Applying Speech Recognition and Language Processing Methods to Transcribe and Structure Physicians' Audio Notes to a Standardized Clinical Report Format

by

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To my parents, my wife, my son and my sister.

Thank you all for your love and support.

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ABSTRACT

Clinical documentation is an audio recording of the clinical encounter by the specialist which is subsequently manually transcribed to be added to the patient's medical record. The current clinical documentation process is tedious, error-prone and time-consuming, more so for specialists working in the emergency department given the rapid turnaround of high-acuity patients. In this thesis, we investigate methods to automate the clinical documentation processes for a pediatric emergency department, leading to the generation of a SOAP report of the clinical encounter. Our approach involves (a) speech recognition to transcribe the audio recording of the clinical encounter to a textual clinical encounter report; and (b) identifying and classifying the sentences within the textual report in terms of the standard SOAP format for clinical reports. For speech recognition, we worked with the DeepSpeech application and used recurrent neural network and n-gram based methods, augmented with medical terminologies and heuristics, to develop domain-specific acoustic and language models. Our approach resulted in a reduction of 49.02% of critical errors as compared to the baseline acoustic and language models provided by DeepSpeech. For generating a SOAP report from the clinical text, we extended an exemplar-based concept detection algorithm to learn a sentence classifier to identify and annotate the clinical sentences in terms of subjective, objective, assessment and plan. Our SOAP classifier achieves a precision of 0.957 (subjective), 0.919 (objective), 0.626 (assessment) and 0.82 (plan).

LIST OF ABBREVIATIONS USED

EHR	Electronic Health Record
EMR	Electronic Medical Record
SR	Speech Recognition
ANN	Artificial Neural Network
DNN	Deep Neural Network
RNN	Recurrent Neural Network
CNN	Convolutional Neural Network
WER	Word Error Rate
CER	Critical Error Rate
SOAP	Subjective Objective Assessment Plan (Acronym)
NLP	Natural Language Processing
CD	Clinical Documentation
LM	Language Model
AM	Acoustic Model
MeSH	Medical Subject Headings (Acronym)

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Chapter 1. INTRODUCTION

Clinical reports are vital in providing quality healthcare. These reports facilitate physicians to recall previous episodes of care given to patients [1]. Moreover, these reports ensure quality healthcare by providing a medium to perform regular audits of the care delivery process [2]. Clinical documentation is a process in which physicians note down encounter synopsis and generate clinical reports. It is a challenging (Section 2.3.1) and tedious process, which can sometimes take twice as much time as it takes for patient interaction [3], [4]. Clinical documentation is done in three modes (Section 2.3.2): hand-written, type-written, and dictations; while adhering to two work-flows (Section 2.3.3): front-end and back-end [6]. Hand-written reports are mostly illegible and unsatisfactory [5]. Type-written and dictations are currently the most common mode of documentation among physicians. In general, the process of clinical documentation poses five major problems (Section 2.3.4) that are caused by either any or all combinations of modes and work-flows. These problems provide motivation for this thesis to work on methods to automate the process of clinical documentation.

1.1 Solution Approach

This thesis focuses on using the physician's dictated audio notes to autonomously generate structured clinical reports. Dictations are given in audio; therefore, Speech Recognition (SR) is used to transcribe audio notes. Transcriptions are then analyzed for SOAP categories, which can be organized to form a standardized clinical report.

After a detailed review of the use of speech recognition in clinical documentation (Section 2.5), this thesis made two recognitions. Firstly, there is a need for more accurate SR systems. Secondly, physicians prefer to dictate in freestyle; hence there is a need to research in the direction of autonomous preparation of reports from transcribed notes. This thesis considers the documentation process from an end-to-end perspective, where physicians can get the ability to dictate in freestyle. Dictated audio notes should firstly transcribe into text using a noise-robust domain-specific SR system. Subsequently, transcribed notes should organize to form a structured clinical report using autonomous language processing techniques. Henceforth, our approach aims to form two separate research objectives, whilst keeping the focus of this thesis on the individual methods within each objective. Figure 1.1 illustrates the solution design for this thesis.

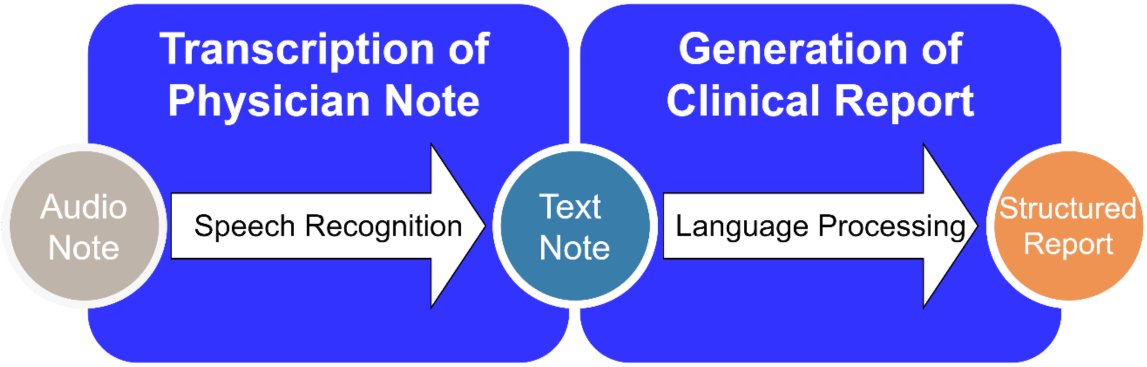


Figure 1.1 Solution approach for clinical documentation

1.2 Research Objectives

This thesis aims to work as a multi-layer solution pipeline, where each layer possesses its own set of problems that needs active rounds of research. Two main research problems are identified that are requisite towards setting a conclusion. These problems act as the objectives of this thesis, which are defined in the subsections below.

1.2.1 First Objective

The first objective of this thesis is “to accurately recognize speech content from physicians’ dictated audio notes”. To facilitate the better achievement of this objective, this research forms a set of three research questions.

1. What are the challenges and shortcomings of SR technology in clinical environments?
2. What are the current advancements and in SR that can address those challenges?
3. What are the steps required to develop robust SR systems in clinical environments?

The first research question is responded to in Section 2.5, which presents a detailed review of the use of SR in clinical documentation, its challenges, shortcomings, and reasons for those shortcomings. For the second question, Section 2.6 and 2.7 presents the current advancements in SR technology that addresses the challenges of noise-robustness and domain-robustness. Finally, this thesis responds to the third question by presenting our methods in Chapter 4, which are evaluated in Chapter 5.

1.2.2 Second Objective

The second objective of this thesis is “to organize transcribed physicians’ dictated audio notes into meaningful categories of the clinical report structure”. To achieve this objective, we investigate algorithms to classify the transcribed text into SOAP categories.

1.3 Research Scope

The main scope of this thesis is limited to research problems within the individual layers of our approached solution pipeline. The feasibility and end-to-end performance of our solution pipeline are not examined in this work.

Clinical reports are of various types since documentation is done in almost every healthcare activity. The scope of this thesis is also limited to the pediatric emergency department that usually generates reports in SOAP (Subjective, Objective, Assessment, and Plan) format; therefore, this thesis follows the SOAP structure.

In the area of speech recognition, this work considers the single-channel audio input. For SR systems, the scope of this thesis is limited to open-sourced systems in the offline domain.

1.4 Thesis Contribution

This thesis spans over two domains of computer science; thus, it contributes to both domains. This thesis reports five contributions that are listed below.

1. This work approaches the process of clinical documentation from an end-to-end perspective. To the best of our knowledge, this perspective has never approached before. This thesis seeks freestyle dictations as input and proceeds to generate a formatted clinical report as output. The operating scope of this solution currently experiments only within emergency departments following SOAP structure. Nevertheless, this solution has the potential to expand in other clinical departments and domains as well.

2. In this work, we demonstrate the use of Project DeepSpeech [7] in the paradigm of the healthcare domain.

3. We apply methods to adapt out-of-domain pre-trained DeepSpeech models and train healthcare domain-specific models without requiring a large healthcare dataset.

4. We propose a method to augment the healthcare domain-specific dataset by generating simulated domain-relevant data using principles of synonym replacement method.

5. Lastly, this thesis contributes by extending an exemplar-based concept detection algorithm to develop a sentence classifier to classify SOAP categories.

1.5 Thesis Organization

This thesis consists of 7 chapters. Chapter 2 provides background details about the individual concepts that are frequently referred to in this thesis. Chapter 3 presents the methodology of this research and all the tools that are used for this research. Chapters 4, 5, and 6 demonstrate the work that is done for each layer of our solution model. Lastly, Chapter 7 constructs a thorough discussion upon the observations, limitations and future work while providing a conclusion to the thesis.

Chapter 2. BACKGROUND AND RELATED WORK

2.1 Health Record

A patient's health record entails chronologically sequenced assortment of a variety of clinical documents, such as clinical reports, lab reports and x-rays, that are generated over time by healthcare professionals providing care services to that patient. These records present medical history and events of care given within the healthcare providers' institution. The term health record is often used conversely with the medical record or medical chart.

2.1.1 Electronic Health Record (EHR)

Electronic Health Record (EHR) are software systems that manage patients' health records electronically. Like health records and medical records, EHR also often gets interchanged with Electronic Medical Record (EMR). However, there exists a subtle difference between both terms. EMR has limited working jurisdiction and can only operate in one provider's institutional domain, while EHR's are designed to serve across multiple institutions i.e., available to multiple providers as well as researchers and policymakers [8], [9].

2.2 Clinical Report

A clinical report is a type of clinical document that appends into a patient's health record. Clinical reports include details of a patient's clinical status and assessments, recorded by healthcare providers during the hospitalization visit or in outpatient care [10]. Clinical reports facilitate communication between healthcare providers [11]. These reports can be of various types, such as progress reports, visit reports and discharge summaries [12]. Clinical reports can be unstructured, semi-structured, or systematically structured [13]. Unstructured and semi-structured reports include information in free texts, which blends relevant and vital information with insignificant details and make retrieval of required information difficult, oftentimes along with adversely increased cognitive load [14]. However, structured reports follow some systematic guidelines to structure the information; thus, important information comes under observation quickly without putting much effort. In this thesis, we work with systematic reports that follow a defined structure.

2.2.1 SOAP

SOAP is a universally accepted method that provides systematic guidelines to write structured clinical reports [13], [15]. SOAP is the acronym for Subjective, Objective, Assessment, and Plan which represents the categories within its structure. SOAP was first theorized over 50 years ago [16] to advise medical students in writing effective reports [17], which later accepted widely among healthcare professionals [16]. Table 2.1 mentions a summary of SOAP guidelines as listed by Sando [13]. There are various benefits that SOAP formatted reports offer above unstructured or semi-structured reports.

1. SOAP reports follow a defined structure. It lowers mental efforts to extract the required information efficiently and quickly [14].

2. SOAP reports are clear, concise, accurate, and allows efficient communications between healthcare providers. Due to this, providers explicitly use these reports to give recommendations to each other [10], [17].

3. SOAP encourages providers to write complete reports by reminding them about specific tasks. This way, SOAP ensures complete reports and enhances the quality of healthcare delivery [16].

4. SOAP reports systematically record encounters of healthcare professionals and patients. Hence, it can also serve as an evaluation tool for accountability, billing, and legal documentation [1], [2], [18].

5. When care delivery requires multiple healthcare providers, effectively written SOAP reports can fasten the delivery process by eliminating the need for redundant history taking episodes for each provider [18].

Table 2.1 Documentation Guidelines of SOAP categories adapted from [13]

Category	**Documentation Guidelines (Semantic concepts for each category)**
Subjective	• Demographics • Patient concerns and complaints • Current health problems • Current medications • Current allergies • Past medical history • Family history • Social history
Objective	• Drugs administered • Physical signs and symptoms • Vital signs • Medication lists • Laboratory data
Assessment	• Active problem list with an assessment of each problem • Actual and potential problems that warrant surveillance • Therapeutic appropriateness including route and method of administration • Goals of therapy for each problem. • Degree of control for each disease stated
Plan	• Adjustments made to drug dosage, frequency, form or route of administration • Patient education and counseling provided • Oral and written consultations to other health care providers • Follow-up Plan • Monitoring parameters

On the one hand, SOAP is appraised for its easy to use guidelines. On the other hand, some studies highlight some limitations as well. Lin [19] questions if swapping the structure of SOAP to APSO increases any efficiency. Moreover, many studies propose extended versions of SOAP. However, all those studies, perhaps only add more guidelines above the basic ones. In this thesis, we focus on the categories of SOAP but not their sequence; therefore, our produced reports can be sequenced in any order to satisfy any structural variation of SOAP. Each SOAP category is further explained in later subsections.

- **SUBJECTIVE**

  The subjective category suggests documenting everything that is coming from the patient's perspective and experiences [16]. It distinguishes between what a patient is thinking about the situation from what healthcare providers believe.

- **OBJECTIVE**

  In the Objective category, providers are guided to include all the observations, examination findings, and diagnostic tests; specifically, those findings that the provider can objectively confirm. Providing objective measures in a separate category allows readers to immediately focus on the relevant and clinically verifiable information without ever needing to know more about the subjective details [18].

- **ASSESSMENT**

  In the Assessment category, providers explicitly mention the diagnosis along with the rationale that leads to the diagnosis. It might also include all those tradeoffs that were considered while reaching to the said diagnosis [16].

- **PLAN**

  The plan category is there to document any treatment plans or directions that the provider might have for the patient or any other provider. This section is also used to write down secondary treatment plans that will get into consideration if the primary plan does not show appropriate results [16].

2.3 Clinical Documentation

Clinical Documentation (CD) is the process where healthcare providers generate clinical reports after every patient encounter. These encounters can be of any purpose and of any length. Even the minor patient-physician interactions must be noted accurately and timely with the same level of responsibility that is usually taken to prepare reports of surgeries and other lifesaving treatments. Clinical documentation is a fundamental skill [13] and is the core responsibility of healthcare providers to generate clinical reports that are accurate and complete. The process of clinical documentation has multiple aspects of details that are defined in later subsections.

2.3.1 Challenges

The goal of the clinical documentation process is to generate high-quality and practical clinical reports to ensure efficient and effective healthcare delivery; however, achieving this goal is a challenging task. Primarily, the process of clinical documentation poses 5 main challenges.

- **ACCURACY**

  The first challenge of clinical documentation is to produce accurate clinical reports. It means that all the contents within a report must reflect the truth, and nothing that is in the report is wrong.

- **COMPLETENESS**

  Completeness is the second challenge, which refers that reports must cover all the aspects of the patient-provider encounter, and no detail goes unnoticed.

- **TURNAROUND TIME**

  Turnaround time is the time that providers take to perform documentation related tasks after finishing one encounter and before starting another encounter. The third challenge of this process is to keep turnaround times as low as possible.

- **PROVIDER THROUGHPUT**

  Throughput reflects the efficiency level of a provider. Documentation related tasks can sometimes take more time and effort than the encounter itself and can overburden the providers, which can lower the quality of healthcare delivery. Therefore, the fourth challenge of the clinical documentation process is to keep provider throughput as high as possible.

- **COST**

  The fifth challenge is to reduce the overall cost. There are two types of costs that are linked with this challenge; setup cost and report generation cost. Setup cost can be defined as the cost it takes to set up any tools that assist with the process, while generation cost can be defined as the cost it takes to generate each report.

2.3.2 Modes

Clinical documentation is usually done in three modes: hand-written, type-written, or voice-dictated. Institutions adopt one of these ways, whereas many of them use multiple modes to create redundancy in the documentation. This section will define each mode in detail.

- **HAND-WRITTEN**

  Classically, clinical reports are produced by hand on a piece of paper. It is the simplest of all modes, and it consists of a plethora of problems around it. Reports prepared by hand are illegible to read and are often never consulted again by providers. Moreover, producing reports in this way takes much time. Handwritten reports are also prone to damage as they exist in physical format, and making a copy is also a hassle.

- **TYPE-WRITTEN**

  Adaption of EHR changes the way clinicians did documentation tasks. EHR’s require the digital entry of information within reports. Healthcare providers use the keyboard and mouse to type-write the reports directly into the software systems of EHR. It reduces the clutter of illegible paper-based reports and makes comprehension easier.

However, healthcare providers are now forced to learn using these new systems. Without learning, there is still low or no impact on documentation times. A study has shown that even with EHR, healthcare providers still spend 38.5% of their time in creating documentation [4].

- **VOICE-DICTATED**

  Voice dictations are not new for healthcare providers. In many institutions' providers are facilitated with dedicated transcriptionists who oversee all the documentation related tasks. Healthcare providers brief transcriptionists about the clinical encounter by giving them dictations, who then complete the reports. This practice shifts the burden of documentation away from providers, who are busy with other crucial tasks. In institutions where no transcriptionist is available, the practice of dictation still benefits providers. They record dictations after encounters and manage their time on more important things when needed. At the end of all encounters or later, when they get time, they then complete the documentation tasks by using pre-recorded dictations.

  A number of newer EHR systems are also now providing voice-enabled options to enter information within reports. These EHR systems use speech recognition technology and allow providers to use their voice to enter information within individual sections of clinical reports. An increasing number of institutions are now implementing voice-enabled EHR systems to facilitate providers; nevertheless, provider adaption of this documentation mode is still a concerning question.

2.3.3 Workflows

Documentation is usually done in two workflows: front-end and back-end. Both workflows start when the provider is finished dealing with patients in an encounter and ends when a report is generated and submitted. Details about both workflows are defined below.

- **FRONT-END**

  In the front-end workflow, the provider is responsible for the proper generation and submission of clinical reports right after the encounter, and before starting any other encounter.

- **BACK-END**

  In the back-end workflow, the provider has the liberty to delay the report generation process to the time of their choosing before a deadline that is set by the institution or any other regulatory body. In this work-flow, the provider can perform encounters back to back to finish patient queues and can then generate all the clinical reports at once.

2.3.4 Problems

To meet all five challenges of clinical documentation is a challenge in itself. Documentation modes and workflows usually focus on a subset of these challenges. Institutions often practice those modes and workflows that are closer to their requirements. In essence, there is nothing at this moment that can offer to meet all five challenges at the same time. Therefore, the current practices of the documentation process fail to meet some challenges and express various problems. There are five major problems. Some of these problems are caused by specific workflow or mode, while others are due to the overall process. The problems are defined below.

- **LOW QUALITY OF CLINICAL REPORTS**

  A major problem in the clinical documentation process is the low quality of clinical reports, which is primarily caused within those institutions that overlook accuracy and completeness in favor of low turnaround times, high throughput, and low costs.

- **HIGH TIME CONSUMPTION**

  Writing a clinical report takes time. In the case of dictated notes, physicians get the ability to postpone the development of reports to increase throughput, while also increasing report turnaround times. With current workflows and modes, this poses a major problem.

- **LOSS OF MINOR CLINICAL ENCOUNTERS**

  Due to the tedious nature of the process, minor encounters are usually ignored, which in turn poses a high risk of lower quality in healthcare delivery.

- **HIGH COST**

  Many institutions employ dedicated transcriptionists and implement advanced EHR systems to facilitate providers with the burden of the documentation process. Both options are costly and require extensive funds.

- **LACK OF OPPORTUNITY TO DEVELOP DATASETS FOR RESEARCH**

  This problem mainly arises due to illegible hand-written reports on paper forms, as patient records become cluttered, and managing them is a hassle [14]. This problem is also present in type-written reports to some extent. Physicians get this habit to copy and paste, and incompleteness is rather common in these reports [20].

2.3.5 Summary

Clinical documentation is the backbone of quality healthcare; however, it often takes more time than treating patients. There are five main challenges of clinical documentation: accuracy, completeness, turnaround time, provider throughput, and cost. Each institution sets policies that focus on a subset of these challenges and practice a workflow and documentation mode that comply with their policies. There are two commonly practiced workflows: front-end and back-end; and three documentation modes: hand-written, type-written and voice-dictated. Currently, no combination of documentation mode and workflow offers to meet all challenges; therefore, the documentation practices raise a number of problems. The five major problems of the clinical documentation process are 1) low quality of reports, 2) high time consumption, 3) loss of minor clinical encounters, 4) high cost, and 5) lack of opportunity to develop datasets for research.

2.4 Speech Recognition

This section provides a background on the fundamental concepts of Speech Recognition (SR). Speech recognition refers to any machine-based method that functions over speech input and processes it into text. SR research is generally categorized into three areas: isolated word recognition, continuous speech recognition, and speech understanding [21]. Isolated word recognition methods are applied to those speech inputs in which speaker utter individual words, separately. However, continuous speech recognition methods are used when speech is continuous and in a natural manner. Speech Understanding, whereas, is used when we are more interested in understanding the sense of speech instead of specific words. In this thesis, we explore methods from continuous speech recognition, as we work with natural and continuous speech.

Speech is recorded in the form of audio signals. These signals are defined as the long arrays of timed sound intensity values. These values represent the acoustic features of the speech in the form of phonemes that are the basic sound units within a language. Phonemes, when combined, form the basis for words and other lexicons within the speech. For efficient recognition, SR requires a prior understanding of such acoustic behaviors, along with the knowledge of grammatical and other rules that exists within the language. This information is provided to SR methods using acoustic and language models that are trained on the speech data from a language. These models are the core components within any SR system. Firstly, acoustic features from input audio are matched with the given acoustic model to identify language units (phonemes) which then produce an estimated sequence of words using the rules from the language model. The robustness of these models is vital in the performance of Recognition. Figure 2.1 illustrates the structure of any SR system in its simplest form.

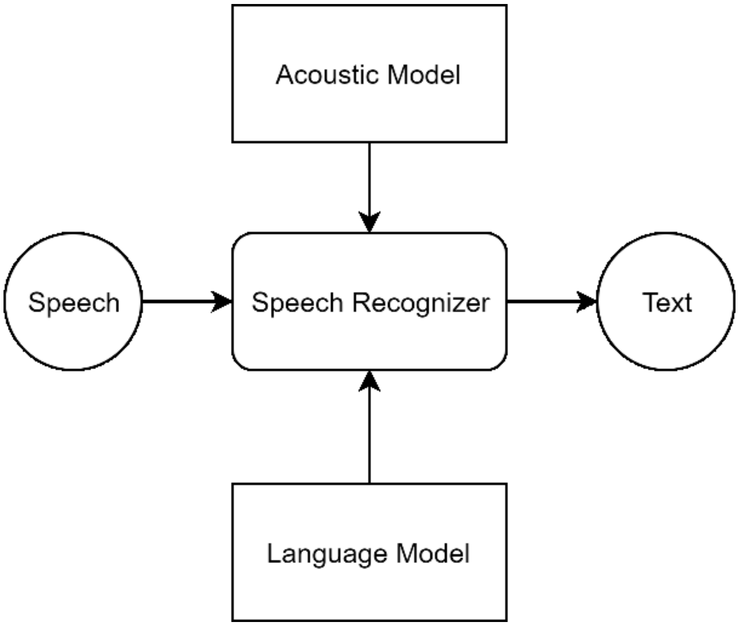


Figure 2.1 Structure of any SR system in its simplest form

When a speech input is given, the objective of SR is to obtain the optimal word sequence for the given speech ($\boldsymbol{X}$), which is a form of well-known maximum *a posteriori* (MAP) problem [22].

Equation 1

$$\widehat{W} = \arg max_{\boldsymbol{W}} P_{\Lambda,\Gamma}(\boldsymbol{W}|\boldsymbol{X})$$

In Equation 1, optimal word sequence $\widehat{W}$ is a word sequence $\boldsymbol{W}$ that maximizes the likelihood for the given speech signal $\boldsymbol{X}$ by the use of an acoustic model $\boldsymbol{\Lambda}$ and language model $\boldsymbol{\Gamma}$. Both models are the components inside the construction of SR systems that are further explained in subsequent sections.

2.4.1 Acoustic Model

The acoustic model forms the basis of any SR system [23]. The purpose of the acoustic model is to provide estimations that a particular phoneme is uttered in a given audio sequence. Acoustic models are either a statistical or machine learning model that maps the relationship between audio signals and linguistic units. These models are trained upon hours of speech data to generalize linguistic relationships effectively.

Audio signals are digitally recorded sound waves, which are made up of sequential samples. The sample rate of an audio file denotes the number of samples recorded in one second. The resolution of a sample refers to the amount of memory (bits) that is used to record each sample. For example, a 10-second audio file of sample rate 16000 Hz and resolution of 16 bits means that it contains a total of 160,000 samples that are recorded in 16 bits each, which translates into a raw size of 312 kilobytes (160,000 x 16 bits) of memory. Audio signals are long arrays; therefore, these signals are segmented into equal intervals, called frames, for processing and model construction. Frames are small but overlapping windows within audio files. Frame size remains fixed throughout the SR system. As an example, for a 16000 Hz audio signal, if we choose a frame of length 256 samples, then the first frame covers from 0th sample to 255th sample, and then the second frame starts from 128th sample and so on.

SR systems extract various types of features from frames. The commonly used features are power spectrum, Mel-frequency cepstral coefficients, and delta features. In continuous speech recognition systems, features within the frames of training audio files base the construction of acoustic models. To perform recognition, a query audio file is extracted for frames, and its features match the acoustic model to get the estimated sequence of linguistic units.

SR systems from their inception are using statistical acoustic models. These systems use the Gaussian Mixture Models (GMM) and Hidden Markov Models (HMMs) to recognize the sequences of phonemes. GMMs detects the phonemes within each frame, and HMMs estimates the likelihood of having detected phonemes given the prior detected sequence. Statistical acoustic models then use estimation maximization algorithms to get the optimal phoneme sequence out of audio signals.

The current advancements in machine learning have enabled researchers to develop end-to-end acoustic models that eliminate the need to use domain expertise as it is required to train the statistical models. End-to-end models take benefit of powerful machine learning techniques, such as Artificial Neural Networks (ANN) and Deep Neural Networks (DNN), to develop acoustic models. These models work on the same inputs, i.e., acoustic features of audio signals; however, a number of current approaches produce direct word sequences, as opposed to traditional models that produce phonemes. In such cases, characters are used as the output sequences.

Since the ultimate goal of SR is to get the optimal word sequence, SR systems take the output of the acoustic model, either statistical model outputting phoneme sequence or machine learning model outputting character sequence, and pass it through decoders to achieve the optimal word sequence. In the decoding part, output sequences are searched in lexicon dictionaries for matching words. In this step, most SR systems also exploit language models to refine the output of acoustic models. The details about language models are in the next subsection.

2.4.2 Language Model

The language model maps the relationship between the words from a given language. In speech recognition, it provides the contextual information of words by assigning a probability distribution over the trained word sequences [24]. It is usually trained on large samples of text from a language. Language models facilitate SR systems to detect connections between the words in a sentence with the help of a pronunciation dictionary [23]. Language models also introduce domain-specific vocabulary to the SR paradigm. It refines the output of SR systems. However, it is not always required for the recognition task. When language models are used in SR systems, their calculated likelihood probabilities are merged with the decoded word sequence probabilities from acoustic models, and then the combined probabilities are used to get the optimal word sequence.

The most common method to construct language models is *n*-gram language modeling, where *n* is the order of language model. An n^{th} order language model calculates the counts for having 1-grams, 2-grams … n-grams from a training corpus. These n-grams occurrence counts are used to calculate the likelihood of having a word $\boldsymbol{W}$ based on the given sequence of n-1 preceding words [23].

Equation 2

$$P(W) = P(W_n|W_1, W_2, W_3 \dots W_{n-1}) = \frac{C(W_1, W_2, W_3 \dots W_n)}{C(W_1, W_2 \dots W_{n-1})}$$

In Equation 2, $P(W_n|W_1, W_2, W_3 \dots W_{n-1})$ denotes the probability of having a word W_n when given a sequence $W_1, W_2, W_3 \dots W_{n-1}$. $C(W_1, W_2, W_3 \dots W_n)$ shows the count of having n-gram within the corpus. $C(W_1, W_2, W_3 \dots W_{n-1})$ shows the count of having (n-1)-gram.

When dealing with probabilities, n-gram based language models are prone to problems such as zero probability problem and out of vocabulary problem. The zero probability problem is due to the unavailability of an n-gram within the training corpus. For these unseen situations, language modeling techniques offer solutions such as smoothing and discounting. In smoothing techniques, n-gram counts are manipulated to give weights to unseen events. Add-one smoothing and add-k smoothing are some examples of smoothing techniques. In discounting techniques, if an n-gram is unseen, then the counts from (n-1)-gram are considered with some discounts. This strategy is also known as backing off.

The out of vocabulary problem arises when a language model does not have a word in its vocabulary. That means not even 1-gram is available for that word. Therefore, solutions to zero probability problems do not work here. A common strategy to tackle the out of vocabulary problem is to use pseudowords such as unknown <UNK>, start <S> and stop </S>. The pseudoword <UNK> is appended with all seen n-1 grams to form a new n-gram, whereas, the pseudowords <S> and </S> are appended in the start and end of each sentence. They are then treated as normal words while calculating probabilities and training n-gram language models.

2.4.3 Evaluation Metric

SR systems are evaluated by investigating differences between their output text and ground truth text. If the SR system works according to expectation, then output text match the ground truth. However, if there are differences, it highlights the system's shortcomings and provides an evaluation of the system. The most commonly adopted evaluation metric for SR is the Word Error Rate (WER) [25].

- **WORD ERROR RATE**

  Word Error Rate (WER) is an evaluation metric that highlights the ratio of mistakes. WER returns a value between 0 and 1, where 0 means that the SR system was not able to recognize a single word correctly, and 1 means that everything was recognized perfectly. Mistakes are counted in the form of insertions, deletions, and substitutions. When comparing output text with ground truth, if a word is missing, then it is inserted, and insertions count is incremented. If a word is in the output sequence and ground truth does not expect to have it, then it is deleted, and deletions count is incremented. If for a word found in output sequence ground truth expects a different word, then it is substituted, and substitutions count is incremented. After finishing comparisons, WER counts all mistakes and divides them by word count of ground truth to get the error rate. WER is commonly expressed as a percentage [25], which can be done by multiplying WER by 100.

$$WER = \frac{I + D + S}{W}$$

$\therefore I = \# \: of \: Insertions$

$\therefore D = \# \: of \: Deletions$

$\therefore S = \# \: of \: Substitutions$

$\therefore W = \# \: of \: words \: in \: Ground \: Truth$

2.5 Speech Recognition in Clinical Documentation

To overcome the challenges of clinical documentation, researchers are looking towards SR technology since the time of its inception [22]. In theory, the idea of using speech to create clinical documentation is quite promising. However, multi-factored evaluations show that it is not as simple to adapt. Changing modes of report generation workflows can open a plethora of issues that may come with the new mode of input. The introduction of EHR reformed the process of clinical documentation when it offered typing as the form of input; however, this input method added up to the already existing issues [26]. With EHR, providers spend roughly double their time in creating documents as compared to care delivery [4]. Many healthcare providers are not very good at operating computer systems, so they still prefer the classical methods of documentation. Since EHR offers much more than the change of input mode, and it is not possible to use handwriting as the method to input notes within EHR, many studies have tried to use SR technology as an alternative to enter notes within EHR. When compared to traditional dictation and transcription methods, speech assisted EHR significantly reduces turnaround times and costs [27]. Consequently, as SR technology is improving, the increasing number of institutions are adopting SR enabled systems to generate clinical reports [27]. However, speech assisted EHR puts the responsibility of the management of note input and report creation upon healthcare providers, which limits the provider adoption of this technology. Therefore, in this section, we investigate the various aspect of SR adoption in documentation workflows and analyze the limitations and shortcomings of SR in the clinical documentation process.

2.5.1 Review Objective

The purpose of this review is to investigate prior efforts of using SR to overcome the challenges and problems of documentation. Therefore, we form three main objectives.

1) To explore previous attempts on using speech as a tool for clinical documentation.
2) To scrutinize the methodology and evaluations of explored attempts.
3) To identify all the factors that limit the intended outcomes of explored attempts.

2.5.2 Literature Exploration

This thesis deals with a problem in the medical domain; therefore, we primarily used PubMed [28] as the source to look for literature. We identified a set of keywords that were combined using 'AND' and 'OR' operators to retrieve the best matching articles. Figure 2.2 shows the query tree that was used to search PubMed to retrieve the relevant studies.

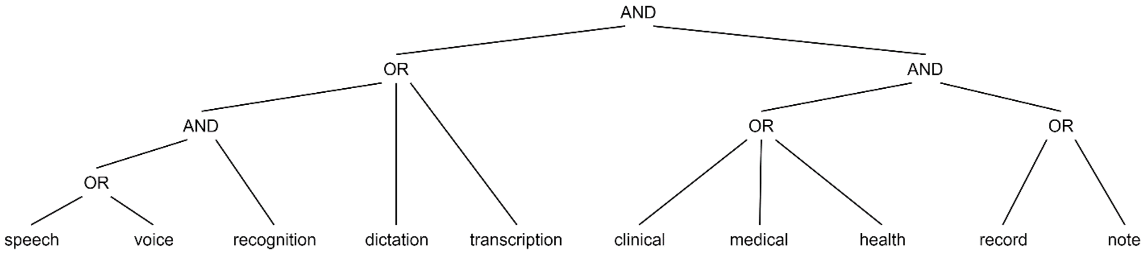


Figure 2.2 Query Tree for Literature search

2.5.3 Analysis

Healthcare providers use dictations in traditional documentation workflows. However, they are now required to use an EHR for report generation. Speech-enabled EHRs contribute more to the challenges of the documentation process. Therefore, in this analysis, we iterate and analyze the impact of SR on the challenges of the clinical documentation process.

- <u>**ACCURACY AND COMPLETENESS**</u>

  Accuracy and completeness reflect the overall quality of the report; therefore, studies usually address these two challenges together. When providers type-write their reports on EHR, they usually make 0.4 mistakes for every 100 words (0.4% error rate) in back-end workflow [29]. Zhou conducted a study to test SR on the same workflow, where he noted an increment of errors by 7.8% [29]. However, he added that reports managed to achieve the same level of quality after a final review from the provider.

  Studies by Hodgson and Goss address the use of SR in front-end workflow. They show similar results to Zhou, where the report quality significantly declined [27], [30].

Although, in a study where experiments were conducted in an ideal environment, with no real-life constraints and stress, 81% of providers reported improvement in the overall quality of reports with the use of SR enabled tools [26].

- **TURNAROUND TIME AND PROVIDER THROUGHPUT**

  Providers spend most of their time to generate reports [29]; this means, an efficient documentation process can reduce turnaround times and boost provider throughput. Studies report that most of the providers are convinced that SR improves efficiency and is easy to use [26], [27]. In back-end workflows, SR has shown to reduce turnaround times and increase productivity [29]. However, when SR is used in front-end workflows, no significant time difference was reported [30].

- **COST**

  In the clinical documentation process, the cost is the aspect that is the least studied in the academic domain. One reason could be that costs are primarily a concern of departments that are not connected with academics. In any case, the cost is a profound variable in the adoption of any solution, and also plays a vital role in the adoption of SR in the clinical documentation process. These days, more and more institutions are tilting towards the adoption of SR enabled solutions since they are thought to reduce costs [27]. A provider adoption survey done in 2018 has also concluded that SR enabled systems can reduce monthly transcription costs by 81% [26]. Since we were not able to find any study that reports any adverse findings in terms of the cost of using SR enabled systems, there is no reason to disbelieve the above-stated opinions.

2.5.4 Findings

The approach to use SR for documentation is not new. Studies from 1981 [31] and 1987 [32] experimented with SR when this technology was developing as a new concept, where they found SR to be worsening the problem. SR technology improved a lot since then. This trend is reflected in the studies done throughout the decade of 1990 [33]–[39]. This trend remains in the decade of the 2000s [40]–[43]. A study done in 2010 [44] reported that about two-thirds of their participants feel that SR can improve report quality and can reduce documentation times as well. Another study that was done in 2012 [45] supports the claim that SR now has the ability to reduce documentation times. Almost all of the recent studies [27], [46]–[49] affirms that SR has the tendency to overcome problems of documentation. However, with all the optimism, SR enabled solutions still lack adaption among healthcare providers [26], [50]. Studies document four main reasons behind the low adoption of SR enabled solutions.

- **HIGH EXPECTATIONS FROM SR ENABLED SYSTEMS.**

  SR systems are viewed as they can dramatically reduce mistakes and documentation times. However, current SR technology still struggles to maintain high accuracy due to real-world issues, such as noise and domain-specific vocabularies. Therefore, noise-robustness and domain-robustness are real challenges of SR that limit the confidence of healthcare providers in SR at this point.

- **RESPONSIBILITY FOR CORRECTIONS.**

  SR systems make mistakes, and physicians are responsible for correcting those mistakes. Due to this, sometimes they spend even more time in corrections. When any machine-based system makes a mistake, humans are expected to correct for those mistakes; however, in this scenario, the overall confidence in SR technology can be increased by making robust systems that do not make mistakes in the first place. The same challenges apply here as well that are mentioned in the above-stated point.

- **CHANGE IN DICTATION STYLE.**

  SR is merely a tool for note entry in many reporting systems. Physicians are responsible for controlling the structure of reports where they have to manually select the report section for which they wish to add the notes. As an example, for the SOAP structured reports, physicians have to select one of the SOAP categories to enter its content at one time. This practice breaks their dictation pace as they have to tailor their dictation style according to the structure of the report. Due to this hassle, physicians prefer recording conventional dictations where they get the ability to record in freestyle at the time of encounter. This hassle also calls for autonomous features that are specialized for documentation tasks, and can intelligently separate the content for different sections of a clinical report from a freestyle recorded dictation.

- **PHYSICIANS' TRAINING**

  Physicians require training to use SR enabled systems efficiently [51]. A 2010 study [44] reported positive response when participants got adequate training, whereas, when they were not satisfied with the training, they reviewed SR enabled systems negatively. Such training includes teaching physicians to enable SR features within the system and other reporting features that are linked to SR.

2.6 Handling Noise in Speech Recognition

SR is an area of interest with more than three decades of active research [22]. In ideal environments where noise and distortions do not interfere with speech signals, the latest developments have enabled SR systems to perform increasingly closer to human speech recognition performance [52]–[54].

Noise is referred to as any phonetic element in the audio signal that is other than the speech signal [55]. In real-life environments that are filled with a huge concentration of noise, SR systems lack that robustness to compete with humans [56]–[58]. This degradation is mainly due to the difference in the acoustic features from input audio to the ones in the trained model [59]. Noise from surroundings changes the acoustic features of speech with unwanted additives from noise. Traditionally, SR-enabled devices used to create an ideal environment using close-talking microphones and other acoustic adjustments. However, with the rise in large-scale hand-held mobile devices, it is not further possible to provide SR with ideal speech inputs. It is inevitable for SR to work in challenging acoustic environments and noise robustness is now a key challenge for SR to maintain its performance levels [60].

Noise robustness is a trending problem in the SR domain. Colossal amounts of methods and techniques have been proposed to provide noise-robust solutions for SR. A number of systematic reviews of noise-robust speech recognition [22], [23], [61] have presented the current advancements in systematic manners. In this review, we explain and analyze techniques about the development of noise-robust systems for domain-specific environments. We are particularly interested in indoor environments where there are reverberant distortions and speech overlaps; nevertheless, this review is not limited to such environments. However, we only review those techniques that deal with single-channel audio signals.

Noise-robustness techniques can be divided into two main groups: feature-space and model-space [22]. Feature-space techniques consider the preprocessing of audio signals to extract clean speech before passing it to SR components. Model-space techniques, on the other hand, deal with the internal construction of noise-robust components. The subsequent sections explain both groups further and provide an analysis of techniques within each group.

2.6.1 Feature-space Techniques

SR works well with clean speech. A straightforward and classic solution is to process the incoming audio to extract clean speech before passing it to the SR system. Feature-space techniques apply this classic solution by using signal processing techniques to enhance the acoustic features of speech. These techniques do not change the acoustic model or any component within SR systems.

Enhancing acoustic features from noisy audio is a difficult problem in single-channel as compared to multi-channel audio spectrum [62], where techniques, such as acoustic beam-forming, are performing close to human transcription performance [63]. However, we do not see such accuracies while using single-channel audio.

Spectral Subtraction [64] and Weiner filtering [65] are classical techniques to filter noise from the audio signals. These methods do not depend upon training [22]; instead, they use statistical tools that estimate the noisy speech spectrum and remove any intensity distribution over that estimated spectrum. These techniques are acceptable when noise is stationary throughout the span, such as noise from wind, fan, or anything that emits a continuous stream of sound. However, their performance degrades with the interaction of varying or convolutional noises such as reverberation and overlapped speeches.

Without prior knowledge of noise or speech patterns, statistical models sometimes over filter the speech signals, consequently clipping and losing acoustic details [66]. There are various learning-based techniques to tackle the problems of reverberation and speech overlap such as Weighted Prediction Error (WPE) using Short-Time Fourier Transform (STFT) domain [67], de-noising auto-encoder [68] and a statistical-neural hybrid Cepstra Minimum Mean Squared Error–Deep Neural Network (CMMSE–DNN) based learning model [69]. However, these techniques shift away from the area of speech recognition while belonging more to the area of signal processing, which is not the working domain of this thesis.

2.6.2 Model-space Techniques

Model-space techniques aim to develop noise-robust SR components, particularly acoustic models. These techniques are linked directly with the objective function of acoustic modeling to absorb the effects of noise and distortion [22]. These techniques have generally shown to achieve higher accuracies in comparison to feature-space techniques. However, in comparison, they use significantly more computational resources.

Noise adaptive training [70] and noise aware training [61] are the candidates of the model-space techniques. In noise adaptive training, acoustic features infused with the noise are relayed directly into the acoustic models, whereas in noise aware training, an estimated noise model is generated to calculate corruption in the training noise [61] which then acts as the mask to filter noise from testing audio. Noise Adaptive techniques are reporting high-performance gains [71]–[73]. Acoustic models trained using ANN-based noise adaptive framework were introduced to the same levels of noise that are expected in the execution life of SR systems, where they have shown performance boosts as high as 20% [74]. Seltzer [61] shows the use of DNN for noise aware training with a relative performance boost of 7.5%. Noise based acoustic training works well on the single-channeled audios and incorporates most of the effects of additive noise. However, models trained using these techniques are not generalizable [68] to use on environments with different noise signatures then of where the models were trained.

The development of current end-to-end SR systems has defined a new state-of-the-art [75]–[78]. These systems are built on the underlined principles of model-space techniques with the goal to tackle the problem of the noise of real environments. These systems train their acoustic models in a data-driven way without relying on any expert domain knowledge [79] such as noise estimates and phonetic dictionaries. Their end-to-end nature allows them to directly train their model based on paired data, where training audio and its corresponding text is paired. However, to achieve higher accuracies, they require vast amounts of training data.

2.6.3 Summary

The problem of noise-robustness in SR is addressed using two types of approaches. The first approach presents techniques that seek treatment to noisy audio before feeding it to SR systems. These techniques span over unsupervised as well as supervised learning. However, they shift the problem to the signal processing domain, where the good signal is enhanced, and undesired signals are suppressed. Variations of such problems are de-noising and noise removal. The second approach seeks the construction of robust SR components, particularly the acoustic model. It shows that noise adaptive training is currently the top-performing technique on which various end-to-end SR systems are constructed. The review has also mentioned that end-to-end systems are setting the current state-of-the-art in the technology of SR.

2.7 Domain-Specific Speech Recognition

In speech recognition, domain entails the combination of the acoustic domain as well as the language domain. The acoustic domain includes speakers, audio channels, and environmental noise. The current state of the art end-to-end SR systems have covered many grounds of robustness over acoustic domains, though domain robustness is still a challenging problem [80]. The problem primarily remains due to the domain-specific language which includes specific words and their relations. Handling the rules of language is the integral responsibility of the language model within SR systems. However, this problem broadens when there is a shortage of domain-specific data and language modeling techniques struggle in training robust language models. Therefore, in this review, we analyze two major techniques that deal with the development of domain-specific language models when domain-relevant data are scarce.

2.7.1 Out-of-Domain Model Adaptation

Model adaptation refers to the use of language models that are trained on one language domain to a different target domain where there is little or no training data available. Various scenarios are linked to model adaptation that we review one by one. A typical scenario is that when the available language model is from the general-purpose domain that seeks adaptation in a specific target domain. In such cases, a direct adaptation of the out-of-domain language model can give domain agnostic behaviors; therefore, it is better in such cases to perform some fine-tuning operations. Another scenario is when the source language model is coming from a domain-specific environment that is different from the domain of the target environment. Lyer [81] experimented with multiple out-of-domain models that were combined to form a single model that improved performance on a general task. You [80] show a 10.4% relative improvement in performance by using an all-rounder approach where multiple domain-specific models were used to train a single language model to apply on a general-purpose target.

Adapted models are combined with domain-specific models by either pooling or interpolation [82]. The pooling technique deals with the creation of one dataset from multiple sources, and then use that dataset to create one combined model [83], whereas, in interpolation, multiple datasets train multiple language models which are then combined using interpolation weights.

2.7.2 Domain Relevant Data Generation

Language models work well when there is sufficient domain-specific training data available. Domain relevant data generation techniques seek various strategies to produce such domain-specific training data when there is a scarcity problem. There are three main types of strategies for data generation: conversion, extraction, and augmentation.

Data conversion strategies seek such data sources that exhibit domain-relevant data in different format or language, then apply techniques to convert such data into the desired format or language. As an example of data conversion, Horia [84] proposes a technique that exploits the use of machine translation to convert domain-relevant data that exhibits in a different language into the language of the target domain.

Data extraction strategies are similar to conversion as it explores domain-relevant data on other platforms, and instead of conversion, it focuses on the extraction of such data from the source platform to the target platform. Abhinav [85] has shown relative progress of 6% by the use of a data extraction technique to extract domain-relevant data from the web and train language models from extracted data.

Data augmentation strategies offer a different way to generate domain-relevant data. It focuses on the augmentation of available information within existing data to generate new data points. Enhancing language models by augmenting domain-specific vocabulary and synonyms have shown a decrement of absolute recognition error by 5.41% in noisy environments of tennis championship while having all variety of noises like emotional outbursts, game noise, crowd noise [86]. Another study shows considerable progress by using models that were created by web extracted and augmented data using pooling [83].

2.7.3 Summary

Domain robustness is a challenge in speech recognition, which is due to the combination of acoustic and language domains. Approaches of noise-robustness, particularly from end-to-end SR systems, considerably address the challenges from the acoustic domain. However, language models still need to be taken care of for robustness. We review two main techniques that deal with the robustness of language models. The first technique seeks adaptation of models from different domains to perform tasks on the target domain. These techniques complement the adaptation process with domain-specific fine-tuning and model enhancements to achieve higher performance. The second technique focuses on the generation of domain-relevant data for language models. This technique exploits various strategies such as data conversion, extraction, and augmentation to artificially generate domain-relevant data that can then be used to generate domain-specific language models.

2.8 Speech Recognition Systems

This section provides an overview of multiple SR systems and toolkits. In this review, we have a special focus on the state-of-the-art end-to-end open-source offline systems. In SR, the term "end-to-end" refers to those systems that recognize text from the given speech without the use of any phonetic representation, which used to be the core of traditional SR systems [79]. Traditional speech recognition systems used to depend on significant human expertise for the development of such representations. End-to-end speech recognition is a recent development that was achieved due to the advancements in Deep Neural Network (DNN). It was first presented in 2014 [87], in which it reports state-of-the-art accuracy on the Wall Street Journal corpus. Later, a number of researchers expanded the end-to-end concept and reported significant performance improvements.

The following SR systems and toolkits are reviewed.

1. Deep Speech
2. ESPnet
3. Wav2Letter++
4. CMUSphinx
5. Kaldi
6. Julius
7. Google Speech-to-Text

2.8.1 Deep Speech

Deep speech is a DNN based end-to-end acoustic modeling technique that uses the Recurrent Neural Network (RNN) to construct a robust SR system. It is built with the focus on noise-robustness, by enabling RNN to consume thousands of hours of unaligned, transcribed audio to train its models. It performs character-level recognition. It was presented in 2014, where it claimed better performance than other commercial SR systems on both, clean and noisy datasets [77]. It outperformed previously established SR systems by achieving 16% WER on the Switchboard corpus [88]. Later in 2015, deep speech presented a state-of-the-art performance in two vastly different languages: English and

Mandarin; and showed that it can be adapted to perform recognition tasks on any other language [76].

Deep speech models are composed of 6 layers (input + 5 layers) (Figure 2.3), where the second last layer is a bi-directional recurrent layer [89]. The output layer in deep speech predicts the character probabilities for the input audio sequence. The structure of deep speech is straightforward and uncomplicated as compared to other RNN based models [87]. Therefore, deep speech depends upon extensive training data to achieve high-performance standards. However, due to simplicity in structure, the RNN model is prone to overfitting; thus, deep speech applies dropout rate in between 5-10% to its layers along with using techniques to synthesize training data with artificial noise.

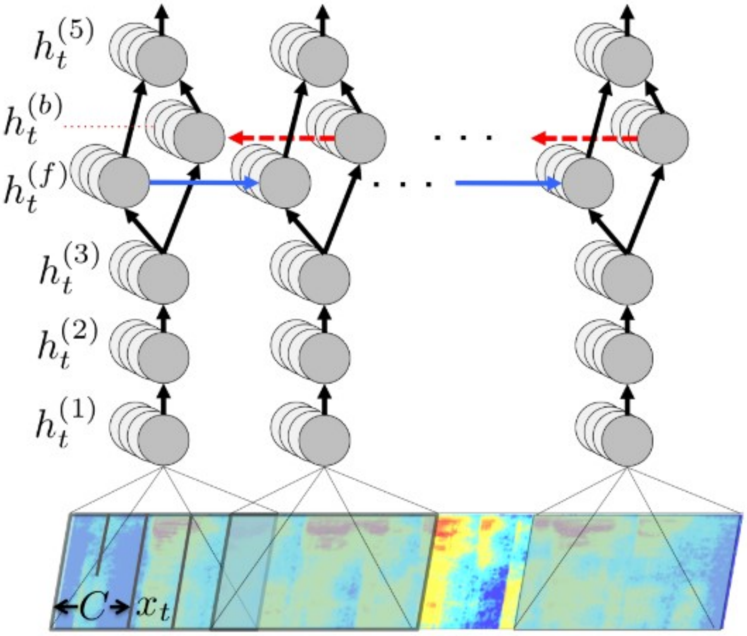


Figure 2.3 Structure of Deep Speech Model [77]

One advantage of deep speech is that it provides techniques to accelerate the training process by using parallelism to enable execution over GPUs. The first technique it provides takes the approach to train a model on many input examples in parallel. Secondly, it provides some techniques to parallelize the overall model training process. Since recurrent layers have a sequential nature, it is challenging to parallelize them; therefore, deep speech approaches to optimize the execution of all other layers.

In November 2017, Mozilla research lab developed project DeepSpeech that implemented the techniques defined above and released the first stable version of an SR system in the open-source domain. Under the hood, DeepSpeech uses TensorFlow [90] neural network toolkit. Training deep speech acoustic model is a compute expensive operation, as it requires a vast amount of data to efficiently learn the domain characteristics; however, it has the ability to run inferences in real-time by using a decent sized GPU due to the native GPU support that TensorFlow provides. To refine its output, DeepSpeech uses an n-gram based language model. The language model generation is not directly handled by DeepSpeech; rather, it is dependent upon the implementations by KenLM [91] language modeling toolkit.

2.8.2 ESPnet

ESPnet is a recent addition to the end-to-end SR systems, presented in 2018 [75]. It is based on a hybrid DNN/HMM approach. It makes use of two vastly different approaches, Connectionist Temporal Classification (CTC) and attention mechanism, in the hybrid manner to train its acoustic models. Although it is a newer edition, it presented comparable performance as compared to the state-of-the-art systems [75].

ESPnet is based on an attention-based encoder-decoder network to perform recognition tasks. Attention-based networks do not require explicit acoustic and language models. However, ESPnet presents a mechanism to develop a hybrid network by fusing the scores from an attention decoder network with CTC decoder. Moreover, it also provides a mechanism to make use of explicit language models. The final proposed recipe of ESPnet works in 6 (1+5) stages (Figure 2.4). Stage 0 prepares the audio data using data preparation scripts from Kaldi toolkit [92], Stage 1 again uses Kaldi to extract features from training data. Stage 2 perform data preparation again, although this time preparation is for training encoders and explicit language models. Stage 3 trains explicit language models. Stage 4 trains SR encoders. Finally, stage 5 performs recognition.

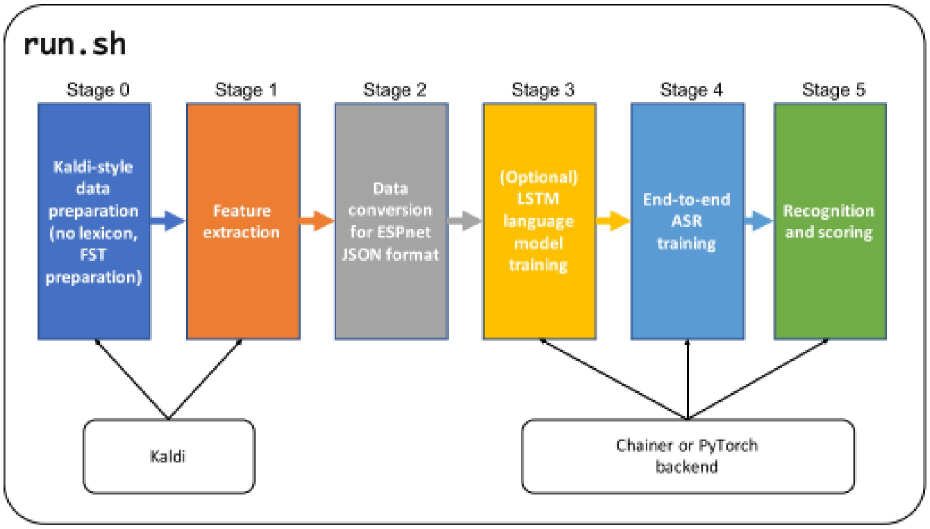

run.sh
Stage 0
Stage 1
Stage 2
Stage 3
Stage 4
Stage 5
Kaldi-style data preparation (no lexicon, FST preparation)
Feature extraction
Data conversion for ESPnet JSON format
(Optional) LSTM language model training
End-to-end ASR training
Recognition and scoring
Kaldi
Chainer or PyTorch backend

Figure 2.4 Processing stages in ESPnet recipe [75]

The first stable version of ESPnet was released in March 2019. It was built on PyTorch [93], which is a neural network toolkit mainly for research purposes. Therefore, it can have some issues in the case of scaling applications. Like deep speech, it is also dependent upon huge datasets for efficient operation.

2.8.3 Wav2Letter++

Wav2Letter++ is the most recently presented end-to-end SR toolkit that is presented in early 2019 [94]. It is developed entirely on C++ by the Facebook research lab to boost performance and speed. It reports the lowest error rates on the same datasets on which deep speech and ESPnet report their performance numbers. The first stable version of Wav2Letter++ was released in early 2019. As it is based on the end-to-end concept, it also depends upon massive training data to train efficient acoustic models. However, until the start of October 2019, it was not offering any pre-trained models with the system.

Wav2Letter++ provides a platform to test various DNN based SR recipes. Recipes in Wav2Letter++ consists of DNN architectures for acoustic modeling and decoding information for language models. Currently, the official repository of Wav2Letter++ provides recipes that use Convolution Neural Network (CNN-DNN) based architectures

[95], [96]. When using architecture from deep speech, Wav2Letter++ reported 5% WER on LibriSpeech clean dataset [94].

2.8.4 CMUSphinx

CMUSphinx is not an end-to-end system, as it is built upon traditional pipelines of speech recognition. It was developed by Carnegie Mellon University (CMU) and was presented in 2004 [97]. We reviewed this system since it has the most recent version of the traditional HMM-based acoustic model, along with a considerable community presence. Even recent studies consider to compare it with leading commercial cloud-based SR [98]. However, with the recent advancements of the end-to-end SR concept, the popularity of CMUSphinx is now fading away.

2.8.5 Kaldi

Kaldi is a speech recognition toolkit, rather than a standalone system, that was presented in early 2011 with the purpose of research [92]. The main focus of Kaldi is towards acoustic model research. However, a number of recent end-to-end systems have borrowed various components from this toolkit [52], [75]. Kaldi toolkit is built upon traditional HMM/GMM based SR pipelines.

2.8.6 Julius

Julius was presented in 2009 as a large-vocabulary continuous speech recognition (LVCSR) system for both research and industrial applications [99]. It was also a traditional system using HMM-based acoustic models. Its main features were the ability to perform real-time processes with low memory usage. However, it was last updated in 2014 and has never updated since.

2.8.7 Google Speech-to-Text

Google speech-to-text [100] is a cloud-based speech recognition service that is currently leading in real life general-purpose speech recognition [98]. It offers services in 120 languages and supports real-time recognition. The cloud service is based on powerful deep neural network models and it offers recognition via easy to use API.

2.8.8 Summary

This review has covered six open-sourced and one cloud-based SR systems. Within open-sourced systems, three are built upon end-to-end concept whereas the remaining three are built upon traditional SR pipelines. This review analyzes these systems upon three factors: performance, ease of use and scalability. We have shown that performance and scalability wise, all end-to-end systems are cutting edge. However, training and using them in domain-specific environments are challenging tasks due to their need for substantial training data. In terms of noise-robustness, end-to-end systems are the best ones along with the reviewed cloud-based system. Due to the dependability of traditional systems on accurate training sets, they usually do not catch up end-to-end systems in real-world environments. When comparing end-to-end systems with each other, DeepSpeech seems to be the most practical one to use at this point.

2.9 SOAP Classification

Classification is the procedure of assigning one or more classes to some entity. Sentence classification is the type of classification that falls under the umbrella of NLP and works on text sentences. It is commonly applied in both medical and non-medical domains. It stems from the document classification, categorization, or segmentation that works on the scope of documents. Some examples of classification in NLP are classifying newspaper articles based on topics and identifying an email as spam. An example of sentence classification is the sentiment analysis of tweets.

This thesis uses sentence classification to assign SOAP categories to the transcription of provider dictations. In a clinical report, subjective and objective sections bare most of the content, whereas the assessment and plan sections are filled with marginally a smaller number of sentences. This trend has shown in the dataset of this thesis which is also affirmed by the dataset class proportion reported by Mowery [101]. This trend creates an imbalanced dataset which may lead to a biased analysis of the performance. Another point to note while dealing with SOAP format is that each category has a semantic definition, and a SOAP formatted report expects its content to adhere to those definitions. In this regard, it is a good idea for a classifier to pick those semantic patterns from the training. Word sequence of a sentence plays a vital role in highlighting those patterns. It means that keeping word sequence intact can positively impact the classification performance.

SOAP classification is attempted before by Mowery [101] in which SVM was used and showed positive gains; however, Mowery did not address the imbalanced nature of SOAP datasets and also did not exploit the sentence sequences in its solution. We were not able to find any other study on SOAP classification to compare the results of this study. Mowery, in its work, also mentioned about this unavailability. However, we reviewed other studies on similar problems in the medical domain. We adapted an exemplar-based concept detection algorithm that is defined by Juckett [102] in an effort to extract concepts from clinical text. This algorithm explicitly takes care of the word sequences and aims to work efficiently on imbalanced datasets.

2.10 Conclusion

In this chapter, we define the clinical documentation process, along with its challenges, modes, and workflows. We discuss the structure of SR systems along with some recent developments that are happening in the SR research domain. A literature review presents the use of SR in the healthcare domain with respect to the challenges of the documentation process. We also present a review of 6 top-of-the-line speech recognition systems. In the end, we review techniques to classify sentences into SOAP categories, where we present an exemplar-based concept detector algorithm with the idea to implement it into a SOAP classifier.

Chapter 3. RESEARCH METHODOLOGY

3.1 Introduction

This chapter describes the methodology undertaken to address the research objectives of this thesis. The process of research started after performing a systematic review of the problem, which led us to define a solution approach that spans over two separate layers and separate domains. The rationale for this multi-layered multi-domain approach is provided in the introductory chapter (Section 1.1). This chapter now highlights all the steps that are taken to form a conclusion within each layer. Figure 3.1 highlights the overall methodology of this thesis.

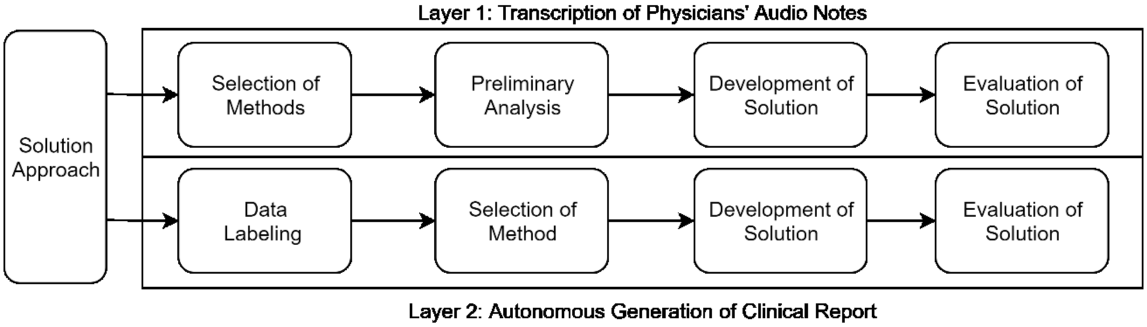


Figure 3.1 Steps in Research Methodology spanning over two layers

3.2 Layer 1: Transcription of Physicians' Audio Notes

The focus of this layer is to achieve higher recognition accuracy in the noise rich environments. It aims to apply the solutions to transcribe physicians' dictation audio files. This layer achieves its objective in four steps.

3.2.1 Selection of Methods

Noise-robustness and domain-robustness are two key challenges towards achieving the first objective of this layer. Both challenges were reviewed in detail (Section 2.6 and 2.7) to explore the top-of-the-line techniques. After a detailed review (Section 2.8), one Speech Recognition (SR) system was selected based on the ability to implement our explored techniques. The selection of the SR system and robustness techniques goes hand in hand to ensure the compatibility between the selections.

- **<u>SPEECH RECOGNITION (SR) SYSTEM</u>**

  We have selected project DeepSpeech [7] in our work. DeepSpeech is an open-source speech recognition engine that is developed by Mozilla. Project DeepSpeech uses acoustic models that are trained on the machine learning techniques of deep speech [77] and language models that are trained using KenLM [91] language modeling toolkit. When the DeepSpeech engine works with a deep speech acoustic model and a KenLM language model, the whole combination becomes a complete speech recognition system.

Name	***Short Name***	***Description***
Project DeepSpeech	DeepSpeech	Speech Recognition Engine requires an acoustic and a language model to perform recognition tasks.
Deep Speech Acoustic Model	Deep speech model OR Acoustic Model	An acoustic model that is developed using Deep Neural Network (DNN) based machine learning techniques.
KenLM Language Model	KenLM Model OR Language model	A language model that is trained using the KenLM toolkit.

Deep speech [77] also provides pre-trained acoustic and language models that have learned from massive datasets. It also provides utilities to train custom models. We selected the release 0.5.1 for our experiments, which is the latest stable release at this point in time.

- **PRE-TRAINED MODELS**

  Pre-trained acoustic and language models provided by DeepSpeech are trained over 3,000 hours of transcribed audio from Fisher [103], LibriSpeech [104] and Switchboard [88] datasets. All datasets are in American English. Details of each dataset are given below.

Corpus Name	Fisher [103]	LibriSpeech [104]	Switchboard [88]
Corpus Size	2,000 hours	1,000 hours	250 hours
Nature of Data	telephone conversations	audiobooks	conversations
Source of Data	16,000 conversations	audiobooks	2,500 conversations by 500 speakers

The pre-trained deep speech model was trained using the following hyperparameters.

Parameter	Layer width	Dropout rate	Learning rate	Language model weight (CTC Decoder)	Word insertion weight (CTC Decoder)
Value	2048	15%	0.00001	0.75	1.85

The language model was trained till 5-grams. The total size of the pre-trained language model is over 4 gigabytes.

3.2.2 Preliminary Analysis

Cloud-based SR systems generally perform better [105] as compared to offline systems, but they do not offer customization options as open-sourced offline SR systems offer. Moreover, in data-sensitive domains, such as the healthcare domain, offline solutions are preferred due to privacy and such concerns. Therefore, in this work, we will be exploring robustness techniques to apply them to an open-sourced offline SR system to maximize accuracy gain. However, we are interested in comparing the performance of the selected SR system with the top-of-the-line cloud SR system in both settings; before and after applying our solution. In this step, we experimented with DeepSpeech and Google Speech [100] using our full dataset.

3.2.3 Development of Solution

This step developed a solution to overcome the challenges of this layer. The solution is motivated by the insights gathered from the preliminary analysis and is based on the reviewed robustness techniques. It proposes methods to maximize accuracy gains using both, acoustic and language models.

3.2.4 Evaluation of solution

SR systems are generally evaluated using Word Error Rate (WER) [25], which gives equal weight to all mistakes. However, in the domain-specific environment, some mistakes can have more impact than others. For example, in the healthcare domain, a mistaken drug name or diagnosis is a critical hazard, in comparison to most of the grammatical mistakes. Therefore, we developed a custom domain-specific evaluation metric, Critical Error Rate (CER), to evaluate such errors. We evaluated our models on both of these evaluation metrics (WER and CER).

- **CRITICAL ERROR RATE (CER)**

  Critical mistakes are defined as those mistakes that involve medical concepts. CER counts critical mistakes and takes its ratio out of all critical concepts within the ground truth. First, it counts all the critical mistakes, and then it divides the count by the number of all medical concepts in the ground truth. CER uses Metamap [106] to query the word to find if it is a critical mistake.

$$CER = \frac{C}{W}$$

$\therefore C = \#\ of\ Critical\ Mistakes$

$\therefore w = \#\ of\ Critical\ Concepts\ in\ Ground\ Truth$

3.3 Layer 2: Autonomous Generation of Clinical Report

A SOAP formatted clinical report contains sections representing all four SOAP categories; therefore, the focus of this layer is to develop a classifier to categorize sentences from the transcription of physicians' notes into one of the SOAP categories. We achieved the objectives for this layer in four steps.

3.3.1 Data Labeling

In the first step, we labeled the dataset for the classification task.

3.3.2 Selection of Method

In this step, an exemplar-based algorithm was selected, which is proposed by Juckett [102] for concept detection within clinical texts.

3.3.3 Development of Solution

The selected algorithm detects concepts at the word level, whereas we aim to work at the sentence level. Thus, in this step, we extended the selected algorithm to give a single confidence score for each class for the given sentence. We also identified four key areas to investigate and develop the solution.

3.3.4 Evaluation of Solution

In this step, we evaluated our solution based on the four independent variables that were formed from the identified areas. For the evaluations, we used Average Precision (AP) as the primary measure of performance. We did not evaluate the area under the ROC curves due to the class imbalance in the dataset.

3.4 Dataset

To achieve the objectives of this research, the IWK health center in Halifax, Nova Scotia, Canada, provided a set of 105 physicians dictated notes, which were then processed into a structured dataset.

3.4.1 Data Collection

Audio clips of clinical dictations were provided by the Pediatric Emergency Department of IWK health center. 20 out of 105 dictation audio clips contained a complete dictated note, whereas the rest of the dictations were chunks of incomplete notes. Only 16 dictations were coupled with gold standard text. In total, all dictations accumulate to 2 hours, 28 minutes, and 14 seconds of audio data. Out of all dictations, 100 were recorded by one person in different areas of the hospital, whereas, remaining five dictations were recorded by different persons.

3.4.2 Dataset Preparation

The dataset was prepared in two steps. In the first step, gold standards were generated and validated. For all those dictation clips where no gold standard was provided, manual transcription process was completed by three fellow researchers of our lab, one of these fellows holds a medical degree that helped us in maintaining the exact vocabulary. Every researcher transcribed all dictation clips; afterward, all three variations were analyzed to generate gold standards. After generating the missing gold standards, all 105 dictations were manually validated.

In the second step, the dataset was structured. All dictation and transcription files were renamed into a sequence of numbers, where a prefix was given to each file. Prefix A was given to all audio clips, and corresponding text files. A dictation and its respective gold standard couple were given the same filename; nevertheless, they had separate extensions (.wav for audio clips, .txt for text files), e.g., (A001.wav, A001.txt).

After setting up all the files for the dataset, we segmented our dataset into two parts. The first part included 100 dictations that were recorded by one person. We called this an original dataset and used it for experiments and analysis. The remaining five dictations form a validation dataset that we used explicitly to validate the final results of our experiments. We did not use the validation dataset at the time of defining, experimenting and refining our methods.

3.5 Research Environment

This research is performed on two computer systems that were used in parallel. Table 3.1 provides a summary of both systems that were used. System 1 was primarily used for review, documentation, and light scripting work where the windows operating system is required. For all the compute-intensive tasks such as model training and fine-tuning, System 2 was used that was equipped with a well-functioning GPU.

Table 3.1 Summary of Research Environment

	System 1	System 2
Processor	Intel Core i7	Intel Core i7
RAM	16GB	20GB
GPU	-	NVIDIA GeForce GTX 960 (2GB VRAM)
Storage	HDD	SSD
Operating System	Windows 10 Pro	Ubuntu 18.04 LTS

Metamap [106] was used to extract medical concepts from texts. In this thesis, vocabulary was limited to MeSH (Medical extended Subject Headings) [107]. Metamap server was initialized on system 2, which was readily available over the network. We were more comfortable working with the JAVA implementation of Metamap client; hence all the scripts that required interaction with Metamap were written in JAVA.

We used Python to experiment with DeepSpeech. We used system 2 for experiments since DeepSpeech uses TensorFlow [90] libraries to run Deep Learning algorithms that facilitate execution over NVIDIA based GPU.

Cloud-based SR systems were tested on the JAVA platform. Exemplar based algorithm in NLP was also implemented in JAVA where results were stored in files which were later analyzed by python scripts using the scikit-learn library to calculate and plot the precision-recall graphs.

3.6 Conclusion

In this chapter, we present the steps we took in each layer of our solution to address both of our objectives. We highlight the methods that are selected in each layer, along with the reasons for such selections. We also mention details about the dataset and working environment that we used throughout our research.

Chapter 4. Speech Recognition – Methods

4.1 Introduction

This chapter presents our methods to explore robust and domain-specific Speech Recognition (SR) for scenarios when there is a shortage of domain-relevant data. In this chapter, methods pertaining to both components: acoustic model and language model; are explored to achieve maximum recognition accuracy. Acoustic models are primarily focused on achieving noise-robustness, as they are directly responsible for dealing with the noise within the feature space. Language models, on the other hand, contribute more to domain-robustness, as they learn from domain-specific language (vocabulary and speech patterns).

4.2 Domain Adaptation

Domain adaptation is a sub-discipline of machine learning which "deals with scenarios in which a model trained on a source distribution is used in the context of a different (but related) target distribution" [108], [109]. In many realistic and low-resourced target domains, where the collection of data is costly and sometimes impossible, training domain-specific models become a challenge. In such scenarios, domain adaptation serves as a highly practical option [110] to bootstrap the model development process [84].

Transfer learning and fine-tuning are two main methods of domain adaptation. In both methods, models that are already trained on one problem domain are used as the starting point to use in another problem domain. However, the difference lies in the way these models are adapted. If the adapted model is shown some training data from a different target domain to learn the domain specifics, this method is referred to as fine-tuning. However, if some or all layers of the adapted model are taken to develop a new model, this method is transfer learning.

4.3 Preliminary Analysis

In this section, we address some fundamental questions that require answers to drive this research. DeepSpeech is a recognition engine that depends on acoustic and language models to perform recognition tasks; however, we have not trained any domain-specific models yet. Therefore, our first logical question is, ‘what will be the performance of DeepSpeech on our dataset by simple domain adaptation of pre-trained (general purpose) models?’; secondly, ‘what type of mistakes do pre-trained models do on a domain-specific dataset?’; and thirdly, ‘how does this performance compare with top-of-the-line commercial cloud-based SR systems like Google SR?’

Table 4.1 Preliminary Results: WER and CER of Cloud and Offline SR

	CER	**WER**
DeepSpeech	49.38%	46.63%
Google	20.18%	21.69%

To answer these questions, all 100 audio clips from our original dataset were transcribed using both SR systems/services (DeepSpeech and Google). Table 4.1 presents the error rates for both systems. In general, we observed that DeepSpeech, with its pre-trained models, made a mistake for almost every two words.

In comparison with the cloud-based SR (Google), DeepSpeech made relatively 114.98% more general mistakes (WER) and 144.69% more critical mistakes (CER). In isolation, DeepSpeech made more critical mistakes than general mistakes, whereas Google was better in recognizing domain critical vocabulary. These differences highlight the domain agnostic behavior of pre-trained models of DeepSpeech.

Table 4.2 Examples mistakes by DeepSpeech during preliminary experiments.

Ground Truth	**DeepSpeech**	**Google**
with the t max of ibuprofen **tracheal palpation**	with a **tax** of age **profane** **trail** at a **patient**	with a t maxx of ibuprofen I killed a **palpation**

The reason for a large number of critical mistakes by DeepSpeech is that its models are not trained on the vocabulary that is deemed critical in our domain. We present some examples of critical mistakes done by both systems/services in Table 4.2. From the example, one can observe that DeepSpeech returned hypotheses that are most common in generally spoken language. For example, ‘t max’ was inferred as ‘tax’, and ‘tracheal’ was conceived as ‘trail’. This behavior is precisely the same that is within the dataset on which the pre-trained language model is trained, i.e., mostly conversational and general speeches. Thus, we should investigate techniques to incorporate more domain-specific vocabulary within the language model.

Google was also not able to conceive many, if not most, of the critical concepts either; however, we observed that such mistakes were less then DeepSpeech. Most of the time, when DeepSpeech made a critical mistake, the audio happens to be valid. For example, in the case of ‘tracheal palpation’, Google recognized ‘palpation’ correctly, while giving a completely out of context hypothesis for ‘tracheal’, but DeepSpeech did not recognize any part of that phrase, which is worse. We verified this specific instance manually and found that the distortion in this audio clip is below the average level of noise within our dataset. Therefore, for better inferences, there is also a need to explore methods to develop accurate acoustic models.

4.4 Acoustic Modeling

In preliminary experiments, the pre-trained acoustic model was not aware of the acoustic environment of the target domain. Therefore, we explored methods to train domain-relevant acoustic models. In this regard, we outlined two research questions. 1) what will be the impact on performance if the pre-trained acoustic model incorporates the acoustic environment of our target domain? and 2) how will DeepSpeech perform with a new acoustic model that is trained solely on our dataset?

Our first question sought domain adaptation of the pre-trained model along with an enhancement method to incorporate the target domain. There are two methods to do it in a machine learning paradigm: transfer learning and fine-tuning. Both of these methods adapt an existing model that is learned in a separate domain. These methods require less training data from the target domain. In our case, the pre-trained acoustic model has already learned from general conversations. Moreover, we do not require any change in the input or output classes. Therefore, we considered using the fine-tuning method to incorporate our target environment within the pre-trained model.

The second question requires the development of a new acoustic model using supervised learning. DeepSpeech is an end-to-end system that relies on large datasets to generalize; therefore, with our dataset of about two and a half hours of audio, we were not able to train the model to the point of convergence. Even after training a new model for 500 epochs, we did not observe any reduction in the error rates, whereas, in comparison, the pre-trained model is only trained for 75 epochs. Hence, we did not pursue this question further.

4.4.1 Audio Pre-Processing

Audio clips in our dataset have an average length of 1:30 mins, whereas the pre-trained model was trained on the audio files that are of sentence length (4-5 seconds). The length of audio has a direct correlation on the memory consumption while training deep speech acoustic models. Therefore, we needed to split the audio clips in shorter chunks to keep the memory allocation under the affordability of our hardware.

A series of considerations were acknowledged before splitting. Firstly, attention was given towards the completion of words in each split. Any cut in between the utterance of a word can make it impossible to recognize that splitting word. Secondly, splits were made in a way to keep the average length around 5 seconds mark.

To effectively break audio clips following all considerations, a silence finding process was used. The idea is that if a cut is made on silence, that is long enough, then the probability of breaking a word will greatly diminish. Audio clips were analyzed to find silences upon various threshold values. There are two thresholds that a silence finder process requires: max intensity level and duration of silence. Both are defined below.

1) **Maximum Intensity Level:** This requires a value for maximum sound intensity level below which everything is considered silence.

2) **Duration of silence:** This requires a value that denotes time in milliseconds of continuous silence to mark it as a valid silence period. Whenever sound intensity drops below the above-defined level a true silence does not need to occur. It is quite possible that while pronouncing a word, the sound intensity drops below the above-defined intensity level for a moment; hence this threshold gives an option to select a duration of silence period, such that only silences of periods more than specific duration will be marked as true silence.

For each audio clip, the silence finding process was executed with varying threshold levels. After each execution, all splits were checked for word completion and the average split length. If any of the considerations failed, thresholds were readjusted, and the process was re-executed. The whole process was performed manually for each audio clip to ensure that speech content preserves even after the splits.

Once all the audio clips were broken into smaller splits, they were then stored in a folder by appending a number from a sequence to their filenames. For Example, the first split of ‘A001.wav’ was given filename ‘A001-01.wav’. All splits were then copied into a folder that was named ‘A001’. After storing all the splits, their corresponding gold standard transcriptions were also modified in such a way that they contain the same number of lines as there are splits, where the nth line has the text for the nth split.

4.4.2 Fine-tuning

Project DeepSpeech provides checkpoints for its pre-trained deep speech model. Checkpoints capture the exact value of all weights and parameters within a model and are stored in a directory. The checkpointing directory within the project DeepSpeech contains the latest values for which the deep speech model was exported. Therefore, we used the provided checkpoints to perform fine-tuning.

Table 4.3 Hyperparameters used for acoustic model fine-tuning

Hyperparameter	Value
audio_sample_rate	16000
train_files	Path/to/train.csv
alphabet_config_path	Path/to/alphabet.txt
export_dir	Path/to/export-directory
checkpoint_dir	Path/to/checkpointing-directory
train_batch_size	5
n_hidden	2048
epochs	1
dropout_rate	0.15
learning_rate	0.0001
lm_alpha	0.75
lm_beta	1.85

The fine-tuning process is the same as model training in DeepSpeech. While training, if a checkpointing directory is defined and the directory contains valid checkpoints, then DeepSpeech starts fine-tuning the existing model; otherwise, it creates a new model. In our scenario, we downloaded the checkpointing directory and started the training process from that directory. Table 4.3 provides a list of hyperparameters that we used. Details about these hyperparameters are as follows.

1. Training files.

   The parameter *train_files* expects a path to a comma-separated file (CSV) that contains three columns: *wav_filename*, *wav_filesize,* and *transcript*. The column *wav_filename* record paths of the audio files that we want to use for training the model, *wav_filesize* note the sizes of each audio file in bytes, and *transcript* have the ground truth of each audio file that other columns enlist. Each row in the CSV represents one audio clip within the dataset.

2. Alphabet file

   The parameter *alphabet_config_path* expects a path to a text file that contains a list of all distinct characters that are within the ground truth.

3. Export directory

   The parameter *export_dir* is used to specify the directory in which we wish to export the trained model. If this parameter is not supplied, then the trained model parameters will be stored in the checkpointing directory only, without exporting the model for inference use.

4. Batch size

   The parameter *train_batch_size* is used to set the batch size of training. The pre-trained deep speech model was trained on a batch size of 24 clips when there were 12 gigabytes of memory available to the developers of the pre-trained model. With one-sixth of that memory available to us and while using audio clips of similar lengths (after splits), we were facing memory exhaustion errors. Therefore, we explored the batch size iteratively by reducing it on each step. We were able to successfully complete the training process by using the batch size of 5 audio clips.

5. Epochs

   For our evaluations, we were interested in analyzing the error rates after each epoch of fine-tuning. Therefore, we executed the training one epoch at a time and exported the trained model after each epoch. After each export, the training was resumed from the same checkpointing directory.

6. Other hyperparameters

   Project DeepSpeech reports the hyperparameters that were used to train the pre-trained model. All other hyperparameters were kept unchanged in this fine-tuning process.

After finishing the fine-tuning process, all generated models are evaluated, whose details are provided in the next chapter.

4.5 Language Modeling

Language is a combination of words (vocabulary) and speech patterns (grammar). Specific domains may have specialized languages; therefore, domain-specific language model plays an important role in the domain-robustness of any SR system. Ideally, language models require training on vast volumes of domain-relevant data [111]. However, in realistic situations, problems arise when there is little or no domain-specific data available [82]. We also observed such problems in our preliminary analysis, when we used the pre-trained model which is an out-of-domain model for our problem domain. Therefore, we explored various methods to develop robust language models that are specific to our target domain.

The main concern is the insufficiency of domain-relevant training data. In the review, we highlight two main techniques to develop domain-specific language models when there are data scarcity problems. The first technique seeks domain adaptation of the out-of-domain language model while enhancing the adapted model using domain-relevant data and using various model combination methods. The second technique, on the other hand, focuses on the generation of domain-relevant data. Therefore, in this work, we experimented with methods from both techniques. We are also interested to see the recognition performance without applying any of these techniques. Hence, we also developed standalone language models using only our original dataset. In summary, we worked on three key tasks to investigate the impact of language modeling techniques.

1) Dataset Augmentation with Domain-Relevant Data.
2) Developing Domain-Specific Language Models
3) Enhancing Pre-Trained Language Model

4.5.1 Dataset Augmentation with Domain Relevant Data

Our dataset includes clinical notes representing narrated cases of patients' diagnosis and treatment, along with rationales and reasons coming from the healthcare provider's perspective. These notes contain domain-specific concepts, for example, diseases, diagnoses, and observations. However, with the limited number of notes having 1966 sentences in total, it is not possible to cover all the concepts within the domain. Therefore, to develop domain-specific and robust language models, it is required to augment our dataset with most of the domain-relevant information.

We reviewed three techniques for data augmentation: extraction, conversion, and generation. Extraction and conversion techniques consider that domain-relevant data is available somewhere else perhaps in a different format, language or source. These considerations are ineffective for sensitive domains like healthcare since such data is usually heavily protected and is available with scrutiny and restrictions. Therefore, the only logical option left is to use data generation techniques to simulate domain-relevant data.

Data generation techniques vary for each domain and require domain knowledge. In the NLP domain, synonym replacement [112] is a simple technique that is also the most natural choice to augment small datasets [113]. In its simplified form, synonym replacement generates new textual units by replacing words from its synonyms. Most implementations of this technique use thesaurus like WordNet [114] or thesaurus.com [115] to get the list of synonyms for replacement. Synonym replacement requires two things for execution: which words in the text should be replaced, and which synonyms should be used for the replacement [113]. In synonym replacement, words to replace are identified from the original dataset, whereas, synonyms are extracted from knowledge sources. Once both: words and synonyms; are identified, then each word is permuted with its synonyms to generate new variations of text.

In this work, we generated domain-relevant data based on the synonym replacement technique. To apply this technique in our domain, we considered *synonyms* as those medical concepts that belong to the same semantic classes. We used MeSH [107] as the knowledge source to extract medical concepts within the healthcare domain. MeSH is a thesaurus that lists medical concepts in a tree hierarchy. Previous work has also shown to use MeSH with the same technique for the data simplification task [116]. We used Metamap [106] to identify medical concepts within our dataset, which is a concept recognizer that annotates medical concepts within texts. Our data generation method consists of three steps.

- **STEP 1: PATTERN EXTRACTION**

Each sentence within our dataset can have multiple medical concepts. We observe that most of the time, these concepts semantically depend on each other, and a replacement can semantically invalidate the sentence. As an example, in the sentence, "She was prescribed a course of cephalexin to treat bacterial infection", there are three medical concepts: "prescribed", "cephalexin" and "bacterial infection". The concepts "cephalexin" and "bacterial infection" belong to *'drug'* and *'disease'* classes respectively and are semantically dependent upon each other. A replacement of the *'disease'* concept "bacterial infection" to another *'disease'* concept "lung cancer" might semantically invalidate the sentence. Therefore, we approached for extracting patterns from the sentences, so that a replacement does not invalidate the semantics. We define that a pattern within a sentence has exactly one medical concept while having maximum neighboring words that are not medical concepts. In our given example, patterns are "She was prescribed a course of", "a course of cephalexin to treat" and "to treat bacterial infection". Since our goal is to generate robust language models, we generated patterns with overlaps to maximize the count of neighbors around the medical concepts.

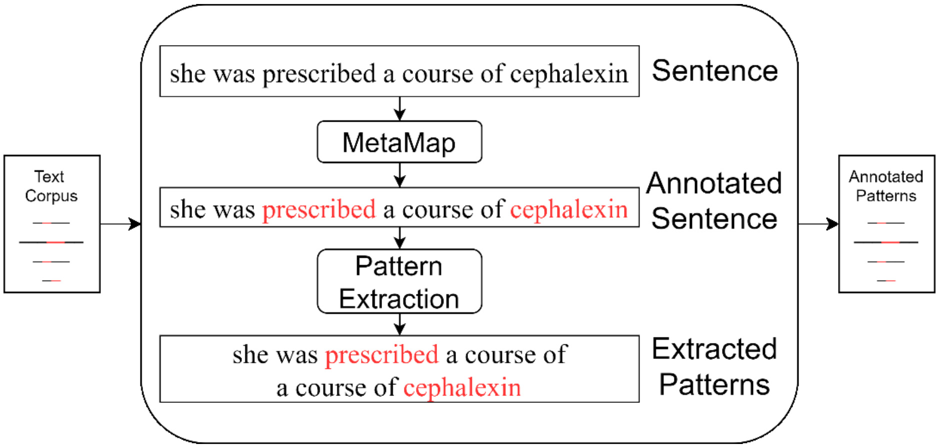


Figure 4.1 Steps of Pattern Extraction

Pattern extraction starts by annotating a sentence using MetaMap by restricting it to use MeSH vocabulary. These annotations are upon the concepts within the sentence. The number of annotations defines the number of patterns that can be extracted from the sentence. Each annotation is then used as the starting point of a new pattern. All the words to the left and right of that annotation that are not part of another annotation are added to that pattern. When the sentence boundary or boundary of another annotation is reached, then the pattern stops growing and is then added to a global list of patterns. This step is repeated with all the annotations to extract all possible patterns from the sentence. Then the whole sentence level work is repeated for all sentences in the dataset. Figure 4.1 illustrates the sentence level pattern extraction along with an example.

- **STEP 2: KNOWLEDGE EXTRACTION**

In this step, we extract *synonyms* from the knowledge source. MeSH classifies each medical concept into 16 root category classes. The concepts within these classes are specific to the healthcare domain and are far from the general-purpose conversational paradigm upon which the pre-trained models were trained. Even our dataset does not account for all concepts from these classes. From preliminary experiments, we observe that most of the mistakes are coming from the concepts of *'disease'* and *'drug'* classes. Therefore, we decide to generate data to cover only these two classes for now. In MeSH, *'disease'* concepts are kept under the root node "Diseases[C]" and *'drug'* concepts under the "Chemical and Drugs[D]" node. We traverse all the child nodes under these two nodes and extract all the concept terms for each child node.

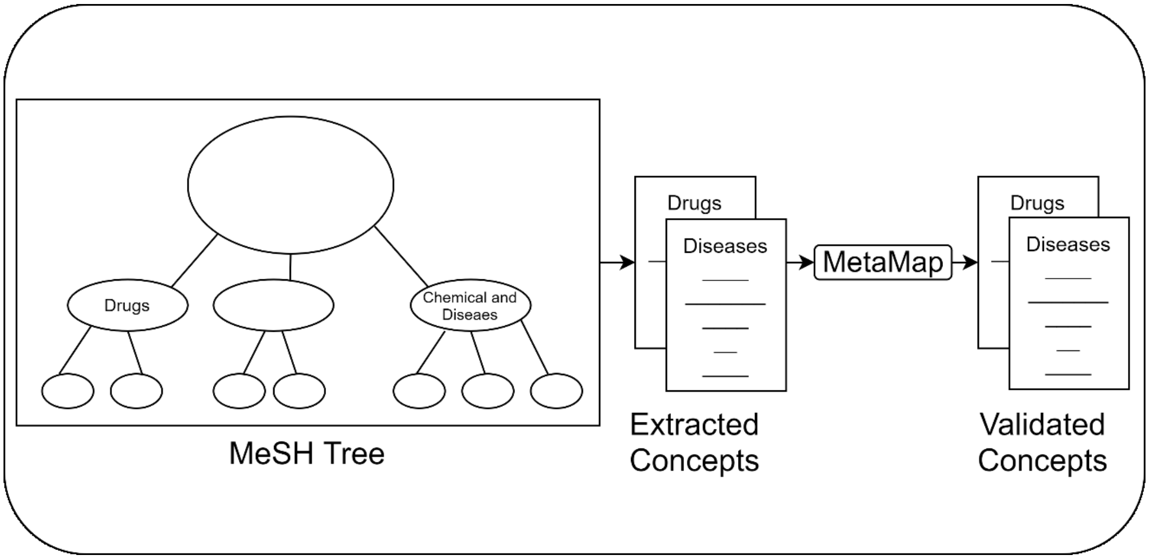


Figure 4.2 Steps of Knowledge Extraction

In MeSH, each medical concept enlists all candidate and qualifier terms, while defining a separate list for the preferred terms of that concept. Many of these terms are closely related to the concept but are not strictly synonymous with the terms that are in use by the physicians. Moreover, root nodes of MeSH include all the concepts that are from all domains of medical science, while for this work we are only interested in those concepts that are applicable in the pediatric emergency departments. As an example, the "Chemical and Drugs[D]" node contains a concept "Propoxur" which is an insecticide. "Propoxur" is not related to pediatric care and is not applicable in our case. Therefore, it is required to filter out such terms from our extracted lists to ensure that the terms are semantically similar to our working domain. To filter the lists, we considered a validation step where only those terms are validated and kept that are semantically closer to our dataset, and all other terms were dropped.

To validate the extracted concepts, we passed each concept term to the Metamap and examined the detected semantic type. If the semantic type matches those that are already existing in our dataset while the semantic type belongs to the same root node from which the term is coming, then we consider that term as valid. We collected all the valid terms for each of the two semantic classes that we extracted. Figure 4.2 depicts the whole process of knowledge extraction. After the extraction and validation of concepts, we get 24,071 concepts from the *'disease'* class and 29,935 concepts from the *'drug'* class.

- **STEP 3: AUGMENTATION**

In this step, we generate simulated data by using patterns and medical concepts extracted in previous steps and then augment the simulated data with our original text corpus. Our strategy in this step is similar to synonym replacement, with a small change that seeks selection of concept list depending upon the class of concept within each pattern. For this step, we know that each pattern has exactly one medical concept within it.

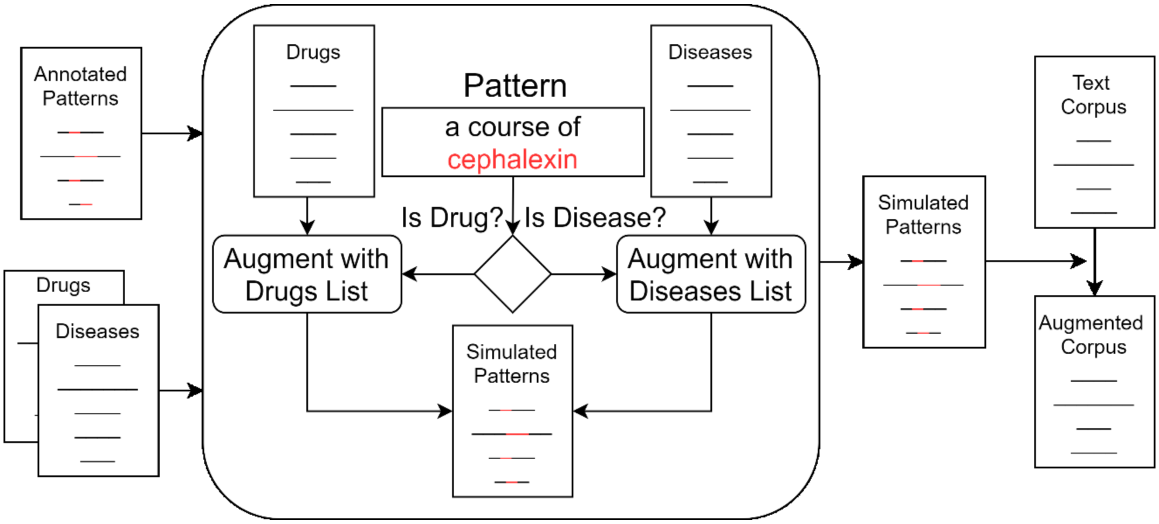


Figure 4.3 Steps to Generate Augmented Corpus

For each pattern from the patterns list, we check the class of the medical concept. If the concept belongs to the *'drug'* class, we select the list of drugs for the augmentation. In case the concept belongs to the *'disease'* class, we select the list of diseases. For anything else, the pattern does not augment. To augment the pattern with the selected list of concepts, each concept within the list is used to replace the existing concept in the pattern to form a simulated variation. Each new variation after the replacement is then recorded in the list of simulated patterns (Figure 4.3). These simulated patterns are then combined with the original text corpus to form an augmented corpus.

Our data augmentation task enabled us to work with two datasets: original and augmented. We use both datasets to evaluate our language modeling methods that we define in later tasks. For the evaluations, we require data augmentation on multiple subsets of our original dataset. Therefore, we develop a utility program using JAVA to automate the augmentation process. Our utility program takes lists of concepts (Drugs and Diseases) and a text dataset, and then it outputs the augmented dataset.

4.5.2 Developing Domain-Specific Language Models

In this task, we develop language models using only the domain-relevant data. For this purpose, we use both datasets: original and augmented. Augmentation is done using the methods presented in the previous task. Language models are created using the KenLM toolkit.

KenLM provides methods to develop n-gram based language models in ARPA [117] format. ARPA is a file format to list down all the calculated probabilities within an n-gram language model. ARPA formatted models are bulky and not efficient to use for inferences; hence, for efficient execution, it is required to convert ARPA models into specific data structures [118]. KenLM also provides functions to convert the ARPA formatted models into PROBING and TRIE data structure based language models [91]. PROBING data structure is faster but uses extensive amounts of memory for inferences. In comparison, the TRIE data structure aims to lower memory consumption. As our compute environment has a limited stack of memory, we adapt the TRIE data structure to develop our language models. Project DeepSpeech also supports TRIE structure by providing a native client to convert the TRIE based language models into efficient binaries that aim speedy execution.

In this task, we use four steps to develop language models. In the first step, we streamline the dataset by removing all leading and trailing whitespaces from all the sentences and converting them into lower case. In the second step, the streamlined dataset trains an ARPA based language model of the 5th order. We use the maximum n-gram order length of 5 because the pre-trained model from DeepSpeech uses the maximum of 5-grams; therefore, we keep the n-gram order similar for valid comparisons. In the third step, the ARPA model converts into a TRIE based model. Finally, the TRIE model converts into DeepSpeech specific binary using its native client.

In this task, we develop language models in two strategies. In the first strategy, we directly use the original dataset to develop the language models. In the second strategy, we apply augmentation methods on our original dataset and then use the augmented dataset to develop the language models.

4.5.3 Enhancing Pre-Trained Language Model

In this task, we enhance the pre-trained language model by incorporating information from our domain-relevant dataset. There are two main reasons to seek this task for the development of robust language models. The first reason is the insufficiency of our domain-relevant dataset. We have only 127 kilobytes of text available in the original dataset. Although after augmenting, we are able to generate about 2 gigabytes of text; however, the pre-trained DeepSpeech model is trained on about 4 gigabytes of text, which is still double. Therefore, we hypothesize that developing language models using text from both data sources can be a better solution. The second reason is due to the preliminary analysis, where DeepSpeech, with its pre-trained language model, made more critical mistakes then general mistakes. From the nature of mistakes, we observed that the pre-trained language model lacks domain-specific vocabulary, evidently due to its training upon an out-of-domain data source. Therefore, we consider a reduction in critical errors by introducing domain-relevant vocabulary in the pre-trained model.

Enhancement of the language model entails combining the information from other data sources (domains) to the existing language model. Language models can be combined by any of two methods: pooling and interpolation. In the pooling method, the corpus of the existing language model is pooled with the text from other data sources. The pooled corpus then trains an enhanced language model. In the interpolation method, a separate language model is trained using the text from each data source. Afterward, all language models; existing and newly trained, are merged using weights that are tuned on some validation text. This validation text is fetched from the target domain.

The interpolation method has some variations [119]. The simplest of all is linear interpolation, in which all intermediary language models (P_i) are combined linearly using tuned weights (λ_i) (Equation 3). These weights are tuned over the validation set such that it maximizes the likelihood operator $P(W|H)$ for the combined model.

Equation 3

$$P(W|H) = \sum_{i} P_i(W|H)\lambda_i$$

KenLM [91] toolkit uses the log-linear interpolation method, which is a slight variation of the linear interpolation method. In the log-linear interpolation method, individual models are merged by applying weights as the power and multiplying the powered models (Equation 4).

Equation 4

$$P(W|H) = \frac{1}{Z_\lambda(H)} \prod_{i} P_i(W|H)^{\lambda_i}$$

After merging all the models, to complete the interpolation probability, the product is divided by a normalizing term $Z_\lambda(H)$ to ensure that the sum of all probabilities over words **W** equals to 1. The normalizing term calculates the product of all words in the vocabulary of all language models (Equation 5).

Equation 5

$$Z_\lambda(H) = \sum_{W} \prod_{i} P_i(W|H)^{\lambda_i}$$

To enhance the pre-trained language model, we experiment with both; pooling and interpolation; methods. Similar to the previous task, we adopt strategies to use both datasets; original and augmented. In total, we develop language models in four strategies, by the combination of methods and datasets. In the first strategy, we use the original dataset to enhance the pre-trained language model using the pooling method. In the second strategy, the same dataset is used with the interpolation method. The third and fourth strategies are similar to the first two, in terms of methods; however, we use augmented dataset in these strategies.

When we use the pooling method, the source corpus of the pre-trained model is pooled with the domain-specific text of our datasets, and then the pooled text trains new language models. When we apply the interpolation method, the pre-trained model remains the first intermediary model, while we train separate models from our datasets and interpolate all intermediaries. All the models developed in this task are trained using the n-gram order of 5, which denotes the maximum n-gram length in the language model.

4.5.4 Summary

In the language modeling phase, we work on three tasks. In the first task, we focus on the generation of artificial domain-relevant data using the principles of the synonym replacement method. We define a three-step method that expects a text corpus to work on, and in turn, it provides an augmented corpus. In the second and third tasks, we provide strategies to develop language models by using both datasets; original and augmented. Both tasks, in combination, develop six strategies to train language models.

1) Training a new language model using the original dataset.
2) Training a new language model using the augmented dataset
3) Enhancing the pre-trained language model using the original dataset using the pooling method.
4) Enhancing the pre-trained language model using the augmented dataset using the pooling method.
5) Enhancing the pre-trained language model using the original dataset using the interpolation method.
6) Enhancing the pre-trained language model using the augmented dataset using the interpolation method.

All these strategies seek the development of n-gram based language models that are of 5th order.

4.6 Discussion

We consider our solution to be replicable in other domains where noise and domain robustness is required, and there is insufficient relevant data available. In the acoustic modeling method, we approached to fine-tune a general-purpose model. As this model is generic, the same method can be applied in any other domain. However, to replicate our language modeling methods, particularly the data augmentation, one will need to look for the domain-specific knowledge sources and concept detection tools for the successful adaptation of these techniques.

4.7 Conclusion

In this chapter, we present our explored techniques and developed methods to train robust and domain-specific models. Our methods focused on those acoustically distorted and sensitive scenarios where there is a shortage of domain-relevant data. We first did the preliminary analysis using pre-trained models of DeepSpeech. We then developed acoustic modeling and language modeling methods by taking insights from the analysis. The acoustic modeling method sought domain adaptation of the pre-built model along with a fine-tuning operation using our dataset. On the other hand, language modeling focus on the generation of domain-relevant data. It worked on a three-step method to generate an augmented dataset, and then it developed six strategies to develop robust language models.

Chapter 5. SPEECH RECOGNITION – EVALUATIONS

5.1 Introduction

This chapter provides a detailed evaluation of the methods that we presented in the previous chapter. Evaluations were done in 2 phases. Figure 5.1 shows the flow of the experiments that we executed for our evaluations.

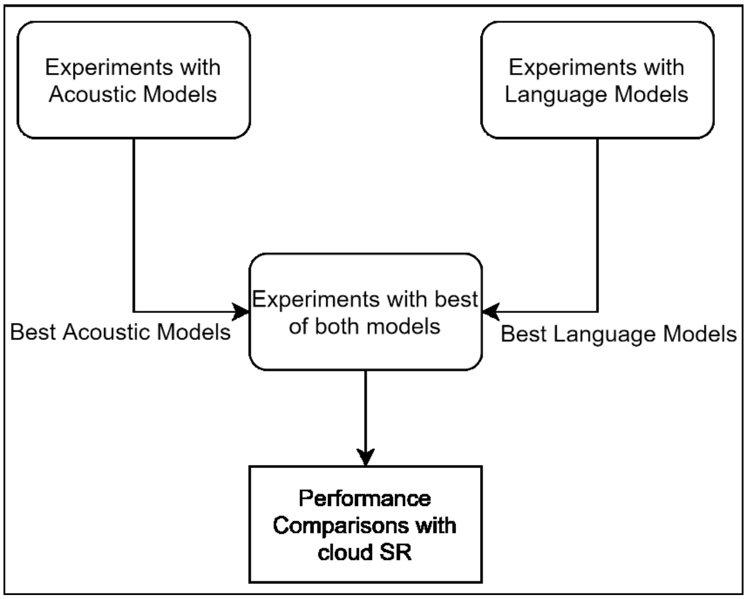

Experiments with Acoustic Models
Experiments with Language Models
Experiments with best of both models
Best Acoustic Models
Best Language Models
Performance Comparisons with cloud SR

Figure 5.1 Flow of experiments

5.2 Setup

5.2.1 Evaluation Phases

Our solution defines methods to enhance both, acoustic and language models within the speech recognition system, therefore our evaluation strategy consisted of two phases.

1) In the first phase, methods pertaining to each model were evaluated in isolation. When evaluating the acoustic modeling method (in Section 0), we used the pre-trained language model for the experiments. Similarly, when evaluating language modeling methods (in Section 5.4), we used the pre-trained acoustic model. For the evaluations in this phase, we did experiments with both, training and testing data to

analyze the performance when models have seen everything as compared to unseen environments. We did not use the testing results to tweak the models, therefore we did not use any separate validation set to test the models in this phase.

2) In the second phase, we evaluated both models in combination. The best performing models from the first phase were selected to perform evaluations in combination. We did not evaluate low performing methods in this phase, particularly due to the fact that the first step of evaluation already gave us such insights. Finally, in this phase, we used our validation set to present the final validation of our trained models.

5.2.2 Cross-Validation

We used 10-fold cross-validation throughout the evaluations. Since we used the same dataset to train both: acoustic and language: models, a conventional method of cross-validation where the dataset shuffles and split into folds each time before conducting an experiment can cause problems; specifically in the second phase of evaluations where we intend to use trained models in combinations. Due to the limited dataset, we also cannot afford to set aside a testing dataset. Therefore, to ensure reliable and valid evaluations, we performed the shuffling and splitting task once, and recorded all the folds. Afterward, we supplied the same folds whenever an experiment used cross-validation.

5.2.3 Interpretation of Results

In the evaluations, we analyze the impact of our methods by examining the difference in performance and comparing it to baselines. As speech recognition systems are primarily evaluated on error rates, we will be considering Word Error Rate (WER) along with our custom metric Critical Error Rate (CER) to measure the performance where a lower error rate means better performance. However, all the crucial decisions are made on the basis of CER. There are two ways to examine the difference in performance. One way is to examine the absolute change in error rates, while the other is to check the relative change with respect to the error rate of baseline. In our evaluations, we have considered both ways to examine our results, however, attention is given to the relative performance differences.

5.3 Evaluating Acoustic Modeling

This section provides an evaluation of our acoustic modeling method. In this method, we fine-tuned the pre-trained acoustic model with our dataset. Fine-tuning was done till 8 epochs. We stopped at the 8th epoch due to the continuous increase in testing error rates. Cross-validation was used to calculate testing error rates. For each of the 10 folds, the pre-trained model was separately fine-tuned, and the error rates from all folds were averaged. This process was repeated at each epoch. Error rates for training cases were calculated directly by using the whole dataset for fine-tuning and using the same data to calculate errors. Figure 5.2 shows the trend of errors on each epoch (horizontal axis) for both error rates (vertical axis) and Table 5.1 lists down the values of error rates

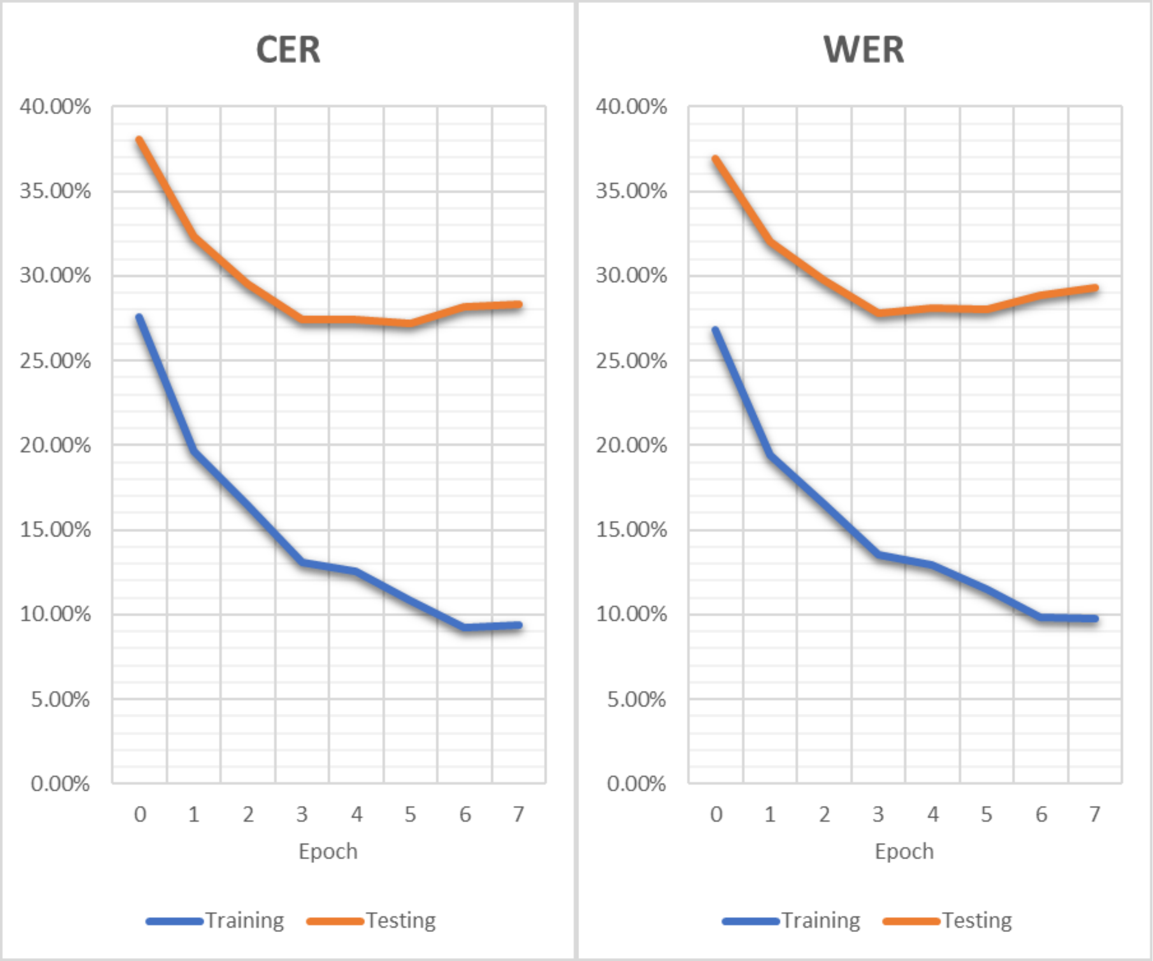


Figure 5.2 Error loss in Acoustic Model training

Table 5.1 Training and testing error rates for Acoustic Model training

		CER		WER	
		Training	**CV Testing**	**Training**	**CV Testing**
nth Epoch	1	27.59%	38.09%	26.84%	36.94%
	2	19.62%	32.31%	19.43%	32.04%
	3	16.47%	29.57%	16.56%	29.77%
	4	13.06%	27.42%	13.53%	**27.83%**
	5	12.57%	27.45%	12.94%	28.11%
	6	10.84%	**27.22%**	11.47%	28.01%
	7	9.25%	28.17%	9.84%	28.86%
	8	9.37%	28.35%	9.75%	29.28%

5.3.1 Analysis

Analysis of error rates in comparison with the number of epochs showed that the model reached a local minima on our dataset on around 4th to 6th epochs. Our analysis of the error rates shows that the 6th epoch is the most efficient (CER: 27.22%) on the basis of CER, while the 4th epoch is the most efficient (WER: 27.83%) on the basis of WER. With the fine-tuning method, we were able to achieve 22.16% absolute and 44.88% relative reduction in CER and 18.8% absolute and 40.32% relative reduction in WER (Table 5.2). As the performance comparison was very close (error difference within a range of 0.2%), models from the 4th to 6th epoch were selected for further evaluations of the second phase.

Table 5.2 Absolute and relative change in error rates after acoustic modeling

	CER	WER
Pre-trained AM	49.38%	46.63%
Pre-trained AM + fine-tuning	27.22%	27.83%
└ **Absolute change**	**-22.16%**	**-18.80%**
└ **Relative change**	**-44.88%**	**-40.32%**

5.4 Evaluating Language Modeling Methods

This section provides an evaluation of our language modeling methods. We provided six strategies to train domain-relevant language models for improved recognition. In our evaluations, we combined all those strategies to develop 8 evaluation scenarios that cover all methods. Table 5.3 provides the details of each evaluation scenario.

Table 5.3 List of scenarios for Language Model evaluations

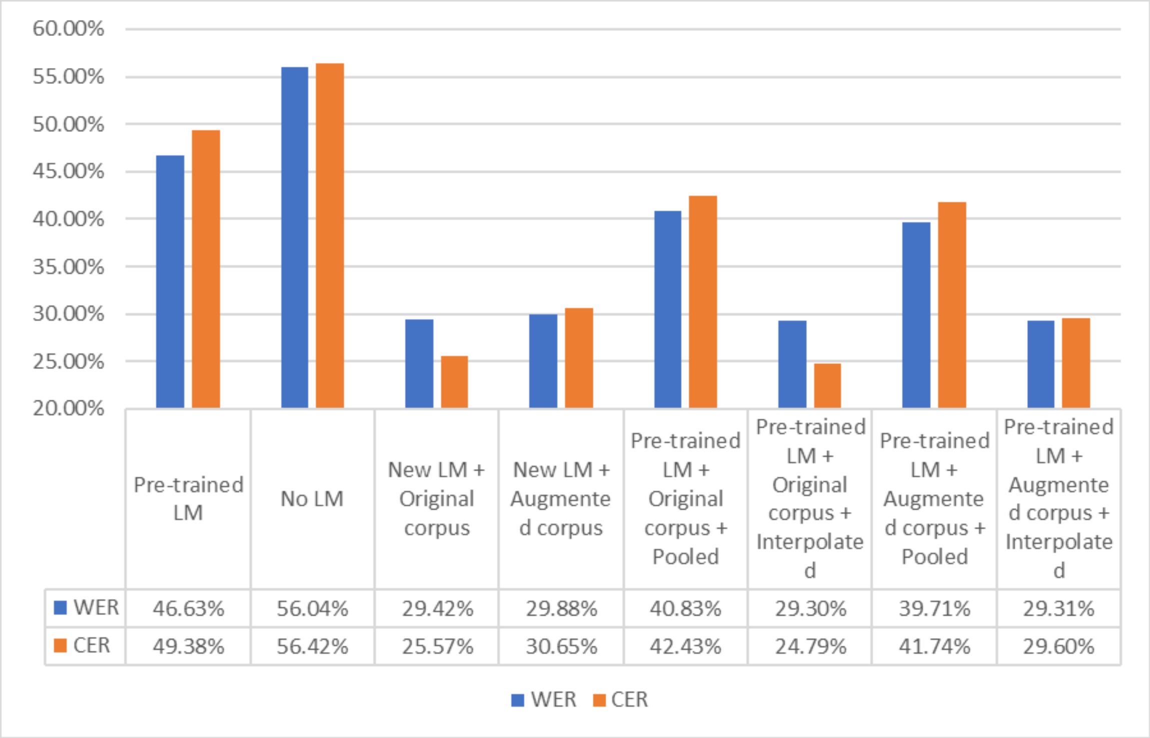
S. No.	**Evaluation Scenario**	**Strategy Details**
1	Pre-trained LM	Baseline: *Performance from the preliminary experiment is considered.*
2	No LM	*No LM is used in this scenario.*
3	New LM + Original in-domain corpus	New LM is trained using the text corpus from the original in-domain dataset.
4	New LM + Augmented in-domain corpus	New LM is trained using the text corpus from the augmented in-domain dataset.
5	Pre-trained LM + Original in-domain corpus + Pooling Method	Pre-trained LM is enhanced using the text corpus from the original in-domain dataset using the pooling method.
6	Pre-trained LM + Original in-domain corpus + Interpolation Method	Pre-trained LM is enhanced using the text corpus from the original in-domain dataset using the interpolation method.
7	Pre-trained LM + Augmented in-domain corpus + Pooling Method	Pre-trained LM is enhanced using the text corpus from the augmented in-domain dataset using the pooling method.
8	Pre-trained LM + Augmented in-domain corpus + Interpolation Method	Pre-trained LM is enhanced using the text corpus from the augmented in-domain dataset using an interpolation method.

Scenario 1 was developed to provide a baseline for this evaluation; therefore, we did not run any experiments in this scenario; instead, the results from preliminary experiments were considered. Scenario 2 was developed to test the performance of DeepSpeech without the use of any language model, as it is not a required component in speech recognition. For the experiments within this scenario, all audio clips from our original dataset were used to calculate error rates. In all other scenarios, language models were trained and tested using training and testing datasets. While evaluating the training error rates, language models were trained using the whole text corpus from the original dataset and all audio clips from the same dataset were used to test those models. While evaluating testing error rates, we used 10-fold cross-validation.

5.4.1 Analysis

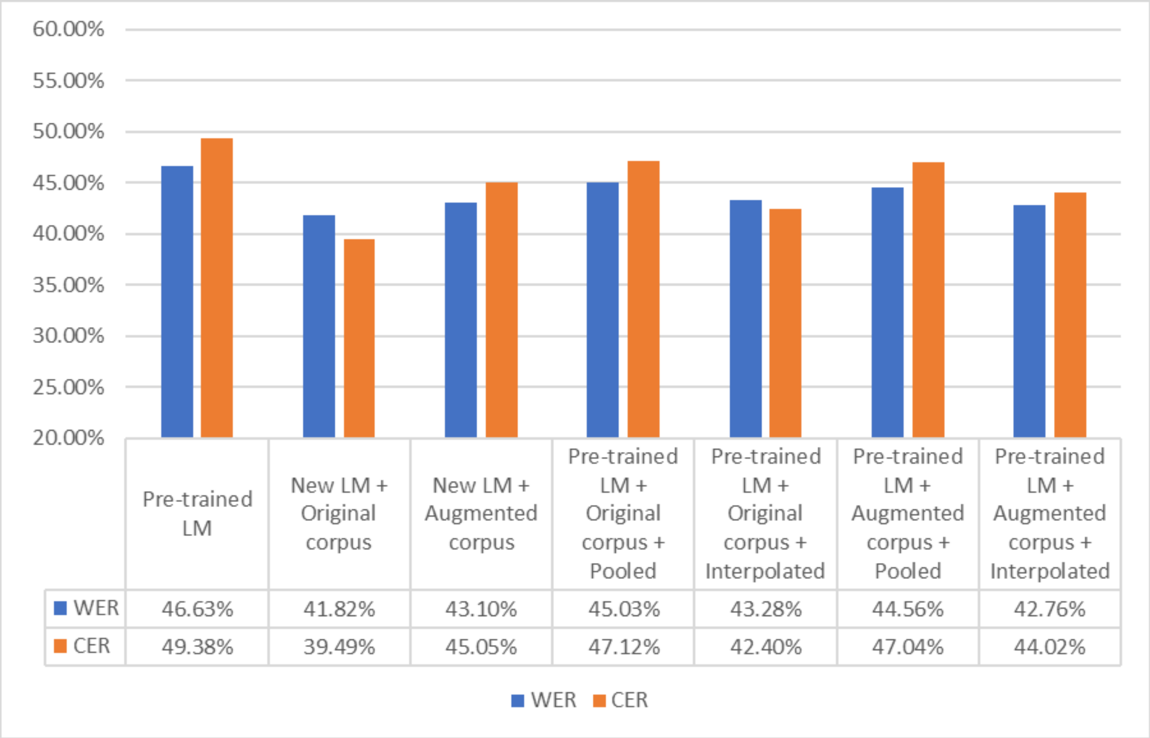
The analysis of our results shows that DeepSpeech did mistakes for more than half the time in scenario 2 when no language model was used. Upon comparing the error rates with baseline, one can see that the average CER increased around 8% and WER increased around 10% when DeepSpeech did not use any language model. This provides evidence of the importance of language models in the process of speech recognition. Moreover, when such language models were used that has already seen the testing data while training, the recognition performance matched the top of the line cloud-based SR (Google). This is not a valid comparison to build a conclusion; nevertheless, it highlights the ability of language models to significantly boost the recognition performance. Table 5.4 shows the error rates for all scenarios when the training dataset was used to test the models that were trained using the corpus from the same dataset. The table also shows error rates from the first 2 scenarios to provide a comparison, even though no language model was trained in those scenarios.

Table 5.4 Training error rates from each evaluation scenario



	Pre-trained LM	No LM	New LM + Original corpus	New LM + Augmented corpus	Pre-trained LM + Original corpus + Pooled	Pre-trained LM + Original corpus + Interpolated	Pre-trained LM + Augmented corpus + Pooled	Pre-trained LM + Augmented corpus + Interpolated
■ WER	46.63%	56.04%	29.42%	29.88%	40.83%	29.30%	39.71%	29.31%
■ CER	49.38%	56.42%	25.57%	30.65%	42.43%	24.79%	41.74%	29.60%

Table 5.5 Cross-validated error rates from each evaluation scenario



	Pre-trained LM	New LM + Original corpus	New LM + Augmented corpus	Pre-trained LM + Original corpus + Pooled	Pre-trained LM + Original corpus + Interpolated	Pre-trained LM + Augmented corpus + Pooled	Pre-trained LM + Augmented corpus + Interpolated
■ WER	46.63%	41.82%	43.10%	45.03%	43.28%	44.56%	42.76%
■ CER	49.38%	39.49%	45.05%	47.12%	42.40%	47.04%	44.02%

Cross-validated experiments show that all our methods improved DeepSpeech performance since we observe lower error rates as compared to the baseline in each experimented scenario. We note a maximum absolute reduction of 4.81% WER and 9.9% CER in our experiments, which translates into a 10.31% relative reduction in WER and 20.04% CER. Table 5.5 presents a bar chart plot and values of error rates in each scenario, while Table 5.6 lists the absolute and relative differences as compared to the baseline.

Table 5.6 Absolute and relative change in error rates compared to baseline

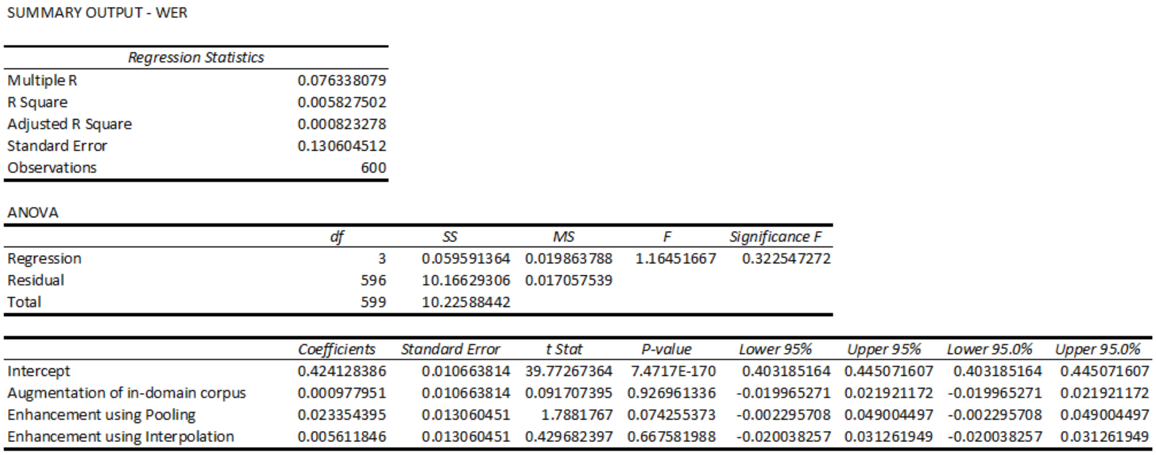
Evaluation Scenario	**Critical Error Rate**	**Absolute Difference (CER)**	**Relative Difference (CER)**	**Word Error Rate**	**Absolute Difference (WER)**	**Relative Difference (WER)**
Baseline *Pre-Trained LM*	49.38%	0.00%	0.00%	46.63%	0.00%	0.00%
New LM + Original corpus	39.49%	**-9.9%**	**-20.04%**	41.82%	**-4.81%**	**-10.31%**
New LM + Augmented corpus	45.05%	-4.33%	-8.77%	43.10%	-3.53%	-7.57%
Pre-trained LM + Original corpus + Pooled	47.12%	-2.26%	-4.59%	45.03%	-1.6%	-3.43%
Pre-trained LM + Original corpus + Interpolated	42.40%	-6.98%	-14.13%	43.28%	-3.35%	-7.18%
Pre-trained LM + Augmented corpus + Pooled	47.04%	-2.35%	-4.75%	44.56%	-2.07%	-4.43%
Pre-trained LM + Augmented corpus + Interpolated	44.02%	-5.36%	-10.86%	42.76%	-3.87%	-8.29%

As we presented multiple methods that are applied in combination with each evaluation scenario, we were interested in analyzing the impact of each individual method on the performance of DeepSpeech. Therefore, we defined four independent variables based on our methods, whose values represent results from each experimented scenario. Table 5.7 lists all variables and their values along with the scenarios that are represented by each value combination. We assigned the value 1 to denote a True or 'Yes', meaning that the respective variable was applied to the scenario, whereas, the value 0 denotes False or 'No'.

Table 5.7 Variables to analyze each experimented method

Variables → Evaluation Scenario ↓	Augmentation of Original corpus	Development of in-domain LM	Enhancement of Pre-Trained LM using Pooling	Enhancement of Pre-Trained LM using Interpolation
3	0	1	0	0
4	1	1	0	0
5	0	0	1	0
6	0	0	0	1
7	1	0	1	0
8	1	0	0	1

Based on these variables, we analyzed the contribution of each method in improving the performance of DeepSpeech. For this analysis, we applied linear regression where the null hypothesis is that there is no change in performance within the different experimented scenarios. Our analysis used only three of these variables since we had to drop the use of variable "*Development of in-domain LM*" due to its direct correlation with other enhancement variables (*"Enhancement of Pre-Trained LM using Pooling"* and *"Enhancement of Pre-Trained LM using Interpolation"*). In scenarios 3 and 4, we experimented with the methods that are based on the dropped variable; however, values from other variables are still able to represent these scenarios (False for both of enhancement variables translates into a True for dropped variable). We applied regression analysis on both error rates individually by keeping them as the dependent variables. Figure 5.3 shows the results summary of regression analysis when WER is taken as the predicted variable. Figure 5.4 shows the results summary of regression analysis for CER. In total 6 scenarios were compared each having 100 observations, therefore the summaries have shown 600 observation count.



SUMMARY OUTPUT - WER

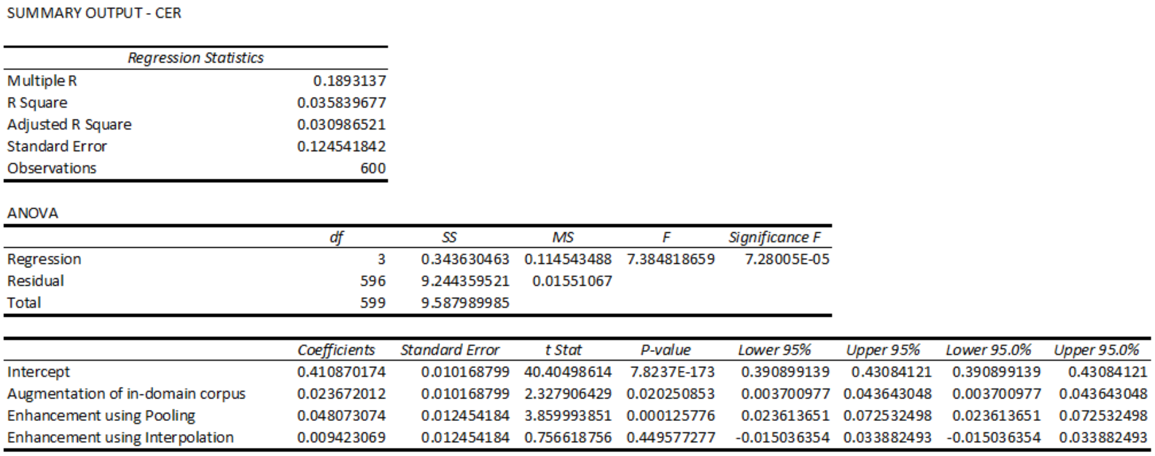
Regression Statistics	
Multiple R	0.076338079
R Square	0.005827502
Adjusted R Square	0.000823278
Standard Error	0.130604512
Observations	600

ANOVA

	df	*SS*	*MS*	*F*	*Significance F*
Regression	3	0.059591364	0.019863788	1.16451667	0.322547272
Residual	596	10.16629306	0.017057539		
Total	599	10.22588442			

	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*	*Lower 95.0%*	*Upper 95.0%*
Intercept	0.424128386	0.010663814	39.77267364	7.4717E-170	0.403185164	0.445071607	0.403185164	0.445071607
Augmentation of in-domain corpus	0.000977951	0.010663814	0.091707395	0.926961336	-0.019965271	0.021921172	-0.019965271	0.021921172
Enhancement using Pooling	0.023354395	0.013060451	1.7881767	0.074255373	-0.002295708	0.049004497	-0.002295708	0.049004497
Enhancement using Interpolation	0.005611846	0.013060451	0.429682397	0.667581988	-0.020038257	0.031261949	-0.020038257	0.031261949

Figure 5.3 Result summary of regression analysis using WER



SUMMARY OUTPUT - CER

Regression Statistics	
Multiple R	0.1893137
R Square	0.035839677
Adjusted R Square	0.030986521
Standard Error	0.124541842
Observations	600

ANOVA

	df	*SS*	*MS*	*F*	*Significance F*
Regression	3	0.343630463	0.114543488	7.384818659	7.28005E-05
Residual	596	9.244359521	0.01551067		
Total	599	9.587989985			

	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*	*Lower 95.0%*	*Upper 95.0%*
Intercept	0.410870174	0.010168799	40.40498614	7.8237E-173	0.390899139	0.43084121	0.390899139	0.43084121
Augmentation of in-domain corpus	0.023672012	0.010168799	2.327906429	0.020250853	0.003700977	0.043643048	0.003700977	0.043643048
Enhancement using Pooling	0.048073074	0.012454184	3.859993851	0.000125776	0.023613651	0.072532498	0.023613651	0.072532498
Enhancement using Interpolation	0.009423069	0.012454184	0.756618756	0.449577277	-0.015036354	0.033882493	-0.015036354	0.033882493

Figure 5.4 Result summary of regression analysis using CER

The ANOVA results from regression analyses reject the null hypothesis when CER is taken as the performance factor, which provides the domain-specific error rate. Due to the importance of critical errors, we argue that some of our methods have a significant impact on the performance of recognition than others, even when there does not seem to have a significant difference in general word errors. However, in these analyses, we were not able to support any single method in providing a significant contribution to error reduction. Therefore, we investigated more on our results to see the combined effects of our methods.

We firstly analyzed the results of those scenarios that applied the augmentation method to compare with those scenarios that used original datasets. We observe that the augmentation method increased error rates as compared to those language models that were created only with our original dataset corpus. However, in those scenarios where we were enhancing the pre-trained language model, the augmentation method did show some reduction in error rates. We noted a maximum of 1.19% relative reduction in WER and 0.18% relative reduction in CER; however, these reductions are not reliable, as we also observe substantial increase (3.81% relative) in critical errors when enhancement is done using an interpolation method. Table 5.8 mentions absolute and relative differences between all scenarios using original and augmented datasets.

Table 5.8 Comparing error rates between original and augmented corpus

	CER			WER		
	New LM	**Pre-Trained LM +Pooling**	**Pre-Trained LM +Interpolation**	**New LM**	**Pre-Trained LM + Pooling**	**Pre-Trained LM +Interpolation**
Original corpus	39.49%	47.12%	42.40%	41.82%	45.03%	43.28%
Augmented corpus	45.05%	47.04%	44.02%	43.10%	44.56%	42.76%
└*Absolute Diff.*	5.57%	-0.08%	1.62%	1.28%	-0.47%	-0.52%
└*Relative Diff.*	14.10%	-0.18%	3.81%	3.05%	-1.03%	-1.19%

Secondly, we analyzed all those scenarios which train new language models to compare with those scenarios that enhance the pre-trained model using the pooling method as well as those using the interpolation method. We note that enhancement, in general, is not effective in reducing error rates; however when interpolation is used to enhance the pre-trained model, we observed 2.29% relative reduction of CER and 0.78% of WER using the augmented corpus. From all other scenarios, a new language model using only the original (un-augmented) corpus gave us the lowest error rates. Table 5.9 and Table 5.10 lists the absolute and relative differences in error rates when using pooling and interpolation methods in comparison to the new domain-specific language modeling method.

Table 5.9 Comparing error rates between new and enhanced pooled model

	CER		WER	
	Using Original Corpus	**Using Augmented Corpus**	**Using Original Corpus**	**Using Augmented Corpus**
New LM	39.49%	45.05%	41.82%	43.10%
└Enhanced LM using Pooling	47.12%	47.04%	45.03%	44.56%
└*Absolute Difference*	7.63%	1.98%	3.21%	1.46%
└*Relative Difference*	19.33%	4.40%	7.67%	3.40%

Table 5.10 Comparing error rates between new and enhanced interpolated model

	CER		WER	
	Using Original Corpus	**Using Augmented Corpus**	**Using Original Corpus**	**Using Augmented Corpus**
New LM	39.49%	45.05%	41.82%	43.10%
└Enhanced LM using Interpolation	42.40%	44.02%	43.28%	42.76%
└*Absolute Difference*	2.92%	-1.03%	1.46%	-0.33%
└*Relative Difference*	7.39%	-2.29%	3.48%	-0.78%

To sum up our analysis, we observe three key performance behaviors of our methods. 1) The pooling method to enhance the pre-trained model has the least impact on the reduction of error rates. 2) The application of the augmentation method on our original dataset, however, did enhance the impact of the pooling method, yet it was not able to surpass the standalone impact of the interpolation method. 3) Nevertheless, the development of simple domain-specific language models has the highest impact, although, enhancement of the pre-trained model seems a more logical option as it provides an opportunity to generate models that are trained on a larger set of information.

To understand these behaviors, we analyzed the construction of the clinical notes from our dataset i.e., our target domain. In the notes, we observe many patterns that were recurring in almost the whole dataset. An instance that we observe that usually occur in the start of every note is, “This is a <age> <weeks/month/year> old <white/black/other ethnicity> <male/female> …”. Some examples that follow this pattern are; “This is a 2 months old white male …”, “This is a 4-year-old black female ...”. Due to many of such patterns that physicians mostly follow while dictating notes, a language model needs to learn them in order to perform efficient recognition. If there happens to be a glitchy output from the acoustic side, a language model will only be able to refine that output if it is already aware of such patterns. The main purpose of language model training is, in fact, to pick the recurring patterns from the training set. Therefore, when we talk about the pre-trained model, it implies that this model has already identified patterns from the datasets on which it was trained. Hence, when we try to enhance the pre-trained model, we try to teach it some new patterns. The pre-trained model was trained on about 4 gigabytes of text, whereas the text from our original dataset all combined is not more than 150 kilobytes. Therefore, we consider that our smaller text corpus was not able to make a significant impact while enhancing the pre-trained model due to the smaller size. The property of the pooling method to give equal weight to all data sources also supports this idea. This also explains the increased impact of error reduction by the use of the augmentation dataset, as it increases the size of the domain-relevant text corpus.

After analysis, we selected language models from all scenarios for the second phase experiments, except those scenarios that implement the pooling method. We dropped the pooling method for further evaluations due to two main reasons. Firstly, it has shown the least performance gains, as we have mentioned above. Secondly, pooling is one of the two model enhancement methods that we experimented with; therefore, we only wanted to continue with one best method of enhancement.

5.5 Combined Evaluation

In this section, we provide our second phase of evaluation. In this phase, no new model was trained, instead, the best performing models; that we selected from previous evaluations; were analyzed further. We selected multiples of both: acoustic and language; models and tested all their combinations on our original dataset using the same cross-validation folds upon which the models were trained. Table 5.11 lists the error rates for all tested combinations in this evaluation phase.

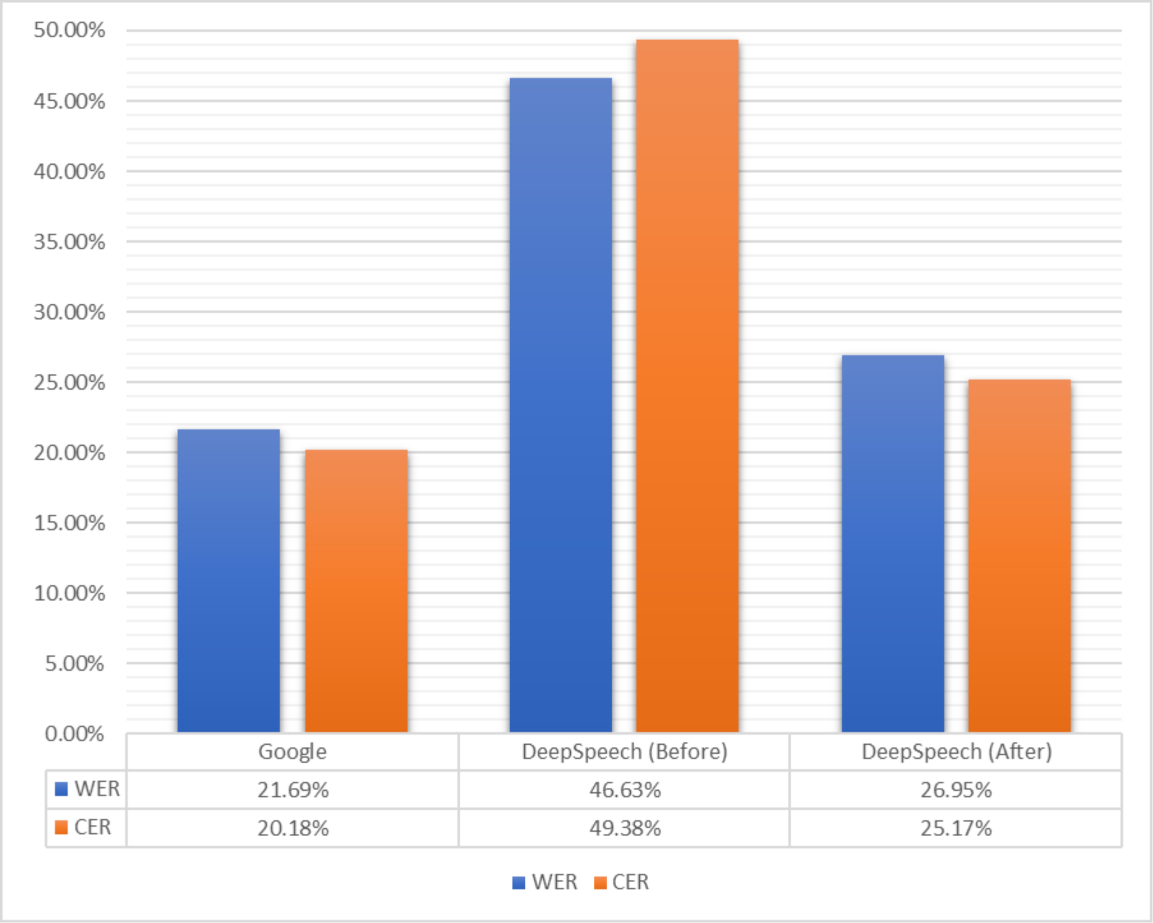
Table 5.11 Error rates after testing with combined models.

	CER			WER		
Acoustic Model → **Language Model ↓**	4th Epoch	5th Epoch	6th Epoch	4th Epoch	5th Epoch	6th Epoch
Pre-trained LM + Original Corpus + Interpolated	26.55%	26.04%	25.51%	28.30%	28.12%	27.90%
Pre-trained LM + Augmented Corpus + Interpolated	25.73%	25.89%	25.17%	26.97%	27.41%	26.95%
New LM + Original Corpus	24.03%	24.28%	24.05%	27.18%	27.51%	27.35%
New LM + Augmented Corpus	26.65%	26.10%	25.74%	27.13%	27.49%	27.23%

5.5.1 Analysis

The combined evaluation showed that we achieved the lowest word error rate (WER: 26.95%) from the combination of the acoustic model of the 6th epoch and the pre-trained language model that is enhanced using augmented corpus. However, this model combination was slightly behind with respect to critical error rates. The lowest critical error rate (CER: 24.03%) was achieved by the 4th epoch acoustic model in combination with a new language model that was trained using only the original dataset.

The analysis of results shows that the language modeling methods of dataset augmentation and model interpolation works best in combination to reduce general error rates. In terms of WER, the augmented interpolated language models performed better than standalone augmented and standalone interpolated models and were also the overall best performing models.



	Google	DeepSpeech (Before)	DeepSpeech (After)
■ WER	21.69%	46.63%	26.95%
■ CER	20.18%	49.38%	25.17%

Table 5.12 Performance comparison of DeepSpeech (before and after) with Google

When analyzing critical errors, we found that the 4th epoch acoustic model did less critical mistakes when combined with new language models, and the 6th epoch acoustic models did less critical mistakes with interpolated language models. However, the lowest critical error rate was achieved by newly trained language models on the original dataset. The augmented interpolated language models were the second-lowest with about 4.7% relative difference.

In the end, we found that all of our acoustic and language modeling methods, in combination, were able to significantly improve the performance of DeepSpeech by reducing error rates from 46.63% to 26.95% WER and from 49.38% to 25.17% CER. This reduction relatively translates into a 42.2% reduction in WER and 49.02% in CER. This improvement enables DeepSpeech to deliver performance that is relatively close to the performance of top-of-the-line cloud-based SR (Google). Table 5.12 shows the error rates of Google, DeepSpech before applying our methods and DeepSpeech after applying our acoustic and language modeling methods.

5.6 Working Examples

In this section, we have provided examples of critical and word errors within the transcribed notes that we observed with the best performing model combinations. In this section, we present a best-case examining transcribed note with the least critical errors, a worst-case examining a note with the most critical errors and two random cases. The two model combinations that we are examining are 1) 4th epoch acoustic model and new language model with the original corpus, and 2) 6th epoch acoustic model and enhanced pre-trained language model with the augmented corpus.

5.6.1 Best Case

In all our 100 notes, the best-transcribed note achieved a CER as low as 6.25% with the 1st model combination where it made only 5 critical mistakes out of 80 total critical concepts. With the 2nd model combination, it achieved 7.5% CER and made 6 critical mistakes. The quality of the corresponding speech in the audio note is found to be clear without any background noise. The dictation is at a normal pace and it appears to be recorded in a closed room with a relaxed environment. Almost all critical mistakes, in this case, were found to be homonyms. For example, “enterovirus” was mistaken as “ether is” and “two older” as “told or”. Table 5.13 lists transcriptions from both model combinations. All the highlighted and bold words and phrases are the errors. The yellow highlights are general word errors, while green highlighted and underlined are critical errors.

Table 5.13 Errors in the best transcribed note

Ground Truth	**AM: 4th Epoch** **LM: New LM + Original Corpus**	**AM: 6th Epoch** **LM: Pre-trained LM + Augmented Corpus + Interpolation**
excerpt seven	*excerpt seven*	*excerpt seven*
past medical history	*past medical history*	*past medical history*
on birth history BLANK was full term	*on birth history BLANK was full term*	*on birth history BLANK was full term*
she had a previous admission for bronchiolitis to the p m u and this was for a r s v positive bronchiolitis on BLANK	*she had a previous admission for bronchiolitis to the p m u and this was for* ***an*** *r s v positive bronchiolitis on BLANK*	*she had a previous admission for bronchiolitis to the p m u and this was for* ***an*** *r s v positive bronchiolitis on BLANK*
she has been followed for peripheral pulmonary artery stenosis by cardiology	*she has been followed* ***per four*** *peripheral pulmonary artery stenosis by cardiology*	*she has been followed for peripheral pulmonary artery* ***talusin*** *cardiology*
she has also had most recently bronchiolitis with human rhinovirus enterovirus on BLANK	*she has also had most recently bronchiolitis with human rhinovirus enterovirus on BLANK*	*she has also had most recently bronchiolitis with human rhinovirus* ***ether is*** *on BLANK*
this required a short admission to i c u for high flow	***is*** *required a short* ***emission*** *to i c u for high flow*	***is*** *required a short admission to i c u for high flow*
medications vitamin d four hundred international units once daily	*medications vitamin d* ***for*** *hundred international units once daily*	*medications vitamin d* **for a** *hundred international units once daily*
allergies no known drug allergies immunizations up to date	*allergies no known drug allergies immunizations up to date*	*allergies no known drug allergies immunizations up to date*
family history BLANK so it is unclear of her family history	*family history BLANK so* ***as on clear*** *of her family history*	*family history BLANK so* ***desone clear*** *of her family history*
social history BLANK lives with mom and two older siblings BLANK and BLANK years old BLANK	*social history BLANK* ***less*** *with mom and* ***told or*** *siblings BLANK and BLANK years old* ***old*** *BLANK*	*social history BLANK* ***lysis*** *with mom and* ***told or*** *siblings BLANK and BLANK years old BLANK*
several family members had been recently	*several family members* ***have*** *been recently*	*several family members* ***have*** *been recently*

5.6.2 Worst Case

In our results, the worst transcription achieved the CER of 59.6% with 2nd model combination and 54.8% CER with 1st model combination. We observed that the quality of the corresponding audio note is significantly lower than other notes. We note high echo and reverberation in the audio while appearing that the speaker is away from the recording device. This audio note was also filled with a high amount of background noise, especially the overlapping noise that is corrupting the speech signals. We hear loud baby cries and parents trying to soothe the baby in the background by talking and playing with the baby. These interruptions reflect on the mistakes. For example, in one place "abdominal pain" is mistaken as "a dona panadol". This transcription is not a homonym for its gold standard. Another similar example is when "upper respiratory tract infection" transcribes into "offer reichstein". These examples show that due to overlapping noise, a lot of speech signal is lost, resulting in a sloppy transcription. Table 5.14 presents the comparison of transcriptions for both model combinations. Green highlights show critical mistakes.

Table 5.14 Errors in the worst transcribed note

Ground Truth	AM: 4th Epoch LM: New LM + Original Corpus	AM: 6th Epoch LM: Pre-trained LM + Augmented Corpus + Interpolation
this is a four year almost five year old female with trisomy twenty one	***he*** *is a four year* ***always*** *five year old female* ***at ten*** *twenty one*	***he*** *is a four year* ***as*** *five year old female* ***as try*** *twenty one*
presenting with two to three week history of upper respiratory tract infection that has lingered awakening with a cough and having the cough during the day and sometimes at night	***is an in a*** *to* ***the*** *three* ***weeks*** *history* ***as offer rather*** *infection* ***of lines waiting*** *with* ***her*** *cough and having* ***(the)*** *cough during the day and* ***some time*** *at night*	***is anion so*** *to three weeks history* ***as offer reichstein of linear waiting*** *with* ***call*** *and having* ***(the)*** *cough during the day* ***had some time (at) tight***
ventolin of no benefit recently	***that on*** *no* ***better we***	***that on*** *no* ***batel rashes***
she has had no fevers with this	*she* ***(has)*** *had no fevers with this*	***(she has) at*** *no fevers with this*

possible headache no other pain	***four** headache **nor her** pain*	***four endantadine***
she has had abdominal pain and vomiting a week ago that resolved over about a day and resulted in multiple episodes of vomiting	*she has had **a do paid** (**and**) vomiting a week **no** that resolved over about a **vein** (**and**) **result is well colitis following***	*she has had **a dona panadol in** a week **no** the resolved over about **ada in result as well colicines following***
she has been on p o steroids for the last five days as per the parents usual approach to acute asthma	*she **says** on p o **per i** for (**the last**) five days **her** the parents usual **got his used for as no***	*she **see n** p o **ser** for (**the last**) five days **her** the parents usual **proctocele for as mopeg***
paragraph past medical history immunizations are up to date	*paragraph past medical history immunizations are (**up to**) date*	***ph** past medical history immunizations (**are**) up to date*
she has had a tetralogy of fallot repaired trisomy twenty one and she is on valproic acid and clobazam for seizure disorder which is quiescent for the last two years	***ten** had **also or care** trisomy twenty one and she (**is**) on **a for** acid **episode** for (**seizure disorder**) which is **a** two years*	***on fenoterol some or paired** trisomy twenty one and she (**is**) on **dolo acidic anorectics** two years*
on exam no respiratory stress normal air entry with no wheeze airway breathing and circulation stable	*on exam no respiratory stress normal **artery** with no **wheezer we** breathing **in certain** stable*	*on exam no respiratory stress normal **reentry** with no **leader we** breathing and circulation stable*
pink soft belly normal left ear normal right ear	***pain saw a day normal as** ear **nor rays***	***pain sagatal** normal **last** ear **nor river***
snotty nose but not dramatically swollen tonsils, slightly red, no pus. not dramatically acute	***not of note a iron in last or or to widened no refused to one week ago i saw so so i group is probably a mild mild being a certain in wide per were more operation the in are work but i do an a b released***	***nodose but no oestro intraorbital red neural perforin was miosis so so iridoids probably mild iletin ceresan viper werner osteoid an a b q resin***

5.6.3 Random Cases

We chose two random notes, in between the above-presented best and worst cases, to analyze the mistakes. Upon examining the corresponding audio recordings, we found that the noise levels remained between the above-defined two example cases. There were no overlapping noises, however, we could listen to some reverberation. On a few occasions, the physician's dictation pace increased dramatically, which directly increased mistakes in transcriptions. On one of such occasions, the phrase "feet swept out from underneath him" was mistaken as "feet slept out from under eat him".

The first random note we examined achieved 11.66% CER with the 1st model combination and 14.4% CER with 2nd model combination. Table 5.15 mentions the transcription we received with both model combinations.

Table 5.15 Errors in the first examined note transcription

Ground Truth	**AM: 4th Epoch** **LM: New LM + Original Corpus**	**AM: 6th Epoch** **LM: Pre-trained LM + Augmented Corpus + Interpolation**
this is an eighteen month old black female	*this is a **ten** month old black female*	*this is a **ten** month old black female*
presenting with a seizure like episode at home	*presenting with a seizure like episode at home*	*presenting with a seizure like episode at home*
child was perfectly well until three days ago when sniffles and cough became apparent	*child was perfectly well until three days ago when sniffles and cough became apparent*	*child was perfectly well until three days ago when sniffles and cough became apparent*
last evening at about eighteen hundred hours the child experienced a mild fever of thirty eight point five	*last evening **(at)** about eighteen hundred hours the child **experience on** mild **(of)** fever thirty eight point five*	*last evening **(at)** about eighteen hundred hours the child **experience** a mild fever (of) thirty eight point five*
this morning on rousing her from her bed and she stiffened exhibited five to fifteen seconds of shaking movements suggestive of	*this morning on **rising** her **for** her bed **if** she stiffened **excited** five to fifteen seconds of **of** shaking **movement** suggestive of*	*this morning on **the rising** her **for** her bed **if** she stiffened **excited** five to fifteen seconds of **of** shaking **movement***

tonic clonic seizure and then settled into a deep sleep from which she roused fifteen minutes later	tonic clonic seizure and **in** settled into a deep sleep **for** which she **was** fifteen minutes later	suggestive of tonic clonic seizure and **intensain** to a deep sleep **for** which she **resistin** **in the** later
by the time she arrived at the i w k emergency she was awake and alert and cranky	**in** time she **wrist** the i w k emergency is she was awake and alert and cranky	**date** she arrived at the i w k emergency i she was awake and alert and cranky
parents have never seen similar seizure activity before	parents have never seen similar seizure activity before	parents have never seen similar seizure activity before
past medical history reveals immunizations up to date and normal birth and pregnancy history with no specialist and no regular medications and no known allergies	past medical history **revealed** immunizations up to date **a** normal birth and pregnancy history with no **specialists** and no regular medications and no known allergies	past medical history reveals immunizations up to date **a** normal birth and pregnancy history with no specialist and no regular medications and no known allergies
family history reveals febrile seizures in dad as a child	family history reveals febrile seizures in dad as a child	family history reveals febrile seizures in **dead** as a child
physical exam revealed a cranky child who settled with care	physical exam revealed a cranky child who settled with care	physical exam revealed a cranky child who settled with care
ear nose and throat exam revealed a red throat with no exudate suggestive of a viral pharyngitis	ear nose and throat exam revealed a red throat with no **x date** suggestive of a viral pharyngitis	ear nose and throat exam revealed a red throat with no **exo date** suggestive of a viral **paris**
ears were normal lungs were clear	ears were normal lungs were clear	ears were normal lungs were clear
cardiac exam was unremarkable	cardiac exam was unremarkable	cardiac exam was unremarkable
abdominal exam was normal	abdominal exam was normal	abdominal exam was normal
neurological exam revealed a child who following ibuprofen was playful and interactive and no focal finding on	neurological exam revealed a child who following ibuprofen was playful and **interim** and no focal findings on	neurological exam revealed a child who following ibuprofen was playful and **interacting** and no focal findings under local exam **is** **cover**

neurological exam was discovered	neurological exam is **descend**	
new paragraph impression is that this is simple febrile seizure	new paragraph impression is that this is simple febrile seizure	new paragraph impression is that this is simple febrile seizure
parents were counseled and reassured	parents were counseled and reassured	parents were counseled and reassured
instructions were given with regards to the delivery of ibuprofen as needed for pain and fever but the parents were cautioned that this would not reduce the risk of further seizures.	instructions were given with regards to the delivery of ibuprofen as needed for pain and fever by the parents were **cousin** that this would not **reduced** the risk of **for other** seizures	instructions were given with regards to the delivery of **i do** **provided** for pain and fever but the parents were **cation** that this would not **reduced** the **rose** of further seizures
we stated the seizure risk at about one or two percent over the rest of this illness	we **stayed** the seizures **(risk)** at about one or two percent over the rest of the illness	we **state** the seizure risk at about one or two percent over the rest of the **sinus**
but cautioned them that further febrile seizures were likely between now and six years of age	but **out on** them that further febrile **i sure** were likely between now and six years of age	but **cation** them that further febrile **tissue** **(were)** likely between **no** and six years of age
her parents were advised to return to the emergency department with further seizures for further assessment	**a** parents were advised to return to the emergency department with rather seizures **refer her** assessment	**a** parents were advised to return to the emergency department with further seizures **refer** assessment
diagnosis viral upper respiratory tract infection with febrile seizure	diagnosis **for** upper respiratory tract infection with febrile seizures	diagnosis **boro** upper **parry** tract infection with febrile seizure

The second random note we examined achieved 22.41% CER with the 1st model combination and 24.13% CER with 2nd model combination. Table 5.16 shows the transcription of the second random note we examined.

Table 5.16 Errors in the second examined note transcription

Ground Truth	**AM: 4th Epoch** **LM: New LM + Original Corpus**	**AM: 6th Epoch** **LM: Pre-trained LM + Augmented Corpus + Interpolation**
excerpt thirty one	*excerpt thirty one*	*excerpt thirty one*
medications at admission	*medications at admission*	*medications at admission*
two hundred and fifty milligrams of amoxil t i d for ten days started on BLANK	***to turn*** *fifty milligrams of* ***a lot p*** *i d for ten days* ***see*** *on BLANK*	***to endrin*** *fifty milligrams of* ***a moban*** *t i d for ten days* ***are*** *on BLANK*
examination at admission	*examination* ***and*** *admission*	*examination* ***and*** *admission*
BLANK was afebrile and vitally stable	*BLANK is* ***a febrile advised this table***	*BLANK was* ***a febrile*** *and* ***vita e table***
head and neck exam was unremarkable cervical lymph nodes were palpable and less than one point five centimeters in diameter	*head and neck exam was unremarkable* ***service*** *lymph nodes* ***with health able*** *and less than one point five centimeters* ***and via***	*head and neck exam was unremarkable* ***service*** *lymph nodes* ***but*** *palpable and less than one point five centimeters* ***and dia***
cardiac exam was normal	*cardiac exam was normal*	*carb exam was normal*
respiratory exam showed increased work of breathing	*respiratory exam showed increased work of* ***everting***	*respiratory exam showed increased work of* ***retin***
intercostal indrawing on the right side	*intercostal indrawing on the right side*	*intercostal* ***in von*** *on* ***vit*** *side*
good air entry bilaterally and course crackles and wheezes throughout both lung fields	***a*** *good air entry bilaterally and course crackles* ***one a throat business***	***a*** *good air entry bilaterally and coarse crackles and* ***tear out pulseless***
her abdominal exam was unremarkable	*her abdominal exam was unremarkable*	*her abdominal exam was unremarkable*
allergies none	*allergies* ***non***	*allergies* ***on***
immunization status	*immunizations status*	*immunizations status*

After reviewing the individual cases, we observed that DeepSpeech was able to understand the domain-specific speech for the most part. However, we noted 3 factors that are prominently linked with the errors.

1) Reverberation

   On average our dataset has low levels of reverberation. However, those audio notes having high reverberation are consistently linked with high numbers of errors.

2) Overlapping Noise

   Similar to reverberations, most of the notes in our dataset have moderate noise levels that do not interfere with the speech. Therefore, such instances skew the performance of transcriptions to a large extent.

3) Dictation Pace

   Within the notes, we observed that the commonly occurring phrases are uttered at a high pace, while complicated sentences are uttered slowly. However, when the speech pace is up, transcription starts to show errors mostly by skipping critical words.

5.7 Final Validation

In this section, we report the results of our acoustic and language models on a separate validation dataset. In the process of dataset preparation (Section 3.4.2), we separated a validation set that we did not use in any of our prior experiments. Therefore, in this final validation, we used our validation dataset upon all of our selected models, which were trained from the whole original dataset. Table 5.17 lists the error rates for all model combinations.

Table 5.17 Error rates on the validation dataset

	CER			WER		
Acoustic Model → **Language Model ↓**	4th Epoch	5th Epoch	6th Epoch	4th Epoch	5th Epoch	6th Epoch
Pre-trained LM + Original Corpus + Interpolated	32.09%	30.52%	30.41%	35.99%	34.39%	34.65%
Pre-trained LM + Augmented Corpus + Interpolated	33.24%	32.04%	33.30%	35.20%	34.23%	35.02%
New LM + Original Corpus	30.98%	29.63%	28.96%	34.99%	34.14%	33.84%
New LM + Augmented Corpus	34.30%	33.89%	34.61%	35.70%	35.34%	35.79%

We observed similar behaviors from the results of the final validation. With respect to WER, the lowest error rates were from the enhanced pre-trained models that use the augmented dataset and newly trained models on the original dataset. The lowest two error rates from these language models only had an absolute difference of 0.09%. However, with respect to CER, we found that newly trained models on the original dataset did a relative maximum of 5% less critical mistakes then the enhanced pre-trained models.

5.8 Discussion

Throughout the evaluations, we observe that newly trained language models on our original (un-augmented) dataset were performing similar to, or sometimes better than those language models that apply our augmentation and model enhancement methods, specifically in regard to critical errors. We consider that this was due to the extremely small size of our dataset, which impacts the performance in two ways.

1) Language modeling is all about vocabulary and speech patterns. Thus, the small size of our dataset does not cover both aspects sufficiently to reflect the target domain. We tried to handle the vocabulary aspect by dataset augmentation method; however, we were not able to introduce more domain-specific speech patterns.

2) The pre-trained model is trained on a significantly larger dataset than ours. Moreover, when our small dataset breaks down into folds for cross-validation, it creates many unseen scenarios for the testing. Thus, all those unseen domain-specific speech patterns get compensation by the prior knowledge of the pre-trained model, which does not reflect our target domain.

In addition to these two reasons, our limited implementation of the augmentation method also hinders the reduction of critical errors. Since our definition of critical errors entails all the domain-specific vocabulary, yet we only used two domain-specific classes (drugs and diseases) to augment our augmentation method. Therefore, all the concepts of remaining domain-specific classes also remain unseen in the experiments with testing folds.

The interpolation method that develops a language model using information from multiple data sources has the ability to adjust in case the volume of data is not similar across all sources. As there is a huge size difference in the data source of the pre-trained language model and our dataset, the interpolation method logically has the means to cope up in this situation. However, interpolation requires a separate tuning set from the target domain to calculate weights for each data source. Since our dataset is already limited, fetching a tuning set from it makes it even smaller. Therefore, we found that in our experiments the interpolation method performed fairly closer to stand-alone models, but they were not able to surpass the performance. Had we had a slightly larger dataset; we consider that the interpolation method would have been the best in performance.

5.9 Conclusion

This chapter presents an evaluation of our defined methods. We have shown that by using the fine-tuning method on the pre-trained deep speech acoustic model, WER relatively decreased by 40.32% CER by 44.88% on our original dataset. After applying the data augmentation method to our dataset and using the interpolation method to enhance the pre-trained language model, we managed to reduce the error rates further relatively by 42.2% WER and 49.02% CER. In our evaluations, we observed that the pooling method to enhance the pre-trained language model had the least impact on the reduction of error rates. Furthermore, when we applied our language modeling methods in isolation, neither of those methods had a reducing impact on error rates. However, when applied in combination, we observed lower error rates when the pre-trained language model was enhanced using the interpolation method and augmented dataset.

Chapter 6. CLASSIFICATION OF TRANSCRIPTION INTO SOAP CATEGORIES

6.1 Introduction

This chapter presents our work to categorize clinical transcriptions as a SOAP structured clinical report. To achieve our second objective, we have selected an exemplar-based concept detection algorithm [102] with the motivation to extend it for SOAP classification. This algorithm was chosen particularly due to its nature of using the word n-gram based approach that we consider working in our problem. In previous work, Mowery [101] have used an n-gram based approach as well and showed positive results. However, their work poses two major limitations. This exemplar-based algorithm takes care of both limitations. Firstly, it makes use of overlapping word grams that fully exploit the sentence sequences. Secondly, since it works on exemplar matching, it should not have an impact on class imbalance.

6.2 Methods

6.2.1 Assigning SOAP categories to Dataset

Our dataset did not provide prior assignments of sentences into SOAP categories; hence we perform data labeling manually on our dataset. We perform this task before working on methods to analyze class proportions of our dataset and to make logical decisions. To label the sentences within our dataset, we referred to the definitions of SOAP categories and related literature to identify the guiding principles for each category. Learning on those principles we skimmed over the dataset looking for commonly occurring patterns within each category. Based on the understanding we developed by these guiding principles and patterns, we heuristically assigned a SOAP label with each sentence within our dataset. The heuristics we applied for each of the SOAP category is given below.

1) Subjective

   Sentences having narrations of tales happened to patients and are from the patient's perspective. Subjective sentences are mostly in the past tense defining a scene involving the patient. There can be some present tense sentences as well in this category that are limited to the responses that are coming from patients. The only exception we have noticed in this category is mostly the first sentence where the physician starts a note by describing the demographics of the patient. Table 6.1 lists the patterns that we observed in the sentences that we labeled as 'Subjective'.

Table 6.1 Patterns observed in subjective category sentences

Patterns	Comments
<Child/He/She> <is/was/has> ...	Since physicians are narrating patients' perspectives, usually a pronoun 'Child', 'He' or 'She' starts a sentence along with a helping word from present or past tense. A tale about patient then follows.
family history ...	When describing the family history, physicians generally start with the phrase itself and then dictate the contents.
immunizations are <up to date>	Physicians are mostly talking about immunizations in every note. For all the notes we examined, we did not find any case where the content changed. However, we think that the phrase 'up to date' will change if a different case happens.
past medical history <is non-contributory/reveals ...>	Similar to family history, physicians start talking about past history with this phrase. If such history is not contributing to the case, then they mention mostly.
this is a <age> <days/months/years> old <boy/girl/male/female> ...	This is the most frequent pattern in all notes and comes at the very start.

2) Objective

Sentences that describe observations of the physician on the patient. These sentences are written in either past or present tense and are usually short in length. They usually start with a laboratory test or examination type and then provide a result to those tests or results. Table 6.2 shows the patterns for which we labeled 'Objective' sentences.

Table 6.2 Patterns observed in objective category sentences

Patterns	Comments
<EXAM NAME> <is/was> <normal/unremarkable/uncomplicated/...>	Subjective sentences are talking about laboratory and physical exam results. Mostly these exams are good, so physicians are noting that down.
<EXAM NAME> reveals ...	In case an exam reveals something, they also mention that.
On exam <child/he/she> <was/has> ...	Mostly for physical exams, physicians simply use 'On exam'.
the rest of exam <was/is> ...	This pattern is also fairly visible in the notes.
<BODY PART> <is/are> <normal/clear/...>	While defining results of physical exam, physicians note down the state of each body part they examined.

3) Assessment

Sentences that describe the assessment of the physician on the patient. These sentences usually have the word 'diagnosis' in them along with a disease or medical condition. Table 6.3 mentions some patters for 'Assessment' sentences

Table 6.3 Patterns observed in assessment category sentences

Patterns	Comments
diagnosis is <DIAGNOSIS>	The word 'diagnosis' is prominent in assessment category sentences.
<Medicine name and dosage> was prescribed	This is a loose pattern that we don't find following a general style. In concept, this pattern mentions about the medications and treatments that are prescribed to the patient.
parents were <reassured/instructed> ...	This pattern mentions all the instructions and reassurances that the physician has given to the parents of the patient which starts with the phrase 'parents were instructed …' and 'parents were reassured that…'

4) Plan

Sentences that describe plans of the physician for the future treatments on the patient. These sentences are usually written in the future tense. Table 6.4 lists the patterns for 'Plan' category sentences.

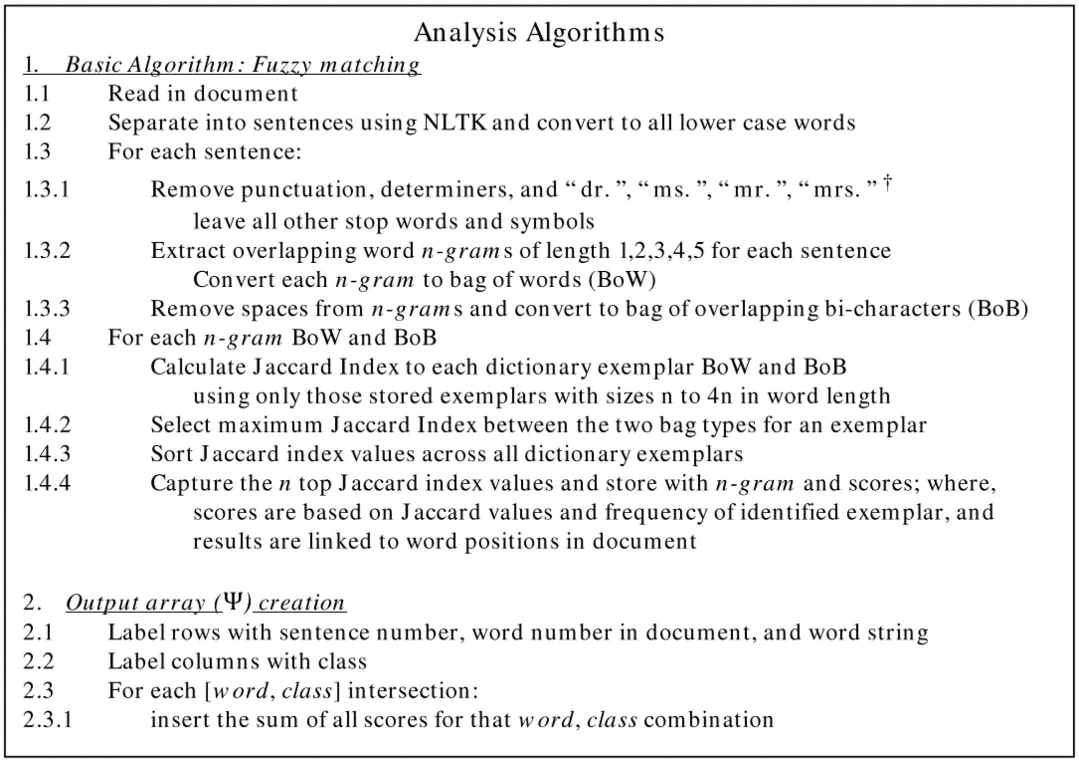
Table 6.4 Patterns observed in plan category sentences

Patterns	Comments
... follow up ...	This is a loose pattern that look for sentences with the phrase 'follow up'. One variation that we observed multiple time is "Follow up as necessary"
<child/parents> <was/were> advised to return if...	This pattern mentions the advice of physician to return if some condition happens.
<Plans for future treatments>	This is also a loose pattern. Generally, it looks for future treatment options. Physician does not seem to follow a strict word sequence for this.

All the sentences from our original dataset are extracted, and each sentence is manually labeled according to the heuristics defined above. The labeled dataset is saved such that features represent sentences and labels consist of one of the SOAP categories. In this process, we observe that there is a class imbalance in our dataset. We note around 47% Subjective, 35.3% Objective, 11% Assessment, and 6.7% Plan sentences in our dataset. The imbalance property of our dataset matches the way clinical reports are usually written. The same spread of classes is shown by Mowery [101] which also supports our observation.

6.2.2 Exemplar-based Concept Detection

Concept detection is a problem in NLP to extract relevant information from text collections. Juckett presents an exemplar-based algorithm to link text to semantically similar classes [102]. It maps each word within the text with probable class assignments. Figure 6.1 highlights the algorithm. The algorithm is named *Fuzzy matching*. Juckett then presents another algorithm *Output array creation* that takes the output values from *Fuzzy matching* to create an array of detected concepts.



```
Analysis Algorithms
1.  Basic Algorithm: Fuzzy matching
1.1      Read in document
1.2      Separate into sentences using NLTK and convert to all lower case words
1.3      For each sentence:
1.3.1        Remove punctuation, determiners, and "dr. ", "ms. ", "mr. ", "mrs. " †
                 leave all other stop words and symbols
1.3.2        Extract overlapping word n-grams of length 1,2,3,4,5 for each sentence
                 Convert each n-gram to bag of words (BoW)
1.3.3        Remove spaces from n-grams and convert to bag of overlapping bi-characters (BoB)
1.4      For each n-gram BoW and BoB
1.4.1        Calculate Jaccard Index to each dictionary exemplar BoW and BoB
                 using only those stored exemplars with sizes n to 4n in word length
1.4.2        Select maximum Jaccard Index between the two bag types for an exemplar
1.4.3        Sort Jaccard index values across all dictionary exemplars
1.4.4        Capture the n top Jaccard index values and store with n-gram and scores; where,
                 scores are based on Jaccard values and frequency of identified exemplar, and
                 results are linked to word positions in document

2.  Output array (Ψ) creation
2.1      Label rows with sentence number, word number in document, and word string
2.2      Label columns with class
2.3      For each [word, class] intersection:
2.3.1        insert the sum of all scores for that word, class combination
```

Figure 6.1 Exemplar based algorithms proposed by Juckett [102]

The *Fuzzy matching* algorithm expects to have some relevant text available that are already categorized by human annotators to train exemplars. Exemplars are defined as the collection of unique text strings that belong to specific semantic classes. In this algorithm, exemplars are stored as Bag of Words (BOW) and Bag of Bi-characters (BOB). For each sentence in the training set, an exemplar pair of BOW and BOB is created. BOW is the set of all words within the training sentence. BOB is created after removing spaces from the sentence and then extracting all overlapping character bi-grams. All generated exemplar BOW and BOB are then stored along with the class assignments of training sentences.

To perform concept detection, the query sentence is first filtered for punctuations and determiners are removed. It then creates overlapping word *n*-grams to the maximum of 5th order (1-gram, 2-gram … 5-gram). Each word *n*-gram is converted into BOW and BOB and stored. It gives a list of BOW and BOB for all possible word *n*-grams (till the order 5) within the query. For each word *n*-gram, exemplars are selected that are of length between *n* and 4*n.* For each selected exemplar, the Jaccard Index [120] of exemplar and word *n*-gram is calculated for both; BOW and BOB, and the larger of these two values is selected. After having similarity values of word *n*-gram with each exemplar, top *n* values are selected. Word *n*-gram and exemplar information for the selected values are then stored.

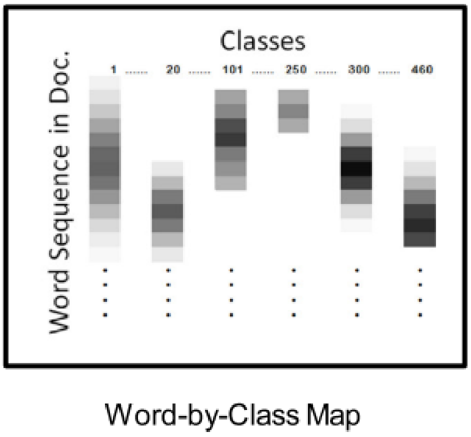


Figure 6.2 Outline of word-class array [102]

After selecting the top *n* values, the algorithm *Output array creation* generates a word-by-class map. Word-by-class map is a two-dimensional array where rows are the words in the query text, and columns are the classes. Each cell within the array gets the score of *word-class* combination. From the stored values in fuzzy matching, all values are selected whose *n*-gram has the *word*, and exemplar belongs to the *class*. All these values are then added, and the resultant value is stored as the *word-class* combination score. Figure 6.2 highlights a word-class matrix as shown in [102].

6.2.3 Exemplar-based Sentence Classification

The second objective of this thesis requires the classification of textual units from transcriptions into one of the SOAP categories. We consider sentences as a textual unit. To achieve our objective, we develop an exemplar-based sentence classification algorithm on the principles of exemplar-based concept detection by extending it to work on whole sentences and provide confidence scores for each class. We use this algorithm due to its nature to exploit word sequences. Moreover, since this algorithm work on exemplars, class imbalance does not make a huge impact. As it selects top *n* scores for each *n*-gram, it can optimally perform as long as there is a minimum of *n* exemplars available for each class.

Juckett took many assumptions during the development of the concept-detection algorithm [102]. Since we adapt and extend this algorithm for a different problem and situation, we identify four key areas that possibly develop an issue. Therefore, we investigate each of those areas to find an optimal solution. After having a solution, we consider each area as an independent variable to test the impact of our solution concerning the original implementation. Details for each identified area are given below.

1) Stop Words

   Stop words removal is a widely accepted and effective pre-processing step in various problems of NLP [121]. However, the concept detection algorithm does not remove stop words from their processing step. Moreover, in the arguments, Juckett [102] does not provide any justification for keeping the stop words. Therefore, in this work, we consider the removal of stop words since it has shown to have significant performance improvements in text categorization tasks [122]. We apply a step to remove stop words and make it optional in our classification algorithm by including it as an input parameter.

2) Maximum word *n*-gram length limit

   In the concept-detection algorithm, the query sentence converts into word-grams of varying lengths from 1-gram to the maximum of 5-grams. There were two reasons given for limiting the maximum *n*-gram length till the 5th order. Frist is that the dataset on which Juckett [102] experimented, had shorter exemplars where 2/3rd of exemplars were of word length five or less. The second reason is that each increasing word-gram length increases the computation time exponentially. In our situation, the dataset has sentences with an average length of 13 words, whereas 2/3rd of sentences are about 17 words or lower. With the same reasoning, we should look at 17-gram exemplars. However, since the magnitude of the difference is more than double, a limit of 17-grams can cause the algorithm to run for much more extended periods. Therefore, we approach not to limit the length of maximum word n-grams in the algorithm; instead, move the limit as an input parameter. There are two reasons for this approach. First, it is easier to evaluate with varying maximum lengths. Second, this enables adaptation of this algorithm to use on a dataset having sentences of different average lengths.

3) Exemplar type

   The concept detection algorithm keeps full-text strings in the exemplars. Juckett [102] does not report the considerations they took while defining exemplars. As we extend the algorithm in our problem domain, we recognize that keeping full-text strings in exemplars can cause some problems.

   The current approach creates one exemplar per text string from the training text. We have a small dataset, in which sentence length ranges from 3 words to 49 words. These text strings come from natural speech and can have larger compound sentences. Creating one exemplar for these larger text strings limits the opportunity to create multiple exemplars. Moreover, due to the longer size of such text strings, they will be skipped in many comparisons with shorter word n-grams, as the algorithm only selects exemplars of length *n* to 4*n* for comparison with any word *n*-gram.

	Size	**Sentence**
A	5	Past medical history is unremarkable
B	5	Immunizations are up to date
C	11	Past medical history shows immunizations are up to date and unremarkable

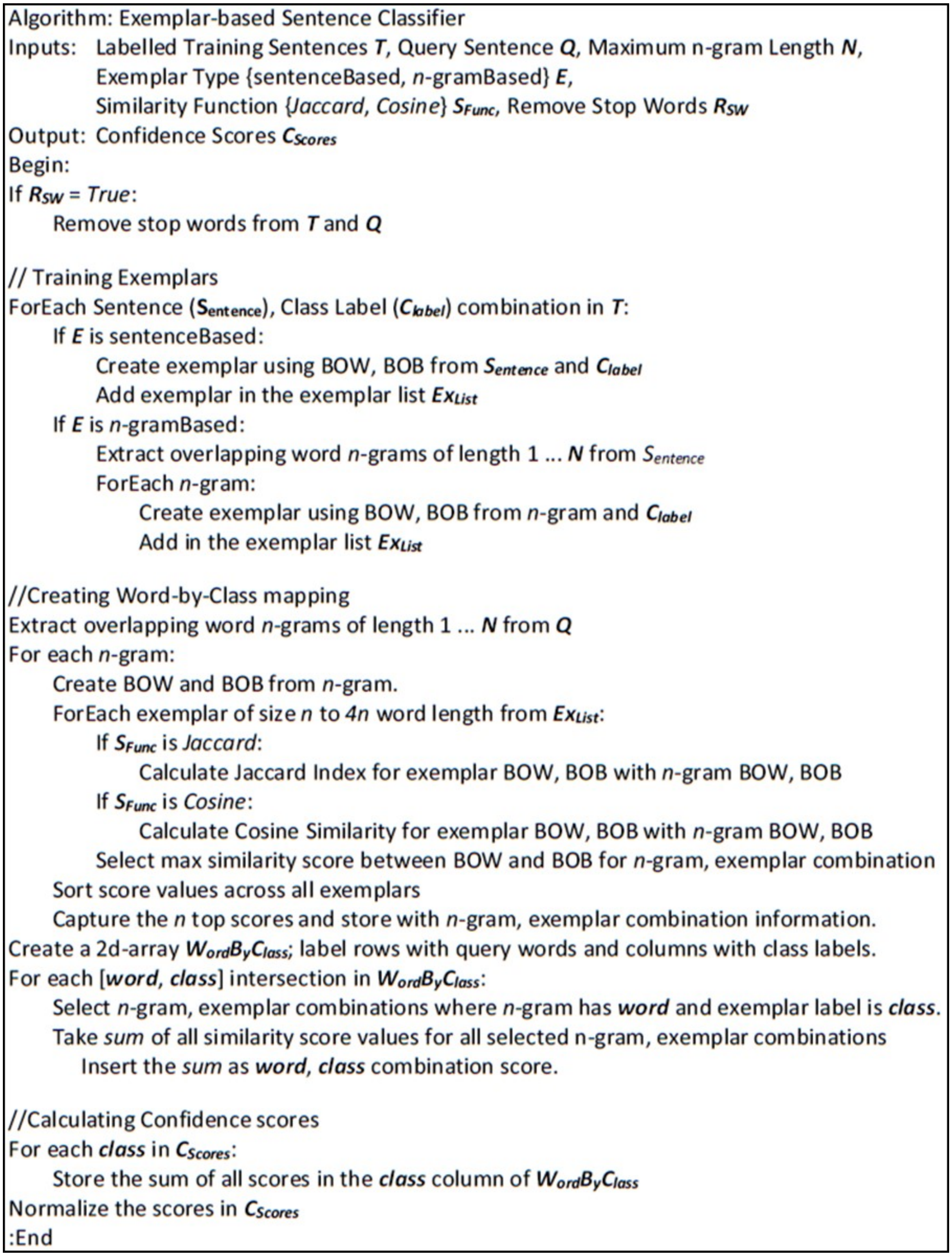
As an example, in the given sentences: A, B and C; sentence C contains semantics of both A and B. However if sentence C is used as exemplar, and sentence A and B are used as query, they will get lower scores since there will only be a partial match among the exemplar and query. Besides, shorter word *n*-grams from the query text, 1-grams, and 2-grams specifically, will get 0 scores since the exemplar will not be selected for comparison as its length is greater than 4 (n=1, 4n=4) and 8 (n=2, 4n=8).

To solve these problems, we consider using word *n*-gram based exemplars. The text strings from the training set converts into word *n*-grams and are stored with the class assignment as exemplars. This way, each overlapped word *n*-gram (sub-string) from the training text string gets an opportunity to have representation. In our algorithm, we implement both types of exemplars and gave options in the input parameter to choose the exemplar type.

4) Similarity function

The concept detection algorithm uses the Jaccard Index as the similarity measure, which does not take word count and sequence for similarity calculations. Cosine similarity [123], on the other hand, is built upon the idea of tf-idf, which takes the count of each dimension in the calculations. Both of these similarity measures are extensively used in the information retrieval domain. However, a comparison of documents retrieved from Google search shows that cosine similarity is the most relevant metric to compare text documents [124]. As we deal with natural speech in our dataset, we hypothesize that cosine similarity will improve the classification performance in comparison with the Jaccard Index. Therefore, we apply both in our algorithm while giving an option to use any one of them in the input parameter.

After investigating all four key areas, we extend the concept detection algorithm into a classifier by applying a two-step process to the word-by-class map output. In the first step, a single score calculates for each class by adding the scores of all words. In the second step, scores of all classes are normalized to get confidence scores in the range of 0 and 1. The pseudocode for the algorithm after the extension is showed in Figure 6.3.



```
Algorithm: Exemplar-based Sentence Classifier
Inputs:   Labelled Training Sentences $T$, Query Sentence $Q$, Maximum n-gram Length $N$,
          Exemplar Type {sentenceBased, $n$-gramBased} $E$,
          Similarity Function {$Jaccard$, $Cosine$} $S_{Func}$, Remove Stop Words $R_{SW}$
Output:   Confidence Scores $C_{Scores}$
Begin:
If $R_{SW}$ = $True$:
    Remove stop words from $T$ and $Q$

// Training Exemplars
ForEach Sentence ($S_{entence}$), Class Label ($C_{label}$) combination in $T$:
    If $E$ is sentenceBased:
        Create exemplar using BOW, BOB from $S_{entence}$ and $C_{label}$
        Add exemplar in the exemplar list $Ex_{List}$
    If $E$ is $n$-gramBased:
        Extract overlapping word $n$-grams of length 1 ... $N$ from $S_{entence}$
        ForEach $n$-gram:
            Create exemplar using BOW, BOB from $n$-gram and $C_{label}$
            Add in the exemplar list $Ex_{List}$

//Creating Word-by-Class mapping
Extract overlapping word $n$-grams of length 1 ... $N$ from $Q$
For each $n$-gram:
    Create BOW and BOB from $n$-gram.
    ForEach exemplar of size $n$ to $4n$ word length from $Ex_{List}$:
        If $S_{Func}$ is $Jaccard$:
            Calculate Jaccard Index for exemplar BOW, BOB with $n$-gram BOW, BOB
        If $S_{Func}$ is $Cosine$:
            Calculate Cosine Similarity for exemplar BOW, BOB with $n$-gram BOW, BOB
        Select max similarity score between BOW and BOB for $n$-gram, exemplar combination
    Sort score values across all exemplars
    Capture the $n$ top scores and store with $n$-gram, exemplar combination information.
Create a 2d-array $W_{ord}B_{y}C_{lass}$; label rows with query words and columns with class labels.
For each [word, class] intersection in $W_{ord}B_{y}C_{lass}$:
    Select $n$-gram, exemplar combinations where $n$-gram has word and exemplar label is class.
    Take sum of all similarity score values for all selected n-gram, exemplar combinations
       Insert the sum as word, class combination score.

//Calculating Confidence scores
For each class in $C_{Scores}$:
    Store the sum of all scores in the class column of $W_{ord}B_{y}C_{lass}$
Normalize the scores in $C_{Scores}$
:End
```

Figure 6.3 Pseudocode for Exemplar-based Sentence Classification Algorithm

6.2.4 Summary

To achieve our objective, we extend the exemplar-based concept detection algorithm for SOAP classification. Five changes are done in this regard. The first change is to give an option in the input parameter to remove stop words. Second, maximum word *n*-gram length is made variable by taking a max length as input. Third, a word *n*-gram based exemplar is developed, and an option is given as an input parameter to select the exemplar type. Fourth, an option is given as an input parameter for similarity matric to use either the Jaccard Index or Cosine Similarity. Fifth, the word-by-class map output is processed using a two-step process to calculate a single confidence score for each class for the query.

6.3 Evaluation

6.3.1 Experimental Setup

We implemented our exemplar-based sentence classifier and then evaluated it on our dataset using four independent variables that correspond to the four proposed improvements. These variables are directly derived from the key areas that we identified and enhanced. One of the independent variables is the maximum word n-gram length limit, for which we did not specify any length; therefore, we experimented with lengths from 1 to 15. All other independent variables have two conditions each that give us 8 cases for experiments. All these cases are given a number. Table 6.5 shows all the cases. Each of these cases is experimented with varying maximum word n-gram length limits, which gave us 120 total conditions to experiment (8 cases x 15 maximum word n-gram length limits).

Table 6.5 Cases based on Stop Word, Similarity Function and Exemplar type

Cases	Stop Word	Similarity Function	Exemplar Type
1	w/ Stop Words	Cosine	Sentence
2			n-gram
3		Jaccard	Sentence
4			n-gram
5	w/o Stop Words	Cosine	Sentence
6			n-gram
7		Jaccard	Sentence
8			n-gram

For each condition, experiments are done in a one-vs-rest method, which means for each SOAP category, a different binary classifier is trained and tested. For instance, when experimenting with the ‘Subjective’ category, all subjective sentences in the dataset are given positive labels (1), and all other sentences are given a negative label (0). The same is repeated for all other categories. Although our classifier can perform multi-class classification, yet we choose this strategy because SOAP categories have a very thin line of separation which can impact the classification performance with our imbalanced dataset. As an example, the sentence “we prescribed him ...” should be an assessment, whereas, with a subtle change “we will prescribe him …” becomes a plan. However, in our dataset, both of these categories have limited sentences. We also observe Mowery [101] applying the same evaluation strategy, due to the same problems.

We conducted all experiments with 5x5 cross-validations. Dataset was randomly shuffled, and 5-fold cross-validation was performed. This process was repeated four more times. For each SOAP category, 25 results were retrieved, which in total gave us 100 results for each condition. Ground truth, confidence score, and condition details were stored from all experiments.

Confidence scores from our classifier show the predicted probability of having a positive label. In this work, we did not specify any mechanism to select any threshold for binary prediction (positive or negative). Therefore, to evaluate our classifier and to compare all the experimental conditions, we used Precision-Recall Curve (PRC), since it provides an accurate evaluation in case of imbalance dataset as compared to Receiver Operating Characteristic (ROC) [125].

Area Under PRC (AUPRC) is represented by Average Precision (AP), where higher AP means better classification performance. In this work, we used AP as the main performance evaluation measure, which also serves as the dependent variable for all our independent variables. We used regression testing to analyze the impact of each independent variable, and based on the results, we selected the most optimal combination of independent variables. We then thoroughly analyze the classification performance of the experimental condition that is according to the selected variables. Three of our independent variables: stop words, similarity function, and exemplar type; are categorical, though has only two values in each. Therefore, we converted them into numerical variables for regression testing.

We analyzed results from all SOAP categories separately as well as in combination. To analyze the overall performance, we took both averages: micro-average and macro-average. In micro-averaging, we directly calculate precision and recall values from overall results, whereas, in macro-averaging, we calculated precision and recall values first for individual categories and then averaged them.

Table 6.6 Conversion of categorical variables to numeric

Independent Variable	Categorical Value	Numeric Value
Maximum word *n*-gram Length Limit	-	1 … 15
Stop Words	w/ Stop Words	0
	w/o Stop Words	1
Similarity Function	Cosine	0
	Jaccard	1
Exemplar Type	Sentence	0
	n-gram	1

In this evaluation, we focus on six main questions.

1. What is the baseline performance of the classifier before improvements?
2. What is the optimal maximum word n-gram length limit for SOAP classification?
3. Does the removal of stop words enhance classification performance?
4. What is the best exemplar type for SOAP classification?
5. What is the best similarity function for SOAP classification?
6. What is the performance of the classifier using optimal conditions?

6.3.2 Results

We experimented with all 120 conditions and analyzed the results to answer the six questions. In this section, we first analyze the baseline performance of the classifier before applying any improvement. Then we analyze the impact of each improvement on the classification performance and select the optimal values for each improvement category. Finally, we analyze the performance of the classifier on the conditions that correspond to the optimal values.

- **<u>BASELINE PERFORMANCE</u>**

We consider case 3 using a maximum word n-gram length limit of 5 as the baseline condition, as this condition equals of classifier without having any improvements. In this condition, we observed an overall micro-averaged AP score of 0.886, while having AP scores of 0.932 for ‘Subjective’, 0.911 for ‘Objective’, 0.563 for ‘Assessment’ and 0.765 for ‘Plan’ category. Figure 6.4 shows the AUPRC for the baseline condition.

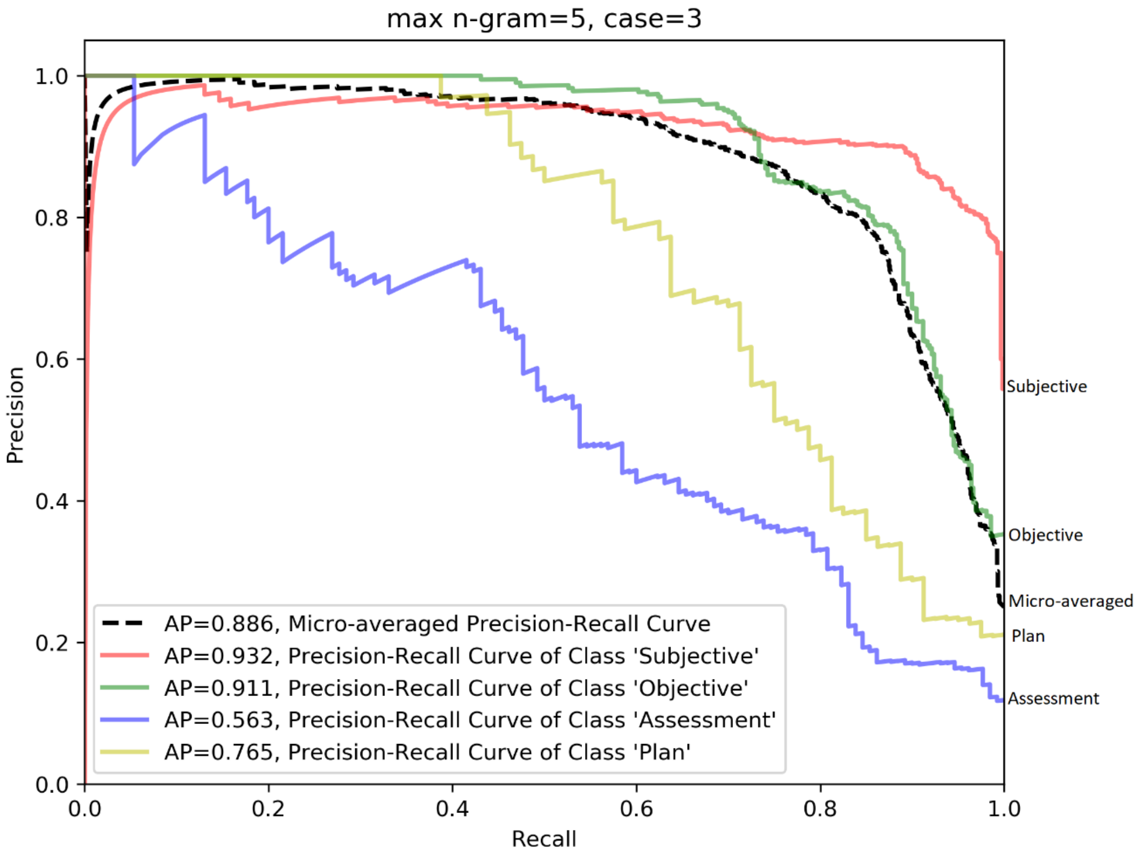


Figure 6.4 Precision-Recall curve of the baseline condition

We compiled a list of example sentences along with their confidence scores from baseline condition and actual SOAP category in Table 6.7. We highlight the top confidence scores while underlined scores show that the highest confidence score is given to the actual SOAP category. The list shows 3 examples each from the ‘Subjective’ and ‘Objective’ category, and 2 examples each from ‘Assessment’ and ‘Plan’ categories.

Table 6.7 Confidence scores of sentences from the baseline condition

	Sentence	**Confidence Scores**				**Actual SOAP Category**
		Subjective	**Objective**	**Assessment**	**Plan**	
1	*paragraph past medical history immunizations are up to date*	**0.88791**	0.0884	0.04866	0.05589	Subjective
2	*immunizations up to date and no significant medical issues*	**0.83285**	0.14976	0.11717	0.11628	Subjective
3	*child was already starting to show return to normal function with crying and purposeful movements*	0.46867	**0.47539**	0.41664	0.35019	Subjective
4	*ear nose and throat exam revealed a runny nose mildly red throat and normal ears*	0.17412	**0.8412**	0.11327	0.13244	Objective
5	*new paragraph family sorry physical exam revealed entirely normal neurological exam with no focal findings*	0.29106	**0.69507**	0.13999	0.14118	Objective
6	*blood work was taken four hours after ingestion revealing non toxic acetaminophen levels*	**0.59756**	0.23034	0.41212	0.14035	Objective
7	*a diagnosis was croup treatment*	0.3143	0.30527	**0.71247**	0.18112	Assessment
8	*i note no allergies*	**0.66861**	0.32717	0.19232	0.07669	Assessment
9	*child will follow up with family doctor*	0.23159	0.17391	0.12547	**0.74356**	Plan
10	*a throat swab was sent today should it be positive we will call her and start her on antibiotics*	0.3523	**0.46499**	0.41026	0.3531	Plan

- **ANALYZING THE IMPACT OF IMPROVEMENTS**

In all experimented conditions, the overall best performance was achieved by the condition using case 1 with maximum word n-gram length limit of 5th order. This condition achieved the highest micro-averaged AP score of 0.897. However, we observed that for individual SOAP categories, different conditions showed better performance for different categories, and no one condition was optimal for all SOAP categories. We list down the highest and lowest AP scores we observed for each SOAP category along with overall combined scores in Table 6.8. The magnitude of different highlights that our suggested improvements are having a major impact on performance, especially with assessment and plan categories.

Table 6.8 Highest and Lowest AP scores for SOAP categories

SOAP Category	Highest AP	Lowest AP	Difference
Subjective	0.957	0.881	0.076
Objective	0.919	0.836	0.083
Assessment	0.626	0.396	0.230
Plan	0.820	0.705	0.115
Micro-Averaged	0.897	0.812	0.085
Macro-Averaged	0.808	0.716	0.092

Results from regression tests on all 120 conditions showed that all independent variables influenced classification performance, except similarity function which is consistently insignificant for all SOAP categories. Table 6.9 highlights the results of regression testing.

Table 6.9 Summary of regression analysis results

Independent Variables →	Max n-gram Length		Stop Words		Similarity Function		Exemplar Type	
SOAP Categories ↓	**P-value**	**T Stat**	**P-value**	**T Stat**	**P-value**	**T Stat**	**P-value**	**T Stat**
Subjective	1.125E-08	6.155	1.554E-19	-10.944	0.512	0.658	0.0725	-1.812
Objective	2.988E-07	5.444	3.503E-10	-6.869	0.189	1.321	2.920E-27	-14.292
Assessment	0.046	-2.019	1.036E-21	-11.874	0.375	-0.891	0.011	-2.584
Plan	0.009	-2.625	0.002	3.215	0.068	-1.841	0.039	-2.090
Micro-Average	3.375E-06	4.885	2.783E-32	-16.585	0.284	1.077	2.596E-11	-7.386
Macro-Average	0.984	-0.020	3.292E-22	-12.087	0.256	-1.141	2.490E-09	-6.469

- **IMPACT OF MAXIMUM N-GRAM LENGTH LIMIT**

Regression analysis showed that changing the maximum n-gram length limit had a significant change in performance. However, the direction of change varied within SOAP categories. We observed that sentences from 'Subjective' and 'Objective' categories were better classified with higher order of n-grams, whereas, 'Assessment' and 'Plan' categories favored shorter n-grams. Figure 6.5 draws the trend line of 6^{th}-degree polynomial after plotting all AP scores for all cases on ordinate with max n-gram lengths on the abscissa.

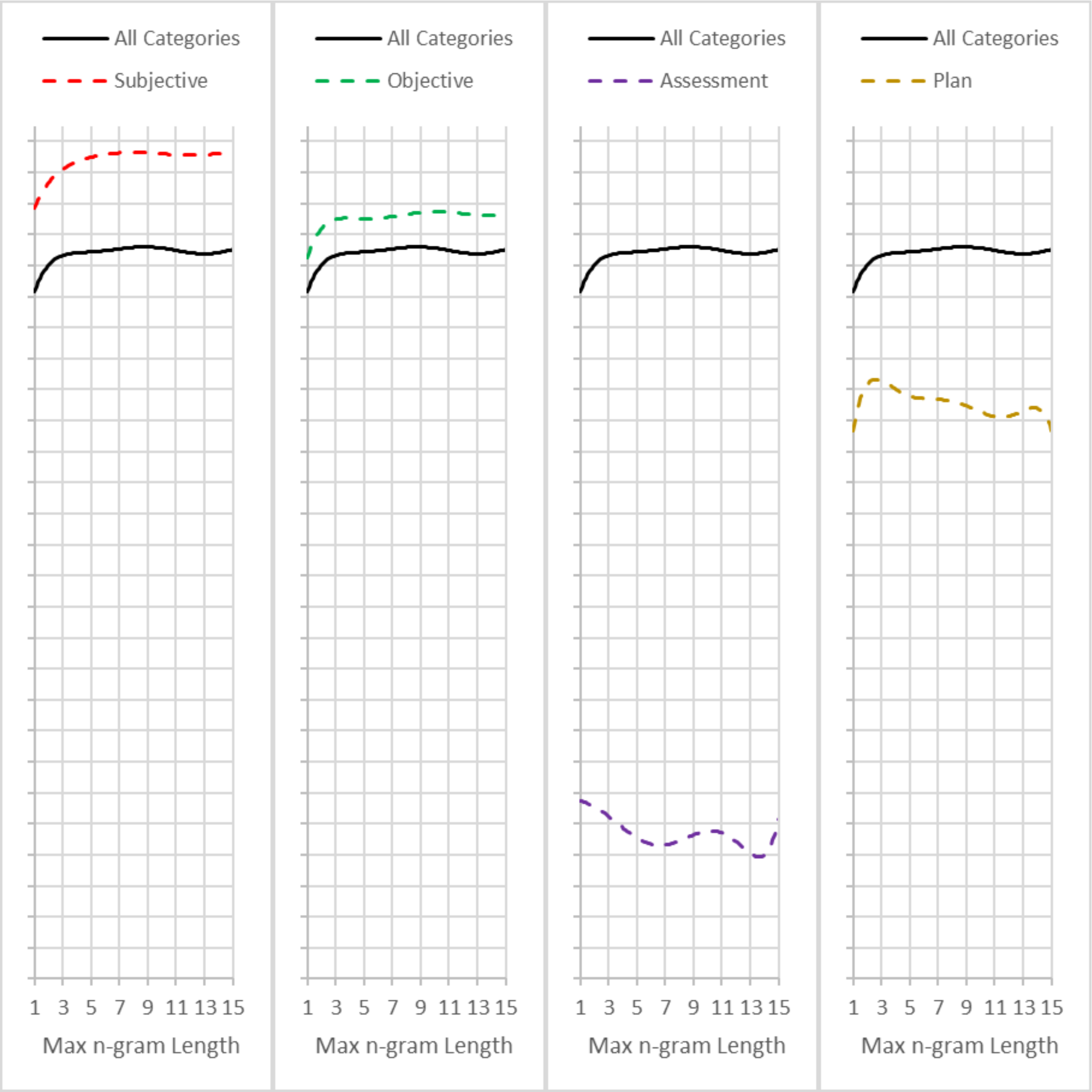


Figure 6.5 All AP scores over n-gram max length

The trend line validates the regression analysis; however, it highlights diminishing increment in AP for ‘Subjective’ and ‘Objective’ categories with the increasing n-gram lengths. For the ‘Assessment’ category, we see continuous declination of performance along n-gram lengths. ‘Plan’ category, however, shows inconsistency, where performance rapidly increased for the first few increments in n-gram lengths, then it started to fall, nevertheless, the fall was not much. These opposite behaviors from SOAP categories regarding max n-gram length explain the high P-value (0.984) for macro-averaged scores.

All 8 cases mostly followed the same trend; however, we did observe some anomalies. In the ‘Subjective’ category, we marked 3 cases to have slight differences. In cases 3 and 8, we saw another spike in scores with the higher values of max n-gram length. In case 5 specifically, we observed that n-gram lengths had no significant impact. We had the same observation about the ‘Objective’ category in case 5. For the ‘Assessment’ category, cases 5 and 6 seemed to have no impact due to n-gram lengths, and case 8 was observed to be favoring larger n-grams. We observed the same behavior with the ‘Plan’ category, where cases 5 and 8 had no impact, whereas, case 6 favored larger n-grams. Overall, case 5 (without stop words, cosine similarity, sentence exemplars) appeared to be immune to the n-gram lengths. We confirmed this observation by applying a t-test on the AP scores which gave us a P-value of 0.196. After analyzing scores, we realized that there cannot be a single selection for max n-gram length; therefore, we picked the best performing max n-gram length from each case (Table 6.10).

Table 6.10 Best performing values for maximum n-gram length for each case

SOAP Categories ↓	All Cases	Case 1	Case 2	Case 3	Case 4	Case 5	Case 6	Case 7	Case 8
Subjective	8	8	9	14	6	11	9	14	15
Objective	11	11	5	11	7	6	7	12	12
Assessment	1	1	3	1	2	15	15	1	15
Plan	6	2	3	2	2	14	8	6	8
Micro-Average	5	5	5	14	7	15	9	10	15
Macro-Average	3	3	3	6	2	15	15	6	15

- **IMPACT OF STOP WORDS REMOVAL**

It is evident from the regression analysis that stop words removal had a significant change in the classification performance for all categories. However, for all the categories except 'Plan', the direction of change is negative (-ve t-stat value). This means that the performance of only the 'Plan' category increased by removing stop words, whereas, all other categories performed better when we keep stop-words in the sentences. Figure 6.6 shows the box plots for AP scores after categorizing them with and without stop words.

In Figure 6.6, all box plots are placed in the same sequence as shown in the legends on the left. To be specific, from left to right, the first 2 plots represents the results from all SOAP categories combined, the second pair represents results only for 'Subjective' category, the third pair represents 'Objective' category, the fourth pair represent 'Assessment' category and the fifth pair represent 'Plan' category. All the blue shaded plots (left on each pair) are made from performance scores when stop words were kept in the sentences. On the other hand, green-shaded plots (right on each pair) are from the scores when stop words were removed. The x mark within plots shows the mean, and the dots outside plots show outliers. While analyzing these plots, we can see that although 'Plan' sentences were better classified without stop words, this performance was not very reliable, since the plot spread is wider along with some outliers.

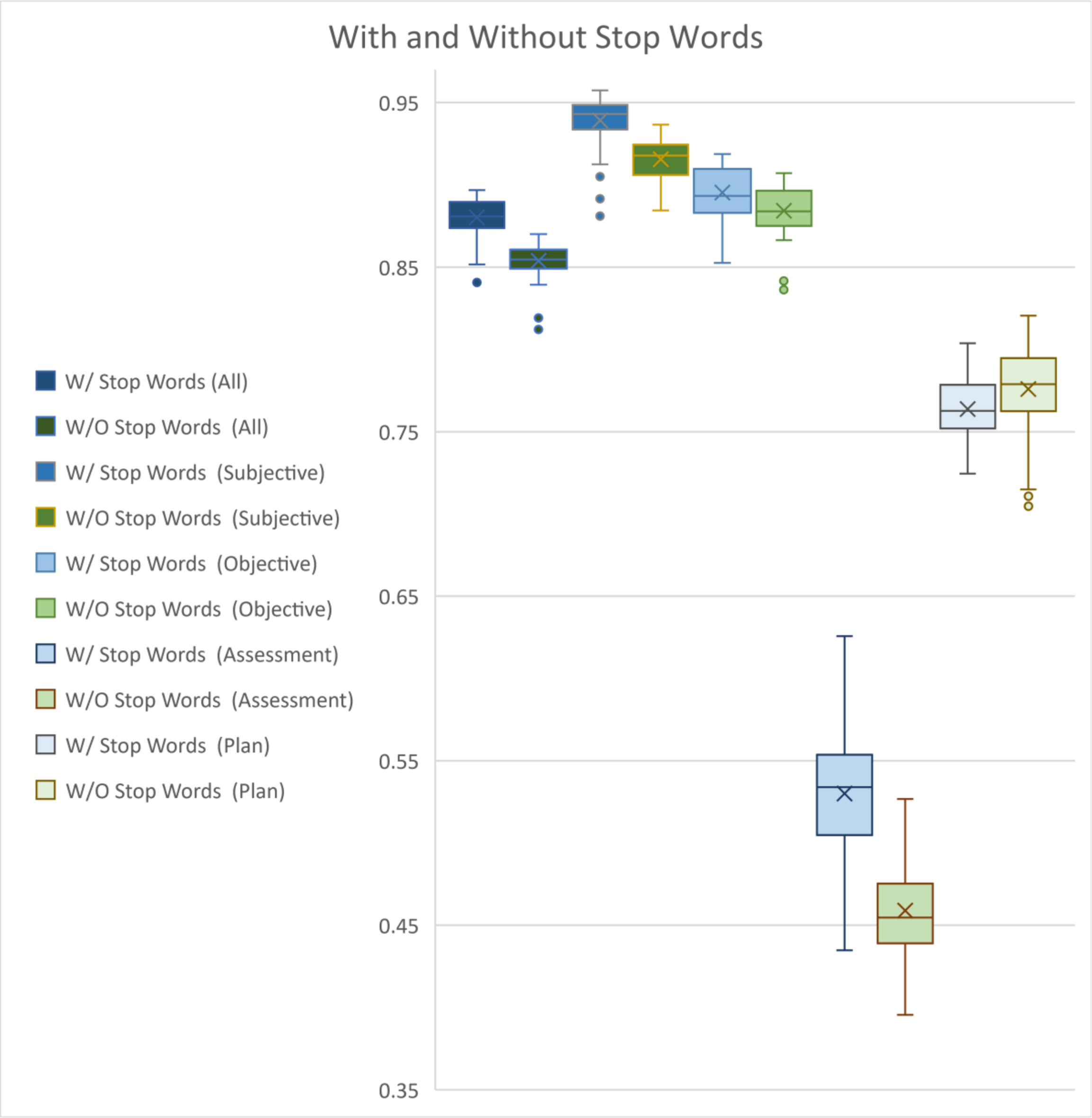


Figure 6.6 Box plots of scores after removing stop words

- **IMPACT OF SIMILARITY FUNCTIONS**

We observed no significant change in performance due to similarity functions. In regression analysis, P-values for all categories were consistently above 0.05, which accepts the null hypothesis. Figure 6.7 shows the box plots distributed over cases using cosine similarity and Jaccard index. The plots are on the same pattern as we saw in the previous figure.

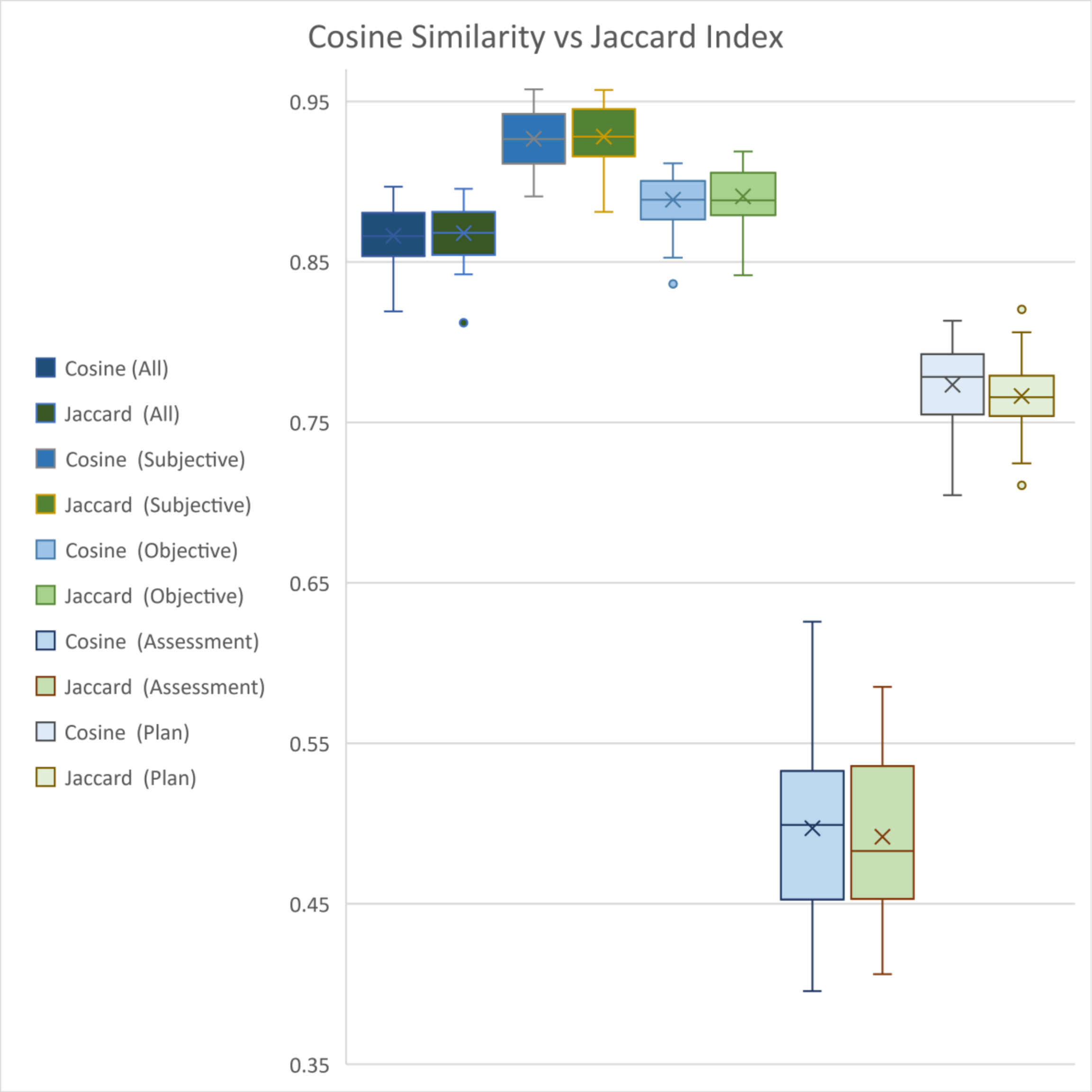


Figure 6.7 Comparing performance based on similarity function (Cosine vs Jaccard)

- **<u>Impact of Exemplar Types</u>**

In our analysis, sentence based exemplars were better than n-gram based exemplars on all SOAP categories. Figure 6.8 shows the box plots for scores based on exemplar-type. Blue shaded plots are for sentence based exemplars and green shaded plots are for n-gram exemplars. These plots validate the results of regression analysis as the mean and median for each blue shaded plot is higher than the corresponding green-shaded plot.

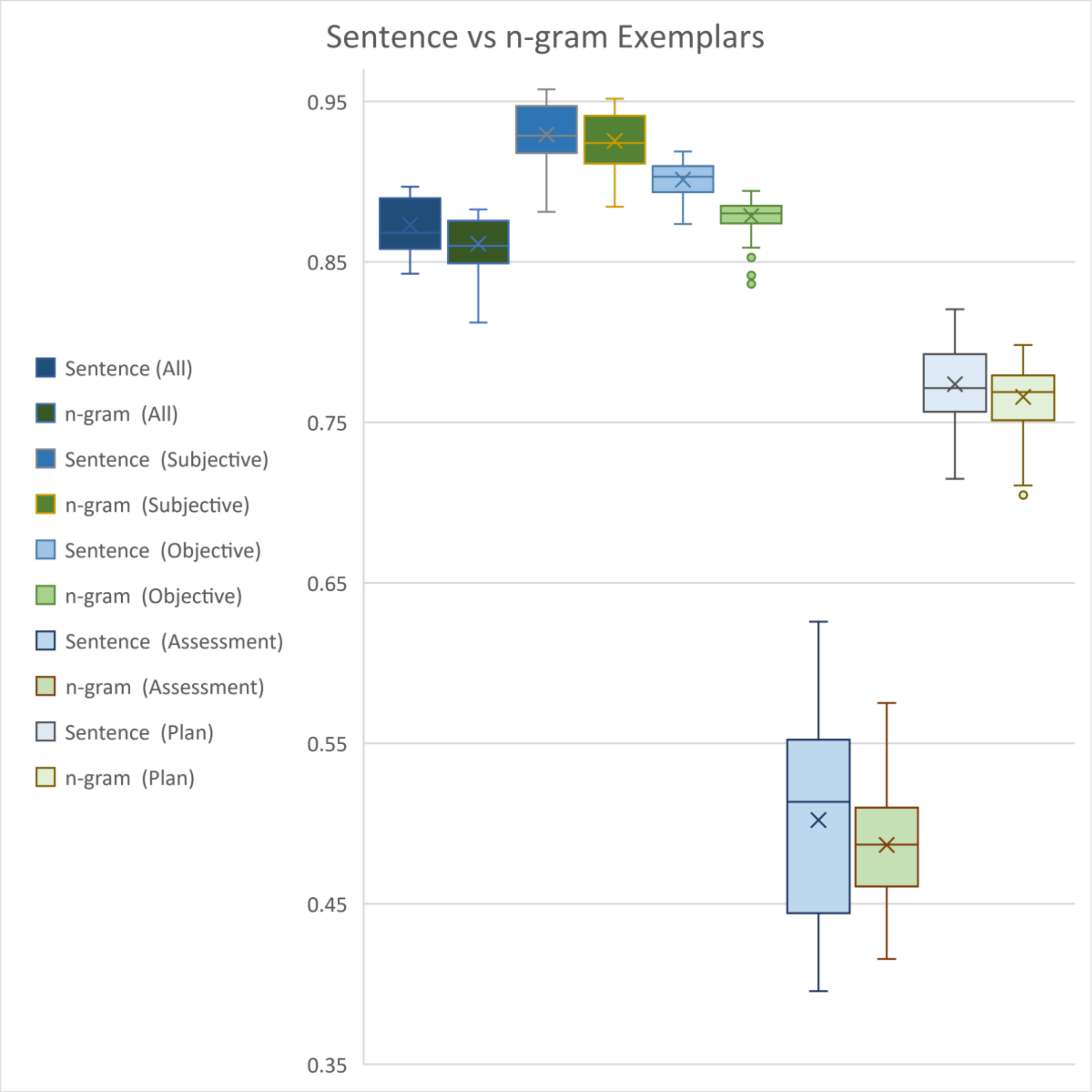


Figure 6.8 Comparing performance based on exemplar type (sentence vs n-gram)

- **OPTIMAL PERFORMANCE**

Results from regression analysis presented that classification performance varied across individual SOAP categories. Therefore, we inspected the optimal performance for each category separately. We select the conditions having the highest AP scores for each category and analyze the improvements that go within that condition. We also calculate the F1 scores for the selected conditions using varying threshold levels. The highest F1 scores are reported with each category. Table 6.11 provides a summary of optimal conditions for each SOAP category along with the magnitude of improvement as compared to baseline performance.

Table 6.11 Summary of optimal conditions for each SOAP category

SOAP Category	Base AP Score	Max AP Score	AP Improved	Optimal Maximum word n-gram length limit	Best Case
Subjective	0.932	0.957	0.025	8	1
Objective	0.911	0.919	0.008	11	3
Assessment	0.563	0.626	0.063	1	1
Plan	0.765	0.82	0.55	6	7

For the 'Subjective' category, we achieved max performance (AP: 0.957) with case 1 using the maximum word n-gram length limit of the 8th order. This means that when our classifier is set to break query sentences in word n-grams till 8-grams, use sentence based exemplar and keep stop words, it will give the best classify 'Subjective' category sentences. Since the similarity function has no significance, we select the condition with cosine similarity as its score was moderately better. Figure 6.9 shows the AUPRC for this condition, where we achieved an F1 score of 0.912.

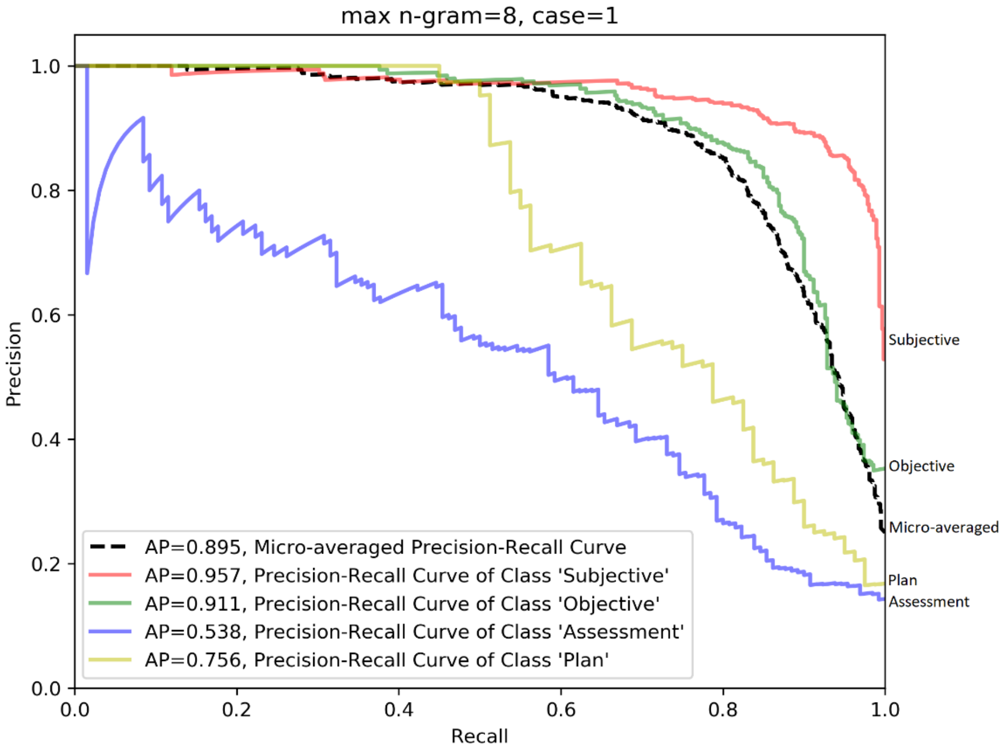


Figure 6.9 Precision-Recall Curve of best performing condition for Subjective

We selected some examples and list them in Table 6.12 showing sentences with their actual SOAP category and confidence scores we obtained using our classifiers with this condition. The top 6 example shows the behavior of this condition on 'Subjective' sentences, while rest shows behavior on other categories. We highlight the top-scoring category while underline shows that our classifier predicted the actual category for the given sentence.

Table 6.12 Confidence scores of sentences from case 1 using 8-gram limit

	Sentence	Confidence Scores				Actual SOAP Category
		Subjective	Objective	Assessment	Plan	
1	*no concussive findings*	**0.80509**	0.296	0.25021	0	Subjective
2	*immediately afterwards paramedics were called on arrival*	0.4717	0.3464	**0.50901**	0.23972	Subjective
3	*no medications*	**0.75963**	0.24037	0.211	0	Subjective
4	*past medical history reveals a healthy athletic male with no significant medical issues*	**0.75253**	0.25061	0.22631	0.17429	Subjective
5	*by the time she arrived at the IWK emergency she was awake and alert and cranky*	**0.51804**	0.41937	0.33357	0.38002	Subjective
6	*family history reveals febrile seizures in dad as a child*	**0.51926**	0.40717	0.30884	0.38605	Subjective
7	*tracheal palpation did not elicit pain*	**0.76971**	0.39352	0.15284	0.24594	Objective
8	*lungs were clear*	0.18333	**0.77103**	0.24431	0.19585	Objective
9	*the likely choice of antibiotics will be amoxicillin*	0.36357	0.37519	**0.42211**	0.57157	Plan
10	*diagnosis fracture radius ulna*	0	0.55951	**0.60422**	0	Assessment

For the ‘Objective’ category, best scores (AP: 0.919) were achieved by condition using case 3 and the maximum word n-gram length limit of 11. We achieved an F1 score of 0.846 in this condition. Figure 6.10 illustrates the AUPRC for this condition. Table 6.13 mentions some examples from this condition, where the top 5 examples show the behavior of this condition over the ‘Objective’ category. The rest of the examples show the performance over other SOAP categories.

Table 6.13 Confidence scores of sentences from case 3 using 11-gram limit

	Sentence	Confidence Scores				Actual SOAP Category
		Subjective	Objective	Assessment	Plan	
1	ear nose and throat exam revealed a red throat with no exudate suggestive of a viral pharyngitis	0.27987	**0.72597**	0.18146	0.1777	Objective
2	blood work was taken four hours after ingestion revealing non toxic acetaminophen levels	**0.62871**	0.20222	0.37966	0.14458	Objective
3	*rest of the physical exam was without comment*	0.20491	**0.83209**	0.15358	0.24458	Objective
4	new paragraph family sorry physical exam revealed entirely normal neurological exam with no focal findings	0.28433	**0.71114**	0.12414	0.12644	Objective
5	*his neurovascular status in the effected limb is normal*	0	**0.67539**	0	0	Objective
6	*past medical history reveals immunizations up to date and normal*	**0.76841**	0.22902	0.15446	0.13135	Subjective

	birth and pregnancy history with no specialist and no regular medications and no known allergies					
7	*diagnosis fracture radius ulna*	0	0.49184	**0.69675**	0	Assessment
8	*chest xray revealed a dense left lower consolidation*	0.34847	**0.69141**	0.21597	0.11372	Assessment
9	*child will follow up with family doctor*	0.29484	0.15295	0.0951	**0.7286**	Plan
10	*parents were counseled and reassured*	0.35712	0.33844	**0.61333**	0.29793	Plan

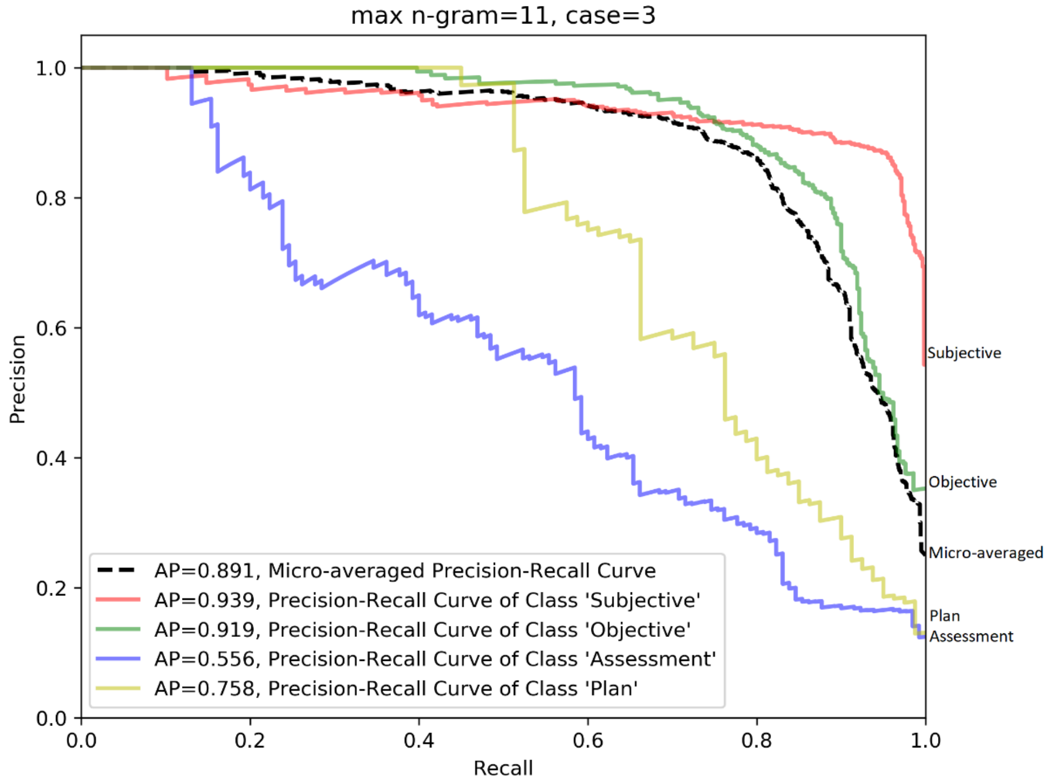


Figure 6.10 Precision-Recall Curve of best performing condition for Objective

For the ‘Assessment’ category, case 1 using maximum word n-gram length limit of 1st order excelled (AP: 0.626) among all other conditions. This condition managed an F1 score of 0.63. Figure 6.11 depicts AUPRC for this condition. Table 6.14 lists example sentences from this condition showing highlighted confidence scores along with the actual SOAP category. Top 5 examples show the behavior of this condition over ‘Assessment’ category sentences, while rest show the behavior over other categories.

Table 6.14 Confidence scores of sentences from case 1 using 1-gram limit

	Sentence	Confidence Scores				Actual SOAP Category
		Subjective	Objective	Assessment	Plan	
1	*a diagnosis was croup treatment*	0.39702	0.299	**0.71162**	0.18063	Assessment
2	*diagnosis is viral respiratory tract infection*	0.41961	0.33547	**0.64259**	0.10616	Assessment
3	*croup instructions were delivered*	0.41324	0.5422	**0.54945**	0.33527	Assessment
4	*i note no allergies*	**0.65644**	0.35877	0.31561	0.14695	Assessment
5	*diagnosis viral upper respiratory tract infection with febrile seizure*	0.44084	0.31599	**0.52301**	0.18636	Assessment
6	*immediately afterwards paramedics were called on arrival*	0.4717	0.3464	**0.50901**	0.23972	Subjective
7	*new paragraph impression is that this is simple febrile seizure*	0.49094	0.33401	**0.5078**	0.33077	Objective
8	*post reduction film showed good placement of the bones*	**0.5516**	0.49871	0.49488	0.31146	Objective
9	*child was hydrated and happy*	0.44425	**0.55868**	0.4596	0.40219	Objective
10	*parents were counseled and reassured*	0.40641	0.38024	**0.54527**	0.38648	Plan

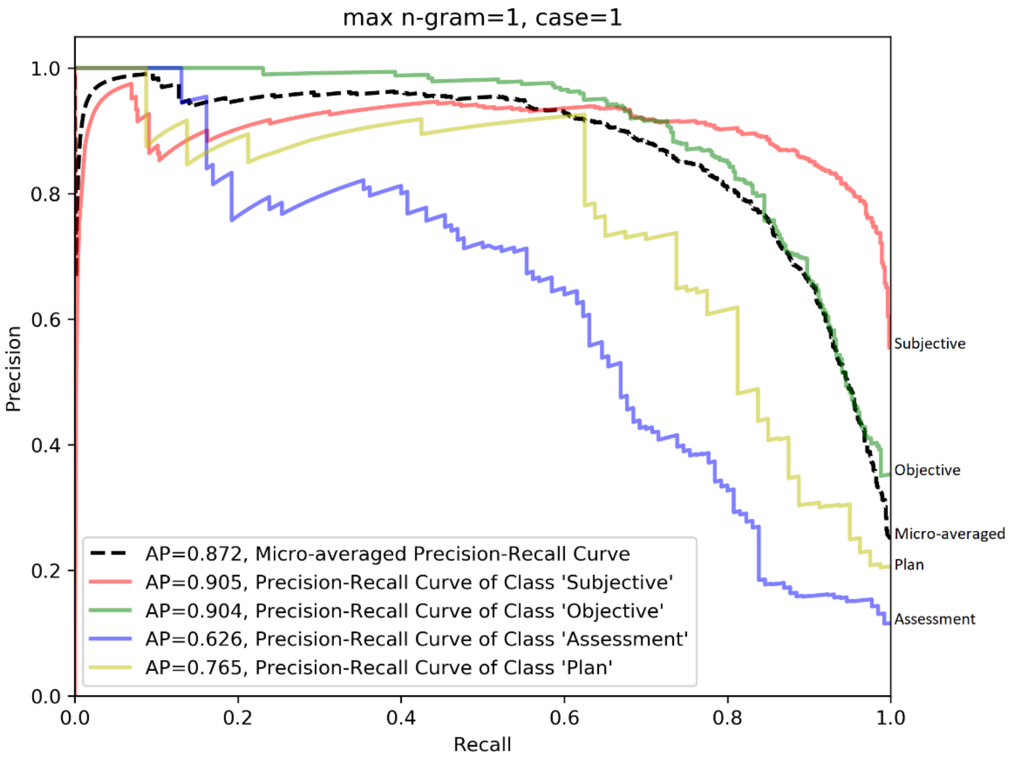


Figure 6.11 Precision-Recall Curve of best performing condition for Assessment

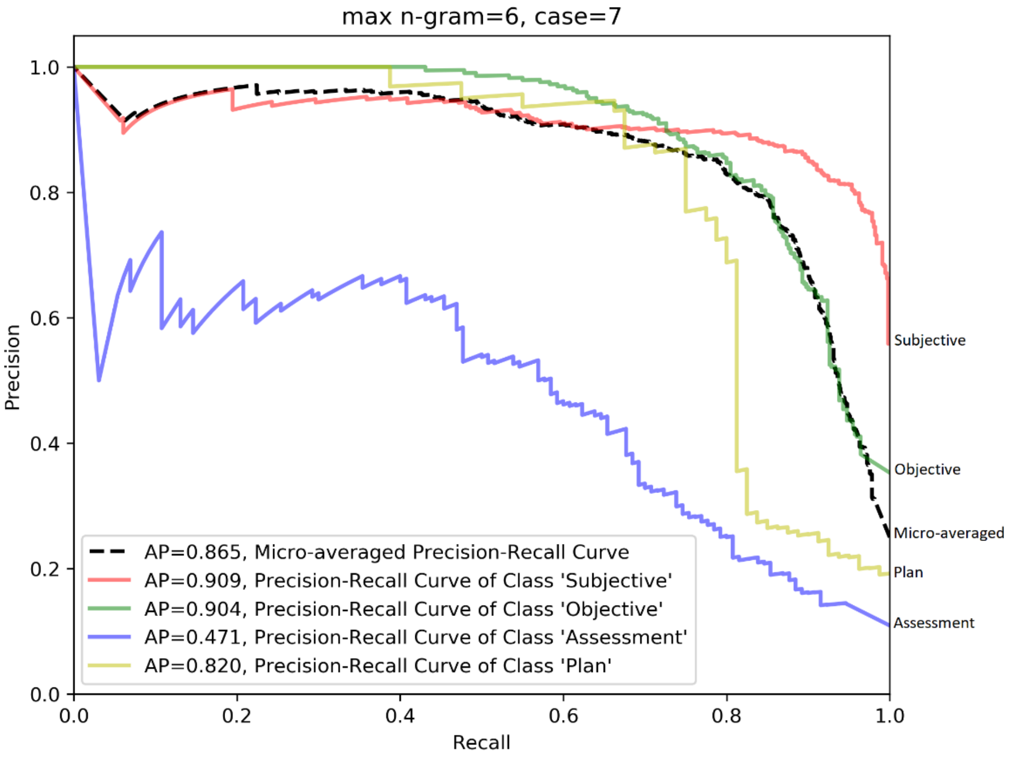


Figure 6.12 Precision-Recall Curve of best performing condition for Plan

For the ‘Plan’ category, we observe case 7 using a maximum word n-gram length limit of 6th order as the best performing condition (AP: 0.82). Figure 6.12 presents the AUPRC for this condition. We achieved an F1 score of 0.805 in this condition. Table 6.15 shows the example sentences for this condition. Top 6 examples show the behavior of this condition over ‘Plan’ category sentences, while others show the behavior over other categories.

Table 6.15 Confidence scores of sentences from case 7 using 6-gram limit

	Sentence	**Confidence Scores**				**Actual SOAP Category**
		Subjective	**Objective**	**Assessment**	**Plan**	
1	*follow up as necessary*	0	0	0	**1**	Plan
2	*child will follow up with family doctor*	0.19748	0.27724	0.17992	**0.73046**	Plan
3	*i have asked mom to follow up with me should she fail to improve over the next few days or should she worsen in any way*	0.39493	0.1183	0	**0.70123**	Plan
4	*child was advised to return if worsening occurred or if she failed to improve significantly over the course of the next seven days*	0.50909	0.27323	0.12239	**0.59619**	Plan
5	*child will follow up with family doctor if there is any other issues*	0.2562	0.2489	0.16498	**0.68693**	Plan
6	*follow up in the next two to three days if she does not improve*	**0.6324**	0.17638	0.16543	0.49534	Plan
7	*her parents are presented with her to the emergency department for further assessment*	0.47742	0.13096	0.36867	**0.52188**	Subjective

8	*child was already starting to show return to normal function with crying and purposeful movements*	**0.5657**	0.35864	0.31614	0.47694	Subjective
9	*she presented to a walk in clinic where she was told that she did not have a concussion*	0.53009	0.36812	0.36995	**0.54721**	Subjective
10	*instructions were given with regards to the delivery of ibuprofen as needed for pain and fever but the parents were cautioned that this would not reduce the risk of further seizures*	0.43787	0.35454	0.3649	**0.44165**	Objective

6.4 Discussion

In this evaluation, we used 238 sentences to evaluate our classifier, which is far less than 4130 sentences that Mowery [101] used in their study; however, we achieved comparable performance in almost all SOAP categories.

The performance of our classifier significantly improved with 'Plan' category sentences when we applied the stop word removal operation. We observe that this change is specifically due to the nature of 'Plan' sentences. Usually, in this category, physicians talk in the future tense. For example, "Child will follow up …" and "We will perform …". In this case, when stop words are removed, the grammatical structure of a sentence becomes more prominent and highlights those keywords like 'will' and 'shall' that be the key identifiers of the future tense.

In our experiments, we also noticed a significant performance change with varying maximum n-gram lengths, which ranged from the lowest overall AP score of 0.81 to the highest of 0.89. We also observed that each SOAP category behaves differently with different n-grams. Juckett [102] has implemented the concept-detection algorithm with the max n-gram length equals to 5 for each class, owing to the small-phrase lengths of their dataset. Using the same principle, we expected better performance with longer n-grams.

In this work, we also evaluated the use of the Jaccard index as the similarity function in comparison to the cosine similarity function. We argued that the Jaccard Index only takes the union of all lexicons for calculations and does not impact with repeated words, and cosine similarity should work better. However, after experiments, our argument failed to achieve support from the results, which made it evident that similarity function has no significant impact on the performance.

6.5 Conclusion

This chapter provides an approach to use an exemplar-based concept detection algorithm to develop a SOAP classifier. This classifier was implemented and was experimented with four independent variables having a total of 120 variations where each variation was tested for each of the SOAP categories separately. These experiments were defined to show a directional insight into our approach, yet due to the small dataset, it does not provide a meaningful conclusion. With the provided dataset, we make two suggestions. The first suggestion is to use the longer n-grams for better classification in ‘Subjective’ and ‘Objective’ categories, whereas shorter n-grams for ‘Assessment’ and ‘Plan’ categories. However, the drawback of longer n-grams is that for each increasing n-gram, processing time increases exponentially. The second suggestion is to make separate classifiers for each of the SOAP categories and remove stop words specifically for Plan category classifiers.

Chapter 7. DISCUSSION

7.1 Introduction

This chapter constructs a thorough discussion based on our work for both of our research objectives. It highlights the observations that we made while performing this research. This chapter then presents a 3-Layer solution framework that is based upon our observations. Afterward, it reports the limitations of this work and provides possible and potential improvements that can be done in the future. Finally, this chapter ends by providing a conclusion towards this thesis.

7.2 Observations

We demonstrated our work on a 2-layer solution model, with the approach of having an end-to-end solution. However, when we observe the output of the first layer, we found no punctuation marks. The reason for this is that SR returns speech in free text format. These texts bare no lexical entities other than words, such as punctuation marks, paragraph indentation. On the other hand, Natural Language Processing (NLP) tasks usually work on text data that are rich with punctuation marks. It means that output from SR systems can create havoc with NLP methods; therefore, it is highly desired to enrich SR output with punctuation marks before transmitting it to our final layer.

While working with the dictations, we also observed that some of them were recorded while patients were still in the room. For our experiments, this created issues because of the increased level of background noise. As we are working towards an end-to-end solution, we made a realization that an autonomous report generation solution will allow providers to record dictations anywhere and anytime. Most of the time, it should be happening right after the encounter, possibly in front of the patient. For such scenarios, we believe that patients will be hearing of what is said, hence they will get the chance to provide clarification for any detail, which will be beneficial in reducing the dictation errors. Fratzke [51] observed the same pattern when they implemented a voice-assisted technology.

7.3 3-Layer Solution Framework

In this thesis, we observed that the output from the first layer is not fully compatible to be used as the input of our second layer. Therefore, to develop a true end-to-end solution, we need to specify a processing layer in between both layers whose purpose should be to streamline the output of the first layer for the next layer.

Sentence boundaries are marked by using a dot, also known as period. This dot shows where a sentence has ended in the text. In our final layer, we are using the sentence as the unit to classify. Therefore, those transcriptions without punctuation marks will certainly have some issues. A quick review shows that there are various solutions available that deal with the punctuation prediction task. We found a punctuation predictor based on a bidirectional recurrent neural network model with attention mechanism [126] that provides pre-trained models based on Wikipedia text. We tested this solution on our dataset and analyzed the results visually. We observed a few mistakes, though it generally felt satisfactory. This simple review of the problem shown us that punctuation prediction is an established problem in the research domain; hence we should give it a separate focus in our solution.

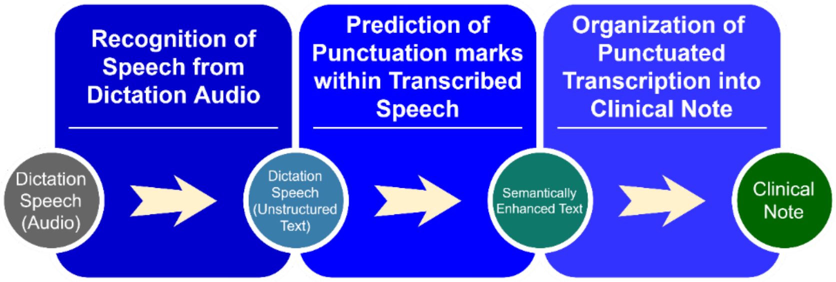

Recognition of Speech from Dictation Audio
Prediction of Punctuation marks within Transcribed Speech
Organization of Punctuated Transcription into Clinical Note
Dictation Speech (Audio)
Dictation Speech (Unstructured Text)
Semantically Enhanced Text
Clinical Note

Figure 7.1 Design for 3-Layer Solution Framework

With all the observations we made in this work, we present a potential 3-layer solution framework for the problem of clinical documentation. All of the layers in this framework are connected as a pipeline. Figure 7.1 represents the design of the 3-layer solution framework. Each layer of this framework is defined below.

1. The first layer of this framework expects physicians recorded audio clips. This layer processes the input audio into text by using a noise and domain robust speech recognition system.

2. In the second layer, the transcriptions from the first layers are analyzed for punctuations. Transcriptions are enriched with predicted punctuations and are given to the third layer.

3. In the third layer, punctuated transcriptions are then classified for clinical reports. Sentences from transcriptions are extracted and then classified for various categories of the report structure.

7.4 Limitations

The size of the dataset possesses the biggest limitation of this work. Due to the small size of the dataset, we had to tweak our experiments accordingly. While experimenting with acoustic models, we initially wanted to train standalone models as well to hold a comparison. However, a few trials with training exhibited the limitations. Therefore, we skipped that scenario from our experiments. Similarly, during the SOAP classification, we sensed a lower level of overall classification performance. The algorithm that we extended and implemented in this layer was tested on a dataset five times in size than ours. Hence, we believe that a lower dataset has introduced a limitation in our work.

Another limitation of this work is that all of the dataset labeling tasks were done by us, without the help of any domain specialist. We perceived the need for a specialist at two points. Firstly, at the time of generating gold standard transcriptions for dictation audios, and secondly, when we labeled the sentences into SOAP categories. While preparing transcriptions, we took help from one of the fellow members of our research group, who has a medical degree. However, we do not consider this fellow a domain specialist since it never practiced in the domain.

7.5 Future Work

This work is primarily experimental; however, it sets a direction for further research. This thesis presents the solutions in terms of research areas that combine to form a solution framework. Particularly, the solution depends on three research areas: continuous speech recognition, punctuation prediction, and sentence classification. Any work that is done in any of these research areas has the potential to enhance the presented solution framework.

Open-sourced offline SR are improving at a rapid pace. While working on this thesis, a new open-sourced offline SR Wav2Letter++ [94] was released reporting better performance then DeepSpeech [76] using similar models and datasets. Wav2Letter++ is developed to scale and work in real-life environments. At the time of our experimentations, its pre-trained models were not released, however, they are available at the time of writing this thesis. Wav2Letter++ is also based on the concept of end-to-end SR, whilst providing features to use custom acoustic models of different architectures. Therefore, we consider that using this toolkit can be a perfect next step towards the enhancement of this work.

At the time of selecting methods for our final layer, we did not explore the sentence classification solutions from other domains. One can argue this as a limitation, but we consider this as the opportunity to move ahead in a logical manner. Since we were only able to find one study that addressed the problem of sentence segmentation for SOAP categories, the next logical step we took was to explore for similar problems within the same (healthcare) domain. Therefore, we consider that this work provides the basis to explore solution ideas from a different domain. We expect that examination of supervised approaches towards text classification for this problem can pose as an appropriate work in this direction.

In the previous subsections, this chapter presented a 3-layer solution framework. We consider that this provides the opportunity to research the problem of clinical documentation in a more systematic way. However, the framework still needs active research and evaluations. Therefore, as future work, this 3-layer solution framework can be enhanced.

7.6 Conclusion

Clinical documentation is a challenging process that poses multiple problems. Researchers are experimenting with speech recognition since its inception to develop efficient solutions. A review suggests that such solutions still lack adoption among healthcare providers. One reason is the lack of accuracy in domain-specific noisy environments. Another reason is that providers still need to intervene and perform manual changes. Therefore, this thesis considers the problem from the end-to-end perspective. It identifies two research objectives and translates them into individual layers of a solution model.

The first layer seeks efficient transcription of dictations in domain-specific and acoustically distorted environments. We selected the DeepSpeech speech recognition system and performed preliminary experiments. We then presented methods to enhance the performance of both: acoustic and language; models. Evaluations show that all our modeling methods improve DeepSpeech performance. We show that by adapting and fine-tuning the pre-trained acoustic model, along with enhancing the pre-trained language model using the augmented corpus from the domain-specific dataset, DeepSpeech can achieve performance levels very close to Google Speech API.

The second layer aims to categorize transcriptions into SOAP categories. We select an exemplar-based concept detection algorithm and extend it to develop a sentence classifier. We identify four areas to enhance and implement our classifier for SOAP classification. Evaluations show that each SOAP category requires a separate setting for optimal performance, and no single set of independent variables will deliver the best performance for all categories.

In this work, we observe that a two-layer solution could not exhibit as an end-to-end solution due to the lack of punctuations in the transcriptions. Therefore, this thesis discusses a 3-layered solution framework that can have the potential to become an end-to-end solution.

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Appendix A. AP Scores for SOAP Classification

Table A.1 Micro-Averaged AP-Scores of All Classes

		Conditions							
		1	2	3	4	5	6	7	8
max n-gram length	1	0.87152	0.84058	0.84252	0.85159	0.85459	0.81910	0.85184	0.81206
	2	0.88061	0.86977	0.86825	0.87163	0.85796	0.84112	0.84968	0.84737
	3	0.89237	0.86801	0.88100	0.87971	0.85346	0.84504	0.86390	0.85155
	4	0.88720	0.87295	0.88759	0.87017	0.86087	0.85578	0.84566	0.84874
	5	**0.89675**	**0.88257**	0.88595	0.87578	0.85288	0.83935	0.86702	0.86095
	6	0.88218	0.87506	0.89358	0.87889	0.86509	0.84752	0.86476	0.84768
	7	0.89209	0.87731	0.89252	**0.88206**	0.85856	0.85403	0.85644	0.85793
	8	0.89512	0.87937	0.89425	0.88162	0.86106	0.85125	0.86177	0.84217
	9	0.89086	0.88086	0.89328	0.87426	0.85684	**0.85889**	0.86656	0.85883
	10	0.88856	0.88010	0.88967	0.87997	0.86259	0.84090	**0.87013**	0.85468
	11	0.89134	0.87508	0.89125	0.87686	0.85885	0.85197	0.85369	0.84510
	12	0.88846	0.87587	0.89400	0.88105	0.85362	0.84972	0.86796	0.85585
	13	0.88870	0.86693	0.89375	0.87600	0.85575	0.83931	0.85644	0.85642
	14	0.87369	0.87150	**0.89542**	0.87421	0.86041	0.85231	0.86727	0.84845
	15	0.88625	0.87110	0.88969	0.87362	**0.86681**	0.85358	0.85403	**0.86945**

Table A.2 Macro-Averaged AP-Scores of All Classes

		Conditions							
		1	2	3	4	5	6	7	8
max n-gram length	1	0.79998	0.75426	0.76915	0.76028	0.76414	0.71638	0.77121	0.72274
	2	0.80459	0.77561	0.79090	**0.79243**	0.75770	0.75826	0.76001	0.75260
	3	**0.80807**	**0.78539**	0.79045	0.78538	0.76450	0.75281	0.76895	0.76315
	4	0.79333	0.78249	0.78759	0.76358	0.76157	0.75335	0.75009	0.75843
	5	0.80807	0.78237	0.79266	0.76794	0.75546	0.75181	0.75882	0.77015
	6	0.78405	0.77931	**0.80132**	0.76689	0.76495	0.75031	**0.77623**	0.75212
	7	0.79768	0.77712	0.79728	0.76820	0.76913	0.75521	0.74464	0.76786
	8	0.79060	0.77587	0.79075	0.77641	0.76729	0.76235	0.76174	0.75969
	9	0.79412	0.77728	0.78958	0.75259	0.76786	0.75242	0.74746	0.76732
	10	0.78881	0.77820	0.78910	0.76923	0.76689	0.76032	0.76641	0.75721
	11	0.79597	0.77398	0.79302	0.77094	0.76086	0.76354	0.76075	0.73879
	12	0.78550	0.77857	0.79082	0.78332	0.74792	0.76637	0.76998	0.76448
	13	0.79340	0.76907	0.79065	0.75373	0.75489	0.74406	0.75701	0.75932
	14	0.77876	0.77184	0.79121	0.76499	0.76382	0.75211	0.75768	0.76184
	15	0.78395	0.76465	0.78830	0.76070	**0.77167**	**0.77614**	0.74695	**0.77150**

Table A.3 AP-Scores of Two Classes (Subjective vs All)

		Conditions							
		1	2	3	4	5	6	7	8
max n-gram length	1	0.90501	0.89149	0.88107	0.90806	0.91505	0.89741	0.89351	0.88440
	2	0.93336	0.92283	0.91246	0.92152	0.92710	0.89072	0.88780	0.91804
	3	0.94239	0.91865	0.92768	0.94003	0.90400	0.90593	0.91811	0.90613
	4	0.94333	0.93144	0.94016	0.93299	0.92555	0.92370	0.90864	0.91680
	5	0.95273	0.94288	0.93150	0.94842	0.92308	0.89751	0.92782	0.92390
	6	0.94767	0.94021	0.94799	**0.95153**	0.92594	0.90369	0.90920	0.91275
	7	0.94967	0.94131	0.94568	0.94773	0.90604	0.92381	0.92287	0.93336
	8	**0.95740**	0.93798	0.94737	0.95101	0.92411	0.91136	0.90881	0.90886
	9	0.94873	**0.95107**	0.94773	0.94274	0.90559	**0.93126**	0.92834	0.92388
	10	0.94585	0.94358	0.94162	0.94536	0.92514	0.90118	0.93022	0.91742
	11	0.94941	0.94000	0.93928	0.94745	**0.92916**	0.91121	0.90954	0.92416
	12	0.95327	0.93872	0.94868	0.94808	0.91769	0.90859	0.92494	0.91523
	13	0.95026	0.93438	0.95207	0.94390	0.92459	0.90395	0.90351	0.92396
	14	0.93729	0.92832	**0.95703**	0.95128	0.91915	0.91917	**0.93349**	0.92274
	15	0.95010	0.93111	0.94280	0.94444	0.92890	0.90565	0.91919	**0.93660**

Table A.4 AP-Scores of Two Classes (Objective vs All)

		Conditions							
		1	2	3	4	5	6	7	8
max n-gram length	1	0.90375	0.85260	0.87347	0.85891	0.87562	0.83632	0.87708	0.84159
	2	0.89769	0.88483	0.89230	0.88298	0.88828	0.87137	0.88961	0.87662
	3	0.90800	0.87393	0.90164	0.88555	0.89864	0.86943	0.88837	0.87976
	4	0.90251	0.88142	0.90932	0.88496	0.89250	0.88372	0.88241	0.88566
	5	0.90749	**0.89293**	0.91095	0.87892	0.87744	0.87557	0.90670	0.87394
	6	0.89953	0.87594	0.91214	0.88282	**0.90129**	0.87362	0.90426	0.87490
	7	0.90831	0.88341	0.90971	**0.89423**	0.89659	**0.88469**	0.88819	0.87681
	8	0.91126	0.89258	0.91615	0.88261	0.88810	0.87390	0.89979	0.86681
	9	0.91129	0.88297	0.91712	0.89106	0.90063	0.87826	0.90311	0.87514
	10	0.91113	0.88707	0.91147	0.89191	0.89916	0.87251	0.90402	0.87803
	11	**0.91130**	0.89220	**0.91876**	0.88074	0.88890	0.87459	0.90308	0.87257
	12	0.90712	0.88976	0.91710	0.88228	0.89269	0.87452	**0.90712**	**0.88933**
	13	0.90656	0.87141	0.91521	0.89360	0.89582	0.87049	0.90602	0.88417
	14	0.90707	0.88522	0.91463	0.87518	0.89538	0.88458	0.90084	0.86635
	15	0.90746	0.88614	0.91403	0.88204	0.89858	0.87836	0.88369	0.88256

Table A.5 AP-Scores of Two Classes (Assessment vs All)

		Conditions							
		1	2	3	4	5	6	7	8
max n-gram length	1	**0.62572**	0.51981	**0.58515**	0.54963	0.48264	0.42715	**0.50811**	0.41564
	2	0.58350	0.52195	0.56644	**0.57512**	0.43244	0.49223	0.47429	0.44123
	3	0.59137	**0.55334**	0.55362	0.53872	0.44582	0.47400	0.47320	0.48630
	4	0.53987	0.53424	0.54579	0.47043	0.43733	0.45967	0.40620	0.45350
	5	0.60639	0.50124	0.56271	0.48171	0.43891	0.45345	0.42155	0.51026
	6	0.51899	0.50746	0.56486	0.47294	0.43950	0.46482	0.47102	0.44875
	7	0.55083	0.49840	0.57151	0.48657	0.48152	0.46541	0.42106	0.47560
	8	0.53778	0.49373	0.55106	0.49727	0.45034	0.46598	0.46191	0.46540
	9	0.55811	0.50911	0.53652	0.43471	0.45231	0.46446	0.44352	0.49112
	10	0.55279	0.52788	0.53187	0.47275	0.43585	0.47011	0.46762	0.45519
	11	0.56682	0.51310	0.55637	0.51224	0.43034	0.49273	0.44681	0.44773
	12	0.54444	0.50459	0.54401	0.54557	0.43188	0.50355	0.44888	0.48709
	13	0.56513	0.49285	0.53277	0.44201	0.39557	0.44036	0.45409	0.45822
	14	0.52844	0.51922	0.53272	0.48407	0.42753	0.42670	0.42524	0.49405
	15	0.54566	0.50524	0.53355	0.45283	**0.49985**	**0.52671**	0.44175	**0.52557**

Table A.6 AP-Scores of Two Classes (Plan vs All)

		Conditions							
		1	2	3	4	5	6	7	8
max n-gram length	1	0.76542	0.75312	0.73690	0.72453	0.78324	0.70465	0.80615	0.74932
	2	**0.80380**	0.77281	**0.79240**	**0.79008**	0.78297	0.77872	0.78832	0.77451
	3	0.79052	**0.79562**	0.77884	0.77720	0.80953	0.76187	0.79611	0.78040
	4	0.78761	0.78287	0.75510	0.76593	0.79089	0.74632	0.80311	0.77775
	5	0.76565	0.79241	0.76548	0.76269	0.78241	0.78070	0.77922	0.77251
	6	0.77001	0.79364	0.78029	0.76025	0.79305	0.75910	**0.82042**	0.77209
	7	0.78190	0.78535	0.76220	0.74425	0.79237	0.74693	0.74642	0.78567
	8	0.75596	0.77918	0.74840	0.77476	0.80662	**0.79814**	0.77646	**0.79768**
	9	0.75836	0.76597	0.75696	0.74186	0.81290	0.73569	0.71488	0.77912
	10	0.74545	0.75426	0.77144	0.76691	0.80741	0.79749	0.76379	0.77821
	11	0.75635	0.75062	0.75767	0.74334	0.79502	0.77564	0.78358	0.71071
	12	0.73718	0.78119	0.75350	0.75734	0.74943	0.77882	0.79898	0.76625
	13	0.75164	0.77764	0.76255	0.73542	0.80356	0.76144	0.76442	0.77093
	14	0.74224	0.75461	0.76046	0.74943	**0.81323**	0.77798	0.77115	0.76423
	15	0.73256	0.73611	0.76280	0.76349	0.75936	0.79384	0.74318	0.74126