

Data Selection for the Training of Deep Neural Network in the Framework of Automatic Speech Recognition



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This thesis is dedicated to
someone
for some special reason

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plenty of waffle, plenty of waffle, plenty of waffle, plenty of waffle, plenty
of waffle, plenty of waffle, plenty of waffle, plenty of waffle.

Abstract

This internship used 200 hours of speech data and their corresponding closed captions obtained from BBC. However, only closed captions are provided by the challenge. In other word, the closed captions are not exactly the same as what audio says. Utilizing the whole dataset generates a bad acoustic model owing to imperfect closed captions. Thus, the objective of the internship is to develop a data selection method to obtain a high performance automatic speech recognition(ASR). Simply put, the ASR must reduce word error rate as small as possible.

A baseline system was developed from a 200 hours random subset of whole training set(train.200). Firstly, a deep neural network was trained on the 100 hours subset of data from train.200 and recognized train.200 to calculate phone matched error rate(PMER), word matched error rate(PMER), and average word duration(AWD). The audio segments were sorted and selected based on PMER and AWD for the next iteration. According to our experiments, baseline system shows decreasing trend of word error rate as well as phone matched error rate threshold. Moreover, I proposed a new algorithm which combines three ASR systems by varying language models. These novel approaches are compared with the baseline system to assess whether it achieves better performance.

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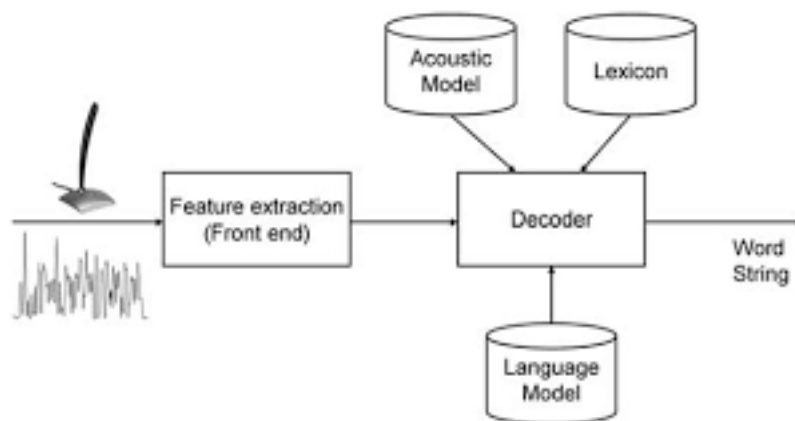
Chapter 1

Introduction

1.1 Motivation

Automatic speech recognition(ASR) is one of the subfield of natural language processing(NLP) with many practical applications. Some examples of practical applications in speech recognition; for example: automatic closed captioning for hearing-disabled persons [20], taking notes of conversations between doctors and patients [10], automatic closed captioning TV broadcasts [34], and many more. This internship will focus on the application of automatic transcription on television broadcasts.

Figure 1.1: automatic speech recognition



Picture 1.1 shows an illustration how the automatic speech recognition works. ASR receives acoustic inputs and outputs a word string. An automatic speech recognition is composed of three components: acoustic model, language model, and lexicon. Acoustic model is a statistical model which represents a relationship between an acoustic input and its corresponding phoneme. Phoneme is a unit (or a group) of sound, for example: /k/, /l/, /sh/, etc. Lexicon is a dictionary which maps from

words to their phonemes. Language model computes the probability of a word string where each word consists of several phonemes. Hence, the lexicon glues the acoustic model and the language model together. These three components work together to search the most likely sentence (from all possible sentences) which represents what people said in the audio.

Despite of the rapid development of speech recognition, there are still many challenges in the field. One of the challenges is training a speech recognizer or adapting a speech recognizer to a new task requires a massive amount of transcribed training data. However, transcribing audio manually is labor intensive and also time consuming. There exist many unlimited supply of training data sources from internet, TV broadcasts, radio, as well as video streaming website, like Youtube. Nevertheless, many of them only possess few corresponding transcriptions or no transcription at all. To build a speech recognition, we can use a training dataset from TV broadcasts which usually have closed captions. Closed captions are close, but not exactly the same as what people said. Furthermore, closed captions are often badly aligned with the audio. These are some examples of good and bad closed captions, as well as noisy utterance.

1. An example of good closed caption. This segment/utterance has the same closed caption as the detailed transcription.
 - Real transcription: That is the very big question that leads to another big question. We're definitely thinking about putting an offer. That's great.
 - Closed caption: That is the very big question that leads to another big question. We're definitely thinking about putting an offer. That's great.
2. An example of bad closed caption. The closed caption is slightly different compared to the real transcription.
 - Real transcription: Russia started badly with the dropping at the hands of Spain. But, they got better and better. Spain looked unstoppable to start with but since then they have looked a little.
 - Closed caption: Russia started badly with at beating at the hands of Spain. Spain looked then they have looked a little
3. Noisy segment. Some segments in training audio may have background noise which makes it hard to be recognized by the ASR. Even, it is sometimes difficult

to be recognized by humans. [Clapping in the background] John Higgins developed very well. He is not five in front.[Still continues clapping in background]

This internship explored how to build a high performance speech recognition system by utilizing less supervision because we did not have correct transcription audio data. The main idea is to use an automatic speech recognizer to automatically transcribe audio data which can be leveraged as a training dataset. The steps of the main idea are as following: firstly, train on all data which are automatically transcribed by other ASR systems, recognize these data with the ASR which we trained, and then compare the decoding transcriptions with the closed captions. Finally, remove all words which do not agree and train only the words which agree.

This idea of using untranscribed data(or unsupervised training) has been proposed by Zavaliagkos and Colthurst in 1998 [35], Kemp and Waibel in 1999 [8]. However, they only utilized small amount of data. Lamel et al were the first who proposed lightly supervised training data with a large amount of training data [13]. In place of utilizing untranscribed data, they trained speech recognition systems by using audio data with closed captions.

Lightly supervised approach is one of the technique to select "good" data. An acoustic model from another task(or another corpus) is utilized to recognize audio data. The decoding results are compared with the closed captions and removed if they disagree. These selected data are trained to generate a new acoustic model which is leveraged to recognize the same or different data. These decoding results are selected again for training a new acoustic model. This internship mainly focuses on the acoustic model component.

The goal of this internship is to try and evaluate the state-of-the-art technique to select the "good" training data. In addition, we proposed multiple other possible solutions to select data. The outcome of this internship will be useful as a training dataset to build a high performance automatic speech recognition.

This internship is expected to contribute in solving data selection problem. Internet has infinitely many audio data, for example: podcast, internet radio, tv broadcast, as well as video streaming. But, mostly they do not have transcriptions at all. In this internship, we conceived speech recognition systems by utilizing TV broadcasts and their corresponding closed captions. In the future, we hope that we use audio data without any transcription as the training dataset.

1.2 Contributions

We make several contributions as following:

1. We give some backgrounds related to speech recognition which helps the readers to understand how the speech recognition works in the nutshell. This background helps to grasp the idea of data selection.
2. We did some literature reviews and summarized the data selection method briefly and completely.
3. We implemented and evaluated the data selection techniques.
4. We proposed new approaches in data selection and assessed the approaches against the current state-of-the-art approach.

1.3 Outlines of the thesis

This report is organized as following. In chapter 2, we elaborate some backgrounds in the automatic speech recognition. The chapter gives necessary backgrounds to the readers how speech recognition works; moreover, the data selection method is further explained. Chapter 3 elaborates the data selection technique which was explored and experimented in this internship. Furthermore, the new data selection methods are also proposed. Chapter 4 tells the setup of experiment and evaluation measurement. Then, chapter 5 shows the result of experiments. Lastly, the report is concluded by chapter 6 which conveys conclusion and some suggestions for future works.

Chapter 2

Background and Literature Review

2.1 Background

2.1.1 Automatic speech recognition

The goal of the automatic speech recognition(ASR) is to search the most likely sentence(\hat{W}) in a language L given acoustic observation O [7]. ASR has been applied in many applications and domains, for example: automatic closed captioning for hearing-disabled persons [20], taking notes of conversations between doctors and patients [10], automatic closed captioning TV broadcasts [34], and many more.

Observation O can be seen as a sequence of sliced acoustic signal. Each successive index represents the consecutive slices of acoustic input.

$$O = o_1, o_2, o_3, \dots, o_t \quad (2.1)$$

A sentence is composed of a sequence of words.

$$W = w_1, w_2, w_3, \dots, w_n \quad (2.2)$$

Thus, an automatic speech recognition can be formalized as following:

$$\hat{W} = \operatorname{argmax}_{W \in L} P(W|O) \quad (2.3)$$

Applying the bayes rule to the equation 2.3 produces the equation bellow. Because observations O do not change for every possible sentence, we can assume $P(O)$ as a constant and ignore it.

$$\hat{W} = \operatorname{argmax}_{W \in L} \frac{P(O|W) \times P(W)}{P(O)} \quad (2.4)$$

$$= \operatorname{argmax}_{W \in L} P(O|W) \times P(W) \quad (2.5)$$

where \hat{W} is the most likely sentence, $P(W)$ is the prior probability of sentence W computed by the language model, and $P(O|W)$ is the observation likelihood calculated by the acoustic model. This internship mainly focuses on the acoustic model. We will discuss the language and acoustic model more in the next subsection.

2.1.2 N-Gram Language model

A language model is a statistical model which computes the probability of word sequence. One of the most common language model is N-gram language model, which we leverage in this internship. The foundation mathematics of N-Gram language model was proposed by Markov in 1913. Then, Shannon re-introduced N-gram to compute the likelihoods of English word sequences [27]. N-gram language model has been applied in many applications, such as: speech recognition [34], handwriting recognition [23], as well as spelling correction [12].

The goal of language model is to compute the probability ($P(w|h)$) of a word w given previous word history h . The way to compute this probability is by using a large corpus and count the relative frequencies. For example: to count the word w_1 given history: w_2, w_3, \dots, w_n , the probability is as following:

$$P(w_1|w_2w_3\dots w_n) = \frac{C(w_1w_2w_3\dots w_n)}{C(w_2w_3\dots w_n)} \quad (2.6)$$

Because we can create infinitely possible sentences, it is more efficient to compute probability by applying the chain rule of probability.

$$\begin{aligned} P(w_1^n) &= P(w_1)P(w_2|w_1)P(w_3|w_1^2)\dots P(w_n|w_1^{n-1}) \\ &= \prod_{k=1}^n P(w_k|w_1^{k-1}) \end{aligned}$$

However, the probability of a word given preceding words is infeasible to be computed. Instead of computing the entire preceding history, N-gram only approximates the probability with last few words. For example: the bigram LM approximates the probability of a word given history by the probability of a word given the last word only $P(w_n|w_{n-1})$. This approximation(or assumption) is called Markov assumption.

A major problem exists in N-Gram language model. Information inside a corpus might be limited. Some word sequences probably do not exist in the corpus, but they are perfectly acceptable word sequences. If we calculate the N-Gram likelihood for these sequences, we will get zero value. The solutions to the problem are backoff and smoothing. Backoff allows the N-gram LM to use the value of lower N-Gram LM if we have zero probability in the higher N-Gram. Smoothing is a technique to avoid zero

probability for every word sequence. If a word sequence does not exist in the corpus, the LM still produces a non-zero value even though it is small. We used Kneser-Ney smoothing [11] which has been implemented in SRILM framework.

To evaluate the performance of a language model(LM), perplexity can be applied to the LM. The intuition behind LM is given two N-gram LM, the better model is the one which predicts test set better than the other. Lower perplexity means that the model is better. Given a language model and a test corpus, perplexity is calculated as following [2] [9]:

$$PP = \exp\left(-\frac{1}{N} \sum_{i=1}^N \log P(w_i|h_i)\right) \quad (2.7)$$

where N is the number of words in test corpus, w_i is the i -th word, and h_i is the history of word w_i .

2.1.3 Acoustic model

The acoustic model(AM) is commonly based on hidden markov model(HMM). Thus, before talking about the acoustic model deeply, it is better to elaborate HMM first.

2.1.3.1 Markov chain

A weighted state finite automaton is a finite state automaton where the arc between nodes has probability how likely the path is taken. Markov chain is one kind of weighted state finite automata which the input sequence determines which state the automaton will go.

Markov chain can be defined formally as following:

- $Q = q_1 q_2 \dots q_N$ a set of states

- $A = \begin{bmatrix} a_{01} a_{02} a_{03} \dots a_{0n} \\ a_{11} a_{12} a_{13} \dots a_{1n} \\ \dots \\ a_{01} a_{02} a_{03} \dots a_{0n} \end{bmatrix}$ is a transition probability matrix where a_{ij} represents the probability of moving from state i to state j . In addition to that, the sum of outgoing probability of every state must be summed into 1. $\sum_{j=1}^n a_{ij} = 1$.

- q_0 and q_F represent initial and final states.

2.1.3.2 Hidden markov model(HMM)

Markov chain is only usable if the event is directly observable in the world. However, we are interested in some events which are not observable or hidden for some problem. For example: acoustic event is observable, but word event is not observable in speech recognition problem. Hidden markov model fixes this problem.

Hidden markov model is formalized as

- $Q = q_1 q_2 \dots q_n$ is a set of states
- $A = \begin{bmatrix} a_{01} a_{02} a_{03} \dots a_{0n} \\ a_{11} a_{12} a_{13} \dots a_{1n} \\ \dots \\ a_{n1} a_{n2} a_{n3} \dots a_{nn} \end{bmatrix}$ is a transition probability matrix where a_{ij} represents the probability of moving from state i to state j such that $\sum_{j=1}^n a_{ij} = 1$ for every i .
- $O = o_1 o_2 \dots o_T$ is a sequence of T observations.
- $B = b_i(o_t)$ is observation likelihoods(or emission probability) where state i emits probability given observation o_t .
- q_0, q_F are initial and final states.

Hidden markov model employs two assumptions:

1. Markov assumption. The state is only dependent to the previous state.

$$P(q_i | q_1 q_2 \dots q_{i-1}) = P(q_i | q_{i-1}) \quad (2.8)$$

2. Output independence assumption. Output observation o_i is only dependent with the state q_i which produces o_i and independent with other states and other observations.

$$P(o_i | o_1 o_2 \dots o_{i-1} o_{i+1} \dots o_T q_1 q_2 \dots q_{i-1} q_{i+1} \dots q_N) = P(o_i | q_i) \quad (2.9)$$

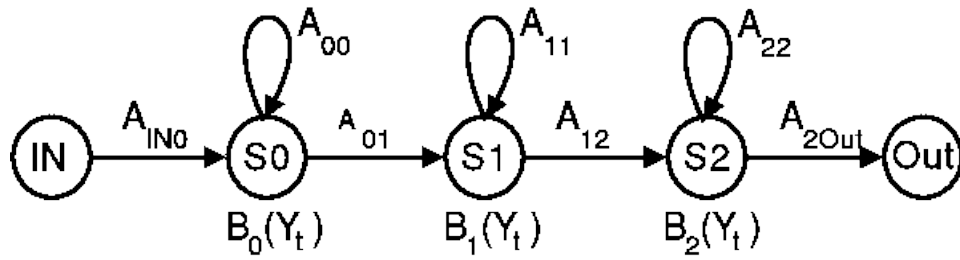
2.1.3.3 Applying HMM to acoustic model

In section 2.1.3.2, HMM is explained. Now, it is time to apply HMM on acoustic model.

1. States

A state in acoustic model can represent a word, a phone, or a sub phone depending on the problem we are trying to solve. For the digit recognition problem, a state represents a sound of one number. A sequence of phone can be represented as a word string. Hence, for more complicated task, like recognizing TV broadcast, it is better to make a state representing a phone or even a sub phone. A sound of a phone is usually influenced by the preceding and successive phone. Therefore, we use three HMM states(for each phone) which capture beginning, middle, and end of the phone. The sub phone state is commonly called as a senone.

Figure 2.1: A triphone HMM model consisting of three emitting states(beginning(S_0), middle(S_1), and end(S_2) of a phone), a transition matrix A , and emission probability(observation likelihood) B [28]



2. Transition matrix

The transition matrix in speech recognition is the probability of moving from the current sub phone state to the successive sub phone state. Unlike HMM, Speech recognition HMM does not allow arbitrary transition because of the sequential nature of language and speech. A state can go to itself or to the next states, but it can not go back to the preceding state. This kind of left-to-right constrained HMM is called Bakis network.

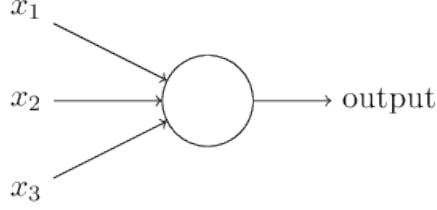
3. Observation

The observation is a sequence of acoustic feature vector. The acoustic input is divided into small chunks and converted into a feature vector.

4. Observation likelihood

Observation likelihood is the probability of a feature vector which is generated by a sub phone state.

Figure 2.2: A perceptron



2.1.4 Deep learning for acoustic model

For our acoustic model, we used deep neural network(DNN) HMM. Beside DNN HMM, there exists gaussian mixture model(GMM) HMM. However, DNN HMM has been proven to outperform GMM DNN in practice [21]. Hence, we only discuss DNN in this report.

2.1.4.1 Feedforward neural network

Feedforward neural network(or sometimes called multilayer perceptron(MLP)) is one kind of neural network. MLP approximates function $f'(\mathbf{x}) = \mathbf{y}$. MLP can be represented as $f(\mathbf{x}; \theta) = \mathbf{y}$ and learn parameters θ which maximizes function approximations.

Perceptron is a kind of artificial neuron developed in 1960 by Frank Rosenblatt [25]. A perceptron receives several inputs(x_1, x_2, \dots, x_n), does weighted sum $\sum_i x_i w_i$, and is thresholded by bias b to make a decision: zero or one.

$$output = \begin{cases} 0, & \text{if } \sum_i x_i w_i + b \leq 0 \\ 1, & \text{if } \sum_i x_i w_i + b > 0 \end{cases} \quad (2.10)$$

A perceptron is too simple to capture non linear pattern. Therefore, the perceptron is modified by applying an activation function into weighted sum. There are several common activation functions, such as:

1. Sigmoid

$$a(x) = \frac{1}{1 + e^{-x}} \quad (2.11)$$

2. Rectified linear unit(relu)

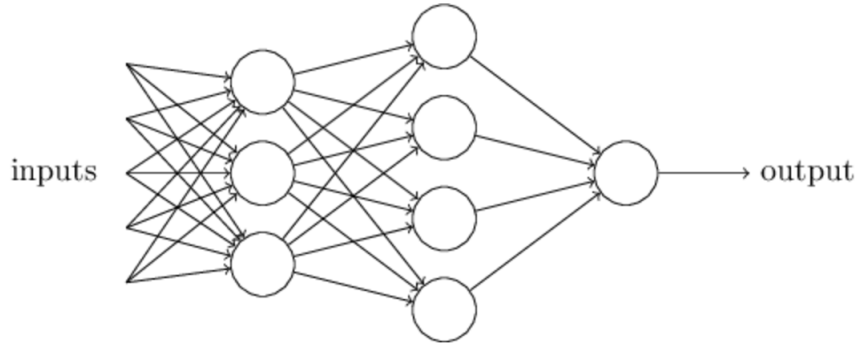
$$a(x) = \max(0, x) \quad (2.12)$$

3. Softmax

$$a(x) = \frac{e^x}{\sum_i e^{x_i}} \quad (2.13)$$

In addition to activation function, we need to make neuron to capture more complex features by stacking many neurons together. This network is called a feed forward multi layer perceptron. This neural network does not have connections between units which form a cycle. It is also called feedforward because the input values are propagated forward to output. The neural network receives inputs, does weighted sum, and applies activation function. The output of the units in one layer is propagated to the units in the next layer until reaching output layer.

Figure 2.3: Multi layer perceptron



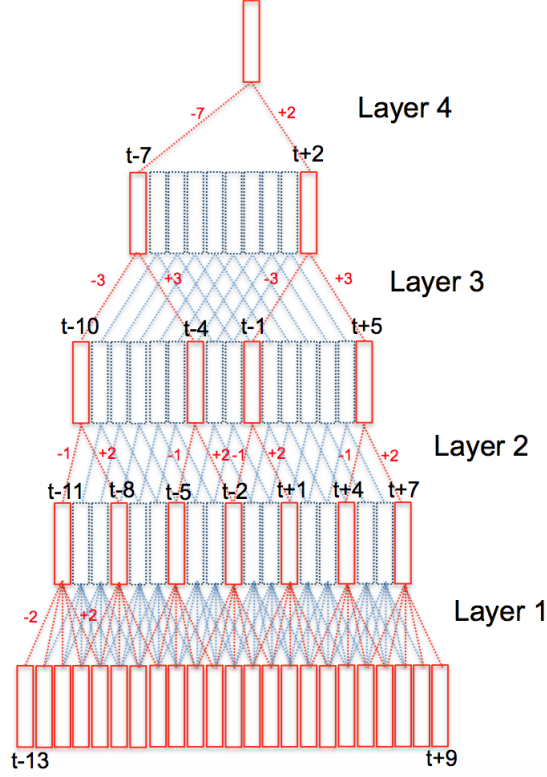
2.1.4.2 Time delay neural network(TDNN)

To model a temporal sequence neural network, like the speech recognition problem, the model must have the following properties: it must have multiple layers to learn complex non linear decision surface, represents relationships between events in time, invariant under translation in time, and does not require precise temporal alignment. From all of these properties, time delay neural network(TDNN) qualifies to model a temporal sequence neural network.

There exist two ways to capture long temporal contexts:

1. Feature representation which present the information of long temporal contexts. The examples of the feature representation are TRAPs [6], multiscale spectro-temporal modulations representation [19], deep scattering spectrum representation [1], and modulation frequency feature representations [32]. These feature representations can use the standard feed forward deep neural network to model the temporal sequence neural network.
2. Acoustic model which can learn long temporal contexts and is trained on short-term feature representations. Recurrent neural network(RNN) [26] and time delay neural network [33] are two state-of-the-art acoustic models which are suitable to model this acoustic model.

Figure 2.4: An example of a TDNN architecture. [21]



Peddinti et al showed that TDNN performs better than RNN in term of parallelization during training [21]. Due to recurrent connections in RNN, RNN is not able to fully utilize parallelization in GPU(general processing unit) the same extent as TDNN. In addition, TDNN has been proven to have lower word error rate compared to RNN [21]. Thus, we will focus more on TDNN and trained acoustic models with TDNN in this internship.

Time delay neural network(TDNN) was first proposed by Waibel et al in 1990 [33].TDNN is suitable to model long term temporal relationship within the range of N delays in short term speech features; for example: MFCC feature representations.

TDNN is basically a feedforward neural network. Learning procedure which we used is backpropagation. There are two passes procedure in the backpropagation. The first pass is forward pass where the neural network receives input, does weighted sum, and applies activation function. The output values from the first layer is forward propagated until reaching the output layer. Then, square error is calculated between the expected value and the output of neural network. The second pass is backward pass where the derived square error value is propagated backward to update weights.

Typical TDNN computes all hidden activation in each layer. Figure 2.4 demon-

strates an architecture of TDNN. TDNN receives acoustic inputs with some delays to the left and right contexts(before and after time t). Usually, the input context is asymmetric, i.e: more time context to the left than right. The main reasons are to reduce the latency of online decoding and improve word error rate. Each layer splice together contiguous temporal windows within a time range; for example: the third layer splices the frames within range $[t - 3, t + 3]$ in the figure 2.4. Furthermore, TDNN applies wider splice when going to higher layers in the networks as shown in the figure 2.4. The reason is we force the higher layer to learn wider temporal contexts.

Training a TDNN is still time consuming. The standard TDNN computes all hidden activation in each layer. Consequently, the training time of TDNN is approximately ten times compared to the standard DNN. Peddinti et al found that there exist large overlaps between input contexts at neighboring time steps; thus, they proposed subsampling [21]. The technique generally only splice no more than two temporal contexts with gap instead of contiguous temporal windows. Figure 2.4 illustrates the procedure of subsampling. In the standard TDNN, all hidden units(red and blue) are calculated. In contrast with subsampling technique, only red hidden units are computed. In consequence, the training time of subsampled TDNN is approximately five times faster than the standard TDNN [21]. Moreover, subsampling is able to reduce the model size. Splicing contiguous temporal contexts will require a massive number of parameters. However, subsampling only splices less temporal contexts than the typical TDNN.

2.1.4.3 Hybrid acoustic model

To train a TDNN or other kinds of DNN acoustic model, one needs to label each acoustic input vector. However, our initial data only have utterance level of start and end time. Even, each word does not have start and end time. Each acoustic input must be labeled with its corresponding senone in order to train a DNN-HMM acoustic model.

GMM acoustic model can bootstrap the labeling process [17]. We can train a GMM-HMM acoustic model with flat start, i.e: without previous phoneme-to-audio alignment. Therefore, the step before training a DNN acoustic model is by training a GMM-HMM acoustic model. Then, force align the training set with the acoustic inputs to generate a sequence of senone which corresponds with the transcription in the segments. The aligned data(the acoustic input with its corresponding senone) is utilized to train a DNN acoustic model.

Training a DNN-HMM is a little bit different than the HMM as explained in 2.1.1. An acoustic model usually models the probability $P(o|y)$ of observation(acoustic input) o given its corresponding senone y . Nonetheless, DNN models the probability of a senone given the observation $P(y|o)$. By applying the bayes rule, $P(o|y)$ can be obtained as the following:

$$P(o|y) = \frac{P(y|o) \times P(o)}{P(y)} \quad (2.14)$$

$P(y)$ can be obtained from distribution of a senone in the training set. By using lexicon, each word in the training set can be mapped into the corresponding senone. However, $P(o)$ is infeasible to be obtained. Luckily, the observation o are fixed and can be seen as a constant. Hence, we can provide HMM with the unnormalized probability..

$$\frac{P(y|o)}{P(y)} \quad (2.15)$$

Applying the hybrid approach has been introduced over 20 years ago [4,24]. Nevertheless, it did not outperform GMM until recently. DNN excels in improving accuracy due to more representational capacity compared to GMM [17]. There are several factors why DNN outperforms GMM just recently.

- The amount of training dataset has increased. DNN usually works well when there exists a massive volume of training data.
- Training DNN can be done on GPU which accelerates the execution time.
- We have more powerful neural network architecture recently with more number of parameters, more hidden layers(deeper network), and better initialization procedure.

Chapter 3

Methodology

3.1 Lightly supervised data selection approach

Despite of the high development in automatic speech recognition, there exist many challenges. One of the main challenge of speech recognition is to reduce development cost when adapting the speech recognition to other task or creating a new speech recognition for a new language. The biggest development cost is to transcribe the audio data with their exact corresponding transcriptions. To generate a "good" speech recognition, one needs a massive number of training audio and their exact transcriptions. However, transcribing audio is labor intensive and time consuming too. There are unlimited supply of audio data in the internet, television, radio, and other sources. Nonetheless, they usually have a few or even no accurate transcription at all. Some television broadcasts have corresponding closed captions. Closed caption means that the transcription is close, but not exactly the same as what the audio says. Even, the closed captions are often badly time-aligned with the audio.

By utilizing these audio data with the corresponding closed captions, we hope to produce a high performance speech recognizer with less supervision. The main idea is to use the automatic speech recognizer to transcribe audio data which will automatically generate transcriptions, which later be used as training data [13]. The steps are as following. Firstly, we train a bootstrap acoustic model trained on a small manually annotated data. Then, recognize the data with closed captions by using the bootstrap model. We compare the decoding result from the bootstrap model with the closed captions and remove the words which do not agree. Finally, we can train a new acoustic model from the filtering.

The idea of using untranscribed audio data has been explored before (Zavaliagkos and Colthurst in 1998 [35] and Kemp & Waibel [8]), which is called as unsupervised

acoustic model training. They utilized small amount of audio data without transcription to train acoustic models. The drawback of their experiments is not using massive volume of training data which is essential to train an acoustic model.

Lightly supervised approach was proposed in 2002 by Lamel et al [13]. In general, the lightly supervised approach operates as following:

1. Train an acoustic model on a small amount of manually annotated data.
2. Recognize(or automatically transcribe) a massive amount of data.
3. Align the automatic transcriptions with the closed captions. Some transcriptions and closed captions might disagree. We can remove or correct these segments.
4. Retrain a new acoustic model using the data which we selected in the previous step.
5. Reiterate from step 2.

These steps can be iterated several times as long as the error rate is decreasing. This method uses the idea of training acoustic model in less supervised manner because the training dataset(closed captions) is not the real detailed transcription.

Using closed caption as training data reduces effort in manual transcription. Detailed transcription process usually takes 20-40 times manual effort compare to live closed captioning. Closed caption is usually produced in real time and less costly compare to the detailed transcription. In addition, the manual transcription is possible to have error [3]. Additionally, some TV broadcasts, such as: CNN headline news, ABC world news tonight, BBC, already have closed captions which can be used as a training dataset. Nevertheless, some problems exist when using the data with closed captions as training dataset. However, training using the closed captions faces several disadvantages compared to the real transcriptions: indication of non speech event, such as: coughing, speaker turn, acoustic conditions: background noise and music. Furthermore, some sentences might be paraphrased, deleted, and changed in word order.

In addition to the closed captions, we can use additional data to build a language model. Other kinds of text are available in internet, such as: news, blog, and closed captions from TV broadcast. However, these data might be less related with the audio data. Some additional sources may be not contemporaneous with the data. Thus, it

provides less supervision. We can interpolate these data with the closed captions to build a more general language model.

Despite the fact that closed captions are not accurate, it has been proven that closed captions provides enough supervision in building automatic speech recognition systems [13]. Lamel found that an increase in training data improves accuracy even though it will increase the model size. Additionally, filter closed captions for the next iteration training set in the lightly supervised technique improves the accuracy slightly. The language model built from closed captions also effectively provides enough supervision in building the ASR. Therefore, lightly supervised technique is our main inspiration to do data selection in this internship.

3.2 State-of-the-art data selection

Some researches have been conducted to investigate the lightly supervised approach to select data in the speech recognition problem [5, 13, 16, 18, 30]. The state-of-the-art data selection was proposed by Lanchantin et al from Cambridge university [15]. Before talking about the state-of-the-art, it is better to discuss some previous related works first.

Lamel et al proposed the lightly supervised approach which harnessed the closed caption as supervision to build a robust speech recognizer [13]. In their experiment, they used a bootstrap acoustic model and biased language model to recognize the audio where the decoding result is compared with the closed caption. Then, the words which do not agree will be removed from training dataset. The new training dataset is utilized to train a new acoustic model. This filtering (removing not-agree words) is called closed caption filtering.

Chan and Woodland explored another way in filtering bad closed captions [5]. They leveraged the confidence measure metric to remove the bad segments. When decoding acoustic inputs, an ASR produces word hypothesis and their corresponding confidence measure. The confidence measure value from each word in each segment is averaged to produce one confidence value per segment. Finally, they determined a threshold confident value to filter out all potentially bad segments, where the confident value is lower than the threshold. Moreover, they also introduced to interpolate two different LMs created from two closed caption datasets and merge them into one single LM. This single LM is used as light supervision when decoding acoustic input together with the acoustic model and the lexicon.

Matias et al applied lightly supervised approach on medical conversation data [18]. There are unlimited supplies of medical speech; however, only informal medical reports are available. The medical reports are not the same as what the physicians said in the audio records. This problem matches perfectly with the lightly supervised approach. They explored frame level filtering in place of word level or segment level filtering. Basically, they forced align and compared the decoding results with the closed captions and mark words which are insertion, deletion, and substitution. All corresponding frames which are associated with those marked words are removed or filtered out from training set to produce a new cleaner training set.

The state-of-the-art data selection was proposed by Lanchantin et al from Cambridge university [15]. They used the lightly supervised approach applied on the multi genre broadcast(MGB) challenge. MGB challenge is a challenge to automatically transcribe TV broadcasts. The challenge only provided TV broadcast audio data and their corresponding closed captions. General TV broadcast data are usually recorded in highly diverse environment speech with background music, non speech event, and sound effect. In addition, some closed captions may be different compared to the real transcription due to deletion, insertion, substitution, and paraphrasing. These factors make the challenge interesting as well as complicated.

Lanchantin et al proposed to tackle the problem inspired from the lightly supervised approach. The lightly supervised approach works as following [14].

1. Trained an acoustic model by selecting a subset of 200 hours training set from the total 1600 hours training set. We called this as AM-v1 which is based on deep neural network.
2. AM-v1 recognized the entire training dataset(1600 hours) which resulted in the decoding result. Compare and force aligned the decoding result with the closed captions. By comparing each segment, they calculated phone matched error rate(PMER) and word matched error rate(WMER) as well as average word duration.
3. By utilizing average word duration and phone matched error rate, they selected 700 hour of data(700hr-v1). The way to select the data is
 - (a) Reject segments which are not in the range of $0.165 \leq AWD \leq 0.66$
 - (b) Sort segments based on PMER and select the top segments until reaching 700 hours set. The threshold for this iteration is 40%. This new selected training data is called 700-v1.

4. Retrain a new acoustic model using the 700-v1. Repeat step 2-4 to create 700-v2, 700-v3 until the data selection algorithm converges.

In every iteration, the language model which they utilized are the same. MGB provides closed captions for each audio and additional text consisting 10 million and 640 million words respectively. From these texts, two language models were built and interpolated into one language model. Furthermore, the merged language model was pruned by 10^{-9} to expedite the decoding process.

A question remains to be asked: when to stop the iteration(the algorithm converges)? The MGB challenge provides a development set which comprises of audio data and their manually transcribed transcriptions. These transcriptions are exactly what people said in the audio with correct time stamp. By recognizing the development set with the ASR system which they built in each iteration, they calculated word error rate(WER). If the WER decreases in the next iteration, continue the iteration. Otherwise, stop the iteration.

3.3 Data

Before talking about the methodology, it is better to talk about the dataset. We have the following dataset:

1. Training set has audio data with their corresponding closed captions.
2. Test set has audio data and their corresponding manual transcriptions. These manual transcriptions are the same as what people said in the audio.
3. Additional text corpus which is utilized for building language model. This additional corpus is different than the closed captions in training set.

3.4 Baseline model

3.4.1 Language model

3.4.2 Acoustic model

3.4.3 Data selection

3.5 Baseline model

3.6 Baseline model

3.6.1 Acoustic model AM.200 and Language Model Version 1 (LM.200.1e-9)

Calculating PMER and WMER for each segment by utilizing AM.200 and LM.200.1e-9:

1. GMM(GMM.200): GMM is trained by using the 200 hours data
2. TDNN(TDNN.200): the result of GMM training(GMM.200) is utilized to build a TDNN(time delay neural network).
3. TDNN graph creation
The language model used is the LM.200.1e-9 and the acoustic model is TDNN.200; furthermore, the dictionary used(Lexicon.200) is the modification of the library provided by MGB(Lexicon.MGB). Words in Lexicon.MGB which do not exist in word.200 are removed from Lexicon.200.
4. TDNN 200 hours of training data recognition
We need to recognize 200 hours data to calculate PMER, WMER, and AWD. This data will be used for data selection of the next iteration.
5. Sclite score PMER and WMER
Use the lattice and graph(produced at step 5 and 3 respectively) to calculate overall PMER and WMER. However, the decoding program does not provide PMER, WMER, and AWD for each segment. Fortunately, the program generates prf file which contains number of correction, insertion, deletion, and substitution for each segment. Two prf files exist after decoding:(ctm_words.filt.filt.prf contains word match error rate and ctm_phones.filt.filt.prf contains phone match error rate). From there, we are able to calculate PMER, WMER, and AWD

of each segments. For the development set, we only need to know the overall PER and WER. In contrast, training set recognition needs PMER, WMER, and AWD for each segment.

version AM0

No.	Description	Result	execution time	extra info
1	GMM.100		3h 30m	20 hosts
2	TDNN.100 training: LM.200.1e-9, GMM.100, Lexicon.200		17h 7m	3 GPU hosts
3	Create a graph from TDNN.200, LM.200.1e-9, Lexicon.200		6m	1 host
4	Create a graph from TDNN.200, LM.7weeks+subtitles.1e-9, Lexicon.200		4h 49m	1 host
5	TDNN.100 recognized train.200		16h 6m	20 hosts
6	TDNN.100 & LM.7weeks+subtitles.1e-9 recognized dev.short	WER 43.9% PER 35.8%	45m	20 hosts

version AM1

No.	Description	Result	execution time	extra info
1	GMM.100		4h 7m	20 hosts
2	TDNN.100 training: LM.200.1e-9, GMM.100, Lexicon.200		20h 1m	3 GPU hosts
3	Create a graph from TDNN.200, LM.200.1e-9, Lexicon.200		5m	1 host
4	Create a graph from TDNN.200, LM.7weeks+subtitles.1e-9, Lexicon.200		3h 7m	1 host
5	TDNN.100 recognized train.200		14h 18m	20 hosts
6	TDNN.100 & LM.7weeks+subtitles.1e-9 recognized dev.short	WER 41.2% PER 33.8%	46m	20 hosts

version AM2

No.	Description	Result	execution time	extra info
1	GMM.100		3h 3m	20 hosts
2	TDNN.100 training: LM.200.1e-9, GMM.100, Lexicon.200		23h 58m	3 GPU hosts
3	Create a graph from TDNN.200, LM.200.1e-9, Lexicon.200		5m	1 host
4	Create a graph from TDNN.200, LM.7weeks+subtitles.1e-9, Lexicon.200		3h 13m	1 host
5	TDNN.100 recognized train.200		15h 51m	20 hosts
6	TDNN.100 & LM.7weeks+subtitles.1e-9 recognized dev.short	WER 40.5% PER 33.3%	36m	20 hosts

version AM2

No.	Description	Result	execution time	extra info
1	GMM.100		3h 3m	20 hosts
2	TDNN.100 training: LM.200.1e-9, GMM.100, Lexicon.200		25h 27m	3 GPU hosts
3	Create a graph from TDNN.200, LM.200.1e-9, Lexicon.200		7m	1 host
4	Create a graph from TDNN.200, LM.7weeks+subtitles.1e-9, Lexicon.200		4h 49m	1 host
5	Create a graph from TDNN.200, LM.genres.1e-9, Lexicon.200		2h 1m each genre	1 host
6	TDNN.100 recognized train.200		15h 52m	20 hosts
7	TDNN.100 & LM.7weeks+subtitles.1e-9 recognized dev.short	WER 40.5% PER 33.3%	38m	20 hosts

3.6.2 Acoustic model(AM.200) and Language Model version 3(LM.genres)

3.6.3 Acoustic model AM.100-v1 and Language Model version 1 (LM.200.1e-9)

3.6.3.1 100 hours selection(100-v1)

How to select 100 hours subset of data for baseline model v1: Section 3.6.1 calculates PMER, WMER, and AWD for each segments. Consequently, we can extract segments(of 200 hours transcriptions) which satisfy $0.165 \leq AWD \leq 0.66$. In the other word, the segments which does not satisfy are removed. Then, segments are sorted based on their PMER in ascending. We can deduce PMER threshold and its total duration by sorting PMER as presented in the following table:

PMER	Total duration	Percentage of total segment duration
0.0	14.83 h	10%
5	29.66 h	20%
10	44.49 h	30%
16	59.32 h	40%
24	74.15 h	50%
33	88.98 h	60%
47	103.81 h	70%
82	118.64 h	80%

The Table 3.6.3.1 shows that 60% of data has 33% PMER with total duration of 88.98 hours of audio. From the table, we conclude that threshold 33 is selected as the threshold to select data for the next iteration.

WMER	Total duration	Percentage of total segment duration
0.0	14.83 h	10%
8	29.66 h	20%
15	44.49 h	30%
23	59.32 h	40%
32	74.15 h	50%
43	88.98 h	60%
58	103.81 h	70%
98	118.64 h	80%

3.6.3.2 Training Acoustic model AM.100-v1

3.6.4 The Second Acoustic model(AM.100-v2) and Language Model version 1 (LM.200.1e-9)

3.7 Comparison

Comparison between different speech recognizer:

No.	Acoustic model	Language Model	PER	WER
1	TDNN.100	LM.7weeks+subtitles.limited.1e-9 Lexicon.7weeks+subtitles	35.8	43.9
2	TDNN.100-v1_decode	LM.7weeks+subtitles.limited.1e-9 Lexicon.7weeks+subtitles	34.3	42.3
3	TDNN.100-v1	LM.7weeks+subtitles.limited.1e-9 Lexicon.7weeks+subtitles	33.8	41.2
4	TDNN.100-v2	LM.7weeks+subtitles.limited.1e-9 Lexicon.7weeks+subtitles	33.3	40.5
5	TDNN.100-v3	LM.7weeks+subtitles.limited.1e-9 Lexicon.7weeks+subtitles	33.3	40.5

Figure 3.1: Average word duration

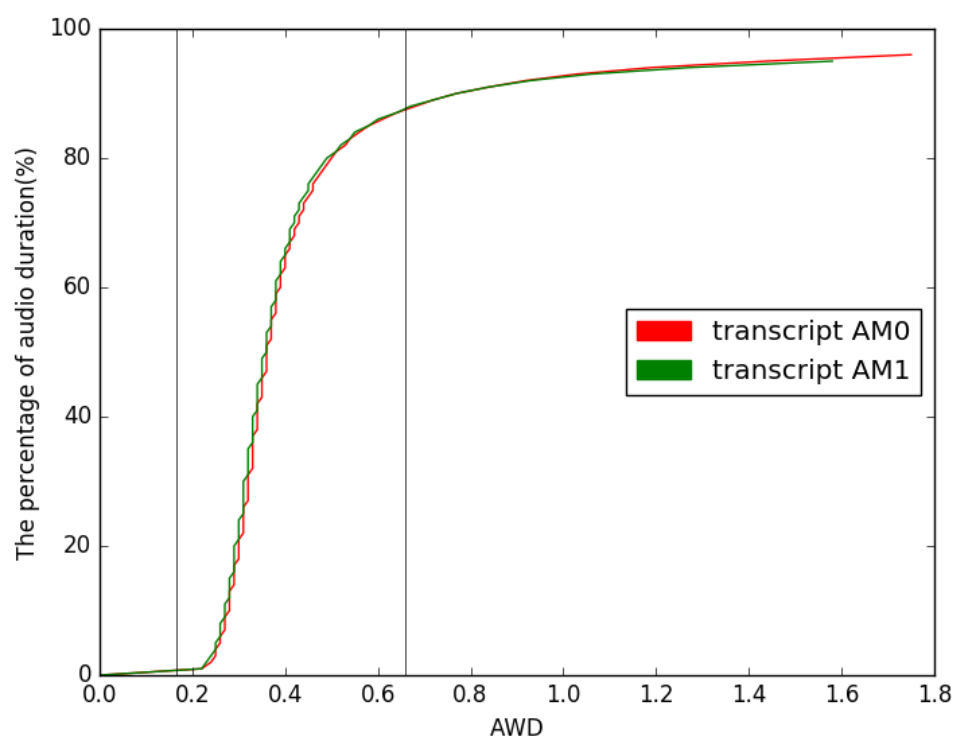


Figure 3.2: Phone match error rate

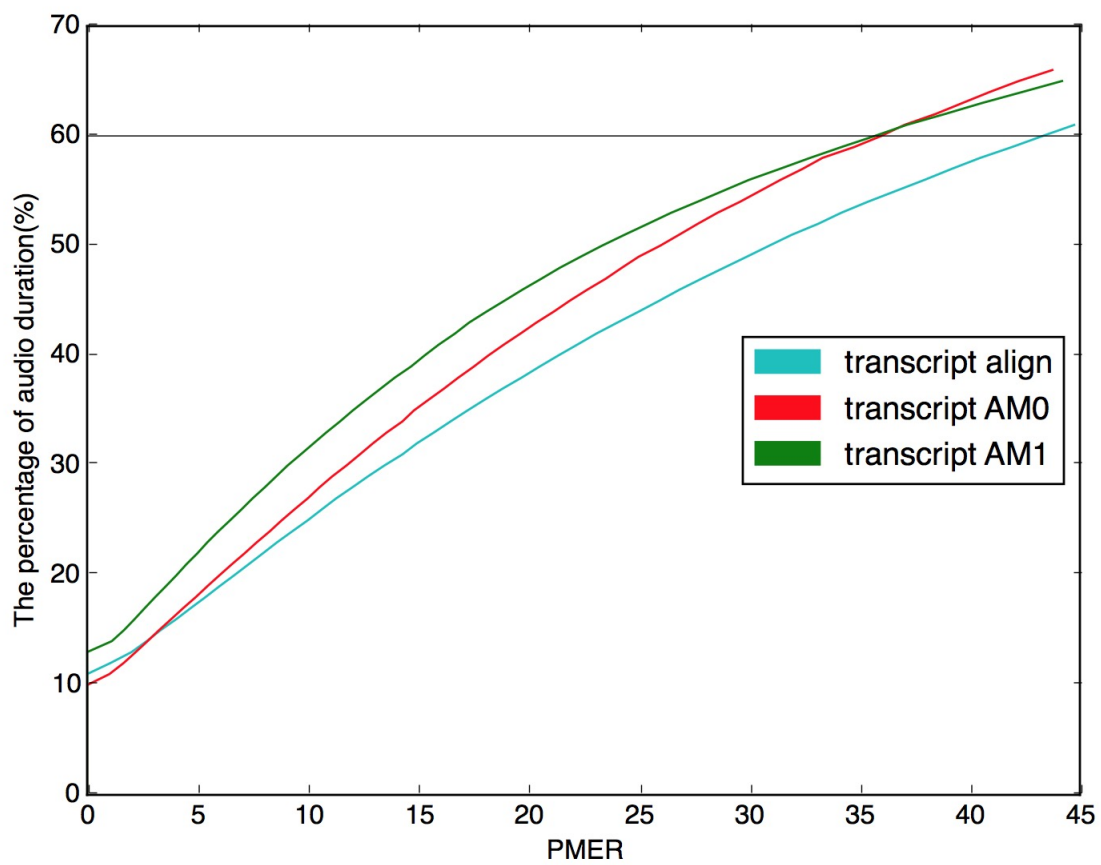
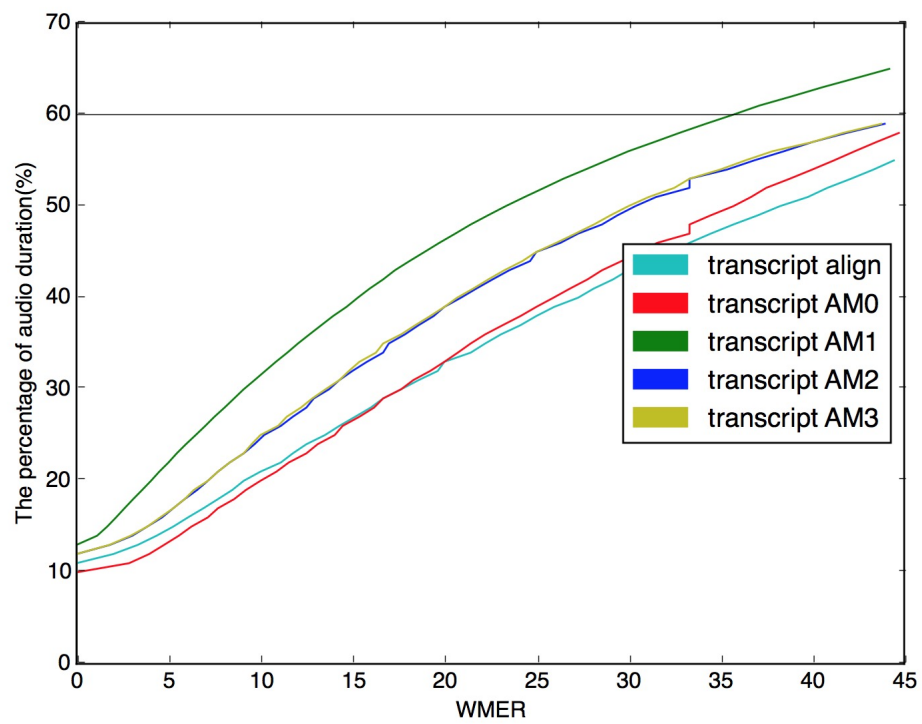


Figure 3.3: Word match error rate



Chapter 4

Implementation

4.1 Data set

For this internship, we used TV broadcasts downloaded from the internet.

- The audio files are taken from TV broadcasts. Total duration of audio is around 200 hours.
- TV broadcast transcriptions(closed captions) of the audio files are provided. The closed captions are close to what the audio says, but not exactly the same as the speakers of the audio said. In addition to the closed captions from 200 hours TV broadcasts, we have the closed captions from 1600 hours of TV broadcasts as well.
- 640 million words of TV subtitles are provided. In addition to that, the 640M subtitles are filtered to avoid overlap with the closed captions from the TV broadcasts.

We prepared two data sets: training set and development set. The training dataset has a total duration of around 200 hours of audio. To evaluate our model, we have a development set. Some metadata are provided in our data, such as: speaker id of the transcript, genre of the show, date and time of the show, as well as television channel where the show was aired. In addition, each segment has start and end time when the segment was shown in the TV broadcast. All files in full training set have closed captions. In contrast, all files in development set have closed captions as well as manually annotated human transcription. The transcript is manually and carefully annotated by human. Thus, the transcript is believed to be the closest transcription spoken by speakers in audio files.

Table 4.1 shows the statistics of the training set and the development set. The second column represents the number of TV shows in each genre; the third column represents the total duration of each genre. Lastly, the forth column(the last column) shows the total duration of speech when the speakers spoke in the audio.

Table 4.1: Dataset duration

No	Data set	#shows	Duration(h)	Aligned speech (h)
1	training set	274	193	149
2	development set	12	8	6

After obtaining 200 hours of data, a 100 hours subset was created by selecting one from two files from 200 training set. The 200 hours and 100 hours training set are named as train.200 and train.100 respectively.

Table 4.2: Statistics of train.200 per genre

Genre	#shows	Duration(h)	Aligned speech(h)
advice	40	26	22
children	51	19	14
comedy	19	8	6
competition	30	21	16
documentary	29	22	14
drama	20	14	10
events	24	38	29
news	61	42	37

4.2 Experiment setup

In this section, we explained how we did the experiments. First, we elaborated how to build language models, then the acoustic model, and lastly how to decode the data set for the data selection and the model evaluation.

4.2.1 Language model

4.2.1.1 Library: SRILM

SRILM is a toolkit which comprises of a collection of executable programs, which are written in C++, for creating and applying statistical language models for speech recognition and other natural language applications [29]. SRILM supports several operations for language model(LM), such as: creating a language model from a text corpus, interpolating several language models into one, pruning a language model, and estimate perplexity of a language model against the test corpus.

The below code is an example how to make a 4-gram language model with input from *CORPUS* and interpolated with Kneser-ney interpolation [11]. The syntax is pretty straightforward and easy to understand. The resulted language model will be written in arpa language model format.

```
ngram-count -order 4 -kndiscount -interpolate -sort -text CORPUS -lm LM
```

4.2.1.2 Execution

This internship experimented with three different kinds of language model for speech recognition. All language models are based on four gram language model. We will describe language model from the most constraint to the less constraint

1. LM.200

This language model, named as LM.200, was produced from the closed captions of 200 hours training set(train.200). LM.200 was pruned by 10^{-9} . Pruning means deleting 4 gram sequences which are less than 10^{-9} . LM.200 was used for the baseline speech recognizer to select the "good" subset of data.

Table 4.3: Statistics of LM.200

No.	File	Information
1	word.200	33,914 words
2	LM.200	uni-gram=33916 bi-gram=402299 tri-gram=111868 4-gram=64801
3	LM.200.1e-9	ngram 1=33916 ngram 2=402299 ngram 3=98566 ngram 4=51215

2. LM.7weeks+subtitles.limited.1e-9

A language model was generated from the closed captions of 1600 hours transcription(7weeks TV broadcast closed captions) and interpolated with a language model from the big TV subtitles with ratio 0.9/0.1. The language model was limited by top 160,000 frequent word list and pruned by 10^{-9} resulting in LM.7weeks+subtitles.limited.1e-9. The language model and together with an acoustic model and a lexicon was utilized to compute error rate of the development set.

No.	File	Information
1	word.160k	160,000 words
2	LM.7weeks	ngram 1=91836 ngram 2=1817881 ngram 3=980925 ngram 4=847736
3	LM.subtitles	ngram 1=756644 ngram 2=27144330 ngram 3=37162518 ngram 4=57912280
4	LM.7weeks+subtitles	ngram 1=768522 ngram 2=27441072 ngram 3=37312673 ngram 4=58183256
5	LM.7weeks+subtitles.limited	ngram 1=160002 ngram 2=24926818 ngram 3=32102763 ngram 4=44253079
5	LM.7weeks+subtitles.limited.1e-9	ngram 1= 160002 ngram 2= 5251197 ngram 3= 3876171 ngram 4= 2453067

3. LM.genres

Eight language models were generated from each genre(LM.documentary, LM.news, LM.events, LM.drama, LM.competition, LM.comedy, LM.children, and LM.advice). Then, each language model was interpolated with the big subtitle LM with ratio 0.9/0.1, limited by the top 160,000 word list, and pruned by 10^{-9} threshold. The language model was used in the new proposed algorithm only.

No.	File	Information
1	LM.documentary	ngram 1=37542 ngram 2=437631 ngram 3=135632 ngram 4=90381
2	LM.news	ngram 1=44588 ngram 2=661625 ngram 3=305473 ngram 4=255125
3	LM.events	ngram 1=23717 ngram 2=306938 ngram 3=125934 ngram 4=95203
4	LM.drama	ngram 1=21345 ngram 2=202078 ngram 3=60920 ngram 4=40073
5	LM.competition	ngram 1=33269 ngram 2=385257 ngram 3=124584 ngram 4=89642
6	LM.comedy	ngram 1=20180 ngram 2=165073 ngram 3=39353 ngram 4=23877
7	LM.children	ngram 1=27029 ngram 2=287141 ngram 3=84063 ngram 4=57851
8	LM.advice	ngram 1=30545 ngram 2=397766 ngram 3=154416 ngram 4=108794

To build language models we mentioned before, we utilized SRILM. In addition to building language models, SRILM is able to interpolate several language models, limit vocabularies of a language models, prune a language model by a threshold, and many more.

4.2.2 Acoustic model

4.2.2.1 Library: Kaldi

Kaldi is a toolkit, written in C++, which comprises several tools which are useful to experiment and build a speech recognition system [22]. Kaldi supports several operations to build a speech recognition system, such as: extracting feature vectors, acoustic modeling, training acoustic models, and creating decoding graph as well as decoding audio inputs into lattices. Kaldi provides several features, such as:

- It support finite state transducer(FST), which is based on OpenFST library. The FST is used to build a decoding graph with the inputs of acoustic model, language model, and lexicon.
- It is extensible and provides complete recipes. Kaldi gives many recipes to build acoustic model, such as: gaussian mixture model, deep neural network, etc.
- It supports linear algebra and utilizes the standard linear algebra library: BLAS and LAPACK.

- It has been tested thoroughly to ensure the quality of the library.

4.2.2.2 Acoustic model implementation

Before training the DNN acoustic model, GMM-HMM must be trained first. GMM-HMM is able to perform force alignment on the flat start(without phoneme-to-audio alignment). The labeling of each acoustic input is compulsory to train the TDNN acoustic model.

We utilized TED-LIUM’s recipe(nnet3 in Kaldi) to train the TDNN acoustic model. The feature vector is extracted with MFCC, consisting of 40 feature values. The TDNN architecture has 6 hidden layers, where each hidden unit utilizes rectified linear unit(RELU) activation function. The TDNN outputs around 9000 output nodes with softmax activation function. Moreover, the TDNN architecture is implemented by leveraging the subsampling technique. Table shows the parameters and subsampling splice configuration we used in the architecture.

Table 4.4: Parameters of theTDNN acoustic model

Parameter	Method
initial learning rate	0.0015
final learning rate	0.00015
mini batch size	512
epoch	3
subsampling splice	
layer 1	$t - 2, t - 1, t, t + 1, t + 2$
layer 2	$t - 1, t + 2$
layer 3	$t - 3, t + 3$
layer 4	$t - 7, t + 2$
layer 5	$t - 3, t + 3$
layer 6	t

4.2.3 Recognition

The last step after training an acoustic model and building a language model is to recognize a data set. The recognition is useful for data selection(computing the new word error rate as well as phone error rate) and evaluate how good our data selection is. In overall, the recognition(or decoding) process works as following:

1. Create a decoding graph from an acoustic model, a language model, and a lexicon. In Kaldi’s implementation, it transforms the acoustic model, the language model, and the lexicon into a weighted finite state transducer(WFST).

2. Decode the dataset by using the WFST. In Kaldi, the decoding process will result in a lattice. Lattice is a decoding graph which represents some variants of the recognition. Providing only one best recognition is not practical; thus lattice is the way to represent the recognition/decoding result.
3. Compute the best path of word or phone in the lattice and calculate the WER as well as PER. Kaldi produces two ctm files(word and phone ctm files) which are the best decoding results which the algorithm can obtain. The ctm file consists of words(or phone) in the transcription with its start and end time relative to the audio. By utilizing sclite, the ctm file(the hypothesized word/phone from the ASR) is compared with the transcriptions(the closed captions or the detailed transcription). Then, the code matches and computes the minimum edit distance to calculate the error rate.

4.2.3.1 Data Selection

To select the good data for the next iteration, the new matched word and phone error rate must be generated from the training set. By running the recognition steps(as explained above) on the training set and comparing the decoding result with the closed captions, a file(the file with the extension of ".prf") is generated. The file contains the number of insertion, deletion, and substitution. By using the error rate equation as bellow, the new matched error rate(WMER and PMER) are computed.

Firstly, the segments are sorted based on the new PMER. Secondly, choose the top 100 hour segments based on the PMER. These selected segments are used for the next iteration.

4.2.3.2 Evaluation

To evaluate how good our data selection is, we need to evaluate the automatic speech recognizer(especially the acoustic model). In every iteration, we train an acoustic model; furthermore, the acoustic model and together with the language model(LM.7weeks+subtitles.limited.1e-9) as well as the lexicon, we recognize the development set. After decoding and computing WER of development set, we compare the WER with the previous iteration. If the new WER is lower, we can continue the iteration; otherwise, stop the iteration.

4.3 Experiment resources

To run our experiment, we utilized grid 5000 server cluster. Grid 5000 is a computing cluster with a focus on parallel and distributed computing [31]. It has several key features:

- It provides a large amount of resources, over 1000 nodes, and massive volume of hard disk.
- The experiment is highly configurable where we can specify number of nodes and the criteria of the nodes which we will use.
- We can do advanced monitoring of memory usage, cpu usage, and the log of our experiment which later be used to analyze the experiment.

The following is the description of resources which we leveraged for this internship based on the tasks:

1. Train acoustic models: 1 computer with GPU and 8 computers without GPU. At least one computer with GPU is compulsory because we can harness GPU to parallelization the computation of DNN training.
2. Create decoding graph only needs one computer because the Kaldi recipe does not need parallelization for this process.
3. Decoding the ASR leverages 20 computers. Usually one computer can recognize one hour of audio within one hour. Therefore, the more computer we use, the faster the decoding process will be.
4. Lastly, the error rate computation and data selection process only utilizes one computer.

Chapter 5

Sample Title

Lorem ipsum dolor sit amet, consectetur adipiscing elit, sed do eiusmod tempor incididunt ut labore et dolore magna aliqua. Ut enim ad minim veniam, quis nostrud exercitation ullamco laboris nisi ut aliquip ex ea commodo consequat. Duis aute irure dolor in reprehenderit in voluptate velit esse cillum dolore eu fugiat nulla pariatur. Excepteur sint occaecat cupidatat non proident, sunt in culpa qui officia deserunt mollit anim id est laborum.

Appendix A

Sample Title

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Appendix B

Sample Title

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