Goodness of Pronunciation Pipelines for OOV Problem

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STUDENT DECLARATION

I hereby declare that this project *Goodness of Pronunciation Pipelines for OOV Problem* is my own work and that, to the best of my knowledge and belief, it contains no material previously published or written by another person nor material which has been accepted for the award of any other degree or diploma of the University or other Institute, except where due acknowledgements has been made in the text.

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Abstract

In the following report we propose a pipeline for Goodness of Pronunciation (GoP) computation solving OOV problem at Testing time using Vocab & Lexicon expansion techniques and Lexicon Transducer re-construction. The pipeline uses different components of ASR system to quantify accent and automatically evaluate them as scores. We use the posteriors of an ASR model trained on native English speech, along with the phone level boundaries to obtain phone level pronunciation scores. We implemented methods to remove $UNK$ and $SPN$ phonemes arising in the GoP output due to absence of words in our Lexicon(Out of Vocabulary(OOV)) from a given utterance by building three pipelines. The Online, Offline and Hybrid pipelines are proposed which take into account time and space complexity concerns with respect to WFST re-construction. The Online method is based per utterance, Offline method pre-incorporates a set of OOV words for a given data set and the Hybrid method combines the above two ideas to expand the lexicon as well work per utterance. We further provide utilities for extracting DNN posterior probabilities to Phone mapping, GoP scores as vectors for each utterance, as well as Phone and Word boundaries to be used for future research purposes.
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1 INTRODUCTION

1.1 What is Speech Recognition

Speech Recognition involves getting a correct transcript given Speech as an input. Over the years many statistical methods have been proposed such as Dynamic Time Warping [1], Linear Predictive Coding [2], Hidden Markov Models [3] and Deep Learning methods such as Deep Belief Networks [4], Recurrent Neural Networks [4], etc for speech recognition. However, most of these methods do not consider accent information of non-native speakers.

1.2 What is Accented Speech Recognition

Accented Speech Recognition is the ability to correctly automatically get a transcription of the Speech which has accent influences. Models are often trained on data sets which lack such diversity. However, humans are diverse, which results in a huge set of accents. Each accent has distinct spectral characteristics such as difference in formants, prosody, pitch which make it distinguishable to the human ear and brain. However, unlike the human brain which can correctly perceive accents, Machine Learning methods still fail to do so. This is the heart of the problem of Speech Recognition and is an important step in democratizing Speech Recognition technology.

1.3 Challenges associated with Accented Speech Recognition

Despite the many advances in Speech Recognition, accented Speech Recognition is a very hot topic. People have proposed numerous methods for solving these problems. Accented Speech recognition has many challenges. In this section we describe the challenges that are present in the field. Many corporations approach the problem of Speech Recognition with the sole view of improving the various benchmarks, without tackling the actual problems. Their methods often lead to algorithmic bias and worsens performance of ASR systems [5], co-operation
between communities is extremely important to mitigate such problems and approach Speech Recognition from a humanitarian perspective. A consequence of poorly performing ASR systems includes the phenomenon of people from small groups feeling excluded and many drop-out due to language barriers. ASR systems perform poorly in cases of code-switching [6], low-resource accented data, dialects [7], etc. One of the biggest challenges for creating Accented Speech Recognition is the absence of high resource, diverse data-sets. Datasets for people with speech impairments is usually very less. These people face difficulties since the common ASR models fail to recognize their impaired Speech. Very few efforts have been made in this direction [8] [9], another problem associated with such databases is the language of collection of data [10]. It is important for data sets to have metadata such as age, gender, [11] other demographic information, if necessary, along with accented speech in multiple languages [12]. Very few data-sets contain Speech of non-native accents which is also very important for making the system robust and adapt to new accents. More such data-sets are required [13]. This makes training models on such data-sets robust to accent variations.
2 EXPERIMENTAL SETUP

We describe the Software and Hardware Requirements for our given experiments.

2.1 Hardware Requirements

We require a machine with at least 12 GB of RAM with an Nvidia GPU of at least 8GB VRAM for training of neural architectures. An Nvidia GPU of RTX 2060 is used in our setup. An Intel Core i7 with 8 cores and 16 threads is utilized. At least 1 TB of memory is required for downloading the required datasets and storing the results of the experiments. The Librispeech (960 hrs.) dataset was used in our experiments, because it has been shown to have more speaker variability, models trained on show better generalization capability.

2.2 Software Requirements

In our machine we require Python2.7, Python3, C++, Perl, shell, bash installed. It is recommended to install a package manager such as conda/pip, etc. for the same. In our experiments we utilize open-source tools and software such as Kaldi and Sequitur-G2P [14]. We chose Kaldi toolkit [15] because of its ability to model complex hybrid ASR architectures based on Hidden Markov Models (HMM) and contains a whole host of other utilities for building an ASR system from scratch. It has a lot more utilities than comparable toolkits such as HTK, CMU Sphinx, etc. Kaldi is very powerful due to its speed which makes it suitable for deployment environments.
3 AUTOMATIC SPEECH RECOGNITION PARADIGMS

There are different methods one can approach Speech Recognition in. This depends primarily on the type of problem we are tackling to solve and the availability of data. In many scenarios we require high interpretability despite high resourced data and might not need fine-grained analysis. Whereas in some cases we have low resourced data and require high accuracy and performance despite the bottleneck of less data. Thus, we can approach the Speech Recognition problem in 2 ways: Statistical/Hybrid Speech Recognition and End-to-End Speech Recognition.

The fundamental problem of Speech Recognition can be represented as:

\[ \hat{W} = \arg\max_{W} P(W|X) \]

where \( W \) is the sequence of words (transcription) and \( X \) is the sequence of acoustic feature vectors (Observations).

3.1 End-to-End Speech Recognition

End-to-End models of Speech recognition involve training Neural Network based models, without any extra modules. These Neural Network components can generalize different patterns present in the observation data and gain linguistic context without the presence of external Linguistic feedback in the form of Lexicons, Grammar Rules, etc. This makes Neural Networks highly desirable for usage in industrial as well as research purposes. The figure below shows a general architecture of End-to-End Speech Recognition system. The input to the model is generally in the form of Mel frequency cepstrum coefficients or other features such as Linear Prediction Coefficients or Spectrogram directly. The recognizer here is the neural network, which learns to model the speech from the features and outputs the result in the form of characters.

However, despite the advances in Speech Recognition Neural Networks itself fail to solve problems without additional information. The problems faced by such techniques are mainly due to the unavailability of high resource data, this includes transcriptions, noise free datasets, specifications including Gender, Age, other information which can affect generalization capabilities. Other problems for End-to-End models can include environmental
factors such as multiple-speakers, channel conditions, absence of Accent variations in the data, prosodical features, etc.

### 3.2 Statistical Speech Recognition

Statistical speech recognition approaches speech recognition problem in a different way than End-to-End models. It has different components, namely the Acoustic Model, Language Model, Dictionary which consists of Lexicons, Vocabulary; a Feature Extraction module and final all these modules are combined to probabilistically decode the final transcription. One of the advantages of this approach is the ability to train robust models using low-resource data.
Also, since we have different modules, each of them can be tuned in a specific way given our problem domain for domain adaptations. This architecture also ensure high interpret ability since each result can be investigated as a series of probabilistic decisions during decoding and encoding phase. We can formulate the Speech Recognition problem as below using Bayes Rule:

\[
\hat{W} = \arg\max_{W} P(X|W).P(W)/P(X)
\]

However, since we want the probability of \(\hat{W}\) and the feature vector can be considered as a constant, so after simplifying:

\[
\hat{W} = \arg\max_{W} P(X|W).P(W)
\]

Where \(W\) is the list of sequences of words, \(X\) is the acoustic observations or feature vectors \(\hat{W}\) the hypothesized word sequence. There are different parts to the Statistical model, these include the Acoustic Model, the Language Model, the Dictionaries. The following modules can be represented by the diagram below:

![Diagram](image)

Figure 3: Different blocks of an ASR system
3.2.1 Acoustic Features

To train our acoustic model responsible for giving the Observation Posteriors given our phonemes, we need to perform feature extraction on our raw signal. In ASR there are numerous different methods for feature extraction, some methods include training the raw signal [16] using CNN and ReLU non-linearity, other features include Perceptual Linear Prediction analysis (PLP) [17], MFCC’s or the features commonly adapted for Speaker adaptation such as I-Vectors, X-Vectors [18], D-vectors. In our setup, we chose an online approach which compute feature extraction on the fly. We used 39 Dim MFCC features with Delta and Double-Delta features. MFCC’s serve as the best baseline feature extraction method because of their ability to model the human cochlea. MFCC’s are also independent in nature thus, this makes it easy to model them since at each timestep t, the vectors are independent of each other i.e $P(O_t|O_{t+x})$ or $P(O_t|O_{t-x})$ is False or simply put features do not have any correlations with each other.

In our given use-case since we need our ASR to be robust, we require two types of feature-extraction methods. One for alignment stage, the other for computing the Deep Neural Network (DNN) posteriors. For the alignment

![Normalized MFCC feature extraction diagram](image)

**Figure 4: Normalized MFCC feature extraction**

be robust, we require two types of feature-extraction methods. One for alignment stage, the other for computing the Deep Neural Network (DNN) posteriors. For the alignment
stage, MFCC’s which have been normalized are sufficient. Another reason we use Mean and Variance features are to initialize the Gaussians of the GMM used per HMM state. This can be helpful for initialization during training HMMs. This makes them noise robust [19] and are also used in the speaker-independent feature extraction stage described below:

![Diagram of feature extraction process](image)

**Figure 5:** I-vector feature extraction

We extract speaker independent I-vectors using the normalized MFCC’s by feeding them to a GMM model trained universally on multiple speakers. Thus, it has learned to model in-speaker and between-speaker variabilities and create a compact low-dimensional vector. In our setup we used 40-dimension MFCC features with delta and double-delta features and 100 dimension I-vector features.
3.2.2 Acoustic Model

This model is responsible for providing the probability estimates after seeing the Observation speech sequence. This model can be a GMM-HMM, DNN-HMM or TDNN-HMM, and other variants. The following model is trained on Speech features, to give the output probabilities. It is represented as $P(X|W)$ i.e., training the model to output the probability of the speech sequence (frame level) given the transcript. Frames here refer to different parts taken from the Speech signal. Each signal is divided into frames and then these are processed by the acoustic model. This $P(X|W)$ usually the probability of observation sequence given the sequence of phonemes i.e. $P(X|P = W)$.

3.2.3 Language Model

The language model predicts the probability of the next word given the previous word. This can be modelled using N-gram approach, or by using other deep neural network based approaches such as RNN, LSTM, etc. This model is trained on a vocabulary of text to estimate the probability of the given word $P(W)$. It is important to use N-gram models which use a variety of smoothing and interpolation methods for unseen sequences, which can be modelled into a $G.fst$ from the language model.

3.2.4 Pronunciation Dictionary

To model the pronunciations, we need to create a dictionary of word and its respective pronunciations. i.e., grapheme and phoneme pairs. This is called the Lexicon. This lexicon is used to generate the list of phones, silence-phones, list of questions for decision tree based state modeling. We use the Silence phone as a way of representing the word boundaries. This is how we model the ASR system, using silences as a way of knowing when a particular word ends or if there are indeed silences due to stuttering. The Librispeech Lexicon has been shown below:
The first 3 entries represent the silence, spoken noise, unknown word, and their respective phonemic mappings. We describe the pipeline to create and modify the lexicon in later sections. Lexicons are extremely useful in variety of ASR related tasks. Such as given the grapheme and phoneme mappings one can train a Grapheme to Phoneme conversion module or using the concept of lexical compression create a corresponding data structure which essentially compressed the learned lexical compression. The same concept is used in the grapheme to phoneme tasks, since after “compression” it can essentially model new sequences to phonemes. Weighted Finite State Automatons (graph) are one such data structure used to represent the lexical information, other forms include the use of Prefix trees, Decision Trees, etc.
3.2.5 Decoding

In this stage we find the likelihood of observing the given word sequence, given the Speech input. This process usually happens after the training has been done, and is usually performed at inference stage, although it does have its applications in the HMM training (forward-backward algorithm) and alignment stage. The Beam Search algorithm is used for alignments since they provide the best time vs cost complexity trade-off. The Figure below shows the training and decoding processes side-by-side. In the training steps, we require transcriptions, lexicons. In the decoding stage, we do not require any transcripts. The algorithms for Decoding include Viterbi and Beam Search. We use the Beam Search algorithm due to the reduced time with which it can find a near optimal solution. The time complexity for Beam Search is reduced from $O(T.N^2)$ to $O(T.K^2)$, where is the beam-width which, $T$ is the time-steps and $N$ is all possible states. Here $K$ is always smaller than $N$. i.e., $K << N$. This is especially useful while performing decoding over a huge graph constructed of multiple Weighted Finite State Automatons.

![Figure 7: Decoding(Left) and Training(Right) procedures.](image)

In our task we are required to construct decoding graphs which in the form of Weighted Finite State Transducers (WFST). We use the term WFST instead of WFSA since it is essentially an automation with inputs and outputs just like an actual transducer converting one quantity to another quantity. The decoding graph consists of 3 parts:
Here $H.fst$ represents a mapping from HMM/GMM states to context-dependent states. $C.fst$ represents a mapping from context-dependent phones or senones to the phones, and $L.fst$ maps phones to the words. We map the $H$ to $C$ to $L$ using composition operations. Composition can be considered just as tensor dot products.

| WFST | Input Sequence       | Output Sequence |
|------|----------------------|-----------------|
| H    | HMM States           | CD Phones       |
| C    | CD Phones            | Phones          |
| L    | Phone Sequence       | Words           |
| G    | Words                | Word sequence   |

Table 1: HCLG Individual WFST components

Figure 8: L.fst

The inputs and outputs of the graph represent the corresponding input sequence and output sequence at each time point. These usually have a probability value concerned with the cost associated with each transition.
However, since WFST’s aren’t deterministic we apply operations to make them deterministic and need to apply minimization operation to reduce redundant paths. Another
important thing required is the need for adding disambiguation symbol #0 and self-loops in
Kaldi to allow for composition of $L.fst$ with $G.fst$. Thus, the $L.fst$ with the disambigua-
tion symbol is usually used during training such as the alignment graphs whereas the actual
decoding is done using a $L.fst$ with added disambiguation symbols. The equation for the
following is represented below:

**Standard ASR WFST Composition:**

$$HCLG = \min(\det(H \circ \min(\det(C \circ \min(\det(L \circ G)))))$$

**Our WFST Composition:**

$$HCL = \min(\det(H \circ \min(\det(C \circ L)))$$

In standard ASR pipeline, we require hypothesis transcript as the output, however, in
our pipeline since we are only concerned with the phoneme sequences and already have
the reference transcript at every speaker’s evaluation the need for a Language model and
subsequent creation of Grammar $G.fst$ is eliminated.

### 3.2.6 Alignment

The alignment is essentially useful for aligning the source speech with our given transcript.
This helps us train the acoustic models using Maximum Likelihood estimates. At each time-
step of an iteration we get the alignments of the observed frames with the states of the HMM
given an utterance. This is obtained while using forward-backward algorithm. Alignments
are extremely helpful for us since we can automatically time align the transcript with the
source speech. This reduces manual labelling effort. We obtain these alignments at phone
level as well as word level.

In the Figure 11 we represent the raw alignments obtained after training a monophone
HMM using GMM with Maximum Likelihood on the Yes/No corpus. Yes, grapheme is
represented as Y and No as simply by N. These are the only phones present. The format of
the above is the File-ID and the alignment vectors. The alignment vectors consist of each
Figure 11: Raw alignments visualized

containing HMM state number, the next number represents the transition to the next state, transition to the same number represents the same state. Each input to the HMM state is essentially a frame, each vector \([\)]\) represents a given phone segment. Within the segment are state number associated with the frame. State numbers not in sequence represent the senones being captured for the given phoneme. The figure has to be read from the top starting with \(SIL\), after \(SIL\) there is blank spaces representing same phone. After \(SIL\) we get an \(N\) phoneme as an output, and then again blank space after which we get another \(N\). Another phonetically time aligned alignment is shown below:

Figure 12: Phone level Conversation Time Mapping file
The given figure shows a .ctm file, this represents the alignment mappings with respect to time durations. The given utterance is taken from a part of an utterance of Librispeech and is read as “...HIS GOSEPL”.
4 HYBRID SPEECH RECOGNITION

As discussed in the above Introduction, besides End-to-End and Statistical approaches another popular approach is the use of Hybrid Speech Recognition systems. These systems have a DNN model and an HMM model. Numerous hybrid approaches have been proposed. These methods combine the best of both approaches. We first describe the GMM-HMM approach to offer an introduction to how a DNN-HMM system would behave.

4.1 GMM-HMM

![GMM-HMM model](image)

Figure 13: GMM-HMM model

The GMM-HMM model is one of the earliest proposed models, although it is statistical in nature and not a hybrid it is important to understand GMM-HMM for the purpose of understanding Hybrid Systems. In this paradigm, each feature vector is modelled by a Gaussian. There are as many Gaussians as the number of HMM states or more. Each component of the GMM represents a Gaussian distribution. We use a 39 component Gaussian Mixture Model. Thus, we have $39 \times 44 \times 3$ mixtures. However, using the concept of tying or combining similar mixtures for similar phonetic states, we can reduce the number of states as well as capture phonetic context dependencies. A Maximum Likelihood approach is used to estimate the training data. At each iteration the Likelihood increases, as we increase the...
Gaussian count. This approach is further improved by using a Decision Tree which asks a set of phonetic questions (E.g., Whether it is a stop? Or whether it is Left Vowel) and then assigns the phone states to a leaf node, thereby capture stress, tone related information as well as reducing the number of states since similar by clustering if they fall into the same leaf node.

Figure 14: Tied state modelling in GMM-HMM

The advantages of this approach are usually related to unseen tri-phones. The states are tied [23] together by clustering the Gaussians of similar phones and the final tied states Gaussians are split to increase the number of mixtures. The GMM serves as an estimator for the HMM states.
4.2 DNN-HMM

In this method instead of using Gaussian Mixture Model as a classifier, we use a DNN [20] as a classifier. The DNN’s final Softmax output layer, is a classifier with as many labels as the number of phones * the number of states per phone e.g. For 44 phones and 3 state HMM, it is 44*3 labels to predict. This label assigns each acoustic frame to an HMM state.

Figure 16: MLP based DNN-HMM model
This assignment is in the form of posteriors \( P(S|O) \). Using these state sequences, and the transition probability \( P(S_2|S_1) \) between states we can get the \( P(O|P) \) i.e \( P(O|P=S_1...S_N) \). Here P is the Phone sequence. The neural network is discriminatively trained using the Cross Entropy Loss function on the predicted labels, which are the individual states to which the frame is assigned to. The advantages of training using Neural Networks are obvious. GMM’s require lot of parameters compared to simple Neural Networks such as RNN, also GMM assume the natural distribution of the data to be Gaussian which might not be true always. Moreover, GMM’s are trained in an unsupervised manner by maximizing the likelihood of the training data.
5 AUTOMATED PIPELINE FOR ACCENT QUANTIFICATION EVALUATION

5.1 Introduction

Pronunciation evaluation is important for developing accent enriched speech recognition systems. An important step towards accent-based Speech modelling is also recognizing how a speakers accent affects the pronunciation, and how this could affect an ASR system. This is beneficial not only as a metric to recognize the pronunciation scores, but also can be used as a tool for automated scoring for assisting L2 learners.

5.2 Pronunciation Evaluation Methods

Pronunciation evaluation methods have two types depending on the availability or in-availability of transcripts these are called Text dependent and Text independent pronunciation evaluation [21]. However, a common drawback of text independent methods includes the absence of a verification agent with respect to the ground truth. There are several methods to evaluate pronunciation of non-native speakers. Out of these the Goodness of Pronunciation (GoP) metric is one of the most used methods. This method proposed by [22] enables us to automatically score pronunciations based on log of posterior probabilities of phonemes normalized by the time. Further modifications proposed include the use of scaled log posteriors [23], or the use of attention-based modelling to predict phoneme duration [24], and transition factor between phoneme segments. Other methods include the use DNN based models instead of GMM’s for GoP [25]. [26] explore how transfer learning approach could be used in GoP task. However, most of these works are based on phoneme level modelling and do not consider senones [28] which allow parameter sharing thus reducing redundant states. Senones unlike tied states, magnify the contextual acoustic information, by not tying similar states but rather clustering them based on their distribution. We use a senone based approach as proposed by [29] which also considers the state transition probabilities (STP) of HMM’s which are often discarded.
5.3 GoP using Senones

As discussed above we use the senone based approach. We discuss the details of the senone based approach:

\[
\text{GoP}(p) = \frac{1}{T} \left| \log \mathcal{P}(p|O) \right|
\]

\[
\text{GoP}(p) = \frac{1}{T} \left[ \sum_{t=1}^{T} \log \mathcal{P}(s_t|O_t) + \sum_{t=2}^{T} \log \mathcal{P}(s_t|s_{t-1}) + (T - 1) \log n \right]
\]

Here the first term represents the probability of belonging to \(s_t\) given the Observation sequence. The second term represents the senone transition probabilities added with the log of number of senones. In the sections below we describe the methods in which we calculate the necessaries for the given equation and build a pipeline around it.
5.4 Overview of Pipeline

In this section we describe the pipeline that we created for automatic computation of Goodness of Pronunciation scores. Another reason to choose the improved GoP metric was it’s Open-Source availability and ease of use. The metric also doesn’t utilize any heavy models based on attention such as transformer layers or stacked RNNs. This make it extremely useful for creating Online pipelines, which would have been difficult due to latency of other large models. This is important since it shows higher correlation to human evaluators. We describe the various stages of our pipeline below:

![GoP pipeline overview](image)

Figure 18: GoP pipeline overview

The complete pipeline overview has been shown above. The MFCC and I-Vector Extraction modules have been already described in the Acoustic Features section. The Forced Alignment module is again described in the previous section. A slight change however is the
use of DNN-HMM based alignment rather than GMM-HMM. The I-Vectors are extracted using a pre-trained speaker independent GMM with a diagonal covariance matrix (only diagonal has standard deviation information, rest are zeros or sparse) to get speaker independent information. The Nnet is a neural network model, an MLP with 25 layers, with outputs being the (senones) tied states of a Context Dependent (Triphone) HMM. In the posterior computation stage, we use a pre-trained DNN-HMM model. For us to automatically evaluate the pronunciation this model was trained on native speech data i.e., Librispeech (960 hours) and Fisher English corpus. This ensures the posterior estimates of the model are with respect to native speech and thus it is useful when non-native speech is used as input to the model. Non-native speech will have a characteristic accent, which will lead to changes in the probability estimates of the senones. This can be considered as removing the native speaker who is the human evaluator and replacing it with a natively trained DNN-HMM.

5.5 Challenges

Before we explain the pipeline, itself we need to understand what challenges one faces while incorporating the GoP equation into our pipeline.

5.5.1 Technical Challenges

As with any code, code breaks and often becomes un-maintainable. Our challenges in the technical domain involved fixing backward compatibility issues, in our experiments we use a robust Grapheme to Phoneme model called SequiturG2P which models the grapheme to phoneme problem using grapheme units and M-gram approach with smoothing and interpolation. We used this to model the lexicon (describe in later sections). The initial challenge with G2P was the issue with backwards compatibility which was fixed by the author of this report. This enabled backwards compatibility across Python2. While preparing the dictionary related files for the given database, there were issues prevalent with respect to single-threaded performance. This would render the entire pipeline unusable and for other users to utilize a single thread. The issue would cause a bug, leading to previously run multiple thread intermediates to be used again or fail in single thread mode. This again was
fixed by the author of this report. Now, we describe one of the biggest issues faced by the authors, which is the problem of Out of Vocabulary occurrences. OOV is a big issue in our pipeline since any OOV occurrence would be mapped entirely as a \textit{SPN} phoneme at testing time. This isn’t ideal when we are trying to build an automated system for phoneme-based pronunciation scoring. On further investigation we found the reason for the issue was with respect to data set (Librispeech, etc), to eliminate some words so as to not expand the Lexicon size. Despite the innocence and factually supported decision, it is not ideal for such cases where accurate phonemic alignments are required for scoring. The pipeline is described in Sections below.

5.5.2 Out of Vocabulary at Testing time Challenges

The OOV pipeline essentially is an automatic pipeline which can generate Lexicons for words which are OOV for our given databases in question. In our case we used the CMUDict and Librispeech database. Any word does not present in either of the two is mapped as SPN during the alignment outputs. Thus, we need to formulate an automated procedure to get these phoneme mappings. This is essentially the method used by us to generate the Lexicon.

1. Compare the vocabulary entries with CMUDict lexicon for corresponding phoneme mapping.

2. Compare the vocabulary entries in (original Librispeech) lexicon.

3. If all words are found, we stop and get list of all mapping in a lexicon file.

4. If words are not found in either database, we automatically generate them.

5. Pass the OOV words to Grapheme to Phoneme model.

6. Append the automatically generated lexicon to lexicon entries which are not OOV.

7. Sort and combine these two into a final lexicon containing all lexicon entries including OOV.
This makes sure that the Lexicon we use in our pipelines models these OOV occurrences and doesn't lead to any errors downstream in Lexicon Transducer compilation and subsequent forced alignment. The final output of our system is a phonetically aligned transcript with GoP probabilities per phoneme of the utterance.

5.5.2.1 Grapheme to Phoneme Conversion For Grapheme to Phoneme conversion, we used Sequitur G2P model. This model uses the concepts of units called graphones which are essentially a unit of grapheme and phoneme together. We use the grapheme to phoneme convertor called Sequitur G2P [17] in essence it finds the Grapheme-Phoneme mappings from the training data (lexicon). These mapping for a particular sequence (of a word) are called alignments or segmentations. A graph of all possible segmentations is constructed and the maximum likelihood $L(g, p, q)$ of the training data (grapheme, phoneme sequence pair) is maximized given our hypothetical segmentation which we are trying to obtain. Once we obtain such a hypothetical alignment, we can update a M-gram model. The M-gram model is essentially a sequence of graphones instead of words. We use a pre-trained 6-gram model. Once the likelihood function saturates, we can use those obtained segmentations to update the M-gram model. However, M-grams are prone to OOV, so an integrated smoothing and
interpolation approach is used. Here, we estimate discount parameters using Maximum Likelihood objective using Expectation Maximization algorithm again on a held-out set not seen during training, and obtain the discount values $d_M$.

For each M-gram. This integrated approach also helps us estimate the back-off distribution of $p_{M-1}(q)$ the lower order M-gram. This basically assigns some probability mass by redistributing it from the grapheme occurs which have extremely high probability mass using discount parameters and the backoff-distribution when necessary. Once the discount parameters are known, and the N-gram updated. A decoding graph is constructed from the segmentations in the form of a Finite State Automata, where each (node) grapheme input corresponds to an output phoneme associated with the previous grapheme history. The weight of each arc has a probability assigned to it which depends on the grapheme sequence’s M-gram probability calculated. The input to this graph will be a sequence of letters from a grapheme, and after doing decoding on the graph a grapheme sequence is obtained. Using this grapheme sequence we can get the phoneme sequence as well. This is our most likely pronunciation. Several methods for decoding can be used. The simplest being First Best Search giving the best path. However, multiple pronunciations (phoneme sequences) are also possible, so after Beam Search through the graph (FSA) we can collect these alternative paths and store them in an array/stack like structure. We can create another graph after getting paths which may have repeated nodes, from this graph we can again do decoding by A* search and get the new rescored values and chose the top-n or the one with best cost.

5.6 Pipeline Methodology

As discussed in the sections above, it is evident that building such a workflow requires a meticulously designed pipeline to enable the automatic score computation of millions of Speech files. Speech files could be in .wav or .flac or .mp3 format. We consider these 3 file formats at present. As discussed in Sections above, the above the pipeline is not well-defined with respect to the cases of Out of Vocabulary occurrences and incorporating this pipeline into our system is challenging. However, we devise 3 simple pipelines which are able to integrate the OOV component into our existing architecture.
5.7 Offline

In this mode the Out of Vocabulary problems are fixed before the execution, i.e., before any inputs are given to the pipeline. This means we pre-compile a set of words that resulted or could result in OOV for a given database. This means that any OOV other than those already present might fail and the process stops. However, it works well in the assumption that no OOV occurs beyond these additions. A very crude assumption which saves executing the OOV pipeline during execution but has its flaws. We describe method for the Offline mode:

![Offline Pipeline Diagram]

Figure 20: Offline Pipeline
1. Collect all Transcripts for Librispeech database. Automatically generate a new vocabulary.

2. From the collected transcripts. Generate a new Lexicon using the Lexicon generation

3. Generate Lexicons from OOV using the pipeline and keep appending it.

4. Get the final Lexicon with OOV lexicon entries. Get list of silence, non-silence phones, other files from the lexicon. Compile the Lexicon L.fst from the Lexicon and place in language model folder.

5. This folder containing the lexicon, phones, L.fst is used every time for Decoding Graph Creation. pipeline.

5.8 Online

In this mode the Out of Vocabulary problems are fixed during the execution, compared to Offline where we pre-compile the Decoding Graph from a pre-appended Lexicon with OOV entries which are known to be encountered. Thus, this method results in automatic creation of Lexicon, the Decoding Graph Composition, and the final output with respect to the given utterance. The Online mode can have 3 variants; however, we settle with these methods because our best method was incompatible with Kaldi’s standard architectures.

5.8.1 Vocabulary Expansion Based

1. Get Transcript for current utterance.

2. Find words from current transcript not in any of the databases available.

3. Add those OOV words to Librispeech-vocabulary. item Regenerate lexicon from appended vocabulary, using Lexicon generation pipeline.

4. Generate the list of silence, non-silence phones, extra-questions for Decision Tree clustering automatically.
5. Compile Lexicon Transducer L.fst from new lexicon. Create the language model folder and use it for computing HCL.fst Decoding graphs.

6. Repeat Steps each time OOV occurs.

5.8.2 Lexicon Expansion Based

1. Get Transcript for current utterance.

2. Find words from current transcript not in any of the databases available.

3. Add those OOV words to Librispeech-vocabulary.

4. Regenerate lexicon from appended vocabulary, using Lexicon generation pipeline.

5. Generate the list of silence, non-silence phones, extra-questions for Decision Tree clustering automatically.

6. Compile Lexicon Transducer L.fst from new lexicon. Create the language model folder and use it for computing HCL.fst Decoding graphs. Repeat Steps each time OOV occurs.
5.9 Hybrid

5.9.1 Lexicon Expansion Based

In Offline mode the lexicon stays constant, in Online mode the Lexicon is appended but changes are never preserved in them. Thus, the change is only present for each utterance and then discarded. This means that the entire process must repeat again and again despite adding for the given utterance the changes are not preserved in memory. We fix this by proposing a hybrid pipeline. In this we follow the same steps as the Online mode but make a conscious decision to preserve the Lexicon. This successfully solves the issue of repeated Online computations and reduces the number of Online runs to one for each unique OOV encountered in the utterance. This pays us dividends by reducing computational cost. The only disadvantage of preserving the Lexicon is the growing size of the Lexicon. We discuss these challenges in Section 5.7. The Hybrid process is described below:

1. Get Transcript for current utterance. Find words from current transcript not in any of the databases available.
2. Generate lexicon for the OOV vocabulary words.

3. Regenerate lexicon from appended vocabulary, using Lexicon generation pipeline. Generate the list of silence, non-silence phones, extra-questions for Decision Tree clustering automatically.

4. Compile Lexicon Transducer L.fst from new lexicon. Create the language model folder and use it for computing HCL.fst Decoding graphs.

5. Repeat Steps 1-7 each time OOV occurs, but do not discard the Lexicon.
6 SUMMARY AND DISCUSSION

We describe three methods by which we can create an optimized pipeline for automatic GoP score computation. The above methods integrate the OOV pipeline by proposing different methods for optimizing the cost associated with the space and time complexity. We also provide utilities to compute Phoneme and Word level alignments, Phoneme posteriors which can be used by researchers in the future for other downstream tasks associated with GoP task, or other tasks. Our method is somewhat of an Hybrid between On-the-fly composition and Fully Composed static WFSTs for decoding since the \( L.fst \) is re-constructed as and when required based on the input utterance.[30] A major problem noted with this method is the presence of dead-states during the decoding phase.

![Figure 24: The vocabulary space denoted as sets.](image)

In this Section we discuss about the consequences of these methods on the Lexicon and Lexicon Transducer. The Offline Lexicon can be considered as a static lexicon, and the others can be considered as a dynamic lexicon. The Offline Lexicon \( L_{Offline} \) is the biggest Lexicon at experiment start. Let us consider the initial Lexicon (without any additions) as \( L_0 \)
which does not contain any additional OOV entries. The other Lexicons $L_{Online}$ and $L_{Hybrid}$ are equal to $L_0$ before experiment start. However, the $L_{Online}$ size can never expand to be that of $L_{Offline}$ since changes to it are discarded after each addition of OOV from a new utterance. After 1 addition provided the same utterance $L_{Hybrid}$ and $L_{Online}$ can be equal as

$$L_{Online} = L_{Online} = L_0.L_{1-entry}$$

where $L_{1-entry}$ denotes the lexicon FST of the given addition.

$$L_{Offline} = L_{Hybrid} = L_0.L_{1-entry}...L_{N-entry}$$

Moreover, a situation can occur such that $L_{Hybrid} >> L_{Offline}$ large number of inputs cause the Hybrid Lexicon to increase in size beyond the Offline lexicon entries. This can occur in real-time since OOV size would be unlimited beyond the scope of the OOV present in the database lexicon, derived from its transcriptions. The following is summarized in the above figure, which represents the given equation visually in the form of the space of vocabulary as sets. The universal set U or an hypothetical lexicon FST $L_U$ containing all possible words known to mankind $L_U \neq L_{Hybrid}$ due to practical limits of space complexity.
7 CONCLUSION AND SCOPE OF FUTURE WORK

In the following project we propose the creation of a pipeline for the use of a Pronunciation evaluation. We further highlight the various issues one faces while formulating a pipeline of automatic score computation. Different methods for the pipeline have been proposed. We propose pipelines to incorporate OOV problem at during Goodness of Pronunciation evaluation/testing time when scores are being computed.

7.1 Conclusion

Traditional ASR systems can be trained to model accent at various stages of the ASR pipeline. Out of Vocabulary can be an issue for ASR systems and solving them can be critical for systems which depend on phoneme or word alignments for downstream tasks. Language modelling using WFST representation can be an technique considered for vocabulary compression. Expanding the Lexicon can lead to state space explosion of the corresponding WFSTs. Thus, there exists a clear trade-off between the size and decoding accuracy. Composing reconstructed (re-compiled) WFSTs can be done in a variety of ways, each having it’s own tradeoff for time vs space complexity.

7.2 Future Work

There are numerous unexplored ideas that arise from our given work. We discuss some of these ideas that could arise as a result or adjacent to our research.

- Further optimization of \( L.fst \) to improve decoding.
- Methods involving On-the-fly Composition of the \( L.fst \) and On-the-fly Rescoring can be easily alleviate some of the concerns during Online computation.
- Explore how the Phoneme posteriors and GoP scores could be used as speech features (vectors as inputs) to Neural Network architectures such as Wav2Vec, HuBERT, etc for improving Accented Speech Recognition and potentially for Prosody related tasks.
• Exploring the generalization capabilities of Neural Network architectures such as RNN and Transformers for posterior computation in GoP.

• Future systems which could potentially utilize LLM’s along with Lexicons for improve GoP.
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