

# Pronunciation Learning for Automatic Speech Recognition

by

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Submitted to the Department of Electrical Engineering and Computer  
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## Abstract

In many ways, the lexicon remains the Achilles heel of modern automatic speech recognizers (ASRs). Unlike stochastic acoustic and language models that learn the values of their parameters from training data, the baseform pronunciations of words in an ASR vocabulary are typically specified manually, and do not change, unless they are edited by an expert. Our work presents a novel generative framework that uses speech data to learn stochastic lexicons, thereby taking a step towards alleviating the need for manual intervention and automatically learning high-quality baseform pronunciations for words. We test our model on a variety of domains: an isolated-word telephone speech corpus, a weather query corpus and an academic lecture corpus. We show significant improvements of 25%, 15% and 2% over expert-pronunciation lexicons, respectively. We also show that further improvements can be made by combining our pronunciation learning framework with acoustic model training.

Thesis Supervisor: James Glass

Title: Principal Research Scientist



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# Chapter 1

## Introduction

In many ways, the lexicon remains the Achilles heel of modern automatic speech recognizers (ASRs). Unlike stochastic acoustic and language models that learn the values of their parameters from training data, the baseform pronunciations of words in an ASR vocabulary are typically specified manually (usually along with the basic phoneme inventory itself), and do not change, unless they are edited by an expert. The lexicon is usually a long list of these hand-crafted pronunciations in the form of dictionary entries that map a word to one or more *canonical* pronunciations.

A more desirable solution would be one whereby the basic linguistic units of a language, and the associated lexical pronunciations could be determined automatically from a large amount of speech data. In this thesis, we discuss methods for the latter, learning the lexical pronunciations of words given both their spelling and spoken utterances of isolated-word and/or continuous speech. This data-driven approach to lexicon generation might discard the notion of canonicalization altogether, and instead generate a stochastic lexicon with pronunciations weighted according to learned statistics.

Like the acoustic and language models, ideally pronunciations would be learned from data closely matching the test domain. In our work, we use the same training data used for Acoustic Model training to learn our pronunciations. Since this data is readily available at no extra cost for all recognizers, we see our work as encouraging lexicon training to become a standard procedure when building an ASR system, while taking a step towards being able to train a speech recognizer entirely from an orthographically transcribed corpus.

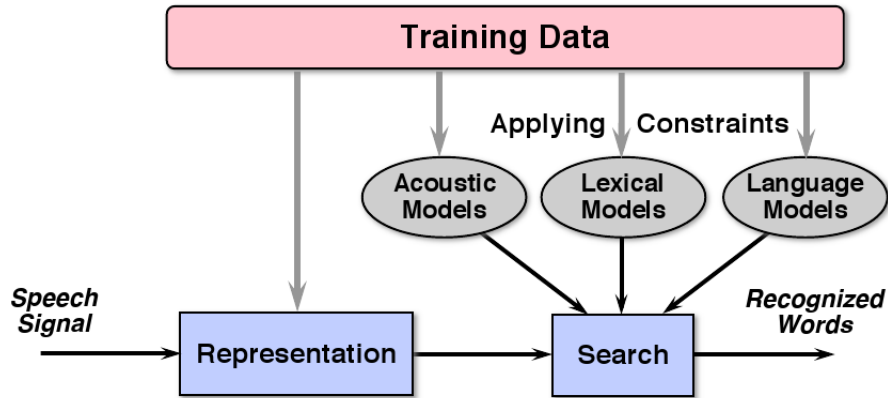


Figure 1-1: Major Components of a Speech Recognition System: The Acoustic Model, Lexicon and the Language Model [1]

## 1.1 Motivation

### 1.1.1 The Lexicon: A Hand-Written ASR Component

ASR is the process of decoding a spoken utterance into a string of words [10]. The spoken utterance is usually modeled as a weighted network of sub-lexical units, which are typically phones. A phone graph which models all speech corresponding to an input acoustic signal is constrained by the acoustic model, the lexicon and the language model. The acoustic model statistically models context-dependent or context-independent phones, typically Gaussian Mixture models are used. It is trained on acoustic-phonetic measurements of transcribed speech data. The lexicon maps words to their phonetic pronunciations, an example entry would be *colonel : k er n ax l*, and is typically crafted manually by experts. The language model statistically models the probability of a word sequence and typically uses n-gram distributions to score sentences. Figure 1-1 illustrates this process.

The fundamental equation of ASR seeks the most likely word sequence  $W^* = w_1^*, \dots, w_K^*$  given an utterance  $u$ :

$$W^* = \arg \max_W P(W|u) = \arg \max_W P(u|W)P(W) \quad (1.1)$$



Where  $P(u|W)$  is the acoustic model and  $P(W)$  is the language model. This equation implicitly implies that to each word corresponds one phonetic representation. A more accurate model would be:

$$P(W|u) = \sum_{B \in \mathcal{B}} P(W, B|u) = \frac{\sum_{B \in \mathcal{B}} P(W, B, u)}{P(u)} = \frac{\sum_{B \in \mathcal{B}} P(W)P(B|W)P(u|B, W)}{P(u)} \quad (1.2)$$

Here  $B$  is a phonetic pronunciation and  $\mathcal{B}$  is the set of all phonetic pronunciations.

$$P(W|u) = \frac{\sum_{B \in \mathcal{B}} P(W)P(B|W)P(u|B)}{P(u)} \quad (1.3)$$

where we assume conditional independence  $P(u|B, W) = P(u|B)$ . Hence:

$$W^* = \arg \max_W P(W|u) = \arg \max_W \sum_{B \in \mathcal{B}} P(u|B)P(B|W)P(W) \quad (1.4)$$

$P(B|W)$  is the lexicon. It assigns a probability to each phonetic pronunciation. Typically all baseforms are weighed equally by setting  $P(B|W) = 1$  for all  $B$  corresponding to  $W$  in the lexicon, even if the lexicon admits multiple pronunciations per word [34, 25]. In this work we propose to learn the lexicon, thereby avoiding the use of experts, as well as having to weight all baseforms equally.

Learning the lexicon from data opens up the possibility of using discriminative training in order to directly optimize on error rate. Discriminative training has been extensively studied for acoustic and language models and has been shown to perform significantly better than maximum likelihood methods. In this thesis, we explore incorporating Discriminative training to enhance our stochastic lexicons.

### 1.1.2 The OOV problem and Dynamic Vocabulary Learning

Almost all speech recognizers have a finite vocabulary pronunciation dictionary. If the recognizer encounters an out of vocabulary (OOV) term, a word that is not in the lexicon, it cannot produce a transcription for it. This limitation is detrimental in many ASR applications. Figure 1-2 demonstrates a potential outcome to an OOV word *euthanasia*. A

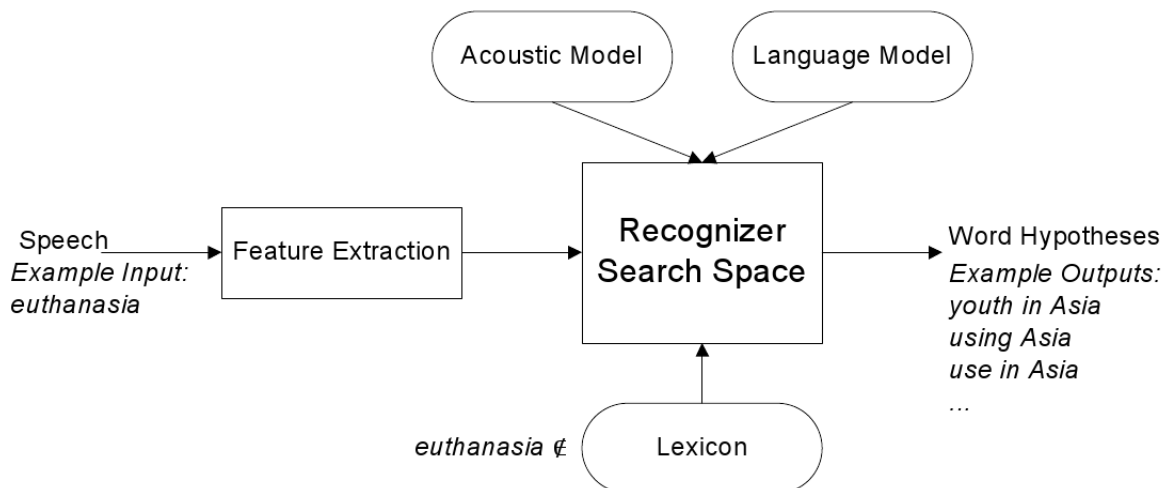


Figure 1-2: Diagram of Speech Recognition System behavior when recognizing an utterance containing an OOV words [10]

misrecognized OOV word can easily cause the surrounding words or even the whole sentence to be misrecognized. Therefore, in order for a ASR systems to be used in the real world, techniques need to be developed to handle the OOV problem. A typical approach is to increase the vocabulary size whether manually or automatically. This cannot completely eliminate OOVs in an open domain recognition task. Other techniques include using confidence scoring to detect OOVs [14], as well as, filler models to hypothesize the pronunciation of an OOV word [6]. In our work, we focus on automatically learning quality baseforms for OOV words in order to expand our lexicon.

The rate of OOV occurrence is tied to the design of the ASR vocabulary. Since constantly increasing the vocabulary size is bound to introduce acoustic ambiguity, ASRs should undergo a paradigm shift from vocabulary design to that of an adaptive system that can dynamically detect and learn new words. In a typical scenario, a speech recognizer remains static while it is deployed. Its acoustic models, language models and lexicon are trained or specified beforehand and remain unchanged while the recognizer is used. In our work, we explore techniques to dynamically expand a recognizer’s lexicon, as well as, improve on the pronunciations already present in the lexicon. This will be done by either automatically collecting new data to be used to retrain the lexicon or using the speech data collected from our speech recognizer’s tasks.

## 1.2 Contributions of this Thesis

This thesis offers the following specific contributions:

- A method for learning better-than-expert word pronunciations given their spellings, as well as, spoken utterances.
  - This method can learn from both isolated-word and continuous speech.
  - This method is robust and hence can learn from cheaply collect noisy speech.
  - This method can supplement the Acoustic and Language models without the use of any additional training data.
- A method for discriminatively training lexicon pronunciation weights for isolated word recognition.
- A method for iteratively training the Acoustic Models, as well as, the Lexicon.

## 1.3 Summary of Each Chapter

The rest of this thesis is organized into 4 chapters. The content of each of the remaining chapters is summarized next:

- **Chapter 2: Background**

Chapter 2 starts with a description of how pronunciation variability is handled in current ASR systems. It then presents a review of the major advances in pronunciation learning for ASR. It also explains some of the mathematical frameworks applied in this thesis.

- **Chapter 3: Learning Pronunciations from Isolated-Word Spoken Examples**

This chapter presents two Bayesian models that learn pronunciations from isolated word examples. It reports on experiments that produce better-than-expert pronunciations for isolated word recognition, as well as, an inherent robustness to real world noisy data.

- **Chapter 4: Discriminative Pronunciation Training for Isolated-Word Speech Recognition**

In this chapter, we improve on our results for isolated-word recognition by discriminatively training our learned pronunciations to minimize WER.

- **Chapter 5: Learning Pronunciations from Continuous Speech**

Here, we explore the use of continuous speech data to learn stochastic lexicons. Building on the work of the previous chapter, we extend our framework to two domains containing spontaneous speech: a weather information retrieval spoken dialogue system and an academic lectures domain. We find that our learned lexicons out-perform expert, hand-crafted lexicons in each domain. We also explore the relationship between the Lexicon and the Acoustic Models by iteratively re-training them. We show improvements on a Book Titles corpus and discuss limitations that should be addressed for these scenarios.

- **Chapter 6: Summary and Future Direction**

This chapter concludes the thesis, and suggests some ideas for future research.

# Chapter 2

## Background

### 2.1 Pronunciation Modeling

Pronunciation variation has been identified as a major cause of errors for a variety of ASR tasks [26]. Pronunciations are typically modeled in a speech recognizer by a phonemic dictionary which may be accompanied by a set of rewrite rules to account for phonological variation.

The ASR system used in this paper incorporates manually crafted phonological rules that account for segmental mismatches between the underlying phonemic baseforms and surface-level phonetic units. These rules have been shown to outperform relying on context-dependent acoustic models to implicitly model phonetic variation [18].

In this work, we model the ASR’s search space using a weighted finite-state transducer (FST) [20]. The FST search space has four primary hierarchical components: the language model ( $G$ ), the phoneme lexicon ( $L$ ), the phonological rules ( $P$ ) that expand the phoneme pronunciations to their phone variations, and the mapping from phone sequences to context-dependent model labels ( $C$ ). The full network can be represented as a composition of these components:

$$N = C \circ P \circ L \circ G \tag{2.1}$$

In this work, we experiment with learning context-independent phoneme pronunciations along with their weights. That is, we try to replace the manually crafted FST  $L$  while keeping

the pronunciations rules FST  $P$  unchanged. We also explore learning phone pronunciations directly, thus avoiding the use of the phonological rewrite rules altogether.

## 2.2 Letter-to-Sound Models

Generating pronunciations for new words has been the subject of much work [9, 7, 22, 33, 28, 5, 23, 21] . The common approach is to use a form of letter-to-sound model to predict the pronunciations of new words using only their spelling. Despite the fact that for some languages, mapping a spelling to a pronunciation is relatively straightforward, English has shown itself to be rather challenging. Many models have been used for this task: in our work, we compare our results to the grapheme model which has been shown to produce state of the art scores for letter-to-sound tasks [7, 36]. We address the mathematical formulation of the grapheme model in this next section.

### 2.2.1 The Graphoneme model

We utilize the joint-multigram approach employed in [9, 7] to model the relationship between graphemes and phonetic units. In this work, we use the term *grapheme* to denote a model that maps graphemes to phones, and *graphoneme* to refer to a model that maps graphemes to phonemes.

We begin by constructing an  $n$ -gram model over graphoneme sequences. We let  $w$  denote a grapheme sequence drawn from the set of all possible grapheme sequences  $\mathcal{W}$  and  $b$  denote a phoneme sequence drawn from the set of all possible phoneme sequences,  $\mathcal{B}$ . A joint model of the letter-to-sound task can be formalized as:

$$b^* = \arg \max_{b \in \mathcal{B}} P(w, b) \tag{2.2}$$

Generally speaking, a graphoneme,  $g = (w, b) \in \mathcal{G} \subseteq \mathcal{W} \times \mathcal{B}$ , is a sub-word unit that maps a grapheme subsequence,  $w$ , to a phoneme subsequence,  $b$ . By analogy, a grapheme is an alternative sub-word unit that maps a grapheme subsequence to a *phone* subsequence. In this work, we restrict our attention to singular graphemes or graphonemes, in which a

mapping is made between at most one grapheme and at most one phonetic unit. The empty subsequence  $\epsilon$  is allowed, however a mapping from  $\epsilon$  to  $\epsilon$  is omitted. Taken together, a sequence of graphonemes,  $g$ , inherently specifies a unique sequence of graphemes  $w$  and phonemes  $b$ ; however, there may be multiple ways to align the pair  $(w, b)$  into various graphoneme sequences  $g \in S(w, b)$ . The following table shows two possible graphoneme segmentations of the word “couple”.

$w$	=	c	o	u	p	l	e	
$b$	=	k	ah		p	ax	l	
	=	k		ah	p	ax	l	
$g_1$	=	c/k	o/ah	u/ $\epsilon$	p/p	$\epsilon$ /ax	l/l	e/ $\epsilon$
$g_2$	=	c/k	o/ $\epsilon$	u/ah	p/p	$\epsilon$ /ax	l/l	e/ $\epsilon$

Given this ambiguity, employing graphonemes in our joint model requires us to marginalize over all possible segmentations. Fortunately, the standard Viterbi approximation has been shown to incur only minor degradation in performance [7].

$$P(w, b) = \sum_{g \in S(w, b)} P(g) \approx \max_{g \in S(w, b)} P(g) \quad (2.3)$$

In our work, we use the open source implementation provided by [7], which runs the Expectation-Maximization (EM) algorithm on a training corpus of word-phoneme pronunciation pairs to automatically infer graphoneme alignments. We then train a standard 5-gram language model over the automatically segmented corpus of graphonemes. This configuration has been shown to produce good results for singular graphonemes [36].

### 2.2.2 Other Work on Letter-to-Sound Prediction

While original work in Grapheme-to-Phoneme conversion consisted of rule-based methods [22], these quickly became overly complicated and tedious for practical use and were soon replaced by data-driven methods. An example of work that utilizes knowledge-based formal linguistic methods in a statistical framework is [33]. As a first step, a hand-written grammar parses words into a set of hand-written linguistically motivated sub-word “spellname” units. Then,

after parsing a large lexicon into these segmented words, a statistical  $n$ -gram model is trained and used later for decoding.

Most other work on letter-to-sound generation can be classified as using a pronunciation by analogy technique or local classification technique. Local classification processes a word spelling sequentially from left-to-right. For each input character a decision is made by looking at the letter’s context using decision trees [30] or neural networks [17]. As for pronunciation by analogy, the main theme is to scan the training lexicon for words or part-of-words that are in some sense similar to the word to be transcribed [28, 5]. The output pronunciation is then chosen to be analogous to the retrieved examples.

While the most recent state-of-the-art work has been on probabilistic approaches such as the joint-sequence model discussed in the previous section. Some have also explored discriminative training in a joint-sequence setting [21], as well as, grapheme-to-phoneme conversion using a Statistical Machine Translation system (SMT) [23].

## 2.3 Using Acoustics to Learn Pronunciations

Other relevant work extends on the idea of letter-to-sound generation by incorporating spoken examples to refine the generated pronunciations [27, 11]. The work of [4] deduces the baseform  $b^*$  given a word or grapheme sequence  $w$  and an utterance  $u$  of the spoken word  $w$ . In this work, a decision tree is used to model  $P(w, b)$  which was later shown to produce poorer results when compared to grapheme models.

The work of [24] adapts the grapheme model parameters using acoustic data and is applied to a name recognition task. Given a training set  $(u_i, w_i)$  of pairs of words  $w$  and spoken examples  $w$ , they maximize the likelihood of their data:

$$\sum_{i=1}^M \log p_{\theta}(u_i, w; \theta) = \sum_{i=1}^M \log \sum_{b \in \mathcal{B}} p_{\theta}(u_i, w, b)$$

by using the standard EM algorithm to adjust  $\theta$ , the grapheme n-gram parameters. They



initially set the parameters of  $\theta$  to those of the grapheme model and iterate until convergence. They also experiment with discriminative training and show that it produces better results than MLE. In our work, we use a similar framework to MLE geared towards predicting a pronunciation for a single word given multiple example utterances.

The work of [35] uses the forced alignment of a phonetic decoder to generate a list of possible pronunciations for words, and then assigns weights using a Minimum-Classification-Error criterion. They then test on a business name query corpus. Curiously, work on pronunciation learning using acoustic examples is rarely applied across the entire lexicon to regularize the pronunciations with respect to the underlying acoustic models. By contrast, in our work we learn pronunciations across all lexical entries rather than the few out-of-vocabulary words for which we do not have an expert opinion. Thus, our test experiments directly compare a learned stochastic lexicon with manually-crafted pronunciations.

## 2.4 Global Linear Models

Here we describe a general framework of linear models that can be applied to a diverse range of tasks, e.g. parsing or ASR hypothesis reranking. We will be modifying this framework to train our pronunciation lexicon.

The framework is outlined in [12]. We learn a mapping from inputs  $x \in X$  to outputs  $y \in Y$  by assuming:

- A set of training examples  $(x_i, y_i)$  for  $i = 1 \dots N$
- A function  $GEN$  which enumerates a set of candidates  $GEN(x)$  for input  $x$
- A representation  $\Phi$  mapping  $(x, y)$  to a feature vector  $\Phi(x, y) \in \mathfrak{R}^d$
- A parameter vector  $\alpha \in \mathfrak{R}^d$

We define a mapping from an input  $x$  to an output  $F(x)$

$$F(x) = \arg \max_{y \in GEN(x)} \Phi(x, y) \cdot \alpha \tag{2.4}$$

To illustrate how Global Linear Models can be applied to discriminative language model training for ASR, we reference the work of [32].

- Each  $(x_i, y_i)$  is an utterance and its reference transcription
- $GEN(x)$  is the outputted word-lattice from a baseline recognizer
- $\Phi(x, y)$  tracks unigram, bigram and trigram word counts in  $y$ , as well as, the score for  $(x, y)$  under the baseline recognizer

To optimize the parameters  $\alpha$ , we consider this variant of the perceptron algorithm:

INPUT: Training examples  $(x_i, y_i)$

INITIALIZATION: Set  $\alpha = 0$

ALGORITHM:

```
for  $t = 1 \dots T, i = 1 \dots N$  do  
     $z_i = \arg \max_{z \in GEN(x_i)} \Phi(x_i, z) \cdot \alpha$   
    if  $z_i \neq y_i$  then  
         $\alpha = \alpha + \Phi(x_i, y_i) - \Phi(x_i, z_i)$   
    end if  
end for
```

OUTPUT:  $\alpha$

For a complete discussion regarding the convergence of this algorithm, as well as, generalization to unseen data, we refer the reader to [12].

## 2.5 Summary

In this chapter, we presented a survey of approaches that handle pronunciation prediction from word spellings, as well as, word spelling supplemented with acoustic examples. We also explained how pronunciation variability is handled in the ASR system used in this thesis. We concluded with a description of Global Linear Models, a mathematical framework used for Discriminative training.

# Chapter 3

## Learning Pronunciations from Isolated-Word Spoken Examples

We first tackle the simplified task of learning word pronunciations from isolated-word speech and testing on isolated-word speech. Our research differs from previous work in the stochastic learning framework. In our case, we use an n-gram graphoneme-based model as the basis for our initial estimate of a pronunciation. The graphoneme model is used as a form of prior to condition our expectation of possible pronunciations of a new word, given its spelling. We then use spoken examples to further refine the pronunciations, and explore two different stochastic pronunciation models: the first cascades all the examples to find a single best pronunciation, while the second creates a pronunciation mixture model (PMM) to consider multiple pronunciations. We compare both approaches on the telephone-based PhoneBook corpus of isolated words [2] and find that they are able to recover expert-level pronunciation baseforms with relatively few example utterances.

### 3.1 Graphone-guided Phonetic Recognition

We begin by exploring a model which incorporates one example utterance with the graphoneme model to find a single high probability baseform. Given a word with grapheme sequence  $w$  and an example utterance of the word  $u$ , we deduce the baseform for  $b^*$  using a

similar framework to that described in [4].

$$b^* = \arg \max_{b \in \mathcal{B}} P(b|w, u) = \arg \max_{b \in \mathcal{B}} P(b, w)p(u|b, w) \quad (3.1)$$

We replace the decision tree originally described in [4] with a graphoneme  $N$ -gram model using independence assumptions and the Viterbi approximation.

$$b^* \approx \arg \max_{b \in \mathcal{B}, g \in \mathcal{S}(w, b)} p(u|b)P(g) \quad (3.2)$$

For each word,  $w$ , a recognizer,  $R_w$ , can be constructed using weighted finite state transducers (FSTs) to model the mapping of acoustic model labels to phoneme sequences, weighted by graphoneme  $n$ -gram parameters.

The procedure described above only incorporates a single example utterance into the pronunciation generation framework. The following sections introduce two methods of utilizing a *set* of  $M$  example utterances,  $u_1^M$ , of a given word,  $w$ .

### 3.1.1 Cascading Recognizers

As in Equation 3.1, we apply Bayes rule with the additional assumption of independence between example utterances given their pronunciations to model the probability of a baseform given the data:

$$b^* = \arg \max_{b \in \mathcal{B}} P(b|w, u_1^M) = \arg \max_{b \in \mathcal{B}} P(b, w) \prod_{i=1}^M p(u_i|b, w)$$

This multiple utterance recognizer can be implemented as a cascade of single utterance recognizers. Figure 3-1 illustrates this approach. While this framework ties up all utterances to predict a single baseform, in this next section, we explore a more parallel approach that can model multiple pronunciations simultaneously.

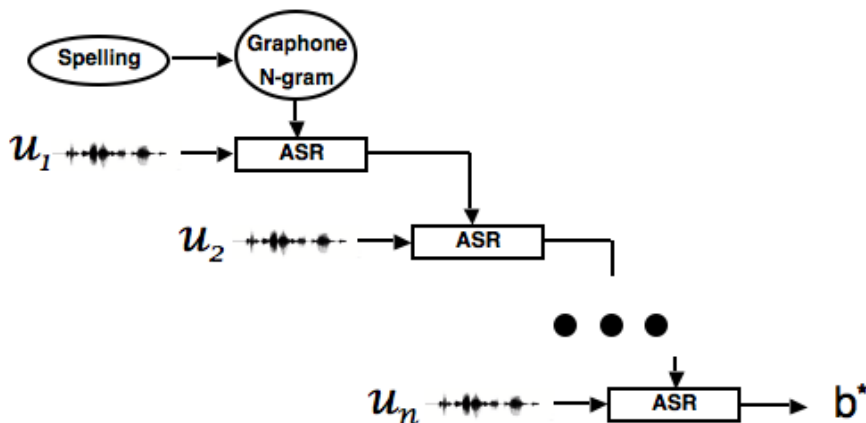


Figure 3-1: Diagram of Cascading Recognizers Model: Each utterance uses recognition results of preceding utterances to decode.

### 3.1.2 Pronunciation Mixture Model

A second formulation of pronunciation generation informed by multiple example utterances is that of a *pronunciation mixture model* (PMM). We parametrize our model with  $\theta_{b,w} = P(b, w)$  under the assumption that a particular word  $w$  and baseform  $b$  have some joint probability, however small, of mapping to one another. In a setup similar to the work described in [24], expectation maximization is used to update these parameters based on the data  $(u_1^M, w)$ . Whereas Li et al. optimize graphoneme language model parameters, our goal here is to directly learn weights for word pronunciations, hence the PMM characterization. We begin by characterizing the log-likelihood of the data.

$$L(\theta) = \sum_{i=1}^M \log p(u_i, w; \theta) = \sum_{i=1}^M \log \sum_{b \in \mathcal{B}} \theta_{w,b} \cdot p(u_i | w, b)$$

The parameters,  $\theta$ , are initialized to our graphoneme  $n$ -gram model scores and run multiple iterations of the EM algorithm. The following equations specify the expectation and maximization steps respectively:

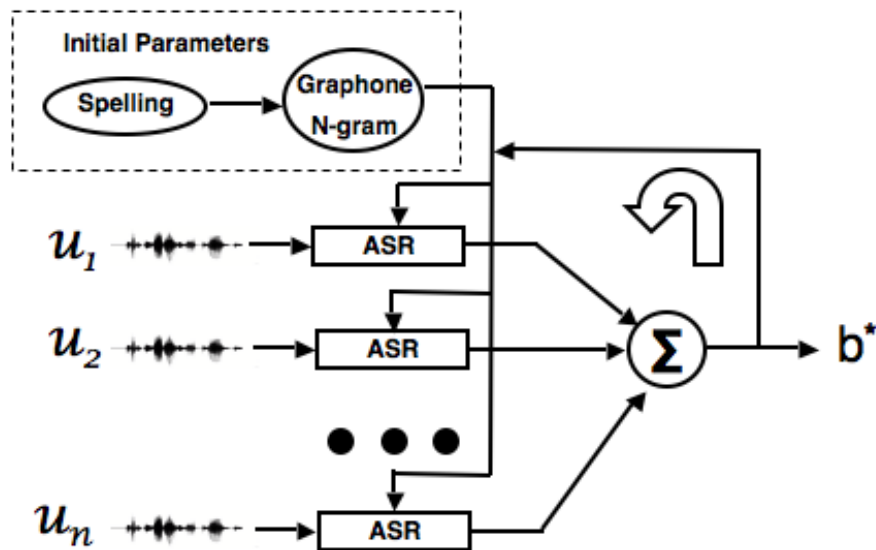


Figure 3-2: Diagram of Pronunciation Mixture Model: Pronunciation weights are initialized with graphoneme letter-to-sound model. All utterances vote in parallel to assign weights for pronunciations (E-step), Votes are then summed and normalized (M-step). New weights are used to initialize the next iteration.

$$\begin{aligned}
 \text{E-step:} \quad & P(b|u_i, w; \theta) = \frac{\theta_{w,b} \cdot p(u_i|b, w)}{\sum_p \theta_{w,p} \cdot p(u_i|b, w)} \\
 \text{M-step:} \quad & \theta_{w,b}^* = \frac{1}{M} \sum_{i=1}^M P(b|u_i, w; \theta)
 \end{aligned}$$

We illustrate this parallel approach in Figure 3-2.

As an initial experiment we pick the baseform  $b$  with the highest weight as the pronunciation of  $w$  and use it unweighted i.e. with a probability of 1.

$$b^* = \arg \max_{b \in \mathcal{B}} P(w, b; \theta^*) = \arg \max_{b \in \mathcal{B}} \theta_{w,b}^* \tag{3.3}$$

In later experiments, we use multiple pronunciations weighted by their mixture probabilities in a stochastic lexicon.

## 3.2 Experimental Setup and Results

### 3.2.1 Experimental Setup

To experiment with the two pronunciation models, we use a landmark-based speech recognizer [15]. MFCC averages are computed over varying durations around hypothesized acoustic-phonetic landmarks to generate 112-dimensional feature vectors, which are then whitened via a PCA rotation. The first 50 principal components are kept as the feature space over which diphone acoustic models are built. Each model is a diagonal Gaussian mixture with up to 75 mixture components trained on a separate corpus of telephone speech. The search space in the recognizer is modeled using a flexible weighted FST toolkit [20].

We consider the task of isolated word recognition using the NYNEX PhoneBook corpus. PhoneBook is a phonetically-rich, isolated-word, telephone-speech database of American English spanning a variety of talkers and telephone transmission characteristics. The core section of PhoneBook consists of a total of 93,667 isolated-word utterances, totalling 23 hours of speech. This breaks down to 7,979 distinct words, each said by an average of 11.7 talkers, with 1,358 talkers each saying up to 75 words. All data were collected in 8-bit mu-law digital form directly from a T1 telephone line. Talkers were adult native speakers of American English chosen to be demographically representative of the U.S [2].

To insure adequate data for our baseline experiments, we chose 2,000 words at random from the subset of the corpus that had example utterances from at least 13 distinct speakers. We held out two of the 13 utterances, one from a male speaker the other from a female speaker, to generate a 4,000 utterance test set.

While the individual recognition experiments described in the next section are limited to the 2,000 selected words, a far larger lexicon was used to train the initial grapheme language model parameters. For this work we used an internal dictionary that contains over 150,000 manually generated entries. To simulate the out-of-vocabulary scenario for which graphemes are typically employed, we removed the 2,000 trial words from our lexicon, and further pruned similarly spelled words using a simple edit distance criterion. We then trained a 5-gram grapheme language model according to the procedures described in [36].

We conduct two baseline experiments to frame our remaining results. The first is a

graphoneme-only baseline in which we performed isolated word recognition over the 4,000 test utterances using a 2,000 word lexicon generated from the graphoneme model alone according to Equation 2.3. Since no acoustic information was used, this provides us with an upper-bound on word error rate (WER) of 16.7%. The second baseline was again the 2,000 word-recognition task; however, this time we explicitly used the manually generated pronunciations originally found in our lexicon [3], giving us a target WER of 12.4%, achievable directly by experts.

It should be noted that about 160 words in the expert-lexicon had multiple baseforms associated with them. For example, the word “youths” was represented as both  $y\ uw\ dh\ z$  and  $y\ uw\ th\ s$ . Initial experiments indicated that allowing multiple baseforms could give an advantage to the expert-lexicon that could be leveraged in the other frameworks. We begin however by choosing only a single pronunciation for inclusion in an automatically generated lexicon. Even so, were able to show the feasibility of recovering and even surpassing the performance of manually generated baseforms.

### 3.2.2 Results using Un-Weighted Pronunciations

Having established our baseline experiments, we evaluated both the cascading recognizer approach and the PMM by varying the number of training utterances for each, and evaluating the WER of the test set against the lexicons produced under each condition. The resulting plot is shown in Figure 3-3. It is encouraging to note that both models perform admirably, achieving expert-level pronunciations with just three example utterances per word.

The cascading recognizer approach of Section 3.1.1 improves slightly faster than the PMM technique. With seven utterances, this model surpasses the expert baseform WER by nearly 1%.

An inherent assumption of this model is that there is a single, correct underlying pronunciation. This fact may explain the slight advantage that this approach has, since our experimental design only allows a single baseform for each word in our automatically generated lexicon. A model which directly computes the single most likely baseform given the data is thus particularly well-suited to the task.

Ideally, a pronunciation generation model would be able to cope with words that have



## Lexicon Adaptation using Acoustic Examples

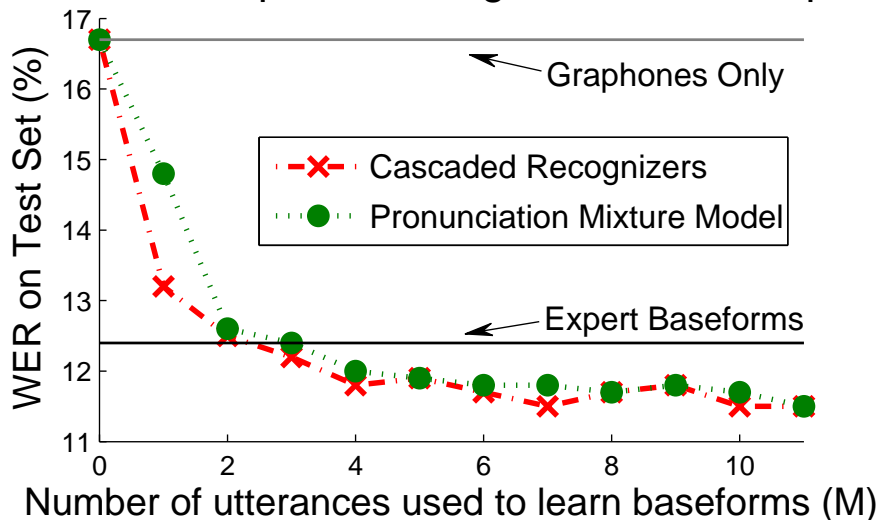


Figure 3-3: Word Error Rate (WER) as a function of the number of example utterances used to adapt the underlying lexicon. We show results for using the Cascaded Recognizers Model, the PMM, the Graphone model and the Expert Dictionary

$\tau$	0.2	0.1	0.05
Avg. # $b$ per $w$	1.25	2.10	2.21
WER (%)	11.2	<b>11.0</b>	11.5

Table 3.1: By varying a threshold  $\tau$  over the weights learned in the PMM, we can incorporate multiple baseform pronunciations for individual words.

multiple pronunciations, such as “either”. It probably does not make sense, for example, to be multiplying the acoustic scores of one utterance pronounced *iy dh er* with a second pronounced *ay dh er*.

Lastly, another potential pitfall of the cascaded recognizers approach is that unless special care is taken to customize the pruning procedure, acoustic variation will inherently cause the pronunciation search space to become successively smaller as the compositions prune low-probability paths. This is especially problematic when considering noisy utterances. Indeed, even with the clean speech comprising the PhoneBook corpus, by the 11th utterance,  $N$ -best lists produced by the cascaded recognizers contained an average of just 10.7 entries.

To illustrate the performance of the PMM, we show in Figure 3-3 the WER obtained by generating a lexicon according to Equation 3.3 (i.e. taking the highest scoring pronunciation and using it unweighted in the lexicon) after two iterations of EM. This stopping

criterion was determined by constructing a development set of 1,500 previously discarded PhoneBook utterances and running recognition using lexicons generated after each EM iteration. Alternatively, EM could have been run to convergence and then smoothed, again with the aid of a development set.

While the PMM requires slightly more data to achieve the lowest reported WER of the cascade approach (11.5%), it is eventually able to do so once all 11 training utterance are incorporated into the mix. It is clear from the figure that with only a single training example EM begins to over-fit the acoustic idiosyncrasies of that particular example. Though not shown in the figure, this effect is magnified for small amounts of training data when EM is run for a third and fourth iteration.

One big advantage of the PMM approach is that it directly models multiple pronunciations for a single word, an avenue we begin to explore with a second set of experiments. We use a simple weight threshold  $\theta_{w,b} > \tau$ , to choose baseforms for inclusion. As in the single baseform case, we initially discard the weights once the baseforms have been chosen, but we ultimately use them during decoding later on in experiments with stochastic lexicons.

Table 3.1 shows WER obtained by recognizers with lexicons trained with all 11 utterances generated under varying values of  $\tau$ . Choosing  $\tau = 0.1$  yields the best reported WER of 11.0%, a 1.4% absolute improvement over the expert-baseline. It's interesting to note that this threshold implies an average of 2.1 pronunciations per word, almost double that of the expert lexicon which has 1.08. We also plot WER using varying thresholds as a function of the number of training utterances used in Figure 3-4. As can be seen, WER improves when using  $\tau = 0.1$  even with less than 11 utterances.

### 3.2.3 Results using Stochastic Lexicon

So far we have been using a threshold to figure out how many baseforms to include per word. During decoding we throw out each baseform's associated score and weight all of them equally. In this part we experiment with including as many baseforms as possible while keeping their associated weight.

We run our experiments on the same test set as before by including the top 100 baseforms. The intuition is that since most of the weight will be concentrated on the top 5 baseforms

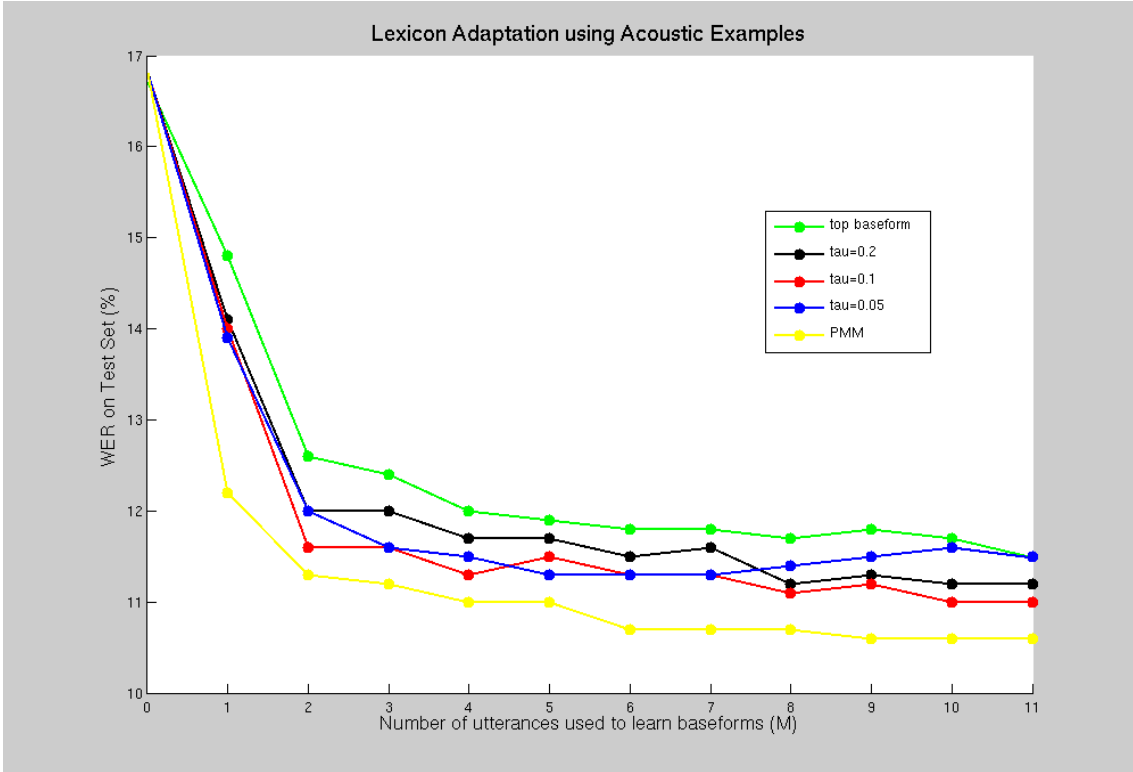


Figure 3-4: Word Error Rate (WER) as a function of the number of example utterances used to adapt the underlying lexicon. We show results for using the un-weighted learned pronunciations while varying the  $\tau$  threshold, as well as, using the PMM (stochastic lexicon)

including an arbitrary large amount should not hurt our scores. Again we notice improvements: the WER for the phoneme PMM drops to 10.6 while the WER for the phone PMM drops to 9.9 which results in a 25% relative improvement over the expert-crafted lexicon. Figure 3-4 plots WER using the stochastic lexicon while training on less than 11 utterances. As can be seen, the stochastic lexicon out-performs using an unweighted lexicon and requires only 6 training examples to achieve its best score.

### 3.3 Training Pronunciations using Noisy Acoustic Examples

While the PhoneBook data used for training simulated ideal training conditions by matching the test data and the AM used, we now show the utility of *un-matched* speech collected cheaply from a cloud-service in generating high-quality pronunciations in a fully automatic

fashion. Models that incorporate acoustic information into lexicon adaptation become particularly useful in domains where acoustic data is cheaper to obtain than expert input. In [24], example utterances of spoken names are obtained in an unsupervised fashion for a voice-dialing application by filtering for interactions where the user confirmed that a call should be placed. Unfortunately, not all domains are amenable to such a convenient context-filter to find self-labeled utterances.

To collect arbitrary acoustic data, we turned to the Amazon Mechanical Turk (AMT) cloud-service. AMT has been described as a work-force in the cloud since it enables *requesters* to post web-based tasks to any *workers* willing to accept micro-payments of as little as \$0.005 upon completion. The service has become popular in the natural language processing community for collecting and annotating corpora, and has recently been gaining use in the speech community. In [29], we were able to collect over 100 hours of read speech, in under four days.

In this work, we used a similar procedure to augment our PhoneBook corpus with another 10 example utterances for each of its 2,000 words at a cost of \$0.01 per utterance. Whereas in [29] we took care to filter the collected speech to obtain high-quality sub-corpora, we took no such precautions when collecting these example utterances. Thus, in addition to other sources of mismatch between the data and our acoustic model, this noisy data poses a challenge to even a recognizer built on expert pronunciations. Due to acoustic mismatch between the utterances and our acoustic models, running the expert baseline recognizer over these 20,000 utterances yields a very high WER of 50.1%. Of course, since we could make no guarantees that the worker even read the word, the true error rate is unknown.

It might seem, then, that using this data to generate valid pronunciations is a dubious exercise. Indeed, this data set confounds the cascading recognizer configuration since a single noisy utterance can throw off the entire cascade. Fortunately, the PMM approach has the nice property that a few noisy scores do not significantly affect the totals.

Repeating a subset of the experiments of the previous section, we again show four iterations of the PMM approach, using the PhoneBook utterances alone, AMT-PhoneBook combined utterances, and the AMT-collected corpus alone. Despite the noisy nature of the cloud-collected corpus, Table 3.2 shows that there is little degradation in WER when using

	# Utts.	Iter.1	2	3	4
Phonebook	11	12.3	11.5	11.7	12.0
AMT	10	12.3	<b>12.0</b>	13.0	15.3
Phonebook+AMT	21	12.3	11.6	11.6	12.0

Table 3.2: PMM results incorporating spoken examples collected via Amazon Mechanical Turk.

all 21 utterances for every word. Perhaps more pleasing is the fact that generating pronunciations based on just the AMT-data still manages to out-perform even the expert generated pronunciations, achieving a WER of 12.0% when using the top un-weighted learned baseform, compared with 12.4% for the experts.

### 3.4 Analysis of Learned Baseforms

In order to quantify some of the differences between the expert and learned baseforms, we ran NIST align software to tabulate differences between the reference expert baseform, and the top choice hypothesis of the PMM model. Of the 2000 baseform pairs, 83% were identical, while the remainder mostly contained a single substitution. Most of the substitutions involved vowels, typically a schwa. Only 2% of the data contained an additional insertion or deletion. Most of these involved retroflexed vowel sequences.

Table 3.3 shows examples of common confusions including vowel and consonant substitutions, vowel/semi-vowel sequence perturbations, syllable deletions, and outright pronunciation corrections. Although the latter were few, it was encouraging to see that they did occur.

Table 3.4 shows the top 10 most confused phoneme pairs, while Table 3.5 and Table 3.6 show the most deleted and inserted phonemes.

### 3.5 Phone Versus Phoneme Pronunciations

As described in Section 2.1, our recognizer uses a lexicon of phoneme transcriptions to decode. This is made possible by the use of a manually crafted pronunciation rules FST [19] that expands sequences of phonemes to all their possible phone realizations. Given the promising

Word	Dictionary Baseform	Top PMM Baseform
parishoners [sic]	p <b>AE</b> r ih sh ax n er z	p <b>AX</b> r ih sh ax n er z
traumatic	tr r <b>AO</b> m ae tf ax kd	tr r <b>AX</b> m ae tf ax kd
winnifred	w ih n ax f r <b>AX</b> dd	w ih n ax f r <b>EH</b> dd
crosby	k r ao <b>Z</b> b iy	k r aa <b>S</b> b iy
melrose	m eh l r ow <b>Z</b>	m eh l r ow <b>S</b>
arenas	<b>ER</b> iy n ax z	<b>AX R</b> iy n ax z
billowy	b ih l <b>OW</b> iy	b ih l <b>AX W</b> iy
whitener	w ay <b>TF AX</b> n er	w ay <b>TD</b> n er
airsickness	eh r <b>SH</b> ih kd n <b>EH</b> s	eh r <b>S</b> ih kd n <b>AX</b> s
Isabel	<b>AX S AA</b> b eh l	<b>IH Z AX</b> b eh l

Table 3.3: Example baseform changes between expert dictionary and top PMM hypothesis. Phonemes involved in the difference have been capitalized.

Confusion Pairs	# of Occurrences
AX ==> IH	37
AO ==> AA	31
ER ==> R	26
R ==> ER	23
AX ==> EH	10
Z ==> S	10
AX ==> AA	10
IH ==> AX	9
AX ==> AH	9
AH ==> AX	6

Table 3.4: Top 10 phoneme confusion pairs for Phonebook lexicon

Deleted Phonemes	# of Occurrences
AX	12
TD	5
Y	4
S	3
AO	2

Table 3.5: Top 5 Deleted Phonemes in Phonebook lexicon

Inserted Phonemes	# of Occurrences
AO	18
AX	11
N	4
TD	2
L	2

Table 3.6: Top 5 Inserted Phonemes in Phonebook lexicon

$\tau$	Iter 1	2	3	4
0.2	13.2			
0.15	12.8	11.9	11.7	
0.1		11.5	11.1	11.1
0.05		11.5	10.7	11.0
0.025			<b>10.3</b>	11.0
0.01			10.8	11.0

Table 3.7: PMM results for learning phone pronunciations from PhoneBook corpus.

results shown in previous sections, we set out to learn phone transcriptions of words which would allow us to bypass the pronunciations rules file and move closer to a fully automatically learned speech recognizer. The FST implementation of the recognizer would then be simplified to  $R = C \circ L \circ G$  where  $L$  is now a lexicon FST that maps phone sequences to words. Note that since we are learning pronunciation in an isolated word setting we avoid having to worry about cross-word pronunciation variation.

To automatically learn phone transcriptions of words we first have to train a *graphone* model instead of the *graphoneme* model we were using previously. This is done by using the pronunciation rules files to expand all the 200k phoneme transcriptions in our expert crafted lexicon to all their phone realizations and train our graphone model on this phone lexicon. We proceed by using our trained graphone model with a modified PMM implementation to learn phone transcriptions. The results are displayed in Table 3.7. The table displays WER scores by varying thresholds for baseform inclusion and number of EM iterations.

We notice that by using a threshold of  $\tau > 0.025$  we achieve significant gains over the phoneme PMM. It is interesting to note that our best phoneme PMM lexicon contained on average 2.1 baseforms per word. When we used the pronunciations rules file to expand these baseforms we ended up with an average of 5.3 baseforms per word. Our new phone

PMM lexicon contains an average of 5.1 baseforms per word which could indicate that our pronunciations rules file tends to overgenerate phone realizations which in turn expands the search space and leads to lower scores.

## 3.6 Summary

In this chapter, we have presented two Bayesian models that learn pronunciations from isolated word examples: The Cascaded Recognizer and the Pronunciation Mixture Model (PMM). We reported on experiments that produce better-than-expert pronunciations for isolated word recognition. We also showed an inherent robustness to real world noisy data when using the PMM. We experimented with using our learned pronunciations in both an unweighted dictionary, as well as, a stochastic lexicon. To understand why our learned pronunciations outperform expert baseforms, we also described some of the differences between our learned pronunciations and the expert pronunciations.



## Chapter 4

# Discriminative Pronunciation Training for Isolated-Word Speech Recognition

As a refinement step, we attempted to adjust the pronunciation weights proposed by the phoneme PMM using discriminative training to directly minimize errors. These new weights are then to be used in a stochastic lexicon during decoding. The hope is that discriminative training can address some of the concerns that maximum likelihood training cannot:

- **Word Confusability:** On average the PMM introduces more pronunciations than the expert lexicon without taking into account that these extra pronunciations might be close to or the same as pronunciations for other words. Hence, the PMM could potentially be increasing word-confusability and therefore increasing WER during testing.
- **Viterbi Decoding:** Our ASR system uses the Viterbi approximation while decoding i.e. it does not marginalize or sum over the probabilities of all pronunciations mapping to a word hypotheses. The Viterbi approximation forces the decoder to select the highest scoring pronunciation for any given word hypotheses. Since the PMM marginalizes over all pronunciations to maximize data likelihood, there is mismatch between our decoding and our training method.

## 4.1 Global Linear Models for Lexicon Learning

In this section, we adapt the approach presented in section 2.4 to discriminatively train the weights of our pronunciation lexicon. Without loss of generality, we can modify Equation 3.1 as follows.

$$w^*, b^* \approx \arg \max_{w,b} P(u|b)P(b, w) \quad (4.1)$$

We now recognize word-pronunciation pairs instead of plain words.

For discriminative training, we consider the model below:

$$w^*, b^* \approx \arg \max_{w,b} \langle \alpha, \Phi(u, b, w) \rangle \quad (4.2)$$

While  $\Phi(u, b, w)$  can represent some complex features such as word, letter, phoneme or letter-phoneme pair ngrams, we only use the ones listed below:

- $\Phi_0(u, b, w) = \log P(u|w) + \log P(b, w)$  the acoustic model score and pronunciations score under our our PMM-lexicon recognizer. We define the rest of the features as:

$$\Phi_{p,l}(u, b, w) = \begin{cases} 1 & \text{if } b = p \text{ and } w = l \\ 0 & \text{otherwise} \end{cases} \quad (4.3)$$

This reduces equation 4.2 to the following:

$$w^*, b^* \approx \arg \max_{w,b} \alpha_0(\log P(u|b) + \log P(b, w)) + \alpha_{b,w} \quad (4.4)$$

The rest of our model is described as follows:

- Our training examples are  $(u_i, w_i)$ . We use the same training set used in our MLE approach, except that now we consider an utterance and its transcription individually, i.e we do not group all utterances of the same word together.
- $GEN(u)$  is an  $n$ -best list or lattice of recognized word-pronunciation pairs  $(b, w)$ , we use our MLE PMM recognizer to generate  $GEN(u)$ .

We optimize the parameters  $\alpha$  as follows:

INPUT: Training examples  $(u_i, w_i)$

INITIALIZATION: Set  $\alpha = 0$

ALGORITHM:

**for**  $t = 1 \dots T, i = 1 \dots N$  **do**

$$(b^*, w^*) = \arg \max_{(b,w) \in GEN(u_i)} \Phi(u_i, b, w) \cdot \alpha$$

$$(b_{oracle}, w_i) = \arg \max_{\substack{(b,w) \in GEN(u_i) \\ w=w_i}} \Phi(u_i, b, w) \cdot \alpha$$

**if**  $w^* \neq w_i$  **then**

$$\alpha = \alpha + \Phi(u_i, b_{oracle}, w_i) - \Phi(u_i, b^*, w^*)$$

**end if**

**end for**

OUTPUT:  $\alpha$

Proof of convergence:

Let  $\overline{GEN}(u_i) = GEN(u_i) - \{(b, w) \mid w = w_i\}$ . In other words  $\overline{GEN}(u_i)$  is the set of incorrect candidates for an utterance  $u_i$ . We will say that a training sequence  $(u_i, w_i)$  for  $i = 1 \dots M$  is separable with margin  $\sigma > 0$  if there exists some vector  $\mathbf{U}$  with  $\|\mathbf{U}\| = 1$  such that

$$\forall i, \forall (p, l) \in \overline{GEN}(u_i), \forall b \text{ s.t. } (b, w_i) \in GEN(u_i) \quad \mathbf{U} \cdot \Phi(u_i, b, w_i) - \mathbf{U} \cdot \Phi(u_i, p, l) \geq \sigma \quad (4.5)$$

The proof is adapted from proofs for the tagging case in [12]. Let  $\alpha^k$  be the weights before the  $k$ 'th mistake is made. It follows that  $\alpha^1 = 0$ . Suppose the  $k$ 'th mistake is made at the  $i$ 'th example. Take  $(b^*, w^*)$  to be the output proposed at this example,  $(b^*, w^*) = \arg \max_{(b,w) \in GEN(u_i)} \Phi(u_i, b, w) \cdot \alpha^k$  and  $b_{oracle}$  to be the highest scoring correct pronunciation under this model,  $(b_{oracle}, w_i) = \arg \max_{\substack{(b,w) \in GEN(u_i) \\ w=w_i}} \Phi(u_i, b, w) \cdot \alpha^k$ . It follows from the algorithm updates that  $\alpha^{k+1} = \alpha^k + \Phi(u_i, b_{oracle}, w_i) - \Phi(u_i, b^*, w^*)$ . We take inner products of both sides with the vector  $\mathbf{U}$ :

$$\mathbf{U} \cdot \alpha^{k+1} = \mathbf{U} \cdot \alpha^k + \mathbf{U} \cdot \Phi(u_i, b_{oracle}, w_i) - \mathbf{U} \cdot \Phi(u_i, b^*, w^*) \geq \mathbf{U} \cdot \alpha^k + \sigma \quad (4.6)$$

where the inequality follows because of the property of  $\mathbf{U}$ . Because  $\alpha^1 = 0$ , and therefore  $\mathbf{U} \cdot \alpha^1 = 0$ , it follows by induction on  $k$  that for all  $k$ ,  $\mathbf{U} \cdot \alpha^{k+1} \geq k\sigma$ . Because  $\mathbf{U} \cdot \alpha^{k+1} \leq \|\mathbf{U}\| \|\alpha^{k+1}\|$ , it follows that  $\|\alpha^{k+1}\| \geq k\sigma$ .

We also derive an upper bound for  $\|\alpha^{k+1}\|^2$ :

$$\begin{aligned} \|\alpha^{k+1}\|^2 &= \|\alpha^k\|^2 + \|\Phi(u_i, b_{oracle}, w_i) - \Phi(u_i, b^*, w^*)\|^2 \\ &\quad + 2\alpha^k \cdot (\Phi(u_i, b_{oracle}, w_i) - \Phi(u_i, b^*, w^*)) \\ &\leq \|\alpha^k\|^2 + R^2 \end{aligned}$$

Where  $R$  is a constant such that

$$\forall i, \forall (p, l) \in \overline{GEN(u_i)}, \forall (b, w) \text{ s.t. } w = w_i \text{ and } (b, w) \in GEN(u_i), \quad \|\Phi(u_i, b, w) - \Phi(u_i, p, l)\| \leq R \quad (4.7)$$

Note that  $2\alpha^k \cdot (\Phi(u_i, b_{oracle}, w_i) - \Phi(u_i, b^*, w^*)) \leq 0$  because  $(b^*, w^*)$  is the highest scoring candidate for  $u_i$  under the parameters  $\alpha^k$ . It follows by induction that  $\|\alpha^{k+1}\|^2 \leq kR^2$ .

Combining the bounds  $\|\alpha^{k+1}\| \geq k\sigma$  and  $\|\alpha^{k+1}\| \leq kR$  give the results for all  $k$  that

$$k^2\sigma^2 \leq \|\alpha^{k+1}\|^2 \leq kR^2 \Rightarrow k \leq \frac{R^2}{\sigma^2} \quad (4.8)$$

## 4.2 Implementing the Algorithm as an FST

Our current implementation of the perceptron relies heavily on the FST toolkit [20].

We first build an FST  $T$  that expands a word to all possible word-pronunciations present in the PMM lexicon. Here a word-pronunciation is basically one entry that is a word concatenated with its pronunciation, i.e. `apple`  $\rightarrow$  `apple_ae_p_ax.l`. By inverting the FST,  $inv(T)$ , we now have an FST that can map word-pronunciations back to words.

$GEN(u)$  is represented as a lattice of word pronunciation pairs  $D_u$  generated by a recognizer that uses the PMM lexicon but is modified so as to hypothesize both a word and its pronunciation. We model the search space of this recognizer in a similar manner to that described in section 2.1:

$$N = C \circ P \circ L' \circ G_T \quad (4.9)$$

Where  $C$  is the context-dependent labels and  $P$  are the pronunciation rules. We modify the baseforms FST  $L'$  so that it can map a string of phones to a word-pronunciation where the pronunciation side matches the input string of phones. Each mapping is weighted by its PMM weight  $P(b|w)$ . We now have to modify the LM FST so that the LM score is still used while maintaining the hypothesized word-pronunciation. This is done by composing  $G$  with  $inv(T)$  and then projecting its input to its output. We call this FST  $G_T$ .

We can also represent our feature vector weights as an FST. We build an FST  $L$  that maps every word-pronunciation  $w_p$  to itself weighted by  $\alpha_{(w,p)}$ . We can now represent Equation 4.2 as:

$$w^*, b^* = \text{bestpath}(\alpha_0 L \circ D) \quad (4.10)$$

Where  $\text{bestpath}(\cdot)$  finds the highest scoring path in a lattice.

Our perceptron algorithm is now implemented as follows:

INPUT: Training examples  $(u_i, w_i)$

INITIALIZATION: Set all arcs weights in  $L$  to zero and  $\alpha_0 = 1$

ALGORITHM:

**for**  $t = 1 \dots T, i = 1 \dots N$  **do**

$(b^*, w^*) = \text{bestpath}(\alpha_0 L \circ D_{u_i})$

**if**  $w^* \neq w_i$  **then**

$(b_{oracle}, w_i) = \text{bestpath}(\alpha_0 L \circ D_{u_i} \circ F_{w_i})$

Update  $\alpha_0$  and  $L$  appropriately.

**end if**

**end for**

Where  $F_{w_i}$  is an FST that only accepts word-pronunciations such that the word side matches  $w_i$ .

iter.	Train	Test	Test-Avg
0	4.7	10.6	n/a
1	4.0	10.2	10.4
2	3.9	10.1	10.4
3	3.0	10.7	10.3
4	2.7	10.4	10.3
5	2.7	10.5	10.2
6	2.6	10.4	10.2
7	2.7	10.9	10.1
8	2.5	10.7	10.1
9	2.6	10.3	10.2
10	2.5	10.4	10.1

Table 4.1: Results for Discriminative training in WER on PhoneBook corpus.

### 4.3 Experimental Setup and Results

We ran the perceptron for multiple iterations on the training set. We report word error rates on the training set and test set. We also test on a refinement of the perceptron algorithm called the “average parameters” method. We define  $\alpha_s^{t,i}$  to be the value for the  $s$ ’th parameter after the  $i$ ’th training example has been processed in pass  $t$  over the training data. Using the “averaged parameters”  $\alpha_s = 1/nT \sum_{t=1..T, i=1..n} \alpha_s^{t,i}$  has been shown to perform significantly better than the final parameters  $\alpha_s^{T,n}$ . The results are shown in Table 4.1. Note here that iteration zero corresponds to using the same lexicon weights learned using the phoneme PMM discussed in section 3.2.3. As expected, WER on the training set goes down with every iteration since we are directly optimizing the feature weights on the training set. WER on the test set goes down until iteration 3 where we begin overfitting. Since the averaged parameters method corresponds to a smoothed out version of the learned parameters, we see a steady decline in WER. The best achievable score is 10.1%.

Using the above described discriminative model results in an improvement in WER. While these results are very promising, we leave further investigations into the approach for future work.

## 4.4 Summary

In this chapter, we introduced a novel mathematical framework for discriminatively training lexicon weights, along with convergence guarantees. We showed that more WER reductions could be achieved using this method. We leave further experiments using more complex features for future work.





# Chapter 5

## Pronunciation Mixture Model for Continuous Speech Recognition

In this chapter, we extend our approach to the more complex task of learning pronunciations from continuous speech and testing on continuous speech. This is a more attractive application than isolated-word speech since continuous data is more readily available.

To extend our isolated-word PMM requires additional considerations. We once again model the sequence of phonetic units as a hidden variable, however, the general ASR problem is now a search for the most likely string of words  $W^* = w_1^*, \dots, w_k^*$  given an utterance  $u$ :

$$W^* = \arg \max_W P(W|u) = \arg \max_W \sum_{B \in \mathcal{B}} P(W, B|u) \quad (5.1)$$

where now,  $B \in \mathcal{B}$  is a sequence of phonemes or phones that might span multiple words and include silence. Thus, for the continuous case, we consider silence to be a phonetic unit and denote it with a '-'. For example, a possible phoneme sequence  $B$  for an utterance with transcription “the boy ate the apple” could be “dh ax b oy - - ey td - dh ah ae p ax l”.

Equation 5.1 can be decomposed as follows:

$$W^* = \arg \max_W \sum_{B \in \mathcal{B}} P(W)P(B|W)P(u|W, B) \quad (5.2)$$

Where  $P(W)$  is the language model,  $P(B|W)$  can be computed using a stochastic lexicon

and  $P(u|W, B)$  can be approximated with the acoustic model  $P(u|B)$ . Note that the speech recognizer used in this thesis uses standard Viterbi approximations during decoding. This reduces Equation 5.2 to the following:

$$W^* = \arg \max_{W, B} P(W)P(B|W)P(u|B) \quad (5.3)$$

## 5.1 EM for Estimating Phoneme Pronunciations

We now extend the Pronunciation Mixture Model (PMM) framework developed for isolated word recognition in Chapter 3 to learn the appropriate weights that can model  $P(B|W)$  in continuous speech.

Our training data is comprised of  $M$  utterances and their transcriptions  $\{u_i, W_i\}$  where  $W_i = w_1^i, \dots, w_{k_i}^i$ . We parameterize the log-likelihood as follows:

$$\sum_{i=1}^M \log P(u_i, W_i | \theta) = \sum_{i=1}^M \log \sum_{B \in \mathcal{B}} \sum_{\psi \in \Psi(W_i, B)} P(u_i, W_i, B, \psi | \theta)$$

where  $\psi$  is an additional hidden variable defined to segment the phonetic sequence  $B$  into  $k$  baseforms while deleting the silences. Thus,  $\psi$  is drawn from possible segmentations  $\Psi(W_i, B)$  and can be indexed to retrieve a particular word-baseform pair. For example:

- $\psi_1(\text{dh ax b oy - - ey td - dh ah ae p ax l}) = \text{dh ax}$
- $\psi_2(\text{dh ax b oy - - ey td - dh ah ae p ax l}) = \text{b oy}$
- $\psi_3(\text{dh ax b oy - - ey td - dh ah ae p ax l}) = \text{ey td}$
- $\psi_4(\text{dh ax b oy - - ey td - dh ah ae p ax l}) = \text{dh ah}$
- $\psi_5(\text{dh ax b oy - - ey td - dh ah ae p ax l}) = \text{ae p ax l}$

We can now further decompose the term as follows:

$$P(u_i, W_i, B, \psi) = P(u_i|B)P(w_1^i, \dots, w_{k_i}^i, b_1, \dots, b_{k_i})$$

where  $b_i = \psi_i(B)$ . Our acoustic models are trained such that when  $\mathcal{B}$  is the *phoneme* alphabet, a pronunciation  $b_i$  is context independent and the equation above can be rewritten as:

$$P(u_i, W_i, B, \psi) = P(u_i|B) \prod_{j=1}^{k_i} \theta_{w_j^i, \psi_j(B)} \quad (5.4)$$

where  $\theta_{w_j^i, b_j} = P(w_j^i, b_j)$ . Our log-likelihood then becomes:

$$\sum_{i=1}^M \log P(u_i, W_i | \theta) = \sum_{i=1}^M \log \sum_{B \in \mathcal{B}} \sum_{\psi \in \Psi(W_i, B)} P(u_i | B) \prod_{j=1}^{k_i} \theta_{w_j^i, \psi_j(B)}$$

The parameters,  $\theta$ , are initialized to our graphoneme n-gram model scores and multiple iterations of the EM algorithm are run.

E-step:

$$\bar{M}_\theta[w, p] = \sum_{i=1}^M \sum_{B \in \mathcal{B}} \sum_{\psi \in \Psi(W_i, B)} P(B, \psi | u_i, W_i, \theta) M[p, w, W_i, B, \psi]$$

M-step:

$$\theta_{w,p}^* = \frac{\bar{M}_\theta[w, p]}{\sum_{w', p' \in V \times \mathcal{B}} \bar{M}_\theta[w', p']}$$

where  $M[p, w, W_i, B, \psi]$  is the number of times word  $w$  appears in  $W_i$  aligned with the pronunciation  $p$ .

$$M[p, w, W_i, B, \psi] = |\{j : \psi_j(B) = p \text{ and } w_j^i = w\}| \quad (5.5)$$

The weights learned are directly used in a stochastic lexicon for decoding continuous speech. The term  $P(B|W)$  in Equation 5.2 can be computed as:

$$P(B|W) = \sum_{\psi \in \Psi(W_i, B)} \prod_{j=1}^k \frac{\theta_{w_j, \psi_j(B)}}{\sum_{p \in \mathcal{B}} \theta_{w_j, p}} \quad (5.6)$$

### 5.1.1 EM for Estimating Phone Pronunciations

The phonetic rules our recognizer applies between the phoneme-based lexicon and the context-dependent acoustic models create context dependencies across words at the *phone* level. A misguided attempt to apply the PMM directly to learning phone pronunciations would ignore the independence assumption made in Equation 5.4, which is no longer valid. In this section, we explore a model that assigns a probability to a word-pronunciation pair given the last phoneme of the previous word’s pronunciation:

$$\begin{aligned} P(w_1, b_1, \dots, w_n, b_n) &= \prod_{i=1}^n P(w_i, b_i | w_1, b_1, \dots, w_{i-1}, b_{i-1}) \\ &\approx \prod_{i=1}^n P(w_i, b_i | b_{i-1}) \\ &\approx \prod_{i=1}^n P(w_i, b_i | LAST(b_{i-1})) \end{aligned}$$

Where  $LAST(b)$  is the last phone in the phone sequence  $b$ . Here we make several independence assumptions, the first is similar to the Markov assumption made in n-gram language modeling, the second references the fact that only the ending of the previous word’s pronunciation can affect the current word’s pronunciation. Our new features  $\theta_{w,b|p} = P(w, b|p)$ , where  $b \in \mathcal{B}$  and  $p$  is a single phone, can now be used in equation 5.4 as follows:

$$P(u_i, W_i, B, \psi) = P(u_i | B) \prod_{j=1}^{|W_i|} \theta_{\psi_j(B), w_j^i | LAST(\psi_{j-1}(b))} \quad (5.7)$$

## 5.2 Implementation Details

Here we discuss some of the issues faced when implementing the continuous speech PPM for phoneme pronunciations. The framework is split into two steps: we first build a constrained-graphoneme recognizer and run it on each training utterance to generate an  $n$ -best list of graphoneme hypotheses for the entire utterance. After creating an  $n$ -best list of graphoneme hypothesis for each utterance, we iterate through the entire list computing expected counts for every word and its pronunciation (E-step) and then normalizing the expected counts into

a probability distributions (M-step).

We first build a graphoneme recognizer for continuous speech. The search space is modelled by the following FST:

$$GR = C \circ P \circ GP^* \tag{5.8}$$

Where  $C$  maps phones to context-dependent model labels and  $P$  are the pronunciation rules. Here  $GP^*$  is our graphoneme  $n$ -gram that has been expanded to allow the recognition of multiple words. This is done by taking the graphoneme  $n$ -gram used for the isolated-word PMM, concatenating it with an FST that emits a  $\#$  symbol and then performing closure on this new FST. The  $\#$  symbol is used as a word boundary. One problem with this approach was that the  $GP^*$  FST was too big to build. To overcome this problem, we pruned out all the paths in the graphoneme  $n$ -gram that do not appear in the top 700 pronunciations for any word in our training set. This significantly reduced the size of  $GP^*$  so that the recognizer search space could be efficiently built.

We then distributively process each utterance and its word-transcription in the training set. We first expand the word transcription into all graphoneme sequences whose letter side match the letters of the transcription and encode those paths as an FST  $L$ . This FST is then composed with the  $GR$  FST in Equation 5.8 to constrain the search space of the graphoneme recognizer. We call this recognizer the constrained-graphoneme recognizer. Recognition is performed on the utterance in question and an  $n$ -best list of 5000 hypotheses is stored on disk. Figure 5-1 shows an example  $n$ -best list for the utterance: “houston texas”. The three scores at the beginning of each line represent the total score, the acoustic model score and the graphoneme  $n$ -gram score respectively. The total score is the log-domain joint probability  $P(u_i, W_i, B, \psi)$  used in Equation 5.4, the AM score is  $P(u_i|B)$  and the graphoneme  $n$ -gram score is  $\prod_j P(w_j, b_j)$ .

After generating an  $n$ -best list for each utterance in our training data, we can proceed with the E-step of the first EM iteration. We keep a double hash table for every word and pronunciation that maps to the expected counts of seeing that word aligned with that specific pronunciation. For every  $n$ -best list, we first normalize the total scores to sum to one by

59.0655 83.9573 -24.8918 **h/hh o/ /y u/uw s/s t/t o/ax n/n # t/t e/eh x/kd /s a/ax s/s**  
55.4080 83.1458 -27.7378 **h/hh o/ /y u/uw s/s t/t o/ax n/n # t/t e/ey x/kd /s a/ax s/s**  
54.4675 83.9573 -29.4899 **h/hh o/ /y u/uw s/s t/t- o/ax n/n # t/t e/eh x/kd /s a/ax s/s**  
50.8100 83.1458 -32.3359 **h/hh o/ /y u/uw s/s t/t- o/ax n/n # t/t e/ey x/kd /s a/ax s/s**  
49.5057 78.9219 -29.4162 **h/hh o/ /y u/uw s/s t/t o/ax n/n # t/t e/eh x/kd /s a/ax s/z**  
47.5087 83.4593 -35.9506 **h/hh o/ /y u/uw s/s t/t o/ax n/m # t/t e/eh x/kd /s a/ax s/s**  
47.2153 83.9573 -36.7420 **h/hh o/ /y u/uw s/s t/t o/ax n/n # t/tf e/eh x/kd /s a/ax s/s**  
47.0608 78.0224 -30.9616 **h/hh o/ u/uw s/s t/t o/ax n/n # t/t e/eh x/kd /s a/ax s/s**  
46.9454 83.9573 -37.0119 **h/hh o/ /y u/uw s/s t/tq o/ n/en # t/t e/eh x/kd /s a/ax s/s**  
46.8134 77.7686 -30.9552 **h/ /y o/ u/uw s/s t/t- o/ax n/n # t/t e/eh x/kd /s a/ax s/s**

Figure 5-1: Constrained Graphoneme Recognizer  $n$ -best hypothesis for “houston texas” along with total, AM and LM score.

computing  $P(B, \psi | u_i, W_i) = \frac{P(u_i, W_i, B, \psi)}{\sum_{P, \psi'} P(u_i, W_i, P, \psi')}$ . We then iterate through the  $n$ -best list and increment the double hashtable for every aligned word-pronunciation with its normalized total score. After computing all the expected counts across all the generated  $n$ -best lists, we normalize the counts according to the M-step equation. We now have a joint-probability distribution for word-pronunciations i.e.  $P(w, b) = \theta_{w,b}$ .

To compute the remaining EM iterations, we again iterate through all the  $n$ -best lists to compute:

$$P(B, \psi, u_i, W_i) = P(B|u_i)P(B, \psi, W) = P(B|u_i) \prod_j \theta_{w_j, b_j} \quad (5.9)$$

Where  $P(B|u_i)$  is the AM score extracted from the  $n$ -best list and  $\theta_{w_j, b_j}$  are the parameters computed during the previous EM iterations.

After computing this joint probability for every hypothesis, we again normalize these probabilities to sum to one and compute expected counts for all the aligned word-pronunciations in the  $n$ -best lists in a similar manner to what was described before. Finally, we once again compute the updated features  $\theta$  using the M-step equation.

## 5.3 Experimental Setup

Experiments using the SUMMIT landmark-based speech recognizer [15] were conducted in two domains: a weather query corpus [13] and an academic lecture corpus [31].

### 5.3.1 Experimental Procedure

To evaluate the performance of our PMM model we used the following procedure for both the weather and lecture domains. We begin by cleaning the acoustic model training set by removing utterances with non-speech artifacts to generate a training set for PMM pronunciations. We then prepare two recognizers, the first based on manually created pronunciations of all the words in the training set and the second a learned PMM recognizer that contains all the pronunciations generated by our PMM model. We then compare the Word Error Rate (WER) of both recognizers on a common test set. Thus, both recognizers use precisely the same vocabulary, but the pronunciations are chosen or weighted either by human or machine. Although the expert-lexicon leaves pronunciations unweighted, it does include a number of entries with multiple pronunciations. To keep the number of PMM pronunciations included in the search space to a reasonable size we use a 0.005 threshold to prune out low probability pronunciations.

The weather query corpus is comprised of relatively short utterances, with an average of 6 words per utterance. After pruning the original training and test sets of all utterances containing non-speech artifacts, we ended up with a 87,600 utterance training set with an 1,805 word vocabulary and a 3,497 utterance test set. The acoustic models used with this corpus were trained on a large data set of telephone speech of which this corpus is a subset.

The lecture corpus contains audio recordings and manual transcriptions for approximately 300 hours of MIT lectures from eight different courses and nearly 100 MITWorld seminars given on a variety of topics [31]. The lecture corpus is a difficult data set for ASR systems because it contains many disfluencies, poorly organized or ungrammatical sentences, and lecture specific keywords [8]. Compared to the weather corpus the sentences are much longer, with about 20 words per utterance on average.

As in the weather domain, we discard utterances that contain non-speech artifacts from

the training set used to train the acoustic model and end up with a 50K utterance training set. We then cleaned the remaining utterances to create a 6,822 utterance test set. We report results on training pronunciations and decoding with back-off maximum likelihood trained Acoustic Models [8]. We leave the use of discriminatively trained models for future work. The back-off maximum likelihood model uses a set of broad phonetic classes to divide the classification problem originating from context-dependent modeling into a set of subproblems. The reported results differ from those in [8] because we use a 25K word vocabulary of all the words in our training set. The original paper uses a 35K word vocabulary with some words absent from the training set.

### **Graphone/Graphoneme Training**

A 150,000 word dictionary of manually generated phoneme pronunciations was used to train the graphoneme  $n$ -gram parameters according to the procedures described in [36].

To train our graphone model, one might be tempted to simply expand the phoneme-based lexicon according to the pronunciation rules learned in Section 2.1. Unfortunately, given the manner in which our acoustic models were trained, the beginnings and endings of pronunciations are context-dependent at the phone level. Thus, we must expand all the sentences in our weather and lecture training corpora first to their phoneme pronunciations using the manually crafted dictionary and then to their phone variations using the pronunciation rules. These phone pronunciations were properly generated since the pronunciation rules had access to the context of a word in a sentence.

### **5.3.2 Experimental Results**

The results for learning pronunciations can be seen in Figure 5.1. A baseline using a lexicon generated directly from graphonemes is shown to be significantly worse than both experts and the PMM. More interestingly, phoneme PMM pronunciations achieve more than a 1.2% WER reduction on the weather test set and a 0.4% WER reductions on the lectures test set over the hand-crafted lexicon. Both results were deemed statistically significant ( $p < 0.001$ ) using the Matched Pair Sentence Segment Word Error test. These results were achieved by running the EM algorithm until convergence which took around 8 iterations. It is important to note that



	Weather	Lectures
Graphoneme L2S	11.2	47.6
Expert	9.5	36.7
Phoneme PMM	8.3	36.3
Phone PMM	8.3	36.1
Context PMM	8.3	37.7

Table 5.1: Results in WER on both the Weather and Lecture corpora using the PMM, the expert dictionary and the Graphoneme model (%)

we are learning these pronunciations without human supervision and hence this technique can be reliably used to predict pronunciations for out-of-vocabulary words from continuous speech. We also show improvement over a baseline of expert crafted pronunciations by training on the same data used for training our acoustic models. This suggests that not only are we learning better-than-expert pronunciations, we are also allowing more information to be extracted from the training set that can complement the acoustic models. This smaller size vocabulary of the weather domain could explain the higher gains achieved: since the PMM includes multiple pronunciations per word, this might make them more confusable a fact that is more apparent in the 25k vocabulary Lecture domain. Another disadvantage of the PMM approach when applied to the Lecture domain is due to the longer sentences present in that corpus. The sheer size of some of the sentences caused the constrained graphoneme recognition step to fail. This happened to about 2k utterances of our 50k utterance training set because no complete path could be found through the FST lattice.

We also test on learning phone pronunciations in a similar context-independent setup as that of phonemes (Section 5.1). The results are referenced as “Phone PMM” in Table 5.1. One advantage of learning phone pronunciations in a context-independent setup is that we are no longer using the pronunciation rules that might be over-expanding the search space. This fact is made apparent in Table 5.2 where we see an increase in the number of pronunciations per word but a smaller search space.

A second reason to favor removal of phonological rules from the recognizer is simply that, when the lexicon is trained appropriately, they appear to be an unnecessary complication. It is also interesting to note that Phone PMM training is faster and requires only 4 EM iterations to achieve convergence. The disadvantage of the direct expansion approach we

Weather Lexicon	Avg # Prons	# States	# Arcs	Size
Expert	1.2	32K	152K	3.5 MB
Phoneme PMM	3.15	51K	350K	7.5 MB
Phone PMM	4.0	47K	231K	5.2 MB
Context PMM	63	253K	936K	22 MB
Lecture Lexicon	Avg. # Prons	# States	# Arcs	Size
Expert	1.2	226K	1.6M	36 MB
Phoneme PMM	1.8	501K	7.6M	154 MB
Phone PMM	2.3	243K	1.2M	28 MB
Context PMM	8.9	565K	2.7M	61MB

Table 5.2: Lexicon statistics for the weather and lecture domains.

have described so far is that phone pronunciations are context-dependent with respect to the underlying acoustic models, a fact that is not represented in the learned lexicon.

We tried to model these cross-word dependencies by using the context-dependent model described in section 5.1.1. Whereas the move from graphonemes to graphones reduces the complexity of our recognizer, incorporating context dependent models grows the search space, as seen in Table 5.2. From the results in Table 5.1, however, it is clear that they are an unnecessary complication, and even hurt performance in the lectures domain. The degradation is likely due to a problem of context sparsity, which is caused by a greater mismatch between training and test in the lecture corpus.

## 5.4 Analysis of Learned Baseforms

We first attempt to measure how much of the expert lexicon the PMM was able to recover. For the 1.8k words in the Weather Corpus vocabulary, the expert lexicon contained 2252 pronunciations (since the expert lexicon allowed multiple pronunciations for some words) of these, 2002 or 88.9% were present in the PMM lexicon with a threshold of 0.005 (all pronunciations with weights less than 0.005 were not included in the PMM lexicon). The average rank of the pronunciations that were found in the PMM lexicon was 1.2 and the average weight was 0.73 . Given that most of the expert pronunciations were included in the PMM with a relatively high weight, we believe that little gain can be achieved by combining the expert lexicon and the PMM lexicon.

Confusion Pairs	# of Occurrences
AX ==> IY	22
AX ==> IH	19
AA ==> AE	16
R ==> ER	15
ER ==> R	14
AA ==> AX	10
IY ==> Y	9
AX ==> EH	9
UW ==> AX	9
AX ==> AA	8

Table 5.3: Top 10 confusion pairs for Weather Domain lexicon

Deleted Phonemes	# of Occurrences
AX	15
AO	13
TD	4
R	3
AA	3

Table 5.4: Top 5 Deleted Phonemes for Weather Corpus lexicon

Similarly to Chapter 3, we again try to quantify some of the differences between the expert and learned baseforms. We run NIST align software to tabulate differences between the reference expert baseform, and the top choice hypothesis of the PMM model for the Weather Corpus lexicon (A list of learned pronunciations is listed in Appendix A). Of the 1805 baseform pairs, 81.5% were identical, while the remainder mostly contained a single substitution. We found the alignment results to be similar to the ones conducted on the isolated-word PMM lexicon. Again, most of the substitutions involved vowels, typically a schwa.

Table 5.3 shows the top 10 most confused phoneme pairs, while Table 5.4 and Table 5.5 show the most deleted and inserted phonemes. About 3.4% and 3.1% of the data contained an additional insertion or deletion, respectively, more than three times the amount observed for the isolated-word case. We found that the increase in deletions could be explained by the fact that during continuous speech speakers are more likely to skip phonemes. Table 5.6 shows some examples where the PMM learned pronunciations with plausible deletions.

Inserted Phonemes	# of Occurrences
AX	13
Y	7
HH	7
IY	6
AO	5

Table 5.5: Top 5 Inserted Phonemes for Weather Corpus lexicon

Word	Dictionary Baseform	Top PMM Baseform
already	ao <b>L</b> r eh df iy	aa r eh df iy
antarctica	ae nt aa r <b>KD</b> t ax k ax	ae nt aa r tf ax k ax
asked	ae s <b>KD</b> t	ae s td
barbara	b aa r b <b>AX</b> r ah	b aa r b r ax
bratislava	b r <b>AA</b> tf ax s l aa v ax	b r tf ax z l aa v ax
clothes	k l ow <b>DH</b> z	k l ow z

Table 5.6: Example phoneme deletions between expert dictionary and top PMM hypothesis for Weather Corpus.

When taking a closer look at the data to explain the increase in insertions, we found that out of the 62 insertions in our PMM lexicon about 16 were either at the beginning or at the end of the pronunciation. Upon closer examination, we found that most of these insertions were happening to words with a low number of occurrence in the training data and were erroneous. We believe that these mistakes are due to words absorbing the pronunciations of other surrounding words. For example, the word “missed” only appeared 3 times in the training set. Of the 3 occurrences, 2 were preceded by the word “I”. In this case, the PMM gave a high probability to the pronunciation “ax m ih s td” i.e. the pronunciation of “I” concatenated with the pronunciation of “missed”. Table 5.7 contains examples of some reasonable insertions, as well as, many erroneous insertions. We also compare the number of times these examples appear in the training set.

### 5.4.1 Non-Native Speaker Pronunciation

In this section, we use the PMM to try to analyze pronunciation differences between native and non-native speakers. We train two PMM lexicons, one on 3k utterances of lectures given by an Indian accented English speaker and the other on 30k utterances of lectures given by

Word	Dictionary Baseform	Top PMM Baseform	# of Occurrences
iran	ax r aa n	<b>AY</b> ax r ae n	16
wow	w aw	w <b>AY</b> aw	19
deep	d iy pd	d iy p <b>AX L</b>	2
guadaloupe	g w aa df ax l uw pd	g w aa df ax l uw <b>P EY</b>	2
towards	t ao r dd z	t ao r dd <b>S IY</b>	1
missed	m ih s td	<b>AX</b> m ih s td	3
rotterdam	r aa tf er d ae m	<b>AX</b> r aa tf er d ae m	1
snowbase	s n ow b ey s	<b>EH</b> s n ow b ey s	1
sea	s iy	<b>S IY</b> s iy	2

Table 5.7: Example of phoneme insertions between expert dictionary and top PMM hypothesis for Weather Corpus.

Confusion Pairs	# of Occurrences
IH ==> AX	8
AE ==> AA	5
S ==> Z	4
AE ==> EH	3
P ==> PD	3

Table 5.8: Top 5 phoneme confusion pairs for Indian accented non-native talker

a Dutch accented English speaker. Note that this data was not part of our original Lecture corpus training set.

We again run NIST alignment on the top pronunciations learned from both speakers with the top pronunciations learned from the entire Lecture corpus. To make sure that the pronunciations learned from the lectures were correctly estimated, we restricted our analysis to words that had at least 5 examples in the training set. For Indian accented speech, we found that out of the 400 words we compared, about 87% of the pronunciations were the same while 12.3% contained substitutions. Only a small fraction of the differences were due to insertions or deletions. Table 5.8 lists the top 5 confusion pairs, mainly vowel substitutions, while Table 5.9 lists 4 word pronunciations that illustrates differences between the native and non-native speaker baseforms. As for Dutch accented speech, we found that out of the 2.5k words we compared, 88.8% of the pronunciations were similar and that most of the changes were again due to substitutions. Table 5.10 lists the top 5 confusion pairs, while Table 5.11 lists some examples.

Word	Native Speaker Pronunciation	Non-Native Speaker Pronunciations
dependent	d <b>AX</b> p <b>EH</b> <b>N</b> <b>D</b> ax n td	d <b>IY</b> p <b>AX</b> <b>DF</b> ax n td
therefore	dh eh r f ao r	dh eh r <b>AX</b> f ao r
vary	v <b>AE</b> r iy	v <b>EH</b> r iy
various	v <b>AE</b> r iy ax s	v <b>EH</b> r iy ax s
only	<b>OW</b> n l iy	<b>AO</b> n l iy
simple	s <b>IH</b> m p ax l	s <b>AX</b> m p ax l
within	w <b>IH</b> dh <b>IH</b> n	w <b>AX</b> dh <b>AX</b> n

Table 5.9: Example of differences between native and Indian accented non-native speaker pronunciations.

Confusion Pairs	# of Occurrences
AX ==> IY	8
AX ==> IH	5
DD ==> TD	4
Z ==> S	3
AA ==> OW	3

Table 5.10: Top 5 phoneme confusion pairs for Dutch accented non-native talker

Word	Native Speaker Pronunciation	Non-Native Speaker Pronunciations
fluid	f l uw <b>AX</b> <b>DD</b>	f l uw <b>IH</b> <b>TD</b>
estimate	eh s t ax m <b>AX</b> td	eh st ax m <b>EY</b> td
reverse	r <b>AX</b> v er s	r <b>IY</b> v er s
pops	p <b>AA</b> pd s	p <b>OW</b> pd s

Table 5.11: Example of differences between native and Dutch accented non-native speaker pronunciations.

## 5.4.2 Slow vs. Fast Speech

We now try to quantify the differences of word pronunciations during fast and slow speech. We conducted the following experiment: We ranked every training utterance in our Lecture corpus training set by its average word duration i.e we divided the total duration of the utterance by the number of words in its reference transcription to compute the average word duration. We then split the training corpus into two parts:

- The “fast speech” training set contained the 25% of the data with the shortest word duration.
- The “slow speech” training set contained the 25% of the data with the longest word duration.

We discarded the remainder of the training data.

After running the PMM on both training sets, we then used the NIST alignment software on the learned baseforms provided they had appeared at least 4 times in both training set. We ended up with a lexicon of 1783 words.

Only about 32% of the baseforms were the same in both the “fast speech” and “slow speech” lexicon. 46% had substitutions, 21% of the baseforms in the “fast speech” lexicon had deletions and 14% had insertions. On average, fast pronunciations contained 5.2 phonemes while slow pronunciations contained 5.4 phonemes. Table 5.12, Table 5.13 and Table 5.14 list some of the top confusion pairs, insertions and deletions. We also tabulate some the example differences in Table 5.15.

## 5.4.3 Word Confusion in Weather Domain and Lecture Domain Lexicon

Since our PMM defines a conditional distribution over words and pronunciations  $P(b|w)$ , by assuming that all words are equally likely i.e.  $P(w) = 1/|V|$  where  $V$  is our vocabulary, we can compute the conditional entropy  $H(b|w)$  and  $H(w|b)$ .

- $H(b|w)$  is a measure of disorder when trying to predict a pronunciation given a word. Hence, it is related to how many pronunciations are allowed per word and how uniform

Confusion Pairs	# of Occurrences
S ==> Z	46
IY ==> AX	38
IH ==> AX	35
R ==> ER	35
AX ==> EH	35
AX ==> IH	33
Z ==> S	26
EH ==> AX	26
ER ==> R	25
IY ==> IH	20

Table 5.12: Top 10 phoneme confusion pairs between “fast” speech and “slow” speech

Inserted Phonemes	# of Occurrences
AX	51
TD	40
DD	20
EH	15
N	14

Table 5.13: Top 5 inserted phonemes in “fast” speech pronunciations

Deleted Phonemes	# of Occurrences
AX	130
IY	33
L	33
TD	27
S	27

Table 5.14: Top 5 deleted phonemes in “fast” speech pronunciations

Word	“Slow” Pronunciation	“Fast” Pronunciation
leadership	l iy df er sh <b>IH PD</b>	l iy df er sh <b>AX</b>
obviously	aa bd v iy ax <b>S</b> l iy	aa bd v iy <b>S</b> ax l iy
learned	l <b>EH R</b> n dd	l <b>ER</b> n dd
thousand	th <b>OW Y AX</b> z ax n dd	th <b>AW</b> z ax n dd

Table 5.15: Examples of pronunciation differences between fast and slow speech pronunciations.



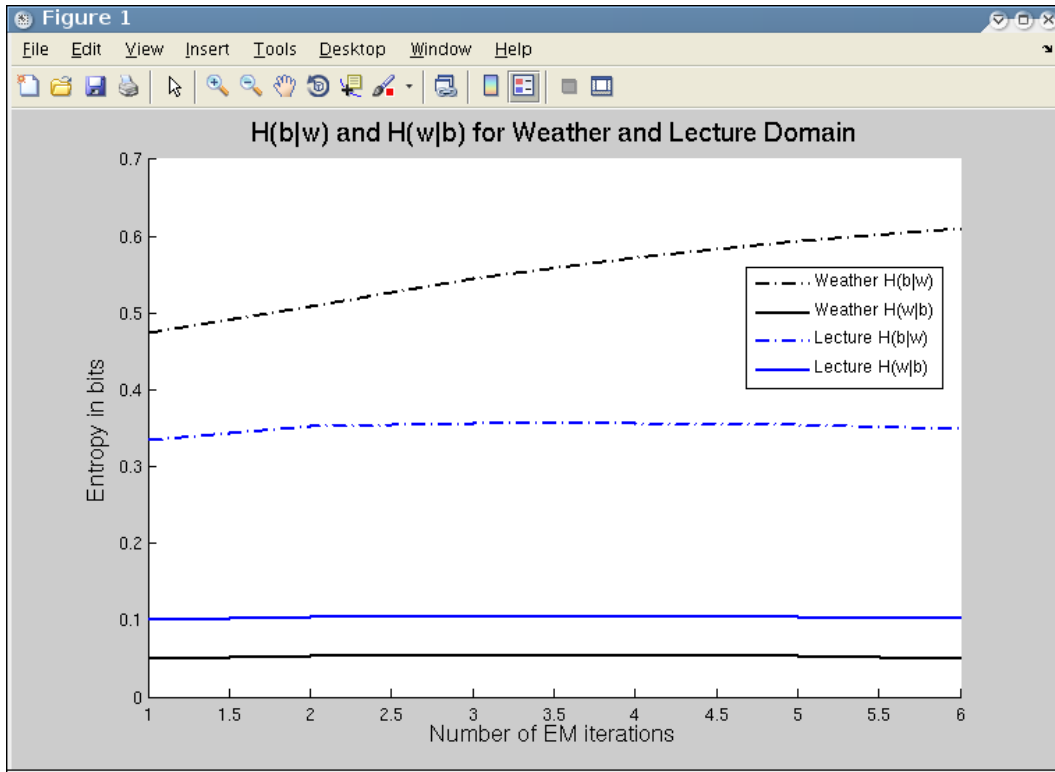


Figure 5-2: Plot of  $H(w|b)$  and  $H(b|w)$  as a function of EM iterations for both the Weather and Lecture domain.

their distribution is.

- $H(w|b)$  is a measure of disorder when trying to predict a word given a pronunciation. This is a measure of how confusable words are when using a stochastic lexicon. In our lexicons we allow different words to map to the same pronunciation, hence  $H(w|b)$  allows us to measure the uncertainty of being able to map back from a pronunciation to the word that generated it.

Figure 5-2 plots  $H(w|b)$  and  $H(b|w)$  as a function of EM iterations for both the Weather lexicon and the Lecture lexicon. As can be seen, while the Weather domain lexicon has a higher  $H(b|w)$  that seems to be increasing with EM iterations, it has a much lower  $H(w|b)$  than the Lecture domain. This confirms our initial concerns that the Lecture domain lexicon allowed for more confusion between words due to its large vocabulary size.

## 5.5 Acoustic Model and Lexicon Co-Training

One of the research activities currently undertaken by the Spoken Language Systems (SLS) research group is utilizing crowd-sourcing for data collection. In this section, we describe applying our PMM model to the E-book (electronic book) corpus. This corpus was collected using Amazon Mechanical Turk (AMT) and contains a large variety of words, including many that have never been used in SLS’s prior speech applications. We first describe the data collection process and then discuss some of the experiments performed on this corpus.

### 5.5.1 Real-World Data

The E-book corpus contains a list of 10K book titles, containing 30K individual words and about 9.5K unique words. The speech data was collected using the WAMI toolkit infrastructure [16] on Amazon Mechanical Turk (AMT). 10 utterances from 10 different speakers were collected for each book title resulting in a total of 100K utterances.

As a final step, the data was then split up into a training set, development set and test set. For each of the 10K titles, 7 utterances from different speakers were kept for training, 1 utterance was used in the development set and the last 2 were held out for testing.

### 5.5.2 Baseline Approach

In this part, we describe the usual procedure to build a speech recognizer for the E-book corpus. As a first attempt, we used our generic Acoustic Models (genericAM) trained on telephone speech, the expert dictionary (expertLexicon) to provide pronunciations for the 9.5K vocabulary, as well as, a Language Model  $n$ -gram trained on the training data. This approach has two limitations: the generic Acoustic Models used do not match the E-book data because they have been trained on a different domain. The other limitation is due to the pronunciation dictionary: about 16% of the 9.5K vocabulary is out-of-vocabulary (OOV), hence the expert dictionary does not contain a pronunciation for those words. To better evaluate the performance of this recognizer, we split our test set into a 17K-utterance in-vocabulary test set (IV-test) where none of the words are OOV and a 3K-utterance OOV test set (OOV-test) where each utterance has at least one OOV word in its reference. Running

the now 8K-vocabulary generic-AM recognizer on the test set we end up with a fairly poor WER of 24.7% on the IV-test and 98.1% on the OOV-test.

In order to improve our baseline performance, we attempt to retrain our AMs using the E-book training set. Retraining AMs requires a training set of utterances and phone-transcribed references. To generate the phone-transcriptions from the original word-transcription, we use a forced-alignment recognizer using our expert dictionary and our generic models. Again since about 16% of the words are OOV, we fail to generate forced-alignments for about 15K of our training utterances. Using these new phone alignments, we can now retrain our Acoustic Models (referred to as expertAM). A significant WER reduction can now be achieved: 11.1% on the IV-test and 90.0% on the OOV-test. The WER on the OOV test set remains high since each utterance has at least one word that is not in the ASR system’s vocabulary.

### 5.5.3 PMM Approach

In this section, we combine our PMM pronunciation acquisition framework with AM training and show improvements over the baseline approach. Using our generic AM, we first run the PMM for two EM iterations on our training set to generate pronunciations for the 9.5K words in our vocabulary. We refer to this lexicon as pmm1em2. We then use this new lexicon and the generic AM to run phone forced-alignment on the training set and retrain new acoustic models (referred to as pmm1em2AM). As a final step we again run the PMM for several iterations using the new retrained AM.

We report our results in Table 5.16. Each row reports on WER for both the in-vocabulary and OOV test set using different AM models and different lexicons. Here pmm1em2AM are the acoustic models trained by running phone forced-alignment using the genericAM and the learned PMM lexicon from EM iteration 2. pmm2em3 is the lexicon learned by running the PMM until EM iteration 3 using the pmm1em2AM Acoustic Models. As can be seen, using this PMM and Acoustic Model Retraining framework can achieve a significant reduction in WER on both the OOV and the IV test sets.

	IV-test	OOV-test
genericAM + expertLexicon	24.7	98.1
<b>expertAM + expertLexicon</b>	<b>11.1</b>	<b>90.0</b>
genericAM + pmm1em1	25.6	26.6
genericAM + pmm1em2	24.1	24.6
genericAM + pmm1em3	23.5	24.6
genericAM + pmm1em4	23.5	24.6
genericAM + pmm1em5	23.3	24.9
genericAM + pmm1em6	23.1	24.9
genericAM + pmm1em7	23.0	25.0
pmm1em2AM + pmm1em2	10.6	14.6
pmm1em2AM + pmm2em1	10.6	13.6
pmm1em2AM + pmm2em2	10.4	13.8
<b>pmm1em2AM + pmm2em3</b>	<b>10.3</b>	<b>14.0</b>
pmm1em2AM + pmm2em4	10.4	14.2

Table 5.16: WER in percentage for E-book domain by iteratively training the acoustic models and the lexicon. A gradual reduction in WER can be observed.

	IV-test	OOV-test
<b>pmm1em2AM + pmm2em3</b>	<b>10.3</b>	<b>14.0</b>
pmm1em4AM + pmm1em4	10.8	14.6
pmm1em3AM + pmm2em1	11.0	13.6
pmm1em3AM + pmm2em2	10.7	13.9
pmm1em3AM + pmm2em3	10.7	14.0

Table 5.17: WER in percentage for E-book domain using pmm1em3. An increase in WER is observed possibly due to overfitting

## Overfitting Concerns

One important issue to address when considering PMM-AM co-training is overfitting. To illustrate this point, we also tried using pmm1em4 to retrain the AMs and observed degradation in performance. The results can be seen in Table 5.17. These initial results indicate that further research into this approach is needed.

## 5.6 Summary

In this Chapter, we generalized our PMM approach to training and testing on continuous speech. We tested and showed WER improvements on both a weather query corpus and

an academic Lecture corpus. After quantifying some of the differences between baseforms learned from continuous speech and expert pronunciations, we used our PMM approach to analyze baseforms learned from fast versus slow speech, as well as, non-native speakers. As a final experiment, we introduced the notion of iteratively co-training the acoustic model and the lexicon using the PMM. After testing on a corpus of book titles collected from AMT, we showed that further improvements can be achieved through this method.



# Chapter 6

## Summary and Future Work

This work has introduced and compared several approaches to generating pronunciations by combining grapheme techniques with acoustic examples. Furthermore, we have shown that even in the presence of significant noise, a pronunciation mixture model can reliably generate improved baseform pronunciations over those generated by experts given both isolated-word and continuous speech. Regardless, we believe that wrapping the lexicon into a statistical framework is a constructive step, which presents exciting new avenues of exploration. We have also shown that the PMM can be trained on the same data as the AM and LM, and hence requires no additional training data to build. These properties make pronunciation training a cheap and effective additional step to building an ASR system. We hope that this thesis, encourages the training of a matched lexicon when training AMs.

Since our findings seem to extend to multiple corpora, the possibility of learning better-than-expert baseforms in arbitrary domains opens up many possibilities for future work. For example, when faced with an out-of-vocabulary word with a known spelling, any system could programmatically post a task to AMT and collect example utterances to generate a high quality entry in the lexicon.

There are two clear directions in which we hope to further this work. The first is to explore acoustic model and lexicon co-training in an iterative fashion, effectively taking a maximum-likelihood step along a set of coordinates in the probability space represented by the recognizer. The second is to move beyond maximum-likelihood, and explore discriminative approaches to pronunciation learning on continuous speech. While we have only talked about

discriminatively training lexicon weights for isolated-word, we hope to generalize this work for continuous speech by developing a framework for simultaneously discriminatively training LM weights, lexicon weights, as well as, word boundary and phone  $n$ -gram weights.

Long term, the ultimate goal of this research might be to infer a phoneme set and learn pronunciations from orthographically transcribed data only. If it were feasible to simultaneously train the lexicon and the acoustic model, large vocabulary speech recognizers could be built for many different languages with little to no expert input, if given enough orthographically transcribed data.



# Appendix A

## Weather Domain Lexicon

The table below lists the 1.8K words present in the Weather Query corpus vocabulary, along with their top PMM pronunciations, associated mixture weights and expert baseforms. We underline the words whose top PMM pronunciation does not match its expert counterpart.

Word	PMM Baseforms	Weight	Expert Baseform	Word	PMM Baseforms	Weight	Expert Baseform
<oh>	ow	1	ow	<uh>	ah_fp	1	ah_fp
<um>	ah_fp m	1	ah_fp m	a	ax	0.64	( ax   ey )
<u>aalten</u>	aa l t iy n	0.58	aa l tq en		ey	0.34	
	ao l tq en	0.27		<u>ababa</u>	ax b ae b aa	0.20	( aa   ae ) b ( aa   ax )
	ao l tf ax n	0.10			aa b ax b aa	0.19	b ( aa   ax )
aberdeen	ae b er d iy n	0.99	ae b er d iy n		ae b ae b ax	0.18	
abilene	ae b ax l iy n	0.97	ae b ax l iy n		ae b ax b ax	0.16	
about	ax b aw td	0.99	ax b aw td		ax b aa b ax	0.15	
abu	aa b uw	0.98	aa b uw	<u>abidjan</u>	ae b iy jh aa n	0.90	aa b iy ( jh   zh ) aa n
<u>accent</u>	ae kd s ax n td	0.99	ae kd s eh n td	able	ey b ax l	0.86	ey b ax l
accumulated	ax k y uw m y ax l ey	0.98	ax k y uw m y ax l ey		y ax b ax l	0.12	
	tf ax dd		tf ax dd				

Word	PMM Baseforms	Weight	Expert Baseform	Word	PMM Baseforms	Weight	Expert Baseform
<b>accumulations</b>	ax k y uw m y ax l ey	0.89	ax k y uw m y ax l ey	above	ax b ah v	0.99	ax b ah v
	sh ax n s		sh ax n z	<b>acapulco</b>	aa k ax p ax l k ow	0.31	( aa   ae ) k ax p ( ow   uh l ) k ow
	ax k y uw m y ax l ey	0.10			aa k ax p ow k ow	0.29	
activity	sh ax n z				ae k ax p ax l k ow	0.11	
<b>addis</b>	ae kd t ih v ax tf iy	0.99	ae kd t ih v ax tf iy		ow k ax p ow k ow	0.11	
	aa df iy s	0.37	( aa   ae ) df ax s	accumulate	ax k y uw m y ax l ey	0.99	ax k y uw m y ax l ey
	aa df ax s	0.20			td		td
	ae df ax s	0.16		accumulation	ax k y uw m y ax l ey	0.94	ax k y uw m y ax l ey
	ae d iy z	0.13			sh ax n		sh ax n
	ae df iy z	0.09		<b>active</b>	ae kd t iy v	0.52	ae kd t ax v
address	ae dr r eh s	0.99	( ae   ax ) dr r eh s		ae kd t ax v	0.39	
advisories	ae dd v ay z ax r iy z	0.93	ae dd v ay z ax r iy z	actually	ae kd ch uw l iy	0.47	ae kd ch ( uw ax l   uw l   ax l ) iy
	ae f g ae n ax s t ae n	0.85	ae f g ae n ax s t ae n		ae kd ch ax l iy	0.36	
afghanistan	ae f t er	0.97	ae f t er		ae kd ch uw ax l iy	0.13	
after	ax g eh n	0.95	ax g eh n	additional	ax d ih sh ax n ax l	0.99	ax d ih sh ax n ax l
again	ax hh eh dd	0.74	ax hh eh dd	adelaide	ae df ax l ey dd	0.35	ae df ax l ey dd
ahead	eh dd	0.23			ae df ax l ay dd	0.15	
	eh r	0.99	eh r		ae dd l ey dd	0.15	
air	eh r l ay n	0.99	eh r l ay n		ae dd l ay dd	0.15	
airline	eh r p l ey n	0.92	eh r p l ey n	advisory	ae dd v ay z ax r iy	0.87	ae dd v ay z ax r iy
airplane	ae kd r ax n	0.98	ae kd r ax n	africa	ae f r ax k ax	0.98	ae f r ax k ax
akron	ae l ax m ow s	0.65	ae l ax m ow ( z   s )	afternoon	ae f t er n uw n	0.97	ae f t er n uw n
alamos	aa l ax m ow s	0.17		ago	ax g ow	0.97	ax g ow
	ae l b ey n iy y ax	0.47	ae l b ey n iy ax	ainsworth	ey n z w er th	0.99	ey n z w er th
	ae l b ey n iy ax	0.39		aires	eh r iy z	0.25	( eh   ae ) r ( iy   eh ) z
	aa l b ey n y ax	0.09			ae r iy z	0.14	
alberta	ae l b er tf ax	0.99	ae l b er tf ax		ay r iy z	0.11	
alert	ax l er td	0.99	ax l er td	airlines	eh r l ay n z	0.99	eh r l ay n z
alexandria	ae l ax gd z ae n dr r iy	0.81	ae l ax ( gd z   kd s ) ae n dr r iy ax	airport	eh r p ao r td	0.99	eh r p ao r td
	ax						
	ae l ax kd s ae n dr r iy	0.10		alabama	ae l ax b ae m ax	0.89	ae l ax b ae m ax
	ax						
<b>algiers</b>	ae l jh y ih r z	0.37	ae l jh ih r z		ae l ax b ae m aa	0.09	
	ae l jh y er z	0.30		alaska	ax l ae s k ax	0.92	ax l ae s k ax
	aa l jh y er z	0.19		albany	ao l b ax n iy	0.94	ao l b ax n iy
all	ao l	0.92	ao l	albuquerque	ae l b ax k er k iy	0.93	ae l b ax k er k iy
along	ax l ao ng	0.98	ax l ao ng	alerts	ax l er td s	0.73	ax l er td s
<b>already</b>	aa r eh df iy	0.98	aa l r eh df iy		r ax l er td s	0.17	
also	ao l s ow	0.73	ao l s ow	algeria	ae l jh ih r iy ax	0.78	ae l jh ih r iy ax
	ao l s ax	0.15			ae l z jh ih r iy ax	0.10	
altoona	ae l t uw n ax	0.91	ae l t uw n ax		ao l jh ax r iy ax	0.10	
<b>altus</b>	ae l tf ax s	0.35	ao l tf ax s	algonquin	ae l g aa ng k w ax n	0.90	( ae   ax ) l g ( aa   ah ) ng k w ax n
	aa l td	0.33			ax l g aa ng k w ax n	0.09	
	ae l t uh z	0.18		allentown	ae l ax n t aw n	0.99	ae l ax n t aw n
amarillo	ae m ax r ih l ow	0.82	ae m ax r ih l ow	alot	ax l aa td	0.85	ax l aa td
american	ax m eh r ax k ax n	0.99	ax m eh r ( ax   ih ) k ax n		l aa td	0.11	
				alright	ao l r ay td	0.74	ao l r ay td
amman	ax m aa n	0.80	ax m aa n		ax l r ay td	0.11	
	ae m aa n	0.11		<b>alto</b>	aa l tf ow	0.87	( ae   aa ) l t ow
amsterdam	ae m s t- er d ae m	0.83	ae m s t- er d ae m	<b>altos</b>	aa l tf ow z s	0.49	( ae   aa ) l t ow z
anaheim	ae n ax hh ay m	0.99	ae n ax hh ay m		ae l tf ow z	0.39	
anchorage	ae ng k r ax jh	0.88	ae ng k ( er   r ) ax jh	am	ae m	0.82	ae m
anderson	ae n d er s ax n	0.51	ae n d er s ax n		m	0.13	
	ih n d er s ax n	0.48		america	ax m eh r ax k ax	0.99	ax m eh r ( ax   ih ) k ax
<b>angola</b>	ae ng g ow ax l aa	0.52	ae ng g ow l ax				
	ae ng g ow l ao	0.46		amherst	ae m hh er s td	0.65	ae m ( hh er   er ) s td
ann	ae n	0.99	ae n		ae m er s td	0.29	
anniston	ae n ax s t ax n	0.90	ae n ax s t ax n	amount	ax m aw n td	0.92	ax m aw n td
another	ax n ah dh er	0.99	ax n ah dh er	an	ax n	0.85	( ax   ae ) n
antarctica	ae nt aa r tf ax k ax	0.60	ae nt aa r ( tf   kd t ) ax k ax		ae n	0.12	
	ae nt aa r kd t ax k ax	0.38		analog	ae n ax l aa gd	0.84	ae n ax l aa gd

Word	PMM Baseforms	Weight	Expert Baseform	Word	PMM Baseforms	Weight	Expert Baseform
antonio	ae n t ow n iy ow	0.78	ae n t ow n iy ow	and	ae n ax l ao gd	0.15	
	ax n t ow n iy ow	0.19			ae n dd	0.61	( ax   ae ) n dd
anything	eh n iy th ih ng	0.92	eh n iy th ih ng		ax n dd	0.18	
anywhere	eh n iy w eh r	0.99	eh n iy w eh r	angeles	ae n	0.10	
appreciate	ax p r iy sh iy ey td	0.45	ax p r iy sh iy ey td		ae n jh ax l ax s	0.97	ae n jh ax l ax s
	p r iy sh iy ey td	0.34		ankara	ae ng k ax r ax	0.45	ae ng k ax r ax
	ax p r ax sh iy ey td	0.20			aa ng k ax r ow	0.18	
april	ey pd r ax l	0.98	ey pd r ax l		aa n k aa r ax	0.12	
arabia	ax r ey b iy ax	0.99	ax r ey b iy ax		ae n k ae r ax	0.11	
arctic	aa r kd t ax kd	0.76	aa r ( tf   kd t ) ax kd		ae ng kd y ax r ax	0.09	
	aa r tf ax kd	0.10		annapolis	ax n ae p ax l ax s	0.97	ax n ae p ax l ax s
	aa r tf ih kd	0.10		annual	ae n y uw ax l	0.60	ae n ( y uh l   y uw ax l )
area	eh r iy ax	0.99	eh r iy ax		ae n y uh l	0.13	
argentina	aa r jh ax n t iy n ax	0.97	aa r jh ax n t iy n ax		ae n y uw w ax l	0.09	
arkansas	aa r k ax n s ao	0.74	aa r k ax n s ao		ae n y ax l	0.09	
	aa r k ax n s ax	0.13		answer	ae n s er	0.71	ae n s er
	aa r k ax n s aa	0.09		antigua	ae n t iy gd w ax	0.77	ae n t iy gd w ax
around	ax r aw n dd	0.96	ax r aw n dd		ae nt iy g ax	0.15	
arthur	aa r th er	0.99	aa r th er	any	eh n iy	0.97	eh n iy
as	ax z	0.75	( ax   ae ) z	anytime	eh n iy t ay m	0.86	eh n iy t ay m
	ae z	0.22		appleton	ae p ax l tf ax n	0.75	ae p ax l tf ax n
asia	ey zh ax	0.92	ey zh ax		ae pd l tf ax n	0.13	
<u>asked</u>	ae s td	0.73	ae s kd td	approximate	ax p r aa kd s ax m ax td	0.99	ax p r aa kd s ax m ( ey   ax ) td
	ae s kd td	0.19		arab	ae r ax bd	0.99	ae r ax bd
aspen	ae s p ax n	0.97	ae s p ax n	arbor	aa r b er	0.99	aa r b er
<u>astoria</u>	ax s t ao r iy ax	0.55	ae s t ao r iy ax	are	aa r	0.97	aa r
	ax s t- ao r iy ax	0.44		areas	eh r iy ax z	0.86	eh r iy ax z
at	ae td	0.95	ae td	arizona	ae r ax z ow n ax	0.98	ae r ax z ow n ax
atlanta	ae td l ae nt ax	0.79	( ax   ae ) td l ae nt ax	arlington	aa r l ih ng t ax n	0.99	aa r l ih ng t ax n
	ax td l ae nt ax	0.20		arrowhead	ae r ow hh eh dd	0.90	ae r ow hh eh dd
au	ow	0.79	ow   ao	aruba	ax r uw b ax	0.93	ax r uw b ax
august	ao g ax s td	0.62	ao g ( ah   ax ) s td	asheville	ae sh v ih l	0.92	ae sh v ih l
	ao g ah s td	0.17		ask	ae s kd	0.96	ae s kd
	aa g ax s td	0.15		asking	ae s k ih ng	0.97	ae s k ih ng
austin	ao s t ax n	0.83	ao s t ax n	assistance	ax s ih s t ax n s	0.96	ax s ih s t ax n s
	aa s t ax n	0.10		asuncion	ax s ah n s iy ow n	0.27	ax s ah n s iy ow n
austria	ao s tr r iy ax	0.79	ao s tr r iy ax		ax s ah n ch ow n	0.23	
	aa s tr r iy ax	0.20			ae s ax n zh ax n	0.23	
average	ae v r ax jh	0.90	ae v r ax ( jh   zh )		ax s ah n sh ax n	0.22	
<u>aware</u>	w eh r	0.68	ax w eh r	athens	ae th ax n z	0.93	ae th ax n z
	ax w eh r	0.31		atlantic	ae td l ae nt ax kd	0.49	( ax   ae ) td l ae nt ax kd
back	b ae kd	0.99	b ae kd		ax td l ae nt ax kd	0.47	
baghdad	b ae gd d ae dd	0.92	b ae gd d ae dd	auckland	ao kd l ax n dd	0.44	ao kd l ax n dd
bahrain	b aa r ey n	0.74	b aa r ey n		aa kd l ax n dd	0.41	
	b aa hh ax r ey n	0.16		augusta	ax g ah s t ax	0.73	( ao   ax ) g ah s t ax
bakersfield	b ey k er z f iy l dd	0.88	b ey k er z f iy l dd		aa g ah s t ax	0.14	
baltimore	b ao l tf ax m ao r	0.98	b ao l tf ax m ao r	australia	ao s tr r ey l y ax	0.78	ao s tr r ey l y ax
bangkok	b ae ng k aa kd	0.94	b ae ng k aa kd	available	ax v ey l ax b ax l	0.65	ax v ey l ax b ax l
bangor	b ae ng g ao r	0.75	b ae ng g ( ao r   er )		ax v ey l b ax l	0.34	
	b ae ng g er	0.12		aviv	ax v iy v	0.95	ax v iy v
barbados	b aa r b ey d ow s	0.83	b aa r b ey d ow s	b	b iy	0.99	b iy
	b aa r b iy df ow z	0.10		bad	b ae dd	0.99	b ae dd
barcelona	b aa r s ax l ow n ax	0.93	b aa r s ax l ow n ax	<u>bahamas</u>	b ax hh aa m ax s	0.72	b ax hh aa m ax z
baseball	b ey s b ao l	0.62	b ey s b ao l		b ax hh aa m ax z	0.26	
	b ey z ax kd b ao l	0.21		baja	b aa hh aa	0.99	b aa hh aa
	m b ey s b ao l	0.12		bali	b aa l iy	0.98	b aa l iy

Word	PMM Baseforms	Weight	Expert Baseform	Word	PMM Baseforms	Weight	Expert Baseform
baton	b ae tq en	0.92	( b ae tq en   b ax t aa n )	<u>bangalore</u>	b ae ng g ax l ao r	0.75	b aa ng g ax l ao r
be	b iy	0.99	b iy		b ay ih ng g ax l ao r	0.23	
beaumont	b ow m aa n td	0.81	b ow m aa n td	bangladesh	b ae ng g l ax d eh sh	0.79	b ae ng g l ax d eh sh
	b aw m ah td	0.11		bar	b aa r	0.99	b aa r
bedford	b eh dd f er dd	0.99	b eh dd f er dd	barbara	b aa r b r ax	0.56	b aa r b ( er   ax r   r ) ( ah   ax )
before	b iy f ao r	0.79	b ( ax   iy ) f ao r		b aa r b ax r ax	0.38	
	b ax f ao r	0.20		barometric	b ae r ax m eh tr r ax kd	0.97	b ae r ax m eh tr r ax kd
beginning	b ax g ih n ih ng	0.99	b ax g ih n ih ng	basel	b aa z ax l	0.58	b ( aa   ae ) z ax l
<u>beirut</u>	b ey r uw td	0.44	b eh r uw td		b ey z ax l	0.11	
	b ey uw td	0.27		bay	b ey	0.96	b ey
	b eh r uw td	0.17		beach	b iy ch	0.97	b iy ch
belfast	b eh l f ae s td	0.70	b eh l f ae s td	<u>become</u>	b ax k ax m	0.97	b ( ax   iy ) k ah m
	b eh l f ae s	0.14		been	b ih n	0.96	b ih n
	b eh l f r ax s td	0.13		begin	b ax g ih n	0.99	b ax g ih n
<u>belgrade</u>	b eh l gd r ey dd	0.49	b eh l g r ( aa   ey ) dd	beijing	b ey zh ih ng	0.57	b ey ( zh   jh ) ih ng
	b eh l g r ey dd	0.29			b ey jh ih ng	0.39	
bellevue	b eh l v y uw	0.97	b eh l v y uw	belarus	b eh l ax r uw s	0.75	b ( eh l   ey l ) ax r uw s
belmont	b eh l m aa n td	0.98	b eh l m aa n td		b iy eh l ax r uw s	0.23	
bend	b eh n dd	0.93	b eh n dd	belgium	b eh l jh ax m	0.93	b eh l jh ax m
berlin	b er l ih n	0.63	b er l ih n	<u>belize</u>	b ax l iy z	0.79	b eh l iy z
	b er l ae n	0.19			b eh l iy z	0.10	
	b er l ax n	0.09		bellingham	bd l iy z	0.09	
bern	b er n	0.96	b er n		b eh l ih ng hh ae m	0.77	b eh l ih ng ( hh ae   hh ax   ax ) m
besides	b ax s ay dd z	0.67	b ( ax   iy ) s ay dd z		b eh l ih ng hh ax m	0.18	
	b iy s ay dd z	0.30		below	b ax l ow	0.87	b ax l ow
bethesda	b ax th eh z d ax	0.49	b ax th eh z d ax	berkeley	b er kd l iy	0.95	b er kd l iy
	b ax t ax z d ax	0.26		bermuda	b er m y uw df ax	0.87	b er m y uw df ax
	b ax s th eh z d ax	0.22		bernardino	b er n ax d iy n ow	0.84	b er n ( aa r   er   ax ) d iy n ow
between	b ax t w iy n	0.95	b ax t w iy n	best	b eh s td	0.99	b eh s td
billings	b ih l ih ng z	0.99	b ih l ih ng z	better	b eh tf er	0.98	b eh tf er
birmingham	b er m ih ng hh ae m	0.92	b er m ih ng ( hh ae   hh ax   ax ) m	big	b ih gd	0.44	b ih gd
blah	b l aa	0.98	b l aa		b ey gd	0.17	
bloomington	b l uw m ih ng t ax n	0.95	b l uw m ih ng t ax n		b ax gd	0.10	
boca	b ow k ax	0.99	b ow k ax	binghamton	b ih ng hh ax m t ax n	0.50	b ih ng ( hh ax   ax ) m t ax n
boise	b oy s iy	0.69	b oy ( z   s ) iy		b ih ng ax m t ax n	0.44	
	b oy z iy	0.24		bismarck	b ih z m aa r kd	0.99	b ih z m aa r kd
bombay	b aa m b ey	0.94	b aa m b ey	blizzard	b l ih z er dd	0.99	b l ih z er dd
bordeaux	b ao r d ow	0.88	b ao r d ow	bluff	b l ah f	0.43	b l ah f
bosnia	b aa z n iy ax	0.40	b aa z n iy ax		b l ax f	0.31	
	b aa z n iy y ax	0.36			b l ao f	0.11	
	b aa z n y ax	0.13		bogota	b ow g ax t aa	0.50	b ow g ax t aa
both	b ow th	0.82	b ow th		b ow gd ax t aa	0.21	
	ow th	0.16			b ow g ax tf aa	0.12	
bowling	b ow l ih ng	0.97	b ow l ih ng	bolivia	b ax l ih v iy ax	0.62	b ( ow l   ax l ) ih v iy ax
bozeman	b ow z m ax n	0.99	b ow z m ax n		b ow l ih v iy ax	0.24	
brasil	b r ax z ih l y ax	0.33	b r ax z ih l ( y ax   iy ax )	bonn	b aa n	0.99	b aa n
	b r ax z ax l iy ax	0.25		borneo	b ao r n iy ow	0.99	b ao r n iy ow
	b r ax z ih l iy ax	0.20		boston	b ao s t ax n	0.71	b ( aa   ao ) s t ax n
	b r ax s iy l iy ax	0.19			b aa s t ax n	0.27	
brazil	b r ax z ih l	0.98	b r ax z ih l	boulder	b ow l df er	0.98	b ow l df er
breezy	b r iy z iy	0.98	b r iy z iy	boy	b oy	0.74	b oy
bring	b r ih ng	0.99	b r ih ng		b oy s ax td s	0.11	
<u>bristol</u>	b r ax s t- ax l	0.50	b r ih s t ax l		b oy sh ax n s	0.09	
	b r ih s t ax l	0.32		bradford	b r ae dd f er dd	0.96	b r ae dd f er dd
british	b r ih tf ax sh	0.82	b r ih tf ax sh	<u>bratislava</u>	b r tf ax z l aa v ax	0.68	b r ( aa   ae ) tf ax ( s   z ) l aa v ax
	b r ax tf ax sh	0.13			b r aa tf ax z l aa v	0.29	

Word	PMM Baseforms	Weight	Expert Baseform	Word	PMM Baseforms	Weight	Expert Baseform
brooklyn	b r uh kd l ax n	0.99	b r uh kd l ax n	breckenridge	b r eh k ax n r ih jh	0.97	b r eh k ax n r ih jh
brunswick	b r ah n z w ih kd	0.71	b r ah n z w ( ax   ih ) kd	bridgeport	b r ih jh p ao r td	0.97	b r ih jh p ao r td
	b r ah n z w ax kd	0.28		<b>brisbane</b>	b r ax z b ax n	0.44	b r ih z b ( ax   ey ) n
bucharest	b uw k ax r eh s td	0.92	b uw k ax r eh s td		b r ih z b ey n	0.37	
<b>buenos</b>	b w eh n ax s	0.59	b w ey n ( ax   ow ) s		b r ih z b ax n	0.09	
	b w ey n ow s	0.19		britain	b r ih tq en	0.99	b r ih tq en
	b w ey n ax s	0.11		brookline	b r uh kd l ay n	0.52	b r uh kd l ay n
bulgaria	b ax l g eh r iy ax	0.99	b ax l g eh r iy ax		b uh kd l ay n	0.16	
burlington	b er l ih ng t ax n	0.96	b er l ih ng t ax n		bd r uh kd l ay n	0.11	
but	b ah td	0.81	b ah td		b r ax k l ay n	0.09	
	b ax td	0.10		brownsville	b r aw n z v ih l	0.87	b r aw n z v ih l
buzzards	b ah z er dd z	0.51	b ah z er dd z	brussels	b r ah s ax l z	0.90	b r ah s ax l z
	b ao z er dd z	0.48		budapest	b uw df ax p eh s td	0.93	b uw df ax p eh s td
bye	b ay	0.98	b ay	buffalo	b ah f ax l ow	0.96	b ah f ax l ow
cairo	k ay r ow	0.90	k ay r ow	burbank	b er b ae ng kd	0.99	b er b ae ng kd
caledonia	k ae l ax d ow n iy ax	0.71	k ae l ax d ow n iy ax	<b>burma</b>	b er m aa	0.53	b er m ax
	k ae l ax d ow n y ax	0.28			b er m ah	0.33	
cali	k aa l iy	0.78	k aa l iy		b ao r m aa	0.13	
	k ae l iy	0.21		butte	b y uw td	0.99	b y uw td
call	k ao l	0.99	k ao l	by	b ay	0.86	b ay
calling	k ao l ih ng	0.97	k ao l ih ng	c	s iy	0.98	s iy
<b>cambridge</b>	k ey m bd r ih jh	0.65	k ey m b r ih jh	calcutta	k ae l k ah tf ax	0.53	k ae l k ah tf ax
	k ey m b r ih jh	0.27			k ae l k aa tf ax	0.38	
can	k ae n	0.64	k ( ae   ax ) n	calgary	k ae l g ax r iy	0.73	k ae l g ax r iy
	k ax n	0.34			k ae l gd r iy	0.16	
canberra	k ae n b eh r ax	0.89	k ae n b ( eh r   er ) ax	california	k ae l ax f ao r n y ax	0.99	k ae l ax f ao r n y ax
cannes	k aa n	0.59	k ( ae n   ae n z   aa n )	called	k ao l dd	0.90	k ao l dd
	k ae n z	0.19			k aa l dd	0.09	
	k aa n z	0.13		cambodia	k ae m b ow df iy ax	0.99	k ae m b ow df iy ax
canyon	k ae n y ax n	0.85	k ae n y ax n	camden	k ae m d ax n	0.99	k ae m d ax n
	k ey n y ax n	0.10		canada	k ae n ax df ax	0.99	k ae n ax df ax
capital	k ae p ax tf ax l	0.99	k ae p ax tf ax l	cancun	k ae n k uw n	0.66	k ae n k uw n
caracas	k ax r aa k ax s	0.75	k ax r aa k ax s		k ae n k ow n	0.30	
	k ae r ae k ax s	0.11		canton	k ae n tq en	0.92	k ae n tq en
caribbean	k ax r ih b iy ax n	0.55	k ( ae r ax   ax r ih ) b iy ax n	cape	k ey pd	0.99	k ey pd
	k ae r ax b iy ax n	0.19		car	k aa r	0.99	k aa r
	k ae r ax b iy ae n	0.13		care	k eh r	0.83	k eh r
	k ax r ih b iy ae n	0.10			k y eh r	0.16	
carlo	k aa r l ow	0.99	k aa r l ow	caribou	k ae r ax b uw	0.96	k ae r ax b uw
carolina	k ae r ax l ay n ax	0.99	k ae r ax l ay n ax	carmel	k aa r m eh l	0.53	k aa r m ( ax l   eh l )
casablanca	k ae s ax b l ae ng k ax	0.27	k ae s ax b l ae ng k ax		k aa r m ax l	0.46	
	k ae s ax b l aa n k ax	0.19		carson	k aa r s ax n	0.99	k aa r s ax n
	k ae s ax b l aa n k ae	0.19		casper	k ae s p er	0.99	k ae s p er
	k aa s ax bd l aa ng k	0.12		<b>cayenne</b>	k ay ae n tf ax dd	0.99	k ay ( ae   eh ) n
	ax						
	k ae s ax bd l ae ng k	0.11		cedar	s iy df er	0.86	s iy df er
	ax						
<b>causes</b>	k aa z ax z	0.90	k ao z ax z		s iy df er uw	0.10	
	k ay z ax z	0.09		center	s eh nt er	0.99	s eh nt er
cayman	k ey m ax n	0.81	k ey m ax n	<b>centigrades</b>	s eh n t iy gd r ey dd z	0.39	s eh nt ax g r ey dd z
	k ey m eh n	0.11			s eh nt ax g r ey dd z	0.34	
celsius	s eh l s iy ax s	0.98	s eh l s iy ax s		s eh n t iy g r ey dd z	0.11	
centigrade	s eh nt ax g r ey dd	0.99	s eh nt ax g r ey dd		s eh nt iy g r ey dd z	0.09	
central	s eh n tr r ax l	0.86	s eh n tr r ax l	champaign	sh ae m p ey n	0.96	sh ae m p ey n
chance	ch ae n s	0.98	ch ae n s	chances	ch ae n s ax z	0.99	ch ae n s ax z
change	ch ey n jh	0.99	ch ey n jh	chapel	ch ae p ax l	0.98	ch ae p ax l
<b>charleston</b>	ch aa r l s t- ax n	0.65	ch aa r l ( s   z ) t ax n	charlotte	sh aa r l ax td	0.99	sh aa r l ax td
	ch aa r l s t ax n	0.32		<b>charlottetown</b>	sh er l ax t aw n	0.54	sh aa r l ax t aw n

Word	PMM Baseforms	Weight	Expert Baseform	Word	PMM Baseforms	Weight	Expert Baseform
charlottesville	sh aa r l ax td s v ih l	0.93	sh aa r l ax td s v ih l	chattanooga	sh ae r l ax t aw n	0.42	
chatham	ch ae tf ax m	0.86	ch ae tf ax m	checking	ch ae tf ax n uw g ax	0.99	ch ae tf ax n uw g ax
check	k ae tf ax m	0.09		<u>chi</u>	ch eh k ih ng	0.95	ch eh k ih ng
<u>cheyenne</u>	ch eh kd	0.97	ch eh kd		ch iy	0.46	k ay
	sh ay ae n	0.42	sh ay eh n	chile	ch ay	0.36	
	s ay eh n	0.14			ch ih l iy	0.56	ch ( iy l ey   ih l ey   ih l iy )
chicago	sh ax k aa g ow	0.99	sh ax k aa g ow		ch ih l ey	0.24	
chill	ch ih l	0.97	ch ih l		ch iy l ey	0.13	
chinese	ch ay n iy z	0.72	ch ay n iy z	china	ch ay n ax	0.96	ch ay n ax
	ch ay n iy z y ax tf ax v	0.17		<u>christchurch</u>	k r ay s td ch er ch	0.94	k r ay s ch er ch
christi	k r ih s t iy	0.99	k r ih s t iy	christmas	k r ih s m ax s	0.95	k r ih s m ax s
church	ch er ch	0.99	ch er ch	<u>cincinnati</u>	s ax n s ax n ae tf iy	0.84	s ih n s ax n ae tf iy
cities	s ih tf iy z	0.99	s ih tf iy z		s ih n s ax n ae tf iy	0.10	
claire	k l eh r	0.99	k l eh r	city	s ih tf iy	0.99	s ih tf iy
clear	k l ih r	0.94	k l ih r	clara	k l ae r ax	0.93	k l ae r ax
cleveland	k l iy v l ax n dd	0.99	k l iy v l ax n dd	clearwater	k l ih r w aa tf er	0.58	k l ih r w ( aa   ao   uh ) tf er
					k l ih r w ao tf er	0.16	
closest	k l ow s ax s td	0.99	k l ow s ax s td	climate	k l ay m ax td	0.99	k l ay m ax td
cloud	k l aw dd	0.84	k l aw dd	clothes	k l ow z	0.99	k l ow ( dh z   z )
cloudy	k l aw df iy	0.89	k l aw df iy	clouds	k l aw dd z	0.83	k l aw dd z
coastal	k ow s t ax l	0.99	k ow s t ax l	coast	k ow s td	0.95	k ow s td
cocoa	k ow k ow	0.99	k ow k ow	coat	k ow td	0.99	k ow td
cold	k ow l dd	0.98	k ow l dd	cod	k aa dd	0.92	k aa dd
coldest	k ow l df ax s td	0.97	k ow l df ax s td	colder	k ow l df er	0.99	k ow l df er
college	k aa l ax jh	0.99	k aa l ax jh	collection	k ax l eh kd sh ax n	0.99	k ax l eh kd sh ax n
cologne	k ax l ow n	0.90	k ax l ow n	collins	k aa l ax n z	0.89	k aa l ax n z
colombo	k ax l ah m b ow	0.99	k ax l ah m b ow		k ao l ax n z	0.09	
colorado	k aa l ax r aa df ow	0.66	k aa l ax r ( ae   aa ) df ow	colombia	k ax l ah m b iy ax	0.72	k ax l ah m b iy ax
					k ax l ah m bd iy ax	0.14	
columbus	k aa l ax r ae df ow	0.32	k ax l ah m b ax s	color	k ax l ah m bd y ax	0.09	
coming	k ax l ah m b ax s	0.92	k ah m ih ng		k ah l er	0.31	k ah l er
computer	k ah m ih ng	0.98	k ah m ih ng		k ah l er z	0.20	
condition	k ax m p y uw tf er	0.95	k ax m p y uw tf er		k aa l er	0.16	
condition	k ax n d ih sh ax n	0.86	k ax n d ih sh ax n		k ax l er	0.12	
congo	k aa ng g ow	0.83	k aa ng g ow	columbia	k aa l r td	0.10	
	k ao ng g ow	0.16			k ax l ah m b iy ax	0.93	k ax l ah m b iy ax
connecticut	k ax n eh tf ax k ax td	0.98	k ax n eh tf ax k ax td	come	k ah m	0.87	k ah m
copenhagen	k ow p ax n hh ey g ax n	0.92	k ow p ax n hh ey g ax n		k ax m	0.12	
cost	k ao s td	0.99	k ao s td	complete	k ax m p l iy td	0.99	k ax m p l iy td
could	k uh dd	0.98	k ( uh   ax ) dd	concord	k aa ng k er dd	0.79	k aa ng k ( er   ao r ) dd
countries	k ah n tr r iy z	0.99	k ah n tr r iy z		k aa ng k ao r dd	0.16	
county	k aw nt iy	0.94	k aw nt iy	conditions	k ax n d ih sh ax n z	0.99	k ax n d ih sh ax n z
course	k ao r s	0.94	k ao r s	connect	k ax n eh kd td	0.99	k ax n eh kd td
cozumel	k aa z ax m eh l	0.43	k ( aa   ow ) z ax m eh l	<u>cool</u>	k ax l	0.56	k uw l
					k uw ax l	0.17	
	k ow z ax m eh l	0.42	( k r iy kd   k r ih kd )		k uw l	0.09	
creek	k aa z ax m ax l	0.13	k r ow ey sh ax	corpus	k ao r p ax s	0.94	k ao r p ax s
croatia	k r iy kd	0.99		costa	k ow s t ax	0.96	k ow s t ax
	k r ow ey sh ax	0.73		count	k aw n td	0.97	k aw n td
	k r ax w ey sh ax	0.21	k r ao s	country	k ah n tr r iy	0.99	k ah n tr r iy
<u>crosse</u>	k r aa s	0.56		couple	k ah p ax l	0.99	k ah p ax l
	k r ao s	0.27		coverage	k ah v r ax jh	0.99	k ah v ( er   r ) ax jh
	k ao s	0.16		created	k r iy ey tf ax dd	0.89	k r iy ey tf ax dd
cruz	k r uw z	0.98	k r uw z	crete	k r iy td	0.97	k r iy td
cupertino	k uw p er t iy n ow	0.95	k uw p er t iy n ow	croix	k r oy	0.98	k r oy
currently	k er ax n td l iy	0.97	k er ax n td l iy	<u>cruces</u>	k r uw s ax z	0.38	k r uw s iy z
cypus	s ay pd r ax s	0.99	s ay pd r ax s				
d	d iy	0.99	d iy				
<u>dakar</u>	d ax k aa r	0.73	d aa k aa r				

Word	PMM Baseforms	Weight	Expert Baseform	Word	PMM Baseforms	Weight	Expert Baseform
dallas	d ae k ao r	0.15			k r uw s ih z	0.19	
	d ae l ax s	0.99	d ae l ax s		k r uw s ax s	0.17	
danbury	d ae n b eh r iy	0.49	d ae n b eh r iy	cuba	k y uw b ax	0.97	k y uw b ax
	d ae m b er iy	0.31		current	k er ax n td	0.96	k er ax n td
	d ae n b er iy	0.15		<u>cyclones</u>	s ay kd l aa n z	0.81	s ay k l ow n z
<u>darwin</u>	d aa r w eh n	0.89	d aa r w ax n		s ay k l aa n z	0.18	
	d aa r w ax n	0.10		czech	ch eh kd	0.97	ch eh kd
database	d ey tf ax b ey s	0.99	d ( ey   ae ) tf ax b ey s	daily	d ey l iy	0.99	d ey l iy
davenport	d ae v ax n p ao r td	0.99	d ae v ax n p ao r td	dakota	d ax k ow tf ax	0.94	d ax k ow tf ax
day	d ey	0.96	d ey	damascus	d ax m ae s k ax s	0.99	d ax m ae s k ax s
days	d ey z	0.96	d ey z	danville	d ae n v ih l	0.99	d ae n v ih l
dayton	d ey tq en	0.99	d ey tq en	data	d ey tf ax	0.74	d ( ey   ae ) tf ax
de	d iy	0.47	d ( eh   ey   iy )		d ae tf ax	0.25	
	d ey	0.44		date	d ey td	0.99	d ey td
death	d eh th	0.88	d eh th	davis	d ey v ax s	0.99	d ey v ax s
	t eh th	0.10		daylight	d ey l ay td	0.99	d ey l ay td
<u>deep</u>	d iy p ax l	0.40	d iy pd	daytime	d ey t ay m	0.99	d ey t ay m
	aa d iy pd	0.40		daytona	d ey t ow n ax	0.97	d ey t ow n ax
	d iy pd	0.11		dearborn	d ih r b ao r n	0.98	d ih r b ao r n
degrees	d iy g r iy z	0.88	d ( ax   iy ) g r iy z	december	d ax s eh m b er	0.65	d ( ax   iy ) s eh m b er
	d ax g r iy z	0.10			d iy s eh m b er	0.31	
delaware	d eh l ax w eh r	0.83	d eh l ax w eh r	define	d ax f ay n	0.84	d ( ax   iy ) f ay n
delmar	d eh l m aa r	0.98	d eh l m aa r		d ax s f ay n	0.14	
denver	d eh n v er	0.99	d eh n v er	del	d eh l	0.97	d eh l
<u>describe</u>	d ax s k r ay bd dd	0.70	d ( ax   iy ) s k- r ay bd	delhi	d eh l iy	0.98	d eh l iy
	d ax s k- r ay bd dd	0.24		denmark	d eh n m aa r kd	0.94	d eh n m aa r kd
<u>detailed</u>	d iy t eh l dd	0.50	d ( ax   iy ) t ey l dd	des	d ax	0.89	d ( ax   eh )
	d iy t ey l dd	0.38		<u>detail</u>	d iy t eh l	0.43	d ( ax   iy ) t ey l
	d iy t eh l	0.09			d iy t ey l	0.27	
dew	d uw	0.96	d uw		d iy t ae l	0.23	
dhabi	d aa b iy	0.99	d aa b iy	detroit	d iy tr r oy td	0.77	d ( ax   iy ) tr r oy td
diego	d iy ey g ow	0.99	d iy ey g ow		d ax tr r oy td	0.20	
different	d ih f r ax n td	0.89	d ih f ( er   r ) ax n td	dewey	d uw iy	0.69	d uw iy
	d ih f er ax	0.09			d uw r iy	0.30	
direction	d ax r eh kd sh ax n	0.96	d ( ay r   ax r ) eh kd sh ax n	did	d ih dd	0.93	d ih dd
distance	d ih s t ax n s	0.99	d ih s t ax n s	difference	d ih f r ax n s	0.99	d ih f ( er   r ) ax n s
djibouti	jh ax b uw tf iy	0.50	jh ax b uw tf iy	<u>digital</u>	d ih jh ax tf ax l	0.85	d ih jh ax t ax l
	d ih jh ax b uw tf iy	0.42		directions	d ax r eh kd sh ax n z	0.99	d ( ay r   ax r ) eh kd sh ax n z
dodge	d aa jh	0.93	d aa jh	district	d ih s tr r ax kd td	0.99	d ih s tr r ax kd td
doing	d uw ih ng	0.82	d uw ih ng	<u>do</u>	d	0.71	d uw
dominican	d ax m ih n ax k ax n	0.89	d ( ax   ow ) m ih n ax k ax n		d uw	0.26	
	d ax m ih n ax k ax	0.10		does	d ah z	0.97	d ah z
dorado	d ax r aa df ow	0.56	d ax r aa df ow	<u>domingo</u>	d ax m ih ng g ow	0.96	d ow m ih ng g ow
	d ax r ey d ow	0.19		done	d ah n	0.91	d ah n
	d ax r ey df ow	0.17		dover	d ow v er	0.99	d ow v er
down	d aw n	0.99	d aw n	drive	dr r ay v	0.99	dr r ay v
driving	dr r ay v ih ng	0.99	dr r ay v ih ng	dry	dr r ay	0.85	dr r ay
dublin	d ah bd l ax n	0.97	d ah bd l ax n		t r ay	0.09	
dude	d uw dd	0.86	d uw dd	dubuque	d ax b y uw kd	0.99	d ax b y uw kd
	d uh dd	0.13		dulles	d ah l ax s	0.85	d ah l ax s
duluth	d ax l uw th	0.91	d ax l uw th		d ow l ax s	0.14	
durham	d ao r ax m	0.64	d ( er   ao r ) ax m	durango	d ax r ae ng g ow	0.39	d ( ax r   ao r ) ae ng g ow
	d er ax m	0.13			d ax r ey n g ow	0.34	
	jh ax r ax m	0.10			d y ao r ae ng g ow	0.10	
dusseldorf	d uw s ax l d ao r f	0.88	d uw s ax l d ao r f	during	d ao r ih ng	0.51	d ( er   ao r ) ih ng
	d ax l s ax l d ao r f	0.11			d er ih ng	0.27	

Word	PMM Baseforms	Weight	Expert Baseform	Word	PMM Baseforms	Weight	Expert Baseform
earlier	er l iy er eh r l iy er	0.72 0.21	er l iy er	e	jh er ih ng iy	0.09 0.95	iy
early	er l iy	0.99	er l iy	earliest	er l iy ax s td	0.99	er l iy ax s td
earthquake	er th k w ey kd	0.89	er th k w ey kd	earth	er th	0.96	er th
east	iy s td	0.96	iy s td	earthquakes	er th k w ey kd s	0.97	er th k w ey kd s
eat	iy td	0.99	iy td	eastern	iy s t er n	0.99	iy s t er n
<b>edinburgh</b>	eh dd en b er ow	0.52	eh df ax n b er ( ax   ow   gd )	ecuador	eh kd w ax d ao r	0.61	eh kd w ax d ao r
	eh df ax n b er ow	0.26			eh kd w ax df ao r	0.28	
	eh dd en b er gd	0.13		edmonton	eh dd m ax n t ax n	0.96	eh dd m ax n t ax n
edward	eh dd w er dd	0.76	eh dd w er dd	effect	ax f eh kd td	0.91	( ax   iy ) f eh kd td
	ey dd w er dd	0.11		eight	ey td	0.99	ey td
egypt	iy jh ax pd td	0.97	iy jh ax pd td	eighth	ey td th	0.72	ey ( td th   th )
eighteenth	ey t iy n th	0.99	ey t iy n th		ey th	0.21	
eighty	ey tf iy	0.99	ey tf iy	either	ay dh er	0.47	( iy   ay ) dh er
el	eh l	0.94	eh l		iy dh er	0.34	
eleventh	ax l eh v ax n th	0.72	ax l eh v ax n th	eleven	ax l eh v ax n	0.88	ax l eh v ax n
	iy l eh v ax n th	0.21			l eh v ax n	0.11	
elmira	eh l m ay r ax	0.88	eh l m ay r ax	elkins	eh l k ax n z	0.99	eh l k ax n z
<b>emergency</b>	ax iy m er jh ax n s iy	0.90	ax m er jh ax n s iy	else	eh l s	0.99	eh l s
end	eh n dd	0.84	eh n dd	emirates	eh m ax r ax td s	0.99	eh m ax r ( ey   ax ) td s
	ih n dd	0.15		england	ih ng g l ax n dd	0.98	ih ng g l ax n dd
english	ih ng g l ax sh	0.98	ih ng g l ax sh	<b>enid</b>	iy n ih dd	0.70	iy n ax dd
enough	ax n ah f	0.91	( ax   iy ) n ah f		iy n ax dd	0.25	
equator	iy k w ey tf er	0.99	( ax   iy ) k w ey tf er	<b>entire</b>	ih n t ay r	0.32	eh n t ay r
<b>essen</b>	ih z eh n	0.95	eh s ax n		eh n t ay r ax	0.29	
estonia	eh s t ow n iy ax	0.44	eh s t ow n iy ax		ih nt ay er	0.12	
	eh s t ow n iy y ax	0.38		erie	eh n t ay r iy	0.11	
eugene	y uw jh iy n	0.99	y uw jh iy n		ih r iy	0.65	ih r iy
evansville	eh v ax n z v ih l	0.99	eh v ax n z v ih l		y ih r iy	0.27	
evening	iy v ax n ih ng	0.78	iy v ( ax n   n ) ih ng	estimated	eh s t ax m ey tf ax dd	0.99	eh s t ax m ey tf ax dd
	iy v n ih ng	0.20		ethiopia	iy th iy ow p iy ax	0.42	iy th iy ow p iy ax
ever	eh v er	0.92	eh v er		iy th iy ow p iy y ax	0.19	
every	eh v r iy	0.80	eh v r iy		iy t iy ow p iy ax	0.18	
	aa f ax r iy	0.19		europa	y ao r ax pd	0.74	y ( er   ao r ) ax pd
exact	eh gd z ae kd td	0.37	eh ( gd   kd ) z ae kd td		y er ax pd	0.11	
	ey gd z ae kd td	0.34		even	iy v ax n	0.99	iy v ax n
	ax gd z ae kd td	0.27		events	iy v eh n td s	0.66	( ax   eh   iy ) v eh n td s
<b>except</b>	eh kd s eh pd	0.90	eh kd s eh pd td		ax v eh n td s	0.33	
<b>exit</b>	eh gd z ih td	0.33	eh ( gd z   kd s ) ax td	everett	eh v r ax td	0.99	eh v ( ax r   r ) ax td
	eh kd z ih td	0.27		everything	eh v r iy th ih ng	0.99	eh v r iy th ih ng
	eh kd s ax s	0.17		exactly	eh gd z ae kd td l iy	0.99	eh ( gd z   kd s ) ae ( kd td   kd ) l iy
	eh kd s ih td	0.16		<b>excuse</b>	kd s k- y uw z	0.63	eh kd s k- y uw z
<b>expanded</b>	iy eh kd s p- ae n d ax dd	0.99	eh kd s p- ae n d ax dd		eh kd s k- y uw z	0.36	
expected	eh kd s p- eh kd t ax dd	0.71	eh kd s p- eh kd t ax dd	expand	eh kd s p- ae n dd	0.56	eh kd s p- ae n dd
	ax kd s p- eh kd t ax dd	0.27			ax kd s p- ae n dd	0.43	
<b>expects</b>	eh kd s p- eh kd s	0.98	eh kd s p- eh kd td s	expect	eh kd s p- eh kd td	0.94	eh kd s p- eh kd td
<b>extended</b>	eh kd s t eh n d ax dd	0.75	eh kd s t- eh n d ax dd	expecting	eh kd s p- eh kd t ih ng	0.89	eh kd s p- eh kd t ih ng
	eh kd s t- eh n d ax dd	0.19		explain	eh kd s p- l ey n	0.57	eh kd s p- l ey n
f	eh f	0.79	eh f		ax kd s p- l ey n	0.16	
	eh ax f	0.13			eh kd s p- l ey n dd	0.12	
factor	f ae kd t er	0.97	f ae kd t er	<b>extreme</b>	eh kd s tr r iy n	0.99	eh kd s tr r iy m
fair	f eh r	0.99	f eh r	fabulous	f ae bd y ax l ax s	0.95	f ae bd ( y ax   y uw ) l ax s
fairfax	f eh r f ae kd s	0.80	f eh r f ae kd s	fahrenheit	f ae r ax n hh ay td	0.80	f ae r ax n hh ay td
fallen	f ao l ax n	0.99	f ao l ax n		f eh r ax n hh ay td	0.17	
falls	f ao l z	0.98	f ao l z	fairbanks	f eh r b ae ng kd s	0.99	f eh r b ae ng kd s
far	f aa r	0.69	f aa r	fall	f ao l	0.96	f ao l



Word	PMM Baseforms	Weight	Expert Baseform	Word	PMM Baseforms	Weight	Expert Baseform
fast	f a o r	0.28		falling	f a o l i h n g	0.99	f a o l i h n g
<u>fayetteville</u>	f a e s t d	0.92	f a e s t d	falmouth	f a w l m a x t h	0.66	f ( a w l   a a l ) m a x t h
	f e y y a x t d v i h l	0.77	f e y a x t d v i h l		f a a l m a x t h	0.16	
	f e y a x t d v i h l	0.11			f a e l m a x t h	0.13	
february	f e h b d y u w e h r i y	0.44	f e h b d ( r u w   y u w ) ( e h r   e r ) i y	fargo	f a a r g o w	0.97	f a a r g o w
	f e h b d r u w e h r i y	0.32		fax	f a e k d s	0.63	f a e k d s
feet	f i y t d	0.99	f i y t d		f f a e k d s	0.36	
fergus	f e r g a x s	0.56	f e r g a x s	fe	f e y	0.96	f e y
	f e r g a x z	0.42		feeling	f i y l i h n g	0.99	f i y l i h n g
few	f y u w	0.97	f y u w	fell	f e h l	0.99	f e h l
fifth	f i h t h	0.51	f i h ( f t h   t h )	fernando	f e r n a e n d o w	0.99	f e r n a e n d o w
	f i h f t h	0.46		fifteenth	f i h f t i y n t h	0.99	f i h f t i y n t h
fiji	f i y j h i y	0.99	f i y j h i y	fifty	f i h f t i y	0.90	f i h f t i y
find	f a y n d d	0.99	f a y n d d	<u>finally</u>	f a y n l i y	0.51	f a y n a x l i y
finished	f i h n a x s h t d	0.80	f i h n a x s h t d		f a y l i y	0.30	
	f i h n i y s h t d	0.12			f a y n d d l i y	0.13	
first	f e r s t d	0.96	f e r s t d	fine	f a y n	0.99	f a y n
flagstaff	f l a e g d s t- a e f	0.95	f l a e g d s t- a e f	finland	f i h n l a x n d d	0.85	f i h n l a x n d d
flight	f l a y t d	0.99	f l a y t d	five	f a y v	0.99	f a y v
flint	f l i h n t d	0.69	f l i h n t d	flash	f l a e s h	0.68	f l a e s h
	f l e h n t d	0.27			f l a e s h s	0.17	
flooding	f l a h d f i h n g	0.90	f l a h d f i h n g		f l a e s h f	0.14	
florence	f l a o r a x n s	0.84	f l a o r a x n s	flights	f l a y t d s	0.98	f l a y t d s
	f l a o r a x n t d s	0.13		flood	f l a h d d	0.99	f l a h d d
<u>flurries</u>	f l a o r i y z	0.99	f l e r i y z	floods	f l a h d d z	0.97	f l a h d d z
flying	f l a y i h n g	0.99	f l a y i h n g	florida	f l a o r a x d f a x	0.53	f l ( a o r a x   a o r ) d f a x
					f l a o r d f a x	0.38	
foggy	f a o g i y	0.66	f ( a a   a o ) g i y	fly	f l a y	0.97	f l a y
	f a a g i y	0.32		fog	f a o g d	0.65	f ( a a   a o ) g d
football	f u h t d b a o l	0.79	f u h t d b a o l		f a a g d	0.28	
	l a x f u h t d b a o l	0.10		following	f a a l o w i h n g	0.99	f a a l o w i h n g
forecast	f a o r k a e s t d	0.99	f a o r k a e s t d	for	f a o r	0.53	f ( a o r   e r   a x r )
forecasts	f a o r k a e s t d s	0.94	f a o r k a e s t d s		f e r	0.42	
forget	f e r g e h t d	0.83	f ( a o r   e r ) g e h t d	forecasted	f a o r k a e s t a x d d	0.99	f a o r k a e s t a x d d
form	f a o r m	0.99	f a o r m	foreign	f a o r a x n	0.85	f a o r a x n
forty	f a o r t f i y	0.99	f a o r t f i y		s f a o r a x n	0.14	
fourteenth	f a o r t i y n t h	0.99	f a o r t i y n t h	forks	f a o r k d s	0.99	f a o r k d s
framingham	f r e y m i h n g h h a e m	0.97	f r e y m i h n g ( h h a e   a x ) m	fort	f a o r t d	0.98	f a o r t d
				four	f a o r	0.97	f a o r
francisco	f r a x n s i h s k o w	0.98	f r ( a x   a e ) n s i h s k o w	fourth	f a o r t h	0.98	f a o r t h
fredericksburg	f r e h d r r a x k d s b e r g d	0.98	f r e h d r r a x k d s b e r g d	france	f r a e n s	0.55	f r a e n s
					f r a e n t d s	0.42	
freeze	f r i y z	0.99	f r i y z	frankfurt	f r a e n g k d f e r t d	0.90	f r a e n g k d f e r t d
french	f r e h n c h	0.86	f r e h n c h	free	f r i y	0.99	f r i y
	f r a e n c h	0.12		freezing	f r i y z i h n g	0.99	f r i y z i h n g
friday	f r a y d f e y	0.99	f r a y d f e y	fresno	f r e h z n o w	0.99	f r e h z n o w
frost	f r a o s t d	0.67	f r a o s t d	from	f r a x m	0.66	f r ( a h   a x ) m
	f r a a s t d	0.26			f r a h m	0.31	
<u>full</u>	f a x l	0.64	f u h l	fuck	f a h k d	0.46	f a h k d
	f a o l	0.34			f a a k d	0.37	
funny	f a h n i y	0.66	f a h n i y	<u>function</u>	f a o n g k d s h a x n	0.53	f a h n g k d s h a x n
	f a h n i y e y t f a x d d	0.32			f a h n g k d s h a x n	0.41	
future	f y u w c h e r	0.99	f y u w c h e r	further	f e r d h e r	0.98	f e r d h e r
gadsden	g a e d d z d a x n	0.99	g a e d d z d a x n	g	j h i y	0.83	j h i y
galaxy	g a e l a x k d s i y	0.70	g a e l a x k d s i y		j h i y i y	0.15	
	g a e l a x k d s i y i y	0.29		gainesville	g e y n z v i h l	0.89	g e y n z v i h l
game	g e y m	0.99	g e y m				
gatwick	g a e t d w i h k d	0.61	g a e t d w ( a x   i h ) k d				
	g a e t d w i y k d	0.37					

Word	PMM Baseforms	Weight	Expert Baseform	Word	PMM Baseforms	Weight	Expert Baseform
geneva	jh ax n iy v ax	0.60	jh ax n iy v ax	galveston	g ey n z v ih l ax l	0.09	
georgetown	jh ih n iy v ax	0.30		garbage	g ae l v ax s t ax n	0.95	g ae l v ax s t ax n
	jh ao r jh t aw n	0.82	jh ao r jh t aw n	general	g aa r b ax jh	0.99	g aa r b ax jh
	jh ao r zh t aw n	0.16			jh eh n ax r ax l	0.51	jh eh n ( ax r   er   r ) ax l
german	jh er m ax n	0.99	jh er m ax n		jh eh n r ax l	0.34	
germany	jh er m ax n iy	0.96	jh er m ax n iy	george	jh ao r jh	0.99	jh ao r jh
getting	g eh tf ih ng	0.48	g eh ( tf ih ng   tq en )	georgia	jh ao r jh ax	0.98	jh ao r jh ax
	g ih tf ih ng	0.38		germantown	jh er m ax n t aw n	0.99	jh er m ax n t aw n
give	g ih v	0.98	g ih v	get	g eh td	0.97	g eh td
glacier	g l ey sh er	0.86	g l ey sh er	gibraltar	jh ax b r ao l tf er	0.99	jh ax b r ao l tf er
glenwood	g l eh n w uh dd	0.81	g l eh n w uh dd	giving	g ih v ih ng	0.85	g ih v ih ng
	g l ax n w uh dd	0.17			jh ih v ih ng	0.14	
going	g ow ih ng	0.73	g ow ih ng	glasgow	g l ae z g ow	0.27	g l ae z g ow
	g uh	0.21			g l ae s k- ow	0.26	
got	g aa td	0.65	g aa td		g l ae s k- aw	0.11	
	g aa	0.22			g l aa s k- ow	0.10	
great	g r ey td	0.98	g r ey td		g l aa s g ow	0.09	
green	g r iy n	0.99	g r iy n	go	g ow	0.98	g ow
greensboro	g r iy n z b er ow	0.63	g r iy n z b ( er   ao r ) ow	good	g uh dd	0.92	g uh dd
grenoble	g r iy n z b ao r ow	0.17		grand	g r ae n dd	0.98	g r ae n dd
	g r iy n z b aa r ow	0.10		greece	g r iy s	0.95	g r iy s
	g r ax n ow b ax l	0.99	g r ax n ( ow   aa ) b ax l	greenland	g r iy n l ax n dd	0.48	g r iy n l ax n dd
ground	g r aw n dd	0.99	g r aw n dd		g r iy n l ae n dd	0.26	
<u>guadaloupe</u>	g w aa df ax l uw p ey	0.99	g w aa df ax l uw pd		g r iy n l ay n dd	0.09	
guangzhou	g w aa ng z ow	0.66	g w aa ng ( z   zh   jh ) ( aw   ow )	greenville	g r iy n v ih l	0.91	g r iy n v ih l
guatemala	g w aa ng zh uw	0.25		groton	g r aa tq en	0.93	g r aa tq en
	g w aa tf ax m aa l ax	0.75	g w aa tf ax m aa l ax	guadalajara	g w aa df ax l ax hh aa r ax	0.36	g w aa df ax l ax hh aa r ax
					g w aa df ax l aa hh aa r ax	0.31	
	g w aa tf ax m aa l aa	0.14			w aa df ax l ax hh aa r ax	0.10	
	w aa tf ax m aa l ax	0.10			g w aa df ax l ax hh ae r ax	0.10	
<u>guiana</u>	g y iy ae n ax	0.30	g ( ay   iy ) ( ae   aa ) n ax	guam	g w aa m	0.81	g w aa m
	g iy ae n ax	0.21		guardia	g w aa r df iy ax	0.92	g w ? aa r df iy ax
	g aa iy ae n ax	0.15		guess	g eh s	0.99	g eh s
	iy ae n ax	0.09		gulf	g ah l f	0.98	g ah l f
	g y aa n ax	0.09		guy	g ay	0.99	g ay
gulfport	g ah l f p ao r td	0.80	g ah l f p ao r td	guys	g ay z	0.74	g ay z
<u>guyana</u>	g y ax n ax	0.49	g ( ay   iy ) ( aa   ae ) n ax		g ay tf ax z	0.25	
	g ay ae n ax	0.49		had	hh ae dd	0.95	hh ae dd
h	ey ch	0.91	ey ch	hail	hh ey l	0.83	hh ey l
hagerstown	hh ey g er z t aw n	0.84	hh ey g er z t aw n	halifax	hh ae l ax f ae kd s	0.93	hh ae l ax f ae kd s
haiti	hh ey tf iy	0.99	hh ey tf iy	hampshire	hh ae m pd sh er	0.99	hh ae m pd sh er
hamburg	hh ae m b er gd	0.95	hh ae m b er gd	hang	hh ae ng	0.80	hh ae ng
hampton	hh ae m pd t ax n	0.99	hh ae m pd t ax n	hanover	hh ae n ow v er	0.99	hh ae n ow v er
hanoi	hh ae n oy	0.74	hh ( ae   ax ) n oy	happened	hh ae p ax n dd	0.99	hh ae p ax n dd
happen	hh ae p ax n	0.99	hh ae p ax n	harare	hh ax r aa r ey	0.72	hh ax r aa r ( ey   ax )
happening	hh ae p ax n ih ng	0.61	hh ae p ax n ih ng		hh ax r aa r ax	0.13	
	hh ae pd n ih ng	0.18			hh ax r aa r iy	0.13	
	hh ae p ax n iy ng	0.12		<u>harriman</u>	hh ae r ax m ih n	0.99	hh ae r ax m ax n
harbor	hh aa r b er	0.92	hh aa r b er	hartford	hh aa r td f er dd	0.98	hh aa r td f er dd
harrisburg	hh ae r ax s b er gd	0.99	hh ae r ax s b er gd	hatteras	hh ae tf ax r ax s	0.86	hh ae tf ( er   ax r ) ax s
has	hh ae z	0.96	hh ae z		hh ae tf er s	0.12	
				have	hh ae v	0.99	hh ae v
havana	hh ax v ae n ax	0.75	hh ax v ae n ax	having	hh ae v ih ng	0.91	hh ae v ih ng
	hh ax v aa n ax	0.11		head	hh eh dd	0.94	hh eh dd
haven	hh ey v ax n	0.98	hh ey v ax n	heard	hh er dd	0.88	hh er dd
hawaii	hh ax w ay iy	0.84	hh ax w ay iy		hh ey dd	0.11	
	hh ax w ay iy iy	0.10					
hear	hh ih r	0.96	hh ih r				

Word	PMM Baseforms	Weight	Expert Baseform	Word	PMM Baseforms	Weight	Expert Baseform
heat	hh iy td	0.95	hh iy td	heathrow	hh iy th r ow	0.52	hh iy th r ow
heavy	hh eh v iy	0.63	hh eh v iy		hh iy td r ow	0.18	
	hh ae v iy	0.33			hh iy tf r ow	0.16	
heights	hh ay td s	0.99	hh ay td s	heidelberg	hh ay df ax l b er gd	0.99	hh ay df ax l b er gd
help	hh eh l pd	0.99	hh eh l pd	hello	hh ax l ow	0.77	hh ( eh   ax ) l ow
helsinki	hh eh l s ih ng k iy	0.86	hh eh l s ih ng k iy		hh eh l ow	0.21	
here	hh ih r	0.37	hh ih r	helpful	hh eh l pd f ax l	0.99	hh eh l pd f ax l
	hh y er	0.32		hemisphere	hh eh m ax s f ih r	0.99	hh eh m ax s f ih r
	y ih r	0.11		hey	hh ey	0.97	hh ey
hi	hh ay	0.95	hh ay	hidden	hh ih dd en	0.99	hh ih dd en
high	hh ay	0.98	hh ay	<b>higher</b>	hh ay er	0.42	hh ay r
highest	hh ay ax s td	0.97	hh ay ax s td		hh ay td er	0.29	
hill	hh ih l	0.89	hh ih l		hh ay eh r	0.22	
hilo	hh iy l ow	0.93	hh iy l ow	highs	hh ay z	0.97	hh ay z
hingham	hh ih ng ax m	0.95	hh ih ng ax m	<b>hills</b>	iy l s	0.37	hh ih l z
hit	hh ih td	0.99	hh ih td		hh ih l z	0.34	
<b>hobart</b>	hh ow ax b aa r td	0.38	hh ow b ( aa r   er ) td		hh ih l s	0.16	
	hh ow b aa r td	0.25			iy l z	0.09	
	hh ow b er td	0.24		hilton	hh ih l tq en	0.99	hh ih l tq en
	hh ax b aa r td	0.11		history	hh ih s t ax r iy	0.34	hh ih s ( t ax r   tr r ) iy
hole	hh ow l	0.66	hh ow l		hh ih s tr r iy	0.33	
	hh ow ax l	0.31			hh ih s t er iy	0.20	
<b>hollywood</b>	hh aa l iy w uh dd	0.88	hh ao l iy w uh dd	ho	hh ow	0.99	hh ow
	hh ao l iy w uh dd	0.10		hold	hh ow l dd	0.87	hh ow l dd
hong	hh aa ng	0.76	hh ( aa   ao ) ng		td hh ow l dd	0.12	
	hh ao ng	0.22		holland	hh aa l ax n dd	0.92	hh aa l ax n dd
hope	hh ow pd	0.75	hh ow pd	honduras	hh aa n d ao r ax s	0.79	hh aa n d ( er   ao r ) ax s
	hh aw pd	0.24			hh aa n d er ax s	0.20	
hotter	hh aa tf er	0.99	hh aa tf er	honolulu	hh aa n ax l uw l uw	0.97	hh aa n ax l uw l uw
hours	aw er z	0.66	aw er z	hot	hh aa td	0.99	hh aa td
how	hh aw	0.99	hh aw	hottest	hh aa tf ax s td	0.96	hh aa tf ax s td
humidity	hh y uw m ih df ax tf	0.99	hh y uw m ih df ax tf	houston	hh y uw s t ax n	0.87	hh y uw s t ax n
	iy		iy				
hundred	hh ah n d er dd	0.66	hh ah n ( d er   dr r ax ) dd	humid	hh y uw m ax dd	0.55	hh y uw m ax dd
	hh ah n dr r ax dd	0.23			hh y uw m ih dd	0.43	
huntington	hh ah nt ih ng t ax n	0.91	hh ah nt ih ng t ax n	hummer	hh ah m er	0.98	hh ah m er
hurricane	hh er ax k ey n	0.93	hh er ax k ey n	hungary	hh ah ng g ax r iy	0.84	hh ah ng g ax r iy
hutchinson	hh ah ch ax n s ax n	0.99	hh ah ch ax n s ax n	huntsville	hh ah n td s v ih l	0.87	hh ah n td s v ih l
i	ay	0.99	ay	hurricanes	hh er ax k ey n z	0.98	hh er ax k ey n z
iceland	ay s l ax n dd	0.92	ay s l ax n dd	hyannis	hh ay ae n ax s	0.97	hh ay ae n ax s
if	ih f	0.72	( ih   ax ) f	ice	ay s	0.48	ay s
	ax f	0.25			ay iy s	0.41	
image	ih m ax jh	0.99	ih m ax jh		ay ay	0.09	
in	ih n	0.91	( ih   ax ) n	idaho	ay df ax hh ow	0.95	ay df ax hh ow
inclement	ih n k l ax m ax n td	0.99	( ih   ax ) n k l ( ax   eh ) m ( ax   eh ) n td	illinois	ih l ax n oy	0.81	ih l ax n oy
	ih n d ax p eh n d ax td s	0.74	ih n d ax p eh n d ax n s	impressive	ax m p r eh s ax v	0.99	( ih   ax ) m p r eh s ax v
<b>independence</b>	ih n d ax p eh n d ax n s	0.20		inches	ih n ch ax z	0.99	ih n ch ax z
india	ih n d iy ax	0.93	ih n d iy ax	including	ih n k l uw df ih ng	0.96	( ih   ax ) n k l uw df ih ng
indianapolis	ih n d iy ax n ae p ax l ax s	0.96	ih n d iy ax n ae p ax l ax s	index	ih n d eh kd s	0.99	ih n d eh kd s
information	ih n f er m ey sh ax n	0.87	ih n f ( ao r   er ) m ey sh ax n	indiana	ih n d iy ae n ax	0.99	ih n d iy ae n ax
	ax n f er m ey sh ax n	0.09		indonesia	ih n d ax n iy zh ax	0.46	ih n d ( ow   ax ) n iy zh ax
<b>inquiring</b>	ax n k w ay ih ng	0.48	( ih ng   ih n ) k w ay r ih ng		ih n d ow n iy zh ax	0.33	
	iy n k w ay r ih ng	0.24		innsbruck	ih n z b r ax kd	0.91	ih n z b r ( uh   ax ) kd
	ih n k w ay er ih ng	0.18		instead	ax n s t- eh dd	0.73	( ih   ax ) n s t- eh dd
interested	ih n tr r ax s t ax dd	0.84	ih ( nt ax   n tr ) r ( eh   ax ) s t ax dd	international	ih nt er n ae sh ax n ax l	0.78	ih nt er n ae ( sh ax   sh ) n ax l
	ih nt ax r ax s t ax dd	0.13			ih nt er n ae sh n ax l	0.18	
internet	ih nt er n eh td	0.52	ih nt er n eh td	iowa	ay ax w ax	0.62	ay ax w ax

Word	PMM Baseforms	Weight	Expert Baseform	Word	PMM Baseforms	Weight	Expert Baseform
<b>iran</b>	ih nt er n eh th td	0.17	( ih r   ay r   ax r ) ( aa   ae ) n	iraq	ay ax w aa	0.17	( ih r   ay r   ax r ) ( aa   ae ) kd
	ih nt er n s td	0.17			ay ow w ax	0.09	
	ih nt er n ax td	0.10			ay r ae kd	0.42	
	ay ax r ae n	0.17			iy r ae kd	0.15	
ireland	y ax r aa n	0.16	ay r l ax n dd	<b>islamabad</b>	ax r aa kd	0.14	er v ( ay   ax ) n ax z l aa m ax b aa dd
	iy r aa n	0.15			ay r aa kd	0.13	
	y ax r ae n	0.13			er v ay n	0.92	
	ax r aa n	0.12			ih z l aa m ax b aa dd	0.48	
is	ay r ae n	0.09	( ih   ax ) z	islands	ih z l aa m ax b ay dd	0.31	ay l ax n dd z ay l z ih s t aa n b uw l
	ay r l ax n dd	0.81			ax z l aa m ax b aa dd	0.18	
	ay r ax l ax n dd	0.11			ay l ax n dd z	0.97	
island	ih z	0.72	ay l ax n dd	<b>istanbul</b>	ay l z	0.99	ih s t ae n b ax l ih s t- ae n b ax l ih s t ax n b ax l ih s t aa n b ax l
	s	0.25			ay l	0.17	
israel	ay l ax n dd	0.99	ih z r ( iy l   iy ax l   ey ax l )	italy	ih s t ae n b ax l	0.35	ih tf ax l iy
	ay l	0.72			ih s t- ae n b ax l	0.20	
it	ax ay ax l	0.22	ih z r ( iy l   iy ax l   ey ax l )	its	ih s t ax n b ax l	0.17	( ih   ax ) td s
	ih z r iy ax l	0.31			ih s t aa n b ax l	0.14	
	ih z r ey ax l	0.21			ih tf ax l iy	0.93	
	ih z r ey l	0.21			ax td s	0.54	
ithaca	ih z r iy l	0.12	ih td	j	ih td s	0.30	jh ey
	ih td	0.99			ih z	0.14	
ivory	ih th ax k ax	0.95	ih th ax k ax	jackson	ih ey	0.98	jh ae kd s ax n
	ay v r iy	0.95			ih th ax k ax	0.98	
jacket	ay v ax ? r iy	0.95	ay v ax ? r iy	jakarta	jh ae kd s ax n	0.91	jh ax k aa r tf ax
	jh ae k ax td	0.99			jh ae k ax td	0.70	
jacksonville	jh ae k ax td	0.99	jh ae k ax td	janeiro	zh ax n eh r ow	0.28	( zh   jh ) ax n eh r ow
	jh ae kd s ax n v ih l	0.95			jh ae kd s ax n v ih l	0.28	
jamaica	jh ax m ey k ax	0.94	jh ax m ey k ax	japan	jh ax n eh r ow	0.94	jh ax p ae n
	jh ax m ey k ax	0.94			jh ax p ae n	0.94	
january	jh ae n y uw eh r iy	0.78	jh ae n y uw eh r iy	jersey	jh er z iy	0.99	jh er z iy
	jh ae n y ao r iy	0.10			jh aa bd	0.80	
jeopardy	jh eh p er df iy	0.67	jh eh p er df iy	<b>john</b>	y aa n	0.66	jh aa n
	jh ax p er df iy	0.28			jh r aa n	0.33	
jerusalem	jh ax r uw s ax l ax m	0.85	jh ax r uw s ax l ax m	<b>jonesboro</b>	jh ow n z b r ow	0.81	jh ow n z b er ow
	jh ax r uw s ax l aa m	0.12			jh ow n z b er ow	0.18	
johannesburg	jh ow hh ae n ax s b er gd	0.85	jh ow hh ae n ax s b er gd	jose	hh ow z ey	0.98	hh ? ow z ey
	jh aa n z	0.72			jh aa n z	0.47	
johns	jh ao n z	0.15	jh ao r dd en	july	jh uh l ay	0.46	jh ( uh l   ax l ) ay
	jh ao r dd en	0.84			jh ax l ay	0.46	
jordan	w aa n	0.99	w aa n	juneau	jh uw n ow	0.99	jh uw n ow
	jh uw n	0.98			jh ah s td	0.57	
juan	jh uw n	0.98	jh uw n	just	jh ax s td	0.34	jh ah s td
	jh uw p ax tf er	0.99			jh ax s td	0.34	
jupiter	k ey	0.99	k ey	<b>kabul</b>	k aa b ax l	0.30	k aa b uh l
	k ey	0.99			k ax b uw ax l	0.17	
kahului	k aa hh ax l uw iy	0.85	k aa hh ax l uw iy	kalamazoo	k ae b uw l	0.14	k ae l ax m ax z uw
	k ae l ax s p- eh l	0.62			k ax b uw	0.12	
kalispell	k ae l ax s p eh l	0.32	k ae l ax s p- eh l	kansas	k ax b uw l	0.10	k ae n z ax s
	k ae td m ae n d uw	0.79			k ae td m ae n d uw	0.98	
katmandu	k ax n t ah k iy	0.99	k ( eh   ax ) n t ah k iy	kenosha	k ae n z ax s	0.97	k ax n ow sh ax
	k iy	0.95			k iy	0.89	
kentucky	k ih l ax m ax n jh aa r ow	0.99	k ih l ax m ax n jh aa r ow	kenosha	k ax n ow sh s ax	0.10	k ax n ow sh ax
	k ay n dd	0.89			k ay n dd	0.96	
kingdom	k ih ng d ax m	0.99	k ih ng d ax m	kenya	k eh n y ax	0.96	k ( eh   iy ) n y ax
	k ih n sh aa s ax	0.60			k iy eh v	0.65	
kinshasa	k ih n sh aa sh sh ax	0.19	k ih n sh aa s ax	kiev	k iy ae f	0.14	k iy eh v
	k ih n sh aa s aa td	0.19			k ih l ih ng t ax n	0.98	
kittyhawk	k ih tf iy hh ao kd	0.75	k ih tf iy hh ao kd	killington	k ay n dd z	0.67	k ay n dd z
	k ih tf iy hh aa	0.23			k ay n dd	0.32	
knowledge	n aa l ax jh	0.90	n aa l ax jh	<b>kingston</b>	k ih ng s t- ax n	0.89	k ih ng s t ax n
	n aa kd s v ih l	0.93			k ih ng s t ax n	0.09	
knoxville	n aa kd s v ih l	0.93	n aa kd s v ih l	kitts	k ih td s	0.99	k ih td s

Word	PMM Baseforms	Weight	Expert Baseform	Word	PMM Baseforms	Weight	Expert Baseform
kong	k aa ng	0.70	k ( aa   ao ) ng	know	n ow	0.99	n ow
	k ao ng	0.19		knox	n aa kd s	0.94	n aa kd s
kosovo	k ow s ax v ow	0.53	k ow s ax v ow	kodiak	k ow df iy ae kd	0.39	k ow df iy ae kd
	k ao s ow v ow	0.13			k ow df iy y ae kd	0.35	
	k ow s ow v ow	0.13			td ow df iy ae kd	0.22	
kuala	k w aa l ax	0.83	k w aa l ax	korea	k ax r iy ax	0.85	k ( ax   ao ) r iy ax
	k w aa l aa	0.16			k ao r iy ax	0.12	
kuwait	k uw w ey td	0.92	k uw w ey td	<b>kourou</b>	k ax r uw	0.52	k uw r uw
l	eh l	0.91	eh l		k ao r uw	0.26	
<b>labor</b>	l ey b ax r	0.99	l ey b er		k ow ao r uw	0.17	
laconia	l ax k ow n iy ax	0.68	l ax k ow n iy ax	kunming	k uh n m ih ng	0.64	k uh n m ih ng
	l ax k ow n iy y ax	0.10			k ah n m ih ng	0.35	
lagos	l aa g ow s	0.59	l aa g ow s	kyoto	k y ow tf ow	0.96	k ( iy   y ) ow tf ow
	l ey g ow s	0.39		la	l ax	0.51	l ( ax   aa )
lake	l ey kd	0.90	l ey kd		l aa	0.32	
lancaster	l ae ng k ax s t er	0.49	l ae ( ng   n ) k ( ax   ae ) s t er	<b>laboratory</b>	l ae bd r ax t er	0.30	l ae bd r ax t ao r iy
	l ae ng k ae s t er	0.40			l ae bd r ax tf er	0.27	
lanka	l aa ng k ax	0.65	l aa ng k ax		l ae bd r ax t er iy	0.23	
	l aa ng k aa	0.18			l ae bd r ax tf er iy	0.14	
large	l aa r jh	0.67	l aa r jh	lafayette	l aa f iy eh td	0.42	l ( aa   ae ) f ( ay   iy ) eh td
	aa r jh	0.32			l aa f ey y eh td	0.14	
las	l aa s	0.94	l aa s		l ae f iy eh td	0.10	
late	l ey td	0.99	l ey td	<b>lahaina</b>	l aa f iy y eh td	0.09	
<b>latest</b>	l ay tf ax s td	0.50	l ey tf ax s td		l aa hh ay n ax	0.69	l ax hh ay n ax
	l ey tf ax s td	0.49			l ax hh ay n ay iy	0.16	
lauderdale	l ao df er d ey l	0.72	l ao df er d ey l		l aa hh ey n ax	0.14	
	l aa df er d ey l	0.21		lakes	l ey kd s	0.77	l ey kd s
lebanon	l eh b ax n aa n	0.84	l eh b ax n ( aa   ax ) n		l ay kd s	0.22	
	l eh b ax n ax n	0.15		languages	l ae ng g w ax jh ax z	0.93	l ae ng g w ax jh ax z
less	l eh s	0.99	l eh s	lansing	l ae n s ih ng	0.86	l ae n s ih ng
level	l eh v ax l	0.83	l eh v ax l	largest	l aa r jh ax s td	0.77	l aa r jh ax s td
	l ax v ax l	0.10			l aa r jh ax td	0.13	
lewiston	l uw ax s t ax n	0.75	l uw ax s t ax n	last	l ae s td	0.95	l ae s td
	l uw ax s t- ax n	0.24		later	l ey tf er	0.94	l ey tf er
lhasa	l aa s ax	0.92	l ( aa   ae ) s ax	latvia	l ae td v iy ax	0.51	l ( aa   ae ) td v iy ax
life	l ay f	0.98	l ay f		l aa td v iy ax	0.48	
<b>lihue</b>	l ax hh uw ey	0.62	l ax hh uw iy	lawrence	l ao r ax n s	0.64	l ao r ax n s
	l ax hh uw iy	0.09			l aa r ax n s	0.29	
likelihood	l ay kd l iy hh uh dd	0.99	l ay kd l iy hh uh dd	leesburg	l iy z b er gd	0.99	l iy z b er gd
lima	l iy m ax	0.59	l iy m ax	let	l eh td	0.46	l eh td
	l iy m aa	0.29			l ax	0.35	
lisbon	l ih z b ax n	0.79	l ih z b ax n		l eh	0.09	
listening	l ih s ax n ih ng	0.71	l ih s ( ax n   n ) ih ng	levels	l eh v ax l z	0.77	l eh v ax l z
	l ax s t ax n ih ng	0.19			l eh v w ax l z	0.15	
little	l ih tf ax l	0.94	l ih tf ax l	lexington	l eh kd s ih ng t ax n	0.78	l eh kd s ih ng t ax n
<b>liverpool</b>	l ih v er p ax l	0.59	l ih v er p uw l	libya	l ih b iy ax	0.63	l ih ( b iy ax   bd y ax )
	l ih v er p ao l	0.11			l ih bd y ax	0.36	
located	l ow k ey tf ax dd	0.94	l ow k ey tf ax dd	lightning	l ay td n ih ng	0.99	l ay td n ih ng
locations	l ow k ey sh ax n z	0.99	l ow k ey sh ax n z	like	l ay kd	0.99	l ay kd
london	l ah n d ax n	0.96	l ah n d ax n	likely	l ay kd l iy	0.98	l ay kd l iy
look	l uh kd	0.98	l uh kd	lincoln	l ih ng k ax n	0.99	l ih ng k ax n
looks	l uh kd s	0.59	l uh kd s	list	l ih s td	0.99	l ih s td
	l uw kd s	0.35		<b>lithuania</b>	l ih th ax w ey n iy ax	0.44	l ih th uw ey n iy ax
lottery	l aa tf er iy	0.99	l aa tf er iy		l ih th ax w ih n iy ax	0.17	
louisiana	l uw iy z iy ae n ax	0.92	l uw iy z iy ae n ax		l ih td th w ey n iy ax	0.16	
low	l ow	0.98	l ow		l ih tf ax w ey n iy ax	0.09	

Word	PMM Baseforms	Weight	Expert Baseform	Word	PMM Baseforms	Weight	Expert Baseform
<b>lower</b>	l ow ao r	0.33	l ow er		l ih td ax w ey n iy ax	0.09	
	l ow er	0.25		live	l ih v	0.82	l ih v
	l aw	0.13			l ax v	0.14	
	l ao r	0.11		local	l ow k ax l	0.96	l ow k ax l
lows	l ow z	0.99	l ow z	location	l ow k ey sh ax n	0.89	l ow k ey sh ax n
<b>lucia</b>	l ax s y ax	0.57	l uw sh ax	logan	l ow g ax n	0.86	l ow g ax n
	l uw sh ax	0.36			l ow g ax n z	0.13	
lumpur	l ah m p ao r	0.94	l ah m p ao r	long	l ao ng	0.96	l ao ng
luxembourg	l ah kd s ax m b er gd	0.63	l ah kd s ax m b er gd	looking	l uh k ih ng	0.99	l uh k ih ng
	l ah kd s ax n b ao r gd	0.24		los	l aa s	0.57	l ( ow   ao   aa ) s
	l ah kd s ax m b ao r gd	0.11			l ao s	0.40	
<b>lyon</b>	l iy aa n	0.74	l ay ax n	louis	l uw ax s	0.99	l uw ( iy   ax s )
	l y ao	0.24		louisville	l uw iy v ih l	0.55	l uw ( ax   iy ) v ( ax   ih ) l
macon	m ey k ax n	0.81	m ey k ax n		l uw ax v ax l	0.28	
	m ay k ax n	0.18			l uw ax v ih l	0.10	
madison	m ae df ax s ax n	0.99	m ae df ax s ax n	lowell	l ow ax l	0.97	l ow ax l
madrid	m ax dr r ih dd	0.76	m ax dr r ih dd	lowest	l ow ax s td	0.99	l ow ax s td
major	m ey jh er	0.99	m ey jh er	lubbock	l ah b ax kd	0.96	l ah b ax kd
malaysia	m ax l ey zh ax	0.94	m ax l ey zh ax	luis	l uw ax s	0.36	l uw ( ax s   iy )
<b>malta</b>	m aa l tf ax	0.50	m ao l tf ax		l uw iy z	0.33	
	m aa l t aa	0.23			l uw iy s	0.10	
	m aa l t ax	0.16		lusaka	l uw s aa k ax	0.99	l uw s ( aa   ae ) k ax
	m aa l tf aa	0.09		lynn	l ih n	0.99	l ih n
<b>managua</b>	m ax n aa gd w ax	0.64	m ax n aa g w ax	m	eh m	0.97	eh m
	m ax n aa gd w ah	0.11		made	m ey dd	0.88	m ey dd
	m aa n aa g w aa	0.09			m ey td	0.09	
manhattan	m ae n hh ae tq en	0.87	m ( ax   ae ) n hh ae tq en	madras	m ax dr r aa s	0.76	m ( aa dr r ax   ax dr r aa ) s
manitoba	m ae n ax t ow b ax	0.96	m ae n ax t ow b ax	maine	m ey n	0.98	m ey n
map	m ae pd	0.99	m ae pd	make	m ey kd	0.99	m ey kd
<b>marine</b>	m ax r iy n	0.97	m er iy n	mali	m aa l iy	0.82	m aa l iy
market	m aa r k ax td	0.99	m aa r k ax td	man	m ae n	0.70	m ae n
marquette	m aa r k eh td	0.42	m aa r k eh td		m ax n	0.15	
	m aa r k ae td	0.30		manchester	m ae n ch eh s t er	0.93	m ae n ch eh s t er
	m aa r kd ae td	0.27		manila	m ax n ih l ax	0.72	m ax n ih l ax
marseille	m aa r s ey	0.63	m aa r s ey		m ax n ax l ax	0.16	
martinique	m aa r tq en iy kd	0.80	m aa r tq en iy kd	many	m eh n iy	0.94	m eh n iy
	m aa r tq en ey iy kd	0.14		march	m aa r ch	0.91	m aa r ch
mass	m ae s	0.99	m ae s	<b>maritime</b>	m eh r ax t ay m	0.99	m ae r ax t ay m
maui	m aw iy	0.84	m aw iy	marlborough	m aa r l b r ow	0.65	m aa r l b ( r   er ) ow
may	m ey	0.97	m ey		m aa r l b er ow	0.23	
mckinley	m ax k ih n l iy	0.99	m ax k ih n l iy	mars	m aa r z	0.86	m aa r z
mean	m iy n	0.91	m iy n	martin	m aa r tq en	0.99	m aa r tq en
meant	m eh n td	0.89	m eh n td	maryland	m eh r ax l ax n dd	0.99	m eh r ax l ax n dd
mediterranean	m eh df ax tf ax r ey n	0.96	m eh df ax tf ax r ey n				
	iy ax n		iy ax n	massachusetts	m ae s ax ch uw s ax td	0.97	m ae s ax ch uw s ax td s
memorial	m ax m ao r iy ax l	0.66	m ax m ao r iy ax l		s		
				maximum	m ae kd s ax m ax m	0.99	m ae kd s ax m ax m
	m ax m ao r ax l	0.33		maybe	m ey b iy	0.91	m ey b iy
menlo	m eh n l ow	0.91	m eh n l ow	me	m iy	0.99	m iy
menu	m eh n y uw	0.73	m eh n y uw	meaning	m iy n ih ng	0.98	m iy n ih ng
	m ey n y uw	0.15		medford	m eh dd f er dd	0.89	m eh dd f er dd
	m ih n y uw	0.11		melbourne	m eh l b er n	0.62	m eh l b er n
message	m eh s ax jh	0.99	m eh s ax jh		m eh l b ao r n	0.36	
mexico	m eh kd s ax k ow	0.97	m eh kd s ax k ow	memphis	m eh m pd f ax s	0.94	m eh m ( f   pd f ) ax s
michigan	m ih sh ax g ax n	0.99	m ih sh ax g ax n	mentioned	m eh n sh ax n dd	0.88	m eh n sh ax n dd
middle	m ih df ax l	0.99	m ih df ax l		m eh n t ax n dd	0.09	
midwest	m ih d w eh s td	0.53	m ( ih   ax ) d w eh s td	meridian	m ax r ih df iy ax n	0.39	m ax r ih df iy ax n
	m ih dd w eh s td	0.38					

Word	PMM Baseforms	Weight	Expert Baseform	Word	PMM Baseforms	Weight	Expert Baseform
might	m ay td	0.99	m ay td		m ax r ih df iy ae n	0.37	
mild	m ay l dd	0.93	m ay l dd		m ax r ih df iy eh n	0.22	
mind	m ay n dd	0.95	m ay n dd	<b>metropolitan</b>	m eh tr r ax p aa l ax tq en	0.58	m eh tr r ax p aa l ax tf ax n
minneapolis	m ih n iy ae p ax l ax s	0.99	m ih n iy ae p ax l ax s		m eh tr r ax p aa l ax tf ax n	0.41	
minot	m ih n ow	0.39	m ( ih n ow   ay n aa td )	miami	m ay ae m iy	0.99	m ay ae m iy
	m ay n aa td	0.28		mid	m ih dd	0.99	m ih dd
	m ay n ae td	0.17		midland	m ih dd l ax n dd	0.88	m ih dd l ax n dd
	m ay n ow	0.13		<b>midwestern</b>	m ih d w eh s t ax n	0.86	m ( ih   ax ) d w eh s t er n
minute	m ih n ax td	0.93	m ih n ax td	milan	m ax l aa n	0.86	m ax l ( aa   ae ) n
mississippi	m ih s ax s ih p iy	0.90	m ih s ax s ih p iy	milwaukee	m ax l w ao k iy	0.84	m ( ih l   ax l ) w ao k iy
missouri	m ax z er iy	0.73	m ax z ( er   ao r ) ( iy   ax )		m ih l w ao k iy	0.09	
	m ax z ao r iy	0.20		minh	m ih n	0.99	m ih n
mogadishu	m ow g ax d iy sh uw	0.99	m ow g ax d iy sh uw	minnesota	m ih n ax s ow tf ax	0.84	m ih n ax s ow tf ax
moment	m ow m ax n td	0.69	m ow m ax n td		m ax n ax s ow tf ax	0.13	
	m aa m ax n td	0.26		<b>minsk</b>	m ih ng td s kd	0.56	m ih n s kd
monday	m ah n d ey	0.98	m ah n d ey		m ih n s kd	0.25	
monica	m aa n ax k ax	0.99	m aa n ax k ax		m iy n td s kd	0.14	
monsoons	m aa n s uw n z	0.96	m aa n s uw n z	<b>missed</b>	ax m ih s td	0.52	m ih s td
monte	m aa nt iy	0.79	m aa nt iy		m ih s td	0.47	
	m ah nt ax	0.18		missoula	m ax z uw l ax	0.75	m ax z uw l ax
monterey	m aa nt ax r ey	0.99	m aa nt ax r ey		m ax z ax l ax	0.20	
<b>montevideo</b>	m aa nt ax v ax d ey eh ow	0.35	m aa nt ax v ( ax d ey ow   ih df iy ow )	mobile	m ow b iy l	0.94	m ow b ( ax l   ay l   iy l )
	m aa nt ax v ih df iy uw	0.28		moines	m oy n	0.95	m oy n
	m aa nt ax v ax d ey ow	0.12		<b>monaco</b>	m aa n ax k ax	0.60	m aa n ax k ow
	m aa nt ax v ih df ey ow	0.11			m aa n ax k ow	0.35	
	m aa nt ax v ih d ey ow	0.10		mongolia	m aa ng g ow l iy ax	0.43	m ( aa   ax ) ( n   ng ) g ow l iy ax
<b>month</b>	m aa n th	0.54	m ah n th		m aa n g ow l iy ax	0.36	
	m ah n th	0.44			m aa n g ow l y ax	0.10	
months	m ah n th s	0.34	m ah n th s	<b>monsoon</b>	m aa n s ax n y ax n	0.48	m aa n s uw n
	m aa n	0.30			m aa n s ax ow n	0.47	
	m aa n th s	0.20		montana	m aa n t ae n ax	0.99	m aa n t ae n ax
montpelier	m aa n p iy l y er	0.62	m aa n p ( iy l y er   ax l y ey )	montego	m aa n t iy g ow	0.82	m aa n t iy g ow
	m aa n td p iy l y er	0.22			m ah n t iy g ow	0.10	
monument	m aa n y ax m ax n td	0.45	m aa n y ax m ax n td	monterrey	m aa nt ax r ey	0.99	m aa nt ax r ey
	m aa n y uw m eh td	0.31		montgomery	m aa n td g ah m r iy	0.35	m aa n td g ah m ( r   ax r ) iy
	m aa n y uw m ax n td	0.21			m ah td g ah m r iy	0.23	
moorhead	m ao r hh eh dd	0.99	m ao r hh eh dd		m aa nt g ah m r iy	0.15	
morning	m ao r n ih ng	0.99	m ao r n ih ng	monthly	m ah n th l iy	0.62	m ah n th l iy
morristown	m ao r ax s t aw n	0.72	m ao r ax s t aw n		m ah n th ax l iy	0.18	
	m aa r ax s t aw n	0.24			m aa n t l iy	0.09	
most	m ow s td	0.89	m ow s td	monticello	m aa nt ax s eh l ow	0.97	m aa nt ax ( ch   s ) eh l ow
mountain	m aw n tq en	0.81	m aw n tq en	montreal	m aa n tr r iy ao l	0.51	m ( aa   ah ) n tr r iy ao l
	m aa n t ax n	0.16			m ah n tr r iy ao l	0.40	
move	m uw v	0.33	m uw v	moon	m uw n	0.76	m uw n
	m aw ey	0.28		more	m ao r	0.99	m ao r
	m ax v ax	0.25		morocco	m ax r aa k ow	0.74	m ( ax   ao ) r aa k ow
movies	m uw v iy z	0.80	m uw v iy z		m aa r aa k ow	0.14	
	m ax l v iy z	0.10			m aa ax r aa k ow	0.11	
much	m ah ch	0.98	m ah ch	moscow	m aa s k ow	0.50	m aa s k ( ow   aw )
music	m y uw z ax kd	0.97	m y uw z ax kd		m aa s k aw	0.42	
my	m ay	0.99	m ay	mount	m aw n td	0.89	m aw n td
myers	m ay r z	0.50	m ay r z	mountains	m aw n tq en z	0.79	m aw n tq en z
	m ay er z	0.29			m aw n tq en s	0.12	
	m ay r ax sh	0.09		movie	m uw v iy	0.71	m uw v iy
n	eh n	0.74	eh n		eh m eh uw v iy	0.28	
	ih n	0.24		mozambique	m ow z ae m b iy kd	0.99	m ow z ae m b iy kd

Word	PMM Baseforms	Weight	Expert Baseform	Word	PMM Baseforms	Weight	Expert Baseform
nairobi	n ay r ow b iy	0.90	n ay r ow b iy	munich	m y uw n ax kd	0.90	m y uw n ax kd
named	n ey m dd	0.99	n ey m dd	muskogee	m ax s k- ow g iy	0.88	m ax s k- ow g iy
<b>nanchang</b>	n ae n dd ch ae ng	0.92	n ae n ch ae ng	<b>myanmar</b>	m ay ae n m aa r	0.66	m ( iy   ay ) ( aa   ax ) n m aa r
nantucket	n ae n t ah k ax td n ae n t ah k eh td	0.78 0.12	n ae n t ah k ax td		m iy ax n m aa r m y aa n m aa r	0.16 0.16	
naples	n ey p ax l z	0.99	n ey p ax l z	myrtle	m er tf ax l	0.98	m er tf ax l
nashville	n ae sh v ih l	0.97	n ae sh v ih l	<b>nagano</b>	n aa g ax n ow n aa g aa n ow	0.47 0.36	n aa g aa n ow
<b>natchez</b>	n ae ch iy z n ae ch ax z n ae ch ax z s	0.66 0.21 0.11	n ae ch ax z	name	n ey m	0.99	n ey m
near	n ih r n y ih r	0.44 0.27	n ih r	names	n ey m z	1	n ey m z
neat	n iy td	0.99	n iy td	nanjing	n ae n jh ih ng	0.98	n ae n jh ih ng
need	n iy dd	0.99	n iy dd	naperville	n ey p er v ih l	0.89	n ey p er v ih l
nepal	n ax p ao l n ey p ao l n ax p aa l n eh p aa l	0.36 0.23 0.19 0.09	n ax p ( aa l   ao l )	nashua	n ae sh uw ax	0.89	n ae sh uw ax
nevada	n ax v ae df ax n ax v aa df ax	0.67 0.32	n ax v ( ae   aa ) df ax	nassau	n ae s ao n ae s ao l n ae s s ao	0.39 0.16 0.13	n ae s ao
new	n uw	0.99	n uw	national	n ae sh ax n ax l n ae sh n ax l	0.80 0.14	n ae sh ( ax n   n ) ax l
<b>newfoundland</b>	n uw f ao n dd l ae n dd n uw f ax n dd l ax n dd n uw f ax n dd l ae n dd n uw f ax n dd l aa n dd	0.30 0.28 0.24 0.09	n uw f ax n dd l ax n dd	nearest	n ih r ax s td n iy ax s td	0.77 0.11	n ih r ax s td
newport	n uw p ao r td	0.89	n uw p ao r td	nebraska	n ax b r ae s k ax	0.99	n ax b r ae s k ax
next	n eh kd s td	0.91	n eh kd s td	neither	n iy dh er	0.45	n ( ay   iy ) dh er
<b>nicaragua</b>	n ih k ax r aa gd w ax n ih k ax r aa gd w aa	0.56 0.35	n ih k ax r aa g w ax		n ay tf er n ay td er	0.17 0.13	
nigeria	n ay jh ih r iy ax	0.94	n ay jh ih r iy ax		n iy dh eh r	0.10	
nighttime	n ay td t ay m	0.99	n ay td t ay m	netherlands	n ay dh er	0.09	n eh dh er l ax n dd z
nineteen	n ay n t iy n	0.99	n ay n t iy n	never	n eh dh er l ax n dd z n eh v er	0.99 0.98	n eh v er
ninety	n ay n d iy n ay nt iy	0.81 0.18	n ay ( nt   n d ) iy	<b>newark</b>	n uw ao r kd	0.68	n ( uw er   uw aa r   ao r ) kd
ninth	n ay n th	0.91	n ay n th		n uw er kd n uw kd	0.14 1	
nome	n ow m	0.93	n ow m	<b>newk</b>	n uw kd	1	
noon	n uw n	0.99	n uw n	news	n uw z	0.99	n uw z
norfolk	n ao r f ax kd n ao r f ao l kd n ao r f ax l kd n ao r f ow kd	0.46 0.20 0.17 0.11	n ao r f ax kd	<b>niagara</b>	n ay ae gd r ax n ay ae g r ax	0.59 0.25	n ay ae g r ax
<b>normally</b>	n ao r ax l iy	0.99	n ao r m ax l iy	nice	n ay s n iy s	0.76 0.23	n ( iy   ay ) s
northeast	n ao r th iy s td n ao r t iy s td	0.74 0.23	n ao r th iy s td	night	n ay td	0.99	n ay td
northern	n ao r dh er n	0.96	n ao r dh er n	nine	n ay n	0.96	n ay n
<b>norway</b>	n ao r w eh ey n ao r w ey	0.52 0.21	n ao r w ey	nineteenth	n ay n t iy n th	0.99	n ay n t iy n th
nothing	n ah th ih ng	0.99	n ah th ih ng	nino	n iy n y ow	0.92	n iy n y ? ow
november	n ow v eh m b er	0.92	n ow v eh m b er	no	n ow	0.99	n ow
number	n ah m b er	0.93	n ah m b er	none	n ah n n aa n	0.81 0.11	n ah n
o	ow ow ax l	0.88 0.10	ow	nope	n ow pd	0.99	n ow pd
<b>obispo</b>	ax b ih s p ow ax b ih z p ow ow b ih s p ow	0.26 0.24 0.13	ax b ih z p ow	normal	n ao r m ax l	0.99	n ao r m ax l
occured	ax k er dd	0.99	ax k er dd	north	n ao r th	0.99	n ao r th
				<b>northeastern</b>	n ao r th hh iy s t er n n ao r th iy s t er n	0.90 0.09	n ao r th iy s t er n
				northwest	n ao r th w eh s td	0.92	n ao r th w eh s td
				not	n aa td ow n ow	0.58 0.16 0.14	n aa td
				nova	n ow v ax	0.99	n ow v ax
				now	n aw	0.95	n aw
				numbers	n ah m b er z n ah m b er z s	0.46 0.25	n ah m b er z



Word	PMM Baseforms	Weight	Expert Baseform	Word	PMM Baseforms	Weight	Expert Baseform
october	aa kd t ow b er	0.97	aa kd t ow b er		n ow m b er z	0.15	
off	ao f	0.88	ao f	oakland	ow kd l ax n dd	0.93	ow kd l ax n dd
	aa f	0.11		occur	ax k er	0.99	ax k er
ogden	aa gd d ax n	0.95	aa gd d ax n	ocean	ow sh ax n	0.86	ow sh ax n
okay	ow k ey	0.92	ow k ey	of	ax v	0.76	( ah   ax ) v
old	ow l dd	0.93	ow l dd	offer	ao f er	0.73	ao f er
omaha	ow m ax hh aa	0.84	ow m ax hh ( aa   ao )		aa f er	0.25	
	ow m ax hh ao	0.12		ohio	ow hh ay ow	0.98	ow hh ay ow
once	w ah n s	0.45	w ah n s	oklahoma	ow kd l ax hh ow m ax	0.98	ow kd l ax hh ow m ax
	w aa n s	0.33		olympia	ax l ih m p iy ax	0.48	( ow   ax ) l ih m p iy ax
	w ah n s eh	0.20			ow l ih m p iy ax	0.36	
only	ow n l iy	0.31	ow n l iy	on	aa n	0.94	( ah   aa ) n
	ao n l iy	0.18		one	w ah n	0.90	w ah n
	ow n iy	0.14			w aa n	0.09	
	ow l iy	0.12		ontario	aa n t eh r iy ow	0.96	aa n t eh r iy ow
	ow ax l iy	0.11		or	ao r	0.93	ao r
	ao l iy	0.09		order	ao r df er	0.80	ao r df er
options	aa pd sh ax n z	0.89	aa pd sh ax n z		ow r df er	0.18	
<b>orange</b>	ao r n jh	0.56	ao r ax n jh	orient	ao r iy ax n td	0.66	ao r iy ( eh   ax ) n td
	ao r ax n jh	0.43			ao r iy eh n	0.22	
oregon	ao r ax g ax n	0.88	ao r ax g ( aa   ax ) n		ao r iy eh nt	0.11	
	ao r ax g aa n	0.10		orleans	ao r l ax n z	0.71	ao r l ( ax   iy   iy ax ) n z
					ao r l iy n z	0.20	
orlando	ao r l ae n d ow	0.98	ao r l ae n d ow	osaka	ow s aa k ax	0.99	ow s aa k ax
<b>orly</b>	w ao r l iy	0.73	ao r l iy	other	ah dh er	0.94	ah dh er
	ao r l iy	0.26		our	aa r	0.43	( aw er   aa r )
oslo	aa z l ow	0.47	aa ( z   s ) l ow		ax ey	0.31	
	aa s l ow	0.46			aa r ey	0.23	
<b>ottawa</b>	aa tf ax w aa	0.57	aa tf ax w ax	outlook	aw td l uh kd	0.92	aw td l uh kd
	aa tf ax w ax	0.34		over	ow v er	0.98	ow v er
out	aw td	0.98	aw td	overnight	ow v er n ay td	0.99	ow v er n ay td
outside	aw td s ay dd	0.91	aw td s ay dd	ozone	ow z ow n	0.79	ow z ow n
overcast	ow v er k ae s td	0.99	ow v er k ae s td		ow z ow n ax td	0.19	
oxford	aa kd s f er dd	0.62	aa kd s f er dd	pacific	p ax s ih f ax kd	0.92	p ax s ih f ax kd
	aa kd s f er td	0.35		palm	p aa m	0.73	p aa l ? m
p	p iy	0.67	p iy		p aa l m	0.23	
	p iy ey	0.26		panama	p ae n ax m aa	0.91	p ae n ax m aa
pakistan	p ae k ax s t ae n	0.62	p ae k ax s t ae n	pardon	p aa r dd en	0.74	p aa r dd en
	p ae k ax s t ax n	0.11			p aa r df ax n	0.17	
	p aa k ax s t aa n	0.10		park	p aa r kd	0.99	p aa r kd
palo	p aa l ow	0.63	p ( ae   aa ) l ow	<b>participating</b>	p ax r tf ax s ax p ey tf	0.77	p aa r t ih s ax p ey tf
	p ae l ow	0.33			ih ng		ih ng
paraguay	p ae r ax g w ay	0.46	p ae r ax g w ( ay   ey )		p ax r t ih s ax p ey tf	0.17	
				pasadena	p ae s ax d iy n ax	0.99	p ae s ax d iy n ax
	p ae r ax g w eh ey	0.22		past	p ae s td	0.99	p ae s td
	p ae r ax g w ey	0.22		<b>paulo</b>	p aa l ow	0.49	p ( aw   ao ) l ow
paris	p ae r ax s	0.97	p ae r ax s		p ao l ow	0.37	
part	p aa r td	0.99	p aa r td	<b>pearson</b>	k er s ax n	0.99	p ih r s ax n
partly	p aa r td l iy	0.94	p aa r td l iy	peking	p iy k ih ng	0.65	p iy k ih ng
paso	p ae s ow	0.85	p ae s ow		p ey k ih ng	0.33	
paul	p ao l	0.97	p ao l	<b>penh</b>	p ae n	0.97	p eh n
paz	p aa z	0.78	p aa z	pensacola	p eh n s ax k ow l ax	0.83	p eh n s ax k ow l ax
	p aa ay z	0.11		<b>peoria</b>	p y ao r iy ax	0.71	p iy ao r iy ax
pegasus	p eh g ax s ax s	0.79	p eh g ax s ax s		p iy ao r iy ax	0.24	
	p ey g ax s ax s	0.16		percentage	p er s eh nt ax jh	0.85	p er s eh nt ax jh
pendleton	p eh n d ax l tf ax n	0.34	p eh n d ax l tf ax n	peru	p er uw	0.36	p er uw
	p eh n dd ax l tf ax n	0.33			p ax r uw	0.25	
	p eh n ax l tf ax n	0.20					

Word	PMM Baseforms	Weight	Expert Baseform	Word	PMM Baseforms	Weight	Expert Baseform
pennsylvania	p eh n s ax l v ey n y ax	0.99	p eh n s ax l v ey n y ax	philadelphia	f ih l ax d eh l f iy ax	0.97	f ih l ax d eh l f iy ax
people	p iy p ax l	0.92	p iy p ax l	phnom	n aa m	0.99	( f n   p n   n ) aa m
percent	p er s eh n td	0.81	p er s eh n td	phone	f ow n	0.91	f ow n
perth	p er th	0.89	p er th	pierre	p iy eh r	0.86	p iy eh r
petersburg	p iy tf er z b er gd	0.98	p iy tf er z b er gd	<u>piscataway</u>	p ih s k ae tf ax w ey	0.38	p ax s k ae tf ax w ey
philippines	f ih l ax p iy n z	0.99	f ih l ax p iy n z		p ax s k ae tf ax w ey	0.37	
phoenix	f iy n ax kd s	0.99	f iy n ax kd s		p ax s k ae tf ax w ay	0.10	
picture	p ih kd ch er	0.99	p ih kd ( ch   sh ) er	pittsfield	p ih td s f iy l dd	0.97	p ih td s f iy l dd
pine	p ay n	0.99	p ay n	place	p l ey s	0.99	p l ey s
pittsburgh	p ih td s b er gd	0.99	p ih td s b er gd	plain	p l ey n	0.98	p l ey n
pizza	p iy td s ax	0.99	p iy td s ax	planet	p l ae n ax td	0.76	p l ae n ax td
places	p l ey s ax z	0.95	p l ey s ax z		p l ae n ey	0.09	
plains	p l ey n z	0.90	p l ey n z	platte	p l ae td	0.86	p l ae td
	p l ay ae n z	0.09			p l ax td	0.12	
planning	p l ae n ih ng	1	p l ae n ih ng	please	p l iy z	0.99	p l iy z
play	p l ey	0.84	p l ey	plymouth	p lih m ax th	0.71	p lih m ax th
	p l ay	0.11			p lih m ax th td	0.09	
plus	p l ah s	0.77	p l ah s	point	p oy n td	0.93	p oy n td
	p l ax s	0.15		<u>pole</u>	p ao l	0.39	p ow l
pocatello	p ow k ax t eh l ow	0.90	p ow k ax t eh l ow		p ow l	0.37	
	p aa k ax t eh l ax	0.09			p ow ax l	0.13	
poland	p ow l ax n dd	0.97	p ow l ax n dd	population	p aa pd y ax l ey sh ax n	0.85	p aa pd y ax l ey sh ax n
pollen	p aa l ax n	0.92	p aa l ax n	portland	p ao r td l ax n dd	0.99	p ao r td l ax n dd
port	p ao r td	0.98	p ao r td	portugal	p ao r ch ax g ax l	0.99	p ao r ch ax g ax l
portsmouth	p ao r td s m ax th	0.96	p ao r td s m ax th	possible	p aa s ax b ax l	0.67	p aa s ax b ax l
possibility	p aa s ax b ih l ax tf iy	0.99	p aa s ax b ih l ax tf iy		p aa s ax b ax l z	0.32	
poughkeepsie	p ax k ih pd s iy	0.95	p ax k ih pd s iy	<u>powell</u>	p ao l	0.49	p aw ax l
prague	p r aa gd	0.73	p r aa gd		p aa ax l	0.39	
	p r aa kd	0.14			p aw ax l	0.11	
predict	p r ax d ih kd td	0.99	p r ax d ih kd td	precipitation	p r ax s ih p ax t ey sh ax n	0.95	p r ax s ih p ax t ey sh ax n
predicting	p r ax d ih kd t ih ng	0.99	p r ax d ih kd t ih ng	predicted	p r ax d ih kd t ax dd	0.99	p r ax d ih kd t ax dd
predictions	p r ax d ih kd sh ax n z	0.99	p r ax d ih kd sh ax n z	prediction	p r ax d ih kd sh ax n	0.99	p r ax d ih kd sh ax n
president	p r eh z ax df ax n td	0.96	p r eh z ax df ax n td	present	p r eh z ax n td	0.99	p r eh z ax n td
pressure	p r eh sh er	0.99	p r eh sh er	presque	p r eh s kd	0.60	p r eh s kd
pretty	p r ih tf iy	0.99	p r ih tf iy		p r eh sh kd	0.31	
prince	p r ih n s	0.73	p r ih n s	pretoria	p r ax t ao r iy ax	0.87	p r ax t ao r iy ax
	p r ax n td s	0.25			p r ax t ao r y ax	0.09	
probability	p r aa b ax b ih l ax tf iy	0.94	p r aa b ax b ih l ax tf iy	price	p r ay s	0.99	p r ay s
program	p r ow gd r ae m	0.99	p r ow gd r ae m	princeton	p r ih n s t ax n	0.90	p r ih n s t ax n
projected	p r ax jh eh kd t ax dd	0.99	p r ax jh eh kd t ax dd	<u>probably</u>	p r aa b ax l iy	0.99	p r aa b ax b l iy
provide	p r ax v ay dd	0.99	p r ax v ay dd	project	p r aa jh eh kd td	0.79	p r ( ax   aa ) jh eh kd td
<u>provincetown</u>	p r aa v ax n s t aw n	0.87	p r aa v ax n s t- aw n		p r aa jh ax kd td	0.16	
	p r aa v ax n s t ax v n	0.12		projection	p r ax jh eh kd sh ax n	0.99	p r ax jh eh kd sh ax n
<u>pueblo</u>	p w eh bd l ow	0.43	p w eh b l ow	providence	p r aa v ax df ax n s	0.93	p r aa v ax df ax n s
	p w eh b l ow	0.40		provo	p r ow v ow	0.99	p r ow v ow
puson	p uw s aa n	0.99	p uw s aa n	puerto	p ao r tf ax	0.59	p ( w eh   ao ) r tf ( ow   ax )
<u>q</u>	k y uw z	0.50	k y uw		p ao r tf ow	0.37	
	k y uw	0.49		pyongyang	p y aa ng y ae ng	0.47	p y ( aa   ah ) ng y ( aa   ae ) ng
quality	k w aa l ax tf iy	0.97	k w aa l ax tf iy		p y ah ng y ae ng	0.25	
queens	k w iy n z	0.90	k w iy n z		p y aa ng y ax ih ng	0.11	
question	k w eh s ch ax n	0.52	k w eh ( s ch   sh ch ? ) ax n	<u>qingdao</u>	ch iy ng d aa ow	0.70	ch iy ng d aw
	k w eh sh ax n	0.29			qh ih ng d aw	0.16	
	k w eh sh ch ax n	0.10		quebec	k ax b eh kd	0.56	k ( ax   w ax ) b eh kd
quincy	k w ih n s iy	0.48	k w ih n ( s   z ) iy		k w ax b eh kd	0.32	
	k w ih n z iy	0.32			k w ax b ae kd	0.09	
	k ih n iy	0.14		<u>query</u>	k r iy	0.34	k w ( ih r   eh r ) iy

Word	PMM Baseforms	Weight	Expert Baseform	Word	PMM Baseforms	Weight	Expert Baseform
quite	k w ay td	0.99	k w ay td		k w eh r iy	0.33	
r	aa r	0.85	aa r		k w ih r iy	0.31	
rain	r ey n	0.99	r ey n	questions	k w eh s ch ax n z	0.62	k w eh ( s ch   sh ch ? ) ax n z
rained	r ey n dd	0.99	r ey n dd		k w eh sh ax n z	0.35	
raining	r ey n ih ng	0.98	r ey n ih ng	quit	k w ih td	0.75	k w ih td
rainy	r ey n iy	0.99	r ey n iy		k w eh td	0.23	
range	r ey n jh	0.97	r ey n jh	<u>quito</u>	k iy tf ow	0.48	k ( iy t   w iy tf ) ow
rapid	r ae p ax dd	0.72	r ae p ax dd		k iy t ow	0.28	
	r ae p ax td	0.17			k w iy tf ow	0.15	
raton	r ax t ow n	0.79	r ax t ow n	<u>rabat</u>	r aa b ao td	0.94	r ax b aa td
reading	r eh df ih ng	0.86	r ( eh   iy ) df ih ng	raincoat	r ey n k ow td	0.96	r ey n k ow td
	r iy df ih ng	0.12		rainfall	r ey n f ao l	0.98	r ey n f ao l
really	r iy l iy	0.83	r iy l iy	rains	r ey n z	0.88	r ey n z
received	r ax s iy v dd	0.99	r ax s iy v dd		r ey n s	0.11	
recognition	r eh k ax gd n ih sh ax n	0.87	r eh k ax gd n ih sh ax n	raleigh	r aa l iy	0.83	r ( aa l   ao l ) iy
	r eh k ax gd n dd ih sh ax n	0.12			r ao l iy	0.10	
record	r eh k er dd	0.99	r ( eh k er   ax k ao r ) dd	ranges	r ey n jh ax z	0.68	r ey n jh ax z
regarding	r iy g aa r df ih ng	0.99	r ( iy   ax ) g aa r df ih ng		r ey n jh iy z s	0.27	
region	r iy jh ax n	0.95	r iy jh ax n	rapids	r ae p ax dd z	0.98	r ae p ax dd z
relative	r eh l ax tf ih v	0.66	r eh l ax tf ( ih   ax ) v	reach	r iy ch	0.80	r iy ch
	r eh l ax tf ax v	0.25			r iy ch s	0.10	
repeat	r ax p iy td	0.50	r ( iy   ax ) p iy td	readings	r iy df ih ng z	0.49	r iy df ih ng z
	r iy p iy td	0.48			r iy ih ng z	0.44	
report	r iy p ao r td	0.55	r ( iy   ax ) p ao r td	<u>receive</u>	r iy s iy v	0.61	r ax s iy v
	r ax p ao r td	0.44			r ax s iy v	0.38	
reports	r iy p ao r td s	0.50	r ( iy   ax ) p ao r td s	recently	r iy s ax n td l iy	0.93	r iy s ax n td l iy
	r ax p ao r td s	0.48		recognize	r eh k ax gd n ay z	0.46	r eh k ax gd n ay z
request	r ax k w eh s td	0.49	r ( iy   ax ) k w eh s td		ax r eh k ax gd n ay z	0.22	
	r iy k w eh s td	0.45			r eh k ax gd n ay z z	0.13	
restart	r iy s t- aa r td	0.99	r iy s t- aa r td	redmond	r eh k ax gd n ay s ax	0.12	
restaurants	r eh s tr r aa n td s	0.59	r eh s ( tr r   t ax r ) ( ax   aa ) n td s		r eh dd m ax n dd	0.99	r eh dd m ax n dd
	r eh s t ax r aa n td s	0.21		regina	r ax jh ay n ax	0.53	r ax ( jh   g ) ( iy   ay ) n ax
reykjavik	r ey kd y ax v ih kd	0.46	r ey kd ( iy ax   y ax ) v ih kd		r iy jh ay n ax	0.28	
	r ey kd jh ax v ih kd	0.19			r ax jh ax n ax	0.10	
	r ey kd y ax v iy kd	0.13		related	r iy l ey tf ax dd	0.75	r ( iy   ax ) l ey tf ax dd
rhodes	r ow dd z	0.91	r ow dd z		r ax l ey dd	0.23	
richmond	r ih ch m ax n dd	0.94	r ih ch m ax n dd	reno	r iy n ow	0.89	r iy n ow
right	r ay td	0.99	r ay td	rephrase	r iy f r ey z	0.99	r ( iy   ax ) f r ey z
rise	r ay z	0.99	r ay z	reported	r ax p ao r tf ax dd	0.59	r ( iy   ax ) p ao r tf ax dd
river	r ih v er	0.91	r ih v er		r iy p ao r tf ax dd	0.29	
road	r ow dd	0.99	r ow dd		r iy p ao r df ax dd	0.10	
rochester	r aa ch eh s t er	0.97	r aa ch eh s t er	republic	r ax p ah bd l ax kd	0.57	r ( iy   ax ) p ah bd l ax kd
rockford	r aa kd f er dd	0.93	r aa kd f er dd		r iy p ah bd l ax kd	0.42	
rocky	r aa k iy	0.99	r aa k iy	rest	r eh s td	0.93	r eh s td
rome	r ow m	0.98	r ow m	restaurant	r eh s tr r aa n td	0.40	r eh s ( tr r   t ax r ) ( ax   aa ) n td
rosa	r ow z ax	0.91	r ow z ax		r eh s tr r ax n td	0.18	
rouge	r uw zh	0.80	r uw zh		r ax s t ax r ax n td	0.15	
	r uw jh	0.18			r eh s t er aa n td	0.09	
rutland	r ah td l ax n dd	0.96	r ah td l ax n dd	reston	r eh s t ax n	0.99	r eh s t ax n
sacramento	s ae kd r ax m eh nt ow	0.98	s ae kd r ax m eh nt ow	rhode	r ow dd	0.99	r ow dd
said	s eh dd	0.81	s eh dd	rica	r iy k ax	0.98	r iy k ax
salem	s ey l ax m	0.99	s ey l ax m	rico	r iy k ow	0.99	r iy k ow
salisbury	s ao l z b eh r iy	0.84	s ao l z b ( er   eh r ) iy	rio	r iy ow	0.94	r iy ow
salvador	s ae l v ax d ao r	0.95	s ae l v ax d ao r	rising	r ay z ih ng	0.90	r ay z ih ng
same	s ey m	0.99	s ey m		ax r ay z ih ng	0.09	
san	s ae n	0.99	s ae n	riyadh	r iy aa dd	0.41	r iy aa dd

Word	PMM Baseforms	Weight	Expert Baseform	Word	PMM Baseforms	Weight	Expert Baseform
sanibel	s ae n ax b eh l	0.83	s ae n ax b ( ax l   eh l )		r iy ae dd	0.24	
santiago	s ae n ax b eh l l	0.16			r iy y ae dd	0.17	
	s aa nt iy aa g ow	0.40	s aa nt iy aa g ow	roanoke	r iy ax dd	0.09	
	s ah nt iy aa g ow	0.29		rock	r ow ax n ow kd	0.90	r ow ax n ow kd
	s ae nt iy aa g ow	0.27		rockville	r aa kd	0.98	r aa kd
sao	s aw	0.83	s aw	<u>romania</u>	r aa kd v ih l	0.93	r aa kd v ih l
	s ow	0.09			r ow m ey n y ax	0.45	r ow m ey n y ax
sarajevo	s ae r ax y ey v ow	0.35	s ( aa r   ae r ) ax y ey v ow		r ah m ey n y ax	0.17	
	s eh r ax y ey v ow	0.25			r ah m ey n iy ax	0.13	
	s aa r ax y ax v ow	0.19		root	r ow m iy n y ax	0.09	
<u>sardinia</u>	s eh r d iy n y ax	0.47	s aa r d iy n ( y ax   iy ax )		r uw td	0.65	r ( uw   uh ) td
	s aa r d iy n y ax	0.26		<u>rotterdam</u>	r uh td	0.34	
	s aa r d iy n iy ax	0.24		russia	ax r aa tf er d ae m	0.93	r aa tf er d ae m
saskatoon	s ae s k ax t uw n	0.99	s ( ae   aa ) s k ax t uw n		r ah sh ax	0.95	r ah sh ax
saturday	s ae tf er df ey	0.99	s ae tf er df ey	s	eh s	0.93	eh s
saudi	s aw df iy	0.71	s ( ao   aw ) df iy	<u>saginaw</u>	s ae g ax n aa	0.64	s ae g ax n ao
	s ao df iy	0.25			s ey g ax n aa	0.25	
savannah	s ax v ae n ax	0.87	s ax v ae n ax	saint	s ae g ax n ao ow	0.09	
<u>scandinavia</u>	s k- ih n d ax n ey v iy ax	0.99	s k- ae n d ax n ey v iy ax	<u>salina</u>	s ey n td	0.97	s ey n td
science	s ay ax n s	1	s ay ax n s		s ax l ay n ax	0.49	s ax l iy n ax
scores	s k- ao r z	0.43	s k- ao r z		s ae l ax n ax	0.15	
	s k- ao r s	0.38		salt	s ao l ay n ax	0.14	
	s k- ao r ax s	0.11		salzburg	s ao l td	0.97	s ao l td
scotland	s k- aa td l ax n dd	0.98	s k- aa td l ax n dd		s ao l td s b er gd	0.61	s ao l td s b er gd
scottsdale	s k- aa td s d ey l	0.83	s k- aa td s d ey l	samoa	s ao l z b er gd	0.38	
scratch	s k- r ae ch	0.89	s k- r ae ch		s ax m ow ax	0.85	s ax m ow ax
	s r ch	0.10		sandusky	s ax b ow ax	0.10	
<u>sea</u>	s iy s iy	0.45	s iy		s ae n d ah s k iy	0.51	s ae n d ah s k iy
	s y uw	0.22		santa	s ax n d ah s k iy	0.42	
	s iy uw	0.20		<u>santo</u>	s ae nt ax	0.99	s ae nt ax
	s iy	0.11			s ae nt ax	0.64	s ae nt ow
season	s iy z ax n	0.99	s iy z ax n	sapporo	s ey nt ax	0.18	
second	s eh k ax n dd	0.96	s eh k ax n dd		s ae nt ow	0.15	
select	s ax l eh kd td	0.99	s ax l eh kd td	sarasota	s ax p ao r ow	0.99	s ( aa   ax ) p ao r ow
senegal	s eh n ax g ao l	0.61	s eh n ax g ao l	saskatchewan	s ae r ax s ow tf ax	0.99	s ae r ax s ow tf ax
	s eh n ax g aa l	0.30			s ae s k ae ch ax w aa n	0.46	s ae s k ae ch ax w aa n
september	s eh pd t eh m b er	0.87	s eh pd t eh m b er		s ax s k ae ch ax w aa n	0.38	
	s ax pd t eh m b er	0.10		satellite	s ax s k- ae ch ax w aa n	0.09	
service	s er v ax s	0.64	s er v ax s	saturn	s ae tf ax l ay td	0.99	s ae tf ax l ay td
	s er v ay s	0.16		sausality	s ae tf er n	0.99	s ae tf er n
	s s er v ax s	0.11		say	s ao s ax l iy tf ow	0.82	s ao s ax l iy tf ow
setting	s eh tf ih ng	0.99	s eh tf ih ng	schedules	s aw td s ax l iy tf ow	0.09	
seventeenth	s eh v ax n t iy n th	0.94	s eh v ax n t iy n th	<u>score</u>	s ey	0.90	s ey
seventy	s eh v ax n d iy	0.89	s eh v ax ( nt   n d ) iy		s k- eh jh ax l z	0.99	s k- eh jh ( uh l   ax l ) z
seville	s ax v ih l	0.86	s ax v ih l		s k- ow	0.38	s k- ao r
	s ax v ih l l	0.12		scotia	s k- ao r	0.33	
shanghai	sh ae ng hh ay	0.82	sh ae ng hh ay	scott's	s k- w ao r	0.27	
shining	sh ay n ih ng	0.91	sh ay n ih ng	scranton	s k- ow sh ax	0.93	s k- ow sh ax
shore	sh ao r	0.99	sh ao r	screwed	s k- aa td s	0.99	s k- aa td s
should	sh uh dd	0.66	sh uh dd	seal	s k- r ae n tq en	0.92	s k- r ae n tq en
	sh ax dd	0.20		seattle	s k- r uw dd	0.99	s k- r uw dd
	ch uh dd	0.11		see	s iy l	0.48	s iy l
showers	sh aw er z	0.87	sh aw er z		s y ax l	0.30	
shut	sh ah td	0.22	sh ah td		s iy ax l	0.12	
	sh aw td	0.21			s iy ae tf ax l	0.99	s iy ae tf ax l
	sh ah td ax	0.15			s iy	0.93	s iy

Word	PMM Baseforms	Weight	Expert Baseform	Word	PMM Baseforms	Weight	Expert Baseform
sically <u>significant</u>	sh ax td	0.14	s ih s ax l iy s ax gd n ih f ax k ax n td	seneca	s eh n ax k ax	0.99	s eh n ax k ax
	sh ah tf ax	0.13		seoul	s ow l	0.73	s ow l
	s ih s ax l iy	0.99		serbia	s ow ax l	0.11	s er b iy ax
	s ax gd n ih f ax kd eh n td	0.42			s er b iy ax	0.88	
	s ax gd n ih f ax kd ae n td	0.23			s er b iy ae m	0.10	
	s ax gd n ih f ax k ax n t ax	0.22					
sioux	s uw	0.84	s uw				
	s s uw	0.09		seven	s eh v ax n	0.99	s eh v ax n
six	s ih kd s	0.96	s ih kd s	seventh	s eh v ax n th	0.99	s eh v ax n th
sixth	s ih kd s th	0.96	s ih kd s th	severe	s ax v ih r	0.94	s ax v ih r
ski	s k- iy	0.89	s k- iy	sex	s eh kd s	0.93	s eh kd s
sky	s k- ay	0.94	s k- ay	shine	sh ay n	0.99	sh ay n
sleet	s l iy td	0.86	s l iy td	shit	sh ih td	0.51	sh ih td
	s l iy iy td	0.13		<u>short</u>	sh ax t s	0.36	
slow	s l ow	0.99	s l ow	show	sh r	0.99	sh ao r td
smith	s m ih th	0.55	s m ih th	shreveport	sh ow	0.94	sh ow
	s m ih td	0.31		siberia	sh r iy v p ao r td	0.96	sh r iy v p ao r td
	s m eh th	0.12		side	s ay b ih r iy ax	0.94	s ay b ih r iy ax
snow	s n ow	0.99	s n ow	<u>singapore</u>	s ay dd	0.99	s ay dd
snowed	s n ow dd	0.99	s n ow dd		s ih ng gd ax p ao r	0.51	s ih ng ax p ao r
snowing	s n ow ih ng	0.99	s n ow ih ng	situation	s ih ng ax p ao r	0.44	
snowstorm	s n ow s t ao r m	0.97	s n ow s t ao r m	sixteenth	s ih ch uw ey sh ax n	0.99	s ih ch uw ey sh ax n
snowy	s n ow iy	0.88	s n ow iy	sixty	s ih kd s t iy n th	0.86	s ih kd s t iy n th
<u>sofia</u>	s ow f iy ao	0.33	s ow f iy ax		s ih kd s t iy	0.67	s ih kd s t iy
	s ow f iy ax	0.30		skiing	s ih kd s t ax	0.14	
	s ow f iy ax b y ax	0.19		sleep	s k- iy ih ng	0.99	s k- iy ih ng
	s ow ax f y ax	0.14			s l iy pd	0.62	s l iy pd
some	s ah m	0.70	s ah m	<u>slovakia</u>	s l iy	0.37	
	s ax m	0.29			s l ow v aa kd y ax	0.46	s l ow v aa k iy ax
something	s ah m th ih ng	0.96	s ah m th ih ng		s l ow v aa kd y uw	0.22	
somewhere	s ah m w eh r	0.84	s ah m w eh r		s l ax v aa k iy ax	0.18	
sorry	s aa r iy	0.62	s ( aa r   ao r ) iy	smart	s l ow v aa k y ax	0.11	
	s ao r iy	0.20		smog	s m aa r td	0.92	s m aa r td
	s aa r ay	0.10			s m aa gd	0.77	s m aa gd
sounds	s aw n dd z	0.99	s aw n dd z	<u>snowbase</u>	s m ao gd	0.22	
southeast	s aw th iy s td	0.95	s aw th iy s td		eh s n ow b ey s	0.53	s n ow b ey s
southern	s ah dh er n	0.94	s ah dh er n	snowfall	s n ow b ey s	0.46	
southwest	s aw th w eh s td	0.95	s aw th w eh s td	snowmass	s n ow f ao l	0.97	s n ow f ao l
<u>space</u>	s p- iy s	0.49	s p- ey s	snowstorms	s n ow m ae s	0.99	s n ow m ae s
	s p- ey sh y ax	0.27			s n ow s t ao r m z	0.78	s n ow s t ao r m z
	s p- ey sh	0.20		so	s n ow ax s t- ao r m z	0.11	
spanish	s p- ae n ax sh	0.56	s p- ae n ax sh		s ow	0.86	s ow
	s p ae n ax sh	0.18		somalia	s ax	0.09	
					s ax m aa l y ax	0.65	s ( ow   ax ) m aa l ( iy ax   y ax )
	s p- ae n ih z	0.11					
	s p- ae n ax s	0.09		someone	s ax m aa l iy ax	0.28	
specific	s p- iy kd	0.99	s p- iy kd		s ah m w ah n	0.55	s ah m w ( ah   ax ) n
speed	s p- ax s ih f ax kd	0.99	s p- ax s ih f ax kd	sometime	s ah m w aa n	0.44	
spell	s p- iy dd	0.99	s p- iy dd		s ah m t ay m	0.66	s ah m t ay m
sports	s p- eh l	0.99	s p- eh l	soon	ax s ah m t ay m	0.33	
spring	s p- ao r td s	0.93	s p- ao r td s		s uw n	0.64	s uw n
spring	s p- r ih ng	0.99	s p- r ih ng	sound	s ax n	0.27	
springs	s p- r ih ng z	0.99	s p- r ih ng z	south	s aw n dd	0.99	s aw n dd
squall	s k- w ao l	0.52	s k- w ao l	southeastern	s aw th	0.99	s aw th
	s k- w aa	0.47			s aw th iy s t er n	0.40	s aw th iy s t er n
sri	s r iy	0.72	( s   sh ) r iy		s aw th iy z t er n	0.35	
	sh r iy	0.21		southernmost	s aw th iy sh t er n	0.21	
					s ah dh er n m ow s td	0.99	s ah dh er n m ow s td

Word	PMM Baseforms	Weight	Expert Baseform	Word	PMM Baseforms	Weight	Expert Baseform
stafford	s t- ae f er dd	0.99	s t- ae f er dd	southwestern	s aw th w eh s t er n	0.99	s aw th w eh s t er n
stapleton	s t- ey p ax l tf ax n	0.51	s t- ey p ax l tf ax n	spain	s p- ey n	0.96	s p- ey n
	s t- ey p ax l tf s ax n	0.33		spartanburg	s p- aa r tq en b er gd	0.99	s p- aa r tq en b er gd
starting	s t- aa r tf ih ng	0.65	s t- aa r tf ih ng	special	s p- eh sh ax l	0.68	s p- eh sh ax l
	s t- ao r tf ih ng	0.33			s p- ey sh eh l	0.22	
<b>statement</b>	s t- ey td m eh n td	0.52	s t- ey td m ax n td	specifically	s p- ax s ih f ax k l iy	0.82	s p- ax s ih f ax k l iy
	s t- ey td m ax n td	0.47			s p- ax s ih f ax kd l iy	0.17	
status	s t- ae tf ax s	0.98	s t- ( ae   ey ) tf ax s	speeds	s p- iy dd z	0.99	s p- iy dd z
stock	s t- aa kd	0.94	s t- aa kd	spokane	s p- ow k ae n	0.92	s p- ow k ( ae   ey ) n
stockville	s t- aa kd v ih l	0.99	s t- aa kd v ih l	spot	s p- aa td	0.99	s p- aa td
storm	s t- ao r m	0.99	s t- ao r m	springfield	s p- r ih ng f iy l dd	0.81	s p- r ih ng f iy l dd
stormy	s t- ao r m iy	0.99	s t- ao r m iy	sprinkles	s p- r ih ng k ax l z	0.72	s p- r ih ng k ax l z
stupid	s t- uw p ax dd	0.68	s t- uw p ax dd		s p- r ih ng kd ax l z	0.27	
	s t- uw p ih td	0.12		square	s k- w eh r	0.99	s k- w eh r
	s t- uw p ih dd	0.09		st	s ey n td	0.99	s ey n td
<b>suburb</b>	s ax b er bd	0.86	s ah b er bd	stamford	s t- ae m f er dd	0.78	s t- ae m f er dd
	s ah b er bd	0.13		start	s t- aa r td	0.85	s t- aa r td
summary	s ah m ax r iy	1	s ah m ax r iy	state	s t- ey td	0.99	s t- ey td
sun	s ah n	0.99	s ah n	states	s t- ey td s	0.98	s t- ey td s
sunlight	s ah n l ay td	0.96	s ah n l ay td	still	s t- ih l	0.98	s t- ih l
sunnyvale	s ah n iy v ey l	0.98	s ah n iy v ey l	stockholm	s t- aa kd hh ow l m	0.58	s t- aa ( k   kd hh ) ow l m
sure	sh er	0.69	sh ( er   ao r )		s t- aa k ow l m	0.39	
	sh ao r	0.21		stop	s t- aa pd	0.91	s t- aa pd
<b>surfing</b>	s er f iy ng	0.73	s er f ih ng	storms	s t- ao r m z	0.98	s t- ao r m z
	s er f iy ng gd	0.25		strasbourg	s tr r ae s b er gd	0.62	s tr r ( ae   ae ) ( z   s ) b ( er   ao r ) gd
sweden	s w iy dd en	0.93	s w iy dd en		s tr r aa s b er gd	0.17	
sydney	s ih dd n iy	0.98	s ih dd n iy	stuttgart	sh t uh td g aa r td	0.48	sh t uh td g aa r td
syria	s ih r iy ax	0.95	s ih r iy ax		s t- uh td g aa r td	0.18	
systems	s ih s t ax m z	0.77	s ih s t ax m z		s t- ax td g aa r td	0.09	
	s s t ax m z	0.11			sh t uw td g aa r td	0.09	
tacoma	t ax k ow m ax	0.86	t ax k ow m ax	suburbs	s ah b er bd z	0.99	s ah b er bd z
tahoe	t aa hh ow	0.99	t aa hh ow	summer	s ah m er	0.90	s ah m er
taiwan	t ay w aa n	0.99	t ay w aa n	sunday	s ah n d ey	0.98	s ah n d ey
talk	t ao kd	0.53	t ao kd	sunny	s ah n iy	0.99	s ah n iy
	t aa kd	0.46		supposed	s ax p ow z dd	0.69	s ax p ow z dd
tallahassee	t ae l ax hh ae s iy	0.84	t ae l ax hh ae s iy		s ax p ax s td	0.15	
<b>tanzania</b>	t ae n z ey n iy ax	0.57	t ae n z ax n iy ax		s ax p ow s td	0.15	
	t ae n z ax n iy y ax	0.14		surf	s er f	0.91	s er f
	t ae n z ax n iy ax	0.13		<b>sweater</b>	s w ah tf er	0.51	s w eh tf er
tasmania	t ae z m ey n iy ax	0.57	t ae z m ey n iy ax		s w eh tf er	0.48	
	t ae z m iy n y ax	0.11		switzerland	s w ih td s er l ax n dd	0.84	s w ih td ( z   s ) er l ax n dd
	t ae z m ey n iy y ax	0.11			s w ih td s ax l ax n dd	0.14	
	t ae z m ey n y ax	0.11		syracuse	s ih r ax k y uw z	0.49	s ih r ax k y uw ( z   s )
tehran	t eh r aa n	0.49	t eh r aa n		s ih r ax k y uw s	0.36	
	t ey r aa n	0.25		system	s ih s t ax m	0.96	s ih s t ax m
	t iy r aa n	0.24		t	t iy	0.97	t iy
<b>telephone</b>	t eh l ax f ao n	0.49	t eh l ax f ow n	<b>tahiti</b>	t ey hh iy tf iy	0.62	t ax hh iy tf iy
	t eh l ax f ow n	0.35			t ax hh iy tf iy	0.27	
	t eh l ax f ao	0.14		taipei	t ay p ey	0.98	t ay p ey
<b>temecula</b>	t ax m eh kd y uw l ax	0.28	t eh m ax k uw l ax	take	t ey kd	0.95	t ey kd
	t ax m eh k uw l ax	0.24		talking	t ao k ih ng	0.66	t ao k ih ng
	t ax m eh k uw l aa	0.13			t aa k ih ng	0.27	
	t ax m eh kd y uw l aa	0.10		tampa	t ae m p ax	0.95	t ae m p ax
temperatures	t eh m p ax ch er z	0.55	t eh m p ( er ax   r ax   ax ) ch er z	taos	t aa ow s	0.38	t aa ow s
	t eh m p r ax ch er z	0.43			t aw s	0.30	
tennessee	t eh n ax s iy	0.75	t eh n ax s iy		t aw z	0.16	

Word	PMM Baseforms	Weight	Expert Baseform	Word	PMM Baseforms	Weight	Expert Baseform
term	t er m	0.99	t er m		t ay ow z	0.10	
territories	t eh r ax t ao r iy z	0.99	t eh r ax t ao r iy z	<b>tegucigalpa</b>	t eh g uw s iy g aa l p ax	0.23	t ax g uw s ( iy   ax ) g aa l p ax
<b>texarkana</b>	t eh kd s er k ae n ax	0.35	t eh kd s aa r k ae n ax		t ax g uw s ax g ae l p ao	0.19	
	t eh kd s aa r k ae n ax	0.24			t ey g uw s iy g aa l p ax	0.18	
	t eh kd s ax k ae n ax	0.19			t ax g uw s ax g aa l p aa m	0.10	
thailand	t ay l ae n dd	0.64	t ay l ( ae   ax ) n dd		t ax g uw s iy g aa l p aa n	0.09	
	t ay l ax n dd	0.34			t ax g uw s iy g aa l p ax	0.09	
thank	th ae ng kd	0.99	th ae ng kd	tel	t eh l	0.99	t eh l
that	dh ae td	0.97	dh ae td	tell	t eh l	0.99	t eh l
<b>them</b>	ax m	0.35	dh eh m	temperature	t eh m p ax ch er	0.60	t eh m p ( er ax   r ax   ax ) ch er
	dh ax m	0.23			t eh m p r ax ch er	0.37	
	dh eh m	0.13		ten	t eh n	0.76	t eh n
there	dh eh r	0.96	dh eh r		ae n	0.10	
they	dh ey	0.95	dh ey	tenth	t eh n th	0.95	t eh n th
things	th ih ng z	0.99	th ih ng z	terrific	t ax r ih f ax kd	0.99	t ax r ih f ax kd
third	th er dd	0.95	th er dd	test	t eh s td	0.72	t eh s td
thirtieth	th er tf iy ax th	0.95	th er tf iy ax th		t ax s td	0.27	
this	dh ih s	0.98	dh ih s	texas	t eh kd s ax s	0.97	t eh kd s ax s
those	dh ow z	0.91	dh ow z	than	dh ae n	0.43	dh ae n
thousand	th aw z ax n dd	0.99	th aw z ax n dd		dh en	0.25	
three	th r iy	0.94	th r iy		dh ax n	0.21	
<b>throughout</b>	th r ax aw td	0.65	th r uw aw td	thanks	th ae ng kd s	0.99	th ae ng kd s
	th r uw aw td	0.34		the	dh ax	0.58	dh ( ax   ah   ih   iy )
thunderstorm	th ah n d er s t- ao r m	0.98	th ah n d er s t- ao r m		dh ah	0.18	
thursday	th er z d ey	0.99	th er z d ey		dh iy	0.11	
tibet	t ax b eh td	0.76	t ax b eh td		dh ih	0.10	
	t ax b ae td	0.22		then	dh eh n	0.69	dh eh n
tides	t ay dd z	0.99	t ay dd z		dh ax n	0.17	
time	t ay m	0.99	t ay m	these	dh iy z	0.97	dh iy z
to	tf ax	0.40	tf ( ax   uw )	thing	th ih ng	0.90	th ih ng
	tf uw	0.24			th	0.09	
	t uw	0.23		think	th ih ng kd	0.99	th ih ng kd
<b>tokyo</b>	t ow kd y ow	0.83	t ow k ( iy   y ) ow	thirteenth	th er t iy n th	0.99	th er t iy n th
toll	t ow l	0.98	t ow l	thirty	th er tf iy	0.99	th er tf iy
tonight	t ax n ay td	0.99	t ax n ay td	thomas	t aa m ax s	0.89	t aa m ax s
topeka	t ax p iy k ax	0.90	t ax p iy k ax	thought	th ao td	0.99	th ao td
	t ax p iy k ae s	0.09		threatening	th r eh tq en ih ng	0.95	th r eh ( tf ax n   tq en   td n ) ih ng
tornados	t ao r n ey df ow z	0.93	t ( ao r   er ) n ey df ow z	through	th r uw	0.92	th r uw
torrence	t ao r ax n s	0.99	t ao r ax n s	thunder	th ah n d er	0.99	th ah n d er
<b>toulouse</b>	t ax l uw z	0.95	t uw l uw z	thunderstorms	th ah n d er s t- ao r m z	0.99	th ah n d er s t- ao r m z
town	t aw n	0.99	t aw n	<b>tianjin</b>	t ih ae n jh ih n	0.42	t ( iy   y ) ( eh   aa ) n jh ih n
traffic	tr r ae f ax kd	0.94	tr r ae f ax kd		t ih n jh ih n	0.38	
travelling	tr r ae v ax l ih ng	0.99	tr r ae v ax l ih ng		t ih ih n jh ih n	0.16	
trenton	tr r eh n tq en	0.97	tr r eh n tq en	tide	t ay dd	0.99	t ay dd
trip	tr r ih pd	0.99	tr r ih pd	timbuktu	t ih m b ax kd t uw	0.39	t ih m b ax kd t uw
tropical	tr r aa p ax k ax l	0.94	tr r aa p ax k ax l		t ih m b ah kd t uw	0.21	
try	tr r ay	0.96	tr r ay		t ax m b ax kd t uw	0.13	
tucson	t uw s aa n	0.94	t uw s aa n	times	t ay m z	0.98	t ay m z
tulsa	t ah l s ax	0.95	t ah l s ax	today	t ax df ey	0.84	t ax df ey
tunisia	t ax n iy zh ax	0.62	t ( ax   uw ) n iy zh ( ax   iy ax )		t ax d ey	0.14	
	t uw n iy zh ax	0.28		toledo	t ax l iy df ow	0.87	t ax l iy df ow
tuscaloosa	t ah s k ax l uw s ax	0.66	t ah s k ax l uw s ax		tf ax l iy df ow	0.10	
	t ah s k ax l uh z ax	0.20		tomorrow	t ax m aa r ow	0.99	t ax m aa r ow
twelve	t w eh l v	0.80	t w eh l v	too	t uw	0.95	t uw
	ey t w eh l v	0.19		tornado	t ao r n ey df ow	0.90	t ( ao r   er ) n ey df ow
twenty	t w eh nt iy	0.98	t w eh nt iy	toronto	t ax r aa nt ow	0.98	t ax r aa nt ow

Word	PMM Baseforms	Weight	Expert Baseform	Word	PMM Baseforms	Weight	Expert Baseform
two	t uw	0.99	t uw	total	t ow tf ax l	0.96	t ow tf ax l
<b>typhoons</b>	t ay f ax l ax n z	0.27	t ay f uw n z	<b>towards</b>	t ao r dd s iy	0.99	t ( ao r   ax w ao r   w ao r ) dd z
	t ay f ao n z	0.21		towns	t aw n z	0.98	t aw n z
	t ay f uw m	0.16		travel	tr r ae v ax l	0.96	tr r ae v ax l
	t ay f uw n s ax z	0.14		traverse	tr r ae v er s	0.95	tr r ( ae   ax ) v er s
	t ay f uw n z	0.12		trinidad	tr r ih n ax d ae dd	0.99	tr r ih n ax d ae dd
u	y uw	0.96	y uw	<b>tripoli</b>	tr r ih p ax l w iy	0.99	tr r ih p ax l iy
ukraine	y uw k r ey n	0.99	y uw k r ey n	troy	tr r oy	0.82	tr r oy
understand	ah n d er s t- ae n dd	0.81	ah n d er s t- ae n dd		ch er oy	0.15	
universe	y uw n ax v er s	0.99	y uw n ax v er s	trying	tr r ay ih ng	0.83	tr r ay ih ng
up	ah pd	0.81	ah pd		tr r ay	0.13	
upper	ah p er	0.88	ah p er	tuesday	t uw z d ey	0.95	t uw z d ey
	ow p er	0.11		tunis	t uw n ax s	0.54	t uw n ax s
uruguay	y ao r ax g w ay	0.50	y ( er   ao r ) ax g w ( ey   ay )		t uw n ih s	0.33	
	y er ax g w ey	0.49			ch uw n ih s	0.12	
use	y uw z	0.90	y uw ( s   z )	turkey	t er k iy	0.99	t er k iy
usually	y uw zh ax l iy	0.44	y uw zh ( uw ax l   ax l   w ax l ) iy	twelfth	t w eh l f th	0.75	t w eh l f th
	y uw zh uw ax l iy	0.22			t w eh l th	0.16	
	y uw zh l iy	0.16		twentieth	t w eh nt iy ax th	0.99	t w eh nt iy ax th
	y uw zh ax l ay	0.15		twin	t w ih n	0.99	t w ih n
utica	y uw tf ax k ax	0.99	y uw tf ax k ax	typhoon	t ay f uw n	0.99	t ay f uw n
v	v iy	0.86	v iy	typically	t ih p ax k ax l iy	0.99	t ih p ax k ( ax l   l ) iy
	v y ax	0.12		uganda	y uw g aa n d ax	0.99	y uw g aa n d ax
vail	v ey l	0.89	v ey l	umbrella	ax m b r eh l ax	0.36	( ax   ah ) m b r eh l ax
valley	v ae l iy	0.97	v ae l iy		ah m bd r eh l ax	0.21	
vegas	v ey g ax s	0.96	v ey g ax s		ax m bd r eh l ax	0.10	
venezuela	v eh n ax z w ey l ax	0.53	v eh n ax z w ey l ax		ah m b r eh l ax	0.10	
	v eh n ax z w eh l ax	0.42		united	y uw n ay tf ax dd	0.99	y uw n ay tf ax dd
vermont	v er m aa n td	0.97	v er m aa n td	until	ax n t ih l	0.99	ax n t ih l
vero	v ih r ow	0.69	v ( ih   eh ) r ow	update	ah pd d ey td	0.99	ah pd d ey td
	v y ih r ow	0.29		urbana	er b ae n ax	0.99	er b ae n ax
vicinity	v ax s ih n ax tf iy	0.97	v ax s ih n ax tf iy	us	ah s	0.54	ah s
vienna	v iy eh n ax	0.87	v iy eh n ax		ax s	0.38	
view	v y uw	0.99	v y uw	<b>useful</b>	uw s f ax l	0.98	y uw s f ax l
virgin	v er jh ax n	0.98	v er jh ax n	utah	y uw t aa	0.78	y uw t ( ao   aa )
visibility	v ih z ax b ih l ax tf iy	0.99	v ih z ax b ih l ax tf iy	<b>uzbekistan</b>	y uw z b eh k ax s t ae n	0.97	uh z b eh k ax s t aa n
voice	v oy s	0.99	v oy s	vacation	v ey k ey sh ax n	0.89	v ey k ey sh ax n
w	d ah b ax l y uw	0.59	d ah b ( ax l   ax ? ) y ( uw   ax )		v ey k y ey sh ax n	0.10	
	d ah b y uw	0.38		vallarta	v ay aa r tf ax	0.60	v ay ( aa   eh ) r tf ax
wait	w ey td	0.73	w ey td		v ay y aa r tf ax	0.25	
	w ah iy	0.11			v ey y aa r tf ax	0.12	
	w ey	0.10		vancouver	v ae n k uw v er	0.73	v ae n k uw v er
<b>wales</b>	w ey l	0.29	w ey l z		v ae ng k uw v er	0.24	
	w ah tf ax l z	0.25		velocity	v ax l aa s ax tf iy	0.82	v ax l aa s ax tf iy
	w ey l ax s	0.23			v ax l ao s ax tf iy	0.17	
	w ey l z	0.21		venice	v eh n ax s	0.88	v eh n ( ax   iy ) s
walnut	w ao l n ah td	0.25	w ao l n ah td	vernal	v er n ax l	0.69	v er n ax l
	w aa n ax td	0.21			v er n ow l	0.19	
	w ao l n ax	0.17			v er t n ao l	0.10	
	w ao l m ax td	0.16		very	v eh r iy	0.99	v eh r iy
	w ao l n ax td	0.13		victoria	v ax kd t ao r iy ax	0.86	v ax kd t ao r iy ax
wanted	w aa nt ax dd	0.83	w aa nt ax dd		v ih kd t ao r iy ax	0.10	
	w ah tf ax dd	0.09		vietnam	v iy eh td n aa m	0.76	v iy ( ax   eh ) td n ( ae   aa ) m
warmer	w ao r m er	0.80	w ao r m er		v iy eh td n ae m	0.17	
warning	w ao r n ih ng	0.99	w ao r n ih ng	<b>vilnius</b>	v ih l ax n ax s	0.48	v ih l n iy ax s
warsaw	w ao r s ao	0.71	w ao r s ao		v ih n iy ax s	0.44	



Word	PMM Baseforms	Weight	Expert Baseform	Word	PMM Baseforms	Weight	Expert Baseform	
was	w ah z	0.59	w ah z	virginia	v er jh ih n y ax	0.99	v er jh ih n y ax	
	w uh z	0.36		vladvostok	v l aa df ax v aa s t aa kd	0.32		v l aa df ax v aa s t aa kd
watch	w aa ch	0.93	w aa ch	v l ae df ax v aa s t aa kd	0.29			
water	w aa tf er	0.63	w ( aa   ao   uh ) ( tf   df ) er	voyager	v oy jh er	0.59	v ( oy ax   ow y ax   ao y ax   oy ) jh er	
	w ao tf er	0.19						
	w aa df er	0.12						
waterloo	w aa tf er l uw	0.78	w ( aa   ao   uh ) ( tf   df ) er l uw	waco	w ey k ow	0.70	w ey k ow	
	w ao tf er l uw	0.21						
waterville	w aa df er v ih l	0.78	w ( aa   ao   uh ) ( tf   df ) er v ih l	wake	w ey kd	0.99	w ey kd	
	w aa tf er v ih l	0.21						
waves	w ey v z	0.98	w ey v z	walla	w aa l ax	0.90	w aa l ax	
wayne	w ey n	0.91	w ey n	want	w aa n td	0.60	w aa n td	
wear	w eh r	0.89	w eh r	w ah	w ah	0.16		
	w ih r er	0.10						
weather	w eh dh er	0.99	w eh dh er	w aa n	w aa n	0.12		
week	w iy kd	0.97	w iy kd	warm	w ao r m	0.99	w ao r m	
weekly	w iy kd l iy	0.99	w iy kd l iy	warmest	w ao r m ax s td	0.99	w ao r m ax s td	
welcome	w eh l k ax m	0.50	w eh l k ax m	warnings	w ao r n ih ng z	0.99	w ao r n ih ng z	
	w ax l k ax m	0.18		<u>warwick</u>	w ao r w eh kd	0.46	w ao r w ax kd	
	w ax l k ow m	0.15			w ao r w ih kd	0.41		
	w ax k ah m	0.10			washington	w aa sh ih ng t ax n	0.98	w aa sh ih ng t ax n
	w eh l ih ng t ax n	0.88		w eh l ih ng t ax n	watches	w aa ch ax z	0.82	w aa ch ax z
west	v eh l ih ng t ax n	0.11	w eh s td	<u>waterbury</u>	w aa tf er b er iy	0.21	w ( aa   ao   uh ) ( tf   df ) er b er iy	
	w eh s td	0.99						
westlake	w eh s l ey kd	0.58	w eh s ( td l   l ) ey kd	watertown	w aa df er t aw n	0.35	w ( aa   ao   uh ) ( tf   df ) er t aw n	
what	w eh s td l ey kd	0.41	w ah td		w ah tf er t aw n	0.22		
	w ah td	0.99						
when	w eh n	0.93	w eh n	w aa tf er t aw n	0.15			
whether	w eh dh er	0.99	w eh dh er	w ao tf er t aw n	0.09			
white	w ay td	0.99	w ay td	w ey v	0.92	w ey v		
who	hh uw	0.86	hh uw	w ey	0.52	w ey		
why	w ay	0.81	w ay	w ey ey	0.20			
wildwood	w ay l dd w uh dd	0.77	w ay l dd w uh dd	w ah oy	0.16			
	w aa l dd w uh dd	0.21						
williamsburg	w ih l y ax m z b er gd	0.76	w ih l y ax m z b er gd	w ah ey	0.09			
	w ih l iy ax m z b er gd	0.12						
<u>wilmington</u>	w ax l m ih ng t ax n	0.67	w ih l m ih ng t ax n	w ey	0.97	w iy		
	w ih l m ih ng t ax n	0.30		wearing	w eh r ih ng	0.68	w eh r ih ng	
win	w ih n	0.98	w ih n	w ih r ey ih ng	0.10			
windiest	w ih n d iy ax s td	0.86	w ih n d iy ax s td	er ih ng	0.10			
	w ih n d iy z s td	0.12		wednesday	w eh n z d ey	0.93	w eh n z d ey	
windsor	w ih n z er	0.36	w ih n z er	<u>weekend</u>	w iy kd eh n dd	0.97	w iy kd eh n dd	
	w ax n z er	0.20			weeks	w iy kd s	0.96	w iy kd s
	w iy n z er	0.19			well	w eh l	0.66	w eh l
	w ih n z	0.10			were	w ax l	0.29	
	w ih n z ao r	0.09			w eh r	w er	0.70	w er
<u>windsurfing</u>	w ih n s er f ih ng	0.53	w ih n dd s er f ih ng	w eh r	0.22			
	w ih n dd s er f ih ng	0.46		western	w eh s t er n	0.94	w eh s t er n	
<u>winnipeg</u>	w ih n ax p ey gd	0.33	w ih n ax p eh gd	wet	w eh td	0.99	w eh td	
	w ih n ax p eh gd	0.33		wheeling	w iy l ih ng	0.99	w iy l ih ng	
	w ih n ax p ey kd	0.20		where	w eh r	0.99	w eh r	
winter	w ih nt er	0.97	w ih nt er	which	w ih ch	0.95	w ih ch	
wish	w ih sh	0.99	w ih sh	whitehorse	w ay td hh ao r s	0.66	w ay td hh ao r s	
within	w ih th ih n	0.38	w ( ax   ih ) ( th   dh ) ih n	w h ow l	w ay td hh ao r s s	0.12		
	w ax th ih n	0.19			whole	hh ow l	0.99	hh ow l
	w ax th ax n	0.18		wichita	w ih ch ax t ao	0.59	w ih ch ax t ao	
					w ih ch ax t aa	0.28		
				will	w ax l	0.92	w ( ax   ih ) l	
				williamsport	w ih l y ax m z p ao r td	0.72	w ih l y ax m z p ao r td	

Word	PMM Baseforms	Weight	Expert Baseform	Word	PMM Baseforms	Weight	Expert Baseform
	w ax td ih n	0.11			w ih l iy ax m z p ao r td	0.18	
wonderful	w ah n d er f ax l	0.55	w ah n d er f ax l	wimbledon	w ih m b ax l df ax n	0.85	w ih m b ax l df ax n
	w aa n d er f ax l	0.44			w ih m b ax l df en	0.12	
<b>woodland</b>	w ah dd l ax n dd	0.51	w uh dd l ( ax   ae ) n dd	wind	w ih n dd	0.98	w ih n dd
	w uh dd l ax n dd	0.42		winds	w ih n dd z	0.93	w ih n dd z
worcester	w uh s t er	0.66	w uh s t er	windsurf	w ih n dd s er f	0.99	w ih n dd s er f
	w ah s t er	0.30		windy	w ih n d iy	0.99	w ih n d iy
<b>world</b>	w ao r l dd	0.59	w er l dd	winston	w ih n s t- ax n	0.61	w ih n s t- ax n
	w er l dd	0.24			w ih n s t ax n	0.30	
would	w uh dd	0.98	w ( uh   ax ) dd	<b>wisconsin</b>	w ax s k- aa n s ax n	0.74	w ax s k aa n s ax n
wrong	r ao ng	0.78	r ao ng		w ax s k aa n s ax n	0.23	
	r aa ng	0.19		with	w ih th	0.38	w ( ax   ih ) ( th   dh )
xian	sh iy aa n	0.45	sh ( ax y   iy ) aa n		w ax th	0.24	
	ch y aa n	0.18			w ih dh	0.23	
	sh ae n	0.11		wonder	w ah n d er	0.72	w ah n d er
	sh iy ae n	0.09			w ah n d er ax	0.27	
<b>yakima</b>	y ae k ax m aa	0.82	y ae k ax m ax	wondering	w ah n d er ih ng	0.96	w ah n d er ih ng
year	y ih r	0.96	y ih r	woods	w uh dd z	0.99	w uh dd z
years	y ih r z	0.43	y ih r z	<b>work</b>	w ao r kd	0.65	w er kd
	y ih r ax z	0.38			w er kd	0.29	
	y er z	0.15		<b>worth</b>	w ao r th	0.54	w er th
yellowstone	y eh l ow s t- ow n	0.91	y eh l ow s t- ow n		w er th	0.45	
yesterday	y eh s t er d ey	0.95	y eh s t er d ey	<b>wow</b>	w ah aw	0.32	w aw
york	y ao r kd	0.99	y ao r kd		w aa ow	0.23	
yoosemite	y ow s eh m ax tf iy	0.52	y ow s eh m ax tf iy		w ah ow	0.21	
	y ow s ax m ax tf iy	0.19		wyoming	w ay ow m ih ng	0.95	w ay ow m ih ng
your	y er	0.79	( y uw r   y ao r   y er )	<b>y</b>	l ay	0.68	w ay
	y ao r	0.19			w ay	0.31	
yukon	y uw k aa n	0.92	y uw k aa n	yeah	y eh	0.56	y ( ae   eh   ey ax )
zaire	z ay ih r	0.31	z ay ( ih r   eh r )		y ae	0.20	
	z ay y er	0.29			y ey ax	0.10	
	z ay iy er	0.23		yearly	y ih r l iy	0.99	y ih r l iy
	z ay er	0.11		yellowknife	y eh l ow n ay f	0.99	y eh l ow n ay f
zealand	z iy l ax n dd	0.97	z iy l ax n dd	yes	y eh s	0.99	y eh s
zimbabwe	z ax m b aa bd w ey	0.52	z ax m b aa bd w ey	yokohama	y ow k ax hh aa m ax	0.48	y ow k ax hh aa m ax
	z ax m b aa bd w eh ey	0.31			y ow k ow hh aa m ax	0.24	
	z ih m b aa bd w ey	0.11			y ow k ow hh aa m aa	0.19	
				yorktown	y ao r kd t aw n	0.99	y ao r kd t aw n
				you	y uw	0.98	y ( uw   ax )
				yugoslavia	y uw g ow s l aa v iy ax	0.96	y uw g ow s l aa v iy ax
				<b>yuma</b>	y uw m ay	0.33	y uw m ax
					y uw m aa	0.33	
					iy y uw m ax	0.16	
					y uw m ax	0.16	
				zambia	z ae m b iy ax	0.68	z ae m b iy ax
					z iy ae m b iy ax	0.17	
					aa m b iy ax	0.14	
				zero	z ih r ow	0.35	z ih r ow
					z iy ow	0.33	
					s ih r ow	0.30	
				zurich	z er ax kd	0.66	z ( er   ao r ) ax kd
					z ao r ax kd	0.15	

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