

NAMETDB THE ORONYM TREE: A VISUAL REPRESENTATION OF  
THE INTELLIGIBILITY OF SONG LYRICS AND OTHER SCRIPTED  
TEXT

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by

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TITLE:                      NameTDB The Oronym Tree: A Visual  
Representation of the Intelligibility of Song  
Lyrics and other scripted text

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## **Abstract**

NameTDB The Oronym Tree: A Visual Representation of the Intelligibility of  
Song Lyrics and other scripted text

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In this project, we developed a visualization of the ambiguity of written prose. Given a textual phrase, our program determines all oronyms for that phrase, or possible ways that that phrase is likely to be misheard. It then creates an oronym parse-tree visualization, with each branch fork indicating that a phonetic sequence can be interpreted in more than one way. Each branch segment represents an orthographic word, and the branch radius is scaled to the word's frequency of use in everyday language.

Given any valid English phrase, our system will first generate all possible correct phonetic sequences for a General American accent. Then, it parses through these phonetic transcriptions depth-first, looking for valid orthographic words for each subsequent phonetic subsequence, generating full and partial phrases from these words. While it is doing so, a tree branch is generated on screen for each possible orthographic divergence. In the event that a branch's phonetic tail is not orthographically interpretable, we visually dead-end the branch by drawing a red sphere. In the event that the entire phonetic sequence can be parsed into a valid orthographic phrase, we indicate this successfully-found oronym with a green sphere.

This visual representation allows users to see how many ways a phrase can be interpreted, and most novelly, where dead-end interpretations of the phrase's phonetic sequence exist. A particularly strong orthographic partial phrase before a phonetic dead-end can mislead a listener, causing them to lose track of the

words in the rest of the phrase.

Our visual representation does not take into account n-gram word-proximity, which causes the visual representation to incorrectly weight some branch paths. However, overall, it does a fairly good job of weighting the likelihood that a listener will follow an oronym branches particular interpretation as they listen to a phrase.

In addition to implementing the visualization, we did a multi-phase user study, incorporating over 500 data points from over 157 test subjects. In it, we tested the validity of our oronym generation by having people read a oronym phrase aloud and send us the recording, and by having people transcribe pre-recorded oronyms. In the first phase, we generated oronym strings for the phrase a nice cold hour, and had over 15 people make approximately 65 recordings of the most common oronym phrases. We then compared their pronunciations to the pronunciations we were expecting, and found that in all cases, the recorded phrase’s phonemics matched our expectations. In the second phase, we selected fifteen of the phase one recordings, and had over 30 different people transcribe each one. In the aggregated transcriptions, the most commonly transcribed phrases roughly corresponded with our metric for the most likely oronym interpretation of the phrase in the recording. Though we are happy with our findings, we believe that we could create even better likelihood metrics with the integration of n-grams, and would suggest this for future work.

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# Chapter 1

## Preliminary Vocabulary

Before we start, there are a few uncommon terms we will use fairly often in this paper. Our paper will make very little sense if you don't know what these things are. We have briefly defined them here.

### 1.1 Mondegreens

A mondegreen is a word or phrase resulting from a misinterpretation of a word or phrase that has been heard[9]. The word was coined by American author Sylvia Wright in her article, "The Death of Lady Mondegreen", published in a 1954 issue of Harper's Bazaar. In it, she describes the origin of the word:

When I was a child, my mother used to read aloud to me from Percy's Reliques, and one of my favorite poems began, as I remember:

Ye Highlands and ye Lowlands,  
Oh, where hae ye been?  
They hae slain the Earl O' Moray,  
And Lady *Mondegreen*.

The fourth line of the quote is actually "and laid him on the green"[18].

Additional commonly-cited mondegreens include[\[5\]](#)[\[14\]](#)[\[16\]](#):

Gladly the Cross-Eyed Bear	Gladly the Cross I'd Bear
Scuse me while I kiss this guy	Scuse me while I kiss the sky
There's a bathroom on the right	There's a bad moon on the rise

## 1.2 Oronyms

Oronyms are phrases that may differ in meaning or spelling, but sound near-identical when spoken. They are similar to mondegreens, and the terms are often used interchangeably. The difference, however, lies in the context. The label "mondegreen" is used more often in regards to music lyrics, where pronunciation can be affected by the addition of music and tone to the phrase. Oronyms, on the other hand, refer to spoken words, not sung lyrics.[\[?\]](#)

Common oronyms include:

i scream	ice cream
an ice cold hour	a nice cold hour
grape ants	gray pants
real eyes	realize

## 1.3 Orthography

Orthography sounds fancy, but it's quite familiar. The word 'orthographic' comes from the Latin *orthographia*, meaning *correct* writing. Orthography itself is the part of language study concerned with letters and spelling. More specifically, it's the standardized system of writing down words in a specific language, using a commonly-accepted set of letters according to accepted usage. [\[10\]](#)

The orthographic symbol set for a language is the commonly-accepted set of letters used to spell words in that language. In English, our orthographic symbol set is the Latin alphabet.

In this paper, when we say "orthographic phrase", we're referring to an sequence of regularly-spelled Webster's-dictionary-type words.

Example: "This is a orthographic phrase."

## 1.4 Phonetics and Phonology

To discover oronyms for a phrase, we must first to translate the root orthographic phrase to a representation that allows us to unambiguously measure pronunciation. Phonology and phonetics are branches of linguistics that deal with pronunciation.

### 1.4.1 Phonetics

Phonetics is a branch of *descriptive* linguistics, and refers to the study of the actual, uttered sound of human speech. It deals with describing the physical phenomena of how these sounds are produced from the vocal tract, how they are transmitted once spoken, and how they are recieved by audience. The building blocks of phonetics are *phones*, which represent atomic sounds.

### 1.4.2 Phonology (aka phonemics)

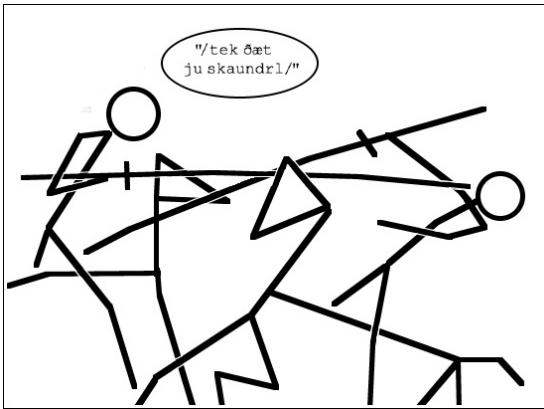
Phonology is a branch of *theoretical* linguistics, and as such, is primarily concered with the abstract grammartical characterization of sounds. It describes

the way that sounds function within a language and give meaning to words. The basis of phonological analysis is the grouping of sounds (*phones*) into distinct units within a languages. These distinct units are called *phonemes*.

These phonemes may contain different phones, depending on the accent of the speaker. For example, native speakers of General American English only generally recognize one ‘L’ sound phoneme. However, there are two different ways that that phoneme manifests itself: the ‘l’ in ”male”, and the ‘l’ in late. This difference is not noticable to a native speaker of American English, because that particular accent will parse any ‘L’ phone as the same ‘L’ phoneme.

### 1.4.3 Phonetics Vs Phonology

As we said previously, though the terms are sometimes used interchangeably, the words ‘phonemic’ and ‘phonetic’ (and their corresponding sound building blocks, ‘phone’ and ‘phoneme’) indicate a different stages of sound parsing. *Phonemes* are idealized sounds; *phones* are the actual sounds that come out of a person’s mouth. Figures [1.1a](#) and [1.1b](#) provide a final, illustrative metaphor of the difference.



(a) Phonology[6]



(b) Phonetics[7]

Figure 1.1: The difference between phonetics and phonology



## 1.5 Phonemic/Phonetic Alphabets

As we stated in section 1.4.1, phonemes are the atomic building blocks of words. Think of phonemes as an alphabet where every meaningful sound has its own letter. The way that we interact with phonemes in a concrete way is by using phonetic alphabets and phonetic dictionaries.

**doc•tor** | 'däktər |  
noun  
1 a qualified practitioner of medicine; a physi  
• a qualified dentist or veterinary surgeon.  
• [ with modifier ] informal a person who giv  
improvements: *the script doctor rewrote the orig*  
2 ( **Doctor** ) a person who holds a doctorate: .

Figure 1.2: The characters to the right of the large bold word "doctor" are IPA symbols.

The most common phonetic alphabet is the IPA (International Phonetic Alphabet). It contains representations of every sound in every known language globally, and allows for cross-cultural pronunciation guidelines. As shown in figure 1.2, IPA representations of orthographic words are found in traditional dictionaries to aid pronunciation.

### 1.5.1 SAMPA

SAMPA (Speech Assessment Methods Phonetic Alphabet) is a computer-readable phonetic alphabet, based upon the symbols found in the more-standard-but-not-easily-computer-readable IPA (International Phonetic Alphabet). It that uses "letters" consisting of 1-2 ASCII characters to represent each phoneme. The ASCII sequences for the SAMPA letter are designed so that any SAMPA sequence deterministically parsible.

We chose to use SAMPA instead of IPA because its ASCII-compliance makes it easy to integrate into other systems.

See [7](#) for a full table of each SAMPA phoneme, its description, and its sub-parts.

For some brief context, the SAMPA spelling of the name ‘Jenee Hughes’ is *dZENi hjuz*. ‘Dr Zoe Wood’ becomes *dAkt@‘r zoui wUd*. ‘Dr John Clements’ becomes *dAkt@‘r dZAn klEm@nts*. ‘Dr Franz Kurfess’ becomes *dAk@‘r fr{nz kʒ‘rfEs*.

# Chapter 2

## Introduction

Human brains are built to come to single conclusions about things that have more than one interpretation. The way that you come to this end conclusion is dependent upon your experiences, cultural immersion, and language familiarity (I CAN TIE IN INDIA HERE!) [17]. When attempting to write English phrases that will be read aloud and heard by people with other linguistic biases than you, it's important to make your prose as deterministically understandable as possible. The first towards this is understanding and identifying how many ways your stuff can be misheard, and why.

### 2.1 You and me...and Leslie?

In the song “*Groovin’ (on a Sunday Afternoon)*”, by the Young Rascals, there’s a part in the bridge that many people hear as “*Life would be ecstasy, you an’ me an’ Leslie*”. In fact, the line is “*Life would be ecstasy, you and me endlessly*”. The confusion lies with the last three syllables of the phrase. The pronunciation of each version, if spoken normally, is as follows:

<b>Alphabetic:</b>	and Les- lie	end- less- ly
<b>SAMPA:</b>	@nd "lEs li	"End l@s li

In the song, the singer is doing what many singers are taught to do, to make it easier to sustain the singing of words that end with unsingable consonants: the unsingable consonant is displaced onto the front of the next word. In this case, the consonant “d” is not singable, so he displaces it onto the next syllable, when he can: “and ME” becomes “an dME”, and “end LESS” becomes “en dLESS”.

Basically, singers are \*born\* to ignore syllable boundaries. So, our singer can effectively think of the sung phrase as:

YOU an dME en dLESS lee

This doesn’t cause confusion for listeners, because they’re used to hearing it. This does mean, however, that lyric placement does not provide an accurate barometer to a listener of where a word actually ends.

In addition, the singer is singing fudging his vowels, like singers are taught to do, so “and” and “end” sound almost indistinguishable. So, really, what listeners are hearing is this:

YOU en dME en dLESS lee

Now, the listener’s brain has to take this syllabic gobbledy-gook, and parse it into something useful. They’ve currently got this mess to deal with (represented in SAMPA syllables):

***ju En dmi En dl@s li***

They parse the first part just fine, because the emphases match:

**you** and **me** *En dl@s li*

But no one says endLESSly. People say ENDlessly. So, the listeners don't recognize it. They have to work with what they have. They already turned one "En d" into an "and", so they do it again:

**you** and **me** and *l@s li*

Now, they're just left with LESS lee. And that fits Leslie, a proper noun that fits in context and in emphasis placement. So, the final heard lyric is:

**you** and **me** and **Les-** lie

The misunderstanding can be traced back to improper emphasis placement. The songwriter probably didn't even think of that, and now he's stuck: a one-hit-wonder with a misunderstood song. We bet that in interview after interview, someone asks him who Leslie is. It's probably very frustrating — especially since he could have just moved the word an eighth note later, and it would have been understood perfectly.

That's the sort of situation this program is going to help avoid.

## 2.2 Why it breaks down

Imagine the case where a jingle-writing company must market a

There are a ton of places where an author must speak to their intended audience through an intermediary source, with whom they may have little to no

contact. When this is the case, it is of the utmost importance to ensure that their written text is as deterministic as possible.

There are two points at which the author's intended phrasing can be muddled : First, when the author's orthographic text becomes an orator's spoken (phonemic) interpretation, and second, when the orator's phonemic interpretation is translated by an audience into a perceived orthographic phrase. Both of these conversions/translations/transmutations/~~ICAN~~"T REMEMBER THE WORK must be made successfully in order for the author's intended meaning to be conveyed.

The phrase "iced ink" undisputedly succeeds in the first translation, but fails on the second. Iced ink can only be pronounced one way, but it can be heard multiple ways—the most notable of which is "I stink", not "iced ink".

The phrase "a nice cold hour" can fail on both parts. First, the orator could have accidentally-capitalized the word Nice, and made it sound like Nice, the city in Rome. An audience would likely hear this as "niece", and would be confused, at best. Even if the orator pronounces the phrase as the author intended, they audience could hear multiple orthographic phrases in the same phonemic sequence: "a nice cold hour", "an ice cold hour", or even "a nigh scold our".

A third, more rare and nefarious type of audience misunderstanding can be caused by parse-tree misdirection, where an audience member is absolutely sure they're hearing one phrase, only to get lost halfway through the lyric

## 2.3 Intended audience

### 1. Playwrights

2. Speechwriters

3. Jingle writers

4. Lyricists

# Chapter 3

## Implementation

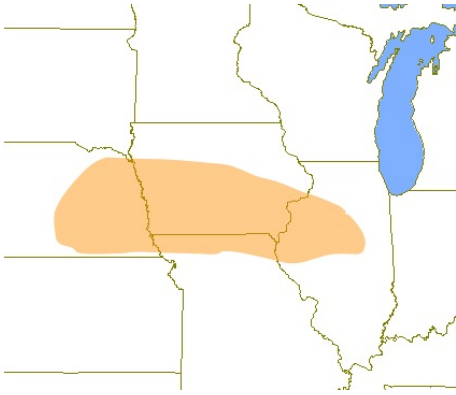
This program has three major functional parts: a custom phonetic dictionary, a command-line oronym generator, and a OpenGL oronym-parse-tree visualization generator.

### 3.1 Customized Phonetic Dictionary

In order to discover oronyms for each phrase, we first needed to determine how each phrase is pronounced. Pronunciation can vary depending on the speakers accent, so it was important for us to (1) chose an accent that we could easily replicate and (2) find a dictionary that supported that accent.

We decided to utilize a General American accent, due to its ubiquity in media and news sources. The General American accent, also known as the "Standard American English" dialect, is not spoken by the majority of people in America, but is used as a sort of "average accent". It most closely resembles the Midwestern accent using in the area in Figure ?? and more commonly recognized as "the





**Figure 3.1:** This is the geographic area whose accent most closely resembles the General American Accent [4]

newscaster accent”. Newscasters learn this accent for national TV, because it is the ”least-accented” of the American accents.

### 3.1.1 Dictionary Options

We considered using three different phonetic dictionaries: the CMU dictionary, LC-STAR dictionary and UNISYN dictionary[8] [1] [15] [12]. We started out by looking at the LC-STAR dictionary, but quickly decided that it wasn’t going to be as useful to us, because the LC-Star project is relatively focused on Speech-to-Speech or Text-to-Speech tech. Also, the website had not been maintained since 2006. We then tried the CMU dictionary, which, for a while, seemed like it was going to work. It had a very simple way of encoding words: first the word, then the identifier number in parens (if needed), then a space, then a one-to-two char code for each sound in the word, with the numbers 0, 1, 2 appended to indicate emphasis (if needed), separated by spaces. An example of a CMU dictionary entry can be seen in Figure 3.2.

ABBREVIATE AH0 B R IY1 V IY0 EY2 T

**Figure 3.2:** Here is the CMU dictionary entry for the word "abbreviate"

The problem that arose with this format, was that there was no explicit definition of where to hyphenate the word when splitting it up. This causes problems if I want to use the word in lyrics, where each note has its own syllable underneath it, and each syllable might have many different sounds. The benefits of the CMU dictionary over some other dictionaries were that (1) it was actively maintained, (2) it included proper nouns, which are often found in lyrics, but not in dictionaries, and (3) it was ridiculously easy to read.

The downsides were that (1) it included no part of speech data or hyphenation data, and (2) it used non-standard symbols for its phonetic alphabet. With the downsides and benefits in mind, the CMU dictionary could not be used in isolation, especially if I someday want to attempt generation of original lyrics (which part of speech data would be vital for).

The UNISYN dictionary is used primarily to phonetically translate words into multiple accents. It has its own formatted dictionary, with a bunch of wildcards in it. They also provide some semi-functioning perl scripts that allow you to specify a dialect you'd like to use (For example, I would say cooking differently than someone from the Deep South, and we both would say it differently than someone from London. However, we're all speaking English. The UNISYN dictionary facilitates this translation).

It had all the information I needed, and then some. However, it was case-insensitive, meaning that it didn't make it easy to differentiate pronunciations for some words. For example, the word "nice" is pronounced differently from the

city "Nice", but they were both stored as "nice" the orthography of UNISYN. The CMU dictionary did. The obvious conclusion, then, was to combine them. I decided that anything that was in the CMU dictionary, but not in the UNISYN dictionary, would be counted as a proper noun. And with that, I started to massage both data sets into mergable forms.

However, I ran into a setback, mentioned in the very first article I found references to both dictionaries in: the dictionaries were inconsistent. They didn't always put stresses in the same place, nor did they always have the same pronunciation. Because of this, it was difficult to match words especially words that were homographic heteronyms (same writing, different sounds, like "Do you know what a buck *does* to *does*?"). Because of this, we decided to use the UNISYN dictionary exclusively.

### 3.1.2 Formatting the dictionary

We used the UNISYN dictionary, using General American SAMPA output, as the base for our phonetic dictionary.

First, we downloaded the dictionary and related files from the UNISYN website.

Once we'd extracted them, we attempted to run the provided perl scripts to turn the UNISYN meta-phonetic symbols into SAMPA phonetic symbols, using the procedure specified in Section 6.1 of the UNISYN Documentation, and the towncode gam (which indicated that we want pronunciations using the *General American* accent)[13].

There were a few errors in translation we fixed manually:

Example:

```
transfer : 2 : VB/VBP : tr{ns"f3'r : tr{nsf3'r : {trans==fer}  
: 7184
```

**Figure 3.3:** Here is an example an entry in our custom phonetic dictionary, using the word "transfer"

- The translation script had erroneously substituted the character `d` instead of the digit `4`, which primarily affected the unique identifiers to disambiguate words and the word-frequency counts. We did a simple search-and-replace to fix this, excluding the orthographic, extended orthographic, and SAMPA spellings.
- The translation script had erroneously substituted the digit `5` instead of the character `l` (lower case L). This interfered with the phonetic/sampa spellings of the words. Fortunately, `5` is not a valid SAMPA phoneme or orthographic letter value, so we removed all instances of it from the ortho, SAMPASpelling, and extendedOrtho columns
- The translation script had erroneously substituted the character sequence `'r\` instead of `'r`. We were able to fix this by simply removing all `\` characters from our output.

### 3.1.3 Custom dictionary fields

Here is the format for the fields in an entry in our custom phonetic dictionary, after we were done with fixing the UNISYN output:

```
<ortho> : <uniqueID> : <partOfSpeech> : <SAMPASpelling> :  
<SAMPAnoEmph> : <extendedOrtho> : <freq>
```

**<ortho>** is the regular spelling of the word

**<uniqueID>** is a number (and optional string) used to differentiate homographs.

**<partOfSpeech>** is used to identify the specific part of speech

**<SAMPAspelling>** is the breakdown of the word, phonetically. It uses the SAMPA alphabet, and separators to show where breaks in the word are, and how they're emphasized. If a separator is ' \$ ', the following phones (until the next separator) are not emphasized. If it's ' % ', then they are the secondary emphasis. If it's ' " ', then they are the primary emphasis.

**<SAMPAnoEmph>** is the same as *jSAMPA*Spelling*i*, but with all emphasis characters stripped out. We chose to add this field so that we could more-easily look up phonetic sequence matches.

**<extendedOrtho>** has no particular use to me, at this time. It indicates the morphological breakdown of the word, allowing for stemming analysis of words. Since we aren't converging that, we never use this field.

**<freq>** is the frequency at which the word occurs in language, according to UNISYN. The frequency count is "taken from a composite of a number of on-line sources of word-frequency. It includes frequencies from the British National Corpus and Maptask, and frequencies derived from Time articles and on-line texts such as Gutenberg. They were weighted to give more importance to sources of spoken speech, and also to increase the numeric frequency of smaller corpuses"[13].

An example of an entry in our custom phonetic dictionary can be seen in **Figure 3.3**.

### 3.1.4 Transferring the dictionary to a sqlite database

Because there are several hundred thousand entries in our phonetic dictionary, it was necessary to have a database, rather than store them all in-program in a multi-dimensional array. We decided to use a SQLite database for this purpose.

To turn the colon-delimited dictionary file into a SQLite database, we decided to use a program called the SQLite Database Browser, an open source, public domain, freeware visual tool to create, design, and edit SQLite3.x database files. We specifically used version 2.0b1 of the program, which was built with version 3.6.18 of the SQLite engine[11].

From that point on, it was just a matter of changing the ':' delimiter in our `phoneticDictionary.csv` to a '|' delimiter, and letting the program convert the pipe-delimited csv into a sqlite database. After letting this process run for a day and a half, it finally spit out a sqlite database file.

## 3.2 Oronym Generation

First, our program takes given an orthographic phrase to find oronyms for.

‘a nice cold hour’

We then tokenize this phrase into its component words, using whitespaces as a delimiter.

‘a’, ‘nice’, ‘cold’, ‘hour’

For each word in the phrase, we query our phonetic dictionary for all possible

SAMPA pronunciations.

<code>'a' → e, @, A</code>
<code>'nice' → naIs, nis</code>
<code>'cold' → kould</code>
<code>'hour' → aU`r</code>

**Figure 3.4:** In this and all subsequent diagrams, a ‘string in quotes’ indicates an orthographic word or phrase, and a monospaced string indicates that it is a SAMPA word or phrase.

Now that we have the pronunciation of each of the words in the form of SAMPA strings, we can list all the possible phonetic permutations of the original phrase.

<code>e naIs kould aU`r</code>
<code>@ naIs kould aU`r</code>
<code>A naIs kould aU`r</code>
<code>e nis kould aU`r</code>
<code>@ nis kould aU`r</code>
<code>A nis kould aU`r</code>

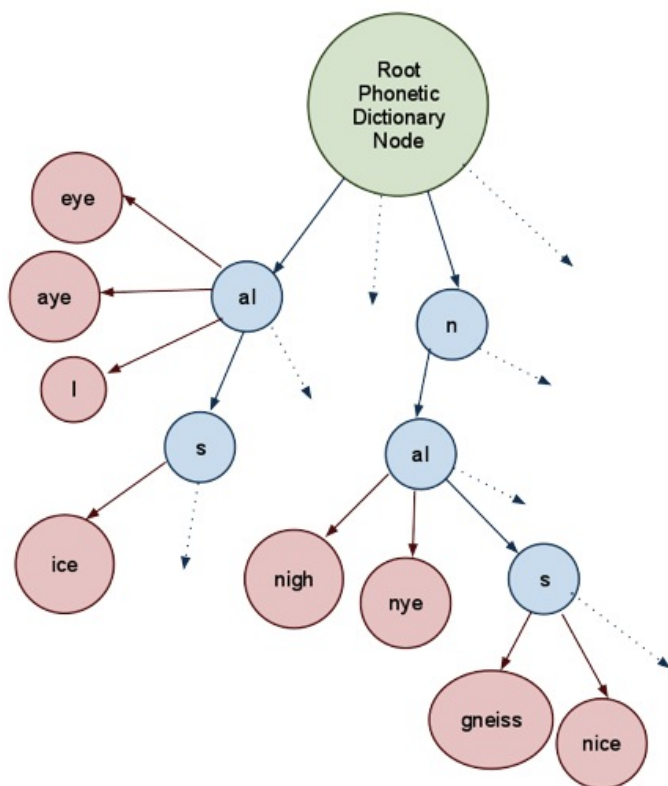
**Figure 3.5:**

Then, for each phonemic phrase, we want to figure out all valid orthographic interpretations. For this, we have to go back to our phonetic dictionary.

The ideal way to think about searching for words in a phonetic sequence is by picturing the phonetic sequence in a tree form. For example, if I had a phonetic tree with the entire dictionary in it, each phonetic tree node would have at least 45 child nodes: one for each phone. A node might also have “word” nodes, if the

phones along the path to that node constructs a valid orthographic word:

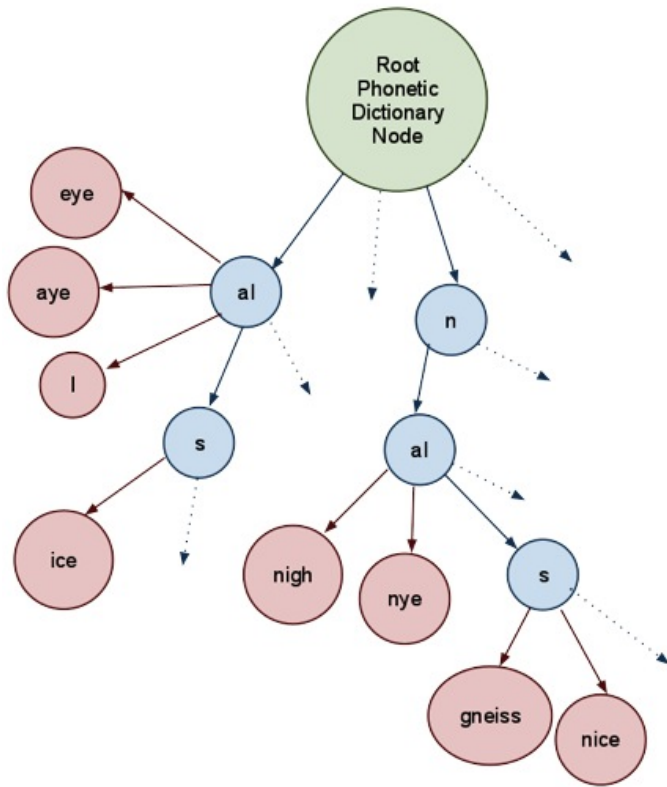
When there are multiple orthographic interpretations at a single phonetic node, the most likely interpretation can be determined by checking the frequency of use for each word. For example, the sequence "n aI s" is much more likely to be "nice" than "gneiss". In figure 3.6, An visual representation of the process of going through an entire dictionary's phonetic tree for nodes along the paths for the SAMPA sequences 'aIs' and 'nice'.



**Figure 3.6:**

We can use this dictionary tree method to discover valid orthographic interpretations for each phonetic sequence. Using the dictionary tree method above, we can orthographically interpret each phonetic transcription of our root orthographic phrase, as shown in figure 3.7:





**Figure 3.7:**

Once we have grabbed all the orthographic interpretations for each phonetic sequence, we combine them all into a orthographic oronym phrase list. This process may leave us with some redundant oronyms, so we de-duplicate that list.

This process gives us a list of all unique and valid oronyms for the original root phrase.

In the case of "a nice cold hour", this returns 290 oronyms.

### 3.2.1 Word Frequency Evaluation

Next, we want to evaluate all our oronyms based on how common each oronym's component words are. For example, "a nice cold hour" is much more likely to be heard "a gneiss cold hour", even though both are phonetically iden-

tical.

To do this, we tokenize each oronym phrase into its component words, using once again using non-newline whitespaces as a delimiter.

### **3.2.2 Step 1: Get all phonetic sequences for a given orthographic phrase**

The first step to discovering the oronyms for the phrase is to determine all the possible pronunciations. The pseudocode to do this is in [??](#).

### **3.2.3 Text-based approach**

## **3.3 Visual Representation**

```

vector< vector < phone > >findAllPhoneSeqsForOrthoPhrase( string orthoPhrase) {
    vector< vector < phone > > allFullPhrasePhoneSeqs
    vector<string> orthoWords = split(orthoPhrase);

    int origNumFullPhrases = 0;
    for ( int i = 0 to orthoWords.size() ) {
        string orthoWord = orthoWords[i] ;
        Vector<vector <phone > > nextWordSampaPhoneSeqs (orthoWord)

        if ( this is the first orthoWord weve looked up this loop ) {
            for( vector<phone> phoneSubSeq: nextWordSampaPhoneSeqs ) {
                allFullPhrasePhoneSeqs[i].append(phoneSubSeq);
            }
        } else {
            origNumFullPhrases = allFullPhrasePhoneSeqs.size();
            if theres more than one vector <phone> in nextWordSampaPhoneSeqs
                then we need to create duplicates of all existing allFullPhrasePhoneSeqs
        }
        for( int m = 0 to allPhrasePhoneSeqs.size() ) {
            int phraseToAppendIndex = m / origNumFullPhrases;
            vector<phone> phoneSeqToAppend = nextWordSampaPhoneSeqs[phraseToAppendIndex]
            append phoneSeqToAppend to the end of allFullPhrasePhoneSeqs[m].
        }
    }

    return allFullPhrasePhoneSeqs;
}

```

**Figure 3.8:** Algorithm to get all phonetic sequences for an orthographic phrase.

```

vector<string> discoverOronymsForPhrase( string origOrthoPhrase, bool includeDeadends,
    vector<string> orthoMisheardAsPhrases;
    vector<vector<phone> > allPhoneSeqsOfOrigPhrase = findAllPhoneSeqsForOrthoPhrase( origOrthoPhrase );

    int numUniquePhoneticInterpretations = allPhoneSeqsOfOrigPhrase.size();
    for(int i = 0; i < numUniquePhoneticInterpretations; i++) {
        vector<phone> curPhoneSeqWithEmph( allPhoneSeqsOfOrigPhrase.at(i) );
        string strOfCurPhoneSeq = phoneVectToString( curPhoneSeqWithEmph );

        //remove emphasis marking for easier lookups
        vector<phone> curPhoneSeq = getNoEmphsPhoneVect( curPhoneSeqWithEmph );

        vector<string> altOrthoPhrases = findOrthoStrsForPhoneSeq( curPhoneSeq );

        for( int j = 0; j < altOrthoPhrases.size(); j++) {
            string altOrthoPhrase = altOrthoPhrases.at(j);

            //ensure it contains valid ortho text in all cases, and if includeDeadends is true
            if ( ( includeDeadends == true && altOrthoPhrase != deadEndDelim1
                && altOrthoPhrase != deadEndDelim2 )
                || ( altOrthoPhrase.find( deadEndDelim1 ) == string::npos
                    && altOrthoPhrase.find( deadEndDelim2 ) == string::npos ) ) {

                orthoMisheardAsPhrases.push_back( altOrthoPhrase );
            }
        }
    }

    //deduplicate orthoMisheardAsPhrases by putting in a set and back again
    set<string> tempSetForDeduplication( orthoMisheardAsPhrases.begin(), orthoMisheardAsPhrases.end() );
    orthoMisheardAsPhrases.assign( tempSetForDeduplication.begin(), tempSetForDeduplication.end() );
    return orthoMisheardAsPhrases;
}

```

**Figure 3.9:** Algorithm to get all oronyms for an orthographic phrase.

```

void buildAndDrawFullTree( string orthoPhrase ) {
    vector< string > fullPhrases = discoverOronymsForPhrase( orthoPhrase , true );
    getMaxAndMinFreqForAllOrthoPhrases( fullPhrases, &maxWordFreq, &minWordFreq);

    //draw the tree's seed

    glPushMatrix();
    {
        glTranslated(0.0, -1.0* DEFAULT_BRANCH_LEN , 0.0);
        materials(GreenShiny);
        drawSphere(DEFAULT_RADIUS);
        materials(allMaterials.at( mat % allMaterials.size () ) );

        drawBranchesAtFork ( fullPhrases, DEFAULT_RADIUS );

    }
    glPopMatrix();
}

```

**Figure 3.10:** Given an orthographic phrase, this function prepares to draw the tree

```

void drawBranchesAtFork( vector< string > fullPhrases, double lastRadius) {

    if( fullPhrases.size() == 0 ) {
        return;
    }

    //use a set to ensure no duplicates
    set< string > firstWords;

    //put the first word of each phrase into the set
    for(int i = 0; i < fullPhrases.size(); i++){
        if( fullPhrases.at(i).size() > 0 ) {
            string firstWord = FirstWord( fullPhrases.at(i) );
            firstWords.insert( firstWord );
        }
    }

    //calculate positioning variables for the spread of branches for firstWord

    set<string>::iterator curFirstWordIter;
    int i = 0;

    //for each firstWord in the set
    for ( curFirstWordIter = firstWords.begin(); curFirstWordIter != firstWords.end();
        string curFirstWord = *curFirstWordIter;

        //calculate the branch radius using the scaled frequency of curFirstWord
        int firstWordFreq = queryDBwithOrthoForFreq ( curFirstWord );
        double firstWordRadius = scaleFreqToRadius( firstWordFreq );

        double newAdditiveRadius = firstWordRadius;

        glPushMatrix();
        {

            //translate and rotate into place

            //if firstWord indicates a dead end ( xxx or fff, defined in wordBreakdown
            if(curFirstWord == deadEndDelim1 || curFirstWord == deadEndDelim2 ) {
                //draw a red sphere at the end of the last branch
            } else if (curFirstWord == successDelim ) {
                //draw a green sphere at the end of the last branch
            } else {

                //draw a branch
                drawBranch( radiansToDegrees( tiltAngle ), curXOffset, curYOffset, new

```

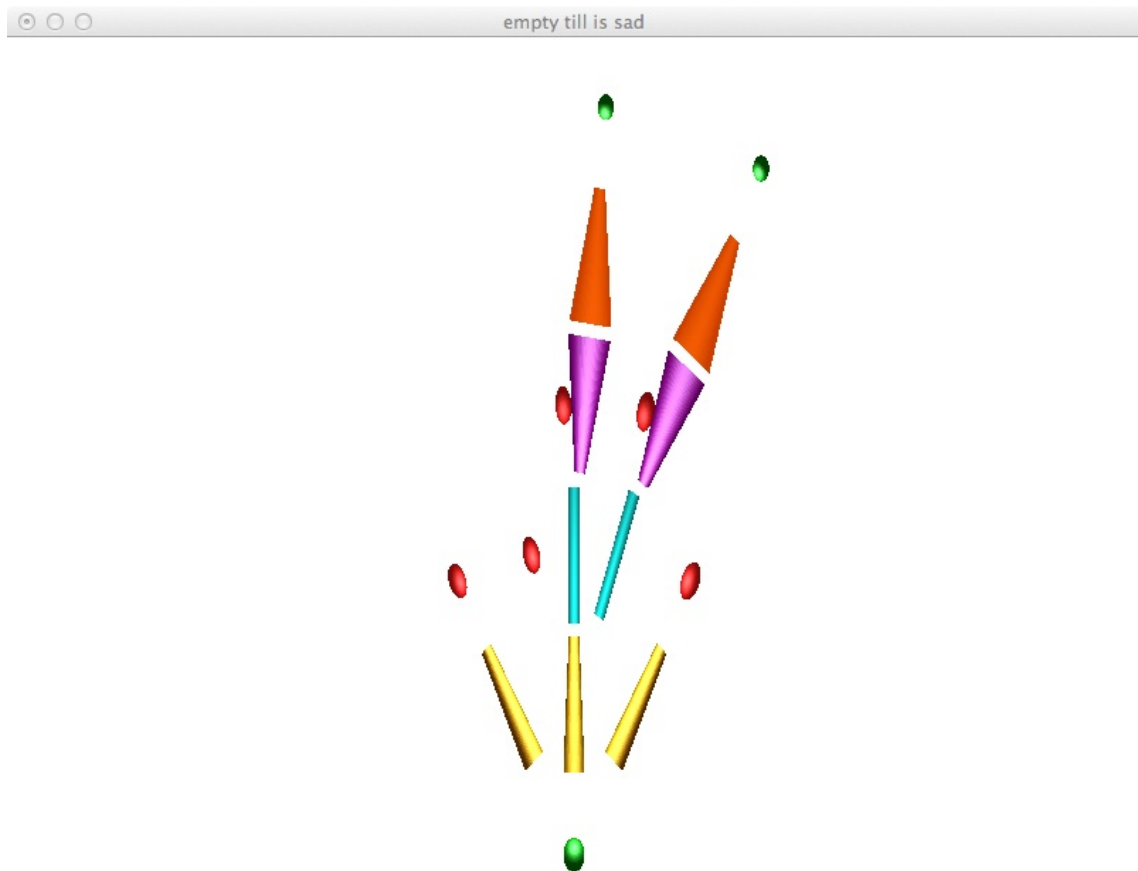
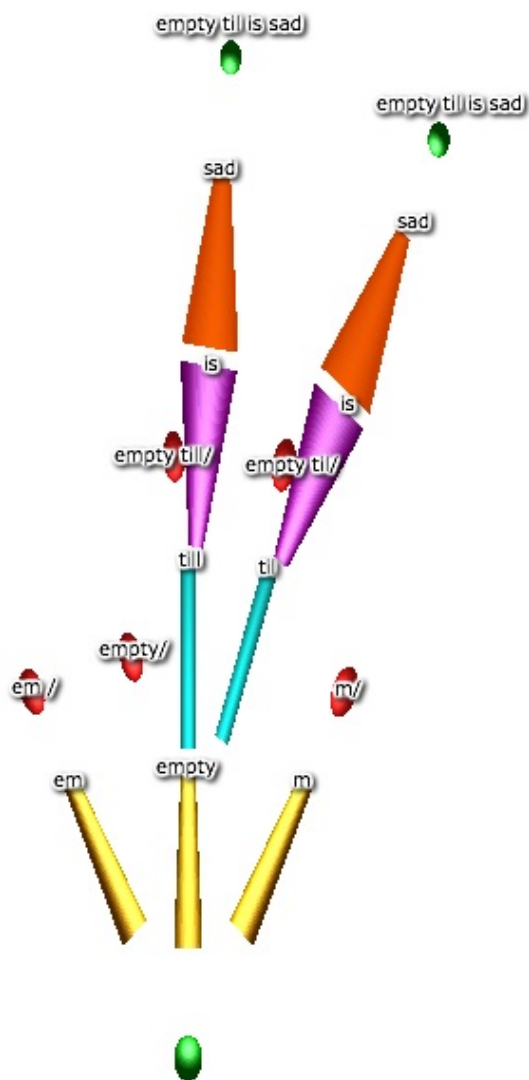


Figure 3.12: This is the parse tree for the phrase "empty till is sad"



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Figure 3.13: This is the annotated parse tree for the phrase "empty till is sad"



Table 3.1: All Oronyms for ‘A Nice Cold Hour’ with frequency values

phrase	total freq	word1	freq1	word2	freq2	word3	freq3	word4	freq4
on i scold our	13185760	on	2774243	i	9937877	scold	217	our	473423
on i scold hour	12784150	on	2774243	i	9937877	scold	217	hour	71813
on i skol dour	12712244	on	2774243	i	9937877	skol	5	dour	119
on i skol dower	12712217	on	2774243	i	9937877	skol	5	dower	92
an i scold our	11205686	an	794169	i	9937877	scold	217	our	473423
an i scold hour	10804076	an	794169	i	9937877	scold	217	hour	71813
an i skol dour	10732170	an	794169	i	9937877	skol	5	dour	119
an i skol dower	10732143	an	794169	i	9937877	skol	5	dower	92
’n’ i scold our	10411517	’n’	0	i	9937877	scold	217	our	473423
’n’ i scold hour	10009907	’n’	0	i	9937877	scold	217	hour	71813
’n’ i skol dour	9938001	’n’	0	i	9937877	skol	5	dour	119
’n’ i skol dower	9937974	’n’	0	i	9937877	skol	5	dower	92
a nice cold our	8253272	a	7536297	nice	190708	cold	52844	our	473423
a niece cold our	8064257	a	7536297	niece	1693	cold	52844	our	473423
a gneiss cold our	8062585	a	7536297	gneiss	21	cold	52844	our	473423
a ne scold our	8017040	a	7536297	ne	7103	scold	217	our	473423
a knee scold our	8016076	a	7536297	knee	6139	scold	217	our	473423
a nigh scold our	8011331	a	7536297	nigh	1394	scold	217	our	473423
a nye scold our	8009974	a	7536297	nye	37	scold	217	our	473423
a nice cold hour	7851662	a	7536297	nice	190708	cold	52844	hour	71813
a nice coal dour	7747572	a	7536297	nice	190708	coal	20448	dour	119
a nice coal dower	7747545	a	7536297	nice	190708	coal	20448	dower	92
Continued on next page									

**Table 3.1 – continued from previous page**

phrase	total freq	word1	freq1	word2	freq2	word3	freq3	word4	freq4
a nice cole dour	7729197	a	7536297	nice	190708	cole	2073	dour	119
a nice cole dower	7729170	a	7536297	nice	190708	cole	2073	dower	92
a nice kohl dour	7728036	a	7536297	nice	190708	kohl	912	dour	119
a nice kohl dower	7728009	a	7536297	nice	190708	kohl	912	dower	92
a niece cold hour	7662647	a	7536297	niece	1693	cold	52844	hour	71813
a gneiss cold hour	7660975	a	7536297	gneiss	21	cold	52844	hour	71813
a ne scold hour	7615430	a	7536297	ne	7103	scold	217	hour	71813
a knee scold hour	7614466	a	7536297	knee	6139	scold	217	hour	71813
a nigh scold hour	7609721	a	7536297	nigh	1394	scold	217	hour	71813
a nye scold hour	7608364	a	7536297	nye	37	scold	217	hour	71813
a niece coal dour	7558557	a	7536297	niece	1693	coal	20448	dour	119
a niece coal dower	7558530	a	7536297	niece	1693	coal	20448	dower	92
a gneiss coal dour	7556885	a	7536297	gneiss	21	coal	20448	dour	119
a gneiss coal dower	7556858	a	7536297	gneiss	21	coal	20448	dower	92
a ne skol dour	7543524	a	7536297	ne	7103	skol	5	dour	119
a ne skol dower	7543497	a	7536297	ne	7103	skol	5	dower	92
a knee skol dour	7542560	a	7536297	knee	6139	skol	5	dour	119
a knee skol dower	7542533	a	7536297	knee	6139	skol	5	dower	92
a niece cole dour	7540182	a	7536297	niece	1693	cole	2073	dour	119
a niece cole dower	7540155	a	7536297	niece	1693	cole	2073	dower	92
a niece kohl dour	7539021	a	7536297	niece	1693	kohl	912	dour	119
a niece kohl dower	7538994	a	7536297	niece	1693	kohl	912	dower	92
Continued on next page									

**Table 3.1 – continued from previous page**

phrase	total freq	word1	freq1	word2	freq2	word3	freq3	word4	freq4
a gneiss cole dour	7538510	a	7536297	gneiss	21	cole	2073	dour	119
a gneiss cole dower	7538483	a	7536297	gneiss	21	cole	2073	dower	92
a nigh skol dour	7537815	a	7536297	nigh	1394	skol	5	dour	119
a nigh skol dower	7537788	a	7536297	nigh	1394	skol	5	dower	92
a gneiss kohl dour	7537349	a	7536297	gneiss	21	kohl	912	dour	119
a gneiss kohl dower	7537322	a	7536297	gneiss	21	kohl	912	dower	92
a nye skol dour	7536458	a	7536297	nye	37	skol	5	dour	119
a nye skol dower	7536431	a	7536297	nye	37	skol	5	dower	92
on aye scold our	3378386	on	2774243	aye	130503	scold	217	our	473423
on e scold our	3356846	on	2774243	e	108963	scold	217	our	473423
on ice cold our	3312712	on	2774243	ice	12202	cold	52844	our	473423
on eye scold our	3274633	on	2774243	eye	26750	scold	217	our	473423
on ay scold our	3254516	on	2774243	ay	6633	scold	217	our	473423
on ice-cold our	3247715	on	2774243	ice-cold	49	our	473423		
on aye scold hour	2976776	on	2774243	aye	130503	scold	217	hour	71813
on e scold hour	2955236	on	2774243	e	108963	scold	217	hour	71813
on ice cold hour	2911102	on	2774243	ice	12202	cold	52844	hour	71813
on aye skol dour	2904870	on	2774243	aye	130503	skol	5	dour	119
on aye skol dower	2904843	on	2774243	aye	130503	skol	5	dower	92
on e skol dour	2883330	on	2774243	e	108963	skol	5	dour	119
on e skol dower	2883303	on	2774243	e	108963	skol	5	dower	92
on eye scold hour	2873023	on	2774243	eye	26750	scold	217	hour	71813

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**Table 3.1 – continued from previous page**

phrase	total freq	word1	freq1	word2	freq2	word3	freq3	word4	freq4
on ay scold hour	2852906	on	2774243	ay	6633	scold	217	hour	71813
on ice-cold hour	2846105	on	2774243	ice-cold	49	hour	71813		
on ice coal dour	2807012	on	2774243	ice	12202	coal	20448	dour	119
on ice coal dower	2806985	on	2774243	ice	12202	coal	20448	dower	92
on eye skol dour	2801117	on	2774243	eye	26750	skol	5	dour	119
on eye skol dower	2801090	on	2774243	eye	26750	skol	5	dower	92
on ice cole dour	2788637	on	2774243	ice	12202	cole	2073	dour	119
on ice cole dower	2788610	on	2774243	ice	12202	cole	2073	dower	92
on ice kohl dour	2787476	on	2774243	ice	12202	kohl	912	dour	119
on ice kohl dower	2787449	on	2774243	ice	12202	kohl	912	dower	92
on ay skol dour	2781000	on	2774243	ay	6633	skol	5	dour	119
on ay skol dower	2780973	on	2774243	ay	6633	skol	5	dower	92
an aye scold our	1398312	an	794169	aye	130503	scold	217	our	473423
an e scold our	1376772	an	794169	e	108963	scold	217	our	473423
an ice cold our	1332638	an	794169	ice	12202	cold	52844	our	473423
an eye scold our	1294559	an	794169	eye	26750	scold	217	our	473423
an ay scold our	1274442	an	794169	ay	6633	scold	217	our	473423
an ice-cold our	1267641	an	794169	ice-cold	49	our	473423		
an aye scold hour	996702	an	794169	aye	130503	scold	217	hour	71813
an e scold hour	975162	an	794169	e	108963	scold	217	hour	71813
ah nice cold our	946271	ah	229296	nice	190708	cold	52844	our	473423
an ice cold hour	931028	an	794169	ice	12202	cold	52844	hour	71813
Continued on next page									

**Table 3.1 – continued from previous page**

phrase	total freq	word1	freq1	word2	freq2	word3	freq3	word4	freq4
an aye skol dour	924796	an	794169	aye	130503	skol	5	dour	119
an aye skol dower	924769	an	794169	aye	130503	skol	5	dower	92
an e skol dour	903256	an	794169	e	108963	skol	5	dour	119
an e skol dower	903229	an	794169	e	108963	skol	5	dower	92
an eye scold hour	892949	an	794169	eye	26750	scold	217	hour	71813
an ay scold hour	872832	an	794169	ay	6633	scold	217	hour	71813
an ice-cold hour	866031	an	794169	ice-cold	49	hour	71813		
an ice coal dour	826938	an	794169	ice	12202	coal	20448	dour	119
an ice coal dower	826911	an	794169	ice	12202	coal	20448	dower	92
an eye skol dour	821043	an	794169	eye	26750	skol	5	dour	119
an eye skol dower	821016	an	794169	eye	26750	skol	5	dower	92
an ice cole dour	808563	an	794169	ice	12202	cole	2073	dour	119
an ice cole dower	808536	an	794169	ice	12202	cole	2073	dower	92
an ice kohl dour	807402	an	794169	ice	12202	kohl	912	dour	119
an ice kohl dower	807375	an	794169	ice	12202	kohl	912	dower	92
an ay skol dour	800926	an	794169	ay	6633	skol	5	dour	119
an ay skol dower	800899	an	794169	ay	6633	skol	5	dower	92
eh nice cold our	783938	eh	66963	nice	190708	cold	52844	our	473423
ah niece cold our	757256	ah	229296	niece	1693	cold	52844	our	473423
ah gneiss cold our	755584	ah	229296	gneiss	21	cold	52844	our	473423
et nice cold our	723706	et	6731	nice	190708	cold	52844	our	473423
o' nice cold our	717438	o'	463	nice	190708	cold	52844	our	473423

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**Table 3.1 – continued from previous page**

phrase	total freq	word1	freq1	word2	freq2	word3	freq3	word4	freq4
ah ne scold our	710039	ah	229296	ne	7103	scold	217	our	473423
ah knee scold our	709075	ah	229296	knee	6139	scold	217	our	473423
ah nigh scold our	704330	ah	229296	nigh	1394	scold	217	our	473423
ah nye scold our	702973	ah	229296	nye	37	scold	217	our	473423
'n' aye scold our	604143	'n'	0	aye	130503	scold	217	our	473423
eh niece cold our	594923	eh	66963	niece	1693	cold	52844	our	473423
eh gneiss cold our	593251	eh	66963	gneiss	21	cold	52844	our	473423
'n' e scold our	582603	'n'	0	e	108963	scold	217	our	473423
eh ne scold our	547706	eh	66963	ne	7103	scold	217	our	473423
eh knee scold our	546742	eh	66963	knee	6139	scold	217	our	473423
ah nice cold hour	544661	ah	229296	nice	190708	cold	52844	hour	71813
eh nigh scold our	541997	eh	66963	nigh	1394	scold	217	our	473423
eh nye scold our	540640	eh	66963	nye	37	scold	217	our	473423
'n' ice cold our	538469	'n'	0	ice	12202	cold	52844	our	473423
et niece cold our	534691	et	6731	niece	1693	cold	52844	our	473423
et gneiss cold our	533019	et	6731	gneiss	21	cold	52844	our	473423
o' niece cold our	528423	o'	463	niece	1693	cold	52844	our	473423
o' gneiss cold our	526751	o'	463	gneiss	21	cold	52844	our	473423
'n' eye scold our	500390	'n'	0	eye	26750	scold	217	our	473423
et ne scold our	487474	et	6731	ne	7103	scold	217	our	473423
et knee scold our	486510	et	6731	knee	6139	scold	217	our	473423
et nigh scold our	481765	et	6731	nigh	1394	scold	217	our	473423
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**Table 3.1 – continued from previous page**

phrase	total freq	word1	freq1	word2	freq2	word3	freq3	word4	freq4
o' ne scold our	481206	o'	463	ne	7103	scold	217	our	473423
et nye scold our	480408	et	6731	nye	37	scold	217	our	473423
'n' ay scold our	480273	'n'	0	ay	6633	scold	217	our	473423
o' knee scold our	480242	o'	463	knee	6139	scold	217	our	473423
o' nigh scold our	475497	o'	463	nigh	1394	scold	217	our	473423
o' nye scold our	474140	o'	463	nye	37	scold	217	our	473423
'n' ice-cold our	473472	'n'	0	ice-cold	49	our	473423		
ah nice coal dour	440571	ah	229296	nice	190708	coal	20448	dour	119
ah nice coal dower	440544	ah	229296	nice	190708	coal	20448	dower	92
ah nice cole dour	422196	ah	229296	nice	190708	cole	2073	dour	119
ah nice cole dower	422169	ah	229296	nice	190708	cole	2073	dower	92
ah nice kohl dour	421035	ah	229296	nice	190708	kohl	912	dour	119
ah nice kohl dower	421008	ah	229296	nice	190708	kohl	912	dower	92
eh nice cold hour	382328	eh	66963	nice	190708	cold	52844	hour	71813
ah niece cold hour	355646	ah	229296	niece	1693	cold	52844	hour	71813
ah gneiss cold hour	353974	ah	229296	gneiss	21	cold	52844	hour	71813
et nice cold hour	322096	et	6731	nice	190708	cold	52844	hour	71813
o' nice cold hour	315828	o'	463	nice	190708	cold	52844	hour	71813
ah ne scold hour	308429	ah	229296	ne	7103	scold	217	hour	71813
ah knee scold hour	307465	ah	229296	knee	6139	scold	217	hour	71813
ah nigh scold hour	302720	ah	229296	nigh	1394	scold	217	hour	71813
ah nye scold hour	301363	ah	229296	nye	37	scold	217	hour	71813

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**Table 3.1 – continued from previous page**

phrase	total freq	word1	freq1	word2	freq2	word3	freq3	word4	freq4
eh nice coal dour	278238	eh	66963	nice	190708	coal	20448	dour	119
eh nice coal dower	278211	eh	66963	nice	190708	coal	20448	dower	92
eh nice cole dour	259863	eh	66963	nice	190708	cole	2073	dour	119
eh nice cole dower	259836	eh	66963	nice	190708	cole	2073	dower	92
eh nice kohl dour	258702	eh	66963	nice	190708	kohl	912	dour	119
eh nice kohl dower	258675	eh	66963	nice	190708	kohl	912	dower	92
ah niece coal dour	251556	ah	229296	niece	1693	coal	20448	dour	119
ah niece coal dower	251529	ah	229296	niece	1693	coal	20448	dower	92
ah gneiss coal dour	249884	ah	229296	gneiss	21	coal	20448	dour	119
ah gneiss coal dower	249857	ah	229296	gneiss	21	coal	20448	dower	92
ah ne skol dour	236523	ah	229296	ne	7103	skol	5	dour	119
ah ne skol dower	236496	ah	229296	ne	7103	skol	5	dower	92
ah knee skol dour	235559	ah	229296	knee	6139	skol	5	dour	119
ah knee skol dower	235532	ah	229296	knee	6139	skol	5	dower	92
ah niece cole dour	233181	ah	229296	niece	1693	cole	2073	dour	119
ah niece cole dower	233154	ah	229296	niece	1693	cole	2073	dower	92
ah niece kohl dour	232020	ah	229296	niece	1693	kohl	912	dour	119
ah niece kohl dower	231993	ah	229296	niece	1693	kohl	912	dower	92
ah gneiss cole dour	231509	ah	229296	gneiss	21	cole	2073	dour	119
ah gneiss cole dower	231482	ah	229296	gneiss	21	cole	2073	dower	92
ah nigh skol dour	230814	ah	229296	nigh	1394	skol	5	dour	119
ah nigh skol dower	230787	ah	229296	nigh	1394	skol	5	dower	92

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**Table 3.1 – continued from previous page**

phrase	total freq	word1	freq1	word2	freq2	word3	freq3	word4	freq4
ah gneiss kohl dour	230348	ah	229296	gneiss	21	kohl	912	dour	119
ah gneiss kohl dower	230321	ah	229296	gneiss	21	kohl	912	dower	92
ah nye skol dour	229457	ah	229296	nye	37	skol	5	dour	119
ah nye skol dower	229430	ah	229296	nye	37	skol	5	dower	92
et nice coal dour	218006	et	6731	nice	190708	coal	20448	dour	119
et nice coal dower	217979	et	6731	nice	190708	coal	20448	dower	92
o' nice coal dour	211738	o'	463	nice	190708	coal	20448	dour	119
o' nice coal dower	211711	o'	463	nice	190708	coal	20448	dower	92
'n' aye scold hour	202533	'n'	0	aye	130503	scold	217	hour	71813
et nice cole dour	199631	et	6731	nice	190708	cole	2073	dour	119
et nice cole dower	199604	et	6731	nice	190708	cole	2073	dower	92
et nice kohl dour	198470	et	6731	nice	190708	kohl	912	dour	119
et nice kohl dower	198443	et	6731	nice	190708	kohl	912	dower	92
o' nice cole dour	193363	o'	463	nice	190708	cole	2073	dour	119
o' nice cole dower	193336	o'	463	nice	190708	cole	2073	dower	92
eh niece cold hour	193313	eh	66963	niece	1693	cold	52844	hour	71813
o' nice kohl dour	192202	o'	463	nice	190708	kohl	912	dour	119
o' nice kohl dower	192175	o'	463	nice	190708	kohl	912	dower	92
eh gneiss cold hour	191641	eh	66963	gneiss	21	cold	52844	hour	71813
'n' e scold hour	180993	'n'	0	e	108963	scold	217	hour	71813
eh ne scold hour	146096	eh	66963	ne	7103	scold	217	hour	71813
eh knee scold hour	145132	eh	66963	knee	6139	scold	217	hour	71813

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**Table 3.1 – continued from previous page**

phrase	total freq	word1	freq1	word2	freq2	word3	freq3	word4	freq4
eh nigh scold hour	140387	eh	66963	nigh	1394	scold	217	hour	71813
eh nye scold hour	139030	eh	66963	nye	37	scold	217	hour	71813
'n' ice cold hour	136859	'n'	0	ice	12202	cold	52844	hour	71813
et niece cold hour	133081	et	6731	niece	1693	cold	52844	hour	71813
et gneiss cold hour	131409	et	6731	gneiss	21	cold	52844	hour	71813
'n' aye skol dour	130627	'n'	0	aye	130503	skol	5	dour	119
'n' aye skol dower	130600	'n'	0	aye	130503	skol	5	dower	92
o' niece cold hour	126813	o'	463	niece	1693	cold	52844	hour	71813
o' gneiss cold hour	125141	o'	463	gneiss	21	cold	52844	hour	71813
'n' e skol dour	109087	'n'	0	e	108963	skol	5	dour	119
'n' e skol dower	109060	'n'	0	e	108963	skol	5	dower	92
'n' eye scold hour	98780	'n'	0	eye	26750	scold	217	hour	71813
eh niece coal dour	89223	eh	66963	niece	1693	coal	20448	dour	119
eh niece coal dower	89196	eh	66963	niece	1693	coal	20448	dower	92
eh gneiss coal dour	87551	eh	66963	gneiss	21	coal	20448	dour	119
eh gneiss coal dower	87524	eh	66963	gneiss	21	coal	20448	dower	92
et ne scold hour	85864	et	6731	ne	7103	scold	217	hour	71813
et knee scold hour	84900	et	6731	knee	6139	scold	217	hour	71813
et nigh scold hour	80155	et	6731	nigh	1394	scold	217	hour	71813
o' ne scold hour	79596	o'	463	ne	7103	scold	217	hour	71813
et nye scold hour	78798	et	6731	nye	37	scold	217	hour	71813
'n' ay scold hour	78663	'n'	0	ay	6633	scold	217	hour	71813

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**Table 3.1 – continued from previous page**

phrase	total freq	word1	freq1	word2	freq2	word3	freq3	word4	freq4
o' knee scold hour	78632	o'	463	knee	6139	scold	217	hour	71813
eh ne skol dour	74190	eh	66963	ne	7103	skol	5	dour	119
eh ne skol dower	74163	eh	66963	ne	7103	skol	5	dower	92
o' nigh scold hour	73887	o'	463	nigh	1394	scold	217	hour	71813
eh knee skol dour	73226	eh	66963	knee	6139	skol	5	dour	119
eh knee skol dower	73199	eh	66963	knee	6139	skol	5	dower	92
o' nye scold hour	72530	o'	463	nye	37	scold	217	hour	71813
'n' ice-cold hour	71862	'n'	0	ice-cold	49	hour	71813		
eh niece cole dour	70848	eh	66963	niece	1693	cole	2073	dour	119
eh niece cole dower	70821	eh	66963	niece	1693	cole	2073	dower	92
eh niece kohl dour	69687	eh	66963	niece	1693	kohl	912	dour	119
eh niece kohl dower	69660	eh	66963	niece	1693	kohl	912	dower	92
eh gneiss cole dour	69176	eh	66963	gneiss	21	cole	2073	dour	119
eh gneiss cole dower	69149	eh	66963	gneiss	21	cole	2073	dower	92
eh nigh skol dour	68481	eh	66963	nigh	1394	skol	5	dour	119
eh nigh skol dower	68454	eh	66963	nigh	1394	skol	5	dower	92
eh gneiss kohl dour	68015	eh	66963	gneiss	21	kohl	912	dour	119
eh gneiss kohl dower	67988	eh	66963	gneiss	21	kohl	912	dower	92
eh nye skol dour	67124	eh	66963	nye	37	skol	5	dour	119
eh nye skol dower	67097	eh	66963	nye	37	skol	5	dower	92
'n' ice coal dour	32769	'n'	0	ice	12202	coal	20448	dour	119
'n' ice coal dower	32742	'n'	0	ice	12202	coal	20448	dower	92

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**Table 3.1 – continued from previous page**

phrase	total freq	word1	freq1	word2	freq2	word3	freq3	word4	freq4
et niece coal dour	28991	et	6731	niece	1693	coal	20448	dour	119
et niece coal dower	28964	et	6731	niece	1693	coal	20448	dower	92
et gneiss coal dour	27319	et	6731	gneiss	21	coal	20448	dour	119
et gneiss coal dower	27292	et	6731	gneiss	21	coal	20448	dower	92
'n' eye skol dour	26874	'n'	0	eye	26750	skol	5	dour	119
'n' eye skol dower	26847	'n'	0	eye	26750	skol	5	dower	92
o' niece coal dour	22723	o'	463	niece	1693	coal	20448	dour	119
o' niece coal dower	22696	o'	463	niece	1693	coal	20448	dower	92
o' gneiss coal dour	21051	o'	463	gneiss	21	coal	20448	dour	119
o' gneiss coal dower	21024	o'	463	gneiss	21	coal	20448	dower	92
'n' ice cole dour	14394	'n'	0	ice	12202	cole	2073	dour	119
'n' ice cole dower	14367	'n'	0	ice	12202	cole	2073	dower	92
et ne skol dour	13958	et	6731	ne	7103	skol	5	dour	119
et ne skol dower	13931	et	6731	ne	7103	skol	5	dower	92
'n' ice kohl dour	13233	'n'	0	ice	12202	kohl	912	dour	119
'n' ice kohl dower	13206	'n'	0	ice	12202	kohl	912	dower	92
et knee skol dour	12994	et	6731	knee	6139	skol	5	dour	119
et knee skol dower	12967	et	6731	knee	6139	skol	5	dower	92
et niece cole dour	10616	et	6731	niece	1693	cole	2073	dour	119
et niece cole dower	10589	et	6731	niece	1693	cole	2073	dower	92
et niece kohl dour	9455	et	6731	niece	1693	kohl	912	dour	119
et niece kohl dower	9428	et	6731	niece	1693	kohl	912	dower	92

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**Table 3.1 – continued from previous page**

phrase	total freq	word1	freq1	word2	freq2	word3	freq3	word4	freq4
et gneiss cole dour	8944	et	6731	gneiss	21	cole	2073	dour	119
et gneiss cole dower	8917	et	6731	gneiss	21	cole	2073	dower	92
et nigh skol dour	8249	et	6731	nigh	1394	skol	5	dour	119
et nigh skol dower	8222	et	6731	nigh	1394	skol	5	dower	92
et gneiss kohl dour	7783	et	6731	gneiss	21	kohl	912	dour	119
et gneiss kohl dower	7756	et	6731	gneiss	21	kohl	912	dower	92
o' ne skol dour	7690	o'	463	ne	7103	skol	5	dour	119
o' ne skol dower	7663	o'	463	ne	7103	skol	5	dower	92
et nye skol dour	6892	et	6731	nye	37	skol	5	dour	119
et nye skol dower	6865	et	6731	nye	37	skol	5	dower	92
'n' ay skol dour	6757	'n'	0	ay	6633	skol	5	dour	119
'n' ay skol dower	6730	'n'	0	ay	6633	skol	5	dower	92
o' knee skol dour	6726	o'	463	knee	6139	skol	5	dour	119
o' knee skol dower	6699	o'	463	knee	6139	skol	5	dower	92
o' niece cole dour	4348	o'	463	niece	1693	cole	2073	dour	119
o' niece cole dower	4321	o'	463	niece	1693	cole	2073	dower	92
o' niece kohl dour	3187	o'	463	niece	1693	kohl	912	dour	119
o' niece kohl dower	3160	o'	463	niece	1693	kohl	912	dower	92
o' gneiss cole dour	2676	o'	463	gneiss	21	cole	2073	dour	119
o' gneiss cole dower	2649	o'	463	gneiss	21	cole	2073	dower	92
o' nigh skol dour	1981	o'	463	nigh	1394	skol	5	dour	119
o' nigh skol dower	1954	o'	463	nigh	1394	skol	5	dower	92
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**Table 3.1 – continued from previous page**

phrase	total freq	word1	freq1	word2	freq2	word3	freq3	word4	freq4
o' gneiss kohl dour	1515	o'	463	gneiss	21	kohl	912	dour	119
o' gneiss kohl dower	1488	o'	463	gneiss	21	kohl	912	dower	92
o' nye skol dour	624	o'	463	nye	37	skol	5	dour	119
o' nye skol dower	597	o'	463	nye	37	skol	5	dower	92

# Chapter 4

## User Study

### 4.1 Structure

We created a multi-wave user study to examine the effectiveness of different parts of our program. I feel like I have multiple personality disorder writing in third person like this.

In the first wave, we had **NUM TO BE COUNTED** people record over 56 different phrases, to see how they pronounced them. This wave served two purposes: one, to gather recordings for the second wave, and two, to see if our phonemic transcriptions were valid.

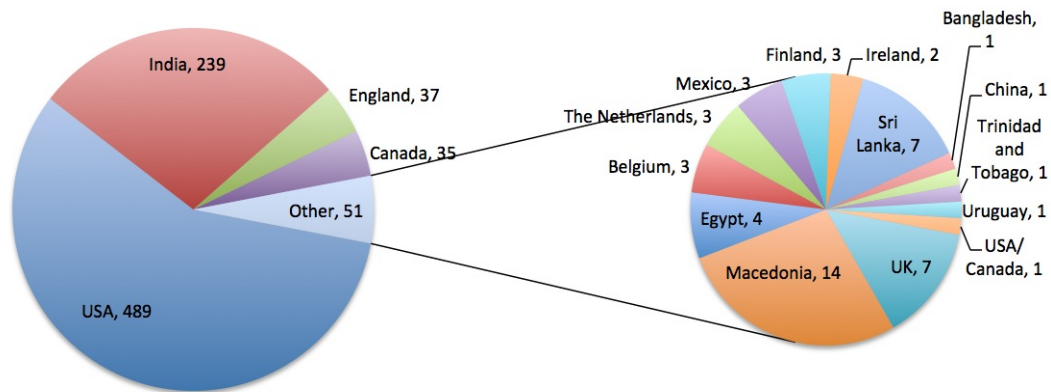


Figure 4.1: Our user study primarily polled people from the United States and India.

## 4.2 Methodology

### 4.2.1 First Wave: Recitation

In this wave of the user study, we used a combination of **NUM TO BE COUNTED** Mechanical Turk workers (hired for \$ 0.10 per task) and volunteers from Reddit.com [2] [3] to record 58 different phrases.

### 4.2.2 Second Wave: Transcription



orthoPhrase	numRecordings	phraseID
a nice cold our	3	A.17.51 a nice cold our
an ice cold our	2	A.17.135 an ice cold our
a nye scold our	2	A.17.69 a nye scold our
ah nye scold our	2	A.18.109 ah nye scold our
an eye scold our	2	A.18.125 an eye scold our
on aye scold our	2	A.18.267 on aye scold our
a nigh scold our	2	A.18.65 a nigh scold our
a nye skol dower	2	A.18.71 a nye skol dower
an aye skol dower	2	A.19.119 an aye skol dower
an eye skol dower	2	A.19.127 an eye skol dower
an ice coal dower	2	A.19.133 an ice coal dower
eh nice coal dower	2	A.20.159 eh nice coal dower
ah nice coal dower	2	A.20.89 ah nice coal dower
fourth wry to	2	B.15.19 fourth wry to
fourth wry too	2	B.16.20 fourth wry too
forth right ooh	2	B.17.1 forth right ooh
fourth rite ooh	2	B.17.13 fourth rite ooh
forth wright ooh	2	B.18.6 forth wright ooh
on i scold our	1	A.16.279 on i scold our
an i scold hour	1	A.17.128 an i scold hour
an i skol dower	1	A.17.131 an i skol dower
an ice-cold our	1	A.17.141 an ice-cold our
on i scold hour	1	A.17.278 on i scold hour
on i skol dower	1	A.17.281 on i skol dower
an aye scold our	1	A.18.117 an aye scold our
an ice cold hour	1	A.18.134 an ice cold hour
an ice-cold hour	1	A.18.140 an ice-cold hour
eh nye scold our	1	A.18.179 eh nye scold our

Response By Country	Num Responses
USA	290
India	124
Britain	32
Canada	28
UK	6
Macedonia	5
Egypt	4
Belgium	3
The Netherlands	3
Mexico	3
Finland	3
Ireland	2
Sri Lanka	2
Bangladesh	1
China	1
Trinidad and Tobago	1
Uruguay	1
USA/Canada	1

**Table 4.2:** Here's a table with the number of responses per country

# Chapter 5

## Results

PUT NGRAMS DIAGRAM HERE: <http://books.google.com/ngrams/graph?content=nice+col>

### 5.0.3 Individual Recording/Transcription Breakdowns

A recording-by-recording transcription breakdown reveals more interesting data. Each bubble charts represent the most common transcriptions for the recorded phrase listed at the top. The size of the bubble and the position along the x axis is indicative of the number of times that phrase was transcribed for this particular recording. The position along the y axis shows how often this phrase was transcribed over all the recordings.

Note that, for the purposes of clarifying these graphs, we did not chart any anomalous transcriptions—that is, transcriptions with only one occurrence in this recording, or transcriptions with less than 5 percent of the recording’s transcriptions with no other occurrences over the entire set of recordings. Doing so did not give us useful visual data, because the bubbles stacked and obscured each other. A full table of the transcriptions per recorded phrase can be found in the appendix

### Global: Most Common Phrase Transcriptions

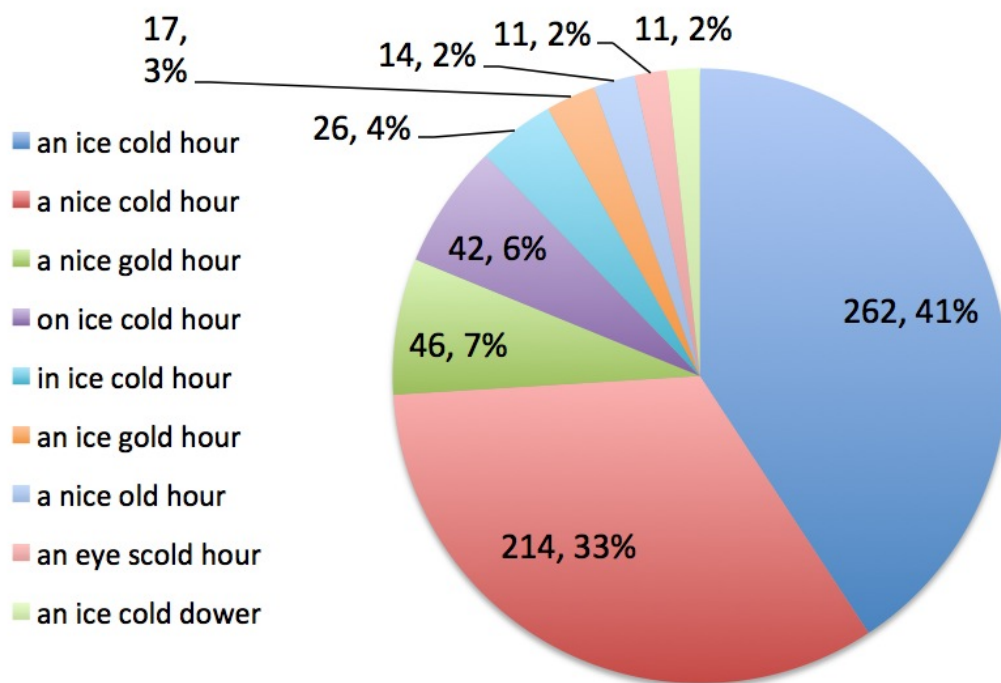


Figure 5.1: Our top two transcriptions were "a nice cold hour" and "an ice cold hour"

## USA: Most Common Phrase Transcriptions

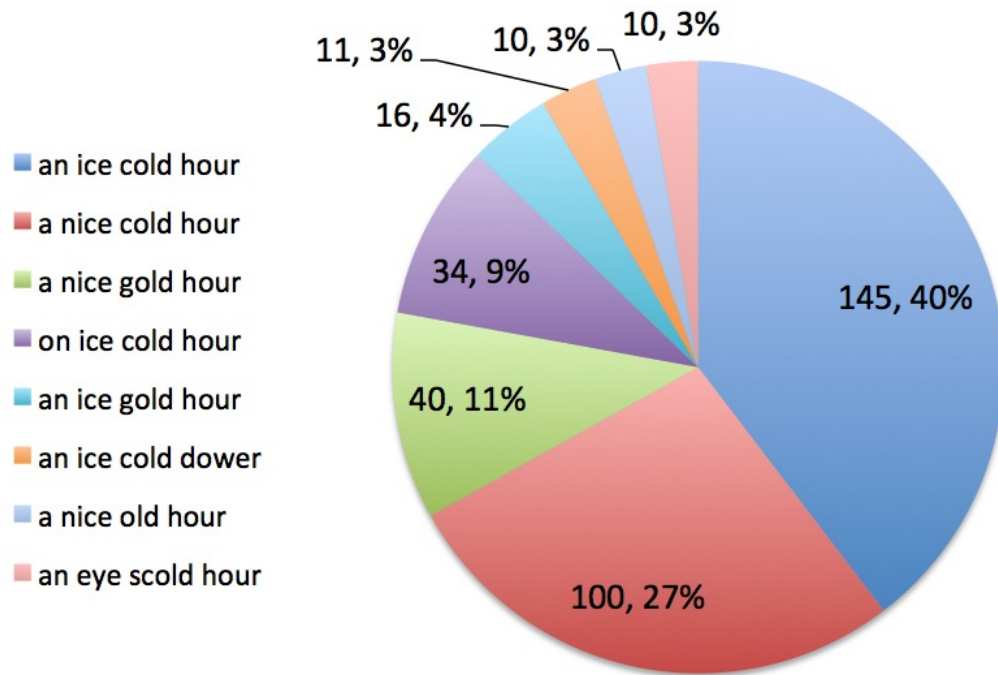


Figure 5.2: Though the breakdown is a bit different than the global transcription breakdown, you can still see the clear trend of "a nice cold hour" and "an ice cold hour" being the most common. There is a slightly larger gap between these two phrase, we hypothesize, because the American transcribers are familiar with what words normally are in proximity to others.

freq	phrase transcribed	total answers
931028	an ice cold hour	262
7851662	a nice cold hour	214
7820004	a nice gold hour	46
2911102	on ice cold hour	42
5503158	in ice cold hour	26
899370	an ice gold hour	17
8013781	a nice old hour	14
892949	an ice cold dower	11
859307	an eye scold hour	11

Table 5.1: You can see, our data isn't too horrible

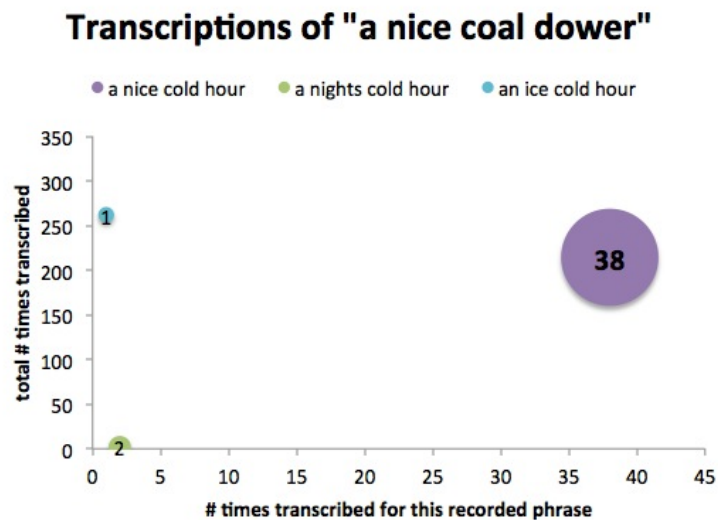


Figure 5.3:

### Transcriptions of "a nice cold our"

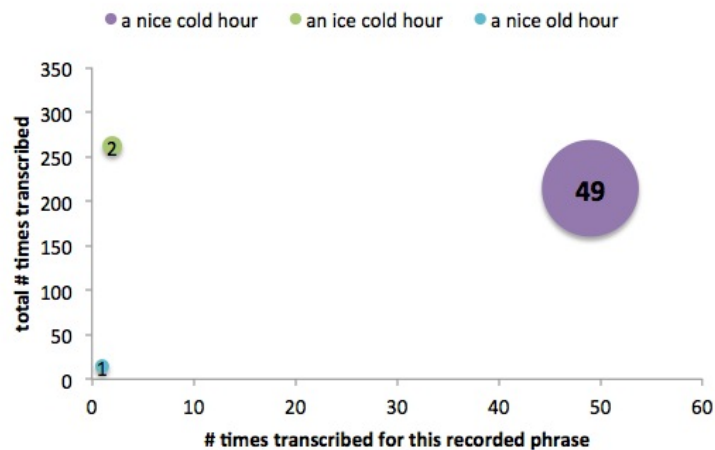


Figure 5.4:

### Transcriptions of "a nigh scold our"

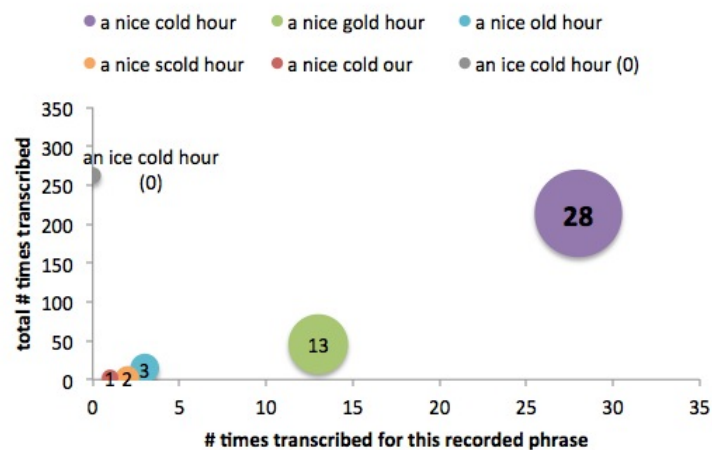


Figure 5.5:

### Transcriptions of "a nye scold hour"

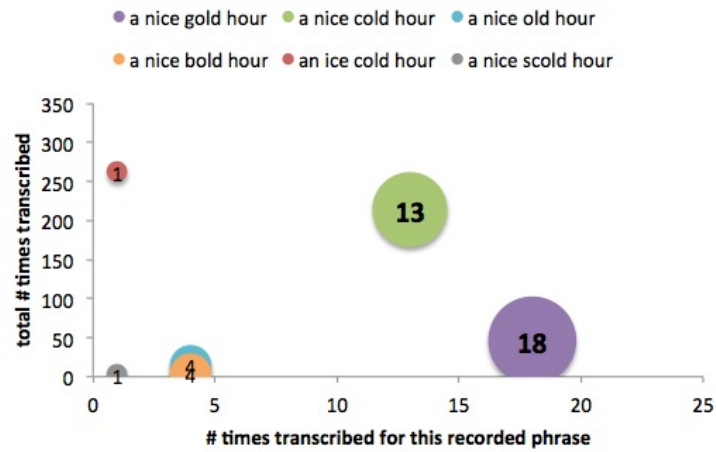


Figure 5.6:

### Transcriptions of "a nye scold our"

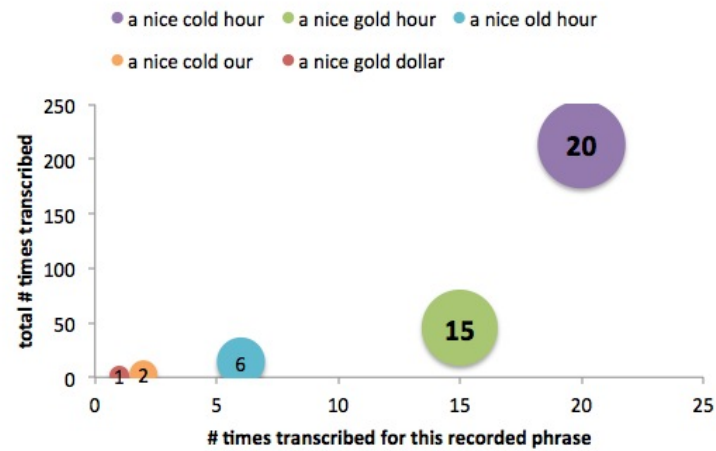


Figure 5.7:



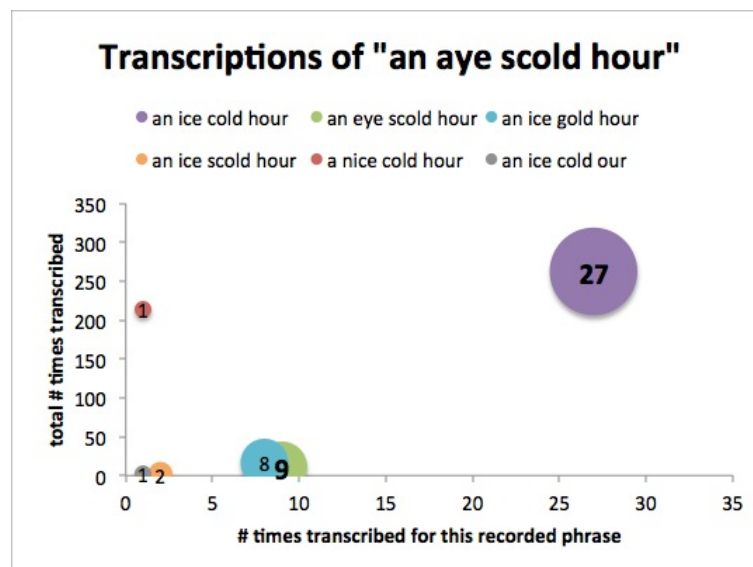


Figure 5.8:

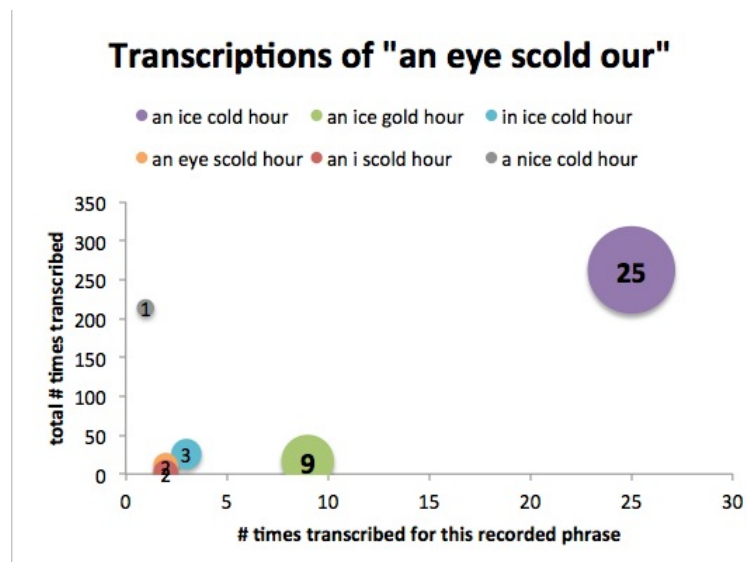


Figure 5.9:

### Transcriptions of "an ice-cold hour"

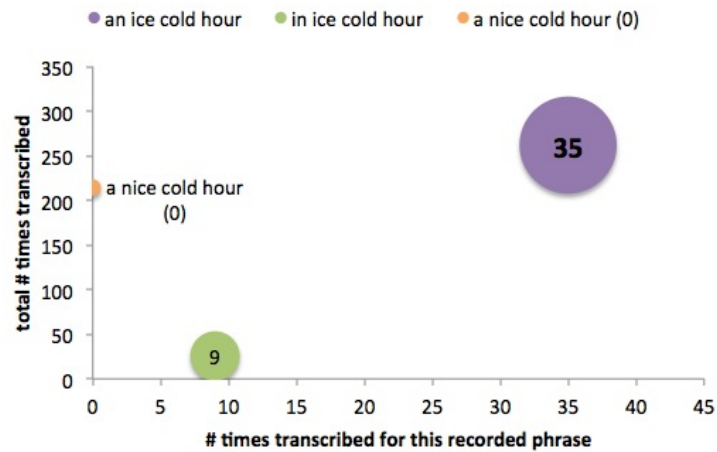


Figure 5.10:

### Transcriptions of "an ice cole dower"

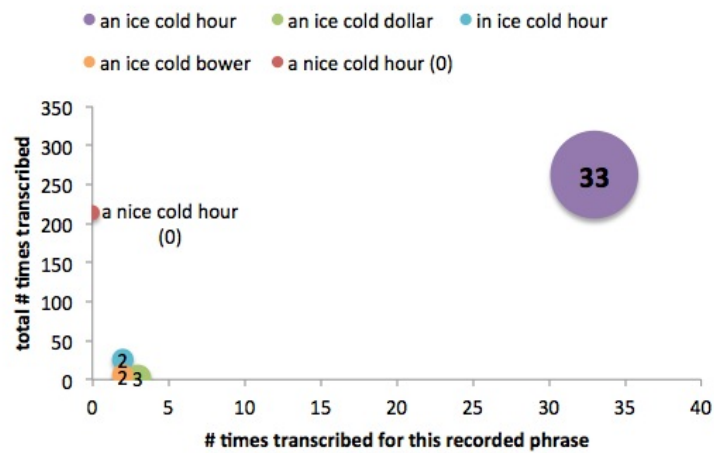


Figure 5.11:

### Transcriptions of "an ice kohl dower"

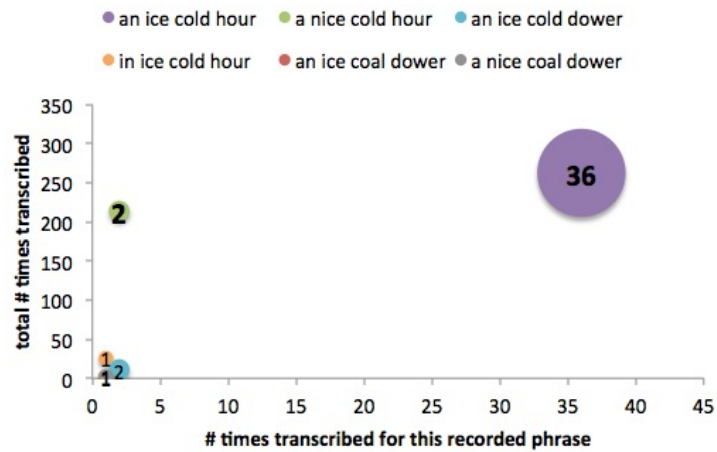


Figure 5.12:

### Transcriptions of "an ice coal dower"

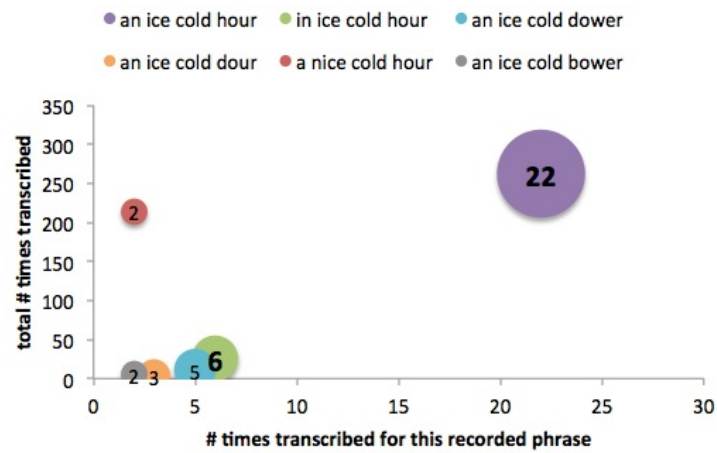


Figure 5.13:

### Transcriptions of "an ice cold our"

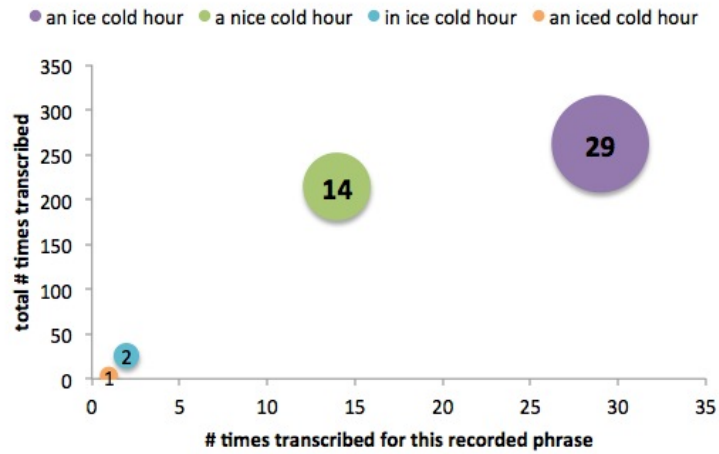


Figure 5.14:

### Transcriptions of "eh nice cole dower"

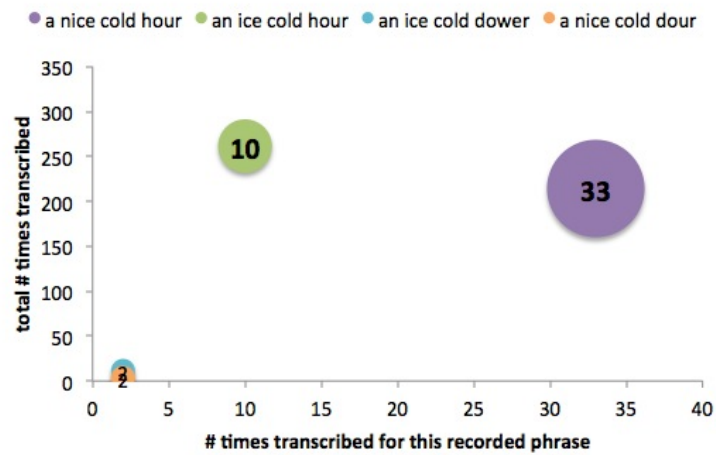


Figure 5.15:

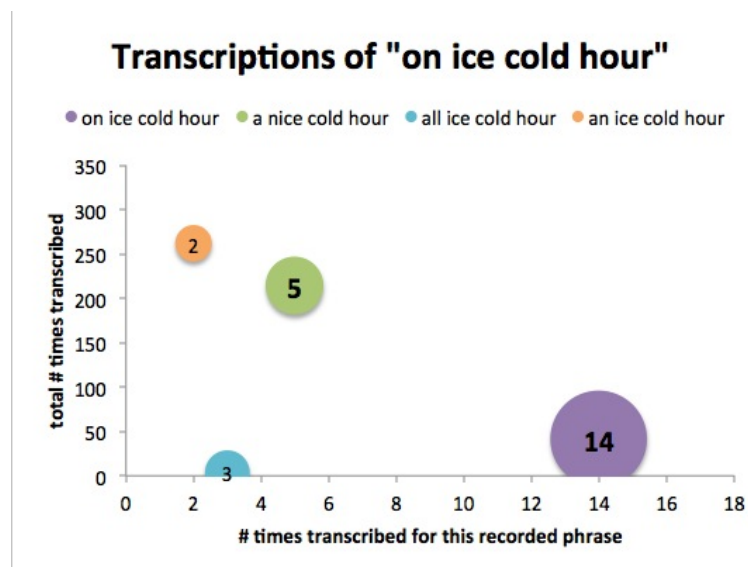


Figure 5.16:

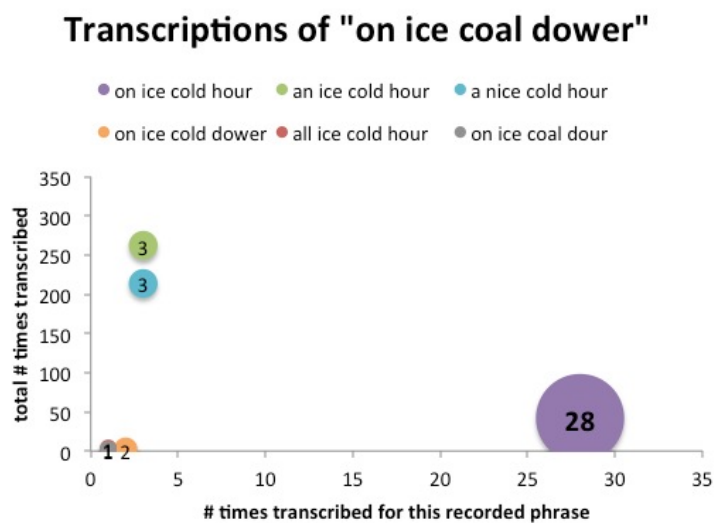


Figure 5.17:

## Chapter 6

### Future Work

## Chapter 7

## Conclusion

SAMPA	Example	Manner of Articulation/ Type	Voiced/ Voiceless	Starts as	Ends as	General type	Weight
p	pen, spin, tip	plosive	voiceless	block	block	Consonant	8
b	but, web	plosive	voiced	block	block	Consonant	7
t	two, sting, bet	plosive	voiceless	block	block	Consonant	8
d	do, odd	plosive	voiced	block	block	Consonant	7
tS	chair, nature, teach	affricate	voiceless	block	continuous frication	Consonant	6
dZ	gin, joy, edge	affricate	voiced	block	continuous frication	Consonant	5
k	cat, kill, skin, queen, thick	plosive	voiceless	block	block	Consonant	8
g	go, get, beg	plosive	voiced	block	block	Consonant	7
f	fool, enough, leaf	fricative	voiceless	continuous frication	continuous frication	Consonant	4
v	voice, have, of	fricative	voiced	continuous frication	continuous frication	Consonant	3
T	thing, breath	fricative	voiceless	continuous frication	continuous frication	Consonant	4
D	this, breathe	fricative	voiced	continuous frication	continuous frication	Consonant	3
s	see, city, pass	fricative	voiceless	continuous frication	continuous frication	Consonant	4
z	zoo, rose	fricative	voiced	continuous frication	continuous frication	Consonant	3
S	she, sure, emo- tion, leash	fricative	voiceless	continuous frication	continuous frication	Consonant	4
Z	pleasure, beige	fricative	voiced	continuous frication	continuous frication	Consonant	3



SAMPA	Example	Manner of Articulation/ Type	Voiced/ Voiceless	Starts as	Ends as	General type	Weight
h	ham	fricative	voiceless	continuous frication	continuous frication	Consonant	4
m	man, ham	nasal	voiced	redirect	redirect	Consonant	1
n	no, tin	nasal	voiced	redirect	redirect	Consonant	1
N	singer, ring	nasal	voiced	redirect	redirect	Consonant	1
l	left, bell	lateral	voiced	continuous	continuous	Consonant	0
r	run, very	approximant	voiced	continuous	continuous	Consonant	0
w	we	semivowel	voiced	continuous	end	Consonant	2
j	yes	semivowel	voiced	continuous	end	Consonant	2
W	what (Scot- tish)	approximant	voiceless	continuous	end	Consonant	3
x	loch (Scottish)	fricative	voiceless	continuous frication	continuous frication	Consonant	4
A	father, not, law	short				Vowel	0.25
I	city	short				Vowel	0.25
E	bed	short				Vowel	0.25
3‘	bird, winner	short				Vowel	0.25
‘r	bird, winner	short				Vowel	0.25
{	lad, cat, ran	short				Vowel	0.25
u	soon, through	short				Vowel	0.25
@	about	short				Vowel	0.25
jU	use, pupil	diphthong		syllabic consonant semivowel	short	Diphthong	0.5
ju	use, pupil	diphthong		syllabic consonant semivowel	short	Diphthong	0.5
i	see	long				Vowel	0.75

SAMPA	Example	Manner of Articulation/ Type	Voiced/ Voiceless	Starts as	Ends as	General type	Weight
V	run, enough	short				Vowel	0.25
U	put	long				Vowel	0.75
e	day	long				Vowel	0.75
O	or, shore	long				Vowel	0.75
a	DNE      in GenAm	long				Vowel	0.75
aI	my, height	diphthong		long	short	Diphthong	1
OI	boy	diphthong		long	short	Diphthong	1
oU	boat	diphthong		short	long	Diphthong	1
ou	boat	diphthong		short	long	Diphthong	1
aU	now	diphthong		long	long	Diphthong	1.5
=	ridden	syllabic consonant semivowel				Vowel	0.25

Table 7.1: Here are the metrics that we use to determine the weights of the phonemes

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