MISHEARD ME ORONYMINATOR: USING ORONYMS TO VALIDATE THE CORRECTNESS OF FREQUENCY DICTIONARIES

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Abstract

Misheard Me Oronyminator: Using Oronyms to Validate the Correctness of Frequency Dictionaries

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In the field of speech recognition, an algorithm must learn to tell the difference between "a nice rock" and "a gneiss rock". These identical-sounding phrases are called oronyms. Word frequency dictionaries are often used by speech recognition systems to help resolve phonetic sequences with more than one possible orthographic phrase interpretation, by looking up which oronym of the root phonetic sequence contains the most common words.

Our paper demonstrates a technique used to validate word frequency dictionary values.We chose to use frequency values from the UNISYN dictionary, which uses tallies each word on a per-occurance basis in a propriatary text corpus.

In the first phase of our user study, we generated oronym strings for the phrase *"a nice cold hour"*, and had over a dozen people make 62 recordings of the most common oronyms for that phrase. In the second phase, we selected 15 of the phase one recordings, and had ∼74 different people transcribe each one, for a total of 953 transcriptions overall.

If the frequency dictionary values for our test phrases accurately reflected the real-world expectations of actual listeners, we would expect that the most commonly transcribed phrases in our user study would roughly correspond with our metric for the most likely oronym interpretation of the root phrase.

During the course of our study, we found that using per-occurance frequency values when computing our overall-phrase-frequency metric caused the end result

to be thrown off by excessively common words, such as “the”, “is”, and “a”. These super-common words had such high per-occurance tallies that they overpowered any effect that any regular word had on a frequency metric. However, when we tally on a document-count basis, instead of a by-occurance basis, we found that this effect was mitigated.

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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. 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[11]. 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"[31].

Additional commonly-cited mondegreens include[7][26][28]:

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.[13]

Common oronyms include:

i scream $\leftrightarrow$ ice cream

an ice cold hour $\leftrightarrow$ a nice cold hour

grape ants $\leftrightarrow$ gray pants

real eyes $\leftrightarrow$ realize

1.3 Orthography

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, its the standardized system of writing down words in a specific language, using a commonly-accepted set of letters according to accepted usage. [14]

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, "orthographic phrase", refers to a sequence of regularly-spelled words found in an English dictionary.

Example: | "This is a orthographic phrase." |

1.4 Corpus

The word corpus is Latin, and means *body.* In general, it's helpful to think of a text corpus as a "body of text" with some special constraints.

In linguistics, the term "corpora" refers to samples from various textual sources.

A "text corpus" refers to a large, structured body of text, consisting of those corpora (a.k.a. samples from various textual sources).

In order for a text corpus to be useful, it must be a representative subset of the larger language it wishes to represent.

To put together a general text corpus for the English language, one should pull from many sources: books, newspapers, movie scripts, magazines, academic literature, etc.

If any single genre is over-represented in the corpora (text samples), then the resultant text corpus can be biased, and not useful for general purposes. For example: if one pulls all their corpora (text samples) from Wikipedia, the resulting text corpus is likely to underrepresent most first-person and second-person nouns and verbs, since those are verboten in Wikipedia articles.

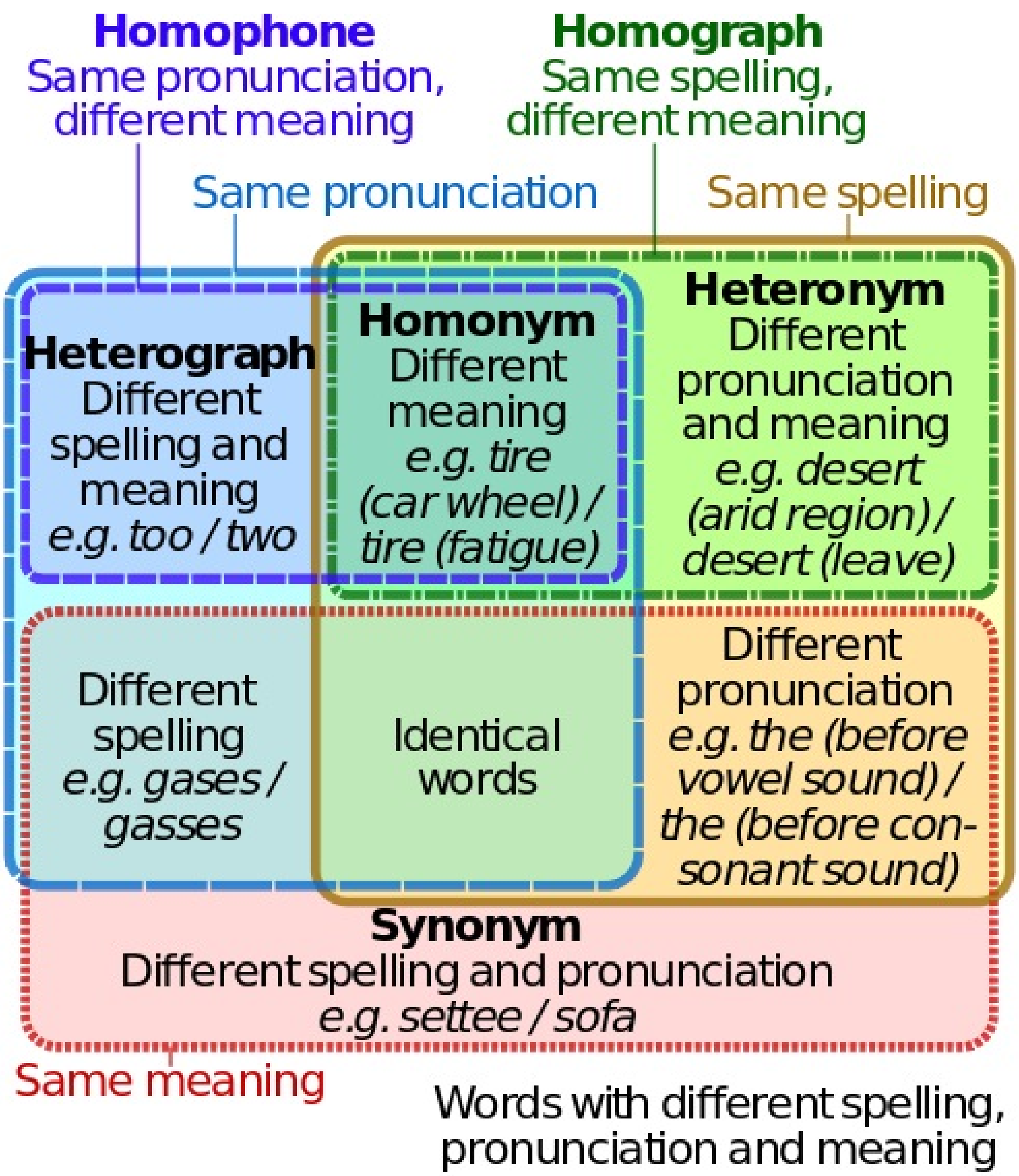
1.4.1 Uses of Text Corpora

A text corpus is generally used as the “control” set for comparing to data from linguistic experiments.

Given a good text corpus, word frequency can be generated simply by counting the number of occurrences of every word that appears in the corpus. This frequency data can be used by other applications, like Melody Matcher, to weight the possibility of resolving homophones[4], by calculating which words have a higher frequency count in the corpus. The higher the frequency, the are more common a word is, and the more likely it is to be heard.

In addition, given a text corpus, one can generate a dictionary of all words in the corpus. This dictionary can then be annotated with data such as part of speech, unique identifiers for homographs, and phonetic spelling.

1.5 Word Categorizations



1.5.1 Homographs

Homographs are orthographic words that are spelled identically. Typically, homographs are also pronounced differently, which makes them homographic heterophones. For example, there are two different pronunciations of “does” : the “multiple female deer” does (doze), and the “third-person singular present indicative form of ‘do”’ does (duhz). If the words are spelled identically AND pronounced identically, then then are homographic homophones, which are commonly known as homonyms.

1.5.2 Heterographs

Heterographs are orthographic words that are spelled differently. Typically, words are only called heterographs if they are also pronounced differently, making them heterographic homophones. The word “does” is a heterographic homophone with two different pronunciations: the “multiple female deer” does (doze), and the “third-person singular present indicative form of ‘do”’ does (duhz). (Most words in the English language are heterographic heterophones; that is, spelled and pronounced uniquely. Because this is the default state of a word set, we rarely describe such words in terms of homo/hetero phones/graphs. As such, the only time a word set is likely to be described as heterographic is if it is also a homophone.

1.5.3 Homophones

Homophones are orthographic words that are pronounced identically, but typically spelled differently. For example, the banes of every grammarian, “there”, “their”, and “they’re”, are heterographic homophones. Alternatively, “to”, “too”, and “two” are also heterographic homophones. If a homophone set is also homographic (that is, spelled identically as well as pronounced identically), then we refer to them as homonyms. As such, the only time the words in a set are likely to be labelled “homophones” is if they are also heterographic.

1.5.4 Homonyms

Homonyms are orthographic words that are pronounced and spelled identically, but defined differently. For example, depending on context, the word “left” can mean left (the opposite of right), or left (the past tense of leave). Homonyms can also be referred to as homographic homophones.

1.6 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.

1.6.1 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 audiences. The building blocks of phonetics are *phones*, which represent atomic sounds.

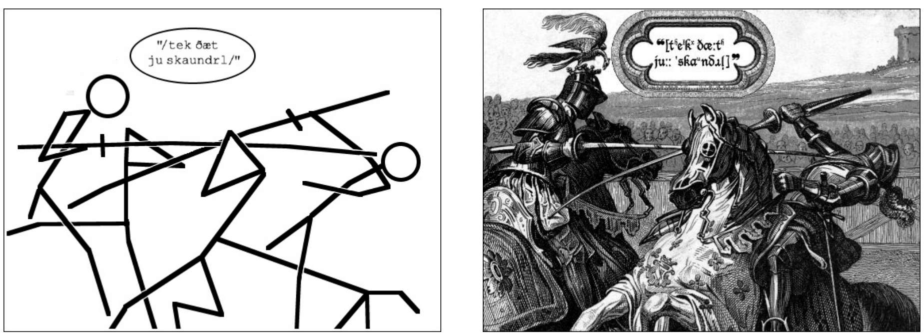
1.6.2 Phonology (aka phonemics)

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.

1.6.3 Phonetics Vs Phonology

As we said previously, though the terms are sometimes used interchangably, 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. Figure 1.1 provides a final, illustrative metaphor of the difference.



(a) Phonology[8] (b) Phonetics[9]

Figure 1.1: The difference between phonetics and phonology

1.7 Phonemic/Phonetic Alphabets

As we stated in section 1.6.2, phonemes are the atomic building blocks of words. In a phonemic alphabet, 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.

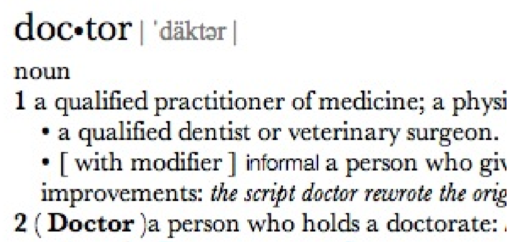


Figure 1.2: The characters to the right of the large bold word "doctor" are IPA symbols.

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.

1.7.1 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 uses "letters" consisting of 1-2 ASCII characters to represent each phoneme. The ASCII sequences corresponding to each of the SAMPA letters are designed so that any SAMPA sequence is deterministically parsible.

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

See table **??** 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 k3`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, cutural immersion, and language familiarity [29]. 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 step towards this is understanding and identifying how many ways a particular textual phrase 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:

Orthographic:	and Les- lie	end- less- ly
SAMPA:	@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 difficult-to-sing 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 boundries. So, our singer can effectively think of the sung phrase as:

YOU an dME en dLESS lee

This does not cause confusion for listeners, because they are 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 eight 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

There are two points at which the author's intendeded phrasing can be muddled : First, when the author's orthographic text becomes an orator's spoken (phonetic) interpretation, and second, when the orator's phonetic interpretation is translated phonetically by an audience into a perceived orthographic phrase. Both of these interpretations must be made succesfully 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 pronouced one way, but it can be heard multiple ways–the most notable of which is “I stink”, not “iced ink”.

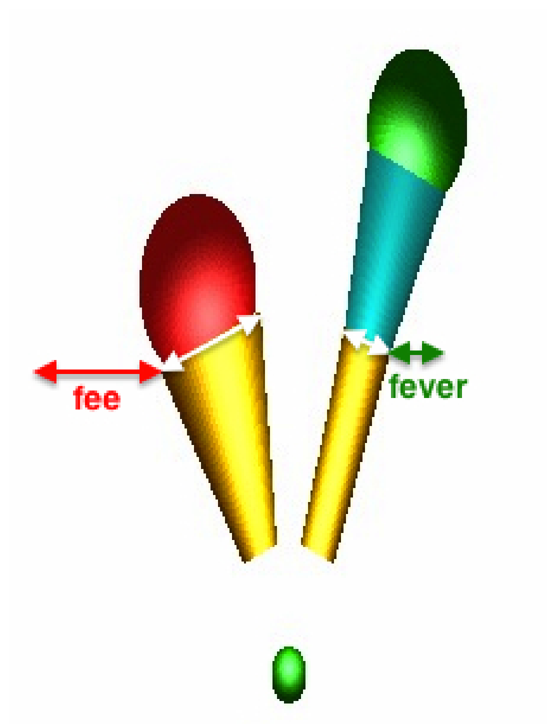
The phrase “a nice cold hour” can fail on both parts. First, the orator could have accidentally-capitalized the word Nice in their head, and made it sound like Nice, the city in France. An audience would likely hear this as “niece”, and would be confused, at best. Even if the orator pronouces the phrase as the author intended, the audience could hear multiple orthographic phrases in the same phonetic 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 because they though they were interpreting a phonetic sequence in a way that resulted in an orthographic dead end. This happens due to the relative frequency of the possible lyrics heard.

For example, when asked to sing along with the Adele song, Rolling in the Deep, people who were starting to sing enthusiastically dropped out around the line “reaching a fever pitch”[20]. Let us consider the phrase “fever pitch”. This phrase has no exact oronyms, but it does have a potential dead end– a listener could hear the first syllable of the phrase as the word “fee”, which has a frequency of 7265. That's more than double the frequency of the word “fever”, which is

3095.

Looking at the oronym parse tree for the phrase “fever pitch” in figure 2.1, we can see that the branch for “fever” ends in a much smaller radius than the branch on the left for the word “fee”. As you can see by the relative size of the end spheres of the branches, the word “fee” even outweighs the last word in the other branch as well (which is “pitch” with a frequency of 5104). Since the human brain is pre-disposed to parse more-familiar words, having that heavily-weighted dead-end branch is likely the cause of the casual listener not being able to memorize the lyrics.



[h]

Figure 2.1: Annotated Oronym Parse tree generated for the phrase “fever pitch”

Chapter 3

Implementation

We present a computer program which takes in a textual phrase in English, determines all oronyms for that phrase, and then visualizes those oronyms in tree form, with branch width scaled by word frequency metrics to indicate the likelihood of interpretation.

To accomplish this, the 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 speaker's 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.

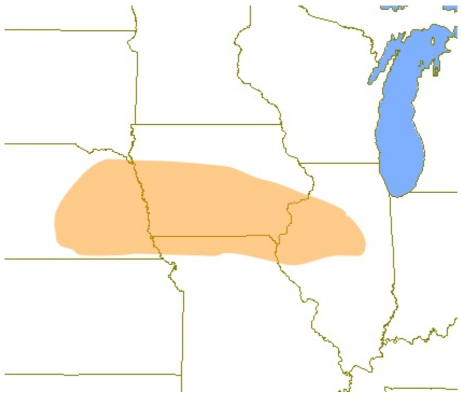


Figure 3.1: This is the geographic area whose accent most closely resembles the General American Accent [6]

3.1.1 Accent Choice

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 most Americans, but is used as an "average accent". It most closely resembles the Midwestern accent used in the area in Figure 3.1, but is more commonly recognized as "the newscaster accent". Newscasters learn this accent for use on national TV, because it is the "least-accented" of the American accents[19].

The downside of using the General American accent is that, while it does give a good approximation of most American's speaking accents, it does not perfectly reflect a "singing accent". Singers tend to elongate syllables, changing emphasis placement in words, and vowels tend to be sung in a more "round" matter[22].For example, though the dictionary pronunciation of the word "baby" is `"be$bi` (bay-bee), in songs, you commonly hear the pronunciation `"be$be` (bay-bay). The `e` sound is easier to sing than the `i` (ee) sound, because the latter requires the the

```
ABBREVIATE  AH0 B R IY1 V IY0 EY2 T
```

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

singer move their mouth and vocal cord position further from neutral than the former does[16].

However, different singers will change pronunication based upon which vowels are easiest for them to sing, so using the General American accent still gives us a fairly good approximation[18].

3.1.2 Dictionary Options

We considered using three different phonetic dictionaries: the CMU dictionary, LC-STAR dictionary and UNISYN dictionary[10] [2] [17]. We started out by looking at the LC-STAR dictionary, but quickly decided that it wasnt going to be as useful to us, because the LC-Star project is relatively focused on Speech-to-Speech or Text-to-Speech tech. In addition, the dictionary is not well-maintained.

The CMU dictionary showed promise, but had a few shortcomings. It had a very simple way of encoding words: first the word, then the identifier number in parentheses (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.

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 for words in song lyrics, where each note has its own syllable underneath it, and each syllable might have many different sounds. In addition, it used non-standard symbols for its phonetic alphabet, which would complicate matters if, in the future, we chose to combine data from other dictionaries with our existing dictionary.

However, unlike some other dictionaries we considered, the CMU dictionary (1) was actively maintained, (2) included proper nouns, which are often found in lyrics, but not in dictionaries, and (3) was ridiculously easy to read.

With the downsides and benefits in mind, the CMU dictionary could not be used in isolation, especially if we wanted to incorporate contextual data from other sources.

The UNISYN dictionary is used primarily to phonetically translate words into multiple accents. It has its own formated dictionary, with a bunch of wild-cards representing different phones. UNISYN provides some semi-functioning perl scripts that allow you to specify a dialect youd like to use (For example, a Californian would say "cooking" differently than someone from the Deep South, and both would say it differently than someone from London. However, they are all speaking English. The UNISYN dictionary facilitates this translation).

It had all the information we needed, and then some. However, it was case-insensitve, meaning that it didn't make it easy to differenciate pronunciations for some words. For example, the word "nice" is pronounced differently from the city "Nice", but they were both stored as "nice" in the orthography of UNISYN. The CMU dictionary did keep track of capitalization. The obvious conclusion, then, was to grab the capitalizations from the CMU dictionary and put them in the UNISYN dictionary, aligning them by pronunciation and part of speech.

However, we ran into a setback, mentioned in the very first article we found

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"

references to both dictionaries in: the dictionaries were inconsistent[27]. They didnt 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[1]. Because of this, we decided to use the UNISYN dictionary exclusively.

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, orthographic spelling of the word.

<uniqueID> is a number (and optional string) used to differentiate homographs[2].

<partOfSpeech> is used to identify the specific part of speech for the word.

[1]Homographic heteronyms are words that are spelled identically by pronouced differently, such as "Do you know what a buck *does* to *does*?"

[2]A homograph shares the same written form as another word but has a different meaning; For example, a farmer would **sow** *(verb)* seeds in a field, but could also raise a **sow** *(noun)* for bacon.

<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 subsequent phones (until the next separator) are not emphasized. If it's `%`, then they are pronounced using secondary emphasis. If it's `"`, then they are given the primary emphasis in the word.

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

<extendedOrtho> allows for stemming analysis of words, for possible use in future work.

<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"[25].

An example of a 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[15].

3.2 Oronym Generation

3.2.1 Step 1: Find all phonemic variations of an orthographic phrase

First, our program takes an orthographic phrase to find oronyms for (Figure 3.4).

‘a nice cold hour’

Figure 3.4: A valid orthographic phrase

We then tokenize this phrase into its component words, using whitespaces as a delimiter (Figure 3.5).

‘a’, ‘nice’, ‘cold’, ‘hour’

Figure 3.5: The root orthographic phrase, tokenized

For each word in the phrase, we query our phonetic dictionary for all possible SAMPA pronunciations (Figure 3.6). .

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

‘a’ → `e, @, A`
‘nice’ → `naIs, nis`
‘cold’ → `kould`
‘hour’ → `aU`r`

Figure 3.6: 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.

phrase(Figure 3.7). .

```
e naIs kould aU`r
@ naIs kould aU`r
A naIs kould aU`r
e nis kould aU`r
@ nis kould aU`r
A nis kould aU`r
```

Figure 3.7:

The pseudocode for this process can be reviewed in figure 3.8.

3.2.2 Step 2: Finding all Orthographic phrases for a Phonemic Sequence

Then, for each phonemic phrase, we want to figure out all valid orthogrpahic 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 phoenetic sequence in a tree form, similar to the tree pictured

```
findAllPhoneSeqsForOrthoPhrase( orthoPhrase ) {
  allFullPhrasePhoneSeqs = empty list of list of phones
  orthoWords = split orthoPhrase on spaces

  origNumFullPhrases = 0
  for( orthoWord in orthoWords with index i ) {
    nextWordSampaPhoneSeqs = possible phone seqs following orthoWord

    if ( orthoWord is the first word in orthoPhrase ) {
      for( phoneSubSeq in nextWordSampaPhoneSeqs ) {
        append phoneSubSeq to allFullPhrasePhoneSeqs[i]
      }
    } else {
      origNumFullPhrases = allFullPhrasePhoneSeqs.size()
      if theres more than one vector <phone> in nextWordSampaPhoneSeqs
        then we need to create duplicates of all existing allFullPhrasePhoneSeqs
    }

    for( m = 0 to allPhrasePhoneSeqs.size() ) {
      phraseToAppendIndex = m / origNumFullPhrases
      phoneSeqToAppend = nextWordSampaPhoneSeqs[phraseToAppendIndex]
      append phoneSeqToAppend to allFullPhrasePhoneSeqs[m]
    }
  }

  return allFullPhrasePhoneSeqs
}
```

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

in abbreviated form in Figure 3.9. 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 construct 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". Figure 3.9 shows a visual representation of traversing an entire dictionary's phonetic tree for nodes along the paths for the SAMPA sequences `aI s` and `n aI s`.

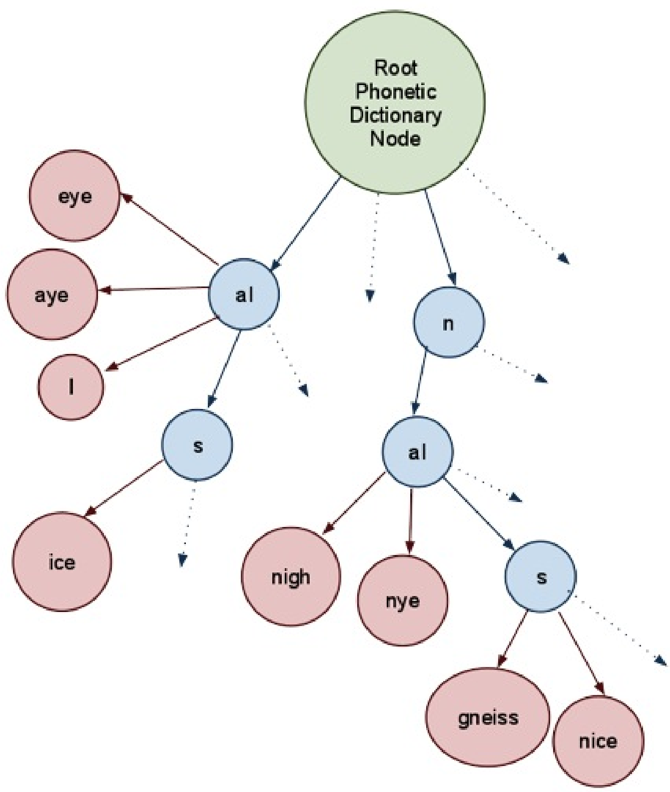


Figure 3.9:

We can use this dictionary tree method to discover all valid orthographic interpretations for any phonetic sequence of our root orthographic phrase, as shown in figure 3.10 for the phrase:

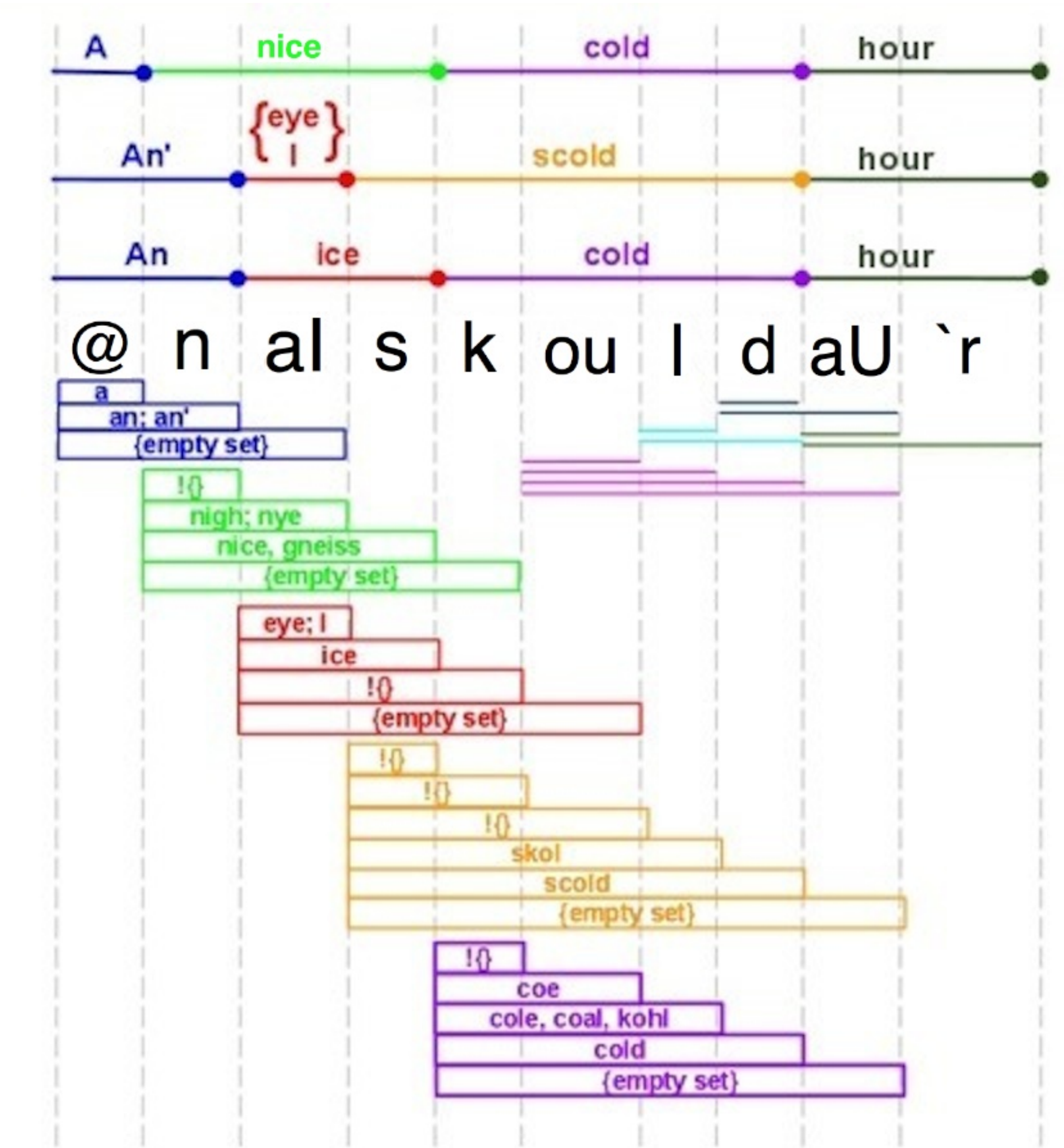


Figure 3.10:

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

After this, we have a list of all unique and valid oronyms for the original root

```
discoverOronymsForPhrase( origOrthoPhrase, includeDeadends ) {
   orthoMisheardAsPhrases = empty list
   allPhoneSeqsOfOrigPhrase = origOrthoPhrase.findAllPhoneSeqs()

   for( curPhoneSeqWithEmph in allPhoneSeqsOfOrigPhrase ) {
      // Remove emphasis marking for easier lookups
      curPhoneSeq = curPhoneSeqWithEmph.stripEmphasis()

      altOrthoPhrases = findOrthoStrsForPhoneSeq( curPhoneSeq )

      for( altOrthoPhrase in altOrthoPhrases ) {
         // Ensure it contains valid ortho text in all cases, and if
         // includeDeadends=false, contains no deadEndDelims so we only add
         // fully valid strings
         if ( ( includeDeadends == true &&
                altOrthoPhrase != deadEndDelim1 &&
                altOrthoPhrase != deadEndDelim2 ) ||
              ( altOrthoPhrase.contains( deadEndDelim1 ) == false &&
                altOrthoPhrase.contains( deadEndDelim2 ) == false ) ) {
            append altOrthoPhrase to orthoMisheardAsPhrases
         }
      }
   }

   orthoMisheardAsPhrases.removeDuplicates()

   return orthoMisheardAsPhrases
}
```

Figure 3.11: Algorithm to get all oronyms for an orthographic phrase.

phrase.

In the case of "a nice cold hour", this returns 290 oronyms, as seen in the first column of figure **??**.

The pseudocode for this process can be reviewed in figure 3.11

3.2.3 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 identical.

To do this, we tokenize each oronym phrase into its component words, once again delimiting by non-newline whitespaces.

Then, we query our phonetic dictionary with each word to get that word's frequency value. We store each word's value separately. When we have retrieved the frequencies for all the words in a phrase, we then sum up all the frequencies to give a combined frequency of the entire phrase.

You can see these frequency counts for the phrase "a nice cold hour" in figure ??.

3.3 Visual Representation

We created two different oronym visualizations. The first, oronym trees, were chosen for their ability to show the phonetic dead ends that may happen during oronym generation. Our particular oronym tree visualization is written in C++ using OpenGL, which allows for future integration into another codebase.

The second visualization shows all valid oronyms of a root phrase using what is known as a sunburst diagram. These sunburst diagrams were created using the ProtoVis library, and use javascript data files with html wrappers. The javascript data files were generated using the same C++ code that the first visualization used, so both visualizations show similar data. However, the oronym sunburst diagrams more easily exhibit the weighting of the different oronym paths with their frequency dictionary values.

3.3.1 Oronym Tree Visualization

We go about building the visual representation of the oronym parse tree in much the same way that we build the textual list of oronyms, with one important caveat: our oronym parse trees may contain oronym fragments. To deal with these we've got to keep track of all our abandoned sub-phrases. For example, for the root oronym phrase "iced ink" (`aI s t I N k`), a listener may hear "I sting"(`aI s t I N`), and then be confused when the phone `k` comes along.

Our algorithm for doing this is recursive, called from a parent function that draws the tree's 'seed' sphere. This parent function is a depth-first traversal of the oronym tree, and is documented in figure 3.23

We start in the parent function by getting all the oronyms of our orthographic phrase, using the process in sections 3.2.1 and 3.2.2. However, instead of ignoring any incomplete orthographic interpretation of a phonetic sequence, as we do in section 3.2.2, we add them to the list of oronyms, keep-

aye sting xxx

aye stink ___SUCCESS!___

ay sting xxx

ay stink ___SUCCESS!___

eye sting xxx

eye stink ___SUCCESS!___

i sting xxx

i stink ___SUCCESS!___

ice ting xxx

ice xxx

iced ink ___SUCCESS!___

Figure 3.12: All partial and complete oronyms for the phrase "iced ink"

ing track of them by appending ‘xxx’
or ‘fff’ to the end of the incomplete
oronym string. For example, as shown in figure 3.12. the phrase “iced ink” may only have has five complete oronyms, but it has six additional oronym fragments, making for 11 possible interpretations.

Then, we tokenize our phrases by whitespace, and look up the frequency of each word, as shown for “iced ink” in figure 3.13. We will later scale our branches’ radii using the maximum and minimum word frequency values found during this run. In this case, the maximum is 9,937,877 for the word “I”, and the minimum is 124 for the word “ting.”

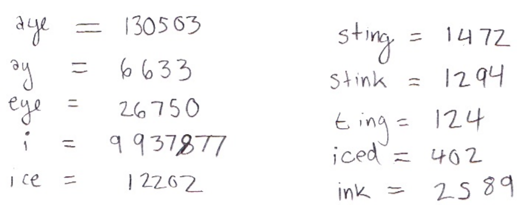


Figure 3.13: Frequency values for all unique words in “iced ink” oronyms

Once we have all partial and complete oronyms, plus the max and min word frequency values found in all those phrases, we pass them into our recursive function, along with the radius of the seed sphere. That radius will be the beginning radius of each root-level branch, as shown in figure 3.14

Inside our recursive function, we pull the first word out of each orthographic phrase, and create a set of unique first words, as seen in figure 3.15.

We then go through this set of unique first words iteratively.

For each word, we look up frequency in the phonetic dictionary. Then, we use the max and min frequencies that we found in our parent function, plus constants

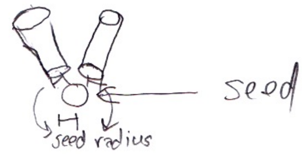


Figure 3.14: Seed Sphere vs branch radius comparison

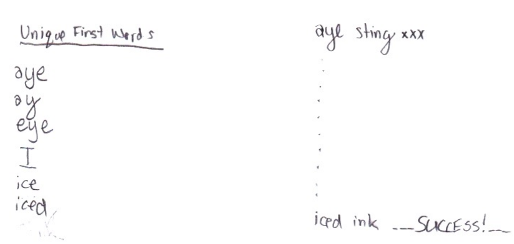


Figure 3.15: All uniqueirst words of "iced ink" oronyms

for max and min radius size, to scale that frequency into a usable radius size.

Then, we check the contents of the word string.

If the word is "xxx" or "fff", then it's not a word at all—just an indication of the dead end of an oronym fragment. In this case, as seen in figure 3.16, we draw a red sphere with the radius of the branch's ancestor, using the radius parameter passed into our recursive function for 'lastRadius'.

If the word is "___SUCCESS!___", that indicates a full oronym has been successfully found, and is terminating at that point. This time, we draw a green sphere using the *lastRadius* parameter for size, as seen in figure 3.17 for the phrase "I stink."

If the word isn't "xxx'.' "fff',' or "___SUCCESS!___", it is a real word, and we draw a cylinder "branch" representing that word. The cylinder's bottom radius is equal to *lastRadius*, and the top radius is equal to the scaled radius that we

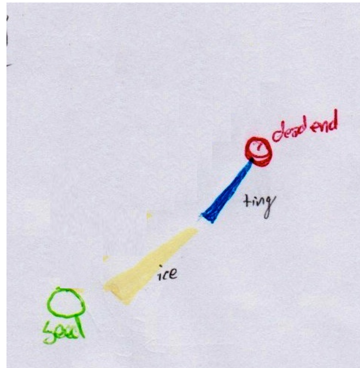


Figure 3.16: Dead end sphere for oronym fragment "ice ting"

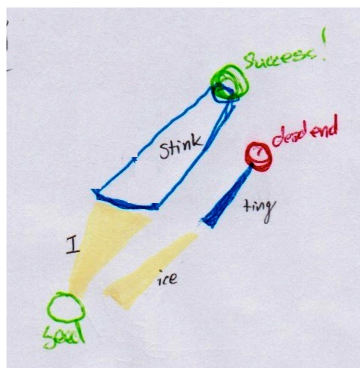


Figure 3.17: Success indicator sphrere for complete oronym "I stink"

derived using the word's frequency. An example of this branch radius scaling is show in figure 3.18.

After we draw the cylinder, we then go through the full list of phrases, and compile a list of all phrases that start with the word we just drew the cylinder for, as in figure 3.19. Then, we remove the first word from each of those phrases, deduplicating the resulting list of "tail" phrases, which is shown in figure 3.20.

Then, we change our material color (so that different levels of branches will be different colors), and make a recursive call to our current function, passing as parameters the scaled radius and the list of tail phrases.

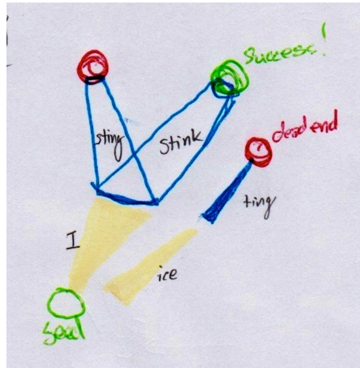


Figure 3.18: Scaled branch radii showing frequency difference

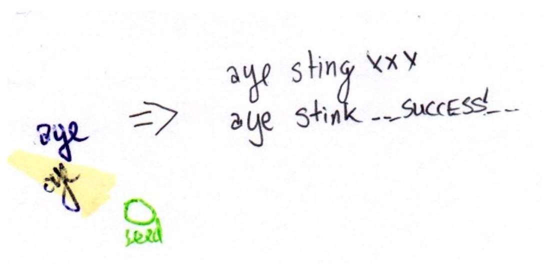


Figure 3.19: All oronym phrases of "iced ink" starting with "aye"

After this recursive call, we change our color material back to whatever it was before the call, and then continue on to the next unique first word in our set, which, in this case, is "ay."

Once we have looped through all our unique first words, we know we're done drawing that set of branches, and we return.

This gives us the oronym parse tree seen in figure 3.21. As shown in figure 3.22 (the annotated version of figure 3.21) each branch on the tree represents a single orthographic word.

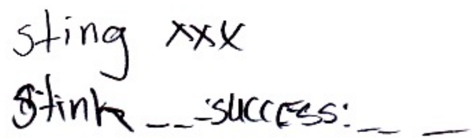


Figure 3.20: Tail phrases for oronyms of "iced ink" that begin with "aye"

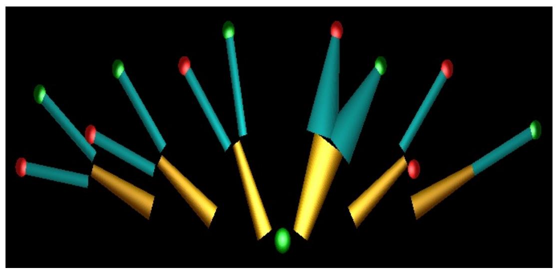


Figure 3.21: Oronym tree for the phrase "iced ink"

3.3.2 Oronym Sunburst Visualization

For our second visualization type, we chose to use sunburst diagrams.

Reading a sunburst diagram

To read a sunburst diagram, start at the very center, which in our case is labelled root. Then, pick any one segment from the first ring surrounding the root. The word contained in this segment will be the first word in your phrase.

Look at all the outer segments that directly touch the first segment you picked. Pick one of those outer segments. The word in that segment is the second word in your phrase.

Continue this process until you reach a segment that has no subsequent outer segments. At this point, you will have compiled a full oronym phrase. The size of

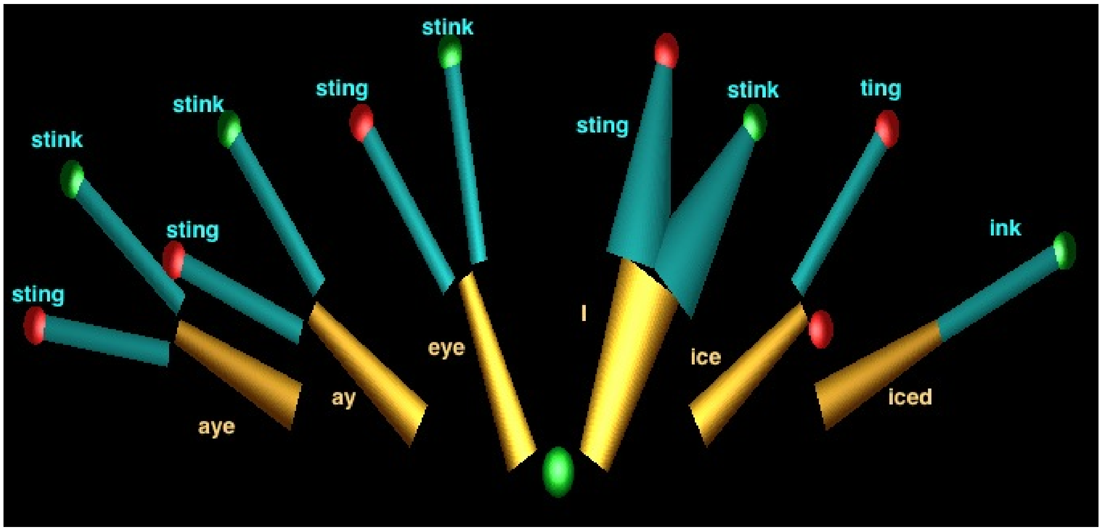


Figure 3.22: Annotated oronym tree for the phrase "iced ink"

the final segment, relative to the rest of the segments in its particular ring, shows you the relative commonness of the phrase whose path ends at that segment.

Sunburst diagram generation

To generate these sunburst diagrams, we modified our existing C++ program to output data in the Protovis js format, seen in figure 3.27.

The labels before the colons are displayed on the diagram in their respective segment, as seen in figure 3.28.

Some minor adjustments were made to the C++ output. The Protovis document format doesnt allow for non-alphanumeric characters to appear in labels, so words like ice-cold or its caused errors. We removed all non-alphanumeric characters so that the sunbursts would generate successfully.

One of the main benefits of the Protovis data format is that, once you have your data, you can trivially generate many different types of graphs. For our

```
buildAndDrawFullTree( orthoPhrase ) {
   fullPhrases = orthoPhrase.discoverOronyms()
   (maxWordFreq, minWordFreq) = fullPhrases.getMaxAndMin()

   // 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 3.23: Given an orthographic phrase, this function prepares to draw the tree

data format, we can general both sunburst and icicle graph views. We chose to use sunburst graphs, but having both options was nice.

Example Sunburst Diagrams

We generated several types of sunburst diagrams, using both artificially-balanced frequency values that gave all paths equal weight and using the frequency values for each path derived from our UNISYN dictionary. A clearer view of how we used sunburst diagrams can be provided with some concrete examples.

Consider the two sunburst diagrams for the oronyms of the phrase “iced ink”, shown in figures 3.29 and 3.30. ”iced ink” has five different oronyms: “iced ink”, “ay stink”, “aye stink”, “eye stink” and “I stink”. The five different outer segments (which are easier to see on the equal-weighted sunburst diagram in

```
drawBranchesAtFork( fullPhrases, lastRadius) {
   if( fullPhrases.size() == 0 ) {
      return
   }

   // Use a set to ensure no duplicates.
   firstWords = empty set

   for( phrase in fullPhrases ) {
      if( phrase.size() > 0 ) {
         firstWords.insert( phrase.firstWord() )
      }
   }

   // Calculate positioning variables for the spread of branches for firstWords.
   for ( curFirstWord in firstWords ) {
      firstWordFreq = curFirstWord.frequency()
      newAdditiveRadius = firstWordFreq.scaleToRadius()

      glPushMatrix()
      {
         // Translate and rotate into place
         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,
                        newAdditiveRadius, lastRadius )

            // Find all phrases in fullPhrases that start with that firstWord
            tailsVect = fullPhrases.findAllWithPrefix(curFirstWord)

            // Change the colors for each branch level

            // Pass those phrases to drawBranchesAtFork
            drawBranchesAtFork( tailsVect, newAdditiveRadius, curXOffset, curYOffset )

            // Change the colors back to ensure consistency for each branch level
         }
      }
      glPopMatrix()
   }
}
```


Figure 3.24: This is the function that facilitates the in-time drawing of the tree as we parse though our oronyms possibilities

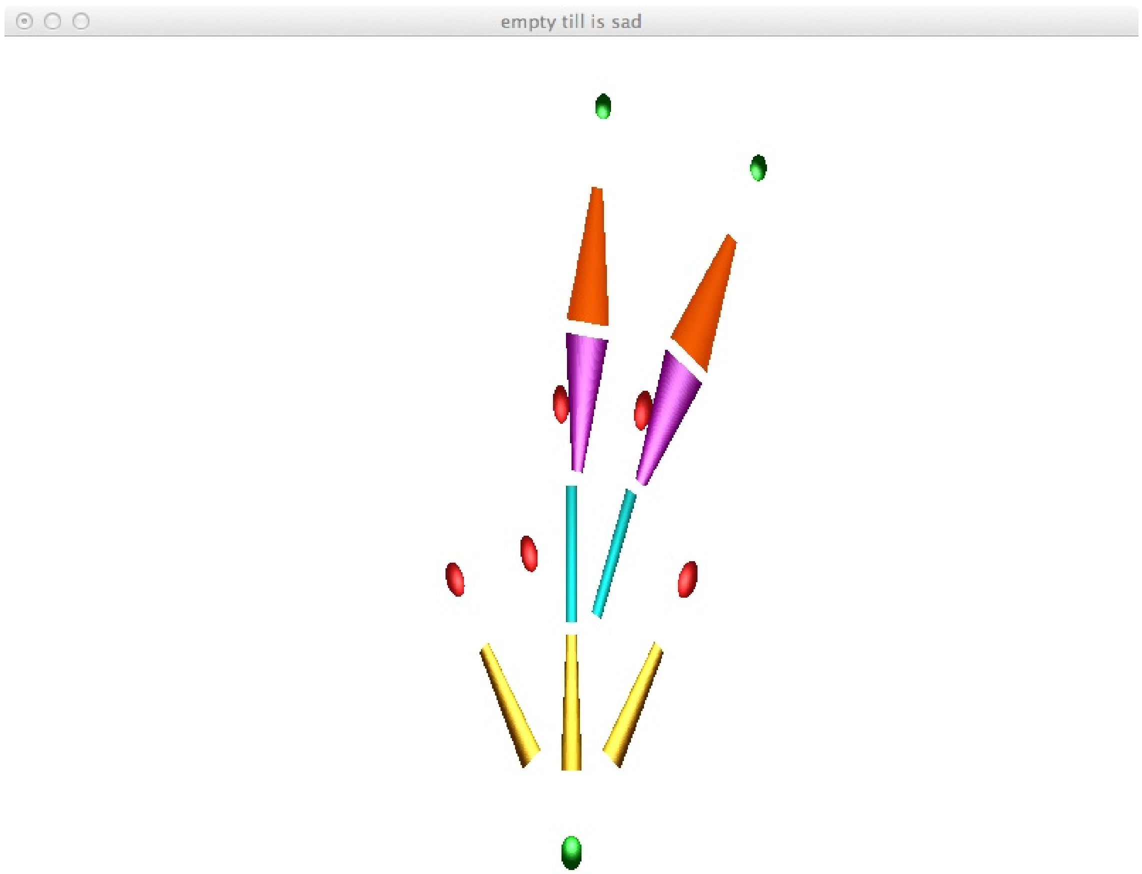


Figure 3.25: This is the parse tree for the phrase "empty till is sad"

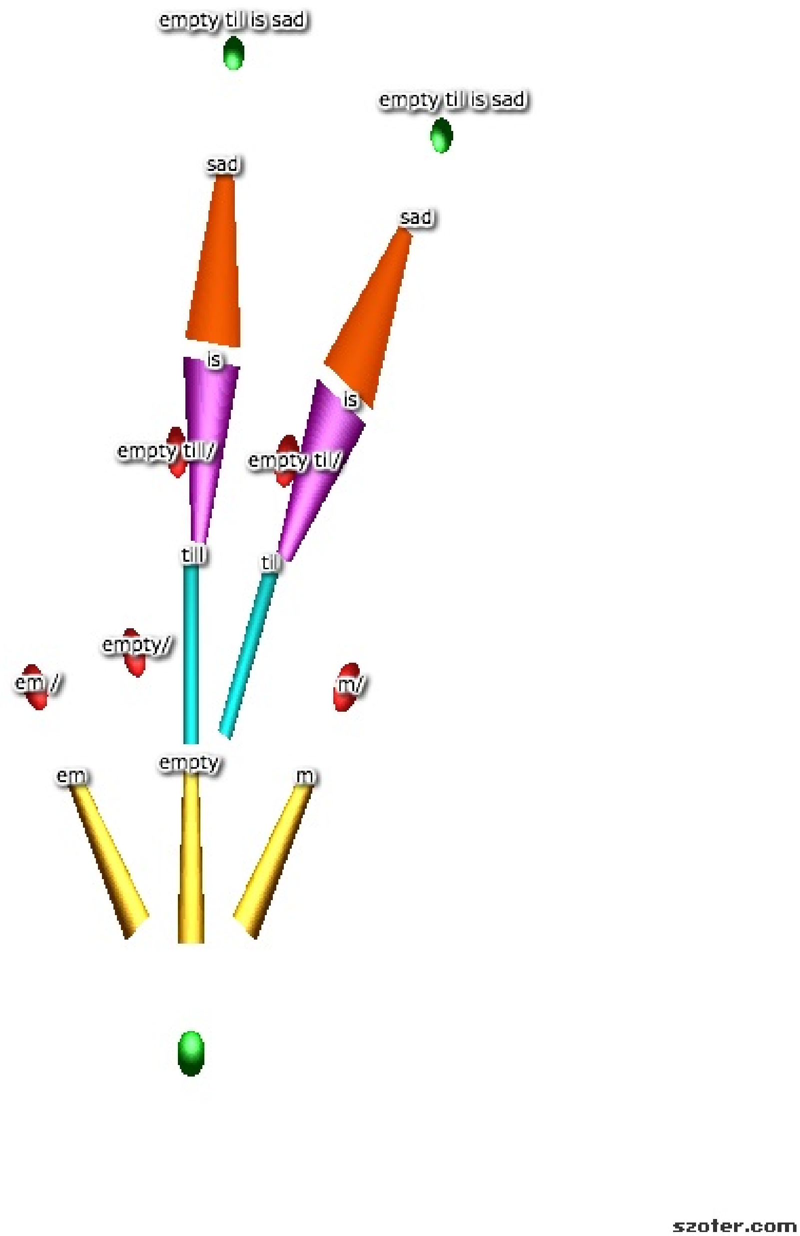


Figure 3.26: This is the annotated parse tree for the phrase "empty till is sad"

```
var root = {
        Child1: {
                Child1A: {
                        Child1Ai: actualCount,
                        Child1Aii: actualCount
                },
                Child1B: {
                        Child1Bi: actualCount
                }
        },
        Child2: {
                Child2A: {
                        Child2Ai: actualCount,
                        Child2Aii: actualCount
                }
        }
};
```

Figure 3.27: Protovis sunburst data format: This example sunburst data file, once the *actualCount* occurances were replaced with actual values, would generate a sunburst diagram

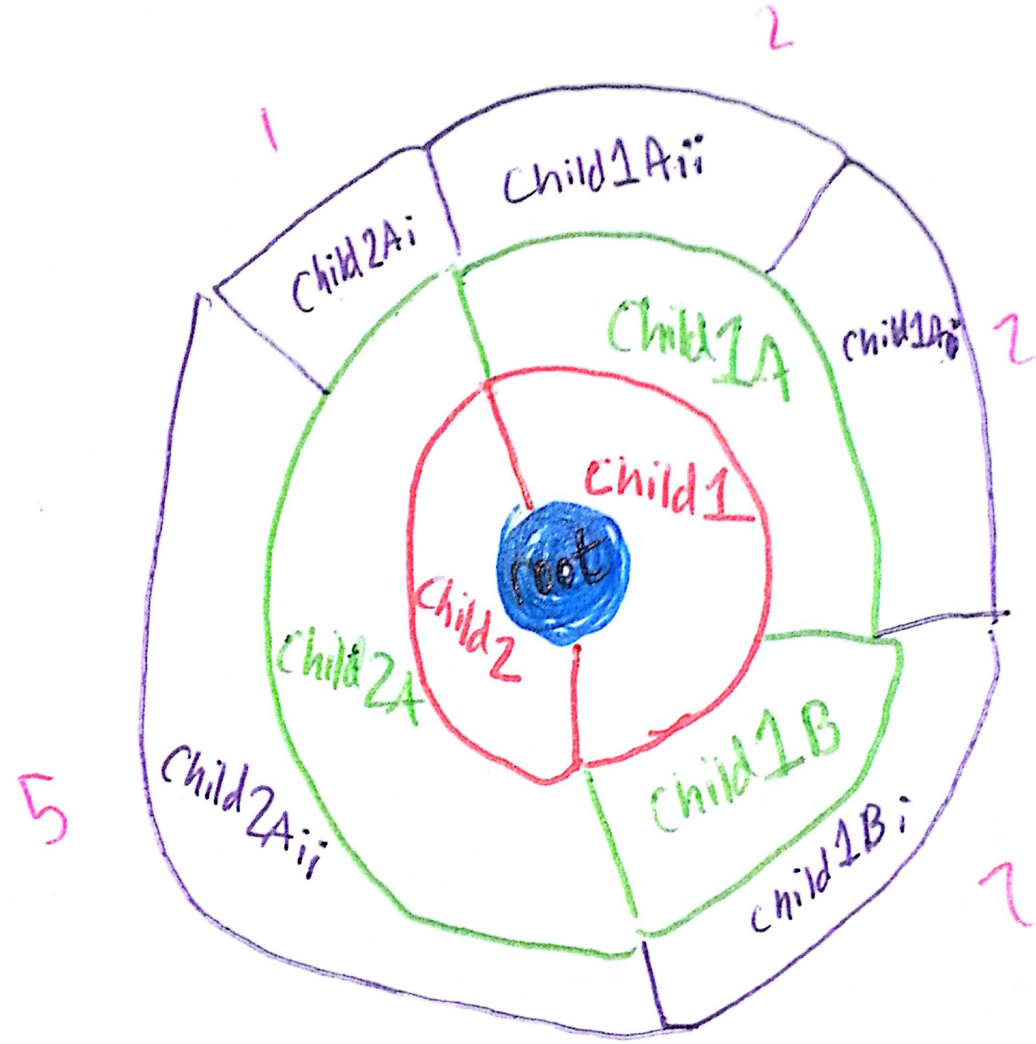


Figure 3.28: This example sunburst diagram is what would be generated by the example data file in figure 3.27

figure 3.29) represent the end word of each of those oronyms. The sunburst diagram that uses the frequency metric (shown in figure 3.30) shows that people are overwhelmingly more likely to hear “I stink” than any other possible oronym.

For a more complicated example, take the phrase “an ice cold hour”. As seen in figure 3.31, the equally-weighted sunburst diagram shows all possible oronym paths. When compared to the sunburst diagram in figure 3.32 that uses the UNISYN-derived frequency metric, we can see that some paths, such as those that begin with the word “a”, are much more likely to be heard than those that begin, for example, with the word “n”.

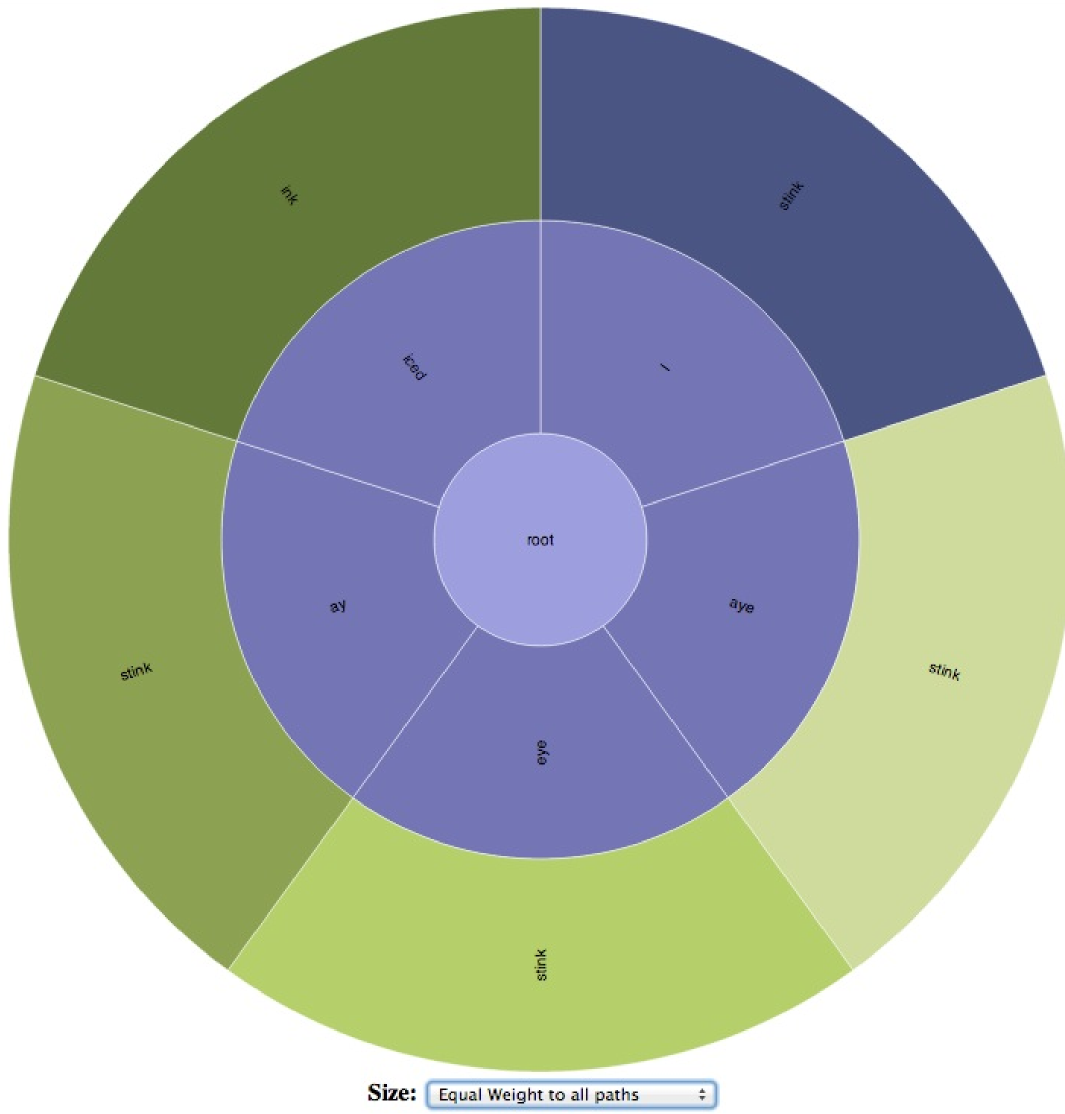


Figure 3.29: Equally-Weighted Sunburst Diagram for the oronyms of "iced ink"

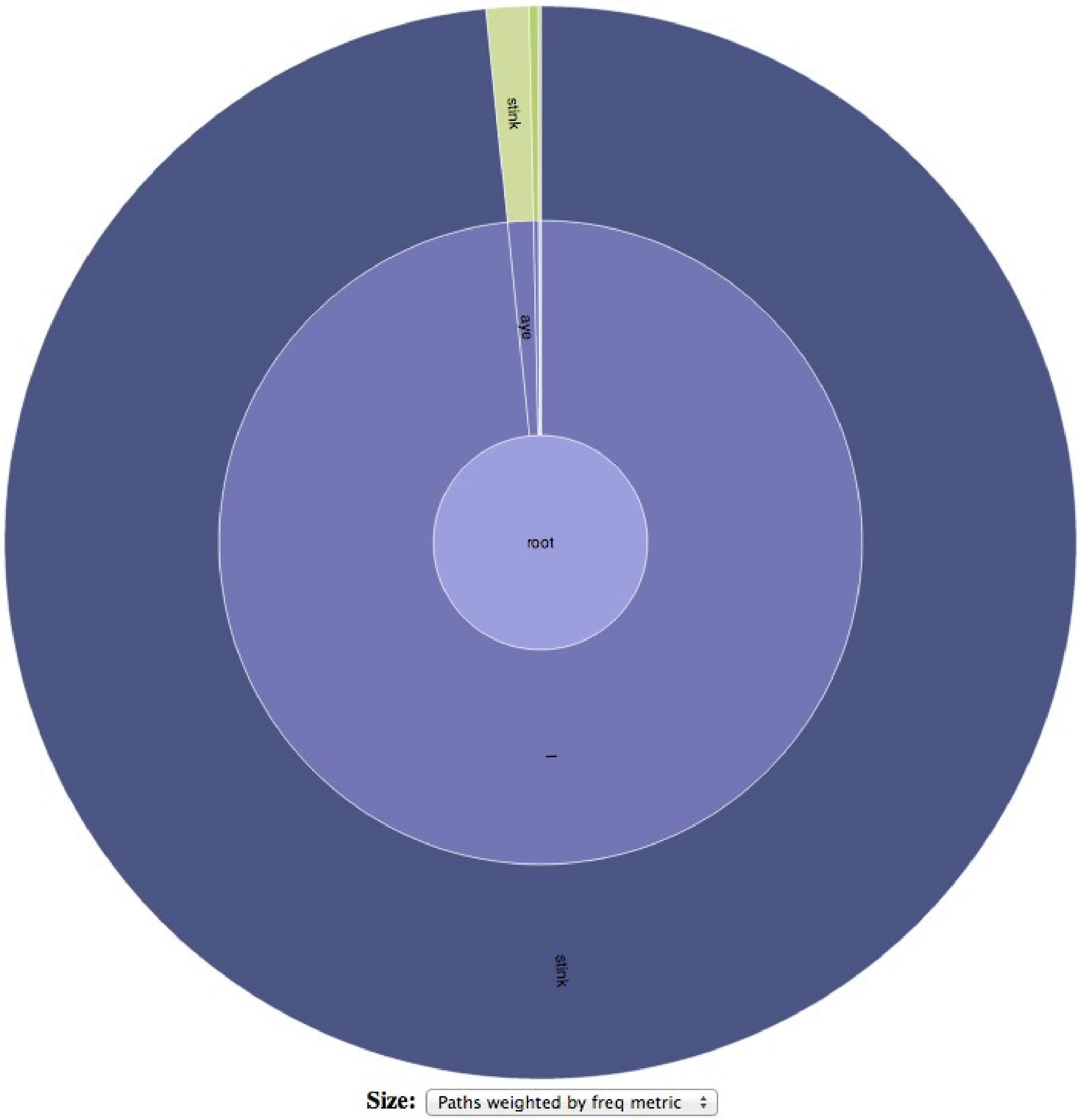


Figure 3.30: Sunburst Diagram for the oronyms of "iced ink" weighted by UNISYN freq metric

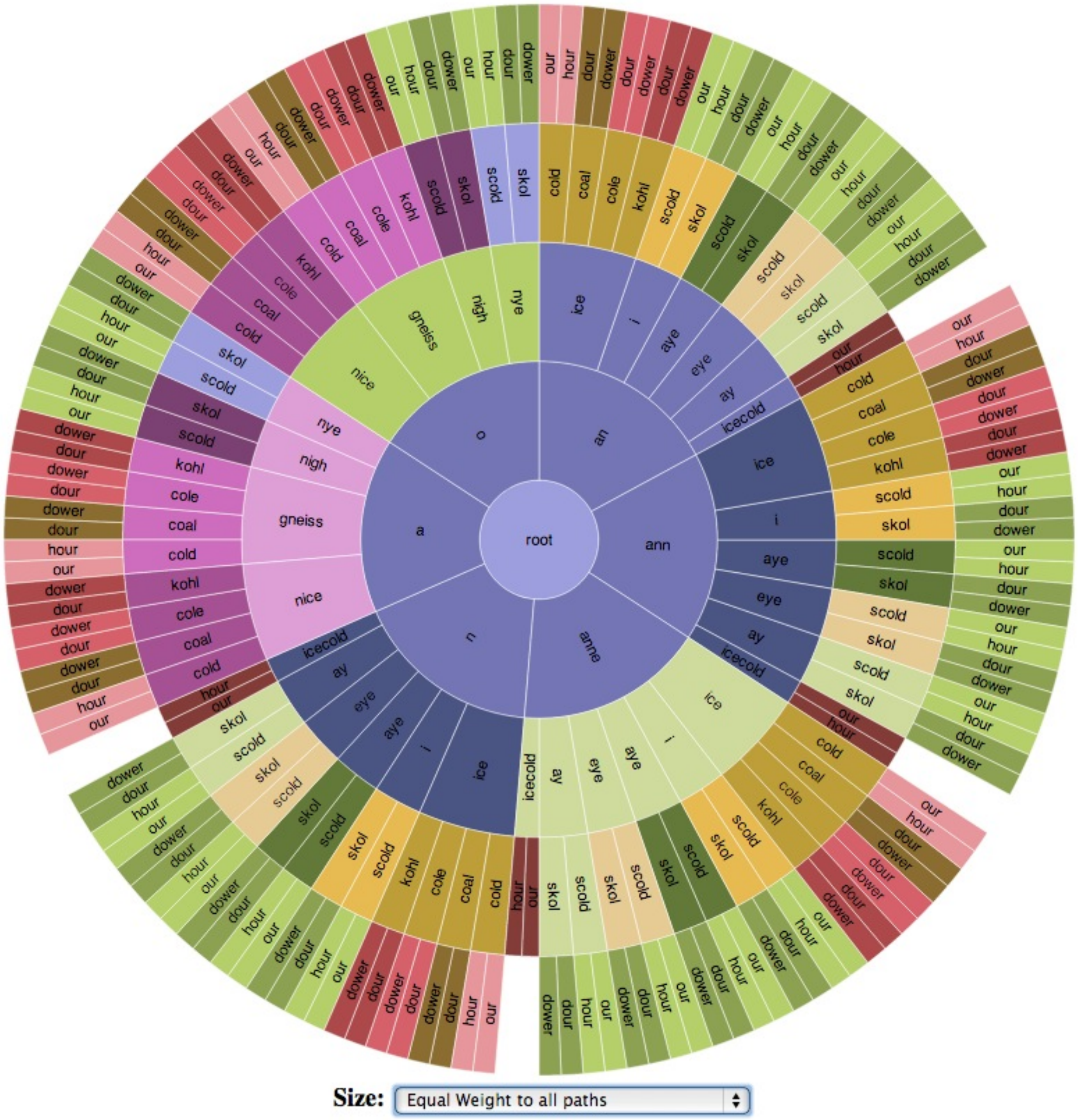


Figure 3.31: Equally-Weighted Sunburst Diagram for the oronyms of “an ice cold hour”

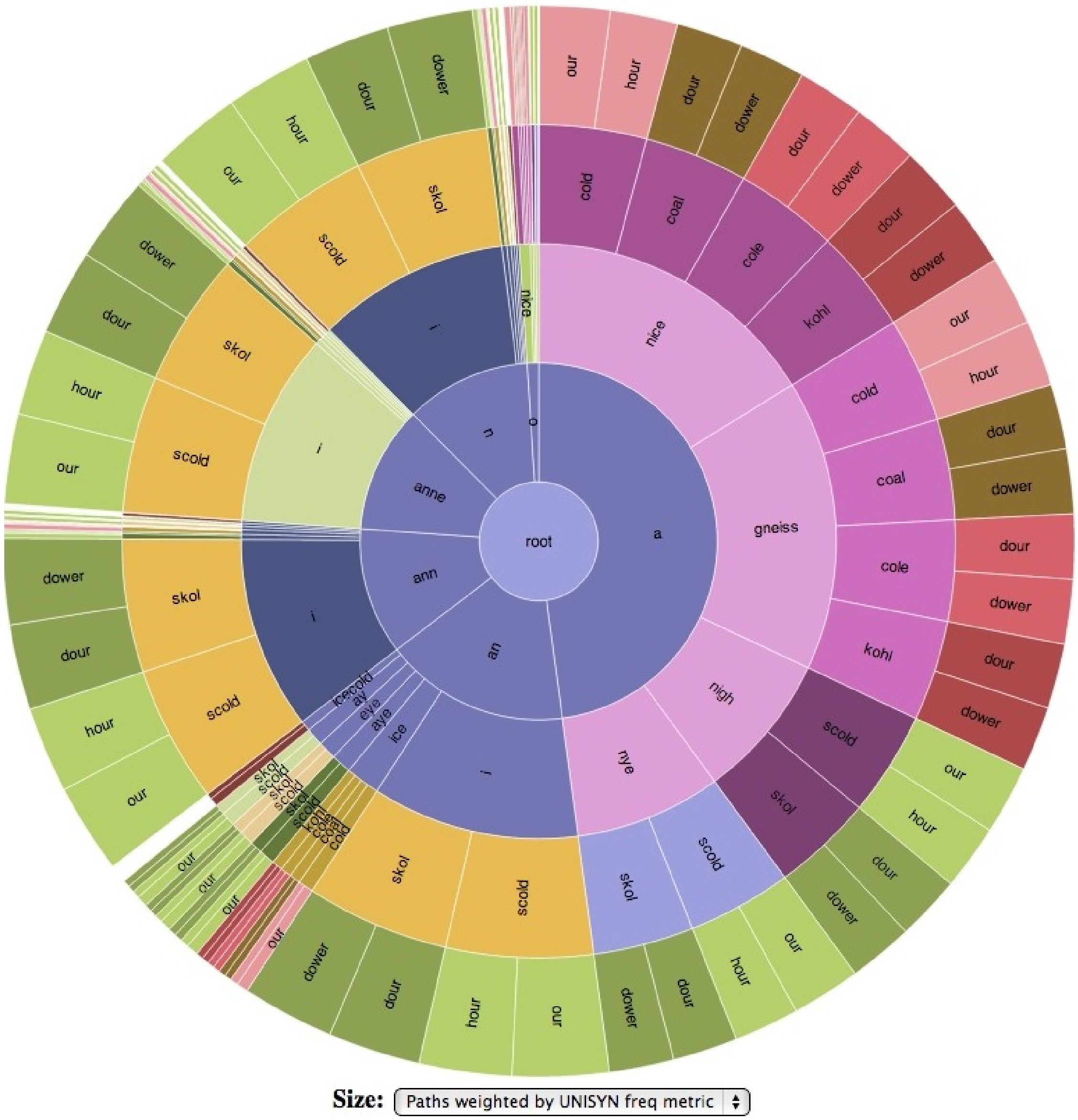


Figure 3.32: Sunburst Diagram for the oronyms of "an ice cold hour" weighted by UNISYN freq metric

Chapter 4

User Study

4.1 Structure

We created a multi-wave user study to examine the correctness of our method of word frequency metric generation, which uses the UNISYN dictionary.

First, we generated oronyms for the phrases “a nice cold hour” and “fourth rye to”. Using the selection criteria outlined in section 4.3.1, we narrowed down our recording options to 48 out of the 290 oronyms generated for “a nice cold hour”, and 10 out of the 39 oronyms generated for “fourth rye to”.

In the first phase, we had a dozen people record over 72 recordings of different phrases. This phase served two purposes: one, to see if our phonemic transcriptions were valid, and two, to gather recordings for the second phase.

In the second phase, we took 15 recordings of oronyms from phase one, and gathered ~74 transcriptions for each recording, resulting in a total of 851 transcriptions. These transcriptions were provided by 208 unique users (127 from the United States). We then compared the observed frequency of transcriptions of the recorded oronym phrases to the calculated frequency metric for oronyms of the original root phrase.

4.2 User Sampling Population

We drew our test subjects from a pool of Amazon Mechanical Turk workers (hired for \$ 0.02 to \$ 0.10 per task) and, for part of phase 1, volunteers from Reddit.com [4] [5].

Amazon Mechanical Turk is an online crowdsourcing service where requesters can hire workers to complete Human Intelligence Tasks, or HITs. The efficacy of using Mechanical Turk for user studies has been widely studied in academia, and specifically proven in the linguistic community [30].

Due to the online nature of Mechanical Turk, we we able to gather an international pool of volunteers. As you can see in figure 4.1, the bulk of our responses came from the United States and India.

4.3 Methodology

4.3.1 First Phase: Recitation

In this wave of the user study, we used a combination of a dozen Mechanical Turk workers (hired for \$ 0.10 per task) to record 72 different phrases. These phrases were oronyms of one of two phrases: phrase A, “a nice cold hour” or phrase B, “ fourth rye to”.

Given that “a nice cold hour” has 290 oronyms, and “ fourth rye to” has 39

, it was necessary to narrow down the number of oronyms recorded in phase one of our user study.

To select which oronyms we would submit to Mechanical Turk for workers to record, we decided to on the following selection criteria: -We discarded oronyms that included words with frequency values of less than 30. Asking a general audience to pronounce uncommon words would likely result in a high rate of unusable recordings. In addition, including uncommon words wouldnt be testing our algorithm—it would be testing the vocabulary of the user study subjects, which is outside the scope of this project. -We discarded all oronym phrases that contained words that capitalize to proper nouns, if that capitalization leadto alternative pronunciations. For example, “nice” maps to the phonetic sequence `n aI s`, but “Nice” maps to the phonetic sequence `n i s` (as in “niece”) . -We discarded oronym phrases that included implicit punctuation. For example, the phrase “Anne I scold our, has an implicit comma between Anne and I. We did this to avoid halting or “dramatic” recording of phrases. -We discarded oronyms with any words whose pronunciation is position specific. For example, the word “ ’n’ ” is pronounced `@ n` when found in “Rock ’n’ Roll, but when on its own, is pronounced `E n`, which doesn’t map back to the original root phrase “an ice cold hour”. We also removed some phrases involving the word “ o’ ”. When pronounced `@`, as it is in “top o the morning, it maps back to the original root phrase, but when found outside of that phrase, as in a last name like O’Donnell, it is pronounced `oU` , and doesn’t map back. -We only chose oronyms for which all pronunciations of the child oronym phrases were also found in the pronunciations of the root oronym phrase. For example, a root phrase that begins with “a” would have an child oronym phrase that begins with “et, using French pronunciation and dropping the trailing `t` . However, “et” can also be pronounced with the `t`, using an American accent, as in the phrase "et al". Since our root phrase doesnt include that `t` sound, any child oronym phrases that begin with "et" have at least one pronunciation not match the root phrases pronunciation. So, we discard all child oronyms that begin with "et.

At the end of this process, we were left with 48 out of the 290 oronyms generated for "a nice cold hour", and 10 out of the 39 oronyms generated for "fourth rye to".

To keep track of the chosen phrases, we assigned each phrase an phraseID, built off of the phrase letter, phrase length, and phrase text. We gave Mechanical Turk workers three minutes to record each phrase and email it to us with the phrase identifier in the subject of the email. The number of recordings per phrase, along with their identifiers, can be seen in table **??**.

We then interpreted the phonetics of each of the recording in SAMPA by ear. In a stunning example of a use case for our project, we discovered that we had unintentionally included some phrases for recording which were not deterministically phonetically parsible, meaning that our oronyms had multiple pronunciations, not all of which mapped back to the original phrase. For example, in some cases, our algorithm mapped the orthographic word "a" to the phoneme `A` (as in "apple". That `A` phoneme can be combined with the subsequent `n` phoneme from the word "nice" to create the SAMPA sequence `A n`, which corresponds with the orthographic word "on". Since that doesn't map back to our original root phrase, we were forced to discard all transcriptions that ended up with that pronunciation. That being said, this fit with our model, and we found no unexpected anomalies when comparing our transcriptions to the expected SAMPA pronunications of each phrase.

4.3.2 Recording Sample Pool

We had originally intended to use all the phase one recordings in phase two, but eventually had to discard all but 15 of the recordings for various reasons, the most common being that the recording was too loud and we wanted to spare our user's ears. Occasionally, the person recording left excessive amounts of space between words that overly-segmented the phrase, interrupting the natural flow of the phonetic sequence and rendering it unusable for our purposes. The recordings for the "fourth rye to" oronyms were all unusable for phase two, because our users tended to insert exclamation points any time they said "ooh" or "too", overloading their microphones or over-segmenting the phrase.

All 15 recordings we used were oronyms for the phrase "a nice cold hour", and were recorded by one man from the midwest, whose accent which made him the best approximation we could get for a General American accent. All other recordings gathered in phase one did not have appropriate accents, and were summarily discarded from further data collection.

4.3.3 Second Wave: Transcription

We hired 208 unique Mechanical Turk workers to transcribe our oronym recordings for \$ 0.02 to \$ 0.03 per transcription. Each of the 15 recordings was transcribed ~74 times, resulting in a total of 851 transcriptions. These transcriptions were provided by 208 unique users (127 from the United States). In addition to transcribing the recording, in each task, the worker was asked what country they were from. We did this to help differentiate native American English speakers from non-native speakers.

Response By Country	Num Responses
USA	506
India	277
Canada	33
England	28
Macedonia	28
Washington	13
Syria	13
UK	11
Sri Lanka	7
Britain	4
Vietnam	4
Egypt	3
Finland	3
Iran	3
Phillipines	3
The Netherlands	2
Mexico	2
“english”	2
Belgium	2
Ireland	2
South Africa	1
West Indies	1
Brazil	1
Uruguay	1
Turkey	1
Bangladesh	1
Trinidad and Tobago	1
China	1

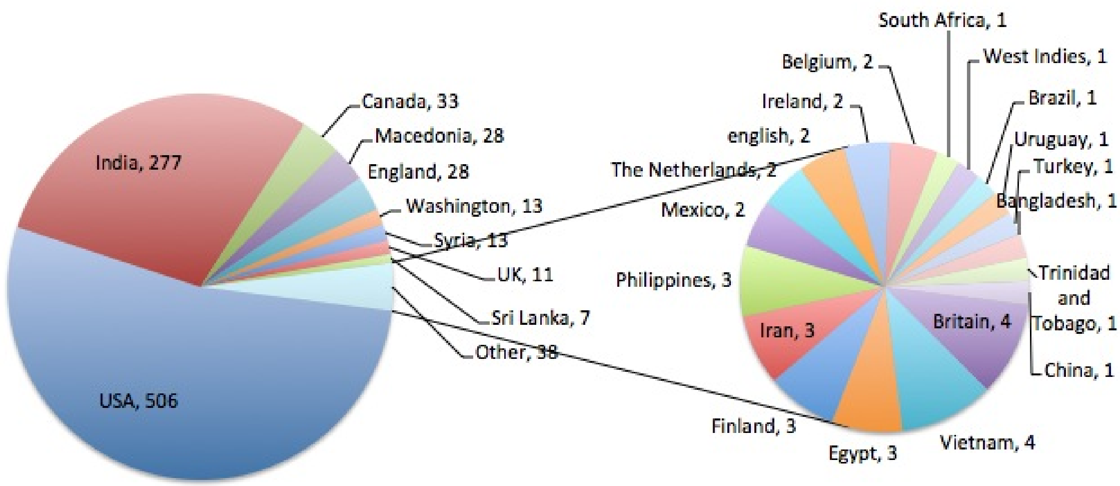


Figure 4.1: Our user study primarily polled people from the United States and India, as can be seen by the number of responses originating from each country.

Chapter 5

Results

5.1 Phase One Results

In this phase, we recorded a dozen users reciting any of the 48 oronyms of the phrase “an ice cold hour”, or any of the 10 oronyms for the phrase “fourth rye to”. Out of 72 recordings, only the recordings of the oronyms of “fourth rye to” were found to diverge from our excepted phonetic patterns, likely due to poor microphone quality not being able to pick up the aspriated *‘f’* sound at the beginning of the phrase[24]. All the oronyms were found to be within reasonable tolerance levels, with 15 recordings from one particular speaker found to be a close enough match to the general American accent to use his recordings in phase two.

5.2 Phase Two Results

We gathered 953 transcriptions for our 15 recorded phrases, with each recording garnering ∼74 transcriptions each. Worldwide, the top four most-frequently transcribed phrases made up for 70% of total transcriptions. The top transcribed phrase worldwide was "an ice cold hour", with 352 transcriptions, followed by "a nice cold hour", with 217 transcriptions. Following that, "a nice gold hour" had 63 transcriptions, and "in ice cold hour" had 38 transcriptions. The breakdown of these top four can be seen in figure 5.1 and table 5.1.

All of the worldwide top transcribed phrases were predicted by our oronym-generator, except for "a nice gold hour". This is a known limitation of our project, though, because we chose to focus on exact phonetic matches. The cold/gold mishearing is a product of phoneme voiced/voiceless pair swapping, which we cover in-depth in section 6.3. It is outside the current scope of our project.

5.2.1 Transcription oronyms' actual frequency vs calculated frequency

Though the most commonly transcribed phrases were found by our oronym generation, figure 5.4 shows an unexpected distribution of the number of times each phrase was transcribed versus the frequency metric that we calculated. We hypothesized that a simple summation of the UNISYN-provided word frequency for each word in a phrase would give a semi-meaningful indicator of whether a phrase's likelyhood to be heard.

Unfortunately, that proved not to be the case. In figure 5.3, we see the sun-

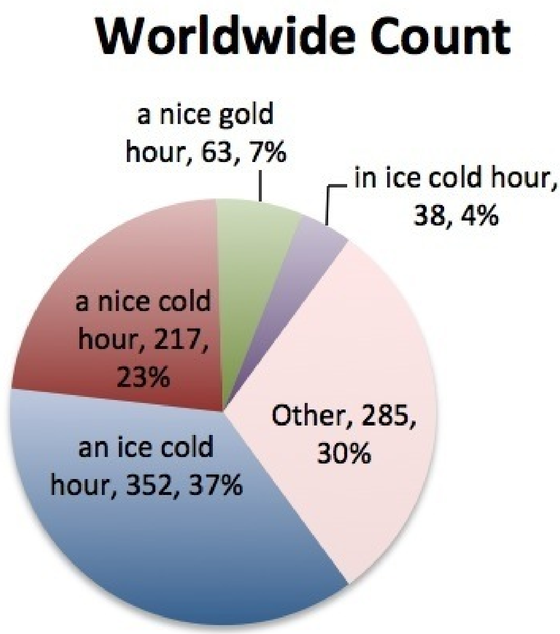


Figure 5.1: Our top two transcriptions were "a nice cold hour" and "an ice cold hour"

predicted freq	phrase transcribed	total answers
931028	an ice cold hour	352
7851662	a nice cold hour	217
0	a nice gold hour	63
5503158	in ice cold hour	38
0	an ice gold hour	18
859307	an eye scold hour	13

Table 5.1: In this table, we list all oronyms that were transcribed more than five times. Out of this list, all but the two containing the word "gold" were predicted by our oronym algorithm. However, we expected that any voiced/voiceless phoneme substitutions, like "cold"/"gold" would be missed by our algorithm.

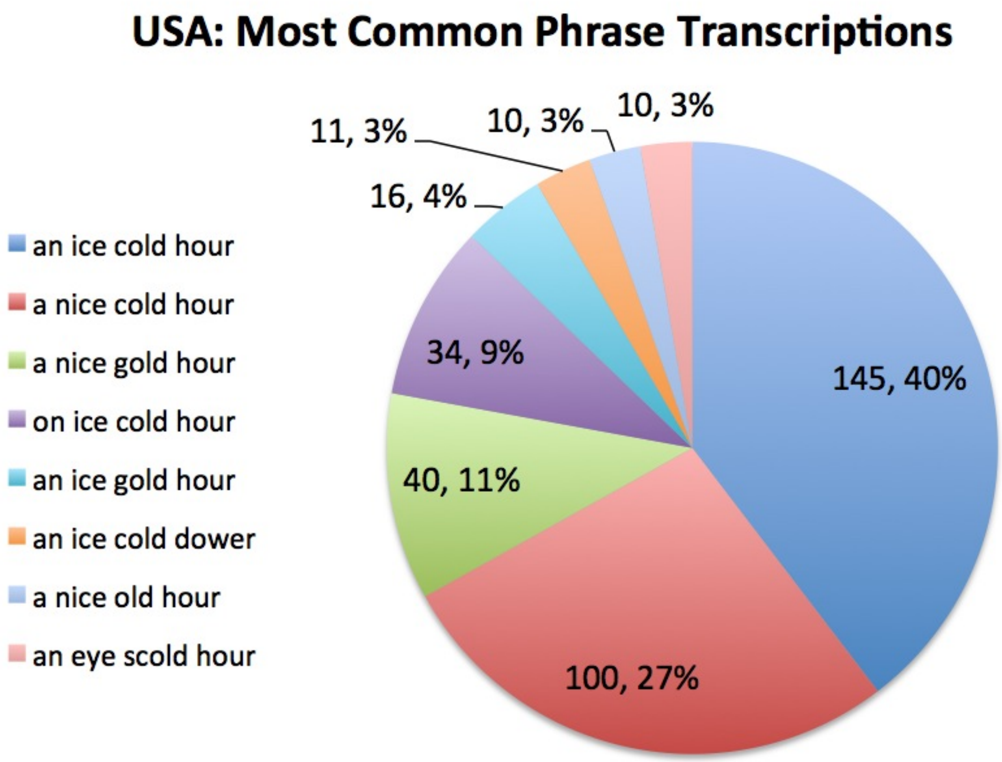


Figure 5.2: Though the breakdown is a bit different than the global transcription breakdown, you can still see the clear trend of "a nice cold hour" and "an ice cold hour" being the most common. There is a slightly larger gap between these two phrase, we hypothesize, because the American transcribers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

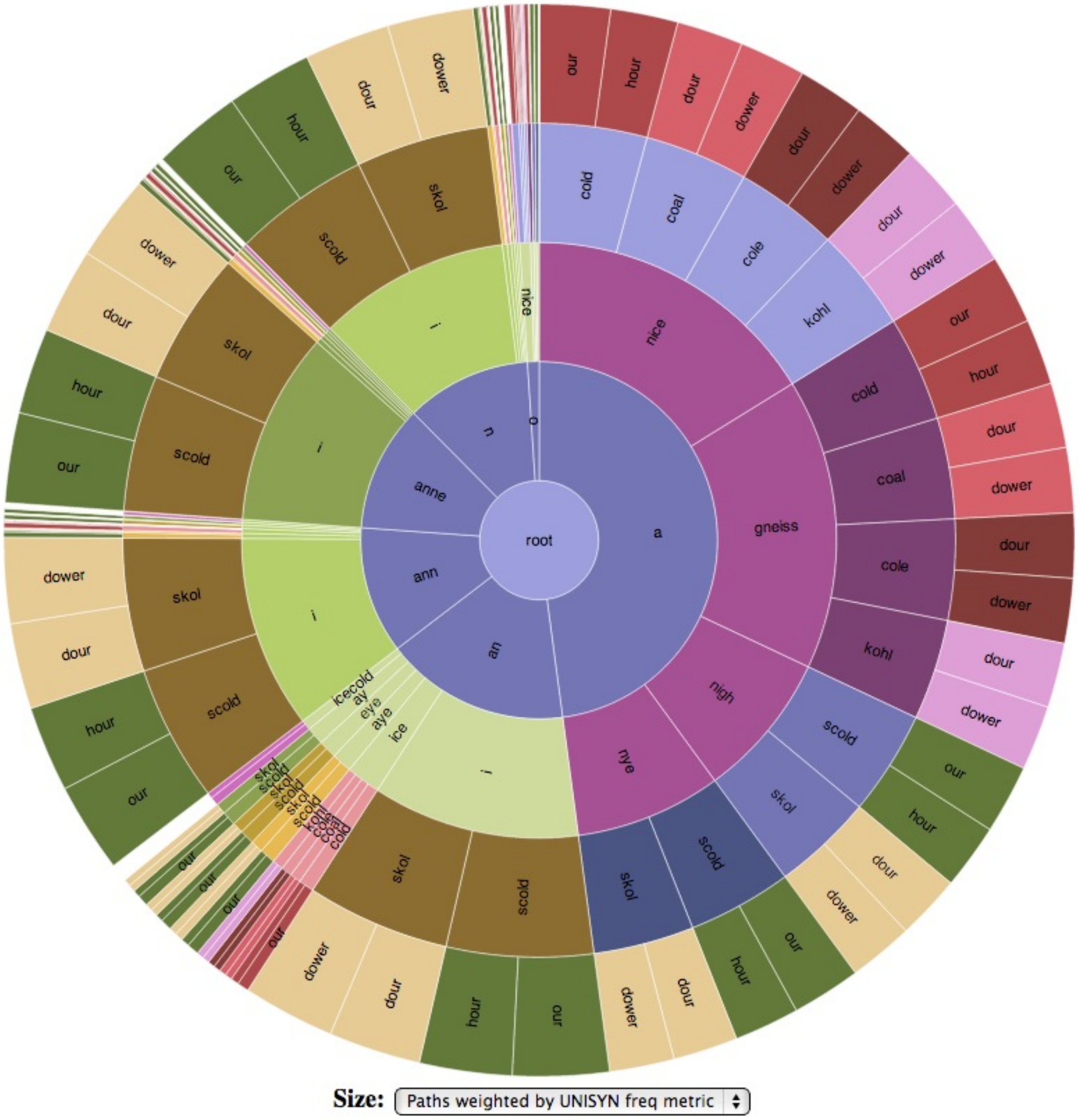


Figure 5.3: Sunburst Chart for A Nice Cold Hour using UNISYN metrics for comparison to observed frequency sunburst

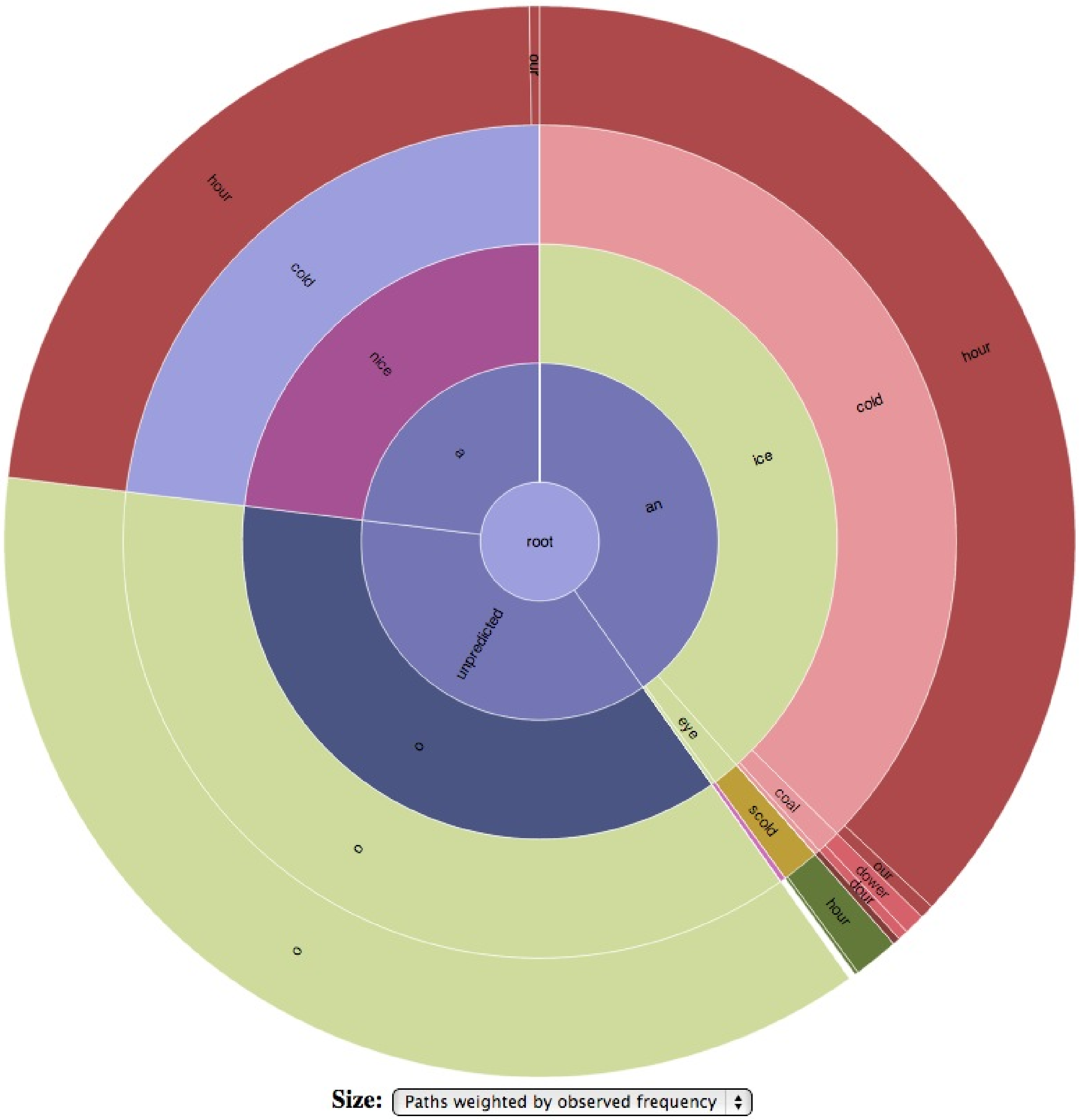


Figure 5.4: Sunburst Chart for A Nice Cold Hour using observed frequencies

burst diagram for the expected distribution of transcribed phrases based upon the UNISYN frequency metric that we calculated. In figure 5.4, we see the sunburst diagram for the transcriptions we observed, with a special slice representing all the transcriptions we did not predict. The unpredicted slice is nearly as large as the slice for “an ice cold hour”, the largest predicted.

5.2.2 Statistical measurement of expected versus observed transcription frequency

A statistical analysis, using a 1-proportion z test, of the observed dataset versus the expected dataset further proves that the UNISYN frequency values were not a good match for reality. Using the top two observed transcriptions as our sample population, we take a look at the phrases “a nice cold hour” and “an ice cold hour” . The phrase “a nice cold hour” has a calculated UNISYN freq metric of 7851662 , and had 125 actual transcriptions observed among people living in the United States. The “an ice cold hour” has a calculated UNISYN freq metric of 931028 , and had 191 actual transcriptions observed among people living in the United States. Therefore, the expected population is 8782690 , and the observed population is 316 .

Given those population, the expected population proportion for “a nice cold hour” would be $7851662 \div 8782690$, or 0.8934 .

In our user study, we found that 125 people transcribed “a nice cold hour” , and 191 people transcribed “an ice cold hour” , for a ratio of 0.65 to 1, where “a nice cold hour” accounts for 39.56% ($p = 0.3956$) of the combined count.

Given the observed population proportion of 0.3956 and the expected population proportion 0.8934 , we did a one-proportion z test with an α of 0.01 . The z value returned was 18.0971 , meaning that the observed population proportion was 18.0971 standard deviations away from the expected population proportion. When we used this z value to compute a p value, we got a value that was so low we can't find a calculator that has enough decimal places to show it without rounding it to zero.

In short, our per-occurance frequency metric predictions don't even remotely match the observed data.

The below is here mostly for my edification: (I'll delete it when my edits are all done.)

Givens for Phrase (1) ("a nice cold hour") :

Calculated metric: 7851662

Actual count: x = 125

Givens for Phrase (2) ("an ice cold hour") :

Calculated metric: 931028

Actual count: x = 191

α = significance Level = 0.01

Calculated sum: 7851662 + 931028 = 8782690

Actual sum: 125 + 191 = 316

p = population proportion of "a nice cold hour" occurrences

p = 7851662 ÷ 8782690 = 0.0000

H_o : p = 0.0000 H_a : p ≠ 0.0000

Actual: 125 ÷ 316 =

1-proportion z-test

z = 18.0971 std deviations away from expected.

If pvalue ¡ α, reject H_o

pvalue $\approx$ 0 ¡ 0.01

So, reject H_o

5.2.3 Observations on Transcription Count per Recording for each transcribed phrase

The Transcription Count by Recording graphs show how many of a occurances of a certain transcription were produced from each recordings. Each graph represents one transcription, and has bars representing each recording, showing the breakdown of where the phrase was transcribed the most often. The graph also compares the observed incidence of those transcriptions with the expected UNISYN frequency metric. The X axis lists the transcribed phrases. The right Y axis corresponds to the smaller, multi-colored bars. Each bar represents the number of times that a transcribed phrase was observed for a particular recording. The left X axis corresponds to the large blue bar behind the smaller bars. The blue bar represents the calculated UNISYN frequency metric for the transcription.

When you compare the bars from the two y axes, some interesting observations appear.

An ice cold hour

When looking at figure 5.5, we notice that all but 12 out of the 362 transcriptions of “an ice cold hour” come from recordings of phrases that similarly begin with “an”. This suggests the existence of some un-measured value related to pronunciation that makes it so that the theoretically identical phonetic sequences of “an ice cold hour” and “a nice cold hour” are heard functionally different.

A nice cold hour

In figure 5.6, we see that while most of the transcriptions of “a nice cold hour” came from recordings of phrases that begin with ’a’, a not-inconsiderable number came from the recordings for the phrases “an ice cold our” and “an ice-cold our”. When taken in regards to the conclusions we drew from figure 5.5 in section 5.2.3, we can conclude that, while listeners appear not to be able to hear an ’an’ as an ’a’, listeners can, under certain circumstances, hear an ’an’ as an ’a’.

In ice cold hour

This chart in figure 5.7 is for the third most common transcription, “in ice cold hour”. Transcriptions of this phrase are fairly evenly distributed among the recordings, though theres a spike of transcriptions on “an ice-cold hour”. Additionally, the transcriptions occur a lot less frequently than the UNISYN frequency metric suggests they should.

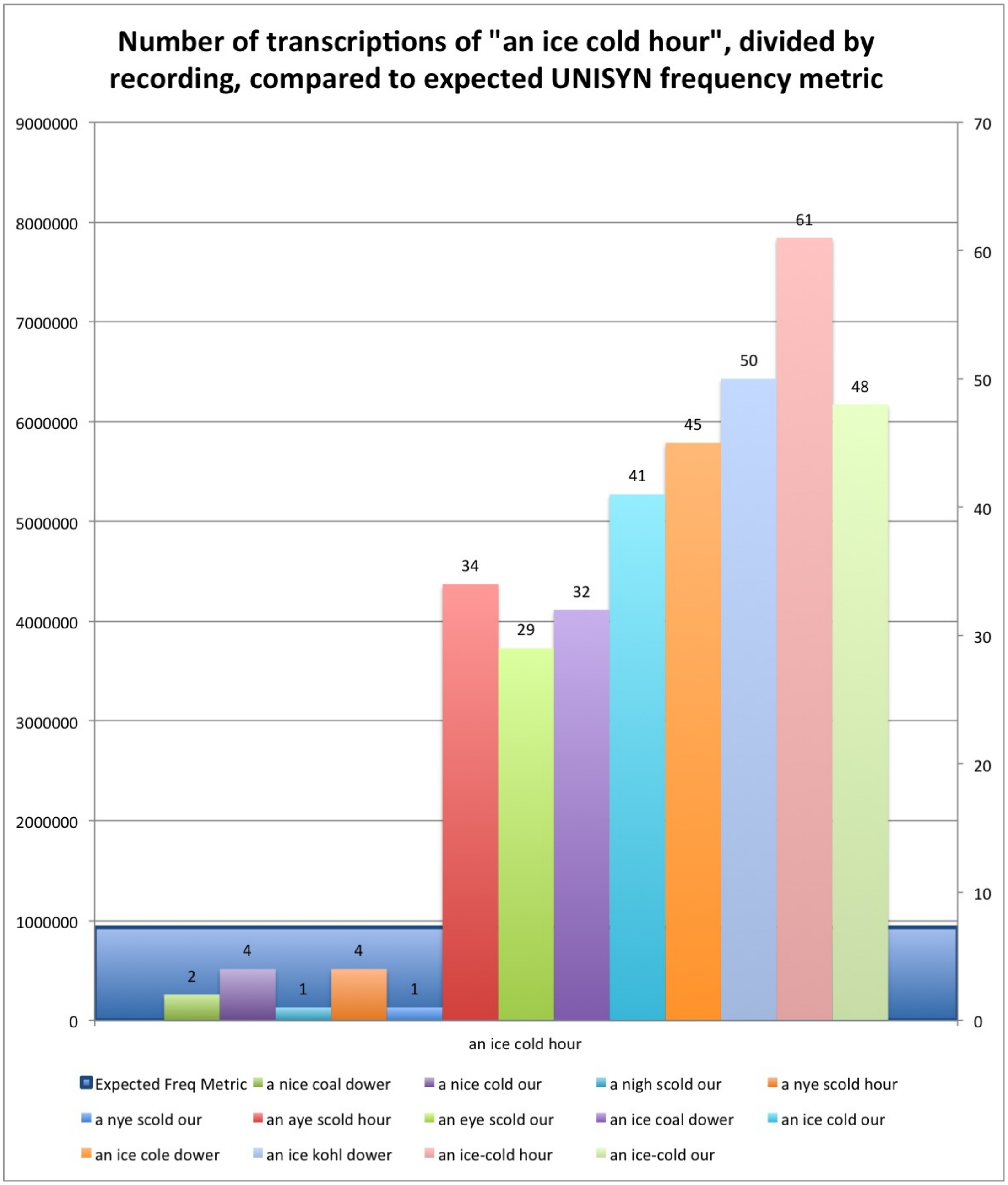


Figure 5.5: This graph represents all transcriptions of the phrase "an ice cold hour", divided into columns based on what recording were transcribed as "an ice cold hour". The large blue bar in the background shows the predicted frequency metric for the phrase in question.

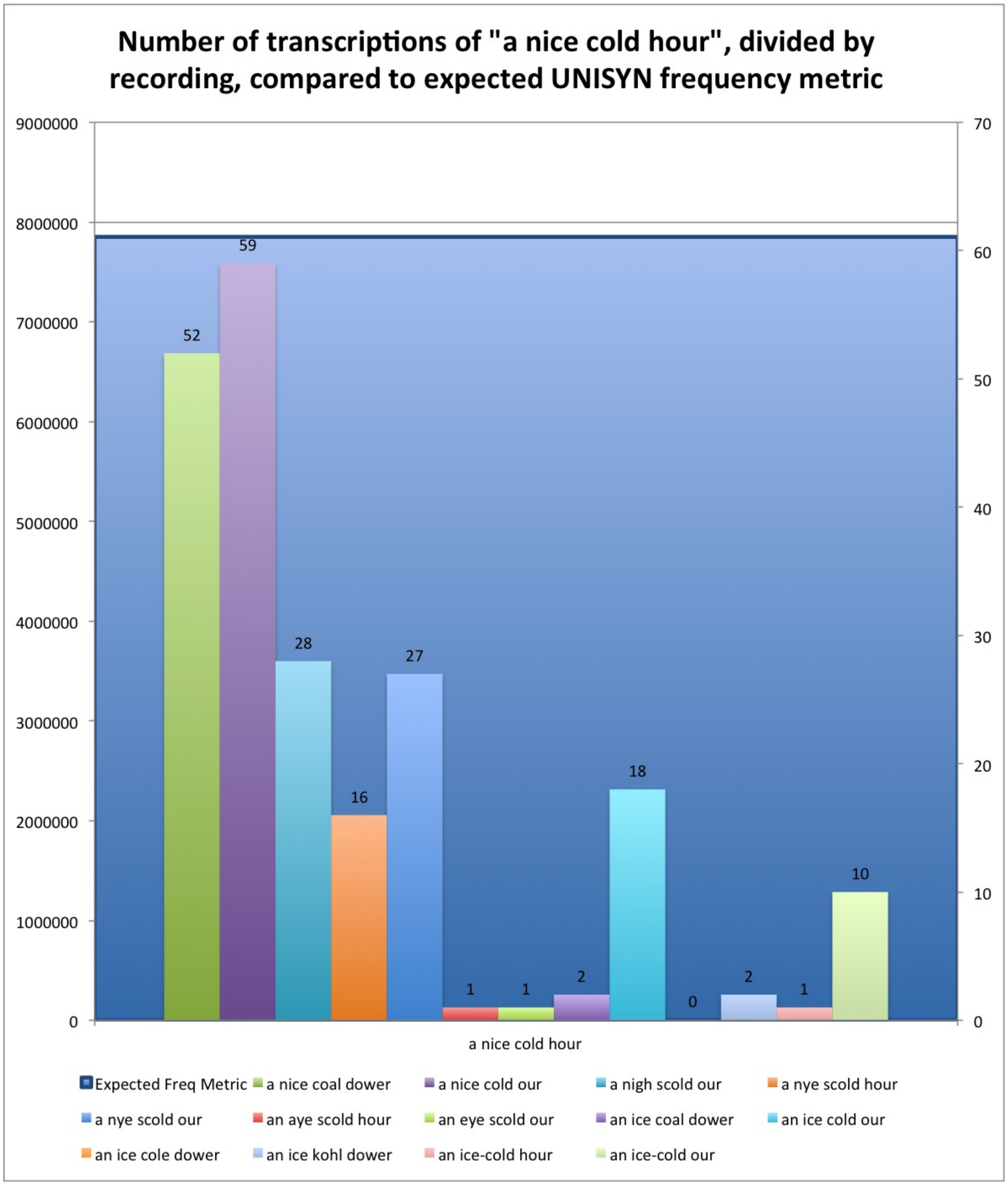


Figure 5.6: This graph represents all transcriptions of the phrase "a nice cold hour", divided into columns based on what recording were transcribed as "a nice cold hour". The large blue bar in the background shows the predicted frequency metric for the phrase in question.

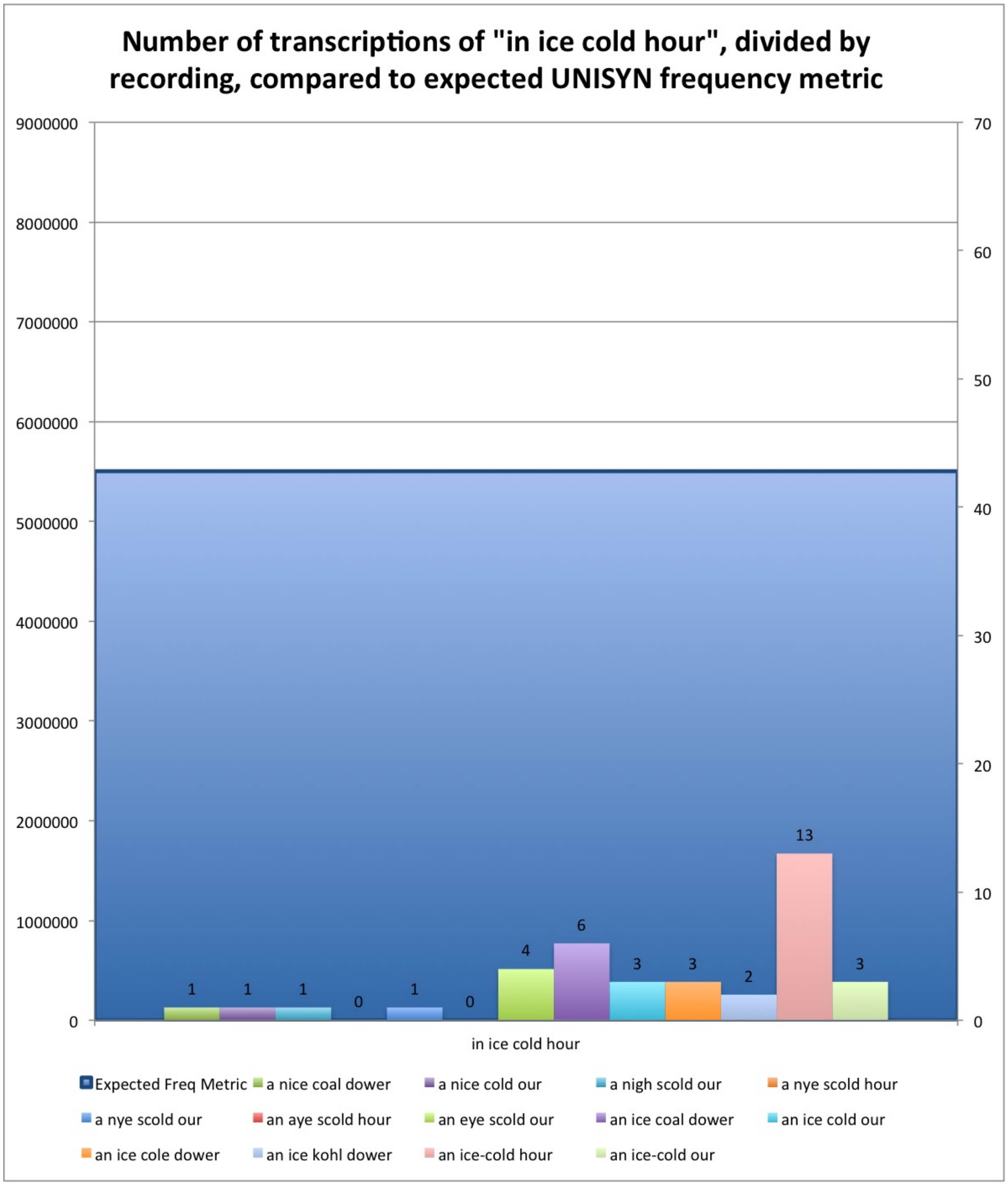


Figure 5.7: This graph represents all transcriptions of the phrase "in ice cold hour", divided into columns based on what recording were transcribed as "in ice cold hour". The large blue bar in the background shows the predicted frequency metric for the phrase in question.

A nice gold hour

The chart in figure 5.8 for the transcriptions of “a nice gold hour” shows that the source recordings of those transcriptions are very specific: only the recordings of “a nye scold our”, “a nye scold hour”, and “a nigh scold our” produce the ’g’/’c’ substitution. In fact, all of our transcriptions that involved the word “gold” arose from these recordings. This suggests that there is some sort of foul magic at play messing with my data.

An ice cold dower

Figure 5.9 shows the transcriptions for the phrase “an ice cold dower”. This phrase features repeated phoneme auto-deletion or auto-insertion, in which two identical adjacent phonemes are blurred into one sound. This can result in the listener putting two phonemes where only one exists (as in this case), or putting one phoneme where two exist. This case, while known to us, is outside the scope of the current project, and suggested for future work.

An eye scold hour

The chart for “an eye scold hour”, shown in figure 5.10 is primarily interesting in that it appears more or less deterministically interpretable. The only recordings that resulted in this phrase were those for an eye scold hour or an aye scold hour. We hypothesize that this has something to do with word emphases, and suggest investigating this for future work.

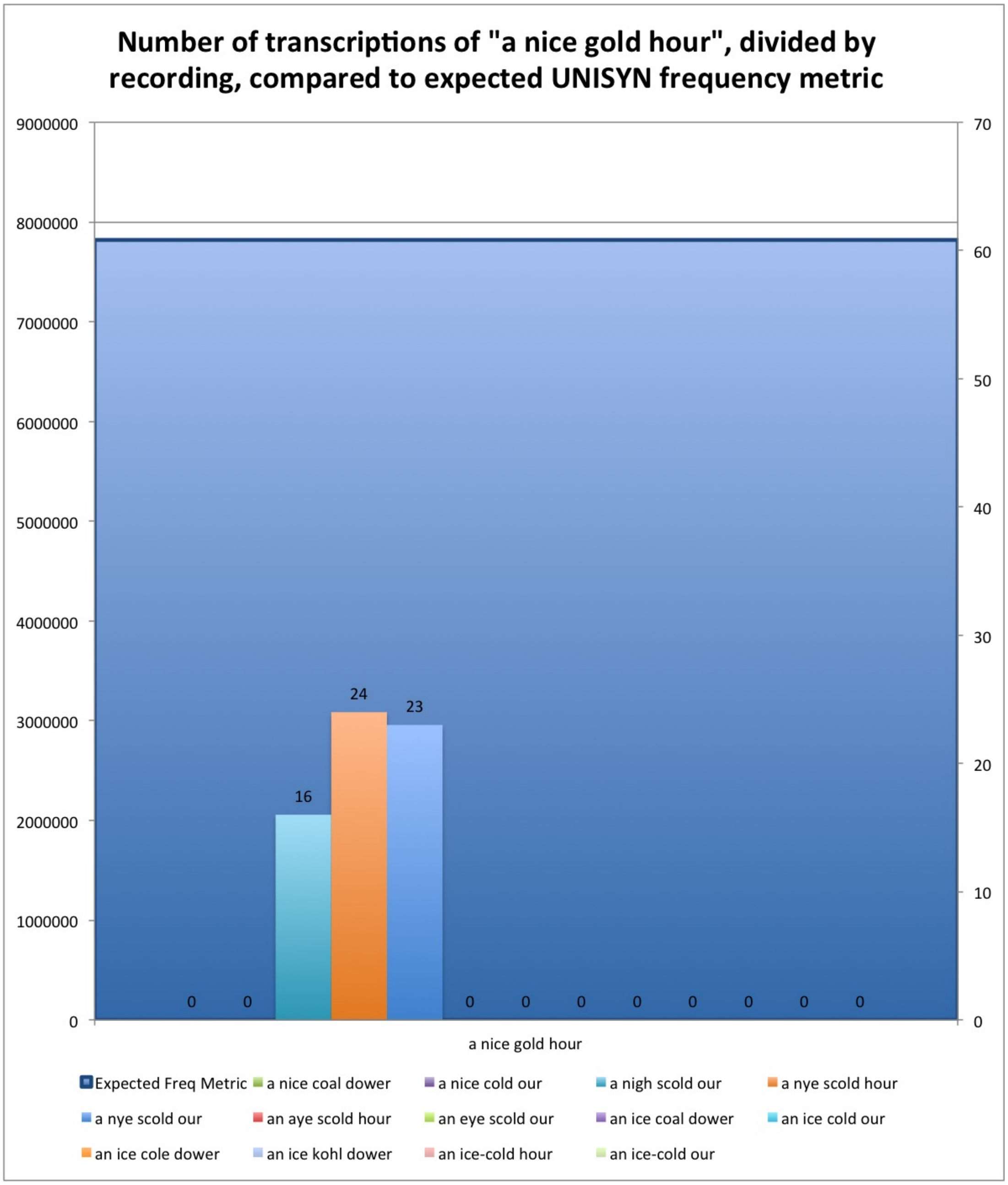


Figure 5.8: This graph represents all transcriptions of the phrase "a nice gold hour", divided into columns based on what recording were transcribed as "a nice gold hour". The large blue bar in the background shows the predicted frequency metric for the phrase in question.

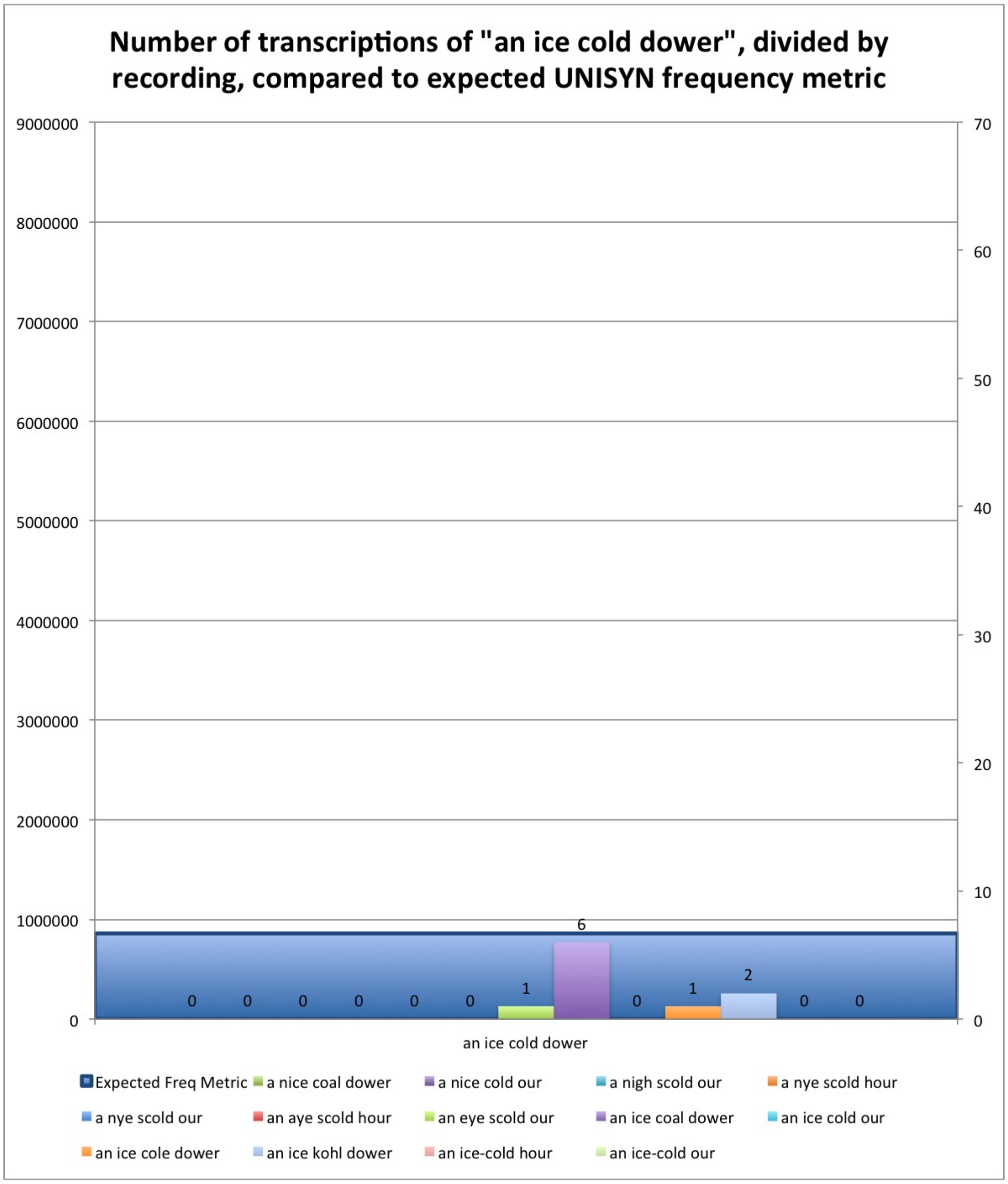


Figure 5.9: This graph represents all transcriptions of the phrase "a nice cold dower", divided into columns based on what recording were transcribed as "a nice cold dower". The large blue bar in the background shows the predicted frequency metric for the phrase in question.

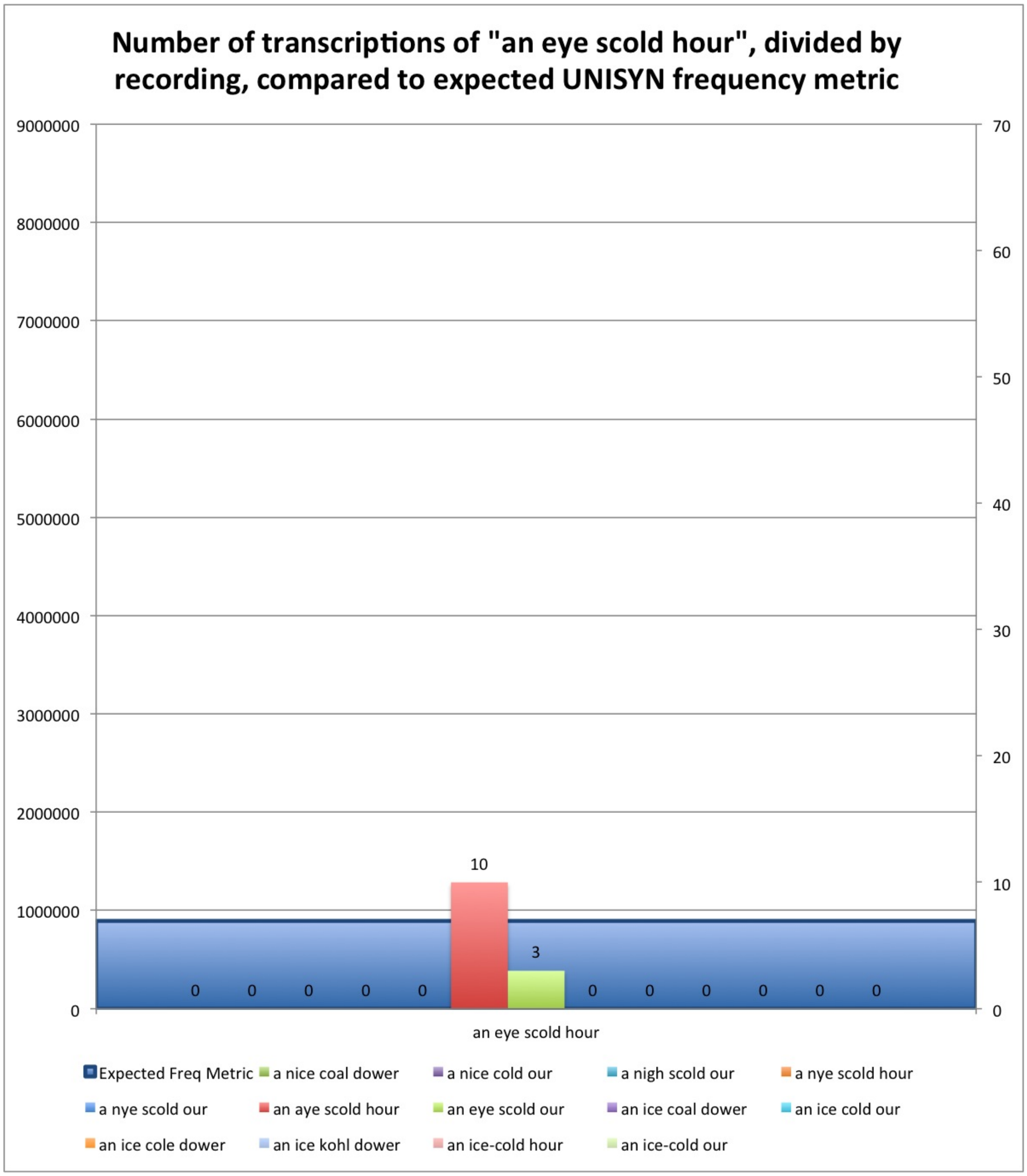


Figure 5.10: This graph represents all transcriptions of the phrase "an eye scold hour", divided into columns based on what recording were transcribed as "an eye scold hour". The large blue bar in the background shows the predicted frequency metric for the phrase in question.

An ice coal dower

The chart for "an ice coal dower" in figure 5.11 is notable in that all its transcriptions came from recordings that began in "an" and ended in "dower", like the phrase itself does. As in 5.10, we suggest that the near-deterministic interpretation has something to do with emphases, and suggest investigating this for future work.

5.2.4 Transcription Breakdown By Country

When comparing transcriptions from countries where English is the dominant language (as shown in figure 5.12) to those from countries where it is not(as shown in figure 5.13), we see some interesting trends.

(1) The most common transcription for both is an ice cold hour, with 36 % native-speaker transcriptions(218) and 24 % non-native(134)

(2) The second most common transcription is also the same for both ("a nice cold hour", but it accounts for a larger percentage of the Non-native pie (24 % compared to the native 22 %)

(3) The third most common transcription differs for native and non-native speakers.

Native speakers transcribed "a nice gold hour" 62 times, accounting for 10 % of all native transcriptions. In comparison, only 1 non-native speaker transcribed that phrase, for a measely 0.2 % of total non-native transcriptions. This brings up an interesting data point—The third most popular transcription for native speakers barely shows up at all in non-native transcriptions. There may be something about common phoneme substitution that native speakers pick up

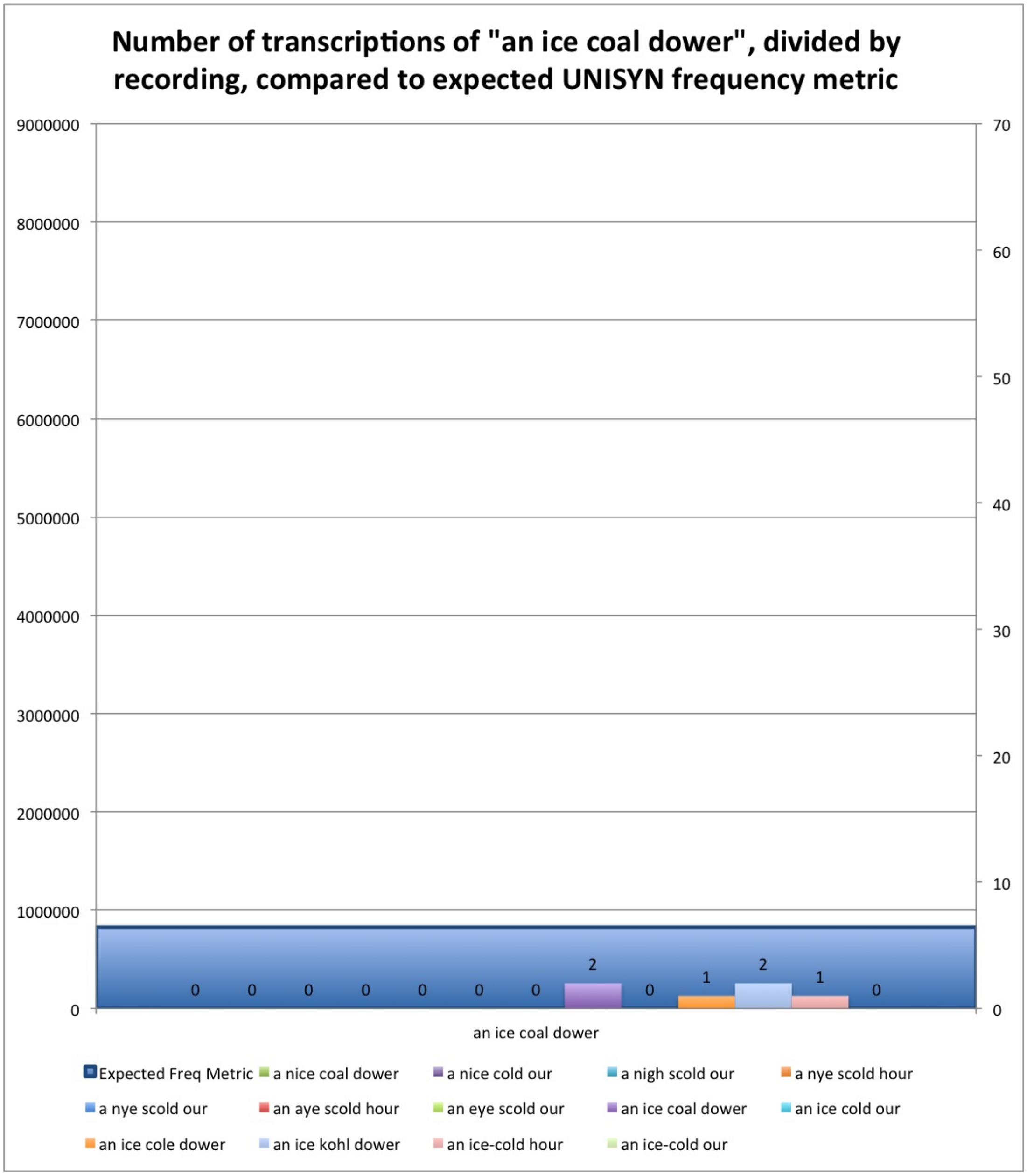


Figure 5.11: This graph represents all transcriptions of the phrase "an ice coal dower", divided into columns based on what recording were transcribed as "an ice coal dower". The large blue bar in the background shows the predicted frequency metric for the phrase in question.

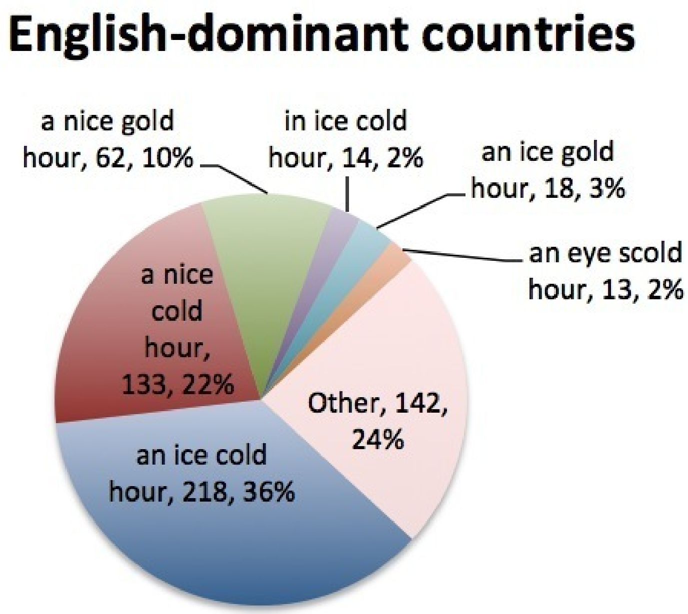


Figure 5.12: Pie Chart of transcriptions from countries that are primarily English-speaking.

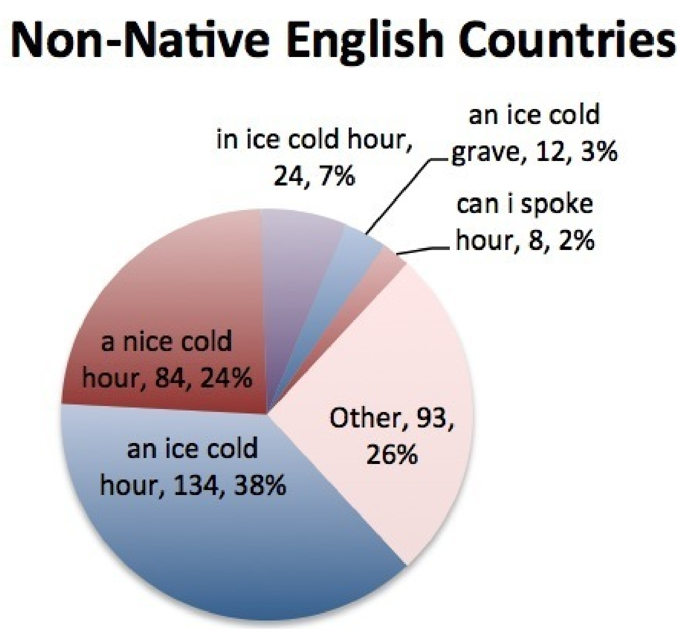


Figure 5.13: Pie Chart of transcriptions from countries that are Non-native English speakers.

on that non-natives dont; specifically, a cold/gold merger.

The third most common transcription for non-native speakers is “in ice cold hour”, which was transcribed 24 times, and makes up 7 % of non-native transcriptions. This phrase was the fifth most common transcription for native speakers, with 14 transcriptions making up 2 % of total transcriptions.

(4) The fourth most common transcription for native speakers was an ice gold hour, getting 3 % of the total with 18 transcriptions (by 14 unique transcribers). This phrase was not transcribed by any non-native speakers. This exhibits the same phone/phoneme substitution that we saw with a nice gold hour.

The fourth (“an ice cold grave”) most common phrase for non-native speakers was only transcribed by one unique worker, and as such, is not going to be taken into serious consideration. The fifth most common phrase (“an ice cold grave”) was also only transcribed by one unique worker, and so cannot be taken into serious consideration.

Chapter 6

Future Work

6.1 Direct Improvements To Misheard Me Oronym ParseTree

Our oronyms trees display all the phonetically-matched oronyms that our users came up with. Unfortunately it also displayed a few that no human in their right mind would think of, and incorrectly weighted some others.

6.2 Places for improvement

In some cases, our phrase-frequency metric did not accurately line up with the actual transcription frequencies from our user studies. We believe that there are two possible reasons for this.

6.2.1 Frequency Validity

Our frequency source data ended up being less than statisfactory, due to several factors, deliniated below.

Corpus Composition deficiencies

The lack of phonemic frequency data is a known defeciency in our source dictionary, UNISYN. According to the authors of the UNISYN lexicon documentation:

> Unfortunately there is currently no method for distinguishing between homographs by frequency. Furthermore, it should be noted that the frequency field, as it was obtained from simple word lists, is not particularly reliable.

[25] The UNISYN frequency count is based upon a large but not exhaustive corpus of text. It has some particularly glaring deficiencies in the medical arena. We find this frustrating, because knowledge about common medical mondegreens could be used to prevent mistakes in patient's treatment plans[21]. Also, it meant that the word "colitis" wasn't in our dictionary, and we therefore couldn't use the example "the girl with colitis goes by"/"the girl with kaleidescope eyes".

Homograph Differentiation

Also, the fact that our program cannot distinguish between words that may be homographs (that is, words that sound different but are spelled the same) makes it improperly weight some phrases over others. For example, take the words for the animals "bucks" and "does". "Bucks" has a frequency of 1133, and "does" has a frequency of 508386. For reference, "deer" has a frequency of 1896.

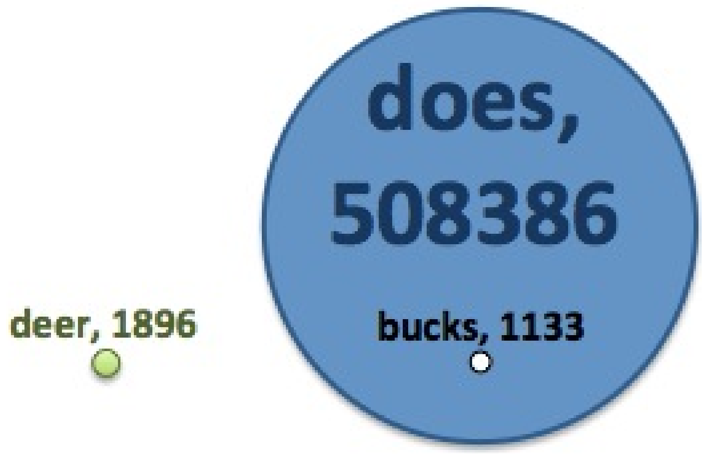


Figure 6.1: Bubble Chart comparison of Frequency for deer, does, and bucks

You can see the relative scale of these in figure 6.1. It seems highly unlikely that the male and female labels for a species would be more common than the actual name of the species, given that we don't see this for sheep (sheep , 13572 , ewe , 186 , ram , 681) or horses (horse , 27559 , mare , 1055 , stallion , 644). What is much more likely is that "bucks" is getting extra hits through its meaning as a slang synonym for dollars (dollars, 8927), and "does" is getting most of its frequency count for the 3rd person present tense of the verb "to do". That seems very likely, given that the frequency for the singular "doe" is only 1077.

Future work on our project would benefit from using a dictionary with some way of distinguishing homographs when counting frequency.

Frequency Dictionary Tallying Methods

In the future, we'd also like to use word frequency values from a dictionary that takes a larger, more-diverse dataset into its frequency count, such as the frequency lists from the Corpus of Contemporary American English[3]. The COCA corpus is entirely focused on word frequency, and as such, does not contain any phonetic data. However, it contains several different ways of determining frequency of words that overcomes some of the shortcomings we ran into trying to compare the semantically-identical words 'a' and 'an'. 'A' is found much for frequently than 'an', but both are just as familiar. In the UNISYN dictionary, we only have contextless frequency counts. In the COCA frequency dictionary, they keep two types of counts: one for how many times the word has been found total, and one for how many documents is has been found in. This way, even though 'a' is found almost seven times as often than 'a' overall, we know that they're equally-familiar words, because they are both found in approximately 160k corpus entries[23].

As a proof of concept, we created a sunburst diagram for "an ice cold hour" using COCA by-document frequency values (shown in figure 6.2), to compare it against the sunburst diagram created using UNISYN frequency values(shown in figure 6.3). The COCA-based sunburst, while still inaccurate, at least has a ratio of phrases beginning with "a" to "an" that is closer to the actual observed ratio (which can be seen back in figure 5.4).

A statistical analysis, using a 1-proportion z test, of the observed dataset frequencies versus a COCA derived-frequency dataset further proves that the COCA frequency values are a better match for the observed data than UNISYN. Using the top two observed transcriptions as our sample population, we take a look at the phrases "a nice cold hour" and "an ice cold hour" . The phrase "a nice cold hour" has a calculated COCA freq metric of 247719 , and had 125 actual transcriptions observed among people living in the United States. The "an ice cold hour" has a calculated COCA freq metric of 227405 , and had 191 actual transcriptions observed among people living in the United States. Therefore, the

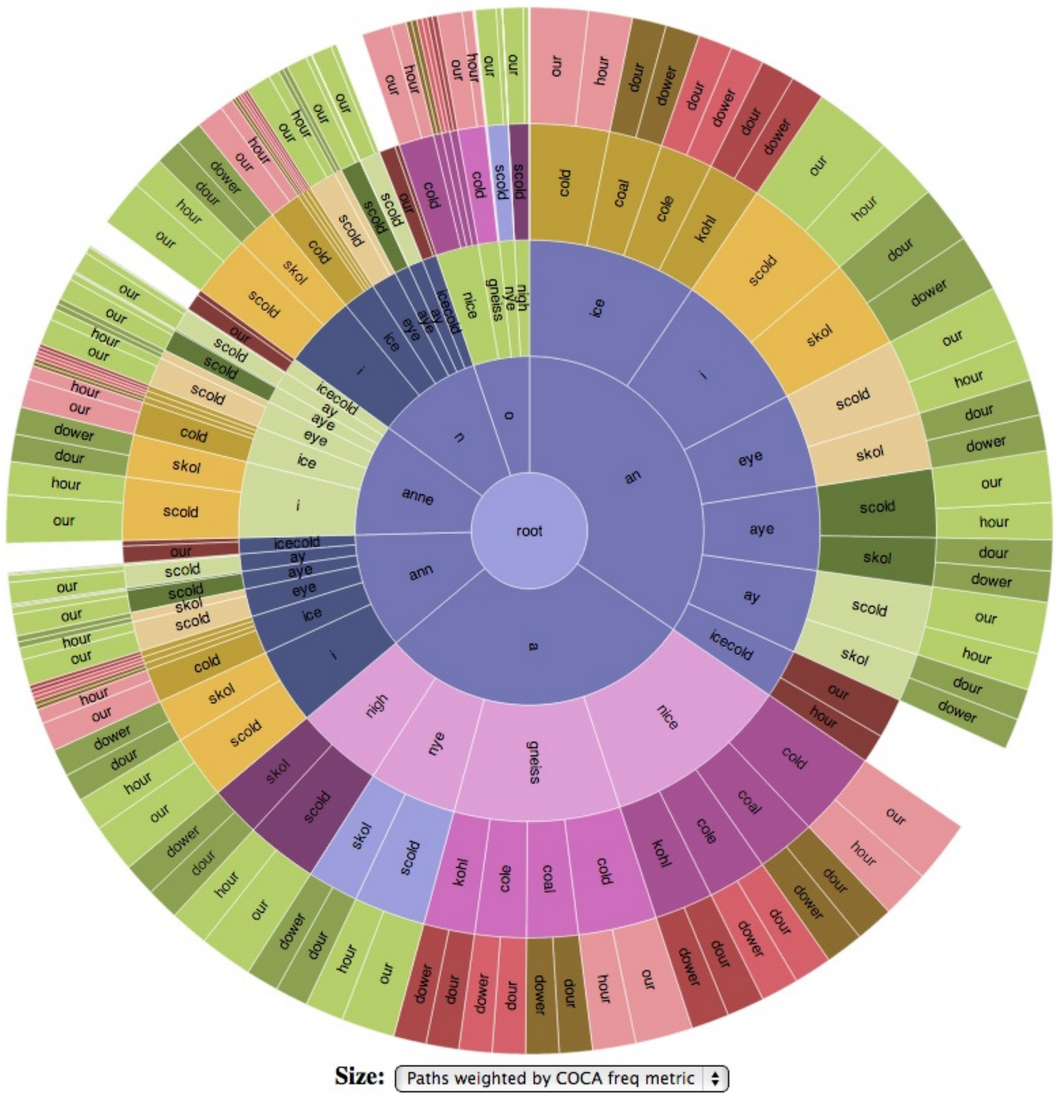


Figure 6.2: Sunburst diagram for "an ice cold hour" using COCA by-document freq metric

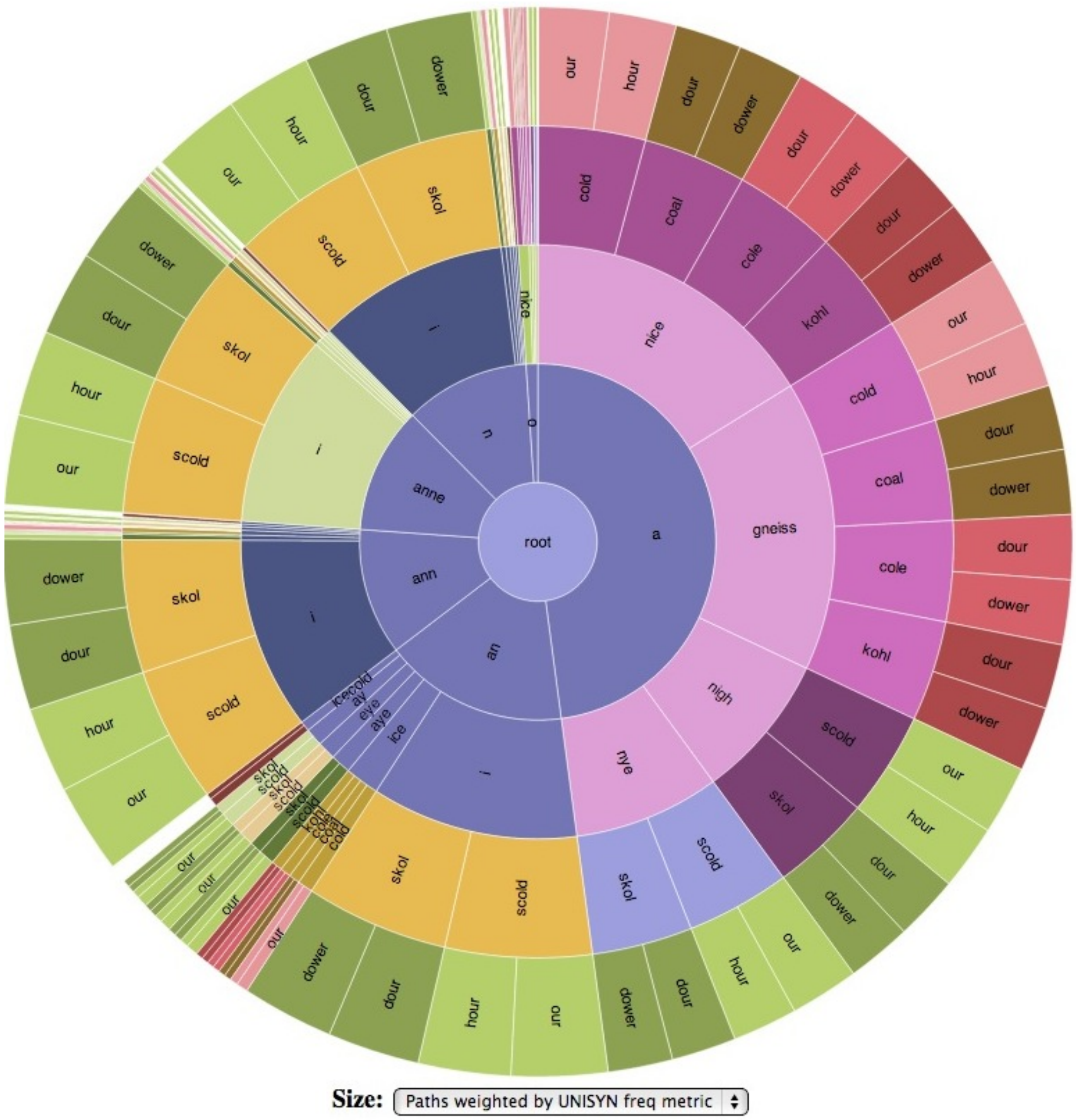


Figure 6.3: Sunburst diagram for "an ice cold hour" using UNISYN freq metric

expected population is 475124 , and the observed population is 316 .

Given those population, the expected population proportion for “a nice cold hour” would be 247719 ÷ 475124 , or 0.4793 .

In our user study, we found that 125 people transcribed “a nice cold hour” , and 191 people transcribed “an ice cold hour” , for a ratio of 0.65 to 1, where “a nice cold hour” accounts for 39.56% (p = 0.3956) of the combined count.

Given the observed population proportion of 0.3956 and the expected population proportion 0.4793 , we did a one-proportion z test with an α of 0.01 . The z value returned was 3.0428 , meaning that the observed population proportion was 3.0428 standard deviations away from the expected population proportion. When we used this z value to compute a p value, we were left with a pvalue of 0.0023 , which is greater than our α of 0.01 . Therefore, there is approximately a 0.01% chance that the observed data could match the COCA predictions, but it's still not incredibly likely. It's significantly more likely than the UNISYN predictions being correct, however.

ALTERNATE COCA stats stuff:

Our COCA-derived document-count frequency metric preditions more closely matched our actual findings. We calculated that “a nice cold hour” had a COCA-derived frequency metric value of 247719 , and “an ice cold hour” had a value of 227405 , giving us a ratio of 1.08 to 1, where “a nice cold hour” accounts for 52.17% (p = 0.5217) of the combined count. When compared to our actual results using a one-sample proportion z test, we got a p-value of 0.0023 , which is slightly better, but not great.

The below is here mostly for my edification: (I'll delete it when my edits are all done.)

Givens for Phrase (1) (“a nice cold hour”) :

Calculated metric: 247719

Actual count: x = 125

Givens for Phrase (2) (“an ice cold hour”) :

Calculated metric: 227405

Actual count: x = 191

α = significance Level = 0.01

Calculated sum: 247719 + 227405 = 475124

Actual sum: 125 + 191 = 316

p = population proportion of “a nice cold hour” occurrences

p = 247719 ÷ 475124 = 0.3956

H_o : p = 0.3956 H_a : p $\neq$ 0.3956

Actual proportion: 125 ÷ 316 = 0.3956

1-proportion z-test

z = 3.0428 std deviations away from expected.

If pvalue ¡ α, reject H_o

pvalue $\approx$ 0.0023 ¿ 0.01

So, accept H_o

6.2.2 Higher-order frequency data

Right now, our program only takes into account the frequency of standalone words, without taking their context into consideration. In the future, we'd like to integrate n-grams into our program. N-grams are a probabilistic model of predicting the next item that will follow in a sequence, based upon frequencies of how often those N items occur in sequence in a corpus of text[12]. A word-level 4-gram, for example, would be a series of four words. Here are some 4-gram phrases, along with counts of how often they occur, from the Google Ngram corpus:

serve as the informational 41
serve as the infrastructure 500
serve as the initial 5331
serve as the initiating 125
serve as the initiation 63
serve as the initiator 81
serve as the injector 56
serve as the inlet 41
serve as the inner 87
serve as the input 1323

[1]

For example, we looked up historical n-gram occurence percentage of n-grams contained in oronyms of our main test phrase "an ice cold hour". As seen in figure 6.4, comparing the 3-grams "a nice cold" and "an ice cold" results in a fairly even split, though the latter phrase is slightly more likely to occur in modern-day settings. When we look at the 2-grams of that 3-gram, we see more interesting trends. In figure 6.5, we see that "a nice" is consistently more frequently found in text than "an ice" is. However, when we compare the 2-grams "ice cold" and "nice cold", as we do in figure 6.6, we see that the phrase "ice cold" is leaps and

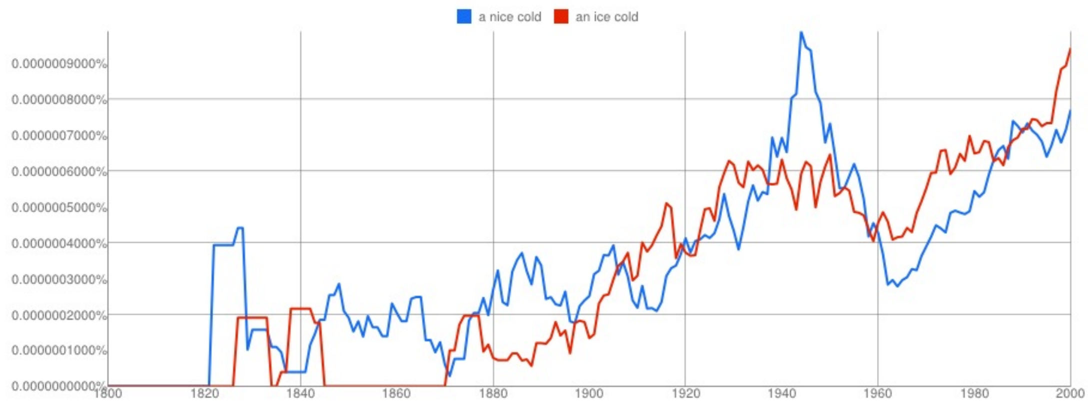


Figure 6.4: Historical N-gram data comparing the three-grams "a nice cold" and "an ice cold"

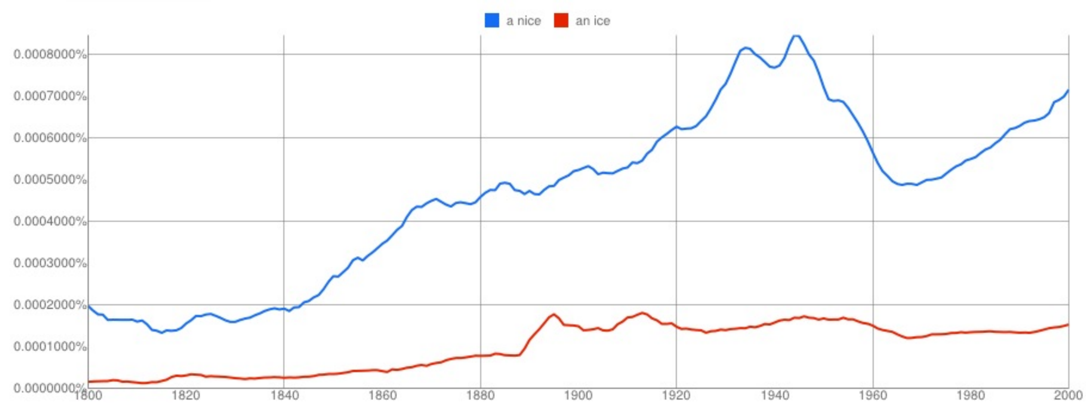


Figure 6.5: Historical N-gram data comparing the two-grams "a nice" and "an ice"

bounds more likely to be encountered in everyday language.

Though we are happy with our findings, we believe that we could create even better likelihood metrics with the integration of several different orders of n-grams, and would suggest this for future work.

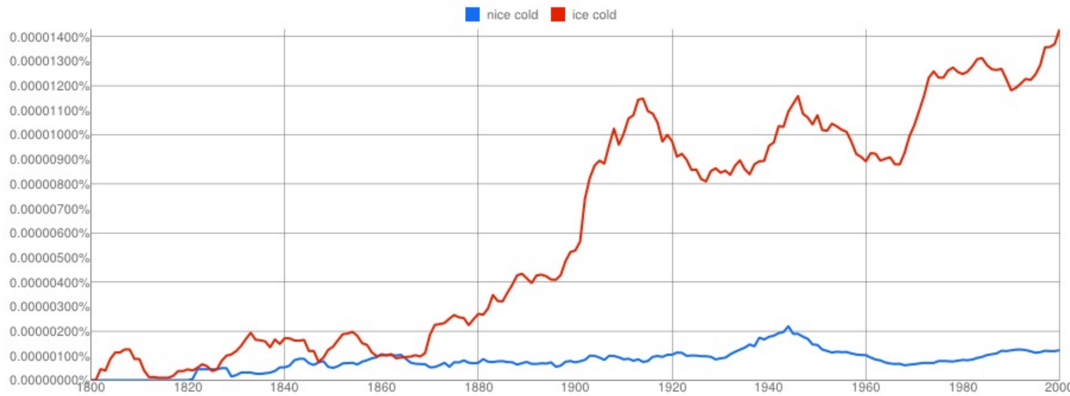


Figure 6.6: Historical N-gram data comparing the two-grams "nice cold" and "ice cold"

6.3 Phoneme swapping

Often when speaking, humans substitute easier-to-say phones for more time-intensive phones. One of the main ways that this substitution occurs is through voiced/voiceless pairs. To voice a phone means to cause the vocal chords to vibrate. Voiced phones are singable, whereas voiceless phones are not. Voiceless phones are like a hiss, and simply direct streams of escaping air. Most consonant phonemes are part of a voice/voiceless pair, such as 't' and 'd'. The word "pretty", when spoken quickly, often uses a 'd' sound instead of a 't' sound, because it's easier to say. Phones are paired when the only differences between their pronuciation is the voicing, aka, when their manner of articulation (i.e. their manner of directing air during the sound), mouth end position, and mouth start position are the same. To view all phones in the SAMPA alphabet, along with enough information to determine whether they are pairs, see table **??**. In our project, we came across an example of phoneme swapping in the "cold"/"gold" transcriptions, which we went over in figure 5.8 and section 5.2.3. For future work, we suggest looking into phoneme swap pairings, and integrating the findings into the existing algorithm.

6.4 Melody Matcher master project

MisheardMe Oronym Tree is a part of the Melody Matcher suite. Melody Matcher is a semi-automated music composition support program. It analyzes English lyrics along with a melody, and alerts the composer of the locations in the song where the lyrics are not deterministically understandable. Basically, it's grammar- and spell-check for songs. This is significant, because very little research has been done specifically on the quantifiable measurement of English-language lyric intelligibility, other than our project.

Melody Matcher aims to replicate the human ability to identify lyrics in a song that are easily misheard. We started on this project, thinking that there would be carefully-specified research on how lyrics match melodies, mathematically. As it turned out, there was very little objective literature on the subject. Because of the lack of objective information of the subject, we had to develop our method from scratch. As we progressed through our work, we went from thinking that understandability depended only on emphasis-matching, to realizing that syllable length played a huge part as well, to realizing that there are many other musical, harmonic, and linguistic factors.

6.4.1 Target Audience and Goals

This program is to be used as a compositional aid by anyone who wants to write songs and make them sound good, technically. It should allow the song writer to focus on more subjective criteria of what makes a song "good", because it will make the structural rules of lyric composition immediately apparent.

Our hope for this project is that it will be useful to burgeoning songwriters, who have the creative spark to make wonderfully poetic lyrics, but lack the "ear" to match their lyrics successfully to music. It should be particularly helpful to songwriters who place a high emphasis on understandability of lyrics (such as parody song writers, or lyricists for musical theater).

Additionally, Melody Matcher will be useful for songwriters for whom English is a second language. While they may be a master lyricist in their native language, writing lyrics in English can be a particular challenge, since so much of lyric-writing is dependent upon knowing the cadence of the language you're writing lyrics in, and since English has no easily-discernible rules for emphasis placement in words.

Melody Matcher analyzes the intelligibility of song lyrics by investigating several root causes:

- Lyric/Music emphasis mismatch, due to:
  - Note intervals
  - Phrase emphases
  - Word emphases
- Word "cramming", due to:
  - Syllable lengths that exceed that of note length
  - Mouth movement delta time intervals
- Word misidentification, due to:
  - Altered pronunciation of words

- Phone similarity
  * Voicing (voiced vs. voiceless)
  * Beginning/end mouth positions
  * Type (Plosive, Fricative, affricate, nasal, lateral, approximant, semivowel)
- Phone sequences with multiple syntactically-correct interpretations

The fully-implemented Melody Matcher program will eventually take into account all of these causes of unintelligibility.

Chapter 7

Conclusion

In this paper, we have demonstrated MisheardMe Oronym Tree, a computer program which takes in textual phrases in English, determines all oronyms for that phrase and then visualizes them with associated information to indicate the likelihood of interpretation. We have demonstrated all three major functional parts: our custom phonetic dictionary, our command-line oronym generator, and our OpenGL oronym-parse-tree visualization generator. Our custom phonetic dictionary has some inconsistencies in word frenquency, due to the source dictionary for it's word frequency values not being generated from a well-sampled corpus. However, it has no major structural flaws, and can be succesfully used for phrase with words with frequencies on the same order of magnitude. Our command-line oronym generator successfully generates all oronyms that are exact phonetic matches for an orthographic phrase. The user studies that we did supported our generated phrases, if not our frequency metrics. Our oronym parse tree visualization had two goals: one, visually represent the likelihood of each oronym interpretation, visualized using wider branches for more common phraseds; and two, to exhibit orthographic phrases that may not have any exact oronyms, but have many dead-end, partial oronyms that could cause ambiguity. Our visualization can successfully do both of those things.

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