

final paper on

**Applications of Decision Trees in Phonetic Recognition**

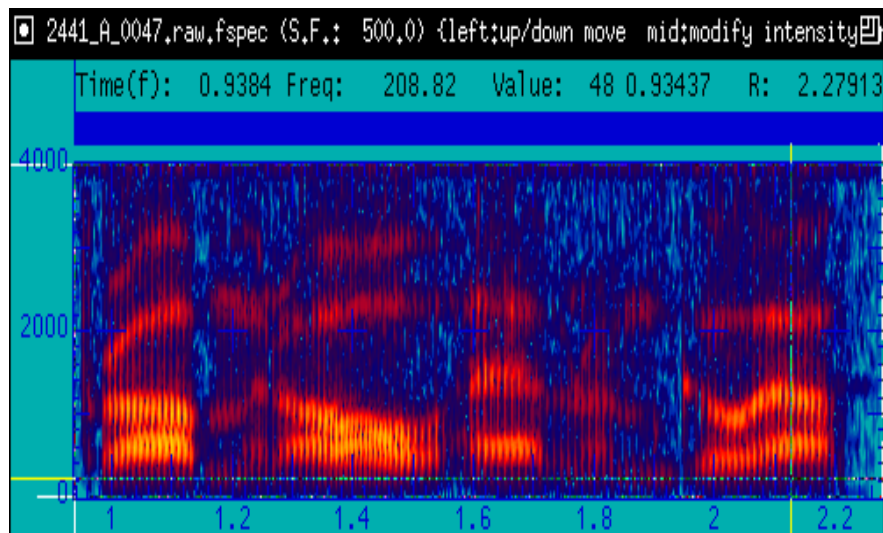
submitted to fulfill the requirements for

**ECE 8993: Fundamentals of Speech Recognition**

submitted to:

Dr. Joseph Picone  
Department of Electrical and Computer Engineering  
413 Simrall, Hardy Rd.  
Mississippi State University  
Mississippi State, Mississippi 39762

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submitted by:

Julie Ngan  
MS in Computer Engineering Candidate  
Department of Electrical and Computer Engineering  
Mississippi State University  
429 Simrall, Hardy Rd.  
Mississippi State, Mississippi 39762  
Tel: 601-325-8335, Fax: 601-325-3149  
Email: ngan@isip.msstate.edu



## ABSTRACT

Recent progress on conversational speech recognition has been painstakingly slow, and has resulted in measurable reductions in word error rate primarily through intricate pronunciation modeling and hand-tailoring of the lexicon.

## 1. INTRODUCTION

Recent progress on conversational speech recognition has been painstakingly slow, and has resulted in measurable reductions in word error rate primarily through intricate pronunciation modeling and hand-tailoring of the lexicon. The primary problem seems to stem from poor acoustic-level matching as a result of a high degree of variability in pronunciations. Three common approaches to overcome this problem are (1) prediction of common alternate pronunciations and incorporation of these as additional paths in the acoustic models, (2) use of acoustic units that specifically model multi-word phrases, and (3) reestimation of the acoustic models in such a way that the models automatically learn such alternate pronunciations.

A really cool equation, that explains everything in life, is as follows:

$$y = mx + b \quad (1)$$

A second equation, that is equally profound, is:

$$y = ax^2 + bx + c \quad (2)$$

I think we need a figure here to explain why this equation is the bomb. See Figure 1, which explains the meaning of life in a block diagram.

The first approach suffers from related problems of intelligent integration of language model and acoustic model scores. The last approach, which is featured in this white paper, requires robust training algorithms that



Figure 1. The meaning of life is depicted here, and explained in a full sentence.

can converge to meaningful solutions in the presence

### 1.1. My First Sub-Heading

I think it is about time to introduce a simple table. In Table X, we see how a table should look. Recent progress on conversational speech recognition has been painstakingly slow, and has resulted in measurable reductions in word error rate primarily through intricate pronunciation modeling and hand-tailoring of the lexicon.

### 1.2. My Second Sub-heading

Recent progress on conversational speech recognition has been painstakingly slow, and has resulted in measurable reductions in word error rate primarily through intricate pronunciation modeling and hand-tailoring of the lexicon.

### 1.3. My Third Sub-Heading

Recent progress on conversational speech recognition has been painstakingly slow, and has resulted in measurable reductions in word error rate primarily through intricate pronunciation modeling and hand-tailoring of

Date	Time	Value
3	4	7
6	6	6
5	5	5

Table 1. This table is really important, so we spend a lot of time explaining it.

the lexicon.

#### 1.4.1. A Really Deep Theory

Recent progress on conversational speech recognition has been painstakingly slow, and has resulted in measurable reductions in word error rate primarily through intricate pronunciation modeling and hand-tailoring of the lexicon.

## 2. DECISION TREES

Recent progress on conversational speech recognition has been painstakingly slow, and has resulted in measurable reductions in word error rate primarily through intricate pronunciation modeling and hand-tailoring of the lexicon.

## 3. APPLICATIONS IN LVCSR

Recent progress on conversational speech recognition has been painstakingly slow, and has resulted in measurable reductions in word error rate primarily through intricate pronunciation modeling and hand-tailoring of the lexicon.

## 4. EXPERIMENTAL SUPPORT

Recent progress on conversational speech recognition has been painstakingly slow, and has resulted in measurable reductions in word error rate primarily through intricate pronunciation modeling and hand-tailoring of the lexicon.

## 5. SUMMARY

Recent progress on conversational speech recognition has been painstakingly slow, and has resulted in measurable reductions in word error rate primarily through intricate pronunciation modeling and hand-tailoring of the lexicon.

## 6. ACKNOWLEDGEMENTS

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## APPENDIX A