Acoustic Classification of Focus in a Web Corpus of Comparatives

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Domain of Inquiry

- Observed correlation between
- i. what has been uttered or is salient in a discourse
- ii. which phonetic material in an utterance is realized with prosodic prominence

Challenges in studying this correlation

- Empirical challenges
- Methodological challenges

Empirical challenge:

What are the objects of study?

How do we identify and/or measure them?

Pragmatics/semantics

Assume: Focus anaphoricity (Rooth 2008)

focus involves a relation to context which is a kind of anaphora

Licensing condition

The antecedent entails the union of the alternative set (focus existential closure)

(I) A: I heard [the quarterback took steroids]₂

B: Yes. In fact, [the WHOLE TEAM_F took steroids] ~2

Focus existential closure: 'some person x took steroids'
Antecedent: 'the quarterback took steroids'

- Phonetics / Phonology
 - abstract, categorical objects nuclear pitch accent? stress?
 - directly observable, gradient measures fundamental frequency? formant extrema? duration?

all (or some combination) of the above?

"a complex of properties that can be related to greater force of articulation, including increased intensity and duration, and shallower spectral tilt" (Ladd 1996:58)

Methodological Challenge:

- We want:
 - to study speech from natural discourse
 - to control for grammatical/pragmatic conditioning
- difficult to recreate real-world context in the lab environment
- traditional speech corpora lack specific focussensitive constructions in sufficient numbers to allow a quantitative analysis

Our goals

- Assemble large, focused datasets of examples where prominence varies in a way that correlates with syntax, semantics, or pragmatics
- Study correlation between lexical/ grammatical/pragmatic context and acoustic realization of prominence

Outline for rest of presentation

- the first dataset
- our datasource
- web harvest methodology (Howell & Rooth 2010)
- classification experiments

First dataset

Search query: ... than I did ...

- Theory makes predictions for the location of prominence
- Antecedent for comparative clause is syntactically obligatory

```
he stayed longer than I did
```

```
-er [[ he stayed d long]<sub>2</sub> than [ l<sub>F</sub> stayed d long ] ~2]
```

[y stayed d-long] antecedent clause [speaker stayed d-long] scope of focus

Licensing condition for focus

The antecedent entails the union of the alternative set (focus existential closure).

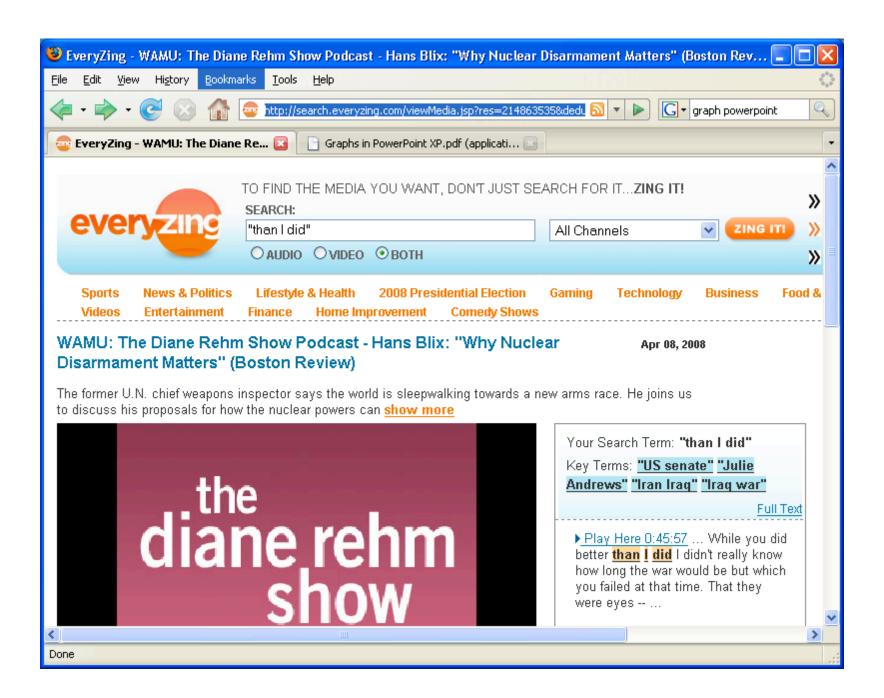
'He stayed d long' entails 'someone stayed d long'

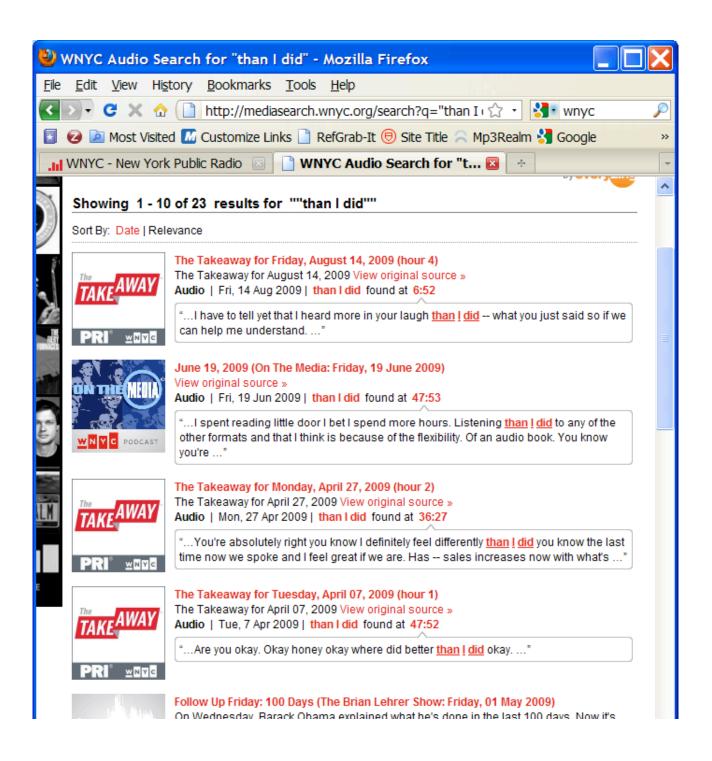
Our Datasource

search.everyzing.com (now defunct)	web l	91 true tokens
multimedia.play.it (now defunct)	web2	127 true tokens
mediasearch.wnyc.org		

Ramp (formerly Everyzing) is a commercial audio indexing service using ASR

Content includes radio and tv programs, podcasts



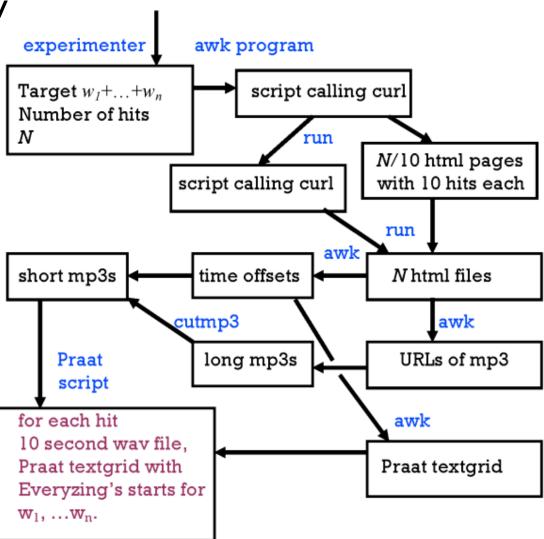


Web Harvest Methodology

Howell & Rooth 2010

- Turn-key procedure using Unix tools (e.g. curl, cutmp3, awk, bash, make)
 - replicates user interaction with website

Workflow

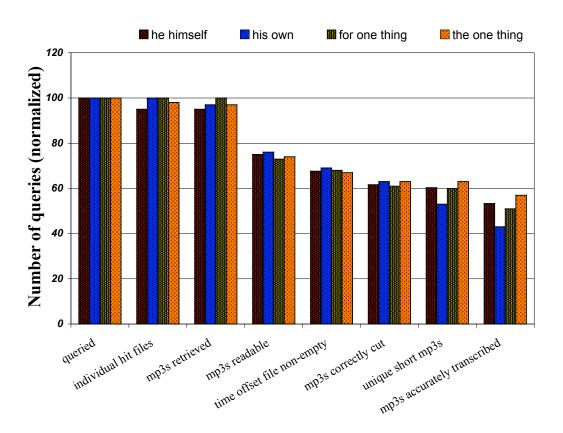


Some steps yet to be automated

- elimination of duplicates common in radio programming
 - -> measure similarity between ASR transcripts and acoustic signals
- phonetic-level annotation
 - -> segmentation by forced alignment using HTK hidden Markov model toolkit
- sentence-level annotation
 - -> sentence-level annotation with commercial transcription service or Amazon Turk

Retrieval efficacy

roughly half or more of hits yield correct, unique speech tokens



Binary Classification Experiment

 Task: Predict focus class from acoustic parameters alone

(1) He stayed longer than I _F did antecedent: he stayed <i>x</i> long	s class
(2) I should have liked that song more than I did _F antecedent: I should have liked that song x much.	ns class
(3) I understand even less than I did before _F antecedent: I understand even x little	ns class

Input for statistical classifiers

- Semantic class:
 - Determined from the TEXT ALONE by co-reference of subjects

If subjects co-refer, ns class

Else, s class

Input for statistical classifiers

- Acoustic features:
 - 308 parameters extracted from string than I did
 - incl. duration, f0, f1, f2, intensity, amplitude, voice quality, spectral tilt
 - means, extrema, range
 - over a vowel, at regular intervals, at times of other events

Questions

- Is the theoretical prediction for location of prominence in comparative clauses confirmed?
- Will the variability in speakers, recording conditions, audio compression, levels of formality, discourse conditions, etc. help or hinder classification compared to laboratory

Questions

- Which set of acoustic features is most predictive?
 - Pitch-first theories privilege f0-related features
 - Stress-first theories privilege stress-related features (duration, intensity, formant extrema)
 - if pitch accents align with stress, then F0 correlates expected
 - however, pitch cues might not be necessary or may be secondary to other stress cues

Machine Learning

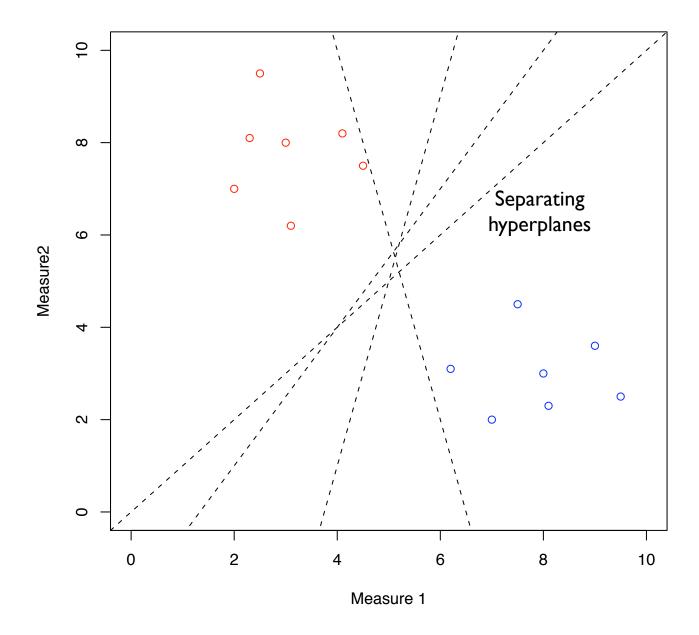
- Linear Discriminant Anaylsis (LDA)
 - minimize within-class distance and maximize between-class distance
 - assumes normal distribution of classes, homogeneity of classes
 - performs best with small number of attributes

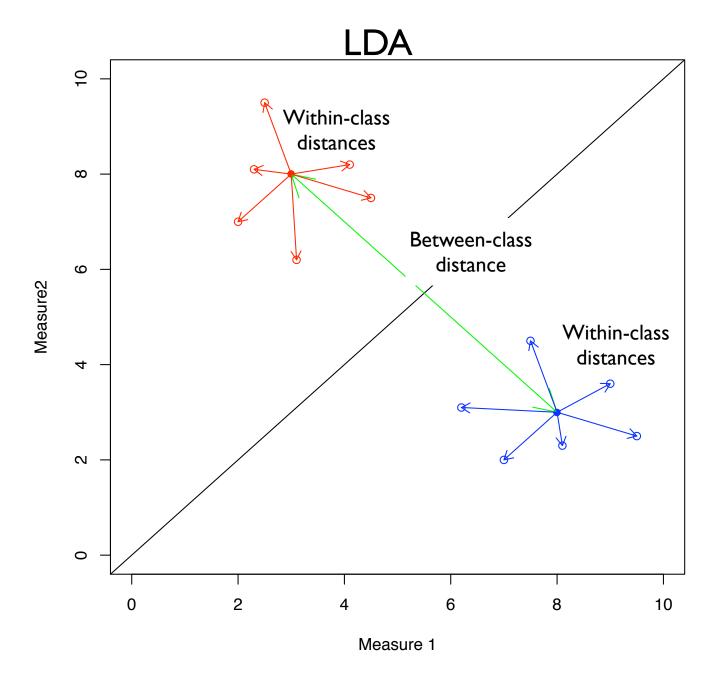
Implementations in R statistical programming environment: package MASS

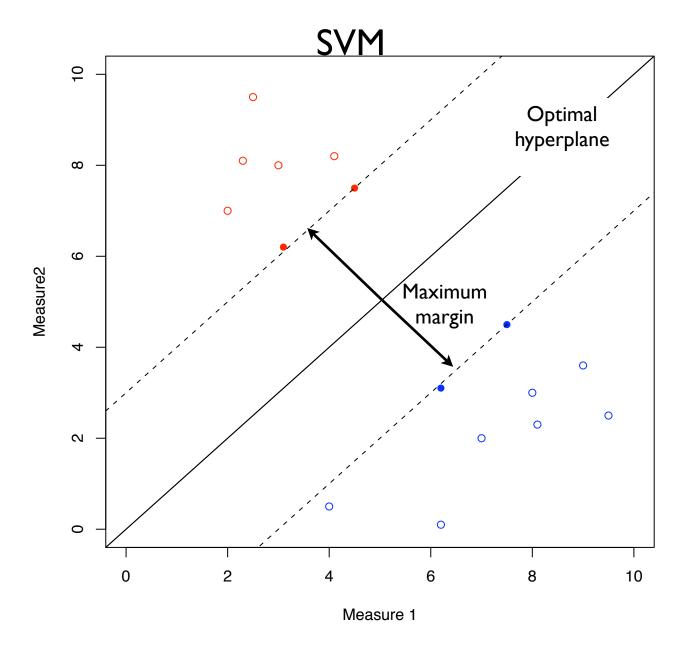
Machine Learning

- Support Vector Machine (SVM)
 - maximize margin between classes
 - works well with large number of attributes: data mapped (using "kernels" to highdimensional featurespace)
 - works well with sparse data: no assumptions of normal distribution and homogeneity

Implementation in R statistical programming environment: libsvm in package e1071







Feature Selection

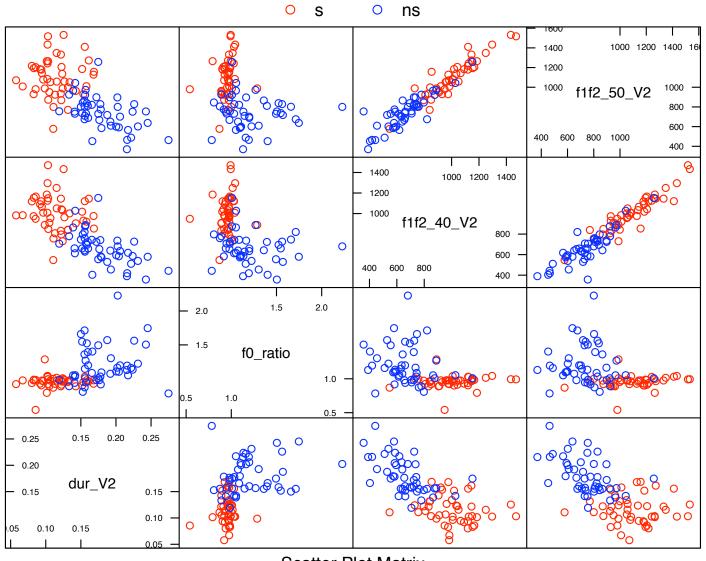
- Many of the features may turn out to be redundant and/or irrelevant
 - e.g. f2-f1 measured at 10% of vowel f2-f1 measured at 20% of vowel
- Manual selection by experimenter
 - theory-informed, trail-and-error
- Automatic selection by algorithm
 - random-forest based algorithm: VarSelRF package

e.g. Automated Feature Selection B

• given all 308 features, VarSelRF selected 4

dur_V2	duration of I
f0_ratio	ratio of f0 maxima in I and did
f1f2_40_V2	f2-f1 at 40% into 1
f1f2_50_V2	f2-f1 at 50% into 1

Automated Feature Selection B



Scatter Plot Matrix

e.g. Hand-picked A

 an experimenter-selected set that turned out to perform well

dur_V2	duration of I
dur_C3	duration of Ist stop closure in did
f0_ratio	ratio of f0 maxima in I and did
f1f2_50_V2	f2-f1 at 50% into 1

Hand-picked A o ns 00 1000 1200 1400 16 1400 1200 1000 f1f2_50_V2 0 800 600 400 600 800 1000 400 0 0 1.5 2.0 2.0 - 1.5 f0_ratio 1.0 0 0.12 0.08 0.10 0.12 0.10 0.08 0.08 dur_C3 0 0.06 0.04 0.06 - 0.25 0.15 0.20 0.25 0 - 0.20 dur_V2 0.15 0.15 0.10 .05 0.10 0.15 0.05

Scatter Plot Matrix

Evaluation of classifier performance

- Baseline accuracy
 - # tokens in largest class of test set
 # tokens in both classes in test set
- Generaliation accuracy
 - # of tokens in test set accurately classified
 # of tokens in test set
- Balanced error rate

```
# incorrect "s" * # incorrect "ns" * 1 * 100
# total "s" # total "ns" 2
```

Classifier Performance

Training set: web1 91 tokens 46:45

Test set: web2 127 tokens 62:65

	Classifier performance on web2			
Feature set	Baseline	SVM (radial kernel)	SVM (linear kernel)	LDA
1. Full set (no. features = 308)	51.2	82.7 (14.3)	85.0 (14.2)	n/a due to collinearity
2. Automated feature selection A (no. features = 16)	51.2	89.8 (10.1)	89.0 (10.3)	90.6 (9.0)
3. Automated feature selection B (no. features = 4)	51.2	86.6 (13.1)	90.6 (9.2)	87.4 (11.9)
4. Hand-picked A (no. features = 4)	51.2	92.9 (6.5)	92.1 (7.1)	91.3 (7.7)
5. Hand-picked B (no. features = 3)	51.2	91.3 (7.7)	92.1 (7.1)	91.3 (7.7)

Theoretical predictions confirmed?

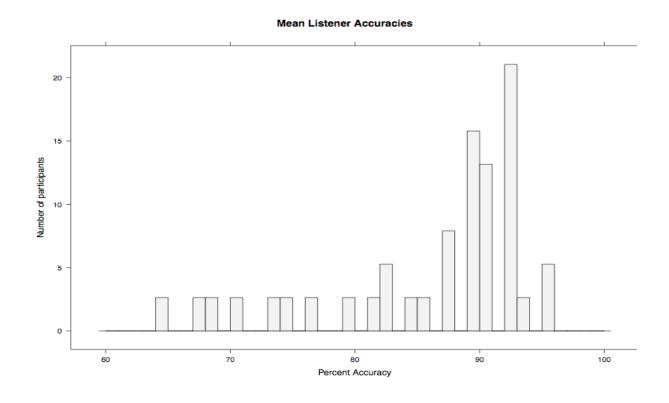
- There seems to be a very robust correlation.
- Are these accuracy and error rates reasonable?

Human classifiers

- Perception experiment (prosodylab @ McGill)
 - 38 participants
 - subset of 64 tokens from web2
- than I did sequence extracted
- Question I:Which is more prominent: I or did?
- Question 2: How confident are you?
 (very uncertain) I 2 3 4 5 6 7 (very confident)

- mean accuracy: 85.9% (64.1-95.3%)
- balanced error rate: 14.1% (4.7-35.9%)
- confidence rating significant predictor of performance

(generalized linear model: σ = 0.031, z= -10.81,p<0.001)



Most predictive acoustic features?

 Models with f0 information performed on par with models lacking it

Hand-picked A: dur_V2, dur_C3, f1f2Time50_V2, f0_ratio

Hand-picked B: dur_V2, dur_C3, f1f2Time50_V2

Feature set	Baseline	SVM (radial)	SVM (linear)	LDA
4. Hand-picked A (no. features = 4)	51.2	92.9 (6.5)	92.1 (7.1)	91.3 (7.7)
5. Hand-picked B (no. features = 3)	51.2	91.3 (7.7)	91.3 (7.7)	90.6 (8.3)

Stress-first

- Results consistent with stress-first accounts of focus
- Note: for theories which assume alignment of pitch events, stress comes "for free"
 - e.g. pitch accents attach to strongest stress in a phrase (Pierrehumbert 1980, Selkirk 1995)

```
p.a. {H*, L*, L+H*, ...}

x

x x x x x x

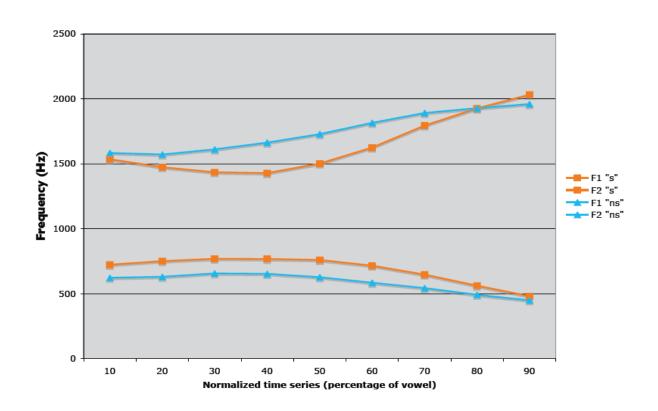
x x x x x x x
```

 Pitch accent type has been argued to correlate with information other than just focus marking (e.g. Ward & Hirschberg 1985, Steedman 2003)

Hyperarticulation

- From a phonetic standpoint, these results also support hyperarticulation theories of prominence (e.g. de Jong 1995, Fowler 1995, Cho 2005)
- The classifiers are good at detecting focused pronouns using local features on pronoun:
 - duration of vowel in "l"
 - distance between f1 and f2 halfway into vowel in "1"

"than I did" Normalized f1 and f2 for "I" (n=91)



Variability: Web vs. Lab

Will the variability in speakers, recording conditions, levels of formality, discourse conditions, etc. help or hinder classification compared to laboratory data?

Production study

- prosodylab @ McGill University
 - 26 participants
 - 16 written stimuli, based on corpus data
 - 12 statements, 4 questions

Classification Experiment 2: Lab-Trained, Web-Tested

Training set: *lab* 394 tokens 193:201

Test set: web1+web2 218 tokens 110:108

		web_1+2: web1 & web2 (web corpus)		
Feature set	Baseline	SVM (RBF)	SVM (linear)	LDA
1. Full set (no. features = 308)	50.5	79.8 (17.4)	73.4 (24.7)	
2. Automated feature selection C (no. features = 43)	50.5	83.9 (15.2)	79.4 (20.6)	
3. Automated feature selection D (no. features = 18)	50.5	81.7 (16.8)	72.9 (27.1)	
4. Hand-picked A (no. features = 3)	50.5	89.4 (9.8)	88.5 (10.3)	88.1 (10.9)
5. Hand-picked B (no. features = 4)	50.5	85.8 (12.9)	88.5 (10.3)	88.1 (10.9)

• Performance did not vary significantly between the declarative and interrogative contexts.

Classification Experiment 2

- Again, predictions of prominence in comparative clauses confirmed
- Again, models without f0 information performed on par with those lacking it
 - -> consistent with stress-first theories of focus
- Classifiers trained on lab data performed on par with classifiers trained on web data
 - -> lab data have sufficient variability to train classifiers
- Are these accuracy rates reasonable?
 - -> perception experiment in progress

Method for future studies

- Find common grammatical or lexical contexts that trigger representations with different prosodic realization, according to relatively well-understood and well-supported theory.
- Correlate the semantic-grammatical categories directly with the speech signal using machine learning
 - Question: How successful are classifiers that lack information about phonemic/morphemic categories (e.g. H*, L+H*)?

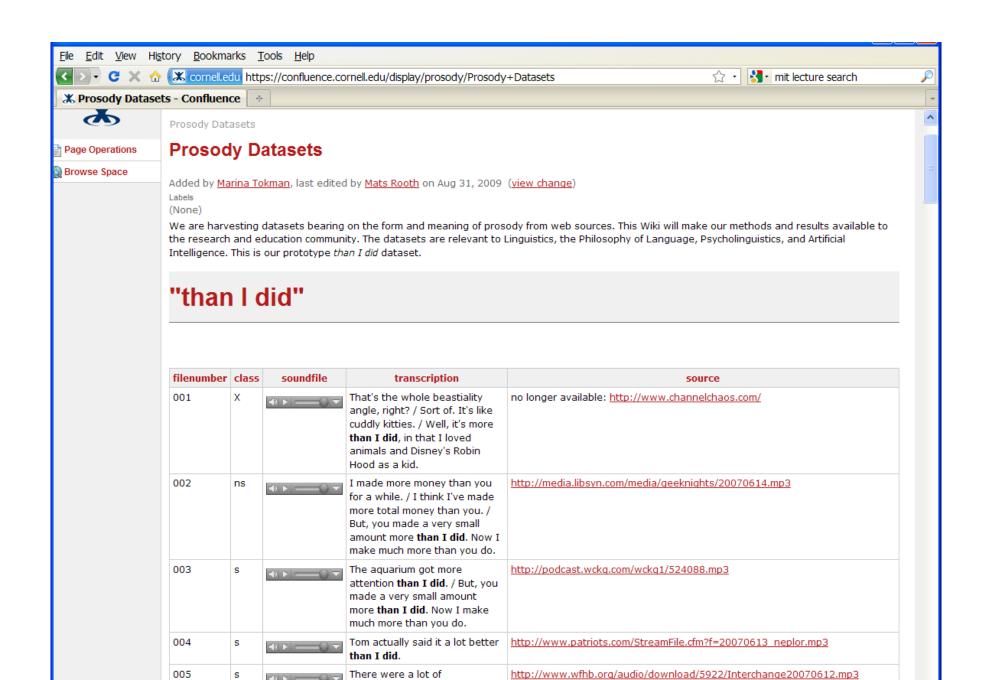
Future directions

- Simple, interactive GUI for aggregation, downloading and processing for web harvest method
- Full comparative paradigm (e.g. than he did, than you do)
 - Which acoustic cues are robust across word and vowel type?
- Second occurrence focus (cf. Howell in prep.)
 - debate over the semantics of focus in contexts favoring pitch-reduction
- Constructions alleged to be inherently contrastive (e.g. in MY opinion, NEXT friday, the President himSELF)
- Constructions alleged to use a particular accent type (e.g. for ONE thing, the ONE thing)

Distribution of datasets

Audio snippets can probably by distributed under fair use.

http://confluence.cornell.edu/display/prosody/ Prosody+Datasets



I should have liked that song I no longer available: http://podcast.971freefm.com/klsx1/520789.mp3

photographers who would shoot more **than I did.**

006

ns