Prosody-Based Detection of *Annoyance* and ***Frustration*** in Communicator Dialogs

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Introduction

- Prosody = rhythm, melody, “tone” of speech
- Largely unused in current ASU systems
- Prior work: prosody aids many tasks:
  - Automatic punctuation
  - Topic segmentation
  - Word recognition
- Today’s talk: detection of user frustration in DARPA Communicator data
  (ROAR project suggested by Jim Bass)

Talk Outline

- Data and labeling
- Prosodic and other features
- Classifier models
- Results
- Conclusions and future directions

Key Questions

- How frequent is annoyance and frustration in Communicator dialogs?
- How reliably can humans label it?
- How well can machines detect it?
- What prosodic or other features are useful?

Data Sources

- Labeled Communicator data from various sites
  - NIST June 2000 collection: 392 dialogs, 7515 utts
  - CMU 1/2001-8/2001 data: 205 dialogs, 5619 utts
  - CU 11/1999-6/2001 data: 240 dialogs, 8765 utts
- Each site used different formats and conventions, so tried to minimize the number of sources, maximize the amount of data.
- *Thanks to NIST, CMU, Colorado, Lucent, UW*

Data Annotation

- 5 undergrads with different backgrounds (emotion should be judged by 'average Joe').
- Labeling jointly funded by SRI and ICSI.
- Each dialog labeled by 2+ people independently in 1st pass (July-Sept 2001), after calibration.
- 2nd "Consensus" pass for all disagreements, by two of the same labelers (0ct-Nov 2001).
- Used customized Rochester Dialog Annotation Tool (DAT), produces SGML output.

Data Labeling

- **Emotion**: neutral, annoyed, frustrated, tired/disappointed, amused/surprised, no-speech/NA
- **Speaking style**: hyperarticulation, perceived pausing between words or syllables, raised voice
- **Repeats and corrections**: repeat/rephrase, repeat/rephrase with correction, correction only
- **Miscellaneous useful events**: self-talk, noise, non-native speaker, speaker switches, etc.

Emotion Samples

❒ Neutral

- *July 30* 1
- *Yes* 2

❒ Disappointed/tired

- *No* 6

❒ *Amused/surprised*

- *No* 7

❒ Annoyed

- *Yes* 3
- *Late morning (HYP)* 8

❒ Frustrated

- *Yes* 4
- *No* 5

- *No, I am … (HYP)* 9
- *There is no Manila...* 10

Emotion Class Distribution

	Count	%
Neutral	17994	.831
Annoyed	1794	.083
No-speech	1437	.066
Frustrated	176	.008
Amused	127	.006
Tired	125	.006
TOTAL	21653	

To get enough data, we grouped annoyed and frustrated, versus else (with speech)

Prosodic Model

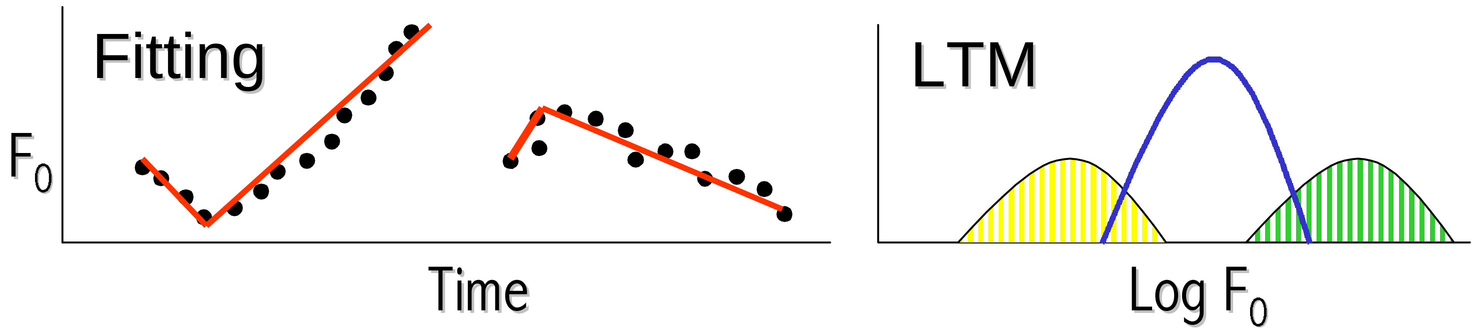
- Used CART-style decision trees as classifiers
- Downsampled to equal class priors (due to low rate of frustration, and to normalize across sites)
- Automatically extracted prosodic features based on recognizer word alignments
- Used automatic feature-subset selection to avoid problem of greedy tree algorithm
- Used 3/4 for train, 1/4th for test, no call overlap

Prosodic Features

- **Duration and speaking rate features**
  - duration of phones, vowels, syllables
  - normalized by phone/vowel means in training data
  - normalized by speaker (all utterances, first 5 only)
  - speaking rate (vowels/time)
- **Pause features**
  - duration and count of utterance-internal pauses at various threshold durations
  - ratio of speech frames to total utt-internal frames

Prosodic Features (cont.)

- **Pitch features**
  - F0-fitting approach developed at SRI (Sönmez)
  - LTM model of F0 estimates speaker's F0 range



  - Many features to capture pitch range, contour shape & size, slopes, locations of interest
  - Normalized using LTM parameters by speaker, using all utts in a call, or only first 5 utts

Features (cont.)

❐ Spectral tilt features

- average of 1st cepstral coefficient
- average slope of linear fit to magnitude spectrum
- difference in log energies btw high and low bands
- extracted from longest normalized vowel region

❐ Other (nonprosodic) features

- position of utterance in dialog
- whether utterance is a repeat or correction
- to check correlations: hand-coded style features including hyperarticulation

Language Model Features

- Train 3-gram LM on data from each class
- LM used word classes (AIRLINE, CITY, etc.) from SRI Communicator recognizer
- Given a test utterance, chose class that has highest LM likelihood (assumes equal priors)
- In prosodic decision tree, use sign of the likelihood difference as input feature
- Finer-grained LM scores cause overtraining

Results: Human and Machine

	Accuracy (%) (chance = 50%)	Kappa (Acc-C)/(1-C)
Each Human with Other Human, overall	71.7	.38
Human with Human "Consensus" (biased)	84.2	.68
Baseline ▶ Prosodic Decision Tree with Consensus	75.6	.51
Tree with Consensus, no repeat/correction	72.9	.46
Tree with Consensus, repeat/correction only	68.7	.37
Language Model features only	63.8	.28

Results (cont.)

- H-H labels agree 72%, **complex decision task**
  - inherent continuum
  - speaker differences
  - relative vs. absolute judgements?
- H labels agree 84% with “consensus” (biased)
- Tree model agrees 76% with consensus-- *better than original labelers with each other*
- Prosodic model makes use of a dialog state feature, but without it it’s still better than H-H
- Language model features alone are not good predictors (dialog feature alone is better)

Baseline Prosodic Tree

duration feature pitch feature other feature

```
REPCO in ec2,rr1,rr2,rex2,inc,ec1,rex1 :  0.7699 0.2301 AF
|    MAXF0_IN_MAXV_N < 126.93:  0.4735 0.5265 N
|    MAXF0_IN_MAXV_N >= 126.93:  0.8296 0.1704 AF
|    |    MAXPHDUR_N < 1.6935:  0.6466 0.3534 AF
|    |    |    UTTPOS < 5.5:  0.1724 0.8276 N
|    |    |    UTTPOS >= 5.5:  0.7008 0.2992 AF
|    |    MAXPHDUR_N >= 1.6935:  0.8852 0.1148 AF
REPCO in 0 :  0.3966 0.6034 N
|    UTTPOS < 7.5:  0.1704 0.8296 N
|    UTTPOS >= 7.5:  0.4658 0.5342 N
|    |    VOWELDUR_DNORM_E_5 < 1.2396:  0.3771 0.6229 N
|    |    |    MINF0TIME < 0.875:  0.2372 0.7628 N
|    |    |    MINF0TIME >= 0.875:  0.5 0.5 AF
|    |    |    |    SYLRATE < 4.7215:  0.562 0.438  AF
|    |    |    |    |    MAXF0_TOPLN < -0.2177:  0.3942 0.6058 N
|    |    |    |    |    MAXF0_TOPLN >= -0.2177:  0.6637 0.3363  AF
|    |    |    |    SYLRATE >= 4.7215:  0.2816 0.7184 N
|    |    VOWELDUR_DNORM_E_5 >= 1.2396:  0.5983 0.4017  AF
|    |    |    MAXPHDUR_N < 1.5395:  0.3841 0.6159 N
|    |    |    |    MINF0TIME < 0.435:  0.1 0.9 N
|    |    |    |    MINF0TIME >= 0.435:  0.4545 0.5455 N
|    |    |    |    |    RISERATIO_DNORM_E_5 < 0.69872:  0.3284 0.6716 N
|    |    |    |    |    RISERATIO_DNORM_E_5 >= 0.69872:  0.6111 0.3889  AF
|    |    |    MAXPHDUR_N >= 1.5395:  0.6728 0.3272  AF
```

Predictors of Annoyed/Frustrated

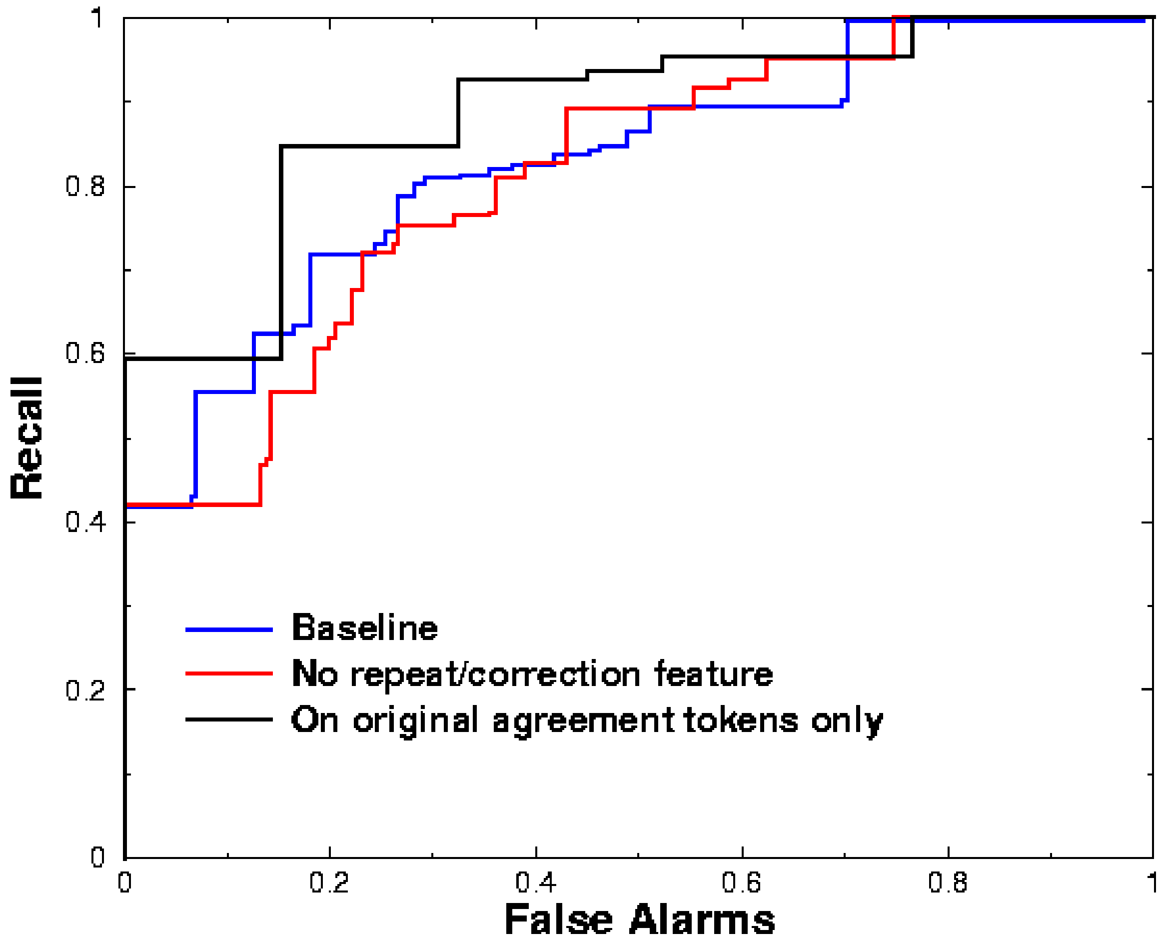
- Prosodic: Pitch features:
  - high maximum fitted F0 in longest normalized vowel
  - high speaker-norm. (1st 5 utts) ratio of F0 rises/falls
  - maximum F0 close to speaker's estimated F0 "topline"
  - minimum fitted F0 late in utterance (no "?" intonation)
- Prosodic: Duration and speaking rate features
  - long maximum phone-normalized phone duration
  - long max phone- & speaker- norm.(1st 5 utts) vowel
  - low syllable-rate (slower speech)
- Other:
  - utterance is repeat, rephrase, explicit correction
  - utterance is after 5-7th in dialog

Effect of Class Definition

	Accuracy (%) (chance = 50%)	Entropy Reduction
Baseline prosody model Consensus labels A,F vs. N,else	75.6	21.6
Tokens on which labelers originally agreed A,F vs. N,else	78.3	26.4
All tokens Consensus labels F vs. A,N,else	82.7	37.0

For less ambiguous tokens, or more extreme tokens
performance is significantly better than our baseline

Error tradeoffs (ROC)



Conclusion

- Emotion labeling is a complex decision task
- Cases that labelers independently agree on are classified with high accuracy
- Extreme emotion (e.g. ‘frustration’) is classified even more accurately
- Classifiers rely heavily on prosodic features, particularly duration and stylized pitch
- Speaker normalizations help, can be online

Conclusions (cont.)

- Two nonprosodic features are important: utterance position and repeat/correction
- Even if repeat/correction not used, prosody still good predictor (better than human-human)
- Language model is an imperfect surrogate feature for the underlying important feature repeat/correction
- Look for other useful dialog features!

Future Directions

- Use realistic <u>data</u> to get more real frustration
- Improve <u>features</u>:
  - use new F0 fitting, capture voice quality
  - base on ASR output (1-best straightforward)
  - optimize online normalizations
- Extend <u>modeling</u>:
  - model frustration *sequences*, include dialog state
  - exploit speaker 'habits'
- Produce <u>prosodically 'tagged'</u> data, using combinations of current feature primitives
- Extend <u>task</u> to other useful emotions & domains.

Thank You