On the Correlation between Perceptual and Contextual Aspects of Laughter in Meetings

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August 9, 2007

Introduction

- what we do:
  - data-driven, language-/text- independent modeling of
  - multi-participant conversation for
  - automatic conversation recognition and understanding
- why?
  - who has the floor when? how many floors are there?
  - who backchannels when? and towards whom?
  - who interrupts who? who asks questions? who gives answers?
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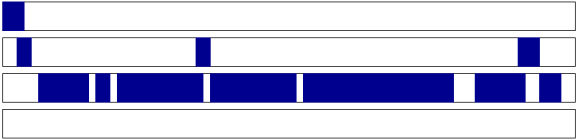
- essentially monologue
- "multi-logue"
- heated "multi-logue"
- a mathematical artifact (the Haar wavelet basis)
- "multi-logue" with laughter



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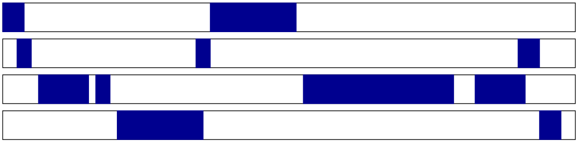

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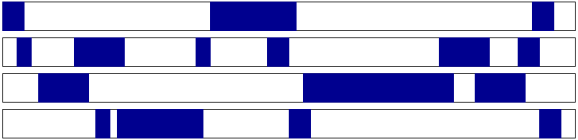

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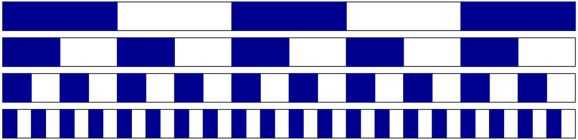

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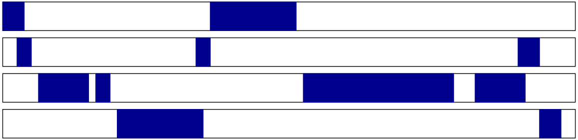

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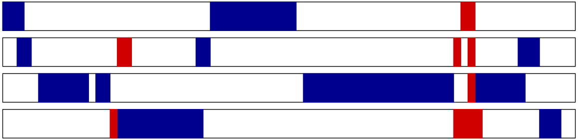

Emotion and Laughter in Conversation

- external observers of conversation appear to agree as to whether participants feel
  - neutral: 82% of utterances
  - positive: 16% of utterances
  - negative: 2% of utterances
- transcribed laughter is strongly predictive of positive valence (92% classification accuracy)
- A FUTURE GOAL: to find laughter in continuous audio
- context does discriminate between speech and laughter
- **does context discriminate between voiced and unvoiced laughter?**

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- naturally occurring project-oriented conversations
- for our purposes, 4 types of meetings:

type	# of meetings	# of possible participants	# of participants		
			mod	min	max
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Bmr	29	15	7	3	9
Bro	23	10	6	4	8
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- rarely, meetings contain additional, uninstrumented participants

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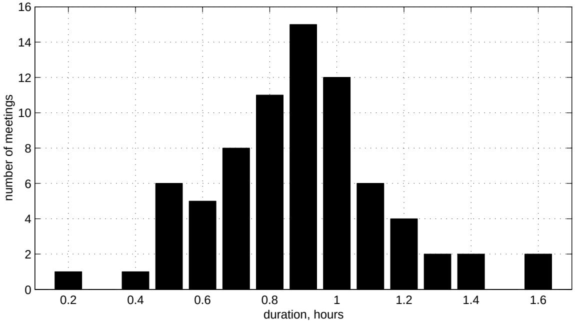

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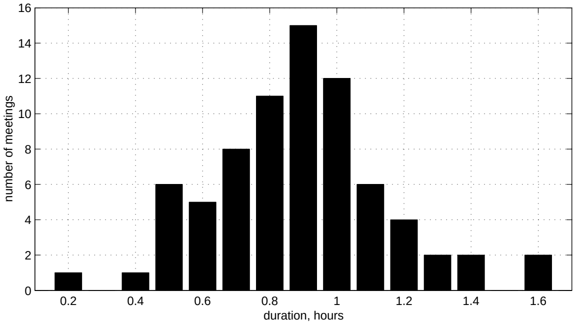

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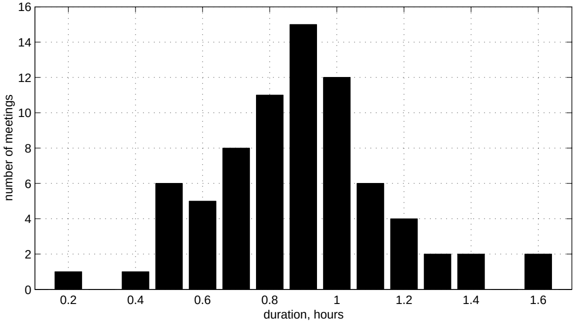

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- the ICSI corpus (audio) is accompanied by orthographic transcription, which includes a relatively rich XML-style mark-up of laughter
- for our purposes, data preprocessing consisted of:
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- orthographic, time-segmented transcription of speaker contributions (`.stm`)

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Bmr011 me011 chanB 3035.301 3036.964 Of beeps, yeah.
Bmr011 fe008 chan8 3035.714 3037.314 <Pause/> of m- one hour of - <...
Bmr011 mn014 chan2 3036.030 3036.640 Yeah.
Bmr011 me013 chan1 3036.280 3037.600 <VocalSound Description="laugh"/>
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- laughter is identified using `VocalSound` and `Comment` tags

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3	4589	inbreath	
4	2223	mouth	
5	970	breath-laugh	√
11	97	laugh-breath	√
46	6	cough-laugh	√
63	3	laugh, "hmmph"	√
69	3	breath while smiling	
75	2	very long laugh	√

- laughter is by far the most common non-verbal vocal sound annotated in this corpus

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- found 12570 non-farfield `VocalSound` instances
  - 11845 were adjacent to a time-stamped utterance boundary or lexical item: endpoints were derived automatically
  - 725 needed to be segmented manually
- found 1108 non-farfield `Comment` instances
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Classifying Voicing of the Segmented Laughter Bouts

- if any portion of the bout is voiced, the bout is voiced
- performed manually for all 13259 bouts by at least one annotator
- interlabeler *k*appa was 0.76-0.79 (we considered this low)
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Voiced vs Unvoiced Laughter by Time

- of 13209 bouts of laughter,
  - voiced: 8687 (65.8%)
  - unvoiced: 4426 (33.5%)
  - *laughed speech*: 96 (0.7%)
- of 5.7 hours of laughter
  - voiced: 4.2 hours (73.7%)
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Voiced vs Unvoiced Laughter by Time

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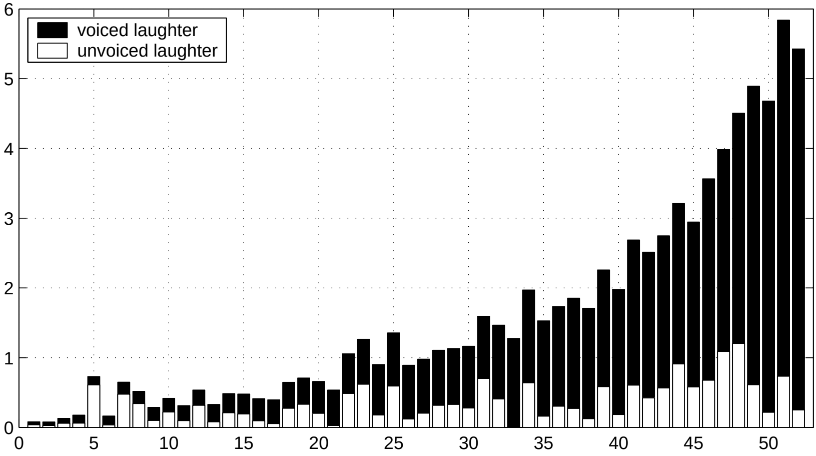
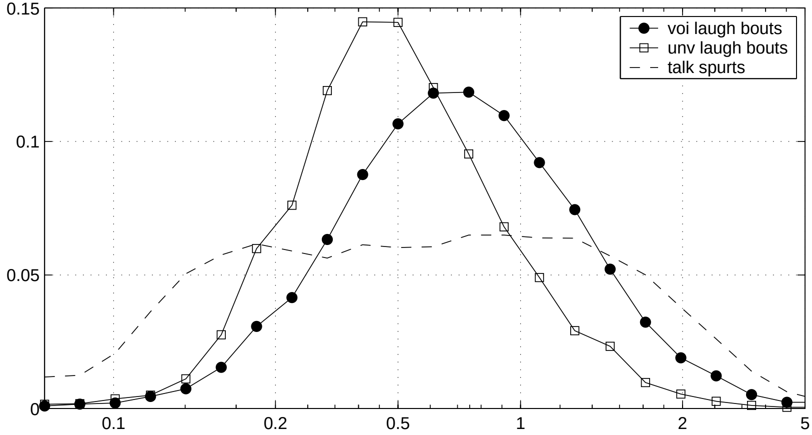


Voiced vs Unvoiced Bout Duration



Analysis of **Laughter-in-Interaction**

- GOAL: characterize the correlation between voicing in laughter and the vocal interaction context in which laughter occurs
  - test for the statistical significance of association
  - test for the strength of association (predictability)

1. discretize (in time) the voiced laughter, unvoiced laughter, and talkspurt segmentations
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- chop up each segmentation into non-overlapping 1 second frames
- for each participant k, declare a frame centered on time t as "on" when participant k vocalizes for at least 10% of that frame's duration
- example:

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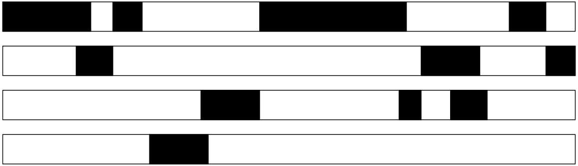

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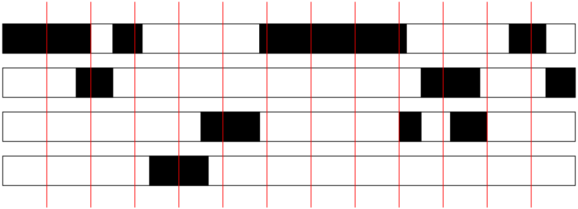

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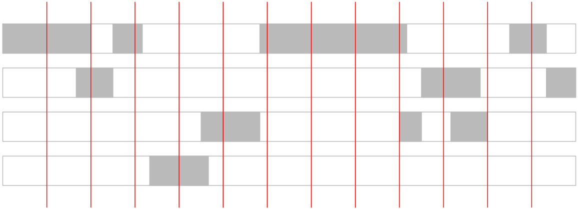

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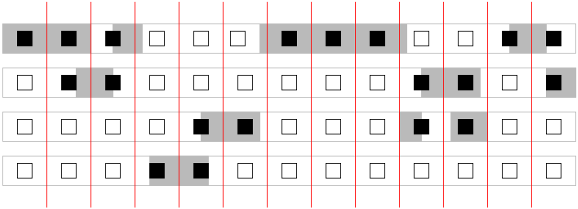

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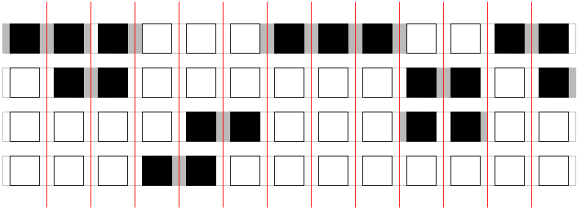

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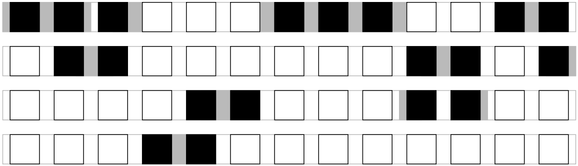

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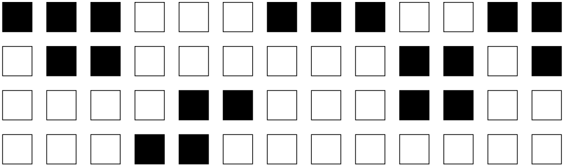

Features Describing Conversational Context

- for each frame t in which participant k laughs:
  - count how many other participants, at times $t-1$, t, and $t+1$, are producing a talk spurt
  - count how many other participants, at times $t-1$, t, and $t+1$, are producing a laugh bout which contains voicing
  - count how many other participants, at times $t-1$, t, and $t+1$, are producing a laugh bout which does not contain voicing
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	speech			voiced laughter			unvoiced laughter					
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2	0	0	1	0	0	1	0	1	1	Y	N	Y
3	0	1	1	0	2	3	1	0	0	N	Y	N
⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮

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- GOAL: correlate context features with the single voicing feature
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  1. significance: a 2×2 χ^2-test
  2. strength: mutual information (or other entropy-related)
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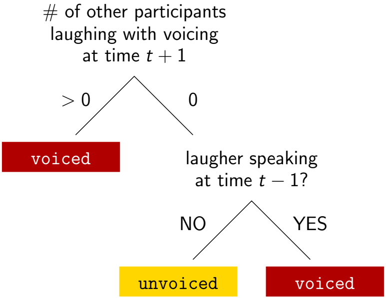
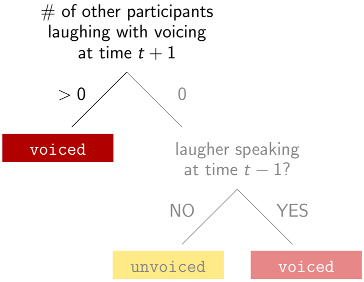
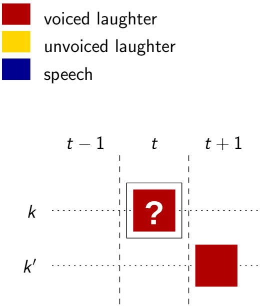


Understanding the Laughter Initiation Decision Tree

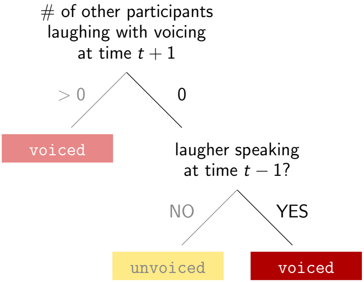
Case 1 when at least one other participant laughs with voicing just after
$\longrightarrow$ **voiced**

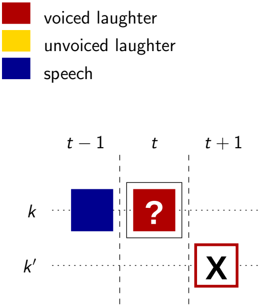




Understanding the Laughter Initiation Decision Tree

Case 2 when no other participants laugh with voicing just after **AND** the laugher speaks just before $\longrightarrow$ **voiced**





Understanding the Laughter Initiation Decision Tree

Case 3 when no other participants laugh with voicing just after **AND** the laugher does not speak just before

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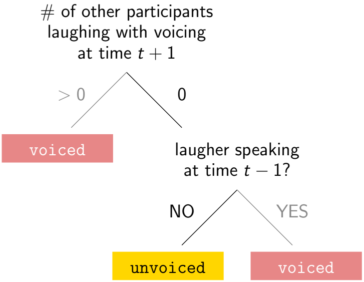

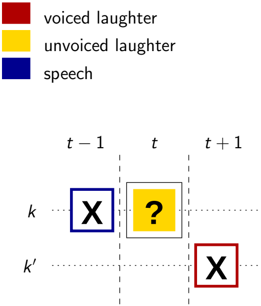

Inferred Decision Tree for Laughter Termination

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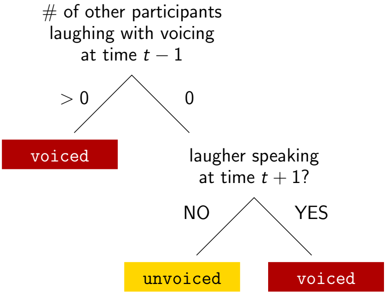

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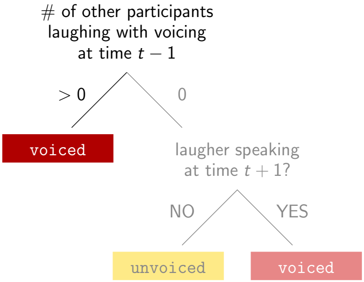

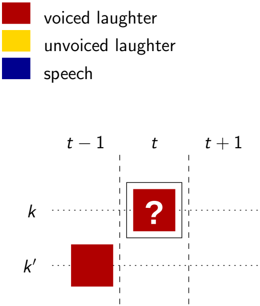

Understanding the Laughter Termination Decision Tree

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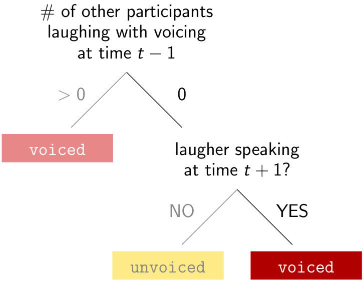

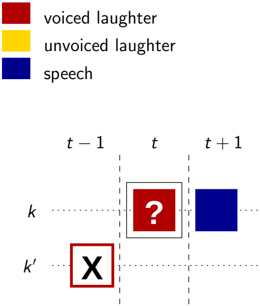

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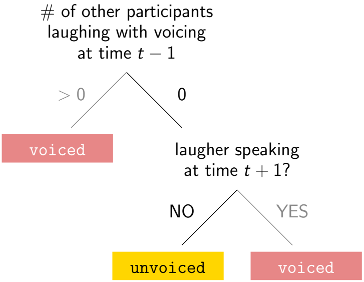

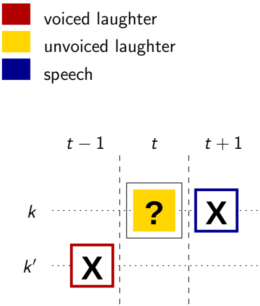

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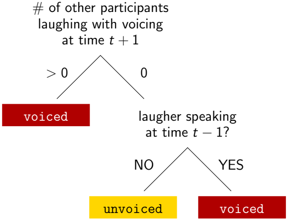

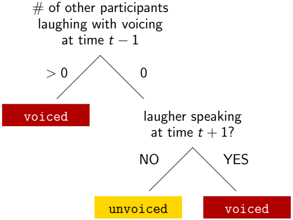

Conclusions I

- of 13209 studied bouts of laughter, 66.5% appear to be voiced and 33.5% appear to be unvoiced
- on average, each participant spends approximately 10% of their vocalization effort on laughter (as opposed to speech)
- bout durations follow a log-normal distribution, as expected
  - the mode of voiced laugh bout durations is approximately twice as large as that of unvoiced laugh bout durations
  - but bout duration does not discriminate between voiced and unvoiced laughter

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1. laughter which begins just before others laugh with voicing and laughter which ends just after others laugh with voicing is likely to be **voiced**
2. when not (1), laughter which begins after the laugher speaks and laughter which ends before the laugher speaks is likely to be **voiced**
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