Introduction	Data	Analysis	Conclusions

Analysis of the Occurrence of Laughter in Meetings

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verbal vocalization

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• primary motivation: meeting understanding



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 laughter detection is particularly important for understanding both interaction and emotion if laughter occurs frequently

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• primary motivation: meeting understanding



- laughter detection is particularly important for understanding both interaction and emotion if laughter occurs frequently
- to date, for meetings, it is not known
 - how much laughter there actually is
 - 2 when it tends to occur

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To find interaction, model participants jointly.

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To find interaction, model participants jointly.

essentially monologue



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To find interaction, model participants jointly.

• "multi-logue"



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To find interaction, model participants jointly.

• "multi-logue" with more participant involvement



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To find interaction, model participants jointly.

• a mathematical artifact (the Haar wavelet basis)



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To find interaction, model participants jointly.

• "multi-logue"



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To find interaction, model participants jointly.

- "multi-logue" with laughter
 - participants tend to wait to speak
 - participants do not wait to laugh



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Three Questions o	f Interest		

What is the quantity of laughter, relative to the quantity of speech?

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Three Questic	ons of Interest		

- What is the quantity of laughter, relative to the quantity of speech?
- Observe the durational distribution of episodes of laughter differ from that of episodes of speech?

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Three Questions	s of Interest		

- What is the quantity of laughter, relative to the quantity of speech?
- Observe the durational distribution of episodes of laughter differ from that of episodes of speech?
- How do meeting participants appear to affect each other in their use of laughter, relative to their use of speech?

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Laugh Bouts vs T	alk Spurts		

• we will contrast the occurrence of laughter ${\cal L}$ with that of speech ${\cal S}$

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Laugh Bouts	vs Talk Spurts		

• we will contrast the occurrence of laughter ${\cal L}$ with that of speech ${\cal S}$

talk spurts contiguous per-participant intervals of speech (Shriberg et al, 2001), containing pauses no longer than 300 ms (as in NIST RT-06s SAD)

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Laugh Bouts	vs Talk Spurts		

 we will contrast the occurrence of laughter *L* with that of speech *S*

talk spurts contiguous per-participant intervals of speech (Shriberg et al, 2001), containing pauses no longer than 300 ms (as in NIST RT-06s SAD)

laugh bouts contiguous per-participant intervals of laughter (Bachorowski et al, 2001), including recovery inhalation

Introduction ○○○●	Data 0000	Analysis 000000	Conclusions
Laugh Bouts	/s Talk Spurts		

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talk spurts contiguous per-participant intervals of speech (Shriberg et al, 2001), containing pauses no longer than 300 ms (as in NIST RT-06s SAD)

- laugh bouts contiguous per-participant intervals of laughter (Bachorowski et al, 2001), including recovery inhalation
- \mathcal{S}/\mathcal{L} islands contiguous per-group intervals in which at least one participant talks/laughs

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Laugh Bouts	vs Talk Spurts		

• we will contrast the occurrence of laughter ${\cal L}$ with that of speech ${\cal S}$



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The ICSI Meeting	Corpus		

 naturally occurring project-oriented conversations with varying number of participants

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The ICSI Meeting	Corpus		

- naturally occurring project-oriented conversations with varying number of participants
- the largest such corpus available

type # of		type # of # of particip		pants
type	meetings	mod	min	max
Bed	15	6	4	7
Bmr	29	7	3	9
Bro	23	6	4	8
other	8	6	5	8

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• rarely, meetings contain additional, uninstrumented participants (we ignore them)

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- rarely, meetings contain additional, uninstrumented participants (we ignore them)
- we use all 75 meetings: 66.3 hours of conversation

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Identifying Laughter in the ICSI Corpus

• laughter is already annotated with rich XML-style mark-up
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- therefore, for our purposes, data preprocessing consists of:

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 - specifying endpoints for identified laughter

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 - identifying laughter in the orthographic transcription
 - specifying endpoints for identified laughter
- orthographic, time-segmented transcription of speaker contributions (.stm)

```
Bmr011 me013 chan1 3029.466 3029.911 Yeah.

Bmr011 me013 chan3 3030.230 3031.140 Film-maker.

Bmr011 fe016 chan0 3030.783 3032.125 <Emphasis> colorful. </Emphasis...

Bmr011 me011 chanB 3035.301 3036.964 Of beeps, yeah.

Bmr011 me013 chan8 3035.714 3037.314 <Pause/> of m- one hour of - <...

Bmr011 me013 chan1 3036.280 3037.600 <VocalSound Description="laugh"/>

Bmr011 me014 chan2 3036.640 3037.15 Yeah.

Bmr011 me015 chan3 3036.940 3037.335 Is -

Bmr011 me011 chanB 3036.964 3038.573 <VocalSound Description="laugh"/>
```

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...9.911 Yeah.
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...2.125 <Emphasis> colorful. </Emphasis> <Comment Description="while laughing"/>
...6.6964 Of beeps, yeah.
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...6.640 Yeah.
...7.600 <VocalSound Description="laugh"/>
...7.115 Yeah.
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```

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Sample VocalSound Instances

Freq	Token	Vocal Sound Description	lleed
Rank	Count	Vocarbound Description	Oseu
1	11515	laugh	
2	7091	breath	
3	4589	inbreath	
4	2223	mouth	
5	970	breath-laugh	\checkmark
11	97	laugh-breath	\checkmark
46	6	cough-laugh	\checkmark
63	3	laugh, "hmmph"	\checkmark
69	3	breath while smiling	
75	2	very long laugh	\checkmark

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Sample VocalSound Instances

Freq	Token	Vocal Sound Description	lleed
Rank	Count	Vocarbound Description	Useu
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2	7091	breath	
3	4589	inbreath	
4	2223	mouth	
5	970	breath-laugh	\checkmark
11	97	laugh-breath	
46	6	cough-laugh	\checkmark
63	3	laugh, "hmmph"	\checkmark
69	3	breath while smiling	
75	2	very long laugh	\checkmark

- laughter is by far the most common non-verbal VocalSound
- idem for Comment instances

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Segmenting Identif	ied Laughter Ins	tances	

• found 12570 non-farfield VocalSound laughs

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Introduction	Data ○○○●	Analysis 000000	Conclusions

- found 12570 non-farfield VocalSound laughs
 - 11845 were adjacent to a time-stamped utterance boundary or lexical item: endpoints were derived automatically
 - 725 needed to be segmented manually

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found 12570 non-farfield VocalSound laughs

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- found 1108 non-farfield Comment laughs
 - all needed to be segmented manually

Introduction	Data	Analysis	Conclusions
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 - 725 needed to be segmented manually
- found 1108 non-farfield Comment laughs
 - all needed to be segmented manually
- manual segmententation performed by one annotator, checked by at least one other annotator

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- found 12570 non-farfield VocalSound laughs
 - 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 laughs
 - all needed to be segmented manually
- manual segmententation performed by one annotator, checked by at least one other annotator
- merging immediately adjacent VocalSound and Comment instances, and removing transcribed instances for which we found counterevidence, resulted in **13259 bouts**

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Speech vs Laughte	r by Time		

• 13259 laugh bouts

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Speech vs Laughte	r by Time		

- 13259 laugh bouts
- 110790 talk spurts

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Introduction	Data 0000	Analysis ●○○○○○	Conclusions
Speech vs Laughte	r by Time		

- 13259 laugh bouts
- 110790 talk spurts
- by personal time:

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Speech vs Laughte	r by Time		

- 13259 laugh bouts
- 110790 talk spurts
- by personal time:
 - 442.6 hours total recorded audio

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Speech vs Laughter	· by Time		

- 13259 laugh bouts
- 110790 talk spurts
- by personal time:
 - 442.6 hours total recorded audio
 - 55.2 hours spent in talk spurts (S), $\equiv 12.47\%$

Introduction	Data 0000	Analysis ●○○○○○	Conclusions
Speech vs Laughter	r by Time		

- 13259 laugh bouts
- 110790 talk spurts
- by personal time:
 - 442.6 hours total recorded audio
 - 55.2 hours spent in talk spurts (S), $\equiv 12.47\%$
 - 5.6 hours spent in laugh bouts (L), $\equiv 1.27\%$

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Speech vs Laughter by Time, by Participant



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Talk Spurt Duration vs Laugh Bout Duration



Kornel Laskowski & Susanne Burger INTERSPEECH 2007, Antwerpen, Belgium

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	Vocalizing Time, hrs					
Vocal Activity	per per		numb voca	er of alizing	simulta ; partici	neously ipants
	part		1	2	3	\geq 4
S	55.2	50.8	46.7	3.8	0.27	0.02
\mathcal{L}	5.6	3.3	2.0	0.7	0.31	0.27
$\mathcal{S}\cap\mathcal{L}$	0.2	0.2	0.2	0.0	0.0	0
$\mathcal{S} \cup \mathcal{L}$	60.3	52.0	45.7	4.8	0.88	0.49

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Introduction	Data 0000	Analysis ○○●○○	Conclusions

	Vocalizing Time, hrs					
Vocal Activity	per per	numb voca	er of alizing	simulta [,] partici	neously pants	
Activity	part	part meet	1	2	3	≥4
S	55.2	50.8	46.7	3.8	0.27	0.02
\mathcal{L}	5.6	3.3	2.0	0.7	0.31	0.27
$\mathcal{S}\cap\mathcal{L}$	0.2	0.2	0.2	0.0	0.0	0
$S \cup L$	60.3	52.0	45.7	4.8	0.88	0.49

 \bullet in ${\cal S}$ only, 84.6% of vocalization is not overlapped

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Introduction	Data 0000	Analysis ○○○●○○	Conclusions

	Vocalizing Time, hrs					
Vocal Activity	per per	number of simultaneously vocalizing participants			neously pants	
	part	meet	1	2	3	≥4
S	55.2	50.8	46.7	3.8	0.27	0.02
\mathcal{L}	5.6	3.3	2.0	0.7	0.31	0.27
$\mathcal{S}\cap\mathcal{L}$	0.2	0.2	0.2	0.0	0.0	0
$\mathcal{S} \cup \mathcal{L}$	60.3	52.0	45.7	4.8	0.88	0.49

 \bullet in ${\cal L}$ only, 35.7% of vocalization is not overlapped

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Introduction	Data 0000	Analysis ○○○●○○	Conclusions

	Vocalizing Time, hrs					
Vocal	per	per	numb	er of	simulta	neously
Activity	nort	moot	VOC	alizing	g partic	ipants
	part	meet	1	2	3	\geq 4
S	55.2	50.8	46.7	3.8	0.27	0.02
\mathcal{L}	5.6	3.3	2.0	0.7	0.31	0.27
$\mathcal{S}\cap\mathcal{L}$	0.2	0.2	0.2	0.0	0.0	0
$\mathcal{S} \cup \mathcal{L}$	60.3	52.0	45.7	4.8	0.88	0.49

• the proportion of "laughed speech" is negligible

Introduction	Data 0000	Analysis ○○○●○○	Conclusions

	Vocalizing Time, hrs					
Vocal	ner	ner	numb	er of	simulta	neously
Activity	port	moot	voca	alizing	; partici	pants
	part	meet	1	2	3	\geq 4
0						
8	55.2	50.8	46.7	3.8	0.27	0.02
S L	55.2 5.6	50.8 3.3	46.7 2.0	3.8 0.7	0.27 0.31	0.02 0.27
\mathcal{S} \mathcal{L} $\mathcal{S} \cap \mathcal{L}$	55.2 5.6 0.2	50.8 3.3 0.2	46.7 2.0 0.2	3.8 0.7 0.0	0.27 0.31 0.0	0.02 0.27 0

 there is ≥3 times as much 3-participant overlap when considering S ∪ L as opposed to S only

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Introduction	Data 0000	Analysis ○○○●○○	Conclusions

	Vocalizing Time, hrs					
Vocal	ner	ner	numb	er of	simulta	neously
Activity	port	moot	voca	alizing	; partici	pants
	part	meet	1	2	3	\geq 4
S	55.2	50.8	46.7	3.8	0.27	0.02
\mathcal{L}	5.6	3.3	2.0	0.7	0.31	0.27
0 - 0						-
$\mathcal{S}\cap\mathcal{L}$	0.2	0.2	0.2	0.0	0.0	0

• there is ≈ 25 times as much 4-participant overlap when considering $S \cup L$ as opposed to S only

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Overlap Dynamics			

• does laughter differ from speech in the way in which overlap arises and is resolved?

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Overlap Dynamics			

- does laughter differ from speech in the way in which overlap arises and is resolved?
- look at transition probabilities under a first-order Markov assumption

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Overlap Dynamics			

- does laughter differ from speech in the way in which overlap arises and is resolved?
- look at transition probabilities under a first-order Markov assumption
 - discretize *L* and *S* segmentations using non-overlapping analysis frames

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Overlap Dynamics			

- does laughter differ from speech in the way in which overlap arises and is resolved?
- look at transition probabilities under a first-order Markov assumption
 - discretize *L* and *S* segmentations using non-overlapping analysis frames
 - Itrain an Extended Degree-of-Overlap (EDO) model on the discretized *L* and *S* segmentations
 - $P({A} \rightarrow {A, B})$
 - $P(\{A,B\} \rightarrow \{A\})$
 - $P({A} \rightarrow {B})$
 - etc.

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Overlap Dynamics			

- does laughter differ from speech in the way in which overlap arises and is resolved?
- look at transition probabilities under a first-order Markov assumption
 - **1** discretize \mathcal{L} and \mathcal{S} segmentations using non-overlapping analysis frames
 - train an Extended Degree-of-Overlap (EDO) model on the discretized \mathcal{L} and \mathcal{S} segmentations
 - $P(\{A\} \rightarrow \{A, B\})$
 - $P(\{A, B\} \rightarrow \{A\})$
 - $P(\{A\} \rightarrow \{B\})$
 - etc.



 \bigcirc compare inferred probabilities for \mathcal{L} and \mathcal{S}

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Overlap Dynamics: Results

Select EDO Transitions		500ms frames		
from (at t)		to (at $t+1$)	${\mathcal S}$	\mathcal{L}
{ <i>A</i> }	\rightarrow	{ <i>A</i> }	82.94	57.96
{ <i>A</i> }	\rightarrow	$\{A, B\}$	6.21	8.43
{ <i>A</i> }	\rightarrow	$\{A, B, C, \cdots\}$	0.39	2.39
$\{A, B\}$	\rightarrow	{ <i>A</i> }	45.49	26.37
$\{A, B\}$	\rightarrow	$\{A, B\}$	40.88	46.93
$\{A, B\}$	\rightarrow	$\{A, B, C, \cdots\}$	4.46	13.65
$\{A, B, C, \cdots\}$	\rightarrow	{ <i>A</i> }	19.24	6.69
$\{A, B, C, \cdots\}$	\rightarrow	$\{A, B\}$	40.94	17.45
$\{A, B, C, \cdots\}$	\rightarrow	$\{A, B, C, \cdots\}$	29.44	71.04

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Overlap Dynamics: Results

Select EDO Transitions		500ms frames		
from (at <i>t</i>)		to (at $t+1$)	${\mathcal S}$	\mathcal{L}
{ <i>A</i> }	\rightarrow	{ <i>A</i> }	82.94	57.96
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{ <i>A</i> }	\rightarrow	$\{A, B, C, \cdots\}$	0.39	2.39
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$\{A, B, C, \cdots\}$	\rightarrow	{ <i>A</i> }	19.24	6.69
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$\{A, B, C, \cdots\}$	\rightarrow	$\{A, B, C, \cdots\}$	29.44	71.04

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Conclusions			

Based on the ICSI meetings,

approximately 9% of vocalizing time is spent on laughter
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Conclusions			

- approximately 9% of vocalizing time is spent on laughter
 - but participants vary widely (0% 30%)

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 - but participants vary widely (0% 30%)
- on average, laughter occurs once a minute

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- approximately 9% of vocalizing time is spent on laughter
 - but participants vary widely (0% 30%)
- on average, laughter occurs once a minute
- Solution is a set of the large majority of ≥3 participant overlap

Introduction	Data 0000	Analysis 000000	Conclusions ●○
Conclusions			

- approximately 9% of vocalizing time is spent on laughter
 - but participants vary widely (0% 30%)
- In average, laughter occurs once a minute
- laughter accounts for the large majority of ≥3 participant overlap
- in contrast to speech, once laughter overlap is incurred, it is most likely to persist

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Conclusions			

- **1** approximately 9% of vocalizing time is spent on laughter
 - but participants vary widely (0% 30%)
- on average, laughter occurs once a minute
- Iaughter accounts for the large majority of ≥3 participant overlap
- in contrast to speech, once laughter overlap is incurred, it is most likely to persist
 - ie. 3-participant speech overlap is 2.5 times more likely than laughter to be resolved within 500 ms

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We would like to t	hank:		

- our annotators: Jörg Brunstein and Matthew Bell
- discussion: Alan Black and Liz Shriberg
- funding: EU CHIL

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