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Exploring the Correlation of Pitch Accents and Semantic Slots for Spoken Language Understanding

Abstract

- prosody provides discourse information available from sp
- pitch accents may help localize important words for SLU: I'd LIKE to book a FLIGHT from SEATTLE to 0 0 0 0 **O** B-fromloc.city_name **O** B
- investigate correlation between pitch accents and slots in
- simulate fully-automated SLU setup by using recognized

Pitch Accent Detection from Audio Only

Model

- trained on subset of the Boston Radio New Corpus (1 hou
- PaIntE and duration features in a random forest binary classical

speaker	accuracy (%)
f1a	73.1
f2b	74.7
f3a	76.7
m1a	73.7
m2b	73.8

Figure 1: PaIntE
[Möhler & Conkie, 1986]
parameters
describe the F0
contour
Table 1: speaker-
independent pitch accent
detection accuracy



Pitch accent detection on recognized text

- recognize same dataset with Kaldi (27% WER)
- apply speaker-independent pitch accent detection models as above
- evaluate against pitch accent labels in the Boston corpus:



	Correlation of Pitch Accents and Semantic Slots in ATIS							
Deech only : MUNICH	 607 utterances from ATIS3 test set recognized with 11.7% WER pitch accents predicted by model trained on all speakers in the Boston dataset 							
-toloc.city name		LIST	FLIGHTS	FROM	DALLAS	TO HO	DUSTON	
Figure 3: we consider how many times a pitch accent lies within the time interval of a word	0	0	0	B-fromloc. city_name	O B-t city	oloc. _name		
text	annotated with a slot label	t ₁	ı ≜ t	2 t	¹ s ▲ t	.4 t ₅ ▲	t ₆	
			accent		accent	acc	ent	
	Results							
ur 20 min)	on original transcription	ons:		on reco	ognized te	ext:		
assifier # files # words # slots			607 6,099 2,452	<pre># files # words # slots</pre>			607 6,212 2,452	
# predicted accents # pred. accents on slots # pred. accents on non-s	slots	3,428 2,218 1,210	# predicted accents# pred. accents on slots# pred. accents on non-slots		3,410 2,173 1,237			
	slots with pred. accent		90.5%	slots wit	h pred. acc	ent	88.7%	
σ* σ 1 b 2	Tables 3 and 4: frequency the original transcriptions (/ of pre left) ar	edicted pitc nd recogniz	h accents ed text (ri	and covera ght)	nge of slots	in ATIS on	

• domain indicators: *flight, flights* (accented only aroung 60% of the time, may be considered given) Table 5: most frequent accented non-slot

FL FLI

W

W

Sł

words in ATIS **References:**

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• G. Möhler and A. Conkie, "Parametric modeling of intonation using vector quantization", in *Proceedings of the third ESCA Workshop on Speech Synthesis*, pp.311-316, 1998 • M. Ostendorf, P. Price, S. Shattuck-Hufnagel, "The Boston University Radio News Corpus", 1995 • J. Pierrehumber and J.Hirschberg, "The intonational structuring of discourse", in 24th Annual Meeting of the ACL, pp. 136-144, 1986

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Pitch accented words not

• question words, imperatives

show speaker's intention

pitch accented (expected)

list, what, please, show, need

function words are not frequently

associated with slots:

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k	accented (%)	frequency
HICH	94.1	32
EASE	93.9	31
ΉΑΤ	90.8	79
IST	87.3	137
EED	78.0	39
ALL .	77.1	37
HOW	75.9	63
ME	74.5	76
I	73.9	78
IGHT	68.4	93
GHTS	57.2	179
ON	51.9	83
ND	42.5	31
ROM	17.4	78
ТО	17.3	87
ΉE	15.8	29

Agreement with Human Labelling

estimate quality of pitch a prediction on ATIS	ccent	# files # words # slots	50 514 201
50 ATIS utterances annot pitch accents by a human	ated with Iabeller	# human-labelled accents # words with predicted accents	235 s 234
agreement in over 70% of cases		agreement: # words	173
			6
 # human-labelled accents # accents on slots # accents on non-slots # slots with no accent 	235 149 86 52	<pre># predicted accents # accents on slots # accents on non-slots # slots with no accent</pre>	234 164 70 37
slots with accent	74.1%	slots with accent	81.6%
	7		8

Tables 6-8: correlation between slots and human-labelled (left) and automatically predicted (right) accents in 50 ATIS files; above: agreement between the two

- accented
- also convey relevant information for SLU

- where performance drops [Mesnil, 2015]
- pitch accent types and/or different slot label types

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Conclusion

• the pitch accent detector trained on part of the Boston corpus does not require pre-transcribed data while yielding comparable results

 \rightarrow we can incorporate pitch accent detection in a SLU system

most words in the ATIS corpus that are labelled with slots are pitch

 \rightarrow expectation of important words to be perceptually prominent many words that are pitch accented and are not labelled with slots

Future Work

different datasets necessary to test generalizability of results

• pitch accent features may help improve slot filling on ASR output,

investigate whether there are correlations between different ToBI