



Universität Stuttgart

Dialog-act classification using Convolutional Neural Networks

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Agenda

- Background
- Models for Dialog-act classification
 - Lexical model
 - Acoustic model
 - Lexico-acoustic model
- Corpora
- Results
- Conclusion
- Future Work

- Dialog-act (DA):
 - Each **utterance** in a dialog has a **performative function** in communication.
 - > Dialog-act is an **act of communication** that expresses certain **attitude**:
 - ▶ statement \rightarrow belief, request \rightarrow desire, apology \rightarrow regret.
 - A dialog-act succeeds if the audience identifies the **speaker's intention**.

Kent Bach(2000)

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Kent Bach(2000)

Speaker	Dialog Act	Utterance
А	Wh-Question	What kind do you have now?
В	Statement	Uh, we have a, a Mazda nine twenty nine and a Ford Crown Victoria and a little two seater CRX
А	Acknowledge	Oh, okay.

A fragment of a labeled switchboard conversation

How to approach the task?:

- Lexical approach
 - Traditional approach, it employs the utterance transcription (word sequence)
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- Acoustic approach
 - Shriberg et al. (2000) was one of the first works that explored the prosody as a potential knowledge source for dialog-act classification.
 - The DAs can be ambiguous if only lexical information is considered Example: *This is your car (?)* \rightarrow Statement or declarative questions
 - In dialog systems, automatic speech recognizers generate noisy transcriptions, the DA classifier must deal with them.

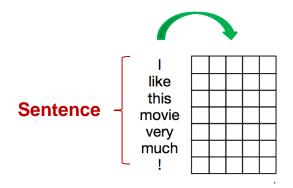
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- Lexico-acoustic approach

- Convolutional Neural Networks (CNN):
 - CNNs are several layers of convolutions with nonlinear activation functions.
 - Each layer applies different filters and combines their results to obtain highlevel features.
 - The last layer is then a classifier that uses these high-level features.
 - Grid-like input format

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Convolutional Neural Networks (CNN):



Word Embeddings

Image source: Zhang. Y., Wallace, B. (2015)

Convolutional Neural Networks (CNN):

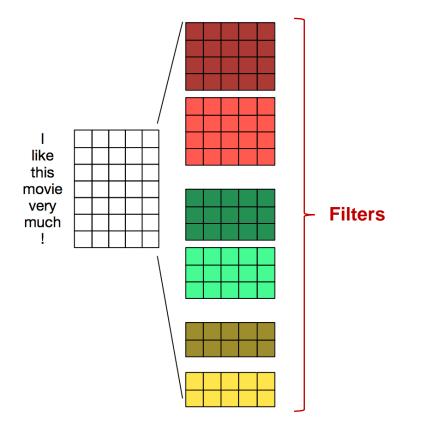
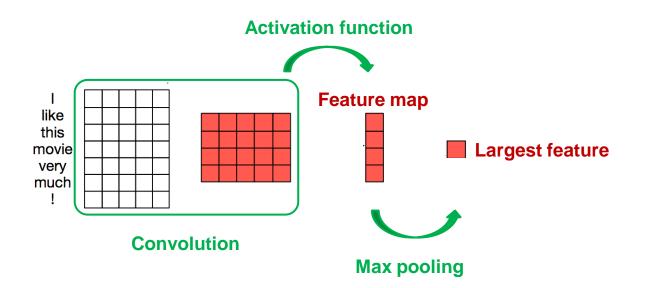


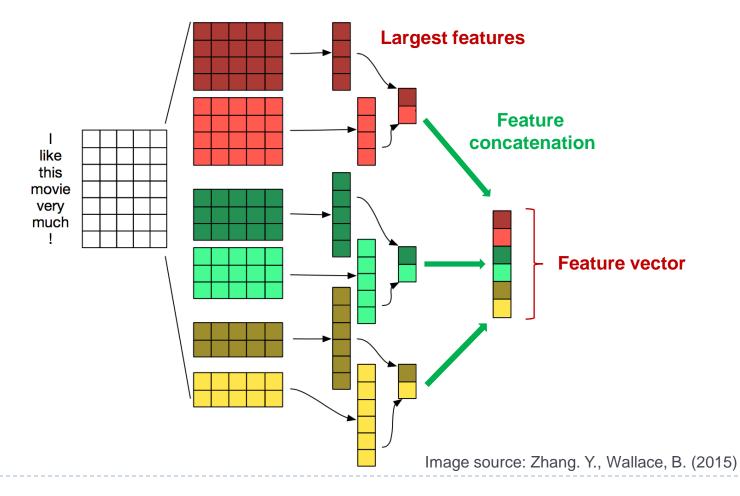
Image source: Zhang. Y., Wallace, B. (2015)

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Convolutional Neural Networks (CNN):

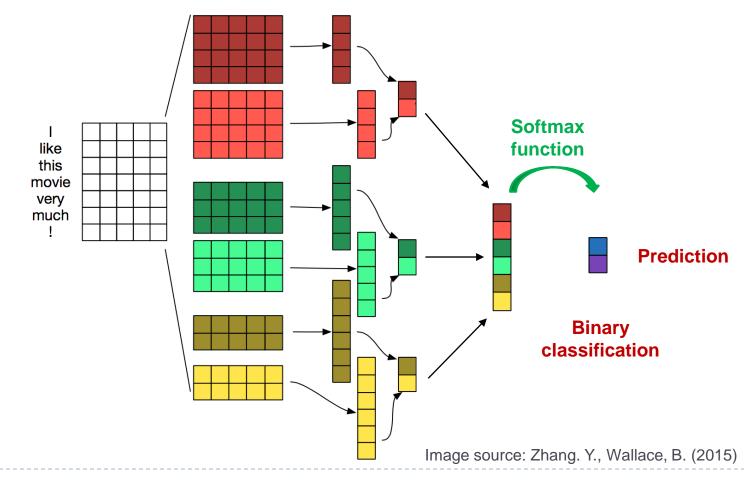


Convolutional Neural Networks (CNN):

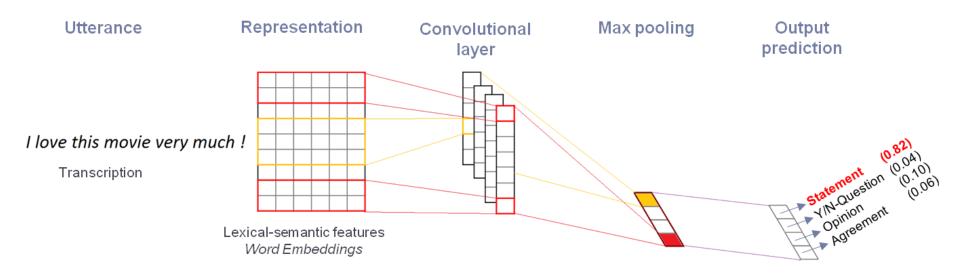


Filters Feature maps

Convolutional Neural Networks (CNN):

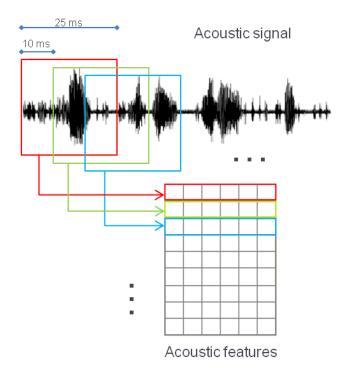


Lexical Model



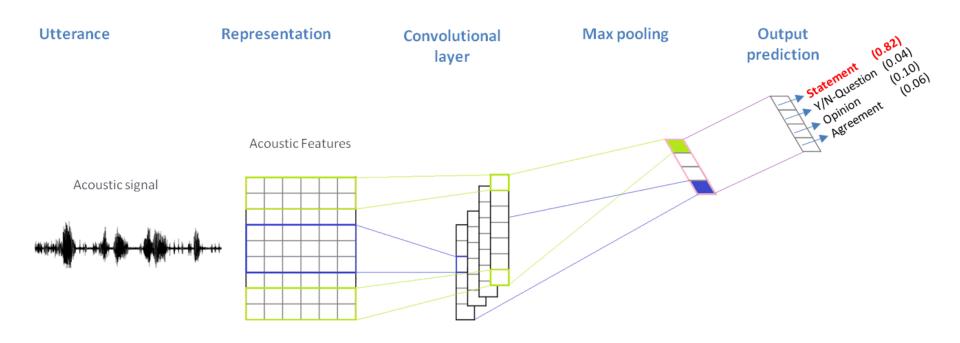
Acoustic Model

Acoustic feature extraction



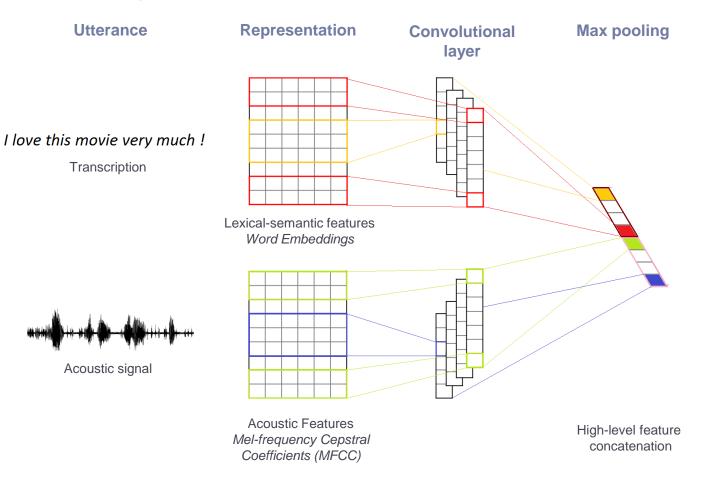
- openSMILE feature sets:
 - Prosodic features: F0, voicing probability and loudness contours
 - LogMel Spectrum
 - Mel-Frequency-Cepstral Coefficients (MFCC)

Acoustic Model



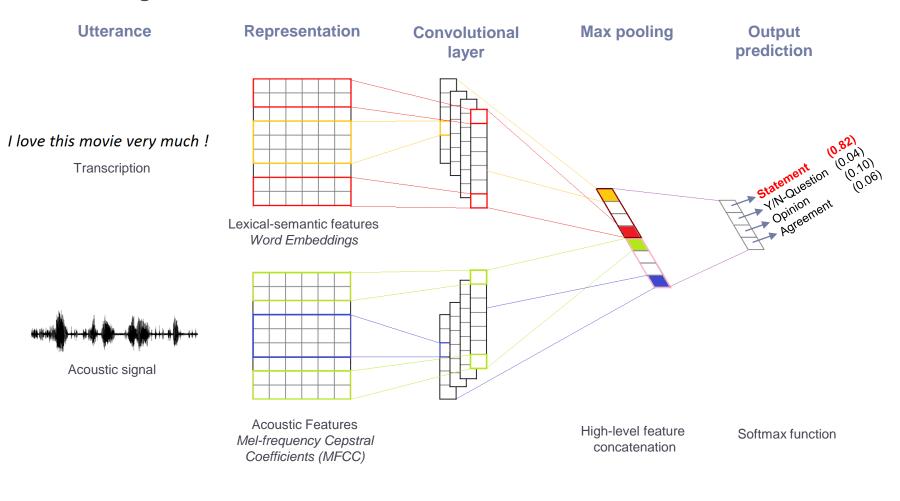
Proposed Model

Dialog-act Classifier – Bi-Convolutional Neural Network



Proposed Model

Dialog-act Classifier – Bi-Convolutional Neural Network



MGK

Corpora

Corpus	Training	Test	Classes	
ATIS	$\sim 5,000$	~ 900	17	
Switchboard	$\sim \! 98,\! 000$	$\sim 10,000$	42	
ICSI	$\sim \! 99,000$	$\sim 10,000$	5	

Results: Lexical Model

Compus	Classes	Time elapsed	Accuracy (%)	
Corpus	Classes	per epoch on avg.		
ATIS	17	$\sim 12 \text{ s}$	94.68	
Switchboard	42	\sim 200 s	71.57	
ICSI	5	$\sim 94s$	84.45	

Table 6.2: Accuracy per corpus on lexical model

Results: Acoustic Model per Feature Set

Epochs	Accuracy (%) per feature set			
	Prosodic	Log-Mel	MFCC	
25	72.40	73.19	74.88	
50	72.51	73.71	73.64	
100	72.62	74.09	75.67	
200	72.74	76.01	76.24	

Epochs	Accuracy (%) per feature set			
	Prosodic	Log Mel	MFCC	
5	52.48	52.46	53.28	
15	52.36	52.35	53.45	
25	52.46	52.69	53.55	
50	52.41	52.78	53.41	

ATIS

Switchboard

Results on ATIS

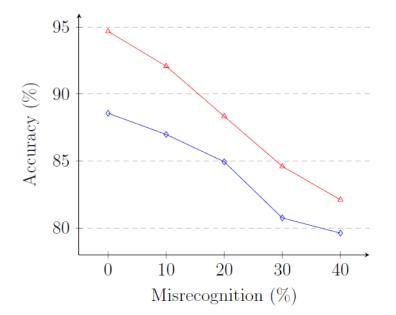
$\mathbf{Accuracy}(\%)$					
Lexical Model	Lexico-acoustic Model				
94.68	74.88	88.57			

Table 6.7: Accuracy on ATIS per model

Lexico-acoustic Model – ASR emulation

→ Lexical Model → Lexico-acoustic Model

Misrecognition (%)	Accuracy (%) per model			
(,,,)	Lexical Model	Lexico-acoustic Model		
0	94.68	88.57		
10	92.08	86.99		
20	88.34	84.95		
30	84.61	80.76		
40	82.12	79.63		



ATIS

MGK

Results on Switchboard

$\mathbf{Accuracy}(\%)$					
Lexical Model	Acoustic Model	Lexico-acoustic Model			
71.57	53.55	72.65			

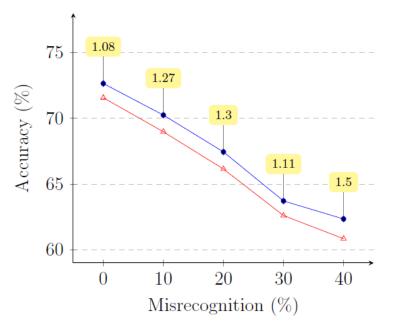
Table 6.10: Accuracy on Switchboard per model

Lexico-acoustic Model - Simulated ASR

← Lexical Model → Lexico-acoustic Model

Misrecognition (%)	Ac F	Improvement	
(,,,)	Lexical Model	Lexico-acoustic Model	
0	71.57	72.65	1.08
10	68.98	70.25	1.27
20	66.15	67.45	1.3
30	62.61	63.72	1.11
40	60.85	62.35	1.5

Switchboard



The acoustic CNN offsets slightly the recognition error

The larger the misrecognition is, the larger improvement the lexico-acoustic model yields.

Lexico-acoustic Model

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Corpus	Classes	CNN			
		Majority Class	Lexical	Acoustic	Bi-CNN
ATIS	17	72.60	94.68	74.88	88.57
Switchboard	42	36.00	71.57	53.55	72.65
ICSI	5	58.90	84.45		

Table 6.12: Accuracy results per model on ATIS, SWBD and ICSI.

Conclusion

- Acoustic Model:
 - MFCC features are more suitable for dialog-act classification.
 - ATIS: accuracy is not significant 3.64% over the majority class.
 - SWBD: accuracy is 17.55% over the majority class.
- Lexico-acoustic Model
 - ATIS: acoustic features worsened the accuracy in 6.5%.
 - SWBD: acoustic features yielded an improvement of 1.08%
 - The acoustic features helped keep the accuracy higher in at least 1.1% regardless of the amount of error (ASR emulation).

Conclusion

- Why contradicting results?
 - In ATIS the utterances are only information requests and the classes are related only to the lexical content,
 - In SWBD the classes are also related to the prosodic content.
 - The utterances in SWBD differ more acoustically themselves and contain phonetic cues that are strongly related to some of the acts.
 - The success of the model depends on the corpus, this is the relation between the prosody in the utterances and the classes.

Future Work

- Combine acoustic feature sets in order to find if there is a more appropriate set
- Train the lexico-acoustic model on ICSI that is similar to SWBD
- Explore Attention Mechanisms on Neural Networks for sentence modeling yielding promising results, in order to highlight words or phrases that are useful for the dialog-act classification.
- Encode sentence context. a Wh-Question is more likely to be followed by a Statement than by another Wh-Question.

Questions...

... Thanks



References

- Kent Bach, Routledge (Firm). Concise Routledge Encyclopedia of Philosophy.
 Psychology Press. Pages 855-856, 2000.
- Yoon Kim. Convolutional Neural Networks for Sentence Classification. 2014.
- Elizabeth Shriberg et al. Can prosody aid the automatic classification of dialog acts in conversational speech? CoRR, cs.CL/0006024, 2000.
- Ye Zhang and Byron C. Wallace. A sensitivity analysis of (and practitioners' guide to) convolutional neural networks for sentence classification. CoRR, abs/1510.03820, 2015.