# SRL4ORL: Semantic Role Labelling for Opinion Role Labelling

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FGOA aims to





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- detect explicit opinion expressions (O)
- measure their intensity (e.g. strong)

John likes that she enjoys being at the Enderly Park.  $O_1$ 



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- measure their intensity (e.g. strong)
- identify their targets (T), entities or propositions at which sentiment is directed

John likes that she enjoys being at the Enderly Park  $O_1$  .

John likes that she enjoys being at the Enderly Park  $O_2$   $T_2$ 





#### FGOA aims to



- detect explicit opinion expressions (O)
- measure their intensity (e.g. strong)
- identify their targets (T), entities or propositions at which sentiment is directed
- identify their holders (H), entities that express an opinion

```
John likes that she enjoys being at the Enderly Park . 
 \mathbf{H_1} \mathbf{O_1} \mathbf{T_1}
```

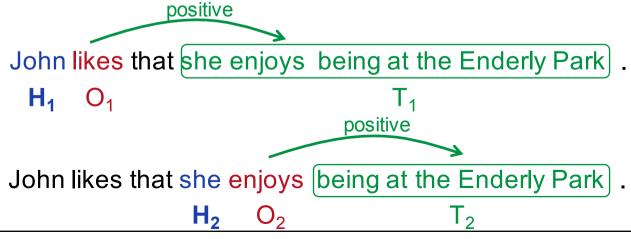
John likes that she enjoys being at the Enderly Park 
$$H_2$$
  $O_2$   $T_2$ 



#### **FGOA** aims to



- detect explicit opinion expressions (O)
- measure their intensity (e.g. strong)
- identify their targets (T), entities or propositions at which sentiment is directed
- identify their holders (H), entities that express an opinion
- classify target-dependent sentiment they express toward their targets





#### **Outline**





#### √ Fine grained-opinion analysis

What are the aims of fine-grained opinion analysis?

Related work

How is FGOA approached?
What kind of data is commonly used?

Semantic Role Labelling (SRL) for Opinion Role Labelling (ORL)

Could we adapt SRL models for ORL?

How well can we predict opinion expressions only?

Could we exploit SRL data?

Preliminary results

Future directions and discussion

### **Approaches to FGOA**



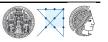


- span-based annotated MPQA corpus (Wiebe et al. 2005)
   ⇒ sequence tagging models with the BIO encoding scheme
- John likes that she enjoys being at the Enderly Park.

```
B-H B-O O B-T I-T I-T I-T I-T I-T Standard methods, CRF and O O O B-H B-O B-T I-T I-T I-T I-T I-T of these sequences
```

#### pipeline models

- first label opinion expressions and then, given an opinion, label its holders and targets (*opinion roles*) (Kim and Hovy, 2006; Kobayashi et al., 2007)
- overlapping entities are handled
- target-dependent sentiment classification not done



#### Joint inference models for FGOA



# AIPH

Joint inference: labelling of opinion entities (expressions,

holders, targets) and classification of relations between them into

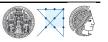
- *is-about*: from a target to its opinion expressions
- *is-from*: from an opinion to its holder

opinion relations

■ Yang and Cardie (2013) (CRF + ILP)

$$\arg \max_{x,u,v} \lambda \sum_{i \in \mathcal{S}} \sum_{z} f_{iz} x_{iz} + (1 - \lambda) \sum_{k} \sum_{i \in \mathcal{O}} \left( \sum_{j \in \mathcal{A}_k} r_{ij} u_{ij} + r_{i\emptyset} v_{ik} \right)$$

- state-of-the-art
- discard entities that contain other entities
- without target-dep. sentiment classification



#### The most recent neural models for FGOA



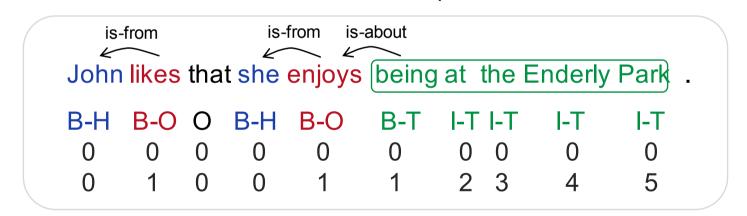
#### Katiyar and Cardie (2016) (LSTM + RLL)



WLL = word-level log likelihood ⇒ standard LSTM

SLL = sentence-level log-likelihood ⇒ the best sequence of opinion entity labels

RLL = relational-level log likelihood ⇒ the best sequence of opinion entity labels and the best sequences of relational distances



- CRF + ILP outperforms LSTM + RLL for extraction of opinion roles
- discard entities that contain other entities, without target-dep. sentiment class.

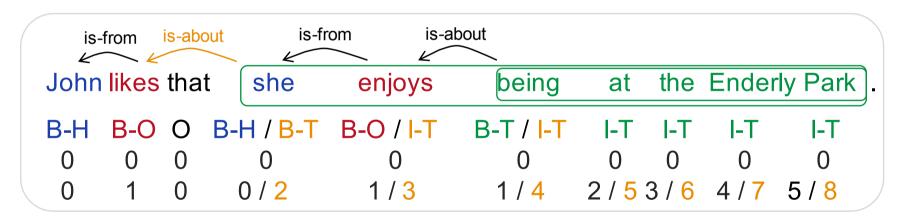
# Where are we 12 years after?



neural models lag behind feature-based models



- (constantly) left as future work
  - handling opinion entities that contain other opinion entities
  - target-dependent sentiment classification



- CRF+ILP & LSTM+RLL achieve ~54% F1 score for classification of is-about rel.
  - ⇒ the models we have at the moment are not close to answering:

Who expressed what kind of sentiment towards what?



### How can we improve?



Can we build simpler models? Using more data?



#### 1. SRL has substantially more data

	train	dev	test-WSJ	test-Brown	test
CoNLL'05	90750	3248	5269	804	6073
MPQA	3458	1224	-	-	313

#### 2. SRL is similar in nature to ORL



The output of **Semantic Role Labeling demo**. Looks familiar?



#### **SRL** and **ORL**: differences



#### related work



- mapping from semantic to opinion roles: Kim and Hovy (2006)
- SRL frame as a feature: Choi et al. (2006)
- ORL poses challenges beyond SRL: Wiegand and Ruppenhofer (2015)

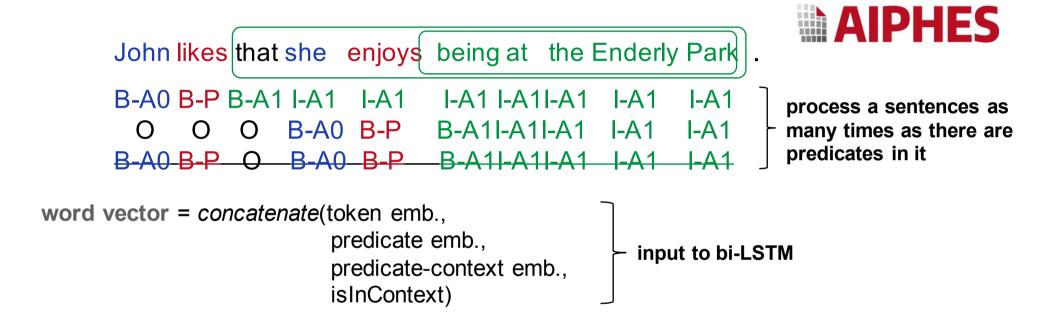
Peter<sub>agent</sub> criticized Mary<sub>patient</sub>.  $\Rightarrow$  (criticize, Peter, holder) & (criticize, Mary, target) Peter<sub>agent</sub> disappoints Mary<sub>patient</sub>.  $\Rightarrow$  (disappoint, Peter, target) & (disappoint, Mary, holder)

- our perspective: how could SRL resources (models, data) be exploited for ORL?
- first step: adapt state-of-the-art SRL model (Zhou and Xu, 2015) for ORL
- challenges:
  - SRL models (usually) presuppose that a predicate is given
  - we can not use sentiment lexical resources to extract opinion expressions:
    - holding himself accountable, demonstrate his concern
    - asked, said...



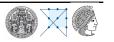
# ZX-SRL model (Zhou and Xu, 2015)





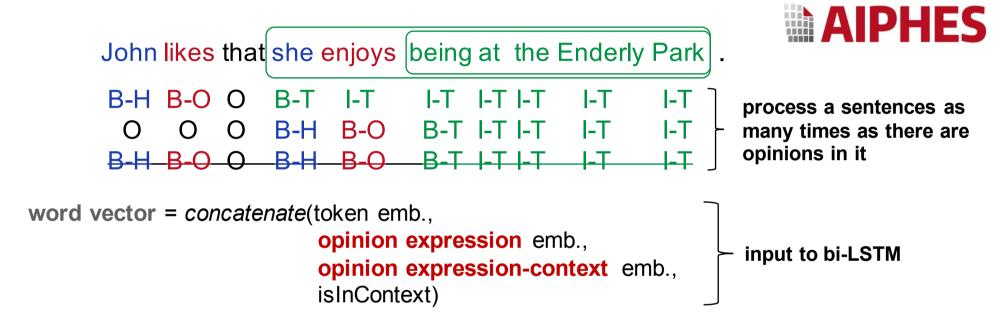
**isInContext** = 1 if the token is in the context, 0 otherwise

- + 1-4 layers of bi-LSTM or bi-GRU
- + CRF layer



#### **ZX-ORL: ZX-SRL for ORL**





**opinion expression-context embedding =** average of embeddings of words in a surrounding window of the opinion expression(context)

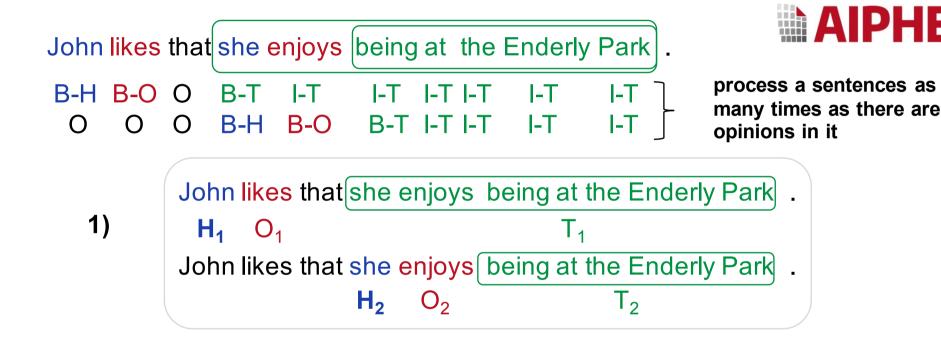
**isInContext** = 1 if the token is in the context, 0 otherwise

- + 1-4 layers of bi-LSTM or bi-GRU
- + CRF layer (with a new set of labels)



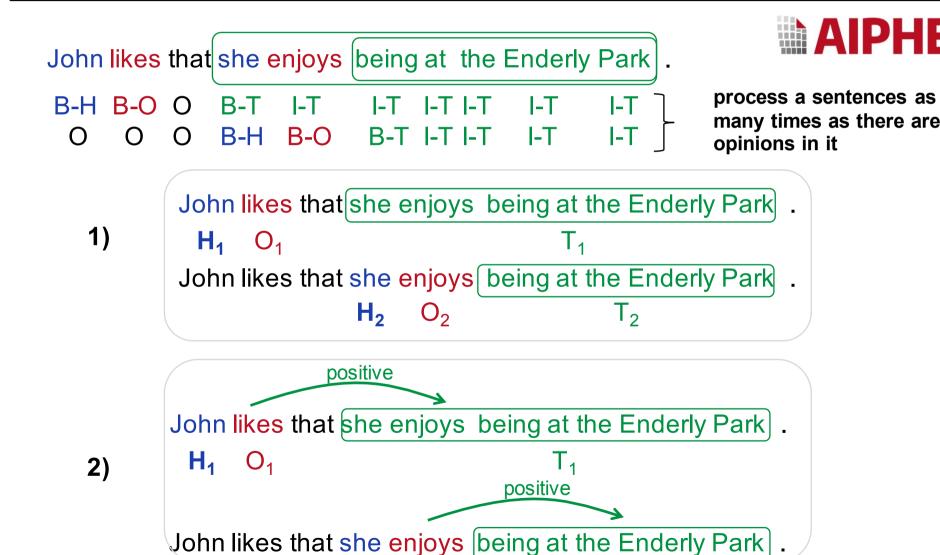
# Oversampling simplifies target-dependent sentiment classification





# Oversampling simplifies target-dependent sentiment classification





# Exp. 1: ZX-ORL with gold opinion expressions



dataset: MPQA 2.0.



model: ZX-ORL with gold opinion expressions

validation technique: 10-fold CV

evaluation metrics:

- binary overlap recall: how many gold entities have an overlapping predicted entity
- binary overlap precision: how many predicted entities have an overlapping gold entity
- proportional overlap recall: measures proportion of the overlap between a gold entity
   and an overlapping predicted entity
- proportional overlap precision: measures proportion of the overlap between a predicted entity and an overlapping gold entity

• f-score = 
$$\frac{2 * precision * recall}{precision + recall}$$

manually chosen HPs

# **Exp 1: ZX-ORL with gold opinion expressions -- results**





	10-fold CV binary overlap f-score			10-fold CV proportional overlap f-score			
	expression	holder	target	expression	holder	target	
ZX-ORL	98.30	73.40	74.08	97.41	71.06	68.84	
CRF	71.17	59.21	59.19	61.67	57.86	53.23	
LSTM+SLL	68.37	62.35	59.65	63.60	60.40	52.01	
CRF+ILP	74.11	67.22	65.40	70.22	65.68	58.72	
LSTM+RLL	71.11	64.71	64.84	65.56	62.18	55.81	

- direct comparison is not possible, our model is given gold opinion expressions!
- ZX-ORL results serve as an upper bound for a future pipeline model
  - opinion extraction ⇒ role extraction ⇒ target-dependent sentiment classification



# **Exp 2.: Predicting opinion expressions only**





#### model variants:

- 1. LSTM
- 2. GRU
- 3. LSTM + CRF
- 4. GRU + CRF
- shallow (1 layer) vs. deep (3 layers)
- HPs tuned with Tree-structured Parzen Estimators (Bergstra et al., 2011)
  - tuned with dev prop. f-score in 50 trails for each out of 8 architectures separately
  - the size of the LSTM/GRU hidden state, value for clipping gradients, word frequency threshold, l<sub>2</sub>-regularization coefficient, keep input probability, keep output probability

# **Exp 2: Predicting opinion expressions only**

#### -- Results



		d	ev	test (onl		
		prop. f-score	binary f-score	prop. f-score	binary f-score	# params
3 layers	LSTM	57.96	70.60	61.30	73.22	113836
	GRU	61.82	70.87	62.59	70.45	615500
	LSTM + CRF	67.19	74.48	67.64	73.23	653692
	GRU + CRF	66.85	74.25	68.98	74.27	1390552
1 layer	LSTM	60.46	69.94	61.69	69.41	204796
	GRU	60.52	70.73	61.65	70.16	175256
	LSTM + CRF	65.89	74.42	67.04	74.09	803220
	GRU + CRF	67.34	73.36	69.35	74.12	458892

■ the shallow GRU + CRF achieves as good performance as the 3-layer GRU + CRF

### **Exp 2: Predicting opinion expressions only** -- 10-fold CV results







	10-fold CV test				
	prop. f-score	binary f-score			
GRU + CRF (1 layer)	66.20	73.43			
Irsoy & Cardie (2014)	66.01	71.72			

- predicting SRL predicates:
  - bi-LSTM model achieved an F1 score of 91.43% on marking words as predicates (or not) (Swayamdipta et al., 2016)
- **next step**: feed predicted opinion expressions to ZX-ORL (no results yet, sorry)



# **Transfer learning from SRL**





#### How about transfer learning from SRL?

- so far: we used the model for SRL (ZX-SRL), but did not use SRL data
- transfer learning: pre-train ZX-SRL and fine-tune it for ORL
  - tuning the new last layer that outputs ORL labels (CRF layer)
  - tuning the full architecture (without the SRL-CRF layer, with the ORL-CRF layer)

# Exp 3: ZX-SRL + fine-tuning



	5-fold CV binary overlap f-score			5-fold CV proportional overlap f-score		
	expression	sion holder target		expression	holder	target
ZX-ORL	98.36	72.84	74.22	96.47	70.47	68.79
ZX-SRL + FT (full)	98.17	63.93	68.80	97.49	61.38	64.19

# Exp 3: ZX-SRL + fine-tuning



	5-fold CV bina	ıry overlap	f-score	5-fold CV prop. overlap f-score			
	expression	holder	target	expression	holder	target	
ZX-ORL	98.36	72.84	74.22	96.47	70.47	68.79	
ZX-SRL + FT (full)	98.17	63.93	68.80	97.49	61.38	64.19	
ZX-SRL + FT CRF	39.53	13.75	13.38	37.34	12.13	13.11	

- the new CRF layer is randomly initialized ⇒ fine-tuning is very sensitive to the choice of the learning rate
- after the first epoch
  - with fine-tuning: 77.35% (opinion expression), 18.59% (holder) and 56.89% (target) binary f-score
  - without fine-tuning: 0%, 0% and 1.17% binary f-score
  - the pre-trained weights are relatively good, but get distorted too quickly and too much



#### **Future directions**





- apply more sophisticated fine-tuning techniques
  - impact of learning rate on fine-tuning: global and local
  - layer-wise transfer
  - restrict ZX-SRL to predict only relevant roles
- deeper analysis to investigate the real impact of SRL for ORL
  - visualization
  - perturbation analysis
- full pipeline model
  - opinion extraction ⇒ role extraction ⇒ target-dependent sentiment classification
  - consider end-to-end learning







# Thank you for your attention!

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### **MPQA** corpus



■ span-based annotated MPQA corpus (Wiebe et al. **2005**)



⇒ sequence tagging models with the BIO encoding scheme

"If the prosecution's key witness is reluctant to testify, how will they proceed?" Mr. Tsvangirai asked. "There is no case to answer."

- explicit opinion annotations allow annotating an implicit opinion as explicit with an "implicit" arg.
- **but**, annotators were not consistent with marking the "implicit" argument

### **MPQA** corpus



■ span-based annotated MPQA corpus (Wiebe et al. **2005**)



⇒ sequence tagging models with the BIO encoding scheme

Asked whether [...], Theishat said that signing the protocol will have a "positive" outcome [...].

He **explained** that both the US and Jordan have different issues to deal with on a national level, including environmental issues.

- "said", "explained" are not sentiment-barring words
- attitude annotations: "e.g., positive sentiments, negative sentiments, agreements, etc., being expressed overall by the private states represented by the direct subjective."

# Ideas for target-dependent sentiment classification





- concatenate target word embeddings ⇒ feed-forward layer of hidden units
- average target word embeddings ⇒ feed-forward layer of hidden units
- process a target sequence with some recurrent architecture or CNN
- process a sentence with some recurrent architecture and concatenate the target embedding with every token embedding

