

Learning Latent Opinions for Aspect-level Sentiment Classification

Bailin Wang*

University of Massachusetts

Wei Lu

Singapore University of Technology
and Design

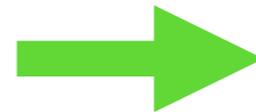
Aspect-level Sentiment Classification

Review

The food is usually good but it certainly isn't a relaxing place to go.

Sentiment

food: positive
place: negative



The food is **usually good** but it **certainly isn't a relaxing** place to go.
positive negative

Problem: requires additional annotations.

Latent Variable: Attention

Review: w_0, w_1, \dots, w_n

The food is usually good

$$p(z=k) \\ 0 \leq k \leq n$$



* Rely on LSTM to capture contextual information implicitly



Explicitly capture the structural dependencies { between target and opinion
between opinion words



Observations:

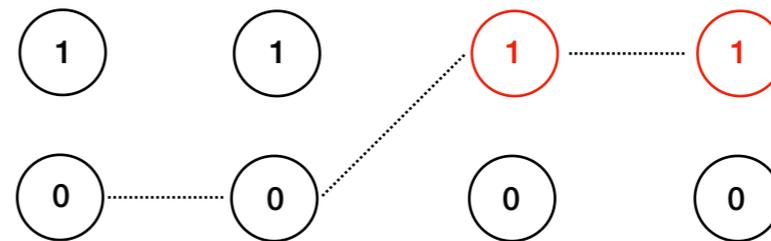
- * may be multiple targets which may hold different sentiments
- * opinions are usually coherent and short span
- * target and its opinion usually closely related in terms of syntactic structure

Segmentation Attention

$$p(z_i) \quad z_i \in \{0,1\}$$

Whether it's a part of the opinion

service is quite terrible

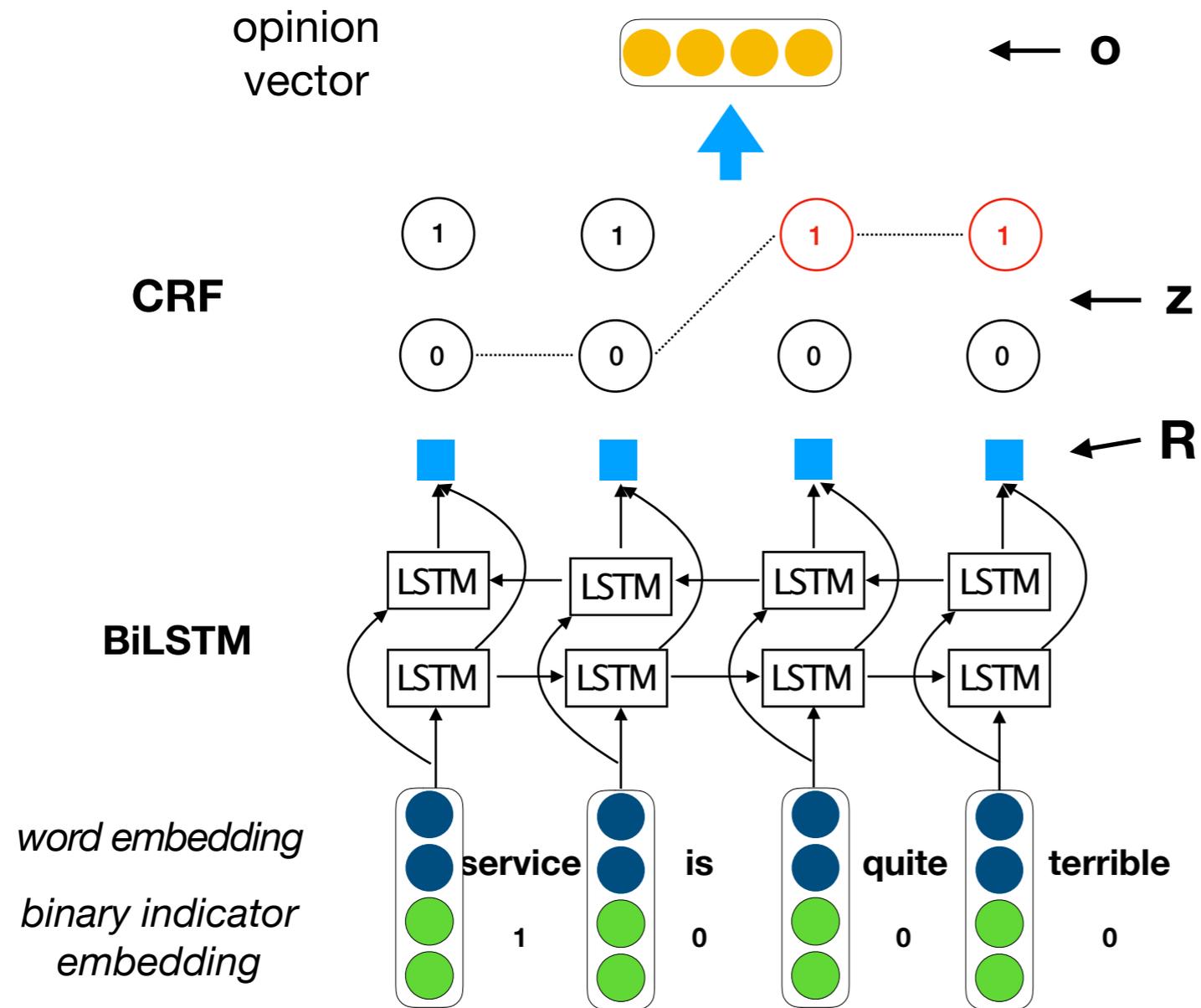


Add first order assumption



Conditional Random Field

Model



Feature Function (g)

$$\mathbf{z} = [z_1, \dots, z_n]$$

$$\mathbf{o} = \sum_{\mathbf{z}} p(\mathbf{z}) g(\mathbf{R}, \mathbf{z})$$



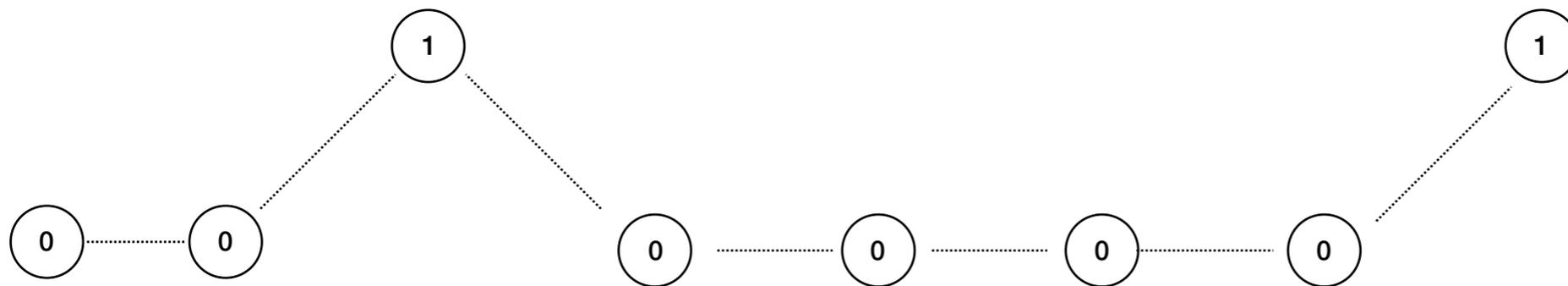
$$g(\mathbf{R}, \mathbf{z}) = \sum_{i=1}^n \mathbb{1}(z_i = 1) \mathbf{r}_i$$

$$\mathbf{o} = \sum_i p(z_i = 1) \mathbf{r}_i$$

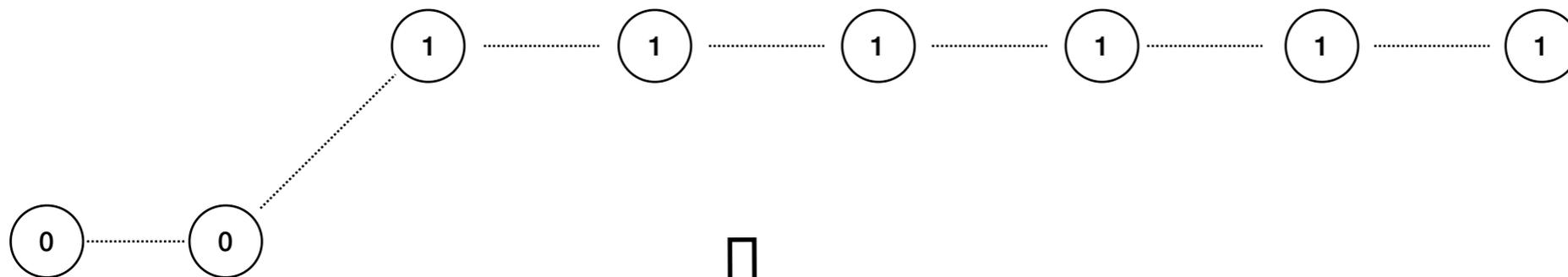
marginal probability

Regularizer

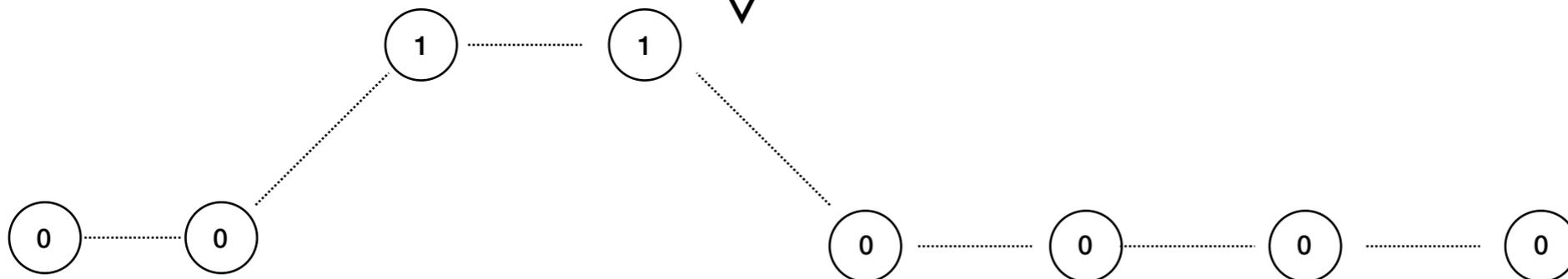
target
↓
service is quite terrible but food is good



↓ **coherent**



↓ **short**



Regularizer

1. punish the state transitions

$$\Omega_1(\mathbf{z}) = \sum_i \sum_{j \neq i} \max(0, \mathbf{W}_{ij}^e - \mathbf{W}_{ii}^e)$$

2. punish the long opinions

$$\Omega_2(\mathbf{z}) = \sum_{i=1}^n p(z_i = 1)$$

Object Function

$$\mathcal{L} = \frac{1}{N} \left[\sum_{i=0}^N -y_i \log p(y_i) + \lambda_1 \Omega_1(\mathbf{z}) + \lambda_2 \Omega_2(\mathbf{z}) \right]$$

Results: SemEval 2014 task 4

Method	Laptop	Restaurant	Twitter
SVM	70.5	80.2	63.4
AdaRNN	-	-	66.3
AT-LSTM	68.9	77.2	-
MemNet	70.3	78.2	68.5
RAM	74.5	80.2	69.4
A-Softmax	68.8	76.9	66.0
SA-Softmax	69.0	77.1	66.2
SA-Softmax-P	69.1	77.8	66.5
A-LSTM	72.7	78.4	68.2
SA-LSTM	74.5	79.8	69.9
SA-LSTM-P	75.1	81.6	69.0

- * A- standard Attention
- * SA- Segmentation Attention
- * P- with regularizers

Conclusions

- * LSTM helps
- * SA- is more beneficial than A-
- * P- helps, especially with LSTM
- * State-of-the-art performance
- * not significant in Twitter (one target)

Results: SemEval 2016 task 5

Method	Restaurant						Hotel Arabic
	English	Spanish	French	Turkish	Russia	Dutch	
XRCE	88.1	-	78.8	-	-	-	-
IIT-TUDA	86.7	83.6	72.2	84.3	73.6	77.0	81.7
LSTM	81.4	75.7	69.8	73.6	73.9	73.6	80.5
HP-LSTM	85.3	81.8	75.4	79.2	77.4	84.8	82.9
A-LSTM	86.5	86.5	81.8	86.2	81.3	85.6	86.5
SA-LSTM	88.1	83.8	81.9	78.6	81.1	86.1	86.7
SA-LSTM-P	88.7	88.0	82.4	83.7	82.8	87.3	86.9

Conclusions

- * SA helps, better with P (regularizer)
- * Language insensitivity
- * Significant improvement, especially for low resource language

Latent Opinions

* *Explicitly extract latent opinions using Viterbi*

* *provide causal explanations of how model works internally*

Method	Laptop		Restaurant	
	Precision	Recall	Precision	Recall
A-Softmax	50.2	44.6	59.7	36.9
SA-Softmax	36.2	68.1	38.5	64.7
SA-Softmax-P	65.5	55.2	42.2	58.3
A-LSTM	48.4	47.9	56.5	53.7
SA-LSTM	25.5	75.4	21.2	78.3
SA-LSTM-P	49.1	58.7	39.4	59.9

Conclusions

* LSTM and SA helps recall opinions

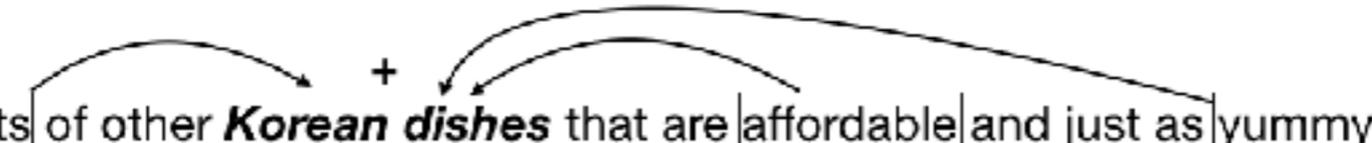
* Regularizer helps balance P and R

* unsupervised extraction of opinions at word-level

* annotations provided by Wang et al. 2016

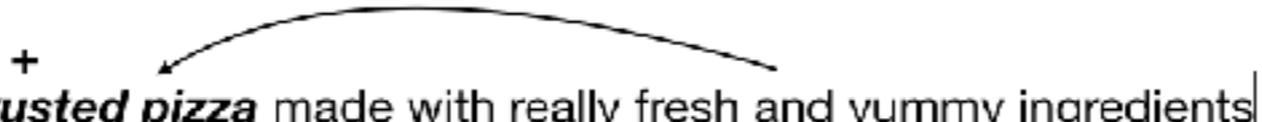
Latent Opinions

1. It also has lots of other **Korean dishes** that are affordable and just as yummy.



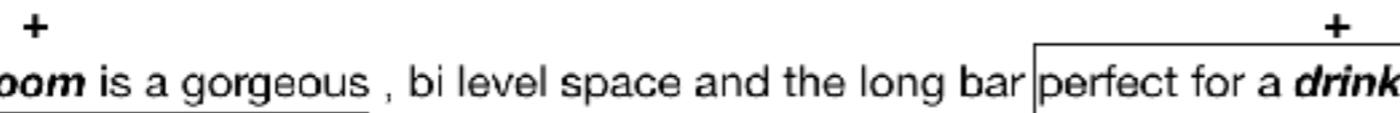
multiple opinions

2. They have **wheat crusted pizza** made with really fresh and yummy ingredients.



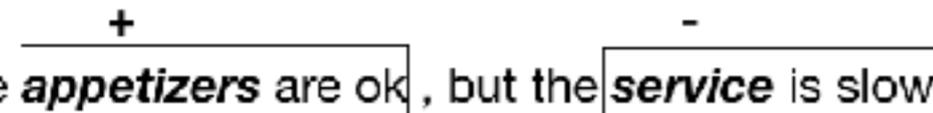
coherent span

3. The room is a gorgeous , bi level space and the long bar perfect for a drink.



same sentiment, different opinion

4. The appetizers are ok , but the service is slow.



different sentiment, different opinion

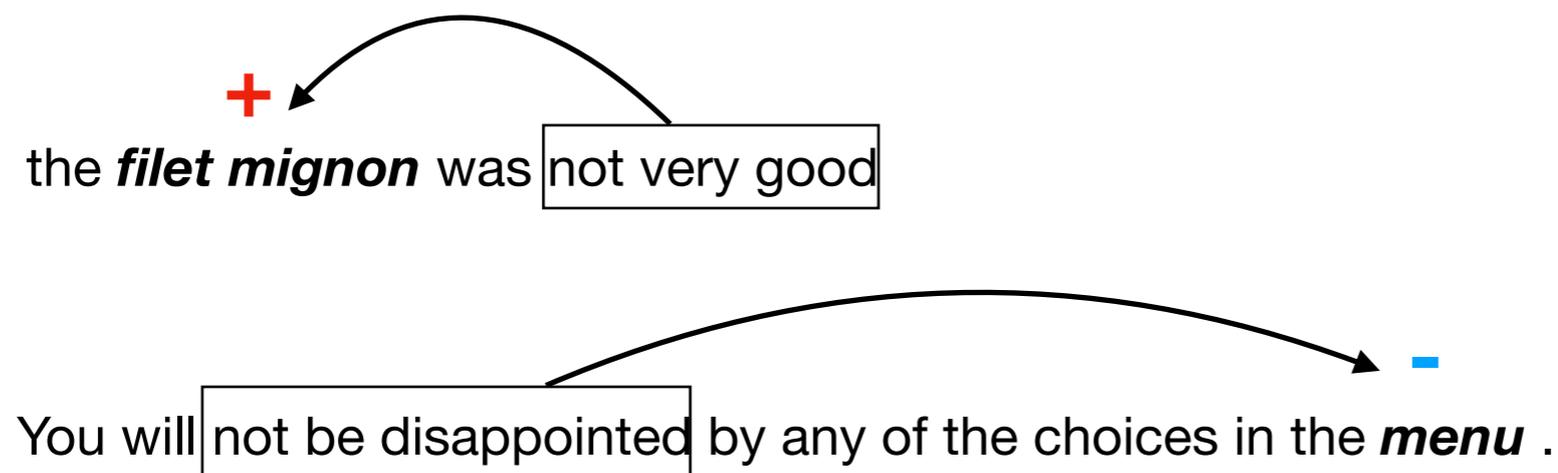
Error Analysis

1. attention error

assign sentiment to intensity words like “really”, “sure”

2. representation error

Negation opinion



Thanks

Code available on Github: <https://github.com/berlino/SA-Sent>