

# Aspect-based Sentiment Classification with Graph Convolutional Networks

Hyunjae Kim

Data Mining & Information Systems Lab.

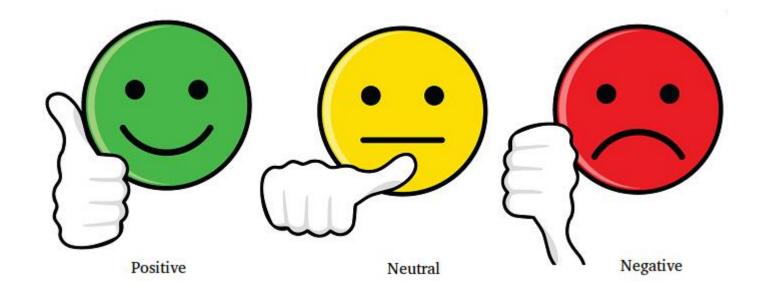
Department of Computer Science and Engineering,

College of Informatics, Korea University

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#### Sentiment Classification





### Aspect-Based Sentiment Classification



Great food but the service was dreadful

Aspects: <u>Food</u>, <u>Service</u>

Sentiments:

 $\underline{Food} \rightarrow \underline{good}$ ,  $\underline{Service} \rightarrow \underline{bad}$ 

### Limitations of Previous Models (1/2)



Attention-based models

Its <u>size</u> is <u>ideal</u> and <u>the weight</u> is <u>acceptable</u>.

Good food bad service

### Limitations of Previous Models (1/2)



CNN-based models

The <u>staff</u> a bit more friendly.

The <u>staff</u> should be a bit more friendly.

## Limitations of Previous Models (2/2)



The <u>staff</u> should be a bit more friendly

CNNs - the sentiment of an aspect is usually determined by key phrases instead of individual words.

#### Solution

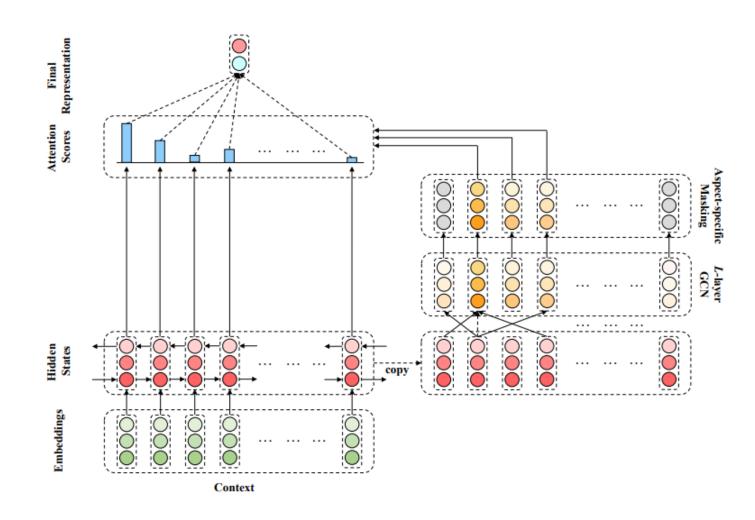


#### **Utilizing GCN!**

- Two papers accepted at EMNLP 2019
  - Aspect-based Sentiment Classification with Aspectspecific <u>Graph Convolutional Networks</u>
  - Syntax-Aware Aspect Level Sentiment Classification with <u>Graph Attention Networks</u>

# Approach 1 (1/3)





## Approach 1 (2/3)



$$\tilde{\mathbf{h}}_i^l = \sum_{j=1}^n \mathbf{A}_{ij} \mathbf{W}^l \mathbf{g}_j^{l-1}$$
 (2)

$$\mathbf{h}_i^l = \text{ReLU}(\tilde{\mathbf{h}}_i^l / (d_i + 1) + \mathbf{b}^l) \tag{3}$$

$$\mathbf{g}_i^l = \mathcal{F}(\mathbf{h}_i^l) \tag{4}$$

$$q_{i} = \begin{cases} 1 - \frac{\tau + 1 - i}{n} & 1 \le i < \tau + 1 \\ 0 & \tau + 1 \le i \le \tau + m \\ 1 - \frac{i - \tau - m}{n} & \tau + m < i \le n \end{cases}$$
 (5)

$$\mathcal{F}(\mathbf{h}_i^l) = q_i \mathbf{h}_i^l \tag{6}$$

position weights

## Approach 1 (3/3)



$$\beta_t = \sum_{i=1}^n \mathbf{h}_t^{c\top} \mathbf{h}_i^L = \sum_{i=\tau+1}^{\tau+m} \mathbf{h}_t^{c\top} \mathbf{h}_i^L$$
 (8)

 Aspect-specific Masking

$$\alpha_t = \frac{\exp(\beta_t)}{\sum_{i=1}^n \exp(\beta_i)}$$
 (9)

 Aspect-specific Attention

$$\mathbf{r} = \sum_{t=1}^{n} \alpha_t \mathbf{h}_t^c \tag{10}$$

$$\mathbf{p} = \operatorname{softmax}(\mathbf{W}_p \mathbf{r} + \mathbf{b}_p) \tag{11}$$

#### Approach 2



$$h_{l+1}^i = \prod_{k=1}^K \sigma(\sum_{j \in n[i]} \alpha_{lk}^{ij} W_{lk} h_l^j)$$
 (1)

$$\alpha_{lk}^{ij} = \frac{exp(f(a_{lk}^{T}[W_{lk}h_{l}^{i}||W_{lk}h_{l}^{j}]))}{\sum_{u \in n[i]} exp(f(a_{lk}^{T}[W_{lk}h_{l}^{i}||W_{lk}h_{l}^{u}]))}$$
(2)

$$H_{l+1} = GAT(H_l, A; \Theta_l) \tag{3}$$

$$H_{l+1}, C_{l+1} = LSTM(GAT(H_l, A; \Theta_l), (H_l, C_l))$$
  
 $H_0, C_0 = LSTM(XW_p + [b_p]_N, (0, 0))$ 

#### **Datasets**



Dataset		# Pos.	# Neu.	# Neg.	
TWITTER	Train	1561	3127	1560	
	Test	173	346	173	
LAP14	Train	994 464		870	
LAI 14	Test	341	169	128	
REST14	Train	2164	637	807	
	Test	728	196	196	
REST15	Train	912	36	256	
1120110	Test	326	34	182	
REST16	Train	1240	69	439	
	Test	469	30	117	

#### Results



Model .	TWITTER		LAP14		REST14		REST15		REST16	
	Acc.	F1	Acc.	F1	Acc.	F1	Acc.	F1	Acc.	F1
SVM	63.40 <sup>‡</sup>	63.30 <sup>‡</sup>	70.49 <sup>‡</sup>	N/A	80.16 <sup>‡</sup>	N/A	N/A	N/A	N/A	N/A
LSTM	69.56	67.70	69.28	63.09	78.13	67.47	77.37	55.17	86.80	63.88
MemNet	71.48	69.90	70.64	65.17	79.61	69.64	77.31	58.28	85.44	65.99
AOA	72.30	70.20	72.62	67.52	79.97	70.42	78.17	57.02	87.50	66.21
IAN	72.50	70.81	72.05	67.38	79.26	70.09	78.54	52.65	84.74	55.21
TNet-LF	72.98	71.43	74.61	70.14	80.42	71.03	78.47	59.47	89.07	70.43
ASCNN	71.05	69.45	72.62	66.72	81.73	73.10	78.47	58.90	87.39	64.56
ASGCN-DT ASGCN-DG	71.53 72.15 <sup>†</sup>	69.68 70.40 <sup>†</sup>	74.14 <sup>†</sup> <b>75.55</b> <sup>†‡</sup>	69.24 <sup>†</sup> <b>71.05</b> <sup>†‡</sup>	<b>80.86</b> <sup>‡</sup> 80.77 <sup>‡</sup>	<b>72.19</b> <sup>‡</sup> 72.02 <sup>‡</sup>	79.34 <sup>†‡</sup> 79.89 <sup>†‡</sup>	60.78 <sup>†‡</sup> 61.89 <sup>†‡</sup>	88.69 <sup>†</sup> <b>88.99</b> <sup>†</sup>	66.64 <sup>†</sup> <b>67.48</b> <sup>†</sup>

a possible reason, supect, conjecture, ...

## Ablation Study



Model	TWITTER		LAP14		REST14		REST15		REST16	
	Acc.	F1	Acc.	F1	Acc.	F1	Acc.	F1	Acc.	F1
BiLSTM+Attn ASGCN-DG	71.24 72.15	69.55 70.40	72.83 75.55		79.85 80.77				87.28 88.99	68.18 67.48
ASGCN-DG w/o pos. ASGCN-DG w/o mask ASGCN-DG w/o GCN	72.64	70.63		66.56	79.02	68.29				61.41

- Removal of pos → performance increases on Twitter and Rest14.
- The GCN does not work well as expected on the datasets not sensitive to syntax information.

# Case Study



Model	Aspect	Attention visualization	Prediction	Label	
MemNet	food	great food but the service was dreadful!	negative <sub>x</sub>	positive	
	staff	The staff should be a bit more friendly.	positive <sub>x</sub>	negative	. (
	Windows 8	Did not enjoy the new Windows 8 and touchscreen functions.	positive <sub>x</sub>	negative	
	food	great food but the service was dreadful!	positive.	positive	
IAN	staff	The staff should be a bit more friendly.	positive, negative		
IAN	Windows 8	Did not enjoy the new Windows 8 and touchscreen functions.	neutral <sub>x</sub>	negative	
	food	great food but the service was dreadful!	positive.	positive	_
A CONNI	staff	The staff should be a bit more friendly.	neutral <sub>x</sub>	negative	,
ASCNN	Windows 8	Did not enjoy the new Windows 8 and touchscreen functions.	negative.	negative	
ASGCN-DG	food	great food but the service was dreadful!	positive.	positive	
	staff	The staff should be a bit more friendly.	negative.	negative	,
	Windows 8	Did not enjoy the new Windows 8 and touchscreen functions.	negative.	negative	
		<u> </u>			

0/3

1/3

2/3

3/3

- long-range
- multi-word

# **GGeut**

