Aspect Based Sentiment Analysis with Gated Convolutional Networks

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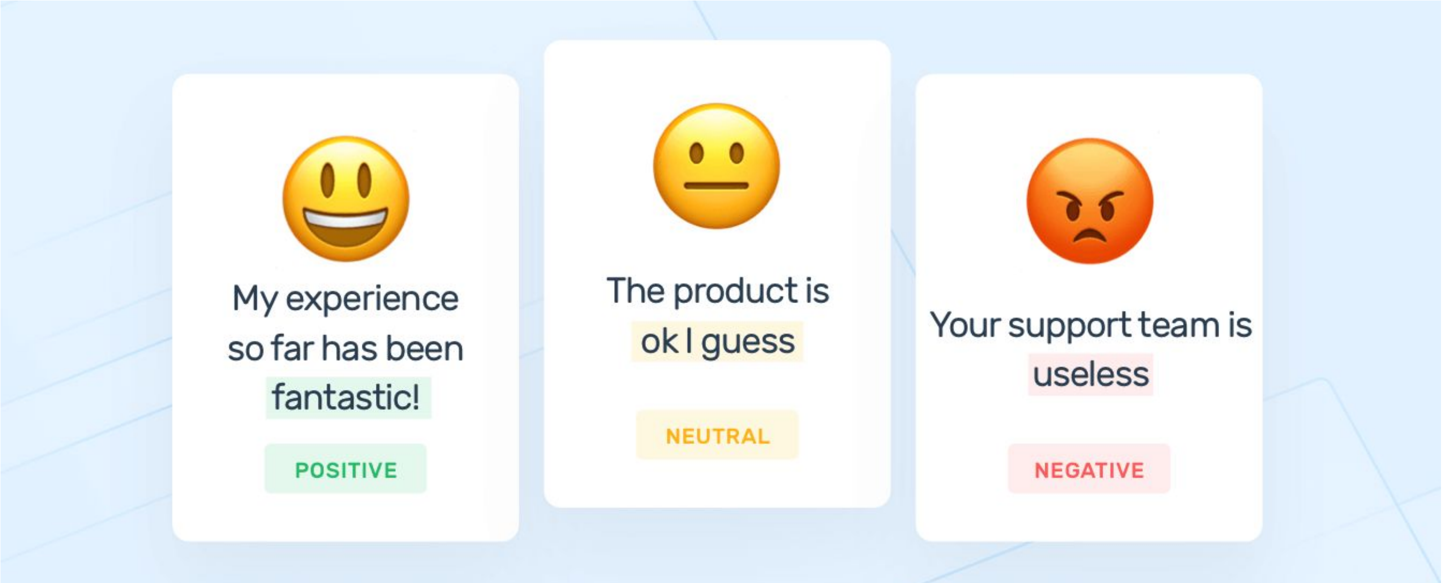
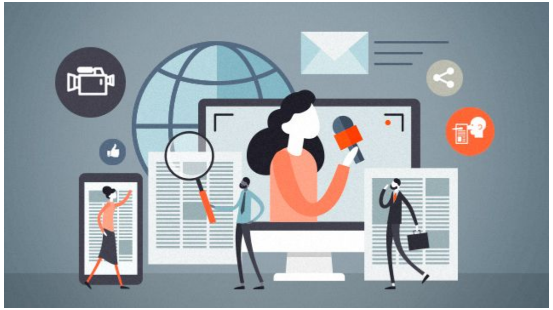
Motivation - Sentiment Analysis

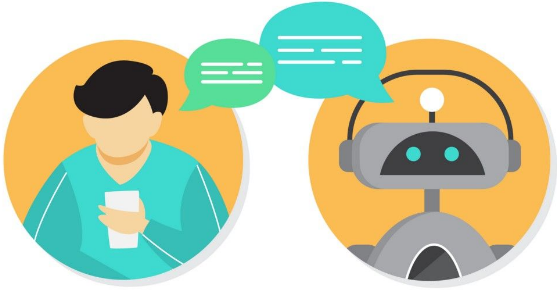


Applications

Business Insights



News Sources



Question Answering

Aspect Based Sentiment Analysis

"Battery life is good, but the screen size is too small."

Aspect: Battery life, **Polarity:** Positive
Aspect: Screen size, **Polarity:** Negative

Problem Statement

Two subtasks:

- Aspect-Category Sentiment Analysis (ACSA)
- Aspect-Term Sentiment Analysis (ATSA)

Sentence
Average to good Thai food, but terrible delivery.
Average to good Thai food, but terrible delivery.

ATSA: Food, Delivery

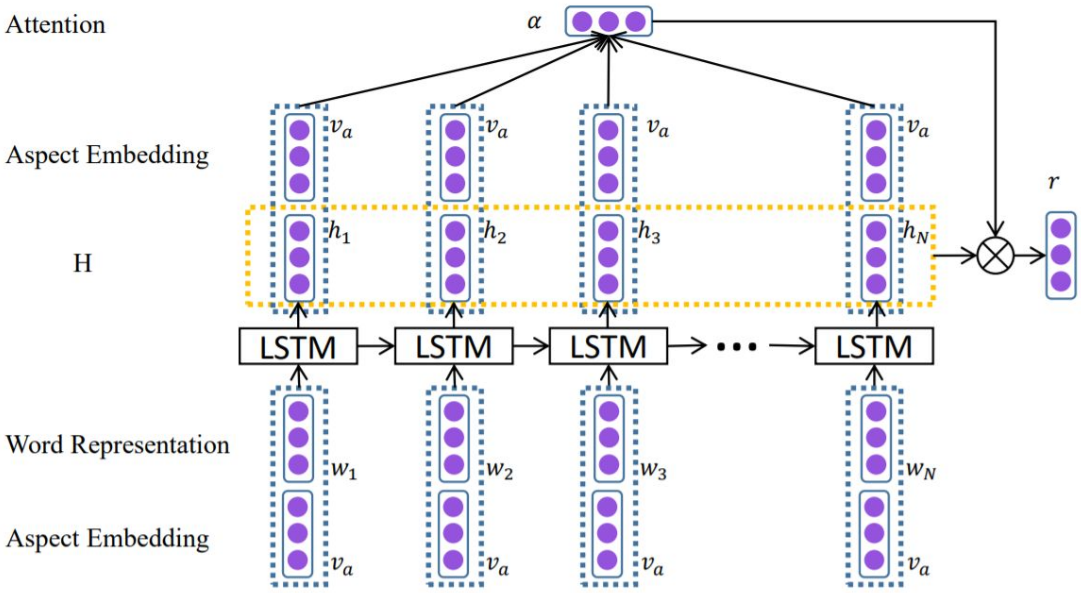
ACSA: Service

Related Work

- Earlier research works: labor-intensive handcraft features
- Neural network-based approaches
- Target-dependent: LSTM & attention mechanisms

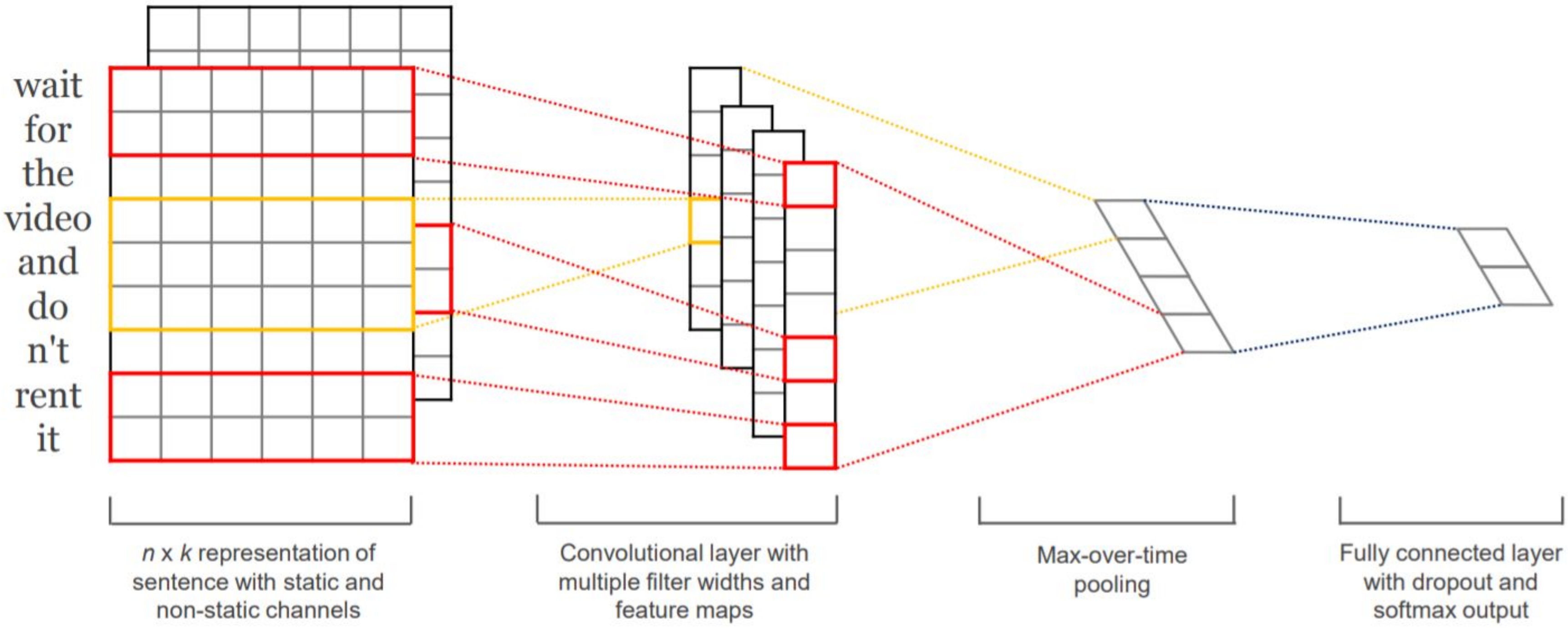
1. NRC-Canada / SVM
2. TD-LSTM
3. ATAE-LSTM
4. IAN
5. RAM
6. CNN
7. GCN

Attention-based LSTM (ATAE-LSTM) Architecture & Limitations



Attention-based LSTM with Aspect Embedding

CNN - Architecture & Limitations



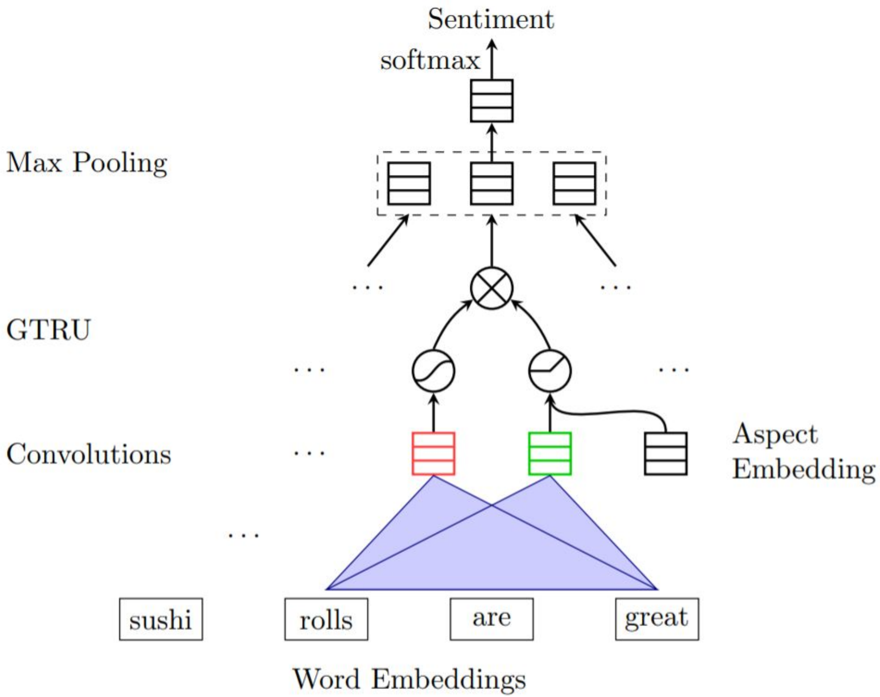
Proposed Approach

- CNN Model with Gating Mechanism
- Gated Tanh-ReLU selectively outputs sentiment features according to a given aspect or entity.
- Simpler than existing models (compared to models with attention)
- Can be trained in parallel - not time dependent unlike LSTM models

Gated Convolutional Network with Aspect Embedding (GCAE) for ACSA

1. Embedding Layer

$$w_i \in \{1, 2, \ldots, V\} \longrightarrow \boldsymbol{v}_i \in \mathbb{R}^D$$



Gated Convolutional Network with Aspect Embedding (GCAE) for ACSA

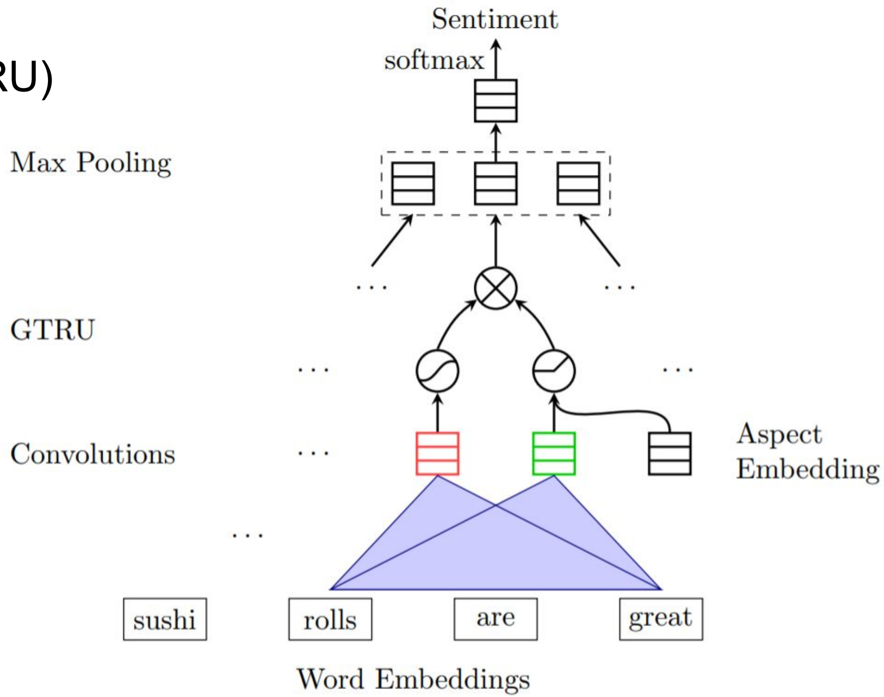
2. Convolutions & Gated Tanh-ReLU Units (GTRU)

$$\mathbf{X} = [\boldsymbol{v}_1, \boldsymbol{v}_2, \ldots, \boldsymbol{v}_L]$$

$$a_i = \mathrm{relu}(\mathbf{X}_{i:i+k} * \mathbf{W}_a + \mathbf{V}_a \boldsymbol{v}_a + b_a)$$

$$s_i = \tanh(\mathbf{X}_{i:i+k} * \mathbf{W}_s + b_s)$$

$$c_i = s_i \times a_i$$



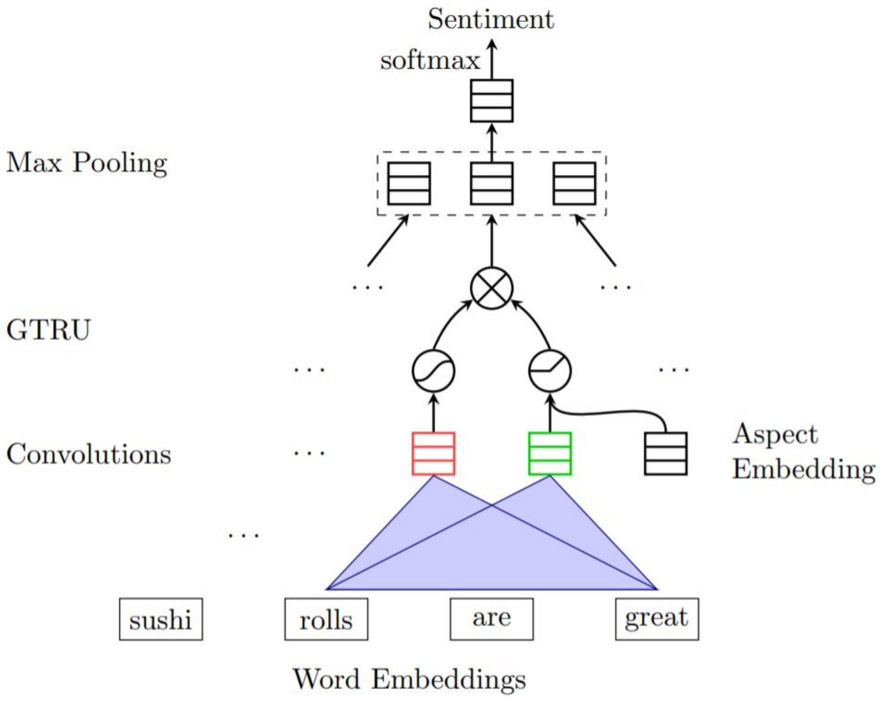
Gated Convolutional Network with Aspect Embedding (GCAE) for ACSA

3. Max-over-time pooling layer
4. Softmax
5. Training - Minimize cross-entropy loss

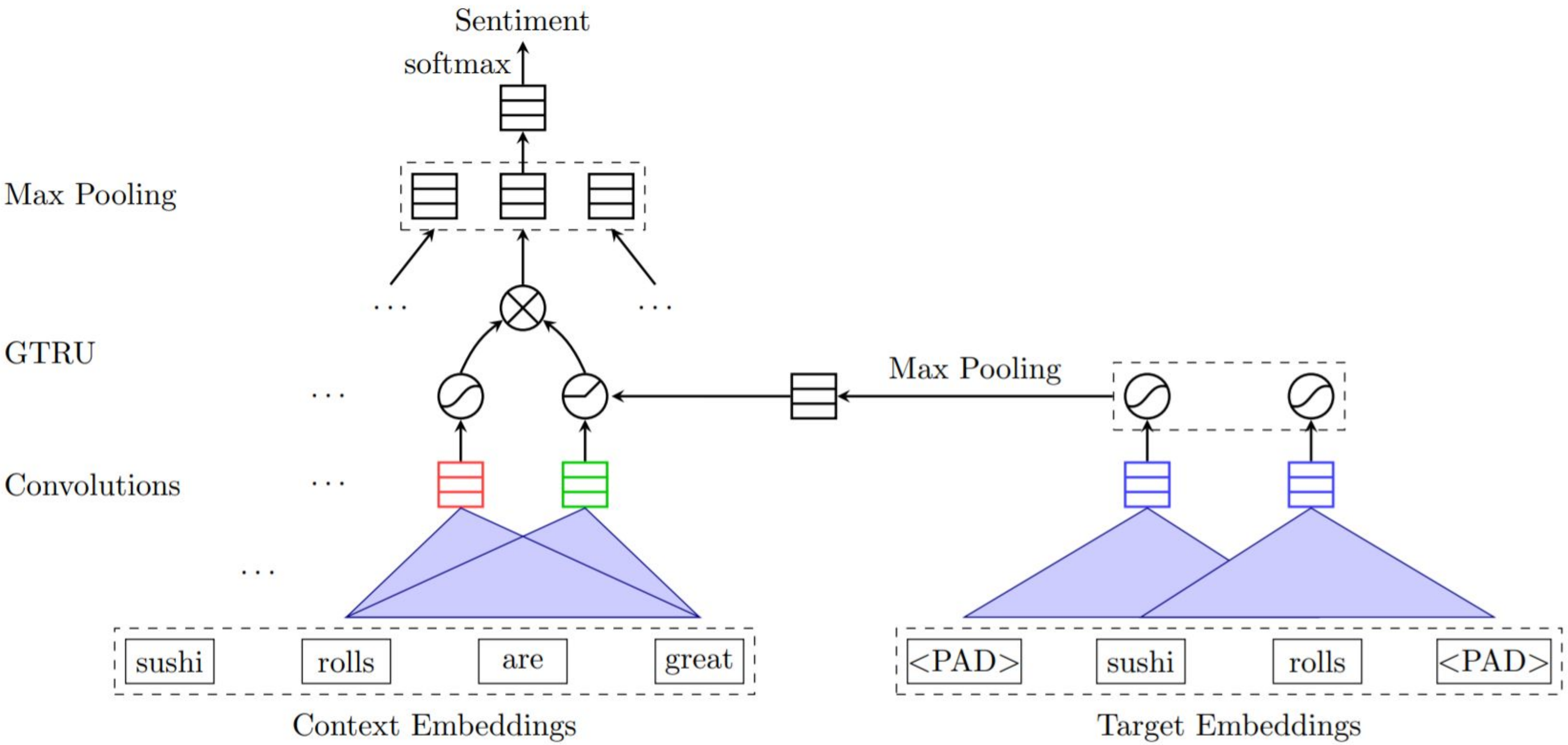
$$\mathcal{L} = -\sum_i \sum_j y_i^j \log \hat{y}_i^j$$

y = ground-truth

$\hat{y}$ = predicted value



GCAE on ATSA



Sentiment
softmax
Max Pooling
GTRU
Convolutions
Max Pooling
sushi
rolls
are
great
Context Embeddings
<PAD>
sushi
rolls
<PAD>
Target Embeddings

Datasets

- SemEval Workshops - customer reviews: Restaurant & Laptop
- **Hard Datasets:** Sentences having multiple aspect labels associated with multiple sentiments

Sentence	aspect category/term	sentiment label
Average to good Thai food, but terrible delivery.	food	positive
Average to good Thai food, but terrible delivery.	delivery	negative

Table 1: Two example sentences in one hard test set of restaurant review dataset of SemEval 2014.

Datasets - ACSA Task

- **Aspects**: food, price, service, ambience, and misc;
- **Sentiment polarities**: positive, negative, neutral, and conflict.
- **Sentence label p**: No. of positive labels - No. of negative labels
  Positive if p>0, Negative if p<0, Neutral if p=0

	Positive		Negative		Neutral		Conflict	
	Train	Test	Train	Test	Train	Test	Train	Test
Restaurant-Large	2710	1505	1198	680	757	241	-	-
Restaurant-Large-Hard	182	92	178	81	107	61	-	-
Restaurant-2014	2179	657	839	222	500	94	195	52
Restaurant-2014-Hard	139	32	136	26	50	12	40	19

Table 2: Statistics of the datasets for ACSA task. The hard dataset is only made up of sentences having multiple aspect labels associated with multiple sentiments.

Datasets - ATSA Task

- Duplicate each sentence n_a times

	Positive		Negative		Neutral		Conflict	
	Train	Test	Train	Test	Train	Test	Train	Test
Restaurant	2164	728	805	196	633	196	91	14
Restaurant-Hard	379	92	323	62	293	83	43	8
Laptop	987	341	866	128	460	169	45	16
Laptop-Hard	159	31	147	25	173	49	17	3

Table 3: Statistics of the datasets for ATSA task.

Implementation Details

- 300-dimension GloVe vectors pre-trained on unlabeled data of 840 billion tokens
- Random initialization - uniform distribution $U(-0.25, 0.25)$
- Adagrad
- Batch size: 32 instances
- Learning Rate: $1e-2$
- Maximal epochs: 30
- 5-fold cross validation

Results - ACSA

Models	Restaurant-Large		Restaurant 2014	
	Test	Hard Test	Test	Hard Test
SVM*	-	-	75.32	-
SVM + lexicons*	-	-	**82.93**	-
ATAE-LSTM	83.91±0.49	66.32±2.28	78.29±0.68	45.62±0.90
CNN	84.28±0.15	50.43±0.38	79.47±0.32	44.94±0.01
GCN	84.48±0.06	50.08±0.31	**79.67±0.35**	44.49±1.52
GCAE	**85.92±0.27**	**70.75±1.19**	79.35±0.34	**50.55±1.83**

Table 4: The accuracy of all models on test sets and on the subsets made up of test sentences that have multiple sentiments and multiple aspect terms. Restaurant-Large dataset is created by merging all the restaurant reviews of SemEval workshops within three years. '*': the results with SVM are retrieved from NRC-Canada (Kiritchenko et al., 2014).

Results - ATSA

Models	Restaurant		Laptop	
	Test	Hard Test	Test	Hard Test
SVM*	77.13	-	63.61	-
SVM + lexicons*	**80.16**	-	**70.49**	-
TD-LSTM	73.44±1.17	56.48±2.46	62.23±0.92	46.11±1.89
ATAE-LSTM	73.74±3.01	50.98±2.27	64.38±4.52	40.39±1.30
IAN	76.34±0.27	55.16±1.97	68.49±0.57	44.51±0.48
RAM	76.97±0.64	55.85±1.60	68.48±0.85	45.37±2.03
GCAE	**77.28±0.32**	**56.73±0.56**	**69.14±0.32**	**47.06±2.45**

Table 5: The accuracy of ATSA subtask on SemEval 2014 Task 4. '*': the results with SVM are retrieved from NRC-Canada (Kiritchenko et al., 2014)

Gating Mechanisms

Gated Tanh Units (**GTU**): $(\mathbf{X} * \mathbf{W} + b) \times \sigma(\mathbf{X} * \mathbf{W}_a + \mathbf{V}\boldsymbol{v}_a + b_a)$

Gated Linear Units (**GLU**): $\tanh(\mathbf{X} * \mathbf{W} + b) \times \sigma(\mathbf{X} * \mathbf{W}_a + \mathbf{V}\boldsymbol{v}_a + b_a)$

Gates	Restaurant-Large		Restaurant 2014	
	Test	Hard Test	Test	Hard Test
GTU	84.62	60.25	79.31	**51.93**
GLU	84.74	59.82	79.12	50.80
GTRU	**85.92**	**70.75**	**79.35**	50.55

Table 7: The accuracy of different gating units on restaurant reviews on ACSA task.

Training Time

- Training time of all models until convergence on a validation set on a desktop machine with a 1080 Ti GPU

Model	ATSA
ATAE	25.28
IAN	82.87
RAM	64.16
TD-LSTM	19.39
GCAE	3.33

Table 6: The time to converge in seconds on ATSA task.

Conclusion

- An efficient CNN with gating mechanisms for ACSA and ATSA tasks.
- GTRU controls the sentiment flow according to the given aspect information
- Performance improvement compared with other neural models by extensive experiments on SemEval datasets.

Future Directions

- LSTM → CNN → CNN with Gating Mechanism
- Transformers with Gating Mechanism for Sentiment Analysis

References

- W. Xue and T. Li, ‘‘Aspect based sentiment analysis with gated convolutional networks,’’ in Proc. ACL, vol. 1, 2018, pp. 2514–2523.
- Maria Pontiki, Dimitrios Galanis, John Pavlopoulos, Haris Papageorgiou, Ion Androutsopoulos, and Suresh Manandhar. 2014. Semeval-2014 task 4: Aspect based sentiment analysis. In SemEval@COLING, pages 27–35, Stroudsburg, PA, USA. Association for Computational Linguistics.
- Dzmitry Bahdanau, Kyunghyun Cho, and Yoshua Bengio. 2014. Neural Machine Translation by Jointly Learning to Align and Translate. In ICLR, pages CoRR abs–1409.0473.
- Yoon Kim. 2014. Convolutional Neural Networks for Sentence Classification. In EMNLP, pages 1746– 1751
- Yequan Wang, Minlie Huang, Xiaoyan Zhu, and Li Zhao. 2016b. Attention-based LSTM for Aspect level Sentiment Classification. In EMNLP, pages 606–615.
- Duyu Tang, Bing Qin, Xiaocheng Feng, and Ting Liu. 2016a. Effective LSTMs for Target-Dependent Sentiment Classification. In COLING, pages 3298– 3307
- A. Kumar, V. T. Narapareddy, V. Aditya Srikanth, L. B. M. Neti and A. Malapati, "Aspect-Based Sentiment Classification Using Interactive Gated Convolutional Network," in IEEE Access, vol. 8, pp. 22445-22453, 2020

Thank You