

Aspect Based Sentiment Analysis using Deep Memory Networks

Andrei Vacariu

Wasifa Chowdhury

Stanley Gan

Outline of Presentation

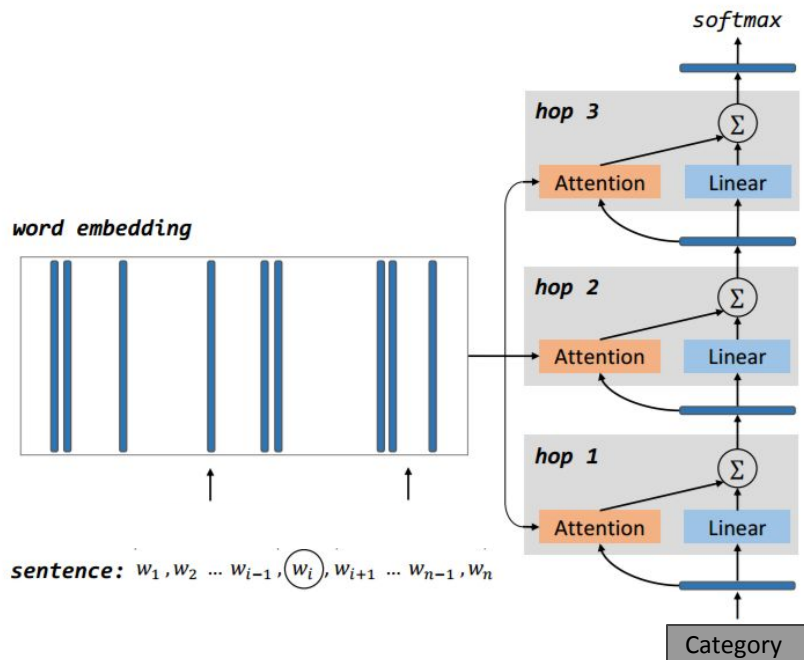
- Review of task
- Network architecture
- Approaches
- Results and comparison
- Future work
- References

Review of Our Task

Semeval Task 4, Subtask 4: Aspect Category Polarity

- Given a set of categories and a review, determine the polarity of each category
- Example
 - Given categories: Food, price
 - Given review: “The restaurant was **too expensive**, but the **menu was great**”
 - Food: **Positive**, Price: **Negative**
- 4 classes of sentiment: Positive, Neutral, Negative, Conflict
- Dataset
 - Restaurant reviews: 3041 training data, 100 test data
 - Laptop reviews: 3045 training data, 100 test data
- Evaluation
 - Accuracy: number of correctly predicted polarity labels/ total number of labels

Network Architecture: Memory Networks



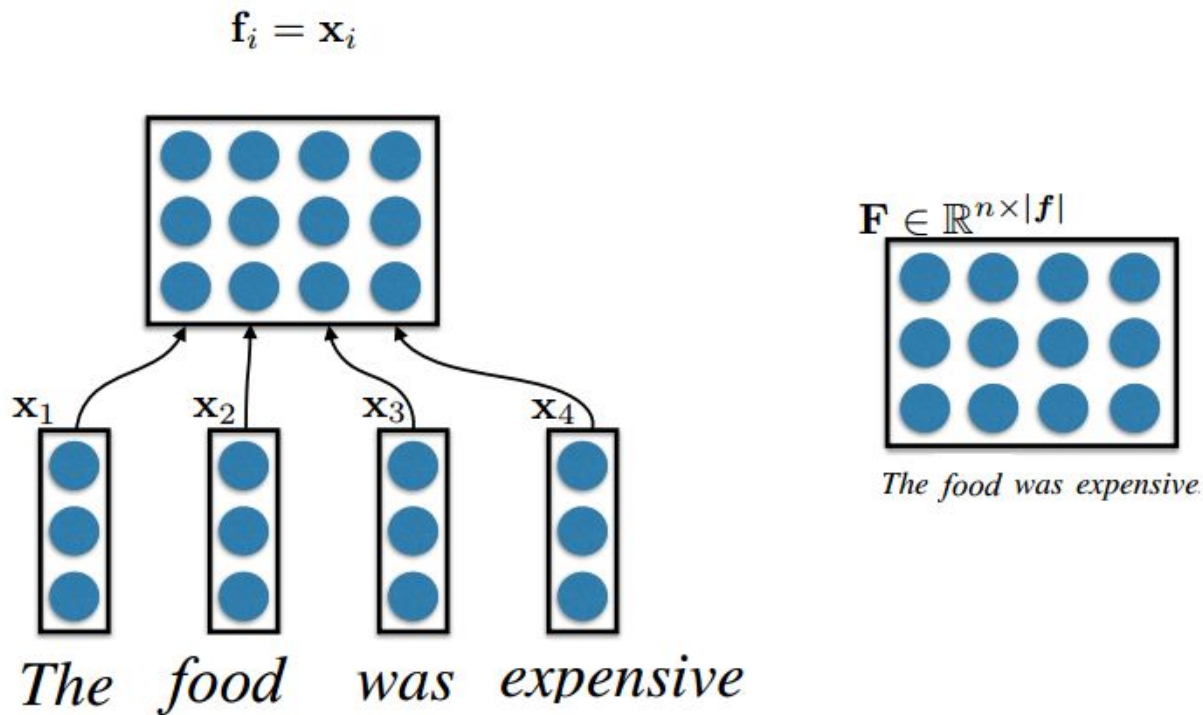
- Aspect category instead of aspect term
- Features of Memory Networks
 - Explicit memory
 - Attention layers and hops
- Using pre-trained GloVe vectors for initial word embeddings

Figure 1: An illustration of our deep memory network with three computational layers (hops) for aspect level sentiment classification.

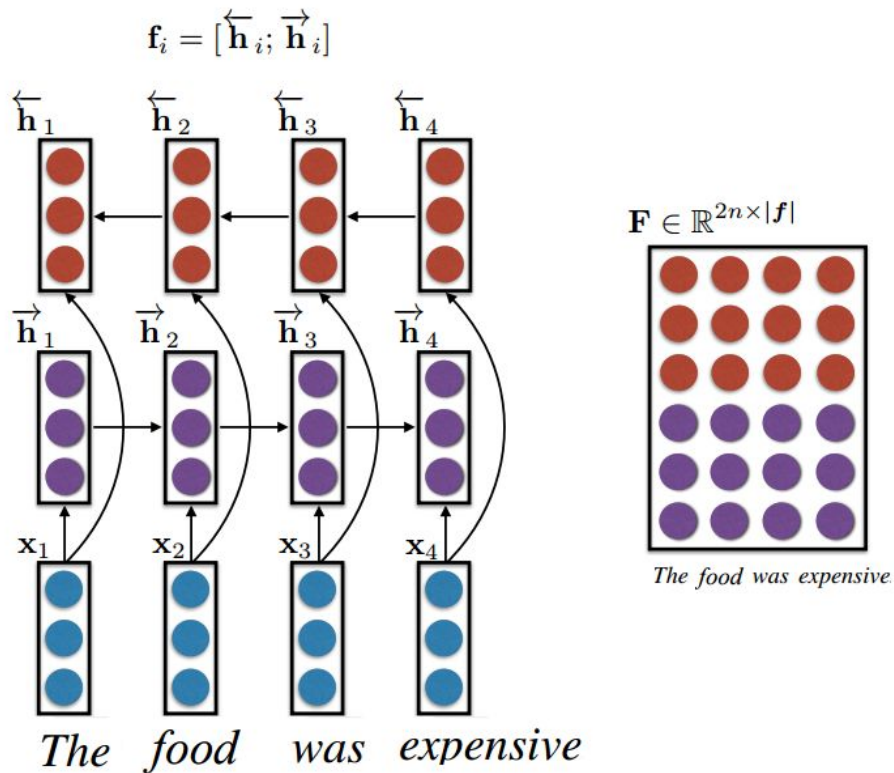
Our Approaches

- Bidirectional LSTM for input representations
- Incorporate aspect into memory vectors
- Linear mapping from pre-trained GloVe vectors to context vectors
- Local attention mechanism
- Incorporate aspect into hop output

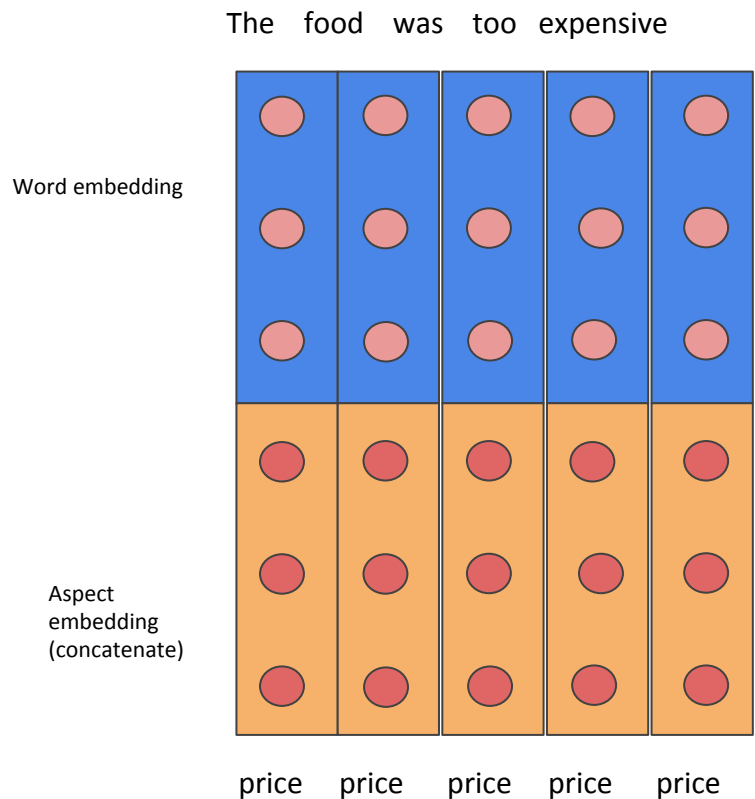
Input Representations



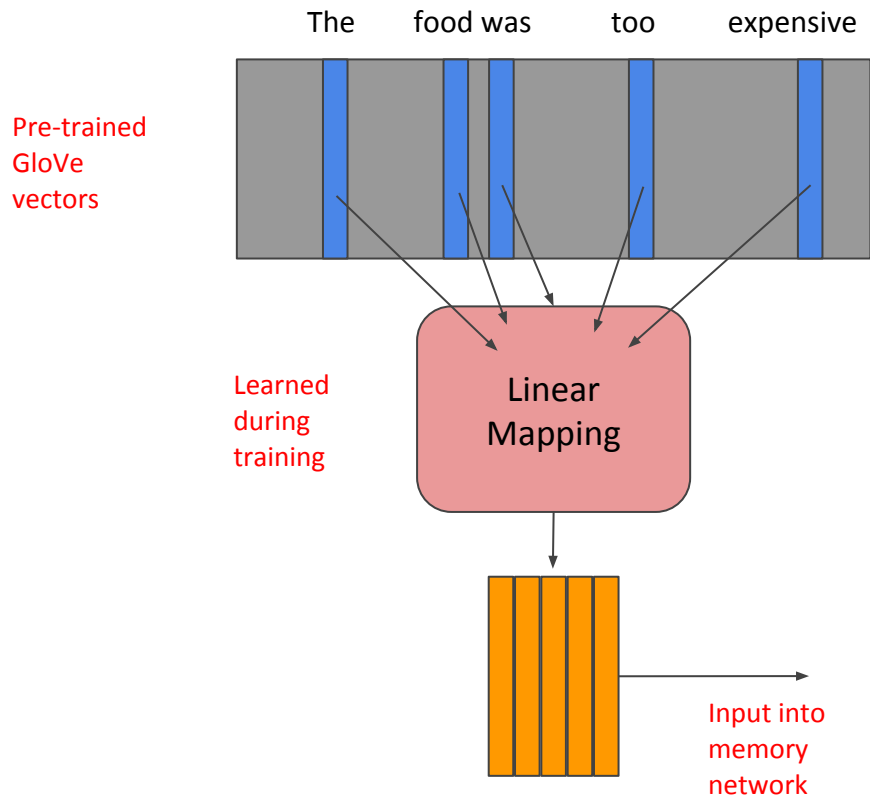
Input Representations: Bidirectional LSTM



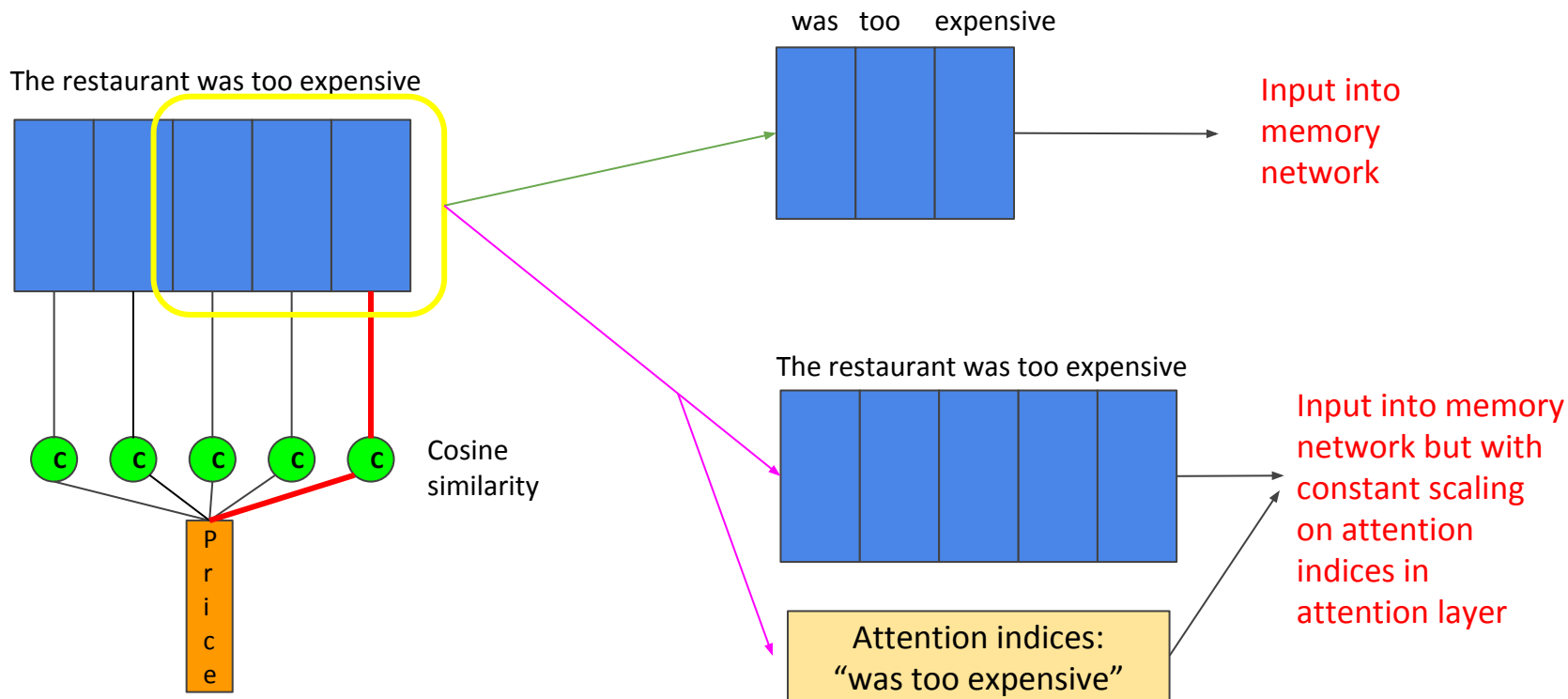
Input Representations: Incorporating Aspect



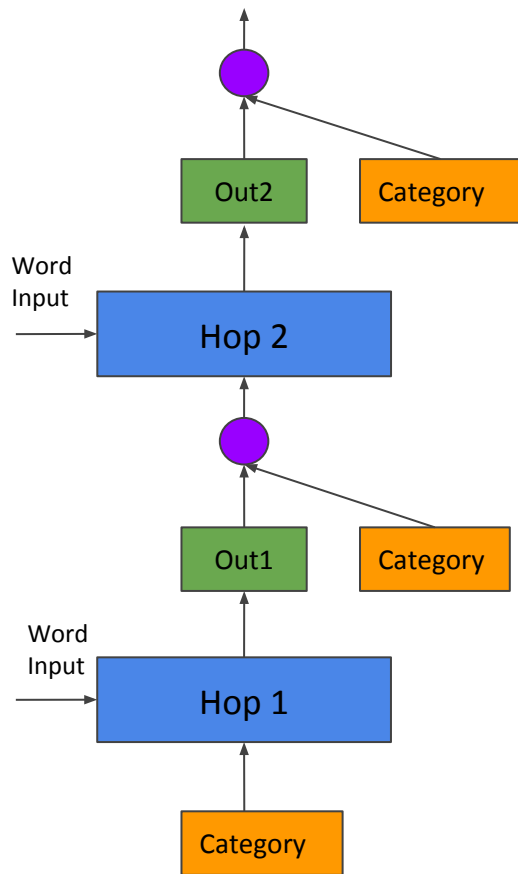
Linear Mapping from GloVe to Context



Local Attention Mechanism



Incorporating Aspect to Hop Output



● = concatenate/linear combination

Concatenate

- Concatenate hop output and category
- Linear layer

Linear Combination

- $\text{New_output}_k = \alpha_k * \text{Category} + (1 - \alpha_k) * \text{Out}_k$
- α_k is learned

Results on Different Configurations

	Laptop			Restaurant		
	2 classes	3 classes	4 classes	2 classes	3 classes	4 classes
BiLSTM	85.93	72.41	66.53	88.93	83.7	75.59
BiLSTM+AC	85.93	71.68	68.28	88.80	83.7	78.42
BiLSTM + AS=2	87.24	72.85	68.44	88.41	84.04	79.2
BiLSTM+AC+AS=2	87.24	73.44	67.81	88.54	84.8	79.49
LA	86.46	69.53	64.69	88.15	79.46	75.59
LA+AC	84.63	69.53	64.38	86.59	80.35	75.10
HopLC + LA	73.44	23.04	63.75	75.78	69.08	64.06
HopLC + LA + AC	73.43	-	61.56	75.78	69.08	64.06
HopConcat + LA	85.93	69.14	68.81	88.93	81.03	71.93
HopConcat + LA + AC	85.16	69.72	63.75	88.41	81.14	72.66
BiLSTM + HopLC + AS=2	-	20.31	51.72	78.71	69.04	64.06
BiLSTM + HopConcat + AS=2	86.72	70.70	63.96	89.45	81.47	75.10

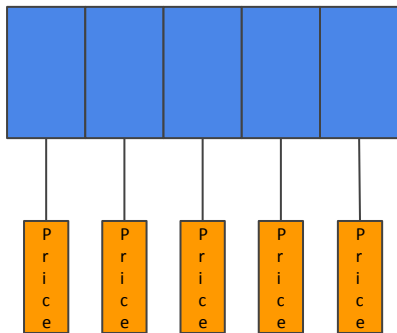
Our Best Configuration vs. State of the Art

2 classes		
	Laptop	Restaurant
Our best	87.24	89.45
ATAE-LSTM	87.6	90.9
AE-LSTM	87.4	89.6

3 classes		
	Laptop	Restaurant
Our best	73.44	84.8
ATAE-LSTM	68.7	77.2
AE-LSTM	68.9	76.6

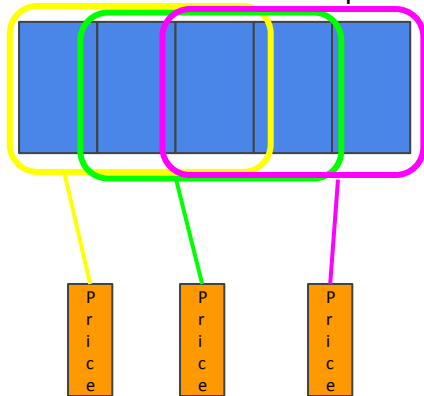
Future Potential Approaches

The restaurant was too expensive



Semantic
relatedness
between
category and
each word

The restaurant was too expensive



Semantic
relatedness
between
category and
multiple words

1. Use GloVe vectors trained on twitter data
2. ConvNet for attention layer

References

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- Dataset: SemEval(Semantic Evaluation) 2014
- Partially implemented TensorFlow code for Deep Memory Networks: https://github.com/ganeshjawahar/mem_absa

Thank you for listening

Q&A?