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Discovering Protagonist of Sentiment with Aspect Reconstructed Capsule Network

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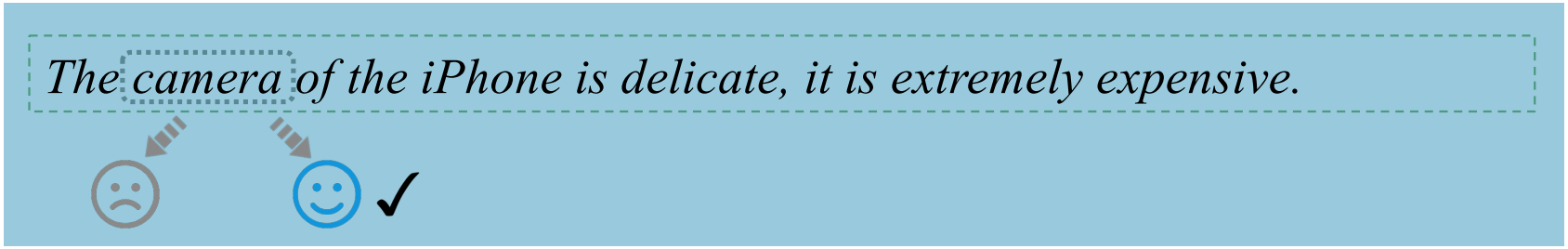
PART ONE

Introduction

Definition

As an essential sub-task of aspect-level sentiment analysis, Aspect-Term level Sentiment Analysis (ATSA) aims to predict the sentiment polarity with respect to given targets appearing in the text.

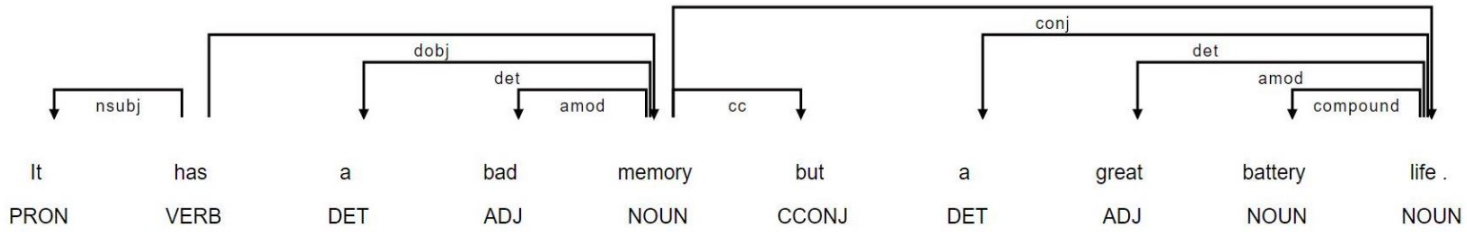


ATSA may ask the sentiment polarity towards the given target “camera”.

Existing Methods

- Conventional approaches incorporated linguistic knowledge into the models.

  Conventional approaches incorporated linguistic knowledge, such as sentiment-lexicon, syntactic parser, and negation words, etc., and feature engineering into the models to facilitate the prediction accuracy.

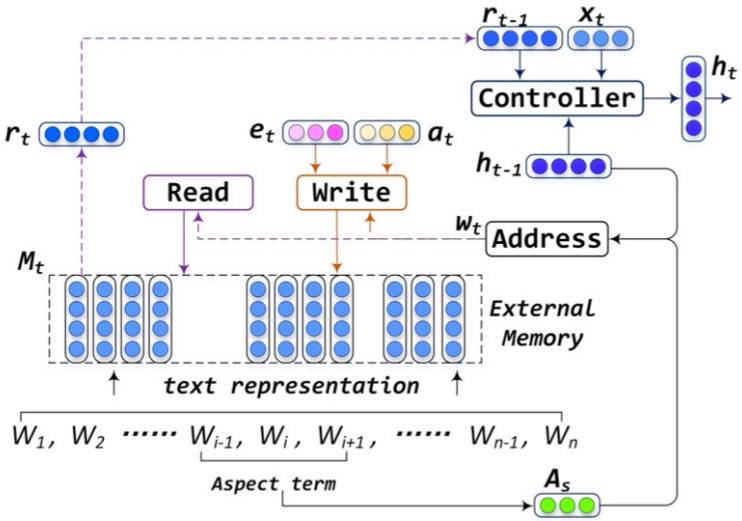


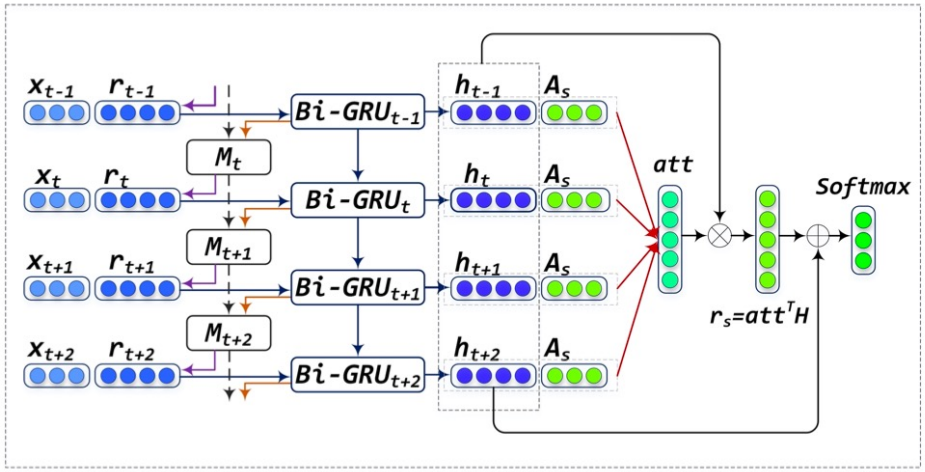
Aspect: memory Sentiment: Negative

Existing Methods

- Methods using supervised deep neural networks.

Mao, Li, Wang, Zhang, Peng, He and Wang: Aspect-Based Sentiment Classification with Attentive Neural Turing Machines. In(IJCAI2019)

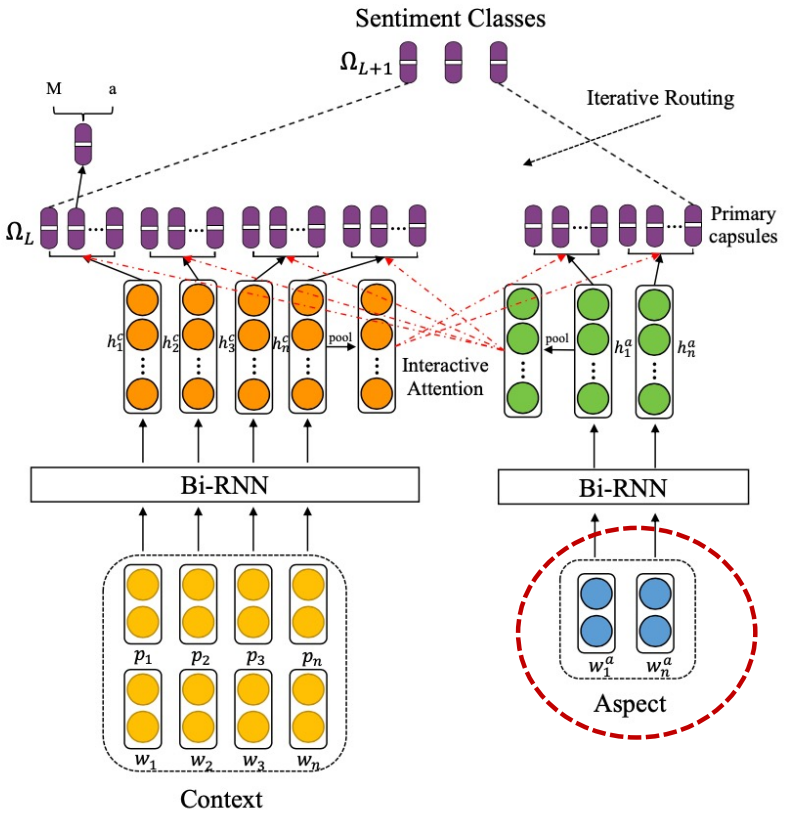




Challenges

- Fully labeled aspect terms and their locations in sentence are explicitly required in both training and test process for recent methods.

Du, Sun, Wang, Qi, Liao, Xu, Liu: Capsule Network with Interactive Attention for Aspect-Level Sentiment Classification. In: EMNLP (2017)



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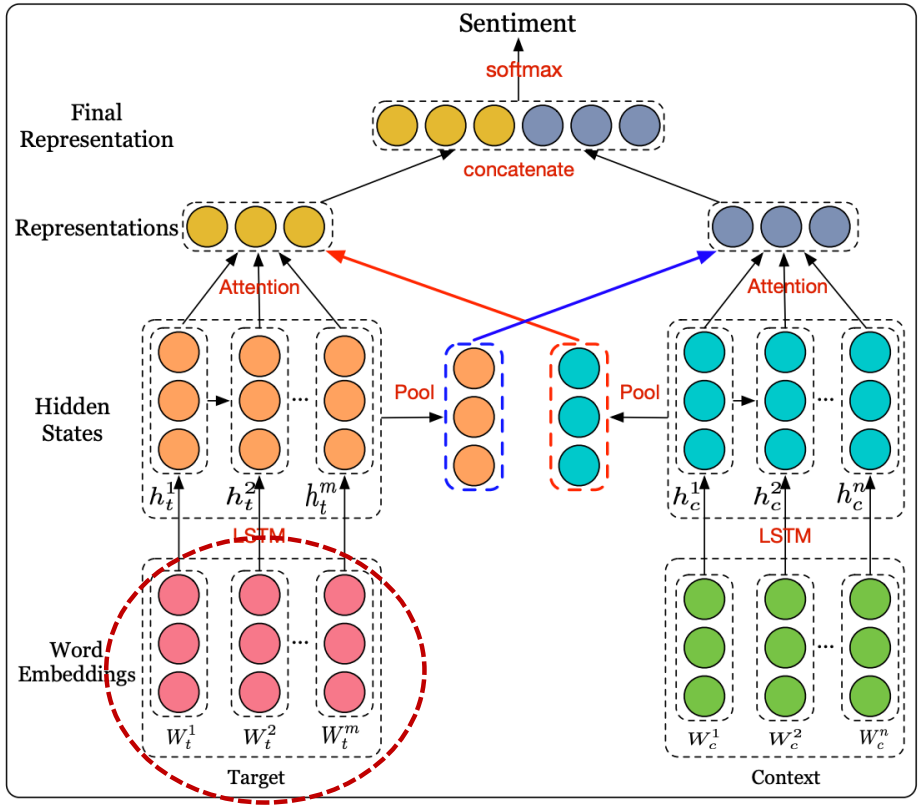
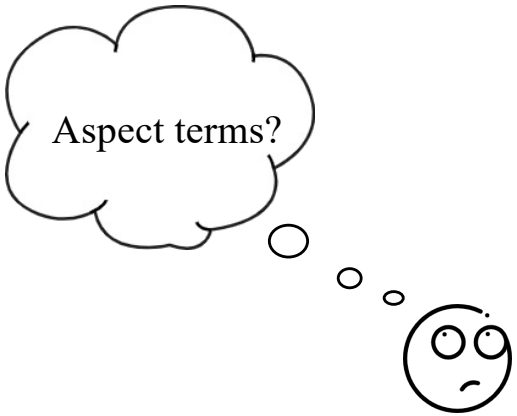
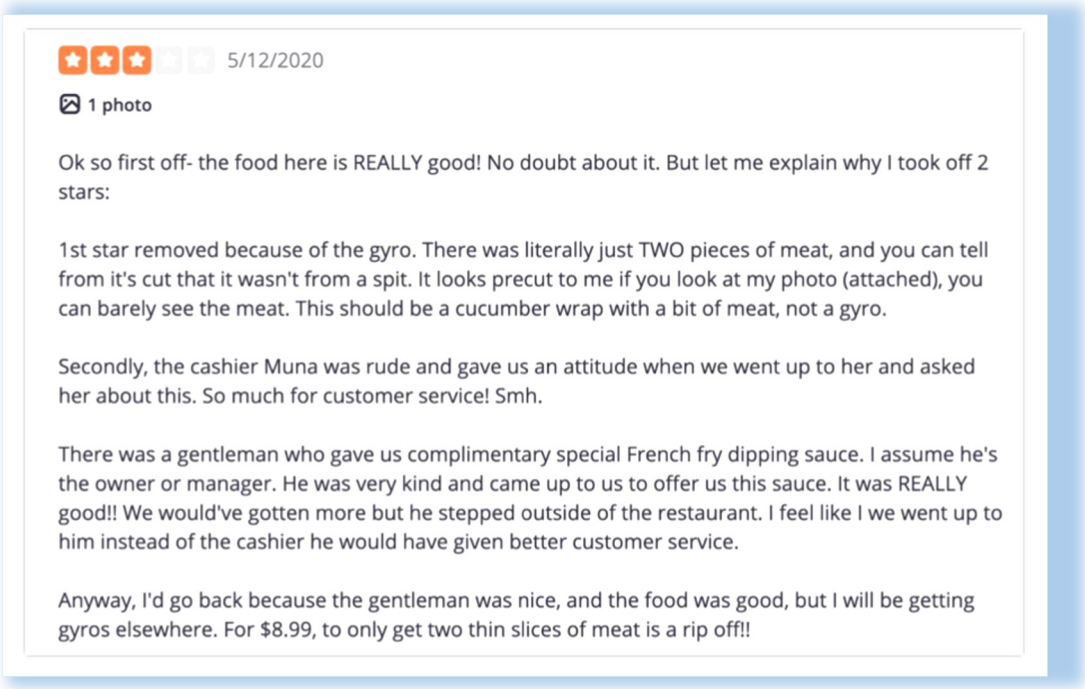
Ma, D., Li, S., Zhang, X., Wang, H.: Interactive attention networks for aspect-level sentiment classification. In: IJCAI (2017)



Challenges

- However, the labeled aspect terms are often difficult to obtain in the practical applications.





5/12/2020

1 photo

Ok so first off- the food here is REALLY good! No doubt about it. But let me explain why I took off 2 stars:

1st star removed because of the gyro. There was literally just TWO pieces of meat, and you can tell from it's cut that it wasn't from a spit. It looks precut to me if you look at my photo (attached), you can barely see the meat. This should be a cucumber wrap with a bit of meat, not a gyro.

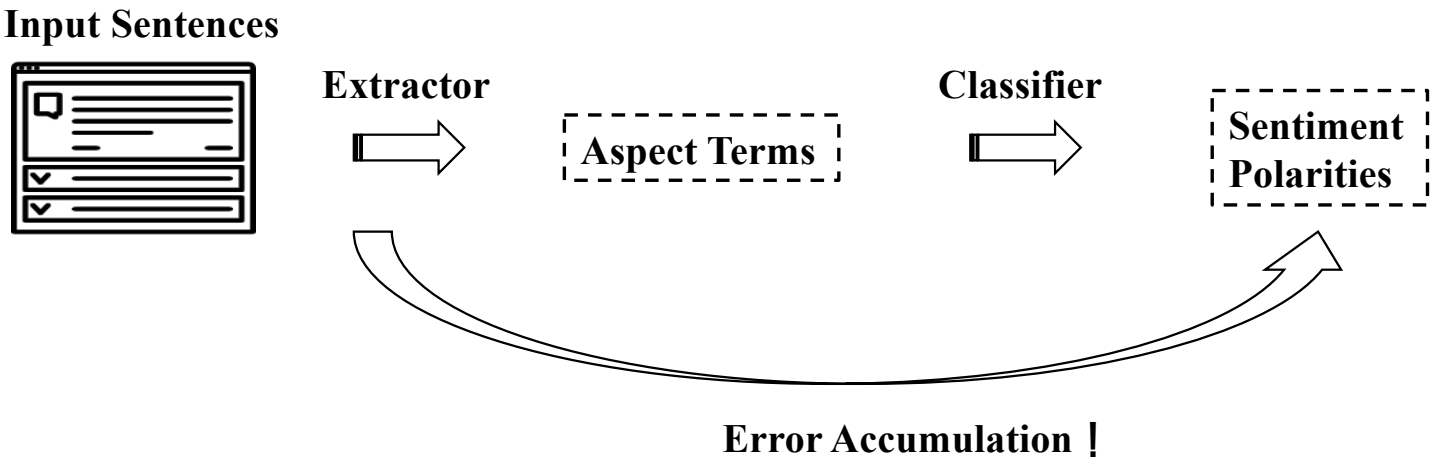
Secondly, the cashier Muna was rude and gave us an attitude when we went up to her and asked her about this. So much for customer service! Smh.

There was a gentleman who gave us complimentary special French fry dipping sauce. I assume he's the owner or manager. He was very kind and came up to us to offer us this sauce. It was REALLY good!! We would've gotten more but he stepped outside of the restaurant. I feel like I we went up to him instead of the cashier he would have given better customer service.

Anyway, I'd go back because the gentleman was nice, and the food was good, but I will be getting gyros elsewhere. For $8.99, to only get two thin slices of meat is a rip off!!

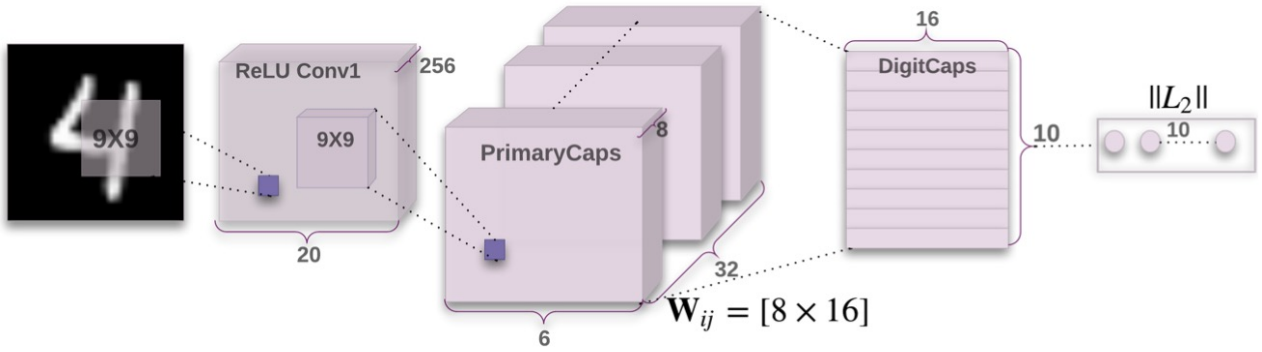
Challenges

- To acquire aspect terms on predicted sentences, automatic aspect term detection may lead to error accumulation, and manually identifying is inefficient even infeasible.



Caspule Network

- Capsule Network is first proposed for image processing. The length of a capsule denotes the probability that the entity exists. And its orientation can encode the properties of the entity, which can be used for the reconstruction of the initial entities.



Contributions

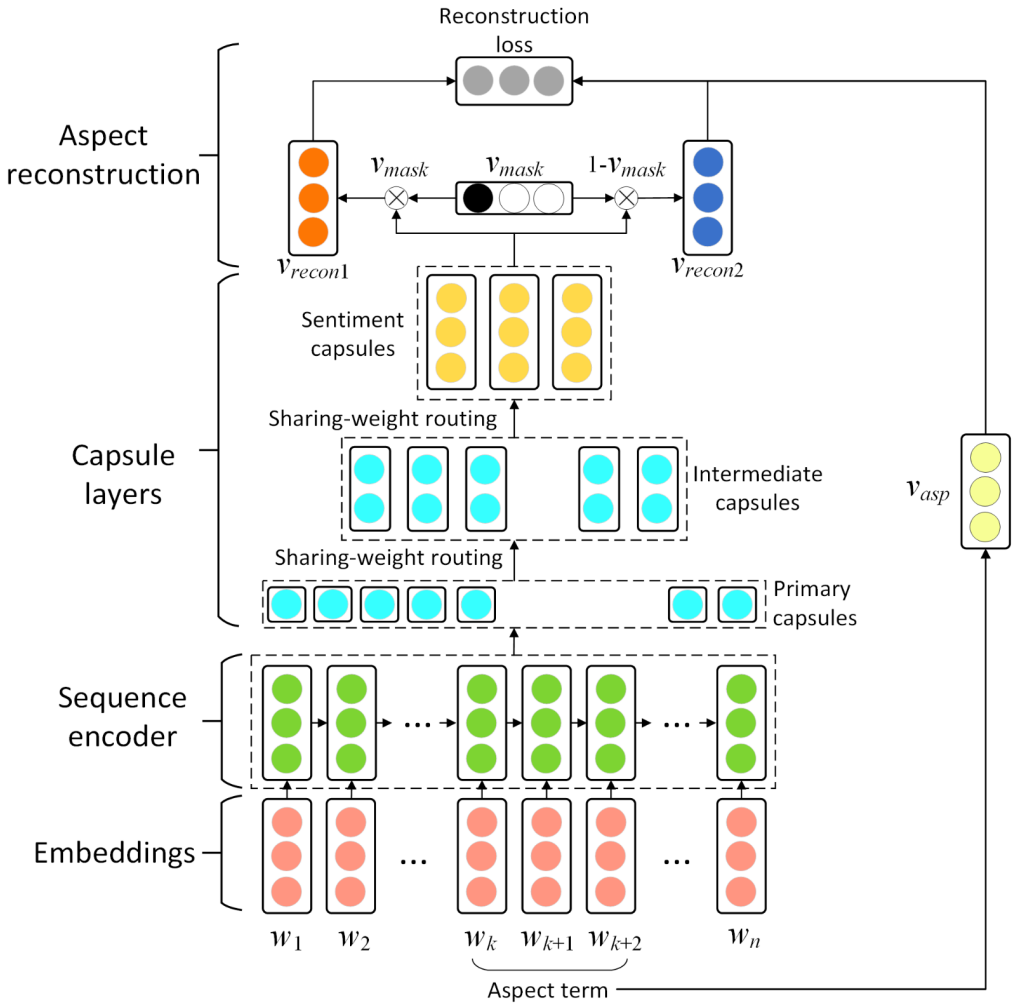
- Inspired by the previous capsule network, we propose CAPSAR (CAPsule network with Sentiment-Aspect Reconstruction) framework by leveraging capsules to denote sentiment categories and enforce the potential aspect information as the corresponding properties.
- To save computational cost, we propose a share-weight routing for capsule network and devise a reconstruction mechanism to reconstruct aspect terms with sentiment capsules.
- We evaluate the proposed model in three widely used benchmarks. The results show the model can surpass SOTA baselines in standard ATSA tasks.

PART TWO

Model

Model Overview

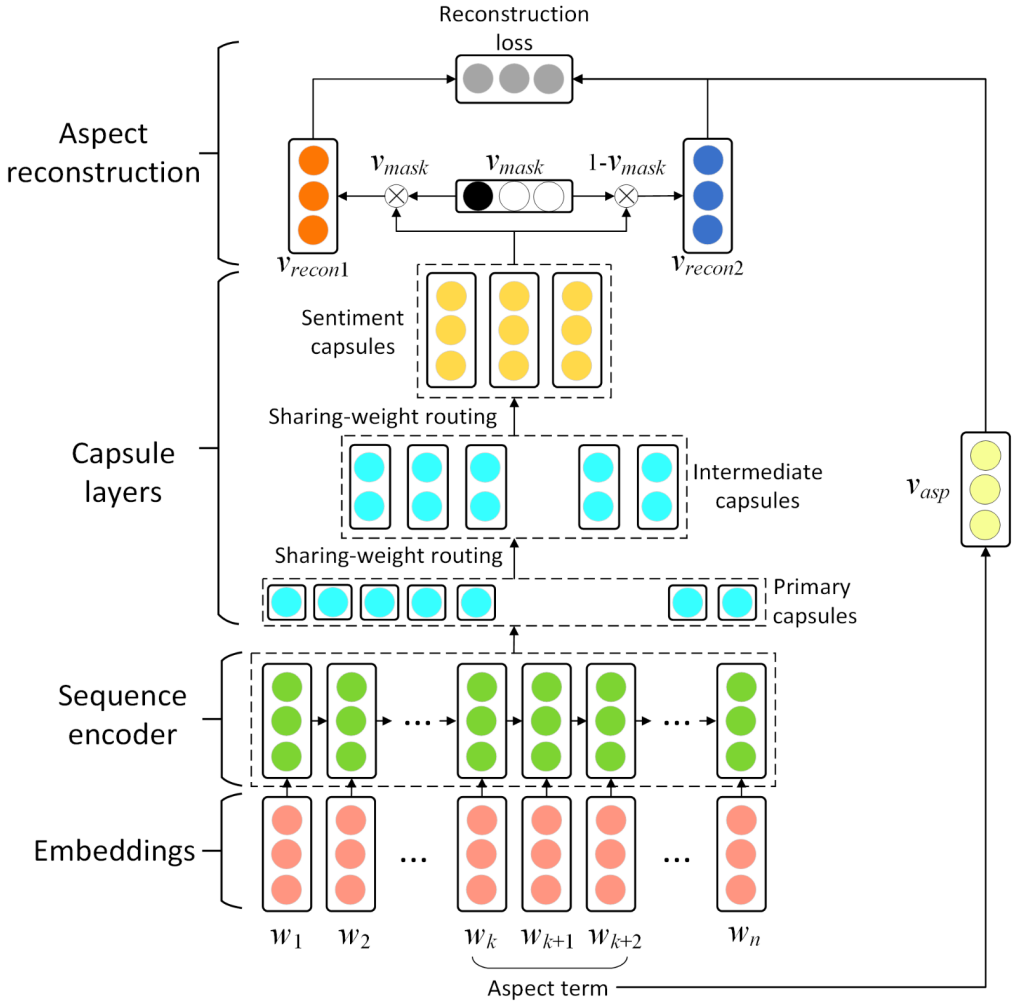
The overall architecture is shown in the right figure. It starts with an embedding representation of words in the given sentence. Then the word embeddings are encoded by a sentence encoder to construct a sentence representation.



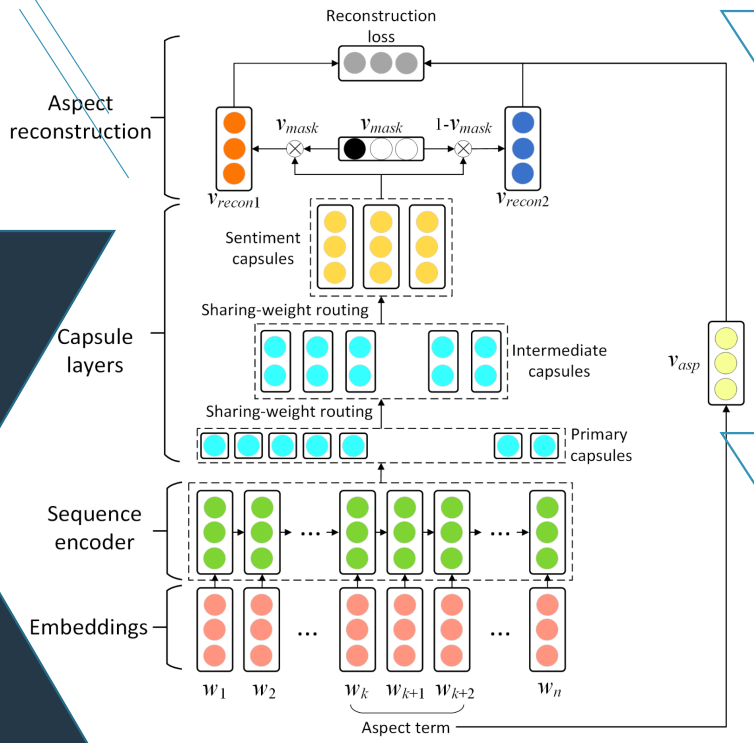
Model Overview

Next, the output of the sequence encoder is fed into a 3-layer capsule network.

The up most capsule layer contains three sentiment capsules, which will be used to reconstruct aspect terms during aspect reconstruction.



Training with Aspect Reconstruction



- Maximize the length of the correct sentiment capsules and we use a margin loss for every given sentence.

$$L_1^{(i)} = v_{mask}^{(i)} \max(0, m^+ - ||v_{prob}^{(i)}||)^2 + (1 - v_{mask}^{(i)}) \max(0, ||v_{prob}^{(i)}|| - m^-)^2$$

- Minimize the distance between reconstructed aspect and the gold aspect by a specifically designed reconstruction loss.

$$L_2^{(i)} = -v_{asp}^{(i)} \frac{v_{recon1}^{(i)}}{||v_{recon1}^{(i)}||} + v_{asp}^{(i)} \frac{v_{recon2}^{(i)}}{||v_{recon2}^{(i)}||}$$

PART THREE

Experiment

Dataset

Three widely used benchmark datasets are adopted in the experiment. Though these three benchmarks are not large-scale datasets, they are the most popular and fair test beds for recent methods.

Dataset	Restaurant		Laptop		Twitter	
	Train	Test	Train	Test	Train	Test
Neg.	807	196	870	128	1562	173
Neu.	637	196	464	169	3124	346
Pos.	2164	728	994	341	1562	173

Main Results

We compare our method with several SOTA approaches. From the following table, we can observe that our proposed model has clear advantages over baselines except the F1 score on Laptop. In addition, the CAPSAR-BERT further improves the performance of BERT.

	Models	Restaurant		Laptop		Twitter	
		Accuracy	F1	Accuracy	F1	Accuracy	F1
Baselines	ATAE-LSTM	0.7720	NA	0.6870	NA	NA	NA
	TD-LSTM	0.7560	NA	0.6810	NA	0.6662*	0.6401*
	IAN	0.7860	NA	0.7210	NA	NA	NA
	MemNet(3)	0.8032	NA	0.7237	NA	0.6850*	0.6691*
	RAM(3)	0.8023	0.7080	0.7449	0.7135	0.6936	0.6730
	MGAN	0.8125	0.7194	0.7539	**0.7247**	0.7254	0.7081
	ANTM	0.8143	0.7120	0.7491	0.7142	0.7011	0.6814
Ablation Test	CAPSAR w/o R	0.8185	0.7216	0.7484	0.7039	0.7255	0.7067
	CAPSAR w/o H	0.8188	0.7226	0.7461	0.7054	0.7298	0.7080
	CAPSAR	**0.8286**	**0.7432**	**0.7593**	0.7221	**0.7368**	**0.7231**
Combine BERT	BERT	0.8476	0.7713	0.7787	0.7371	0.7537	0.7383
	CAPSAR-BERT	**0.8594**	**0.7867**	**0.7874**	**0.7479**	**0.7630**	**0.7511**

Case Study

Sentence	CAPSAR	ANTM	MGAN	RAM
1. The [**chocolate raspberry cake**]$_{\text{Pos}}$ is heavenly - not too sweet , but full of [**flavor**]$_{\text{Pos}}$.	(Pos,Pos)	(Pos,Neg✗)	(Neg✗,Pos)	(Pos,Neg✗)
2. Not only was the sushi fresh , they also served other [**entrees**]$_{\text{Neu}}$ allowed each guest something to choose from and we all left happy (try the [**duck**]$_{\text{Pos}}$!	(Neu,Pos)	(Pos✗,Pos)	(Pos✗,Pos)	(Pos✗,Pos)
3. The [**baterry**]$_{\text{Pos}}$ is very longer .	Pos	Neg✗	Pos	Neg✗
4. [**Startup times**]$_{\text{Neg}}$ are incredibly long : over two minutes.	Neg	Neg	Pos✗	Pos✗
5. However I chose two day [**shipping**]$_{\text{Neg}}$ and it took over a week to arrive.	Neu✗	Neu✗	Pos✗	Pos✗

PART FOUR

Conclusion

- **Task**: aspect-term level sentiment analysis.
- **Model**: we proposed a CAPSAR which is piled up hierarchical capsule layers equipped with a shared-weight routing algorithm to capture key features for predicting sentiment polarities.
- **Experiment**: experimental results on three real-world benchmarks demonstrate the effectiveness of the proposed model.

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Thanks for listening~

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