Improving Review Representations with User Attention and Product Attention for Sentiment Classification

Zhen Wu, Xin-Yu Dai, Cunyan Yin, Shujian Huang, Jiajun Chen

National Key Laboratory for Novel Software Technology, Nanjing University, Nanjing, 210023, China

Collaborative Innovation Center of Novel Software Technology and Industrialization, Nanjing, 210023, China

wuz@nlp.nju.edu.cn,{daixinyu,yincy,huangsj,chenjj}@nju.edu.cn

Motivation

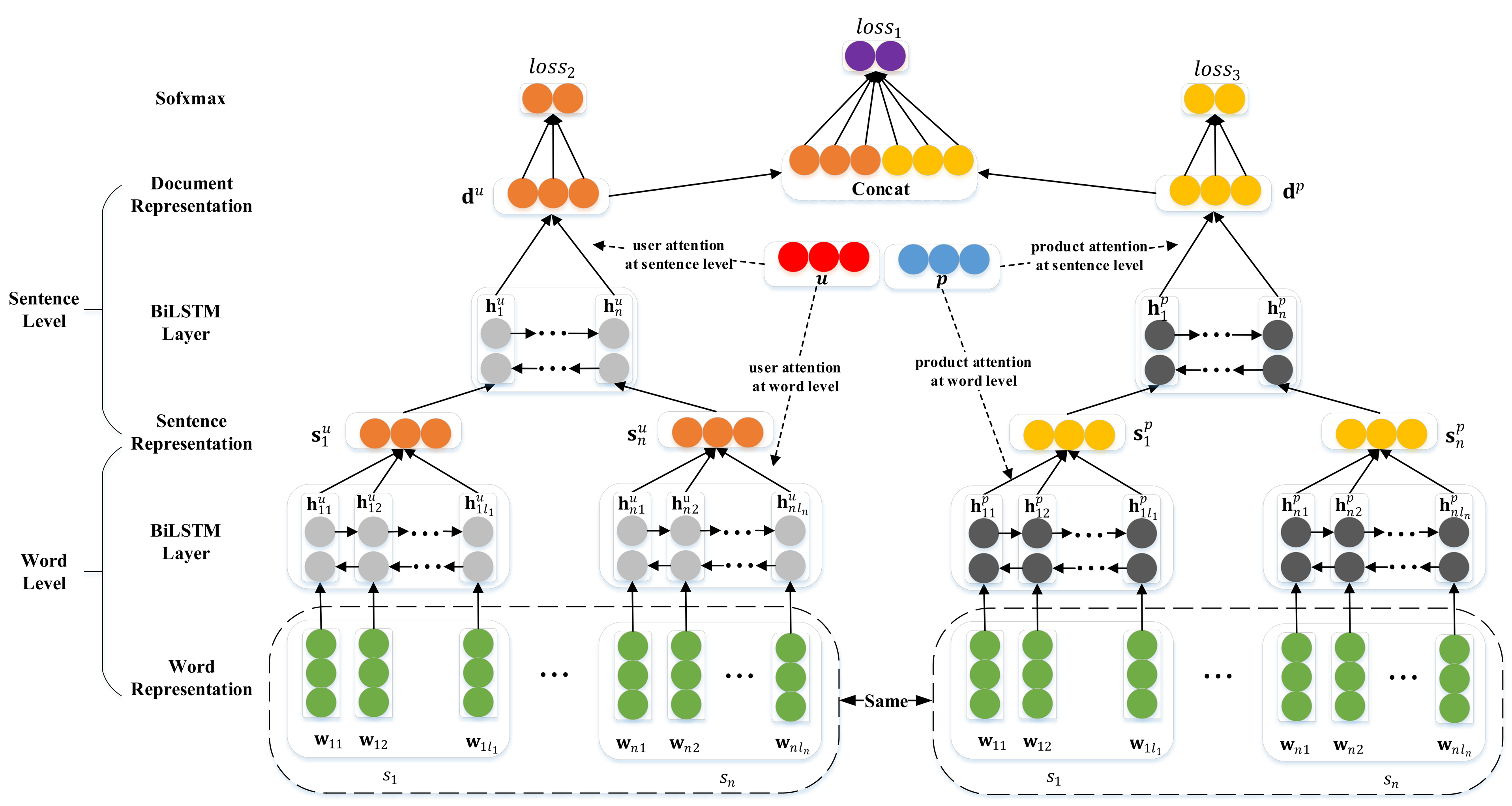
- Previous Methods
  - Incorporate user and product information into sentiment classification indistinguishably.
- Our Observation
  - In reviews, some words or sentences show strong user's preference, and some others tend to indicate product's characteristic.
  - Opinions (rational evaluation) are more related to products and emotions (emotional evaluation) are more centered on users.

> The bar area is definitely good 'people watching' and i love the modern contemporary d´ecor.
>
> ■ user's emotion (emotional evaluation) ■ product's characteristic (rational evaluation)

- Idea
  - Use attention mechanism to model review representations from two views: from the user and product perspective respectively.

Proposed Model

- Framework



- Hierarchical Attention
  - user information
  - product information
- Combined Strategy
  - Add a softmax classifier respectively to three review representations: d_u, d_p, and [d_u; d_p].
  - The loss_2 and loss_3 are designed to learn to review representations from two orthogonal views, from users and products, respectively.
- Loss Function

$$L = \lambda_1 loss_1 + \lambda_2 loss_2 + \lambda_3 loss_3$$

Experiments

- Datasets

Datasets	#classes	#docs	#users	#products	#docs/user	#docs/product	#sens/doc	#words/sen
IMDB	10	84,919	1,310	1,635	64.82	51.94	16.08	24.54
Yelp 2013	5	78,966	1,631	1,633	48.42	48.36	10.89	17.38
Yelp 2014	5	231,163	4,818	4,194	47.97	55.11	11.41	17.26

- Metrics
  - Accuracy $Accuracy = \frac{T}{N}$
  - RMSE $RMSE = \sqrt{\frac{\sum_{i=1}^{N}(gd_i - pr_i)^2}{N}}$

- Effect of User and Product Information

Models	IMDB		Yelp 2013		Yelp 2014	
	Acc.	RMSE	Acc.	RMSE	Acc.	RMSE
NSC+LA(BiLSTM)	0.490	1.325	0.638	0.691	0.646	0.678
HUA	0.521	1.300	0.649	0.691	0.663	0.661
HPA	0.493	1.326	0.641	0.681	0.646	0.678
HUAPA	**0.546**	**1.245**	**0.678**	**0.642**	**0.686**	**0.626**

▲ NSC+LA only uses review text. Besides local text, HUA uses user information, HPA incorporates product information, and HUAPA considers user and product information meanwhile.

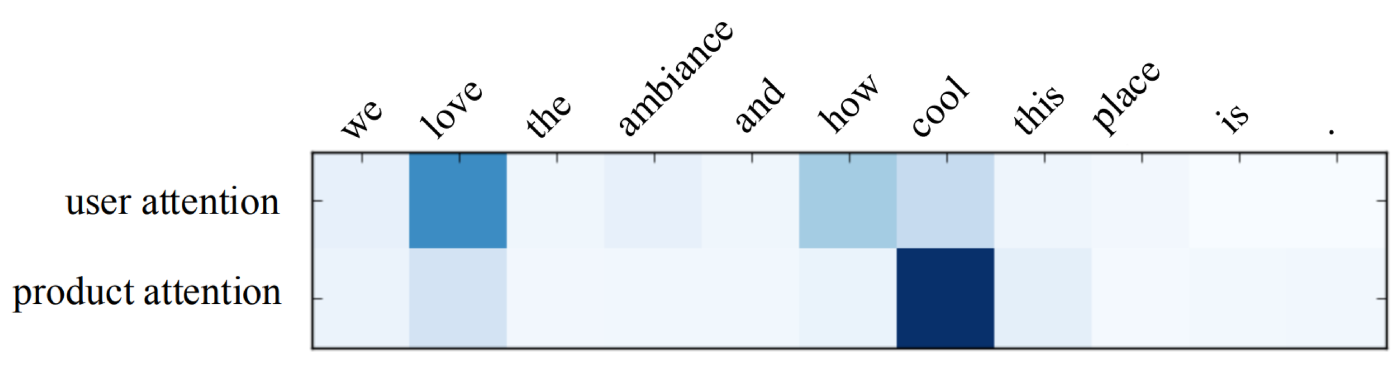
- Effect of the Different Weighted Loss

λ_1	λ_2	λ_2	IMDB		Yelp 2013		Yelp 2014	
			Acc.	RMSE	Acc.	RMSE	Acc.	RMSE
1.0	0.0	0.0	0.538	1.229	0.669	0.658	0.675	0.647
0.7	0.3	0.0	0.541	1.239	0.672	0.644	0.680	0.641
0.7	0.0	0.3	0.540	1.287	0.675	0.646	0.679	0.633
0.4	0.3	0.3	**0.546**	**1.245**	**0.678**	**0.642**	**0.686**	**0.626**

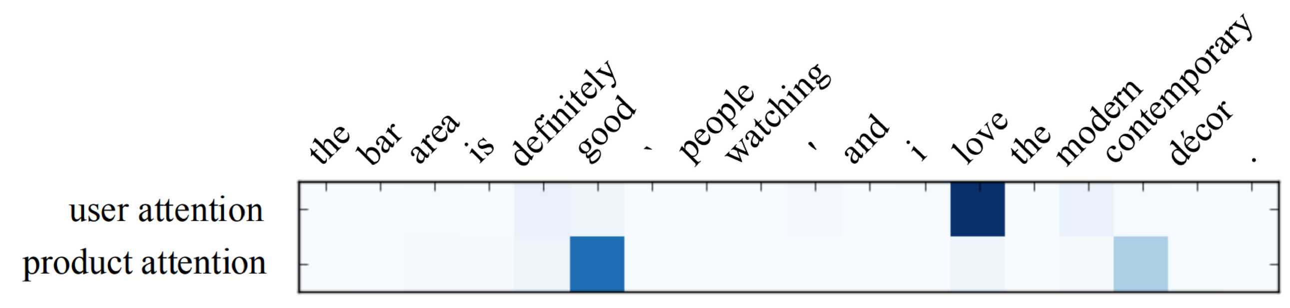
- Overall Results

Models	IMDB		Yelp 2013		Yelp 2014	
	Acc.	RMSE	Acc.	RMSE	Acc.	RMSE
Models without user and product information						
Majority	0.196	2.495	0.411	1.060	0.392	1.097
Trigram	0.399	1.783	0.569	0.814	0.577	0.804
TextFeature	0.402	1.793	0.556	0.845	0.572	0.800
AvgWordvec+SVM	0.304	1.985	0.526	0.898	0.530	0.893
SSWE+SVM	0.312	1.973	0.549	0.849	0.557	0.851
Paragraph Vector	0.341	1.814	0.554	0.832	0.564	0.802
RNTN+Recurrent	0.400	1.764	0.574	0.804	0.582	0.821
UPNN(CNN and no UP)	0.405	1.629	0.577	0.812	0.585	0.808
NSC	0.443	1.465	0.627	0.701	0.637	0.686
NSC+LA	0.487	1.381	0.631	0.706	0.630	0.715
NSC+LA(BiLSTM)	0.490	1.325	0.638	0.691	0.646	0.678
Models with user and product information						
Trigram+UPF	0.404	1.764	0.570	0.803	0.576	0.789
TextFeature+UPF	0.402	1.774	0.561	1.822	0.579	0.791
JMARS	N/A	1.773	N/A	0.985	N/A	0.999
UPNN(CNN)	0.435	1.602	0.596	0.784	0.608	0.764
UPNN(NSC)	0.471	1.443	0.631	0.702	N/A	N/A
LUPDR	0.488	1.451	0.639	0.694	0.639	0.688
NSC+UPA	0.533	1.281	0.650	0.692	0.667	0.654
NSC+UPA(BiLSTM)	0.529	1.247	0.655	0.672	0.669	0.654
HUAPA	**0.550**	**1.185**	**0.683**	**0.628**	**0.686**	**0.626**

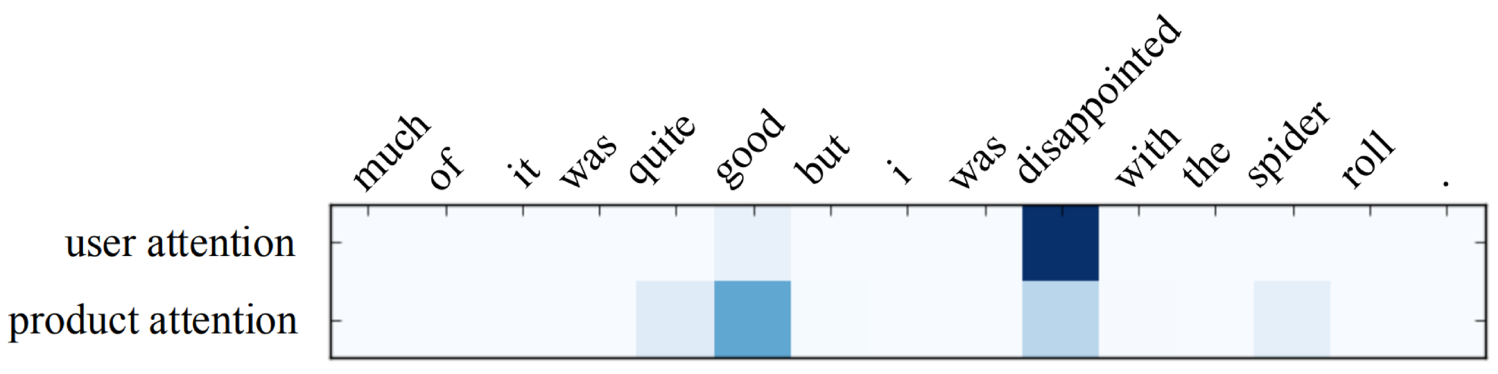
Case Study for Visualization of Attention



review 1: we love the ambiance and how cool this place is.



review 2: the bar area is definitely good `people watching' and i love the modern contemporary décor.



review 3: much of it was quite good but I was disappointed with the spider roll.

▲ In review 3, the word "good" indicates the product's positive characteristic, and the word "disappointed" shows user's negative sentiment. Our model catches the inconsistency between user's emotion and product's characteristic.