Capturing User and Product Information for Sentiment Classification via Hierarchical Separated Attention and Neural Collaborative Filtering

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Motivation

Sentiment classification which aims to predict a user's sentiment about a product is becoming more and more useful and important. Some neural network methods achieved improvement by capturing user and product information.

However, these methods fail to incorporate user preferences and product characteristics reasonably and effectively. What's more, these methods all only use the explicit influences observed in texts and ignore the implicit interaction influences between user and product which cannot be observed in texts. In this paper, we propose a novel neural network model **HUPSA-NCF(Hierarchical User Product Separated Attention and Neural Collaborative Filtering Net- work)** to address these issues.

The Proposed Model

1. Task Formalizations

We suppose U,P,D is the set of users,products and review documents respectively. A review d ∈ D which written by u ∈ U for p ∈ P consists of n sentences {s1, s2, ...sn} and the i−th sentence si consists of li words {w1i , w2i , ..., wi }. Then our task can be formalized as follows: a user u writes a review d for p and give a rating r, we should predict the rating r based on the information of (d, u, p).

2. Model Architecture

The architecture of HUPSA-NCF model is shown in Fig. 1. The model consists of two components: hierarchical user product separated attention network(HUPSA) and neural collaborative filtering network(NCF).

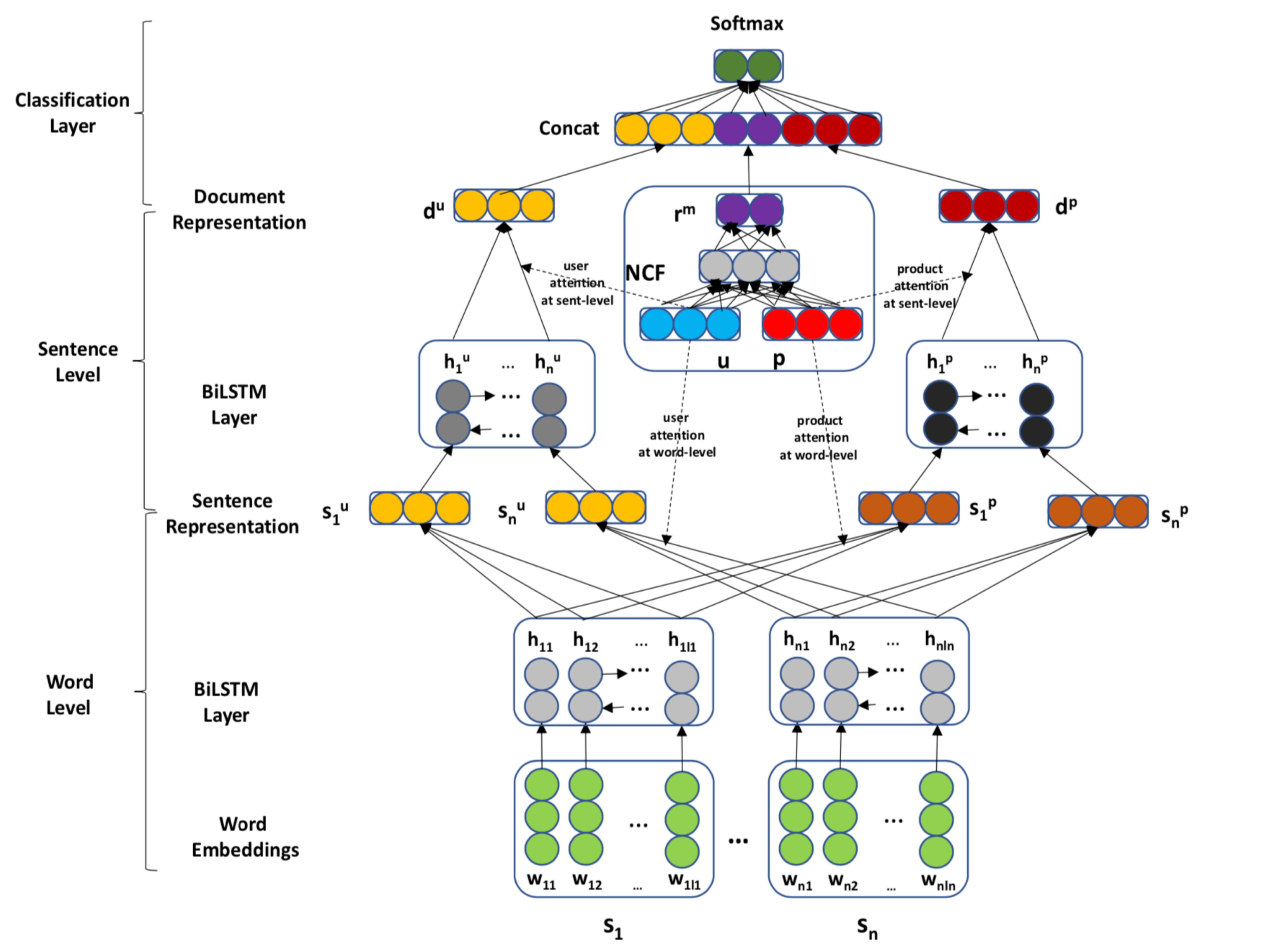

Fig. 1. The architecture of Hierarchical User Product Separated Attention and Neural Collaborative Filtering Network(HUPSA-NCF).

HUPSA-NCF:

- HUPSA is used to incorporate user preferences and product characteristics into text representations. HUPSA applies BiLSTM to encode the review in word-level and sentence-level. To incorporate user and product information, it uses hierarchical user attention and product attention separately to get user-specific text representation and product-specific text representation respectively.
- NCF applies a multilayer perception (three-layers perception in experiments) to capture and encode the implicit interaction representation between user and product.
- Finally we concatenate user-specific text representation, product-specific text representation and implicit interaction representation to get the complete review semantic representation as the features of classification.

Experiments

Datasets:

Table 1. Statistics of IMDB, Yelp2013 and Yelp2014 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:

$$Accuracy = \frac{T}{N} \qquad RMSE = \sqrt{\frac{\sum_{i=1}^{N}(r_i - \hat{r}_i)^2}{N}}$$

Experiments Setting:

- We use stanford CoreNLP for sentence splitting and word tokenization.
- We pretrain 200-dimensional word embeddings with SkipGram on the three datasets respectively and they will be fine-tune during training.
- User embedding dimension and product embedding dimension are set to 200 and are randomly initialized to a uniform distribution U (−0.01, 0.01).
- We set the dimension of hidden state in LSTM unit to 100 and get 200 dimensional output hidden state because of bidirection.
- Hyper parameters are tuned on validation set and Adam is used to update parameters during training.
- Finally,we select best configuration based on performance of validation set and evaluate the configuration on test set.

Experiments Results and Analysis:

Table 2. Reviews sentiment classification results. Acc.(higher is better) and RMSE(lower is better) are the evaluation metrics. The best performances are in **bold**.

Models	IMDB		Yelp 2013		Yelp 2014	
	Acc.	RMSE	Acc.	RMSE	Acc.	RMSE
Models without user and product information						
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+RNN	0.400	1.764	0.574	0.804	0.582	0.821
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	0.822	0.579	0.791
JMARS	N/A	1.773	N/A	0.985	N/A	0.999
UPNN	0.435	1.602	0.596	0.784	0.608	0.764
UPDMN	0.465	1.351	0.639	0.662	0.613	0.720
NSC-UPA	0.533	1.281	0.650	0.692	0.667	0.654
HUAPA	0.550	1.185	0.683	0.628	0.686	0.626
HUPSA-NCF	**0.561**	**1.096**	**0.694**	**0.608**	**0.702**	**0.603**

We have some important findings from Table2.

- Firstly, we find both NSC-UPA and HUAPA perform better that UPNN and UPDMN, and they both use attention mechanism. It indicates that attention mechanism is more effective in incorporating user and product information.
- Secondly, we find the way of using attention mechanism also effects the performance of models. HUAPA performs better than NSC-UPA because it separates user and product attention.
- Lastly, we find our model HUPSA-NCF achieves best performance, because HUPSA-NCF incorporates user and product information more reasonably and effectively by using user attention and product attention separately. What's more, HUPAS-NCF uses a multilayer perception as neural collaborative filtering to capture implicit interaction information between user and product.

Table 3. Effect of different ways of using attention mechanism on Acc. and RMSE.

Models	IMDB		Yelp 2013		Yelp 2014	
	Acc.	RMSE	Acc.	RMSE	Acc.	RMSE
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
HUPSA	0.554	1.124	0.688	0.612	0.691	0.621
HUPSA-NCF	**0.561**	**1.096**	**0.694**	**0.608**	**0.702**	**0.603**

Table 3 shows the effect of different ways of using attention mechanism:

NSC-UPA(BiLSTM) uses user and product joint attention to incorporate user and product information simultaneously, but HUAPA separates user attention and product attention completely to incorporate user and product information respectively. According to experimental results, the second way of using attention is more reasonable because user and product have very different influences on reviews. HUPSA gets better performance than HUAPA, because HUAPA can not fine-tune word embeddings during training while our HUPSA can fine-tune by sharing word-level hidden states in user attention and product attention. HUPSA-NCF achieves better performance than HUPSA, this comparison validates the effectiveness of neural collaborative filtering.

Conclusion:

In this paper, we propose a novel neural network model HUPSA-NCF for document-level sentiment classification. To incorporate user and product information into text representations reasonably and effectively, HUPSA-NCF uses user attention and product attention separately to BiLSTM layers. Then, HUPAS-NCF uses a multilayer perception as neural collaborative filtering to capture and encode implicit interaction representation between user and product. Finally, HUPSA-NCF concatenates explicit text representations and implicit interaction representation for final classification. Experimental results show that HUPSA-NCF outperforms other state-of-the-art methods on IMDB and Yelp datasets.