Dual Memory Network Model for Biased Product Review Classification

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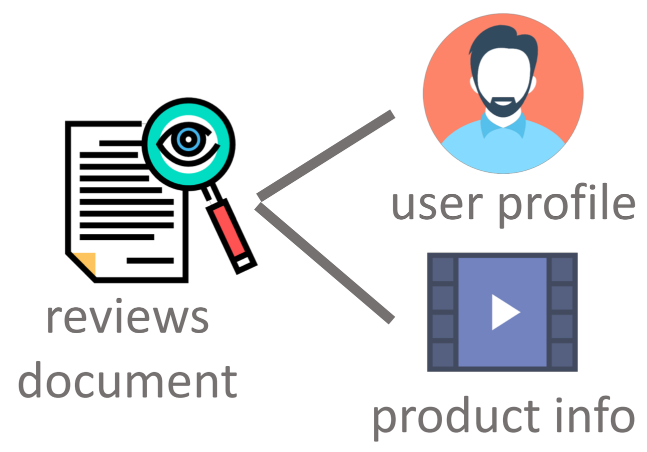
Abstract

In sentiment analysis (SA) of product reviews, both user and product information are proven to be useful. Current tasks handle user profile and product information in a unified model which may not be able to learn salient features of users and products effectively. In this work, we propose a dual user and product memory network (DUPMN) model to learn user profiles and product reviews using separate memory networks. Then, the two representations are used jointly for sentiment prediction. The use of separate models aims to capture user profiles and product information more effectively. Compared to state-of-the art unified prediction models, the evaluations on three benchmark datasets, IMDB, Yelp13, and Yelp14, show that our dual learning model gives performance gain of 0.6%, 1.2%, and 0.9%, respectively. The improvements are also deemed very significant measured by p-values.

Introduction

A **user profile** is defined by the collection of reviews a user writes.
Product information defined for a product is the collection of reviews for this product.



We can consider user profile and product information in sentiment analysis, while they are fundamentally different. We should not consider them as single united representation.

Related Works

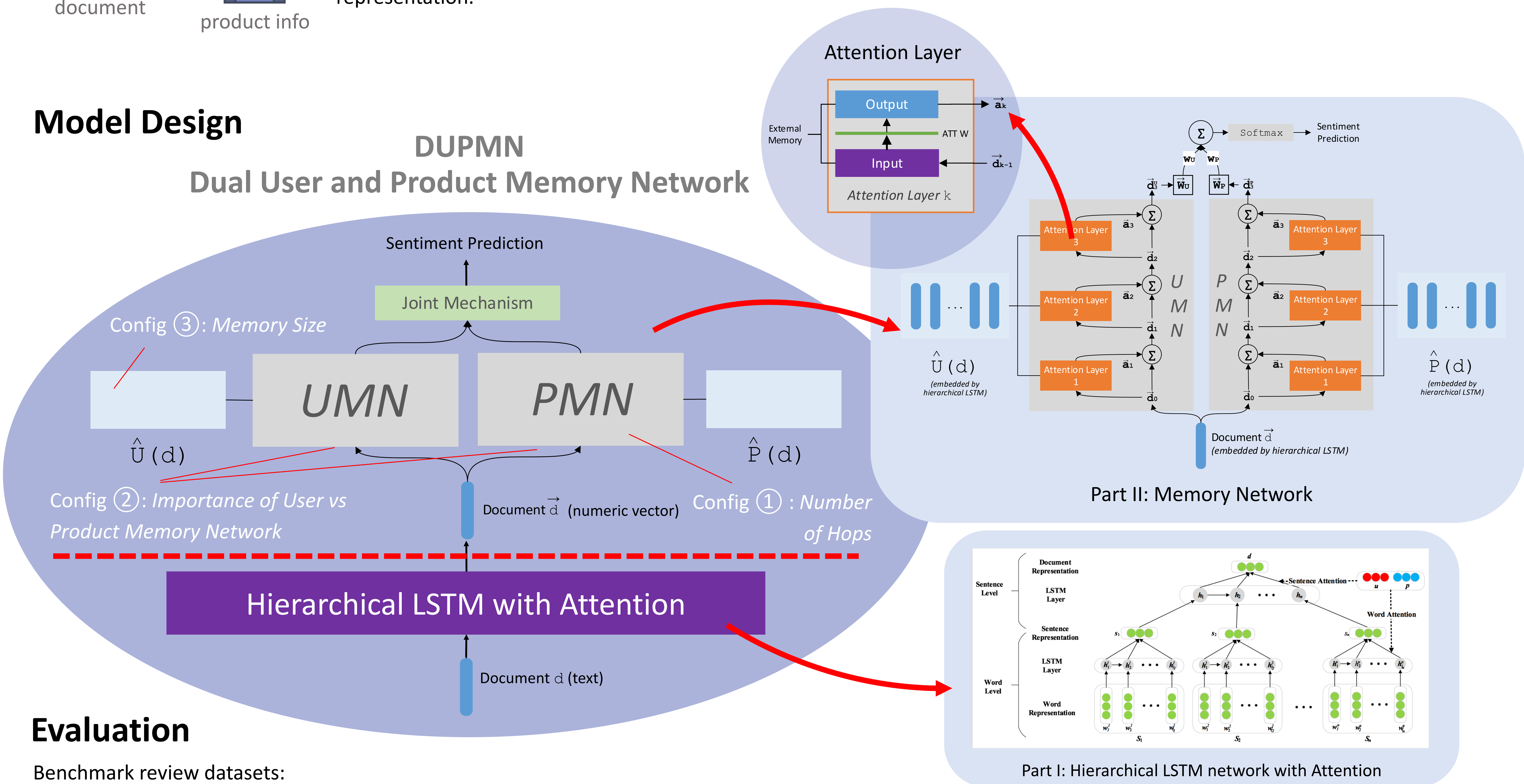
Linear or kernel methods on lexical features
Traditional Way

NN as classifier for text classification
RNN, LSTM
Neural-network-based Approaches

Focus more on important text and add more associate data like eye-tracking data
Attention

Utilizing **User Profile** and **Product Information** as single representation

Model Design



Evaluation

Benchmark review datasets:
IMDB, Yelp13 and Yelp14

DUPMN vs Comparison Models

	IMDB			Yelp13			Yelp14		
Model	Acc	RMSE	MAE	Acc	RMSE	MAE	Acc	RMSE	MAE
Majority	0.196	2.495	1.838	0.392	1.097	0.779	0.411	1.060	0.744
Trigram	0.399	1.783	1.147	0.577	0.804	0.487	0.569	0.814	0.513
TextFeature	0.402	1.793	1.134	0.572	0.800	0.490	0.556	0.845	0.520
AvgWordvec	0.304	1.985	1.361	0.530	0.893	0.562	0.526	0.898	0.568
SSWE	0.312	1.973	N/A	0.549	0.849	N/A	0.557	0.851	N/A
RNTN+RNN	0.400	1.734	N/A	0.574	0.804	N/A	0.582	0.821	N/A
CLSTM	0.421	1.549	N/A	0.592	0.729	N/A	0.637	0.686	N/A
LSTM+LA	0.443	1.465	N/A	0.627	0.701	N/A	0.637	0.686	N/A
LSTM+CBA	0.489	1.365	N/A	0.638	0.697	N/A	0.641	0.678	N/A
UPNN	0.435	1.602	0.979	0.608	0.764	0.447	0.596	0.784	0.464
UPDMN	0.465	1.351	0.853	0.613	0.720	0.425	0.639	0.662	0.369
InterSub	0.476	1.392	N/A	0.623	0.714	N/A	0.635	0.690	N/A
LSTM+UPA	0.533	1.281	N/A	0.650	0.692	N/A	0.667	0.654	N/A
DUPMN	**0.539**	**1.279**	**0.734**	**0.662**	**0.667**	**0.375**	**0.676**	**0.639**	**0.351**

Outperforms the state-of-the-art model

DUPMN with Different Configurations

Config ①: *Number of Hops*

- Smaller hop works better

Config ②: *Importance of User vs Product Memory Network*

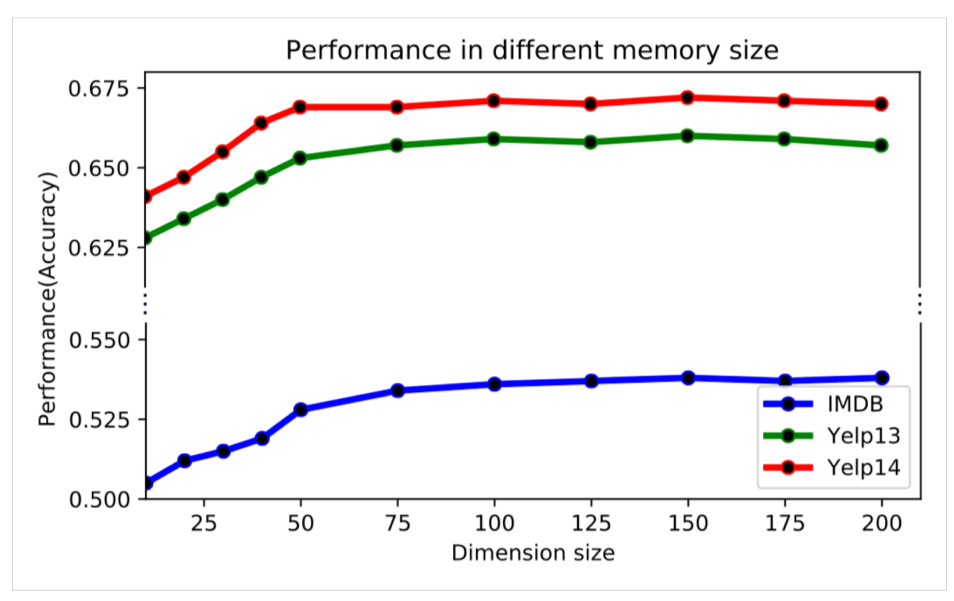
- User profile influences sentiments of movie reviews more
- Product information influences sentiments of restaurants reviews more

IMDB		Yelp13		Yelp14	
w'_U	w'_P	w'_U	w'_P	w'_U	w'_P
0.534	0.466	0.475	**0.525**	0.436	**0.564**

Average joint weight for three datasets

Config ③: *Memory Size*

- Larger memory helps until 75



Performance vs Memory Size

Key References

Huimin Chen, Maosong Sun, Cunchao Tu, Yankai Lin, and Zhiyuan Liu. 2016. Neural sentiment classification with user and product attention. EMNLP.

Sainbayar Sukhbaatar, Jason Weston, Rob Fergus, et al. 2015. End-to-end memory networks. In Advances in neural information processing systems, pages 2440–2448.

Acknowledgement

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Code, dataset and more are available at:
derek.ma/proj/dupmn