A Sentiment Analysis Method to Better Utilize User Profile and Product Information

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Abstract

We proposed a new Joint User and Product Memory Network (JUPMN) utilizing user profile and product information in separate ways into sentiment classification. Inspired by the successful utilization of memory network, our model first creates document representations using hierarchical LSTM model and then feeds the document vectors into new carefully designed user and product memory networks to reflect corresponding features. The evaluation of JUPMN on three benchmark review datasets shows that JUPMN outperforms the state-of-the-art model and further analysis of experimental results is employed.
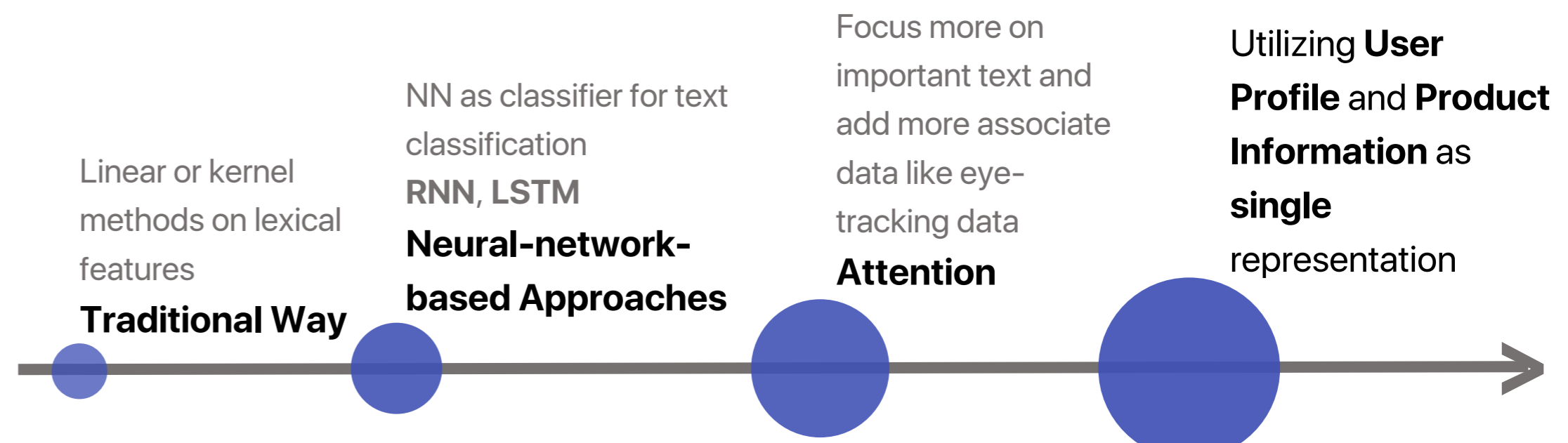
Introduction

Task: Sentiment Analysis.
Input: a paragraph of reviewing text
Output: ratings/sentiment

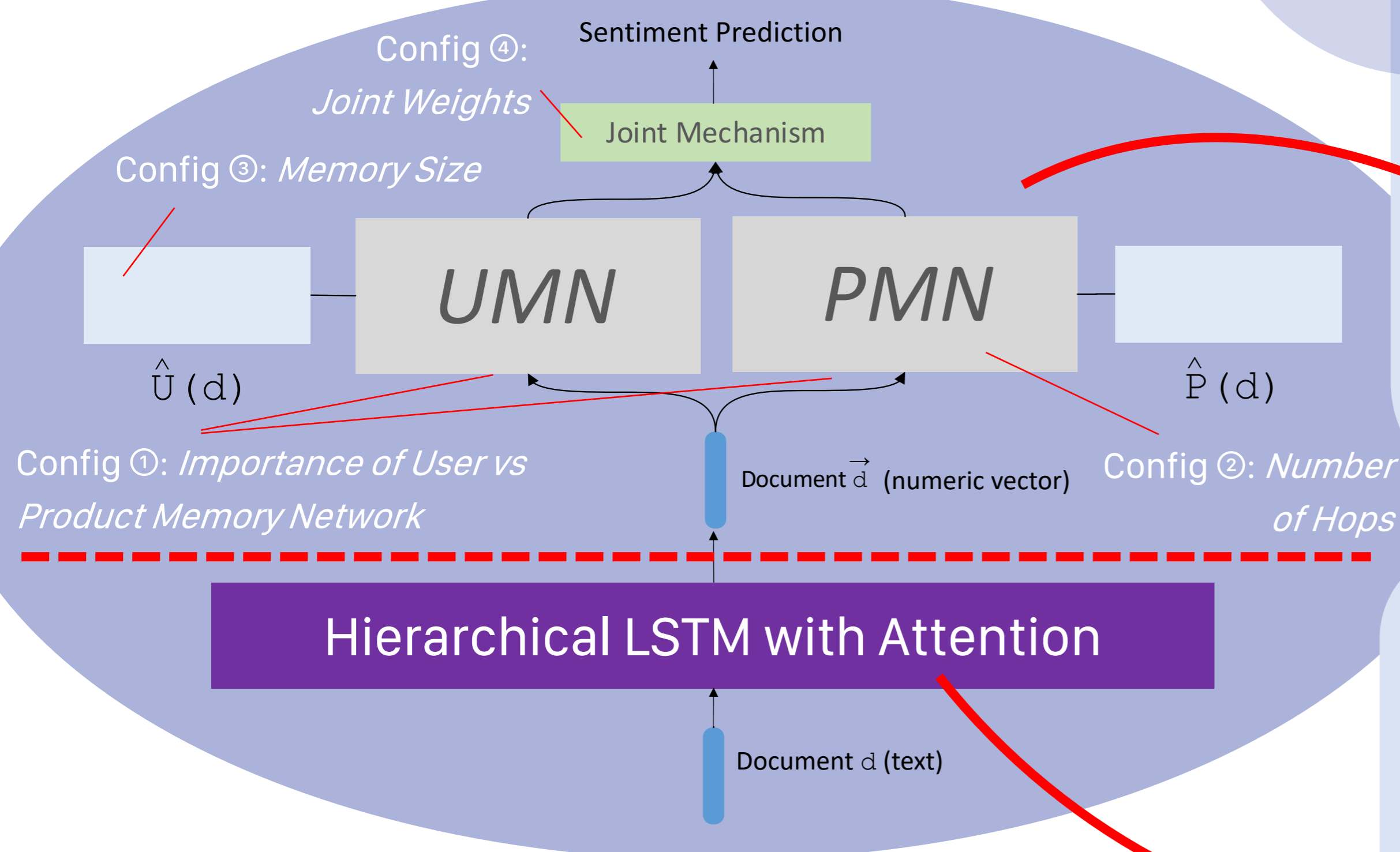reviews document → user profile, product info
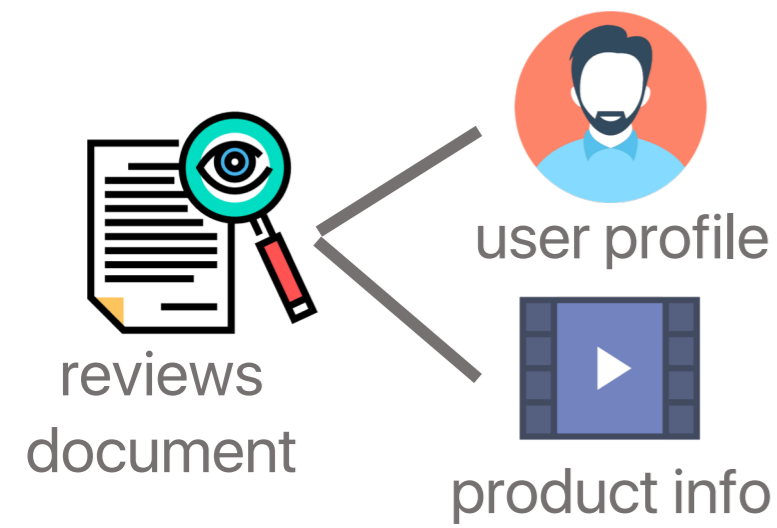
Can consider user profile and product information, while they are fundamentally different. We should not consider them as single united representation
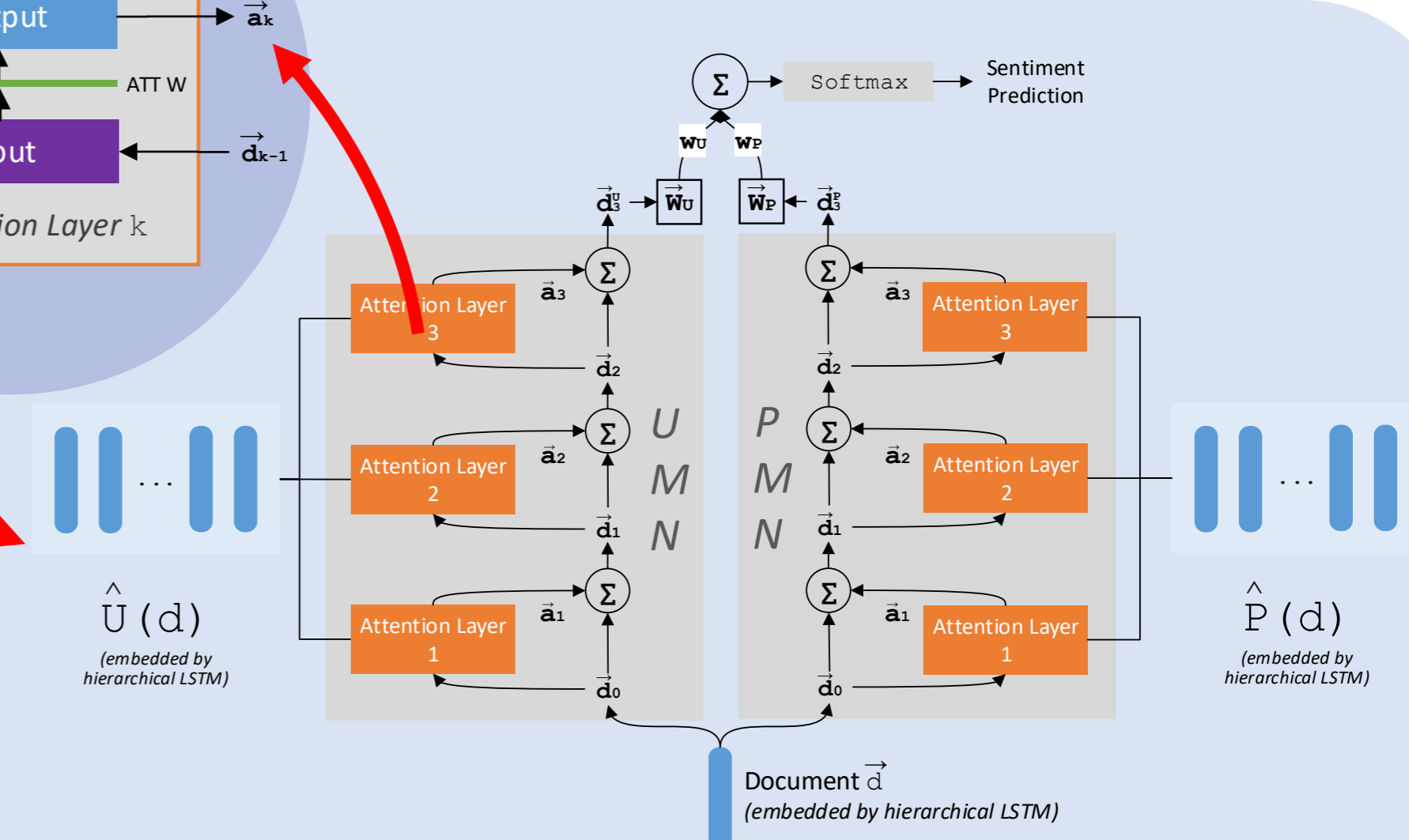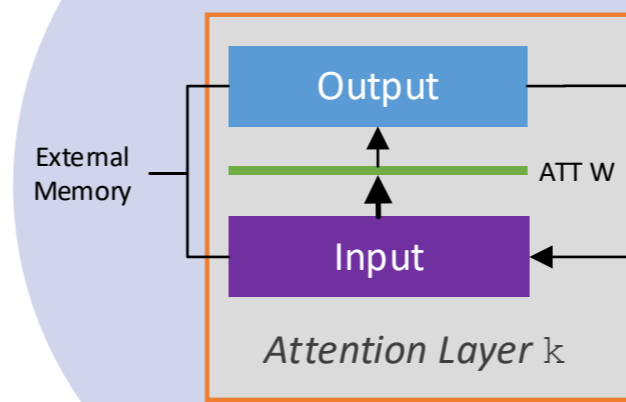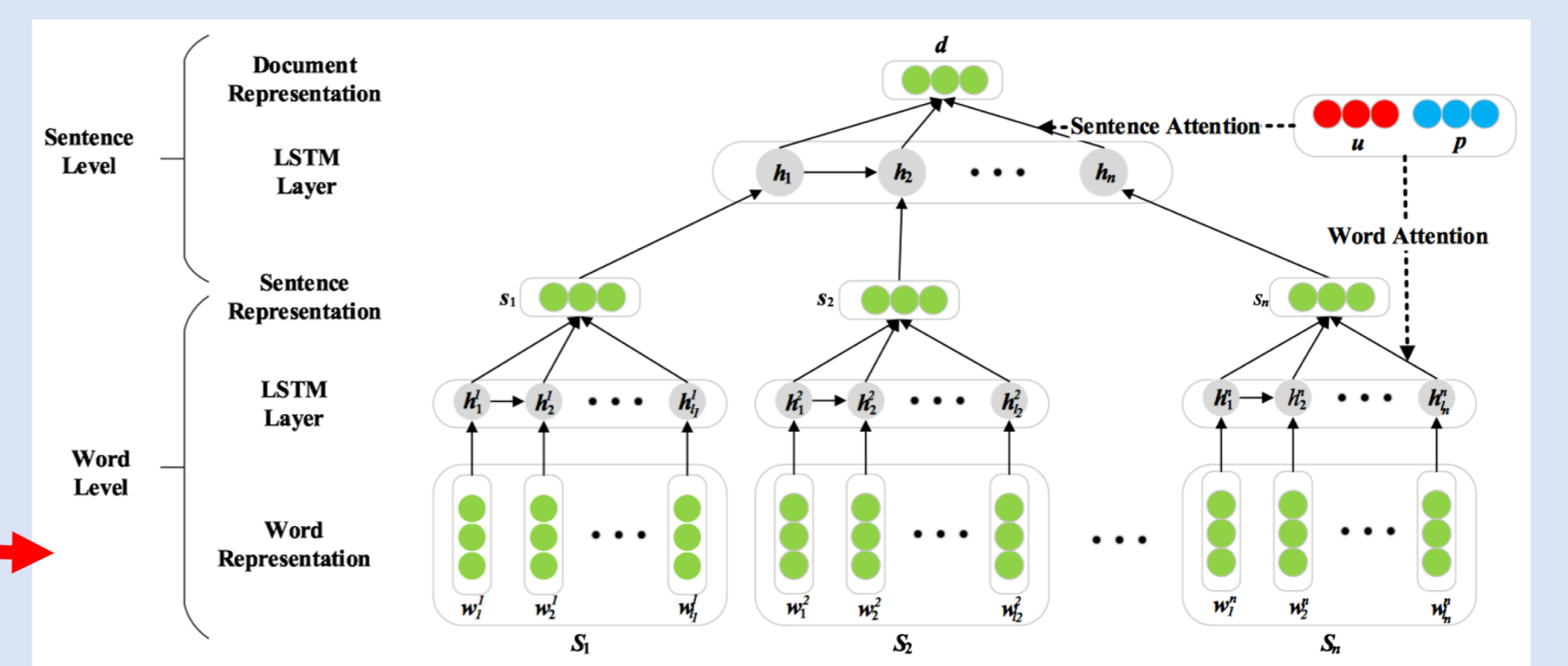
Related Works

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

JUPMN
Joint User and Product Memory Network

Config ④: *Joint Weights*

Config ③: *Memory Size*

Sentiment Prediction

Joint Mechanism

UMN   PMN

$\hat{U}(d)$ $\hat{P}(d)$

Config ①: *Importance of User vs Product Memory Network*

Document $\vec{d}$ (numeric vector)

Config ②: *Number of Hops*

Hierarchical LSTM with Attention

Document d (text)

Attention Layer

External Memory — Output — ATT W — Input — $\vec{a}_k$, $\vec{d}_{k-1}$
Attention Layer k

Σ — Softmax — Sentiment Prediction
W_U, W_P

$\hat{U}(d)$ *(embedded by hierarchical LSTM)*   U M N   P M N $\hat{P}(d)$ *(embedded by hierarchical LSTM)*

Attention Layer 3, Attention Layer 2, Attention Layer 1

Document $\vec{d}$ *(embedded by hierarchical LSTM)*

Part II: Memory Network

Part I: Hierarchical LSTM network with Attention

Evaluation

Benchmark datasets: IMDB, Yelp13 and Yelp14

IMDb   yelp

Left: document number statistics
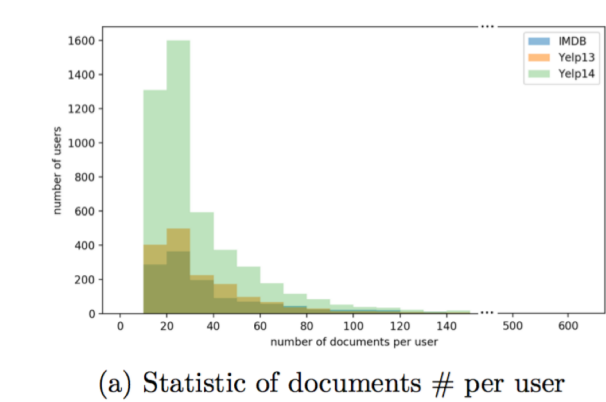
(a) Statistic of documents # per user

JUPMN vs Comparison Models

Model	IMDB			Yelp13			Yelp14		
	Acc	RMSE	MAE	Acc	RMSE	MAE	Acc	RMSE	MAE
Majority	0.196	2.495	1.838	0.392	1.097	0.779	0.411	1.06	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
UPN(K)	0.435	1.602	0.979	0.608	0.764	0.447	0.596	0.784	0.464
UPDMN(K)	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
JUPMN	**0.539**	1.283	**0.725**	**0.662**	**0.667**	**0.375**	**0.676**	**0.641**	**0.351**

Outperforms the state-of-the-art model
Best accuracy, RMSE and MAE

Config ①: *Importance of User vs Product Memory Network*

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

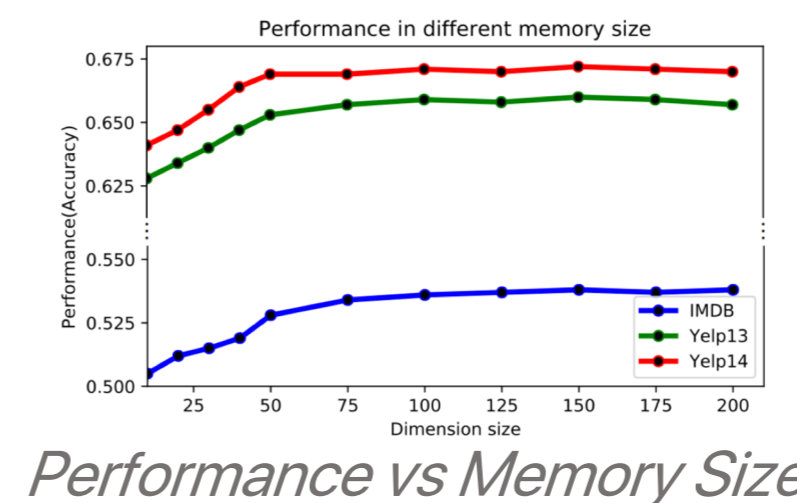|	IMDB		Yelp13		Yelp14	
	w'_U	w'_P	w'_U	w'_P	w'_U	w'_P
	0.534	0.466	0.475	**0.525**	0.436	**0.564**

Average joint weight for three datasets

Config ②: *Number of Hops*

- Smaller hop works better

Config ③: *Memory Size*

- Larger memory helps until 75

Performance vs Memory Size

JUPMN with Different Configurations

(a) 10 users who give average highest ratings (b) 10 users who give average lowest ratings

(a) 10 movies with average highest ratings (b) 10 movies with average lowest ratings

(a) 10 users who give average highest ratings (b) 10 users who give average lowest ratings

(a) 10 restaurants with average high-est ratings (b) 10 restaurants with average low-est ratings

Config ④: *Joint Weights*

- Weighted version works better
- Weight help to balance the influences of UMN and PMN