Learning Semantic Representations of Users and Products for Document Level Sentiment Classification

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1. The Task

- We target at document-level sentiment classification
  - Given a document as input, the task is to predict the overall sentiment polarity

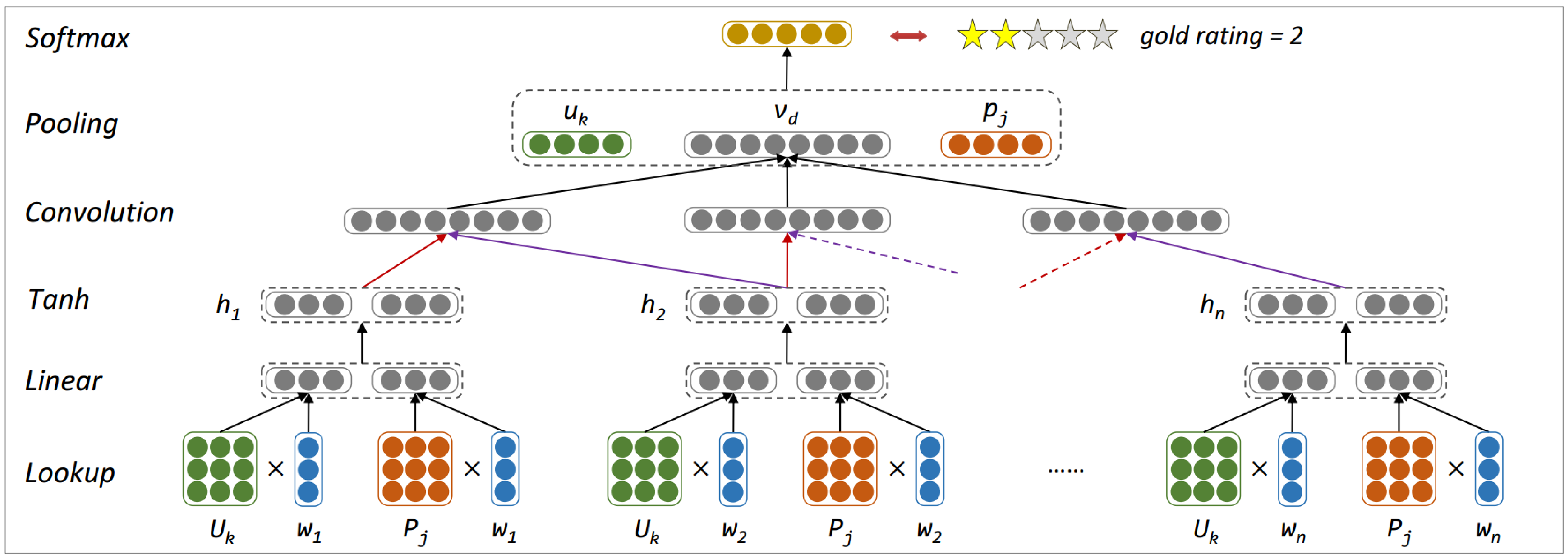
THE TRUTH YOU NEED TO KNOW ABOUT THE 12" MACBOOK RETINA

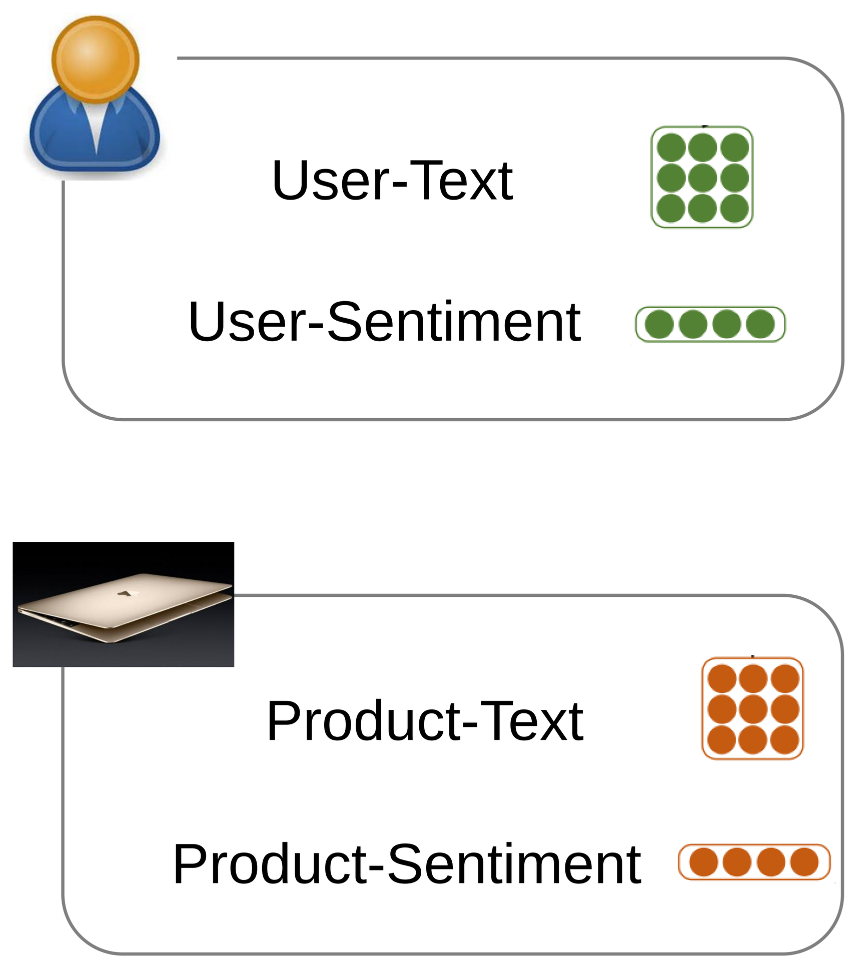
Not since the tech press slammed the original iPad ("Who need this?" "Nothing but a big iPod Touch!") have I seen such a wrong-headed rush to criticize a new Apple product. It's like watching a lunatic mob roam the village at night with torches and pitchforks, shouting: "Kill the beast!" And here's what's so bizarre about the criticism: the Macbook Air has always been compromised compared to the Macbook Pro. Worse screen, fewer ports, less available memory, slower processors. But everyone understands that these are the trade-offs if you want a thinner, lighter laptop. Now the new Macbook 12' takes thin and light to a whole new level, with a much better screen, while the main compromises vs. the Air are the reduction to one port and a slower processor... and the press has reacted like Apple shot someone's dog.

2. Basic Idea

- The basic idea
  - **Users** who write the review and **products** which are evaluated are important for inferring the sentiment of a text
  - We develop a deep learning method to use semantics of **texts**, **users** and **products** for sentiment classification

3. The Approach





4. Experiment

- We derive 3 datasets from IMDB and Yelp Dataset Challenge 2013 and 2014.

Dataset	#users	#products	#reviews	#docs/user	#docs/product	#sents/doc	#words/doc
IMDB	1,310	1,635	84,919	64.82	51.94	16.08	394.6
Yelp 2014	4,818	4,194	231,163	47.97	55.11	11.41	196.9
Yelp 2013	1,631	1,633	78,966	48.42	48.36	10.89	189.3

	IMDB			Yelp 2014			Yelp 2013		
	Acc	MAE	RMSE	Acc	MAE	RMSE	Acc	MAE	RMSE
Majority	0.196	1.838	2.495	0.392	0.779	1.097	0.411	0.744	1.060
Trigram	0.399	1.147	1.783	0.577	0.487	0.804	0.569	0.513	0.814
TextFeature	0.402	1.134	1.793	0.572	0.490	**0.800**	0.556	0.520	0.845
AvgWordvec + SVM	0.304	1.361	1.985	0.530	0.562	0.893	0.526	0.568	0.898
SSWE + SVM	0.312	1.347	1.973	0.557	0.523	0.851	0.549	0.529	0.849
Paragraph Vector	0.341	1.211	1.814	0.564	0.496	0.802	0.554	0.515	0.832
RNTN + Recurrent	0.400	1.133	1.764	0.582	**0.478**	0.821	0.574	0.489	**0.804**
UPNN (no UP)	**0.405**	**1.030**	**1.629**	**0.585**	0.483	0.808	**0.577**	**0.485**	0.812
Trigram + UPF	0.404	1.132	1.764	0.576	0.471	0.789	0.570	0.491	0.803
TextFeature + UPF	0.402	1.129	1.774	0.579	0.476	0.791	0.561	0.509	0.822
JMARS	N/A	1.285	1.773	N/A	0.710	0.999	N/A	0.699	0.985
UPNN (full)	**0.435**	**0.979**	**1.602**	**0.608**	**0.447**	**0.764**	**0.596**	**0.464**	**0.784**
UPNN $-\ u_k - p_j$	0.409	1.021	1.622	0.585	0.483	0.808	0.572	0.491	0.823
UPNN $-\ U_k - P_j$	0.426	0.993	1.607	0.597	0.465	0.789	0.585	0.482	0.802
UPNN $-\ U_k - u_k$	0.324	1.209	1.743	0.577	0.475	0.778	0.566	0.505	0.828
UPNN $-\ P_j - p_j$	0.397	1.075	1.712	0.595	0.462	0.776	0.590	0.476	0.802

- Semantic representations of users and products can improve classification accuracy.
- User/product vectors are more powerful than user/product matrices.
- User representations are more useful than product representations.

Datasets and codes are available at http://ir.hit.edu.cn/~dytang/