Modeling User Leniency and Product Popularity for Sentiment Classification

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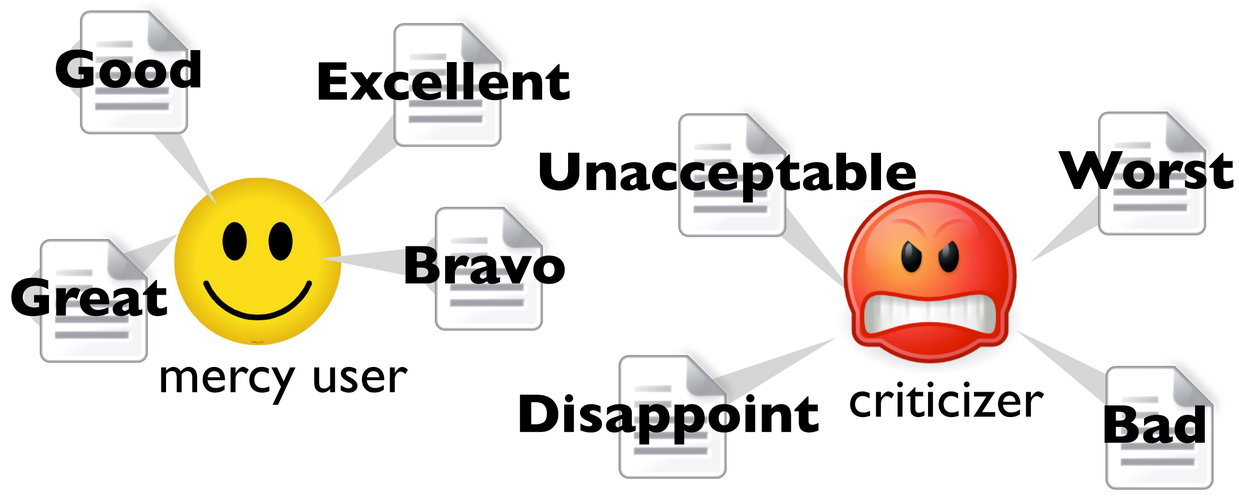
Existing methods to sentiment classification

- Classical methods for sentiment classification consider only the textual features
- Recent user- and product-aware methods:
  - use a tensor to project each user and product onto (Li+, 2011)
  - combine user-specific classifiers to classify a review of the test user (Seroussi+, 2010)
  - use a user network for sentiment classification (Tan+, 2011)

Difficult to handle reviews written by newly emerging users or on newly emerging products

Motivation : Biased sentiment in real-world

In real-world, sentiment written by a user or on a product is often biased toward positive or negative
e.g., intolerant users tend to complaint



we take advantage of these biases

Our method : Global model for collective sentiment classification

Global model

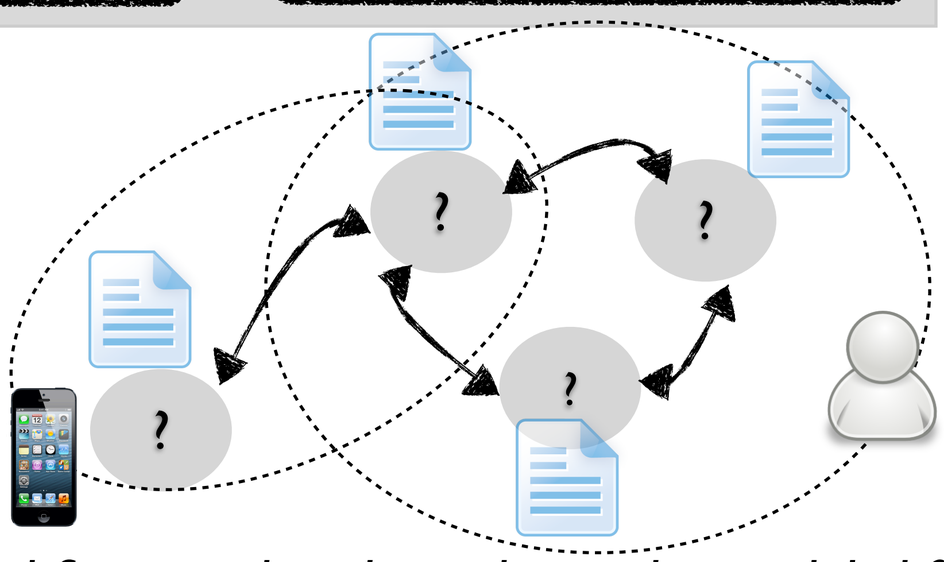
Novel global model collectively classifies a set of reviews while computing polarity biases for each user and product

We represent biases as two global features

- **User leniency**: The pos/neg ratio of the user's other reviews
- **Product popularity**: The pos/neg ratio of the product's other reviews

Global features introduce dependencies among labels if the reviews are written:

1. by the same user
2. on the same product



ISSUE:

How to compute the global features that depend on unknown labels?

Decoding strategy

Adopt two-stage decoding to compute global features (Krishnan & Manning, 2006)

Stage-1:

For each review:

Estimate label by using local textual features

Stage-2:

For each review:

1. *compute global features using the labels in stage-1*
2. *estimate label by using local and global features*

Can handle reviews written by emerging users or on emerging products

Experiment

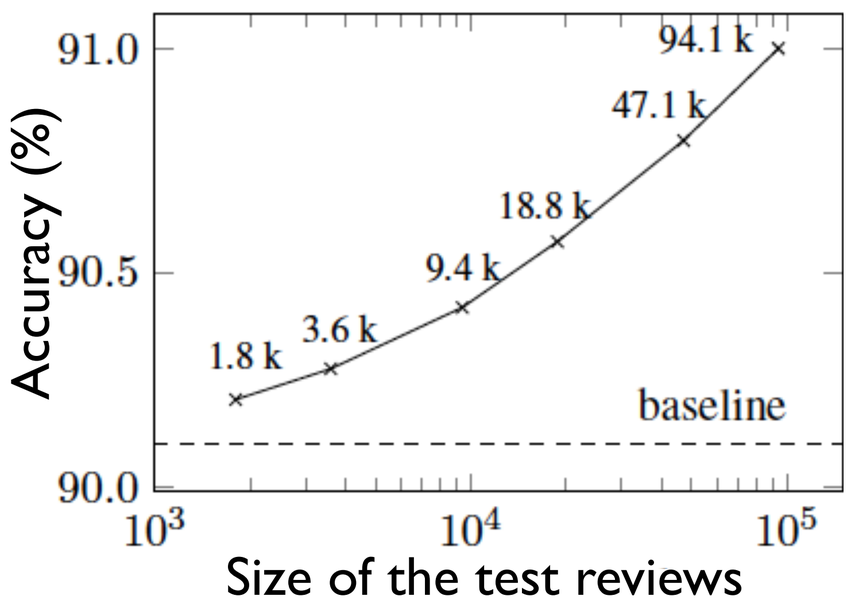
- Data: 180k reviews in Blitzer dataset and 50k reviews in Maas dataset
- We adopted a confidence-weighted local classifier (Dredze+, 2008)

method \ dataset	Blitzer	Maas
Seroussi+ 2010†	89.37%	n/a
Maas+ 2011	n/a	88.89%
baseline*	90.13%	91.41%
proposed	**91.02%**	**92.68%**

† Maas+ 2011 is cited result which uses a data split different to ours

* Minor change of baseline compared to the paper

Impact of # reviews processed at once



More reviews, more accurate

Future work

- Deploy other decoding strategies such as easiest-first (Tsuruoka & Tsujii, 2005)
- Introduce other global dependencies
- Automatically detect global dependencies

A more detailed version of this paper will appear in PACLIC27