Thumbs Up? Sentiment Classification using Machine Learning Techniques

Pang, Lee, Vaithyanathan - EMNLP 2002

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IE @ Technion

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Agenda

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   - Sentiment analysis
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3. Methods
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Introduction

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- Recent (2002) works sort documents according to their **subject**
  - e.g., sports vs. politics
- Yet crucial part of online posted articles is their **sentiment**
  - provide useful insights for readers automatically
  - e.g., product review is negative or positive

Topic classification

Current (2002) techniques for non-topic text categorization

- Source style with features as stylistic variation (Biber, 1988)
  - e.g., author, publisher (NY times vs. Daily News)
- Genre of text (Finn et al., 2002)
  - e.g., editorial 'subjective' genre
- Is subjective language used? (Wiebe et al., 2001)
- Does text contains opinion expressing?

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  - Q: What are our expected challenges?
  - A: Topics are identifiable by key words alone, while sentiment requires more **understanding**
- e.g., "How could anyone sit through this movie?"
  - Can you mark any negative word?
- Previous (2002) techniques:
  - Cognitive linguistic models (Sack, 1994)
  - Discriminant word lexicons (Tong, 2001)
  - Semantic orientation of words (Turney and Littman, 2002)

Problem

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- e.g., Zero-one loss: $L(x, y, f_w) = \mathbf{1}\{f_w\hat{(}x) \neq y\}$
  - w denotes learned parameters

Data: IMDB Movie Reviews

- Lucky for us: user rating provides us **supervised** learning
- Converted into three categories (or topics):
  - *Positive*, *negative*, (and *neutral* - not used)
- Avoid bias issues:
  - 20 reviews per author per sentiment
  - 752 negative vs 1301 positive
  - total of 144 reviewers

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Human	Proposed words	Accuracy	Ties [1]
1	positive (5): dazzling, brilliant.. negative (5): suck, terrible..	58%	75%
2	positive (11): gripping, spectacular.. negative (6): cliched, boring..	64%	39%

Table: Baseline results for human word lists, data is balanced (700 vs. 700)

[1] Documents percentage where sentiments rated equally

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Methods

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Then each document d is represented by $\overrightarrow{d} := (n_1(d), ..., n_m(d))$.

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- $\overrightarrow{d_2} = (0, 0, 1, 1, 2)$

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- A_1: Some estimates are zero, can smooth (e.g., add-one smoothing)
- A_2: Short documents vs. long documents (propose: tf-idf)

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aka logistic regression

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Fit procedure

- Training data used to estimate distribution F
- λ's are set to maximize entropy of induced distribution

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Alternative fitting procedure:

Definition (Gradient descent)

$$w = w - \alpha * \frac{\partial L(X,w)}{\partial w}\text{ , Update till convergence}$$

Results

Results and discussion

ID	Features	count	freq/pres	NB	ME	SVM
1	unigrams	16165	freq	78.7%	NA	72.8%
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  - Hence from this point authors use presence (**binarized occurrences**)

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- Position based on dividing text into quarters.

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(2018)

- We have tried to reproduce the experiment for the best setting reported

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unigrams	16165	77.48%	**81.52%**	48.19%	**82.75%**

Table: Original vs. our results

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unigrams	16165	77.48%	**81.52%**	48.19%	**82.75%**

Table: Original vs. our results

- MLP is 2-layer neural network with 100 Relu neurons
- **No tuning** was used (sklearn 0.19.2 default parameters)
  - Plus not all described processing steps applied
- Notebook is available here

Classifier comparison
(2018)

- Let's observe our classifiers decision boundaries for some toy datasets

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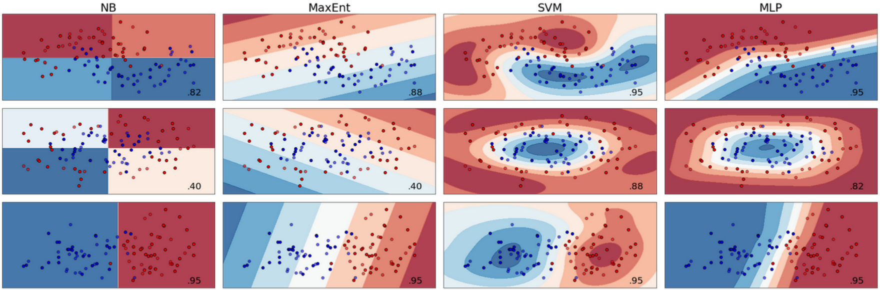

- Accuracy is reported

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Review example

"This film should be brilliant. It sounds like a great plot, the actors are first grade, and the supporting cast is good as well, and Stallone is attempting to deliver a good performance. However, it can't hold up."

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  - Apply feature selection algorithms
- Contrarily, performance isn't comparable to topic classification

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- Authors suggest determining the **focus** of each sentence, if is on/off topic.

Thank you for participating!
Questions?