Thumbs Up? Sentiment Classification using Machine Learning Techniques

Pang, Lee, Vaithyanathan - EMNLP 2002

Slides by: Dor Cohen, Itai Gat

IE @ Technion

October 16, 2018

Agenda

Introduction

Topic classification

- Recent (2002) works sort documents according to their **subject**
  - e.g., sports vs. politics

Topic classification

- 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

Sentiment analysis

- This work: apply topic classification techniques on sentiment analysis
  - Q: What are our expected challenges?

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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?

Sentiment analysis
Motivation

- Should we watch this movie?

Sentiment analysis

Motivation

A Star Is Born (2018) ★ 8.4/10 46,238

R | 2h 16min | Drama , Music , Romance | 5 October 2018 (USA)

- Should we watch this movie?
- Ideally: read each review and decide

★ 10/10

Amazing!

gastraube 31 August 2018

This movie is perfect, it made me cry from the beginning to the end, it deserves several Oscar's nominations. Lady Gaga is a true astist.

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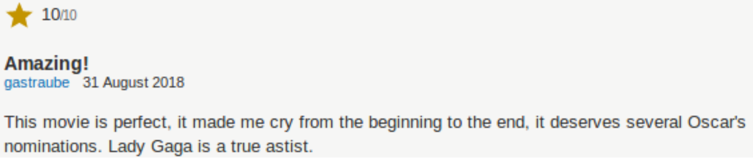

Problem

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

Data: IMDB Movie Reviews

- Lucky for us: user rating provides **supervised** learning
- Converted into 3 categories:
  - *Positive*, *negative*, (*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

Human based sentiment classifiers

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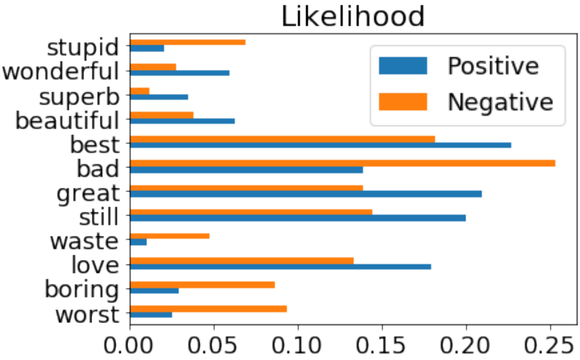
Human	Proposed words	Accuracy	Ties
3+Stats	positive (7): love, wonderful.. negative (7): bad, worst, '?', '!',..	69%	16%

Table: Results where words (total 14) were chosen based on data statistics

Human based sentiment classifiers

(2018) Data analysis

We reproduced the analysis, following are example estimates



- Note words occurrences were binarized

Methods

Bag of words

Framework details

Theorem (1)

Let $\{f_1, ..f_m\}$ *denote set of m features that can appear in document.*

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Definition (BOW)

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

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Example

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- d_2: "Act boring"

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- A_2: Short vs. long documents

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Assume the following Bow model with 4 documents for each class:

	act	audio	boring	rocks
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aka logistic regression

Definition (MaxEnt estimator)

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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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<u>Alternative fitting procedure:</u>

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%
2	unigrams	16165	pres	81.0%	80.4%	**82.9%**

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  - Hence from this point authors use presence (**binarized occurrences**)

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- Position based on dividing text into quarters.

Reproduce results

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(2018)

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

Features	count	NB	ME	SVM	MLP
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unigrams	16165	77.48%	**81.52%**	80.66%	**82.75%**

Table: Original vs. our results

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unigrams	16165	77.48%	**81.52%**	80.66%	**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

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(2018)

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

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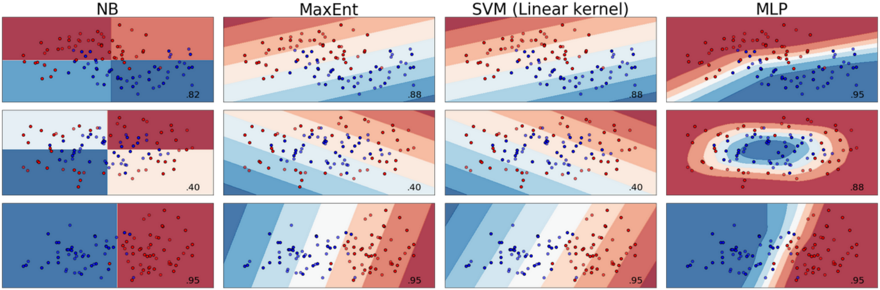

- Accuracy is reported

Conclusions

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- Contrarily, performance isn't comparable to topic classification

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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?