Thumbs Up? Sentiment Classification using Machine Learning Techniques

Pang, Lee, Vaithyanathan - EMNLP 2002

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Agenda

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   - Sentiment analysis
2. Problem
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Introduction

Topic classification

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  - 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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- This work: apply topic classification techniques on sentiment analysis
  - Q: What are our expected challenges?
  - A: Topics are identifiable by key words alone
    detecting sentiment requires more **understanding**
- e.g., "How could anyone sit through this movie?"
  - Can you mark any negative word?

Sentiment analysis

Motivation

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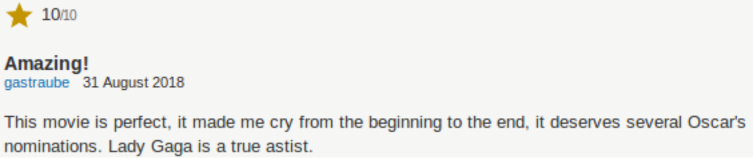

Sentiment analysis

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.

★ 2/10

Directing and acting miscarriage

dailynewsandinformations 5 October 2018

Maybe only the sound on this film is up to par...everything else is drown in mediocrity...

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

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Human based sentiment classifiers

Should we worry about high rate of ties?

- Proposed list is relatively short (usually effect is 0 vs. 0)
  - Not necessarily the reason for low accuracy!
- Authors propose their list
  - Backed up with statistics

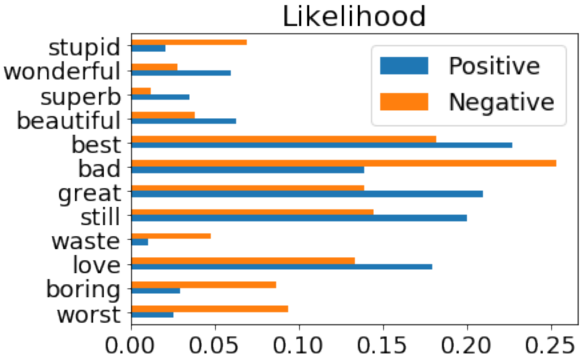
Human	Proposed words	Accuracy	Ties
3+Stats	positive (7): love, wonderful.. negative (7): bad, worst, '?', '!',..	69%	16%

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

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Definition (BOW)

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

Bag of words

Example

- d_1: "Audio rocks"
- d_2: "Act boring"

	act	audio	boring	rocks
mapping	0	1	2	3
d1	0	1	0	1
d2	1	0	1	0

- d_3: "Boring effects", $d_3^{bow} = ?$

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- A_1: Estimates could be zero
- A_2: Short vs. long documents

Naive bayes example

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

	act	audio	boring	rocks
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- $P(d|neg) = \frac{1}{4}^0 * \frac{1}{4}^0 * \frac{3}{4}^1 * \frac{1}{4}^0 = \frac{3}{4}$

SVM vs. Logistic regression

- Can view both parametrically: $f(x_i, W) = Wx_i + b$
- **Train** with gradient descent:
  - Initialize parameters
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Methods differ in their loss functions:

Definition (SVM loss)

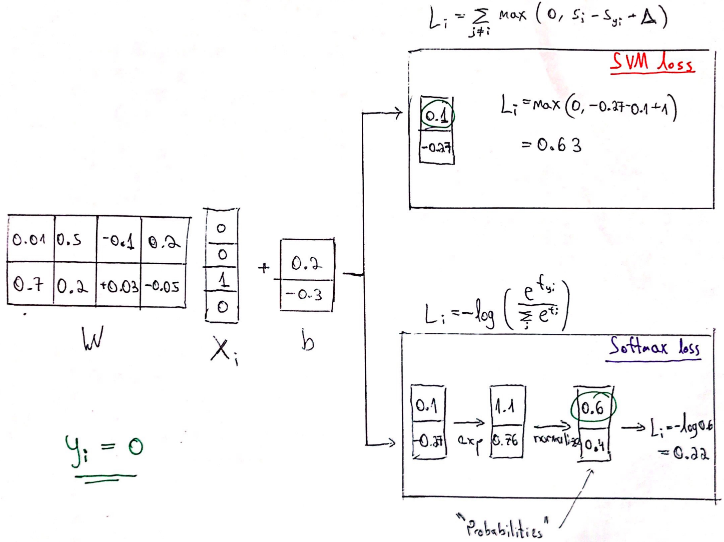
$L_i = \sum_{j \neq i} max(0, s_j - s_{y_i} + \delta)$, where $s_j = f(x_i, W)_j$

Definition (Softmax loss)

$L_i = -log(\frac{e^{f_{y_i}}}{\sum_j e^{f_j}})$

SVM vs. Logistic regression

Evaluate loss example



Results

Results and discussion

Using feature presence

ID	Features	count	NB	ME	SVM
2	unigrams	16165	81.0%	80.4%	**82.9%**
3	uni+bigrams	32330	80.6%	80.8	**82.7%**
4	bigrams	16165	77.3%	77.4%	77.1%
5	unigrams+POS	16695	81.5%	80.4%	**81.9%**
6	adjectives	2633	77.0%	77.7%	75.1%
7	top 2633 unigrams	2633	80.3%	81.0%	81.4%
8	unigram+position	22430	81.0%	80.1%	**81.6%**

Table: 3-fold average accuracies, unigram/bigrams appear at least 4/7 times on corpus. Expressions with negation words were handled with unified "NOT" tag.

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- Adding bigrams doesn't improve results; Bigrams alone is worse
- Part-of-speech: "I love this movie" vs. "This is a love story"
- Position based on dividing text into quarters.

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- Unigrams presence setting achieves the best performance
  - Apply feature selection algorithms
- Contrarily, performance isn't comparable to topic classification

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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- Difficult for bag-of-words classifiers.
- Authors suggest determining the **focus** of each sentence

Reproduce results

Reproduce results
(2018)

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

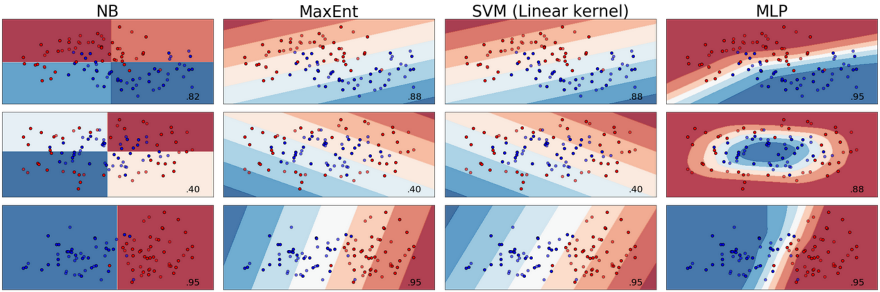
Features	count	NB	ME	SVM	MLP
unigrams	16165	81.0%	80.4%	**82.9%**	NA
unigrams	16165	77.48%	**81.52%**	80.66%	**82.75%**

Table: Original vs. our results

- **No tuning** (sklearn 0.19.2 default parameters)
- MLP: 2-layer neural network, 100 Relu neurons, sigmoid
- Notebook is available ▸ here

Classifier comparison
(2018)

- Our classifiers decision boundaries for some toy datasets



- Accuracy is reported

Thank you for participating!
Questions?