Thumbs Up? Sentiment Classification using Machine Learning Techniques

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Problem definition

Topic classification

Sentiment analysis

Motivation

- Should we watch this movie?

Sentiment analysis

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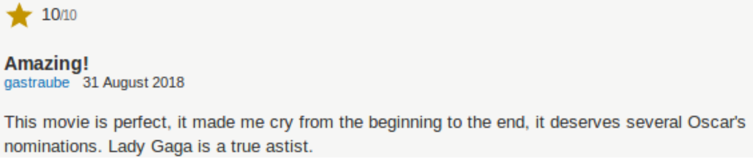
- Ideally: read each review and decide



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...

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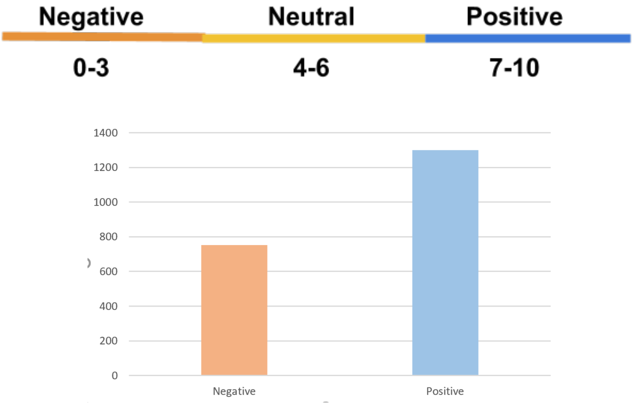
- Evaluate by loss function
- e.g., Zero-one loss: $L(x, y, f_w) = \mathbf{1}\{f_w(x) \neq y\}$
  - w denotes learned parameters

Data: IMDB Movie Reviews

- User rating provides **supervised** learning:



Human based sentiment classifiers

- **Hypothesis:** certain words indicate on sentiment type
- **Test:** count positive vs. negative words

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

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

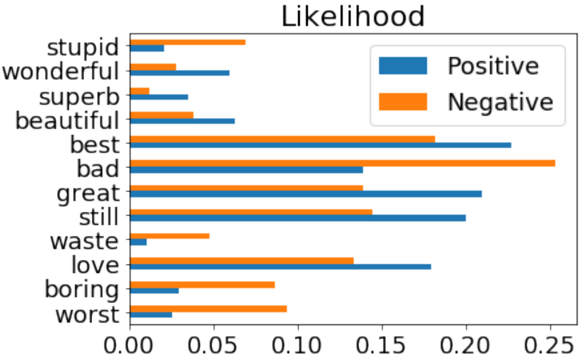
Human	Proposed words	Accuracy	Ties
3+Stats	positive (7): love, wonderful.. negative (7): bad, worst, '?', '!',..	69%	16%

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
Example

- d_1: "Great soundtrack, boring actors"
- d_2: "Annoying soundtrack, great actors"

	actors	soundtrack	boring	annoying	great
d1	1	1	1	0	1
d2	1	1	0	1	1

- d_3: "Great soundtrack, great actors, great popcorn."
- $d_3^{bow} =?$

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- d_3^{bow}=(1,1,0,0,3)

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  - Hence $\widehat{P(d|c)} = \prod_{i=1}^{m} P(f_i|c)^{n_i(d)}$

Naive bayes example

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

	act	audio	boring	rocks
mapping	0	1	2	3
positive	1	3	1	3
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- Recall $\widehat{P(d|c)} = \prod_{i=1}^{m} P(f_i|c)^{n_i(d)}$
- $P(d|pos) = \frac{1}{4}^0 * \frac{1}{4}^0 * \frac{1}{4}^1 * \frac{1}{4}^0 = \frac{1}{4}$
- $P(d|neg) = \frac{1}{4}^0 * \frac{1}{4}^0 * \frac{3}{4}^1 * \frac{1}{4}^0 = \frac{3}{4}$

SVM vs. Logistic regression

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

Definition (SVM loss)

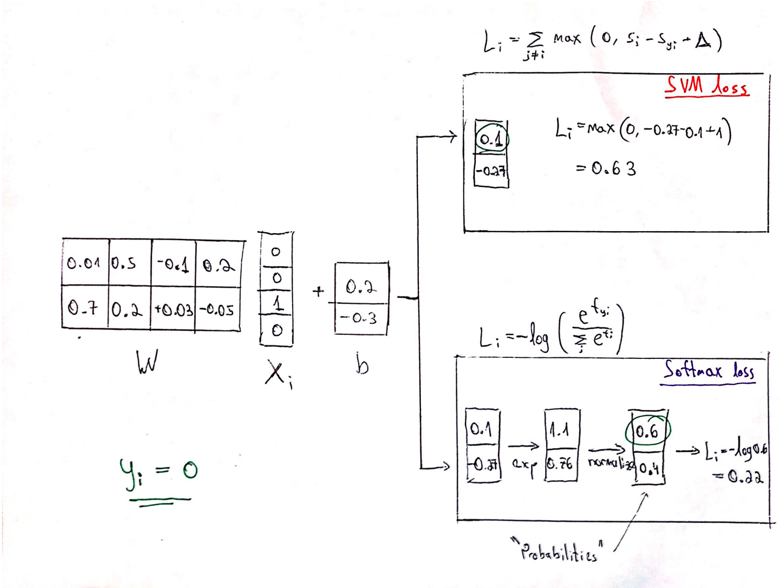
$L_i = \sum_{j \neq i} max(0, s_j - s_{y_i} + \delta)$, where $s_j = f(x_i, W)_j$

Definition (Softmax loss)

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

SVM vs. Logistic regression

Evaluate loss example



Results

Experimental setup

Features:

- d: "Audio quality rocks"
- Unigram: {'audio', 'rocks',.. }
- Bigram: {'audio quality',.. }
- N-gram !

Setup

- Unigram/bigram appear at least 4/7 times
- Uniform class distributions
- 3-fold average accuracies
- Unified NOT tag

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%
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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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  - 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

Thank you for participating!
Questions?