Natural language processing and Sentiment analysis

Rolando P. Hong Enriquez

JUST EAT

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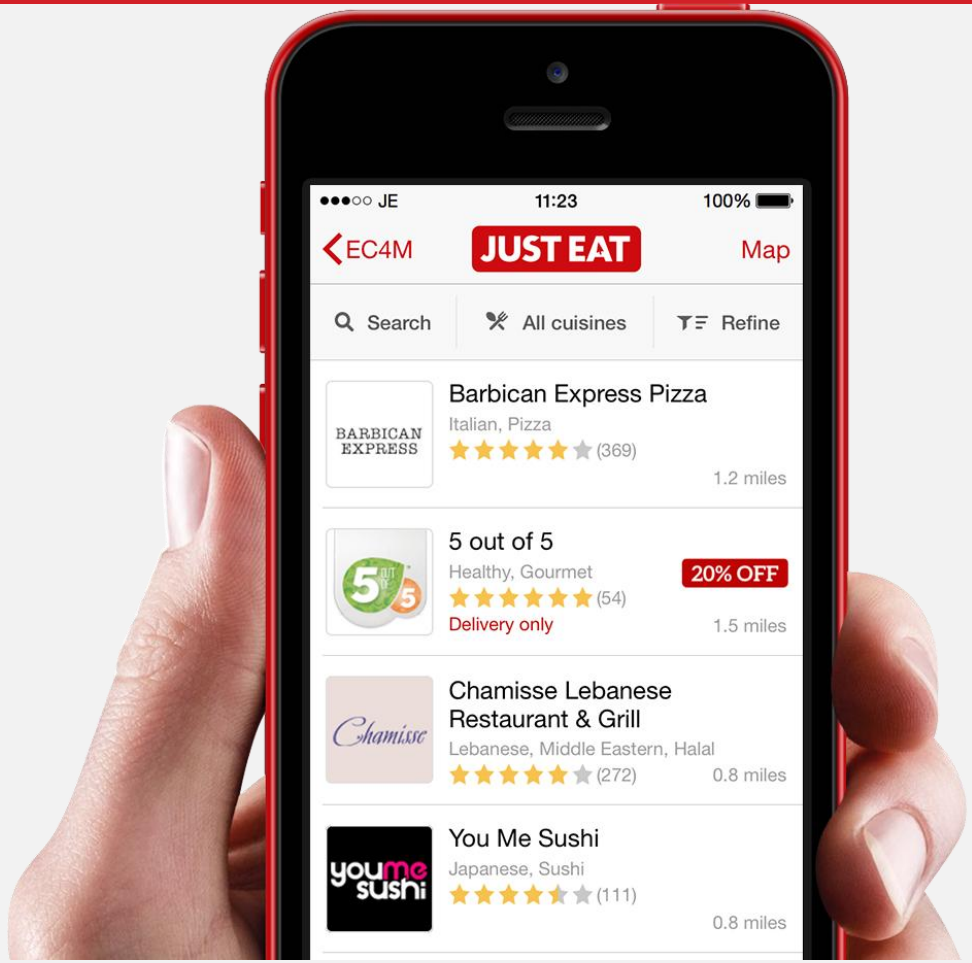
JUST EAT



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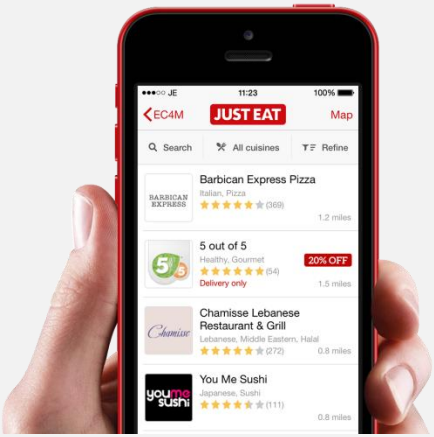

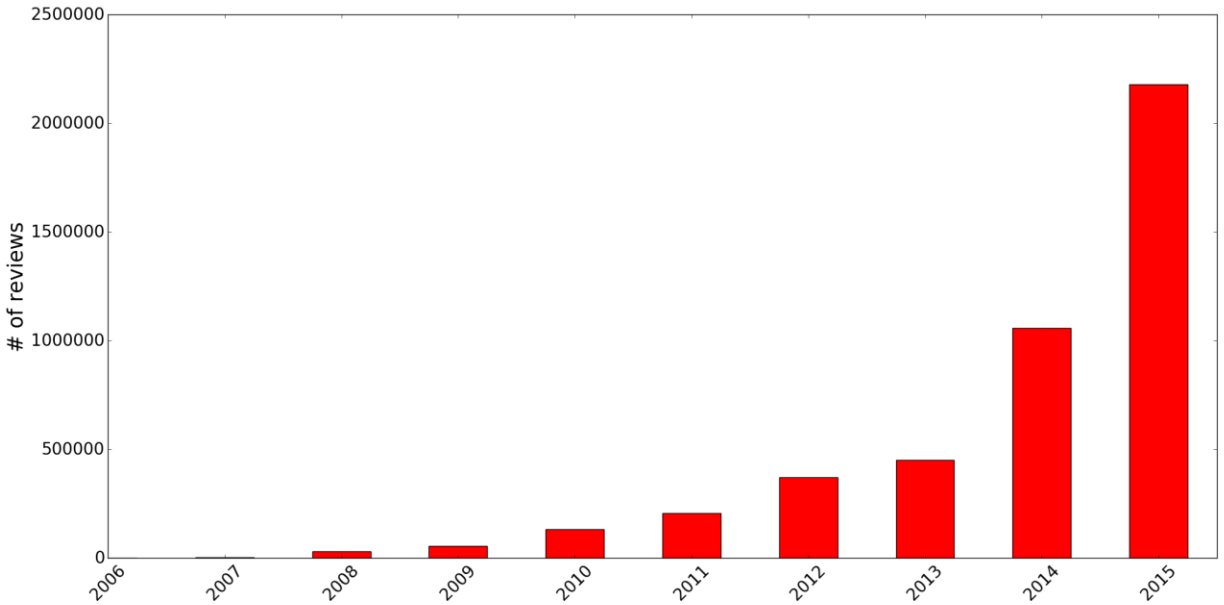

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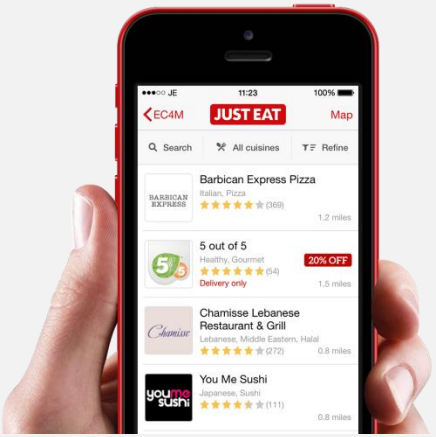
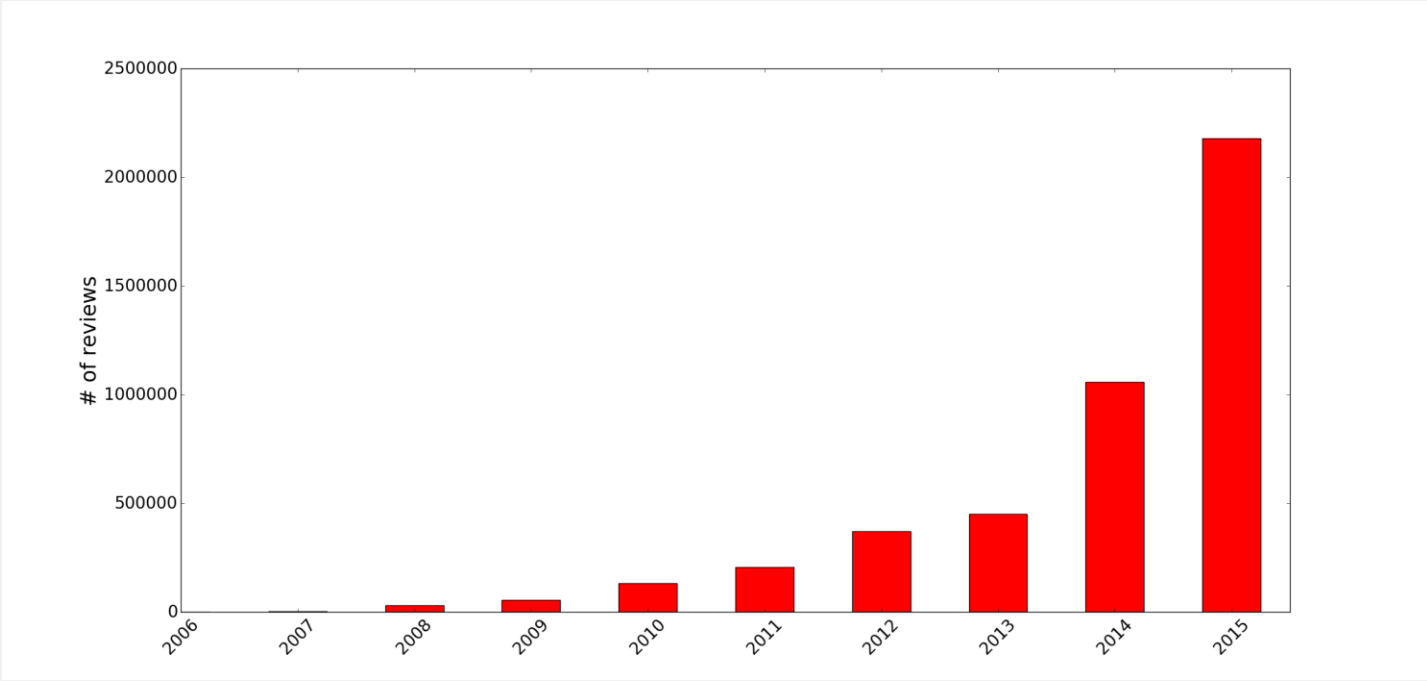
How can we efficiently analyze the sentiment in these data?





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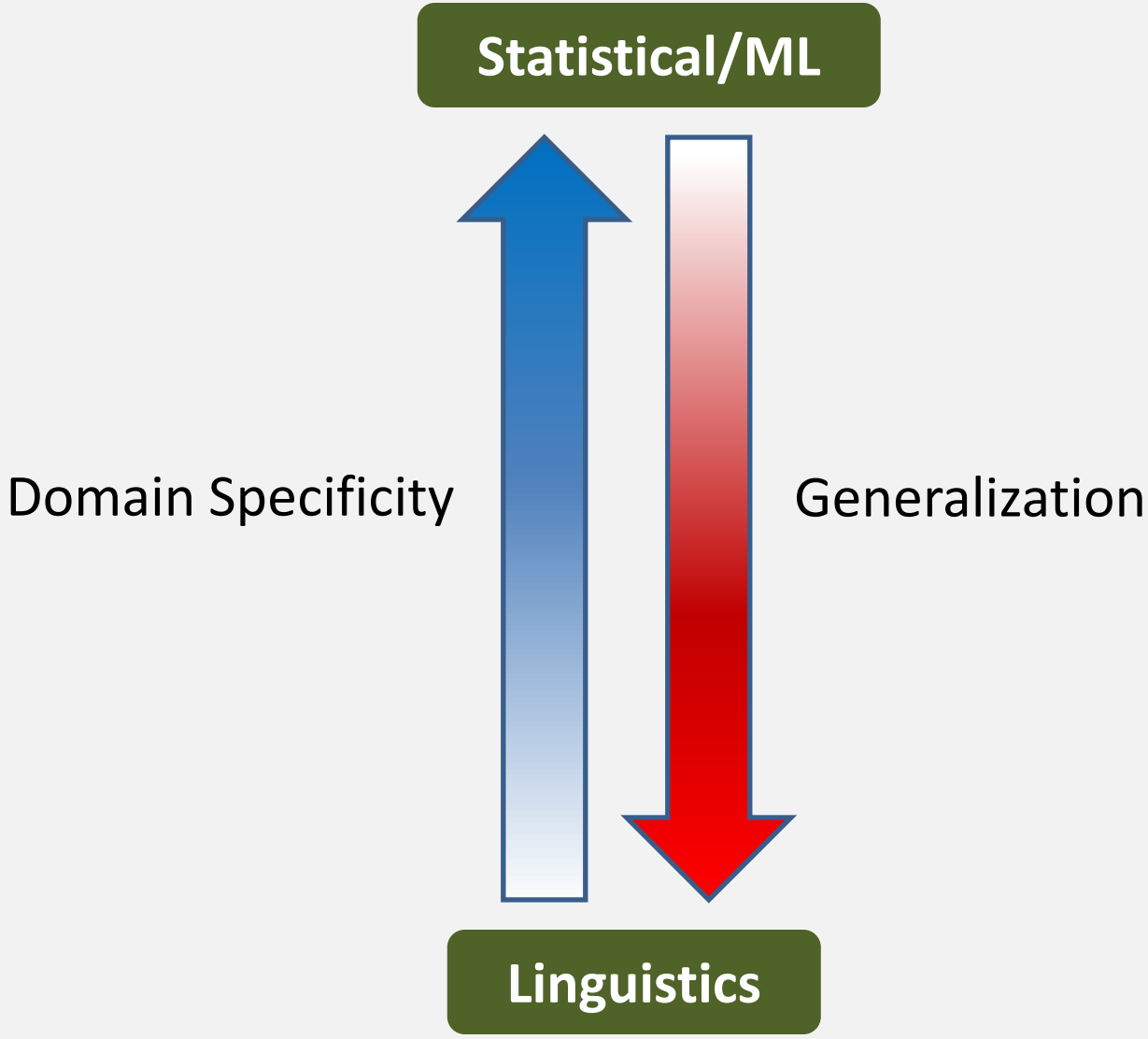
Two Approaches



Two Approaches

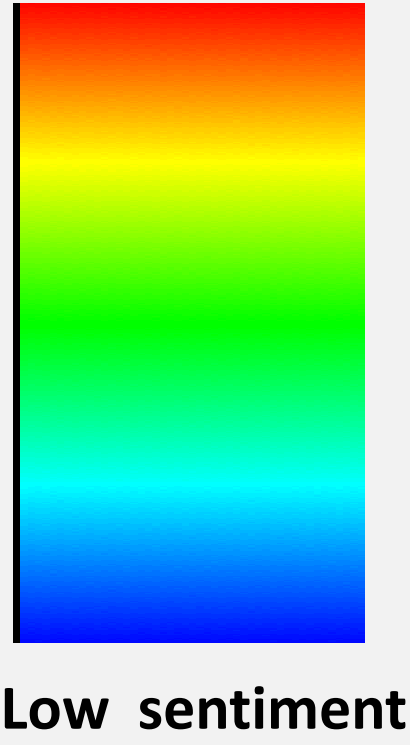
Statistical/ML

+

Linguistics

Goal

['word1' 'word2' 'word3']



THE PIPELINE

["Wheeeen I am alone, a NormallY enjoy a good pizza!! ☺"]

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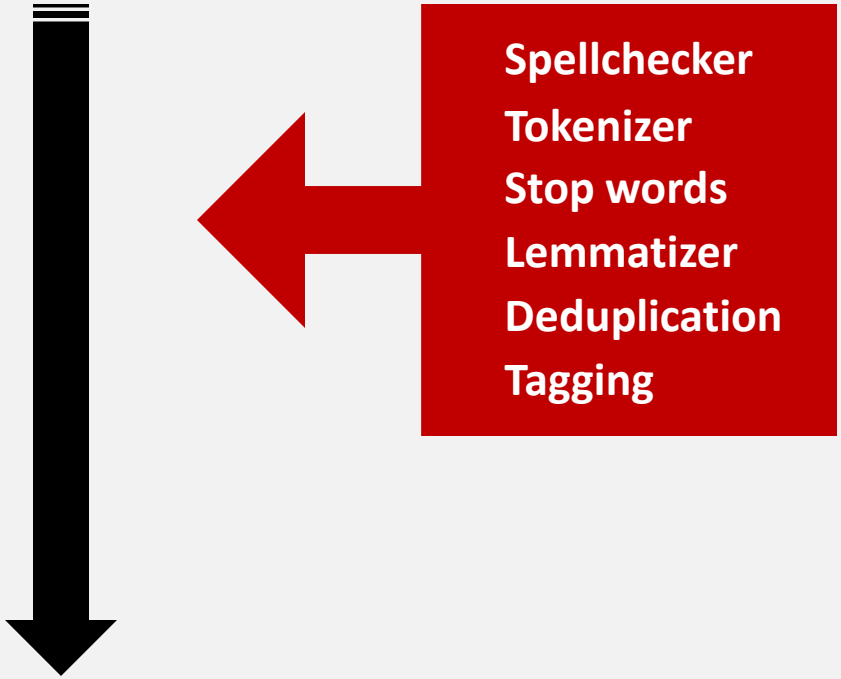

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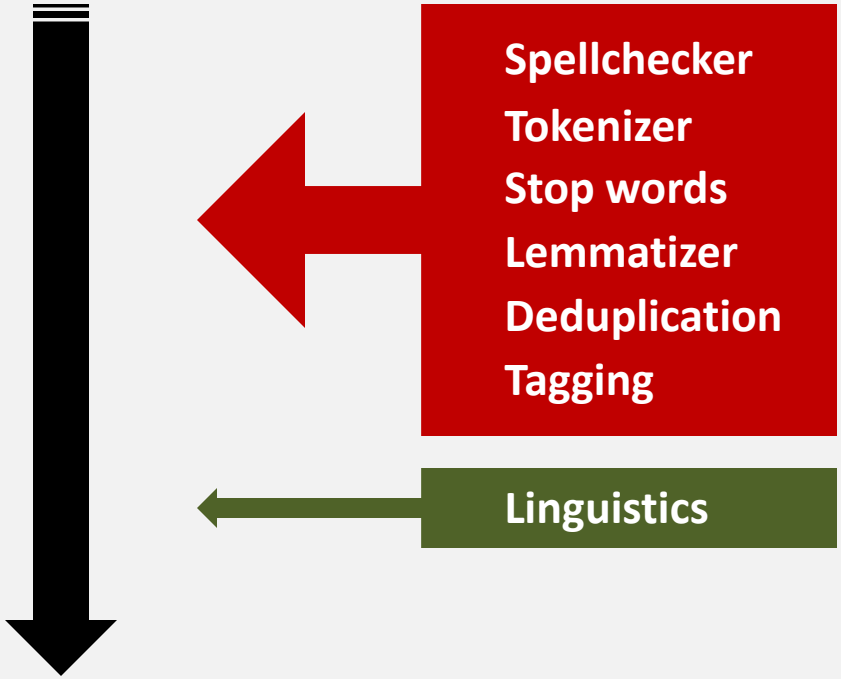

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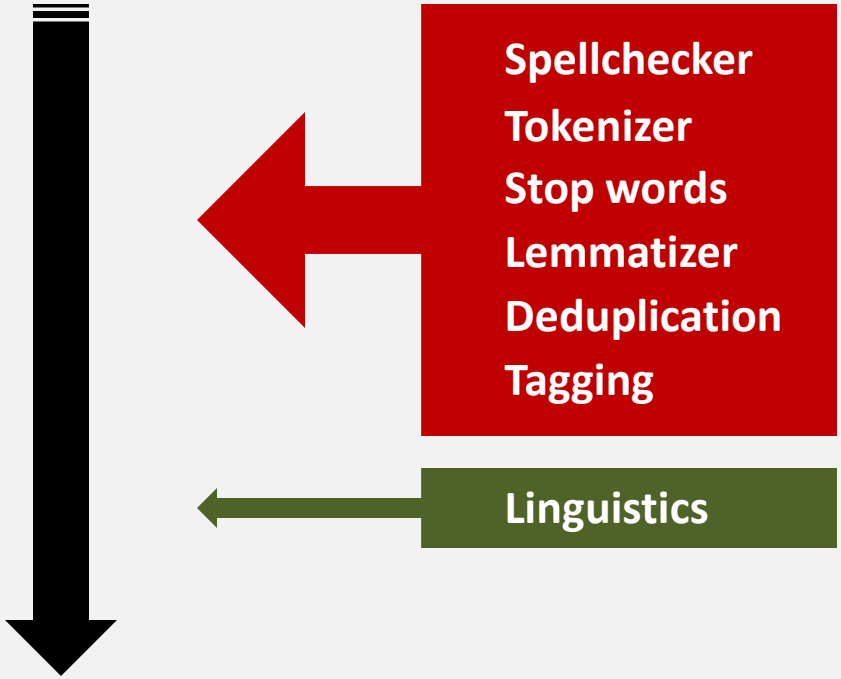

['alone' 'enjoy' 'good']

THE PIPELINE

["She runs a lot!!
When I run that much
I normally need to enjoy a good pizza alone in the evening."]

THE PIPELINE

["She runs a lot!!
When I run that much
I normally need to enjoy a good pizza alone in the evening."]

Tokenize

[“She runs a lot!!
When I run that much
I normally need to enjoy a good pizza alone in the evening.”]

Tokenize

[‘She’ ‘runs’ ‘a’ lot’ ‘!’ ‘!’ ‘When’ ‘I’ ‘run’ ‘that’ ‘much’
‘I’ ‘normally’ ‘need’ ‘to’ ‘enjoy’ ‘a’ ‘good’ ‘pizza’
‘alone’ ‘in’ ‘the’ ‘evening’ ’.’]

Remove stop words

['She' 'runs' 'a' lot' '!' '!' 'When' 'I' 'run' 'that' 'much'
'I' 'normally' 'need' 'to' 'enjoy' 'a' 'good' 'pizza'
'alone' 'in' 'the' 'evening' '.']

Remove stop words

['She' 'runs' 'lot' 'I' 'run' 'much' 'I' 'normally'
'need' 'enjoy' 'good' 'pizza' 'alone' 'evening']

Lemmatize

['She' 'runs' 'lot' 'I' 'run' 'much' 'I' 'normally'
'need' 'enjoy' 'good' 'pizza' 'alone' 'evening']

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Lemmatize

['She' 'run' 'lot' 'I' 'run' 'much' 'I' 'normally'
'need' 'enjoy' 'good' 'pizza' 'alone' 'evening']

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Eliminate duplicates

['She' 'run' 'lot' 'I' 'run' 'much' 'I' 'normally'
'need' 'enjoy' 'good' 'pizza' 'alone' 'evening']

Eliminate duplicates

['She' 'run' 'lot' 'much' 'I' 'normally' 'need' 'enjoy' 'good' 'pizza' 'alone' 'evening']

Tagging

['She' 'run' 'lot' 'much' 'I' 'normally' 'need' 'enjoy' 'good' 'pizza' 'alone' 'evening']

- Verbs & Adverbs
- Adjectives
- Nouns & Personal Pronouns

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Eliminate objective parts

['She' 'run' 'lot' 'much' 'I' 'normally' 'need' 'enjoy' 'good' 'pizza' 'alone' 'evening']

- Verbs & Adverbs
- Adjectives
- Nouns & Personal Pronouns

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Eliminate objective parts

['run' 'lot' 'much' 'normally' 'need' 'enjoy' 'good' 'alone']

Verbs & Adverbs

Adjectives

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Valence Aware Dictionary for sEntiment Reasoning [1]

['run' 'lot' 'much' 'normally' 'need' 'enjoy'
'good' 'alone']

Verbs & Adverbs

Adjectives

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[1] https://github.com/cjhutto/vaderSentiment

VADER

['run' 'lot' 'much' 'normally' 'need' 'enjoy' 'good' 'alone']

Verbs & Adverbs

Adjectives

VADER: A Parsimonious Rule-based Model for Sentiment Analysis of Social Media Text

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cjhutto@gatech.edu gilbert@cc.gatech.edu

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VADER

['run' 'lot' 'much' 'normally' 'need' 'enjoy' 'good' 'alone']

VADER score ≠ 0

Rolando P. Hong Enriquez

VADER

['enjoy' 'good' 'alone']

VADER score ≠ 0

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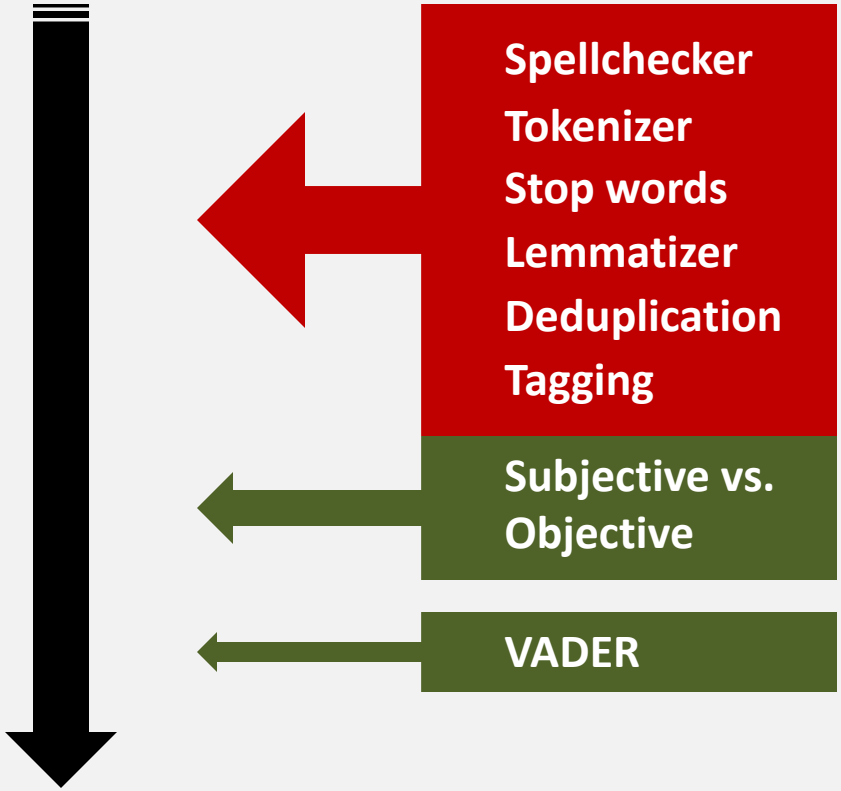
THE PIPELINE

["Wheeeen I am alone, a NormallY enjoy a good pizza!! ☺"]



['alone' 'enjoy' 'good']

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Binarize

1 2 3 4 5

[‘play’ ‘funny’ ‘sad’ ‘good’ ‘bad’] **Minimal Dictionary**

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Binarize

1 2 3 4 5

[‘play’ ‘funny’ ‘sad’ ‘good’ ‘bad’] **Minimal Dictionary**

‘This food is very good’ **Review**

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Binarize

1 2 3 4 5

[‘play’ ‘funny’ ‘sad’ ‘good’ ‘bad’] **Minimal Dictionary**

‘This food is very good’ **Review**

[0 0 0 1 0] **Binarized Review**

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Small Intro to ML models

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ML models

Discriminative

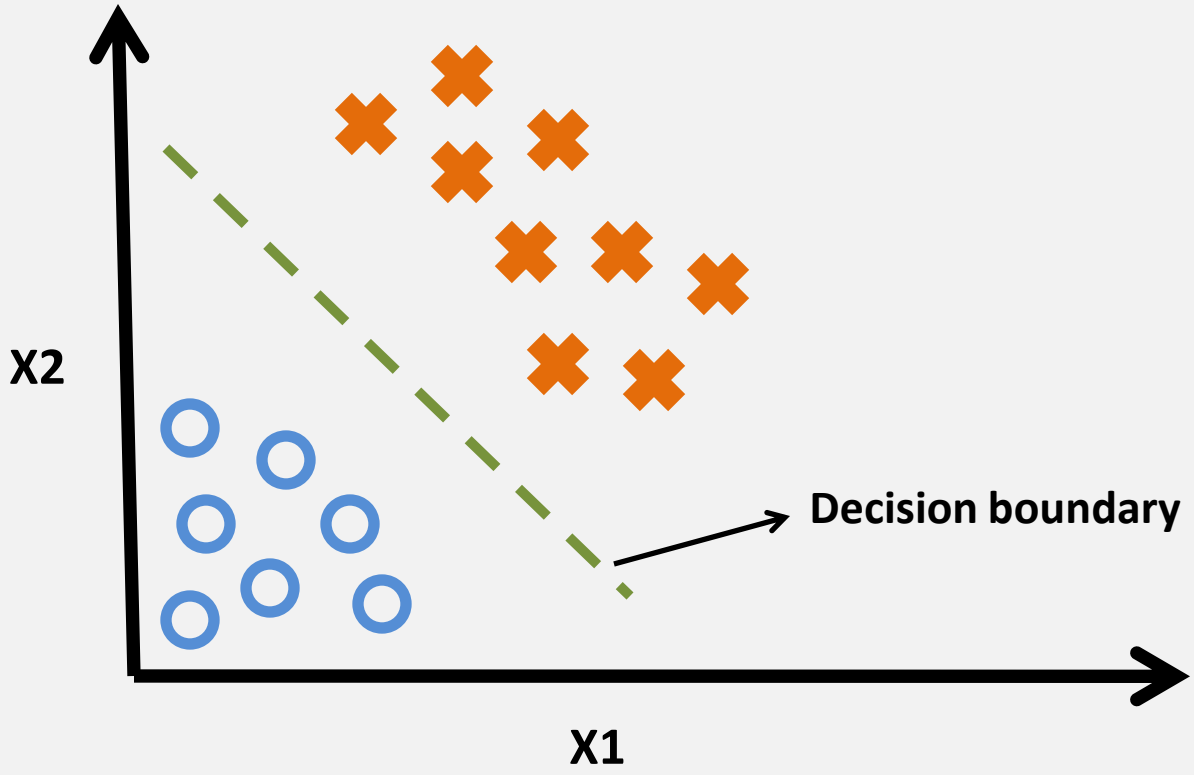
e.g., Linear/Logistic Regression

Generative

e.g., Naïve Bayes

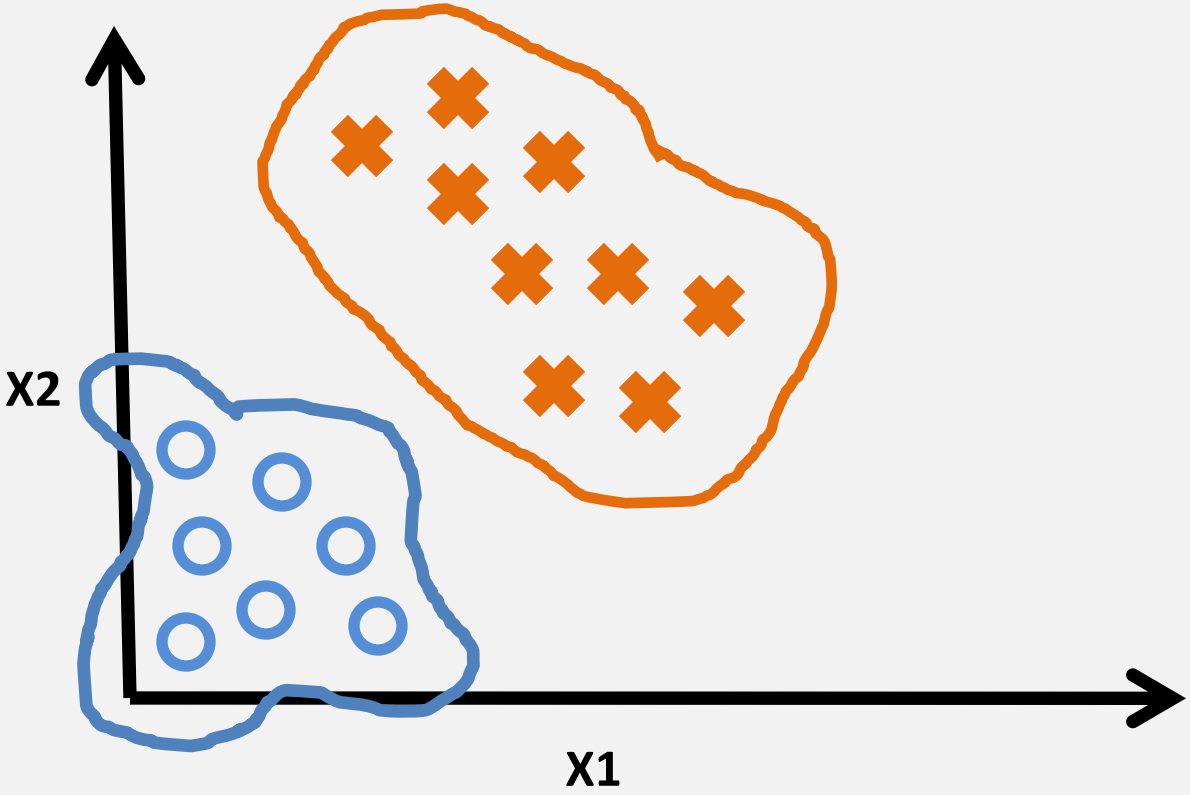
ML models

Discriminative



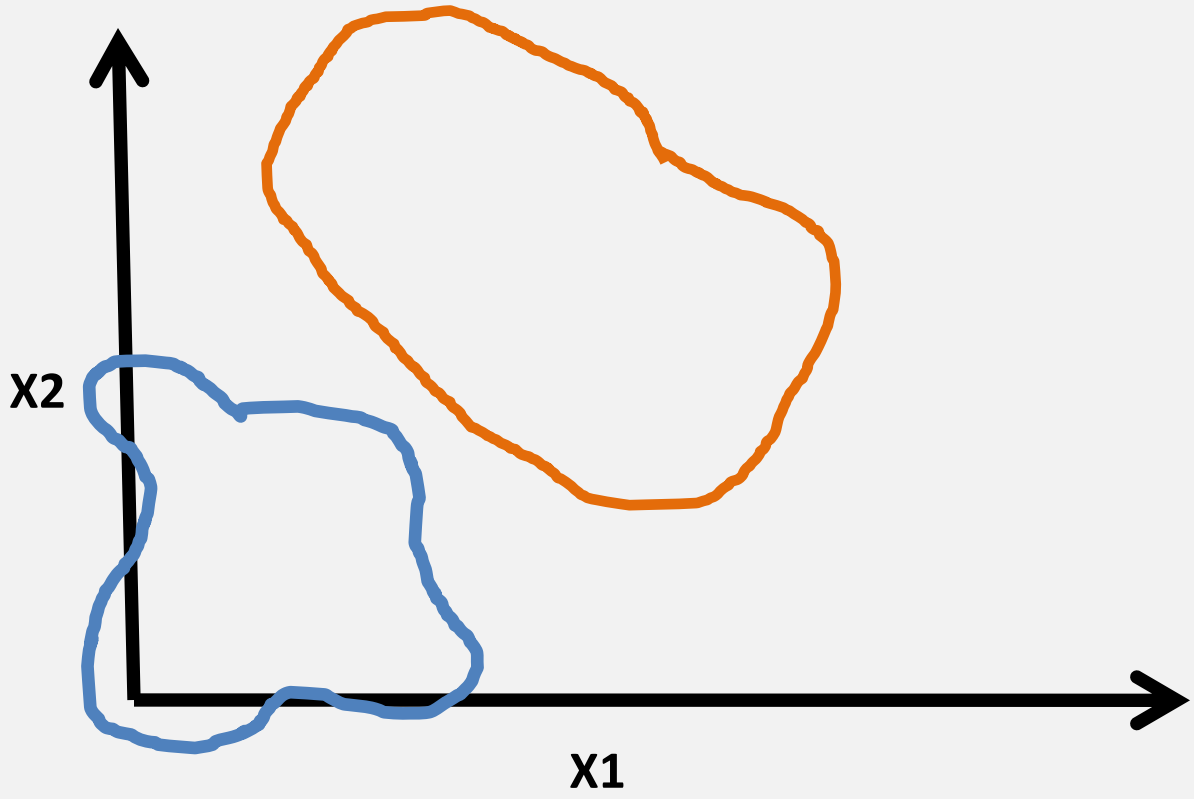
ML models

Generative



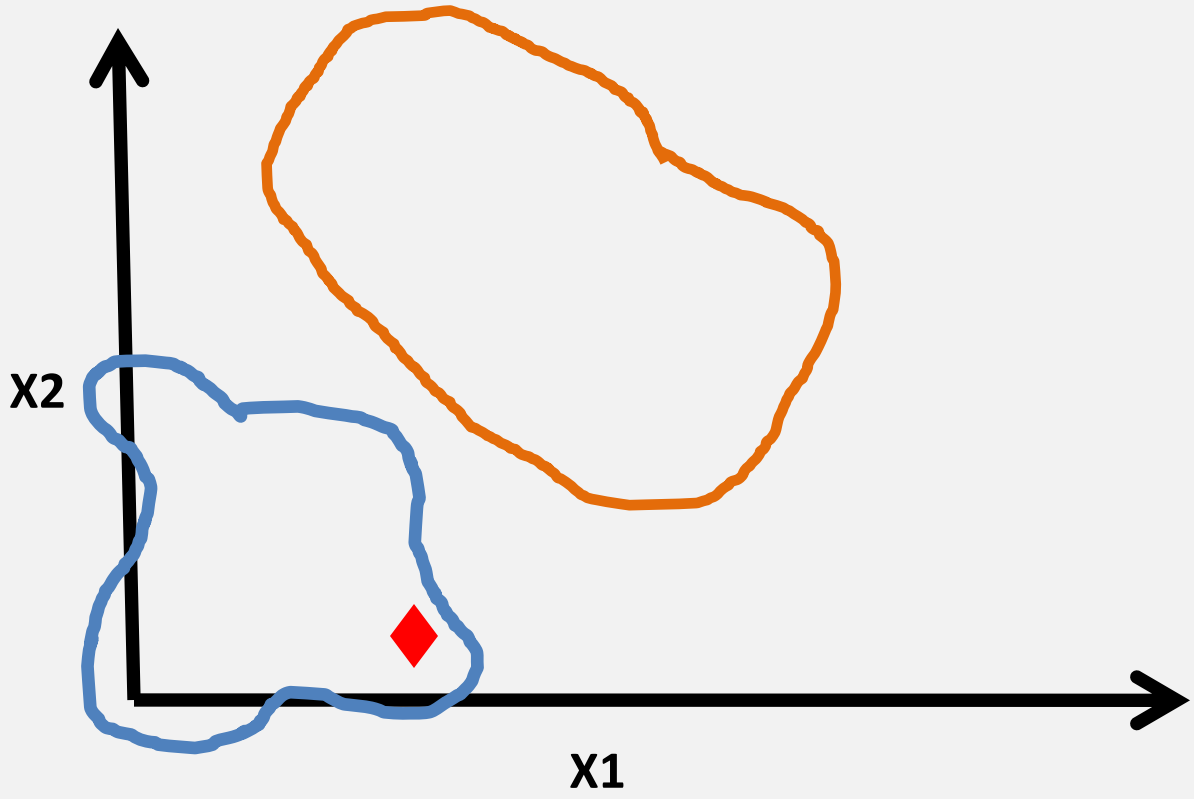
ML models

Generative

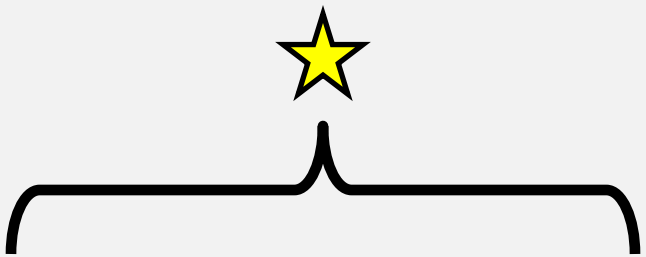


ML models

Generative



Training data



[1 1 0 1 0] **Review 1**

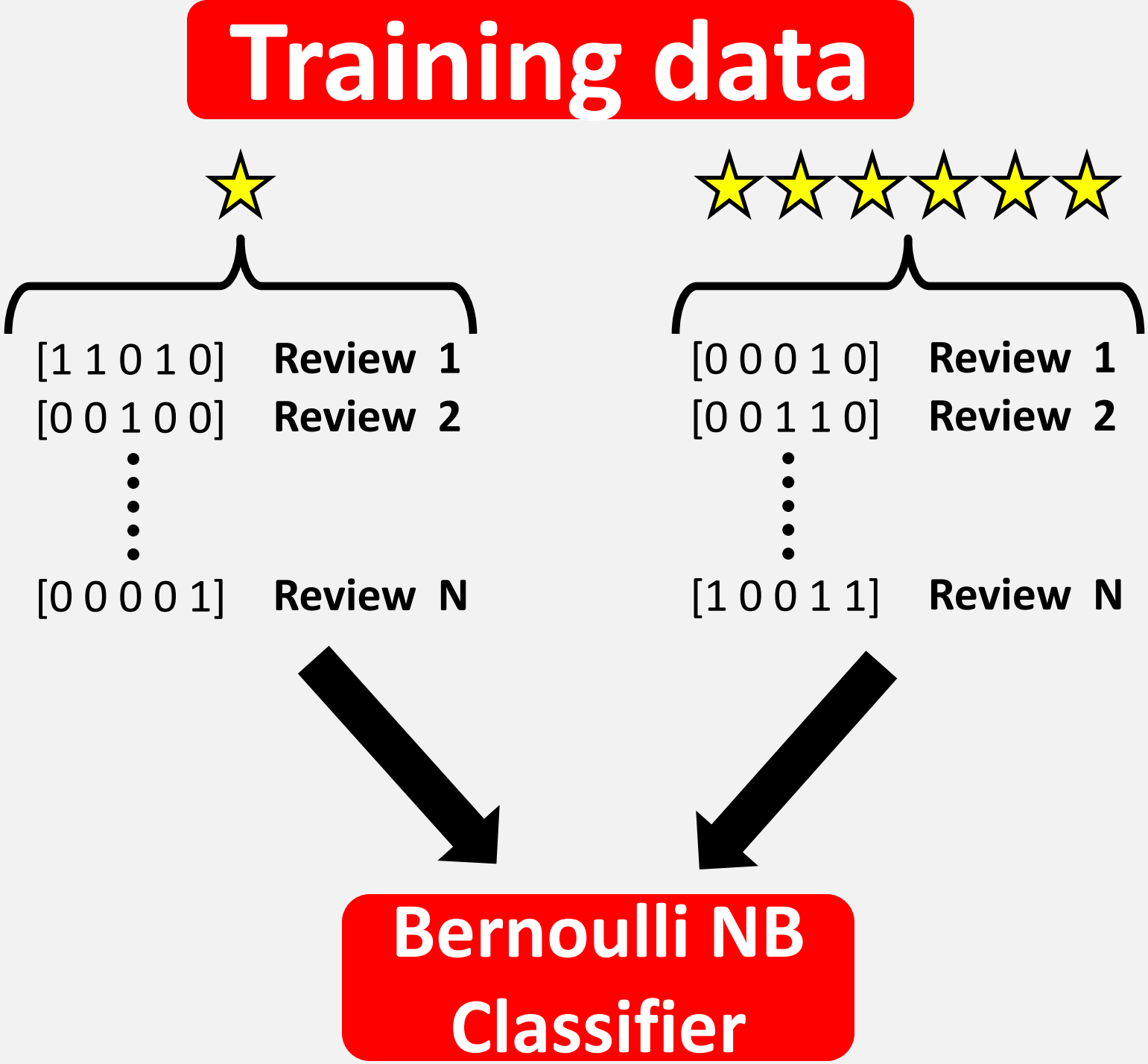
[0 0 1 0 0] **Review 2**

[0 0 0 0 1] **Review N**

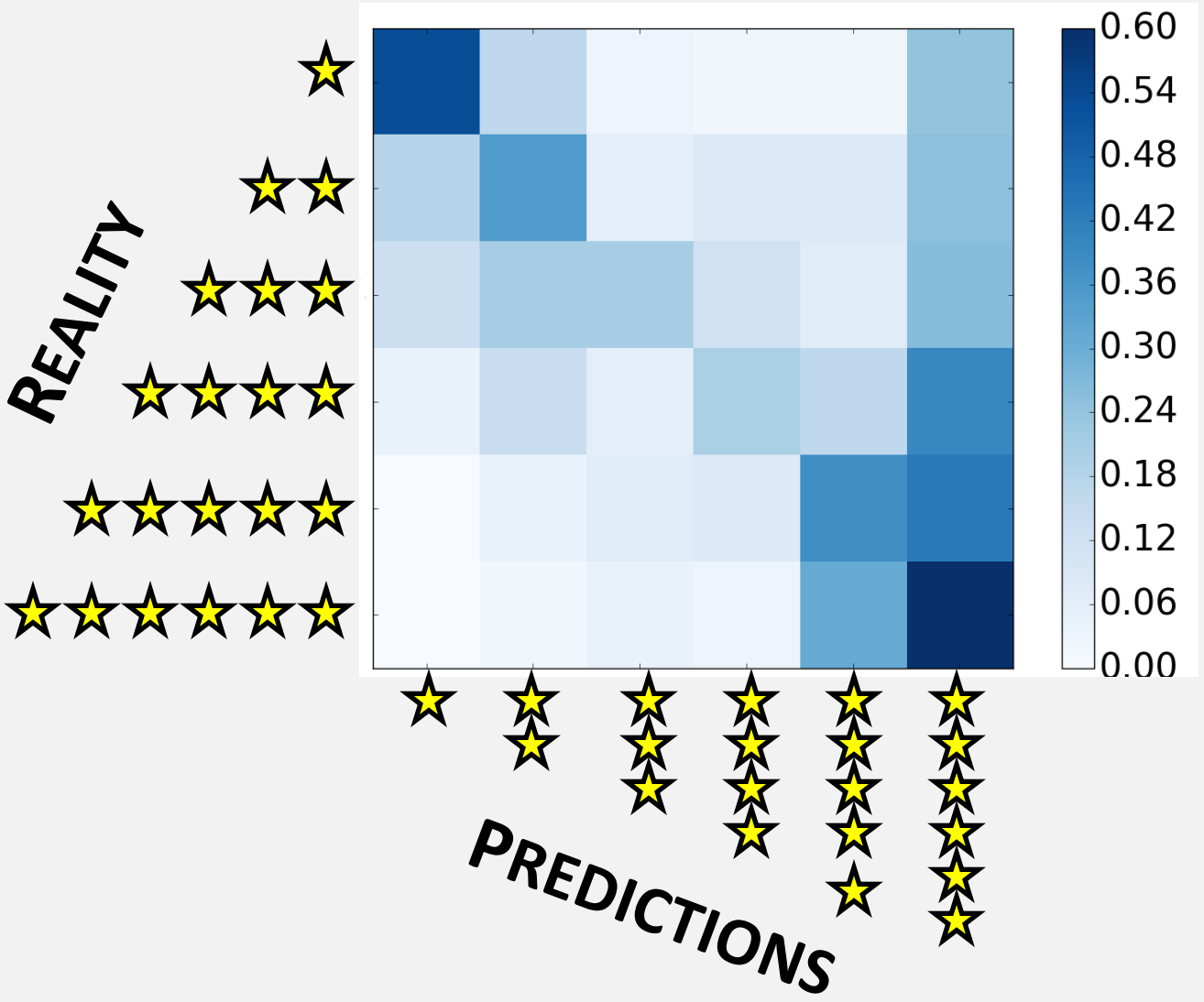
[0 0 0 1 0] **Review 1**

[0 0 1 1 0] **Review 2**

[1 0 0 1 1] **Review N**

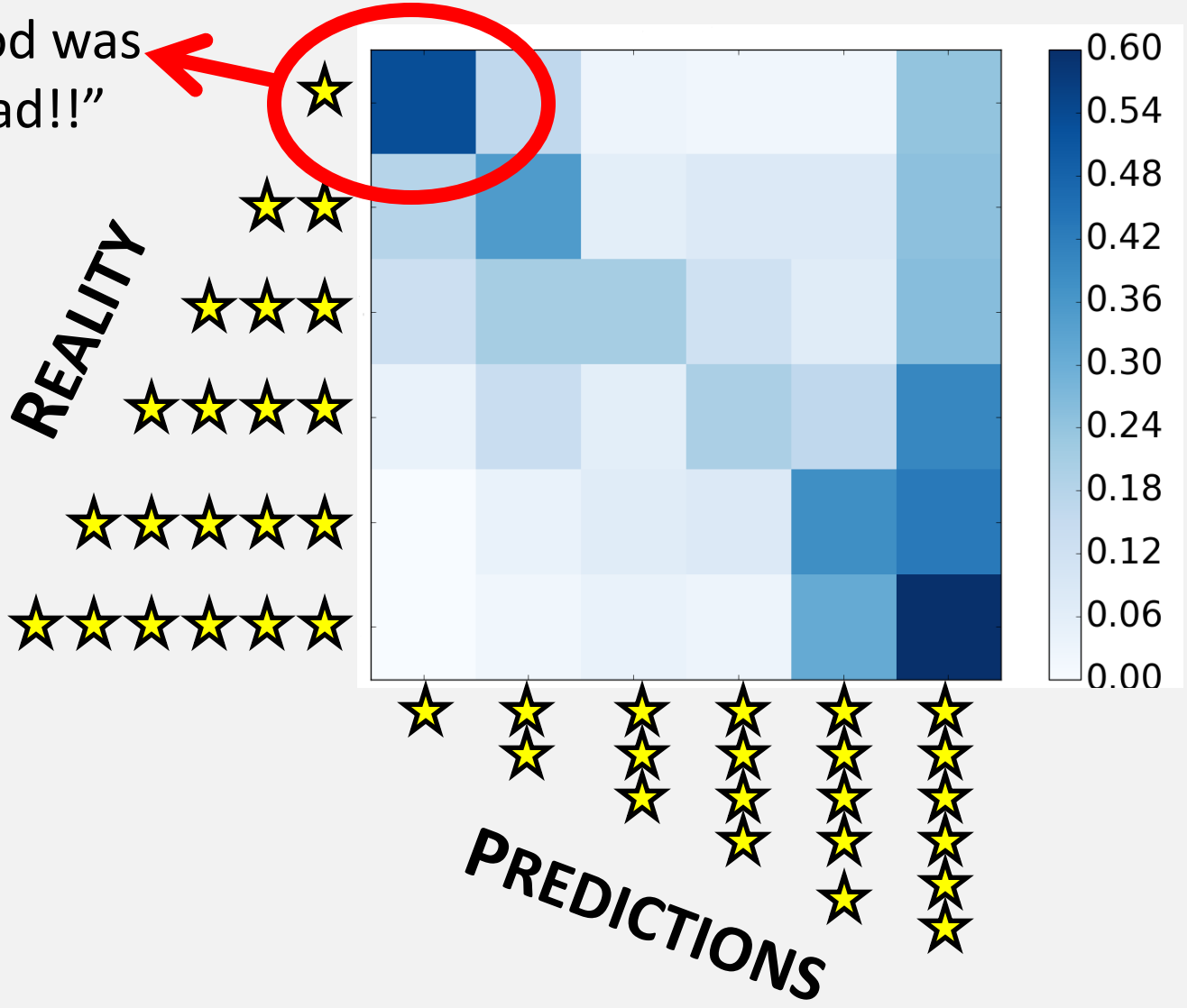

Training data
[1 1 0 1 0] Review 1
[0 0 1 0 0] Review 2
[0 0 0 0 1] Review N
[0 0 0 1 0] Review 1
[0 0 1 1 0] Review 2
[1 0 0 1 1] Review N
Bernoulli NB Classifier

Testing the Classifier

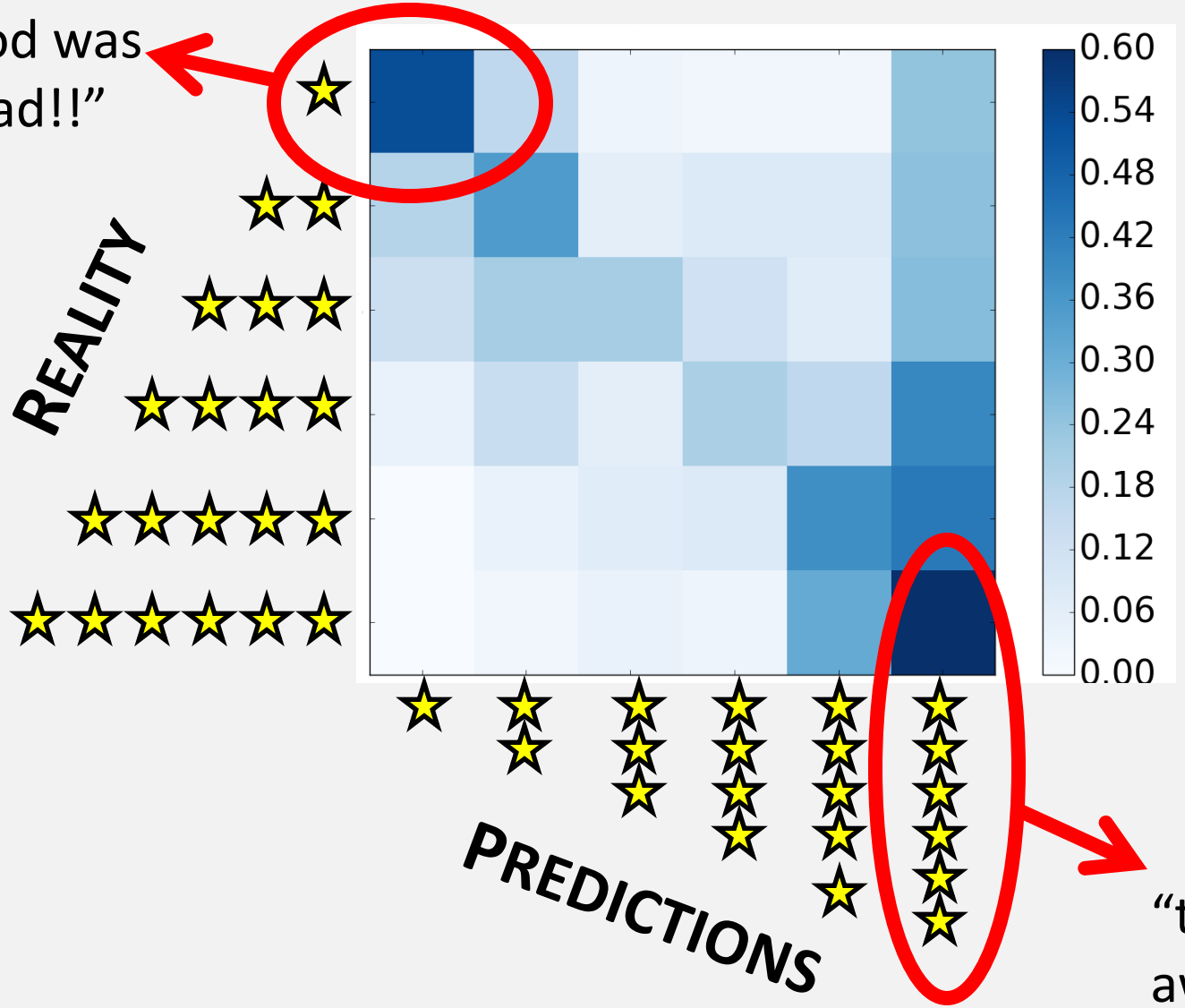


Testing the Classifier

“the food was really bad!!”



Testing the Classifier



Some comparisons

Fang and Zhan *Journal of Big Data* (2015) 2:5
DOI 10.1186/s40537-015-0015-2

Journal of Big Data
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METHODOLOGY Open Access

Sentiment analysis using product review data

Xing Fang* and Justin Zhan

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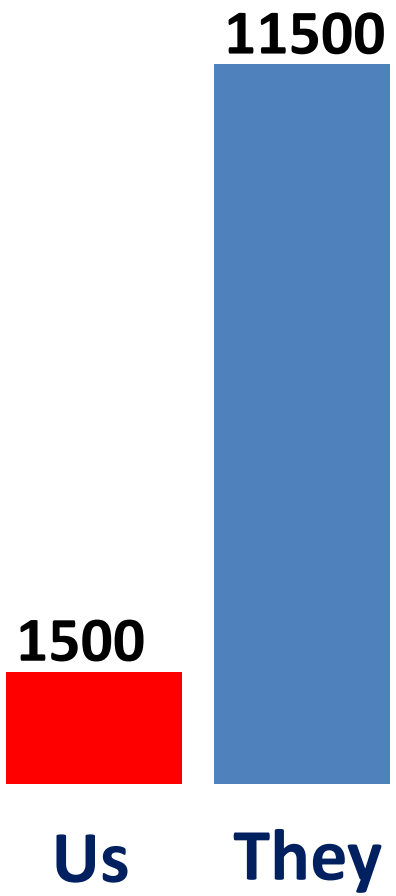
Number of features



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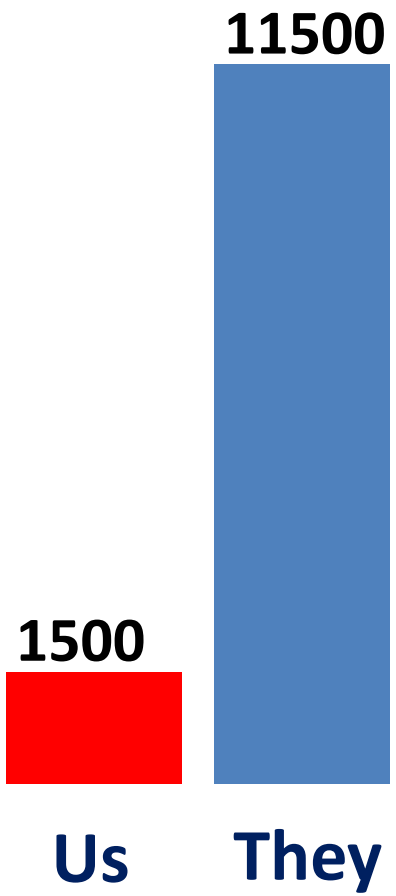
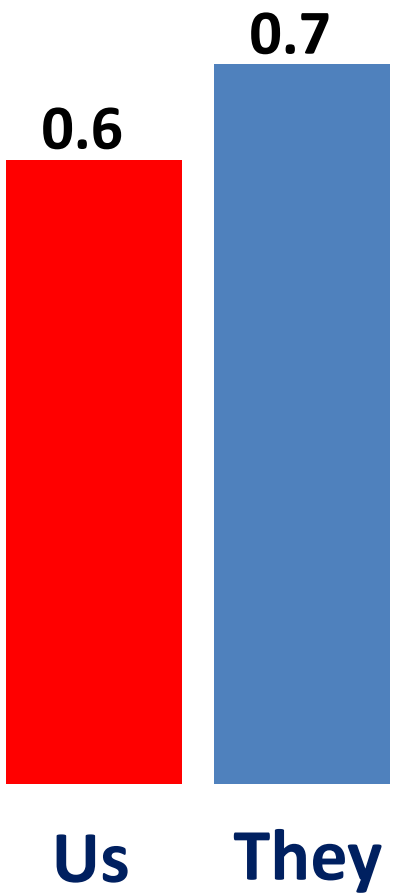
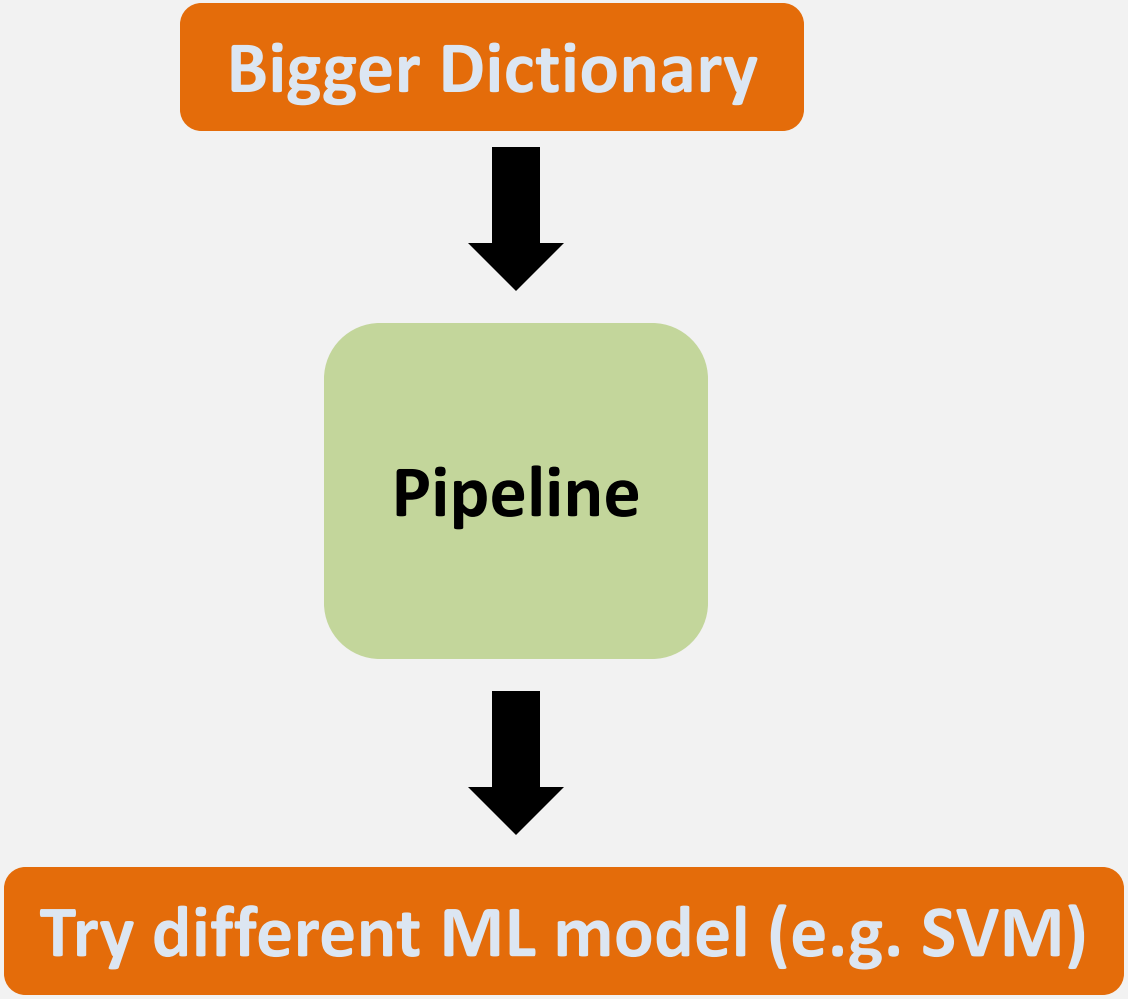


F1 scores



Improving



Thank you

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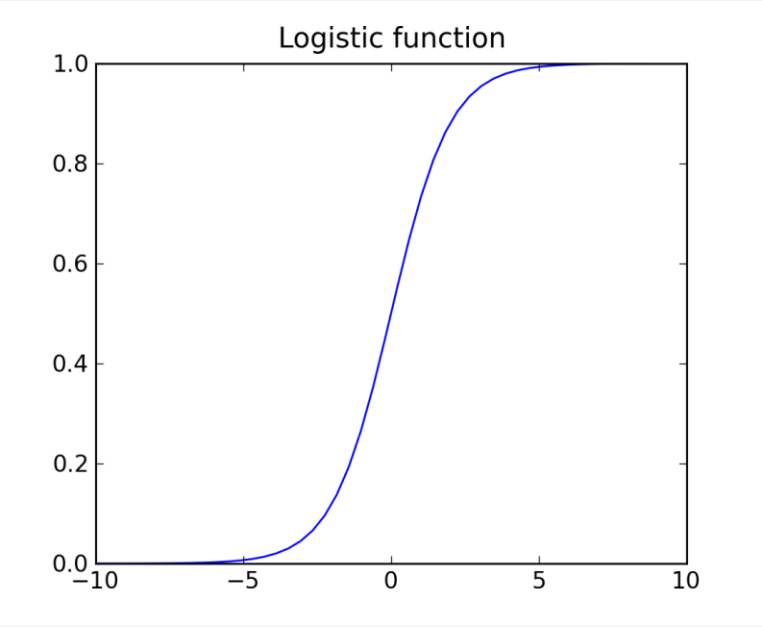
ML models

What does all that means from the perspective of probabilities?

ML models

Discriminative

p(y|x) **Estimates "directly" the probability of y given x**



$$y = \frac{1}{1+e^{x}}$$

$$y = \begin{Bmatrix} 0 \\ 1 \end{Bmatrix}$$ **Classifying in classes '0' and '1'**

e.g., y = 1 if x > 0

ML models

Generative

p(x|y) **Estimates “directly” the probability of y given x**