Text Classification

CS4248 Natural Language Processing

Week 04

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Slides adapted from An Introduction to Natural Language Processing, Computational Linguistics, and Speech Recognition, Prof. Hwee Tou Ng (NUS), and Dan Jurafsky (Stanford)

Recap of Week 03

Language Models

N-grams

Perplexity: Evaluating Language Models

Unknown Words Redux

- Smoothing
- Backoff
- Interpolation
- Kneser-Ney

Announcements

Assignment #1 Due

Assignment #2 Out

Project Team Formation Announced – Due Next Week

Midterm to be offered both online and offline

Week 04 Agenda

Text Classification

Case Study: Sentiment Analysis

TF-IDF

Vector Space Model

Naïve Bayes
and a Runthrough (time permitting)

Evaluating Text Classification

Text Classification

What is Text Classification?

Text Classification

A mapping h from input data x (drawn from instance space $\mathcal{X}$) to a label (or labels) y from some enumerable output space $\mathcal{Y}$

- $\mathcal{X}$ = set of all documents
- $\mathcal{Y}$ = {english, mandarin, greek, …}
- x = a single document

$h(x) = y$

E.g. Lh(μῆνιν ἄειδε θεὰ) = greek

Slide adapted from David Bamman (UCB)

Text Classification

Let $h(x)$ be the “true” mapping (unknown).

How do we find the best $\hat{h}(x)$ to approximate $h(x)$?

- Rule Based (Decision Rules)

if x has characters in
unicode point range 0370-03FF:
$\hat{h}(x)$ = greek

- Supervised learning
  - Given training data in the form of $< x, y >$ pairs, learn $\hat{h}(x)$

Slide adapted from David Bamman (UCB)

Subject Classification

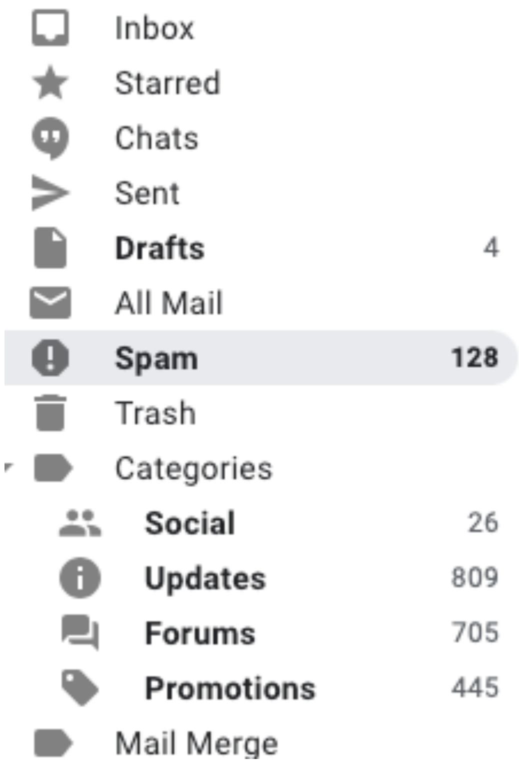
?

MeSH Subject Category Hierarchy

- Antagonists and Inhibitors
- Blood Supply
- Chemistry
- Drug Therapy
- Embryology
- Epidemiology
- …

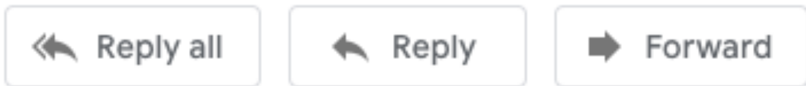
Slide adapted from Dan Jurafsky (Stanford)

Spam Detection

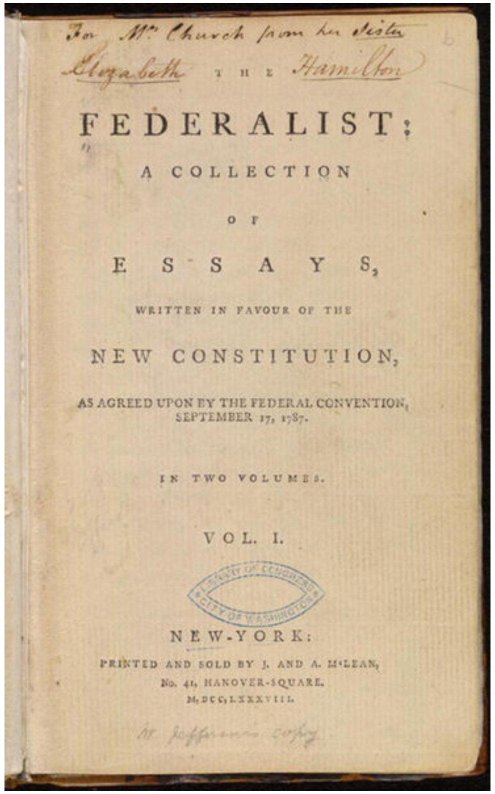


REPLY 01-02-2021

I'm Ivan Maslyaev, the Vice President General Counsel and member of LUKOIL Management Committee. I have a file that has something to do with a member of your family. Get back for more details



Authorship Attribution



For Mrs Church from her Sister Elizabeth Hamilton

THE FEDERALIST:

A COLLECTION OF ESSAYS, WRITTEN IN FAVOUR OF THE NEW CONSTITUTION, AS AGREED UPON BY THE FEDERAL CONVENTION, SEPTEMBER 17, 1787.

IN TWO VOLUMES.

VOL. I.

NEW-YORK:

PRINTED AND SOLD BY J. AND A. M'LEAN, No. 41, HANOVER-SQUARE.

M,DCC,LXXXVIII.

Who wrote which Federalist papers?

1787-8: anonymous essays try to convince New York to ratify U.S Constitution: Jay, Madison, Hamilton.

Authorship of 12 of the letters was in dispute.

1963: solved by Mosteller and Wallace using Bayesian methods

Slide adapted from Dan Jurafsky (Stanford)

Positive or Negative Movie Review?

…zany characters and richly applied satire, and some great plot twists

It was pathetic. The worst part about it was the boxing scenes…

…awesome caramel sauce and sweet toasty almonds. I love this place!

…awful pizza and ridiculously overpriced…

Slide adapted from Dan Jurafsky (Stanford)

Positive or Negative Movie Review?

+ *…zany characters and richly applied satire, and some great plot twists*
− *It was pathetic. The worst part about it was the boxing scenes…*
+ *…awesome caramel sauce and sweet toasty almonds. I love this place!*
− *…awful pizza and ridiculously overpriced…*

Slide adapted from Dan Jurafsky (Stanford)

The Text Classification Problem

Given a document $\boldsymbol{x} = (w_1, w_2, \ldots, w_{|x|}) \in \mathcal{V}^*$

predict a label $y \in \mathcal{Y}$

where $\mathcal{Y}$ is an enumerated, fixed set of classes.

N.B.: Our SLP3 textbook uses d for x and c for y. We'll use both interchangeably.

Slide adapted from Dan Jurafsky (Stanford)

Sample Text Classification Tasks

task	x	y
language ID	text	{english, mandarin, greek, …}
spam classification	email	{spam, not spam}
authorship attribution	text	{jk rowling, james joyce, …}
genre classification	novel	{detective, romance, gothic, …}
sentiment analysis	text	{postive, negative, neutral, mixed}

and many more…

Slide adapted from Dan Jurafsky (Stanford)

Case Study: Sentiment Analysis

Sample Text Classfication Problem

Adapted from David Bamman (UCB)

Sentiment Analysis

Product ratings

Five Stars
I needed the book for my natural language processing class. needless to say, I learnt a lot.
Published on November 27, 2014 by Kamran

Encyclopedic Treatment of NLP
Daniel Jurafsky and James Martin have assembled an incredible mass of information about natural language processing.Foundations of Statistical Natural Language Processing Read more
Published on April 25, 2012 by John M. Ford

Political opinion mining

Sentiment Analysis

Movie Reviews

Movie: Soul
Year: 2020

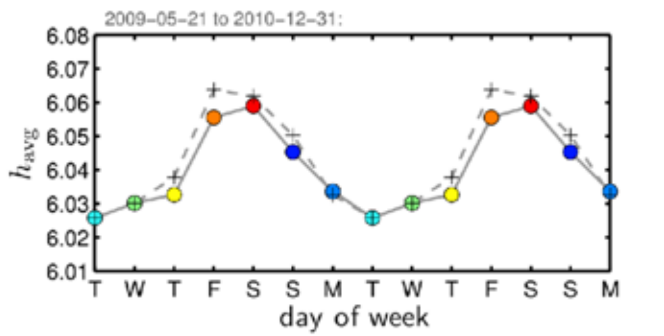
This inventive tale stars Jamie Foxx as a jazz musician caught in a world that human souls pass through on their way into and out of life. Full review

A.O. Scott
The NYTimes

Soul strives to help us remember that life itself is a blessing, even when it doesn't go as we planned. Full review

Paul Asay
Plugged In

Sentiment as Tone

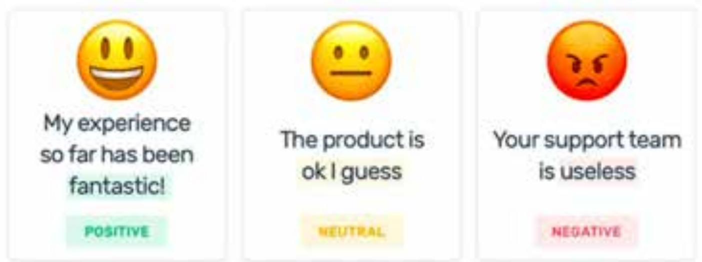


Dodds et al. (2011). "Temporal patterns of happiness and information in a global social network: Hedonometrics and Twitter" (PLoS One)

Sentiment Analysis

The sentiment expressed in a text refers to the author's subjective or emotional attitude towards the central topic of the text.

Sentiment analysis is a classic application of text classification, and is typically approached with a BoW classifier.



Sentiment Analysis

Some linguistic phenomena require going beyond the bag-of-words:

This is not the worst thing that can happen.

I didn't like this movie.

How should we deal with negation?

- prepend the prefix NOT to every word after a token of logical negation until the next punctuation mark.

"*I didn't* NOT_*like* NOT_*this* NOT_*movie.*"

Sentiment Analysis

Sometimes words are a good indicator of sentiment (*love*, *amazing*, *hate*, *terrible*); but …

Many times it requires deep world and contextual knowledge:

- *It would be nice if you acted like you understood.*
- *Valentine's Day is being marketed as a Date Movie. I think it's more of a First-Date Movie. If your date likes it, do not date that person again. And if you like it, there may not be a second date.* - *Robert Ebert*

Adadpted from David Bamman (UCB)

Sentiment Analysis

Lack of training data?

- Use external dictionaries:
  E.g.: General Inquirer, MPQA, LIWC, AFINN, etc.

pos	neg
unlimited	lag
prudent	contortions
superb	fright
closeness	lonely
impeccably	tenuously
fast-paced	plebeian
treat	mortification

Adadpted from David Bamman (UCB)

$tf-idf$

How does a word contribute meaning to a document?

Adapted from CS3245

Word–Document Count Matrices

Store the number of occurrences of a term in a document:

- Each document is a **count vector** in $\mathcal{N}^V$: a column below

	Antony and Cleopatra	Julius Caesar	The Tempest	Hamlet	Othello
Antony	157	73	0	0	0
Brutus	4	157	0	1	0
Caesar	232	227	0	2	1
Calpurnia	0	10	0	0	0
Cleopatra	57	0	0	0	0
mercy	2	0	3	5	5
worser	2	0	1	1	1

Adapted from CS3245

Term frequency tf

- The term frequency $tf_{w,d}$ of word w in document d is defined as the number of times that w occurs in d.
- We want to use tf when computing a representation of a document. But how?
- Raw term frequency is not what we want:
  - Relevance does not increase proportionally with term frequency.
  - A document with 10 occurrences of the term is more relevant than a document with 1 occurrence. But not 10 times more relevant.

Note: frequency = count

Adapted from CS3245

Solution: log frequency weighting

The log frequency weight of word w in d is

$$w_{t,d} = \begin{cases} 1 + \log_{10} \mathrm{tf}_{t,d}, & \text{if } \mathrm{tf}_{t,d} > 0 \\ 0, & \text{otherwise} \end{cases}$$

e.g. 0 → 0, 1 → 1, 2 → 1.3, 10 → 2, 1000 → 4, etc. t.

Adapted from CS3245

Document frequency

Rare terms are more informative than frequent terms

- Recall stop words
- Consider a term in the query that is rare in the collection (e.g., *arachnocentric*)

A document containing this term is very likely to be relevant to the query *arachnocentric*

- We want a high weight for rare terms like *arachnocentric*.

Adapted from CS3245

Document frequency, continued

Frequent words are less informative than **rare words**

Consider a word that is frequent in the collection (e.g., *high, increase, line*). How important is that word in characterizing it ($\mathcal{R}$)?

Document frequency, continued

Frequent words are less informative than **rare words**

Consider a word that is frequent in the collection (e.g., *high, increase, line*). How important is that word in characterizing it ($\mathcal{R}$)?

A document containing such a word is more important to characterize it a document that doesn't have it.

For such words , we want high positive weights for them but lower than the weights for rare words.

We will use document frequency (df) to capture this.

Adapted from CS3245

idf weight

df_w is the document frequency of w : the number of documents that contain w

- df_w is an inverse measure of the informativeness of w
- $df_w \leq N$

We define the idf (inverse document frequency) of w by

$$idf_w = \log \ (N/df_w)$$

- We use $\log(N/df_w)$ instead of N/df_w to "dampen" the effect of idf.

Adapted from CS3245

NUS School of Computing

Example: suppose $N = 1$ million

term	df_t	idf_t
calpurnia	1	6
animal	100	4
sunday	1,000	3
fly	10,000	2
under	100,000	1
the	1,000,000	0

$$idf_w = \log_{10}(N/df_w)$$

There is one idf value for each term w in a collection.

Adapted from CS3245

Collection vs. Document frequency

The collection frequency of w is the number of occurrences of w in the collection, counting multiple occurrences.

Example:

Word	Collection frequency	Document frequency
insurance	10440	3997
try	10422	8760

Which word is a better term to characterize a document (and should get a higher weight)?

Adapted from CS3245

$tf-idf$ weighting

The $tf-idf$ weight of a term is the product of its tf weight and its idf weight.

$$weight_{w,d} = (1 + \log tf_{w,d}) \times \log(N/df_w)$$

Best known weighting scheme NLP/IR

- Note: the "-" in $tf-idf$ is a hyphen, not a minus sign!
- Alternative names: $tf \cdot idf$, $tf \times idf$

Increases with the number of occurrences within a document

Increases with the rarity of the word in the collection

Adapted from CS3245

Count → Weight Matrix

	Antony and Cleopatra	Julius Caesar	The Tempest	Hamlet	Othello
Antony	5.25	3.18	0	0	0
Brutus	1.21	6.1	0	1	0
Caesar	8.59	2.54	0	1.51	0.25
Calpurnia	0	1.54	0	0	0
Cleopatra	2.85	0	0	0	0
mercy	1.51	0	1.9	0.12	5.25
worser	1.37	0	0.11	4.15	0.25

Each document is now represented by a real-valued vector of $tf - idf$ weights $\in \mathcal{R}^{|V|}$

Adapted from CS3245

Vector Space Model

Documents as vectors

So we have a $|V|$-dimensional vector space

Words are axes of the space

Documents are points or vectors in this space

High-dimensional: tens of thousands of dimensions; each dictionary term is a dimension

These are very sparse vectors – most entries are zero.

We'll see vector representations for words (vs. sentences) again later in word embeddings

Slide Credits: Dan Jurafsky (Stanford)

1st Try: Dot product

The dot product between two vectors is a scalar:

$$\text{dot product}(\mathbf{v}, \mathbf{w}) = \mathbf{v} \cdot \mathbf{w} = \sum_{i=1}^{N} v_i w_i = v_1 w_1 + v_2 w_2 + \ldots + v_N w_N$$

The dot product tends to be high when the two vectors have large values in the same dimensions

Dot product can be a similarity metric between vectors

Nice!

Slide Credits: Dan Jurafsky (Stanford)

Problem with raw dot product

Dot product favors long vectors.

Dot product is higher if a vector is longer (has higher values in many dimension).

Vector length:

$$|\mathbf{v}| = \sqrt{\sum_{i=1}^{N} v_i^2}$$

Frequent words (*of*, *the*, *you*) have long vectors (since they occur many times with other words).

So the dot product overly favors frequent words. Not good.

Slide Credits: Dan Jurafsky (Stanford)

Better: cosine for computing word similarity

$$\text{cosine}(\vec{v},\vec{w}) = \frac{\vec{v}\cdot\vec{w}}{|\vec{v}||\vec{w}|} = \frac{\sum_{i=1}^{N} v_i w_i}{\sqrt{\sum_{i=1}^{N} v_i^2}\sqrt{\sum_{i=1}^{N} w_i^2}}$$

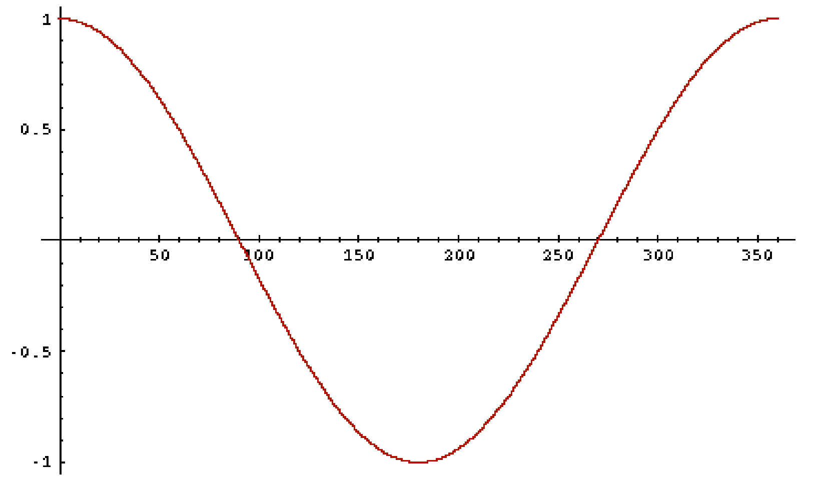
Slide Credits: Dan Jurafsky (Stanford)

Cosine as a similarity metric

–1: vectors point in opposite directions

+1: vectors point in same directions

0: vectors are orthogonal



But since raw frequency values are non-negative, the cosine for term-term matrix vectors ranges from 0–1

Slide Credits: Dan Jurafsky (Stanford)

Cosine examples

$$\cos(\vec{v},\vec{w}) = \frac{\vec{v}\bullet\vec{w}}{|\vec{v}||\vec{w}|} = \frac{\vec{v}}{|\vec{v}|}\bullet\frac{\vec{w}}{|\vec{w}|} = \frac{\sum_{i=1}^{N} v_i w_i}{\sqrt{\sum_{i=1}^{N} v_i^2}\sqrt{\sum_{i=1}^{N} w_i^2}}$$

	pie	data	computer
cherry	442	8	2
digital	5	1683	1670
information	5	3982	3325

$$\cos(\text{cherry},\text{information}) =$$

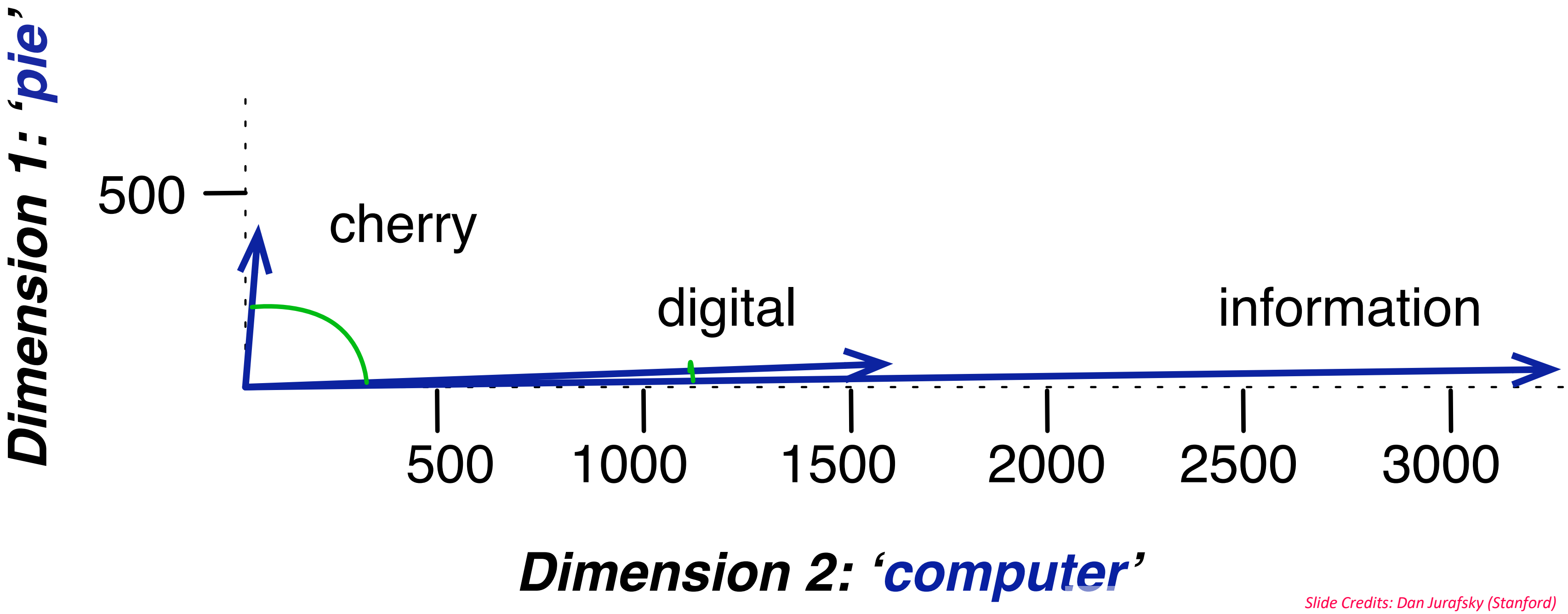
$$\frac{442*5+8*3982+2*3325}{\sqrt{442^2+8^2+2^2}\sqrt{5^2+3982^2+3325^2}} = .017$$

$$\cos(\text{digital},\text{information}) =$$

$$\frac{5*5+1683*3982+1670*3325}{\sqrt{5^2+1683^2+1670^2}\sqrt{5^2+3982^2+3325^2}} = .996$$

Slide Credits: Dan Jurafsky (Stanford)

Visualizing cosines (well, angles)



Slide Credits: Dan Jurafsky (Stanford)

Naïve Bayes

Back to Reverend Thomas Bayes for Text Classification

Slide Credits: CS3245 IR and Dan Jurafsky (Stanford)

Naïve Bayes Intuition

Simple ("naïve") classification method based on Bayes rule.

Relies on a very simple representation of document:

The **Bag of Words** (BoW)

Completely compatible with the vector space model!

Slide adapted from CS324 IR and Dan Jurafsky (Stanford)

The Bag of Words Representation

I love this movie! It's sweet, but with satirical humor. The dialogue is great and the adventure scenes are fun... It manages to be whimsical and romantic while laughing at the conventions of the fairy tale genre. I would recommend it to just about anyone. I've seen it several times, and I'm always happy to see it again whenever I have a friend who hasn't seen it yet!

it	6
I	5
the	4
to	3
and	3
seen	2
yet	1
would	1
whimsical	1
times	1
sweet	1
satirical	1
adventure	1
genre	1
fairy	1
humor	1
have	1
great	1
…	…

Slide adapted from CS324 IR and Dan Jurafsky (Stanford)

Bayes' Rule

$$P(y|\boldsymbol{w}) = \frac{P(\boldsymbol{w}|y)P(y)}{P(\boldsymbol{w})}$$

Slide adapted from CS3244 Machine Learning

Bayes' Rule

$$P(y|\mathbf{w}) = \frac{P(\mathbf{w}|y)P(y)}{P(\mathbf{w})}$$

Slide adapted from CS3244 Machine Learning

Bayes' Rule

Likelihood: How probable is the data given that our document is a member of y?

Prior: How probable is a document to be a member of class y seeing any data?

$$P(y|\boldsymbol{w}) = \frac{P(\boldsymbol{w}|y)P(y)}{P(\boldsymbol{w})}$$

Posterior: How probable is the instance classified as a member of class y?

Marginal: How probable is the evidence under any class?

Slide adapted from CS3244 Machine Learning

Naïve Bayes

Likelihood: How probable is the data given that our document is a member of y?

Prior: How probable is a document to be a member of class y seeing any data?

$$P(y|\boldsymbol{w}) = P(w_1|y) \times P(w_2|y) \times \cdots \times P(w_n|y) \times P(y)$$

Posterior: How probable is the instance classified as a member of class y?

Marginal: To think about. Where did it go?

Slide adapted from CS3244 Machine Learning

Naïve Bayes: Self-Check

$$P(y|\boldsymbol{w}) = P(\boldsymbol{w}|y) \times P(y)$$

$$P(y|\boldsymbol{w}) \propto P(w_1|y) \times P(w_2|y) \times \cdots \times P(w_n|y) \times P(y)$$

What two assumptions did we make?

1.

2.

Slide adapted from CS3244 Machine Learning

Naïve Bayes: Self-Check

$$P(y|\boldsymbol{w}) = P(\boldsymbol{w}|y) \times P(y)$$

$$P(y|\boldsymbol{w}) \propto P(w_1|y) \times P(w_2|y) \times \cdots \times P(w_n|y) \times P(y)$$

What two assumptions did we make?

1. Bag of Words: Position doesn't matter
2. Conditional Independence: no interaction between words. i.e., all $P(w_i|y)$ don't give any information

Slide adapted from CS3245I Machine Learning

NUS School of Computing

Naïve Bayes Classifier

$$c_{MAP} = \underset{c \in \mathcal{C}}{\operatorname{argmax}} P(c|d)$$

Maximum a posteriori or mostly likely class

$$= \underset{c \in \mathcal{C}}{\operatorname{argmax}} \frac{P(d|c)P(c)}{P(d)}$$

Bayes rule

$$= \underset{c \in \mathcal{C}}{\operatorname{argmax}} P(d|c)P(c)$$

Dropping the P(d) in the denominator

$$= \underset{c \in \mathcal{C}}{\operatorname{argmax}} \overbrace{P(f_1, f_2, ..., f_n|c)}^{\text{likelihood}} \overbrace{P(c)}^{\text{prior}}$$

Document d represented as features $f_1, ..., f_n$ (such as word counts) BoW assumption

$$= \underset{c \in \mathcal{C}}{\operatorname{argmax}} P(f_1|c)P(f_2|c)...P(f_n)|c)P(c)$$

Independence Assumption

$$c_{NB} = \underset{c \in \mathcal{C}}{\operatorname{argmax}} P(c) \prod_{f \in \mathcal{F}} P(f|c)$$

Equation for NB classifier

Slide Credits: David Bamman (UCB)

Maximum Likelihood Estimates

In relative frequency estimation, the parameters are set to empirical frequencies. Estimating $P(w|c)$:

$$\hat{P}(w_i|c_j) = \frac{count(w_i, c_j)}{\sum_{w \in \mathcal{V}} count(w, c_j)}$$

Fraction of times word w_i appears among all words of in all documents of topic c_j

Estimating $P(c)$:

$$\hat{P}(c_j) = \frac{N_{c_j}}{N_{doc}}$$

N_{c_j} = the number of documents in our dataset with class c_j
N_{doc} = the total number of documents

Slide Credits: David Bamman (UCB)

Other Issues We've Seen Before

1. **Sparsity**: Multiplying small probabilities leads to numerical underflow.

   Solution: transform to the equivalent addition of log probabilities.

$$c_{NB} = \underset{c \in \mathcal{C}}{\operatorname{argmax}} \log P(c) + \sum_{f \in \mathcal{F}} \log P(f|c)$$

2. **Out of Vocabulary**: There will be new words seen during test time.

   Solution: Smoothing, Backoff and Interpolation; Subword (BPE) Counting

$$\frac{count(w_i, c_j) + \alpha}{\sum_{w \in \mathcal{V}} count(w, c_j) + |V|\alpha}$$

α = smoothing hyperparameter.
Laplace (add-1) smoothing: $\alpha = 1$

Summary: Multinomial NB Classifier

function TRAIN NAIVE BAYES(D, C) **returns** log $P(c)$ and log $P(w|c)$

for each class $c \in C$ # Calculate $P(c)$ terms
  N_{doc} = number of documents in D
  N_c = number of documents from D in class c
  $logprior[c] \leftarrow \log \frac{N_c}{N_{doc}}$
  $V \leftarrow$ vocabulary of D
  $bigdoc[c] \leftarrow$ **append**(d) **for** d $\in$ D **with** class c
  for each word w in V # Calculate $P(w|c)$ terms
    $count(w,c) \leftarrow$ # of occurrences of w in $bigdoc[c]$
    $loglikelihood[w,c] \leftarrow \log \frac{count(w,c) + 1}{\sum_{w' \text{ in } V} (count(w',c) + 1)}$
return *logprior*, *loglikelihood*, V

function TEST NAIVE BAYES(*testdoc*, *logprior*, *loglikelihood*, C, V) **returns** best c

for each class $c \in C$
  $sum[c] \leftarrow logprior[c]$
  for each position i in *testdoc*
    $word \leftarrow testdoc[i]$
    if $word \in V$
      $sum[c] \leftarrow sum[c] + loglikelihood[word,c]$
return $\text{argmax}_c\ sum[c]$

N.B.: Our SLP3 textbook uses d for x and c for y. We'll use both interchangeably.

Naïve Bayes Runthrough

Weather Dataset

	Outlook	Temperature	Humidity	Windy	Play Golf
1	Rainy	Hot	High	False	No
2	Rainy	Hot	High	True	No
3	Overcast	Hot	High	False	Yes
4	Sunny	Mild	High	False	Yes
5	Sunny	Cool	Normal	False	Yes
6	Sunny	Cool	Normal	True	No
7	Overcast	Cool	Normal	True	Yes
8	Rainy	Mild	High	False	No
9	Rainy	Cool	Normal	False	Yes
10	Sunny	Mild	Normal	False	Yes
11	Rainy	Mild	Normal	True	Yes
12	Overcast	Mild	High	True	Yes
13	Overcast	Hot	Normal	False	Yes
14	Sunny	Mild	High	True	No

Slide adapted from CS3244 Machine Learning

Frequency Table

		Play Golf	
		Yes	No
Outlook	Sunny	3	2
	Overcast	4	0
	Rainy	2	3

Outlook	Temperature	Humidity	Windy	Play Golf
Rainy	Hot	High	False	No
Rainy	Hot	High	True	No
Overcast	Hot	High	False	Yes
Sunny	Mild	High	False	Yes
Sunny	Cool	Normal	False	Yes
Sunny	Cool	Normal	True	No
Overcast	Cool	Normal	True	Yes
Rainy	Mild	High	False	No
Rainy	Cool	Normal	False	Yes
Sunny	Mild	Normal	False	Yes
Rainy	Mild	Normal	True	Yes
Overcast	Mild	High	True	Yes
Overcast	Hot	Normal	False	Yes
Sunny	Mild	High	True	No

Slide adapted from CS3244 Machine Learning

Likelihood Table

		Play Golf		
		Yes	No	
Outlook	Sunny	3/9	2/5	5/14
	Overcast	4/9	0/5	4/14
	Rainy	2/9	3/5	5/14
		9/14	5/14	

Slide adapted from CS3244 Machine Learning

Likelihood Table

$$P(x_i|y) = P(Sunny|Yes) = \frac{3}{9}$$

$$P(x_i) = P(Sunny) = \frac{5}{14}$$

		Play Golf		
		Yes	No	
Outlook	Sunny	3/9	2/5	5/14
	Overcast	4/9	0/5	4/14
	Rainy	2/9	3/5	5/14
		9/14	5/14	

$$P(y) = P(Yes) = \frac{9}{14}$$

$$P(y|x) = P(Yes|Sunny) = \frac{3}{9} \times \frac{9}{14} \div \frac{5}{14} = \frac{3}{5}$$

Slide adapted from CS3244 Machine Learning

All of the likelihood tables

These statistics make up the model representation for NB, our h.

		Play Golf	
		Yes	No
Outlook	Sunny	3/9	2/5
	Overcast	4/9	0/5
	Rainy	2/9	3/5

		Play Golf	
		Yes	No
Temperature	Hot	2/9	2/5
	Mild	4/9	2/5
	Cool	3/9	1/5

		Play Golf	
		Yes	No
Windy	True	3/9	3/5
	False	6/9	2/5

		Play Golf	
		Yes	No
Humidity	High	3/9	4/5
	Normal	6/9	1/5

Slide adapted from CS3244 Machine Learning

Applying NB at test time

Outlook	Temperature	Humidity	Windy	Play Golf
Overcast	Cool	High	True	?

		Play Golf	
		Yes	No
Outlook	Sunny	4/12	3/8
	Overcast	5/12	1/8
	Rainy	3/12	4/8

		Play Golf	
		Yes	No
Temperature	Hot	3/12	3/8
	Mild	5/12	3/8
	Cool	4/12	2/8

		Play Golf	
		Yes	No
Windy	True	4/11	4/7
	False	7/11	3/7

		Play Golf	
		Yes	No
Humidity	High	4/11	5/7
	Normal	7/11	2/7

		Play Golf	
		Yes	No
Outlook	Sunny	3/9	2/5
	Overcast	4/9	0/5
	Rainy	2/9	3/5

		Play Golf	
		Yes	No
Temperature	Hot	2/9	2/5
	Mild	4/9	2/5
	Cool	3/9	1/5

		Play Golf	
		Yes	No
Windy	True	3/9	3/5
	False	6/9	2/5

		Play Golf	
		Yes	No
Humidity	High	3/9	4/5
	Normal	6/9	1/5

Slide adapted from CS3244 Machine Learning

Applying NB at test time

Outlook	Temperature	Humidity	Windy	Play Golf
Overcast	Cool	High	True	?

$$P(Yes|x) = P(Overcast|Yes)\times P(Cool|Yes)\times P(High|Yes)\times P(True|Yes)\times P(Yes)$$

$$P(No|x) = P(Overcast|No)\times P(Cool|No)\times P(High|No)\times P(True|No)\times P(No)$$

		Play Golf	
		Yes	No
Outlook	Sunny	3/9	2/5
	Overcast	4/9	0/5
	Rainy	2/9	3/5

		Play Golf	
		Yes	No
Temperature	Hot	2/9	2/5
	Mild	4/9	2/5
	Cool	3/9	1/5

		Play Golf	
		Yes	No
Humidity	High	3/9	4/5
	Normal	6/9	1/5

		Play Golf	
		Yes	No
Windy	True	3/9	3/5
	False	6/9	2/5

Slide adapted from CS3244 Machine Learning

Applying NB at test time

Outlook	Temperature	Humidity	Windy	Play Golf
Overcast	Cool	High	True	?

$$P(Yes|x) = P(Overcast|Yes) \times P(Cool|Yes) \times P(High|Yes) \times P(True|Yes) \times P(Yes)$$

$$P(Yes|x) = \frac{4}{9} \times \frac{3}{9} \times \frac{3}{9} \times \frac{3}{9} \times \frac{9}{14} = 0.010582$$

$$\frac{0.0010582}{0.0010582 + 0.0} = 1.0$$

$$P(No|x) = P(Overcast|No) \times P(Cool|No) \times P(High|No) \times P(True|No) \times P(No)$$

$$P(No|x) = \frac{0}{5} \times \frac{1}{5} \times \frac{4}{5} \times \frac{3}{5} \times \frac{5}{14} = 0.0$$

$$\frac{0.0}{0.0010582 + 0.0} = 0.0$$

		Play Golf	
		Yes	No
Outlook	Sunny	3/9	2/5
	Overcast	4/9	0/5
	Rainy	2/9	3/5

		Play Golf	
		Yes	No
Temperature	Hot	2/9	2/5
	Mild	4/9	2/5
	Cool	3/9	1/5

		Play Golf	
		Yes	No
Humidity	High	3/9	4/5
	Normal	6/9	1/5

		Play Golf	
		Yes	No
Windy	True	3/9	3/5
	False	6/9	2/5

Slide adapted from CS3244 Machine Learning

Laplace Smoothed Frequency Table

		Play Golf	
		Yes	No
Outlook	Sunny	3+1=4 (4/12)	2+1=3 (3/8)
	Overcast	4+1=5 (5/12)	0+1=1 (1/8)
	Rainy	2+1=3 (3/12)	3+1=4 (4/8)

Priors
$P(\text{Yes}) = 9+1\ (10/14+2)$
$P(\text{No}) = 5+1\ (6/14+2)$

We smooth the priors separately from the likelihoods.

Slide adapted from CS3244 Machine Learning

Smoothed Frequency Table

NUS School of Computing

		Play Golf	
		Yes	No
Outlook	Sunny	3+1=4 (4/12)	2+1=3 (3/8)
	Overcast	4+1=5 (5/12)	0+1=1 (1/8)
	Rainy	2+1=3 (3/12)	3+1=4 (4/8)

Priors
P(Yes) = 9+1 (10/16)
P(No) = 5+1 (6/16)

$$P(Yes|x) = P(Overcast|Yes) \times P(Cool|Yes) \times P(High|Yes) \times P(True|Yes) \times P(Yes)$$

$$P(Yes|x) = \frac{5}{12} \times \frac{4}{12} \times \frac{4}{11} \times \frac{4}{11} \times \frac{10}{16} = 0.01147$$

$$P(No|x) = P(Overcast|No) \times P(Cool|No) \times P(High|No) \times P(True|No) \times P(No)$$

$$P(No|x) = \frac{1}{8} \times \frac{2}{8} \times \frac{5}{7} \times \frac{4}{7} \times \frac{6}{16} = 0.00478$$

		Play Golf	
		Yes	No
Outlook	Sunny	4/12	3/8
	Overcast	5/12	1/8
	Rainy	3/12	4/8

		Play Golf	
		Yes	No
Temperature	Hot	3/12	3/8
	Mild	5/12	3/8
	Cool	4/12	2/8

		Play Golf	
		Yes	No
Humidity	High	4/11	5/7
	Normal	7/11	2/7

		Play Golf	
		Yes	No
Windy	True	4/11	4/7
	False	7/11	3/7

Slide adapted from CS3244 Machine Learning

Applying Smoothed NB at test time

Outlook	Temperature	Humidity	Windy	Play Golf
Overcast	Cool	High	True	?

$$P(Yes|x) = \frac{5}{12} \times \frac{4}{12} \times \frac{4}{11} \times \frac{4}{11} \times \frac{10}{16} = 0.01147$$

$$\frac{0.1147}{0.1147 + 0.00478} = 0.95$$

$$P(No|x) = \frac{1}{8} \times \frac{2}{8} \times \frac{5}{7} \times \frac{4}{7} \times \frac{6}{16} = 0.00478$$

$$\frac{0.001147}{0.1147 + 0.00478} = 0.05$$

		Play Golf	
		Yes	No
Outlook	Sunny	4/12	3/8
	Overcast	5/12	1/8
	Rainy	3/12	4/8

		Play Golf	
		Yes	No
Temperature	Hot	3/12	3/8
	Mild	5/12	3/8
	Cool	4/12	2/8

		Play Golf	
		Yes	No
Humidity	High	4/11	5/7
	Normal	7/11	2/7

		Play Golf	
		Yes	No
Windy	True	4/11	4/7
	False	7/11	3/7

Slide adapted from CS3244 Machine Learning

Applying Smoothed NB at test time

Outlook	Temperature	Humidity	Windy	Play Golf
Overcast	Cool	High	True	Yes

$$P(Yes|x) = \frac{5}{12} \times \frac{4}{12} \times \frac{4}{11} \times \frac{4}{11} \times \frac{10}{16} = 0.01147$$

$$\frac{0.1147}{0.1147 + 0.00478} = 0.95$$

max

$$P(No|x) = \frac{1}{8} \times \frac{2}{8} \times \frac{5}{7} \times \frac{4}{7} \times \frac{6}{16} = 0.00478$$

$$\frac{0.001147}{0.1147 + 0.00478} = 0.05$$

		Play Golf	
		Yes	No
Outlook	Sunny	4/12	3/8
	Overcast	5/12	1/8
	Rainy	3/12	4/8

		Play Golf	
		Yes	No
Temperature	Hot	3/12	3/8
	Mild	5/12	3/8
	Cool	4/12	2/8

		Play Golf	
		Yes	No
Humidity	High	4/11	5/7
	Normal	7/11	2/7

		Play Golf	
		Yes	No
Windy	True	4/11	4/7
	False	7/11	3/7

Slide adapted from CS3244 Machine Learning

Naïve Bayes Summary

Naïve Bayes is a LM!

Let's relate to last week's lecture on Language Models, which assigns a probability to a sentence.

$$P(its,\ water,\ is,\ so,\ transparent,\ that)$$

Naïve Bayes then:

Naïve Bayes is a LM!

Let's relate to last week's lecture on Language Models, which assigns a probability to a sentence.

$$P(its, water, is, so, transparent, that)$$

Naïve Bayes then:

- Makes a non-contextual decision (unigram model)
- Treats each class like a separate language model*

Naïve Bayes Summary

Naïve Bayes is a class-specific language model.

Good baseline: Robust, fast to train, and has and low storage requirements.

NB makes strong assumptions that features are:

- conditionally independent of each other
- order doesn't matter

Evaluating Classifications

Going beyond Accuracy

National University of Singapore
School of Computing

Accuracy

Our basic metric is accuracy: how often is our classifier right?

$$acc(y, \hat{y}) = \frac{1}{N}\sum_{i=1}^{N}[y^{(i)} = \hat{y}]$$

Slides adapted from Diyi Yang (GaTech) and David Bamman (UCB)

Beyond Right and Wrong

For any set of labels, there are 2 ways to be wrong:

- False positive (FP): the system incorrectly predicts the label
- False negative (FN): the system incorrectly fails to predict the label.

Similarly, there are 2 ways to be right:

- True positive (TP): the system correctly predicts the label.
- True negative (TN): the system correctly predicts the label does not apply to it.

Slides adapted from Diyi Yang (GaTech)

The Binary Confusion Matrix

		Actual Values	
		+ve	–ve
Predicted Values	+ve		
	–ve		

Recall

Recall is the fraction of positive instances which were correctly classified:

Actual Values

		+ve	−ve
Predicted Values	+ve		
	−ve		

$$r = \frac{TP}{TP + FN}$$

Question: What is Accuracy?

Slides adapted from Diyi Yang (GaTech)

Precision

Precision is the fraction of positive predictions that were correct:

Actual Values

		+ve	−ve
Predicted Values	+ve		
	−ve		

$$p = \frac{TP}{TP + FP}$$

How do you generalize this to k classes?

Slides adapted from Diyi Yang (GaTech)

Precision/Recall

You can get high recall for a class (but low precision) by calling all documents as that class!

Recall is a non-decreasing function of the number of docs classified to that class.

In most systems, precision decreases when the # of documents assigned to a class increases; i.e., when recall increases

This is not a theorem, but a result with strong empirical confirmation

A combined measure: *F*

We can combine precision and recall into a single measure to rule them all (actually multiple ways to do this).

$$F = \frac{2 \cdot p \cdot r}{p + r}$$

Use a harmonic mean, not an arithmetic mean. Why?