Text Classification with Naive Bayes

CS 485, Spring 2024
Applications of Natural Language Processing
https://people.cs.umass.edu/~brenocon/cs485_s24/

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upcoming

- Question: Can anyone access the Moodle page now? (All it has is a link to Echo360 lecture video recordings)
- Brendan's OH: **Monday, 11am-noon**, room CS 238. Starting 2/12
  - Come to discuss anything—in this course or otherwise!
  - Can add alternate meetings—please ask (but I'm busy after class)
- Chloe's OH: **Tuesday**, time TBA
- HW1 released tomorrow; due in 1.5 weeks

- Tuesday, 6-7pm: Hands-on Python setup & tutorial, run by Pracha, one of your UCAs
  - Location: Hasbrouck HAS0138
  - Python installation with anaconda, and basics of the python environment.
  - How to run python with command line, and how to create parameter for command line (w and w/o argparse library).
  - How to to use Jupyter notebook.

roadmap

- Introduce text classification
- Method #1: Manually-defined rules and keywords
- Method #2: Supervised learning
    - Naive Bayes model
    - next week: logistic regression model

text classification

- input: some text **x** (e.g., sentence, document)
- output: a label **y** (from a finite, smallish, label set)
- goal: learn a mapping function *f* from **x** to **y**

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fyi: basically every NLP problem reduces to learning a mapping function with various definitions of **x** and **y**!

problem	**x**	**y**
sentiment analysis	text from reviews (e.g., IMDB)	{positive, negative}
topic identification	documents	{sports, news, health, …}
author identification	books	{Tolkien, Shakespeare, …}
spam identification	emails	{spam, not spam}

… many more!

input **x**:

From European Union <info@eu.org>
Subject
Reply to [redacted]

Please confirm to us that you are the owner of this very email address with your copy of identity card as proof.

YOU EMAIL ID HAS WON $10,000,000.00 ON THE ONGOING EUROPEAN UNION COMPENSATION FOR SCAM VICTIMS. CONTACT OUR EMAIL:
CONTACT US NOW VIA EMAIL: [redacted] NOW TO CLAIM YOUR COMPENSATION

label **y**: **spam** or **not spam**

we'd like to learn a mapping f such that
$f(\mathbf{x})$ = **spam**

Demo: Keyword count classifier

- Let's consider this task:
  sentiment classification of movie reviews
- Can *manually defined* keyword lists be a useful indicator of text sentiment?
  - For each category, define set of words
  - Predict a category if many of its words are used
- Let's try manually defined keywords!
  - Sending link on Piazza/email

f can be hand-designed rules

- if “won $10,000,000” in **x**, **y** = **spam**
- if “CS485” in **x**, **y** = **not spam**

what are the drawbacks of this method?

f can be **learned** from data

- given **training data** (already-labeled **x,y** pairs) learn *f* by maximizing the likelihood of the training data

- this is known as **supervised learning**

training data:

x (email text)	**y** (spam or not spam)
learn how to fly in 2 minutes	spam
send me your bank info	spam
CS585 Gradescope consent poll	not spam
click here for trillions of $$$	spam

… ideally many more examples!

heldout data:

x (email text)	**y** (spam or not spam)
CS485 important update	not spam
ancient unicorns speaking english!!!	spam

training data:

x (email text)	**y** (spam or not spam)
learn how to fly in 2 minutes	spam
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heldout data:

x (email text)	**y** (spam or not spam)
CS485 important update	not spam
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learn mapping function on training data,
measure its accuracy on heldout data

probability review

- random variable X takes value x with probability $p(X = x)$; shorthand $p(x)$
- joint probability: $p(X = x, Y = y)$
- conditional probability: $p(X = x \mid Y = y)$

$$= \frac{p(X = x, Y = y)}{p(Y = y)}$$

- when does $p(X = x, Y = y) = p(X = x) \cdot p(Y = y)$?

probability of some input text

- goal: assign a probability to a sentence
  - sentence: sequence of *tokens*
    $p(w_1, w_2, w_3, \ldots, w_n)$
  - $w_i \in V$ where V is the **vocabulary** (*types*)
- some constraints:

non-negativity: for any $w \in V$, $p(w) \geq 0$

probability distribution, sums to 1: $\sum_{w \in V} p(w) = 1$

toy sentiment example

- vocabulary V: {i, hate, love, the, movie, actor}
- training data (movie reviews):
  - i hate the movie
  - i love the movie
  - i hate the actor
  - the movie i love
  - i love love love love love the movie
  - hate movie
  - i hate the actor i love the movie

labels:
positive
negative

bag-of-words representation

i hate the actor i love the movie

bag-of-words representation

i hate the actor i love the movie

word	count
i	2
hate	1
love	1
the	2
movie	1
actor	1

bag-of-words representation

i hate the actor i love the movie

word	count
i	2
hate	1
love	1
the	2
movie	1
actor	1

equivalent representation to:

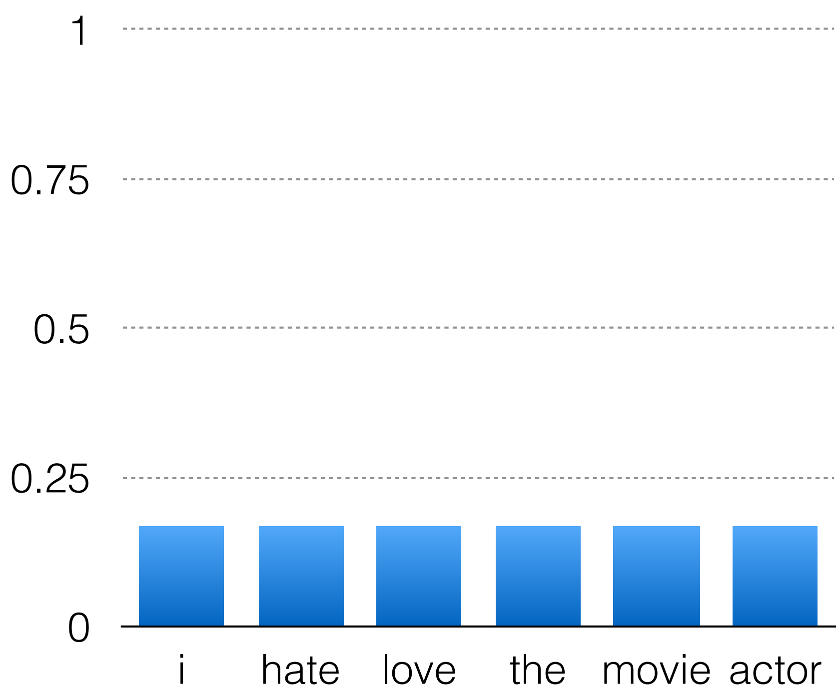
actor i i the the love movie hate

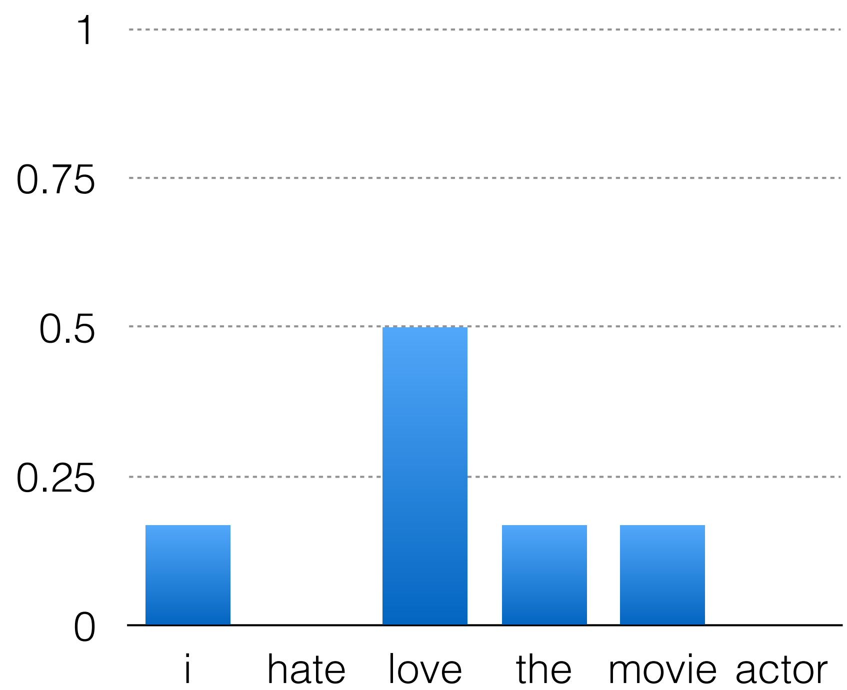
naive Bayes

- assumption: each word is independent of all other words, conditional on document label

- given labeled data, we can use naive Bayes to estimate probabilities for unlabeled data
- goal: infer probability distribution that generated the labeled data for each label

which of the below word distributions looks like one found in positive reviews?



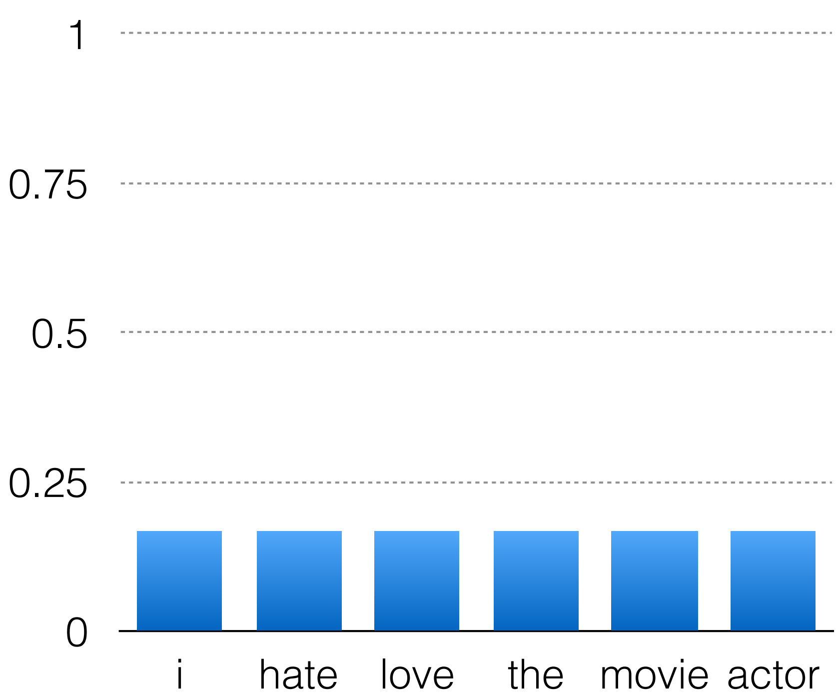


… back to our reviews

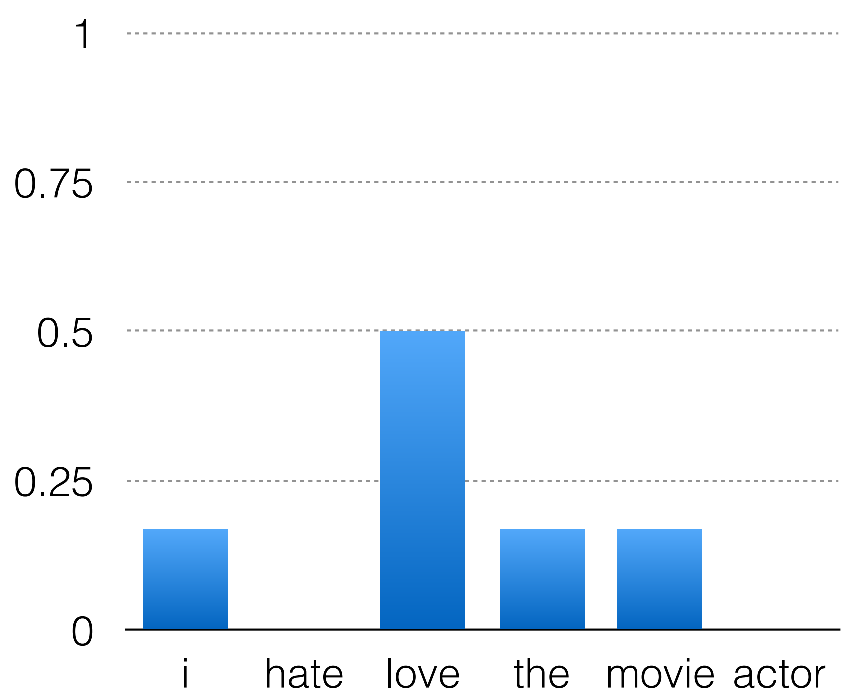
$$p(\text{i love love love love love the movie})$$

$$= p(\text{i}) \cdot p(\text{love})^5 \cdot p(\text{the}) \cdot p(\text{movie})$$

= 5.95374181e-7



= 1.4467592e-4



logs to avoid underflow

$p(w_1) \cdot p(w_2) \cdot p(w3) \ \ldots \cdot p(w_n)$
can get really small esp. with large *n*

$$\log \prod p(w_i) = \sum \log p(w_i)$$

$p(\text{i}) \cdot p(\text{love})^5 \cdot p(\text{the}) \cdot p(\text{movie})$ = 5.95374181e-7

$\log p(\text{i}) + 5 \log p(\text{love}) + \log p(\text{the}) + \log p(\text{movie})$

= -14.3340757538

[This implementation trick is very common in ML and NLP]

class conditional probabilities

Bayes rule (ex: x = sentence, y = label in {pos, neg})

$$p(y \mid x) = \frac{p(y) \cdot P(x \mid y)}{p(x)}$$

our predicted label is the one with the highest posterior probability, i.e.,

class conditional probabilities

Bayes rule (ex: *x* = sentence, *y* = label in {pos, neg})

prior likelihood

posterior

$$p(y \mid x) = \frac{p(y) \cdot P(x \mid y)}{p(x)}$$

our predicted label is the one with the highest posterior probability, i.e.,

$$\hat{y} = \arg\max_{y \in Y} p(y) \cdot P(x \mid y)$$

what happened to the denominator???

argmax notation

computing the prior…

- i hate the movie
- i love the movie
- i hate the actor
- the movie i love
- i love love love love love the movie
- hate movie
- i hate the actor i love the movie

$p(y)$ lets us encode inductive bias about the labels

we can estimate it from the data by simply counting…

label y	count	p(Y=y)	log(p(Y=y))
POS	3	0.43	-0.84
NEG	4	0.57	-0.56

computing the likelihood…

p(X | y=POS)

word	count	p(w l y)
i	3	0.19
hate	0	0.00
love	7	0.44
the	3	0.19
movie	3	0.19
actor	0	0.00
total	**16**	

p(X | y=NEG)

word	count	p(w l y)
i	4	0.22
hate	4	0.22
love	1	0.06
the	4	0.22
movie	3	0.17
actor	2	0.11
total	**18**	

$p(X \mid y=\text{POS})$

word	count	p(w l y)
i	3	0.19
hate	0	0.00
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$p(X \mid y=\text{NEG})$

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new review X_{new}: love love the movie

$$\log p(X_{\text{new}} \mid \text{POS}) = \sum_{w \in X_{\text{new}}} \log p(w \mid \text{POS}) = -4.96$$

$$\log p(X_{\text{new}} \mid \text{NEG}) = -8.91$$

posterior probs for X_{new}

$$\log p(\text{POS} \mid X_{\text{new}}) \propto \log P(\text{POS}) + \log p(X_{\text{new}} \mid \text{POS})$$
$$= -0.84 - 4.96 = -5.80$$

$$\log p(\text{NEG} \mid X_{\text{new}}) \propto -0.56 - 8.91 = -9.47$$

What does NB predict?

Naive Bayes

y - doc class/label
x - doc text
w - word

- Assumptions

Prior for class: $P(y)$

Likelihood for text: $P(x|y) = \prod_{i=1}^{N_{tok}} P(w_i|y)$

- Steps to use

vector $|V| \times K$

  - 1. Training: learn p(y) and p(w|y) parameters for all classes and words, based on their counts in labeled training data
  - 2. Prediction: given learned parameters, for new doc, use Bayes Rule to predict posterior probability of class labels

$x^{(new)}$

$$P(y=SCUBA|x) = \frac{p(y=S)\, p(x|y=S)}{p(x)}$$

what if we see no positive training documents containing the word "awesome"?

$$p(\text{awesome}\,|\,\text{POS}) = 0$$

$$p(\text{mare is awesome}\,|\,\text{POS}) =$$

$$= p(\text{mare}\,|\,+)\;p(\text{is}\,|\,+)\;\underbrace{p(\text{awesome}\,|\,+)}_{0}$$

$$= 0$$

Add-α (pseudocount) smoothing

"Relative Freq. Estimate"

$$\text{unsmoothed } P(w_i \mid y) = \frac{\text{count}(w_i, y)}{\sum_{w \in V} \text{count}(w, y)}$$

Toks in y

$$\text{smoothed } P(w_i \mid y) = \frac{\text{count}(w_i, y) + \alpha}{\sum_{w \in V} \text{count}(w, y) + \alpha \mid V \mid}$$

$\alpha = 1$ $\alpha = \frac{1}{|V|}$

what happens if we do add-α smoothing as α increases?

Example: Training

	Cat	Documents
Training	-	just plain boring
	-	entirely predictable and lacks energy
	-	no surprises and very few laughs
	+	very powerful
	+	the most fun film of the summer
Test	?	predictable with no fun

Add-1

$$P(y=+) = \frac{2}{5}$$

$$P(y=-) = \frac{3}{5}$$

$$p(\text{predictable} \mid +) = \frac{0+1}{9+\alpha|V|} = \frac{1}{29}$$

$|V| = 20$

Example: Prediction

Model Parameters

New doc x = "I love"

P(+) = .5

P(–) = .5

w	P(w|+)	P(w|-)
I	0.1	0.2
love	0.1	0.001
this	0.01	0.01
fun	0.05	0.005
film	0.1	0.1
...	...	...

$P(+)\,P(\text{I love}\mid +)$

$= .5\;P(\text{I}\mid +)\,P(\text{love}\mid +)$

$= .5 \times .1 \times .1 = \frac{5}{1000}$

$P(-)\,P(\text{I love}\mid -)$

$= .5 \times .2 \times .001$

= smaller

Other details

"I love love love" = $p(I)[p(love)]^3$

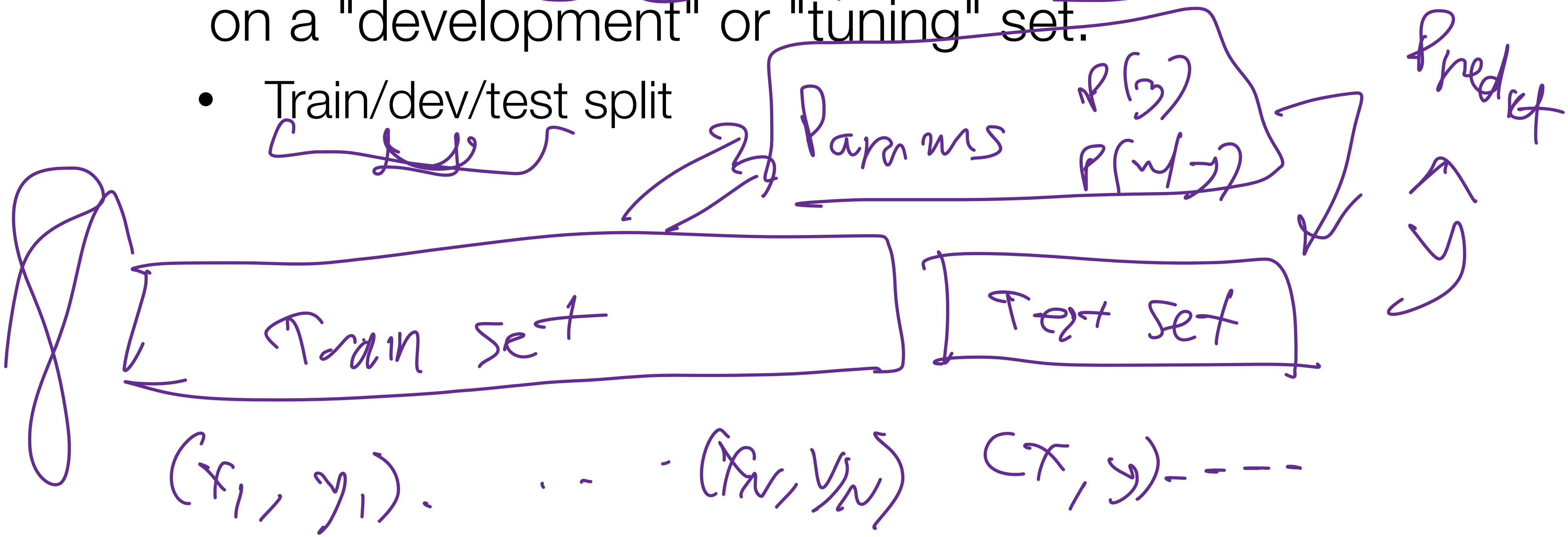
- Binarization
  - Issue: overcounting word repetitions
  - Solution:

Pretend a word count is just 1

- Negation handling
  - Issue:
  - Solution: heuristic

Evaluation

- Must assess accuracy on held-out data.
    - Train/test split
    - (Alternative: cross-validation)
- Must tune hyperparameters (e.g. pseudocount) on a "development" or "tuning" set.
    - Train/dev/test split



Overusing test sets