Lecture 5
Text Classification with Naive Bayes

CS 490A, Fall 2021
9/14 and 9/16 lectures
https://people.cs.umass.edu/~brenocon/cs490a_f21/

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text classification

- input: some text **x** (e.g., sentence, document)
- output: a label **y** (from a finite 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
$f(\mathbf{x}) = \textbf{spam}$

f can be hand-designed rules

- if “won $10,000,000” in **x**, **y** = **spam**
- if “CS490A Fall 2020” 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)
CS585 important update	not spam
ancient unicorns speaking english!!!	spam

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learn mapping function on training data, measure its accuracy on heldout data

- stopped here 9/14

9/16 lecture notes

- COVID reports and masking policy.
  - **Do not come to class if you are sick or possibly exposed**
  - **Always wear your mask**
- Office hours on webpage
  >=3 different timeslots every week!
- Today: Text classification continued
  - Laptops out for a little non-coding activity shortly!
  - Paper exercise later

How to do text classification?

- Questions
  - Can word counts a useful indicator of text sentiment?
  - Can *manually defined* keyword lists be a useful indicator of text sentiment?
- Pang et al. 2002: compare human-supplied keywords against machine learning, evaluated on movie reviews
- Let's try manually defined keywords!
  - go to: **http://brenocon.com/sw**

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learn how to fly in 2 minutes	spam
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x (email text)	**y** (spam or not spam)
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learn mapping function on training data, measure its accuracy on heldout data

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

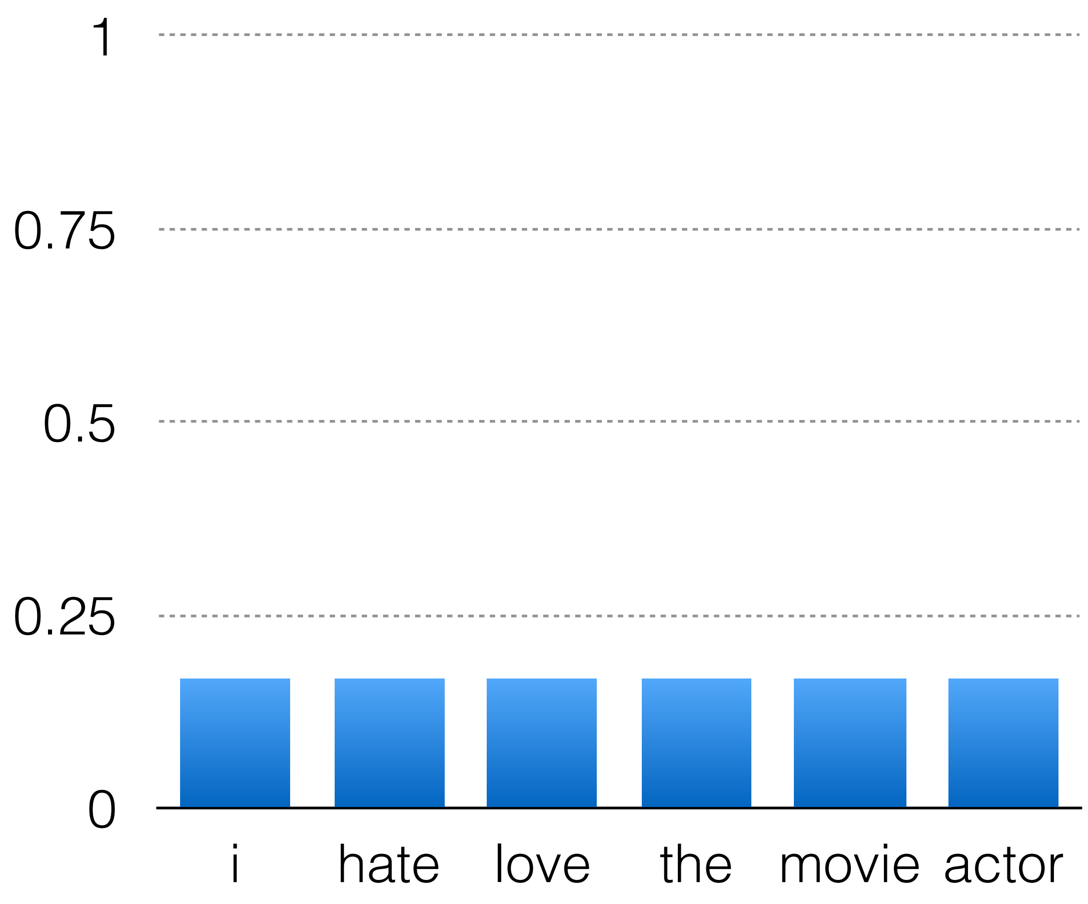
equivalent representation to:

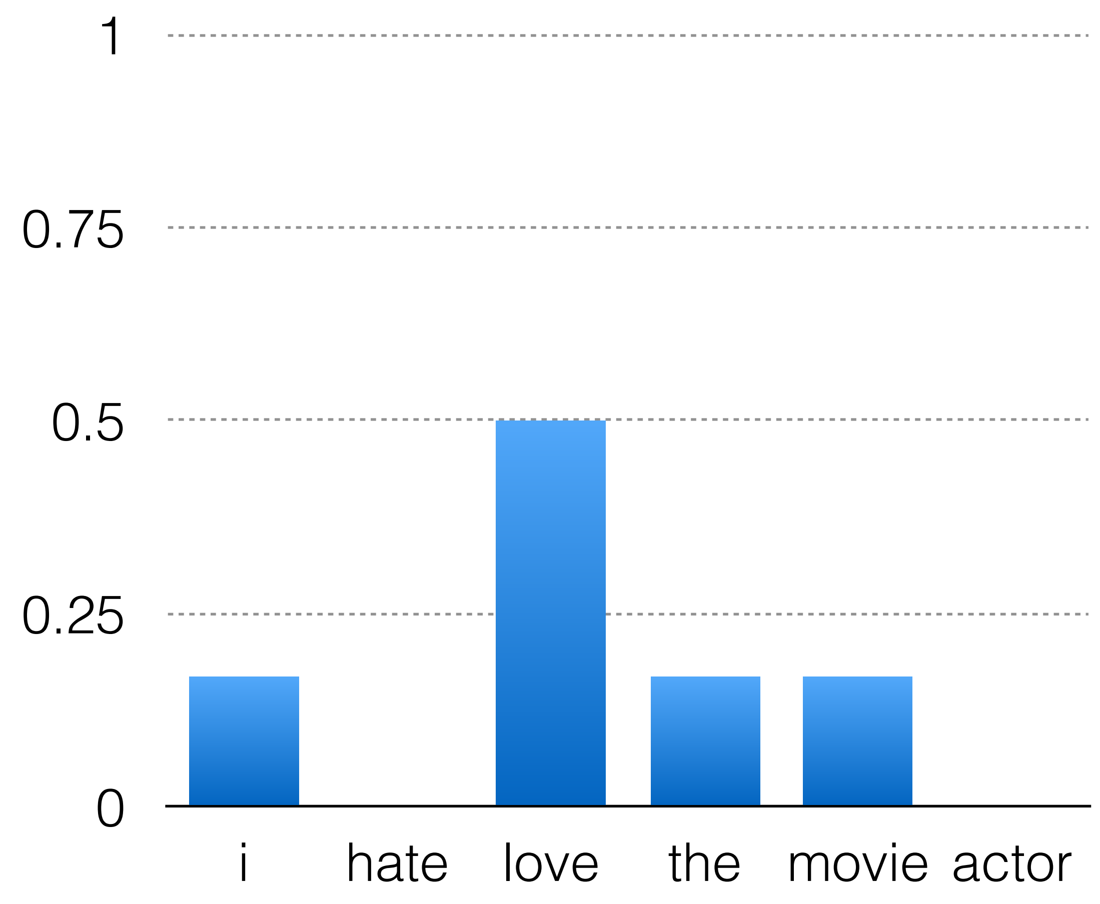
actor i i the the love movie hate

naive Bayes

- represents input text as a bag of words
- assumption: each word is independent of all other words
- 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 distributions was most likely generated in positive reviews?



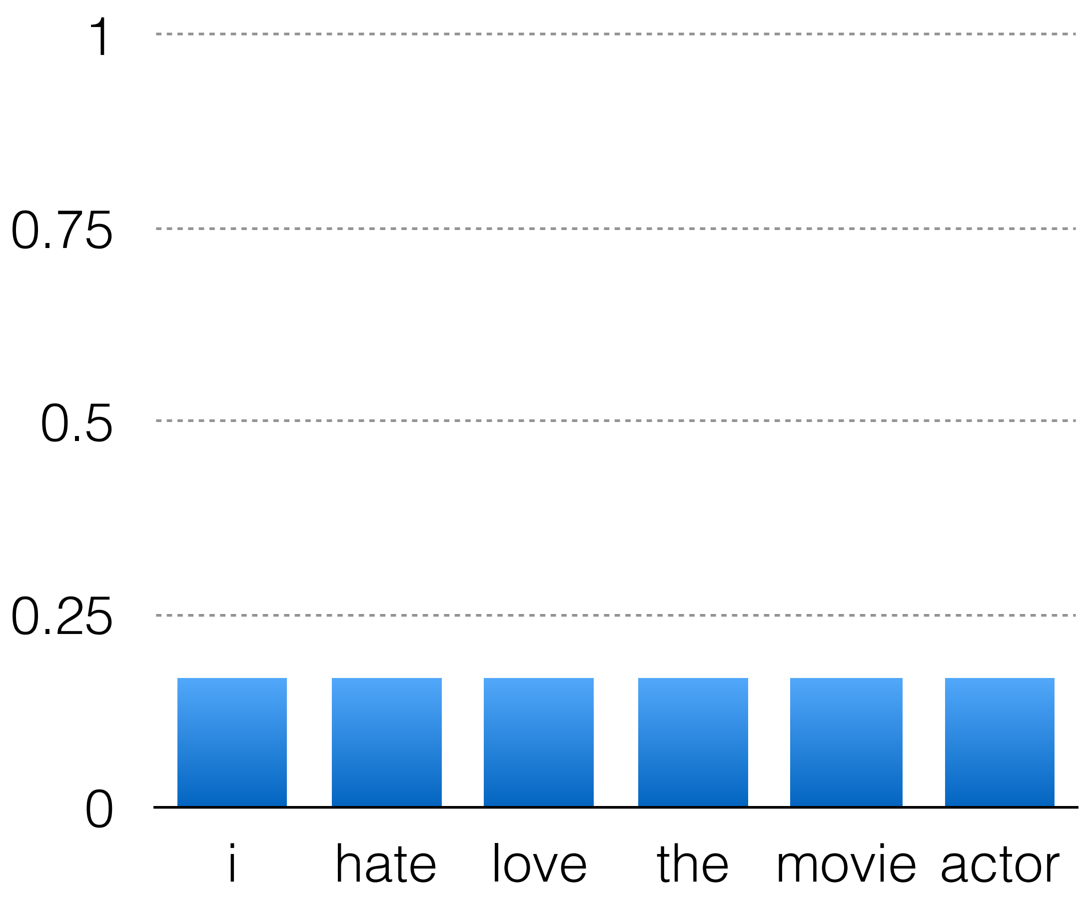


… back to our reviews

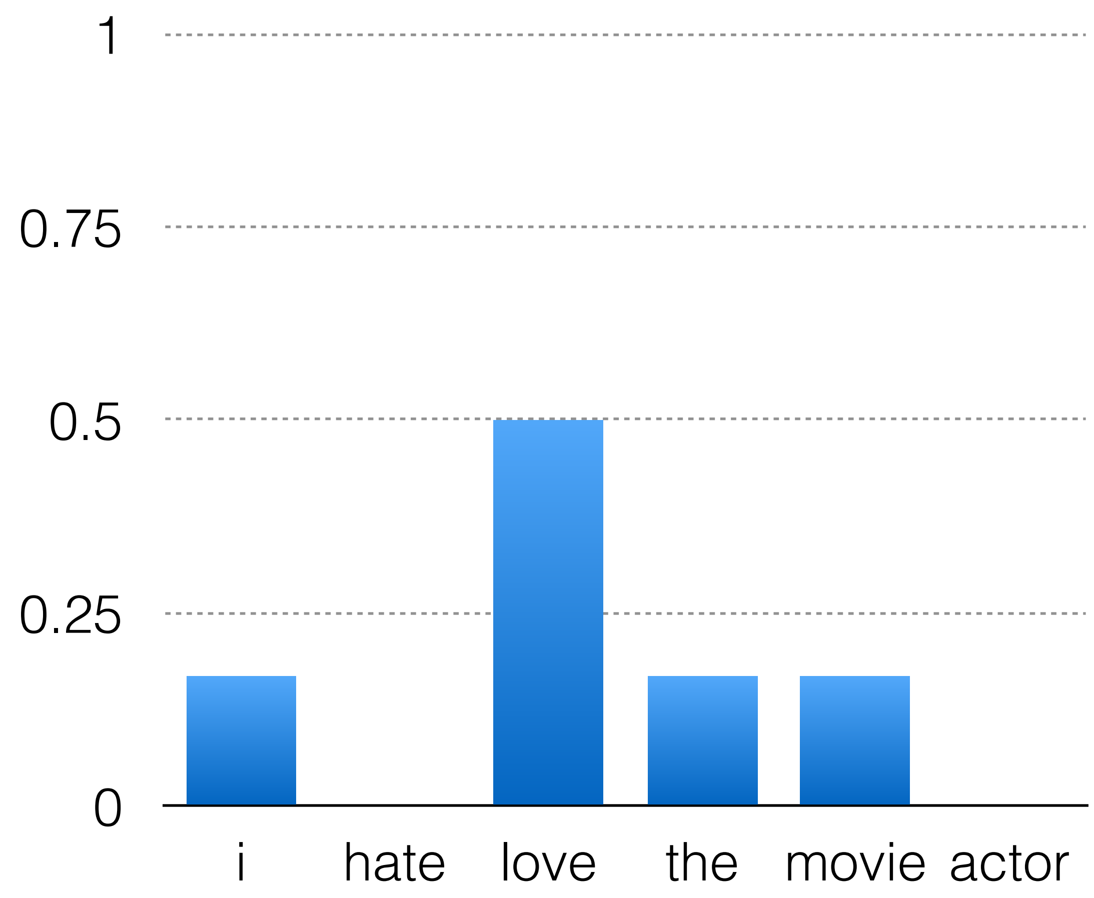
$$p(\text{i love love love love love the movie})$$

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

= 5.95374181e-7



= 1.4467592e-4



logs to avoid underflow

$p(w_1) \cdot p(w_2) \cdot p(w3) \ \dots \cdot p(w_n)$
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})

$$\overset{\text{posterior}}{p(y \mid x)} = \frac{\overset{\text{prior}}{p(y)} \cdot \overset{\text{likelihood}}{P(x \mid y)}}{p(x)}$$

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???

remember the independence assumption!

maximum a posteriori (MAP) class

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

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

$$= \arg\max_{y \in Y} \log p(y) + \sum_{w \in x} \log P(w \mid y)$$

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))
positive	3	0.43	-0.84
negative	4	0.57	-0.56

computing the likelihood…

p(X | y=positive)

word	count	p(w | 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=negative)

word	count	p(w | 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**	

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

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**	

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

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**	

new review X_{new}: love love the movie

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

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

posterior probs for X_{new}

$$\log p(\text{positive} \,|\, X_{\text{new}}) \propto \log P(\text{positive}) + \log p(X_{\text{new}} \,|\, \text{positive})$$
$$= -0.84 - 4.96 = -5.80$$

$$\log p(\text{negative} \,|\, X_{\text{new}}) \propto -0.56 - 8.91 = -9.47$$

What does NB predict?

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

$$p(\text{awesome} \mid \text{positive}) = 0$$

Add-α (pseudocount) smoothing

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

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

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

Evaluation

- Must assess accuracy on held-out data. Either:
  - Train/test split
  - Cross validation
- Must tune hyperparameters (e.g. pseudocount) on a "development" or "tuning" set.
  - Train/dev/test split
- Significance testing for evaluation metric: given that the test set was small, could results have been due to chance?