CS 1671 / CS 2071 / ISSP 2071
Human Language Technologies

Session 8: Logistic regression part 1

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Quiz

- Go to **Quizzes > Quiz 02-09** on Canvas
- You have until **1:10pm** to complete it
- Allowed resources
  - Textbook
  - Your notes (on a computer or physical)
  - Course slides and website
- Resources not allowed
  - Generative AI
  - Internet searches

What do you call a bad dream about machine learning?

A logistic nightmare

Course logistics: project

- Consider which projects you'd like to work on from the list of project options
- Project Match Day is **next class, Wed Feb 11**. You will form groups of ~5 students around projects from the project list
    - We'll "match" in a few rounds, where groups that are too large or too small will join other groups
    - Come with multiple project preferences
- If you're really excited about an idea, talk to others who might be interested

Course logistics: quiz

- Next in-class quiz is next class, **Wed Feb 11**
  - Session 8 (today): J+M 4-4.3
- Lowest quiz score in the course will be dropped
- If you won't be in class, let me know and I can accommodate

Course logistics: homework

- Homework 1 is **due Thu Feb 12 at 11:59pm**
- Homework 1 covers text processing and regular expressions in Python

PyLing
Pitt Python Linguistics Group

- Computational linguistics group on campus
- Practice NLP skills related to this class with fun tutorials and guest speakers (with food, too! 🍕)
- Next meeting is **Wed Feb 11, 6-7:15pm at CL 2818** (linguistics department conference room)
  - Tour of **computational linguistics certificate** which is going live this semester! 🎉
  - Also text analysis of NLP conference proceedings (how much are dominated by LLMs? What other areas are prevalent?)
- Contact Na-Rae Han, naraehan@pitt.edu to get on their mailing list

Lecture overview: Logistic regression part 1

- Coding activity: build your own n-gram LM
- Text classification
- Input to classification: features from text
- Logistic regression
- Binary classification with logistic regression

Coding activity: build your own n-gram LM

N-gram document representations on JupyterHub

1. Go to this nbgitpuller link (also available on course website)
2. Start a server with **TEACH – 6 CPUs, 48 GB**
3. Load custom environment at **/ix1/cs1671-2026s/class_env**
    1. If you have multiple accounts on the CRCD, put in **cs1671-2026s** for Account
4. This should pull the cs1671_spring2026_jupyterhub folder into your JupyterLab
5. Open **session7_ngram_lm.ipynb**

Text classification

Text classification

"My dear Mr. Bennet," said his lady to him one day, "have you heard that Netherfield Park is let at last?"

ROMANCE

Pride and Prejudice

DIALOG

Is this spam?

Subject: **Important notice!**
From: Stanford University <newsforum@stanford.edu>
Date: October 28, 2011 12:34:16 PM PDT
To: undisclosed-recipients:;

Greats News!

You can now access the latest news by using the link below to login to Stanford University News Forum.

http://www.123contactform.com/contact-form-StanfordNew1-236335.html

Click on the above link to login for more information about this new exciting forum. You can also copy the above link to your browser bar and login for more information
about the new services.

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Slide adapted from Jurafksy & Martin

What is the subject of this medical article?

MEDLINE Article


Brain and Cognition

Syntactic frame and verb bias in aphasia: Plausibility judgments of undergoer-subject sentences

?

MeSH Subject Category Hierarchy

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

Slide adapted from Jurafksy & Martin

Text Classification

We have a set of documents that we want to *classify* into a small set *classes*.

Applications:

- **Topic classification:** you have a set of news articles that you want to classify as finance, politics, or sports.
- **Sentiment detection:** you have a set of movie reviews that you want to classify as good, bad, or neutral.
- **Language Identification:** you have a set of documents that you want to classify as English, Mandarin, Arabic, or Hindi.
- **Reading level:** you have a set of articles that you want to classify as kindergarten, 1st grade, ...12th grade.
- **Author identification:** you have a set of fictional works that you want to classify as Shakespeare, James Joyce, ...
- **Genre identification:** you have a set of documents that you want to classify as report, editorial, advertisement, blog, ...

Slide credit: David Mortensen

Example: Sentiment Detection

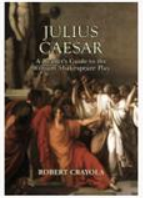
	Cat	Documents
Training	-	just plain boring
	-	entirely predictable and lacks energy
	-	no surprises and very few laughs
	+	very powerful
	+	the most fun film of the summer
Test	?	predictable with no fun

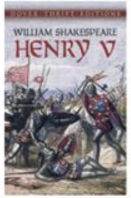
Slide credit: David Mortensen

Input to classification tasks: features

Term-document matrix

- Each cell is the count of term t in a document d ($tf_{t,d}$).
- Each document is a count vector in $\mathbb{N}^V$, a column below.





	As You Like It	Twelfth Night	Julius Caesar	Henry V
battle	1	1	8	15
soldier	2	2	12	36
fool	37	58	1	5
clown	6	117	0	0

Slide credit: David Mortensen

Movie Ratings

- A training set of movie reviews (with star ratings 1 - 5)
- A set of features for each message (considered as a bag of words)
  - For each word: Number of occurrences
  - Whether phrases such as *Excellent*, *sucks*, *blockbuster*, *biggest*, *Star Wars*, *Disney*, *Adam Sandler*, ...are in the review

Slide credit: David Mortensen

Spam Detection

- A training set of email messages (marked *Spam* or *Not-Spam*)
- A set of features for each message
  - For each word: Number of occurrences
  - Whether phrases such as “Nigerian Prince”, “email quota full”, “won ONE HUNDRED MILLION DOLLARS” are in the message
  - Whether it is from someone you know
  - Whether it is a reply to your message
  - Whether it is from your domain (e.g., `cmu.edu`)

Slide credit: David Mortensen

Logistic regression

What Goes into a (Discriminative) ML Classifier?

1. A feature representation
2. A classification function
3. An objective function
4. An algorithm for optimizing the objective function

Slide credit: David Mortensen

What Goes into Logistic Regression?

GENERAL	IN LOGISTIC REGRESSION
feature representation	represent each observation $\mathbf{x}^{(i)}$ as a **vector of features** $[x_1, x_2, \ldots x_n]$
classification function	**sigmoid function** (logistic function)
objective function	**cross-entropy loss**
optimization function	(stochastic) **gradient descent**

Slide credit: David Mortensen

The Two Phases of Logistic Regression

train learn **w** (a vector of weights, one for each feature) and b (a bias) using **stochastic gradient descent** and **cross-entropy loss**.

test given a test example x, we compute $p(y|x)$ using the learned weights w and b and return the label ($y = 1$ or $y = 0$) that has higher probability.

Slide credit: David Mortensen

Binary classification with logistic regression

Text classification with logistic regression

Given a series of input/output pairs:

$$(x^i, y^i)$$

For each observation x^i

- We represent x^i by a feature vector $[x_1, x_2, \ldots, x_n]$
- We compute an output: a predicted class $y^i \in \{0, 1\}$
    - Get to the predicted class by estimating $p(y|x)$, i.e. $p(y=1|x)$ and $p(y=0|x)$

For sentiment analysis (classification):

- $y^i = 1$ is positive sentiment, $y^i = 0$ is negative sentiment

Reminder: the Dot Product

We will see the dot product a lot. It is the **sum** of the element-wise **product** of two vectors of the same dimensionality.

$$\begin{bmatrix} 2 & 7 & 1 \end{bmatrix} \cdot \begin{bmatrix} 8 \\ 2 \\ 8 \end{bmatrix} = 2 \cdot 8 + 7 \cdot 2 + 1 \cdot 8 = 38 \tag{3}$$

Moving on...

Slide credit: David Mortensen

Features in Logistic Regression

For feature x_i, weight w_i tells us how important x_i is

- x_i = "review contains awesome": $w_i = +10$
- x_j = "review contains abysmal": $w_j = -10$
- x_k = "review contains mediocre": $w_k = -2$

Slide credit: David Mortensen

Logistic Regression for One Observation x

input observation feature vector $x = [x_1, x_2, \ldots, x_n]$

weights one per feature $W = [w_1, w_2, \ldots, w_n]$ plus w_0, which is the **bias** b

output a predicted class $\hat{y} \in \{0, 1\}$

Slide credit: David Mortensen

How to Do Classification

For each feature x_i, weight w_i tells us the importance of x_i (and we also have the bias b that shifts where the function crosses the x-axis)

We'll sum up all the weighted features and the bias

$$z = \left(\sum_{i=1}^{n} w_i x_i \right) + b$$

$$z = \mathbf{w} \cdot \mathbf{x} + b$$

Slide credit: David Mortensen

A Most Important Formula

We compute

$$z = \mathbf{w} \cdot \mathbf{x} + b$$

If z is high, we say $y = 1$; if low, then $y = 0$.

orchids A classifiers for cymbidiums should return $y = 1$ when the input is a cymbidium and $y = 0$ otherwise.

sentiment A classifier for positive sentiment show return $y = 1$ when the input has positive sentiment (when the emotions of the writer towards the topic are positive) and $y = 0$ otherwise.

Remember this formula.

Slide credit: David Mortensen

But We Want a Probabilistic Classifier

What does "sum is high" even mean?

Can't our classifier be like Naive Bayes and give us a probability?

What we really want:

- $p(y = 1|x; \theta)$
- $p(y = 0|x; \theta)$

Where x is a vector of features and $\theta = (w, b)$ (the weights and the bias).

Slide credit: David Mortensen

The Problem: z isn't a Probability!

z is just a number:

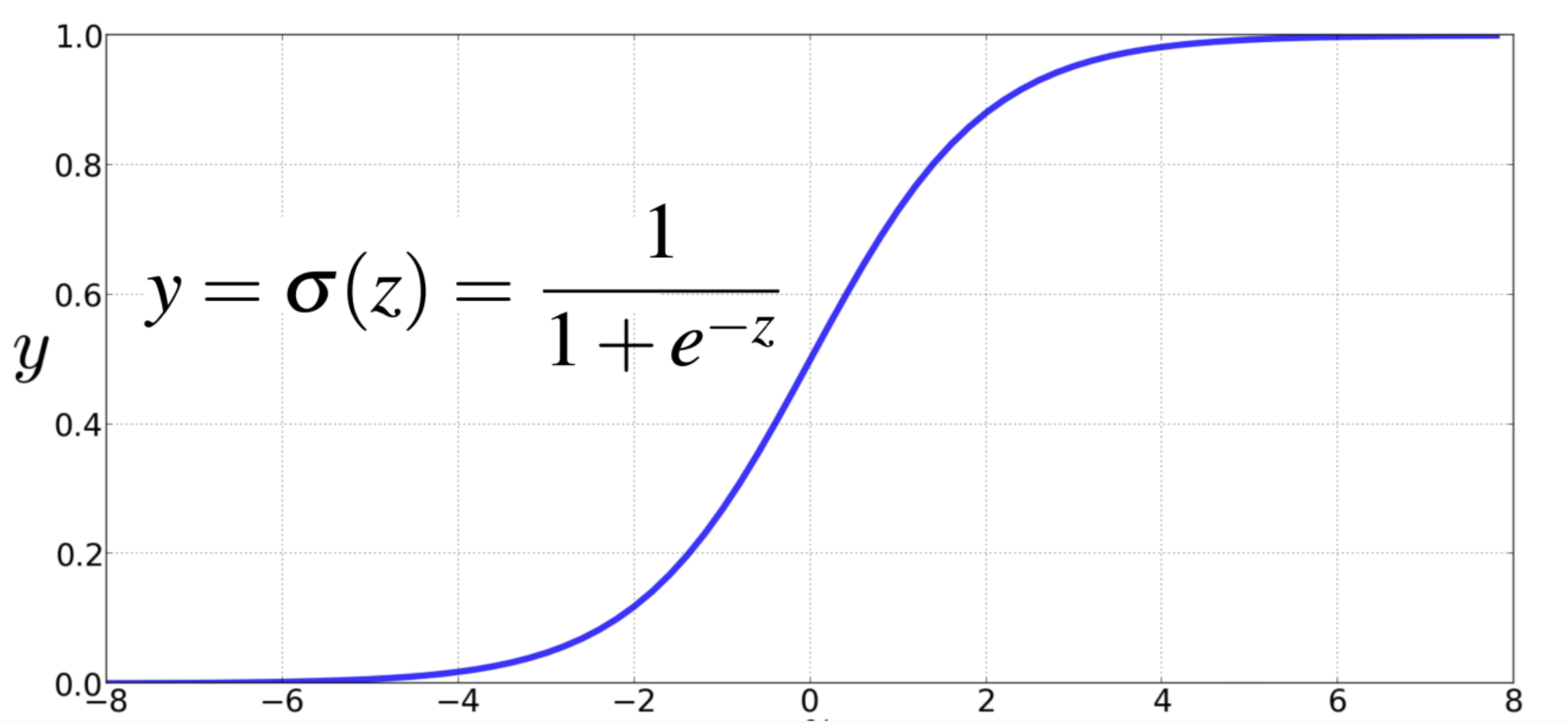
$$z = w \cdot x + b$$

Solution: use a function of z that goes from 0 to 1, like the **logistic function** or **sigmoid function**:

$$\hat{y} = \sigma(z) = \frac{1}{1 + e^{-z}} = \frac{1}{1 + \exp(-z)}$$

Slide credit: David Mortensen

The Sigmoid Function



Slide credit: David Mortensen

Logistic Regression in Three Easy Steps

1. Compute $w \cdot x + b$
2. Pass it through the sigmoid function: $\sigma(w \cdot x + b)$
3. Treat the result as a probability

Slide credit: David Mortensen

Making Probabilities with Sigmoids

$$\begin{aligned}
P(y=1) &= \sigma(w \cdot x + b) \\
&= \frac{1}{1+\exp(-(w \cdot x + b))} \\
P(y=0) &= 1 - \sigma(w \cdot x + b) \\
&= 1 - \frac{1}{1+\exp(-(w \cdot x + b))} \\
&= \frac{\exp(-(w \cdot x + b))}{1+\exp(-(w \cdot x + b))}
\end{aligned}$$

Slide credit: David Mortensen

From Probability to Classification

$$y = \begin{cases} 1 & P(y = 1|x) > 0.5 \\ 0 & \text{otherwise} \end{cases}$$

0.5 here is called the **decision boundary**

Slide credit: David Mortensen

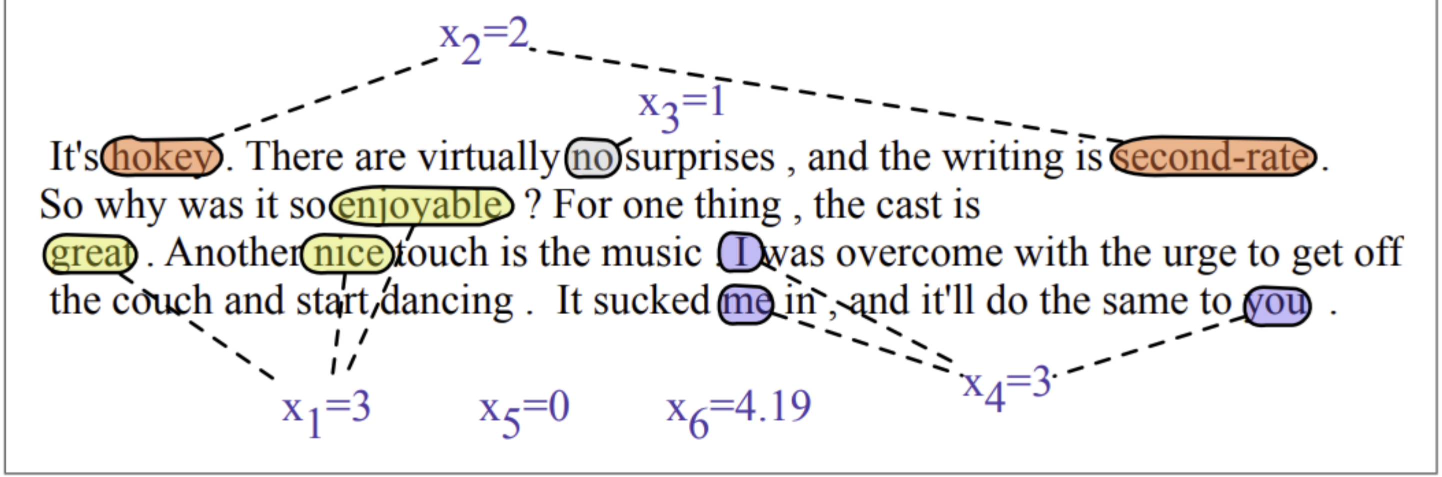
Sentiment Classification: Movie Review

It’s hokey . There are virtually no surprises , and the writing is second-rate . So why was it so enjoyable ? For one thing , the cast is great . Another nice touch is the music . I was overcome with the urge to get off the couch and start dancing . It sucked me in , and it’ll do the same to you .

Slide credit: David Mortensen

Sentiment classification: feature engineering

Var	Definition
x_1	count(positive lexicon words $\in$ doc)
x_2	count(negative lexicon words $\in$ doc)
x_3	$\begin{cases} 1 & \text{if ``no''} \in \text{doc} \\ 0 & \text{otherwise} \end{cases}$
x_4	count(1st and 2nd pronouns $\in$ doc)
x_5	$\begin{cases} 1 & \text{if ``!''} \in \text{doc} \\ 0 & \text{otherwise} \end{cases}$
x_6	$\ln$(word count of doc)



Var	Definition	Value in Fig. 5.2
x_1	count(positive lexicon) $\in$ doc)	3
x_2	count(negative lexicon) $\in$ doc)	2
x_3	$\begin{cases} 1 & \text{if "no"} \in \text{doc} \\ 0 & \text{otherwise} \end{cases}$	1
x_4	$\text{count}(\text{1st and 2nd pronouns} \in \text{doc})$	3
x_5	$\begin{cases} 1 & \text{if "!"} \in \text{doc} \\ 0 & \text{otherwise} \end{cases}$	0
x_6	$\log(\text{word count of doc})$	$\ln(66) = 4.19$

Classifying Sentiment for Input x

Var	Definition	Val
x_1	count(positive lexicon) $\in$ doc	3
x_2	count(negative lexicon) $\in$ doc	2
x_3	$\begin{cases} 1 & \text{if "no"} \in \text{doc} \\ 0 & \text{otherwise} \end{cases}$	1
x_4	count(1st & 2nd pronouns) $\in$ doc	3
x_5	$\begin{cases} 1 & \text{if "!"} \in \text{doc} \\ 0 & \text{otherwise} \end{cases}$	0
x_6	$\log$(word count of doc)	$\ln(66) = 4.19$

Suppose $w = [2.5,$ -5.0, $-1.2, 0.5, 2.0, 0.7]$ **and** $b = 0.1$

Slide credit: David Mortensen

Performing the calculations

$w = [2.5, -5.0, -1.2, 0.5, 2.0, 0.7]$ and $b = 0.1$

Var	Val
x_1	3
x_2	2
x_3	1
x_4	3
x_5	0
x_6	$\ln(66) = 4.19$

$$p(+|x) = P(Y=1|x) \quad = \quad \sigma(w \cdot x + b)$$

$$p(-|x) = P(Y=0|x) \quad =$$

Slide credit: David Mortensen