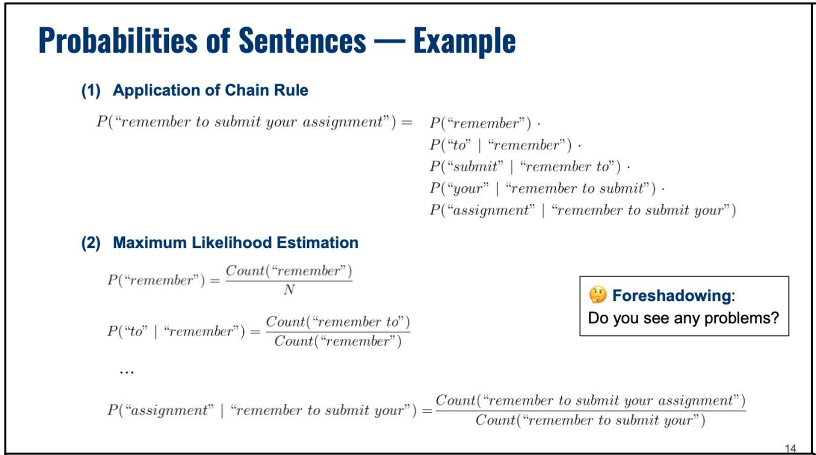
NUS | Computing
National University of Singapore

CS4248: Natural Language Processing

Lecture 4 — Text Classification

Recap of Week 03



Probabilities of Sentences — Example

(1) Application of Chain Rule

$$P(\text{“remember to submit your assignment”}) = P(\text{“remember”}) \cdot P(\text{“to”} \mid \text{“remember”}) \cdot P(\text{“submit”} \mid \text{“remember to”}) \cdot P(\text{“your”} \mid \text{“remember to submit”}) \cdot P(\text{“assignment”} \mid \text{“remember to submit your”})$$

(2) Maximum Likelihood Estimation

$$P(\text{“remember”}) = \frac{Count(\text{“remember”})}{N}$$

$$P(\text{“to”} \mid \text{“remember”}) = \frac{Count(\text{“remember to”})}{Count(\text{“remember”})}$$

…

$$P(\text{“assignment”} \mid \text{“remember to submit your”}) = \frac{Count(\text{“remember to submit your assignment”})}{Count(\text{“remember to submit your”})}$$

🤔 **Foreshadowing**: Do you see any problems?

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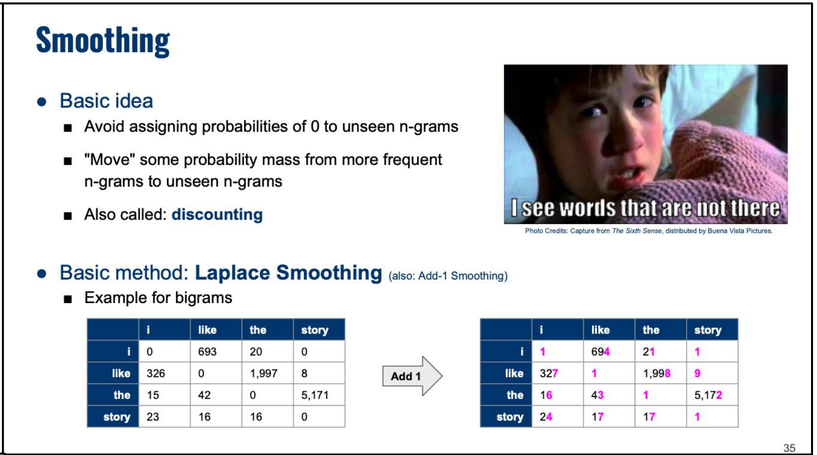

Smoothing

- Basic idea
  - Avoid assigning probabilities of 0 to unseen n-grams
  - "Move" some probability mass from more frequent n-grams to unseen n-grams
  - Also called: **discounting**

I see words that are not there

Photo Credits: Capture from *The Sixth Sense*, distributed by Buena Vista Pictures.

- Basic method: **Laplace Smoothing** (also: Add-1 Smoothing)
  - Example for bigrams

	i	like	the	story
i	0	693	20	0
like	326	0	1,997	8
the	15	42	0	5,171
story	23	16	16	0

Add 1

	i	like	the	story
i	1	694	21	1
like	327	1	1,998	9
the	16	43	1	5,172
story	24	17	17	1

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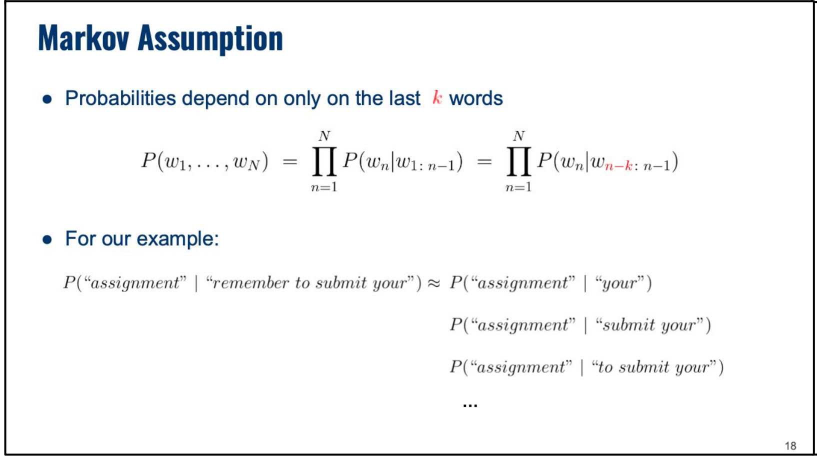

Markov Assumption

- Probabilities depend on only on the last k words

$$P(w_1, \ldots, w_N) = \prod_{n=1}^{N} P(w_n|w_{1:n-1}) = \prod_{n=1}^{N} P(w_n|w_{n-k:n-1})$$

- For our example:

$$P(\text{“assignment”} \mid \text{“remember to submit your”}) \approx P(\text{“assignment”} \mid \text{“your”})$$

$$P(\text{“assignment”} \mid \text{“submit your”})$$

$$P(\text{“assignment”} \mid \text{“to submit your”})$$

…

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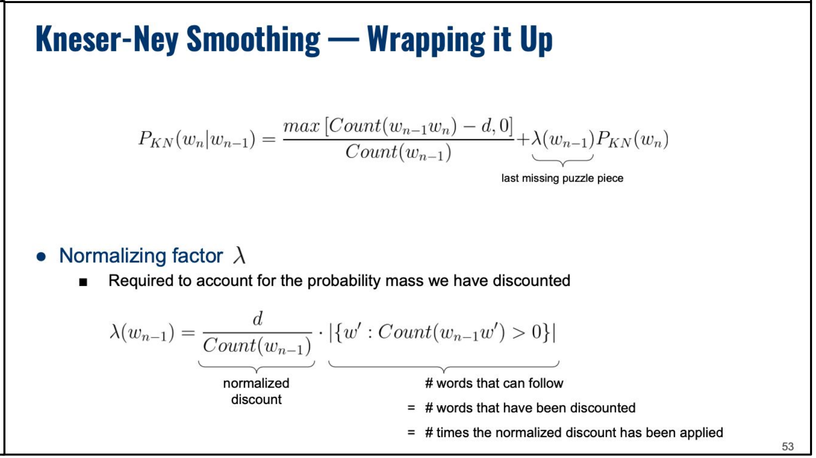

Kneser-Ney Smoothing — Wrapping it Up

$$P_{KN}(w_n|w_{n-1}) = \frac{max\left[Count(w_{n-1}w_n) - d, 0\right]}{Count(w_{n-1})} + \underbrace{\lambda(w_{n-1})}_{\text{last missing puzzle piece}} P_{KN}(w_n)$$

- Normalizing factor λ
  - Required to account for the probability mass we have discounted

$$\lambda(w_{n-1}) = \underbrace{\frac{d}{Count(w_{n-1})}}_{\text{normalized discount}} \cdot \underbrace{|\{w' : Count(w_{n-1}w') > 0\}|}_{\text{\# words that can follow}}$$

= # words that have been discounted

= # times the normalized discount has been applied

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- **Text Classification**
  - **Common Applications**
  - Formal Setup
- Naive Bayes Classifier
  - Basic Intuition & BoW Representation
  - Definition & Practical Considerations
  - Complete Runthrough
  - Discussion & Limitations
- Evaluation of Classifiers
- Vector Space Model
  - Vector Representation of Documents
  - Document Similarity

Text Classification — Motivation

- Very common machine learning task: **classification**
  - Focus in the context of NLP: classification of text documents
  - Task: given a text document, assign document a class
    (in general, the set of classes are finite and predefined)

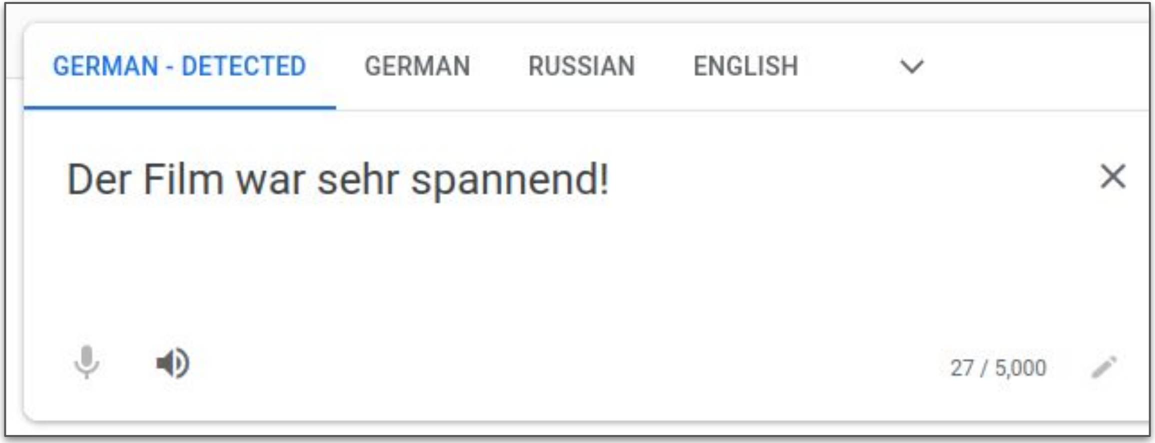
- Examples

Task	Classes (examples)
language detection	{english, malay, chinese, tamil, german, …}
spam detection	{spam, not spam}
subject/genre classification	{biology, chemistry, geology, psychology, ...}
authorship attribution	{stephen king, dan brown, jk rowling, …}
sentiment analysis	{positive, negative, neutral, mixed}
…	…

Text Classification — Language Detection

- Identification of the language
  - Relatively straightforward in case of unique alphabets/characters
  - More tricky in case of (closely) related languages

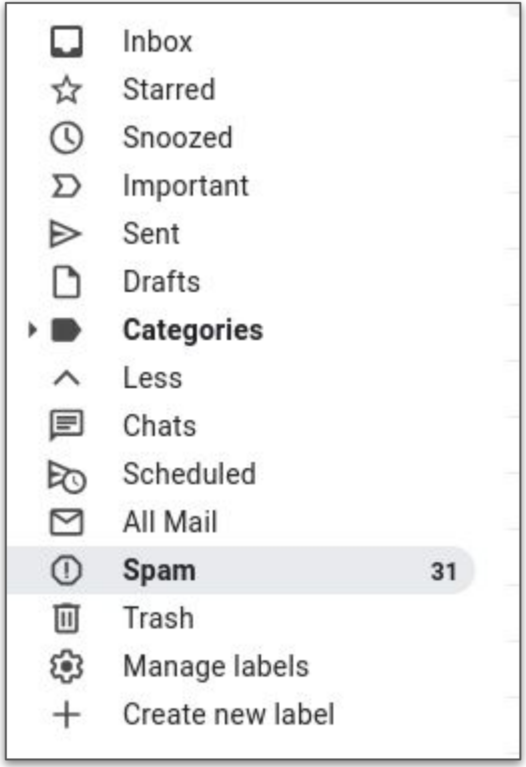
Example: Google Translate



Der Film war sehr spannend!

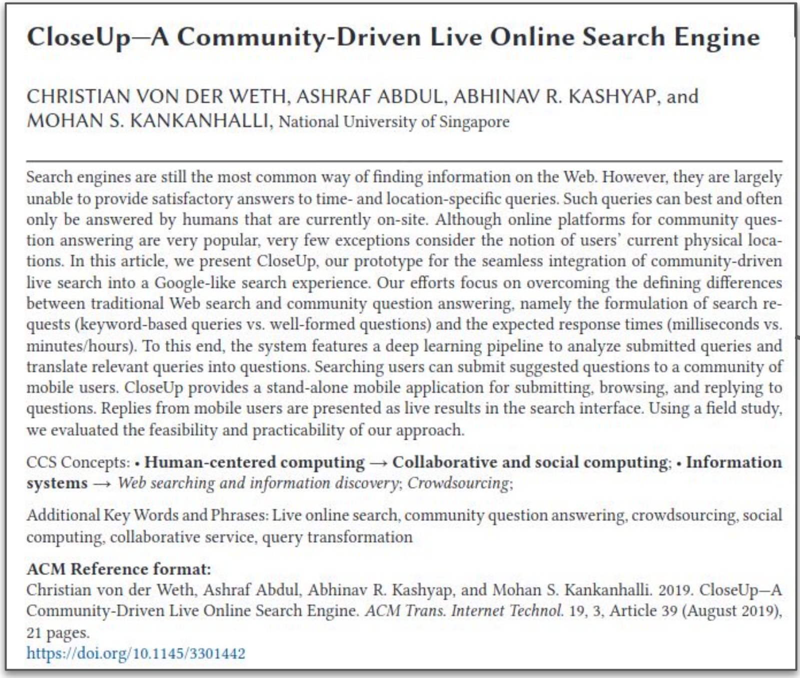
Text Classification — Email Spam Detection

- Email, messenger, SMS spam
  - Mostly annoying (e.g., ads)
  - Security risks (e.g., phishing, malicious attachments)



Text Classification — Subject Classification

- Typical application:
  - Automated organization of huge volumes of documents



CloseUp—A Community-Driven Live Online Search Engine

CHRISTIAN VON DER WETH, ASHRAF ABDUL, ABHINAV R. KASHYAP, and MOHAN S. KANKANHALLI, National University of Singapore

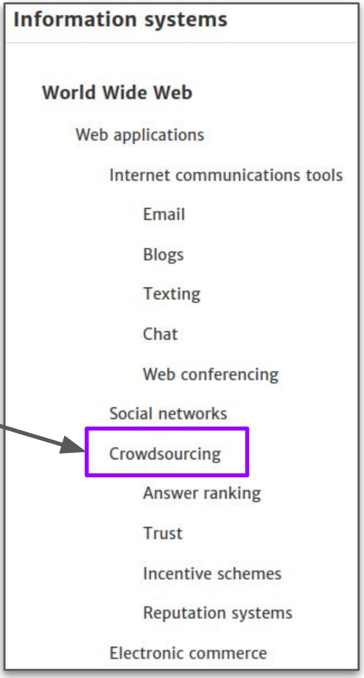
Search engines are still the most common way of finding information on the Web. However, they are largely unable to provide satisfactory answers to time- and location-specific queries. Such queries can best and often only be answered by humans that are currently on-site. Although online platforms for community question answering are very popular, very few exceptions consider the notion of users' current physical locations. In this article, we present CloseUp, our prototype for the seamless integration of community-driven live search into a Google-like search experience. Our efforts focus on overcoming the defining differences between traditional Web search and community question answering, namely the formulation of search requests (keyword-based queries vs. well-formed questions) and the expected response times (milliseconds vs. minutes/hours). To this end, the system features a deep learning pipeline to analyze submitted queries and translate relevant queries into questions. Searching users can submit suggested questions to a community of mobile users. CloseUp provides a stand-alone mobile application for submitting, browsing, and replying to questions. Replies from mobile users are presented as live results in the search interface. Using a field study, we evaluated the feasibility and practicability of our approach.

CCS Concepts: • **Human-centered computing → Collaborative and social computing**; • **Information systems** → *Web searching and information discovery; Crowdsourcing*;

Additional Key Words and Phrases: Live online search, community question answering, crowdsourcing, social computing, collaborative service, query transformation

ACM Reference format:
Christian von der Weth, Ashraf Abdul, Abhinav R. Kashyap, and Mohan S. Kankanhalli. 2019. CloseUp—A Community-Driven Live Online Search Engine. *ACM Trans. Internet Technol.* 19, 3, Article 39 (August 2019), 21 pages.
https://doi.org/10.1145/3301442

ACM Computing Classification System (very small snippet)

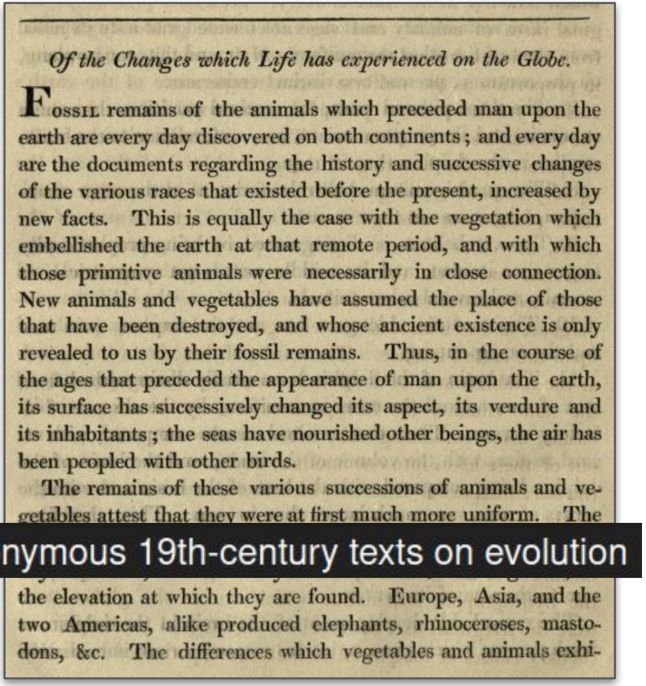


Information systems

- **World Wide Web**
  - Web applications
    - Internet communications tools
      - Email
      - Blogs
      - Texting
      - Chat
      - Web conferencing
    - Social networks
    - Crowdsourcing
      - Answer ranking
      - Trust
      - Incentive schemes
      - Reputation systems
    - Electronic commerce

Text Classification — Authorship Attribution

- NLP/AI meets Linguistic Forensics
  - Anonymously written documents
  - Documents written under a pseudonym
- Observation — underlying assumption:
  - People have unique writing styles
  - Vocabulary, frequent phrases, sentence lengths, typos, etc.



Of the Changes which Life has experienced on the Globe.

FOSSIL remains of the animals which preceded man upon the earth are every day discovered on both continents; and every day are the documents regarding the history and successive changes of the various races that existed before the present, increased by new facts. This is equally the case with the vegetation which embellished the earth at that remote period, and with which those primitive animals were necessarily in close connection. New animals and vegetables have assumed the place of those that have been destroyed, and whose ancient existence is only revealed to us by their fossil remains. Thus, in the course of the ages that preceded the appearance of man upon the earth, its surface has successively changed its aspect, its verdure and its inhabitants; the seas have nourished other beings, the air has been peopled with other birds.

The remains of these various successions of animals and vegetables attest that they were at first much more uniform. The

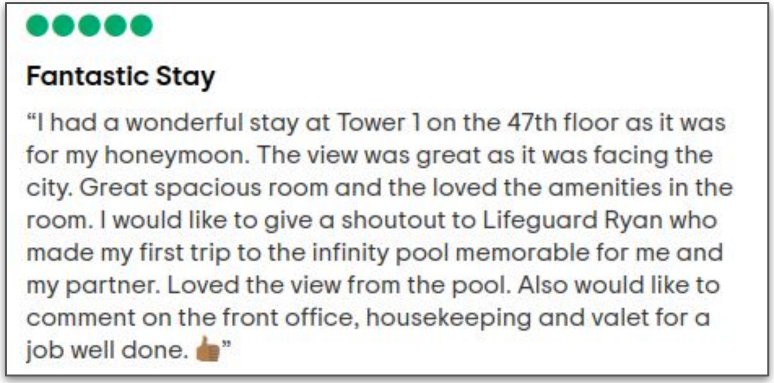
the elevation at which they are found. Europe, Asia, and the two Americas, alike produced elephants, rhinoceroses, mastodons, &c. The differences which vegetables and animals exhi-

AI reveals authors of anonymous 19th-century texts on evolution

Source: https://www.intelligentcio.com/eu/2018/08/28/ai-reveals-authors-of-anonymous-19th-century-texts-on-evolution/

Text Classification — Sentiment Analysis

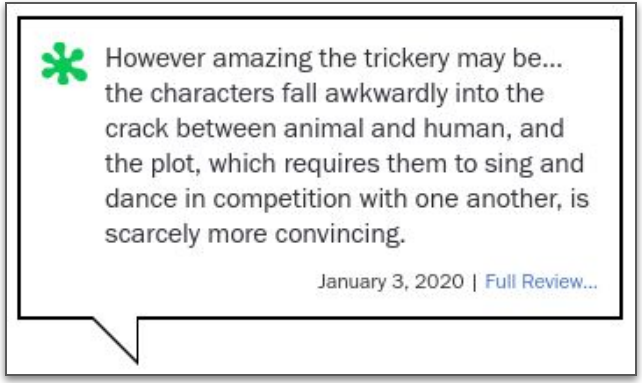
- Sentiment Analysis:
  - An author’s subjective or emotional attitude towards the central topic of the text
  - Very commonly applied to assess online users opinions about product and services
    (e.g., product reviews, hotel/restaurant reviews, movie/song/book reviews)
  - Also: consumer feedback, brand monitoring, political views, trend analysis, etc.



●●●●●

Fantastic Stay

“I had a wonderful stay at Tower 1 on the 47th floor as it was for my honeymoon. The view was great as it was facing the city. Great spacious room and the loved the amenities in the room. I would like to give a shoutout to Lifeguard Ryan who made my first trip to the infinity pool memorable for me and my partner. Loved the view from the pool. Also would like to comment on the front office, housekeeping and valet for a job well done. 👍”



However amazing the trickery may be... the characters fall awkwardly into the crack between animal and human, and the plot, which requires them to sing and dance in competition with one another, is scarcely more convincing.

January 3, 2020 | Full Review...

🏃‍♀️🏃🏃‍♂️ Positive or Negative Movie Reviews

Let’s label the keywords and the sentiment of the four lines below.

...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...

🏃‍♀️🏃🏃‍♂️ Positive or Negative Movie Reviews

Let’s label the keywords and the sentiment of the four lines below.

+ *...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...*

🏃‍♀️🏃🏃‍♂️ In-Lecture Activity (5 mins)

- Question: What are applications where text classification may be ethically questionable or even harmful?
  - Brainstorm with your peers; there is no right or wrong answer here

- Post your answer to Canvas > Discussions > [In-Lecture Interaction] L1

  (One student of your group can post the reply. Make sure to include your group members' names)

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Text Classification

- Formal setup
  - X — set of all documents; $x \in X$ — a single document
  - Y — set of all classes (or class labels); $y \in Y$ — a single class (or class label)

- Classification task
  - Mapping h from input space X to output space Y $\quad h : X \rightarrow Y$

$$h(x) = y$$

e.g., $h(\text{“}The\ movie\ \ is\ great.\text{”}) = \text{“}positive\text{”}$

"True" mapping which is unknown in practice

Note: A document might be assigned to more than one class ➜ **multilabel classification**

Note 2: Our SLP3 textbook uses d for x and c for y. We'll use both interchangeably.

Text Classification

- Goal of a classification task
  - Find the best $\hat{h}(x)$ to approximate the true mapping $h(x)$ ➜ **But how?**

- Two main approaches

(1) **Rule-based** (decision rules)

$$IF\ \ \text{“}good\text{”} \in x\ \ OR\ \ \text{“}great\text{”} \in x\ \ OR\ \ \text{“}nice\text{”} \in x\ \ OR\ \ \ldots$$
$$h(x) = \text{“}positive\text{”}$$
$$ELSE\ IF\ \ \text{“}bad\text{”} \in x\ \ OR\ \ \text{“}boring\text{”} \in x\ \ OR\ \ \text{“}dumb\text{”} \in x\ \ OR\ \ \ldots$$
$$h(x) = \text{“}negative\text{”}$$

(2) Supervised Learning (machine learning classifiers)

- Automatically learn $\hat{h}(x)$ based on a dataset of $\langle x, y \rangle$ pairs

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Naive Bayes Classifier — Intuition

- Simple (“naive”) probabilistic classifier based on Bayes Rule
  - Given a document x, for each class y_i compute $P(y_i|x)$
  - Assign document to class y with the highest probability $P(y_i|x)$ ➜ $y_{NB} = \underset{y_i \in Y}{\operatorname{argmax}}\, P(y_i|x)$
  - Calculate $P(y_i|x)$ using Bayes Rule ➜ $P(y_i|x) = \dfrac{P(x|y_i)P(y_i)}{P(x)}$

- Example (sentiment analysis)

$$P(\mathbf{pos} \mid \text{“}The\, movie\, is\, really\, funny\text{”}) \overset{\substack{\text{hopefully :)}\\ \downarrow}}{>} P(\mathbf{neg} \mid \text{“}The\, movie\, is\, really\, funny\text{”})$$

- Relies on a very simple representation of documents: **Bag-of-Words (BoW)**

Bag-of-Word (BoW) Representation

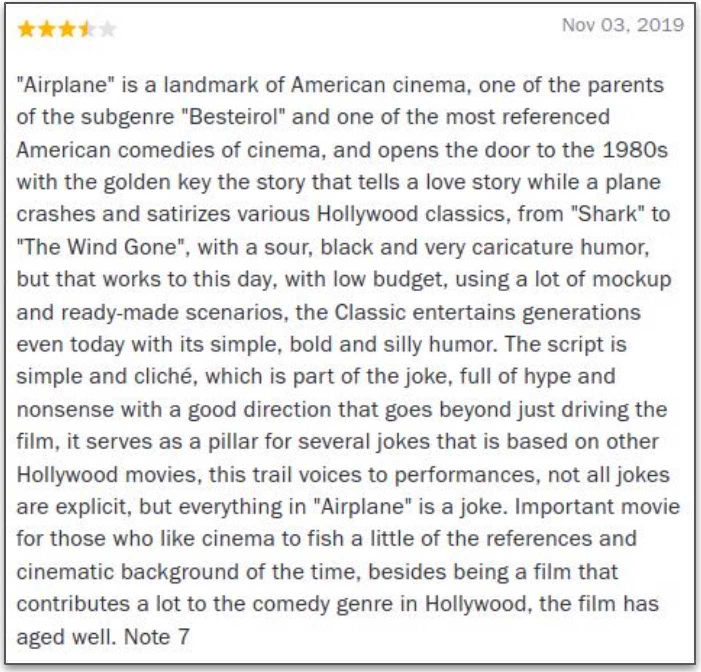
- Simplifying assumptions
  - Represent a document as a bag (i.e., multiset) of words (i.e., we also keep track of the word counts)
  - Ignore any word order or any other grammar

- BoW representation affected by
  - Tokenization
  - Normalization

Choice depending on the application/task

Bag-of-Words Representation — Example

Movie review for "*Airplane!*" (1980)

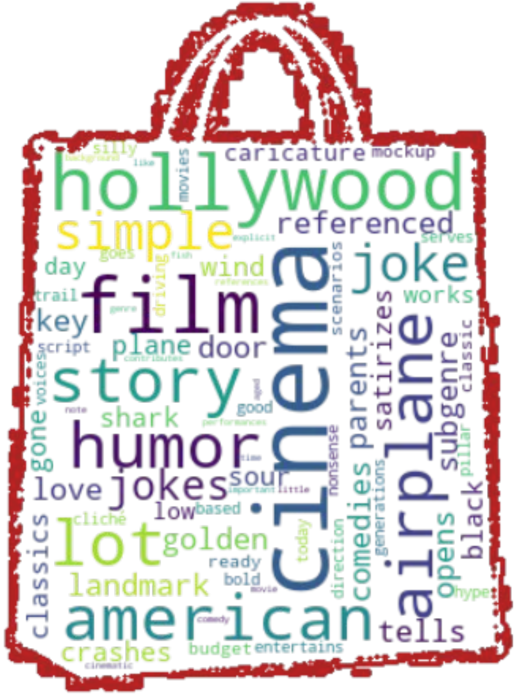


★★★½☆ Nov 03, 2019

"Airplane" is a landmark of American cinema, one of the parents of the subgenre "Besteirol" and one of the most referenced American comedies of cinema, and opens the door to the 1980s with the golden key the story that tells a love story while a plane crashes and satirizes various Hollywood classics, from "Shark" to "The Wind Gone", with a sour, black and very caricature humor, but that works to this day, with low budget, using a lot of mockup and ready-made scenarios, the Classic entertains generations even today with its simple, bold and silly humor. The script is simple and cliché, which is part of the joke, full of hype and nonsense with a good direction that goes beyond just driving the film, it serves as a pillar for several jokes that is based on other Hollywood movies, this trail voices to performances, not all jokes are explicit, but everything in "Airplane" is a joke. Important movie for those who like cinema to fish a little of the references and cinematic background of the time, besides being a film that contributes a lot to the comedy genre in Hollywood, the film has aged well. Note 7

Normalization steps:

- Removal of non-words
- Removal of stopwords
- Case-folding (lowercase)



🏃‍♀️ 🏃 🏃‍♂️ Quick Quiz

For which NLP task is a BoW representation of documents arguably **least problematic**? Why?

A Machine Translation

B Document Categorization

C Syntactic Parsing

D Sentiment Analysis

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Naive Bayes Classifier — Annotated

- Basic setup
  - Document $x \in X$ with $x = w_1, w_2, \ldots, w_n$ (BoW representation)
  - Class label $y \in Y$

$$\underbrace{P(y|w_1, w_2, \ldots, w_n)}_{\textbf{Posterior: }\text{Probability of class } y \text{ given document } x} = \frac{\overbrace{P(w_1, w_2, \ldots, w_n|y)}^{\textbf{Likelihood: }\text{Probability of } x \text{ given that it belongs to class } y}\overbrace{P(y)}^{\textbf{Prior: }\text{Probability that } x \text{ belongs to class } y \text{ without seeing any data}}}{\underbrace{P(w_1, w_2, \ldots, w_n)}_{\textbf{Marginal: }\text{Probability of } x \text{ under any class}}}$$

Naive Bayes Classifier

- Observation
  - We are not really interested in the exact values of $P(y_i|x)$
  - We only care about the difference between $P(y_i|x)$ and $P(y_j|x)$

$$\frac{P(w_1, w_2, \dots, w_n|y_i)P(y_i)}{P(w_1, w_2, \dots, w_n)} \overset{?}{\gtreqless} \frac{P(w_1, w_2, \dots, w_n|y_j)P(y_j)}{P(w_1, w_2, \dots, w_n)}$$

The **marginal** does not affect the result of comparison!

$$P(y|w_1, w_2, \dots, w_n) \propto P(w_1, w_2, \dots, w_n|y)P(y)$$

Naive Bayes Classifier — The “Naive” Part

- Simplifying assumption
  - All words $w_1, w_2, \dots, w_n$ are independent from each other
  - Obviously does not hold, but still achieves good results in practice

$$P(y|w_1, w_2, \dots, w_n) \propto P(w_1, w_2, \dots, w_n|y)P(y)$$

“Naive” assumption

$$P(y|w_1, w_2, \dots, w_n) \propto P(w_1|y)P(w_2|y)\dots P(w_n|y)P(y) = P(y)\prod_{i=1}^{n} P(w_i|y)$$

How to calculate these probabilities?

Naive Bayes Classifier — Maximum Likelihood Estimates

- **Prior** $P(y)$

$$\hat{P}(y) = \frac{N_y}{N}$$

# documents of class y

# documents (total)

- **Likelihood** $P(w_i|y)$

$$\hat{P}(w_i|y) = \frac{Count(w_i, y)}{\sum_{w \in V} Count(w, y)}$$

# occurrences of w_i in documents of class y

# words (total) in documents of class y

Does this look familiar?

Naive Bayes Classifier — Practical Considerations

- Risk of arithmetic underflow ➜ Calculate log probabilities

$$P(y|w_1, w_2, \ldots, w_n) \propto P(y) \prod_{i=1}^{n} P(w_i|y) \quad ➜ \quad \log P(y|w_1, w_2, \ldots, w_n) \propto \log P(y) + \sum_{i=1}^{n} \log P(w_i|y)$$

- Out-of-vocabulary (OOV) words + unrepresented classes
  - Unseen words w_i during test/prediction time ➜ $Count(w_i, y) = 0$ ➜ $P(w_i|y) = 0$
  - No document of class y ➜ $P(y) = 0$

e.g.: Add-k Smoothing:

$$\hat{P}(w_i|y) = \frac{Count(w_i, y) + k}{\sum_{w \in V} Count(w, y) + k|V|} \qquad \hat{P}(y) = \frac{N_y + k}{N + k|Y|}$$

Deriving the NB Classifier in One Slide

$$y_{MAP} = \arg\max_{y \in \mathcal{Y}} P(y|x)$$

Most likely class (*Maximum a priori*)

$$= \arg\max_{y \in \mathcal{Y}} \frac{P(x|y) \cdot P(y)}{P(x)}$$

Bayes Rule

$$= \arg\max_{y \in \mathcal{Y}} P(x|y) \cdot P(y)$$

Dropping the prior ***P(w)*** in the denominator

$$= \arg\max_{y \in \mathcal{Y}} P(w_1, \ldots, w_n|y) \cdot P(y)$$

Doc represented as words w_1, ... , w_m (such as word counts) using BoW assumption

$$= \arg\max_{y \in \mathcal{Y}} P(w_1|y) \cdot \ldots \cdot P(w_n|y) \cdot P(y)$$

Independence Assumption

$$= \arg\max_{y \in \mathcal{Y}} \prod_{i=1}^{N} P(w_i|y) \cdot P(y)$$

Equation for Naive Bayes

NB Algorithm Summary

```
$\textbf{TrainNaiveBayes}(D, \mathcal{Y})$ returns $logP(y)$ and $logP(w|y)$ :
$N \leftarrow |D|$
for each class $y \in \mathcal{Y}$ : // calc prior terms
  $N[y] \leftarrow D_y$
  $logprior[y] \leftarrow log(|N[y]|/N)$
  $V \leftarrow$ vocabulary of $D$
  $bigdoc[y] \leftarrow$ append$(d)$ forall $d \in N[y]$
  for each word $w \in V$ : // calc likelihood terms
    $c(w, y) \leftarrow$ # of occurrences of$w$ in $bigdoc[y]$
    $loglikelihood[w, y] \leftarrow log \frac{c(w, y) + 1}{\sum_{w' \in V}(c(w', y) + 1)}$
return $logprior,\ loglikelihood, V$
```

```
$\textbf{TestNaiveBayes}(x, logprior,$
  $loglikelihood, \mathcal{Y}, V)$
  returns $y$ :
for each class $y \in \mathcal{Y}$ :
  $sum[y] \leftarrow logprior[y]$
  for each position $i$ in $x$ :
    $w \leftarrow x_i$
    if $w \in V$ :
      $sum[y] + = loglikelihood[w, c]$
return $argmax_y(sum[y])$
```

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Naive Bayes Classifier — Runthrough

- Sentiment Analysis
  - Documents: movie reviews
  - Two classes: “pos”, “neg”

$$V = \{funny,\ boring,\ movie,\ cast,\ good\}$$

$$|V| = 5$$

Example corpus

(greyed-out words/tokens removed during normalization)

Review	Class
very good and funny movie!	pos
what a funny cast!	pos
a very boring movie and boring cast	neg
very boring cast!	neg
such a funny movie!	pos
really good cast, really good movie.	pos
boring…such a boring movie!!!	neg

Naive Bayes Classifier — Runthrough

- Calculating **priors** (with Laplace Smoothing)
  - Number of reviews $N = 7$
  - Number of positive reviews $N_{pos} = 4$
  - Number of negative reviews $N_{neg} = 3$

$$P(pos) = \frac{N_{pos} + 1}{N + |Y|} = \frac{4 + 1}{7 + 2} = \frac{5}{9}$$

$$P(neg) = \frac{N_{neg} + 1}{N + |Y|} = \frac{3 + 1}{7 + 2} = \frac{4}{9}$$

P(pos)	P(neg)
5/9	4/9

Naive Bayes Classifier — Runthrough

- Calculating **likelihoods** (with Laplace Smoothing)

$$\hat{P}(funny|pos) = \frac{Count(funny, pos) + 1}{\sum_{w \in V} Count(w, pos) + |V|} = \frac{3+1}{11+5} = \frac{4}{16}$$

$$\hat{P}(funny|neg) = \frac{Count(funny, neg) + 1}{\sum_{w \in V} Count(w, neg) + |V|} = \frac{0+1}{9+5} = \frac{1}{14}$$

...

w_i	$P(w_i|pos)$	$P(w_i|neg)$
funny	**4/16**	**1/14**
boring	1/16	6/14
movie	4/16	3/14
cast	3/16	3/14
good	4/16	1/14

We have the **priors** and **likelihoods** ➜ Naive Bayes Classifier done training

🏃‍♀️🏃 Naive Bayes Classifier — Inference

P(pos)	P(neg)
5/9	4/9

- Predict the class for a new review

Review	**Class**
a funny movie and cast	**???**

w_i	$P(w_i \mid pos)$	$P(w_i \mid neg)$
funny	4/16	1/14
boring	1/16	6/14
movie	4/16	3/14
cast	3/16	3/14
good	4/16	1/14

➜ Label review with ?

🏃‍♀️🏃 Naive Bayes Classifier — Inference

P(pos)	P(neg)
5/9	4/9

- Predict the class for a new review

Review	Class
a funny movie and cast	**???**

w_i	$P(w_i \mid pos)$	$P(w_i \mid neg)$
funny	4/16	1/14
boring	1/16	6/14
movie	4/16	3/14
cast	3/16	3/14
good	4/16	1/14

$$P(pos|funny, movie, cast) \propto P(pos)P(funny|pos)P(movie|pos)P(cast|pos) = \frac{5}{9} \cdot \frac{4}{16} \cdot \frac{4}{16} \cdot \frac{3}{16} = 0.0065$$

$$P(neg|funny, movie, cast) \propto P(neg)P(funny|neg)P(movie|neg)P(cast|neg) = \frac{4}{9} \cdot \frac{1}{14} \cdot \frac{3}{14} \cdot \frac{3}{14} = 0.0015$$

$P(pos|funny, movie, cast) > P(neg|funny, movie, cast)$ ➜ Label review with “pos”

🏃‍♀️🏃🏃‍♂️ How does NB compare with LM? (5 mins)

- Question: How does NB differ from an LM in its assumptions?
  What are its pros? Its cons?

- Post your answer to Canvas > Discussions > [In-Lecture Interaction] L1
  (One student of your group can post the reply. Make sure to include your group members' names)

Outline

- Text Classification
  - Common Applications
  - Formal setup
- **Naive Bayes Classifier**
  - Basic Intuition & BoW Representation
  - Definition & Practical Considerations
  - Complete Runthrough
  - **Discussion & Limitations**
- Evaluation of Classifiers
- Vector Space Model
  - Vector Representation of Documents
  - Document Similarity

Naive Bayes Classifier + BoW — Discussion

- Naive Bayes vs. Language Models
  - Naive Bayes makes a non-contextual decision (unigram model; but can be extended to larger n-grams)
  - Naive Bayes is an LM! It treats each class like a separate language model
- Biggest **pro**: simplicity
  - Easy to understand & implement, fast, not very data hungry, interpretable results
- Biggest **con**: assumption of conditional independence
  - For most types of data, the features are typically not independent
  - For text classification (features = words) it actually often works well in practice
    (particularly with some additional "tweaking" of the data)

Naive Bayes Classifier + BoW — Limitations

- Example: Sentiment Analysis
  - BoW incapable to handle some relevant linguistic phenomena
  - Most prominently: **negation** (typically flips the sentiment)

Particularly a problem if "not" is removed as a stopword

$$P(pos|\text{“}the\ movie\ is\ very\ funny.\text{”}) \approx P(pos|\text{“}the\ movie\ is\ {\color{red}not}\ very\ funny.\text{”})$$

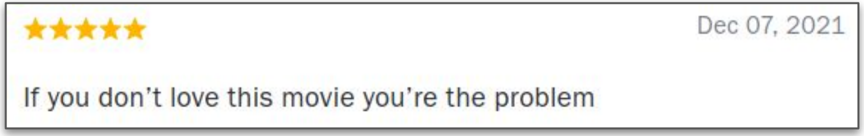
- Possible countermeasure (to handle negation)
  - Add prefix “NOT” to every word between negation word and next punctuation mark
    (**Note:** this is a common heuristic which is neither trivial nor perfect — but if often works well)

$$\text{“}the\ movie\ is\ not\ very\ funny.\text{”} \rightarrow \text{“}the\ movie\ is\ not\ NOT\_very\ NOT\_funny.\text{”}$$

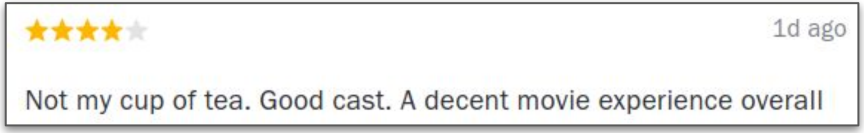
🤔 **To think about:** Where would this simple heuristic fail? Examples?

Naive Bayes Classifier + BoW — Limitations

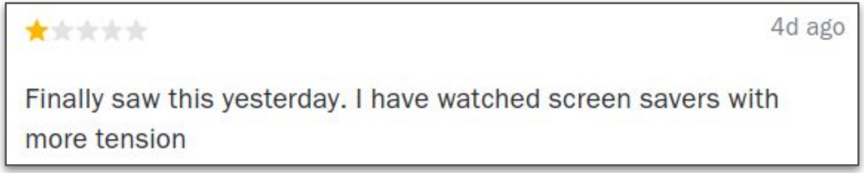
- Example: Sentiment Analysis
  - Sentiment is often expressed/conveyed in phrases or idioms (not just individual words)
  - Other challenges: modals (e.g., *may*, *might*), conditionals (e.g., *if*), questions, literary devices (e.g., sarcasm)
  - Often requires deep world and contextual knowledge


★★★★★ Dec 07, 2021

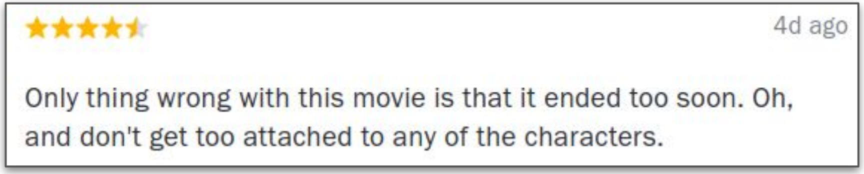
If you don't love this movie you're the problem


★★★★☆ 1d ago

Not my cup of tea. Good cast. A decent movie experience overall


★☆☆☆☆ 4d ago

Finally saw this yesterday. I have watched screen savers with more tension


★★★★★ 4d ago

Only thing wrong with this movie is that it ended too soon. Oh, and don't get too attached to any of the characters.

Note: These challenges are not limited to the Naive Bayes classifier, but more prominent due to NB's BoW approach

Naive Bayes Classifier — Summary

- Naive Bayes = class-specific language model
  - Probabilistic classifier based on Bayes Rule
- Good baseline
  - Robust, fast to train, low storage requirements
  - Works actually pretty well for many text classification tasks
    (e.g., sentiment analysis over reviews which often contain very indicative words)
- Strong assumption: conditional independence
  - Requires careful assessment if this assumption (at least somewhat) holds
  - Maybe some tweaks possible address this issue (e.g., negation handling)

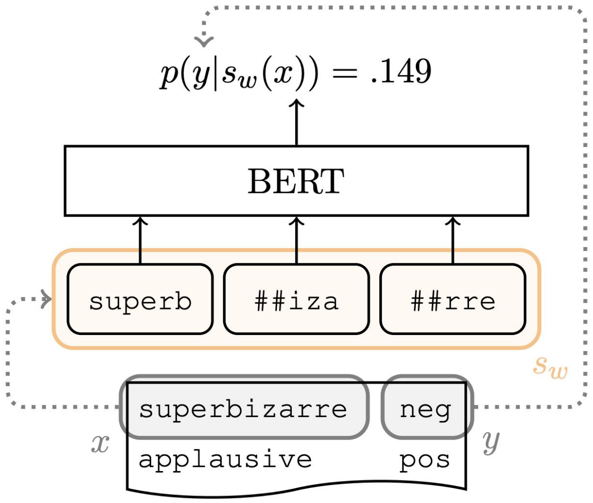
Break

Cody Blakeney
@code_star

Do you guys ever think about tokenizers?

Prithviraj (Raj) Ammanabrolu @rajammanabrolu · Sep 26, 2023
If there's one thing standing in the way of AGI, it's tokenizers

BERT thinks the sentiment of “superbizarre” is positive because its tokenization contains the token “superb”



(a) BERT (s_w)

[Hofmann *et al.* (2021) Superbizarre Is Not Superb: Derivational Morphology Improves BERT’s Interpretation of Complex Words]

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  - Motivation & Goals
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Pre-Lecture Activity from Last Week

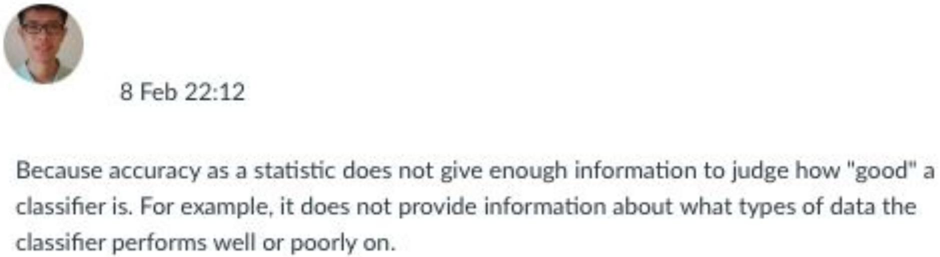
- Assigned Task
  - Post a 1–2 sentence answer to the following question into the Pre-Lecture Discussion (you will find the thread on Canvas > Discussions)

"When we want to evaluate classifiers,
*why is **accuracy** alone often not a good metric?"*

Side notes:

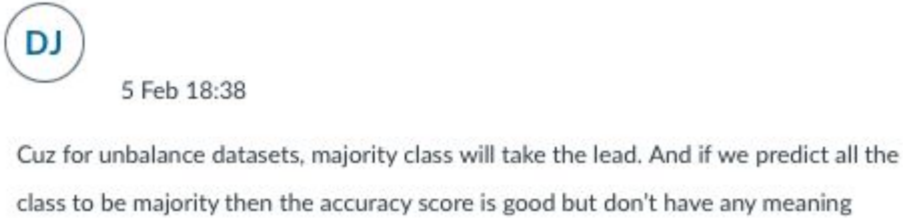
- This task is meant as a warm-up to provide some context for the next lecture
- No worries if you get lost; we will talk about this in the next lecture
- You can just copy-&-paste others' answers, but his won't help you learn better

Pre-Lecture Activity from Last Week



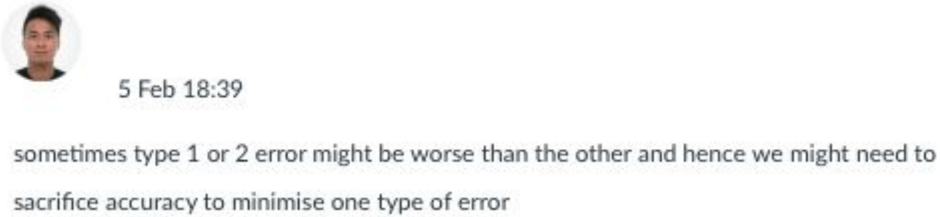
8 Feb 22:12

Because accuracy as a statistic does not give enough information to judge how "good" a classifier is. For example, it does not provide information about what types of data the classifier performs well or poorly on.



5 Feb 18:38

Cuz for unbalance datasets, majority class will take the lead. And if we predict all the class to be majority then the accuracy score is good but don't have any meaning



5 Feb 18:39

sometimes type 1 or 2 error might be worse than the other and hence we might need to sacrifice accuracy to minimise one type of error

Evaluating Classifiers — Error Types

- Recall from Week 02: Two basic types of errors
  - Assume there are only 2 classes: **Positive (1)** & **Negative (0)** ➜ binary classification
  - There are 2 ways for a classifier to get it wrong

The classifier incorrectly predicts the label ➜ **False Positives** (Type I Errors)

The classifier incorrectly fails to predict the label ➜ **False Negatives** (Type II Errors)

  - Analogously, there are 2 ways to get it right

The classifier correctly predicts the label ➜ **True Positives**

The classifier incorrectly fails to predict the label ➜ **True Negatives**

Classification: Evaluation — Confusion Matrix

actual labels

predicted labels

	1	0
1	🟩	🟥
0	🟥	🟩

True Positives (TP): Number of positive classes that have been correctly predicted as positive

True Negatives (TN): Number of negative classes that have been correctly predicted as negative

False Positives (FP): Number of negative classes that have been incorrectly predicted as positive

False Negatives (FN): Number of positive classes that have been incorrectly predicted as negative

Classification: Evaluation — Confusion Matrix

		actual labels	
		1	**0**
predicted labels	**1**	True Positives (TP)	False Positives (FP)
	0	False Negatives (FN)	True Negatives (TN)

True Positives (TP): Number of positive classes that have been correctly predicted as positive

True Negatives (TN): Number of negative classes that have been correctly predicted as negative

False Positives (FP): Number of negative classes that have been incorrectly predicted as positive

False Negatives (FN): Number of positive classes that have been incorrectly predicted as negative

Classification: Evaluation — Popular Metrics

- Accuracy

$$Accuracy = \frac{TP + TN}{TP + FP + TN + TF}$$

actual labels

predicted labels

	1	0
1	TP	FP
0	FN	TN

Classification: Evaluation — Popular Metrics

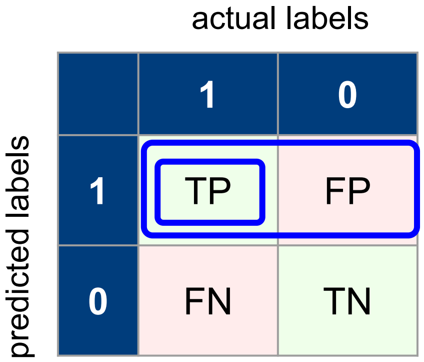
- Precision, Recall, F1 Score

Harmonic Mean of Precision and Recall

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

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

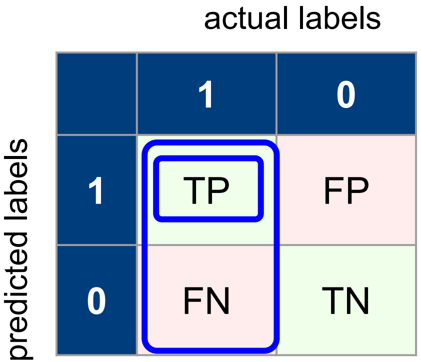
$$F1 = 2 \cdot \frac{Precision \cdot Recall}{Precision + Recall}$$



actual labels

predicted labels

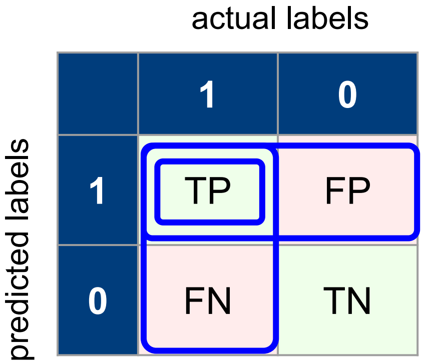
	1	0
1	TP	FP
0	FN	TN



actual labels

predicted labels

	1	0
1	TP	FP
0	FN	TN



actual labels

predicted labels

	1	0
1	TP	FP
0	FN	TN

Which is more important?

Precision or Recall?

http://
Search
Go

Classification: Evaluation — Why so Many Measures?

- Observation: FP and FN not always equally problematic

$$Precision = \frac{TP}{TP + FP} \qquad Recall = \frac{TP}{TP + FN}$$

- Example: COVID 19 pre-vaccine
  (e.g., from social media content posted by users)
  - BAD: misclassifying a high-risk person
  - OK-ish: misclassifying a healthy person

Recall > Precision

- Example: Web Search Results
  (e.g., for search engines such as Google)
  - BAD: showing an irrelevant result
  - OK: missing a relevant article in result

Recall < Precision

Classification: Evaluation — Why so Many Measures?

- Problem: (Highly) imbalanced datasets

- Example use case: COVID-19 test (binary “classifier”)
  - Most people in a population are not infected
  - Assume a test that always(!) returns “negative”

actual labels

predicted labels

	1	0
1	0	0
0	200	10,000

$$Accuracy = \frac{0 + 10000}{0 + 0 + 10000 + 200} = 98\%$$

➜ Very high accuracy despite “useless” test

🏃‍♀️🏃🏃‍♂️ Why Harmonic? (5 mins)

- Question: Why do we calculate the F1 score using the Harmonic Mean?
  - Post your answer to Canvas > Discussions > [In-Lecture Interaction] L1
    (one student of your group can post the reply, but include your group members' names)

Why the Harmonic Mean?

$$F1 = 2 \cdot \frac{Precision \cdot Recall}{Precision + Recall}$$

Why not, e.g., Average?

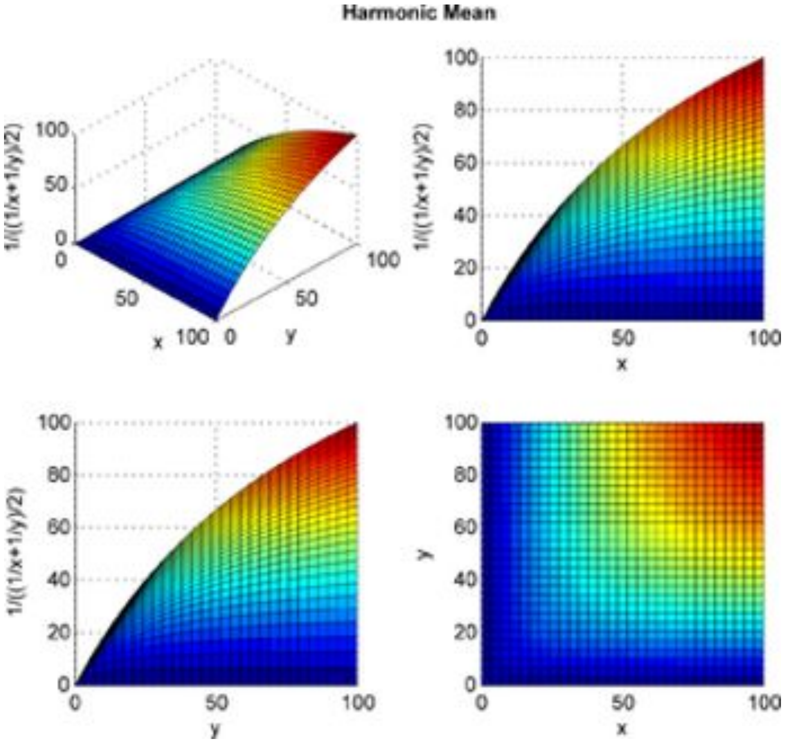
$$F1 = \frac{Precision + Recall}{2}$$

😎 **Pro Tip**: It's not a competition,
but about discussions and sharing ideas

🏃‍♀️🏃🏃‍♂️Why Harmonic?

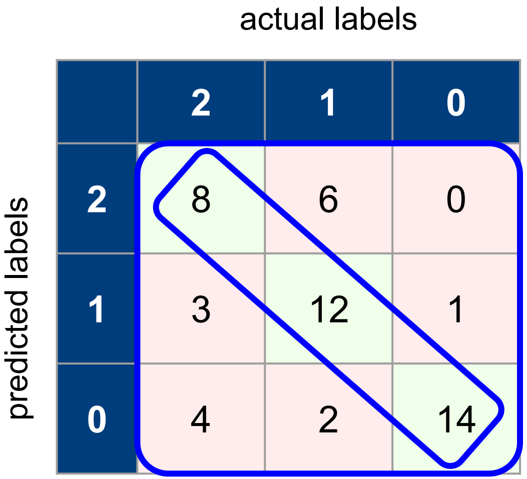
Arithmetic mean also uses only the 0.5–1.0 range if used.

It can be trivially easy to score well on one metric, we want only non-trivial combinations of both to score well.



Classification: Evaluation — Beyond 2 Classes

- Example: 3 classes, 50 samples



actual labels

predicted labels

	2	1	0
2	8	6	0
1	3	12	1
0	4	2	14

$$Accuracy = \frac{8+12+14}{8+12+14+6+3+1+4+2} = 0.68$$

Multiclass Evaluation — One-vs-Rest Confusion Matrices

- Example:

actual labels

predicted labels

	2	1	0
2	8	6	0
1	3	12	1
0	4	2	14

2-vs-Rest

	2	$\bar{2}$
2	8	6
$\bar{2}$	7	29

$$F1 = 0.55$$

1-vs-Rest

	1	$\bar{1}$
1	12	4
$\bar{1}$	8	26

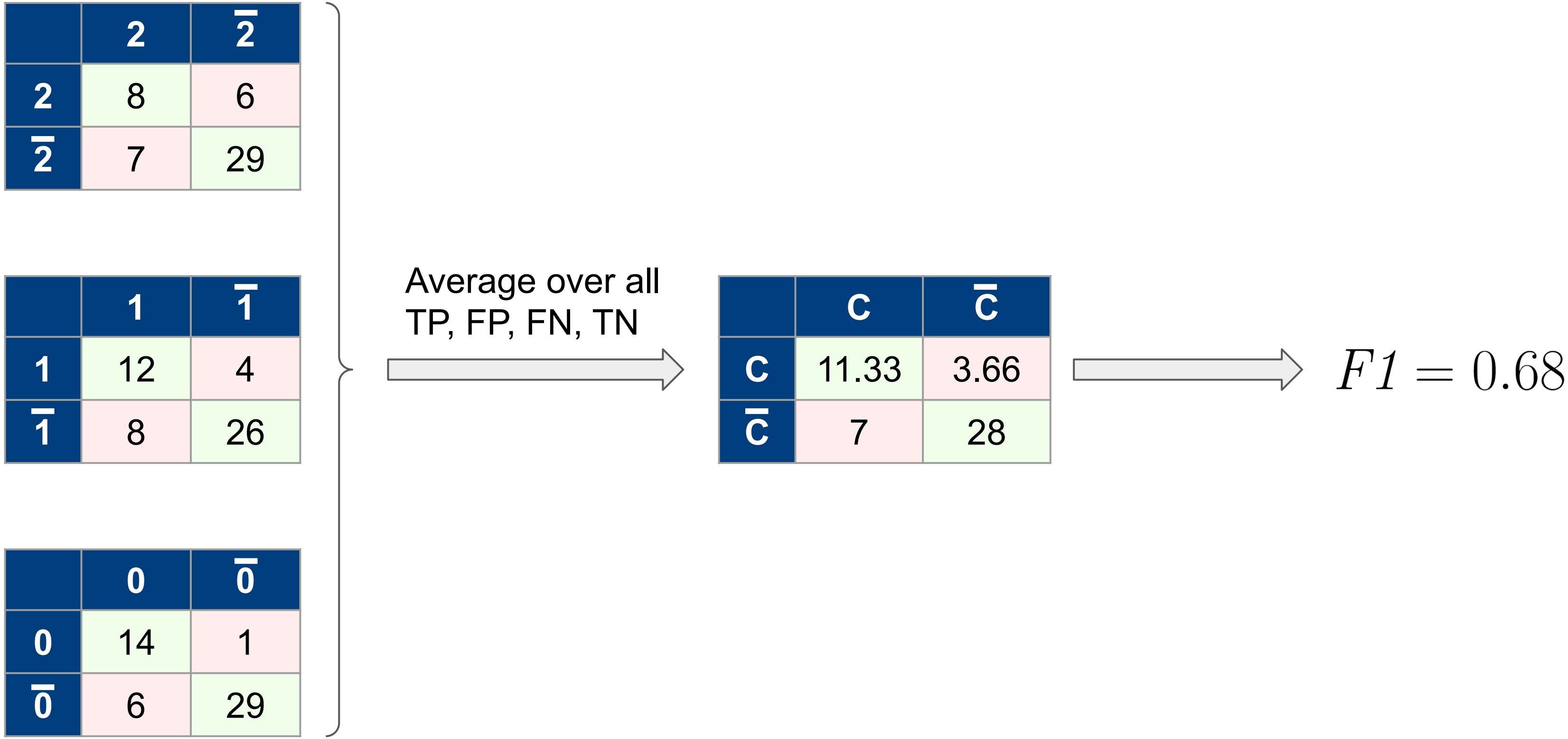
$$F1 = 0.66$$

0-vs-Rest

	0	$\bar{0}$
0	14	1
$\bar{0}$	6	29

$$F1 = 0.80$$

One-vs-Rest — Micro Averaging



	2	$\bar{2}$
2	8	6
$\bar{2}$	7	29

	1	$\bar{1}$
1	12	4
$\bar{1}$	8	26

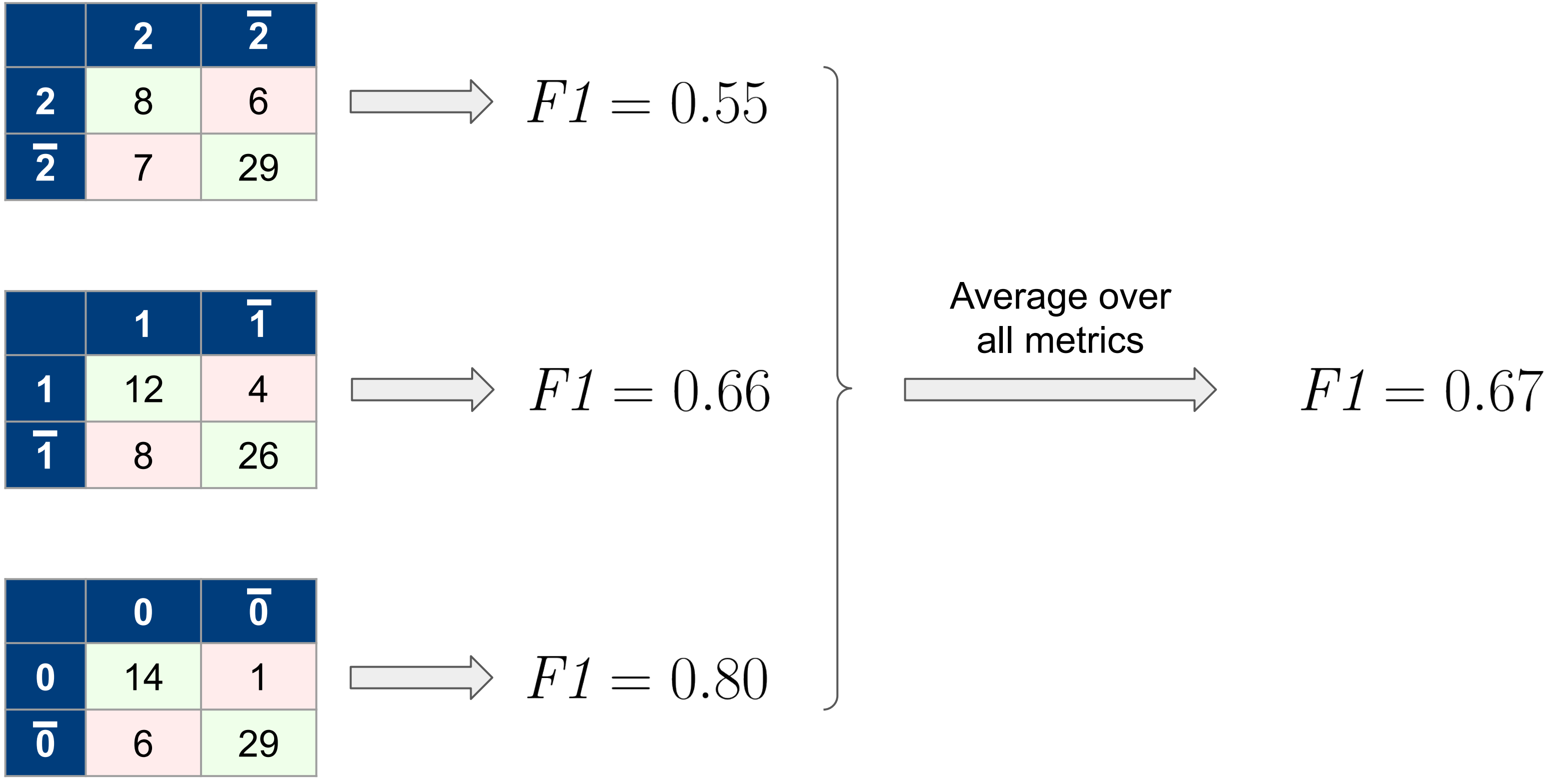
	0	$\bar{0}$
0	14	1
$\bar{0}$	6	29

Average over all TP, FP, FN, TN

	C	$\bar{C}$
C	11.33	3.66
$\bar{C}$	7	28

$$F1 = 0.68$$

One-vs-Rest — Macro Averaging



	2	$\overline{2}$
2	8	6
$\overline{2}$	7	29

$$F1 = 0.55$$

	1	$\overline{1}$
1	12	4
$\overline{1}$	8	26

$$F1 = 0.66$$

	0	$\overline{0}$
0	14	1
$\overline{0}$	6	29

$$F1 = 0.80$$

Average over all metrics

$$F1 = 0.67$$

One-vs-Rest — Macro vs. Micro Averaging

- Both methods use One-vs-Rest confusion matrices
  - All introduced metrics applicable

- Micro-averaging
  - Averaging over TP, FP, FN, TN values of all One-vs-Rest confusion matrices
  - Favors bigger classes (since average over counts)

- Macro-averaging
  - Averaging over metrics derived from each One-vs-Rest confusion matrix
  - Treats all class equally (since metrics are normalized)

🏃‍♀️ 🏃 🏃‍♂️ Micro / Macro 1

A **2-class** classifier and a **10-class** classifier have a f1-score of 0.6: Which classifier does a **better** job?

A The 2-class classifier

B The 10-class classifier

C Both are equally good

D Not comparable

🏃‍♀️🏃🏃‍♂️ Micro / Macro 2

Which has the larger value?

Micro average

or

Macro average

A Micro

B Macro

C It depends

D What? I wasn’t paying attention…

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  - **Vector Representation of Documents**
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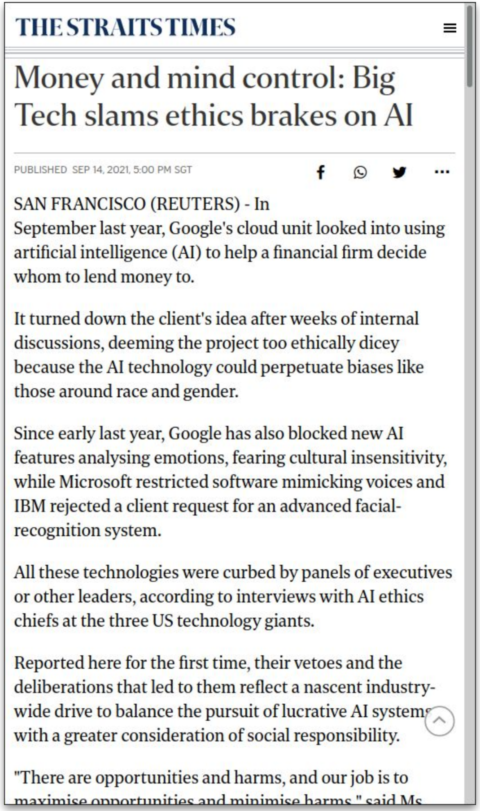
Vector Space Model — Motivation

- Most algorithms do not work on raw text — common requirements
  - Numerical input
  - Standardized/canonical input

- Feature extraction ➜ vectorization of text data
  - Represent each text document as a vector of equal size
  - Vector elements = numerical values derived from text



THE STRAITS TIMES

Money and mind control: Big Tech slams ethics brakes on AI

PUBLISHED SEP 14, 2021, 5:00 PM SGT

SAN FRANCISCO (REUTERS) - In September last year, Google's cloud unit looked into using artificial intelligence (AI) to help a financial firm decide whom to lend money to.

It turned down the client's idea after weeks of internal discussions, deeming the project too ethically dicey because the AI technology could perpetuate biases like those around race and gender.

Since early last year, Google has also blocked new AI features analysing emotions, fearing cultural insensitivity, while Microsoft restricted software mimicking voices and IBM rejected a client request for an advanced facial-recognition system.

All these technologies were curbed by panels of executives or other leaders, according to interviews with AI ethics chiefs at the three US technology giants.

Reported here for the first time, their vetoes and the deliberations that led to them reflect a nascent industry-wide drive to balance the pursuit of lucrative AI systems with a greater consideration of social responsibility.

"There are opportunities and harms, and our job is to maximise opportunities and minimise harms," said Ms

???

(0.42, 0.02, 0.53, 0.91, 0.21, 0.74, 0.04, …, 0.16, 0.76)

“Manual” Approach — Handcrafted Features

- Example: Sentiment Analysis
  - Length of text document (number of tokens or characters)
  - Number of positive and negative emoticons
  - Number of words associated with positive or negative mood

Finding good features can be tricky in practice

- 2 movie reviews
  - R_1: *“The movie was so boring - I hated it after just 20 minutes! :(((”*
  - R_2: *“Dune is a such a brilliant and beautiful movie!”*

	# char	#tokens	#emoticons+	#emoticons–	# words+	# words–
R_1	64	15	0	1	0	2
R_2	47	10	0	0	2	0

Vector Space Model

- Idea: Vectorize documents based on vocabulary (➜ BoW representation)
  - Length each document vector is the size of corpus vocabulary V
  - Vectors for all documents in dataset D form the document-term matrix

- Document-term matrix
  - Set of documents $d_1, d_2, \ldots, d_{|D|}$
  - Set of unique terms $t_1, t_2, \ldots, t_{|V|}$

➜ weight $w_{t,d}$: matrix value depending on representation

	d_1	d_2	d_3	d_4	d_5	…	$d_{\|D\|}$
t_1							
t_2							
t_3							
t_4		$w_{4,2}$					
…							
$t_{\|V\|}$							

Vector Space Model — Example Corpus

d_1 : *Dogs chase cats and other dogs.*

d_2 : *Cats chase other cats.*

d_3 : *There is a car chase on the TV.*

d_4 : *My dog watches other dogs on TV.*

d_5 : *My dog and cat sit in the car.*

Normalization steps:

- Removal of non-words
- Removal of stopwords
- Case-folding (lowercase)
- Lemmatization

d_1 : *dog chase cat dog*

d_2 : *cat chase cat*

d_3 : *car chase tv*

d_4 : *dog watch dog tv*

d_5 : *dog cat sit car*

➜ Vocabulary V = {*car*, *cat*, *chase*, *dog*, *sit*, *tv*, *watch*}

Document–Term Matrix with Binary Weights

d_1 : dog chase cat dog
d_2 : cat chase cat
d_3 : car chase tv
d_4 : dog watch dog tv
d_5 : dog cat sit car

- Matrix elements are either 0 or 1
  - $w_{t,d} = 1$: document d contains term t
  - $w_{t,d} = 0$: otherwise

- Interpretation
  - Weights reflect presence or absence of a term in a document
  - No differentiation between words of a document
  - Suitable for basic filtering of documents (e.g., find all documents containing “dog”)

	d_1	d_2	d_3	d_4	d_5
car	0	0	1	0	1
cat	1	1	0	0	1
chase	1	1	1	0	0
dog	1	0	0	1	1
sit	0	0	0	0	1
tv	0	0	1	1	0
watch	0	0	0	1	0

Document–Term Matrix with Term Frequencies

d_1 : dog chase cat dog
d_2 : cat chase cat
d_3 : car chase tv
d_4 : dog watch dog tv
d_5 : dog cat sit car

- Matrix elements are integers
  - $w_{t,d}$: # occurrences of term t in document d

    ➜ **term frequency** $tf_{t,d}$

- Interpretation
  - Assumption: more frequent terms in a document are more important

BUT: Does “more frequent” always mean “more important”?

	d_1	d_2	d_3	d_4	d_5
car	0	0	1	0	1
cat	1	**2**	0	0	1
chase	1	1	1	0	0
dog	**2**	0	0	**2**	1
sit	0	0	0	0	1
tv	0	0	1	1	0
watch	0	0	0	1	0

$tf_{t,d}$ as a Indicator for a Term's Importance

- Consideration 1: Relative importance
  - Assume 2 documents d_1 and d_2 containing the term *"NLP"*
  - d_1 contains *“NLP”* 100 times, d_2 contains *“NLP”* 10 times

$tf_{NLP,d_1} > tf_{NLP,d_2}$ ➜ d_1 more important than d_2 w.r.t. *“NLP”* ✓

But is d_1 really 10x more important than d_2?

➜ Extension: Use a sublinear function to model importance based on $tf_{t,d}$

- Common: **logarithm**
- Different functions possible and not always required

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

$tf_{t,d}$ as a Indicator for a Term's Importance

- Consideration 2: Cross-document importance
  - Assume a document d_1 containing the term *"NLP"* many times
  - Let *"NLP"* also be frequent in many to most other documents

Is *"NLP"* really important (i.e., characteristic, informative) for d_1?

- Intuition — example: "dog watch dog tv"
  - "dog" appears 2x in the document, but also in 3/5 of the other documents
  - "watch" appears 1x in the document, but also only in this document

$tf_{t,d}$ as a Indicator for a Term's Importance

➜ Extension: **Inverse Document Frequency** idf_t as an additional factor

- Document frequency df_t : # documents containing t
- Inverse measure of a terms importance, relevance, informativeness

➜ Inverse Document Frequency: $$idf_t = \log \frac{|D|}{df_t}$$

Again, log to dampen the effect of the inverse document frequency

Document-Term Matrix with $tf\text{-}idf$ Weights

- Putting it all together

$$w_{t,d} = (1 + \log_{10} tf_{t,d}) \cdot \log_{10} \frac{|D|}{df_t}$$

- Side notes
  - No real theoretic underpinning, but $tf\text{-}idf$ works best in practice
  - Not all definitions of $tf\text{-}idf$ apply a sublinear scaling of $tf_{t,d}$
  - Alternative names: $tf \cdot idf$, $tf \times idf$
  - There are different weighting functions for calculating $tf\text{-}idf$

Document-Term Matrix with $tf\text{-}idf$ Weights

d_1 : dog chase cat dog
d_2 : cat chase cat
d_3 : car chase tv
d_4 : dog watch dog tv
d_5 : dog cat sit car

$$w_{t,d} = (1 + \log_{10} tf_{t,d}) \cdot \log_{10} \frac{|D|}{df_t}$$

- Example

$$w_{dog,d_4} = (1 + \log_{10} 2) \cdot \log_{10} \frac{5}{3} = (1 + 0.3) \cdot 0.22 = 0.29$$

$$w_{watch,d_4} = (1 + \log_{10} 1) \cdot \log_{10} \frac{5}{1} = (1 + 0) \cdot 0.7 = 0.7$$

Document-Term Matrix with $tf\text{-}idf$ Weights

- Matrix elements = $tf\text{-}idf$ weights

d_1 : dog chase cat dog
d_2 : cat chase cat
d_3 : car chase tv
d_4 : dog watch dog tv
d_5 : dog cat sit car

$$w_{t,d} = (1 + \log_{10} tf_{t,d}) \cdot \log_{10} \frac{|D|}{df_t}$$

➜

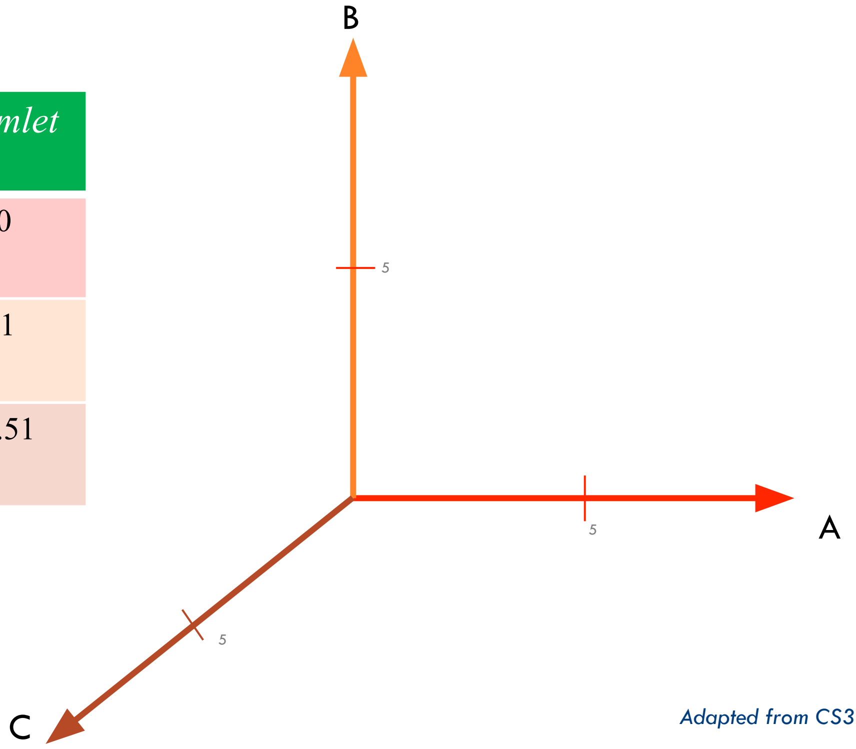
	d_1	d_2	d_3	d_4	d_5
car	0	0	0.4	0	0.4
cat	0.22	0.29	0	0	0.22
chase	0.22	0.22	0.22	0	0
dog	0.29	0	0	0.29	0.22
sit	0	0	0	0	0.7
tv	0	0	0.4	0.4	0
watch	0	0	0	0.7	0

Outline

- Text Classification
  - Common Applications
  - Formal setup
- Naive Bayes Classifier
  - Basic Intuition & BoW Representation
  - Definition & Practical Considerations
  - Complete Runthrough
  - Discussion & Limitations
- Evaluation of Classifiers
- **Vector Space Model**
  - Vector Representation of Documents
  - **Document Similarity**

Vector Space

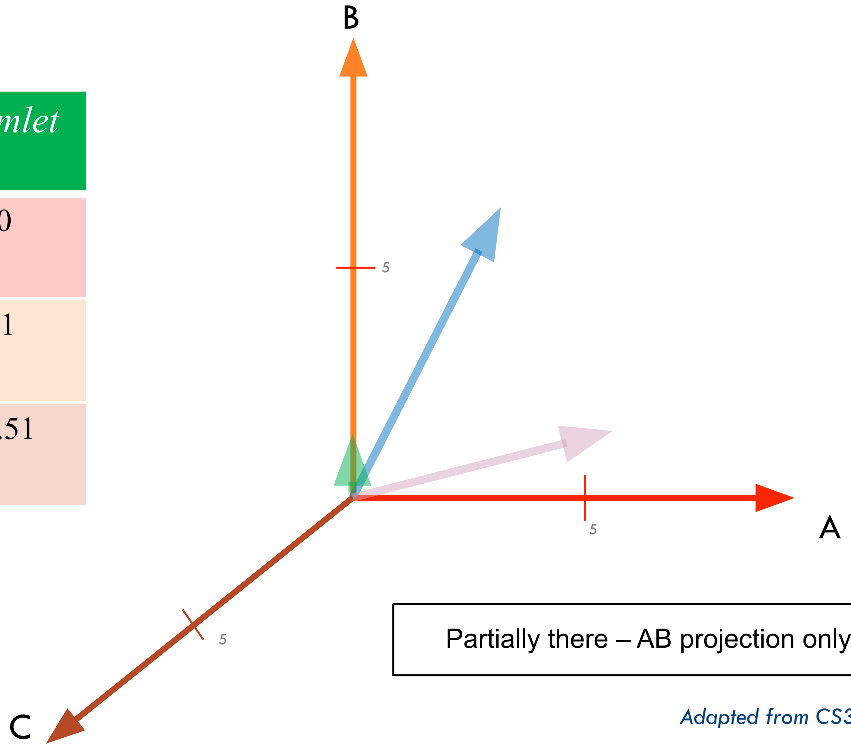
	Antony & Cleopatra	*Julius Caesar*	*Hamlet*
Antony	5.25	3.18	0
Brutus	1.21	6.1	1
Caesar	8.59	2.54	1.51



Adapted from CS3245

Vector Space

	Antony & Cleopatra	*Julius Caesar*	*Hamlet*
Antony	5.25	3.18	0
Brutus	1.21	6.1	1
Caesar	8.59	2.54	1.51

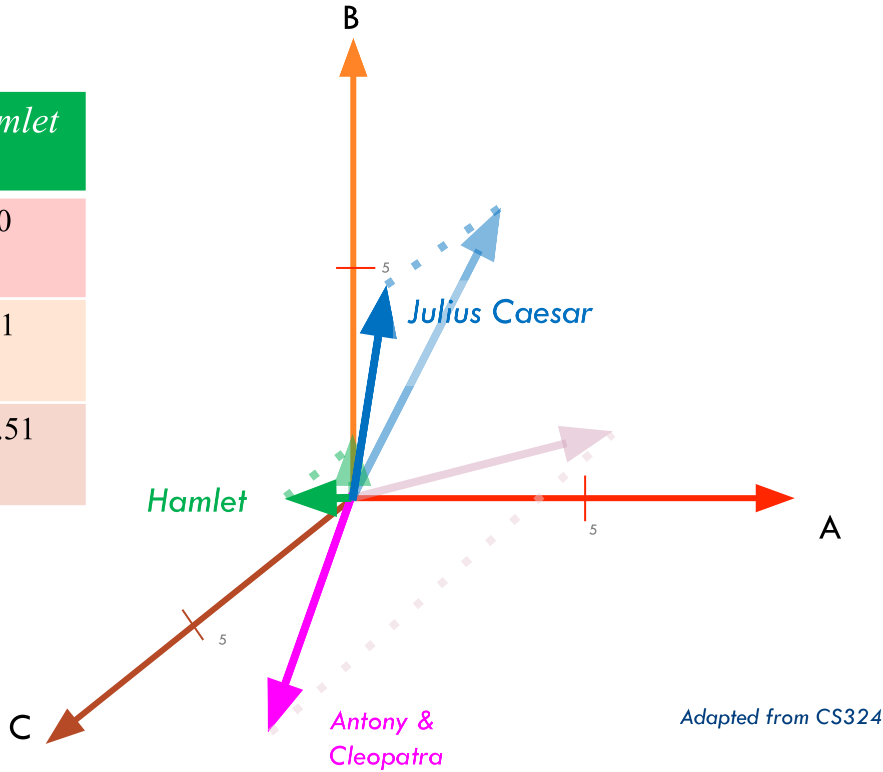


Partially there – AB projection only.

Adapted from CS3245

Vector Space

	Antony & Cleopatra	*Julius Caesar*	*Hamlet*
Antony	5.25	3.18	0
Brutus	1.21	6.1	1
Caesar	8.59	2.54	1.51



Adapted from CS3245

Vector Space Model — Document Similarity

- Vector Space Model
  - $|V|$-dimensional vector space
  - Words are axes (i.e., dimensions) of the space
    (each word in vocabulary represent a axis/dimensions)
  - Documents are points or vectors in this space
  - In practice: very high-dimensional space
    (typically tens of thousands of dimensions)

➜ Document vectors are typically very sparse
(i.e., most entries in the vectors are zero)

➜ How can we calculate the **similarity** between text documents

- Many NLP tasks rely on "some meaningful" metric quantifying document similarity
- Using Vector Space Model: document similarity ➜ vector similarity

Document Similarity

- Approach 1: Dot Product
  - The dot product between two vectors v and w is defined as

$$dot(v, w) = v \cdot w = v_1 w_1 + v_2 w_2 + \ldots v_n w_n = \sum_{i=1}^{n} v_i w_i$$

- Interpretation
  - $dot(v, w)$ is high if v and w have large values in the same dimensions

➜ $dot(v, w)$ represents a similarity metric between vectors, but…

Document Similarity

- Limitations of Dot Product
  - $dot(v, w)$ is higher if a vector has higher values in many dimensions

$$dot(v, w) = \sum_{i=1}^{n} v_i w_i$$

➜ $dot(v, w)$ favors long vectors

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

- Effects in document vectors
  - $dot(v, w)$ favors frequent words
    (since they occur many times with other documents)
  - $dot(v, w)$ favors long documents
    (since the raw term frequencies are higher)

➜ $dot(v, w)$ overly favors frequent words

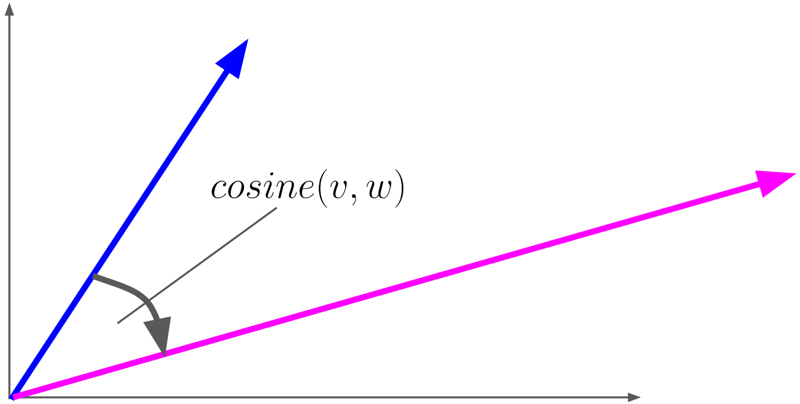
Document Similarity — Cosine Similarity

- Approach 2: Cosine Similarity (dot product normalized by length of vectors)

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

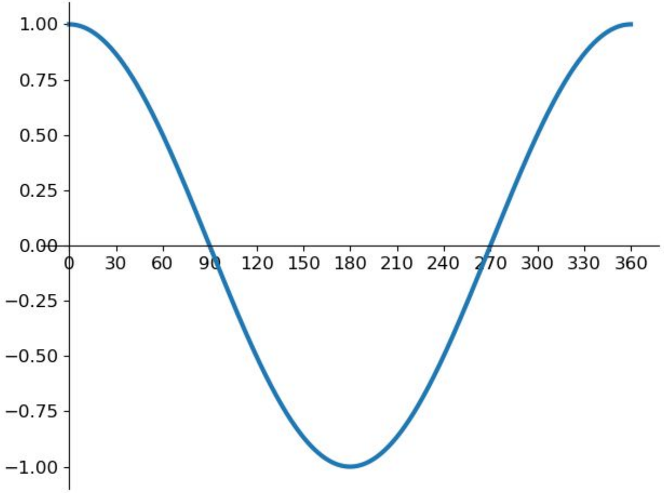
- Geometric interpretation
  - $cosine(v,w)$ measures the angle between vectors

$dot(v,w)$ cares about angle and length



Document Similarity — Cosine Similarity

- Cosine as a similarity metric
  - $cosine(v, w) = -1$
    vectors point in opposite directions
  - $cosine(v, w) = 1$
    vectors point in the same direction
  - $cosine(v, w) = 0$
    vectors are orthogonal



- Cosine similarity for document vectors
  - Vector entries are all positive

➜ $0 \leq cosine(u, v) \leq 1$

Document Similarity — Cosine Similarity

d_1 : dog chase cat dog
d_2 : cat chase cat
d_3 : car chase tv
d_4 : dog watch dog tv
d_5 : dog cat sit car

	d_1	d_2	d_3	d_4	d_5
car	0	0	0.4	0	0.4
cat	0.22	0.29	0	0	0.22
chase	0.22	0.22	0.22	0	0
dog	0.29	0	0	0.29	0.22
sit	0	0	0	0	0.7
tv	0	0	0.4	0.4	0
watch	0	0	0	0.7	0

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

$$cosine(d_1, d_2) = \frac{(0.22 \cdot 0.29) + (0.22 \cdot 0.22)}{\sqrt{0.22^2 + 0.22^2 + 0.29^2} \cdot \sqrt{0.29^2 + 0.22^2}} = 0.72$$

(only non-zero components included)

Document Similarity — Cosine Similarity

d_1 : *dog chase cat dog*
d_2 : *cat chase cat*
d_3 : *car chase tv*
d_4 : *dog watch dog tv*
d_5 : *dog cat sit car*

	d_1	d_2	d_3	d_4	d_5
car	0	0	0.4	0	0.4
cat	0.22	0.29	0	0	0.22
chase	0.22	0.22	0.22	0	0
dog	0.29	0	0	0.29	0.22
sit	0	0	0	0	0.7
tv	0	0	0.4	0.4	0
watch	0	0	0	0.7	0

All pairwise cosine similarities

	d_1	d_2	d_3	d_4	d_5
d_1	1	0.72	0.19	0.23	0.31
d_2		1	0.22	0	0.20
d_3			1	0.31	0.31
d_4				1	0.09
d_5					1

Vector Space Model

- Representing documents as vectors
  - Meaningful way to compute similarities between documents (e.g., for ranking documents in information retrieval, clustering)
  - Valid input for other text classifiers beyond Naive Bayes (document vectors have no numerical values)
- Limitation: BoW representation of documents
  - Does not consider sequential order of words in a sentence

Summary

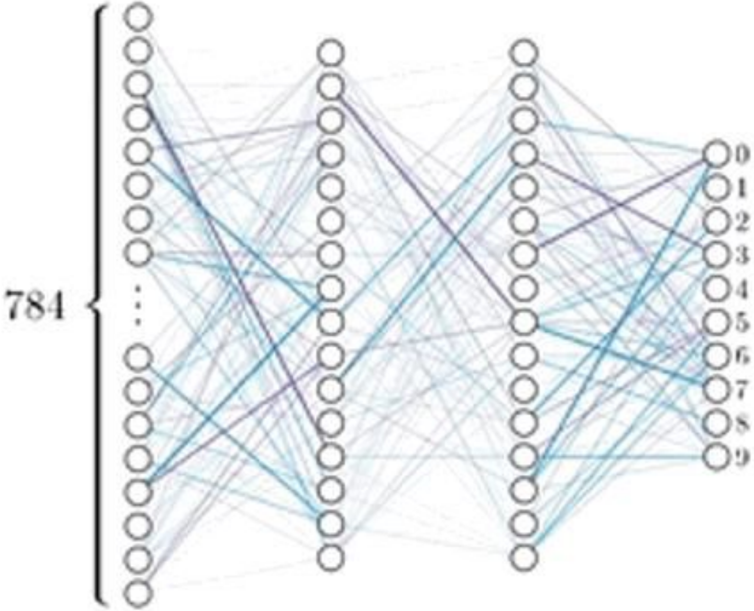
- Text Classification
  - Very fundamental NLP task
    (very fundamental machine learning task, in general)
  - Supervised machine learning task ➜ we need training data

- Baseline classifier: Naive Bayes
  - Very simple classifier related to language models ➜ works directly over words
  - Relies on Bag-of-Word Representation of documents (incl. its limitations)

- Vector Space Model
  - Derive meaningful vector representation of documents from their vocabulary
  - Definition of meaningful similarity between documents ➜ import for many NLP tasks

Outlook for Next Week: Connectionist ML

Training in progress. . .



Pre-Lecture Activity for Next Week

- Assigned Task (due before Feb 16)
  - ■ Post a 1–2 sentence answer to the following question into the Pre-Lecture Discussion (you will find the thread on Canvas > Discussions)

“What is a common myth about neural networks?”

Read some blog posts or online articles, and cite them with the links in your answer

Side notes:

- This task is meant as a warm-up to provide some context for the next lecture
- No worries if you get lost; we will talk about this in the next lecture
- You can just copy-&-paste others' answers but this won't help you learn better