Natural Language Processing (NLP)

Today’s objectives and plan

Morning: NLP and Information Retrieval

- Text Featurization
  - Text processing pipeline
  - Bag of words and TF-IDF
- Morning assignment: Build a basic text processing pipeline to compare NYT articles using nltk and sklearn

Afternoon: Document Classification with Naïve Bayes

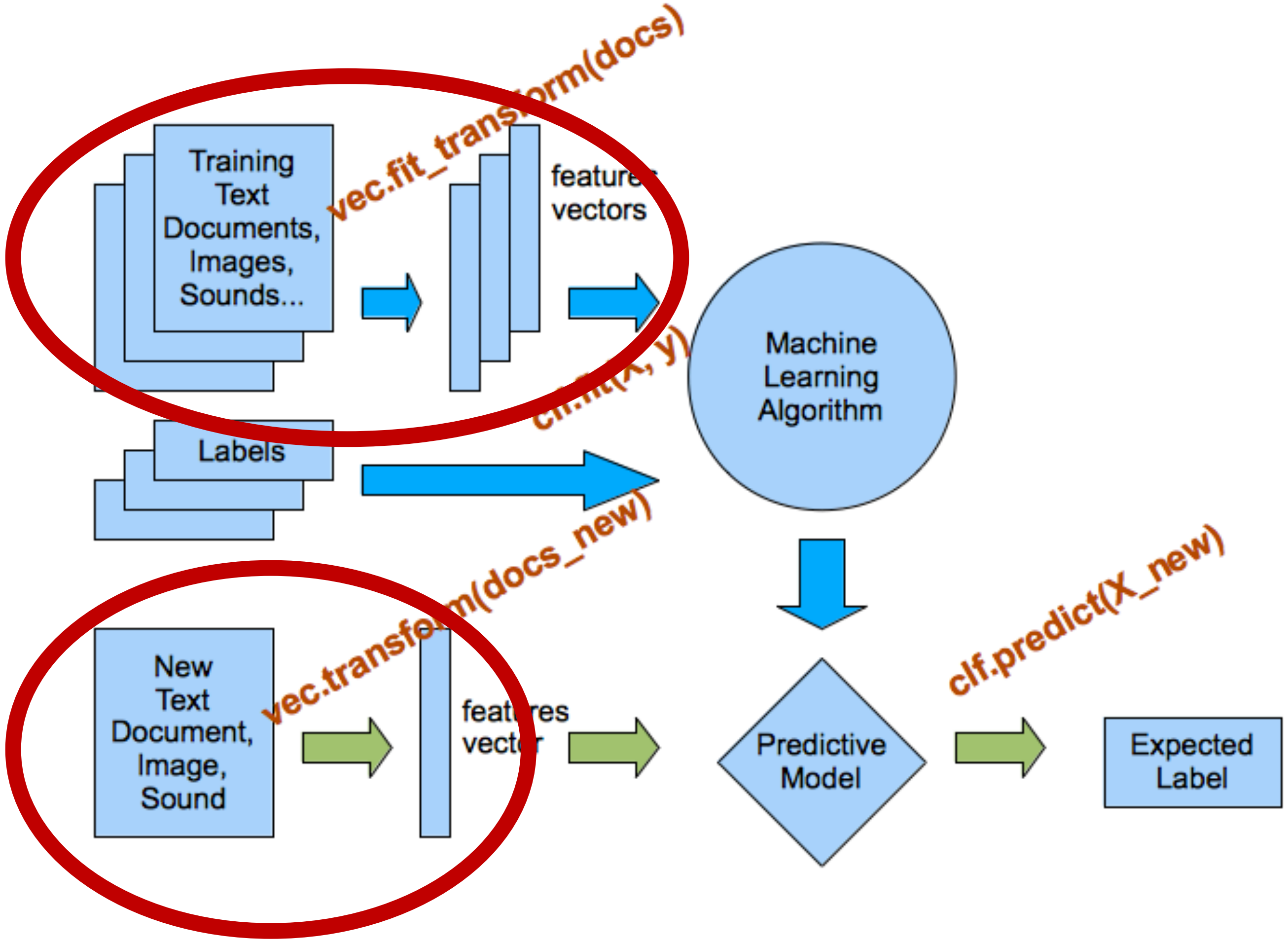
- Reviews
  - Bayes’ Rule
  - MAP Estimation
  - Independence and Conditional Independence
- Naïve Bayes Classifier
- Document Classification with Naïve Bayes
- Pair programming: (1) Implementing Naive Bayes Classifier and Document Classification; (2) Applications of tf-idf and cosine similarity

Morning: NLP and Information Retrieval

Motivation

- You’re Google News, and you want to group news articles by topic
- You’re a legal tech firm, and you need to sift through 1,000,000 pages of legal documents to find the relevant ones

Text Featurization



Text Featurization Pipeline

- Tokenization
  - Take the document and split it into a list of tokens
- Lower case conversion
- Stop words removal
- Stemming/Lemmatization
  - Reduce words to their root form
  - Stemming (crude character-based method)
    - E.g., “walked” → “walk”
  - Lemmatization (based on the lexicon; performs better than stemming)
    - E.g., “people” → “person”, “better” → “good”
- Bag of words/N-grams

Terminology

- Corpus:
  - a dataset of text; e.g., newspaper articles, tweets
- Document:
  - a single entry from our corpus; e.g., article, sentence, tweet
- Vocabulary:
  - all the words that appear in our corpus
- Token:
  - an entity; e.g., a word

Sample sentence

Students are learning from other students

Tokenization

- Take the document and split it into a list of tokens

Students are learning from other students

↓

[‘Students’, ‘are’, ‘learning’, ‘from’, ‘other’, ‘students’]

Lower case conversion

[‘Students’, ‘are’, ‘learning’, ‘from’, ‘other’, ‘students’]

↓

[‘students’, ‘are’, ‘learning’, ‘from’, ‘other’, ‘students’]

Stop word removal

- Words we ignore in our analysis that are too common to be useful

(sklearn and nltk have standard list of stop words)

[‘students’, ‘are’, ‘learning’, ‘from’, ‘other’, ‘students’]

↓

[‘students’, ‘learning’, ‘other’, ‘students’]

Stemming/Lemmatization

- Reduce words to their root form
  - Stemming (crude character-based method)
  - Lemmatization (based on the lexicon; performs better than stemming)

[‘students’, ‘learning’, ‘other’, ‘students’]

↓

[‘student’, ‘learn’, ‘other’, ‘student’]

With a corpus made of 3 documents:

1. Students are learning from other students
2. I am teaching at Galvanize
3. There are students learning at Galvanize

1. [‘student’, ‘learn’, ‘other’, ‘student’]
2. [‘teach’, ‘galvanize’]
3. [‘student’, ‘learn’, ‘galvanize’]

Bag of words

- A document represented as a vector of word counts is called a “bag of words”
- Vector for our corpus:

(galvanize, learn, other, student, teach)

document	galvanize	learn	other	student	teach
[‘student’, ‘learn’, ‘other’, ‘student’]					
[‘teach’, ‘galvanize’]					
[‘student’, ‘learn’, ‘galvanize’]					

Bag of words

- A document represented as a vector of word counts is called a “bag of words”
- Vector for our corpus:

(galvanize, learn, other, student, teach)

document	galvanize	learn	other	student	teach
[‘student’, ‘learn’, ‘other’, ‘student’]	0	1	1	2	0
[‘teach’, ‘galvanize’]	1	0	0	0	1
[‘student’, ‘learn’, ‘galvanize’]	1	1	0	1	0

Issues with bags of words

- Bags of words are naïve
  - Word counts
    - Counts emphasize results from longer documents
  - Every word has equal weighting
    - But “other” and “student” have different predictive power

- Is there a better way to featurize?

Term frequencies (TF)

- Normalize counts within a document to frequency

$$\mathrm{tf}(\mathrm{t}, \mathrm{d}) = \frac{\text{total count of term t in document d}}{\text{total count of all terms in document d}}$$

document	galvanize	learn	other	student	teach
[‘student’, ‘learn’, ‘other’, ‘student’]					
[‘teach’, ‘galvanize’]					
[‘student’, ‘learn’, ‘galvanize’]					

Term frequencies (TF)

- Normalize counts within a document to frequency

$$\mathrm{tf(t, d)} = \frac{\text{total count of term t in document d}}{\text{total count of all terms in document d}}$$

document	galvanize	learn	other	student	teach
['student', 'learn', 'other', 'student']	0	$\frac{1}{4} = .25$	$\frac{1}{4} = .25$	$\frac{2}{4} = .5$	0
['teach', 'galvanize']	$\frac{1}{2} = .5$	0	0	0	$\frac{1}{2} = .5$
['student', 'learn', 'galvanize']	$\frac{1}{3} = .333$	$\frac{1}{3} = .333$	0	$\frac{1}{3} = .333$	0

Issues with term frequencies

- Words found in only one document should have highest weighting
- Words found in every documents should have lowest weighting

Inverse document frequencies (IDF)

$$\mathrm{idf(t, D)} = \log \frac{\text{total count of documents in corpus D}}{\text{count of documents containing term t}}$$

document	galvanize	learn	other	student	teach
[‘student’, ‘learn’, ‘other’, ‘student’]					
[‘teach’, ‘galvanize’]					
[‘student’, ‘learn’, ‘galvanize’]					
$idf(t, D)$					

Inverse document frequencies (IDF)

$$\mathrm{idf(t, D)} = \log \frac{\text{total count of documents in corpus D}}{\text{count of documents containing term t}}$$

document	galvanize	learn	other	student	teach
['student', 'learn', 'other', 'student']		X	X	X	
['teach', 'galvanize']	X				X
['student', 'learn', 'galvanize']	X	X		X	
$idf(t, D)$	$\log\frac{3}{2} = .405$	$\log\frac{3}{2} = .405$	$\log\frac{3}{1} = 1.10$	$\log\frac{3}{2} = .405$	$\log\frac{3}{1} = 1.10$

TF-IDF

$$\text{tf–idf}(\text{t}, \text{d}, \text{D}) = \text{tf}(\text{t}, \text{d}) \cdot \text{idf}(\text{t}, \text{D})$$

document	galvanize	learn	other	student	teach
[‘student’, ‘learn’, ‘other’, ‘student’]					
[‘teach’, ‘galvanize’]					
[‘student’, ‘learn’, ‘galvanize’]					

TF-IDF

$$\mathrm{tf{-}idf}(\mathrm{t}, \mathrm{d}, \mathrm{D}) = \mathrm{tf}(\mathrm{t}, \mathrm{d}) \cdot \mathrm{idf}(\mathrm{t}, \mathrm{D})$$

document	galvanize	learn	other	student	teach
[‘student’, ‘learn’, ‘other’, ‘student’]	0	$.25\times.405 = .101$	$.25\times1.10 = .275$	$.5\times.405 = .203$	0
[‘teach’, ‘galvanize’]	$.5\times.405 = .203$	0	0	0	$.25\times1.10 = .275$
[‘student’, ‘learn’, ‘galvanize’]	$.333\times.405 = .135$	$.333\times.405 = .135$	0	$.333\times.405 = .135$	0

Comparing TF-IDF vectors of documents: Cosine Similarity

$$\text{similarity} = \cos\theta = \frac{\mathrm{A} \cdot \mathrm{B}}{\|\mathrm{A}\|\|\mathrm{B}\|}$$

- [‘student’, ‘learn’, ‘other’, ‘student’] vs. [‘teach’, ‘galvanize’]

  → (0, .101, .275, .203, 0) vs. (.203, 0, 0, 0, .275)

  → $\text{similarity} = \frac{0}{.36 \times .34} = 0$
- [‘student’, ‘learn’, ‘other’, ‘student’] vs. [‘student’, ‘learn’, ‘galvanize’]

  → (0, .101, .275, .203, 0) vs. (.135, .135, 0, .135, 0)

  → $\text{similarity} = \frac{0.041}{.36 \times .23} = .34$

N-grams

- Bag of words lose word order
- What to do when it matters?

- N-grams attempt to retain some of it:

[‘student’, ‘learn’, ‘other’, ‘student’]

→ (student, learn), (learn, other), (other, student) *(2-grams)*

→ (student, learn, other), (learn, other, student) *(3-grams)*

Advanced NLP Problem Types

- Sentiment analysis
  - http://nlp.stanford.edu/sentiment/index.html
- Machine translation
  - https://medium.com/s-c-a-l-e/how-baidu-mastered-mandarin-with-deep-learning-and-lots-of-data-1d94032564a5

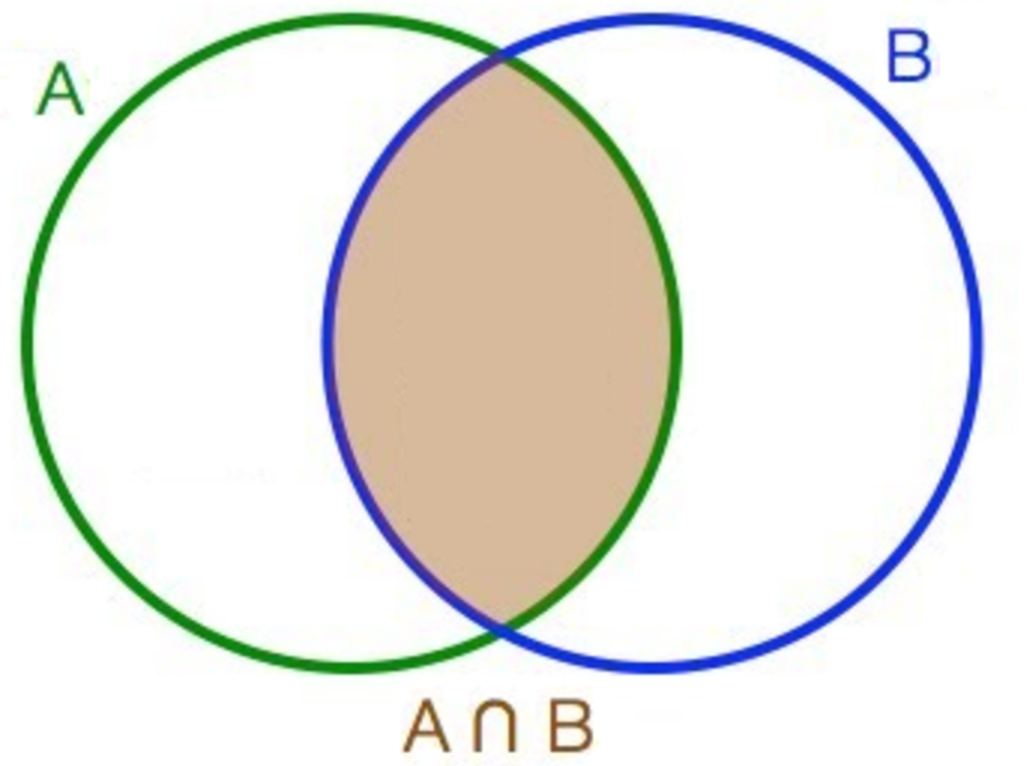
Morning assignment

Afternoon: Document Classification with Naïve Bayes

Bayes’ Rule Review

Conditional Probability Review

$$P(B \mid A) = \frac{P(A \cap B)}{P(A)}$$



Bayes' Rule

likelihood of the evidence "E" if the hypothesis "H" is true

prior probability of "H"

posterior probability of "H" given the evidence

$$P(H \mid E) = \frac{P(E \mid H)P(H)}{P(E)}$$

prior probability that the evidence itself is true (but also a normalizing constant)

Bayes' Rule after expanding $P(E)$

$$P(H \mid E) = \frac{P(E \mid H)P(H)}{P(E \mid H)P(H) + P(E \mid H^c)P(H^c)}$$

- $E = E \cap (H \cup H^c) = (E \cap H) \cup (E \cap H^c)$
- $P(E) = P(E \cap H) + P(E \cap H^c)$ (independent events)
- $P(E) = P(E \mid H)P(H) + P(E \mid H^c)P(H^c)$

Poll: Relating Prior Knowledge/Belief to Data

You have a drawer of 100 coins, 10 of which are biased

P(head | fair) = .5

P(head | biased) = .25

You randomly choose a coin and flip it three times. It comes up heads all three times

- **What is P(fair | H, H, H)?**

Poll: Relating Prior Knowledge/Belief to Data (cont.)

$$\mathrm{P}(\mathrm{fair} \mid \mathrm{H}, \mathrm{H}, \mathrm{H})$$

$$= \frac{\mathrm{P}(\mathrm{H}, \mathrm{H}, \mathrm{H} \mid \mathrm{fair})\mathrm{P}(\mathrm{fair})}{\mathrm{P}(\mathrm{H}, \mathrm{H}, \mathrm{H} \mid \mathrm{fair})\mathrm{P}(\mathrm{fair}) + \mathrm{P}(\mathrm{H}, \mathrm{H}, \mathrm{H} \mid \mathrm{biased})\mathrm{P}(\mathrm{biased})}$$

$$= \frac{.5^3 \times .9}{.5^3 \times .9 + .25^3 \times .1} = .986$$

Relating Prior Knowledge/Belief to Data (cont.)

$$\mathrm{P}(\mathrm{biased} \mid \mathrm{H}, \mathrm{H}, \mathrm{H})$$

$$= \frac{\mathrm{P}(\mathrm{H}, \mathrm{H}, \mathrm{H} \mid \mathrm{biased})\mathrm{P}(\mathrm{biased})}{\mathrm{P}(\mathrm{H}, \mathrm{H}, \mathrm{H} \mid \mathrm{biased})\mathrm{P}(\mathrm{biased}) + \mathrm{P}(\mathrm{H}, \mathrm{H}, \mathrm{H} \mid \mathrm{fair})\mathrm{P}(\mathrm{fair})}$$

$$= \frac{.25^3 \times .1}{.25^3 \times .1 + .5^3 \times .9} = .014$$

MAP Estimation Review

MAP Estimation Review

- Recall Bayes' Rule:

$$\mathrm{P}(\mathrm{H} \mid \mathrm{E}) = \frac{\mathrm{P}(\mathrm{E} \mid \mathrm{H})\mathrm{P}(\mathrm{H})}{\mathrm{P}(\mathrm{E})}$$

- MAP finds H to maximize $\mathrm{P}(\mathrm{H} \mid \mathrm{E})$

$$\underset{\mathrm{H}}{\operatorname{argmax}}\, \mathrm{P}(\mathrm{H} \mid \mathrm{E}) = \underset{\mathrm{H}}{\operatorname{argmax}} \frac{\mathrm{P}(\mathrm{E} \mid \mathrm{H})\mathrm{P}(\mathrm{H})}{\mathrm{P}(\mathrm{E})} = \underset{\mathrm{H}}{\operatorname{argmax}}\, \mathrm{P}(\mathrm{E} \mid \mathrm{H})\mathrm{P}(\mathrm{H})$$

(prior is constant)

Poll: Relating Prior Knowledge/Belief to Data

You have a drawer of 100 coins, 10 of which are biased

P(head | fair) = .5

P(head | biased) = .25

You randomly choose a coin and flip it three times. It comes up heads all three times

- **Which coin type (fair or unfair) is most probable under the posterior?**

Poll: Relating Prior Knowledge/Belief to Data (cont.)

$$\underset{\text{coin}}{\operatorname{argmax}} \mathrm{P}(\text{coin} \mid \mathrm{H}, \mathrm{H}, \mathrm{H})?$$

$$\underset{\text{coin}}{\operatorname{argmax}} \mathrm{P}(\text{coin} \mid \mathrm{H}, \mathrm{H}, \mathrm{H}) = \underset{\text{coin}}{\operatorname{argmax}} \mathrm{P}(\mathrm{H}, \mathrm{H}, \mathrm{H} \mid \text{coin}) \mathrm{P}(\text{coin})$$

$$\mathrm{P}(\mathrm{H}, \mathrm{H}, \mathrm{H} \mid \text{fair}) \mathrm{P}(\text{fair}) = .5^3 \times .9 = .113$$
$$\mathrm{P}(\mathrm{H}, \mathrm{H}, \mathrm{H} \mid \text{biased}) \mathrm{P}(\text{biased}) = .25^3 \times .1 = .00156$$
$$\downarrow$$
$$\underset{\text{coin}}{\operatorname{argmax}} \mathrm{P}(\text{coin} \mid \mathrm{H}, \mathrm{H}, \mathrm{H}) = \text{fair}$$

Independence and Conditional Independence Review

Independence

If A and B are independent,

$$P(B \mid A) = P(B)$$

Then using Bayes' rule:

$$\frac{P(A \cap B)}{P(A)} = P(B)$$

$$\downarrow$$

$$P(A \cap B) = P(A)P(B)$$

Conditional Independence

$$P(A \cap B \mid C) = P(A \mid C)P(B \mid C)$$

Naïve Bayes Classifier

Derivation

$$\underset{y}{\operatorname{argmax}}\, P(y \mid X)?$$

$$P(y \mid X) = \frac{P(X \mid y)P(y)}{P(X)} \text{ (Bayes' rule)}$$

$$\underset{y}{\operatorname{argmax}}\, P(y \mid X) = \underset{y}{\operatorname{argmax}}\, P(X \mid y)P(y) \text{ (MAP estimation)}$$

$$P(X \mid y) = P(x_1 \mid y)P(x_2 \mid y) \ldots P\left(x_p \mid y\right) = \prod_{j=1}^{p} P\left(x_j \mid y\right)$$

Naïve Bayes Classifier is MAP estimation combined with conditional independence

$$\underset{y}{\operatorname{argmax}} P(y \mid X) = \underset{y}{\operatorname{argmax}} P(y) \prod_{j=1}^{p} P\left(x_j \mid y\right)$$

Document Classification with Naïve Bayes

Motivation

How to predict what topic a given document is about?

E.g.,

"the cat jumped over the tree"

- Q: How can we decide whether this document is fiction or non-fiction?
- A: Use word counts from corpus of label fiction and non-fiction documents to train a Naïve Bayes classifier

Document Classification with Naïve Bayes

$$\underset{y}{\operatorname{argmax}} P(y \mid X) = \underset{y}{\operatorname{argmax}} P(y) \prod_{j=1}^{p} P\left(x_j \mid y\right)$$

$$\downarrow$$

$$\underset{\text{topic}}{\operatorname{argmax}} P(\text{topic} \mid \text{document}) = \underset{\text{topic}}{\operatorname{argmax}} P(\text{topic}) \prod_{\text{word}} P(\text{word} \mid \text{topic})^{c_{\text{word}}}$$

(c_{word} = number of times a word appears in the document)

Corpus

Fiction	**Non-fiction**
“the cat in the hat”	“the Giants won the game”
“the cow jumped over the moon”	“the candidate won the election”
“the cat in the tree”	
(total count of all words in the topic = 16)	(total count of all words in the topic = 10)

(total count of distinct words on all documents = 13 (vocabulary))

Prior distributions

$$\mathrm{P}(\text{topic} = \text{"fiction"}) = \frac{\text{count of fiction documents}}{\text{total count of documents}} = \frac{3}{5} = .6$$

Conditional distributions

$$\mathrm{P(w \mid t)} = \frac{\text{total count of word w in all documents of topic t}}{\text{total count of all words in all documents of topic t}}$$

"the cat in the hat"
"the cow jumped over the moon"
"the cat in the tree"

$$P(word = \text{"the"} \mid fiction) = \frac{6}{16}$$

$$P(word = \text{"cat"} \mid fiction) = \frac{2}{16}$$

$$P(word = \text{"jumped"} \mid fiction) = \frac{1}{16}$$

$$P(word = \text{"over"} \mid fiction) = \frac{1}{16}$$

$$P(word = \text{"tree"} \mid fiction) = \frac{1}{16}$$

“the cat jumped over the tree”

$$P(\text{topic} = \text{"fiction"} \mid \text{document} = \text{"the cat jumped over the tree"})$$
$$=$$
$$P(\text{topic} = \text{"fiction"})$$
$$\cdot\, P(\text{word} = \text{"the"} \mid \text{fiction})^2$$
$$\cdot\, P(\text{word} = \text{"cat"} \mid \text{fiction})$$
$$\cdot\, P(\text{word} = \text{"jumped"} \mid \text{fiction})$$
$$\cdot\, P(\text{word} = \text{"over"} \mid \text{fiction})$$
$$\cdot\, P(\text{word} = \text{"tree"} \mid \text{fiction})$$

“the cat jumped over the tree” (cont.)

$$\mathrm{P}(\text{topic} = \text{"fiction"} \mid \text{document} = \text{"the cat jumped over the tree"})$$

$$= \frac{3}{5} \times \left(\frac{6}{16}\right)^2 \times \frac{2}{16} \times \frac{1}{16} \times \frac{1}{16} \times \frac{1}{16}$$

$$= \frac{216}{83886080}$$

$$= 2.6 \times 10^{-6}$$

(problem #1: very small number; risk of numerical overflow)

“the cat jumped over the tree” (cont.)

$$P(\text{topic} = \text{"non−fiction"} \mid \text{document} = \text{"the cat jumped over the tree"})$$

$$= \frac{2}{5} \times \left(\frac{4}{10}\right)^2 \times \frac{0}{10} \times \frac{0}{10} \times \frac{0}{10} \times \frac{0}{10}$$

$$= \frac{0}{5000000}$$

$$= 0$$

(problem #2: unknown words, e.g., “cat” have a 0 conditional probability

→ $P(\text{topic} \mid \text{document}) = 0$)

Log transformation to address problem #1

- Use log probabilities instead:

$$\log \mathrm{P}(\mathrm{topic} \mid \mathrm{document}) = \log \mathrm{P}(\mathrm{topic}) + \sum_{\mathrm{word}} \mathrm{c}_{\mathrm{word}} \log \mathrm{P}(\mathrm{word} \mid \mathrm{topic})$$

Laplace (add α, e.g., 1) smoothing to address problem #2

- Add α to each word's frequency
- As if we saw each word one more time than we actually did

$$\mathrm{P(w \mid t)} = \frac{\text{(total count of word w in all documents of topic t)} + \alpha}{\text{(total count of all words in all documents of topic t)} + \alpha\text{(total count of distinct words in all documents)}}$$

“the cat jumped over the tree” (take 2)

$$\log \mathrm{P}(\text{topic} = \text{"fiction"} \mid \text{document} = \text{"the cat jumped over the tree"})$$
$$= \log\frac{3}{5} + 2\times\log\frac{6+1}{16+13} + \log\frac{2+1}{16+13} + \log\frac{1+1}{16+13} + \log\frac{1+1}{16+13} + \log\frac{1+1}{16+13} = -13.6$$

$$\log \mathrm{P}(\text{topic} = \text{"non−fiction"} \mid \text{document} = \text{"the cat jumped over the tree"})$$
$$= \log\frac{2}{5} + 2\times\log\frac{4+1}{10+13} + \log\frac{0+1}{10+13} + \log\frac{0+1}{10+13} + \log\frac{0+1}{10+13} + \log\frac{0+1}{10+13} = -16.5$$

$$\downarrow$$

$$\operatorname*{argmax}_{\text{topic}} \log \mathrm{P}(\text{topic} \mid= \text{"the cat jumped over the tree"}) = \text{fiction}$$

When to use Naïve Bayes?

- Pros
  - Good with “wide data” (i.e., more features p than observations n)
  - Fast to train and predict (also good at online learning, i.e., when new documents are added to the corpus, you just need to increment the word counts)
  - Simple to implement
- Cons
  - Can be hampered by irrelevant features
  - Probabilistic estimates are unreliable because of naïve assumption
  - Often outperformed by other models

Afternoon pairing