Natural Language Processing and Text Classification

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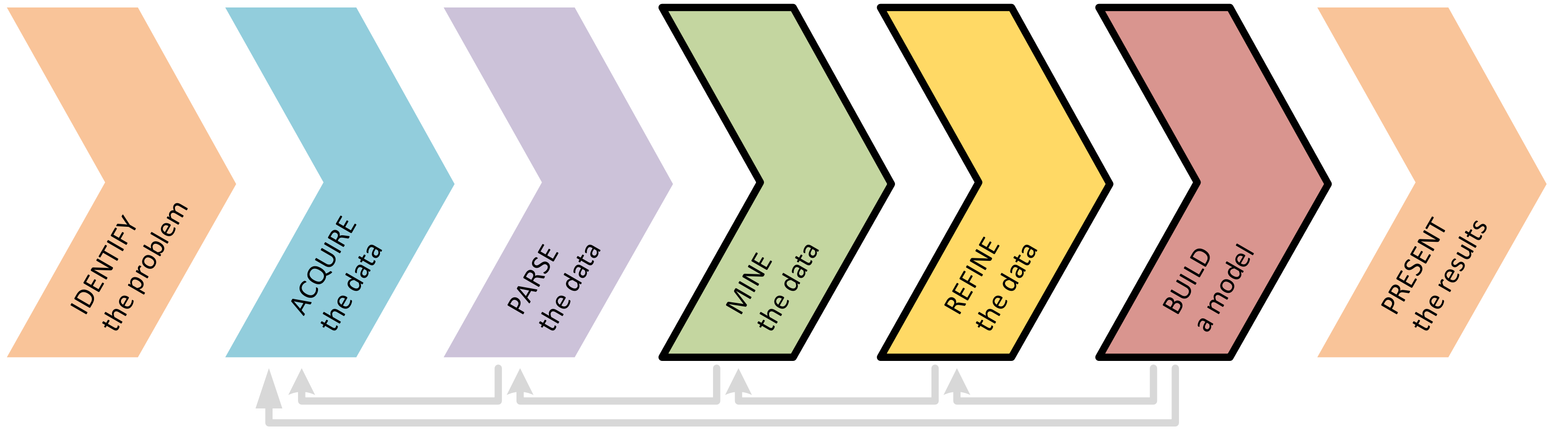
GENERAL ASSEMBLY

Where does Natural Language Processing fits in the course?

Unit 1 – Research Design and Data Analysis	*Research Design*	*Data Visualization in Pandas*	*Statistics*	*Exploratory Data Analysis in Pandas*
Unit 2 – Foundations of Modeling	Linear Regression	Classification Models	Evaluating Model Fit	Presenting Insights from Data Models
Unit 3 – Data Science in the Real World	*Decision Trees and Random Forests*	*Time Series Data*	*Natural Language Processing*	*Databases*



Learning Objectives

After this lesson, you should be able to:

- Define natural language processing
- List common tasks associated with
  - Use-cases
  - Tokenization
  - Stemming and lemmatization
  - Tagging and parsing
- Demonstrate how to classify text or documents using scikit-learn

Outline

- Review (decision trees and random forests)
- Natural Language Processing
  - Understanding and Generation
  - NLP is hard…
  - Tokenization
  - Stemming and Lemmatization
  - Tagging and Parsing
- Natural Language Processing in Python
  - Demo – Tokenizing, Tagging, and Parsing with *spacy*
- Text Classification
  - Bag-of-words classification
  - Text Processing with *scikit-learn*
  - Term Frequency and Inverse Document Frequency (TF-IDF)
- Unit Project 4's Presentations (cont.)
- Lab
- Office hours in class for final projects
- Review
- In-flight
  - Final Project 2 (due next session on 4/12)

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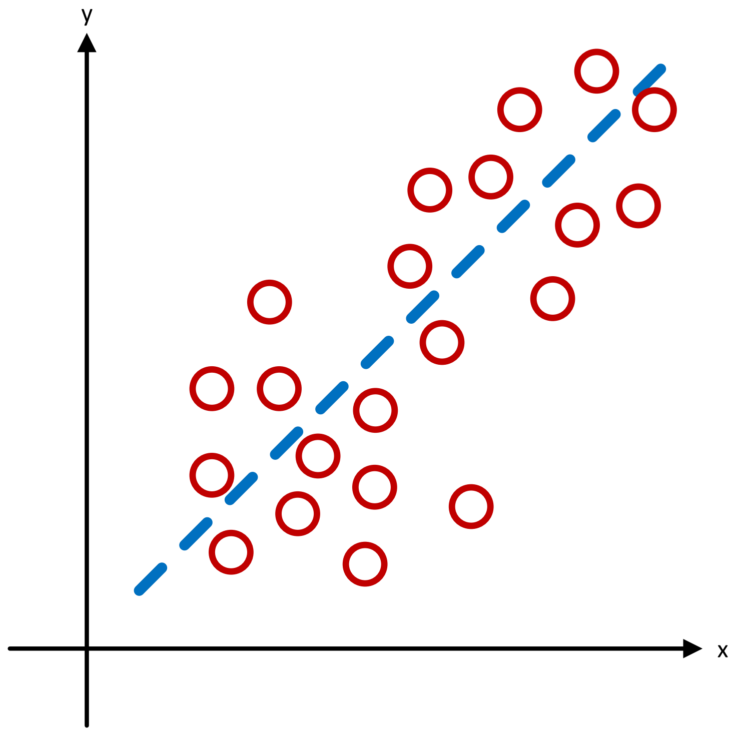
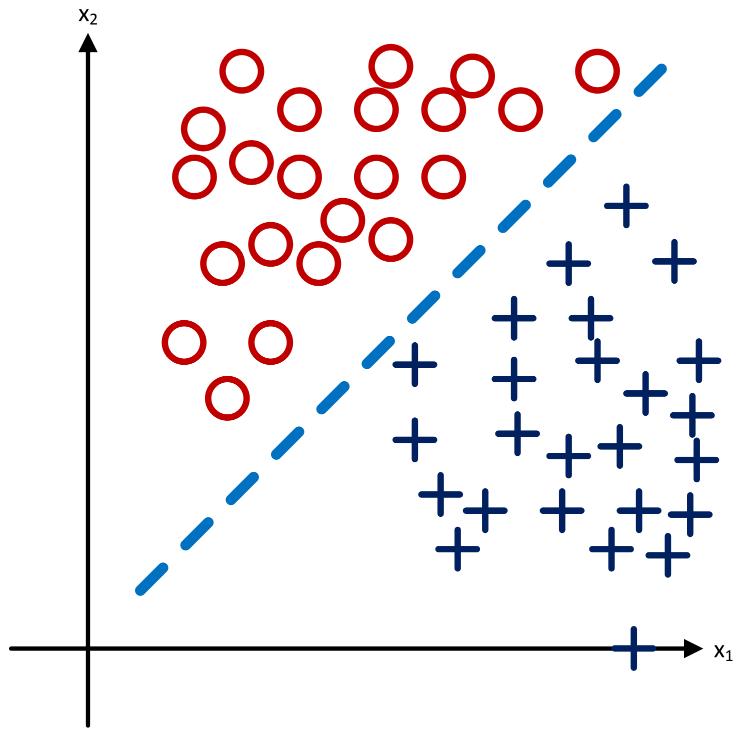
Review

Classification and regression differ in what they are trying to predict

Regression



Classification



Review

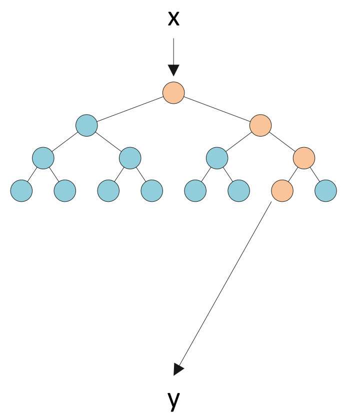
- What are decision trees?
  - What does training involve?
  - What are some common problems with decision trees?

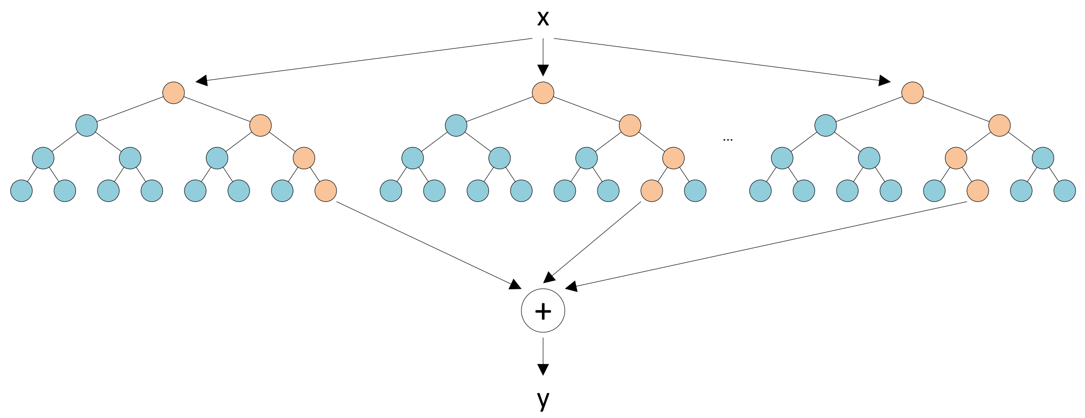
- What are random forests?
  - What are some common problems with random forests?

Review (cont.)

- Decision trees are models that ask a series of questions. The next question depends upon the answer to the previous question

- Random forest models are ensembles of decision trees that are randomized in the way they are created





Review (cont.)

Decision Trees

- Decision trees are weak learners that are easy to overfit

Random Forests

- Random forests are strong models that are made up of a collection of decision trees
  - They are non-linear (as opposed to logistic regression)
  - They are mostly black-boxes (no coefficients, although we do have a measure of feature importance)
  - They can be used for classification or regression

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Q & A

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Pre-Work

Pre-Work

Before this lesson, you should already be able to:

- Experience with *scikit-learn* classifiers, specifically random forests and decision trees
- Install the Python package *spacy* with `pip install spacy`
- Run the *spacy* download data command with `python -m spacy.en.download --force all`

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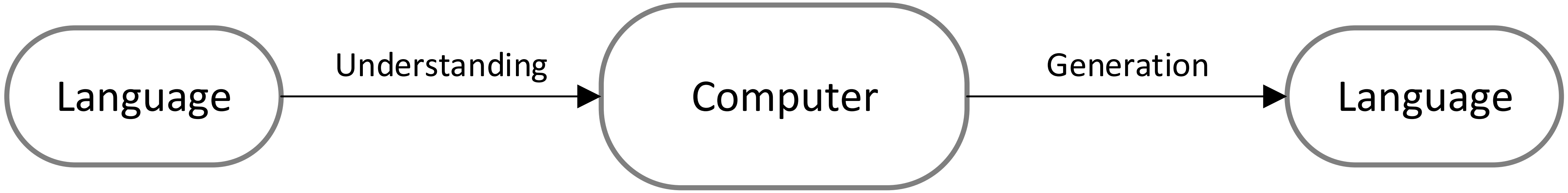
Natural Language Processing

What is Natural Language Processing?

- Natural Language Processing (NLP) is the study of the computational treatment of natural (human) language, i.e., teaching computers how to understand (and generate) human language

Basic NLP Pipeline: Understanding and Generation



NLP is tasked with extracting meaning and information from (text) documents

Understanding

- For most tasks, a fair amount of pre-processing is required to make the text digestible for our algorithms. We typically need to *add structure* to our *unstructured* data

Generation

- These tasks may range from simple classification tasks, such as deciding what category a piece of text falls into, to more complex tasks like translating or summarizing text

What are some real-world examples of NLP?

- Search engines (E.g., Google and Bing)
- Natural language assistants (E.g., Apple's Siri uses voice recognition to record a command and then various fairly advanced NLP engines to identify the question asked and possible answers)
- Machine translation (E.g., Google Translate)
- Question answering (E.g., IBM's Watson)
- News digest (E.g., Yahoo!)

Computers are confused by (human) language

- E.g., “Children make delicious snacks”

- *Are* Children delicious snacks?

- Do children *prepare* delicious snacks?

Each genre of text (e.g., blogs, emails, press releases, chats) presents different challenges to NLP

- E.g., newspapers news headlines
  - “Red tape holds up new bridges”
  - “Government head seeks arms”
  - “Blair wins on budget, more lies ahead”

Tokenization

Tokenization is the task of separating a sentence into its constituent parts, or *tokens*

- Determining the “words” of a sentence seems easy but can quickly become complicated with unusual punctuation (common in social media) or different language conventions

- What sort of difficulties may there be with the following sentence?
  - “The L.A. Lakers won the NBA championship in 2010, defeating the Boston Celtics”

“The L.A. Lakers won the NBA championship in 2010, defeating the Boston Celtics”

- To perform a proper analysis, we need to be able to identify that:
    - The periods in “L.A.” don’t mark the end of a sentence but an abbreviation
    - “L.A. Lakers” and “Boston Celtics” are one concept.
    - “2010” is the word used, not “2010,”

Tokenization Examples

Sentence	Tokens
My house is located in Uptown.	[My, house, is, located, in, Uptown]
The Lakers are my favorite team.	[The, Lakers, are, my, favorite, team]
Data Science is the future!	[Data, Science, is, the, future]
GA has many locations.	[GA, has, many, locations]

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Stemming and Lemmatization

Stemming and lemmatization help identify common roots of words

- How would you describe the relationship between the terms ‘bad’ and ‘badly’ or ‘different’ and ‘differences’?

Stemming is a crude process of removing common endings from words

- To stem a word is to reduce it to a base form, called the *stem*, after removing various suffixes and endings and, sometimes, performing some additional transformations
- In practice, prefixes are sometimes preserved, so ‘rescan’ will not be stemmed to ‘scan’

- E.g.,
  - badly → bad
  - computing → comput
  - computed → comput
  - wipes → wip
  - wiped → wip
  - wiping → wip

Lemmatization is a more refined process that uses specific language and grammar rules to derive the root of a word

- This is useful for words that do not share an obvious root such as ‘best’ and ‘better’

- E.g.,
  - best → good
  - better → good
  - good → good
  - wiping → wipe
  - hidden → hide
  - shouted → shout

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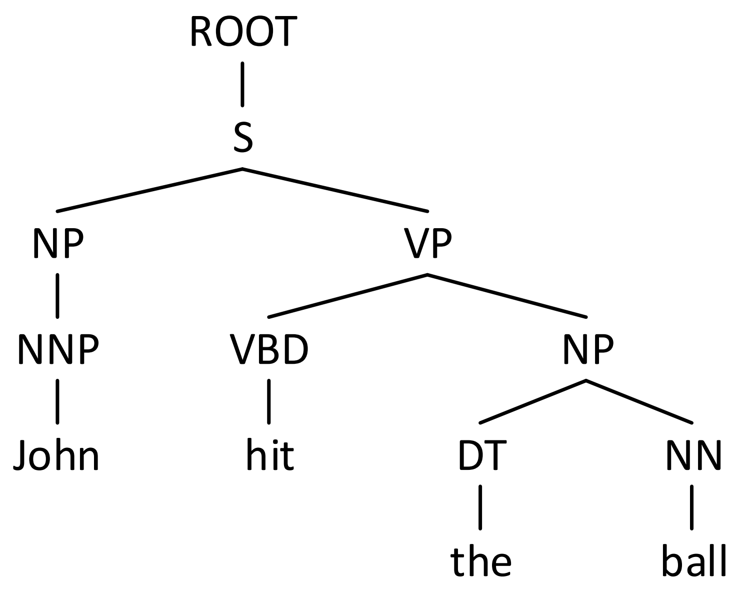
Tagging and Parsing

Tagging and Parsing

- In order to understand the various elements of a sentence, we need to *tag* important topics and *parse* their dependencies



DT - Determiner
NN - Noun, singular or mass
NNP - Proper noun, singular
NP - Noun phrase
S - Simple declarative clause
VBD - Verb, past tense
VP - Verb phrase

Tagging and Parsing (cont.)

- Our goal is to identify the *actors* and *actions* in the text in order to make informed decisions

- E.g., if we are processing financial news, we might need to identify which companies are involved and any actions they are taking
- E.g., if we are writing an assistant application, we might need to identify specific command phrases in order to determine what is being asked (e.g. “Siri, when is my next appointment?”)

Tagging and parsing is made up of a few overlapping subtasks

- Parts of speech tagging: What are the parts of speech in a sentence? (e.g. noun, verb, adjective)
- Named entity recognition: Can we identify *specific* proper nouns? Can we pick out people and locations?
- Chunking: Can we identify the pieces of the sentence that go together in meaningful chunks? (e.g. noun or verb phrases)

Tagging

```
John/NNP hit/VBD the/DT ball/NN
```

Parsing

```
(ROOT
  (S
    (NP (NNP John))
    (VP (VBD hit)
      (NP (DT the) (NN ball)))))
```

These subtasks are very difficult because language is complex and ever changing

- Most often, we are looking for heuristics to search through large amounts of text data
  - The results may not be perfect and that’s okay
- These techniques rely on rule-based systems but more recent research has focused on more flexible systems, focusing on words used rather than on the structure of the sentence
- We’ll see an example of these modern approaches in the next class

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Natural Language Processing in Python

Natural Language Processing in Python

- Most NLP techniques require pre-processing large collections of annotated text in order to learn specific language rules
  - There are many tools available for English and other popular languages
  - Each tool typically requires a large amount of data and large databases of special use-cases like language inconsistencies and slang
- In Python, two popular NLP packages are *nltk* and *spacy*
  - *nltk* is more popular but not as advanced and well maintained; *spacy* is more modern but not available for commercial use

Demo – Tokenizing, tagging, and Parsing with *spacy*

Tokenizing, tagging, and parsing with *spacy*

- *spacy* has 3 pre-processing engines:
  - A tokenizer: to identify the word tokens
  - A tagger: to identify the concepts described by the words
  - A parser: to identify the phrases and links between different words
- Each of these engines can be overridden with a different, specialized tool
  - You can even write your own and use them in place of the defaults

We’ll be using *spacy* to tokenize, tag, and parse “John hit the ball”

- `nlp_toolkit` runs each of the individual pre-processing tools

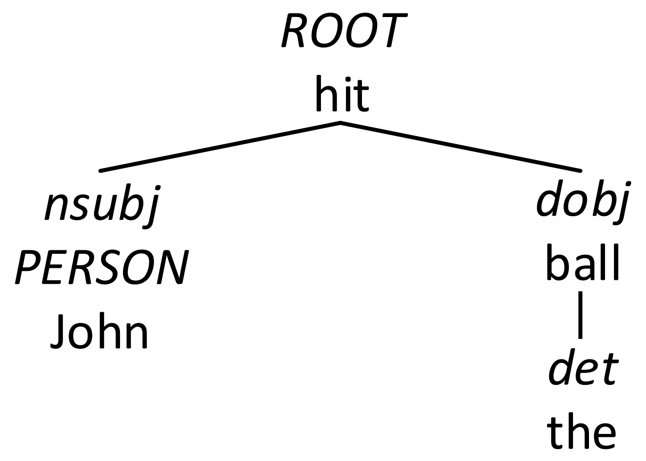
```
from spacy.en import English
nlp_toolkit = English()

sentence = u'John hit the ball'
parsed = nlp_toolkit(sentence)

for (i, word) in enumerate(parsed):
    print word
    print "\tParent: {}".format(word.head.lemma_)
    print "\tPhrase type: {}".format(word.dep_)
    print "\tKnown entity type: {}".format(word.ent_type_ if word.ent_type_ else 'n/a')
    print "\tLemma: {}".format(word.lemma_)
```

“John hit the ball” after tokenization, tagging, and parsing

```
John
          Parent: hit
          Phrase type: nsubj
          Known entity type: PERSON
          Lemma: john
hit
          Parent: hit
          Phrase type: ROOT
          Known entity type: n/a
          Lemma: hit
the
          Parent: ball
          Phrase type: det
          Known entity type: n/a
          Lemma: the
ball
          Parent: hit
          Phrase type: dobj
          Known entity type: n/a
          Lemma: ball
```

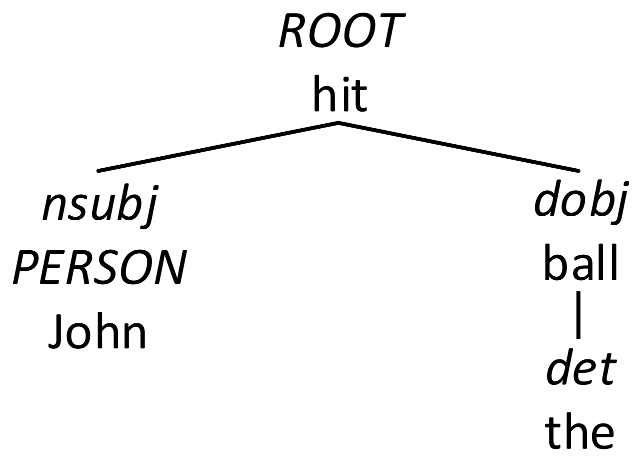


nsubj: link between a verb and an NP subject
  e.g. 'Clinton defeated Dole' - nsubj(defeated,Clinton)

dobj: link between a verb and one of its accusative objects
  e.g. 'she gave me a raise' - dobj(gave,raise)

det: link from a noun to its determiner
  e.g. 'the man' - det(man,the), 'which man' - det(man,which)

"John hit the ball" after tokenization, tagging, and parsing (cont.)



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e.g. 'she gave me a raise' - dobj(gave,raise)

det: link from a noun to its determiner
e.g. 'the man' - det(man,the), 'which man' - det(man,which)

- In this output,
  - "John" is identified as a person (PERSON)
  - We identify that "hit" is at its root as it is the action "John" took

Text Classification

Text Classification

- Text classification is the task of predicting what category or topic a piece of text is from

- For example, we may want to identify whether an article is a sports or business story
- Or whether has positive or negative sentiment

Text Classification

- Typically, this is done by using the text as features and the label as the target output. This is referred to as *bag-of-words* classification
- To include text as features, we usually create a binary feature for each word, i.e. does this piece of text contain that word?

- As we do this, we need to consider several things
  - Does order of words matter?
  - Does punctuation matter?
  - Does upper or lower case matter?

“John hit the ball”

- To create binary text features, we first create a vocabulary to account for all possible words in our universe:

$$x = \left(x_{aardvark}, \dots, x_{ball}, \dots, x_{hit}, \dots, x_{John}, \dots, x_{the}, \dots, x_{zyzzogeton}\right)$$

- “John hit the ball”

$$x = \left(\underbrace{\dots}_{0}, \underbrace{x_{ball}}_{1}, \underbrace{\dots}_{0}, \underbrace{x_{hit}}_{1}, \underbrace{\dots}_{0}, \underbrace{x_{John}}_{1}, \underbrace{\dots}_{0}, \underbrace{x_{the}}_{1}, \underbrace{\dots}_{0}\right)$$

Codealong - Text Processing with *scikit-learn*

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Term Frequency and Inverse Document Frequency (TF-IDF)

TF-IDF

- An alternative bag-of-words approach to `CountVectorizer` is a Term Frequency - Inverse Document Frequency (TF-IDF) representation
- TF-IDF uses the product of two intermediate values, the Term Frequency and Inverse Document Frequency

Term Frequency (TF)

- *Term Frequency* is equivalent to `CountVectorizer` features but using frequencies, not counts

$$tf(t,d) = \frac{number\ of\ occurences\ of\ term\ t\ in\ document\ d}{number\ of\ terms\ in\ document\ d}$$

- *Term Frequency* assigns high weight to frequent words (words that appear frequently) in a documents

Inverse Document Frequency (IDF)

- *Document Frequency* is the percentage of documents that a particular word appears in
- *Inverse Document Frequency* is *Document Frequency*'s inverse

$$idf(t, D) = \frac{total\ number\ of\ documents\ D}{number\ of\ documents\ term\ t\ appears\ in\ them}$$

- *Inverse Document Frequency* assigns high weight to rare words in all the documents

TF-IDF (cont.)

- Combining,

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

- The intuition behind *TF-IDF* is to assign high weight to words that either
  - appear frequently in this document or
  - appear rarely in other documents (and are therefore specific to this document)

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Lab

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Review

Review

- Natural language processing (NLP) is the task of pulling meaning and information from text
- This typically involves many sub problems including tokenization, cleaning (stemming and lemmatization), and parsing
- After we have structured our text, we can identify features for other tasks, including classification, summarization, and translation
- In *scikit-learn*, we use vectorizers to create text features for classification, such as `CountVectorizer` and `TfIdfVectorizer`

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Pre-Work

Pre-Work

Before the next lesson, you should already be able to:

- Install *gensim* with `pip install gensim`
- Recall and apply *unsupervised learning* techniques
- Recall probability distributions, specifically discrete multinomial distributions
- Recall NLP essentials, including experience with *spacy*
- BONUS: Setup Twitter API credentials using the provided instructions

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Q & A

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Exit Ticket

Don’t forget to fill out your exit ticket here

Sources

- Introduction to Natural Language Processing, University of Michigan