GENERAL ASSEMBLY

NATURAL LANGUAGE PROCESSING AND TEXT CLASSIFICATION

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LEARNING OBJECTIVES

- Define natural language processing
- List common tasks associated with:
  - use-cases
  - tokenization
  - tagging
  - parsing
- Demonstrate how to classify text or documents using scikit-learn

COURSE

PRE-WORK

PRE-WORK REVIEW

- Experience with scikit-learn classifiers, specifically random forests and decision trees
- Install the Python package `spacy` with `conda install spacy`
- Run the `spacy` download data command (may require admin privileges)

```
python -m spacy download en
```

OPENING

NATURAL LANGUAGE PROCESSING AND TEXT CLASSIFICATION

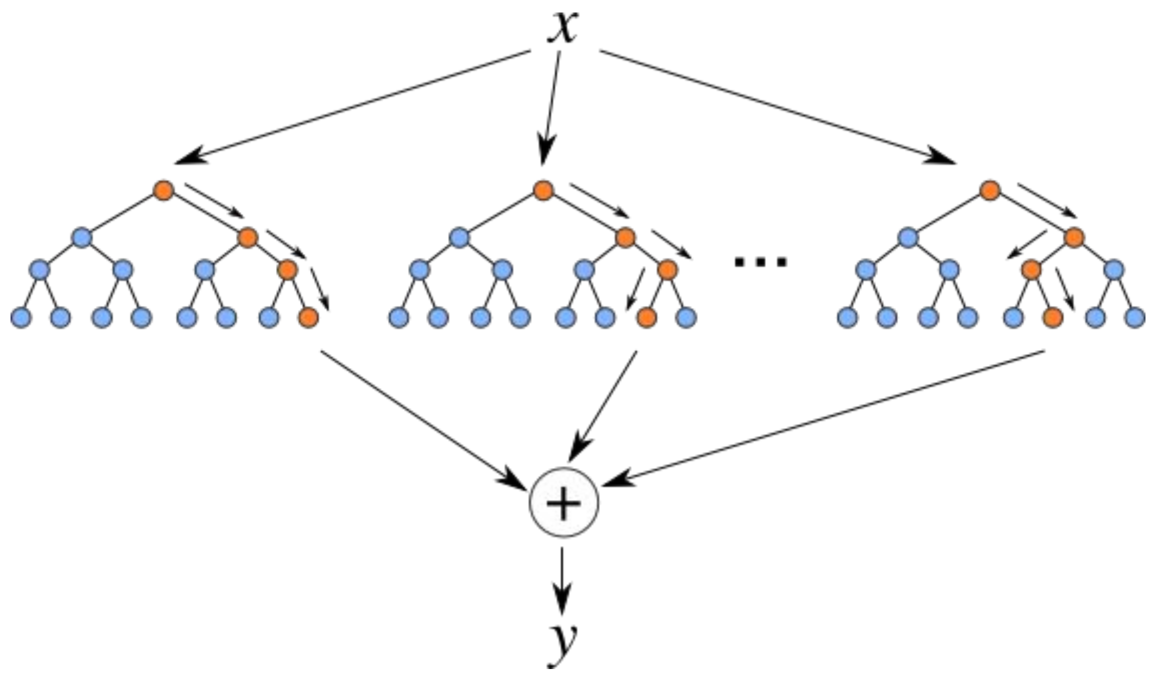
REVIEW: DECISION TREES AND RANDOM FORESTS

- What are decision trees?
- What are random forests?

REVIEW: DECISION TREES AND RANDOM FORESTS

- 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: DECISION TREES AND RANDOM FORESTS

- 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
- Decision trees are **weak** learners that are easy to overfit
- Random forests are **strong** models that are made up of a collection of decision trees

INTRODUCTION

NATURAL LANGUAGE PROCESSING

WHAT IS NATURAL LANGUAGE PROCESSING (NLP)?

- Natural language processing is the task of extracting meaning and information from text documents

- There are many types of information we might want to extract.

- These tasks may range from:
    - *simple* classification tasks - e.g. deciding what category a piece of text falls into
    - to more *complex* tasks - e.g. translating or summarizing text

- Most tasks require pre-processing to make text usable by our algos
    - We typically need to *add structure* to our *unstructured data*

WHAT IS NATURAL LANGUAGE PROCESSING (NLP)?

- Many AI assistant systems are typically powered by fairly advanced NLP engines

- A system like ***Siri*** uses *voice-to-transcription* to record a command and then various *NLP algorithms* to identify the question asked and possible answers

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

TOKENIZATION

- What sort of difficulties can you find in the following sentence?
  - “The L.A. Lakers won the NBA championship in 2010, defeating the Boston Celtics.”

TOKENIZATION EXAMPLES

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.]

LEMMATIZATION AND STEMMING

- How would you describe the relationship between the terms ‘bad’ and ‘badly’ or ‘different’ and ‘differences’?
- *Stemming* and *lemmatization* help identify common roots of words
- *Stemming* is a crude process of removing common endings from sentences, such as ‘s’, ‘es’, ‘ly’, ‘ing’, and ‘ed’
- Example: *Porter stemmer* function

LEMMATIZATION AND STEMMING

- 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 *'better'* and *'best'*
- What are some other examples of words that do not share an obvious root?

LEMMATIZATION AND STEMMING EXAMPLES

Lemmatization	**Stemming**
shouted → shout	badly → bad
best → good	computing → comput
better → good	computed → comput
good → good	wipes → wip
wiping → wipe	wiped → wip
hidden → hide	wiping → wip

ACTIVITY: KNOWLEDGE CHECK

EXERCISE

ANSWER THE FOLLOWING QUESTIONS

1. What other words or phrases might cause problems with stemming? Why?

2. What other words or phrases might cause problems with lemmatization? Why?

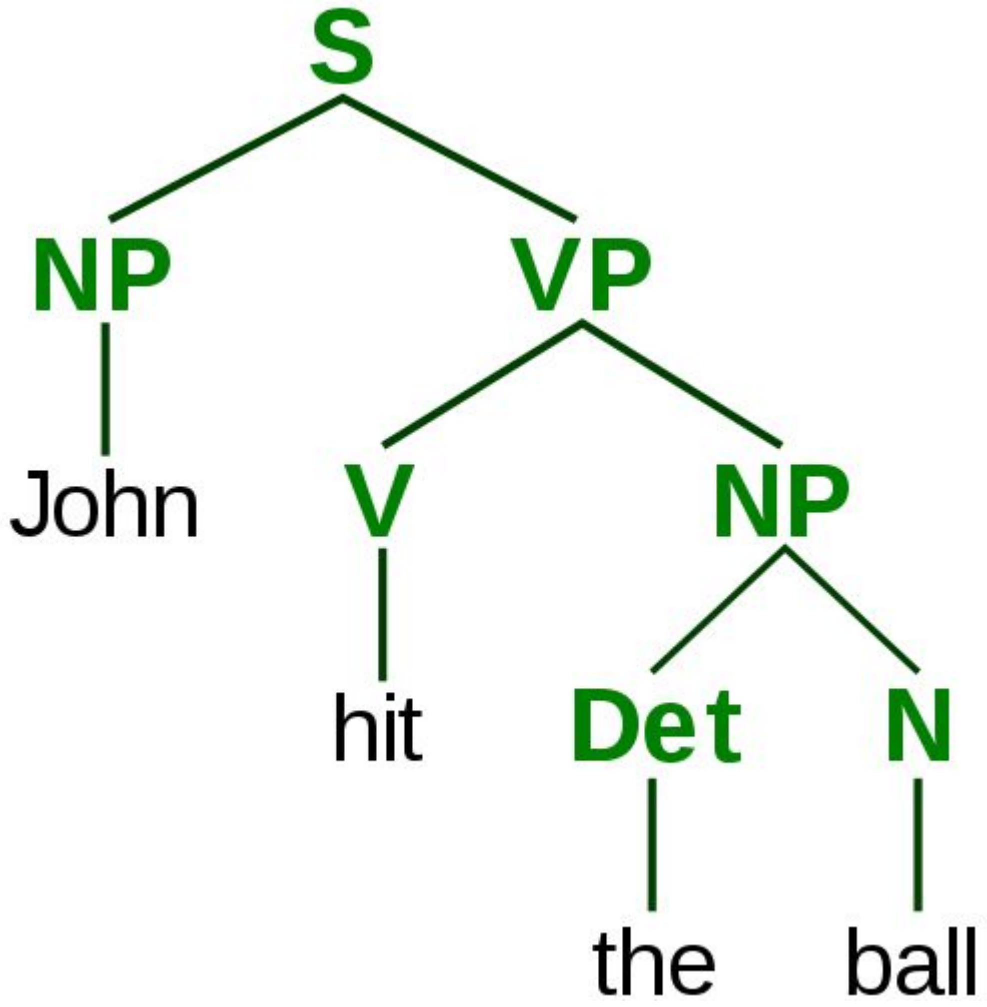
DELIVERABLE

Answers to the above questions

PARSING AND TAGGING

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

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



PARSING AND TAGGING

- If we are processing financial news, we might need to identify which *companies* are involved and which *actions* they are taking
- 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?”

PARSING AND TAGGING

- Tagging and parsing is made up of a few overlapping *sub-problems*:
    - **“Parts of speech” tagging**:
        - What are the parts of speech in a sentence (e.g. noun, verb, adjective, etc)?
    - **Chunking**:
        - Can we identify the pieces of the sentence that go together in meaningful chunks (e.g. noun or verb *phrases*)?
    - **Named entity recognition**:
        - Can we identify *specific* proper nouns?
        - Can we pick out people and locations?

ACTIVITY: KNOWLEDGE CHECK

EXERCISE

ANSWER THE FOLLOWING QUESTIONS

1. How might NLP be applied within your current jobs or final projects?
2. What are some other potential NLP use-cases?

DELIVERABLE

Answers to the above questions

DEMO

NATURAL LANGUAGE PROCESSING WITH ‘SPACY’

NATURAL LANGUAGE PROCESSING WITH ‘SPACY’

- 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, including language inconsistencies and slang

NATURAL LANGUAGE PROCESSING WITH 'SPACY'

- 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

NATURAL LANGUAGE PROCESSING WITH ‘SPACY’

- We’ll be using `spacy` to process some news article titles
  - First load the NLP toolkit by specifying the language:

```
import spacy
nlp_toolkit = spacy.load('en')
```

- This toolkit 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

NATURAL LANGUAGE PROCESSING WITH ‘SPACY’

- The first title is “IBM Sees Holographic Calls, Air Breathing Batteries”

- From this, we may wish to extract several pieces of information:
    - this title references a company and that company is referencing a new possible product -- air-breathing batteries

NATURAL LANGUAGE PROCESSING WITH ‘SPACY’

- We can use spacy to get information about this title

```
title = "IBM sees holographic calls, air breathing batteries"
parsed = nlp_toolkit(title)

for (i, word) in enumerate(parsed):
  print("Word: {}".format(word))
  print("\t Phrase type: {}".format(word.dep_))
  print("\t Is the word a known entity type? {}".format(word.ent_type_  if 
word.ent_type_ else "No"))
  print("\t Lemma: {}".format(word.lemma_))
  print("\t Parent of this word: {}".format(word.head.lemma_))
```

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

NATURAL LANGUAGE PROCESSING WITH ‘SPACY’

- The output will look similar to this:

```
Word: IBM
   Phrase type: nsubj
   Is the word a known entity type? ORG
   Lemma: ibm
   Parent of this word: see
Word: sees
   Phrase type: ROOT
   Is the word a known entity type? No
   Lemma: see
   Parent of this word: see
Word: holographic
   Phrase type: amod
   Is the word a known entity type? No
   Lemma: holographic
   Parent of this word: call
```

NATURAL LANGUAGE PROCESSING WITH ‘SPACY’

- In this output:
  - “IBM” is identified as an organization (ORG)
  - We identify a phrase: “holographic calls”
  - We identify a compound noun phrase: “air breathing batteries”
  - We identify that “see” is at the root as an action “IBM” is taking
  - We can see that “batteries” was lemmatized to “battery”

NATURAL LANGUAGE PROCESSING WITH ‘SPACY’

- We can use this output to find all titles that discuss an organization

```
def references_organization(title):
  parsed = nlp_toolkit(title)
  return any([word.ent_type_ == 'ORG' for word in parsed])

data['references_organization'] = data['title'].fillna('').map(references_organization)

data[data['references_organization']][['title']].head()
```

ACTIVITY: KNOWLEDGE CHECK

EXERCISE

COMPLETE THE FOLLOWING TASK

1. Using the code on the previous slide, write a function to identify titles that mention an organization (ORG) **<u>and</u>** a person (PERSON)

   - **Hint:** use the Python '*and*' operator

DELIVERABLE

New function

COMMON PROBLEMS IN NLP

- These subtasks are very difficult, because language is complex and changes frequently

- 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!

- Older techniques rely on *rule-based systems*
  - More recent techniques use *flexible systems*, focusing on the words used rather than the structure of the sentence

- We’ll see an example of these ‘modern’ approaches in the next class

INTRODUCTION

TEXT CLASSIFICATION

TEXT CLASSIFICATION

- Text classification is the task of predicting which category or topic a text sample is from

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

- Typically, this is done by using the text as features and the label as the target output (i.e. *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?

TEXT CLASSIFICATION

- To create binary text features, we first create a vocabulary to account for all possible words in our universe
- As we do this, we need to consider several things
    - Does order of words matter?
    - Does punctuation matter?
    - Does upper or lower case matter?

TEXT CLASSIFICATION

- This table illustrates features created from the following passage:

“It’s a great advantage not to drink among hard drinking people.”

Feature	Value
it’s	1
great	1
good	0
advantage	1
not	1
think	0
drink	1
from	0
hard	1
drinking	1

Feature	Value
people	1
withhold	0
random	0
smoke	0
among	1
whenever	0
thoughtful	0
inexhaustible	0
men	0
Nick	0

ACTIVITY: KNOWLEDGE CHECK

EXERCISE

ANSWER THE FOLLOWING QUESTIONS

Discuss your answers to the following questions and explain your reasoning.

1. Does word order matter?
2. Does word case (e.g. upper or lower) matter?
3. Does punctuation matter?

DELIVERABLE

Answers to the above questions

ACTIVITY: KNOWLEDGE CHECK

EXERCISE

ANSWER THE FOLLOWING QUESTIONS

1. What is “bag-of-words” classification and when should it be used?
2. What are some benefits to this approach?

DELIVERABLE

Answers to the above questions

DEMO

TEXT PROCESSING IN SCIKIT-LEARN

TEXT PROCESSING IN SCIKIT-LEARN

- Scikit-learn has many pre-processing utilities that simplify tasks required to convert text into features for a model
- These can be found in the `sklearn.preprocessing.text` package
- We will use the StumbleUpon dataset again to perform text classification
    - This time, we will use the text content itself to predict whether a page is ‘evergreen’ or not
- Open the starter code notebook to follow along

COUNTVECTORIZER

- `CountVectorizer` converts a collection of text into a matrix of features

- Each **row** will be a *sample* (an article or piece of text) and each **column** will be a *text feature* (usually a count or binary feature per word)

- `CountVectorizer` takes a column of text and creates a new dataset
  - It generates a feature for every word in all of the pieces of text

- **REMEMBER**: Using all of the words can be useful, but we may need to use *regularization* to avoid overfitting
  - Otherwise, rare words may cause the model to overfit and not generalize (e.g. “suuuuuper”)

COUNTVECTORIZER

- Instantiate a new `CountVectorizer`

```
from sklearn.feature_extraction.text import CountVectorizer

vectorizer = CountVectorizer(max_features = 1000,
                             ngram_range=(1, 2),
                             stop_words='english',
                             binary=True)
```

COUNTVECTORIZER PARAMETERS

- There are several parameters to utilize

- `ngram_range` - a range of word phrases to use
  - `(1,1)` means use all single words
  - `(1,2)` means use all contiguous pairs of word
  - `(1,3)` means use all triples

- `stop_words=’english’`
  - Stop words are non-content words (e.g. ‘to’, ‘the’, ‘it’, etc)
  - They aren’t helpful for prediction, so they get removed

COUNTVECTORIZER PARAMETERS

- `max_features=1000`
  - Maximum number of words to consider (uses the first `N` most frequent)

- `binary=True`
  - To use a dummy column as the entry (1 or 0, as opposed to the count)
  - This is useful if you think a word appearing 10 times is no more important than whether the word appears at all

COUNTVECTORIZER

- Vectorizers are like other models in scikit-learn
    - We create a vectorizer object with the parameters of our feature space
    - We `fit` a vectorizer to learn the vocabulary
    - We `transform` a set of text into that feature space

COUNTVECTORIZER

- **Note**: there is a distinction between *`fit`* and *`transform`*
  - We `fit` from our *training set*
    - This is part of the model building process, so we don’t look at our test set
  - We `transform` our *test set* using our model fit on the training set

COUNTVECTORIZER EXAMPLE

```
titles = data['title'].fillna('')

from sklearn.feature_extraction.text import CountVectorizer

vectorizer = CountVectorizer(max_features = 1000,
                             ngram_range=(1, 2),
                             stop_words='english',
                             binary=True)

# Use `fit` to learn the vocabulary of the titles vectorizer.fit(titles)

# Use `tranform` to generate the sample X word matrix - one column per
feature (word or n-grams)
X = vectorizer.transform(titles)
```

RANDOM FOREST PREDICTION MODEL

- Build a random forest model to predict the "evergreen-ness" of a website using the title features

```
from sklearn.ensemble import RandomForestClassifier

model = RandomForestClassifier(n_estimators = 20)

# Use `fit` to learn the vocabulary of the titles vectorizer.fit(titles)

# Use `tranform` to generate the sample X word matrix - one column per feature (word or n-grams)
X = vectorizer.transform(titles)
y = data['label']

from sklearn.cross_validation import cross_val_score

scores = cross_val_score(model, X, y, scoring='roc_auc')
print('CV AUC {}, Average AUC {}'.format(scores, scores.mean()))
```

TERM FREQUENCY - INVERSE DOCUMENT FREQUENCY

- 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 - INVERSE DOCUMENT FREQUENCY

- *Term Frequency* is equivalent to `CountVectorizer` features, just the number of times a word appears in the document (i.e. count)
- *Document Frequency* is the percentage of documents that a particular word appears in
- For example, “the” would be 100% while “Syria” is much lower
- *Inverse Document Frequency* is just 1/Document Frequency

TERM FREQUENCY - INVERSE DOCUMENT FREQUENCY

- Therefore, TF-IDF = Term Frequency * Inverse Document Frequency ***or*** TF-IDF = Term Frequency / Document Frequency

- The intuition is that the words that have high weight are those that either appear ***frequently*** in this document or appear ***rarely*** in other documents (and are *therefore* unique to this document)

- This is a good alternative to using a static set of “stop” words

```
from sklearn.feature_extraction.text import TfidfVectorizer
vectorizer = TfidfVectorizer()
```

ACTIVITY: KNOWLEDGE CHECK

EXERCISE

ANSWER THE FOLLOWING QUESTIONS

1. What does **TF-IDF** stand for?
2. What does this function do and why is it useful?
3. Use `TfidfVectorizer` to create a feature representation of the StumbleUpon titles in `starter_code`

DELIVERABLE

Answers to the above questions and feature representation

INDEPENDENT PRACTICE

TEXT CLASSIFICATION IN SCIKIT-LEARN

ACTIVITY: TEXT CLASSIFICATION IN SCIKIT-LEARN

EXERCISE

DIRECTIONS (30 minutes)

1. Use the text features of `title` with one or more feature sets from the previous random forest model
   - Train this model to see if it improves AUC
2. Use the `body` text instead of the `title`
   - Does this give an improvement?
3. Use `TfIdfVectorizer` instead of `CountVectorizer`
   - Does this give an improvement?

Check:
- Were you able to prepare a model that uses both quantitative features and text features?
- Does this model improve the AUC?

DELIVERABLE

Three new models

CONCLUSION

TOPIC REVIEW

LET’S REVIEW

- Natural language processing (NLP) is the task of pulling meaning and information from text

- This typically involves many subproblems 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`

COURSE

BEFORE NEXT CLASS

BEFORE NEXT CLASS

DUE DATE

- Final Project, Part 2 due: Thurs - 5/3 (*Next class)*

LESSON

Q & A

LESSON

EXIT TICKET

DON’T FORGET TO FILL OUT YOUR EXIT TICKET