

IS434

Social Analytics & Applications

Lab 9: Text Analysis

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Lab 9 – Get Lab files from eLearn

- eLearn → Content → Labs → **Lab9.zip**
- Unzip it.
- Port all files/directories over to your EC2 instance!

Lab9_News_TextAnalysis.ipynb

```
import nltk

##### Section 1 #####
# NLTK package comes with many books, on which we can perform text analysis.

# Which books are available?
print(nltk.corpus.gutenberg.fileids())

# Let's download 'Emma' by author Jane Austen.
# It returns a LIST of words.
emma_words = nltk.corpus.gutenberg.words('austen-emma.txt')
print(emma_words[:5])

# How many words are in this book?
print(len(emma_words))

# We can also download this book - broken down by 'sentences'.
emma_sentences = nltk.corpus.gutenberg.sents('austen-emma.txt')
print(emma_sentences[:5])

# How many sentences are in this book?
print(len(emma_sentences))

# What is the longest sentence's length?
longest_sentence = max(len(s) for s in emma_sentences)
print(longest_sentence)

# Let's have a look at this sentence.
for sentence in emma_sentences:
    if len(sentence) == longest_sentence:
        print(sentence)
```

Lab9_News_TextAnalysis.ipynb

```
##### Section 1 #####

# Specify input file
news_article_path = 'StraitsTimes1.txt'

# Open the file, read in all the news content and make a single sentence.
news_article_file = open(news_article_path, 'r')
news_content = ''
# Read one line at a time
for line in news_article_file:
    if len(line.strip()) > 0:
        news_content = news_content + line + ' '

# See what it looks like.
print_(news_content)

# Let's lower-case all words.
news_content = news_content.lower()

# See what it looks like.
print_(news_content)

##### Section 2 #####
# sent_tokenize() function takes a text blob and breaks it into 'sentences'.
news_sentences = sent_tokenize(news_content)
print_(news_sentences)
# How many sentences are in this news article?
print_(len(news_sentences))

##### Section 3 #####
# word_tokenize() function takes a text blob and breaks it into 'words'.
news_words = word_tokenize(news_content)
print_(news_words)
# How many words are in this news article?
print_(len(news_words))
```

Do you notice...
punctuations and
stop words?

Stop Words

This is a partial list. Click on Help in the text to see a full listing.

Stopwords

a	it	these
about	its	they
again	itself	this
all	just	those
almost	kg	through
also	km	thus
although	made	to
always	mainly	upon
among	make	use
an	may	used
and	mg	using
another	might	various
any	ml	very
are	mm	was
as	most	we
at	mostly	were

Words that don't represent any **entity** or **sentiment**.

→ In most cases, they don't mean anything.

Frequent appearance of “a”, “an”, “the”, “it” in English phrases... more frequent than entities or sentiment words.

Entities are... people, company names (e.g. “Donald Trump”).

Sentiment words are... adjectives or emotion-indicating words (e.g. “awesome”, “awful”, “bad”, “good”)

So... what do we do with them?

→ We **remove them**. This is part of **data cleaning**.

```
##### Section 3 #####  
# word_tokenize() function takes a text blob and breaks it into 'words'.  
tokenizer = RegexpTokenizer(r'\w+')  
#news_words = word_tokenize(news_content)  
news_words = tokenizer.tokenize(news_content)  
print_(news_words)  
# How many words are in this news article?  
print_(len(news_words))
```

Go back to **Section 3** and use **RegexpTokenizer**.
Using this **tokenizer** will remove all the **punctuations**.

Don't forget to import it...

```
from nltk.tokenize import sent_tokenize, word_tokenize, RegexpTokenizer  
from nltk.corpus import stopwords
```

You can also use this instead of FOR loop a few lines below.



```
##### Section 4 #####
# Let's load up English corpus from NLTK package.
stop_words = stopwords.words('english')
# See what words are inside.
print_(stop_words)

##### Section 5 #####
# Let's remove stop words from the news content.
#news_words_filtered = [w for w in news_words if not w in stop_words]

news_words_filtered = []

for w in news_words:
    if w not in stop_words:
        news_words_filtered.append(w)

# After removing stop words, how many words remain?
print_(len(news_words_filtered))
```

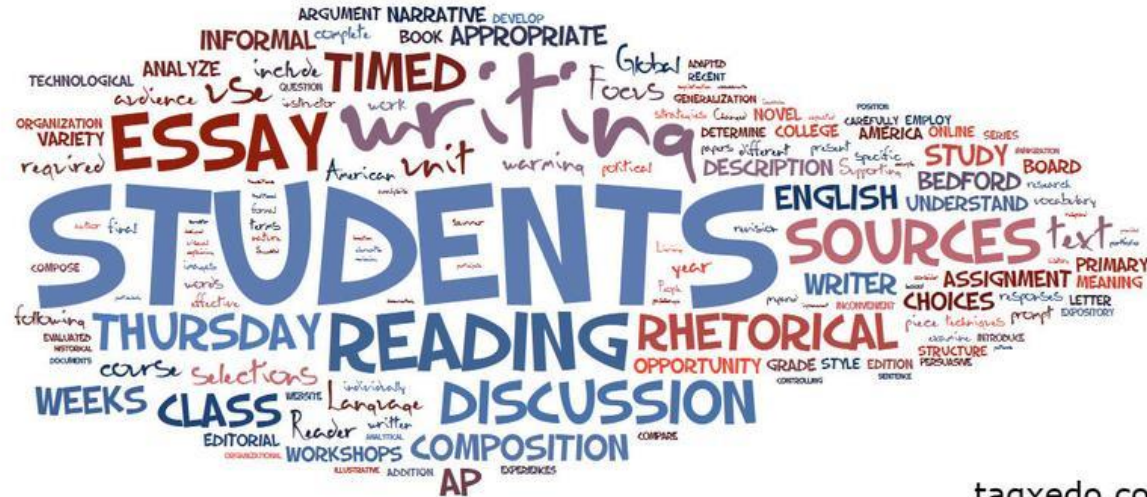
Stemming

I was taking a **ride** in the car.
I was **riding** in the car.

- If we're simply trying to figure out... what are people's favorite **activities** from a large number of **tweets** or **blogs**;
- “**ride**”, “**riding**” → these two words mean the **same** in our analysis.
- **This is just one example**. Can you imagine... every word in English language, tense and variations...
- Porter **stemmer** is one of the most widely used stemming algorithms, developed in 1979.
- We will use **stemmer(s)** to standardize words.


```
##### Section 6 #####  
# Let's create a Porter Stemmer object.  
porter_stemmer = PorterStemmer()  
  
# Let's test out this stemmer.  
some_words = ["ride", "rides", "riding"]  
for w in some_words:  
    print(porter_stemmer.stem(w))  
  
# Let's stem all the words in our news article.  
news_words_filtered_stemmed = []  
for w in news_words_filtered:  
    news_words_filtered_stemmed.append(porter_stemmer.stem(w))  
  
print(news_words_filtered_stemmed)
```

Word Cloud



tagxedo.com

- Word Cloud = Weighted List
 - Weight = Term frequency
- Can easily see frequently mentioned terms
- Cannot see term-to-term associations
- A bit of cleaning... (stop words, punctuations) is needed.
 - We did this step already.

Word Cloud

- Install (if you don't have it) **wordcloud** package and **Pillow** package in Anaconda.
- Google search “Cabin Sketch” font. Download the font and install it in your local computer.
 - <https://www.fontsquirrel.com/fonts/cabinsketch>
- For tutorials:
 - Windows: <http://www.softwareok.com/?seite=faq-Windows-8&faq=87>
 - Mac: <http://www.fontspring.com/support/installing/how-do-i-install-fonts-on-my-mac>

```
##### Section 7 #####
```

```
# Word Cloud takes a string. Convert our list of words into a string.
```

```
words_joined = " ".join([w for w in news_words_filtered_stemmed])
```

```
# Create a word cloud
```

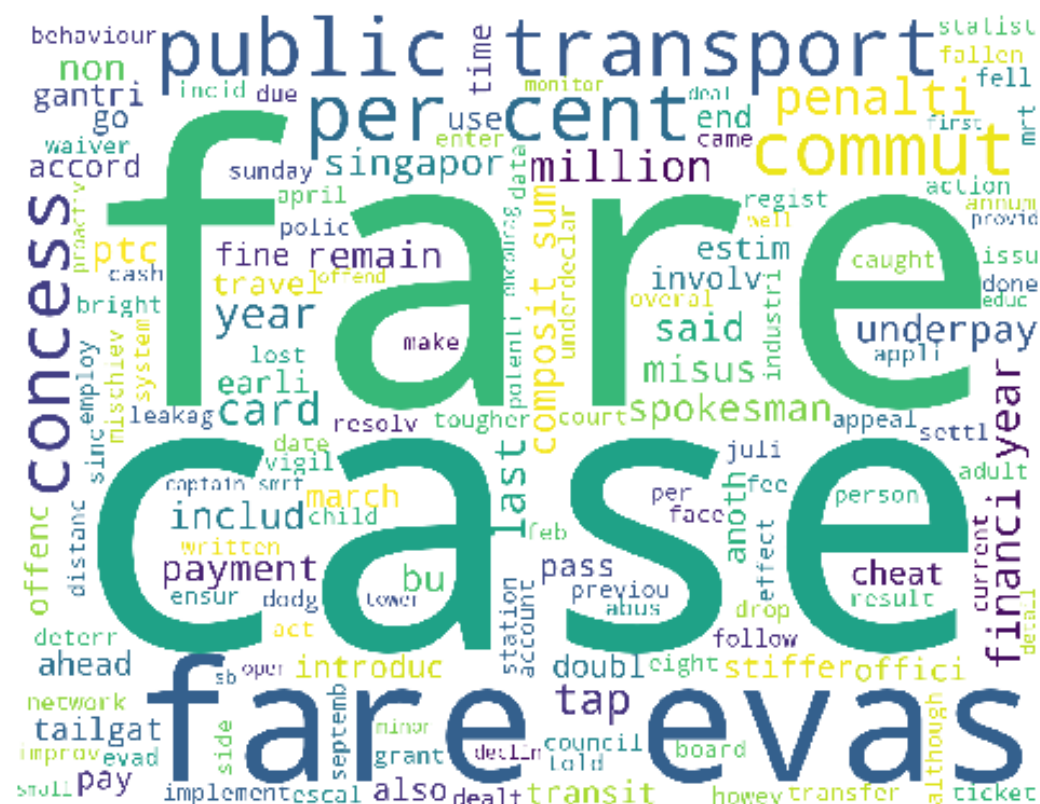
```
my_wordcloud = WordCloud(background_color='white',
                          width=1800,
                          height=1400).generate(words_joined)
```

```
plt.imshow(my_wordcloud)
```

```
plt.axis('off')
```

```
plt.show()
```

```
plt.savefig('WordCloud.png', dpi=300)
```



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Sentiment Analysis – Rule-Based (Part 1)

- **Lab9_SentimentAnalysis1.ipynb**
 - **Corpus/Corpora** (inside **dict/** and **dict2/** directories)
 - Positive corpus
 - Negative corpus
 - Incrementer corpus
 - Decrementer corpus
 - Inverter corpus
 - **Before you run this code, you need to do the following**
 - Go to EC2 Linux command line
 - Go to your **Anaconda's bin directory**. For example:
> `cd /home/ec2-user/anaconda/bin`
 - You need to **download** the below **dictionary**
> `python -m nltk.downloader averaged_perceptron_tagger`
- You will see messages like this upon successful download:

```
[nltk_data] Downloading package averaged_perceptron_tagger to
[nltk_data] /home/ec2-user/nltk_data...
[nltk_data] Unzipping taggers/averaged_perceptron_tagger.zip.
```


Sentiment Analysis – Rule-Based (Part 1)

- Run **Cell 2 & Cell 3**
 - [Cell 2] Load up libraries & specify the location of **dictionaries**
 - [Cell 3] Defines helper **Classes** and **functions**
- Scroll all the way to the bottom... to the **LAST CELL** in the Jupyter workbook.
 - Here is a sample restaurant review. Clearly, it is a negative review. Let's perform sentiment scoring on this.
- **run_analysis(____)** function will take a review comment (which can span multiple sentences).
- **run_analysis()** performs the following:
 1. Split the review comment into one or more sentences.
 2. Part-Of-Speech (POS) tagging will be done on each sentence.
 3. Calculates **sentiment score** based on +ve/-ve corpora.
 - But what about incrementers and decrementers?
 4. Calculates **sentiment score** based on +ve/-ve corpora & incrementer/decrementer corpora.
 5. Calculates **sentiment score** based on +ve/-ve corpora & incrementer/decrementer corpora & inverter corpus.

Sentiment Analysis – Rule-Based (Part 2)

- **Lab9_SentimentAnalysis2.ipynb**
- In **Part 1**, all positives received **+1** and all negatives received **-1**.
- In **Part 2**, there are **3 levels** of **positivity** and **3 levels** of **negativity**.
- You can define a scale of your own. For example, you might define **5 levels** of positivity/negativity.

```
excellent: [positive3]
good: [positive2]
okay: [positive1]
```

okay < good < excellent

```
lousy: [negative2]
awful: [negative3]
mediocre: [negative1]
```

mediocre < lousy < awful

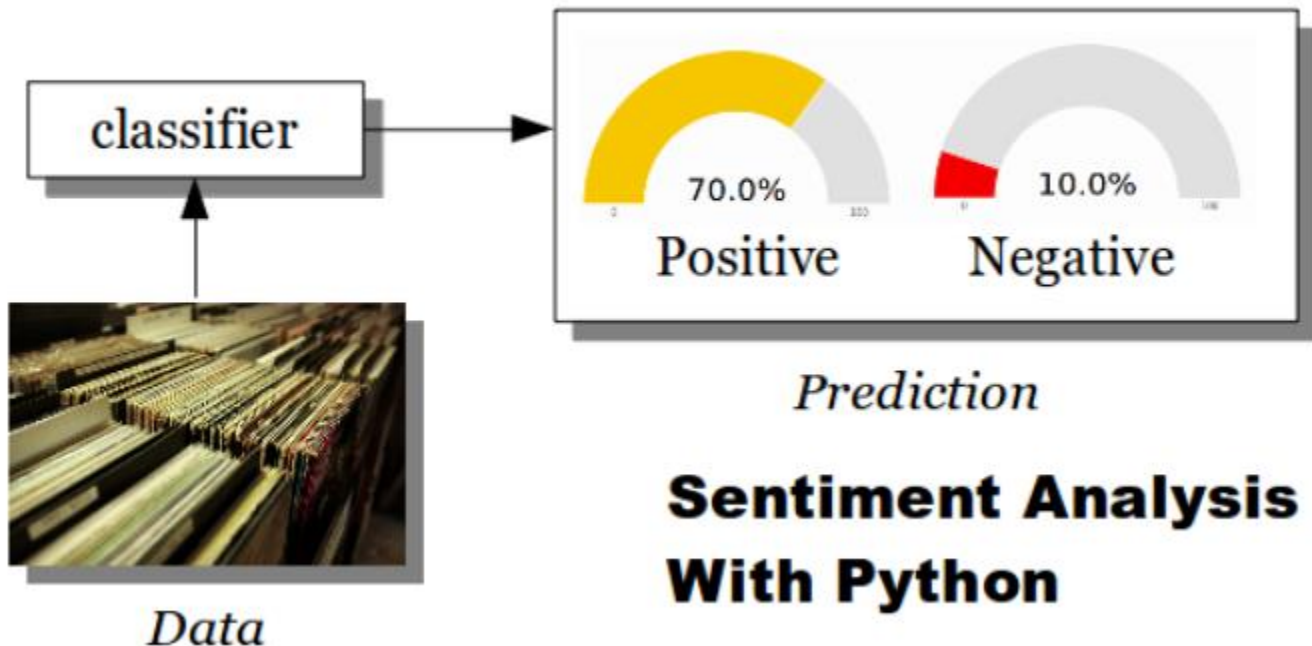
- The **sentiment dictionaries** for **Part 2** are located in **dict2/** directory.

Lab 9: Yelp Restaurant Review Challenge

- Copy **Lab9_SentimentAnalysis2.ipynb** into a new file called **“Lab9_SentimentAnalysis2_Yelp.ipynb”**.
- This new script must:
 1. Read from **Yelp_Food_Input.txt**.
 2. Use appropriate **chart(s)** to summarize the customer reviews.
 1. How many restaurant reviews are there?
 2. Word Cloud
 3. Top 20 **words/terms** mentioned in the review comments
 3. For each restaurant review, compute and assign a **sentiment score**.
 4. Use appropriate **chart(s)** to summarize sentiment analysis results. Are there more positive comments than negative comments? What does the distribution (of sentiment scores) look like? (e.g. boxplot)
 5. Post one or more charts with description to **Twitter** using hashtag **#is434**

Lab 9 – Sentiment Classification

- **Lab9_SentimentClassification1.ipynb**
- Given a movie review or a tweet, it can be automatically classified in categories.
- These categories can be user defined (positive, negative) or whichever classes you want.



Lab 9 – Sentiment Classification

- **Lab9_SentimentClassification2.ipynb**
- Here, we will use **IMDB** movie reviews as the baseline dataset (training/testing) to build **Sentiment Classification** model.
 - This dataset comes with **NLTK package**.
- In doing so, we will use **Naïve Bayes** algorithm.

$$P(c | x) = \frac{P(x | c)P(c)}{P(x)}$$

Diagram illustrating the Naïve Bayes formula components:

- $P(c | x)$ is labeled **Posterior Probability** (indicated by a downward arrow).
- $P(x | c)$ is labeled **Likelihood** (indicated by an upward arrow).
- $P(c)$ is labeled **Class Prior Probability** (indicated by an upward arrow).
- $P(x)$ is labeled **Predictor Prior Probability** (indicated by a downward arrow).

$$P(c | X) = P(x_1 | c) \times P(x_2 | c) \times \cdots \times P(x_n | c) \times P(c)$$

Lab 9: Topic Modeling

- Files
 - Lab9_TopicModeling_V1.ipynb
 - Lab9_TopicModeling_V2.ipynb
- What is topic modeling?
 - Technique to extract **hidden topics** from **large volumes of text**
 - *Examples: feeds from **social media**, **customer reviews** of businesses, **emails of customer complaints**, etc.*
 - It is very time-consuming to read through large volumes of text and compile the topics.
 - Latent Dirichlet Allocation (LDA) is one of the automated algorithms that can read through text documents and automatically output **topics**.
- For you to do:
 - Try each script above. Both are very well commented – please read the tutorial comments.
 - Note that topic modeling is a very memory-intensive task. Running the above scripts on a large file on a **micro EC2 instance** may lead to a “Dead Kernel”.
 - Solutions
 - Try the scripts on your local laptop computer’s Jupyter first.
 - So that you understand what the scripts do.
 - You can try the scripts on a larger EC2 instance (e.g. xLarge).
 - Note that the AWS Free Tier does NOT include > micro EC2.
 - Using larger capacity servers will be charged to your account.

Kernel Restarting

The kernel appears to have died. It will restart automatically.