Natural Language

Processing

Data Science, Spring 2021

1. Our mod of the day.

1. Our mod of the day.

2. Project 2

- 1. Our mod of the day.
- 2. Project 2
- 3. An equation you were promised

Our moderator

Our moderator

1. Anubhav!





1. Spend some time on your PDF generation!

An equation you were promised:

$$(1+\frac{\lambda}{N})^{-2}$$

An equation you were promised:

Let's say you had a variable where half the data was missing $(\lambda = 0.5)$ and you used N = 5 for the number of generated data sets:

$$(1 + \frac{0.5}{5})^{-2} = 1.049$$

An equation you were promised:

How much better would it be if you used an 'infinite' number of generated data sets?

$$(1 + \frac{0.5}{\infty})^{-2} = 1$$

Part I: Text Classification

Why?

1. Determine if something is spam

- 1. Determine if something is spam
- 2. Sentiment

- 1. Determine if something is spam
- 2. Sentiment
- 3. Authorship

- 1. Determine if something is spam
- 2. Sentiment
- 3. Authorship
- 4. Time period of authorship

- 1. Determine if something is spam
- 2. Sentiment
- 3. Authorship
- 4. Time period of authorship
- 5. What else?

1. A set of classes $Y = \{y_1, y_2, y_3, \dots, y_n\}$

- 1. A set of classes $Y = \{y_1, y_2, y_3, ..., y_n\}$
- 2. Some document $w \in Doc$

- 1. A set of classes $Y = \{y_1, y_2, y_3, ..., y_n\}$
- 2. Some document $w \in Doc$
- **3**. Classification is a function: $classify : Doc \rightarrow Y$



There are many ways to implement such a function:



There are many ways to implement such a function: 1. Rule-based approach (blacklists, keywords, etc.)

Classification

There are many ways to implement such a function:

- 1. Rule-based approach (blacklists, keywords, etc.)
- 2. Supervised learning

1. Input:

1. Input:

1.1 Document $w \in Doc$

1. Input:

- 1.1 Document $w \in Doc$
- 1.2 Classes $Y = \{y_1, y_2, y_3, \dots, y_n\}$

1. Input:

- 1.1 Document $w \in Doc$
- 1.2 Classes $Y = \{y_1, y_2, y_3, \dots, y_n\}$
- **1.3** Training set $T = \{(w_1, y_1), (w_2, y_2), (w_3, y_3) \dots, (w_n, y_n)\}$

1. Input:

- 1.1 Document $w \in Doc$
- 1.2 Classes $Y = \{y_1, y_2, y_3, \dots, y_n\}$
- **1.3** Training set $T = \{(w_1, y_1), (w_2, y_2), (w_3, y_3) \dots, (w_n, y_n)\}$

2. Output

1. Input:

- 1.1 Document $w \in Doc$
- 1.2 Classes $Y = \{y_1, y_2, y_3, \dots, y_n\}$
- **1.3** Training set $T = \{(w_1, y_1), (w_2, y_2), (w_3, y_3) \dots, (w_n, y_n)\}$

2. Output

2.1 classify : $Doc \rightarrow Y$

- 1. Input:
 - 1.1 Document $w \in Doc$
 - 1.2 Classes $Y = \{y_1, y_2, y_3, \dots, y_n\}$
 - **1.3** Training set $T = \{(w_1, y_1), (w_2, y_2), (w_3, y_3) \dots, (w_n, y_n)\}$
- 2. Output
 - **2.1** classify : $Doc \rightarrow Y$
- 3. What's the downside?

Part II: Representation

What's a word cloud actually tell you?

What's a word cloud actually tell you?1. Technical name: Bag of Words

What's a word cloud actually tell you?

- 1. Technical name: Bag of Words
- 2. FYI: 'Bag of Words' is also a good insult to call someone

If we created a Bag of Words for the descriptions of the various CMSC courses what might we see?

1. tf_{ij} : The frequency of word j in document i

tf_{ij}: The frequency of word j in document i
More general than bag of words.

- 1. tf_{ij} : The frequency of word j in document i
- 2. More general than bag of words.
- 3. Some adjustments:

- 1. tf_{ij} : The frequency of word j in document i
- 2. More general than bag of words.
- 3. Some adjustments:

3.1 $\log(1 + tf_{ij})$: Reduce impact of outliers

- 1. tf_{ij} : The frequency of word j in document i
- 2. More general than bag of words.
- 3. Some adjustments:
 - 3.1 $\log(1 + tf_{ij})$: Reduce impact of outliers
 - 3.2 $\frac{tf_{ij}}{max_j tf_{ij}}$: Normalize by most common word

1. You can use term frequency to train classifiers!

You can use term frequency to train classifiers!
Linear classifiers: "How Dickensian is this novel?"

- 1. You can use term frequency to train classifiers!
- 2. Linear classifiers: "How Dickensian is this novel?"
- 3. Think of some examples.

1. Inverse term frequency is a thing, too!

- 1. Inverse term frequency is a thing, too!
- 2. What do you think that means?

Inverse Term Frequency

$$idf_j = \log(\frac{\#Doc}{\#Doc \ni j})$$

Part III: Advice

NLTK in Python

NLTK in Python

1. I strongly recommend that you do the assigned reading on NLTK

NLTK in Python

- 1. I strongly recommend that you do the assigned reading on NLTK
- 2. You don't have to worry about implementing these things!

Thanks for your time!

:)