

# 9/24: Sentiment Analysis

Discord: <a href="https://discord.gg/68VpV6">https://discord.gg/68VpV6</a>

# A Quick Development Tip

## **Development Tip: Github!**

- Whenever you do any project of whatever size, it's always a good idea to have it somewhere on your GitHub
- For example, if you complete any of our notebooks, create a repository and upload it to your GitHub!

## Steps to do this for SIGNLL

1) Create a new repository (title it something like SIGNLL 2020)

- Create a folder inside the repository for each project
- 3) Organize your repository!!!

#### Extra help:

https://reproducible-science-curriculum.github.io/sharing-RR-Jupyter/01-sharing-github/

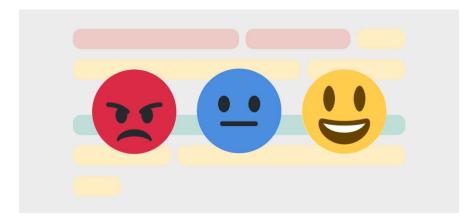
# Sentiment Analysis

How can we extract emotion from text?

#### What is Sentiment Analysis?

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Sentiment analysis is the interpretation and classification of emotions (positive, negative and neutral) within text data using text analysis techniques



#### How do we know?



Which tweet is positive? Which is negative? Why?

#### **Classifying Words**





negative tweet

12:00 PM · Jun 1, 2020





positive tweet

12:00 PM · Jun 1, 2020

## **Organizing These Words**

We can organize our tweets using this data table:

Word	Negative Tweet Count	Positive Tweet Count
l	1	Ο
hate	1	Ο
stupid	1	0
Purdue	1	O
UIUC	0	1
is	0	1
the	0	1
best!	O	1

## **Sentiment Analysis Steps**

- 1) Process and clean up our tweets
- 2) Organize them into a dictionary
- 3) Create and train a model using logistic regression
- 4) Verify our results with test data

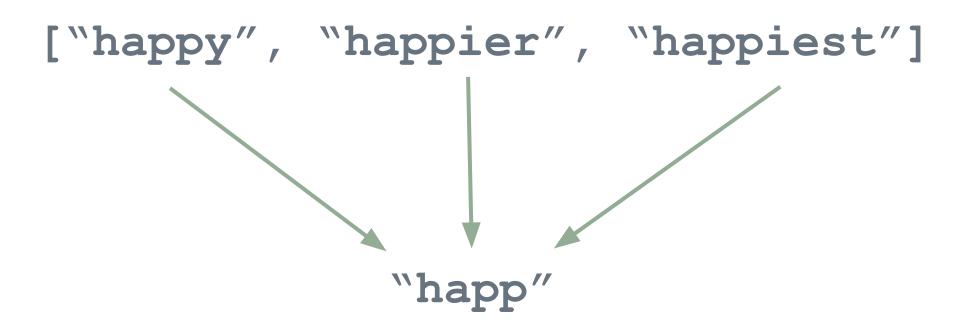
#### **Multiple Word Definitions**

Do these tweets basically mean the same thing?



#### **Word Tokenization**

Fortunately, we can run a built-in algorithm to make sure that these words all mean the same thing



#### **Stopwords**

There are also some words that add no meaning to the sentence, such as:

Since these words don't help us that much, we can remove them from our tweets

Note: We'll also being doing this with punctuation and twitter symbols (@, #, etc.)

#### **Step 1: Processing our tweet**

After tokenizing, removing stop words, and some other steps (like removing punctuation), we can convert our tweet to useful data for the computer:



#### Step 2: Building our dictionary

#### Recall our data table from earlier:

Word	Negative Tweet Count	Positive Tweet Count
l	1	Ο
hate	1	Ο
stupid	1	0
Purdue	1	O
UIUC	0	1
is	0	1
the	0	1
best!	O	1

#### **Dictionary Conversion**

Instead of having separate columns for positive tweet count and negative tweet count, we can represent them as a single list of length 2:

$$\{n_{neg} \ n_{pos}\}$$

This is useful because we can represent our dictionary with the following key/value pair:

$$word: \{n_{neg} \ n_{pos}\}$$

#### **Example Dictionary**

A common dictionary of tweets might look like:

```
Sample Tweet Dictionary:
-----
{'excit': [4, 28], 'aw': [30, 2], 'angri': [5, 3],
'want': [185, 69], 'wish': [91, 113]}
```

(This is for the words <u>exciting</u>, <u>awful</u>, <u>angry</u>, <u>want</u>, and <u>wish</u>. The real dictionary would have many many more words)

## Step 3: Training our model

Since we are predicting categorical data (whether the tweet is positive or negative), we can use **logistic regression**!

#### Reminder: logistic gradient descent equation:

```
def log_grad_descent(x, actual_y, thetas, learning_rate, m, num_iterations):
    # perform the algorithm for the specified number of iterations
    for iteration in range(num_iterations):
        # calculate our sigmoided predicted output
        pred_output = sigmoid(x @ thetas)
        # get the derivative of this value
        gradients = lin_reg_derivative(pred_output, actual_y, x, m)
        # adjust our thetas
        thetas = thetas - learning_rate * gradients
    return thetas
```

#### Representing our tweets as numbers

To use logistic regression, we need to represent our tweets as numbers

We can do this by using three parameters from our dictionary:

$$\{1 \sum count_{neg} \sum count_{pos}\}$$

The first parameter is used for the intercept, while the second and third parameters add all of negative and positive counts for each word in the tweet, respectively

#### Tweet representation example



```
Tokens: ["wish", "friend", "like"]
```

```
"wish": [63, 29]
+
  "friend": [30, 40]
+
  "like": [182, 187]
```

$$tweet_val = [1, 275, 256]$$

#### **Logistic Gradient Descent**

Now that we have all of our tweets represented as numbers, we can run logistic gradient descent as normal!

$$y = \begin{cases} 1 & neg_0 & pos_0 \\ 1 & neg_1 & pos_1 \\ \dots & \dots & \dots \\ 1 & neg_{m-1} & pos_{m-1} \end{cases} \cdot \{\Theta_0 \Theta_1 \Theta_2\}$$
$$y = sigmoid(y)$$

## Step 4: Testing our model

There's two ways we can test our model: with the training set or our own custom inputs

It's always a good idea to verify your data with the test set before using custom inputs

One common metric for an <u>evenly</u> distributed dataset is accuracy, defined as:

$$accuracy = \frac{n_{correct}}{n_{total}}$$

# Tasks to Complete

 Work on the notebook (twitter\_code.zip) in the google drive folder https://drive.google.com/drive/folders/1XinmyYovhzV

https://drive.google.com/drive/folders/1XinmyYoyhzVS Nvzz7Djzoxkvg3rnekD1?usp=sharing

Try to work on it collaboratively! You might meet some people you could do a project with in the future

As always, let us know if you need any help!

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