

# Kagan ILTER Sentiment Analysis with 55.000 Tweets

Springboard Data Science Career Track
Capstone Project-2

### **Problem Definition**

The scope of this project is to predict the sentiment of a short twitter text and categorize them over 3 sentiments (positive, negative, neutral)



Companies/
Organizations

Social Media Influencers

Ecommerce traders

Websites / applications

### **Data Information**

- Dataset is acquired from <a href="https://data.world/crowdflower/sentiment-analysis-in-text">https://data.world/crowdflower/sentiment-analysis-in-text</a>
- 4 features and 55.000 data points/samples.
- Contains labels for the emotional content (such as happiness, sadness, and anger)
- Target Feature is 'sentiment'



	tweet_id	sentiment	author	content
0	1956967341	empty	xoshayzers	@tiffanylue i know i was listenin to bad habit earlier and i started freakin at his part =[
1	1956967666	sadness	wannamama	Layin n bed with a headache ughhhhwaitin on your call
2	1956967696	sadness	coolfunky	Funeral ceremonygloomy friday
3	1956967789	enthusiasm	czareaquino	wants to hang out with friends SOON!
4	1956968416	neutral	xkilljoyx	@dannycastillo We want to trade with someone who has Houston tickets, but no one will.
5	1956968477	worry	XXXPEACHESXXX	Re-pinging @ghostridah14: why didn't you go to prom? BC my bf didn't like my friends
6	1956968487	sadness	ShansBee	I should be sleep, but im not! thinking about an old friend who I want. but he's married now. damn, & me 2! scandalous!

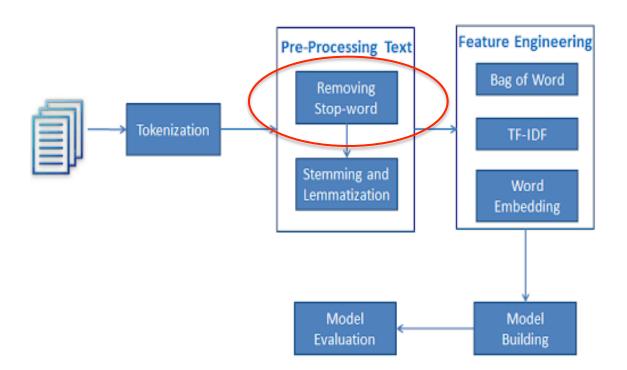
Anger, boredom, hate, worry, sadness : Negative

Happiness, fun, love, surprise, enthusiasm, relief : Positive

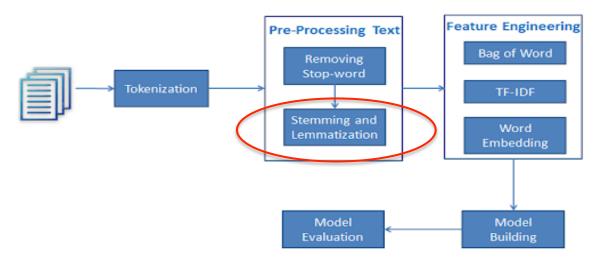
Empty, neutral : Neutral

### Cleaning the tweet texts:

- Removing special characters,
- Punctuations,
- Accented characters,
- Html tags,
- Spaces,
- Tickers
- Hyperlinks
- Usernames
- Stopwords

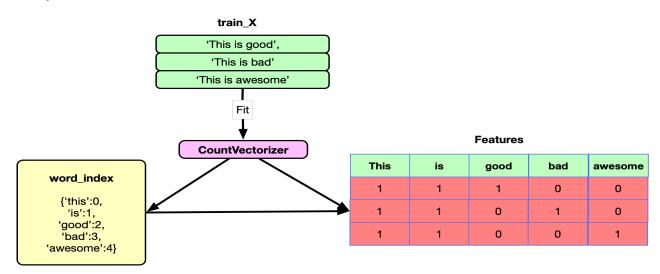


Stemming and lemmatization:



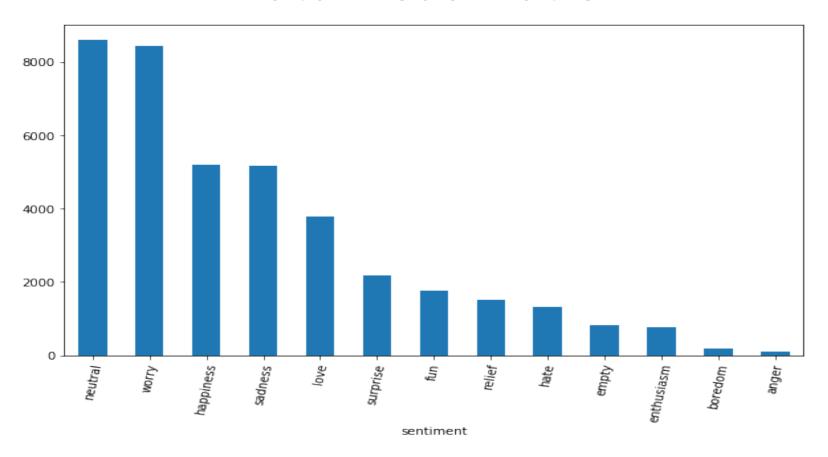
- Missing Values, outliers, duplicates:
  - No missing values
  - 173 repeating duplicates

- Bag of Words (Plus n-grams) (CountVectorizing in ScikitLearn):
  - A mathematical model to represent unstructured text (or any other data) as numeric vectors



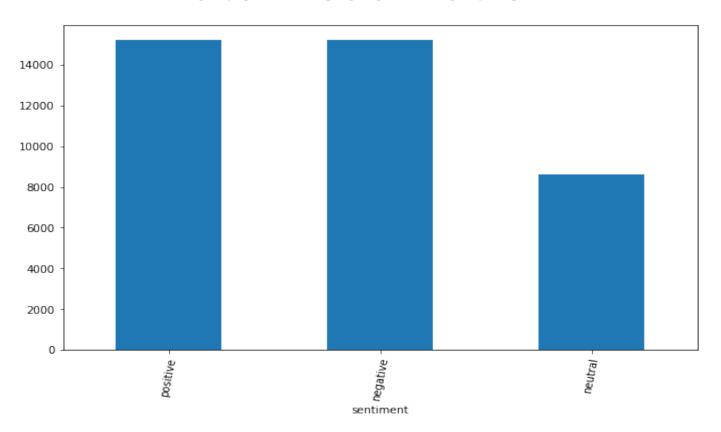
you	youll	your	youre	youtube	youve	yr	yum	yummy	ûï
0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0

### **Data Visualization**



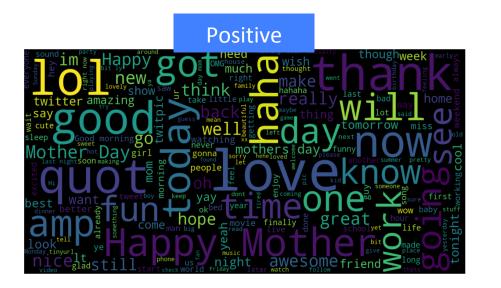
The distribution of emotions in the data set (imbalanced)

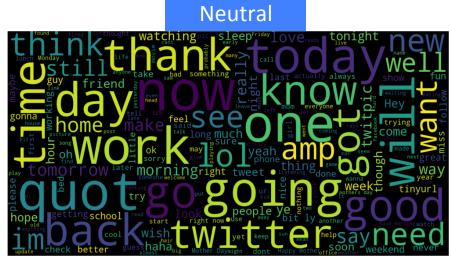
### **Data Visualization**



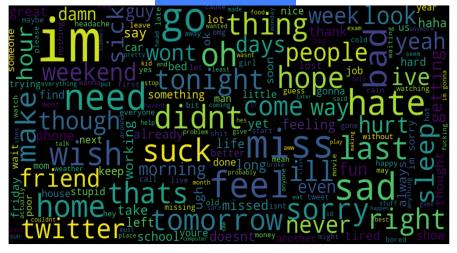
The distribution of 3 sentiments

### **Data Visualization**



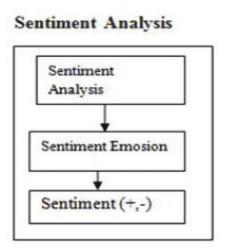


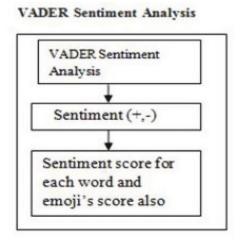
### Negative



# **Data Comparison with NLTK Vader**

➤ NLTK Vader is a parsimonious rule-based model for sentiment analysis of social media text. With Vader, we can compare our dataset's classification with the Vader classification

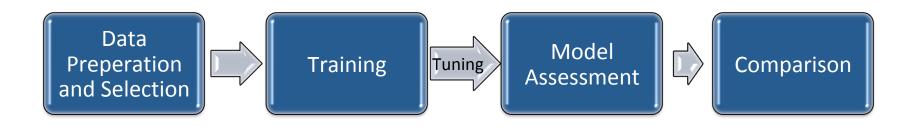




- ➤ If the Vader compound result is lower than -0.05, the text is categorized as negative sentiment. Higher than 0.05 is a positive sentiment.
- As a result of Vader comparison, we realized that our dataset's classification is better than Vader's classification.

# **Predictive Modeling**

Supervised learning multi-class classification



- Subset of whole data: 30%
  - Logistic regression,
  - Naive bayes,
  - Linear svm,
  - Random forest,
  - Gradient boosting,
  - Xgboosting
  - Deep learning

Logistic Regression for 13 emotions

Logistic Regression is one of the basic and popular algorithm to solve a classification problem. Because of the imbalanced features, the accuracy is low.

Accuracy: 0.2208

#### Logistic Regression for 3 sentiments



 $\overline{\Box}$ 



Negative

Neutral

Positive

#### Linear SVC with Count Vectorizing

The objective of a Linear SVC (Support Vector Classifier) is to fit to the data providde, returning a "best fit" hyperplane that divides, or categorizes ourdata.

Accuracy: 0.6156

#### Naïve Bayes with Count Vectorizing

Naive Bayes classifiers are a collection of classification algorithms based on Bayes' Theorem. It is not a single algorithm but a family of algorithms where all of them share a common principle, i.e. every pair of features being classified is independent of each other.

#### Random Forest with Count Vectorizing

A random forest is a meta estimator that fits a number of decision tree classifiers on various sub-samples of the dataset and uses averaging to improve the predictive accuracy and control over-fitting. We used random forest with a 'balanced' class weight

Accuracy: 0.6156

#### Gradient Boosting with Count Vectorizing

Gradient boosting classifiers are a group of machine learning algorithms that combine many weak learning models together to create a strong predictive model.

#### **➤** Word frequencies with Tf-Idf:

TF-IDF are word frequency scores that try to highlight words that are more interesting, e.g. frequent in a document but not across documents.

#### Logistic Regression with Tf-idf

	precision	recall	f1-score	support
negative neutral positive	0.71 0.43 0.61	0.72 0.41 0.62	0.72 0.42 0.61	6124 2917 4317
accuracy macro avg weighted avg	0.58 0.62	0.58 0.62	0.62 0.58 0.62	13358 13358 13358

#### > Pipeline

A pipeline consists of a chain of processing elements (processes, threads, coroutines, functions, etc.), arranged so that the output of each element is the input of the next. We used scikit-learn pipeline models.

#### We used:

- Count Vectorizer
- Tr-Idf Transformer
- Multimnomial Naïve Bayes model as a classifier

#### Grid Search

We applied a grid-searching model for scanning the data to configure optimal parameters for our model. With the best parameters below, the accuracy is:

#### Deep Learning Algorithm

Deep Learning (which includes Recurrent Neural Networks, Convolution neural Networks and others) is an important type of Machine Learning approach.

We used Keras deep learning frame and Tensorflow in our NLP text classification model.

```
Epoch 1/5
- 336s - loss: 0.8706 - acc: 0.5974
Epoch 2/5
- 333s - loss: 0.7893 - acc: 0.6472
Epoch 3/5
- 333s - loss: 0.7533 - acc: 0.6618
Epoch 4/5
- 333s - loss: 0.7174 - acc: 0.6812
Epoch 5/5
- 333s - loss: 0.6860 - acc: 0.6964
```

### **Conclusion**

- ➤ We have chosen a difficult and informal text in order to make it harder to analyze the sentiment (general text, not a review or a sentiment pool data)
- The distribution of the features are not balanced. In order to deal with this problem, we concatenated additional 15 thousands row data set, we limited the categorization, we applied random forest hyper-tuning and feature engineering.
- ➤ We used random forest model to balance the distribution and Grid Search with 5-fold cross validation technique to deal with the overfitting problem. Because of the reasons mentioned above, our best score is 0.68 after applying Tf-idf and deep learning algorithm.
- Most important things for an effective sentiment analysis of short social media texts are data preprocessing, feature engineering and choosing the best model

### **Future Works**

- For increasing the accuracy of our model, it is very important to find additional balanced data sets, and applying effective feature engineering techniques.
- Applying Word2vec or Phrase modeling could also improves the model.
- ➤ Categorization of sentiments in 2 classes (such as bad or not bad) could also give higher results.
- ➤ Run time for these kinds of data with decision tree models and deep learning models is relatively long. Decreasing the run time with more efficient computers or cloud systems could be used for increasing the effectiveness.

# **Thank You**