Disaster Tweet Detection

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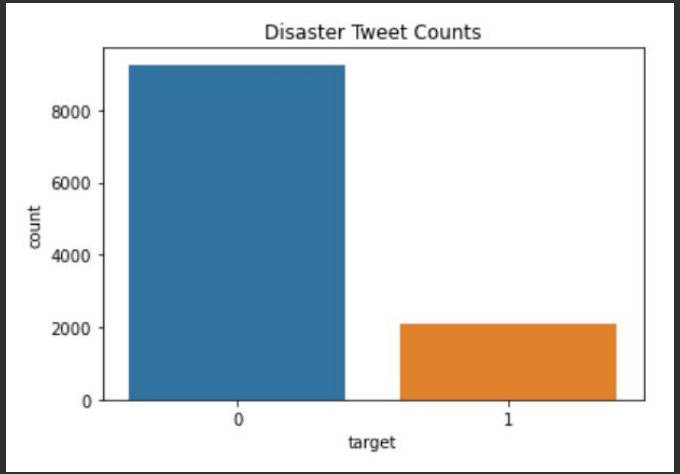
How can we build an NLP model that is able to classify tweets as disasters with high accuracy?

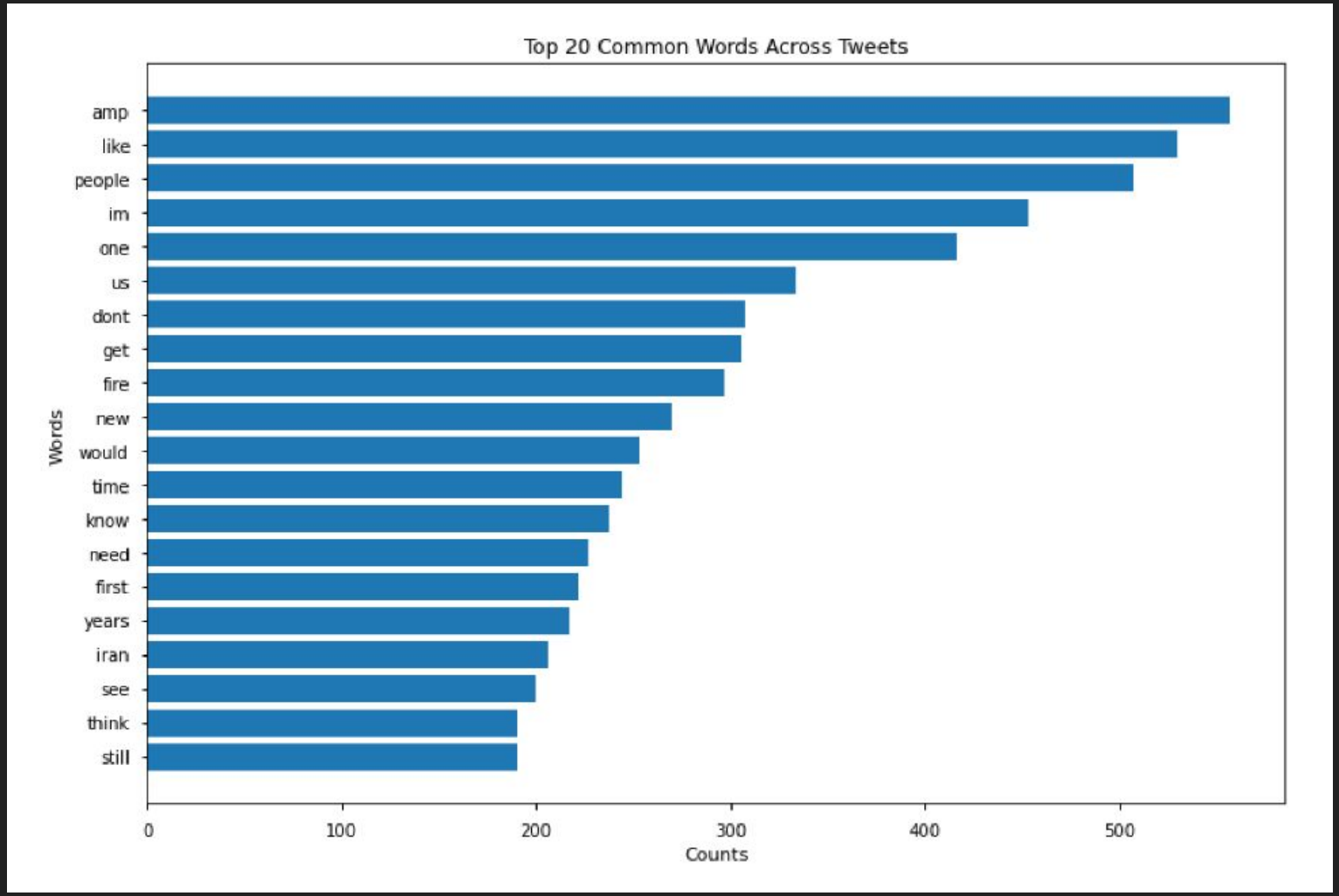
Data Wrangling

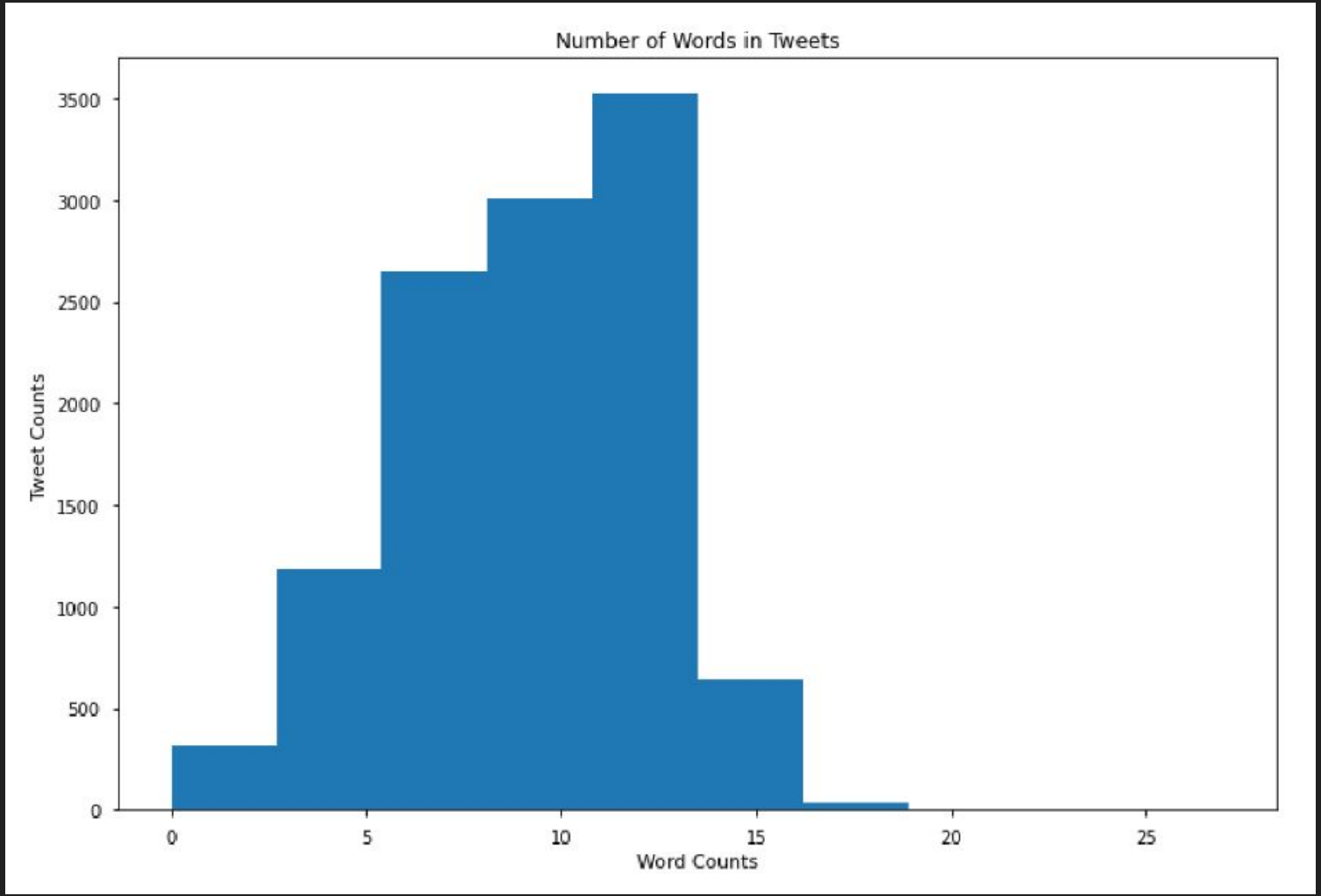
- Import data
- Check for balanced target classes
- Data cleaning
  - Converting text to lowercase
  - Regular expression string removal
  - Tokenized text
  - Remove stop words

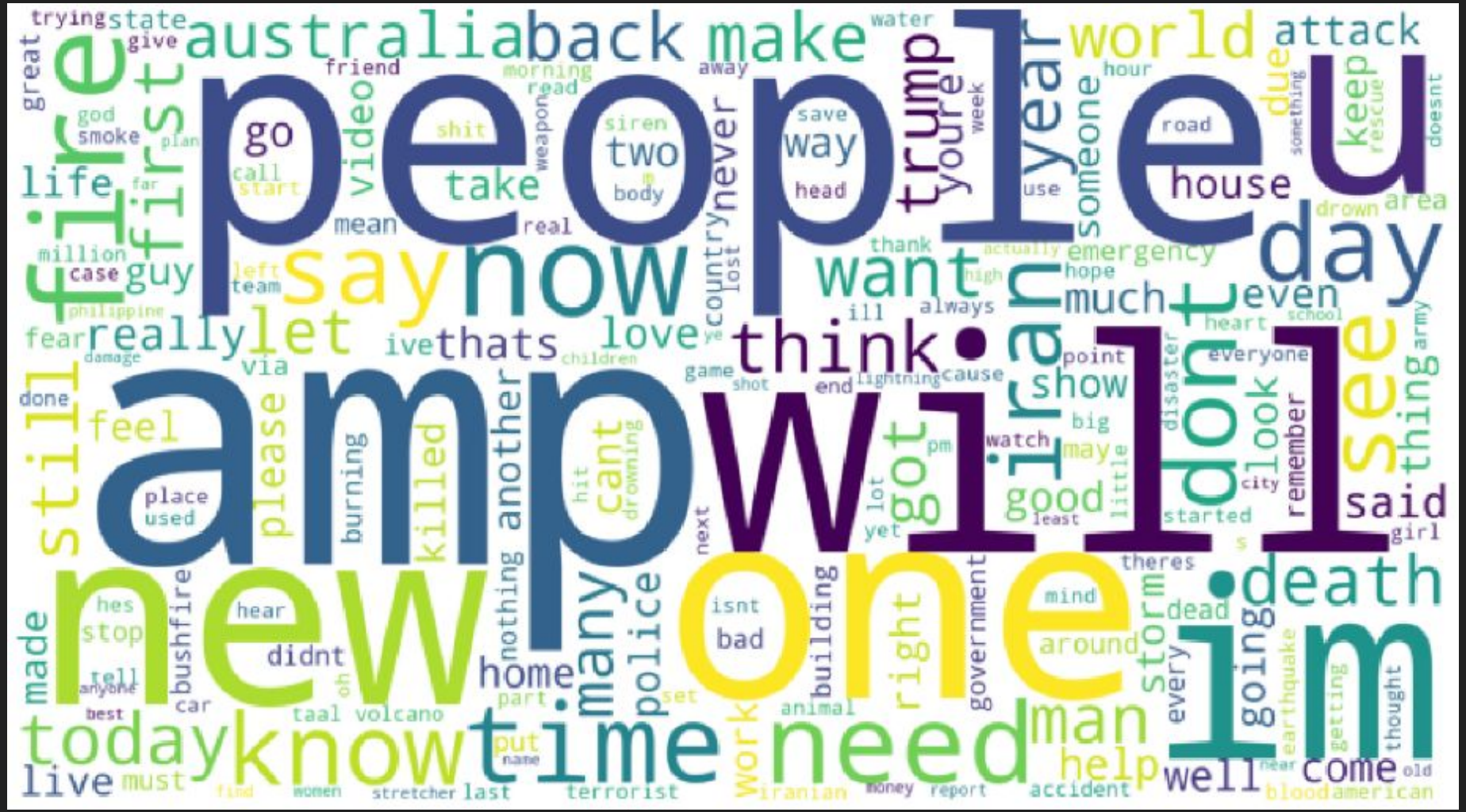


EDA

- Create some plots:
  - Top 20 Words → hbar plot
  - Words per Tweet → histogram
  - Word Cloud


Top 20 Common Words Across Tweets
amp
like
people
im
one
us
dont
get
fire
new
would
time
know
need
first
years
iran
see
think
still
Words
0
100
200
300
400
500
Counts


Number of Words in Tweets
Tweet Counts
3500
3000
2500
2000
1500
1000
500
0
0
5
10
15
20
25
Word Counts


people
amp
will
new
one
australia
fire
back
make
world
attack
first
go
video
two
take
way
trump
year
keep
house
life
say
now
want
day
really
let
love
thats
think
iran
dont
see
much
even
still
feel
please
killed
another
cant
got
show
look
thing
said
death
im
today
know
time
need
many
police
right
work
man
help
well
come
live
made
bushfire
home
didnt
bad
building
government
storm
going
dead
around
stop
tell
car
taal volcano
terrorist
iranian
accident
bloodamerican
u

Preprocessing

- Remove unused columns
- Remove one null row
- Split data into train/test sets
  - 80/20
- Create vectorizers
  - Count
  - TFIDF
- Fit with training features (tweets)
- Transformed training and test features

Modeling

- Tried 5 different classification models
  - Logistic Regression
  - Random Forest
  - KNN
  - SVM
  - Gradient Boosting

Model Hyperparameters

Logistic Regression:

- penalty = l2
- max_iter = 500
- C = 0.1
- solver = lbfgs

KNN:

- n_neighbors = 6
- n_jobs = -1

Gradient Boosting:

- n_estimators = 100
- max_depth = 10
- max_features = auto
- learning_rate =0.1

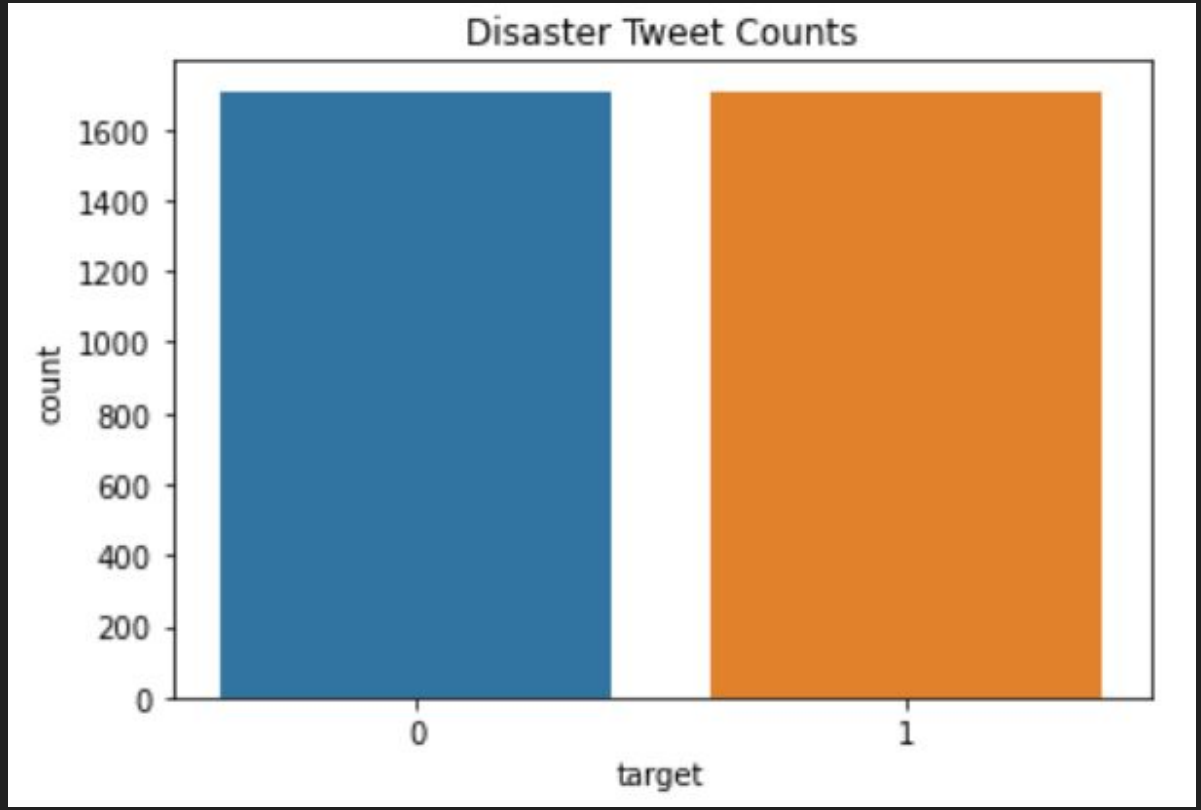
Random Forest:

- n_estimators = 500
- n_jobs = -1

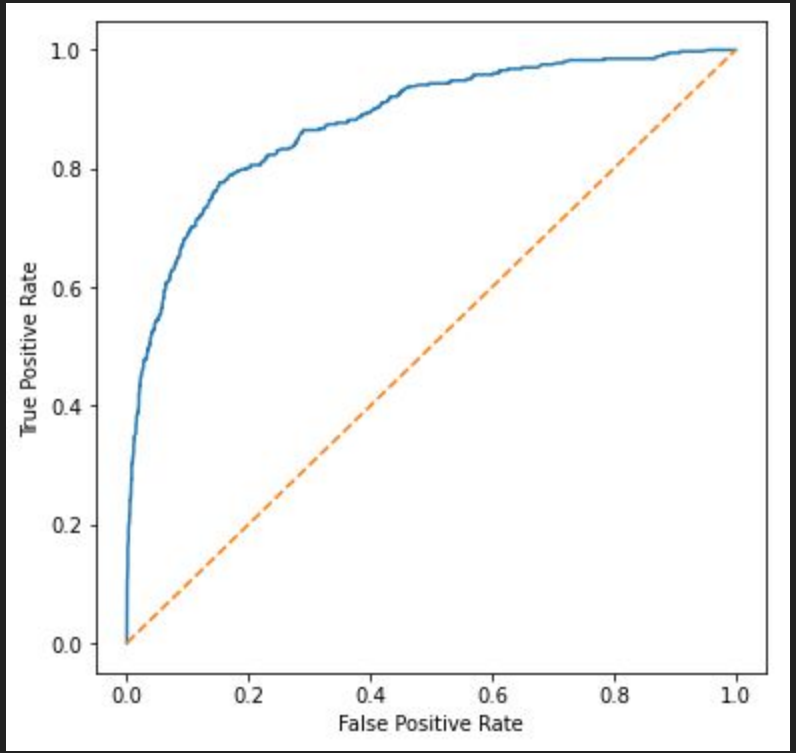
SVM:

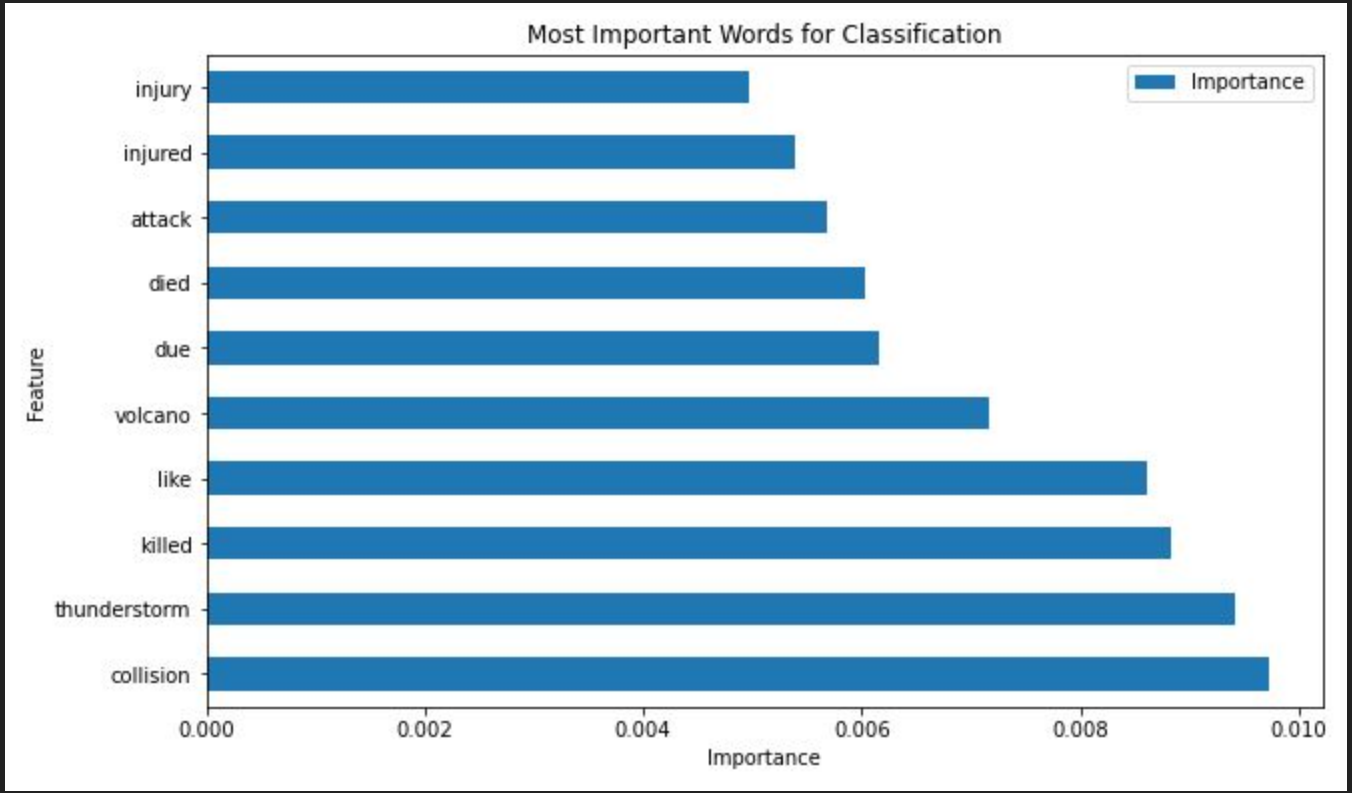
- C= 1
- gamma= 1

Vectorizer	Model	Recall
Count	Logistic Regression	**0.54**
TFIDF	Logistic Regression	0.36
Count	Random Forest	0.49
TFIDF	Random Forest	0.49
Count	KNN	0.20
TFIDF	KNN	0.18
Count	SVM	0.19
TFIDF	SVM	0.44
Count	Gradient Boosting	0.36
TFIDF	Gradient Boosting	0.36


Disaster Tweet Counts
count
1600
1400
1200
1000
800
600
400
200
0
0
1
target

Imbalanced/Balanced	Vectorizer	Model	Recall
Imbalanced	Count	Logistic Regression	**0.54**
Imbalanced	TFIDF	Logistic Regression	0.36
Imbalanced	Count	Random Forest	0.49
Imbalanced	TFIDF	Random Forest	0.49
Imbalanced	Count	KNN	0.20
Imbalanced	TFIDF	KNN	0.18
Imbalanced	Count	SVM	0.19
Imbalanced	TFIDF	SVM	0.44
Imbalanced	Count	Gradient Boosting	0.36
Imbalanced	TFIDF	Gradient Boosting	0.36
Balanced	Count	Logistic Regression	0.75
Balanced	TFIDF	Logistic Regression	0.77
Balanced	Count	Random Forest	**0.78**
Balanced	TFIDF	Random Forest	0.75
Balanced	Count	KNN	0.26
Balanced	TFIDF	KNN	0.20
Balanced	Count	SVM	0.29
Balanced	TFIDF	SVM	0.76
Balanced	Count	Gradient Boosting	0.72
Balanced	TFIDF	Gradient Boosting	0.70


True Positive Rate
False Positive Rate
0.0
0.2
0.4
0.6
0.8
1.0


Most Important Words for Classification
Importance
injury
injured
attack
died
due
volcano
like
killed
thunderstorm
collision
Feature
0.000
0.002
0.004
0.006
0.008
0.010
Importance

Future Scope

- Best model can be used by disaster relief organizations
- Explore more models
  - Deep Learning Neural Networks
- Plot word clouds for subsetted data (TP, TN, FP, FN)
- Similar projects