Philipps Universität Marburg

Introduction to Natural Language Processing

Natural Language Processing with Disaster Tweets

Predict which Tweets are about real disasters & which ones are not

Son Nghiem
Report + Coding

Kien Nguyen
Slides + Coding

Visit our Project

Data Description

Size: ~11K Tweets

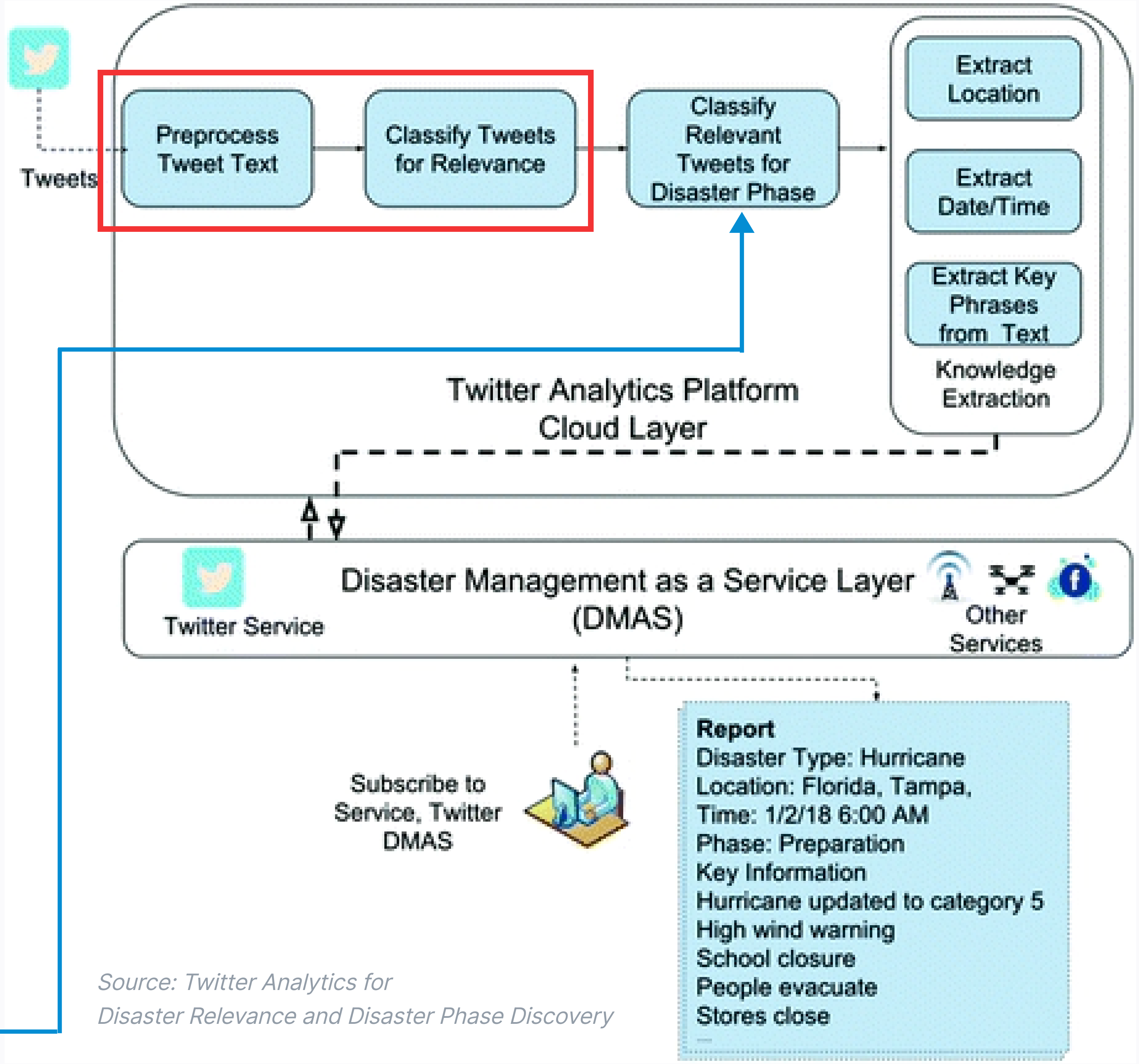
(70% Training + 30% Test)

Evaluation Metric

$$F_\beta = \frac{(\beta^2 + 1)PR}{\beta^2 P + R}$$

Set **Beta** = **0.5**

(**P**recision is *more important* than **R**ecall)



Source: Twitter Analytics for Disaster Relevance and Disaster Phase Discovery

Features of Interest

BEFORE

URL
Punctuation
Hashtag
Mention
— count per Tweet

Most common — Hashtags, Keywords, Locations, Named entity types

AFTER

Character
Word
Unique word
Average word length
— count per Tweet

Most common — Unigrams, Bigrams, Trigrams, Fourgrams

Transformation

Relabel mislabeled samples (training set only)

Convert POS tags to Wordnet format

text	target	relabeled target	cleaned text	tokenized	lowercased	lowercased text	...	text without stopwords	pos tags	wordnet pos	lemmatized	lemmatized text
Our Deeds are the Reason of this #earthquake M...	1	1	Our Deeds are the Reason of this earthquake Ma...	[Our, Deeds, are, the, Reason, of, this, earth...	[our, deeds, are, the, reason, of, this, earth...	our deeds are the reason of this earthquake ma...	...	deeds reason earthquake may allah forgive us	[(deeds, NNS), (reason, NN), (earthquake, NN),...	[(deeds, n), (reason, n), (earthquake, n), (ma...	[deed, reason, earthquake, may, allah, forgive...	deed reason earthquake may allah forgive u

Remove URLs, HTML tags, Emojis, punctuation marks

Apply Wordnet lemmatizer

Adding Potential Indicators

Potential Indicators

lemmatized text	url count	character count	bigram	disaster bigram count	non disaster bigram count
deed reason earthquake may allah forgive u	-0.934365	-0.492126	[allah forgive, deeds reason, earthquake may, ...	-0.483609	-0.960491

Standardized values

From most common N-grams to Disaster/Non-Disaster N-gram count

The greater the number N, the more disaster-relevant/irrelevant the most common N-grams in Disaster/Non-Disaster Tweets become, but also the less frequent they are.

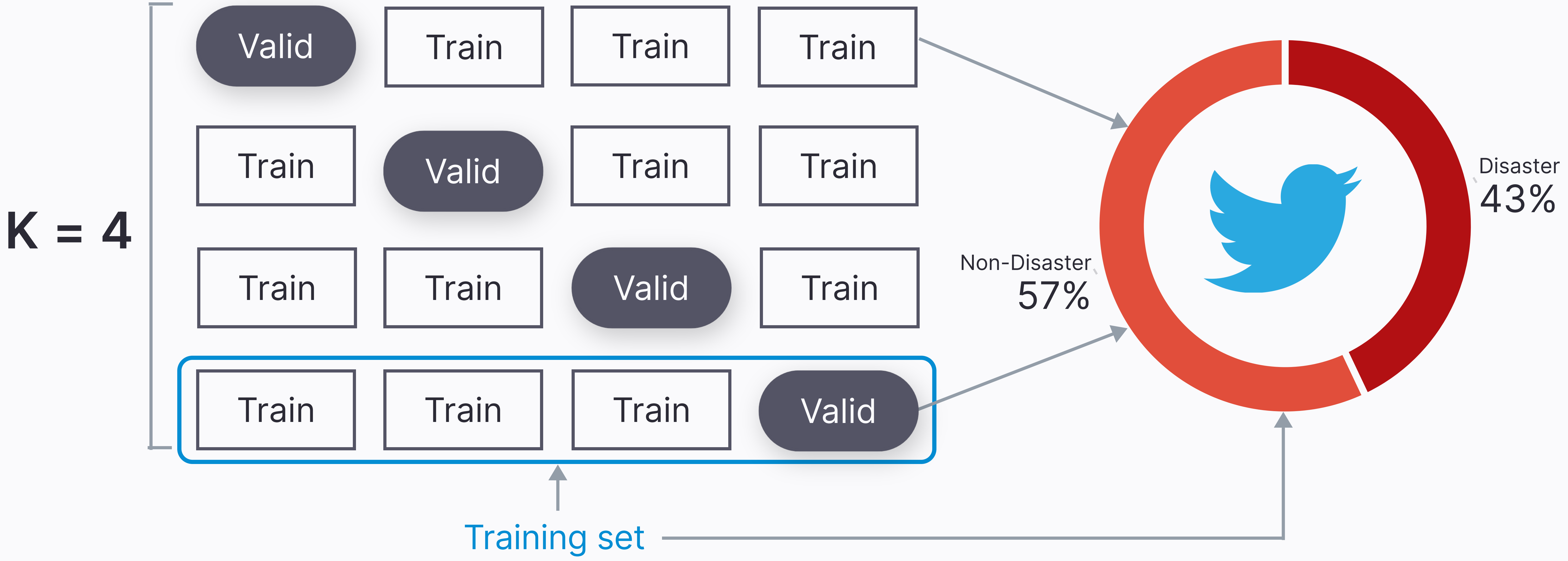
Problem

Is having any of the most common N-grams in Disaster Tweets suitable as a potential indicator?
No, as for large N, many Disaster Tweets will be flagged as *No*.

Solution

Create two lists of disaster-relevant & -irrelevant [N]-grams from the most common [N+2]-grams in Disaster & Non-Disaster Tweets

Stratified Cross Validation



Embedders

	Implementation	Vector Dimension
Bag-of-Words	• Use *sklearn.CountVectorizer* to **embed Tweets**	Vocabulary size
TF-IDF	• Use *sklearn.TfidfVectorizer* to **embed Tweets**	Vocabulary size
GloVe	• Download the pretrained corpus model *glove.twitter.27B.50d.txt* • **Embed words then Tweets** by using the model	50
Word2Vec	• Download the pretrained corpus model *word2vec-google-news-300* • **Embed words then Tweets** by using the model	300
Sentence-BERT	• *Continue training* the fine-tuned model *paraphrase-MiniLM-L6-v2* on labeled pairs of Disaster & Non-Disaster Tweets • Use the continue-trained model to **embed Tweets**	384

Classifiers

Logistic Regression

L2 Regularization

Inverse of regularization strength **C** = **1.0**

Multilayer Perceptron

ReLU activation

One hidden layer (**100** neurons)

Max #Iterations **200**

Constant learning rate **0.001**

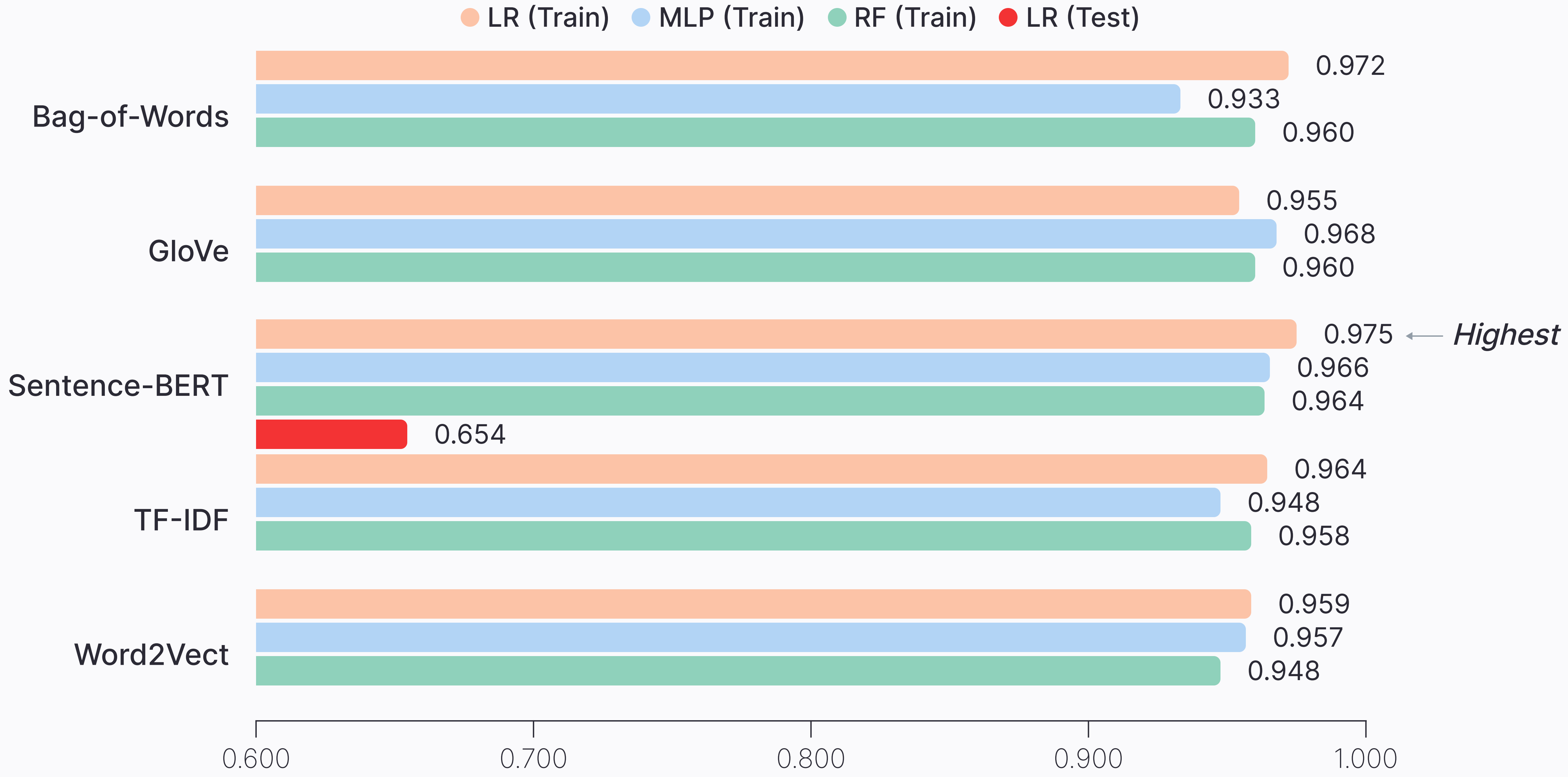
Random Forest

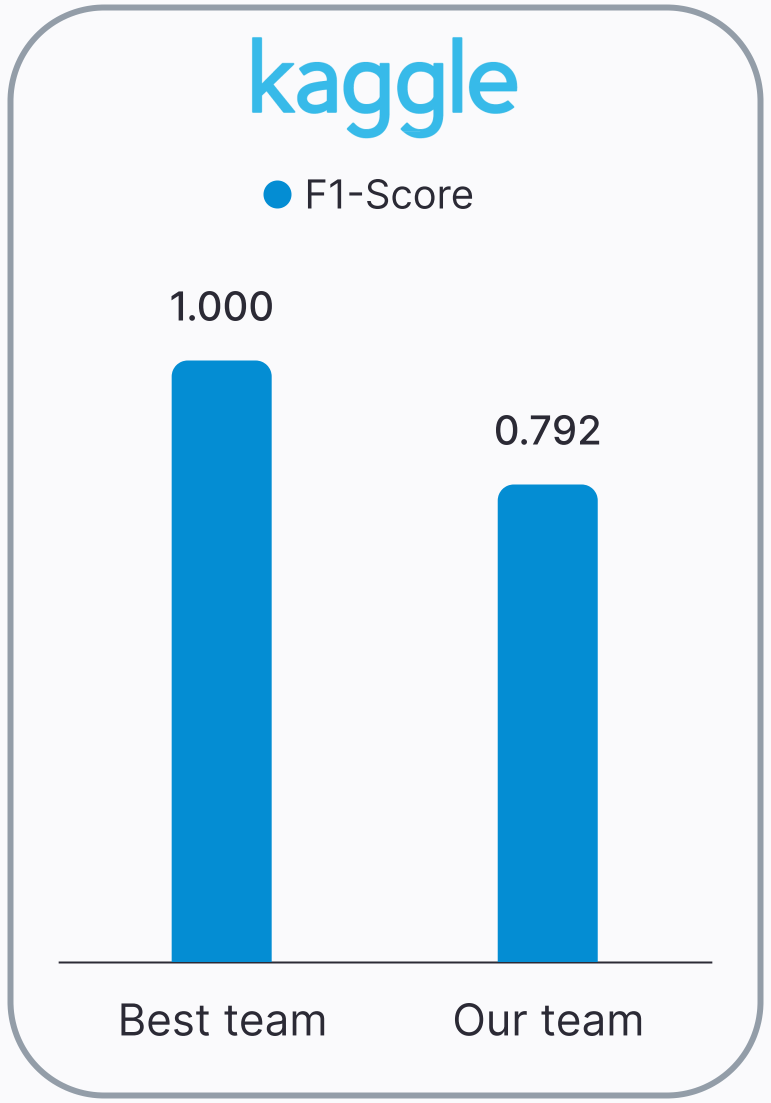
100 Decision Trees

Gini Impurity as split criteria

Build trees **with Bootstrapping**

Results


LR (Train)
MLP (Train)
RF (Train)
LR (Test)
Bag-of-Words
0.972
0.933
0.960
GloVe
0.955
0.968
0.960
Sentence-BERT
0.975
Highest
0.966
0.964
0.654
TF-IDF
0.964
0.948
0.958
Word2Vect
0.959
0.957
0.948
0.600
0.700
0.800
0.900
1.000


kaggle
F1-Score
1.000
0.792
Best team
Our team

Discussion

PROBLEM	OPTIMIZATION
Human error during labeling test set	Label test set with a gold standard model
No hyperparameter tuning for Logistic Regression Classifier	Hyperparameter Optimization with Random Search & Grid Search
Only one training epoch for Sentence-BERT Embedder	Increase the number of training epochs
Inaccurate & incomplete training samples for Sentence-BERT Embedder	Preprocess samples before training
Possibility of added potential indicators being insignificant	Treat potential indicator choices as hyperparameters during fine-tuning
Possibility of overfitting data and inadequately cleaned Tweets	Apply stronger regularization and stricter data cleaning