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

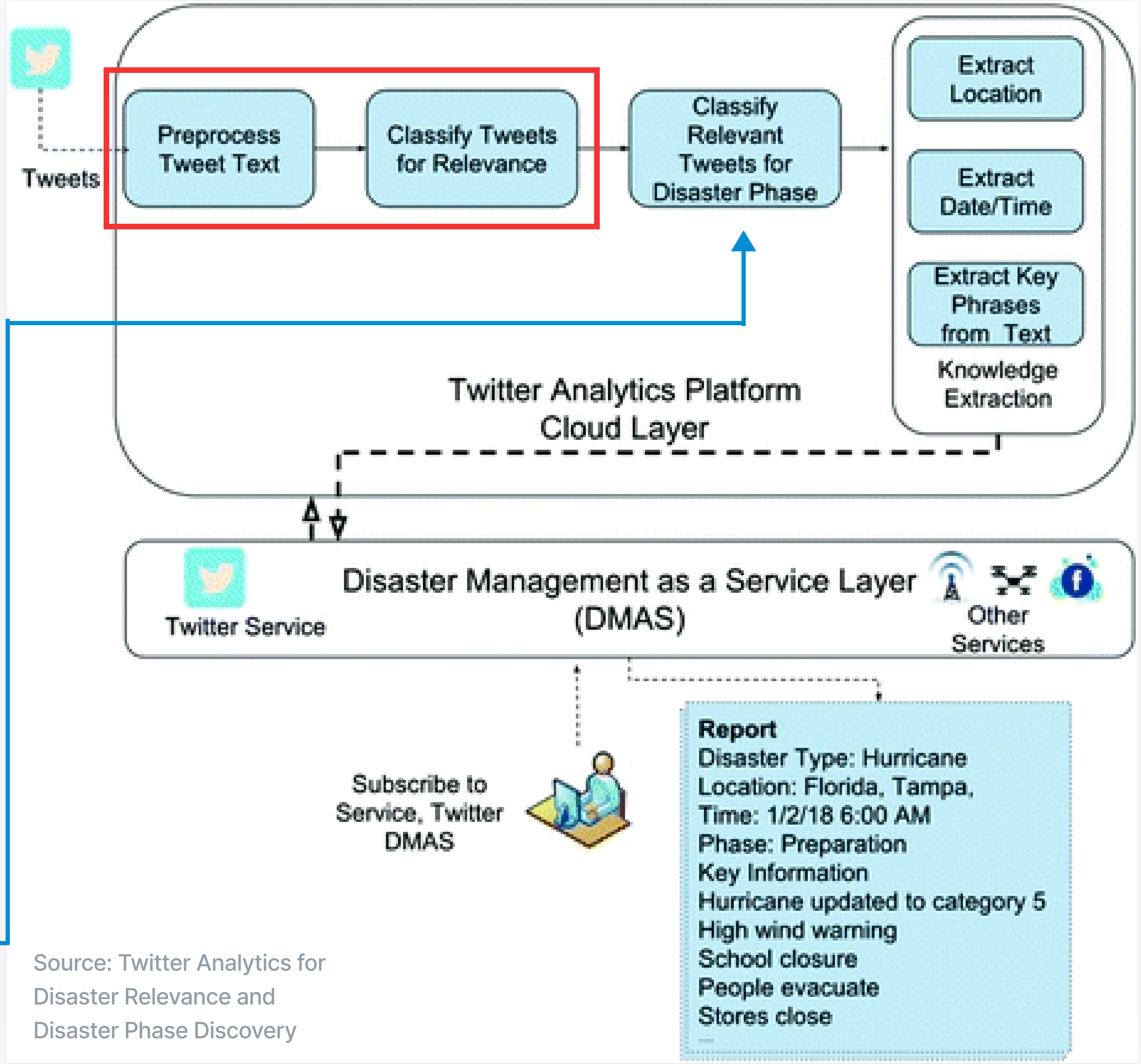
(70% Training + 30% Test)

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

Philipps Universität Marburg

Data Analysis · **Data Preprocessing** · Applying Models · Evaluation

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.

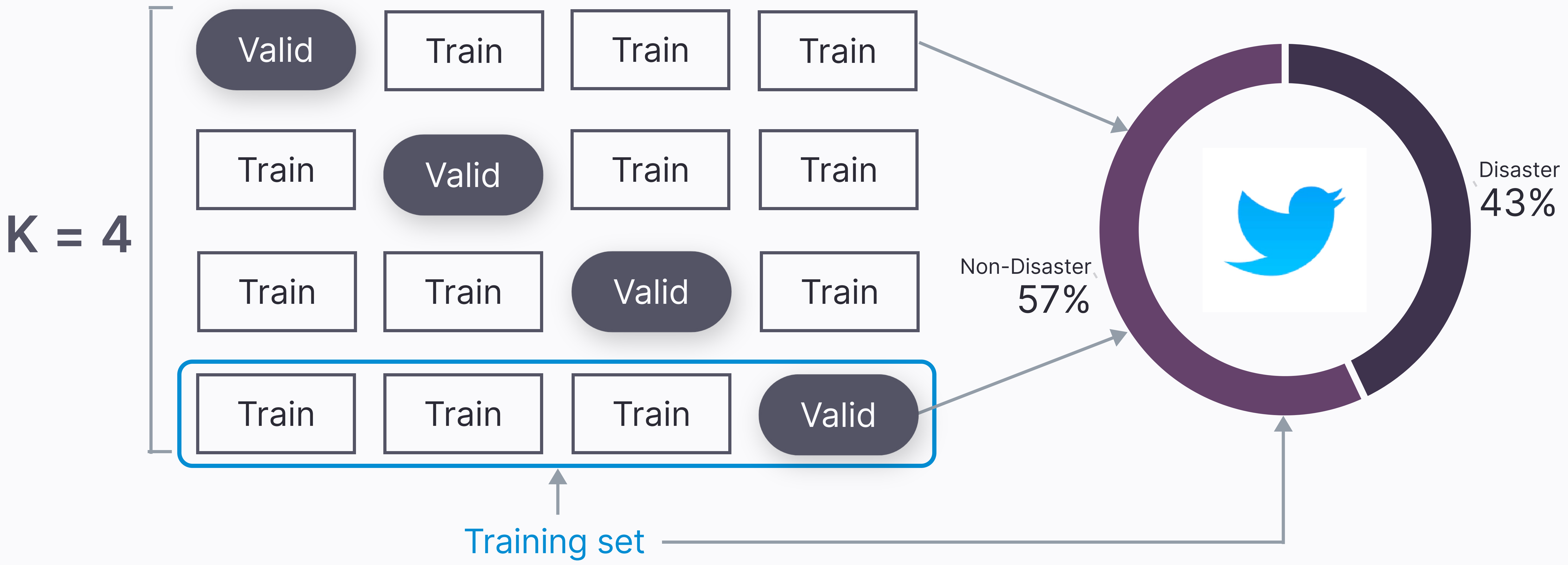
Problem:

- "Has any of the most common N-grams in Disaster Tweets" as potential indicator?
  ⇒ For high N, many Disaster Tweets will be flagged as "No"

Solution:

1. Create two lists of disaster-relevant/irrelevant N-grams from the most common [N+2]-grams in Disaster/Non-Disaster Tweets
2. Count the number of N-grams of each Tweet in each of those lists

Stratified Cross Validation



Embedders

	Implementation	Vector Dimension
Bag-of-Words	• Use "sklearn.CountVectorizer" to embed Tweets directly	Vocabulary length
GloVe	• Download the pretrained corpus model "glove.twitter.27B.50d.txt" • Embed every word by using the downloaded model • Embed every Tweet by taking the mean vector of all the words in a Tweet as its embedding	50 (constant)
Sentence-BERT	• Continue training the fine-tuned Sentence Transformer model "paraphrase-MiniLM-L6-v2" on pairs of Disaster and/or Non-Disaster Tweets in training set • Use the continue-trained model to embed Tweets directly	384 (constant)

Embedders

	Implementation	Vector Dimension
TF-IDF	• Use "sklearn.TfidfVectorizer" to embed Tweets directly	Vocabulary length
Word2Vec	• Download the pretrained corpus model "word2vec-google-news-300" • Embed every word by using the downloaded model • Embed every Tweet by taking the mean vector of all the words in a Tweet as its embedding	300 (constant)

Classifiers

Logistic Regression

L2 Regularization

Multilayer Perceptron

ReLU activation

One hidden layer with **100** neurons

Max #Iterations **200**

Constant learning rate **0.001**

Random Forest

100 Decision Trees

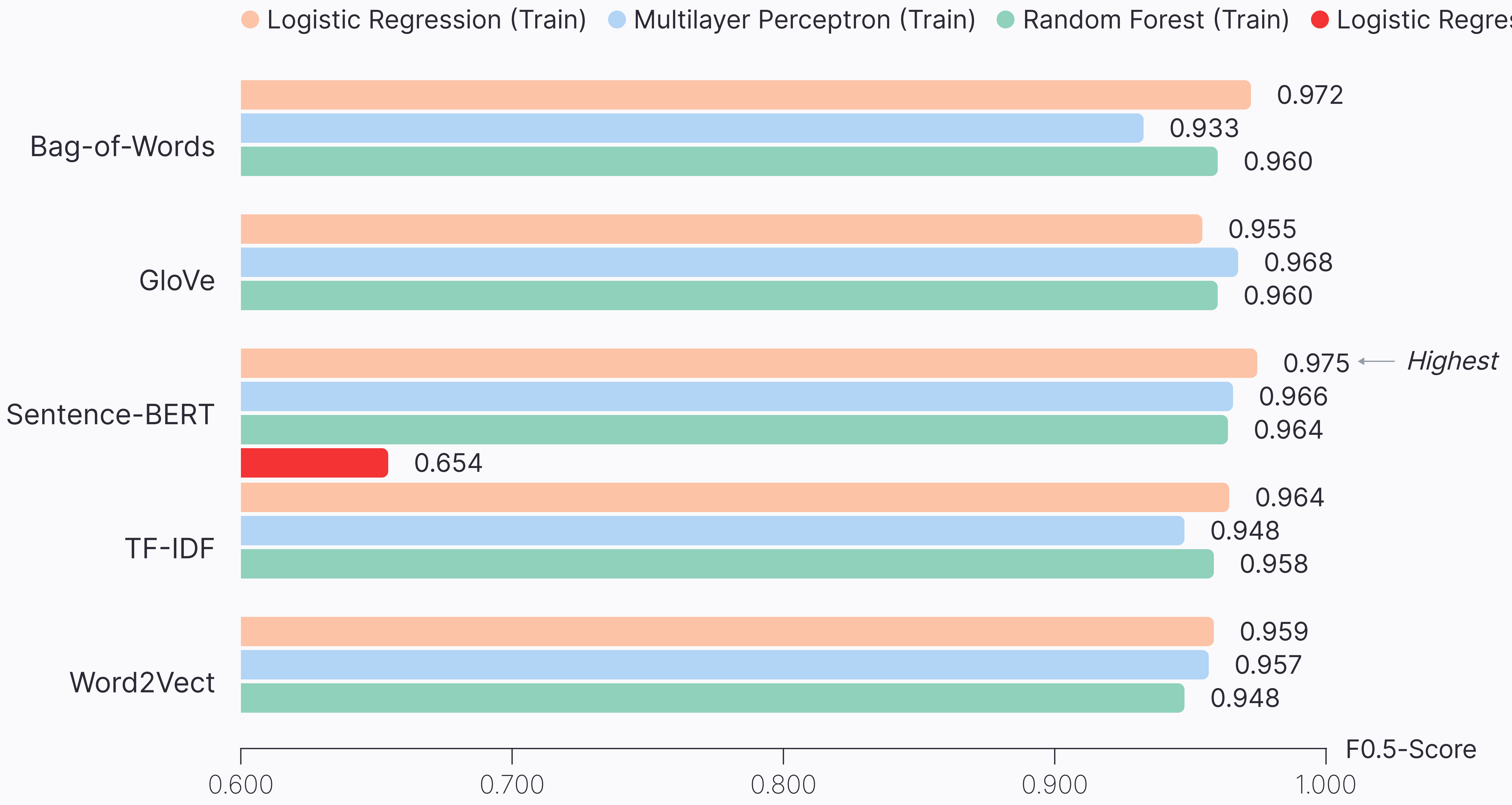
Gini Impurity as split criteria

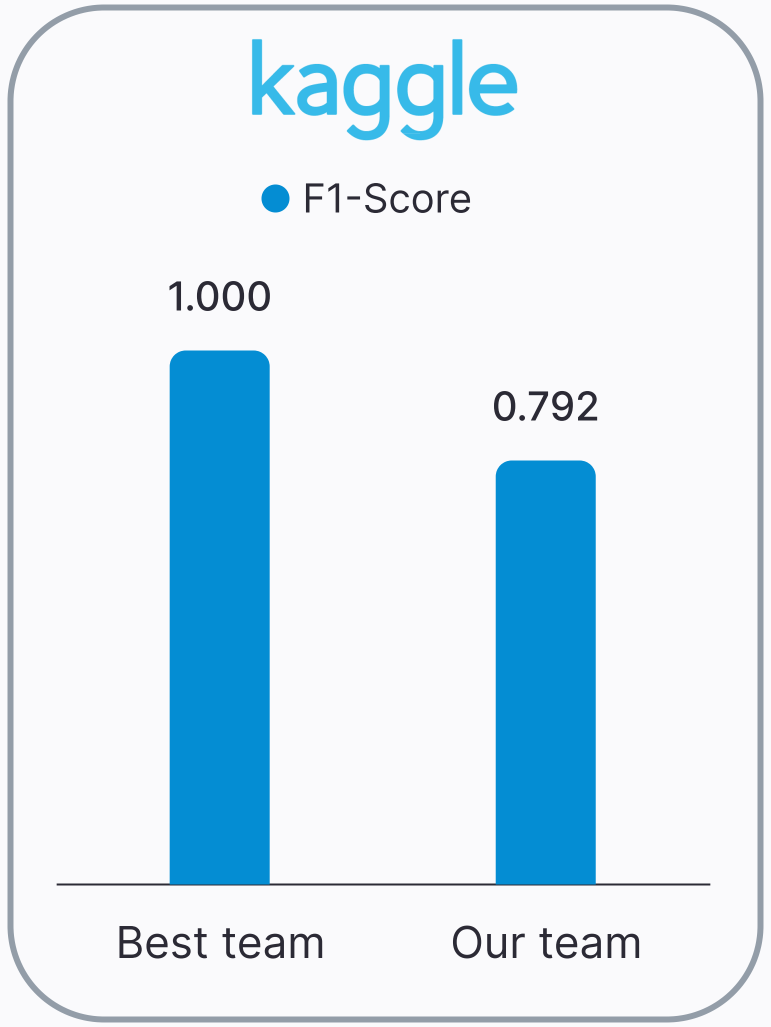
Build trees **with Bootstrapping**

Philipps Universität Marburg

Data Analysis · Data Preprocessing · Applying Models · **Evaluation**

Results





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 for Sentence-BERT Embedder
Inaccurate & incomplete training samples for Sentence-BERT model	Evaluate samples systematically before training Sentence-BERT model
Possibility of added potential indicators being insignificant	Treat potential indicator choices as hyperparameters during fine-tuning