CAPITOL

Classifying American Political Ideologies Through Online Language

Universita' degli Studi di Pavia
Bachelor degree in Artificial Intelligence
A.Y. 2024-45

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INTRODUCTION

1

Project Objective:

Classify American political ideologies by analysing tweets to distinguish between democratic and republican content.

2

Model Development:

Developed and evaluated models for binary classification using labeled political tweets focusing on text content to identify political affiliation.

3

Text Representation Approaches:

2 main text representation approaches were explored: TF-IDF vectorisation with traditional classifiers and pretrained word embeddings with LSTM networks.

DATASET

DATASET

ind...	date object	id int64	username object	text object
0 - ...	2021-04-19 ... 0% 2021-07-09 ... 0% 29358 others 100%	135168...		
0	2021-10-13 19:47:44	14483...	SenatorHassan	Happy th birthday to the @USN
1	2021-06-30 14:53:13	14102...	SenatorMenendez	The greatest generation's inves
2	2021-08-08 01:11:29	14241...	SenBillCassidy	Thanks to @SenTedCruz and @
3	2021-04-14 14:02:49	13823...	SenBlumenthal	/ To get lasting change we cant
4	2021-12-11 16:06:38	14697...	SenatorBraun	Today were celebrating years o
5	2021-05-11 17:18:50	13921...	SenJeffMerkley	The #ForthePeopleAct includes
6	2021-08-10 16:22:55	14251...	SenBlumenthal	Todays strong, bipartisan vote i
7	2021-08-12 01:13:26	14256...	SenatorHagerty	Supporting crime victims requir
8	2021-12-11 16:27:51	14697...	SenBillCassidy	We in Louisiana know how natu
9	2021-01-20 13:55:04	13518...	CoryBooker	Today we start anew.

Using 2 features:
tweets text and labels 0, 1 for Democrat and Republican

PoliticalTweets from Hugging Face:

DATA ANALYSIS

49.3% vs 50.7%

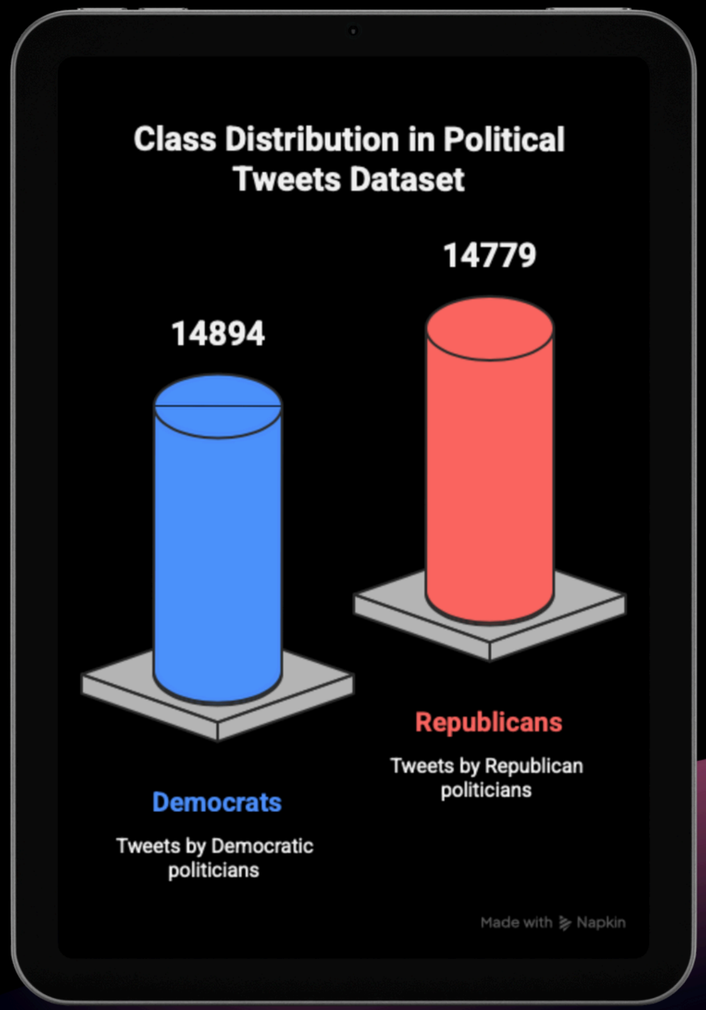
Class distribution

25-40 words

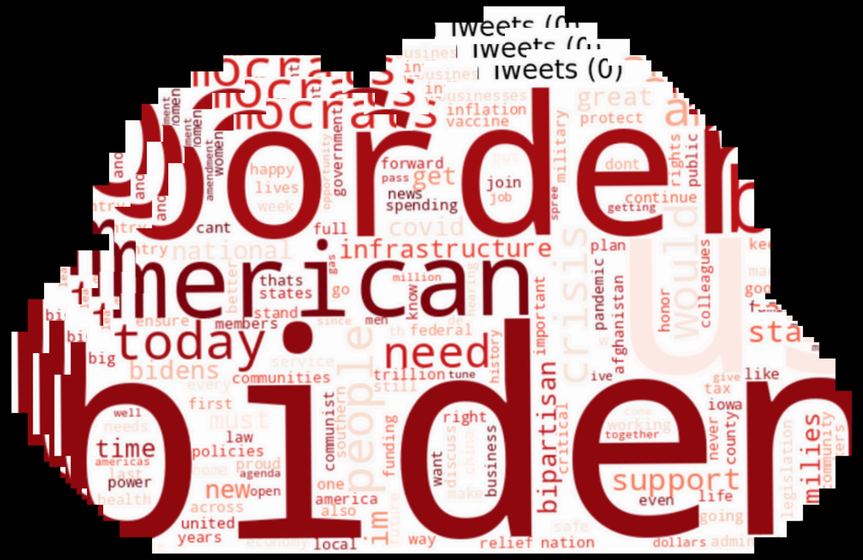
Word Count Skewness

214.82 chars

Average tweet length



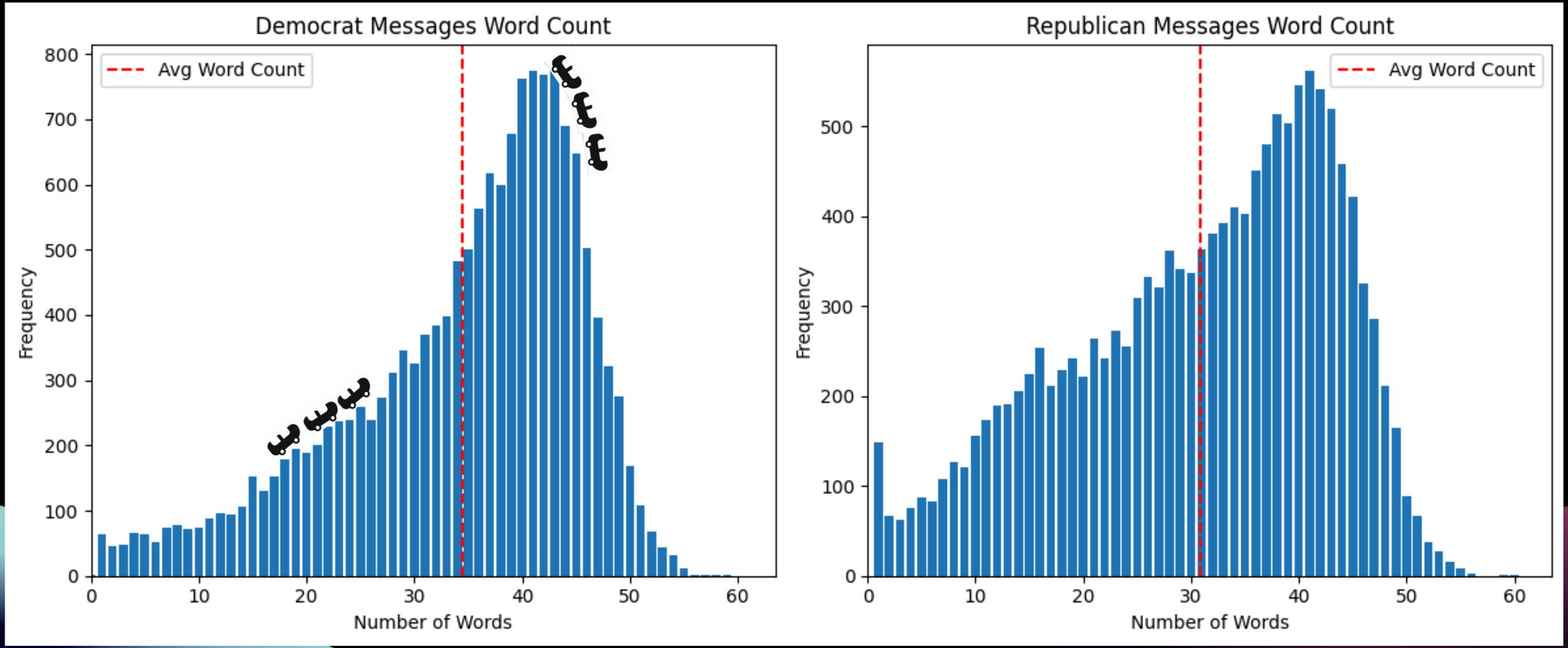
WORD CLOUD

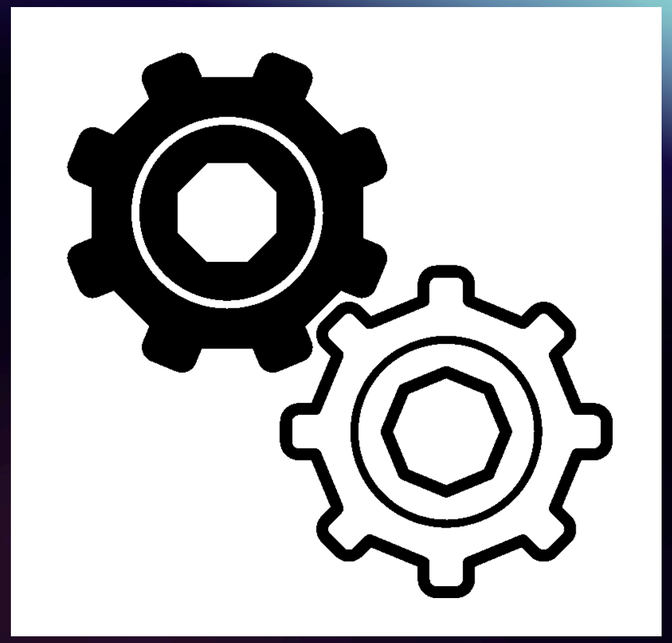


GOP.

DEMOCRATS

WORD COUNT


Democrat Messages Word Count
Avg Word Count
Frequency
Number of Words
0
100
200
300
400
500
600
700
800
0
10
20
30
40
50
60
Republican Messages Word Count
Avg Word Count
Frequency
Number of Words
0
100
200
300
400
500
0
10
20
30
40
50
60

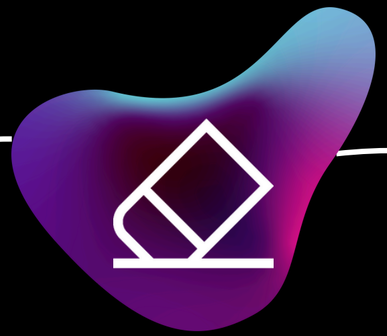


PREPROCESSING

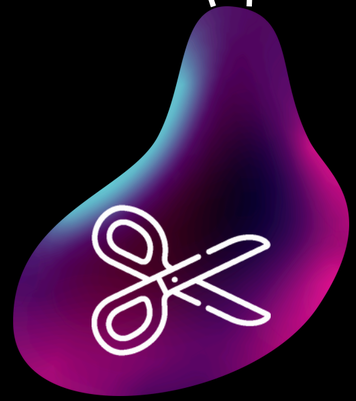
PREPROCESSING PIPELINE

Text normalisation

Hashtag preprocessing



Emoji removal

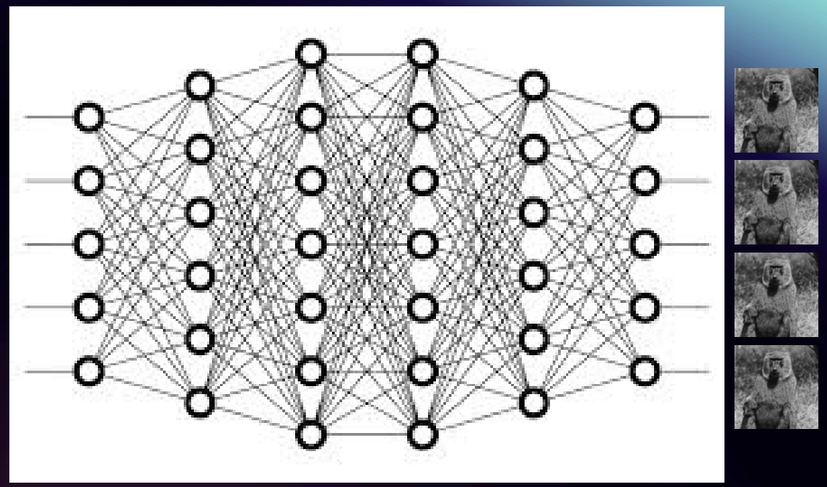


Regex cleaning

Stopwords filtering

PREPROCESSING PIPELINE

```python
def clean_text(text):
    text = str(text).lower()
    hashtags = re.findall(r"#\w+", text)
    for tag in hashtags:
        split_words = wordninja.split(tag.lstrip("#"))
        text = text.replace(tag, " ".join(split_words))
    text = emoji.replace_emoji(text, replace='')
    text = re.sub(r'\n', '', text)                                  # newline
    text = re.sub(r'@\w+', '', text)                                # menzioni (@user)
    text = re.sub(r'http\S+|www\S+|https\S+', '', text, flags=re.MULTILINE)  # link
    text = re.sub(r'\w*\d\w*', '', text)                            # parole con numeri
    text = re.sub(r'[^\x00-\x7F]+', '', text)                       # caratteri n
    text = re.sub('[%s]' % re.escape(string.punctuation), '', text) # punteggiat
    return text
```



MODELS AND ARCHITECTURES

FEATURE REPRESENTATION

TF-IDF vectorisation

Sparse vectors

No word order

No semantics

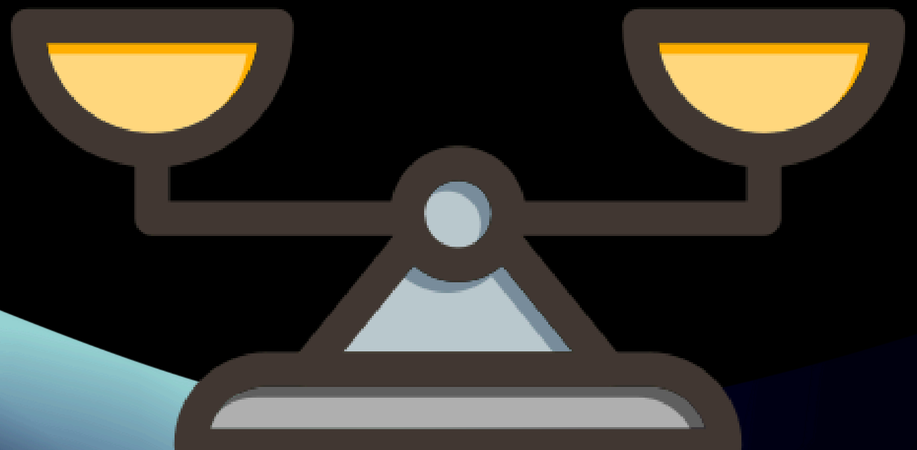
VS

Pretrained word embeddings

Dense vectors

Neural network architecture

Capture semantic relationships



MODEL ARCHITECTURES

TF-IDF	TF-IDF	GloVe	FastText
XGBoost	Logistic Regression	LSTM	LSTM

TF-IDF

$$w_{i,j} = tf_{i,j} \cdot \log\left(\frac{N}{df_i}\right)$$

- “The - is not a minus, it’s an hyphen”
- Count the number of occurrences in a document (x_train).
- Offset by the number of documents in the corpus that contain the word
- It's a numerical statistic that is intended to reflect how important a word is to a document in a collection or corpus

```python
X_train = list(df_train['text_cleaned'])
X_test = list(df_test['text_cleaned'])

# TF-IDF stands for:
# TF = Term Frequency: how often a word appears in a document.
# IDF = Inverse Document Frequency: how rare a word is across all documents.
# a high TF-IDF value = a term that's frequent in this document and rare elsewhere

vectorizer = CountVectorizer(vocabulary = vocab) # matrix of token counts
transformer = TfidfTransformer()

# TD-IDF for training data
X_train = vectorizer.fit_transform(X_train)
X_tfidf_train = transformer.fit_transform(X_train)

# TD-IDF for test data
X_test = vectorizer.transform(X_test)
X_tfidf_test = transformer.transform(X_test)

print(X_tfidf_train.shape, X_tfidf_test.shape)
```

TF-IDF

XGBoost

- Model that trains a fixed number of decision trees. Each tree is trained on a subset of the data.

```python
# XGBOOST MODEL

pipe = Pipeline([
    ('model', xgb.XGBClassifier(
        learning_rate=0.1,
        max_depth=11,
        n_estimators=80,
        use_label_encoder=False,
        eval_metric='auc'
    ))
])

pipe.fit(X_train, y_train)

y_pred_class_xgb = pipe.predict(X_test)
y_pred_train_xgb = pipe.predict(X_train)

print('Train: {}'.format(accuracy_score(y_train, y_pred_train_xgb)))
print('Test: {}'.format(accuracy_score(y_test, y_pred_class_xgb)))

acc_train_xgb = accuracy_score(y_train, y_pred_train_xgb)
acc_test_xgb = accuracy_score(y_test, y_pred_class_xgb)
report_xgb = classification_report(y_test, y_pred_class_xgb)

print("XGBoost classification report:")
print(report_xgb)

conf_xgb = confusion_matrix(y_test, y_pred_class_xgb)
print(conf_xgb)
```

TF-IDF

Logistic Regression

- Supervised learning algorithm for classification. Models the probability that an input belongs to a class using the logistic (sigmoid) function.

```
# LOGISTIC REGRESSION MODEL

pipe = Pipeline([
    ('model', LogisticRegression(
        solver='lbfgs',
        max_iter=1000,
        multi_class='auto'
    ))])

pipe.fit(X_train, y_train)

y_pred_class_log = pipe.predict(X_test)
y_pred_train_log = pipe.predict(X_train)

print('Train: {}'.format(accuracy_score(y_train, y_pred_train_log)))
print('Test: {}'.format(accuracy_score(y_test, y_pred_class_log)))

acc_train_log = accuracy_score(y_train, y_pred_train_log)
acc_test_log = accuracy_score(y_test, y_pred_class_log)
report_log = classification_report(y_test, y_pred_class_log)

print("Logistic Regression classification report:")
print(report_log)

conf_log = confusion_matrix(y_test, y_pred_class_log)
print(conf_log)
```

GloVe

- Unsupervised learning algorithm for word embeddings. It builds vectors by aggregating global word-word co-occurrence statistics from a corpus.

glove.6B.100d.txt (347.12 MB)

This preview is truncated due to the large file size. Create a Notebook or download this file to see the full content. **Download** **Create Notebook**

```
the -0.038194 -0.24487 0.72812 -0.39961 0.083172 0.043953 -0.39141 0.3344 -0.57545 0.087459 0.28787 -0.06731 0.30906 -0.26384 -0.13231 -0.20757 0.33395 -0.33848 -0.31743 -0.48336 0.1464 -0.37304 0.34577 0.052041 0.44946 -0
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- -1.2557 0.61036 0.56793 -0.96596 -0.45249 -0.071696 0.57122 -0.31292 -0.43814 0.90622 0.06961 -0.053104 0.25029 0.27841 0.77724 0.26329 0.56874 -1.1171 -0.078268 -0.51317 0.8071 0.99214 0.22753 1.0847 0.88292 0.17221 -0.
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was 0.13717 -0.54287 0.19419 -0.29953 0.17545 0.084672 0.67752 0.098295 -0.035611 0.21334 0.51663 0.20687 0.44082 -0.33655 0.56025 -0.6879 0.51957 -0.21258 -0.52708 -0.12249 0.33099 0.026448 0.59067 0.0065469 0.45405 -0.3
said -0.13128 -0.452 0.043399 -0.99798 -0.21053 -0.95868 -0.24609 0.48413 0.18178 0.475 -0.22305 0.30064 0.43496 -0.3605 0.20245 -0.52594 -0.34708 0.0075873 -1.0497 0.18673 0.57369 0.43814 0.098659 0.3877 -0.2258 0.41911 0
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```

FastText

- Word embedding model by Facebook. Extends Word2Vec by representing words as bags of character n-grams, capturing subword information.

$$h_w = \sum_{g \in w} x_g$$

mang erai ange
man ang era gera
nge ger rai nger

Character n-grams

+

mangerai

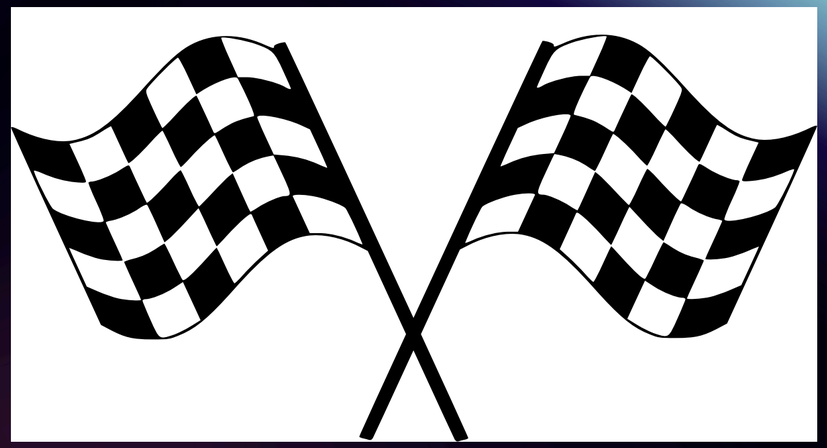
Word itself

Glove or FastText

LSTM

- Subtype of Recurrent Neural Networks (RNN). Used to recognize patterns in data sequences.
- Take as input also the embedding matrix

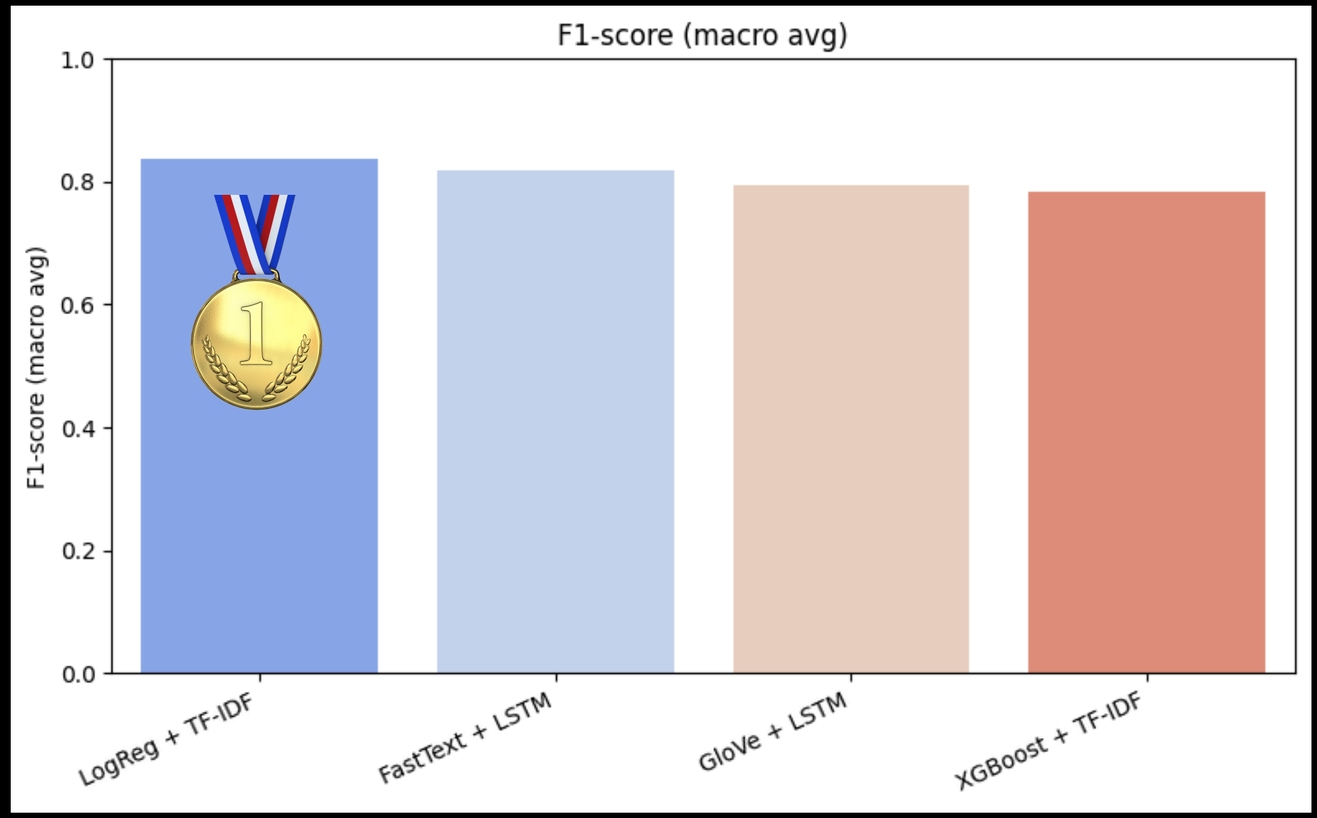
```python
def create_model(embedding_matrix,
                 LOSS = 'binary_crossentropy',
                 learning_rate=0.01,
                 hidden_act='relu',
                 dropout_rate=0.2):

    text_input = Input(shape=(max_len,), name='text_input')

    # Embedding layer suitable for both GloVe and FastText
    embedding = Embedding(input_dim=vocab_size,
                          output_dim=embedding_matrix.shape[1],
                          weights=[embedding_matrix],
                          input_length=max_len,
                          trainable=False,
                          name='embedding')(text_input)
    # RNN layer
    lstm = LSTM(units=128,
                activation='tanh',
                recurrent_activation='sigmoid',
                kernel_initializer='glorot_uniform',
                return_sequences=False,
                name='lstm')(embedding)

    # Dense layers with dropout
    x = Dense(64, activation=hidden_act, kernel_initializer='he_uniform', kernel_regularizer='l2')(lstm)
    x = Dropout(dropout_rate)(x)

    x = Dense(32, activation=hidden_act, kernel_initializer='he_uniform', kernel_regularizer='l2')(x)
    x = Dropout(dropout_rate)(x)

    # Output layer for binary classification
    output = Dense(1, activation='sigmoid', name='output')(x)

    model = Model(inputs=text_input, outputs=output)
    model.compile(
        optimizer=Adam(learning_rate=learning_rate),
        loss=LOSS,
        metrics=['accuracy']
    )

    return model
```



RESULTS

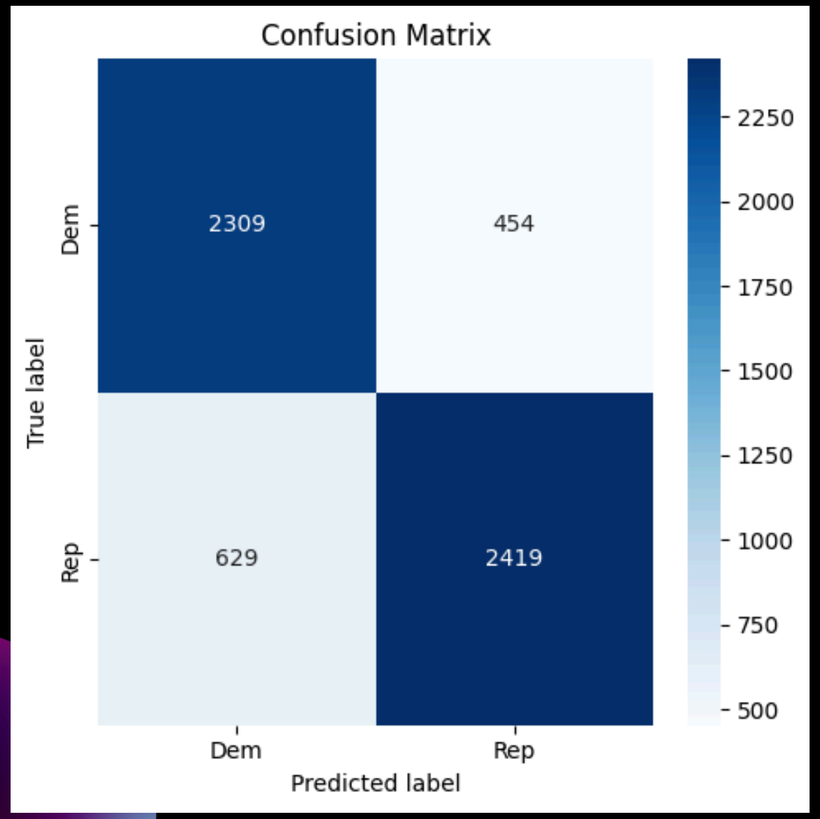
AND THE WINNER IS...

TF-IDF + Logistic Regression!

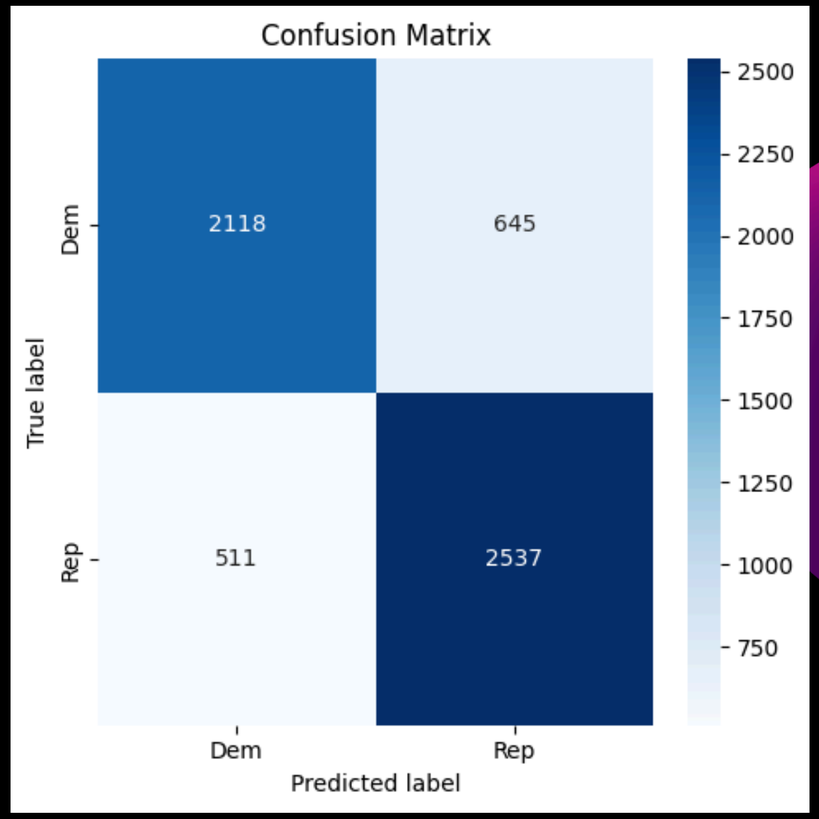


...2nd and 3rd place...

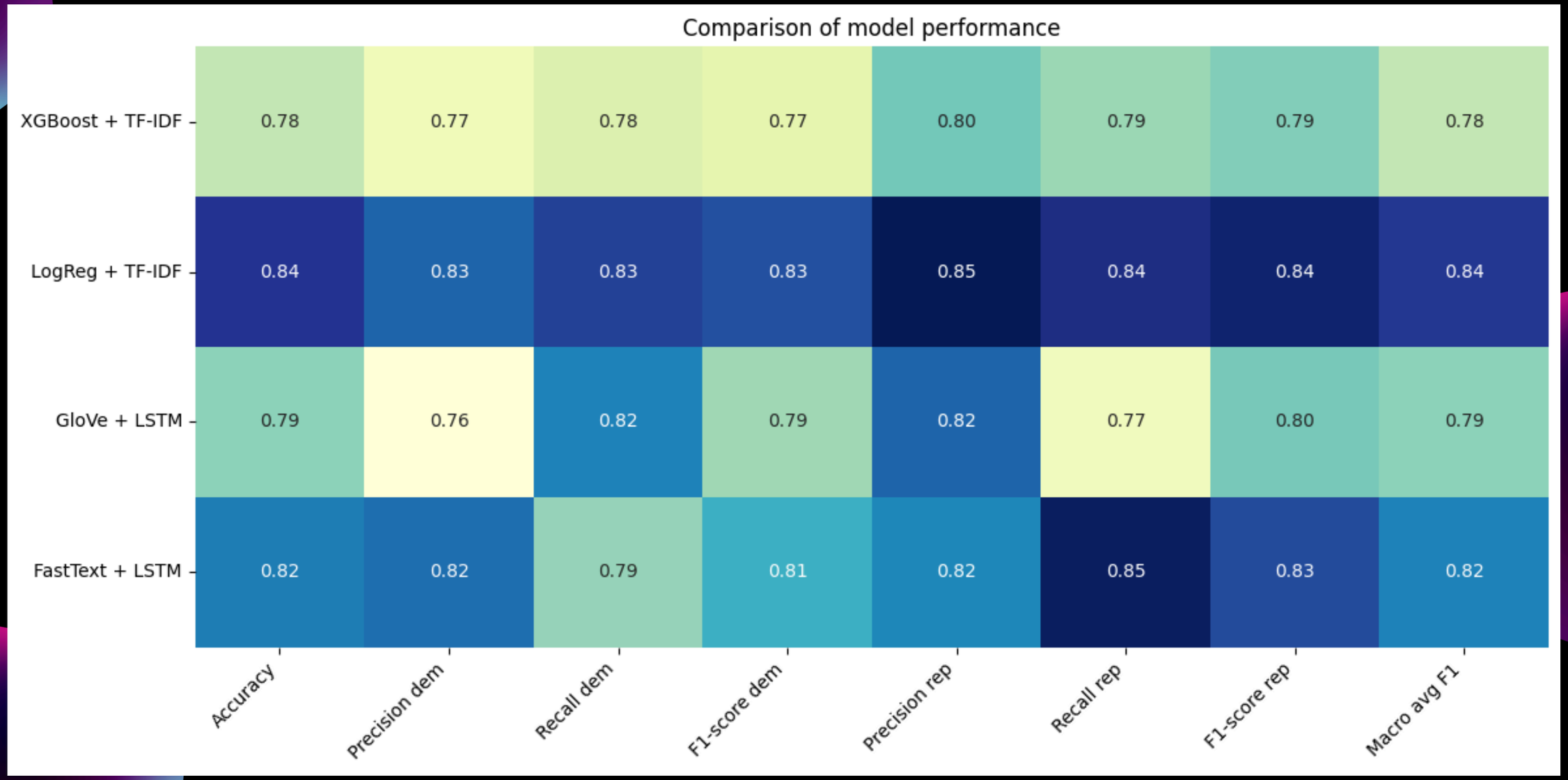
FastText + LSTM



GloVe + LSTM



RESULTS AND ANALYSIS



SOURCES

GLOVE:
HTTPS://NLP.STANFORD.EDU/PROJECTS/GLOVE/

HUGGINGFACE:
HTTPS://HUGGINGFACE.CO/DATASETS/JACOBVS/POLITICALTWEETS

CANVA:
HTTPS://WWW.CANVA.COM

DEEPNOTE:
HTTPS://DEEPNOTE.COM

THANK YOU FOR THE ATTENTION!