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Project Deadline: 11/25/2021

Problem Description

The term hate speech is any form of expression (verbal, written, or behavioral communication) that attacks or uses derogatory or discriminatory language against a person or group. This hate could be towards religion, ethnicity, nationality, race, color, ancestry, sex, or other identity factors. In this problem, we need to build a machine learning model that predicts which tweets have hate speech in them.

Hate Speech Detection is generally a task of sentiment classification. To classify hate speech from a piece of text, we need to train the model on data used to classify sentiments. So for the task of the hate speech detection model, we will use Twitter tweets to identify tweets containing hate speech.

Business Understanding

Organizations need to consider customers' mentality and what type of audience they are offering their products to, but dealing with the immediacy of user feedback is not an easy task, especially when the speech turns offensive. Our goal is to build a machine learning model with an f1-score higher than or equal to 0.95 to help organizations automatically detect hate speech within tweets.

Project Lifecycle

Figure 1: Project Lifecycle

Data Intake Report

Name: Hate Speech Detection
Report date: 11/25/2021
Internship Batch: NLP02
Version:1.0
Data intake by: Alaa Eddine Osta
Data intake reviewer:
Data storage location: https://github.com/Osta-Alaa/Hate-Speech-Detection

Tabular data details: df

Total number of observations	31962
Total number of files	1
Total number of features	3
Base format of the file	.csv
Size of the data	749.2+ KB

Data Understanding

	id	label	tweet
0	1	0	@user when a father is dysfunctional and is s...
1	2	0	@user @user thanks for #lyft credit i can't us...
2	3	0	bihday your majesty
3	4	0	#model i love u take with u all the time in ...
4	5	0	factsguide: society now #motivation
...	...	...	...
31957	31958	0	ate @user isz that youuu?ð□□□ð□□□□ð□□□□ð□□□□ð□□□□ð...
31958	31959	0	to see nina turner on the airwaves trying to...
31959	31960	0	listening to sad songs on a monday morning otw...
31960	31961	1	@user #sikh #temple vandalised in in #calgary,...
31961	31962	0	thank you @user for you follow

31962 rows × 3 columns

Figure 1: Data Frame of the Data

Observations from Figure 1:

- There is a lot of noise in the data ()
- There are three total columns in the dataset
- The number of observations is equal to 31962

```
RangeIndex: 31962 entries, 0 to 31961
Data columns (total 3 columns):
 #   Column  Non-Null Count  Dtype 
---  ------  --------------  ----- 
 0   id      31962 non-null  int64 
 1   label   31962 non-null  int64 
 2   tweet   31962 non-null  object
dtypes: int64(2), object(1)
memory usage: 749.2+ KB
```

Figure 2: Data Frame Information

Observations from Figure 2:

- There are no null values in the dataset
- The data type of the tweet column is String object
- The data type of both id and label columns is int64
- The size of the data is 749.2+ KB

	label	count	percentage
0	0	29720	92.98542
1	1	2242	7.01458

Figure 3: The number of examples each class has

Observations from Figure 3:

- The data given is unbalanced where the number of data samples labeled 0 is about 13 times higher than the samples labeled 1, which causes an overfitting problem for models, as they mostly predict zeros.

To overcome the data set problems we observed we can consider the following approaches:

- Cleaning data (removing noise from data)
- Transforming data (transforming data into numerical values)
- Using pre-trained vectorizers for data transformation
- Using a pre-trained Transformer and fine-tuning it to the given data

EDA

0.1 Importing Modules

```
%%capture
!pip install 'transformers == 4.6.0'
```

```
import zipfile
import pandas as pd
import numpy as np
import re
import random
import matplotlib.pyplot as plt
from wordcloud import WordCloud
import seaborn as sns
from sklearn.feature_extraction import text
from sklearn.model_selection import train_test_split
from sklearn.metrics import f1_score, accuracy_score
import xgboost as xgb
import numpy as np
import tensorflow_hub as hub
import tensorflow as tf
from sklearn.feature_extraction.text import TfidfVectorizer
from sklearn.pipeline import Pipeline
from sklearn.naive_bayes import MultinomialNB
from sklearn.ensemble import RandomForestClassifier
from sklearn.linear_model import LogisticRegression
from sklearn.linear_model import SGDClassifier
from tensorflow.keras import layers
from sklearn.metrics import accuracy_score, precision_recall_fscore_support
from sklearn.metrics import confusion_matrix
from transformers import DistilBertTokenizerFast
from transformers import TFDistilBertForSequenceClassification, TFTrainer,
 ↪TFTrainingArguments
```

0.2 Loading Data

```
zip_path= "/content/drive/MyDrive/Hate Speech Detection Data/train_E6oV31V.csv.
↪zip"
```

```
# Create function to unzip a zipfile into current working directory
def unzip_data(filename):
  """
  Unzips filename into the current working directory.

  Args:
    filename (str): a filepath to a target zip folder to be unzipped.
  """
  zip_ref = zipfile.ZipFile(filename, "r")
  zip_ref.extractall()
  zip_ref.close()
unzip_data(zip_path)
```

```
# Read csv file
df = pd.read_csv("/content/train_E6oV31V.csv")
```

0.3 Exploring Data

```
# Check data
df
```

```
          id  label                                              tweet
0          1      0   @user when a father is dysfunctional and is s…
1          2      0  @user @user thanks for #lyft credit i can't us…
2          3      0                                bihday your majesty
3          4      0  #model   i love u take with u all the time in …
4          5      0             factsguide: society now    #motivation
…        …    …                                                …
31957  31958      0  ate @user isz that youuu?ð  ð  ð  ð  ð  ð…
31958  31959      0    to see nina turner on the airwaves trying to…
31959  31960      0  listening to sad songs on a monday morning otw…
31960  31961      1  @user #sikh #temple vandalised in in #calgary,…
31961  31962      0                           thank you @user for you follow

[31962 rows x 3 columns]
```

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 31962 entries, 0 to 31961
Data columns (total 3 columns):
 #   Column  Non-Null Count  Dtype
---  ------  --------------  -----
```

```
 0   id      31962 non-null  int64
 1   label   31962 non-null  int64
 2   tweet   31962 non-null  object
dtypes: int64(2), object(1)
memory usage: 749.2+ KB
```

```
# Drop the id column
df = df.drop('id',axis=1)
df.head()
```

```
   label                                              tweet
0      0   @user when a father is dysfunctional and is s…
1      0  @user @user thanks for #lyft credit i can't us…
2      0                                bihday your majesty
3      0  #model   i love u take with u all the time in …
4      0             factsguide: society now    #motivation
```

```
# Check how many examples each class has
df.label.value_counts()
```

```
0    29720
1     2242
Name: label, dtype: int64
```

```
df_Stat=df[['label','tweet']].groupby('label').count().reset_index()
df_Stat.columns=['label','count']
df_Stat['percentage']=(df_Stat['count']/df_Stat['count'].sum())*100
df_Stat
```

```
   label  count  percentage
0      0  29720    92.98542
1      1   2242     7.01458
```

```
# Shuffle the data
df_shuffled = df.sample(frac=1, random_state=42)
df_shuffled.head()
```

```
       label                                              tweet
12227      0   @user â my mom says my smile is captivatingâ…
14709      0  in 3 days i will be meeting my sis-n-law, coun…
19319      0  hating the conservative homophobes using this …
4308       0  awee if this doesn't  #scream    #friday #acewe…
24055      0   fathersday  #fatherÃ¢Ã Ã s #day #god! #Ã Ã« #…
```

```
# Remove symbols from tweets and lower case all characters
def process_tweet(tweet):
    return " ".join(re.sub("(@[A-Za-z0-9]+)|([^0-9A-Za-z \t])", " ",tweet.
 ↪lower()).split())
```

```
df_shuffled['processed_tweets'] = df_shuffled['tweet'].apply(process_tweet)
df_shuffled.head()
```

```
       label  ...                                   processed_tweets
12227      0  ...  my mom says my smile is captivating i says hap…
14709      0  ...  in 3 days i will be meeting my sis n law coune…
19319      0  ...  hating the conservative homophobes using this …
4308       0  ...  awee if this doesn t scream friday acewellstuc…
24055      0  ...  fathersday father s day god tony a smith buy t…

[5 rows x 3 columns]
```

```
# Visualize some random examples
random_index = random.randint(0, len(df_shuffled)-10) # create random indexes
for row in df_shuffled[["processed_tweets", "label"]][random_index:
↪random_index+10].itertuples():
  _, tweet, label = row
  print(f"Label: {label}", "(hate speech)" if label > 0 else "(normal speech)")
  print(f"Tweet:\n{tweet}\n")
  print("---\n")
```

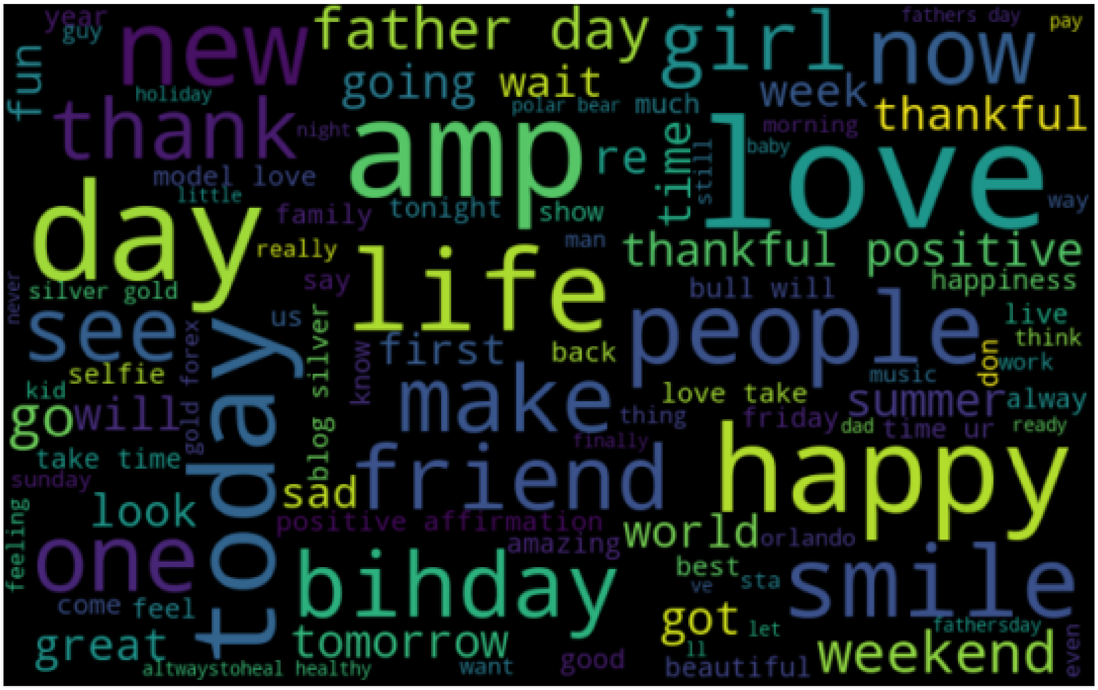
```
Label: 0 (normal speech)
Tweet:
remember when used to lead on impoant social issues 29 years later they re
afraid to even talk abt cannabis whathappened

---

Label: 0 (normal speech)
Tweet:
i think everything in my life right now is a leapoffaith and i m not scared im
sta betting on yourself

---

Label: 1 (hate speech)
Tweet:
isn t it time we realized what we ve done hate exploitation read america s
history

---

Label: 0 (normal speech)
Tweet:
thanks kidsrehab

---
```

```
Label: 0 (normal speech)
Tweet:
is that a jet engine in your pocket or are you just to see me via

---

Label: 0 (normal speech)
Tweet:
cause we lost

---

Label: 0 (normal speech)
Tweet:
ramadan to all mussulmanic twitter friends blesessing month n happy

---

Label: 0 (normal speech)
Tweet:
absolutely disgusted with andover kfc disgusting service the food was cold and
horrible and over cooked very

---

Label: 0 (normal speech)
Tweet:
being ignored confused disappointed after so many years i can t see a change
sadly i tried to trust

---

Label: 0 (normal speech)
Tweet:
luth nurses begin indefinite strike

---
```

```
# Visualize the most frequent words in normal tweets
normal_words = ' '.join([word for word in␣
↪df_shuffled['processed_tweets'][df_shuffled['label'] == 0]])
wordcloud = WordCloud(width = 800, height = 500, max_font_size = 110,max_words␣
↪= 100).generate(normal_words)
print('Normal speech words')
plt.figure(figsize= (12,8))
plt.imshow(wordcloud, interpolation = 'bilinear',cmap='viridis')
```

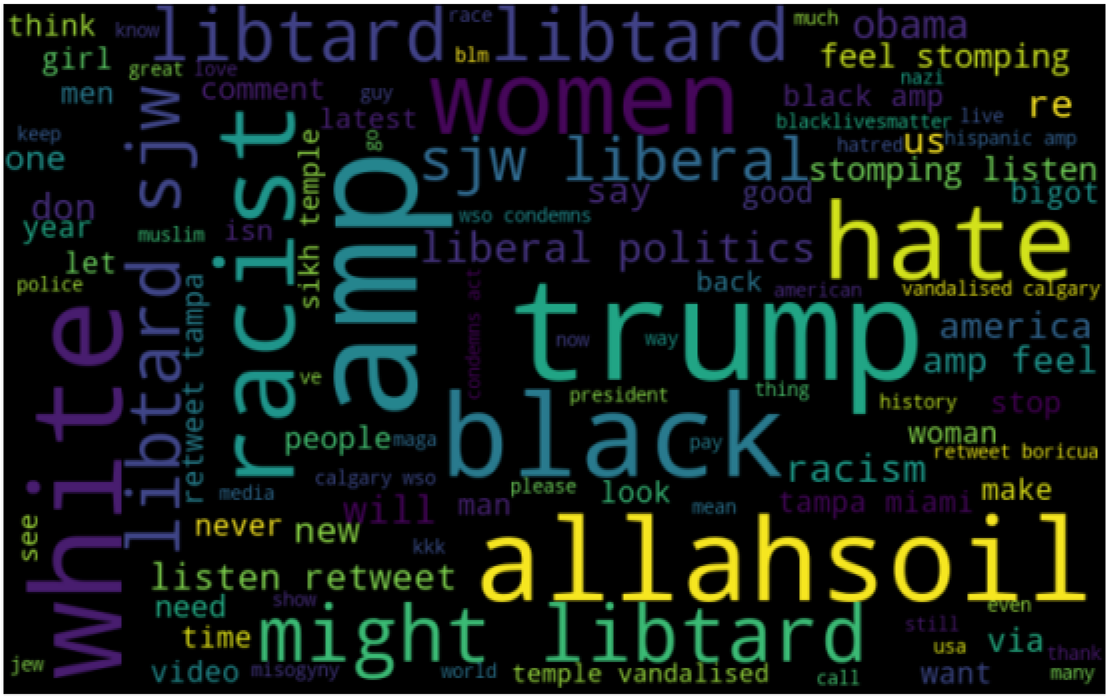
```
plt.axis('off');
```

Normal speech words




```
# Visualize the most frequent words in hate tweets
normal_words = ' '.join([word for word in df_shuffled['processed_tweets'][df_shuffled['label'] == 1]])
wordcloud = WordCloud(width = 800, height = 500, max_font_size = 110,max_words = 100).generate(normal_words)
print('Hate speech words')
plt.figure(figsize= (12,8))
plt.imshow(wordcloud, interpolation = 'bilinear',cmap='viridis')
plt.axis('off');
```

Hate speech words




```
# Import stopwords with scikit-learn
stopwords = text.ENGLISH_STOP_WORDS
# Get the top used words from normal tweets excluding stopwords, numbers, and␣
 ↪strings with length of one character
normal_words = pd.Series(' '.
 ↪join(df_shuffled['processed_tweets'][df_shuffled['label'] == 0].apply(lambda␣
 ↪x: ' '.join(item for item in str(x).split() if item not in stopwords and not␣
 ↪item.isdigit() and len(item)>1))).split()).value_counts()[:30]
normal_words
```

```
love         2796
day          2346
happy        1694
amp          1476
just         1288
life         1163
time         1127
today        1080
thankful      952
positive      934
new           931
like          920
bihday        872
good          841
```

```
people       792
smile        745
father       650
want         626
don          616
fun          614
healthy      609
weekend      604
work         604
summer       571
family       536
make         532
friday       530
beautiful    523
friends      517
best         513
dtype: int64
```

```python
# Get the top used words from hate tweets excluding stopwords, numbers, and␣
 ↪strings with length of one character
hate_words = pd.Series(' '.
 ↪join(df_shuffled['processed_tweets'][df_shuffled['label'] == 1].apply(lambda␣
 ↪x: ' '.join(item for item in str(x).split() if item not in stopwords and not␣
 ↪item.isdigit() and len(item)>1))).split()).value_counts()[:30]
hate_words
```

```
amp          300
trump        213
libtard      149
white        140
like         139
black        134
racist       108
politics      97
people        95
allahsoil     92
liberal       82
just          79
women         78
sjw           74
new           72
obama         72
hate          72
retweet       67
racism        66
don           63
feel          59
```

```
listen        57
america       54
stomping      48
right         48
race          47
men           46
miami         46
woman         43
comments      39
dtype: int64
```

```python
# Creating a dataframe to represent top 30 normal and hate used words
d1 = pd.DataFrame(normal_words.index,columns = ['Normal_Words'])
d2 = pd.DataFrame(normal_words.values,columns = ['Normal_Count'])
d3 = pd.DataFrame(hate_words.index,columns = ['Hate_Words'])
d4 = pd.DataFrame(hate_words.values,columns = ['Hate_Count'])
word_freq_df = pd.concat([d1,d2,d3,d4], axis = 1)
word_freq_df
```

	Normal_Words	Normal_Count	Hate_Words	Hate_Count
0	love	2796	amp	300
1	day	2346	trump	213
2	happy	1694	libtard	149
3	amp	1476	white	140
4	just	1288	like	139
5	life	1163	black	134
6	time	1127	racist	108
7	today	1080	politics	97
8	thankful	952	people	95
9	positive	934	allahsoil	92
10	new	931	liberal	82
11	like	920	just	79
12	bihday	872	women	78
13	good	841	sjw	74
14	people	792	new	72
15	smile	745	obama	72
16	father	650	hate	72
17	want	626	retweet	67
18	don	616	racism	66
19	fun	614	don	63
20	healthy	609	feel	59
21	weekend	604	listen	57
22	work	604	america	54
23	summer	571	stomping	48
24	family	536	right	48

```
25         make          532       race          47
26       friday          530        men          46
```

0.4 Splitting Data into Training and Validation Sets

```
# Use train_test_split to split training data into training and validation sets
train_sentences, val_sentences, train_labels, val_labels =␣
↪train_test_split(list(df_shuffled["processed_tweets"]),
                                                                                    ␣
↪list(df_shuffled["label"]),
                                                                                    ␣
↪test_size=0.2, # use 10% of training data for validation
                                                                                    ␣
↪random_state=42)
```

```
# Find the average number of tokens (words) in the training and validation␣
↪tweets
round (sum([len(i.split()) for i in train_sentences])/len(train_sentences)),␣
↪round (sum([len(i.split()) for i in val_sentences])/len(val_sentences))
```

```
(13, 13)
```

0.5 Running a Series of Modeling Experiments

```
# Create tokenization and modeling pipeline


# XGBClassifier
pipeline_xgb = Pipeline([
    ('tfidf', TfidfVectorizer()),
    ('model', xgb.XGBClassifier(use_label =False)),])

model_0 = pipeline_xgb.fit(train_sentences, train_labels)

model_0_score = model_0.score(val_sentences, val_labels)

print(f"Our model_0 (XGBClassifier) achieves an accuracy of:{model_0_score*100:.
↪2f}%")


# MultinomialNB
model_1 = Pipeline([
                    ("tfidf", TfidfVectorizer()), # Convert words to numbers␣
↪using tfidf
                    ("clf", MultinomialNB()) # model the text
])
```

```
model_1.fit(train_sentences, train_labels)
score_1 = model_1.score(val_sentences, val_labels)
print(f"Our model_1 (MultinomialNB) achieves an accuracy of:{score_1*100:.2f}%")


# RandomForestClassifier
model_2 = Pipeline([
                    ("tfidf", TfidfVectorizer()), # Convert words to numbers␣
 ↪using tfidf
                    ("clf", RandomForestClassifier()) # model the text
])

model_2.fit(train_sentences, train_labels)
score_2 = model_2.score(val_sentences, val_labels)
print(f"Our model_2 (RandomForestClassifier) achieves an accuracy of:
 ↪{score_2*100:.2f}%")


# LogisticRegression
model_3 = Pipeline([
                    ("tfidf", TfidfVectorizer()), # Convert words to numbers␣
 ↪using tfidf
                    ("clf", LogisticRegression()) # model the text
])

model_3.fit(train_sentences, train_labels)
score_3 = model_3.score(val_sentences, val_labels)
print(f"Our model_3 (LogisticRegression) achieves an accuracy of:{score_3*100:.
 ↪2f}%")
```

```
# SGDClassifier
model_4 = Pipeline([
                    ("tfidf", TfidfVectorizer()), # Convert words to numbers␣
 ↪using tfidf
                    ("clf", SGDClassifier()) # model the text
])

model_4.fit(train_sentences, train_labels)
score_4 = model_4.score(val_sentences, val_labels)
print(f"Our model_4 (SGDClassifier) achieves an accuracy of:{score_4*100:.2f}%")
```

```
Our model_0 (XGBClassifier) achieves an accuracy of:94.17%
Our model_1 (MultinomialNB) achieves an accuracy of:93.52%
Our model_2 (RandomForestClassifier) achieves an accuracy of:96.15%
Our model_3 (LogisticRegression) achieves an accuracy of:94.81%
```

Our model_4 (SGDClassifier) achieves an accuracy of:95.10%

```
# Create a Keras Layer using the USE pretrained layer from tensorflow hub
sentence_encoder_layer = hub.KerasLayer("https://tfhub.dev/google/
↪universal-sentence-encoder/4",
                                        input_shape=[],
                                        dtype=tf.string,
                                        trainable=False,
                                        name="USE"
                                        )
# Create model using the Sequential API
model_5 = tf.keras.Sequential([
  sentence_encoder_layer,
  layers.Dense(64, activation="relu"),
  layers.Dense(1, activation="sigmoid")
], name = "model_5_USE")

# Compile
model_5.compile(loss="binary_crossentropy",
                optimizer=tf.keras.optimizers.Adam(),
                metrics=["accuracy"])
model_5.summary()
```

```
Model: "model_5_USE"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 USE (KerasLayer)            (None, 512)               256797824

 dense_2 (Dense)             (None, 64)                32832

 dense_3 (Dense)             (None, 1)                 65

=================================================================
Total params: 256,830,721
Trainable params: 32,897
Non-trainable params: 256,797,824
_________________________________________________________________
```

```python
# Train a classifier on top of USE pretrained embeddings
model_5_history = model_5.fit(train_sentences,
                              train_labels,
                              epochs=15,
                              validation_data=(val_sentences, val_labels)
                              )
```

```
Epoch 1/15
800/800 [==============================] - 21s 23ms/step - loss: 0.1770 -
accuracy: 0.9437 - val_loss: 0.1368 - val_accuracy: 0.9487

Epoch 2/15
800/800 [==============================] - 18s 22ms/step - loss: 0.1223 -
accuracy: 0.9565 - val_loss: 0.1302 - val_accuracy: 0.9504
Epoch 3/15
800/800 [==============================] - 17s 22ms/step - loss: 0.1118 -
accuracy: 0.9594 - val_loss: 0.1246 - val_accuracy: 0.9529
Epoch 4/15
800/800 [==============================] - 17s 22ms/step - loss: 0.1023 -
accuracy: 0.9623 - val_loss: 0.1192 - val_accuracy: 0.9564
Epoch 5/15
800/800 [==============================] - 17s 22ms/step - loss: 0.0936 -
accuracy: 0.9659 - val_loss: 0.1152 - val_accuracy: 0.9570
Epoch 6/15
800/800 [==============================] - 17s 22ms/step - loss: 0.0852 -
accuracy: 0.9689 - val_loss: 0.1137 - val_accuracy: 0.9587
Epoch 7/15
800/800 [==============================] - 17s 21ms/step - loss: 0.0777 -
accuracy: 0.9719 - val_loss: 0.1118 - val_accuracy: 0.9592
Epoch 8/15
800/800 [==============================] - 17s 22ms/step - loss: 0.0713 -
accuracy: 0.9741 - val_loss: 0.1102 - val_accuracy: 0.9598
Epoch 9/15
800/800 [==============================] - 17s 22ms/step - loss: 0.0649 -
accuracy: 0.9777 - val_loss: 0.1108 - val_accuracy: 0.9592
Epoch 10/15
800/800 [==============================] - 17s 21ms/step - loss: 0.0589 -
accuracy: 0.9804 - val_loss: 0.1123 - val_accuracy: 0.9598
```

```
Epoch 11/15
800/800 [==============================] - 17s 22ms/step - loss: 0.0534 -
accuracy: 0.9824 - val_loss: 0.1144 - val_accuracy: 0.9606
Epoch 12/15
800/800 [==============================] - 17s 21ms/step - loss: 0.0479 -
accuracy: 0.9850 - val_loss: 0.1143 - val_accuracy: 0.9601
Epoch 13/15
800/800 [==============================] - 17s 21ms/step - loss: 0.0431 -
accuracy: 0.9863 - val_loss: 0.1151 - val_accuracy: 0.9592
Epoch 14/15
800/800 [==============================] - 17s 21ms/step - loss: 0.0381 -
accuracy: 0.9893 - val_loss: 0.1171 - val_accuracy: 0.9612
Epoch 15/15
800/800 [==============================] - 17s 21ms/step - loss: 0.0340 -
accuracy: 0.9906 - val_loss: 0.1214 - val_accuracy: 0.9615
```

```python
# Make predictions with USE TF Hub Model
model_5_pred_probs = model_5.predict(val_sentences)
```

```python
# Making predictions on validation data
y0_predict = model_0.predict(val_sentences)
y1_predict = model_1.predict(val_sentences)
y2_predict = model_2.predict(val_sentences)
y3_predict = model_3.predict(val_sentences)
y4_predict = model_4.predict(val_sentences)
y5_predict = tf.squeeze(tf.round(model_5_pred_probs))
```

0.6 Creating an Evaluation Function for Model Experiments

```python
# Function to evaluate: accuracy, precision, recall, f1-score
def calculate_results(y_true,y_pred):
  """
  Calculates model accuracy, precision, recall and f1 score of a binary␣
↪classification model
  """
  # Calculate model accuracy
  model_accuracy = accuracy_score(y_true, y_pred) * 100
  # Calculate model precision, recall and f1-score using "weighted" average
  model_precision, model_recall, model_f1, _ =␣
↪precision_recall_fscore_support(y_true, y_pred, average="weighted")
  model_results = {"accuracy": model_accuracy,
                  "precision": model_precision,
                  "recall": model_recall,
                  "f1": model_f1}
  return model_results
```

```python
# Get baseline results
model_0_results = calculate_results(y_true=val_labels,
                                    y_pred= y0_predict)
model_0_results
```

```
{'accuracy': 94.16549350852495,
 'f1': 0.9240085458148133,
 'precision': 0.9416924045330635,
 'recall': 0.9416549350852494}
```

```python
# Get model_1 results
model_1_results = calculate_results(y_true=val_labels,
                                    y_pred= y1_predict)
model_1_results
```

```
{'accuracy': 93.52416705771938,
 'f1': 0.9103555383590493,
 'precision': 0.9394690355064025,
 'recall': 0.9352416705771938}
```

```python
# Get model_2 results
model_2_results = calculate_results(y_true=val_labels,
                                    y_pred= y2_predict)
model_2_results
```

```
{'accuracy': 96.15204129516658,
 'f1': 0.9560442219920248,
 'precision': 0.9607553645482917,
 'recall': 0.9615204129516659}
```

```python
# Get model_3 results
model_3_results = calculate_results(y_true=val_labels,
                                    y_pred= y3_predict)
model_3_results
```

```
{'accuracy': 94.80681995933051,
 'f1': 0.9359882323688977,
 'precision': 0.9466040133565261,
 'recall': 0.9480681995933051}
```

```python
# Get model_4 results
model_4_results = calculate_results(y_true=val_labels,
                                    y_pred= y4_predict)
model_4_results
```

```
{'accuracy': 95.10402002189895,
 'f1': 0.9401526202494138,
 'precision': 0.9511041686353916,
 'recall': 0.9510402002189895}
```

```python
# Get model_5 results
model_5_results = calculate_results(y_true = val_labels,
                                    y_pred = y5_predict)
model_5_results
```

```
{'accuracy': 96.15204129516658,
 'f1': 0.9595563153708081,
 'precision': 0.9589536629357007,
 'recall': 0.9615204129516659}
```

0.7 Comparing the Performance of the Models

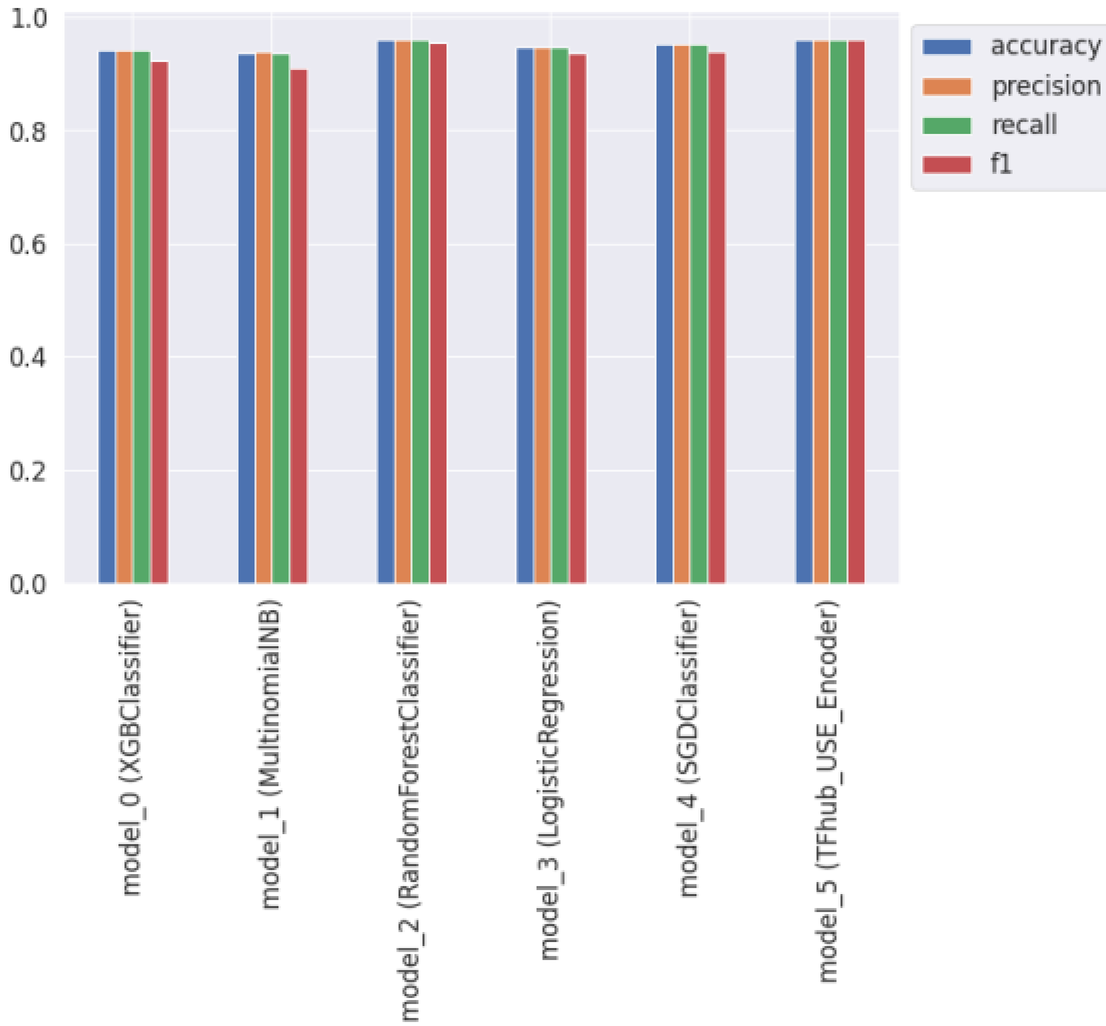
```python
models_results_df = pd.DataFrame(data={'model_0 (XGBClassifier)':␣
 ↪model_0_results,
                                       'model_1 (MultinomialNB)':␣
 ↪model_1_results,
```

```python
                                       'model_2 (RandomForestClassifier)' :␣
 ↪model_2_results,
                                       'model_3 (LogisticRegression)':␣
 ↪model_3_results,
                                       'model_4 (SGDClassifier)' :␣
 ↪model_4_results,
                                       'model_5 (TFhub_USE_Encoder)' :␣
 ↪model_5_results}).transpose()
models_results_df
```

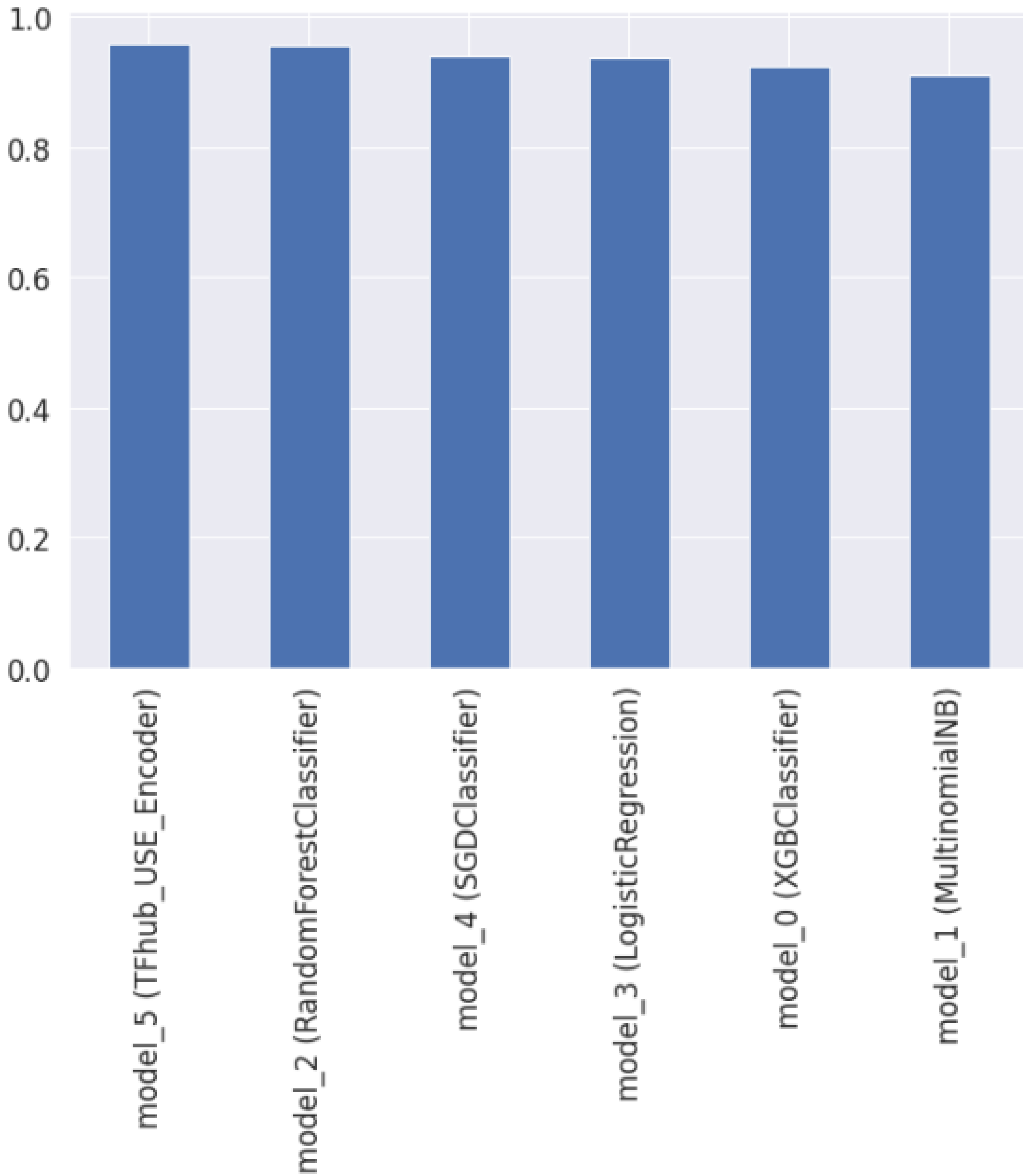
	accuracy	precision	recall	f1
model_0 (XGBClassifier)	94.165494	0.941692	0.941655	0.924009
model_1 (MultinomialNB)	93.524167	0.939469	0.935242	0.910356
model_2 (RandomForestClassifier)	96.152041	0.960755	0.961520	0.956044
model_3 (LogisticRegression)	94.806820	0.946604	0.948068	0.935988
model_4 (SGDClassifier)	95.104020	0.951104	0.951040	0.940153
model_5 (TFhub_USE_Encoder)	96.152041	0.958954	0.961520	0.959556

```python
# Reduce the accuracy to the same scale as other metrics
models_results_df["accuracy"]= models_results_df["accuracy"]/100
```

```python
# Plot and compare all of the model results
models_results_df.plot(kind="bar", figsize=(10,7)).legend(bbox_to_anchor=(1.0,1.
 ↪0));
```




```python
# Sort model results by f1-score
models_results_df.sort_values("f1", ascending=False)["f1"].plot(kind="bar",␣
 ↪figsize=(10, 7));
```




```
# Confusion matrix
cm_0 = confusion_matrix(val_labels, y0_predict)
cm_0
```

```
array([[5922,    6],
       [ 367,   98]])
```

```
cm_1 = confusion_matrix(val_labels, y1_predict)
cm_1
```

```
array([[5928,    0],
       [ 414,   51]])
```

```
cm_2 = confusion_matrix(val_labels, y2_predict)
cm_2
```

```
array([[5913,   15],
       [ 231,  234]])
```

```
cm_3 = confusion_matrix(val_labels, y3_predict)
cm_3
```

```
array([[5915,   13],
       [ 319,  146]])
```

```
cm_4 = confusion_matrix(val_labels, y4_predict)
cm_4
```

```
array([[5920,    8],
       [ 305,  160]])
```

```
cm_5 = confusion_matrix(val_labels, y5_predict)
cm_5
```

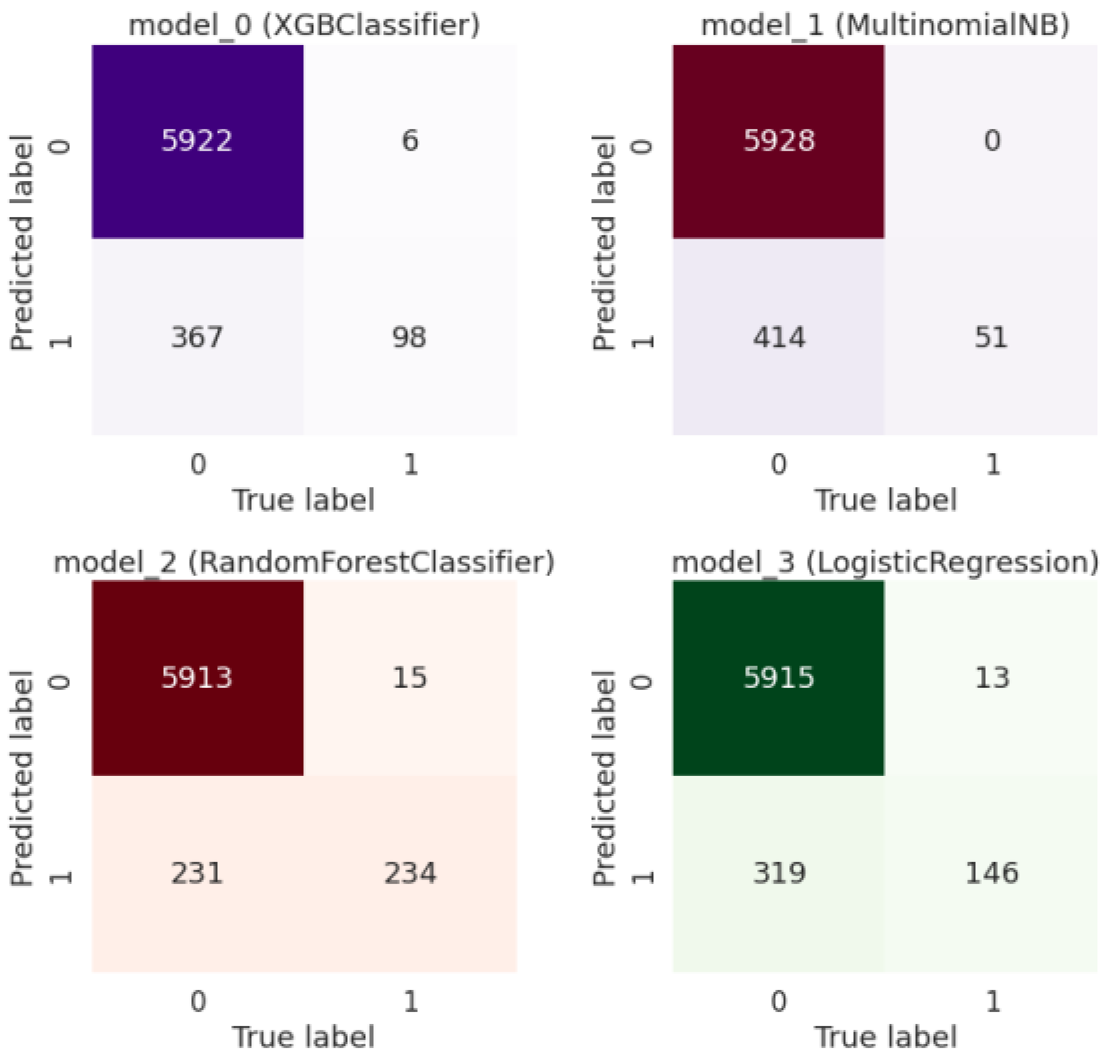
```
array([[5851,   77],
       [ 169,  296]])
```

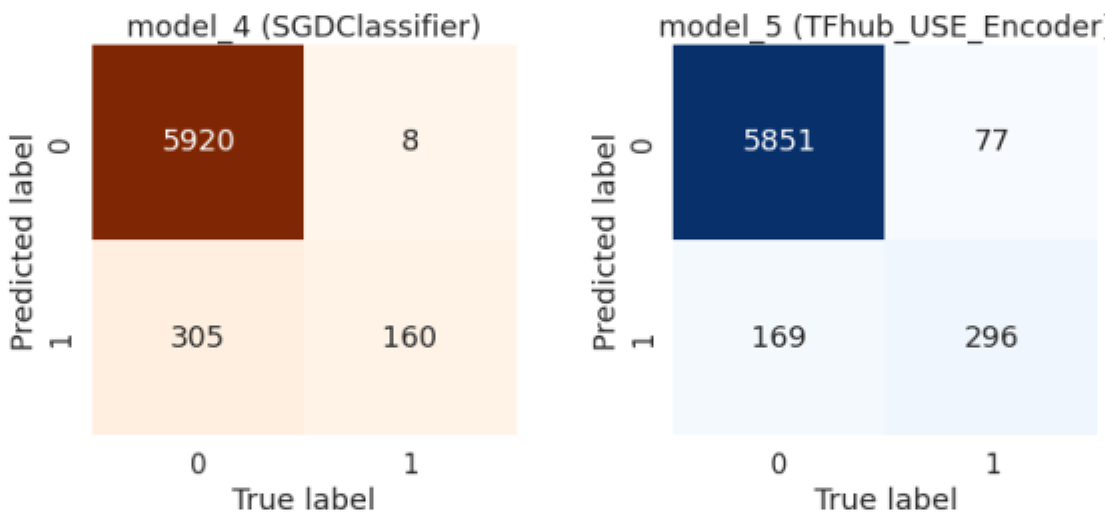
```
sns.set(font_scale=1.5)
# Plot the confusion matrix for each model
fig, axs = plt.subplots(3, 2,figsize=(10, 14))
sns.heatmap(confusion_matrix(val_labels, y0_predict),
                  annot=True,
                  cbar=False,
                  fmt='d',
                  ax=axs[0, 0],
                  cmap= 'Purples'
                     )
axs[0, 0].set_title('model_0 (XGBClassifier)')
axs[0, 0].set_xlabel("True label")
axs[0, 0].set_ylabel("Predicted label")

sns.heatmap(confusion_matrix(val_labels, y1_predict),
                  annot=True,
                  cbar=False,
                  fmt='d',
                  ax=axs[0, 1],
                  cmap='PuRd'
                     )
```

```
axs[0, 1].set_title('model_1 (MultinomialNB)')
axs[0, 1].set_xlabel("True label")
axs[0, 1].set_ylabel("Predicted label")


sns.heatmap(confusion_matrix(val_labels, y2_predict),
                  annot=True,
                  cbar=False,
                  fmt='d',
                  ax=axs[1, 0],
                  cmap='Reds'
                     )
axs[1, 0].set_title('model_2 (RandomForestClassifier)')
axs[1, 0].set_xlabel("True label")
axs[1, 0].set_ylabel("Predicted label")


sns.heatmap(confusion_matrix(val_labels, y3_predict),
                  annot=True,
                  cbar=False,
                  fmt='d',
                  ax=axs[1, 1],
                  cmap='Greens'
                     )
axs[1, 1].set_title('model_3 (LogisticRegression)')
axs[1, 1].set_xlabel("True label")
axs[1, 1].set_ylabel("Predicted label")
```

```
sns.heatmap(confusion_matrix(val_labels, y4_predict),
                  annot=True,
                  cbar=False,
                  fmt='d',
                  ax=axs[2, 0],
                  cmap='Oranges'
                     )
axs[2, 0].set_title('model_4 (SGDClassifier)')
axs[2, 0].set_xlabel("True label")
axs[2, 0].set_ylabel("Predicted label")


sns.heatmap(confusion_matrix(val_labels, y5_predict),
                  annot=True,
                  cbar=False,
                  fmt='d',
                  ax=axs[2, 1],
```

```
                    cmap='Blues'
                       )
axs[2, 1].set_title('model_5 (TFhub_USE_Encoder)')
axs[2, 1].set_xlabel("True label")
axs[2, 1].set_ylabel("Predicted label")
plt.tight_layout();
```






```python
# Save the best model
model_5.save('tfhub_use_encoder.h5')
```

0.8 Finding the Most Wrong Examples

```python
# Create DataFrame with validation sentences and best performing model␣
↪prediction labels + probabilities
val_df = pd.DataFrame({"text": val_sentences,
                       "target": val_labels,
                       "pred": y5_predict,
                       "pred_prob": tf.squeeze(model_5_pred_probs)})
val_df.head()
```

```
                                         text  ...     pred_prob
0                 turn it in abc for 20 20 sobering  ...  5.430939e-02
1  oh no thursdays is noodle day what have you do...  ...  7.533444e-05
2             here we go let s do this people icrs2016  ...  5.501849e-03
3  water in me and around me sam sierra michael b...  ...  2.714794e-05
4           awesome beginner gopro mounts super to use  ...  9.277188e-07

[5 rows x 4 columns]
```

```python
# Find the wrong predictions and sort by predictio probabilities
most_wrong = val_df[val_df["target"] !=val_df["pred"]].sort_values("pred_prob",␣
↪ascending=False)
most_wrong
```

```
                                                   text  ...  pred_prob
4272  lgbtqhatestrumppay but luvs homophobic misogyn...  ...   0.998966
4506  the makes the trump candidacy wohwhile donaldt...  ...   0.994312
558   what lies these dt suppoers are spreading look...  ...   0.992918
1344  ali spoke the truth about white folks period f...  ...   0.992009
6054  i award thee most cucked tweet in history prep...  ...   0.991659
…                                                   …  …          …
2382  this newyearseve may our resolutions b 2 end p...  ...   0.000192
5222  2 99 2016release ebook book the summer that me...  ...   0.000079
1063  funny can t get rid of 7 1stammendment so many...  ...   0.000040
5568                 good afternoon sweety send me letter  ...   0.000026
1153                 i m blessedt iconic lovebeingalegend  ...   0.000001

[246 rows x 4 columns]
```

```python
# False positives
most_wrong.head()
```

```
                                                   text  ...  pred_prob
4272  lgbtqhatestrumppay but luvs homophobic misogyn...  ...   0.998966

4506  the makes the trump candidacy wohwhile donaldt...  ...   0.994312
558   what lies these dt suppoers are spreading look...  ...   0.992918
1344  ali spoke the truth about white folks period f...  ...   0.992009
6054  i award thee most cucked tweet in history prep...  ...   0.991659

[5 rows x 4 columns]
```

```python
# False negative
most_wrong.tail()
```

```
                                                   text  ...  pred_prob
2382  this newyearseve may our resolutions b 2 end p...  ...   0.000192
5222  2 99 2016release ebook book the summer that me...  ...   0.000079
1063  funny can t get rid of 7 1stammendment so many...  ...   0.000040
5568                 good afternoon sweety send me letter  ...   0.000026
1153                 i m blessedt iconic lovebeingalegend  ...   0.000001

[5 rows x 4 columns]
```

```python
# Check the false positives (model predicted 1 when should've been 0)
for row in most_wrong[:10].itertuples():
  _, text, target, pred, pred_prob = row
  print(f"Target: {target}, Pred: {pred}, Prob: {pred_prob}")
  print(f"Text:\n{text}\n")
  print("---\n")
```

```
Target: 0, Pred: 1.0, Prob: 0.998965859413147
Text:
lgbtqhatestrumppay but luvs homophobic misogynist antisemitic death cult
masquerading as a religion

---

Target: 0, Pred: 1.0, Prob: 0.9943115711212158
Text:
the makes the trump candidacy wohwhile donaldtrumphastinyhands
tinydancerfoinyhands

---

Target: 0, Pred: 1.0, Prob: 0.9929178357124329
Text:
what lies these dt suppoers are spreading looks like propaganda from the 1930s

---

Target: 0, Pred: 1.0, Prob: 0.9920094013214111
Text:
ali spoke the truth about white folks period facts idiot moron
theverycoreofamerica

---

Target: 0, Pred: 1.0, Prob: 0.9916594624519348
Text:
i award thee most cucked tweet in history prep the bull you insufferable faggot
sbc16

---

Target: 0, Pred: 1.0, Prob: 0.9753319621086121
Text:
straight white men are viciously under attack they are often the real victims

---
```

```
Target: 0, Pred: 1.0, Prob: 0.9751490950584412
Text:
reason 638 on why i don t suppo modern day feminism it s no longer about women s
rights in america

---

Target: 0, Pred: 1.0, Prob: 0.9630975127220154
Text:
i can t believe any american would vote for her so many scandals

---

Target: 0, Pred: 1.0, Prob: 0.9623082876205444
Text:
prayfororlando can we show love amp not hate by clifton w 0

---

Target: 0, Pred: 1.0, Prob: 0.9607369899749756
Text:
just herd you re podcast no man deserves to be called a man after he rapes a
women scumofthreah

---
```

```python
# Check the false negatives (model predicted 0 when should've been 1)
for row in most_wrong[-10:].itertuples():
```

```python
  _, text, target, pred, pred_prob = row
  print(f"Target: {target}, Pred: {pred}, Prob: {pred_prob}")
  print(f"Text:\n{text}\n")
  print("---\n")
```

```
Target: 1, Pred: 0.0, Prob: 0.0011675811838835864
Text:
great aicle of truth about trc needs comments back up why it s needed
indignenous via

---

Target: 1, Pred: 0.0, Prob: 0.0008611972443759441
Text:
now ask yourself if you really want to follow i m done

---
```

Target: 1, Pred: 0.0, Prob: 4.03911508328747e-05
Text:
funny can t get rid of 7 1stammendment so many distractions and lousy qb maybe next year probab

---

Target: 1, Pred: 0.0, Prob: 0.000704584876075387
Text:
ouuh fuck it bustymilf

Target: 1, Pred: 0.0, Prob: 0.0004778062575496733
Text:
you can still be

Target: 1, Pred: 0.0, Prob: 0.0004640818515326828
Text:
note i was just able to pop this zit on my neck that s been there for days i ve beensqueezing it for days

---

Target: 1, Pred: 0.0, Prob: 0.00019191103638149798
Text:
this newyearseve may our resolutions b 2 end problems like amp domesticviolence by turning 2 god of love

---

Target: 1, Pred: 0.0, Prob: 7.872624701121822e-05
Text:
2 99 2016release ebook book the summer that melted everything a novel by tiffany mcdaniel via

---

Target: 1, Pred: 0.0, Prob: 4.03911508328747e-05
Text:
funny can t get rid of 7 1stammendment so many distractions and lousy qb maybe next year probab

---

Target: 1, Pred: 0.0, Prob: 2.6166002498939633e-05
Text:
good afternoon sweety send me letter

Target: 1, Pred: 0.0, Prob: 1.3290167544255382e-06
Text:
i m blessedt iconic lovebeingalegend

0.9 Another Option: Using DistilBertTokenizerFast

```
tokenizer = DistilBertTokenizerFast.from_pretrained('distilbert-base-uncased')
```

```
Downloading:   0%|          | 0.00/232k [00:00<?, ?B/s]

Downloading:   0%|          | 0.00/466k [00:00<?, ?B/s]

Downloading:   0%|          | 0.00/28.0 [00:00<?, ?B/s]
```

```
train_encodings = tokenizer(train_sentences, truncation=True, padding=True)
val_encodings = tokenizer(val_sentences, truncation=True, padding=True)
```

```
train_dataset = tf.data.Dataset.from_tensor_slices((
    dict(train_encodings),
    train_labels
))
val_dataset = tf.data.Dataset.from_tensor_slices((
    dict(val_encodings),
    val_labels
))
```

```
train_dataset
```

```
<TensorSliceDataset shapes: ({input_ids: (46,), attention_mask: (46,)}, ()),
types: ({input_ids: tf.int32, attention_mask: tf.int32}, tf.int32)>
```

```python
len(val_labels)
```

6393

```python
training_args = TFTrainingArguments(
    output_dir='./results',          # output directory
    num_train_epochs=3,              # total number of training epochs
    per_device_train_batch_size=16,  # batch size per device during training
    per_device_eval_batch_size=64,   # batch size for evaluation
    warmup_steps=500,                # number of warmup steps for learning rate␣
 ↪scheduler
    weight_decay=0.01,               # strength of weight decay
    logging_dir='./logs',            # directory for storing logs
    logging_steps=10,
)

with training_args.strategy.scope():
    model_6 = TFDistilBertForSequenceClassification.
 ↪from_pretrained("distilbert-base-uncased")

trainer = TFTrainer(
    model=model_6,                       # the instantiated  Transformers␣
 ↪model to be trained
    args=training_args,                  # training arguments, defined above
    train_dataset=train_dataset,         # training dataset
    eval_dataset=val_dataset             # evaluation dataset
)

trainer.train()
```

```python
score_6 = trainer.evaluate(val_dataset)
score_6
```

{'eval_loss': 0.12932125091552735}

```python
trainer.predict(val_dataset)
```

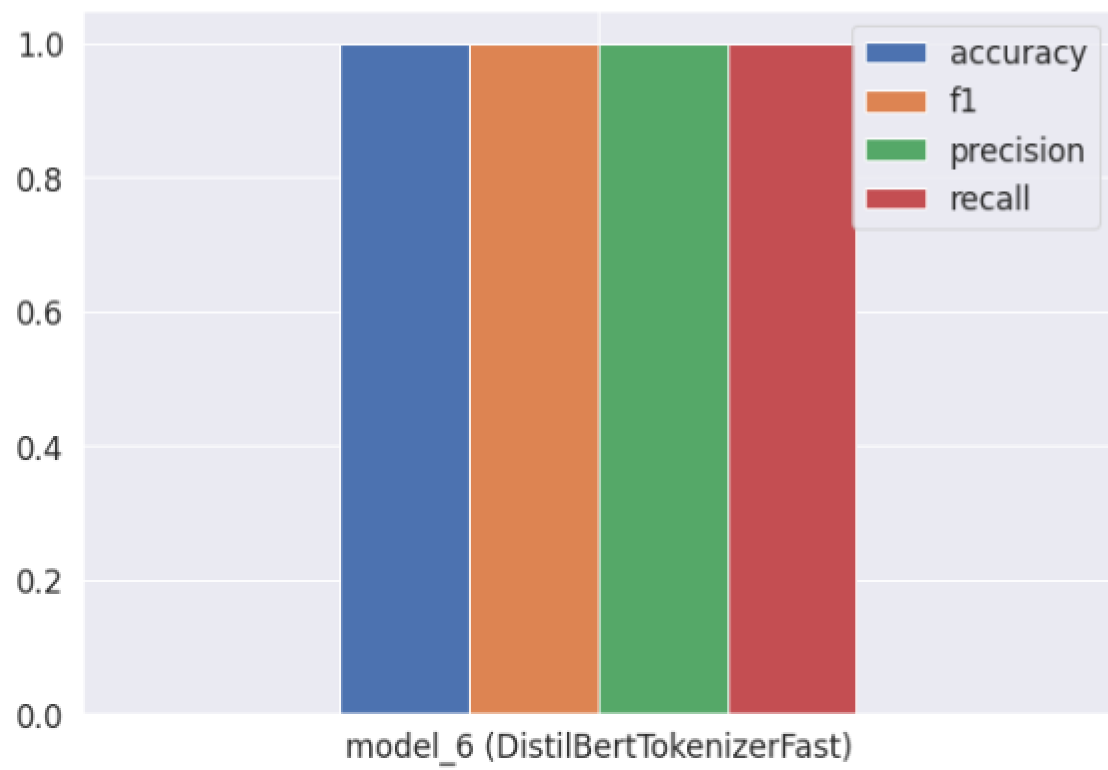
```
PredictionOutput(predictions=array([[ 3.2038417, -3.2720242],
       [ 4.1385026, -4.1992965],
       [ 3.5704398, -3.624197 ],
       …,
       [ 4.1603084, -4.2755566],
       [ 4.133188 , -4.2293296],
       [ 4.1415644, -4.2415414]], dtype=float32), label_ids=array([0, 0, 0, …,
0, 0, 0], dtype=int32), metrics={'eval_loss': 0.1284922504425049})
```

```
y6_predict=trainer.predict(val_dataset)[1]
```

```
# Get model_6 results
model_6_results = calculate_results(y_true=val_labels,
                                    y_pred= y6_predict)
model_6_results
```

```
{'accuracy': 100.0, 'f1': 1.0, 'precision': 1.0, 'recall': 1.0}
```

```
model_6_results_df=pd.DataFrame(data={'model_6 (DistilBertTokenizerFast)':␣
 ↪model_6_results}).transpose()
# Reduce the accuracy to the same scale as other metrics
model_6_results_df["accuracy"]= model_6_results_df["accuracy"]/100
model_6_results_df.plot(kind="bar", figsize=(10, 7))
plt.xticks(rotation='horizontal');
```



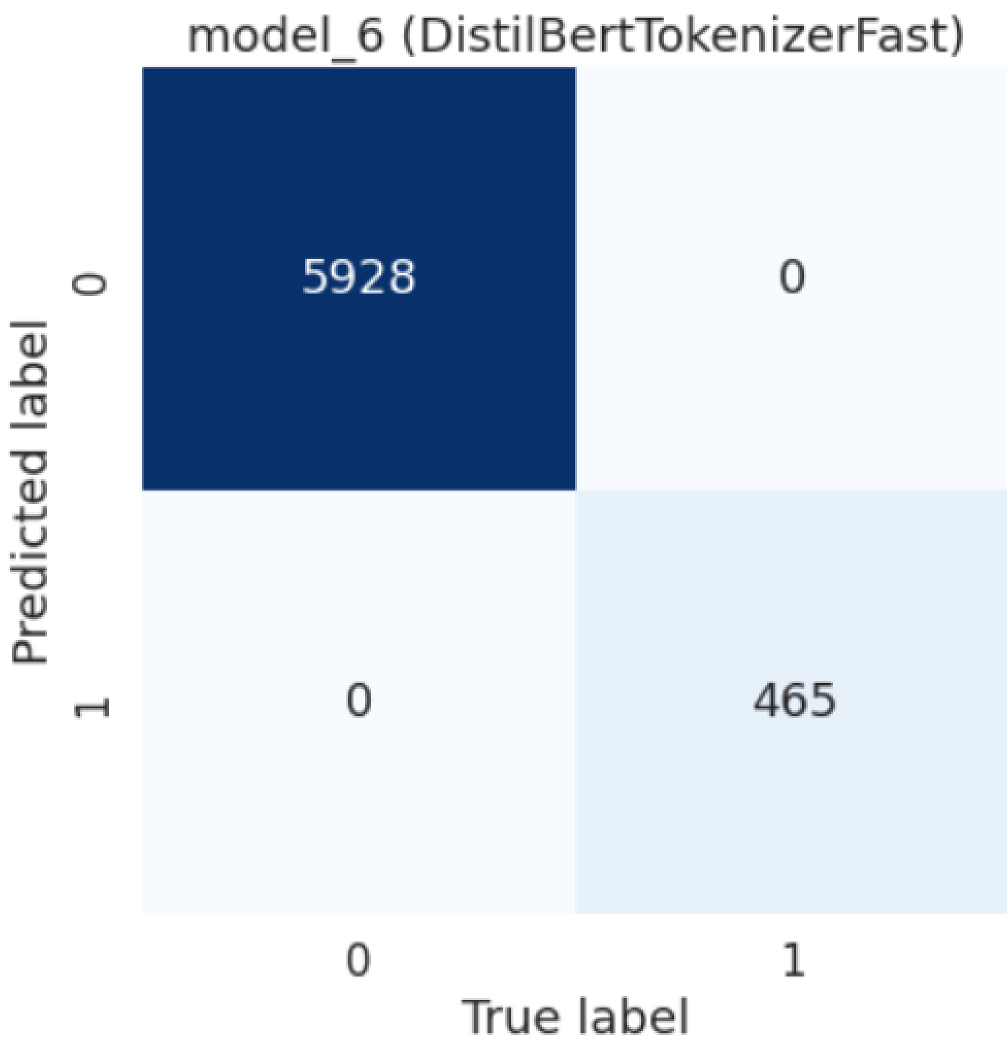

```
np.unique(val_labels,return_counts=True)
```

```
(array([0, 1]), array([5928,  465]))
```

```
cm_6 = confusion_matrix(val_labels, y6_predict)
cm_6
```

```
array([[5928,    0],
       [   0,  465]])
```

```
# Plot the confusion matrix for model_6
plt.figure(figsize=(6,6))
sns.heatmap(confusion_matrix(val_labels, y6_predict),
                  annot=True,
                  cbar=False,
                  fmt='d',
                  cmap='Blues'
                     )
plt.title('model_6 (DistilBertTokenizerFast)')
plt.xlabel('True label')
plt.ylabel('Predicted label');
```




```
trainer.save_model("distilbert_model")
```

Recommendation

- Collect more hate tweets data.
- Check the most wrong predictions as shown in the EDA and fix some wrong labels.
- Although model_5 was the best performing model in the early stage of experimenting, it was beaten later by model_6 (DistilBertTokenizerFast) which gave a perfect f1-score of one. So I would recommend using model_6.