Group Name: AO Name: Alaa Eddine Osta

Email: ostaalaaeddine@gmail.com

Country: Lebanon

College: Üsküdar University

Specialization: NLP

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?ถ\\\\\\\\\\\\\\\\\\\\\\\\\\\\\\\\\\
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

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	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, u
→TFTrainingArguments
```

# 0.2 Loading Data

```
# 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_E6oV3lV.csv")
```

## 0.3 Exploring Data

```
# Check data
df
```

	id	label	tweet
0	1	0	Quser 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	Quser #sikh #temple vandalised in in #calgary,
31961	31962	0	thank you @user for you follow

```
df.info()
```

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

[31962 rows x 3 columns]

```
id
            31962 non-null int64
1 label 31962 non-null int64
   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
      O Quser when a father is dysfunctional and is s...
       O @user @user thanks for #lyft credit i can't us...
2
                                       bihday your majesty
       0 #model
3
                  i love u take with u all the time in ...
                    factsguide: society now
                                               #motivation
# Check how many examples each class has
df.label.value_counts()
     29720
      2242
1
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 29720
                92.98542
         2242
1
      1
                   7.01458
# Shuffle the data
df_shuffled = df.sample(frac=1, random_state=42)
df_shuffled.head()
       label
12227
               Quser â my mom says my smile is captivatingâ...
14709
           0 in 3 days i will be meeting my sis-n-law, coun...
           O hating the conservative homophobes using this ...
19319
4308
           O awee if this doesn't #scream #friday #acewe...
               fathersday #fatherâÂÂs #day #god! #ë #...
24055
# 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
           0 ... my mom says my smile is captivating i says hap ...
12227
           0 ... in 3 days i will be meeting my sis n law coune ...
14709
           0 ... hating the conservative homophobes using this ...
19319
4308
           0 ... awee if this doesn t scream friday acewellstuc...
           0 ... fathersday father s day god tony a smith buy t...
24055
[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)
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)
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)
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

```
The solution of the state of th
```

Hate speech words

```
think know ibtard blm libtard much obama feel stomping mazi girl great love media latest WOMEN black amp reblacklivesmatter live reblacklivesmatter li
```

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
               745
smile
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
```

```
# 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_tous: ' '.join(item for item in str(x).split() if item not in stopwords and not tous item.isdigit() and len(item)>1))).split()).value_counts()[:30]

hate_words
```

```
300
amp
trump
              213
libtard
              149
white
              140
like
              139
black
              134
              108
racist
politics
               97
people
               95
allahsoil
               92
liberal
               82
               79
just
women
               78
               74
sjw
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
```

```
# 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)),

oround (sum([len(i.split()) for i in val_sentences])/len(val_sentences))
```

(13, 13)

#### 0.5 Running a Series of Modeling Experiments

```
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
1)
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:
\rightarrow{score_2*100:.2f}%")
# LogisticRegression
model_3 = Pipeline([
                    ("tfidf", TfidfVectorizer()), # Convert words to numbers
→using tfidf
                    ("clf", LogisticRegression()) # model the text
1)
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
1)
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%
```

```
# 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

-----

```
# 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 -

800/800 [============ ] - 17s 21ms/step - loss: 0.0777 -

800/800 [============ ] - 17s 22ms/step - loss: 0.0713 -

800/800 [======== ] - 17s 22ms/step - loss: 0.0649 -

800/800 [=========== ] - 17s 21ms/step - loss: 0.0589 -

accuracy: 0.9689 - val\_loss: 0.1137 - val\_accuracy: 0.9587

accuracy: 0.9719 - val\_loss: 0.1118 - val\_accuracy: 0.9592

accuracy: 0.9741 - val\_loss: 0.1102 - val\_accuracy: 0.9598

accuracy: 0.9777 - val\_loss: 0.1108 - val\_accuracy: 0.9592

accuracy: 0.9804 - val\_loss: 0.1123 - val\_accuracy: 0.9598

Epoch 7/15

Epoch 8/15

Epoch 9/15

Epoch 10/15

```
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
accuracy: 0.9850 - val_loss: 0.1143 - val_accuracy: 0.9601
Epoch 13/15
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
accuracy: 0.9906 - val_loss: 0.1214 - val_accuracy: 0.9615
# Make predictions with USE TF Hub Model
model_5_pred_probs = model_5.predict(val_sentences)
# Making predictions on validation data
```

```
# 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

```
# 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}
# 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}
# 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}
# 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}
```

```
# 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}
# 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

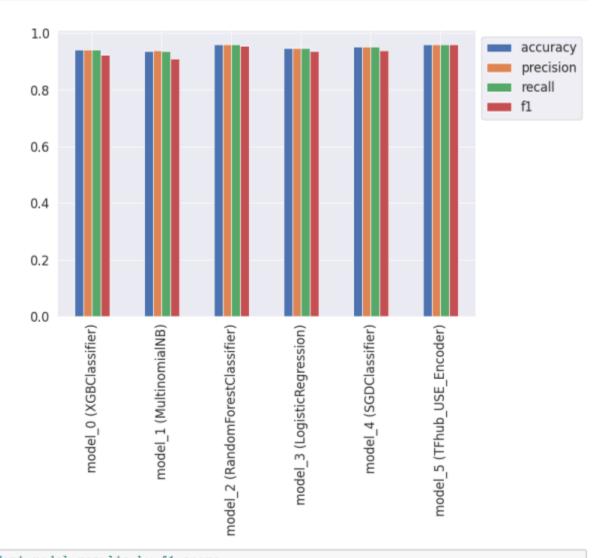
```
models_results_df = pd.DataFrame(data={'model_0 (XGBClassifier)':u
→model_0_results,
                                       'model_1 (MultinomialNB)': __
→model_1_results,
```

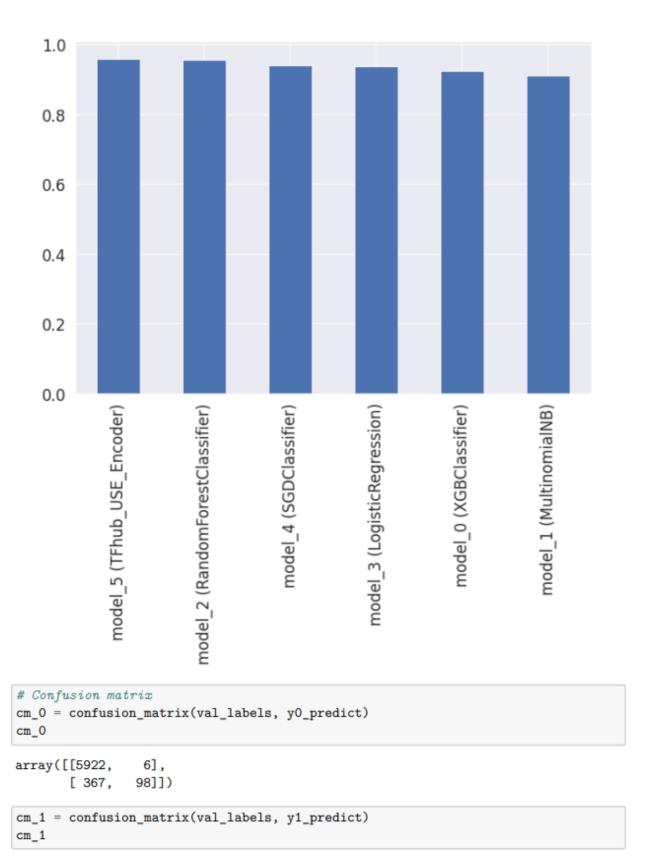
```
'model_2 (RandomForestClassifier)' : __
-model_2_results,
                                         'model_3 (LogisticRegression)': u
-model_3_results,
                                         'model_4 (SGDClassifier)' : ...
-model_4_results,
                                         'model_5 (TFhub_USE_Encoder)' : ...
→model_5_results}).transpose()
models_results_df
```

```
accuracy precision recall
                                                                   f1
                               94.165494 0.941692 0.941655 0.924009
model_0 (XGBClassifier)
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
                               95.104020 0.951104 0.951040 0.940153
model_4 (SGDClassifier)
model_5 (TFhub_USE_Encoder)
                              96.152041 0.958954 0.961520 0.959556
```

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

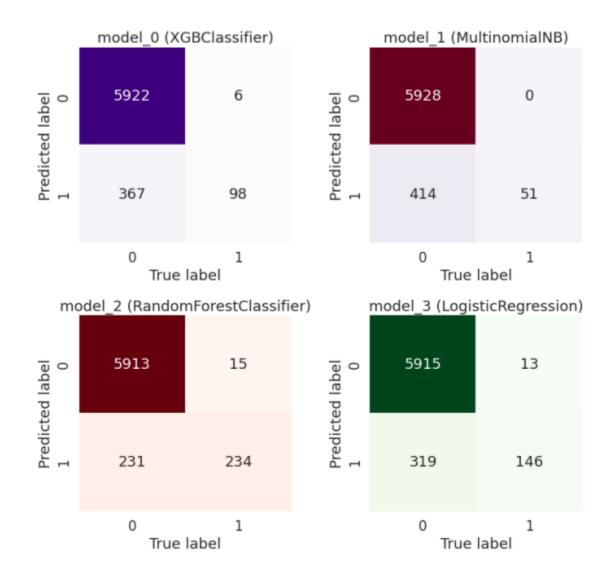
```
# Plot and compare all of the model results
models_results_df.plot(kind="bar", figsize=(10,7)).legend(bbox_to_anchor=(1.0,1.
--0));
```

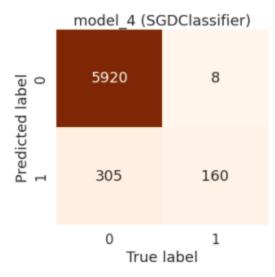


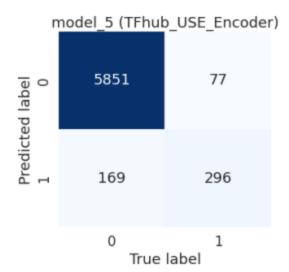


```
array([[5928,
                 0],
       [ 414,
                51]])
cm_2 = confusion_matrix(val_labels, y2_predict)
cm_2
array([[5913,
               15],
       [ 231, 234]])
cm_3 = confusion_matrix(val_labels, y3_predict)
cm_3
array([[5915, 13],
       [ 319, 146]])
cm_4 = confusion_matrix(val_labels, 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],
```







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

# 0.8 Finding the Most Wrong Examples

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

[5 rows x 4 columns]

```
# Find the wrong predictions and sort by predictio probabilities
most_wrong = val_df[val_df["target"] !=val_df["pred"]].sort_values("pred_prob",u
 →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
      what lies these dt suppoers are spreading look ... ...
558
                                                             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
                   i m blessedt iconic lovebeingalegend ...
1153
                                                               0.000001
[246 rows x 4 columns]
# 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
      what lies these dt suppoers are spreading look... ...
558
                                                            0.992918
      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]
# 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]
```

```
# 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
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
what lies these dt suppoers are spreading looks like propaganda from the 1930s
Target: 0, Pred: 1.0, Prob: 0.9920094013214111
ali spoke the truth about white folks period facts idiot moron
theverycoreofamerica
Target: 0, Pred: 1.0, Prob: 0.9916594624519348
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
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
prayfororlando can we show love amp not hate by clifton w 0
Target: 0, Pred: 1.0, Prob: 0.9607369899749756
just herd you re podcast no man deserves to be called a man after he rapes a
women scumofthreah
 # Check the false negatives (model predicted 0 when should've been 1)
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: 1, Pred: 0.0, Prob: 0.001167581183835864
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
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
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]
              0%|
                            | 0.00/466k [00:00<?, ?B/s]
Downloading:
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,)}, ()),</pre>
types: ({input_ids: tf.int32, attention_mask: tf.int32}, tf.int32)>
```

```
len(val_labels)
```

```
6393
 training_args = TFTrainingArguments(
    output_dir='./results',
                                    # output directory
                                    # total number of training epochs
    num_train_epochs=3,
    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_
 \rightarrowscheduler
    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
                                        # training arguments, defined above
    args=training_args,
    train_dataset=train_dataset,
                                        # training dataset
                                        # evaluation dataset
     eval_dataset=val_dataset
 )
 trainer.train()
score_6 = trainer.evaluate(val_dataset)
score_6
{'eval_loss': 0.12932125091552735}
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_proba=trainer.predict(val_dataset)[0]
y6_predict=np.argmax(y6_predict_proba,axis=-1)
```

```
{'accuracy': 96.5274519005162,

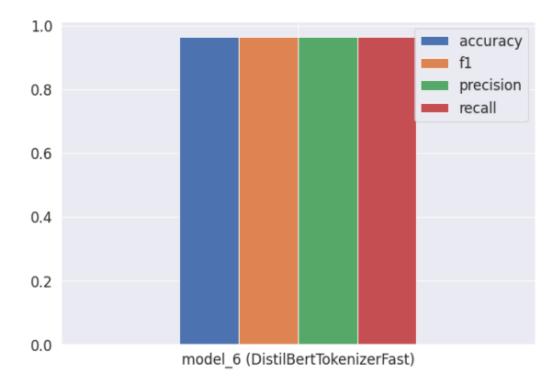
'f1': 0.9644764593802877,

'precision': 0.9639728208229673,

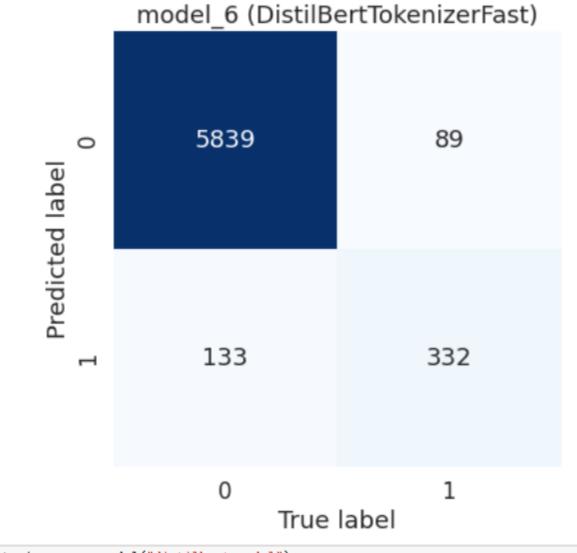
'recall': 0.9652745190051619}
```

accuracy f1 precision recall model\_6 (DistilBertTokenizerFast) 96.527452 0.964476 0.963973 0.965275

```
# 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([[5839,
               89],
       [ 133, 332]])
# 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 an f1-score of 0.964. So I would recommend using model 6.