2022 Datahacks Project Report - Intermediate

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Goal: Predict successful deals for each company on Shark Tank tv show

Dataset: Train, Test

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Package Import

In [1]:
```python
import re
import os
import csv
import nltk
import warnings
import tqdm
import numpy as np
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt
import tensorflow as tf
from tensorflow.keras.utils import to_categorical
from tensorflow import keras
from tensorflow.keras import layers, Sequential
from keras.layers import Dense, Bidirectional, LSTM, Dropout
from keras.models import Model
from keras.layers.embeddings import Embedding
from tensorflow.keras.metrics import Recall, Precision
from tensorflow.keras.preprocessing.text import Tokenizer
from tensorflow.keras.preprocessing.sequence import pad_sequences
from wordcloud import WordCloud, STOPWORDS, ImageColorGenerator
from xgboost import XGBClassifier
from nltk.corpus import stopwords
from nltk.stem import WordNetLemmatizer
from nltk.corpus import stopwords
from sklearn.model_selection import train_test_split
from sklearn.metrics import accuracy_score
from sklearn import tree
from sklearn.feature_extraction.text import CountVectorizer
from sklearn.feature_extraction.text import TfidfVectorizer
from sklearn.neighbors import KNeighborsClassifier
from sklearn.metrics import classification_report
from sklearn.ensemble import RandomForestClassifier
from sklearn.metrics import roc_auc_score
warnings.filterwarnings('ignore')
```

```
C:\Users\ziyuw\AppData\Local\Programs\Python\Python310\lib\site-packages\xgboost\compat.py:36: FutureWarning: pandas.Int64Index is deprecated and will be removed from pandas in a future version. Use pandas.Index with the appropriate dtype instead.
  from pandas import MultiIndex, Int64Index
```

EDA

Data Process

In [2]:
```python
train = pd.read_csv('./train.csv')
train.head()
```

Out[2]:

	Season_Epi_code	Pitched_Business_Identifier	Pitched_Business_Desc	Deal_Status	Deal_Shark
0	826	Laid Brand	hair-care products made with pheromones . Laid...	0	NaN
1	826	Wine & Design	painting classes with wine served . Wine & Des...	1	KOL
2	824	Peoples Design	a mixing bowl with a built-in scoop . Peoples ...	1	LG
3	824	Rumi Spice	saffron imported from Afghanistan . Rumi Spice...	1	MC
4	824	Wallet Buckle	a belt buckle that holds credit cards . The Wa...	1	RH

Column Rename and Information

In [3]:
```python
df = train.copy()
df.rename(columns = {'Pitched_Business_Desc':'Des', \
    'Pitched_Business_Identifier':'Brand', \
        'Season_Epi_code':'Episode',\
            'Deal_Status':'Status',\
                'Deal_Shark':'Shark'}, inplace = True)
```

In [4]:
```python
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 530 entries, 0 to 529
Data columns (total 5 columns):
 #   Column   Non-Null Count  Dtype
---  ------   --------------  -----
 0   Episode  530 non-null    int64
 1   Brand    530 non-null    object
 2   Des      530 non-null    object
 3   Status   530 non-null    int64
 4   Shark    283 non-null    object
dtypes: int64(2), object(3)
memory usage: 20.8+ KB
```

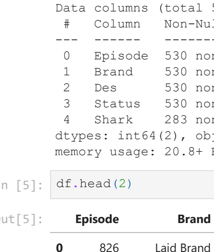
In [5]:
```python
df.head(2)
```

Out[5]:

	Episode	Brand	Des	Status	Shark
0	826	Laid Brand	hair-care products made with pheromones . Laid...	0	NaN
1	826	Wine & Design	painting classes with wine served . Wine & Des...	1	KOL

In [6]:
```python
sns.countplot(x ='Status', data = df)
```

Out[6]:
```
<AxesSubplot:xlabel='Status', ylabel='count'>
```



Obviously, the Description column takes most weights to predict the Status.

In [7]:
```python
print("Null-Value Num for Desciption: " + str(df.Des.isnull().sum()))
```

```
Null-Value Num for Desciption: 0
```

In [8]:
```python
df["Episode"] = df["Episode"].apply(lambda x: int(x))
print("Null-Value Num For Epi-code: " + str(df.Episode.isnull().sum()))
```

```
Null-Value Num For Epi-code: 0
```

Collect, Clean, and Standardize

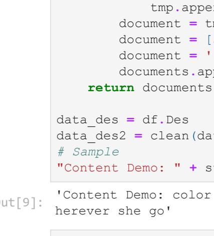
In [9]:
```python
def clean(X):
    '''Column Clean'''
    documents = []
    stemmer = WordNetLemmatizer()
    for sen in range(0, len(X)):
        # Remove special characters
        document = re.sub(r'\W', ' ', str(X[sen]))
        # remove single characters
        document = re.sub(r'\s+[a-zA-Z]\s+', ' ', document)
        # Remove single characters from the start
        document = re.sub(r'\^[a-zA-Z]\s+', ' ', document)
        # Substituting multiple spaces with single
        document = re.sub(r'\s+', ' ', document, flags=re.I)
        # Removing prefixed 'b'
        document = re.sub(r'^b\s+', '', document)
        # Converting to Lowercase
        document = document.lower()
        # Lemmatization
        document = document.split()
        # remove single char again of special char
        tmp = []
        for w in document:
            chs = [c for c in w if ord(c) >= 48 and ord(c) <= 122]
            w = ''.join(chs)
            tmp.append(w)
        document = tmp
        document = [stemmer.lemmatize(word) for word in document]
        document = ' '.join(document)
        documents.append(document)
    return documents

data_des = df.Des
data_des2 = clean(data_des)
# Sample
"Content Demo: " + str(data_des2[0][104:])
```

Out[9]:
```
'Content Demo: color in addition to protecting and hydrating hair  the pheromone help girl  exude confidence wherever she go'
```

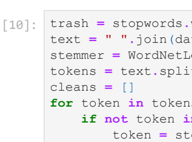
In [10]:
```python
trash = stopwords.words('english')
text = " ".join(data_des2).lower()
stemmer = WordNetLemmatizer()
tokens = text.split()
cleans = []
for token in tokens:
    if not token in trash:
        token = stemmer.lemmatize(token)
        cleans.append(token)
freq = nltk.FreqDist(cleans)
freq.plot(16, cumulative = False, color = '#8B0A40')
```

Out[10]:
```
<AxesSubplot:xlabel='Samples', ylabel='Counts'>
```

In [11]:
```python
des_len = []
for i in data_des2:
    des_len.append(len(i.split(" ")))
plt.bar(range(len(des_len)), des_len, fc = '#36648B')
plt.show()
```



In [12]:
```python
wordcloud = WordCloud(max_font_size = 120, max_words = 30, \
    background_color = "#EDEDED").generate(" ".join(cleans))
plt.imshow(wordcloud, interpolation = 'bilinear')
plt.axis("off")
plt.show()
```



From the above visualizations, the words with high frequency have normal meanings.

Feature Enineering

In [ ]:

NLP Model

CountVector and XGBoost

In [13]:
```python
len(data_des)
```

Out[13]:
```
530
```

In [14]:
```python
cv = CountVectorizer(max_features = 2000, encoding = "utf-8",
      ngram_range = (2, 3), stop_words = 'english')
```

In [15]:
```python
X = cv.fit_transform(data_des).toarray()
y = df['Status']
X_train, X_test, y_train, y_test = train_test_split(X, y, \
      test_size = 0.20, random_state = 0)
count_df = pd.DataFrame(X_train, columns = cv.get_feature_names_out())
```

In [16]:
```python
count_df['tiket'] = y_train
model = XGBClassifier(use_label_encoder = False, eval_metric = 'mlogloss')
model.fit(X_train, y_train)

# make predictions for test data
y_pred = model.predict(X_test)
predictions = [round(value) for value in y_pred]
# evaluate predictions
accuracy = accuracy_score(y_test, predictions)

print('Models with CountVector Feature:\n')
print('XGBoost Classifier Model:\n')
print('Test-set Accuracy:', accuracy)
```

```
Models with CountVector Feature:

XGBoost Classifier Model:

Test-set Accuracy: 0.5566037735849056
```

We found that in XGBoost Model, it reaches the best accuracy for y_test when we use the 2-gram. Furthermore, about the stopwords in English, we found that XGBoost is poor at classifying words with stop words and may do better if synonyms are processed. We are not sure whether in test data the performance will be better.

XGBoost are good at allocating rate for each tree to decrease weight, but the running is slow since it has to presort all features and generate more classifier levels.

TF-IDF and Decision Tree

In [17]:
```python
dff = df.copy() # copy to prevent catastrophe
```

In [18]:
```python
def TFIDFModels(Model, text):

    x_train, x_test, y_train, y_test = train_test_split(dff['Des'], dff['Status'],\
         test_size = 0.2, random_state = 50)

    vect      = TfidfVectorizer(min_df = 5, max_df = 0.7, \
        sublinear_tf = True, use_idf = True)
    train_vect= vect.fit_transform(x_train)
    test_vect = vect.transform(x_test)

    model     = Model
    model.fit(train_vect, y_train)
    predicted = model.predict(test_vect)
    accuracy  = model.score(train_vect, y_train)
    report = classification_report(y_test, predicted, output_dict=True)

    print(text)
    print('Test-set Accuracy:', accuracy_score(y_test, predicted))
    print('\n')
```

In [19]:
```python
def KNN_TFIDF():
    # x, y
    x_train, x_test, y_train, y_test = train_test_split(dff['Des'], dff['Status'],\
         test_size = 0.2, random_state = 50)
    # TF-IDF
    vect      = TfidfVectorizer(min_df = 5, max_df = 0.7, \
        sublinear_tf = True, use_idf = True)
    train_vect= vect.fit_transform(x_train)
    test_vect = vect.transform(x_test)

    for k in [1,2]: # 1-gram, 2-gram
        model = KNeighborsClassifier(n_neighbors = k)
        model.fit(train_vect, y_train)

        predicted = model.predict(test_vect)
        accuracy  = model.score(train_vect, y_train)
        report = classification_report(y_test, predicted, output_dict=True)

        print("Classification for k = {} is:".format(k))
        print('Test-set Accuracy:', accuracy_score(y_test, predicted))
        print('\n')
```

In [20]:
```python
from sklearn import svm
SupportVectorClassifier = svm.SVC(C = 2, kernel='poly')

print('Models with TF-IDF Feature:\n')

# Support Vector
svm = TFIDFModels(Model = SupportVectorClassifier,\
    text = 'Support Vector Classifier Model:\n')

# Decision Tree
DecTree = TFIDFModels(Model = tree.DecisionTreeClassifier()\
    ,text = 'Decision Tree Classifier Model:\n')
knn_tfidf = KNN_TFIDF()
```

```
Models with TF-IDF Feature:

Support Vector Classifier Model:

Test-set Accuracy: 0.6415094339622641


Decision Tree Classifier Model:

Test-set Accuracy: 0.5


Classification for k = 1 is:
Test-set Accuracy: 0.6509433962264151


Classification for k = 2 is:
Test-set Accuracy: 0.46226415094339623
```

We can see that Support Vector and 1-gram Decision Tree have similar performance.

Random Forest

In [21]:
```python
test = pd.read_csv("./test.csv")
```

In [22]:
```python
x_train, y_train = df['Des'], df['Status']
vect = CountVectorizer(max_features=1000 , ngram_range=(2,2))
vct   = vect.fit(x_train)
train_vect = vct.transform(x_train)
test_vect = vct.transform(test.Pitched_Business_Desc)
rf = RandomForestClassifier()
rf.fit(train_vect,y_train)
y_pred = rf.predict_proba(test_vect)
```

In [23]:
```python
step_factor = 0.05
threshold = 0.2
roc_score = 0
predicted_proba = rf.predict_proba(train_vect) # probability of prediction
while threshold <= 0.8: # check best threshold
    temp_thresh = threshold
    predicted = (predicted_proba [:,1] >= temp_thresh).astype('int')
    print('Threshold', round(temp_thresh, 2), \
    '-- score', round(roc_auc_score(y_train, predicted), 2))
    if roc_score < roc_auc_score(y_train, predicted): #store the threshold for best classification
        roc_score = roc_auc_score(y_train, predicted)
        thrsh_score = threshold
    threshold = threshold + step_factor
print('---Optimum Threshold ---', thrsh_score, \
    '--ROC--', round(roc_score,2))
```

```
Threshold 0.2 -- score 0.76
Threshold 0.25 -- score 0.85
Threshold 0.3 -- score 0.9
Threshold 0.35 -- score 0.93
Threshold 0.4 -- score 0.94
Threshold 0.45 -- score 0.94
Threshold 0.5 -- score 0.95
Threshold 0.55 -- score 0.95
Threshold 0.6 -- score 0.95
Threshold 0.65 -- score 0.95
Threshold 0.7 -- score 0.94
Threshold 0.75 -- score 0.92
---Optimum Threshold --- 0.49999999999999994 --ROC-- 0.95
```

We pick 0.6 as from 0.55-0.7 performs roughly same.

In [24]:
```python
y_pred = y_pred[:, 1]
rf_out = []
for i in range(len(y_pred)):
  if y_pred[i] >= 0.6:
    rf_out.append(1)
  else:
    rf_out.append(0)
rf_output = pd.DataFrame(rf_out)
rf_out[:10]
```

Out[24]:
```
[0, 0, 0, 0, 0, 0, 1, 0, 0, 0]
```

LSTM

In [25]:
```python
data2 = pd.read_csv('train.csv')
data2.rename(columns = {'Pitched_Business_Desc':'Des', \
    'Pitched_Business_Identifier':'Brand', \
        'Season_Epi_code':'Episode',\
            'Deal_Status':'Status',\
                'Deal_Shark':'Shark'}, inplace = True)
data2 = data2[['Des','Status']]
data2['Des'] = clean(data2['Des'])
```

In [26]:
```python
X, y = data2['Des'], data2['Status']
tokenizer = Tokenizer()
tokenizer.fit_on_texts(X)
X = tokenizer.texts_to_sequences(X)
X = np.array(X)
y = np.array(y)
# pad sequences at the beginning of each sequence with 0's
# for example if SEQUENCE_LENGTH=4:
# [[5, 3, 2], [5, 1, 2, 3], [3, 4]]
# will be transformed to:
# [[0, 5, 3, 2], [5, 1, 2, 3], [0, 0, 3, 4]]
X = pad_sequences(X, maxlen = 100)
y = to_categorical(y)
X_train, X_test, y_train, y_test = train_test_split(X, y, \
    test_size = 0.2, random_state=7)
```

In [27]:
```python
def get_model(tokenizer, lstm_units):
    """
    Constructs the model
    """
    # get the GloVe embedding vectors
    model = Sequential()
    model.add(Embedding(len(tokenizer.word_index)+1,
              100,
              trainable=False,
              input_length= 100))

    model.add(LSTM(lstm_units, recurrent_dropout=0.2))
    model.add(Dropout(0.3))
    model.add(Dense(2, activation="softmax"))
    # compile as rmsprop optimizer
    # aswell as with recall metric
    model.compile(optimizer="rmsprop", loss="categorical_crossentropy",
                  metrics=["accuracy"])
    model.summary()
    return model
```

In [28]:
```python
model = get_model( tokenizer = tokenizer, lstm_units = 128)
model.fit(X_train, y_train, validation_data = (X_test, y_test),
          batch_size=16, epochs=12, verbose=1)
```

```
Model: "sequential"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 embedding (Embedding)       (None, 100, 100)          340700

 lstm (LSTM)                 (None, 128)               117248

 dropout (Dropout)           (None, 128)               0

 dense (Dense)               (None, 2)                 258

=================================================================
Total params: 458,206
Trainable params: 117,506
Non-trainable params: 340,700
_________________________________________________________________
Epoch 1/12
27/27 [==============================] - 5s 84ms/step - loss: 0.6922 - accuracy: 0.5425 - val_loss: 0.6999 - val_accuracy: 0.4340
Epoch 2/12
27/27 [==============================] - 2s 65ms/step - loss: 0.6849 - accuracy: 0.5825 - val_loss: 0.7096 - val_accuracy: 0.4528
Epoch 3/12
27/27 [==============================] - 2s 62ms/step - loss: 0.6733 - accuracy: 0.5920 - val_loss: 0.7115 - val_accuracy: 0.4528
Epoch 4/12
27/27 [==============================] - 2s 62ms/step - loss: 0.6649 - accuracy: 0.6061 - val_loss: 0.7745 - val_accuracy: 0.5000
Epoch 5/12
27/27 [==============================] - 2s 63ms/step - loss: 0.6600 - accuracy: 0.5825 - val_loss: 0.7074 - val_accuracy: 0.4717
Epoch 6/12
27/27 [==============================] - 2s 62ms/step - loss: 0.6654 - accuracy: 0.6108 - val_loss: 0.7127 - val_accuracy: 0.5189
Epoch 7/12
27/27 [==============================] - 2s 61ms/step - loss: 0.6507 - accuracy: 0.6250 - val_loss: 0.8135 - val_accuracy: 0.4811
Epoch 8/12
27/27 [==============================] - 2s 72ms/step - loss: 0.6658 - accuracy: 0.6156 - val_loss: 0.7374 - val_accuracy: 0.5000
Epoch 9/12
27/27 [==============================] - 2s 89ms/step - loss: 0.6363 - accuracy: 0.6132 - val_loss: 0.7209 - val_accuracy: 0.5000
Epoch 10/12
27/27 [==============================] - 2s 87ms/step - loss: 0.6440 - accuracy: 0.6415 - val_loss: 0.7304 - val_accuracy: 0.5000
Epoch 11/12
27/27 [==============================] - 2s 91ms/step - loss: 0.6184 - accuracy: 0.6792 - val_loss: 0.7390 - val_accuracy: 0.5000
Epoch 12/12
27/27 [==============================] - 2s 86ms/step - loss: 0.6682 - accuracy: 0.6722 - val_loss: 0.7650 - val_accuracy: 0.5000
```

Out[28]:
```
<keras.callbacks.History at 0x1c13cb02f80>
```

In [29]:
```python
result = model.evaluate(X_test, y_test)
```

```
4/4 [==============================] - 0s 15ms/step - loss: 0.7650 - accuracy: 0.5000
```

We found that LSTM does not perform so well in the small dataset. The reason is not clear but we did not have enough time to embed vectors which may affect accuracy.

From above, we decide to use TF-IDF that perform slightly better in train set.

In [31]:
```python
test = pd.read_csv("./test.csv")
vect      = TfidfVectorizer(min_df = 5, max_df = 0.8,\
    sublinear_tf = True, use_idf = True)
train_vect= vect.fit_transform(df['Des'])
test_vect = vect.transform(test.Pitched_Business_Desc)
SupportVectorClassifier.fit(train_vect, df['Status'])
predicted = SupportVectorClassifier.predict(test_vect)
tf_out = pd.DataFrame(predicted)
tf_out.rename(columns = {0:'Pred'}, inplace = True)
tf_out.head()
file = 'output.csv'
if(os.path.exists(file) and os.path.isfile(file)):
    os.remove(file)
tf_out.to_csv('output.csv', index = False)
print("Prediction saved.")
```

```
Prediction saved.
```