IT350 DA Assignment 5

YELP Dataset

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In [4]:
```
# importing libraries
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import tensorflow as tf
from sklearn.decomposition import PCA
from sklearn.preprocessing import StandardScaler
!pip install gensim
from gensim.parsing.preprocessing import remove_stopwords
from gensim.utils import simple_preprocess
from gensim.parsing.porter import PorterStemmer
from sklearn.model_selection import train_test_split
from gensim import corpora

data_path = "./yelp.csv"
```

```
Collecting gensim
  Downloading gensim-4.0.1-cp38-cp38-win_amd64.whl (23.9 MB)
Requirement already satisfied: Cython==0.29.21 in c:\users\harsh\anaconda3\lib\site-packages (from gensim) (0.29.21)
Requirement already satisfied: scipy>=0.18.1 in c:\users\harsh\anaconda3\lib\site-packages (from gensim) (1.5.2)
Collecting smart-open>=1.8.1
  Downloading smart_open-5.0.0-py3-none-any.whl (56 kB)
Requirement already satisfied: numpy>=1.11.3 in c:\users\harsh\anaconda3\lib\site-packages (from gensim) (1.19.2)
Installing collected packages: smart-open, gensim
Successfully installed gensim-4.0.1 smart-open-5.0.0
C:\Users\harsh\anaconda3\lib\site-packages\gensim\similarities\__init__.py:15: UserWarning: The gensim.similarities.levenshtein submodule is disabled, because the optional Levenshtein package <https://pypi.org/project/python-Levenshtein/> is unavailable. Install Levenhstein (e.g. `pip install python-Levenshtein`) to suppress this warning.
  warnings.warn(msg)
```

In [5]:
```
# Reading the data
data_raw = pd.read_csv(data_path)
print("Number of rows per star rating:")
print(data_raw['stars'].value_counts())

# Function to map stars to sentiment
def map_sentiment(stars_received):
    if stars_received <= 2:
        return 0          #negative review
    elif stars_received == 3:
        return 1          #neutral review
    else:
        return 2          #positive review
# Mapping stars to sentiment into three categories
data_raw['sentiment'] = [ map_sentiment(x) for x in data_raw['stars']]

remove_stopwords("Restaurant had a really good service!!")
remove_stopwords("I did not like the food!")
remove_stopwords("This product is not good!")
# Tokenizing
data_raw['tokenized_text'] = [simple_preprocess(line, deacc=True) for line in data_raw['text']]
porter_stemmer = PorterStemmer()
data_raw['stemmed_tokens'] = [[porter_stemmer.stem(word) for word in tokens] for tokens in data_raw['tokenized_text'] ]
```

```
Number of rows per star rating:
4    3526
5    3337
3    1461
2     927
1     749
Name: stars, dtype: int64
```

In [6]:
```
# Train Test Split Function
def split_train_test(data_raw, test_size=0.3, shuffle_state=True):
    X_train, X_test, Y_train, Y_test = train_test_split(data_raw[['business_id', 'cool', 'date', 'funny', 'review_id', 'stars', 'text', 'useful', 'user_id', '
    print("Value counts for Train sentiments")
    print(Y_train.value_counts())
    print("Value counts for Test sentiments")
    print(Y_test.value_counts())
    X_train = X_train.reset_index()
    X_test = X_test.reset_index()
    Y_train = Y_train.to_frame()
    Y_train = Y_train.reset_index()
    Y_test = Y_test.to_frame()
    Y_test = Y_test.reset_index()
    return X_train, X_test, Y_train, Y_test

X_train, X_test, Y_train, Y_test = split_train_test(data_raw)
```

```
Value counts for Train sentiments
2    4822
0    1155
1    1023
Name: sentiment, dtype: int64
Value counts for Test sentiments
2    2041
0     521
1     438
Name: sentiment, dtype: int64
```

In [7]:
```
def make_dict(data_raw, padding=True):
    if padding:
        review_dict = corpora.Dictionary([['pad']])
        review_dict.add_documents(data_raw['stemmed_tokens'])
    else:
        review_dict = corpora.Dictionary(data_raw['stemmed_tokens'])
    return review_dict

# Making the dictionary(vocalubary)
review_dict = make_dict(data_raw, padding=False)
```

In [8]:
```
VOCAB_SIZE = len(review_dict)
NUM_LABELS = 3

# Function to make bow vector to be used as input to network
def make_bow_vector(review_dict, sentence):
    # vec = torch.zeros(VOCAB_SIZE, dtype=torch.float64, device=device)
    vec = np.zeros(VOCAB_SIZE, dtype=np.float64)
    for word in sentence:
        vec[review_dict.token2id[word]] += 1
    return vec.reshape(1, -1)

x_train = [make_bow_vector(review_dict, row['stemmed_tokens']) for index, row in X_train.iterrows()]
x_test = [make_bow_vector(review_dict, row['stemmed_tokens']) for index, row in X_test.iterrows()]
x_train = np.array(x_train)
x_train = np.reshape(x_train, (x_train.shape[0], -1))
y_train = Y_train['sentiment'].to_numpy()
x_test = np.array(x_test)
x_test = np.reshape(x_test, (x_test.shape[0], -1))
y_test = Y_test['sentiment'].to_numpy()
```

In [9]:
```
print(x_test.shape)
print(y_test.shape)
```

```
(3000, 19608)
(3000,)
```

In [15]:
```
def yelp_backprop(inputshape, classes):
  model = tf.keras.Sequential()
  input_shape = (inputshape)
  #Input layer
  model.add(tf.keras.layers.InputLayer(input_shape=input_shape))
  # model.add(tf.keras.layers.Flatten())

  #First hidden layer
  model.add(tf.keras.layers.Dense(32, activation='sigmoid'))

  #Second hidden layer
  model.add(tf.keras.layers.Dense(32, activation='sigmoid'))

  #Output layer
  model.add(tf.keras.layers.Dense(classes, activation='sigmoid'))

  return model
```

In [16]:
```
model = yelp_backprop(x_train.shape[-1], 3)
optimizer = tf.keras.optimizers.SGD(learning_rate=0.1)
model.compile(optimizer=optimizer, metrics=['accuracy'], loss='sparse_categorical_crossentropy')
model.summary()
history = model.fit(x = x_train, y = y_train, batch_size=32, epochs=20, validation_data=(x_test, y_test), )
```

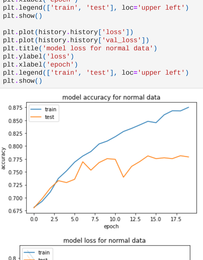
```
Model: "sequential_2"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
dense_6 (Dense)              (None, 32)                627488
_________________________________________________________________
dense_7 (Dense)              (None, 32)                1056
_________________________________________________________________
dense_8 (Dense)              (None, 3)                 99
=================================================================
Total params: 628,643
Trainable params: 628,643
Non-trainable params: 0
_________________________________________________________________
Epoch 1/20
219/219 [==============================] - 2s 7ms/step - loss: 0.9049 - accuracy: 0.6454 - val_loss: 0.8129 - val_accuracy: 0.6803
Epoch 2/20
219/219 [==============================] - 1s 5ms/step - loss: 0.7897 - accuracy: 0.6932 - val_loss: 0.7529 - val_accuracy: 0.6980
Epoch 3/20
219/219 [==============================] - 1s 5ms/step - loss: 0.7316 - accuracy: 0.7057 - val_loss: 0.6909 - val_accuracy: 0.7183
Epoch 4/20
219/219 [==============================] - 1s 5ms/step - loss: 0.6621 - accuracy: 0.7347 - val_loss: 0.6456 - val_accuracy: 0.7330
Epoch 5/20
219/219 [==============================] - 1s 5ms/step - loss: 0.6206 - accuracy: 0.7463 - val_loss: 0.6762 - val_accuracy: 0.7293
Epoch 6/20
219/219 [==============================] - 1s 5ms/step - loss: 0.5697 - accuracy: 0.7720 - val_loss: 0.6402 - val_accuracy: 0.7357
Epoch 7/20
219/219 [==============================] - 1s 5ms/step - loss: 0.5592 - accuracy: 0.7780 - val_loss: 0.5686 - val_accuracy: 0.7697
Epoch 8/20
219/219 [==============================] - 1s 5ms/step - loss: 0.5219 - accuracy: 0.7901 - val_loss: 0.6006 - val_accuracy: 0.7533
Epoch 9/20
219/219 [==============================] - 1s 5ms/step - loss: 0.4921 - accuracy: 0.8023 - val_loss: 0.5531 - val_accuracy: 0.7680
Epoch 10/20
219/219 [==============================] - 1s 5ms/step - loss: 0.4789 - accuracy: 0.8089 - val_loss: 0.5468 - val_accuracy: 0.7757
Epoch 11/20
219/219 [==============================] - 1s 5ms/step - loss: 0.4456 - accuracy: 0.8188 - val_loss: 0.5700 - val_accuracy: 0.7743
Epoch 12/20
219/219 [==============================] - 1s 5ms/step - loss: 0.4315 - accuracy: 0.8293 - val_loss: 0.6114 - val_accuracy: 0.7397
Epoch 13/20
219/219 [==============================] - 1s 6ms/step - loss: 0.4146 - accuracy: 0.8352 - val_loss: 0.6314 - val_accuracy: 0.7607
Epoch 14/20
219/219 [==============================] - 1s 6ms/step - loss: 0.3924 - accuracy: 0.8445 - val_loss: 0.5555 - val_accuracy: 0.7700
Epoch 15/20
219/219 [==============================] - 1s 6ms/step - loss: 0.3703 - accuracy: 0.8600 - val_loss: 0.5545 - val_accuracy: 0.7810
Epoch 16/20
219/219 [==============================] - 1s 6ms/step - loss: 0.3751 - accuracy: 0.8561 - val_loss: 0.5926 - val_accuracy: 0.7757
Epoch 17/20
219/219 [==============================] - 1s 6ms/step - loss: 0.3588 - accuracy: 0.8673 - val_loss: 0.5518 - val_accuracy: 0.7773
Epoch 18/20
219/219 [==============================] - 1s 6ms/step - loss: 0.3368 - accuracy: 0.8698 - val_loss: 0.5737 - val_accuracy: 0.7757
Epoch 19/20
219/219 [==============================] - 1s 6ms/step - loss: 0.3315 - accuracy: 0.8686 - val_loss: 0.5662 - val_accuracy: 0.7813
Epoch 20/20
219/219 [==============================] - 1s 5ms/step - loss: 0.3226 - accuracy: 0.8775 - val_loss: 0.6351 - val_accuracy: 0.7790
```

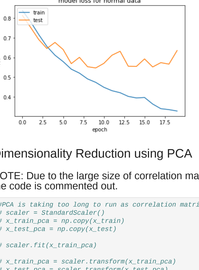
In [17]:
```
score = model.evaluate(x_test, y_test, verbose=0)
print('Test loss:', score[0])
print('Test accuracy:', score[1])
```

```
Test loss: 0.6351478899588446
Test accuracy: 0.7789999842643738
```

In [18]:
```
plt.plot(history.history['accuracy'])
plt.plot(history.history['val_accuracy'])
plt.title('model accuracy for normal data')
plt.ylabel('accuracy')
plt.xlabel('epoch')
plt.legend(['train', 'test'], loc='upper left')
plt.show()

plt.plot(history.history['loss'])
plt.plot(history.history['val_loss'])
plt.title('model loss for normal data')
plt.ylabel('loss')
plt.xlabel('epoch')
plt.legend(['train', 'test'], loc='upper left')
plt.show()
```





Dimensionality Reduction using PCA

NOTE: Due to the large size of correlation matrix generated in this dataset, the PCA is taking too much time to run on the RAM. Therefore the code is commented out.

In [ ]:
```
#PCA is taking too long to run as correlation matrix is too large to accomodate in RAM
# scaler = StandardScaler()
# x_train_pca = np.copy(x_train)
# x_test_pca = np.copy(x_test)

# scaler.fit(x_train_pca)

# x_train_pca = scaler.transform(x_train_pca)
# x_test_pca = scaler.transform(x_test_pca)
# pca = PCA(0.95)
# pca.fit(x_train)
# print("PCA number of components: ",pca.n_components_)
# x_train_pca = pca.transform(x_train_pca)
# x_test_pca = pca.transform(x_test_pca)

# pca_model = yelp_backprop(pca.n_components_.item(), 10)
# pca_model.compile(optimizer='adam', metrics=['accuracy'], loss='sparse_categorical_crossentropy')
# pca_model.summary()
# pca_history = pca_model.fit(x = x_train_pca, y = Y_train, batch_size=32, epochs=10, validation_data=(x_test_pca, Y_test))
```