LSTM

```
%pip install lime
%pip install shap
%pip install minisom
# Imports
import numpy
import shap
from minisom import MiniSom
from keras.datasets import imdb, mnist
from keras.models import Sequential
from keras.layers import Dense
from keras.layers import LSTM
from keras.layers import Embedding
from keras.preprocessing import sequence
from keras.preprocessing.sequence import pad_sequences
import tensorflow as tf
import keras
import cv2
import numpy as np
from keras.datasets import mnist
from keras.models import Sequential , load_model
from keras.layers import Dense, Dropout, Flatten, Conv2D, MaxPooling2D
from tensorflow.keras.utils import plot model
import pandas as pd
from sklearn.decomposition import PCA
from sklearn import datasets
from sklearn.preprocessing import MinMaxScaler
import matplotlib.pyplot as plt
from sklearn import datasets
from keras.layers import Input, Dense
from keras.models import Model
from sklearn.model_selection import train_test_split
from sklearn.metrics import accuracy_score
from sklearn.datasets import load_breast_cancer
from sklearn.model selection import train test split
from sklearn.preprocessing import LabelEncoder
from xgboost import XGBClassifier
import lime
import lime.lime_tabular
import warnings
warnings.filterwarnings ('ignore')
#fix random seed for reproducibility
numpy.random.seed(7)
# limiting the vocab to 5000 words
top_words= 5000
# Q - load the dataset
(X_train, y_train), (X_test, y_test) = imdb.load_data(num_words = top_words)
     Downloading data from <a href="https://storage.googleapis.com/tensorflow/tf-keras-datasets/imdb.npz">https://storage.googleapis.com/tensorflow/tf-keras-datasets/imdb.npz</a>
     print(X_train[1]) # This is the first training example: Word indices in form of numbers
print(type(X_train[1])) # List of numbers that represents words from a vocab
print(len(X train[1])) # Number of words
print(y_train[1]) # Sentiment of the review
print(type(y_train[1])) # Type of value
     [1, 194, 1153, 194, 2, 78, 228, 5, 6, 1463, 4369, 2, 134, 26, 4, 715, 8, 118, 1634, 14, 394, 20, 13, 119, 954, 189, 102, 5, 20
     <class 'list'>
     189
     <class 'numpy.int64'>
max_review_length = 400 # Every review will be of this length
X_train = pad_sequences(X_train, maxlen = max_review_length)
X_test = pad_sequences(X_test, maxlen = max_review_length)
print(X train.shape)
```

```
(25000, 400)
embedding_vector_length = 32 # every review will be represented in the form of 32 element vectors
model = Sequential()
model.add(Embedding(top_words + 1, embedding_vector_length, input_length = max_review_length))
model.add(LSTM(10))
model.add(Dense(1, activation='sigmoid'))
model.compile(loss=['binary_crossentropy'], optimizer='adam', metrics=['accuracy']) #Question
hist=model.fit(X_train, y_train, epochs=10, batch_size=256,verbose=1, validation_data=(X_test,y_test))
scores = model.evaluate(X_test, y_test, verbose=0)
scores # Firsst is loss and second is accuracy
     [0.371402382850647, 0.8652799725532532]
print("Accuracy: %.2f%%" % (scores[1]*100)) #Question
     Accuracy: 86.53%
import matplotlib.pyplot as plt
#Question
# PLOT epoch v/s accuracy
y1=hist.history['accuracy'] # the accuracy for each epoch
y2=hist.history['val_accuracy'] # the validation accuracy for each epoch
plt.plot(y1)
plt.plot(y2)
import matplotlib.pyplot as plt
# Plot epoch vs Loss
#auestion
y1=hist.history['loss']
y2=hist.history['val_loss']
plt.plot(y1)
plt.plot(y2)
pred=model.predict(X_test)
print(pred)
```

CNN

```
(x_train, y_train), (x_test, y_test) = mnist.load_data()
x_train= x_train.reshape(60000,28,28)  # 60000 images of size 28,28
x_test= x_test.reshape(x_test.shape[0],28,28)  # x_test.shape[0] is numebr of images.
input_shape=(28,28,1)  # 1 is number of channels. eg RGB. this one is black and white

y_train=keras.utils.to_categorical(y_train,10)  # converts categories to one hot encoded vectors
y_test=keras.utils.to_categorical(y_test,10)
x_train= x_train.astype('float32')
x_test= x_test.astype('float32')
for i in range(10):
   plt.imshow(x_train[i])
   plt.subplot(5,2,i+1)

x_train /= 255
x_test /=255
model = None
# Q
batch size = 64 # told in question
```

```
num_classes = 10
def build_model(optimizer):
 model= Sequential()
  model.add(Conv2D(32, kernel_size = (3,3), activation = 'relu', input_shape = input_shape))
  model.add(MaxPooling2D(pool_size=(2,2)))
  model.add(Conv2D(32, kernel_size = (3,3), activation = 'relu'))
  model.add(MaxPooling2D(pool_size=(2,2)))
  model.add(Dropout(0.25))
  model.add(Flatten())
  model.add(Dense(256, activation='relu'))
  model.add(Dropout(0.25))
  model.add(Dense(10, activation='softmax'))
  model.compile(loss=keras.losses.categorical_crossentropy, optimizer=optimizer, metrics = ['accuracy'])
  model.summary()
  return model
optimizers = ['Adadelta', 'Adagrad', 'Adam', 'RMSprop', 'SGD']
for i in optimizers:
  model = build model(i) # added this
  plot_model(model, to_file="mnist model"+ '.jpg', show_shapes=True)
  \verb|hist=model.fit(x_train, y_train, batch_size=batch_size, epochs=1, verbose=1, validation_data=(x_test, y_test))|
  y1=hist.history['accuracy']
  y2=hist.history['val_accuracy']
  plt.plot(y1)
  plt.plot(y2)
keras.models.save_model(model, "mnist.h5", save_format="h5")
def predict_image(model,img):
  img = np.reshape(img,(1,28,28)) # 1 image of 28,28
  pred = model.predict(img)
  img = img.astype('float32')
 img = img / 255
  print(pred)
  answer = np.argmax(pred)
 print(answer)
m = load_model('/content/mnist.h5')
predict_image(m, x_test[7])
plt.imshow(x_test[7],cmap='gray')
PCA
iris = datasets.load_iris() # Loading data
X = iris.data
y = iris.target
print("X:",X[0])
target_names = iris.target_names
     X: [5.1 3.5 1.4 0.2]
scaler = MinMaxScaler()
scaler.fit(X)
X_scaled = scaler.transform(X) # scaling values from 0-1
def plot3clusters(X, title, vtitle):
    So what we want to do here is we have different data points on a piece of paper. we want to give colors to different tyeps of d
    .....
    plt.figure()
    # picking a color for a group
    colors = ['navy','turquoise','darkorange']
    # i = unique identifier for the group
    for color, i, target_name in zip(colors, [0,1,2], target_names):
        \# if any data point label = i, get its x and y cordinate and build its scatter plot
        plt.scatter(X[y==i, 0], X[y==i, 1], color=color, label=target_name)
        plt.legend(loc='upper left')
```

plt.title(title)

```
plt.xlabel(vtitle + "1") # PC1
    plt.ylabel(vtitle + "2") # PC2
    plt.show()

pca = PCA()
pca_transformed = pca.fit_transform(X_scaled)

# Displaying new Transformed Values
print("Pca transformed: ", pca_transformed[0])

# Calling the plotting function
plot3clusters(pca_transformed[:, :2], 'PCA', 'PC')
```

Autoencoders

```
iris = datasets.load iris()
X = iris.data
y = iris.target
print("X:",X[0])
target names = iris.target names
# Scaling the data
scaler = MinMaxScaler()
scaler.fit(X)
X_scaled = scaler.transform(X)
     X: [5.1 3.5 1.4 0.2]
def plot3clusters(X, title, vtitle):
    plt.figure()
    colors = ['navy','turquoise','darkorange']
    for color, i, target_name in zip(colors, [0,1,2], target_names):
        plt.scatter(X[y==i, 0], X[y==i, 1], color=color, label=target_name)
        plt.legend(loc='upper left')
        plt.title(title)
        plt.xlabel(vtitle + "1")
        plt.ylabel(vtitle + "2")
        plt.show()
# this is the size of our encoded representations
input_dim = X_scaled.shape[1] # Total number of features (4)
encoding_dim = 2 # the dimension will be reduced to 2
# this is our input placeholder
input_img = Input(shape=(4,))
# <KerasTensor: shape=(None, 4) dtype=float32 (created by layer 'input_2')>
# "encoded" representation of the input
encoded = Dense(encoding_dim,activation='sigmoid')(input_img) # input img will be compressed to 2 dims
# "decoded" lossy reconstruction of the input
decoded = Dense(input_dim,activation='sigmoid')(encoded)
# Map an input to reconstruction
autoencoder = Model(input_img,decoded) # specified input = img, decoded= output
autoencoder.compile(optimizer='adam',loss='mse')
print(autoencoder.summary())
history = autoencoder.fit(X_scaled,X_scaled,epochs=2000,batch_size=16,shuffle=True,validation_split=0.1,verbose=0)
# X = Y since the goal is re-construction and 10% data for validation
# Plot the loss
plt.plot(history.history['loss'])
plt.plot(history.history['val_loss'])
plt.title('model train vs validation loss')
plt.ylabel('loss')
plt.xlabel('epoch')
plt.legend(['train','validation'],loc='upper right')
plt.show()
# Use the encoded layer to encode the training input
```

```
encoder = Model(input_img,encoded) # Encoder model that takes input image and shrinks it
encoded_input = Input(shape=(encoding_dim,)) # this is a way to give encoded input to decoder (we already know what dimensions we
decoder_layer = autoencoder.layers[-1] # last layer of the autoencoder is the decoder layer that gives reconstructed output
decoder = Model(encoded_input,decoder_layer(encoded_input)) # input is encoded data and output is decoder layer (resconstructor)
encoded_data = encoder.predict(X_scaled)
```

plot3clusters(encoded_data[:,:2],'Non-Linear sigmoid-based AE','AE')

< XAI

LIME

```
data = load_breast_cancer()
df = pd.DataFrame(data.data, columns=data.feature_names)
df['target'] = data.target
print(df.head())

# Information about dataset
df.info()

# Setting up the data for modelling
y=df['target'].to_frame() # define Y (Given)
X=df[df.columns.difference(['target'])] # define X (Given)

# Question - do train-test-split
X_train, X_test, y_train, y_test = train_test_split(X,y, test_size = 0.2, random_state=42)
# Question - Build XBGoost classifier
model = XGBClassifier(random_state=42)
# Train with training data
model.fit(X_train, y_train.values.ravel())
```

XGBClassifier

XGBClassifier(base_score=None, booster=None, callbacks=None, colsample_bylevel=None, colsample_bynode=None, colsample_bytree=None, device=None, early_stopping_rounds=None, enable_categorical=False, eval_metric=None, feature_types=None, gamma=None, grow_policy=None, importance_type=None, interaction_constraints=None, learning_rate=None, max_bin=None, max_cat_threshold=None, max_cat_to_onehot=None, max_delta_step=None, max_depth=None, max_leaves=None, min_child_weight=None, missing=nan, monotone_constraints=None, multi_strategy=None, n_estimators=None, n_jobs=None, num_parallel_tree=None, random_state=42, ...)

Explain a single data point say at 5th index of out data.

```
data_point = 5
explanation = explainer.explain_instance(df.loc[data_point, data.feature_names].astype(int).values,predictor_function, num_feature
explanation.show_in_notebook(show_table=True)
```

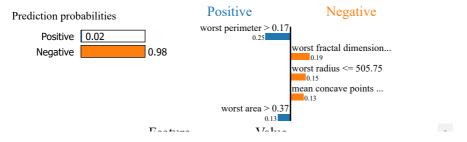
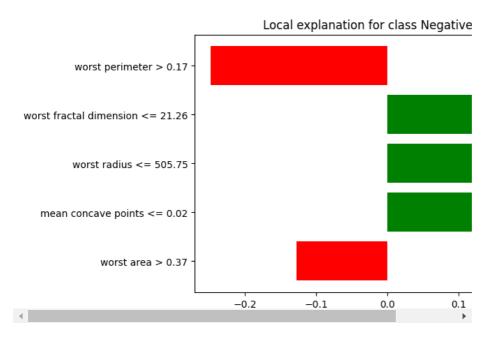


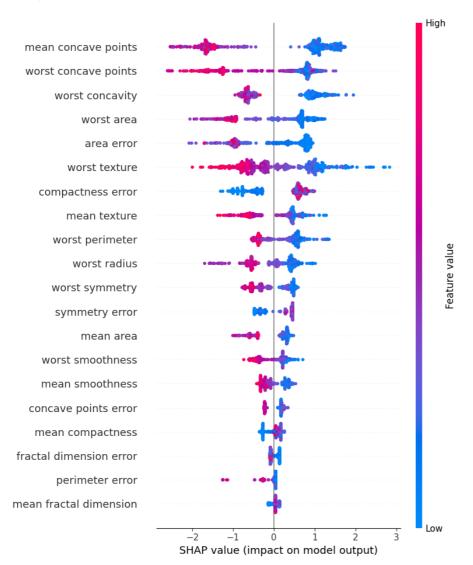
figure = explanation.as_pyplot_figure()



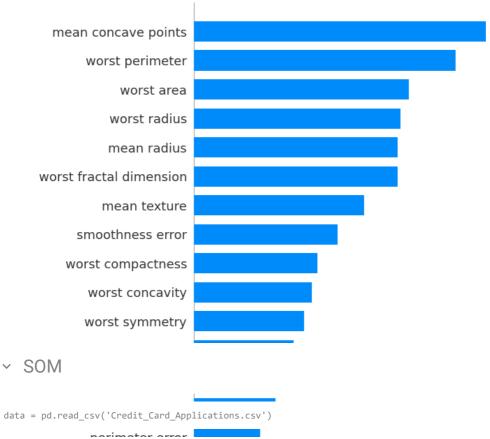
√ SHAP

```
# Loading the data to work with
data = load_breast_cancer()
df = pd.DataFrame(data.data, columns=data.feature_names)
df['target'] = data.target
df.head()
df.info()
# Setting up the data for modelling
y=df['target'].to_frame() # define Y
X \! = \! df[df.columns.difference(['target'])] \ \# \ define \ X
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.20, random_state=42) # create train and test
X_train,X_test, y_train, y_test = train_test_split(X, y, test_size = 0.2, random_state = 42)
model = XGBClassifier(random_state=42,gpu_id=0) # build classifier Gradient Boosted decision trees
model.fit(X_train,y_train.values.ravel())
# Given
y_pred = model.predict(X_test)
accuracy = accuracy_score(y_test, y_pred)
print("Accuracy: %.2f%%" % (accuracy * 100.0))
# aues
explainer = shap.TreeExplainer(model)
shap_values = explainer.shap_values(X)
expected_value = explainer.expected_value
```

shap.summary_plot(shap_values, X)



shap.summary_plot(shap_values, X,plot_type="bar", feature_names=data.feature_names)



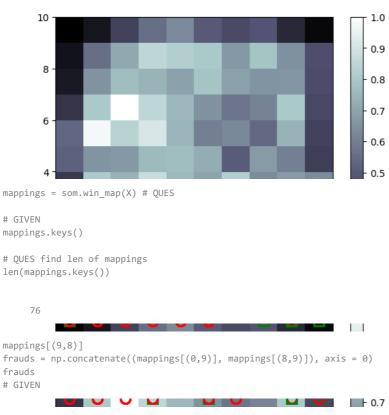
data = pd.read_csv('Credit_Card_Applications.csv') narimatar arrar

data.head()

	CustomerID	A1	A2	А3	Α4	A5	A6	A7	A8	А9	A10	A11	A12	A13	A14	Cl
0	15776156	1	22.08	11.46	2	4	4	1.585	0	0	0	1	2	100	1213	
1	15739548	0	22.67	7.00	2	8	4	0.165	0	0	0	0	2	160	1	
2	15662854	0	29.58	1.75	1	4	4	1.250	0	0	0	1	2	280	1	
3	15687688	0	21.67	11.50	1	5	3	0.000	1	1	11	1	2	0	1	
4	15715750	1	20.17	8.17	2	6	4	1.960	1	1	14	0	2	60	159	
				U.,	,		U.Z	,	U.4		0.0		0.0		1.0	•

```
# Ques shape of data
data.shape
     (690, 16)
# Ques: Info of data
data.info()
# Defining X variables for the input of SOM (GIVEN)
X = data.iloc[:, 1:14].values
y = data.iloc[:, -1].values
# QUES- convert X variable into pd.dataframe
pd.DataFrame(X)
sc = MinMaxScaler(feature_range = (0, 1)) # GIVEN
# Ques: Apply fit_transform
X = sc.fit_transform(X)
pd.DataFrame(X) #GIVEN
```

```
# Set the hyper parameters (GIVEN)
som grid rows = 10
som_grid_columns = 10
iterations = 20000
sigma = 1
learning_rate = 0.5
# QUES : SOM MODEL
som = MiniSom(x = som_grid_rows,y = som_grid_columns,input_len = 13, sigma=1, learning_rate=0.5)
# Initializing the weights
som.random_weights_init(X)
# QUES: train som
som.train_random(X,iterations)
# giveNM
# Returns the distance map from the weights:
som.distance_map()
from pylab import plot, axis, show, pcolor, colorbar, bone
bone()
pcolor(som.distance_map().T)  # Distance map as background
colorbar()
show()
bone()
pcolor(som.distance_map().T)
colorbar() #gives legend
markers = ['o', 's']
                                  # if the observation is fraud then red circular color or else green square
colors = ['r', 'g']
for i, x in enumerate(X):
   w = som.winner(x)
    plot(w[0] + 0.5,
        W[1] + 0.5,
        markers[y[i]],
        markeredgecolor = colors[y[i]],
        markerfacecolor = 'None',
         markersize = 10,
        markeredgewidth = 2)
show()
# GIVENN
```



	0	1	2	3	4	5	6	7	8	9	10	11	12	
0	1.0	37.58	0.000	2.0	8.0	4.0	0.000	0.0	0.0	0.0	0.0	3.0	184.0	11.
1	1.0	23.17	0.000	2.0	8.0	4.0	0.000	0.0	0.0	0.0	0.0	3.0	184.0	
3	1.0	33.67	2.165	2.0	8.0	4.0	1.500	0.0	0.0	0.0	0.0	3.0	120.0	
4	1.0	20.42	0.000	2.0	8.0	4.0	0.000	0.0	0.0	0.0	0.0	3.0	184.0	
5	1.0	29.58	4.500	2.0	9.0	4.0	7.500	1.0	1.0	2.0	1.0	2.0	330.0	
6	1.0	23.08	2.500	2.0	8.0	4.0	1.085	1.0	1.0	11.0	1.0	2.0	60.0	
7	1.0	39.58	13.915	2.0	9.0	4.0	8.625	1.0	1.0	6.0	1.0	2.0	70.0	
8	1.0	63.33	0.540	2.0	8.0	4.0	0.585	1.0	1.0	3.0	1.0	2.0	180.0	
9	1.0	27.83	1.500	2.0	9.0	4.0	2.000	1.0	1.0	11.0	1.0	2.0	434.0	
10	1.0	56.75	12.250	2.0	7.0	4.0	1.250	1.0	1.0	4.0	1.0	2.0	200.0	