Assignment No : 4
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Problem Statement:

Use Autoencoder to implement anomaly detection. Build the model by using:

a. Import required libraries

b. Upload / access the dataset

c. Encoder converts it into latent representation

d. Decoder networks convert it back to the original input

e. Compile the models with Optimizer, Loss, and Evaluation Metrics

Objective:

The objective of anomaly detection is to find unexpected or rare events in data streams

Methodology:

1.Deep Learning

2.TensorFlow

Required libraries:

Pandas , Numpy , matplotlib , seaborn , Sklearn.

Theory:

What is deep learning?

Deep learning is a type of machine learning and artificial intelligence (AI) that imitates the way humans gain certain types of knowledge. Deep learning is an important element of data science, which includes statistics and predictive modeling. It is extremely beneficial to data scientists who are tasked with collecting, analyzing and interpreting large amounts of data; deep learning makes this process faster and easier.

What is anomaly detection?

Anomaly detection is a mathematical process used by data scientists to detect abnormalities within supervised and unsupervised numerical data based on how different a data point is from its surrounding data points or from the standard deviation. There are many different anomaly detection techniques, sometimes called outlier detection algorithms, that each have different criteria for outlier detection and are therefore used for different use cases. Anomaly detection is used across all the major data science technologies such as, Python and Scikit-learn (SKlearn). All forms of anomaly detection rely on first building an understanding of standard results, or normal instances, using time series data. Time series data is essentially a collection of values of the same variable over a period of time. This does not typically mean constant or the same but rather changing in an expected way. Each technique uses different estimator criteria to form the benchmark.

We need to create a single fully-connected neural layer as encoder and as decoder model, compile the models with Optimizer, Loss and Evaluation Metrics. The loss function is usually either the mean- squared error or cross-entropy between the output and the input, which we call 'Reconstruction Loss'. It penalizes the network for creating outputs different from the input. Then, we need to fit our model with the test data.

STEPS TO CREATE A SIMPLE AUTOENCODER

We will build a simple single fully-connected neural layer as encoder and as decoder to read a number present in the image

Let's define the size of the Encoded representation.

encoding_dim=32 #Assuming the input size= 100000

encoded=Dense(encoding_dim, activation='relu')(input_img) "encoded" is the encoded representation of the input

decoded=Dense(activation='sigmoid')(encoded) # 'decoded' is the lossy reconstruction of the input

autoencoder=model(input_img, decoded) #this model maps an input to its reconstruction Lets

create a separate encoder model

encoder=model(input_img, encoded) #this model maps an input to its encoded representation

Lets create a separate decoded model

encoded_input=Input (shape=(encoding_dim,)) # create a placeholder for an encoded (32-dimensional) input

decoded_layer=autoencoder.layers[-1] #retrieve the last layer of the autoencoder model

decoder=model(encoded_input, decoder_layer(encoded_input)) create the decoder model Now, lets train

our autoencoder to reconstruct the digits

autoencoder.compile(optimizer='ada', loss='mae')

Prepare train data: x_train and test data: x_test

lets train our autoencoder for 20 epochs

autoencoder.fit(x_train,x_train, epochs=20, shuffle=True, validation_data=(x_test, x_test))

Now, we will try to visualize the reconstructed input and encoded representation

encoded_img=encoder.predict(x_test)

decoded_img=decoded.predict(encoded_img)

In [1]:

```
#
Synthetic dataset
from sklearn.datasets import make_classification
```

In [2]:

```
#
Data
processing
import pandas as pd
import numpy as np
from collections import Counter
```

In [3]:

```
#
```

Visualization
```
import matplotlib.pyplot as plt
import seaborn as sns
```

In [4]:

#

Model and performance
```
#!pip install tensorflow
import tensorflow as tf
from tensorflow.keras import layers, losses
from sklearn.model_selection import train_test_split
from sklearn.metrics import classification_report
```

In [5]:

#

Create an imbalanced dataset
```
X, y = make_classification(n_samples=100000, n_features=32, n_informative=32,
                           n_redundant=0, n_repeated=0, n_classes=2,
                          n_clusters_per_class=1,
                          weights=[0.995, 0.005],
                           class_sep=0.5, random_state=0)
```

In [6]:

#

Train test split
```
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42 )
# Check the number of records
print('The number of records in the training dataset is', X_train.shape[0]) print('The
number of records in the test dataset is', X_test.shape[0]) print(f"The training dataset
has {sorted(Counter(y_train).items())[0][1]} records for the majority class and
{sorted(Counter(y_train).items())[1][1]} records for the minority clas s.")
```

```
The number of records in the training dataset is 80000
The number of records in the test dataset is 20000
The training dataset has 79200 records for the majority class and 800 records for the min
ority class.
```

In [7]:

#
Keep
only

```
the normal data for the training dataset
X_train_normal = X_train[np.where(y_train == 0)]
# Input layer
input = tf.keras.layers.Input(shape=(32,))
# Encoder layers
encoder = tf.keras.Sequential([
  layers.Dense(16, activation='relu'),
  layers.Dense(8, activation='relu'),
  layers.Dense(4, activation='relu')])(input)
# Decoder layers
decoder = tf.keras.Sequential([
      layers.Dense(8, activation="relu"),
      layers.Dense(16, activation="relu"),
      layers.Dense(32, activation="sigmoid")])(encoder)
# Create the autoencoder
autoencoder = tf.keras.Model(inputs=input, outputs=decoder)
```

In [8]:

#

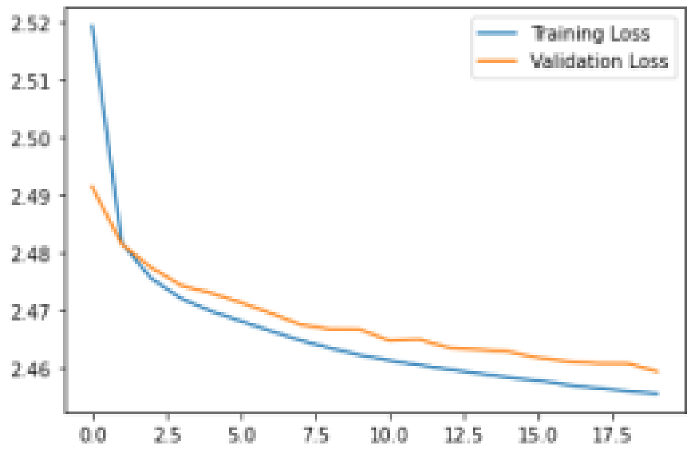
```
Compile the autoencoder
autoencoder.compile(optimizer='adam', loss='mae')
# Fit the autoencoder
history = autoencoder.fit(X_train_normal, X_train_normal,
          epochs=20,
          batch_size=64,
          validation_data=(X_test, X_test),
          shuffle=True)
```

```
Epoch 1/20
1238/1238 [==============================] - 4s 3ms/step - loss: 2.5194 - val_loss: 2.491 5
Epoch 2/20
1238/1238 [==============================] - 3s 3ms/step - loss: 2.4817 - val_loss: 2.481 5
Epoch 3/20
1238/1238 [==============================] - 3s 3ms/step - loss: 2.4755 - val_loss: 2.477 4
Epoch 4/20
1238/1238 [==============================] - 3s 2ms/step - loss: 2.4721 - val_loss: 2.474 4
Epoch 5/20
1238/1238 [==============================] - 3s 3ms/step - loss: 2.4699 - val_loss: 2.473 1
Epoch 6/20
1238/1238 [==============================] - 3s 3ms/step - loss: 2.4682 - val_loss: 2.471 4
Epoch 7/20
  1238/1238 [==============================] - 3s 3ms/step - loss: 2.4665 - val_loss: 2.469
      ============================== - s mssep - oss: . - va_oss: . 6
     Epoch 8/20
     1238/1238 [==============================] - 3s 2ms/step - loss: 2.4649 -
     val_loss: 2.467 6
     Epoch 9/20
     1238/1238 [==============================] - 3s 2ms/step - loss: 2.4635 -
     val_loss: 2.466 8
     Epoch 10/20
     1238/1238 [==============================] - 3s 2ms/step - loss: 2.4623 -
     val_loss: 2.466 7
     Epoch 11/20
     1238/1238 [==============================] - 3s 3ms/step - loss: 2.4614 -
     val_loss: 2.464 8
     Epoch 12/20
```

```
1238/1238 [==============================] - 3s 3ms/step - loss: 2.4606 -
val_loss: 2.465 0
Epoch 13/20
1238/1238 [==============================] - 3s 3ms/step - loss: 2.4598 -
val_loss: 2.463 5
Epoch 14/20
1238/1238 [==============================] - 5s 4ms/step - loss: 2.4591 -
val_loss: 2.463 2
Epoch 15/20
1238/1238 [==============================] - 3s 2ms/step - loss: 2.4584 -
val_loss: 2.462 9
Epoch 16/20
1238/1238 [==============================] - 3s 3ms/step - loss: 2.4579 -
val_loss: 2.461 8
Epoch 17/20
1238/1238 [==============================] - 3s 3ms/step - loss: 2.4571 -
val_loss: 2.461 2
Epoch 18/20
1238/1238 [==============================] - 3s 2ms/step - loss: 2.4565 -
val_loss: 2.460 9
Epoch 19/20
1238/1238 [==============================] - 3s 2ms/step - loss: 2.4561 -
val_loss: 2.460 9
Epoch 20/20
1238/1238 [==============================] - 3s 3ms/step - loss: 2.4556 -
val_loss: 2.459 4
```

In [9]:

```
plt.plot(history.history["loss"], label="Training Loss")
plt.plot(history.history["val_loss"] , label="Validation Loss")
plt.legend();
```



In [10]:

```
# Predict anomalies/outliers in the training dataset
prediction = autoencoder.predict(X_test)
```

```
625/625 [==============================] - 1s 1ms/step
```

In [11]:

```
# Get the mean absolute error between actual and reconstruction/prediction
prediction_loss = tf.keras.losses.mae(prediction, X_test)
```

In [12]:

#

```
Check the prediction loss threshold for 2% of outliers
loss_threshold = np.percentile(prediction_loss, 98)
print(f'The prediction loss threshold for 2% of outliers is {loss_threshold:.2f}')
```

```
The prediction loss threshold for 2% of outliers is 3.45
```

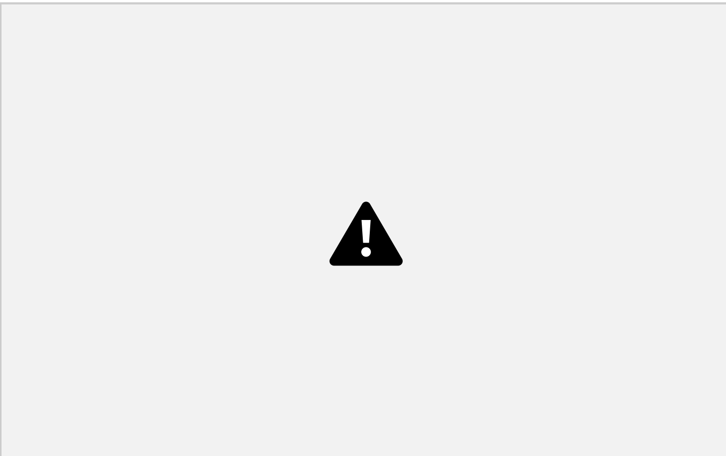
In [13]:

#

```
Visualize the threshold
sns.histplot(prediction_loss, bins=30, alpha=0.8)
plt.axvline(x=loss_threshold, color='orange')
```

Out[13]:

```
<matplotlib.lines.Line2D at 0x7fd45a64b490>
```



In [14]:

#

```
Check the model performance at 2% threshold
threshold_prediction = [0 if i < loss_threshold else 1 for i in prediction_loss]
```

In [15]:

# #

```
Check the prediction performance
print(classification_report(y_test, threshold_prediction))
```

```
              precision recall f1-score support

           0 0.99 0.98 0.98 19803
           1 0.00 0.01 0.00 197

    accuracy 0.97 20000
```

```
   macro avg 0.50 0.49 0.49 20000
weighted avg 0.98 0.97 0.98 20000
```