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

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

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

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

```
# 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)
```

```
# 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 class.")
```

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



```
# 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'),
```

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```

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)

```

```

# 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)

```

```

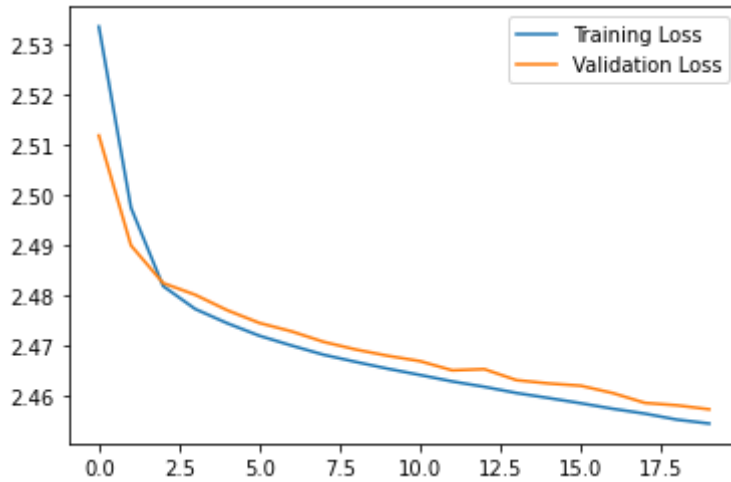
Epoch 1/20
1238/1238 [=====] - 4s 2ms/step - loss: 2.5335 - val_loss: 2.4720
Epoch 2/20
1238/1238 [=====] - 3s 2ms/step - loss: 2.4975 - val_loss: 2.4720
Epoch 3/20
1238/1238 [=====] - 3s 2ms/step - loss: 2.4819 - val_loss: 2.4720
Epoch 4/20
1238/1238 [=====] - 3s 2ms/step - loss: 2.4773 - val_loss: 2.4720
Epoch 5/20
1238/1238 [=====] - 3s 2ms/step - loss: 2.4745 - val_loss: 2.4720
Epoch 6/20
1238/1238 [=====] - 3s 2ms/step - loss: 2.4720 - val_loss: 2.4720
Epoch 7/20
1238/1238 [=====] - 3s 2ms/step - loss: 2.4701 - val_loss: 2.4720
Epoch 8/20
1238/1238 [=====] - 3s 2ms/step - loss: 2.4682 - val_loss: 2.4720
Epoch 9/20
1238/1238 [=====] - 3s 2ms/step - loss: 2.4668 - val_loss: 2.4720
Epoch 10/20
1238/1238 [=====] - 3s 3ms/step - loss: 2.4654 - val_loss: 2.4720
Epoch 11/20
1238/1238 [=====] - 3s 2ms/step - loss: 2.4642 - val_loss: 2.4720
Epoch 12/20
1238/1238 [=====] - 3s 2ms/step - loss: 2.4629 - val_loss: 2.4720
Epoch 13/20
1238/1238 [=====] - 3s 2ms/step - loss: 2.4619 - val_loss: 2.4720
Epoch 14/20
1238/1238 [=====] - 3s 2ms/step - loss: 2.4606 - val_loss: 2.4720
Epoch 15/20
1238/1238 [=====] - 3s 2ms/step - loss: 2.4596 - val_loss: 2.4720
Epoch 16/20
1238/1238 [=====] - 3s 3ms/step - loss: 2.4586 - val_loss: 2.4720
Epoch 17/20
1238/1238 [=====] - 3s 2ms/step - loss: 2.4575 - val_loss: 2.4720
Epoch 18/20
1238/1238 [=====] - 3s 2ms/step - loss: 2.4565 - val_loss: 2.4720
Epoch 19/20
1238/1238 [=====] - 3s 2ms/step - loss: 2.4553 - val_loss: 2.4720

```

Epoch 20/20

1238/1238 [=====] - 3s 2ms/step - loss: 2.4546 - val_loss: 2.4546

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



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

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

```
# 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

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

<matplotlib.lines.Line2D at 0x7f092615e5d0>

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

```
# # 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

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