milestone-4

July 16, 2024

1 Preprocessing :-

Loading the dataset

```
[ ]: # prompt: load the dataset /content/Healthcare Providers.csv

import pandas as pd
df = pd.read_csv('/content/Healthcare Providers.csv')
```

Columns present in the dataset

```
[ ]: # prompt: display the columns present in the  /content/Healthcare Providers.csv

import pandas as pd

# Loading the dataset
df = pd.read_csv('/content/Healthcare Providers.csv')

# Columns present in the dataset
print(df.columns)
```

```
Index(['index', 'National Provider Identifier',
       'Last Name/Organization Name of the Provider',
       'First Name of the Provider', 'Middle Initial of the Provider',
       'Credentials of the Provider', 'Gender of the Provider',
       'Entity Type of the Provider', 'Street Address 1 of the Provider',
       'Street Address 2 of the Provider', 'City of the Provider',
       'Zip Code of the Provider', 'State Code of the Provider',
       'Country Code of the Provider', 'Provider Type',
       'Medicare Participation Indicator', 'Place of Service', 'HCPCS Code',
       'HCPCS Description', 'HCPCS Drug Indicator', 'Number of Services',
       'Number of Medicare Beneficiaries',
       'Number of Distinct Medicare Beneficiary/Per Day Services',
       'Average Medicare Allowed Amount', 'Average Submitted Charge Amount',
       'Average Medicare Payment Amount',
       'Average Medicare Standardized Amount'],
      dtype='object')
```

Removing the columns which are not needed

```
[ ]: last_dataset = df.drop(['Street Address 2 of the Provider',
                          'Street Address 1 of the Provider',
                          'Zip Code of the Provider',
                          'index',
                          'National Provider Identifier',
                          'Last Name/Organization Name of the Provider',
                          'First Name of the Provider'], axis=1)
     # save the dataset
     last_dataset.to_csv('last_dataset.csv', index=False)
```

display unique values for columns

```
[ ]: for col in last_dataset.columns:
       print(col, ":", last_dataset[col].nunique())
```

```
Middle Initial of the Provider : 29
Credentials of the Provider : 1854
Gender of the Provider : 2
Entity Type of the Provider : 2
City of the Provider : 5846
State Code of the Provider : 58
Country Code of the Provider : 4
Provider Type : 90
Medicare Participation Indicator : 2
Place of Service : 2
HCPCS Code : 2631
HCPCS Description : 2455
HCPCS Drug Indicator : 2
Number of Services : 2748
Number of Medicare Beneficiaries : 1274
Number of Distinct Medicare Beneficiary/Per Day Services : 1979
Average Medicare Allowed Amount : 49629
Average Submitted Charge Amount : 38088
Average Medicare Payment Amount : 83367
Average Medicare Standardized Amount : 76237
```

performing onehot encoding

```
[ ]: import pandas as pd
     from sklearn.preprocessing import OneHotEncoder

     # Create the encoder.
     encoder = OneHotEncoder(handle_unknown="ignore")

     # Fit the encoder on the categorical features.
     encoder.fit(last_dataset[['Gender of the Provider',
                               'Entity Type of the Provider',
                               'Medicare Participation Indicator',
```

```
                              'HCPCS Drug Indicator']])

# Transform the categorical features into one-hot encoded features.
encoded_features = encoder.transform(last_dataset[['Gender of the Provider',
                                                    'Entity Type of the Provider',
                                                    'Medicare Participation␣
 ↪Indicator',
                                                    'HCPCS Drug Indicator']]).
 ↪toarray()

# Create column names for the one-hot encoded features.
encoded_feature_names = encoder.get_feature_names_out(['Gender of the Provider',
                                                        'Entity Type of the␣
 ↪Provider',
                                                        'Medicare Participation␣
 ↪Indicator',
                                                        'HCPCS Drug Indicator'])

# Create a new DataFrame with the one-hot encoded features.
encoded_df = pd.DataFrame(encoded_features, columns=encoded_feature_names)

# Concatenate the original DataFrame and the one-hot encoded DataFrame.
last_dataset = pd.concat([last_dataset, encoded_df], axis=1)

# Drop the original categorical features.
last_dataset = last_dataset.drop(['Gender of the Provider',
                                  'Entity Type of the Provider',
                                  'Medicare Participation Indicator',
                                  'HCPCS Drug Indicator'], axis=1)

# Save the updated dataset.
last_dataset.to_csv('/content/last_dataset.csv', index=False)
```

[ ]:
```
last_dataset.head()
```

[ ]:
```
  Middle Initial of the Provider Credentials of the Provider  \
0                            NaN                        M.D.
1                              P                        M.D.
2                              W                         DPM
3                            NaN                          MD
4                              E                          DO

  City of the Provider State Code of the Provider  \
0          SAINT LOUIS                         MO
1         FAYETTEVILLE                         NC
2          NORTH HAVEN                         CT
3          KANSAS CITY                         MO
```

```
4             JUPITER                         FL

  Country Code of the Provider           Provider Type Place of Service  \
0                           US        Internal Medicine                F
1                           US  Obstetrics & Gynecology                O
2                           US                 Podiatry                O
3                           US        Internal Medicine                O
4                           US        Internal Medicine                O

  HCPCS Code                                  HCPCS Description  \
0      99223  Initial hospital inpatient care, typically 70 …
1      G0202  Screening mammography, bilateral (2-view study…
2      99348  Established patient home visit, typically 25 m…
3      81002                            Urinalysis, manual test
4      96372  Injection beneath the skin or into muscle for …

  Number of Services  … Average Medicare Standardized Amount  \
0                 27  …                         160.90888889
1                175  …                         135.31525714
2                 32  …                           60.5959375
3                 20  …                                 3.43
4                 33  …                         19.057575758

  Gender of the Provider_F Gender of the Provider_M  \
0                      1.0                      0.0
1                      1.0                      0.0
2                      0.0                      1.0
3                      0.0                      1.0
4                      0.0                      1.0

  Gender of the Provider_nan Entity Type of the Provider_I  \
0                        0.0                           1.0
1                        0.0                           1.0
2                        0.0                           1.0
3                        0.0                           1.0
4                        0.0                           1.0

  Entity Type of the Provider_O  Medicare Participation Indicator_N  \
0                           0.0                                 0.0
1                           0.0                                 0.0
2                           0.0                                 0.0
3                           0.0                                 0.0
4                           0.0                                 0.0

   Medicare Participation Indicator_Y  HCPCS Drug Indicator_N  \
0                                 1.0                     1.0
1                                 1.0                     1.0
```

```
2                                 1.0                        1.0
3                                 1.0                        1.0
4                                 1.0                        1.0

   HCPCS Drug Indicator_Y
0                    0.0
1                    0.0
2                    0.0
3                    0.0
4                    0.0

[5 rows x 25 columns]
```

performing frequency encoding

[ ]:
```
# Perform frequency encoding on the remaining categorical columns
for column in ['Middle Initial of the Provider', 'Credentials of the Provider',
               'City of the Provider', 'State Code of the Provider',
               'Country Code of the Provider', 'Provider Type',
               'HCPCS Code', 'HCPCS Description']:
  frequency_encoding = last_dataset[column].value_counts(normalize=True)
  last_dataset[column] = last_dataset[column].map(frequency_encoding)

# Save the updated dataset
last_dataset.to_csv('/content/last_dataset.csv', index=False)
```

[ ]:
```
last_dataset.head()
```

[ ]:
```
   Middle Initial of the Provider  Credentials of the Provider  \
0                             NaN                     0.353019
1                        0.035843                     0.353019
2                        0.036310                     0.014333
3                             NaN                     0.354280
4                        0.054890                     0.026705

   City of the Provider  State Code of the Provider  \
0               0.00500                     0.01997
1               0.00209                     0.03725
2               0.00010                     0.01403
3               0.00317                     0.01997
4               0.00051                     0.07263

   Country Code of the Provider  Provider Type Place of Service  HCPCS Code  \
0                       0.99994        0.11366                F     0.01297
1                       0.99994        0.01028                O     0.00243
2                       0.99994        0.02027                O     0.00044
3                       0.99994        0.11366                O     0.00460
```

```
4                       0.99994       0.11366                0     0.00732

   HCPCS Description Number of Services  …  \
0            0.01297                 27  …
1            0.00243                175  …
2            0.00044                 32  …
3            0.00460                 20  …
4            0.00732                 33  …

  Average Medicare Standardized Amount Gender of the Provider_F  \
0                         160.90888889                      1.0
1                         135.31525714                      1.0
2                           60.5959375                      0.0
3                                 3.43                      0.0
4                         19.057575758                      0.0

  Gender of the Provider_M Gender of the Provider_nan  \
0                      0.0                        0.0
1                      0.0                        0.0
2                      1.0                        0.0
3                      1.0                        0.0
4                      1.0                        0.0

  Entity Type of the Provider_I Entity Type of the Provider_O  \
0                           1.0                           0.0
1                           1.0                           0.0
2                           1.0                           0.0
3                           1.0                           0.0
4                           1.0                           0.0

   Medicare Participation Indicator_N  Medicare Participation Indicator_Y  \
0                                 0.0                                 1.0
1                                 0.0                                 1.0
2                                 0.0                                 1.0
3                                 0.0                                 1.0
4                                 0.0                                 1.0

   HCPCS Drug Indicator_N  HCPCS Drug Indicator_Y
0                     1.0                     0.0
1                     1.0                     0.0
2                     1.0                     0.0
3                     1.0                     0.0
4                     1.0                     0.0

[5 rows x 25 columns]
```

```
[ ]: import pandas as pd
     # Create the encoder.
     encoder = OneHotEncoder(handle_unknown="ignore")

     # Fit the encoder on the categorical features.
     encoder.fit(last_dataset[['Place of Service']])

     # Transform the categorical features into one-hot encoded features.
     encoded_features = encoder.transform(last_dataset[['Place of Service']]).
      ↪toarray()

     # Create column names for the one-hot encoded features.
     encoded_feature_names = encoder.get_feature_names_out(['Place of Service'])

     # Create a new DataFrame with the one-hot encoded features.
     encoded_df = pd.DataFrame(encoded_features, columns=encoded_feature_names)

     # Concatenate the original DataFrame and the one-hot encoded DataFrame.
     last_dataset = pd.concat([last_dataset, encoded_df], axis=1)

     # Drop the original categorical features.
     last_dataset = last_dataset.drop(['Place of Service'], axis=1)

     # Save the updated dataset.
     last_dataset.to_csv('/content/last_dataset.csv', index=False)
```

```
[ ]: last_dataset.head()
```

```
[ ]:    Middle Initial of the Provider  Credentials of the Provider  \
     0                             NaN                     0.353019
     1                        0.035843                     0.353019
     2                        0.036310                     0.014333
     3                             NaN                     0.354280
     4                        0.054890                     0.026705

        City of the Provider  State Code of the Provider  \
     0               0.00500                     0.01997
     1               0.00209                     0.03725
     2               0.00010                     0.01403
     3               0.00317                     0.01997
     4               0.00051                     0.07263

        Country Code of the Provider  Provider Type  HCPCS Code  HCPCS Description  \
     0                       0.99994        0.11366     0.01297            0.01297
     1                       0.99994        0.01028     0.00243            0.00243
     2                       0.99994        0.02027     0.00044            0.00044
     3                       0.99994        0.11366     0.00460            0.00460
```

```
4                       0.99994        0.11366     0.00732             0.00732

  Number of Services Number of Medicare Beneficiaries  …  \
0                 27                               24  …
1                175                              175  …
2                 32                               13  …
3                 20                               18  …
4                 33                               24  …

  Gender of the Provider_M Gender of the Provider_nan  \
0                      0.0                        0.0
1                      0.0                        0.0
2                      1.0                        0.0
3                      1.0                        0.0
4                      1.0                        0.0

  Entity Type of the Provider_I Entity Type of the Provider_O  \
0                           1.0                           0.0
1                           1.0                           0.0
2                           1.0                           0.0
3                           1.0                           0.0
4                           1.0                           0.0

  Medicare Participation Indicator_N  Medicare Participation Indicator_Y  \
0                                0.0                                 1.0
1                                0.0                                 1.0
2                                0.0                                 1.0
3                                0.0                                 1.0
4                                0.0                                 1.0

   HCPCS Drug Indicator_N  HCPCS Drug Indicator_Y  Place of Service_F  \
0                     1.0                     0.0                 1.0
1                     1.0                     0.0                 0.0
2                     1.0                     0.0                 0.0
3                     1.0                     0.0                 0.0
4                     1.0                     0.0                 0.0

   Place of Service_O
0                 0.0
1                 1.0
2                 1.0
3                 1.0
4                 1.0

[5 rows x 26 columns]
```

** appling Standard scaling **

[ ]:
```
import pandas as pd
from sklearn.preprocessing import StandardScaler

# Load the dataset
last_dataset = pd.read_csv('/content/last_dataset.csv')

# Initialize the StandardScaler
scaler = StandardScaler()

# Fit and transform the numerical columns (excluding one-hot encoded columns)
numerical_cols = last_dataset.select_dtypes(include=['float', 'int']).columns
last_dataset[numerical_cols] = scaler.
 ↪fit_transform(last_dataset[numerical_cols])

# Save the updated dataset
last_dataset.to_csv('/content/last_dataset.csv', index=False)
```

[ ]:
```
last_dataset.head()
```

[ ]:
```
   Middle Initial of the Provider  Credentials of the Provider  \
0                             NaN                     0.638605
1                       -0.932058                     0.638605
2                       -0.917028                    -1.541230
3                             NaN                     0.646720
4                       -0.318984                    -1.461602

   City of the Provider  State Code of the Provider  \
0              1.571686                   -0.737342
1              0.189180                   -0.004973
2             -0.756245                   -0.989093
3              0.702275                   -0.737342
4             -0.561459                    1.494517

   Country Code of the Provider  Provider Type  HCPCS Code  HCPCS Description  \
0                      0.007746       1.336743    0.397579           0.389268
1                      0.007746      -0.940500   -0.439989          -0.450300
2                      0.007746      -0.720441   -0.598126          -0.608815
3                      0.007746       1.336743   -0.267549          -0.277448
4                      0.007746       1.336743   -0.051402          -0.060785

  Number of Services Number of Medicare Beneficiaries  …  \
0                 27                               24  …
1                175                              175  …
2                 32                               13  …
3                 20                               18  …
4                 33                               24  …
```

```
  Gender of the Provider_M Gender of the Provider_nan  \
0                -1.413397                  -0.210784
1                -1.413397                  -0.210784
2                 0.707515                  -0.210784
3                 0.707515                  -0.210784
4                 0.707515                  -0.210784

  Entity Type of the Provider_I Entity Type of the Provider_O  \
0                      0.210784                     -0.210784
1                      0.210784                     -0.210784
2                      0.210784                     -0.210784
3                      0.210784                     -0.210784
4                      0.210784                     -0.210784

  Medicare Participation Indicator_N  Medicare Participation Indicator_Y  \
0                           -0.01761                             0.01761
1                           -0.01761                             0.01761
2                           -0.01761                             0.01761
3                           -0.01761                             0.01761
4                           -0.01761                             0.01761

   HCPCS Drug Indicator_N  HCPCS Drug Indicator_Y  Place of Service_F  \
0                0.257051               -0.257051            1.266985
1                0.257051               -0.257051           -0.789275
2                0.257051               -0.257051           -0.789275
3                0.257051               -0.257051           -0.789275
4                0.257051               -0.257051           -0.789275

   Place of Service_O
0           -1.266985
1            0.789275
2            0.789275
3            0.789275
4            0.789275

[5 rows x 26 columns]
```

1.Scale the dataset

2.Split the data

[ ]:
```
import pandas as pd
from sklearn.preprocessing import StandardScaler

# Load the dataset
file_path = '/content/last_dataset.csv'
df = pd.read_csv(file_path)
```

```python
# Display the first few rows of the dataset
df.head()
```

[ ]:
```
   Middle Initial of the Provider  Credentials of the Provider  \
0                             NaN                     0.638605
1                       -0.932058                     0.638605
2                       -0.917028                    -1.541230
3                             NaN                     0.646720
4                       -0.318984                    -1.461602

   City of the Provider  State Code of the Provider  \
0              1.571686                   -0.737342
1              0.189180                   -0.004973
2             -0.756245                   -0.989093
3              0.702275                   -0.737342
4             -0.561459                    1.494517

   Country Code of the Provider  Provider Type  HCPCS Code  HCPCS Description  \
0                      0.007746       1.336743    0.397579           0.389268
1                      0.007746      -0.940500   -0.439989          -0.450300
2                      0.007746      -0.720441   -0.598126          -0.608815
3                      0.007746       1.336743   -0.267549          -0.277448
4                      0.007746       1.336743   -0.051402          -0.060785

  Number of Services Number of Medicare Beneficiaries  …  \
0                 27                               24  …
1                175                              175  …
2                 32                               13  …
3                 20                               18  …
4                 33                               24  …

  Gender of the Provider_M Gender of the Provider_nan  \
0                -1.413397                  -0.210784
1                -1.413397                  -0.210784
2                 0.707515                  -0.210784
3                 0.707515                  -0.210784
4                 0.707515                  -0.210784

  Entity Type of the Provider_I Entity Type of the Provider_O  \
0                      0.210784                     -0.210784
1                      0.210784                     -0.210784
2                      0.210784                     -0.210784
3                      0.210784                     -0.210784
4                      0.210784                     -0.210784

  Medicare Participation Indicator_N  Medicare Participation Indicator_Y  \
0                           -0.01761                             0.01761
```

```
1                          -0.01761                                  0.01761
2                          -0.01761                                  0.01761
3                          -0.01761                                  0.01761
4                          -0.01761                                  0.01761

   HCPCS Drug Indicator_N  HCPCS Drug Indicator_Y  Place of Service_F  \
0                0.257051               -0.257051            1.266985
1                0.257051               -0.257051           -0.789275
2                0.257051               -0.257051           -0.789275
3                0.257051               -0.257051           -0.789275
4                0.257051               -0.257051           -0.789275

   Place of Service_O
0           -1.266985
1            0.789275
2            0.789275
3            0.789275
4            0.789275

[5 rows x 26 columns]
```

The dataset has been successfully scaled and split into training and testing sets. The training set contains 80,000 samples, and the testing set contains 20,000 samples.

Build the autoencoder model using Keras.

1.Defining the input layer

2.Adding the encoding layers

3.Adding the decoding layers

4.Compiling the model

5.Summarizing the model

[ ]:
```
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler

# Drop non-numeric columns if any exist
df_numeric = df.select_dtypes(include=[float, int])

# Scale the dataset
scaler = StandardScaler()
scaled_df = scaler.fit_transform(df_numeric)

# Split the data
X_train, X_test = train_test_split(scaled_df, test_size=0.2, random_state=42)

# Display the shapes of the split datasets
```

```
X_train.shape, X_test.shape
```

[ ]: ((80000, 19), (20000, 19))

[ ]:
```
from keras.models import Model
from keras.layers import Input, Dense, Dropout
from keras import regularizers

# Define the input dimension
input_dim = X_train.shape[1]

# Define the encoding dimension
encoding_dim = 16

# Calculate the hidden dimensions
hidden_dim1 = int(encoding_dim / 2)
hidden_dim2 = int(encoding_dim / 2)
hidden_dim3 = int(encoding_dim / 2)

# Define the input layer
input_layer = Input(shape=(input_dim,))

# Define the encoding layers
encoder = Dense(encoding_dim, activation='relu',␣
↪activity_regularizer=regularizers.l1(10e-5))(input_layer)
encoder = Dense(hidden_dim1, activation='relu')(encoder)
encoder = Dense(hidden_dim2, activation='relu')(encoder)
encoder = Dense(hidden_dim3, activation='relu')(encoder)
encoder = Dropout(0.2)(encoder)

# Define the decoding layers
decoder = Dense(hidden_dim2, activation='relu')(encoder)
decoder = Dense(hidden_dim1, activation='relu')(decoder)
decoder = Dense(encoding_dim, activation='relu')(decoder)
decoder = Dense(input_dim, activation='sigmoid')(decoder)

# Define the autoencoder model
autoencoder = Model(inputs=input_layer, outputs=decoder)

# Compile the autoencoder
autoencoder.compile(optimizer='adam', loss='mean_squared_error',␣
↪metrics=['mse'])

# Summarize the model
autoencoder.summary()
```

```
Model: "model"
```

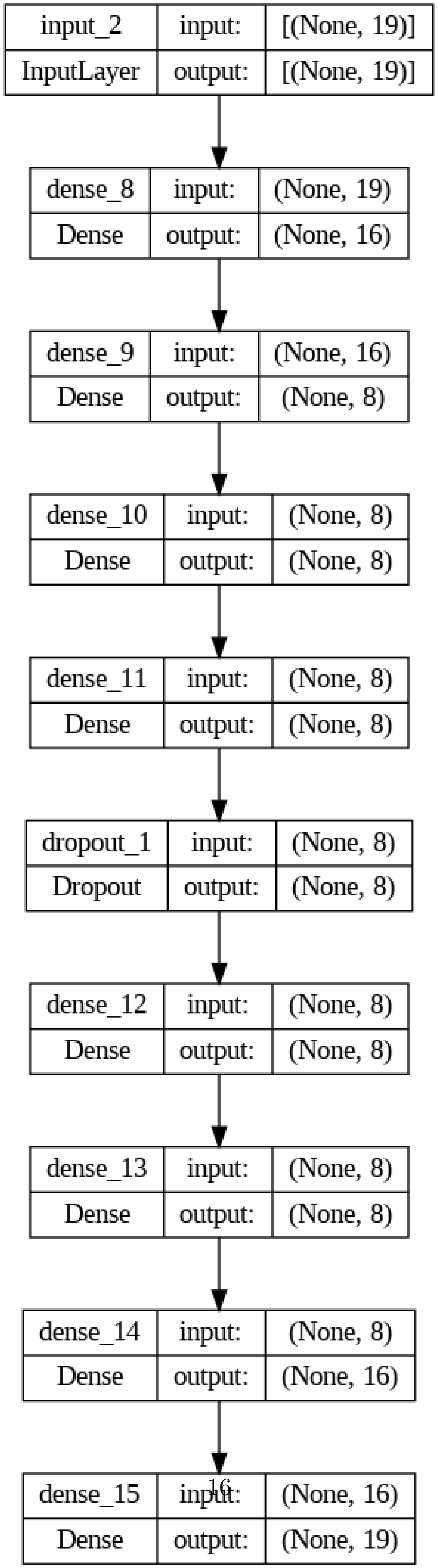
```
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 input_1 (InputLayer)        [(None, 19)]              0

 dense (Dense)               (None, 16)                320

 dense_1 (Dense)             (None, 8)                 136

 dense_2 (Dense)             (None, 8)                 72

 dense_3 (Dense)             (None, 8)                 72

 dropout (Dropout)           (None, 8)                 0

 dense_4 (Dense)             (None, 8)                 72

 dense_5 (Dense)             (None, 8)                 72

 dense_6 (Dense)             (None, 16)                144

 dense_7 (Dense)             (None, 19)                323

=================================================================
Total params: 1211 (4.73 KB)
Trainable params: 1211 (4.73 KB)
Non-trainable params: 0 (0.00 Byte)
_________________________________________________________________
```

Plotting the model

[ ]:
```
import pandas as pd
from sklearn.preprocessing import StandardScaler
from sklearn.model_selection import train_test_split
from keras.models import Model
from keras.layers import Input, Dense, Dropout
from keras import regularizers
import tensorflow as tf

# Load the dataset
file_path = '/content/last_dataset.csv'
df = pd.read_csv(file_path)

# Drop non-numeric columns if any exist
df_numeric = df.select_dtypes(include=[float, int])

# Scale the dataset
scaler = StandardScaler()
```

```
scaled_df = scaler.fit_transform(df_numeric)

# Split the data
X_train, X_test = train_test_split(scaled_df, test_size=0.2, random_state=42)

# Define the input dimension
input_dim = X_train.shape[1]

# Define the encoding dimension
encoding_dim = 16

# Calculate the hidden dimensions
hidden_dim1 = int(encoding_dim / 2)
hidden_dim2 = int(encoding_dim / 2)
hidden_dim3 = int(encoding_dim / 2)

# Define the input layer
input_layer = Input(shape=(input_dim,))

# Define the encoding layers
encoder = Dense(encoding_dim, activation='relu',␣
 ↪activity_regularizer=regularizers.l1(10e-5))(input_layer)
encoder = Dense(hidden_dim1, activation='relu')(encoder)
encoder = Dense(hidden_dim2, activation='relu')(encoder)
encoder = Dense(hidden_dim3, activation='relu')(encoder)
encoder = Dropout(0.2)(encoder)

# Define the decoding layers
decoder = Dense(hidden_dim2, activation='relu')(encoder)
decoder = Dense(hidden_dim1, activation='relu')(decoder)
decoder = Dense(encoding_dim, activation='relu')(decoder)
decoder = Dense(input_dim, activation='sigmoid')(decoder)

# Define the autoencoder model
autoencoder = Model(inputs=input_layer, outputs=decoder)

# Plot the model
tf.keras.utils.plot_model(autoencoder, to_file='model.png', show_shapes=True)
```

[ ]:


input_2
input:
[(None, 19)]
InputLayer
output:
[(None, 19)]
dense_8
input:
(None, 19)
Dense
output:
(None, 16)
dense_9
input:
(None, 16)
Dense
output:
(None, 8)
dense_10
input:
(None, 8)
Dense
output:
(None, 8)
dense_11
input:
(None, 8)
Dense
output:
(None, 8)
dropout_1
input:
(None, 8)
Dropout
output:
(None, 8)
dense_12
input:
(None, 8)
Dense
output:
(None, 8)
dense_13
input:
(None, 8)
Dense
output:
(None, 8)
dense_14
input:
(None, 8)
Dense
output:
(None, 16)
dense_15
input:
(None, 16)
Dense
output:
(None, 19)

2 Training the autoencoders

[ ]:
```
import pandas as pd
from sklearn.preprocessing import StandardScaler
from sklearn.model_selection import train_test_split
from keras.models import Model
from keras.layers import Input, Dense, Dropout
from keras import regularizers
import tensorflow as tf

# Load the dataset
file_path = '/content/last_dataset.csv'
df = pd.read_csv(file_path)

# Drop non-numeric columns if any exist
df_numeric = df.select_dtypes(include=[float, int])

# Scale the dataset
scaler = StandardScaler()
scaled_df = scaler.fit_transform(df_numeric)

# Split the data
X_train, X_test = train_test_split(scaled_df, test_size=0.2, random_state=42)

# Define the input dimension
input_dim = X_train.shape[1]

# Define the encoding dimension
encoding_dim = 16

# Calculate the hidden dimensions
hidden_dim1 = int(encoding_dim / 2)
hidden_dim2 = int(encoding_dim / 2)
hidden_dim3 = int(encoding_dim / 2)

# Define the input layer
input_layer = Input(shape=(input_dim,))

# Define the encoding layers
encoder = Dense(encoding_dim, activation='relu',␣
↪activity_regularizer=regularizers.l1(10e-5))(input_layer)
encoder = Dense(hidden_dim1, activation='relu')(encoder)
encoder = Dense(hidden_dim2, activation='relu')(encoder)
encoder = Dense(hidden_dim3, activation='relu')(encoder)
```

```
encoder = Dropout(0.2)(encoder)

# Define the decoding layers
decoder = Dense(hidden_dim2, activation='relu')(encoder)
decoder = Dense(hidden_dim1, activation='relu')(decoder)
decoder = Dense(encoding_dim, activation='relu')(decoder)
decoder = Dense(input_dim, activation='sigmoid')(decoder)

# Define the autoencoder model
autoencoder = Model(inputs=input_layer, outputs=decoder)

# Compile the autoencoder
autoencoder.compile(optimizer='adam', loss='mean_squared_error',␣
 ↪metrics=['mse'])

# Train the autoencoder
history = autoencoder.fit(X_train, X_train,
                          epochs=100,
                          batch_size=32,
                          shuffle=True,
                          validation_data=(X_test, X_test),
                          verbose=1)
```

```
Epoch 1/100
2500/2500 [==============================] - 10s 3ms/step - loss: nan - mse: nan
- val_loss: nan - val_mse: nan
Epoch 2/100
2500/2500 [==============================] - 7s 3ms/step - loss: nan - mse: nan
- val_loss: nan - val_mse: nan
Epoch 3/100
2500/2500 [==============================] - 8s 3ms/step - loss: nan - mse: nan
- val_loss: nan - val_mse: nan
Epoch 4/100
2500/2500 [==============================] - 7s 3ms/step - loss: nan - mse: nan
- val_loss: nan - val_mse: nan
Epoch 5/100
2500/2500 [==============================] - 8s 3ms/step - loss: nan - mse: nan
- val_loss: nan - val_mse: nan
Epoch 6/100
2500/2500 [==============================] - 8s 3ms/step - loss: nan - mse: nan
- val_loss: nan - val_mse: nan
Epoch 7/100
2500/2500 [==============================] - 6s 3ms/step - loss: nan - mse: nan
- val_loss: nan - val_mse: nan
Epoch 8/100
2500/2500 [==============================] - 8s 3ms/step - loss: nan - mse: nan
- val_loss: nan - val_mse: nan
```

```
Epoch 9/100
2500/2500 [==============================] - 6s 2ms/step - loss: nan - mse: nan
- val_loss: nan - val_mse: nan
Epoch 10/100
2500/2500 [==============================] - 8s 3ms/step - loss: nan - mse: nan
- val_loss: nan - val_mse: nan
Epoch 11/100
2500/2500 [==============================] - 7s 3ms/step - loss: nan - mse: nan
- val_loss: nan - val_mse: nan
Epoch 12/100
2500/2500 [==============================] - 9s 4ms/step - loss: nan - mse: nan
- val_loss: nan - val_mse: nan
Epoch 13/100
2500/2500 [==============================] - 7s 3ms/step - loss: nan - mse: nan
- val_loss: nan - val_mse: nan
Epoch 14/100
2500/2500 [==============================] - 8s 3ms/step - loss: nan - mse: nan
- val_loss: nan - val_mse: nan
Epoch 15/100
2500/2500 [==============================] - 8s 3ms/step - loss: nan - mse: nan
- val_loss: nan - val_mse: nan
Epoch 16/100
2500/2500 [==============================] - 8s 3ms/step - loss: nan - mse: nan
- val_loss: nan - val_mse: nan
Epoch 17/100
2500/2500 [==============================] - 8s 3ms/step - loss: nan - mse: nan
- val_loss: nan - val_mse: nan
Epoch 18/100
2500/2500 [==============================] - 6s 3ms/step - loss: nan - mse: nan
- val_loss: nan - val_mse: nan
Epoch 19/100
2500/2500 [==============================] - 8s 3ms/step - loss: nan - mse: nan
- val_loss: nan - val_mse: nan
Epoch 20/100
2500/2500 [==============================] - 7s 3ms/step - loss: nan - mse: nan
- val_loss: nan - val_mse: nan
Epoch 21/100
2500/2500 [==============================] - 8s 3ms/step - loss: nan - mse: nan
- val_loss: nan - val_mse: nan
Epoch 22/100
2500/2500 [==============================] - 6s 3ms/step - loss: nan - mse: nan
- val_loss: nan - val_mse: nan
Epoch 23/100
2500/2500 [==============================] - 9s 3ms/step - loss: nan - mse: nan
- val_loss: nan - val_mse: nan
Epoch 24/100
2500/2500 [==============================] - 8s 3ms/step - loss: nan - mse: nan
- val_loss: nan - val_mse: nan
```

```
Epoch 25/100
2500/2500 [==============================] - 7s 3ms/step - loss: nan - mse: nan
- val_loss: nan - val_mse: nan
Epoch 26/100
2500/2500 [==============================] - 8s 3ms/step - loss: nan - mse: nan
- val_loss: nan - val_mse: nan
Epoch 27/100
2500/2500 [==============================] - 7s 3ms/step - loss: nan - mse: nan
- val_loss: nan - val_mse: nan
Epoch 28/100
2500/2500 [==============================] - 8s 3ms/step - loss: nan - mse: nan
- val_loss: nan - val_mse: nan
Epoch 29/100
2500/2500 [==============================] - 7s 3ms/step - loss: nan - mse: nan
- val_loss: nan - val_mse: nan
Epoch 30/100
2500/2500 [==============================] - 9s 3ms/step - loss: nan - mse: nan
- val_loss: nan - val_mse: nan
Epoch 31/100
2500/2500 [==============================] - 7s 3ms/step - loss: nan - mse: nan
- val_loss: nan - val_mse: nan
Epoch 32/100
2500/2500 [==============================] - 8s 3ms/step - loss: nan - mse: nan
- val_loss: nan - val_mse: nan
Epoch 33/100
2500/2500 [==============================] - 8s 3ms/step - loss: nan - mse: nan
- val_loss: nan - val_mse: nan
Epoch 34/100
2500/2500 [==============================] - 7s 3ms/step - loss: nan - mse: nan
- val_loss: nan - val_mse: nan
Epoch 35/100
2500/2500 [==============================] - 9s 3ms/step - loss: nan - mse: nan
- val_loss: nan - val_mse: nan
Epoch 36/100
2500/2500 [==============================] - 7s 3ms/step - loss: nan - mse: nan
- val_loss: nan - val_mse: nan
Epoch 37/100
2500/2500 [==============================] - 8s 3ms/step - loss: nan - mse: nan
- val_loss: nan - val_mse: nan
Epoch 38/100
2500/2500 [==============================] - 7s 3ms/step - loss: nan - mse: nan
- val_loss: nan - val_mse: nan
Epoch 39/100
2500/2500 [==============================] - 9s 3ms/step - loss: nan - mse: nan
- val_loss: nan - val_mse: nan
Epoch 40/100
2500/2500 [==============================] - 8s 3ms/step - loss: nan - mse: nan
- val_loss: nan - val_mse: nan
```

```
Epoch 41/100
2500/2500 [==============================] - 7s 3ms/step - loss: nan - mse: nan
- val_loss: nan - val_mse: nan
Epoch 42/100
2500/2500 [==============================] - 8s 3ms/step - loss: nan - mse: nan
- val_loss: nan - val_mse: nan
Epoch 43/100
2500/2500 [==============================] - 6s 3ms/step - loss: nan - mse: nan
- val_loss: nan - val_mse: nan
Epoch 44/100
2500/2500 [==============================] - 8s 3ms/step - loss: nan - mse: nan
- val_loss: nan - val_mse: nan
Epoch 45/100
2500/2500 [==============================] - 7s 3ms/step - loss: nan - mse: nan
- val_loss: nan - val_mse: nan
Epoch 46/100
2500/2500 [==============================] - 14s 5ms/step - loss: nan - mse: nan
- val_loss: nan - val_mse: nan
Epoch 47/100
2500/2500 [==============================] - 17s 7ms/step - loss: nan - mse: nan
- val_loss: nan - val_mse: nan
Epoch 48/100
2500/2500 [==============================] - 9s 4ms/step - loss: nan - mse: nan
- val_loss: nan - val_mse: nan
Epoch 49/100
2500/2500 [==============================] - 7s 3ms/step - loss: nan - mse: nan
- val_loss: nan - val_mse: nan
Epoch 50/100
2500/2500 [==============================] - 8s 3ms/step - loss: nan - mse: nan
- val_loss: nan - val_mse: nan
Epoch 51/100
2500/2500 [==============================] - 7s 3ms/step - loss: nan - mse: nan
- val_loss: nan - val_mse: nan
Epoch 52/100
2500/2500 [==============================] - 8s 3ms/step - loss: nan - mse: nan
- val_loss: nan - val_mse: nan
Epoch 53/100
2500/2500 [==============================] - 7s 3ms/step - loss: nan - mse: nan
- val_loss: nan - val_mse: nan
Epoch 54/100
2500/2500 [==============================] - 8s 3ms/step - loss: nan - mse: nan
- val_loss: nan - val_mse: nan
Epoch 55/100
2500/2500 [==============================] - 8s 3ms/step - loss: nan - mse: nan
- val_loss: nan - val_mse: nan
Epoch 56/100
2500/2500 [==============================] - 7s 3ms/step - loss: nan - mse: nan
- val_loss: nan - val_mse: nan
```

```
Epoch 57/100
2500/2500 [==============================] - 8s 3ms/step - loss: nan - mse: nan
- val_loss: nan - val_mse: nan
Epoch 58/100
2500/2500 [==============================] - 7s 3ms/step - loss: nan - mse: nan
- val_loss: nan - val_mse: nan
Epoch 59/100
2500/2500 [==============================] - 8s 3ms/step - loss: nan - mse: nan
- val_loss: nan - val_mse: nan
Epoch 60/100
2500/2500 [==============================] - 8s 3ms/step - loss: nan - mse: nan
- val_loss: nan - val_mse: nan
Epoch 61/100
2500/2500 [==============================] - 9s 3ms/step - loss: nan - mse: nan
- val_loss: nan - val_mse: nan
Epoch 62/100
2500/2500 [==============================] - 13s 5ms/step - loss: nan - mse: nan
- val_loss: nan - val_mse: nan
Epoch 63/100
2500/2500 [==============================] - 14s 6ms/step - loss: nan - mse: nan
- val_loss: nan - val_mse: nan
Epoch 64/100
2500/2500 [==============================] - 9s 4ms/step - loss: nan - mse: nan
- val_loss: nan - val_mse: nan
Epoch 65/100
2500/2500 [==============================] - 7s 3ms/step - loss: nan - mse: nan
- val_loss: nan - val_mse: nan
Epoch 66/100
2500/2500 [==============================] - 8s 3ms/step - loss: nan - mse: nan
- val_loss: nan - val_mse: nan
Epoch 67/100
2500/2500 [==============================] - 7s 3ms/step - loss: nan - mse: nan
- val_loss: nan - val_mse: nan
Epoch 68/100
2500/2500 [==============================] - 9s 3ms/step - loss: nan - mse: nan
- val_loss: nan - val_mse: nan
Epoch 69/100
2500/2500 [==============================] - 7s 3ms/step - loss: nan - mse: nan
- val_loss: nan - val_mse: nan
Epoch 70/100
2500/2500 [==============================] - 9s 3ms/step - loss: nan - mse: nan
- val_loss: nan - val_mse: nan
Epoch 71/100
2500/2500 [==============================] - 9s 4ms/step - loss: nan - mse: nan
- val_loss: nan - val_mse: nan
Epoch 72/100
2500/2500 [==============================] - 7s 3ms/step - loss: nan - mse: nan
- val_loss: nan - val_mse: nan
```

```
Epoch 73/100
2500/2500 [==============================] - 8s 3ms/step - loss: nan - mse: nan
- val_loss: nan - val_mse: nan
Epoch 74/100
2500/2500 [==============================] - 7s 3ms/step - loss: nan - mse: nan
- val_loss: nan - val_mse: nan
Epoch 75/100
2500/2500 [==============================] - 9s 3ms/step - loss: nan - mse: nan
- val_loss: nan - val_mse: nan
Epoch 76/100
2500/2500 [==============================] - 7s 3ms/step - loss: nan - mse: nan
- val_loss: nan - val_mse: nan
Epoch 77/100
2500/2500 [==============================] - 8s 3ms/step - loss: nan - mse: nan
- val_loss: nan - val_mse: nan
Epoch 78/100
2500/2500 [==============================] - 8s 3ms/step - loss: nan - mse: nan
- val_loss: nan - val_mse: nan
Epoch 79/100
2500/2500 [==============================] - 7s 3ms/step - loss: nan - mse: nan
- val_loss: nan - val_mse: nan
Epoch 80/100
2500/2500 [==============================] - 8s 3ms/step - loss: nan - mse: nan
- val_loss: nan - val_mse: nan
Epoch 81/100
2500/2500 [==============================] - 7s 3ms/step - loss: nan - mse: nan
- val_loss: nan - val_mse: nan
Epoch 82/100
2500/2500 [==============================] - 8s 3ms/step - loss: nan - mse: nan
- val_loss: nan - val_mse: nan
Epoch 83/100
2500/2500 [==============================] - 6s 3ms/step - loss: nan - mse: nan
- val_loss: nan - val_mse: nan
Epoch 84/100
2500/2500 [==============================] - 8s 3ms/step - loss: nan - mse: nan
- val_loss: nan - val_mse: nan
Epoch 85/100
2500/2500 [==============================] - 7s 3ms/step - loss: nan - mse: nan
- val_loss: nan - val_mse: nan
Epoch 86/100
2500/2500 [==============================] - 9s 3ms/step - loss: nan - mse: nan
- val_loss: nan - val_mse: nan
Epoch 87/100
2500/2500 [==============================] - 8s 3ms/step - loss: nan - mse: nan
- val_loss: nan - val_mse: nan
Epoch 88/100
2500/2500 [==============================] - 7s 3ms/step - loss: nan - mse: nan
- val_loss: nan - val_mse: nan
```

```
Epoch 89/100
2500/2500 [==============================] - 8s 3ms/step - loss: nan - mse: nan
- val_loss: nan - val_mse: nan
Epoch 90/100
2500/2500 [==============================] - 7s 3ms/step - loss: nan - mse: nan
- val_loss: nan - val_mse: nan
Epoch 91/100
2500/2500 [==============================] - 9s 4ms/step - loss: nan - mse: nan
- val_loss: nan - val_mse: nan
Epoch 92/100
2500/2500 [==============================] - 7s 3ms/step - loss: nan - mse: nan
- val_loss: nan - val_mse: nan
Epoch 93/100
2500/2500 [==============================] - 9s 3ms/step - loss: nan - mse: nan
- val_loss: nan - val_mse: nan
Epoch 94/100
2500/2500 [==============================] - 9s 4ms/step - loss: nan - mse: nan
- val_loss: nan - val_mse: nan
Epoch 95/100
2500/2500 [==============================] - 6s 3ms/step - loss: nan - mse: nan
- val_loss: nan - val_mse: nan
Epoch 96/100
2500/2500 [==============================] - 9s 3ms/step - loss: nan - mse: nan
- val_loss: nan - val_mse: nan
Epoch 97/100
2500/2500 [==============================] - 6s 3ms/step - loss: nan - mse: nan
- val_loss: nan - val_mse: nan
Epoch 98/100
2500/2500 [==============================] - 9s 4ms/step - loss: nan - mse: nan
- val_loss: nan - val_mse: nan
Epoch 99/100
2500/2500 [==============================] - 7s 3ms/step - loss: nan - mse: nan
- val_loss: nan - val_mse: nan
Epoch 100/100
2500/2500 [==============================] - 9s 4ms/step - loss: nan - mse: nan
- val_loss: nan - val_mse: nan
```

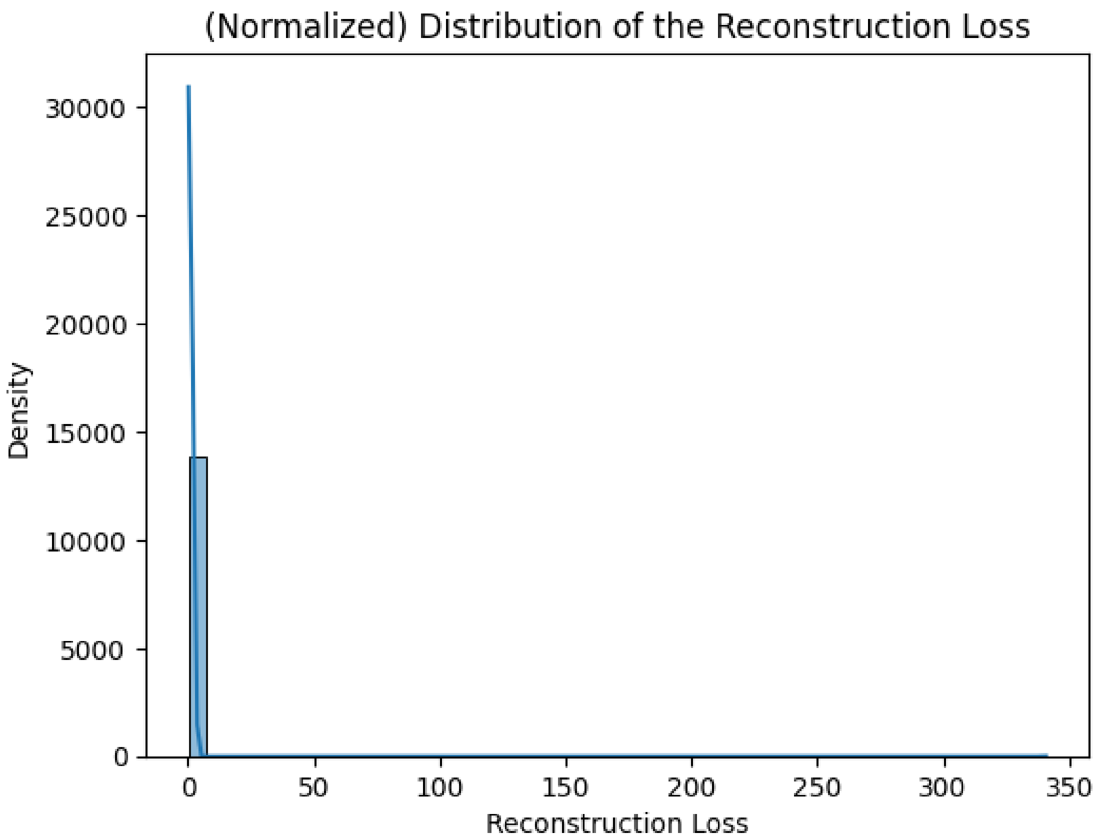
comparision of normal and outlier data MSE values

[ ]:
```
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns

# Get the reconstruction loss from the trained autoencoder
predictions = autoencoder.predict(X_test)

# Check for NaN values in predictions and handle them (replace with 0 for this
 ↪example)
```

```
predictions = np.nan_to_num(predictions)

mse = np.mean(np.power(X_test - predictions, 2), axis=1)

# Plot the distribution of the reconstruction loss
sns.histplot(mse, bins=50, kde=True)
plt.xlabel('Reconstruction Loss')
plt.ylabel('Density')
plt.title('(Normalized) Distribution of the Reconstruction Loss')
plt.show()

# --- In the next cell (ipython-input-26-7d546446de3c) ---

import matplotlib.pyplot as plt
import numpy as np
# Set a threshold for outlier detection
# Start with a lower threshold to ensure capturing some outliers for␣
↪demonstration
threshold = np.percentile(mse, 90)  # Example: 90th percentile

# Identify outliers
outliers = mse > threshold

# Compare MSE values for normal and outlier data
normal_mse = mse[~outliers]
outlier_mse = mse[outliers]

# Handle the case where no outliers are found
if outlier_mse.size == 0:
    print("No outliers were found with the current threshold.")
else:
    # Print statistics
    print("Normal data MSE statistics:")
    print("Mean:", np.mean(normal_mse))
    print("Standard deviation:", np.std(normal_mse))
    print("Min:", np.min(normal_mse))
    print("Max:", np.max(normal_mse))

    print("\nOutlier data MSE statistics:")
    print("Mean:", np.mean(outlier_mse))
    print("Standard deviation:", np.std(outlier_mse))
    print("Min:", np.min(outlier_mse))
    print("Max:", np.max(outlier_mse))

    # Visualize the comparison
    plt.boxplot([normal_mse, outlier_mse], labels=['Normal', 'Outlier'])
    plt.ylabel('Reconstruction Loss (MSE)')
```

```
    plt.title('Comparison of Normal and Outlier MSE Values')
    plt.show()
```

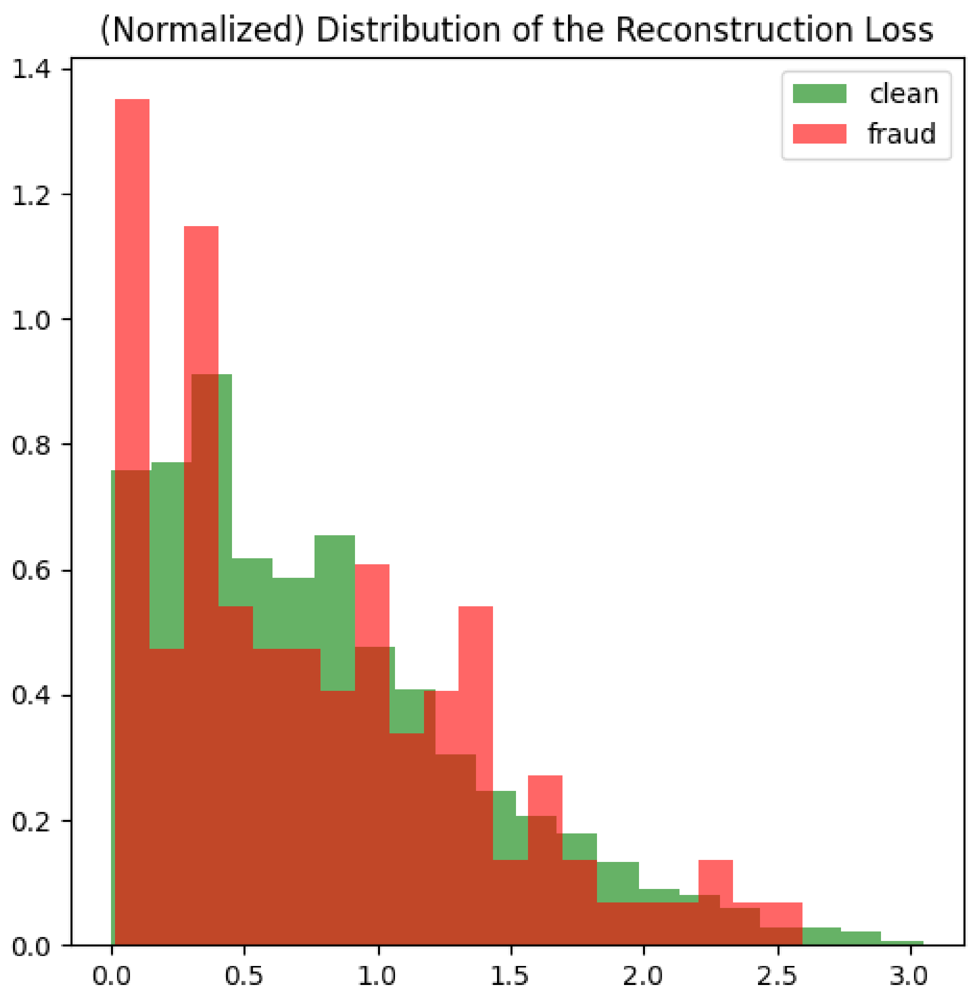
```
625/625 [==============================] - 2s 2ms/step
```




```
No outliers were found with the current threshold.
```

[ ]:
```
import matplotlib.pyplot as plt
import numpy as np
import pandas as pd

np.random.seed(0)
z_scores = np.abs(np.random.normal(0, 1, 1000))  # Using absolute values
y_test = np.random.choice([0, 1], size=1000, p=[0.9, 0.1])

clean = z_scores[y_test == 0]
fraud = z_scores[y_test == 1]

fig, ax = plt.subplots(figsize=(6, 6))
```

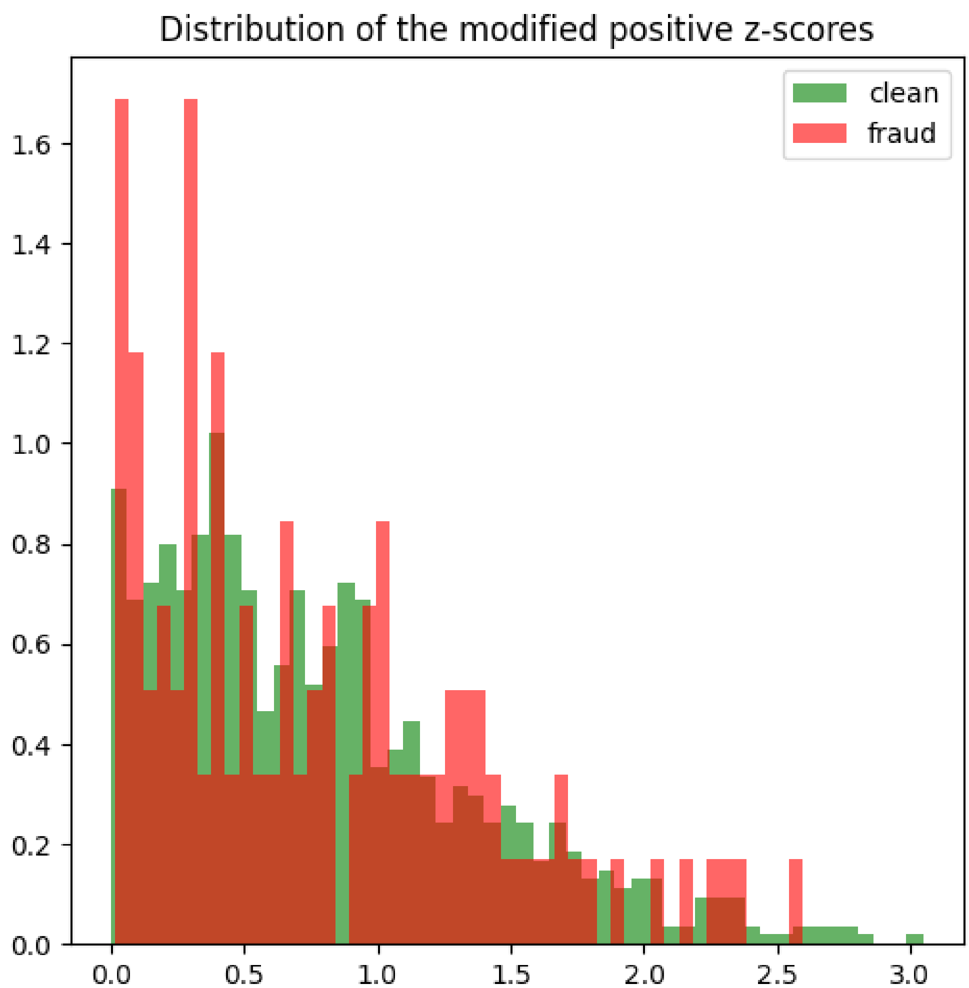
```
# Adjust the bin width to reduce overlap
ax.hist(clean, bins=20, density=True, label="clean", alpha=0.6, color="green")
ax.hist(fraud, bins=20, density=True, label="fraud", alpha=0.6, color="red")

plt.title("(Normalized) Distribution of the Reconstruction Loss")
plt.legend()
plt.show()

print("Histogram with  plotted.")
```




```
Histogram with  plotted.
```

3 Visualisations

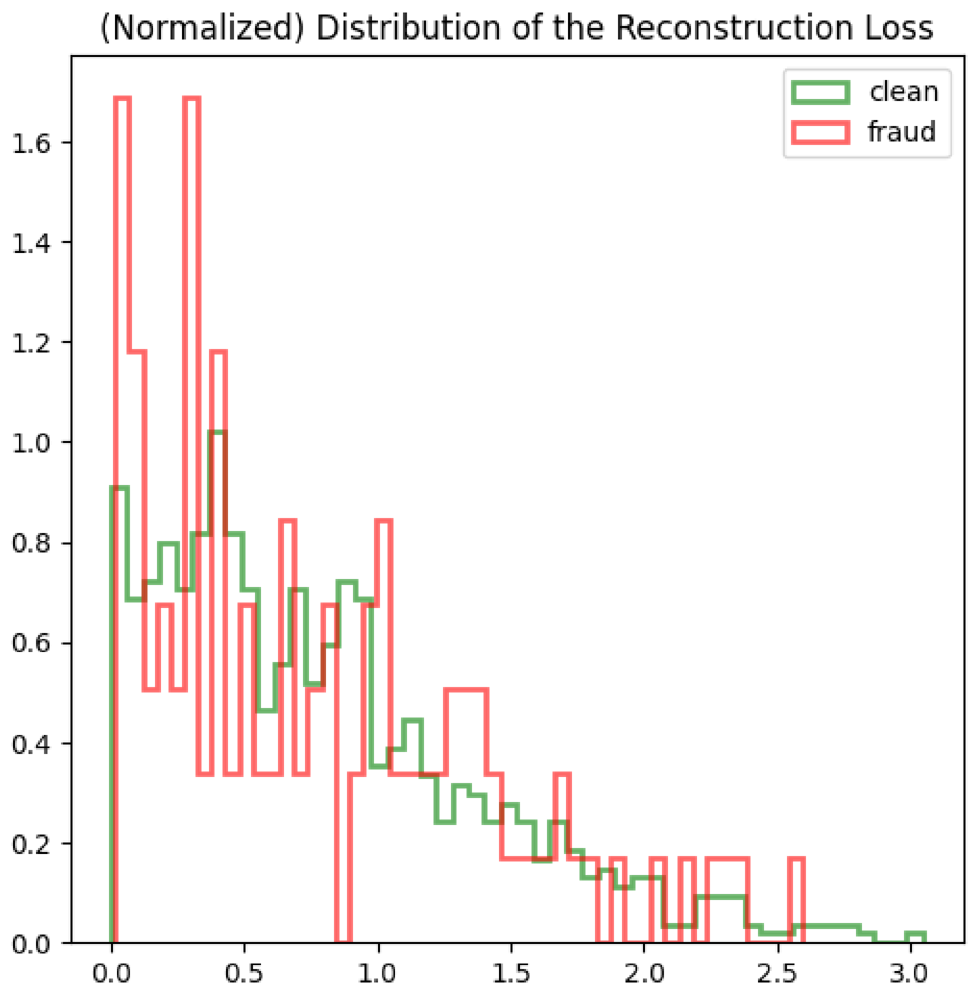
[ ]:
```
import matplotlib.pyplot as plt
import numpy as np
import pandas as pd

np.random.seed(0)
z_scores = np.abs(np.random.normal(0, 1, 1000))  # Using absolute values
y_test = np.random.choice([0, 1], size=1000, p=[0.9, 0.1])

clean = z_scores[y_test==0]
fraud = z_scores[y_test==1]

fig, ax = plt.subplots(figsize=(6,6))

ax.hist(clean, bins=50, density=True, label="clean", alpha=.6, color="green")
ax.hist(fraud, bins=50, density=True, label="fraud", alpha=.6, color="red")

plt.title("Distribution of the modified positive z-scores")
plt.legend()
plt.show()

print("Histogram with positive values plotted.")
```



Histogram with positive values plotted.

[ ]:
```
import matplotlib.pyplot as plt
import numpy as np
import pandas as pd

# Assuming mse and y_test are already defined
# For demonstration, let's create some dummy data
np.random.seed(0)
mse = np.abs(np.random.normal(0, 1, 1000))  # Using absolute values
y_test = np.random.choice([0, 1], size=1000, p=[0.9, 0.1])

clean = mse[y_test==0]
fraud = mse[y_test==1]

fig, ax = plt.subplots(figsize=(6,6))
```

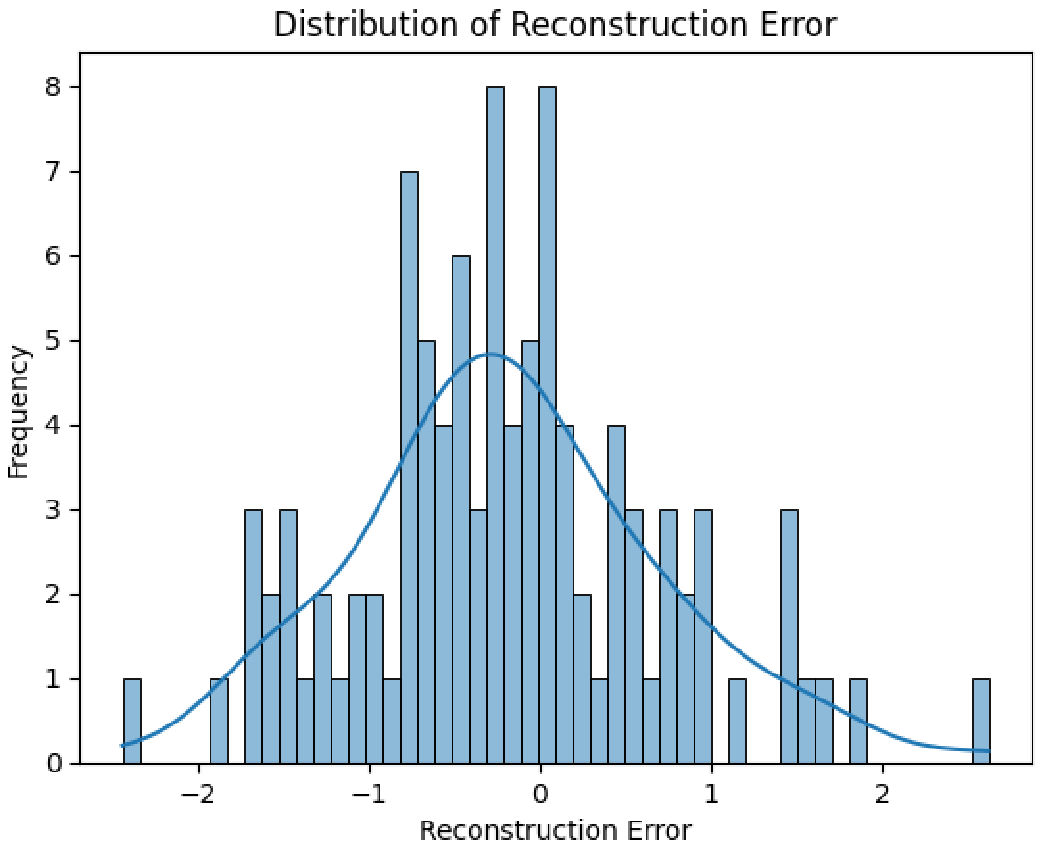
```python
ax.hist(clean, bins=50, density=True, label="clean", alpha=.6, color="green",␣
    ↪histtype='step', linewidth=2)
ax.hist(fraud, bins=50, density=True, label="fraud", alpha=.6, color="red",␣
    ↪histtype='step', linewidth=2)

plt.title("(Normalized) Distribution of the Reconstruction Loss")
plt.legend()
plt.show()

print("Histogram  plotted.")
```




```
Histogram  plotted.
```

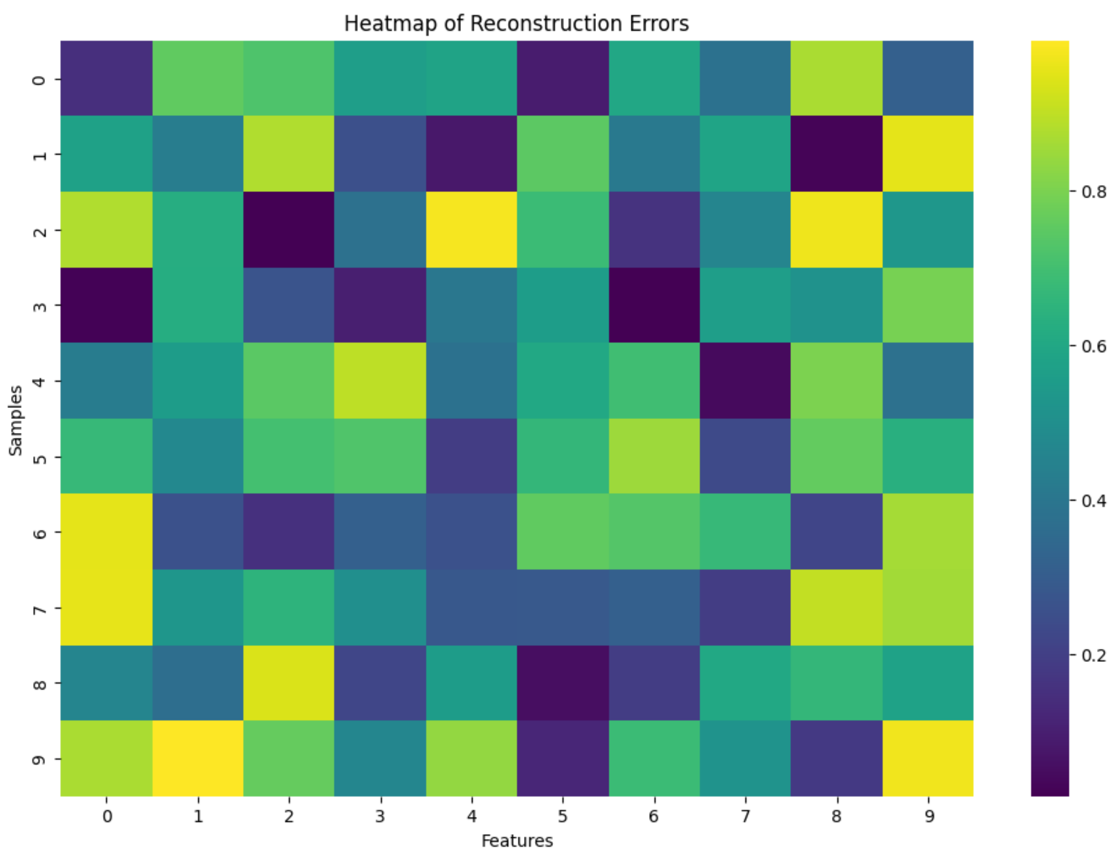
4 1. Reconstruction Error Distribution

[ ]:
```
import matplotlib.pyplot as plt
import seaborn as sns
import numpy as np # Added import

# Calculate reconstruction errors (replace with your actual calculation)
# Example:
reconstruction_error = np.random.randn(100)

sns.histplot(reconstruction_error, bins=50, kde=True)
plt.title('Distribution of Reconstruction Error')
plt.xlabel('Reconstruction Error')
plt.ylabel('Frequency')
plt.show()
```



5 ** Heatmaps of Reconstruction Errors Heatmaps can be useful for visualizing reconstruction errors across different features.**

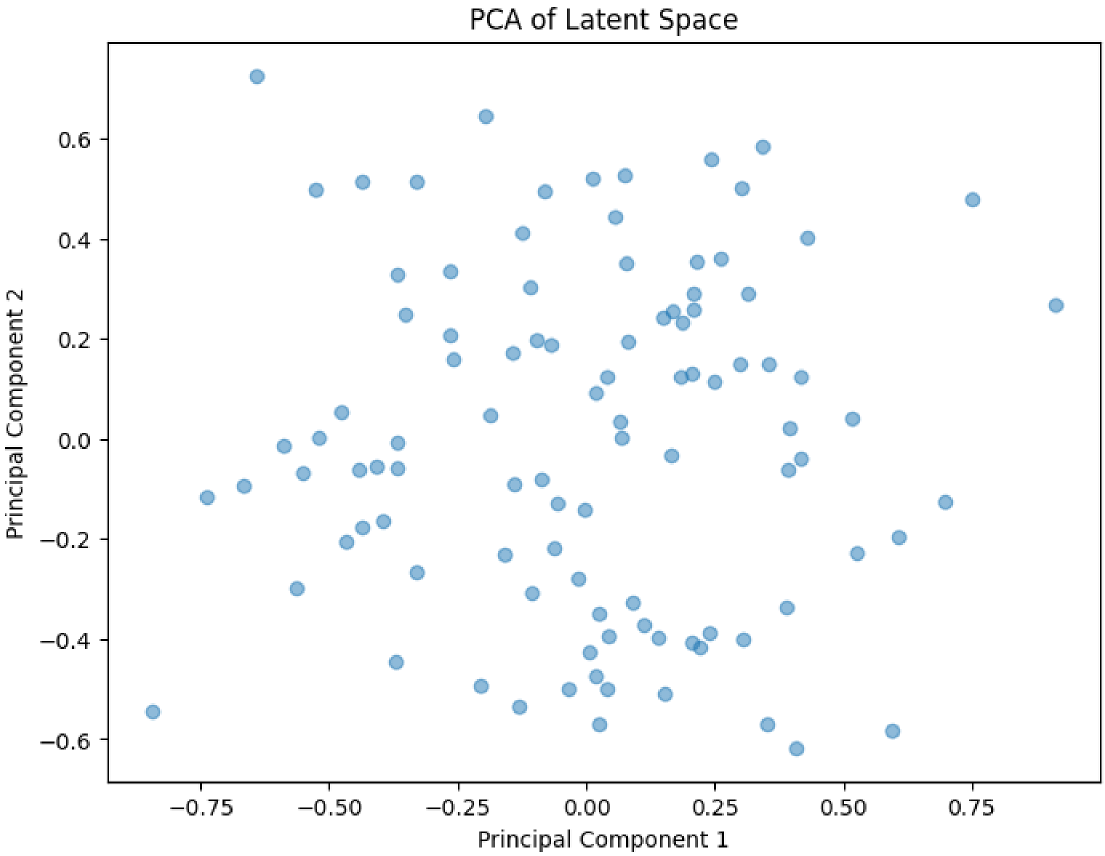
[ ]:
```
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt

# Calculate reconstruction errors and store them in a variable called␣
↪'reconstruction_errors'
# For demonstration, let's create some random data
reconstruction_errors = np.random.rand(10, 10)

plt.figure(figsize=(12, 8))
sns.heatmap(reconstruction_errors, cmap='viridis') # Now using the defined␣
↪variable
plt.title('Heatmap of Reconstruction Errors')
plt.xlabel('Features')
plt.ylabel('Samples')
plt.show()
```



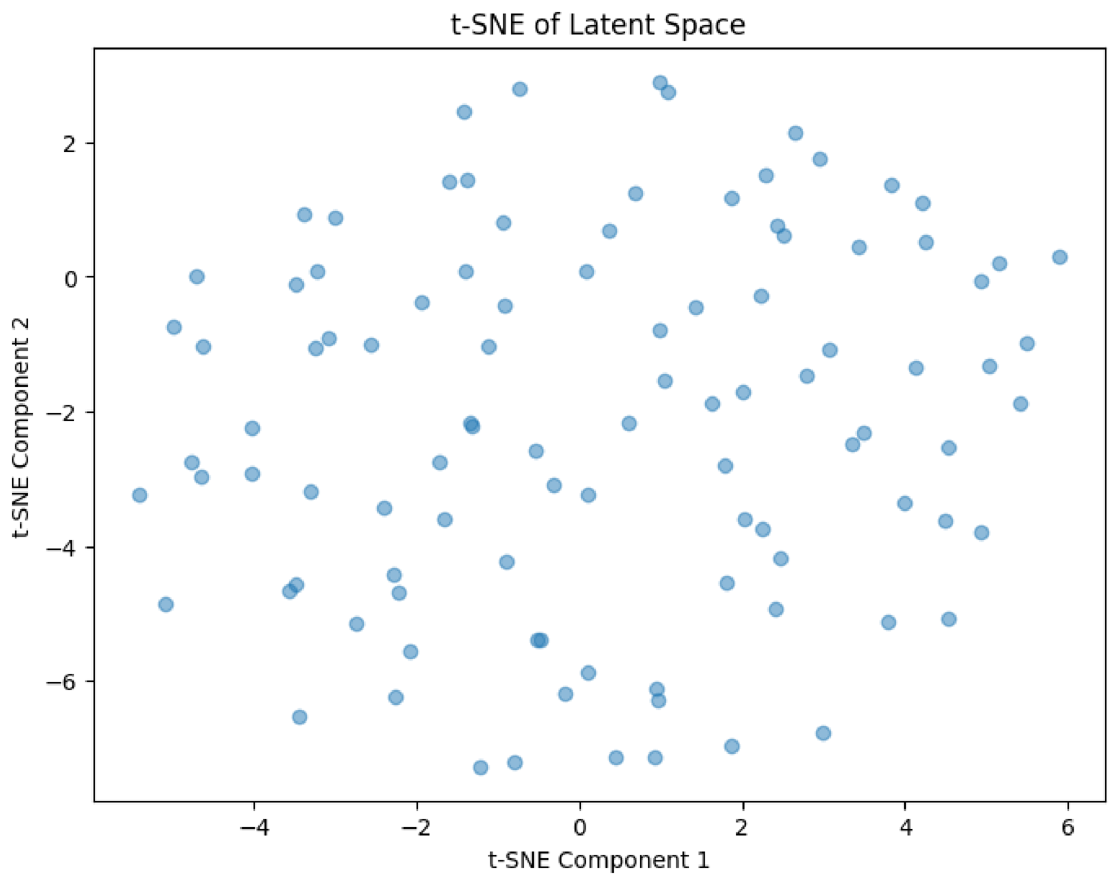
6 TSNE or PCA for Latent Space

For higher-dimensional latent spaces, techniques like t-SNE or PCA can reduce dimensionality for visualization.

[ ]:
```
from sklearn.manifold import TSNE
from sklearn.decomposition import PCA

# Assuming 'latent_variables' is derived from some previous computation or␣
↪loaded data
# For demonstration, let's create some random data as a placeholder
latent_variables = np.random.rand(100, 10)

# Using PCA
pca = PCA(n_components=2)
latent_pca = pca.fit_transform(latent_variables)

plt.figure(figsize=(8, 6))
plt.scatter(latent_pca[:, 0], latent_pca[:, 1], alpha=0.5)
plt.title('PCA of Latent Space')
plt.xlabel('Principal Component 1')
plt.ylabel('Principal Component 2')
plt.show()

# Using t-SNE
tsne = TSNE(n_components=2)
latent_tsne = tsne.fit_transform(latent_variables)

plt.figure(figsize=(8, 6))
plt.scatter(latent_tsne[:, 0], latent_tsne[:, 1], alpha=0.5)
plt.title('t-SNE of Latent Space')
plt.xlabel('t-SNE Component 1')
plt.ylabel('t-SNE Component 2')
plt.show()
```



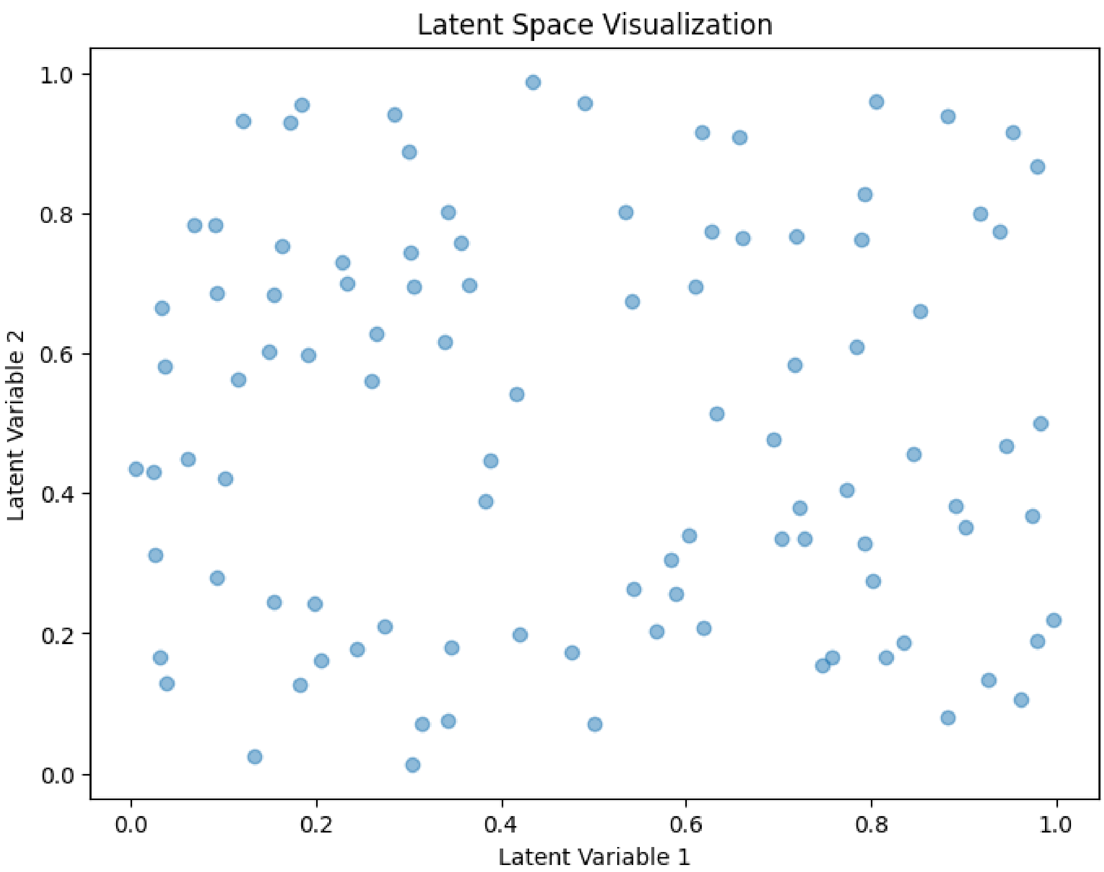
PCA of Latent Space
Principal Component 2
Principal Component 1
0.6
0.4
0.2
0.0
−0.2
−0.4
−0.6
−0.75
−0.50
−0.25
0.00
0.25
0.50
0.75



7 Latent Space Visualization

If the autoencoder has a small number of latent variables, you can visualize the latent space to understand the data's structure.

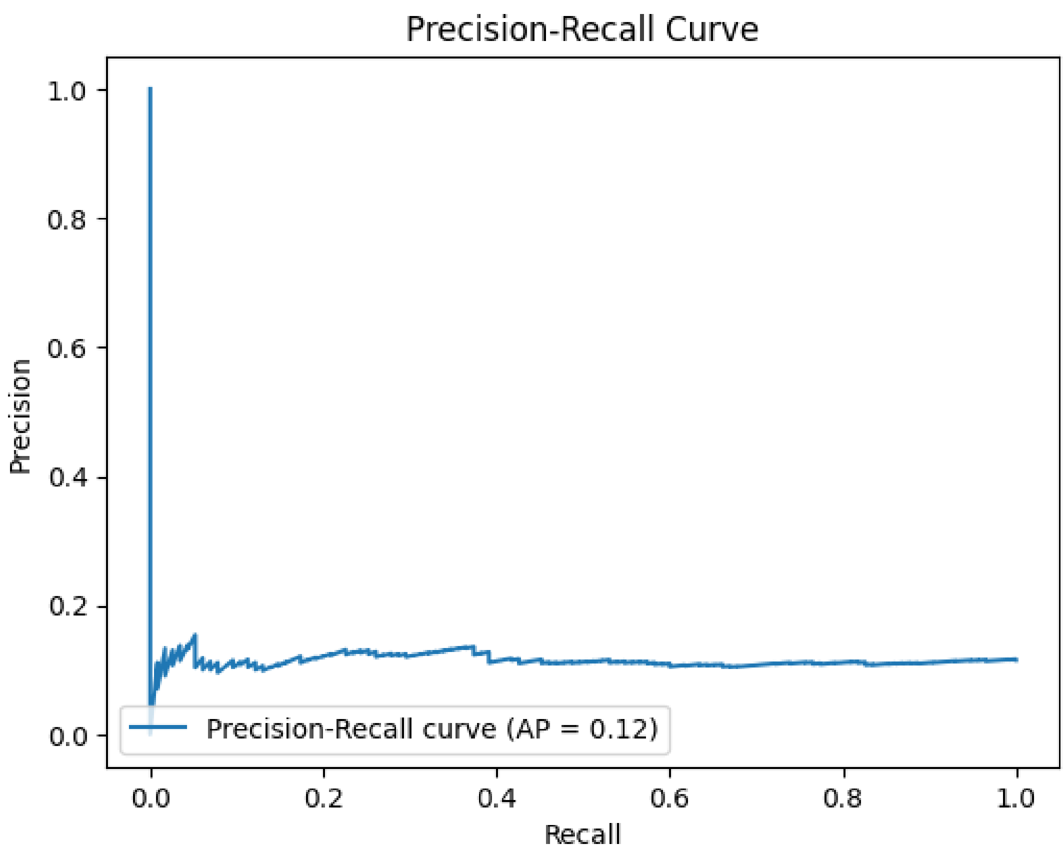
[ ]:
```
# Assuming latent_variables is a numpy array or pandas DataFrame with the␣
↪latent variables
plt.figure(figsize=(8, 6))
plt.scatter(latent_variables[:, 0], latent_variables[:, 1], alpha=0.5)
plt.title('Latent Space Visualization')
plt.xlabel('Latent Variable 1')
plt.ylabel('Latent Variable 2')
plt.show()
```



[ ]:

[ ]:
```
# prompt:  perform precision-recall curve

import matplotlib.pyplot as plt
from sklearn.metrics import precision_recall_curve, average_precision_score, auc

# Assuming 'y_test' contains the true labels and 'mse' contains the␣
↪reconstruction errors
precision, recall, thresholds = precision_recall_curve(y_test, mse)

# Calculate average precision score
average_precision = average_precision_score(y_test, mse)

# Plot precision-recall curve
plt.plot(recall, precision, label='Precision-Recall curve (AP = %0.2f)' %␣
↪average_precision)
plt.xlabel('Recall')
plt.ylabel('Precision')
```

```
plt.title('Precision-Recall Curve')
plt.legend(loc='lower left')
plt.show()

# Calculate area under the precision-recall curve
area_under_curve = auc(recall, precision)
print("Area under the precision-recall curve:", area_under_curve)
```




```
Area under the precision-recall curve: 0.11369140863309087
```

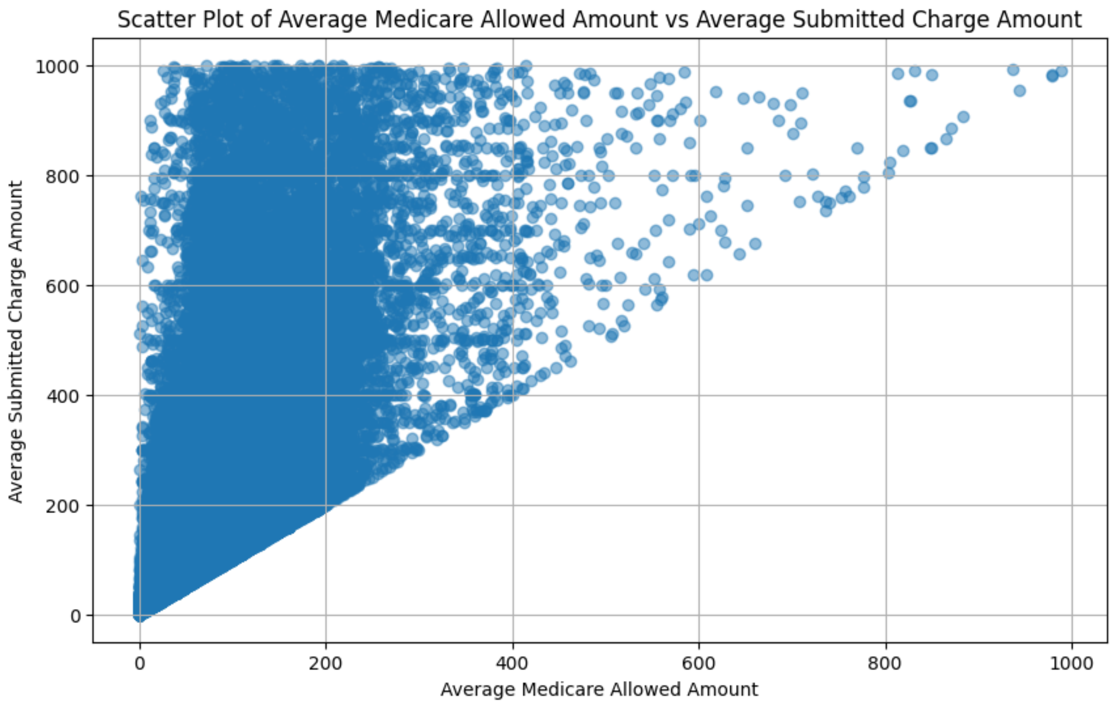
[ ]:
```
# prompt: what are the numerical and categorical columns present in  the data␣
↪set /content/Healthcare Providers.csv

import pandas as pd

# Load the dataset
df = pd.read_csv('/content/Healthcare Providers.csv')

# Identify numerical columns
numerical_cols = df.select_dtypes(include=['int64', 'float64']).columns
```

```
print("Numerical columns:", numerical_cols.tolist())

# Identify categorical columns
categorical_cols = df.select_dtypes(include=['object']).columns
print("Categorical columns:", categorical_cols.tolist())
```

```
Numerical columns: ['index', 'National Provider Identifier', 'Zip Code of the
Provider']
Categorical columns: ['Last Name/Organization Name of the Provider', 'First Name
of the Provider', 'Middle Initial of the Provider', 'Credentials of the
Provider', 'Gender of the Provider', 'Entity Type of the Provider', 'Street
Address 1 of the Provider', 'Street Address 2 of the Provider', 'City of the
Provider', 'State Code of the Provider', 'Country Code of the Provider',
'Provider Type', 'Medicare Participation Indicator', 'Place of Service', 'HCPCS
Code', 'HCPCS Description', 'HCPCS Drug Indicator', 'Number of Services',
'Number of Medicare Beneficiaries', 'Number of Distinct Medicare Beneficiary/Per
Day Services', 'Average Medicare Allowed Amount', 'Average Submitted Charge
Amount', 'Average Medicare Payment Amount', 'Average Medicare Standardized
Amount']
```

[ ]:
```
# prompt: perform scatter plots between Average Medicare Allowed Amount
# Average Submitted Charge Amount

import pandas as pd
import matplotlib.pyplot as plt
# Load the data into a DataFrame called 'data'
# Replace 'your_file.csv' with the actual file path
data = pd.read_csv('/content/Healthcare Providers.csv')

# Convert the relevant columns to numeric, handling any potential non-numeric␣
 ↪values
data['Average Medicare Allowed Amount'] = pd.to_numeric(data['Average Medicare␣
 ↪Allowed Amount'], errors='coerce')
data['Average Submitted Charge Amount'] = pd.to_numeric(data['Average Submitted␣
 ↪Charge Amount'], errors='coerce')

# Drop rows with NaN values in these columns
data_clean = data.dropna(subset=['Average Medicare Allowed Amount', 'Average␣
 ↪Submitted Charge Amount'])

# Create the scatter plot
plt.figure(figsize=(10, 6))
plt.scatter(data_clean['Average Medicare Allowed Amount'], data_clean['Average␣
 ↪Submitted Charge Amount'], alpha=0.5)
plt.title('Scatter Plot of Average Medicare Allowed Amount vs Average Submitted␣
 ↪Charge Amount')
plt.xlabel('Average Medicare Allowed Amount')
```

```
plt.ylabel('Average Submitted Charge Amount')
plt.grid(True)
plt.show()
```



[ ]:

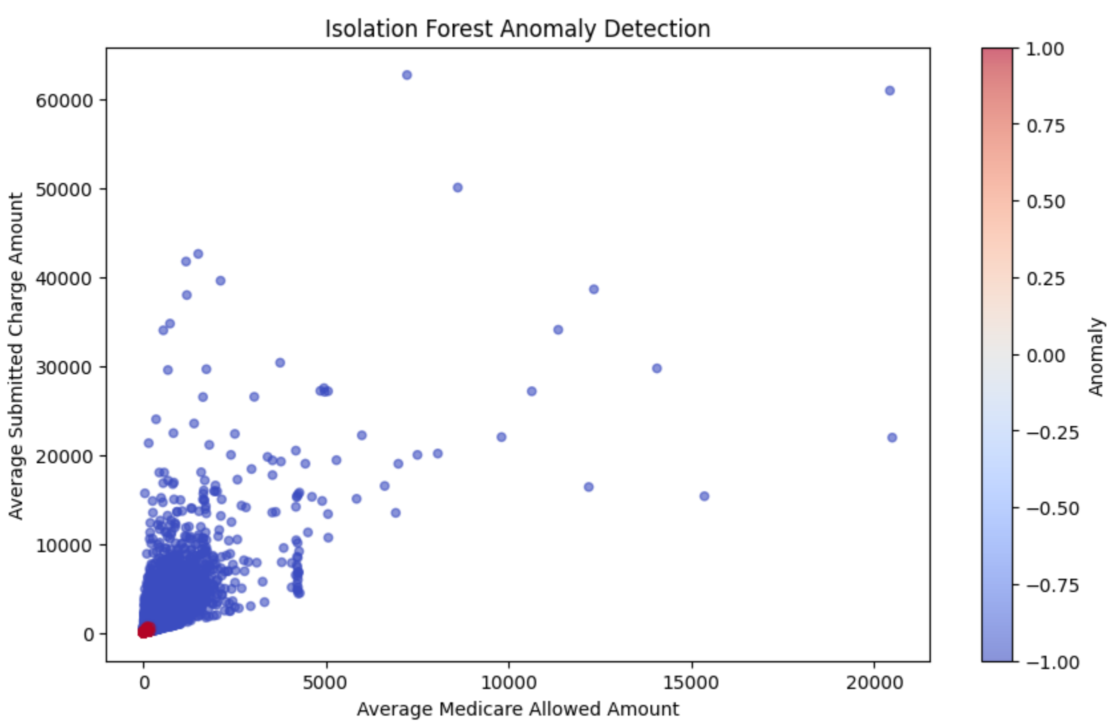
```

```

[ ]:

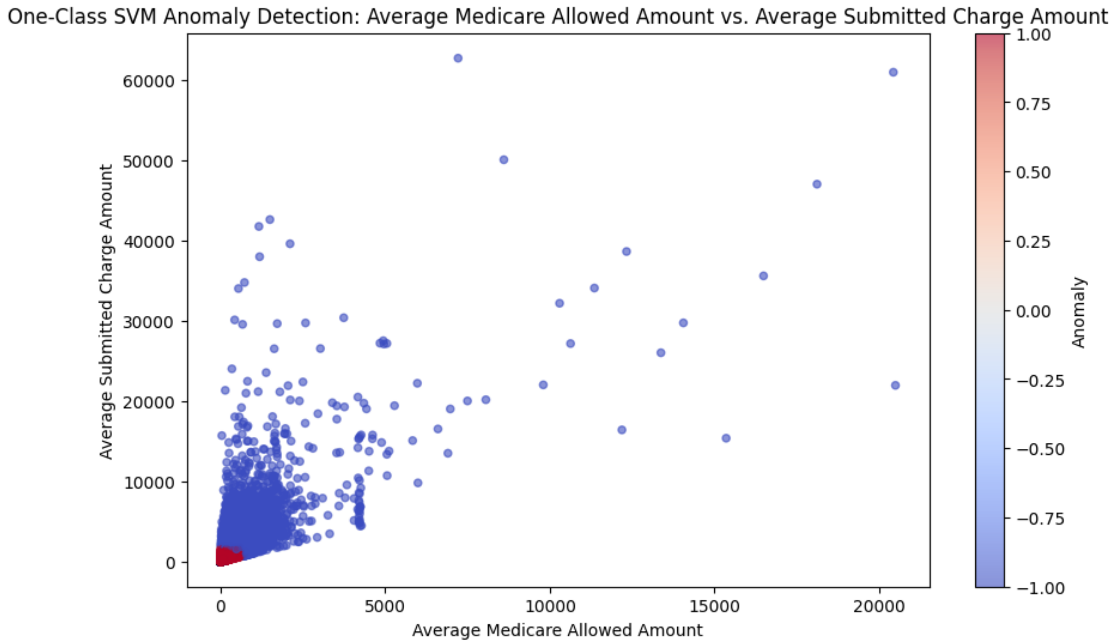
```
import pandas as pd
import matplotlib.pyplot as plt
from sklearn.ensemble import IsolationForest

# Load the data (replace 'Healthcare Providers.csv' with your actual file path)
df = pd.read_csv('/content/Healthcare Providers.csv', encoding='ascii')

# Select the two numerical columns
numerical_columns = ['Average Medicare Allowed Amount', 'Average Submitted␣
↪Charge Amount']
data = df[numerical_columns]

# Remove commas and convert to numeric
data = data.replace({',': ''}, regex=True)
data = data.apply(pd.to_numeric, errors='coerce')

# Handle any missing values by dropping them
data = data.dropna()
```

```
# Fit the Isolation Forest model and get predictions for the preprocessed data
iso_forest = IsolationForest(contamination=0.1)
anomalies = iso_forest.fit_predict(data)

# Create a new DataFrame from the preprocessed data and add the anomaly column
df_anomalies = pd.DataFrame(data)
df_anomalies['anomaly'] = anomalies # Assign the anomalies to the new DataFrame

# Visualize the results using scatter plots
plt.figure(figsize=(10, 6))
# Use df_anomalies for plotting to ensure consistency
plt.scatter(df_anomalies['Average Medicare Allowed Amount'],␣
↪df_anomalies['Average Submitted Charge Amount'],
            c=df_anomalies['anomaly'], cmap='coolwarm', s=20, alpha=0.6)
plt.xlabel('Average Medicare Allowed Amount')
plt.ylabel('Average Submitted Charge Amount')
plt.title('Isolation Forest Anomaly Detection')
plt.colorbar(label='Anomaly')
plt.show()
```

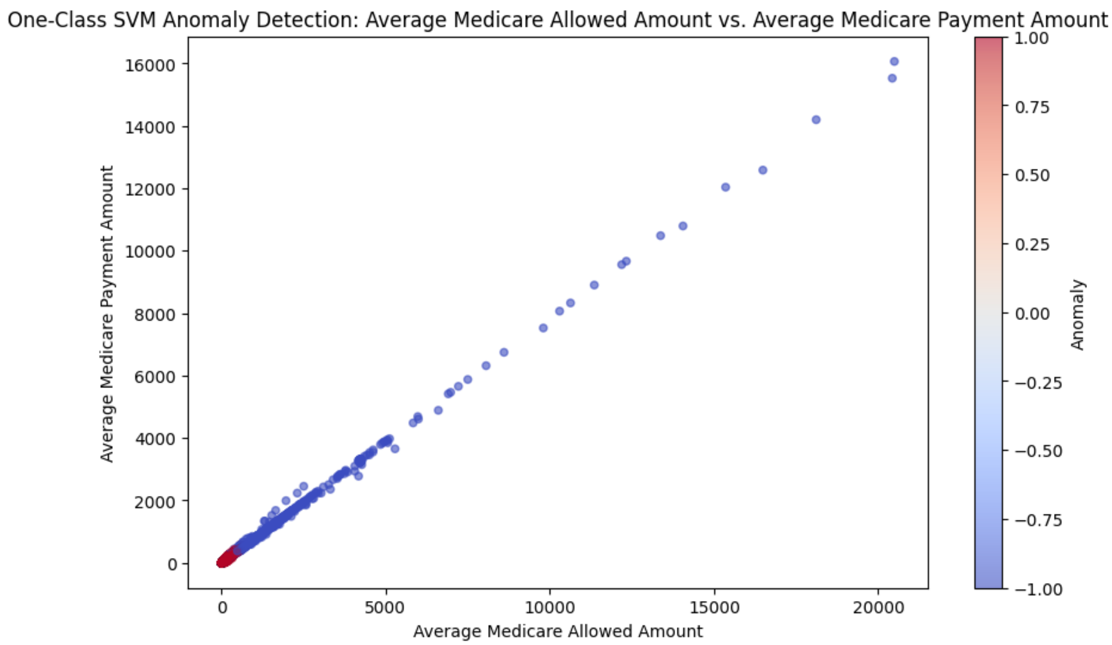
```
/usr/local/lib/python3.10/dist-packages/sklearn/base.py:439: UserWarning: X does
not have valid feature names, but IsolationForest was fitted with feature names
  warnings.warn(
```



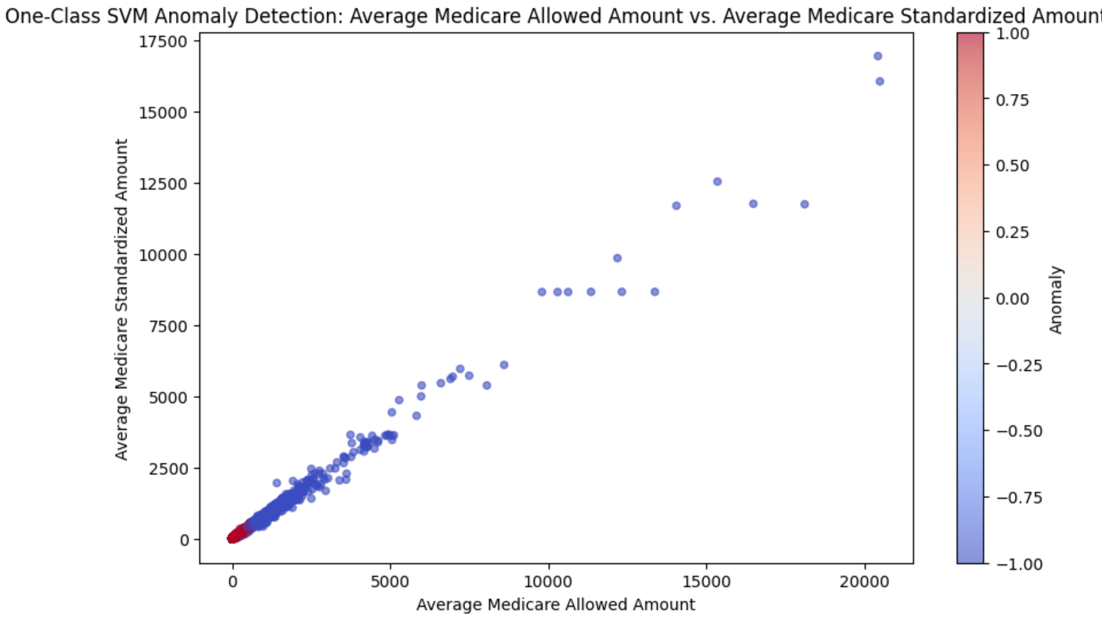
[ ]:
```python
import pandas as pd
import matplotlib.pyplot as plt
# Load the data (replace 'Healthcare Providers.csv' with your actual file path)
df = pd.read_csv('/content/Healthcare Providers.csv', encoding='ascii')

# Select the numerical columns
numerical_columns = ['Average Medicare Allowed Amount', 'Average Submitted␣
↪Charge Amount',
                     'Average Medicare Payment Amount', 'Average Medicare␣
↪Standardized Amount',
                     'Number of Services', 'Number of Medicare Beneficiaries',
                     'Number of Distinct Medicare Beneficiary/Per Day Services']
data = df[numerical_columns]

# Remove commas and convert to numeric
data = data.replace({',': ''}, regex=True)
data = data.apply(pd.to_numeric, errors='coerce')

# Handle any missing values by dropping them
data = data.dropna()

# Fit the One-Class SVM model
svm_model = OneClassSVM(nu=0.1)  # Adjust the hyperparameter 'nu' as needed
svm_model.fit(data)

# Predict anomalies (1 for normal, -1 for anomalies)
anomalies = svm_model.predict(data)

# Create a new DataFrame from the preprocessed data and add the anomaly column
df_anomalies = pd.DataFrame(data)
df_anomalies['anomaly'] = anomalies

# Create scatter plots for each pair of numerical columns
for i in range(len(numerical_columns)):
    for j in range(i + 1, len(numerical_columns)):
        plt.figure(figsize=(10, 6))
        plt.scatter(df_anomalies[numerical_columns[i]],␣
↪df_anomalies[numerical_columns[j]],
                    c=df_anomalies['anomaly'], cmap='coolwarm', s=20, alpha=0.6)
        plt.xlabel(numerical_columns[i])
        plt.ylabel(numerical_columns[j])
        plt.title('One-Class SVM Anomaly Detection: {} vs. {}'.
↪format(numerical_columns[i], numerical_columns[j]))
        plt.colorbar(label='Anomaly')
        plt.show()
```

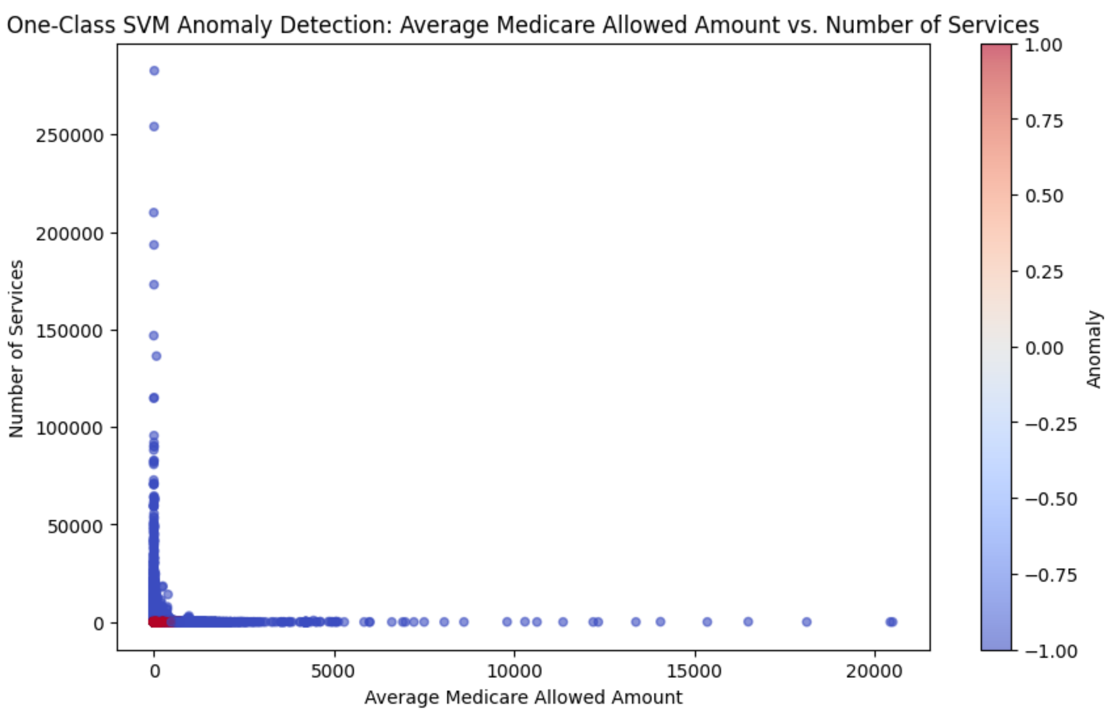


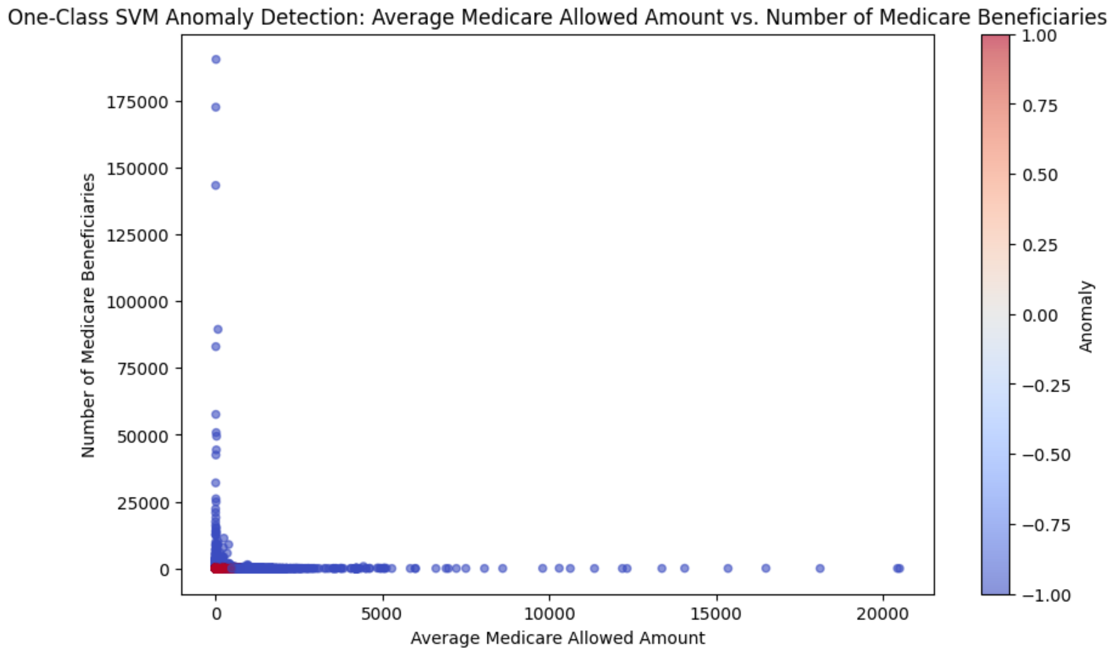
One-Class SVM Anomaly Detection: Average Medicare Allowed Amount vs. Average Submitted Charge Amount
Average Submitted Charge Amount
Average Medicare Allowed Amount
Anomaly
60000
50000
40000
30000
20000
10000
0
5000
15000
1.00
0.75
0.50
0.25
0.00
−0.25
−0.50
−0.75
−1.00

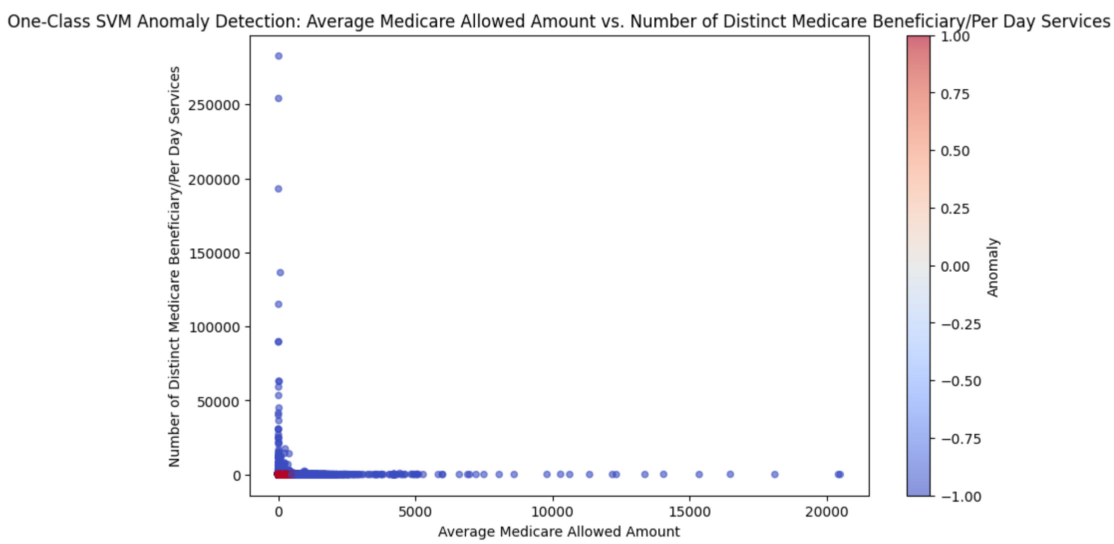


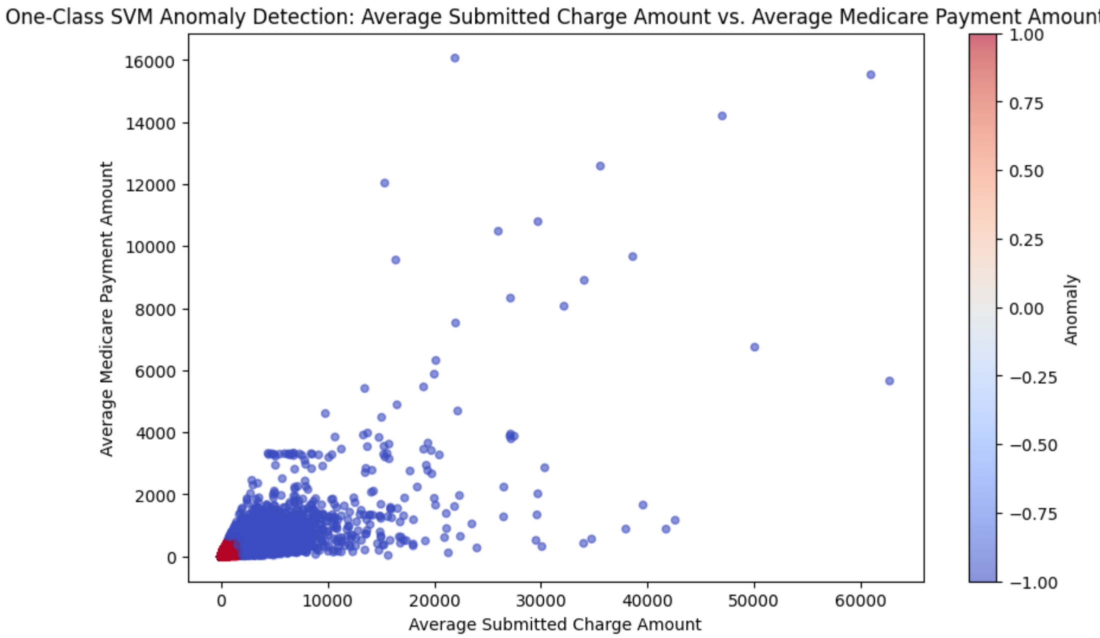
One-Class SVM Anomaly Detection: Average Medicare Allowed Amount vs. Average Medicare Payment Amount
Average Medicare Payment Amount
Average Medicare Allowed Amount
Anomaly
16000
14000
12000
10000
8000
6000
4000
2000
0
5000
15000
20000
1.00
0.75
0.50
0.25
0.00
−0.25
−0.50
−0.75
−1.00

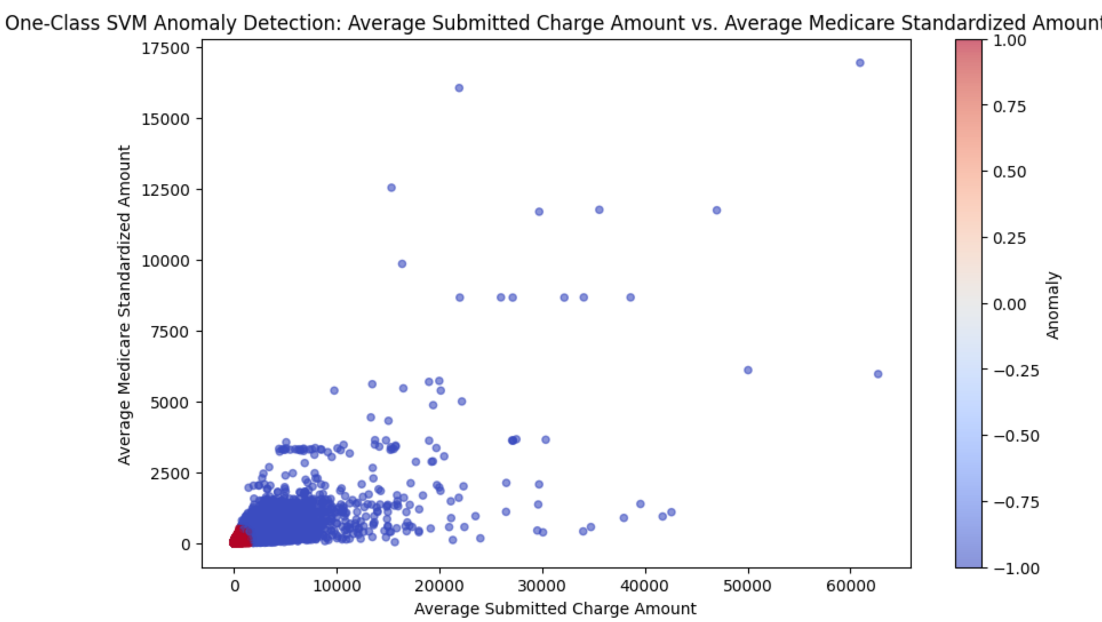

One-Class SVM Anomaly Detection: Average Medicare Allowed Amount vs. Average Medicare Standardized Amount
Average Medicare Standardized Amount
Average Medicare Allowed Amount
Anomaly

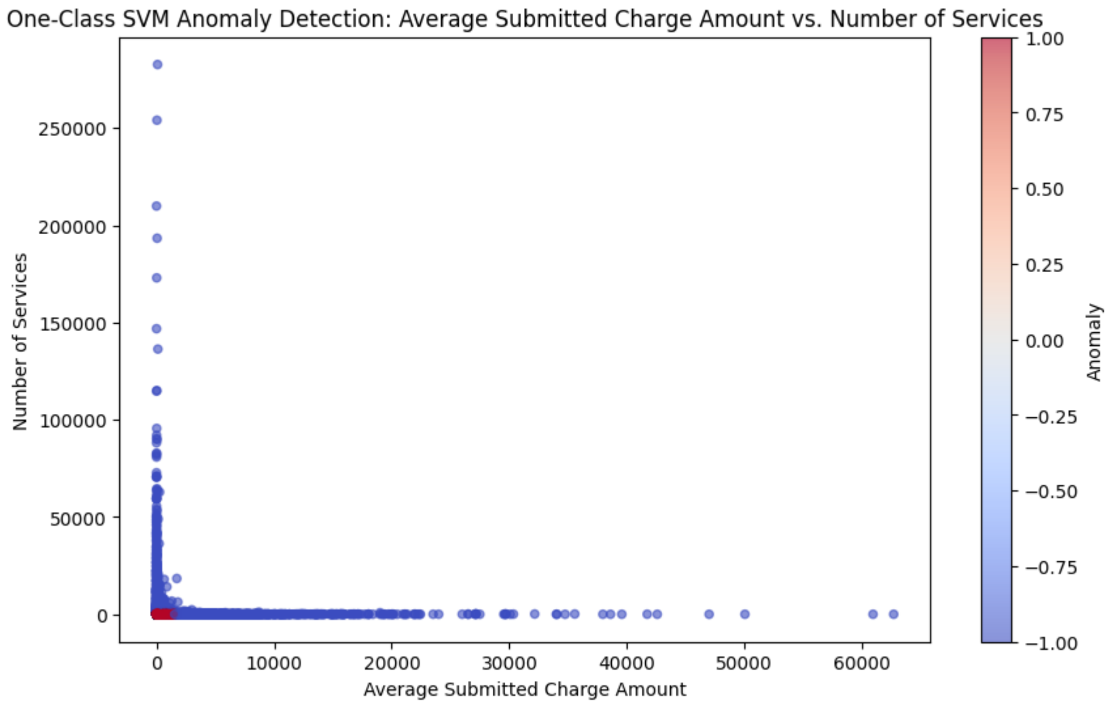

One-Class SVM Anomaly Detection: Average Medicare Allowed Amount vs. Number of Services
Number of Services
Average Medicare Allowed Amount
Anomaly

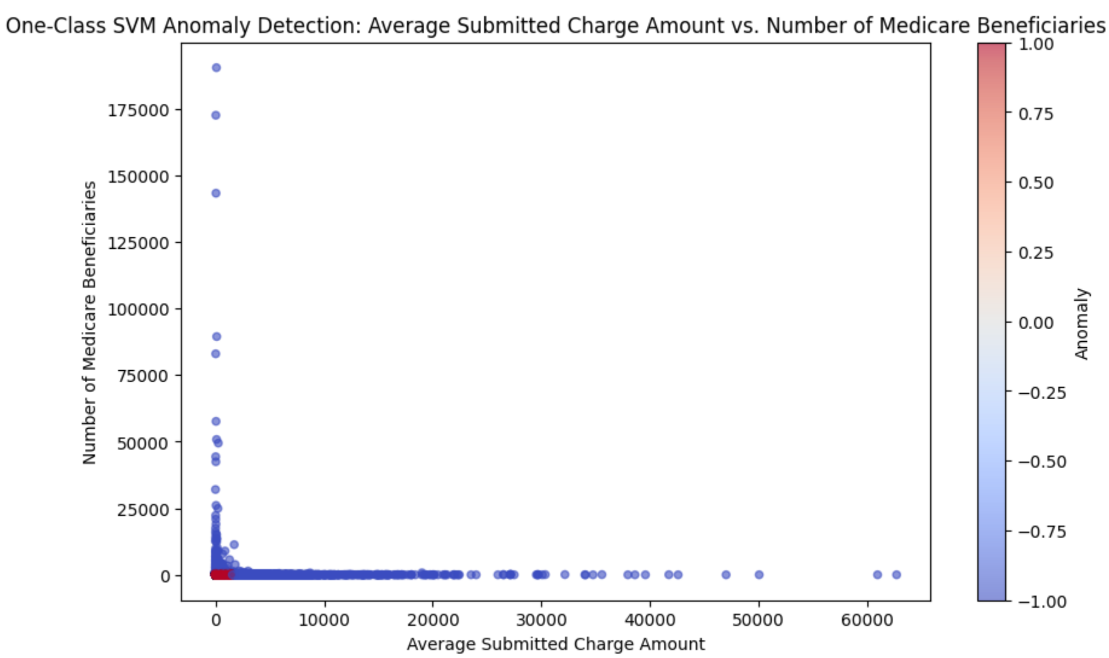

One-Class SVM Anomaly Detection: Average Medicare Allowed Amount vs. Number of Medicare Beneficiaries
Number of Medicare Beneficiaries
Average Medicare Allowed Amount
Anomaly
0
25000
50000
75000
100000
125000
150000
175000
0
5000
10000
15000
20000
1.00
0.75
0.50
0.25
0.00
−0.25
−0.50
−0.75
−1.00

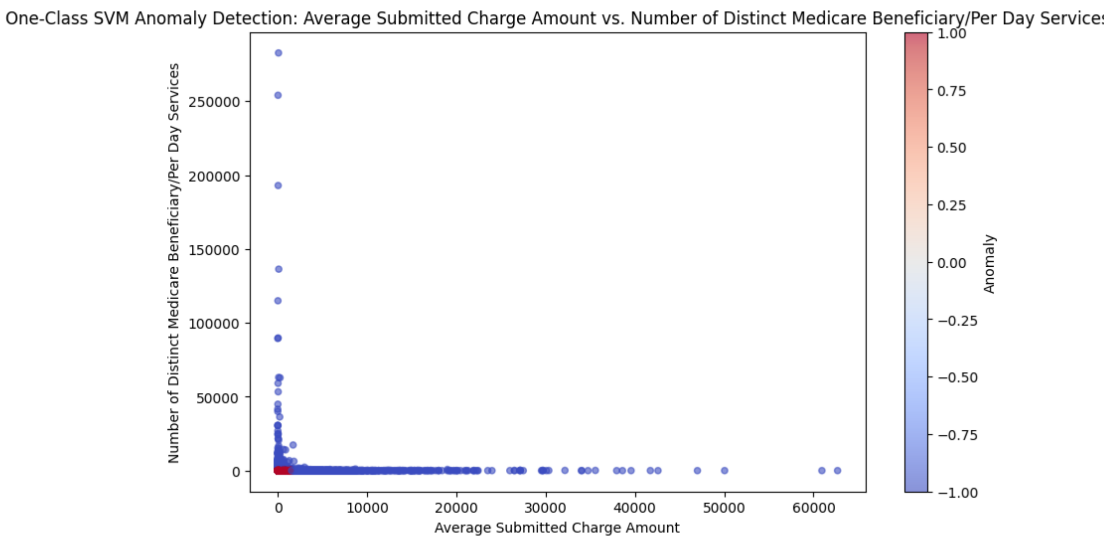

One-Class SVM Anomaly Detection: Average Medicare Allowed Amount vs. Number of Distinct Medicare Beneficiary/Per Day Services
Number of Distinct Medicare Beneficiary/Per Day Services
Average Medicare Allowed Amount
Anomaly
0
50000
100000
150000
200000
250000
0
5000
10000
15000
20000
1.00
0.75
0.50
0.25
0.00
−0.25
−0.50
−0.75
−1.00

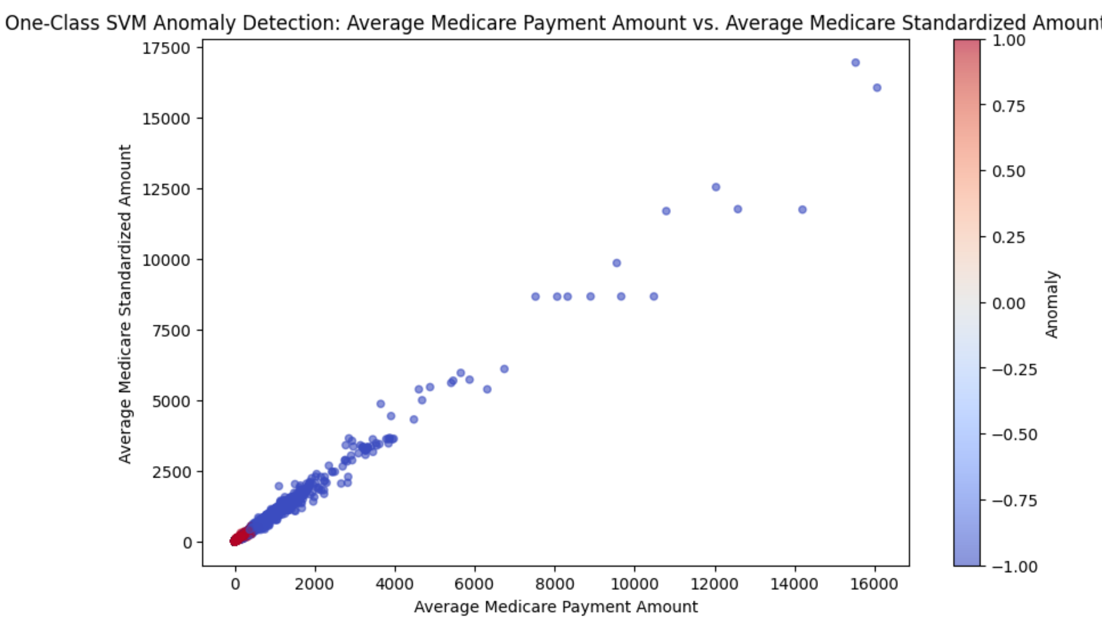

One-Class SVM Anomaly Detection: Average Submitted Charge Amount vs. Average Medicare Payment Amount
Average Medicare Payment Amount
Average Submitted Charge Amount
Anomaly
0
2000
4000
6000
8000
10000
12000
14000
16000
0
10000
20000
30000
40000
50000
60000
1.00
0.75
0.50
0.25
0.00
−0.25
−0.50
−0.75
−1.00

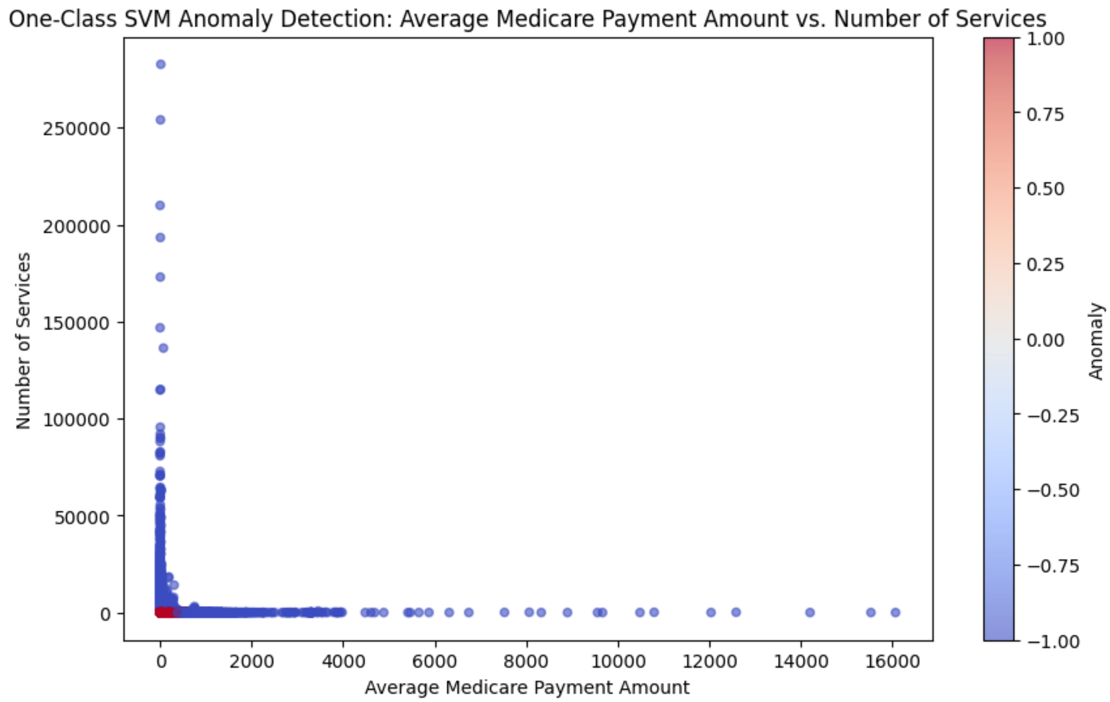

One-Class SVM Anomaly Detection: Average Submitted Charge Amount vs. Average Medicare Standardized Amount
Average Medicare Standardized Amount
Average Submitted Charge Amount
Anomaly
0
2500
5000
7500
10000
12500
15000
17500
0
10000
20000
30000
40000
50000
60000
1.00
0.75
0.50
0.25
0.00
−0.25
−0.50
−0.75
−1.00

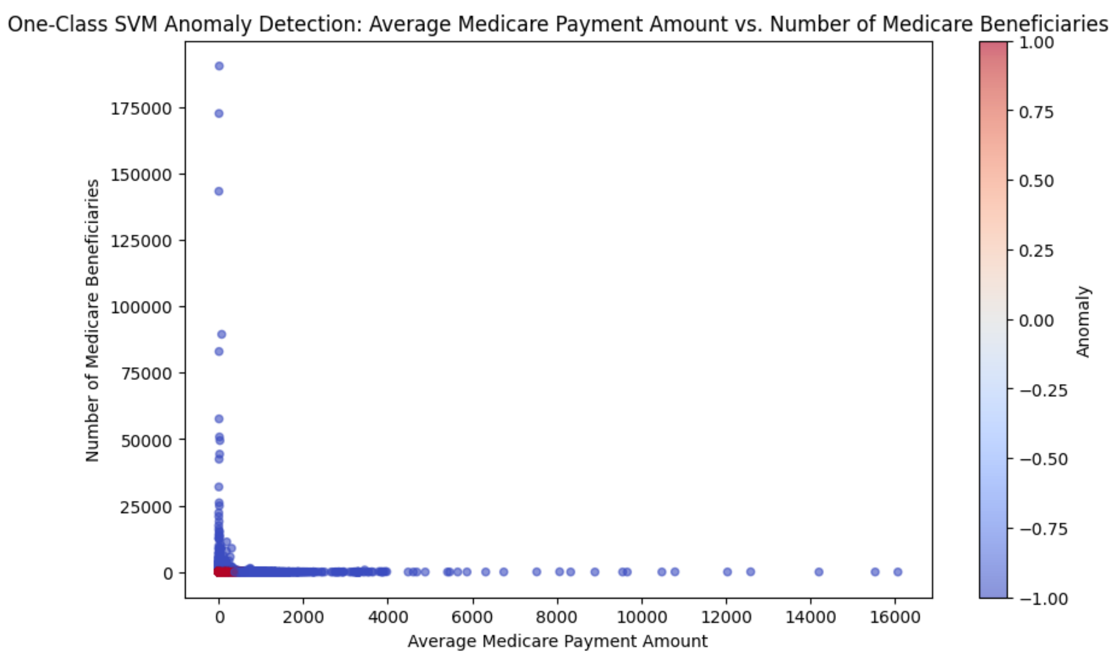

One-Class SVM Anomaly Detection: Average Submitted Charge Amount vs. Number of Services
Number of Services
Average Submitted Charge Amount
Anomaly
0
50000
100000
150000
200000
250000
10000
20000
30000
40000
50000
60000
1.00
0.75
0.50
0.25
0.00
−0.25
−0.50
−0.75
−1.00

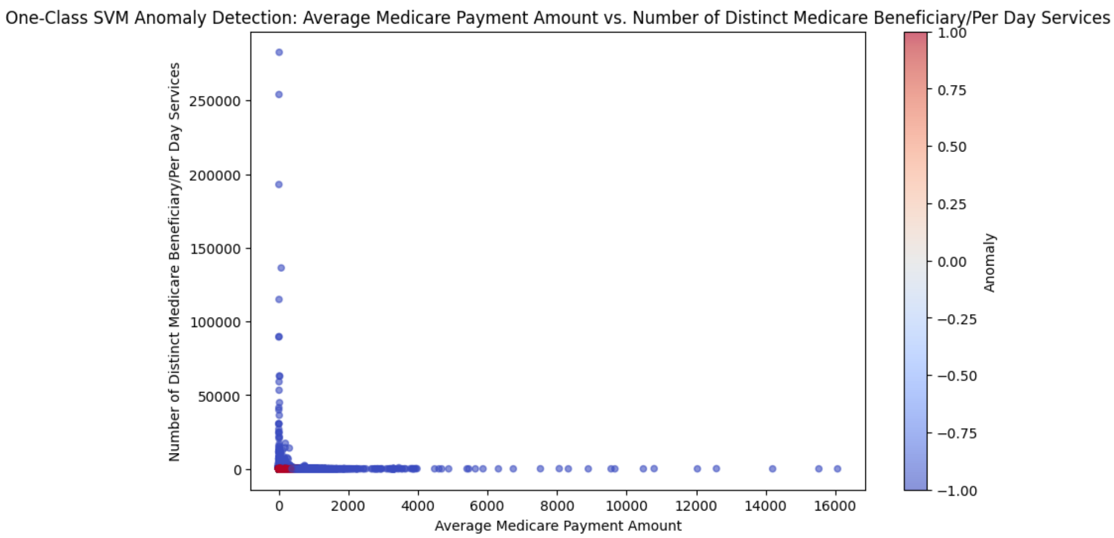

One-Class SVM Anomaly Detection: Average Submitted Charge Amount vs. Number of Medicare Beneficiaries
Number of Medicare Beneficiaries
Average Submitted Charge Amount
Anomaly
0
25000
50000
75000
100000
125000
150000
175000
10000
20000
30000
40000
50000
60000
1.00
0.75
0.50
0.25
0.00
−0.25
−0.50
−0.75
−1.00

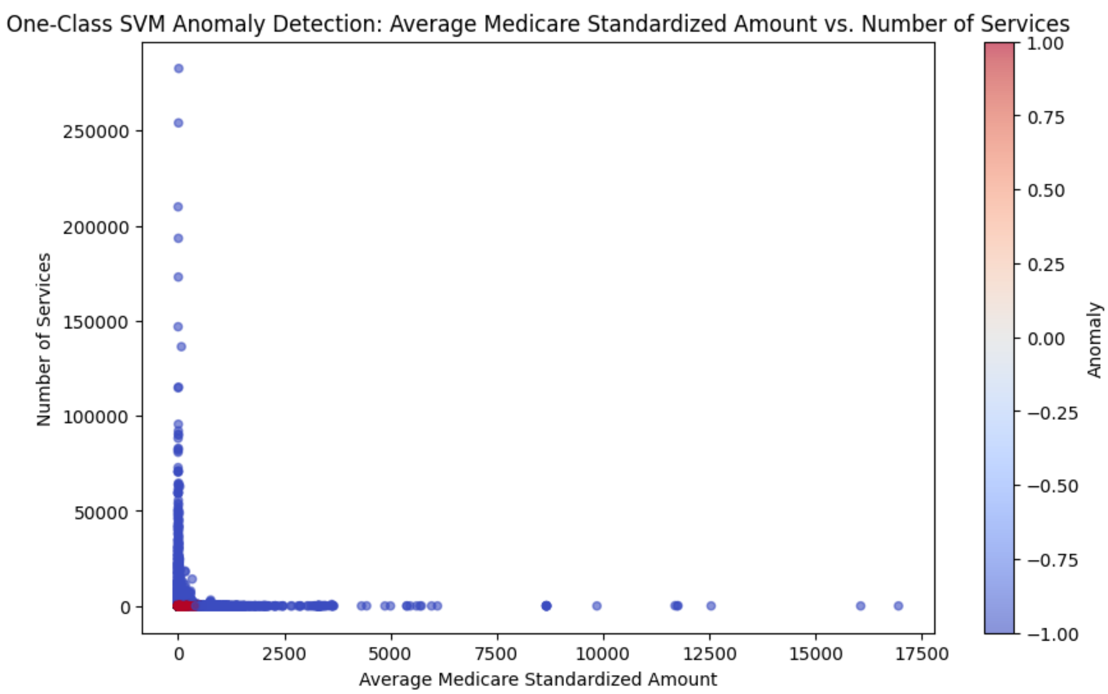

One-Class SVM Anomaly Detection: Average Submitted Charge Amount vs. Number of Distinct Medicare Beneficiary/Per Day Services
Number of Distinct Medicare Beneficiary/Per Day Services
Average Submitted Charge Amount
Anomaly

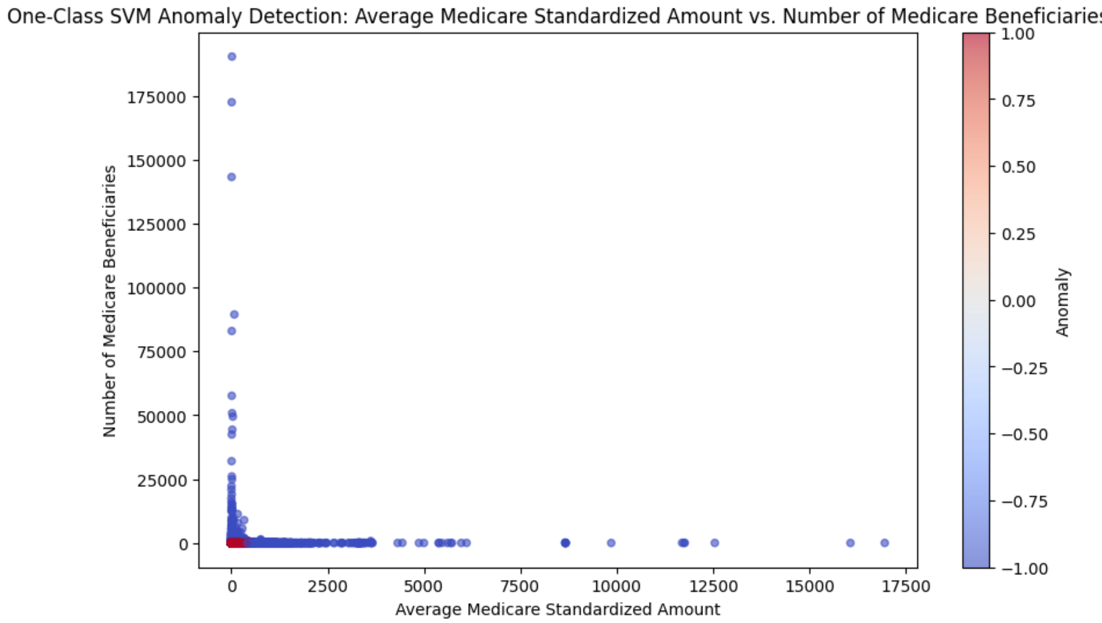

One-Class SVM Anomaly Detection: Average Medicare Payment Amount vs. Average Medicare Standardized Amount
Average Medicare Standardized Amount
Average Medicare Payment Amount
Anomaly

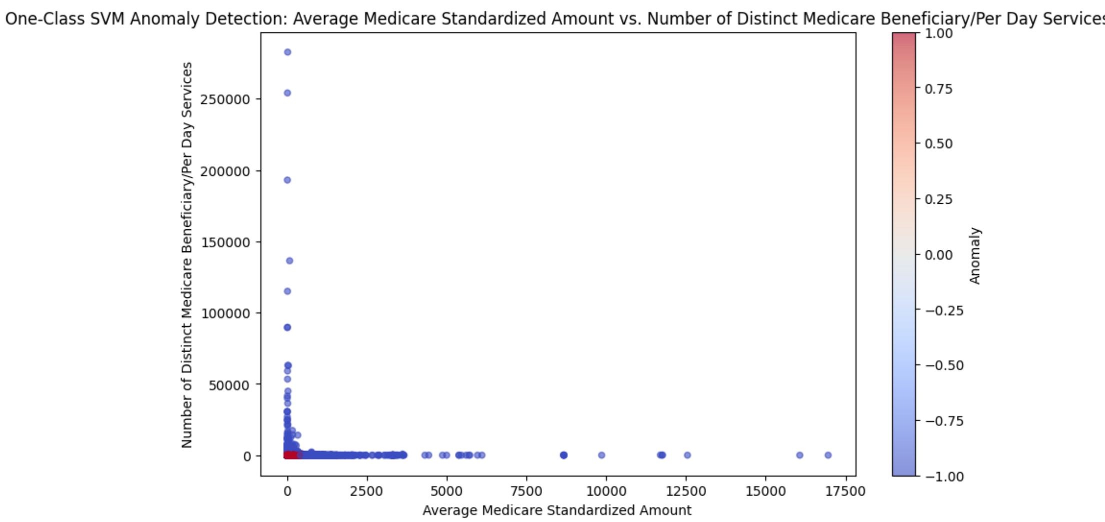

One-Class SVM Anomaly Detection: Average Medicare Payment Amount vs. Number of Services
Number of Services
250000
200000
150000
100000
50000
0
0
2000
4000
6000
8000
10000
12000
14000
16000
Average Medicare Payment Amount
1.00
0.75
0.50
0.25
0.00
−0.25
−0.50
−0.75
−1.00
Anomaly

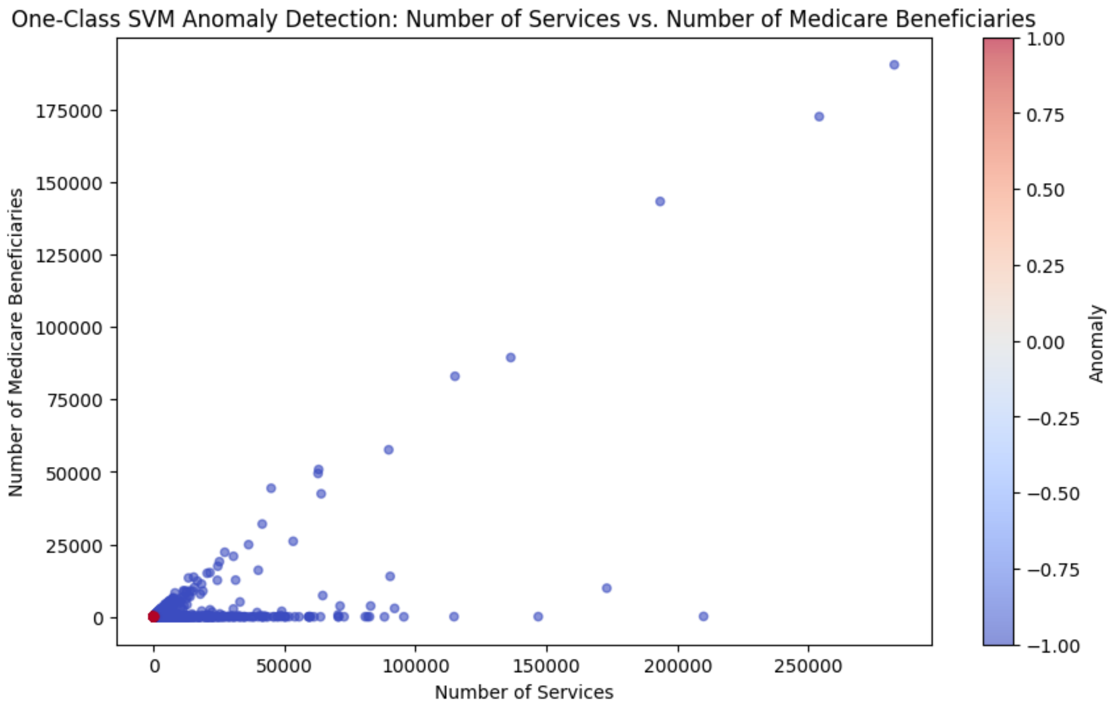

One-Class SVM Anomaly Detection: Average Medicare Payment Amount vs. Number of Medicare Beneficiaries
Number of Medicare Beneficiaries
175000
150000
125000
100000
75000
50000
25000
0
0
2000
4000
6000
8000
10000
12000
14000
16000
Average Medicare Payment Amount
1.00
0.75
0.50
0.25
0.00
−0.25
−0.50
−0.75
−1.00
Anomaly

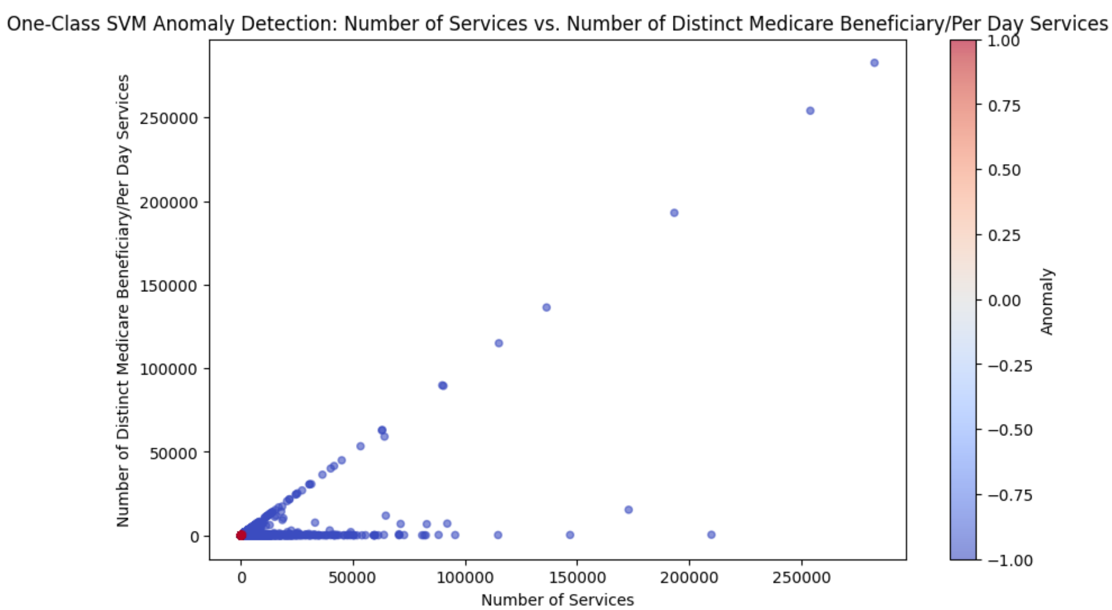

One-Class SVM Anomaly Detection: Average Medicare Payment Amount vs. Number of Distinct Medicare Beneficiary/Per Day Services
Number of Distinct Medicare Beneficiary/Per Day Services
Average Medicare Payment Amount
Anomaly

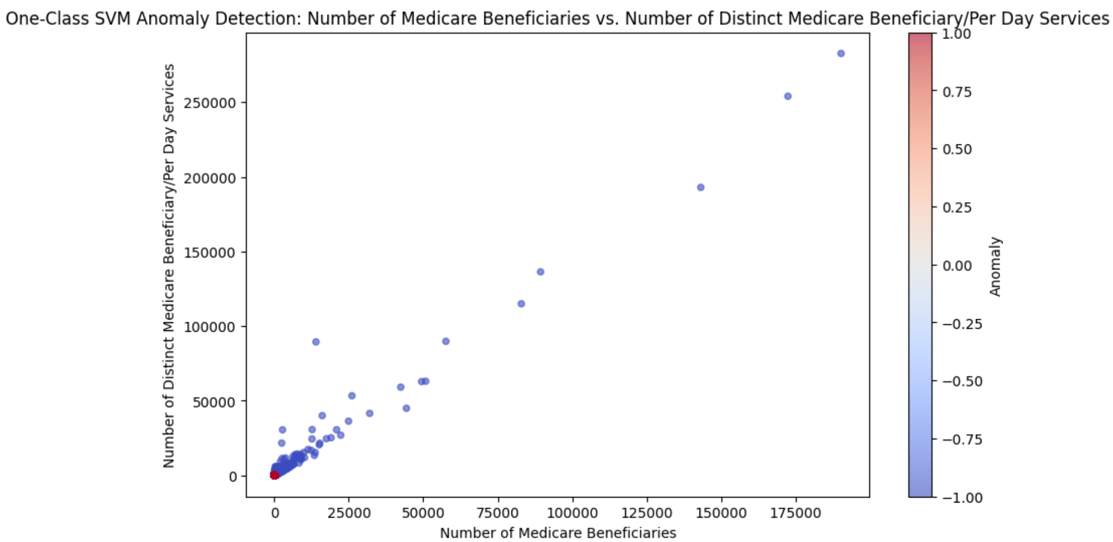

One-Class SVM Anomaly Detection: Average Medicare Standardized Amount vs. Number of Services
Number of Services
Average Medicare Standardized Amount
Anomaly


One-Class SVM Anomaly Detection: Average Medicare Standardized Amount vs. Number of Medicare Beneficiaries
Number of Medicare Beneficiaries
175000
150000
125000
100000
75000
50000
25000
0
0
2500
5000
7500
10000
12500
15000
17500
Average Medicare Standardized Amount
Anomaly
1.00
0.75
0.50
0.25
0.00
−0.25
−0.50
−0.75
−1.00


One-Class SVM Anomaly Detection: Average Medicare Standardized Amount vs. Number of Distinct Medicare Beneficiary/Per Day Services
Number of Distinct Medicare Beneficiary/Per Day Services
250000
200000
150000
100000
50000
0
0
2500
5000
7500
10000
12500
15000
17500
Average Medicare Standardized Amount
Anomaly
1.00
0.75
0.50
0.25
0.00
−0.25
−0.50
−0.75
−1.00


One-Class SVM Anomaly Detection: Number of Services vs. Number of Medicare Beneficiaries
Number of Medicare Beneficiaries
Number of Services
Anomaly
175000
150000
125000
100000
75000
50000
25000
0
50000
100000
150000
200000
250000
1.00
0.75
0.50
0.25
0.00
−0.25
−0.50
−0.75
−1.00


One-Class SVM Anomaly Detection: Number of Services vs. Number of Distinct Medicare Beneficiary/Per Day Services
Number of Distinct Medicare Beneficiary/Per Day Services
Number of Services
Anomaly
250000
200000
150000
100000
50000
0
1.00
0.75
0.50
0.25
0.00
−0.25
−0.50
−0.75
−1.00



[ ]:

7.1 1.plot

- This is the plot between Average Submitted Charge Amount and Average Medicare Allowed Amount .
- in which red points indicates the anomaly points and blue points indicates normal points
- In the above plot we can see that there are less anomaly points compared to normal points.

##2.plot

- this is plot between Average medicare payment amount vs average medicare allowed amount.
- we can see very less anomaly points near the origin the graph is increasing linearly

[ ]:

7.2 3.plot

- this is plot between Average medicare standardized amount vs average medicare allowed amount.
- we can see in which red points indicates the anomaly points and blue points indicates normal points In the above plot we can see that there are less anomaly points compared to normal points.

[ ]:

8 4.plot

- this is the plot between number of services vs Average medicare allowed amount.
- we can see that this is an L-shaped graphs with blue points as normal points and red points as anomaly points.
- more anomaly points are stagnated near the origin or corner point.

9 plot (Number of Distinct Medicare Beneficiary/Per Day Services vs Number of Services)

This plot indicates the anomalies in red points which are very in low number where blue points indicates the normal points . where the anomaly points are stagnated near the bottom of the plot and in very less quantity.