In [4]:
```
import pandas as pd
import numpy as np
from sklearn.ensemble import IsolationForest
from sklearn.preprocessing import StandardScaler

# Generate synthetic input data
def generate_synthetic_data(num_samples=1000, num_features=10):
    input_data = pd.DataFrame(np.random.rand(num_samples, num_features), columns=[f"Param_{i}" for i in range(num_features)])
    return input_data

# Generate synthetic output data
def generate_synthetic_output_data(num_samples=1000, num_features=10):
    output_data = pd.DataFrame(np.random.rand(num_samples, num_features), columns=[f"Output_{i}" for i in range(num_features)])
    return output_data

# Combine input and output data
def combine_data(input_data, output_data):
    combined_data = pd.concat([input_data, output_data], axis=1)
    return combined_data

# Add labels for normal (0) and anomalous (1) instances (for demonstration purposes)
def add_labels(combined_data):
    labels = np.random.choice([0, 1], combined_data.shape[0], p=[0.9, 0.1])
    combined_data['Label'] = labels
    return combined_data

# Train Anomaly Detection Model
def train_anomaly_detection_model(X):
    scaler = StandardScaler()
    X_scaled = scaler.fit_transform(X)
    model = IsolationForest(contamination=0.1)
    model.fit(X_scaled)
    return model, scaler

# Detect Anomalies
def detect_anomalies(model, scaler, X):
    X_scaled = scaler.transform(X)
    anomaly_scores = model.decision_function(X_scaled)
    anomalies = X[anomaly_scores < 0]
    return anomalies

# Main function
```

```python
def main():
    # Generate synthetic data
    input_data = generate_synthetic_data()
    output_data = generate_synthetic_output_data()
    combined_data = combine_data(input_data, output_data)
    combined_data = add_labels(combined_data)

    # Separate features (input parameters) and labels (normal/anomalous)
    X = combined_data.drop(columns=['Label'])
    y = combined_data['Label']

    # Train the Isolation Forest model
    model, scaler = train_anomaly_detection_model(X)

    # Detect anomalies
    anomalies = detect_anomalies(model, scaler, X)

    # Attribute anomalies to input parameters
    print("Detected Anomalies and Associated Input Parameters:")
    print(anomalies)

if __name__ == "__main__":
    main()
```

```
Detected Anomalies and Associated Input Parameters:
      Param_0   Param_1   Param_2   Param_3   Param_4   Param_5   Param_6  \
9    0.373619  0.523891  0.458947  0.397743  0.063730  0.035476  0.217454
35   0.249847  0.977465  0.075599  0.828821  0.803463  0.115456  0.755909
44   0.487150  0.847950  0.555109  0.843295  0.916070  0.855491  0.903528
49   0.971506  0.517546  0.923174  0.970287  0.638183  0.802911  0.222971
54   0.728867  0.776440  0.165720  0.754091  0.229420  0.100416  0.944693
..        ...       ...       ...       ...       ...       ...       ...
956  0.467387  0.959664  0.205710  0.883587  0.046438  0.833457  0.111528
968  0.503881  0.508471  0.168583  0.926844  0.988468  0.403991  0.877893
969  0.785114  0.067192  0.780781  0.989739  0.262879  0.812794  0.495174
974  0.904738  0.933732  0.528457  0.410756  0.108080  0.206150  0.603131
992  0.702878  0.027581  0.973305  0.898575  0.609201  0.576620  0.722840

      Param_7   Param_8   Param_9  Output_0  Output_1  Output_2  Output_3  \
9    0.953366  0.273424  0.183319  0.754242  0.274445  0.731072  0.865271
35   0.637978  0.424942  0.025548  0.883200  0.166919  0.994589  0.967766
44   0.527089  0.447496  0.238215  0.858818  0.124091  0.632654  0.159753
49   0.019705  0.452995  0.012095  0.653944  0.722167  0.750385  0.593910
54   0.033561  0.189116  0.895423  0.731845  0.329830  0.322451  0.987044
..        ...       ...       ...       ...       ...       ...       ...
956  0.536480  0.991037  0.826937  0.895998  0.786051  0.898643  0.101381
968  0.881734  0.520357  0.584539  0.149961  0.962244  0.369921  0.990900
969  0.124663  0.770697  0.470776  0.579502  0.449319  0.996775  0.668907
974  0.531644  0.120329  0.442265  0.396251  0.973254  0.959463  0.831393
992  0.928565  0.309920  0.227814  0.556328  0.858425  0.074748  0.641955

     Output_4  Output_5  Output_6  Output_7  Output_8  Output_9
9    0.971792  0.429194  0.071656  0.956931  0.684073  0.726071
35   0.115018  0.665646  0.976086  0.961977  0.973451  0.929021
44   0.897138  0.926135  0.956596  0.636495  0.750033  0.892406
49   0.929369  0.940385  0.117542  0.036720  0.516448  0.689520
54   0.894043  0.607489  0.522893  0.079489  0.040176  0.042844
..        ...       ...       ...       ...       ...       ...
956  0.355852  0.103582  0.490416  0.761773  0.993900  0.322237
968  0.033588  0.536816  0.135261  0.441323  0.188842  0.222262
969  0.102519  0.106989  0.998960  0.974041  0.287018  0.832620
974  0.030818  0.145599  0.621994  0.694895  0.055607  0.376918
992  0.172852  0.456959  0.068847  0.949223  0.629865  0.896485

[100 rows x 20 columns]
```

In [5]:
```python
import pandas as pd
import numpy as np
```

```python
from sklearn.ensemble import IsolationForest
from sklearn.preprocessing import StandardScaler

# Generate synthetic input data
def generate_synthetic_data(num_samples=1000, num_features=10):
    input_data = pd.DataFrame(np.random.rand(num_samples, num_features), columns=[f"Param_{i}" for i in range(num_features)])
    return input_data

# Generate synthetic output data
def generate_synthetic_output_data(num_samples=1000, num_features=10):
    output_data = pd.DataFrame(np.random.rand(num_samples, num_features), columns=[f"Output_{i}" for i in range(num_features)])
    return output_data

# Combine input and output data
def combine_data(input_data, output_data):
    combined_data = pd.concat([input_data, output_data], axis=1)
    return combined_data

# Add labels for normal (0) and anomalous (1) instances (for demonstration purposes)
def add_labels(combined_data):
    labels = np.random.choice([0, 1], combined_data.shape[0], p=[0.9, 0.1])
    combined_data['Label'] = labels
    return combined_data

# Train Anomaly Detection Model
def train_anomaly_detection_model(X):
    scaler = StandardScaler()
    X_scaled = scaler.fit_transform(X)
    model = IsolationForest(contamination=0.2)  # Adjusting contamination parameter
    model.fit(X_scaled)
    return model, scaler

# Detect Anomalies
def detect_anomalies(model, scaler, X):
    X_scaled = scaler.transform(X)
    anomaly_scores = model.decision_function(X_scaled)
    anomalies = X[anomaly_scores < 0]
    return anomalies, anomaly_scores

# Introduce a single anomaly point
def introduce_anomaly(input_data):
    # Randomly select a sample index
    sample_index = np.random.randint(len(input_data))
    # Randomly select a feature to modify
```

```
    feature_index = np.random.randint(input_data.shape[1])
    # Modify the selected feature to be an outlier
    input_data.iloc[sample_index, feature_index] = np.random.uniform(10, 100)  # Introduce an outlier value

# Main function
def main():
    # Generate synthetic data
    input_data = generate_synthetic_data()
    output_data = generate_synthetic_output_data()
    combined_data = combine_data(input_data, output_data)
    combined_data = add_labels(combined_data)

    # Introduce a single anomaly point
    introduce_anomaly(input_data)

    # Separate features (input parameters) and labels (normal/anomalous)
    X = combined_data.drop(columns=['Label'])
    y = combined_data['Label']

    # Train the Isolation Forest model
    model, scaler = train_anomaly_detection_model(X)

    # Detect anomalies
    anomalies, anomaly_scores = detect_anomalies(model, scaler, X)

    # Attribute anomalies to input parameters
    print("Detected Anomalies and Associated Input Parameters:")
    print(anomalies)

    # Print anomaly scores for better understanding
    print("Anomaly Scores:")
    print(anomaly_scores)

if __name__ == "__main__":
    main()
```

```
Detected Anomalies and Associated Input Parameters:
      Param_0   Param_1   Param_2   Param_3   Param_4   Param_5   Param_6  \
4    0.618505  0.637171  0.867521  0.607513  0.629929  0.955639  0.087959
23   0.051528  0.143883  0.973025  0.043450  0.112233  0.370276  0.514020
28   0.841420  0.079416  0.086965  0.664293  0.073049  0.171927  0.429242
34   0.931978  0.452632  0.607655  0.093561  0.820377  0.566907  0.145616
38   0.645346  0.114850  0.852864  0.160029  0.047593  0.620928  0.619135
..        ...       ...       ...       ...       ...       ...       ...
951  0.500845  0.584086  0.709531  0.365690  0.011646  0.663590  0.544716
959  0.156106  0.967400  0.858553  0.006368  0.975924  0.972859  0.990856
967  0.514864  0.259170  0.569415  0.281872  0.839993  0.904481  0.230719
982  0.870316  0.535779  0.998064  0.690232  0.168478  0.406485  0.995727
991  0.474052  0.750486  0.016644  0.120507  0.054973  0.795602  0.026742

      Param_7   Param_8   Param_9  Output_0  Output_1  Output_2  Output_3  \
4    0.964010  0.186162  0.047111  0.976300  0.731951  0.887619  0.602825
23   0.841312  0.704487  0.774927  0.957975  0.566776  0.106240  0.991186
28   0.012893  0.730089  0.447185  0.740372  0.004039  0.033326  0.660867
34   0.467599  0.320766  0.993687  0.528683  0.810893  0.975494  0.027399
38   0.993277  0.687756  0.974232  0.863091  0.066547  0.971391  0.772259
..        ...       ...       ...       ...       ...       ...       ...
951  0.526545  0.870413  0.990188  0.208612  0.353077  0.845473  0.152377
959  0.363958  0.373598  0.859677  0.524029  0.508831  0.519714  0.420809
967  0.143223  0.804430  0.641939  0.732454  0.925090  0.917735  0.193333
982  0.935499  0.791591  0.798320  0.981275  0.355561  0.731150  0.662638
991  0.916820  0.195405  0.172175  0.171427  0.408264  0.916373  0.727844

     Output_4  Output_5  Output_6  Output_7  Output_8  Output_9
4    0.295072  0.611045  0.883665  0.466569  0.359218  0.128722
23   0.191706  0.056468  0.412216  0.761770  0.050948  0.515207
28   0.670942  0.774473  0.538448  0.314458  0.029330  0.238740
34   0.727009  0.849852  0.931294  0.747743  0.511225  0.331043
38   0.297075  0.282151  0.634965  0.754780  0.275155  0.972502
..        ...       ...       ...       ...       ...       ...
951  0.120027  0.211044  0.500164  0.034344  0.544111  0.895308
959  0.306221  0.114447  0.790007  0.769196  0.702549  0.991425
967  0.611181  0.770993  0.922450  0.032975  0.055652  0.219322
982  0.306291  0.282188  0.922268  0.732862  0.772506  0.709338
991  0.336959  0.524113  0.687377  0.978939  0.245946  0.688913

[200 rows x 20 columns]
Anomaly Scores:
[ 1.91612165e-02  3.03009981e-02  1.33512119e-02  1.09528129e-02
 -9.23221207e-04  1.45555509e-02  2.41212273e-02  5.00171238e-02
```

```
 1.40947786e-02  8.34505439e-03  4.21370756e-02  1.05725546e-02
 1.19585864e-02  5.79365288e-03  1.55995640e-02  1.69132635e-02
 3.76249442e-02  1.25383847e-03  4.26943183e-02  4.06376687e-02
 3.29407521e-02  3.13862858e-02  2.20726733e-02 -8.33620162e-03
 3.57752714e-02  2.58564122e-02  2.24297031e-02  3.51245163e-02
-2.71658881e-02  1.64608217e-02  1.10807165e-02  3.03370516e-02
 2.02320870e-02  1.86555981e-02 -2.54837587e-03  2.93574251e-03
 1.31276608e-03  6.91845493e-03 -2.72328019e-02  9.49669211e-03
 2.34360263e-02  3.43472967e-02  2.92154814e-02  2.91943811e-02
 7.94716093e-04  4.38317163e-02  4.95204127e-02  1.24371207e-02
 1.47663447e-02  9.11947857e-03 -2.28635265e-02 -4.04583218e-02
-8.01707524e-03  2.20899645e-02  3.08343398e-02  5.22454452e-02
 2.16631298e-02  2.74779532e-02 -9.96546370e-03 -1.82315796e-02
 2.01507482e-02  2.52972377e-02 -2.42809791e-03  7.56693669e-03
 5.58201919e-02  2.36152482e-02  2.24573650e-02 -1.32308847e-02
 5.25903391e-02 -1.90577622e-02  5.32954495e-03  1.58012640e-02
 4.61228740e-02  3.19476897e-03  2.22004950e-02 -2.16157471e-02
 2.63949537e-02 -8.72471721e-03 -5.83494125e-03  2.33576711e-02
 5.31556931e-02  4.71721301e-02  1.94635357e-02  1.87050524e-02
-5.51146182e-02  5.28276527e-02  2.15169924e-02  3.20602894e-02
 2.08480184e-02 -7.37471904e-03 -6.72041447e-03 -3.07848655e-02
 2.41851337e-02  2.97019134e-02  3.50692498e-02  2.06766772e-02
 6.58011735e-03  7.13074777e-03  2.46237288e-02  6.50629079e-02
-1.10515065e-02  3.60262263e-02  6.35400231e-02  3.12220670e-03
-1.25795062e-02  3.29530213e-02  2.68535319e-02  3.81648635e-03
 3.16798556e-02 -1.87956323e-05  7.09973023e-03  4.42685048e-02
-3.99762547e-03  1.06785606e-02  4.94627003e-03  2.27395130e-02
-1.10529033e-03  1.64495195e-02  5.23867358e-02  7.40871222e-03
 5.55927870e-02 -2.23550011e-02 -1.21820753e-03  3.55907533e-03
 1.69932858e-02 -6.31798665e-03  4.17920117e-02  3.05687814e-02
 2.48377111e-02  2.52296974e-02 -1.21255334e-02 -5.44916462e-02
-1.20059873e-02  3.91912481e-02  9.49214282e-03  3.63518188e-02
 4.22421153e-02  3.45271252e-02  2.61745859e-02  8.56173945e-03
 5.21723583e-03  8.97847873e-03  3.02037913e-02 -2.15536496e-02
 4.81668893e-02 -1.14836823e-02  1.50230826e-02 -1.25501473e-02
 3.81829773e-02  5.04396903e-02  2.63713768e-03 -1.63770894e-02
 2.58317438e-02  2.42242043e-02  4.23822788e-02  2.23390950e-02
 4.62837288e-02  7.03173994e-03  3.50743042e-02 -4.95556757e-03
 7.76138448e-03  3.44149387e-02  1.80759540e-02  3.08627551e-02
 3.51607787e-02  3.39538701e-02  1.61634961e-02  3.81584728e-02
 3.12614723e-02  1.35393575e-02  1.88076050e-02  3.28760988e-02
-1.17384485e-02  1.23376023e-02  2.92766125e-02  1.55725341e-02
-1.86829034e-02  1.44636532e-02  3.63083822e-02  3.54815272e-02
-1.19599686e-02  4.98357014e-02  3.67592921e-02  2.50952191e-02
```

```
 1.47400130e-02  4.53449845e-02  4.34510087e-02  3.00854376e-02
-1.57786252e-02  5.25971741e-02  5.08160084e-02 -4.60858463e-03
-8.16250220e-04  4.82935116e-02 -1.07517519e-02  1.97036089e-02
 2.97516763e-02  4.94989292e-02  4.14245696e-02  2.16045764e-02
-6.20877099e-03  2.57344123e-02  3.48080438e-02  3.91694354e-02
 2.76275064e-02  1.97971828e-02  2.47049057e-02  5.41901144e-02
-4.67350688e-03  5.27351086e-02  3.48038509e-02  5.64451095e-02
 2.03600752e-02  3.81461689e-02  3.50622959e-02  2.22416482e-02
-1.00846740e-02  3.69123181e-03  4.11177589e-02 -1.57314997e-02
 1.91037667e-02 -9.82542355e-03  1.60597653e-02  8.39862056e-03
 6.86206558e-03 -1.37552929e-02  3.80992051e-02 -2.50910853e-02
 4.28425710e-02  2.34344585e-02  3.64956940e-02 -5.42648940e-03
 6.25171039e-02 -7.96750556e-03  3.83043899e-02  1.52673495e-02
 6.92026866e-03 -7.30575817e-03 -8.48483620e-03  3.95829435e-02
 1.71454516e-02 -2.93407396e-02  3.50530416e-02 -1.57002380e-02
 2.07386415e-02  4.90243464e-02  2.26445734e-02  4.97480639e-02
 2.85731217e-02  6.16793143e-02  4.76784817e-02  1.52962738e-02
 2.13509947e-02  2.55941314e-02  1.65436287e-02 -1.82711283e-02
-3.45041670e-02 -1.15635135e-02  1.57836592e-02  2.21698159e-02
-6.85000049e-03  7.00662430e-03  1.44615000e-02  1.87782297e-02
 1.33484573e-02  1.40816520e-03  4.44635030e-02  5.24160415e-03
 1.16750145e-02  3.13717690e-02 -4.42773708e-03  5.83294629e-03
 4.92789519e-02 -1.87028141e-04  1.43226686e-02  2.34509623e-02
 5.93017183e-02  2.63938904e-03 -7.81431428e-03  3.39490563e-02
 5.52522631e-02  3.61325776e-02  2.74490102e-02  2.64763355e-02
 4.54783862e-02 -2.41795282e-02  2.32117108e-02  7.05763354e-02
 4.08510575e-02  1.70850290e-02  5.68384525e-02  1.28235695e-02
 2.32618802e-02 -1.31686315e-02  3.50601690e-02 -2.44500156e-03
 4.17294728e-02  2.83049291e-02  2.40554574e-02 -7.57285647e-03
 4.59078904e-02  2.62013103e-02  4.62086602e-02  2.00668407e-02
 2.84563097e-02  1.01811537e-02  4.81357574e-02  1.96267333e-02
-1.44304886e-02  2.91959037e-02  7.24610570e-02  3.75577628e-02
 1.64933779e-02  1.92349562e-02  4.55540168e-02  2.88148554e-02
-2.36766902e-03  5.43719385e-03  4.09114473e-02  1.97622244e-02
 3.20442294e-02  2.95310157e-02  6.76283104e-02  2.28887092e-02
-6.21154996e-03  3.28430344e-02  2.07348533e-03  3.58823578e-03
 3.91682902e-02  2.04696728e-02  2.89772326e-02  9.07127012e-03
 8.39396817e-03 -5.04787199e-03  4.26087204e-02 -1.72633269e-02
 2.00870674e-02 -9.52624463e-03 -1.39049542e-02  2.91446533e-02
 9.53472263e-03  1.53756814e-02  2.30802777e-02  1.19161818e-02
 2.39040686e-03  2.85329554e-02 -3.38721700e-04  2.97382370e-02
 3.30491889e-03 -1.23438870e-02  1.57123380e-02  6.32768213e-03
 1.25713481e-02 -3.49262537e-03  3.17643556e-02  1.82878036e-02
 2.42989667e-03  7.17483550e-03 -7.98315474e-03  1.40709711e-02
```

```
  2.54193657e-02  3.16322161e-02  5.50429053e-03  2.28946810e-02
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```

In [6]:

```
import pandas as pd
import numpy as np
from sklearn.ensemble import IsolationForest
from sklearn.preprocessing import StandardScaler
import matplotlib.pyplot as plt

# Generate synthetic input data
def generate_synthetic_data(num_samples=1000, num_features=10):
    input_data = pd.DataFrame(np.random.rand(num_samples, num_features), columns=[f"Param_{i}" for i in range(num_features)])
    return input_data

# Generate synthetic output data
def generate_synthetic_output_data(num_samples=1000, num_features=10):
    output_data = pd.DataFrame(np.random.rand(num_samples, num_features), columns=[f"Output_{i}" for i in range(num_features)])
    return output_data
```

```
# Combine input and output data
def combine_data(input_data, output_data):
    combined_data = pd.concat([input_data, output_data], axis=1)
    return combined_data

# Add labels for normal (0) and anomalous (1) instances (for demonstration purposes)
def add_labels(combined_data):
    labels = np.random.choice([0, 1], combined_data.shape[0], p=[0.9, 0.1])
    combined_data['Label'] = labels
    return combined_data

# Train Anomaly Detection Model
def train_anomaly_detection_model(X):
    scaler = StandardScaler()
    X_scaled = scaler.fit_transform(X)
    model = IsolationForest(contamination=0.2)  # Adjusting contamination parameter
    model.fit(X_scaled)
    return model, scaler

# Detect Anomalies
def detect_anomalies(model, scaler, X):
    X_scaled = scaler.transform(X)
    anomaly_scores = model.decision_function(X_scaled)
    anomalies = X[anomaly_scores < 0]
    return anomalies, anomaly_scores

# Introduce a single anomaly point
def introduce_anomaly(input_data):
    # Randomly select a sample index
    sample_index = np.random.randint(len(input_data))
    # Randomly select a feature to modify
    feature_index = np.random.randint(input_data.shape[1])
    # Modify the selected feature to be an outlier
    input_data.iloc[sample_index, feature_index] = np.random.uniform(10, 100)  # Introduce an outlier value

# Main function
def main():
    # Generate synthetic data
    input_data = generate_synthetic_data()
    output_data = generate_synthetic_output_data()
    combined_data = combine_data(input_data, output_data)
    combined_data = add_labels(combined_data)
```

```
    # Introduce a single anomaly point
    introduce_anomaly(input_data)

    # Separate features (input parameters) and labels (normal/anomalous)
    X = combined_data.drop(columns=['Label'])
    y = combined_data['Label']

    # Train the Isolation Forest model
    model, scaler = train_anomaly_detection_model(X)

    # Detect anomalies
    anomalies, anomaly_scores = detect_anomalies(model, scaler, X)

    # Attribute anomalies to input parameters
    print("Detected Anomalies and Associated Input Parameters:")
    print(anomalies)

    # Print anomaly scores for better understanding
    print("Anomaly Scores:")
    print(anomaly_scores)

    # Plot the data
    plt.figure(figsize=(10, 6))
    plt.scatter(X.iloc[:, 0], X.iloc[:, 1], c='blue', label='Normal')
    plt.scatter(anomalies.iloc[:, 0], anomalies.iloc[:, 1], c='red', label='Anomaly')
    plt.title('Anomaly Detection')
    plt.xlabel('Param_0')
    plt.ylabel('Param_1')
    plt.legend()
    plt.show()

if __name__ == "__main__":
    main()
```

```
Detected Anomalies and Associated Input Parameters:
      Param_0   Param_1   Param_2   Param_3   Param_4   Param_5   Param_6  \
1    0.269433  0.174979  0.077705  0.602672  0.597216  0.026760  0.023951
3    0.966983  0.790079  0.318552  0.331646  0.187686  0.783909  0.894212
12   0.390558  0.176587  0.760337  0.942936  0.685665  0.175049  0.833466
31   0.741915  0.174758  0.192586  0.207072  0.389676  0.793043  0.119279
33   0.177792  0.427721  0.267397  0.290301  0.738031  0.240358  0.193914
..        ...       ...       ...       ...       ...       ...       ...
978  0.591462  0.906786  0.893805  0.312934  0.457809  0.997479  0.049039
981  0.990107  0.031651  0.703082  0.462667  0.512648  0.271073  0.882756
987  0.212526  0.246732  0.749004  0.796429  0.131574  0.083924  0.637055
995  0.093487  0.856259  0.020522  0.219777  0.157860  0.570508  0.896833
999  0.262828  0.153760  0.934506  0.821004  0.843708  0.117329  0.540056

      Param_7   Param_8   Param_9  Output_0  Output_1  Output_2  Output_3  \
1    0.369546  0.871171  0.024360  0.723362  0.771840  0.764669  0.039672
3    0.950407  0.525350  0.620333  0.118333  0.107301  0.939969  0.177488
12   0.691544  0.777841  0.186936  0.175976  0.144475  0.098472  0.512232
31   0.784178  0.968382  0.736066  0.021012  0.826942  0.906810  0.575027
33   0.724522  0.588097  0.910106  0.532127  0.085812  0.970835  0.856643
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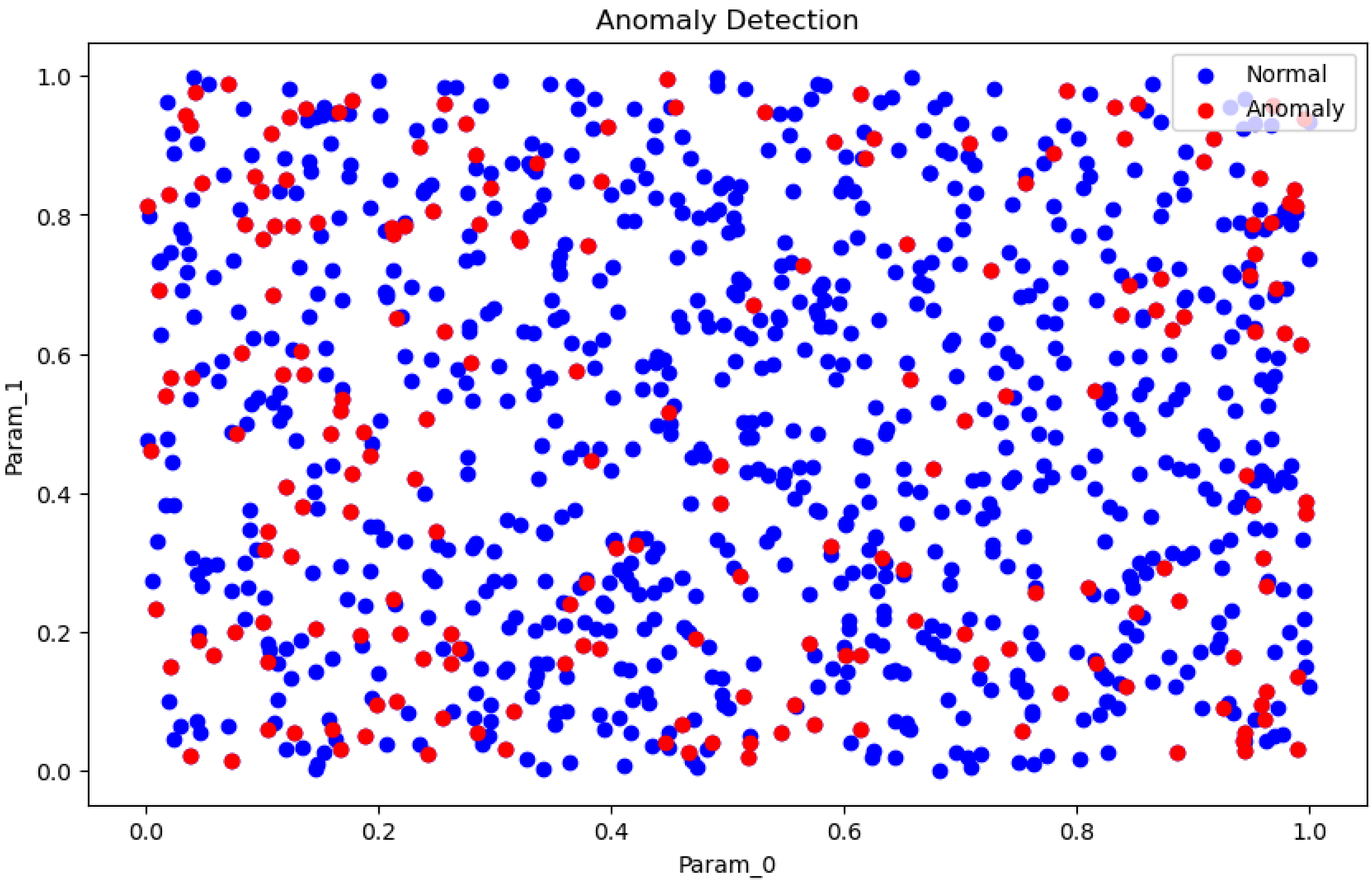

In [7]:
```
import pandas as pd
import numpy as np
from sklearn.ensemble import IsolationForest
from sklearn.preprocessing import StandardScaler
import matplotlib.pyplot as plt

# Generate synthetic linear input data
def generate_synthetic_linear_data(num_samples=1000, num_features=2):
    # Generate normal data
```

```
    normal_data = np.random.multivariate_normal(mean=[0] * num_features, cov=np.eye(num_features), size=num_samples // 2)
    # Generate anomalous data with larger means
    anomalous_data = np.random.multivariate_normal(mean=[5] * num_features, cov=np.eye(num_features), size=num_samples // 2)
    # Combine normal and anomalous data
    input_data = np.vstack([normal_data, anomalous_data])
    # Create DataFrame
    input_df = pd.DataFrame(input_data, columns=[f"Param_{i}" for i in range(num_features)])
    return input_df

# Combine input and output data
def combine_data(input_data, output_data):
    combined_data = pd.concat([input_data, output_data], axis=1)
    return combined_data

# Add labels for normal (0) and anomalous (1) instances (for demonstration purposes)
def add_labels(combined_data):
    labels = np.zeros(combined_data.shape[0])
    labels[combined_data.index >= len(combined_data) // 2] = 1
    combined_data['Label'] = labels
    return combined_data

# Train Anomaly Detection Model
def train_anomaly_detection_model(X):
    scaler = StandardScaler()
    X_scaled = scaler.fit_transform(X)
    model = IsolationForest(contamination=0.2)  # Adjusting contamination parameter
    model.fit(X_scaled)
    return model, scaler

# Detect Anomalies
def detect_anomalies(model, scaler, X):
    X_scaled = scaler.transform(X)
    anomaly_scores = model.decision_function(X_scaled)
    anomalies = X[anomaly_scores < 0]
    return anomalies, anomaly_scores

# Main function
def main():
    # Generate synthetic linear data
    input_data = generate_synthetic_linear_data()
    output_data = generate_synthetic_output_data()
    combined_data = combine_data(input_data, output_data)
    combined_data = add_labels(combined_data)
```

```
    # Separate features (input parameters) and labels (normal/anomalous)
    X = combined_data.drop(columns=['Label'])
    y = combined_data['Label']

    # Train the Isolation Forest model
    model, scaler = train_anomaly_detection_model(X)

    # Detect anomalies
    anomalies, anomaly_scores = detect_anomalies(model, scaler, X)

    # Attribute anomalies to input parameters
    print("Detected Anomalies and Associated Input Parameters:")
    print(anomalies)

    # Print anomaly scores for better understanding
    print("Anomaly Scores:")
    print(anomaly_scores)

    # Plot the data
    plt.figure(figsize=(10, 6))
    plt.scatter(X.iloc[:, 0], X.iloc[:, 1], c='blue', label='Normal')
    plt.scatter(anomalies.iloc[:, 0], anomalies.iloc[:, 1], c='red', label='Anomaly')
    plt.title('Anomaly Detection')
    plt.xlabel('Param_0')
    plt.ylabel('Param_1')
    plt.legend()
    plt.show()

if __name__ == "__main__":
    main()
```

```
Detected Anomalies and Associated Input Parameters:
      Param_0   Param_1  Output_0  Output_1  Output_2  Output_3  Output_4  \
15  -0.067048 -1.299877  0.269003  0.883226  0.031323  0.207199  0.924561
17  -1.517448  0.297219  0.819503  0.934716  0.842444  0.646991  0.900911
20  -0.347480 -0.286925  0.990135  0.218513  0.794114  0.807884  0.720131
34  -0.311511 -2.595183  0.736017  0.961269  0.384719  0.054391  0.623530
36  -0.575799  0.870014  0.380717  0.886608  0.781413  0.837296  0.094904
..        ...       ...       ...       ...       ...       ...       ...
986  6.712362  5.342779  0.367629  0.455001  0.590722  0.354632  0.239059
989  4.839333  5.106471  0.696720  0.755370  0.694504  0.757833  0.947876
991  6.085540  6.512511  0.797662  0.606869  0.951235  0.172630  0.706002
995  5.046684  6.083548  0.307216  0.273463  0.915843  0.156375  0.898815
997  5.128804  6.322682  0.359049  0.817091  0.480006  0.032831  0.213836

     Output_5  Output_6  Output_7  Output_8  Output_9
15   0.911050  0.865518  0.512451  0.989371  0.230062
17   0.225670  0.541067  0.038256  0.684707  0.910804
20   0.539466  0.160104  0.865492  0.834229  0.870954
34   0.076548  0.295868  0.916897  0.092868  0.352490
36   0.853387  0.963980  0.960916  0.924431  0.693259
..        ...       ...       ...       ...       ...
986  0.916443  0.884248  0.821852  0.735735  0.076648
989  0.809106  0.044920  0.828304  0.979552  0.069561
991  0.728285  0.011597  0.200813  0.244864  0.650694
995  0.029749  0.129061  0.672359  0.503548  0.177645
997  0.714911  0.820785  0.029243  0.583544  0.371347

[200 rows x 12 columns]
Anomaly Scores:
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```

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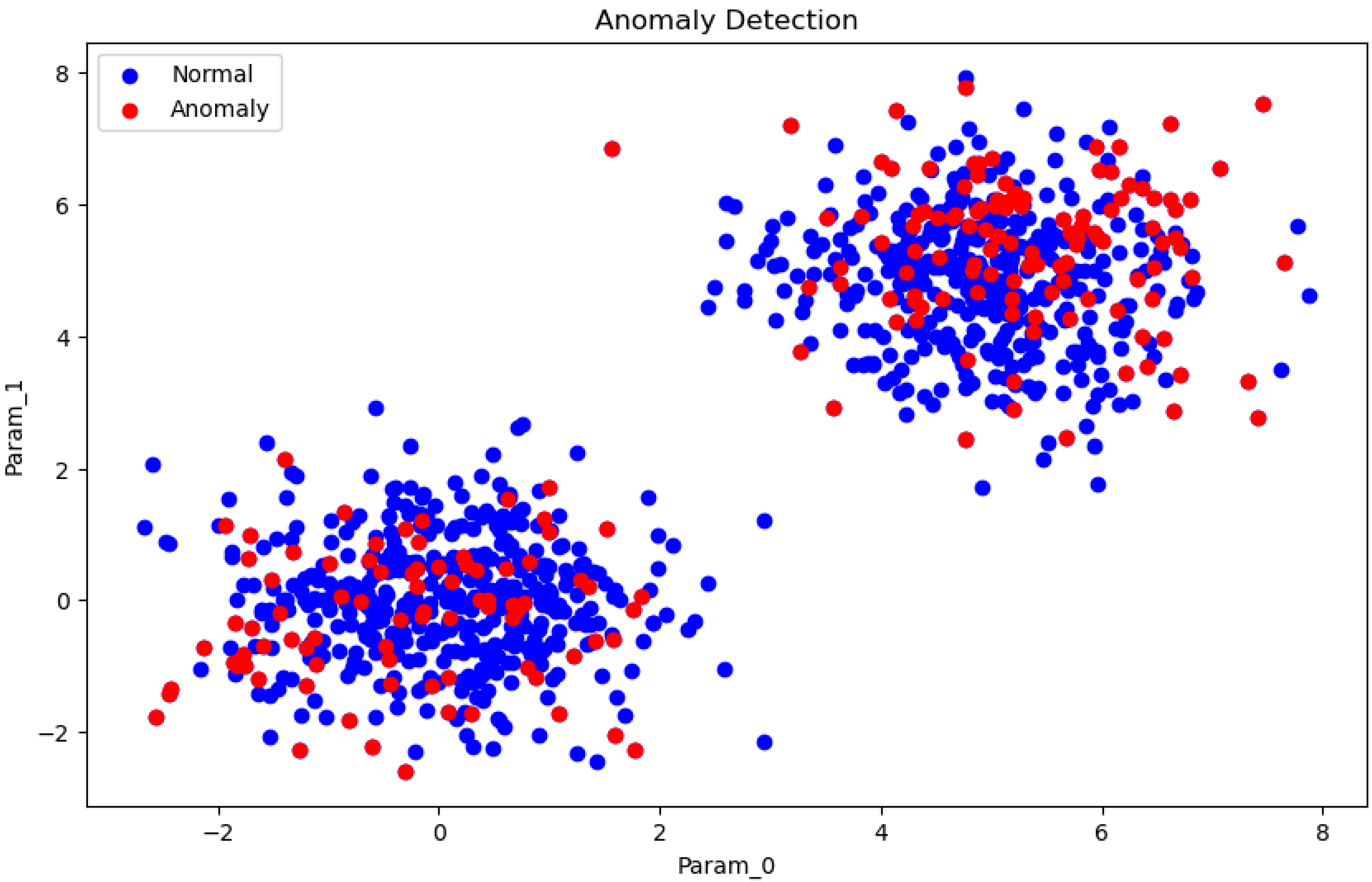
```



In [8]:
```
import pandas as pd
import numpy as np
from sklearn.ensemble import IsolationForest
from sklearn.preprocessing import StandardScaler
import matplotlib.pyplot as plt

# Generate synthetic linear input data with anomalies as peaks
def generate_synthetic_data(num_samples=1000, num_features=2, num_anomalies=5):
    # Generate normal data along a straight line
```

```
    normal_data = np.zeros((num_samples // 2, num_features))
    normal_data[:, 0] = np.linspace(0, 10, num_samples // 2)
    # Generate anomalous data with peaks
    peak_indices = np.random.choice(np.arange(num_samples // 2), num_anomalies, replace=False)
    anomalous_data = normal_data.copy()
    anomalous_data[peak_indices, 1] = np.random.uniform(10, 20, num_anomalies)  # Introduce peaks
    # Combine normal and anomalous data
    input_data = np.vstack([normal_data, anomalous_data])
    # Create DataFrame
    input_df = pd.DataFrame(input_data, columns=[f"Param_{i}" for i in range(num_features)])
    return input_df

# Combine input and output data
def combine_data(input_data, output_data):
    combined_data = pd.concat([input_data, output_data], axis=1)
    return combined_data

# Add labels for normal (0) and anomalous (1) instances (for demonstration purposes)
def add_labels(combined_data):
    labels = np.zeros(combined_data.shape[0])
    labels[combined_data.index >= len(combined_data) // 2] = 1
    combined_data['Label'] = labels
    return combined_data

# Train Anomaly Detection Model
def train_anomaly_detection_model(X):
    scaler = StandardScaler()
    X_scaled = scaler.fit_transform(X)
    model = IsolationForest(contamination=0.2)  # Adjusting contamination parameter
    model.fit(X_scaled)
    return model, scaler

# Detect Anomalies
def detect_anomalies(model, scaler, X):
    X_scaled = scaler.transform(X)
    anomaly_scores = model.decision_function(X_scaled)
    anomalies = X[anomaly_scores < 0]
    return anomalies, anomaly_scores

# Attribute Anomalies to Input Parameters
def attribute_anomalies_to_input_params(anomalies, num_features):
    param_cols = [f"Param_{i}" for i in range(num_features)]
    anomalous_params = []
    for index, row in anomalies.iterrows():
```

```
        peak_param = param_cols[np.argmax(row.values)]
        anomalous_params.append(peak_param)
    return anomalous_params

# Main function
def main():
    # Generate synthetic data
    num_anomalies = 5  # Number of anomalies (peaks)
    input_data = generate_synthetic_data(num_anomalies=num_anomalies)
    output_data = generate_synthetic_output_data()
    combined_data = combine_data(input_data, output_data)
    combined_data = add_labels(combined_data)

    # Separate features (input parameters) and labels (normal/anomalous)
    X = combined_data.drop(columns=['Label'])
    y = combined_data['Label']

    # Train the Isolation Forest model
    model, scaler = train_anomaly_detection_model(X)

    # Detect anomalies
    anomalies, anomaly_scores = detect_anomalies(model, scaler, X)

    # Attribute anomalies to input parameters
    anomalous_params = attribute_anomalies_to_input_params(anomalies, X.shape[1])

    # Print detected anomalies and associated input parameters
    print("Detected Anomalies and Associated Input Parameters:")
    for anomaly, param in zip(anomalies.values, anomalous_params):
        print(f"Anomaly at {param} with values: {anomaly}")

    # Plot the data
    plt.figure(figsize=(10, 6))
    plt.scatter(X.iloc[:, 0], X.iloc[:, 1], c='blue', label='Normal')
    plt.scatter(anomalies.iloc[:, 0], anomalies.iloc[:, 1], c='red', label='Anomaly')
    plt.title('Anomaly Detection')
    plt.xlabel('Param_0')
    plt.ylabel('Param_1')
    plt.legend()
    plt.show()

if __name__ == "__main__":
    main()
```

```
Detected Anomalies and Associated Input Parameters:
Anomaly at Param_3 with values: [0.02004008 0.         0.75521642 0.89889631 0.49347171 0.59772141
 0.76103673 0.3345103  0.8967086  0.04603444 0.14706828 0.28893039]
Anomaly at Param_2 with values: [0.04008016 0.         0.98320534 0.20382382 0.82236021 0.95009918
 0.26084998 0.54521939 0.35039937 0.89448954 0.16927938 0.51213148]
Anomaly at Param_8 with values: [0.08016032 0.         0.51693427 0.02257237 0.07674248 0.1303302
 0.13218285 0.49263346 0.56951599 0.13749038 0.51791763 0.15312111]
Anomaly at Param_3 with values: [0.14028056 0.         0.11511384 0.5515752  0.07231511 0.19207045
 0.00320195 0.20165888 0.31294055 0.49023607 0.09940901 0.02841908]
Anomaly at Param_6 with values: [0.16032064 0.         0.93430153 0.71161879 0.30969767 0.83521417
 0.96042133 0.74264656 0.6720086  0.788403   0.05419516 0.06761205]
Anomaly at Param_7 with values: [3.00601202e-01 0.00000000e+00 1.20546894e-01 8.64788133e-01
 5.54123204e-01 2.61303826e-01 7.64829119e-01 9.17083292e-01
 1.13131347e-02 7.69229706e-01 3.71758532e-01 7.86516086e-04]
Anomaly at Param_6 with values: [0.42084168 0.         0.48575652 0.85674168 0.18539273 0.91636294
 0.92539323 0.71906878 0.10582015 0.67796965 0.01061243 0.55627576]
Anomaly at Param_11 with values: [0.44088176 0.         0.73595615 0.95710528 0.5074111  0.82061342
 0.67451779 0.22310632 0.41576155 0.73014146 0.04142384 0.97903445]
Anomaly at Param_8 with values: [0.52104208 0.         0.68453927 0.59151628 0.18786422 0.20986781
 0.80598016 0.60438613 0.98631299 0.58163434 0.37198698 0.96028463]
Anomaly at Param_3 with values: [0.6012024  0.         0.07460186 0.99386914 0.2227416  0.36540452
 0.85026154 0.7198889  0.90719786 0.47963024 0.79057171 0.74526271]
Anomaly at Param_9 with values: [0.62124248 0.         0.05678223 0.78296325 0.17266683 0.62584142
 0.57541836 0.69035366 0.42050799 0.95965925 0.57543149 0.95793784]
Anomaly at Param_7 with values: [0.68136273 0.         0.35056377 0.05547138 0.82319081 0.33557969
 0.33502592 0.93930716 0.83922742 0.05539396 0.22303657 0.89655729]
Anomaly at Param_5 with values: [0.70140281 0.         0.23654966 0.1587339  0.36485486 0.99932889
 0.83500137 0.05091929 0.78401087 0.03677032 0.7588926  0.75891072]
Anomaly at Param_0 with values: [0.74148297 0.         0.0394174  0.40925086 0.23149922 0.15111214
 0.63002355 0.23102702 0.30866937 0.05464882 0.53113627 0.17575207]
Anomaly at Param_9 with values: [0.82164329 0.         0.19264334 0.0466409  0.23100302 0.28460318
 0.13086878 0.2475695  0.31405938 0.97992062 0.29462538 0.06988597]
Anomaly at Param_11 with values: [0.86172345 0.         0.25326316 0.26758158 0.88672655 0.65563714
 0.52363942 0.04790706 0.9254656  0.25627983 0.83437837 0.99715264]
Anomaly at Param_0 with values: [1.04208417 0.         0.04085147 0.3141559  0.48821989 0.83562897
 0.8524957  0.73630363 0.66586969 0.08327017 0.64681262 0.94146822]
Anomaly at Param_0 with values: [1.22244489 0.         0.41086777 0.1715899  0.18064803 0.12609967
 0.96604864 0.9327941  0.59749496 0.11048638 0.48688824 0.23137755]
Anomaly at Param_0 with values: [1.42284569 0.         0.04275277 0.6814625  0.05930595 0.90751862
 0.15888433 0.6067539  0.83533921 0.03114544 0.46520634 0.47816994]
Anomaly at Param_0 with values: [1.46292585 0.         0.76666725 0.08385865 0.58278272 0.05226126
 0.70426472 0.95927212 0.96556183 0.12909219 0.03479222 0.50804408]
Anomaly at Param_0 with values: [1.50300601 0.         0.8119703  0.56479716 0.1801277  0.1289516
 0.62210236 0.06222119 0.80315598 0.17150282 0.94016038 0.13124573]
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Anomaly at Param_0 with values: [1.54308617 0.         0.7762311  0.64118841 0.1175418  0.14738645
 0.72231415 0.14353587 0.10248335 0.3420441  0.1114363  0.03239994]
Anomaly at Param_0 with values: [1.58316633 0.         0.80355492 0.21753867 0.11759083 0.12319842
 0.449485   0.31502298 0.92417866 0.60790594 0.17616509 0.11633951]
Anomaly at Param_0 with values: [1.62324649 0.         0.83327965 0.54496173 0.38285668 0.01134954
 0.80282695 0.18419393 0.93911393 0.05382119 0.2846149  0.15290268]
Anomaly at Param_0 with values: [1.64328657 0.         0.10446096 0.18353107 0.2299003  0.65830143
 0.40953125 0.91028164 0.9683724  0.13764381 0.12431663 0.9559946 ]
Anomaly at Param_0 with values: [1.68336673 0.         0.49813983 0.65339957 0.70691685 0.17111867
 0.761857   0.20262271 0.9730166  0.646927   0.97300335 0.99148382]
Anomaly at Param_0 with values: [1.76352705 0.         0.64904226 0.28832465 0.96753655 0.16810685
 0.30297654 0.04250813 0.51824818 0.92535134 0.11420286 0.20052706]
Anomaly at Param_0 with values: [1.96392786 0.         0.09506713 0.0592882  0.75142219 0.03211963
 0.60096338 0.01656805 0.42230887 0.01689854 0.85901677 0.70822174]
Anomaly at Param_0 with values: [2.10420842 0.         0.03510606 0.96508854 0.90143226 0.00362097
 0.43274353 0.4113207  0.55465674 0.91321322 0.57853425 0.98910526]
Anomaly at Param_0 with values: [2.18436874 0.         0.80891609 0.90569784 0.9066008  0.34092911
 0.78459032 0.61533433 0.96439242 0.01787579 0.00235223 0.45362554]
Anomaly at Param_0 with values: [2.3246493  0.         0.34187092 0.99878662 0.99919992 0.7620199
 0.10199749 0.99777976 0.32881671 0.70973505 0.46048745 0.05719751]
Anomaly at Param_0 with values: [2.64529058e+00 0.00000000e+00 1.00864703e-01 8.22516791e-01
 1.36519109e-01 9.96990556e-01 6.27162298e-04 9.98909553e-01
 2.11247660e-01 6.51012932e-01 3.75659350e-01 8.57060645e-01]
Anomaly at Param_0 with values: [2.76553106 0.         0.19958882 0.71661287 0.11798414 0.23772531
 0.0083957  0.45366285 0.97957918 0.87436311 0.0379415  0.33744599]
Anomaly at Param_0 with values: [2.86573146 0.         0.99358571 0.70673893 0.00808774 0.06645071
 0.08812772 0.33336582 0.07798395 0.63786961 0.30325897 0.53260206]
Anomaly at Param_0 with values: [3.0260521  0.         0.20058578 0.65749492 0.20155744 0.01706896
 0.9884488  0.84013725 0.20949846 0.380205   0.98401514 0.49353756]
Anomaly at Param_0 with values: [3.08617234 0.         0.85361122 0.61760116 0.16745823 0.70344416
 0.3036453  0.99809362 0.05858536 0.75531352 0.46862079 0.95830999]
Anomaly at Param_0 with values: [3.10621242 0.         0.98662454 0.46460891 0.25874483 0.01011223
 0.98953915 0.9802023  0.30711158 0.58226791 0.27585883 0.39078051]
Anomaly at Param_0 with values: [3.18637275 0.         0.59850893 0.63206191 0.07291304 0.12585682
 0.97817146 0.89552243 0.81659729 0.24464639 0.24344163 0.40472955]
Anomaly at Param_0 with values: [3.56713427 0.         0.25451598 0.18180894 0.5884609  0.49114888
 0.91215986 0.9788917  0.96053898 0.813395   0.65512797 0.07540933]
Anomaly at Param_0 with values: [3.66733467 0.         0.52891637 0.76372988 0.85216176 0.04720908
 0.01288896 0.87130917 0.60468714 0.02574665 0.96879762 0.88215079]
Anomaly at Param_0 with values: [3.70741483 0.         0.85167822 0.19655991 0.02887055 0.04219396
 0.27887003 0.06473398 0.28228613 0.84092289 0.83272778 0.95456914]
Anomaly at Param_0 with values: [3.98797595 0.         0.90198047 0.77773634 0.97769038 0.35896728
 0.7907562  0.10281931 0.15034743 0.96308601 0.25598549 0.94419056]
Anomaly at Param_0 with values: [4.06813627 0.         0.20406248 0.97268279 0.41433587 0.06703284
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 0.1057936  0.19249457 0.73683364 0.03940423 0.2498615  0.12912769]
Anomaly at Param_0 with values: [4.30861723 0.         0.90740183 0.54782959 0.97667101 0.94140967
 0.83860397 0.55877496 0.00647853 0.15356387 0.3302666  0.01488512]
Anomaly at Param_0 with values: [4.52905812 0.         0.0468966  0.31977808 0.04715293 0.05299821
 0.97276548 0.20348715 0.81595674 0.55448691 0.44524217 0.80003894]
Anomaly at Param_0 with values: [4.58917836 0.         0.46983911 0.94417403 0.886478   0.74755404
 0.01034377 0.36007572 0.95596925 0.23943278 0.8142334  0.01720236]
Anomaly at Param_0 with values: [4.68937876 0.         0.06519337 0.43118628 0.38972997 0.07066033
 0.69289956 0.12088851 0.91790174 0.22411381 0.13132443 0.11610497]
Anomaly at Param_0 with values: [4.86973948 0.         0.03104232 0.14668908 0.15528877 0.13255776
 0.15980235 0.1315485  0.21507587 0.79413319 0.75527083 0.99995596]
Anomaly at Param_0 with values: [4.92985972 0.         0.03896599 0.46442808 0.61206916 0.52661558
 0.08520171 0.96757921 0.14316748 0.17715184 0.85334284 0.84564245]
Anomaly at Param_0 with values: [5.07014028 0.         0.89292967 0.24072661 0.21068844 0.82651527
 0.80517734 0.8000029  0.79014848 0.77136194 0.0344262  0.15903871]
Anomaly at Param_0 with values: [5.61122244 0.         0.01409977 0.97865358 0.09773122 0.85237139
 0.00739902 0.18853443 0.99833661 0.52614901 0.84916002 0.32545748]
Anomaly at Param_0 with values: [5.75150301 0.         0.03025938 0.20062567 0.51361597 0.01894027
 0.99955589 0.47959442 0.74568753 0.0765661  0.6781016  0.9556017 ]
Anomaly at Param_0 with values: [6.21242485 0.         0.02817807 0.14853301 0.55430068 0.81671298
 0.60383148 0.94497448 0.44700444 0.80588119 0.01330739 0.09797949]
Anomaly at Param_0 with values: [6.71342685 0.         0.13859008 0.2059865  0.85000647 0.83803949
 0.3038428  0.04981456 0.72359116 0.86952436 0.98019136 0.89351543]
Anomaly at Param_0 with values: [6.75350701 0.         0.09515212 0.60050343 0.30903971 0.14346234
 0.55862739 0.91363868 0.95083882 0.87259206 0.02383923 0.75940379]
Anomaly at Param_0 with values: [6.77354709 0.         0.76080888 0.14361673 0.03887217 0.16350316
 0.56836677 0.94366983 0.67080282 0.47619952 0.79728734 0.88683777]
Anomaly at Param_0 with values: [6.95390782 0.         0.19736825 0.70497174 0.59210135 0.76395297
 0.95132627 0.11699329 0.83215086 0.96028266 0.08689309 0.99175161]
Anomaly at Param_0 with values: [6.99398798 0.         0.64935606 0.16671067 0.05498306 0.81960341
 0.09626486 0.72816398 0.84291029 0.85652238 0.98800398 0.82321081]
Anomaly at Param_0 with values: [7.0741483  0.         0.04856004 0.49716026 0.31284809 0.79701732
 0.77180748 0.9295728  0.20402918 0.13890284 0.02788757 0.09279685]
Anomaly at Param_0 with values: [7.4749499  0.         0.97738371 0.34609255 0.78365483 0.0191961
 0.90693712 0.41270878 0.01738525 0.38514327 0.47452367 0.04859381]
Anomaly at Param_0 with values: [7.51503006 0.         0.41830094 0.34729753 0.03105575 0.16661886
 0.92138041 0.99450323 0.76528935 0.52357048 0.90572282 0.40240414]
Anomaly at Param_0 with values: [7.6753507  0.         0.64298808 0.12612429 0.82376966 0.67462816
 0.12308172 0.9756081  0.98347552 0.76911943 0.51970117 0.39313623]
Anomaly at Param_0 with values: [7.95591182e+00 0.00000000e+00 5.66603216e-02 6.89912803e-01
 4.68619783e-01 9.92897028e-01 1.22074453e-01 9.83618456e-01
 4.71601694e-02 1.26155524e-01 5.85263503e-03 6.42638722e-01]
Anomaly at Param_0 with values: [8.15631263 0.         0.57330302 0.03736925 0.24774556 0.19463912
 0.11295028 0.31764549 0.74450691 0.91898458 0.21125835 0.98983773]
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Anomaly at Param_0 with values: [8.29659319 0.         0.97945816 0.18410982 0.48400352 0.41575421
 0.29702042 0.82641235 0.01783691 0.52928819 0.46746218 0.98811047]
Anomaly at Param_0 with values: [8.31663327 0.         0.02654883 0.3924831  0.9234416  0.79398828
 0.86762833 0.54910381 0.73288657 0.98751589 0.52801647 0.26460454]
Anomaly at Param_0 with values: [8.39679359 0.         0.08068356 0.76682166 0.62949252 0.58955382
 0.58301207 0.97092926 0.74517449 0.83826291 0.08469578 0.83546971]
Anomaly at Param_0 with values: [8.41683367 0.         0.90387497 0.67098212 0.62019549 0.15544828
 0.87597932 0.89159144 0.18656383 0.031452   0.55162309 0.87933729]
Anomaly at Param_0 with values: [8.51703407e+00 0.00000000e+00 1.92450022e-02 4.61862118e-01
 2.59791376e-01 2.44795415e-01 5.79358708e-01 6.57767637e-01
 6.55715118e-01 6.25313370e-01 3.10187227e-02 7.14435690e-03]
Anomaly at Param_0 with values: [8.71743487 0.         0.35084752 0.86140968 0.37314906 0.30901767
 0.88796741 0.92465765 0.73502009 0.05160769 0.96173686 0.74791312]
Anomaly at Param_0 with values: [8.83767535e+00 0.00000000e+00 5.34717083e-02 5.14201345e-01
 5.73508274e-01 5.01290705e-03 8.46050628e-01 1.92095585e-02
 2.50455968e-01 5.52416105e-01 2.80319575e-01 9.83288434e-01]
Anomaly at Param_0 with values: [8.85771543e+00 0.00000000e+00 4.80855096e-01 3.10513043e-01
 4.98635494e-01 3.40638376e-01 1.56752560e-01 2.76186648e-02
 8.33663418e-01 2.31797142e-01 2.10579872e-01 2.76610000e-03]
Anomaly at Param_0 with values: [8.93787575 0.         0.22089901 0.82101819 0.02473713 0.26069879
 0.82981528 0.63754335 0.22835778 0.86398556 0.26467678 0.96675453]
Anomaly at Param_0 with values: [9.17835671e+00 0.00000000e+00 7.83681881e-02 6.72657435e-03
 3.85195444e-01 7.08226456e-01 7.64577541e-01 1.02780940e-01
 2.14184890e-01 3.96094108e-02 6.20006267e-01 9.39297540e-01]
Anomaly at Param_0 with values: [9.29859719 0.         0.18600023 0.44428876 0.97123323 0.68882707
 0.37024346 0.97620135 0.132514   0.63736935 0.89250453 0.74269874]
Anomaly at Param_0 with values: [9.51903808 0.         0.2097885  0.08625889 0.01595488 0.31934007
 0.5054826  0.60204792 0.1468744  0.1089424  0.78462389 0.03873296]
Anomaly at Param_0 with values: [9.53907816 0.         0.07689731 0.13361886 0.1636436  0.30453827
 0.24157315 0.09213721 0.67254146 0.68590031 0.94023608 0.60182453]
Anomaly at Param_0 with values: [9.5991984  0.         0.95613135 0.83030249 0.16626098 0.39208681
 0.6580113  0.94612718 0.98611462 0.24211541 0.12979136 0.3643758 ]
Anomaly at Param_0 with values: [9.65931864 0.         0.89125781 0.44082566 0.9516856  0.10711502
 0.88688543 0.17341869 0.28267927 0.5698517  0.1791366  0.03513506]
Anomaly at Param_0 with values: [9.71943888 0.         0.04792761 0.58086556 0.39783821 0.14219954
 0.22163937 0.99818674 0.54858035 0.38136083 0.61206174 0.82980309]
Anomaly at Param_0 with values: [9.75951904 0.         0.77076115 0.19555449 0.35526958 0.06048416
 0.88315243 0.98880768 0.66990572 0.31251233 0.89183724 0.46990573]
Anomaly at Param_0 with values: [9.81963928 0.         0.89780129 0.3900297  0.06156023 0.98533893
 0.91563546 0.17599745 0.03511118 0.37153431 0.38029956 0.65374921]
Anomaly at Param_0 with values: [9.89979960e+00 0.00000000e+00 5.62237295e-01 8.89840185e-01
 6.65553000e-01 6.66839837e-01 9.10853161e-04 1.66131547e-01
 9.36586498e-01 4.38530379e-02 9.50549990e-01 9.28041653e-01]
Anomaly at Param_0 with values: [9.91983968 0.         0.11765994 0.99184097 0.55007392 0.02568672
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 0.81426923 0.72699114 0.41504715 0.84027246 0.44433541 0.9751335 ]
Anomaly at Param_0 with values: [9.97995992e+00 0.00000000e+00 1.87550938e-01 7.06872569e-01
 4.66878744e-03 3.17867906e-01 3.84454729e-01 2.77076600e-01
 4.08904456e-01 4.44536847e-02 9.13770764e-01 5.55831318e-01]
Anomaly at Param_0 with values: [10.          0.          0.1912041   0.75164067  0.08443762  0.95768843
  0.82717353  0.32988517  0.31132282  0.04356535  0.95988448  0.58103282]
Anomaly at Param_6 with values: [0.         0.         0.87401815 0.63550018 0.39340616 0.70281175
 0.96112383 0.02496675 0.22996521 0.94388219 0.41029621 0.82338213]
Anomaly at Param_4 with values: [0.04008016 0.         0.54335464 0.02429304 0.96561233 0.87179245
 0.93877289 0.02956327 0.53179248 0.1829727  0.4695745  0.07313879]
Anomaly at Param_10 with values: [0.1002004  0.         0.64070293 0.81666278 0.18718536 0.52712017
 0.21511791 0.79030359 0.07169686 0.90406023 0.92228142 0.82747796]
Anomaly at Param_11 with values: [0.14028056 0.         0.33307293 0.94071978 0.21946918 0.65291113
 0.32178486 0.58914924 0.77809387 0.34481804 0.03700048 0.96972379]
Anomaly at Param_4 with values: [0.16032064 0.         0.75009424 0.1873771  0.96981623 0.39947214
 0.10202165 0.05852885 0.65207964 0.08397693 0.21128993 0.47225386]
Anomaly at Param_8 with values: [2.20440882e-01 0.00000000e+00 2.22059899e-04 3.92410818e-01
 4.26204928e-01 1.68277141e-02 5.52625017e-01 6.94174403e-01
 9.78677861e-01 1.04268510e-01 1.70789440e-01 5.00204479e-01]
Anomaly at Param_3 with values: [0.3006012  0.         0.06137467 0.87219087 0.05630914 0.16966519
 0.75315552 0.16180771 0.42615389 0.09350018 0.79478566 0.78527922]
Anomaly at Param_4 with values: [0.32064128 0.         0.37496925 0.85483216 0.96821814 0.02200933
 0.25404674 0.58803413 0.06957063 0.64961186 0.5030236  0.92712055]
Anomaly at Param_5 with values: [0.34068136 0.         0.11189397 0.37055437 0.13924792 0.9282853
 0.40892001 0.03744473 0.69493444 0.32282415 0.21307373 0.53025639]
Anomaly at Param_6 with values: [0.38076152 0.         0.04925783 0.79685182 0.27836102 0.76126149
 0.85786554 0.08428669 0.48798023 0.70356548 0.45424393 0.69973942]
Anomaly at Param_7 with values: [0.44088176 0.         0.24236435 0.07325894 0.39158413 0.12670627
 0.08108814 0.93095203 0.43578062 0.4320358  0.02166701 0.45131275]
Anomaly at Param_9 with values: [0.46092184 0.         0.5223221  0.03809586 0.14748562 0.06149949
 0.54233371 0.45784024 0.78167486 0.90900238 0.56239483 0.36170053]
Anomaly at Param_2 with values: [0.54108216 0.         0.94079314 0.50168041 0.38915036 0.86534063
 0.85937375 0.14299432 0.01999199 0.68399524 0.16010927 0.71218087]
Anomaly at Param_6 with values: [0.6012024  0.         0.48722667 0.96126439 0.39183937 0.14818884
 0.9673902  0.87723769 0.91320767 0.08260297 0.76522109 0.63189986]
Anomaly at Param_3 with values: [0.62124248 0.         0.93674874 0.95485017 0.87604408 0.03727902
 0.00216953 0.71899172 0.58567078 0.03903103 0.28402726 0.14096397]
Anomaly at Param_7 with values: [0.66132265 0.         0.88169456 0.85629966 0.38278263 0.76002492
 0.88300903 0.90439915 0.07150678 0.43180649 0.39607176 0.14234305]
Anomaly at Param_2 with values: [0.74148297 0.         0.95194693 0.10575034 0.14558745 0.14749122
 0.83648806 0.09993617 0.9189744  0.80792486 0.64545529 0.03499827]
Anomaly at Param_5 with values: [0.80160321 0.         0.902628   0.79908289 0.01443136 0.9882829
 0.23834052 0.61153435 0.64891161 0.06015911 0.07503734 0.57282865]
Anomaly at Param_11 with values: [0.90180361 0.         0.61465868 0.58593675 0.16732127 0.92418667
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 0.80248766 0.03094288 0.84891838 0.42491478 0.22301525 0.93428906]
Anomaly at Param_0 with values: [1.00200401 0.         0.93322393 0.27371403 0.35768436 0.2524071
 0.9746502  0.98122917 0.9186464  0.5175521  0.95626101 0.03789661]
Anomaly at Param_0 with values: [1.04208417 0.         0.96350811 0.26328399 0.26087826 0.0239195
 0.07021482 0.5964302  0.8126931  0.87592099 0.61324145 0.23422379]
Anomaly at Param_0 with values: [1.16232465 0.         0.59363122 0.25839551 0.01350556 0.41303927
 0.12127993 0.92076652 0.72634995 0.19591549 0.67974835 0.90680037]
Anomaly at Param_0 with values: [1.18236473 0.         0.00776104 0.80667698 0.5313615  0.33768637
 0.04514967 0.31434543 0.64098978 0.81515438 0.01566382 0.9516987 ]
Anomaly at Param_0 with values: [1.24248497 0.         0.8140726  0.3933358  0.33490919 0.86520088
 0.04255271 0.03647007 0.5849538  0.48764858 0.05514546 0.01825447]
Anomaly at Param_0 with values: [1.40280561 0.         0.52302207 0.84411204 0.10801333 0.39817633
 0.14898748 0.00346987 0.08300794 0.07479915 0.42876281 0.77606787]
Anomaly at Param_1 with values: [1.44288577e+00 1.36806800e+01 4.64379706e-01 4.46847700e-01
 6.90661431e-01 5.89452738e-01 1.58915670e-02 5.51880269e-01
 8.94330434e-01 5.64022822e-03 7.22458879e-01 6.03397966e-01]
Anomaly at Param_0 with values: [1.52304609 0.         0.86359233 0.48239933 0.99277819 0.05172541
 0.1327411  0.98513166 0.29828996 0.85522932 0.79446051 0.86299436]
Anomaly at Param_0 with values: [1.58316633 0.         0.12319209 0.01680579 0.30027275 0.64424327
 0.81234685 0.72371139 0.37944404 0.81365215 0.9212792  0.97423438]
Anomaly at Param_0 with values: [1.60320641 0.         0.98719278 0.36169857 0.14381887 0.71584694
 0.22081131 0.08161579 0.4329939  0.93193138 0.06117693 0.06767232]
Anomaly at Param_0 with values: [1.64328657 0.         0.65443091 0.8867573  0.87896458 0.09303048
 0.4074333  0.9841692  0.45839699 0.65555988 0.8283803  0.45550184]
Anomaly at Param_0 with values: [1.66332665 0.         0.18849568 0.03838865 0.75263149 0.96839293
 0.15721895 0.20760166 0.60298231 0.36224958 0.29670428 0.20991102]
Anomaly at Param_0 with values: [1.68336673 0.         0.16498331 0.01722074 0.87938263 0.94385902
 0.10303204 0.12702349 0.72025901 0.41149024 0.54735942 0.47929404]
Anomaly at Param_0 with values: [1.76352705 0.         0.80008867 0.68975856 0.29270235 0.53057245
 0.31428174 0.07855488 0.96374645 0.61291374 0.94565099 0.17198279]
Anomaly at Param_0 with values: [1.78356713 0.         0.02730839 0.2944499  0.31063193 0.03631435
 0.2037783  0.81785468 0.98545885 0.05035773 0.21290292 0.75218611]
Anomaly at Param_0 with values: [1.80360721 0.         0.19004208 0.63570165 0.67584905 0.88808043
 0.23565595 0.97129596 0.14202113 0.76552554 0.17986592 0.05274565]
Anomaly at Param_0 with values: [2.0240481  0.         0.39056833 0.06325403 0.86458696 0.05161321
 0.21279719 0.36289314 0.91722885 0.66390418 0.28169483 0.1909606 ]
Anomaly at Param_0 with values: [2.18436874 0.         0.61752339 0.29862572 0.19418064 0.05770644
 0.31934947 0.96157549 0.37083191 0.3465093  0.96515954 0.98023205]
Anomaly at Param_0 with values: [2.20440882 0.         0.24630834 0.0770228  0.85176161 0.91981701
 0.69521582 0.927771   0.33306125 0.12545583 0.96934593 0.8883013 ]
Anomaly at Param_0 with values: [2.3246493  0.         0.80597518 0.4587298  0.06837597 0.78325301
 0.27704993 0.90854899 0.41457228 0.87885735 0.02534813 0.81651809]
Anomaly at Param_0 with values: [2.34468938e+00 0.00000000e+00 5.92121924e-02 4.16907717e-03
 8.14960881e-01 2.06074066e-03 7.40656293e-02 8.22797607e-01
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 1.76198962e-01 1.57827210e-01 3.88894498e-01 6.68502880e-01]
Anomaly at Param_0 with values: [2.4248497  0.         0.18124789 0.55522545 0.11345489 0.52391022
 0.94211461 0.79191526 0.94092167 0.70587968 0.71707189 0.97362015]
Anomaly at Param_1 with values: [2.48496994e+00 1.87814345e+01 4.15017808e-01 4.74215194e-03
 6.74885122e-01 8.28865975e-01 5.00971750e-01 4.65897724e-01
 1.59068168e-01 3.95759544e-01 5.63124667e-01 9.53996077e-01]
Anomaly at Param_0 with values: [2.54509018 0.         0.03961347 0.75155626 0.04507035 0.17863998
 0.22994466 0.86605029 0.29511358 0.44183839 0.04163817 0.48493917]
Anomaly at Param_0 with values: [2.9258517  0.         0.00306183 0.6665158  0.10273353 0.93069574
 0.07447253 0.21062976 0.28406917 0.76567043 0.08700553 0.6619258 ]
Anomaly at Param_0 with values: [3.06613226 0.         0.09143964 0.30168379 0.0348496  0.47546407
 0.07932177 0.01622106 0.54637667 0.23831503 0.86311646 0.866213  ]
Anomaly at Param_0 with values: [3.08617234 0.         0.21825783 0.4874921  0.34901016 0.81492782
 0.16301285 0.21053652 0.33935031 0.93235134 0.99105642 0.04243816]
Anomaly at Param_0 with values: [3.18637275 0.         0.27232381 0.97174783 0.87223619 0.17500951
 0.69735433 0.77747624 0.03415937 0.8051107  0.54978404 0.99088815]
Anomaly at Param_0 with values: [3.22645291 0.         0.13852963 0.14790079 0.2507164  0.04160463
 0.71873142 0.00369051 0.79189373 0.09196363 0.58292324 0.05254933]
Anomaly at Param_0 with values: [3.32665331 0.         0.88251738 0.1333682  0.90046928 0.60998531
 0.41628306 0.04035297 0.86282851 0.97279668 0.15392635 0.25065622]
Anomaly at Param_0 with values: [3.46693387 0.         0.00399205 0.95157962 0.81198835 0.11835913
 0.17697089 0.24888827 0.97995693 0.98779842 0.11782438 0.69979478]
Anomaly at Param_0 with values: [3.48697395 0.         0.88582721 0.39628213 0.891328   0.0043467
 0.82327356 0.70226214 0.24553211 0.08637029 0.89945124 0.08604513]
Anomaly at Param_1 with values: [ 3.62725451 11.64935088  0.33603003  0.20894111  0.21896909  0.01890022
  0.82770317  0.608947    0.22937953  0.09830489  0.81504082  0.38259727]
Anomaly at Param_0 with values: [3.66733467 0.         0.04748514 0.18660653 0.5914     0.09345869
 0.11935862 0.46043577 0.88240204 0.23416511 0.1773182  0.99622024]
Anomaly at Param_0 with values: [3.72745491 0.         0.09107446 0.78231183 0.62941673 0.8549838
 0.51658258 0.14434948 0.96988903 0.18414938 0.19899595 0.01885777]
Anomaly at Param_0 with values: [3.92785571 0.         0.38784868 0.08231382 0.12237031 0.56172189
 0.89112176 0.07702188 0.72784189 0.71848256 0.99098048 0.71711445]
Anomaly at Param_0 with values: [4.12825651 0.         0.48558967 0.29383223 0.89463772 0.03601262
 0.77771508 0.96114855 0.9878384  0.33086333 0.9740369  0.40364499]
Anomaly at Param_0 with values: [4.18837675 0.         0.93179    0.21762132 0.93686332 0.79196674
 0.13635192 0.94770368 0.75173513 0.70242875 0.8751332  0.18447877]
Anomaly at Param_0 with values: [4.34869739 0.         0.83453031 0.32611047 0.88177078 0.11866225
 0.16583136 0.14991975 0.86668546 0.49980931 0.90974581 0.04357207]
Anomaly at Param_0 with values: [4.40881764 0.         0.3589465  0.60207802 0.18557561 0.21404306
 0.73619878 0.70590745 0.97002051 0.90816465 0.68971141 0.04495145]
Anomaly at Param_0 with values: [4.4488978  0.         0.26892417 0.95418818 0.46807845 0.5824104
 0.0208092  0.77788623 0.2952084  0.91906244 0.03880414 0.96883405]
Anomaly at Param_0 with values: [4.52905812 0.         0.11604764 0.56912524 0.05103427 0.70117942
 0.20075205 0.85090588 0.9463676  0.72999584 0.93923084 0.60464673]
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Anomaly at Param_0 with values: [4.78957916e+00 0.00000000e+00 6.51275783e-01 9.76275620e-01
 1.92637711e-04 5.87958253e-01 3.54640188e-01 8.10406880e-01
 3.20478780e-02 4.17783825e-01 3.74100685e-01 6.20126021e-02]
Anomaly at Param_1 with values: [5.23046092e+00 1.34097926e+01 6.18018679e-01 6.84801402e-01
 7.85319791e-04 9.94879747e-01 7.27329008e-01 9.45873556e-01
 5.95620931e-01 3.12874931e-01 7.05137866e-01 1.55566783e-01]
Anomaly at Param_0 with values: [5.33066132 0.         0.89932269 0.81382651 0.47903235 0.92833713
 0.85636138 0.78492509 0.06283207 0.09672387 0.05409286 0.02689989]
Anomaly at Param_0 with values: [5.43086172 0.         0.13186762 0.96026132 0.93918976 0.62451235
 0.27629749 0.79259087 0.04064042 0.5879725  0.91779238 0.07232331]
Anomaly at Param_0 with values: [5.4509018  0.         0.03897382 0.41320187 0.10968827 0.00683318
 0.68395423 0.96925425 0.15194889 0.61993537 0.12564288 0.47654494]
Anomaly at Param_0 with values: [5.49098196 0.         0.78278363 0.67461699 0.91516167 0.70983064
 0.79411303 0.89034263 0.04234102 0.90087196 0.91089757 0.41096602]
Anomaly at Param_0 with values: [5.63126253 0.         0.39893933 0.13821745 0.15211757 0.9416008
 0.30294713 0.10126676 0.82525651 0.49861926 0.0384658  0.02300901]
Anomaly at Param_0 with values: [5.65130261 0.         0.01522997 0.14958261 0.12539984 0.2158971
 0.35762006 0.68948165 0.78721062 0.83123419 0.15968372 0.45855094]
Anomaly at Param_0 with values: [5.71142285 0.         0.73457016 0.76620937 0.996176   0.58619407
 0.04704363 0.49391405 0.89944595 0.06533556 0.32364371 0.91971362]
Anomaly at Param_0 with values: [5.73146293e+00 0.00000000e+00 1.95670769e-01 9.76383343e-02
 3.36722646e-01 3.18947170e-01 1.09393824e-04 1.67933302e-01
 7.92215142e-01 4.76040048e-01 9.82073228e-01 2.50854238e-01]
Anomaly at Param_0 with values: [5.75150301 0.         0.03494561 0.18260482 0.09988348 0.32786521
 0.84302393 0.96067344 0.76289476 0.09523787 0.6374905  0.82037114]
Anomaly at Param_0 with values: [5.89178357 0.         0.04785425 0.95721588 0.25571083 0.97556236
 0.96673402 0.88153243 0.27272875 0.79108009 0.87808027 0.25606255]
Anomaly at Param_0 with values: [5.91182365 0.         0.91100416 0.765148   0.06402455 0.04723138
 0.01569364 0.9494992  0.49059441 0.55507276 0.3048433  0.93688668]
Anomaly at Param_0 with values: [5.93186373 0.         0.25838727 0.86825671 0.21611064 0.97039154
 0.07478156 0.85796047 0.80768684 0.82364157 0.07252074 0.37103801]
Anomaly at Param_0 with values: [5.97194389e+00 0.00000000e+00 5.75748333e-03 9.58150981e-02
 3.64467115e-02 5.98366887e-01 9.54576745e-01 1.64521382e-01
 1.48792144e-02 6.30772940e-01 4.55869967e-01 5.93198999e-01]
Anomaly at Param_0 with values: [6.05210421 0.         0.48098605 0.90006442 0.16832959 0.41918527
 0.31209845 0.933323   0.82213339 0.44872443 0.01631519 0.05545353]
Anomaly at Param_0 with values: [6.31262525 0.         0.02586754 0.12264702 0.32671997 0.74299267
 0.85657626 0.73515521 0.14818384 0.65968002 0.99819177 0.81007391]
Anomaly at Param_0 with values: [6.35270541 0.         0.58894293 0.36016504 0.70214333 0.01058895
 0.8003841  0.89983276 0.05811191 0.6530486  0.7847762  0.99311447]
Anomaly at Param_0 with values: [6.61322645 0.         0.04396855 0.06089359 0.77592196 0.18456742
 0.68371943 0.55822634 0.06348368 0.98159737 0.01936248 0.0464334 ]
Anomaly at Param_1 with values: [ 6.93386774 12.60419624  0.74633112  0.19530319  0.07301913  0.56085055
  0.09630265  0.59715547  0.16050856  0.62815669  0.50190434  0.25356522]
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Anomaly at Param_0 with values: [7.07414830e+00 0.00000000e+00 4.99421526e-02 9.31428013e-01
 6.73041002e-01 1.15506387e-03 6.26180793e-01 8.28307953e-02
 8.27848950e-01 2.81591655e-01 1.59495800e-01 9.84869691e-01]
Anomaly at Param_0 with values: [7.59519038 0.         0.61312683 0.71031176 0.02434074 0.40821327
 0.85396141 0.56251149 0.87313934 0.4012411  0.90844892 0.98993715]
Anomaly at Param_0 with values: [7.89579158 0.         0.94460904 0.01726258 0.2761116  0.29879603
 0.1215384  0.24487828 0.34750788 0.23999127 0.75891983 0.14012069]
Anomaly at Param_0 with values: [8.05611222 0.         0.25573907 0.49936855 0.22199774 0.16373438
 0.05726339 0.74354445 0.03810451 0.04202593 0.02818971 0.21775089]
Anomaly at Param_0 with values: [8.09619238 0.         0.81643874 0.97881674 0.07767153 0.05112777
 0.81554405 0.94190398 0.61692145 0.85711993 0.1460428  0.42337197]
Anomaly at Param_0 with values: [8.15631263 0.         0.31694743 0.07031455 0.15261826 0.52021612
 0.97084174 0.87245984 0.66188404 0.35455529 0.95999835 0.41359054]
Anomaly at Param_0 with values: [8.19639279 0.         0.03918717 0.66088311 0.891147   0.97147699
 0.92499251 0.43431778 0.02077604 0.51078034 0.14674727 0.28176347]
Anomaly at Param_0 with values: [8.25651303 0.         0.32948349 0.51208581 0.13331689 0.76010355
 0.87901862 0.00838611 0.33948767 0.73225154 0.84268543 0.94022871]
Anomaly at Param_0 with values: [8.27655311 0.         0.03303515 0.92736724 0.56910428 0.0458011
 0.67287666 0.03792439 0.18385288 0.86861163 0.56806766 0.37178545]
Anomaly at Param_0 with values: [8.33667335 0.         0.26656964 0.94876266 0.03071256 0.9667451
 0.49904142 0.3684413  0.10460198 0.17749767 0.0966723  0.80587659]
Anomaly at Param_0 with values: [8.53707415 0.         0.91824837 0.12449682 0.24856247 0.22844966
 0.66616142 0.97296701 0.36598482 0.3057489  0.70600458 0.1162356 ]
Anomaly at Param_0 with values: [8.69739479 0.         0.8336438  0.17033012 0.19523715 0.83676771
 0.54610058 0.04973287 0.04270574 0.89462404 0.05338302 0.83608089]
Anomaly at Param_0 with values: [8.73747495e+00 0.00000000e+00 1.55056847e-01 5.76556287e-03
 6.35689246e-01 4.42147975e-02 3.60935929e-02 2.25593014e-01
 7.47509889e-01 2.87609522e-01 3.07761135e-01 1.35205987e-01]
Anomaly at Param_0 with values: [8.75751503 0.         0.86948194 0.48188044 0.09271421 0.93681824
 0.33196665 0.6341107  0.05793923 0.96873667 0.67922836 0.1433667 ]
Anomaly at Param_0 with values: [8.83767535e+00 0.00000000e+00 8.81203083e-03 4.20289802e-01
 2.69915180e-01 3.63025774e-01 9.07463252e-01 1.70974122e-01
 7.82434372e-01 5.33374979e-02 5.12762663e-01 2.41735520e-01]
Anomaly at Param_0 with values: [8.95791583 0.         0.22027974 0.01121824 0.6560195  0.94691235
 0.13131147 0.95362862 0.83616141 0.52947326 0.54440483 0.36821185]
Anomaly at Param_0 with values: [8.99799599e+00 0.00000000e+00 8.31701096e-01 6.18463762e-01
 4.30050351e-01 9.18892303e-01 1.38478321e-01 8.42320363e-03
 9.09058466e-01 9.30304932e-01 7.65111933e-01 9.61157093e-02]
Anomaly at Param_0 with values: [9.03807615 0.         0.20926824 0.26498757 0.01955338 0.17608906
 0.41150748 0.93843092 0.11004585 0.74783626 0.18655533 0.19202525]
Anomaly at Param_0 with values: [9.19839679 0.         0.88696198 0.96693533 0.45118865 0.73813406
 0.99507826 0.72984636 0.90154812 0.46762852 0.39747448 0.9751087 ]
Anomaly at Param_0 with values: [9.27855711 0.         0.84221783 0.60084363 0.88657107 0.22425955
 0.27488481 0.39227577 0.02850783 0.01438478 0.09343889 0.24522145]
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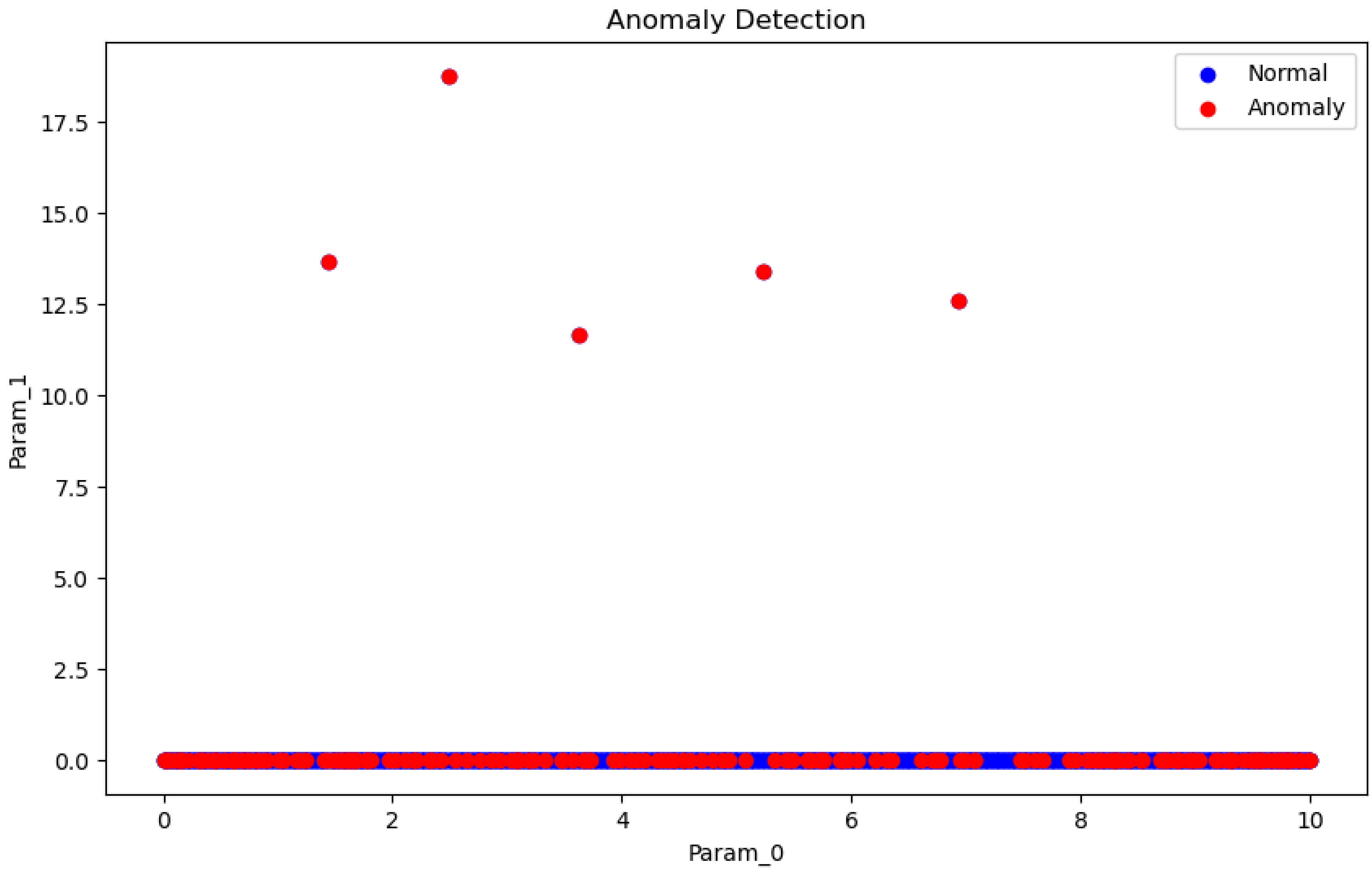
Anomaly at Param_0 with values: [9.29859719 0.         0.49236715 0.77132216 0.03640152 0.56636991
 0.48281418 0.02913269 0.50645109 0.07096663 0.86397188 0.02442856]
Anomaly at Param_0 with values: [9.33867735 0.         0.61643814 0.2670295  0.78022061 0.37491338
 0.93870841 0.93056699 0.80520039 0.49054277 0.72630794 0.97791875]
Anomaly at Param_0 with values: [9.41883768 0.         0.26085172 0.45285711 0.96026353 0.98253584
 0.42214715 0.48287794 0.08983497 0.08211588 0.83630631 0.97936863]
Anomaly at Param_0 with values: [9.47895792 0.         0.241241   0.73650084 0.71680195 0.87322985
 0.30252421 0.04006702 0.84768902 0.77266407 0.08953884 0.92979927]
Anomaly at Param_0 with values: [9.498998   0.         0.55836758 0.08694633 0.31786806 0.95790515
 0.29686455 0.94448354 0.4299713  0.06042927 0.13559328 0.55666786]
Anomaly at Param_0 with values: [9.55911824 0.         0.10075062 0.03272998 0.38037755 0.13421837
 0.99347314 0.84297041 0.95953207 0.55480855 0.37793857 0.7161304 ]
Anomaly at Param_0 with values: [9.57915832 0.         0.84671032 0.06922341 0.86429682 0.95123172
 0.53973486 0.10746226 0.38485752 0.40627761 0.17743616 0.02343697]
Anomaly at Param_0 with values: [9.65931864 0.         0.62083057 0.93326707 0.01550651 0.12869228
 0.4088235  0.1762291  0.31761353 0.19439244 0.11397262 0.8911424 ]
Anomaly at Param_0 with values: [9.71943888 0.         0.79442625 0.80795953 0.51257699 0.19947906
 0.04513852 0.97017043 0.07651925 0.12724286 0.48108451 0.60730787]
Anomaly at Param_0 with values: [9.75951904e+00 0.00000000e+00 1.41726883e-01 6.86568128e-01
 4.09642300e-02 6.11698620e-01 8.91559646e-01 6.13091739e-01
 1.88715982e-01 1.49036364e-03 3.40177107e-01 9.29574231e-01]
Anomaly at Param_0 with values: [9.77955912 0.         0.65214021 0.66624141 0.13821274 0.44199155
 0.01866014 0.81795398 0.11933527 0.27451557 0.22701653 0.84304438]
Anomaly at Param_0 with values: [9.81963928 0.         0.57821601 0.10600244 0.26676406 0.25647969
 0.76776058 0.78673527 0.69233121 0.99113871 0.01627593 0.89761273]
Anomaly at Param_0 with values: [9.83967936 0.         0.57145911 0.87426747 0.74907435 0.32908539
 0.99038384 0.7892481  0.09111362 0.40771868 0.23802511 0.23406467]
```



In [9]:
```
import pandas as pd
import numpy as np
from sklearn.ensemble import IsolationForest
from sklearn.preprocessing import StandardScaler
import matplotlib.pyplot as plt

# Generate synthetic linear input data with anomalies as peaks
def generate_synthetic_data(num_samples=1000, num_features=2, num_anomalies=5):
    # Generate normal data along a straight line
```

```
    normal_data = np.zeros((num_samples // 2, num_features))
    normal_data[:, 0] = np.linspace(0, 10, num_samples // 2)
    # Generate anomalous data with peaks
    peak_indices = np.random.choice(np.arange(10, num_samples // 2 - 10), num_anomalies, replace=False)
    anomalous_data = normal_data.copy()
    for idx in peak_indices:
        peak_height = np.random.uniform(10, 20)
        anomalous_data[idx, 1] = peak_height  # Introduce peaks
    # Combine normal and anomalous data
    input_data = np.vstack([normal_data, anomalous_data])
    # Create DataFrame
    input_df = pd.DataFrame(input_data, columns=[f"Param_{i}" for i in range(num_features)])
    return input_df

# Combine input and output data
def combine_data(input_data, output_data):
    combined_data = pd.concat([input_data, output_data], axis=1)
    return combined_data

# Add labels for normal (0) and anomalous (1) instances (for demonstration purposes)
def add_labels(combined_data):
    labels = np.zeros(combined_data.shape[0])
    labels[combined_data.index >= len(combined_data) // 2] = 1
    combined_data['Label'] = labels
    return combined_data

# Train Anomaly Detection Model
def train_anomaly_detection_model(X):
    scaler = StandardScaler()
    X_scaled = scaler.fit_transform(X)
    model = IsolationForest(contamination=0.2)  # Adjusting contamination parameter
    model.fit(X_scaled)
    return model, scaler

# Detect Anomalies
def detect_anomalies(model, scaler, X):
    X_scaled = scaler.transform(X)
    anomaly_scores = model.decision_function(X_scaled)
    anomalies = X[anomaly_scores < 0]
    return anomalies, anomaly_scores

# Attribute Anomalies to Input Parameters
def attribute_anomalies_to_input_params(anomalies, num_features):
    param_cols = [f"Param_{i}" for i in range(num_features)]
```

```
    anomalous_params = []
    for index, row in anomalies.iterrows():
        peak_param = param_cols[np.argmax(row.values)]
        anomalous_params.append(peak_param)
    return anomalous_params

# Main function
def main():
    # Generate synthetic data
    num_anomalies = 5  # Number of anomalies (peaks)
    input_data = generate_synthetic_data(num_anomalies=num_anomalies)
    output_data = generate_synthetic_output_data()
    combined_data = combine_data(input_data, output_data)
    combined_data = add_labels(combined_data)

    # Separate features (input parameters) and labels (normal/anomalous)
    X = combined_data.drop(columns=['Label'])
    y = combined_data['Label']

    # Train the Isolation Forest model
    model, scaler = train_anomaly_detection_model(X)

    # Detect anomalies
    anomalies, anomaly_scores = detect_anomalies(model, scaler, X)

    # Attribute anomalies to input parameters
    anomalous_params = attribute_anomalies_to_input_params(anomalies, X.shape[1])

    # Print detected anomalies and associated input parameters
    print("Detected Anomalies and Associated Input Parameters:")
    for anomaly, param in zip(anomalies.values, anomalous_params):
        print(f"Anomaly at {param} with values: {anomaly}")

    # Plot the data
    plt.figure(figsize=(10, 6))
    plt.scatter(X.iloc[:500, 0], X.iloc[:500, 1], c='blue', label='Normal')
    plt.scatter(X.iloc[500:, 0], X.iloc[500:, 1], c='red', label='Anomaly')
    plt.title('Anomaly Detection')
    plt.xlabel('Param_0')
    plt.ylabel('Param_1')
    plt.legend()
    plt.show()
```

```
if __name__ == "__main__":
    main()
```

```
Detected Anomalies and Associated Input Parameters:
Anomaly at Param_7 with values: [0.02004008 0.         0.3238764  0.18156293 0.66987191 0.12317434
 0.57397965 0.95217758 0.3799149  0.22035342 0.8026723  0.60881978]
Anomaly at Param_2 with values: [0.04008016 0.         0.92686203 0.66156875 0.3305858  0.21445464
 0.80895926 0.18500334 0.18189087 0.78638586 0.78150899 0.27676128]
Anomaly at Param_7 with values: [0.08016032 0.         0.6420195  0.13339393 0.22740177 0.5683864
 0.02756397 0.95604609 0.77598898 0.79193111 0.72736295 0.49598609]
Anomaly at Param_8 with values: [0.1002004  0.         0.18764323 0.42442291 0.41877326 0.22506445
 0.75055237 0.02370974 0.84027283 0.72714939 0.15881036 0.83749224]
Anomaly at Param_6 with values: [0.12024048 0.         0.3338712  0.81986528 0.55530161 0.57932602
 0.90809422 0.11371098 0.40035791 0.02785534 0.52792231 0.62132032]
Anomaly at Param_5 with values: [0.2004008  0.         0.39990171 0.00821683 0.49250724 0.98722604
 0.31285368 0.25145602 0.80282527 0.27167188 0.01366128 0.71814521]
Anomaly at Param_7 with values: [0.22044088 0.         0.45102301 0.92053444 0.4912475  0.23457717
 0.55147475 0.97601568 0.03338358 0.82104427 0.62985014 0.50108842]
Anomaly at Param_6 with values: [0.24048096 0.         0.57751682 0.36169195 0.07564476 0.42268062
 0.92285691 0.90810947 0.83151588 0.2623253  0.43215541 0.19631585]
Anomaly at Param_2 with values: [0.32064128 0.         0.99586393 0.60120903 0.02969876 0.75022324
 0.67878386 0.1007224  0.64662377 0.5653994  0.59344459 0.86727687]
Anomaly at Param_8 with values: [0.34068136 0.         0.25873974 0.47638445 0.93858544 0.79392247
 0.06100966 0.51757602 0.95819292 0.17101207 0.24009822 0.84328873]
Anomaly at Param_2 with values: [0.38076152 0.         0.96528115 0.11669092 0.20396015 0.2537849
 0.31060078 0.64236285 0.52136361 0.20028243 0.20879596 0.96152042]
Anomaly at Param_7 with values: [0.46092184 0.         0.84768764 0.82802937 0.7618378  0.74438067
 0.20885803 0.94486957 0.38040436 0.49672085 0.14797822 0.56804686]
Anomaly at Param_9 with values: [0.58116232 0.         0.69430058 0.51449151 0.91950602 0.32745983
 0.26235844 0.78528332 0.00322253 0.9859098  0.88087298 0.26973227]
Anomaly at Param_4 with values: [0.6012024  0.         0.0298097  0.25900857 0.97326222 0.02873356
 0.53836798 0.67873835 0.8114422  0.78790551 0.75286058 0.24825868]
Anomaly at Param_5 with values: [0.62124248 0.         0.09444169 0.03767276 0.68119111 0.98443995
 0.65504053 0.13932214 0.62158308 0.18568346 0.45846564 0.56894249]
Anomaly at Param_4 with values: [0.68136273 0.         0.52786201 0.02407859 0.9587599  0.06681469
 0.93734827 0.16336909 0.46016152 0.67120991 0.1352872  0.4833423 ]
Anomaly at Param_5 with values: [0.70140281 0.         0.11731562 0.76598714 0.40191053 0.99467281
 0.09477281 0.82081832 0.80681471 0.70093682 0.28510666 0.76023531]
Anomaly at Param_7 with values: [0.96192385 0.         0.54061468 0.05405273 0.64635233 0.15654262
 0.55704308 0.9853732  0.96545114 0.50441677 0.92758215 0.08903749]
Anomaly at Param_8 with values: [0.98196393 0.         0.69251349 0.51711168 0.90898807 0.16033602
 0.98489733 0.51480263 0.99268001 0.18903548 0.51446724 0.07634447]
Anomaly at Param_0 with values: [1.16232465e+00 0.00000000e+00 7.72604827e-01 2.67092500e-01
 7.57261102e-01 6.34250296e-01 8.43293086e-01 7.54395147e-02
 3.35261466e-01 3.60326632e-04 5.19998745e-01 8.97400493e-01]
Anomaly at Param_0 with values: [1.38276553 0.         0.49226314 0.09002161 0.53918061 0.87194681
 0.96045813 0.89315563 0.77937446 0.33296852 0.884814   0.66083002]
```

```
Anomaly at Param_0 with values: [1.44288577 0.         0.8811941  0.67613228 0.73329372 0.81455161
 0.59846271 0.90811458 0.70143679 0.98413613 0.28964367 0.11970507]
Anomaly at Param_0 with values: [1.48296593 0.         0.81421555 0.95351071 0.28096572 0.5873698
 0.93036768 0.46512092 0.01557544 0.28456716 0.73589764 0.20846452]
Anomaly at Param_0 with values: [1.50300601 0.         0.99685936 0.27048724 0.310297   0.99528214
 0.91542463 0.19411698 0.57628529 0.26036364 0.05388204 0.73002697]
Anomaly at Param_0 with values: [1.52304609 0.         0.09621512 0.39646425 0.77758201 0.29703555
 0.65918902 0.04067437 0.34835861 0.88489433 0.91067433 0.96420673]
Anomaly at Param_0 with values: [1.58316633 0.         0.02201093 0.28560596 0.35547962 0.75730669
 0.51598379 0.96107906 0.88888869 0.8265766  0.86172136 0.78205138]
Anomaly at Param_0 with values: [1.62324649 0.         0.90424452 0.29024578 0.34907125 0.97109128
 0.00710446 0.20091585 0.44466017 0.18791349 0.74869781 0.8328855 ]
Anomaly at Param_0 with values: [1.86372745 0.         0.85097327 0.87637021 0.18900022 0.899652
 0.82327344 0.97746675 0.7927799  0.57441836 0.44447242 0.36467772]
Anomaly at Param_0 with values: [1.88376754e+00 0.00000000e+00 8.63665859e-01 2.04439319e-01
 6.05191820e-01 2.40493883e-01 6.59493837e-01 2.91958749e-04
 8.10548056e-01 2.32991241e-01 6.83817652e-01 7.56445670e-01]
Anomaly at Param_0 with values: [1.9238477  0.         0.2565433  0.40831973 0.38049522 0.22426361
 0.0882877  0.0056444  0.45788655 0.28500029 0.88883097 0.03075573]
Anomaly at Param_0 with values: [2.20440882 0.         0.22702184 0.05210427 0.03955311 0.60450806
 0.91312374 0.73688384 0.33992682 0.11007063 0.53358055 0.88355108]
Anomaly at Param_0 with values: [2.36472946 0.         0.58493897 0.57249248 0.00381303 0.94959293
 0.01744479 0.00743312 0.86685369 0.55617843 0.57823818 0.74510858]
Anomaly at Param_0 with values: [2.44488978 0.         0.88898956 0.1786272  0.89355727 0.93101045
 0.19215513 0.05285726 0.05057861 0.28965484 0.89026347 0.96641121]
Anomaly at Param_0 with values: [2.56513026 0.         0.06375691 0.57175989 0.33275475 0.02328725
 0.78474711 0.28484568 0.00515408 0.69888305 0.36700497 0.897285  ]
Anomaly at Param_0 with values: [2.66533066 0.         0.45014087 0.54195818 0.96663297 0.90214174
 0.07671491 0.98799081 0.72975986 0.05886316 0.92099019 0.17404829]
Anomaly at Param_0 with values: [2.7254509  0.         0.88609402 0.98445571 0.45313064 0.35278374
 0.49573668 0.04570668 0.35725491 0.02620873 0.88285652 0.01912048]
Anomaly at Param_0 with values: [2.88577154 0.         0.9337145  0.18964438 0.27344068 0.45428998
 0.96151757 0.21898396 0.8150397  0.21445407 0.13389433 0.83262044]
Anomaly at Param_0 with values: [3.42685371 0.         0.51825567 0.92333551 0.75444404 0.24491862
 0.06704758 0.38857617 0.14070524 0.048624   0.10833087 0.56476738]
Anomaly at Param_0 with values: [3.46693387 0.         0.73297915 0.92044313 0.04115069 0.82610553
 0.75379726 0.04376979 0.50374678 0.23975806 0.05342314 0.16425843]
Anomaly at Param_0 with values: [3.60721443 0.         0.87589753 0.02193352 0.1691251  0.90522055
 0.87533989 0.13736161 0.18775794 0.81572458 0.32377442 0.80572923]
Anomaly at Param_0 with values: [4.10821643 0.         0.25850305 0.94414938 0.38653622 0.23581153
 0.06512086 0.84244208 0.82992452 0.68131725 0.01867719 0.31363451]
Anomaly at Param_0 with values: [4.16833667 0.         0.6307001  0.98943705 0.40275191 0.6281335
 0.95482613 0.00683585 0.94146295 0.90116901 0.83107723 0.63930594]
Anomaly at Param_0 with values: [4.22845691 0.         0.92639032 0.81344151 0.24904243 0.06607478
```

```
 0.16187389 0.27776794 0.93301815 0.69611198 0.53631948 0.03937665]
Anomaly at Param_0 with values: [4.46893788 0.         0.98859472 0.04141267 0.04949608 0.74805238
 0.06314952 0.30766012 0.81386987 0.21205472 0.91781655 0.91206054]
Anomaly at Param_0 with values: [4.50901804 0.         0.71715682 0.96472152 0.03056252 0.3161499
 0.5348912  0.00645124 0.77481601 0.7760771  0.23885083 0.55244896]
Anomaly at Param_0 with values: [4.54909820e+00 0.00000000e+00 9.48307717e-01 6.33702236e-01
 6.46140424e-01 3.15975795e-03 5.12119945e-01 9.24320912e-01
 1.86746431e-01 1.64944673e-01 7.21114959e-01 9.16281864e-01]
Anomaly at Param_0 with values: [4.62925852 0.         0.98806092 0.92236029 0.9774002  0.22440112
 0.44621784 0.24132055 0.84091598 0.08705132 0.31587293 0.94834282]
Anomaly at Param_0 with values: [4.72945892 0.         0.09654606 0.16220555 0.95918296 0.43787806
 0.23092467 0.33380516 0.12854218 0.9832529  0.54359942 0.9630057 ]
Anomaly at Param_0 with values: [5.09018036 0.         0.83673435 0.95696912 0.12075766 0.64253352
 0.53900457 0.08381521 0.84081525 0.14318042 0.3697418  0.97756923]
Anomaly at Param_0 with values: [5.13026052 0.         0.86696986 0.97216931 0.75035977 0.936921
 0.01763668 0.53289015 0.19619628 0.31983233 0.18273579 0.65631969]
Anomaly at Param_0 with values: [5.29058116 0.         0.8337196  0.09409091 0.27286929 0.74939778
 0.2537374  0.96841924 0.73561149 0.27663627 0.83303782 0.06162911]
Anomaly at Param_0 with values: [5.53106212 0.         0.9532389  0.8658435  0.66753688 0.24599744
 0.43824167 0.76444363 0.92347166 0.40992434 0.87495496 0.9305921 ]
Anomaly at Param_0 with values: [6.15230461 0.         0.94490519 0.73393962 0.30496218 0.58077607
 0.0417029  0.35702988 0.82447108 0.19426048 0.06726407 0.00640327]
Anomaly at Param_0 with values: [6.17234469e+00 0.00000000e+00 9.99526999e-01 8.88663551e-01
 5.24493608e-03 3.74575498e-02 6.09518745e-01 9.99651000e-01
 5.30501066e-01 5.07639253e-01 5.36912361e-01 4.41811558e-02]
Anomaly at Param_0 with values: [6.19238477 0.         0.95933799 0.08460143 0.4442686  0.34275544
 0.140388   0.02698351 0.22077322 0.3484831  0.21032958 0.95410221]
Anomaly at Param_0 with values: [6.61322645 0.         0.24135497 0.06680173 0.07923654 0.07276214
 0.88010668 0.30823111 0.09041987 0.01221314 0.35639021 0.9766559 ]
Anomaly at Param_0 with values: [7.03406814e+00 0.00000000e+00 9.08830615e-01 6.62508882e-01
 8.38941963e-01 5.35632358e-01 7.69715137e-01 1.11390436e-01
 5.01654565e-01 1.21459929e-03 9.62521223e-01 7.10989638e-01]
Anomaly at Param_0 with values: [7.05410822 0.         0.07243246 0.9739766  0.51441164 0.94128513
 0.02652054 0.75432419 0.18380329 0.51462529 0.22686542 0.36923251]
Anomaly at Param_0 with values: [7.11422846 0.         0.50593461 0.43543273 0.05844143 0.52495623
 0.99912902 0.94166717 0.71940206 0.5614695  0.71104392 0.86838267]
Anomaly at Param_0 with values: [7.1743487  0.         0.89079773 0.3678975  0.68813358 0.05276825
 0.3477706  0.39967059 0.80402405 0.00883169 0.41224177 0.95949408]
Anomaly at Param_0 with values: [7.33466934 0.         0.9939058  0.92872989 0.77215521 0.2337169
 0.72706481 0.76824275 0.84407099 0.96374202 0.79759961 0.78276798]
Anomaly at Param_0 with values: [7.41482966e+00 0.00000000e+00 9.71354501e-01 9.00553596e-01
 2.17170566e-01 5.73383498e-01 8.23922905e-01 2.21395148e-01
 5.41531010e-01 9.90620688e-01 3.66280167e-03 2.37037124e-01]
Anomaly at Param_0 with values: [7.79559118 0.         0.8686833  0.5966034  0.95920143 0.55071183
```

```
 0.09900858 0.84555545 0.92801797 0.07645444 0.49312681 0.5639015 ]
Anomaly at Param_0 with values: [7.8757515  0.         0.25009129 0.67804392 0.87600995 0.05182283
 0.01555246 0.88069245 0.73871278 0.55566358 0.94515869 0.29144086]
Anomaly at Param_0 with values: [7.99599198 0.         0.99713875 0.90294346 0.87548578 0.49583234
 0.08169006 0.26298666 0.20320444 0.77408565 0.74256162 0.68136593]
Anomaly at Param_0 with values: [8.05611222e+00 0.00000000e+00 8.60013824e-02 9.71039098e-01
 2.41914968e-01 6.03597051e-04 4.94414507e-01 7.28375978e-01
 6.18886498e-01 4.10629358e-01 3.87135774e-01 9.08048041e-01]
Anomaly at Param_0 with values: [8.15631263 0.         0.97719538 0.82729096 0.0770962  0.99496566
 0.32858021 0.16444999 0.04534037 0.55668848 0.49525938 0.70491155]
Anomaly at Param_0 with values: [8.27655311 0.         0.67596031 0.96192779 0.37753614 0.1075785
 0.94348979 0.5339536  0.88074967 0.25882259 0.84892773 0.71745607]
Anomaly at Param_0 with values: [8.37675351 0.         0.05550327 0.18990274 0.68515434 0.98405323
 0.05997838 0.26123899 0.39621821 0.49166886 0.9635117  0.3158305 ]
Anomaly at Param_0 with values: [8.43687375 0.         0.68173268 0.03662546 0.58099425 0.09043562
 0.91076966 0.0825041  0.04022031 0.10915603 0.06692632 0.82976993]
Anomaly at Param_0 with values: [8.55711423 0.         0.89577851 0.14242733 0.98773249 0.16611231
 0.93088264 0.34293202 0.90427331 0.3358668  0.52108419 0.99981591]
Anomaly at Param_0 with values: [8.99799599 0.         0.67753063 0.58206641 0.20350892 0.86286898
 0.74656049 0.03464281 0.61882409 0.01723956 0.96451086 0.37002591]
Anomaly at Param_0 with values: [9.03807615 0.         0.22776642 0.9510659  0.96531856 0.62095575
 0.94845953 0.49296566 0.38358232 0.53780639 0.8109299  0.96050509]
Anomaly at Param_0 with values: [9.05811623 0.         0.97755109 0.986881   0.69645431 0.70454065
 0.4814781  0.86641245 0.2432472  0.09257706 0.15142614 0.31191819]
Anomaly at Param_0 with values: [9.17835671 0.         0.42143612 0.7252116  0.12538943 0.22690205
 0.34767109 0.92743485 0.92241523 0.89952685 0.65071496 0.90454962]
Anomaly at Param_0 with values: [9.23847695e+00 0.00000000e+00 9.91345390e-02 3.66955531e-02
 4.06457573e-01 6.53106248e-01 5.41775402e-01 3.79084933e-01
 6.94226737e-03 4.92907844e-01 3.45101621e-02 6.69453428e-03]
Anomaly at Param_0 with values: [9.47895792 0.         0.96845889 0.7871335  0.55331126 0.72029952
 0.04930695 0.34467546 0.10785832 0.87142258 0.01986509 0.04391095]
Anomaly at Param_0 with values: [9.55911824 0.         0.37125694 0.82086038 0.82063396 0.52289978
 0.78659207 0.97726191 0.01452399 0.48631234 0.78700864 0.92939709]
Anomaly at Param_0 with values: [9.65931864 0.         0.99148353 0.14626954 0.75231826 0.18368776
 0.75185217 0.97847459 0.03845709 0.19097501 0.30454885 0.705493  ]
Anomaly at Param_0 with values: [9.6993988  0.         0.21943094 0.72738804 0.96247448 0.84917269
 0.49898812 0.09428666 0.78270994 0.18314951 0.37442101 0.93615883]
Anomaly at Param_0 with values: [9.75951904 0.         0.03545815 0.90795611 0.50618982 0.84772544
 0.09414039 0.12590576 0.62222962 0.61139133 0.06275523 0.93285062]
Anomaly at Param_0 with values: [9.7995992  0.         0.67760366 0.72014095 0.11939603 0.01218016
 0.62200181 0.18214978 0.32693173 0.01891574 0.37515039 0.22599629]
Anomaly at Param_0 with values: [9.85971944 0.         0.47187896 0.59314886 0.86064262 0.98025436
 0.98630158 0.75424617 0.66767396 0.94936015 0.6278737  0.30326133]
Anomaly at Param_0 with values: [9.87975952 0.         0.96156979 0.93843152 0.64966678 0.64772338
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 0.41597475 0.21563672 0.19394656 0.93319866 0.01823195 0.46266875]
Anomaly at Param_0 with values: [9.91983968 0.         0.42501885 0.41254666 0.01509793 0.34581996
 0.69362083 0.0652273  0.40406205 0.09268141 0.28953706 0.15452205]
Anomaly at Param_6 with values: [0.         0.         0.65006275 0.78389921 0.07942234 0.79663241
 0.86091048 0.71963596 0.1190374  0.50959337 0.72910471 0.2996493 ]
Anomaly at Param_7 with values: [0.04008016 0.         0.0400581  0.62428352 0.07016448 0.28012326
 0.28105531 0.97317625 0.82981875 0.90982368 0.42039623 0.88639028]
Anomaly at Param_9 with values: [0.06012024 0.         0.19669817 0.26010704 0.73413154 0.28490217
 0.96571013 0.13809754 0.03980832 0.97683417 0.56847877 0.42211308]
Anomaly at Param_5 with values: [0.1002004  0.         0.10256081 0.7500656  0.90499355 0.93089939
 0.35249956 0.35856361 0.60007003 0.68462521 0.5573443  0.02922252]
Anomaly at Param_4 with values: [0.14028056 0.         0.38120704 0.90283594 0.99697193 0.01084273
 0.40878509 0.98184495 0.6262661  0.45801847 0.29929823 0.74362699]
Anomaly at Param_6 with values: [0.18036072 0.         0.373382   0.69514026 0.15018808 0.06656805
 0.95402294 0.00120238 0.1446701  0.19544152 0.52964942 0.56790265]
Anomaly at Param_11 with values: [0.2004008  0.         0.92835908 0.72493308 0.95775352 0.89373774
 0.6850293  0.34134895 0.85089399 0.39186486 0.41605341 0.98844706]
Anomaly at Param_4 with values: [0.28056112 0.         0.13597549 0.01676025 0.8936876  0.04290806
 0.80453078 0.65724269 0.33072103 0.59746109 0.25140711 0.42056228]
Anomaly at Param_4 with values: [0.4008016  0.         0.31707662 0.20214389 0.93447645 0.71134015
 0.22232595 0.17657265 0.60710075 0.08555691 0.14900373 0.15963861]
Anomaly at Param_6 with values: [0.42084168 0.         0.08065241 0.20950431 0.8316043  0.24438536
 0.99609416 0.07442672 0.71237849 0.90459321 0.95609357 0.4541819 ]
Anomaly at Param_3 with values: [0.44088176 0.         0.8621976  0.93241734 0.65708726 0.62145308
 0.37577049 0.02916519 0.51469001 0.06004516 0.29128928 0.25035599]
Anomaly at Param_8 with values: [0.52104208 0.         0.41474227 0.31044459 0.4627292  0.56334061
 0.93822474 0.16940667 0.99782733 0.48793203 0.82269954 0.44802126]
Anomaly at Param_9 with values: [0.64128257 0.         0.05695959 0.13755806 0.24282242 0.23608773
 0.54742438 0.89491631 0.12747727 0.96023124 0.20547393 0.45184045]
Anomaly at Param_8 with values: [0.70140281 0.         0.82758392 0.5111265  0.4941749  0.00747663
 0.23829894 0.72965993 0.95490059 0.0617105  0.66646151 0.02127061]
Anomaly at Param_2 with values: [0.78156313 0.         0.92784099 0.27365688 0.79287004 0.77977261
 0.27768519 0.88169506 0.20338623 0.04749028 0.65873094 0.73640724]
Anomaly at Param_4 with values: [0.84168337 0.         0.8471338  0.4184577  0.9925714  0.10236925
 0.10838417 0.03834812 0.22593839 0.75004044 0.7517143  0.10815192]
Anomaly at Param_2 with values: [0.88176353 0.         0.94555021 0.79476474 0.51998861 0.89957437
 0.25889533 0.35243712 0.46285732 0.02695088 0.21021672 0.47342523]
Anomaly at Param_5 with values: [0.92184369 0.         0.4253194  0.4810821  0.96469669 0.98568303
 0.94623731 0.84821906 0.88911469 0.08904537 0.13578668 0.74814818]
Anomaly at Param_0 with values: [1.06212425 0.         0.7020712  0.96776057 0.997303   0.13189151
 0.20923679 0.10812923 0.16554722 0.74109599 0.6082519  0.06189086]
Anomaly at Param_0 with values: [1.08216433 0.         0.96832147 0.95689221 0.35574467 0.02431444
 0.79153355 0.21986807 0.60018937 0.24075893 0.40274431 0.0556525 ]
Anomaly at Param_0 with values: [1.18236473 0.         0.4714447  0.00923865 0.72909472 0.93968723
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 0.95938604 0.22886122 0.09733591 0.95853085 0.16709101 0.17313008]
Anomaly at Param_0 with values: [1.24248497 0.         0.43527826 0.89396169 0.58861301 0.7885253
 0.00631263 0.79116523 0.0949453  0.14285113 0.72922863 0.37112504]
Anomaly at Param_0 with values: [1.32264529 0.         0.50967917 0.90515305 0.18958418 0.80224196
 0.02299988 0.32550807 0.41593739 0.69556611 0.11573556 0.89449086]
Anomaly at Param_0 with values: [1.42284569 0.         0.11076676 0.02434196 0.07216878 0.39211509
 0.85865545 0.07573906 0.21532665 0.64947322 0.0900649  0.5664047 ]
Anomaly at Param_0 with values: [1.44288577 0.         0.95302124 0.00648743 0.93457194 0.75395539
 0.53296392 0.40313624 0.2711272  0.89401298 0.84295384 0.00311568]
Anomaly at Param_0 with values: [1.48296593 0.         0.31451089 0.01649147 0.03869403 0.74539901
 0.71315097 0.92729617 0.24966889 0.80063944 0.07962008 0.3302904 ]
Anomaly at Param_0 with values: [1.58316633 0.         0.0018199  0.90039027 0.95850088 0.52899494
 0.71745575 0.10697713 0.32009238 0.99921604 0.58632697 0.04810929]
Anomaly at Param_0 with values: [1.72344689 0.         0.3603496  0.72173125 0.26826824 0.22330647
 0.06246857 0.96363623 0.96293181 0.84198742 0.93228552 0.6988777 ]
Anomaly at Param_0 with values: [1.82364729 0.         0.22088916 0.83595038 0.96081894 0.63860258
 0.06883453 0.60838504 0.00190484 0.51618284 0.55490295 0.88183634]
Anomaly at Param_1 with values: [ 1.84368737 16.57902939  0.6070662   0.38058353  0.66940092  0.91103128
  0.44584221  0.40619724  0.98447669  0.84846913  0.96752018  0.12637973]
Anomaly at Param_0 with values: [1.86372745 0.         0.54516219 0.5406229  0.1136117  0.01677179
 0.00853406 0.88425895 0.87886999 0.96622015 0.5714903  0.00583203]
Anomaly at Param_0 with values: [2.06412826 0.         0.73447564 0.43337524 0.04766301 0.02006998
 0.09360066 0.95841338 0.5251634  0.67719753 0.02628253 0.71540346]
Anomaly at Param_0 with values: [2.08416834 0.         0.76575547 0.40601103 0.74599316 0.94698671
 0.62977155 0.32733602 0.86288609 0.99804007 0.46302697 0.98900568]
Anomaly at Param_0 with values: [2.20440882 0.         0.67280571 0.03476903 0.15666916 0.18532695
 0.86218608 0.21399883 0.02628601 0.15631663 0.7430194  0.57795629]
Anomaly at Param_0 with values: [2.36472946 0.         0.8858219  0.99487786 0.03639613 0.97347207
 0.72978025 0.68310953 0.52401703 0.07566972 0.16720738 0.61510547]
Anomaly at Param_0 with values: [2.38476954 0.         0.08996064 0.8319921  0.12473033 0.31100986
 0.0207935  0.04792976 0.72478565 0.3297417  0.37739528 0.55648196]
Anomaly at Param_0 with values: [2.40480962 0.         0.99456655 0.86089097 0.02122907 0.62678457
 0.57054822 0.17169759 0.46368604 0.15304783 0.65851462 0.48002289]
Anomaly at Param_0 with values: [2.54509018 0.         0.4492632  0.90995308 0.85978774 0.22616528
 0.23179648 0.04422847 0.73110882 0.84793944 0.35906265 0.96879065]
Anomaly at Param_0 with values: [2.70541082 0.         0.12131574 0.23526354 0.99820225 0.783283
 0.99052206 0.75891661 0.21544863 0.08399727 0.85813062 0.84808268]
Anomaly at Param_0 with values: [2.86573146 0.         0.22529545 0.96848798 0.16595464 0.0234946
 0.1004816  0.43692607 0.98084177 0.10624209 0.86754816 0.87990126]
Anomaly at Param_0 with values: [2.88577154 0.         0.69577401 0.8959706  0.5191204  0.86211341
 0.39553213 0.53887369 0.87267027 0.01694767 0.99135406 0.14604595]
Anomaly at Param_0 with values: [2.9258517  0.         0.51992086 0.37894938 0.77187317 0.88746181
 0.0112291  0.73345642 0.14687407 0.99129703 0.65581127 0.7499468 ]
Anomaly at Param_0 with values: [3.0260521  0.         0.39217848 0.00357126 0.04053623 0.37194124
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 0.98971543 0.47016996 0.33687124 0.09929094 0.42676879 0.06769494]
Anomaly at Param_1 with values: [3.12625251e+00 1.80059806e+01 5.73735270e-01 4.10397818e-01
 7.22155897e-01 8.69975442e-03 6.13092737e-01 8.12985124e-01
 8.17005910e-01 6.60681824e-01 8.95592753e-01 6.65182905e-01]
Anomaly at Param_1 with values: [ 3.14629259 11.38460118  0.28857345  0.8050551   0.47408844  0.49483365
  0.6959092   0.93836906  0.52588697  0.71350278  0.78407035  0.1264693 ]
Anomaly at Param_0 with values: [3.16633267 0.         0.99355206 0.65485194 0.49195587 0.28231269
 0.31349637 0.07253817 0.9313958  0.27358138 0.09077996 0.15259781]
Anomaly at Param_0 with values: [3.18637275 0.         0.25153159 0.32005222 0.17248545 0.65905935
 0.03744966 0.13759166 0.09539609 0.92719947 0.93250876 0.06780476]
Anomaly at Param_0 with values: [3.24649299 0.         0.23072482 0.69968659 0.62079778 0.96633294
 0.05689207 0.31117108 0.88960864 0.10628836 0.95830011 0.94045739]
Anomaly at Param_0 with values: [3.46693387 0.         0.13430559 0.95153288 0.34622264 0.34912317
 0.82349808 0.34570198 0.81403718 0.79796047 0.16997487 0.92695235]
Anomaly at Param_0 with values: [3.54709419 0.         0.06046314 0.2313268  0.99935423 0.2715183
 0.61096097 0.98763579 0.8890784  0.33232374 0.04436474 0.95572521]
Anomaly at Param_0 with values: [3.72745491 0.         0.26806328 0.54196267 0.7586178  0.97907483
 0.68340772 0.01774071 0.2589845  0.08180075 0.908592   0.59843437]
Anomaly at Param_0 with values: [3.86773547 0.         0.67975858 0.51073156 0.01235511 0.86161709
 0.06121972 0.43633274 0.09220546 0.59463277 0.82932797 0.96599085]
Anomaly at Param_0 with values: [4.10821643 0.         0.85279509 0.01842965 0.13771115 0.96377948
 0.79369299 0.02175338 0.86195416 0.95831232 0.13849358 0.81505805]
Anomaly at Param_0 with values: [4.14829659 0.         0.95858957 0.57224028 0.28980756 0.81121158
 0.91985447 0.67189736 0.70621274 0.17782753 0.94540568 0.37692255]
Anomaly at Param_0 with values: [4.20841683 0.         0.05393033 0.14931931 0.02069271 0.76649507
 0.08522872 0.83010243 0.09123144 0.92796781 0.78408519 0.76296993]
Anomaly at Param_0 with values: [4.24849699 0.         0.77395029 0.39889957 0.45712101 0.17486756
 0.92862813 0.1874366  0.97311896 0.01553797 0.57668151 0.3114917 ]
Anomaly at Param_0 with values: [4.32865731 0.         0.52048315 0.98751369 0.78444198 0.22398881
 0.28714896 0.97035947 0.92824767 0.80518849 0.6406806  0.04239339]
Anomaly at Param_0 with values: [4.36873747 0.         0.13885287 0.98683705 0.80997328 0.09090416
 0.46288779 0.06199627 0.79366799 0.88363796 0.9504001  0.89890382]
Anomaly at Param_0 with values: [4.38877756 0.         0.81319321 0.54390996 0.11830778 0.87852485
 0.54876864 0.08681704 0.98845354 0.84173522 0.4167219  0.06537887]
Anomaly at Param_0 with values: [4.50901804 0.         0.21354462 0.0146215  0.5898113  0.20146959
 0.79364713 0.08628625 0.82376794 0.12094877 0.83146535 0.83403848]
Anomaly at Param_0 with values: [4.88977956 0.         0.34629245 0.89060573 0.367803   0.08523354
 0.07793551 0.95832226 0.97455583 0.48795731 0.75605967 0.27322769]
Anomaly at Param_0 with values: [4.92985972 0.         0.05315847 0.41111168 0.87377914 0.04429266
 0.90675651 0.44653208 0.99790747 0.40376569 0.01720593 0.39253591]
Anomaly at Param_0 with values: [5.03006012 0.         0.91820553 0.83012028 0.95999077 0.06907535
 0.76844704 0.40339249 0.94201008 0.30150631 0.62379339 0.06158776]
Anomaly at Param_0 with values: [5.09018036 0.         0.80914273 0.40070037 0.89137277 0.3880678
 0.71795905 0.04782364 0.06126658 0.01768347 0.90525575 0.27331325]
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Anomaly at Param_0 with values: [5.29058116 0.         0.54959583 0.20705449 0.58719516 0.01919872
 0.1677791  0.06612479 0.93781331 0.67135961 0.24866278 0.05521542]
Anomaly at Param_0 with values: [5.4509018  0.         0.24406604 0.96170892 0.86510806 0.08658127
 0.90440804 0.91871977 0.24571849 0.03919507 0.28944937 0.04775088]
Anomaly at Param_0 with values: [5.47094188 0.         0.2512206  0.42148816 0.78249145 0.07275227
 0.03311627 0.54058417 0.28562132 0.08759216 0.93892483 0.16011693]
Anomaly at Param_0 with values: [5.61122244e+00 0.00000000e+00 3.71947445e-01 8.94167789e-01
 9.91184002e-02 1.40966290e-01 8.26184565e-01 4.46641150e-01
 2.60739432e-01 1.66582119e-03 1.25231663e-01 1.40452212e-01]
Anomaly at Param_0 with values: [5.65130261 0.         0.22865032 0.04002158 0.26453659 0.83495248
 0.232699   0.82039365 0.88055533 0.03409085 0.16973833 0.40889015]
Anomaly at Param_0 with values: [5.75150301 0.         0.01855837 0.05856476 0.40117046 0.50060624
 0.31905041 0.81683372 0.11947173 0.93001638 0.064961   0.94881463]
Anomaly at Param_0 with values: [5.85170341 0.         0.0450972  0.87775659 0.11709784 0.2213405
 0.91968302 0.91032215 0.48989699 0.08987616 0.89448263 0.72478386]
Anomaly at Param_1 with values: [ 5.91182365 11.70552788  0.3094366   0.77420559  0.5281358   0.27740873
  0.17345392  0.48445867  0.98003483  0.64806222  0.65577335  0.41592747]
Anomaly at Param_0 with values: [5.97194389 0.         0.32737508 0.02983673 0.21348584 0.15919411
 0.01431842 0.88963543 0.10429047 0.21541465 0.42326317 0.90317504]
Anomaly at Param_1 with values: [ 5.99198397 19.99832504  0.67532083  0.02027969  0.73577918  0.68394206
  0.42639015  0.89904494  0.70253038  0.84363389  0.91960154  0.26019566]
Anomaly at Param_0 with values: [6.07214429 0.         0.70500672 0.91626177 0.07934282 0.12638447
 0.38958391 0.83153395 0.86616262 0.07654196 0.59911196 0.94101942]
Anomaly at Param_0 with values: [6.09218437 0.         0.83953334 0.06353787 0.2097009  0.50089018
 0.04576661 0.00987267 0.80418987 0.88784358 0.31402152 0.57292191]
Anomaly at Param_0 with values: [6.13226453 0.         0.87380822 0.86626553 0.02667227 0.40493614
 0.89381439 0.30931638 0.76545745 0.85966014 0.9335822  0.58833453]
Anomaly at Param_0 with values: [6.21242485e+00 0.00000000e+00 9.09131853e-01 8.23866162e-01
 9.37427335e-02 8.05035290e-02 8.15223253e-01 6.97296379e-02
 6.19321413e-01 5.67409884e-01 3.67130174e-03 2.33380321e-03]
Anomaly at Param_0 with values: [6.25250501 0.         0.56809174 0.10803385 0.50268576 0.01831163
 0.92189809 0.95951082 0.02809417 0.00822224 0.43622416 0.63768545]
Anomaly at Param_0 with values: [6.59318637 0.         0.2418947  0.66505715 0.71050323 0.95202787
 0.94068842 0.48510618 0.67883792 0.01150518 0.78069886 0.93584575]
Anomaly at Param_0 with values: [7.03406814 0.         0.59148624 0.77707809 0.39233685 0.98684439
 0.76651968 0.01289528 0.07934915 0.06885628 0.16344964 0.39320209]
Anomaly at Param_0 with values: [7.29458918 0.         0.1655582  0.98003085 0.09707072 0.12684037
 0.0598923  0.21742723 0.88121543 0.34790031 0.52470366 0.18373267]
Anomaly at Param_0 with values: [7.33466934 0.         0.68929026 0.83901149 0.64617819 0.27939261
 0.99969435 0.3962788  0.88272928 0.1219625  0.59693823 0.9886487 ]
Anomaly at Param_0 with values: [7.35470942 0.         0.15535446 0.97496584 0.57015705 0.07435128
 0.25263409 0.93648183 0.28495496 0.70060575 0.05298626 0.09363088]
Anomaly at Param_0 with values: [7.45490982 0.         0.70341499 0.98265572 0.91855256 0.29288121
 0.45272987 0.49911384 0.90992763 0.06739647 0.68778543 0.15748879]
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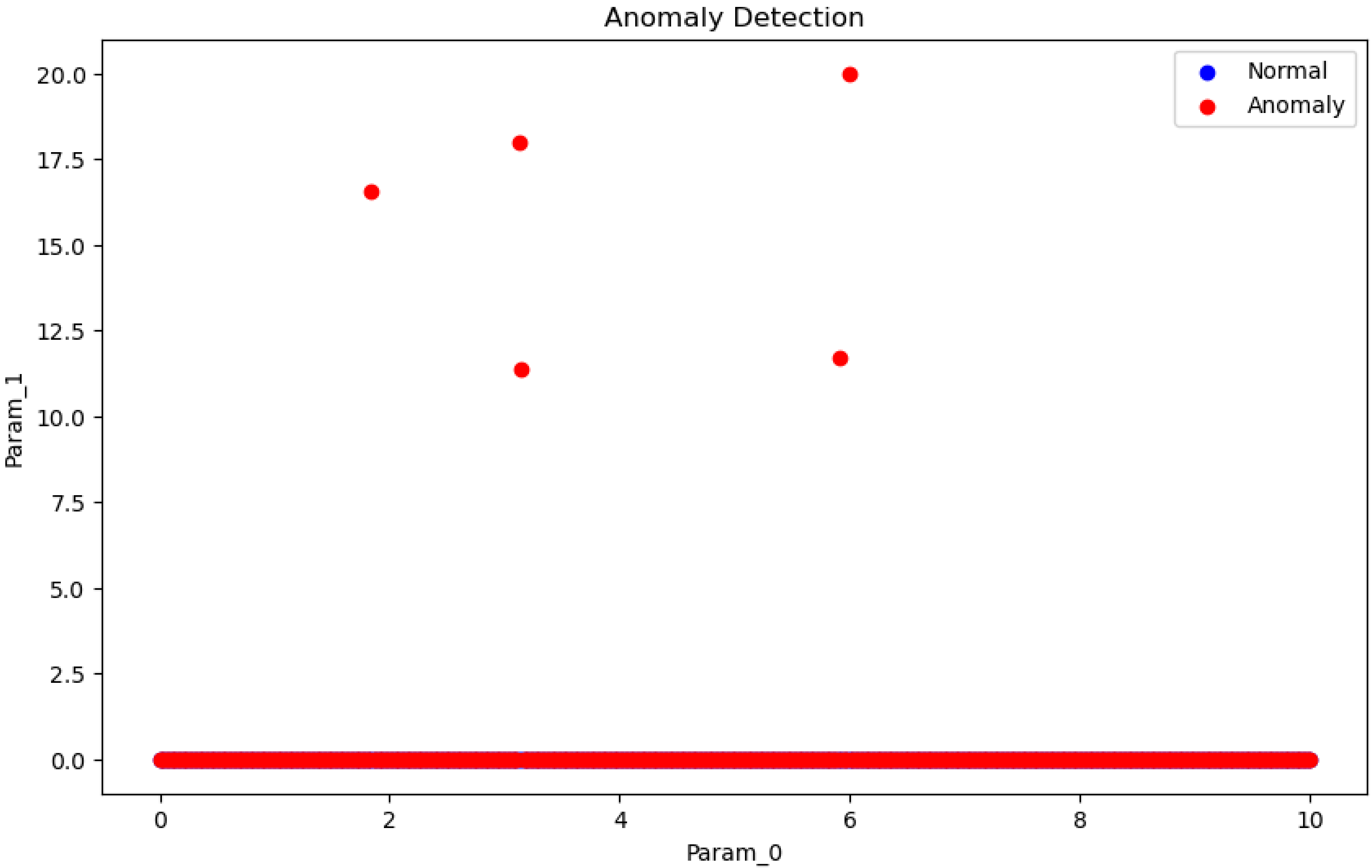
Anomaly at Param_0 with values: [7.51503006 0.         0.51903346 0.13610438 0.50665257 0.91545474
 0.02489525 0.87916255 0.42887698 0.99235754 0.92112091 0.40038081]
Anomaly at Param_0 with values: [7.53507014 0.         0.75461675 0.96122885 0.26123036 0.74518136
 0.46717337 0.22117975 0.9715489  0.16701925 0.26706474 0.60596991]
Anomaly at Param_0 with values: [7.65531062 0.         0.54639147 0.53680057 0.10935491 0.30134229
 0.86282315 0.07820153 0.90787774 0.19490621 0.03971007 0.21386462]
Anomaly at Param_0 with values: [7.93587174 0.         0.87116508 0.66245922 0.11635023 0.5435636
 0.07573855 0.99541899 0.13597671 0.99966373 0.44021033 0.83386469]
Anomaly at Param_0 with values: [8.17635271 0.         0.89021604 0.88306187 0.96356798 0.93807888
 0.93628334 0.78317412 0.58761774 0.89729244 0.77575486 0.89679993]
Anomaly at Param_0 with values: [8.21643287 0.         0.11508331 0.44444569 0.77028386 0.64111141
 0.0122075  0.73378361 0.28737972 0.7293552  0.89888612 0.87445711]
Anomaly at Param_0 with values: [8.25651303e+00 0.00000000e+00 8.58767666e-01 8.04963237e-01
 2.78719967e-01 2.96500410e-01 4.74667042e-01 8.82591441e-01
 8.87889383e-01 6.75114647e-01 6.88451041e-03 7.98815942e-01]
Anomaly at Param_0 with values: [8.73747495 0.         0.97056562 0.19372983 0.85868435 0.34054917
 0.9204561  0.0768529  0.63966188 0.54961758 0.85568594 0.03074284]
Anomaly at Param_0 with values: [8.87775551 0.         0.98808865 0.86667713 0.29148229 0.1121987
 0.45344605 0.72310783 0.29742253 0.16058808 0.1101031  0.14534936]
Anomaly at Param_0 with values: [8.89779559e+00 0.00000000e+00 7.79103178e-01 1.33967160e-01
 7.73124329e-03 9.58411124e-01 1.58487275e-01 3.24568619e-01
 2.94167800e-01 4.71154092e-01 9.98475514e-01 7.67479527e-01]
Anomaly at Param_0 with values: [8.95791583 0.         0.14538791 0.01251    0.42197261 0.35291421
 0.53458195 0.17211998 0.89585751 0.89732668 0.02304213 0.66453354]
Anomaly at Param_0 with values: [9.11823647 0.         0.08360651 0.62229112 0.92766404 0.61802721
 0.87741775 0.42059348 0.6312296  0.05640744 0.93854749 0.65725072]
Anomaly at Param_0 with values: [9.15831663e+00 0.00000000e+00 2.01830919e-01 8.76956521e-03
 1.03184724e-01 2.07174355e-01 8.90444840e-01 7.12685383e-01
 9.78226160e-01 2.72127814e-01 1.95220072e-01 3.32914693e-02]
Anomaly at Param_0 with values: [9.21843687e+00 0.00000000e+00 1.50251631e-01 1.51292846e-02
 9.20223010e-01 6.09665760e-03 5.95848985e-01 9.10628728e-01
 8.27159030e-01 3.20775543e-01 7.08651525e-01 9.80026844e-01]
Anomaly at Param_0 with values: [9.25851703 0.         0.50307576 0.98931237 0.4658508  0.04915241
 0.35364509 0.96873339 0.27802243 0.08897689 0.78574303 0.4774074 ]
Anomaly at Param_0 with values: [9.29859719e+00 0.00000000e+00 2.18093210e-01 9.99629824e-01
 9.95761610e-01 3.87445757e-01 9.83983348e-01 2.64922295e-01
 8.64150360e-03 5.03351222e-01 7.57775750e-01 4.07597587e-01]
Anomaly at Param_0 with values: [9.33867735e+00 0.00000000e+00 4.75545404e-01 8.79527350e-01
 1.53148178e-03 8.57992871e-01 8.13889111e-01 6.62932400e-01
 3.00432025e-01 1.98921004e-01 4.93627096e-02 6.98152004e-01]
Anomaly at Param_0 with values: [9.45891784 0.         0.29145226 0.92319975 0.71089195 0.04101157
 0.81699828 0.25863262 0.96564816 0.97638823 0.92105768 0.82562207]
Anomaly at Param_0 with values: [9.57915832e+00 0.00000000e+00 1.96702788e-01 5.67107902e-01
 6.58301794e-01 8.92260272e-01 9.59272112e-01 3.26334981e-01
```

```
 6.14332785e-01 9.17088428e-01 6.84926695e-01 5.09100615e-03]
Anomaly at Param_0 with values: [9.59919840e+00 0.00000000e+00 1.56054034e-01 6.63907166e-01
 1.90328154e-03 9.17146960e-01 6.38817784e-01 6.76080127e-01
 2.57259655e-01 2.29562249e-02 2.13274443e-01 6.81581467e-01]
Anomaly at Param_0 with values: [9.63927856 0.         0.31006252 0.49432117 0.22190824 0.0721957
 0.39694499 0.01483972 0.5115323  0.1149119  0.10523028 0.68405134]
Anomaly at Param_0 with values: [9.67935872 0.         0.82382436 0.79305212 0.60849468 0.67199576
 0.52452998 0.96745905 0.10275463 0.51151365 0.81548417 0.78117624]
Anomaly at Param_0 with values: [9.73947896 0.         0.22168294 0.9440217  0.27237267 0.07847116
 0.67925519 0.80126948 0.13288115 0.2928424  0.93749304 0.35016965]
Anomaly at Param_0 with values: [9.75951904 0.         0.11712954 0.30047173 0.74122748 0.65962346
 0.16894964 0.92448207 0.05512825 0.69398072 0.90712923 0.9688022 ]
Anomaly at Param_0 with values: [9.81963928 0.         0.2234985  0.25134314 0.23094135 0.07631006
 0.97445188 0.59231925 0.99666733 0.42277107 0.74179767 0.46545706]
Anomaly at Param_0 with values: [9.83967936 0.         0.26171948 0.82808185 0.91751761 0.05237122
 0.95669634 0.63787032 0.47093667 0.54118814 0.70417162 0.9498704 ]
Anomaly at Param_0 with values: [9.87975952 0.         0.39979715 0.92432156 0.33143104 0.77836065
 0.3483057  0.66193205 0.94893066 0.35778607 0.87562985 0.93804353]
Anomaly at Param_0 with values: [9.8997996  0.         0.02189637 0.09717738 0.01860148 0.81747444
 0.5030038  0.49858157 0.90906289 0.20909593 0.07345623 0.21940409]
Anomaly at Param_0 with values: [9.93987976 0.         0.63868097 0.41695299 0.11042683 0.91064561
 0.56527129 0.98249965 0.66716441 0.36240382 0.57307492 0.98718184]
Anomaly at Param_0 with values: [10.          0.          0.70591218  0.98224816  0.06498602  0.49821343
  0.67636051  0.6169243   0.82562676  0.53124467  0.67844395  0.09152391]
```



In [10]:
```
import pandas as pd
import numpy as np
from sklearn.ensemble import IsolationForest
from sklearn.preprocessing import StandardScaler
import matplotlib.pyplot as plt

# Generate synthetic linear input data with anomalies as peaks
def generate_synthetic_data(num_samples=1000, num_features=2, num_anomalies=5):
    # Generate normal data along a straight line
```

```
    normal_data = np.zeros((num_samples // 2, num_features))
    normal_data[:, 0] = np.linspace(0, 10, num_samples // 2)
    # Generate anomalous data with peaks
    peak_indices = np.random.choice(np.arange(10, num_samples // 2 - 10), num_anomalies, replace=False)
    anomalous_data = normal_data.copy()
    for idx in peak_indices:
        peak_height = np.random.uniform(10, 20)
        anomalous_data[idx, 1] = peak_height  # Introduce peaks
    # Combine normal and anomalous data
    input_data = np.vstack([normal_data, anomalous_data])
    # Create DataFrame
    input_df = pd.DataFrame(input_data, columns=[f"Param_{i}" for i in range(num_features)])
    return input_df

# Combine input and output data
def combine_data(input_data, output_data):
    combined_data = pd.concat([input_data, output_data], axis=1)
    return combined_data

# Add labels for normal (0) and anomalous (1) instances (for demonstration purposes)
def add_labels(combined_data):
    labels = np.zeros(combined_data.shape[0])
    labels[combined_data.index >= len(combined_data) // 2] = 1
    combined_data['Label'] = labels
    return combined_data

# Train Anomaly Detection Model
def train_anomaly_detection_model(X):
    scaler = StandardScaler()
    X_scaled = scaler.fit_transform(X)
    model = IsolationForest(contamination=0.05)  # Adjusting contamination parameter
    model.fit(X_scaled)
    return model, scaler

# Detect Anomalies
def detect_anomalies(model, scaler, X):
    X_scaled = scaler.transform(X)
    anomaly_scores = model.decision_function(X_scaled)
    anomalies = X[anomaly_scores < 0]
    return anomalies, anomaly_scores

# Attribute Anomalies to Input Parameters
def attribute_anomalies_to_input_params(anomalies, num_features):
    param_cols = [f"Param_{i}" for i in range(num_features)]
```

```
    anomalous_params = []
    for index, row in anomalies.iterrows():
        peak_param = param_cols[np.argmax(row.values)]
        anomalous_params.append(peak_param)
    return anomalous_params

# Main function
def main():
    # Generate synthetic data
    num_anomalies = 5  # Number of anomalies (peaks)
    input_data = generate_synthetic_data(num_anomalies=num_anomalies)
    output_data = generate_synthetic_output_data()
    combined_data = combine_data(input_data, output_data)
    combined_data = add_labels(combined_data)

    # Separate features (input parameters) and labels (normal/anomalous)
    X = combined_data.drop(columns=['Label'])
    y = combined_data['Label']

    # Train the Isolation Forest model
    model, scaler = train_anomaly_detection_model(X)

    # Detect anomalies
    anomalies, anomaly_scores = detect_anomalies(model, scaler, X)

    # Attribute anomalies to input parameters
    anomalous_params = attribute_anomalies_to_input_params(anomalies, X.shape[1])

    # Print detected anomalies and associated input parameters
    print("Detected Anomalies and Associated Input Parameters:")
    for anomaly, param in zip(anomalies.values, anomalous_params):
        print(f"Anomaly at {param} with values: {anomaly}")

    # Plot the data
    plt.figure(figsize=(10, 6))
    plt.scatter(X.iloc[:500, 0], X.iloc[:500, 1], c='blue', label='Normal')
    plt.scatter(X.iloc[500:, 0], X.iloc[500:, 1], c='red', label='Anomaly')
    plt.title('Anomaly Detection')
    plt.xlabel('Param_0')
    plt.ylabel('Param_1')
    plt.legend()
    plt.show()
```

```
if __name__ == "__main__":
    main()
```

```
Detected Anomalies and Associated Input Parameters:
Anomaly at Param_11 with values: [0.08016032 0.         0.24533028 0.01371245 0.10461545 0.38214508
 0.26069717 0.33266187 0.26009608 0.99300222 0.93585304 0.99502947]
Anomaly at Param_6 with values: [0.2004008  0.         0.10692244 0.90183682 0.52495503 0.74853319
 0.95363414 0.11718789 0.769375   0.08658057 0.87677584 0.47497353]
Anomaly at Param_7 with values: [0.36072144 0.         0.12936808 0.01201644 0.90258305 0.98702518
 0.73564935 0.99935081 0.09741268 0.52738777 0.54049758 0.41177667]
Anomaly at Param_10 with values: [0.4008016  0.         0.92014997 0.72089045 0.99558813 0.85642871
 0.03663851 0.64836888 0.77694051 0.20644792 0.99949117 0.09861882]
Anomaly at Param_5 with values: [0.70140281 0.         0.86631132 0.85290488 0.81639081 0.9522071
 0.69226405 0.94879198 0.63397241 0.71276207 0.83071722 0.07154633]
Anomaly at Param_0 with values: [1.58316633 0.         0.80869085 0.88861827 0.13212903 0.91479392
 0.134821   0.09696469 0.94291151 0.28995064 0.00271907 0.35750532]
Anomaly at Param_0 with values: [1.88376754 0.         0.92028529 0.23813486 0.03370704 0.2288335
 0.96538595 0.03180056 0.17416567 0.76372666 0.21033785 0.05761298]
Anomaly at Param_0 with values: [2.68537074 0.         0.95086383 0.02455845 0.9999432  0.11451739
 0.71717648 0.93058581 0.37054487 0.12869688 0.69640118 0.9044396 ]
Anomaly at Param_0 with values: [3.10621242 0.         0.87536045 0.67623199 0.26288173 0.51915976
 0.99401377 0.79058763 0.03384564 0.91702179 0.93846994 0.09363305]
Anomaly at Param_0 with values: [6.05210421 0.         0.97768818 0.96472012 0.75481156 0.12561322
 0.99198105 0.01885476 0.76004561 0.58521642 0.94168744 0.91869154]
Anomaly at Param_0 with values: [6.9739479  0.         0.859499   0.5795378  0.93732711 0.0442025
 0.44351106 0.87777275 0.16099139 0.97058456 0.02600827 0.10162245]
Anomaly at Param_0 with values: [7.43486974e+00 0.00000000e+00 8.19857529e-01 1.70105301e-01
 5.89215141e-01 3.65930299e-03 9.70538967e-01 9.60883895e-01
 9.81881515e-01 9.92613155e-01 6.90948919e-01 2.67023123e-01]
Anomaly at Param_0 with values: [8.0761523  0.         0.86165679 0.83715988 0.43851575 0.13536663
 0.94515896 0.94632166 0.96781518 0.04046981 0.75750922 0.12194528]
Anomaly at Param_0 with values: [8.59719439 0.         0.62182939 0.38412721 0.14921959 0.19360581
 0.09102836 0.8589497  0.30961998 0.02332029 0.97114371 0.96481152]
Anomaly at Param_0 with values: [8.79759519 0.         0.02842827 0.19238855 0.97780115 0.68326232
 0.95497517 0.64164748 0.72216765 0.05093098 0.01465526 0.84123874]
Anomaly at Param_0 with values: [8.91783567 0.         0.93296933 0.53964196 0.96874122 0.11022433
 0.18357359 0.02103922 0.0280314  0.45683149 0.91104449 0.3232783 ]
Anomaly at Param_0 with values: [9.25851703 0.         0.58986951 0.95283541 0.16834718 0.55789914
 0.65844615 0.41092997 0.18515798 0.08083218 0.99584941 0.08164421]
Anomaly at Param_0 with values: [9.35871743 0.         0.89865355 0.04843248 0.0245642  0.70847338
 0.98939375 0.35796068 0.28818327 0.0485864  0.47482147 0.11800672]
Anomaly at Param_0 with values: [9.61923848e+00 0.00000000e+00 5.89977177e-01 8.39488536e-03
 9.58841842e-01 2.92486936e-01 5.14638354e-01 3.35196051e-02
 1.58366049e-01 9.08153400e-01 4.31777275e-01 9.97872707e-01]
Anomaly at Param_0 with values: [9.67935872e+00 0.00000000e+00 9.21547269e-01 1.25489596e-01
 9.21807810e-01 9.68852482e-04 1.87325052e-01 9.41875704e-01
 9.50383795e-01 7.82365719e-01 9.62381003e-02 7.29709969e-01]
```

```
Anomaly at Param_0 with values: [9.85971944 0.         0.86978291 0.86905421 0.85826519 0.82741238
 0.85662141 0.02960683 0.89714668 0.42834532 0.49177806 0.05056753]
Anomaly at Param_0 with values: [9.87975952e+00 0.00000000e+00 9.76441992e-01 2.35099747e-01
 7.48214449e-03 5.74365250e-01 6.83247022e-02 5.10629113e-01
 8.63230661e-01 9.18386958e-01 9.88940603e-01 5.90808317e-01]
Anomaly at Param_3 with values: [0.06012024 0.         0.06405814 0.91080659 0.52869904 0.04161664
 0.02180646 0.02190782 0.16807674 0.67985554 0.6961425  0.84747906]
Anomaly at Param_10 with values: [0.22044088 0.         0.93469066 0.74673286 0.75306622 0.68725458
 0.36044868 0.69254511 0.69042312 0.02494434 0.9507538  0.04846967]
Anomaly at Param_11 with values: [0.26052104 0.         0.02531576 0.01204523 0.40545651 0.83313218
 0.16049782 0.14047196 0.0464434  0.07536497 0.59670352 0.83822336]
Anomaly at Param_4 with values: [0.28056112 0.         0.73732321 0.32601451 0.96331059 0.53599356
 0.16064647 0.83599844 0.00908006 0.01055674 0.90117841 0.37426361]
Anomaly at Param_6 with values: [0.48096192 0.         0.88825062 0.79299286 0.40424017 0.09849248
 0.9689783  0.01615614 0.12643148 0.06034959 0.03253054 0.25199259]
Anomaly at Param_3 with values: [0.54108216 0.         0.0386455  0.96524607 0.00510505 0.45533427
 0.02096321 0.40038227 0.81548829 0.45062307 0.89877613 0.1956174 ]
Anomaly at Param_1 with values: [1.08216433e+00 1.20485151e+01 8.03820648e-01 2.58883587e-01
 1.08424837e-01 5.68268054e-01 7.78397249e-01 3.22599325e-01
 9.11766709e-02 1.07560572e-01 8.48448259e-03 3.21018337e-01]
Anomaly at Param_0 with values: [1.20240481 0.         0.08287325 0.10033701 0.87928823 0.93103765
 0.90365026 0.84458306 0.17977345 0.69709383 0.98062367 0.94877644]
Anomaly at Param_0 with values: [1.26252505 0.         0.98912024 0.04252951 0.93520104 0.10992825
 0.33448068 0.21934125 0.89764438 0.19702749 0.09918067 0.29884597]
Anomaly at Param_0 with values: [1.38276553 0.         0.34937357 0.18117111 0.97617047 0.4129037
 0.61845199 0.91468844 0.37860248 0.9557514  0.88458704 0.14562664]
Anomaly at Param_0 with values: [2.24448898 0.         0.90895432 0.16874367 0.17795622 0.84098616
 0.18966605 0.96146584 0.98229489 0.2809736  0.94067334 0.09620977]
Anomaly at Param_1 with values: [ 2.6252505  19.10660052  0.27404541  0.42371559  0.09535465  0.64891086
  0.97328768  0.2189145   0.83661229  0.20165703  0.75796817  0.9858643 ]
Anomaly at Param_0 with values: [2.88577154 0.         0.16268806 0.91067463 0.37696733 0.12876196
 0.858482   0.30880406 0.04195197 0.06723729 0.05603414 0.0343913 ]
Anomaly at Param_0 with values: [3.56713427 0.         0.94128828 0.80140777 0.97474989 0.77621041
 0.96571354 0.90800455 0.21388723 0.31287855 0.33392304 0.85561856]
Anomaly at Param_1 with values: [ 6.19238477 10.05787363  0.38779329  0.32303527  0.23244686  0.51754889
  0.11936399  0.87864659  0.3882584   0.98137778  0.97613584  0.16239942]
Anomaly at Param_0 with values: [6.85370741 0.         0.80945683 0.54324733 0.92056743 0.97674773
 0.9797103  0.0744368  0.48403966 0.81522203 0.011286   0.03162212]
Anomaly at Param_0 with values: [7.09418838e+00 0.00000000e+00 9.99216566e-01 5.64471896e-01
 6.66551920e-03 6.32426840e-01 9.53181343e-01 1.48789987e-01
 1.28703448e-01 9.47863871e-01 1.35663607e-01 6.33605794e-01]
Anomaly at Param_0 with values: [7.89579158 0.         0.9460955  0.7537428  0.01461075 0.81131358
 0.2522072  0.99789179 0.14117285 0.61127715 0.34048991 0.98140271]
Anomaly at Param_0 with values: [8.59719439e+00 0.00000000e+00 3.00042806e-03 1.77296668e-01
```

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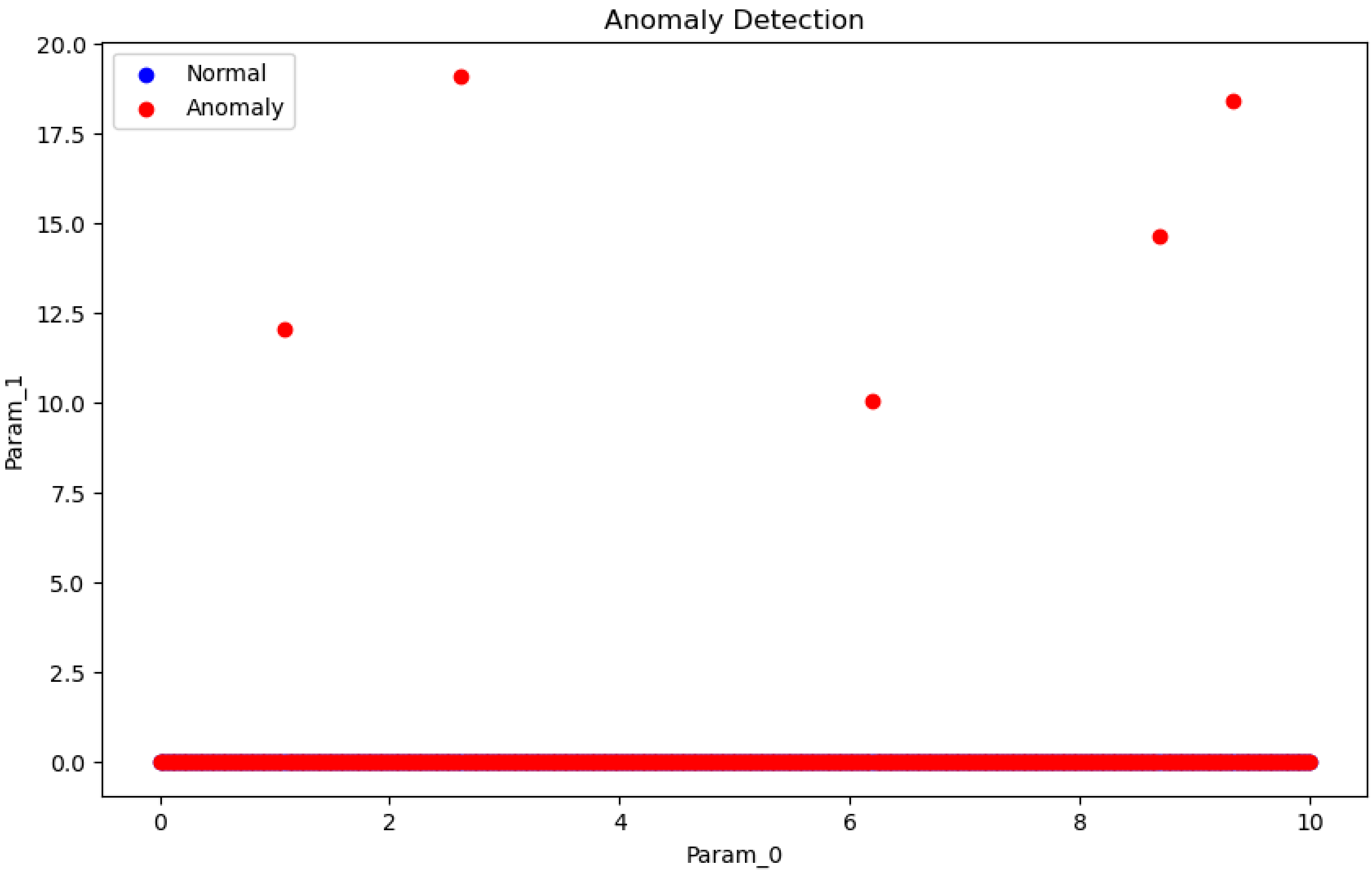
 8.31141424e-01 3.16970742e-01 6.60407787e-01 9.81293139e-01
 8.55534307e-01 1.82133626e-01 5.17650447e-01 7.29063017e-01]
Anomaly at Param_1 with values: [ 8.69739479 14.62383097  0.54352758  0.90013186  0.86025222  0.0990981
  0.4108271   0.161535    0.10707867  0.128995    0.03099744  0.19523184]
Anomaly at Param_0 with values: [8.95791583 0.         0.21415706 0.68555115 0.32553061 0.64089828
 0.06103848 0.99442245 0.04581869 0.0367387  0.15488082 0.97522151]
Anomaly at Param_0 with values: [9.15831663e+00 0.00000000e+00 2.79499330e-01 7.00458783e-01
 9.12753139e-01 3.65176858e-02 6.57068126e-01 8.59462900e-02
 2.52943756e-03 6.97543138e-01 1.37121306e-02 9.83220872e-01]
Anomaly at Param_0 with values: [9.37875752 0.         0.22701713 0.57693263 0.43228641 0.54567518
 0.22207517 0.41242704 0.96645591 0.05996369 0.95807846 0.04083107]
Anomaly at Param_0 with values: [9.57915832e+00 0.00000000e+00 4.53619981e-03 1.19433496e-01
 5.32423950e-01 8.37131732e-01 4.21543302e-03 3.42822285e-01
 8.31993670e-01 1.49804214e-01 4.01070629e-01 9.88703303e-01]
Anomaly at Param_0 with values: [9.5991984  0.         0.35910981 0.87682143 0.92095805 0.99781107
 0.37917054 0.95922324 0.50937444 0.68156195 0.90341826 0.62423783]
Anomaly at Param_0 with values: [9.71943888e+00 0.00000000e+00 7.91826934e-02 2.41512934e-01
 9.55380943e-03 3.79998839e-02 4.53250086e-01 3.67196617e-02
 9.38367436e-01 1.24951971e-01 5.28843964e-01 8.85459996e-01]
Anomaly at Param_0 with values: [9.83967936 0.         0.43465098 0.41685886 0.01823758 0.90799376
 0.40566423 0.96340631 0.15582784 0.64727704 0.96698064 0.29046798]
Anomaly at Param_0 with values: [9.93987976 0.         0.29492602 0.1067786  0.91912252 0.24410458
 0.99475002 0.06978878 0.54984586 0.23734527 0.96056842 0.19128947]
```



In [11]:
```
import pandas as pd
import numpy as np
from sklearn.ensemble import IsolationForest
from sklearn.preprocessing import StandardScaler
import matplotlib.pyplot as plt

# Generate synthetic linear input data with anomalies as peaks
def generate_synthetic_data(num_samples=1000, num_features=2, num_anomalies=2):
    # Generate normal data along a straight line
```

```
    normal_data = np.zeros((num_samples // 2, num_features))
    normal_data[:, 0] = np.linspace(0, 10, num_samples // 2)
    # Generate anomalous data with peaks
    peak_indices = np.random.choice(np.arange(10, num_samples // 2 - 10), num_anomalies, replace=False)
    anomalous_data = normal_data.copy()
    for idx in peak_indices:
        peak_height = np.random.uniform(10, 20)
        anomalous_data[idx, 1] = peak_height  # Introduce peaks
    # Combine normal and anomalous data
    input_data = np.vstack([normal_data, anomalous_data])
    # Create DataFrame
    input_df = pd.DataFrame(input_data, columns=[f"Param_{i}" for i in range(num_features)])
    return input_df

# Combine input and output data
def combine_data(input_data, output_data):
    combined_data = pd.concat([input_data, output_data], axis=1)
    return combined_data

# Add labels for normal (0) and anomalous (1) instances (for demonstration purposes)
def add_labels(combined_data):
    labels = np.zeros(combined_data.shape[0])
    labels[combined_data.index >= len(combined_data) // 2] = 1
    combined_data['Label'] = labels
    return combined_data

# Train Anomaly Detection Model
def train_anomaly_detection_model(X):
    scaler = StandardScaler()
    X_scaled = scaler.fit_transform(X)
    model = IsolationForest(contamination=0.05)  # Adjusting contamination parameter
    model.fit(X_scaled)
    return model, scaler

# Detect Anomalies
def detect_anomalies(model, scaler, X):
    X_scaled = scaler.transform(X)
    anomaly_scores = model.decision_function(X_scaled)
    anomalies = X[anomaly_scores < 0]
    return anomalies, anomaly_scores

# Attribute Anomalies to Input Parameters
def attribute_anomalies_to_input_params(anomalies, num_features):
    param_cols = [f"Param_{i}" for i in range(num_features)]
```

```
    anomalous_params = []
    for index, row in anomalies.iterrows():
        peak_param = param_cols[np.argmax(row.values)]
        anomalous_params.append(peak_param)
    return anomalous_params

# Main function
def main():
    # Generate synthetic data
    num_anomalies = 2  # Number of anomalies (peaks)
    input_data = generate_synthetic_data(num_anomalies=num_anomalies)
    output_data = generate_synthetic_output_data()
    combined_data = combine_data(input_data, output_data)
    combined_data = add_labels(combined_data)

    # Separate features (input parameters) and labels (normal/anomalous)
    X = combined_data.drop(columns=['Label'])
    y = combined_data['Label']

    # Train the Isolation Forest model
    model, scaler = train_anomaly_detection_model(X)

    # Detect anomalies
    anomalies, anomaly_scores = detect_anomalies(model, scaler, X)

    # Attribute anomalies to input parameters
    anomalous_params = attribute_anomalies_to_input_params(anomalies, X.shape[1])

    # Print detected anomalies and associated input parameters
    print("Detected Anomalies and Associated Input Parameters:")
    for anomaly, param in zip(anomalies.values, anomalous_params):
        print(f"Anomaly at {param} with values: {anomaly}")

    # Plot the data
    plt.figure(figsize=(10, 6))
    plt.scatter(X.iloc[:500, 0], X.iloc[:500, 1], c='blue', label='Normal')
    plt.scatter(X.iloc[500:, 0], X.iloc[500:, 1], c='red', label='Anomaly')
    plt.title('Anomaly Detection')
    plt.xlabel('Param_0')
    plt.ylabel('Param_1')
    plt.legend()

    # Highlight anomalies
    for idx, (x, y) in enumerate(anomalies.values):
```

```
        plt.text(x, y, f'Anomaly {idx + 1}', fontsize=10, color='black', ha='center', va='bottom')

    plt.show()

if __name__ == "__main__":
    main()
```

```
Detected Anomalies and Associated Input Parameters:
Anomaly at Param_7 with values: [0.         0.         0.1258592  0.48566718 0.50426056 0.13195439
 0.31759915 0.99781182 0.82330069 0.84365967 0.06440306 0.17920679]
Anomaly at Param_6 with values: [0.42084168 0.         0.03150008 0.46896658 0.62434219 0.17303498
 0.98835703 0.30460749 0.1245096  0.01524144 0.36846873 0.15269691]
Anomaly at Param_9 with values: [0.74148297 0.         0.31761901 0.76474006 0.87973039 0.48154747
 0.03429154 0.10507266 0.07756108 0.93008292 0.21458753 0.04324451]
Anomaly at Param_11 with values: [0.88176353 0.         0.86165108 0.24201512 0.61459291 0.00877277
 0.18243698 0.86896314 0.15679643 0.78693731 0.07589981 0.90943055]
Anomaly at Param_0 with values: [2.70541082 0.         0.9109371  0.69227682 0.02158502 0.01865652
 0.11020885 0.41707361 0.96764514 0.16654567 0.72442359 0.08083575]
Anomaly at Param_0 with values: [2.84569138e+00 0.00000000e+00 7.74750701e-01 1.68744950e-01
 1.72995395e-01 2.38048090e-03 9.66531431e-01 1.26662533e-01
 6.73693145e-02 7.83246919e-01 7.54327426e-02 9.95339443e-01]
Anomaly at Param_0 with values: [3.08617234 0.         0.01482426 0.97703392 0.4616035  0.74174326
 0.10164756 0.88042928 0.58675626 0.10376635 0.08303048 0.83233024]
Anomaly at Param_0 with values: [3.60721443 0.         0.27292993 0.01281695 0.97815891 0.96162554
 0.64407905 0.91632604 0.99964637 0.29111607 0.91312913 0.23810899]
Anomaly at Param_0 with values: [3.80761523 0.         0.00576358 0.02241889 0.04991287 0.42891032
 0.79936546 0.86582717 0.99408036 0.49640447 0.93433671 0.10170438]
Anomaly at Param_0 with values: [3.86773547 0.         0.29516357 0.86546482 0.89235273 0.02622882
 0.15061716 0.79245436 0.82451955 0.14949785 0.81843761 0.90488402]
Anomaly at Param_0 with values: [4.34869739 0.         0.99495234 0.0654372  0.93224901 0.44417977
 0.20557789 0.69225501 0.92954954 0.72000611 0.6869922  0.98890021]
Anomaly at Param_0 with values: [5.85170341e+00 0.00000000e+00 1.73362811e-01 1.79369733e-03
 1.02145211e-01 9.45521703e-01 8.18567263e-02 2.65488148e-05
 3.89910427e-01 5.86732632e-01 8.23889575e-01 4.02773297e-02]
Anomaly at Param_0 with values: [5.97194389 0.         0.75541184 0.92743032 0.7887738  0.92979814
 0.0497657  0.62088048 0.84646469 0.92627902 0.84258008 0.84195137]
Anomaly at Param_0 with values: [6.07214429e+00 0.00000000e+00 6.68908069e-02 9.04133343e-01
 3.03730973e-01 1.87257880e-01 8.08019464e-01 2.33005551e-03
 9.86092386e-01 9.66035286e-01 2.84407320e-01 9.36044898e-01]
Anomaly at Param_0 with values: [6.11222445e+00 0.00000000e+00 1.90154639e-01 9.83853698e-01
 1.53841510e-01 8.51983025e-01 1.76547078e-01 8.91479292e-01
 2.75744700e-01 2.84417426e-03 9.96128130e-01 7.23262947e-01]
Anomaly at Param_0 with values: [6.39278557e+00 0.00000000e+00 9.37304313e-01 1.30976671e-01
 2.82702256e-01 7.29505880e-02 9.35072777e-01 9.00492005e-01
 2.37515497e-01 1.16778868e-02 4.22261049e-03 7.44715389e-01]
Anomaly at Param_0 with values: [6.61322645 0.         0.09042715 0.8583583  0.68717209 0.91838605
 0.05367367 0.26634074 0.0748063  0.8664719  0.84839915 0.95277705]
Anomaly at Param_0 with values: [7.41482966 0.         0.02037809 0.02061254 0.97698553 0.3903203
 0.24415402 0.97684749 0.28681473 0.06122663 0.24400916 0.29961474]
Anomaly at Param_0 with values: [7.43486974 0.         0.78539885 0.90959697 0.99309821 0.34249141
 0.0465877  0.29348377 0.68674915 0.11633775 0.08292631 0.53763275]
```

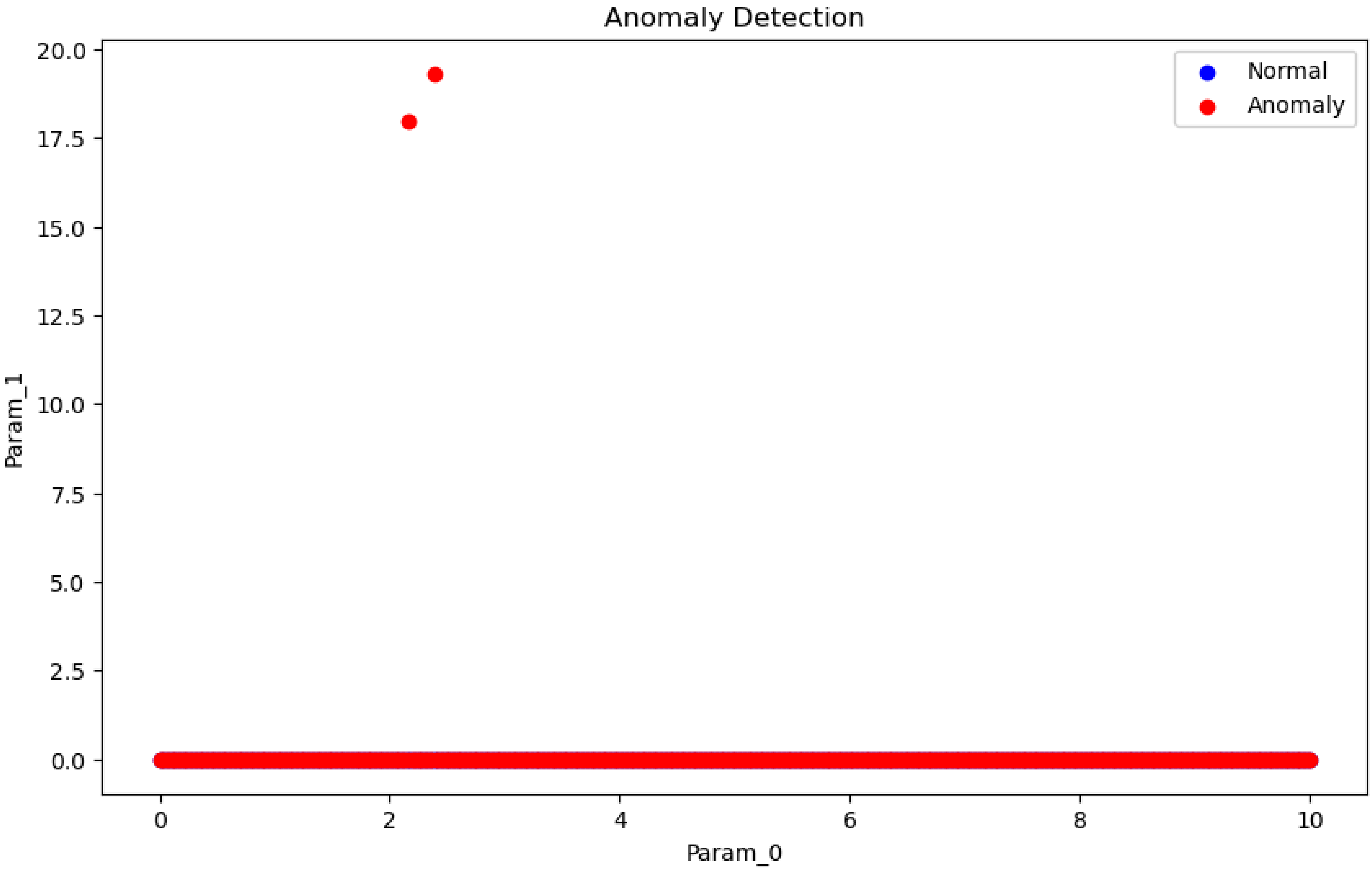
```
Anomaly at Param_0 with values: [8.65731463 0.         0.31570728 0.83792475 0.49948112 0.84177461
 0.07666738 0.28974212 0.94365526 0.93749529 0.16519736 0.03107739]
Anomaly at Param_0 with values: [8.69739479 0.         0.61734723 0.95469008 0.12054568 0.69902225
 0.11559194 0.12424693 0.04143101 0.89143482 0.85986182 0.98480348]
Anomaly at Param_0 with values: [9.15831663 0.         0.19062716 0.98723014 0.78287998 0.99320028
 0.45008132 0.89999403 0.15746721 0.03347335 0.9408716  0.23772578]
Anomaly at Param_0 with values: [9.21843687 0.         0.6496555  0.76051756 0.64309772 0.12575221
 0.25540536 0.06614983 0.94266172 0.55855476 0.97678617 0.0655637 ]
Anomaly at Param_0 with values: [9.8997996  0.         0.92933603 0.72498969 0.09138654 0.62151842
 0.93580925 0.9958231  0.82830464 0.89526035 0.10546791 0.501452  ]
Anomaly at Param_11 with values: [0.04008016 0.         0.0293255  0.44526153 0.16642118 0.42052078
 0.05314618 0.77825449 0.02792296 0.41875375 0.84862798 0.99230301]
Anomaly at Param_4 with values: [0.2004008  0.         0.4901242  0.46987665 0.93605194 0.01268526
 0.89762143 0.82770201 0.87389413 0.85575381 0.39178348 0.04406148]
Anomaly at Param_11 with values: [0.4008016  0.         0.73300305 0.93761562 0.65003945 0.56693633
 0.09622278 0.75482602 0.08084162 0.84912797 0.26952994 0.99066259]
Anomaly at Param_5 with values: [0.58116232 0.         0.06068647 0.59017371 0.97508662 0.99826312
 0.07597485 0.38190058 0.11216115 0.61135612 0.12311857 0.46797807]
Anomaly at Param_3 with values: [0.74148297 0.         0.38940522 0.95938817 0.16654627 0.46716543
 0.02905432 0.45281133 0.00411293 0.11685271 0.8907284  0.94995193]
Anomaly at Param_10 with values: [0.90180361 0.         0.83497609 0.41071238 0.3014162  0.49550398
 0.88974054 0.04171528 0.00134542 0.01854056 0.98043189 0.47012696]
Anomaly at Param_0 with values: [1.10220441 0.         0.99458925 0.17052696 0.0478891  0.00304543
 0.08874085 0.08991836 0.4769019  0.95057009 0.67094955 0.94252509]
Anomaly at Param_0 with values: [1.86372745 0.         0.03207729 0.90865681 0.89338777 0.18320906
 0.24398278 0.76739386 0.43880997 0.93039336 0.81048792 0.09637637]
Anomaly at Param_0 with values: [2.24448898 0.         0.83322144 0.15034186 0.54067423 0.84465607
 0.95500319 0.01883461 0.85648485 0.10648738 0.20823727 0.94747379]
Anomaly at Param_1 with values: [ 2.38476954 19.31702353  0.02945374  0.40961698  0.7168528   0.86690512
  0.93049984  0.94426066  0.2805925   0.98212992  0.57787141  0.21001649]
Anomaly at Param_0 with values: [3.20641283 0.         0.10522181 0.67167526 0.95683197 0.27500248
 0.30240752 0.3924228  0.97980834 0.80895258 0.98831944 0.54850607]
Anomaly at Param_0 with values: [4.04809619 0.         0.64853438 0.98158828 0.84464139 0.06923779
 0.03892665 0.19767926 0.86437601 0.78534983 0.08222648 0.08144853]
Anomaly at Param_0 with values: [5.43086172 0.         0.17536505 0.86833344 0.67501903 0.36941486
 0.04891491 0.15106942 0.98573083 0.13413019 0.25385153 0.98236928]
Anomaly at Param_0 with values: [5.63126253e+00 0.00000000e+00 9.64381900e-01 9.41417219e-01
 9.83077924e-01 8.58601032e-01 2.88364139e-01 5.82181907e-01
 6.04436280e-01 9.74156372e-01 5.60939877e-03 5.36629762e-01]
Anomaly at Param_0 with values: [5.67134269 0.         0.18014748 0.98729595 0.98308126 0.86886906
 0.77740355 0.95170465 0.10557335 0.01378884 0.6264424  0.21594994]
Anomaly at Param_0 with values: [7.11422846e+00 0.00000000e+00 1.07804663e-02 9.02094464e-01
 3.00372874e-01 7.79016707e-01 1.14683194e-04 4.39273459e-01
 9.68393674e-01 2.62948607e-01 8.43223143e-01 1.52430859e-01]
```

```
Anomaly at Param_0 with values: [7.15430862 0.         0.59360667 0.91062646 0.56395731 0.80855853
 0.17770666 0.89490683 0.90504664 0.91927855 0.96938447 0.94993177]
Anomaly at Param_0 with values: [7.55511022 0.         0.05332852 0.87763815 0.79261571 0.09490998
 0.62277476 0.94392021 0.50276788 0.24122696 0.9578635  0.11302275]
Anomaly at Param_0 with values: [7.6753507  0.         0.11624599 0.57950134 0.21698428 0.18142143
 0.72075411 0.44805149 0.99631703 0.94292511 0.77263658 0.025231  ]
Anomaly at Param_0 with values: [8.81763527 0.         0.93615019 0.20493607 0.72588923 0.81358683
 0.04399931 0.78843494 0.87787688 0.91017424 0.1911802  0.07923977]
Anomaly at Param_0 with values: [9.13827655 0.         0.11110182 0.82939654 0.1561256  0.86810315
 0.19730932 0.96434815 0.00942706 0.84665901 0.91850922 0.3347108 ]
Anomaly at Param_0 with values: [9.19839679 0.         0.73771035 0.99340032 0.39483119 0.69610671
 0.86535451 0.09578601 0.86540325 0.06466088 0.01899436 0.0464077 ]
Anomaly at Param_0 with values: [9.35871743 0.         0.96973347 0.46687147 0.95531763 0.66961535
 0.02551287 0.11118916 0.22937273 0.82863835 0.84764208 0.0520206 ]
Anomaly at Param_0 with values: [9.37875752 0.         0.76960541 0.91458619 0.93399992 0.40674295
 0.03477361 0.129239   0.66180327 0.33802515 0.13111077 0.76498825]
Anomaly at Param_0 with values: [9.43887776 0.         0.9586177  0.16183942 0.46680568 0.01837958
 0.36559294 0.01789449 0.95044901 0.95071226 0.25911225 0.28669745]
Anomaly at Param_0 with values: [9.71943888 0.         0.78297653 0.31497596 0.8547793  0.25400252
 0.63284794 0.04145888 0.33642025 0.96429191 0.06974142 0.15622566]
```

```
---------------------------------------------------------------------------
ValueError                                Traceback (most recent call last)
Cell In[11], line 103
    100     plt.show()
    102 if __name__ == "__main__":
--> 103     main()

Cell In[11], line 97, in main()
     94 plt.legend()
     96 # Highlight anomalies
---> 97 for idx, (x, y) in enumerate(anomalies.values):
     98     plt.text(x, y, f'Anomaly {idx + 1}', fontsize=10, color='black', ha='center', va='bottom')
    100 plt.show()

ValueError: too many values to unpack (expected 2)
```



In [12]:
```
import pandas as pd
from sklearn.ensemble import IsolationForest
from sklearn.preprocessing import StandardScaler
import matplotlib.pyplot as plt

# Function to read .inp files
def read_inp_file(file_path):
    # Read .inp file into DataFrame
    data = pd.read_csv(file_path, delimiter=' ', header=None)  # Assuming space-separated values
```

```
    return data

# Function to preprocess data
def preprocess_data(data):
    # Implement data preprocessing steps as needed
    # For demonstration, let's assume we are dropping any rows with missing values
    data.dropna(inplace=True)
    return data

# Combine input and output data
def combine_data(input_data, output_data):
    combined_data = pd.concat([input_data, output_data], axis=1)
    return combined_data

# Train Anomaly Detection Model
def train_anomaly_detection_model(X):
    scaler = StandardScaler()
    X_scaled = scaler.fit_transform(X)
    model = IsolationForest(contamination=0.05)  # Adjusting contamination parameter
    model.fit(X_scaled)
    return model, scaler

# Detect Anomalies
def detect_anomalies(model, scaler, X):
    X_scaled = scaler.transform(X)
    anomaly_scores = model.decision_function(X_scaled)
    anomalies = X[anomaly_scores < 0]
    return anomalies, anomaly_scores

# Main function
def main():
    # Read input test case file (.inp)
    input_test_case_file = read_inp_file("input_test_case_file.inp")

    # Read reference file (if available)
    reference_file = read_inp_file("reference_file.inp")

    # Preprocess data
    input_data = preprocess_data(input_test_case_file)
    reference_data = preprocess_data(reference_file) if reference_file is not None else None

    # Combine data
    combined_data = input_data if reference_data is None else combine_data(input_data, reference_data)
```

```
    # Separate features (input parameters) and labels (output data, if available)
    X = combined_data.drop(columns=['Label']) if 'Label' in combined_data.columns else combined_data

    # Train the Isolation Forest model
    model, scaler = train_anomaly_detection_model(X)

    # Detect anomalies
    anomalies, anomaly_scores = detect_anomalies(model, scaler, X)

    # Visualize results
    plt.scatter(X.iloc[:, 0], X.iloc[:, 1], c='blue', label='Normal')
    if not anomalies.empty:
        plt.scatter(anomalies.iloc[:, 0], anomalies.iloc[:, 1], c='red', label='Anomaly')
    plt.title('Anomaly Detection')
    plt.xlabel('Feature 1')
    plt.ylabel('Feature 2')
    plt.legend()
    plt.show()

if __name__ == "__main__":
    main()
```

```
---------------------------------------------------------------------------
FileNotFoundError                         Traceback (most recent call last)
Cell In[12], line 74
     71     plt.show()
     73 if __name__ == "__main__":
---> 74     main()

Cell In[12], line 42, in main()
     40 def main():
     41     # Read input test case file (.inp)
---> 42     input_test_case_file = read_inp_file("input_test_case_file.inp")
     44     # Read reference file (if available)
     45     reference_file = read_inp_file("reference_file.inp")

Cell In[12], line 9, in read_inp_file(file_path)
      7 def read_inp_file(file_path):
      8     # Read .inp file into DataFrame
----> 9     data = pd.read_csv(file_path, delimiter=' ', header=None)  # Assuming space-separated values
     10     return data

File ~\anaconda3\lib\site-packages\pandas\util\_decorators.py:211, in deprecate_kwarg.<locals>._deprecate_kwarg.<locals>.wrapper
(*args, **kwargs)
    209     else:
    210         kwargs[new_arg_name] = new_arg_value
--> 211 return func(*args, **kwargs)

File ~\anaconda3\lib\site-packages\pandas\util\_decorators.py:331, in deprecate_nonkeyword_arguments.<locals>.decorate.<locals>.
wrapper(*args, **kwargs)
    325 if len(args) > num_allow_args:
    326     warnings.warn(
    327         msg.format(arguments=_format_argument_list(allow_args)),
    328         FutureWarning,
    329         stacklevel=find_stack_level(),
    330     )
--> 331 return func(*args, **kwargs)

File ~\anaconda3\lib\site-packages\pandas\io\parsers\readers.py:950, in read_csv(filepath_or_buffer, sep, delimiter, header, nam
es, index_col, usecols, squeeze, prefix, mangle_dupe_cols, dtype, engine, converters, true_values, false_values, skipinitialspac
e, skiprows, skipfooter, nrows, na_values, keep_default_na, na_filter, verbose, skip_blank_lines, parse_dates, infer_datetime_fo
rmat, keep_date_col, date_parser, dayfirst, cache_dates, iterator, chunksize, compression, thousands, decimal, lineterminator, q
uotechar, quoting, doublequote, escapechar, comment, encoding, encoding_errors, dialect, error_bad_lines, warn_bad_lines, on_bad
_lines, delim_whitespace, low_memory, memory_map, float_precision, storage_options)
    935 kwds_defaults = _refine_defaults_read(
```

```
    936     dialect,
    937     delimiter,
   (...)
    946     defaults={"delimiter": ","},
    947 )
    948 kwds.update(kwds_defaults)
--> 950 return _read(filepath_or_buffer, kwds)

File ~\anaconda3\lib\site-packages\pandas\io\parsers\readers.py:605, in _read(filepath_or_buffer, kwds)
    602 _validate_names(kwds.get("names", None))
    604 # Create the parser.
--> 605 parser = TextFileReader(filepath_or_buffer, **kwds)
    607 if chunksize or iterator:
    608     return parser

File ~\anaconda3\lib\site-packages\pandas\io\parsers\readers.py:1442, in TextFileReader.__init__(self, f, engine, **kwds)
   1439     self.options["has_index_names"] = kwds["has_index_names"]
   1441 self.handles: IOHandles | None = None
-> 1442 self._engine = self._make_engine(f, self.engine)

File ~\anaconda3\lib\site-packages\pandas\io\parsers\readers.py:1735, in TextFileReader._make_engine(self, f, engine)
   1733     if "b" not in mode:
   1734         mode += "b"
-> 1735 self.handles = get_handle(
   1736     f,
   1737     mode,
   1738     encoding=self.options.get("encoding", None),
   1739     compression=self.options.get("compression", None),
   1740     memory_map=self.options.get("memory_map", False),
   1741     is_text=is_text,
   1742     errors=self.options.get("encoding_errors", "strict"),
   1743     storage_options=self.options.get("storage_options", None),
   1744 )
   1745 assert self.handles is not None
   1746 f = self.handles.handle

File ~\anaconda3\lib\site-packages\pandas\io\common.py:856, in get_handle(path_or_buf, mode, encoding, compression, memory_map,
is_text, errors, storage_options)
    851 elif isinstance(handle, str):
    852     # Check whether the filename is to be opened in binary mode.
    853     # Binary mode does not support 'encoding' and 'newline'.
    854     if ioargs.encoding and "b" not in ioargs.mode:
    855         # Encoding
--> 856         handle = open(
```

```
                handle,
                ioargs.mode,
                encoding=ioargs.encoding,
                errors=errors,
                newline="",
            )
        else:
            # Binary mode
            handle = open(handle, ioargs.mode)

FileNotFoundError: [Errno 2] No such file or directory: 'input_test_case_file.inp'
```

In [13]:

```
import pandas as pd
import numpy as np
from sklearn.ensemble import IsolationForest
from sklearn.preprocessing import StandardScaler
import matplotlib.pyplot as plt

# Function to generate random synthetic data
def generate_random_data(num_samples, num_features):
    return pd.DataFrame(np.random.rand(num_samples, num_features), columns=[f"Param_{i}" for i in range(num_features)])

# Function to introduce anomalies in the input test case data
def introduce_anomalies(input_data, num_anomalies):
    anomaly_indices = np.random.choice(input_data.index, num_anomalies, replace=False)
    input_data.loc[anomaly_indices] += 5  # Add anomaly value to selected rows
    return input_data

# Function to train anomaly detection model
def train_anomaly_detection_model(X):
    scaler = StandardScaler()
    X_scaled = scaler.fit_transform(X)
    model = IsolationForest(contamination=0.05)  # Adjusting contamination parameter
    model.fit(X_scaled)
    return model, scaler

# Function to detect anomalies
def detect_anomalies(model, scaler, X):
    X_scaled = scaler.transform(X)
    anomaly_scores = model.decision_function(X_scaled)
    anomalies = X[anomaly_scores < 0]
    return anomalies, anomaly_scores

# Function to find root cause
```

```python
def find_root_cause(anomalies, reference_data):
    root_causes = []
    for idx, anomaly in anomalies.iterrows():
        reference_diff = reference_data - anomaly.values.reshape(1, -1)
        param_responsible = reference_diff.abs().sum(axis=1).idxmin()
        root_causes.append(param_responsible)
    return pd.DataFrame(root_causes, columns=['Param_Responsible'])

# Main function
def main():
    # Generate random synthetic data for input test case and reference
    input_test_case_data = generate_random_data(100, 5)  # 100 samples, 5 features
    reference_data = generate_random_data(100, 5)  # 100 samples, 5 features

    # Introduce anomalies in the input test case data
    input_test_case_data = introduce_anomalies(input_test_case_data, 2)  # Introduce 2 anomalies

    # Train the Isolation Forest model
    model, scaler = train_anomaly_detection_model(reference_data)

    # Detect anomalies
    anomalies, _ = detect_anomalies(model, scaler, input_test_case_data)

    # Find root cause
    root_causes = find_root_cause(anomalies, reference_data)

    # Print anomalies and root causes
    print("Detected Anomalies and Associated Root Causes:")
    for idx, anomaly in anomalies.iterrows():
        param_responsible = root_causes.iloc[idx]['Param_Responsible']
        print(f"Anomaly {idx + 1}:")
        print("Anomaly values:", anomaly.values)
        print("Parameter responsible for anomaly:", param_responsible)
        print()

    # Visualize results
    plt.scatter(reference_data.iloc[:, 0], reference_data.iloc[:, 1], c='blue', label='Reference Data')
    plt.scatter(input_test_case_data.iloc[:, 0], input_test_case_data.iloc[:, 1], c='green', label='Input Test Case Data')
    if not anomalies.empty:
        plt.scatter(anomalies.iloc[:, 0], anomalies.iloc[:, 1], c='red', label='Anomaly')
    plt.title('Anomaly Detection')
    plt.xlabel('Feature 1')
    plt.ylabel('Feature 2')
    plt.legend()
```

```
    plt.show()

if __name__ == "__main__":
    main()
```

```
Detected Anomalies and Associated Root Causes:
Anomaly 5:
Anomaly values: [0.84640619 0.94830113 0.20421459 0.99795038 0.54657483]
Parameter responsible for anomaly: 29

Anomaly 8:
Anomaly values: [0.35736883 0.94066562 0.16798572 0.13615151 0.0331756 ]
Parameter responsible for anomaly: 8

Anomaly 10:
Anomaly values: [0.79363751 0.13994504 0.0641665  0.93932776 0.86354884]
Parameter responsible for anomaly: 61

Anomaly 11:
Anomaly values: [0.93803381 0.33019673 0.64103234 0.93917272 0.81074354]
Parameter responsible for anomaly: 25

Anomaly 15:
Anomaly values: [0.90452094 0.32802782 0.99625152 0.99374145 0.44690197]
Parameter responsible for anomaly: 70
```

```
---------------------------------------------------------------------------
IndexError                                Traceback (most recent call last)
Cell In[13], line 80
     77     plt.show()
     79 if __name__ == "__main__":
---> 80     main()

Cell In[13], line 62, in main()
     60 print("Detected Anomalies and Associated Root Causes:")
     61 for idx, anomaly in anomalies.iterrows():
---> 62     param_responsible = root_causes.iloc[idx]['Param_Responsible']
     63     print(f"Anomaly {idx + 1}:")
     64     print("Anomaly values:", anomaly.values)

File ~\anaconda3\lib\site-packages\pandas\core\indexing.py:1073, in _LocationIndexer.__getitem__(self, key)
   1070 axis = self.axis or 0
   1072 maybe_callable = com.apply_if_callable(key, self.obj)
-> 1073 return self._getitem_axis(maybe_callable, axis=axis)

File ~\anaconda3\lib\site-packages\pandas\core\indexing.py:1625, in _iLocIndexer._getitem_axis(self, key, axis)
   1622     raise TypeError("Cannot index by location index with a non-integer key")
   1624 # validate the location
-> 1625 self._validate_integer(key, axis)
   1627 return self.obj._ixs(key, axis=axis)

File ~\anaconda3\lib\site-packages\pandas\core\indexing.py:1557, in _iLocIndexer._validate_integer(self, key, axis)
   1555 len_axis = len(self.obj._get_axis(axis))
   1556 if key >= len_axis or key < -len_axis:
-> 1557     raise IndexError("single positional indexer is out-of-bounds")

IndexError: single positional indexer is out-of-bounds
```

In [14]:

```python
import pandas as pd
import numpy as np
from sklearn.ensemble import IsolationForest
from sklearn.preprocessing import StandardScaler
import matplotlib.pyplot as plt

# Function to generate random synthetic data
def generate_random_data(num_samples, num_features):
    return pd.DataFrame(np.random.rand(num_samples, num_features), columns=[f"Param_{i}" for i in range(num_features)])

# Function to introduce anomalies in the input test case data
```

```
def introduce_anomalies(input_data, num_anomalies):
    anomaly_indices = np.random.choice(input_data.index, num_anomalies, replace=False)
    input_data.loc[anomaly_indices] += 5  # Add anomaly value to selected rows
    return input_data

# Function to train anomaly detection model
def train_anomaly_detection_model(X):
    scaler = StandardScaler()
    X_scaled = scaler.fit_transform(X)
    model = IsolationForest(contamination=0.05)  # Adjusting contamination parameter
    model.fit(X_scaled)
    return model, scaler

# Function to detect anomalies
def detect_anomalies(model, scaler, X):
    X_scaled = scaler.transform(X)
    anomaly_scores = model.decision_function(X_scaled)
    anomalies = X[anomaly_scores < 0]
    return anomalies, anomaly_scores

# Function to find root cause
def find_root_cause(anomalies, reference_data):
    root_causes = []
    for idx, anomaly in anomalies.iterrows():
        reference_diff = reference_data - anomaly.values.reshape(1, -1)
        if not reference_diff.empty:
            param_responsible = reference_diff.abs().sum(axis=1).idxmin()
            root_causes.append(param_responsible)
    return pd.DataFrame(root_causes, columns=['Param_Responsible'])

# Main function
def main():
    # Generate random synthetic data for input test case and reference
    input_test_case_data = generate_random_data(100, 5)  # 100 samples, 5 features
    reference_data = generate_random_data(100, 5)  # 100 samples, 5 features

    # Introduce anomalies in the input test case data
    input_test_case_data = introduce_anomalies(input_test_case_data, 2)  # Introduce 2 anomalies

    # Train the Isolation Forest model
    model, scaler = train_anomaly_detection_model(reference_data)

    # Detect anomalies
    anomalies, _ = detect_anomalies(model, scaler, input_test_case_data)
```

```python
    # Find root cause
    if not anomalies.empty:
        root_causes = find_root_cause(anomalies, reference_data)

        # Print anomalies and root causes
        print("Detected Anomalies and Associated Root Causes:")
        for idx, anomaly in anomalies.iterrows():
            param_responsible = root_causes.iloc[idx]['Param_Responsible']
            print(f"Anomaly {idx + 1}:")
            print("Anomaly values:", anomaly.values)
            print("Parameter responsible for anomaly:", param_responsible)
            print()

    # Visualize results
    plt.scatter(reference_data.iloc[:, 0], reference_data.iloc[:, 1], c='blue', label='Reference Data')
    plt.scatter(input_test_case_data.iloc[:, 0], input_test_case_data.iloc[:, 1], c='green', label='Input Test Case Data')
    if not anomalies.empty:
        plt.scatter(anomalies.iloc[:, 0], anomalies.iloc[:, 1], c='red', label='Anomaly')
    plt.title('Anomaly Detection')
    plt.xlabel('Feature 1')
    plt.ylabel('Feature 2')
    plt.legend()
    plt.show()

if __name__ == "__main__":
    main()
```

```
Detected Anomalies and Associated Root Causes:
Anomaly 6:
Anomaly values: [0.92946386 0.73734147 0.76529037 0.02973688 0.98755829]
Parameter responsible for anomaly: 22

Anomaly 9:
Anomaly values: [0.92678443 0.07306134 0.91156482 0.00754676 0.06200752]
Parameter responsible for anomaly: 15

Anomaly 15:
Anomaly values: [0.29151497 0.03923192 0.03997434 0.92882721 0.86726372]
Parameter responsible for anomaly: 70

Anomaly 19:
Anomaly values: [0.61077139 0.96361843 0.52038347 0.4468301  0.97225776]
Parameter responsible for anomaly: 18
```

```
---------------------------------------------------------------------------
IndexError                                Traceback (most recent call last)
Cell In[14], line 82
     79     plt.show()
     81 if __name__ == "__main__":
---> 82     main()

Cell In[14], line 64, in main()
     62 print("Detected Anomalies and Associated Root Causes:")
     63 for idx, anomaly in anomalies.iterrows():
---> 64     param_responsible = root_causes.iloc[idx]['Param_Responsible']
     65     print(f"Anomaly {idx + 1}:")
     66     print("Anomaly values:", anomaly.values)

File ~\anaconda3\lib\site-packages\pandas\core\indexing.py:1073, in _LocationIndexer.__getitem__(self, key)
   1070 axis = self.axis or 0
   1072 maybe_callable = com.apply_if_callable(key, self.obj)
-> 1073 return self._getitem_axis(maybe_callable, axis=axis)

File ~\anaconda3\lib\site-packages\pandas\core\indexing.py:1625, in _iLocIndexer._getitem_axis(self, key, axis)
   1622     raise TypeError("Cannot index by location index with a non-integer key")
   1624 # validate the location
-> 1625 self._validate_integer(key, axis)
   1627 return self.obj._ixs(key, axis=axis)

File ~\anaconda3\lib\site-packages\pandas\core\indexing.py:1557, in _iLocIndexer._validate_integer(self, key, axis)
   1555 len_axis = len(self.obj._get_axis(axis))
   1556 if key >= len_axis or key < -len_axis:
-> 1557     raise IndexError("single positional indexer is out-of-bounds")

IndexError: single positional indexer is out-of-bounds
```

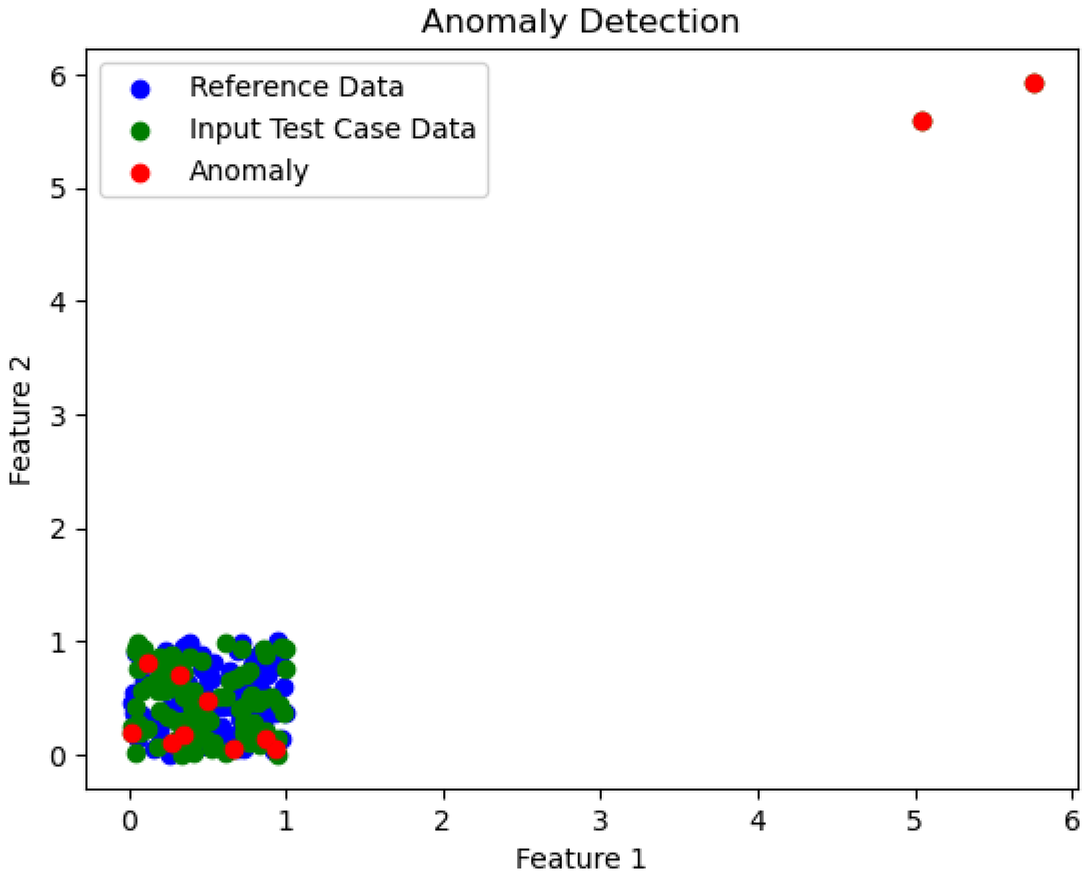
In [15]:

```
import pandas as pd
import numpy as np
from sklearn.ensemble import IsolationForest
from sklearn.preprocessing import StandardScaler
import matplotlib.pyplot as plt

# Function to generate random synthetic data
def generate_random_data(num_samples, num_features):
    return pd.DataFrame(np.random.rand(num_samples, num_features), columns=[f"Param_{i}" for i in range(num_features)])

# Function to introduce anomalies in the input test case data
```

```
def introduce_anomalies(input_data, num_anomalies):
    anomaly_indices = np.random.choice(input_data.index, num_anomalies, replace=False)
    input_data.loc[anomaly_indices] += 5  # Add anomaly value to selected rows
    return input_data

# Function to train anomaly detection model
def train_anomaly_detection_model(X):
    scaler = StandardScaler()
    X_scaled = scaler.fit_transform(X)
    model = IsolationForest(contamination=0.05)  # Adjusting contamination parameter
    model.fit(X_scaled)
    return model, scaler

# Function to detect anomalies
def detect_anomalies(model, scaler, X):
    X_scaled = scaler.transform(X)
    anomaly_scores = model.decision_function(X_scaled)
    anomalies = X[anomaly_scores < 0]
    return anomalies, anomaly_scores

# Function to find root cause
def find_root_cause(anomalies, reference_data):
    root_causes = []
    for idx, anomaly in anomalies.iterrows():
        reference_diff = reference_data - anomaly.values.reshape(1, -1)
        if not reference_diff.empty:
            param_responsible = reference_diff.abs().sum(axis=1).idxmin()
            root_causes.append(param_responsible)
    return pd.DataFrame(root_causes, columns=['Param_Responsible'])

# Main function
def main():
    # Generate random synthetic data for input test case and reference
    input_test_case_data = generate_random_data(100, 5)  # 100 samples, 5 features
    reference_data = generate_random_data(100, 5)  # 100 samples, 5 features

    # Introduce anomalies in the input test case data
    input_test_case_data = introduce_anomalies(input_test_case_data, 2)  # Introduce 2 anomalies

    # Train the Isolation Forest model
    model, scaler = train_anomaly_detection_model(reference_data)

    # Detect anomalies
    anomalies, _ = detect_anomalies(model, scaler, input_test_case_data)
```

```
    # Find root cause
    if not anomalies.empty:
        root_causes = find_root_cause(anomalies, reference_data)

        # Print anomalies and root causes
        print("Detected Anomalies and Associated Root Causes:")
        for idx, anomaly in anomalies.iterrows():
            if idx < len(root_causes):  # Check if index is within bounds
                param_responsible = root_causes.iloc[idx]['Param_Responsible']
                print(f"Anomaly {idx + 1}:")
                print("Anomaly values:", anomaly.values)
                print("Parameter responsible for anomaly:", param_responsible)
                print()

    # Visualize results
    plt.scatter(reference_data.iloc[:, 0], reference_data.iloc[:, 1], c='blue', label='Reference Data')
    plt.scatter(input_test_case_data.iloc[:, 0], input_test_case_data.iloc[:, 1], c='green', label='Input Test Case Data')
    if not anomalies.empty:
        plt.scatter(anomalies.iloc[:, 0], anomalies.iloc[:, 1], c='red', label='Anomaly')
    plt.title('Anomaly Detection')
    plt.xlabel('Feature 1')
    plt.ylabel('Feature 2')
    plt.legend()
    plt.show()

if __name__ == "__main__":
    main()
```

```
Detected Anomalies and Associated Root Causes:
Anomaly 3:
Anomaly values: [6.70272935e-01 5.04429372e-02 2.87087548e-01 7.33152797e-05
 5.24137150e-02]
Parameter responsible for anomaly: 61
```



In [16]:

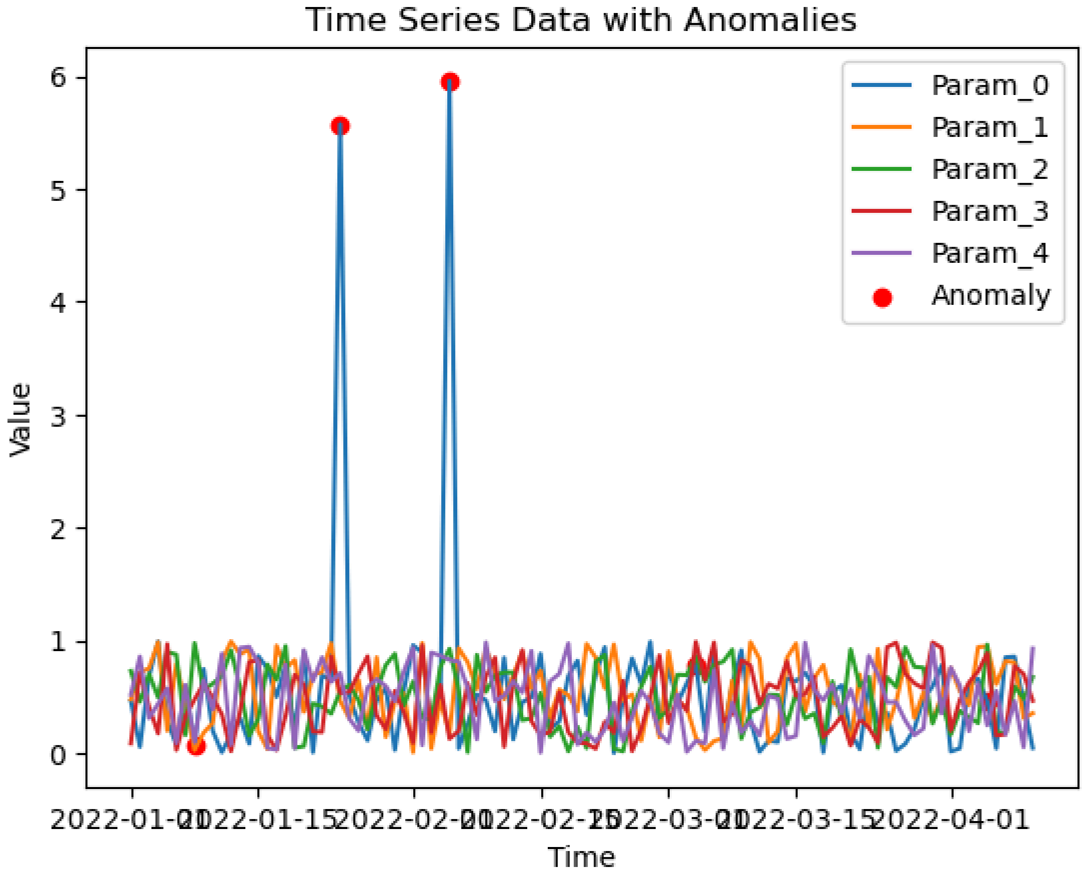
```
import pandas as pd
import numpy as np
from sklearn.ensemble import IsolationForest
from sklearn.preprocessing import StandardScaler
import matplotlib.pyplot as plt

# Function to generate random synthetic time series data
def generate_time_series_data(num_samples, num_features):
    date_range = pd.date_range(start='2022-01-01', periods=num_samples, freq='D')
    data = pd.DataFrame(np.random.rand(num_samples, num_features), columns=[f"Param_{i}" for i in range(num_features)], index=dat
    return data

# Function to introduce anomalies in the time series data
def introduce_anomalies(data, num_anomalies):
    anomaly_indices = np.random.choice(data.index, num_anomalies, replace=False)
```

```
    data.loc[anomaly_indices, 'Param_0'] += 5  # Add anomaly value to selected rows and feature 'Param_0'
    return data

# Function to train anomaly detection model
def train_anomaly_detection_model(X):
    scaler = StandardScaler()
    X_scaled = scaler.fit_transform(X)
    model = IsolationForest(contamination=0.05)  # Adjusting contamination parameter
    model.fit(X_scaled)
    return model, scaler

# Function to detect anomalies
def detect_anomalies(model, scaler, X):
    X_scaled = scaler.transform(X)
    anomaly_scores = model.decision_function(X_scaled)
    anomalies = X[anomaly_scores < 0]
    return anomalies, anomaly_scores

# Main function
def main():
    # Generate random synthetic time series data
    num_samples = 100
    num_features = 5
    time_series_data = generate_time_series_data(num_samples, num_features)

    # Introduce anomalies in the time series data
    time_series_data = introduce_anomalies(time_series_data, 2)  # Introduce 2 anomalies

    # Train the Isolation Forest model
    model, scaler = train_anomaly_detection_model(time_series_data)

    # Detect anomalies
    anomalies, _ = detect_anomalies(model, scaler, time_series_data)

    # Print detected anomalies
    print("Detected Anomalies:")
    print(anomalies)

    # Visualize time series data with anomalies
    for feature in time_series_data.columns:
        plt.plot(time_series_data.index, time_series_data[feature], label=feature)
    plt.scatter(anomalies.index, anomalies['Param_0'], c='red', label='Anomaly')  # Assuming 'Param_0' is the feature with anomal
    plt.title('Time Series Data with Anomalies')
    plt.xlabel('Time')
```

```
    plt.ylabel('Value')
    plt.legend()
    plt.show()

if __name__ == "__main__":
    main()
```

Detected Anomalies:

	Param_0	Param_1	Param_2	Param_3	Param_4
2022-01-08	0.071306	0.025621	0.975895	0.475648	0.095065
2022-01-24	5.577340	0.460556	0.552697	0.531557	0.709475
2022-02-05	5.961443	0.174558	0.925054	0.126403	0.826554
2022-03-04	0.787794	0.138230	0.865067	0.987831	0.106702
2022-04-05	0.461920	0.947836	0.962256	0.885512	0.245318



In [21]:
```
import pandas as pd
import numpy as np
from sklearn.ensemble import IsolationForest
from sklearn.preprocessing import StandardScaler
import matplotlib.pyplot as plt

# Function to generate random synthetic time series data
def generate_time_series_data(num_samples, num_features):
    date_range = pd.date_range(start='2022-01-01', periods=num_samples, freq='D')
    data = pd.DataFrame(np.random.rand(num_samples, num_features), columns=[f"Param_{i}" for i in range(num_features)], index=dat
    return data

# Function to introduce anomalies in the time series data
def introduce_anomalies(data, num_anomalies):
    anomaly_indices = np.random.choice(data.index, num_anomalies, replace=False)
    data.loc[anomaly_indices, 'Param_0'] += 5  # Add anomaly value to selected rows and feature 'Param_0'
    return data

# Function to train anomaly detection model
def train_anomaly_detection_model(X):
    scaler = StandardScaler()
    X_scaled = scaler.fit_transform(X)
    model = IsolationForest(contamination=0.05)  # Adjusting contamination parameter
    model.fit(X_scaled)
    return model, scaler

# Function to detect anomalies
def detect_anomalies(model, scaler, X):
    X_scaled = scaler.transform(X)
    anomaly_scores = model.decision_function(X_scaled)
    anomalies = X[anomaly_scores < 0]
    return anomalies, anomaly_scores

# Function to find root cause
def find_root_cause(anomalies, reference_data):
    root_causes = []
    for anomaly in anomalies.values:  # Iterate over anomaly values directly
        reference_diff = reference_data - anomaly.reshape(1, -1)
        param_responsible = reference_diff.abs().sum(axis=1).idxmin()
        root_causes.append(param_responsible)
    return pd.DataFrame(root_causes, columns=['Param_Responsible'])

# Main function
```

```python
def main():
    # Generate random synthetic time series data
    num_samples = 100
    num_features = 5
    time_series_data = generate_time_series_data(num_samples, num_features)

    # Introduce anomalies in the time series data
    time_series_data = introduce_anomalies(time_series_data, 2)  # Introduce 2 anomalies

    # Train the Isolation Forest model
    model, scaler = train_anomaly_detection_model(time_series_data)

    # Detect anomalies
    anomalies, _ = detect_anomalies(model, scaler, time_series_data)

    # Find root cause
    root_causes = find_root_cause(anomalies, time_series_data)

    # Print detected anomalies and their root causes
    print("Detected Anomalies and Associated Root Causes:")
    for idx, anomaly in anomalies.iterrows():
        param_responsible = root_causes.iloc[idx]['Param_Responsible']
        print(f"Anomaly {idx + 1}:")
        print("Anomaly values:", anomaly.values)
        print("Parameter responsible for anomaly:", param_responsible)
        print()

    # Visualize time series data with anomalies
    for feature in time_series_data.columns:
        plt.plot(time_series_data.index, time_series_data[feature], label=feature)
    plt.scatter(anomalies.index, anomalies['Param_0'], c='red', label='Anomaly')  # Assuming 'Param_0' is the feature with anomal
    plt.title('Time Series Data with Anomalies')
    plt.xlabel('Time')
    plt.ylabel('Value')
    plt.legend()
    plt.show()

if __name__ == "__main__":
    main()
```

```
Detected Anomalies and Associated Root Causes:
```

```
---------------------------------------------------------------------------
TypeError                                 Traceback (most recent call last)
Cell In[21], line 82
     79     plt.show()
     81 if __name__ == "__main__":
---> 82     main()

Cell In[21], line 65, in main()
     63 print("Detected Anomalies and Associated Root Causes:")
     64 for idx, anomaly in anomalies.iterrows():
---> 65     param_responsible = root_causes.iloc[idx]['Param_Responsible']
     66     print(f"Anomaly {idx + 1}:")
     67     print("Anomaly values:", anomaly.values)

File ~\anaconda3\lib\site-packages\pandas\core\indexing.py:1073, in _LocationIndexer.__getitem__(self, key)
   1070 axis = self.axis or 0
   1072 maybe_callable = com.apply_if_callable(key, self.obj)
-> 1073 return self._getitem_axis(maybe_callable, axis=axis)

File ~\anaconda3\lib\site-packages\pandas\core\indexing.py:1622, in _iLocIndexer._getitem_axis(self, key, axis)
   1620 key = item_from_zerodim(key)
   1621 if not is_integer(key):
-> 1622     raise TypeError("Cannot index by location index with a non-integer key")
   1624 # validate the location
   1625 self._validate_integer(key, axis)

TypeError: Cannot index by location index with a non-integer key
```

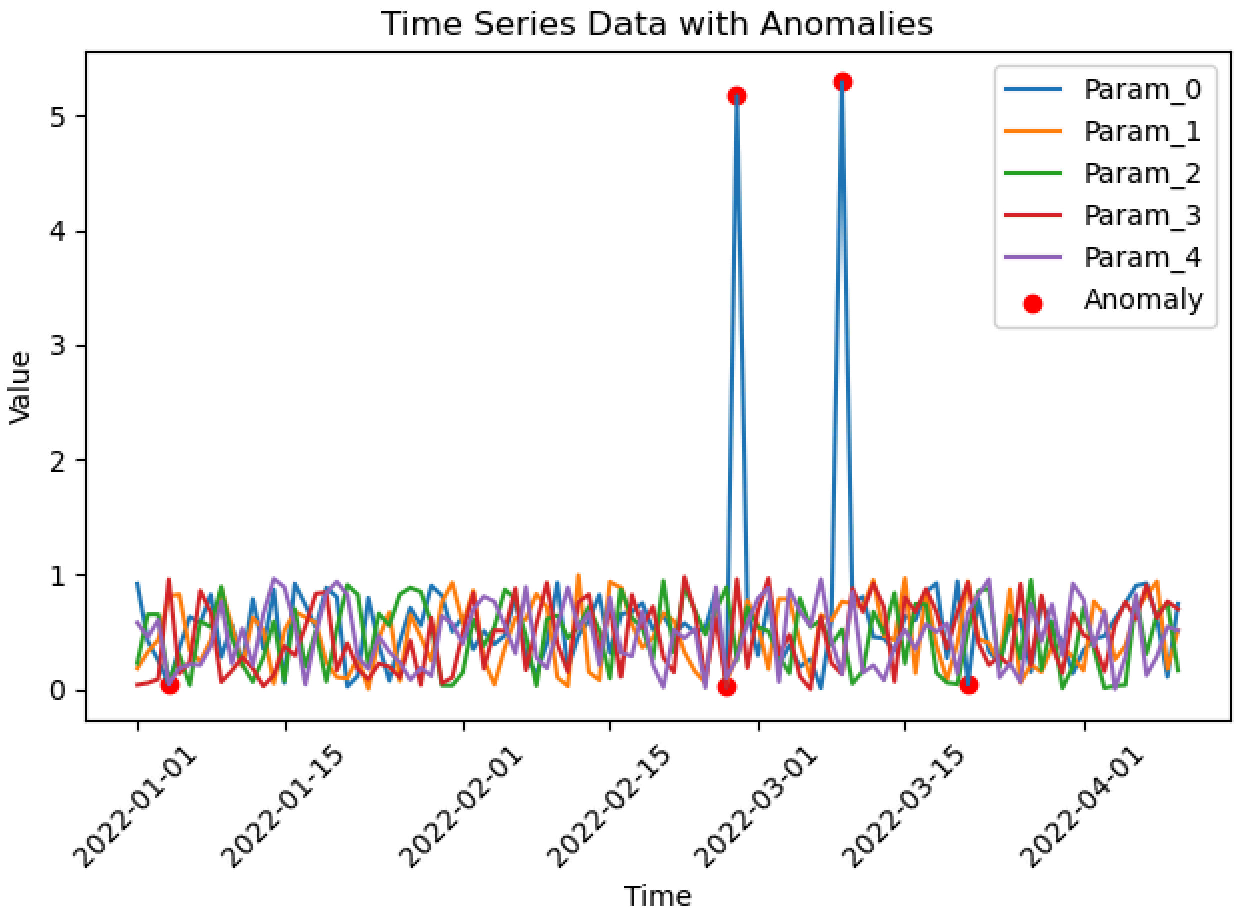
In [24]:

```
import pandas as pd
import numpy as np
from sklearn.ensemble import IsolationForest
from sklearn.preprocessing import StandardScaler
import matplotlib.pyplot as plt

# Function to generate random synthetic time series data
def generate_time_series_data(num_samples, num_features):
    date_range = pd.date_range(start='2022-01-01', periods=num_samples, freq='D')
    data = pd.DataFrame(np.random.rand(num_samples, num_features), columns=[f"Param_{i}" for i in range(num_features)], index=dat
    return data

# Function to introduce anomalies in the time series data
def introduce_anomalies(data, num_anomalies):
    anomaly_indices = np.random.choice(data.index, num_anomalies, replace=False)
```

```
    data.loc[anomaly_indices, 'Param_0'] += 5  # Add anomaly value to selected rows and feature 'Param_0'
    return data

# Function to train anomaly detection model
def train_anomaly_detection_model(X):
    scaler = StandardScaler()
    X_scaled = scaler.fit_transform(X)
    model = IsolationForest(contamination=0.05)  # Adjusting contamination parameter
    model.fit(X_scaled)
    return model, scaler

# Function to detect anomalies
def detect_anomalies(model, scaler, X):
    X_scaled = scaler.transform(X)
    anomaly_scores = model.decision_function(X_scaled)
    anomalies = X[anomaly_scores < 0]
    return anomalies, anomaly_scores

# Function to find root cause
def find_root_cause(anomalies, reference_data):
    root_causes = []
    for anomaly in anomalies.values:  # Iterate over anomaly values directly
        reference_diff = reference_data - anomaly.reshape(1, -1)
        param_responsible = reference_diff.abs().sum(axis=1).idxmin()
        root_causes.append(param_responsible)
    return pd.DataFrame(root_causes, columns=['Param_Responsible'])

# Main function
def main():
    # Generate random synthetic time series data
    num_samples = 100
    num_features = 5
    time_series_data = generate_time_series_data(num_samples, num_features)

    # Introduce anomalies in the time series data
    time_series_data = introduce_anomalies(time_series_data, 2)  # Introduce 2 anomalies

    # Train the Isolation Forest model
    model, scaler = train_anomaly_detection_model(time_series_data)

    # Detect anomalies
    anomalies, _ = detect_anomalies(model, scaler, time_series_data)

    # Find root cause
```

```
    root_causes = find_root_cause(anomalies, time_series_data)

    # Print detected anomalies and their root causes
    print("Detected Anomalies and Associated Root Causes:")
    for idx, anomaly in enumerate(anomalies.values):
        param_responsible = root_causes.iloc[idx]['Param_Responsible']
        print(f"Anomaly {idx + 1}:")
        print("Anomaly values:", anomaly)
        print("Parameter responsible for anomaly:", param_responsible)
        print()

    # Visualize time series data with anomalies
    # Visualize time series data with anomalies
    for feature in time_series_data.columns:
        plt.plot(time_series_data.index, time_series_data[feature], label=feature)
    plt.scatter(anomalies.index, anomalies['Param_0'], c='red', label='Anomaly')  # Assuming 'Param_0' is the feature with anomal
    plt.title('Time Series Data with Anomalies')
    plt.xlabel('Time')
    plt.ylabel('Value')
    plt.xticks(rotation=45)  # Rotate x-axis labels by 45 degrees
    plt.legend()
    plt.tight_layout()  # Adjust layout to prevent overlapping labels
    plt.show()


if __name__ == "__main__":
    main()
```

```
Detected Anomalies and Associated Root Causes:
Anomaly 1:
Anomaly values: [0.0428647  0.81448495 0.06259475 0.95983442 0.04346884]
Parameter responsible for anomaly: 2022-01-04 00:00:00

Anomaly 2:
Anomaly values: [0.02133482 0.06019207 0.89080889 0.02039263 0.0974947 ]
Parameter responsible for anomaly: 2022-02-26 00:00:00

Anomaly 3:
Anomaly values: [5.17464335 0.2995789  0.25114401 0.96127727 0.2723835 ]
Parameter responsible for anomaly: 2022-02-27 00:00:00

Anomaly 4:
Anomaly values: [5.2961784  0.76556617 0.52311879 0.13261397 0.13026826]
Parameter responsible for anomaly: 2022-03-09 00:00:00

Anomaly 5:
Anomaly values: [0.04279362 0.9424787  0.51491926 0.93511191 0.66854519]
Parameter responsible for anomaly: 2022-03-21 00:00:00
```


Time Series Data with Anomalies
Param_0
Param_1
Param_2
Param_3
Param_4
Anomaly
Value
0
1
2
3
4
5
2022-01-01
2022-01-15
2022-02-01
2022-02-15
2022-03-01
2022-03-15
2022-04-01
Time

```
In [ ]:
```