MILESTONE-3

Anomaly Detection

Data set

In [ ]:
```python
import pandas as pd
import matplotlib.pyplot as plt
data = pd.read_csv("Healthcare Providers.csv")
data.head()
```

Out[ ]:

	index	National Provider Identifier	Last Name/Organization Name of the Provider	First Name of the Provider	Middle Initial of the Provider	Credentials of the Provider	Gender of the Provider	Entity Type of the Provider	Street Address 1 of the Provider	Street Address 2 of the Provider	...	HCPCS Code	HCPCS Description	HCPCS Drug Indicator	Number of Services	Number of Medicare Beneficiaries	Number of Distinct Medicare Beneficiary/Per Day Services	
0	8774979	1891106191	UPADHYAYULA	SATYASREE	NaN	M.D.	F	I	1402 S GRAND BLVD	FDT 14TH FLOOR	...	99223	Initial hospital inpatient care, typically 70 ...	N	27	24	27	200
1	3354385	1346202256	JONES	WENDY	P	M.D.	F	I	2950 VILLAGE DR	NaN	...	G0202	Screening mammography, bilateral (2-view study...	N	175	175	175	
2	3001884	1306820956	DUROCHER	RICHARD	W	DPM	M	I	20 WASHINGTON AVE	STE 212	...	99348	Established patient home visit, typically 25 m...	N	32	13	32	
3	7594822	1770523540	FULLARD	JASPER	NaN	MD	M	I	5746 N BROADWAY ST	NaN	...	81002	Urinalysis, manual test	N	20	18	20	
4	746159	1073627758	PERROTTI	ANTHONY	E	DO	M	I	875 MILITARY TRL	SUITE 200	...	96372	Injection beneath the skin or into muscle for ...	N	33	24	31	

5 rows × 27 columns

Information about the dataset

In [ ]:
```python
# information about the dataset
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 100000 entries, 0 to 99999
Data columns (total 27 columns):
 #   Column                                                    Non-Null Count   Dtype
---  ------                                                    --------------   -----
 0   index                                                     100000 non-null  int64
 1   National Provider Identifier                              100000 non-null  int64
 2   Last Name/Organization Name of the Provider               100000 non-null  object
 3   First Name of the Provider                                95745 non-null   object
 4   Middle Initial of the Provider                            70669 non-null   object
 5   Credentials of the Provider                               92791 non-null   object
 6   Gender of the Provider                                    95746 non-null   object
 7   Entity Type of the Provider                               100000 non-null  object
 8   Street Address 1 of the Provider                          100000 non-null  object
 9   Street Address 2 of the Provider                          40637 non-null   object
 10  City of the Provider                                      100000 non-null  object
 11  Zip Code of the Provider                                  100000 non-null  float64
 12  State Code of the Provider                                100000 non-null  object
 13  Country Code of the Provider                              100000 non-null  object
 14  Provider Type                                             100000 non-null  object
 15  Medicare Participation Indicator                          100000 non-null  object
 16  Place of Service                                          100000 non-null  object
 17  HCPCS Code                                                100000 non-null  object
 18  HCPCS Description                                         100000 non-null  object
 19  HCPCS Drug Indicator                                      100000 non-null  object
 20  Number of Services                                        100000 non-null  object
 21  Number of Medicare Beneficiaries                          100000 non-null  object
 22  Number of Distinct Medicare Beneficiary/Per Day Services  100000 non-null  object
 23  Average Medicare Allowed Amount                           100000 non-null  object
 24  Average Submitted Charge Amount                           100000 non-null  object
 25  Average Medicare Payment Amount                           100000 non-null  object
 26  Average Medicare Standardized Amount                      100000 non-null  object
dtypes: float64(1), int64(2), object(24)
memory usage: 20.6+ MB
```

In [ ]:
```python
irrelevant_columns=['Entity Type of the Provider',
                    'Street Address 1 of the Provider',
                    'Street Address 2 of the Provider',
                    'Zip Code of the Provider',
                    'Medicare Participation Indicator',
                    'Place of Service',
                    'HCPCS Code',
                    'HCPCS Description',
                    'HCPCS Drug Indicator',
                    'Country Code of the Provider']
```

In [ ]:
```python
data.head()
```

Out[ ]:

	index	National Provider Identifier	Last Name/Organization Name of the Provider	First Name of the Provider	Middle Initial of the Provider	Credentials of the Provider	Gender of the Provider	Entity Type of the Provider	Street Address 1 of the Provider	Street Address 2 of the Provider	...	HCPCS Code	HCPCS Description	HCPCS Drug Indicator	Number of Services	Number of Medicare Beneficiaries	Number of Distinct Medicare Beneficiary/Per Day Services	
0	8774979	1891106191	UPADHYAYULA	SATYASREE	NaN	M.D.	F	I	1402 S GRAND BLVD	FDT 14TH FLOOR	...	99223	Initial hospital inpatient care, typically 70 ...	N	27	24	27	2
1	3354385	1346202256	JONES	WENDY	P	M.D.	F	I	2950 VILLAGE DR	NaN	...	G0202	Screening mammography, bilateral (2-view study...	N	175	175	175	
2	3001884	1306820956	DUROCHER	RICHARD	W	DPM	M	I	20 WASHINGTON AVE	STE 212	...	99348	Established patient home visit, typically 25 m...	N	32	13	32	
3	7594822	1770523540	FULLARD	JASPER	NaN	MD	M	I	5746 N BROADWAY ST	NaN	...	81002	Urinalysis, manual test	N	20	18	20	
4	746159	1073627758	PERROTTI	ANTHONY	E	DO	M	I	875 MILITARY TRL	SUITE 200	...	96372	Injection beneath the skin or into muscle for ...	N	33	24	31	

5 rows × 27 columns

In [ ]:

```python
numeric_columns = [
    'Number of Services',
    'Number of Medicare Beneficiaries',
    'Number of Distinct Medicare Beneficiary/Per Day Services',
    'Average Medicare Allowed Amount',
    'Average Submitted Charge Amount',
    'Average Medicare Payment Amount',
    'Average Medicare Standardized Amount'
]

for column in numeric_columns:
    data[column] = pd.to_numeric(data[column], errors='coerce')


data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 100000 entries, 0 to 99999
Data columns (total 27 columns):
 #   Column                                                    Non-Null Count   Dtype  
---  ------                                                    --------------   -----  
 0   index                                                     100000 non-null  int64  
 1   National Provider Identifier                              100000 non-null  int64  
 2   Last Name/Organization Name of the Provider               100000 non-null  object 
 3   First Name of the Provider                                95745 non-null   object 
 4   Middle Initial of the Provider                            70669 non-null   object 
 5   Credentials of the Provider                               92791 non-null   object 
 6   Gender of the Provider                                    95746 non-null   object 
 7   Entity Type of the Provider                               100000 non-null  object 
 8   Street Address 1 of the Provider                          100000 non-null  object 
 9   Street Address 2 of the Provider                          40637 non-null   object 
 10  City of the Provider                                      100000 non-null  object 
 11  Zip Code of the Provider                                  100000 non-null  float64
 12  State Code of the Provider                                100000 non-null  object 
 13  Country Code of the Provider                              100000 non-null  object 
 14  Provider Type                                             100000 non-null  object 
 15  Medicare Participation Indicator                          100000 non-null  object 
 16  Place of Service                                          100000 non-null  object 
 17  HCPCS Code                                                100000 non-null  object 
 18  HCPCS Description                                         100000 non-null  object 
 19  HCPCS Drug Indicator                                      100000 non-null  object 
 20  Number of Services                                        97347 non-null   float64
 21  Number of Medicare Beneficiaries                          99595 non-null   float64
 22  Number of Distinct Medicare Beneficiary/Per Day Services  98500 non-null   float64
 23  Average Medicare Allowed Amount                           99255 non-null   float64
 24  Average Submitted Charge Amount                           93277 non-null   float64
 25  Average Medicare Payment Amount                           99534 non-null   float64
 26  Average Medicare Standardized Amount                      99530 non-null   float64
dtypes: float64(8), int64(2), object(17)
memory usage: 20.6+ MB
```

Missing values

In [ ]:

```python
# missing values
print(data.isnull().sum())
```

```
index                                                           0
National Provider Identifier                                    0
Last Name/Organization Name of the Provider                     0
First Name of the Provider                                   4255
Middle Initial of the Provider                              29331
Credentials of the Provider                                  7209
Gender of the Provider                                       4254
City of the Provider                                            0
State Code of the Provider                                      0
Provider Type                                                   0
Number of Services                                              0
Number of Medicare Beneficiaries                                0
Number of Distinct Medicare Beneficiary/Per Day Services        0
Average Medicare Allowed Amount                                 0
Average Submitted Charge Amount                                 0
Average Medicare Payment Amount                                 0
Average Medicare Standardized Amount                            0
dtype: int64
```

Check for duplicates

In [ ]:

```python
# Check for duplicates
print(data.duplicated().sum())
data.head()
```

```
0
```

Out[ ]:

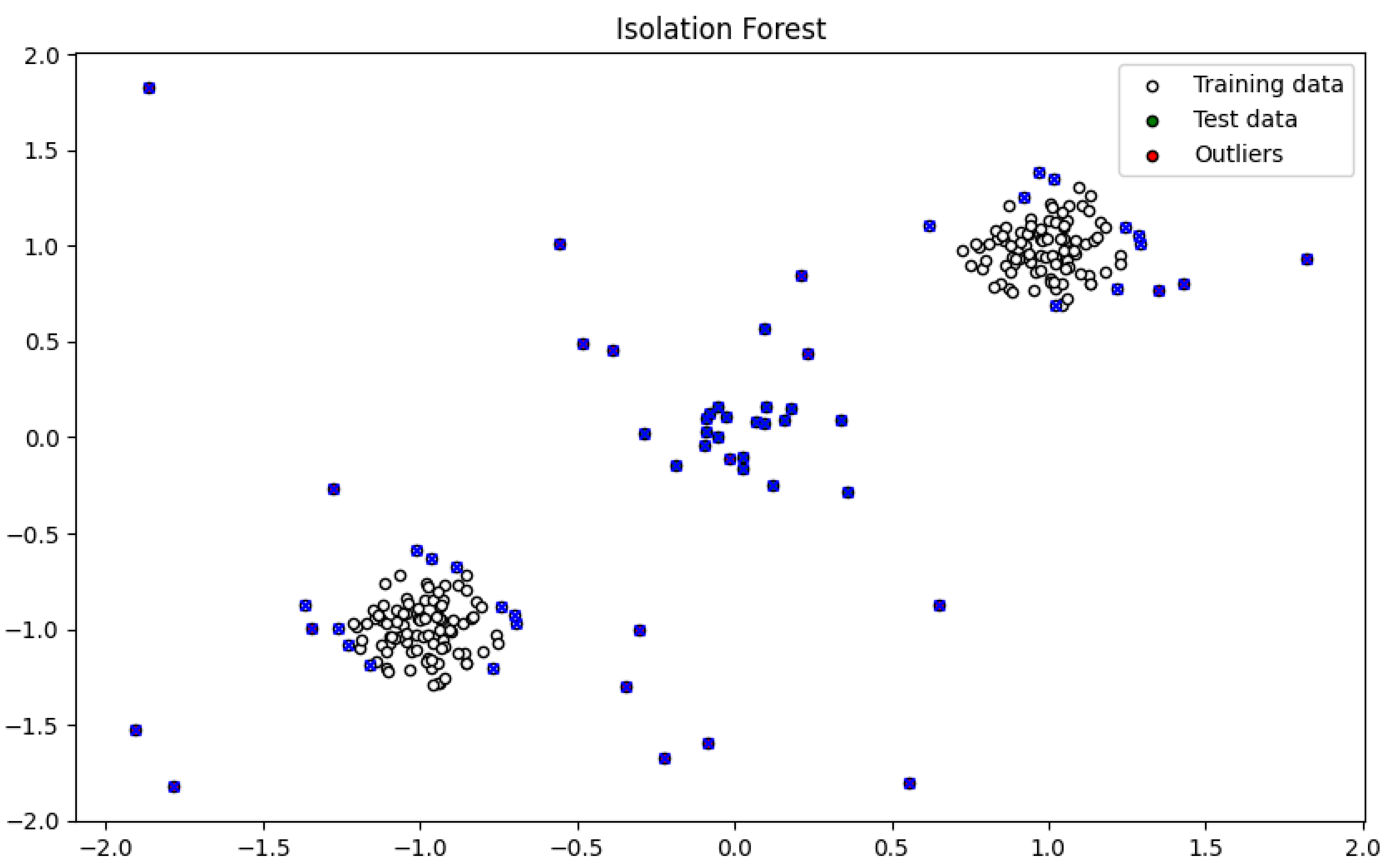
index	National Provider Identifier	Last Name/Organization Name of the Provider	First Name of the Provider	Middle Initial of the Provider	Credentials of the Provider	Gender of the Provider	City of the Provider	State Code of the Provider	Provider Type	Number of Services	Number of Medicare Beneficiaries	Number of Distinct Medicare Beneficiary/Per Day Services	Average Medicare Allowed Amount	Average Submitted Charge Amount	Av Me Pa Ar
0	8774979	1891106191	UPADHYAYULA	SATYASREE	NaN	M.D.	F	SAINT LOUIS	MO	Internal Medicine	27	24	27	200.58777778	305.21111111	157.262
1	3354385	1346202256	JONES	WENDY	P	M.D.	F	FAYETTEVILLE	NC	Obstetrics & Gynecology	175	175	175	123.73	548.8	
2	3001884	1306820956	DUROCHER	RICHARD	W	DPM	M	NORTH HAVEN	CT	Podiatry	32	13	32	90.65	155	64.43
3	7594822	1770523540	FULLARD	JASPER	NaN	MD	M	KANSAS CITY	MO	Internal Medicine	20	18	20	3.5	5	
4	746159	1073627758	PERROTTI	ANTHONY	E	DO	M	JUPITER	FL	Internal Medicine	33	24	31	26.52	40	19.5393

Isolation Forest

This code snippet demonstrates using the Isolation Forest algorithm to detect anomalies in a synthetic dataset. First, a dataset is generated with training, test, and outlier data, combining points clustered around specific centers and uniformly distributed outliers. The data is then standardized using StandardScaler to ensure equal feature contribution. The Isolation Forest model is trained on the standardized training data and subsequently used to predict anomalies in the training, test, and outlier data. Anomalies are labeled as -1, while normal points are labeled as 1. Finally, the results are visualized with a plot that displays the training data in white, test data in green, outliers in red, and detected anomalies marked with blue 'x's. This visualization helps illustrate how effectively the model identifies anomalies across different datasets.

In [ ]:

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

# Generating a synthetic dataset
rng = np.random.RandomState(42)
X = 0.3 * rng.randn(100, 2)
X_train = np.r_[X + 2, X - 2]
X_test = 0.3 * rng.randn(20, 2)
X_outliers = rng.uniform(low=-4, high=4, size=(20, 2))

# Standardizing the data
scaler = StandardScaler()
X_train = scaler.fit_transform(X_train)
X_test = scaler.transform(X_test)
X_outliers = scaler.transform(X_outliers)

# Isolation Forest
iso_forest = IsolationForest(contamination=0.1, random_state=rng)
iso_forest.fit(X_train)

# Predicting anomalies
y_pred_train_iso = iso_forest.predict(X_train)
y_pred_test_iso = iso_forest.predict(X_test)
y_pred_outliers_iso = iso_forest.predict(X_outliers)

# Plotting results
def plot_results(X_train, X_test, X_outliers, y_pred_train, y_pred_test, y_pred_outliers, title):
    plt.figure(figsize=(10, 6))
    plt.title(title)
    plt.scatter(X_train[:, 0], X_train[:, 1], c='white', s=20, edgecolor='k', label="Training data")
    plt.scatter(X_test[:, 0], X_test[:, 1], c='green', s=20, edgecolor='k', label="Test data")
    plt.scatter(X_outliers[:, 0], X_outliers[:, 1], c='red', s=20, edgecolor='k', label="Outliers")
    plt.scatter(X_train[y_pred_train == -1][:, 0], X_train[y_pred_train == -1][:, 1], c='blue', s=20, edgecolor='k', marker='x')
    plt.scatter(X_test[y_pred_test == -1][:, 0], X_test[y_pred_test == -1][:, 1], c='blue', s=20, edgecolor='k', marker='x')
    plt.scatter(X_outliers[y_pred_outliers == -1][:, 0], X_outliers[y_pred_outliers == -1][:, 1], c='blue', s=20, edgecolor='k', marker='x')
    plt.legend()
    plt.show()

plot_results(X_train, X_test, X_outliers, y_pred_train_iso, y_pred_test_iso, y_pred_outliers_iso, "Isolation Forest")
```



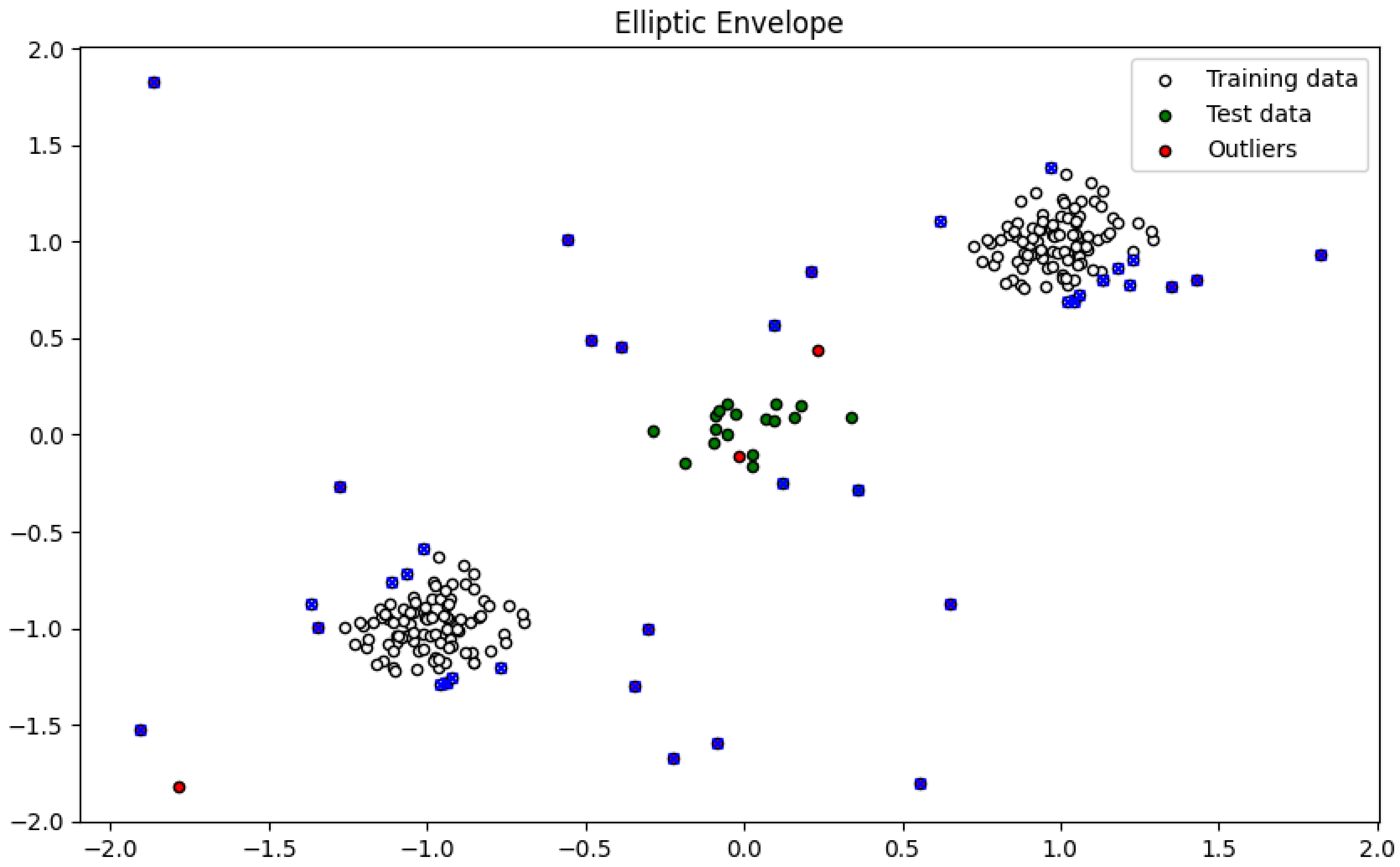
Elliptic Envelope

This code demonstrates using the Elliptic Envelope algorithm to detect anomalies in a synthetic dataset. A dataset is generated with training, test, and outlier data, which is then standardized using StandardScaler to ensure consistent feature scaling. The Elliptic Envelope model is trained on the standardized training data and predicts anomalies in the training, test, and outlier datasets. Anomalies are labeled as -1, while normal points are labeled as 1. The results are visualized in a plot, where training data points are shown in white, test data in green, outliers in red, and detected anomalies marked with blue 'x's. This visualization illustrates the model's effectiveness in identifying anomalies across different data sets.

In [ ]:

```python
import numpy as np
import pandas as pd
```

```
import matplotlib.pyplot as plt
from sklearn.covariance import EllipticEnvelope
from sklearn.preprocessing import StandardScaler

# Generating a synthetic dataset
rng = np.random.RandomState(42)
X = 0.3 * rng.randn(100, 2)
X_train = np.r_[X + 2, X - 2]
X_test = 0.3 * rng.randn(20, 2)
X_outliers = rng.uniform(low=-4, high=4, size=(20, 2))

# Standardizing the data
scaler = StandardScaler()
X_train = scaler.fit_transform(X_train)
X_test = scaler.transform(X_test)
X_outliers = scaler.transform(X_outliers)

# Elliptic Envelope
ell_env = EllipticEnvelope(contamination=0.1)
ell_env.fit(X_train)

# Predicting anomalies
y_pred_train_ell = ell_env.predict(X_train)
y_pred_test_ell = ell_env.predict(X_test)
y_pred_outliers_ell = ell_env.predict(X_outliers)

# Plotting results
def plot_results(X_train, X_test, X_outliers, y_pred_train, y_pred_test, y_pred_outliers, title):
    plt.figure(figsize=(10, 6))
    plt.title(title)
    plt.scatter(X_train[:, 0], X_train[:, 1], c='white', s=20, edgecolor='k', label="Training data")
    plt.scatter(X_test[:, 0], X_test[:, 1], c='green', s=20, edgecolor='k', label="Test data")
    plt.scatter(X_outliers[:, 0], X_outliers[:, 1], c='red', s=20, edgecolor='k', label="Outliers")
    plt.scatter(X_train[y_pred_train == -1][:, 0], X_train[y_pred_train == -1][:, 1], c='blue', s=20, edgecolor='k', marker='x')
    plt.scatter(X_test[y_pred_test == -1][:, 0], X_test[y_pred_test == -1][:, 1], c='blue', s=20, edgecolor='k', marker='x')
    plt.scatter(X_outliers[y_pred_outliers == -1][:, 0], X_outliers[y_pred_outliers == -1][:, 1], c='blue', s=20, edgecolor='k', marker='x')
    plt.legend()
    plt.show()

plot_results(X_train, X_test, X_outliers, y_pred_train_ell, y_pred_test_ell, y_pred_outliers_ell, "Elliptic Envelope")
```



One-Class SVM

This code snippet demonstrates using the One-Class SVM algorithm to detect anomalies in a synthetic dataset. It starts by generating a dataset with training, test, and outlier data. The data is then standardized using StandardScaler to ensure consistent scaling. A One-Class SVM model is trained on the standardized training data and used to predict anomalies in the training, test, and outlier data. The anomalies are labeled as -1, while normal points are labeled as 1. Finally, the results are visualized in a plot where the training data points are shown in white, test data in green, outliers in red, and detected anomalies marked with blue 'x's. This visualization helps to illustrate how well the model identifies anomalies across different datasets.

In [ ]:

```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
from sklearn.svm import OneClassSVM
from sklearn.preprocessing import StandardScaler

# Generating a synthetic dataset
rng = np.random.RandomState(42)
X = 0.3 * rng.randn(100, 2)
X_train = np.r_[X + 2, X - 2]
X_test = 0.3 * rng.randn(20, 2)
X_outliers = rng.uniform(low=-4, high=4, size=(20, 2))

# Standardizing the data
scaler = StandardScaler()
X_train = scaler.fit_transform(X_train)
X_test = scaler.transform(X_test)
X_outliers = scaler.transform(X_outliers)

# One-class SVM
one_svm = OneClassSVM(nu=0.1, kernel="rbf", gamma=0.1)
one_svm.fit(X_train)

# Predicting anomalies
y_pred_train_svm = one_svm.predict(X_train)
y_pred_test_svm = one_svm.predict(X_test)
y_pred_outliers_svm = one_svm.predict(X_outliers)

# Plotting results
def plot_results(X_train, X_test, X_outliers, y_pred_train, y_pred_test, y_pred_outliers, title):
    plt.figure(figsize=(10, 6))
    plt.title(title)
    plt.scatter(X_train[:, 0], X_train[:, 1], c='white', s=20, edgecolor='k', label="Training data")
    plt.scatter(X_test[:, 0], X_test[:, 1], c='green', s=20, edgecolor='k', label="Test data")
    plt.scatter(X_outliers[:, 0], X_outliers[:, 1], c='red', s=20, edgecolor='k', label="Outliers")
    plt.scatter(X_train[y_pred_train == -1][:, 0], X_train[y_pred_train == -1][:, 1], c='blue', s=20, edgecolor='k', marker='x')
    plt.scatter(X_test[y_pred_test == -1][:, 0], X_test[y_pred_test == -1][:, 1], c='blue', s=20, edgecolor='k', marker='x')
    plt.scatter(X_outliers[y_pred_outliers == -1][:, 0], X_outliers[y_pred_outliers == -1][:, 1], c='blue', s=20, edgecolor='k', marker='x')
    plt.legend()
    plt.show()
```

```
plot_results(X_train, X_test, X_outliers, y_pred_train_svm, y_pred_test_svm, y_pred_outliers_svm, "One-Class SVM")
```