Milestone-3

```
# import library
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
import warnings
warnings.filterwarnings('ignore')
```

Tasks of Milestone - 3

- To perform Isolation forest with the visualization of anomalies.
- To perform Elliptic Envelope algorithm with visualization.
- To perform OneClassSvm algorithms.

Read the data

```
# preprocessed dataset for visulization of categorical features
org_df=pd.read_csv('preprocessed.csv')
org_df.head()
```

	Credentials of the Provider	Gender of the Provider	Entity Type of the Provider	City of the Provider	State Code of the Provider	Country Code of the Provider	Provider Type	Part
0	MD	F	I	SAINT LOUIS	MO	US	Internal Medicine	
1	MD	F	I	FAYETTEVILLE	NC	US	Obstetrics & Gynecology	
2	DPM	M	I	NORTH HAVEN	CT	US	Podiatry	
3	MD	M	I	KANSAS CITY	MO	US	Internal Medicine	
4	DO	M	I	JUPITER	FL	US	Internal Medicine	

```
# Encoded dataset for the machine learning model training and anomay detectiona
df=pd.read_csv('encoded.csv')
df.head()
```

	Credentials of the Provider	City of the Provider	State Code of the Provider	Provider Type	HCPCS Code	Number of Services	Number of Medicare Beneficiaries	Nu I I Benefic: Day :
0	73827	500	1997	11366	1297	27.0	24.0	
1	73827	209	3725	1028	243	175.0	175.0	
2	1915	10	1403	2027	44	32.0	13.0	
3	73827	317	1997	11366	460	20.0	18.0	
4	6176	51	7263	11366	732	33.0	24.0	

5 rows × 27 columns

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 100000 entries, 0 to 99999
Data columns (total 27 columns):
 #   Column                                                Non-Null Count   Dtype
---  ------                                                --------------   -----
 0   Credentials of the Provider                           100000 non-null  int64
 1   City of the Provider                                  100000 non-null  int64
 2   State Code of the Provider                            100000 non-null  int64
 3   Provider Type                                         100000 non-null  int64
 4   HCPCS Code                                            100000 non-null  int64
 5   Number of Services                                    100000 non-null  float64
 6   Number of Medicare Beneficiaries                      100000 non-null  float64
 7   Number of Distinct Medicare Beneficiary/Per Day Services  100000 non-null  float64
 8   Average Medicare Allowed Amount                       100000 non-null  float64
 9   Average Submitted Charge Amount                       100000 non-null  float64
 10  Average Medicare Payment Amount                       100000 non-null  float64
 11  Average Medicare Standardized Amount                  100000 non-null  float64
 12  Gender of the Provider_F                              100000 non-null  bool
 13  Gender of the Provider_M                              100000 non-null  bool
 14  Gender of the Provider_O                              100000 non-null  bool
 15  Entity Type of the Provider_I                         100000 non-null  bool
 16  Entity Type of the Provider_O                         100000 non-null  bool
 17  Country Code of the Provider_DE                       100000 non-null  bool
 18  Country Code of the Provider_JP                       100000 non-null  bool
 19  Country Code of the Provider_TR                       100000 non-null  bool
 20  Country Code of the Provider_US                       100000 non-null  bool
 21  Medicare Participation Indicator_N                    100000 non-null  bool
 22  Medicare Participation Indicator_Y                    100000 non-null  bool
 23  Place of Service_F                                    100000 non-null  bool
 24  Place of Service_O                                    100000 non-null  bool
 25  HCPCS Drug Indicator_N                                100000 non-null  bool
 26  HCPCS Drug Indicator_Y                                100000 non-null  bool
dtypes: bool(15), float64(7), int64(5)
memory usage: 10.6 MB
```

Standardized the data

```
# Standardized the data
from sklearn.preprocessing import StandardScaler
ss=StandardScaler()

numerical_cols=df.iloc[:,:12].columns
scaled_data=ss.fit_transform(df[numerical_cols])
temp_df=pd.DataFrame(scaled_data,columns=df.iloc[:,:12].columns)
temp_df.head()
```

	Credentials of the Provider	City of the Provider	State Code of the Provider	Provider Type	HCPCS Code	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	Sta
0	0.594983	1.571686	-0.737342	1.336743	0.397579	-0.085301	-0.059308	-0.070183	0.385450	-0.046433	0.400082	
1	0.594983	0.189180	-0.004973	-0.940500	-0.439989	-0.025939	0.076775	0.020049	0.086673	0.182805	0.207649	
2	-1.684316	-0.756245	-0.989093	-0.720441	-0.598126	-0.083296	-0.069222	-0.067135	-0.041922	-0.187794	-0.064687	
3	0.594983	0.702275	-0.737342	1.336743	-0.267549	-0.088109	-0.064716	-0.074451	-0.380709	-0.328957	-0.370166	

```
scaled_df=temp_df.join(df.iloc[:,12:])
scaled_df.head()
```

	Credentials of the Provider	City of the Provider	State Code of the Provider	Provider Type	HCPCS Code	Number of Services	Number of Medicare Beneficiaries	Number of Distinct Medicare Beneficiary/Per Day Services	Average Medicare Allowed Amount	Average Submitted Charge Amount	...	Coun Code of Provider
0	0.594983	1.571686	-0.737342	1.336743	0.397579	-0.085301	-0.059308	-0.070183	0.385450	-0.046433	...	F
1	0.594983	0.189180	-0.004973	-0.940500	-0.439989	-0.025939	0.076775	0.020049	0.086673	0.182805	...	F
2	-1.684316	-0.756245	-0.989093	-0.720441	-0.598126	-0.083296	-0.069222	-0.067135	-0.041922	-0.187794	...	F
3	0.594983	0.702275	-0.737342	1.336743	-0.267549	-0.088109	-0.064716	-0.074451	-0.380709	-0.328957	...	F
4	-1.549260	-0.561459	1.494517	1.336743	-0.051402	-0.082895	-0.059308	-0.067744	-0.291221	-0.296019	...	F

5 rows × 27 columns

```
scaled_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 100000 entries, 0 to 99999
Data columns (total 27 columns):
 #   Column                                                   Non-Null Count   Dtype
---  ------                                                   --------------   -----
 0   Credentials of the Provider                              100000 non-null  float64
 1   City of the Provider                                     100000 non-null  float64
 2   State Code of the Provider                               100000 non-null  float64
 3   Provider Type                                            100000 non-null  float64
 4   HCPCS Code                                               100000 non-null  float64
 5   Number of Services                                       100000 non-null  float64
 6   Number of Medicare Beneficiaries                         100000 non-null  float64
 7   Number of Distinct Medicare Beneficiary/Per Day Services 100000 non-null  float64
 8   Average Medicare Allowed Amount                          100000 non-null  float64
 9   Average Submitted Charge Amount                          100000 non-null  float64
 10  Average Medicare Payment Amount                          100000 non-null  float64
 11  Average Medicare Standardized Amount                     100000 non-null  float64
 12  Gender of the Provider_F                                 100000 non-null  bool
 13  Gender of the Provider_M                                 100000 non-null  bool
 14  Gender of the Provider_O                                 100000 non-null  bool
 15  Entity Type of the Provider_I                            100000 non-null  bool
 16  Entity Type of the Provider_O                            100000 non-null  bool
 17  Country Code of the Provider_DE                          100000 non-null  bool
 18  Country Code of the Provider_JP                          100000 non-null  bool
 19  Country Code of the Provider_TR                          100000 non-null  bool
 20  Country Code of the Provider_US                          100000 non-null  bool
 21  Medicare Participation Indicator_N                       100000 non-null  bool
 22  Medicare Participation Indicator_Y                       100000 non-null  bool
 23  Place of Service_F                                       100000 non-null  bool
 24  Place of Service_O                                       100000 non-null  bool
 25  HCPCS Drug Indicator_N                                   100000 non-null  bool
 26  HCPCS Drug Indicator_Y                                   100000 non-null  bool
dtypes: bool(15), float64(12)
memory usage: 10.6 MB
```

Anomaly detection

1- Isolation Forest

```
from sklearn.ensemble import IsolationForest
# Step 1: Use the scaled dataset (final_df)
# Step 2: Apply Isolation Forest
iso_forest=IsolationForest(n_estimators=200,contamination=0.01,random_state=42)
iso_forest.fit(scaled_df)
anomaly_labels=iso_forest.predict(scaled_df)
```

```
df[anomaly_labels==-1]
```

	Credentials of the Provider	City of the Provider	State Code of the Provider	Provider Type	HCPCS Code	Number of Services	Number of Medicare Beneficiaries	Number of Distinct Medicare Beneficiary/Per Day Services	Average Medicare Allowed Amount	Average Submitted Charge Amount	...	Co Pr
221	73827	592	1997	447	17	13.0	13.0	13.0	1686.694615	6785.660000	...	
224	73827	7	3333	507	645	78.0	78.0	78.0	191.303846	209.564359	...	
340	73827	298	787	512	19	19.0	18.0	18.0	1311.228947	6343.348421	...	
375	73827	244	1994	999	3	13.0	13.0	13.0	3102.210000	7884.615385	...	
439	73827	406	1753	1745	24	149.0	57.0	149.0	4213.732148	7374.000000	...	
...	...	...	...	...	...	...	...	...	...	...	...	
99640	73827	96	1423	512	6	27.0	23.0	25.0	777.024815	1525.000000	...	
99678	73827	2	3333	1240	438	4140.0	2995.0	4140.0	13.320000	82.169345	...	
99774	73827	28	1520	512	5	13.0	13.0	13.0	550.430769	3408.050000	...	
99914	73827	5	7775	512	13	34.0	25.0	34.0	3605.580000	8500.000000	...	
99932	73827	23	6361	12537	8	16.0	15.0	16.0	18112.740000	47000.000000	...	

1000 rows × 27 columns

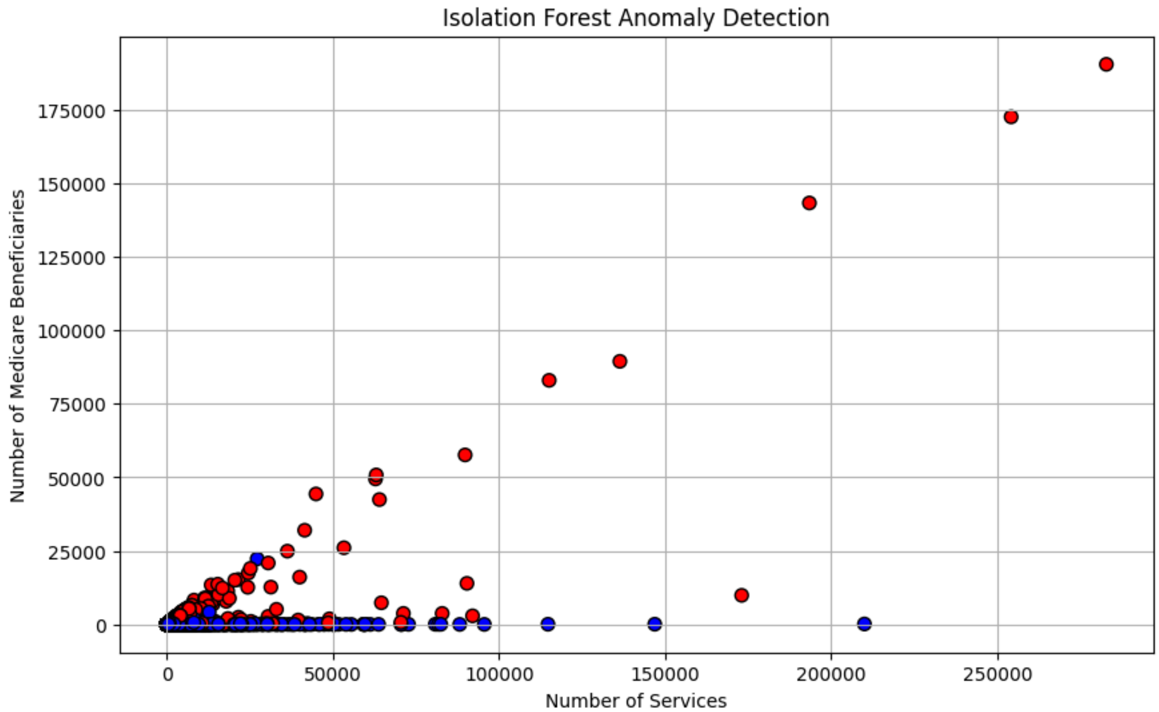
- These above are the rows which are anomalies in the dataset
- There are 1000 anomalies present in the dataset

Visualization for the isolation forest results

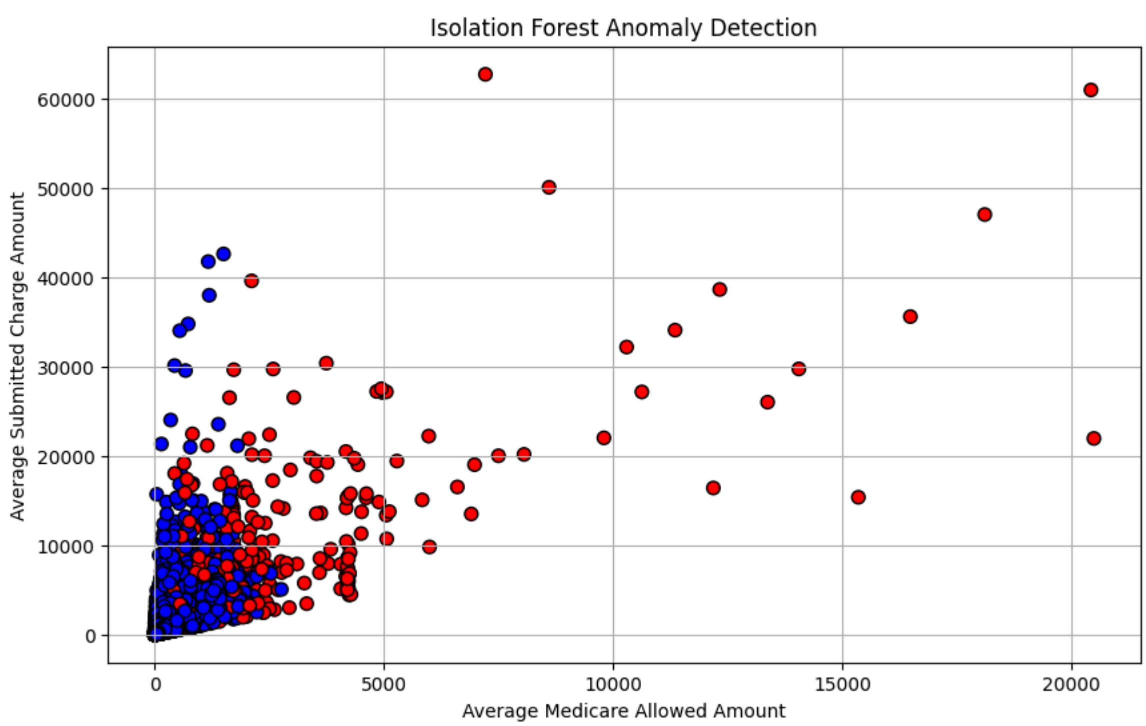
Scatter plots for the isolation forest

```
# Map the anomaly labels to colors
colors = np.array(['b', 'r'])  # Normal points: blue, Anomalies: orange
anomaly_colors = np.where(anomaly_labels == 1, colors[0], colors[1])
```

```
# Plot the graph of the result of Isolation forest b/w 'Number of Services' and 'Number of Medicar
# Step 3: Visualize the results
features = df[['Number of Services', 'Number of Medicare Beneficiaries']].values
plt.figure(figsize=(10, 6))
plt.scatter(features[:, 0], features[:, 1], c=anomaly_colors, marker='o', edgecolor='k', s=50)
plt.title('Isolation Forest Anomaly Detection')
plt.xlabel('Number of Services')
plt.ylabel('Number of Medicare Beneficiaries')
plt.grid(True)
plt.show()
```




```
# plot the graph between 'Average Medicare Allowed Amount' and 'Average Submitted Charge Amount'
plt.figure(figsize=(10, 6))
plt.scatter(x=df.loc[:,'Average Medicare Allowed Amount'],
            y=df.loc[:,'Average Submitted Charge Amount'],c=anomaly_colors, marker='o', edgecolor='
plt.title('Isolation Forest Anomaly Detection')
plt.xlabel('Average Medicare Allowed Amount')
plt.ylabel('Average Submitted Charge Amount')
plt.grid(True)
plt.show()
```



- Above plot shows that the red point are the anomalies and the blue points are the Normal datapoint.

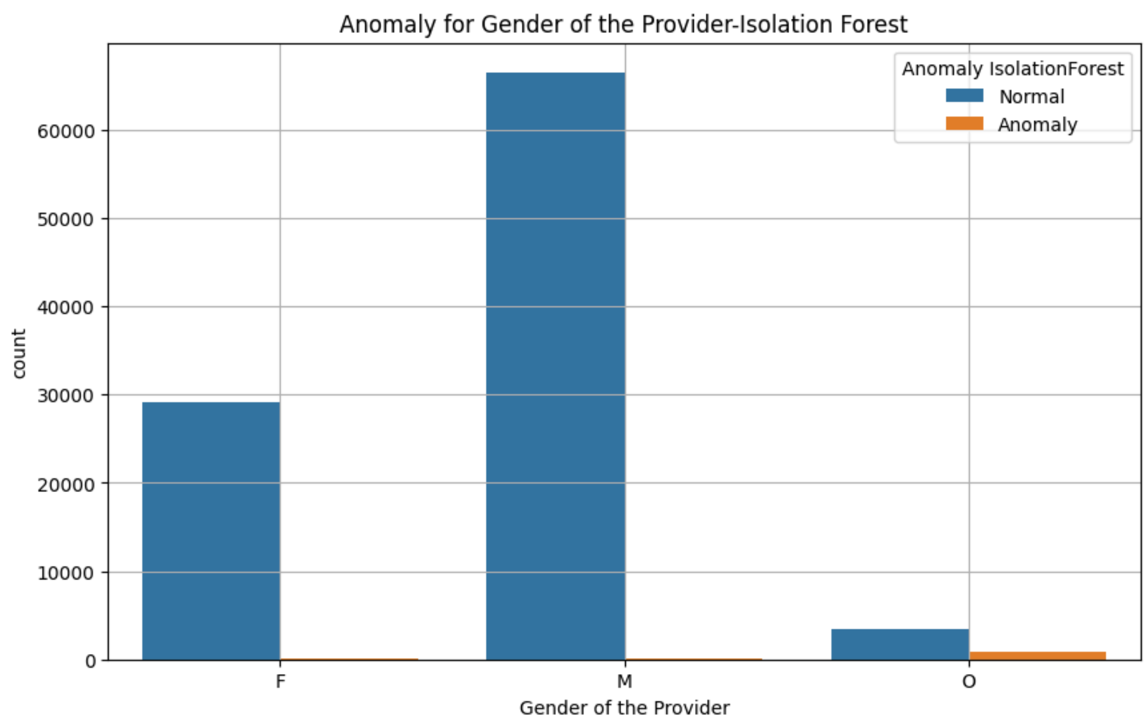
Bar plot for the catogorical features

```
# Create a column as Amomaly Isolations forest which is having Normal and Anomaly category for eac
org_df['Anomaly IsolationForest']=anomaly_labels
org_df['Anomaly IsolationForest'] = org_df['Anomaly IsolationForest'].replace({1: 'Normal', -1: 'A
```

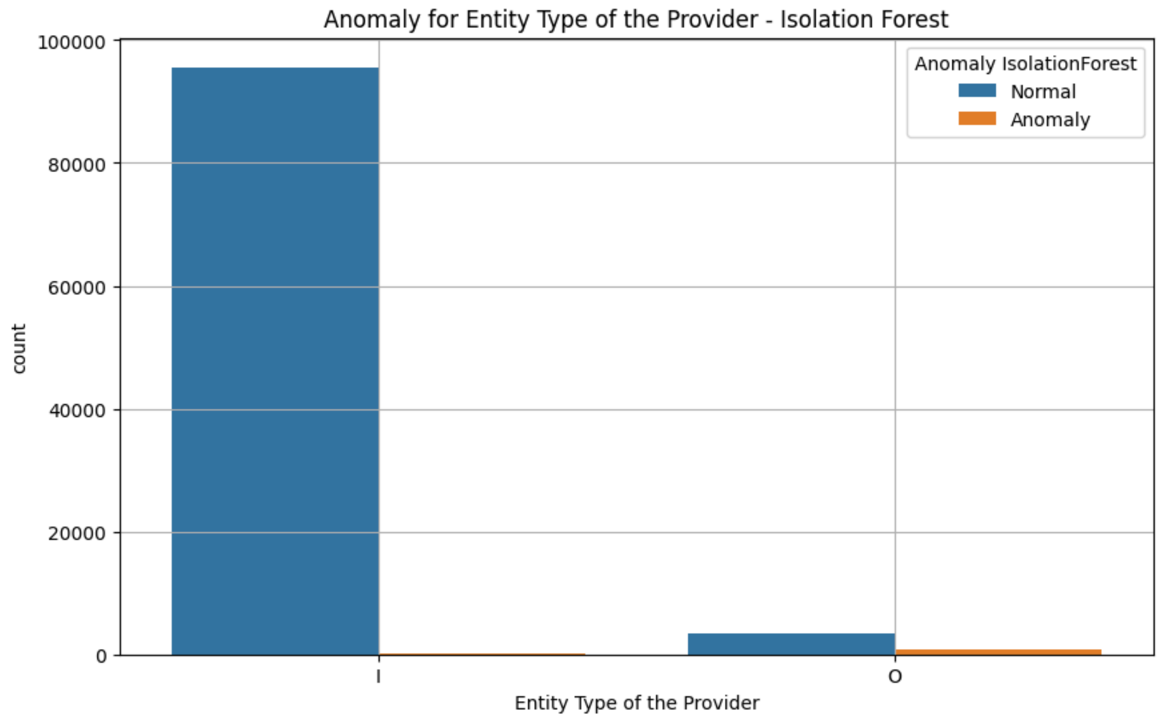
```
org_df.head()
```

	Credentials of the Provider	Gender of the Provider	Entity Type of the Provider	City of the Provider	State Code of the Provider	Country Code of the Provider	Provider Type	Medicare Participation Indicator	Place of Service	HCPCS Code	HCPCS Drug Indicator	Number of Services
0	MD	F	I	SAINT LOUIS	MO	US	Internal Medicine	Y	F	99223	N	27.0
1	MD	F	I	FAYETTEVILLE	NC	US	Obstetrics & Gynecology	Y	O	G0202	N	175.0
2	DPM	M	I	NORTH HAVEN	CT	US	Podiatry	Y	O	99348	N	32.0
3	MD	M	I	KANSAS CITY	MO	US	Internal Medicine	Y	O	81002	N	20.0
4	DO	M	I	JUPITER	FL	US	Internal Medicine	Y	O	96372	N	33.0

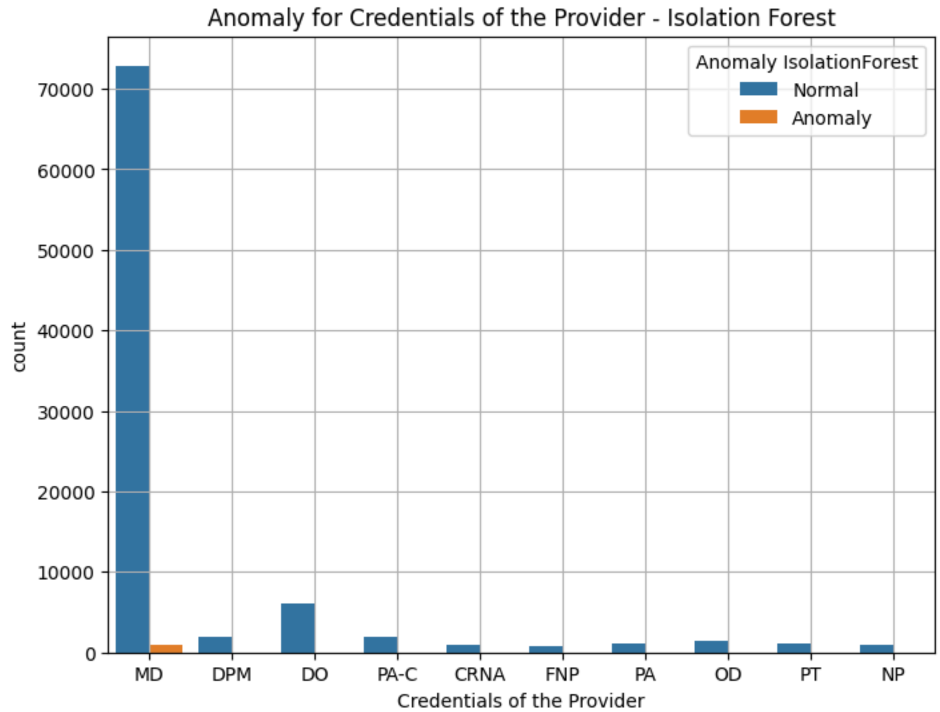
```
# count plot for Gender of the Provider
plt.figure(figsize=(10, 6))
sns.countplot(org_df,x='Gender of the Provider',hue='Anomaly IsolationForest')
plt.title('Anomaly for Gender of the Provider-Isolation Forest')
plt.grid(True)
plt.show()
```



```
# count plot for Entity Type of the Provider
plt.figure(figsize=(10, 6))
sns.countplot(org_df,x='Entity Type of the Provider',hue='Anomaly IsolationForest')
plt.title('Anomaly for Entity Type of the Provider - Isolation Forest')
plt.grid(True)
plt.show()
```




```
# Identify the top 10 categories
top_10_categories = org_df['Credentials of the Provider'].value_counts().head(10).index
top_10_data = org_df[org_df['Credentials of the Provider'].isin(top_10_categories)]
# count plot for the top 10 Provider type
plt.figure(figsize=(8, 6))
sns.countplot(top_10_data,x='Credentials of the Provider',hue='Anomaly IsolationForest')
plt.title('Anomaly for Credentials of the Provider - Isolation Forest')
plt.grid(True)
plt.show()
```



- In All the above bar plots blue bara shows the count of normal points
- The orange bars shows the count of anomalies present in the dataset for the different categories

2- Elliptic Envelope

```
# Apply Elliptic Envelope
from sklearn.covariance import EllipticEnvelope
elliptic_env = EllipticEnvelope(contamination=0.01, random_state=42)
elliptic_env.fit(scaled_df)
anomaly_predictions = elliptic_env.predict(scaled_df)
```

```
df[anomaly_predictions==-1]
```

	Credentials of the Provider	City of the Provider	State Code of the Provider	Provider Type	HCPCS Code	Number of Services	Number of Medicare Beneficiaries	Number of Distinct Medicare Beneficiary/Per Day Services	Average Medicare Allowed Amount	Average Submitted Charge Amount	...	Cc Pr
79	6176	13	1997	3098	49	1568.0	20.0	22.0	12.528068	15.000000	...	
120	73827	118	2792	1745	27	15000.0	12.0	20.0	1.060300	3.900000	...	
234	73827	124	1136	727	90	1620.0	19.0	27.0	16.891630	35.666667	...	
337	73827	60	2020	2495	33	5234.0	26.0	60.0	5.974026	10.387658	...	
563	73827	611	2858	1794	21	70700.0	22.0	311.0	0.023652	0.130000	...	
...	...	...	...	...	...	...	...	...	...	...	...	
99576	113	634	2791	12537	12	15600.0	77.0	78.0	0.210269	1.000000	...	
99593	73827	40	171	1745	37	1970.0	59.0	197.0	21.903467	88.970000	...	
99872	73827	400	4561	727	6	43000.0	14.0	113.0	7.481456	8.000000	...	
99914	73827	5	7775	512	13	34.0	25.0	34.0	3605.580000	8500.000000	...	
99932	73827	23	6361	12537	8	16.0	15.0	16.0	18112.740000	47000.000000	...	

1000 rows × 27 columns

- according to the Ellopic envelope algorithm, The no of present of anomalies present in the dataset are 1000.
- Above rows are the one which is anomalies in the dataset.

```
# Create a column as Anomaly Elliptic Envelope
org_df['Anomaly EllipticEnvelope']=anomaly_predictions
org_df['Anomaly EllipticEnvelope'] = org_df['Anomaly EllipticEnvelope'].replace({1: 'Normal', -1:
```

```
org_df.head()
```

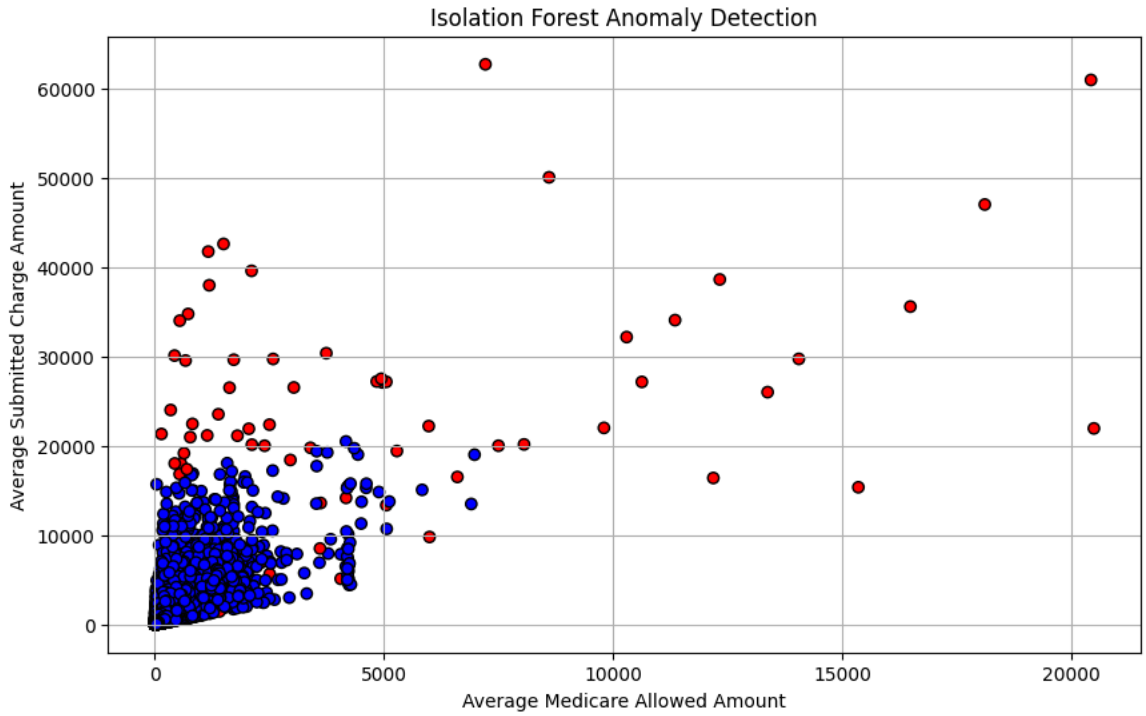
	Credentials of the Provider	Gender of the Provider	Entity Type of the Provider	City of the Provider	State Code of the Provider	Country Code of the Provider	Provider Type	Medicare Participation Indicator	Place of Service	HCPCS Code	HCPCS Drug Indicator	Number of Services
0	MD	F	I	SAINT LOUIS	MO	US	Internal Medicine	Y	F	99223	N	27.0
1	MD	F	I	FAYETTEVILLE	NC	US	Obstetrics & Gynecology	Y	O	G0202	N	175.0
2	DPM	M	I	NORTH HAVEN	CT	US	Podiatry	Y	O	99348	N	32.0
3	MD	M	I	KANSAS CITY	MO	US	Internal Medicine	Y	O	81002	N	20.0
4	DO	M	I	JUPITER	FL	US	Internal Medicine	Y	O	96372	N	33.0

Visualization for the Elliptic Envelope results

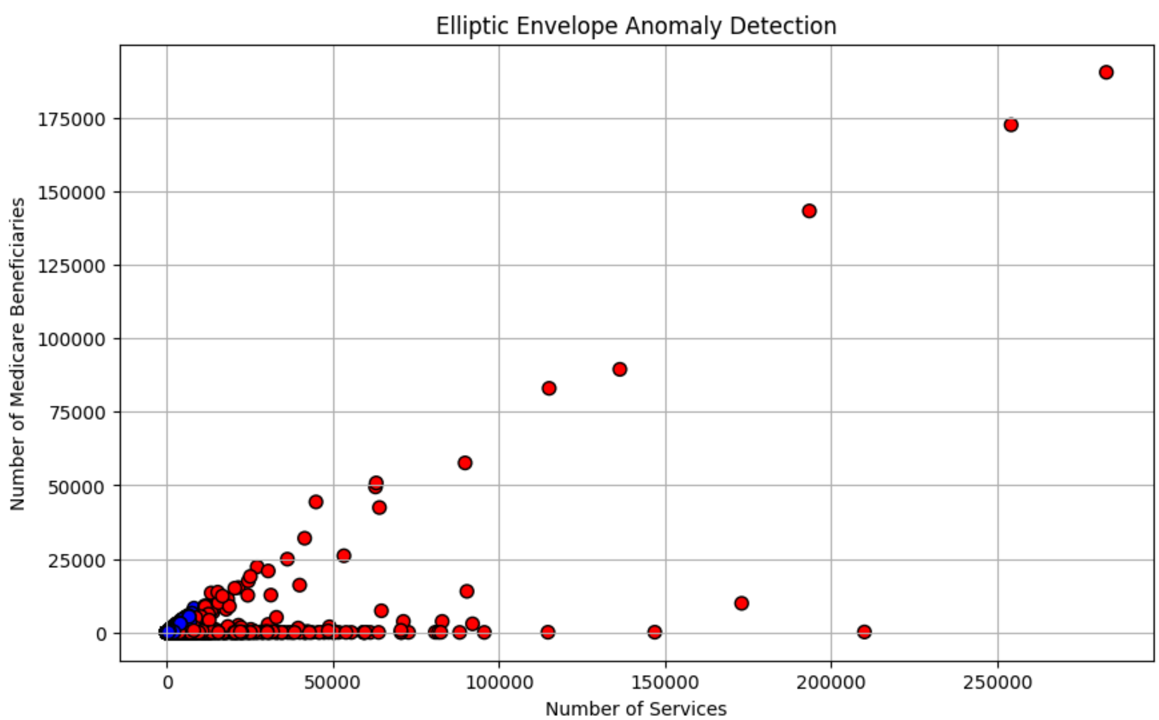
Scatter plots for the different features having normal and anomalous points

```
# Map the anomaly labels to colors
colors = np.array(['b', 'r'])  # Normal points: blue, Anomalies: red
anomaly_col = np.where(anomaly_predictions == 1, colors[0], colors[1])
```

```
# Visualize the results
features = df[['Average Medicare Allowed Amount', 'Average Submitted Charge Amount']].values
plt.figure(figsize=(10, 6))
plt.scatter(features[:, 0], features[:, 1], c=anomaly_col, marker='o', edgecolor='k')
plt.title('Isolation Forest Anomaly Detection')
plt.xlabel('Average Medicare Allowed Amount')
plt.ylabel('Average Submitted Charge Amount')
plt.grid(True)
plt.show()
```



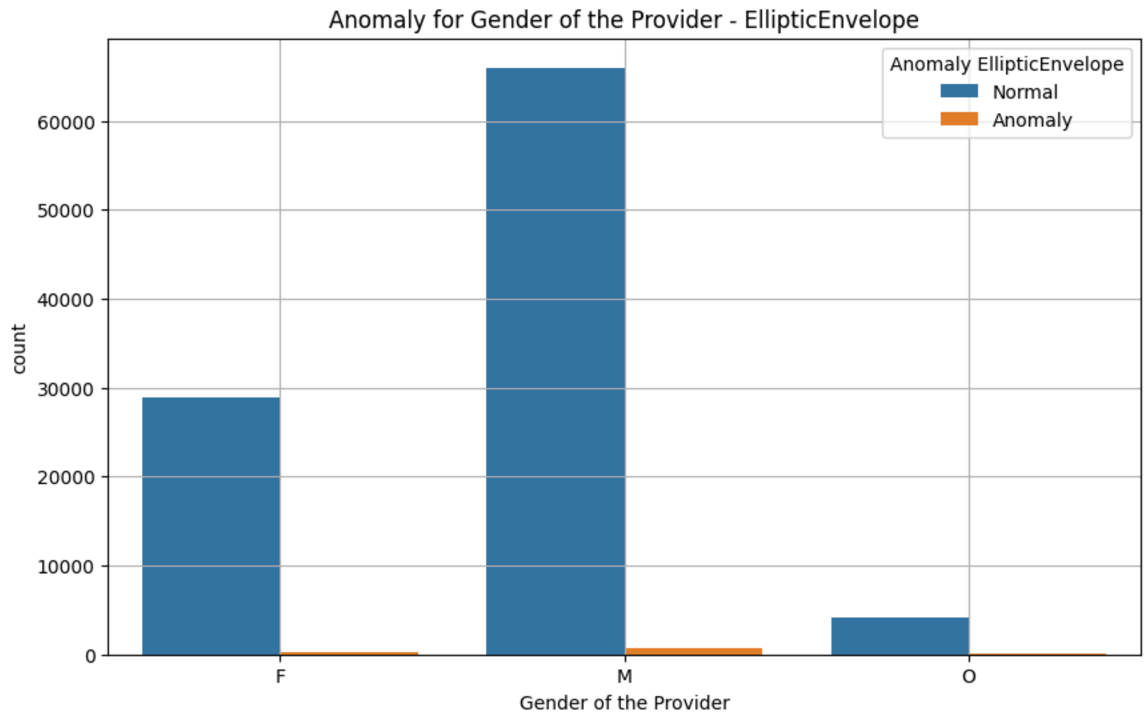

```
# scatter plot for 'Number of Services and NUmber of Medicare Beneficiaries'
features = df[['Number of Services', 'Number of Medicare Beneficiaries']].values
plt.figure(figsize=(10, 6))
plt.scatter(features[:, 0], features[:, 1], c=anomaly_col, marker='o', edgecolor='k', s=50)
plt.title('Elliptic Envelope Anomaly Detection')
plt.xlabel('Number of Services')
plt.ylabel('Number of Medicare Beneficiaries')
plt.grid(True)
plt.show()
```



- In the above plot we can see the two region in which there are two type of points red and blue
- Red points shows the anomalies and Blue points shows the normal transaction in the dataset.

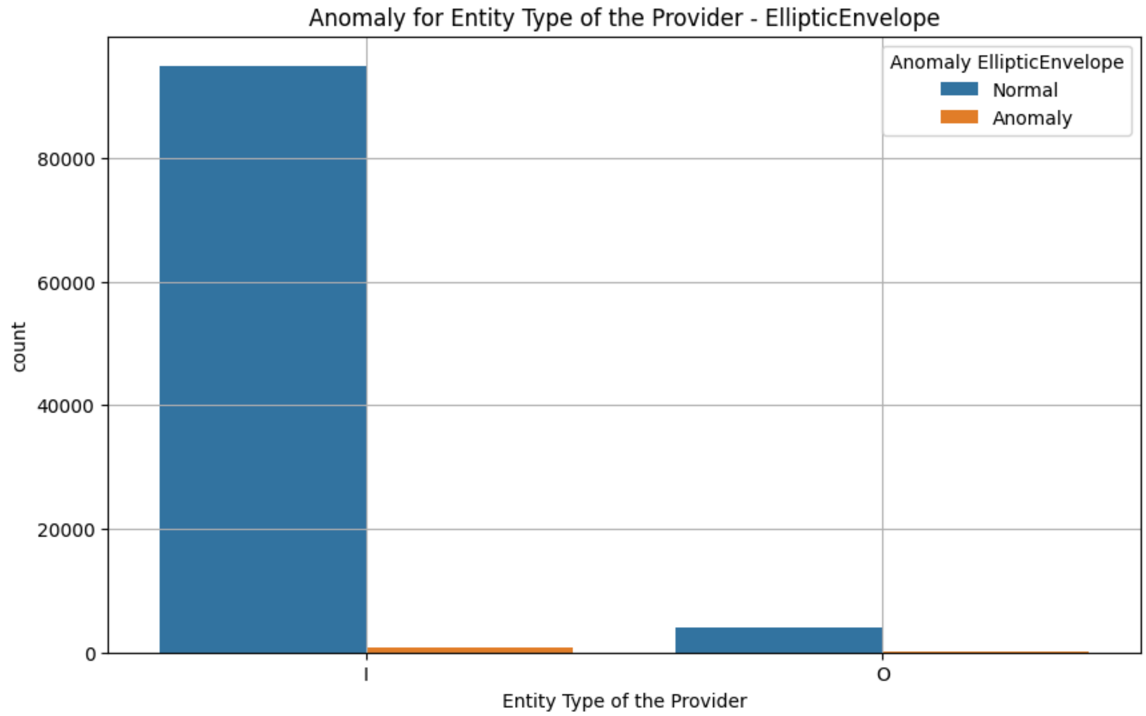
Barplot for the different features

```
# plot for 'Gender of the Provider'
plt.figure(figsize=(10, 6))
sns.countplot(org_df,x='Gender of the Provider',hue='Anomaly EllipticEnvelope')
plt.title('Anomaly for Gender of the Provider - EllipticEnvelope')
plt.grid(True)
plt.show()
```



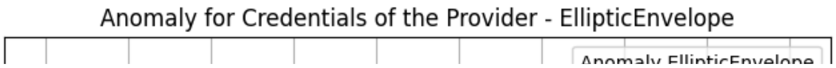
- The above pot shows the count plot for the gender of the provider
- There are three type of Gender of the provider- Male, Female and Organization
- clearly we can see the normal and anomalies count for the gender of the providers

```
plt.figure(figsize=(10, 6))
sns.countplot(org_df,x='Entity Type of the Provider',hue='Anomaly EllipticEnvelope')
plt.title('Anomaly for Entity Type of the Provider - EllipticEnvelope')
plt.grid(True)
plt.show()
```



- According to the above plot we can see the type of provider individual and organization.
- I category stands for individual type of provider.
- O category stands for organization type of provider.
- Blue and orange bars shows us the count of normal and fraudulent transactions in the dataset.

```
# Identify the top 10 categories
top_10_categories = org_df['Credentials of the Provider'].value_counts().head(10).index
top_10_data = org_df[org_df['Credentials of the Provider'].isin(top_10_categories)]
# count plot for the top 10 Provider type
plt.figure(figsize=(8, 6))
sns.countplot(top_10_data,x='Credentials of the Provider',hue='Anomaly EllipticEnvelope')
plt.title('Anomaly for Credentials of the Provider - EllipticEnvelope')
plt.grid(True)
plt.show()
```



- The above plot shows that the top 10 credentials of the provider.
- Also shows the normal and anomalies count of credential of the provider.

OneClassSvm

```
from sklearn.svm import OneClassSVM

# Apply One-Class SVM
oneclass_svm = OneClassSVM(nu=0.2, kernel='rbf', gamma='scale')
oneclass_svm.fit(scaled_df)
anomaly_labels_oc = oneclass_svm.predict(scaled_df)
```

```
df[anomaly_labels_oc==-1]
```

```
# Create a column as Anomaly Elliptic Envelope
org_df['Anomaly OneClassSvm']=anomaly_labels_oc
org_df['Anomaly OneClassSvm'] = org_df['OneClassSvm'].replace({1: 'Normal', -1: 'Anomaly'})
```

Visualization of OneClassSvm anomalies

Scattor plots