INFOSYS SPRINGBOARD INTERNSHIP

MileStone 3

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In [1]:
```
import pandas as pd
import matplotlib.pyplot as plt
import warnings
warnings.filterwarnings('ignore')

data = pd.read_csv("/Users/rudranighosh/Downloads/Healthcare Providers.csv")
data.head()
```

Out[1]:

	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	HC Descrip
0	8774979	1891106191	UPADHYAYULA	SATYASREE	NaN	M.D.	F	I	1402 S GRAND BLVD	FDT 14TH FLOOR	...	99223	Initial hos inpatient typically
1	3354385	1346202256	JONES	WENDY	P	M.D.	F	I	2950 VILLAGE DR	NaN	...	G0202	Scree mammogra bilatera view stu
2	3001884	1306820956	DUROCHER	RICHARD	W	DPM	M	I	20 WASHINGTON AVE	STE 212	...	99348	Establi patient h visit, typ 25
3	7594822	1770523540	FULLARD	JASPER	NaN	MD	M	I	5746 N BROADWAY ST	NaN	...	81002	Urina manua
4	746159	1073627758	PERROTTI	ANTHONY	E	DO	M	I	875 MILITARY TRL	SUITE 200	...	96372	Inje beneat skin o muscle

5 rows × 27 columns

In [2]:
```
# 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 [3]:
```
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']

data=data.drop(columns=irrelevant_columns)
```

Columns that have no relevance in our assignment have been dropped

In [4]:
```
data.head()
```

Out[4]:

	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	Numbe Medic Beneficia
0	8774979	1891106191	UPADHYAYULA	SATYASREE	NaN	M.D.	F	SAINT LOUIS	MO	Internal Medicine	27	
1	3354385	1346202256	JONES	WENDY	P	M.D.	F	FAYETTEVILLE	NC	Obstetrics & Gynecology	175	
2	3001884	1306820956	DUROCHER	RICHARD	W	DPM	M	NORTH HAVEN	CT	Podiatry	32	
3	7594822	1770523540	FULLARD	JASPER	NaN	MD	M	KANSAS CITY	MO	Internal Medicine	20	
4	746159	1073627758	PERROTTI	ANTHONY	E	DO	M	JUPITER	FL	Internal Medicine	33	

Data Preprocessing

In [5]:
```
# Merging the name columns into a single column
data['Full Name'] = data['First Name of the Provider'].fillna('') + ' ' + \
                    data['Middle Initial of the Provider'].fillna('') + ' ' + \
                    data['Last Name/Organization Name of the Provider'].fillna('')
data['Full Name'] = data['Full Name'].str.strip()

data = data.drop(columns=['Last Name/Organization Name of the Provider',
                          'First Name of the Provider',
                          'Middle Initial of the Provider'])

full_name_column = data.pop('Full Name')

data.insert(1, 'Full Name', full_name_column)


data.head()
```

Out[5]:

	index	Full Name	National Provider Identifier	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	M
0	8774979	SATYASREE UPADHYAYULA	1891106191	M.D.	F	SAINT LOUIS	MO	Internal Medicine	27	24	27	200.5
1	3354385	WENDY P JONES	1346202256	M.D.	F	FAYETTEVILLE	NC	Obstetrics & Gynecology	175	175	175	
2	3001884	RICHARD W DUROCHER	1306820956	DPM	M	NORTH HAVEN	CT	Podiatry	32	13	32	
3	7594822	JASPER FULLARD	1770523540	MD	M	KANSAS CITY	MO	Internal Medicine	20	18	20	
4	746159	ANTHONY E PERROTTI	1073627758	DO	M	JUPITER	FL	Internal Medicine	33	24	31	

A new column "Full Name" has been created to merge first name, middle name and last name

In [6]:
```
# Uniform format of credentials
data['Credentials of the Provider'] = data['Credentials of the Provider'].str.replace(r'\.', '', regex=True).str.upper()
data.head()
```

Out[6]:

	index	Full Name	National Provider Identifier	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	M
0	8774979	SATYASREE UPADHYAYULA	1891106191	MD	F	SAINT LOUIS	MO	Internal Medicine	27	24	27	200.5
1	3354385	WENDY P JONES	1346202256	MD	F	FAYETTEVILLE	NC	Obstetrics & Gynecology	175	175	175	
2	3001884	RICHARD W DUROCHER	1306820956	DPM	M	NORTH HAVEN	CT	Podiatry	32	13	32	
3	7594822	JASPER FULLARD	1770523540	MD	M	KANSAS CITY	MO	Internal Medicine	20	18	20	
4	746159	ANTHONY E PERROTTI	1073627758	DO	M	JUPITER	FL	Internal Medicine	33	24	31	

"Credentials of the Provider" column now follows a uniform format. Such that MD and M.D and M.D. are all treated as the same unit

Converting Object to Numeric Type

In [7]:
```
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 15 columns):
 #   Column                                                    Non-Null Count   Dtype  
---  ------                                                    --------------   -----  
 0   index                                                     100000 non-null  int64  
 1   Full Name                                                 100000 non-null  object 
 2   National Provider Identifier                              100000 non-null  int64  
 3   Credentials of the Provider                               92791 non-null   object 
 4   Gender of the Provider                                    95746 non-null   object 
 5   City of the Provider                                      100000 non-null  object 
 6   State Code of the Provider                                100000 non-null  object 
 7   Provider Type                                             100000 non-null  object 
 8   Number of Services                                        97347 non-null   float64
 9   Number of Medicare Beneficiaries                          99595 non-null   float64
 10  Number of Distinct Medicare Beneficiary/Per Day Services  98500 non-null   float64
 11  Average Medicare Allowed Amount                           99255 non-null   float64
 12  Average Submitted Charge Amount                           93277 non-null   float64
 13  Average Medicare Payment Amount                           99534 non-null   float64
 14  Average Medicare Standardized Amount                      99530 non-null   float64
dtypes: float64(7), int64(2), object(6)
memory usage: 11.4+ MB
```

Looking for Missing Values and imputing them with Mean

In [8]:
```
# missing values
print(data.isnull().sum())
```

```
index                                                          0
Full Name                                                      0
National Provider Identifier                                   0
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                                          2653
Number of Medicare Beneficiaries                             405
Number of Distinct Medicare Beneficiary/Per Day Services    1500
Average Medicare Allowed Amount                              745
Average Submitted Charge Amount                             6723
Average Medicare Payment Amount                              466
Average Medicare Standardized Amount                         470
dtype: int64
```

In [9]:
```
# Imputation of numeric missing values with mean
data[numeric_columns] = data[numeric_columns].fillna(data[numeric_columns].mean())

print(data.isnull().sum())
```

```
index                                                          0
Full Name                                                      0
National Provider Identifier                                   0
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
```

Imputation of categorical columns with mode

In [10]:
```
categorical_columns = ['Credentials of the Provider',
                   'Gender of the Provider',
                   'City of the Provider',
                  'State Code of the Provider']

for column in categorical_columns:
    data[column].fillna(data[column].mode()[0], inplace=True)

print(data.isnull().sum())
```

```
index                                                       0
Full Name                                                   0
National Provider Identifier                                0
Credentials of the Provider                                 0
Gender of the Provider                                      0
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
```

Looking for Duplicate Values

```
In [11]: # Check for duplicates
         print(data.duplicated().sum())

         0
```

```
In [12]: data.head()
```

Out[12]:

	index	Full Name	National Provider Identifier	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	Av Me Al Ar
0	8774979	SATYASREE UPADHYAYULA	1891106191	MD	F	SAINT LOUIS	MO	Internal Medicine	27.0	24.0	27.0	200.5
1	3354385	WENDY P JONES	1346202256	MD	F	FAYETTEVILLE	NC	Obstetrics & Gynecology	175.0	175.0	175.0	123.7
2	3001884	RICHARD W DUROCHER	1306820956	DPM	M	NORTH HAVEN	CT	Podiatry	32.0	13.0	32.0	90.6
3	7594822	JASPER FULLARD	1770523540	MD	M	KANSAS CITY	MO	Internal Medicine	20.0	18.0	20.0	3.5
4	746159	ANTHONY E PERROTTI	1073627758	DO	M	JUPITER	FL	Internal Medicine	33.0	24.0	31.0	26.5

Encoding some Categorical Columns using Frequency Encoder

```
In [13]: def frequency_encode(df, columns):
             for column in columns:
                 freq_encoding = df[column].value_counts() / len(df)
                 new_column_name = column + '_Freq'
                 df.insert(df.columns.get_loc(column) + 1, new_column_name, df[column].map(freq_encoding))
             return df

         columns_to_encode=['Credentials of the Provider',
                            'Gender of the Provider',
                            'Provider Type',
                           'State Code of the Provider']

         data = frequency_encode(data, columns_to_encode)

         df=data

         data.head()
```

Out[13]:

	index	Full Name	National Provider Identifier	Credentials of the Provider	Credentials of the Provider_Freq	Gender of the Provider	Gender of the Provider_Freq	City of the Provider	State Code of the Provider	State Code of the Provider_Freq	Provider Type
0	8774979	SATYASREE UPADHYAYULA	1891106191	MD	0.73827	F	0.29105	SAINT LOUIS	MO	0.01997	Internal Medicine
1	3354385	WENDY P JONES	1346202256	MD	0.73827	F	0.29105	FAYETTEVILLE	NC	0.03725	Obstetrics & Gynecology
2	3001884	RICHARD W DUROCHER	1306820956	DPM	0.01915	M	0.70895	NORTH HAVEN	CT	0.01403	Podiatry
3	7594822	JASPER FULLARD	1770523540	MD	0.73827	M	0.70895	KANSAS CITY	MO	0.01997	Internal Medicine
4	746159	ANTHONY E PERROTTI	1073627758	DO	0.06176	M	0.70895	JUPITER	FL	0.07263	Internal Medicine

```
In [14]: df.columns

Out[14]: Index(['index', 'Full Name', 'National Provider Identifier',
                'Credentials of the Provider', 'Credentials of the Provider_Freq',
                'Gender of the Provider', 'Gender of the Provider_Freq',
                'City of the Provider', 'State Code of the Provider',
                'State Code of the Provider_Freq', 'Provider Type',
                'Provider Type_Freq', 'Number of Services',
                'Number of Medicare Beneficiaries',
                'Number of Distinct Medicare Beneficiary/Per Day Services',
                'Average Medicare Allowed Amount', 'Average Submitted Charge Amount',
                'Average Medicare Payment Amount',
                'Average Medicare Standardized Amount'],
               dtype='object')
```

Performing Standardization on Numerical Columns

```
In [15]: from sklearn.preprocessing import StandardScaler

         data_copy=data.copy()

         standardization_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',
                                  'Credentials of the Provider_Freq',
                                  'Gender of the Provider_Freq',
                                  'State Code of the Provider_Freq' ]

         # Standardization
         standard_scaler = StandardScaler()
         data[standardization_columns] = standard_scaler.fit_transform(data[standardization_columns])
```

```
print("Standardized DataFrame:")
data.head()
```

```
Standardized DataFrame:
```

Out[15]:

	index	Full Name	National Provider Identifier	Credentials of the Provider	Credentials of the Provider_Freq	Gender of the Provider	Gender of the Provider_Freq	City of the Provider	State Code of the Provider	State Code of the Provider_Freq	Provider Type
0	8774979	SATYASREE UPADHYAYULA	1891106191	MD	0.594983	F	-1.560716	SAINT LOUIS	MO	-0.737342	Internal Medicine
1	3354385	WENDY P JONES	1346202256	MD	0.594983	F	-1.560716	FAYETTEVILLE	NC	-0.004973	Obstetrics & Gynecology
2	3001884	RICHARD W DUROCHER	1306820956	DPM	-1.684316	M	0.640731	NORTH HAVEN	CT	-0.989093	Podiatry
3	7594822	JASPER FULLARD	1770523540	MD	0.594983	M	0.640731	KANSAS CITY	MO	-0.737342	Internal Medicine
4	746159	ANTHONY E PERROTTI	1073627758	DO	-1.549260	M	0.640731	JUPITER	FL	1.494517	Internal Medicine

FINAL DATASET

In [16]:
```
anomaly_detection_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',
    'Credentials of the Provider_Freq',
    'Gender of the Provider_Freq',
    'State Code of the Provider_Freq',
    'Provider Type_Freq'
]

X = data[anomaly_detection_columns]

X
```

Out[16]:

	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	Credentials of the Provider_Freq	Gender of the Provider_Freq	State Code of the Provider_Freq
0	-0.497577	-0.444753	-0.482232	1.098226	0.621012	0.972452	1.003321	0.594983	-1.560716	-0.737342
1	0.503328	1.040098	0.554599	0.352134	1.940981	0.549955	0.722789	0.594983	-1.560716	-0.004973
2	-0.463762	-0.552921	-0.447204	0.031012	-0.192958	-0.047975	-0.096209	-1.684316	0.640731	-0.989093
3	-0.544917	-0.503753	-0.531272	-0.814992	-1.005784	-0.718674	-0.722804	0.594983	0.640731	-0.737342
4	-0.456999	-0.444753	-0.454210	-0.591527	-0.816125	-0.541578	-0.551510	-1.549260	0.640731	1.494517
...	...	...	...	...	...	...	...	...	...	...
99995	-0.544917	-0.484087	-0.531272	-0.020219	0.126753	-0.088807	-0.078095	-1.709831	-1.560716	0.142517
99996	0.239576	0.371423	0.281380	-0.254193	-0.252286	-0.426514	-0.354403	-1.729577	-1.560716	-1.140399
99997	-0.605783	-0.572588	-0.594322	-0.674428	-0.439269	-0.601485	-0.600151	0.594983	0.640731	-0.737342
99998	-0.599020	-0.562754	-0.587316	-0.552503	-0.680654	-0.427351	-0.482868	0.594983	-1.560716	1.112228
99999	3.303156	0.066586	3.440912	-0.474250	-0.778910	-0.429474	-0.476378	0.594983	-1.560716	1.112228

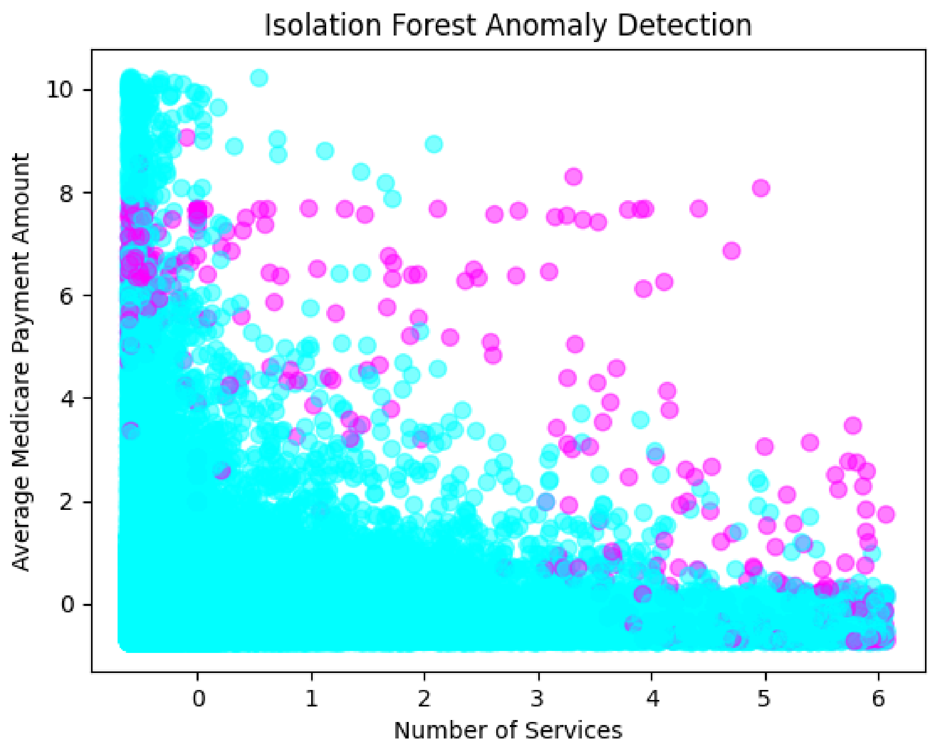
100000 rows × 11 columns

ISOLATION FOREST

In [20]:
```
from sklearn.ensemble import IsolationForest

# Isolation Forest
isolation_forest = IsolationForest(contamination=0.005, random_state=0)
isolation_forest.fit(X)
data['IsolationForest'] = isolation_forest.predict(X)
data['IsolationForest'] = data['IsolationForest'].map({1: 0, -1: 1})
print("Isolation Forest anomalies detected:", data['IsolationForest'].sum())
```

```
Isolation Forest anomalies detected: 500
```

In [21]:
```
# Scatter plot between 'Number of Services' and 'Average Medicare Payment Amount'
plt.scatter(data['Number of Services'], data['Average Medicare Payment Amount'],
               c=data['IsolationForest'], cmap='cool', s=50, alpha=0.5)
plt.title('Isolation Forest Anomaly Detection')
plt.xlabel('Number of Services')
plt.ylabel('Average Medicare Payment Amount')
plt.show()
```



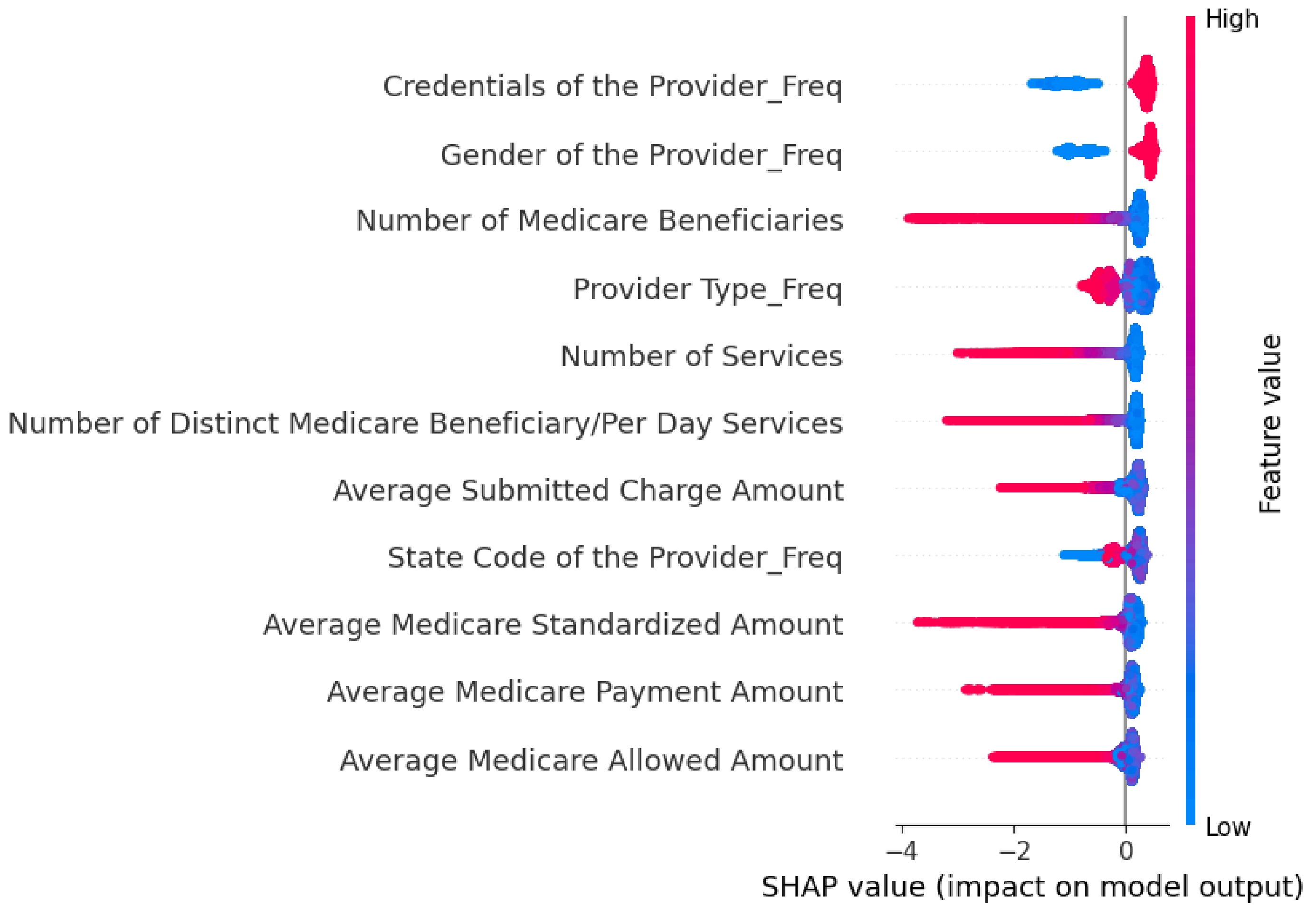
Using contamination as 0.005 and random_state as 0, the Isolation Forest model detected 500 anomalies

SHAP ANALYSIS OF IsolationForest Model

```
In [23]: import shap
         from sklearn.ensemble import IsolationForest

         # SHAP model's output
         explainer = shap.Explainer(isolation_forest, X)
         shap_values = explainer(X)
```

```
100%|===================| 99764/100000 [06:32<00:00]
```

```
In [24]: # SHAP summary plot
         shap.summary_plot(shap_values, X, feature_names=anomaly_detection_columns)
```



INTERPRETATION

- The following columns tend to negatively affect the output:

- 'Number of Services',
- 'Number of Medicare Beneficiaries',
- 'Number of Distinct Medicare Beneficiary/Per Day Services',
- 'Average Medicare Allowed Amount',
- 'Average Medicare Payment Amount',
- 'Average Medicare Standardized Amount',

- this shows the tendency of fraud increases with higher values in such columns

---

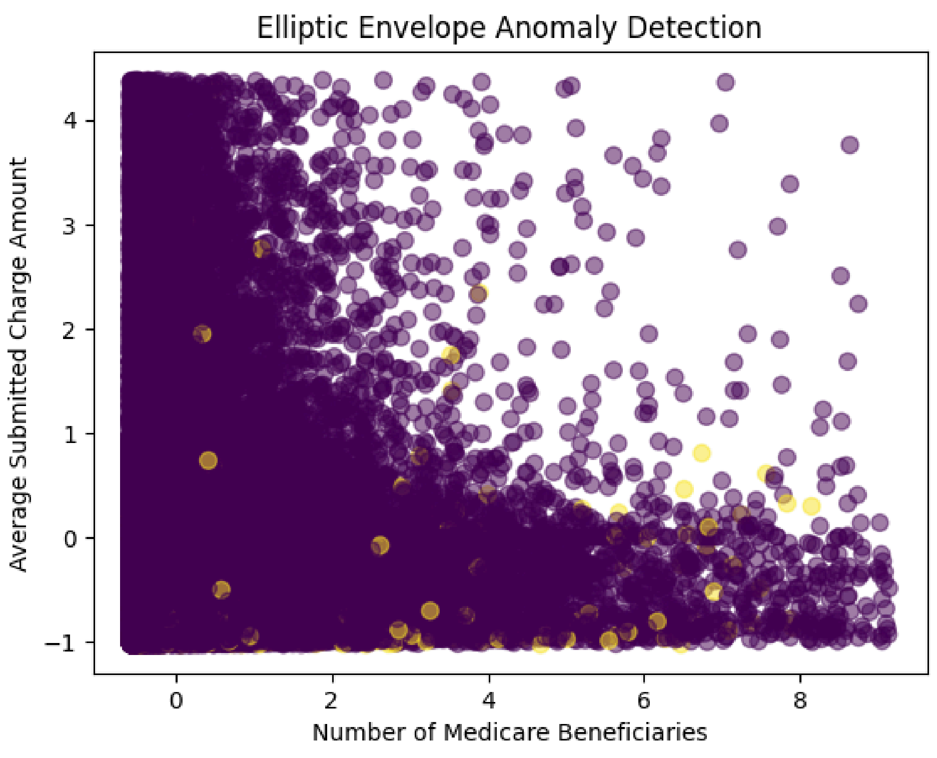
ELLIPTIC ENVELOPE

```
In [17]: from sklearn.covariance import EllipticEnvelope

         # Elliptic Envelope
         elliptic_envelope = EllipticEnvelope(contamination=0.007, random_state=42)
```

```
elliptic_envelope.fit(X)
data['EllipticEnvelope'] = elliptic_envelope.predict(X)
data['EllipticEnvelope'] = data['EllipticEnvelope'].map({1: 0, -1: 1})
print("Elliptic Envelope anomalies detected:", data['EllipticEnvelope'].sum())
```

```
Elliptic Envelope anomalies detected: 700
```

In [28]:
```
plt.scatter(data['Number of Medicare Beneficiaries'], data['Average Submitted Charge Amount'],
            c=data['EllipticEnvelope'], cmap='viridis', s=50, alpha=0.5)
plt.title('Elliptic Envelope Anomaly Detection')
plt.xlabel('Number of Medicare Beneficiaries')
plt.ylabel('Average Submitted Charge Amount')
plt.show()
```

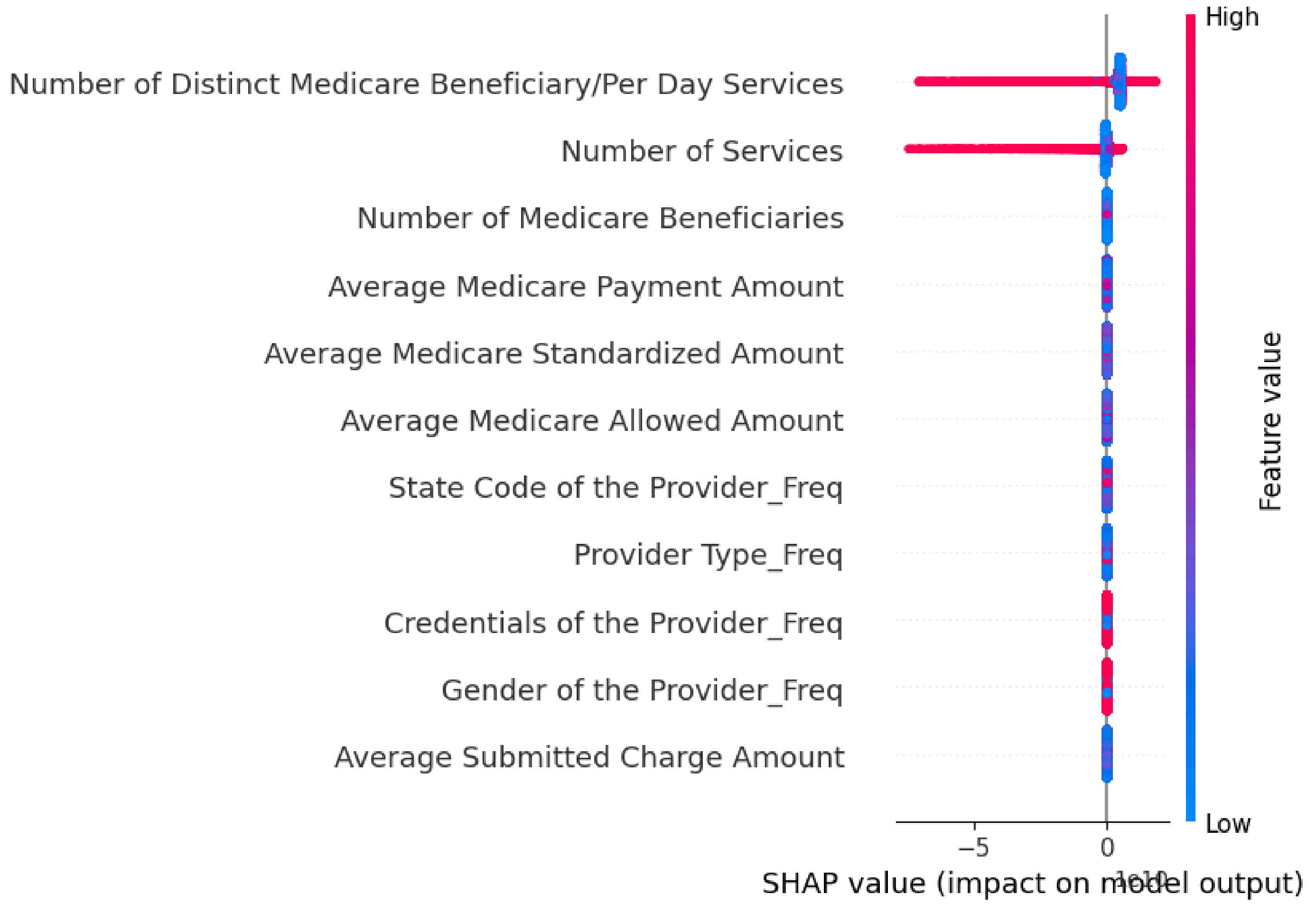


Using contamination as 0.007 and random_state as 42, the Elliptic Envelope model detected 700 anomalies

SHAP ANALYSIS OF EllipticEnvelope in combination with IsolationForest

In [20]:
```
import shap

K = 10
background_data = shap.sample(X, K)

# Initializing SHAP explainer with sampled background data
explainer = shap.KernelExplainer(elliptic_envelope.decision_function, background_data)

# Compute SHAP values
shap_values = explainer.shap_values(X)

# Plot the SHAP summary plot
shap.summary_plot(shap_values, X, feature_names=anomaly_detection_columns)
```

```
100%|████████████████████████████████| 100000/100000 [1:22:16<00:00, 20.26it/s]
```



INTERPRETATION

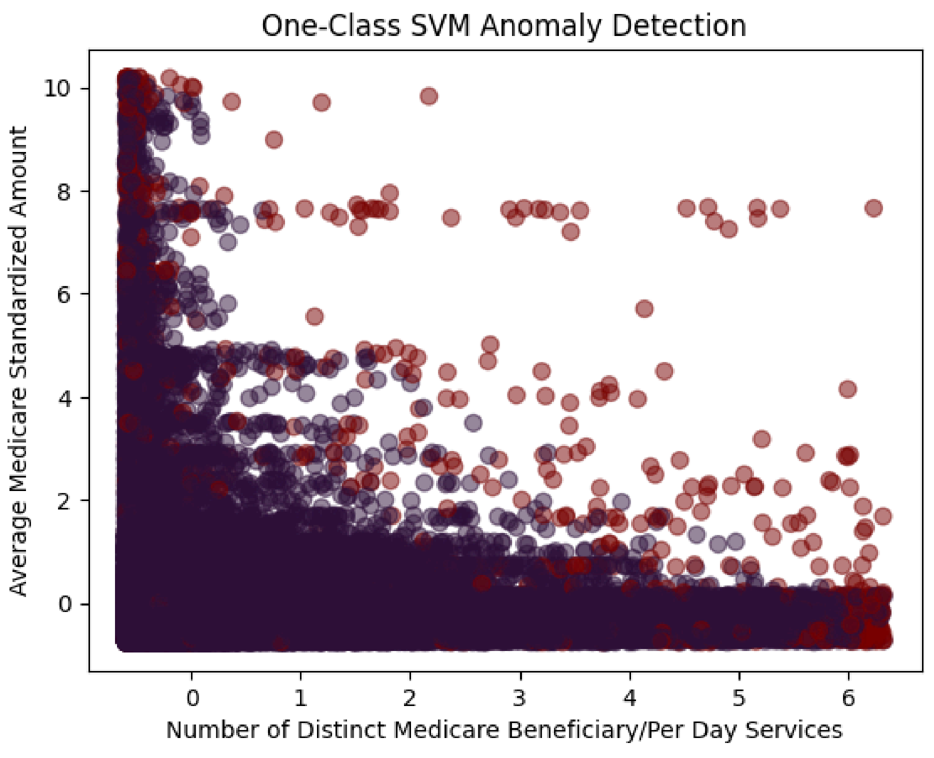
- Higher Number of Services tends to negatively affect the output, this shows the tendency of fraud increases with increase in number of services
- 'Number of Distinct Medicare Beneficiary/Per Day Services' also tends to negatively affect the output, this means the tendency of fraud increases with increase in Number of Distinct Medicare Beneficiary/Per Day Services

ONE CLASS SVM

```
In [17]: from sklearn.svm import OneClassSVM

         # One-Class SVM
         one_class_svm = OneClassSVM(gamma='auto', nu=0.01)
         one_class_svm.fit(X)
         data['OneClassSVM'] = one_class_svm.predict(X)
         data['OneClassSVM'] = data['OneClassSVM'].map({1: 0, -1: 1})
         print("One-Class SVM anomalies detected:", data['OneClassSVM'].sum())
```

```
One-Class SVM anomalies detected: 1012
```

```
In [18]: plt.scatter(data['Number of Distinct Medicare Beneficiary/Per Day Services'], data['Average Medicare Standardized Amount'],
                     c=data['OneClassSVM'], cmap='turbo', s=50, alpha=0.5)
         plt.title('One-Class SVM Anomaly Detection')
         plt.xlabel('Number of Distinct Medicare Beneficiary/Per Day Services')
         plt.ylabel('Average Medicare Standardized Amount')
         plt.show()
```

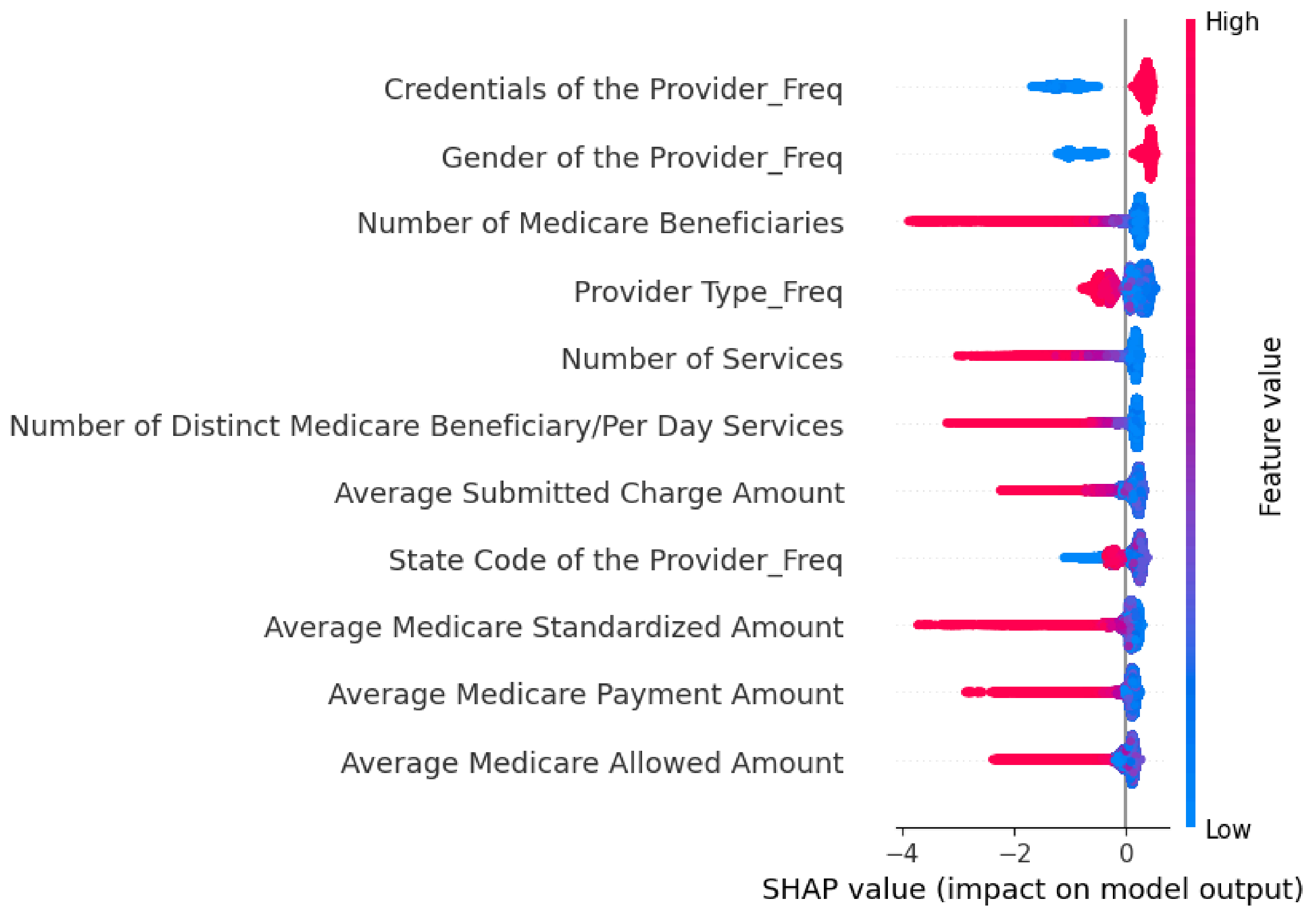


Using One-Class SVM model and setting gamma as 'auto' and nu as 0.01, 1012 anomalies have been detected

SHAP ANALYSIS OF OneClassSVM in combination with IsolationForest

```
In [19]: import shap
         from sklearn.ensemble import IsolationForest

         # Convert predictions to binary labels
         data['OneClassSVM'] = data['OneClassSVM'].apply(lambda x: 1 if x == -1 else 0)

         # Fit the Isolation Forest model
         isolation_forest = IsolationForest(contamination=0.005, random_state=0)
         isolation_forest.fit(X)

         # Perform SHAP analysis on the Isolation Forest model
         explainer = shap.Explainer(isolation_forest, X)
         shap_values = explainer(X)

         # Plot the SHAP summary plot
         shap.summary_plot(shap_values, X, feature_names=anomaly_detection_columns)
```

```
100%|===================| 99922/100000 [06:42<00:00]
```



INTERPRETATION

- The following columns tend to negatively affect the output:

- 'Number of Services',
- 'Number of Medicare Beneficiaries',
- 'Number of Distinct Medicare Beneficiary/Per Day Services',
- 'Average Medicare Allowed Amount',
- 'Average Medicare Payment Amount',
- 'Average Medicare Standardized Amount',

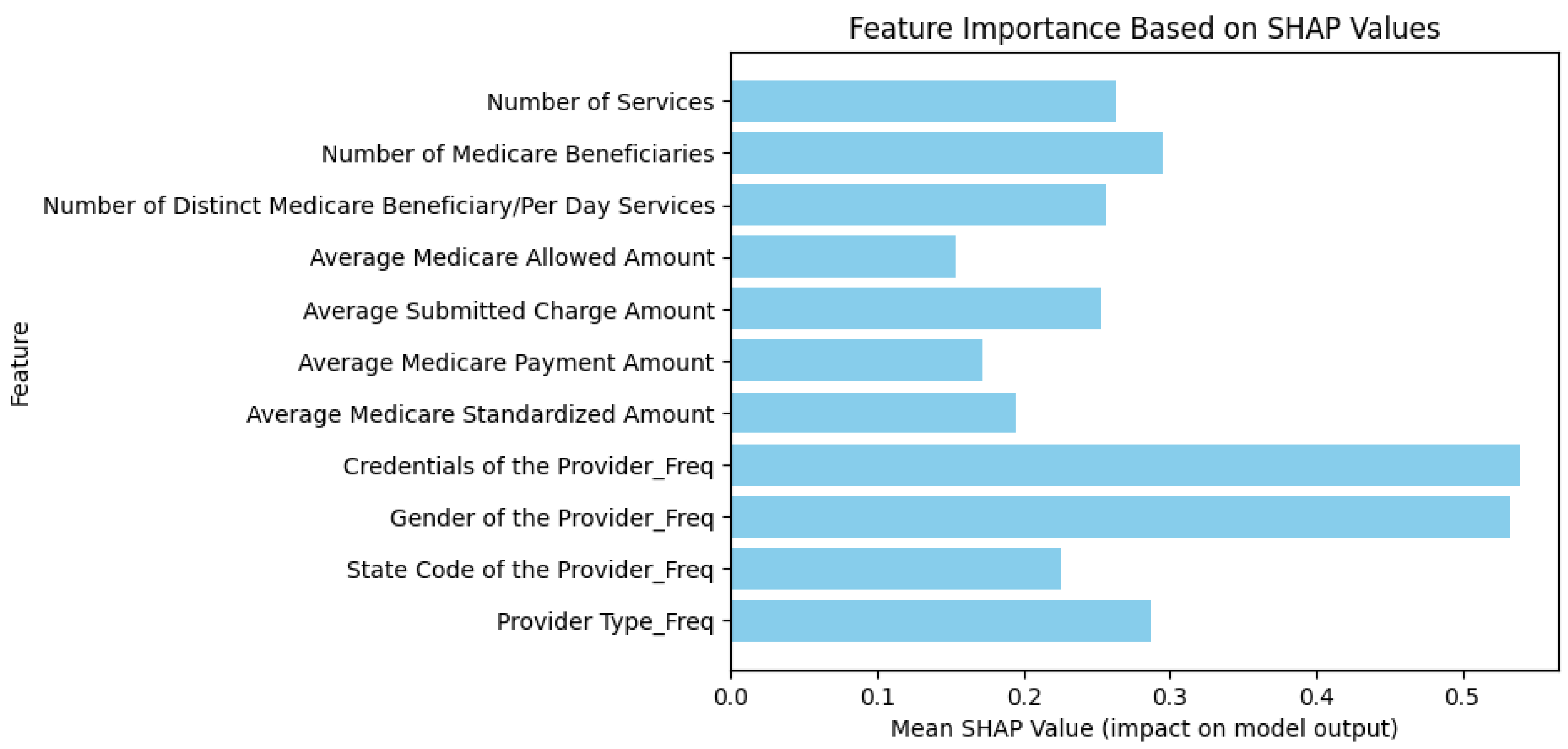
- this shows the tendency of fraud increases with higher values in such columns

---

FURTHER INTERPRETATION :

The following bargraph shows the dependence on every feature in making prediction

In [34]:
```python
import numpy as np

# Converting SHAP values to numpy array
shap_values_array = np.array(shap_values.values)
shap_values_summary = np.abs(shap_values_array).mean(axis=0)

# Plot of the summarized SHAP values as a stacked bar plot
plt.barh(anomaly_detection_columns, shap_values_summary, color='skyblue')
plt.xlabel('Mean SHAP Value (impact on model output)')
plt.ylabel('Feature')
plt.title('Feature Importance Based on SHAP Values')
plt.gca().invert_yaxis()
plt.show()
```

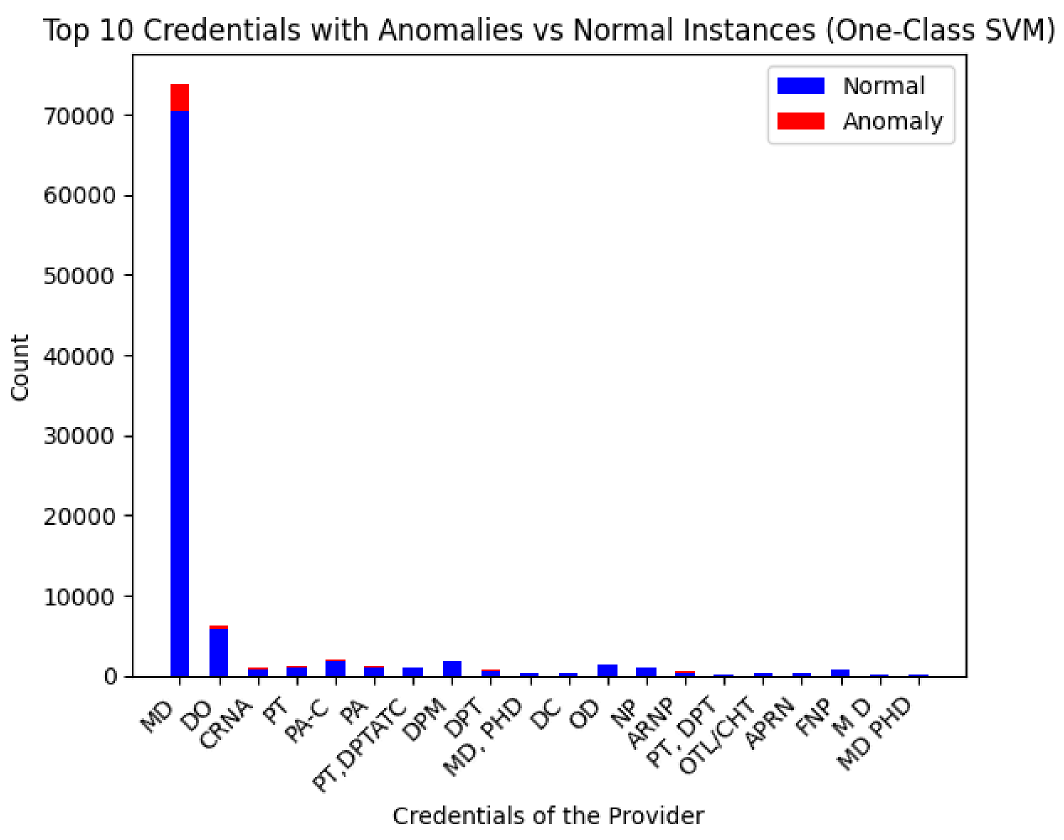


From the above graph, we can see that 'Credentials of the Provider_Freq', and 'Gender of the Provider_Freq' have the highest impact in the model output.

Visualization of Anamolies in the 'Credentials of the Provider_Freq' and 'Gender of the Provider_Freq' columns using stacked bar graphs

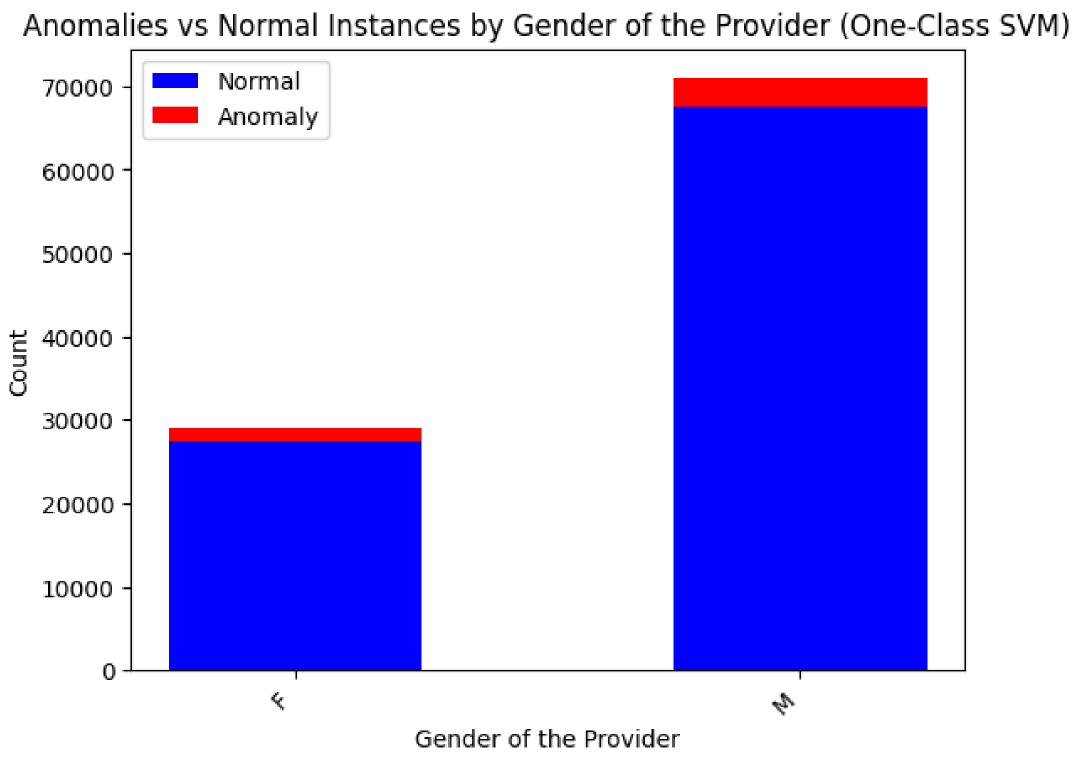
In [36]:
```
import matplotlib.pyplot as plt
import seaborn as sns

# Ensure One-Class SVM Anomaly Labels are Correctly Applied
one_class_svm = OneClassSVM(gamma='auto', nu=0.05)
one_class_svm.fit(X)
data['OneClassSVM'] = one_class_svm.predict(X)
data['OneClassSVM'] = data['OneClassSVM'].map({1: 0, -1: 1})
print("One-Class SVM anomalies detected:", data['OneClassSVM'].sum())

# Group the data by 'Credentials of the Provider_Freq' and 'OneClassSVM'
credentials_grouped = data.groupby(['Credentials of the Provider_Freq', 'OneClassSVM']).size().unstack().fillna(0)
credentials_grouped.columns = ['Normal', 'Anomaly'] if credentials_grouped.shape[1] == 2 else (['Normal'] if 0 in credentials_grou
credentials_grouped = credentials_grouped.reset_index()

#top 10 credentials with most anomalies
top_credentials = credentials_grouped.sort_values(by='Anomaly', ascending=False).head(20)

credentials_mapping = data[['Credentials of the Provider', 'Credentials of the Provider_Freq']].drop_duplicates()
credentials_mapping_dict = credentials_mapping.set_index('Credentials of the Provider_Freq')['Credentials of the Provider'].to_dic

# Mapping the frequency-encoded values back to the original values for labels
top_credentials['Credentials of the Provider'] = top_credentials['Credentials of the Provider_Freq'].map(credentials_mapping_dict)

# stacked bar plot for 'Credentials of the Provider'
bar_width = 0.5
bars1 = plt.bar(top_credentials['Credentials of the Provider'], top_credentials['Normal'], color='blue', label='Normal', width=bar
bars2 = plt.bar(top_credentials['Credentials of the Provider'], top_credentials['Anomaly'], bottom=top_credentials['Normal'], colo
plt.xlabel('Credentials of the Provider')
plt.ylabel('Count')
plt.title('Top 10 Credentials with Anomalies vs Normal Instances (One-Class SVM)')
plt.xticks(rotation=45, ha='right')
plt.legend()
plt.show()
```

```
One-Class SVM anomalies detected: 5000
```



We can see that most anomolies are present with Credential 'MD'

In [38]:
```
# Grouping the data by 'Gender of the Provider_Freq' and 'OneClassSVM'
gender_grouped = data.groupby(['Gender of the Provider_Freq', 'OneClassSVM']).size().unstack().fillna(0)
gender_grouped.columns = ['Normal', 'Anomaly'] if gender_grouped.shape[1] == 2 else (['Normal'] if 0 in gender_grouped.columns els
gender_grouped = gender_grouped.reset_index()

gender_mapping = data[['Gender of the Provider', 'Gender of the Provider_Freq']].drop_duplicates()
gender_mapping_dict = gender_mapping.set_index('Gender of the Provider_Freq')['Gender of the Provider'].to_dict()

# Mapping the frequency-encoded values back to the original values for labels
gender_grouped['Gender of the Provider'] = gender_grouped['Gender of the Provider_Freq'].map(gender_mapping_dict)

#stacked bar plot for 'Gender of the Provider'
bar_width = 0.5
bars1 = plt.bar(gender_grouped['Gender of the Provider'], gender_grouped['Normal'], color='blue', label='Normal', width=bar_width)
bars2 = plt.bar(gender_grouped['Gender of the Provider'], gender_grouped['Anomaly'], bottom=gender_grouped['Normal'], color='red',
plt.xlabel('Gender of the Provider')
plt.ylabel('Count')
plt.title('Anomalies vs Normal Instances by Gender of the Provider (One-Class SVM)')
plt.xticks(rotation=45, ha='right')
plt.legend()
plt.show()
```



We can see that more anomolies are present when Gender is Male

```
In [ ]:
```