INFOSYS SPRINGBOARD

Building Anomaly Detection System using Python

Problem:

In this project, we delve deep into the thriving sector of **Security** by analyzing a **Anomaly detection on Healthcare Dataset** from a USA-based Health Service Providers, available at the kaggle. This dataset documents all transactions between patients and service providers. Our primary objective is to amplify the efficiency of Healthcare System and avoid fraudulent transactions in **Healthcare system**. We aim to transform the data into a -centric dataset that will facilitate the Base for Anomaly Detection system of patient providing better service , ultimately enhancing security ,efficiency and patient service.

Step 1 | Setup and Initialization

In [1]:
```
#importing necessary libraries
#loading dataset

import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
import numpy as np
from matplotlib.colors import LinearSegmentedColormap

hdata = pd.read_csv(r'C:\Users\tmbha\Downloads\ifosys_springboard\hdata.csv')
```

Step 2 | Initial Data Analysis

In [2]:
```
hdata
```

Out[2]:

	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	Str Add 2 of Provi
0	8774979	1891106191	UPADHYAYULA	SATYASREE	NaN	M.D.	F	I	1402 S GRAND BLVD	1 FLC
1	3354385	1346202256	JONES	WENDY	P	M.D.	F	I	2950 VILLAGE DR	N
2	3001884	1306820956	DUROCHER	RICHARD	W	DPM	M	I	20 WASHINGTON AVE	STE
3	7594822	1770523540	FULLARD	JASPER	NaN	MD	M	I	5746 N BROADWAY ST	N
4	746159	1073627758	PERROTTI	ANTHONY	E	DO	M	I	875 MILITARY TRL	SU
...	...	...	...	...	...	...	...	...	...	
99995	3837311	1386938868	PAPES	JOAN	NaN	PT	F	I	324 E BALTIMORE ST	N
99996	2079360	1215091327	HAYNER	MARGARET	S	ARNP	F	I	645 NW 4TH ST	N
99997	8927965	1902868185	VALENCIA	DANA	NaN	M.D.	M	I	3009 N BALLAS RD	SU 2
99998	8854571	1891941183	GONZALEZ-LAMOS	RAFAELA	NaN	NaN	F	I	2365 BOSTON POST RD	SU
99999	3547535	1356772156	RAMEZANI	ELIIAN	NaN	NaN	F	I	444 MIDDLE NECK RD APT 1H	N

100000 rows × 27 columns

In [3]:

```
hdata.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 [4]:
```python
hdata.describe(include='object').T
```

Out[4]:

	count	unique	top	freq
Last Name/Organization Name of the Provider	100000	42820	PATEL	557
First Name of the Provider	95745	13022	MICHAEL	2350
Middle Initial of the Provider	70669	29	A	8152
Credentials of the Provider	92791	1854	MD	32874
Gender of the Provider	95746	2	M	66641
Entity Type of the Provider	100000	2	I	95746
Street Address 1 of the Provider	100000	51928	200 1ST ST SW	244
Street Address 2 of the Provider	40637	10024	SUITE 200	1624
City of the Provider	100000	5846	NEW YORK	1061
State Code of the Provider	100000	58	CA	7775
Country Code of the Provider	100000	4	US	99994
Provider Type	100000	90	Diagnostic Radiology	12537
Medicare Participation Indicator	100000	2	Y	99969
Place of Service	100000	2	O	61616
HCPCS Code	100000	2631	99213	4578
HCPCS Description	100000	2455	Established patient office or other outpatient...	4578
HCPCS Drug Indicator	100000	2	N	93802
Number of Services	100000	2748	13	3018
Number of Medicare Beneficiaries	100000	1274	11	4791
Number of Distinct Medicare Beneficiary/Per Day Services	100000	1979	12	3210
Average Medicare Allowed Amount	100000	49629	3	1017
Average Submitted Charge Amount	100000	38088	150	970
Average Medicare Payment Amount	100000	83367	2.94	623
Average Medicare Standardized Amount	100000	76237	25.32	1630

In [5]:
```python
hdata.describe()
```

Out[5]:

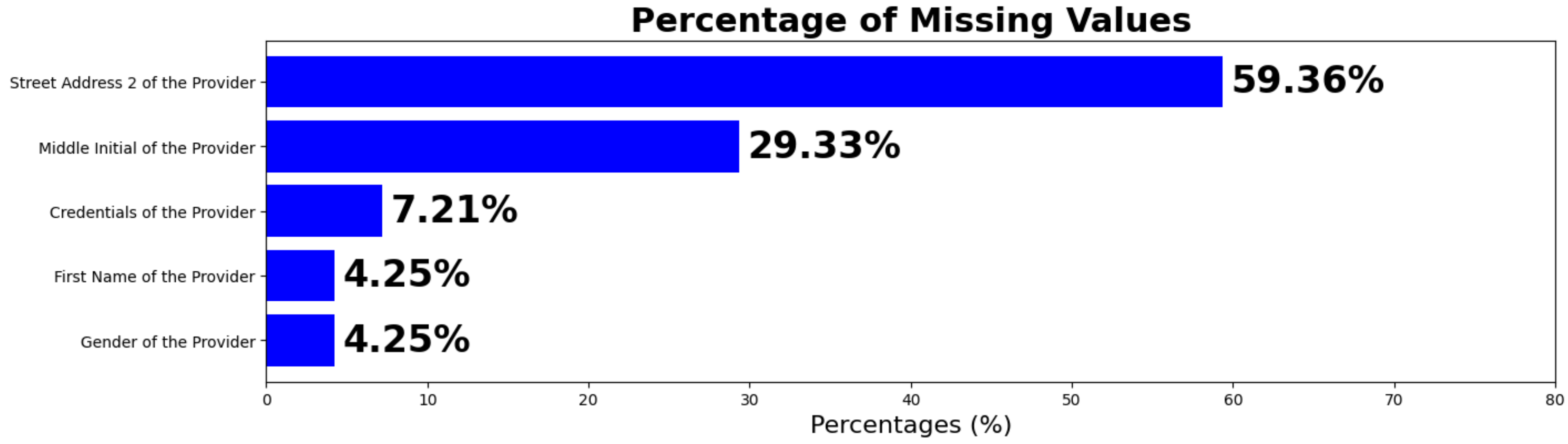
	index	National Provider Identifier	Zip Code of the Provider
count	1.000000e+05	1.000000e+05	1.000000e+05
mean	4.907646e+06	1.498227e+09	4.163820e+08
std	2.839633e+06	2.874125e+08	3.082566e+08
min	2.090000e+02	1.003001e+09	6.010000e+02
25%	2.458791e+06	1.245669e+09	1.426300e+08
50%	4.901266e+06	1.497847e+09	3.633025e+08
75%	7.349450e+06	1.740374e+09	6.819881e+08
max	9.847440e+06	1.993000e+09	9.990166e+08

Step 3 | Data Cleaning & Transformation

Step 3.1 | Handling Missing Values

In [6]:

```
# Calculating the percentage of missing values for each column
missing_data = hdata.isnull().sum()

missing_percentage = (missing_data[missing_data > 0] / hdata.shape[0]) * 100

# Prepare values
missing_percentage.sort_values(ascending=True, inplace=True)

# Plot the barh chart
fig, ax = plt.subplots(figsize=(15, 4))
ax.barh(missing_percentage.index, missing_percentage, color='blue')

# Annotate the values and indexes
for i, (value, name) in enumerate(zip(missing_percentage, missing_percentage.index)):
    ax.text(value+0.5, i, f"{value:.2f}%", ha='left', va='center', fontweight='bold', fontsize=24, color='black')

# Set x-axis limit
ax.set_xlim([0, 80])

# Add title and xlabel
plt.title("Percentage of Missing Values", fontweight='bold', fontsize=22)
plt.xlabel('Percentages (%)', fontsize=16)
plt.show()

#print(missing_data)
```



Handling Missing Values Strategy:

- `Street Address 2 of the Provider` **(59.36% missing values)**
  - The `Street Address 2 of the Provider` column contains nearly a 60% of missing data. This column is not essential for Anomaly Detection and creating system. Imputing such a large percentage of missing values might introduce significant bias or noise into the analysis. We will Drop this column.
- `Middle Initial of the Provider` **(29.33% missing values)**

- The `Middle Initial of the Provider` column has a major percentage of missing values. However, it has importance but we cannot fill these missing values are unique as middile initial can any , we also drop this column.

- `Credentials of the Provider` **(7.21% missing values)**
  - The `Credentials of the Provider` column has a small 7.21% percentage of missing values. However, it has importance but we can fill these missing values with highest occurrence/frequently occurring of value in the column.
- `First Name of the Provider` **(4.25% missing values)**
  - The `First Name of the Provider` column has a small 7.21% percentage of missing values. we will drop this column as we cannot randomaly give name to any person which is not present in the record.
- `Gender of the Provider` **(7.25% missing values)**
  - The `Gender of the Provider` column has a small 7.21% percentage of missing values. However, it has importance but we can fill these missing values with highest occurrence/frequently occurring of value in the column.

By removing columns with missing values in the `Street Address 2 of the Provider`, `First Name of the Provider` and `Middle Initial of the Provider` columns, and filling missing values in `Credentials of the Provider` and `Gender of the Provider` we aim to construct a cleaner and more reliable dataset, which is essential for achieving accurate anomaly detection and creating an effective anomaly detection system.

In [7]:
```
#replacing null values in Credentials of the Provider and Gender of the Provider by frequent item in that column
#finding frequent value

print('Frequent value in "Credentials of the Provider" is  ',hdata["Credentials of the Provider"].mode()[0])
print('Frequent value in "Gender of the Provider" is  ' ,hdata['Gender of the Provider'].mode()[0])

#replacing null values missing values
hdata["Credentials of the Provider"] = hdata["Credentials of the Provider"].fillna(hdata["Credentials of the Prov
hdata["Gender of the Provider"] = hdata["Gender of the Provider"].fillna(hdata["Gender of the Provider"].mode()[

hdata.info()
```

```
Frequent value in "Credentials of the Provider" is   MD
Frequent value in "Gender of the Provider" is   M
<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                                100000 non-null  object
 6   Gender of the Provider                                     100000 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 [8]:
```
# dot removing from Credentials of the Provider

dot_columns = ['Credentials of the Provider']
```

```python
for col in dot_columns:
    hdata[col]=hdata[col].str.replace('.','')

hdata.head(5).T
```

Out[8]:

	0	1	2	3	4
index	8774979	3354385	3001884	7594822	746159
National Provider Identifier	1891106191	1346202256	1306820956	1770523540	1073627758
Last Name/Organization Name of the Provider	UPADHYAYULA	JONES	DUROCHER	FULLARD	PERROTTI
First Name of the Provider	SATYASREE	WENDY	RICHARD	JASPER	ANTHONY
Middle Initial of the Provider	NaN	P	W	NaN	E
Credentials of the Provider	MD	MD	DPM	MD	DO
Gender of the Provider	F	F	M	M	M
Entity Type of the Provider	I	I	I	I	I
Street Address 1 of the Provider	1402 S GRAND BLVD	2950 VILLAGE DR	20 WASHINGTON AVE	5746 N BROADWAY ST	875 MILITARY TRL
Street Address 2 of the Provider	FDT 14TH FLOOR	NaN	STE 212	NaN	SUITE 200
City of the Provider	SAINT LOUIS	FAYETTEVILLE	NORTH HAVEN	KANSAS CITY	JUPITER
Zip Code of the Provider	631041004.0	283043815.0	64732343.0	641183998.0	334585700.0
State Code of the Provider	MO	NC	CT	MO	FL
Country Code of the Provider	US	US	US	US	US
Provider Type	Internal Medicine	Obstetrics & Gynecology	Podiatry	Internal Medicine	Internal Medicine
Medicare Participation Indicator	Y	Y	Y	Y	Y
Place of Service	F	O	O	O	O
HCPCS Code	99223	G0202	99348	81002	96372
HCPCS Description	Initial hospital inpatient care, typically 70 ...	Screening mammography, bilateral (2-view study...	Established patient home visit, typically 25 m...	Urinalysis, manual test	Injection beneath the skin or into muscle for ...
HCPCS Drug Indicator	N	N	N	N	N
Number of Services	27	175	32	20	33
Number of Medicare Beneficiaries	24	175	13	18	24
Number of Distinct Medicare Beneficiary/Per Day Services	27	175	32	20	31
Average Medicare Allowed Amount	200.58777778	123.73	90.65	3.5	26.52
Average Submitted Charge Amount	305.21111111	548.8	155	5	40
Average Medicare Payment Amount	157.26222222	118.83	64.4396875	3.43	19.539393939
Average Medicare Standardized Amount	160.90888889	135.31525714	60.5959375	3.43	19.057575758

Step 3.2 |Merging columns

In [9]:

```python
#merging names of provider
def combine_columns(row):
    return  str(row['Last Name/Organization Name of the Provider'])+ ' '+ str(row['First Name of the Provider'])
hdata['Name'] = hdata.apply(combine_columns, axis=1)

#merging names of Address
```

```python
def combine_address(row):
    return  str(row['Street Address 1 of the Provider'])+ ' '+ str(row['Street Address 2 of the Provider'])
hdata['Full Address'] = hdata.apply(combine_address, axis=1)

hdata.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 100000 entries, 0 to 99999
Data columns (total 29 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                             100000 non-null  object 
 6   Gender of the Provider                                  100000 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 
 27  Name                                                    100000 non-null  object 
 28  Full Address                                            100000 non-null  object 
dtypes: float64(1), int64(2), object(26)
memory usage: 22.1+ MB
```

In [10]:
```python
DropCols = ['index', 'National Provider Identifier','Last Name/Organization Name of the Provider',
       'First Name of the Provider', 'Middle Initial of the Provider','Street Address 1 of the Provider',
       'Street Address 2 of the Provider','Zip Code of the Provider',"HCPCS Code"]
df = hdata.drop(DropCols, axis = 1)
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 100000 entries, 0 to 99999
Data columns (total 20 columns):
 #   Column                                                  Non-Null Count   Dtype 
---  ------                                                  --------------   ----- 
 0   Credentials of the Provider                             100000 non-null  object
 1   Gender of the Provider                                  100000 non-null  object
 2   Entity Type of the Provider                             100000 non-null  object
 3   City of the Provider                                    100000 non-null  object
 4   State Code of the Provider                              100000 non-null  object
 5   Country Code of the Provider                            100000 non-null  object
 6   Provider Type                                           100000 non-null  object
 7   Medicare Participation Indicator                        100000 non-null  object
 8   Place of Service                                        100000 non-null  object
 9   HCPCS Description                                       100000 non-null  object
 10  HCPCS Drug Indicator                                    100000 non-null  object
 11  Number of Services                                      100000 non-null  object
 12  Number of Medicare Beneficiaries                        100000 non-null  object
 13  Number of Distinct Medicare Beneficiary/Per Day Services  100000 non-null  object
 14  Average Medicare Allowed Amount                         100000 non-null  object
 15  Average Submitted Charge Amount                         100000 non-null  object
 16  Average Medicare Payment Amount                         100000 non-null  object
 17  Average Medicare Standardized Amount                    100000 non-null  object
 18  Name                                                    100000 non-null  object
 19  Full Address                                            100000 non-null  object
dtypes: object(20)
memory usage: 15.3+ MB
```

Step 3.3 | Transforming Object values to Numeric

In [11]:
```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 Standard
df[numeric_columns].describe(include='object').T
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 100000 entries, 0 to 99999
Data columns (total 20 columns):
 #   Column                                                     Non-Null Count   Dtype
---  ------                                                     --------------   -----
 0   Credentials of the Provider                                100000 non-null  object
 1   Gender of the Provider                                     100000 non-null  object
 2   Entity Type of the Provider                                100000 non-null  object
 3   City of the Provider                                       100000 non-null  object
 4   State Code of the Provider                                 100000 non-null  object
 5   Country Code of the Provider                               100000 non-null  object
 6   Provider Type                                              100000 non-null  object
 7   Medicare Participation Indicator                           100000 non-null  object
 8   Place of Service                                           100000 non-null  object
 9   HCPCS Description                                          100000 non-null  object
 10  HCPCS Drug Indicator                                       100000 non-null  object
 11  Number of Services                                         100000 non-null  object
 12  Number of Medicare Beneficiaries                           100000 non-null  object
 13  Number of Distinct Medicare Beneficiary/Per Day Services   100000 non-null  object
 14  Average Medicare Allowed Amount                            100000 non-null  object
 15  Average Submitted Charge Amount                            100000 non-null  object
 16  Average Medicare Payment Amount                            100000 non-null  object
 17  Average Medicare Standardized Amount                       100000 non-null  object
 18  Name                                                       100000 non-null  object
 19  Full Address                                               100000 non-null  object
dtypes: object(20)
memory usage: 15.3+ MB
```

Inferences from the numeric_columns Data:

- All the quantaties from the numeric_columns are showing general description , indicating that these are the object type containing numeric value.
- The numeric_columns shows there is no missing values hence we can convert it in numeric data type .

In [12]:
```
#converted object data types to numeric

#removed comma
def remove_comma(x):
    return x.replace(",","")

#converted object data type to numeric
for col in numeric_columns:
    df[col] = pd.to_numeric(df[col].apply(lambda x: remove_comma(x)))

df.describe()
```

Out[12]:

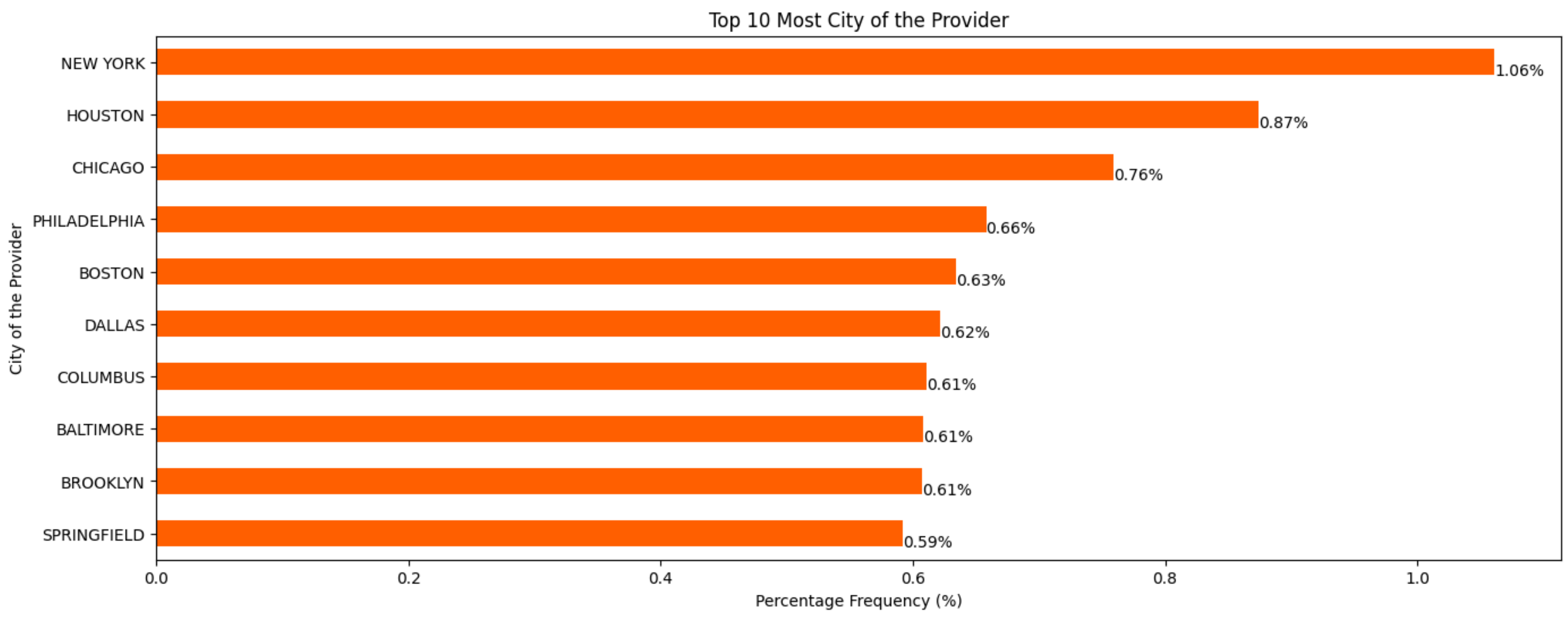
	Number of Services	Number of Medicare Beneficiaries	Number of Distinct Medicare Beneficiary/Per Day Services	Average Medicare Allowed Amount	Average Submitted Charge Amount	Average Medicare Payment Amount	Average Medicare Standardized Amount
count	100000.000000	100000.000000	100000.000000	100000.000000	100000.000000	100000.000000	100000.000000
mean	239.671424	89.809310	142.115680	101.434155	354.550451	77.358795	78.030693
std	2493.187089	1109.616902	1640.227228	257.242779	1062.608271	199.718813	200.045458
min	11.000000	11.000000	11.000000	0.010000	0.010000	0.008679	0.008679
25%	21.000000	17.000000	20.000000	24.270000	57.647876	19.335228	20.121849
50%	43.000000	32.000000	40.000000	65.095000	146.000000	47.020176	47.841094
75%	118.000000	75.000000	106.000000	113.160000	298.932111	84.894452	84.879560
max	282739.000000	190306.000000	282737.000000	20494.000000	62694.000000	16067.300000	16957.148000

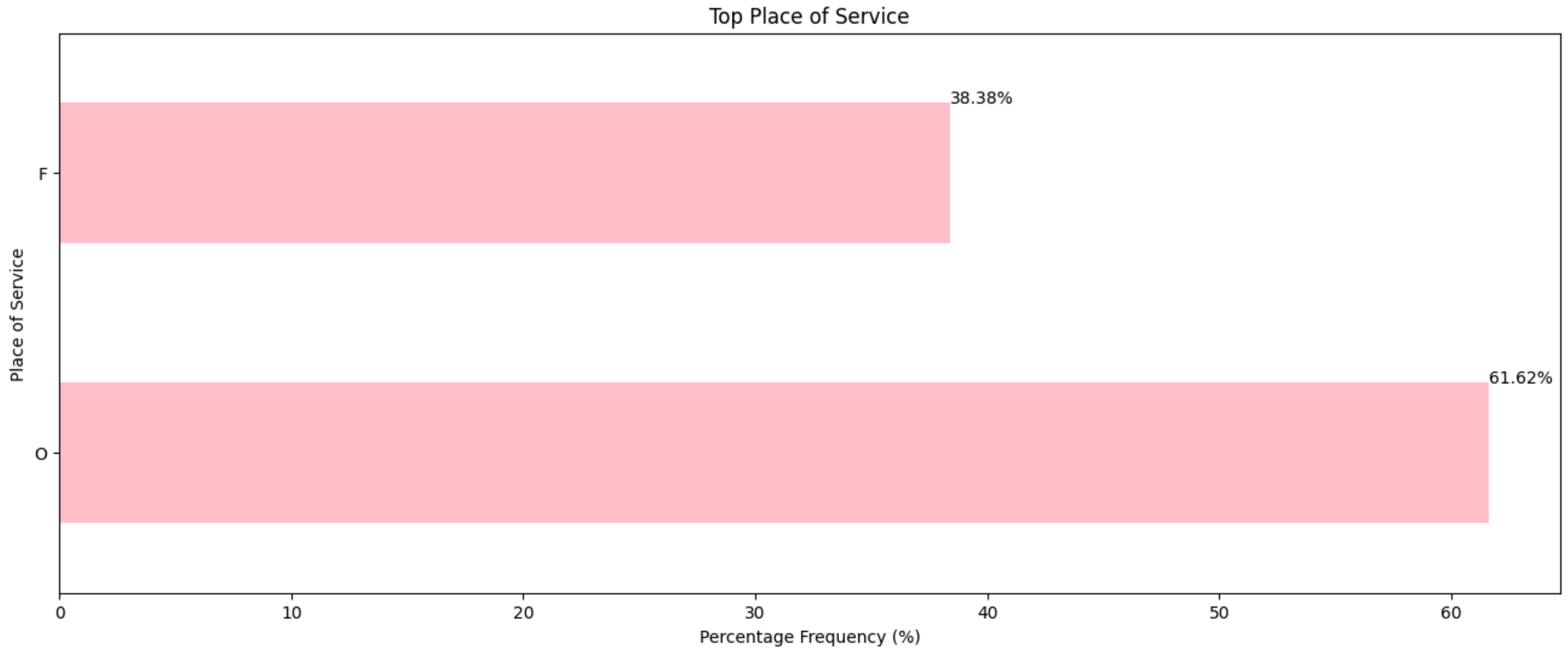
Step 4 | Visualizations

Step 4.1 | Univariate Analysis

In [13]:
```
# Finding the top 10 most frequent City of the Provider

top_10 = df['City of the Provider'].value_counts(normalize=True).head(10) * 100
```

```python
# Plotting the top 10 most frequent stock codes

plt.figure(figsize=(16, 6))
top_10.plot(kind='barh', color='#ff6200')

# Adding the percentage frequency on the bars

for index, value in enumerate(top_10):
    plt.text(value, index+0.25, f'{value:.2f}%', fontsize=10)

plt.title('Top 10 Most City of the Provider')
plt.xlabel('Percentage Frequency (%)')
plt.ylabel('City of the Provider')
plt.gca().invert_yaxis()
plt.show()

# Finding  Place of Service

top_10 = df['Place of Service'].value_counts(normalize=True)*100

# Plotting the top 10 most frequent stock codes

plt.figure(figsize=(16, 6))
top_10.plot(kind='barh', color='pink')

# Adding the percentage frequency on the bars

for index, value in enumerate(top_10):
    plt.text(value, index+0.25, f'{value:.2f}%', fontsize=10)

plt.title('Top Place of Service')
plt.xlabel('Percentage Frequency (%)')
plt.ylabel('Place of Service')
#plt.gca().invert_yaxis()
plt.show()
```





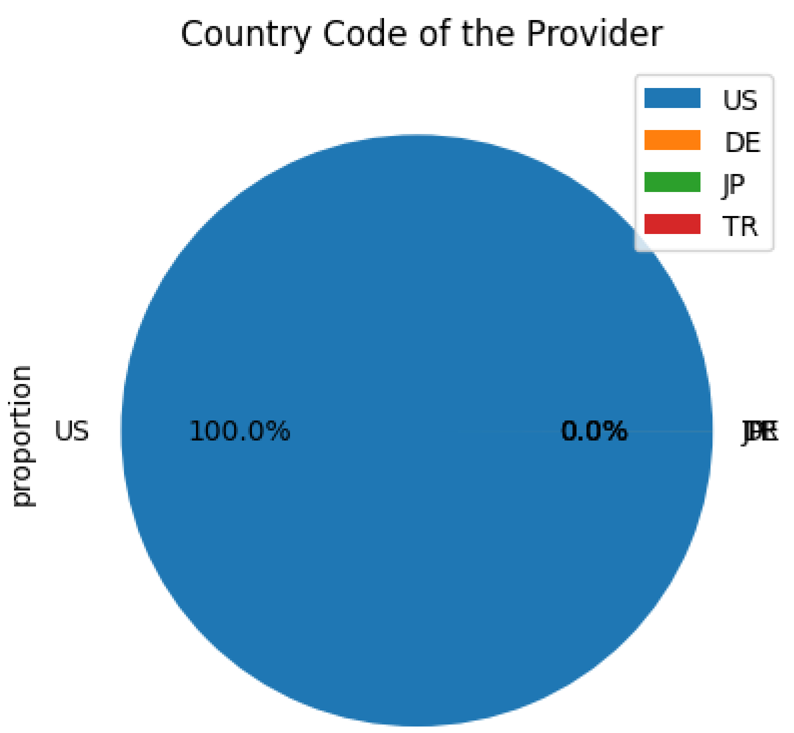
Inference:

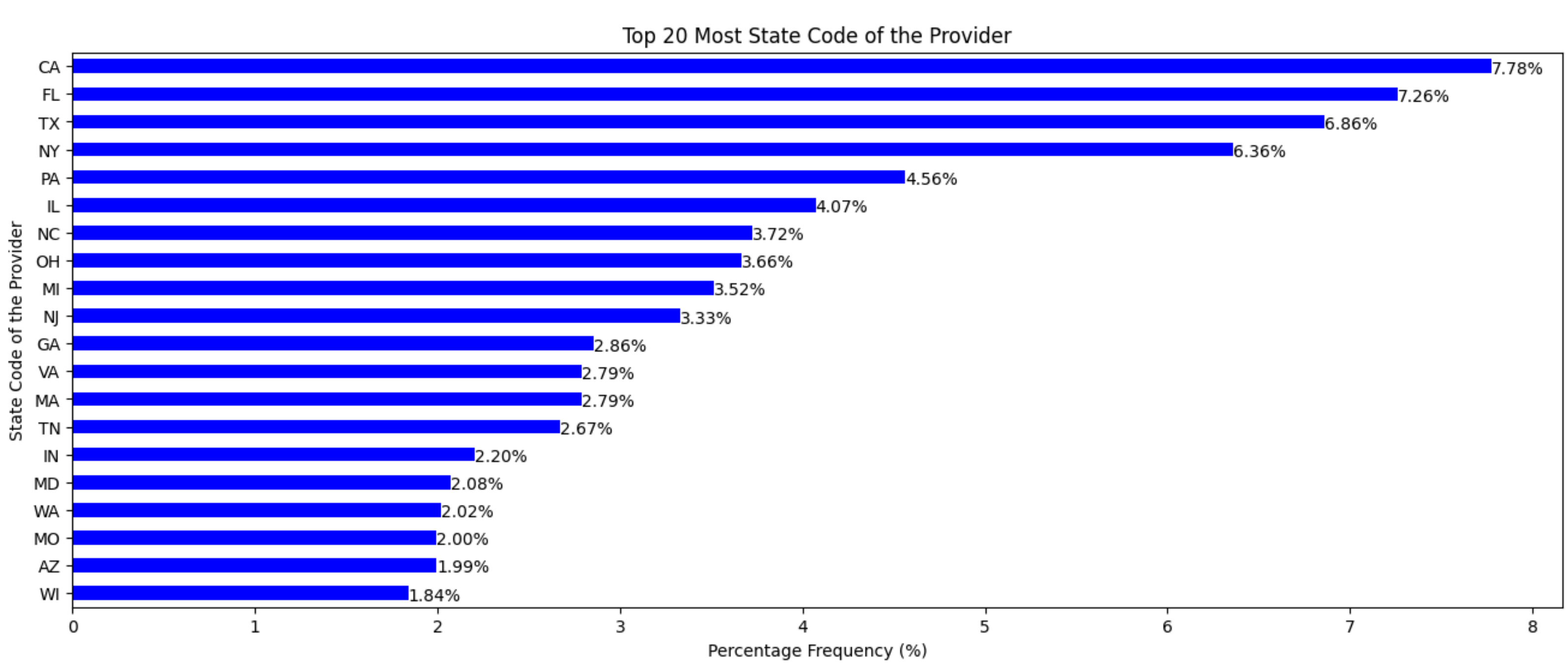
The output indicates the following:

- The service Provider contributions by city **NEW YORK** contributes **1.06%** followed by HOUSTON and CHICAGO.

- The place of service is mostly **Non-facility** which is around **61.62%** where as **Facility** low number around **38.38%** in the dataset. It shows many service providers also provide services outside facility

In [14]:
```
# Finding the top Country Code of the Provider

top_10 = df['Country Code of the Provider'].value_counts(normalize=True).head()

# Plotting

top_10.plot(kind='pie' ,autopct='%1.1f%%')
plt.title(' Country Code of the Provider')
plt.legend()
plt.show()

# Finding the top 20 most State Code of the Provider

top_10 = df['State Code of the Provider'].value_counts(normalize=True).head(20) * 100

# Plotting the top 20 State Code of the Provider

plt.figure(figsize=(16, 6))
top_10.plot(kind='barh', color='blue')

# Adding the percentage frequency on the bars

for index, value in enumerate(top_10):
    plt.text(value, index+0.25, f'{value:.2f}%', fontsize=10)

plt.title('Top 20 Most State Code of the Provider')
plt.xlabel('Percentage Frequency (%)')
plt.ylabel('State Code of the Provider')
plt.gca().invert_yaxis()
plt.show()
```





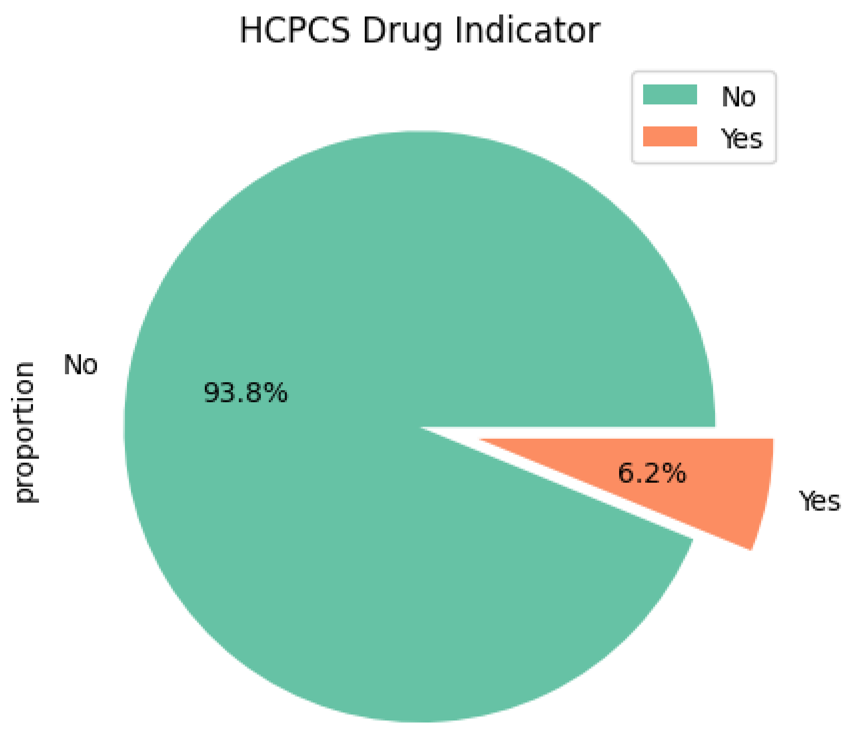
Inference:

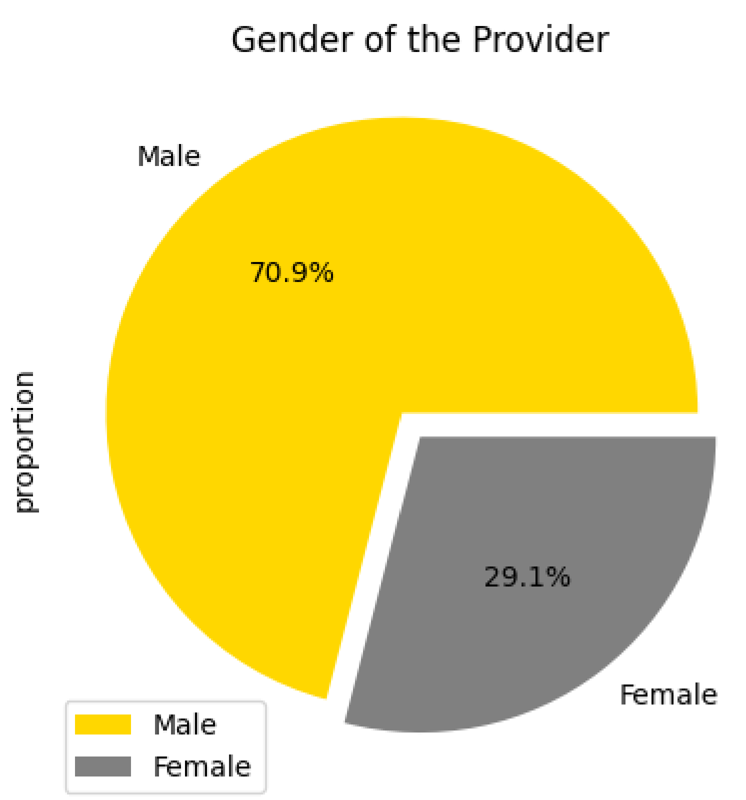
The output indicates the following:

- The Country of providers is dominated by **US** holds almost all **100.00%** records in dataset, other are only 3-4 in numbers.

- Threre are large part of Service providers comes from the state of **California** which is around **7.78%** of total providers followed by **Florida, Texas, Newyork** has contribution around **7.26%, 6.86%, 6.36%** respectively State-wise in the dataset.

In [15]:
```
# Plotting the HCPCS Drug Indicator
top_1 = df['HCPCS Drug Indicator'].value_counts(normalize=True).head()
mylabels = ["No","Yes"]
myexplode = [0,0.2]
top_1.plot(kind='pie',labels=mylabels, explode=myexplode,  autopct='%1.1f%%' , colors=sns.color_palette('Set
plt.title('HCPCS Drug Indicator')
plt.legend()
plt.show()

# Plotting the top  most frequent gender
top_1 = df['Gender of the Provider'].value_counts(normalize=True).head()
mylabels = ["Male","Female"]
myexplode = [0.1,0]
top_1.plot(kind='pie',  labels=mylabels , explode=myexplode, autopct='%1.1f%%' ,colors=['gold','grey'])
plt.title('Gender of the Provider')
plt.legend()
plt.show()
```





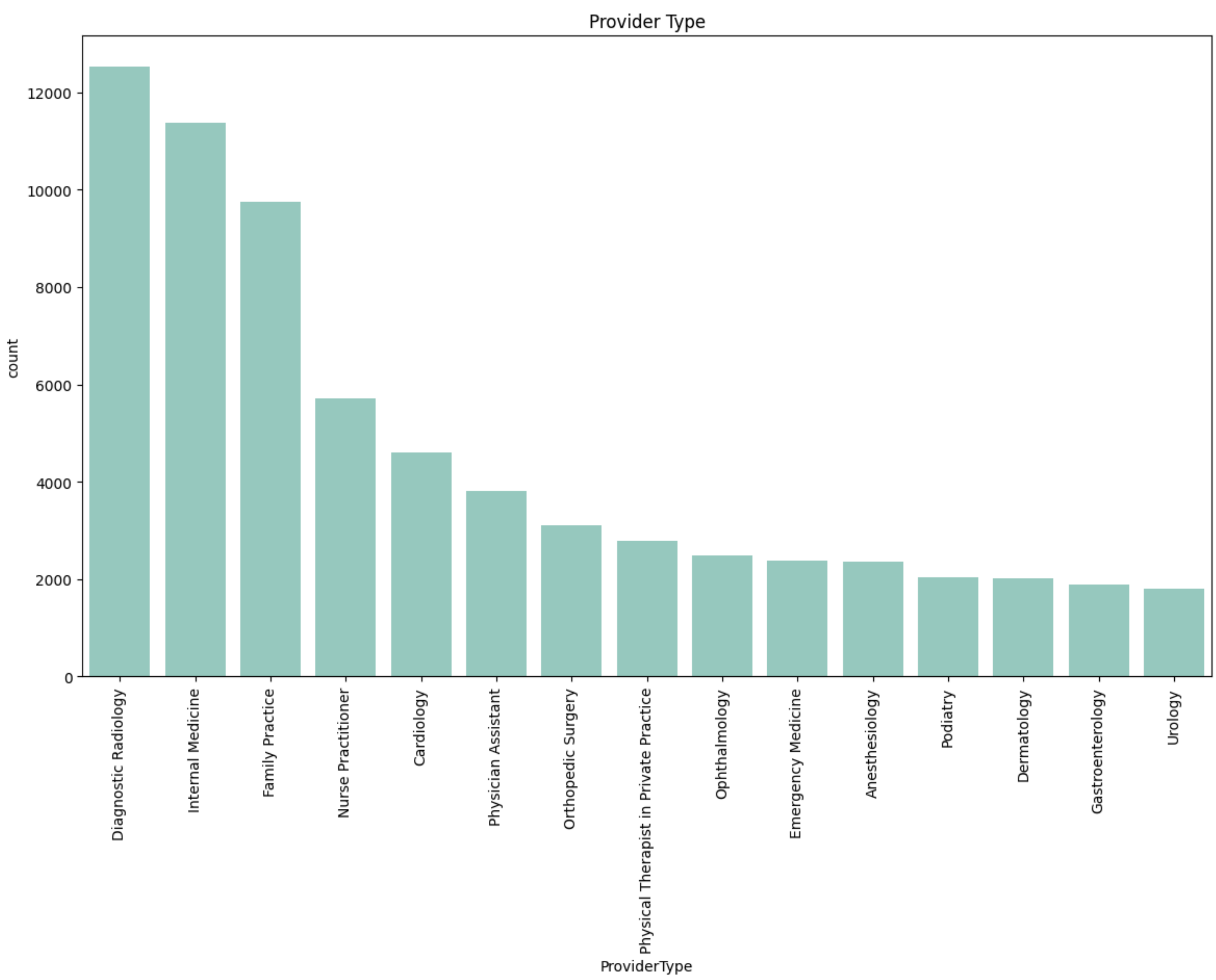
Inference:

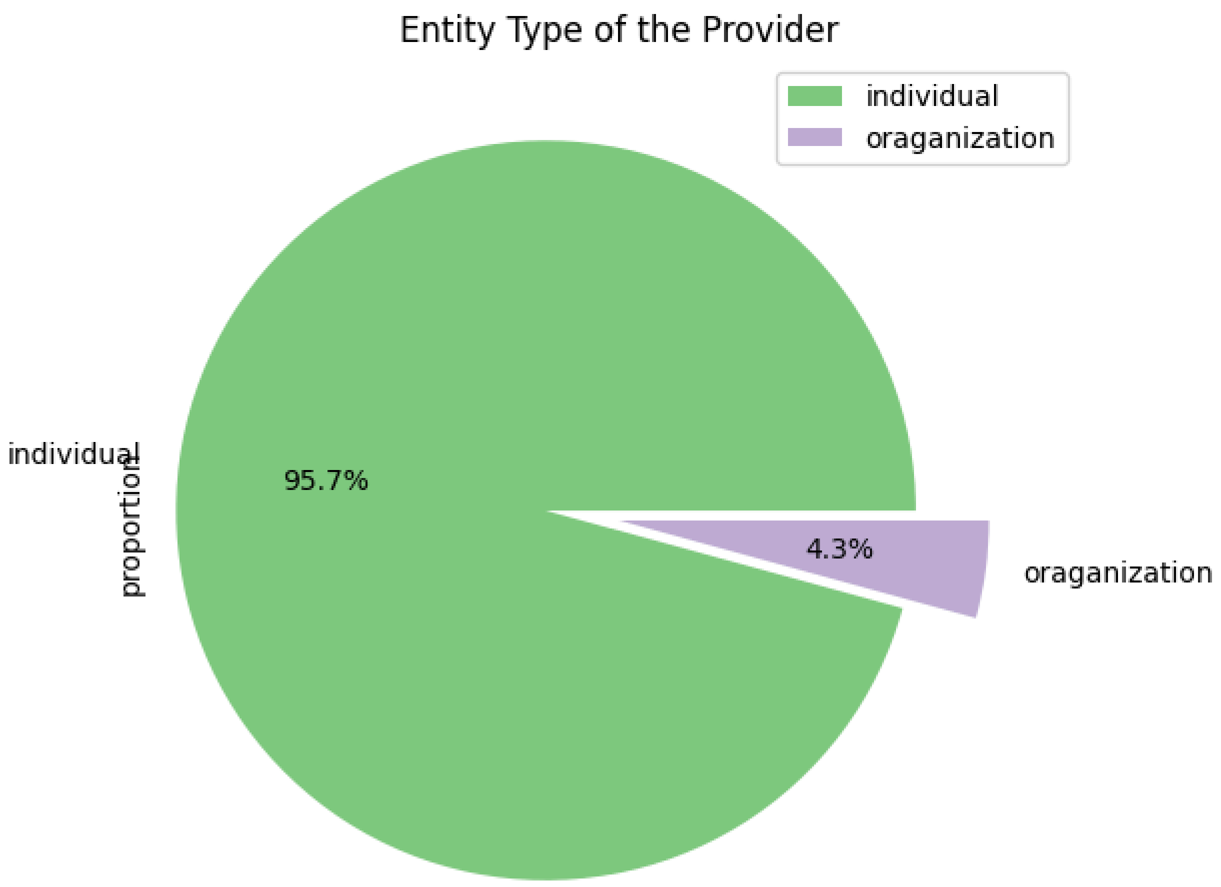
The output indicates the following:

- The HCPCS Drug Indicator of **No** holds more than **93.8%** and **Yes** has around **6.2%** records in dataset.

- Threre are large part Gender type are **Male** which is around **70.9%** total patient and **Females** has significantly low contribution around **29.1%** in the dataset.

In [16]:
```
#plotting provider type and the count using countplot
sns.set_palette("Set3",15)
df.rename(columns={'Provider Type':'ProviderType'},inplace=True)
plt.figure(figsize=(14, 8))
group_count= 15
sns.countplot(x='ProviderType', data=df, order= df.ProviderType.value_counts().iloc[:group_count].index)
plt.title('Provider Type')
plt.xticks(rotation=90)
plt.show()

# Plotting the top  most frequent gender
top_1 = df['Entity Type of the Provider'].value_counts(normalize=True).head()
plt.figure(figsize=(8, 6))
mylabels = ["individual","oraganization"]
myexplode = [0.2,0]
top_1.plot(kind='pie',  labels=mylabels, explode=myexplode,autopct='%1.1f%%', colors=sns.color_palette('Acc
plt.title('Entity Type of the Provider')
plt.legend()
plt.show()
```





Inference:

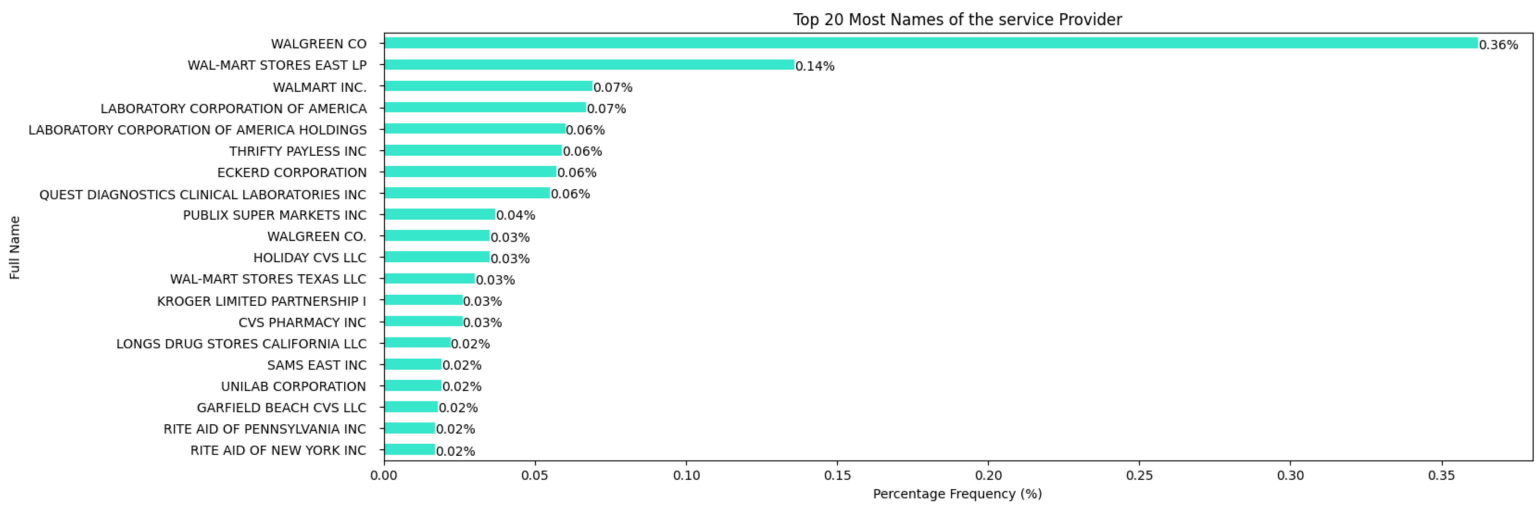
The output indicates the following:

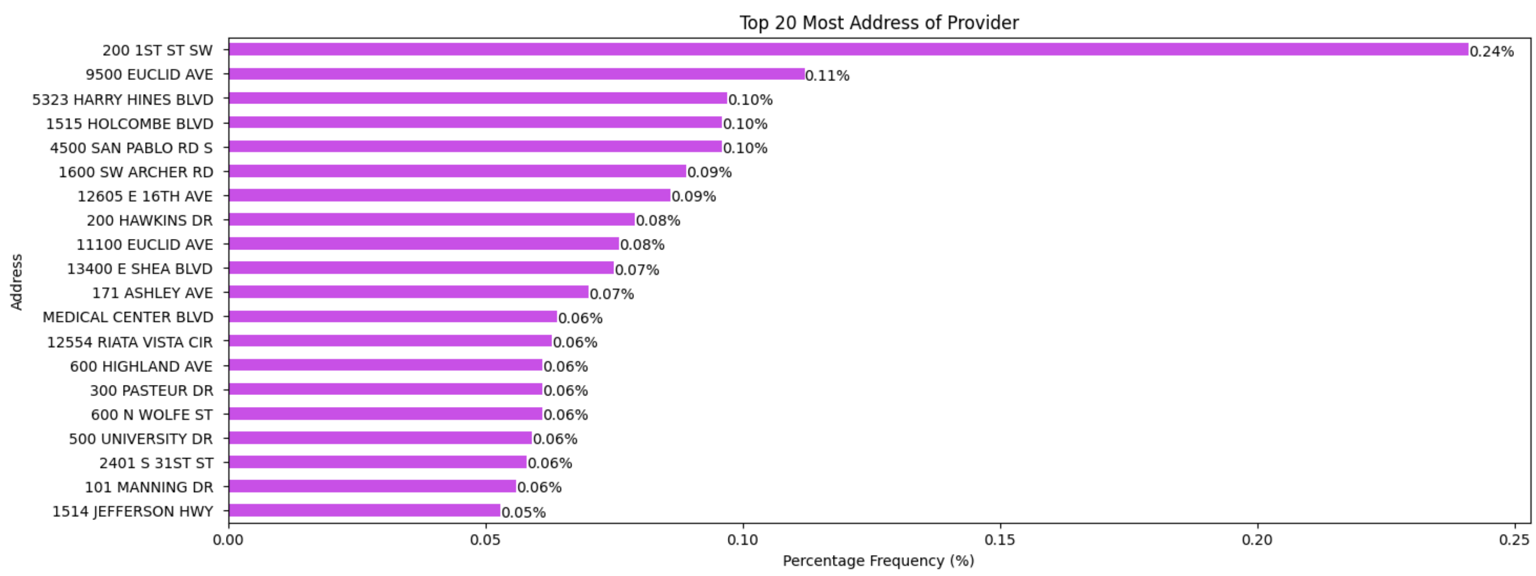
- The majority of Provider type is **Diagonostic Radiology** which holds more than **12000** count followed by **internal medicine** which has around **11000** records Top 10 contributes around 50% overall.
- Threre are large part entity type of providers are **individual** around **95.7%** providers are registered as individual. It indicates that most providers pratice individually and provide services

In [17]:

```
#remove nan from name and address column

df['Name'] = df['Name'].str.replace("nan","")
df['Full Address'] = df['Full Address'].str.replace("nan","")

#Name
top_10 = df['Name'].value_counts(normalize=True).head(20) * 100

# Plotting the top 20 Names of the Provider

plt.figure(figsize=(16, 6))
top_10.plot(kind='barh', color='#3AE6CA')

# Adding the percentage frequency on the bars

for index, value in enumerate(top_10):
    plt.text(value, index+0.25, f'{value:.2f}%', fontsize=10)

plt.title('Top 20 Most Names of the service Provider')
plt.xlabel('Percentage Frequency (%)')
plt.ylabel('Full Name')
plt.gca().invert_yaxis()
plt.show()

#Address
top_10 = df['Full Address'].value_counts(normalize=True).head(20) * 100

# Plotting the top 20 Names of the Provider

plt.figure(figsize=(16, 6))
top_10.plot(kind='barh', color='#C853E8')

# Adding the percentage frequency on the bars

for index, value in enumerate(top_10):
    plt.text(value, index+0.25, f'{value:.2f}%', fontsize=10)

plt.title('Top 20 Most Address of Provider')
plt.xlabel('Percentage Frequency (%)')
```

```
plt.ylabel('Address')
plt.gca().invert_yaxis()
plt.show()
```





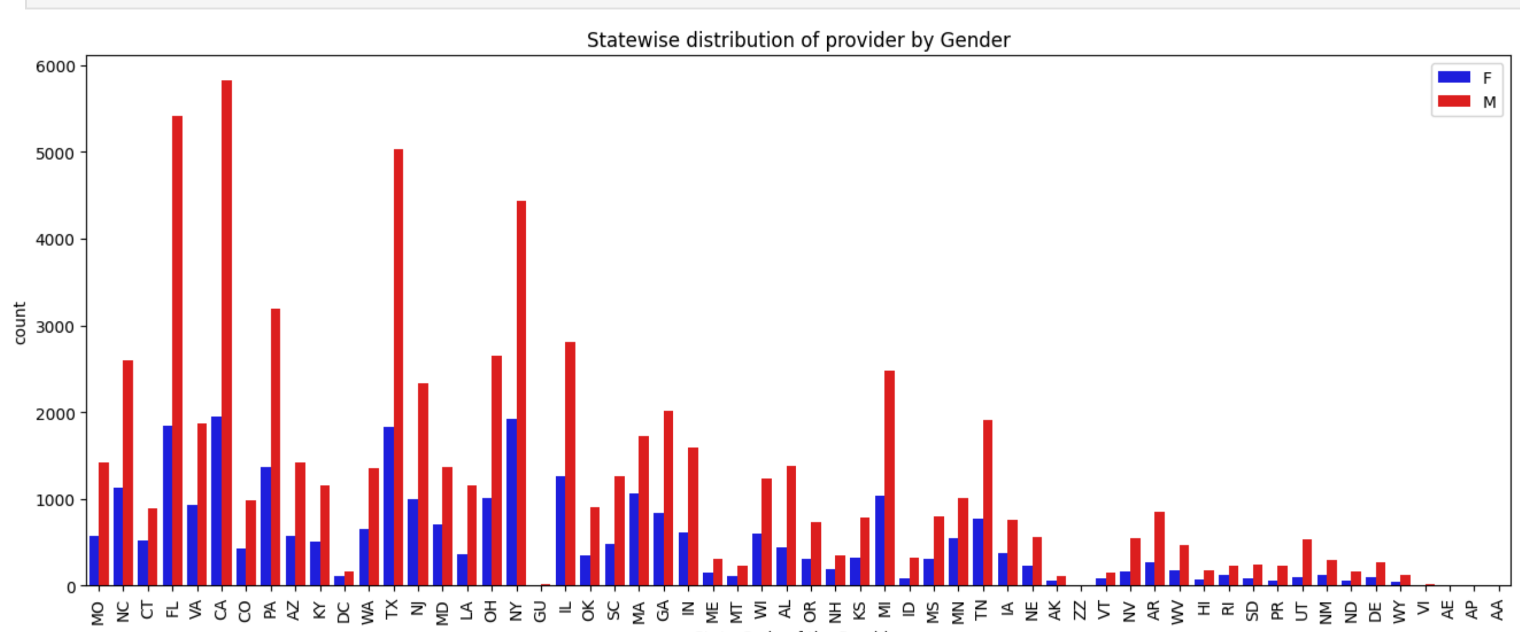
Inference:

The output indicates the following:

- The majority of service provider is WALGREEN co. which has around 0.36% around 360 out of 100000 entries.
- The 200 1ST ST SW is the most commonly found address of the provider in the dataset around 0.24% i.e.240 entries are found . Also almost majority addresses don't have null value at second line of address

Step 4.2 | Bivariate Analysis

In [19]:
```
plt.figure(figsize=(16, 6))
sns.countplot(data=df, x="State Code of the Provider", hue="Gender of the Provider" ,palette=['blue','re
plt.xticks(rotation=90)
plt.title("Statewise distribution of provider by Gender")
plt.legend()
plt.show()
```



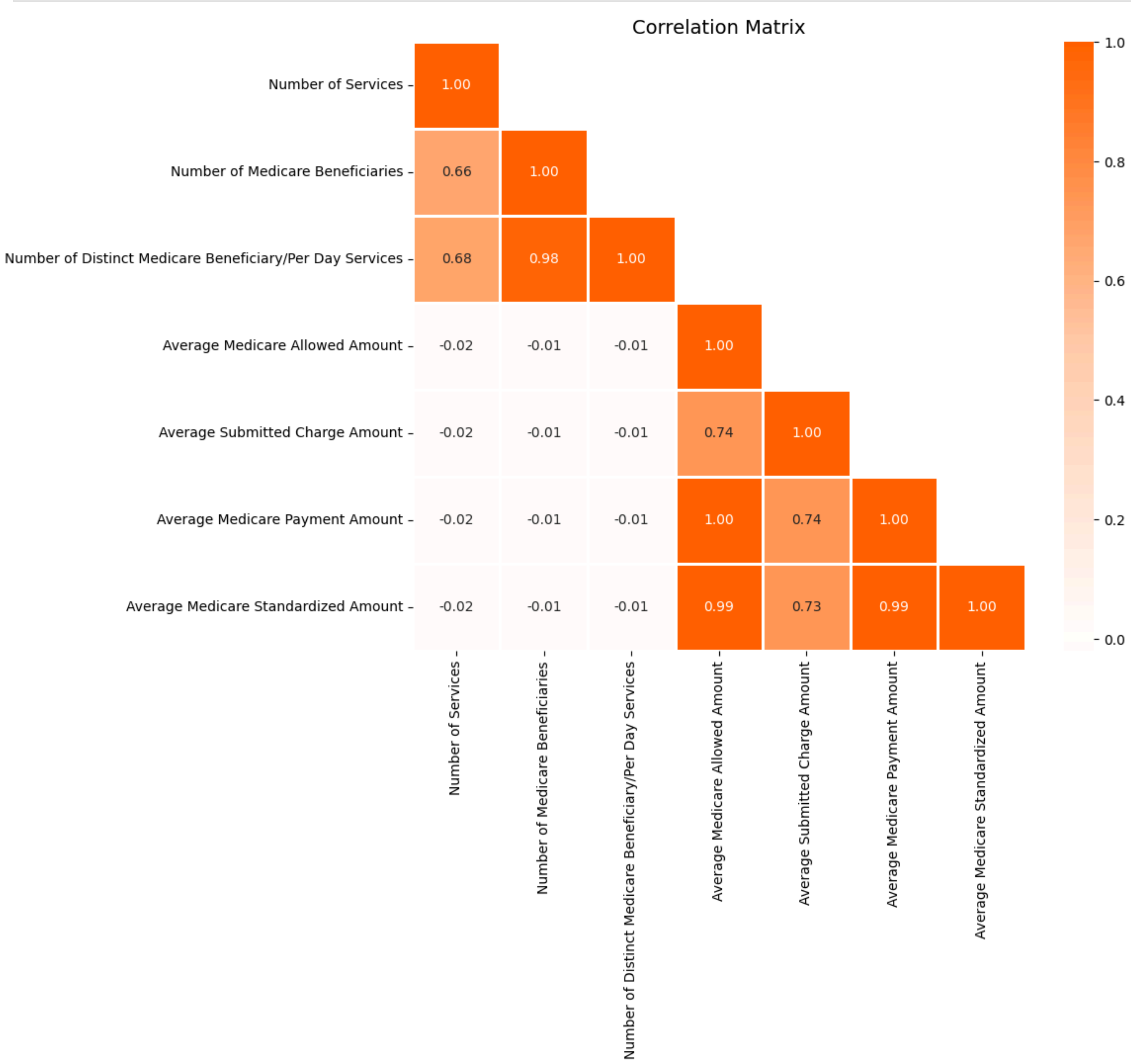
Inference:

The output indicates the following:

- The highest no of providers is highest for male in California and Florida which is above 5000 .
- The highest Number of provider female is in Florida , California ,Texas and Newyork above 1500 females are evenly distributed.

| Correlation Analysis

In [20]:
```
# Calculate the correlation matrix
correlation = df. corr(numeric_only = True)

# Define a custom colormap
colors = ['#ff6200', '#ffcaa8', 'white', '#ffcaa8', '#ff6200']
my_cmap = LinearSegmentedColormap.from_list('custom_map', colors, N=256)

# Create a mask to only show the lower triangle of the matrix (since it's mirrored around its
# top-left to bottom-right diagonal)
mask = np.zeros_like(correlation)
mask[np.triu_indices_from(mask, k=1)] = True

# Plot the heatmap
plt.figure(figsize=(10, 8))
sns.heatmap(correlation, mask=mask, cmap=my_cmap, annot=True, center=0, fmt='.2f', linewidths=2)
plt.title('Correlation Matrix', fontsize=14)
plt.show()
```



Inference:

Looking at the heatmap, we can see that there are some pairs of variables that have high correlations, for instance:

- `Number of Medicare Beneficiaries` and `Number of Services`

- `Number of Distinct Medicare Beneficiary/Per Day Services` and `Number of Services`
- `Number of Distinct Medicare Beneficiary/Per Day Services` and `Number of Medicare Beneficiaries`
- `Average Submitted Charge Amount` and `Average Medicare Allowed Amount`
- `Average Medicare Payment Amount ` and `Average Medicare Allowed Amount`
- `Average Medicare Standardized Amount ` and `Average Medicare Allowed Amount`
- `Average Medicare Payment Amount ` and `Average Submitted Charge Amount`
- `Average Medicare Standardized Amount ` and `Average Submitted Charge Amount`
- `Average Medicare Standardized Amount ` and `Average Medicare Payment Amount`

These high correlations indicate that these variables move closely together, implying a degree of multicollinearity.

In [21]:
```
df.sample(10).T
```

Out[21]:

	84830	94113	53692	23401	27497	12051	68648	
Credentials of the Provider	MD	MD	MD	MD	MD	MD PHD	MD	
Gender of the Provider	M	M	F	M	F	F	M	
Entity Type of the Provider	I	I	I	I	I	I	I	
City of the Provider	NEW BERN	MIRAMAR BEACH	BILLINGS	BOSTON	NORTH RIVERSIDE	BUFFALO	RIVERVIEW	LAD
State Code of the Provider	NC	FL	MT	MA	IL	NY	FL	
Country Code of the Provider	US	US	US	US	US	US	US	
ProviderType	Radiation Oncology	Family Practice	Internal Medicine	Diagnostic Radiology	Family Practice	Pathology	Urology	Ph As
Medicare Participation Indicator	Y	Y	Y	Y	Y	Y	Y	
Place of Service	F	F	O	F	O	F	O	
HCPCS Description	Radiation treatment management, 5 treatments	Established patient office or other outpatient...	Established patient office or other outpatient...	Ultrasound of abdomen	Established patient office or other outpatient...	Bone marrow, smear interpretation	Electronic assessment of bladder emptying	Eme depa prob hi
HCPCS Drug Indicator	N	N	N	N	N	N	N	
Number of Services	483.0	72.0	22.0	23.0	51.0	35.0	36.0	
Number of Medicare Beneficiaries	124	56	22	22	45	33	36	
Number of Distinct Medicare Beneficiary/Per Day Services	483	72	22	23	51	35	36	
Average Medicare Allowed Amount	182.550207	51.89	115.0	29.745217	78.11	49.92	14.426389	
Average Submitted Charge Amount	626.0	58.244583	157.090909	270.0	105.0	100.0	32.0	
Average Medicare Payment Amount	142.651594	37.202361	63.987727	21.313478	49.196471	39.14	10.259444	77.1
Average Medicare Standardized Amount	148.509731	37.046528	66.185909	21.068261	46.375098	40.24	10.388333	75.9
Name	MILLER SETH	JIMENEZ JOSE R	KALE KARI V	YOON LUKE S	SATO MAKI	ZHANG NAN	BAKER MARK B	MC GL
Full Address	2000 NEUSE BLVD	7720 US HIGHWAY 98 W SUITE 350	2675 CENTRAL AVE	55 FRUIT ST FND 216	7222 W CERMAK RD SUITE 700	100 HIGH ST	6043 WINTHROP COMMERCE AVE SUITE 201	HIG