Project1-EDA

January 27, 2020

1 Project 1 - Clustering

1.0.1 Charlie Marshall

1.0.2 Professor Klabjan

1.0.3 IEMS 308

1.0.4 27 January 2019

In [1]:
```
##### Loading significant packages #############
import os
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import matplotlib.cm as cm
import seaborn as sns
from scipy import stats
from sklearn.cluster import KMeans
from sklearn import preprocessing
from sklearn.metrics import silhouette_score, silhouette_samples
from scipy.cluster.hierarchy import dendrogram, linkage
```

In [2]:
```
##### Loading Medicare Provider Payment Data ###############
df = pd.read_csv("Medicare_Provider_Util_Payment_PUF_CY2017/Medicare_Provider_Util_Payn
df = df.drop([0])      # Dropping copyright statement
df.head()
```

```
/Users/charlesmarshall/anaconda3/lib/python3.7/site-packages/IPython/core/interactiveshell.py:3
  interactivity=interactivity, compiler=compiler, result=result)
```

Out[2]:

	npi	nppes_provider_last_org_name	nppes_provider_first_name	\
1	1003000126	ENKESHAFI	ARDALAN	
2	1003000126	ENKESHAFI	ARDALAN	
3	1003000126	ENKESHAFI	ARDALAN	
4	1003000126	ENKESHAFI	ARDALAN	
5	1003000126	ENKESHAFI	ARDALAN	

```
  nppes_provider_mi nppes_credentials nppes_provider_gender nppes_entity_code  \
1               NaN             M.D.                      M                 I
2               NaN             M.D.                      M                 I
3               NaN             M.D.                      M                 I
4               NaN             M.D.                      M                 I
5               NaN             M.D.                      M                 I

  nppes_provider_street1 nppes_provider_street2 nppes_provider_city  ...  \
1           900 SETON DR                    NaN          CUMBERLAND  ...
2           900 SETON DR                    NaN          CUMBERLAND  ...
3           900 SETON DR                    NaN          CUMBERLAND  ...
4           900 SETON DR                    NaN          CUMBERLAND  ...
5           900 SETON DR                    NaN          CUMBERLAND  ...

  hcpcs_code                                hcpcs_description  \
1      99217               Hospital observation care discharge
2      99218    Hospital observation care typically 30 minutes
3      99219    Hospital observation care typically 50 minutes
4      99220  Hospital observation care typically 70 minutes...
5      99221  Initial hospital inpatient care, typically 30 ...

  hcpcs_drug_indicator line_srvc_cnt bene_unique_cnt bene_day_srvc_cnt  \
1                    N         100.0            96.0             100.0
2                    N          26.0            25.0              26.0
3                    N          52.0            51.0              52.0
4                    N          59.0            59.0              59.0
5                    N          16.0            16.0              16.0

  average_Medicare_allowed_amt average_submitted_chrg_amt  \
1                    73.398800                 325.780000
2                   100.080000                 449.000000
3                   136.380000                 614.000000
4                   190.363729                 755.932203
5                   101.680000                 462.812500

  average_Medicare_payment_amt  average_Medicare_standard_amt
1                    56.827200                      57.492400
2                    78.460000                      79.306154
3                   102.807692                     103.895385
4                   141.293559                     142.865763
5                    79.710000                      80.750000

[5 rows x 26 columns]
```

1.1 Removing Outliers of Numerical Data

All data points outside 3 standard devaitions from the mean are removed

```
In [3]: # Removes all outliers from numerical columns
        # Constrains will contain `True` or `False` depending on if it is a value below the th
        # Drop (inplace) values set to be rejected
        def drop_numerical_outliers(df, z_thresh=3):
            constrains = df.select_dtypes(include=[np.number]).apply(lambda x: np.abs(stats.zs
            df.drop(df.index[~constrains], inplace=True)

        drop_numerical_outliers(df)
```

1.2 Start Explanatory Data Analysis

```
In [4]: df.shape

Out[4]: (9689357, 26)

In [5]: df.info()

<class 'pandas.core.frame.DataFrame'>
Int64Index: 9689357 entries, 1 to 9847443
Data columns (total 26 columns):
npi                                  int64
nppes_provider_last_org_name         object
nppes_provider_first_name            object
nppes_provider_mi                    object
nppes_credentials                    object
nppes_provider_gender                object
nppes_entity_code                    object
nppes_provider_street1               object
nppes_provider_street2               object
nppes_provider_city                  object
nppes_provider_zip                   object
nppes_provider_state                 object
nppes_provider_country               object
provider_type                        object
medicare_participation_indicator     object
place_of_service                     object
hcpcs_code                           object
hcpcs_description                    object
hcpcs_drug_indicator                 object
line_srvc_cnt                        float64
bene_unique_cnt                      float64
bene_day_srvc_cnt                    float64
average_Medicare_allowed_amt         float64
average_submitted_chrg_amt           float64
average_Medicare_payment_amt         float64
average_Medicare_standard_amt        float64
dtypes: float64(7), int64(1), object(18)
memory usage: 1.9+ GB
```

```
In [6]: df.describe()
```

Out[6]:

	npi	line_srvc_cnt	bene_unique_cnt	bene_day_srvc_cnt
count	9.689357e+06	9.689357e+06	9.689357e+06	9.689357e+06
mean	1.499871e+09	1.606119e+02	7.431467e+01	1.183432e+02
std	2.877043e+08	5.503218e+02	1.361547e+02	2.506905e+02
min	1.003000e+09	7.500000e+00	1.100000e+01	1.100000e+01
25%	1.255302e+09	2.100000e+01	1.700000e+01	2.000000e+01
50%	1.497987e+09	4.300000e+01	3.300000e+01	4.100000e+01
75%	1.740680e+09	1.180000e+02	7.600000e+01	1.070000e+02
max	1.993000e+09	1.561200e+04	3.590000e+03	6.096000e+03

	average_Medicare_allowed_amt	average_submitted_chrg_amt
count	9.689357e+06	9.689357e+06
mean	8.450123e+01	2.701615e+02
std	9.290735e+01	4.035712e+02
min	6.035380e-05	6.035380e-05
25%	2.411000e+01	5.700000e+01
50%	6.364000e+01	1.436972e+02
75%	1.114200e+02	2.880000e+02
max	9.309430e+02	3.544182e+03

	average_Medicare_payment_amt	average_Medicare_standard_amt
count	9.689357e+06	9.689357e+06
mean	6.422428e+01	6.483764e+01
std	7.217548e+01	7.248741e+01
min	0.000000e+00	0.000000e+00
25%	1.908958e+01	1.988481e+01
50%	4.633478e+01	4.719936e+01
75%	8.317672e+01	8.334863e+01
max	7.234023e+02	7.258472e+02

```
In [7]: df.corr()
```

Out[7]:

	npi	line_srvc_cnt	bene_unique_cnt
npi	1.000000	0.000278	0.000329
line_srvc_cnt	0.000278	1.000000	0.404730
bene_unique_cnt	0.000329	0.404730	1.000000
bene_day_srvc_cnt	0.000358	0.513464	0.814087
average_Medicare_allowed_amt	-0.000769	-0.083963	-0.045585
average_submitted_chrg_amt	-0.000168	-0.081258	-0.059439
average_Medicare_payment_amt	-0.000711	-0.083876	-0.047775
average_Medicare_standard_amt	-0.000728	-0.084124	-0.047955

	bene_day_srvc_cnt
npi	0.000358
line_srvc_cnt	0.513464
bene_unique_cnt	0.814087

```
bene_day_srvc_cnt                    1.000000
average_Medicare_allowed_amt        -0.066698
average_submitted_chrg_amt          -0.086088
average_Medicare_payment_amt        -0.069676
average_Medicare_standard_amt       -0.069581

                           average_Medicare_allowed_amt  \
npi                                           -0.000769
line_srvc_cnt                                 -0.083963
bene_unique_cnt                               -0.045585
bene_day_srvc_cnt                             -0.066698
average_Medicare_allowed_amt                   1.000000
average_submitted_chrg_amt                     0.718817
average_Medicare_payment_amt                   0.992497
average_Medicare_standard_amt                  0.988778

                           average_submitted_chrg_amt  \
npi                                          -0.000168
line_srvc_cnt                                -0.081258
bene_unique_cnt                              -0.059439
bene_day_srvc_cnt                            -0.086088
average_Medicare_allowed_amt                  0.718817
average_submitted_chrg_amt                    1.000000
average_Medicare_payment_amt                  0.715348
average_Medicare_standard_amt                 0.708221

                           average_Medicare_payment_amt  \
npi                                           -0.000711
line_srvc_cnt                                 -0.083876
bene_unique_cnt                               -0.047775
bene_day_srvc_cnt                             -0.069676
average_Medicare_allowed_amt                   0.992497
average_submitted_chrg_amt                     0.715348
average_Medicare_payment_amt                   1.000000
average_Medicare_standard_amt                  0.992823

                           average_Medicare_standard_amt
npi                                           -0.000728
line_srvc_cnt                                 -0.084124
bene_unique_cnt                               -0.047955
bene_day_srvc_cnt                             -0.069581
average_Medicare_allowed_amt                   0.988778
average_submitted_chrg_amt                     0.708221
average_Medicare_payment_amt                   0.992823
average_Medicare_standard_amt                  1.000000
```

1.3 EDA of Numerical Data

Starting with EDA with an analysis of the numerical features in the data, with a goal of understanding the distributions of the data.

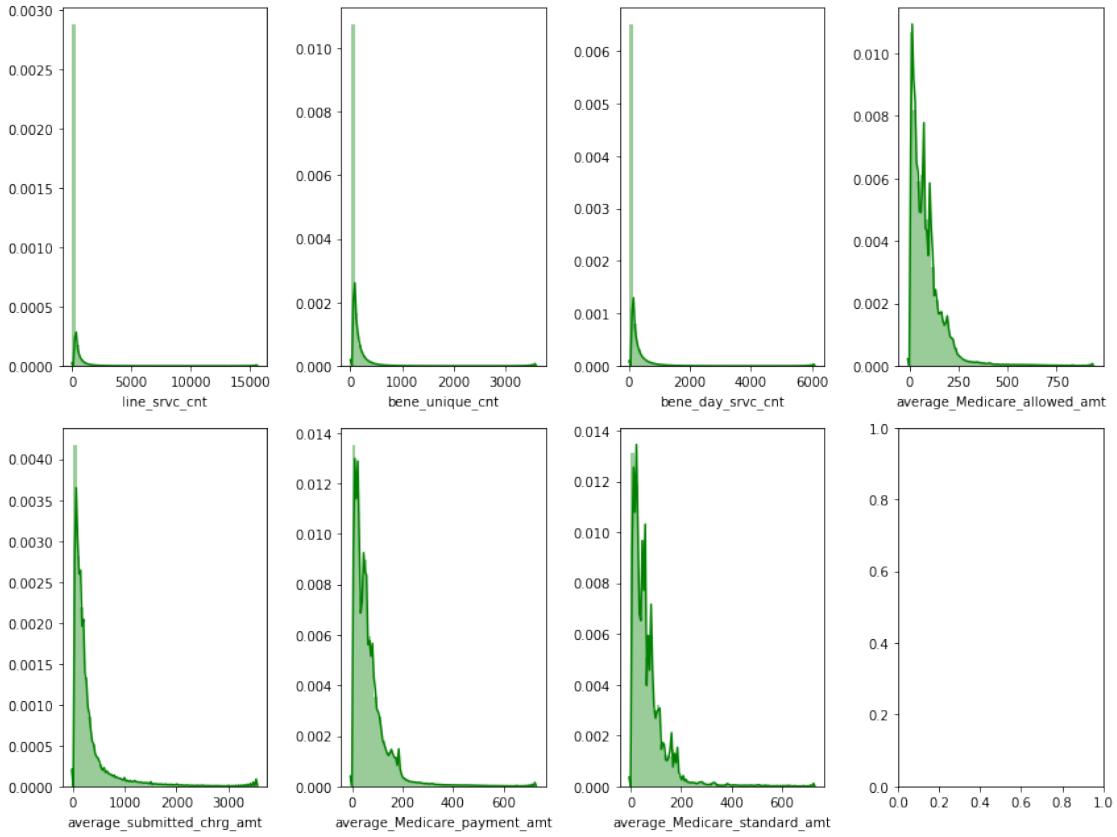
```
In [8]: df_num = df.select_dtypes(include = ['float64'])
        df_num.info()
        df_num.describe()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 9689357 entries, 1 to 9847443
Data columns (total 7 columns):
line_srvc_cnt                   float64
bene_unique_cnt                 float64
bene_day_srvc_cnt               float64
average_Medicare_allowed_amt    float64
average_submitted_chrg_amt      float64
average_Medicare_payment_amt    float64
average_Medicare_standard_amt   float64
dtypes: float64(7)
memory usage: 591.4 MB
```

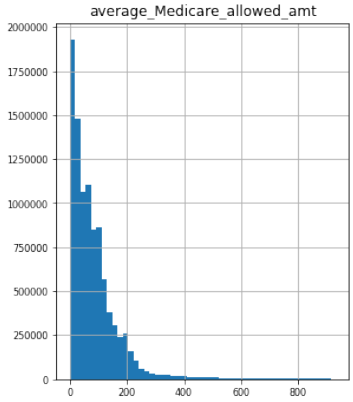
```
Out[8]:        line_srvc_cnt  bene_unique_cnt  bene_day_srvc_cnt  \
        count   9.689357e+06     9.689357e+06       9.689357e+06
        mean    1.606119e+02     7.431467e+01       1.183432e+02
        std     5.503218e+02     1.361547e+02       2.506905e+02
        min     7.500000e+00     1.100000e+01       1.100000e+01
        25%     2.100000e+01     1.700000e+01       2.000000e+01
        50%     4.300000e+01     3.300000e+01       4.100000e+01
        75%     1.180000e+02     7.600000e+01       1.070000e+02
        max     1.561200e+04     3.590000e+03       6.096000e+03

               average_Medicare_allowed_amt  average_submitted_chrg_amt  \
        count                  9.689357e+06                9.689357e+06
        mean                   8.450123e+01                2.701615e+02
        std                    9.290735e+01                4.035712e+02
        min                    6.035380e-05                6.035380e-05
        25%                    2.411000e+01                5.700000e+01
        50%                    6.364000e+01                1.436972e+02
        75%                    1.114200e+02                2.880000e+02
        max                    9.309430e+02                3.544182e+03

               average_Medicare_payment_amt  average_Medicare_standard_amt
        count                  9.689357e+06                   9.689357e+06
        mean                   6.422428e+01                   6.483764e+01
        std                    7.217548e+01                   7.248741e+01
        min                    0.000000e+00                   0.000000e+00
        25%                    1.908958e+01                   1.988481e+01
```

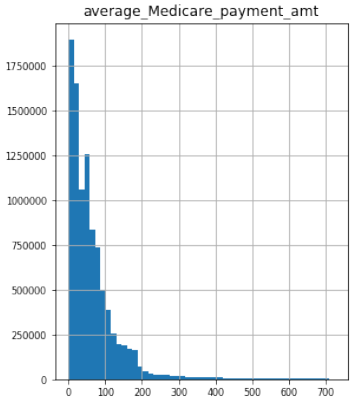
50%	4.633478e+01	4.719936e+01
75%	8.317672e+01	8.334863e+01
max	7.234023e+02	7.258472e+02

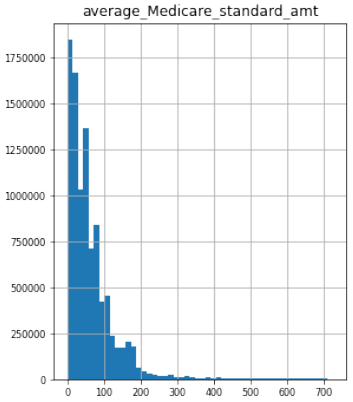
In [207]:
```
fig, axes = plt.subplots(round(len(df_num.columns) / 3), 4, figsize=(12,9))

    for i, ax in enumerate(fig.axes):
        if i < len(df_num.columns):
            sns.distplot(df_num.iloc[:,i], color='g', ax=ax) #hist_kws={'alpha': 0.4})

    fig.tight_layout()
```

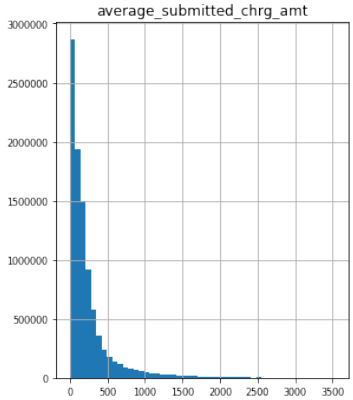


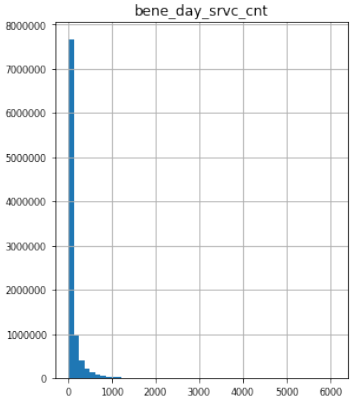
In [10]:
```
df_num.hist(figsize=(16, 20), bins = 50, xlabelsize=8, ylabelsize=8);
```

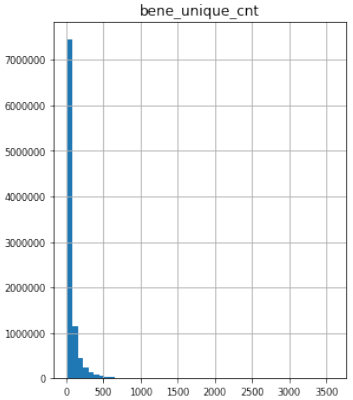


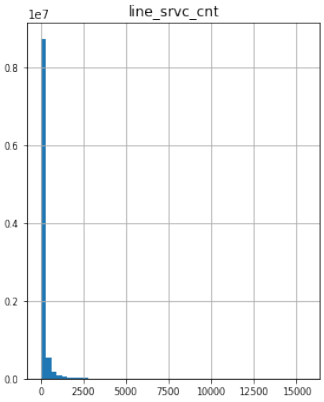












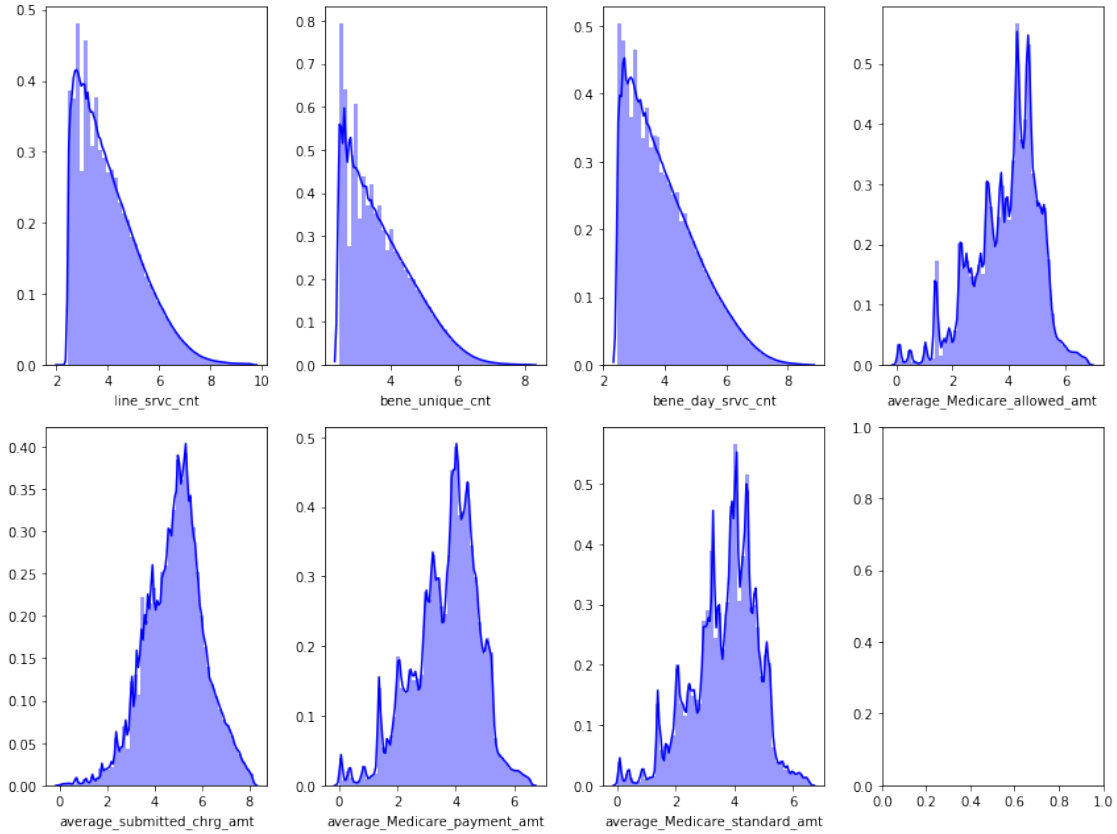

```
In [11]: logx = np.log(df_num+1)
         logx.describe()
```

Out[11]:

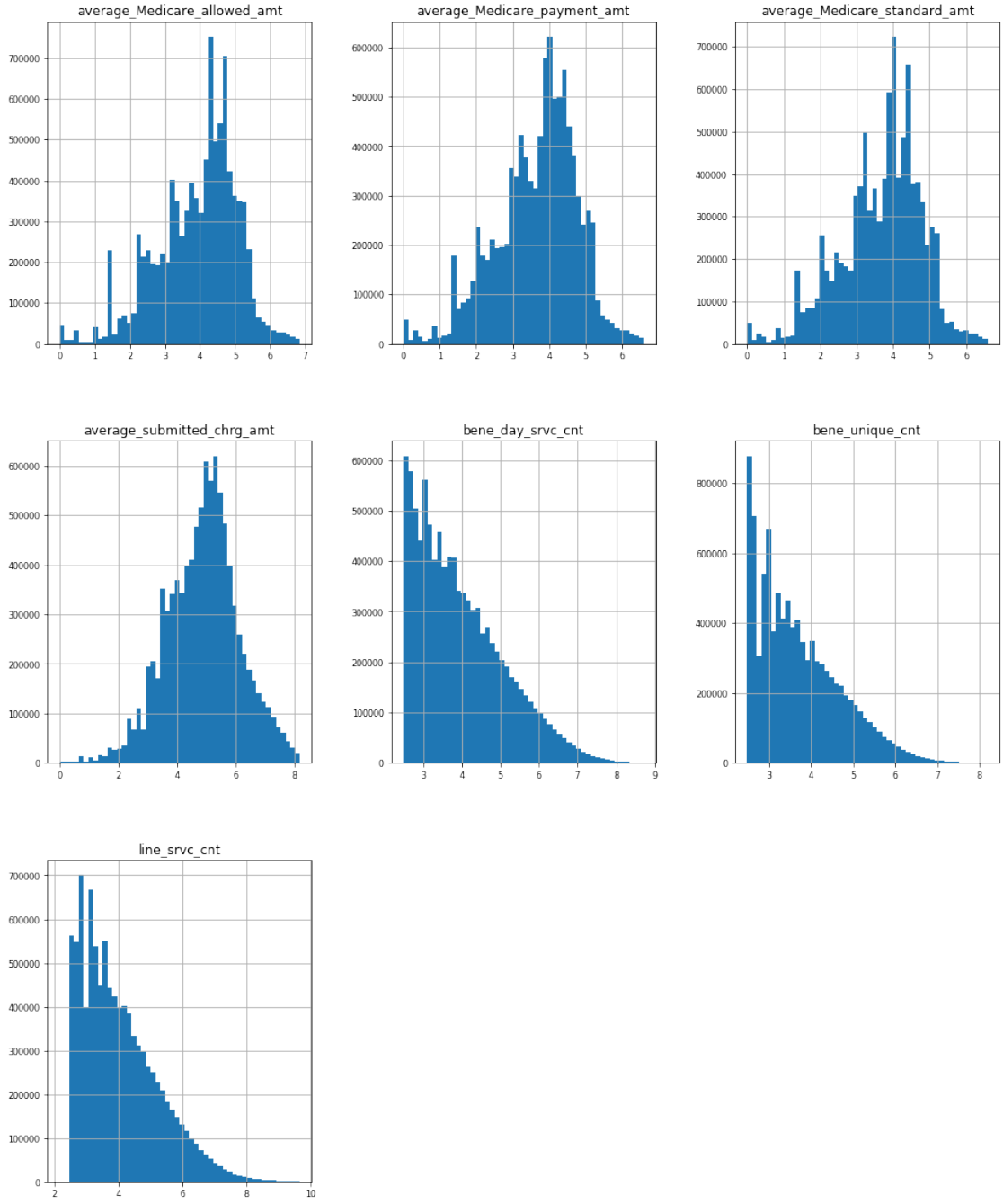
	line_srvc_cnt	bene_unique_cnt	bene_day_srvc_cnt	\
count	9.689357e+06	9.689357e+06	9.689357e+06	
mean	4.049679e+00	3.719968e+00	3.969712e+00	
std	1.209221e+00	9.754828e-01	1.133209e+00	

```
min     2.140066e+00     2.484907e+00       2.484907e+00
25%     3.091042e+00     2.890372e+00       3.044522e+00
50%     3.784190e+00     3.526361e+00       3.737670e+00
75%     4.779123e+00     4.343805e+00       4.682131e+00
max     9.655859e+00     8.186186e+00       8.715552e+00

       average_Medicare_allowed_amt  average_submitted_chrg_amt  \
count                  9.689357e+06                9.689357e+06
mean                   3.923733e+00                4.892136e+00
std                    1.142726e+00                1.230041e+00
min                    6.035198e-05                6.035198e-05
25%                    3.223266e+00                4.060443e+00
50%                    4.168833e+00                4.974644e+00
75%                    4.722242e+00                5.666427e+00
max                    6.837272e+00                8.173345e+00

       average_Medicare_payment_amt  average_Medicare_standard_amt
count                  9.689357e+06                   9.689357e+06
mean                   3.667014e+00                   3.681859e+00
std                    1.103607e+00                   1.099124e+00
min                    0.000000e+00                   0.000000e+00
25%                    3.000201e+00                   3.039022e+00
50%                    3.857245e+00                   3.875346e+00
75%                    4.432918e+00                   4.434959e+00
max                    6.585347e+00                   6.588716e+00
```

In [12]:
```
fig, axes = plt.subplots(round(len(df_num.columns) / 3), 4, figsize=(12,9))

for i, ax in enumerate(fig.axes):
    if i < len(df_num.columns):
        sns.distplot(logx.iloc[:,i], color='b', ax=ax) #bins=100, hist_kws={'alpha':

fig.tight_layout()
```



In [13]: logx.hist(figsize=(16, 20), bins = 50, xlabelsize=8, ylabelsize=8);

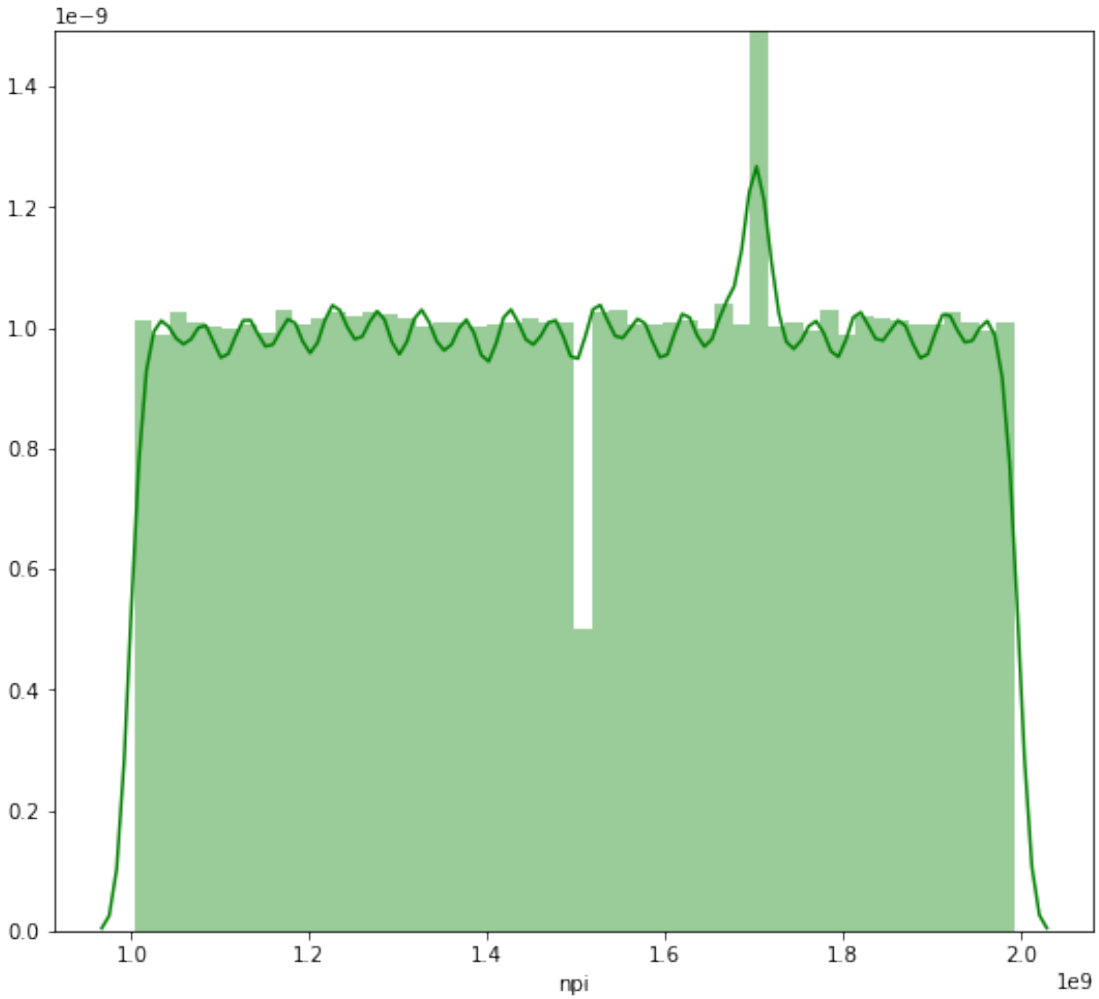


1.4 EDA of Non-Numeric Data

```
In [14]: print(df['npi'].describe())
         plt.figure(figsize=(9, 8))
         sns.distplot(df['npi'], color='g', hist_kws={'alpha': 0.4});
```

```
count    9.689357e+06
mean     1.499871e+09
```

```
std      2.877043e+08
min      1.003000e+09
25%      1.255302e+09
50%      1.497987e+09
75%      1.740680e+09
max      1.993000e+09
Name: npi, dtype: float64
```




```
In [204]: print(df['nppes_credentials'].describe())
          #print(set(df['nppes_credentials']))

          # This output is extremely large, so it is left commented
```

```
count     8997201
unique      15968
```

```
top            MD
freq      3184587
Name: nppes_credentials, dtype: object
```

```
In [205]: print(df['nppes_provider_state'].describe())
          print(set(df['nppes_provider_state']))
```

```
count     9689357
unique         61
top            CA
freq       745862
Name: nppes_provider_state, dtype: object
{'OR', 'AP', 'WA', 'XX', 'HI', 'WV', 'WI', 'OH', 'MN', 'ND', 'IA', 'NE', 'UT', 'CO', 'TX', 'CT
```

```
In [17]: print(df['nppes_provider_country'].describe())
         print(set(df['nppes_provider_country']))
```

```
count     9689357
unique         25
top            US
freq      9688765
Name: nppes_provider_country, dtype: object
{'MX', 'TH', 'TR', 'NO', 'TT', 'CR', 'SA', 'JP', 'US', 'CA', 'LB', 'AG', 'IN', 'CN', 'PK', 'DE
```

```
In [206]: print(df['hcpcs_code'].describe())
          #print(set(df['hcpcs_code']))

          # With 5652 unique values, this output is also very long so it is commented out to s
```

```
count     9689357
unique       5652
top         99213
freq       457817
Name: hcpcs_code, dtype: object
```

```
In [19]: print(df['provider_type'].describe())
         print(set(df['provider_type']))
```

```
count                  9689357
unique                      94
top       Diagnostic Radiology
freq                    1235785
Name: provider_type, dtype: object
{'Vascular Surgery', 'Pharmacy', 'Pathology', 'Neurosurgery', 'Plastic and Reconstructive Surg
```

1.5 EDA of Categorical Data

Selecting which categorical factors are appropriate to use in clustering.

```
In [20]: df_not_num = df.select_dtypes(include = ['O'])
         print('There is {} non numerical features including:\n{}'.format(len(df_not_num.columns
```

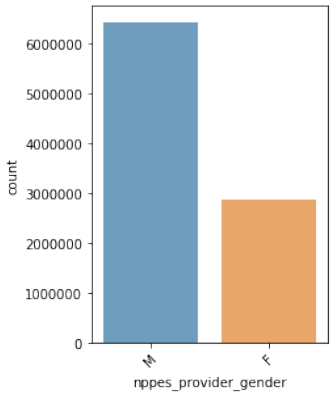
```
There is 18 non numerical features including:
['nppes_provider_last_org_name', 'nppes_provider_first_name', 'nppes_provider_mi', 'nppes_credo
```

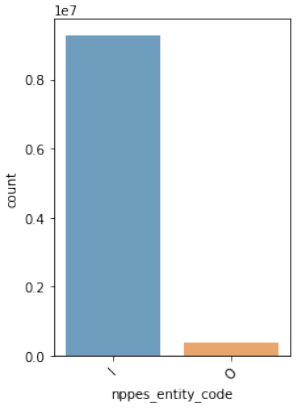
```
In [21]: df_imp_cat = df[['nppes_provider_gender', 'nppes_entity_code', 'nppes_provider_state'
         print('There is {} non numerical features which are important or not too large in size
         df_imp_cat.info()
         df_imp_cat.describe()
```

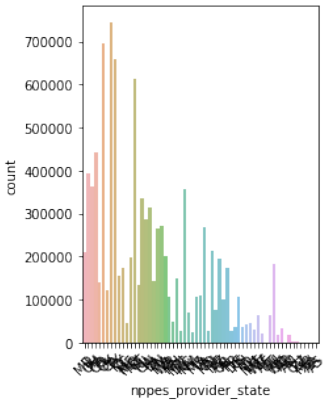
```
There is 18 non numerical features which are important or not too large in size including:
['nppes_provider_last_org_name', 'nppes_provider_first_name', 'nppes_provider_mi', 'nppes_credo
<class 'pandas.core.frame.DataFrame'>
Int64Index: 9689357 entries, 1 to 9847443
Data columns (total 8 columns):
nppes_provider_gender               object
nppes_entity_code                   object
nppes_provider_state                object
nppes_provider_country              object
provider_type                       object
medicare_participation_indicator    object
place_of_service                    object
hcpcs_drug_indicator                object
dtypes: object(8)
memory usage: 665.3+ MB
```

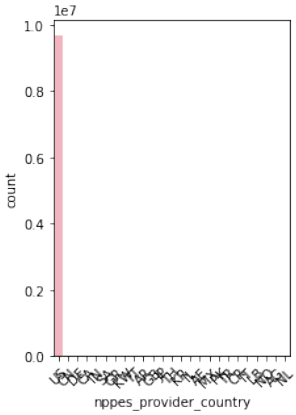
```
Out[21]:        nppes_provider_gender nppes_entity_code nppes_provider_state  \
         count                9295989           9689357              9689357
         unique                     2                 2                   61
         top                        M                 I                   CA
         freq                 6429582           9295989               745862

                nppes_provider_country         provider_type  \
         count                 9689357               9689357
         unique                     25                    94
         top                        US  Diagnostic Radiology
         freq                 9688765               1235785

                medicare_participation_indicator place_of_service hcpcs_drug_indicator
         count                           9689357          9689357              9689357
         unique                                2                2                    2
         top                                   Y                O                    N
         freq                            9686063          6029489              9088521
```

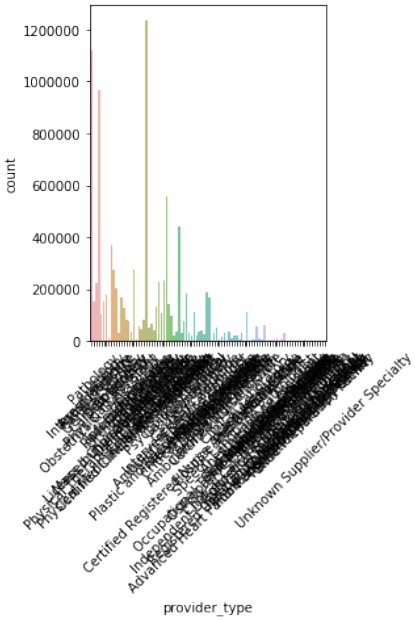
```
In [22]: fig, axes = plt.subplots(round(len(df_imp_cat.columns) / 3), 3, figsize=(12,18))

         for i, ax in enumerate(fig.axes):
             if i < len(df_imp_cat.columns):
                 ax.set_xticklabels(ax.xaxis.get_majorticklabels(), rotation=45)
                 sns.countplot(x=df_imp_cat.columns[i], alpha=0.7, data=df_imp_cat, ax=ax)

         fig.tight_layout()
```

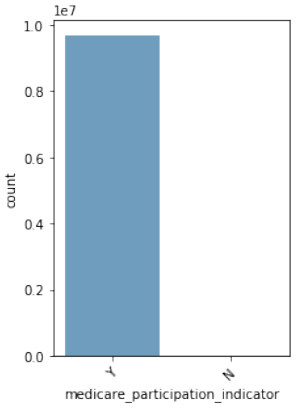

count
nppes_provider_gender
M
F

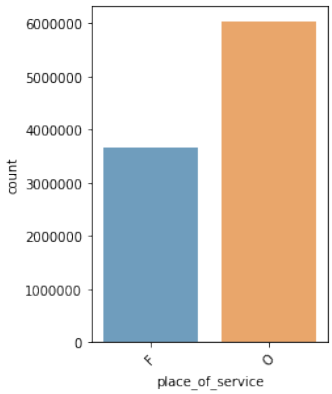

1e7
count
nppes_entity_code
I
O

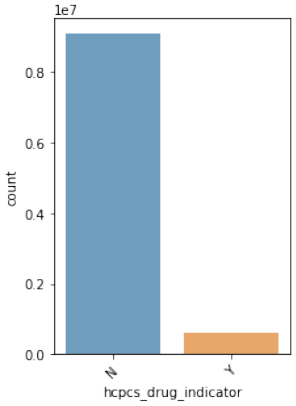

count
nppes_provider_state

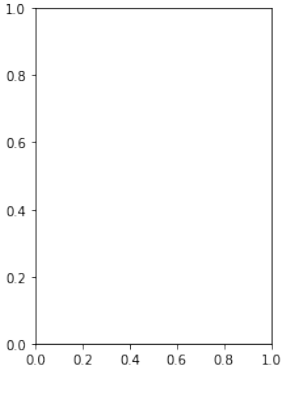

1e7
count
nppes_provider_country


count
provider_type
Unknown Supplier/Provider Specialty

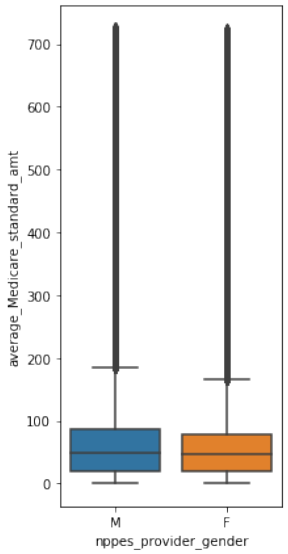

1e7
count
medicare_participation_indicator
Y
N

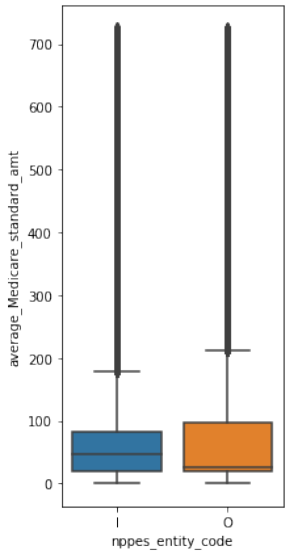

count
place_of_service
F
O

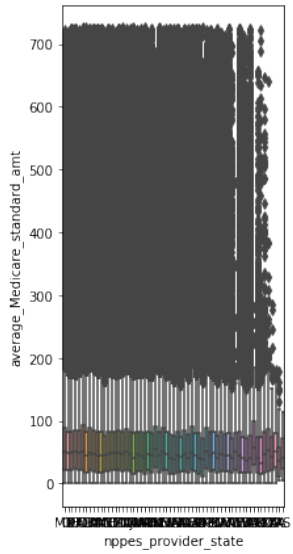

1e7
count
hcpcs_drug_indicator
N
Y

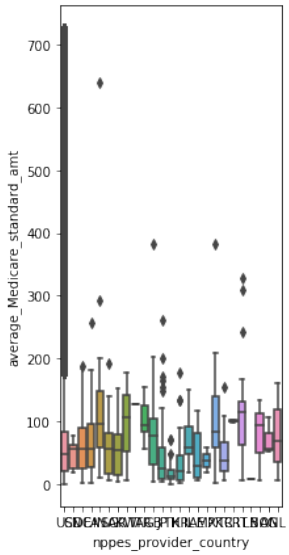


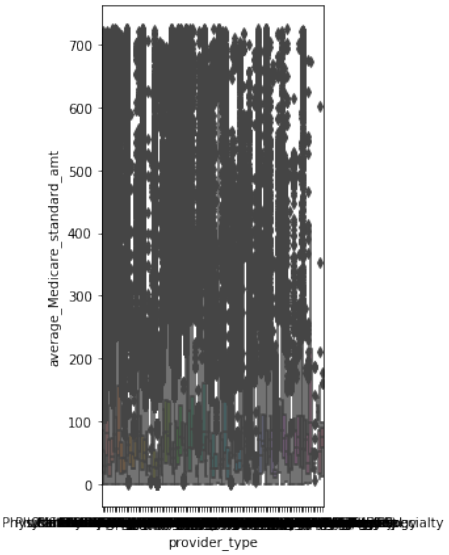
```
In [23]: fig, axes = plt.subplots(round(len(df_imp_cat.columns) / 3), 3, figsize=(12,18))

         for i, ax in enumerate(fig.axes):
             if i < len(df_imp_cat.columns):
                 sns.boxplot(x=df_imp_cat.columns[i], y='average_Medicare_standard_amt', data=
                 #plt.setp(ax.artists, alpha=.5, linewidth=2, edgecolor="k")
                 plt.xticks(rotation=45)

         fig.tight_layout()
```

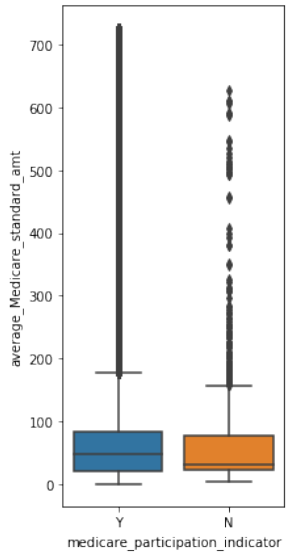

average_Medicare_standard_amt
nppes_provider_gender
M
F

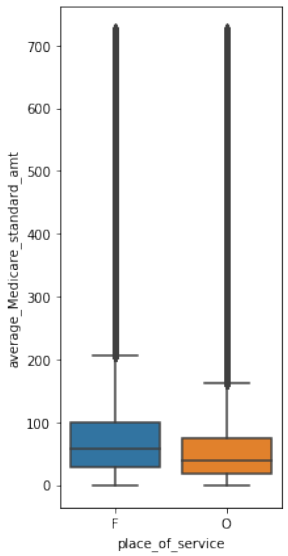

average_Medicare_standard_amt
nppes_entity_code
I
O

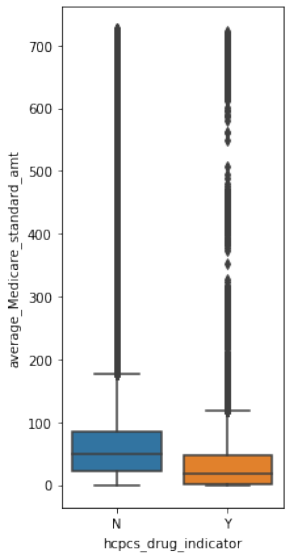

average_Medicare_standard_amt
nppes_provider_state

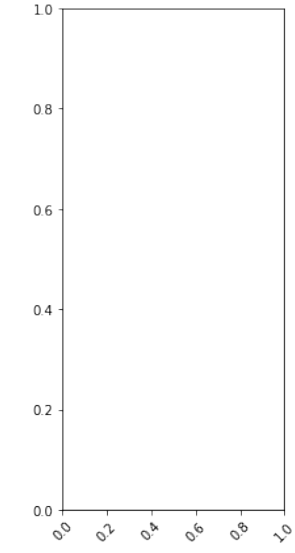

average_Medicare_standard_amt
nppes_provider_country


average_Medicare_standard_amt
provider_type

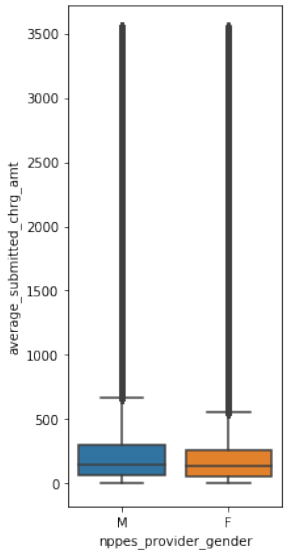

average_Medicare_standard_amt
Y
N
medicare_participation_indicator

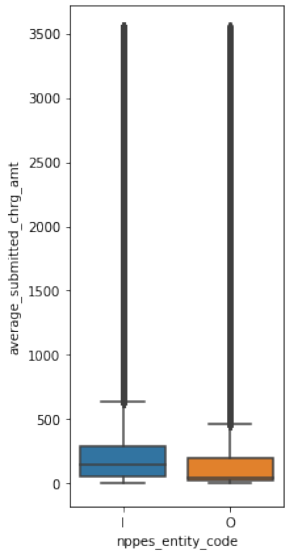

average_Medicare_standard_amt
F
O
place_of_service

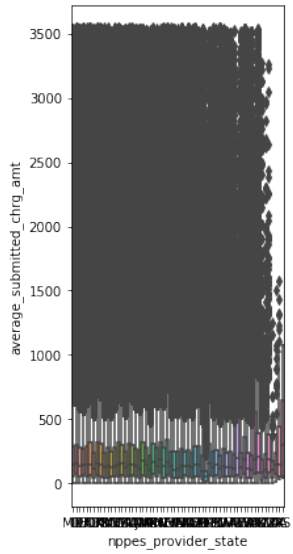

average_Medicare_standard_amt
N
Y
hcpcs_drug_indicator

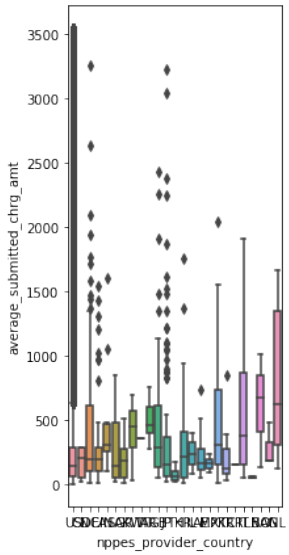


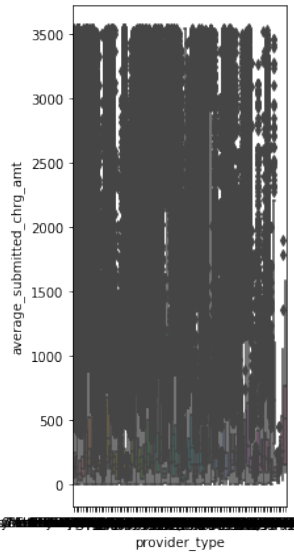
```
In [24]: fig, axes = plt.subplots(round(len(df_imp_cat.columns) / 3), 3, figsize=(12,18))

         for i, ax in enumerate(fig.axes):
             if i < len(df_imp_cat.columns):
                 sns.boxplot(x=df_imp_cat.columns[i], y='average_submitted_chrg_amt', data=df,
                 #plt.setp(ax.artists, alpha=.5, linewidth=2, edgecolor="k")
                 plt.xticks(rotation=45)

         fig.tight_layout()
```

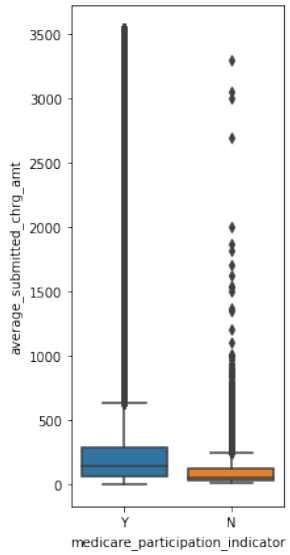

average_submitted_chrg_amt
0
500
1000
1500
2000
2500
3000
3500
M
F
nppes_provider_gender

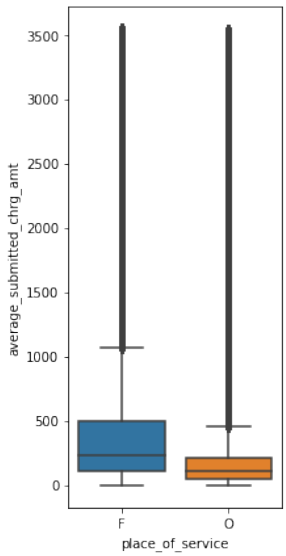

average_submitted_chrg_amt
0
500
1000
1500
2000
2500
3000
3500
I
O
nppes_entity_code

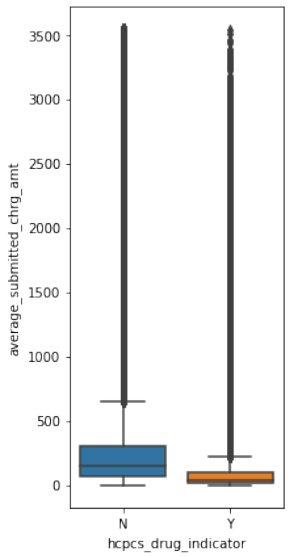

average_submitted_chrg_amt
0
500
1000
1500
2000
2500
3000
3500
nppes_provider_state

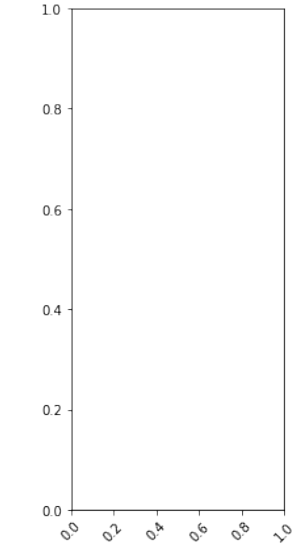

average_submitted_chrg_amt
0
500
1000
1500
2000
2500
3000
3500
nppes_provider_country


average_submitted_chrg_amt
0
500
1000
1500
2000
2500
3000
3500
provider_type


average_submitted_chrg_amt
0
500
1000
1500
2000
2500
3000
3500
Y
N
medicare_participation_indicator


average_submitted_chrg_amt
0
500
1000
1500
2000
2500
3000
3500
F
O
place_of_service


average_submitted_chrg_amt
0
500
1000
1500
2000
2500
3000
3500
N
Y
hcpcs_drug_indicator


0.0
0.2
0.4
0.6
0.8
1.0

```
In [25]: # Creating a dummy variable for gender
         pd.get_dummies(df['nppes_provider_gender'],prefix='gender')
         df = pd.concat([df,pd.get_dummies(df['nppes_provider_gender'],prefix='gender')],axis=

In [26]: # Creating a dummy variable for the entity code
         pd.get_dummies(df['nppes_entity_code'],prefix='entity_code')
         df = pd.concat([df,pd.get_dummies(df['nppes_entity_code'],prefix='entity_code')],axis=

In [27]: # Creating a dummy variable for the entity code
         pd.get_dummies(df['hcpcs_drug_indicator'],prefix='drug_indicator')
         df = pd.concat([df,pd.get_dummies(df['hcpcs_drug_indicator'],prefix='drug_indicator')]

In [28]: # Creating a dummy variable for the participation indicator
         pd.get_dummies(df['medicare_participation_indicator'],prefix='participation_indicator
         df = pd.concat([df,pd.get_dummies(df['medicare_participation_indicator'],prefix='parti

In [29]: # Creating a dummy variable for the participation indicator
         pd.get_dummies(df['place_of_service'],prefix='place_of_service')
         df = pd.concat([df,pd.get_dummies(df['place_of_service'],prefix='place_of_service')],a

In [30]: df.shape

Out[30]: (9689357, 36)

In [31]: df.head(5)

Out[31]:
           npi nppes_provider_last_org_name nppes_provider_first_name  \
1  1003000126                    ENKESHAFI                   ARDALAN
2  1003000126                    ENKESHAFI                   ARDALAN
3  1003000126                    ENKESHAFI                   ARDALAN
4  1003000126                    ENKESHAFI                   ARDALAN
5  1003000126                    ENKESHAFI                   ARDALAN

  nppes_provider_mi nppes_credentials nppes_provider_gender nppes_entity_code  \
1               NaN             M.D.                     M                 I
2               NaN             M.D.                     M                 I
3               NaN             M.D.                     M                 I
4               NaN             M.D.                     M                 I
5               NaN             M.D.                     M                 I

  nppes_provider_street1 nppes_provider_street2 nppes_provider_city  ...  \
1          900 SETON DR                    NaN          CUMBERLAND  ...
2          900 SETON DR                    NaN          CUMBERLAND  ...
3          900 SETON DR                    NaN          CUMBERLAND  ...
4          900 SETON DR                    NaN          CUMBERLAND  ...
5          900 SETON DR                    NaN          CUMBERLAND  ...
```

```
  gender_F gender_M entity_code_I entity_code_O drug_indicator_N  \
1        0        1             1             0                 1
2        0        1             1             0                 1
3        0        1             1             0                 1
4        0        1             1             0                 1
5        0        1             1             0                 1

  drug_indicator_Y participation_indicator_N participation_indicator_Y  \
1                0                         0                         1
2                0                         0                         1
3                0                         0                         1
4                0                         0                         1
5                0                         0                         1

  place_of_service_F  place_of_service_O
1                  1                   0
2                  1                   0
3                  1                   0
4                  1                   0
5                  1                   0

[5 rows x 36 columns]
```

1.6 Start Clustering

Group by hcpcs codes 999201 - 99215, which are associated with new and returning outpatient visits. These codes are significant because they represent the most commonly used hcpcs codes. Then, I will cluster on gender, entity code, participation indicator, and drug indicator.

```
In [111]: df_clust = []
          df_clust = df.loc[df['hcpcs_code'] > '99200']
          df_clust = df_clust.loc[df_clust['hcpcs_code'] < '99215']
          df_clust = df_clust.reset_index(drop=True)
          df_clust.head()
```

```
Out[111]:           npi nppes_provider_last_org_name nppes_provider_first_name  \
          0  1003000142                      KHALIL                    RASHID
          1  1003000142                      KHALIL                    RASHID
          2  1003000142                      KHALIL                    RASHID
          3  1003000142                      KHALIL                    RASHID
          4  1003000142                      KHALIL                    RASHID

            nppes_provider_mi nppes_credentials nppes_provider_gender nppes_entity_code  \
          0               NaN             M.D.                      M                 I
          1               NaN             M.D.                      M                 I
          2               NaN             M.D.                      M                 I
          3               NaN             M.D.                      M                 I
```

```
4               NaN             M.D.                     M                 I

      nppes_provider_street1 nppes_provider_street2 nppes_provider_city  ...  \
0  4126 N HOLLAND SYLVANIA RD             SUITE 220              TOLEDO  ...
1  4126 N HOLLAND SYLVANIA RD             SUITE 220              TOLEDO  ...
2  4126 N HOLLAND SYLVANIA RD             SUITE 220              TOLEDO  ...
3  4126 N HOLLAND SYLVANIA RD             SUITE 220              TOLEDO  ...
4  4126 N HOLLAND SYLVANIA RD             SUITE 220              TOLEDO  ...

  gender_F gender_M entity_code_I entity_code_O drug_indicator_N  \
0        0        1             1             0                 1
1        0        1             1             0                 1
2        0        1             1             0                 1
3        0        1             1             0                 1
4        0        1             1             0                 1

  drug_indicator_Y participation_indicator_N participation_indicator_Y  \
0                0                         0                         1
1                0                         0                         1
2                0                         0                         1
3                0                         0                         1
4                0                         0                         1

  place_of_service_F  place_of_service_O
0                  0                   1
1                  0                   1
2                  0                   1
3                  1                   0
4                  0                   1

[5 rows x 36 columns]
```

In [116]:
```
pay_ratio = logx['average_Medicare_allowed_amt']/logx['average_submitted_chrg_amt']
pay_ratio = pay_ratio.reset_index(drop=True)
pay_ratio.head()
```

Out[116]:
```
0    0.744382
1    0.755562
2    0.766590
3    0.792572
4    0.754399
dtype: float64
```

In [117]:
```
df_clust['pay_ratio'] = pay_ratio
df_clust.head()
```

Out[117]:
```
          npi nppes_provider_last_org_name nppes_provider_first_name  \
0  1003000142                      KHALIL                    RASHID
1  1003000142                      KHALIL                    RASHID
```

```
2  1003000142                      KHALIL                    RASHID
3  1003000142                      KHALIL                    RASHID
4  1003000142                      KHALIL                    RASHID

  nppes_provider_mi nppes_credentials nppes_provider_gender nppes_entity_code  \
0               NaN             M.D.                      M                 I
1               NaN             M.D.                      M                 I
2               NaN             M.D.                      M                 I
3               NaN             M.D.                      M                 I
4               NaN             M.D.                      M                 I

       nppes_provider_street1 nppes_provider_street2 nppes_provider_city  ...  \
0  4126 N HOLLAND SYLVANIA RD              SUITE 220              TOLEDO  ...
1  4126 N HOLLAND SYLVANIA RD              SUITE 220              TOLEDO  ...
2  4126 N HOLLAND SYLVANIA RD              SUITE 220              TOLEDO  ...
3  4126 N HOLLAND SYLVANIA RD              SUITE 220              TOLEDO  ...
4  4126 N HOLLAND SYLVANIA RD              SUITE 220              TOLEDO  ...

  gender_M entity_code_I entity_code_O drug_indicator_N drug_indicator_Y  \
0        1             1             0                1                0
1        1             1             0                1                0
2        1             1             0                1                0
3        1             1             0                1                0
4        1             1             0                1                0

  participation_indicator_N participation_indicator_Y place_of_service_F  \
0                         0                         1                 0
1                         0                         1                 0
2                         0                         1                 0
3                         0                         1                 1
4                         0                         1                 0

  place_of_service_O  pay_ratio
0                  1   0.744382
1                  1   0.755562
2                  1   0.766590
3                  0   0.792572
4                  1   0.754399

[5 rows x 37 columns]
```

In [118]:
```
train_ind = df_clust.sample(frac = 0.9, random_state = 0).index
train = df_clust.loc[train_ind,:]
test = df_clust[~df_clust.index.isin(train_ind)]
```

In [119]:
```
train.describe()
```

Out[119]:
```
                 npi  line_srvc_cnt  bene_unique_cnt  bene_day_srvc_cnt  \
count  1.370557e+06   1.370557e+06     1.370557e+06       1.370557e+06
```

mean	1.499709e+09	1.554753e+02	9.443000e+01	1.554671e+02
std	2.877891e+08	2.629306e+02	1.249527e+02	2.629181e+02
min	1.003000e+09	7.500000e+00	1.100000e+01	1.100000e+01
25%	1.245678e+09	2.500000e+01	2.200000e+01	2.500000e+01
50%	1.497965e+09	6.000000e+01	4.900000e+01	6.000000e+01
75%	1.740721e+09	1.670000e+02	1.160000e+02	1.670000e+02
max	1.993000e+09	6.058000e+03	3.503000e+03	6.057000e+03

	average_Medicare_allowed_amt	average_submitted_chrg_amt	\
count	1.370557e+06	1.370557e+06	
mean	9.284059e+01	1.939008e+02	
std	4.154348e+01	1.192317e+02	
min	1.000000e-02	1.000000e-02	
25%	6.770000e+01	1.153279e+02	
50%	8.425000e+01	1.661438e+02	
75%	1.097500e+02	2.400000e+02	
max	2.726200e+02	3.519767e+03	

	average_Medicare_payment_amt	average_Medicare_standard_amt	\
count	1.370557e+06	1.370557e+06	
mean	6.348889e+01	6.494087e+01	
std	3.064066e+01	3.027190e+01	
min	0.000000e+00	0.000000e+00	
25%	4.327579e+01	4.594652e+01	
50%	5.728633e+01	5.784425e+01	
75%	7.666340e+01	7.816500e+01	
max	2.614739e+02	1.805492e+02	

	gender_F	gender_M	entity_code_I	entity_code_O	\
count	1.370557e+06	1.370557e+06	1.370557e+06	1.370557e+06	
mean	3.608387e-01	6.391460e-01	9.999847e-01	1.532224e-05	
std	4.802440e-01	4.802484e-01	3.914334e-03	3.914334e-03	
min	0.000000e+00	0.000000e+00	0.000000e+00	0.000000e+00	
25%	0.000000e+00	0.000000e+00	1.000000e+00	0.000000e+00	
50%	0.000000e+00	1.000000e+00	1.000000e+00	0.000000e+00	
75%	1.000000e+00	1.000000e+00	1.000000e+00	0.000000e+00	
max	1.000000e+00	1.000000e+00	1.000000e+00	1.000000e+00	

	drug_indicator_N	drug_indicator_Y	participation_indicator_N	\
count	1370557.0	1370557.0	1.370557e+06	
mean	1.0	0.0	4.479930e-04	
std	0.0	0.0	2.116111e-02	
min	1.0	0.0	0.000000e+00	
25%	1.0	0.0	0.000000e+00	
50%	1.0	0.0	0.000000e+00	
75%	1.0	0.0	0.000000e+00	
max	1.0	0.0	1.000000e+00	

```
       participation_indicator_Y  place_of_service_F  place_of_service_O  \
count               1.370557e+06        1.370557e+06        1.370557e+06
mean                9.995520e-01        1.259517e-01        8.740483e-01
std                 2.116111e-02        3.317951e-01        3.317951e-01
min                 0.000000e+00        0.000000e+00        0.000000e+00
25%                 1.000000e+00        0.000000e+00        1.000000e+00
50%                 1.000000e+00        0.000000e+00        1.000000e+00
75%                 1.000000e+00        0.000000e+00        1.000000e+00
max                 1.000000e+00        1.000000e+00        1.000000e+00

          pay_ratio
count  1.370557e+06
mean   7.973866e-01
std    1.360340e-01
min    3.049488e-03
25%    7.288828e-01
50%    8.157591e-01
75%    8.869255e-01
max    1.000000e+00
```

```
In [120]: set(train['hcpcs_code'])
```

```
Out[120]: {'99201',
           '99202',
           '99203',
           '99204',
           '99205',
           '99211',
           '99212',
           '99213',
           '99214'}
```

```
In [121]: train.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 1370557 entries, 1401931 to 1440521
Data columns (total 37 columns):
npi                                1370557 non-null int64
nppes_provider_last_org_name       1370532 non-null object
nppes_provider_first_name          1370516 non-null object
nppes_provider_mi                  1018444 non-null object
nppes_credentials                  1327933 non-null object
nppes_provider_gender              1370536 non-null object
nppes_entity_code                  1370557 non-null object
nppes_provider_street1             1370554 non-null object
nppes_provider_street2             611032 non-null object
nppes_provider_city                1370557 non-null object
nppes_provider_zip                 1370557 non-null object
nppes_provider_state               1370557 non-null object
```

```
nppes_provider_country               1370557 non-null object
provider_type                        1370557 non-null object
medicare_participation_indicator     1370557 non-null object
place_of_service                     1370557 non-null object
hcpcs_code                           1370557 non-null object
hcpcs_description                    1370557 non-null object
hcpcs_drug_indicator                 1370557 non-null object
line_srvc_cnt                        1370557 non-null float64
bene_unique_cnt                      1370557 non-null float64
bene_day_srvc_cnt                    1370557 non-null float64
average_Medicare_allowed_amt         1370557 non-null float64
average_submitted_chrg_amt           1370557 non-null float64
average_Medicare_payment_amt         1370557 non-null float64
average_Medicare_standard_amt        1370557 non-null float64
gender_F                             1370557 non-null uint8
gender_M                             1370557 non-null uint8
entity_code_I                        1370557 non-null uint8
entity_code_O                        1370557 non-null uint8
drug_indicator_N                     1370557 non-null uint8
drug_indicator_Y                     1370557 non-null uint8
participation_indicator_N            1370557 non-null uint8
participation_indicator_Y            1370557 non-null uint8
place_of_service_F                   1370557 non-null uint8
place_of_service_O                   1370557 non-null uint8
pay_ratio                            1370557 non-null float64
dtypes: float64(8), int64(1), object(18), uint8(10)
memory usage: 305.9+ MB
```

1.6.1 Removing all factors except those which will be clustered on

```
In [122]: train = train[['bene_day_srvc_cnt', 'pay_ratio']]
          train.head()
```

Out[122]:

	bene_day_srvc_cnt	pay_ratio
1401931	58.0	0.890901
245413	290.0	0.889787
1226995	474.0	0.828879
126031	144.0	0.768402
312578	212.0	0.909610

```
In [123]: train.describe()
```

Out[123]:

	bene_day_srvc_cnt	pay_ratio
count	1.370557e+06	1.370557e+06
mean	1.554671e+02	7.973866e-01
std	2.629181e+02	1.360340e-01
min	1.100000e+01	3.049488e-03
25%	2.500000e+01	7.288828e-01

```
50%          6.000000e+01   8.157591e-01
75%          1.670000e+02   8.869255e-01
max          6.057000e+03   1.000000e+00
```

```
In [124]: scaler = preprocessing.StandardScaler().fit(train)
          dfNorm = scaler.transform(train)
```

```
In [125]: train.head()
```

Out[125]:

	bene_day_srvc_cnt	pay_ratio
1401931	58.0	0.890901
245413	290.0	0.889787
1226995	474.0	0.828879
126031	144.0	0.768402
312578	212.0	0.909610

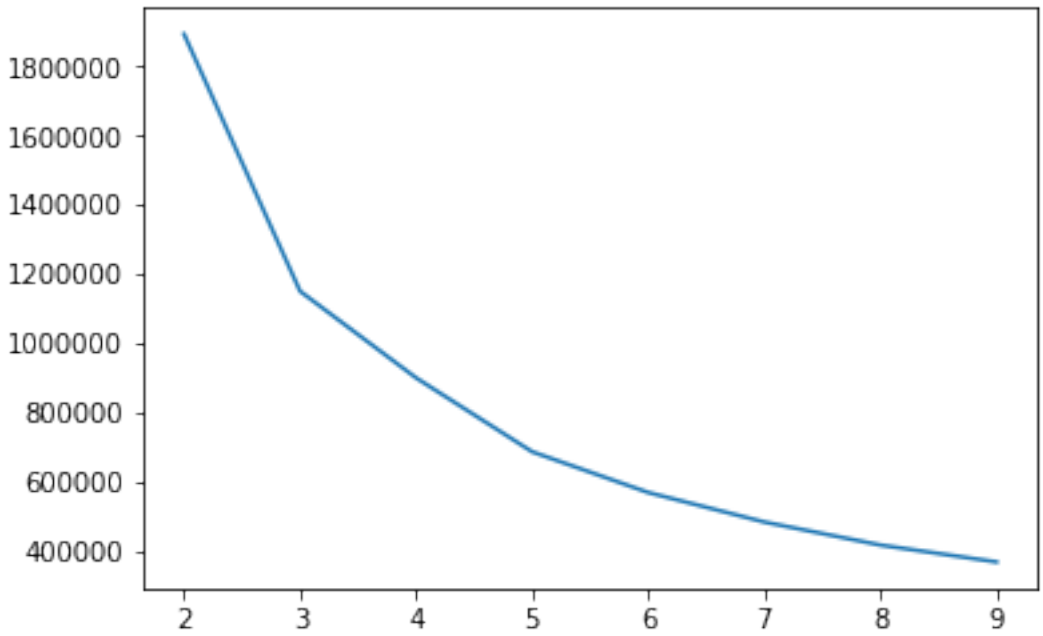
```
In [126]: maxClusters = 10
          sse = []
          for nClusters in range(2,maxClusters):
              kmeans = KMeans(n_clusters=nClusters, random_state=0).fit(dfNorm)
              sse.append(kmeans.inertia_)
```

```
In [127]: print(sse)
```

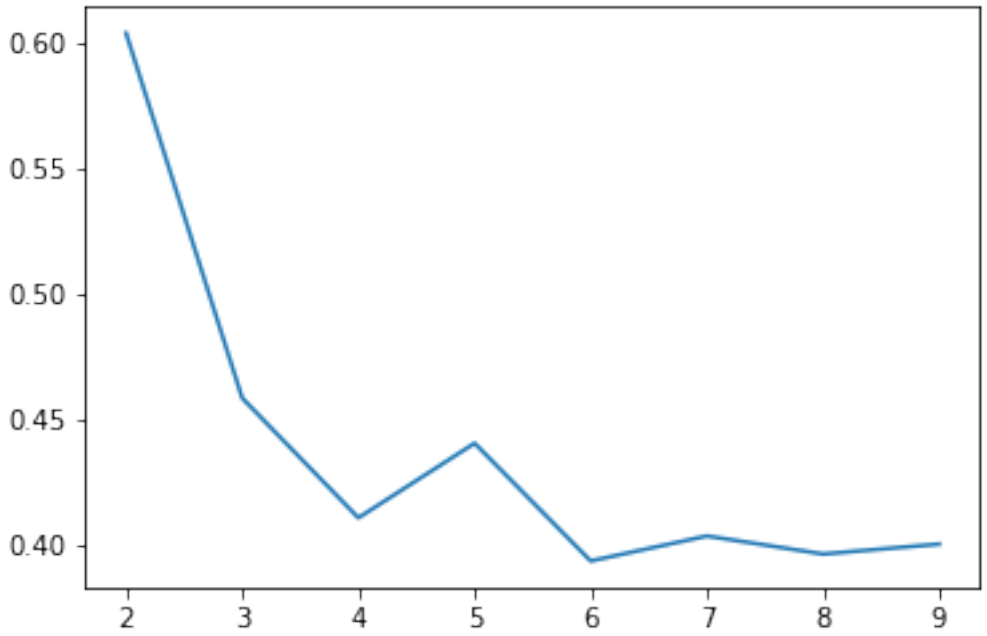
```
[1893657.8781051266, 1149673.0292939371, 898902.3803362981, 685103.9830502096, 567278.25903933
```

```
In [128]: plt.plot(range(2,maxClusters),sse)
```

```
Out[128]: [<matplotlib.lines.Line2D at 0x1a4ea3fcf8>]
```



```
In [129]: silh = []
          for nClusters in range(2,maxClusters):
              kmeans = KMeans(n_clusters=nClusters, random_state=0).fit(dfNorm)
              silhouette_avg = silhouette_score(dfNorm, kmeans.labels_, sample_size = 10000)
              silh.append(silhouette_avg)

In [130]: print(silh)

[0.603865802545504, 0.4585196885202319, 0.41084431257905807, 0.440537862972748, 0.3936657277865

In [131]: plt.plot(range(2,maxClusters),silh)

Out[131]: [<matplotlib.lines.Line2D at 0x1a4e90c5c0>]
```

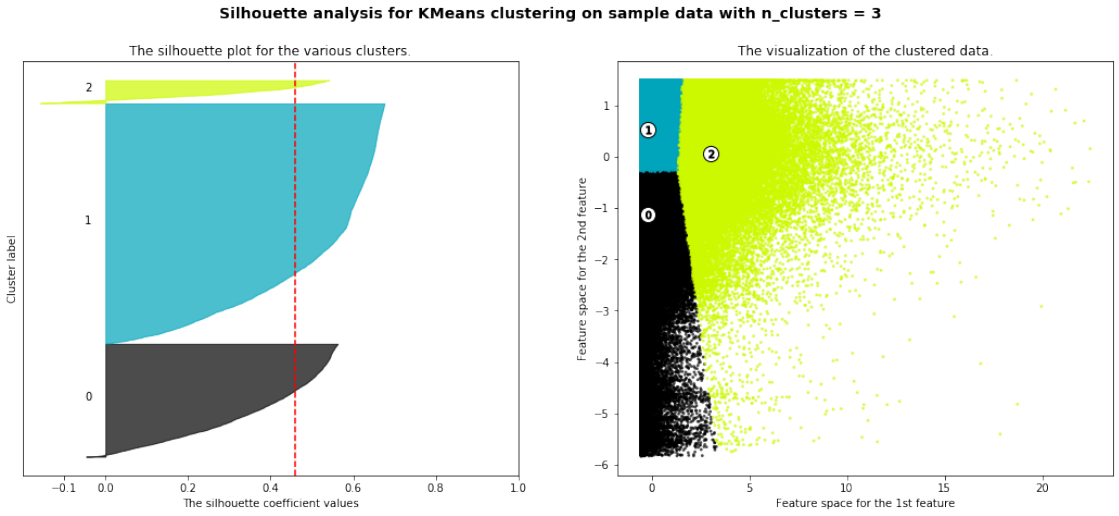


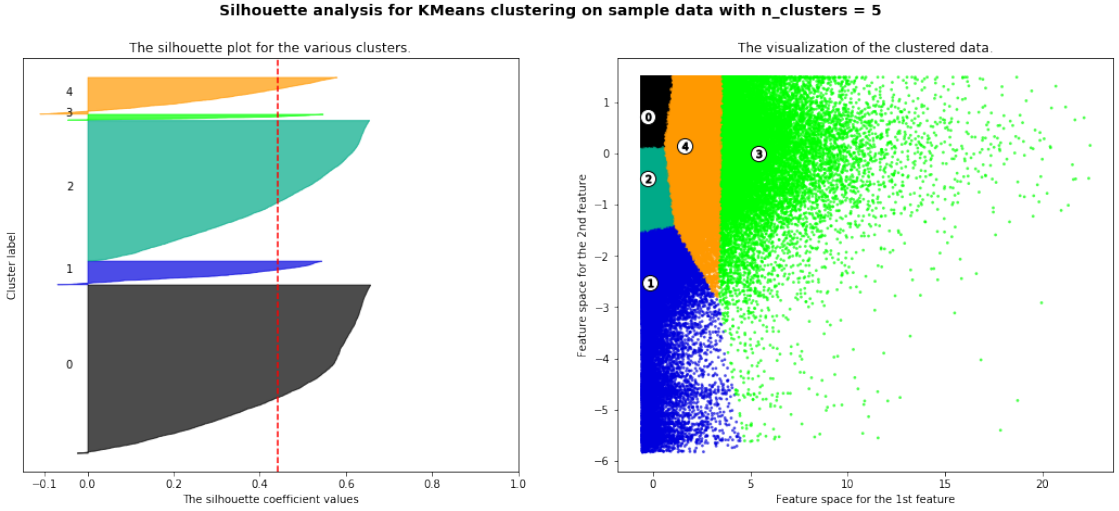

```
In [132]: range_n_clusters = [3, 5]

          for n_clusters in range_n_clusters:
              # Create a subplot with 1 row and 2 columns
              fig, (ax1, ax2) = plt.subplots(1, 2)
              fig.set_size_inches(18, 7)

              # The 1st subplot is the silhouette plot
```

```
# The silhouette coefficient can range from -1, 1 but in this example all
# lie within [-0.1, 1]
#ax1.set_xlim([-0.1, 1])
# The (n_clusters+1)*10 is for inserting blank space between silhouette
# plots of individual clusters, to demarcate them clearly.
#ax1.set_ylim([0, len(dfNorm) + (n_clusters + 1) * 10])

# Initialize the clusterer with n_clusters value and a random generator
# seed of 10 for reproducibility.
kmeans = KMeans(n_clusters=n_clusters, random_state=0)
cluster_labels = kmeans.fit_predict(dfNorm)

# The silhouette_score gives the average value for all the samples.
# This gives a perspective into the density and separation of the formed
# clusters
silhouette_avg = silhouette_score(dfNorm, kmeans.labels_, sample_size = 10000)
print("For n_clusters =", n_clusters,
      "The average silhouette_score is :", silhouette_avg)

indices = np.random.choice(dfNorm.shape[0], 10000, replace = False)

# Compute the silhouette scores for each sample
sample_silhouette_values = silhouette_samples(dfNorm[indices], kmeans.labels_[ind

y_lower = 10
for i in range(n_clusters):
    # Aggregate the silhouette scores for samples belonging to
    # cluster i, and sort them
    ith_cluster_silhouette_values = sample_silhouette_values[kmeans.labels_[indi
    ith_cluster_silhouette_values.sort()

    size_cluster_i = ith_cluster_silhouette_values.shape[0]
    y_upper = y_lower + size_cluster_i

    color = cm.nipy_spectral(float(i) / n_clusters)

    ax1.fill_betweenx(np.arange(y_lower, y_upper), 0, ith_cluster_silhouette_valu

    # Label the silhouette plots with their cluster numbers at the middle
    ax1.text(-0.05, y_lower + 0.5 * size_cluster_i, str(i))

    # Compute the new y_lower for next plot
    y_lower = y_upper + 10  # 10 for the 0 samples

ax1.set_title("The silhouette plot for the various clusters.")
ax1.set_xlabel("The silhouette coefficient values")
ax1.set_ylabel("Cluster label")
```

```
            # The vertical line for average silhouette score of all the values
            ax1.axvline(x=silhouette_avg, color="red", linestyle="--")

            ax1.set_yticks([])  # Clear the yaxis labels / ticks
            ax1.set_xticks([-0.1, 0, 0.2, 0.4, 0.6, 0.8, 1])

            # 2nd Plot showing the actual clusters formed
            colors = cm.nipy_spectral(cluster_labels.astype(float) / n_clusters)
            ax2.scatter(dfNorm[:, 0], dfNorm[:, 1], marker='.', s=30, lw=0, alpha=0.7, c=colo

            # Labeling the clusters
            centers = kmeans.cluster_centers_
            # Draw white circles at cluster centers
            ax2.scatter(centers[:, 0], centers[:, 1], marker='o',
                        c="white", alpha=1, s=200, edgecolor='k')

            for i, c in enumerate(centers):
                ax2.scatter(c[0], c[1], marker='$%d$' % i, alpha=1,
                            s=50, edgecolor='k')

            ax2.set_title("The visualization of the clustered data.")
            ax2.set_xlabel("Feature space for the 1st feature")
            ax2.set_ylabel("Feature space for the 2nd feature")

            plt.suptitle(("Silhouette analysis for KMeans clustering on sample data "
                          "with n_clusters = %d" % n_clusters),
                         fontsize=14, fontweight='bold')

        plt.show()
```

```
For n_clusters = 3 The average silhouette_score is : 0.46045892385587306
For n_clusters = 5 The average silhouette_score is : 0.44074056522550153
```





1.7 K-Means Clustering

```
In [133]: labels = KMeans(n_clusters=3, random_state=0).fit_predict(dfNorm)

In [134]: train['Clusters'] = labels

In [135]: train['Clusters'].value_counts()

Out[135]: 1    873195
          0    410814
          2     86548
          Name: Clusters, dtype: int64

In [136]: train.groupby('Clusters').mean()

Out[136]:           bene_day_srvc_cnt  pay_ratio
          Clusters
          0                105.597080   0.644874
          1                100.448195   0.868207
          2                947.276806   0.806798
```

Analyzing the clusters based on zip codes. The zip codes are broken down to their first digit to represent a specific region of the U.S.

```
In [187]: #df_a = []
          #df_a = df.loc[df['hcpcs_code'] > '99200']
          #df_a = df_a.loc[df_a['hcpcs_code'] < '99215']
          #print(df_a.iloc[:,10])
          #df_a.loc[0, 'nppes_provider_zip']
          df_a = df_clust.loc[train_ind,:]
          df_a.head()
```

Out[187]:

	npi	nppes_provider_last_org_name	nppes_provider_first_name
1401931	1922011782	NASUR	ALI
245413	1164428801	CARTER	WILLIAM
1226995	1801854757	WILSON	JOHN
126031	1083648703	MALL	RONALD
312578	1205836533	KALLET	CYNTHIA

	nppes_provider_mi	nppes_credentials	nppes_provider_gender
1401931	M	M.D.	M
245413	H	MD	M
1226995	W	DO	M
126031	M	DO	M
312578	E	DO	F

	nppes_entity_code	nppes_provider_street1
1401931	I	3270 JOE BATTLE BLVD STE 380
245413	I	6201 CENTREVILLE RD
1226995	I	2011 N COLLINS BLVD
126031	I	3800 EAST BAY DRIVE
312578	I	3328 S SMITHVILLE RD

	nppes_provider_street2	nppes_provider_city	...	gender_M
1401931	NaN	EL PASO	...	1
245413	STE 100	CENTREVILLE	...	1
1226995	SUITE 609	RICHARDSON	...	1
126031	EAST BAY MEDICAL CENTER	LARGO	...	1
312578	NaN	DAYTON	...	0

	entity_code_I	entity_code_O	drug_indicator_N	drug_indicator_Y
1401931	1	0	1	0
245413	1	0	1	0
1226995	1	0	1	0
126031	1	0	1	0
312578	1	0	1	0

	participation_indicator_N	participation_indicator_Y
1401931	0	1
245413	0	1
1226995	0	1
126031	0	1
312578	0	1

	place_of_service_F	place_of_service_O	pay_ratio
1401931	0	1	0.890901
245413	0	1	0.889787
1226995	0	1	0.828879
126031	0	1	0.768402
312578	0	1	0.909610

```
[5 rows x 37 columns]
```

```
In [188]: def region(str):
              str = str[0]
              return(str)
```

```
In [189]: #train = train.reset_index(drop=True)
          df_a['nppes_provider_zip'] = df_a['nppes_provider_zip'].astype(str)
```

```
In [190]: zip = []
          for i in range(len(df_a)):
              i = df_a.iloc[i,10]
              zip.append(region(i))
```

```
In [191]: zip_array = pd.DataFrame(np.array([zip]).T)
          zip_array.head()
```

```
Out[191]:    0
          0  7
          1  2
          2  7
          3  3
          4  4
```

```
In [192]: #zip_array = pd.DataFrame(np.array([zip]).T)
          #zip_array = zip_array.reset_index(drop = True)
          df_a = df_a.reset_index(drop = True)
          df_a['zip'] = zip_array
          #df = pd.concat([df,pd.get_dummies(df['place_of_service'],prefix='place_of_service')
          #set(df_a['zip'])
          df_a.head()
```

```
Out[192]:          npi nppes_provider_last_org_name nppes_provider_first_name  \
          0  1922011782                      NASUR                       ALI
          1  1164428801                     CARTER                   WILLIAM
          2  1801854757                     WILSON                      JOHN
          3  1083648703                       MALL                    RONALD
          4  1205836533                     KALLET                   CYNTHIA

            nppes_provider_mi nppes_credentials nppes_provider_gender nppes_entity_code  \
          0                 M             M.D.                       M                 I
          1                 H               MD                       M                 I
          2                 W               DO                       M                 I
          3                 M               DO                       M                 I
          4                 E               DO                       F                 I

                  nppes_provider_street1   nppes_provider_street2 nppes_provider_city  \
          0  3270 JOE BATTLE BLVD STE 380                      NaN             EL PASO
```

```
1           6201 CENTREVILLE RD                  STE 100         CENTREVILLE
2           2011 N COLLINS BLVD                SUITE 609          RICHARDSON
3           3800 EAST BAY DRIVE  EAST BAY MEDICAL CENTER               LARGO
4          3328 S SMITHVILLE RD                      NaN              DAYTON

   ... entity_code_I entity_code_O drug_indicator_N drug_indicator_Y  \
0  ...             1             0                1                 0
1  ...             1             0                1                 0
2  ...             1             0                1                 0
3  ...             1             0                1                 0
4  ...             1             0                1                 0

  participation_indicator_N participation_indicator_Y place_of_service_F  \
0                         0                         1                  0
1                         0                         1                  0
2                         0                         1                  0
3                         0                         1                  0
4                         0                         1                  0

  place_of_service_O pay_ratio  zip
0                  1  0.890901    7
1                  1  0.889787    2
2                  1  0.828879    7
3                  1  0.768402    3
4                  1  0.909610    4

[5 rows x 38 columns]
```

```
In [193]: train.head()
```

```
Out[193]:    bene_day_srvc_cnt  pay_ratio  Clusters
0               58.0   0.890901         1
1              290.0   0.889787         1
2              474.0   0.828879         1
3              144.0   0.768402         1
4              212.0   0.909610         1
```

```
In [194]: finalDF = pd.concat([train,df_a['zip']],axis=1)
          finalDF.head()
```

```
Out[194]:    bene_day_srvc_cnt  pay_ratio  Clusters zip
0               58.0   0.890901         1   7
1              290.0   0.889787         1   2
2              474.0   0.828879         1   7
3              144.0   0.768402         1   3
4              212.0   0.909610         1   4
```

```
In [195]: for i in range(3):
              print("Cluster:", i)
              print(finalDF.loc[finalDF.Clusters == i]['zip'].value_counts())
```

```
Cluster: 0
3    60383
1    53396
2    53051
4    49759
9    48902
7    46641
6    38003
8    31419
5    26298
0     2959
M        1
P        1
N        1
Name: zip, dtype: int64
Cluster: 1
3    128321
2    113310
1    113074
4    105110
9    104643
7     98528
6     81115
8     67047
5     55754
0      6280
M         4
N         4
L         2
A         2
B         1
Name: zip, dtype: int64
Cluster: 2
3    17137
2    12914
7    11853
9    10200
1     9961
4     8684
6     6990
8     6153
5     2148
0      508
Name: zip, dtype: int64
```

```
In [196]: finalDF = pd.concat([finalDF,pd.get_dummies(finalDF['zip'],prefix='zip')],axis=1)
          finalDF.head()
```

Out[196]:

	bene_day_srvc_cnt	pay_ratio	Clusters	zip	zip_0	zip_1	zip_2	zip_3	\
0	58.0	0.890901	1	7	0	0	0	0	
1	290.0	0.889787	1	2	0	0	1	0	
2	474.0	0.828879	1	7	0	0	0	0	
3	144.0	0.768402	1	3	0	0	0	1	
4	212.0	0.909610	1	4	0	0	0	0	

	zip_4	zip_5	zip_6	zip_7	zip_8	zip_9	zip_A	zip_B	zip_L	zip_M	\
0	0	0	0	1	0	0	0	0	0	0	
1	0	0	0	0	0	0	0	0	0	0	
2	0	0	0	1	0	0	0	0	0	0	
3	0	0	0	0	0	0	0	0	0	0	
4	1	0	0	0	0	0	0	0	0	0	

	zip_N	zip_P
0	0	0
1	0	0
2	0	0
3	0	0
4	0	0

In [197]:
```
finalDF.drop(['zip','zip_A','zip_B','zip_L','zip_M','zip_P','zip_N'],axis=1, inplace=
finalDF.head()
```

Out[197]:

	bene_day_srvc_cnt	pay_ratio	Clusters	zip_0	zip_1	zip_2	zip_3	zip_4	\
0	58.0	0.890901	1	0	0	0	0	0	
1	290.0	0.889787	1	0	0	1	0	0	
2	474.0	0.828879	1	0	0	0	0	0	
3	144.0	0.768402	1	0	0	0	1	0	
4	212.0	0.909610	1	0	0	0	0	1	

	zip_5	zip_6	zip_7	zip_8	zip_9
0	0	0	1	0	0
1	0	0	0	0	0
2	0	0	1	0	0
3	0	0	0	0	0
4	0	0	0	0	0

In [198]:
```
finalDF.groupby('Clusters').mean()
```

Out[198]:

Clusters	bene_day_srvc_cnt	pay_ratio	zip_0	zip_1	zip_2	\
0	105.597080	0.644874	0.007203	0.129976	0.129136	
1	100.448195	0.868207	0.007192	0.129495	0.129765	
2	947.276806	0.806798	0.005870	0.115092	0.149212	

Clusters	zip_3	zip_4	zip_5	zip_6	zip_7	zip_8	zip_9
0	0.146984	0.121123	0.064014	0.092507	0.113533	0.076480	0.119037

```
1          0.146956  0.120374  0.063851  0.092894  0.112836  0.076784  0.119839
2          0.198006  0.100337  0.024819  0.080764  0.136953  0.071093  0.117854
```

```
In [209]: df_b = df_clust.loc[train_ind,:]
          data = pd.concat([train,df_b['hcpcs_code']],axis=1)
          data = pd.concat([data,pd.get_dummies(data['hcpcs_code'],prefix='hcpcs')],axis=1)
          data.groupby('Clusters').mean()
```

```
Out[209]:           bene_day_srvc_cnt  pay_ratio  hcpcs_99201  hcpcs_99202  hcpcs_99203  \
          Clusters
          0.0              105.597080   0.644874     0.002707     0.028276     0.105198
          1.0              100.448195   0.868207     0.002751     0.028492     0.105417
          2.0              947.276806   0.806798     0.002242     0.028793     0.105791

                    hcpcs_99204  hcpcs_99205  hcpcs_99211  hcpcs_99212  hcpcs_99213  \
          Clusters
          0.0          0.106148     0.036627     0.018230     0.078649     0.271174
          1.0          0.105928     0.037138     0.018009     0.078888     0.270620
          2.0          0.105745     0.036743     0.018914     0.078015     0.270509

                    hcpcs_99214
          Clusters
          0.0          0.252494
          1.0          0.253026
          2.0          0.253640
```

1.8 Testing

```
In [199]: test = test[['bene_day_srvc_cnt', 'pay_ratio']]
          test.head()
```

```
Out[199]:     bene_day_srvc_cnt  pay_ratio
          4               330.0   0.754399
          26               29.0   0.807190
          38              214.0   0.928515
          54               21.0   0.978910
          75               45.0   0.798416
```

```
In [200]: scaler2 = preprocessing.StandardScaler().fit(test)
          dfNorm2 = scaler.transform(test)
```

```
In [201]: labels2 = KMeans(n_clusters=3, random_state=0).fit_predict(dfNorm2)
          test['Clusters'] = labels2
          test['Clusters'].value_counts()
```

```
Out[201]: 2    97165
          1    45202
          0     9917
          Name: Clusters, dtype: int64
```

```
In [202]: test.groupby('Clusters').mean()
```

Out[202]:

Clusters	bene_day_srvc_cnt	pay_ratio
0	937.753151	0.807853
1	106.421486	0.643872
2	99.052457	0.867735

```
In [ ]:
```