Bronx Buildings Dataset Analysis

August 17, 2020

0.0.1 Main objective of the analysis that also specifies whether your model will be focused on clustering or dimensionality reduction and the benefits that your analysis brings to the business or stakeholders of this data.

The models created are focused in clustering buildings in Bronx borough, New York City. The idea is to find out different sizes of buildings within this area in order for NYC City Planning purposes and maintainence.

0.0.2 Brief description of the data set you chose, a summary of its attributes, and an outline of what you are trying to accomplish with this analysis.

We will use PLUTO dataset for this project.

The Primary Land Use Tax Lot Output (PLUTO™) data file was developed by the New York City Department of City Planning's Information Technology Division (ITD)/Database and Application Development Section.

It has 20 known features and the description as below:

Field	Description
Lot	The number of the tax lot
ZipCode	The zip code that the tax lot is located in
Address	An address for the tax lot
LotArea	Total area of the tax lot, expressed in square feet rounded to the nearest integer
BldgArea	The total gross area in square feet
ResArea	An estimate of the exterior dimensions of the portion of the structure(s) allocated for residential use
OfficeArea	An estimate of the exterior dimensions of the portion of the structure(s) for office use
RetailArea	An estimate of the exterior dimensions of the portion of the structure(s) allocated for retail use
NumBldgs	The number of buildings on the tax lot.
NumFloors	The number of full and partial stories starting from the ground floor.
LotDepth	The tax lot's depth measured in feet
BldgDepth	The building's depth, which is the effective perpendicular distance, measured in feet.
YearBuilt	The year construction of the building was completed
YearAlter1	The year of the second most recent alteration

Field	Description
BuiltFAR	The Built Floor Area Ratio (FAR) is the total building floor area divided by the area of the tax lot
ResidFAR	The Maximum Allowable Residential Floor Area Ratio
CommFAR	The Maximum Allowable Commercial Floor Area Ratio
FacilFAR	The Maximum Allowable Community Facility Floor Area Ratio
XCoord	The X coordinate of the XY coordinate pair which depicts the approximate location of the lot
YCoord	The Y coordinate of the XY coordinate pair which depicts the approximate location of the lot

0.0.3 Brief summary of data exploration and actions taken for data cleaning or feature engineering.

The data will be loaded and explored. There will be missing data treatment and removing unwanted categorical features since this is clustering.

There will be some visualizations done to see each features and correlation.

0.0.4 Import Libraries

[1]:
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns

%matplotlib inline
sns.set(style='darkgrid',font_scale=1.2)

from sklearn.preprocessing import StandardScaler
from sklearn.cluster import AgglomerativeClustering
from sklearn.cluster import KMeans, DBSCAN
from sklearn.metrics import silhouette_score, adjusted_rand_score

from sklearn.decomposition import PCA, KernelPCA

import scipy.cluster.hierarchy as sch

from mpl_toolkits.mplot3d import Axes3D

pd.set_option('display.max_columns', None)
pd.set_option('display.max_rows', 10 )


np.random.seed(0)
```

[2]:
```
df = pd.read_csv("BXMod.csv", low_memory=False)
```

[3]:
```
df
```

[3]:
```
         Lot  ZipCode                   Address  LotArea  BldgArea  ResArea  \
0          1  10454.0  122 BRUCKNER BOULEVARD     15000         0        0
1          4  10454.0  126 BRUCKNER BOULEVARD     13770       752        0
2         10  10454.0  138 BRUCKNER BOULEVARD     35000     39375        0
3         17  10454.0  144 BRUCKNER BOULEVARD      2500     12500    12500
4         18  10454.0  148 BRUCKNER BOULEVARD      1875      8595     6876
…      …      …                         …       …        …       …
89849   100      NaN                      NaN        0         0        0
89850   150      NaN                      NaN        0         0        0
89851   200      NaN                      NaN        0         0        0
89852  8900      NaN                      NaN        0         0        0
89853  8900      NaN                      NaN        0         0        0

       OfficeArea  RetailArea  NumBldgs  NumFloors  LotDepth  BldgDepth  \
0               0           0         1        0.0     200.0        0.0
1             272           0         2        1.0     100.0       16.0
2               0           0         1        2.0     200.0      200.0
3               0           0         1        5.0     100.0       85.0
4               0        1719         1        5.0      75.0       70.0
…             …           …         …          …         …
89849           0           0         0        0.0       0.0        0.0
89850           0           0         0        0.0       0.0        0.0
89851           0           0         0        0.0       0.0        0.0
89852           0           0         0        0.0       0.0        0.0
89853           0           0         0        0.0       0.0        0.0

       YearBuilt  YearAlter1  BuiltFAR  ResidFAR  CommFAR  FacilFAR  \
0              0           0      0.00      6.02      5.0       6.5
1           1931        1994      0.05      6.02      5.0       6.5
2           1931           0      1.13      6.02      5.0       6.5
3           1931        2001      5.00      6.02      5.0       6.5
4           1920        2009      4.58      6.02      5.0       6.5
…            …           …         …         …        …
89849          0           0      0.00      0.00      0.0       0.0
89850          0           0      0.00      6.02      3.4       6.5
89851          0           0      0.00      0.00      0.0       0.0
89852          0           0      0.00      0.00      0.0       0.0
89853          0           0      0.00      0.00      0.0       0.0

          XCoord    YCoord
0      1005957.0  232162.0
1      1006076.0  232156.0
2      1006187.0  232036.0
3      1006299.0  232033.0
4      1006363.0  232040.0
```

```
…          …        …
89849        NaN       NaN
89850        NaN       NaN
89851        NaN       NaN
89852        NaN       NaN
89853        NaN       NaN

[89854 rows x 20 columns]
```

[4]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 89854 entries, 0 to 89853
Data columns (total 20 columns):
 #   Column      Non-Null Count  Dtype
---  ------      --------------  -----
 0   Lot         89854 non-null  int64
 1   ZipCode     89525 non-null  float64
 2   Address     89785 non-null  object
 3   LotArea     89854 non-null  int64
 4   BldgArea    89854 non-null  int64
 5   ResArea     89854 non-null  int64
 6   OfficeArea  89854 non-null  int64
 7   RetailArea  89854 non-null  int64
 8   NumBldgs    89854 non-null  int64
 9   NumFloors   89854 non-null  float64
 10  LotDepth    89854 non-null  float64
 11  BldgDepth   89854 non-null  float64
 12  YearBuilt   89854 non-null  int64
 13  YearAlter1  89854 non-null  int64
 14  BuiltFAR    89854 non-null  float64
 15  ResidFAR    89854 non-null  float64
 16  CommFAR     89854 non-null  float64
 17  FacilFAR    89854 non-null  float64
 18  XCoord      86595 non-null  float64
 19  YCoord      86595 non-null  float64
dtypes: float64(10), int64(9), object(1)
memory usage: 13.7+ MB
```

[5]:
```
df.shape
```

[5]: (89854, 20)

0.0.5 Data Preprocessing

Remove all categorical and string features from dataset before clustering

[6]:
```python
df.describe(include='all')
```

[6]:
```
                Lot       ZipCode       Address       LotArea      BldgArea  \
count  89854.000000  89525.000000         89785  8.985400e+04  8.985400e+04
unique          NaN           NaN         87017           NaN           NaN
top             NaN           NaN  SHORE DRIVE            NaN           NaN
freq            NaN           NaN            42           NaN           NaN
mean     111.493601  10464.280726           NaN  1.023904e+04  8.113609e+03
…               …             …             …             …             …
min        1.000000  10451.000000           NaN  0.000000e+00  0.000000e+00
25%       20.000000  10460.000000           NaN  2.188000e+03  1.598000e+03
50%       41.000000  10465.000000           NaN  2.508000e+03  2.226000e+03
75%       73.000000  10469.000000           NaN  4.250000e+03  3.288000e+03
max     9978.000000  11370.000000           NaN  7.425000e+07  1.354011e+07

            ResArea    OfficeArea    RetailArea      NumBldgs     NumFloors  \
count  8.985400e+04  8.985400e+04   89854.00000  89854.000000  89854.000000
unique          NaN           NaN           NaN           NaN           NaN
top             NaN           NaN           NaN           NaN           NaN
freq            NaN           NaN           NaN           NaN           NaN
mean   5.720876e+03  5.057144e+02     349.91691      1.184778      2.273265
…               …             …             …             …             …
min    0.000000e+00  0.000000e+00       0.00000      0.000000      0.000000
25%    1.152000e+03  0.000000e+00       0.00000      1.000000      2.000000
50%    1.760000e+03  0.000000e+00       0.00000      1.000000      2.000000
75%    2.616000e+03  0.000000e+00       0.00000      1.000000      3.000000
max    1.321140e+07  1.311800e+06  598908.00000    251.000000     44.000000

           LotDepth     BldgDepth    YearBuilt    YearAlter1      BuiltFAR  \
count  89854.000000  89854.000000  89854.00000  89854.000000  89854.000000
unique          NaN           NaN          NaN           NaN           NaN
top             NaN           NaN          NaN           NaN           NaN
freq            NaN           NaN          NaN           NaN           NaN
mean     105.978085     48.229342   1805.69515    176.591782      1.107134
…               …             …            …             …             …
min        0.000000      0.000000      0.00000      0.000000      0.000000
25%       95.000000     35.000000   1920.00000      0.000000      0.550000
50%      100.000000     44.670000   1931.00000      0.000000      0.860000
75%      102.420000     55.000000   1960.00000      0.000000      1.250000
max     8000.000000   1300.000000   2017.00000   2017.000000    259.800000

           ResidFAR       CommFAR      FacilFAR        XCoord         YCoord
count  89854.000000  89854.000000  89854.000000  8.659500e+04   86595.000000
unique          NaN           NaN           NaN           NaN            NaN
top             NaN           NaN           NaN           NaN            NaN
freq            NaN           NaN           NaN           NaN            NaN
mean       1.674844      0.130644      2.853723  1.021686e+06  249975.676667
```

```
…             …            …            …              …              …
min    0.000000     0.000000     0.000000   1.002677e+06  227527.000000
25%    0.900000     0.000000     2.000000   1.014310e+06  241918.000000
50%    1.100000     0.000000     2.000000   1.023321e+06  248586.000000
75%    2.430000     0.000000     4.800000   1.027126e+06  258036.500000
max   10.000000     9.000000    10.000000   1.047777e+06  272275.000000

[11 rows x 20 columns]
```

[7]:

```
df.columns
```

[7]:

```
Index(['Lot', 'ZipCode', 'Address', 'LotArea', 'BldgArea', 'ResArea',
       'OfficeArea', 'RetailArea', 'NumBldgs', 'NumFloors', 'LotDepth',
       'BldgDepth', 'YearBuilt', 'YearAlter1', 'BuiltFAR', 'ResidFAR',
       'CommFAR', 'FacilFAR', 'XCoord', 'YCoord'],
      dtype='object')
```

[8]:

```
df.drop(columns=['Lot', 'ZipCode', 'Address','YearBuilt',␣
 ↪'YearAlter1','XCoord', 'YCoord'],inplace=True)
```

[9]:

```
df
```

[9]:

```
       LotArea  BldgArea  ResArea  OfficeArea  RetailArea  NumBldgs  \
0        15000         0        0           0           0         1
1        13770       752        0         272           0         2
2        35000     39375        0           0           0         1
3         2500     12500    12500           0           0         1
4         1875      8595     6876           0        1719         1
…          …         …        …          …          …
89849        0         0        0           0           0         0
89850        0         0        0           0           0         0
89851        0         0        0           0           0         0
89852        0         0        0           0           0         0
89853        0         0        0           0           0         0

       NumFloors  LotDepth  BldgDepth  BuiltFAR  ResidFAR  CommFAR  FacilFAR
0            0.0     200.0        0.0      0.00      6.02      5.0       6.5
1            1.0     100.0       16.0      0.05      6.02      5.0       6.5
2            2.0     200.0      200.0      1.13      6.02      5.0       6.5
3            5.0     100.0       85.0      5.00      6.02      5.0       6.5
4            5.0      75.0       70.0      4.58      6.02      5.0       6.5
…            …         …         …         …         …         …        …
89849        0.0       0.0        0.0      0.00      0.00      0.0       0.0
89850        0.0       0.0        0.0      0.00      6.02      3.4       6.5
89851        0.0       0.0        0.0      0.00      0.00      0.0       0.0
89852        0.0       0.0        0.0      0.00      0.00      0.0       0.0
89853        0.0       0.0        0.0      0.00      0.00      0.0       0.0
```

```
[89854 rows x 13 columns]
```

[10]:

```
#Replace all zeros with NaNs since zero figure means data not available
df = df.replace(to_replace=0, value=np.nan)
```

[11]:

```
df
```

[11]:

```
       LotArea  BldgArea  ResArea  OfficeArea  RetailArea  NumBldgs  \
0      15000.0       NaN      NaN         NaN         NaN       1.0
1      13770.0     752.0      NaN       272.0         NaN       2.0
2      35000.0   39375.0      NaN         NaN         NaN       1.0
3       2500.0   12500.0  12500.0         NaN         NaN       1.0
4       1875.0    8595.0   6876.0         NaN      1719.0       1.0
…          …        …       …           …           …         …
89849      NaN       NaN      NaN         NaN         NaN       NaN
89850      NaN       NaN      NaN         NaN         NaN       NaN
89851      NaN       NaN      NaN         NaN         NaN       NaN
89852      NaN       NaN      NaN         NaN         NaN       NaN
89853      NaN       NaN      NaN         NaN         NaN       NaN

       NumFloors  LotDepth  BldgDepth  BuiltFAR  ResidFAR  CommFAR  FacilFAR
0            NaN     200.0        NaN       NaN      6.02      5.0       6.5
1            1.0     100.0       16.0      0.05      6.02      5.0       6.5
2            2.0     200.0      200.0      1.13      6.02      5.0       6.5
3            5.0     100.0       85.0      5.00      6.02      5.0       6.5
4            5.0      75.0       70.0      4.58      6.02      5.0       6.5
…            …        …         …           …        …        …
89849        NaN       NaN        NaN       NaN       NaN      NaN       NaN
89850        NaN       NaN        NaN       NaN      6.02      3.4       6.5
89851        NaN       NaN        NaN       NaN       NaN      NaN       NaN
89852        NaN       NaN        NaN       NaN       NaN      NaN       NaN
89853        NaN       NaN        NaN       NaN       NaN      NaN       NaN

[89854 rows x 13 columns]
```

0.0.6 Treat Missing Values

[12]:

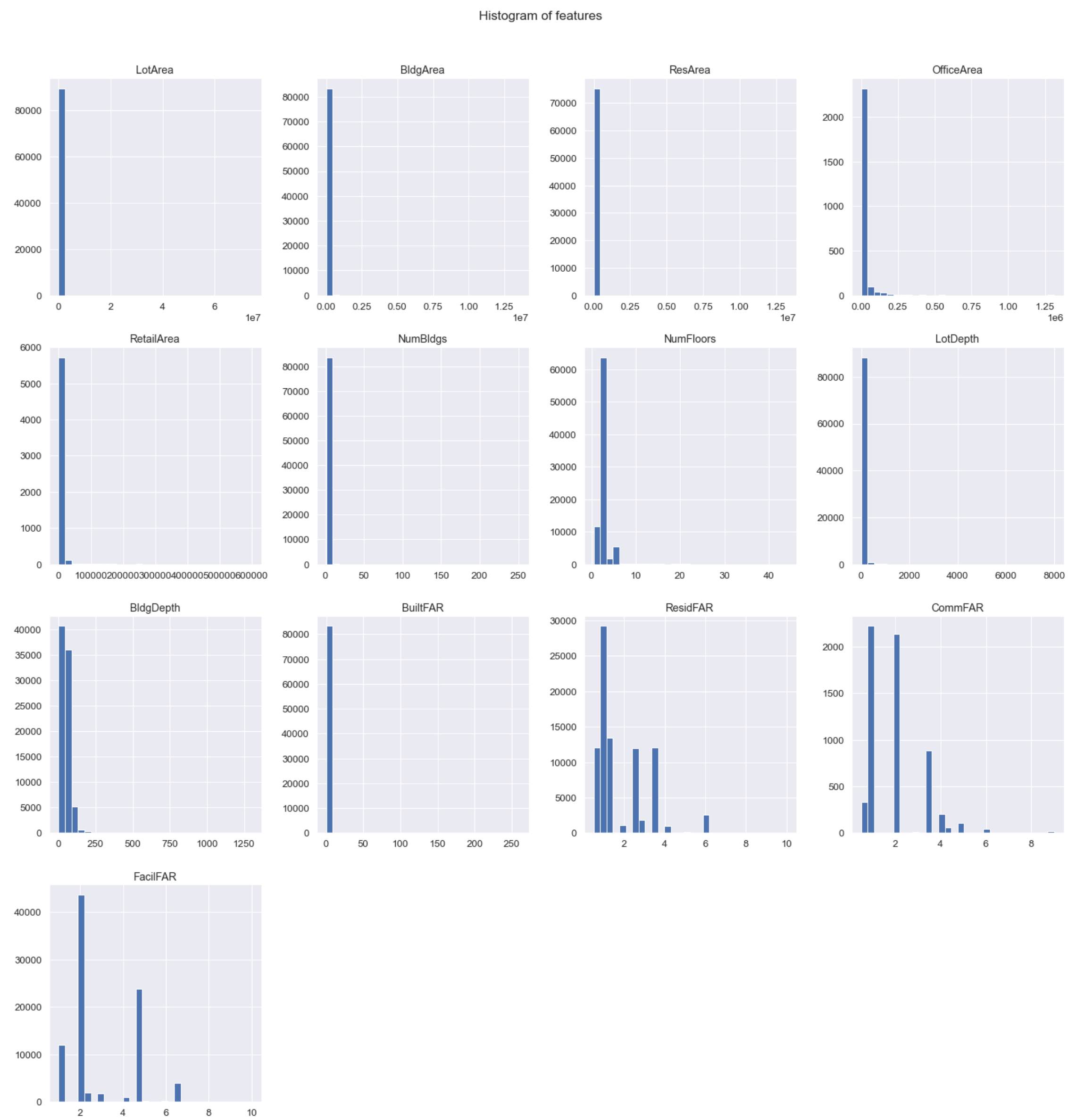
```
df.isnull().sum()
```

[12]:

```
LotArea         301
BldgArea       6423
ResArea       14487
OfficeArea    87319
RetailArea    83962
                …
BldgDepth      6687
```

```
BuiltFAR        6521
ResidFAR        4358
CommFAR        83828
FacilFAR        1104
Length: 13, dtype: int64
```

[13]:
```
df.hist(bins=30, figsize=(20,20))
plt.suptitle("Histogram of features", y=1.04)
plt.tight_layout()
plt.show()
```



Some of the features are right skewed

[14]:
```
df.columns
```

[14]:
```
Index(['LotArea', 'BldgArea', 'ResArea', 'OfficeArea', 'RetailArea',
       'NumBldgs', 'NumFloors', 'LotDepth', 'BldgDepth', 'BuiltFAR',
       'ResidFAR', 'CommFAR', 'FacilFAR'],
      dtype='object')
```

[15]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 89854 entries, 0 to 89853
Data columns (total 13 columns):
 #   Column      Non-Null Count  Dtype
---  ------      --------------  -----
 0   LotArea     89553 non-null  float64
 1   BldgArea    83431 non-null  float64
 2   ResArea     75367 non-null  float64
 3   OfficeArea  2535 non-null   float64
 4   RetailArea  5892 non-null   float64
 5   NumBldgs    83783 non-null  float64
 6   NumFloors   83305 non-null  float64
 7   LotDepth    89595 non-null  float64
 8   BldgDepth   83167 non-null  float64
 9   BuiltFAR    83333 non-null  float64
 10  ResidFAR    85496 non-null  float64
 11  CommFAR     6026 non-null   float64
 12  FacilFAR    88750 non-null  float64
dtypes: float64(13)
memory usage: 8.9 MB
```

We need to drop OfficeArea, RetailArea and CommFAR since there are too many missing values

[16]:
```
df.drop(columns=['OfficeArea', 'RetailArea', 'CommFAR'],inplace=True)
```

[17]:
```
df
```

[17]:
```
        LotArea  BldgArea  ResArea  NumBldgs  NumFloors  LotDepth  BldgDepth  \
0       15000.0       NaN      NaN       1.0        NaN     200.0        NaN
1       13770.0     752.0      NaN       2.0        1.0     100.0       16.0
2       35000.0   39375.0      NaN       1.0        2.0     200.0      200.0
3        2500.0   12500.0  12500.0       1.0        5.0     100.0       85.0
4        1875.0    8595.0   6876.0       1.0        5.0      75.0       70.0
…           …        …       …        …          …         …         …
89849       NaN       NaN      NaN       NaN        NaN       NaN        NaN
89850       NaN       NaN      NaN       NaN        NaN       NaN        NaN
89851       NaN       NaN      NaN       NaN        NaN       NaN        NaN
89852       NaN       NaN      NaN       NaN        NaN       NaN        NaN
89853       NaN       NaN      NaN       NaN        NaN       NaN        NaN
```

```
       BuiltFAR  ResidFAR  FacilFAR
0           NaN      6.02       6.5
1          0.05      6.02       6.5
2          1.13      6.02       6.5
3          5.00      6.02       6.5
4          4.58      6.02       6.5
…          …        …        …
89849       NaN       NaN       NaN
89850       NaN      6.02       6.5
89851       NaN       NaN       NaN
89852       NaN       NaN       NaN
89853       NaN       NaN       NaN

[89854 rows x 10 columns]
```

[18]:
```
df.isnull().sum()
```

[18]:
```
LotArea        301
BldgArea      6423
ResArea      14487
NumBldgs      6071
NumFloors     6549
LotDepth       259
BldgDepth     6687
BuiltFAR      6521
ResidFAR      4358
FacilFAR      1104
dtype: int64
```

[19]:
```
# Drop all NaNs
df.dropna(inplace=True)
```

[20]:
```
df
```

[20]:
```
        LotArea   BldgArea    ResArea  NumBldgs  NumFloors  LotDepth  \
3        2500.0    12500.0    12500.0       1.0        5.0    100.00
4        1875.0     8595.0     6876.0       1.0        5.0     75.00
25       2500.0     6784.0     6784.0       1.0        4.0    100.00
28       2500.0    11500.0     9176.0       1.0        5.0    100.00
37     204540.0  1306230.0  1306230.0       4.0       16.0    487.58
…          …          …          …        …          …          …
89836    4244.0     1336.0     1336.0       2.0        2.0    119.00
89837    4122.0     1432.0     1432.0       2.0        2.0    115.58
89838    8400.0     1720.0     1720.0       2.0        2.0    112.00
89839    3891.0     1512.0     1512.0       2.0        2.0    109.08
89840    1900.0     1044.0     1044.0       1.0        2.0     76.00
```

```
       BldgDepth  BuiltFAR  ResidFAR  FacilFAR
3           85.0      5.00      6.02       6.5
4           70.0      4.58      6.02       6.5
25          75.0      2.71      3.00       3.0
28          96.0      4.60      3.00       3.0
37          48.0      6.39      2.43       4.8
…            …         …         …         …
89836       28.0      0.31      0.50       1.0
89837       28.0      0.35      0.50       1.0
89838       30.0      0.20      0.50       1.0
89839       28.0      0.39      0.50       1.0
89840       29.0      0.55      0.90       2.0

[74193 rows x 10 columns]
```

[21]:
```
df.reset_index(drop=True, inplace=True)
```

[22]:
```
df
```

[22]:
```
        LotArea   BldgArea    ResArea  NumBldgs  NumFloors  LotDepth  \
0        2500.0    12500.0    12500.0       1.0        5.0    100.00
1        1875.0     8595.0     6876.0       1.0        5.0     75.00
2        2500.0     6784.0     6784.0       1.0        4.0    100.00
3        2500.0    11500.0     9176.0       1.0        5.0    100.00
4      204540.0  1306230.0  1306230.0       4.0       16.0    487.58
…          …          …          …         …          …         …
74188    4244.0     1336.0     1336.0       2.0        2.0    119.00
74189    4122.0     1432.0     1432.0       2.0        2.0    115.58
74190    8400.0     1720.0     1720.0       2.0        2.0    112.00
74191    3891.0     1512.0     1512.0       2.0        2.0    109.08
74192    1900.0     1044.0     1044.0       1.0        2.0     76.00

       BldgDepth  BuiltFAR  ResidFAR  FacilFAR
0           85.0      5.00      6.02       6.5
1           70.0      4.58      6.02       6.5
2           75.0      2.71      3.00       3.0
3           96.0      4.60      3.00       3.0
4           48.0      6.39      2.43       4.8
…            …         …         …         …
74188       28.0      0.31      0.50       1.0
74189       28.0      0.35      0.50       1.0
74190       30.0      0.20      0.50       1.0
74191       28.0      0.39      0.50       1.0
74192       29.0      0.55      0.90       2.0

[74193 rows x 10 columns]
```

0.0.7 Save a copy as csv file

[23]:
```
#df.to_csv('bronxusa.csv',index=False)
```

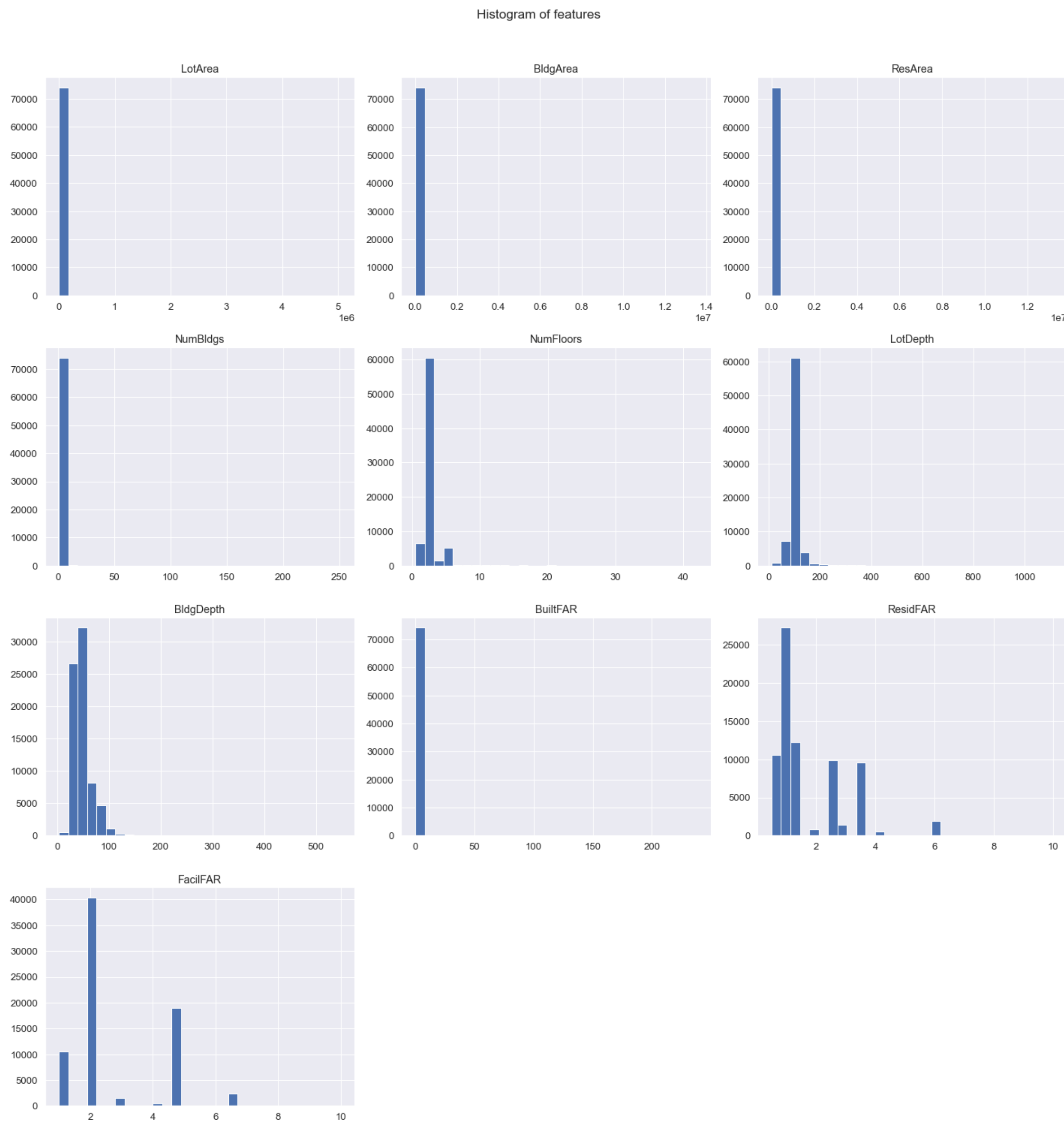
0.0.8 Data Visualization

[24]:
```
df = pd.read_csv('bronxusa.csv')
```

[25]:
```
df.shape
```

[25]:
```
(74193, 10)
```

[26]:
```
df.hist(bins=30, figsize=(20,20))
plt.suptitle("Histogram of features", y=1.04)
plt.tight_layout()
plt.show()
```



This graph was redone to exclude those dropped features. Still right skewed for some features

[27]:
```
df.corr()
```

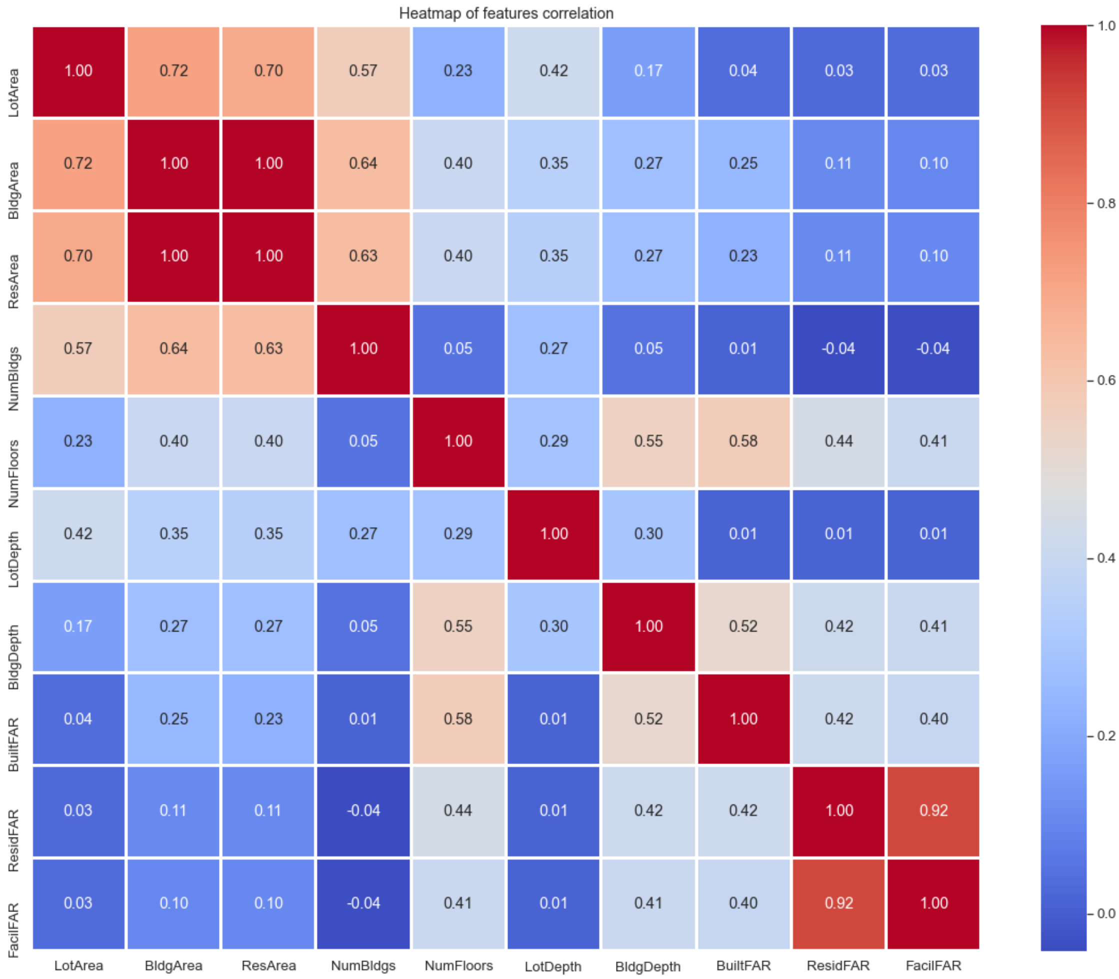
[27]:

	LotArea	BldgArea	ResArea	NumBldgs	NumFloors	LotDepth	\
LotArea	1.000000	0.716683	0.697126	0.569469	0.226378	0.420397	
BldgArea	0.716683	1.000000	0.996520	0.637119	0.401753	0.351594	
ResArea	0.697126	0.996520	1.000000	0.634960	0.402663	0.348293	
NumBldgs	0.569469	0.637119	0.634960	1.000000	0.053902	0.272675	
NumFloors	0.226378	0.401753	0.402663	0.053902	1.000000	0.290620	
LotDepth	0.420397	0.351594	0.348293	0.272675	0.290620	1.000000	
BldgDepth	0.167923	0.274446	0.274174	0.048424	0.549174	0.299683	

```
BuiltFAR   0.039064  0.251014  0.225913  0.013802   0.577994  0.013681
ResidFAR   0.030626  0.110594  0.111445 -0.042254   0.440021  0.014560
FacilFAR   0.031475  0.104173  0.104661 -0.037867   0.408788  0.014024

           BldgDepth  BuiltFAR  ResidFAR  FacilFAR
LotArea     0.167923  0.039064  0.030626  0.031475
BldgArea    0.274446  0.251014  0.110594  0.104173
ResArea     0.274174  0.225913  0.111445  0.104661
NumBldgs    0.048424  0.013802 -0.042254 -0.037867
NumFloors   0.549174  0.577994  0.440021  0.408788
LotDepth    0.299683  0.013681  0.014560  0.014024
BldgDepth   1.000000  0.520624  0.417760  0.407543
BuiltFAR    0.520624  1.000000  0.420006  0.397036
ResidFAR    0.417760  0.420006  1.000000  0.917245
FacilFAR    0.407543  0.397036  0.917245  1.000000
```

[28]:

```
plt.figure(figsize=(20,16))
plt.title("Heatmap of features correlation")
sns.heatmap(df.corr(),cmap="coolwarm",annot=True,fmt='.2f',linewidths=2)
plt.show()
```



BldgArea vs ResArea, ResidFAR vs FacilFAR are highly correlated to each other.

[29]:
```
sns.pairplot(df.sample(500))
plt.suptitle("Pairplot of features", y=1.05, va='top', size=20)
plt.show()
```

We will use a small sample out from the dataset to save time and faster computation

[30]:
```
df = df.copy()
```

[31]:
```
df1 = df.sample(frac=0.05, random_state=0)
```

[32]:
```
df1
```

[32]:

	LotArea	BldgArea	ResArea	NumBldgs	NumFloors	LotDepth	BldgDepth	\
64589	4000.0	1692.0	1692.0	2.0	2.0	100.00	30.0	
6125	2500.0	4095.0	4095.0	1.0	3.0	100.00	65.0	
19575	2400.0	1200.0	1200.0	1.0	2.0	60.00	25.0	

```
4627    3822.0    1920.0   1280.0       2.0         3.0     101.00        32.0
73108   2052.0    1600.0   1200.0       1.0         2.0      54.00        20.0
…         …         …        …          …          …          …
1041    2311.0    3960.0   3960.0       1.0         3.0      92.59        50.0
62226   4750.0    2112.0   2112.0       1.0         2.0      95.00        48.0
50126   1692.0    1674.0   1116.0       1.0         2.0      94.00        31.0
64293   2358.0    1944.0   1296.0       1.0         2.0     100.00        36.0
53670   4892.0    2128.0   1064.0       2.0         1.5      97.83        38.0

       BuiltFAR  ResidFAR  FacilFAR
64589      0.42      0.60       1.0
6125       1.64      3.44       4.8
19575      0.50      0.90       2.0
4627       0.50      2.43       4.8
73108      0.78      0.60       1.0
…           …        …        …
1041       1.71      2.43       4.8
62226      0.44      0.90       2.0
50126      0.99      0.90       2.0
64293      0.82      0.60       1.0
53670      0.43      1.25       2.0

[3710 rows x 10 columns]
```

[33]:
```
df1.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 3710 entries, 64589 to 53670
Data columns (total 10 columns):
 #   Column     Non-Null Count  Dtype
---  ------     --------------  -----
 0   LotArea    3710 non-null   float64
 1   BldgArea   3710 non-null   float64
 2   ResArea    3710 non-null   float64
 3   NumBldgs   3710 non-null   float64
 4   NumFloors  3710 non-null   float64
 5   LotDepth   3710 non-null   float64
 6   BldgDepth  3710 non-null   float64
 7   BuiltFAR   3710 non-null   float64
 8   ResidFAR   3710 non-null   float64
 9   FacilFAR   3710 non-null   float64
dtypes: float64(10)
memory usage: 318.8 KB
```

[34]:
```
df1.shape
```

[34]: (3710, 10)

[35]:
```
df1.describe()
```

[35]:

	LotArea	BldgArea	ResArea	NumBldgs	NumFloors
count	3710.000000	3710.000000	3710.000000	3710.000000	3710.000000
mean	3912.093261	5867.001887	5518.797305	1.254987	2.458170
std	10344.737538	17985.009647	17795.169652	1.160692	1.167185
min	765.000000	450.000000	450.000000	1.000000	0.500000
25%	2136.500000	1704.250000	1368.000000	1.000000	2.000000
50%	2500.000000	2247.000000	2000.000000	1.000000	2.000000
75%	3435.000000	3140.750000	2774.250000	1.000000	3.000000
max	519774.000000	332298.000000	332298.000000	64.000000	29.000000

	LotDepth	BldgDepth	BuiltFAR	ResidFAR	FacilFAR
count	3710.000000	3710.000000	3710.000000	3710.00000	3710.000000
mean	100.438235	47.968871	1.143394	1.60886	2.689650
std	26.627235	19.320822	0.940854	1.16742	1.482658
min	15.080000	13.000000	0.050000	0.50000	1.000000
25%	95.000000	36.000000	0.630000	0.90000	2.000000
50%	100.000000	45.000000	0.890000	1.10000	2.000000
75%	100.182500	54.000000	1.290000	2.43000	4.800000
max	700.000000	300.000000	11.630000	6.02000	6.500000

[36]:
```
df1.reset_index(drop=True, inplace=True)
```

[37]:
```
df1
```

[37]:

	LotArea	BldgArea	ResArea	NumBldgs	NumFloors	LotDepth	BldgDepth
0	4000.0	1692.0	1692.0	2.0	2.0	100.00	30.0
1	2500.0	4095.0	4095.0	1.0	3.0	100.00	65.0
2	2400.0	1200.0	1200.0	1.0	2.0	60.00	25.0
3	3822.0	1920.0	1280.0	2.0	3.0	101.00	32.0
4	2052.0	1600.0	1200.0	1.0	2.0	54.00	20.0
…	…	…	…	…	…	…	…
3705	2311.0	3960.0	3960.0	1.0	3.0	92.59	50.0
3706	4750.0	2112.0	2112.0	1.0	2.0	95.00	48.0
3707	1692.0	1674.0	1116.0	1.0	2.0	94.00	31.0
3708	2358.0	1944.0	1296.0	1.0	2.0	100.00	36.0
3709	4892.0	2128.0	1064.0	2.0	1.5	97.83	38.0

	BuiltFAR	ResidFAR	FacilFAR
0	0.42	0.60	1.0
1	1.64	3.44	4.8
2	0.50	0.90	2.0
3	0.50	2.43	4.8
4	0.78	0.60	1.0
…	…	…	…
3705	1.71	2.43	4.8

```
3706        0.44       0.90        2.0
3707        0.99       0.90        2.0
3708        0.82       0.60        1.0
3709        0.43       1.25        2.0

[3710 rows x 10 columns]
```

[38]:
```
#Save a copy of subset data
#df1.to_csv("bronxtraining.csv", index=False)
```

0.0.9 Summary of training at least three variations of the unsupervised model you selected. For example, you can use different clustering techniques or different hyperparameters.

We will be using 3 models of clustering: Hierarchical, K-Means and DBScan. Plots will be generated to make comparisons and results before chossing the final model.

0.0.10 Scaling the data for training

[39]:
```
X = df1.iloc[:,0:11]
```

[40]:
```
X
```

[40]:
```
      LotArea  BldgArea  ResArea  NumBldgs  NumFloors  LotDepth  BldgDepth  \
0      4000.0    1692.0   1692.0       2.0        2.0    100.00       30.0
1      2500.0    4095.0   4095.0       1.0        3.0    100.00       65.0
2      2400.0    1200.0   1200.0       1.0        2.0     60.00       25.0
3      3822.0    1920.0   1280.0       2.0        3.0    101.00       32.0
4      2052.0    1600.0   1200.0       1.0        2.0     54.00       20.0
…         …         …        …         …          …         …         …
3705   2311.0    3960.0   3960.0       1.0        3.0     92.59       50.0
3706   4750.0    2112.0   2112.0       1.0        2.0     95.00       48.0
3707   1692.0    1674.0   1116.0       1.0        2.0     94.00       31.0
3708   2358.0    1944.0   1296.0       1.0        2.0    100.00       36.0
3709   4892.0    2128.0   1064.0       2.0        1.5     97.83       38.0

      BuiltFAR  ResidFAR  FacilFAR
0         0.42      0.60       1.0
1         1.64      3.44       4.8
2         0.50      0.90       2.0
3         0.50      2.43       4.8
4         0.78      0.60       1.0
…          …         …        …
3705      1.71      2.43       4.8
3706      0.44      0.90       2.0
3707      0.99      0.90       2.0
3708      0.82      0.60       1.0
```

```
3709      0.43      1.25       2.0

[3710 rows x 10 columns]
```

[41]:
```python
X.values
```

[41]:
```
array([[4.000e+03, 1.692e+03, 1.692e+03, …, 4.200e-01, 6.000e-01,
        1.000e+00],
       [2.500e+03, 4.095e+03, 4.095e+03, …, 1.640e+00, 3.440e+00,
        4.800e+00],
       [2.400e+03, 1.200e+03, 1.200e+03, …, 5.000e-01, 9.000e-01,
        2.000e+00],
       …,
       [1.692e+03, 1.674e+03, 1.116e+03, …, 9.900e-01, 9.000e-01,
        2.000e+00],
       [2.358e+03, 1.944e+03, 1.296e+03, …, 8.200e-01, 6.000e-01,
        1.000e+00],
       [4.892e+03, 2.128e+03, 1.064e+03, …, 4.300e-01, 1.250e+00,
        2.000e+00]])
```

[42]:
```python
scaler = StandardScaler()
```

[43]:
```python
X_transform = scaler.fit_transform(X)
```

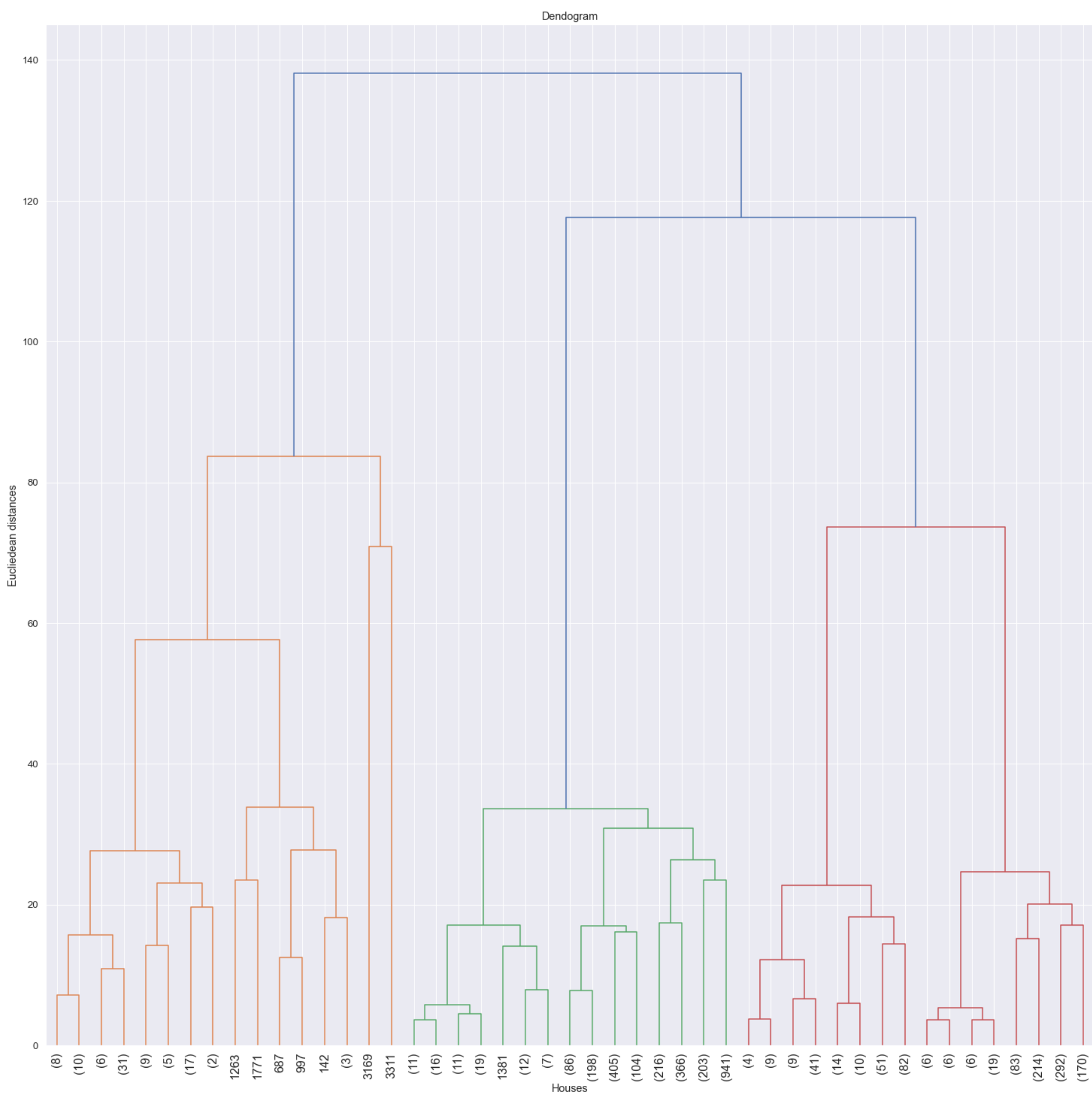
[44]:
```python
X_transform
```

[44]:
```
array([[ 0.00849887, -0.23216916, -0.21507596, …, -0.76897308,
        -0.86429556, -1.13976197],
       [-0.13652194, -0.09853988, -0.08002111, …,  0.52789663,
         1.56874747,  1.4235479 ],
       [-0.14618999, -0.25952897, -0.24272764, …, -0.68393244,
        -0.60728397, -0.46520674],
       …,
       [-0.21463981, -0.23317013, -0.24744865, …, -0.16305854,
        -0.60728397, -0.46520674],
       [-0.15025057, -0.21815561, -0.23733219, …, -0.3437699 ,
        -0.86429556, -1.13976197],
       [ 0.09473791, -0.20792349, -0.25037119, …, -0.758343  ,
        -0.30743712, -0.46520674]])
```

0.1 Hierarchical Clustering Method

0.1.1 Plot Dendogram to find optimal number of clusters

[45]:
```python
plt.figure(figsize=(25,25))
dendogram = sch.dendrogram(sch.linkage(X_transform,method='ward'),truncate_mode='level',
                            color_threshold=None,p=5,leaf_font_size=16)
plt.title("Dendogram")
plt.xlabel("Houses")
plt.ylabel("Eucliedean distances")
plt.show()
```



We choose nclusters = 3 since highest difference height

0.1.2 Fitting hierachical cluster

[46]:
```
hc = AgglomerativeClustering(n_clusters=3,affinity='euclidean',linkage='ward')
```

[47]:
```
y_hc = hc.fit_predict(X_transform)
```

[48]:
```
y_hc
```

[48]:
```
array([2, 1, 2, …, 2, 2, 2], dtype=int64)
```

[49]:
```
y = pd.DataFrame(y_hc,columns=['Cluster'])
```

[50]:
```
y
```

[50]:
```
      Cluster
0           2
1           1
2           2
3           1
4           2
…         …
3705        1
3706        2
3707        2
3708        2
3709        2

[3710 rows x 1 columns]
```

[51]:
```
y['Cluster'].unique()
```

[51]:
```
array([2, 1, 0], dtype=int64)
```

[52]:
```
y['Cluster'].value_counts()
```

[52]:
```
2    2596
1    1016
0      98
Name: Cluster, dtype: int64
```

[53]:
```
np.where(y_hc == 0)
```

[53]:
```
(array([  42,  100,  132,  142,  425,  486,  515,  560,  582,  598,  681,
         687,  711,  797,  823,  829,  837,  896,  903,  907,  919,  973,
         997, 1024, 1027, 1053, 1070, 1078, 1121, 1192, 1263, 1421, 1475,
        1507, 1537, 1550, 1555, 1597, 1598, 1638, 1663, 1737, 1769, 1771,
        1776, 1791, 1794, 1806, 1813, 1962, 1997, 2011, 2030, 2059, 2078,
```

```
       2137, 2247, 2265, 2375, 2394, 2401, 2412, 2428, 2459, 2485, 2511,
       2541, 2544, 2569, 2586, 2664, 2689, 2696, 2712, 2723, 2755, 2771,
       2787, 2818, 2900, 2958, 3052, 3126, 3158, 3169, 3198, 3220, 3237,
       3262, 3307, 3311, 3363, 3387, 3420, 3455, 3595, 3612, 3636],
      dtype=int64),)
```

[54]:
```
np.where(y_hc == 1)
```

[54]:
```
(array([   1,    3,   13, …, 3689, 3690, 3705], dtype=int64),)
```

[55]:
```
np.where(y_hc == 2)
```

[55]:
```
(array([   0,    2,    4, …, 3707, 3708, 3709], dtype=int64),)
```

[56]:
```
newdf = pd.concat([df1,y],axis=1)
```

[57]:
```
newdf
```

[57]:
```
      LotArea  BldgArea  ResArea  NumBldgs  NumFloors  LotDepth  BldgDepth  \
0      4000.0    1692.0   1692.0       2.0        2.0    100.00       30.0
1      2500.0    4095.0   4095.0       1.0        3.0    100.00       65.0
2      2400.0    1200.0   1200.0       1.0        2.0     60.00       25.0
3      3822.0    1920.0   1280.0       2.0        3.0    101.00       32.0
4      2052.0    1600.0   1200.0       1.0        2.0     54.00       20.0
…         …        …        …         …          …         …         …
3705   2311.0    3960.0   3960.0       1.0        3.0     92.59       50.0
3706   4750.0    2112.0   2112.0       1.0        2.0     95.00       48.0
3707   1692.0    1674.0   1116.0       1.0        2.0     94.00       31.0
3708   2358.0    1944.0   1296.0       1.0        2.0    100.00       36.0
3709   4892.0    2128.0   1064.0       2.0        1.5     97.83       38.0

      BuiltFAR  ResidFAR  FacilFAR  Cluster
0         0.42      0.60       1.0        2
1         1.64      3.44       4.8        1
2         0.50      0.90       2.0        2
3         0.50      2.43       4.8        1
4         0.78      0.60       1.0        2
…          …         …        …
3705      1.71      2.43       4.8        1
3706      0.44      0.90       2.0        2
3707      0.99      0.90       2.0        2
3708      0.82      0.60       1.0        2
3709      0.43      1.25       2.0        2

[3710 rows x 11 columns]
```

[58]:
```
newdf["Cluster"].value_counts()
```

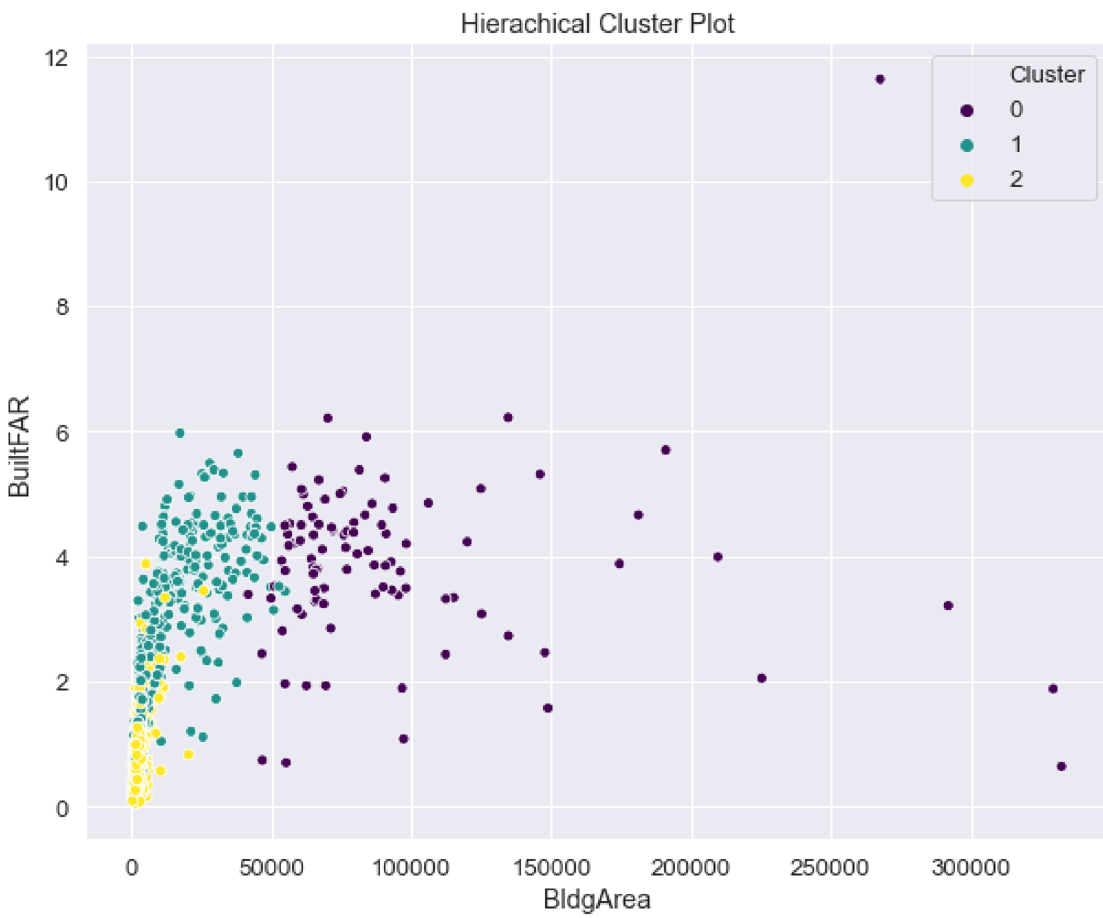
[58]:
```
2    2596
1    1016
0      98
Name: Cluster, dtype: int64
```

[59]:
```
meandf = newdf.groupby(by='Cluster').mean()
```

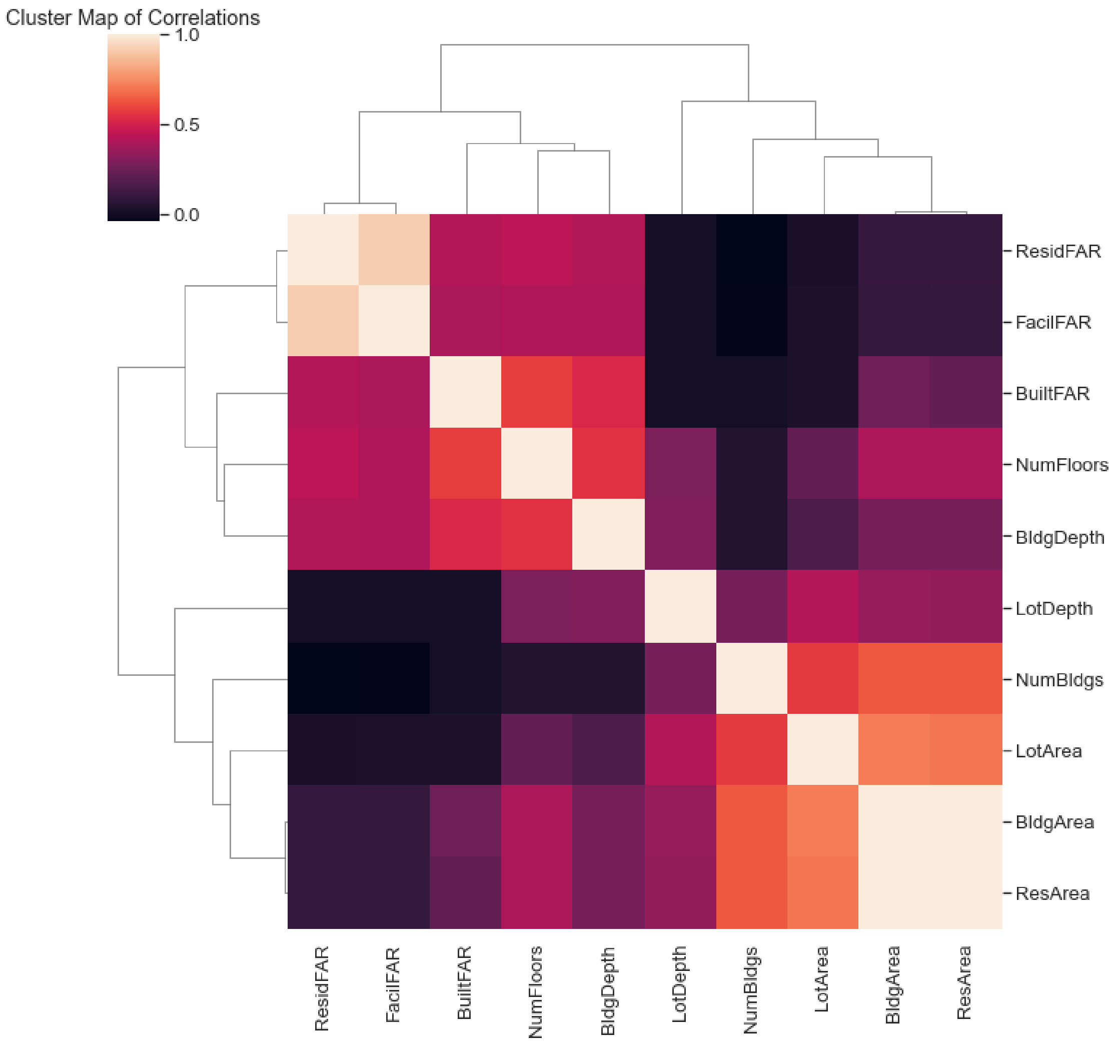
[60]:
```
meandf
```

[60]:
```
              LotArea      BldgArea       ResArea  NumBldgs  NumFloors  \
Cluster
0        32548.540816  94210.234694  92732.285714  2.071429   6.438776
1         3174.352362   6598.432087   6248.693898  1.134843   2.936270
2         3119.786980   2245.750000   1940.793914  1.271186   2.120786

           LotDepth   BldgDepth  BuiltFAR  ResidFAR  FacilFAR
Cluster
0        151.512857  105.316939  3.911122  3.753265  4.953061
1         97.545423   56.014951  1.703701  3.093996  4.784646
2         99.642311   42.654954  0.819622  0.946668  1.784284
```

[61]:
```
x_axis = newdf['BldgArea']
y_axis = newdf['BuiltFAR']
plt.figure(figsize=(10,8))
sns.scatterplot(x_axis,y_axis,hue=newdf['Cluster'],palette='viridis')
plt.title('Hierachical Cluster Plot')
plt.show()
```



[62]:
```
sns.clustermap(df.corr())
plt.title("Cluster Map of Correlations")
plt.show()
```



Analysis: Based on cluster plot, there are 3 clusters found.

Cluster 0: Largest Sized Buildings based on high values of area

Cluster 1: Medium Sized Buildings based on BldgArea value

Cluster 2: Small Sized Buildings based on BldgArea value

0.2 K-Means Clustering Method

0.2.1 Using Elbow Method to find optimal number of clusters

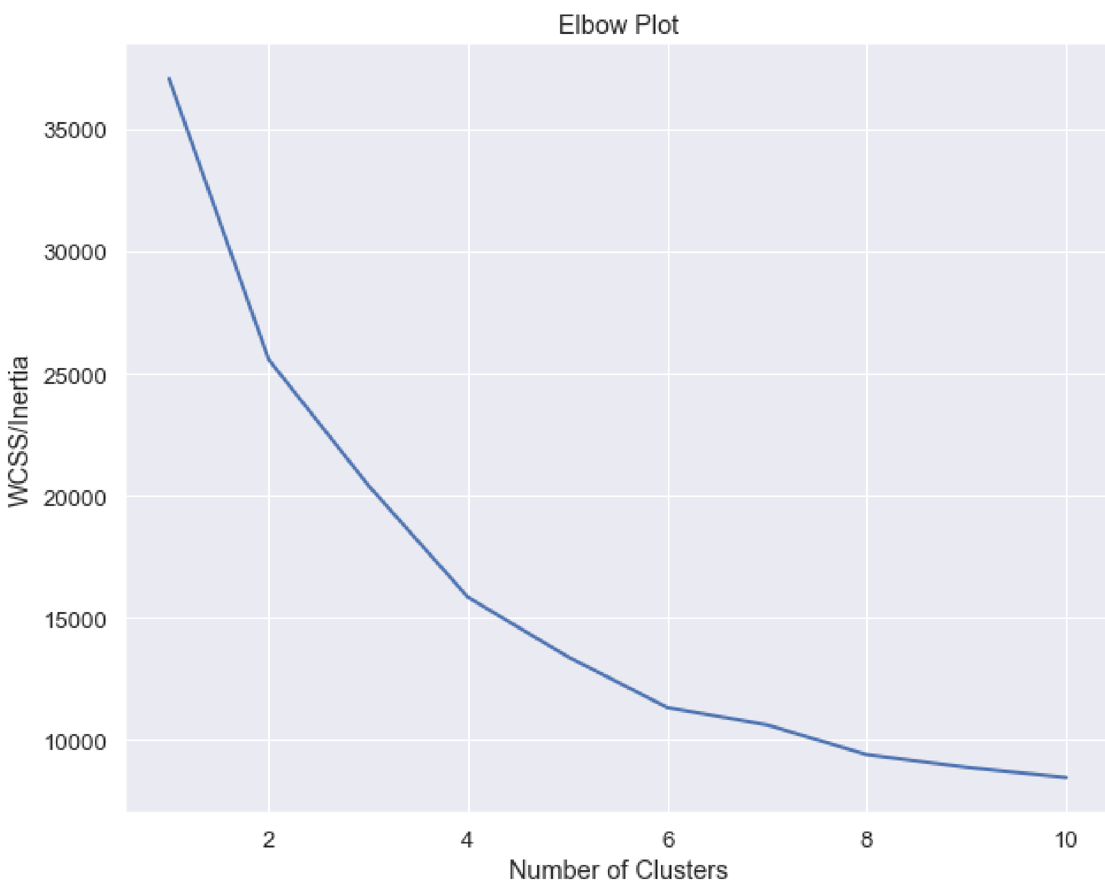
[63]:
```
wcss = []

for i in range(1,11):
    kmeans = KMeans(n_clusters=i,init='k-means++',random_state=0, n_init=10)
    kmeans.fit(X_transform)
```

```
    wcss.append(kmeans.inertia_)
```

[64]:
```
wcss
```

[64]:
```
[37099.999999999876,
 25584.590147780338,
 20428.26509162942,
 15841.129949552638,
 13407.952781423644,
 11326.132619965483,
 10614.038214797878,
 9397.209301852517,
 8876.393122036905,
 8461.425393352614]
```

[65]:
```
plt.figure(figsize=(10,8))
plt.plot(range(1,11),wcss,linewidth=2)
plt.title("Elbow Plot")
plt.xlabel("Number of Clusters")
plt.ylabel("WCSS/Inertia")
plt.show()
```



Choose number of clusters = 4

0.2.2 Execute K-Means after determining the suitable cluster

[66]:
```
kmeans = KMeans(n_clusters=4,init='k-means++',random_state=0, n_init=10)
```

[67]:
```
kmeans.fit(X_transform)
```

[67]:
```
KMeans(n_clusters=4, random_state=0)
```

0.2.3 Results

[68]:
```
df_segm_kmeans = df1.copy()
```

[69]:
```
df_segm_kmeans
```

[69]:
```
       LotArea  BldgArea  ResArea  NumBldgs  NumFloors  LotDepth  BldgDepth  \
0       4000.0    1692.0   1692.0       2.0        2.0    100.00       30.0
1       2500.0    4095.0   4095.0       1.0        3.0    100.00       65.0
2       2400.0    1200.0   1200.0       1.0        2.0     60.00       25.0
3       3822.0    1920.0   1280.0       2.0        3.0    101.00       32.0
4       2052.0    1600.0   1200.0       1.0        2.0     54.00       20.0
…          …         …        …         …          …         …          …
3705    2311.0    3960.0   3960.0       1.0        3.0     92.59       50.0
3706    4750.0    2112.0   2112.0       1.0        2.0     95.00       48.0
3707    1692.0    1674.0   1116.0       1.0        2.0     94.00       31.0
3708    2358.0    1944.0   1296.0       1.0        2.0    100.00       36.0
3709    4892.0    2128.0   1064.0       2.0        1.5     97.83       38.0

       BuiltFAR  ResidFAR  FacilFAR
0          0.42      0.60       1.0
1          1.64      3.44       4.8
2          0.50      0.90       2.0
3          0.50      2.43       4.8
4          0.78      0.60       1.0
…             …         …         …
3705       1.71      2.43       4.8
3706       0.44      0.90       2.0
3707       0.99      0.90       2.0
3708       0.82      0.60       1.0
3709       0.43      1.25       2.0

[3710 rows x 10 columns]
```

[70]:
```
df_segm_kmeans['Segment K-Means'] = kmeans.labels_
```

[71]:
```python
df_segm_kmeans
```

[71]:

```
      LotArea  BldgArea  ResArea  NumBldgs  NumFloors  LotDepth  BldgDepth  \
0      4000.0    1692.0   1692.0       2.0        2.0    100.00       30.0
1      2500.0    4095.0   4095.0       1.0        3.0    100.00       65.0
2      2400.0    1200.0   1200.0       1.0        2.0     60.00       25.0
3      3822.0    1920.0   1280.0       2.0        3.0    101.00       32.0
4      2052.0    1600.0   1200.0       1.0        2.0     54.00       20.0
…         …         …        …         …          …         …
3705   2311.0    3960.0   3960.0       1.0        3.0     92.59       50.0
3706   4750.0    2112.0   2112.0       1.0        2.0     95.00       48.0
3707   1692.0    1674.0   1116.0       1.0        2.0     94.00       31.0
3708   2358.0    1944.0   1296.0       1.0        2.0    100.00       36.0
3709   4892.0    2128.0   1064.0       2.0        1.5     97.83       38.0

      BuiltFAR  ResidFAR  FacilFAR  Segment K-Means
0         0.42      0.60       1.0                1
1         1.64      3.44       4.8                3
2         0.50      0.90       2.0                1
3         0.50      2.43       4.8                3
4         0.78      0.60       1.0                1
…          …         …        …              …
3705      1.71      2.43       4.8                3
3706      0.44      0.90       2.0                1
3707      0.99      0.90       2.0                1
3708      0.82      0.60       1.0                1
3709      0.43      1.25       2.0                1

[3710 rows x 11 columns]
```

[72]:
```python
df_segm_analysis = df_segm_kmeans.groupby(['Segment K-Means']).mean()
```

[73]:
```python
df_segm_analysis
```

[73]:

```
                       LotArea       BldgArea        ResArea   NumBldgs  \
Segment K-Means
0                180035.833333  237477.500000  237477.500000  15.500000
1                  3118.099037    2236.654721    1933.893256   1.271291
2                 12799.708502   47828.773279   46730.153846   1.093117
3                  2529.763341    3159.960557    2887.554524   1.153132

                 NumFloors    LotDepth   BldgDepth  BuiltFAR  ResidFAR  \
Segment K-Means
0                 6.833333  426.120000  146.333333  1.738333  3.196667
1                 2.120062   99.642173   42.637480  0.818609  0.946686
2                 5.696356  113.152955   91.912915  3.990688  3.509231
3                 2.517691   96.924490   50.742181  1.301125  3.046705
```

```
                FacilFAR
Segment K-Means
0               5.083333
1               1.784200
2               4.828340
3               4.785963
```

[ ]:
```
#df_segm_kmeans.groupby(['Segment K-Means','NumFloors']).count()
```

[ ]:
```
#df_segm_kmeans.groupby(['Segment K-Means','NumFloors']).size()
```

Analysis:

Cluster 0 has largest areas, floors and numbers = Extra Large (XL)

Cluster 1 has average areas values overall = Medium 1 (M1)

Cluster 2 has large areas overall = Large (L)

Cluster 3 has average areas values overall = Medium 2 (M2)

[74]:
```
df_segm_analysis.rename({0: 'XL',
                         1: 'M1',
                         2: 'L',
                         3: 'M2',
                         },inplace=True)
```

[75]:
```
df_segm_analysis
```

[75]:
```
                       LotArea       BldgArea        ResArea   NumBldgs  \
Segment K-Means
XL               180035.833333  237477.500000  237477.500000  15.500000
M1                 3118.099037    2236.654721    1933.893256   1.271291
L                 12799.708502   47828.773279   46730.153846   1.093117
M2                 2529.763341    3159.960557    2887.554524   1.153132

                 NumFloors    LotDepth   BldgDepth  BuiltFAR  ResidFAR  \
Segment K-Means
XL                6.833333  426.120000  146.333333  1.738333  3.196667
M1                2.120062   99.642173   42.637480  0.818609  0.946686
L                 5.696356  113.152955   91.912915  3.990688  3.509231
M2                2.517691   96.924490   50.742181  1.301125  3.046705

                 FacilFAR
Segment K-Means
XL               5.083333
M1               1.784200
L                4.828340
```

```
M2               4.785963
```

[76]:
```
df_segm_kmeans['Labels'] = df_segm_kmeans['Segment K-Means'].map({0: 'XL',
                                                                  1: 'M1',
                                                                  2: 'L',
                                                                  3: 'M2'})
```

[77]:
```
df_segm_kmeans
```

[77]:
```
      LotArea  BldgArea  ResArea  NumBldgs  NumFloors  LotDepth  BldgDepth  \
0      4000.0    1692.0   1692.0       2.0        2.0    100.00       30.0
1      2500.0    4095.0   4095.0       1.0        3.0    100.00       65.0
2      2400.0    1200.0   1200.0       1.0        2.0     60.00       25.0
3      3822.0    1920.0   1280.0       2.0        3.0    101.00       32.0
4      2052.0    1600.0   1200.0       1.0        2.0     54.00       20.0
…         …         …        …        …          …         …         …
3705   2311.0    3960.0   3960.0       1.0        3.0     92.59       50.0
3706   4750.0    2112.0   2112.0       1.0        2.0     95.00       48.0
3707   1692.0    1674.0   1116.0       1.0        2.0     94.00       31.0
3708   2358.0    1944.0   1296.0       1.0        2.0    100.00       36.0
3709   4892.0    2128.0   1064.0       2.0        1.5     97.83       38.0

      BuiltFAR  ResidFAR  FacilFAR  Segment K-Means Labels
0         0.42      0.60       1.0                1     M1
1         1.64      3.44       4.8                3     M2
2         0.50      0.90       2.0                1     M1
3         0.50      2.43       4.8                3     M2
4         0.78      0.60       1.0                1     M1
…          …         …         …                …      …
3705      1.71      2.43       4.8                3     M2
3706      0.44      0.90       2.0                1     M1
3707      0.99      0.90       2.0                1     M1
3708      0.82      0.60       1.0                1     M1
3709      0.43      1.25       2.0                1     M1

[3710 rows x 12 columns]
```

0.2.4 Plot the clusters

[78]:
```
x_axis = df_segm_kmeans['BldgArea']
y_axis = df_segm_kmeans['BuiltFAR']
plt.figure(figsize=(10,8))
sns.
 ↪scatterplot(x_axis,y_axis,hue=df_segm_kmeans['Labels'],palette=['g','r','c','m'])
plt.title('Segmentation K-Means')
plt.show()
```

[79]:
```
# x_axis = df_segm_kmeans['BldgArea']
# y_axis = df_segm_kmeans['BuiltFAR']
# z_axis = df_segm_kmeans['BldgDepth']

# fig = plt.figure(figsize=(10,8))
# ax = fig.add_subplot(111, projection='3d')
# ax.scatter3D(x_axis,y_axis,z_axis,c=z_axis, cmap='viridis')

# ax.set_xlabel('BldgArea')
# ax.set_ylabel('BuiltFAR')
# ax.set_zlabel('BldgDepth')

# plt.show()
```

0.3 DBSCAN method

[80]:
```
epsilon = 0.3
minimumSamples = 50
db = DBSCAN(eps=epsilon, min_samples=minimumSamples).fit(X_transform)
```

[81]:
```
labels= db.labels_
labels
```

[81]:
```
array([-1, -1, -1, …,  0,  1, -1], dtype=int64)
```

[82]:
```
y = pd.DataFrame(labels,columns=['Cluster'])
```

[83]:
```
y
```

[83]:
```
      Cluster
0          -1
1          -1
2          -1
3          -1
4          -1
…         …
3705       -1
3706       -1
3707        0
3708        1
3709       -1

[3710 rows x 1 columns]
```

[84]:
```
y.value_counts()
```

[84]:
```
Cluster
-1         2884
 0          662
 2           94
 1           70
dtype: int64
```

[85]:
```
dbdf = pd.concat([df1,y],axis=1)
```

[86]:
```
dbdf
```

[86]:
```
      LotArea  BldgArea  ResArea  NumBldgs  NumFloors  LotDepth  BldgDepth  \
0      4000.0    1692.0   1692.0       2.0        2.0    100.00       30.0
1      2500.0    4095.0   4095.0       1.0        3.0    100.00       65.0
2      2400.0    1200.0   1200.0       1.0        2.0     60.00       25.0
3      3822.0    1920.0   1280.0       2.0        3.0    101.00       32.0
```

```
4      2052.0    1600.0   1200.0       1.0        2.0      54.00        20.0
…        …         …        …          …          …        …
3705   2311.0    3960.0   3960.0       1.0        3.0      92.59        50.0
3706   4750.0    2112.0   2112.0       1.0        2.0      95.00        48.0
3707   1692.0    1674.0   1116.0       1.0        2.0      94.00        31.0
3708   2358.0    1944.0   1296.0       1.0        2.0     100.00        36.0
3709   4892.0    2128.0   1064.0       2.0        1.5      97.83        38.0

      BuiltFAR  ResidFAR  FacilFAR  Cluster
0         0.42      0.60       1.0       -1
1         1.64      3.44       4.8       -1
2         0.50      0.90       2.0       -1
3         0.50      2.43       4.8       -1
4         0.78      0.60       1.0       -1
…          …         …         …         …
3705      1.71      2.43       4.8       -1
3706      0.44      0.90       2.0       -1
3707      0.99      0.90       2.0        0
3708      0.82      0.60       1.0        1
3709      0.43      1.25       2.0       -1

[3710 rows x 11 columns]
```

[87]:
```python
dbdf["Cluster"].value_counts()
```

[87]:
```
-1    2884
 0     662
 2      94
 1      70
Name: Cluster, dtype: int64
```

-1 are Outliers, hence need to be removed from table

[88]:
```python
dbdf
```

[88]:
```
      LotArea  BldgArea  ResArea  NumBldgs  NumFloors  LotDepth  BldgDepth  \
0      4000.0    1692.0   1692.0       2.0        2.0    100.00       30.0
1      2500.0    4095.0   4095.0       1.0        3.0    100.00       65.0
2      2400.0    1200.0   1200.0       1.0        2.0     60.00       25.0
3      3822.0    1920.0   1280.0       2.0        3.0    101.00       32.0
4      2052.0    1600.0   1200.0       1.0        2.0     54.00       20.0
…        …         …        …          …          …        …
3705   2311.0    3960.0   3960.0       1.0        3.0     92.59       50.0
3706   4750.0    2112.0   2112.0       1.0        2.0     95.00       48.0
3707   1692.0    1674.0   1116.0       1.0        2.0     94.00       31.0
3708   2358.0    1944.0   1296.0       1.0        2.0    100.00       36.0
3709   4892.0    2128.0   1064.0       2.0        1.5     97.83       38.0
```

```
      BuiltFAR  ResidFAR  FacilFAR  Cluster
0         0.42      0.60       1.0       -1
1         1.64      3.44       4.8       -1
2         0.50      0.90       2.0       -1
3         0.50      2.43       4.8       -1
4         0.78      0.60       1.0       -1
…          …         …        …        …
3705      1.71      2.43       4.8       -1
3706      0.44      0.90       2.0       -1
3707      0.99      0.90       2.0        0
3708      0.82      0.60       1.0        1
3709      0.43      1.25       2.0       -1

[3710 rows x 11 columns]
```

[89]:
```
db2 = dbdf[dbdf["Cluster"] != -1]
```

[90]:
```
db2
```

[90]:
```
      LotArea  BldgArea  ResArea  NumBldgs  NumFloors  LotDepth  BldgDepth  \
8      1710.0    1539.0   1188.0       1.0        2.0     95.00      33.00
9      1699.0    1728.0   1152.0       1.0        2.0     90.00      32.00
12     1900.0    1980.0   1440.0       1.0        2.0    100.00      36.00
14     4257.0    2484.0   2484.0       1.0        2.0    100.00      46.33
17     2720.0    1820.0   1280.0       1.0        2.0    109.98      35.00
…        …        …        …        …        …        …        …
3696   1710.0    1849.0   1296.0       1.0        2.0     95.00      34.00
3699   3092.0    1782.0   1188.0       1.0        2.0    100.00      30.00
3700   1966.0    1975.0   1406.0       1.0        2.0    100.00      37.00
3707   1692.0    1674.0   1116.0       1.0        2.0     94.00      31.00
3708   2358.0    1944.0   1296.0       1.0        2.0    100.00      36.00

      BuiltFAR  ResidFAR  FacilFAR  Cluster
8         0.90      0.90       2.0        0
9         1.02      0.90       2.0        0
12        1.04      0.90       2.0        0
14        0.58      0.90       2.0        0
17        0.67      0.90       2.0        0
…          …         …        …        …
3696      1.08      0.90       2.0        0
3699      0.58      0.90       2.0        0
3700      1.00      1.25       2.0        0
3707      0.99      0.90       2.0        0
3708      0.82      0.60       1.0        1

[826 rows x 11 columns]
```

[91]:
```
db2['Cluster'].value_counts()
```

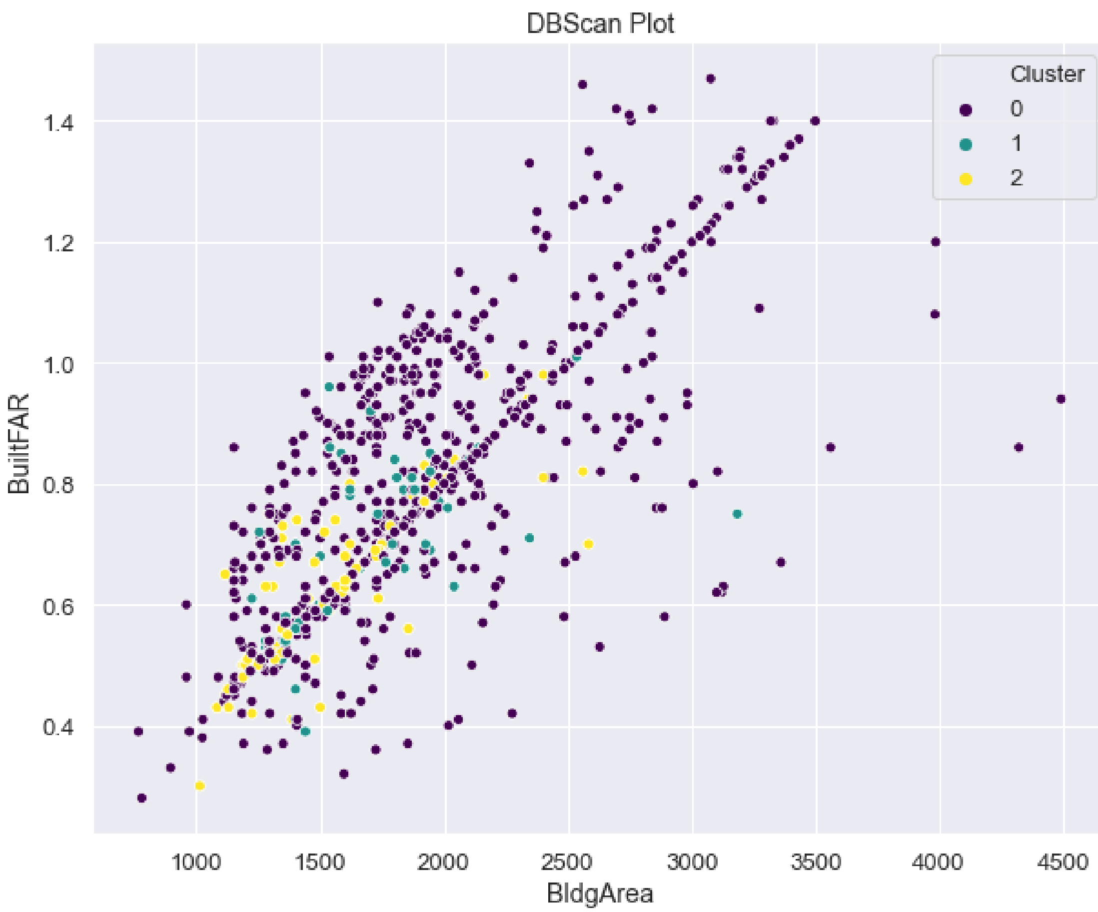
[91]:
```
0    662
2     94
1     70
Name: Cluster, dtype: int64
```

[92]:
```
meandb = db2.groupby(by='Cluster').mean()
```

[93]:
```
meandb
```

[93]:
```
             LotArea     BldgArea      ResArea  NumBldgs  NumFloors  \
Cluster
0        2413.030211  1975.611782  1601.099698       1.0   1.995227
1        2464.071429  1662.914286  1360.100000       1.0   2.000000
2        2483.595745  1567.340426  1414.872340       2.0   1.997340

          LotDepth  BldgDepth  BuiltFAR  ResidFAR  FacilFAR
Cluster
0        99.116526  40.402175  0.840136  1.011329       2.0
1        98.834857  35.477429  0.684571  0.598571       1.0
2        98.965319  37.320957  0.636277  0.944149       2.0
```

[94]:
```
x_axis = db2['BldgArea']
y_axis = db2['BuiltFAR']
plt.figure(figsize=(10,8))
sns.scatterplot(x_axis,y_axis,hue=db2['Cluster'],palette='viridis')
plt.title('DBScan Plot')
plt.show()
```



Analysis of DBSCAN Plot:

The clusters 0, 1 and 2 are totally mixed up together, hence the model is unable to differentiate the data

0.3.1 A paragraph explaining which of your Unsupervised Learning models you recommend as a final model that best fits your needs in terms.

We would recommend Hierarchical Model since there is more clearer separation of clusters and the mean values of building features are clearly seen.

0.3.2 Summary Key Findings and Insights, which walks your reader through the main findings of your modeling exercise

The summary concludes with the best clustering model to be implemented with clear separation of clusters.

0.3.3 Suggestions for next steps in analyzing this data, which may include suggesting revisiting this model or adding specific data features to achieve a better model

There are other clustering methods can be used: Mean Shift, HDBSCAN, OPTICS methods which need to be explored in future. Another method is compress the dataset using Principal Component Analysis and then use the 3 models to see any result improvements.