Using Machine Learning to Create Price Prediction for Tokyo Based Real Estate Company with Python

Part A: Data Processing and Exploratory Data Analysis (EDA)

By Shahin Karami

This Notebook is split into 2 steps. Step 1 will take Real Estate Data from Tokyo Japan (data is sourced from Kaggle) and prepare it for EDA, Correlation analysis, and eventually Regression analysis using Machine Learning. I will focus on removing unnecessary columns, duplicate values and missing values. Once the data is properly cleaned I move to Step 2, which is to conduct basic EDA with the help of `SweetViz`. I also remove outliers using the Median Absolute Deviation. By the conclusion of this notebook I will have prepped the data for all forms of analysis, and will have taken the first step in that analysis via EDA.

Step 1: Data Preprocessing

First I will prep the data for EDA.

1 - Imports and Data Import

The data used for this project comes Kaggle. The Kaggle Dataset has real estate data from all 47 prefectures in Japan. For this project I use a subsample of the Tokyo prefecture data that only has 20,000 data points.

In [1]:
```
import pickle
import matplotlib
from scipy.stats import median_abs_deviation

import pandas as pd
import numpy as np
import sweetviz as sv
import seaborn as sns

import matplotlib.pyplot as plt
import matplotlib.mlab as mlab
from matplotlib.pyplot import figure

plt.style.use('ggplot')
%matplotlib inline
```

In [2]:
```
df = pd.read_csv('TokyoSub.csv')
```

---

2 - Removing Unessasary Columns

First I observe the dimensionality of the data, then I proceed to remove the columns that I will not be using for EDA.

In [3]:
```
df.shape
```

Out[3]:
```
(20000, 35)
```

In [4]:
```
df = df.drop(['MunicipalityCode', 'Prefecture', 'Region', 'DistrictName', 'NearestStation','MinT
              'AreaIsGreaterFlag', 'FrontageIsGreaterFlag', 'TotalFloorArea',
              'TotalFloorAreaIsGreaterFlag', 'PrewarBuilding', 'Purpose', 'Classification', 'Bre
              'CityPlanning', 'CoverageRatio', 'FloorAreaRatio', 'Period', 'Year','Quarter','Rem
```

In [5]:
```
df.head(5)
```

Out[5]:

	Type	Municipality	TimeToNearestStation	TradePrice	FloorPlan	Area	LandShape	Frontage
0	Pre-owned Condominiums, etc.	Chiyoda Ward	4	40000000	1LDK	30	NaN	NaN
1	Pre-owned Condominiums, etc.	Chiyoda Ward	4	130000000	3LDK	80	NaN	NaN
2	Residential Land(Land and Building)	Chiyoda Ward	2	400000000	NaN	110	Trapezoidal Shaped	9.0
3	Residential Land(Land and Building)	Chiyoda Ward	1	180000000	NaN	50	Rectangular Shaped	5.2
4	Pre-owned Condominiums, etc.	Chiyoda Ward	4	100000000	2LDK	65	NaN	NaN

---

3 - Change Column's Name

I rename some columns to make the data easier to interpret. I change the name of the column based on the following:

- `TimeToNearestStation` : `MinuteToClosestStation`
- `TradePrice` : `Price`

In [6]:
```
col_name = ['Type', 'Municipality','MinuteToClosestStation',
       'Price', 'FloorPlan', 'Area', 'LandShape', 'Frontage',
       'BuildingYear', 'Structure', 'Use', 'Direction', 'Renovation']

df.columns = col_name
df.head(5)
```

Out[6]:

	Type	Municipality	MinuteToClosestStation	Price	FloorPlan	Area	LandShape	Frontag
0	Pre-owned Condominiums, etc.	Chiyoda Ward	4	40000000	1LDK	30	NaN	Nal
1	Pre-owned Condominiums, etc.	Chiyoda Ward	4	130000000	3LDK	80	NaN	Nal
2	Residential Land(Land and Building)	Chiyoda Ward	2	400000000	NaN	110	Trapezoidal Shaped	9.
3	Residential Land(Land and Building)	Chiyoda Ward	1	180000000	NaN	50	Rectangular Shaped	5.
4	Pre-owned Condominiums, etc.	Chiyoda Ward	4	100000000	2LDK	65	NaN	Nal

---

4 - Dealing with Missing Values

I create a for loop to iterate among all columns to determine whether they have any `NaN` or not. This Loop provides the number of null values in every single column as well as the percentage of null values.

In [7]:

```
for col in df.columns:
    number_null = df.loc[: , col].isnull().sum()
    perc_null = (number_null / df.shape[0]) * 100
    print('{} -- {} -- {}%'.format(col, number_null, round(perc_null,3)))
```

```
Type -- 0 -- 0.0%
Municipality -- 0 -- 0.0%
MinuteToClosestStation -- 137 -- 0.685%
Price -- 0 -- 0.0%
FloorPlan -- 3153 -- 15.765%
Area -- 0 -- 0.0%
LandShape -- 16848 -- 84.24%
Frontage -- 17053 -- 85.265%
BuildingYear -- 710 -- 3.55%
Structure -- 488 -- 2.44%
Use -- 2208 -- 11.04%
Direction -- 16847 -- 84.235%
Renovation -- 4917 -- 24.585%
```

The result above shows we have a wide range of `NaN` present in the data. Some features contain a small amount of `NaN` while other contain a large amount of NaNs. Since I have a large dataset I have created a trivial breakdown of how I will go about it the `NaN` within each feature:

Numerical Features:

- between 0% and 30%, I impute with mean or median.

- More than 30%, I drop the rows.

Categorical Features:

- less than 5%, I drop the rows.
- between 5% and 30%, I impute with mode.
- More than 30%, create a new label as `Other`.

NOTE: *By no means do I claim this method to be the 'correct' method. However, for the sake of this project this method will suffice.*

I first focus on the categorical values. I impute `Renovation`, `FloorPlan` and `Use` with mode.

In [8]:
```
mode_Renovation = df['Renovation'].mode()[0]
mode_Use = df['Use'].mode()[0]
mode_FloorPlan = df['FloorPlan'].mode()[0]

print(mode_Renovation)
print(mode_Use)
print(mode_FloorPlan)
```

```
Not yet
House
1K
```

In [9]:
```
df['Renovation'] = df['Renovation'].fillna('Not yet')
df['Use'] = df['Use'].fillna('House')
df['FloorPlan'] = df['FloorPlan'].fillna('1K')
```

Then, I created a new label for missing values in `LandShape` and `Direction`.

In [10]:
```
df['LandShape'] = df['LandShape'].fillna('Other LandShape')
df['Direction'] = df['Direction'].fillna('Other Direction')
```

Lastly, I drop any row with `NaNs` in the `Structure` columns

In [11]:
```
df = df.dropna(subset = ['Structure'])
```

Now, I will shift my focus to the Numerical Features. I will impute `MinuteToClosestStation` and `BuildingYear`. However, before doing this, I must make sure about distribution shape of these columns to see whether they are right-skewed or left-skewed. It can be helpful when I want to decide choosing mean or median for imputing. Also, I will check the data type of theses variables to confirm their numerical type.

In [12]:
```
print(df['MinuteToClosestStation'].dtypes)
print(df['BuildingYear'].dtypes)
```

```
object
float64
```

`MinuteToClosestStation` is an object type. This means there are some non-numerical values in this column. This should be handled first. Below we will confirm the presense of non-numerical values and instruct python to coerce those instances as a `NaN`.

In [13]:
```
df['MinuteToClosestStation'].unique()
```

Out[13]:
```
array(['4', '2', '1', nan, '3', '5', '6', '0', '7', '11', '10', '8', '9',
       '12', '30-60minutes', '13', '14', '16', '15', '19', '18', '21',
       '2H-', '17'], dtype=object)
```

In [14]:
```
df['MinuteToClosestStation'] = pd.to_numeric(df['MinuteToClosestStation'], errors='coerce')
df['MinuteToClosestStation'].unique()
```

Out[14]:
```
array([ 4.,  2.,  1., nan,  3.,  5.,  6.,  0.,  7., 11., 10.,  8.,  9.,
       12., 13., 14., 16., 15., 19., 18., 21., 17.])
```

Now we can see its distribution to determine whether to use Mean or Median

In [15]:
```
skewness_MTCS = round(df['MinuteToClosestStation'].skew() ,3)
print('Skewness :' , skewness_MTCS)

def approximately_zero(skewness, tolerance= 1):
    if abs(skewness) <= tolerance:
        print("The data is not heavily skewed, use the Mean. ")
    else:
        print("The data is heavily skewed, use the Median. ")
    return

approximately_zero(skewness_MTCS)
```

```
Skewness : 1.103
The data is heavily skewed, use the Median.
```

The result above tells me that I should opt to use the Median when I impute.

In [16]:
```
df['MinuteToClosestStation'] = df['MinuteToClosestStation'].fillna(df['MinuteToClosestStation'].
```

Next I run the same process for `BuildingYear`

In [17]:
```
skewness_BY = round(df['BuildingYear'].skew() ,3)
print('Skewness :' , skewness_BY)

approximately_zero(skewness_BY)
```

```
Skewness : -0.933
The data is not heavily skewed, use the Mean.
```

The result above tells me that I should opt to use the Mean when I impute.

In [18]:
```
df['BuildingYear'] = df['BuildingYear'].fillna(df['BuildingYear'].mean()).round(0)
```

The last change i need to do is to drop the `NaNs` found in the `Frontage` columns

In [19]:
```
df = df.dropna(subset = ['Frontage'])
```

Now that I have completed all imputions I conduct I final check in the updated data.

In [20]:
```
for col in df.columns:
    number_null = df.loc[: , col].isnull().sum()
    perc_null = (number_null / df.shape[0]) * 100
    print('{} - {} - %{}'.format(col, number_null, round(perc_null,3)))
```

```
Type - 0 - %0.0
Municipality - 0 - %0.0
MinuteToClosestStation - 0 - %0.0
Price - 0 - %0.0
FloorPlan - 0 - %0.0
Area - 0 - %0.0
LandShape - 0 - %0.0
Frontage - 0 - %0.0
BuildingYear - 0 - %0.0
Structure - 0 - %0.0
Use - 0 - %0.0
Direction - 0 - %0.0
Renovation - 0 - %0.0
```

---

5 - Removing any Duplicates Entries.

Now that all the `NaNs` have been handled, I can focus on removing any potential duplicated. I will first check to see if the data contains duplicates, then proceed accordingly.

In [21]:
```
duplicate_rows = df.duplicated()

if duplicate_rows.any():
    print("The DataFrame has duplicate rows.")
else:
    print("The DataFrame does not have duplicate rows.")
```

```
The DataFrame has duplicate rows.
```

Since we have duplicates rows, lets find them and list them out in a DataFrame

In [22]:
```
duplicate_rows = df[df.duplicated(keep = False)]
duplicate_rows = pd.DataFrame(duplicate_rows)
duplicate_rows
```

Out[22]:

	Type	Municipality	MinuteToClosestStation	Price	FloorPlan	Area	LandShape	Frontag
4986	Residential Land(Land and Building)	Chuo Ward	2.0	230000000	1K	80	Rectangular Shaped	7
4994	Residential Land(Land and Building)	Chuo Ward	2.0	230000000	1K	80	Rectangular Shaped	7
9353	Residential Land(Land and Building)	Minato Ward	1.0	360000000	1K	160	Rectangular Shaped	8
9354	Residential Land(Land and Building)	Minato Ward	1.0	360000000	1K	160	Rectangular Shaped	8
14686	Residential Land(Land and Building)	Shinjuku Ward	5.0	59000000	1K	50	Rectangular Shaped	7
14690	Residential Land(Land and Building)	Shinjuku Ward	5.0	59000000	1K	50	Rectangular Shaped	7
18342	Residential Land(Land and Building)	Shinjuku Ward	4.0	400000000	1K	145	Semi-rectangular Shaped	9
18343	Residential Land(Land and Building)	Shinjuku Ward	4.0	400000000	1K	145	Semi-rectangular Shaped	9

Now I check the shape of the data before and after dropping the duplicates. Finally I confirm that the data doesnt have any duplicates.

In [23]:

```
print("before: ", df.shape)

df = df.drop_duplicates(keep='first')
print("after: ", df.shape)
```

```
before:  (2765, 13)
after:  (2761, 13)
```

In [24]:

```
duplicate_rows = df.duplicated()

if duplicate_rows.any():
    print("The DataFrame has duplicate rows.")
else:
    print("The DataFrame does not have duplicate rows.")
```

```
The DataFrame does not have duplicate rows.
```

---

6 - Checking the Numerical Variables

Now I want to check each numerical variable for any possible non-numerical values. This check is nessasary as numeric values can be classified as an `int`, `float`, or even a `str` The columns that are of intrest are: `Area`, `Frontage`, `MinuteToClosestStation`, `BuildingYear`, `Price`. Since I only have five numerical variables to check, I will manually check each one

In [25]:
```
print(df.Area.apply(type).value_counts())
print(df.Frontage.apply(type).value_counts())
print(df.MinuteToClosestStation.apply(type).value_counts())
print(df.BuildingYear.apply(type).value_counts())
print(df.Price.apply(type).value_counts())
```

```
<class 'int'>    2761
Name: Area, dtype: int64
<class 'float'>    2761
Name: Frontage, dtype: int64
<class 'float'>    2761
Name: MinuteToClosestStation, dtype: int64
<class 'float'>    2761
Name: BuildingYear, dtype: int64
<class 'int'>    2761
Name: Price, dtype: int64
```

Luckily, each numerical variable consist of either an `int` or `float`. Moreover, each variable has exactly 2761 values, which is the number of rows that our current dataframe, as seen below.

In [26]:
```
df.shape
```

Out[26]:
```
(2761, 13)
```

---

7 - Checking the Categorical Variables

Lastly, I will check the values of the categoreical variable. These variables are: `Type`, `Municipality`, `FloorPlan`, `LandShape`, `Structure`, `Direction`, `Use`, `Renovation`. It is important to check the categorical variables as some may have multiple values according to the documentations found on the Kaggle page associated with the data found here.

Type

In [27]:
```
print(df['Type'].unique())
```

```
['Residential Land(Land and Building)']
```

In [28]:
```
print(df['Type'].value_counts())
```

```
Residential Land(Land and Building)    2761
Name: Type, dtype: int64
```

Municipality

In [29]:
```
print(df['Municipality'].unique())
```

```
['Chiyoda Ward' 'Chuo Ward' 'Minato Ward' 'Shinjuku Ward' 'Bunkyo Ward']
```

In [30]:
```
print(df['Municipality'].value_counts())
```

```
Shinjuku Ward    1015
Minato Ward       660
Chuo Ward         581
Chiyoda Ward      434
Bunkyo Ward        71
Name: Municipality, dtype: int64
```

FloorPlan

In [31]:
```
print(df['FloorPlan'].unique())
```

```
['1K']
```

In [32]:
```
print(df['FloorPlan'].value_counts())
```

```
1K    2761
Name: FloorPlan, dtype: int64
```

LandShape

In [33]:
```
print(df['LandShape'].unique())
```

```
['Trapezoidal Shaped' 'Rectangular Shaped' 'Semi-rectangular Shaped'
 'Semi-trapezoidal Shaped' 'Irregular Shaped' 'Semi-shaped'
 'Semi-square Shaped' 'Flag-shaped etc.' 'Square Shaped' 'Other LandShape']
```

In [34]:
```
print(df['LandShape'].value_counts())
```

```
Semi-rectangular Shaped    1014
Rectangular Shaped          731
Irregular Shaped            423
Semi-trapezoidal Shaped     197
Semi-square Shaped          157
Semi-shaped                 111
Trapezoidal Shaped           78
Flag-shaped etc.             28
Square Shaped                21
Other LandShape               1
Name: LandShape, dtype: int64
```

Structure

In [35]:
```
print(df['Structure'].unique())
```

```
['S' 'RC' 'SRC' 'W' 'LS' 'S, LS' 'B' 'SRC, RC' 'S, W' 'RC, W' 'RC, S'
 'W, B']
```

It seems that some of the `Structure` values are a combination of two different Structure types (ex. `'S, LS'`). For simplicity my strategy will be to split these values up and only keep the first Structure type (ex. split `'S, LS'` and only keep `'S'`)

In [36]:
```
df['Structure'] = df['Structure'].apply(lambda x: x.split(',')[0])
```

In [37]:
```
print(df['Structure'].value_counts())
```

```
RC      1014
W        795
S        551
SRC      348
LS        50
B          3
Name: Structure, dtype: int64
```

Direction

In [38]:
```
print(df['Direction'].unique())
```

```
['Northwest' 'Southwest' 'South' 'Northeast' 'East' 'Southeast' 'West'
 'North' 'No facing road']
```

In [39]:
```
print(df['Direction'].value_counts())
```

```
Northwest         382
Southwest         373
Southeast         371
West              344
Northeast         335
South             329
East              307
North             304
No facing road     16
Name: Direction, dtype: int64
```

Use

In [40]:
```
print(df['Use'].unique())
```

```
['Office, Shop' 'Housing Complex, Office' 'House, Office, Workshop'
 'House, Office, Shop' 'Other' 'Office, Warehouse' 'Parking Lot'
 'Office, Parking Lot' 'Housing Complex, Office, Shop' 'House' 'Office'
 'Housing Complex' 'Housing Complex, Shop' 'House, Shop' 'Warehouse, Shop'
 'Housing Complex, Office, Warehouse, Shop' 'House, Workshop, Shop'
 'Warehouse' 'House, Office' 'Office, Warehouse, Parking Lot'
 'House, Factory, Office, Shop' 'House, Office, Other' 'Shop'
 'House, Office, Warehouse, Shop' 'Office, Other'
 'Office, Warehouse, Shop' 'House, Warehouse, Shop, Other' 'Workshop'
 'House, Office, Parking Lot' 'Office, Workshop, Warehouse' 'Factory'
 'House, Warehouse' 'House, Housing Complex, Factory, Warehouse'
 'Office, Parking Lot, Shop' 'House, Factory, Office'
 'Housing Complex, Office, Warehouse, Parking Lot'
 'House, Office, Warehouse' 'House, Workshop' 'House, Office, Shop, Other'
 'House, Parking Lot' 'House, Parking Lot, Shop'
 'Housing Complex, Parking Lot' 'Housing Complex, Warehouse'
 'House, Factory' 'Warehouse, Parking Lot' 'Office, Warehouse, Other'
 'Housing Complex, Office, Parking Lot, Shop'
 'House, Office, Parking Lot, Shop' 'House, Other'
 'House, Warehouse, Shop' 'Shop, Other' 'House, Workshop, Warehouse, Shop'
 'House, Housing Complex, Office, Shop'
 'Housing Complex, Office, Warehouse' 'Office, Shop, Other'
 'House, Office, Warehouse, Parking Lot' 'Housing Complex, Other'
 'Workshop, Warehouse, Parking Lot' 'Factory, Office, Warehouse'
 'Factory, Office' 'House, Housing Complex, Factory, Office'
 'House, Workshop, Warehouse' 'Office, Workshop, Shop'
 'Housing Complex, Workshop' 'Office, Workshop' 'House, Shop, Other'
 'House, Office, Workshop, Shop'
 'House, Housing Complex, Office, Warehouse'
 'Housing Complex, Office, Workshop' 'House, Housing Complex, Office'
 'House, Warehouse, Other' 'House, Housing Complex, Shop'
 'House, Housing Complex, Workshop'
 'House, Housing Complex, Factory, Office, Workshop, Warehouse'
 'Housing Complex, Factory, Office, Parking Lot'
 'House, Housing Complex, Parking Lot'
 'House, Warehouse, Parking Lot, Shop' 'Housing Complex, Factory, Office'
 'Office, Parking Lot, Other' 'Housing Complex, Office, Parking Lot'
 'Housing Complex, Parking Lot, Shop'
 'Housing Complex, Workshop, Warehouse'
 'Housing Complex, Office, Warehouse, Parking Lot, Shop'
 'Housing Complex, Factory'
 'Housing Complex, Office, Warehouse, Shop, Other'
 'House, Housing Complex, Workshop, Shop'
 'Housing Complex, Warehouse, Parking Lot' 'House, Housing Complex'
 'Parking Lot, Shop' 'Housing Complex, Warehouse, Shop'
 'House, Housing Complex, Office, Workshop' 'Parking Lot, Other'
 'Workshop, Shop' 'House, Warehouse, Parking Lot'
 'House, Office, Parking Lot, Shop, Other'
 'House, Housing Complex, Parking Lot, Other'
 'House, Parking Lot, Shop, Other' 'Office, Warehouse, Parking Lot, Shop'
 'House, Office, Parking Lot, Other' 'Factory, Workshop'
 'Housing Complex, Office, Other'
 'House, Office, Warehouse, Parking Lot, Shop' 'Workshop, Warehouse'
 'Housing Complex, Factory, Shop'
 'House, Workshop, Warehouse, Parking Lot'
 'House, Office, Warehouse, Shop, Other' 'Factory, Office, Other'
 'Office, Workshop, Warehouse, Parking Lot'
 'Housing Complex, Workshop, Shop' 'Office, Parking Lot, Shop, Other'
 'House, Housing Complex, Office, Warehouse, Parking Lot']
```

Like with the `Structure` column, `Use` has entries that have a combination of values. Again, I will split them up and only consider the first `Use` value.

In [41]:
```
df['Use'] = df['Use'].apply(lambda x: x.split(',')[0])
```

In [42]:
```
print(df['Use'].value_counts())
```

```
House               1300
Office               705
Housing Complex      559
Shop                 117
Other                 43
Warehouse             18
Factory                9
Parking Lot            6
Workshop               4
Name: Use, dtype: int64
```

Renovation

In [43]:
```
print(df['Renovation'].unique())
```

```
['Not yet']
```

In [44]:
```
print(df['Renovation'].value_counts())
```

```
Not yet    2761
Name: Renovation, dtype: int64
```

Step 2 Exploratory Data Analysis (EDA)

Now that the Data is properly cleaned I can conduct Exploratory Data Analysis. Once this is completed I can move to Corraltion analysis and building a ML model (which will be done in a seperate Notebook).

1 - Discriptive Statical Analysis with SweetViz package

I recently discovered the SweetViz package. SweetViz is an open-source Python library that generates beautiful, high-density visualizations to kickstart EDA (Exploratory Data Analysis) with just two lines of code. Output is a fully self-contained HTML application or can be embedded within a Jupyter Notebook.

I opt to include the SweetViz visualization within the notebook. The great thing about SweetViz output is that it is fully interactive. Each tab contains basic statistical analysis of a Variable from the DataFrame. The `ASSOCIATIONS` button will provide a correlation matrix.

In [45]:
```
analyze_report = sv.analyze(df)
analyze_report.show_notebook()
```

```
                                    |          | [  0%]   00:00 -> (? left)
```

SweetVIZ

2.1.4

Get updates, docs & report issues here

Created & maintained by Francois Bertrand

Graphic design by Jean-Francois Hains

DataFrame

2761
0
1.6 MB
13
8
5
0

ASSOCIATIONS

DataFrame

1 Type

VALUES:	2,761 (100%)
MISSING:	---
DISTINCT:	1 (<1%)

Residential Land

2 Municipality

VALUES:	2,761 (100%)
MISSING:	---
DISTINCT:	5 (<1%)

3 MinuteToClosestStation

VALUES:	2,761 (100%)
MISSING:	---
DISTINCT:	17 (<1%)
ZEROES:	10 (<1%)

MAX	16.0
95%	9.0
Q3	6.0
AVG	4.6
MEDIAN	4.0
Q1	3.0
5%	1.0
MIN	0.0

RANGE	16.0
IQR	3.00
STD	2.58
VAR	6.68
KURT.	0.076
SKEW	0.724
SUM	12,597

4 Price

---

2 - Focusing in on Numerical Variables

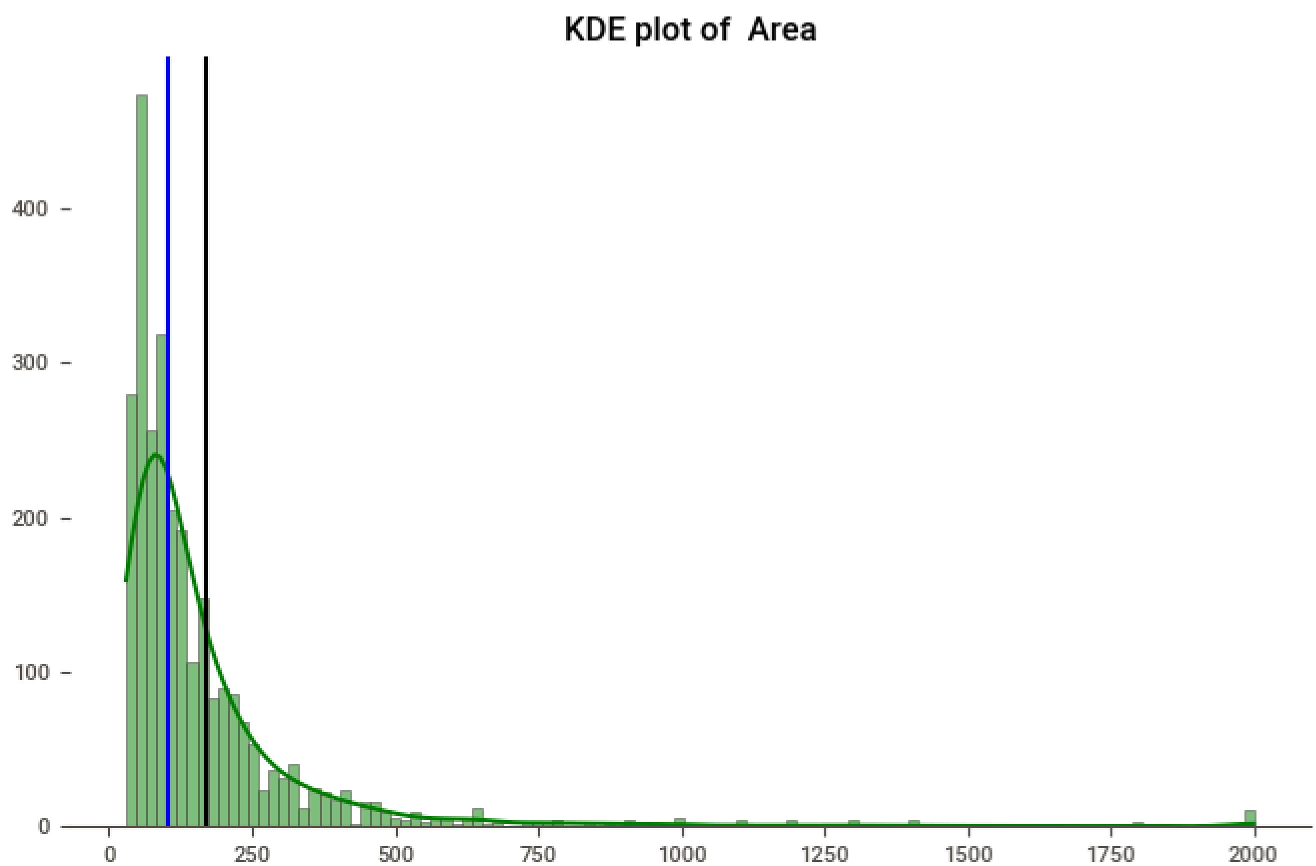
I feel it is important to focus in on the Numerical variables a bit more than what SweetViz has outputted. Specifically I will create a KDE plot for each Numerical Variables as well as provide a written interpretation for each Numerical Variables. Below I will generate a KDE for the Numerical variables as well as provide some interpretations using the SweetViz output.

First I create a function to plot the KDE along with the Mean in black and median in blue

In [46]:
```
def kde_plot(var):
```

```
    plt.figure(figsize = (8,5))
    sns.histplot(df[var], kde = True, color= 'green')
    sns.despine(left = True)

    mean = df[var].mean()
    median = df[var].median()

    plt.axvline(mean, color ='black', linestyle ='solid')
    plt.axvline(median, color ='blue', linestyle ='solid')
    plt.xlabel('')
    plt.ylabel('')
    plt.title("KDE plot of  {}".format(var))
    plt.legend

    return plt.show()
```

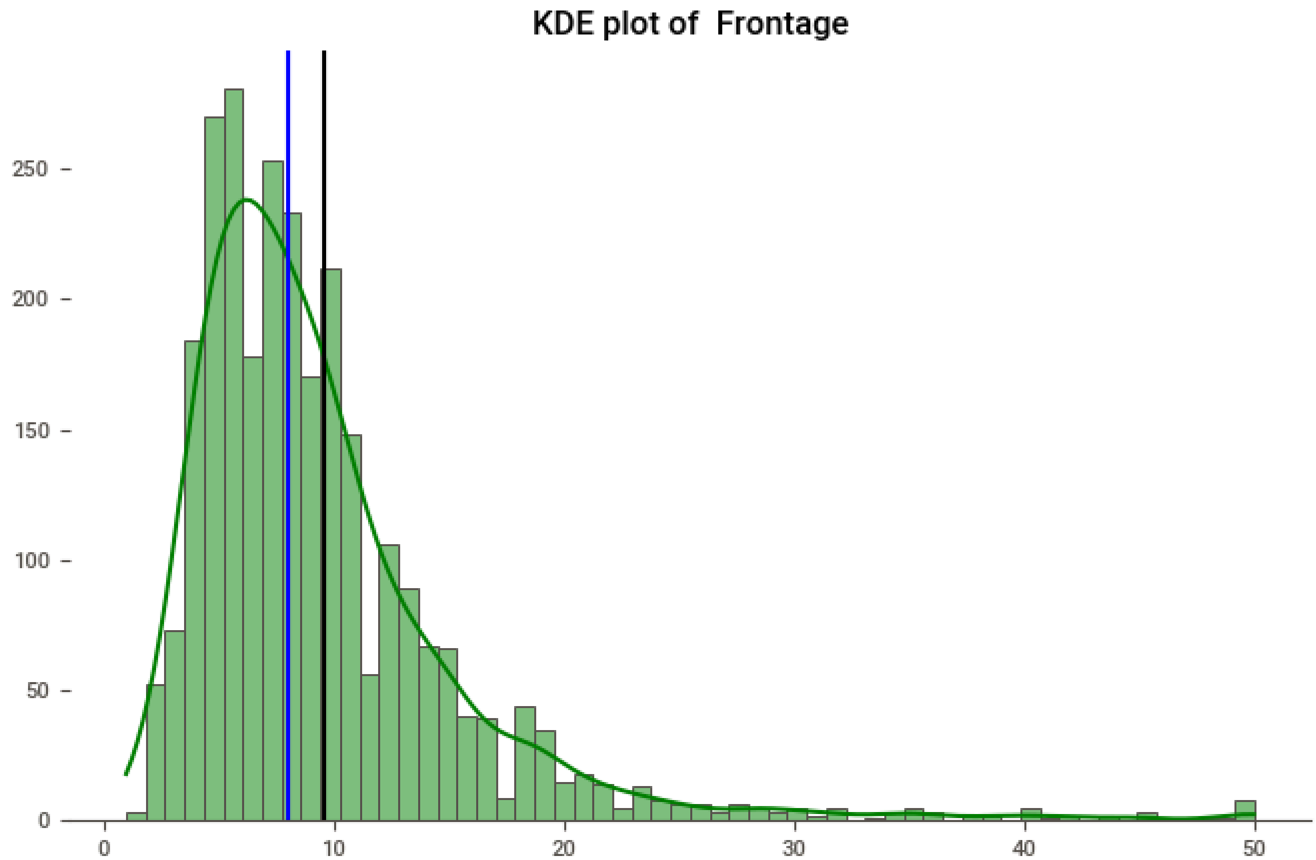
In [47]:
```
kde_plot('Area')
```



Notes on Area:

- The average Area is 170 square meters
- Maximum: 2000 square meters
- Minimum: 30 square meters
- Half of the real estate are less than 105 square meters
- 25% of the real estate have an area less than 65 square meters
- 75% of the real estate have an area greater than 190 square meters
- 50% of the real estate have an area between 65 and 190 square meters
- The KDE clearly shows that Area is skewed right

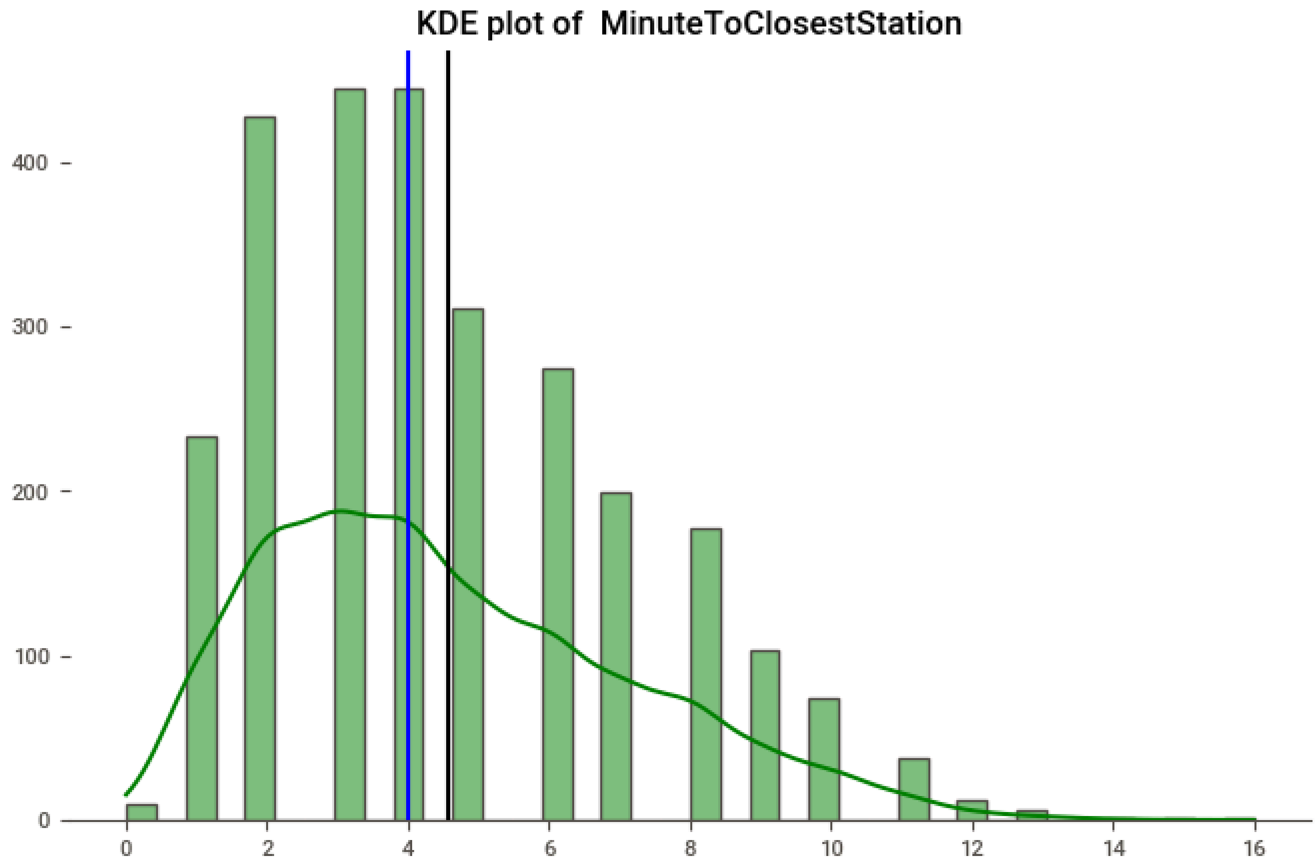
In [48]:
```
kde_plot('Frontage')
```



Notes on Frontage:

- The average Frontage is 9.6 meters
- Maximum: 50 meters
- Minimum: 1 meters
- Half of the real estate have Frontage that is less than 8 meters
- 25% of the real estate have Frontage that is less than 5.5 meters
- 75% of the real estate have Frontage that is greater than 11.5 meters
- 50% of the real estate have Frontage that is between 5.5 and 11.5 meters
- The KDE clearly shows that Frontage is skewed right

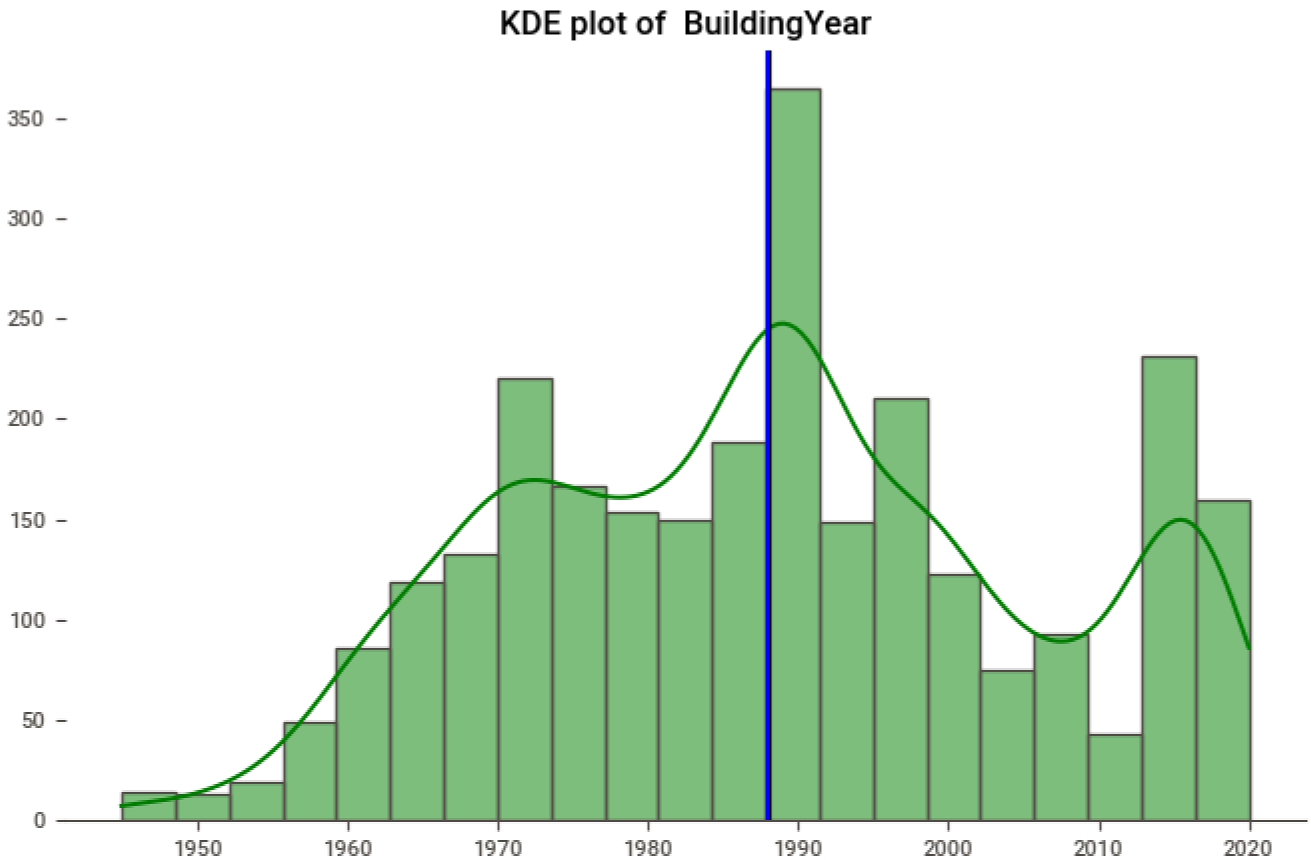
In [49]:
```
kde_plot('MinuteToClosestStation')
```



Notes on MinuteToClosestStation:

- The average time to nearest station is 4.6 minutes
- Maximum: 16 minutes to nearest station
- Minimum: less than 1 minute to nearest station
- Half of the real estate is less than 4 minutes to the nearest station
- 25% of the real estate is less than 3 minutes to the nearest station
- 75% of the real estate is greater than 6 minutes to the nearest station
- 50% of the real estate is between 3 and 6 minutes to the nearest station
- The KDE shows that the time to the nearest station resembles a normal distribution but is skewed right

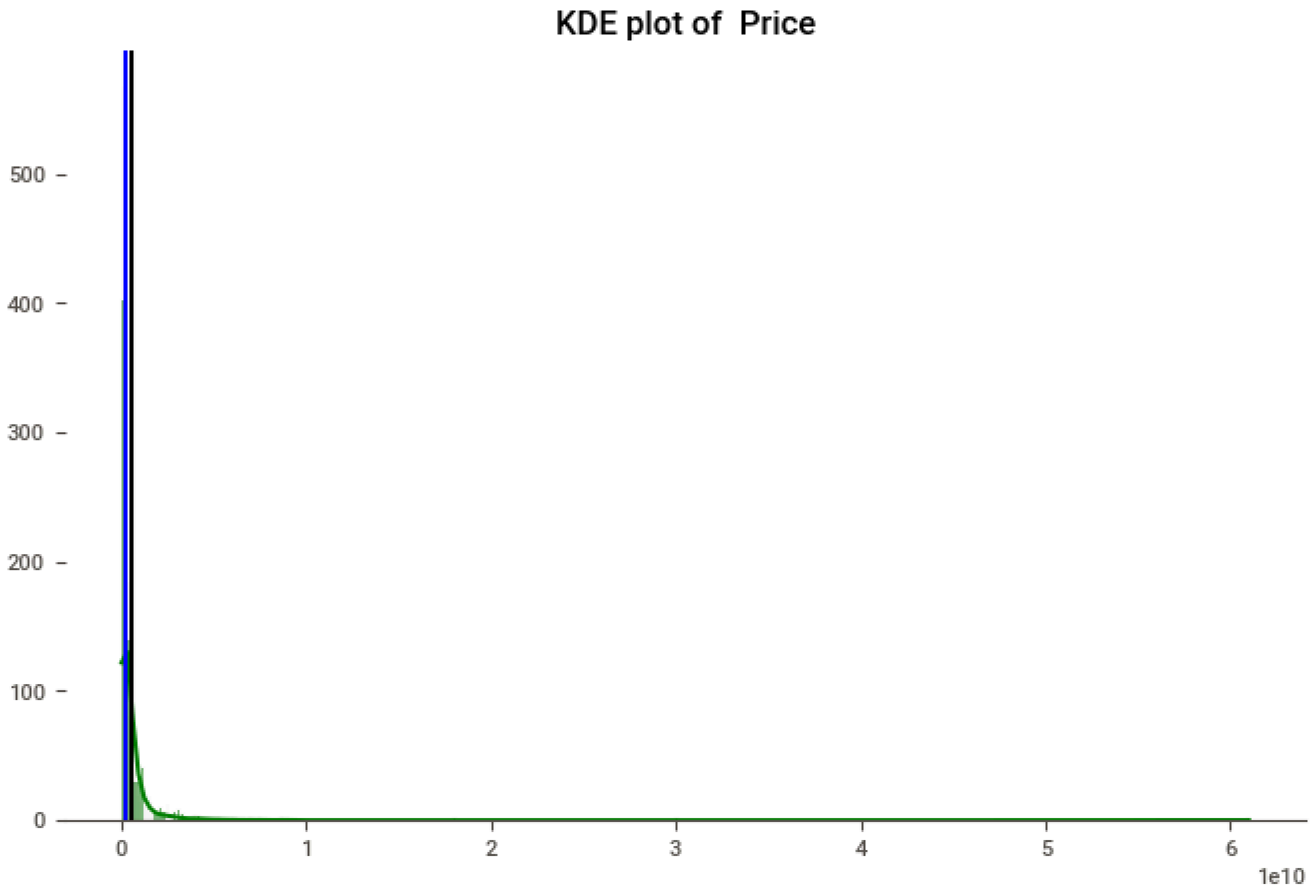
In [50]:
```
kde_plot('BuildingYear')
```



Notes on BuildingYear:

- The average year to build is 1987
- Maximum: The newest house was built in 2020
- Minimum: The oldest house was built in 1945
- Half of all the real estate was built before 1988
- 25% of all the real estate was built before or on 1974
- 75% of all the real estate was built before or on 2000
- 50% of all the real estate was built between 1974 and 2000
- The KDE shows that the distribution of building year is somewhere between a normal and bimodal distribution

In [51]:
```
kde_plot('Price')
```



Notes on Price:

- The average price was 0.5 billion Yen
- Maximum: 61 Billion Yen
- Minimum: 0Billion Yen
- Half of all the real estate is worth less than 0.2 billion Yen
- 25% of all the real estate is worth less than 0.1 billion Yen
- 75% of all the real estate is worth less than 0.5 billion Yen
- 50% of all the real estate is worth between 0.1 and 0.5
- The KDE shows that the distribution of price is extremely skewed right

---

Now I will present the real estate with the maximum and minimums of each numerical value. This is just so we can conduct some more of a visual analysis of the properties with maximum and minimum numerical traits.

Minimum Area

In [52]:
```
df[df['Area'] == df['Area'].min()]
```

Out[52]:

	Type	Municipality	MinuteToClosestStation	Price	FloorPlan	Area	LandShape	Frontag
419	Residential Land(Land and Building)	Chiyoda Ward	2.0	17000000	1K	30	Rectangular Shaped	4
2461	Residential Land(Land and Building)	Chuo Ward	1.0	320000000	1K	30	Rectangular Shaped	3
2499	Residential Land(Land and Building)	Chuo Ward	2.0	190000000	1K	30	Semi-rectangular Shaped	4
2525	Residential Land(Land and Building)	Chuo Ward	2.0	120000000	1K	30	Trapezoidal Shaped	5
3387	Residential Land(Land and Building)	Chuo Ward	2.0	50000000	1K	30	Rectangular Shaped	3
3388	Residential Land(Land and Building)	Chuo Ward	2.0	51000000	1K	30	Rectangular Shaped	3
5213	Residential Land(Land and Building)	Chuo Ward	3.0	150000000	1K	30	Semi-rectangular Shaped	3
5832	Residential Land(Land and Building)	Chuo Ward	3.0	36000000	1K	30	Rectangular Shaped	3
8425	Residential Land(Land and Building)	Minato Ward	8.0	43000000	1K	30	Semi-shaped	5
9040	Residential Land(Land and Building)	Minato Ward	4.0	27000000	1K	30	Semi-rectangular Shaped	7
9714	Residential Land(Land and Building)	Minato Ward	6.0	23000000	1K	30	Semi-rectangular Shaped	4
10367	Residential Land(Land and Building)	Minato Ward	4.0	24000000	1K	30	Semi-rectangular Shaped	3
11721	Residential Land(Land	Chuo Ward	4.0	9000000	1K	30	Semi-rectangular	4

	Type	Municipality	MinuteToClosestStation	Price	FloorPlan	Area	LandShape	Frontag
	and Building)						Shaped	
11993	Residential Land(Land and Building)	Shinjuku Ward	5.0	4500000	1K	30	Semi-square Shaped	3
12579	Residential Land(Land and Building)	Shinjuku Ward	4.0	17000000	1K	30	Rectangular Shaped	3
13260	Residential Land(Land and Building)	Shinjuku Ward	5.0	47000000	1K	30	Semi-trapezoidal Shaped	4
14636	Residential Land(Land and Building)	Chuo Ward	4.0	33000000	1K	30	Semi-rectangular Shaped	7
15144	Residential Land(Land and Building)	Shinjuku Ward	3.0	22000000	1K	30	Semi-rectangular Shaped	4
16219	Residential Land(Land and Building)	Minato Ward	2.0	40000000	1K	30	Irregular Shaped	3
16628	Residential Land(Land and Building)	Shinjuku Ward	5.0	20000000	1K	30	Rectangular Shaped	3
17544	Residential Land(Land and Building)	Shinjuku Ward	4.0	20000000	1K	30	Semi-rectangular Shaped	4
18388	Residential Land(Land and Building)	Chuo Ward	2.0	170000000	1K	30	Rectangular Shaped	3
18406	Residential Land(Land and Building)	Shinjuku Ward	0.0	140000000	1K	30	Irregular Shaped	7
18527	Residential Land(Land and Building)	Shinjuku Ward	8.0	21000000	1K	30	Semi-shaped	6
19082	Residential Land(Land and Building)	Bunkyo Ward	5.0	39000000	1K	30	Irregular Shaped	7

	Type	Municipality	MinuteToClosestStation	Price	FloorPlan	Area	LandShape	Frontag
19750	Residential Land(Land and Building)	Bunkyo Ward	5.0	37000000	1K	30	Rectangular Shaped	4
19988	Residential Land(Land and Building)	Bunkyo Ward	6.0	40000000	1K	30	Rectangular Shaped	3
19989	Residential Land(Land and Building)	Bunkyo Ward	6.0	36000000	1K	30	Rectangular Shaped	3

Maximum Area

In [53]:
```
df[df['Area'] == df['Area'].max()]
```

Out[53]:

	Type	Municipality	MinuteToClosestStation	Price	FloorPlan	Area	LandShape	Front
1053	Residential Land(Land and Building)	Chiyoda Ward	6.0	7000000000	1K	2000	Rectangular Shaped	
6465	Residential Land(Land and Building)	Minato Ward	1.0	30000000000	1K	2000	Irregular Shaped	
6662	Residential Land(Land and Building)	Minato Ward	7.0	7500000000	1K	2000	Irregular Shaped	
9930	Residential Land(Land and Building)	Minato Ward	3.0	6600000000	1K	2000	Semi-rectangular Shaped	
11060	Residential Land(Land and Building)	Minato Ward	9.0	4700000000	1K	2000	Irregular Shaped	
15053	Residential Land(Land and Building)	Minato Ward	6.0	7000000000	1K	2000	Semi-square Shaped	
15142	Residential Land(Land and Building)	Minato Ward	1.0	4000000000	1K	2000	Semi-rectangular Shaped	
15812	Residential Land(Land and Building)	Chuo Ward	7.0	14000000000	1K	2000	Semi-shaped	
17597	Residential Land(Land and Building)	Shinjuku Ward	5.0	3900000000	1K	2000	Semi-shaped	
17778	Residential Land(Land and Building)	Shinjuku Ward	9.0	4400000000	1K	2000	Irregular Shaped	
18711	Residential Land(Land and Building)	Minato Ward	4.0	61000000000	1K	2000	Irregular Shaped	

Minimum Frontage

In [54]:

```
df[df['Frontage'] == df['Frontage'].min()]
```

Out[54]:

	Type	Municipality	MinuteToClosestStation	Price	FloorPlan	Area	LandShape	Frontage
17351	Residential Land(Land and Building)	Shinjuku Ward	8.0	7600000	1K	40	Flag-shaped etc.	1.0

Maximum Frontage

In [55]:
```
df[df['Frontage'] == df['Frontage'].max()]
```

Out[55]:

	Type	Municipality	MinuteToClosestStation	Price	FloorPlan	Area	LandShape	Front
6465	Residential Land(Land and Building)	Minato Ward	1.0	30000000000	1K	2000	Irregular Shaped	
9930	Residential Land(Land and Building)	Minato Ward	3.0	6600000000	1K	2000	Semi-rectangular Shaped	
15812	Residential Land(Land and Building)	Chuo Ward	7.0	14000000000	1K	2000	Semi-shaped	
16263	Residential Land(Land and Building)	Minato Ward	3.0	2700000000	1K	1300	Semi-rectangular Shaped	
16268	Residential Land(Land and Building)	Shinjuku Ward	6.0	1900000000	1K	1400	Semi-rectangular Shaped	
17597	Residential Land(Land and Building)	Shinjuku Ward	5.0	3900000000	1K	2000	Semi-shaped	
17778	Residential Land(Land and Building)	Shinjuku Ward	9.0	4400000000	1K	2000	Irregular Shaped	
18711	Residential Land(Land and Building)	Minato Ward	4.0	61000000000	1K	2000	Irregular Shaped	

Minimum Time to Nearest Station

In [56]:
```
df[df['MinuteToClosestStation'] == df['MinuteToClosestStation'].min()]
```

Out[56]:

	Type	Municipality	MinuteToClosestStation	Price	FloorPlan	Area	LandShape	Fronta
3722	Residential Land(Land and Building)	Chuo Ward	0.0	3800000000	1K	390	Semi-rectangular Shaped	1
4961	Residential Land(Land and Building)	Chuo Ward	0.0	140000000	1K	50	Semi-rectangular Shaped	
5181	Residential Land(Land and Building)	Chuo Ward	0.0	2500000000	1K	470	Irregular Shaped	1
5259	Residential Land(Land and Building)	Chuo Ward	0.0	58000000	1K	60	Rectangular Shaped	
5790	Residential Land(Land and Building)	Chuo Ward	0.0	110000000	1K	45	Rectangular Shaped	
13500	Residential Land(Land and Building)	Chuo Ward	0.0	200000000	1K	55	Semi-rectangular Shaped	
14363	Residential Land(Land and Building)	Shinjuku Ward	0.0	2300000000	1K	240	Semi-trapezoidal Shaped	1
18406	Residential Land(Land and Building)	Shinjuku Ward	0.0	140000000	1K	30	Irregular Shaped	
18614	Residential Land(Land and Building)	Minato Ward	0.0	2300000000	1K	300	Rectangular Shaped	1
19603	Residential Land(Land and Building)	Minato Ward	0.0	520000000	1K	75	Trapezoidal Shaped	

Maximum Time to Nearest Station

In [57]:
```
df[df['MinuteToClosestStation'] == df['MinuteToClosestStation'].max()]
```

Out[57]:

	Type	Municipality	MinuteToClosestStation	Price	FloorPlan	Area	LandShape	Frontag
19975	Residential Land(Land and Building)	Minato Ward	16.0	110000000	1K	85	Semi-square Shaped	8.

Minimum Building Year

In [58]:

```
df[df['BuildingYear'] == df['BuildingYear'].min()]
```

Out[58]:

	Type	Municipality	MinuteToClosestStation	Price	FloorPlan	Area	LandShape	Fronta
504	Residential Land(Land and Building)	Chiyoda Ward	1.0	80000000	1K	55	Rectangular Shaped	
505	Residential Land(Land and Building)	Chiyoda Ward	1.0	100000000	1K	55	Rectangular Shaped	
2580	Residential Land(Land and Building)	Chuo Ward	1.0	2400000000	1K	125	Semi-square Shaped	1
3339	Residential Land(Land and Building)	Chuo Ward	2.0	22000000	1K	35	Rectangular Shaped	
3357	Residential Land(Land and Building)	Chuo Ward	4.0	18000000	1K	40	Rectangular Shaped	[illegible]
3364	Residential Land(Land and Building)	Chuo Ward	3.0	55000000	1K	75	Semi-rectangular Shaped	
3417	Residential Land(Land and Building)	Chuo Ward	3.0	18000000	1K	35	Rectangular Shaped	
3472	Residential Land(Land and Building)	Chuo Ward	4.0	16000000	1K	40	Rectangular Shaped	[illegible]
7875	Residential Land(Land and Building)	Minato Ward	9.0	490000000	1K	640	Semi-rectangular Shaped	2
13458	Residential Land(Land and Building)	Shinjuku Ward	4.0	300000000	1K	310	Semi-rectangular Shaped	1
17626	Residential Land(Land and Building)	Minato Ward	3.0	700000000	1K	340	Irregular Shaped	1
19954	Residential Land(Land and Building)	Bunkyo Ward	4.0	9000000	1K	35	Rectangular Shaped	

Maximum Building Year

In [59]:
```
df[df['BuildingYear'] == df['BuildingYear'].max()]
```

Out[59]:

	Type	Municipality	MinuteToClosestStation	Price	FloorPlan	Area	LandShape	Frontage
17895	Residential Land(Land and Building)	Shinjuku Ward	5.0	76000000	1K	75	Flag-shaped etc.	2.5

Minimum Price

In [60]:
```
df[df['Price'] == df['Price'].min()]
```

Out[60]:

	Type	Municipality	MinuteToClosestStation	Price	FloorPlan	Area	LandShape	Frontage	B
7392	Residential Land(Land and Building)	Minato Ward	4.0	520000	1K	45	Semi-rectangular Shaped	5.0	

Maximum Price

In [61]:
```
df[df['Price'] == df['Price'].max()]
```

Out[61]:

	Type	Municipality	MinuteToClosestStation	Price	FloorPlan	Area	LandShape	Front
18711	Residential Land(Land and Building)	Minato Ward	4.0	61000000000	1K	2000	Irregular Shaped	

---

3 - Outliers

In the previous sections, we saw some variables have outliers, and before wrapping up the EDA I want to address this issue. The biggest outliers are seen in `Price` and looking at the correlation matrix in the SweetViz dashboard I see that `Price` is correlated to Area. So, with some feature engineering I will handle these outliers. To start, I will first create a new feature Price per Area: `PPA`

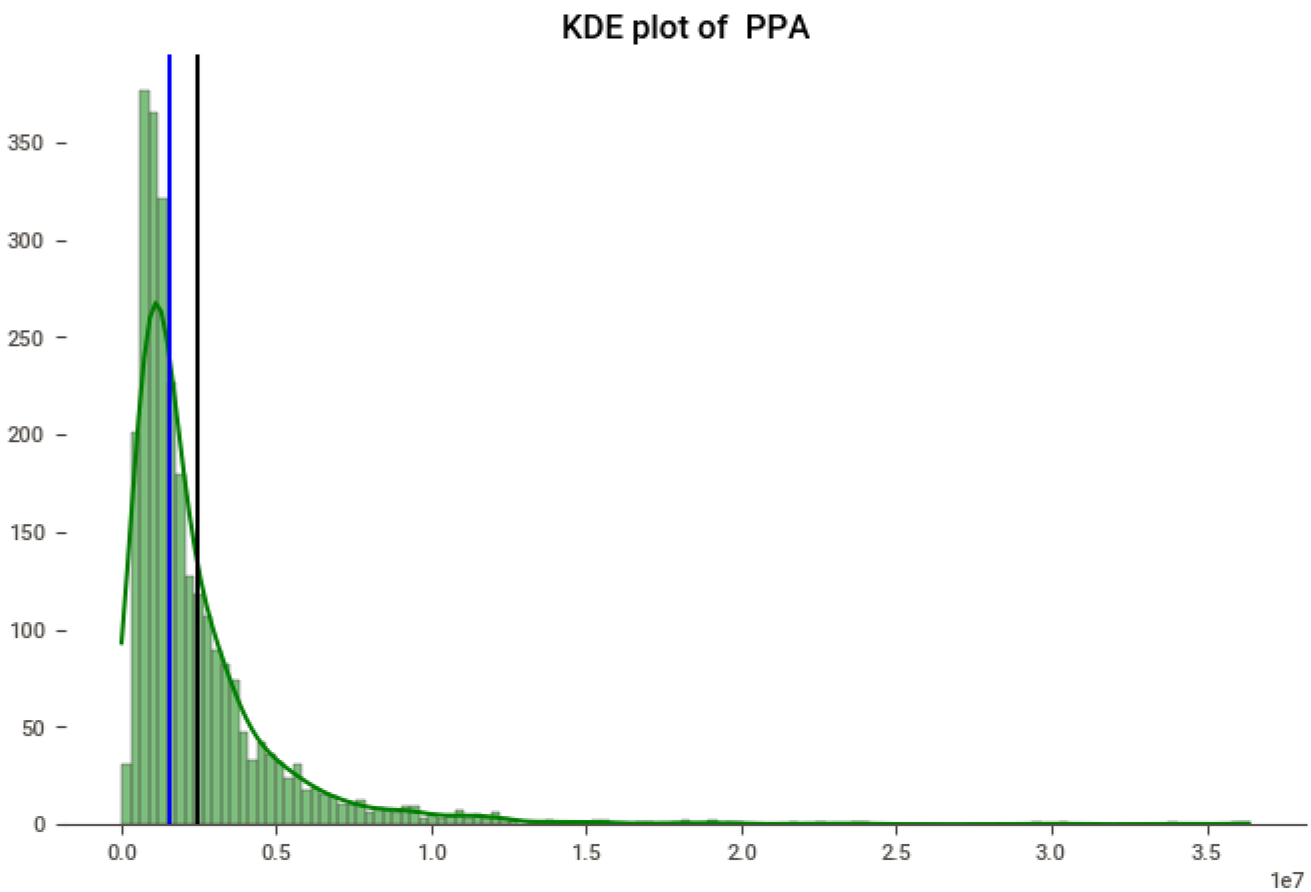
In [62]:
```
df['PPA'] = df['Price'] / df['Area']
df.head(2)
```

Out[62]:

	Type	Municipality	MinuteToClosestStation	Price	FloorPlan	Area	LandShape	Frontage	B
2	Residential Land(Land and Building)	Chiyoda Ward	2.0	400000000	1K	110	Trapezoidal Shaped	9.0	
3	Residential Land(Land and Building)	Chiyoda Ward	1.0	180000000	1K	50	Rectangular Shaped	5.2	

Now the KDE of `PPA`

In [63]:
```
kde_plot('PPA')
```



The KDE shows that `PPA` is extremely right skewed and contains very large outlier. Therfore we cannot methods like z-score, as `PPA` does not behave normally. Instead, I will use the Median Absolute Deviation (MAD) technique. This is a robust method for distribution with a heavy outlier effect. More information on the MAD can be found here. I will calculate the MAD of `PPA` using the `scipy.stats` library below.

In [64]:
```
median_abs_deviation(df["PPA"])
```

Out[64]: 788888.8888888889

Now, I filter dataset (removing outlier) based on the MAD technique.

In [65]:
```
median_prices = {"Tokyo": median_abs_deviation(df["PPA"])}
```

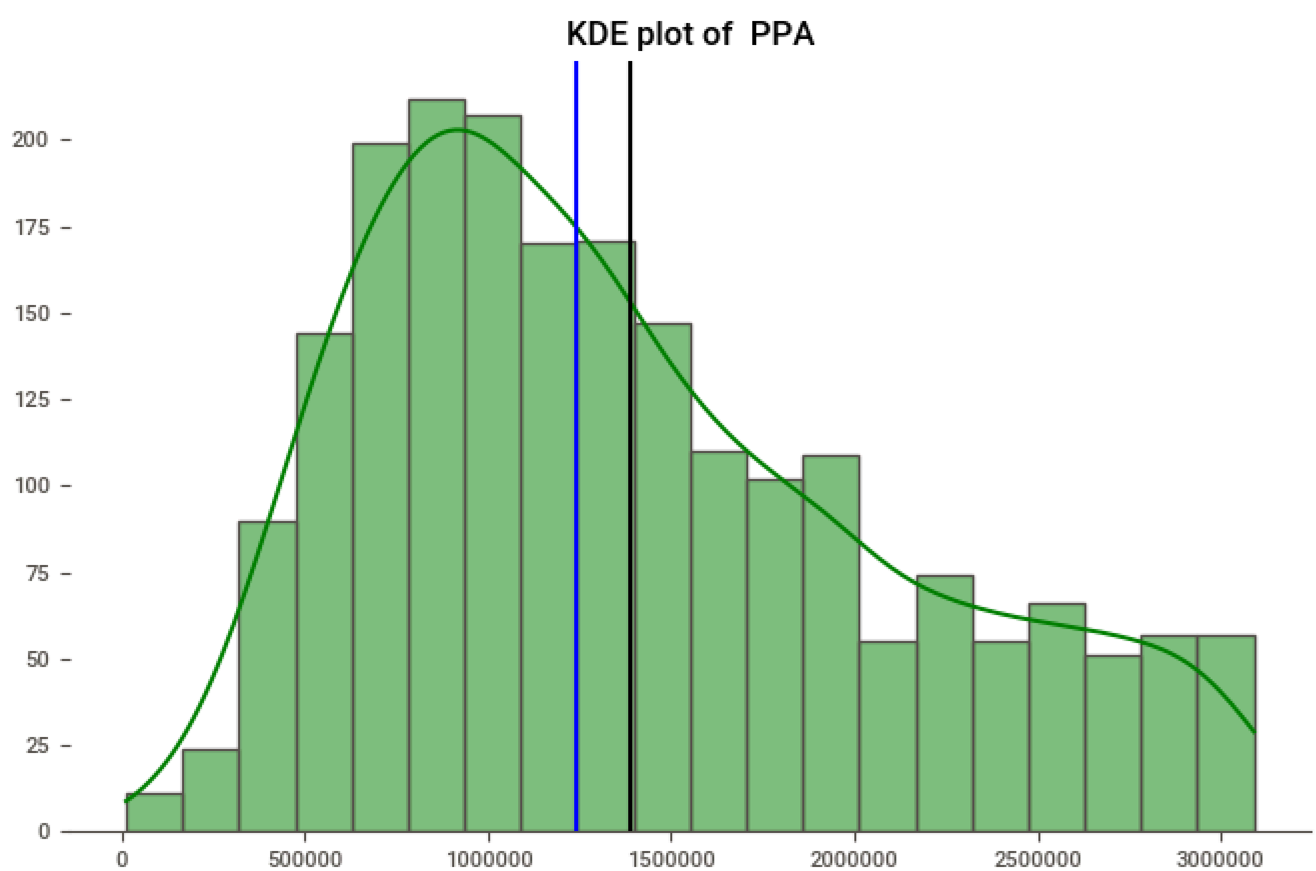
```
#call province median from the dictionary
Median = median_prices["Tokyo"]

#difference between each price_per_area with the called median
df['Median_Diff'] = 0

for index, row in df.iterrows():
    median_diff = abs(row['PPA'] - Median)
    df.at[index, 'Median_Diff'] = median_diff

#calculate the median of new column
MAD = df['Median_Diff'].median()

#determine treshold
threshold = MAD * 3

#detect and filter rows based on outlier
df = df[~(df['Median_Diff'] > threshold)]

#remove the differenece column
df = df.drop(['Median_Diff'], axis=1)
```

In [66]:
```
df.shape
```

Out[66]:
```
(2111, 14)
```

Note that the shape of the Dataframe has been reduced, an indication that outliers have been removed. We can check the KDE of `PPA` once again and visually confirm the removal of extreme outliers.

In [67]:
```
kde_plot('PPA')
```



Now that we removed outliers based on `PPA` we can remove the `PPA` column, reset the index, and proceed to save our processed dataframe using the `pickle` package.

In [68]:
```
df=df.drop(['PPA'], axis=1)
```

In [69]:
```
df = df[df.Use != 'Parking Lot']
```

---

4 - Saving Data using `pickle`

This concludes the first part of this project. Using the `pickle` package I will save our current dataframe. In the next part I will continue this project.

In [929...
```
with open('TokyoSub_Final.pickle', 'wb') as file:
    pickle.dump(df, file)
```
