COMP 4605 SPRING 2021

Project: Analyzing Airbnb House Data in Istanbul And Amount Of Waste in Istanbul

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Abstract

Since 2008, Airbnb has gained a serious position in the real estate market with the use of tourists. In this research, together with the 2020 Istanbul Airbnb Open Data, it was a research where I compared the amount of household waste between 2004 and 2020 according to Istanbul districts, analyzed and answered my hypotheses.

Importing Libraries

In [1]:
```
import pandas as pd
import numpy as np
import seaborn as sea
import matplotlib.pyplot as plt
import matplotlib.image as mpimg
from sklearn.linear_model import LinearRegression
from sklearn.preprocessing import PolynomialFeatures
from sklearn.model_selection import train_test_split
from scipy import stats
```

First of all we need to load datasets

I am merging two datasets which are Istanbul Airbnb dataset and Amount of Waste in Istanbul

In [2]:
```
a = pd.read_csv("listings.csv")
b = pd.read_csv("evselatik.csv")
data = pd.merge(a, b,
                   on='neighbourhood',
                   how='left')
```

In [3]:
```
data.head(100)
```

Out[3]:

	id	name	host_id	host_name	neighbourhood_group	neighbourhood	latitude	longitude	room_type	price	...	2011	201
0	4826	The Place	6603	Kaan	NaN	Uskudar	41.05650	29.05367	Entire home/apt	720	...	194,205	197,94
1	20815	The Bosphorus from The Comfy Hill	78838	Gülder	NaN	Besiktas	41.06984	29.04545	Entire home/apt	816	...	108,720	111,26
2	27271	LOVELY APT. IN PERFECT LOCATION	117026	Mutlu	NaN	Beyoglu	41.03254	28.98153	Entire home/apt	233	...	125,928	124,27
3	28277	Duplex Apartment with Terrace	121607	Alen	NaN	Sisli	41.04471	28.98567	Hotel room	761	...	163,506	170,53
4	28318	Cosy home overlooking Bosphorus	121721	Aydin	NaN	Sariyer	41.09048	29.05559	Entire home/apt	823	...	114,470	117,48
...	...	...	...	...	...	...	...	...	...	...	...	...	..
95	265772	Furnished Flats & Historical Room	1393796	Hülya	NaN	Sisli	41.05458	28.98672	Private room	274	...	163,506	170,53
96	270561	Room minuet 2TRAM Street,Yusufpasha اتفضلوااهل...	1351134	Bãśmä	NaN	Fatih	41.01077	28.94512	Private room	96	...	229,842	240,95
97	270883	only 10 minutes to Sultanahmet	1417732	Tayfun	NaN	Fatih	41.02480	28.94738	Entire home/apt	384	...	229,842	240,95
98	271439	Charming Delightful Studio@Centre 3	466302	Demir	NaN	Beyoglu	41.02669	28.97594	Entire home/apt	213	...	125,928	124,27
99	274454	Galateia Apartments,1 BR up to 4	1435301	Galateia	NaN	Beyoglu	41.02961	28.97643	Entire home/apt	1310	...	125,928	124,27

100 rows × 34 columns

Before starting analyze, I start by extracting data that won't work for me in my analysis and filling the 0 value for null values

In [4]:
```
data.drop(['name','id','host_id','host_name','last_review','neighbourhood_group'], axis=1, inplace=True)
data['reviews_per_month'].fillna(0, inplace=True)
a.drop(['name','id','host_id','host_name','last_review','neighbourhood_group'], axis=1, inplace=True)
a['reviews_per_month'].fillna(0, inplace=True)
```

Lets check data types of dataset before use them

In [5]:
```
data.dtypes
```

Out[5]:
```
neighbourhood                      object
latitude                          float64
longitude                         float64
room_type                          object
price                               int64
minimum_nights                      int64
number_of_reviews                   int64
reviews_per_month                 float64
calculated_host_listings_count      int64
availability_365                    int64
Veri Türü (Data Type)              object
2004                               object
2005                               object
2006                               object
2007                               object
2008                               object
2009                               object
2010                               object
2011                               object
2012                               object
2013                               object
2014                               object
2015                               object
2016                               object
2017                               object
2018                               object
2019                               object
2020                               object
dtype: object
```

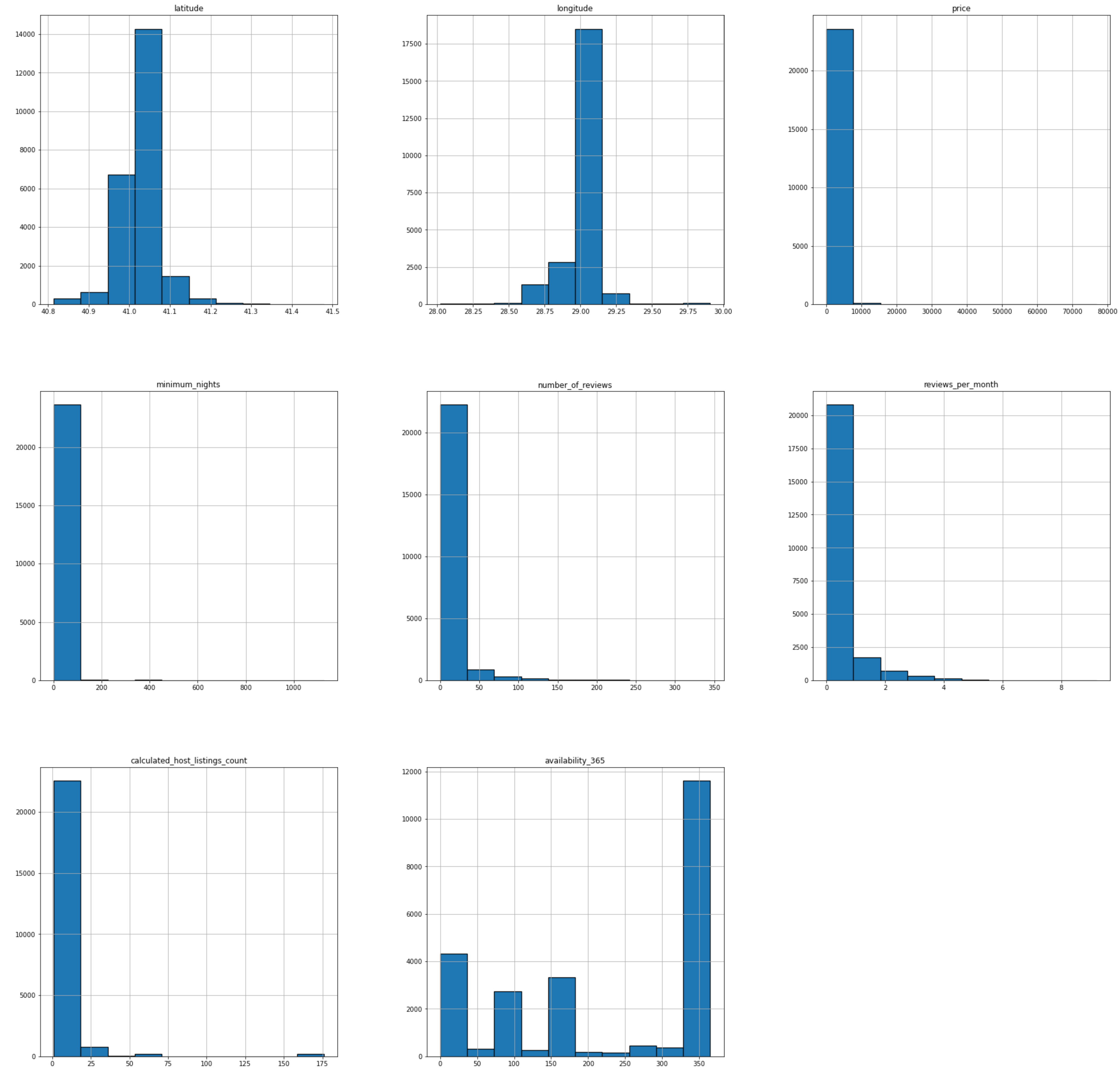
In [6]:
```
data.describe()
```

Out[6]:

	latitude	longitude	price	minimum_nights	number_of_reviews	reviews_per_month	calculated_host_listings_count	availability_:
count	23728.000000	23728.000000	23728.000000	23728.000000	23728.000000	23728.000000	23728.000000	23728.000
mean	41.028416	28.982111	484.643248	4.525202	7.870828	0.339794	5.861767	227.709
std	0.045713	0.127503	1973.884093	27.614191	23.229127	0.718269	16.535368	146.607
min	40.813960	28.019010	0.000000	1.000000	0.000000	0.000000	1.000000	0.000
25%	41.005120	28.973210	137.000000	1.000000	0.000000	0.000000	1.000000	89.000
50%	41.031850	28.983485	247.000000	1.000000	0.000000	0.000000	2.000000	302.000
75%	41.048530	29.020050	446.000000	3.000000	4.000000	0.300000	5.000000	365.000
max	41.479030	29.907780	76922.000000	1125.000000	345.000000	9.200000	176.000000	365.000

Let's examine the distribution of data by column by extracting histogram of our data

In [7]:
```
data.hist(edgecolor="black", linewidth=1.2, figsize=(30, 30));
```



In [8]:
```
categorical_col = []
for column in data.columns:
    if column == "neighbourhood" or column == "room_type":
        categorical_col.append(column)
categorical_col
```

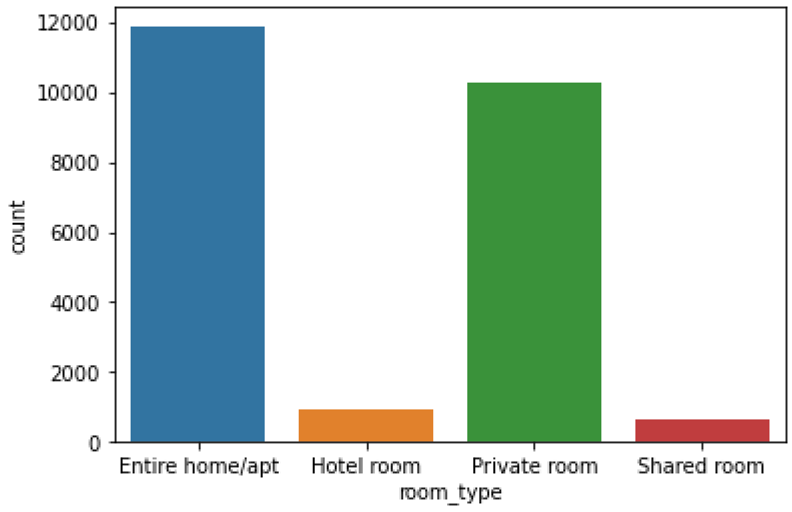
Out[8]:
```
['neighbourhood', 'room_type']
```

Which house type is the most in the listings?

At first, when we examined our dataset, we noticed that there were advertisements for different room types.

Let's examine which type of room is on the dataset using bar char. Looking at the results, we see that we have the most home listings in general and the least shared room listings

In [9]:
```
compareRoom = sea.countplot(x="room_type", data=data)
```



We need to check the data we have for anything that's not worth it. In this way, we can achieve more realistic results in our analysis.

In [10]:
```
data.isnull().sum()
```

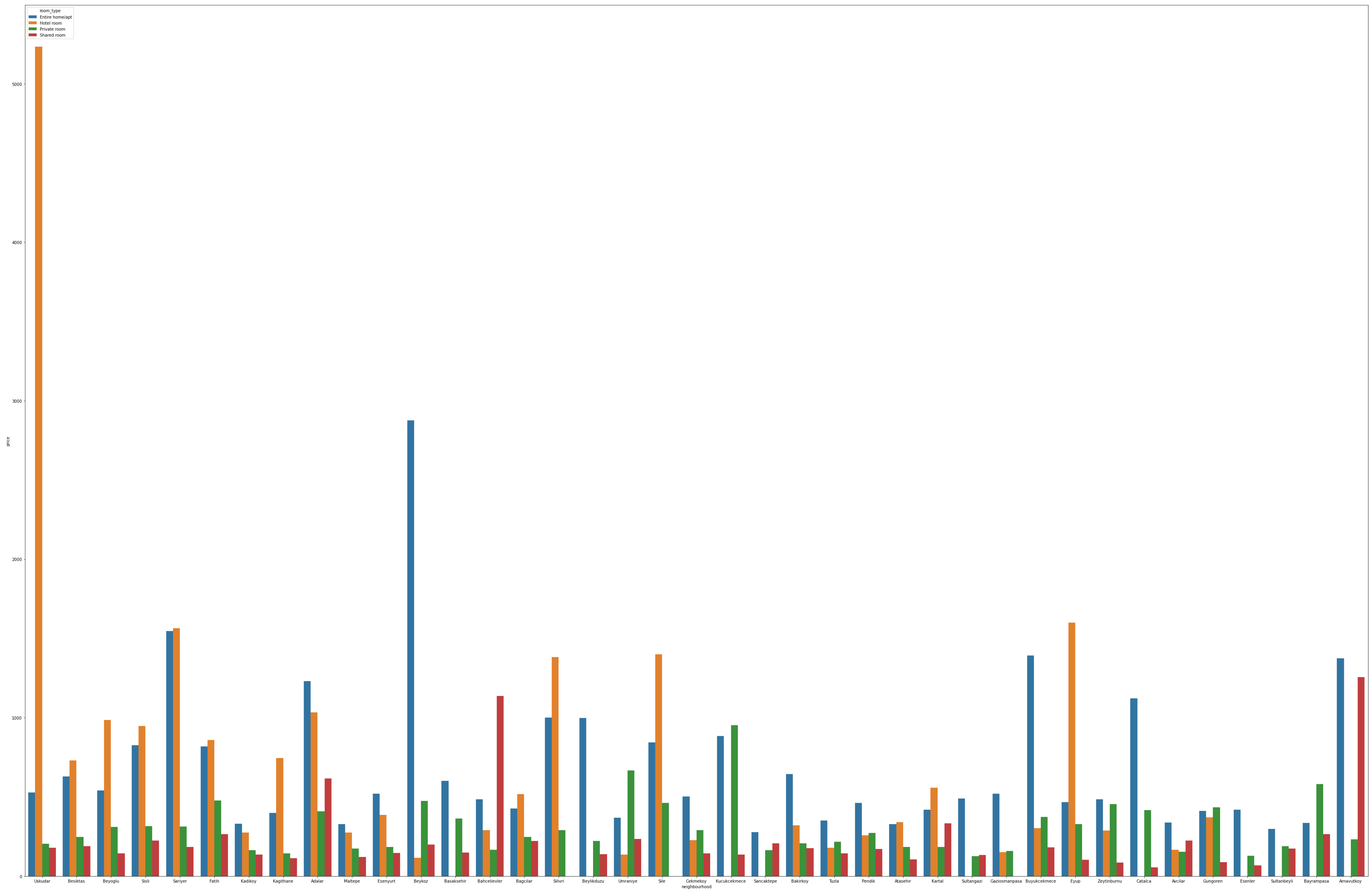
Out[10]:
```
neighbourhood                     0
latitude                          0
longitude                         0
room_type                         0
price                             0
minimum_nights                    0
number_of_reviews                 0
reviews_per_month                 0
calculated_host_listings_count    0
availability_365                  0
Veri Türü (Data Type)             0
2004                              0
2005                              0
2006                              0
2007                              0
2008                              0
2009                              0
2010                              0
2011                              0
2012                              0
2013                              0
2014                              0
2015                              0
2016                              0
2017                              0
2018                              0
2019                              0
2020                              0
dtype: int64
```

According the result we can see that we do not have any null value so We can move forward more reliably

Let's examine the changes in the prices of room typæes according to the districts with the help of graphics. In this way, we can find the district for the type of house we want in accordance with our budget.

In [11]:
```
plt.figure(figsize=(60, 40))
neighbourhood = data.neighbourhood
price = data.price
roomType = data.room_type
sea.barplot(x=neighbourhood, y=price, hue=roomType, ci=None)
```

Out[11]:
```
<AxesSubplot:xlabel='neighbourhood', ylabel='price'>
```



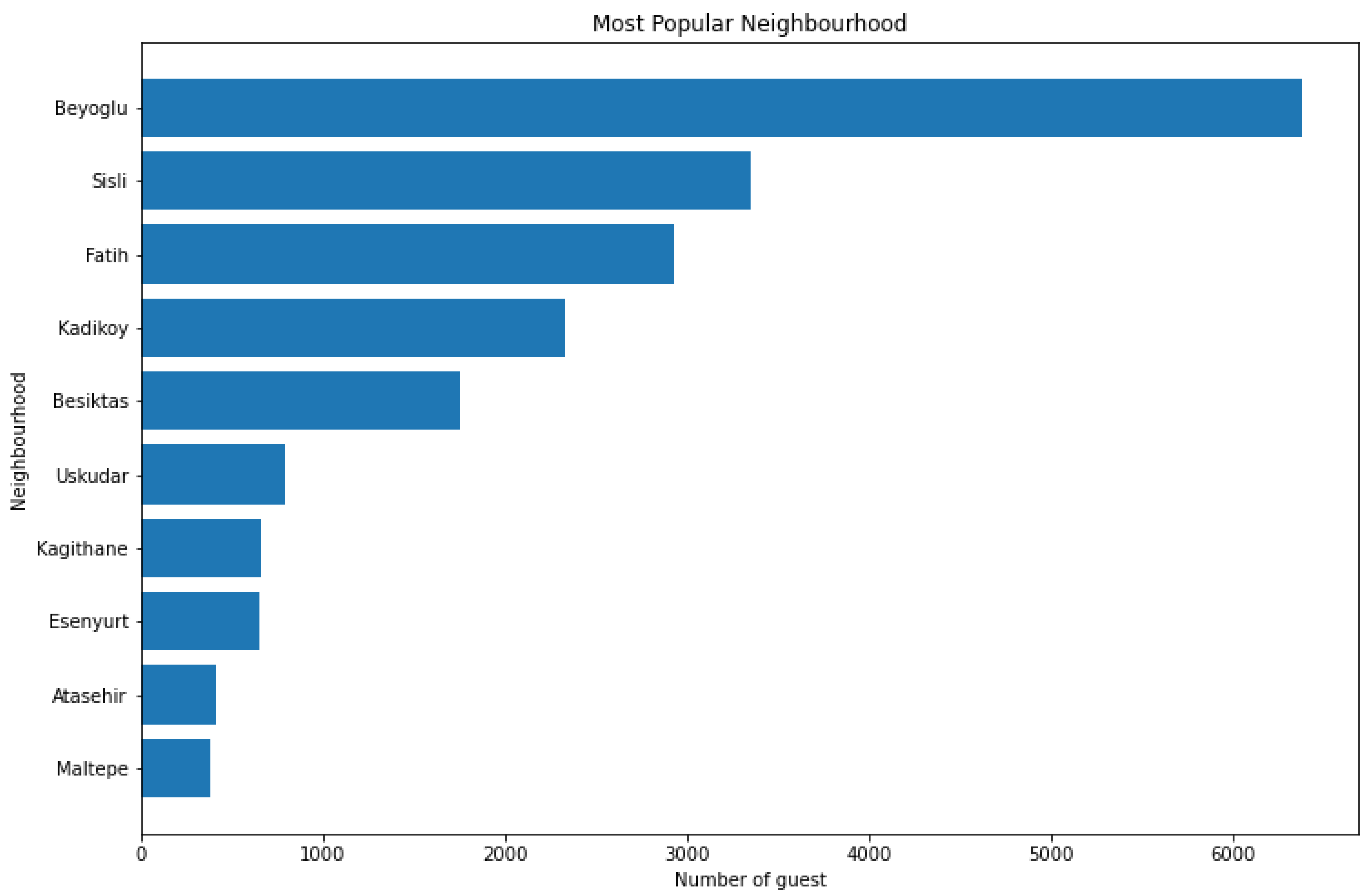
According to our data, we see that the most expensive hotel is in Üsküdar, the most expensive house advertisement is in Beykoz, the most expensive private room is in Küçükçekmece and the most expensive common room is in Arnavutköy.

Which neighborhood has the most home listings?

Let's examine the 10 neighbourhood that host the top 10 neighbourhood

In [12]:
```
dataNeighbour = data.neighbourhood.value_counts()[:10]
plt.figure(figsize=(12, 8))
xNeighbour = list(dataNeighbour.index)
yNeighbour = list(dataNeighbour.values)
xNeighbour.reverse()
yNeighbour.reverse()
plt.title("Most Popular Neighbourhood")
plt.ylabel("Neighbourhood")
plt.xlabel("Number of guest")

plt.barh(xNeighbour, yNeighbour)
```

Out[12]:
```
<BarContainer object of 10 artists>
```



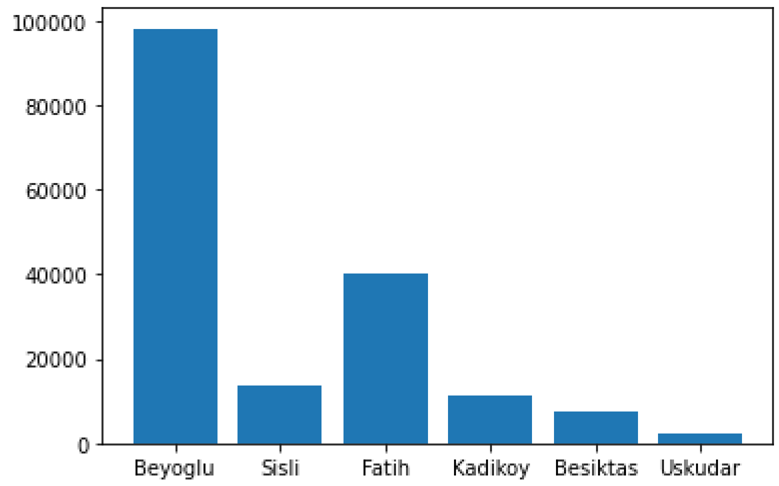
According to result we can see the most popular neighbourhood is Beyoglu

We saw the famous neighbourhood on top so they can be famous but, let's check their reviews number for top 5 neighbourhood

Is there a direct proportion between popularity and reviews of number?

In [13]:
```
BeyogluReviews = data[data['neighbourhood'] == "Beyoglu"].sum().number_of_reviews
SisliReviews = data[data['neighbourhood'] == "Sisli"].sum().number_of_reviews
FatihReviews = data[data['neighbourhood'] == "Fatih"].sum().number_of_reviews
KadikoyReviews = data[data['neighbourhood'] == "Kadikoy"].sum().number_of_reviews
BesiktasReviews = data[data['neighbourhood'] == "Besiktas"].sum().number_of_reviews
UskudarReviews = data[data['neighbourhood'] == "Uskudar"].sum().number_of_reviews

neighbourhoods = ["Beyoglu", "Sisli", "Fatih", "Kadikoy", "Besiktas", "Uskudar"]
neighbourhoodsReviews = [BeyogluReviews,SisliReviews,FatihReviews,KadikoyReviews,BesiktasReviews,UskudarReviews
print("Reviews number of Beyoglu:",BeyogluReviews)
print("Reviews number of Sisli:",SisliReviews)
print("Reviews number of Fatih:",FatihReviews)
print("Reviews number of Kadikoy:",KadikoyReviews)
print("Reviews number of Besiktas:",BesiktasReviews)
print("Reviews number of Uskudar:",UskudarReviews)

plt.bar(neighbourhoods,neighbourhoodsReviews)
plt.show()
```

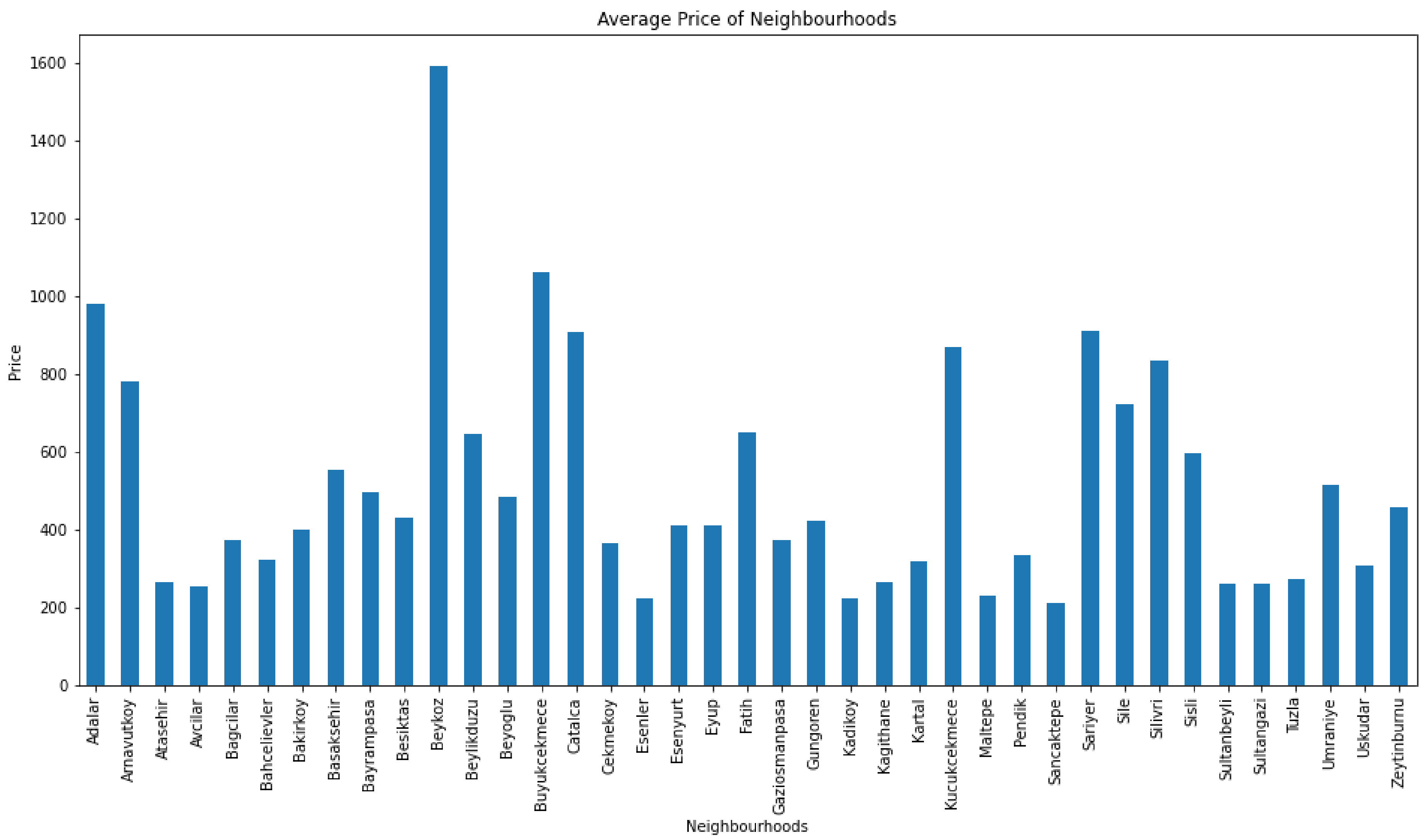
```
Reviews number of Beyoglu: 98178
Reviews number of Sisli: 13580
Reviews number of Fatih: 40209
Reviews number of Kadikoy: 11198
Reviews number of Besiktas: 7519
Reviews number of Uskudar: 2165
```



What are the price averages by neighborhood?

In [14]:
```
neighbourhoodPrice = data["price"].groupby([data.neighbourhood]).mean()
plt.figure(figsize=(16, 8))
priceBar = neighbourhoodPrice.plot(kind = "bar")
priceBar.set_xlabel('Neighbourhoods')
priceBar.set_ylabel('Price')
priceBar.set_title("Average Price of Neighbourhoods")
```

Out[14]:
```
Text(0.5, 1.0, 'Average Price of Neighbourhoods')
```

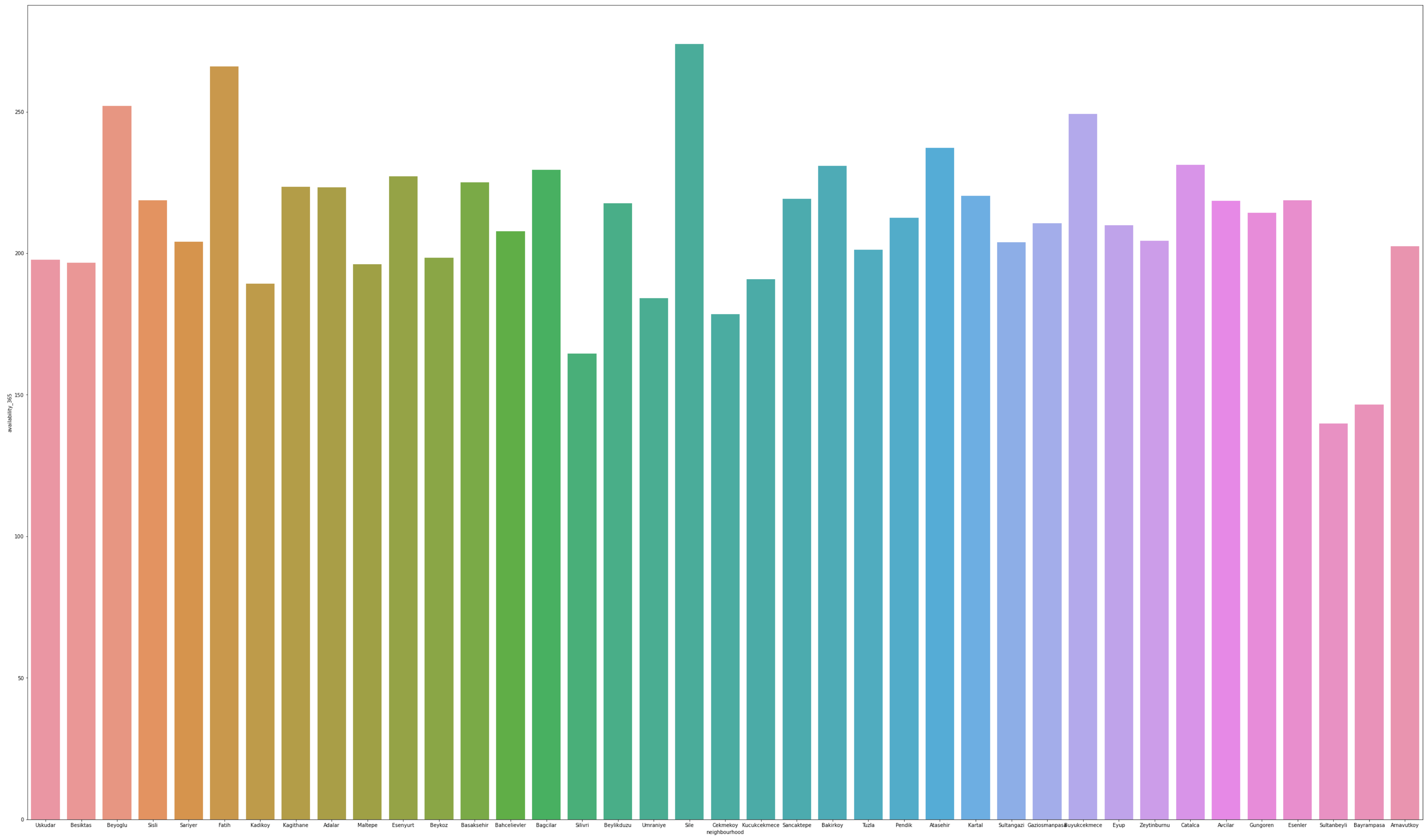


According to popularity, we saw that while Sisli was in the second place, Fatih was in the third place, but when we look at the reviews of the number, we see that Fatih has more reviews. Thus, we cannot say for sure that the most popular place has the most reviews.

Let's examine the annual occupancy by neighbourhood.

In [15]:
```
plt.figure(figsize=(50, 30))
sea.barplot(x=neighbourhood, y=data.availability_365, data=data, ci=None)
```

Out[15]: <AxesSubplot:xlabel='neighbourhood', ylabel='availability_365'>



See what Istanbul looks like by uploading a map view of Istanbul.

In [16]:
```
img = mpimg.imread('istanbul.png')
np.save("istanbul",img)
plt.figure(figsize=(16,8))
plt.imshow(img)
```

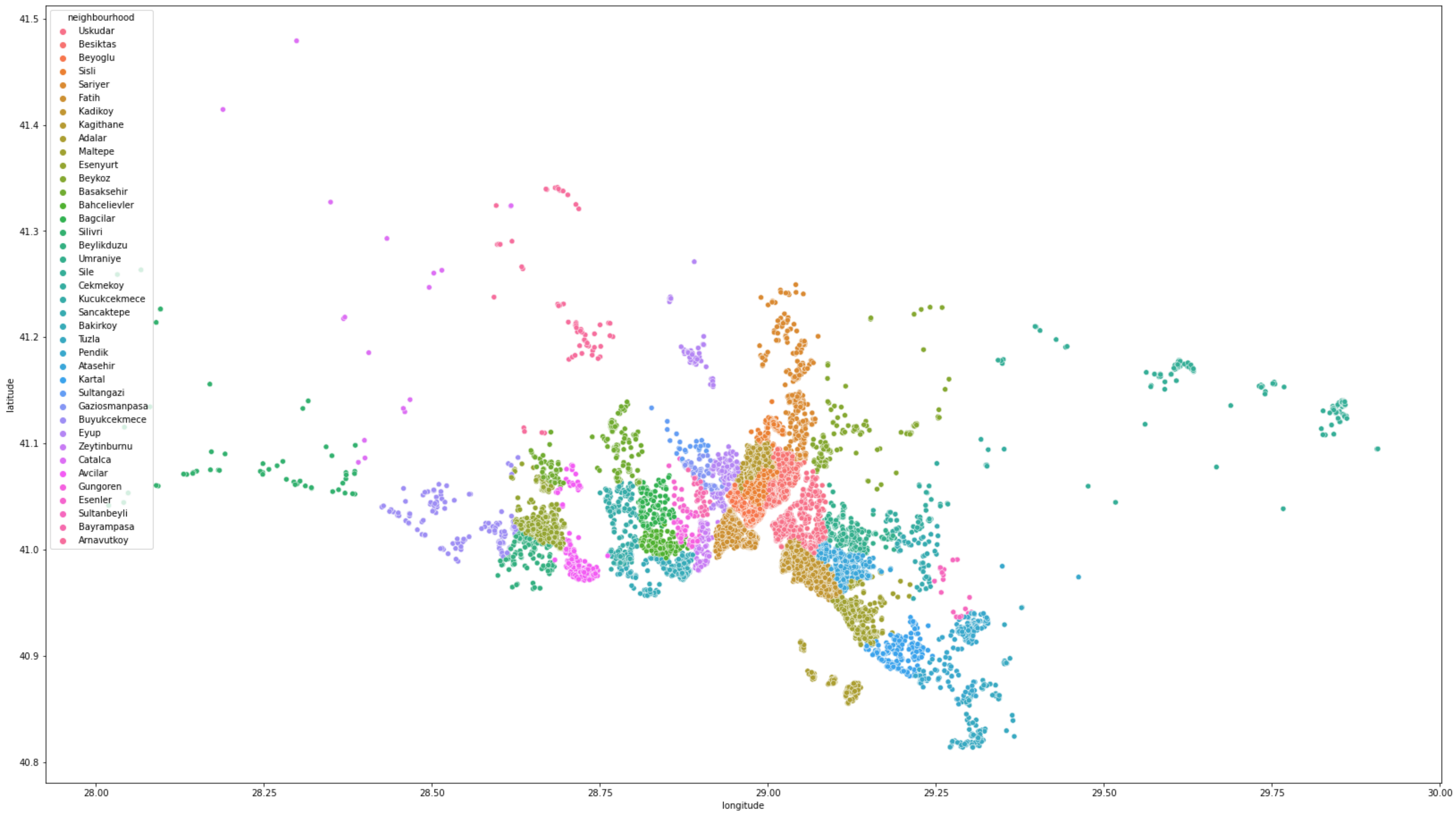
Out[16]: <matplotlib.image.AxesImage at 0x7ff891464b80>

Now, let's try to map according to the latitude and longitude of our own data.

Let's map according to our neighbourhoods at first and have information about the locations of the neighbourhoods.

In [17]:
```
plt.figure(figsize=(28, 16))
sea.scatterplot(x=data.longitude,y=data.latitude,hue=data.neighbourhood)
```

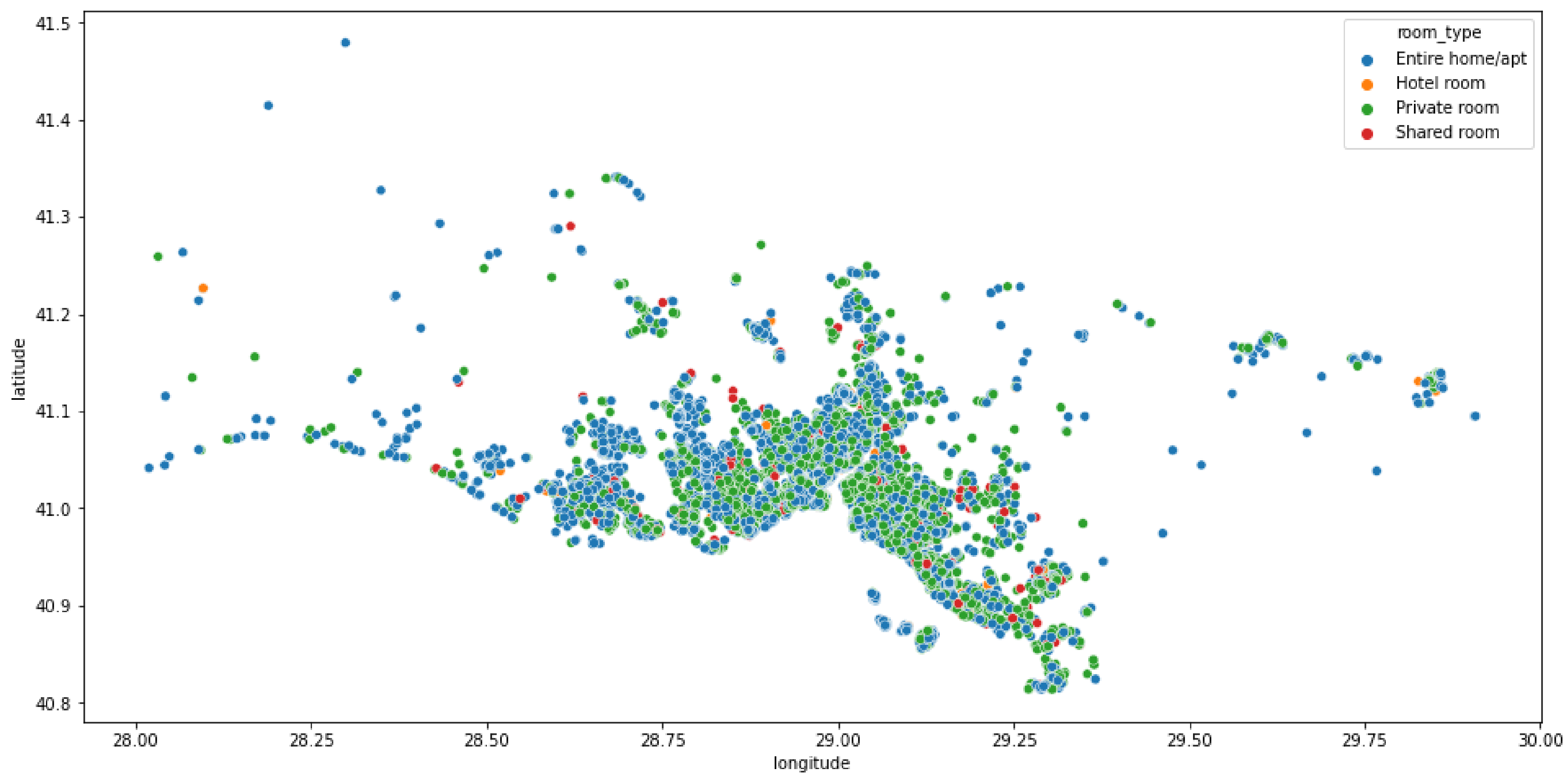
Out[17]: <AxesSubplot:xlabel='longitude', ylabel='latitude'>



Mapping according to room types

In [18]:
```
plt.figure(figsize=(16,8))
sea.scatterplot(x=data.longitude,y=data.latitude,hue=data.room_type)
```

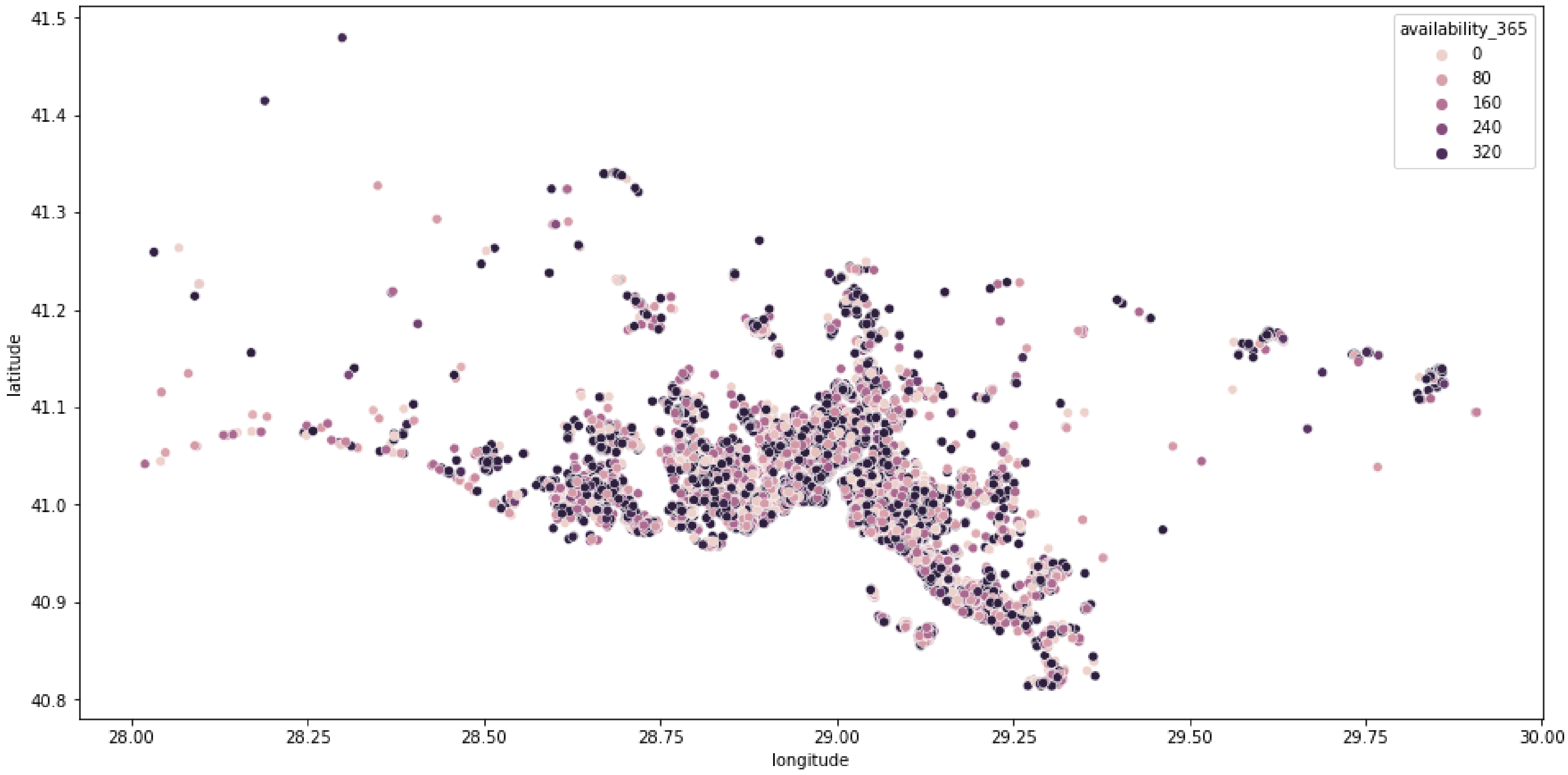
Out[18]: <AxesSubplot:xlabel='longitude', ylabel='latitude'>



Mapping by yearly availability

In [19]:
```
plt.figure(figsize=(16,8))
sea.scatterplot(x=data.longitude,y=data.latitude,hue=data.availability_365)
```

Out[19]: <AxesSubplot:xlabel='longitude', ylabel='latitude'>



Let's examine the ads under the price of 1000

In [20]:
```
price = data[data["price"]<1000]
price
```

Out[20]:

	neighbourhood	latitude	longitude	room_type	price	minimum_nights	number_of_reviews	reviews_per_month	calculated_host_listings_count
0	Uskudar	41.05650	29.05367	Entire home/apt	720	1	1	0.01	1
1	Besiktas	41.06984	29.04545	Entire home/apt	816	365	41	0.33	2
2	Beyoglu	41.03254	28.98153	Entire home/apt	233	30	13	0.19	1
3	Sisli	41.04471	28.98567	Hotel room	761	3	0	0.00	19
4	Sariyer	41.09048	29.05559	Entire home/apt	823	3	0	0.00	1
...	...	...	...	...	...	...	...	...	...
23723	Avcilar	40.97870	28.72668	Private room	171	1	0	0.00	2
23724	Sisli	41.11798	29.00886	Entire home/apt	597	1	0	0.00	15
23725	Beyoglu	41.03839	28.98831	Private room	144	1	0	0.00	7
23726	Esenyurt	41.01065	28.67427	Entire home/apt	603	2	0	0.00	1
23727	Sile	41.17426	29.60997	Private room	103	1	0	0.00	1

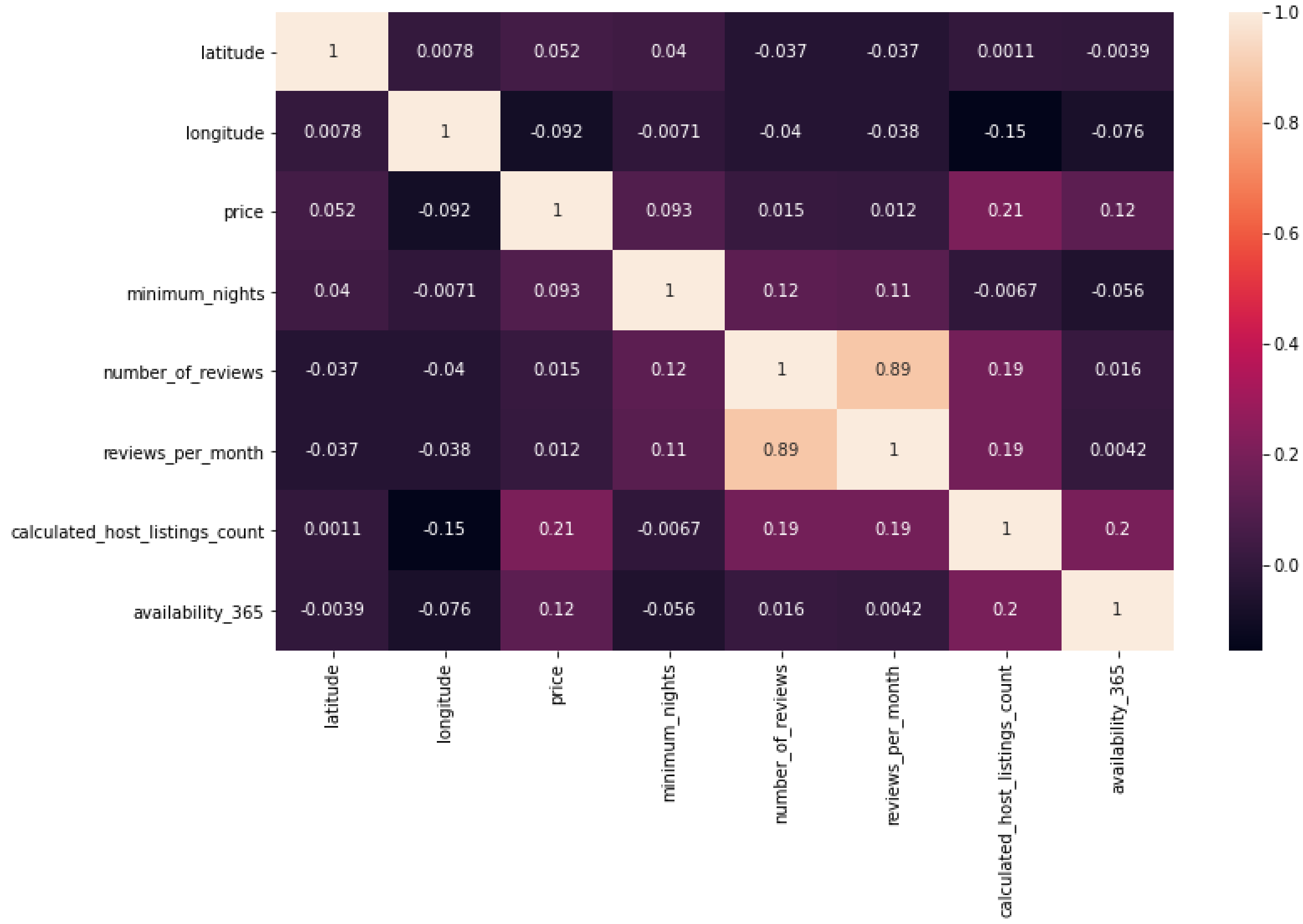
22156 rows × 28 columns

Correlation

Now let's examine the relationship between the columns in our data with correlation.

In [21]:
```
corr = data.corr(method='kendall')
plt.figure(figsize=(12,7))
sea.heatmap(corr, annot=True)
data.columns
```

Out[21]:
```
Index(['neighbourhood', 'latitude', 'longitude', 'room_type', 'price',
       'minimum_nights', 'number_of_reviews', 'reviews_per_month',
       'calculated_host_listings_count', 'availability_365',
       'Veri Türü (Data Type)', '2004', '2005', '2006', '2007', '2008', '2009',
       '2010', '2011', '2012', '2013', '2014', '2015', '2016', '2017', '2018',
       '2019', '2020'],
      dtype='object')
```

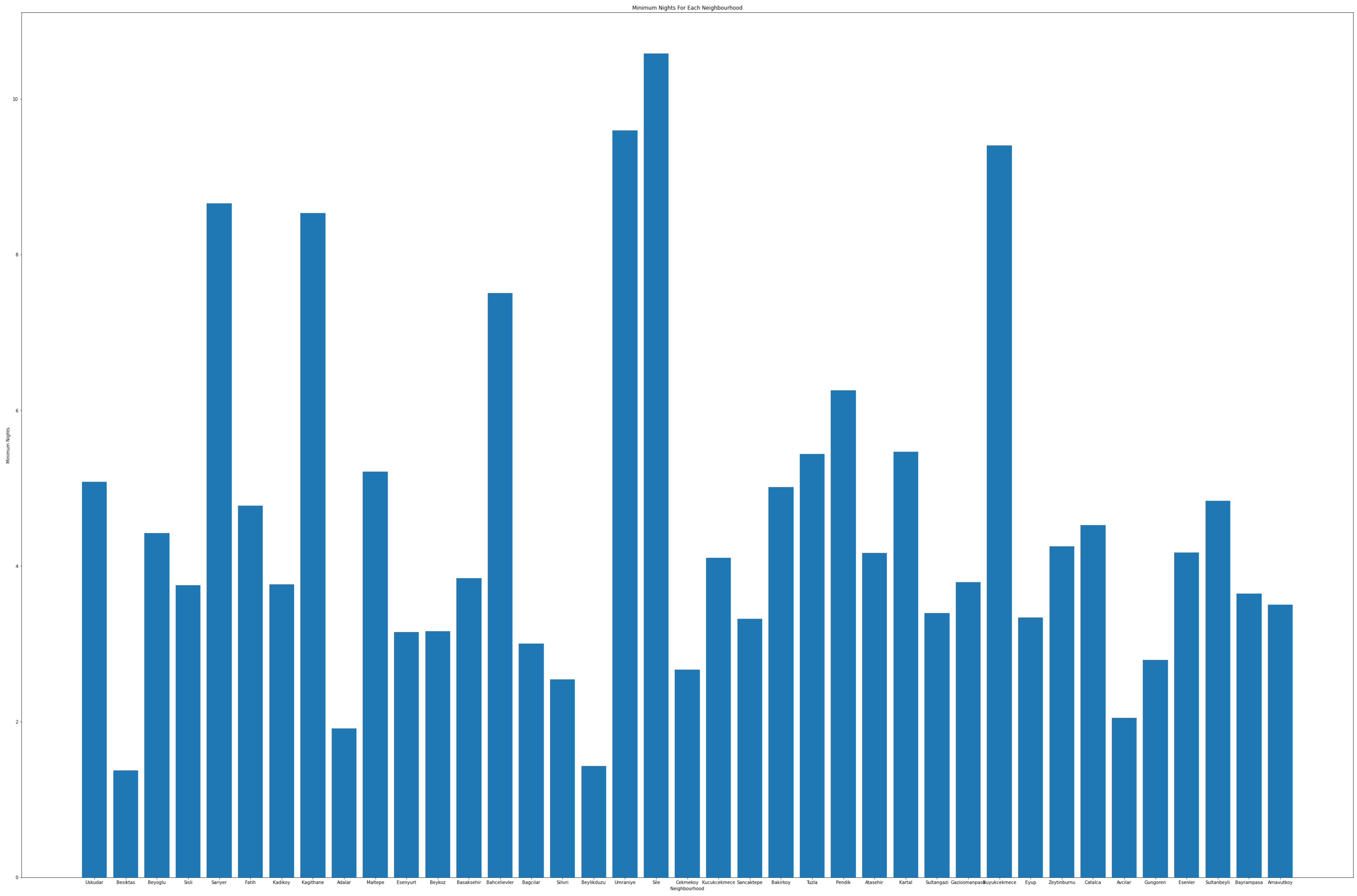


There is the highest correlation relationship between number_of_reviews and reviews_per_mounth. This means that we can interpret that the two are interconnected and have a directly proportional relationship with each other.

According to the correlation table, we can say that there are generally small relationships between them for our other columns. Our columns longitude and calculated_host_listings_count have the greatest negative correlation. However, since this value is -0.15, we can say that they have a small negative relationship.

There is a minimum number of days to be rented for each ad to be rented. These can take different forms such as 1-3-5-10. Let's take a look at how many days we need to rent on average for each district. In this review, we need to remove the same districts in order not to experience confusion while taking the average of each data.

In [22]:
```
plt.figure(figsize=(54, 36))
meanNightMean = data['minimum_nights'].groupby([data.neighbourhood]).mean()
NeighbourhoodsKey = data.neighbourhood
NeighbourhoodsKey = NeighbourhoodsKey.drop_duplicates()
plt.bar(NeighbourhoodsKey, meanNightMean)
plt.xlabel('Neighbourhood')
plt.ylabel('Minimum Nights')
plt.title('Minimum Nights For Each Neighbourhood')
plt.show()
```



Which district is the amount of household waste the most?

Since the waste amounts are not given in number type in our data, let's first convert it to float type and then find the maximum value and find the most domestic waste amount in which neighbourhood.

Type *Markdown* and LaTeX: α^2

In [23]:
```
wasteOf20 = data.iloc[:,[0,27]]
wasteOf20 = wasteOf20.drop_duplicates()
tmp = []
def convert(val):
    new_val = val.replace(',','.')
    new_val = float(new_val)
    tmp.append(new_val)

wasteOf20['2020'].apply(convert)
maxTmp = max(tmp)
maxTmp = str(maxTmp)
maxTmp = maxTmp.replace(".", ",")
maxData = wasteOf20[wasteOf20['2020'] == maxTmp]
maxData
```

Out[23]:

	neighbourhood	2020
62	Esenyurt	384,469

Based on our investigation, we have obtained the information that the highest amount of waste is in Esenyurt with 384,469.

Which neighbourhood has the highest average wage?

First of all, we need to extract the one-night data from the districts. Because the increase in the night price plays an important role in the increase in the price. We collected the average of our data in places where the minimum night is 1 by grouping them according to districts. Now, let's find out which is the maximum wage among these values and get its information.

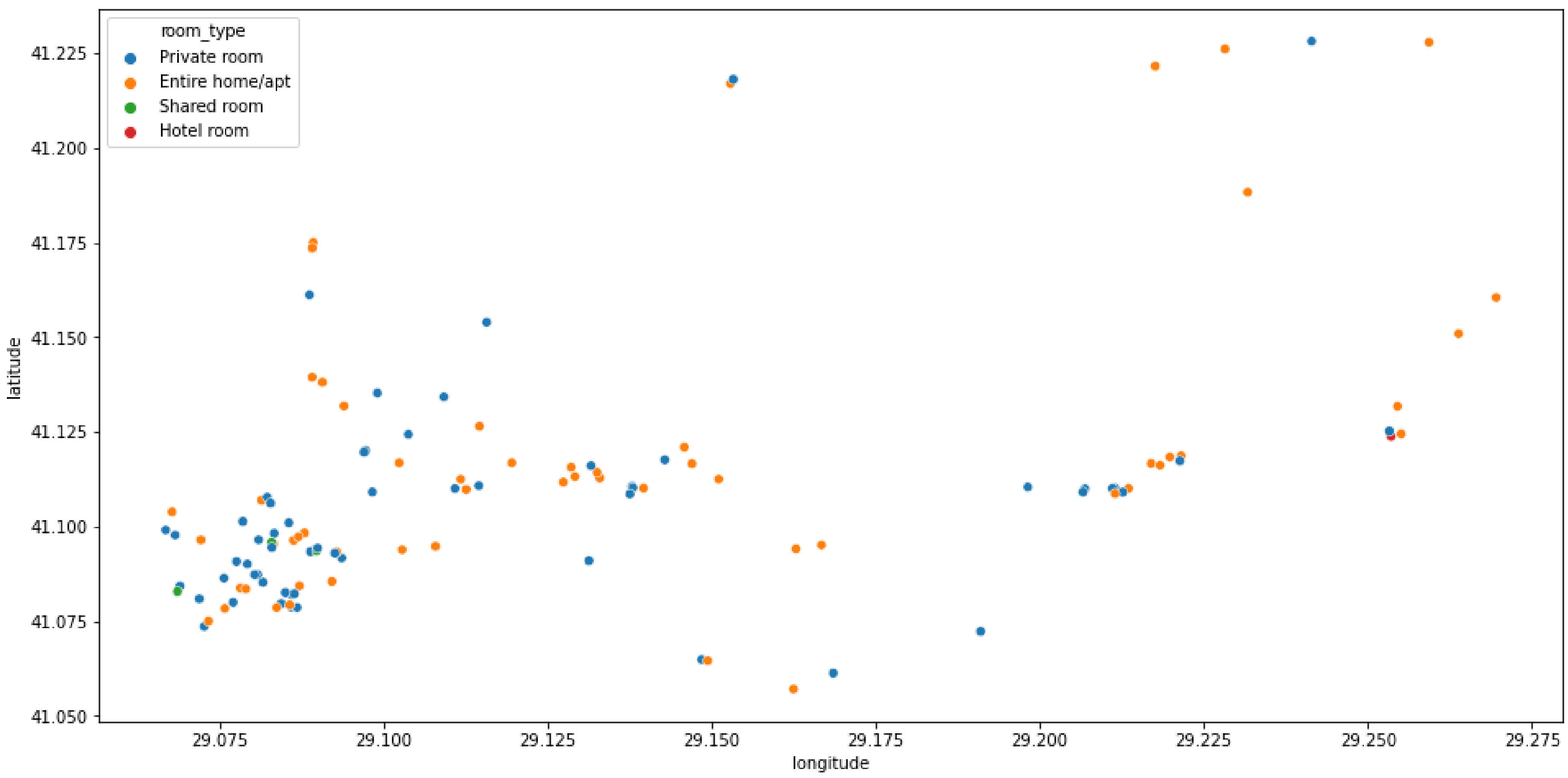
In [24]:
```
meanNeighborhood = data[data["minimum_nights"] == 1].groupby([data.neighbourhood]).mean()
#meanNeighborhood.sort_values(by=['price'],inplace = True)
mostExpensiveValue = meanNeighborhood['price'].max()
expensiveNeighborhood = meanNeighborhood[meanNeighborhood["price"] == mostExpensiveValue]
expensiveNeighborhood
```

Out[24]:

	latitude	longitude	price	minimum_nights	number_of_reviews	reviews_per_month	calculated_host_listings_count	availability
neighbourhood								
Beykoz	41.104999	29.125939	1118.014925	1.0	1.253731	0.092537	4.089552	175.94

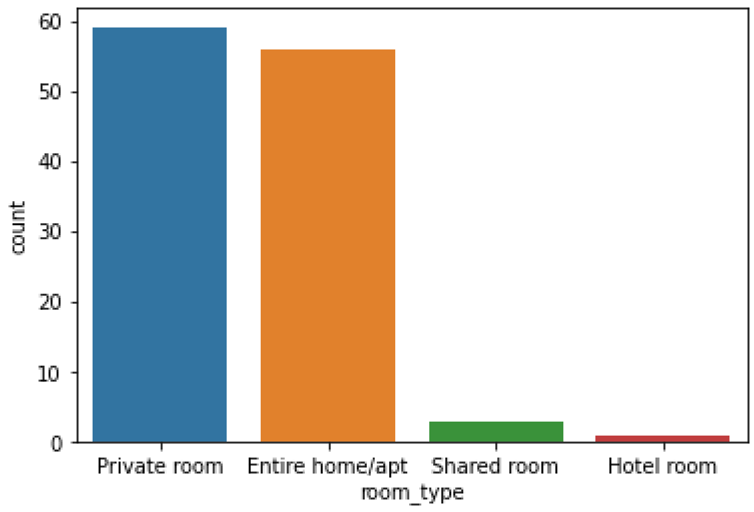
In [25]:
```
BeykozDatas = data[data["neighbourhood"] == "Beykoz"]
BeykozDatas
plt.figure(figsize=(16,8))
sea.scatterplot(x=BeykozDatas.longitude,y=BeykozDatas.latitude,hue=BeykozDatas.room_type)
```

Out[25]: <AxesSubplot:xlabel='longitude', ylabel='latitude'>



Let's examine the distribution of room types in Beykoz, our most expensive neighborhood.

In [26]:
```
BeykozRoomType = sea.countplot(x="room_type", data=BeykozDatas)
```



In [27]:
```
BeykozDatas.describe()
```

Out[27]:

	latitude	longitude	price	minimum_nights	number_of_reviews	reviews_per_month	calculated_host_listings_count	availability_365
count	119.000000	119.000000	119.000000	119.000000	119.000000	119.000000	119.000000	119.000000
mean	41.111041	29.128309	1594.420168	3.151261	1.865546	0.115462	3.941176	198.445378
std	0.034636	0.057700	4669.803214	5.177590	5.447631	0.266731	17.160407	137.848154
min	41.057050	29.066820	41.000000	1.000000	0.000000	0.000000	1.000000	0.000000
25%	41.090855	29.084750	117.000000	1.000000	0.000000	0.000000	1.000000	88.000000
50%	41.108550	29.102410	281.000000	1.000000	0.000000	0.000000	1.000000	179.000000
75%	41.117480	29.153075	1001.000000	2.000000	1.000000	0.090000	2.000000	362.500000
max	41.228260	29.269530	34618.000000	30.000000	37.000000	1.470000	176.000000	365.000000

How much on average do we have to pay to rent a house in the most expensive neighborhood?

In [28]:
```
BeykozRoomTypePricesMean = BeykozDatas.price.groupby([BeykozDatas.room_type]).mean()
BeykozRoomTypePricesMean
```

Out[28]:
```
room_type
Entire home/apt    2875.303571
Hotel room          117.000000
Private room        474.661017
Shared room         199.000000
Name: price, dtype: float64
```

According to our research, we learned that Beykoz is the most expensive neighbourhood with an average price of 1118.

Regression analysis to predict the price

Let's convert room types and neighbourhood into columns and boolean values for better prediction and analysis.

splitting the dataset into test and training data

In [29]:
```
data2 = pd.get_dummies(a, columns=categorical_col)
data2.head()
```

Out[29]:

	latitude	longitude	price	minimum_nights	number_of_reviews	reviews_per_month	calculated_host_listings_count	availability_365	neighbourhood_
0	41.05650	29.05367	720	1	1	0.01	1	365	
1	41.06984	29.04545	816	365	41	0.33	2	279	
2	41.03254	28.98153	233	30	13	0.19	1	289	
3	41.04471	28.98567	761	3	0	0.00	19	365	
4	41.09048	29.05559	823	3	0	0.00	1	88	

5 rows × 51 columns

Let's check the columns of seperated data

In [30]:
```
data2.columns
```

Out[30]:
```
Index(['latitude', 'longitude', 'price', 'minimum_nights', 'number_of_reviews',
       'reviews_per_month', 'calculated_host_listings_count',
       'availability_365', 'neighbourhood_Adalar', 'neighbourhood_Arnavutkoy',
       'neighbourhood_Atasehir', 'neighbourhood_Avcilar',
       'neighbourhood_Bagcilar', 'neighbourhood_Bahcelievler',
       'neighbourhood_Bakirkoy', 'neighbourhood_Basaksehir',
       'neighbourhood_Bayrampasa', 'neighbourhood_Besiktas',
       'neighbourhood_Beykoz', 'neighbourhood_Beylikduzu',
       'neighbourhood_Beyoglu', 'neighbourhood_Buyukcekmece',
       'neighbourhood_Catalca', 'neighbourhood_Cekmekoy',
       'neighbourhood_Esenler', 'neighbourhood_Esenyurt', 'neighbourhood_Eyup',
       'neighbourhood_Fatih', 'neighbourhood_Gaziosmanpasa',
       'neighbourhood_Gungoren', 'neighbourhood_Kadikoy',
       'neighbourhood_Kagithane', 'neighbourhood_Kartal',
       'neighbourhood_Kucukcekmece', 'neighbourhood_Maltepe',
       'neighbourhood_Pendik', 'neighbourhood_Sancaktepe',
       'neighbourhood_Sariyer', 'neighbourhood_Sile', 'neighbourhood_Silivri',
       'neighbourhood_Sisli', 'neighbourhood_Sultanbeyli',
       'neighbourhood_Sultangazi', 'neighbourhood_Tuzla',
       'neighbourhood_Umraniye', 'neighbourhood_Uskudar',
       'neighbourhood_Zeytinburnu', 'room_type_Entire home/apt',
       'room_type_Hotel room', 'room_type_Private room',
       'room_type_Shared room'],
      dtype='object')
```

Let's check mean for each columns

In [31]:
```
print(data2.describe().loc["mean", :])
```

```
latitude                           41.028416
longitude                          28.982111
price                             484.643248
minimum_nights                      4.525202
number_of_reviews                   7.870828
reviews_per_month                   0.339794
calculated_host_listings_count      5.861767
availability_365                  227.709921
neighbourhood_Adalar                0.007544
neighbourhood_Arnavutkoy            0.002950
neighbourhood_Atasehir              0.017448
neighbourhood_Avcilar               0.009145
neighbourhood_Bagcilar              0.007460
neighbourhood_Bahcelievler          0.009988
neighbourhood_Bakirkoy              0.012517
neighbourhood_Basaksehir            0.011800
neighbourhood_Bayrampasa            0.001433
neighbourhood_Besiktas              0.073668
neighbourhood_Beykoz                0.005015
neighbourhood_Beylikduzu            0.005184
neighbourhood_Beyoglu               0.268543
neighbourhood_Buyukcekmece          0.005774
neighbourhood_Catalca               0.000759
neighbourhood_Cekmekoy              0.002318
neighbourhood_Esenler               0.000885
neighbourhood_Esenyurt              0.027605
neighbourhood_Eyup                  0.010115
neighbourhood_Fatih                 0.123609
neighbourhood_Gaziosmanpasa         0.003582
neighbourhood_Gungoren              0.003034
neighbourhood_Kadikoy               0.098238
neighbourhood_Kagithane             0.028026
neighbourhood_Kartal                0.008302
neighbourhood_Kucukcekmece          0.008429
neighbourhood_Maltepe               0.015973
neighbourhood_Pendik                0.009103
neighbourhood_Sancaktepe            0.002234
neighbourhood_Sariyer               0.015383
neighbourhood_Sile                  0.006406
neighbourhood_Silivri               0.002318
neighbourhood_Sisli                 0.141183
neighbourhood_Sultanbeyli           0.000885
neighbourhood_Sultangazi            0.001011
neighbourhood_Tuzla                 0.004383
neighbourhood_Umraniye              0.009609
neighbourhood_Uskudar               0.033463
neighbourhood_Zeytinburnu           0.004678
room_type_Entire home/apt           0.499326
room_type_Hotel room                0.040206
room_type_Private room              0.432021
room_type_Shared room               0.028447
Name: mean, dtype: float64
```

Let's check standart deviation for each columns

In [32]:
```
print(data2.describe().loc["std", :])
```

```
latitude                               0.045713
longitude                              0.127503
price                               1973.884093
minimum_nights                        27.614191
number_of_reviews                     23.229127
reviews_per_month                      0.718269
calculated_host_listings_count        16.535368
availability_365                     146.607077
neighbourhood_Adalar                   0.086529
neighbourhood_Arnavutkoy               0.054236
neighbourhood_Atasehir                 0.130935
neighbourhood_Avcilar                  0.095195
neighbourhood_Bagcilar                 0.086048
neighbourhood_Bahcelievler             0.099443
neighbourhood_Bakirkoy                 0.111179
neighbourhood_Basaksehir               0.107989
neighbourhood_Bayrampasa               0.037827
neighbourhood_Besiktas                 0.261236
neighbourhood_Beykoz                   0.070642
neighbourhood_Beylikduzu               0.071813
neighbourhood_Beyoglu                  0.443211
neighbourhood_Buyukcekmece             0.075767
neighbourhood_Catalca                  0.027533
neighbourhood_Cekmekoy                 0.048090
neighbourhood_Esenler                  0.029737
neighbourhood_Esenyurt                 0.163840
neighbourhood_Eyup                     0.100064
neighbourhood_Fatih                    0.329142
neighbourhood_Gaziosmanpasa            0.059746
neighbourhood_Gungoren                 0.055003
neighbourhood_Kadikoy                  0.297643
neighbourhood_Kagithane                0.165050
neighbourhood_Kartal                   0.090741
neighbourhood_Kucukcekmece             0.091423
neighbourhood_Maltepe                  0.125372
neighbourhood_Pendik                   0.094977
neighbourhood_Sancaktepe               0.047210
neighbourhood_Sariyer                  0.123072
neighbourhood_Sile                     0.079782
neighbourhood_Silivri                  0.048090
neighbourhood_Sisli                    0.348218
neighbourhood_Sultanbeyli              0.029737
neighbourhood_Sultangazi               0.031788
neighbourhood_Tuzla                    0.066060
neighbourhood_Umraniye                 0.097555
neighbourhood_Uskudar                  0.179845
neighbourhood_Zeytinburnu              0.068237
room_type_Entire home/apt              0.500010
room_type_Hotel room                   0.196445
room_type_Private room                 0.495368
room_type_Shared room                  0.166251
Name: std, dtype: float64
```

In [33]:
```
z=data2.drop(['price'],axis=1)
w=data2['price']
Z_train, Z_test, W_train, W_test = train_test_split(z, w, test_size=0.30, random_state=42)
data2.columns
```

Out[33]:
```
Index(['latitude', 'longitude', 'price', 'minimum_nights', 'number_of_reviews',
       'reviews_per_month', 'calculated_host_listings_count',
       'availability_365', 'neighbourhood_Adalar', 'neighbourhood_Arnavutkoy',
       'neighbourhood_Atasehir', 'neighbourhood_Avcilar',
       'neighbourhood_Bagcilar', 'neighbourhood_Bahcelievler',
       'neighbourhood_Bakirkoy', 'neighbourhood_Basaksehir',
       'neighbourhood_Bayrampasa', 'neighbourhood_Besiktas',
       'neighbourhood_Beykoz', 'neighbourhood_Beylikduzu',
       'neighbourhood_Beyoglu', 'neighbourhood_Buyukcekmece',
       'neighbourhood_Catalca', 'neighbourhood_Cekmekoy',
       'neighbourhood_Esenler', 'neighbourhood_Esenyurt', 'neighbourhood_Eyup',
       'neighbourhood_Fatih', 'neighbourhood_Gaziosmanpasa',
       'neighbourhood_Gungoren', 'neighbourhood_Kadikoy',
       'neighbourhood_Kagithane', 'neighbourhood_Kartal',
       'neighbourhood_Kucukcekmece', 'neighbourhood_Maltepe',
       'neighbourhood_Pendik', 'neighbourhood_Sancaktepe',
       'neighbourhood_Sariyer', 'neighbourhood_Sile', 'neighbourhood_Silivri',
       'neighbourhood_Sisli', 'neighbourhood_Sultanbeyli',
       'neighbourhood_Sultangazi', 'neighbourhood_Tuzla',
       'neighbourhood_Umraniye', 'neighbourhood_Uskudar',
       'neighbourhood_Zeytinburnu', 'room_type_Entire home/apt',
       'room_type_Hotel room', 'room_type_Private room',
       'room_type_Shared room'],
      dtype='object')
```

In [34]:
```
from sklearn import metrics
linear=LinearRegression()
linear.fit(Z_train,W_train)
W_pred=linear.predict(Z_test)
metrics.r2_score(W_test,W_pred)
```

Out[34]:
```
0.026905103978877798
```

The accuracy we got is 0.02%.Our model is predicting that how price is varying in Istanbul on different features.

Let's minimize data to make a price estimate for the latitude of Üsküdar district by taking only the latitude from our data.

In [35]:
```
data2.head(2)
X = data2.iloc[:,[0]]
y = data2.price.values.reshape(-1,1)
X = X.values.reshape(-1,1)
print(X.shape)
print(y.shape)
```

```
(23728, 1)
(23728, 1)
```

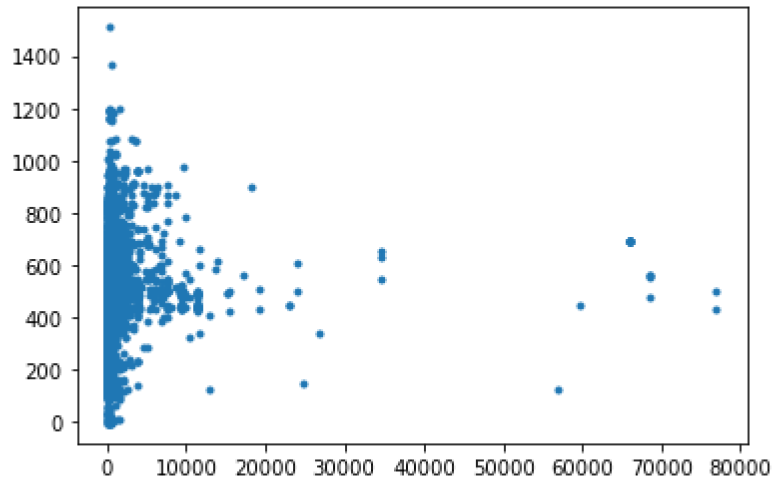
In [36]:
```
from sklearn.linear_model import LinearRegression
regression = LinearRegression()
regression.fit(X,y)
print(regression.predict(np.array([[41.09048]])))
```

```
[[625.83962352]]
```

When we predicted based on the latitude of Üsküdar district, we estimated the price of 625.

Let's visualize our price and predict

In [37]:
```
plt.plot(y,regression.predict(X), '.')
plt.show()
```



Let's examine our error mean by using metrics

Mean Absolute Error (MAE) shows the difference between predictions and actual values.

In [38]:
```
def errors(real, predicted):
    mae = metrics.mean_absolute_error(real, predicted)
    print('MAE:', mae)
errors(y, regression.predict(X))
```

```
MAE: 423.24458020223574
```

Now, let's examine the annual domestic waste numbers according to the districts in Istanbul, which is our second dataset.

In [39]:
```
b.head(15)
```

Out[39]:

	neighbourhood	Veri Türü (Data Type)	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	
0	Adalar	Miktar (Ton) (Amount)	7,834	10,615	17,228	12,102	12,232	13,228	11,884	12,109	12,077	12,886	23,531	12,004	12,711	
1	Arnavutkoy	Miktar (Ton) (Amount)	14,742	17,055	29,874	31,163	30,187	39,603	51,041	53,779	59,294	64,386	74,446	88,765	88,435	
2	Atasehir	Miktar (Ton) (Amount)	99,570	108,725	116,350	115,838	108,804	57,172	136,509	145,206	153,265	169,790	173,099	179,390	183,933	1
3	Avcilar	Miktar (Ton) (Amount)	76,741	68,579	102,550	113,784	106,832	121,277	113,793	115,190	119,614	132,095	147,880	183,128	171,638	1
4	Bahcelievler	Miktar (Ton) (Amount)	165,395	186,014	200,850	198,891	193,768	208,109	189,725	187,098	190,638	214,657	217,869	212,794	217,714	2
5	Bagcilar	Miktar (Ton) (Amount)	192,223	205,455	244,660	249,504	231,711	262,991	232,660	231,675	234,106	261,596	269,005	262,812	280,921	2
6	Bakirkoy	Miktar (Ton) (Amount)	79,952	96,202	100,950	102,793	95,940	115,591	110,031	105,868	120,737	148,860	152,493	159,072	156,268	1
7	Basaksehir	Miktar (Ton) (Amount)	51,544	53,788	61,680	63,725	60,990	42,982	106,894	130,057	137,093	161,729	181,877	179,829	197,563	2
8	Bayrampasa	Miktar (Ton) (Amount)	84,695	90,010	104,328	104,432	97,047	116,542	110,824	106,486	110,285	117,746	123,775	127,707	129,597	1
9	Besiktas	Miktar (Ton) (Amount)	96,470	102,525	113,975	113,856	103,750	119,804	111,013	108,720	111,260	121,377	129,396	128,561	128,516	1
10	Beykoz	Miktar (Ton) (Amount)	61,959	72,943	80,509	78,233	74,756	88,563	89,784	87,680	89,926	101,156	107,285	114,926	118,972	1
11	Beylikduzu	Miktar (Ton) (Amount)	6,220	5,358	5,936	6,511	6,586	64,238	74,229	78,774	82,433	91,621	102,467	106,671	108,265	1
12	Beyoglu	Miktar (Ton) (Amount)	109,798	118,299	125,129	121,735	112,843	132,064	121,908	125,928	124,270	134,704	142,168	133,197	131,076	1
13	Buyukcekmece	Miktar (Ton) (Amount)	5,326	4,589	5,083	5,575	5,640	72,844	71,773	75,967	86,283	94,039	97,743	99,499	98,712	1
14	Catalca	Miktar (Ton) (Amount)	0	0	0	0	0	17,636	19,418	20,280	21,782	15,380	25,155	34,172	27,365	

We do not need to use some columns, that's why we can drop them for better analysis and predict

In [40]:
```
b_copy = b.copy()
b_copy2 = b.copy()
b_copy.drop(['Veri Türü (Data Type)','neighbourhood'], axis=1, inplace=True)
b_copy2.drop(['Veri Türü (Data Type)'], axis=1, inplace=True)
```

Since our columns do not come in number type in our data, let's move on by converting them to integer type and numpy array format first. Then we will fix (-1,1) with reshape to be able to regress.

In [41]:
```
columns = b_copy.columns
columns = np.array(columns)
columnsPlot = []
for p in columns:
    columnsPlot.append(int(p))
columns = columns.reshape(-1,1)
columnsPlot = np.array(columnsPlot)
columnsPlot
```

Out[41]:
```
array([2004, 2005, 2006, 2007, 2008, 2009, 2010, 2011, 2012, 2013, 2014,
       2015, 2016, 2017, 2018, 2019, 2020])
```

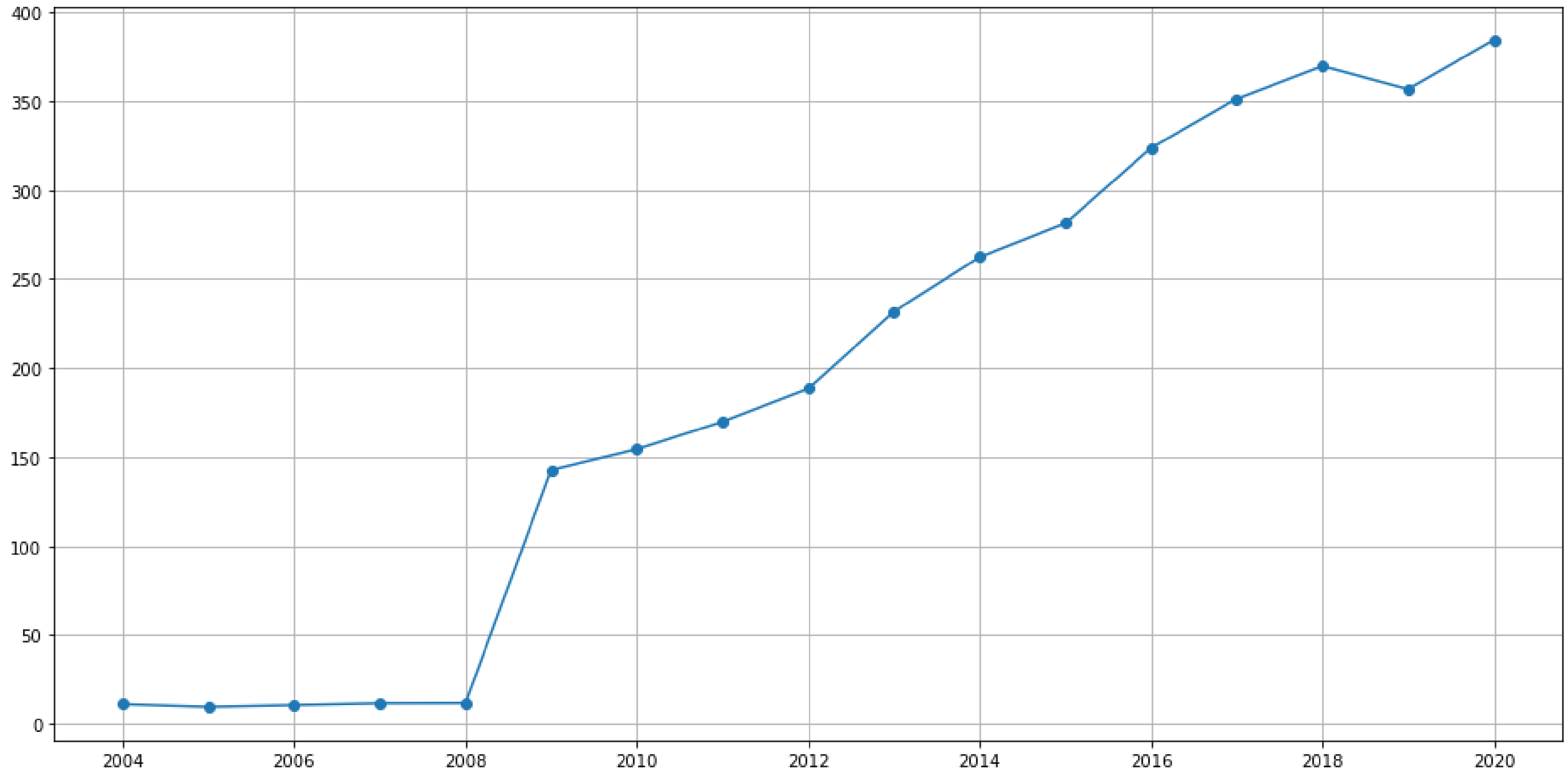
In our previous analyzes, we saw that the highest amount of domestic waste was in Esenyurt, so let's

choose Esenyurt again and make our predictions accordingly.

In [42]:
```
esenyurtWaste = []
tmp = b_copy.values[17]
tmp = np.array(tmp)
for value in tmp:
    newValue = value.replace(',','.')
    esenyurtWaste.append(float(newValue))
esenyurtWaste = np.array(esenyurtWaste)
esenyurtWaste = esenyurtWaste.reshape(-1,1)
```

Let's visualize our data

In [43]:
```
plt.figure(figsize=(16, 8))
plt.grid()
plt.plot(columnsPlot,esenyurtWaste, marker = 'o')
plt.show()
```



Now, according to the data we have, let's estimate for 2021 and 2022 using linear regression.

In [44]:
```
regression = LinearRegression()
regression.fit(columns,esenyurtWaste)
print(regression.predict([[2021]]))
print(regression.predict([[2022]]))
```

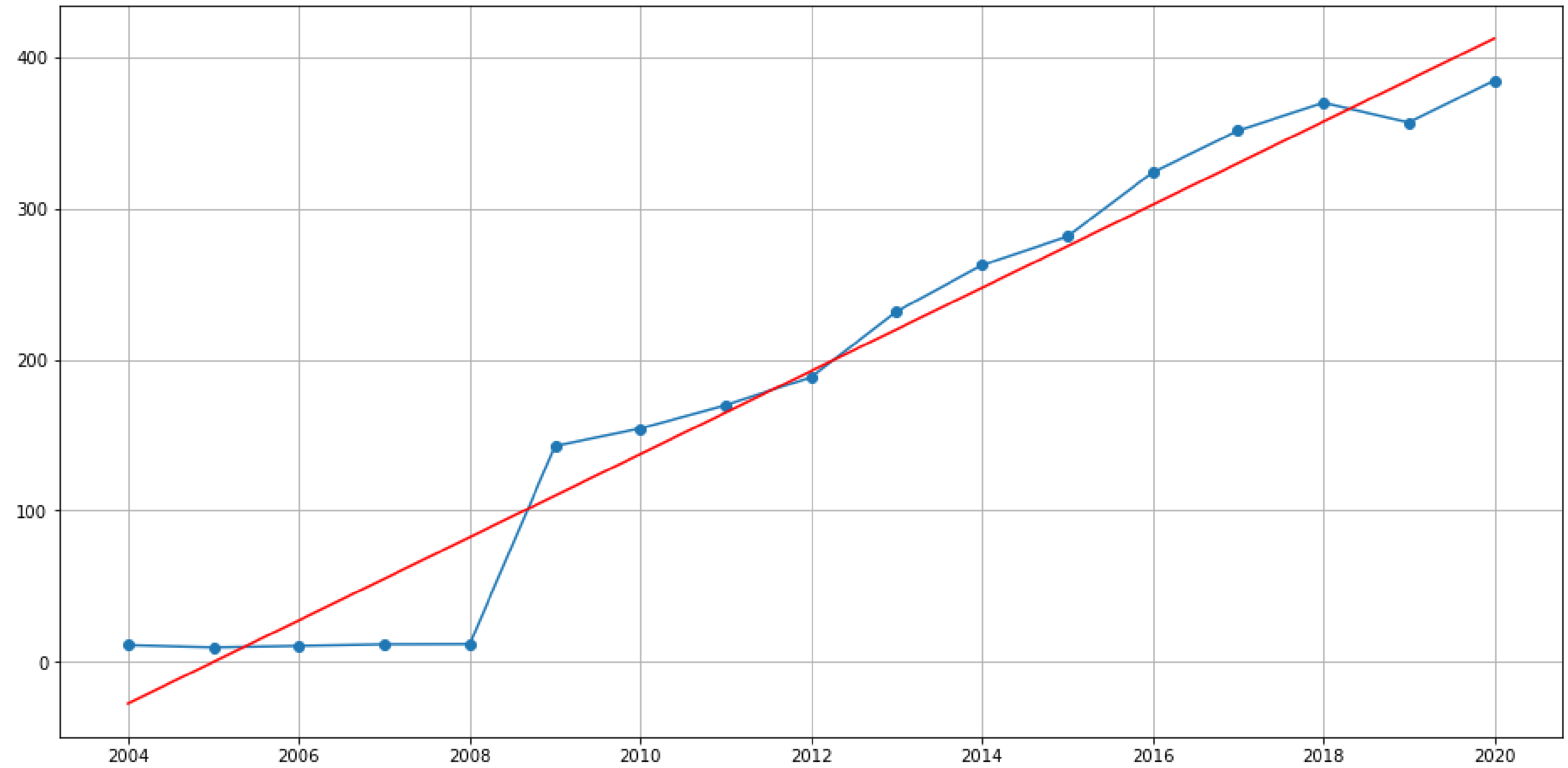
```
[[439.7835]]
[[467.26743137]]
```

Let's create a series by using arange function to create an array containing numbers starting from the specified starting value and incrementing the number of steps each time up to the end value

We need to give the next value of maximum point where arange does not include the maximum point in the array

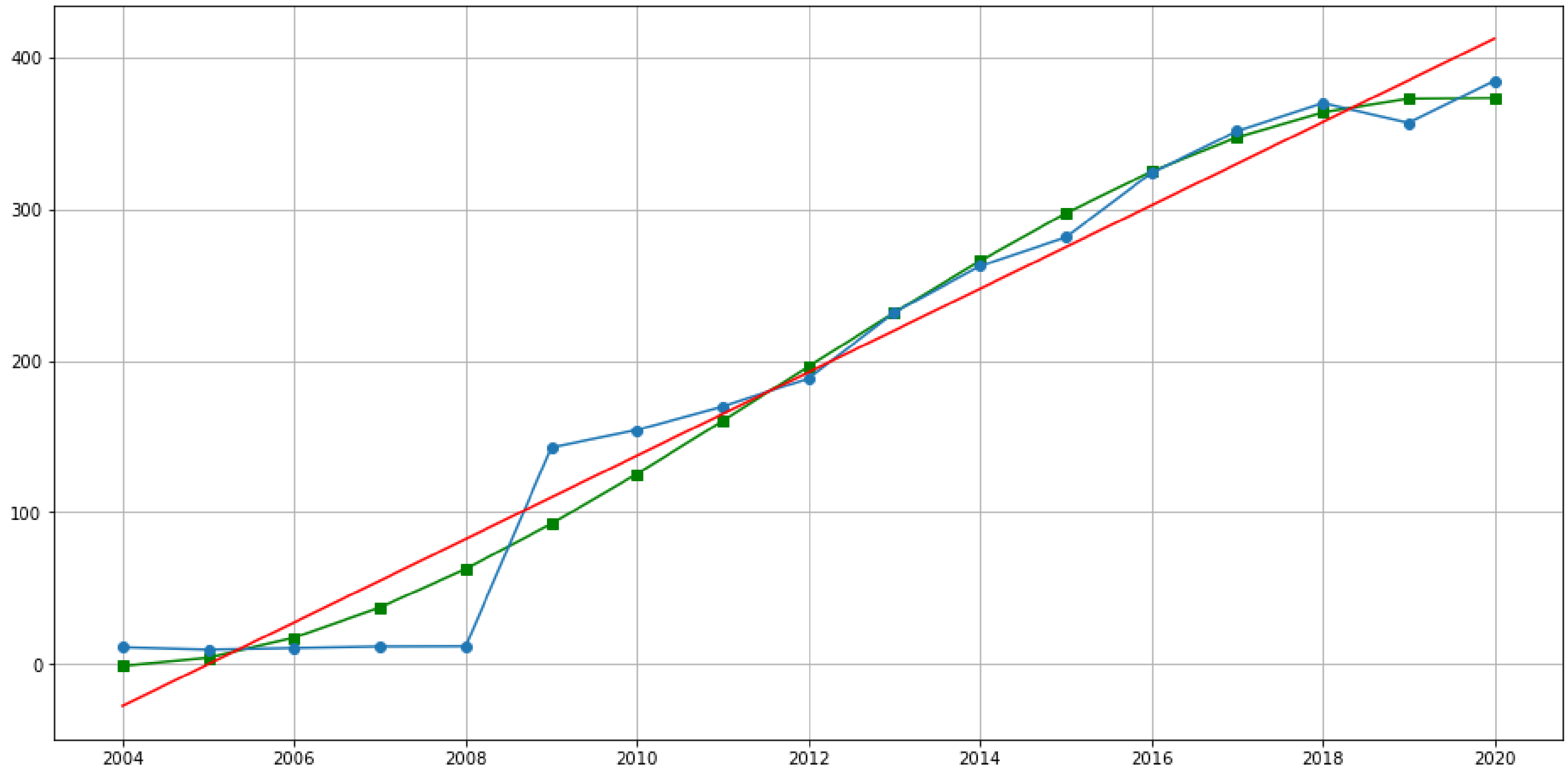
Now let's draw a linear plot for our price by years.

In [45]:
```
tmp2 = np.arange(min(columnsPlot),max(columnsPlot)+1).reshape(-1,1)
plt.figure(figsize=(16, 8))
plt.grid()
plt.plot(columnsPlot,esenyurtWaste, marker = 'o')
plt.plot(tmp2,regression.predict(tmp2),color="red")
plt.show()
```



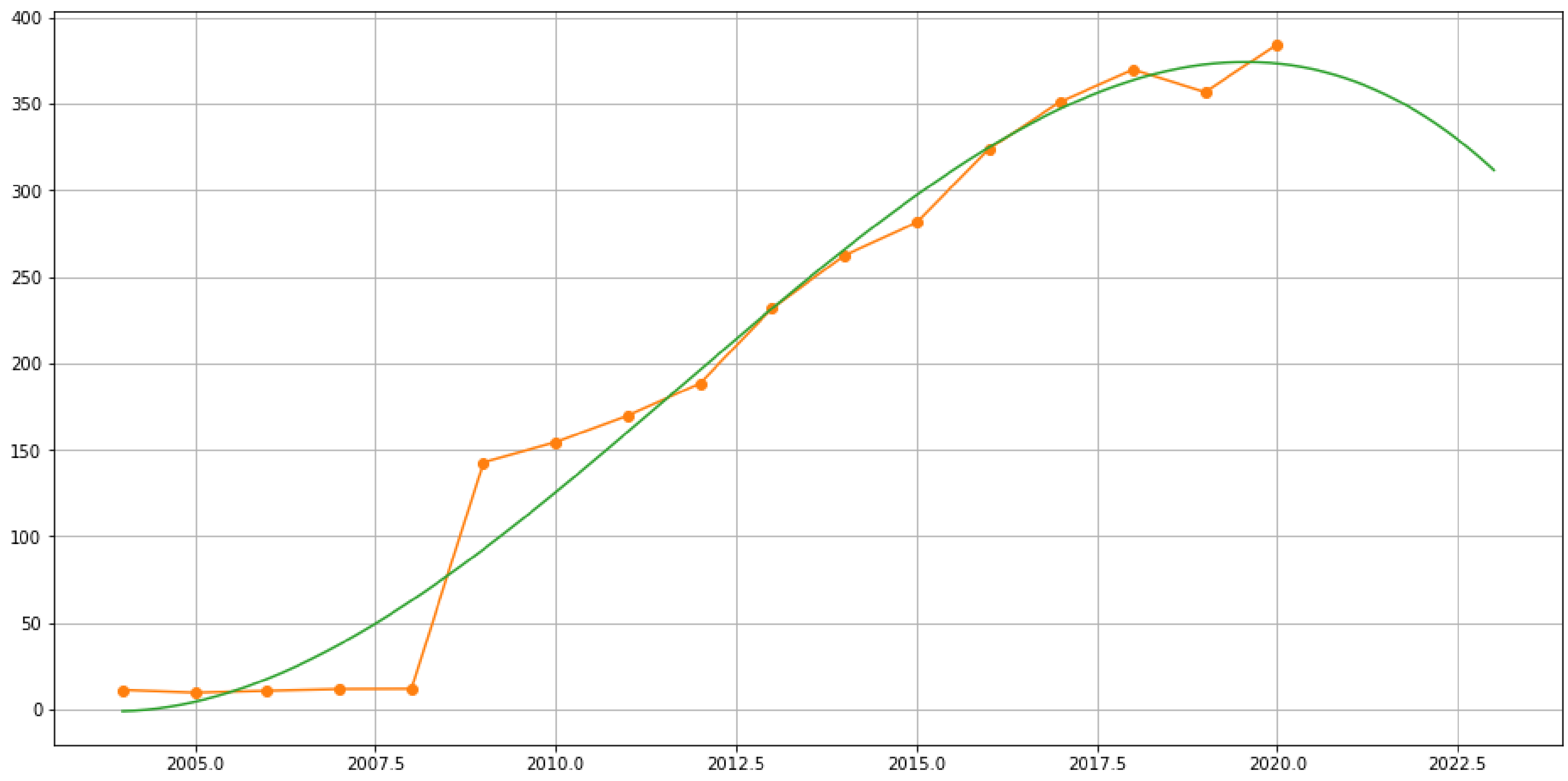
We did our investigations using linear regression. Let's examine it using polynomial regression.

In [46]:
```
regression2 = LinearRegression()
columns_copy = columns.copy()
esenyurtWaste_copy = esenyurtWaste.copy()
regression2.fit(columns_copy,esenyurtWaste_copy)
regressionPoly = PolynomialFeatures(degree = 4)
columnsPoly = regressionPoly.fit_transform(columns_copy)
regression2.fit(columnsPoly,esenyurtWaste_copy)

plt.figure(figsize=(16, 8))
plt.grid()
plt.plot(tmp2,regression2.predict(columnsPoly), 'gs-')
plt.plot(columnsPlot,esenyurtWaste, marker = 'o')
plt.plot(tmp2,regression.predict(tmp2),color="red")
plt.show()
```



In [47]:
```
from sklearn.pipeline import make_pipeline
plt.figure(figsize=(16, 8))
xfit = np.linspace(2004,2023,2023).reshape(-1,1)
poly_model = make_pipeline(PolynomialFeatures(4),LinearRegression())
poly_model.fit(columnsPlot.reshape(17,1),esenyurtWaste)
yfit = poly_model.predict(xfit)
plt.plot(columnsPlot, esenyurtWaste,'.')
plt.plot(columnsPlot,esenyurtWaste, marker = 'o')
plt.grid()
plt.plot(xfit, yfit);

estimate1 = regression2.predict(regressionPoly.fit_transform([[2021]]))
estimate2 = regression2.predict(regressionPoly.fit_transform([[2022]]))
estimate3 = regression2.predict(regressionPoly.fit_transform([[2023]]))
print(estimate1,estimate2,estimate3)
```

```
[[363.98431838]] [[343.87940633]] [[311.69155514]]
```



Hypothesis

Waste is higher in the district where real estate advertisements are the most.

In our previous examinations, we saw that Beyoğlu had the most advertisements. Let's compare our values and apply our tests for Beyoğlu and Esenyurt, where the most household waste is located.

In [48]:
```
BeyogluWaste = b_copy['2020'].values[12]
EsenyurtWaste = b_copy['2020'].values[17]
print("Waste of Beyoglu for 20020:",BeyogluWaste)
print("Waste of Esenyurt for 20020:",EsenyurtWaste)
```

```
Waste of Beyoglu for 20020: 115,602
Waste of Esenyurt for 20020: 384,469
```

When we look at the number of waste, we see that although Beyoglu has much more ads than Esenyurt, it has less than half of Esenyurt in terms of domestic waste.

The amount of domestic waste in 2019 is more than the amount of domestic waste in 2020

In [49]:
```
tmp20 = b_copy['2020']
tmp19 = b_copy['2019']
waste20 = []
waste19 = []
for value in tmp20:
    newValue = value.replace(',','.')
    waste20.append(float(newValue))
for value in tmp19:
    newValue = value.replace(',','.')
    waste19.append(float(newValue))
```

Shapiro Test

Now let's apply the shapiro test and evaluate our hypothesis.

In [50]:
```
shapiro_result = stats.shapiro(waste20)
shapiroTable = {'DF':[len(shapiro_result) - 1],
         'Test Statistic':[shapiro_result[0]],
         'p-Value':[shapiro_result[1]]}
result = pd.DataFrame(shapiroTable)
result
```

Out[50]:

	DF	Test Statistic	p-Value
0	1	0.934116	0.024403

For waste of 2020, we see that our p-value is less than 0.05 and according to this result, we can say that it does not have a normal distribution.

In [51]:
```
shapiro_result = stats.shapiro(waste19)
shapiroTable = {'DF':[len(shapiro_result) - 1],
         'Test Statistic':[shapiro_result[0]],
         'p-Value':[shapiro_result[1]]}
result = pd.DataFrame(shapiroTable)
result
```

Out[51]:

	DF	Test Statistic	p-Value
0	1	0.951832	0.094731

For waste of 2019, we see that the p value is greater than 0.05 and according to this result, we can say that it has a normal distribution. Now, let's apply the additional t-test for the correctness of our hypothesis.

In [52]:
```
print(stats.ttest_ind(waste19, waste20, equal_var=True))
```

```
Ttest_indResult(statistic=0.015396264768454803, pvalue=0.9877563899244018)
```

In the t-test, we see that the p-value value is greater than 0.05. Based on this result, I accept the N0 hypothesis.

Previously, we found the 6 neighbourhood with the most advertisements. Now, let's examine the amount of domestic waste in these 6 neighbourhood year by year and observe the change between 2019 and 2020.

First, let's pull our relevant data from our dataset and the relevant columns of this data.

In [53]:
```
# 'Beyoglu', 'Sisli', 'Fatih', 'Kadikoy', 'Besiktas', 'Uskudar'
Beyoglu_data = b_copy2[b_copy2["neighbourhood"] == "Beyoglu"]
Sisli_data = b_copy2[b_copy2["neighbourhood"] == "Sisli"]
Fatih_data = b_copy2[b_copy2["neighbourhood"] == "Fatih"]
Kadikoy_data = b_copy2[b_copy2["neighbourhood"] == "Kadikoy"]
Besiktas_data = b_copy2[b_copy2["neighbourhood"] == "Besiktas"]
Uskudar_data = b_copy2[b_copy2["neighbourhood"] == "Uskudar"]
Beyoglu_data = Beyoglu_data.iloc[:,[1,2,3,4,5,6,7,8,9,10,11,12,13,14,15,16,17]]
Sisli_data = Sisli_data.iloc[:,[1,2,3,4,5,6,7,8,9,10,11,12,13,14,15,16,17]]
Fatih_data = Fatih_data.iloc[:,[1,2,3,4,5,6,7,8,9,10,11,12,13,14,15,16,17]]
Kadikoy_data = Kadikoy_data.iloc[:,[1,2,3,4,5,6,7,8,9,10,11,12,13,14,15,16,17]]
Besiktas_data = Besiktas_data.iloc[:,[1,2,3,4,5,6,7,8,9,10,11,12,13,14,15,16,17]]
Uskudar_data = Uskudar_data.iloc[:,[1,2,3,4,5,6,7,8,9,10,11,12,13,14,15,16,17]]
```

I am converting it to numpy array format in order to be able to operate on our data more easily.

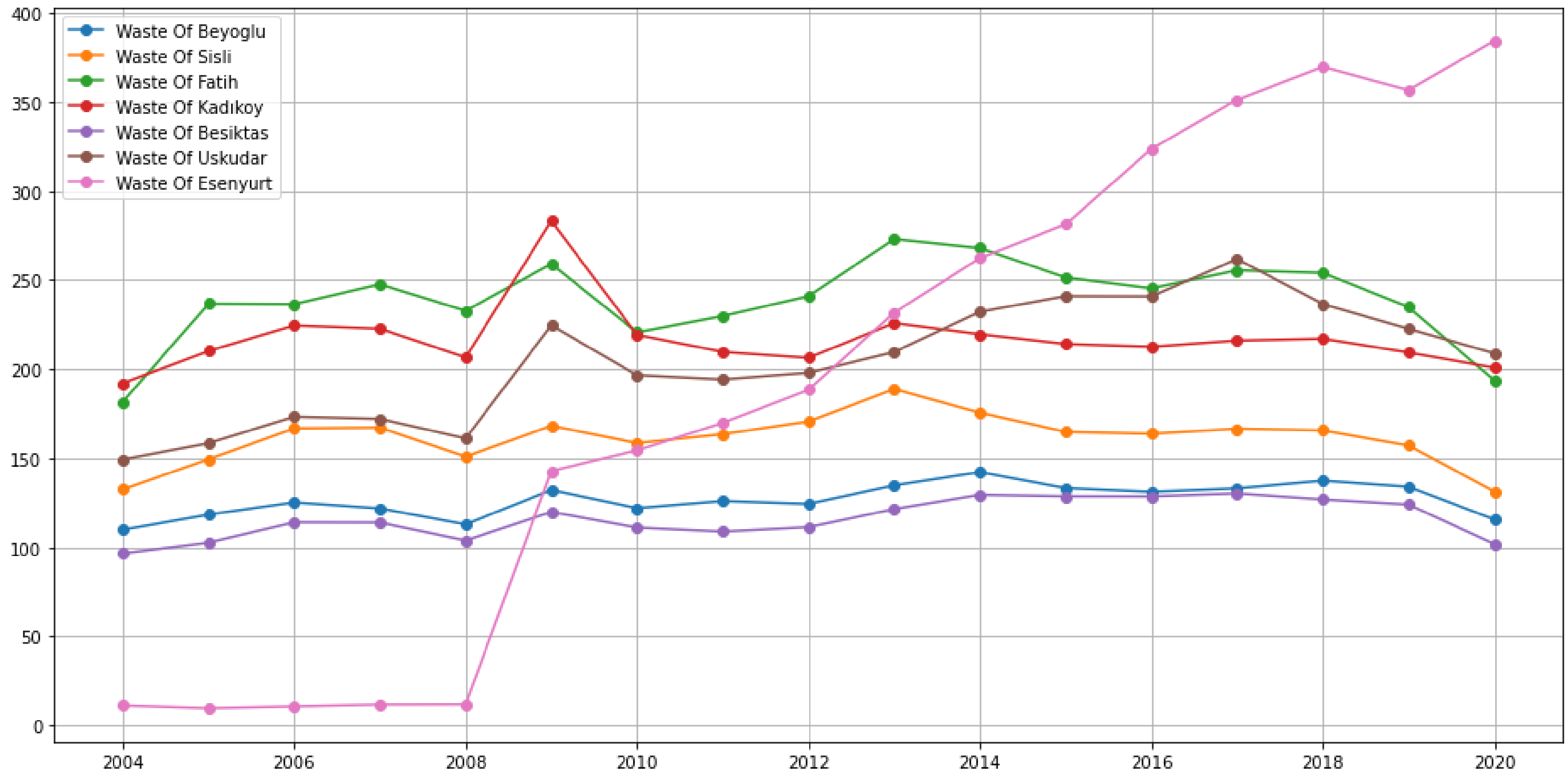
In [54]:
```
Beyoglu_data = np.array(Beyoglu_data)
Sisli_data = np.array(Sisli_data)
Fatih_data = np.array(Fatih_data)
Kadikoy_data = np.array(Kadikoy_data)
Besiktas_data = np.array(Besiktas_data)
Uskudar_data = np.array(Uskudar_data)
```

Now let's do our operations on our data and divide it into different arrays.

In [55]:
```
Beyoglu_waste = []
Sisli_waste = []
Fatih_waste = []
Kadikoy_waste = []
Besiktas_waste = []
Uskudar_waste = []
Beyoglu_data = Beyoglu_data.reshape(17,1)
Sisli_data = Sisli_data.reshape(17,1)
Fatih_data = Fatih_data.reshape(17,1)
Kadikoy_data = Kadikoy_data.reshape(17,1)
Besiktas_data = Besiktas_data.reshape(17,1)
Uskudar_data = Uskudar_data.reshape(17,1)
for val in Beyoglu_data:
    val = str(val[0])
    newValue = val.replace(',','.')
    Beyoglu_waste.append(float(newValue))
for val in Sisli_data:
    val = str(val[0])
    newValue = val.replace(',','.')
    Sisli_waste.append(float(newValue))
for val in Fatih_data:
    val = str(val[0])
    newValue = val.replace(',','.')
    Fatih_waste.append(float(newValue))
for val in Kadikoy_data:
    val = str(val[0])
    newValue = val.replace(',','.')
    Kadikoy_waste.append(float(newValue))
for val in Besiktas_data:
    val = str(val[0])
    newValue = val.replace(',','.')
    Besiktas_waste.append(float(newValue))
for val in Uskudar_data:
    val = str(val[0])
    newValue = val.replace(',','.')
    Uskudar_waste.append(float(newValue))
Beyoglu_waste = np.array(Beyoglu_waste)
Beyoglu_waste = Beyoglu_waste.reshape(-1,1)
Sisli_waste = np.array(Sisli_waste)
Sisli_waste = Sisli_waste.reshape(-1,1)
Fatih_waste = np.array(Fatih_waste)
Fatih_waste = Fatih_waste.reshape(-1,1)
Kadikoy_waste = np.array(Kadikoy_waste)
Kadikoy_waste = Kadikoy_waste.reshape(-1,1)
Besiktas_waste = np.array(Besiktas_waste)
Besiktas_waste = Besiktas_waste.reshape(-1,1)
Uskudar_waste = np.array(Uskudar_waste)
Uskudar_waste = Uskudar_waste.reshape(-1,1)
```

Finally, let's divide the data we have obtained and in addition to these, let's add the district of Esenyurt, which has the most domestic waste, to our graph.

In [56]:
```
plt.figure(figsize=(16, 8))
plt.grid()
plt.plot(columnsPlot,Beyoglu_waste, marker = 'o')
plt.plot(columnsPlot,Sisli_waste, marker = 'o')
plt.plot(columnsPlot,Fatih_waste, marker = 'o')
plt.plot(columnsPlot,Kadikoy_waste, marker = 'o')
plt.plot(columnsPlot,Besiktas_waste, marker = 'o')
plt.plot(columnsPlot,Uskudar_waste, marker = 'o')
plt.plot(columnsPlot,esenyurtWaste, marker = 'o')
plt.legend(['Waste Of Beyoglu','Waste Of Sisli','Waste Of Fatih','Waste Of Kadıkoy',
            'Waste Of Besiktas','Waste Of Uskudar','Waste Of Esenyurt'])
plt.show()
```



We have observed the changes in the amount of domestic waste for the 6 most popular neighborhoods and Esenyurt neighborhoods with the most domestic waste. For the 6 most popular neighborhoods, we observe a decline between 2019 and 2020.

Conclusion

As a result, by answering multiple questions about our airbnb data, we examined the factors affecting house prices about our data and about districts. We have seen that the price averages depending on the districts and the prices of the houses change depending on the characteristics. We had the opportunity to make different comparisons for all districts by visualizing our data. In addition to our Airbnb data, we added the amount of household waste to our airbnb data and tried to find an interaction between them. One of our hypotheses was that the amount of waste might be higher in the district with too many advertisements. When we checked our values, we saw that this was not the case. In addition, we made predictions for the coming years depending on the amount of waste and made our visualizations accordingly.

References

[https://medium.com/codex/house-price-prediction-with-machine-learning-in-python-cf9df744f7ff (https://medium.com/codex/house-price-prediction-with-machine-learning-in-python-cf9df744f7ff)](https://medium.com/codex/house-price-prediction-with-machine-learning-in-python-cf9df744f7ff)