In [31]:

```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
%matplotlib inline
import seaborn as sns
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import LabelEncoder
import warnings
from scipy import stats
import math
warnings.filterwarnings('ignore')
```

In [4]:

```
df = pd.read_csv("/content/real_estate.csv")
```

In [5]:

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 414 entries, 0 to 413
Data columns (total 8 columns):
 #   Column                               Non-Null Count  Dtype  
---  ------                               --------------  -----  
 0   transaction_date                     414 non-null    float64
 1   house_age                            414 non-null    int64  
 2   distance_to_the_nearest_MRT_station  414 non-null    float64
 3   number_of_convenience_stores         414 non-null    int64  
 4   latitude                             414 non-null    float64
 5   longitude                            414 non-null    float64
 6   house_price_of_unit_area             414 non-null    float64
 7   house_age_square                     414 non-null    int64  
dtypes: float64(5), int64(3)
memory usage: 26.0 KB
```

In [6]:

```
df.columns
```

Out[6]:

```
Index(['transaction_date', 'house_age', 'distance_to_the_nearest_MRT_station',
       'number_of_convenience_stores', 'latitude', 'longitude',
       'house_price_of_unit_area', 'house_age_square'],
      dtype='object')
```

In [7]:

```
# for convenience, I rename to shorten attributes's name
df.columns = ['transaction_date', 'house_age', 'distance',
       'number_stores', 'latitude', 'longitude',
       'house_price', 'house_age_square']
```

In [8]:

```
"""
Dataset includes 8 attributes, non-null values:
continuous attributes : transaction_date, distance_to_the_nearest_MRT_station, latitude,
longitude, house_price_of_unit_area
categorical attribites: house_age, number_of_convenience_stores, house_age_square ( = hou
se_age * house_age)
"""
continuous = ["transaction_date", "distance", "latitude", "longitude", "house_price"]
categorical = ["house_age", "number_stores", "house_age_square"]
```

In [9]:

```
df.describe()
```

Out[9]:

	transaction_date	house_age	distance	number_stores	latitude	longitude	house_price	house_age_square
count	414.000000	414.000000	414.000000	414.000000	414.000000	414.000000	414.000000	414.000000
mean	2013.148971	17.292271	1083.885689	4.094203	24.969030	121.533361	37.980193	427.166667
std	0.281967	11.333769	1262.109595	2.945562	0.012410	0.015347	13.606488	459.166535
min	2012.667000	0.000000	23.382840	0.000000	24.932070	121.473530	7.600000	0.000000
25%	2012.917000	9.000000	289.324800	1.000000	24.963000	121.528085	27.700000	81.000000
50%	2013.167000	16.000000	492.231300	4.000000	24.971100	121.538630	38.450000	256.000000
75%	2013.417000	28.000000	1454.279000	6.000000	24.977455	121.543305	46.600000	784.000000
max	2013.583000	43.000000	6488.021000	10.000000	25.014590	121.566270	117.500000	1849.000000

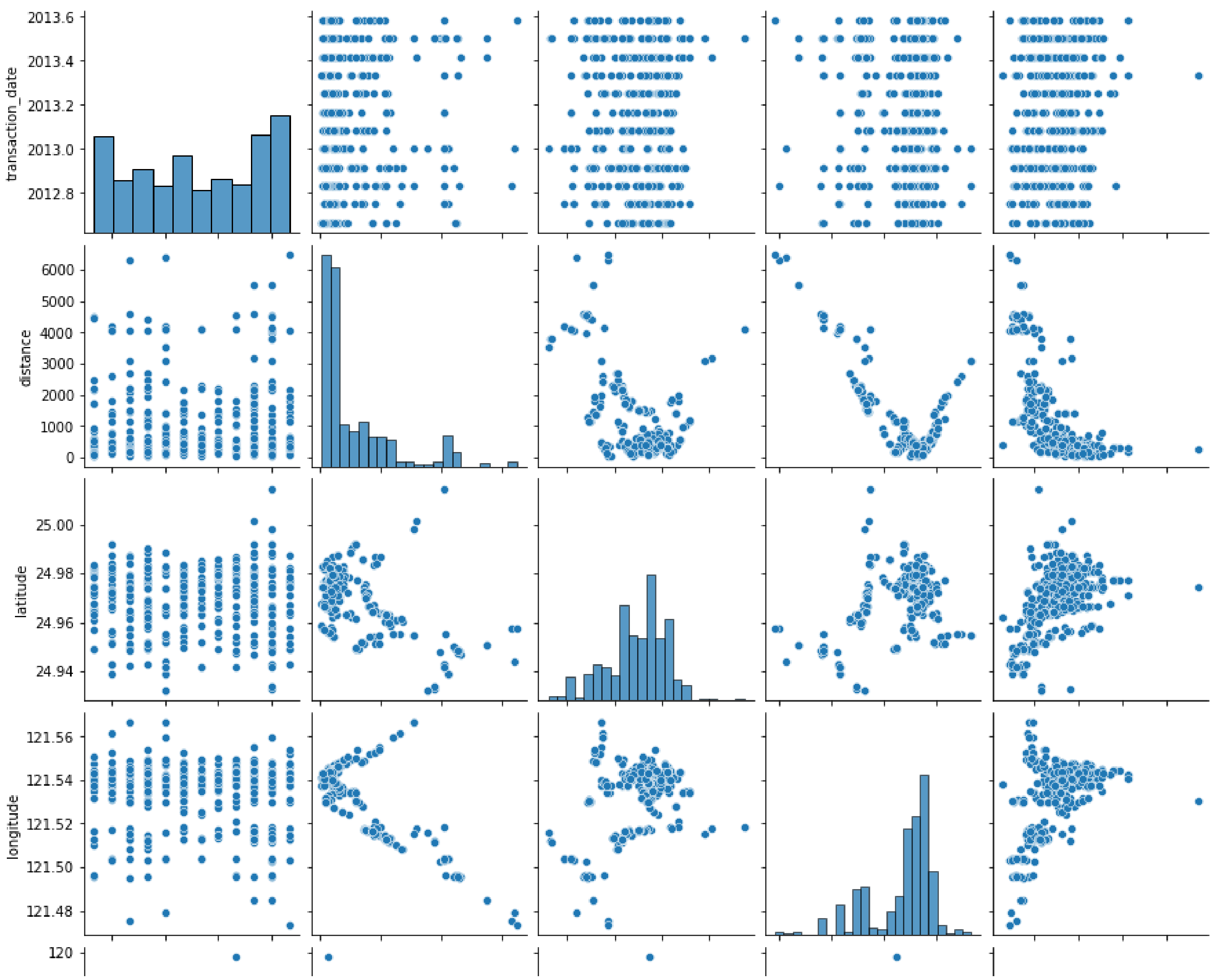
In [10]:

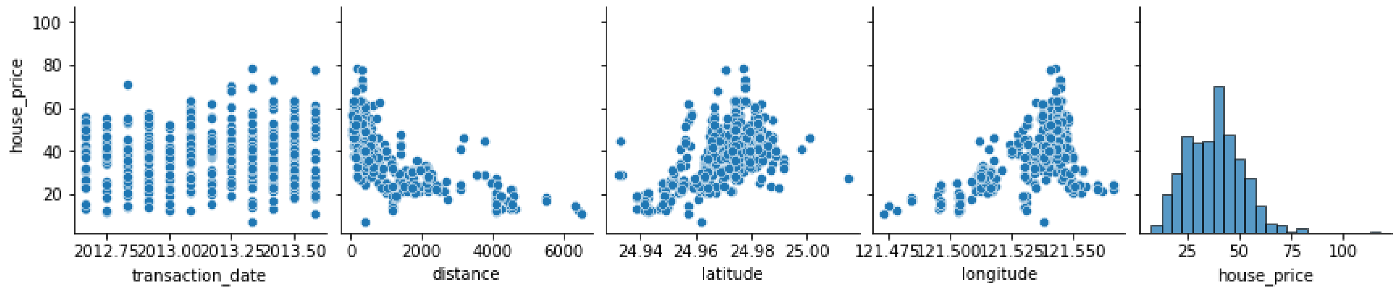
```
def function_to_pair_plot(df):
    plt.figure(dpi=120)
    sns.pairplot(df)
    plt.show()
```

In [11]:

```
# pair-plot attributes from continuous set to see how correlated each pair of them is
function_to_pair_plot(df[continuous])
```

<Figure size 720x480 with 0 Axes>





In [12]:

```
"""
The cross line of chart above is histogram of each attributes.
- house_price and latitude are likely normal distributions
- house_price is slightly skew at the right side
- latitude is likely skew at the left side

"""
```

Out[12]:

```
'\nThe cross line of chart above is histogram of each attributes. \n- house_price_of_unit_area and latitude are likely normal distributions\n'
```

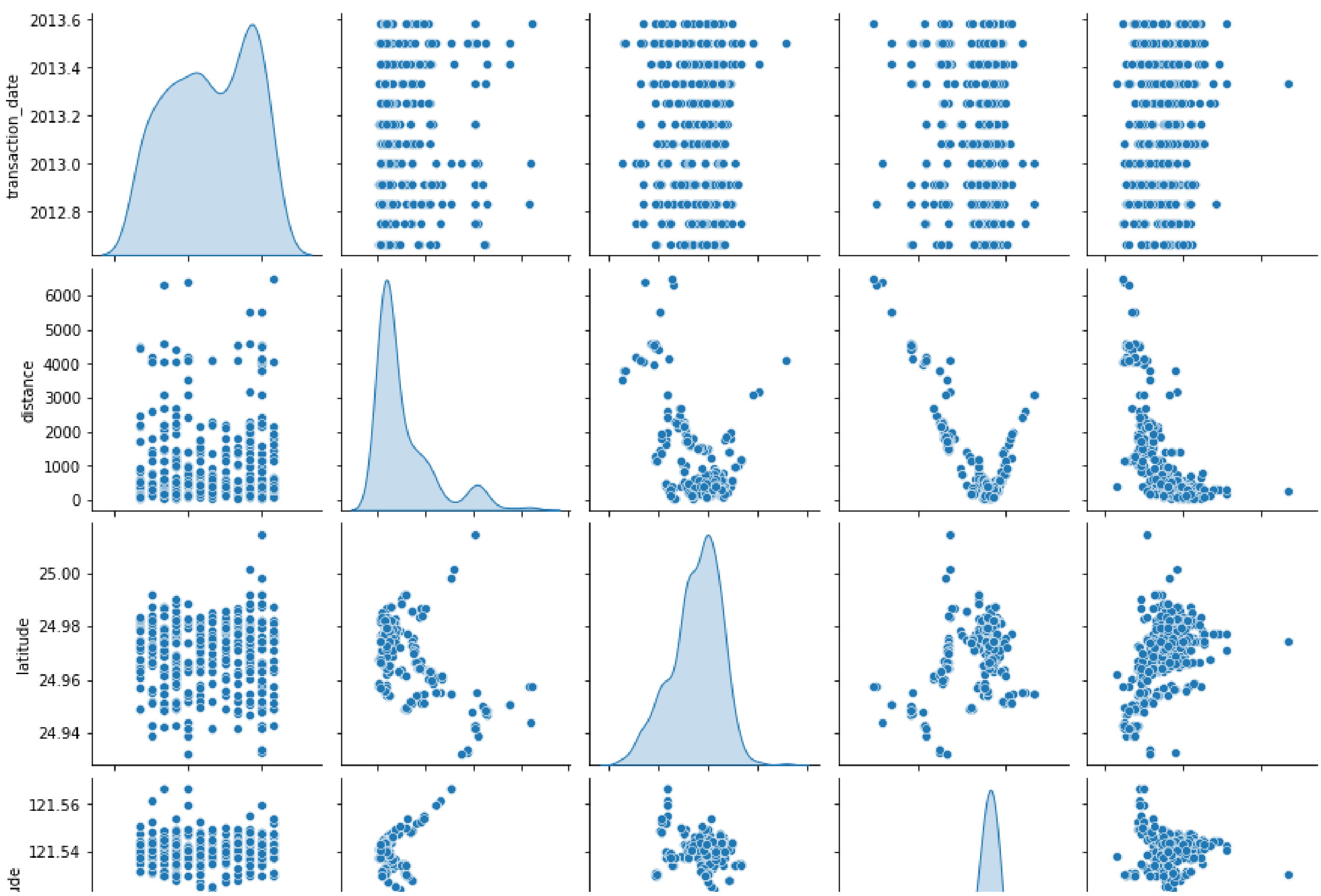
In [13]:

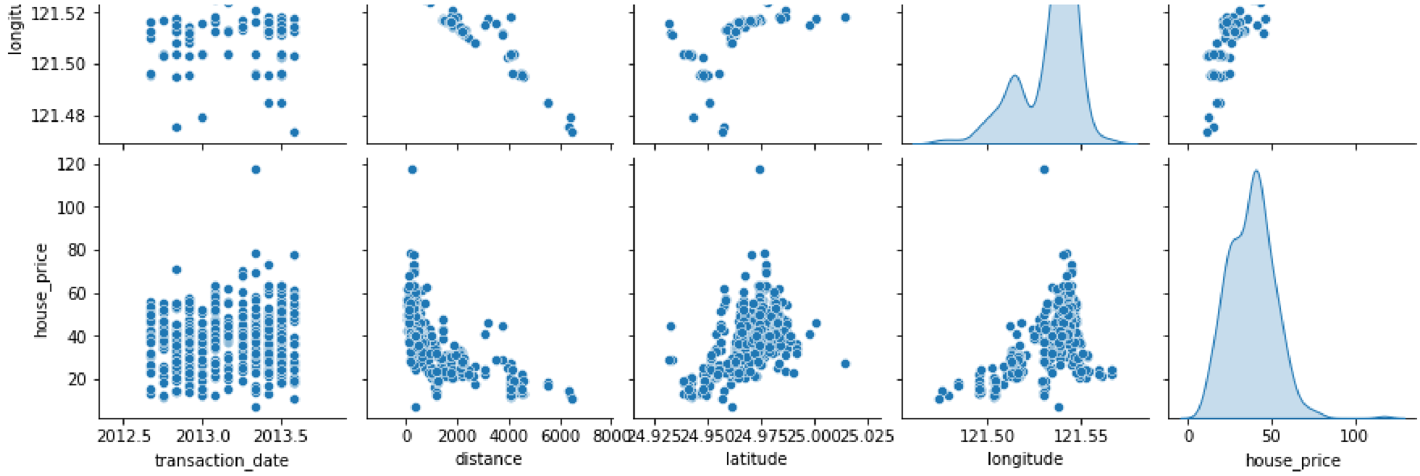
```
def function_to_pair_plot_kde(df):
    plt.figure(dpi=120)
    sns.pairplot(df, diag_kind="kde")
    plt.show()
```

In [14]:

```
"""
We might want to see the KDE of them:
"""
function_to_pair_plot_kde(df[continuous])
```

<Figure size 720x480 with 0 Axes>



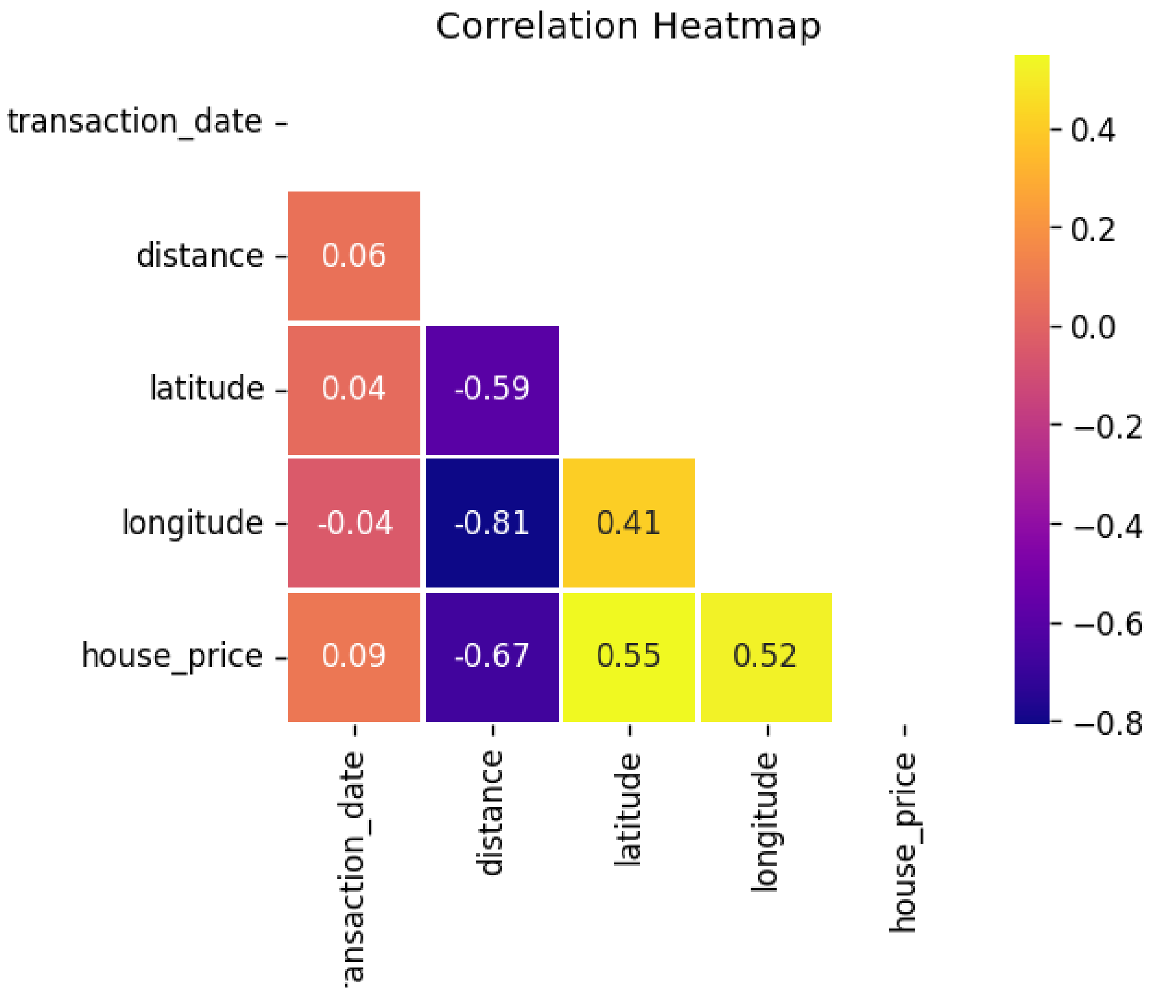


In [15]:

```
def plot_heatmap(df):
    plt.figure(dpi = 120,figsize= (5,4))
    mask = np.triu(np.ones_like(df.corr(),dtype = bool))
    sns.heatmap(df.corr(),mask = mask, fmt = ".2f",annot=True,lw=1,cmap = 'plasma')
    plt.yticks(rotation = 0)
    plt.xticks(rotation = 90)
    plt.title('Correlation Heatmap')
    plt.show()
```

In [16]:

```
plot_heatmap(df[continuous])
"""
Plot Correlation Heatmap to find out the exact correlation metrics
There are obviously some extreme correlations here. For instance, distance is negatively
correlated with the rest (-0.59, -0.81, -0.67) except transaction_date.
house_price is the same as distance
transaction_date is likely not correlated with the rest.

"""
```



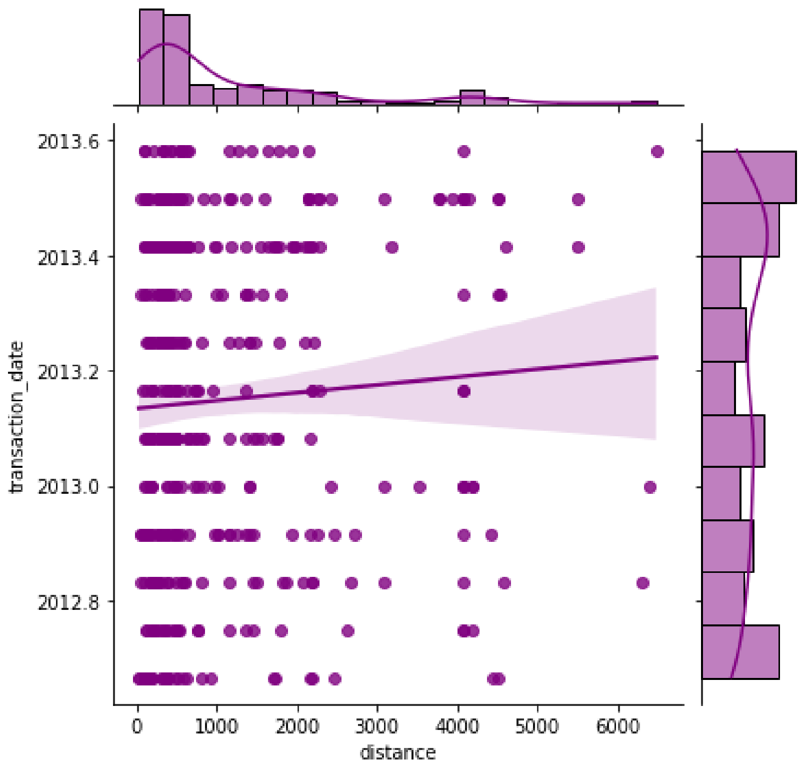
Out[16]:

```
'\nPlot Correlation Heatmap to find out the exact correlation metrics\nThere are obviousl
y some extreme correlations here. For instance, distance is negatively correlated with th
e rest (-0.59, -0.81, -0.67) except transaction_date.\nhouse_price is the same as distanc
e\ntransaction_date is likely not correlated with the rest.\n\n'
```

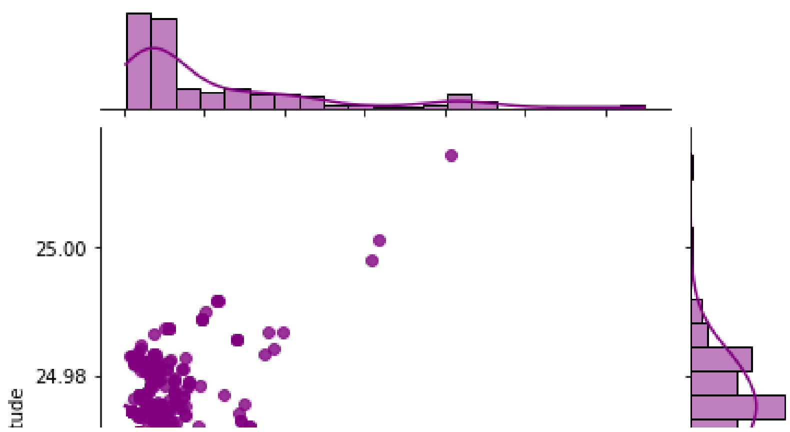
In [17]:

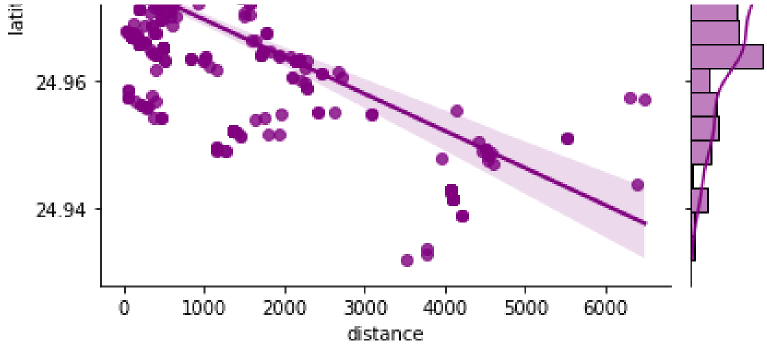
```
"""
intuitively, linear line below indicates the negative correlation of distance with other
continuous variables
"""
plt.figure(dpi = 100, figsize = (5,4))
print("Distance with other continuous variables \n")
for i in  df[continuous].columns:
    if i != 'distance':
        print(f"Correlation between Distance and {i} ==> ",df[continuous].corr().loc['di
stance'][i])
        sns.jointplot(x='distance',y=i,data= df[continuous] ,kind = 'reg',color = 'purpl
e')
        plt.show()
```

```
Distance with other continuous variables

Correlation between Distance and transaction_date ==>  0.06087995314209762 6

&lt;Figure size 500x400 with 0 Axes&gt;
```

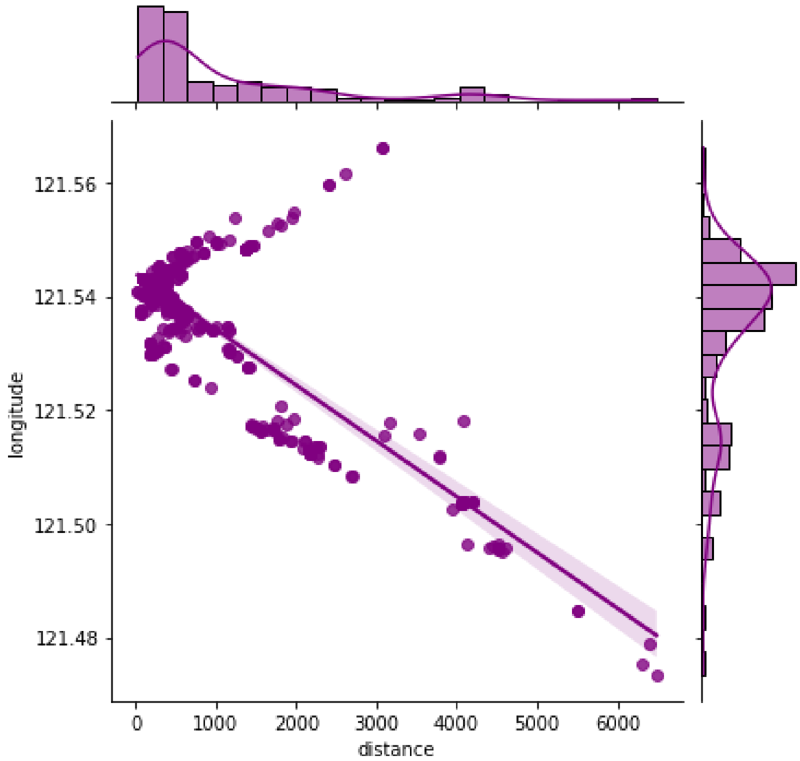



```
Correlation between Distance and latitude ==>  -0.5910665729874615
```

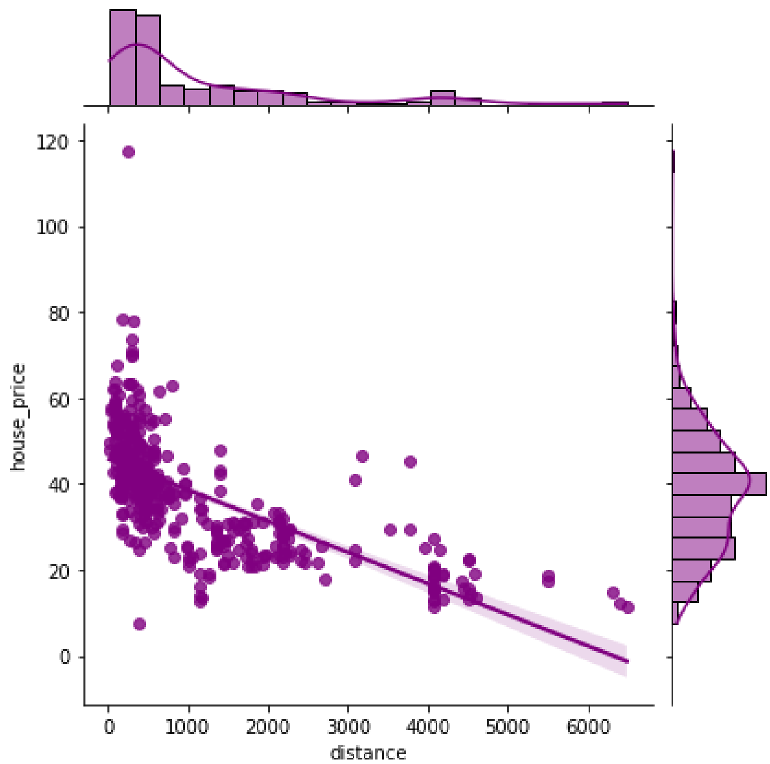





```
Correlation between Distance and longitude ==>  -0.8063167695693655
```




```
Correlation between Distance and house_price ==>  -0.6736128553689181
```

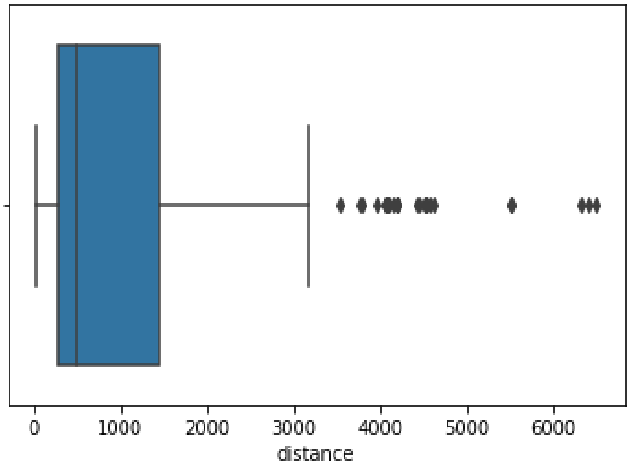


In [18]:

```
sns.boxplot(df["distance"])
```

Out[18]:

<matplotlib.axes._subplots.AxesSubplot at 0x7feaf7bdf810>



In [20]:

```
"""
The outliers of distance lie in range 3000 (heavily skew at the right side)
"""
```

Out[20]:

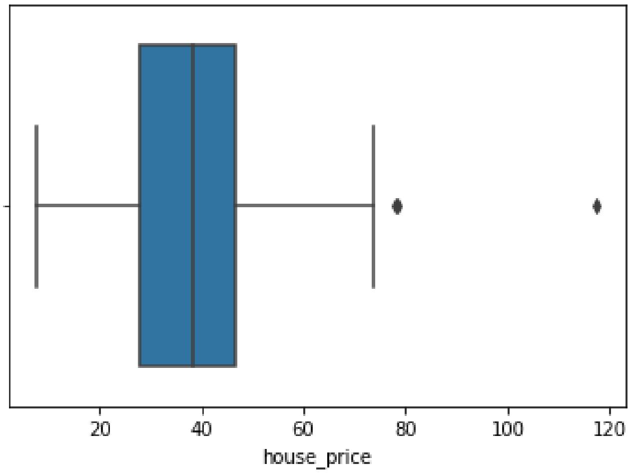
'\nThe outliers of distance lie in range 3000 (heavily skew at the right side)\n'

In [24]:

```
"""
Do similarly with other continuous variables, we have:
"""
sns.boxplot(df["house_price"])
```

Out[24]:

<matplotlib.axes._subplots.AxesSubplot at 0x7feaeeca7a10>

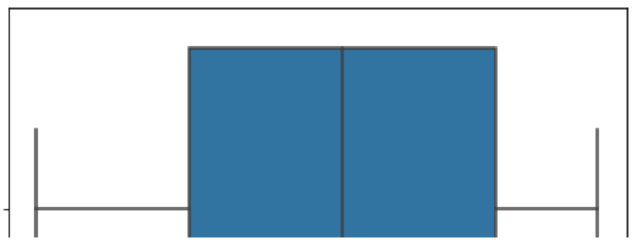


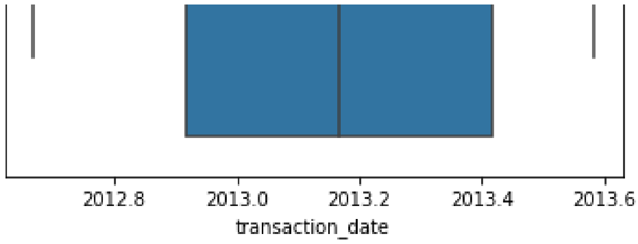
In [115]:

```
sns.boxplot(df["transaction_date"])
```

Out[115]:

<matplotlib.axes._subplots.AxesSubplot at 0x7fead9018610>



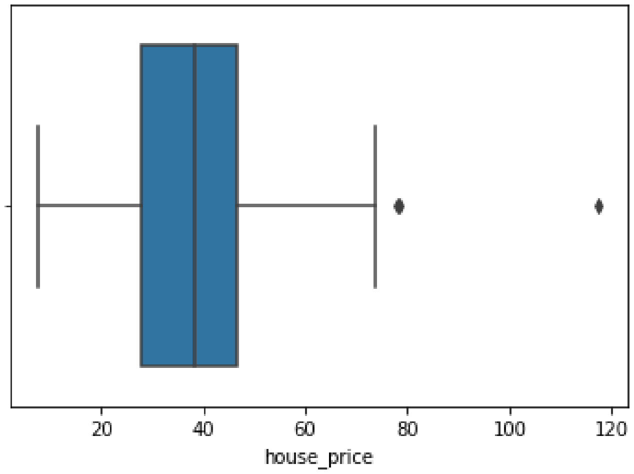


In [25]:

```
sns.boxplot(df["house_price"])
```

Out[25]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x7feaf7bca710>
```

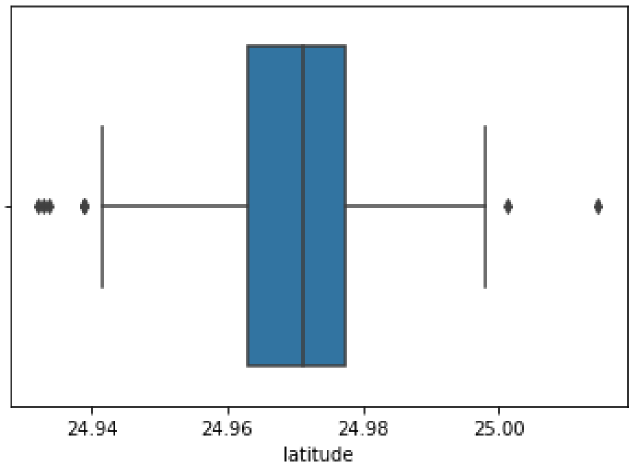


In [26]:

```
sns.boxplot(df["latitude"])
# frew outliers
```

Out[26]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x7feaed9523d0>
```

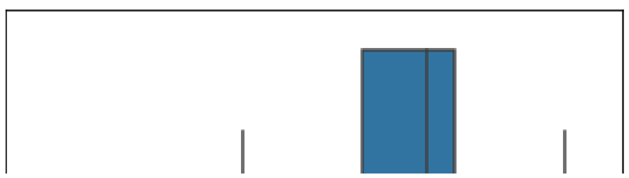


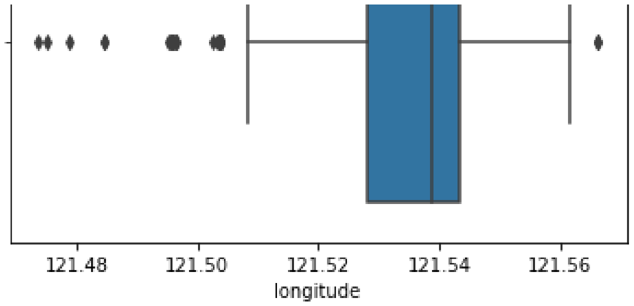
In [27]:

```
sns.boxplot(df["longitude"])
# many outliers
```

Out[27]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x7feaed8bac90>
```





In [34]:

```
def statistic_numbers(distribution):
    """
    return:
    sample mean
    mode
    skewness
    z-score
    """
    return np.mean(distribution), stats.mode(distribution), stats.skew(distribution), st
ats.zscore(distribution)
```

In [35]:

```
mean_dis, mode_dis, skew_dis, _ = statistic_numbers(df.distance)
print("mean : ", mean_dis)
print("mode : ", mode_dis)
print("skew : ", skew_dis)
```

```
mean :  1083.8856889130436
mode :  ModeResult(mode=array([289.3248]), count=array([13]))
skew :  1.8819063601148036
```

In [21]:

```
df.columns
```

Out[21]:

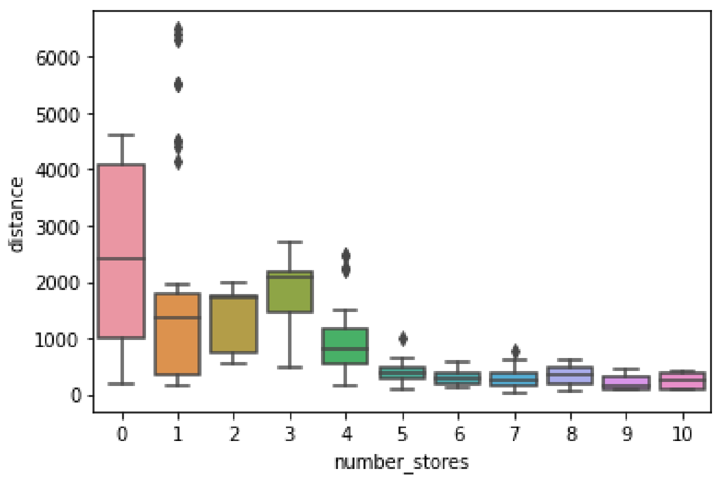
```
Index(['transaction_date', 'house_age', 'distance', 'number_stores',
       'latitude', 'longitude', 'house_price', 'house_age_square'],
      dtype='object')
```

In [28]:

```
"""
For categorical attributes, we perform box-plot one continuous variable to each of them
For example, I will perform boxplot of number_stores
"""
sns.boxplot(x="number_stores", y="distance", data=df)
```

Out[28]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x7feaed864ed0>
```



In [39]:

```
df.groupby('number_stores').count()
```

Out[39]:

number_stores	transaction_date	house_age	distance	latitude	longitude	house_price	house_age_square
0	67	67	67	67	67	67	67
1	46	46	46	46	46	46	46
2	24	24	24	24	24	24	24
3	46	46	46	46	46	46	46
4	31	31	31	31	31	31	31
5	67	67	67	67	67	67	67
6	37	37	37	37	37	37	37
7	31	31	31	31	31	31	31
8	30	30	30	30	30	30	30
9	25	25	25	25	25	25	25
10	10	10	10	10	10	10	10

In [42]:

```
df.groupby('house_age').count().head(5)
# house_age_square is the same
```

Out[42]:

house_age	transaction_date	distance	number_stores	latitude	longitude	house_price	house_age_square
0	17	17	17	17	17	17	17
1	11	11	11	11	11	11	11
2	8	8	8	8	8	8	8
3	14	14	14	14	14	14	14
4	13	13	13	13	13	13	13

In [37]:

```
df.describe()
```

Out[37]:

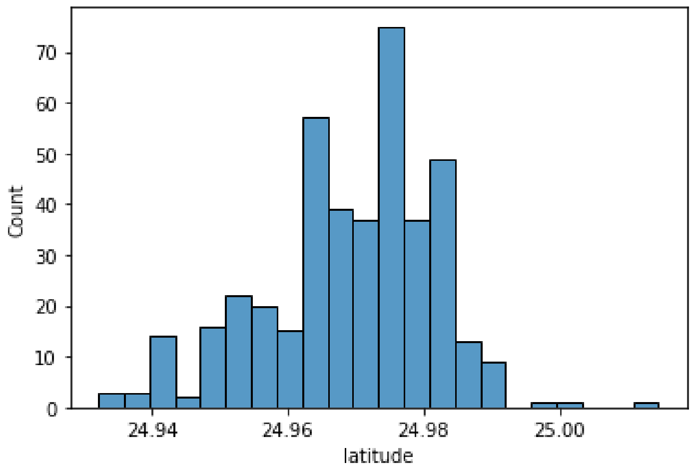
	transaction_date	house_age	distance	number_stores	latitude	longitude	house_price	house_age_square
count	414.000000	414.000000	414.000000	414.000000	414.000000	414.000000	414.000000	414.000000
mean	2013.148971	17.292271	1083.885689	4.094203	24.969030	121.533361	37.980193	427.166667
std	0.281967	11.333769	1262.109595	2.945562	0.012410	0.015347	13.606488	459.166535
min	2012.667000	0.000000	23.382840	0.000000	24.932070	121.473530	7.600000	0.000000
25%	2012.917000	9.000000	289.324800	1.000000	24.963000	121.528085	27.700000	81.000000
50%	2013.167000	16.000000	492.231300	4.000000	24.971100	121.538630	38.450000	256.000000
75%	2013.417000	28.000000	1454.279000	6.000000	24.977455	121.543305	46.600000	784.000000
max	2013.583000	43.000000	6488.021000	10.000000	25.014590	121.566270	117.500000	1849.000000

In [76]:

```
sns.histplot(df.latitude)
```

Out[76]:

<matplotlib.axes._subplots.AxesSubplot at 0x7fead9816750>

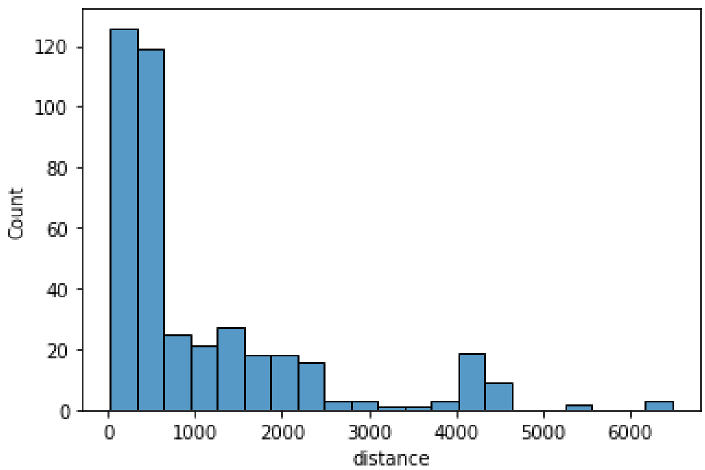


In [71]:

```
sns.histplot(df.distance)
```

Out[71]:

<matplotlib.axes._subplots.AxesSubplot at 0x7fead991e950>



In [78]:

```
"""
muy_latitude = 24.96
muy_distance = 1083.89

For latitude,
We can clearly see that the latitude is likely a normal distribution, and mean of it is b
igger than 24.9 . Then it's obvious that the mean will be in range (24.9, 25).
Hence, I want to test if it's always that the mean is bigger than 24.9 or not

For distance, there is a imbalance between the value < 1000 and the rest. Unlike latitude
, when observe on histogram of distance, it's hard to tell where the mean is supposed to
lie in.
Hence, I want to test if it is bigger than a number, for example 1080
"""
```

Out[78]:

```
"\nmuy_latitude = 24.96\nmuy_distance = 1083.89\n\nFor latitude,\nWe can clearly see that
the latitude is likely a normal distribution, and mean of it is bigger than 24.9 . Then i
t's obvious that the mean will be in range (24.9, 25).\nHence, I want to test if it's alw
ays that the mean is bigger than 24.9 or not\n\nFor distance, there is a imbalance betwee
n the value < 1000 and the rest. Unlike latitude, when observe on histogram of distance,
it's hard to tell where the mean is supposed to lie in.\nHence, I want to test if it is b
igger than a number, for example 1500\n"
```

In [97]:

```
# Hypothesis testing for mean of latitude. We want to test if mean of latitude is bigger
than 24 or not
"""
Null hypothesis H0: mean of latitude = 24.9
Alternative hypothesis Ha: mean of latitude > 24.9
alpha = 0.05
"""
alpha = 0.05
N = 414
s = 0.012410
muy0 = 24.9
muy_x = 24.969030
z_score = (muy_x - muy0) / (s/math.sqrt(N))
print(z_score)
qt = stats.t.ppf(1-alpha, N)
if abs(z_score) > qt:
  print("Reject H0. Support Ha. Hence, we have temporarily accepted alternative hypothesi
s, that the mean cannot be 24.9 ")
else:
  print("Failed to reject H0. ")
```

```
113.17910686586961
Reject H0. Support Ha. Hence, we have temporarily accept alternative hypothesis, that is
mean > 24.9
```

In [99]:

```
# Hypothesis testing for mean of distance
"""
Null hypothesis H0: mean of distance = 1080
Alternative hypothesis Ha: mean of distance > 1080
"""
alpha = 0.05
N = 414
s = 1262.109595
muy0 = 1080
muy_x = 1083.885689
z_score = (muy_x - muy0) / (s/math.sqrt(N))
print(z_score)
qt = stats.t.ppf(1-alpha, N)
if abs(z_score) > qt:
  print("Reject H0. Support Ha. Hence, we have temporarily accept alternative hypothesis"
)
else:
  print("Failed to reject H0. Hence, the mean of distance can be 1080 ")
```

```
0.06264279690338559
Failed to reject H0. Hence, the mean of distance can be 1080
```

In [113]:

```
"""
proportion of number_stores is 2 = 0.058, it's small. I want to test if proportion of it
has a chance to be bigger or not. I test it with 0.12
proportion of house_age is 0.019. It's near 0.02. I  want to test if proportion of it has
a chance to 0.02 or not.
"""
```

Out[113]:

```
"\nproportion of number_stores is 2 = 0.058, it's small. I want to test if proportion of
it has a chance to be bigger or not. I test it with 0.12\nproportion of house_age is 0.01
9. It's near 0.02. I  want to test if proportion of it has a chance to 0.02 or not.\n"
```

In [109]:

```
# Hypothesis testing for proportion of number_stores
"""
Null hypothesis H0: proportion of number_stores where number_stores is 2 = 0.12
```

```
Alternative hypothesis Ha: proportion of number_stores where number_stores is 2 != 0.12
"""
df_test_pro = df[df['number_stores'] == 2]
alpha = 0.05
N = 414
p = len(df_test_pro) / N
p0 = 0.12
z_score = (p - p0) / math.sqrt(p0 * (1 - p0) / N)
print(z_score)

if z_score <= -1.645:
  print("Reject H0")
else:
  print("Failed to reject H0")
```

```
-3.8838539462273576
Reject H0
```

In [111]:

```
# Hypothesis testing for proportion of house_age
"""
Null hypothesis H0: proportion of house_age where house_age is 50 = 0.02
Alternative hypothesis Ha: proportion of house_age where house_age is 50 != 0.02
"""
df_test_pro_age = df[df['house_age'] == 10]
alpha = 0.05
N = 414
p = len(df_test_pro_age) / N
p0 = 0.02
z_score = (p - p0) / math.sqrt(p0 * (1 - p0) / N)
print(z_score)
if z_score <= -1.645:
  print("Reject H0")
else:
  print("Failed to reject H0")
```

```
-0.09829463743659829
Failed to reject H0
```

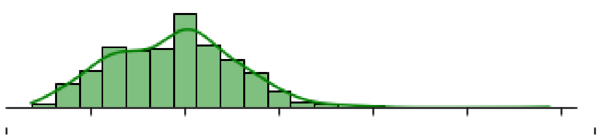
In [43]:

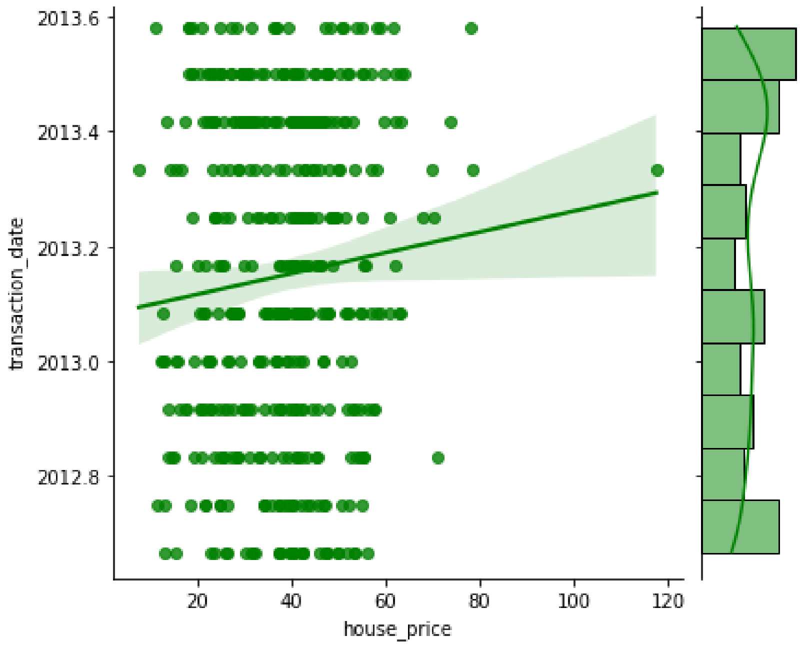
```
import statsmodels.api as sm
from statsmodels.formula.api import ols
```

In [116]:

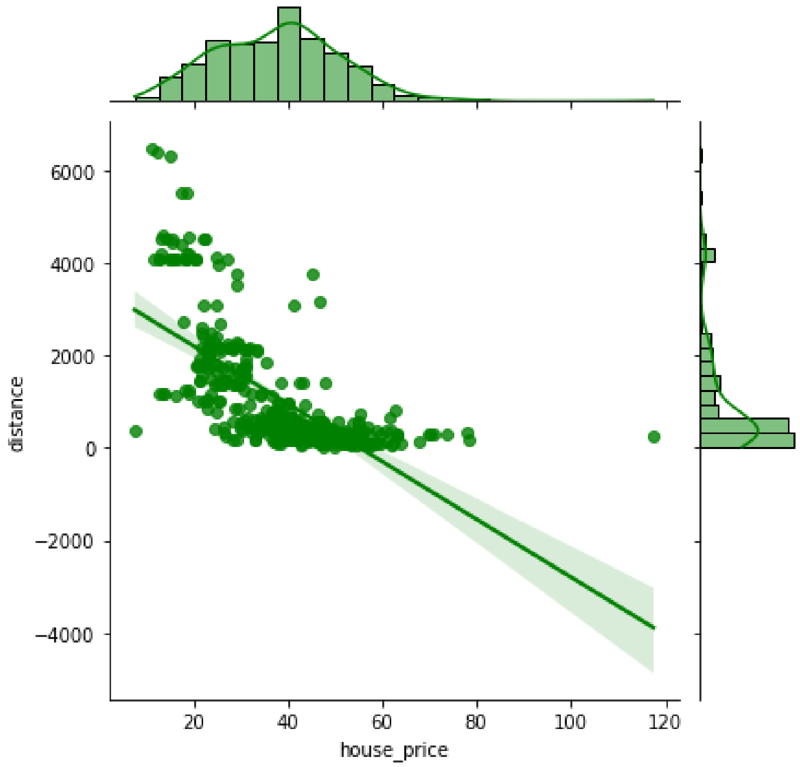
```
"""
I want to investigate the relationship between house_price and the rest and construct a l
inear regression model for it
We perform some charts first to see how other variables affect house_price
"""
plt.figure(dpi = 100, figsize = (5,4))
print("house_price with other continuous variables \n")
for i in  df[continuous].columns:
    if i != 'house_price':
        print(f"Correlation between house_price and {i} ==> ",df[continuous].corr().loc[
'house_price'][i])
        sns.jointplot(x='house_price',y=i,data= df[continuous] ,kind = 'reg',color = 'gr
een')
        plt.show()
```

```
house_price with other continuous variables

Correlation between house_price and transaction_date ==>  0.08749060640257195

<Figure size 500x400 with 0 Axes>
```

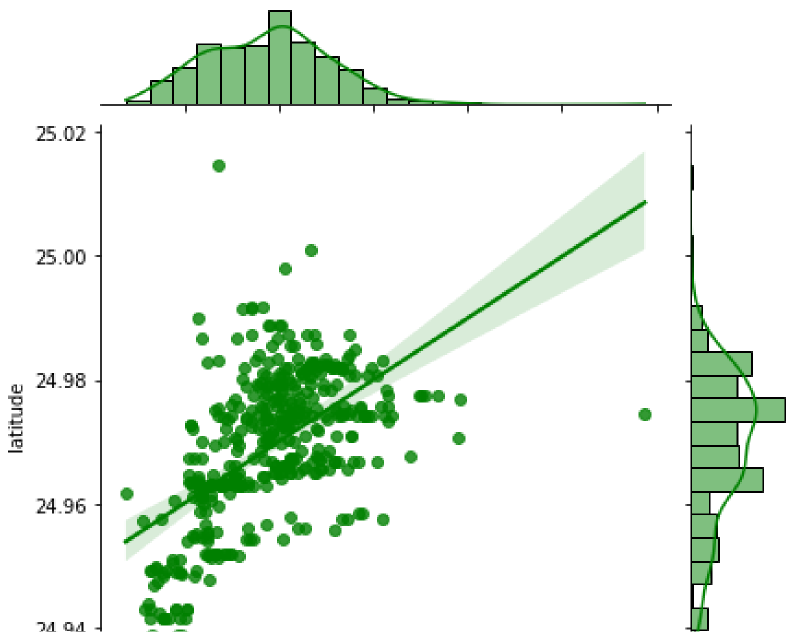




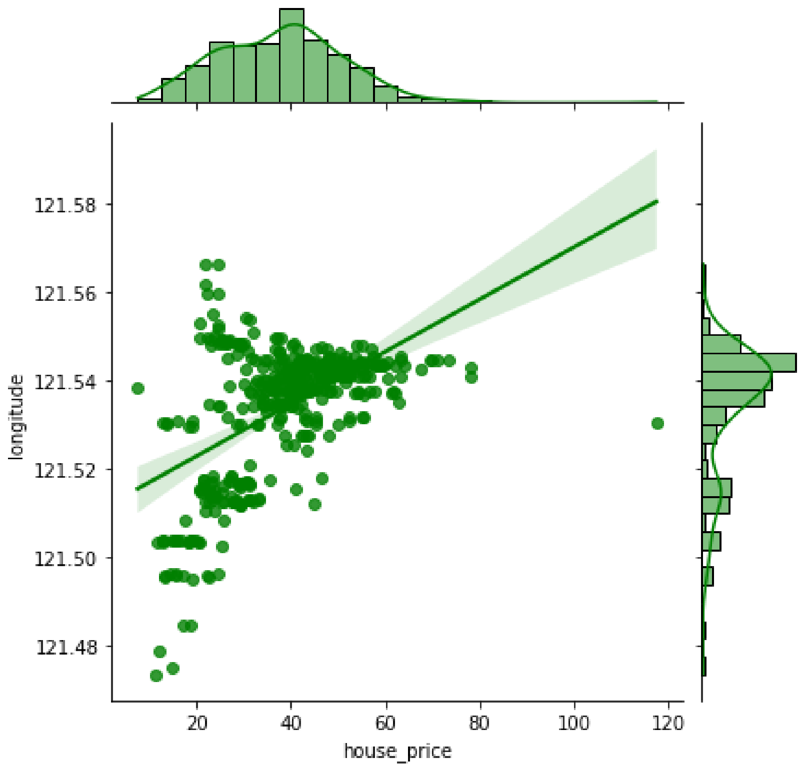
Correlation between house_price and distance ==> -0.6736128553689181



Correlation between house_price and latitude ==> 0.5463066525035899




```
Correlation between house_price and longitude ==>  0.5232865070287729
```



In [ ]:

```
"""
Latitude and longitude and transaction_date affects the house_price positively. That mean
s, if they increases, house_price will increase as well.
But distance is opposite. If it's more far away, the house_price will decrease
"""
```

In [53]:

```
predictors = ["transaction_date", "distance", "latitude", "longitude"]
df_X = df[predictors]
df_y = df["house_price"]
```

In [46]:

```
df_X = sm.add_constant(df_X)
```

In [48]:

```
model = sm.OLS(df_y, df_X).fit()
predictions = model.predict(df_X)

print_model = model.summary()
print(print_model)
```

```
                            OLS Regression Results
==============================================================================
Dep. Variable:            house_price   R-squared:                       0.500
Model:                            OLS   Adj. R-squared:                  0.496
Method:                 Least Squares   F-statistic:                     102.4
Date:                Tue, 21 Dec 2021   Prob (F-statistic):           2.41e-60
Time:                        07:15:34   Log-Likelihood:                -1524.1
No. Observations:                 414   AIC:                             3058.
Df Residuals:                     409   BIC:                             3078.
Df Model:                           4
Covariance Type:            nonrobust
=========================================================================================
```

```
                        coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------------
const             -1.465e+04   7391.540     -1.981      0.048   -2.92e+04    -115.958
transaction_date      5.4981      1.697      3.240      0.001       2.162       8.834
distance             -0.0062      0.001     -8.453      0.000      -0.008      -0.005
latitude            233.8133     48.134      4.858      0.000     139.193     328.433
longitude           -18.2321     52.877     -0.345      0.730    -122.177      85.713
==============================================================================
Omnibus:                      154.918   Durbin-Watson:                   2.147
Prob(Omnibus):                  0.000   Jarque-Bera (JB):             1165.554
Skew:                           1.394   Prob(JB):                    8.00e-254
Kurtosis:                      10.733   Cond. No.                     3.71e+07
==============================================================================

Warnings:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specifie
d.
[2] The condition number is large, 3.71e+07. This might indicate that there are
strong multicollinearity or other numerical problems.
```

In [49]:

```
"""
assume that:
house_price = b0 * const + b1 * transaction_date + b2 * distance  + b3 * latitude + b4 *
longitude

b1, b2, b3, b4 represents the difference in the predicted value of the response variable
for each one-unit change in the predictor variable
In this problem, suppose that all the predictors are constants:
- If transaction_date increases one unit, the house_price increases in b1.
Similarly:
- If distance increases one unit, the house_price increases in b2
- If latitude increases one unit, the house_price increases in b3
- If longitude increases one unit, the house_price increases in b4

if all predictors are 0, house_price = b0

"""
```

Out[49]:

```
'\nassume that:\nhouse_price = b0 * const + b1 * transaction_date + b2 * distance  + b3 *
latitude + b4 * longitude\n\nb1, b2, b3, b4 represents the difference in the predicted va
lue of the response variable for each one-unit change in the predictor variable\nIn this
problem, suppose that all the predictors are constants:\n- If transaction_date increases
one unit, the house_price increases in b1.\nSimilarly:\n- If distance increases one unit,
the house_price increases in b2\n- If latitude increases one unit, the house_price increa
ses in b3\n- If longitude increases one unit, the house_price increases in b4\n\nif all p
redictors are 0, house_price = b0 \n\n'
```

In [58]:

```
# Construct 95% confidence interval
# There are 414 observations and 5 predictors, so that degree of freedom is 409
def CI(predictor = "const" ,alpha = 0.05, df = 409):
  qt = stats.t.ppf(1-alpha, df)
  print(qt)
  if predictor == "const":
    return (-1.465e+04 - qt * 7391.540, -1.465e+04 + qt * 7391.540)
  elif (predictor == "transaction_date"):
    return (5.4981 - qt * 1.697, 5.4981 + qt * 1.697 )
  elif (predictor == "distance"):
    return  (-0.0062 - qt * 0.001, -0.0062 + qt * 0.001 )
  elif (predictor == "latitude"):
    return  ( 233.8133 - qt * 48.134, 233.8133 + qt * 48.134 )
  elif (predictor == "longitude"):
    return  (-18.2321  - qt * 52.877 , -18.2321  + qt * 52.877 )
```

In [63]:

```
print("95% confidence interval of {}".format("intercept"))
```

```
print(CI(predictor = "const", alpha=0.05, df=409 ))
print("\n")
for value in predictors:
  print("95% confidence interval of {}".format(value))
  print(CI(predictor = value, alpha=0.05, df=409 ))
  print("\n")
```

```
95% confidence interval of intercept
1.6485877281964472
(-26835.602136473168, -2464.397863526832)


95% confidence interval of transaction_date
1.6485877281964472
(2.700446625250629, 8.29575337474937)


95% confidence interval of distance
1.6485877281964472
(-0.007848587728196446, -0.004551412271803553)


95% confidence interval of latitude
1.6485877281964472
(154.4601782909922, 313.1664217090078)


95% confidence interval of longitude
1.6485877281964472
(-105.40447330384355, 68.94027330384354)
```