In [28]:
```
import pandas as pd
import numpy as np
```

In [29]:
```
data=pd.read_csv(r"D:\ML\real_estate_price_size_year_view  3rd march new.csv")
data
```

Out[29]:

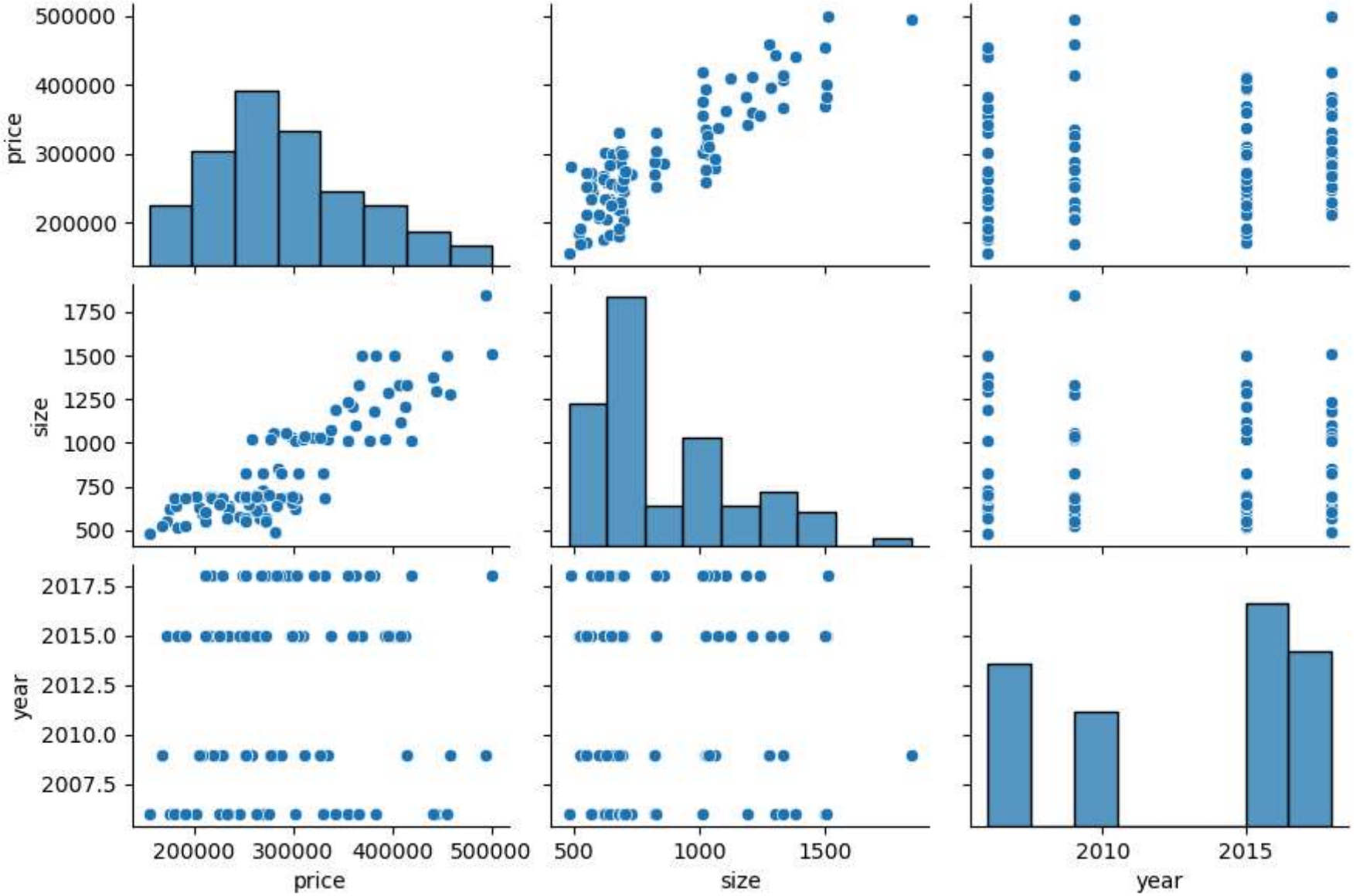
	price	size	year	view
0	234314.144	643.09	2015	No sea view
1	228581.528	656.22	2009	No sea view
2	281626.336	487.29	2018	Sea view
3	401255.608	1504.75	2015	No sea view
4	458674.256	1275.46	2009	Sea view
...	...	...	...	...
95	252460.400	549.80	2009	Sea view
96	310522.592	1037.44	2009	No sea view
97	383635.568	1504.75	2006	No sea view
98	225145.248	648.29	2015	No sea view
99	274922.856	705.29	2006	Sea view

100 rows × 4 columns

In [30]:
```
import seaborn as sns
sns.pairplot(data,height=2,aspect=1.5)
```

```
D:\Anaconda\Lib\site-packages\seaborn\axisgrid.py:118: UserWarning: The figure layout has changed to tight
  self._figure.tight_layout(*args, **kwargs)
```

Out[30]:
```
<seaborn.axisgrid.PairGrid at 0x25de5e06150>
```



In [31]:
```
data.describe()
```

Out[31]:

	price	size	year
count	100.000000	100.000000	100.000000
mean	292289.470160	853.024200	2012.600000
std	77051.727525	297.941951	4.729021
min	154282.128000	479.750000	2006.000000
25%	234280.148000	643.330000	2009.000000
50%	280590.716000	696.405000	2015.000000
75%	335723.696000	1029.322500	2018.000000
max	500681.128000	1842.510000	2018.000000

In [32]:
```
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 100 entries, 0 to 99
Data columns (total 4 columns):
 #   Column  Non-Null Count  Dtype  
---  ------  --------------  -----  
 0   price   100 non-null    float64
 1   size    100 non-null    float64
 2   year    100 non-null    int64  
 3   view    100 non-null    object 
dtypes: float64(2), int64(1), object(1)
memory usage: 3.3+ KB
```

In [33]:
```
data1=pd.get_dummies(data)
data1
```

Out[33]:

	price	size	year	view_No sea view	view_Sea view
0	234314.144	643.09	2015	True	False
1	228581.528	656.22	2009	True	False
2	281626.336	487.29	2018	False	True
3	401255.608	1504.75	2015	True	False
4	458674.256	1275.46	2009	False	True
...	...	...	...	...	...
95	252460.400	549.80	2009	False	True
96	310522.592	1037.44	2009	True	False
97	383635.568	1504.75	2006	True	False
98	225145.248	648.29	2015	True	False
99	274922.856	705.29	2006	False	True

100 rows × 5 columns

In [44]:

```
x=data1.drop('price',axis='columns' )
x
```

Out[44]:

	size	year	view_No sea view	view_Sea view
0	643.09	2015	True	False
1	656.22	2009	True	False
2	487.29	2018	False	True
3	1504.75	2015	True	False
4	1275.46	2009	False	True
...	...	...	...	...
95	549.80	2009	False	True
96	1037.44	2009	True	False
97	1504.75	2006	True	False
98	648.29	2015	True	False
99	705.29	2006	False	True

100 rows × 4 columns

In [45]:

```
y=data1.price
print(x)
print(y)
```

```
       size  year  view_No sea view  view_Sea view
0    643.09  2015              True          False
1    656.22  2009              True          False
2    487.29  2018             False           True
3   1504.75  2015              True          False
4   1275.46  2009             False           True
..      ...   ...               ...            ...
95   549.80  2009             False           True
96  1037.44  2009              True          False
97  1504.75  2006              True          False
98   648.29  2015              True          False
99   705.29  2006             False           True

[100 rows x 4 columns]
0     234314.144
1     228581.528
2     281626.336
3     401255.608
4     458674.256
         ...
95    252460.400
96    310522.592
97    383635.568
98    225145.248
99    274922.856
Name: price, Length: 100, dtype: float64
```

In [46]:
```
from sklearn.model_selection import train_test_split
x_train, x_test, y_train, y_test=train_test_split(x,y,test_size=0.4, random_state=2)
```

In [47]:
```
print(x_train)
print(x_test)
print(y_train)
print(y_test)
```

	size	year	view_No sea view	view_Sea view
12	694.52	2015	True	False
53	727.88	2006	False	True
87	1028.41	2009	False	True
54	647.50	2015	False	True
95	549.80	2009	False	True
32	597.90	2009	True	False
19	1027.76	2018	True	False
26	570.89	2018	False	True
60	828.16	2018	True	False
55	1508.84	2018	False	True
9	694.52	2009	True	False
96	1037.44	2009	True	False
17	623.94	2006	False	True
59	569.17	2015	False	True
57	1283.85	2015	False	True
41	682.26	2018	True	False
64	685.48	2015	False	True
45	698.29	2015	False	True
97	1504.75	2006	True	False
8	682.26	2018	False	True
71	643.41	2006	True	False
94	698.29	2006	False	True
90	694.52	2018	True	False
98	648.29	2015	True	False
86	479.75	2006	True	False
80	681.07	2006	True	False
50	647.50	2015	True	False
52	1021.95	2009	True	False
66	1009.25	2006	False	True
88	601.66	2018	True	False
70	1021.95	2009	True	False
46	633.19	2009	True	False
68	685.48	2018	False	True
69	1496.36	2006	False	True
81	1122.34	2015	False	True
58	827.84	2006	False	True
33	525.81	2015	True	False
38	685.48	2018	False	True
51	1021.95	2015	False	True
42	823.21	2009	False	True
4	1275.46	2009	False	True
67	549.80	2015	False	True
39	698.29	2015	True	False

37	570.25	2006	False	True
20	620.71	2015	False	True
31	681.07	2006	True	False
63	1021.95	2009	False	True
47	698.29	2006	True	False
85	1009.25	2018	False	True
93	698.29	2018	True	False
49	617.05	2015	False	True
34	857.54	2018	True	False
7	620.82	2006	True	False
75	685.48	2018	False	True
82	681.07	2006	True	False
43	1334.10	2009	True	False
22	1207.45	2015	False	True
72	656.22	2015	False	True
15	1379.72	2006	False	True
40	1021.95	2015	True	False

	size	year	view_No sea view	view_Sea view
83	643.09	2018	False	True
30	1010.33	2006	True	False
56	1032.06	2018	True	False
24	525.81	2009	True	False
16	690.54	2018	True	False
23	518.38	2015	True	False
2	487.29	2018	False	True
27	1334.10	2015	False	True
28	681.07	2015	False	True
13	1009.25	2018	True	False
99	705.29	2006	False	True
92	694.52	2015	False	True
76	1183.46	2018	False	True
14	1300.96	2006	False	True
0	643.09	2015	True	False
21	549.69	2015	True	False
3	1504.75	2015	True	False
29	1496.36	2015	True	False
61	698.50	2015	True	False
79	1188.62	2006	False	True
35	622.97	2018	False	True
11	1842.51	2009	False	True
84	685.48	2018	False	True
44	1060.36	2018	True	False
73	549.80	2015	True	False
5	575.19	2006	False	True

```
25  1103.30  2018             False           True
77  1334.10  2006              True          False
74   685.48  2018              True          False
62  1205.62  2015              True          False
65   827.09  2015              True          False
1    656.22  2009              True          False
18   681.07  2006              True          False
48   633.19  2015             False           True
36   823.21  2006              True          False
78   682.26  2009             False           True
6    570.89  2015             False           True
89  1236.93  2018              True          False
91  1071.55  2015              True          False
10  1060.36  2009              True          False
12    215472.104
53    269523.056
87    327252.112
54    255629.160
95    252460.400
32    207742.248
19    299416.976
26    271793.312
60    251188.824
55    500681.128
9     218630.608
96    310522.592
17    234178.160
59    251332.592
57    395242.096
41    217468.224
64    302393.384
45    300061.480
97    383635.568
8     331101.344
71    181587.576
94    262477.856
90    251140.656
98    225145.248
86    154282.128
80    180307.216
50    225656.120
52    258637.008
66    355251.200
88    211904.536
```

```
70    276875.632
46    204302.976
68    294582.944
69    454512.760
81    408637.816
58    330677.128
33    191486.896
38    292965.216
51    393069.760
42    287350.000
4     458674.256
67    271726.752
39    245747.200
37    233493.208
20    268125.080
31    225452.320
63    334938.872
47    201778.048
85    376253.808
93    266684.248
49    262423.504
34    285223.176
7     175716.480
75    286161.600
82    190909.056
43    414682.648
22    412569.472
72    298926.496
15    440201.616
40    310045.712
Name: price, dtype: float64
83    282683.544
30    301635.728
56    320345.520
24    168047.264
16    248337.600
23    183459.488
2     281626.336
27    406852.304
28    297760.440
13    418753.008
99    274922.856
92    298170.880
76    382120.152
```

```
14    444192.008
0     234314.144
21    171795.240
3     401255.608
29    368988.432
61    263311.696
79    342988.456
35    302000.920
11    494778.992
84    303597.216
44    293044.496
73    211724.096
5     245050.280
25    362519.720
77    365863.936
74    228313.024
62    359674.440
65    304587.272
1     228581.528
18    225451.984
48    257828.416
36    269225.920
78    251560.040
6     265129.064
89    354512.112
91    338078.168
10    279555.096
Name: price, dtype: float64
```

In [48]:
```
from sklearn.linear_model import LinearRegression
```

In [49]:
```
equation=LinearRegression()
```

In [50]:
```
equation.fit(x_train, y_train)
```

Out[50]:
```
▾ LinearRegression
LinearRegression()
```

In [51]:
```
equation.intercept_
```

Out[51]:
```
-5778726.325474448
```

In [52]:
```
equation.coef_
```

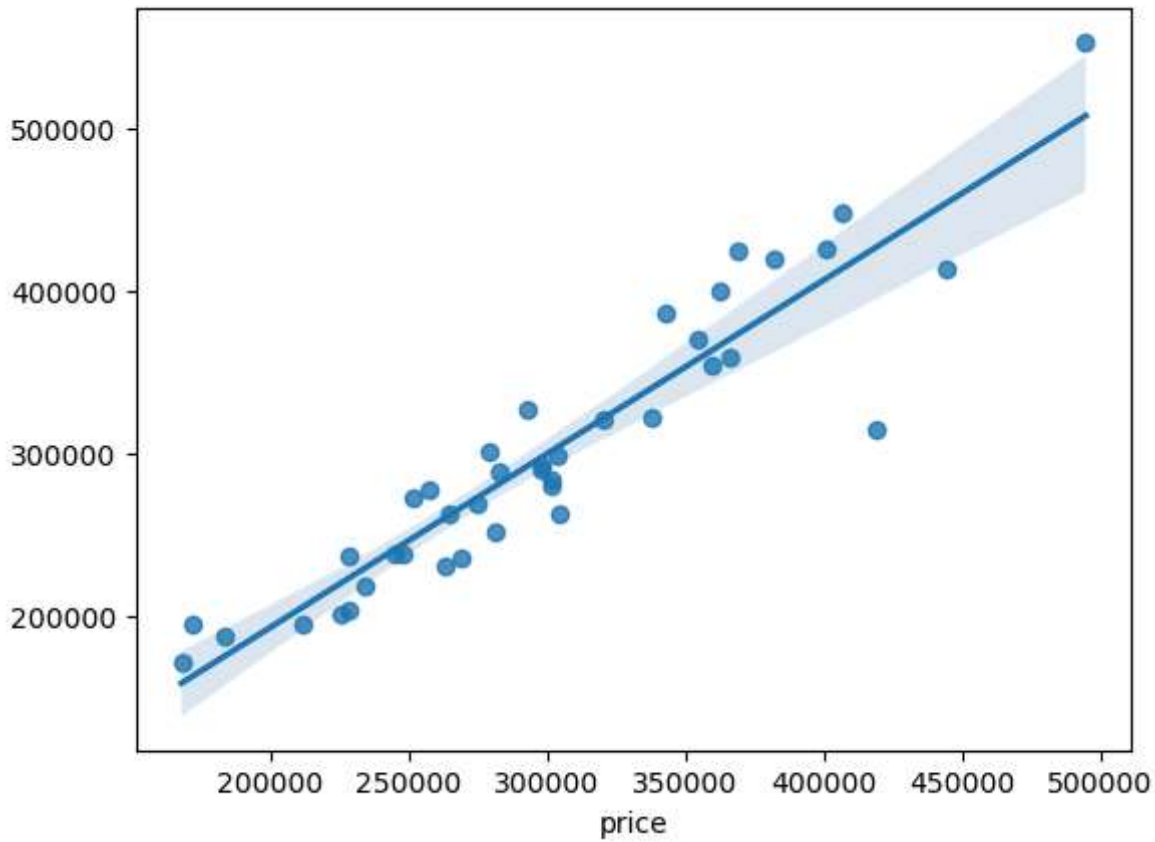
Out[52]:
```
array([   242.12526906,   2914.12242819, -31226.44185297,  31226.44185297])
```

In [53]:
```
y_test_predicted=equation.predict(x_test)
y_test_predicted
```

Out[53]:
```
array([288907.51573793, 280403.2467037 , 320634.09793863, 171831.07862285,
       237943.47604893, 187516.82244284, 251184.39881823, 447476.13062718,
       289361.06617231, 315111.22055134, 268998.23833529, 292617.65104118,
       419744.74738039, 413224.99735682, 217712.26474743, 195097.76461714,
       426341.92408649, 424310.49307906, 231128.4259061 , 386024.64463052,
       284035.95532442, 553090.30410134, 299171.20589342, 327486.24305305,
       195124.39839674, 237497.74083046, 400335.98581247, 358796.14506756,
       236718.32218748, 353914.99235229, 262263.31425465, 203406.63496109,
       200681.08061269, 277768.10828967, 235096.76635702, 272164.46067337,
       262683.70402717, 370238.30181114, 321453.25752928, 301259.14119938])
```

In [54]:
```
sns.regplot(x=y_test, y=y_test_predicted)
```

Out[54]:
```
<Axes: xlabel='price'>
```


500000
400000
300000
200000
200000
250000
300000
350000
400000
450000
500000
price

In [ ]:

In [ ]: