HOUSING PRICE IN THE STATE OF WASHINGTON

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

In [2]:
```
df = pd.read_csv('home_data.csv')
print(df.shape)
print(df.dtypes)

#Rest set the price column for avoiding crash on the regression model later
df['price_new'] = df['price']/1000
```

```
(21613, 21)
id                 int64
date              object
price              int64
bedrooms           int64
bathrooms        float64
sqft_living        int64
sqft_lot           int64
floors           float64
waterfront         int64
view               int64
condition          int64
grade              int64
sqft_above         int64
sqft_basement      int64
yr_built           int64
yr_renovated       int64
zipcode            int64
lat              float64
long             float64
sqft_living15      int64
sqft_lot15         int64
dtype: object
```

In [3]:
```
df.head()
```

Out[3]:

	id	date	price	bedrooms	bathrooms	sqft_living	sqft_lot	floors	wate
0	7129300520	20141013T000000	221900	3	1.00	1180	5650	1.0	
1	6414100192	20141209T000000	538000	3	2.25	2570	7242	2.0	
2	5631500400	20150225T000000	180000	2	1.00	770	10000	1.0	
3	2487200875	20141209T000000	604000	4	3.00	1960	5000	1.0	
4	1954400510	20150218T000000	510000	3	2.00	1680	8080	1.0	

5 rows × 22 columns

In [4]:
```python
df_numeric = df.select_dtypes(include='number')
numeric_cols = df_numeric.columns.values
print(numeric_cols)
print(df_numeric)
```

```
['id' 'price' 'bedrooms' 'bathrooms' 'sqft_living' 'sqft_lot' 'floors'
 'waterfront' 'view' 'condition' 'grade' 'sqft_above' 'sqft_basement'
 'yr_built' 'yr_renovated' 'zipcode' 'lat' 'long' 'sqft_living15'
 'sqft_lot15' 'price_new']
               id   price  bedrooms  bathrooms  sqft_living  sqft_lot  floors  \
0      7129300520  221900         3       1.00         1180      5650     1.0
1      6414100192  538000         3       2.25         2570      7242     2.0
2      5631500400  180000         2       1.00          770     10000     1.0
3      2487200875  604000         4       3.00         1960      5000     1.0
4      1954400510  510000         3       2.00         1680      8080     1.0
...           ...     ...       ...        ...          ...       ...     ...
21608   263000018  360000         3       2.50         1530      1131     3.0
21609  6600060120  400000         4       2.50         2310      5813     2.0
21610  1523300141  402101         2       0.75         1020      1350     2.0
21611   291310100  400000         3       2.50         1600      2388     2.0
21612  1523300157  325000         2       0.75         1020      1076     2.0

       waterfront  view  condition  ...  sqft_above  sqft_basement  yr_built  \
0               0     0          3  ...        1180              0      1955
1               0     0          3  ...        2170            400      1951
2               0     0          3  ...         770              0      1933
3               0     0          5  ...        1050            910      1965
4               0     0          3  ...        1680              0      1987
...           ...   ...        ...  ...         ...            ...       ...
21608           0     0          3  ...        1530              0      2009
21609           0     0          3  ...        2310              0      2014
21610           0     0          3  ...        1020              0      2009
21611           0     0          3  ...        1600              0      2004
21612           0     0          3  ...        1020              0      2008

       yr_renovated  zipcode      lat     long  sqft_living15  sqft_lot15  \
0                 0    98178  47.5112 -122.257           1340        5650
1              1991    98125  47.7210 -122.319           1690        7639
2                 0    98028  47.7379 -122.233           2720        8062
3                 0    98136  47.5208 -122.393           1360        5000
4                 0    98074  47.6168 -122.045           1800        7503
...             ...      ...      ...      ...            ...         ...
21608             0    98103  47.6993 -122.346           1530        1509
21609             0    98146  47.5107 -122.362           1830        7200
21610             0    98144  47.5944 -122.299           1020        2007
21611             0    98027  47.5345 -122.069           1410        1287
21612             0    98144  47.5941 -122.299           1020        1357

       price_new
0        221.900
1        538.000
2        180.000
3        604.000
4        510.000
...          ...
21608    360.000
```

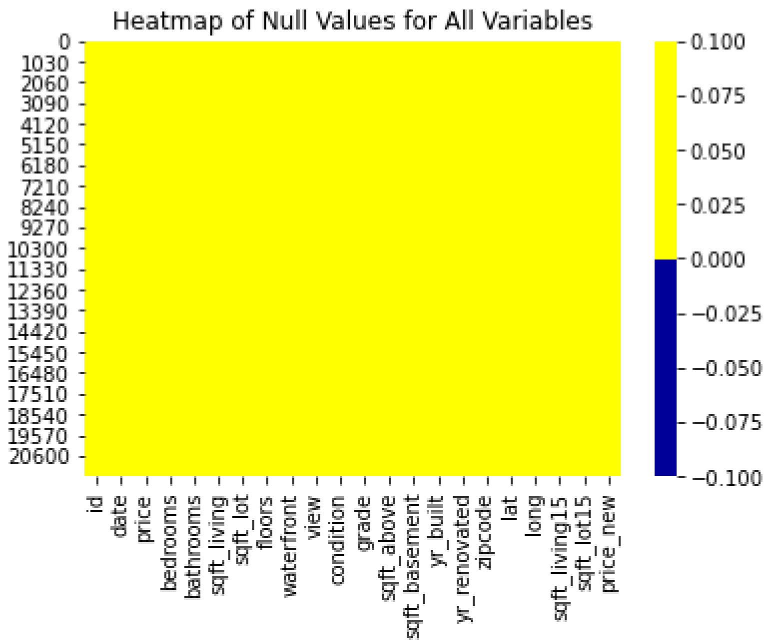
```
21609    400.000
21610    402.101
21611    400.000
21612    325.000

[21613 rows x 21 columns]
```

In [5]:
```
print(df.isnull().sum())
```

```
id               0
date             0
price            0
bedrooms         0
bathrooms        0
sqft_living      0
sqft_lot         0
floors           0
waterfront       0
view             0
condition        0
grade            0
sqft_above       0
sqft_basement    0
yr_built         0
yr_renovated     0
zipcode          0
lat              0
long             0
sqft_living15    0
sqft_lot15       0
price_new        0
dtype: int64
```

Checking if there is any missing values in our dataset for all variables.

In [6]:
```python
cols = df.columns[:]
plt.title('Heatmap of Null Values for All Variables')
colors = ['#000099', '#ffff00']
sns.heatmap(df[cols].isnull(), cmap=sns.color_palette(colors))
plt.show()
```



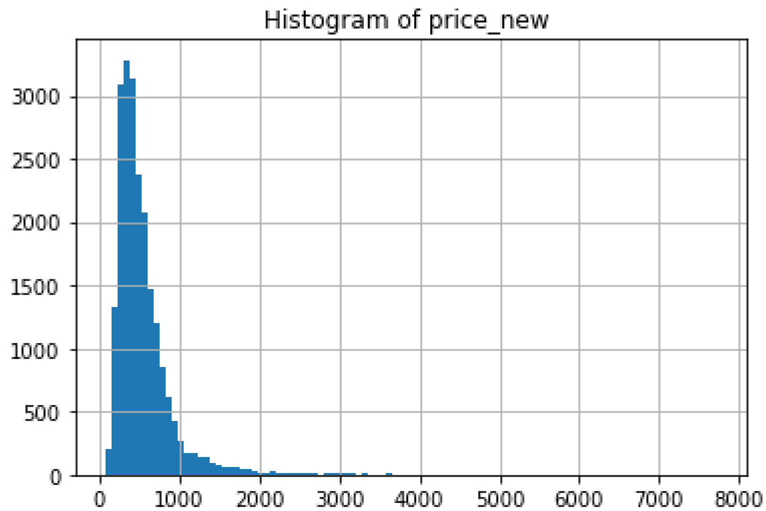
We are dropping the last 4 columns because we are not considering using these variables for our analysis.

In [7]:
```python
cols_to_drop = ['lat','long','sqft_living15','sqft_lot15']
df = df.drop(cols_to_drop, axis=1)
```

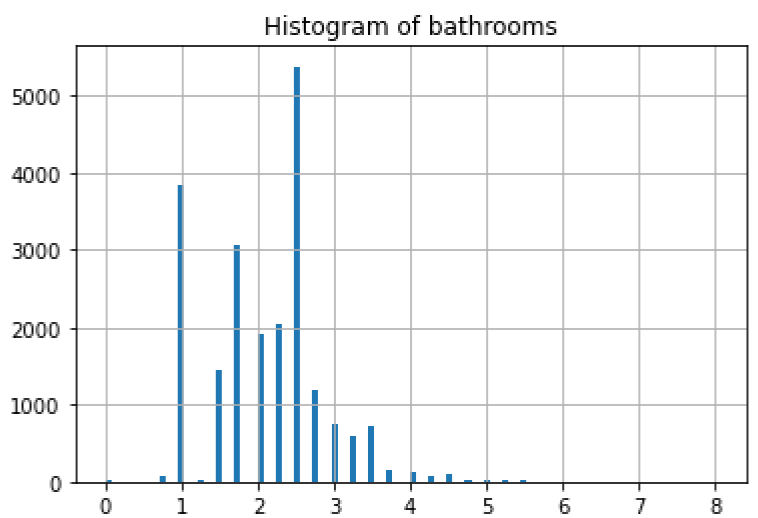
Chosen dependent variable as 'price_new', independent variables as 'grade', 'sqft_living', 'floors', & 'bathrooms'.

Histogram

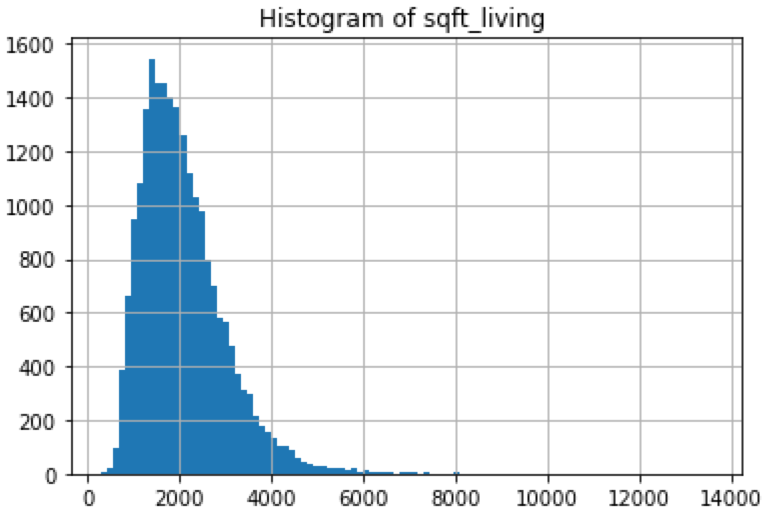
In [8]:
```
# 1. histogram of price_new. to detect outliers
plt.title('Histogram of price_new ')
df.price_new.hist(bins=100)
plt.show()
```



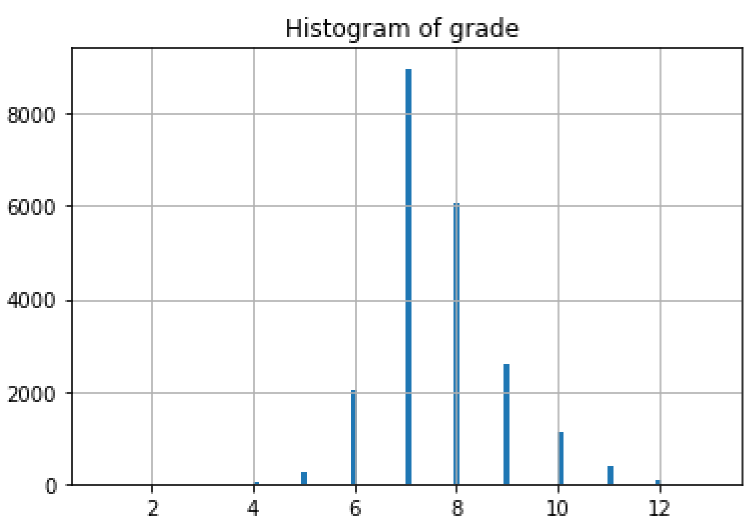
In [9]:
```
# 2. histogram of bedrooms. to detect outliers
plt.title('Histogram of bathrooms')
df.bathrooms.hist(bins=100)
plt.show()
```



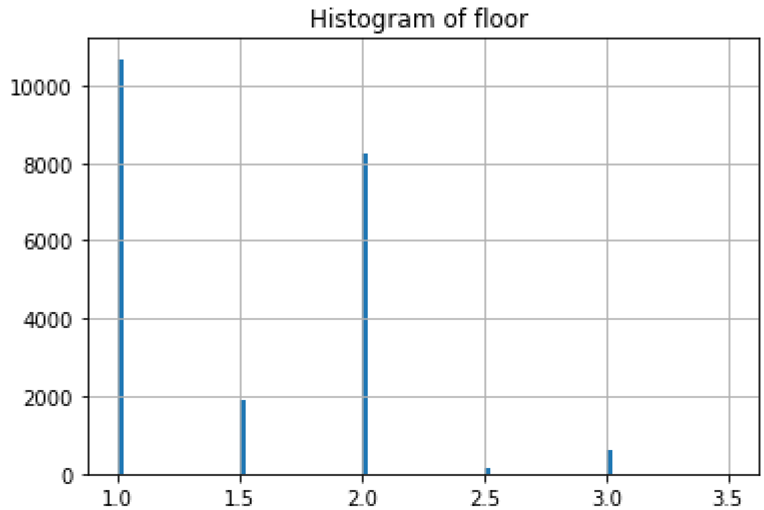
In [10]:
```
# 3. histogram of sqft_living. to detect outliers
plt.title('Histogram of sqft_living ')
df.sqft_living.hist(bins=100)
plt.show()
```



In [11]:
```
# 4. histogram of grade. to detect outliers
df.grade.hist(bins=100)
plt.title('Histogram of grade ')
plt.show()
```

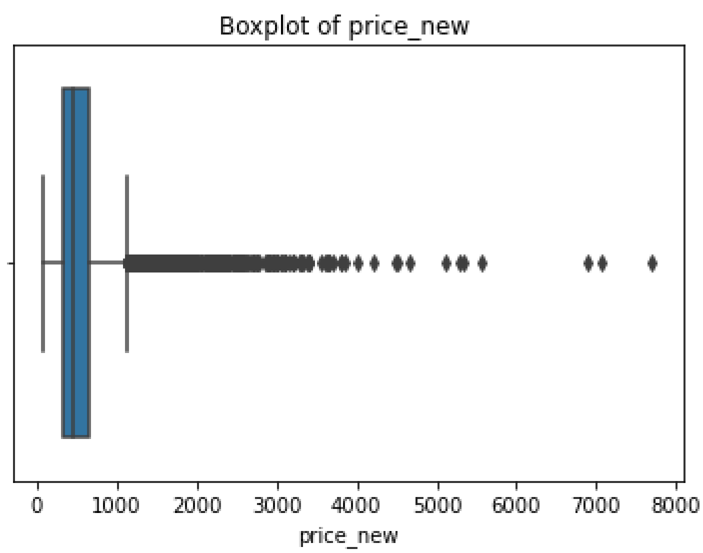


In [12]:
```python
# 5. histogram of floor. to detect outliers
df.floors.hist(bins=100)
plt.title('Histogram of floor ')
plt.show()
```



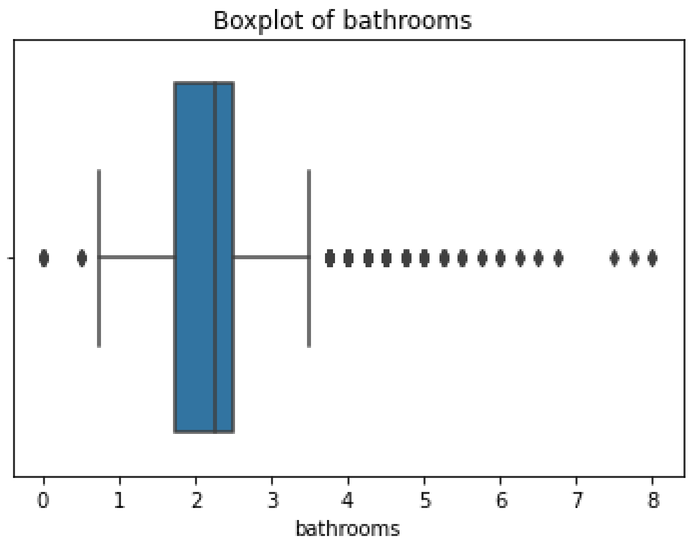
Boxplots

In [13]:
```python
# 1. box plot of price_new to detect outliers
plt.title('Boxplot of price_new ')
sns.boxplot(data=df,x='price_new')
plt.show()
```



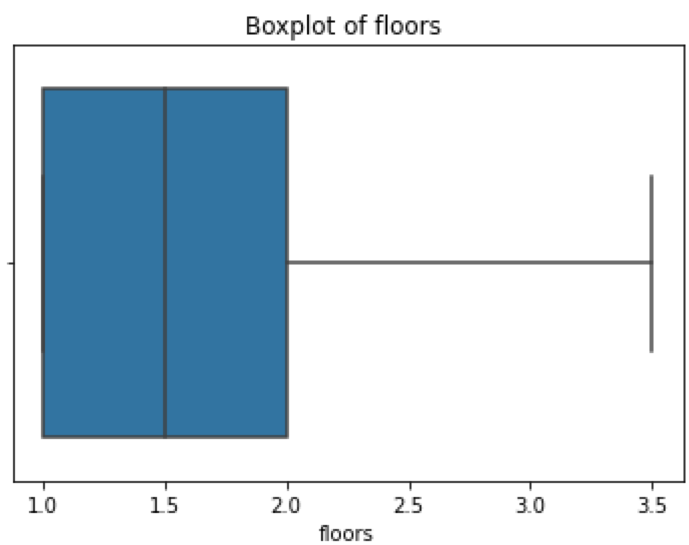
In [14]:

```
# 2. box plot of bathrooms to detect outliers
plt.title('Boxplot of bathrooms ')
sns.boxplot(data=df,x='bathrooms')
plt.show()
```

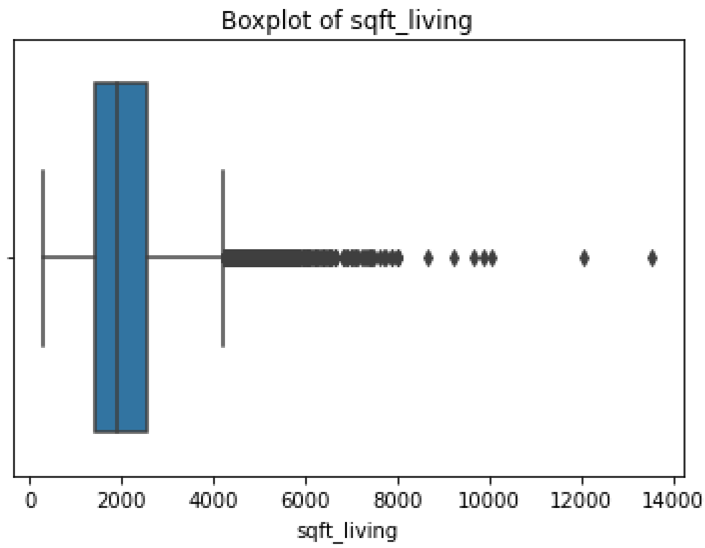


In [15]:

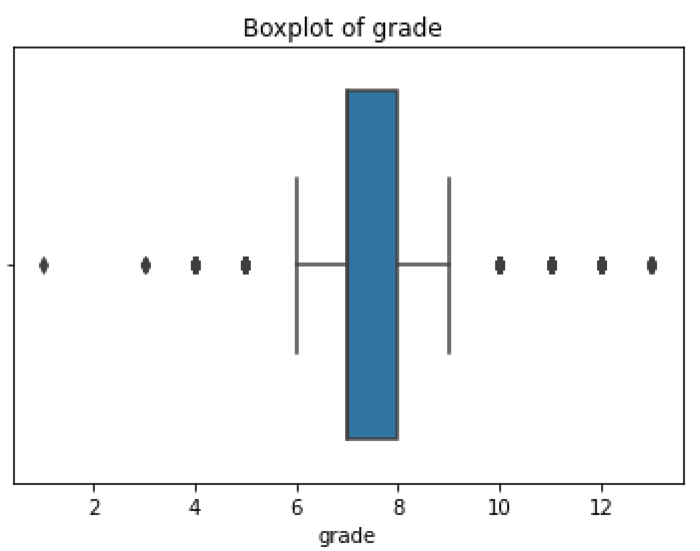
```
# 3. box plot of floors to detect outliers
plt.title('Boxplot of floors ')
sns.boxplot(data=df,x='floors')
plt.show()
```



In [16]:
```python
# 4. box plot of sqft_living to detect outliers
plt.title('Boxplot of sqft_living')
sns.boxplot(data=df,x='sqft_living')
plt.show()
```



In [17]:
```python
# 5. box plot of grade to detect outliers
plt.title('Boxplot of grade ')
sns.boxplot(data=df,x='grade')
plt.show()
```



More detail information of the boxplot:

In [18]:
```
df['grade'].describe()
```

Out[18]:
```
count    21613.000000
mean         7.656873
std          1.175459
min          1.000000
25%          7.000000
50%          7.000000
75%          8.000000
max         13.000000
Name: grade, dtype: float64
```

In [19]:
```
df['sqft_living'].describe()
```

Out[19]:
```
count    21613.000000
mean      2079.899736
std        918.440897
min        290.000000
25%       1427.000000
50%       1910.000000
75%       2550.000000
max      13540.000000
Name: sqft_living, dtype: float64
```

In [20]:
```
df['floors'].describe()
```

Out[20]:
```
count    21613.000000
mean         1.494309
std          0.539989
min          1.000000
25%          1.000000
50%          1.500000
75%          2.000000
max          3.500000
Name: floors, dtype: float64
```

In [21]:
```
df['bathrooms'].describe()
```

Out[21]:
```
count    21613.000000
mean         2.114757
std          0.770163
min          0.000000
25%          1.750000
50%          2.250000
75%          2.500000
max          8.000000
Name: bathrooms, dtype: float64
```

In [22]:
```python
df['price_new'].describe()
```

Out[22]:
```
count    21613.000000
mean       540.088142
std        367.127196
min         75.000000
25%        321.950000
50%        450.000000
75%        645.000000
max       7700.000000
Name: price_new, dtype: float64
```

we are checking if there is any repetition on our data. We found out that the repetition mostly are in the variable of 'waterfront' and 'yr_renovated'.

However, we are not going to use those two variables.

In [23]:
```python
num_rows = len(df.index)
low_information_cols = []

for col in df.columns:
    cnts = df[col].value_counts(dropna=False)
    top_pct = (cnts/num_rows).iloc[0]

    if top_pct > 0.95:
        low_information_cols.append(col)
        print('{0}: {1:.5f}%'.format(col, top_pct*100))
        print(cnts)
        print()
```

```
waterfront: 99.24582%
0    21450
1      163
Name: waterfront, dtype: int64

yr_renovated: 95.77106%
0       20699
2014       91
2013       37
2003       36
2000       35
        ...
1934        1
1959        1
1951        1
1948        1
1944        1
Name: yr_renovated, Length: 70, dtype: int64
```

In [24]:
```
df_dedupped = df.drop('id', axis=1).drop_duplicates()
print(df.shape)
print(df_dedupped.shape)
```

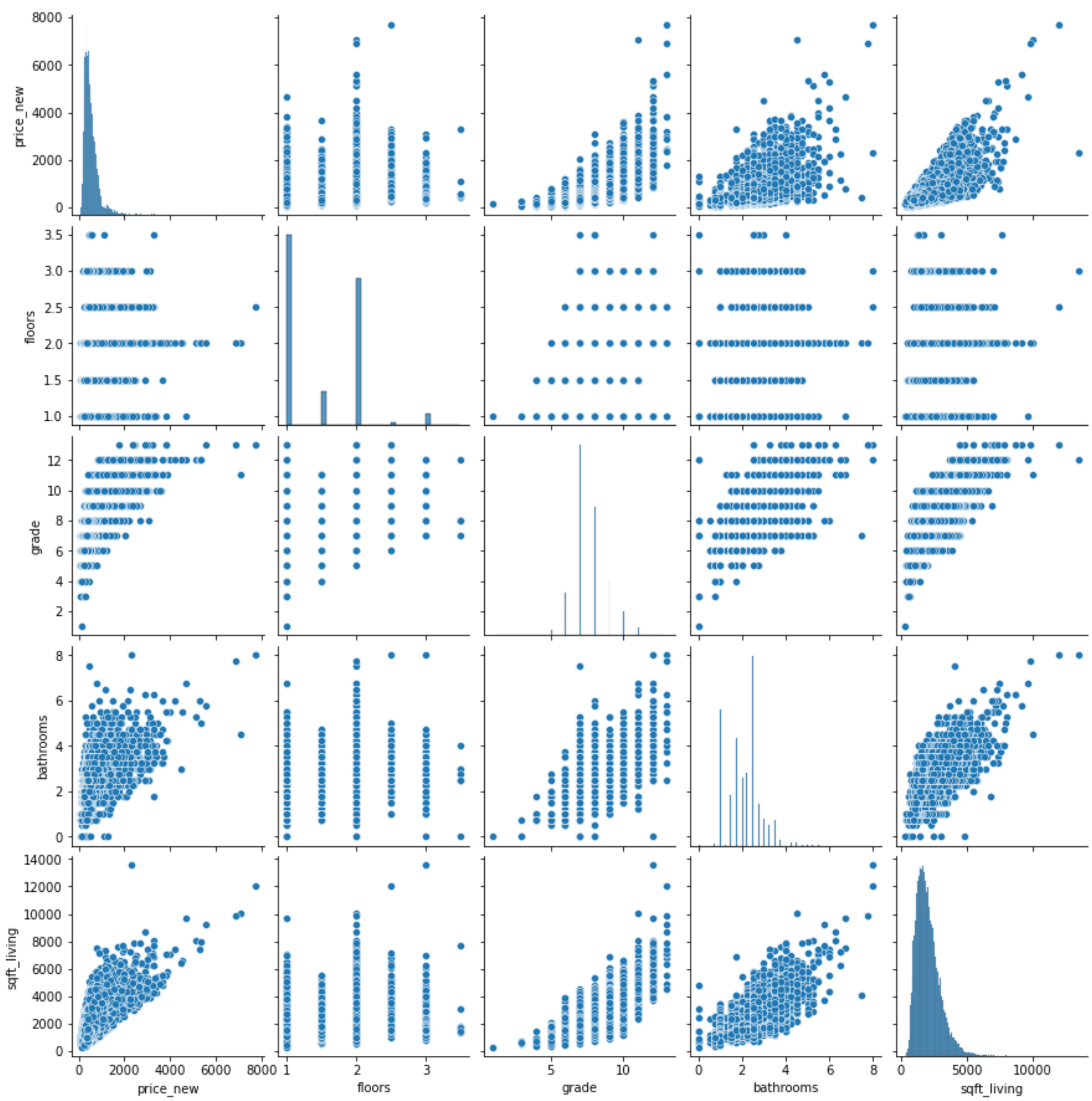
```
(21613, 18)
(21613, 17)
```

There is no duplicate house records in this dataset

Pairplot

In [25]:
```
sns.pairplot(df[['price_new','floors','grade','bathrooms','sqft_living']])
```

Out[25]: `<seaborn.axisgrid.PairGrid at 0x119190e80>`



Regression model

```
In [26]: import patsy
import statsmodels.api as sm
import statsmodels.formula.api as smf

#our dataframe is called df
df.head(5)
```

Out[26]:

	id	date	price	bedrooms	bathrooms	sqft_living	sqft_lot	floors	wate
0	7129300520	20141013T000000	221900	3	1.00	1180	5650	1.0	
1	6414100192	20141209T000000	538000	3	2.25	2570	7242	2.0	
2	5631500400	20150225T000000	180000	2	1.00	770	10000	1.0	
3	2487200875	20141209T000000	604000	4	3.00	1960	5000	1.0	
4	1954400510	20150218T000000	510000	3	2.00	1680	8080	1.0	

```
In [27]: #1. Specify the regression
#price=β0+β1grade+β2sqft_living+β3floors+β4bathrooms+ε. #this is a mathematical e
#2. Create the model
#Using the statsmodel syntax, we have
#price ~ grade + sqft_living + floors + bathrooms

#WE are creating four different regression models
# #model 1
price_model1= smf.ols('price_new ~ grade', data=df) #running our main explanatory
# #model 2
price_model2= smf.ols('price_new ~ grade + sqft_living', data=df) #adding sqft_li
# #model 3
price_model3 = smf.ols('price_new ~ grade + sqft_living + floors', data=df) #add
# #model 4
price_model4 = smf.ols('price_new ~ grade + sqft_living + floors + bathrooms', da
```

```
In [28]: #use .fit() method to estimate the model fit for OLS
results1 = price_model1.fit() #model 1 fitting
results2 = price_model2.fit() #model 2 fitting
results3 = price_model3.fit() #model 3 fitting
results4 = price_model4.fit() #model 4 fitting
```

We print the summary and check the P values for all the independent variables to see if they are statistical significance.

In [29]:
```
print(results1.summary())
print(results2.summary())
print(results3.summary())
print(results4.summary())
```

```
                            OLS Regression Results
==============================================================================
=
Dep. Variable:              price_new   R-squared:                       0.44
5
Model:                            OLS   Adj. R-squared:                  0.44
5
Method:                 Least Squares   F-statistic:                1.736e+0
4
Date:                Sun, 04 Apr 2021   Prob (F-statistic):              0.0
0
Time:                        11:35:34   Log-Likelihood:          -1.5194e+0
5
No. Observations:               21613   AIC:                        3.039e+0
5
Df Residuals:                   21611   BIC:                        3.039e+0
5
Df Model:                           1
Covariance Type:            nonrobust
```

We reorganized the summary from above and put important results for all models into one summary table.

In [30]:

```
from statsmodels.iolib.summary2 import summary_col #create regression table

table = summary_col(
    [results1, results2, results3, results4],
    model_names = ['Model 1', 'Model 2', 'Model 3','Model 4'],
    stars=True, #level of significance
    regressor_order = ['Intercept', 'grade', 'sqft_living', 'floors', 'bathroom',
    float_format='%0.2f',
    drop_omitted = False #
    )

table.add_title('Does higher grade have a higher housing price?') # RQ: How does
# controlling sqft_living, floors, and bathrooms

print(table.as_text())

# The 'w' is for 'write'.
fout = open('table1.txt', 'w')
fout.write(table.as_text())
fout.close()
```

```
      Does higher grade have a higher housing price?
===========================================================
                Model 1     Model 2    Model 3    Model 4
-----------------------------------------------------------
Intercept      -1056.04*** -598.11*** -602.58*** -601.35***
               (12.26)     (13.30)    (13.26)    (13.24)
grade          208.46***   98.55***   107.64***  109.45***
               (1.58)      (2.24)     (2.35)     (2.36)
sqft_living                0.18***    0.18***    0.20***
                           (0.00)     (0.00)     (0.00)
floors                                -43.96***  -34.65***
                                      (3.54)     (3.76)
bathrooms                                        -26.67***
                                                 (3.65)
R-squared      0.45        0.53       0.54       0.54
R-squared Adj. 0.45        0.53       0.54       0.54
===========================================================
Standard errors in parentheses.
* p<.1, ** p<.05, ***p<.01
```