Business Problem

1. To develop a model for ACME Real Estate Agency to accurately predict a value of a house based on avaliable data. This will help their clients, either buy or sell their homes at a fair price.

2. To identify if renovations can be made to improve the selling price of the house.

Methodology

We will employ Linear Regression to develop a model and predict values of house based on past data

Dataset

We will use the King County House Sales dataset : `kc_house_data.csv`

In [1]:
```
#importing relevant libraries
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
%matplotlib inline
import warnings
warnings.filterwarnings('ignore')
```

In [2]:
```
#importing the dataset
df = pd.read_csv('kc_house_data.csv')
df.head()
```

Out[2]:

	id	date	price	bedrooms	bathrooms	sqft_living	sqft_lot	floors	waterfro
0	7129300520	20141013T000000	221900.0	3	1.00	1180	5650	1.0	
1	6414100192	20141209T000000	538000.0	3	2.25	2570	7242	2.0	
2	5631500400	20150225T000000	180000.0	2	1.00	770	10000	1.0	
3	2487200875	20141209T000000	604000.0	4	3.00	1960	5000	1.0	
4	1954400510	20150218T000000	510000.0	3	2.00	1680	8080	1.0	

5 rows × 21 columns

Using the `date` info to categorize seasons to check for possible seasonal differences in the sale prices.

In [3]:
```
#getting the month data first
df['date'] = df['date'].astype('datetime64[ns]')
df['month_of_sale'] = df['date'].dt.month
```

In [4]:
```
# creating a dict to convert the numeric value into month
months  = {1 : 'January',
           2 : 'February',
           3 : 'March',
           4 : 'April',
           5 : 'May',
           6 : 'June',
           7 : 'July',
           8 : 'August',
           9 : 'September',
           10 : 'October',
           11 : 'November',
           12 : 'December'}

#applying it to the df
df['month_of_sale'] = df['month_of_sale'].map(months)
```

In [5]:
```
# defining seasons and adding to the df
seasons = {'March' : 'Spring',
          'April' : 'Spring',
          'May' : 'Spring',
          'June' : 'Summer',
          'July' : 'Summer',
          'August' : 'Summer',
          'September' : 'Autumn',
          'October' : 'Autumn',
          'November' : 'Autumn',
          'December' : 'Winter',
          'January' : 'Winter',
          'February' : 'Winter'}

#applying it to the df
df['season'] = df['month_of_sale'].map(seasons)
```

In [6]:
```
df.head()
```

Out[6]:

	id	date	price	bedrooms	bathrooms	sqft_living	sqft_lot	floors	waterfront	view	.
0	7129300520	2014-10-13	221900.0	3	1.00	1180	5650	1.0	0	0	.
1	6414100192	2014-12-09	538000.0	3	2.25	2570	7242	2.0	0	0	.
2	5631500400	2015-02-25	180000.0	2	1.00	770	10000	1.0	0	0	.
3	2487200875	2014-12-09	604000.0	4	3.00	1960	5000	1.0	0	0	.
4	1954400510	2015-02-18	510000.0	3	2.00	1680	8080	1.0	0	0	.

5 rows × 23 columns

In [7]:
```
#creating a copy of the df for the analysis
df1 = df.copy()
df1.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 21613 entries, 0 to 21612
Data columns (total 23 columns):
 #   Column         Non-Null Count  Dtype
---  ------         --------------  -----
 0   id             21613 non-null  int64
 1   date           21613 non-null  datetime64[ns]
 2   price          21613 non-null  float64
 3   bedrooms       21613 non-null  int64
 4   bathrooms      21613 non-null  float64
 5   sqft_living    21613 non-null  int64
 6   sqft_lot       21613 non-null  int64
 7   floors         21613 non-null  float64
 8   waterfront     21613 non-null  int64
 9   view           21613 non-null  int64
 10  condition      21613 non-null  int64
 11  grade          21613 non-null  int64
 12  sqft_above     21611 non-null  float64
 13  sqft_basement  21613 non-null  int64
 14  yr_built       21613 non-null  int64
 15  yr_renovated   21613 non-null  int64
 16  zipcode        21613 non-null  int64
 17  lat            21613 non-null  float64
 18  long           21613 non-null  float64
 19  sqft_living15  21613 non-null  int64
 20  sqft_lot15     21613 non-null  int64
 21  month_of_sale  21613 non-null  object
 22  season         21613 non-null  object
dtypes: datetime64[ns](1), float64(6), int64(14), object(2)
memory usage: 3.8+ MB
```

In [8]:
```
#imputing the median value for sqft_above
median = df1['sqft_above'].median
df1['sqft_above'].fillna(median,inplace=True)
```

In [9]:
```
# removing the id column since it is not relevant for the analysis
df1.drop('id',axis=1,inplace=True)
```

Since, `season` is of `object` data type, it needs to be converted into an integer to show up in the heat map. For this, we will employ `OneHotEncoder`.

In [10]:
```
# importing the relevant library
from sklearn.preprocessing import OneHotEncoder
seasons = df1[['season']]

#instantiate
encoder_seasons = OneHotEncoder(categories='auto',sparse=False,handle_unknown='ignore')

#fit it to the data
encoder_seasons.fit(seasons)

#inspecting the categories
encoder_seasons.categories_
```

Out[10]: [array(['Autumn', 'Spring', 'Summer', 'Winter'], dtype=object)]

In [11]:
```
#transforming the data
seasons_encoded = encoder_seasons.transform(seasons)
seasons_encoded
```

Out[11]:
```
array([[1., 0., 0., 0.],
       [0., 0., 0., 1.],
       [0., 0., 0., 1.],
       ...,
       [0., 0., 1., 0.],
       [0., 0., 0., 1.],
       [1., 0., 0., 0.]])
```

In [12]:
```
#converting the encoded values into a df
seasons_encoded_df = pd.DataFrame(data=seasons_encoded,index=df1.index)
seasons_encoded_df.head()
```

Out[12]:

	0	1	2	3
0	1.0	0.0	0.0	0.0
1	0.0	0.0	0.0	1.0
2	0.0	0.0	0.0	1.0
3	0.0	0.0	0.0	1.0
4	0.0	0.0	0.0	1.0

In [13]:
```
#renaming the columns to readability
seasons_encoded_df.rename(columns = {0:'Autumn',1:'Spring',2:'Summer',3:'Winter'},inpla
```

In [14]:
```
# adding the encoded values to df1
df1 = pd.concat([df1,seasons_encoded_df],axis=1)
df1.head()
```

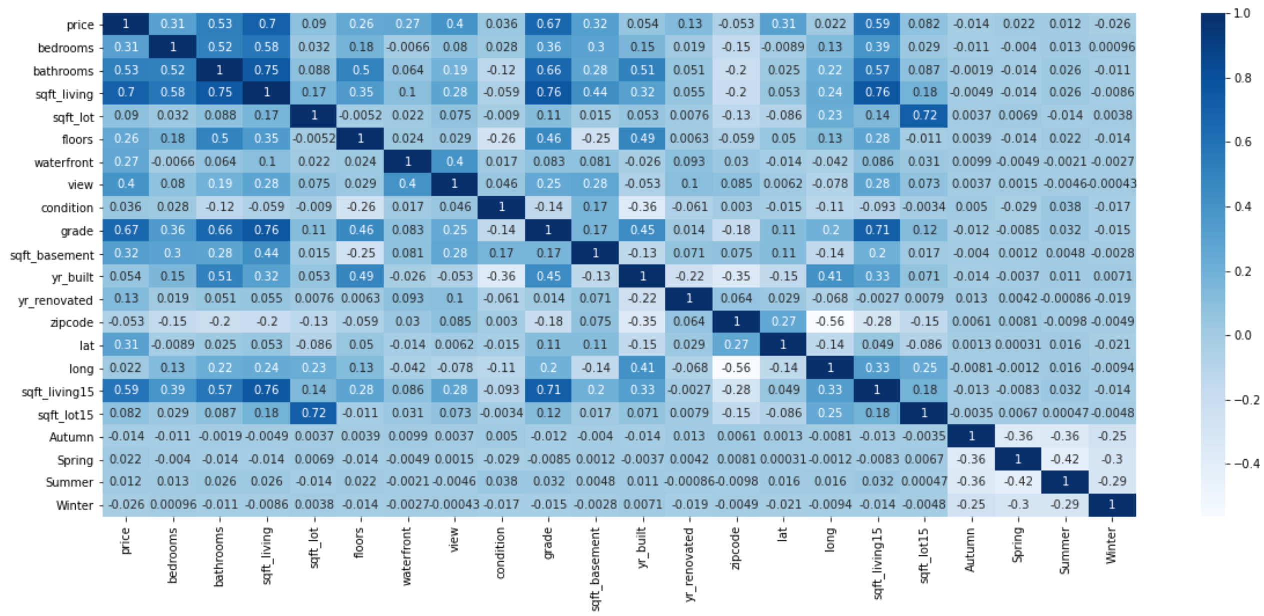
Out[14]:

	date	price	bedrooms	bathrooms	sqft_living	sqft_lot	floors	waterfront	view	condition	...
0	2014-10-13	221900.0	3	1.00	1180	5650	1.0	0	0	3	...
1	2014-12-09	538000.0	3	2.25	2570	7242	2.0	0	0	3	...
2	2015-02-25	180000.0	2	1.00	770	10000	1.0	0	0	3	...
3	2014-12-09	604000.0	4	3.00	1960	5000	1.0	0	0	5	...
4	2015-02-18	510000.0	3	2.00	1680	8080	1.0	0	0	3	...

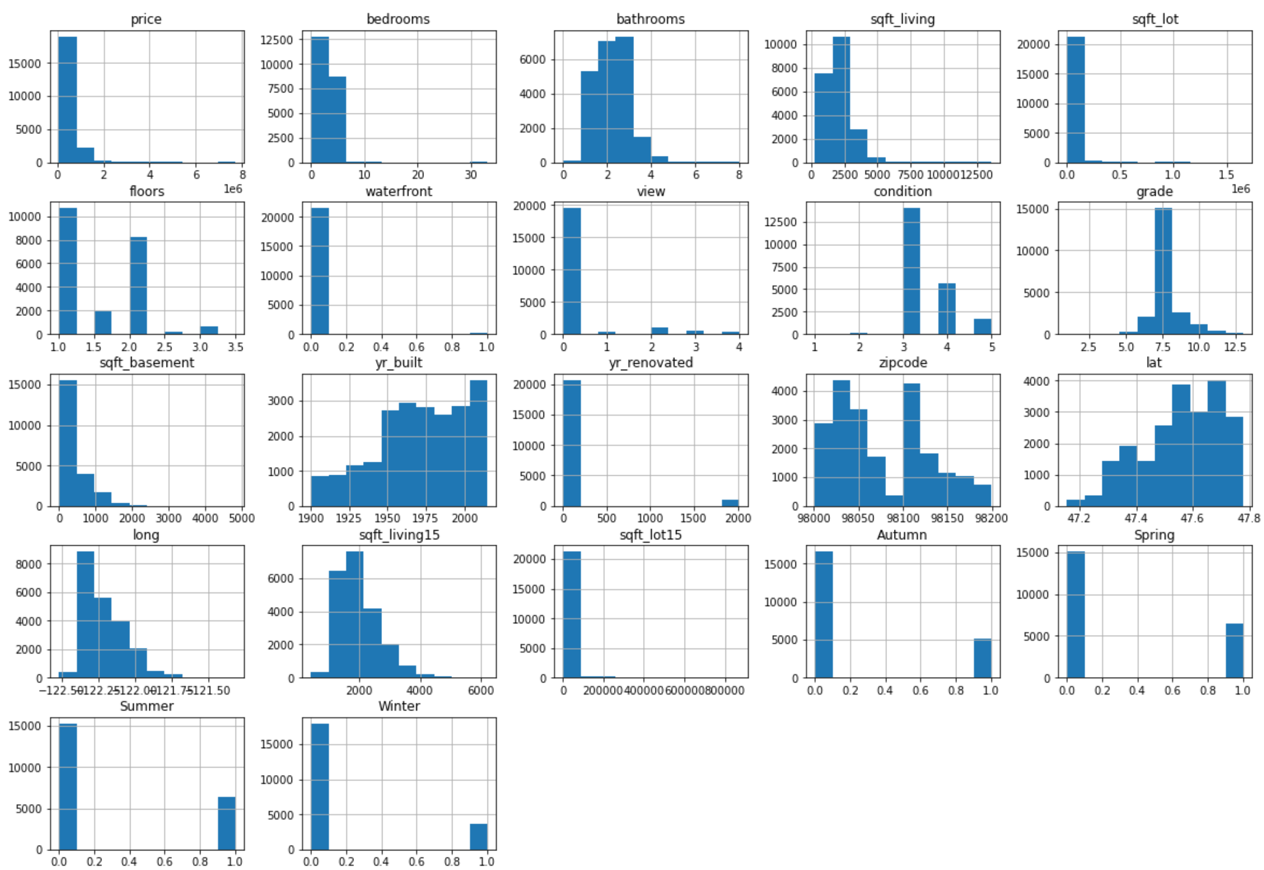
5 rows × 26 columns

In [15]:
```
# Looking at the updated heatmap
import seaborn as sns
fig,ax = plt.subplots(figsize=(20,8))
```

```python
corr = df1.corr()
sns.heatmap(corr,cmap='Blues',annot=True);
```



In [16]:
```python
# viewing the distribution of the variables
fig,ax = plt.subplots(figsize=(20,14))
pd.plotting.hist_frame(df1,ax=ax);
```



Building the model with `statsmodel` - baseline

In [17]:
```python
#import the library
from statsmodels.formula.api import ols
import statsmodels.api as sm
```

In [18]:
```python
# droppping irrelevant data
df1.drop(['date','month_of_sale','season'],axis=1,inplace=True)
df1.drop('sqft_above',axis=1,inplace=True) # since it is high correlation with sqft_liv
```

In [19]:
```python
#building the baseline model
outcome = 'price'
predictors = df1.drop('price',axis=1)
predictors_sum = '+'.join(predictors.columns)

f = outcome + '~' + predictors_sum
model_baseline = ols(formula=f,data=df1).fit()

model_baseline.summary()
```

Out[19]:

OLS Regression Results

Dep. Variable:	price	**R-squared:**	0.701
Model:	OLS	**Adj. R-squared:**	0.701
Method:	Least Squares	**F-statistic:**	2530.
Date:	Wed, 19 Oct 2022	**Prob (F-statistic):**	0.00
Time:	08:47:18	**Log-Likelihood:**	-2.9456e+05
No. Observations:	21613	**AIC:**	5.892e+05
Df Residuals:	21592	**BIC:**	5.893e+05
Df Model:	20		
Covariance Type:	nonrobust		

	coef	**std err**	**t**	**P>|t|**	**[0.025**	**0.975]**
Intercept	5.416e+06	2.34e+06	2.314	0.021	8.28e+05	1e+07
bedrooms	-3.595e+04	1888.466	-19.035	0.000	-3.96e+04	-3.22e+04
bathrooms	4.13e+04	3247.692	12.717	0.000	3.49e+04	4.77e+04
sqft_living	181.6648	3.662	49.612	0.000	174.488	188.842
sqft_lot	0.1272	0.048	2.658	0.008	0.033	0.221
floors	6984.6495	3589.681	1.946	0.052	-51.390	1.4e+04
waterfront	5.838e+05	1.73e+04	33.694	0.000	5.5e+05	6.18e+05
view	5.276e+04	2136.214	24.699	0.000	4.86e+04	5.69e+04
condition	2.708e+04	2350.074	11.524	0.000	2.25e+04	3.17e+04
grade	9.574e+04	2149.002	44.552	0.000	9.15e+04	1e+05
sqft_basement	-31.4945	4.352	-7.236	0.000	-40.025	-22.964
yr_built	-2619.2555	72.527	-36.114	0.000	-2761.414	-2477.097
yr_renovated	19.7768	3.649	5.419	0.000	12.624	26.929

zipcode	-583.9780	32.925	-17.737	0.000	-648.513	-519.443
lat	6.029e+05	1.07e+04	56.262	0.000	5.82e+05	6.24e+05
long	-2.152e+05	1.31e+04	-16.416	0.000	-2.41e+05	-1.9e+05
sqft_living15	21.6406	3.442	6.288	0.000	14.895	28.387
sqft_lot15	-0.3856	0.073	-5.272	0.000	-0.529	-0.242
Autumn	1.346e+06	5.85e+05	2.300	0.021	1.99e+05	2.49e+06
Spring	1.375e+06	5.85e+05	2.349	0.019	2.28e+05	2.52e+06
Summer	1.348e+06	5.85e+05	2.303	0.021	2.01e+05	2.49e+06
Winter	1.348e+06	5.85e+05	2.304	0.021	2.01e+05	2.5e+06

Omnibus:	18430.723	**Durbin-Watson:**	1.990
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	1899541.916
Skew:	3.576	**Prob(JB):**	0.00
Kurtosis:	48.367	**Cond. No.**	1.01e+20

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
[2] The smallest eigenvalue is 2.15e-26. This might indicate that there are
strong multicollinearity problems or that the design matrix is singular.

In [20]:
```
print('R-squared value for baseline model = ',model_baseline.rsquared)
```

```
R-squared value for baseline model =  0.7009279563815052
```

In [21]:
```
#Looking at the summary statistics for each variable
df1.describe()
```

Out[21]:

	price	bedrooms	bathrooms	sqft_living	sqft_lot	floors	waterfro
count	2.161300e+04	21613.000000	21613.000000	21613.000000	2.161300e+04	21613.000000	21613.00000
mean	5.400881e+05	3.370842	2.114757	2079.899736	1.510697e+04	1.494309	0.0075
std	3.671272e+05	0.930062	0.770163	918.440897	4.142051e+04	0.539989	0.0865
min	7.500000e+04	0.000000	0.000000	290.000000	5.200000e+02	1.000000	0.0000
25%	3.219500e+05	3.000000	1.750000	1427.000000	5.040000e+03	1.000000	0.0000
50%	4.500000e+05	3.000000	2.250000	1910.000000	7.618000e+03	1.500000	0.0000
75%	6.450000e+05	4.000000	2.500000	2550.000000	1.068800e+04	2.000000	0.0000
max	7.700000e+06	33.000000	8.000000	13540.000000	1.651359e+06	3.500000	1.0000

8 rows × 22 columns

From the above, we can see that the `standard deviaton` for `[sqft living,sqft_lot,sqft_living15,sqft_lot15,yr_renovated]` are quite high

In [22]:
```
# examining yr_renovated
df1['yr_renovated'].value_counts()
```

Out[22]:
```
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
```

Looks like `yr_renovated` has 20699 rows of 0 values, indicating that nearly 96% of the houses in the dataset have not been renovated. Hence, we can factor it out from our analysis - model_1

In [23]:
```
#dropping yr_renovated
df1.drop('yr_renovated',axis=1,inplace=True)
```

In [24]:
```
#running the model again
outcome = 'price'
predictors = df1.drop('price',axis=1)
predictors_sum = '+'.join(predictors.columns)

f = outcome + '~' + predictors_sum
model_1 = ols(formula=f,data=df1).fit()

model_1.summary()
```

Out[24]:

OLS Regression Results

Dep. Variable:	price	**R-squared:**	0.701
Model:	OLS	**Adj. R-squared:**	0.700
Method:	Least Squares	**F-statistic:**	2658.
Date:	Wed, 19 Oct 2022	**Prob (F-statistic):**	0.00
Time:	08:47:18	**Log-Likelihood:**	-2.9457e+05
No. Observations:	21613	**AIC:**	5.892e+05
Df Residuals:	21593	**BIC:**	5.893e+05
Df Model:	19		
Covariance Type:	nonrobust		

	coef	std err	t	P>|t|	[0.025	0.975]
Intercept	6.338e+06	2.34e+06	2.713	0.007	1.76e+06	1.09e+07
bedrooms	-3.628e+04	1888.690	-19.210	0.000	-4e+04	-3.26e+04

bathrooms	4.363e+04	3221.336	13.543	0.000	3.73e+04	4.99e+04
sqft_living	181.6754	3.664	49.583	0.000	174.494	188.857
sqft_lot	0.1236	0.048	2.583	0.010	0.030	0.217
floors	8009.7234	3587.048	2.233	0.026	978.844	1.5e+04
waterfront	5.89e+05	1.73e+04	34.025	0.000	5.55e+05	6.23e+05
view	5.313e+04	2136.560	24.865	0.000	4.89e+04	5.73e+04
condition	2.488e+04	2316.347	10.743	0.000	2.03e+04	2.94e+04
grade	9.616e+04	2149.027	44.746	0.000	9.19e+04	1e+05
sqft_basement	-31.2853	4.355	-7.184	0.000	-39.821	-22.749
yr_built	-2744.6428	68.783	-39.903	0.000	-2879.463	-2609.823
zipcode	-588.7554	32.935	-17.876	0.000	-653.310	-524.201
lat	6.006e+05	1.07e+04	56.055	0.000	5.8e+05	6.22e+05
long	-2.126e+05	1.31e+04	-16.214	0.000	-2.38e+05	-1.87e+05
sqft_living15	20.6390	3.439	6.001	0.000	13.898	27.380
sqft_lot15	-0.3800	0.073	-5.193	0.000	-0.523	-0.237
Autumn	1.577e+06	5.84e+05	2.699	0.007	4.32e+05	2.72e+06
Spring	1.605e+06	5.84e+05	2.748	0.006	4.6e+05	2.75e+06
Summer	1.578e+06	5.84e+05	2.702	0.007	4.34e+05	2.72e+06
Winter	1.578e+06	5.84e+05	2.702	0.007	4.34e+05	2.72e+06

Omnibus:	18429.820	**Durbin-Watson:**	1.990
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	1896654.926
Skew:	3.577	**Prob(JB):**	0.00
Kurtosis:	48.332	**Cond. No.**	1.18e+20

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
[2] The smallest eigenvalue is 1.56e-26. This might indicate that there are
strong multicollinearity problems or that the design matrix is singular.

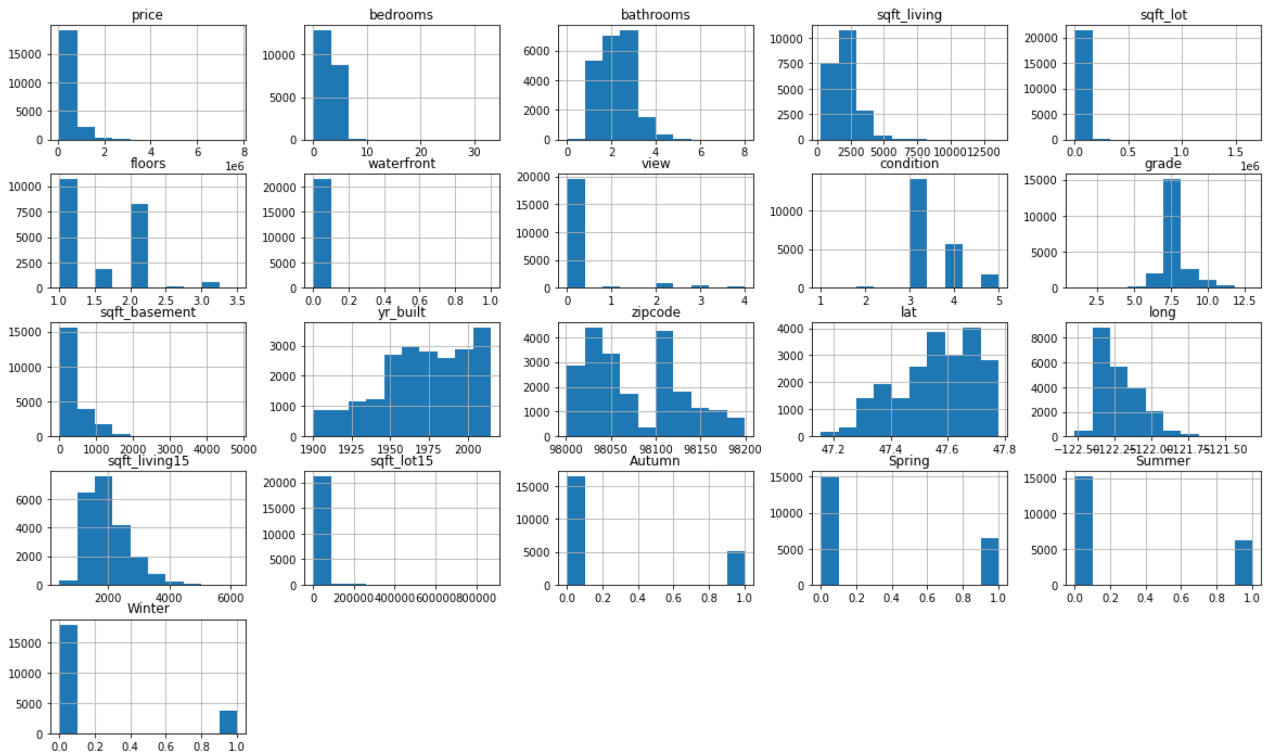
In [25]:
```
print('R-squared value for the baseline model = ',model_baseline.rsquared)
print('R-squared value for model_1 = ',model_1.rsquared, ' - removing yr_renovated ')
```

```
R-squared value for the baseline model =  0.7009279563815052
R-squared value for model_1 =  0.7005211415851306  - removing yr_renovated
```

Let's look at the predictor variables and get an idea of how they are distributed. For linear regression, while normality of the predictors

is not an assumption, but it does help the model if the predictors are normally distributed

In [26]:
```
#visualizing the distribution of the variables
fig,ax = plt.subplots(figsize=(20,12))
pd.plotting.hist_frame(df1,ax= ax);
```



transforming `price` using log transform - model_2

In [27]:
```
#transforming price
df1['price'] = df1['price'].map(lambda x : np.log(x))

# modelling with the transformed price
outcome = 'price'
predictors = df1.drop('price',axis=1)
predictors_sum = '+'.join(predictors.columns)

f = outcome + '~' + predictors_sum
model_2 = ols(formula=f,data=df1).fit()

model_2.summary()
```

Out[27]:

OLS Regression Results

Dep. Variable:	price	**R-squared:**	0.772
Model:	OLS	**Adj. R-squared:**	0.771
Method:	Least Squares	**F-statistic:**	3838.
Date:	Wed, 19 Oct 2022	**Prob (F-statistic):**	0.00
Time:	08:47:21	**Log-Likelihood:**	-856.18
No. Observations:	21613	**AIC:**	1752.

Df Residuals:	21593	**BIC:**	1912.
Df Model:	19		
Covariance Type:	nonrobust		

	coef	std err	t	P>|t|	[0.025	0.975]
Intercept	-2.2382	2.927	-0.765	0.445	-7.976	3.500
bedrooms	-0.0131	0.002	-5.546	0.000	-0.018	-0.008
bathrooms	0.0737	0.004	18.247	0.000	0.066	0.082
sqft_living	0.0001	4.59e-06	29.793	0.000	0.000	0.000
sqft_lot	4.633e-07	6e-08	7.723	0.000	3.46e-07	5.81e-07
floors	0.0775	0.004	17.238	0.000	0.069	0.086
waterfront	0.3823	0.022	17.622	0.000	0.340	0.425
view	0.0609	0.003	22.755	0.000	0.056	0.066
condition	0.0597	0.003	20.562	0.000	0.054	0.065
grade	0.1594	0.003	59.198	0.000	0.154	0.165
sqft_basement	1.5e-05	5.46e-06	2.749	0.006	4.31e-06	2.57e-05
yr_built	-0.0036	8.62e-05	-42.227	0.000	-0.004	-0.003
zipcode	-0.0007	4.13e-05	-15.938	0.000	-0.001	-0.001
lat	1.3958	0.013	103.963	0.000	1.369	1.422
long	-0.1554	0.016	-9.460	0.000	-0.188	-0.123
sqft_living15	9.658e-05	4.31e-06	22.411	0.000	8.81e-05	0.000
sqft_lot15	-2.57e-07	9.17e-08	-2.803	0.005	-4.37e-07	-7.72e-08
Autumn	-0.5734	0.732	-0.784	0.433	-2.008	0.861
Spring	-0.5234	0.732	-0.715	0.475	-1.958	0.911
Summer	-0.5681	0.732	-0.776	0.438	-2.003	0.866
Winter	-0.5733	0.732	-0.783	0.433	-2.008	0.861

Omnibus:	401.199	**Durbin-Watson:**	1.986
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	835.932
Skew:	-0.038	**Prob(JB):**	3.02e-182
Kurtosis:	3.960	**Cond. No.**	1.18e+20

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
[2] The smallest eigenvalue is 1.56e-26. This might indicate that there are
strong multicollinearity problems or that the design matrix is singular.

```
In [28]: print('R-squared value for the baseline_model = ',model_baseline.rsquared)
         print('R-squared value for model_1 = ',model_1.rsquared, ' - removing yr_renovated ')
         print('R-squared value for model_2 = ',model_2.rsquared, ' - transforming price using l
```

```
R-squared value for the baseline_model =  0.7009279563815052
R-squared value for model_1 =  0.7005211415851306  - removing yr_renovated
R-squared value for model_2 =  0.7715173571062647  - transforming price using log transf
orm
```

Since transforming `price` increased the R^2 values, we can try transforming some of the other variables to see if it improves the model

```
In [29]: #transforming the following varibale
         df1['sqft_living'] = df1['sqft_living'].map(lambda x: np.log(x))
```

```
In [30]: # modelling with transformed sqft_living
         outcome = 'price'
         predictors = df1.drop('price',axis=1)
         predictors_sum = '+'.join(predictors.columns)

         f = outcome + '~' + predictors_sum
         model_3 = ols(formula=f,data=df1).fit()

         model_3.summary()
```

Out[30]:

OLS Regression Results

Dep. Variable:	price	**R-squared:**	0.774
Model:	OLS	**Adj. R-squared:**	0.773
Method:	Least Squares	**F-statistic:**	3882.
Date:	Wed, 19 Oct 2022	**Prob (F-statistic):**	0.00
Time:	08:47:22	**Log-Likelihood:**	-759.52
No. Observations:	21613	**AIC:**	1559.
Df Residuals:	21593	**BIC:**	1719.
Df Model:	19		
Covariance Type:	nonrobust		

	coef	std err	t	P>|t|	[0.025	0.975]
Intercept	-6.1405	2.921	-2.102	0.036	-11.867	-0.414
bedrooms	-0.0241	0.002	-9.824	0.000	-0.029	-0.019
bathrooms	0.0732	0.004	18.362	0.000	0.065	0.081
sqft_living	0.3182	0.010	33.010	0.000	0.299	0.337
sqft_lot	5.014e-07	5.96e-08	8.407	0.000	3.85e-07	6.18e-07
floors	0.0728	0.004	16.233	0.000	0.064	0.082
waterfront	0.3955	0.022	18.329	0.000	0.353	0.438
view	0.0638	0.003	23.911	0.000	0.059	0.069

condition	0.0551	0.003	19.084	0.000	0.049	0.061
grade	0.1609	0.003	61.242	0.000	0.156	0.166
sqft_basement	1.133e-05	5.39e-06	2.101	0.036	7.59e-07	2.19e-05
yr_built	-0.0038	8.5e-05	-45.105	0.000	-0.004	-0.004
zipcode	-0.0006	4.11e-05	-15.466	0.000	-0.001	-0.001
lat	1.3967	0.013	104.536	0.000	1.371	1.423
long	-0.1630	0.016	-9.964	0.000	-0.195	-0.131
sqft_living15	9.748e-05	4.22e-06	23.111	0.000	8.92e-05	0.000
sqft_lot15	-2.273e-07	9.12e-08	-2.491	0.013	-4.06e-07	-4.84e-08
Autumn	-1.5487	0.730	-2.120	0.034	-2.980	-0.117
Spring	-1.4990	0.730	-2.052	0.040	-2.931	-0.067
Summer	-1.5443	0.730	-2.114	0.034	-2.976	-0.113
Winter	-1.5486	0.730	-2.120	0.034	-2.980	-0.117

Omnibus:	333.208	**Durbin-Watson:**	1.984
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	634.777
Skew:	0.054	**Prob(JB):**	1.44e-138
Kurtosis:	3.833	**Cond. No.**	1.17e+20

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
[2] The smallest eigenvalue is 1.59e-26. This might indicate that there are
strong multicollinearity problems or that the design matrix is singular.

In [31]:

```
print('R-squared value for the baseline_model = ',model_baseline.rsquared)
print('R-squared value for model_1 = ',model_1.rsquared, ' - removing yr_renovated ')
print('R-squared value for model_2 = ',model_2.rsquared, ' - transforming price using l
print('R-squared value for model_3 = ',model_3.rsquared, ' - transforming sqft_living u
```

```
R-squared value for the baseline_model =  0.7009279563815052
R-squared value for model_1 =  0.7005211415851306  - removing yr_renovated
R-squared value for model_2 =  0.7715173571062647  - transforming price using log transf
orm
R-squared value for model_3 =  0.7735521196953915  - transforming sqft_living using log
transform
```

In [32]:

```
#transforming sqft_lot
df1['sqft_lot'] = df1['sqft_lot'].map(lambda x: np.log(x))

outcome = 'price'
predictors = df1.drop('price',axis=1)
predictors_sum = '+'.join(predictors.columns)

f = outcome + '~' + predictors_sum
```

```python
model_4 = ols(formula=f,data=df1).fit()

model_4.summary()
```

Out[32]:

OLS Regression Results

Dep. Variable:	price	**R-squared:**	0.774
Model:	OLS	**Adj. R-squared:**	0.774
Method:	Least Squares	**F-statistic:**	3901.
Date:	Wed, 19 Oct 2022	**Prob (F-statistic):**	0.00
Time:	08:47:22	**Log-Likelihood:**	-720.17
No. Observations:	21613	**AIC:**	1480.
Df Residuals:	21593	**BIC:**	1640.
Df Model:	19		
Covariance Type:	nonrobust		

	coef	**std err**	**t**	**P>|t|**	**[0.025**	**0.975]**
Intercept	1.7481	2.967	0.589	0.556	-4.067	7.563
bedrooms	-0.0237	0.002	-9.675	0.000	-0.028	-0.019
bathrooms	0.0702	0.004	17.602	0.000	0.062	0.078
sqft_living	0.3542	0.010	35.466	0.000	0.335	0.374
sqft_lot	-0.0387	0.003	-12.235	0.000	-0.045	-0.032
floors	0.0468	0.005	9.493	0.000	0.037	0.056
waterfront	0.4091	0.022	18.957	0.000	0.367	0.451
view	0.0655	0.003	24.600	0.000	0.060	0.071
condition	0.0546	0.003	18.946	0.000	0.049	0.060
grade	0.1616	0.003	61.630	0.000	0.156	0.167
sqft_basement	-3.692e-06	5.5e-06	-0.671	0.502	-1.45e-05	7.1e-06
yr_built	-0.0040	8.53e-05	-46.796	0.000	-0.004	-0.004
zipcode	-0.0007	4.11e-05	-16.073	0.000	-0.001	-0.001
lat	1.3751	0.013	102.573	0.000	1.349	1.401
long	-0.1139	0.017	-6.859	0.000	-0.146	-0.081
sqft_living15	0.0001	4.24e-06	24.048	0.000	9.36e-05	0.000
sqft_lot15	9.347e-07	8.36e-08	11.184	0.000	7.71e-07	1.1e-06
Autumn	0.4237	0.742	0.571	0.568	-1.030	1.877
Spring	0.4726	0.742	0.637	0.524	-0.981	1.926
Summer	0.4275	0.742	0.576	0.564	-1.026	1.881
Winter	0.4243	0.742	0.572	0.567	-1.029	1.878

Omnibus:	407.305	**Durbin-Watson:**	1.986
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	799.046
Skew:	0.097	**Prob(JB):**	3.09e-174
Kurtosis:	3.922	**Cond. No.**	1.16e+20

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
[2] The smallest eigenvalue is 1.57e-26. This might indicate that there are
strong multicollinearity problems or that the design matrix is singular.

In [33]:

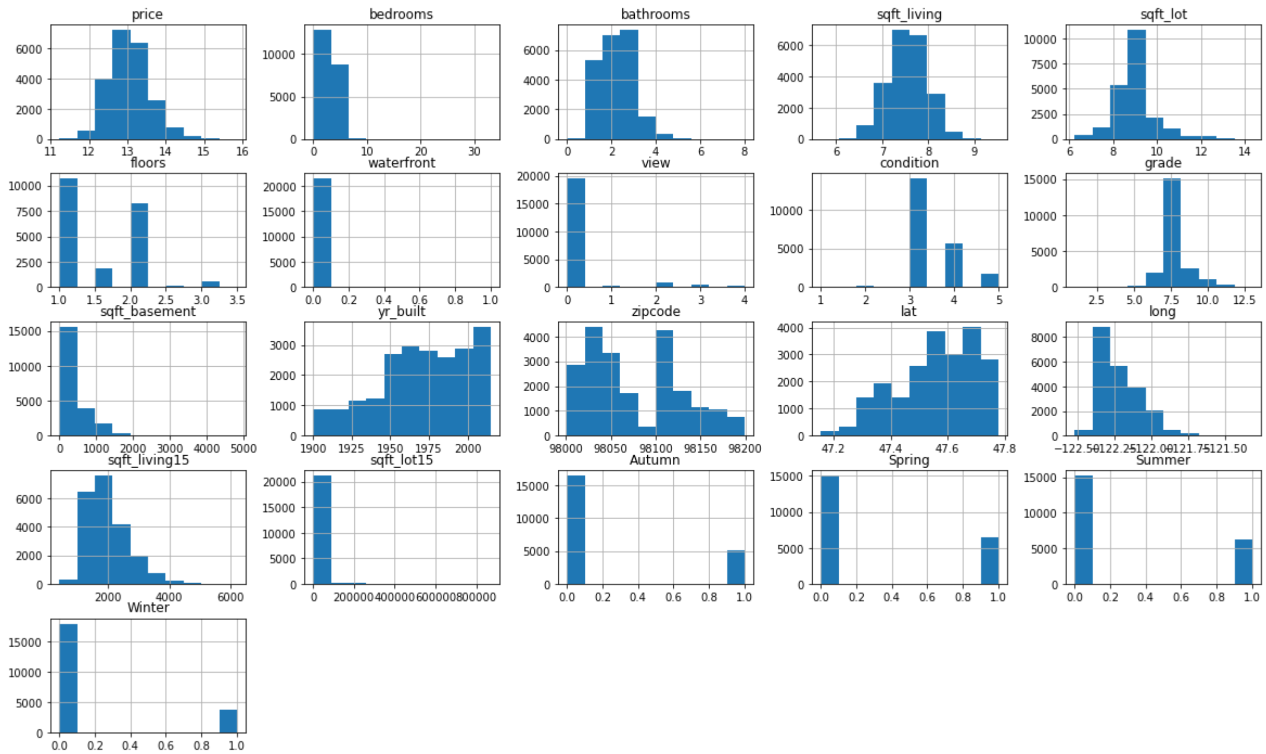
```
print('R-squared value for the baseline_model = ',model_baseline.rsquared)
print('R-squared value for model_1 = ',model_1.rsquared, ' - removing yr_renovated ')
print('R-squared value for model_2 = ',model_2.rsquared, ' - transforming price using l
print('R-squared value for model_3 = ',model_3.rsquared, ' - transforming sqft_living u
print('R-squared value for model_4 = ',model_4.rsquared, ' - transforming sqft_lot usin
```

```
R-squared value for the baseline_model =  0.7009279563815052
R-squared value for model_1 =  0.7005211415851306  - removing yr_renovated
R-squared value for model_2 =  0.7715173571062647  - transforming price using log transf
orm
R-squared value for model_3 =  0.7735521196953915  - transforming sqft_living using log
transform
R-squared value for model_4 =  0.7743750042560188  - transforming sqft_lot using log tra
nsform
```

Since transforming variables does not seem to yield appreciable increase in the R^2 value, we can try scaling to see if we can get any gains.

In [34]:

```
#visualizing the distribution of the variables
fig,ax = plt.subplots(figsize=(20,12))
pd.plotting.hist_frame(df1,ax= ax);
```



We can scale `sqft_lot15` and `sqft_living15` looking at the visualization above

In [35]:
```
#importing the library
from sklearn import preprocessing
```

In [36]:
```
scale = preprocessing.MinMaxScaler().fit(df1[['sqft_living15','sqft_lot15']])
scale_values = scale.transform(df1[['sqft_living15','sqft_lot15']])
scale_values
```

Out[36]:
```
array([[0.16193426, 0.00574235],
       [0.22216486, 0.00802712],
       [0.3994149 , 0.00851302],
       ...,
       [0.10686629, 0.00155764],
       [0.17398038, 0.00073057],
       [0.10686629, 0.00081098]])
```

In [37]:
```
scale_df = pd.DataFrame(scale_values)
scale_df.rename(columns = {0:'sqft_living15',1:'sqft_lot15'},inplace=True)
scale_df
```

Out[37]:

	sqft_living15	sqft_lot15
0	0.161934	0.005742
1	0.222165	0.008027
2	0.399415	0.008513
3	0.165376	0.004996
4	0.241094	0.007871
...	...	...

	sqft_living15	sqft_lot15
21608	0.194631	0.000986
21609	0.246257	0.007523
21610	0.106866	0.001558
21611	0.173980	0.000731
21612	0.106866	0.000811

21613 rows × 2 columns

In [38]:

```
#replacing the values with the scaled values in the df
df1['sqft_living15'] = scale_df['sqft_living15']
df1['sqft_lot15'] = scale_df['sqft_lot15']
```

In [39]:

```
#using scaled values
outcome = 'price'
predictors = df1.drop('price',axis=1)
predictors_sum = '+'.join(predictors.columns)

f = outcome + '~' + predictors_sum
model_5 = ols(formula=f,data=df1).fit()

model_5.summary()
```

Out[39]:

OLS Regression Results

Dep. Variable:	price	**R-squared:**	0.774
Model:	OLS	**Adj. R-squared:**	0.774
Method:	Least Squares	**F-statistic:**	3901.
Date:	Wed, 19 Oct 2022	**Prob (F-statistic):**	0.00
Time:	08:47:25	**Log-Likelihood:**	-720.17
No. Observations:	21613	**AIC:**	1480.
Df Residuals:	21593	**BIC:**	1640.
Df Model:	19		
Covariance Type:	nonrobust		

	coef	std err	t	P>|t|	[0.025	0.975]
Intercept	1.7811	2.966	0.600	0.548	-4.033	7.595
bedrooms	-0.0237	0.002	-9.675	0.000	-0.028	-0.019
bathrooms	0.0702	0.004	17.602	0.000	0.062	0.078
sqft_living	0.3542	0.010	35.466	0.000	0.335	0.374
sqft_lot	-0.0387	0.003	-12.235	0.000	-0.045	-0.032
floors	0.0468	0.005	9.493	0.000	0.037	0.056
waterfront	0.4091	0.022	18.957	0.000	0.367	0.451

view	0.0655	0.003	24.600	0.000	0.060	0.071
condition	0.0546	0.003	18.946	0.000	0.049	0.060
grade	0.1616	0.003	61.630	0.000	0.156	0.167
sqft_basement	-3.692e-06	5.5e-06	-0.671	0.502	-1.45e-05	7.1e-06
yr_built	-0.0040	8.53e-05	-46.796	0.000	-0.004	-0.004
zipcode	-0.0007	4.11e-05	-16.073	0.000	-0.001	-0.001
lat	1.3751	0.013	102.573	0.000	1.349	1.401
long	-0.1139	0.017	-6.859	0.000	-0.146	-0.081
sqft_living15	0.5919	0.025	24.048	0.000	0.544	0.640
sqft_lot15	0.8137	0.073	11.184	0.000	0.671	0.956
Autumn	0.4320	0.742	0.582	0.560	-1.022	1.886
Spring	0.4808	0.742	0.648	0.517	-0.973	1.934
Summer	0.4357	0.742	0.588	0.557	-1.018	1.889
Winter	0.4326	0.742	0.583	0.560	-1.021	1.886

Omnibus:	407.305	**Durbin-Watson:**	1.986
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	799.046
Skew:	0.097	**Prob(JB):**	3.09e-174
Kurtosis:	3.922	**Cond. No.**	1.14e+20

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
[2] The smallest eigenvalue is 1.59e-26. This might indicate that there are
strong multicollinearity problems or that the design matrix is singular.

In [40]:

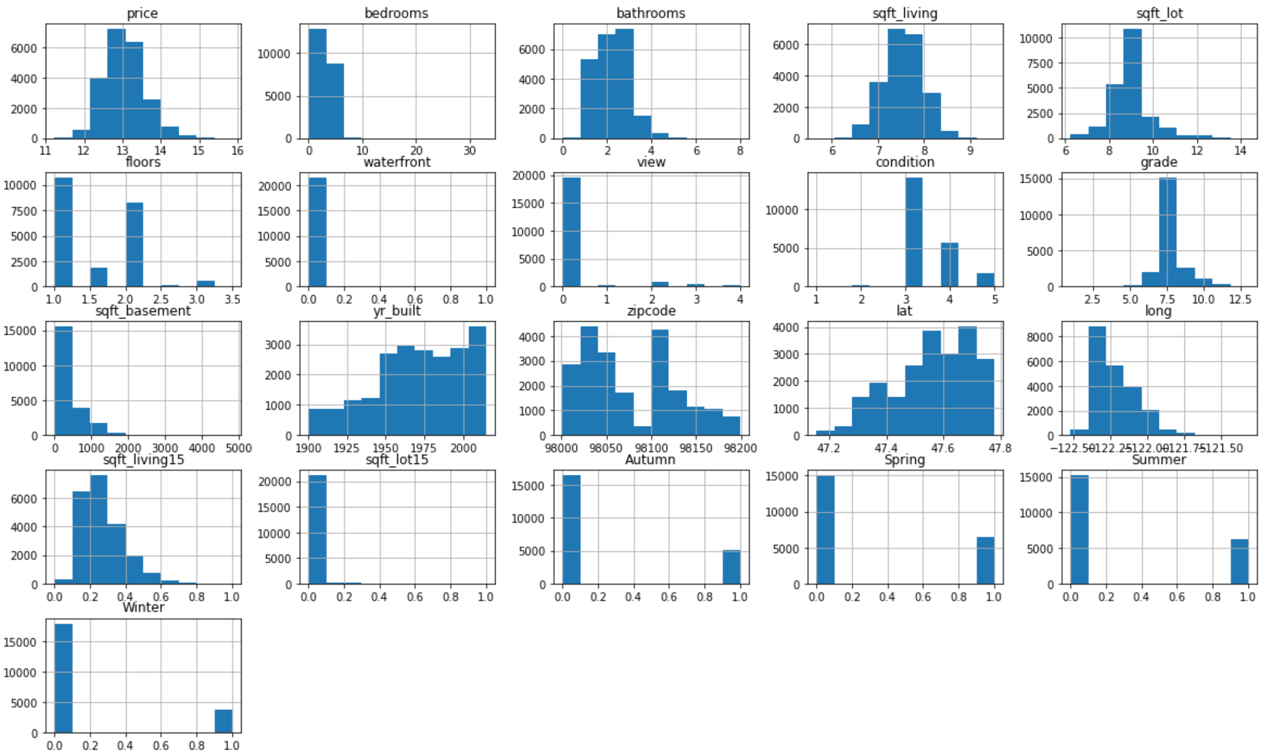
```
print('R-squared value for the baseline_model = ',model_baseline.rsquared)
print('R-squared value for model_1 = ',model_1.rsquared, ' - removing yr_renovated ')
print('R-squared value for model_2 = ',model_2.rsquared, ' - transforming price using l
print('R-squared value for model_3 = ',model_3.rsquared, ' - transforming sqft_living u
print('R-squared value for model_4 = ',model_4.rsquared, ' - transforming sqft_lot usin
print('R-squared value for model_5 = ',model_5.rsquared, ' - using scaled values')
```

```
R-squared value for the baseline_model =  0.7009279563815052
R-squared value for model_1 =  0.7005211415851306  - removing yr_renovated
R-squared value for model_2 =  0.7715173571062647  - transforming price using log transf
orm
R-squared value for model_3 =  0.7735521196953915  - transforming sqft_living using log
transform
R-squared value for model_4 =  0.7743750042560188  - transforming sqft_lot using log tra
nsform
R-squared value for model_5 =  0.7743750042560187  - using scaled values
```

As we can see from the above, there is no change in the

R^2 value after using the scaled values

In [41]:
```
#visualizing the distribution of the variables
fig,ax = plt.subplots(figsize=(20,12))
pd.plotting.hist_frame(df1,ax= ax);
```



Based on the p-values from the summary statistics, we can remove all the seasons and the size of the basement thereby concluding that they do not factor in the selling price of a house

In [42]:
```
df1.drop(['Autumn','Spring','Summer','Winter','sqft_basement'],inplace=True,axis=1)
```

In [43]:
```
#modelling with the new df
outcome = 'price'
predictors = df1.drop(['price'],axis=1)
predictors_sum = '+'.join(predictors.columns)

f = outcome + '~' + predictors_sum
model_6 = ols(formula=f,data=df1).fit()

model_6.summary()
```

Out[43]:

OLS Regression Results

Dep. Variable:	price	**R-squared:**	0.773
Model:	OLS	**Adj. R-squared:**	0.773
Method:	Least Squares	**F-statistic:**	4894.
Date:	Wed, 19 Oct 2022	**Prob (F-statistic):**	0.00
Time:	08:47:28	**Log-Likelihood:**	-801.05

No. Observations:	21613	**AIC:**	1634.
Df Residuals:	21597	**BIC:**	1762.
Df Model:	15		
Covariance Type:	nonrobust		

	coef	std err	t	P>|t|	[0.025	0.975]
Intercept	2.5104	3.699	0.679	0.497	-4.741	9.761
bedrooms	-0.0233	0.002	-9.496	0.000	-0.028	-0.018
bathrooms	0.0695	0.004	17.576	0.000	0.062	0.077
sqft_living	0.3507	0.009	38.789	0.000	0.333	0.368
sqft_lot	-0.0390	0.003	-12.564	0.000	-0.045	-0.033
floors	0.0474	0.004	10.951	0.000	0.039	0.056
waterfront	0.4080	0.022	18.841	0.000	0.366	0.450
view	0.0654	0.003	24.873	0.000	0.060	0.071
condition	0.0534	0.003	18.513	0.000	0.048	0.059
grade	0.1620	0.003	61.994	0.000	0.157	0.167
yr_built	-0.0040	8.55e-05	-46.705	0.000	-0.004	-0.004
zipcode	-0.0007	4.12e-05	-15.973	0.000	-0.001	-0.001
lat	1.3740	0.013	102.532	0.000	1.348	1.400
long	-0.1108	0.017	-6.706	0.000	-0.143	-0.078
sqft_living15	0.5941	0.025	24.159	0.000	0.546	0.642
sqft_lot15	0.8251	0.073	11.363	0.000	0.683	0.967

Omnibus:	399.658	**Durbin-Watson:**	1.983
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	766.103
Skew:	0.105	**Prob(JB):**	4.39e-167
Kurtosis:	3.898	**Cond. No.**	2.12e+08

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
[2] The condition number is large, 2.12e+08. This might indicate that there are
strong multicollinearity or other numerical problems.

In [44]:

```
print('R-squared value for the baseline_model = ',model_baseline.rsquared)
print('R-squared value for model_1 = ',model_1.rsquared, ' - removing yr_renovated ')
print('R-squared value for model_2 = ',model_2.rsquared, ' - transforming price using l
print('R-squared value for model_3 = ',model_3.rsquared, ' - transforming sqft_living u
print('R-squared value for model_4 = ',model_4.rsquared, ' - transforming sqft_lot usin
```

```
print('R-squared value for model_5 = ',model_5.rsquared, ' - using scaled values')
print('R-squared value for model_6 = ',model_6.rsquared, ' - dropping seasons and the b
```

```
R-squared value for the baseline_model =  0.7009279563815052
R-squared value for model_1 =  0.7005211415851306  - removing yr_renovated
R-squared value for model_2 =  0.7715173571062647  - transforming price using log transf
orm
R-squared value for model_3 =  0.7735521196953915  - transforming sqft_living using log
transform
R-squared value for model_4 =  0.7743750042560188  - transforming sqft_lot using log tra
nsform
R-squared value for model_5 =  0.7743750042560187  - using scaled values
R-squared value for model_6 =  0.7726801965727106  - dropping seasons and the basement
```

Model diagnostics

In [45]:

```
#getting predicted values
y_preds = model_6.fittedvalues
y_preds
```

Out[45]:

```
0        12.518129
1        13.299370
2        12.846288
3        12.940788
4        12.970565
           ...
21608    13.150331
21609    12.890803
21610    12.465554
21611    12.889894
21612    12.477357
Length: 21613, dtype: float64
```

In [46]:

```
#R^2 values
r_squared = model_6.rsquared
r_squared
```

Out[46]:

```
0.7726801965727106
```

In [47]:

```
# calculating the root mean squared error.
# this will tell us how far off the model is from the predicted
# since, we have log-transformed the values, we will have to undo this to get the real-

from sklearn.metrics import mean_squared_error
MSE = round(mean_squared_error(y_true = np.exp(df1['price']), y_pred = np.exp(model_6.f
print(f'mean_squared_error = {MSE}')
RMSE = round(np.sqrt(MSE),2)
print(f'root_mean_squared_error = {RMSE}')
```

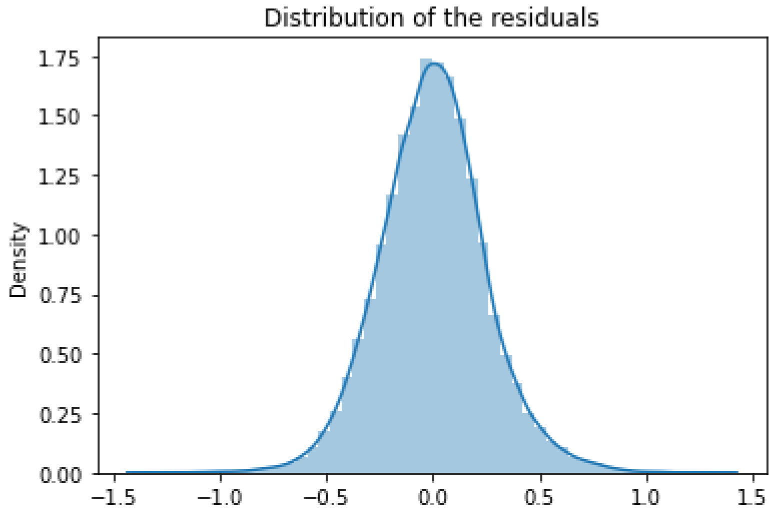
```
mean_squared_error = 33979601170.15
root_mean_squared_error = 184335.57
```

Based on the RMSE value, the model will be off by an average of USD 184,335 when it comes to predicting the price of a house

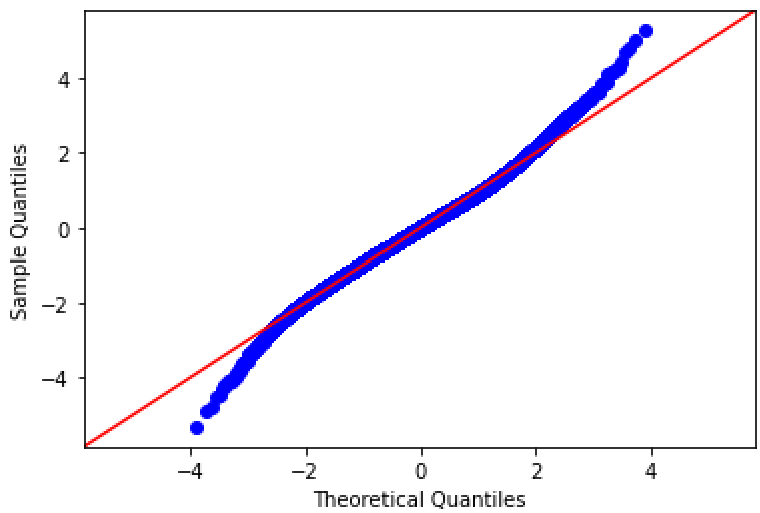
Checking if the model fullfills linear regression assumptions

1. Distribution of the model residuals is normal

In [48]:
```
residuals = model_6.resid
p = sns.distplot(residuals,kde=True)
p = plt.title('Distribution of the residuals')
```



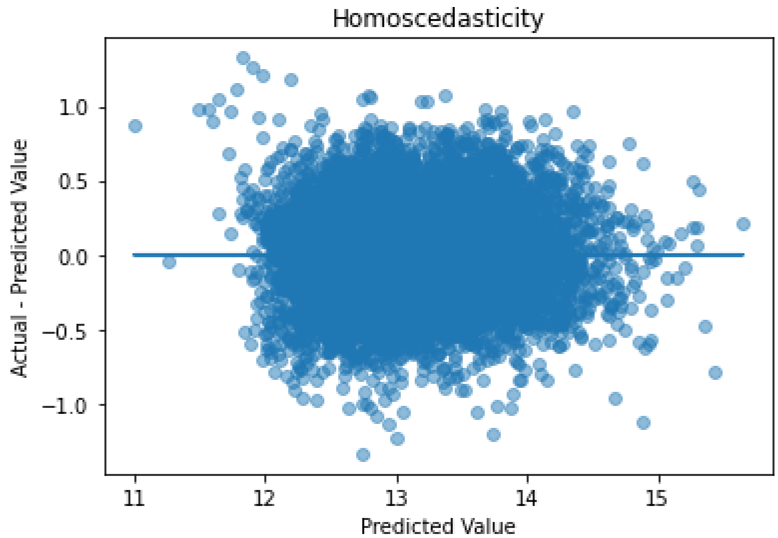
In [49]:
```
# Q-Q plots
import scipy.stats as stats
residuals = model_6.resid
fig = sm.graphics.qqplot(residuals, dist=stats.norm, line='45', fit=True)
fig.show()
```



2. Homoscedastic - the residuals have equal variances over the entire regression model

In [50]:
```
fig, ax = plt.subplots()

ax.scatter(y_preds, residuals, alpha=0.5)
ax.plot(y_preds, [0 for i in range(len(df1['price']))])
ax.set_xlabel("Predicted Value")
ax.set_ylabel("Actual - Predicted Value");
ax.set_title ('Homoscedasticity');
```

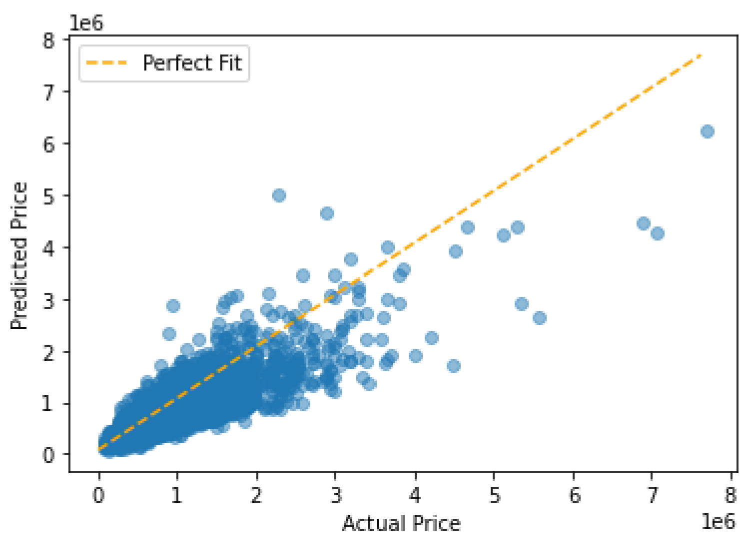


3. Checking to see if there is a linear relationship

In [51]:

```
predicted_values = model_6.fittedvalues
fig, ax = plt.subplots(sharex=True,sharey=True)

perfect_line = np.arange(np.exp(df1['price']).min(), np.exp(df1['price']).max())
ax.scatter(np.exp(df1['price']), np.exp(predicted_values), alpha=0.5)
ax.plot(perfect_line, linestyle="--", color="orange", label="Perfect Fit")
ax.set_xlabel("Actual Price")
ax.set_ylabel("Predicted Price")
ax.legend();
```



Model Interpretation

Since we have have transformed `price` , `sqft_lot` , `sqft_living` we need to exponentiate the same to get their natural values

Interpreting log transformed dependent and independent varibles :

Interpret the coefficient as the percent increase in the dependent variable for every 1% increase in the independent variable. Example: the coefficient is 0.198. For every 1% increase in the independent variable, our dependent variable increases by about 0.20%. For x percent increase, calculate 1.x to the power of the coefficient, subtract 1, and multiply by 100. Example: For every 20% increase in the independent variable, our dependent variable increases by about (1.20 0.198 – 1) * 100 = 3.7 percent.

Source

> https://data.library.virginia.edu/interpreting-log-transformations-in-a-linear-model/

Factors affecting re-sale value

In [52]:
```
# bedrooms -  interpreted differenty since it was not log-transformed
percent_increase = round((np.exp(model_6.params[1])-1)*100,2)
print(f'Expected precentage increase in the house value if the number of bedrooms is in
```

```
Expected precentage increase in the house value if the number of bedrooms is increased b
y 1  is -2.3%
```

In [53]:
```
# bathrooms -  interpreted differenty since it was not log-transformed
percent_increase = round((np.exp(model_6.params[2])-1)*100,2)
print(f'Expected precentage increase in the house value if the number of bathrooms is i
```

```
Expected precentage increase in the house value if the number of bathrooms is increased
by 1  is 7.2%
```

In [54]:
```
#sqft_living was log_transfomed along with price
# calculating % increase in price for a 10% increase in the sqft_living
percent_increase = round(((1.10**model_6.params[3])-1)*100,2)
print(f'Expected precentage increase in the house value when the living area is increas
```

```
Expected precentage increase in the house value when the living area is increased by 10%
is 3.4%
```

In [55]:
```
#sqft_lot was log_transfomed along with price
# calculating % increase in price for a 10% increase in the sqft_lot
percent_increase = round(((1.10**model_6.params[4])-1)*100,2)
print(f'Expected precentage increase in the house value when the sqft_lot is increased
```

```
Expected precentage increase in the house value when the sqft_lot is increased by 10% is
-0.37%
```

In [56]:
```
# floors -  interpreted differenty since it was not log-transformed
percent_increase = round((np.exp(model_6.params[5])-1)*100,2)
print(f'Expected precentage increase in the house value if the number of floors is incr
```

```
Expected precentage increase in the house value if the number of floors is increased by
1 unit is 4.85%
```

In [57]:
```
# waterfront -  interpreted differenty since it was not log-transformed
percent_increase = round((np.exp(model_6.params[6])-1)*100,2)
print(f'Expected precentage increase in the house value if the house is on the waterfro
```

```
Expected precentage increase in the house value if the house is on the waterfront is 50.
38%
```

In [58]:
```
# view -  interpreted differenty since it was not log-transformed
percent_increase = round((np.exp(model_6.params[7])-1)*100,2)
print(f'Expected precentage increase in the house value if the view is increased by 1 u
```

```
Expected precentage increase in the house value if the view is increased by 1 unit is 6.
76%
```

In [59]:
```python
# condition -  interpreted differenty since it was not log-transformed
percent_increase = round((np.exp(model_6.params[8])-1)*100,2)
print(f'Expected precentage increase in the house value when condition is increased by
```

```
Expected precentage increase in the house value when condition is increased by 1 unit is
5.49%
```

In [60]:
```python
# grade -  interpreted differenty since it was not log-transformed
percent_increase = round((np.exp(model_6.params[9])-1)*100,2)
print(f'Expected precentage increase in the house value when condition is increased by
```

```
Expected precentage increase in the house value when condition is increased by 1 unit is
17.58%
```

In [61]:
```python
# yr_built -  interpreted differenty since it was not log-transformed
percent_increase = round((np.exp(model_6.params[10])-1)*100,2)
print(f'Expected precentage increase in the house value when condition is increased by
```

```
Expected precentage increase in the house value when condition is increased by 1 unit is
-0.4%
```

In [62]:
```python
#sqft_living15 was log_transfomed along with price
percent_increase = round(((1.10**model_6.params[14])-1)*100,2)
print(f'Expected precentage increase in the house value when sqft_living15 is increased
```

```
Expected precentage increase in the house value when sqft_living15 is increased by 10% i
s 5.83%
```

In [63]:
```python
#sqft_lot15 was log_transfomed along with price
percent_increase = round(((1.10**model_6.params[15])-1)*100,2)
print(f'Expected precentage increase in the house value when sqft_lot15 is increased by
```

```
Expected precentage increase in the house value when sqft_lot15 is increased by 10% is
8.18%
```

The developed model will be off by an average of USD 184,335 when it comes to predicting the price of a house.

A unit increase in the `grade` i.e materials that go into the building of the house will yield an increase of `17.6%`

By adding an extra `bathroom`, the sale price goes up by `7.2%`

A unit increase in the `condition` of the house i.e maintenance will yield an increase of approx. `5.5%`

By increasing the `sqft_living` of the house by 10%, selling price goes by `3.4%`

Conclusions

1. The model is not very accurate since the predicted values are off by USD 184,335. Other modelling techniques may yield more

accurate predictions. More data might be help the current model as well

2. Build quality, number of bathrooms and overall condition of the house play the biggest factors when it comes to the resale value of a house