```
In [64]:
```

```
# Importing essential libraries
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
plt.style.use('ggplot')
import seaborn as sns
sns.set context(context='notebook',
                font scale=1,
                rc=None)
sns.set style('darkgrid')
from sklearn.model selection import train test split
from sklearn.linear_model import LinearRegression
from sklearn.metrics import mean squared error
from sklearn.model_selection import cross_val_score
from sklearn.metrics import r2 score
import warnings
warnings.filterwarnings('ignore')
```

In [6]:

```
path='/content/kc_house_data.csv'
df=pd.read_csv(path)
df.head(10)
```

Out[6]:

	id	date	price	bedrooms	bathrooms	sqft_living	sqft_lot	floors	waterfront	view	 grade	S
0	7129300520	20141013T000000	221900.0	3	1.00	1180	5650	1.0	0	0	 7	
1	6414100192	20141209T000000	538000.0	3	2.25	2570	7242	2.0	0	0	 7	
2	5631500400	20150225T000000	180000.0	2	1.00	770	10000	1.0	0	0	 6	
3	2487200875	20141209T000000	604000.0	4	3.00	1960	5000	1.0	0	0	 7	
4	1954400510	20150218T000000	510000.0	3	2.00	1680	8080	1.0	0	0	 8	
5	7237550310	20140512T000000	1225000.0	4	4.50	5420	101930	1.0	0	0	 11	
6	1321400060	20140627T000000	257500.0	3	2.25	1715	6819	2.0	0	0	 7	
7	2008000270	20150115T000000	291850.0	3	1.50	1060	9711	1.0	0	0	 7	
8	2414600126	20150415T000000	229500.0	3	1.00	1780	7470	1.0	0	0	 7	
9	3793500160	20150312T000000	323000.0	3	2.50	1890	6560	2.0	0	0	 7	

10 rows × 21 columns

In [22]:

```
print(f'Sum of duplicated values: {df.duplicated().sum()}')
print(f'No. of Rows: {df.shape[0]} and No. of Columns: {df.shape[1]}')
print('_'*70)
null_values=[]
null_percentage=[]
dtypes=[]
```

```
for i in df.columns:
   null_count=df[i].isna().sum()
   null_per=(null_count/len(df))*100
   null_values.append(null_count)
   null_percentage.append(null_per)
   dtypes.append(df[i].dtype)

missing_data={
        'Columns':df.columns,
        'missing_values':null_values,
        'missing_percentage':null_percentage,
        'data_type':dtypes
}

missing_df=pd.DataFrame(missing_data)
missing_df
```

Sum of duplicated values: 0 No. of Rows: 21613 and No. of Columns: 20 $\,$

Out[22]:

	Columns	missing_values	missing_percentage	data_type
0	date	0	0.0	object
1	price	0	0.0	float64
2	bedrooms	0	0.0	int64
3	bathrooms	0	0.0	float64
4	sqft_living	0	0.0	int64
5	sqft_lot	0	0.0	int64
6	floors	0	0.0	float64
7	waterfront	0	0.0	int64
8	view	0	0.0	int64
9	condition	0	0.0	int64
10	grade	0	0.0	int64
11	sqft_above	0	0.0	int64
12	sqft_basement	0	0.0	int64
13	yr_built	0	0.0	int64
14	yr_renovated	0	0.0	int64
15	zipcode	0	0.0	int64
16	lat	0	0.0	float64
17	long	0	0.0	float64
18	sqft_living15	0	0.0	int64
19	sqft_lot15	0	0.0	int64

In [25]:

```
from math import ceil
df[['bedrooms', 'bathrooms']] = df[['bedrooms', 'bathrooms']].applymap(ceil)
```

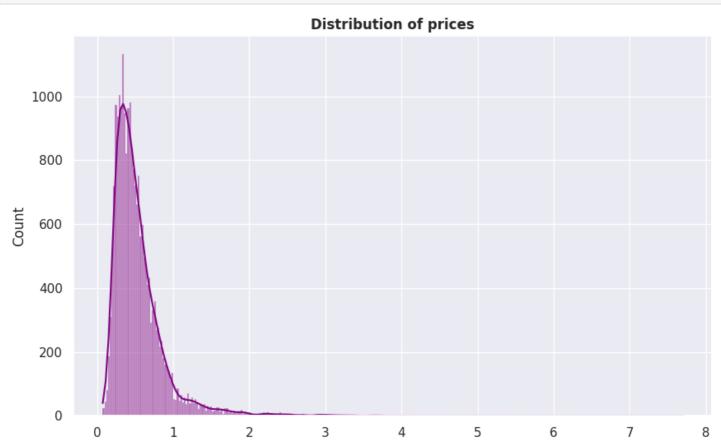
In [27]:

```
df.drop('date', axis=1).describe().T\
    .style.bar(subset=['mean'],color='orange')\
    .background_gradient(subset=['std'], cmap='Blues')\
    .background_gradient(subset=['50%'], cmap='BuGn')
```

Out[27]:

	count	mean	std	min	25%	50%	75%	
price	21613.000000	540088.141767	367127.196483	75000.000000	321950.000000	450000.000000	645000.000000	770
bedrooms	21613.000000	3.370842	0.930062	0.000000	3.000000	3.000000	4.000000	
bathrooms	21613.000000	2.439273	0.923593	0.000000	2.000000	3.000000	3.000000	
sqft_living	21613.000000	2079.899736	918.440897	290.000000	1427.000000	1910.000000	2550.000000	1;
sqft_lot	21613.000000	15106.967566	41420.511515	520.000000	5040.000000	7618.000000	10688.000000	165 ⁻
floors	21613.000000	1.494309	0.539989	1.000000	1.000000	1.500000	2.000000	
waterfront	21613.000000	0.007542	0.086517	0.000000	0.000000	0.000000	0.000000	
view	21613.000000	0.234303	0.766318	0.000000	0.000000	0.000000	0.000000	
condition	21613.000000	3.409430	0.650743	1.000000	3.000000	3.000000	4.000000	
grade	21613.000000	7.656873	1.175459	1.000000	7.000000	7.000000	8.000000	
sqft_above	21613.000000	1788.390691	828.090978	290.000000	1190.000000	1560.000000	2210.000000	9
sqft_basement	21613.000000	291.509045	442.575043	0.000000	0.000000	0.000000	560.000000	4
yr_built	21613.000000	1971.005136	29.373411	1900.000000	1951.000000	1975.000000	1997.000000	1
yr_renovated	21613.000000	84.402258	401.679240	0.000000	0.000000	0.000000	0.000000	1
zipcode	21613.000000	98077.939805	53.505026	98001.000000	98033.000000	98065.000000	98118.000000	98
lat	21613.000000	47.560053	0.138564	47.155900	47.471000	47.571800	47.678000	
long	21613.000000	-122.213896	0.140828	-122.519000	-122.328000	-122.230000	-122.125000	
sqft_living15	21613.000000	1986.552492	685.391304	399.000000	1490.000000	1840.000000	2360.000000	(
sqft_lot15	21613.000000	12768.455652	27304.179631	651.000000	5100.000000	7620.000000	10083.000000	87 ⁻

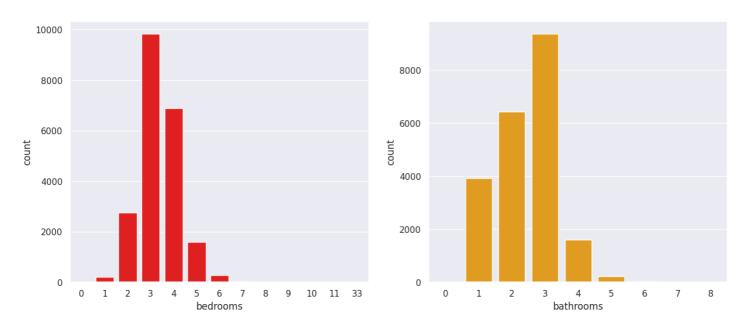
In [30]:



price 1e6

In [33]:

Distribution of Bedrooms and Bathrooms



In [36]:

```
correlation=df.drop('date',axis=1).corr()

plt.figure(figsize=(20, 6))
sns.heatmap(correlation,cmap='tab10',annot=True,fmt='.2f',cbar=True)

plt.title('Relation among different parameters',fontweight='bold')
plt.show()
```

```
Relation among different parameters
                                                                                                                                                                                                                   1.0
    bedrooms
                                                                                                                                                                -0.01
   bathrooms
                                                                                                                                                                                           0.08
                                                                                                                                                                                                                  - 0.8
    sqft_living
                                                                                                                                            0.06
                                                                                                                                                               0.05
                                                                                                                                                                        0.24
       sqft_lot
                                                                                                                                                                -0.09
                                                                                                                                                                                                                   0.6
         floors
    waterfront
                                                                                                                                                                                                                  0.4
                                     -0.14
0.66
     condition
                                                        0.11
                                                                                                                                                               0.11
                                                                                                                                                                                           0.12
        grade
                                                                                                                                                                                                                  - 0.2
   sqft_above
sqft_basement
                                                                                                                                                                                                                  - 0.0
       yr_built
 yr_renovated
       zipcode
                                                                                                                                                                                                                  - -0.2
                                                                           -0.04
          long
                                                                                                                                                                                                                    -0.4
                                                                                                                                   0.33
 sqft_living15
    sqft_lot15
                                                                                                                                     yr built
                                                                                                                                                                                             lot15
                                                                                                                  above
                                                                                                                           basement
                                                                                                                                                        zipcode
                                                                                                                                                                                             sdft
                                                                                                                           sqft
```

In [42]:

```
print(f'As \'sqft_living\' is highly coorelated with price, therefore:')
print('-'*70)
```

```
sns.scatterplot(data=df, x='price', y='sqft_living')
plt.title('Scatter plot for price and sqft')
plt.show()
```

As 'sqft_living' is highly coorelated with price, therefore:



In [43]:

```
print(f'As \'sqft_above\' is highly coorelated with price, therefore:')
print('-'*70)

sns.scatterplot(data=df,x='price',y='sqft_above')
plt.title('Scatter plot for price and sqft')

plt.show()
```

As 'sqft_above' is highly coorelated with price, therefore:



```
0 1 2 3 4 5 6 7 8 price le6
```

In [44]:

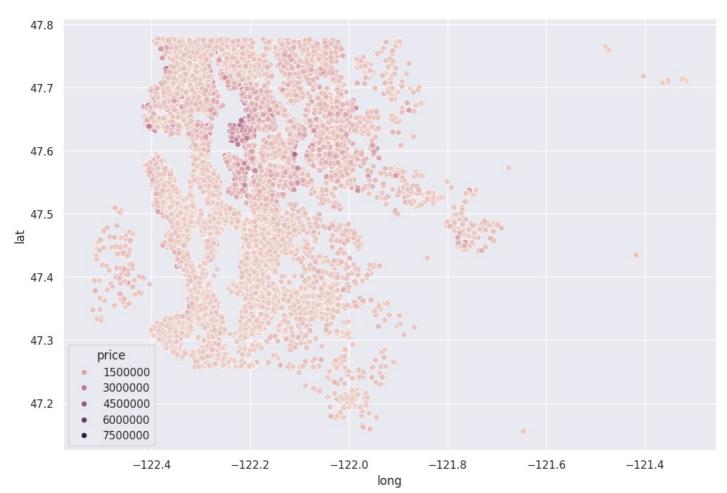
```
print('Location of houses according to prices and lattitude+longitude')
print('_'*80)

plt.figure(figsize=(12, 8))
sns.scatterplot(x='long', y='lat', data=df, hue='price')
```

Location of houses according to prices and lattitude+longitude

Out[44]:

```
<Axes: xlabel='long', ylabel='lat'>
```



In []:

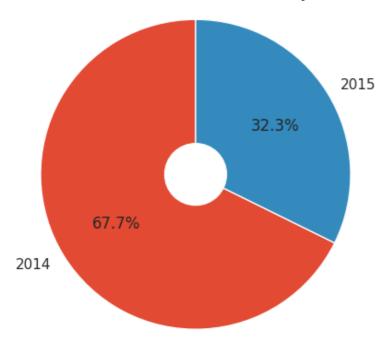
```
df['date'] = df['date'].apply(pd.to_datetime)
df['year'] = df['date'].apply(lambda x: x.year)
df['month'] = df['date'].apply(lambda x: x.month)
```

In [54]:

```
ax.axis('equal')
plt.title('Number of Houses sold over the years')
plt.show()
```

Total number of houses sold: 21613

Number of Houses sold over the years



In [56]:

```
X=df[['bedrooms','bathrooms','sqft_living','sqft_above']]
y=df['price']
```

In [59]:

```
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2)
print(f'X Shape: {X_train.shape} & X D\'type: {type(X_train)}')
print(f'y Shape: {y_train.shape} & y D\'type: {type(y_train)}')
```

X Shape: (17290, 4) & X D'type: <class 'pandas.core.frame.DataFrame'>
y Shape: (17290,) & X D'type: <class 'pandas.core.series.Series'>

In [62]:

```
model = LinearRegression()
model.fit(X_train, y_train)

y_pred = model.predict(X_test)

mse = mean_squared_error(y_test, y_pred)
print(f'Mean Squared Error: {mse}')
```

Mean Squared Error: 68742845084.2156

In [63]:

```
r2 = model.score(X_test, y_test)
print(f'R<sup>2</sup> Score: {r2}')
```

R² Score: 0.5072385997429594

In [65]:

```
scores = cross_val_score(model, X, y, cv=5, scoring='r2')
```

In [66]:

. . ,

print(scores)

[0.5093702 0.51151308 0.49026996 0.4999815 0.51130422]

'Score is being compromised because of outliers being present.