Final Project Submission

Please fill out:

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- Student pace: Part Time
- Scheduled project review date/time: Monday, February 25 (5:30PM)
- Instructor name: Eli Thomas
- Blog post URL:

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

Business Problem

Background

Machine learning is taking over the real estate sector, so this data analysis is quite common for commercial real estate firms. https://www.wsj.com/articles/how-to-buy-a-house-the-wall-street-way-1537102800 (https://www.wsj.com/articles/how-to-buy-a-house-the-wall-street-way-1537102800)

At the time the data was collected, the Seattle housing market was booming. Houses across the area jumped anywhere from 5.4% to 18.9% in value from the previous year. For King County as a whole, the median home price jumped 6.1%. https://www.seattletimes.com/business/real-estate/home-prices-in-seattle-pop-nearly-19-percent-for-the-year/ (https://www.seattletimes.com/business/real-estate/home-prices-in-seattle-pop-nearly-19-percent-for-the-year/)

King County is the most populous county in Washington. The 2010 April Census recorded that the population of King County was 1,931,249. In 2000, the median home value stood at $235,000.

By 2016, the median home value was $407,400.

https://www.kingcounty.gov/~/media/depts/executive/performance-strategy-budget/regional-planning/Demographics/Dec-2018-Update/KC-Profile2018.ashx?la=en (https://www.kingcounty.gov/~/media/depts/executive/performance-strategy-budget/regional-planning/Demographics/Dec-2018-Update/KC-Profile2018.ashx?la=en)

Objective: The goal is to find what features (or variables) are the best predictors of housing value and which ones are irrelvant. Our findings will inform recommendations to a business in terms of what features they should focus on before purchasing a house.

Understanding the Data

Let's take a look at our data and get a taste for the provided variables.

In [2]:
```
df = pd.read_csv("kc_house_data.csv")
df.head(30)
```

Out[2]:

	id	date	price	bedrooms	bathrooms	sqft_living	sqft_lot	floors	waterfront
0	7129300520	10/13/2014	221900.0	3	1.00	1180	5650	1.0	NaN
1	6414100192	12/9/2014	538000.0	3	2.25	2570	7242	2.0	0.0
2	5631500400	2/25/2015	180000.0	2	1.00	770	10000	1.0	0.0
3	2487200875	12/9/2014	604000.0	4	3.00	1960	5000	1.0	0.0
4	1954400510	2/18/2015	510000.0	3	2.00	1680	8080	1.0	0.0
5	7237550310	5/12/2014	1230000.0	4	4.50	5420	101930	1.0	0.0
6	1321400060	6/27/2014	257500.0	3	2.25	1715	6819	2.0	0.0
7	2008000270	1/15/2015	291850.0	3	1.50	1060	9711	1.0	0.0
8	2414600126	4/15/2015	229500.0	3	1.00	1780	7470	1.0	0.0
9	3793500160	3/12/2015	323000.0	3	2.50	1890	6560	2.0	0.0
10	1736800520	4/3/2015	662500.0	3	2.50	3560	9796	1.0	NaN

In [3]:
```
df.columns
```

Out[3]:
```
Index(['id', 'date', 'price', 'bedrooms', 'bathrooms', 'sqft_living',
       'sqft_lot', 'floors', 'waterfront', 'view', 'condition', 'grade',
       'sqft_above', 'sqft_basement', 'yr_built', 'yr_renovated', 'zipcod
e',
       'lat', 'long', 'sqft_living15', 'sqft_lot15'],
      dtype='object')
```

In [4]:
```
df.describe()
```

Out[4]:

	id	price	bedrooms	bathrooms	sqft_living	sqft_lot	
count	2.159700e+04	2.159700e+04	21597.000000	21597.000000	21597.000000	2.159700e+04	21597.
mean	4.580474e+09	5.402966e+05	3.373200	2.115826	2080.321850	1.509941e+04	1.
std	2.876736e+09	3.673681e+05	0.926299	0.768984	918.106125	4.141264e+04	0.
min	1.000102e+06	7.800000e+04	1.000000	0.500000	370.000000	5.200000e+02	1.
25%	2.123049e+09	3.220000e+05	3.000000	1.750000	1430.000000	5.040000e+03	1.
50%	3.904930e+09	4.500000e+05	3.000000	2.250000	1910.000000	7.618000e+03	1.
75%	7.308900e+09	6.450000e+05	4.000000	2.500000	2550.000000	1.068500e+04	2.
max	9.900000e+09	7.700000e+06	33.000000	8.000000	13540.000000	1.651359e+06	3.

What's the problem?

We have a lot of interesting features in the dataset. Before going into data cleaning, let's examine each variable one-by-one to fully understand what it is and how it might affect housing prices. Throughout the examination, I will classify variables as location (where the house located), property (space properties of the house), and house (specific characteristics of the house).

ID: the index of our dataframe

Price: Our dependent variable that we're framing our analysis around.

Bedrooms: *House* - the number of bedrooms in the house. I fully expect this to play a role in a house's price as it's one of the first features a potential buyer looks at.

Bathrooms: *House* - the number of bathrooms in the house. Again, I expect the number of bathrooms to postively correlate with a house's price.

SqFt Living: *House* - this indicates the square footage of the actual house. This will probably play a significant role in a house's price.

SqFt Lot: *Property* - this indicates the square footage of the house's lot. While I expect this to postively correlate with a house's value, I think it will less so than the house's square footage.

Floors: *House* - the number of levels in a house. It seems most houses simply fall between 1-3 floors, so I don't think this will be an important feature.

Waterfront: *Property* - waterfront tells us if a property sits on a waterfront. While the general thinking is waterfront properties cost more than non-waterfront properties, I'm unsure if it will play a significant influence on sales price compared to other variables in our dataset.

View: *Miscellaneous* - this indicates the number of times a house was viewed. I don't think this plays a role in sale price.

Condition: *House* - condition is a grade for what kind of shape a house is in. It seems that this is on a particular scale. If so, we'll need to ensure it's a categorical variable.

Grade: *House* - the overall grade given to a house in accordance with the King County grading system. When researching the grading system [https://info.kingcounty.gov/assessor/esales/Glossary.aspx?type=r](https://info.kingcounty.gov/assessor/esales/Glossary.aspx?type=r%5D), the term "grade" is said to be, "Classification by construction quality which refers to the types of materials used and the quality of workmanship. Buildings of better quality (higher grade) cost more to build per unit of measure and command higher value." From this, I expect grade to be a significant factor for sales prices in King County.

SqFt Above: *House* - square footage of the house apart from the basement. I expect this relationship is captured in other variables.

SqFt Basement: *House* - square footage of the house's basement. Again, there are a lot of square footage variables so we can likely delete some since their relationships probably overlap.

Yr Built: *House* - this tells us what year the house was built. I'm unsure if this will play any role in a house's sale price.

Yr Renovated: *House* - this tells us IF and WHEN a house was renovated. I don't expect this to play much significance compared to other features.

Zip Code: *Location* - zip code tells us what neighborhood a house is located. This could potentially have some significance. Housing values could rise or fall depending on the local school's quality, crime rates, proximity to Seattle (nearest city), etc.

Latitude: *Location* - the latitude coordinate of the house.

Longitude *Location* - the longitude coordinate of the house.

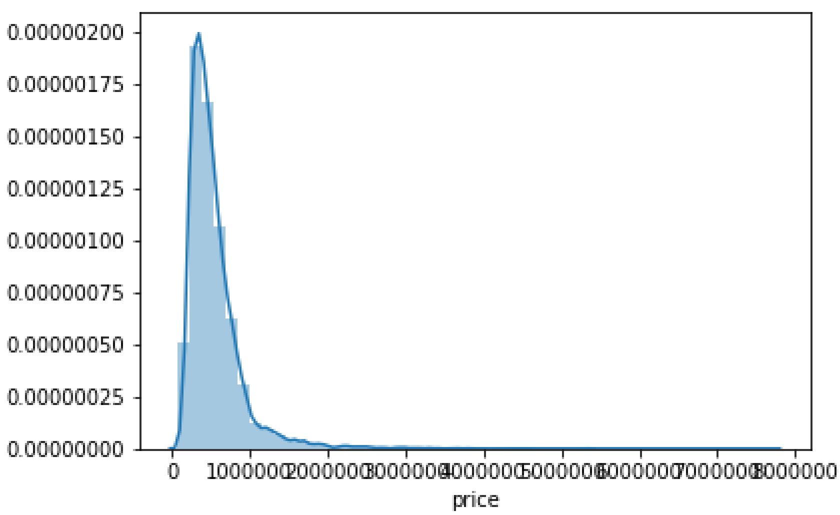
SqFt Living15: *House* - the square footage of the house in 2015. If it's different from the original square footage variable, it implies renovations were made.

SqFt Lot15: *Property* - the square footage of the lot size in 2015. Again, it implies renovations were made.

Before we begin data cleaning, let's explore the major part of our analysis - Sales Price

In [5]:
```
sns.distplot(df['price']);
```

```
/Users/Derek/anaconda3/lib/python3.7/site-packages/scipy/stats/stats.py:1
713: FutureWarning: Using a non-tuple sequence for multidimensional index
ing is deprecated; use `arr[tuple(seq)]` instead of `arr[seq]`. In the fu
ture this will be interpreted as an array index, `arr[np.array(seq)]`, wh
ich will result either in an error or a different result.
  return np.add.reduce(sorted[indexer] * weights, axis=axis) / sumval
```



Housing prices are positively skewed (aka it deviates from a normal distribution -- something that needs fixing later). Let's check out some more specific attributes.

In [6]:
```
print("Skewness: %f" % df['price'].skew())
print("Kurtosis: %f" % df['price'].kurt())
```

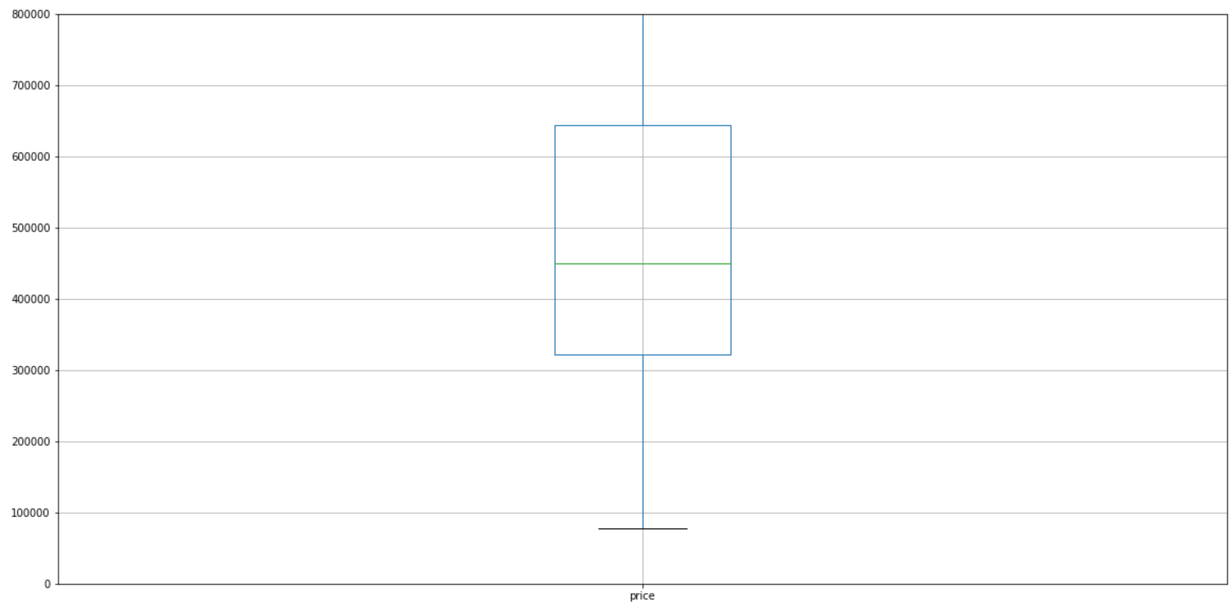
```
Skewness: 4.023365
Kurtosis: 34.541359
```

A skewness value of 4.02 confirms that the sales price is highly skewed.

The kurtosis is extremely high, indicating that it is leptokurtic. This confirms our plot above -- the distribution is long and the tails are flat. We have some outliers that need dealing with.

In [7]:
```
fig = df.boxplot('price', figsize=(20,10))
fig.axis(ymin=0, ymax=800000);

print("Average: %f" % df['price'].mean())
print("Median: %f" % df['price'].median())
```

```
Average: 540296.573506
Median: 450000.000000
```



The average sales price is $540,296.

The median sales price is $450,000.

These findings fall in line with our plot showing how the distribution is postively skewed.

Scrubbing

One of the first things we'll aim to clean is any missing data from the dataset.

In [8]:
```
print(df.info())
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 21597 entries, 0 to 21596
Data columns (total 21 columns):
id               21597 non-null int64
date             21597 non-null object
price            21597 non-null float64
bedrooms         21597 non-null int64
bathrooms        21597 non-null float64
sqft_living      21597 non-null int64
sqft_lot         21597 non-null int64
floors           21597 non-null float64
waterfront       19221 non-null float64
view             21534 non-null float64
condition        21597 non-null int64
grade            21597 non-null int64
sqft_above       21597 non-null int64
sqft_basement    21597 non-null object
yr_built         21597 non-null int64
yr_renovated     17755 non-null float64
zipcode          21597 non-null int64
lat              21597 non-null float64
long             21597 non-null float64
sqft_living15    21597 non-null int64
sqft_lot15       21597 non-null int64
dtypes: float64(8), int64(11), object(2)
memory usage: 3.5+ MB
None
```

Immediate Observations

We have null values in 3 features: waterfront, view, and yr_renovated.

We'll need to treated the following variables as categorical:
- Waterfront (0 or 1 indicating whether or not the house is on the waterfront)
- View (scale of 0-4 (how many times a house was viewed)
- Condition (another scale rating what condition the house is in)
- Grade (another scale quantifying the quality of the house)
- Zip Code (this can be a variable that is one-hot encoded later on)

We'll likely treat the following as numerical (and be sure to check for any outliers later on):
- Bedrooms
- Bathrooms
- SqFt in the living space
- SqFt of the lot
- Floors
- SqFt outside of the basement
- SqFt of the basement
- Year built

- Year renovated (if applicable)
- Latitude
- Longitude

In [9]:
```
1 df.isnull().sum()
```

Out[9]:
```
id                  0
date                0
price               0
bedrooms            0
bathrooms           0
sqft_living         0
sqft_lot            0
floors              0
waterfront       2376
view               63
condition           0
grade               0
sqft_above          0
sqft_basement       0
yr_built            0
yr_renovated     3842
zipcode             0
lat                 0
long                0
sqft_living15       0
sqft_lot15          0
dtype: int64
```

So we see we have missing data from the following variables:

- Waterfront
- View
- Year Renovated

Let's check out some more specifics to determine what corrective actions need to be taken.

In [10]:

```
cols = ['waterfront', 'view', 'yr_renovated']
for col in cols:
    print("Value Counts for " + col + ':\n')
    print(df[col].value_counts(dropna=False).head(5), '\n')
    print("Unique values for " + col + ':\n')
    print(df[col].unique(), '\n')
    print("% of null values: ", round(((df[col].isnull().sum()/df.shape
    print('------------------------------\n')
```

```
Value Counts for waterfront:

 0.0    19075
NaN      2376
 1.0      146
Name: waterfront, dtype: int64

Unique values for waterfront:

[nan  0.  1.]

% of null values:  11.0
-------------------------------

Value Counts for view:

0.0    19422
2.0      957
3.0      508
1.0      330
4.0      317
Name: view, dtype: int64

Unique values for view:

[ 0. nan  3.  4.  2.  1.]

% of null values:  0.29
-------------------------------

Value Counts for yr_renovated:

 0.0       17011
NaN         3842
 2014.0       73
 2003.0       31
 2013.0       31
Name: yr_renovated, dtype: int64

Unique values for yr_renovated:

[   0. 1991.   nan 2002. 2010. 1992. 2013. 1994. 1978. 2005. 2003. 1984.
 1954. 2014. 2011. 1983. 1945. 1990. 1988. 1977. 1981. 1995. 2000. 1999.
 1998. 1970. 1989. 2004. 1986. 2007. 1987. 2006. 1985. 2001. 1980. 1971.
 1979. 1997. 1950. 1969. 1948. 2009. 2015. 1974. 2008. 1968. 2012. 1963.
 1951. 1962. 1953. 1993. 1996. 1955. 1982. 1956. 1940. 1976. 1946. 1975.
 1964. 1973. 1957. 1959. 1960. 1967. 1965. 1934. 1972. 1944. 1958.]
```

```
% of null values:  17.79
-------------------------------
```

The percentages above show that deleting waterfront/yr_renovated will cost us significant data points. However, deleting null values from view will only delete .2%. It's probably best to just delete the null values from the view category.

In [11]:
```
print(df['waterfront'].unique())
19221/21597 #entries under Waterfront divided by total entries
```

```
[nan  0.  1.]
```

Out[11]:
```
0.8899847201000138
```

We see from the percentage above that approximately 89% of the waterfront column isn't null.

Therefore, we'd be deleting a lot of good data if we simply delete the column.

In addition, it's difficult to just assume what these values should be. By replacing them with 0s or 1s, we could significantly alter the effect waterfront has on price. Therefore, our best bet is probably just deleting all the rows with null values. While we are deleting a lot of data, it still leaves us with 19,000+ data points and keeps the integrity of the waterfront column intact.

In [12]:
```
df = df[df.waterfront == df.waterfront]
df.shape
```

Out[12]:
```
(19221, 21)
```

The cell above removed all rows that contained null values in the waterfront column. We decreased our dataset from 21,597 houses to 19,221 houses.

In [13]:
```
df.head()
```

Out[13]:

	id	date	price	bedrooms	bathrooms	sqft_living	sqft_lot	floors	waterfront
1	6414100192	12/9/2014	538000.0	3	2.25	2570	7242	2.0	0.0
2	5631500400	2/25/2015	180000.0	2	1.00	770	10000	1.0	0.0
3	2487200875	12/9/2014	604000.0	4	3.00	1960	5000	1.0	0.0
4	1954400510	2/18/2015	510000.0	3	2.00	1680	8080	1.0	0.0
5	7237550310	5/12/2014	1230000.0	4	4.50	5420	101930	1.0	0.0

5 rows × 21 columns

In [14]:
```
df.isnull().sum()
```

Out[14]:
```
id                  0
date                0
price               0
bedrooms            0
bathrooms           0
sqft_living         0
sqft_lot            0
floors              0
waterfront          0
view               57
condition           0
grade               0
sqft_above          0
sqft_basement       0
yr_built            0
yr_renovated     3412
zipcode             0
lat                 0
long                0
sqft_living15       0
sqft_lot15          0
dtype: int64
```

Awesome! We successfully deleted the nulls from the waterfront column. Let's continue on to the view column.

In [15]:
```
df['view'].unique()
```

Out[15]:
```
array([ 0., nan,  3.,  4.,  2.,  1.])
```

We see from our unique values that view ranges from 0-4.

In [16]:
```
df['view'].isnull().sum()/df.shape[0]
```

Out[16]:
```
0.0029655064772904634
```

If we delete the null values from the view column, we'll only be deleting .2% of our total data points. In this case, it's probably just easiest to do that!

In [17]:
```
df = df[df.view == df.view]
df['view'].value_counts()
```

Out[17]:
```
0.0    17312
2.0      836
3.0      435
1.0      291
4.0      290
Name: view, dtype: int64
```

The null values from the view column are gone! Now to check out the pesky nulls in the year renovated column.

In [18]:
```
df['yr_renovated'].unique()
```

Out[18]:
```
array([1991.,    nan,    0., 2002., 2010., 1992., 2013., 1994., 1978.,
       2005., 2003., 1984., 1954., 2014., 2011., 1983., 1990., 1988.,
       1977., 1981., 1995., 2000., 1999., 1998., 1970., 1989., 2004.,
       1986., 2007., 1987., 2006., 1985., 2001., 1980., 1971., 1945.,
       1979., 1997., 1950., 1969., 1948., 2009., 2015., 2008., 2012.,
       1968., 1963., 1951., 1962., 1953., 1993., 1955., 1996., 1982.,
       1956., 1940., 1976., 1946., 1975., 1964., 1973., 1957., 1959.,
       1960., 1965., 1967., 1934., 1972., 1944., 1958., 1974.])
```

In [19]:
```
print(df['yr_renovated'].isnull().sum()/df['yr_renovated'].notnull().su
```

```
0.21583555386372288
```

We see that over 20% of our data will be deleted if we're to delete the year renovated column.

To start, let's change 'yr_renovated" to a categorical variable -- indicating whether or not a house was renovated at all. We'll also make the assumption that a null value indicates a house was never renovated. If a house was renovated, it was likely recorded. So we will replace null values with 0s, which indicates a house was not renovated.

In [20]:
```
df['yr_renovated'] = df['yr_renovated'].mask(df['yr_renovated'] > .5, 1
df['yr_renovated'].fillna(0, inplace=True)
```

We changed the yr_renovated column to a categorical variable. We'll also change all null values to 0, indicated those houses were not renovated. We're now able to keep the column and keep that additional 20% of our data.

In [21]:
```
df.isnull().sum()
```

Out[21]:
```
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
dtype: int64
```

Now that we deleted all the null values, let's fix some columns' data types.

In [22]:
```
df.drop(df[df['sqft_basement'] == '?'].index, inplace=True)
df['sqft_basement'] = df['sqft_basement'].astype(float).astype(int)
```

In [23]:
```
#df['zipcode'] = df['zipcode'].astype('category')
#df['view'] = df['view'].astype('category')
#df['waterfront'] = df['waterfront'].astype('category')
#df['condition'] = df['condition'].astype('category')
#df['grade'] = df['grade'].astype('category')
#df['zipcode'] = df['zipcode'].astype('category')
#df['yr_renovated'] = df['yr_renovated'].astype('category')
```

In [24]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 18749 entries, 1 to 21596
Data columns (total 21 columns):
id               18749 non-null int64
date             18749 non-null object
price            18749 non-null float64
bedrooms         18749 non-null int64
bathrooms        18749 non-null float64
sqft_living      18749 non-null int64
sqft_lot         18749 non-null int64
floors           18749 non-null float64
waterfront       18749 non-null float64
view             18749 non-null float64
condition        18749 non-null int64
grade            18749 non-null int64
sqft_above       18749 non-null int64
sqft_basement    18749 non-null int64
yr_built         18749 non-null int64
yr_renovated     18749 non-null float64
zipcode          18749 non-null int64
lat              18749 non-null float64
long             18749 non-null float64
sqft_living15    18749 non-null int64
sqft_lot15       18749 non-null int64
dtypes: float64(8), int64(12), object(1)
memory usage: 3.1+ MB
```

Looking back, we actually don't seem to need date or the ID column, so let's delete those as well to minimize the data we're looking at.

In [25]:
```
df.drop(columns=['date', 'id'], axis=1, inplace=True)
df.head(4)
```

Out[25]:

	price	bedrooms	bathrooms	sqft_living	sqft_lot	floors	waterfront	view	condition	grade
1	538000.0	3	2.25	2570	7242	2.0	0.0	0.0	3	7
2	180000.0	2	1.00	770	10000	1.0	0.0	0.0	3	6
3	604000.0	4	3.00	1960	5000	1.0	0.0	0.0	5	7
4	510000.0	3	2.00	1680	8080	1.0	0.0	0.0	3	8

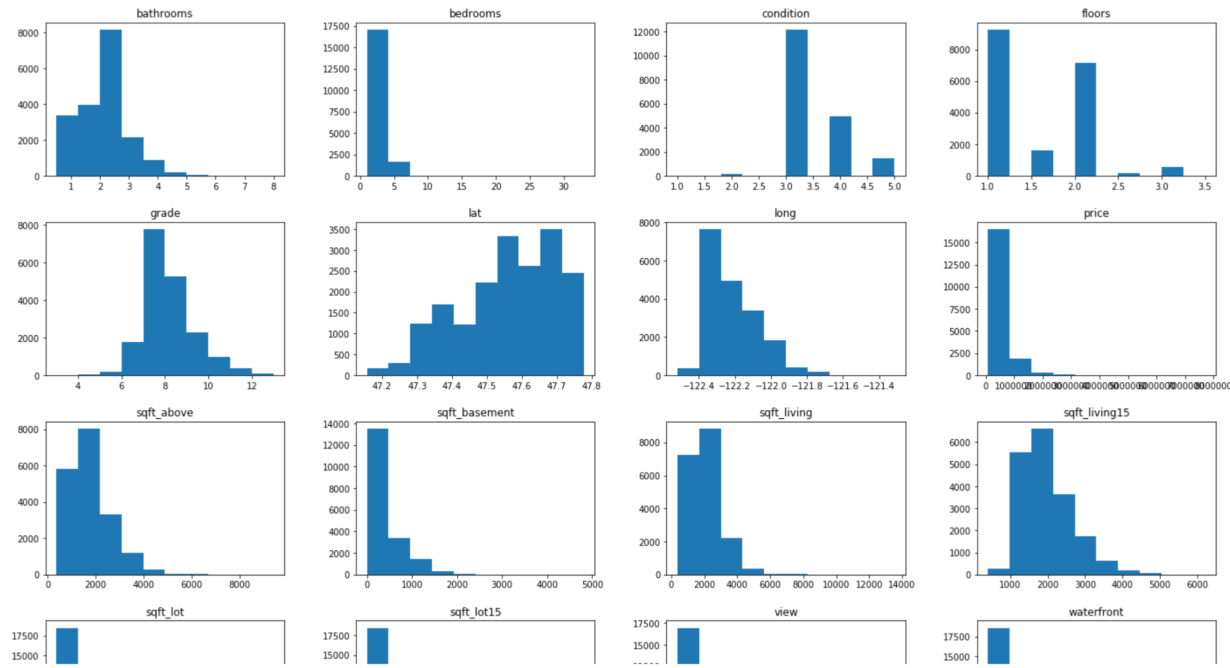
While there are some categorical variables we can one-hot encode, it's easier to create some visuals in the exploratory data analysis phase so let's skip that for now. Although there's certainly going to be some more data cleaning as we explore the data, we've done enough to get started.

Exploratory Data Analysis

First things first, let's create some histograms to check out the initial pattern of our data and see how skewed each feature is.

In [26]:
```
import warnings
warnings.filterwarnings('ignore')
```

In [27]:
```
df.hist(figsize=(24,20), grid=False);
```



Initial Observations

Bathrooms, bedrooms, floors are both ositively skewed. However, our bathroom data points look much more like a normal distribution than our bedroom data points do.
Price is VERY positively skewed and seems to have a long tail (aka a number of outliers (expensive houses) that are affecting our average sales price). This will require some further exploring if we want to modify the data and set our model up for success.
Unsurprisingly, most of the square footage features have the same distribution. Each is positively skewed with a long tail (indicating a larger number of outliers). We should expect that some of the features will be deleted, as there will definitely be some multicollinearity between them.
Latitude is negatively skewed while longitude is positively skewed. Both need to be normalized.
There isn't much to say about the floor data. Most houses have 1-2 floors. However, since the distribution of floors is so small for our specific dataset, we may want to consider changing this to a categorical variable.
The year built feature is negatively skewed, indicating that an influx of houses were built over the past few years.

Rather than rely on our own eye, let's get some more specific measurements on the skewness and kurtosis.

Examining the Continuous Variables

In [28]:
```
cols = ['bedrooms', 'bathrooms', 'floors', 'price', 'sqft_above', 'sqft
        , 'sqft_living', 'sqft_living15', 'sqft_lot', 'sqft_lot15', 'yr_
for col in cols:
    print("Skewness values for " + col + ':\n')
    print(df[col].skew(), '\n')
    print("Kurtosis values for " + col + ':\n')
    print(df[col].kurt(), '\n')
    print('------------------------------\n')
```

```
Skewness values for bedrooms:

2.244187624571679

Kurtosis values for bedrooms:

56.96344219888979

-------------------------------

Skewness values for bathrooms:

0.5285021675760262

Kurtosis values for bathrooms:

1.3372747987449616

-------------------------------

Skewness values for floors:

0.6106137903831421

Kurtosis values for floors:

-0.49968790646923145

-------------------------------

Skewness values for price:

4.0930927997007664

Kurtosis values for price:

35.514598884546466

-------------------------------

Skewness values for sqft_above:

1.4636764653166006

Kurtosis values for sqft_above:

3.5469204452825815
```

```
-------------------------------
Skewness values for sqft_basement:
1.603162039835526
Kurtosis values for sqft_basement:
2.925470002468078
-------------------------------
Skewness values for sqft_living:
1.5089498418666263
Kurtosis values for sqft_living:
5.602403712148688
-------------------------------
Skewness values for sqft_living15:
1.1212030427771582
Kurtosis values for sqft_living15:
1.6842055451626354
-------------------------------
Skewness values for sqft_lot:
13.305032366570126
Kurtosis values for sqft_lot:
301.8849642592416
-------------------------------
Skewness values for sqft_lot15:
9.81978555221999
Kurtosis values for sqft_lot15:
162.07704626803485
-------------------------------
Skewness values for yr_built:
-0.4745350985519742
Kurtosis values for yr_built:
```

```
-0.6477567061564709

------------------------------
```

Immediate Observations

Bedrooms: The kurtosis value for bedrooms is HUGE! It must have some serious outliers. It's also postively skewed, so we'll need to fix this before we perform any modeling.

Bathrooms: A slight, positive skew. Nothing major, but it's high enough that we'll need to normalize it. Kurtosis value is low enough that we can ignore it.

Price: As we saw earlier, price needs to be normalized and some outliers need to be taken care of.

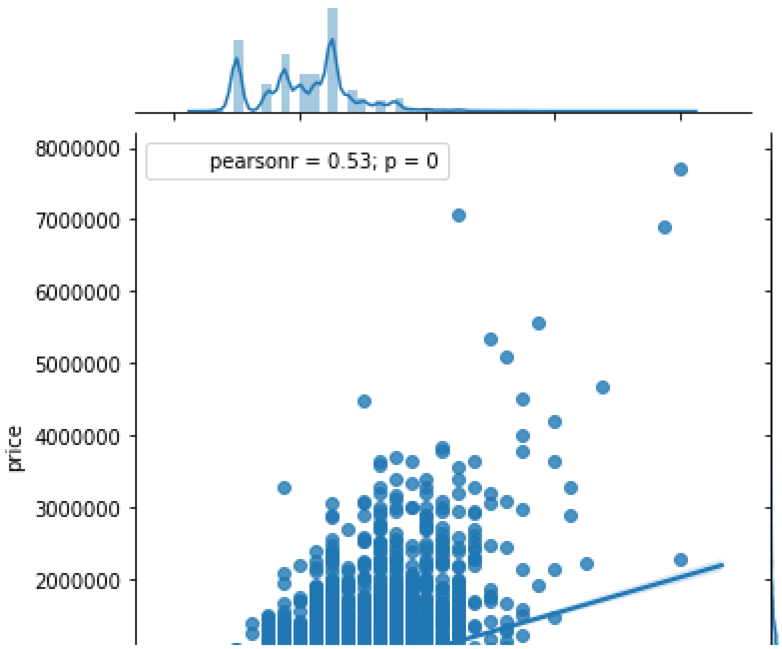
As noted above (and confirmed by the skewness and kurtosis), all square footage features are positively skewed and have a leptokurtic distribution (especially the square footage of property lots).

The year built feature is negatively skewed (as more houses were built in the past two decades) and has a platykurtic distribution (lack of outliers).

Visualizing Linear Relationships with Price using Seaborn Joint Plots

To get a better idea of each feature's relationship with price, let's use Seaborn joint plots. To help get a visual depiction of how linear each relationship is (as well as quantify their correlations and significance), we'll added fitted regression lines and pearson correlation coefficients.

In [29]:
```
cont_vars = df[['bathrooms', 'bedrooms', 'floors', 'price', 'sqft_above
                'sqft_living', 'sqft_living15', 'sqft_lot','sqft_lot15'
                'yr_built', 'lat','long']]

from scipy.stats import pearsonr
for col in cont_vars:
    sns.jointplot(x=col, y='price', data=cont_vars, kind='reg', stat_fu
```



Immediate Observations

Price: It's even clearer that some house prices are significant outliers as it is a long tailed distribution. It's also evident because our median house value is 450,000 and the average value is 541,622.

Bathrooms: Postive correlation with price. We also see the data is bimodal.

Bedrooms: Weak correlation with price. However, we still have that stubborn 33-bedroom home, so let's delete that and see if our Pearson coefficient improves.

Floors: An ordinal value. Weak correlation. Another bimodal feature as most of the values are 1 or 2 floors. As we see in our fitted linear regression line, the number of floors generates little impact on a home's value.

Square Footage (Above): Now we're getting somewhere! With a strong, positive correlation, we see the square footage of a home (aside from the basement) has a linear relationship with a home's value. Bigger home means pricier home is a common intuition, however, so this isn't too surprising.

Square Footage (Basement): An interesting insight here. The size of a home's basement doesn't have a positive correlation or linear relationship with the home's price. Even homes with no basement rise quite high in price.

Square Footage (Living): No surprise. A very strong, positive correlation and an obvious linear relationship price. We'll need to investigate to see how much multicollinearity there is between this square footage variable and the others, as it's unlikely we can do modeling with all of them.

Square Footage (Lot): Interesting note that the lot size generates no linear relationship with price. A lot of values here equal zero. We can interpret these values as apartments or townhomes, considering this means they have no yard. In addition, there are some large lots with much smaller pricetags. For all we know, these could be big, empty lots!

Year Built: Another interesting insight. Year built demonstrates no linear relationship with price.

Latitude & Longitude: A weak correlation, but the jointplot does provide some good intel. It seems as the latitude increase, so does housing price. When we look at the map of King County, Seattle is at its northern boundary. One can make a guess that being closer to a major city increases a home's value. However, there are other factors at play here, which damper its impact. An example might be longitude, in which this could be capturing how close a house is to the water.

Dealing with the Outliers

To deal with the outliers are in our data, we'll need to define what an outlier is and how we translate that across all features. The easiest way to do this is to find z-scores for all data points and create a cut-off, or threshold, for where we want to delete data that deviates far from the average.

Z-scores will help us recenter the data and look for data points that stray too far from the average (in the case of z-scores -- 0). We'll start by setting a threshold of 3 and see how many outliers that eliminates.

In [30]:

```
from scipy import stats

z = np.abs(stats.zscore(cont_vars))
print(z)
```

```
[[0.17231267 0.40351205 0.9359521  ... 0.68427968 1.15928992 0.74751969]
 [1.45261955 1.48182552 0.91619481 ... 1.298113   1.28110828 0.13568783]
 [1.147272   0.67480143 0.91619481 ... 0.20685376 0.28378921 1.27397966]
 ...
 [0.49729911 0.67480143 0.9359521  ... 1.46413694 0.3565919  1.05343562]
 [1.777606   1.48182552 0.9359521  ... 1.29362769 0.24673338 0.60523321]
 [1.777606   1.48182552 0.9359521  ... 1.25952583 0.24457093 0.60523321]]
```

Above, we converted all continuous/ordinal variables into z-scores. Now, we'll place a threshold on the z-scores to see how many outliers we identify across the data.

If we're to use the threshold of three standard deviations to detect outliers, we'll be deleting 1,300 data points. Rather, let's increase the threshold to 4 standard deviations and see what we get.

In this case, we'll be deleting approximately 650 data points across the 13 continuous/ordinal features.

In [31]:
```
650/18749
```

Out[31]:
```
0.034668515654168224
```

This amounts to 3.5% of the data points. Since this is a minor percentange of our data, let's go ahead and delete the outliers and check whether or not it affected features' correlations to price.

In [32]:
```
cont_vars = cont_vars[(np.abs(stats.zscore(cont_vars)) < 4).all(axis=1)
print(cont_vars.shape)
```

```
(18101, 13)
```

Now that we deleted all outliers that had z-scores 4 standard deviations above the mean, we'll need to add these newly scrubbed columns back to our original dataframe and drop the old columns.

In [33]:
```
df.drop(['bedrooms', 'bathrooms', 'floors', 'price', 'sqft_above', 'sqf
        , 'sqft_living', 'sqft_living15', 'sqft_lot', 'sqft_lot15',
          'yr_built', 'lat', 'long'], axis=1, inplace=True)
```

Boom! All former columns were dropped from the dataframe!

In [34]:
```
print(df.head())
print(cont_vars.head())
```

```
   waterfront  view  condition  grade  yr_renovated  zipcode
1         0.0   0.0          3      7           1.0    98125
2         0.0   0.0          3      6           0.0    98028
3         0.0   0.0          5      7           0.0    98136
4         0.0   0.0          3      8           0.0    98074
5         0.0   0.0          3     11           0.0    98053
   bathrooms  bedrooms  floors     price  sqft_above  sqft_basement  \
1       2.25         3     2.0  538000.0        2170            400
2       1.00         2     1.0  180000.0         770              0
3       3.00         4     1.0  604000.0        1050            910
4       2.00         3     1.0  510000.0        1680              0
8       1.00         3     1.0  229500.0        1050            730

   sqft_living  sqft_living15  sqft_lot  sqft_lot15  yr_built      lat  \
1         2570           1690      7242        7639      1951  47.7210
2          770           2720     10000        8062      1933  47.7379
3         1960           1360      5000        5000      1965  47.5208
4         1680           1800      8080        7503      1987  47.6168
8         1780           1780      7470        8113      1960  47.5123

      long
1 -122.319
2 -122.233
3 -122.393
4 -122.045
8 -122.337
```

Everything looks good. Let's go ahead and combine these dataframes so we begin to normalize the data and check for multicollinearity.

In [35]:
```python
df2 = cont_vars.join(df, how='left')
df2.head()
```

Out[35]:

	bathrooms	bedrooms	floors	price	sqft_above	sqft_basement	sqft_living	sqft_living15	sqf
1	2.25	3	2.0	538000.0	2170	400	2570	1690	7
2	1.00	2	1.0	180000.0	770	0	770	2720	1(
3	3.00	4	1.0	604000.0	1050	910	1960	1360	5
4	2.00	3	1.0	510000.0	1680	0	1680	1800	8
8	1.00	3	1.0	229500.0	1050	730	1780	1780	7

All looks good! Now that outliers are deleted and we've got the remaining data all pieced back together, let's analyze if there is any multicollinearity between features.

Checking Multicollinearity

As we perform a regression analysis, the goal is to evaluate the impact that an independent variable has on the dependent variable of interest. However, a regression analysis assumes that the average change in the dependent variable for each 1 unit change in a predictor holds all other variables constant. If predictors strongly correlate with one another, we cannot assume other variables stay constant. Therefore, it's important to check for and eliminate multicollinearity before modeling, as it can influence our coefficients.

To understand the correlation between features, let's create a dataset that removes our dependent variable of interest (price).

In [36]:
```python
predictors = df2.drop(['price'], axis=1)
```

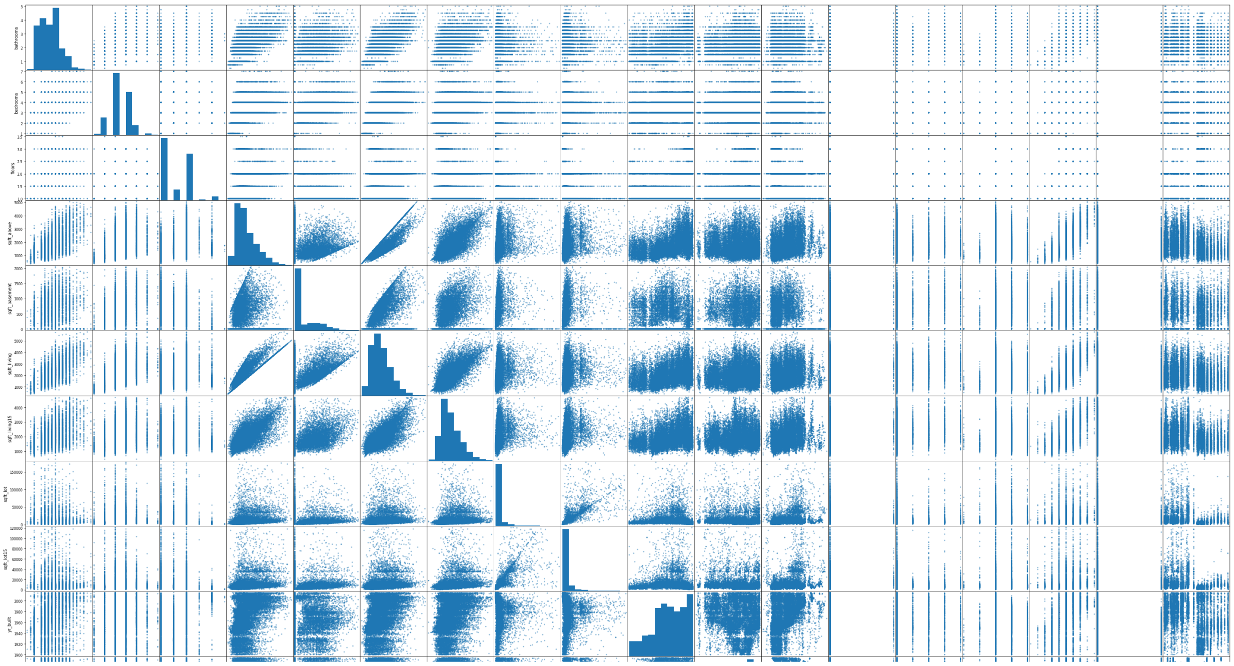
In [37]:
```python
predictors.head()
```

Out[37]:

	bathrooms	bedrooms	floors	sqft_above	sqft_basement	sqft_living	sqft_living15	sqft_lot	sqft_
1	2.25	3	2.0	2170	400	2570	1690	7242	
2	1.00	2	1.0	770	0	770	2720	10000	
3	3.00	4	1.0	1050	910	1960	1360	5000	
4	2.00	3	1.0	1680	0	1680	1800	8080	
8	1.00	3	1.0	1050	730	1780	1780	7470	

Great. Now it's identify how correlated the predictors are with one another and get an idea of which features we need to eliminate.

In [38]:
```
pd.plotting.scatter_matrix(predictors,figsize = [50,50]);
```

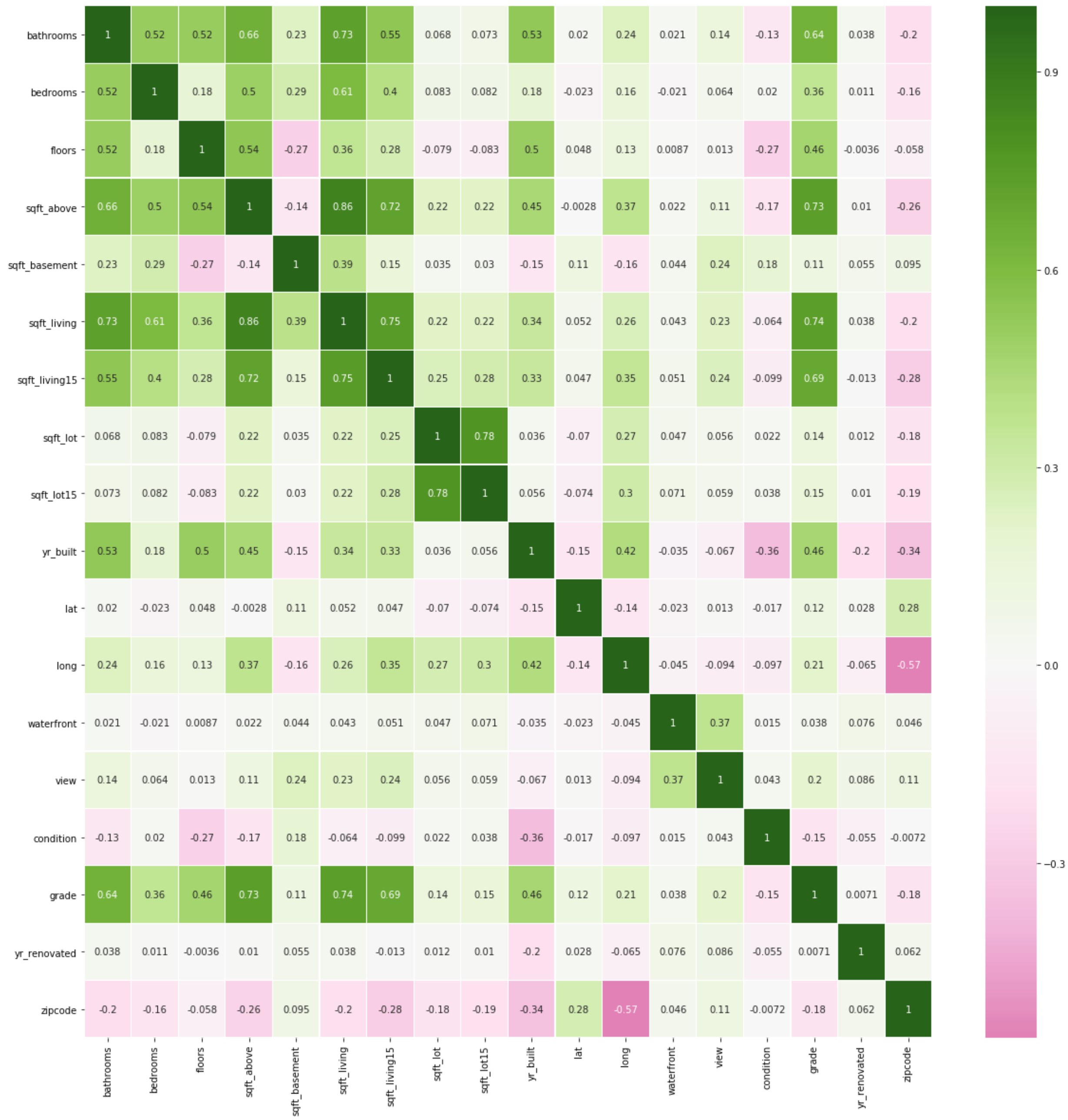


In [39]:
```
predictors.corr()
```

Out[39]:

	bathrooms	bedrooms	floors	sqft_above	sqft_basement	sqft_living	sqft_living1
bathrooms	1.000000	0.515622	0.516377	0.655528	0.233637	0.730042	0.54608
bedrooms	0.515622	1.000000	0.179493	0.495662	0.285272	0.607762	0.40159
floors	0.516377	0.179493	1.000000	0.540538	-0.274430	0.362194	0.27660
sqft_above	0.655528	0.495662	0.540538	1.000000	-0.135780	0.860994	0.72436
sqft_basement	0.233637	0.285272	-0.274430	-0.135780	1.000000	0.386999	0.15186
sqft_living	0.730042	0.607762	0.362194	0.860994	0.386999	1.000000	0.75212
sqft_living15	0.546087	0.401598	0.276607	0.724368	0.151860	0.752129	1.00000
sqft_lot	0.068224	0.083474	-0.078859	0.217911	0.034617	0.220581	0.25052
sqft_lot15	0.072652	0.082378	-0.082819	0.221241	0.030129	0.221376	0.28044
yr_built	0.532308	0.176199	0.500979	0.446374	-0.146460	0.340252	0.33398
lat	0.019712	-0.022818	0.048413	-0.002828	0.107213	0.052408	0.04706
long	0.237812	0.155987	0.130713	0.366590	-0.162351	0.257839	0.35468
waterfront	0.020796	-0.020633	0.008682	0.021784	0.043808	0.042764	0.05073
view	0.139442	0.064118	0.013057	0.112329	0.241563	0.228555	0.24208
condition	-0.134610	0.019718	-0.269502	-0.166939	0.177061	-0.064472	-0.09865
grade	0.639831	0.359434	0.463539	0.733812	0.111393	0.740144	0.69393
yr_renovated	0.038448	0.010612	-0.003585	0.010246	0.055079	0.037812	-0.01338
zipcode	-0.201990	-0.160801	-0.057607	-0.262645	0.094775	-0.195789	-0.27835

In [40]:
```
fig, ax = plt.subplots(figsize=(20,20))
sns.heatmap(predictors.corr(), annot=True, cmap='PiYG' , center=0, line
```



Based on the scatter matrix and our correlation chart, there are definitely some features that need to be eliminated (specifically the square footage variables).

How will we define what the threshold for multicollinearity is? Typically, a strong correlation is considered around .7 - .8, so if we use this general consensus, let's set our threshold at .70.

In [41]:
```
abs(predictors.corr()) > 0.70
```

Out[41]:

	bathrooms	bedrooms	floors	sqft_above	sqft_basement	sqft_living	sqft_living15	s
bathrooms	True	False	False	False	False	True	False	
bedrooms	False	True	False	False	False	False	False	
floors	False	False	True	False	False	False	False	
sqft_above	False	False	False	True	False	True	True	
sqft_basement	False	False	False	False	True	False	False	
sqft_living	True	False	False	True	False	True	True	
sqft_living15	False	False	False	True	False	True	True	
sqft_lot	False	False	False	False	False	False	False	
sqft_lot15	False	False	False	False	False	False	False	
yr_built	False	False	False	False	False	False	False	
lat	False	False	False	False	False	False	False	
long	False	False	False	False	False	False	False	
waterfront	False	False	False	False	False	False	False	
view	False	False	False	False	False	False	False	
condition	False	False	False	False	False	False	False	
grade	False	False	False	True	False	True	False	
yr_renovated	False	False	False	False	False	False	False	
zipcode	False	False	False	False	False	False	False	

Immediate Observations

All of the square footage variables are heavily correlate, so some will need to be dropped. In the next section, we'll inspect what property size features should be kept.

Question #1

Does square footage matter when purchasing a home? Specifically, does square footage matter in terms of living space, property, or both?

Before buying a home, it's important to be knowledgeable about whether or not square footage plays a factor in a home's value (both in terms of the house and the property). This can assist in the decision of whether or not to buy within cities or suburbs, and whether one should buy primarily a large home or small home.

We also ask this question in order to help inform our decision of what square footage variable to include in the final model. This analysis will lend a hand to deciding what square footage feature plays the most important feature in a home's value.

Our features include the following:

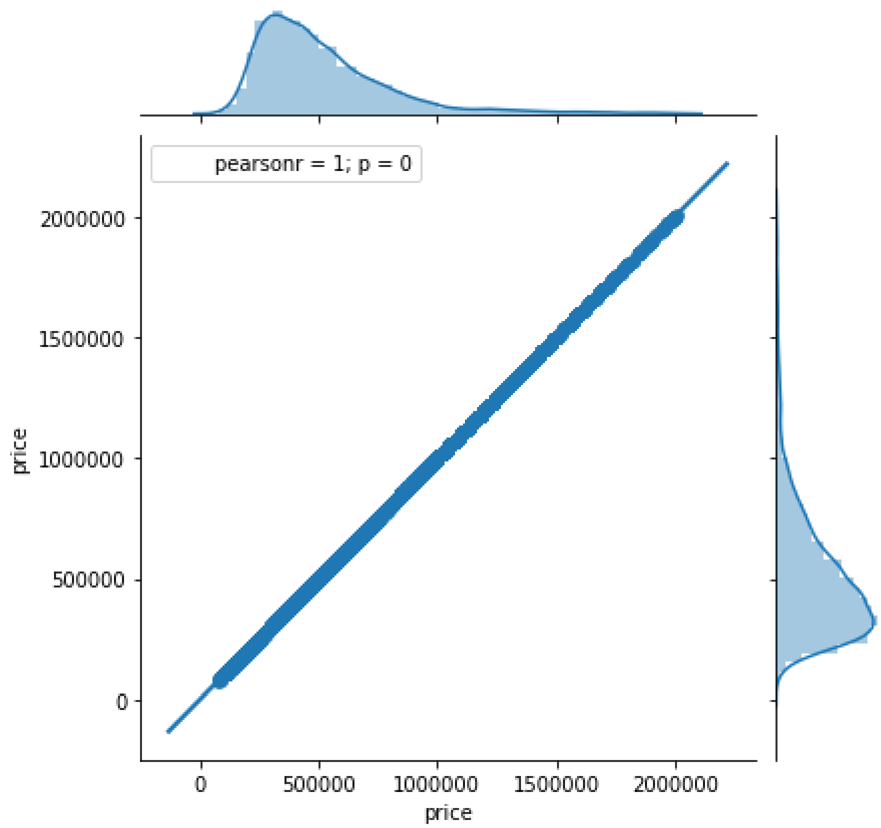
Square footage of the living space Square footage of the basement Square footage of the living space, not including the basement Square footage of the lot Square footage of the living space in 2015 Square footage of the lot in 2015

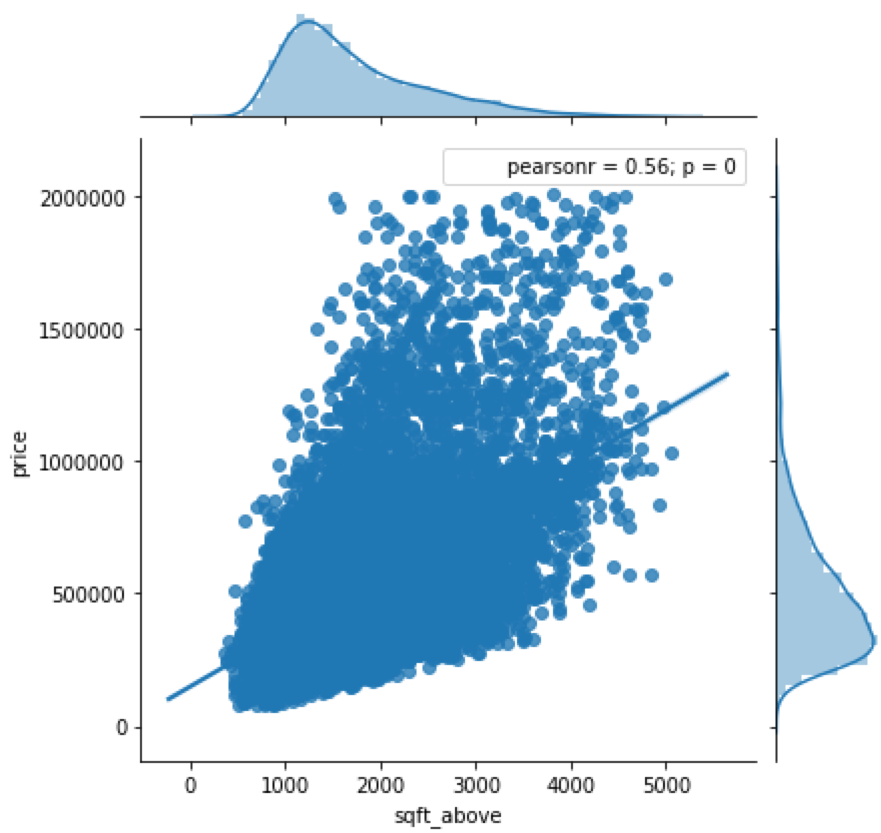
Before we jump in, let's create a dataframe of just these variables.

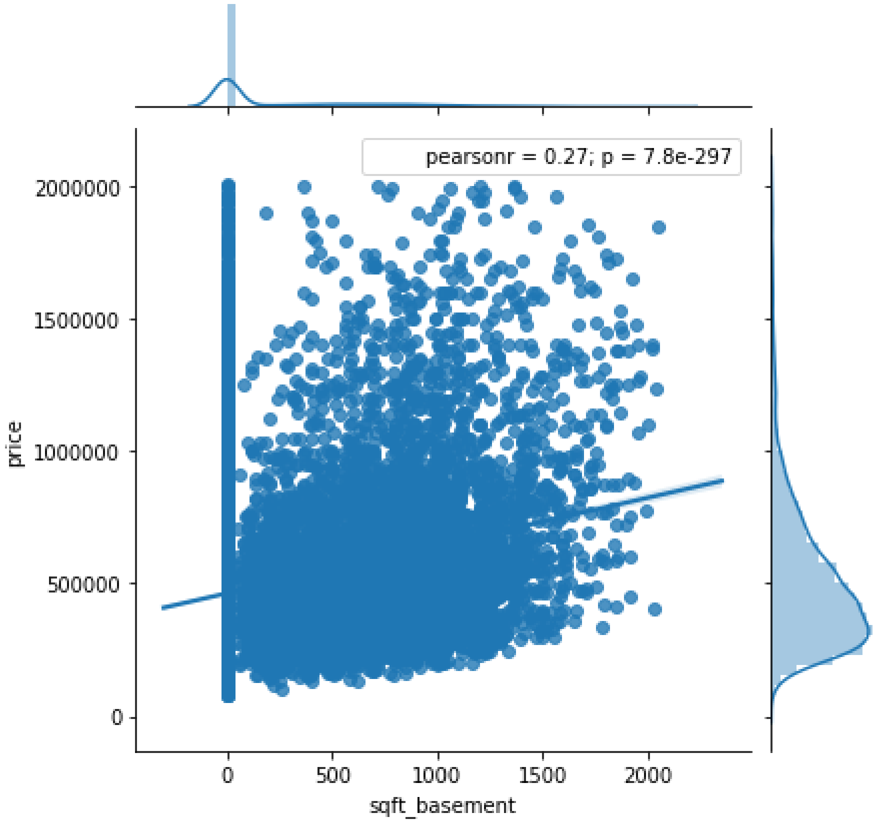
In [42]:
```
sqft = df2[['price','sqft_above', 'sqft_basement', 'sqft_living', 'sqft
            'sqft_lot15']]

```

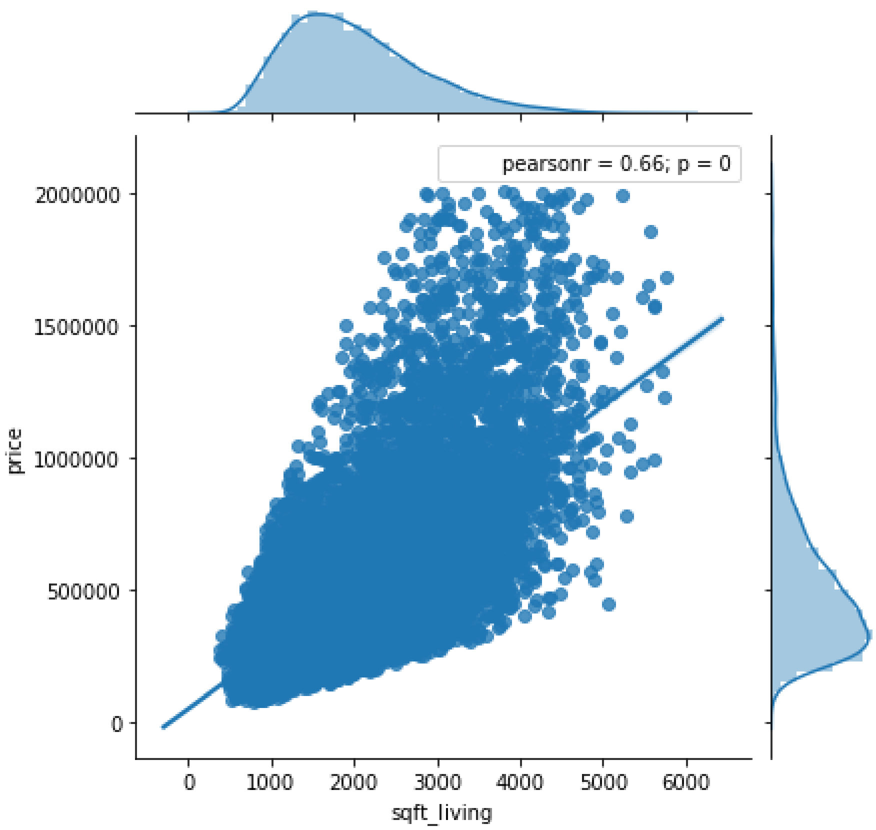
We also added price to quickly run some correlations and get a chance to see how each specific measurement is correlated to home price.

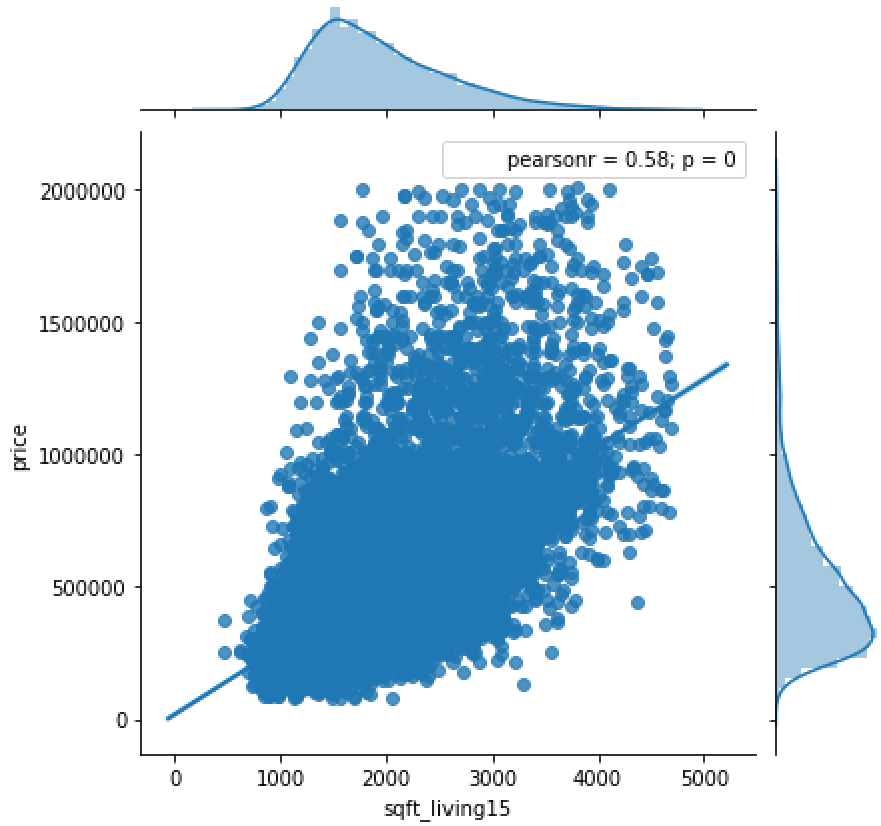
In [43]:
```python
for col in sqft:
    sns.jointplot(x=col, y='price', data=sqft, kind='reg', stat_func=pe
```

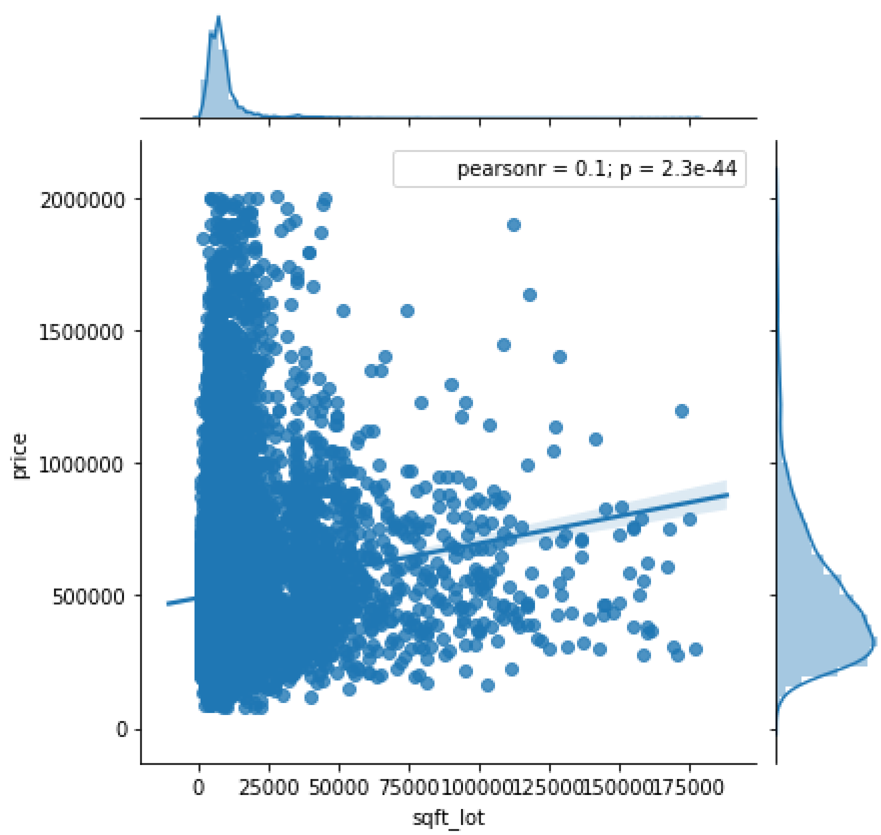


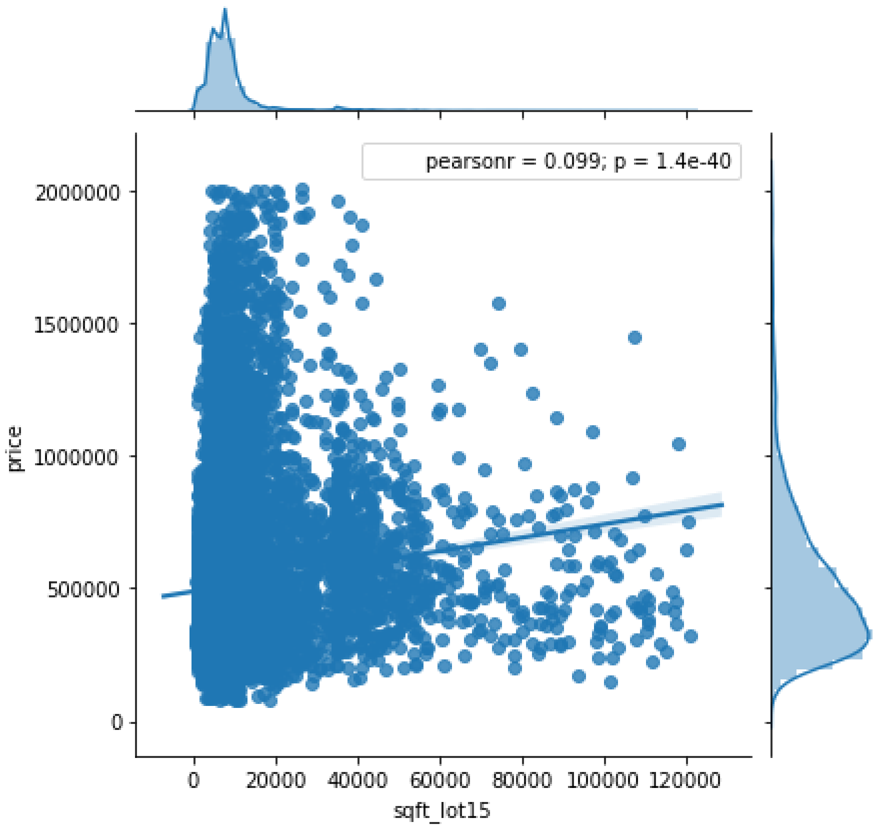



pearsonr = 0.27; p = 7.8e-297
price
2000000
1500000
1000000
500000
0
0
500
1000
1500
2000
sqft_basement


pearsonr = 0.66; p = 0
price
2000000
1500000
1000000
500000
0
0
1000
2000
3000
4000
5000
6000
sqft_living


pearsonr = 0.58; p = 0
2000000
1500000
1000000
500000
0
price
0
1000
2000
3000
4000
5000
sqft_living15


pearsonr = 0.1; p = 2.3e-44
2000000
1500000
1000000
500000
0
price
0
25000
50000
75000
100000
125000
150000
175000
sqft_lot



Interestingly enough, we see that square footage of a living space is positively correlated with a home's price. The sqft_above feature also positively correlates with price.

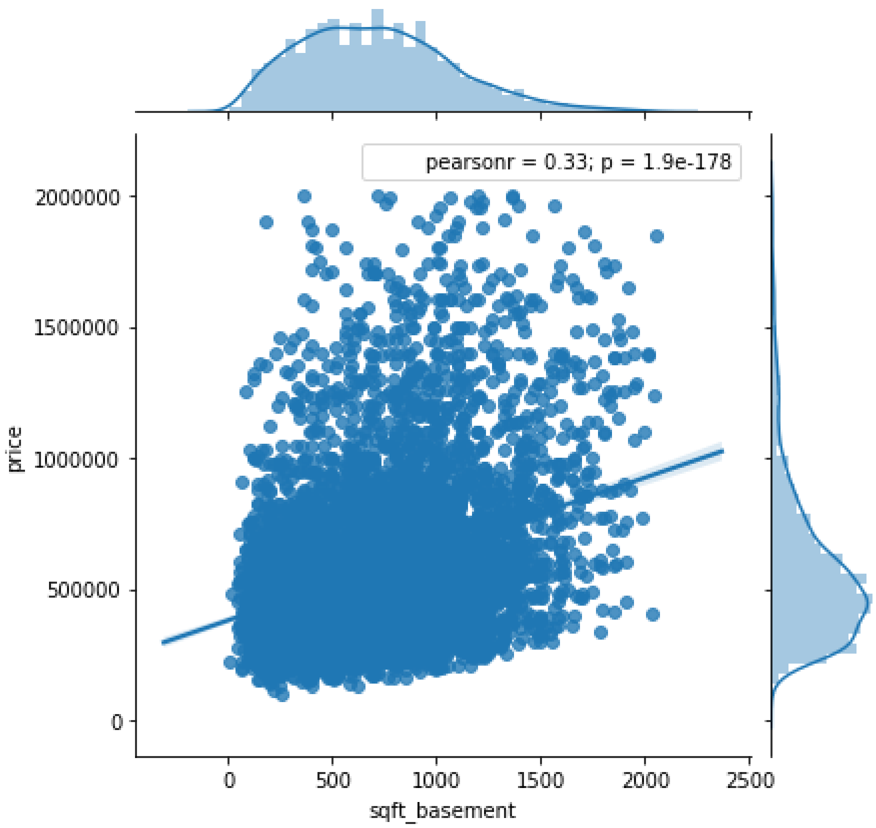
The lot square footage has no correlation to price whatsoever. Assuming the lot sizes that equal zero are apartments, it's apparent that apartment value can vary greatly. From this point on, it's safe to disregard lot size.

The basement feature seems to have a weak, positive correlation with price (it would've been valuable to have data on whether or not the basement is finished). However, it's tough to get a read on whether or not the size of the basement correlates with price when so many homes with no basements are in our data.

Out of curiosity, let's check the correlation measurement again when we eliminate homes with no basements.

In [44]:
```
basement = df2[['price','sqft_basement']]
basement.drop(basement[basement['sqft_basement'] == 0].index, inplace=T
sns.jointplot(x='sqft_basement', y='price', data=basement, kind='reg',
```

Out[44]: <seaborn.axisgrid.JointGrid at 0x1a2285d8d0>



While eliminating houses with no basements did increase the correlation with price, it still remains relatively weak. Let's disregard the basement feature and move on to the living area measurements.

Square Footage Living v. Square Footage Above

Eliminating all other features, we leave ourselves with living space square footage and living space square footage (excluding the basement). Let's get an initial reading on the correlations between these two features and price.

In [45]:
```
sqft.head()
sqft = sqft.drop(['sqft_basement', 'sqft_living15', 'sqft_lot', 'sqft_l

```

In [46]:
```
sqft.corr()
```

Out[46]:

	price	sqft_above	sqft_living
price	1.000000	0.562492	0.661437
sqft_above	0.562492	1.000000	0.860994
sqft_living	0.661437	0.860994	1.000000

From the analysis, we find that the entire living space square footage has a very stronger correlation with price. While the square footage of the house outside of the basement does still have a positive correlation with price, it doesn't nearly correlate as highly. This shows that disregarding basements in their entirety does lead to miscalculations. Although living space square footage correlates with a number of features, it is definitely something we want in our final model as it will likely be heavily predicted of house value.

Our Findings

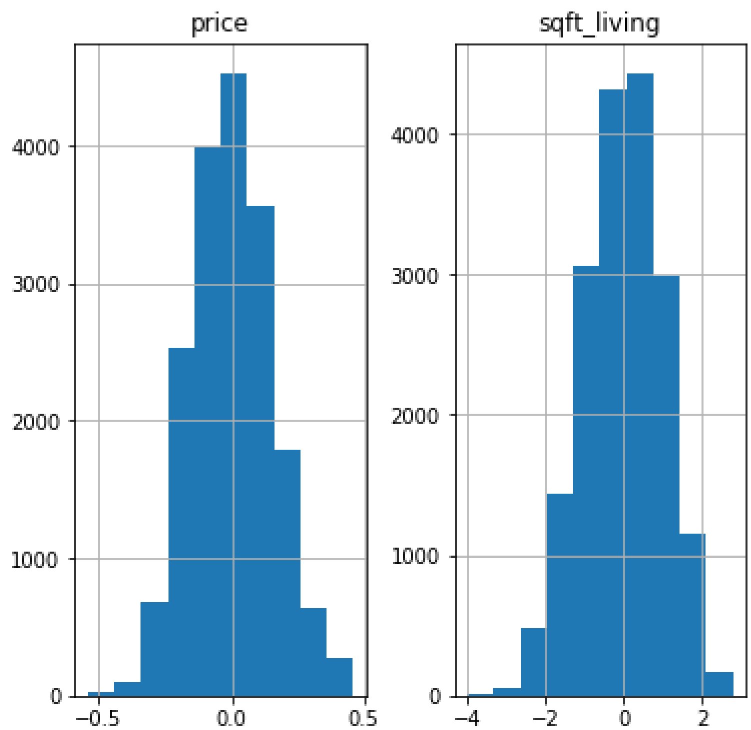
Property square footage plays little role in a home's value. A basement isn't a make-or-break feature. Living space square footage is the most influential feature of any of our square footage measurements.

In [47]:
```
print("Price Skewness:", (sqft['price'].skew()))
print("Price Kurtosis:", (sqft['price'].kurt()))
print("Living Space SqFt Skewness:", (sqft['sqft_living'].skew()))
print("Living Space SqFt Kurtosis:", (sqft['sqft_living'].kurt()))
```

```
Price Skewness: 1.7677623567956724
Price Kurtosis: 4.3737995207129945
Living Space SqFt Skewness: 0.8096351381708555
Living Space SqFt Kurtosis: 0.5427766676197536
```

Our earlier adjustment for outliers decreased the skewness and kurtosis for both variables. However, both data is still positively skewed. This will require normalizing both price and the square footage of the living space. However, the kurtosis scores show that our outlier adjustment significantly decreased the length of distribution tails for living space. However, it seems that the distribution tail for price is on the high side. This will be dealt with through log transformations.

In [48]:
```
data_log = pd.DataFrame([])
data_log["price"] = np.log(sqft["price"])
data_log["sqft_living"] = np.log(sqft["sqft_living"])

logprice = data_log["price"]
logsqft = data_log["sqft_living"]

scaled_price = (logprice-np.mean(logprice))/(max(logprice)-min(logprice
scaled_sqft = (logsqft-np.mean(logsqft))/np.sqrt(np.var(logsqft))

data_cont_scaled = pd.DataFrame([])
data_cont_scaled["price"]= scaled_price
data_cont_scaled["sqft_living"]= scaled_sqft

data_cont_scaled.hist(figsize  = [6, 6]);
```



In [49]:
```
print("Price Skewness:", data_cont_scaled["price"].skew())
print("Price Kurtosis:", data_cont_scaled["price"].kurt())
print("Sqft Skewness:", data_cont_scaled["sqft_living"].skew())
print("Sqft Kurtosis:", data_cont_scaled["sqft_living"].kurt())
```

```
Price Skewness: 0.17996151721851544
Price Kurtosis: -0.017497001760833353
Sqft Skewness: -0.1772458899479632
Sqft Kurtosis: -0.28328189217260835
```

After scaling and log-transforming price and square foot, we can run a regression on the features to get a closer look at the relationship between price and living space square footage.

In [50]:
```
import statsmodels.api as sm
from statsmodels.formula.api import ols
```

In [51]:
```
f = 'price~sqft_living'
model = ols(formula=f, data=data_cont_scaled).fit()
model.summary()
```

Out[51]:

OLS Regression Results

Dep. Variable:	price	**R-squared:**	0.410
Model:	OLS	**Adj. R-squared:**	0.410
Method:	Least Squares	**F-statistic:**	1.259e+04
Date:	Sat, 02 Mar 2019	**Prob (F-statistic):**	0.00
Time:	10:51:16	**Log-Likelihood:**	13179.
No. Observations:	18101	**AIC:**	-2.635e+04
Df Residuals:	18099	**BIC:**	-2.634e+04
Df Model:	1		
Covariance Type:	nonrobust		

	coef	std err	t	P>|t|	[0.025	0.975]
Intercept	2.923e-14	0.001	3.37e-11	1.000	-0.002	0.002
sqft_living	0.0974	0.001	112.207	0.000	0.096	0.099

Omnibus:	175.660	**Durbin-Watson:**	1.995
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	116.142
Skew:	0.048	**Prob(JB):**	6.03e-26
Kurtosis:	2.620	**Cond. No.**	1.00

Warnings:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.

Between the high T-score and the low P-value, we can safely assume that living space square footage plays an important part in determining a home's value.

We intepret this coefficient as, **"The model predicts a 1% increase in living space square footage leads to an increase in price by .1%."**

Question #2: Does zip code (city) affect a home's value?

In [52]:
```
zipcode = df2[['price', 'zipcode', 'grade']]
zipcode.head()
```

Out[52]:

	price	zipcode	grade
1	538000.0	98125	7
2	180000.0	98028	6
3	604000.0	98136	7
4	510000.0	98074	8
8	229500.0	98146	7

To make our analysis more accurate, it's likely a good idea to convert the zip codes to the actual cities they're located in. This will allow us to minimize the categories and get a better picture of what houses cost in each city. We'll also be able to tell what cities have the highest graded homes.

To obtain zip codes with matching cities, we'll be using the index provided here: httphttps://www.zip-codes.com/county/wa-king.asp://ciclt.net/sn/clt/capitolimpact/gw_ziplist.aspx?ClientCode=capitolimpact&State=wa&StName=Washington&StFIPS=53&FIPS=53033 (https://www.zip-codes.com/county/wa-king.asp://ciclt.net/sn/clt/capitolimpact/gw_ziplist.aspx?ClientCode=capitolimpact&State=wa&StName=Washington&StFIPS=53&FIPS=53033)

In [53]:
```
zipcode['zipcode'] = zipcode['zipcode'].astype('str')
```

In [54]:
```
zipcode['zipcode'].replace('98001', 'Auburn', inplace=True)
zipcode['zipcode'].replace('98002', 'Auburn', inplace=True)
zipcode['zipcode'].replace('98003', 'Federal_Way', inplace=True)
zipcode['zipcode'].replace('98004', 'Bellevue', inplace=True)
zipcode['zipcode'].replace('98005', 'Bellevue', inplace=True)
zipcode['zipcode'].replace('98006', 'Bellevue', inplace=True)
zipcode['zipcode'].replace('98007', 'Bellevue', inplace=True)
zipcode['zipcode'].replace('98008', 'Bellevue', inplace=True)
zipcode['zipcode'].replace('98009', 'Bellevue', inplace=True)
zipcode['zipcode'].replace('98010', 'Black_Diamond', inplace=True)
zipcode['zipcode'].replace('98011', 'Bothell', inplace=True)
zipcode['zipcode'].replace('98013', 'Burton', inplace=True)
zipcode['zipcode'].replace('98014', 'Carnation', inplace=True)
zipcode['zipcode'].replace('98015', 'Bellevue', inplace=True)
zipcode['zipcode'].replace('98019', 'Duvall', inplace=True)
zipcode['zipcode'].replace('98022', 'Enumclaw', inplace=True)
zipcode['zipcode'].replace('98023', 'Federal_Way', inplace=True)
zipcode['zipcode'].replace('98024', 'Fall_City', inplace=True)
zipcode['zipcode'].replace('98025', 'Hobart', inplace=True)
zipcode['zipcode'].replace('98027', 'Issaquah', inplace=True)
zipcode['zipcode'].replace('98028', 'Kenmore', inplace=True)
zipcode['zipcode'].replace('98029', 'Issaquah', inplace=True)
zipcode['zipcode'].replace('98030', 'Kent', inplace=True)
zipcode['zipcode'].replace('98031', 'Kent', inplace=True)
zipcode['zipcode'].replace('98032', 'Kent', inplace=True)
zipcode['zipcode'].replace('98033', 'Kirkland', inplace=True)
zipcode['zipcode'].replace('98034', 'Kirkland', inplace=True)
zipcode['zipcode'].replace('98035', 'Kent', inplace=True)
zipcode['zipcode'].replace('98038', 'Maple_Valley', inplace=True)
zipcode['zipcode'].replace('98039', 'Medina', inplace=True)
zipcode['zipcode'].replace('98040', 'Mercer_Island', inplace=True)
zipcode['zipcode'].replace('98041', 'Bothell', inplace=True)
zipcode['zipcode'].replace('98042', 'Kent', inplace=True)
zipcode['zipcode'].replace('98045', 'North_Bend', inplace=True)
zipcode['zipcode'].replace('98047', 'Pacific', inplace=True)
zipcode['zipcode'].replace('98050', 'Preston', inplace=True)
zipcode['zipcode'].replace('98051', 'Ravensdale', inplace=True)
zipcode['zipcode'].replace('98052', 'Redmond', inplace=True)
zipcode['zipcode'].replace('98053', 'Redmond', inplace=True)
zipcode['zipcode'].replace('98055', 'Renton', inplace=True)
zipcode['zipcode'].replace('98056', 'Renton', inplace=True)
zipcode['zipcode'].replace('98057', 'Renton', inplace=True)
zipcode['zipcode'].replace('98058', 'Renton', inplace=True)
zipcode['zipcode'].replace('98059', 'Renton', inplace=True)
zipcode['zipcode'].replace('98062', 'Seahurst', inplace=True)
zipcode['zipcode'].replace('98063', 'Federal_Way', inplace=True)
zipcode['zipcode'].replace('98064', 'Kent', inplace=True)
zipcode['zipcode'].replace('98065', 'Snoqualmie', inplace=True)
zipcode['zipcode'].replace('98070', 'Vashon', inplace=True)
zipcode['zipcode'].replace('98071', 'Auburn', inplace=True)
zipcode['zipcode'].replace('98072', 'Woodinville', inplace=True)
zipcode['zipcode'].replace('98073', 'Redmond', inplace=True)
zipcode['zipcode'].replace('98074', 'Sammamish', inplace=True)
zipcode['zipcode'].replace('98075', 'Sammamish', inplace=True)
zipcode['zipcode'].replace('98077', 'Woodinville', inplace=True)
zipcode['zipcode'].replace('98083', 'Kirkland', inplace=True)
```

```
zipcode['zipcode'].replace('98089', 'Kent', inplace=True)
zipcode['zipcode'].replace('98092', 'Auburn', inplace=True)
zipcode['zipcode'].replace('98093', 'Federal_Way', inplace=True)
zipcode['zipcode'].replace('98101', 'Seattle', inplace=True)
zipcode['zipcode'].replace('98102', 'Seattle', inplace=True)
zipcode['zipcode'].replace('98103', 'Seattle', inplace=True)
zipcode['zipcode'].replace('98104', 'Seattle', inplace=True)
zipcode['zipcode'].replace('98105', 'Seattle', inplace=True)
zipcode['zipcode'].replace('98106', 'Seattle', inplace=True)
zipcode['zipcode'].replace('98107', 'Seattle', inplace=True)
zipcode['zipcode'].replace('98108', 'Seattle', inplace=True)
zipcode['zipcode'].replace('98109', 'Seattle', inplace=True)
zipcode['zipcode'].replace('98111', 'Seattle', inplace=True)
zipcode['zipcode'].replace('98112', 'Seattle', inplace=True)
zipcode['zipcode'].replace('98113', 'Seattle', inplace=True)
zipcode['zipcode'].replace('98114', 'Seattle', inplace=True)
zipcode['zipcode'].replace('98115', 'Seattle', inplace=True)
zipcode['zipcode'].replace('98116', 'Seattle', inplace=True)
zipcode['zipcode'].replace('98117', 'Seattle', inplace=True)
zipcode['zipcode'].replace('98118', 'Seattle', inplace=True)
zipcode['zipcode'].replace('98119', 'Seattle', inplace=True)
zipcode['zipcode'].replace('98121', 'Seattle', inplace=True)
zipcode['zipcode'].replace('98122', 'Seattle', inplace=True)
zipcode['zipcode'].replace('98124', 'Seattle', inplace=True)
zipcode['zipcode'].replace('98125', 'Seattle', inplace=True)
zipcode['zipcode'].replace('98126', 'Seattle', inplace=True)
zipcode['zipcode'].replace('98127', 'Seattle', inplace=True)
zipcode['zipcode'].replace('98129', 'Seattle', inplace=True)
zipcode['zipcode'].replace('98131', 'Seattle', inplace=True)
zipcode['zipcode'].replace('98133', 'Seattle', inplace=True)
zipcode['zipcode'].replace('98134', 'Seattle', inplace=True)
zipcode['zipcode'].replace('98136', 'Seattle', inplace=True)
zipcode['zipcode'].replace('98138', 'Seattle', inplace=True)
zipcode['zipcode'].replace('98139', 'Seattle', inplace=True)
zipcode['zipcode'].replace('98141', 'Seattle', inplace=True)
zipcode['zipcode'].replace('98144', 'Seattle', inplace=True)
zipcode['zipcode'].replace('98145', 'Seattle', inplace=True)
zipcode['zipcode'].replace('98146', 'Seattle', inplace=True)
zipcode['zipcode'].replace('98148', 'Seattle', inplace=True)
zipcode['zipcode'].replace('98154', 'Seattle', inplace=True)
zipcode['zipcode'].replace('98155', 'Seattle', inplace=True)
zipcode['zipcode'].replace('98158', 'Seattle', inplace=True)
zipcode['zipcode'].replace('98160', 'Seattle', inplace=True)
zipcode['zipcode'].replace('98161', 'Seattle', inplace=True)
zipcode['zipcode'].replace('98164', 'Seattle', inplace=True)
zipcode['zipcode'].replace('98165', 'Seattle', inplace=True)
zipcode['zipcode'].replace('98166', 'Seattle', inplace=True)
zipcode['zipcode'].replace('98168', 'Seattle', inplace=True)
zipcode['zipcode'].replace('98170', 'Seattle', inplace=True)
zipcode['zipcode'].replace('98174', 'Seattle', inplace=True)
zipcode['zipcode'].replace('98175', 'Seattle', inplace=True)
zipcode['zipcode'].replace('98177', 'Seattle', inplace=True)
zipcode['zipcode'].replace('98178', 'Seattle', inplace=True)
zipcode['zipcode'].replace('98181', 'Seattle', inplace=True)
zipcode['zipcode'].replace('98185', 'Seattle', inplace=True)
zipcode['zipcode'].replace('98188', 'Seattle', inplace=True)
zipcode['zipcode'].replace('98190', 'Seattle', inplace=True)
```

```
zipcode['zipcode'].replace('98191', 'Seattle', inplace=True)
zipcode['zipcode'].replace('98194', 'Seattle', inplace=True)
zipcode['zipcode'].replace('98195', 'Seattle', inplace=True)
zipcode['zipcode'].replace('98198', 'Seattle', inplace=True)
zipcode['zipcode'].replace('98199', 'Seattle', inplace=True)
zipcode['zipcode'].replace('98224', 'Baring', inplace=True)
zipcode['zipcode'].replace('98288', 'Skykomish', inplace=True)
```

In [55]:
```
zipcode['zipcode'].value_counts()
```

Out[55]:
```
Seattle          7660
Renton           1346
Bellevue         1151
Kent             1046
Kirkland          829
Redmond           820
Auburn            763
Federal_Way       678
Sammamish         672
Issaquah          609
Maple_Valley      480
Woodinville       385
Snoqualmie        263
Kenmore           249
Mercer_Island     217
Bothell           170
Enumclaw          169
North_Bend        162
Duvall            144
Vashon             75
Black_Diamond      71
Carnation          68
Fall_City          47
Medina             27
Name: zipcode, dtype: int64
```

In [56]:
```
zipcode['zipcode'] = zipcode['zipcode'].astype('category')
```

Now we have a much better idea of where our data is coming from! We see the the majority of houses are in the Seattle-area. On the other end, we have 27 houses from Medina. After some research, I found that billionaires such as Bill Gates and Jeff Bezos own homes here, so we can safely assume 27 houses are pricey!

In [57]:
```
Medina = zipcode.loc[zipcode['zipcode'] == 'Medina']
print("The average home in Medina sold for: $", Medina['price'].mean())
```

```
The average home in Medina sold for: $ 1450555.5555555555
```

Well...our assumption was correct! The average home was sold for just under $1.5 million.

Let's take a look at average home prices within each of these cities. After that, we can take a look at what the average graded home is within each city.

In [58]:
```
pd.set_option('float_format', '{:f}'.format)
zipcode.groupby('zipcode', as_index=False)['price'].mean().sort_values(
```

Out[58]:

	zipcode	price
14	Medina	1450555.555556
15	Mercer_Island	1063399.612903
1	Bellevue	808963.009557
19	Sammamish	713662.976190
17	Redmond	638970.606098
12	Kirkland	611171.510253
23	Woodinville	598655.057143
9	Issaquah	587304.794745
21	Snoqualmie	518159.212928
20	Seattle	516541.802219
3	Bothell	492879.947059
22	Vashon	467609.600000
10	Kenmore	456413.453815
4	Carnation	431286.455882
5	Duvall	417537.236111
7	Fall_City	417173.829787
16	North_Bend	394806.746914
18	Renton	393595.168648
2	Black_Diamond	385730.887324
13	Maple_Valley	354177.645833
11	Kent	295155.219885
8	Federal_Way	283419.095870
0	Auburn	281358.736566
6	Enumclaw	280613.236686

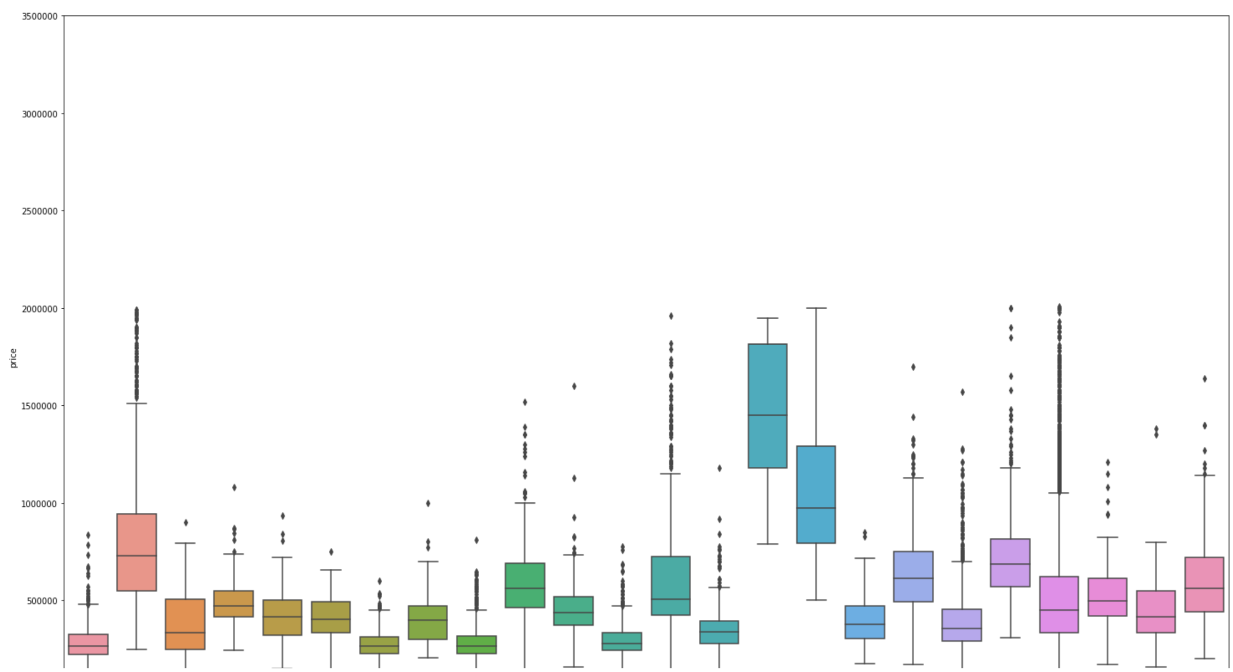
We see a broad range of home values according to what city a home is located. Let's see if this list matches with the list of cities with the highest graded homes.

In [59]:
```
zipcode.groupby('zipcode', as_index=False)['grade'].mean().sort_values(
```

Out[59]:

	zipcode	grade
19	Sammamish	8.818452
15	Mercer_Island	8.801843
14	Medina	8.555556
23	Woodinville	8.332468
1	Bellevue	8.271937
9	Issaquah	8.201970
17	Redmond	8.154878
21	Snoqualmie	7.806084
3	Bothell	7.794118
12	Kirkland	7.721351
10	Kenmore	7.590361

In [60]:
```
var = 'zipcode'
data = zipcode
f, ax = plt.subplots(figsize=(25, 15))
fig = sns.boxplot(x=var, y="price", data=data)
fig.axis(ymin=0, ymax=3500000);
```



Immediate Observations

We find that most of the expensive cities/areas also contain the highest graded homes. The five most expensive areas cities (Medina, Mercer Island, Bellevue, Sammamish, and Redmond) also had some of the highest graded homes.

Meanwhile, all the cheapest cities/neighborhoods also include some of the lowest graded homes (Enumclaw, Auburn, Federal Way, and Kent).

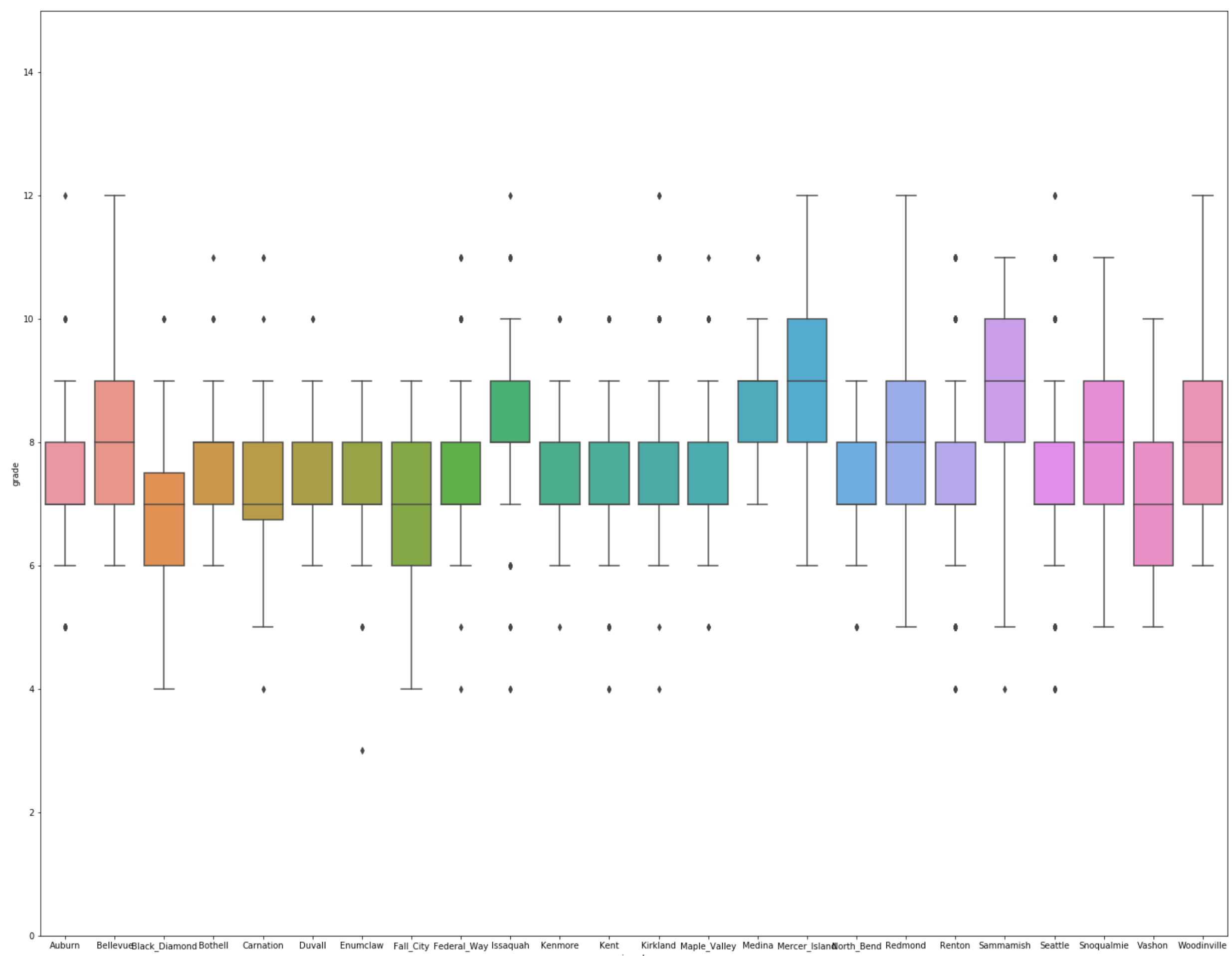
Two immediate outliers: **Seattle and Vashon**

Seatte ranked as the 10th most expensive city, but finished 20th when it came to highest graded homes. One could possible infer this is due to proximity to the city: living closer to a metro area raises the cost of a home despite its inferior quality.

Vashon, on the other hand, is a remote island. Unlike Mercer, it doesn't have a bridge to the mainland. Based on the data, we found that Vashon is the 12th most expensive area, but only ranks 21st when it comes to home grade. This could likely be due to its proximity to Seattle. According to the New York Times and other sources, Vashon is only 22 minutes away from downtown Seattle and its economy is centered around commuters into Seattle.

In [61]:

```
var = 'zipcode'
data = zipcode
f, ax = plt.subplots(figsize=(25, 20))
fig = sns.boxplot(x=var, y="grade", data=data)
fig.axis(ymin=0, ymax=15);
```



In [62]:

```
z_dummies = pd.get_dummies(zipcode['zipcode'], prefix='zip')
```

In [63]:
```
z_dummies.head()
```

Out[63]:

	zip_Auburn	zip_Bellevue	zip_Black_Diamond	zip_Bothell	zip_Carnation	zip_Duvall	zip_Enumcla
1	0	0	0	0	0	0	
2	0	0	0	0	0	0	
3	0	0	0	0	0	0	
4	0	0	0	0	0	0	
8	0	0	0	0	0	0	

5 rows × 24 columns

In [64]:
```
zipcode = zipcode.drop(['zipcode'], axis=1)
zipcode = zipcode.drop(['grade'], axis=1)
```

In [65]:
```
zipcode = pd.concat([zipcode, z_dummies], axis=1)
```

In [66]:
```
zipcode.head()
```

Out[66]:

	price	zip_Auburn	zip_Bellevue	zip_Black_Diamond	zip_Bothell	zip_Carnation	zip_Duva
1	538000.000000	0	0	0	0	0	
2	180000.000000	0	0	0	0	0	
3	604000.000000	0	0	0	0	0	
4	510000.000000	0	0	0	0	0	
8	229500.000000	0	0	0	0	0	

5 rows × 25 columns

In [67]:
```
import statsmodels.api as sm
import statsmodels.formula.api as smf
import scipy.stats as stats
import statsmodels.stats.api as sms
```

In [68]:
```
cols_zip = [col for col in zipcode if col.startswith('zip')]


values = [['ind_var','r_sq','int','slope','p_val']]
high_zips = []
for idx, val in enumerate(zipcode):
    print('Price ~ ' + val)
    print('--------------')
    f = 'price~' + val
    model = smf.ols(formula=f, data=zipcode,).fit()
    values.append([val, (model.rsquared).round(2), model.params[0], mod
    #let's only look closely at r^2 higher than .01
    if (model.rsquared).round(3) >= .01:
        print("HIGH R^2")
        print(values[idx+1])
        high_zips.append(val)
print('\n\n', 'Zipcodes with r-squared over .1:',  high_zips)
print(len(high_zips))
```

```
Price ~ price
--------------
HIGH R^2
['price', 1.0, 3.7834979593753815e-10, 1.0, 0.0]
Price ~ zip_Auburn
--------------
HIGH R^2
['zip_Auburn', 0.03, 523323.6822586227, -241964.9456924398, 2.66992138583
8346e-122]
Price ~ zip_Bellevue
--------------
HIGH R^2
['zip_Bellevue', 0.08, 493035.17964601784, 315927.82991088904, 0.0]
Price ~ zip_Black_Diamond
--------------
Price ~ zip_Bothell
--------------
Price ~ zip_Carnation
--------------
Price ~ zip_Duvall
--------------
Price ~ zip_Enumclaw
--------------
Price ~ zip_Fall_City
--------------
Price ~ zip_Federal_Way
--------------
HIGH R^2
['zip_Federal_Way', 0.03, 522063.05297595105, -238643.95710574338, 2.8102
010463327503e-106]
Price ~ zip_Issaquah
--------------
Price ~ zip_Kenmore
--------------
Price ~ zip_Kent
--------------
HIGH R^2
['zip_Kent', 0.04, 526492.5452360013, -231337.32535072515, 7.977259135903
```

```
856e-151]
Price ~ zip_Kirkland
--------------
Price ~ zip_Maple_Valley
--------------
Price ~ zip_Medina
--------------
HIGH R^2
['zip_Medina', 0.02, 511723.8972557266, 938831.6582998359, 2.587737277590
0376e-68]
Price ~ zip_Mercer_Island
--------------
HIGH R^2
['zip_Mercer_Island', 0.05, 506447.383303512, 556952.2295997071, 1.384780
0043646223e-190]
Price ~ zip_North_Bend
--------------
Price ~ zip_Redmond
--------------
HIGH R^2
['zip_Redmond', 0.01, 507152.7586366527, 131817.84746091109, 9.8573980135
52564e-40]
Price ~ zip_Renton
--------------
HIGH R^2
['zip_Renton', 0.01, 522726.56651745766, -129131.39786961042, 6.774676123
3781e-60]
Price ~ zip_Sammamish
--------------
HIGH R^2
['zip_Sammamish', 0.02, 505392.2312811981, 208270.74490928193, 1.80285443
40557784e-80]
Price ~ zip_Seattle
--------------
Price ~ zip_Snoqualmie
--------------
Price ~ zip_Vashon
--------------
Price ~ zip_Woodinville
--------------


 Zipcodes with r-squared over .1: ['price', 'zip_Auburn', 'zip_Bellevue',
'zip_Federal_Way', 'zip_Kent', 'zip_Medina', 'zip_Mercer_Island', 'zip_Re
dmond', 'zip_Renton', 'zip_Sammamish']
10
```

In [69]:

```
new_zips = zipcode.drop(['price'], axis=1)
```

In [70]:
```
for col in new_zips:
    f = "price~" + col
    model = smf.ols(formula=f, data = zipcode).fit()
    print(model.summary())
```

```
                            OLS Regression Results
==========================================================================
=====
Dep. Variable:                  price   R-squared:
0.030
Model:                            OLS   Adj. R-squared:
0.030
Method:                 Least Squares   F-statistic:
561.6
Date:                Sat, 02 Mar 2019   Prob (F-statistic):           2.67
e-122
Time:                        10:51:23   Log-Likelihood:             -2.524
6e+05
No. Observations:               18101   AIC:                          5.04
9e+05
Df Residuals:                   18099   BIC:                          5.04
9e+05
Df Model:                           1
Covariance Type:            nonrobust
```

We find nine cities/neighborhoods that might have a significant impact on price:

- Auburn
- Bellevue
- Federal Way
- Kent
- Medina
- Mercer Island
- Redmond
- Renton
- Sammamish

Modeling

Let's set up a dataframe to use for modeling. In this initial dataframe, we'll keep our new zipcode variables, along with living space square footage, and keep some others that don't highly correlate with the aforementioned square footage feature. After we test these variables out, we'll take a look at our initial R^2 to see our results. If it isn't to our liking, we can recalibrate.

In [71]:
```
df2.head()
df2 = df2.drop(['zipcode', 'sqft_above', 'sqft_basement', 'sqft_living1
                'sqft_lot'], axis=1)
```

In [72]:
```
df2.head()
```

Out[72]:

	bathrooms	bedrooms	floors	price	sqft_living	sqft_lot15	yr_built	lat	
1	2.250000	3	2.000000	538000.000000	2570	7639	1951	47.721000	-122.3
2	1.000000	2	1.000000	180000.000000	770	8062	1933	47.737900	-122.2
3	3.000000	4	1.000000	604000.000000	1960	5000	1965	47.520800	-122.3
4	2.000000	3	1.000000	510000.000000	1680	7503	1987	47.616800	-122.0
8	1.000000	3	1.000000	229500.000000	1780	8113	1960	47.512300	-122.3

In [73]:
```
df2.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 18101 entries, 1 to 21596
Data columns (total 14 columns):
bathrooms        18101 non-null float64
bedrooms         18101 non-null int64
floors           18101 non-null float64
price            18101 non-null float64
sqft_living      18101 non-null int64
sqft_lot15       18101 non-null int64
yr_built         18101 non-null int64
lat              18101 non-null float64
long             18101 non-null float64
waterfront       18101 non-null float64
view             18101 non-null float64
condition        18101 non-null int64
grade            18101 non-null int64
yr_renovated     18101 non-null float64
dtypes: float64(8), int64(6)
memory usage: 2.7 MB
```

In [74]:
```
df2.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 18101 entries, 1 to 21596
Data columns (total 14 columns):
bathrooms        18101 non-null float64
bedrooms         18101 non-null int64
floors           18101 non-null float64
price            18101 non-null float64
sqft_living      18101 non-null int64
sqft_lot15       18101 non-null int64
yr_built         18101 non-null int64
lat              18101 non-null float64
long             18101 non-null float64
waterfront       18101 non-null float64
view             18101 non-null float64
condition        18101 non-null int64
grade            18101 non-null int64
yr_renovated     18101 non-null float64
dtypes: float64(8), int64(6)
memory usage: 2.7 MB
```

In [75]:
```
df_final = pd.concat([df2, new_zips], axis=1)
```

In [76]:
```
df_final.head()
df_final = df_final.drop(['sqft_lot15'], axis=1)
df_final = df_final.drop(['bathrooms'], axis=1)  #dropping because of c
```

In [77]:
```
for col in df_final.iloc[:, 11:].columns:
    df_final[col] = df_final[col].astype('category')
df_final['yr_renovated'] = df_final['yr_renovated'].astype('category')
df_final['waterfront'] = df_final['waterfront'].astype('category')
df_final['floors'] = df_final['floors'].astype('int')
df_final['view'] = df_final['view'].astype('category')
```

In [78]:
```
data_log = pd.DataFrame([])

data_log["price"] = np.log(df_final["price"])
data_log["sqft_living"] = np.log(df_final["sqft_living"])


logprice = data_log["price"]
logsqft = data_log["sqft_living"]


scaled_price = (logprice-np.mean(logprice))/(max(logprice)-min(logprice
scaled_sqft = (logsqft-np.mean(logsqft))/np.sqrt(np.var(logsqft))



data_final_scaled = pd.DataFrame([])
data_final_scaled["price"]= scaled_price
data_final_scaled["sqft_living"]= scaled_sqft
```

In [79]:
```
df_final = df_final.drop(['price', 'sqft_living'], axis=1)
```

In [80]:
```
df_final = pd.concat([df_final, data_final_scaled], axis=1)
```

In [81]:
```
features = df_final.drop(['price'], axis=1)
```

In [83]:
```
df_final.head()
```

Out[83]:

	bedrooms	floors	yr_built	lat	long	waterfront	view	condition	grade	yr_rei
1	3	2	1951	47.721000	-122.319000	0.000000	0.000000	3	7	1
2	2	1	1933	47.737900	-122.233000	0.000000	0.000000	3	6	0
3	4	1	1965	47.520800	-122.393000	0.000000	0.000000	5	7	0
4	3	1	1987	47.616800	-122.045000	0.000000	0.000000	3	8	0
8	3	1	1960	47.512300	-122.337000	0.000000	0.000000	3	7	0

5 rows × 36 columns

In [84]:
```
df_final.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 18101 entries, 1 to 21596
Data columns (total 36 columns):
bedrooms             18101 non-null int64
floors               18101 non-null int64
yr_built             18101 non-null int64
lat                  18101 non-null float64
long                 18101 non-null float64
waterfront           18101 non-null category
view                 18101 non-null category
condition            18101 non-null int64
grade                18101 non-null int64
yr_renovated         18101 non-null category
zip_Auburn           18101 non-null category
zip_Bellevue         18101 non-null category
zip_Black_Diamond    18101 non-null category
zip_Bothell          18101 non-null category
zip_Carnation        18101 non-null category
zip_Duvall           18101 non-null category
zip_Enumclaw         18101 non-null category
zip_Fall_City        18101 non-null category
zip_Federal_Way      18101 non-null category
zip_Issaquah         18101 non-null category
zip_Kenmore          18101 non-null category
zip_Kent             18101 non-null category
zip_Kirkland         18101 non-null category
zip_Maple_Valley     18101 non-null category
zip_Medina           18101 non-null category
zip_Mercer_Island    18101 non-null category
zip_North_Bend       18101 non-null category
zip_Redmond          18101 non-null category
zip_Renton           18101 non-null category
zip_Sammamish        18101 non-null category
zip_Seattle          18101 non-null category
zip_Snoqualmie       18101 non-null category
zip_Vashon           18101 non-null category
zip_Woodinville      18101 non-null category
price                18101 non-null float64
sqft_living          18101 non-null float64
dtypes: category(27), float64(4), int64(5)
memory usage: 2.5 MB
```

In [102]:
```
model = 'price ~ grade + waterfront + sqft_living + yr_built + lat'
smf.ols(formula=model, data=df_final).fit().summary()
```

Out[102]:

OLS Regression Results

Dep. Variable:	price	**R-squared:**	0.721
Model:	OLS	**Adj. R-squared:**	0.721
Method:	Least Squares	**F-statistic:**	9369.
Date:	Sat, 02 Mar 2019	**Prob (F-statistic):**	0.00
Time:	11:58:06	**Log-Likelihood:**	19966.
No. Observations:	18101	**AIC:**	-3.992e+04
Df Residuals:	18095	**BIC:**	-3.987e+04
Df Model:	5		
Covariance Type:	nonrobust		

	coef	std err	t	P>|t|	[0.025	0.975]
Intercept	18.5656	0.227	81.957	0.000	19.010	18.122

Immediate Observations

The R^2 value tells us that our model explains 72% of the variation in price.

The coefficients all have a p-value of less than .05, so they are significant. An increase in latitude (living in the northern section of King County), grade, and square footage all show an increase in a home's value. Being on the waterfront also has a significant, positive impact on a home's value.

In [103]:
```
df_model = df_final[['price', 'grade', 'waterfront', 'sqft_living', 'y
```

Train-Test-Split

In order to get a good sense of how well our model will be doing on new instances, we'll have to perform a so-called "train-test-split". We'll take a sample of the data that serves as input to "train" our model - fit a linear regression and compute the parameter estimates for our variables, and calculate how well our predictive performance is doing comparing the actual targets y and the fitted ŷ obtained by our model.

In [110]:
```
y = df_model[["price"]]
X = df_model.drop(["price"], axis=1)
```

In [111]:
```
from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size =
```

In [112]:
```
print(len(X_train), len(X_test), len(y_train), len(y_test))
```

```
14480 3621 14480 3621
```

In [113]:
```
from sklearn.linear_model import LinearRegression
linreg = LinearRegression()
linreg.fit(X_train, y_train)

y_hat_train = linreg.predict(X_train)
y_hat_test = linreg.predict(X_test)
```

Let's take a look at the residuals.

In [114]:
```
train_residuals = y_hat_train - y_train
test_residuals = y_hat_test - y_test
```

In [115]:
```
mse_train = np.sum((y_train-y_hat_train)**2)/len(y_train)
mse_test =np.sum((y_test-y_hat_test)**2)/len(y_test)
print('Train Mean Squarred Error:', mse_train)
print('Test Mean Squarred Error:', mse_test)
```

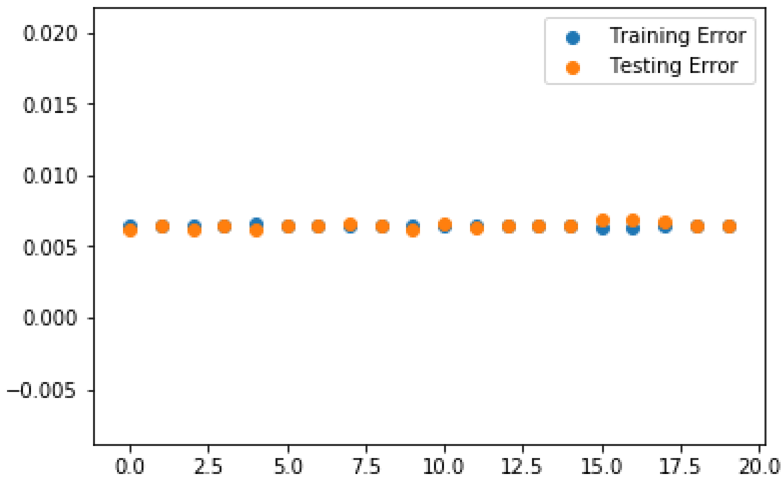
```
Train Mean Squarred Error: price    0.006503
dtype: float64
Test Mean Squarred Error: price    0.006232
dtype: float64
```

In [116]:
```
from sklearn.metrics import mean_squared_error

train_mse = mean_squared_error(y_train, y_hat_train)
test_mse = mean_squared_error(y_test, y_hat_test)
print('Train Mean Squarred Error:', train_mse)
print('Test Mean Squarred Error:', test_mse)
```

```
Train Mean Squarred Error: 0.006503365305877629
Test Mean Squarred Error: 0.006231654389598581
```

Luckily, there isn't much of a difference between the MSE of the test set and the MSE of the training set.

In [118]:
```
linreg = LinearRegression()

num = 20
train_err = []
test_err = []
for i in range(num):
    X_train, X_test, y_train, y_test = train_test_split(X, y, test_siz
    linreg.fit(X_train, y_train)
    y_hat_train = linreg.predict(X_train)
    y_hat_test = linreg.predict(X_test)
    train_err.append(mean_squared_error(y_train, y_hat_train))
    test_err.append(mean_squared_error(y_test, y_hat_test))
plt.scatter(list(range(num)), train_err, label='Training Error')
plt.scatter(list(range(num)), test_err, label='Testing Error')
plt.legend();
```



Conclusions & Next Steps

The overall takeaways can be summarized as the following:

1. Living space square footage is far more important than lot square footage. - We found extensive data to support the notion that when purchasing a home, it's far more important to focus on how big the actual house/apartment is versus the property size.

2. The most expensive zip codes also contain the highest graded homes. - There was extensive overlap between the most expensive areas and the areas with the highest graded homes. The two exceptions to this rule were Seattle and Vashon, which contained expensive homes but ranked toward the bottom of home grade averages.

3. King County covers a wide variety of areas - King County covers a diverse set of areas in Washington, including Medina (where the average home sold for 1.5 million) and Enumclaw (where the average home sold for just under 290,000).

4. The phrase "Location, Location, Location" holds true. - A variety of data told us that the location of a house does, in fact, alter its value.

Based on the preliminary analysis that was conducted here, there are a lot of interesting things to investigate if we wanted to proceed further.

1. Historical Context - What role does the local/national economy play in a home's value? How have homes depreciated/appreciated in the county? What do the houses that gained the most value over the past ten years have in common? Does this information tell us actionable business trends?

2. Further Exploring Location - Does the proximity to Seattle affect home values? What about proximity to transportation centers?

3. Investigate Job Availabilty on Home Price - Can we find an occurence where a major corporation placed an office in the county and see how it affected home values over the years (this could likely be rolled over into finding out how much Amazon's new headquarters in Crystal City will affect home values in the D.C. area)?