King County Housing with Multiple Linear Regression

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Notebook 2: Data Preparation ¶

This notebook contains a breakdown of the step-by-step processes that we used to compile, scrub, and transform our data. It includes variations of narrowing our scope and explorations into the impacts that our different transformations have on the data. For the actual full process of how the data was obtained, and a full description of each data set, please see our first notebook, 'business_problem_and_data_understanding'.

In [1]:
```
# importing the packages we will be using for this project
import pandas as pd
# setting pandas display to avoid scientific notation in my dataframes
pd.options.display.float_format = '{:.2f}'.format
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
import sklearn

from bs4 import BeautifulSoup
import json
import requests

import folium

import haversine as hs

import statsmodels.api as sm
from statsmodels.formula.api import ols
from statsmodels.stats import diagnostic as diag
from statsmodels.stats.outliers_influence import variance_inflation_factor

from sklearn.metrics import r2_score
from sklearn.linear_model import LinearRegression
from sklearn.neighbors import NearestNeighbors
from sklearn.model_selection import train_test_split
from sklearn.metrics import mean_squared_error, r2_score, mean_absolute_error

import scipy.stats as stats

import pylab

%matplotlib inline
```

King County Houses

In [2]:
```
# reading the csv file
df = pd.read_csv('data/kc_house_data.csv')
# previewing the DataFrame
df.head()
```

Out[2]:

	id	date	price	bedrooms	bathrooms	sqft_living	sqft_lot	floors	waterfront	view	...	grade	sqft_above	sqft_basement	yr_built	yr_renovated	zipcode	lat	long	sqft_living15	sqft_lot15
0	7129300520	10/13/2014	221900.00	3	1.00	1180	5650	1.00	nan	0.00	...	7	1180	0.0	1955	0.00	98178	47.51	-122.26	1340	5650
1	6414100192	12/9/2014	538000.00	3	2.25	2570	7242	2.00	0.00	0.00	...	7	2170	400.0	1951	1991.00	98125	47.72	-122.32	1690	7639
2	5631500400	2/25/2015	180000.00	2	1.00	770	10000	1.00	0.00	0.00	...	6	770	0.0	1933	nan	98028	47.74	-122.23	2720	8062
3	2487200875	12/9/2014	604000.00	4	3.00	1960	5000	1.00	0.00	0.00	...	7	1050	910.0	1965	0.00	98136	47.52	-122.39	1360	5000
4	1954400510	2/18/2015	510000.00	3	2.00	1680	8080	1.00	0.00	0.00	...	8	1680	0.0	1987	0.00	98074	47.62	-122.05	1800	7503

5 rows × 21 columns

In [3]:
```
# generating descriptive statistics
df.describe()
```

Out[3]:

	id	price	bedrooms	bathrooms	sqft_living	sqft_lot	floors	waterfront	view	condition	grade	sqft_above	yr_built	yr_renovated	zipcode	lat	long	sqft_living15	sc
count	21597.00	21597.00	21597.00	21597.00	21597.00	21597.00	21597.00	19221.00	21534.00	21597.00	21597.00	21597.00	21597.00	17755.00	21597.00	21597.00	21597.00	21597.00	2
mean	4580474287.77	540296.57	3.37	2.12	2080.32	15099.41	1.49	0.01	0.23	3.41	7.66	1788.60	1971.00	83.64	98077.95	47.56	-122.21	1986.62	1
std	2876735715.75	367368.14	0.93	0.77	918.11	41412.64	0.54	0.09	0.77	0.65	1.17	827.76	29.38	399.95	53.51	0.14	0.14	685.23	2
min	1000102.00	78000.00	1.00	0.50	370.00	520.00	1.00	0.00	0.00	1.00	3.00	370.00	1900.00	0.00	98001.00	47.16	-122.52	399.00	
25%	2123049175.00	322000.00	3.00	1.75	1430.00	5040.00	1.00	0.00	0.00	3.00	7.00	1190.00	1951.00	0.00	98033.00	47.47	-122.33	1490.00	
50%	3904930410.00	450000.00	3.00	2.25	1910.00	7618.00	1.50	0.00	0.00	3.00	7.00	1560.00	1975.00	0.00	98065.00	47.57	-122.23	1840.00	
75%	7308900490.00	645000.00	4.00	2.50	2550.00	10685.00	2.00	0.00	0.00	4.00	8.00	2210.00	1997.00	0.00	98118.00	47.68	-122.12	2360.00	1
max	9900000190.00	7700000.00	33.00	8.00	13540.00	1651359.00	3.50	1.00	4.00	5.00	13.00	9410.00	2015.00	2015.00	98199.00	47.78	-121.31	6210.00	87

In [4]:
```
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
```

Narrowing down our price range

In [5]:
```
std = df.price.std()
print('std: ',std)
mean = df.price.mean()
print('mean: ', mean)
std_1 = mean + std
std_1m = mean - std
print('mean +1 std: ',std_1)
print('mean -1 std: ',std_1m)
```

```
std:  367368.1401013945
mean:  540296.5735055795
mean +1 std:  907664.713606974
mean -1 std:  172928.433404185
```

In [6]:
```
df = df.loc[(df['price']<std_1) & (df['price']>std_1m)]
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 19205 entries, 0 to 21596
Data columns (total 21 columns):
id               19205 non-null int64
date             19205 non-null object
price            19205 non-null float64
bedrooms         19205 non-null int64
bathrooms        19205 non-null float64
sqft_living      19205 non-null int64
sqft_lot         19205 non-null int64
floors           19205 non-null float64
waterfront       17082 non-null float64
view             19149 non-null float64
condition        19205 non-null int64
grade            19205 non-null int64
sqft_above       19205 non-null int64
sqft_basement    19205 non-null object
yr_built         19205 non-null int64
yr_renovated     15798 non-null float64
zipcode          19205 non-null int64
lat              19205 non-null float64
long             19205 non-null float64
sqft_living15    19205 non-null int64
sqft_lot15       19205 non-null int64
dtypes: float64(8), int64(11), object(2)
memory usage: 3.2+ MB
```

In [7]:
```
#dropping unnecessary columns
drop = ['id','date', 'yr_built', 'bedrooms', 'bathrooms','sqft_lot', 'floors', 'waterfront', 'view', 'condition', 'sqft_above', 'sqft_basement', 'yr_built', 'yr_
renovated', 'zipcode', 'sqft_living15', 'sqft_lot15']
df = df.drop(columns = drop, axis=1)
```

In [8]:
```
df.columns
```

Out[8]:
```
Index(['price', 'sqft_living', 'grade', 'lat', 'long'], dtype='object')
```

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

Out[9]:
```
price          0
sqft_living    0
grade          0
lat            0
long           0
dtype: int64
```

King County Parks

In [10]:
```
# importing park data
# reading the csv file
king_parks = pd.read_csv('data/ParkAddresses_wLatLong.csv', index_col='ID')
# previewing the DataFrame
king_parks.head()
```

Out[10]:

ID	Address	Combined	Lat	Long
0.00	Auburn Black Diamond Rd and SE Green Valley Rd...	47.301182311345315, -122.17491469179195	47.30	-122.17
1.00	NE 165th St and 179th Pl NE Redmond WA 98072	47.74702351303733, -122.09810603412113	47.75	-122.10
2.00	NaN	NaN	nan	nan
3.00	NE 138th and Juanita Drive NE Kirkland WA 98028	47.72417796430824, -122.2384511052857	47.72	-122.24
4.00	S 284th Pl and 37th Ave S Federal Way WA 98003	47.34814028865613, -122.2811067550002	47.35	-122.28

In [11]:
```
#create function to find distances between all points in DF and return matrix
def find_distance(dataframe):
    """
    Calculates distance between points of interest and houses.

    Generates a distance matrix for distances between houses and points of interest.
    Calculates distance from each point in dataframe (df) to point of interest.
    Converts latitude and longitude to radians in order to calculate distance.
    Returns values as kilometers.

    Parameters:
    dataframe (Pandas DataFrame object): user input name of Pandas DataFrame.

    Returns:
    Matrix of distances.

    """
    dist = sklearn.neighbors.DistanceMetric.get_metric('haversine')

    #convert lat and long to radians
    dataframe[['lat_radians','long_radians']] = (np.radians(dataframe.loc[:,['Lat','Long']]))

    #create list matrix (results in km)
    dist_matrix = (dist.pairwise
    (df[['lat_radians_A','long_radians_A']],
     dataframe[['lat_radians','long_radians']])*6371)

    #return a matrix DataFrame
    return pd.DataFrame(dist_matrix)
```

In [12]:
```
#convert lat and long to radians in housing data
df[['lat_radians_A','long_radians_A']] = (np.radians(df.loc[:,['lat','long']]))
```

In [13]:
```
park_matrix = find_distance(king_parks)
```

In [14]:
```
#find min distance in each row
park_min_matrix = park_matrix.where(park_matrix.values == park_matrix.min(
    axis=1)[:,None]).drop_duplicates()
```

In [15]:
```
#create a new column with only min distance and remove the rest
park_min_matrix['min_dist_park'] = park_min_matrix[park_min_matrix.columns[0:]].apply(
    lambda x: ','.join(x.dropna().astype(str)),
    axis=1)
nearest_park = park_min_matrix['min_dist_park']
```

In [16]:
```
df = df.join(nearest_park)
```

In [17]:
```
df.head()
```

Out[17]:

	price	sqft_living	grade	lat	long	lat_radians_A	long_radians_A	min_dist_park
0	221900.00	1180	7	47.51	-122.26	0.83	-2.13	2.038307293948517
1	538000.00	2570	7	47.72	-122.32	0.83	-2.13	5.052057710119824
2	180000.00	770	6	47.74	-122.23	0.83	-2.13	1.337990461344532
3	604000.00	1960	7	47.52	-122.39	0.83	-2.14	2.448557143643891
4	510000.00	1680	8	47.62	-122.05	0.83	-2.13	2.6728316989804743

In [18]:
```
df['min_dist_park']= df['min_dist_park'].astype('float64')
```

King County Top Schools

In [19]:
```
# importing school data
# for entire data obtaining process, please see other notebook

# reading the csv file
top_schools_df = pd.read_csv('data/top_schools.csv')
# previewing the DataFrame
top_schools_df.head()
```

Out[19]:

	Unnamed: 0	year	ncessch	school_name	state_name	lea_name	zip_location	latitude	longitude	county_code	school_level	school_type
0	43	2015	530039000058	Ardmore Elementary School	Washington	Bellevue School District	98008	47.64	-122.12	53033.00	Primary	Regular school
1	44	2015	530039000060	Bellevue High School	Washington	Bellevue School District	98004	47.60	-122.20	53033.00	High	Regular school
2	45	2015	530039000062	Bennett Elementary School	Washington	Bellevue School District	98008	47.62	-122.10	53033.00	Primary	Regular school
3	46	2015	530039000063	Cherry Crest Elementary School	Washington	Bellevue School District	98005	47.64	-122.17	53033.00	Primary	Regular school
4	47	2015	530039000064	Chinook Middle School	Washington	Bellevue School District	98004	47.63	-122.21	53033.00	Middle	Regular school

In [20]:
```
top_schools_df.drop(columns = 'Unnamed: 0', axis=1, inplace=True)
```

In [21]:
```
top_schools_df.head()
```
Out[21]:

	year	ncessch	school_name	state_name	lea_name	zip_location	latitude	longitude	county_code	school_level	school_type
0	2015	530039000058	Ardmore Elementary School	Washington	Bellevue School District	98008	47.64	-122.12	53033.00	Primary	Regular school
1	2015	530039000060	Bellevue High School	Washington	Bellevue School District	98004	47.60	-122.20	53033.00	High	Regular school
2	2015	530039000062	Bennett Elementary School	Washington	Bellevue School District	98008	47.62	-122.10	53033.00	Primary	Regular school
3	2015	530039000063	Cherry Crest Elementary School	Washington	Bellevue School District	98005	47.64	-122.17	53033.00	Primary	Regular school
4	2015	530039000064	Chinook Middle School	Washington	Bellevue School District	98004	47.63	-122.21	53033.00	Middle	Regular school

In [22]:
```
#geographic distance calculator
#function that identifies the distance between a point of interest and house
def distance_to(point_of_interest):
    """
    Calculates distance between point of interest and a house.

    Takes in coordinates for point of interest as latitude and longitude.
    Calculates distance from each point in dataframe (df) to point of interest.
    Uses haversine formula to calculate distance and return as kilometers.
    Can set distances as new column of dataframe by using df['new_column']=distance_to(point_of_interest).

    Parameters:
    point_of_interest (float): user input coordinates (latitude,longitude).

    Returns:
    Distances in kilometers, using haversine formula.

    """
    distance = df[['lat','long']].apply(lambda x: hs.haversine(x.tolist(), point_of_interest), axis=1)
    return distance
```
In [23]:
```
top_school_coordinates = []
x = round(top_schools_df.latitude, 2)
y = round(top_schools_df.longitude, 2)
top_school_coordinates = list(zip(x,y))
```
In [24]:
```
for i in range(len(top_school_coordinates)):
    df[f'top_school_{i}'] = distance_to(top_school_coordinates[i])

top_school_cols = []
for i in range(len(top_school_coordinates)):
    top_school_cols.append(f'top_school_{i}')
    df['closest_distance_to_top_school'] = df[top_school_cols].min(axis=1)
```
In [25]:
```
df.drop(columns = top_school_cols, axis=1, inplace=True)
rad_cols = ['lat_radians_A', 'long_radians_A']
df.drop(columns=rad_cols, axis=1, inplace=True)
df.head()
```
Out[25]:

	price	sqft_living	grade	lat	long	min_dist_park	closest_distance_to_top_school
0	221900.00	1180	7	47.51	-122.26	2.04	0.26
1	538000.00	2570	7	47.72	-122.32	5.05	0.68
2	180000.00	770	6	47.74	-122.23	1.34	2.00
3	604000.00	1960	7	47.52	-122.39	2.45	1.73
4	510000.00	1680	8	47.62	-122.05	2.67	1.18

King County Top 10 Coffee Shops

In [26]:
```
def get_keys(path):
    """Retrieves API key from files as api_key."""
    with open(path) as f:
        return json.load(f)

keys = get_keys("/Users/dtunnicliffe/.secret/yelp_api.json")
api_key = keys['api_key']

term = 'coffee'
location = 'King County, WA'
SEARCH_LIMIT = 10
espresso = pd.DataFrame([])
def yelp(term, location, SEARCH_LIMIT):
    """
    Creates a new dataframe of information retrieved from yelp API query.

    Searches businesses and returns top results based on criteria provided.
    Makes API call as if searching on yelp.
    Returns relevant information for businesses such as name, location, price range, and rating out of 5 stars.

    Parameters:
    term (str): user input term to search for.
    location (str): user input city, state, or zip code to search within.
    SEARCH_LIMIT (int): user input number of results to return.

    Returns:
    New dataframe populated with requested information.

    """
    global espresso
    url = 'https://api.yelp.com/v3/businesses/search'
    headers = {
    'Authorization': f'Bearer {api_key}',
    }
    url_params = {
    'term': term.replace(' ', '+'),
    'location': location.replace(' ', '+'),
    'limit': SEARCH_LIMIT,
    'sort_by': 'rating'
    }
    response = requests.get(url, headers=headers, params=url_params)
    df_temp = pd.DataFrame.from_dict(response.json()['businesses'])
    espresso = espresso.append(df_temp)
    return espresso
```

In [27]:
```python
espresso = yelp(term, location, SEARCH_LIMIT)
```

In [28]:
```python
espresso.head()
```

Out[28]:

	id	alias	name	image_url	is_closed	url	review_count	categories	rating	coordinates	transactions	pric
0	S6CXIQ5KrMpTPZf1eNMa2w	five-stones-coffee-company-redmond	Five Stones Coffee Company	https://s3-media3.fl.yelpcdn.com/bphoto/OmzSO6...	False	https://www.yelp.com/biz/five-stones-coffee-co...	415	[{'alias': 'coffee', 'title': 'Coffee & Tea'}]	4.50	{'latitude': 47.67583, 'longitude': -122.12471}	[delivery]	$
1	v7xfqk9f7N8A98AQ2kddWg	anchorhead-coffee-bellevue-3	Anchorhead Coffee	https://s3-media3.fl.yelpcdn.com/bphoto/ErNP7S...	False	https://www.yelp.com/biz/anchorhead-coffee-bel...	70	[{'alias': 'coffeeroasteries', 'title': 'Coffe...	4.50	{'latitude': 47.61509, 'longitude': -122.194026}	[delivery]	Na
2	t2DOOFh-oJLddtpxbVlDrQ	huxdotter-coffee-north-bend	Huxdotter Coffee	https://s3-media3.fl.yelpcdn.com/bphoto/MdLMtc...	False	https://www.yelp.com/biz/huxdotter-coffee-nort...	83	[{'alias': 'coffee', 'title': 'Coffee & Tea'},...	4.50	{'latitude': 47.493445, 'longitude': -121.787556}	[]	
3	-MzbuOLr2kAoqlQY8w7ECA	pioneer-coffee-north-bend-north-bend	Pioneer Coffee - North Bend	https://s3-media3.fl.yelpcdn.com/bphoto/5SpY3i...	False	https://www.yelp.com/biz/pioneer-coffee-north-...	75	[{'alias': 'coffeeroasteries', 'title': 'Coffe...	4.50	{'latitude': 47.4956976441376, 'longitude': -1...	[]	
4	oUk6IZAFQ37R5OK0etWocg	the-north-bend-bakery-north-bend	The North Bend Bakery	https://s3-media1.fl.yelpcdn.com/bphoto/weMpOC...	False	https://www.yelp.com/biz/the-north-bend-bakery...	158	[{'alias': 'bakeries', 'title': 'Bakeries'}, {...	4.00	{'latitude': 47.4950561, 'longitude': -121.786...	[]	

In [29]:
```python
great_coffee_coordinates = []
x = [round(coordinate['latitude'], 2) for coordinate in espresso['coordinates']]
y = [round(coordinate['longitude'], 2) for coordinate in espresso['coordinates']]
great_coffee_coordinates = list(zip(x,y))
```

In [30]:
```python
for i in range(len(great_coffee_coordinates)):
    df[f'great_coffee_{i}'] = distance_to(great_coffee_coordinates[i])

great_coffee_cols = []
for i in range(len(great_coffee_coordinates)):
    great_coffee_cols.append(f'great_coffee_{i}')
    df['closest_distance_to_great_coffee'] = df[great_coffee_cols].min(axis=1)
```

In [31]:
```python
#dropping unnecessary columns
df = df.drop(columns = great_coffee_cols, axis=1)
df.head()
```

Out[31]:

	price	sqft_living	grade	lat	long	min_dist_park	closest_distance_to_top_school	closest_distance_to_great_coffee
0	221900.00	1180	7	47.51	-122.26	2.04	0.26	8.39
1	538000.00	2570	7	47.72	-122.32	5.05	0.68	14.81
2	180000.00	770	6	47.74	-122.23	1.34	2.00	10.63
3	604000.00	1960	7	47.52	-122.39	2.45	1.73	15.80
4	510000.00	1680	8	47.62	-122.05	2.67	1.18	8.55

King County Churches of Scientology

In [32]:
```python
#locations pulled from scientology-seattle.org
church_of_scientology_mission = (47.818100, -122.315430)
church_of_scientology_washington = (47.622380, -122.361020)
church_of_scientology_life_improvement_center = (47.615060, -122.327580)
```

In [33]:
```python
#function that identifies the distance between a point of interest and house
def distance_to(point_of_interest):
    """
    Calculates distance between point of interest and a house.

    Takes in coordinates for point of interest as latitude and longitude.
    Calculates distance from each point in dataframe (df) to point of interest.
    Uses haversine formula to calculate distance and return as kilometers.
    Can set distances as new column of dataframe by using df['new_column']=distance_to(point_of_interest).

    Parameters:
    point_of_interest (float): user input coordinates (latitude,longitude).

    Returns:
    Distances in kilometers, using haversine formula.

    """
    distance = df[['lat','long']].apply(lambda x: hs.haversine(x.tolist(), point_of_interest), axis=1)
    return distance
```

In [34]:
```python
#creating new columns of distances from houses to point of interest
df['distance_to_scientology_m'] = distance_to(church_of_scientology_mission)
df['distance_to_scientology_w'] = distance_to(church_of_scientology_washington)
df['distance_to_scientology_l'] = distance_to(church_of_scientology_life_improvement_center)
df['closest_distance_to_scientology'] = df[['distance_to_scientology_m',
                                            'distance_to_scientology_w',
                                            'distance_to_scientology_l']].min(axis=1)
```

In [35]:
```python
sci_cols = ['distance_to_scientology_m', 'distance_to_scientology_w',
            'distance_to_scientology_l']
df.drop(columns = sci_cols, axis=1, inplace=True)
```

In [36]:
```python
df.head()
```

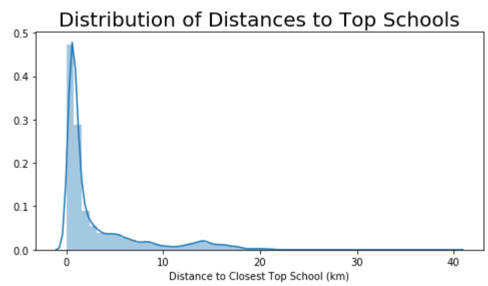
Out[36]:

	price	sqft_living	grade	lat	long	min_dist_park	closest_distance_to_top_school	closest_distance_to_great_coffee	closest_distance_to_scientology
0	221900.00	1180	7	47.51	-122.26	2.04	0.26	8.39	12.71
1	538000.00	2570	7	47.72	-122.32	5.05	0.68	14.81	10.80
2	180000.00	770	6	47.74	-122.23	1.34	2.00	10.63	10.84
3	604000.00	1960	7	47.52	-122.39	2.45	1.73	15.80	11.55
4	510000.00	1680	8	47.62	-122.05	2.67	1.18	8.55	21.18

Log-Transforming Features

In [37]:
```python
plt.figure(figsize=(8,4))
sns.distplot(df['closest_distance_to_top_school'])
plt.title("Distribution of Distances to Top Schools", fontsize=20)
plt.xlabel('Distance to Closest Top School (km)');
print("Skewness:", df['closest_distance_to_top_school'].skew())
print("Kurtosis:", df['closest_distance_to_top_school'].kurt())
```

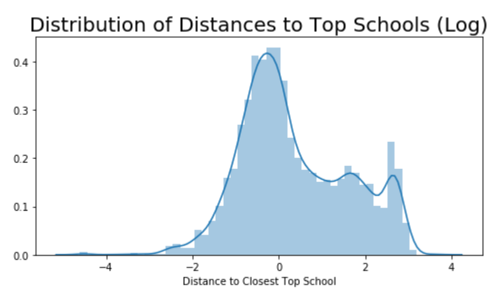
```
Skewness: 2.07081534646944
Kurtosis: 4.115792045291801
```



In [38]:
```python
# removing zeroes for log transformation
df.loc[df['closest_distance_to_top_school']==0.00, 'closest_distance_to_top_school']=0.01
#natural log transformation for 'closest_distance_to_top_school'.
df['log_school'] = df['closest_distance_to_top_school'].map(lambda x: np.log(x))
```

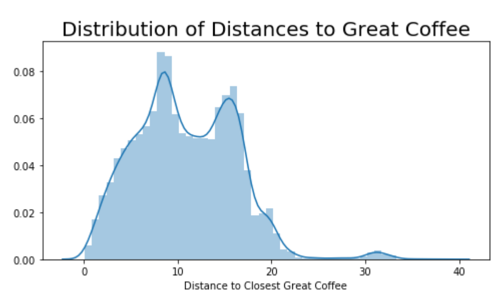
In [39]:
```python
plt.figure(figsize=(8,4))
sns.distplot(df['log_school'])
plt.title("Distribution of Distances to Top Schools (Log)", fontsize=20)
plt.xlabel('Distance to Closest Top School');
print("Skewness:", df['log_school'].skew())
print("Kurtosis:", df['log_school'].kurt())
```

```
Skewness: 0.31498656015781384
Kurtosis: -0.4837932278849535
```



In [40]:
```python
plt.figure(figsize=(8,4))
sns.distplot(df['closest_distance_to_great_coffee'])
plt.title("Distribution of Distances to Great Coffee", fontsize=20)
plt.xlabel('Distance to Closest Great Coffee');
print("Skewness:", df['closest_distance_to_great_coffee'].skew())
print("Kurtosis:", df['closest_distance_to_great_coffee'].kurt())
```

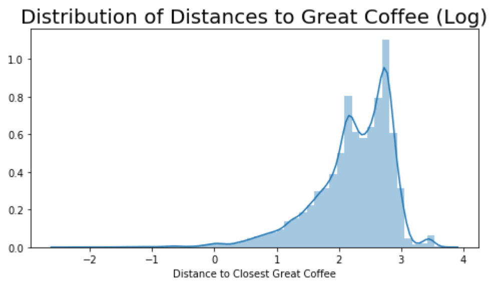
```
Skewness: 0.5463096986202912
Kurtosis: 0.8549832443796928
```



In [41]:
```python
# removing zeroes for log transformation
df.loc[df['closest_distance_to_great_coffee']==0.00, 'closest_distance_to_top_school']=0.01
#natural log transformation for 'closest_distance_to_great_coffee'.
df['log_coffee'] = df['closest_distance_to_great_coffee'].map(lambda x: np.log(x))
```

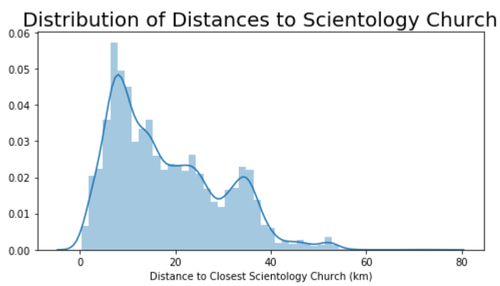
In [42]:
```python
plt.figure(figsize=(8,4))
sns.distplot(df['log_coffee'])
plt.title("Distribution of Distances to Great Coffee (Log)", fontsize=20)
plt.xlabel('Distance to Closest Great Coffee');
print("Skewness:", df['log_coffee'].skew())
print("Kurtosis:", df['log_coffee'].kurt())
```

```
Skewness: -1.3133207595110006
Kurtosis: 2.7702815633450766
```



In [43]:
```python
plt.figure(figsize=(8,4))
sns.distplot(df['closest_distance_to_scientology'])
plt.title("Distribution of Distances to Scientology Church", fontsize=20)
plt.xlabel('Distance to Closest Scientology Church (km)');
print("Skewness:", df['closest_distance_to_scientology'].skew())
print("Kurtosis:", df['closest_distance_to_scientology'].kurt())
```

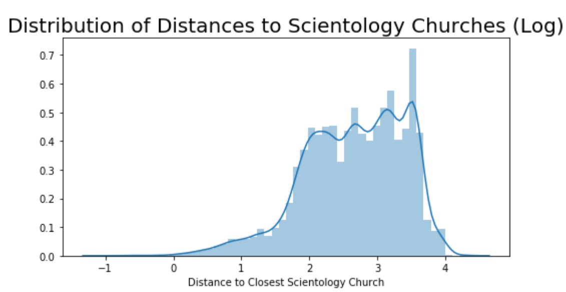
```
Skewness: 0.729624297126709
Kurtosis: -0.13070775209001573
```



In [44]:
```python
# removing zeroes for log transformation
df.loc[df['closest_distance_to_scientology']==0.00, 'closest_distance_to_scientology']=0.01
#natural log transformation for 'closest_distance_to_scientology'.
df['log_scientology'] = df['closest_distance_to_scientology'].map(lambda x: np.log(x))
```

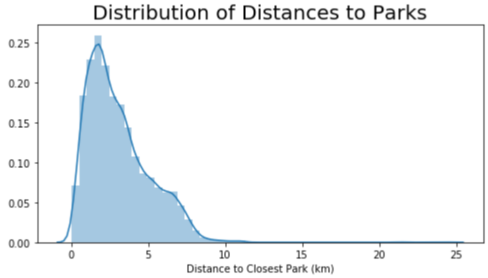
In [45]:
```python
plt.figure(figsize=(8,4))
sns.distplot(df['log_scientology'])
plt.title("Distribution of Distances to Scientology Churches (Log)", fontsize=20)
plt.xlabel('Distance to Closest Scientology Church');
print("Skewness:", df['log_scientology'].skew())
print("Kurtosis:", df['log_scientology'].kurt())
```

```
Skewness: -0.6186336629179573
Kurtosis: 0.16752897590293658
```



```
In [46]: plt.figure(figsize=(8,4))
         sns.distplot(df['min_dist_park'])
         plt.title("Distribution of Distances to Parks", fontsize=20)
         plt.xlabel('Distance to Closest Park (km)');
         print("Skewness:", df['min_dist_park'].skew())
         print("Kurtosis:", df['min_dist_park'].kurt())
```

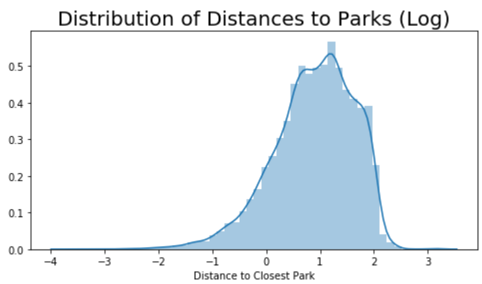
```
Skewness: 1.205427367383708
Kurtosis: 3.9928978255283716
```




```
In [47]: # removing zeroes for log transformation
         df.loc[df['min_dist_park']==0.00, 'min_dist_park']=0.01
         #natural log transformation for 'min_dist_park'.
         df['log_park'] = df['min_dist_park'].map(lambda x: np.log(x))
```

```
In [48]: plt.figure(figsize=(8,4))
         sns.distplot(df['log_park'])
         plt.title("Distribution of Distances to Parks (Log)", fontsize=20)
         plt.xlabel('Distance to Closest Park');
         print("Skewness:", df['log_park'].skew())
         print("Kurtosis:", df['log_park'].kurt())
```

```
Skewness: -0.697074959578087
Kurtosis: 0.6535881306866189
```




```
In [49]: df.isnull().sum()
```

```
Out[49]: price                                 0
         sqft_living                           0
         grade                                 0
         lat                                   0
         long                                  0
         min_dist_park                      2712
         closest_distance_to_top_school        0
         closest_distance_to_great_coffee      0
         closest_distance_to_scientology       0
         log_school                            0
         log_coffee                            0
         log_scientology                       0
         log_park                           2712
         dtype: int64
```

```
In [50]: df.dropna(inplace=True)
         df.isnull().sum()
```

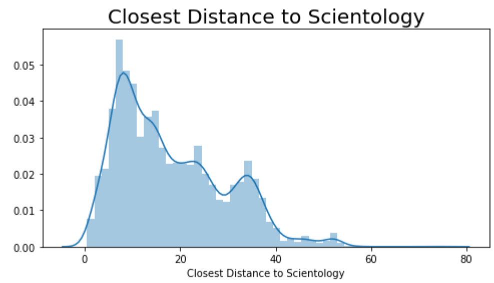
```
Out[50]: price                               0
         sqft_living                         0
         grade                               0
         lat                                 0
         long                                0
         min_dist_park                       0
         closest_distance_to_top_school      0
         closest_distance_to_great_coffee    0
         closest_distance_to_scientology     0
         log_school                          0
         log_coffee                          0
         log_scientology                     0
         log_park                            0
         dtype: int64
```

```
In [51]: # saving copy of DataFrame as csv file
         #df.to_csv('./data/all_features_with_logs.csv')
```

Quantile Tranformation

In [54]:
```
plt.figure(figsize=(8,4))
sns.distplot(df['closest_distance_to_scientology'])
plt.title("Closest Distance to Scientology", fontsize=20)
plt.xlabel('Closest Distance to Scientology');
print("Skewness:", df['closest_distance_to_scientology'].skew())
print("Kurtosis:", df['closest_distance_to_scientology'].kurt())
```

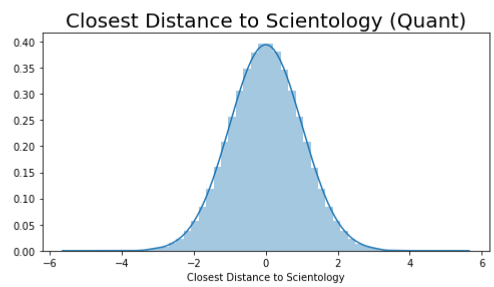
```
Skewness: 0.7554175937501574
Kurtosis: -0.04297248665931219
```



In [55]:
```
from sklearn.preprocessing import QuantileTransformer
qt = QuantileTransformer(output_distribution='normal')
to_transform= ['sqft_living', 'closest_distance_to_great_coffee', 'min_dist_park', 'closest_distance_to_top_school', 'closest_distance_to_scientology', 'price']
df[to_transform] = qt.fit_transform(df[to_transform])
```

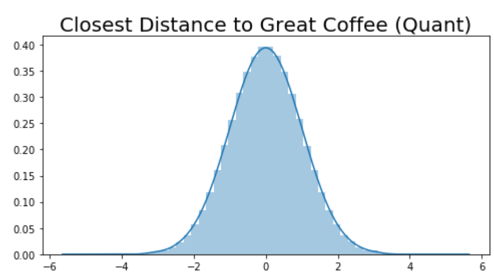
In [56]:
```
plt.figure(figsize=(8,4))
sns.distplot(df['closest_distance_to_scientology'])
plt.title("Closest Distance to Scientology (Quant)", fontsize=20)
plt.xlabel('Closest Distance to Scientology');
print("Skewness:", df['closest_distance_to_scientology'].skew())
print("Kurtosis:", df['closest_distance_to_scientology'].kurt())
```

```
Skewness: 0.003628284074277272
Kurtosis: 0.04166152893410047
```

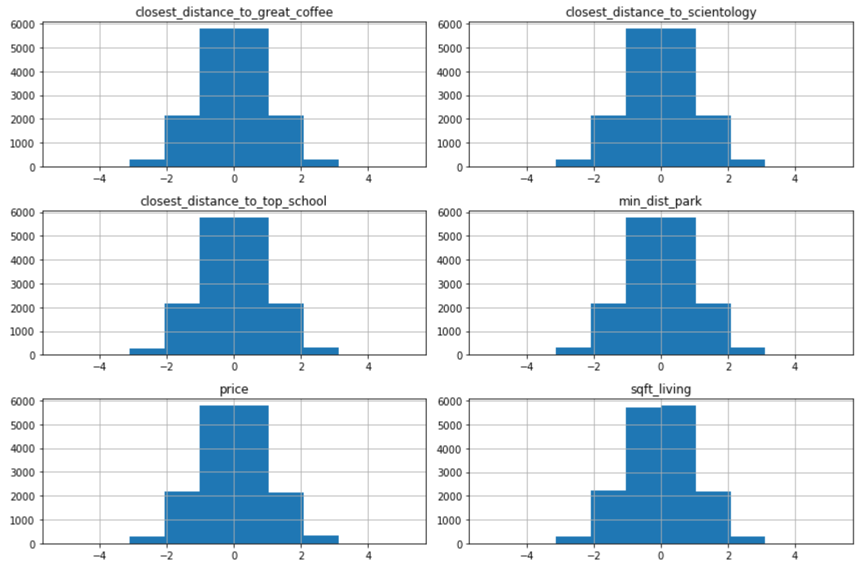


In [57]:
```
plt.figure(figsize=(8,4))
sns.distplot(df['closest_distance_to_great_coffee'])
plt.title("Closest Distance to Great Coffee (Quant)", fontsize=20)
plt.xlabel('Closest Distance to Great Coffee');
print("Skewness:", df['closest_distance_to_great_coffee'].skew())
print("Kurtosis:", df['closest_distance_to_great_coffee'].kurt())
```

```
Skewness: -0.0020929964852480346
Kurtosis: 0.023398255870954454
```



In [58]:
```
df[['sqft_living', 'closest_distance_to_great_coffee', 'min_dist_park', 'closest_distance_to_top_school', 'closest_distance_to_scientology', 'price']].hist(figsi
ze=(12, 8))
plt.tight_layout();
```



In [59]:
```
grade_dums = pd.get_dummies(df.grade, prefix='grade', drop_first=True)
```

In [60]:
```
df = df.drop(['grade'], axis=1)
df = pd.concat([df, grade_dums], axis=1)
df.head()
```

Out[60]:

	price	sqft_living	lat	long	min_dist_park	closest_distance_to_top_school	closest_distance_to_great_coffee	closest_distance_to_scientology	log_school	log_coffee	...	log_park	grade_4	grade_5	grade_6	grac
0	-1.60	-1.08	47.51	-122.26	-0.31	-1.61	-0.36	-0.24	-1.34	2.13	...	0.71	0	0	0	
1	0.49	0.94	47.72	-122.32	0.92	-0.50	0.65	-0.40	-0.38	2.70	...	1.62	0	0	0	
2	-2.54	-2.14	47.74	-122.23	-0.84	0.36	0.05	-0.39	0.69	2.36	...	0.29	0	0	1	
3	0.78	0.17	47.52	-122.39	-0.08	0.30	0.89	-0.33	0.55	2.76	...	0.90	0	0	0	
4	0.37	-0.22	47.62	-122.05	0.02	0.08	-0.32	0.37	0.16	2.15	...	0.98	0	0	0	

5 rows × 21 columns

In [61]:
```
df['interaction'] = df['closest_distance_to_top_school'] * df['closest_distance_to_scientology']
features = ['sqft_living', 'closest_distance_to_great_coffee', 'min_dist_park', 'closest_distance_to_top_school', 'closest_distance_to_scientology', 'interactio
n', 'grade_4', 'grade_5', 'grade_6', 'grade_7', 'grade_8', 'grade_9', 'grade_10', 'grade_11']
target = ['price']
X = df[features]
y = df[target]

# running an iteration of the model with interaction column and using train_test_split
X_train, X_test, y_train, y_test = train_test_split(X,y, random_state=1)

lm9 = LinearRegression().fit(X_train, y_train)
lm9_preds = lm9.predict(X_test)

print('R^2: ', r2_score(y_test, lm9_preds))
```

```
R^2:  0.6336201486861495
```

By quantile tranforming our data to achieve a more normal distribution, we are able to achieve a higher R2 score.

In [62]:
```
# saving copy of dataframe as csv file
#df.to_csv('./data/all_features_quant_transformed.csv')
```

Price Per Square Foot

While we were happy with the increasing R2 score, we wanted to experiment with a new possibility: making a predictive model for price per square foot, as opposed to just price. By honing on in on this target, our goal was to more accurately predict the value of a home based on our features.

In [63]:
```
# reading the csv file
df = pd.read_csv('data/kc_house_data.csv')
# previewing the DataFrame
df.head()
```

Out[63]:

	id	date	price	bedrooms	bathrooms	sqft_living	sqft_lot	floors	waterfront	view	...	grade	sqft_above	sqft_basement	yr_built	yr_renovated	zipcode	lat	long	sqft_living15	sqft_lot15
0	7129300520	10/13/2014	221900.00	3	1.00	1180	5650	1.00	nan	0.00	...	7	1180	0.0	1955	0.00	98178	47.51	-122.26	1340	5650
1	6414100192	12/9/2014	538000.00	3	2.25	2570	7242	2.00	0.00	0.00	...	7	2170	400.0	1951	1991.00	98125	47.72	-122.32	1690	7639
2	5631500400	2/25/2015	180000.00	2	1.00	770	10000	1.00	0.00	0.00	...	6	770	0.0	1933	nan	98028	47.74	-122.23	2720	8062
3	2487200875	12/9/2014	604000.00	4	3.00	1960	5000	1.00	0.00	0.00	...	7	1050	910.0	1965	0.00	98136	47.52	-122.39	1360	5000
4	1954400510	2/18/2015	510000.00	3	2.00	1680	8080	1.00	0.00	0.00	...	8	1680	0.0	1987	0.00	98074	47.62	-122.05	1800	7503

5 rows × 21 columns

In [64]:
```
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
```

In [65]:
```
# creating price per sqft column
df['price_per_sqft'] = (df['price'] / df['sqft_living'])
df.head()
```

Out[65]:

	id	date	price	bedrooms	bathrooms	sqft_living	sqft_lot	floors	waterfront	view	...	sqft_above	sqft_basement	yr_built	yr_renovated	zipcode	lat	long	sqft_living15	sqft_lot15	price_
0	7129300520	10/13/2014	221900.00	3	1.00	1180	5650	1.00	nan	0.00	...	1180	0.0	1955	0.00	98178	47.51	-122.26	1340	5650	
1	6414100192	12/9/2014	538000.00	3	2.25	2570	7242	2.00	0.00	0.00	...	2170	400.0	1951	1991.00	98125	47.72	-122.32	1690	7639	
2	5631500400	2/25/2015	180000.00	2	1.00	770	10000	1.00	0.00	0.00	...	770	0.0	1933	nan	98028	47.74	-122.23	2720	8062	
3	2487200875	12/9/2014	604000.00	4	3.00	1960	5000	1.00	0.00	0.00	...	1050	910.0	1965	0.00	98136	47.52	-122.39	1360	5000	
4	1954400510	2/18/2015	510000.00	3	2.00	1680	8080	1.00	0.00	0.00	...	1680	0.0	1987	0.00	98074	47.62	-122.05	1800	7503	

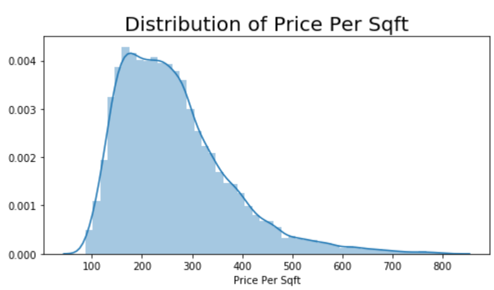
5 rows × 22 columns

In [66]:
```
df.price_per_sqft.describe()
```

Out[66]:
```
count   21597.00
mean      264.14
std       110.00
min        87.59
25%       182.29
50%       244.64
75%       318.33
max       810.14
Name: price_per_sqft, dtype: float64
```

In [67]:
```
plt.figure(figsize=(8,4))
sns.distplot(df['price_per_sqft'])
plt.title("Distribution of Price Per Sqft", fontsize=20)
plt.xlabel('Price Per Sqft');
print("Skewness:", df['price_per_sqft'].skew())
print("Kurtosis:", df['price_per_sqft'].kurt())
```

```
Skewness: 1.2469211620378835
Kurtosis: 2.0993152010383684
```



Narrowing down our data

We opted to use price per square foot as the factor by which to narrow our data. We removed outliers and focused on our main data by filtering for data within 1.5 standard deviations from the mean for price per square foot.

In [68]:
```
# finding the data that lies within 1.5 standard deviations from the mean
std = df.price_per_sqft.std()
print('std: ',std)
mean = df.price_per_sqft.mean()
print('mean: ', mean)
std_1 = mean + std
std_1m = mean - std
std_15 = mean + (1.5*std)
std_15m = mean - (1.5*std)
print('mean +1 std: ',std_1)
print('mean -1 std: ',std_1m)
print('mean +1.5 std: ',std_15)
print('mean -1.5 std: ',std_15m)
```

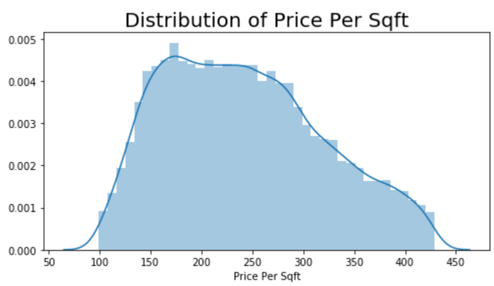
```
std:  110.00006067814525
mean:  264.1433683790251
mean +1 std:  374.14342905717035
mean -1 std:  154.14330770087986
mean +1.5 std:  429.143459396243
mean -1.5 std:  99.14327736180724
```

In [69]:
```
std = df.price_per_sqft.std()
mean = df.price_per_sqft.mean()
std_1 = mean + std
std_1m = mean - std
std_15 = mean + (1.5*std)
std_15m = mean - (1.5*std)
# removing outliers
# focusing on data within 1.5 standard deviations from the mean
df = df.loc[(df['price_per_sqft']<std_15) & (df['price_per_sqft']>std_15m)]
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 19785 entries, 0 to 21596
Data columns (total 22 columns):
id                19785 non-null int64
date              19785 non-null object
price             19785 non-null float64
bedrooms          19785 non-null int64
bathrooms         19785 non-null float64
sqft_living       19785 non-null int64
sqft_lot          19785 non-null int64
floors            19785 non-null float64
waterfront        17586 non-null float64
view              19728 non-null float64
condition         19785 non-null int64
grade             19785 non-null int64
sqft_above        19785 non-null int64
sqft_basement     19785 non-null object
yr_built          19785 non-null int64
yr_renovated      16312 non-null float64
zipcode           19785 non-null int64
lat               19785 non-null float64
long              19785 non-null float64
sqft_living15     19785 non-null int64
sqft_lot15        19785 non-null int64
price_per_sqft    19785 non-null float64
dtypes: float64(9), int64(11), object(2)
memory usage: 3.5+ MB
```

In [70]:
```
plt.figure(figsize=(8,4))
sns.distplot(df['price_per_sqft'])
plt.title("Distribution of Price Per Sqft", fontsize=20)
plt.xlabel('Price Per Sqft');
print("Skewness:", df['price_per_sqft'].skew())
print("Kurtosis:", df['price_per_sqft'].kurt())
```

```
Skewness: 0.37133132146882725
Kurtosis: -0.6982023030383484
```



In [71]:
```
#dropping unnecessary columns
drop = ['id','date', 'yr_built', 'bedrooms', 'bathrooms','sqft_lot', 'floors', 'waterfront', 'view', 'condition', 'sqft_above', 'sqft_basement', 'yr_built', 'yr_
renovated', 'zipcode', 'sqft_living15', 'sqft_lot15']
df = df.drop(columns = drop, axis=1)
```

In [72]:
```
df.columns
```

Out[72]:
```
Index(['price', 'sqft_living', 'grade', 'lat', 'long', 'price_per_sqft'], dtype='object')
```

In [73]:
```
df.isnull().sum()
```

Out[73]:
```
price             0
sqft_living       0
grade             0
lat               0
long              0
price_per_sqft    0
dtype: int64
```

Now that we had all new parameters, we needed to pull in the data again so that it was filtered for outliers based on our new target variable, price per square foot.

King County Parks

In [74]:
```
# importing park data REVISED
# now including only parks (removing forests, natural areas, and trail heads)
# for entire data scraping process, please see other notebook

# reading the csv file
king_parks = pd.read_csv('data/ParkAddresses_Revised_wLatLong.csv', index_col='ID')
# previewing the DataFrame
king_parks.head()
```

Out[74]:

ID	Name	Address	Combined	Lat	Long
0	NaN	NaN	NaN	nan	nan
1	NaN	NaN	NaN	nan	nan
2	NaN	NaN	NaN	nan	nan
3	Big Finn Hill Park	NE 138th and Juanita Drive NE Kirkland WA 98028	47.72417796430824, -122.2384511052857	47.72	-122.24
4	NaN	NaN	NaN	nan	nan

In [75]:
```
king_parks.isnull().sum()
```

Out[75]:
```
Name        85
Address     85
Combined    85
Lat         85
Long        85
dtype: int64
```

In [76]:
```
king_parks.dropna(inplace=True)
```

In [77]:
```
#create function to find distances between all points in DF and return matrix
def find_distance(dataframe):
    """
    Calculates distance between points of interest and houses.

    Generates a distance matrix for distances between houses and points of interest.
    Calculates distance from each point in dataframe (df) to point of interest.
    Converts latitude and longitude to radians in order to calculate distance.
    Returns values as kilometers.

    Parameters:
    dataframe (Pandas DataFrame object): user input name of Pandas DataFrame.

    Returns:
    Matrix of distances.

    """
    dist = sklearn.neighbors.DistanceMetric.get_metric('haversine')

    #convert lat and long to radians
    dataframe[['lat_radians','long_radians']] = (np.radians(dataframe.loc[:,['Lat','Long']]))

    #create list matrix (results in km)
    dist_matrix = (dist.pairwise
    (df[['lat_radians_A','long_radians_A']],
     dataframe[['lat_radians','long_radians']])*6371)

    #return a matrix DataFrame
    return pd.DataFrame(dist_matrix)
```

In [78]:
```
#convert lat and long to radians in housing data
df[['lat_radians_A','long_radians_A']] = (np.radians(df.loc[:,['lat','long']]))
```

In [79]:
```
park_matrix = find_distance(king_parks)
```

In [80]:
```
#find min distance in each row
park_min_matrix = park_matrix.where(park_matrix.values == park_matrix.min(
    axis=1)[:,None]).drop_duplicates()
```

In [81]:
```
#create a new column with only min distance and remove the rest
park_min_matrix['min_dist_park'] = park_min_matrix[park_min_matrix.columns[0:]].apply(
    lambda x: ','.join(x.dropna().astype(str)),
    axis=1)
nearest_park = park_min_matrix['min_dist_park']
```

In [82]:
```
df = df.join(nearest_park)
```

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

Out[83]:

	price	sqft_living	grade	lat	long	price_per_sqft	lat_radians_A	long_radians_A	min_dist_park
0	221900.00	1180	7	47.51	-122.26	188.05	0.83	-2.13	2.038307293948517
1	538000.00	2570	7	47.72	-122.32	209.34	0.83	-2.13	5.6653668000626025
2	180000.00	770	6	47.74	-122.23	233.77	0.83	-2.13	1.337990461344532
3	604000.00	1960	7	47.52	-122.39	308.16	0.83	-2.14	2.448557143643891
4	510000.00	1680	8	47.62	-122.05	303.57	0.83	-2.13	3.723027946782503

In [84]:
```
df['min_dist_park']= df['min_dist_park'].astype('float64')
```

King County Top Schools

In [85]:
```
# importing school data
# for entire data obtaining process, please see other notebook

# reading the csv file
top_schools_df = pd.read_csv('data/top_schools.csv')
# previewing the DataFrame
top_schools_df.head()
```

Out[85]:

	Unnamed: 0	year	ncessch	school_name	state_name	lea_name	zip_location	latitude	longitude	county_code	school_level	school_type
0	43	2015	530039000058	Ardmore Elementary School	Washington	Bellevue School District	98008	47.64	-122.12	53033.00	Primary	Regular school
1	44	2015	530039000060	Bellevue High School	Washington	Bellevue School District	98004	47.60	-122.20	53033.00	High	Regular school
2	45	2015	530039000062	Bennett Elementary School	Washington	Bellevue School District	98008	47.62	-122.10	53033.00	Primary	Regular school
3	46	2015	530039000063	Cherry Crest Elementary School	Washington	Bellevue School District	98005	47.64	-122.17	53033.00	Primary	Regular school
4	47	2015	530039000064	Chinook Middle School	Washington	Bellevue School District	98004	47.63	-122.21	53033.00	Middle	Regular school

In [86]:
```
top_schools_df.drop(columns = 'Unnamed: 0', axis=1, inplace=True)
```

In [87]:
```
top_schools_df.head()
```

Out[87]:

	year	ncessch	school_name	state_name	lea_name	zip_location	latitude	longitude	county_code	school_level	school_type
0	2015	530039000058	Ardmore Elementary School	Washington	Bellevue School District	98008	47.64	-122.12	53033.00	Primary	Regular school
1	2015	530039000060	Bellevue High School	Washington	Bellevue School District	98004	47.60	-122.20	53033.00	High	Regular school
2	2015	530039000062	Bennett Elementary School	Washington	Bellevue School District	98008	47.62	-122.10	53033.00	Primary	Regular school
3	2015	530039000063	Cherry Crest Elementary School	Washington	Bellevue School District	98005	47.64	-122.17	53033.00	Primary	Regular school
4	2015	530039000064	Chinook Middle School	Washington	Bellevue School District	98004	47.63	-122.21	53033.00	Middle	Regular school

In [88]:
```
top_school_coordinates = []
x = round(top_schools_df.latitude, 2)
y = round(top_schools_df.longitude, 2)
top_school_coordinates = list(zip(x,y))
```

In [89]:
```
for i in range(len(top_school_coordinates)):
    df[f'top_school_{i}'] = distance_to(top_school_coordinates[i])

top_school_cols = []
for i in range(len(top_school_coordinates)):
    top_school_cols.append(f'top_school_{i}')
    df['closest_distance_to_top_school'] = df[top_school_cols].min(axis=1)
```

In [90]:
```
df.drop(columns = top_school_cols, axis=1, inplace=True)
rad_cols = ['lat_radians_A', 'long_radians_A']
df.drop(columns=rad_cols, axis=1, inplace=True)
df.head()
```

Out[90]:

	price	sqft_living	grade	lat	long	price_per_sqft	min_dist_park	closest_distance_to_top_school
0	221900.00	1180	7	47.51	-122.26	188.05	2.04	0.26
1	538000.00	2570	7	47.72	-122.32	209.34	5.67	0.68
2	180000.00	770	6	47.74	-122.23	233.77	1.34	2.00
3	604000.00	1960	7	47.52	-122.39	308.16	2.45	1.73
4	510000.00	1680	8	47.62	-122.05	303.57	3.72	1.18

King County Top 10 Coffee Shops

In [91]:
```
def get_keys(path):
    """Retrieves API key from files as api_key."""
    with open(path) as f:
        return json.load(f)

keys = get_keys("/Users/dtunnicliffe/.secret/yelp_api.json")
api_key = keys['api_key']

term = 'coffee'
location = 'King County, WA'
SEARCH_LIMIT = 10
espresso = pd.DataFrame([])
def yelp(term, location, SEARCH_LIMIT):
    """
    Creates a new dataframe of information retrieved from yelp API query.

    Searches businesses and returns top results based on criteria provided.
    Makes API call as if searching on yelp.
    Returns relevant information for businesses such as name, location, price range, and rating out of 5 stars.

    Parameters:
    term (str): user input term to search for.
    location (str): user input city, state, or zip code to search within.
    SEARCH_LIMIT (int): user input number of results to return.

    Returns:
    New dataframe populated with requested information.

    """
    global espresso
    url = 'https://api.yelp.com/v3/businesses/search'
    headers = {
    'Authorization': f'Bearer {api_key}',
    }
    url_params = {
    'term': term.replace(' ', '+'),
    'location': location.replace(' ', '+'),
    'limit': SEARCH_LIMIT,
    'sort_by': 'rating'
    }
    response = requests.get(url, headers=headers, params=url_params)
    df_temp = pd.DataFrame.from_dict(response.json()['businesses'])
    espresso = espresso.append(df_temp)
    return espresso
```

In [92]:
```python
espresso = yelp(term, location, SEARCH_LIMIT)
```

In [93]:
```python
espresso.head()
```

Out[93]:

	id	alias	name	image_url	is_closed	url	review_count	categories	rating	coordinates	transactions	pric
0	S6CXIQ5KrMpTPZf1eNMa2w	five-stones-coffee-company-redmond	Five Stones Coffee Company	https://s3-media3.fl.yelpcdn.com/bphoto/OmzSO6...	False	https://www.yelp.com/biz/five-stones-coffee-co...	415	[{'alias': 'coffee', 'title': 'Coffee & Tea'}]	4.50	{'latitude': 47.67583, 'longitude': -122.12471}	[delivery]	$
1	v7xfqk9f7N8A98AQ2kddWg	anchorhead-coffee-bellevue-3	Anchorhead Coffee	https://s3-media3.fl.yelpcdn.com/bphoto/ErNP7S...	False	https://www.yelp.com/biz/anchorhead-coffee-bel...	70	[{'alias': 'coffeeroasteries', 'title': 'Coffe...	4.50	{'latitude': 47.61509, 'longitude': -122.194026}	[delivery]	Na
2	t2DOOFh-oJLddtpxbVlDrQ	huxdotter-coffee-north-bend	Huxdotter Coffee	https://s3-media3.fl.yelpcdn.com/bphoto/MdLMtc...	False	https://www.yelp.com/biz/huxdotter-coffee-nort...	83	[{'alias': 'coffee', 'title': 'Coffee & Tea'},...	4.50	{'latitude': 47.493445, 'longitude': -121.787556}	[]	
3	-MzbuOLr2kAoqlQY8w7ECA	pioneer-coffee-north-bend-north-bend	Pioneer Coffee - North Bend	https://s3-media3.fl.yelpcdn.com/bphoto/5SpY3i...	False	https://www.yelp.com/biz/pioneer-coffee-north-...	75	[{'alias': 'coffeeroasteries', 'title': 'Coffe...	4.50	{'latitude': 47.4956976441376, 'longitude': -1...	[]	
4	oUk6IZAFQ37R5OK0etWocg	the-north-bend-bakery-north-bend	The North Bend Bakery	https://s3-media1.fl.yelpcdn.com/bphoto/weMpOC...	False	https://www.yelp.com/biz/the-north-bend-bakery...	158	[{'alias': 'bakeries', 'title': 'Bakeries'}, {...	4.00	{'latitude': 47.4950561, 'longitude': -121.786...	[]	

In [94]:
```python
great_coffee_coordinates = []
x = [round(coordinate['latitude'], 2) for coordinate in espresso['coordinates']]
y = [round(coordinate['longitude'], 2) for coordinate in espresso['coordinates']]
great_coffee_coordinates = list(zip(x,y))
```

In [95]:
```python
for i in range(len(great_coffee_coordinates)):
    df[f'great_coffee_{i}'] = distance_to(great_coffee_coordinates[i])

great_coffee_cols = []
for i in range(len(great_coffee_coordinates)):
    great_coffee_cols.append(f'great_coffee_{i}')
    df['closest_distance_to_great_coffee'] = df[great_coffee_cols].min(axis=1)
```

In [96]:
```python
#dropping unnecessary columns
df = df.drop(columns = great_coffee_cols, axis=1)
df.head()
```

Out[96]:

	price	sqft_living	grade	lat	long	price_per_sqft	min_dist_park	closest_distance_to_top_school	closest_distance_to_great_coffee
0	221900.00	1180	7	47.51	-122.26	188.05	2.04	0.26	8.39
1	538000.00	2570	7	47.72	-122.32	209.34	5.67	0.68	14.81
2	180000.00	770	6	47.74	-122.23	233.77	1.34	2.00	10.63
3	604000.00	1960	7	47.52	-122.39	308.16	2.45	1.73	15.80
4	510000.00	1680	8	47.62	-122.05	303.57	3.72	1.18	8.55

King County Churches of Scientology

In [97]:
```python
#locations pulled from scientology-seattle.org
church_of_scientology_mission = (47.818100, -122.315430)
church_of_scientology_washington = (47.622380, -122.361020)
church_of_scientology_life_improvement_center = (47.615060, -122.327580)
```

In [98]:
```python
#creating new columns of distances from houses to point of interest
df['distance_to_scientology_m'] = distance_to(church_of_scientology_mission)
df['distance_to_scientology_w'] = distance_to(church_of_scientology_washington)
df['distance_to_scientology_l'] = distance_to(church_of_scientology_life_improvement_center)
df['closest_distance_to_scientology'] = df[['distance_to_scientology_m',
                                            'distance_to_scientology_w',
                                            'distance_to_scientology_l']].min(axis=1)
```

In [99]:
```python
sci_cols = ['distance_to_scientology_m', 'distance_to_scientology_w',
            'distance_to_scientology_l']
df.drop(columns = sci_cols, axis=1, inplace=True)
```

In [100]:
```python
df.head()
```

Out[100]:

	price	sqft_living	grade	lat	long	price_per_sqft	min_dist_park	closest_distance_to_top_school	closest_distance_to_great_coffee	closest_distance_to_scientology
0	221900.00	1180	7	47.51	-122.26	188.05	2.04	0.26	8.39	12.71
1	538000.00	2570	7	47.72	-122.32	209.34	5.67	0.68	14.81	10.80
2	180000.00	770	6	47.74	-122.23	233.77	1.34	2.00	10.63	10.84
3	604000.00	1960	7	47.52	-122.39	308.16	2.45	1.73	15.80	11.55
4	510000.00	1680	8	47.62	-122.05	303.57	3.72	1.18	8.55	21.18

Quantile Transformation

In [101]:
```
df.isnull().sum()
```

Out[101]:
```
price                                0
sqft_living                          0
grade                                0
lat                                  0
long                                 0
price_per_sqft                       0
min_dist_park                     2290
closest_distance_to_top_school       0
closest_distance_to_great_coffee     0
closest_distance_to_scientology      0
dtype: int64
```

In [102]:
```
df.dropna(inplace=True)
```

In [103]:
```
df.corr()
```

Out[103]:

	price	sqft_living	grade	lat	long	price_per_sqft	min_dist_park	closest_distance_to_top_school	closest_distance_to_great_coffee	closest_distance_to_scientology
price	1.00	0.76	0.71	0.37	0.07	0.52	-0.01	-0.35	-0.22	-0.30
sqft_living	0.76	1.00	0.76	0.08	0.22	-0.10	-0.00	-0.09	-0.17	0.04
grade	0.71	0.76	1.00	0.11	0.22	0.12	-0.01	-0.10	-0.19	0.03
lat	0.37	0.08	0.11	1.00	-0.10	0.54	-0.01	-0.66	-0.18	-0.72
long	0.07	0.22	0.22	-0.10	1.00	-0.18	-0.01	0.01	-0.38	0.63
price_per_sqft	0.52	-0.10	0.12	0.54	-0.18	1.00	-0.00	-0.50	-0.10	-0.55
min_dist_park	-0.01	-0.00	-0.01	-0.01	-0.01	-0.00	1.00	0.01	-0.01	-0.00
closest_distance_to_top_school	-0.35	-0.09	-0.10	-0.66	0.01	-0.50	0.01	1.00	0.34	0.66
closest_distance_to_great_coffee	-0.22	-0.17	-0.19	-0.18	-0.38	-0.10	-0.01	0.34	1.00	0.11
closest_distance_to_scientology	-0.30	0.04	0.03	-0.72	0.63	-0.55	-0.00	0.66	0.11	1.00

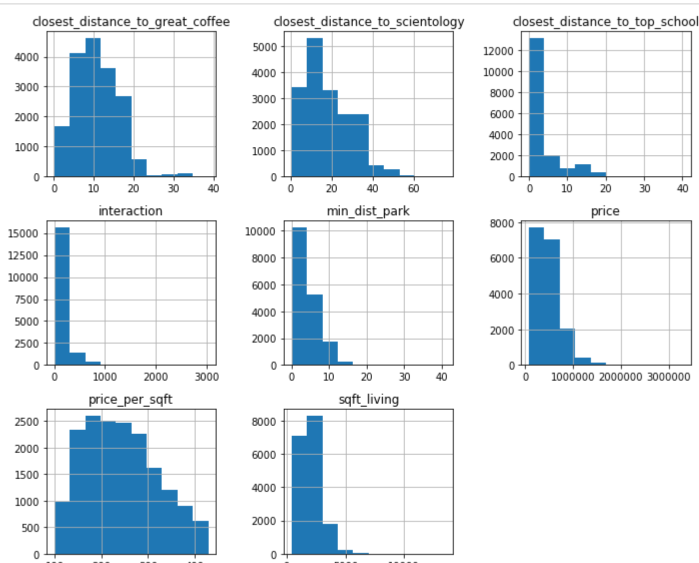
Since closest distance to top school and closest distance to scientology have multicolinearity, creating 'interaction' column to account for this relationship.

In [104]:
```
df['interaction'] = df['closest_distance_to_top_school'] * df['closest_distance_to_scientology']
df.head()
```

Out[104]:

	price	sqft_living	grade	lat	long	price_per_sqft	min_dist_park	closest_distance_to_top_school	closest_distance_to_great_coffee	closest_distance_to_scientology	interaction
0	221900.00	1180	7	47.51	-122.26	188.05	2.04	0.26	8.39	12.71	3.33
1	538000.00	2570	7	47.72	-122.32	209.34	5.67	0.68	14.81	10.80	7.37
2	180000.00	770	6	47.74	-122.23	233.77	1.34	2.00	10.63	10.84	21.71
3	604000.00	1960	7	47.52	-122.39	308.16	2.45	1.73	15.80	11.55	19.97
4	510000.00	1680	8	47.62	-122.05	303.57	3.72	1.18	8.55	21.18	24.98

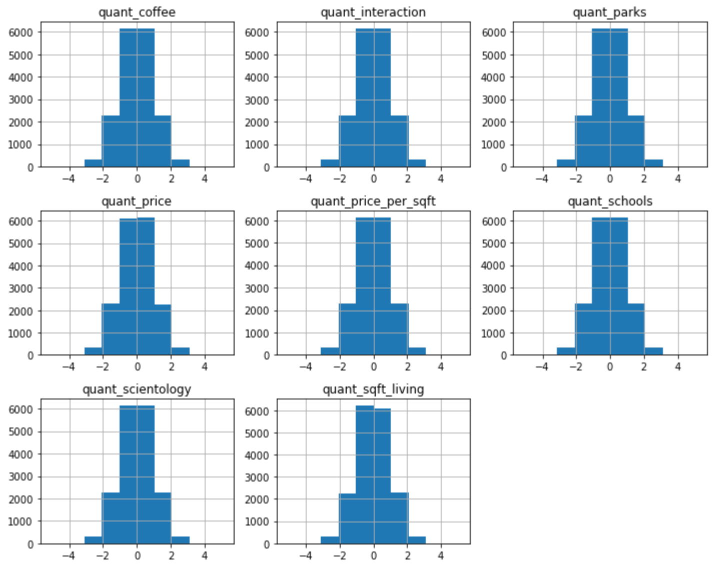
In [105]:
```
df[['price_per_sqft', 'sqft_living', 'closest_distance_to_great_coffee', 'min_dist_park', 'closest_distance_to_top_school', 'closest_distance_to_scientology', 'price', 'interaction']].hist(figsize=(10,8))
plt.tight_layout();
```



Our features and target do not illustrate normal distrubtions.

In [106]:
```
# quantile-transforming our features and target
from sklearn.preprocessing import QuantileTransformer
qt = QuantileTransformer(output_distribution='normal')
df['quant_sqft_living'] = qt.fit_transform(df[['sqft_living']])
df['quant_coffee'] = qt.fit_transform(df[['closest_distance_to_great_coffee']])
df['quant_parks'] = qt.fit_transform(df[['min_dist_park']])
df['quant_schools'] = qt.fit_transform(df[['closest_distance_to_top_school']])
df['quant_scientology'] = qt.fit_transform(df[['closest_distance_to_scientology']])
df['quant_price'] = qt.fit_transform(df[['price']])
df['quant_price_per_sqft'] = qt.fit_transform(df[['price_per_sqft']])
df['quant_interaction'] = qt.fit_transform(df[['interaction']])
```

```
In [107]: df[['quant_sqft_living', 'quant_coffee', 'quant_parks', 'quant_schools', 'quant_scientology', 'quant_price', 'quant_price_per_sqft', 'quant_interaction' ]].hist(
          figsize=(10, 8))
          plt.tight_layout();
```



Our quantile transformation led to a much more normal distribution for our features and target.

```
In [108]: grade_dums = pd.get_dummies(df.grade, prefix='grade', drop_first=True)
```

```
In [109]: df = df.drop(['grade'], axis=1)
          df = pd.concat([df, grade_dums], axis=1)
          df.head()
```

Out[109]:

	price	sqft_living	lat	long	price_per_sqft	min_dist_park	closest_distance_to_top_school	closest_distance_to_great_coffee	closest_distance_to_scientology	interaction	...	quant_interaction	grade_5	grade_
0	221900.00	1180	47.51	-122.26	188.05	2.04	0.26	8.39	12.71	3.33	...	-1.11	0	
1	538000.00	2570	47.72	-122.32	209.34	5.67	0.68	14.81	10.80	7.37	...	-0.50	0	
2	180000.00	770	47.74	-122.23	233.77	1.34	2.00	10.63	10.84	21.71	...	0.08	0	
3	604000.00	1960	47.52	-122.39	308.16	2.45	1.73	15.80	11.55	19.97	...	0.05	0	
4	510000.00	1680	47.62	-122.05	303.57	3.72	1.18	8.55	21.18	24.98	...	0.16	0	

5 rows × 27 columns

```
In [110]: # saving copy of dataframe as csv file
          #df.to_csv('./data/all_features_ppsqft_quant.csv')
```