King County Housing with Multiple Linear Regression

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Notebook 1: Business Problem and Data Understading

This notebook contains an introduction to our project, our business problem, the full process of how all our data were obtained, and an exploration of our data with EDA.

Overview

We have been tasked with analyzing the data of houses in King County. Our goal is to make predictions about the sale price of houses based on certain variables or features, so that they can be used to make profitable decisions by a housing development company. After careful consideration and evaluation of our data, and many iterations of our linear regression models, we have determined that sqare-feet of living space, building grade, and proximity to top schools, great coffee shops, and churches of scientology all are correlated with a higher selling price for a house in King County.

Business Problem

Our stakeholders in a housing development company are searching for the qualities that lead to higher home sale prices. We will be reviewing building grade, square-footage of living space, and location-related factors such as proximity to schools, coffee shops, parks, and scientology churches to determine which factors are highly correlated with home sale prices.

Hypotheses

Null hypothesis (H0): There is no relationship between our features and our target variable, price. Alternative hypothesis (Ha): There is a relationship between our features and our target variable, price.

We will be using a significance level (alpha) of 0.05 to make our determination, and will make our final recommendations accordingly.

Data Understanding

We utilized a few different data sources for our model so that we could obtain a comprehensive and accurate prediction of home prices.

- King County House Data: a dataset that we were provided at the onset of the project. This file contains data for 21,597 homes built in King County from 1900 to 2015. Each home in the set contains information regarding features such as number of bedrooms/bathrooms, number of floors, square footage, zip code, condition, and more.
- Urban Institute Education Data: The Urban Institute is a nonprofit research organization. Their Education Data Explorer "...harmonizes data from all major federal datasets, including the US Department of Education Common Core of Data, the US Department of Education Civil Rights Data Collection, the US Department of Education EDFacts, the US Census Bureau Small Area Income and Poverty Estimates, the US Department of Education Integrated Postsecondary Education Data System, the US Department of Education College Scorecard, and the National Historical Geographic Information System." Custom-generated report provides descriptors such as name and location (lat,long) of school, zip code, and which school district it belongs to.
- Niche.com: school rankings for top King County school districts.
- Yelp API: Used to obtain the top-rated coffee shops for King County.
- Web-scraped data from KingCounty.gov parks website (https://www.kingcounty.gov/services/parks-recreation/parks/parks-and-natural-lands/parksatoz.aspx (https://www.kingcounty.gov/services/parks-recreation/parks/parks-and-natural-lands/parksatoz.aspx))
- Scientology church location information from scientology-seattle.org.
- Building grade categorical descriptions from https://info.kingcounty.gov/assessor/esales/Glossary.aspx?type=r (https://info.kingcounty.gov/assessor/esales/Glossary.aspx?type=r).

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 House Data

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]:

```
# getting info for DataFrame
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 [4]:

```
df.shape
```

Out[4]:

```
(21597, 21)
```

In [5]:

```
df.price.describe()
```

Out[5]:

```
count     21597.00
mean     540296.57
std      367368.14
min       78000.00
25%      322000.00
50%      450000.00
75%      645000.00
max     7700000.00
Name: price, dtype: float64
```

This dataset contains a wide price range for houses from 78,000 dollars all the way up to almost 8 million dollars. The mean house price is 540,297 dollars, while the median house price is 450,000 dollars.

In [6]:
```
# checking the dispersion of years built
df.yr_built.describe()
```

Out[6]:
```
count    21597.00
mean      1971.00
std         29.38
min       1900.00
25%       1951.00
50%       1975.00
75%       1997.00
max       2015.00
Name: yr_built, dtype: float64
```

In [7]:
```
# getting counts for each value in condition column
df['condition'].value_counts()
```

Out[7]:
```
3    14020
4     5677
5     1701
2      170
1       29
Name: condition, dtype: int64
```

In [8]:
```
# getting counts for each value in zipcode column
df['zipcode'].value_counts()
```

Out[8]:
```
98103    602
98038    589
98115    583
98052    574
98117    553
        ...
98102    104
98010    100
98024     80
98148     57
98039     50
Name: zipcode, Length: 70, dtype: int64
```

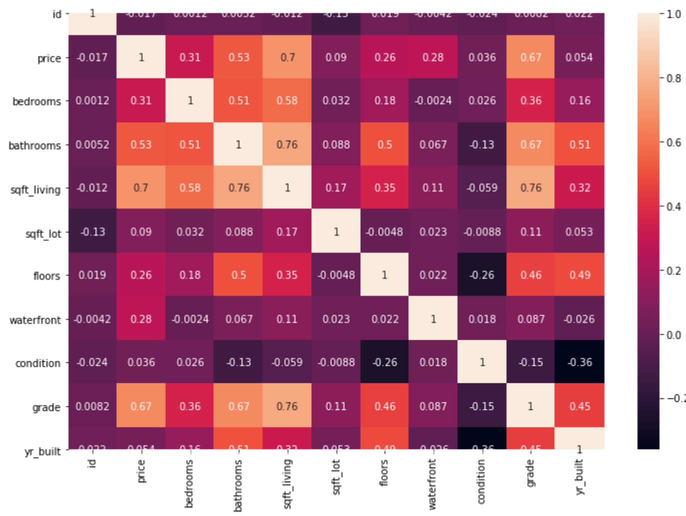
In [9]:
```
# getting descriptive statistics for square footage
df['sqft_living'].describe()
```

Out[9]:
```
count    21597.00
mean      2080.32
std        918.11
min        370.00
25%       1430.00
50%       1910.00
75%       2550.00
max      13540.00
Name: sqft_living, dtype: float64
```

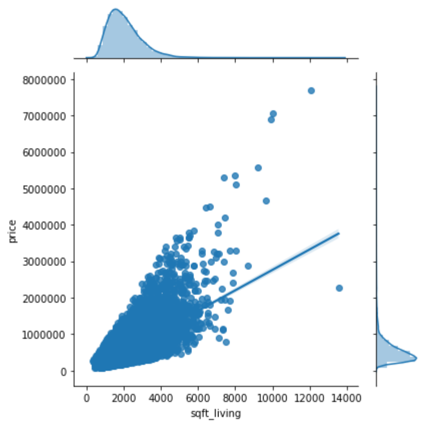
The mean square-feet of living space is 2,080 square feet, but there are houses as small as 370 sqft and as large as 13,540 sqft in this dataset.

In [10]:
```
# remove unwanted columns
drop_vars = ['date', 'view', 'sqft_above', 'sqft_basement', 'yr_renovated',
             'zipcode', 'lat', 'long', 'sqft_living15', 'sqft_lot15']
df_corr = df.drop(columns=drop_vars)

# generate heatmap to display correlations
corr = df_corr.corr()
f, ax = plt.subplots(figsize=(12, 8))
sns.heatmap(corr, annot=True);
```

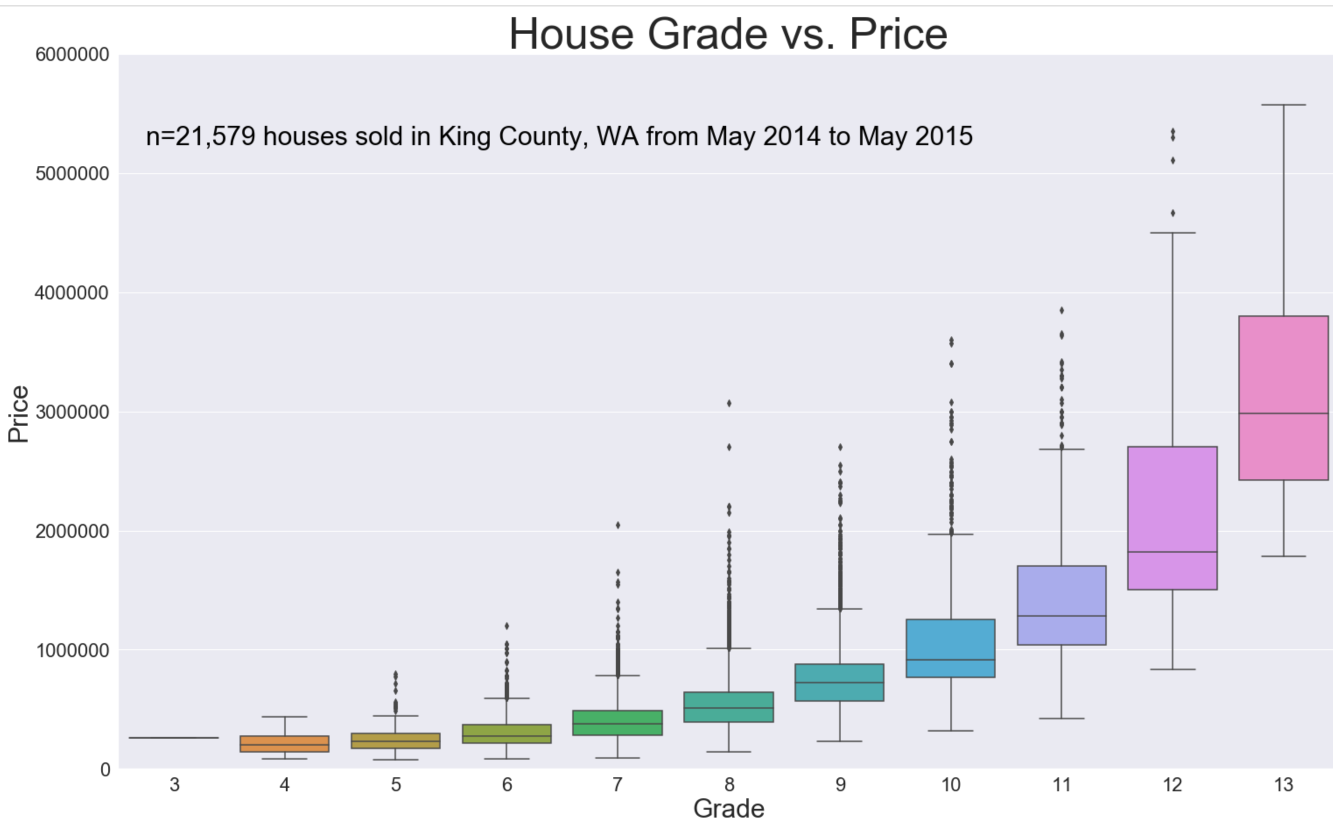


In [11]:
```
# examining the relationship between sqft_living and price
sns.jointplot('sqft_living','price', data=df, kind='reg')
plt.tight_layout()
plt.savefig('./visualizations/sqft_reg.png');
```



The visualization above demonstrates that there seems to be a relatively strong linear relationship between square feet of living space and the price of a house.

In [12]:
```
#grade
plt.figure(figsize=(25,15))
sns.set(font_scale=2)
pal = sns.color_palette("husl", 8)
ax = sns.boxplot(x="grade", y="price", data=df)
ax.set_title('House Grade vs. Price', fontsize=50)
ax.set_ylabel('Price', fontsize=30)
ax.set_xlabel('Grade', fontsize=30)
ax.set_ylim(bottom=0, top=6000000)
ax.text(.7, .9, 'n=21,579 houses sold in King County, WA from May 2014 to May 2015',
        color='black', fontsize=30,
        horizontalalignment='right',
        verticalalignment='top',
        transform=ax.transAxes);
plt.savefig('./visualizations/grade.png');
```



When we look at grade, we can see that as the categorical building grade designation improves, the house price does indeed rise as well. This makes sense, as the definition for a building grade of 13 is, "Generally custom designed and built. Mansion level. Large amount of highest quality cabinet work, wood trim, marble, entry ways etc." We can see in the boxplots above that the mean house price for a home with a grade of 13 is far above even the max value for any other grade. In contrast, the definition of a building grade of 3 is, "Falls short of minimum building standards. Normally cabin or inferior structure." We can see this clearly demonstrated in the selling prices of houses on the lower end of grade.

In [13]:
```
df.grade.value_counts()
```

Out[13]:
```
7     8974
8     6065
9     2615
6     2038
10    1134
11     399
5      242
12      89
4       27
13      13
3        1
Name: grade, dtype: int64
```

The most common building grade is a 7, which is defined as, "Average grade of construction and design."

Urban Institute Education Data

King County Schools

We began by calculcating the distance from each home to a school, to see if there was a connection between school proximity and house price.

In [14]:
```
# loading and previewing school data
schools = pd.read_csv('data/EducationDataPortal_11.22.2020_schools.csv')
schools.head()
```

Out[14]:

	year	ncessch	school_name	state_name	lea_name	zip_location	latitude	longitude	county_code	school_level	school_type
0	2015	530000100376	Black Diamond Elementary	Washington	Enumclaw School District	98010	47.31	-122.00	53033.00	Primary	Regular school
1	2015	530000100377	Byron Kibler Elementary School	Washington	Enumclaw School District	98022	47.21	-122.00	53033.00	Primary	Regular school
2	2015	530000100379	Enumclaw Sr High School	Washington	Enumclaw School District	98022	47.19	-122.01	53033.00	High	Regular school
3	2015	530000100382	Southwood Elementary School	Washington	Enumclaw School District	98022	47.19	-122.01	53033.00	Primary	Regular school
4	2015	530000100383	Westwood Elementary School	Washington	Enumclaw School District	98022	47.23	-122.06	53033.00	Primary	Regular school

In [15]:
```
# getting value counts for school county codes
schools.county_code.value_counts()
```

Out[15]:
```
53033.00    518
53053.00    284
53061.00    223
53063.00    175
53011.00    135
53077.00    113
53035.00     80
53067.00     79
53073.00     69
53005.00     61
53025.00     55
53015.00     48
53057.00     48
53041.00     46
53065.00     42
53027.00     41
53007.00     39
53021.00     36
53047.00     33
53071.00     30
53009.00     29
53029.00     26
53075.00     26
53039.00     22
53045.00     22
53017.00     21
53037.00     20
53049.00     20
53043.00     16
53031.00     15
53001.00     15
53055.00     14
53019.00     12
53003.00     12
53059.00     11
53051.00      9
53013.00      4
53023.00      2
53069.00      2
Name: county_code, dtype: int64
```

In [16]:
```
# filtering dataframe to show only King County schools
# King County's county code is 53033 as per county website
schools = schools.loc[schools['county_code']==53033]
schools.head()
```

Out[16]:

	year	ncessch	school_name	state_name	lea_name	zip_location	latitude	longitude	county_code	school_level	school_type
0	2015	530000100376	Black Diamond Elementary	Washington	Enumclaw School District	98010	47.31	-122.00	53033.00	Primary	Regular school
1	2015	530000100377	Byron Kibler Elementary School	Washington	Enumclaw School District	98022	47.21	-122.00	53033.00	Primary	Regular school
2	2015	530000100379	Enumclaw Sr High School	Washington	Enumclaw School District	98022	47.19	-122.01	53033.00	High	Regular school
3	2015	530000100382	Southwood Elementary School	Washington	Enumclaw School District	98022	47.19	-122.01	53033.00	Primary	Regular school
4	2015	530000100383	Westwood Elementary School	Washington	Enumclaw School District	98022	47.23	-122.06	53033.00	Primary	Regular school

In [17]:
```
schools.shape
```

Out[17]:
```
(518, 11)
```

In [18]:
```
# resetting index after filtering
schools.reset_index(inplace=True)
schools.head()
```

Out[18]:

	index	year	ncessch	school_name	state_name	lea_name	zip_location	latitude	longitude	county_code	school_level	school_type
0	0	2015	530000100376	Black Diamond Elementary	Washington	Enumclaw School District	98010	47.31	-122.00	53033.00	Primary	Regular school
1	1	2015	530000100377	Byron Kibler Elementary School	Washington	Enumclaw School District	98022	47.21	-122.00	53033.00	Primary	Regular school
2	2	2015	530000100379	Enumclaw Sr High School	Washington	Enumclaw School District	98022	47.19	-122.01	53033.00	High	Regular school
3	3	2015	530000100382	Southwood Elementary School	Washington	Enumclaw School District	98022	47.19	-122.01	53033.00	Primary	Regular school
4	4	2015	530000100383	Westwood Elementary School	Washington	Enumclaw School District	98022	47.23	-122.06	53033.00	Primary	Regular school

In [19]:
```
# dropping extra index column
schools.drop(columns='index', inplace=True, axis=1)
```

In [20]:
```
schools.head()
```

Out[20]:

	year	ncessch	school_name	state_name	lea_name	zip_location	latitude	longitude	county_code	school_level	school_type
0	2015	530000100376	Black Diamond Elementary	Washington	Enumclaw School District	98010	47.31	-122.00	53033.00	Primary	Regular school
1	2015	530000100377	Byron Kibler Elementary School	Washington	Enumclaw School District	98022	47.21	-122.00	53033.00	Primary	Regular school
2	2015	530000100379	Enumclaw Sr High School	Washington	Enumclaw School District	98022	47.19	-122.01	53033.00	High	Regular school
3	2015	530000100382	Southwood Elementary School	Washington	Enumclaw School District	98022	47.19	-122.01	53033.00	Primary	Regular school
4	2015	530000100383	Westwood Elementary School	Washington	Enumclaw School District	98022	47.23	-122.06	53033.00	Primary	Regular school

In [21]:
```
# checking for duplicates
schools.school_name.duplicated().sum()
```

Out[21]: 11

In [22]:
```
# showing duplicates for school name
schools.loc[schools.school_name.duplicated()==True]
```

Out[22]:

	year	ncessch	school_name	state_name	lea_name	zip_location	latitude	longitude	county_code	school_level	school_type
28	2015	530030002904	Special Ed School	Washington	Auburn School District	98002	47.31	-122.22	53033.00	Other	Special education school
123	2015	530354000522	Cascade Middle School	Washington	Highline School District	98146	47.50	-122.35	53033.00	Middle	Regular school
125	2015	530354000524	Chinook Middle School	Washington	Highline School District	98188	47.44	-122.28	53033.00	Middle	Regular school
160	2015	530354003373	Gateway to College	Washington	Highline School District	98146	47.50	-122.34	53033.00	High	Other/alternative school
203	2015	530396000628	Panther Lake Elementary School	Washington	Kent School District	98031	47.41	-122.20	53033.00	Primary	Regular school
321	2015	530591001993	Sunrise Elementary	Washington	Northshore School District	98052	47.73	-122.11	53033.00	Primary	Regular school
333	2015	530723001071	Hazelwood Elementary School	Washington	Renton School District	98056	47.54	-122.18	53033.00	Primary	Regular school
337	2015	530723001076	Lakeridge Elementary School	Washington	Renton School District	98178	47.50	-122.24	53033.00	Primary	Regular school
411	2015	530771001229	Olympic View Elementary School	Washington	Seattle Public Schools	98115	47.70	-122.32	53033.00	Primary	Regular school
456	2015	530771003361	Rainier View Elementary School	Washington	Seattle Public Schools	98178	47.50	-122.26	53033.00	Primary	Regular school
482	2015	530792003445	Head Start	Washington	Shoreline School District	98133	47.75	-122.34	53033.00	Primary	Regular school

In [23]:
```
# reviewing duplicates
schools.loc[schools.school_name=='Panther Lake Elementary School']
```

Out[23]:

	year	ncessch	school_name	state_name	lea_name	zip_location	latitude	longitude	county_code	school_level	school_type
99	2015	530282001767	Panther Lake Elementary School	Washington	Federal Way School District	98003	47.29	-122.33	53033.00	Primary	Regular school
203	2015	530396000628	Panther Lake Elementary School	Washington	Kent School District	98031	47.41	-122.20	53033.00	Primary	Regular school

In [24]:
```
schools.loc[schools.school_name=='Cascade Middle School']
```

Out[24]:

	year	ncessch	school_name	state_name	lea_name	zip_location	latitude	longitude	county_code	school_level	school_type
12	2015	530030000033	Cascade Middle School	Washington	Auburn School District	98002	47.33	-122.21	53033.00	Middle	Regular school
123	2015	530354000522	Cascade Middle School	Washington	Highline School District	98146	47.50	-122.35	53033.00	Middle	Regular school

In [25]:
```
schools.loc[schools.school_name=='Sunrise Elementary']
```

Out[25]:

	year	ncessch	school_name	state_name	lea_name	zip_location	latitude	longitude	county_code	school_level	school_type
5	2015	530000100478	Sunrise Elementary	Washington	Enumclaw School District	98022	47.19	-122.01	53033.00	Primary	Regular school
321	2015	530591001993	Sunrise Elementary	Washington	Northshore School District	98052	47.73	-122.11	53033.00	Primary	Regular school

When reviewing the 11 duplicates for "school_name", it was apparent that these were not duplicate entries, but rather, different institutions with the same name in different school districts.

In [26]:
```
# checking for null values
schools.isnull().sum()
```

Out[26]:
```
year            0
ncessch         0
school_name     0
state_name      0
lea_name        0
zip_location    0
latitude        0
longitude       0
county_code     0
school_level    0
school_type     0
dtype: int64
```

In [27]:
```
school_coordinates = []
x = round(schools.latitude, 2)
y = round(schools.longitude, 2)
school_coordinates = list(zip(x,y))
```

In [28]:
```python
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 [29]:
```python
for i in range(len(school_coordinates)):
    df[f'school_{i}'] = distance_to(school_coordinates[i])

school_cols = []
for i in range(len(school_coordinates)):
    school_cols.append(f'school_{i}')
    df['closest_distance_to_school'] = df[school_cols].min(axis=1)
```

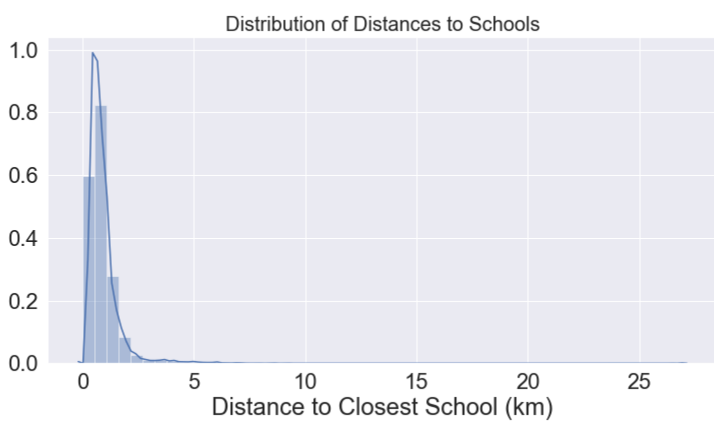
In [30]:
```python
df.closest_distance_to_school.describe()
```

Out[30]:
```
count    21597.00
mean         0.88
std          0.77
min          0.00
25%          0.47
50%          0.71
75%          1.06
max         26.95
Name: closest_distance_to_school, dtype: float64
```

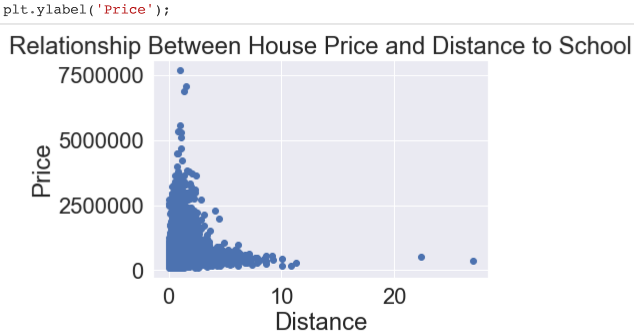
The closest distance to a school is 0.00 km (house located at the exact same latitude and longitude as a school building). The farthest distance is 26.95 km.

In [31]:
```python
plt.figure(figsize=(12,6))
sns.distplot(df['closest_distance_to_school'])
plt.title("Distribution of Distances to Schools", fontsize=20)
plt.xlabel('Distance to Closest School (km)');
print("Skewness:", df['closest_distance_to_school'].skew())
print("Kurtosis:", df['closest_distance_to_school'].kurt())
```

```
Skewness: 6.218078338828554
Kurtosis: 108.62323888858803
```



In [32]:
```python
plt.scatter(x=df['closest_distance_to_school'], y=df['price'])
plt.title('Relationship Between House Price and Distance to School')
plt.xlabel('Distance')
plt.ylabel('Price');
```



As expected, there seemed to be a negative correlation between distance to a school and the price of a house. As the distance between a house and a school decreased, the house price increased.

In [33]:
```python
#dropping unnecessary columns
drop = ['date','id','yr_built', 'yr_renovated', 'sqft_above', 'sqft_basement', 'sqft_living15', 'sqft_lot15']
df_cleaned = df.drop(columns = drop, axis=1)
```

In [34]:
```python
df_cleaned = df_cleaned.drop(columns = school_cols, axis=1)
```

In [35]:
```
df_cleaned.head()
```

Out[35]:

	price	bedrooms	bathrooms	sqft_living	sqft_lot	floors	waterfront	view	condition	grade	zipcode	lat	long	closest_distance_to_school
0	221900.00	3	1.00	1180	5650	1.00	nan	0.00	3	7	98178	47.51	-122.26	0.26
1	538000.00	3	2.25	2570	7242	2.00	0.00	0.00	3	7	98125	47.72	-122.32	0.68
2	180000.00	2	1.00	770	10000	1.00	0.00	0.00	3	6	98028	47.74	-122.23	0.32
3	604000.00	4	3.00	1960	5000	1.00	0.00	0.00	5	7	98136	47.52	-122.39	1.73
4	510000.00	3	2.00	1680	8080	1.00	0.00	0.00	3	8	98074	47.62	-122.05	1.18

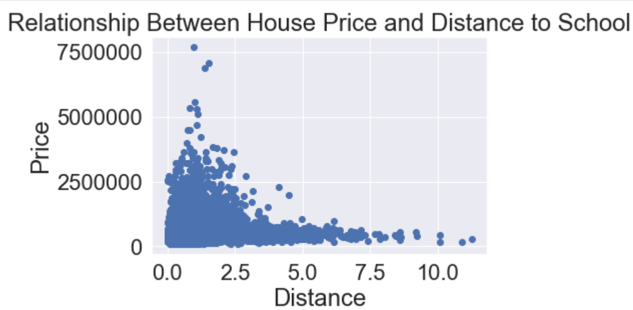
In [36]:
```
df_cleaned.corr()
```

Out[36]:

	price	bedrooms	bathrooms	sqft_living	sqft_lot	floors	waterfront	view	condition	grade	zipcode	lat	long	closest_distance_to_school
price	1.00	0.31	0.53	0.70	0.09	0.26	0.28	0.40	0.04	0.67	-0.05	0.31	0.02	0.07
bedrooms	0.31	1.00	0.51	0.58	0.03	0.18	-0.00	0.08	0.03	0.36	-0.15	-0.01	0.13	0.00
bathrooms	0.53	0.51	1.00	0.76	0.09	0.50	0.07	0.19	-0.13	0.67	-0.20	0.02	0.22	0.10
sqft_living	0.70	0.58	0.76	1.00	0.17	0.35	0.11	0.28	-0.06	0.76	-0.20	0.05	0.24	0.15
sqft_lot	0.09	0.03	0.09	0.17	1.00	-0.00	0.02	0.08	-0.01	0.11	-0.13	-0.09	0.23	0.35
floors	0.26	0.18	0.50	0.35	-0.00	1.00	0.02	0.03	-0.26	0.46	-0.06	0.05	0.13	0.04
waterfront	0.28	-0.00	0.07	0.11	0.02	0.02	1.00	0.41	0.02	0.09	0.03	-0.01	-0.04	0.09
view	0.40	0.08	0.19	0.28	0.08	0.03	0.41	1.00	0.05	0.25	0.09	0.01	-0.08	0.11
condition	0.04	0.03	-0.13	-0.06	-0.01	-0.26	0.02	0.05	1.00	-0.15	0.00	-0.02	-0.11	-0.03
grade	0.67	0.36	0.67	0.76	0.11	0.46	0.09	0.25	-0.15	1.00	-0.19	0.11	0.20	0.12
zipcode	-0.05	-0.15	-0.20	-0.20	-0.13	-0.06	0.03	0.09	0.00	-0.19	1.00	0.27	-0.56	-0.18
lat	0.31	-0.01	0.02	0.05	-0.09	0.05	-0.01	0.01	-0.02	0.11	0.27	1.00	-0.14	-0.12
long	0.02	0.13	0.22	0.24	0.23	0.13	-0.04	-0.08	-0.11	0.20	-0.56	-0.14	1.00	0.33
closest_distance_to_school	0.07	0.00	0.10	0.15	0.35	0.04	0.09	0.11	-0.03	0.12	-0.18	-0.12	0.33	1.00

In [37]:
```
df_cleaned = df_cleaned.loc[df_cleaned.closest_distance_to_school<20]
```

In [38]:
```
plt.scatter(x=df_cleaned['closest_distance_to_school'], y=df_cleaned['price'])
plt.title('Relationship Between House Price and Distance to School')
plt.xlabel('Distance')
plt.ylabel('Price');
```



With outliers removed, we are able to more clearly visualize this relationship.

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

Out[39]:

	price	bedrooms	bathrooms	sqft_living	sqft_lot	floors	waterfront	view	condition	grade	zipcode	lat	long	closest_distance_to_school
price	1.00	0.31	0.53	0.70	0.09	0.26	0.28	0.40	0.04	0.67	-0.05	0.31	0.02	0.07
bedrooms	0.31	1.00	0.51	0.58	0.03	0.18	-0.00	0.08	0.03	0.36	-0.15	-0.01	0.13	0.01
bathrooms	0.53	0.51	1.00	0.76	0.09	0.50	0.07	0.19	-0.13	0.67	-0.20	0.02	0.22	0.11
sqft_living	0.70	0.58	0.76	1.00	0.17	0.35	0.11	0.28	-0.06	0.76	-0.20	0.05	0.24	0.16
sqft_lot	0.09	0.03	0.09	0.17	1.00	-0.00	0.02	0.08	-0.01	0.11	-0.13	-0.09	0.23	0.37
floors	0.26	0.18	0.50	0.35	-0.00	1.00	0.02	0.03	-0.26	0.46	-0.06	0.05	0.13	0.04
waterfront	0.28	-0.00	0.07	0.11	0.02	0.02	1.00	0.41	0.02	0.09	0.03	-0.01	-0.04	0.10
view	0.40	0.08	0.19	0.28	0.08	0.03	0.41	1.00	0.05	0.25	0.09	0.01	-0.08	0.11
condition	0.04	0.03	-0.13	-0.06	-0.01	-0.26	0.02	0.05	1.00	-0.15	0.00	-0.02	-0.11	-0.03
grade	0.67	0.36	0.67	0.76	0.11	0.46	0.09	0.25	-0.15	1.00	-0.19	0.11	0.20	0.13
zipcode	-0.05	-0.15	-0.20	-0.20	-0.13	-0.06	0.03	0.09	0.00	-0.19	1.00	0.27	-0.56	-0.19
lat	0.31	-0.01	0.02	0.05	-0.09	0.05	-0.01	0.01	-0.02	0.11	0.27	1.00	-0.13	-0.12
long	0.02	0.13	0.22	0.24	0.23	0.13	-0.04	-0.08	-0.11	0.20	-0.56	-0.13	1.00	0.33
closest_distance_to_school	0.07	0.01	0.11	0.16	0.37	0.04	0.10	0.11	-0.03	0.13	-0.19	-0.12	0.33	1.00

King County Top Schools

There was only a correlation of 0.07 between proximity to a school and house price. So we narrowed this down to the top 8 school districts in King County, as per rankings on Niche.com, to see if there was a stronger correlation between house price and a highly ranked school.

In [40]:
```
schools.lea_name.value_counts()
```

Out[40]:
```
Seattle Public Schools                          107
Lake Washington School District                  53
Federal Way School District                      48
Kent School District                             43
Highline School District                         43
Bellevue School District                         30
Renton School District                           29
Issaquah School District                         27
Auburn School District                           22
Northshore School District                       22
Shoreline School District                        19
Snoqualmie Valley School District                12
Enumclaw School District                          9
Riverview School District                         9
Tahoma School District                            9
Tukwila School District                           7
Vashon Island School District                     5
Mercer Island School District                     5
Mary Walker School District                       4
Lake Washington Institute of Technology           3
Skykomish School District                         2
South Seattle Community College (CC Dist #6)      1
University of Washington (17904)                  1
Renton Technical College                          1
Excel Public Charter School LEA                   1
Seattle Central Community College                 1
First Place Scholars Charter School District      1
Summit Public School: Sierra                      1
Rainier Prep Charter School District              1
Green River Community College                     1
Monroe School District                            1
Name: lea_name, dtype: int64
```

In [41]:
```
from bs4 import BeautifulSoup
# url for Niche.com King County school district ranking
url = f"https://www.niche.com/k12/search/best-school-districts/c/king-county-wa/"
response = requests.get(url)
# creating soup
soup = BeautifulSoup(response.text, 'lxml')
soup.findAll('section')
```

Out[41]:
```
[<section class="container"> <div class="customer-logo-wrapper"> <div class="customer-logo"> <img alt="Logo" src="http://a.niche.com/wp-content/themes/niche-abo
ut/images/about-home/stacked-green.svg"/> </div> </div> <div class="page-title-wrapper"> <div class="page-title"> <h1>Please verify you are a human</h1> </div>
</div> <div class="content-wrapper"> <div class="content"> <div id="px-captcha"> </div> <p> Access to this page has been denied because we believe you are using
automation tools to browse the website.  </p> <p> This may happen as a result of the following: </p> <ul> <li> Javascript is disabled or blocked by an extension
(ad blockers for example) </li> <li> Your browser does not support cookies </li> </ul> <p> Please make sure that Javascript and cookies are enabled on your brow
ser and that you are not blocking them from loading.  </p> <p> Reference ID: #fcdc0bf0-3e4f-11eb-b56d-b1d3df0409d6 </p> </div> </div> <div class="page-footer-wr
apper"> <div class="page-footer"> <p> Powered by <a href="https://www.perimeterx.com/whywasiblocked">PerimeterX</a> , Inc.  </p> </div> </div> </section>]
```

I attempted to web-scrape the data for the highest-ranked school districts in King County from Niche.com, but I was unable to do so due to being blocked by their server. So instead, I manually entered the eight school districts that were ranked in the A range (A+, A, A-) into a list.

In [42]:
```
top_schools = ['Mercer Island School District', 'Bellevue School District',
               'Lake Washington School District', 'Issaquah School District',
               'Tahoma School District', 'Shoreline School District',
               'Vashon Island School District', 'Snoqualmie Valley School District',
               'Seattle Public Schools']
```

In [43]:
```
top_schools_df = schools.loc[schools['lea_name'].isin(top_schools)]
top_schools_df.head()
```

Out[43]:

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

In [44]:
```
# saving copy of DataFrame as csv file
#top_schools_df.to_csv('./data/top_schools.csv')
```

In [45]:
```
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 [46]:
```
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)
```

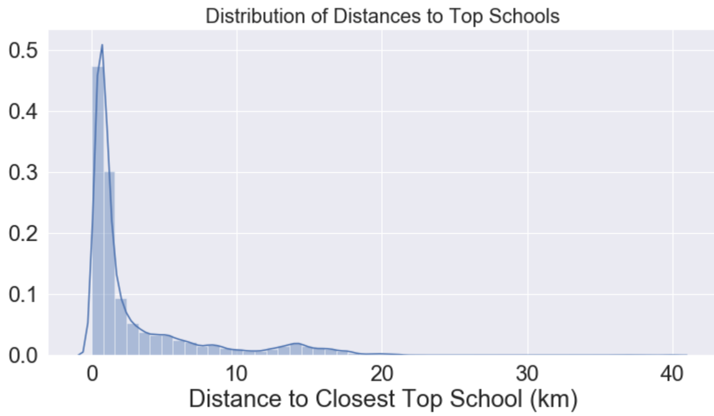
In [47]:
```
df.closest_distance_to_top_school.describe()
```

Out[47]:
```
count   21597.00
mean        3.09
std         4.41
min         0.00
25%         0.60
50%         1.05
75%         3.43
max        40.09
Name: closest_distance_to_top_school, dtype: float64
```

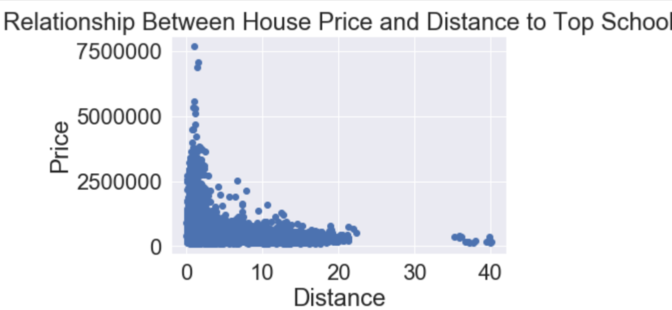
The closest distance from a house to a top school is 0.00 km (house located at the exact same latitude and longitude as a school building). The farthest distance is 40.09 km.

In [48]:
```
plt.figure(figsize=(12,6))
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: 2.2762581074960346
Kurtosis: 5.809128777092479
```



In [49]:
```
plt.scatter(x=df['closest_distance_to_top_school'], y=df['price'])
plt.title('Relationship Between House Price and Distance to Top School')
plt.xlabel('Distance')
plt.ylabel('Price');
```



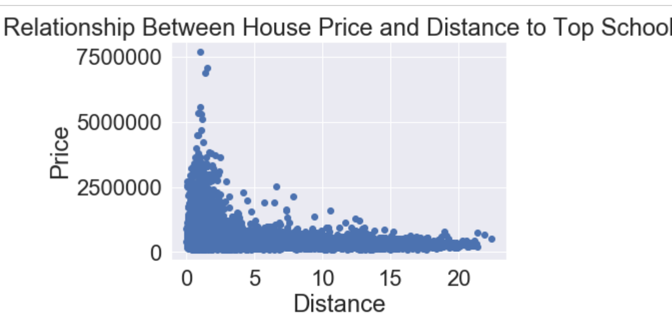
In [50]:
```
#dropping unnecessary columns
drop = ['date','id','yr_built', 'yr_renovated', 'sqft_above', 'sqft_basement', 'sqft_living15', 'sqft_lot15']
df_cleaned = df.drop(columns = drop, axis=1)
```

In [51]:
```
df_cleaned = df_cleaned.drop(columns = school_cols, axis=1)
```

In [52]:
```
df_cleaned = df_cleaned.drop(columns = top_school_cols, axis=1)
```

In [53]:
```
df_cleaned = df_cleaned.loc[df_cleaned.closest_distance_to_top_school<30]
```

In [54]:
```
plt.scatter(x=df_cleaned['closest_distance_to_top_school'], y=df_cleaned['price'])
plt.title('Relationship Between House Price and Distance to Top School')
plt.xlabel('Distance')
plt.ylabel('Price')
plt.savefig('./visualizations/school_price.png');
```

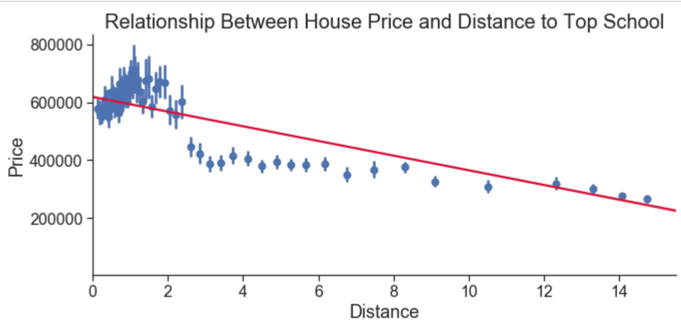


In [55]:
```
df_cleaned.corr()
```

Out[55]:

	price	bedrooms	bathrooms	sqft_living	sqft_lot	floors	waterfront	view	condition	grade	zipcode	lat	long	closest_distance_to_school	closest_distance_to_top_school
price	1.00	0.31	0.53	0.70	0.09	0.26	0.28	0.40	0.04	0.67	-0.05	0.31	0.03	0.07	-0.30
bedrooms	0.31	1.00	0.51	0.58	0.03	0.18	-0.00	0.08	0.03	0.36	-0.16	-0.01	0.14	0.01	-0.00
bathrooms	0.53	0.51	1.00	0.76	0.09	0.50	0.07	0.19	-0.13	0.67	-0.21	0.03	0.23	0.11	-0.05
sqft_living	0.70	0.58	0.76	1.00	0.17	0.35	0.11	0.28	-0.06	0.76	-0.20	0.05	0.25	0.16	-0.06
sqft_lot	0.09	0.03	0.09	0.17	1.00	-0.00	0.02	0.08	-0.01	0.11	-0.13	-0.09	0.23	0.36	0.11
floors	0.26	0.18	0.50	0.35	-0.00	1.00	0.02	0.03	-0.26	0.46	-0.06	0.05	0.13	0.04	-0.10
waterfront	0.28	-0.00	0.07	0.11	0.02	0.02	1.00	0.41	0.02	0.09	0.03	-0.01	-0.04	0.10	0.00
view	0.40	0.08	0.19	0.28	0.08	0.03	0.41	1.00	0.05	0.25	0.09	0.01	-0.08	0.11	-0.02
condition	0.04	0.03	-0.13	-0.06	-0.01	-0.26	0.02	0.05	1.00	-0.15	0.00	-0.01	-0.11	-0.03	0.01
grade	0.67	0.36	0.67	0.76	0.11	0.46	0.09	0.25	-0.15	1.00	-0.19	0.11	0.21	0.13	-0.10
zipcode	-0.05	-0.16	-0.21	-0.20	-0.13	-0.06	0.03	0.09	0.00	-0.19	1.00	0.27	-0.57	-0.19	-0.29
lat	0.31	-0.01	0.03	0.05	-0.09	0.05	-0.01	0.01	-0.01	0.11	0.27	1.00	-0.14	-0.12	-0.69
long	0.03	0.14	0.23	0.25	0.23	0.13	-0.04	-0.08	-0.11	0.21	-0.57	-0.14	1.00	0.33	-0.00
closest_distance_to_school	0.07	0.01	0.11	0.16	0.36	0.04	0.10	0.11	-0.03	0.13	-0.19	-0.12	0.33	1.00	0.16
closest_distance_to_top_school	-0.30	-0.00	-0.05	-0.06	0.11	-0.10	0.00	-0.02	0.01	-0.10	-0.29	-0.69	-0.00	0.16	1.00

In [56]:
```
sns.set_style('ticks')
sns.lmplot(x='closest_distance_to_top_school', y='price', data=df_cleaned, aspect=2, line_kws={'color': 'crimson'}, x_bins=75)
plt.title('Relationship Between House Price and Distance to Top School', fontsize=20)
plt.xlabel('Distance', fontsize=18)
plt.ylabel('Price', fontsize=18)
plt.xticks(fontsize=16)
plt.yticks(fontsize=16);
#plt.ylim(100000,750000)
plt.xlim(0, 15.5);
plt.tight_layout()
plt.savefig('./visualizations/price_school_2.png')
```



When we look at the distance to a school and price, there is not much of a correlation there at all. However, once we narrow it down to the top schools, we start to see a stronger negative correlation. So as the distance to a top school decreases, the house price increases.

Proximity to Coffee Shops via Yelp API

We speculated that there may be a relationship between good coffee shops and higher home prices. We used the Yelp API to obtain the data for the top 50 highest-rated coffee shops and used the provided latitudes and longitudes to calculate their distances from each home.

In [57]:
```
import requests
import json
```

In [58]:
```
def get_keys(path):
    """Retrieves API key from files as api_key."""
    with open(path) as f:
        return json.load(f)
```

In [59]:
```
keys = get_keys("/Users/dtunnicliffe/.secret/yelp_api.json")
api_key = keys['api_key']
```

In [60]:
```python
term = 'coffee'
location = 'King County, WA'
SEARCH_LIMIT = 50
mochas = 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 mochas
    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'])
    mochas = mochas.append(df_temp)
    return mochas
```

In [61]:
```python
mochas = yelp(term, location, SEARCH_LIMIT)
```

In [62]:
```python
mochas.shape
```

Out[62]:
```
(50, 16)
```

In [63]:
```python
mochas.head()
```

Out[63]:

	id	alias	name	image_url	is_closed	url	review_count	categories	rating	coordinates	transactions	loc
0	h1dhP2ZRiMGE2RdpUtputg	coffeeholic-house-seattle	Coffeeholic House	https://s3-media1.fl.yelpcdn.com/bphoto/m5L0vl...	False	https://www.yelp.com/biz/coffeeholic-house-sea...	254	[{'alias': 'coffee', 'title': 'Coffee & Tea'}]	4.50	{'latitude': 47.55723, 'longitude': -122.28596}	[]	{'addr '3 Huds 'addr
1	PJakGoM3gkStlwG5AvPadw	mighty-mugs-coffee-kent	Mighty Mugs Coffee	https://s3-media1.fl.yelpcdn.com/bphoto/xKBXSp...	False	https://www.yelp.com/biz/mighty-mugs-coffee-ke...	102	[{'alias': 'coffee', 'title': 'Coffee & Tea'},...	5.00	{'latitude': 47.4408184523004, 'longitude': -1...	[]	{'addr '18 Valley 'addres
2	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]	{'addr '8102 Av 'addr
3	0ms-mWSw4ywRDM4Yn11r7g	lamppost-coffee-roasters-bonney-lake	Lamppost Coffee Roasters	https://s3-media2.fl.yelpcdn.com/bphoto/d4pn9O...	False	https://www.yelp.com/biz/lamppost-coffee-roast...	27	[{'alias': 'coffeeroasteries', 'title': 'Coffe...	5.00	{'latitude': 47.167816, 'longitude': -122.1612...	[delivery]	{'addr '200 'addr
4	EWqgeiGor-aVJlMLc8iSKw	boon-boona-coffee-renton	Boon Boona Coffee	https://s3-media3.fl.yelpcdn.com/bphoto/tVH2Gx...	False	https://www.yelp.com/biz/boon-boona-coffee-ren...	209	[{'alias': 'coffeeroasteries', 'title': 'Coffe...	4.50	{'latitude': 47.4797895, 'longitude': -122.206...	[delivery, pickup]	{'addr '724 'addr

In [64]:
```python
coffee_coordinates = []
x = [round(coordinate['latitude'], 2) for coordinate in mochas['coordinates']]
y = [round(coordinate['longitude'], 2) for coordinate in mochas['coordinates']]
coffee_coordinates = list(zip(x,y))
```

In [65]:
```python
for i in range(len(coffee_coordinates)):
    df_cleaned[f'coffee_{i}'] = distance_to(coffee_coordinates[i])

coffee_cols = []
for i in range(len(coffee_coordinates)):
    coffee_cols.append(f'coffee_{i}')
    df_cleaned['closest_distance_to_good_coffee'] = df_cleaned[coffee_cols].min(axis=1)
```

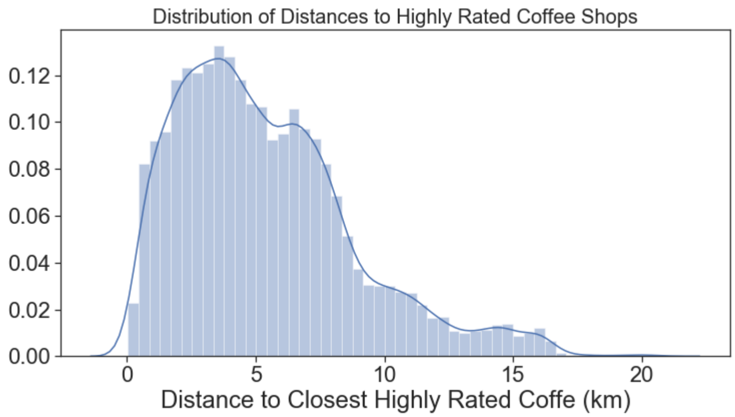
In [66]:
```python
df_cleaned.closest_distance_to_good_coffee.describe()
```

Out[66]:
```
count    21580.00
mean         5.39
std          3.46
min          0.03
25%          2.77
50%          4.79
75%          7.29
max         20.80
Name: closest_distance_to_good_coffee, dtype: float64
```

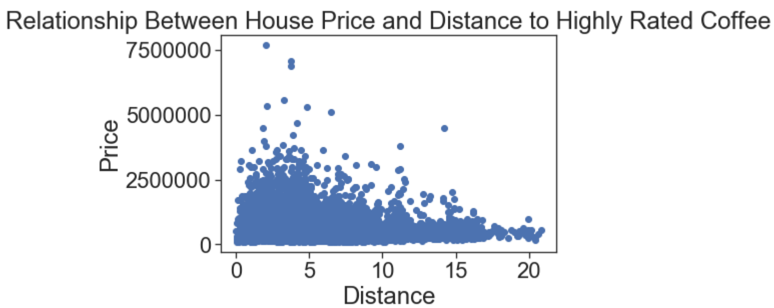
The closest distance to a highly rated coffee shop is 0.03 km. The farthest distance is 22.89 km.

In [67]:
```python
plt.figure(figsize=(12,6))
sns.distplot(df_cleaned['closest_distance_to_good_coffee'])
plt.title("Distribution of Distances to Highly Rated Coffee Shops", fontsize=20)
plt.xlabel('Distance to Closest Highly Rated Coffe (km)');
print("Skewness:", df_cleaned['closest_distance_to_good_coffee'].skew())
print("Kurtosis:", df_cleaned['closest_distance_to_good_coffee'].kurt())
```

```
Skewness: 0.9710209137999876
Kurtosis: 0.8312576020439337
```



In [68]:
```python
plt.scatter(x=df_cleaned['closest_distance_to_good_coffee'], y=df_cleaned['price'])
plt.title('Relationship Between House Price and Distance to Highly Rated Coffee')
plt.xlabel('Distance')
plt.ylabel('Price');
```



In [69]:
```python
#dropping unnecessary columns
df_cleaned = df_cleaned.drop(columns = coffee_cols, axis=1)
df_cleaned.head()
```

Out[69]:

	price	bedrooms	bathrooms	sqft_living	sqft_lot	floors	waterfront	view	condition	grade	zipcode	lat	long	closest_distance_to_school	closest_distance_to_top_school	closest_distance_to_good_coffee
0	221900.00	3	1.00	1180	5650	1.00	nan	0.00	3	7	98178	47.51	-122.26	0.26	0.26	4.39
1	538000.00	3	2.25	2570	7242	2.00	0.00	0.00	3	7	98125	47.72	-122.32	0.68	0.68	10.38
2	180000.00	2	1.00	770	10000	1.00	0.00	0.00	3	6	98028	47.74	-122.23	0.32	2.00	10.63
3	604000.00	4	3.00	1960	5000	1.00	0.00	0.00	5	7	98136	47.52	-122.39	1.73	1.73	8.88
4	510000.00	3	2.00	1680	8080	1.00	0.00	0.00	3	8	98074	47.62	-122.05	1.18	1.18	8.00

In [70]:
```python
optimal = df_cleaned.loc[(df_cleaned['price']>180000) & (df_cleaned['price']<700000)]
optimal.corr()
```

Out[70]:

	price	bedrooms	bathrooms	sqft_living	sqft_lot	floors	waterfront	view	condition	grade	zipcode	lat	long	closest_distance_to_school	closest_distance_to_top_school	closest_d
price	1.00	0.19	0.32	0.44	0.07	0.21	0.03	0.14	0.01	0.47	0.03	0.47	0.07	0.06	-0.42	
bedrooms	0.19	1.00	0.46	0.59	0.02	0.11	-0.04	0.01	0.02	0.26	-0.16	-0.10	0.14	-0.00	0.09	
bathrooms	0.32	0.46	1.00	0.67	0.03	0.49	-0.04	0.04	-0.16	0.56	-0.23	-0.10	0.24	0.08	0.07	
sqft_living	0.44	0.59	0.67	1.00	0.14	0.28	-0.02	0.10	-0.08	0.60	-0.23	-0.13	0.28	0.14	0.12	
sqft_lot	0.07	0.02	0.03	0.14	1.00	-0.05	0.02	0.10	0.01	0.04	-0.14	-0.11	0.22	0.39	0.13	
floors	0.21	0.11	0.49	0.28	-0.05	1.00	-0.02	-0.03	-0.29	0.43	-0.06	-0.01	0.11	0.02	-0.05	
waterfront	0.03	-0.04	-0.04	-0.02	0.02	-0.02	1.00	0.29	0.01	-0.03	0.02	-0.04	-0.06	0.12	0.03	
view	0.14	0.01	0.04	0.10	0.10	-0.03	0.29	1.00	0.02	0.07	0.09	-0.07	-0.07	0.12	0.07	
condition	0.01	0.02	-0.16	-0.08	0.01	-0.29	0.01	0.02	1.00	-0.20	-0.01	-0.03	-0.07	-0.01	0.02	
grade	0.47	0.26	0.56	0.60	0.04	0.43	-0.03	0.07	-0.20	1.00	-0.19	-0.02	0.20	0.09	0.04	
zipcode	0.03	-0.16	-0.23	-0.23	-0.14	-0.06	0.02	0.09	-0.01	-0.19	1.00	0.31	-0.56	-0.18	-0.35	
lat	0.47	-0.10	-0.10	-0.13	-0.11	-0.01	-0.04	-0.07	-0.03	-0.02	0.31	1.00	-0.16	-0.13	-0.69	
long	0.07	0.14	0.24	0.28	0.22	0.11	-0.06	-0.07	-0.07	0.20	-0.56	-0.16	1.00	0.32	-0.00	
closest_distance_to_school	0.06	-0.00	0.08	0.14	0.39	0.02	0.12	0.12	-0.01	0.09	-0.18	-0.13	0.32	1.00	0.16	
closest_distance_to_top_school	-0.42	0.09	0.07	0.12	0.13	-0.05	0.03	0.07	0.02	0.04	-0.35	-0.69	-0.00	0.16	1.00	
closest_distance_to_good_coffee	-0.01	-0.04	-0.11	-0.05	0.01	-0.13	0.09	0.06	0.02	-0.04	0.32	0.36	-0.49	0.03	0.02	

Unfortunately, there was no observable relationship between house price and distance to a highly rated coffee shop.

Top 10 Highest-Rated Coffee Shops from Yelp API

We then gathered data for the top 10 highest-rated coffee shops in King County, as per the Yelp API, and tried to find a connection between house price and distance from a very highly-rated coffee shop.

In [71]:
```python
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 [72]:
```python
espresso = yelp(term, location, SEARCH_LIMIT)
```

In [73]:
```python
espresso.shape
```

Out[73]:
```
(10, 16)
```

In [74]:
```python
espresso.head(10)
```

Out[74]:

	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	oUk6lZAFQ37R5OK0etWocg	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...	[]	
5	9DJY3ndAM0E6T7qGtrq0kg	issaquah-coffee-company-issaquah	Issaquah Coffee Company	https://s3-media4.fl.yelpcdn.com/bphoto/PDXXmy...	False	https://www.yelp.com/biz/issaquah-coffee-compa...	355	[{'alias': 'coffee', 'title': 'Coffee & Tea'},...	4.00	{'latitude': 47.5396224396688, 'longitude': -1...	[delivery]	
6	kybVpzGFcYov1d0X00vDjQ	candor-coffee-renton	Candor Coffee	https://s3-media4.fl.yelpcdn.com/bphoto/NUupoy...	False	https://www.yelp.com/biz/candor-coffee-renton?...	20	[{'alias': 'coffee', 'title': 'Coffee & Tea'},...	4.50	{'latitude': 47.441603, 'longitude': -122.220055}	[]	Na
7	9yDshpKSd3mjYs2JUY5JbQ	espresso-chalet-index	Espresso Chalet	https://s3-media1.fl.yelpcdn.com/bphoto/vkm9Vg...	False	https://www.yelp.com/biz/espresso-chalet-index...	65	[{'alias': 'coffee', 'title': 'Coffee & Tea'}]	4.00	{'latitude': 47.8085589918289, 'longitude': -1...	[]	
8	Abtd76-NMG-MNlaOklCxMg	the-bindlestick-snoqualmie	The Bindlestick	https://s3-media1.fl.yelpcdn.com/bphoto/bpncBp...	False	https://www.yelp.com/biz/the-bindlestick-snoqu...	64	[{'alias': 'coffee', 'title': 'Coffee & Tea'},...	4.00	{'latitude': 47.52869, 'longitude': -121.82507}	[]	
9	U0zB-UuDQCYZWilcG_ju7A	cafe-minee-snoqualmie	Cafe Minee	https://s3-media4.fl.yelpcdn.com/bphoto/YQdJgn...	False	https://www.yelp.com/biz/cafe-minee-snoqualmie...	64	[{'alias': 'bakeries', 'title': 'Bakeries'}, {...	4.00	{'latitude': 47.52747, 'longitude': -121.82406}	[]	

In [75]:
```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 [76]:
```
for i in range(len(great_coffee_coordinates)):
    df_cleaned[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_cleaned['closest_distance_to_great_coffee'] = df_cleaned[great_coffee_cols].min(axis=1)
```

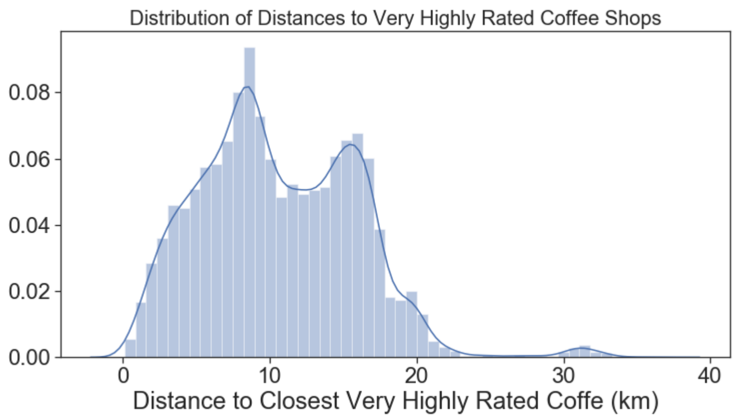
In [77]:
```
df_cleaned.closest_distance_to_great_coffee.describe()
```

Out[77]:
```
count    21580.00
mean        10.60
std          5.32
min          0.09
25%          6.66
50%          9.94
75%         14.71
max         36.98
Name: closest_distance_to_great_coffee, dtype: float64
```

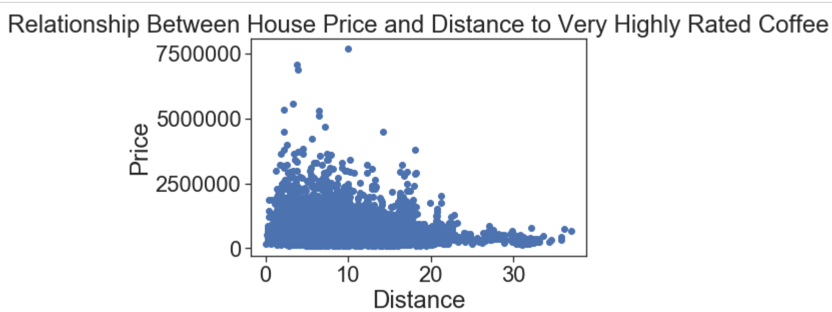
The closest distance to a very highly rated coffee shop is 0.09 km. The farthest distance is 39.19 km.

In [78]:
```
plt.figure(figsize=(12,6))
sns.distplot(df_cleaned['closest_distance_to_great_coffee'])
plt.title("Distribution of Distances to Very Highly Rated Coffee Shops", fontsize=20)
plt.xlabel('Distance to Closest Very Highly Rated Coffe (km)');
print("Skewness:", df_cleaned['closest_distance_to_great_coffee'].skew())
print("Kurtosis:", df_cleaned['closest_distance_to_great_coffee'].kurt())
```

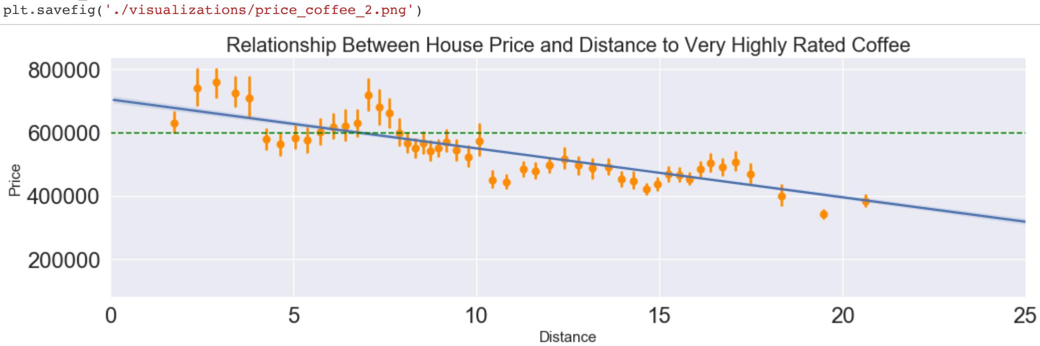
```
Skewness: 0.5729380397094243
Kurtosis: 0.7979295440671059
```



In [79]:
```
plt.scatter(x=df_cleaned['closest_distance_to_great_coffee'], y=df_cleaned['price'])
plt.title('Relationship Between House Price and Distance to Very Highly Rated Coffee')
plt.xlabel('Distance')
plt.ylabel('Price');
```



In [80]:
```
# plotting house price by distance to highly rated coffee
sns.set_style('darkgrid')
sns.lmplot(x='closest_distance_to_great_coffee', y='price', data=df_cleaned, aspect=3, x_bins=50, scatter_kws={'color': 'darkorange'})
plt.title('Relationship Between House Price and Distance to Very Highly Rated Coffee', fontsize=20)
plt.xlabel('Distance', fontsize=15)
plt.ylabel('Price', fontsize=15)
plt.xlim(0, 25)
plt.axhline(y=600000, ls='--', c='green');
plt.tight_layout()
plt.savefig('./visualizations/price_coffee_2.png')
```



In [81]:
```python
#dropping unnecessary columns
df_cleaned = df_cleaned.drop(columns = great_coffee_cols, axis=1)
df_cleaned.head()
```

Out[81]:

	price	bedrooms	bathrooms	sqft_living	sqft_lot	floors	waterfront	view	condition	grade	zipcode	lat	long	closest_distance_to_school	closest_distance_to_top_school	closest_distance_to_good_coffee
0	221900.00	3	1.00	1180	5650	1.00	nan	0.00	3	7	98178	47.51	-122.26	0.26	0.26	4.39
1	538000.00	3	2.25	2570	7242	2.00	0.00	0.00	3	7	98125	47.72	-122.32	0.68	0.68	10.38
2	180000.00	2	1.00	770	10000	1.00	0.00	0.00	3	6	98028	47.74	-122.23	0.32	2.00	10.63
3	604000.00	4	3.00	1960	5000	1.00	0.00	0.00	5	7	98136	47.52	-122.39	1.73	1.73	8.88
4	510000.00	3	2.00	1680	8080	1.00	0.00	0.00	3	8	98074	47.62	-122.05	1.18	1.18	8.00

In [82]:
```python
df_cleaned.corr()
```

Out[82]:

	price	bedrooms	bathrooms	sqft_living	sqft_lot	floors	waterfront	view	condition	grade	zipcode	lat	long	closest_distance_to_school	closest_distance_to_top_school	closest_d
price	1.00	0.31	0.53	0.70	0.09	0.26	0.28	0.40	0.04	0.67	-0.05	0.31	0.03	0.07	-0.30	
bedrooms	0.31	1.00	0.51	0.58	0.03	0.18	-0.00	0.08	0.03	0.36	-0.16	-0.01	0.14	0.01	-0.00	
bathrooms	0.53	0.51	1.00	0.76	0.09	0.50	0.07	0.19	-0.13	0.67	-0.21	0.03	0.23	0.11	-0.05	
sqft_living	0.70	0.58	0.76	1.00	0.17	0.35	0.11	0.28	-0.06	0.76	-0.20	0.05	0.25	0.16	-0.06	
sqft_lot	0.09	0.03	0.09	0.17	1.00	-0.00	0.02	0.08	-0.01	0.11	-0.13	-0.09	0.23	0.36	0.11	
floors	0.26	0.18	0.50	0.35	-0.00	1.00	0.02	0.03	-0.26	0.46	-0.06	0.05	0.13	0.04	-0.10	
waterfront	0.28	-0.00	0.07	0.11	0.02	0.02	1.00	0.41	0.02	0.09	0.03	-0.01	-0.04	0.10	0.00	
view	0.40	0.08	0.19	0.28	0.08	0.03	0.41	1.00	0.05	0.25	0.09	0.01	-0.08	0.11	-0.02	
condition	0.04	0.03	-0.13	-0.06	-0.01	-0.26	0.02	0.05	1.00	-0.15	0.00	-0.01	-0.11	-0.03	0.01	
grade	0.67	0.36	0.67	0.76	0.11	0.46	0.09	0.25	-0.15	1.00	-0.19	0.11	0.21	0.13	-0.10	
zipcode	-0.05	-0.16	-0.21	-0.20	-0.13	-0.06	0.03	0.09	0.00	-0.19	1.00	0.27	-0.57	-0.19	-0.29	
lat	0.31	-0.01	0.03	0.05	-0.09	0.05	-0.01	0.01	-0.01	0.11	0.27	1.00	-0.14	-0.12	-0.69	
long	0.03	0.14	0.23	0.25	0.23	0.13	-0.04	-0.08	-0.11	0.21	-0.57	-0.14	1.00	0.33	-0.00	
closest_distance_to_school	0.07	0.01	0.11	0.16	0.36	0.04	0.10	0.11	-0.03	0.13	-0.19	-0.12	0.33	1.00	0.16	
closest_distance_to_top_school	-0.30	-0.00	-0.05	-0.06	0.11	-0.10	0.00	-0.02	0.01	-0.10	-0.29	-0.69	-0.00	0.16	1.00	
closest_distance_to_good_coffee	-0.10	-0.06	-0.12	-0.09	0.01	-0.13	0.07	0.05	0.00	-0.09	0.33	0.30	-0.45	0.04	0.05	
closest_distance_to_great_coffee	-0.22	-0.15	-0.17	-0.21	0.06	-0.06	0.01	0.05	0.05	-0.20	0.25	-0.18	-0.41	0.07	0.33	

We found that, similar to good schools, there was a negative correlation between house price and proximity to a very highly-rated coffee shop. As distance to a great coffee shop decreases, house price increases.

Proximity to Scientology Churches

We had heard a theory that homes located near scientology churches tend to be higher in price, due to the fact that scientologists are known for investing funds in their surrounding communities. While certainly unique, we wanted to explore this feature and see if there was any connection between house price and proximity to a church of scientology.

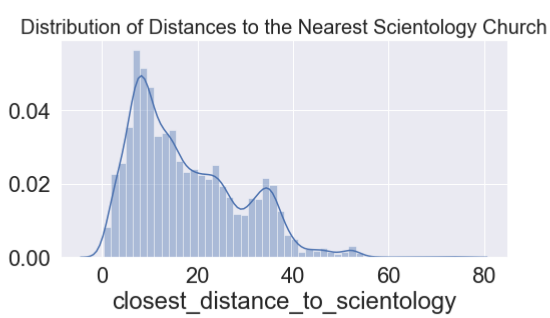
In [83]:
```python
#locations pulled from scientology-seattle.org
church_of_scientology_mission = (47.818100, -122.315430)
church_of_scientology_washington = (47.622380, -122.361020)
church_of_scientology_life_improvement_center = (47.615060, -122.327580)
```

In [84]:
```python
# creating a dataframe to investigate scientology proximity
scientology = pd.read_csv('./data/kc_house_data.csv')

# creating new columns of distances from houses to scientology churches
# running our haversine calculator function on these points
scientology['distance_to_scientology_m'] = distance_to(church_of_scientology_mission)
scientology['distance_to_scientology_w'] = distance_to(church_of_scientology_washington)
scientology['distance_to_scientology_l'] = distance_to(church_of_scientology_life_improvement_center)
scientology['closest_distance_to_scientology'] = scientology[['distance_to_scientology_m',
                                                          'distance_to_scientology_w',
                                                          'distance_to_scientology_l']].min(axis=1)
```

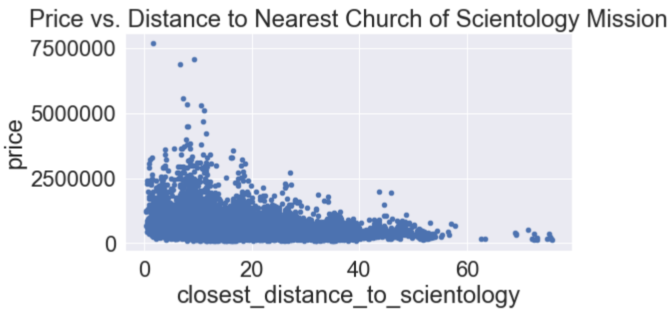
In [85]:
```python
plt.figure(figsize=(8,4))
sns.distplot(scientology['closest_distance_to_scientology'])
plt.title("Distribution of Distances to the Nearest Scientology Church", fontsize=20);
print("Distribution appears to deviate slightly from a normal distribution.")
print("Displays a positive skewness.")
print("Skewness:", scientology['closest_distance_to_scientology'].skew())
print("Kurtosis:", scientology['closest_distance_to_scientology'].kurt())
```

```
Distribution appears to deviate slightly from a normal distribution.
Displays a positive skewness.
Skewness: 0.8119816020278896
Kurtosis: 0.1550669496730026
```



In [86]:
```
#church of scientology vs price plot
plot1 = pd.concat([scientology['price'], scientology['closest_distance_to_scientology']], axis=1)
plot1.plot.scatter(x='closest_distance_to_scientology', y='price', figsize=(8,4))
plt.title("Price vs. Distance to Nearest Church of Scientology Mission");
```

```
'c' argument looks like a single numeric RGB or RGBA sequence, which should be avoided as value-mapping will have precedence in case its length matches with 'x'
& 'y'.  Please use a 2-D array with a single row if you really want to specify the same RGB or RGBA value for all points.
```



In [87]:
```
scientology.corr()
```

Out[87]:

	id	price	bedrooms	bathrooms	sqft_living	sqft_lot	floors	waterfront	view	condition	...	yr_renovated	zipcode	lat	long	sqft_living15	sqft_lot15	distance_to_scientology_m
id	1.00	-0.02	0.00	0.01	-0.01	-0.13	0.02	-0.00	0.01	-0.02	...	-0.01	-0.01	-0.00	0.02	-0.00	-0.14	0.01
price	-0.02	1.00	0.31	0.53	0.70	0.09	0.26	0.28	0.40	0.04	...	0.13	-0.05	0.31	0.02	0.59	0.08	-0.29
bedrooms	0.00	0.31	1.00	0.51	0.58	0.03	0.18	-0.00	0.08	0.03	...	0.02	-0.15	-0.01	0.13	0.39	0.03	0.02
bathrooms	0.01	0.53	0.51	1.00	0.76	0.09	0.50	0.07	0.19	-0.13	...	0.05	-0.20	0.02	0.22	0.57	0.09	0.03
sqft_living	-0.01	0.70	0.58	0.76	1.00	0.17	0.35	0.11	0.28	-0.06	...	0.06	-0.20	0.05	0.24	0.76	0.18	0.00
sqft_lot	-0.13	0.09	0.03	0.09	0.17	1.00	-0.00	0.02	0.08	-0.01	...	0.00	-0.13	-0.09	0.23	0.14	0.72	0.15
floors	0.02	0.26	0.18	0.50	0.35	-0.00	1.00	0.02	0.03	-0.26	...	0.00	-0.06	0.05	0.13	0.28	-0.01	-0.01
waterfront	-0.00	0.28	-0.00	0.07	0.11	0.02	0.02	1.00	0.41	0.02	...	0.09	0.03	-0.01	-0.04	0.09	0.03	0.01
view	0.01	0.40	0.08	0.19	0.28	0.08	0.03	0.41	1.00	0.05	...	0.10	0.09	0.01	-0.08	0.28	0.07	-0.02
condition	-0.02	0.04	0.03	-0.13	-0.06	-0.01	-0.26	0.02	0.05	1.00	...	-0.06	0.00	-0.02	-0.11	-0.09	-0.00	-0.02
grade	0.01	0.67	0.36	0.67	0.76	0.11	0.46	0.09	0.25	-0.15	...	0.02	-0.19	0.11	0.20	0.71	0.12	-0.06
sqft_above	-0.01	0.61	0.48	0.69	0.88	0.18	0.52	0.08	0.17	-0.16	...	0.02	-0.26	-0.00	0.34	0.73	0.20	0.08
yr_built	0.02	0.05	0.16	0.51	0.32	0.05	0.49	-0.03	-0.05	-0.36	...	-0.23	-0.35	-0.15	0.41	0.33	0.07	0.24
yr_renovated	-0.01	0.13	0.02	0.05	0.06	0.00	0.00	0.09	0.10	-0.06	...	1.00	0.07	0.03	-0.07	-0.00	0.00	-0.05
zipcode	-0.01	-0.05	-0.15	-0.20	-0.20	-0.13	-0.06	0.03	0.09	0.00	...	0.07	1.00	0.27	-0.56	-0.28	-0.15	-0.37
lat	-0.00	0.31	-0.01	0.02	0.05	-0.09	0.05	-0.01	0.01	-0.02	...	0.03	0.27	1.00	-0.14	0.05	-0.09	-0.96
long	0.02	0.02	0.13	0.22	0.24	0.23	0.13	-0.04	-0.08	-0.11	...	-0.07	-0.56	-0.14	1.00	0.34	0.26	0.38
sqft_living15	-0.00	0.59	0.39	0.57	0.76	0.14	0.28	0.09	0.28	-0.09	...	-0.00	-0.28	0.05	0.34	1.00	0.18	0.03
sqft_lot15	-0.14	0.08	0.03	0.09	0.18	0.72	-0.01	0.03	0.07	-0.00	...	0.00	-0.15	-0.09	0.26	0.18	1.00	0.16
distance_to_scientology_m	0.01	-0.29	0.02	0.03	0.00	0.15	-0.01	0.01	-0.02	-0.02	...	-0.05	-0.37	-0.96	0.38	0.03	0.16	1.00
distance_to_scientology_w	0.01	-0.28	0.07	0.09	0.09	0.24	0.00	-0.01	-0.07	-0.07	...	-0.09	-0.55	-0.65	0.69	0.15	0.27	0.80
distance_to_scientology_l	0.00	-0.30	0.05	0.07	0.07	0.24	-0.00	-0.01	-0.07	-0.07	...	-0.09	-0.51	-0.64	0.64	0.12	0.27	0.78
closest_distance_to_scientology	0.01	-0.28	0.05	0.08	0.07	0.23	0.01	-0.01	-0.07	-0.07	...	-0.08	-0.53	-0.72	0.65	0.12	0.26	0.85

23 rows × 23 columns

Like schools and coffee shops, there appears to be a negative correlation between proximity to a scientology church and the price of a house. As distance from a home to a scientology church decreases, house price tends to increase.

Web-scraped Data for Proximity to Parks

We hypthesized that being close to a park may have a correlation with house price as well. We web-scraped data to investigate this possibility.

In [88]:
```
# web-scraping park data from kingcounty.gov
url_parks = 'https://www.kingcounty.gov/services/parks-recreation/parks/parks-and-natural-lands/parksatoz.aspx'
html_parks = requests.get(url_parks)
soup_parks = BeautifulSoup(html_parks.content, 'html.parser')
addresses = soup_parks.findAll('strong')
```

In [89]:
```
park_addresses = []
for item in addresses:
    park_addresses.append(item.text.strip())

unwanted = ['Access','Use','Useful Links','Acreage:','Usage:','','Accessibility:',
            'Length:','Use:','Access:','Useful links','.','Trail length:','Helpful links']
park_addresses = [x for x in park_addresses if x not in unwanted]
```

In [90]:
```
names = soup_parks.findAll('a', class_ = 'collapsed')
```

In [91]:
```
park_names = []
for item in names:
    park_names.append(item.text.strip())
```

In [92]:
```
# removing inconsistent data
# no addresses listed for these particular parks
park_names.pop(0)
park_names.pop(27)
park_names.pop(7)
park_names.pop(41)
park_names.pop(62)
park_names.pop(-39)
```

Out[92]: 'Rattlesnake Mountain Scenic Area'

In [93]:
```
print(len(park_names))
print(len(park_addresses))
```

```
158
158
```

In [94]:
```
parks = dict(zip(park_names, park_addresses))
```

In [95]:
```
parks_df = pd.DataFrame.from_dict(parks, orient = 'index')
# saving to csv file
# parks_df.to_csv('./data/ParkAddresses_wLatLong.csv')
```

In [96]:
```
# 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[96]:

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 [97]:
```
king_parks.dropna(inplace=True)
```

In [98]:
```
#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 miles)
    dist_matrix = (dist.pairwise
    (df[['lat_radians_A','long_radians_A']],
     dataframe[['lat_radians','long_radians']])*3959)

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

In [99]:
```
#convert lat and long to radians in housing data
df[['lat_radians_A','long_radians_A']] = (np.radians(df.loc[:,['lat','long']]))
```

In [100]:
```
park_matrix = find_distance(king_parks)
```

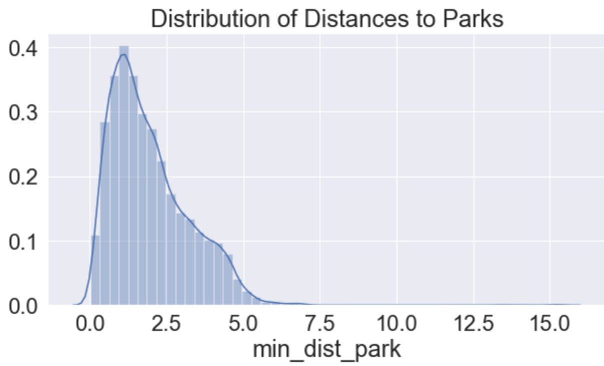
In [101]:
```
#find min distance in each row
park_min_matrix = park_matrix.where(park_matrix.values == park_matrix.min(
    axis=1)[:,None]).drop_duplicates()
```

In [102]:
```
#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 [103]:
```
data2 = df.join(nearest_park)
data2['min_dist_park']= data2['min_dist_park'].astype('float64')
```

In [104]:
```
# data2[['min_dist_park']].to_csv('data/park_distance.csv')
```

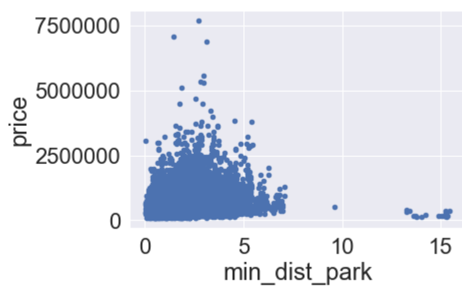
In [105]:
```
plt.figure(figsize=(10,5))
sns.distplot(data2['min_dist_park'])
plt.title('Distribution of Distances to Parks');
```



In [106]:
```
data2.plot.scatter(x='min_dist_park', y='price');
print('corr. price and parks: ' + str(data2['price'].corr(data2['min_dist_park'])))
```

```
'c' argument looks like a single numeric RGB or RGBA sequence, which should be avoided as value-mapping will have precedence in case its length matches with 'x' & 'y'.  Please use a 2-D array with a single row if you really want to specify the same RGB or RGBA value for all points.
```

```
corr. price and parks: 0.1640772485169492
```



It was not yet clear whether there was a relationship between proximity to a park and the price of a home. As we continued our exploration, removed outliers, narrowed down our data, and revised our park list to eliminate forests and trail heads, we began to see more of a connection.

Please see our next notebook, 'data_preparation', for the cleaning, compiling, and transformations of our data.

In [ ]: