```
In [1]:
# Initialize Otter
import otter
grader = otter.Notebook("proj1a.ipynb")
```

Project 1A: Exploring Cook County Housing

Due Date: Thursday, March 10th, 11:59 PM PDT

Collaboration Policy

Data science is a collaborative activity. While you may talk with others about the homework, we ask that you **write your solutions individually**. If you do discuss the assignments with others please **include their names** in the collaborators cell below.

```
In [10]:
!jupyter-nbconvert --to PDFviaHTML proj1a.ipynb
```

```
[NbConvertApp] Converting notebook proj1a.ipynb to PDFviaHTML
[NbConvertApp] Writing 496298 bytes to proj1a.pdf
```

Collaborators: *list names here*

Introduction

This project explores what can be learned from an extensive housing data set that is embedded in a dense social context in Cook County, Illinois.

Here in part A, we will guide you through some basic exploratory data analysis (EDA) to understand the structure of the data. Next, you will be adding a few new features to the dataset, while cleaning the data as well in the process.

In part B, you will specify and fit a linear model for the purpose of prediction. Finally, we will analyze the error of the model and brainstorm ways to improve the model's performance.

Score Breakdown

Question	Part	Points
1	1	1
1	2	1
1	3	1
1	4	1
2	1	1
2	2	1
3	1	3
3	2	1
3	3	1
4	-	2
5	1	1
5	2	2
5	3	2
6	1	1
6	2	2
6	3	1
6	4	2
6	5	1
7	1	1
7	2	2
Total	-	28

```
In [2]:
import numpy as np

import pandas as pd
from pandas.api.types import CategoricalDtype

%matplotlib inline
import matplotlib.pyplot as plt
import seaborn as sns

import warnings
warnings.filterwarnings("ignore")

import zipfile
import os

from ds100_utils import run_linear_regression_test

# Plot settings
plt.rcParams['figure.figsize'] = (12, 9)
plt.rcParams['font.size'] = 12
```

The Data

The data set consists of over 500 thousand records from Cook County, Illinois, the county where Chicago is located. The data set we will be working with has 61 features in total; the 62nd is sales price, which you will predict with linear regression in the next part of this project. An explanation of each variable can be found in the included `codebook.txt` file. Some of the columns have been filtered out to ensure this assignment doesn't become overly long when dealing with data cleaning and formatting.

The data are split into training and test sets with 204,792 and 68,264 observations, respectively, but we will only be working on the training set for this part of the project.

Let's first extract the data from the `cook_county_data.zip`. Notice we didn't leave the `csv` files directly in the directory because they take up too much space without some prior compression.

```
In [3]:
with zipfile.ZipFile('cook_county_data.zip') as item:
    item.extractall()
```

Let's load the training data.

```
In [4]:
training_data = pd.read_csv("cook_county_train.csv", index_col='Unnamed: 0')
```

As a good sanity check, we should at least verify that the data shape matches the description.

```
In [5]:
# 204792 observations and 62 features in training data
assert training_data.shape == (204792, 62)
# Sale Price is provided in the training data
assert 'Sale Price' in training_data.columns.values
```

The next order of business is getting a feel for the variables in our data. A more detailed description of each variable is included in `codebook.txt` (in the same directory as this notebook). **You should take some time to familiarize yourself with the codebook before moving forward.**

Let's take a quick look at all the current columns in our training data.

```
In [6]:
training_data.columns.values
```

```
Out[6]:
array(['PIN', 'Property Class', 'Neighborhood Code', 'Land Square Feet',
       'Town Code', 'Apartments', 'Wall Material', 'Roof Material',
       'Basement', 'Basement Finish', 'Central Heating', 'Other Heating',
       'Central Air', 'Fireplaces', 'Attic Type', 'Attic Finish',
       'Design Plan', 'Cathedral Ceiling', 'Construction Quality',
       'Site Desirability', 'Garage 1 Size', 'Garage 1 Material',
       'Garage 1 Attachment', 'Garage 1 Area', 'Garage 2 Size',
       'Garage 2 Material', 'Garage 2 Attachment', 'Garage 2 Area',
       'Porch', 'Other Improvements', 'Building Square Feet',
       'Repair Condition', 'Multi Code', 'Number of Commercial Units',
       'Estimate (Land)', 'Estimate (Building)', 'Deed No.', 'Sale Price',
       'Longitude', 'Latitude', 'Census Tract',
       'Multi Property Indicator', 'Modeling Group', 'Age', 'Use',
       "O'Hare Noise", 'Floodplain', 'Road Proximity', 'Sale Year',
       'Sale Quarter', 'Sale Half-Year', 'Sale Quarter of Year',
       'Sale Month of Year', 'Sale Half of Year', 'Most Recent Sale',
       'Age Decade', 'Pure Market Filter', 'Garage Indicator',
       'Neigborhood Code (mapping)', 'Town and Neighborhood',
       'Description', 'Lot Size'], dtype=object)
```

```
In [7]:
training_data['Description'][0]
```

```
Out[7]:
'This property, sold on 09/14/2015, is a one-story houeshold located at 2950 S LYMAN ST.It has a total of 6 ro
oms, 3 of which are bedrooms, and 1.0 of which are bathrooms.'
```

Part 1: Contextualizing the Data

Let's try to understand the background of our dataset before diving into a full-scale analysis.

Question 1

Part 1

Based on the columns present in this data set and the values that they take, what do you think each row represents? That is, what is the granularity of this data set?

Each row represents a different property along with its specifications in the Cook County of Illinois.

Part 2

Why do you think this data was collected? For what purposes? By whom?

This question calls for your speculation and is looking for thoughtfulness, not correctness.

I think this data was collected by the Federal Government for tax purposes or for census purposes because the data also inludes the use and census tracker of the property.

Part 3

Certain variables in this data set contain information that either directly contains demographic information (data on people) or could when linked to other data sets. Identify at least one demographic-related variable and explain the nature of the demographic data it embeds.

One demographic-related variable that is contained in the data set is the town and neigborhood variable. This variable indicates the area in which the property is located in, and when linked to another data set (probably one such as income) or recent sale price, the data might show how different areas correlate to higher sale prices/or a higher income bracket for the people occupying the property.

Part 4

Craft at least two questions about housing in Cook County that can be answered with this data set and provide the type of analytical tool you would use to answer it (e.g. "I would create a ***plot of*** and ***" or "I would calculate the*** [summary statistic] for _ **and** __"). Be sure to reference the columns that you would use and any additional data sets you would need to answer that question.

1. Do more expensive properties have more land square feet and is the relationship linear? I would plot these two together using a scatterplot then create a regression line. Then I would use a residual plot to determine if there are any strange patterns.
2. Do newer properties in Cook County, Illinois (in terms of the column Age) have more central air conditioning (Central Air) than older properties? I would create a plot here and because the Age is quantitative and the Central Air is categorical, I would create a KDE plot to show they relationship. The x would be the Age, and the hue would be Central Air and then I would examine the distributions for present and non-present air conditioning.

Part 2: Exploratory Data Analysis

This data set was collected by the Cook County Assessor's Office in order to build a model to predict the monetary value of a home (if you didn't put this for your answer for Question 1 Part 2, please don't go back and change it - we wanted speculation!). You can read more about data collection in the CCAO's Residential Data Integrity Preliminary Report. In part 2 of this project you will be building a linear model that predict sales prices using training data but it's important to first understand how the structure of the data informs such a model. In this section, we will make a series of exploratory visualizations and feature engineering in preparation for that prediction task.

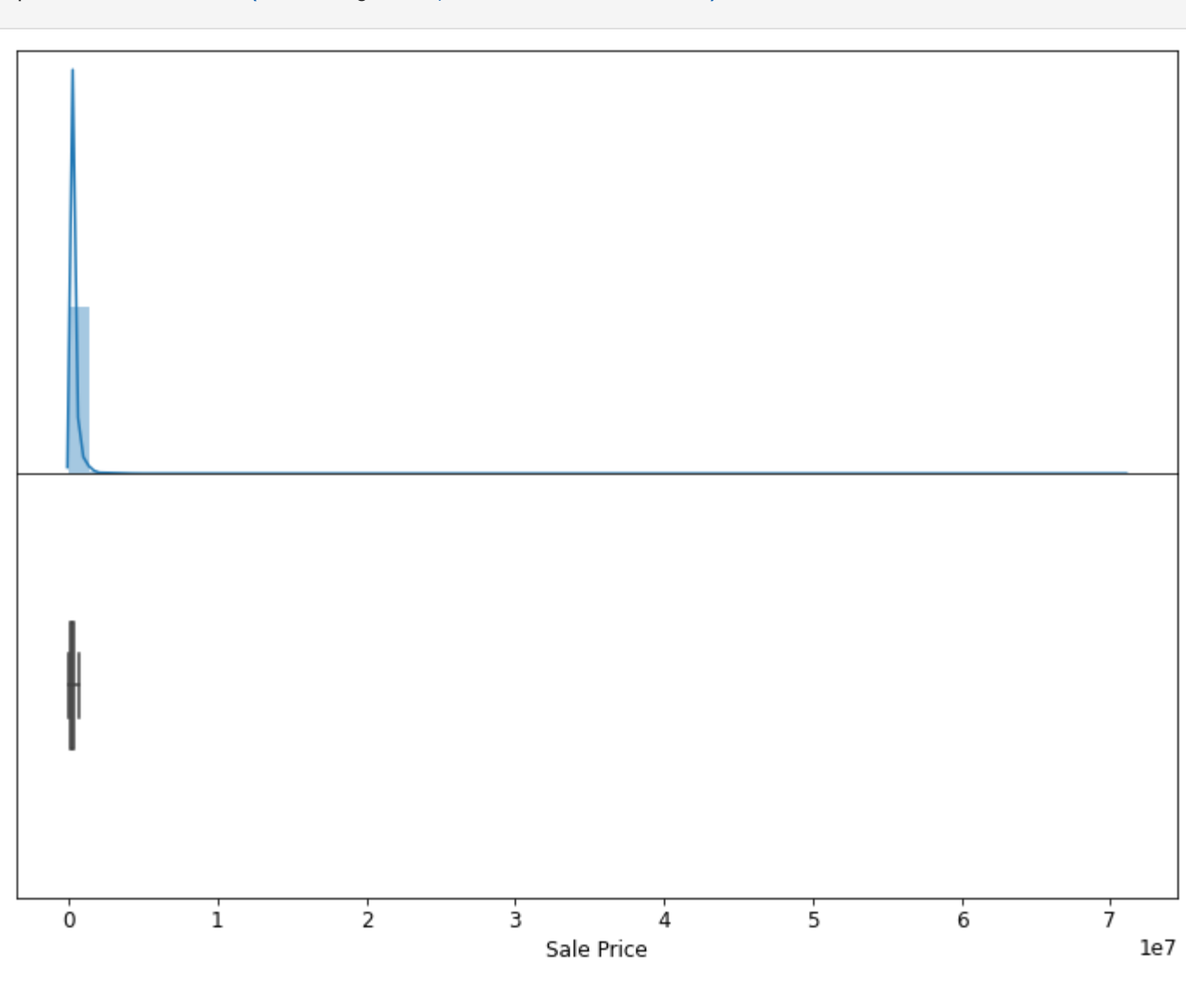
Note that we will perform EDA on the **training data**.

Sale Price

We begin by examining the distribution of our target variable `SalePrice`. At the same time, we also take a look at some descriptive statistics of this variable. We have provided the following helper method `plot_distribution` that you can use to visualize the distribution of the `SalePrice` using both the histogram and the box plot at the same time. Run the following 2 cells and describe what you think is wrong with the visualization.

```
In [8]:
def plot_distribution(data, label):
    fig, axs = plt.subplots(nrows=2)

    sns.distplot(
        data[label],
        ax=axs[0]
    )
    sns.boxplot(
        data[label],
        width=0.3,
        ax=axs[1],
        showfliers=False,
    )

    # Align axes
    spacer = np.max(data[label]) * 0.05
    xmin = np.min(data[label]) - spacer
    xmax = np.max(data[label]) + spacer
    axs[0].set_xlim((xmin, xmax))
    axs[1].set_xlim((xmin, xmax))

    # Remove some axis text
    axs[0].xaxis.set_visible(False)
    axs[0].yaxis.set_visible(False)
    axs[1].yaxis.set_visible(False)

    # Put the two plots together
    plt.subplots_adjust(hspace=0)

    # Adjust boxplot fill to be white
    axs[1].artists[0].set_facecolor('white')
```

```
In [9]:
plot_distribution(training_data, label='Sale Price')
```



Question 2

Part 1

Identify one issue with the visualization above and briefly describe one way to overcome it. You may also want to try running `training_data['Sale Price'].describe()` in a different cell to see some specific summary statistics on the distribution of the target variable. Make sure to delete the cell afterwards as the autograder may not work otherwise.

One issue with the visualiation above is that the scale of the x axis Sale Price is much too large for the actual Sale Price distribution, making the distribution look very compact and difficult to understand. Yes, the max is 7.1 le7, but the other data barely even comes close to that. Instead of using the min and max as the axis limit's, we could try and use the quartiles defined by describe method, or just choosing a smaller max and a larger min by applying log.

```
In [10]:
training_data['Sale Price'].describe()
```

```
Out[10]:
count    2.047920e+05
mean     2.451646e+05
std      3.628694e+05
min      1.000000e+00
25%      4.520000e+04
50%      1.750000e+05
75%      3.120000e+05
max      7.100000e+07
Name: Sale Price, dtype: float64
```

Part 2

To zoom in on the visualization of most households, we will focus only on a subset of `Sale Price` for this assignment. In addition, it may be a good idea to apply log transformation to `Sale Price`. In the cell below, reassign `training_data` to a new dataframe that is the same as the original one **except with the following changes**:

- `training_data` should contain only households whose price is at least $500.
- `training_data` should contain a new `Log Sale Price` column that contains the log-transformed sale prices.

Note: This also implies from now on, our target variable in the model will be the log transformed sale prices from the column `Log Sale Price`.

Note: You should **NOT** remove the original column `Sale Price` as it will be helpful for later questions.

To ensure that any error from this part does not propagate to later questions, there will be no hidden test here.

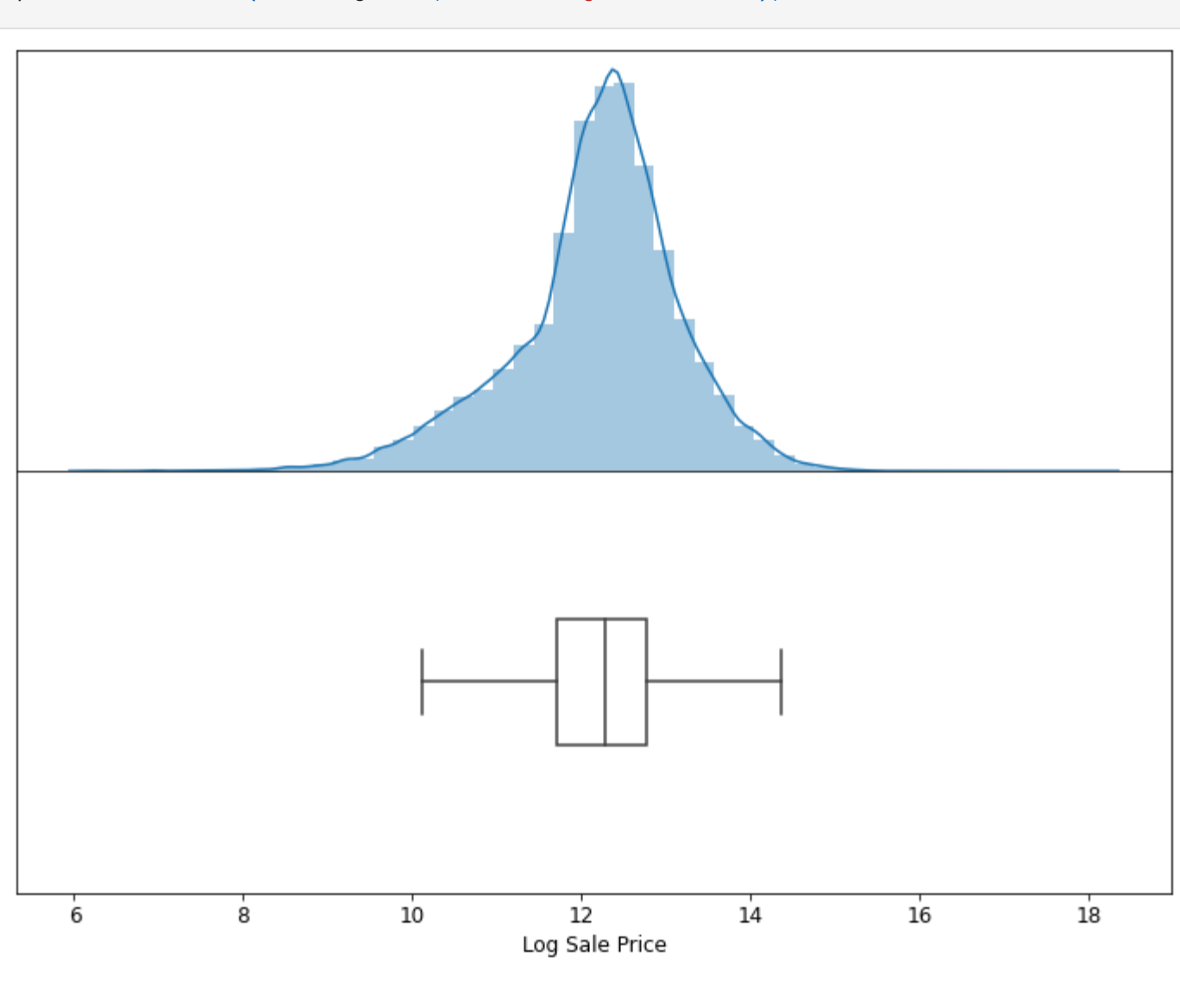
```
In [11]:
training_data = training_data[training_data["Sale Price"] >= 500]
training_data["Log Sale Price"] = np.log(training_data["Sale Price"])
```

```
In [12]:
grader.check("q2b")
```

Out[12]: **q2b** passed!

Let's create a new distribution plot on the log-transformed sale price.

```
In [13]:
plot_distribution(training_data, label='Log Sale Price');
```



Question 3

Part 1

To check your understanding of the graph and summary statistics above, answer the following `True` or `False` questions:

1. The distribution of `Log Sale Price` in the training set is symmetric.
2. The mean of `Log Sale Price` in the training set is greater than the median.
3. At least 25% of the houses in the training set sold for more than $200,000.00.

The provided tests for this question do not confirm that you have answered correctly; only that you have assigned each variable to `True` or `False`.

```
In [14]:
# These should be True or False
q3statement1 = False
q3statement2 = False
q3statement3 = True
```

```
In [15]:
grader.check("q3a")
```

Out[15]: **q3a** passed!

Part 2

Next, we want to explore if any there is any correlation between `Log Sale Price` and the total area occupied by the household. The `codebook.txt` file tells us the column `Building Square Feet` should do the trick -- it measures "(from the exterior) the total area, in square feet, occupied by the building".

Before creating this jointplot however, let's also apply a log transformation to the `Building Square Feet` column.

In the following cell, create a new column `Log Building Square Feet` in our `training_data` that contains the log transformed area occupied by each household.

You should NOT remove the original `Building Square Feet` column this time as it will be used for later questions.

To ensure that any errors from this part do not propagate to later questions, there will be no hidden tests here.

```
In [16]:
training_data["Log Building Square Feet"] = np.log(training_data["Building Square Feet"])
```

```
In [17]:
grader.check("q3b")
```

Out[17]: **q3b** passed!

Part 3

As shown below, we created a joint plot with `Log Building Square Feet` on the x-axis, and `Log Sale Price` on the y-axis. In addition, we fit a simple linear regression line through the bivariate scatter plot in the middle.

Based on the following plot, does there exist a correlation between `Log Sale Price` and `Log Building Square Feet`? Would `Log Building Square Feet` make a good candidate as one of the features for our model?

Joint Plot

There does seem to be a slight positive correlation between the Log Sale Price and Log Building Square Feet. Log Building Square Feet would make a good candidate as one of the features for our model.

Question 4

Continuing from the previous part, as you explore the data set, you might still run into more outliers that prevent you from creating a clear visualization or capturing the trend of the majority of the houses.

For this assignment, we will work to remove these outliers from the data as we run into them. Write a function `remove_outliers` that removes outliers from a data set based off a threshold value of a variable. For example, `remove_outliers(training_data, 'Building Square Feet', upper=8000)` should return a data frame with only observations that satisfy `Building Square Feet` less than or equal to 8000.

The provided tests check that training_data was updated correctly, so that future analyses are not corrupted by a mistake. However, the provided tests do not check that you have implemented remove_outliers correctly so that it works with any data, variable, lower, and upper bound.

```
In [18]:
def remove_outliers(data, variable, lower=-np.inf, upper=np.inf):
    """
    Input:
      data (data frame): the table to be filtered
      variable (string): the column with numerical outliers
      lower (numeric): observations with values lower than this will be removed
      upper (numeric): observations with values higher than this will be removed

    Output:
      a data frame with outliers removed

    Note: This function should not change mutate the contents of data.
    """
    data = data[data[variable] <= upper]
    data = data[data[variable] >= lower]
    return data
```

```
In [19]:
grader.check("q4")
```

Out[19]: **q4** passed!

Part 3: Feature Engineering

In this section we will walk you through a few feature engineering techniques.

Bedrooms

Let's start simple by extracting the total number of bedrooms as our first feature for the model. You may notice that the `Bedrooms` column doesn't actually exist in the original dataframe! Instead, it is part of the `Description` column.

Question 5

Part 1

Let's take a closer look at the `Description` column first. Compare the description across a few rows together at the same time. For the following list of variables, how many of them can be extracted from the `Description` column? Assign your answer as an integer to the variable `q4a`.

- The date the property was sold on
- The number of stories the property contains
- The previous owner of the property
- The address of the property
- The number of garages the property has
- The total number of rooms inside the property
- The total number of bedrooms inside the property
- The total number of bathrooms inside the property

```
In [20]:
q5a = 6
```

```
In [21]:
grader.check("q5a")
```

Out[21]: **q5a** passed!

```
In [22]:
training_data["Description"].values
```

```
Out[22]:
array(['This property, sold on 05/23/2018, is a one-story houeshold located at 2844 N LOWELL AVE.It has a tota
l of 6 rooms, 3 of which are bedrooms, and 1.0 of which are bathrooms.',
       'This property, sold on 02/18/2016, is a one-story houeshold located at 11415 S PRAIRIE AVE.It has a to
tal of 7 rooms, 3 of which are bedrooms, and 1.0 of which are bathrooms.',
       'This property, sold on 07/23/2013, is a one-story with partially livable attics houeshold located at 2
012 DOBSON ST.It has a total of 5 rooms, 3 of which are bedrooms, and 1.5 of which are bathrooms.',
       ...,
       'This property, sold on 01/31/2014, is a one-story houeshold located at 3525 S 55TH AVE.It has a total
of 5 rooms, 3 of which are bedrooms, and 2.0 of which are bathrooms.',
       'This property, sold on 02/22/2018, is a one-story houeshold located at 8430 N OSCEOLA AVE.It has a tot
al of 5 rooms, 3 of which are bedrooms, and 1.0 of which are bathrooms.',
       'This property, sold on 04/22/2014, is a one-story houeshold located at 4209 W 47TH ST.It has a total o
f 4 rooms, 2 of which are bedrooms, and 1.0 of which are bathrooms.'],
      dtype=object)
```

Part 2

Write a function `add_total_bedrooms(data)` that returns a copy of `data` with an additional column called `Bedrooms` that contains the total number of bathrooms (as integers) for each house. **Treat missing values as zeros if necessary**. Remember that you can make use of vectorized code here; you shouldn't need any `for` statements.

Hint: You should consider inspecting the `Description` column to figure out if there is any general structure within the text. Once you have noticed a certain pattern, you are set with the power of Regex!

```
In [46]:
def add_total_bedrooms(data):
    """
    Input:
      data (data frame): a data frame containing at least the Description column.
    """
    with_rooms = data.copy()
    with_rooms["Bedrooms"] = with_rooms["Description"].str.findall(r"(\d)\sof which are bedrooms")
    with_rooms["Bedrooms"] = with_rooms["Bedrooms"].apply(lambda x: int(x[0])).fillna(0)
    return with_rooms


training_data = add_total_bedrooms(training_data)
```

```
In [47]:
grader.check("q5b")
```

Out[47]: **q5b** passed!

Part 3

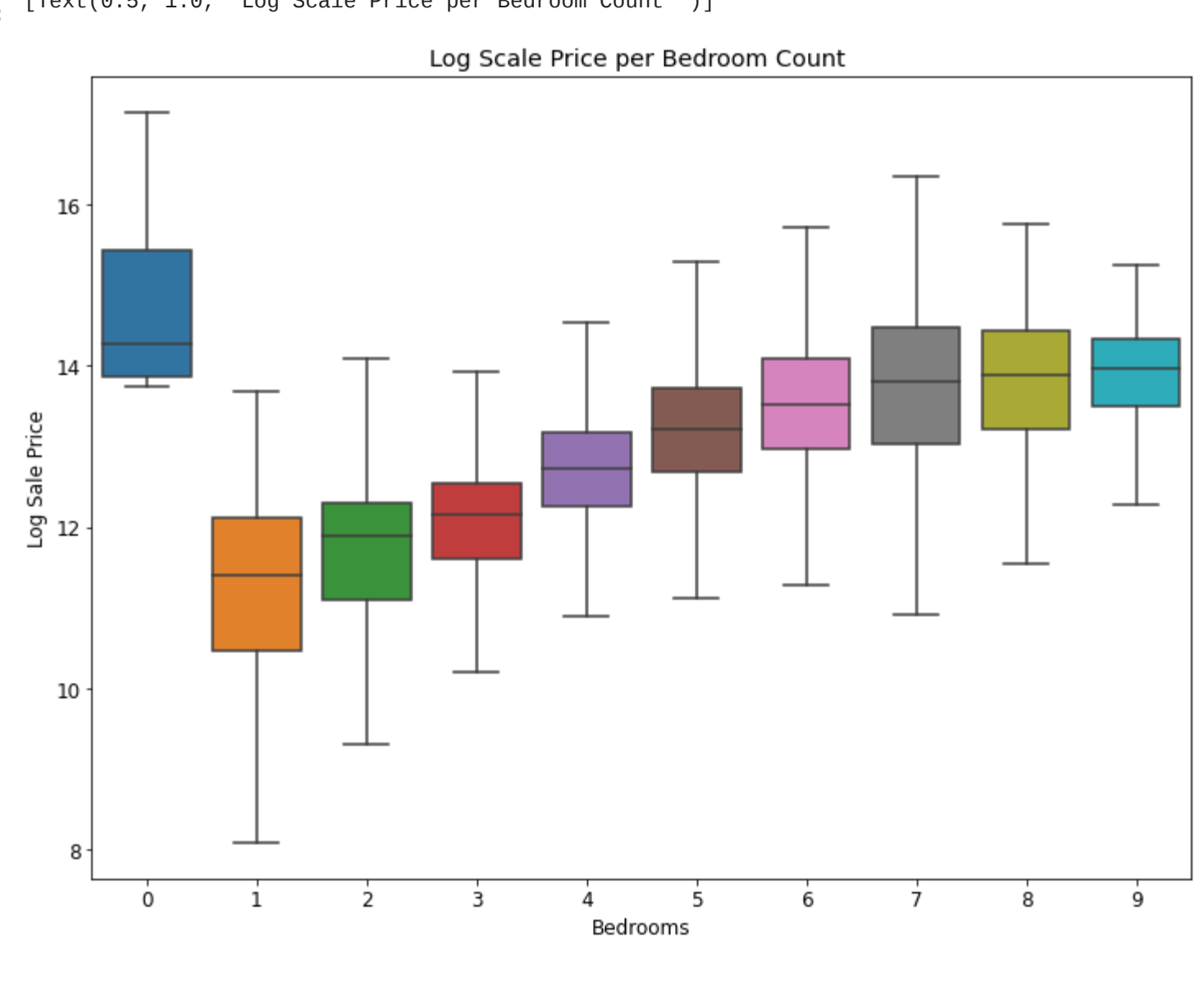
Create a visualization that clearly and succintly shows if there exists an association between `Bedrooms` and `Log Sale Price`. A good visualization should satisfy the following requirements:

- It should avoid overplotting.
- It should have clearly labeled axes and succinct title.
- It should convey the strength of the correlation between the sale price and the number of rooms.

Hint: A direct scatter plot of the sale price against the number of rooms for all of the households in our training data might risk overplotting.

```
In [48]:
sns.boxplot(x="Bedrooms", y="Log Sale Price", data=training_data, showfliers = False).set(title="Log Scale Pri
```

```
Out[48]:
[Text(0.5, 1.0, 'Log Scale Price per Bedroom Count ')]
```



Question 6

Now, let's take a look at the relationship between neighborhood and sale prices of the houses in our data set. Notice that currently we don't have the actual names for the neighborhoods. Instead we will use a similar column `Neighborhood Code` (which is a numerical encoding of the actual neighborhoods by the Assessment office).

Part 1

Before creating any visualization, let's quickly inspect how many different neighborhoods we are dealing with.

Assign the variable `num_neighborhoods` with the total number of neighborhoods in `training_data`.

```
In [49]:
num_neighborhoods = len(training_data["Neighborhood Code"].unique())
num_neighborhoods
```

Out[49]: 193

```
In [50]:
grader.check("q6a")
```

Out[50]: **q6a** passed!

Part 2

If we try directly plotting the distribution of `Log Sale Price` for all of the households in each neighborhood using the `plot_categorical` function from the next cell, we would get the following visualization. overplot

```
In [51]:
def plot_categorical(neighborhoods):
    fig, axs = plt.subplots(nrows=2)

    sns.boxplot(
        x='Neighborhood Code',
        y='Log Sale Price',
        data=neighborhoods,
        ax=axs[0],
    )

    sns.countplot(
        x='Neighborhood Code',
        data=neighborhoods,
        ax=axs[1],
    )

    # Draw median price
    axs[0].axhline(
        y=training_data['Log Sale Price'].median(),
        color='red',
        linestyle='dotted'
    )

    # Label the bars with counts
    for patch in axs[1].patches:
        x = patch.get_bbox().get_points()[:, 0]
        y = patch.get_bbox().get_points()[1, 1]
        axs[1].annotate(f'{int(y)}', (x.mean(), y), ha='center', va='bottom')

    # Format x-axes
    axs[1].set_xticklabels(axs[1].xaxis.get_majorticklabels(), rotation=90)
    axs[0].xaxis.set_visible(False)

    # Narrow the gap between the plots
    plt.subplots_adjust(hspace=0.01)
```

Oh no, looks like we have run into the problem of overplotting again!

You might have noticed that the graph is overplotted because **there are actually quite a few neighborhoods in our dataset**! For the clarity of our visualization, we will have to zoom in again on a few of them. The reason for this is our visualization will become quite cluttered with a super dense x-axis.

Assign the variable `in_top_20_neighborhoods` to a copy of `training_data` that contains only neighborhoods with the top 20 number of houses.

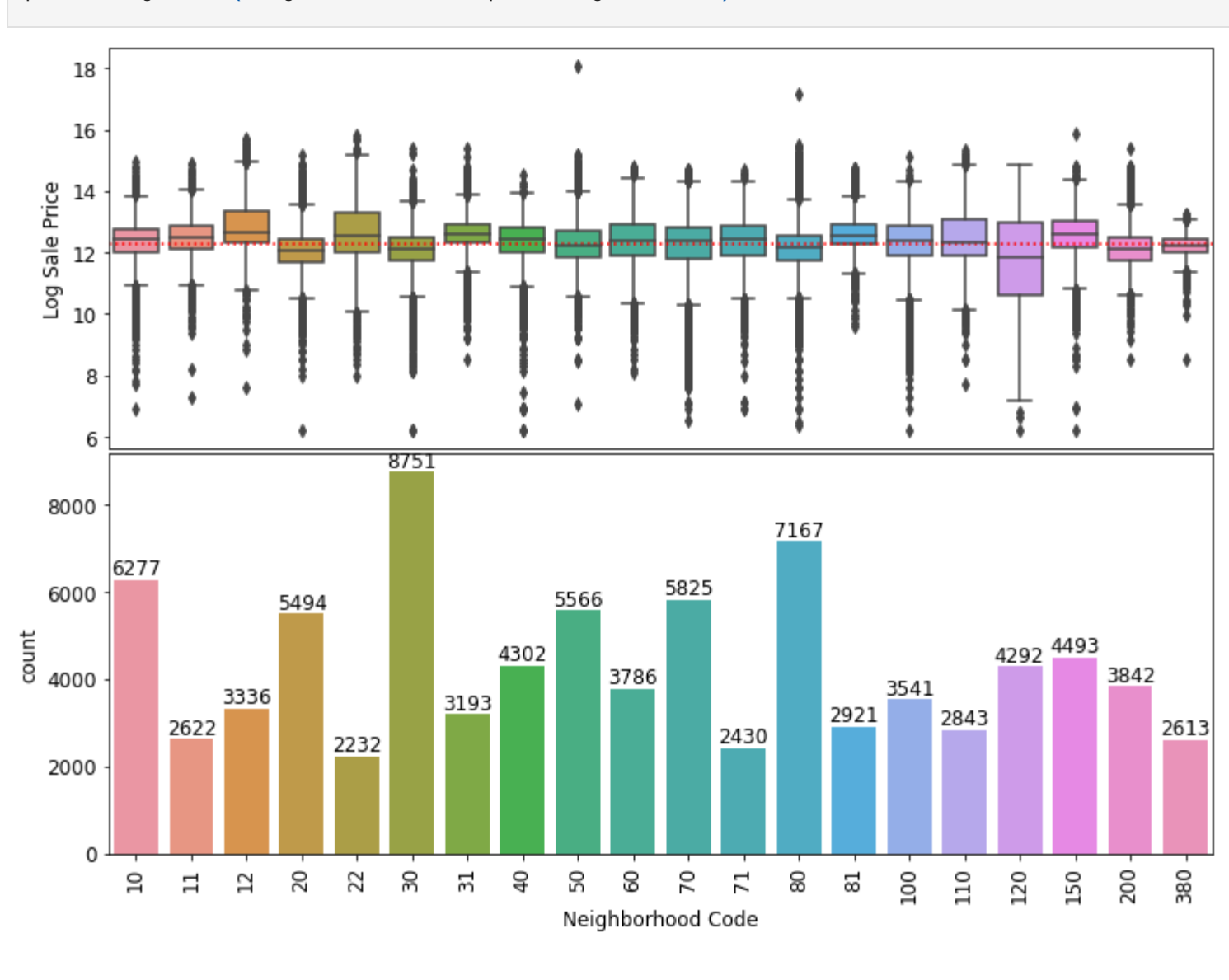
```
In [52]:
in_top_20_neighborhoods = training_data.groupby("Neighborhood Code").size().sort_values(ascending=False).head(
in_top_20_neighborhoods = training_data[training_data["Neighborhood Code"].isin(in_top_20_neighborhoods.index)
```

```
In [53]:
grader.check("q6b")
```

Out[53]: **q6b** passed!

Let's create another of the distribution of sale price within in each neighborhood again, but this time with a narrower focus!

```
In [54]:
plot_categorical(neighborhoods=in_top_20_neighborhoods)
```



Part 3

It looks a lot better now than before, right? Based on the plot above, what can be said about the relationship between the houses' `Log Sale Price` and their neighborhoods?

Looking at the plot above, we can see that the the relationship beween the Log Sale Price and their Neighborhoods is pretty similar and close to a median of a little higher than 12 for the majority of the top 20 neighborhoods. Some of the lower density neighborhoods are a little more expensive, such as 12, 110, and 22.

Part 4

One way we can deal with the lack of data from some neighborhoods is to create a new feature that bins neighborhoods together. Let's categorize our neighborhoods in a crude way: we'll take the top 3 neighborhoods measured by median `Log Sale Price` and identify them as "expensive neighborhoods"; the other neighborhoods are not marked.

Write a function that returns list of the neighborhood codes of the top `n` most pricy neighborhoods as measured by our choice of aggregating function. For example, in the setup above, we would want to call `find_expensive_neighborhoods(training_data, 3, np.median)` to find the top 3 neighborhoods measured by median `Log Sale Price`.

In [55]:

```
def find_expensive_neighborhoods(data, n=3, metric=np.median):
    """
    Input:
      data (data frame): should contain at least a string-valued 'Neighborhood Code'
        and a numeric 'Sale Price' column
      n (int): the number of top values desired
      metric (function): function used for aggregating the data in each neighborhood.
        for example, np.median for median prices

    Output:
      a list of the the neighborhood codes of the top n highest-priced neighborhoods as measured by the metric
    """
    neighborhoods = data.groupby("Neighborhood Code").agg({"Log Sale Price": metric}).sort_values(by="Log Sale
    # This makes sure the final list contains the generic int type used in Python3, not specific ones used in
    return [int(code) for code in neighborhoods]

expensive_neighborhoods = find_expensive_neighborhoods(training_data, 3, np.median)
expensive_neighborhoods
```

Out[55]:

```
[44, 94, 93]
```

In [56]:

```
grader.check("q6d")
```

Out[56]:

q6d passed!

Part 5

We now have a list of neighborhoods we've deemed as higher-priced than others. Let's use that information to write a function `add_expensive_neighborhood` that adds a column `in_expensive_neighborhood` which takes on the value 1 if the house is part of `expensive_neighborhoods` and the value 0 otherwise. This type of variable is known as an **indicator variable**.

Hint: `pd.Series.astype` may be useful for converting True/False values to integers.

In [57]:

```
def add_in_expensive_neighborhood(data, neighborhoods):
    """
    Input:
      data (data frame): a data frame containing a 'Neighborhood Code' column with values
        found in the codebook
      neighborhoods (list of strings): strings should be the names of neighborhoods
        pre-identified as expensive
    Output:
      data frame identical to the input with the addition of a binary
      in_expensive_neighborhood column
    """
    data['in_expensive_neighborhood'] = np.where(data["Neighborhood Code"].isin(neighborhoods), 1, 0)
    return data

expensive_neighborhoods = find_expensive_neighborhoods(training_data, 3, np.median)
training_data = add_in_expensive_neighborhood(training_data, expensive_neighborhoods)
```

In [58]:

```
grader.check("q6e")
```

Out[58]:

q6e passed!

Question 7

In the following question, we will take a closer look at the `Roof Material` feature of the dataset and examine how we can incorporate categorical features into our linear model.

Part 1

If we look at `codebook.txt` carefully, we can see that the Assessor's Office uses the following mapping for the numerical values in the `Roof Material` column.

```
Central Heating (Nominal):

        1    Shingle/Asphalt
        2    Tar&Gravel
        3    Slate
        4    Shake
        5    Tile
        6    Other
```

Write a function `substitute_roof_material` that replaces each numerical value in `Roof Material` with their corresponding roof material. Your function should return a new DataFrame, not modify the existing DataFrame.

Hint: the DataFrame.replace method may be useful here.

In [59]:

```
def substitute_roof_material(data):
    """
    Input:
      data (data frame): a data frame containing a 'Roof Material' column.  Its values
                         should be limited to those found in the codebook
    Output:
      data frame identical to the input except with a refactored 'Roof Material' column
    """
    data = data.copy()
    mapping = {1: "Shingle/Asphalt", 2: "Tar&Gravel", 3: "Slate", 4: "Shake", 5: "Tile", 6: "Other"}
    data["Roof Material"].replace(mapping, inplace=True)
    return data

training_data = substitute_roof_material(training_data)
training_data.head()
```

Out[59]:

	PIN	Property Class	Neighborhood Code	Land Square Feet	Town Code	Apartments	Wall Material	Roof Material	Basement	Basement Finish	...	Log Sale Price	Bu
1	13272240180000	202	120	3780.0	71	0.0	2.0	Shingle/Asphalt	1.0	1.0	...	12.560244	6.9
2	25221150230000	202	210	4375.0	70	0.0	2.0	Shingle/Asphalt	2.0	3.0	...	9.998798	6.8
3	10251130030000	203	220	4375.0	17	0.0	3.0	Shingle/Asphalt	1.0	3.0	...	12.323856	7.0
4	31361040550000	202	120	8400.0	32	0.0	3.0	Shingle/Asphalt	2.0	3.0	...	10.025705	6.8
6	30314240080000	203	181	10890.0	37	0.0	1.0	Shingle/Asphalt	1.0	3.0	...	11.512925	7.4

5 rows × 72 columns

In [60]:

```
grader.check("q7a")
```

Out[60]:

q7a passed!

Part 2

An Important Note on One Hot Encoding

Unfortunately, simply fixing these missing values isn't sufficient for using `Roof Material` in our model. Since `Roof Material` is a categorical variable, we will have to one-hot-encode the data. Notice in the example code below that we have to pre-specify the categories. For more information on categorical data in pandas, refer to this link. For more information on why we want to use one-hot-encoding, refer to this link.

Complete the following function `ohe_roof_material` that returns a dataframe with the new column one-hot-encoded on the roof material of the household. These new columns should have the form `x0_MATERIAL`. Your function should return a new DataFrame, not modify the existing DataFrame.

Note: You should **avoid using `pd.get_dummies`** in your solution as it will remove your original column and is therefore not as reusable as your constructed data preprocessing pipeline. Instead, you can one-hot-encode one column into multiple columns **using Scikit-learn's One Hot Encoder**.

In [61]:

```
from sklearn.preprocessing import OneHotEncoder

def ohe_roof_material(data):
    """
    One-hot-encodes roof material.  New columns are of the form x0_MATERIAL.
    """
    categories = ["Shingle/Asphalt", "Tar&Gravel", "Slate", "Shake", "Tile", "Other"]
    for value in categories:
        data["x0_" + value] = (data["Roof Material"] == value).astype(int)
    return data

training_data = ohe_roof_material(training_data)
training_data.filter(regex='^x0').head(10)
```

Out[61]:

	x0_Shingle/Asphalt	x0_Tar&Gravel	x0_Slate	x0_Shake	x0_Tile	x0_Other
1	1	0	0	0	0	0
2	1	0	0	0	0	0
3	1	0	0	0	0	0
4	1	0	0	0	0	0
6	1	0	0	0	0	0
7	1	0	0	0	0	0
8	0	1	0	0	0	0
9	1	0	0	0	0	0
10	1	0	0	0	0	0
11	1	0	0	0	0	0

In [62]:

```
grader.check("q7b")
```

Out[62]:

q7b passed!

Congratulations! You have finished Project 1A!

In Project 1B, you will focus on building a linear model to predict home prices. You will be well-prepared to build such a model: you have considered what is in this data set, what it can be used for, and engineered some features that should be useful for prediction. Creating a house-pricing model for Cook County has some challenging social implications to think, though, however. This will be addressed in an upcoming lecture and next week's discussion.

To double-check your work, the cell below will rerun all of the autograder tests.

In [63]:

```
grader.check_all()
```

Out[63]:

```
q2b results: All test cases passed!

q3a results: All test cases passed!

q3b results: All test cases passed!

q4 results: All test cases passed!

q5a results: All test cases passed!

q5b results: All test cases passed!

q6a results: All test cases passed!

q6b results: All test cases passed!

q6d results: All test cases passed!

q6e results: All test cases passed!

q7a results: All test cases passed!

q7b results: All test cases passed!
```

Submission

Make sure you have run all cells in your notebook in order before running the cell below, so that all images/graphs appear in the output. The cell below will generate a zip file for you to submit. **Please save before exporting!**

In [65]:

```
# Save your notebook first, then run this cell to export your submission.
grader.export()
```

Your submission has been exported. Click here to download the zip file.