# hw2

September 17, 2018

Before you turn this problem in, make sure everything runs as expected. First, **restart the kernel** (in the menubar, select Kernel→Restart) and then **run all cells** (in the menubar, select Cell→Run All).

Make sure you fill in any place that says YOUR CODE HERE or "YOUR ANSWER HERE", as well as your name and collaborators below:

```
In [1]: NAME = "Benjamin Liu"
        COLLABORATORS = ""
```

---

# 1 Homework 2: Bike Sharing

## 1.1 EDA and Visualization

## 1.2 Due Date: Tuesday 9/25, 11:59 PM

## 1.3 Course Policies

Here are some important course policies. These are also located at http://www.ds100.org/fa18/.

**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** at the top of your solution.

## 1.4 Introduction

This assignment includes both specific tasks to perform and open-ended questions to investigate. The open-ended questions ask you to think creatively and critically about how the plots you have created provide insight into the data.

After completing this assignment, you should be comfortable with:

- reading plaintext delimited data into pandas
- wrangling data for analysis
- using EDA to learn about your data
- making informative plots

### 1.5 Grading

Grading is broken down into autograded answers and free response.

For autograded answers, the results of your code are compared to public and/or hidden tests.

For free response, readers will evaluate how well you answered the question and/or fulfilled the requirements of the question.

For plots, your plots should be *similar* to the given examples. We will tolerate small variations such as color differences or slight variations in scale. However it is in your best interest to make the plots as similar as possible as similarity is subject to the readers.

**Note that for ALL plotting questions from here on out, we will expect appropriate titles, axis labels, legends, etc. The following question serves as a good guideline on what is "enough": If I directly downloaded the plot and viewed it, would I be able to tell what was being visualized without knowing the question?**

### 1.6 Submission - IMPORTANT, PLEASE READ

For this assignment and future assignments (homework and projects) you will also submit your free response and plotting questions to gradescope. To do this, you can download as PDF (File->Download As->PDF via Latex (.pdf)). You are responsible for submitting and tagging your answers in gradescope. For each free response and plotting question, please include:

1. Relevant code used to generate the plot or inform your insights
2. The written free response or plot

We are doing this to make it easier on our graders and for you, in the case you need to submit a regrade request. Gradescope (as of now) is still better for manual grading.

#### 1.6.1 Score breakdown

| Question | Points |
|---|---|
| Question 1a | 2 |
| Question 1b | 1 |
| Question 1c | 2 |
| Question 2a | 2 |
| Question 2b | 2 |
| Question 2c | 2 |
| Question 2d | 2 |
| Question 3a | 5 |
| Question 3b | 3 |
| Question 3c | 2 |
| Question 4a | 4 |
| Question 4b | 3 |
| Question 5a | 2 |
| Question 5b | 2 |
| Question 6a | 1 |
| Question 6b | 4 |
| Question 6c | 2 |
| Total | 41 |

In [2]:
```python
# Run this cell to set up your notebook.  Make sure ds100_utils.py is in this assignment's folder
import seaborn as sns
import csv
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import zipfile
from pathlib import Path
import ds100_utils

# Default plot configurations
%matplotlib inline
plt.rcParams['figure.figsize'] = (16,8)
plt.rcParams['figure.dpi'] = 150
sns.set()

from IPython.display import display, Latex, Markdown
```

## 1.7 Loading Bike Sharing Data

The data we are exploring is data on bike sharing in Washington D.C.
The variables in this data frame are defined as:

| Variable | Description |
|---|---|
| instant | record index |
| dteday | date |
| season | 1. spring 2. summer 3. fall 4. winter |
| yr | year (0: 2011, 1:2012) |
| mnth | month ( 1 to 12) |
| hr | hour (0 to 23) |
| holiday | whether day is holiday or not |
| weekday | day of the week |
| workingday | if day is neither weekend nor holiday |
| weathersit | 1. clear or partly cloudy 2. mist and clouds 3. light snow or rain 4. heavy rain or snow |
| temp | normalized temperature in Celsius (divided by 41) |
| atemp | normalized "feels-like" temperature in Celsius (divided by 50) |
| hum | normalized percent humidity (divided by 100) |
| windspeed | normalized wind speed (divided by 67) |
| casual | count of casual users |
| registered | count of registered users |
| cnt | count of total rental bikes including casual and registered |

### 1.7.1 Download the Data

In [3]:
```python
# Run this cell to download the data.  No further action is needed
```

```
data_url = 'https://github.com/DS-100/fa18/raw/gh-pages/assets/datasets/hw2-bikeshare.zip'
file_name = 'data.zip'
data_dir = '.'

dest_path = ds100_utils.fetch_and_cache(data_url=data_url, data_dir=data_dir, file=file_name)
print('Saved at {}'.format(dest_path))

zipped_data = zipfile.ZipFile(dest_path, 'r')

data_dir = Path('data')
zipped_data.extractall(data_dir)


print("Extracted Files:")
for f in data_dir.glob("*"):
    print("\t",f)
```

```
Using version already downloaded: Fri Sep 14 22:49:27 2018
MD5 hash of file: 2bcd2ca89278a8230f4e9461455c0811
Saved at data.zip
Extracted Files:
         data/bikeshare.txt
```

### 1.7.2 Examining the file contents

Can you identify the file format? (No answer required.)

In [4]:
```
# Run this cell to look at the top of the file.  No further action is needed
for line in ds100_utils.head(data_dir/'bikeshare.txt'):
    print(line,end="")
```

```
instant,dteday,season,yr,mnth,hr,holiday,weekday,workingday,weathersit,temp,atemp,hum,windspeed,casual,regist
1,2011-01-01,1,0,1,0,0,6,0,1,0.24,0.2879,0.81,0,3,13,16
2,2011-01-01,1,0,1,1,0,6,0,1,0.22,0.2727,0.8,0,8,32,40
3,2011-01-01,1,0,1,2,0,6,0,1,0.22,0.2727,0.8,0,5,27,32
4,2011-01-01,1,0,1,3,0,6,0,1,0.24,0.2879,0.75,0,3,10,13
```

### 1.7.3 Size

Is the file big? How many records do we expect to find? (No answers required.)

In [5]:
```
# Run this cell to view some metadata.  No further action is needed
print("Size:", (data_dir/"bikeshare.txt").stat().st_size, "bytes")
print("Line Count:", ds100_utils.line_count(data_dir/"bikeshare.txt"), "lines")
```

```
Size: 1156736 bytes
Line Count: 17380 lines
```

### 1.7.4 Loading the data

The following code loads the data into a Pandas DataFrame.

In [6]:
```
# Run this cell to load the data. No further action is needed
bike = pd.read_csv(data_dir/'bikeshare.txt')
bike.head()
```

Out[6]:
```
   instant      dteday  season  yr  mnth  hr  holiday  weekday  workingday  \
0        1  2011-01-01       1   0     1   0        0        6           0
1        2  2011-01-01       1   0     1   1        0        6           0
2        3  2011-01-01       1   0     1   2        0        6           0
3        4  2011-01-01       1   0     1   3        0        6           0
4        5  2011-01-01       1   0     1   4        0        6           0

   weathersit  temp   atemp   hum  windspeed  casual  registered  cnt
0           1  0.24  0.2879  0.81        0.0       3          13   16
1           1  0.22  0.2727  0.80        0.0       8          32   40
2           1  0.22  0.2727  0.80        0.0       5          27   32
3           1  0.24  0.2879  0.75        0.0       3          10   13
4           1  0.24  0.2879  0.75        0.0       0           1    1
```

Below, we show the shape of the file. You should see that the size of the dataframe matches the number of lines in the file, minus the header row.

In [7]:
```
bike.shape
```

Out[7]:
```
(17379, 17)
```

---

## 1.8 1: Data Preparation

A few of the variables that are numeric/integer actually encode categorical data. These include holiday, weekday, workingday, and weathersit. In the following problem, we will convert these four variables to strings specifying the categories. In particular, use 3-letter labels (Sun, Mon, Tue, Wed, Thu, Fri, and Sat) for weekday. You may simply use yes/no for holiday and workingday.

In this exercise we will *mutate* the data frame, **overwriting the corresponding variables in the data frame.** However, our notebook will effectively document this in-place data transformation for future readers. Make sure to leave the underlying datafile bikeshare.txt unmodified.

### 1.8.1 Question 1

**Question 1a (Decoding weekday, workingday, and weathersit)** Decode the holiday, weekday, workingday, and weathersit fields:

1. holiday: Convert to yes and no. Hint: There are fewer holidays...
2. weekday: It turns out that Monday is the day with the most holidays. Mutate the 'weekday' column to use the 3-letter label ('Sun', 'Mon', 'Tue', 'Wed', 'Thu', 'Fri', and 'Sat' ...) instead of its current numerical values. Assume 0 corresponds to Sun, 1 to Mon and so on.

3. workingday: Convert to yes and no.
4. weathersit: You should replace each value with one of Clear, Mist, Light, or Heavy.

Note if you want to revert the changes run the cell that reloads the csv.

**Hint:** One approach is to use the replace method of the pandas DataFrame class. We haven't discussed how to do this so you'll need to look at the documentation. The most concise way is with the approach described in the documentation as "nested-dictonaries", though there are many possible solutions.

In [8]:
```
# Modify holiday weekday, workingday, and weathersit here
# Hint: one strategy involves df.replace(...)

# YOUR CODE HERE
### BEGIN Solution
holiday_dict = {1: "yes", 0: "no"}
weekday_dict = {1: "Mon", 2: "Tue", 3: "Wed", 4: "Thu", 5: "Fri", 6: "Sat", 0: "Sun"}
workingday_dict = {0: "no", 1: "yes"}
weathersit_dict = {1: "Clear", 2: "Mist", 3: "Light", 4: "Heavy"}
def to_holiday(x):
    return holiday_dict[x]
def to_weekday(x):
    return weekday_dict[x]
def to_workingday(x):
    return workingday_dict[x]
def to_weathersit(x):
    return weathersit_dict[x]
bike['holiday'] = bike['holiday'].map(to_holiday)
bike['weekday'] = bike['weekday'].map(to_weekday)
bike['workingday'] = bike['workingday'].map(to_workingday)
bike['weathersit'] = bike['weathersit'].map(to_weathersit)
### END Solution
# raise NotImplementedError()
```

In [9]:
```
bike.head()
```

Out[9]:
```
   instant      dteday  season  yr  mnth  hr holiday weekday workingday  \
0        1  2011-01-01       1   0     1   0      no     Sat         no
1        2  2011-01-01       1   0     1   1      no     Sat         no
2        3  2011-01-01       1   0     1   2      no     Sat         no
3        4  2011-01-01       1   0     1   3      no     Sat         no
4        5  2011-01-01       1   0     1   4      no     Sat         no

  weathersit  temp   atemp   hum  windspeed  casual  registered  cnt
0      Clear  0.24  0.2879  0.81        0.0       3          13   16
1      Clear  0.22  0.2727  0.80        0.0       8          32   40
2      Clear  0.22  0.2727  0.80        0.0       5          27   32
3      Clear  0.24  0.2879  0.75        0.0       3          10   13
4      Clear  0.24  0.2879  0.75        0.0       0           1    1
```

In [10]:
```
assert isinstance(bike, pd.DataFrame)
assert bike['holiday'].dtype == np.dtype('O')
assert list(bike['holiday'].iloc[370:375]) == ['no', 'no', 'yes', 'yes', 'yes']
assert bike['weekday'].dtype == np.dtype('O')
assert bike['workingday'].dtype == np.dtype('O')
assert bike['weathersit'].dtype == np.dtype('O')
```

**Question 1b (Holidays)** How many entries in the data correspond to holidays? Set the variable num_holidays to this value.

In [11]:
```
num_holidays = bike[bike['holiday']=="yes"].shape[0]

# YOUR CODE HERE
# raise NotImplementedError()
```

In [12]:
```
assert 400 <= num_holidays <= 550
```

**Question 1c (Computing Daily Total Counts)** The granularity of this data is at the hourly level. However, for some of the analysis we will also want to compute daily statistics. In particular, in the next few questions we will be analyzing the daily number of registered and unregistered users.

Construct a data frame with the following columns: * casual: total number of casual riders for each day * registered: total number of registered riders for each day * workingday: whether that day is a working day or not (yes or no)

**Hint**: groupby and agg. For the agg method, please check the documentation for examples on applying different aggregations per column. If you use the capability to do different aggregations by column, you can do this task with a single call to groupby and agg. For the workingday column we can take any of the values since we are grouping by the day, thus the value will be the same within each group. Take a look at the 'first' or 'last' aggregation functions.

In [13]:
```
daily_counts = (
    bike[['dteday', 'casual', 'registered', 'workingday']]
    .groupby('dteday')
    .agg({'casual': "sum", 'registered': "sum", 'workingday': "first"})
)
daily_counts.head()
# YOUR CODE HERE
# raise NotImplementedError()
```

Out[13]:

| dteday | casual | registered | workingday |
|---|---|---|---|
| 2011-01-01 | 331 | 654 | no |
| 2011-01-02 | 131 | 670 | no |
| 2011-01-03 | 120 | 1229 | yes |
| 2011-01-04 | 108 | 1454 | yes |
| 2011-01-05 | 82 | 1518 | yes |

In [14]:
```
daily_counts.shape
```

Out[14]: (731, 3)

In [15]:
```
assert np.round(daily_counts['casual'].mean()) == 848.0
assert np.round(daily_counts['casual'].var()) == 471450.0
```

---

## 1.9 2: Exploring the Distribution of Riders

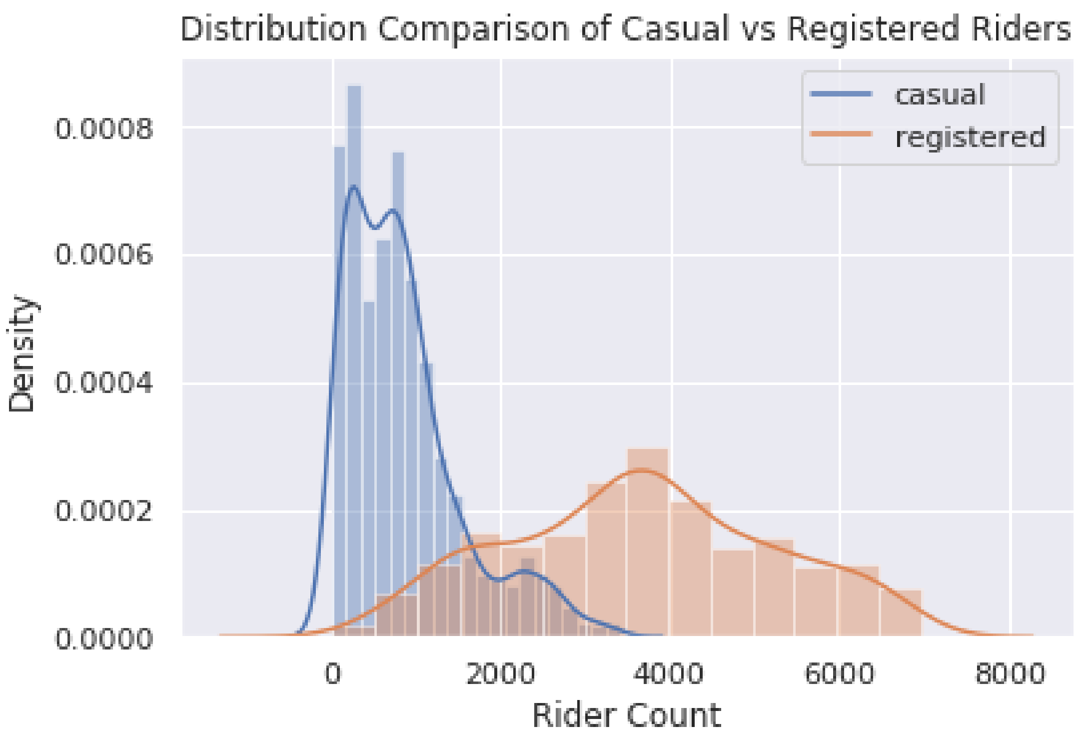
Let's begin by comparing the distribution of the daily counts of casual and registered riders.

### 1.9.1 Question 2

**Question 2a** Use the sns.distplot function to create a plot that overlays the distribution of the daily counts of casual and registered users. The temporal granularity of the records should be daily counts, which you should have after completing question 1c.

Include a legend, xlabel, ylabel, and title. You may want to look at the seaborn plotting tutorial if you're not sure how to add these. After creating the plot, look at it and make sure you understand what the plot is actually telling us, e.g on a given day, the most likely number of registered riders we expect is ~4000, but it could be anywher from almost none to 7000.

In [16]:
```
### BEGIN Solution
ax = sns.distplot(daily_counts['casual'], kde_kws={"label": "casual"})
sns.distplot(daily_counts['registered'], kde_kws={"label": "registered"});
ax.set_xlabel("Rider Count")
ax.set_ylabel("Density")
ax.set_title("Distribution Comparison of Casual vs Registered Riders");
### END Solution

# YOUR CODE HERE
# raise NotImplementedError()
```




### 1.9.2 Question 2b

In the cell below, descibe the differences you notice between the density curves for casual and registered riders. Consider concepts such as modes, symmetry, skewness, tails, gaps and outliers. Include a comment on the spread of the distributions.

In [17]:
```
q2b = " \
    The mode of the casual rider counts is significantly smaller than registered's. \
    The distribution of registered rider counts is symmetric bell shape while the casual rider distribution sk
    The spread of registered rider counts is wider than casual riders'  \
    The casual rider counts only have one-side tail. \
"

q2b

# YOUR CODE HERE
# raise NotImplementedError()
```

Out[17]: "     The mode of the casual rider counts is significantly smaller than registered's.     The distribution of

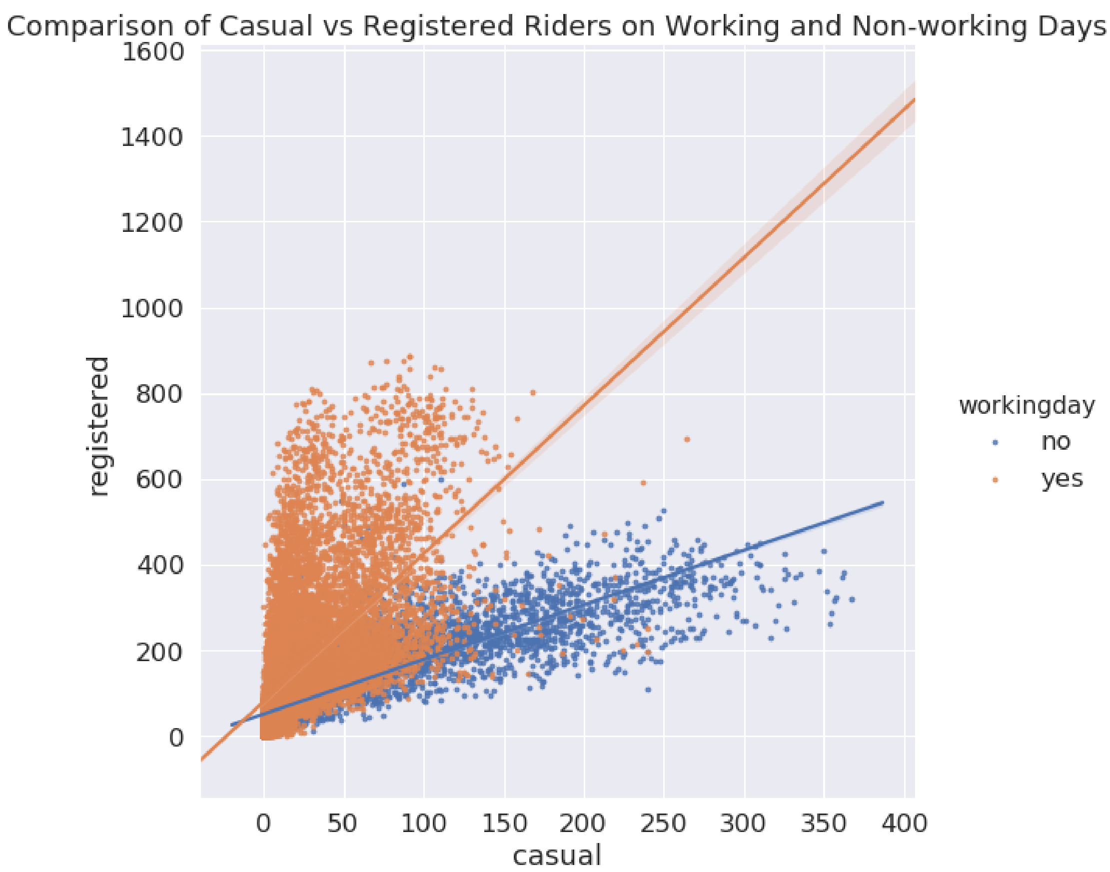
### 1.9.3 Question 2c

The density plots do not show us how the daily counts for registered and casual riders vary together. Use sns.lmplot to make a scatter plot to investigate the relationship between casual and registered counts. The lmplot function will also try to draw a linear regression line (just as you saw in Data 8). Color the points in the scatterplot according to whether or not the day is working day. There are many points in the scatter plot so make them small to help with over plotting. Also make sure to set fit_reg=True to generate the linear regression line. You can set the height parameter if you want to adjust the size of the lmplot. Make sure to include a title.

**Hints:** * Checkout this helpful tutorial on lmplot.

- You will need to set x, y, and hue and the scatter_kws.

In [18]:
```
# Make the font size a bit bigger
sns.set(font_scale=1.5)
### BEGIN Solution
ax = sns.lmplot(data=bike, x='casual', y='registered', hue='workingday', height=8, scatter_kws={'s': 8})
# ax = sns.lmplot(data=daily_counts, x='casual', y='registered', hue='workingday', height=8, scatter_k
ax = plt.gca();
ax.set_title("Comparison of Casual vs Registered Riders on Working and Non-working Days");
### END Solution

# YOUR CODE HERE
# raise NotImplementedError()
```



### 1.9.4 Question 2d

What does this scatterplot seem to reveal about the relationship (if any) between casual and registered riders and whether or not the day is on the weekend?

Why might we be concerned with overplotting in examining this relationship? By "overplotting", we're referring to the term used in chapter 6.5 of the textbook.

```
In [19]: q2d = " \
           On the weekend, there will be relatively more casual rides. \
           In general, the more casual riders, the more registered riders, but this relationship does't not imply caus
           There are many marks that make it difficult to tell where the data lie. In addition, some of the points o
         "
         q2d

         # YOUR CODE HERE
         # raise NotImplementedError()
```

---

## 1.10 3: Visualization

### 1.10.1 Question 3

**Question 3a Bivariate Kernel Density Plot** The scatter plot you made in question 2c makes clear the separation between the work days and non-work days. However, the overplotting makes it difficult to see the density of the joint counts. To address this issue, let's try visualizing the data with another technique, the bivariate kernel density estimate.

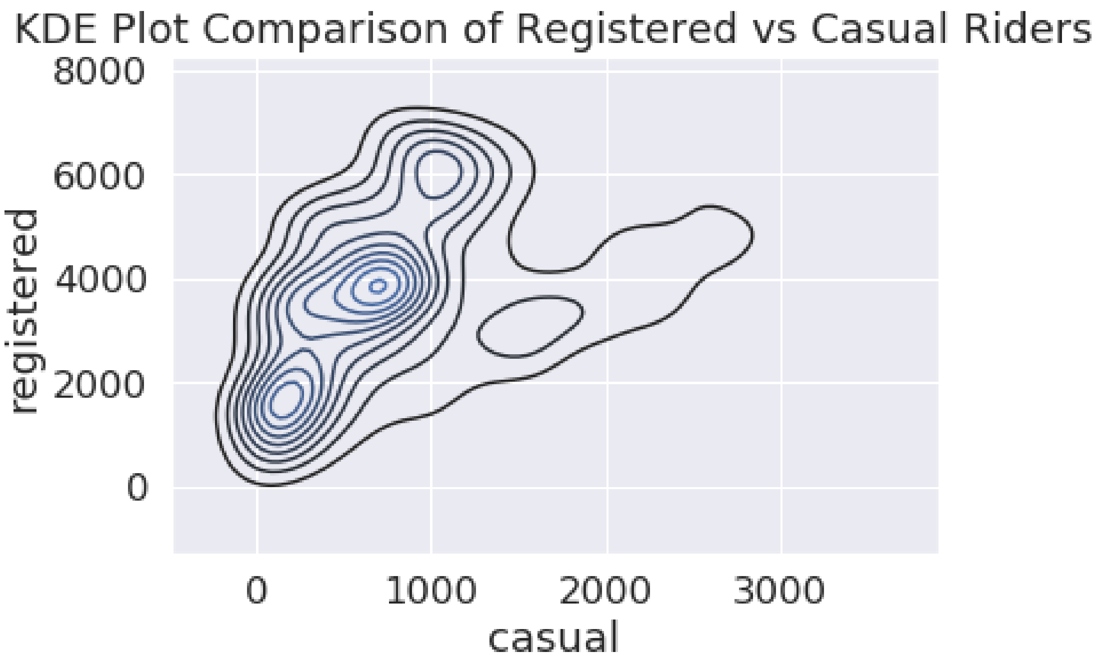
You will want to read up on the documentation for sns.kdeplot which can be found at https://seaborn.pydata.org/generated/seaborn.kdeplot.html

The result we wish to achieve should be a plot that looks something like this:

You can think of this plot as an overhead countour or topographical map, where the "high" regions are those with more data points, and "low" regions are those with fewer data points.

A basic kde plot of all the data is quite easy to generate. However, this plot includes both weekend and weekday data, which isn't what we want (see example figure above).

```
In [20]: sns.kdeplot(daily_counts['casual'], daily_counts['registered'])
         plt.title('KDE Plot Comparison of Registered vs Casual Riders');
```




Generating the plot with weekend and weekday separated can be complicated so we will provide a walkthrough below, feel free to use whatever method you wish however if you do not want to follow the walkthrough.

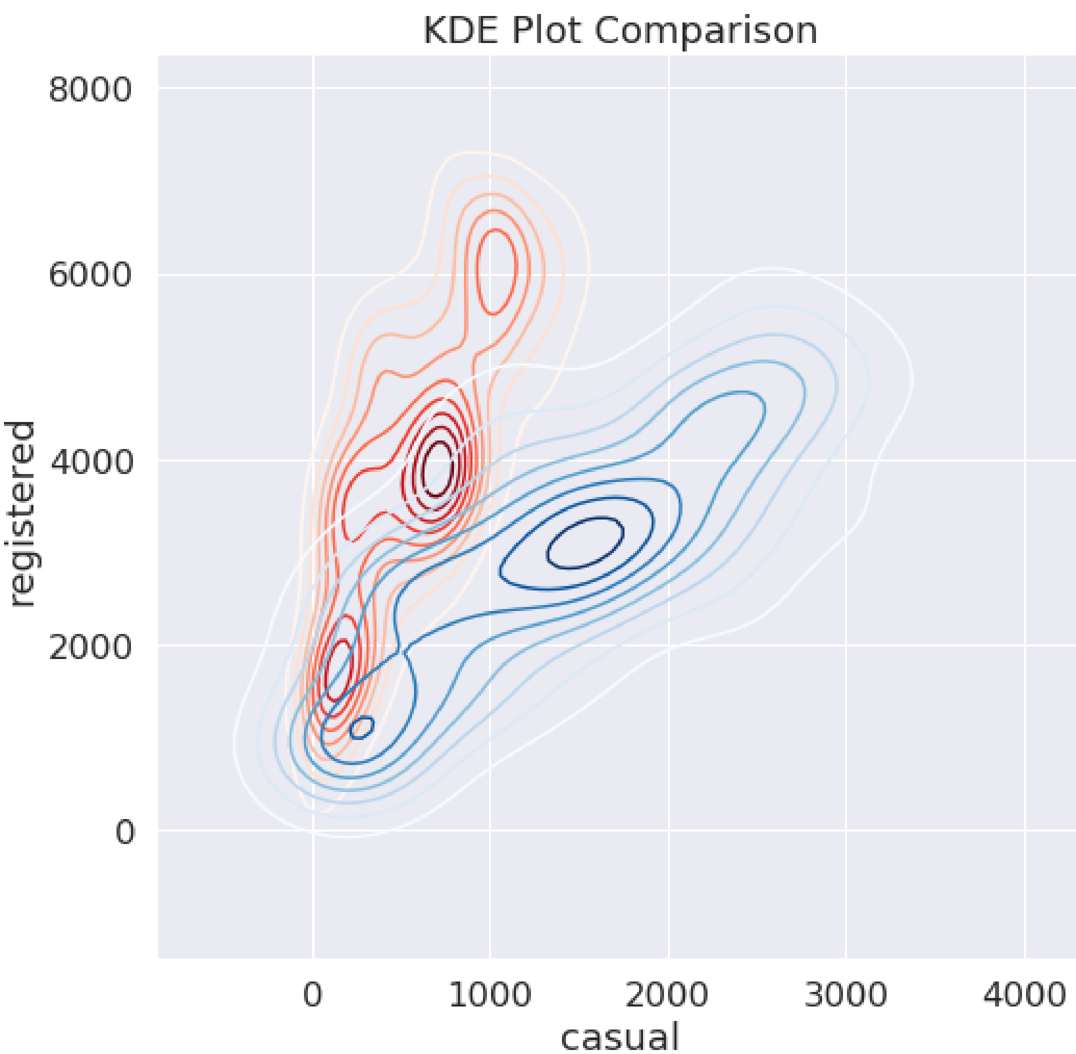
**Hints:** * You can use loc with a boolean array and column names at the same time, as seen in lecture 2. * You will need to call kdeplot twice. * Check out this tutorial to see an example of how to set colors for each dataset and how to create a legend. The legend part uses some weird matplotlib syntax that we haven't learned! You'll probably find creating the legend annoying, but it's a good exercise to learn how to use examples to get the look you want. * You will want to set the cmap parameter of kdeplot to "Reds" and "Blues" (or whatever two contrasting colors you'd like).

After you get your plot working, experiment by setting shade=True in kdeplot to see the difference between the shaded and unshaded version. Please submit your work with shade=False.

In [21]:
```
# is_workingday = (daily_counts['workingday']=='yes')
# is_workingday
```

In [22]:
```
import matplotlib.patches as mpatches  # see the tutorial for how we use mpatches to generate this figure

# Set 'is_workingday' to a boolean array that is true for all working_days
is_workingday = (daily_counts['workingday']=='yes')

# Bivariate KDEs require two data inputs.
# In this case, we will need the daily counts for casual and registered riders on weekdays
# Hint: use loc and is_workingday to splice out the relevant rows and column (casual/registered).
casual_weekday = daily_counts.loc[is_workingday, 'casual']
registered_weekday = daily_counts.loc[is_workingday, 'registered']
```

```python
# Use sns.kdeplot on the two variables above to plot the bivariate KDE for weekday rides

# Repeat the same steps above but for rows corresponding to non-workingdays
casual_weekend = daily_counts.loc[~is_workingday, 'casual']
registered_weekend = daily_counts.loc[~is_workingday, 'registered']

plt.figure(figsize=(8, 8))
# Use sns.kdeplot on the two variables above to plot the bivariate KDE for weekday rides
sns.kdeplot(casual_weekday, registered_weekday, legend=True, cmap="Reds")
sns.kdeplot(casual_weekend, registered_weekend, legend=True, cmap="Blues")
plt.title("KDE Plot Comparison");

# YOUR CODE HERE
# raise NotImplementedError()
```



**Question 3b** What does the contour plot suggest about the relationship between casual and registered riders for work days? For non-work days? Do you feel like it's easier to see the relationship on this countour plot, or on the plot you created for 2c? Why?

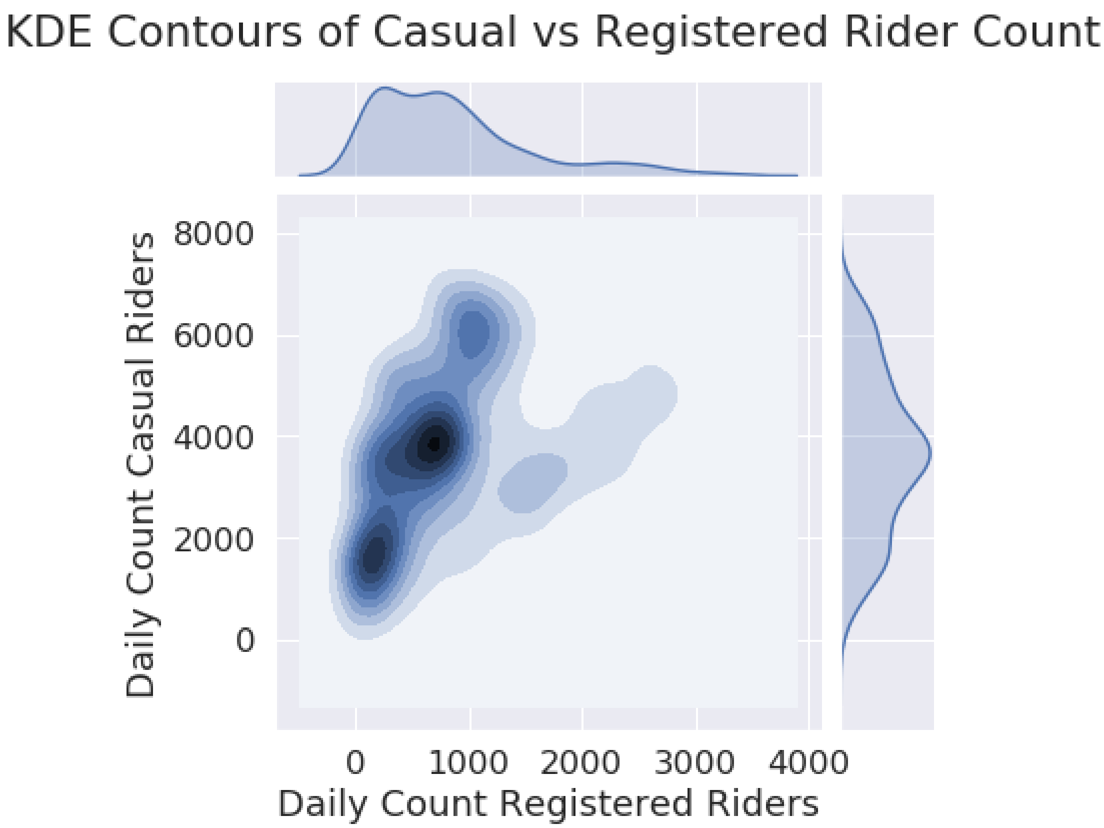
In [23]:
```
q3b = " \
    Both during workdays and non-workdays, the casual riders and registered riders are positive correlated.
    It is easier to see the relationship with the contour plot because there is no points overlapping and I hav
"
q3b
# YOUR CODE HERE
# raise NotImplementedError()
```

Out[23]:
```
'      Both during workdays and non-workdays, the casual riders and registered riders are positive correlat
```

**Question 3c** As an alternative approach to visualizing the data, construct the following set of three plots where the main plot shows the contours of the kernel density estimate of daily counts for registered and casual riders plotted together, and the two "margin" plots (at the top and right of the figure) provide the univariate kernel density estimate of each of these variables. Note that this plot makes it harder see the linear relationships between casual and registered for the two different conditions (weekday vs. weekend).

**Hints**: * The seaborn plotting tutorial has examples that may be helpful. * Take a look at `sns.jointplot` and its `kind` parameter. * `set_axis_labels` can be used to rename axes on the contour plot. * `plt.suptitle` from lab 1 can be handy for setting the title where you want. * `plt.subplots_adjust(top=0.9)` can help if your title overlaps with your plot

In [24]:
```
### BEGIN Solution
ax = sns.jointplot(data=daily_counts, x='casual', y='registered', kind='kde')
ax.set_axis_labels("Daily Count Registered Riders", "Daily Count Casual Riders")
plt.suptitle("KDE Contours of Casual vs Registered Rider Count")
plt.subplots_adjust(top=0.9);
### END Solution

# YOUR CODE HERE
# raise NotImplementedError()
```




---

## 1.11 4: Exploring Ride Sharing and Time

### 1.11.1 Question 4

**Question 4a** Plot number of riders for each day in the month of June in 2011.

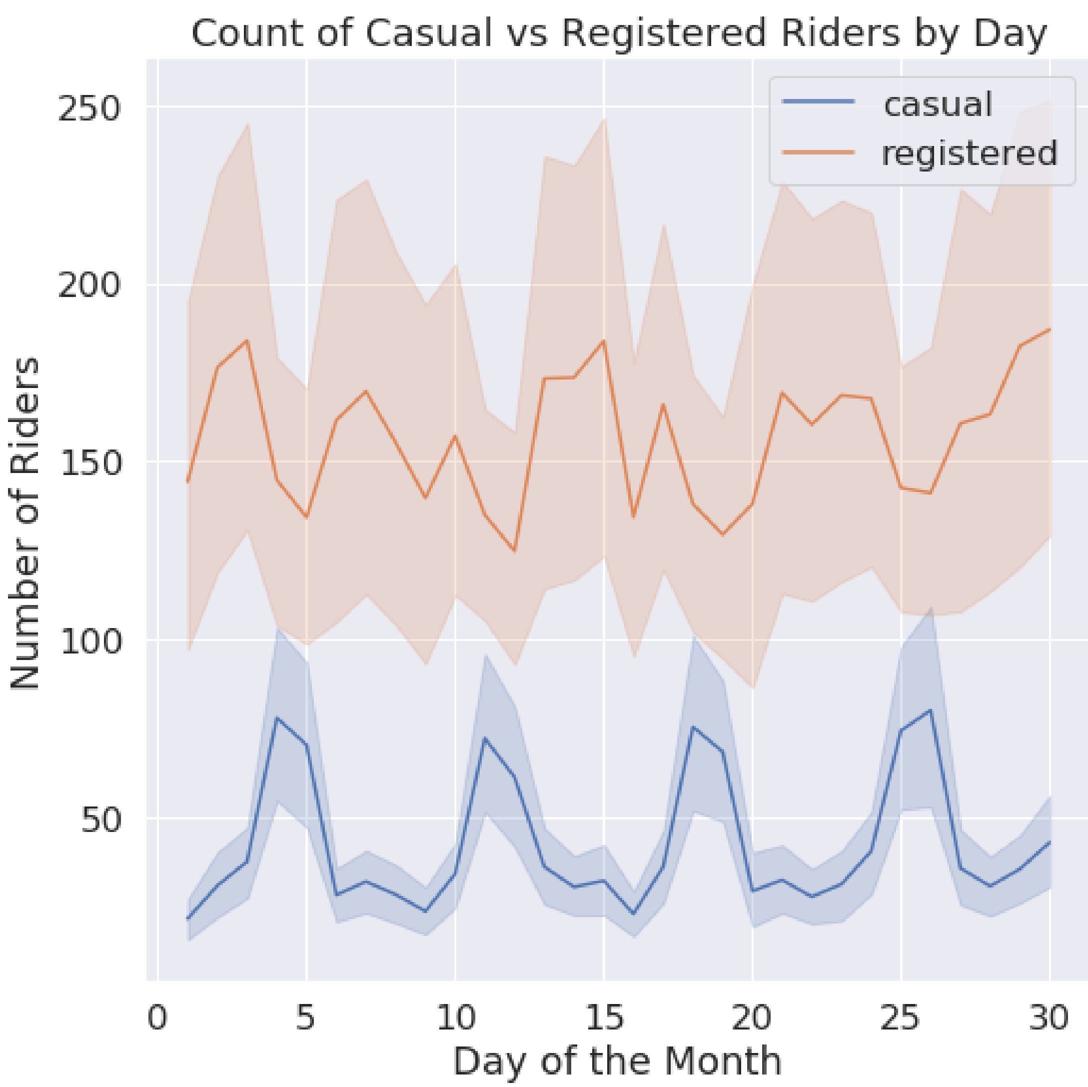
Make sure to add descriptive x-axis and y-axis labels and create a legend to distinguish the line for casual riders and the line for registered riders. The end result should look like the figure below. The shaded region is a bootstrap confidence interval similar to what you learned about in Data 8.

Make sure to include xlabel, ylabel, a legend, and a title.

**Hints:** * Add a new Series to the bike datafame correpsonding to the day. You can do something similar to what you did in hw1 when you created the postal_code_5 Seres. * Make sure your day series is of type int. One way is to use the map method of the Series class, i.e. s.map(int). * Use sns.lineplot.

```
In [25]: ### BEGIN Solution
         plt.figure(figsize=(8, 8))
         # daily_counts['day']=daily_counts.index.str[-2:].map(int)
         # daily_counts['year_mnth']=daily_counts.index.str[:-3]
         # June_2011 = daily_counts[daily_counts['year_mnth']=="2011-06"]
```

```
bike['day']=bike['dteday'].str[-2:].map(int)
bike['year_mnth']=bike['dteday'].str[:-3]
June_2011 = bike[bike['year_mnth']=="2011-06"]
# June_2011
# daily_counts.drop(columns=["day"], inplace=True)
ax = sns.lineplot(data=June_2011, x='day', y='casual')
sns.lineplot(data=June_2011, x='day', y='registered');
ax.set_xlabel("Day of the Month")
ax.set_ylabel("Number of Riders")
ax.set_title("Count of Casual vs Registered Riders by Day");
plt.legend(("casual", "registered"));
### END Solution

# YOUR CODE HERE
# raise NotImplementedError()
```



**Question 4b** This plot has several interesting features. How do the number of casual and registered riders compare for different days of the month? What is an interesting trend and pattern you notice between the lines? Why do you think the confidence interval for the registered riders is, on average, wider than the confidence interval for casual riders?

In [26]:
```
q4b = " \
    There is clear periodic pattern of both casual riders. \
    The number of registered riders is bigger than the casual riders. \
    When registered rides reach peak, the casual and vice versa. And the shaded area for registered rides is
    The CI for the registered riders is wider than the CI of casual riders. \
"
q4b
# YOUR CODE HERE
# raise NotImplementedError()
```

Out[26]:
```
'     There is clear periodic pattern of both casual riders.     The number of registered riders is bigger tha
```

---

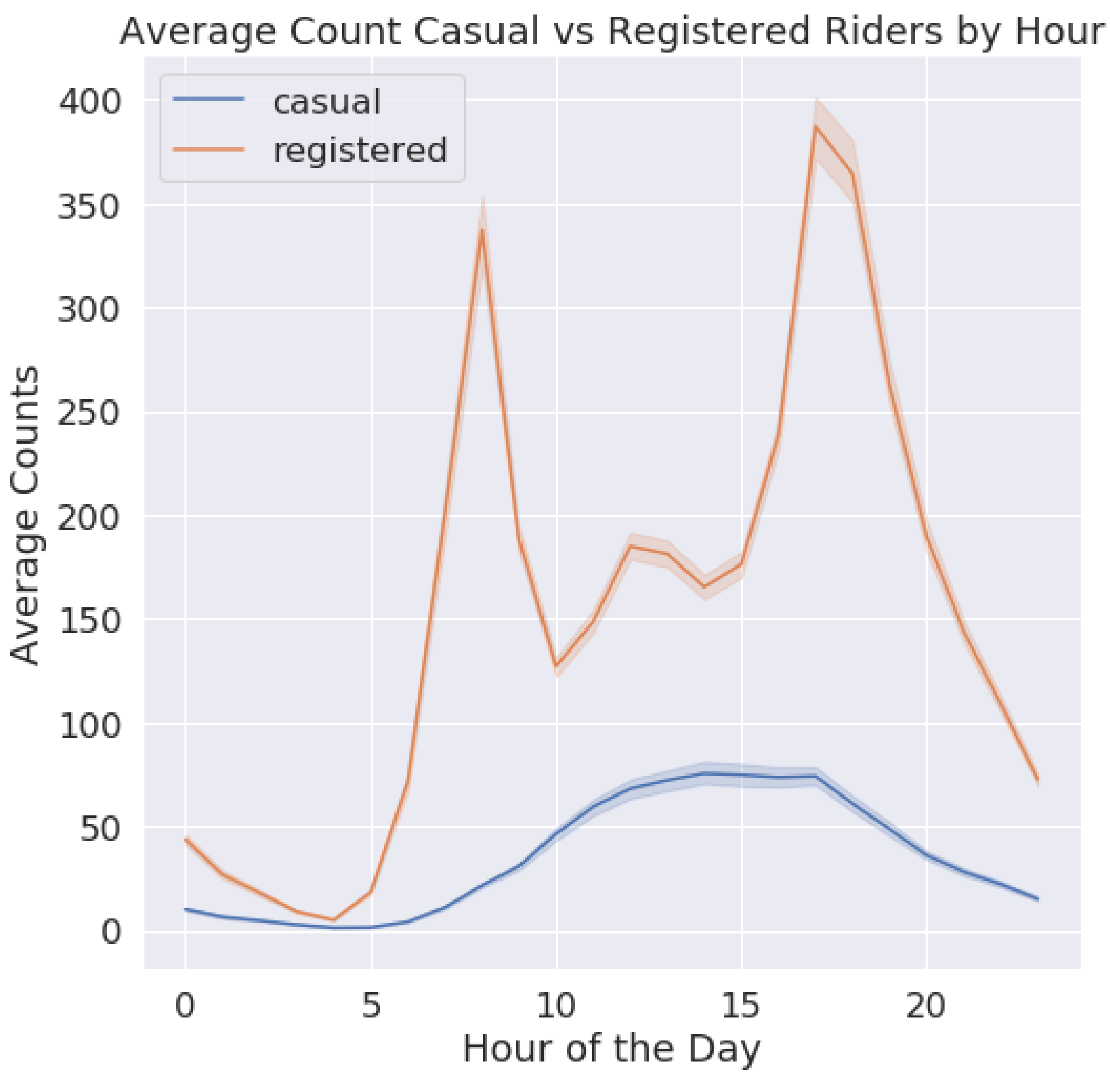
## 1.12 5: Understanding Daily Patterns

### 1.12.1 Question 5

**Question 5a** Let's examine the behavior of riders by plotting the average number of riders for each hour of the day over the **entire dataset** (not just June 2011), stratified by rider type.

Your plot should look like the following:

In [27]:
```
### BEGIN Solution
plt.figure(figsize=(8, 8))
ax = sns.lineplot(data=bike, x='hr', y='casual', estimator='mean')
sns.lineplot(data=bike, x='hr', y='registered', estimator='mean')
ax.set_xlabel("Hour of the Day")
ax.set_ylabel("Average Counts")
ax.set_title("Average Count Casual vs Registered Riders by Hour");
plt.legend(("casual", "registered"));
### END Solution

# YOUR CODE HERE
# raise NotImplementedError()
```




**Question 5b** What can you observe from the plot? Hypothesize about the meaning of the peaks in the registered riders' distribution.

```
In [28]: q5b = " \
            For casual riders, the number of rides increase slowly and reach its peak at 1pm-4pm and then graduall
            For registered riders, there are two spikes (9am and 5pm) in the rides counts. One hypothesis for the sp
         "
         q5b
         # YOUR CODE HERE
         # raise NotImplementedError()
```

```
Out[28]: '      For casual riders, the number of rides increase slowly and reach its peak at 1pm-4pm and then gradu
```

### 1.13 6: Exploring Ride Sharing and Weather

Now let's examine how the weather is affecting rider's behavior. First let's look at how the proportion of casual riders changes as weather changes.

#### 1.13.1 Question 6

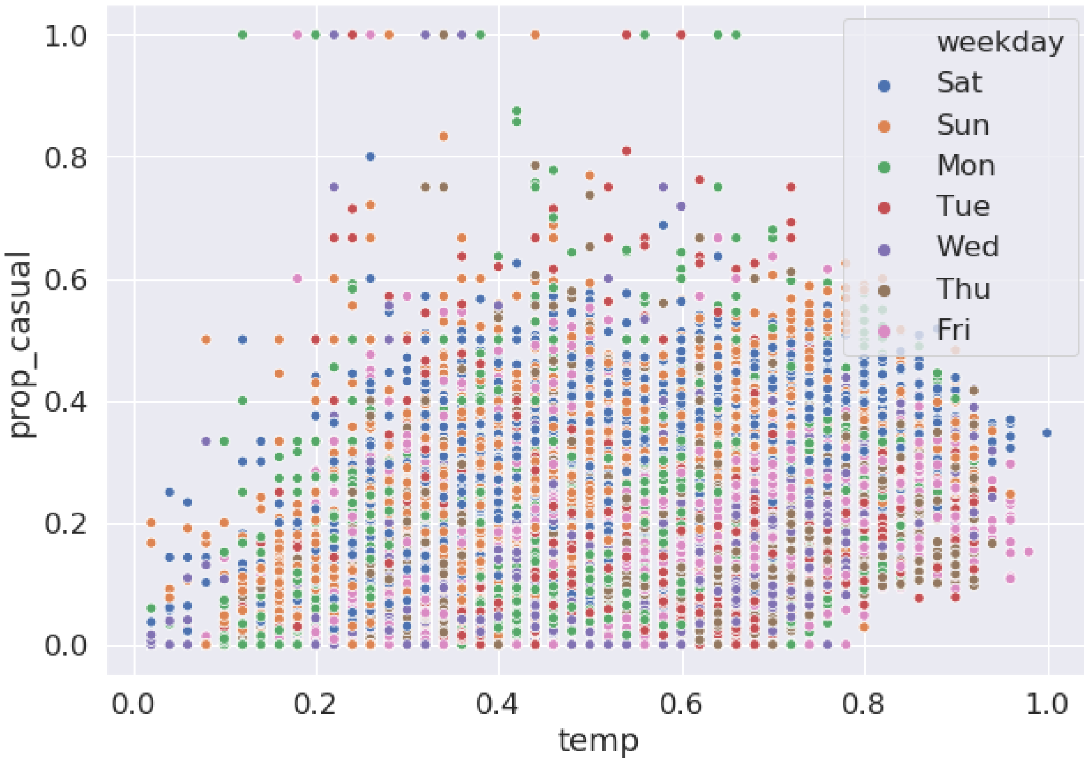
**Question 6a** Create a new column prop_casual in the bike dataframe representing the proportion of casual riders out of all riders.

```
In [29]: bike['prop_casual'] = bike['casual']/bike['cnt']

         # YOUR CODE HERE
         # raise NotImplementedError()
```

```
In [30]: assert int(bike["prop_casual"].sum()) == 2991

         ### BEGIN HIDDEN TEST
         assert np.round(bike["prop_casual"].mean(), 2) == 0.17
         ### END HIDDEN TEST
```

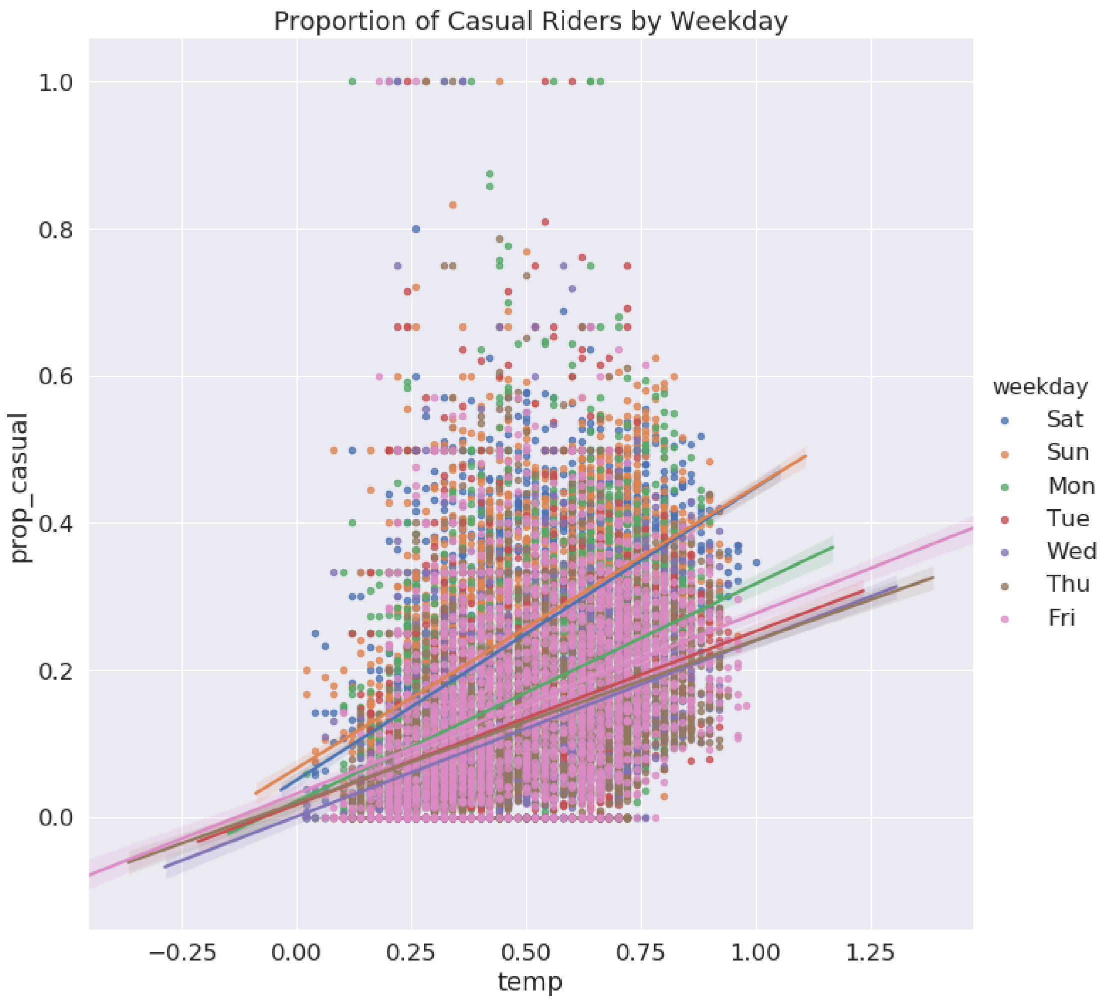
**Question 6b** In order to examine the relationship between proportion of casual riders and temperature, we can create a scatterplot using sns.scatterplot. We can even use color/hue to encode the information about day of week. Run the cell below, and you'll see we end up with a big mess that is impossible to interpret.

```
In [31]: plt.figure(figsize=(10, 7))
         sns.scatterplot(data=bike, x="temp", y="prop_casual", hue="weekday");
```



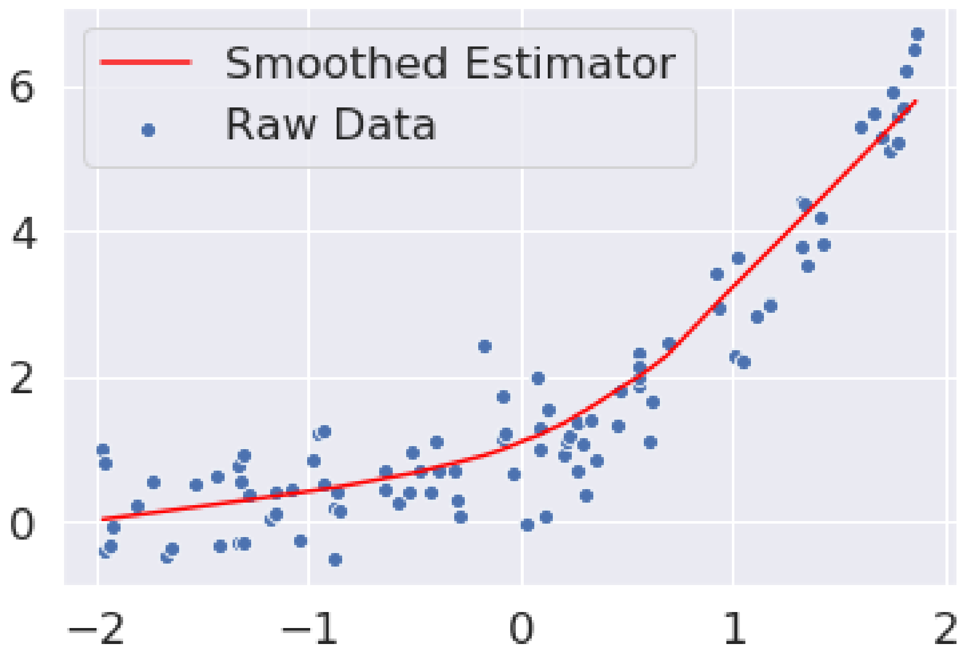

We could attempt linear regression using sns.lmplot as shown below, which hint at some relationships between temperature and proportional casual, but the plot is still fairly unconvincing.

```
In [32]: sns.lmplot(data=bike, x="temp", y="prop_casual", hue="weekday", scatter_kws={"s": 20}, height=10)
         plt.title("Proportion of Casual Riders by Weekday");
```




A better approach is to use the "Local Smoothing" technique described in lecture. We saw an example of this with cherry blossom race times. As a reminder, the basic idea is that for each x value, we compute some sort of representative y value that captures the data close to that x value. One technique for local smoothing is "Locally Weighted Scatterplot Smoothing" or LOWESS. An example is below. The red curve shown is a smoothed version of the scatterplot.

In [33]:
```
from statsmodels.nonparametric.smoothers_lowess import lowess
# Make noisy data
xobs = np.sort(np.random.rand(100)*4.0 - 2)
yobs = np.exp(xobs) + np.random.randn(100) / 2.0
sns.scatterplot(xobs, yobs, label="Raw Data")

# Predict 'smoothed' valued for observations
ysmooth = lowess(yobs, xobs, return_sorted=False)
sns.lineplot(xobs, ysmooth, label="Smoothed Estimator", color='red')
plt.legend();
```




In our case with the bike ridership data, we want 7 curves, one for each day of the week. The x-axis will be the temperature and the y-axis will be a smoothed version of the proportion of casual riders.

You should use statsmodels.nonparametric.smoothers_lowess.lowess just like the example above. Unlike the example above, plot ONLY the lowess curve. Do not plot the actual data, which would result in overplotting. For this problem, the simplest way is to use a loop.

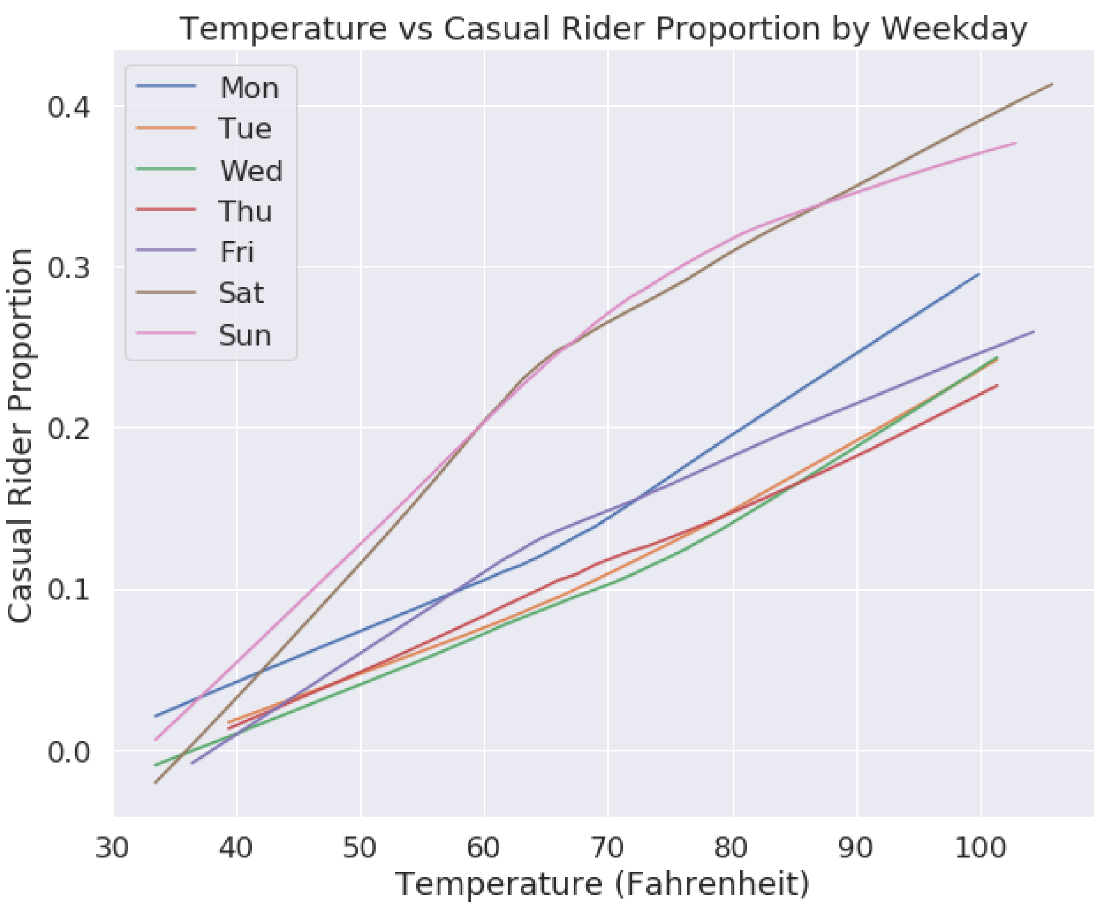
**Hints:** * Start by just plotting only one day of the week to make sure you can do that first.

- lowess expects y coordinate first, then x coordinate.
- Look at the top of this homework notebook for a description of the temperature field to know how to convert to fahrenheit. By default, the temperature field ranges from 0.0 to 1.0.

Note: If you prefer putting your plot in Celsius, that's fine as well!

In [34]:
```
from statsmodels.nonparametric.smoothers_lowess import lowess

plt.figure(figsize=(10,8))
### BEGIN Solution
x_obs, y_obs, y_smooth={}, {}, {}
for ky in weekday_dict:
    weekday = weekday_dict[ky];
    selected = bike[bike['weekday']==weekday]
    x_obs[weekday] = selected['temp']*41*(9/5) + 32 # change from oC to oF
    y_obs[weekday] = selected['prop_casual']
    y_smooth[weekday] = lowess(y_obs[weekday], x_obs[weekday], return_sorted=False)
```

```
    sns.lineplot(x_obs[weekday], y_smooth[weekday], label=weekday)
plt.legend()
plt.xlabel("Temperature (Fahrenheit)")
plt.ylabel("Casual Rider Proportion")
plt.title("Temperature vs Casual Rider Proportion by Weekday");
### END Solution

# YOUR CODE HERE
# raise NotImplementedError()
```




**Question 6c** What do you see from the curve plot? How is prop_casual changing as a function of temperature? Do you notice anything else interesting?

In [35]:
```
q6c = " \
    The curve of Sat and Sun are very closed and the curve for the rest are very similar. It is like Sat and S
    The prop of casual has a positive relationship with temperature. \
"

q6c
```

```
# YOUR CODE HERE
# raise NotImplementedError()
```

Out[35]: '     The curve of Sat and Sun are very closed and the curve for the rest are very similar. It is like Sat an

### 1.14 Submission - IMPORTANT, PLEASE READ

For this assignment and future assignments (homework and projects) you will also submit your free response and plotting questions to gradescope. To do this, you can download as PDF (File->Download As->PDF via Latex (.pdf)). You are responsible for submitting and tagging your answers in gradescope. For each free response and plotting question, please include:

1. Relevant code used to generate the plot or inform your insights
2. The written free response or plot

We are doing this to make it easier on our graders and for you, in the case you need to submit a regrade request. Gradescope (as of now) is still better for manual grading.

### 1.15 Submission

You're done!

Before submitting this assignment, ensure to:

1. Restart the Kernel (in the menubar, select Kernel->Restart & Run All)
2. Validate the notebook by clicking the "Validate" button

Finally, make sure to **submit** the assignment via the Assignments tab in Datahub