Homework 3: Bike Sharing

Exploratory Data Analysis (EDA) and Visualization

Due Date: Friday October 18, 11:59 PM

Course Policies

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.

Introduction

This assignment includes both specific tasks to perform and open-ended questions to investigate. The open-ended questions ask you to think 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

Grading

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?

Submission

For this assignment and future assignments (homework and projects) you will need to upload a single document to Gradescope. To do this, you can

1. download as HTML (`File->Export Notebook As->HTML (.html)`)
2. Print HTML to PDF (.pdf)
3. Upload to Gradescope -- tagging your responses.

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.

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	4
Question 3b	3
Question 4a	2
Question 4b	2
Question 5a	1
Question 5b	4
Total	29

In [59]:

```
# Run this cell to set up your notebook.  Make sure ds-ua-112_utils.py is in t
his 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 IPython.display import Image
from pathlib import Path
import ds_ua_112_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
```

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

Download the Data

In [60]:
```
# Run this cell to download the data.  No further action is needed

data_url = 'https://cims.nyu.edu/~policast/bikeshare.zip'
file_name = 'data.zip'
data_dir = '.'

dest_path = ds_ua_112_utils.fetch_and_cache(data_url=data_url, data_dir=data_d
ir, 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: Mon Oct  7 20:53:18 2019
MD5 hash of file: fe4d1444ec7354d027a220f46dde42b1
Saved at data.zip
Extracted Files:
         data/bikeshare.txt
         data/data
```

Examining the file contents

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

In [61]:
```
# Run this cell to look at the top of the file.  No further action is needed
for line in ds_ua_112_utils.head(data_dir/'bikeshare.txt'):
    print(line,end="")
```

```
instant,dteday,season,yr,mnth,hr,holiday,weekday,workingday,weathersit,temp,a
temp,hum,windspeed,casual,registered,cnt
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
```

Size

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

In [62]:
```
# 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:", ds_ua_112_utils.line_count(data_dir/"bikeshare.txt"), "li
nes")
```

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

Loading the data

The following code loads the data into a Pandas DataFrame.

In [63]:
```
# Run this cell to load the data.  No further action is needed
bike = pd.read_csv(data_dir/'bikeshare.txt')
bike.head(10)
```

Out[63]:

	instant	dteday	season	yr	mnth	hr	holiday	weekday	workingday	weathersit	temp	ater
0	1	2011-01-01	1	0	1	0	0	6	0	1	0.24	0.28
1	2	2011-01-01	1	0	1	1	0	6	0	1	0.22	0.27
2	3	2011-01-01	1	0	1	2	0	6	0	1	0.22	0.27
3	4	2011-01-01	1	0	1	3	0	6	0	1	0.24	0.28
4	5	2011-01-01	1	0	1	4	0	6	0	1	0.24	0.28
5	6	2011-01-01	1	0	1	5	0	6	0	2	0.24	0.25
6	7	2011-01-01	1	0	1	6	0	6	0	1	0.22	0.27
7	8	2011-01-01	1	0	1	7	0	6	0	1	0.20	0.25
8	9	2011-01-01	1	0	1	8	0	6	0	1	0.24	0.28
9	10	2011-01-01	1	0	1	9	0	6	0	1	0.32	0.34

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 [64]:
```
bike.shape
```

Out[64]: (17379, 17)

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.

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 [65]:
```
# Modify holiday weekday, workingday, and weathersit here
# Hint: one strategy involves df.replace(...)
bike['holiday'] = bike['holiday'].replace({0: "no", 1: "yes"})
bike['weekday'] = bike['weekday'].replace({0: "Sun", 1: "Mon", 2: "Tue", 3: "W
ed",
                                           4: "Thu", 5: "Fri", 6: "Sat"})
bike['workingday'] = bike['workingday'].replace({0: "no", 1: "yes"})
bike['weathersit'] = bike['weathersit'].replace({1: "Clear", 2: "Mist", 3: "Li
ght", 4: "Heavy"})
bike.head()
### BEGIN SOLUTION
#TODO
### END SOLUTION
```

Out[65]:

	instant	dteday	season	yr	mnth	hr	holiday	weekday	workingday	weathersit	temp	ater
0	1	2011-01-01	1	0	1	0	no	Sat	no	Clear	0.24	0.28
1	2	2011-01-01	1	0	1	1	no	Sat	no	Clear	0.22	0.27
2	3	2011-01-01	1	0	1	2	no	Sat	no	Clear	0.22	0.27
3	4	2011-01-01	1	0	1	3	no	Sat	no	Clear	0.24	0.28
4	5	2011-01-01	1	0	1	4	no	Sat	no	Clear	0.24	0.28

In [66]:
```
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')

# Hidden tests
assert bike.shape == (17379, 17) or bike.shape == (17379, 18)
assert list(bike['weekday'].iloc[::2000]) == ['Sat', 'Tue', 'Mon', 'Mon', 'Mo
n', 'Sun', 'Sun', 'Sat', 'Sun']
assert list(bike['workingday'].iloc[::2000]) == ['no', 'yes', 'yes', 'yes', 'y
es', 'no', 'no', 'no', 'no']
assert list(bike['weathersit'].iloc[::2000]) == ['Clear', 'Clear', 'Clear', 'C
lear', 'Clear', 'Clear', 'Clear', 'Clear', 'Clear']
```

Question 1b (Holidays)

How many entries in the data correspond to holidays? Set the variable `num_holidays` to this value.

In [67]:
```
num_holidays = len(bike.loc[bike.holiday == "yes"])
num_holidays

### BEGIN SOLUTION
#TODO
### END SOLUTION
```

Out[67]: 500

In [68]:
```
assert 400 <= num_holidays <= 550

### BEGIN HIDDEN TESTS
assert num_holidays == 500
### END HIDDEN TESTS
```

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 (https://pandas.pydata.org/pandas-docs/stable/generated/pandas.core.groupby.DataFrameGroupBy.agg.html)](https://pandas.pydata.org/pandas-docs/stable/generated/pandas.core.groupby.DataFrameGroupBy.agg.html) 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 [69]:
```
x = bike.groupby('dteday').sum()
permy = x['casual']
permz = x['registered']
temp = bike.groupby('dteday').agg('first')
temp2 = temp['workingday']
daily_counts = pd.DataFrame(columns=["casual", "registered", "workingday"])
daily_counts['casual'] = permy
daily_counts['registered'] = permz
daily_counts['workingday'] = temp2
### BEGIN SOLUTION
daily_counts.head(12)

#TODO
### END SOLUTION
```

Out[69]:

	casual	registered	workingday
dteday			
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
2011-01-06	88	1518	yes
2011-01-07	148	1362	yes
2011-01-08	68	891	no
2011-01-09	54	768	no
2011-01-10	41	1280	yes
2011-01-11	43	1220	yes
2011-01-12	25	1137	yes

In [70]:
```
assert np.round(daily_counts['casual'].mean()) == 848.0
assert np.round(daily_counts['casual'].var()) == 471450.0

### BEGIN HIDDEN TESTS
assert np.round(daily_counts['registered'].mean()) == 3656.0
assert np.round(daily_counts['registered'].var()) == 2434400.0
assert sorted(list(daily_counts['workingday'].value_counts())) == [231, 500]
### END HIDDEN TESTS
```

2: Exploring the Distribution of Riders

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

Question 2

Question 2a

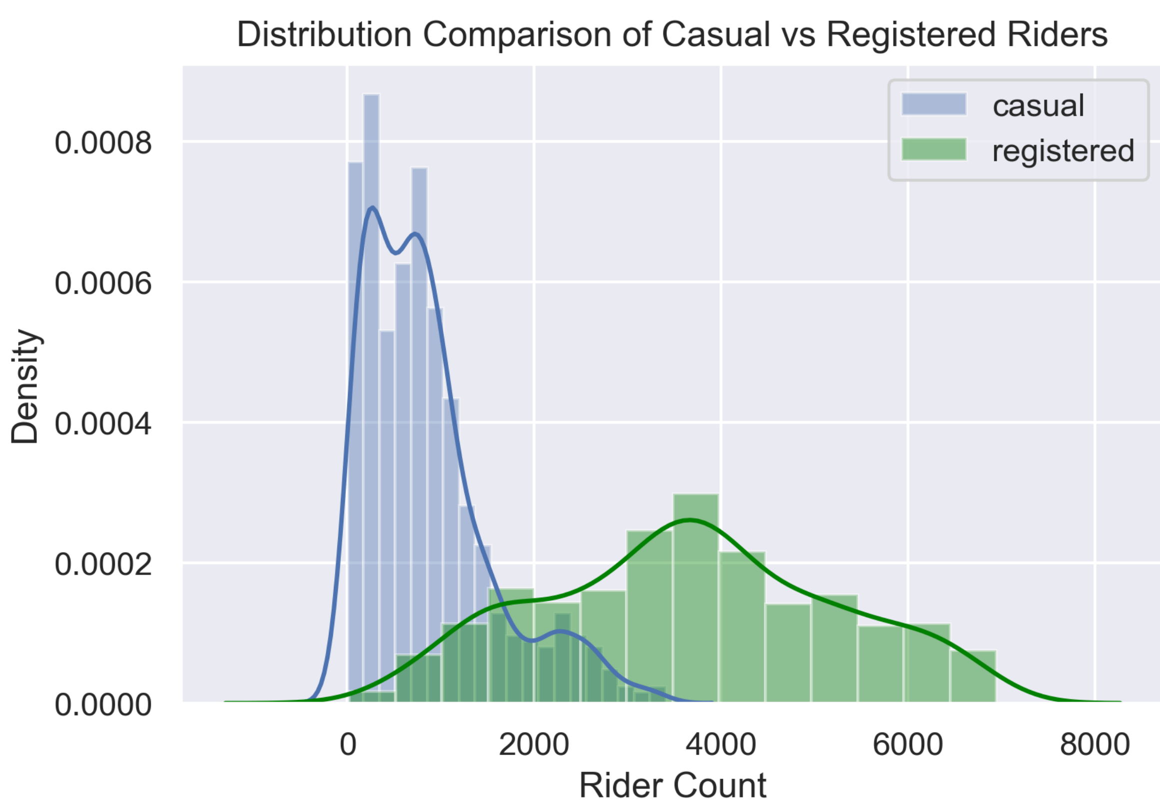
Use the `sns.distplot` (https://seaborn.pydata.org/generated/seaborn.distplot.html) function to create a plot that overlays the distribution of the daily counts of `casual` and `registered` users. The temporal granularity of the records should be daily counts, which you should have after completing question 1c.

Include a legend, xlabel, ylabel, and title. You may want to look at the seaborn plotting tutorial (https://seaborn.pydata.org/tutorial/distributions.html) 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.

IMAGE

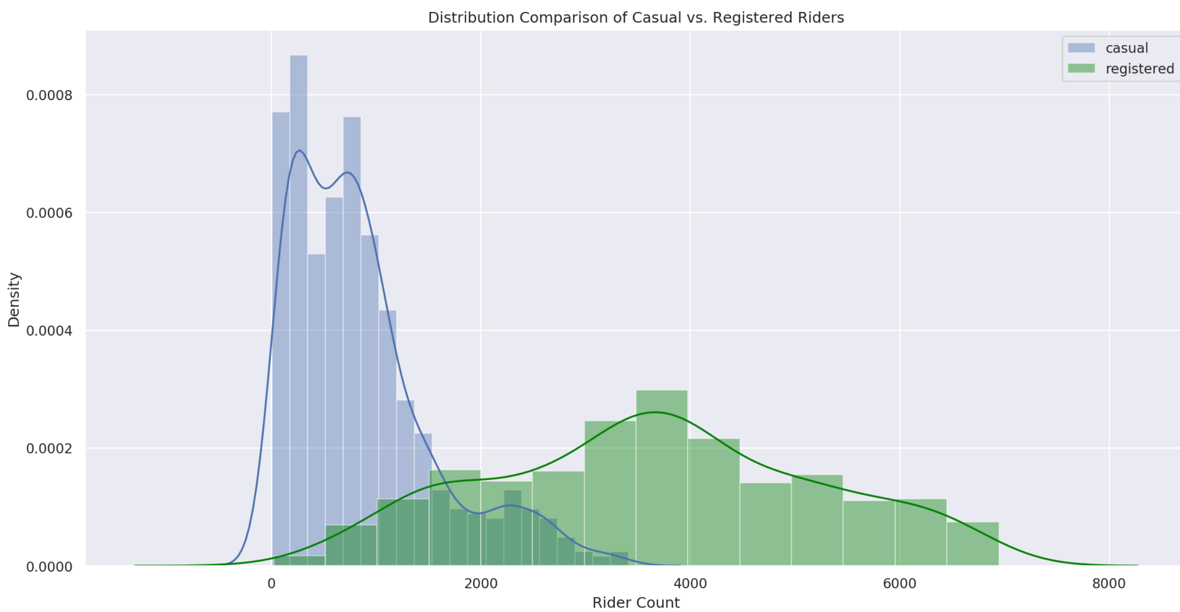
In [34]:
```
Image(filename='images/casual_v_registered.png', embed=True, height=10, width=700)
```

Out[34]:



In [72]:
```
x = sns.distplot(daily_counts['casual'], label="casual")
x = sns.distplot(daily_counts['registered'], color="green", label="registered"
)
x.set_xlabel("Rider Count")
x.set_ylabel("Density")
x.set_title("Distribution Comparison of Casual vs. Registered Riders")
plt.legend()
### BEGIN SOLUTION
#TODO
### END SOLUTION
```

Out[72]: <matplotlib.legend.Legend at 0x2b1957eb1048>



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 [36]:
```
q2b = "From this graph, we can see that the casual riders plot is skewed to the right and looks to have around two peaks. On the other hand, the registered plot looks to be a normal, symmetric distribution. In addition, these graphs differ because range for casual biking is a lot smaller than the registered plot."
q2b

### BEGIN SOLUTION
#TODO

### END SOLUTION
```

Out[36]:
```
'From this graph, we can see that the casual riders plot is skewed to the right and looks to have around two peaks. On the other hand, the registered plot looks to be a normal, symmetric distribution. In addition, these graphs differ because range for casual biking is a lot smaller than the registered plot.'
```

Question 2c

The density plots do not show us how the daily counts for registered and casual riders vary together. Use `sns.lmplot` (https://seaborn.pydata.org/generated/seaborn.lmplot.html) 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.

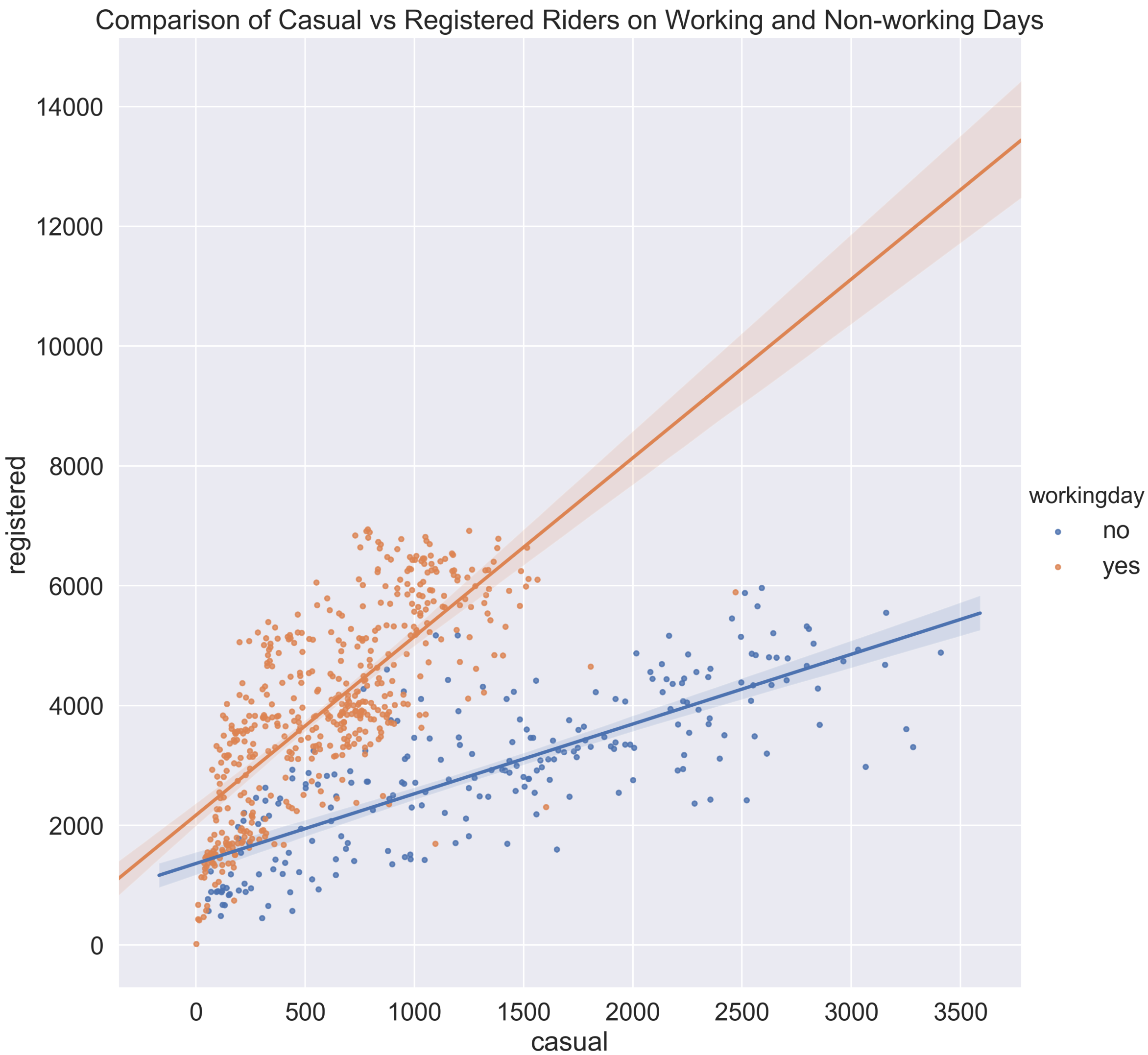
Hints:

- Checkout this helpful tutorial on `lmplot` (https://seaborn.pydata.org/tutorial/regression.html).
- You will need to set `x` , `y` , and `hue` and the `scatter_kws` .

IMAGE

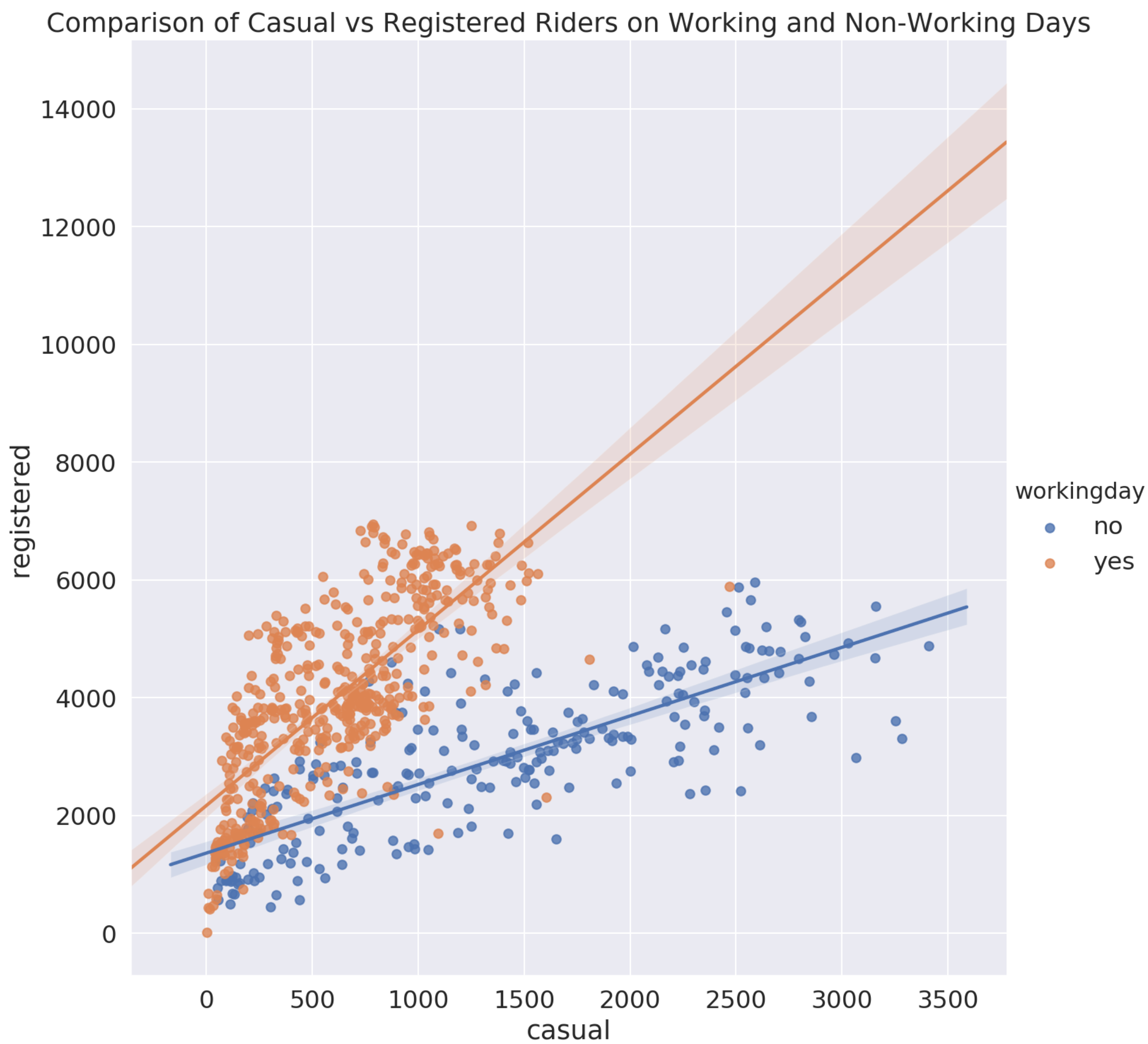
In [37]:
```python
Image(filename='images/casual_registered_working_nonworking.png', embed=True,
height=10, width=700)
```

Out[37]:



In [76]:
```
# Make the font size a bit bigger
...
### BEGIN SOLUTION
#TODO
sns.set(font_scale=1.5)
y = sns.lmplot(x="casual", y="registered", hue="workingday", data=daily_counts
, fit_reg=True, height=10)
y = plt.gca()
y.set_title("Comparison of Casual vs Registered Riders on Working and Non-Work
ing Days")

y = sns.set(font_scale=1.5)
### END SOLUTION
```



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 (http://www.textbook.ds100.org/ch/06/viz_principles_2.html)](http://www.textbook.ds100.org/ch/06/viz_principles_2.html).

In [39]:
```
q2d = "Based on the line of best fit for both casual and registered riders, th
e relationship appears to be linear but it depends on whether or not it is a w
orkingday. If it is a workingday, there are many more registered riders, and v
ice versa for non-workingdays. We might be concerned about overplotting in thi
s plot because due to the large amount of data points, we may not be able to s
ee some points that are covered by other points of data. For instance, some of
the points in this plot overlap with eachother, and if they are different in c
olor, some points may not be visible."
q2d
### BEGIN SOLUTION
#TODO
### END SOLUTION
```

Out[39]:
```
'Based on the line of best fit for both casual and registered riders, the rel
ationship appears to be linear but it depends on whether or not it is a worki
ngday. If it is a workingday, there are many more registered riders, and vice
versa for non-workingdays. We might be concerned about overplotting in this p
lot because due to the large amount of data points, we may not be able to see
some points that are covered by other points of data. For instance, some of t
he points in this plot overlap with eachother, and if they are different in c
olor, some points may not be visible.'
```

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).

3: Exploring Ride Sharing and Time

Question 3

Question 3a

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.

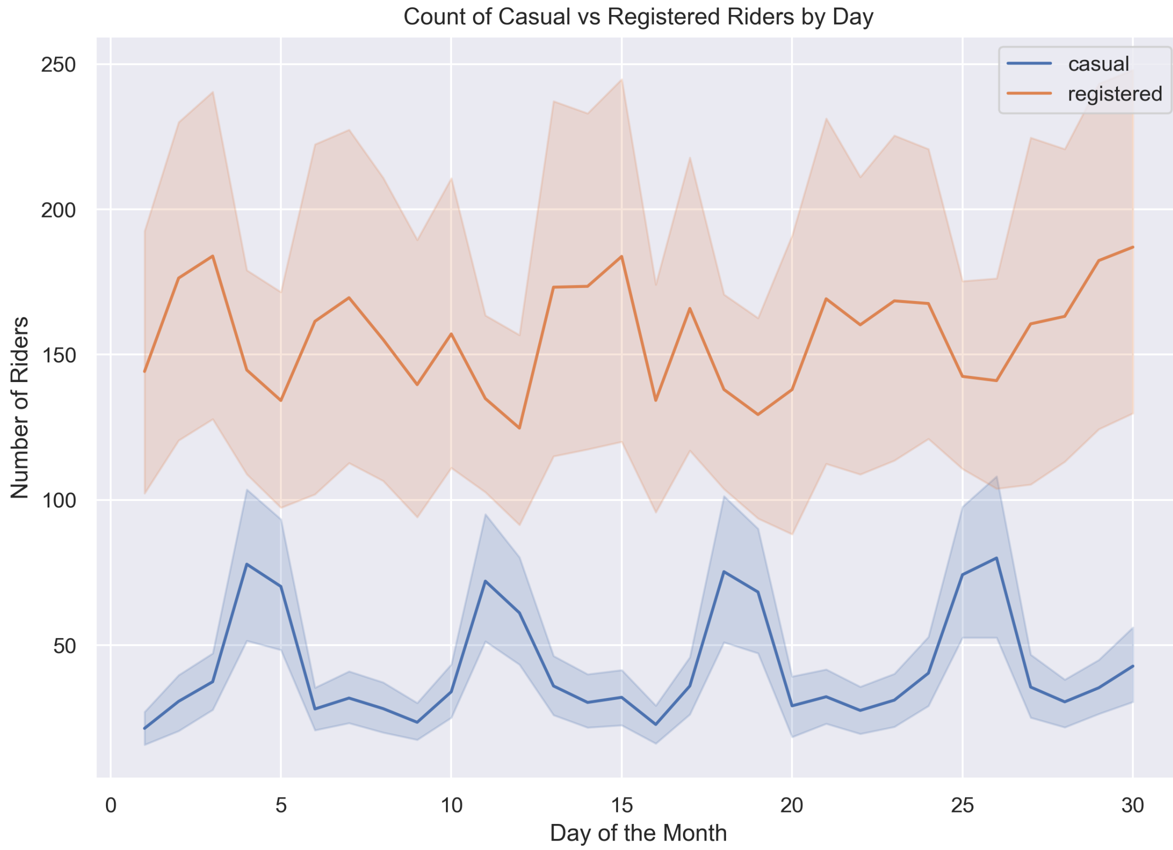
Hints:

- 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`.

IMAGE

In [40]:
```
Image(filename='images/june_riders.png', embed=True, height=10, width=700)
```

Out[40]:

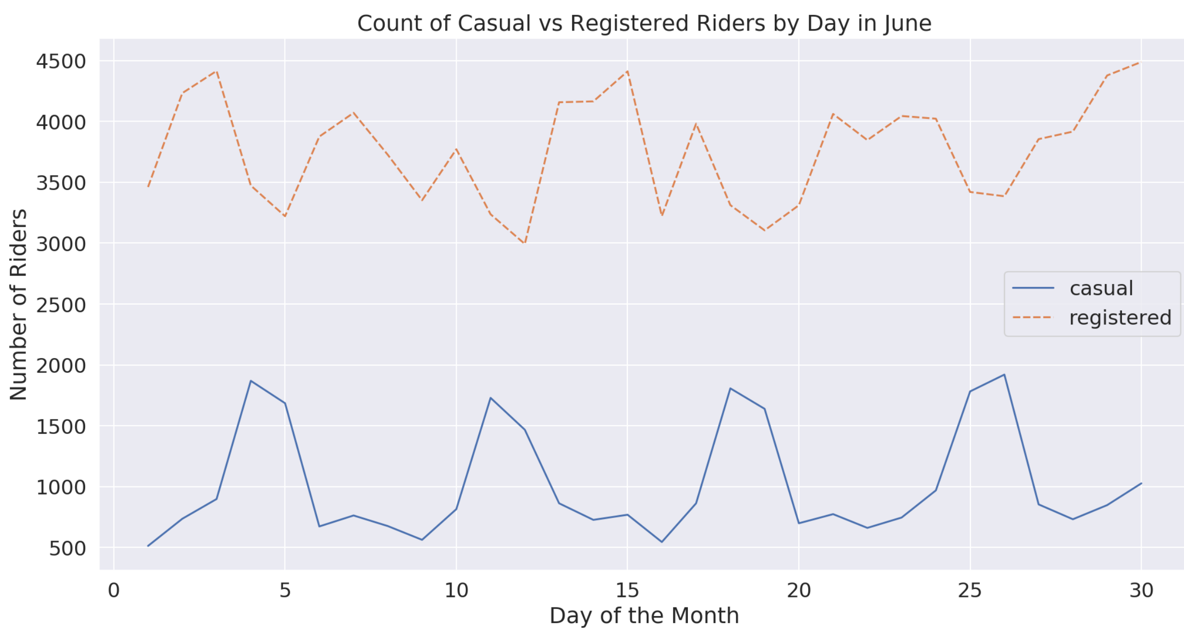


In [41]:
```
import seaborn as sns; sns.set();
```

In [81]:
```
temp = bike['dteday'].str[8:10]
temp = temp.map(int)
bike['day'] = temp
june = bike.loc[(bike.mnth == 6) & (bike.yr == 0)]
june = june.groupby('day').sum()
df = pd.DataFrame(columns=['casual', 'registered'])
df['casual'] = june['casual']
df['registered'] = june['registered']


plot = sns.lineplot(data=df)
plot.set_xlabel("Day of the Month")
plot.set_ylabel("Number of Riders")
plot.set_title("Count of Casual vs Registered Riders by Day in June")
plot
### BEGIN SOLUTION
#TODO
### END SOLUTION
```

Out[81]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x2b1957f90cf8>
```



Question 3b

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 [43]:
```
q3b = "We can see that on this graph, the casual riders peaks on the weekends
 of the month while the registered riders peaks in the weekdays. On the weeken
ds, the difference between the number of casual riders and registered riders i
s the smallest"
q3b
### BEGIN SOLUTION
#TODO
### END SOLUTION
```

Out[43]:
```
'We can see that on this graph, the casual riders peaks on the weekends of th
e month while the registered riders peaks in the weekdays. On the weekends, t
he difference between the number of casual riders and registered riders is th
e smallest'
```

4: Understanding Daily Patterns

Question 4

Question 4a

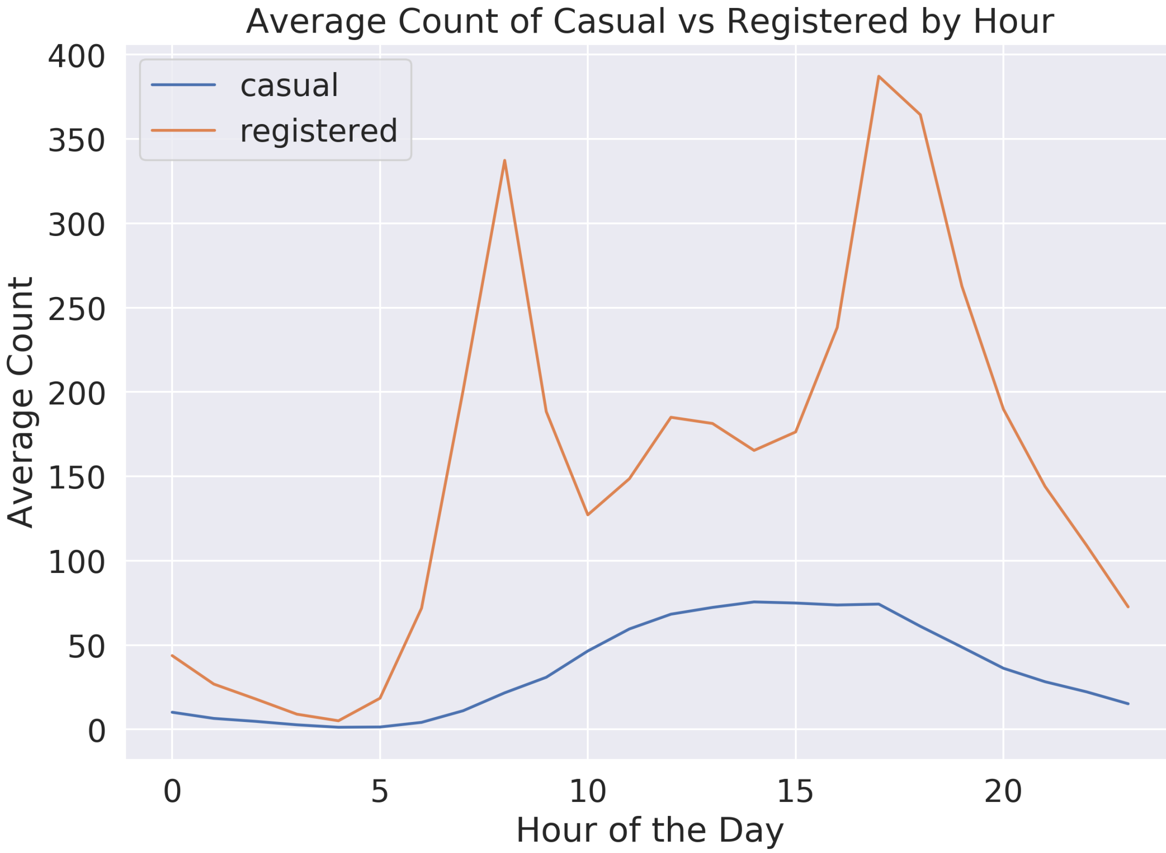
Let's examine the behavior of riders by plotting the average number of riders for each hour of the day over the **entire dataset** (not just June 2011), stratified by rider type.

Your plot should look like the following:

IMAGE

In [44]:
```
Image(filename='images/diurnal_bikes.png', embed=True, height=10, width=700)
```

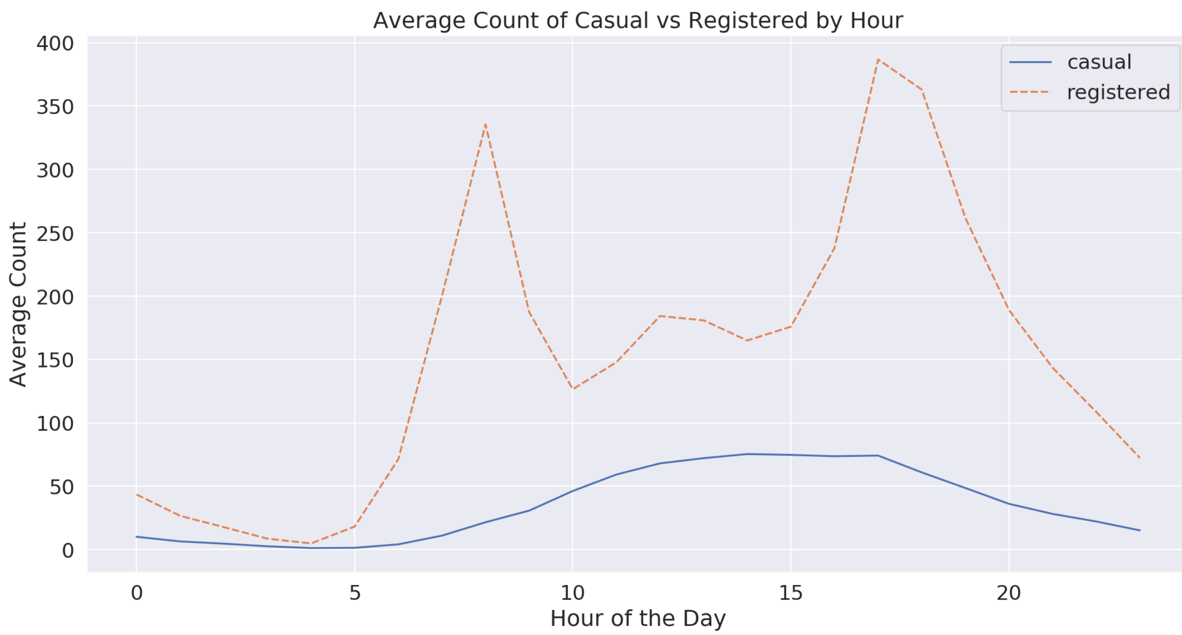
Out[44]:



In [82]:
```
...
temp = bike['hr'].map(int)
bike['hr'] = temp
array = bike.groupby('hr').sum()
df = pd.DataFrame(columns=['casual', 'registered'])
days = bike.groupby('dteday')
df['casual'] = array.casual/(len(days))
df['registered'] = array.registered/(len(days))

graph = sns.lineplot(data=df)
graph.set_xlabel('Hour of the Day')
graph.set_ylabel('Average Count')
graph.set_title('Average Count of Casual vs Registered by Hour')
### BEGIN SOLUTION
#TODO
### END SOLUTION
```

Out[82]:
```
Text(0.5, 1.0, 'Average Count of Casual vs Registered by Hour')
```



Question 4b

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

In [84]:
```
q4b = "We can hypothesize that from the peaks (in the registered bikers), the
 average count of bikers is highest around 8-9 am and 5-6 pm. This is most lik
ely attributed to the standard 9am-5pm workday commute, where people would bik
e to work and bike home afterwards. On the other hand, the casual riders peaks
around 2-4pm, and this is possibly because this time frame is usually after lu
nch and when the weather is warmer."
q4b
### BEGIN SOLUTION
#TODO
### END SOLUTION
```

Out[84]:
```
'We can hypothesize that from the peaks (in the registered bikers), the avera
ge count of bikers is highest around 8-9 am and 5-6 pm. This is most likely a
ttributed to the standard 9am-5pm workday commute, where people would bike to
work and bike home afterwards. On the other hand, the casual riders peaks aro
und 2-4pm, and this is possibly because this time frame is usually after lunc
h and when the weather is warmer.'
```

5: 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.

Question 5

Question 5a

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

In [85]:
```
...
bike['prop_casual'] = (bike.casual / bike.cnt)
bike.head()
### BEGIN SOLUTION
#TODO
### END SOLUTION
```

Out[85]:

	instant	dteday	season	yr	mnth	hr	holiday	weekday	workingday	weathersit	temp	ater
0	1	2011-01-01	1	0	1	0	no	Sat	no	Clear	0.24	0.28
1	2	2011-01-01	1	0	1	1	no	Sat	no	Clear	0.22	0.27
2	3	2011-01-01	1	0	1	2	no	Sat	no	Clear	0.22	0.27
3	4	2011-01-01	1	0	1	3	no	Sat	no	Clear	0.24	0.28
4	5	2011-01-01	1	0	1	4	no	Sat	no	Clear	0.24	0.28

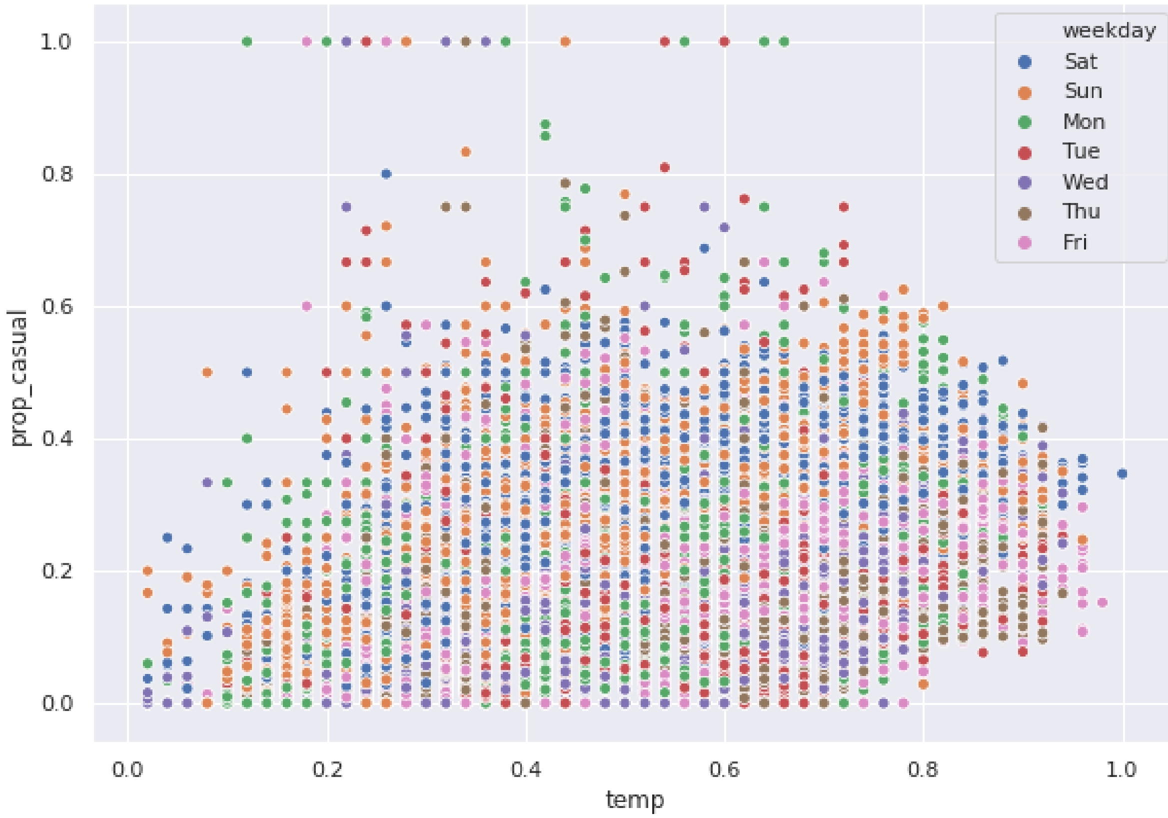
In [48]:
```
assert int(bike["prop_casual"].sum()) == 2991

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

Question 5b

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 [49]:
```
plt.figure(figsize=(10, 7))
sns.scatterplot(data=bike, x="temp", y="prop_casual", hue="weekday");
```

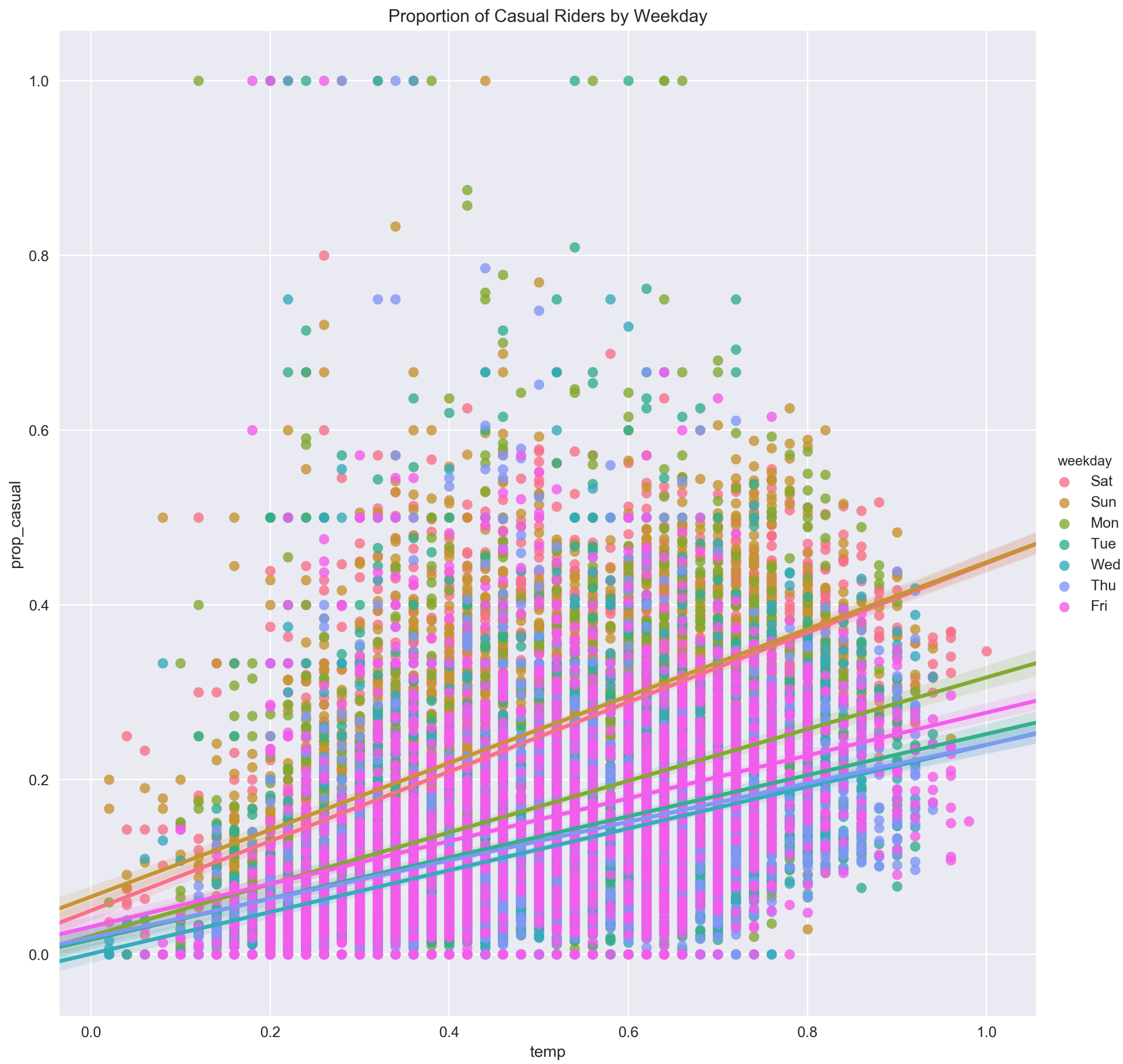


We could attempt linear regression using `sns.lmplot` as shown below, which hint at some relationships between temperature and proportional casual, but the plot is still fairly unconvincing.

IMAGE

In [50]:
```
Image(filename='images/curveplot_temp_prop_casual_2.png', embed=True, height=1
0, width=700)
```

Out[50]:

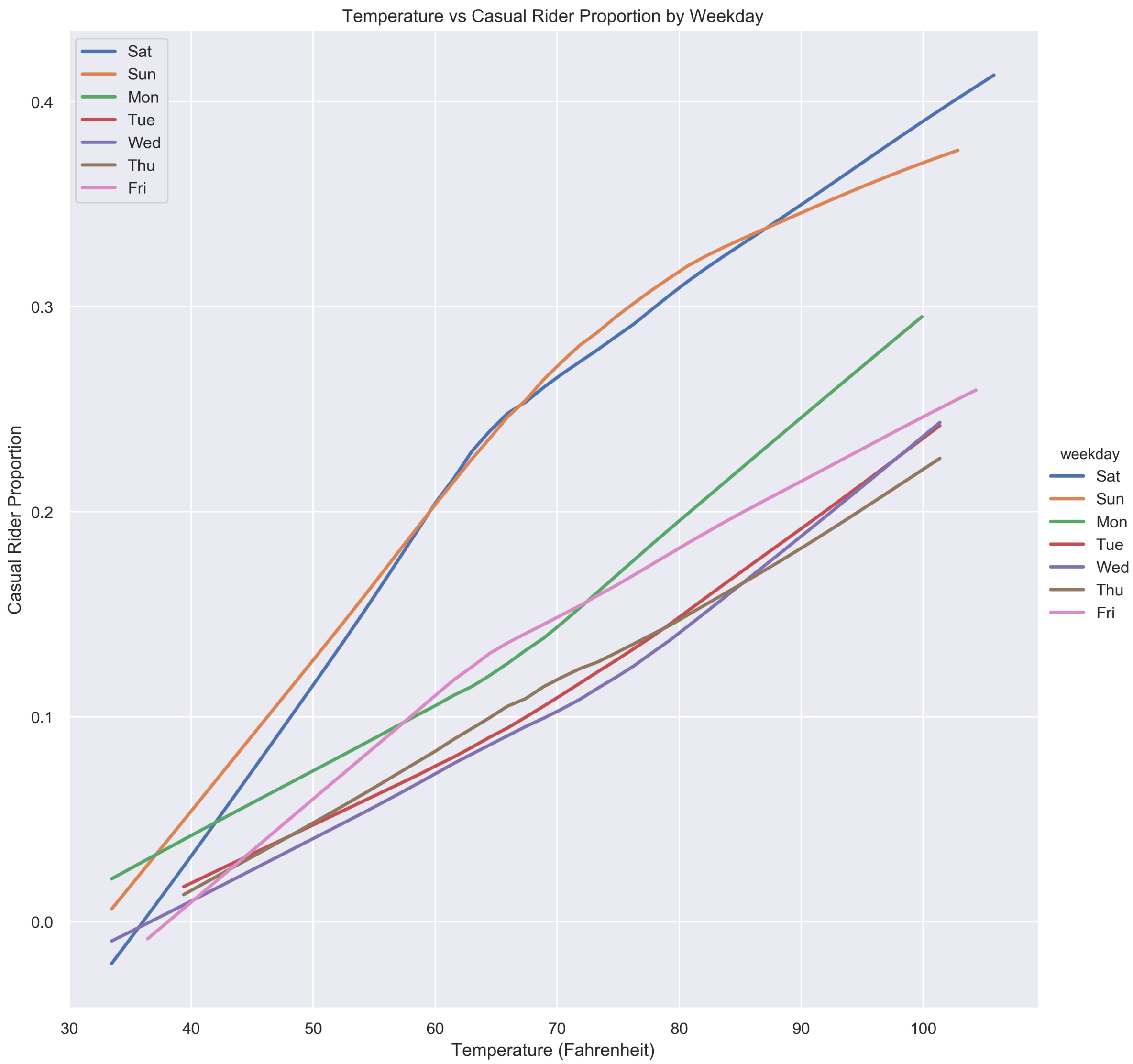


In our case with the bike ridership data, we want 7 curves, one for each day of the week. The x-axis will be the temperature and the y-axis will be some version of the proportion of casual riders. We want to remove the underlying scatter-plot.

IMAGE

In [51]:
```
Image(filename="images/curveplot_temp_prop_casual.png", embed=True, height=10,
width=700)
```

Out[51]:



Hints:

- Start by just plotting only one day of the week to make sure you can do that first.
- Try taking `lowess = True` in `sns.lmplot` for a better fit to the trends over the 7 curves. This will allow the curves to wiggle between points.
- 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!

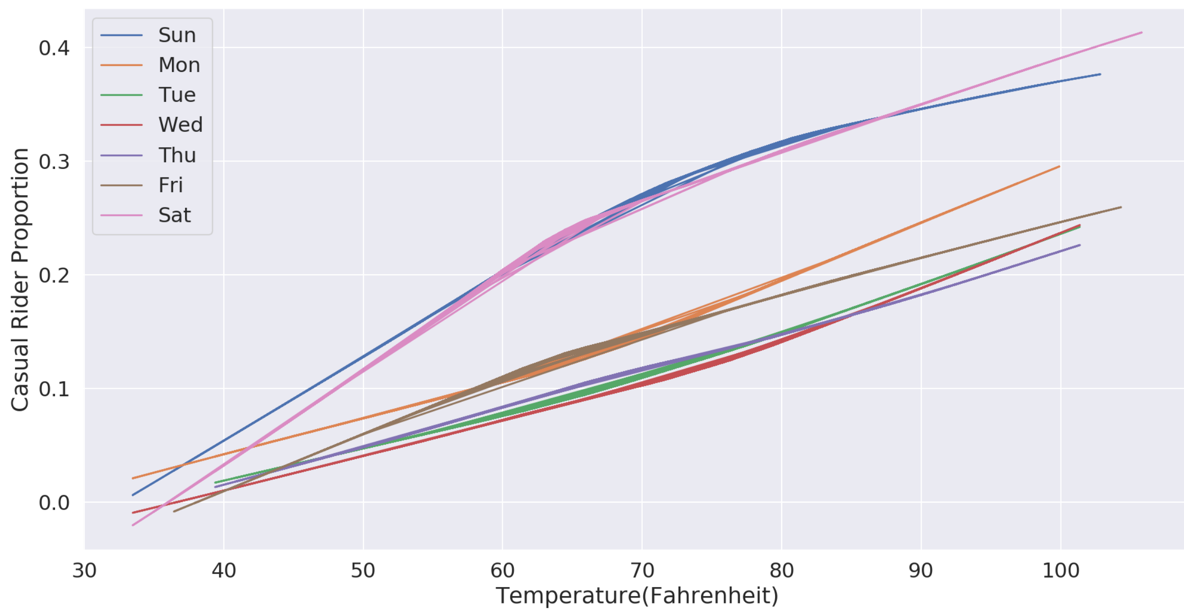
In [87]:
```
from statsmodels.nonparametric.smoothers_lowess import lowess

day = ['Sun', 'Mon', 'Tue', 'Wed', 'Thu', 'Fri', 'Sat']

for i in range(len(day)):
    x = bike[bike["weekday"] == day[i]].copy()
    x["temp"] = (x["temp"] * 41) * (9/5) + 32
    y = lowess(x["prop_casual"], x["temp"] * 41, return_sorted=False)
    plt.plot(x["temp"], y, label=day[i])
    plt.legend()

plt.xlabel("Temperature(Fahrenheit)")
plt.ylabel("Casual Rider Proportion")
plt.figure(figsize=(10,8))
### BEGIN SOLUTION
#TODO
### END SOLUTION
```

Out[87]: <Figure size 1500x1200 with 0 Axes>



<Figure size 1500x1200 with 0 Axes>

Question 5b

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 [53]:
```
q5c = "As the temperature increases, we can see that proportion of casual bike
rs begins to rise. This may be attributed to because of nice/warm weather, the
average person is more inclined to go outside and enjoy the weather through ac
tivities such as biking. It can also be noted that the proportion of casual bi
kers is higher on the weekends, where people would probably have more time to
 be biking."
q5c
### BEGIN SOLUTION
#TODO
### END SOLUTION
```

Out[53]:
```
'As the temperature increases, we can see that proportion of casual bikers be
gins to rise. This may be attributed to because of nice/warm weather, the ave
rage person is more inclined to go outside and enjoy the weather through acti
vities such as biking. It can also be noted that the proportion of casual bik
ers is higher on the weekends, where people would probably have more time to
be biking.'
```