

0.0.1 Question 0

Question 0A What is the granularity of the data (i.e. what does each row represent)?

Bicycle rental status and related information(weather, windspeed, casual and registered users) every hour in each day from 2011 to 2012

Question 0B For this assignment, we'll be using this data to study bike usage in Washington D.C. Based on the granularity and the variables present in the data, what might some limitations of using this data be? What are two additional data categories/variables that you can collect to address some of these limitations?

we don't know where are the bikes rental and what kind of people rent the bicycles. Therefore, location and major people are two data categories we can add in order to know where is the rental hotspot and what major people use them.

0.0.2 Question 2

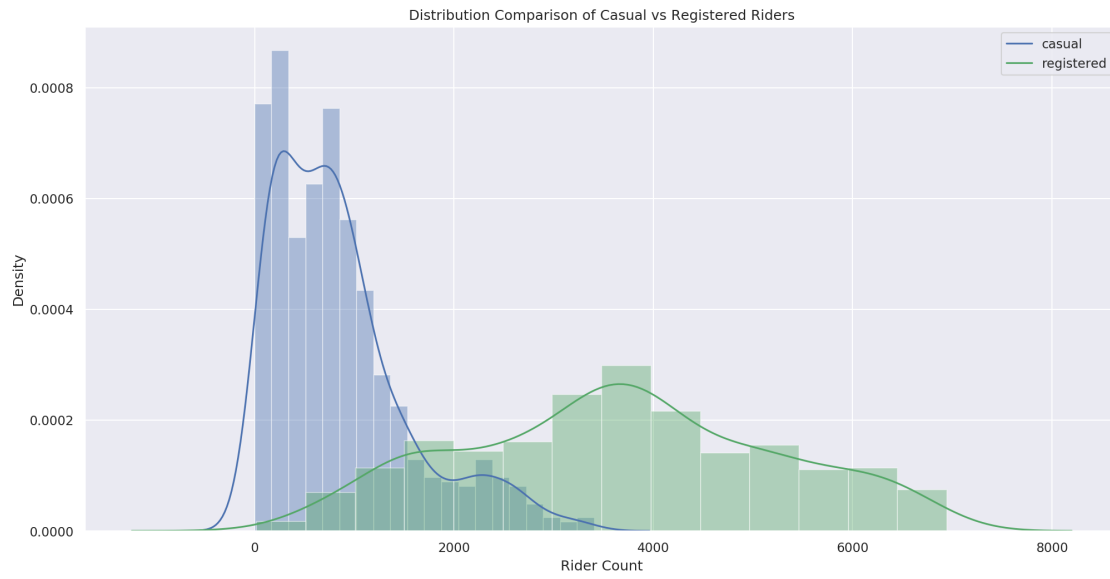
Question 2a Use the `sns.distplot` function to create a plot that overlays the distribution of the daily counts of bike users, using blue to represent `casual` riders, and green to represent `registered` riders. The temporal granularity of the records should be daily counts, which you should have after completing question 1c. **You can ignore all warnings that say `distplot` is a deprecated function.**

Include a legend, xlabel, ylabel, and title. Read 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 anywhere from nearly 0 to 7000.

```
In [16]: sns.distplot(daily_counts['casual'], color = 'b')
         sns.distplot(daily_counts['registered'], color = 'g')
         plt.xlabel('Rider Count')
         plt.title('Distribution Comparison of Casual vs Registered Riders')
         plt.legend(['casual', 'registered'])
```

```
/opt/conda/lib/python3.8/site-packages/seaborn/distributions.py:2551: FutureWarning: `distplot` is a deprecated alias for `displot`.
warnings.warn(msg, FutureWarning)
/opt/conda/lib/python3.8/site-packages/matplotlib/cbook/__init__.py:1402: FutureWarning: Support for multi-dimensional arrays is deprecated.
ndim = x[:, None].ndim
/opt/conda/lib/python3.8/site-packages/matplotlib/axes/_base.py:276: FutureWarning: Support for multi-dimensional arrays is deprecated.
x = x[:, np.newaxis]
/opt/conda/lib/python3.8/site-packages/matplotlib/axes/_base.py:278: FutureWarning: Support for multi-dimensional arrays is deprecated.
y = y[:, np.newaxis]
/opt/conda/lib/python3.8/site-packages/seaborn/distributions.py:2551: FutureWarning: `distplot` is a deprecated alias for `displot`.
warnings.warn(msg, FutureWarning)
/opt/conda/lib/python3.8/site-packages/matplotlib/cbook/__init__.py:1402: FutureWarning: Support for multi-dimensional arrays is deprecated.
ndim = x[:, None].ndim
/opt/conda/lib/python3.8/site-packages/matplotlib/axes/_base.py:276: FutureWarning: Support for multi-dimensional arrays is deprecated.
x = x[:, np.newaxis]
/opt/conda/lib/python3.8/site-packages/matplotlib/axes/_base.py:278: FutureWarning: Support for multi-dimensional arrays is deprecated.
y = y[:, np.newaxis]
```

```
Out[16]: <matplotlib.legend.Legend at 0x7fd79326fc10>
```



0.0.3 Question 2b

In the cell below, describe 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.

Registered is symmetry, unimodal, has wider gaps with smaller density and the curve rises smoothly, the rider count distributed from 0 to 8000(larger standard deviation). Casual is asymmetry, multimodal, has tight gaps with bigger density and the curve rises fastly, the rider count distributed from 0 to 4000(smaller standard deviation) and skewed to the right.

0.0.4 Question 2c

The density plots do not show us how the 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. This time, let's use the `bike` DataFrame to plot hourly counts instead of daily 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 a working day (your colors do not have to match ours exactly, but they should be different based on whether the day is a working day).

There are many points in the scatter plot, so make them small to help reduce overplotting. 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`.

Hints: * Checkout this helpful [tutorial on lmplot](#).

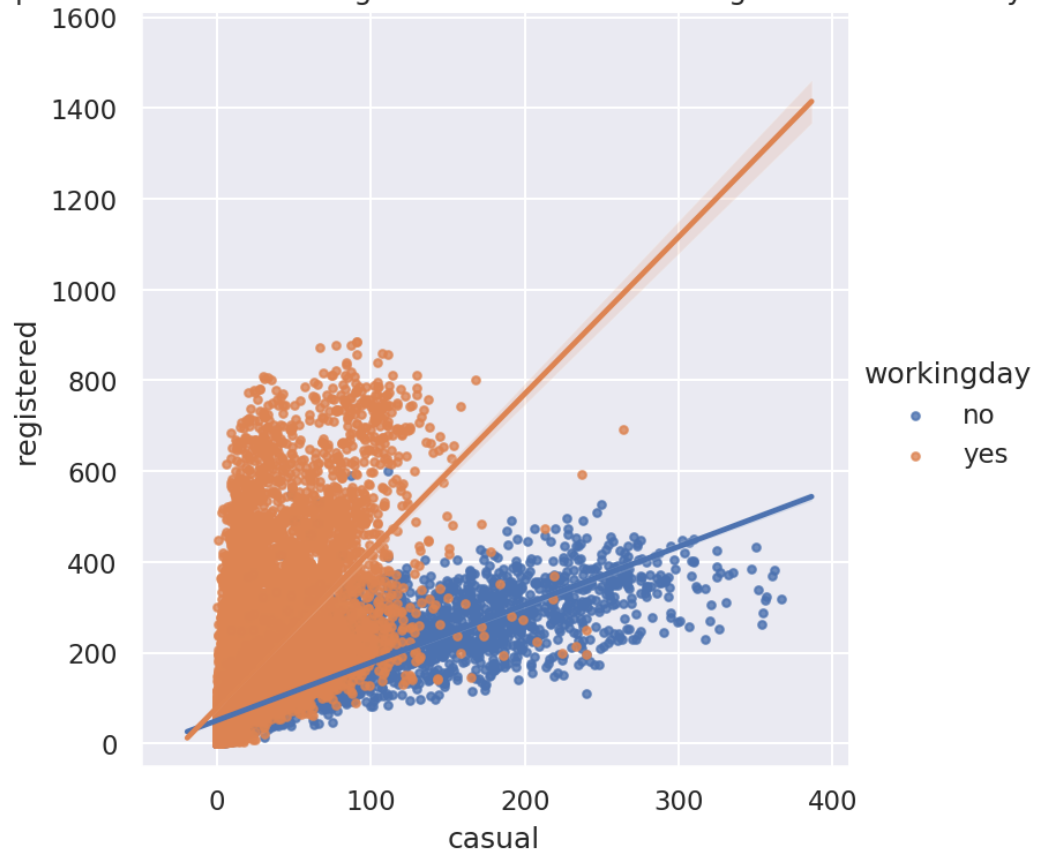
- You will need to set `x`, `y`, and `hue` and the `scatter_kws`.

```
In [17]: # Make the font size a bit bigger
sns.set(font_scale=1)
```

```
sns.lmplot(x="casual", y="registered", hue="workingday", height = 5, fit_reg=True, data=bike,
plt.xlim(-50,410)
plt.ylim(-50,1610)
plt.title("Comparison of Casual vs Registered Riders on Working and Non-work Days")
```

```
Out[17]: Text(0.5, 1, 'Comparison of Casual vs Registered Riders on Working and Non-work Days')
```

Comparison of Casual vs Registered Riders on Working and Non-work Days



0.0.5 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? What effect does [overplotting](#) have on your ability to describe this relationship?

In workday, the proportion of registered users is much larger than casual users. In non-work day, the proportion of registered users has dropped a lot but is still higher than casual users. There are many points at the bottom left of this figure are overplotting. Overplotting makes us difficult to distinguish its data.

Generating the plot with weekend and weekday separated can be complicated so we will provide a walk-through below, feel free to use whatever method you wish 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 * You will need to call `kdeplot` twice. * Check out this [guide](#) to see an example of how to create a legend. In particular, look at how the example in the guide makes use of the `label` argument in the call to `plt.plot()` and what the `plt.legend()` call does. This is 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). You are required for this question to use two sets of contrasting colors for your plots.

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 [19]: # Set 'is_workingday' to a boolean array that is true for all working_days
is_workingday = daily_counts[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 workdays
casual_workday = is_workingday['casual']
registered_workday = is_workingday['registered']

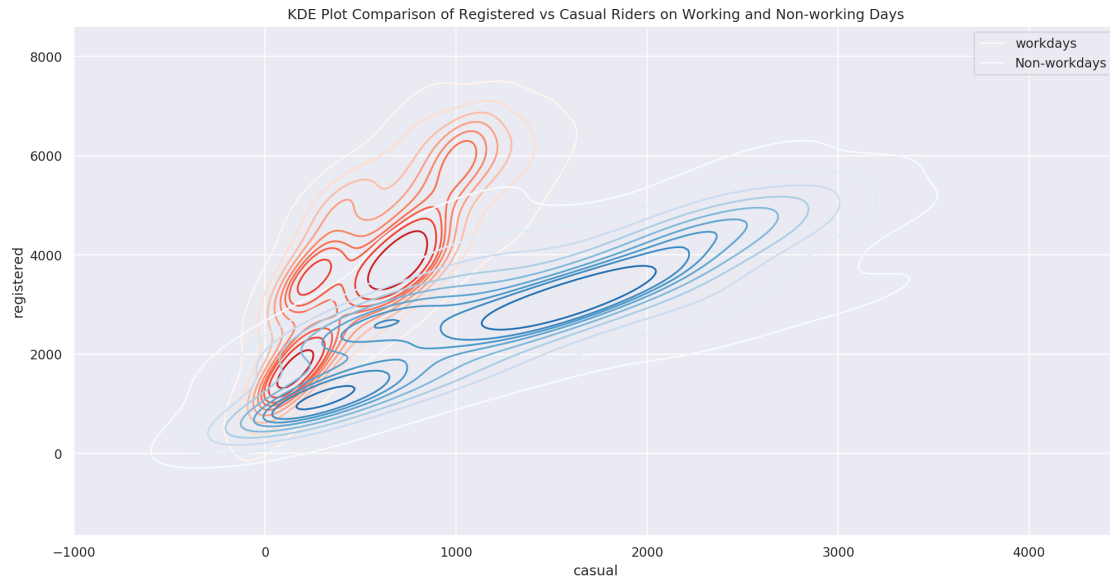
# Use sns.kdeplot on the two variables above to plot the bivariate KDE for weekday rides
sns.kdeplot(x=casual_workday, y=registered_workday, shade=False, label = 'workdays', cmap = 'R

# Repeat the same steps above but for rows corresponding to non-workingdays
casual_non_workday = daily_counts[daily_counts['workingday'] == 'no']['casual']
registered_non_workday = daily_counts[daily_counts['workingday'] == 'no']['registered']

# Use sns.kdeplot on the two variables above to plot the bivariate KDE for non-workingday rides
sns.kdeplot(x=casual_non_workday, y=registered_non_workday, shade=False, label = 'Non-workdays

#sns.kdeplot(x='casual', y='registered', hue = 'workingday', data = daily_counts, shade=False)
plt.title('KDE Plot Comparison of Registered vs Casual Riders on Working and Non-working Days')
plt.legend()
```

```
Out[19]: <matplotlib.legend.Legend at 0x7fd790934b80>
```



Question 3b What additional details can you identify from this contour plot that were difficult to determine from the scatter plot?

We can see the areas where the two overlap and the density of their distribution. This allows us to better understand the relationship between workdays and non-workdays.

0.1 4: Joint Plot

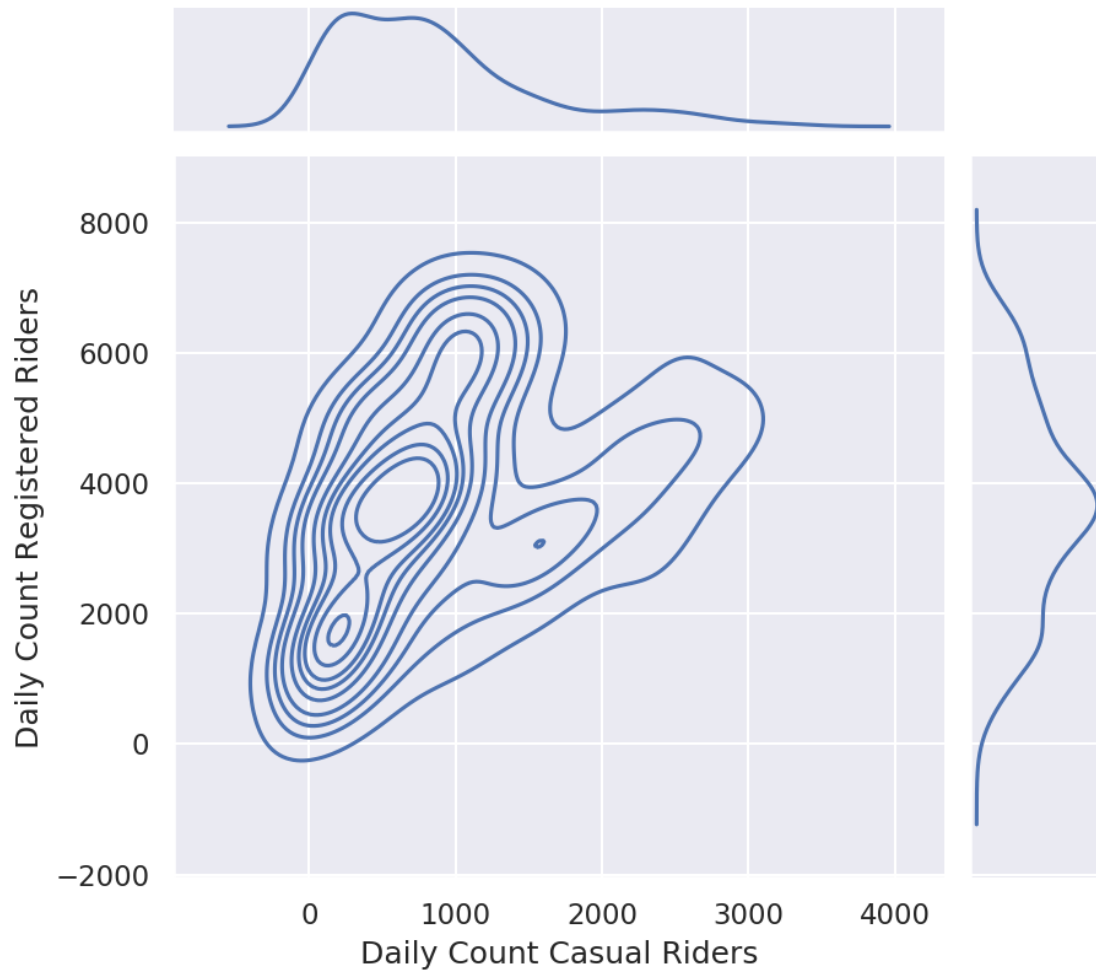
As an alternative approach to visualizing the data, construct the following set of three plots where the main plot shows the contours of the kernel density estimate of daily counts for registered and casual riders plotted together, and the two "margin" plots (at the top and right of the figure) provide 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 [20]: sns.jointplot(data = daily_counts, x="casual", y="registered", kind = 'kde').set_axis_labels('Casual', 'Registered')
plt.suptitle('KDE Contours of Casual vs Registered Riders Count')
plt.subplots_adjust(top=0.9)
```

```
/opt/conda/lib/python3.8/site-packages/matplotlib/cbook/__init__.py:1402: FutureWarning: Support for multi-dimensional arrays is deprecated.
  ndim = x[:, None].ndim
/opt/conda/lib/python3.8/site-packages/matplotlib/axes/_base.py:276: FutureWarning: Support for multi-dimensional arrays is deprecated.
  x = x[:, np.newaxis]
/opt/conda/lib/python3.8/site-packages/matplotlib/axes/_base.py:278: FutureWarning: Support for multi-dimensional arrays is deprecated.
  y = y[:, np.newaxis]
/opt/conda/lib/python3.8/site-packages/matplotlib/cbook/__init__.py:1402: FutureWarning: Support for multi-dimensional arrays is deprecated.
  ndim = x[:, None].ndim
/opt/conda/lib/python3.8/site-packages/matplotlib/axes/_base.py:276: FutureWarning: Support for multi-dimensional arrays is deprecated.
  x = x[:, np.newaxis]
/opt/conda/lib/python3.8/site-packages/matplotlib/axes/_base.py:278: FutureWarning: Support for multi-dimensional arrays is deprecated.
  y = y[:, np.newaxis]
```

KDE Contours of Casual vs Registered Riders Count



0.2 5: Understanding Daily Patterns

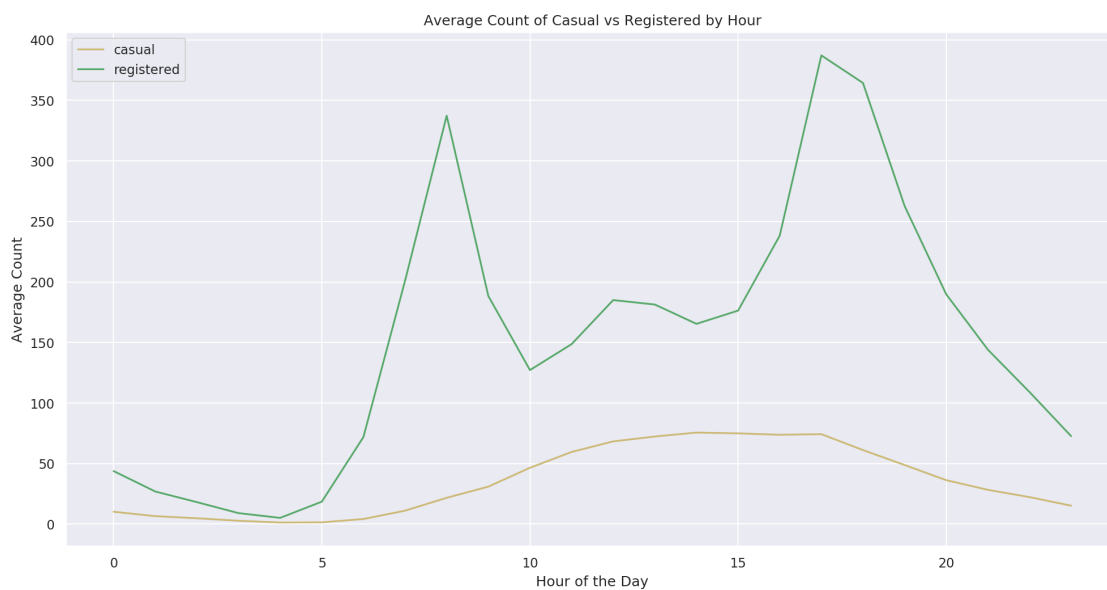
0.2.1 Question 5

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**, stratified by rider type.

Your plot should look like the plot below. While we don't expect your plot's colors to match ours exactly, your plot should have different colored lines for different kinds of riders.

```
In [21]: bike.groupby('hr').mean()[['casual', 'registered']].plot(color = ['y', 'g']).legend(loc = 2)
plt.xlabel('Hour of the Day')
plt.ylabel('Average Count')
plt.title('Average Count of Casual vs Registered by Hour')
```

```
Out[21]: Text(0.5, 1.0, 'Average Count of Casual vs Registered by Hour')
```



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

There are several peaks on registered line. The peak of registered user is during commuting time. This makes sense for me, registered users are usually those who use it frequently. The commuting time is just the time of traffic jam. Using bicycles will save time greatly, so the peak of registered users is at commuting time. The peak from 10 am to 15 am is lunch time for people. Casual users are usually those who are not used frequently. They will avoid commuting hour, so their peak is between 10 and 20.

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.

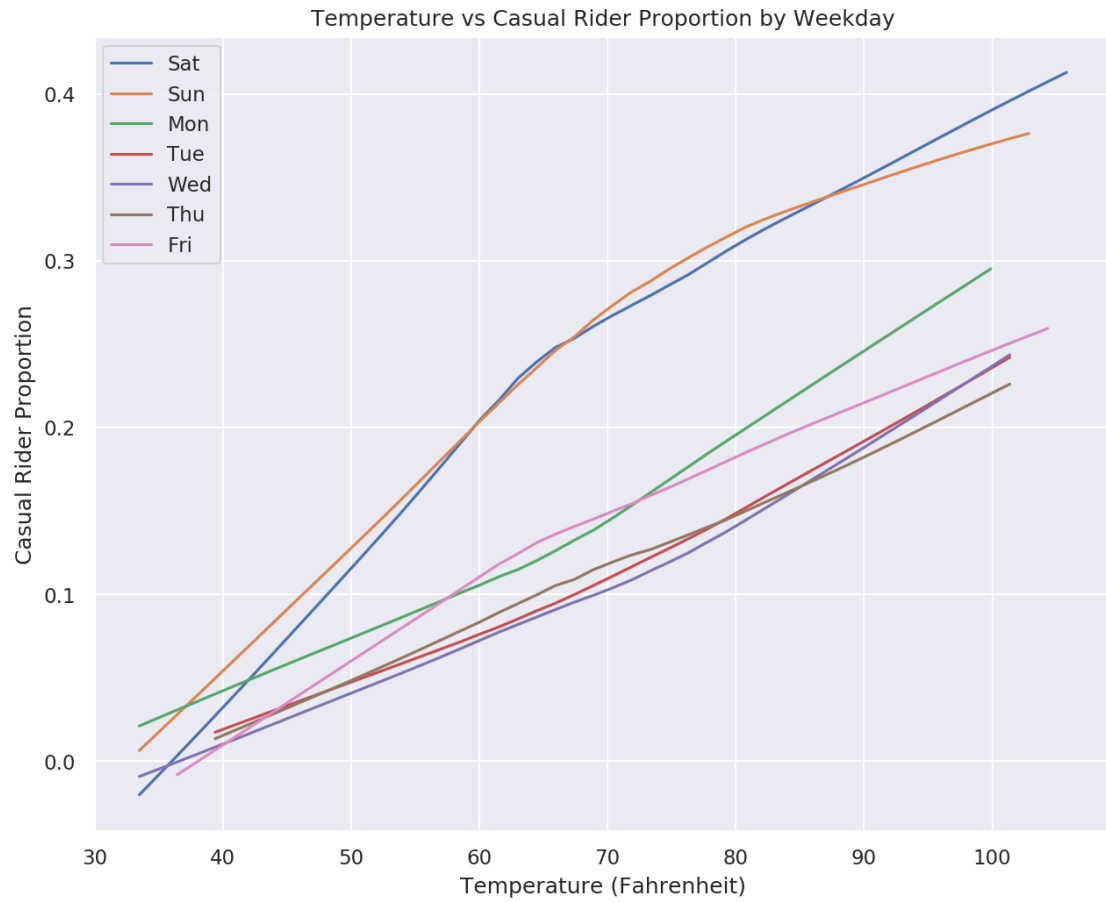
You do not need to match the colors on our sample plot as long as the colors in your plot make it easy to distinguish which day they represent.

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

- The `lowess` function 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. In case you need it, $\text{Fahrenheit} = \text{Celsius} * \frac{9}{5} + 32$.

Note: If you prefer plotting temperatures in Celsius, that's fine as well!

```
In [27]: from statsmodels.nonparametric.smoothers_lowess import lowess
plt.figure(figsize=(10,8))
for i in ['Sat', 'Sun', 'Mon', 'Tue', 'Wed', 'Thu', 'Fri']:
    temp = bike[bike['weekday'] == i]
    toF = temp['temp'] * 41 * (9/5) + 32
    sns.lineplot(x = toF, y = lowess(temp['prop_casual'], toF, return_sorted=False), label=i)
plt.title("Temperature vs Casual Rider Proportion by Weekday")
plt.xlabel('Temperature (Fahrenheit)')
plt.ylabel('Casual Rider Proportion')
plt.show()
```



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?

With the increase in temperature, the proportion of casual rider is also increasing. 60~80 degree fahrenheit is the turning point for the proportion of casual rider. Non-workingdays has higher the proportion of casual rider than workingdays.

0.2.2 Question 7

Question 7A Imagine you are working for a Bike Sharing Company that collaborates with city planners, transportation agencies, and policy makers in order to implement bike sharing in a city. These stakeholders would like to reduce congestion and lower transportation costs. They also want to ensure the bike sharing program is implemented equitably. In this sense, equity is a social value that is informing the deployment and assessment of your bike sharing technology.

Equity in transportation includes: improving the ability of people of different socio-economic classes, genders, races, and neighborhoods to access and afford the transportation services, and assessing how inclusive transportation systems are over time.

Do you think the `bike` data as it is can help you assess equity? If so, please explain. If not, how would you change the dataset? You may discuss how you would change the granularity, what other kinds of variables you'd introduce to it, or anything else that might help you answer this question.

No, we only know the number of people who use it, but we don't know who is using it in the dataset. In order to get more information about who ride a bike, the dataset should include user genders, races and the location that we can use it to study the relationship between the rich and poor areas. We can even introduce the unit price list of public transportation to compare with the price of bicycle rental to analyze why people use/don't use bicycles.

Question 7B Bike sharing is growing in popularity and new cities and regions are making efforts to implement bike sharing systems that complement their other transportation offerings. The goals of these efforts are to have bike sharing serve as an alternate form of transportation in order to alleviate congestion, provide geographic connectivity, reduce carbon emissions, and promote inclusion among communities.

Bike sharing systems have spread to many cities across the country. The company you work for asks you to determine the feasibility of expanding bike sharing to additional cities of the U.S.

Based on your plots in this assignment, what would you recommend and why? Please list at least two reasons why, and mention which plot(s) you drew your analysis from.

Note: There isn't a set right or wrong answer for this question, feel free to come up with your own conclusions based on evidence from your plots!

A city with a very large number of workers, this will improve people's traffic jams during commuting, we can see in the graph "Average Count of Casual vs Registered by Hour" in question 5, registered users have the peaks in the commuting time. And cities where the weather is hot all year round, we know from the graph "Temperature vs Casual Rider Proportion by Weekday" in question 6, with the increase in temperature, the proportion of tourists is also increasing. Therefore if the city is hot, the more casual users.

