0.0.1 Question 0

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

The granularity of the data represents the instance of bike being used/rented and data regarding the date and weather at the time of use.

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?

Two additional data that can be collected is, more detail on the users outside of just casual or registered (demographics) and possibly the path they took or how long they used the bike for.

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 = 'blue', label = 'casual')
         sns.distplot(daily_counts['registered'], color = 'green', label = 'registered')
         plt.xlabel('Rider Count')
         plt.ylabel('Density')
         plt.title('Distribution Comparsion of Casual vs Registered Riders')
         plt.legend();
```

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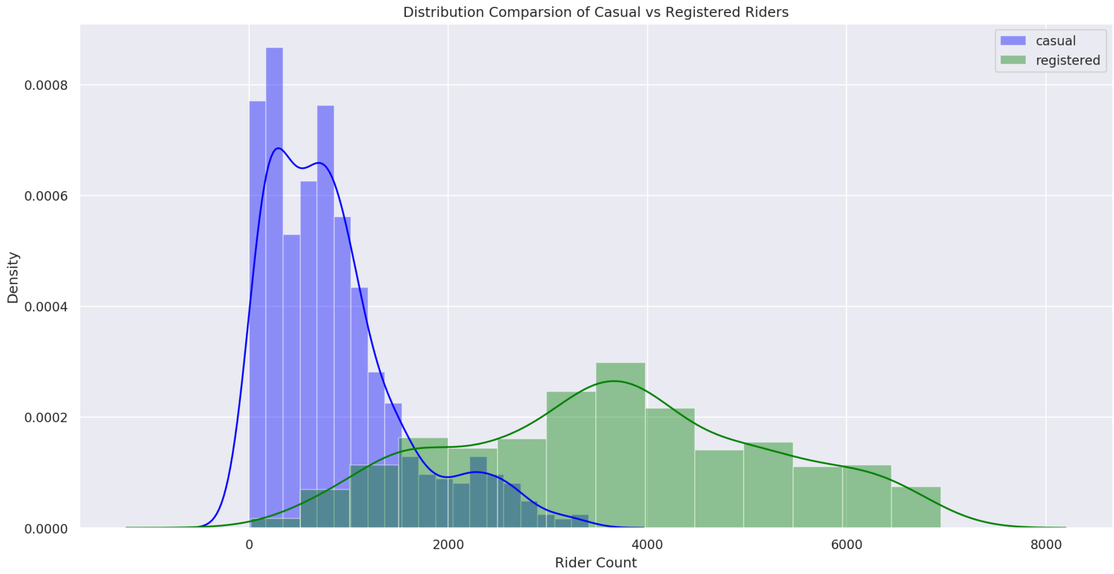


Distribution Comparsion of Casual vs Registered Riders
casual
registered
Density
0.0000
0.0002
0.0004
0.0006
0.0008
0
2000
4000
6000
8000
Rider Count

0.0.3 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.

The density curve for casual riders is bimodal while the registered riders is unimodal. The density curves for casual is skewed to the right while the registered riders seems closer to a normal curve and is somewhat symmetrical.

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.

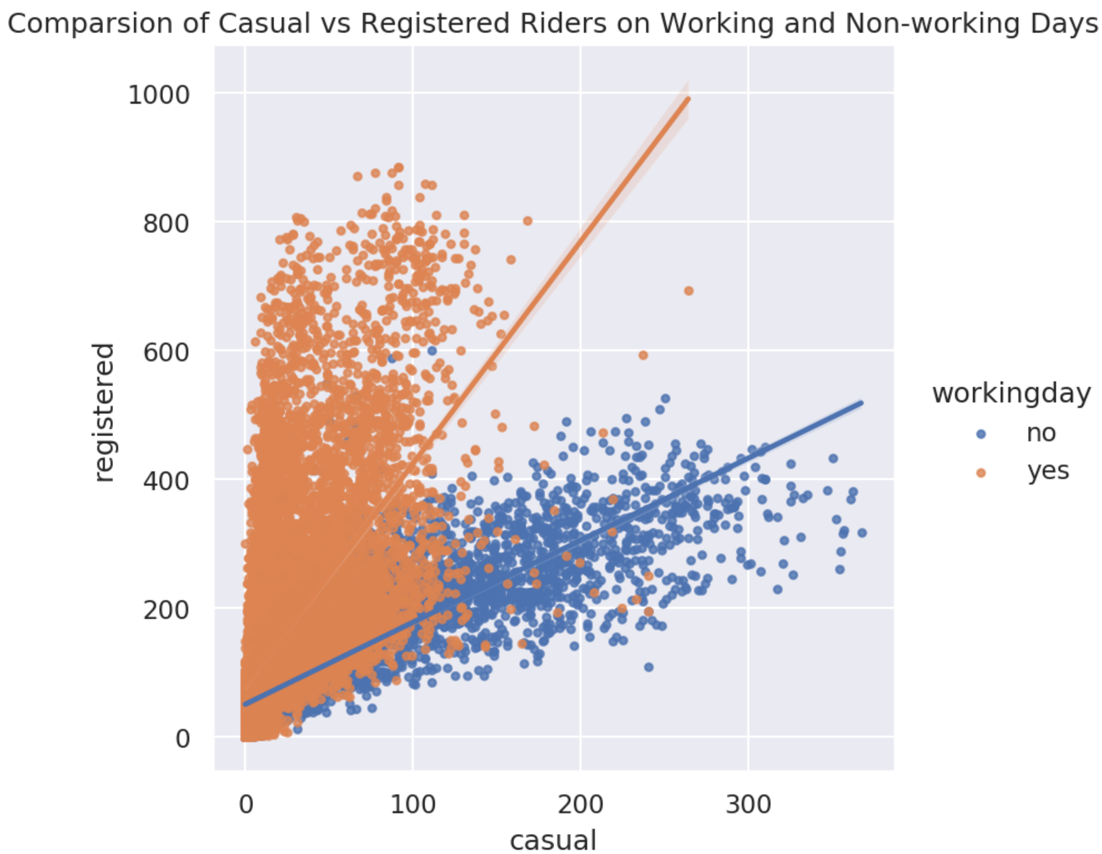
The lmplot function will also try to draw a linear regression line (just as you saw in Data 8). Color the points in the scatterplot according to whether or not the day is a working day (your colors do not have to match ours exactly, but they should be different based on whether the day is a working day).

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', data = bike, fit_reg = True, sca
         plt.title('Comparsion of Casual vs Registered Riders on Working and Non-working Days');
```


Comparsion of Casual vs Registered Riders on Working and Non-working Days
registered
1000
800
600
400
200
0
casual
0
100
200
300
workingday
no
yes

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?

There seems to be a somewhat linear relationship between the two types of riders and this relationship is based on whether it is on the weekday or weekend. Overplotting makes it difficult to accurately describe this relationship because it is difficult to discern the different points in some areas.

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.

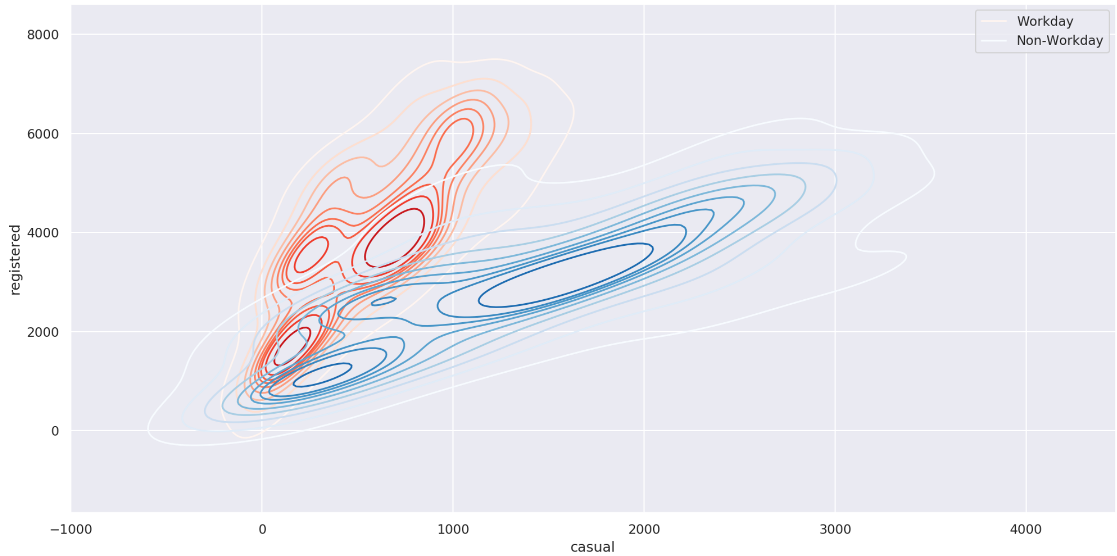
Hints: * You can use `loc` with a boolean array and column names at the same time * You will need to call kdeplot twice. * Check out this guide to see an example of how to create a legend. In particular, look at how the example in the guide makes use of the `label` argument in the call to `plt.plot()` 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['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 = daily_counts.loc[is_workingday, 'casual']
registered_workday = daily_counts.loc[is_workingday, 'registered']

# Use sns.kdeplot on the two variables above to plot the bivariate KDE for weekday rides
sns.kdeplot(casual_workday, registered_workday, cmap = 'Reds', label = 'Workday', shade = Fals

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

# Use sns.kdeplot on the two variables above to plot the bivariate KDE for non-workingday ride
sns.kdeplot(casual_non_workday, registered_non_workday, cmap = 'Blues', label = 'Non-Workday',
plt.legend()
```

```
/opt/conda/lib/python3.8/site-packages/seaborn/_decorators.py:36: FutureWarning: Pass the following var
  warnings.warn(
/opt/conda/lib/python3.8/site-packages/seaborn/_decorators.py:36: FutureWarning: Pass the following var
  warnings.warn(
```

Out[19]: `<matplotlib.legend.Legend at 0x7fad105e3c40>`


Workday
Non-Workday
registered
8000
6000
4000
2000
0
−1000
0
1000
2000
3000
4000
casual

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

From this contour plot we could see more clearly the linear relationship between the two types. Furthermore, it seems that the variability on non-workdays is higher than workdays and workday seems to be trimodal and non-workdays bimodal.

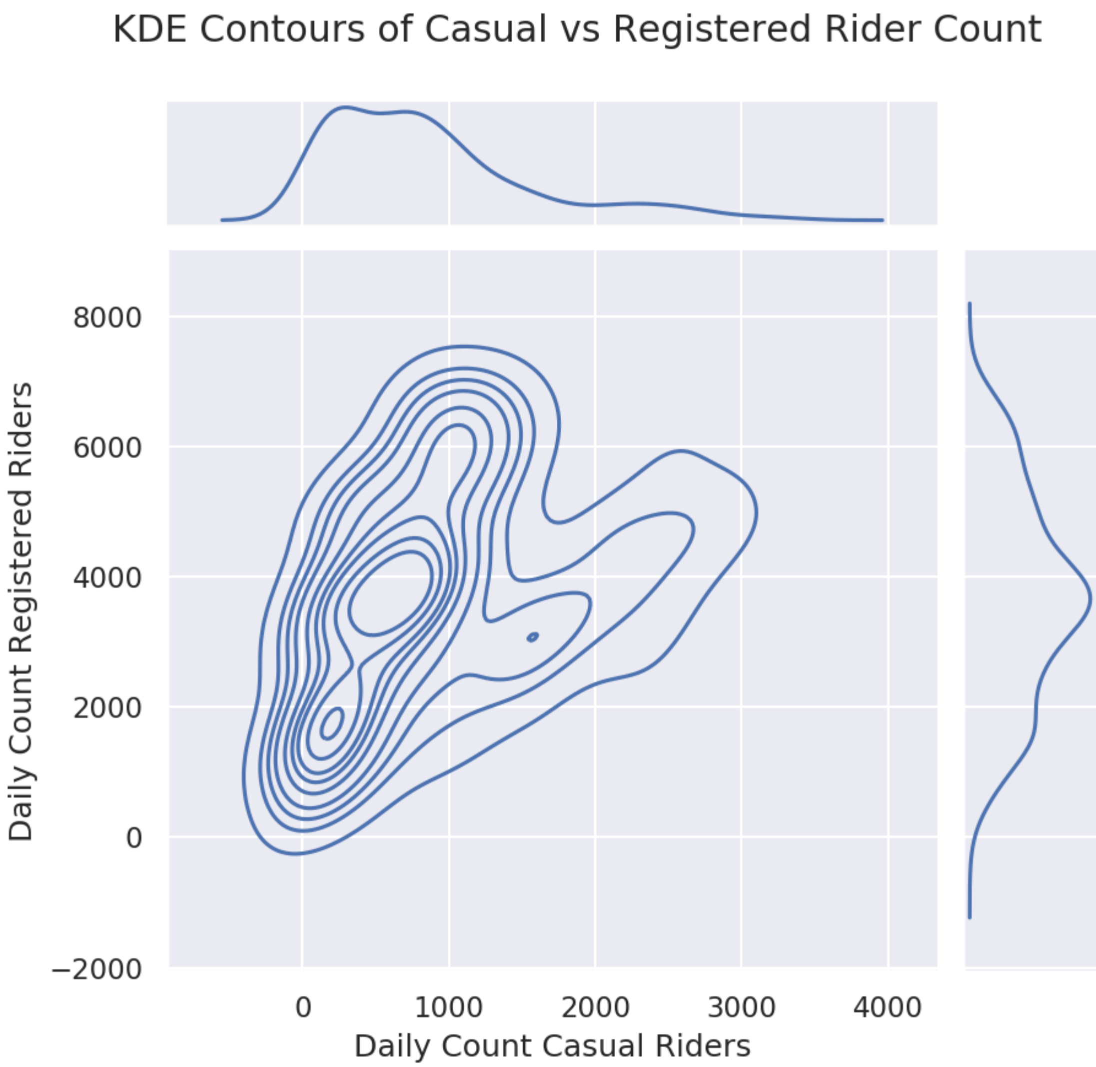
0.1 4: Joint Plot

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]: jointplot = sns.jointplot(data = daily_counts, x ='casual', y ='registered', kind = 'kde')
         jointplot.set_axis_labels('Daily Count Casual Riders', 'Daily Count Registered Riders')
         plt.suptitle('KDE Contours of Casual vs Registered Rider Count')
         plt.subplots_adjust(top = 0.9)
```

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


KDE Contours of Casual vs Registered Rider Count
8000
6000
4000
2000
0
−2000
Daily Count Registered Riders
0
1000
2000
3000
4000
Daily Count Casual Riders

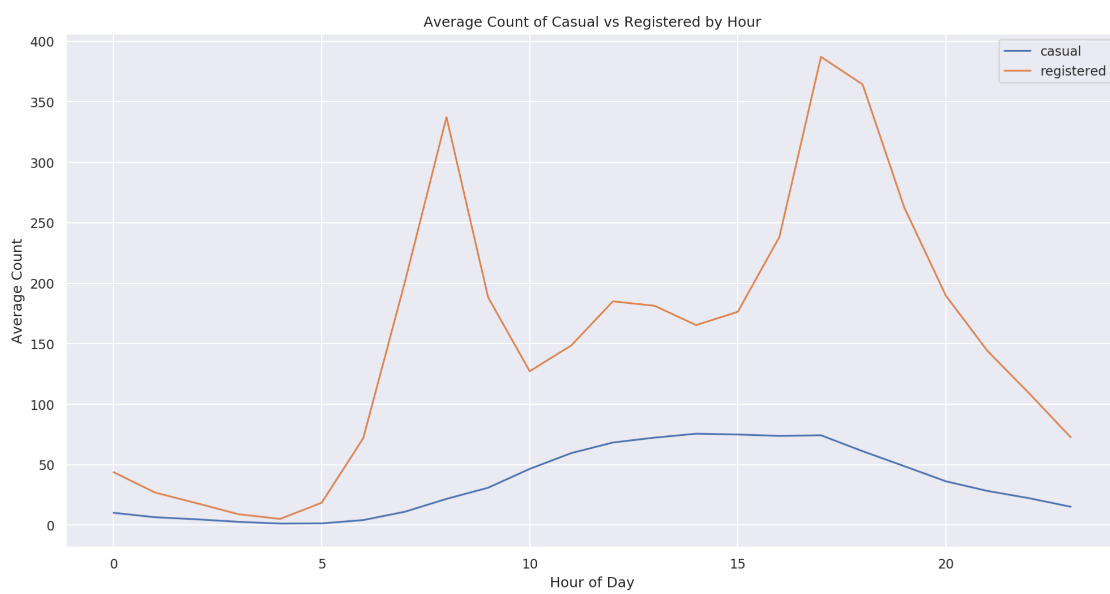
0.2 5: Understanding Daily Patterns

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 [37]:
```
avg_per_hr = bike.groupby('hr').agg(np.average)
sns.lineplot(x = avg_per_hr.index, y = avg_per_hr['casual'], label = 'casual')
sns.lineplot(x = avg_per_hr.index, y = avg_per_hr['registered'], label = 'registered')
plt.xlabel('Hour of Day')
plt.ylabel('Average Count')
plt.title('Average Count of Casual vs Registered by Hour')
plt.legend();
```



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

From the plot above one can hypothesize that casual riders appear to ride mostly in the day with a peak around mid-afternoon. Meanwhile, registered riders ride more overall throughout the day with peaks in the morning and even around commute times and during the day, most likely around lunch hours.

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.

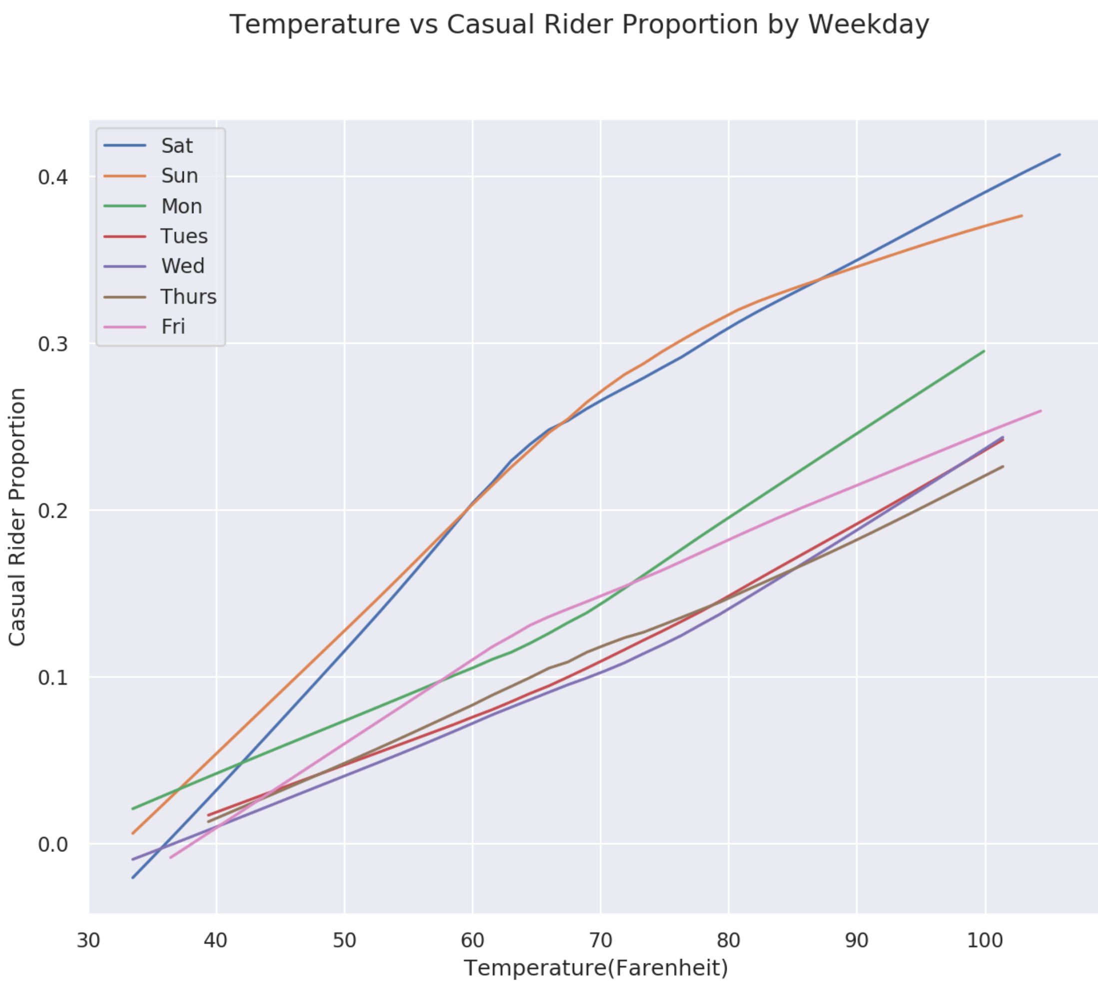
You do not need to match the colors on our sample plot as long as the colors in your plot make it easy to distinguish which day they represent.

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, Fahrenheit $=$ Celsius $* \frac{9}{5} + 32$.

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

In [28]:
```
from statsmodels.nonparametric.smoothers_lowess import lowess

plt.figure(figsize=(10,8))

days = ['Sat', 'Sun', 'Mon', 'Tues', 'Wed', 'Thurs', 'Fri' ]
bike['fahrenheit'] = (bike['temp'] * 41) * (9/5) + 32

for day in days:
    temp = bike[bike['weekday'] == day]['fahrenheit']
    prop_casual = bike[bike['weekday'] == day]['prop_casual']
    smoothed = lowess(prop_casual, temp, return_sorted = False)
    sns.lineplot(x = temp, y = smoothed, label = day)

plt.xlabel('Temperature(Farenheit)')
plt.ylabel('Casual Rider Proportion')
plt.suptitle('Temperature vs Casual Rider Proportion by Weekday')
plt.legend();
```


Temperature vs Casual Rider Proportion by Weekday
Sat
Sun
Mon
Tues
Wed
Thurs
Fri
Casual Rider Proportion
0.4
0.3
0.2
0.1
0.0
30
40
50
60
70
80
90
100
Temperature(Farenheit)

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?

Prop_casual increases as temperature increases for every weekday. This increase is most noticeable during the weekend. Other interesting observations are the lines are non-linear and the slope for the weekend is the highest.

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, the current bike data will not help assess equity in transportation. I would change the granularity by introducing income level, gender and race of the users, basically the demographics and socio-economic levels of the users to better assess equity.

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 you 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!

I would recommended that the bike sharing systems should be expanded but the cities would need to meet certain requirements for the bike sharing system to be feasible. According to the line plot of Temperature vs Casual Rider Proportion, it would be better for the bike sharing system to be implemented in warmer cities as it seems that there are more casual riders with higher temperatures. Furthermore, according to the line plot of Average Count Casual vs Registered by Hour, first of all there are more registered riders and second of all, usage spikes in commute times. Therefore, it would be better in cities that are more densely populated such as New York, where commuting is a hassle.