Data Visualization with Seaborn

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Data file: Cars dataset

In this report, I will explore cars attributes using the Cars dataset from CORGIS Datasets Project. The first step is to read in the csv file and perform some simple data validation.

In [60]:
```
%matplotlib inline
```

In [17]:
```
import numpy as np
import pandas as pd
import matplotlib as mpl
import matplotlib.pyplot as plt
import seaborn as sns
sns.set(style="whitegrid", rc={'figure.figsize':(11.7,8.27)}, color_codes=True)
```

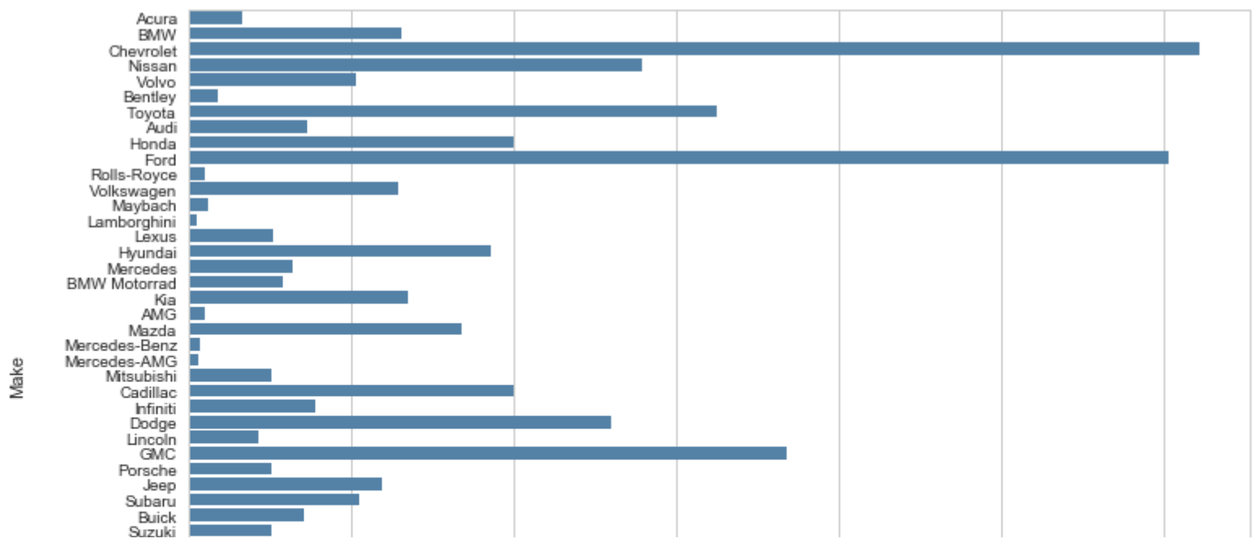
In [61]:
```
cars = pd.read_csv('/Users/libingyi/Documents/MSAN/MSAN622/data/cars2.csv')
# There are only 49 records in 2009, which is too few comparing to other years.
# So choose not to include these records.
cars = cars[cars['Year']!=2009]

# Four-wheel drive is the same as all-wheel drive.
# So rename it as all-wheel drive .
cars['Driveline'] = np.where(cars['Driveline']=='Four-wheel drive', \
                             'All-wheel drive', cars['Driveline'])

cars.head(3)
```

Out[61]:

	City mpg	Classification	Driveline	Engine Type	Fuel Type	Height	Highway mpg	Horsepower	Hybrid	ID	Length	Make	Model Year	Number of Forward Gears	Torque	Transmission	Width	Year
12	20	Automatic transmission	Front-wheel drive	Acura 3.5L 6 Cylinder 280 hp 254 ft-lbs	Gasoline	172	29	280	False	2012 Acura TL	63	Acura	2012 Acura TL	6	254	6 Speed Automatic Select Shift	87	2012
13	18	Automatic transmission	All-wheel drive	Acura 3.7L 6 Cylinder 305 hp 273 ft-lbs	Gasoline	172	26	305	False	2012 Acura TL SH-AWD	63	Acura	2012 Acura TL	6	273	6 Speed Automatic Select Shift	87	2012
14	12	Automatic transmission	All-wheel drive	BMW 4.4L 8 cylinder 555hp 500 ft-lbs Turbo	Gasoline	226	17	555	False	2010 BMW X5 M SUV	243	BMW	2010 BMW X5	6	500	6 Speed Automatic Select Shift	201	2010

Now the dataset is prepared. It is important to know which makes are included in this dataset, so a bar plot will be useful.

In [50]:
```
## bar plot
sns.countplot(y="Make", data=cars, color="steelblue");
```

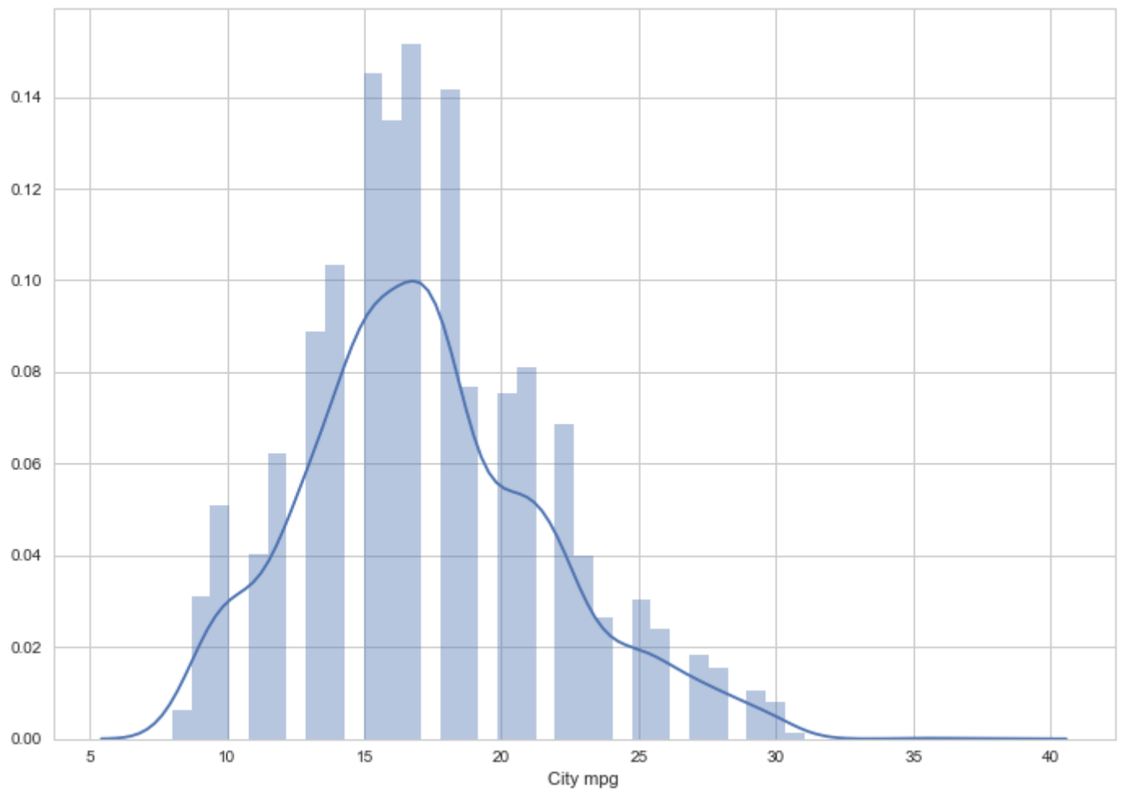


It is clear to see that this dataset mainly consists of American makes. For example, Chevrolet, Ford and GMC have the most records, and the main Germany makes, like BMW, Audi and Mercedes-Benz have only a few records.

Besides the origin, mpg is another key factor of vehicles. Here is the overall average city mpg for all cars in this dataset.

In [51]:
```
## histogram
sns.distplot(cars['City mpg'])
```

Out[51]: `<matplotlib.axes._subplots.AxesSubplot at 0x10a4764e0>`



One can see that the most common city mpg for a car falls between 15 and 20.

It is reasonable to believe that the types of transmission and driveline will affct a vehicle's mpg. A faceted histogram will be useful to show such relationships.

In [54]:
```
## facet histogram
g = sns.FacetGrid(cars, row="Classification", col="Driveline", margin_titles=True)
bins = np.linspace(5, 40, 15)
g.map(plt.hist, "City mpg", color="steelblue", bins=bins, lw=0)
```

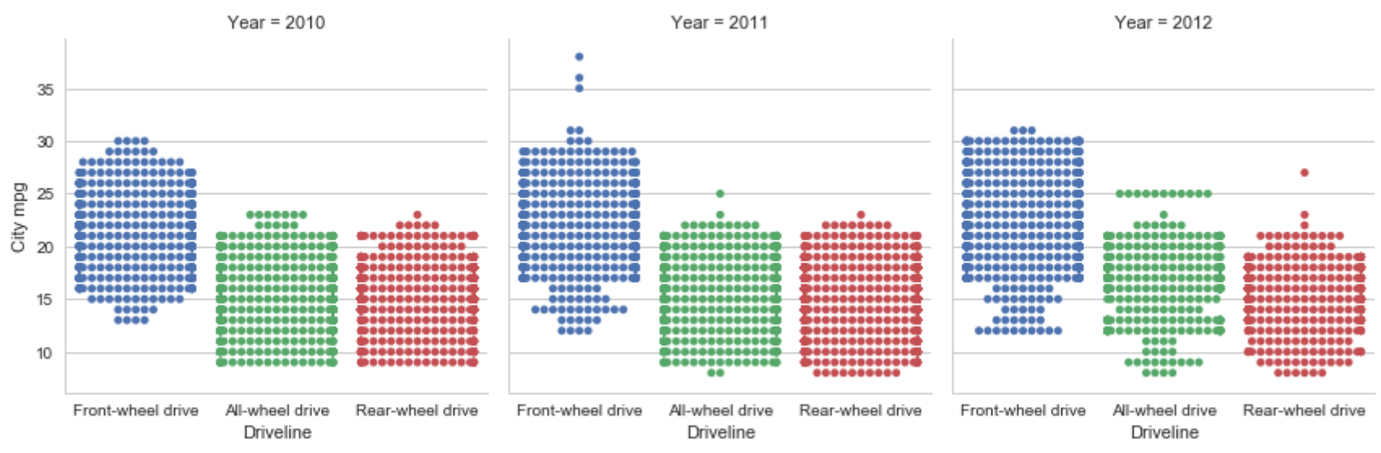
Out[54]: <seaborn.axisgrid.FacetGrid at 0x1a1f4fda90>

According to the distribution, one can see that front-wheel drive vehicles tend to have higher average of city mpg (greater than 20) than all-wheel drive and rear-wheel drive vehicles. However, due to the lack of data, no conclusion can be drawed on the impact of transmission types on the mpg.

A swarm plot can show the distribution of city mpg of different types of driveline more clearly.

In [57]:
```
sns.factorplot(x="Driveline", y="City mpg",
               col="Year", data=cars, kind="swarm")
```

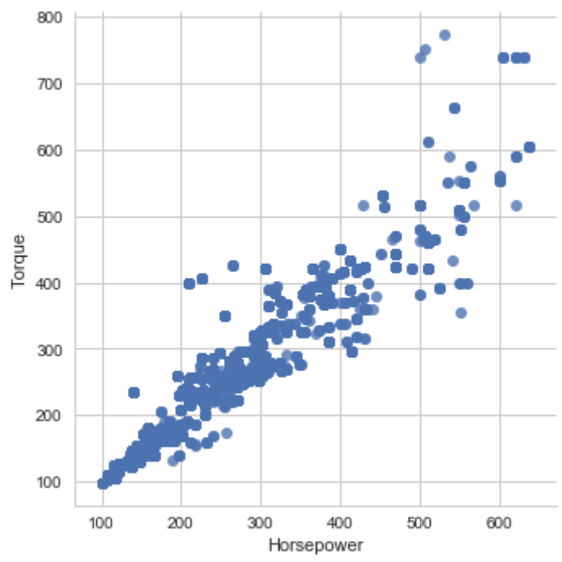
Out[57]: <seaborn.axisgrid.FacetGrid at 0x1a1c55d240>



Based on the swarm plot, one can easily see that front-wheel drive vehicles have a higher average of city mpg. And all-wheel drive vehicles and rear-wheel drive vehicles have similar city mpg.

Driveline types may also affects the horsepower and torque of a vehicle other than mpg. Here is a scatter plot of horsepower and torque of all vehicles in the dataset.

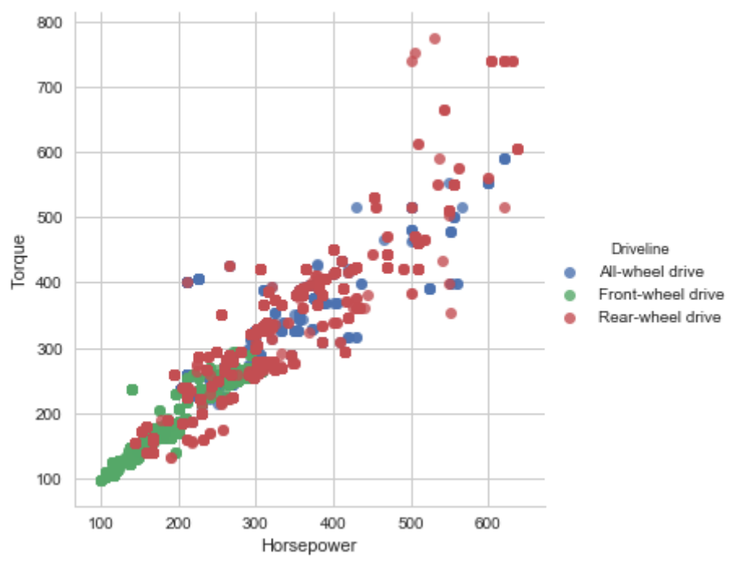
In [58]:
```
##bivarite scatter plot
sns.lmplot(x="Horsepower", y="Torque", data=cars, fit_reg=False);
```



From this plot, one can see that horsepower and torque has a positive relationship.

And here is the same scatter plot with different types of driveline showed in different colors.

In [37]:
```
##trivariate scatter plot
sns.lmplot(x="Horsepower", y="Torque", hue='Driveline', data=cars, fit_reg=False);
```

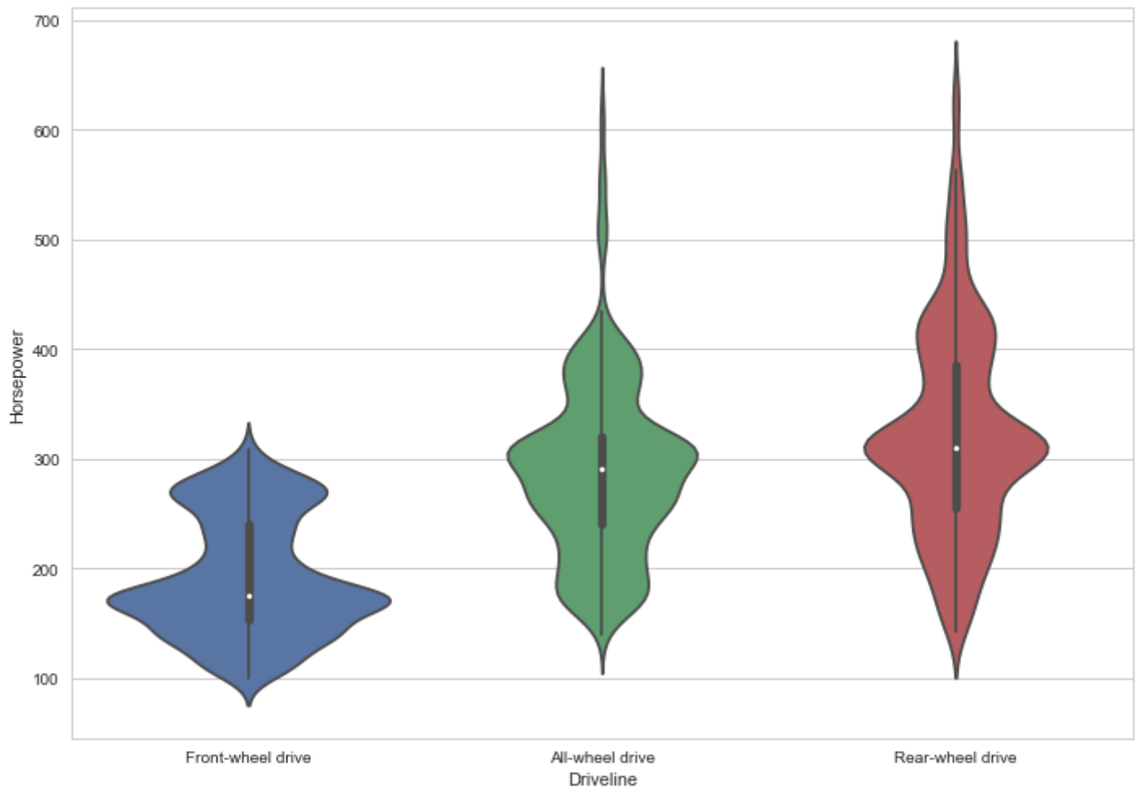


One can see that front-wheel drive vehicles have smaller horsepower and torque, while rear-wheel drive vehicles tend to have the highest torque.

However, in the above scatter plot, most dots representing all-wheel drive vehicles and real-wheel vehicles are overlapped. In order to distinguish whether they have similar distributions, a violin plot can be useful.

In [59]:
```
sns.violinplot(x=cars['Driveline'], y=cars['Horsepower'])
```

Out[59]: <matplotlib.axes._subplots.AxesSubplot at 0x1a1ca14908>



Based on the violin plot, one can see that all-wheel drive and rear-wheel drive vehicles do have similar distribution of horsepower. And front-wheel drive vehicles overall, of course, have lower horsepower.