```
In [1]: %matplotlib inline
    # Dependencies and Setup
    import pandas as pd
    import matplotlib.pyplot as plt
```

```
In [2]: # Read the csv files into pandas as dataframes
    data_file = "data/city_data.csv"
    city_df = pd.read_csv(data_file)
    data_file2 = "data/ride_data.csv"
    ride_df = pd.read_csv(data_file2)
    city_df.head()
```

Out[2]:

	city	driver_count	type
0	Richardfort	38	Urban
1	Williamsstad	59	Urban
2	Port Angela	67	Urban
3	Rodneyfort	34	Urban
4	West Robert	39	Urban

In [3]: ride_df.head()

Out[3]:

	city	date	fare	ride_id
0	Lake Jonathanshire	2018-01-14 10:14:22	13.83	5739410935873
1	South Michelleport	2018-03-04 18:24:09	30.24	2343912425577
2	Port Samanthamouth	2018-02-24 04:29:00	33.44	2005065760003
3	Rodneyfort	2018-02-10 23:22:03	23.44	5149245426178
4	South Jack	2018-03-06 04:28:35	34.58	3908451377344

```
In [4]: # Merge dataframes then sort by city
    merge_df = pd.merge(city_df,ride_df,on="city",how="outer")
    merge_df = merge_df.sort_values("city")
    merge_df.head()
```

Out[4]:

	city	driver_count	type	date	fare	ride_id
1523	Amandaburgh	12	Urban	2018-01-11 02:22:07	29.24	7279902884763
1522	Amandaburgh	12	Urban	2018-02-10 20:42:46	36.17	6455620849753
1529	Amandaburgh	12	Urban	2018-03-13 12:52:31	13.88	6222134922674
1524	Amandaburgh	12	Urban	2018-01-21 04:12:54	9.26	5528427024492
1525	Amandaburgh	12	Urban	2018-04-19 16:30:12	6.27	4400632718421

```
In [5]: # Slice the city_df by Urban city type
    city_urban = city_df.loc[city_df["type"]=="Urban"]
    city_urban.sort_values("city")
    # Driver_count per city for urban city type
    drivers_urban = city_urban["driver_count"].tolist()
    drivers_urban = [each*5 for each in drivers_urban]
    city_urban.head()
```

Out[5]:

	city	driver_count	type
0	Richardfort	38	Urban
1	Williamsstad	59	Urban
2	Port Angela	67	Urban
3	Rodneyfort	34	Urban
4	West Robert	39	Urban

```
In [6]: # Slice the city_df by Rural city type
    city_rural = city_df.loc[city_df["type"]=="Rural"]
    city_rural.sort_values("city")
    # Driver_count per city by Rural type
    drivers_rural = city_rural["driver_count"].tolist()
    drivers_rural = [each*5 for each in drivers_rural]
    drivers_rural
    city_rural.head()
```

Out[6]:

	city	driver_count	type
102	South Jennifer	7	Rural
103	West Heather	4	Rural
104	Newtonview	1	Rural
105	North Holly	8	Rural
106	Michaelberg	6	Rural

```
In [7]: # Slice the city_df by suburban city type
    city_sub = city_df.loc[city_df["type"]=="Suburban"]
    city_sub.sort_values("city")
    # Driver_count per city by suburban type
    drivers_sub= city_sub["driver_count"].tolist()
    drivers_sub = [each*5 for each in drivers_sub]
    city_sub.head()
```

Out[7]:

	city	driver_count	type
66	Port Shane	7	Suburban
67	Lake Ann	3	Suburban
68	Lake Scott	23	Suburban
69	Colemanland	23	Suburban
70	New Raymond	17	Suburban

```
In [8]: # Slice merged df by urban type
    urban_df = merge_df.loc[merge_df["type"]=="Urban"]
    urban_df.sort_values("city")
    # Groupby city
    group_urban = urban_df.groupby("city")
    # Number of rides per city-Urban
    rides_city_urban = group_urban["type"].count()
    rides_city_urban
    # Average fare per city-Urban
    avgfare_urban = round(group_urban["fare"].mean(),2)
    avgfare_urban
```

Out[8]: city

city	
Amandaburgh	24.64
Barajasview	25.33
Carriemouth	28.31
Christopherfurt	24.50
Deanville	25.84
East Kaylahaven	23.76
Erikaland	24.91
Grahamburgh	25.22
Huntermouth	28.99
Hurleymouth	25.89
Jerryton	25.65
Johnton	26.79
Joneschester	22.29
Justinberg	23.69
Karenberg	26.34
Karenside	27.45
Lake Danielberg	24.84
Lake Jonathanshire	23.43
Lake Scottton	23.81
Leahton	21.24
Liumouth	26.15
Loganberg	25.29
Martinezhaven	22.65
New Jacobville	26.77
New Kimberlyborough	22.59
New Paulton	27.82
New Paulville	21.68
North Barbara	23.49
North Jasmine	25.21
North Jason	22.74
North Jason	22.74
North Jason Port Johnbury	22.74 23.01
North Jason Port Johnbury Port Samanthamouth	22.74 23.01 25.64
North Jason Port Johnbury	22.74 23.01
North Jason Port Johnbury Port Samanthamouth	22.74 23.01 25.64
North Jason Port Johnbury Port Samanthamouth Raymondhaven	22.74 23.01 25.64 21.48
North Jason Port Johnbury Port Samanthamouth Raymondhaven Reynoldsfurt Richardfort	22.74 23.01 25.64 21.48 21.92 22.37
North Jason Port Johnbury Port Samanthamouth Raymondhaven Reynoldsfurt Richardfort Roberthaven	22.74 23.01 25.64 21.48 21.92 22.37 23.73
North Jason Port Johnbury Port Samanthamouth Raymondhaven Reynoldsfurt Richardfort Roberthaven Robertport	22.74 23.01 25.64 21.48 21.92 22.37 23.73 23.06
North Jason Port Johnbury Port Samanthamouth Raymondhaven Reynoldsfurt Richardfort Roberthaven Robertport Rodneyfort	22.74 23.01 25.64 21.48 21.92 22.37 23.73 23.06 28.62
North Jason Port Johnbury Port Samanthamouth Raymondhaven Reynoldsfurt Richardfort Roberthaven Robertport Rodneyfort Rogerston	22.74 23.01 25.64 21.48 21.92 22.37 23.73 23.06 28.62 22.10
Port Johnbury Port Samanthamouth Raymondhaven Reynoldsfurt Richardfort Roberthaven Robertport Rodneyfort Rogerston Royland	22.74 23.01 25.64 21.48 21.92 22.37 23.73 23.06 28.62 22.10 20.57
Port Johnbury Port Samanthamouth Raymondhaven Reynoldsfurt Richardfort Roberthaven Robertport Rodneyfort Rogerston Royland Simpsonburgh	22.74 23.01 25.64 21.48 21.92 22.37 23.73 23.06 28.62 22.10 20.57 23.36
Port Johnbury Port Samanthamouth Raymondhaven Reynoldsfurt Richardfort Roberthaven Robertport Rodneyfort Rogerston Royland	22.74 23.01 25.64 21.48 21.92 22.37 23.73 23.06 28.62 22.10 20.57
Port Johnbury Port Samanthamouth Raymondhaven Reynoldsfurt Richardfort Roberthaven Robertport Rodneyfort Rogerston Royland Simpsonburgh	22.74 23.01 25.64 21.48 21.92 22.37 23.73 23.06 28.62 22.10 20.57 23.36
Port Johnbury Port Samanthamouth Raymondhaven Reynoldsfurt Richardfort Roberthaven Robertport Rodneyfort Rogerston Royland Simpsonburgh South Evanton	22.74 23.01 25.64 21.48 21.92 22.37 23.73 23.06 28.62 22.10 20.57 23.36 26.73
Port Johnbury Port Samanthamouth Raymondhaven Reynoldsfurt Richardfort Roberthaven Robertport Rodneyfort Rogerston Royland Simpsonburgh South Evanton South Jack South Karenland	22.74 23.01 25.64 21.48 21.92 22.37 23.73 23.06 28.62 22.10 20.57 23.36 26.73 22.97 26.54
Port Johnbury Port Samanthamouth Raymondhaven Reynoldsfurt Richardfort Roberthaven Robertport Rodneyfort Rogerston Royland Simpsonburgh South Evanton South Jack South Karenland South Latoya	22.74 23.01 25.64 21.48 21.92 22.37 23.73 23.06 28.62 22.10 20.57 23.36 26.73 22.97 26.54 20.09
Port Johnbury Port Samanthamouth Raymondhaven Reynoldsfurt Richardfort Roberthaven Robertport Rodneyfort Rogerston Royland Simpsonburgh South Evanton South Jack South Karenland South Latoya South Michelleport	22.74 23.01 25.64 21.48 21.92 22.37 23.73 23.06 28.62 22.10 20.57 23.36 26.73 22.97 26.54 20.09 24.45
Port Johnbury Port Samanthamouth Raymondhaven Reynoldsfurt Richardfort Roberthaven Robertport Rodneyfort Rogerston Royland Simpsonburgh South Evanton South Jack South Karenland South Latoya South Phillip	22.74 23.01 25.64 21.48 21.92 22.37 23.73 23.06 28.62 22.10 20.57 23.36 26.73 22.97 26.54 20.09 24.45 28.57
Port Johnbury Port Samanthamouth Raymondhaven Reynoldsfurt Richardfort Roberthaven Robertport Rodneyfort Rogerston Royland Simpsonburgh South Evanton South Jack South Karenland South Latoya South Phillip Valentineton	22.74 23.01 25.64 21.48 21.92 22.37 23.73 23.06 28.62 22.10 20.57 23.36 26.73 22.97 26.54 20.09 24.45 28.57 24.64
Port Johnbury Port Samanthamouth Raymondhaven Reynoldsfurt Richardfort Roberthaven Robertport Rodneyfort Rogerston Royland Simpsonburgh South Evanton South Jack South Karenland South Latoya South Phillip Valentineton West Angela	22.74 23.01 25.64 21.48 21.92 22.37 23.73 23.06 28.62 22.10 20.57 23.36 26.73 22.97 26.54 20.09 24.45 28.57 24.64 25.99
Port Johnbury Port Samanthamouth Raymondhaven Reynoldsfurt Richardfort Roberthaven Robertport Rodneyfort Rogerston Royland Simpsonburgh South Evanton South Jack South Karenland South Latoya South Michelleport South Phillip Valentineton West Angela West Anthony	22.74 23.01 25.64 21.48 21.92 22.37 23.73 23.06 28.62 22.10 20.57 23.36 26.73 22.97 26.54 20.09 24.45 28.57 24.64 25.99 24.74
Port Johnbury Port Samanthamouth Raymondhaven Reynoldsfurt Richardfort Roberthaven Robertport Rodneyfort Rogerston Royland Simpsonburgh South Evanton South Jack South Karenland South Latoya South Michelleport South Phillip Valentineton West Angela West Anthony West Christopherberg	22.74 23.01 25.64 21.48 21.92 22.37 23.73 23.06 28.62 22.10 20.57 23.36 26.73 22.97 26.54 20.09 24.45 28.57 24.64 25.99 24.74 24.42
Port Johnbury Port Samanthamouth Raymondhaven Reynoldsfurt Richardfort Roberthaven Robertport Rodneyfort Rogerston Royland Simpsonburgh South Evanton South Jack South Karenland South Latoya South Michelleport South Phillip Valentineton West Angela West Anthony West Christopherberg West Ericstad	22.74 23.01 25.64 21.48 21.92 22.37 23.73 23.06 28.62 22.10 20.57 23.36 26.73 22.97 26.54 20.09 24.45 28.57 24.64 25.99 24.74
Port Johnbury Port Samanthamouth Raymondhaven Reynoldsfurt Richardfort Roberthaven Robertport Rodneyfort Rogerston Royland Simpsonburgh South Evanton South Jack South Karenland South Latoya South Michelleport South Phillip Valentineton West Angela West Anthony West Christopherberg	22.74 23.01 25.64 21.48 21.92 22.37 23.73 23.06 28.62 22.10 20.57 23.36 26.73 22.97 26.54 20.09 24.45 28.57 24.64 25.99 24.74 24.42
Port Johnbury Port Samanthamouth Raymondhaven Reynoldsfurt Richardfort Roberthaven Robertport Rodneyfort Rogerston Royland Simpsonburgh South Evanton South Jack South Karenland South Latoya South Michelleport South Phillip Valentineton West Angela West Anthony West Christopherberg West Ericstad	22.74 23.01 25.64 21.48 21.92 22.37 23.73 23.06 28.62 22.10 20.57 23.36 26.73 22.97 26.54 20.09 24.45 28.57 24.64 25.99 24.74 24.42 22.35
Port Johnbury Port Samanthamouth Raymondhaven Reynoldsfurt Richardfort Roberthaven Robertport Rodneyfort Rogerston Royland Simpsonburgh South Evanton South Jack South Karenland South Latoya South Michelleport South Phillip Valentineton West Angela West Anthony West Christopherberg West Gabriel	22.74 23.01 25.64 21.48 21.92 22.37 23.73 23.06 28.62 22.10 20.57 23.36 26.73 22.97 26.54 20.09 24.45 28.57 24.64 25.99 24.74 24.42 22.35 20.35

```
West Patrickchester 28.23
West Robert 25.12
West Samuelburgh 21.77
Williamsstad 24.36
Williamsview 26.60
```

Name: fare, Length: 66, dtype: float64

```
In [9]: # Slice merged df by rural type
    rural_df = merge_df.loc[merge_df["type"]=="Rural"]
    rural_df.sort_values("city")
    # Groupby city
    group_rural = rural_df.groupby("city")
    # Number of rides per city-Rural
    rides_city_rural = group_rural["type"].count()
    rides_city_rural
    # Average fare per city-Rural
    avgfare_rural = round(group_rural["fare"].mean(),2)
    avgfare_rural
```

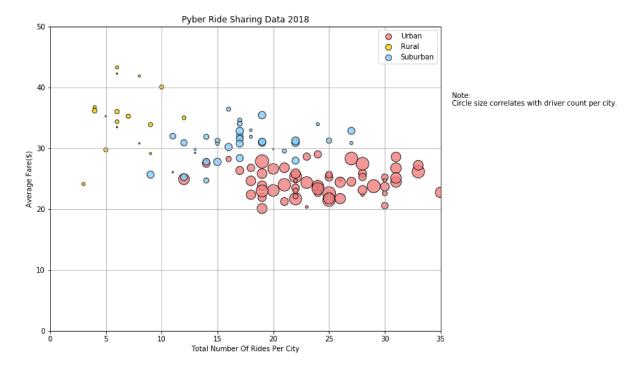
Out[9]: city

Bradshawfurt	40.06
Garzaport	24.12
Harringtonfort	33.47
Jessicaport	36.01
Lake Jamie	34.36
Lake Latoyabury	26.06
Michaelberg	35.00
New Ryantown	43.28
Newtonview	36.75
North Holly	29.13
North Jaime	30.80
Penaborough	35.25
Randallchester	29.74
South Jennifer	35.26
South Marychester	41.87
South Saramouth	36.16
Taylorhaven	42.26
West Heather	33.89
Name: fare, dtype:	float64

```
In [10]: # Slice merged of by Suburban type
         sub_df = merge_df.loc[merge_df["type"]=="Suburban"]
         sub_df.sort_values("city")
         # Groupby city
         group_sub = sub_df.groupby("city")
         # Number of rides per city-Suburban
         rides_city_sub = group_sub["type"].count()
         rides city sub
         # Average fare per city-Suburban
         avgfare_sub = round(group_sub["fare"].mean(),2)
         avgfare sub
Out[10]: city
         Barronchester
                                36.42
         Bethanyland
                                32.96
                               35.44
         Brandonfort
         Colemanland
                               30.89
         Davidfurt
                               32.00
         East Aaronbury
                               25.66
         East Danielview
                                31.56
         East Kentstad
                                29.82
                               30.84
         East Marymouth
         Grayville
                               27.76
         Josephside
                               32.86
         Lake Ann
                                30.89
         Lake Omar
                               28.07
         Lake Robertside
                               31.26
         Lake Scott
                                31.89
         Lewishaven
                               25.24
         Lewisland
                                34.61
         Mezachester
                               30.76
         Myersshire
                                30.20
         New Olivia
                               34.05
         New Raymond
                               27.96
         New Shannonberg
                               28.38
         Nicolechester
                               30.91
         North Jeffrey
                                29.24
         North Richardhaven
                               24.70
         North Timothy
                                31.26
         Port Shane
                                31.08
         Rodriguezview
                               30.75
         Sotoville
                                31.98
         South Brenda
                               33.96
         South Teresa
                                31.22
         Veronicaberg
                               32.83
                                27.78
         Victoriaport
         West Hannah
                                29.55
         West Kimmouth
                                29.87
         Williamsonville
                                31.88
         Name: fare, dtype: float64
```

Bubble Plot of Ride Sharing Data

```
In [11]: # Create scatterplots for each city type dataframes
         # Scatter plot for urban
         fig = plt.figure(figsize=(10,8))
         plt.grid(True)
         sct urban = plt.scatter(x=rides city urban,y=avgfare urban,marker="o",
                                  color="lightcoral",s=10*drivers urban,edgecolor='blac
         k', linewidths=1,alpha=0.8,label="Urban")
         # Scatter plot for rural
         sct rural = plt.scatter(x=rides city rural,y=avgfare rural,marker="o",
                                  color="gold",s=10*drivers_rural,edgecolor='black',line
         widths=1,alpha=0.8,label="Rural")
         # Scatter plot for Suburban
         sct_sub = plt.scatter(x=rides_city_sub,y=avgfare_sub,marker="o",
                                color="lightskyblue",s=10*drivers_sub,edgecolor='black',
         linewidths=1,alpha=0.8,label="Suburban")
         # Set the legends then set equal sizes for legend pts
         lgnd = plt.legend(handles=[sct_urban,sct_rural,sct_sub],loc="best")
         lgnd.legendHandles[0]._sizes = [70]
         lgnd.legendHandles[1]. sizes = [70]
         lgnd.legendHandles[2]. sizes = [70]
         # Set texts and positions on the chart
         plt.text(36,37,'Note:\nCircle size correlates with driver count per city.',fon
         tsize=10)
         # Set x and y axis
         plt.xlim(0,35)
         plt.ylim(0,50)
         # axis labels and title
         plt.title("Pyber Ride Sharing Data 2018")
         plt.xlabel("Total Number Of Rides Per City")
         plt.ylabel("Average Fare($)")
         plt.savefig("mypyber.png",bbox inches='tight')
         plt.show()
```



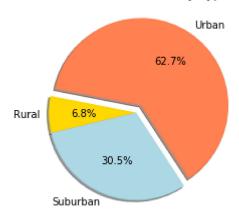
Total Fares by City Type

```
In [12]: # Pie charts
# Total fares for all the city types combined
total_fare = round(ride_df["fare"].sum(),2)
# Total fares for Urban
grouped_type = merge_df.groupby("type")
total_fare_type = grouped_type["fare"].sum()
# % total fares for each city type
percent_fare_type = [(x/total_fare)*100 for x in total_fare_type]
percent_fare_type
```

Out[12]: [6.811492974983412, 30.463872062732218, 62.72463496228453]

Out[13]: Text(0.5, 1.0, '% Of Total Fares Per City Type')





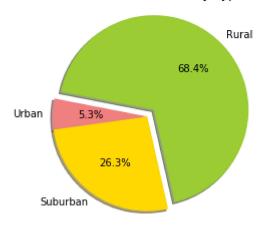
Total Rides by City Type

Out[14]: [5.263157894736842, 26.31578947368421, 68.42105263157895]

```
In [15]:
        # Labels for the sections of our pie chart
         labels = ["Urban", "Suburban", "Rural"]
         # Value per section of the pie chart
         percent_rides_type
         # Colors per section of the pie chart
         colors = ["lightcoral", "gold", "yellowgreen"]
         # Set matplotlib to seperate the "Python" section from the others
         explode = [0, 0, 0.1]
         # Create the pie chart and automatically set to find the percentages of each p
         art of the pie chart
         plt.pie(percent_rides_type, explode=explode, labels=labels, colors=colors,
                 autopct="%1.1f%%", shadow=True, startangle=169)
         plt.title("% Of Total Rides Per City Type")
         # Set the matplotlib to show a pie chart with equal axes
         plt.axis("equal")
```

Out[15]: (-1.1052772830989732, 1.1863127973827317, -1.1127278884131324, 1.191025342591955)





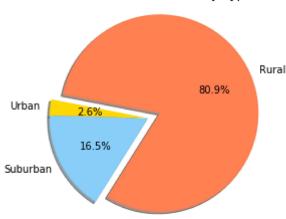
Total Drivers by City Type

```
In [16]: # % of total drivers per City Type
          # Total drivers for all cities combined
          total_drivers = city_df["driver_count"].sum()
          # Total drivers for urban
          # Groupby city type and city
          grouped_city_type = city_df.groupby("type")
          total drivers type = grouped city type["driver count"].sum()
          # % Total drivers per city type
          percent drivers type = [(x/\text{total drivers})*100 \text{ for } x \text{ in total drivers type}]
          percent_drivers_type
```

Out[16]: [2.6236125126135215, 16.481668348469558, 80.89471913891691]

```
In [17]: # Labels for the sections of our pie chart
         labels = ["Urban", "Suburban", "Rural"]
         # Values per section of the pie chart
         percent_drivers_type
         # Colors per section of the pie chart
         colors = ["gold", "lightskyblue", "coral"]
         # Set matplotlib to seperate the "Python" section from the others
         explode = [0, 0, 0.13]
         # Create the pie chart and automatically set to find the percentages of each p
         art of the pie chart
         plt.pie(percent_drivers_type, explode=explode, labels=labels, colors=colors,
                 autopct="%1.1f%%", shadow=True, startangle=169)
         plt.title("% Of Total Drivers Per City Type")
         # Set matplotlib to show a pie chart with equal axes
         plt.axis("equal")
```

Out[17]: (-1.1107992489998582, 1.231274009892694, -1.054002478011723, 1.15775304700421



7)