pyber

March 22, 2018

1 Pyber Data Analysis

1.1 Part 1: Bubble Plot

In [109]:
```
import pandas as pd
from matplotlib import pyplot as plt
import seaborn

seaborn.set()
seaborn.set_palette(seaborn.xkcd_palette([
    "gold",
    "light sky blue",
    "coral",
]))
seaborn.set_style({"axes.facecolor": "darkgray"})
```

In [110]:
```
fare_data = pd.read_csv("ride_data.csv")
fare_data.head()
```

Out[110]:

	city	date	fare	ride_id
0	Sarabury	2016-01-16 13:49:27	38.35	5403689035038
1	South Roy	2016-01-02 18:42:34	17.49	4036272335942
2	Wiseborough	2016-01-21 17:35:29	44.18	3645042422587
3	Spencertown	2016-07-31 14:53:22	6.87	2242596575892
4	Nguyenbury	2016-07-09 04:42:44	6.28	1543057793673

In [111]:
```
city_data = pd.read_csv("city_data.csv")
city_data.head()
```

Out[111]:

	city	driver_count	type
0	Kelseyland	63	Urban
1	Nguyenbury	8	Urban
2	East Douglas	12	Urban
3	West Dawnfurt	34	Urban
4	Rodriguezburgh	52	Urban

In [112]:
```
avg_fare_per_city = fare_data.groupby("city").mean()
avg_city_fare_typed = avg_fare_per_city.join(city_data.set_index("city"))
avg_city_fare_typed.head()
```

```
Out[112]:                     fare       ride_id  driver_count      type
          city
          Alvarezhaven  23.928710  5.351586e+12            21     Urban
          Alyssaberg    20.609615  3.536678e+12            67     Urban
          Anitamouth    37.315556  4.195870e+12            16  Suburban
          Antoniomouth  23.625000  5.086800e+12            21     Urban
          Aprilchester  21.981579  4.574788e+12            49     Urban
```

```
In [113]: total_rides_per_city = fare_data["city"].value_counts()
          total_rides_per_city.head()
```

```
Out[113]: Port Johnstad    34
          Swansonbury      34
          Port James       32
          South Louis      32
          Arnoldview       31
          Name: city, dtype: int64
```

```
In [114]: city_summary = avg_city_fare_typed.join(total_rides_per_city)
          city_summary = city_summary.drop("ride_id", axis=1)
          city_summary.columns = ["avg_fare", "driver_count", "type", "ride_count"]
          city_summary.head()
```

```
Out[114]:                avg_fare  driver_count      type  ride_count
          Alvarezhaven  23.928710            21     Urban          31
          Alyssaberg    20.609615            67     Urban          26
          Anitamouth    37.315556            16  Suburban           9
          Antoniomouth  23.625000            21     Urban          22
          Aprilchester  21.981579            49     Urban          19
```

```
In [115]: urban_cities = city_summary[city_summary.type == "Urban"]
          suburban_cities = city_summary[city_summary.type == "Suburban"]
          rural_cities = city_summary[city_summary.type == "Rural"]
```

```
In [116]: for df in [urban_cities, suburban_cities, rural_cities]:
              plt.scatter(
                  df["driver_count"],
                  df["avg_fare"],
                  s=df["ride_count"]*5,
                  alpha=0.65,
                  label=df.iloc[0]["type"]
              )
          plt.xlabel("Drivers per City")
          plt.ylabel("Average Fare per City")
          plt.title("Driver Count")
          plt.legend()
          plt.show()
```

1.2 Part 2: Pie Charts

1.2.1 Fares by City Type

In [117]:
```
typed_fares = fare_data.join(city_data[["city", "type"]].set_index("city"), on="city"
typed_fares.sample(10)
```

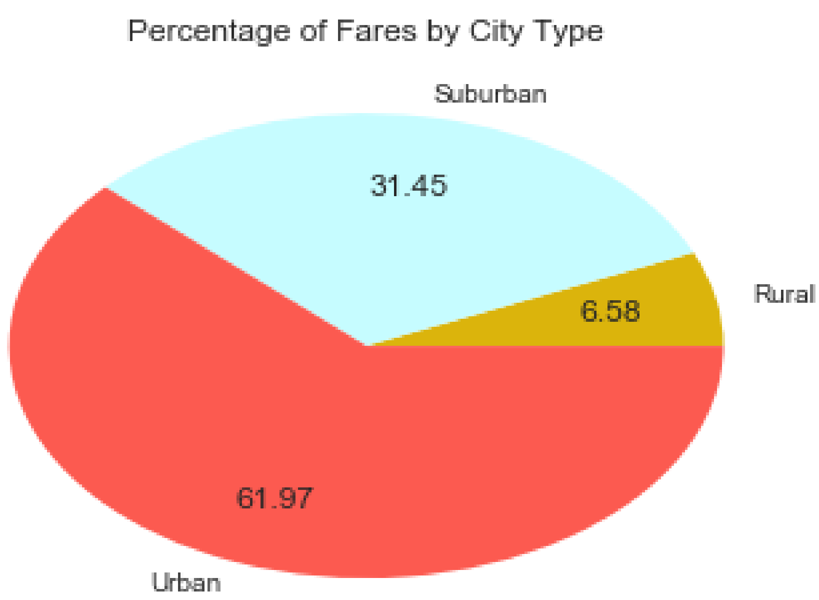
Out[117]:

	city	date	fare	ride_id	type
1675	New Brandonborough	2016-04-26 19:15:18	27.95	7273596757686	Suburban
695	Smithhaven	2016-10-12 05:55:43	4.57	8478436402439	Urban
1793	Martinmouth	2016-09-13 05:50:40	39.92	155794037869	Suburban
1429	Eriktown	2016-11-10 08:31:17	39.15	4715353076775	Urban
1804	Port Alexandria	2016-05-11 17:15:14	38.47	7189369952182	Suburban
1973	Port Alexandria	2016-08-10 12:16:09	31.75	11622863980	Suburban
2221	Lake Brenda	2016-07-26 22:43:47	21.61	906508038494	Suburban
166	Lake Jeffreyland	2016-04-10 15:48:48	38.54	7589586454429	Urban
585	Lake Sarashire	2016-08-01 09:48:56	25.32	1733794141848	Urban
722	New David	2016-08-09 11:20:33	44.44	6236880541676	Urban

In [118]:
```
fare_per_type = typed_fares.groupby("type").sum()["fare"]
total_fares = sum(typed_fares["fare"])
percent_fare_per_type = fare_per_type / total_fares
percent_fare_per_type
```

```
Out[118]: type
          Rural       0.065798
          Suburban    0.314458
          Urban       0.619745
          Name: fare, dtype: float64
```

```
In [119]: fare_pie = plt.pie(
              percent_fare_per_type,
              labels=percent_fare_per_type.index,
              autopct='%.2f',
              pctdistance=0.7
          )
          plt.title("Percentage of Fares by City Type")
          plt.show()
```

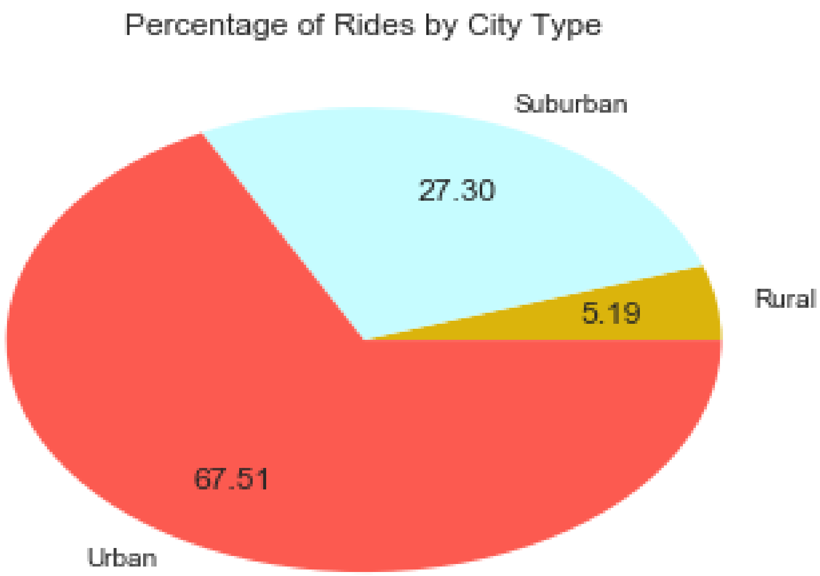


1.2.2 Rides by City Type

```
In [120]: rides_per_type = city_summary.groupby("type").sum()["ride_count"]
          total_rides = sum(city_summary["ride_count"])
          percent_rides_per_type = rides_per_type / total_rides
          percent_rides_per_type
```

```
Out[120]: type
          Rural       0.051932
          Suburban    0.272954
          Urban       0.675114
          Name: ride_count, dtype: float64
```

In [121]:
```
ride_pie = plt.pie(
    percent_rides_per_type,
    labels=percent_rides_per_type.index,
    autopct='%.2f',
    pctdistance=0.7
)
plt.title("Percentage of Rides by City Type")
plt.show()
```



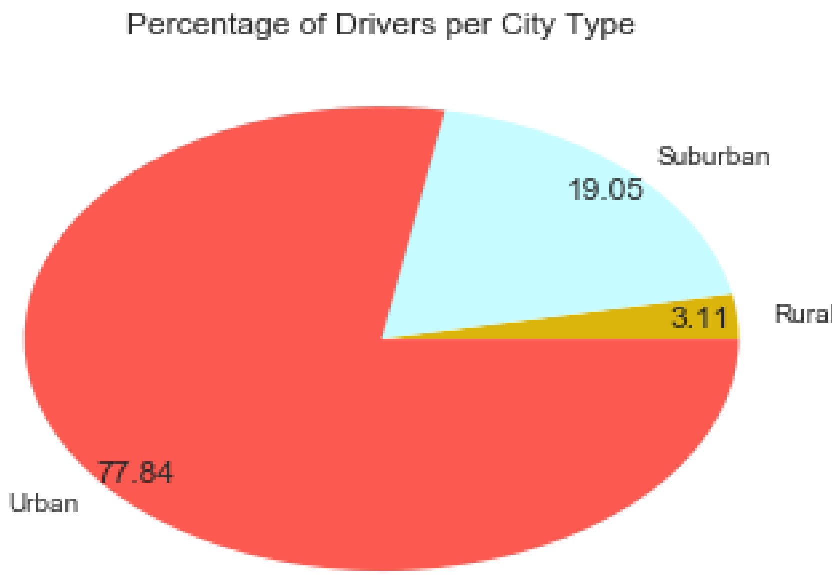
1.2.3 Drivers by City Type

In [122]:
```
drivers_per_type = city_data.groupby("type").sum()["driver_count"]
total_drivers = sum(city_data["driver_count"])
percent_drivers_per_type = drivers_per_type / total_drivers
percent_drivers_per_type
```

Out[122]:
```
type
Rural       0.031054
Suburban    0.190505
Urban       0.778441
Name: driver_count, dtype: float64
```

In [123]:
```
driver_pie = plt.pie(
    percent_drivers_per_type,
    labels=percent_drivers_per_type.index,
    autopct='%.2f',
```

```
        pctdistance=0.9
    )
    plt.title("Percentage of Drivers per City Type")
    plt.show()
```



1.3 Conclusions

A few trends were noticed. While more than 75% of the drivers are in urban settings, closer to 60% of the total fares were received in urban settings. Combining this observation with that of the bubble plot above, it appears that ride fares in suburban and rural settings are generally higher than those in urban settings.

This could be because the distance to travel is greater in the suburban and rural areas (speculation), but it also appears that those areas have much fewer drivers, driving the scarcity and thus, presumably, the price up.