

# Leased vs. Owned Product Comparison



Data Analysis Collaborated by:

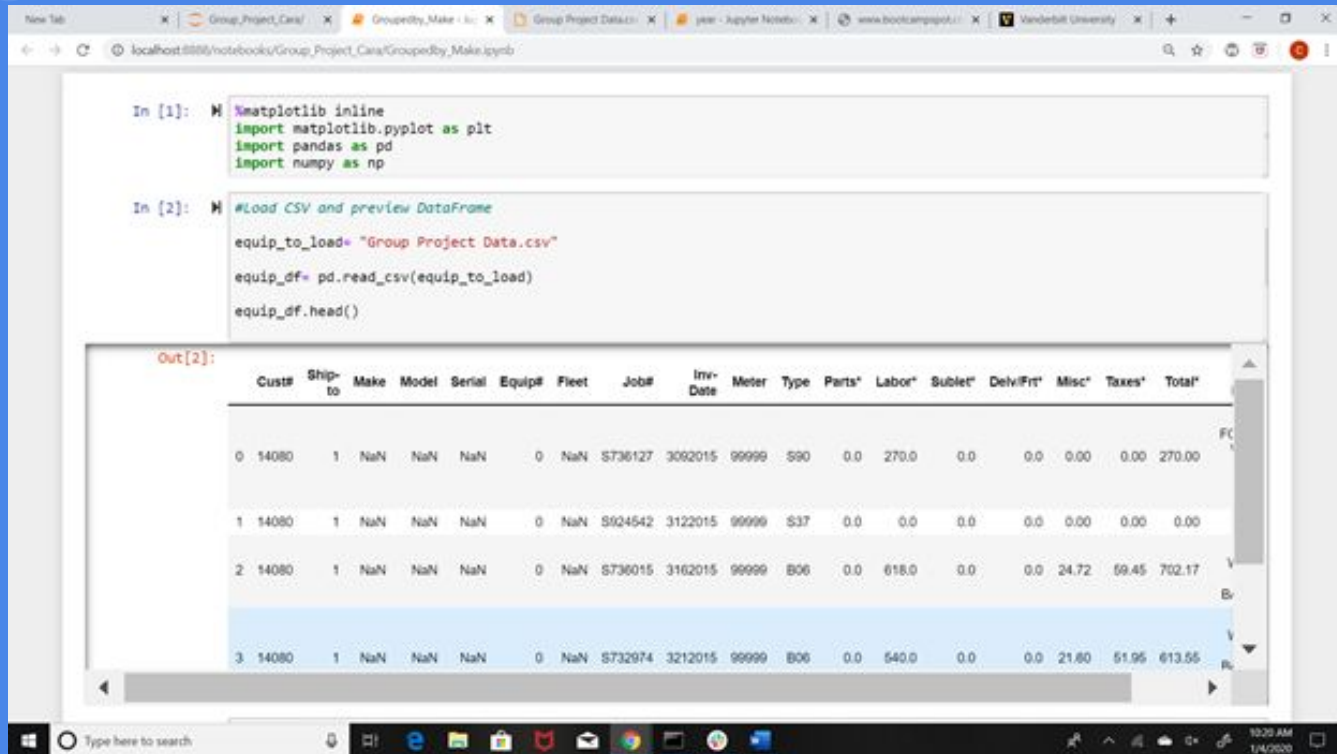
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- Joshua Cohen
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*\*All raw data was compiled from customer product and maintenance costs csv from 2015 to present.*

# **Executive Summary**

Analysis was performed based on company data provided by the finance department. We scrubbed data dated back to 2015 until present, to compare the cost efficiency of leased vs. owned equipment.

# Data Sourcing



The screenshot shows a Jupyter Notebook interface with two input cells and one output cell. The first input cell contains code to import matplotlib, pandas, and numpy. The second input cell contains code to load a CSV file and preview its first few rows. The output cell displays the first four rows of the loaded data as a table.

```
In [1]: %matplotlib inline
import matplotlib.pyplot as plt
import pandas as pd
import numpy as np

In [2]: #Load CSV and preview DataFrame
equip_to_load = "Group Project Data.csv"
equip_df = pd.read_csv(equip_to_load)
equip_df.head()
```

Out[2]:

	Cust#	Ship-to	Make	Model	Serial	Equip#	Fleet	Job#	Inv-Date	Meter	Type	Parts*	Labor*	Sublet*	Delv/Frt*	Misc*	Taxes*	Total*
0	14080	1	NaN	NaN	NaN	0	NaN	S736127	3092015	99999	S90	0.0	270.0	0.0	0.0	0.00	0.00	270.00
1	14080	1	NaN	NaN	NaN	0	NaN	S924542	3122015	99999	S37	0.0	0.0	0.0	0.0	0.00	0.00	0.00
2	14080	1	NaN	NaN	NaN	0	NaN	S736015	3162015	99999	B06	0.0	618.0	0.0	0.0	24.72	69.45	702.17
3	14080	1	NaN	NaN	NaN	0	NaN	S732974	3212015	99999	B06	0.0	540.0	0.0	0.0	21.80	51.95	613.55

[illegible]

```
New Tab | Group Project_Cars | Group Project_Make | Group Project_Data | jupyter - Jupyter Notebook | www.bootcampproject.com | Vanderbilt University |
localhost:8888/notebooks/Group Project_Cars/Groupedby_Make.ipynb

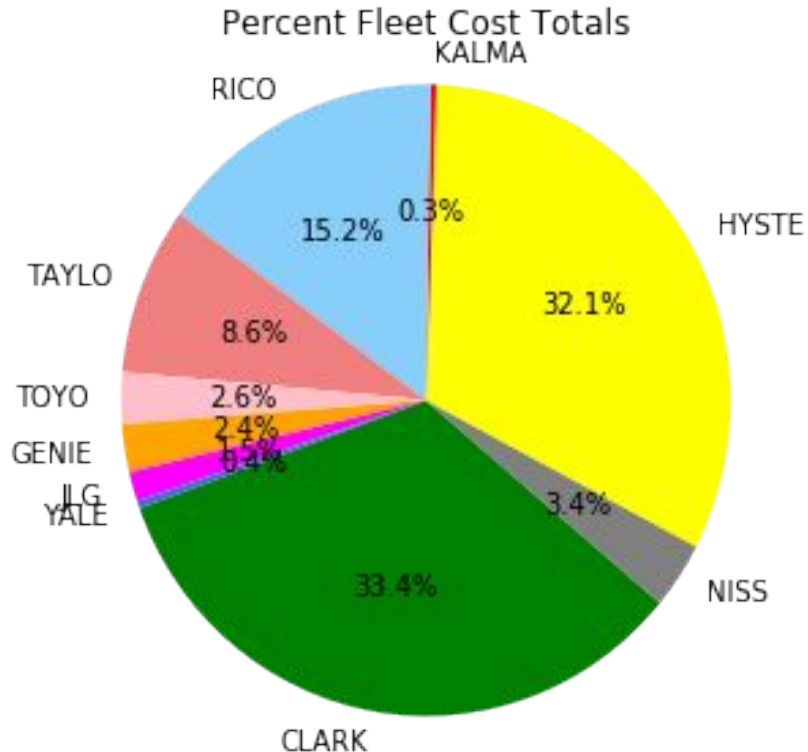
In [6]: # Type = updated_Make["type"].unique()
Type

Out[6]: array(['SUV', 'S11', 'S10', 'S12', 'S13', 'S14', 'S15'], dtype=object)

In [7]: # Color, Size, Price, Fuel, Make, Model, Year, Mile
updated_make_P = updated_Make.groupby('Make').agg({'color': lambda x: x.unique(), 'size': lambda x: x.unique(), 'price': lambda x: x.unique(), 'fuel': lambda x: x.unique(), 'make': lambda x: x.unique(), 'model': lambda x: x.unique(), 'year': lambda x: x.unique(), 'mile': lambda x: x.unique()})
updated_make_P

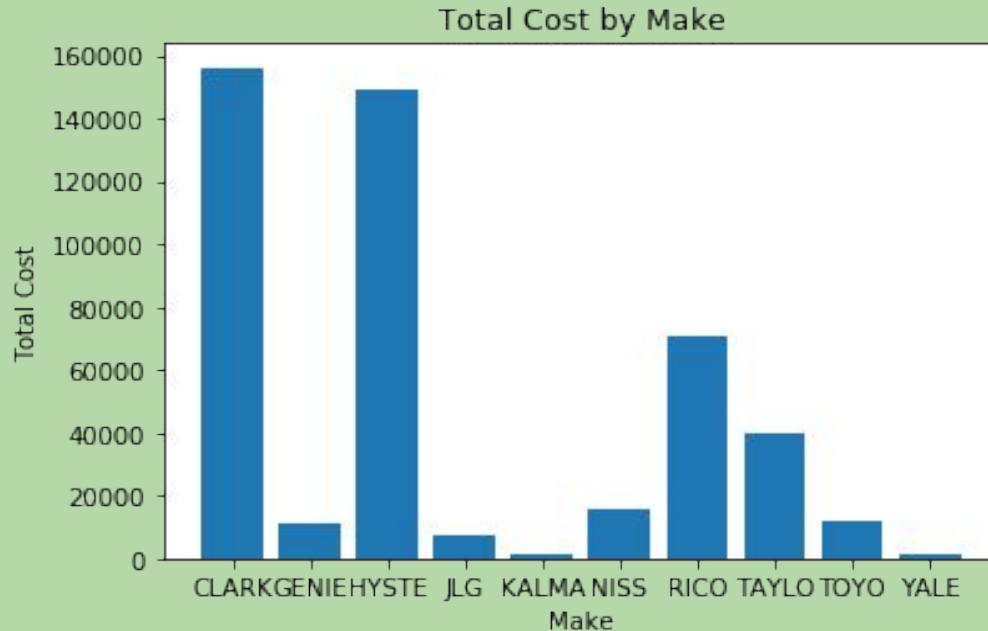
Out[7]:
   Color  Size  Price  Fuel  Make  Model  Year  Mile  Year  Mile  Year  Mile  Year  Mile
0  SUV    S11    10000  Gas  Ford  Focus  2010  10000  2010  10000  2010  10000  2010  10000
1  SUV    S12    10000  Gas  Ford  Focus  2011  10000  2011  10000  2011  10000  2011  10000
2  SUV    S13    10000  Gas  Ford  Focus  2012  10000  2012  10000  2012  10000  2012  10000
3  SUV    S14    10000  Gas  Ford  Focus  2013  10000  2013  10000  2013  10000  2013  10000
4  SUV    S15    10000  Gas  Ford  Focus  2014  10000  2014  10000  2014  10000  2014  10000
5  SUV    S16    10000  Gas  Ford  Focus  2015  10000  2015  10000  2015  10000  2015  10000
6  SUV    S17    10000  Gas  Ford  Focus  2016  10000  2016  10000  2016  10000  2016  10000
7  SUV    S18    10000  Gas  Ford  Focus  2017  10000  2017  10000  2017  10000  2017  10000
8  SUV    S19    10000  Gas  Ford  Focus  2018  10000  2018  10000  2018  10000  2018  10000
9  SUV    S20    10000  Gas  Ford  Focus  2019  10000  2019  10000  2019  10000  2019  10000
10 SUV    S21    10000  Gas  Ford  Focus  2020  10000  2020  10000  2020  10000  2020  10000
11 SUV    S22    10000  Gas  Ford  Focus  2021  10000  2021  10000  2021  10000  2021  10000
12 SUV    S23    10000  Gas  Ford  Focus  2022  10000  2022  10000  2022  10000  2022  10000
13 SUV    S24    10000  Gas  Ford  Focus  2023  10000  2023  10000  2023  10000  2023  10000
14 SUV    S25    10000  Gas  Ford  Focus  2024  10000  2024  10000  2024  10000  2024  10000
15 SUV    S26    10000  Gas  Ford  Focus  2025  10000  2025  10000  2025  10000  2025  10000
16 SUV    S27    10000  Gas  Ford  Focus  2026  10000  2026  10000  2026  10000  2026  10000
17 SUV    S28    10000  Gas  Ford  Focus  2027  10000  2027  10000  2027  10000  2027  10000
18 SUV    S29    10000  Gas  Ford  Focus  2028  10000  2028  10000  2028  10000  2028  10000
19 SUV    S30    10000  Gas  Ford  Focus  2029  10000  2029  10000  2029  10000  2029  10000
20 SUV    S31    10000  Gas  Ford  Focus  2030  10000  2030  10000  2030  10000  2030  10000
21 SUV    S32    10000  Gas  Ford  Focus  2031  10000  2031  10000  2031  10000  2031  10000
22 SUV    S33    10000  Gas  Ford  Focus  2032  10000  2032  10000  2032  10000  2032  10000
23 SUV    S34    10000  Gas  Ford  Focus  2033  10000  2033  10000  2033  10000  2033  10000
24 SUV    S35    10000  Gas  Ford  Focus  2034  10000  2034  10000  2034  10000  2034  10000
25 SUV    S36    10000  Gas  Ford  Focus  2035  10000  2035  10000  2035  10000  2035  10000
26 SUV    S37    10000  Gas  Ford  Focus  2036  10000  2036  10000  2036  10000  2036  10000
27 SUV    S38    10000  Gas  Ford  Focus  2037  10000  2037  10000  2037  10000  2037  10000
28 SUV    S39    10000  Gas  Ford  Focus  2038  10000  2038  10000  2038  10000  2038  10000
29 SUV    S40    10000  Gas  Ford  Focus  2039  10000  2039  10000  2039  10000  2039  10000
30 SUV    S41    10000  Gas  Ford  Focus  2040  10000  2040  10000  2040  10000  2040  10000
31 SUV    S42    10000  Gas  Ford  Focus  2041  10000  2041  10000  2041  10000  2041  10000
32 SUV    S43    10000  Gas  Ford  Focus  2042  10000  2042  10000  2042  10000  2042  10000
33 SUV    S44    10000  Gas  Ford  Focus  2043  10000  2043  10000  2043  10000  2043  10000
34 SUV    S45    10000  Gas  Ford  Focus  2044  10000  2044  10000  2044  10000  2044  10000
35 SUV    S46    10000  Gas  Ford  Focus  2045  10000  2045  10000  2045  10000  2045  10000
36 SUV    S47    10000  Gas  Ford  Focus  2046  10000  2046  10000  2046  10000  2046  10000
37 SUV    S48    10000  Gas  Ford  Focus  2047  10000  2047  10000  2047  10000  2047  10000
38 SUV    S49    10000  Gas  Ford  Focus  2048  10000  2048  10000  2048  10000  2048  10000
39 SUV    S50    10000  Gas  Ford  Focus  2049  10000  2049  10000  2049  10000  2049  10000
40 SUV    S51    10000  Gas  Ford  Focus  2050  10000  2050  10000  2050  10000  2050  10000
41 SUV    S52    10000  Gas  Ford  Focus  2051  10000  2051  10000  2051  10000  2051  10000
42 SUV    S53    10000  Gas  Ford  Focus  2052  10000  2052  10000  2052  10000  2052  10000
43 SUV    S54    10000  Gas  Ford  Focus  2053  10000  2053  10000  2053  10000  2053  10000
44 SUV    S55    10000  Gas  Ford  Focus  2054  10000  2054  10000  2054  10000  2054  10000
45 SUV    S56    10000  Gas  Ford  Focus  2055  10000  2055  10000  2055  10000  2055  10000
46 SUV    S57    10000  Gas  Ford  Focus  2056  10000  2056  10000  2056  10000  2056  10000
47 SUV    S58    10000  Gas  Ford  Focus  2057  10000  2057  10000  2057  10000  2057  10000
48 SUV    S59    10000  Gas  Ford  Focus  2058  10000  2058  10000  2058  10000  2058  10000
49 SUV    S60    10000  Gas  Ford  Focus  2059  10000  2059  10000  2059  10000  2059  10000
50 SUV    S61    10000  Gas  Ford  Focus  2060  10000  2060  10000  2060  10000  2060  10000
51 SUV    S62    10000  Gas  Ford  Focus  2061  10000  2061  10000  2061  10000  2061  10000
52 SUV    S6
```

# Make Percentages of Total Cost



- Percentages Pie Chart gives a better perspective CLARK and HYSTE surpass other Fleets in total cost.
- RICO and TAYLO are a distant third and fourth cost total in overall comparison.

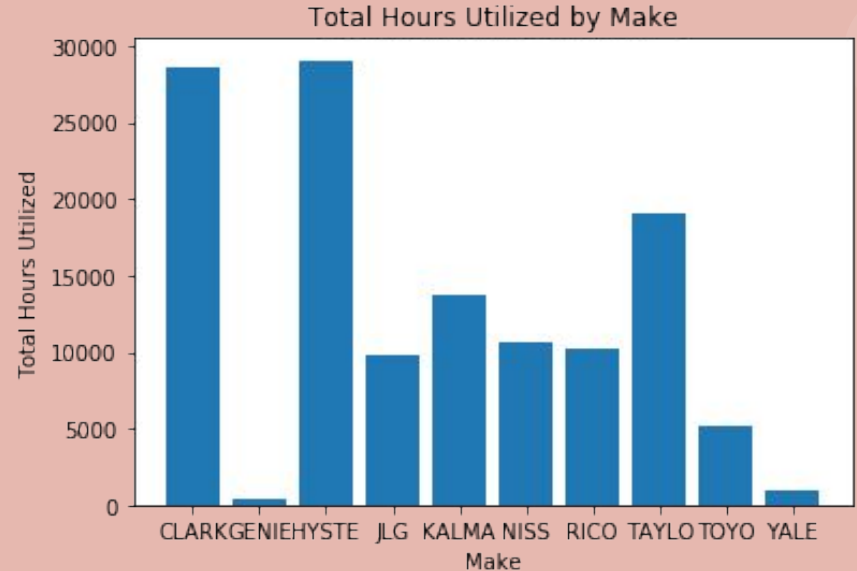
# Analysing Data by Make and Their Total Cost



- CLARK and HYTE had the total cost amongst fleets/makes.
- However, further depth of calculations was needed to provide the the cost efficiency of each make.

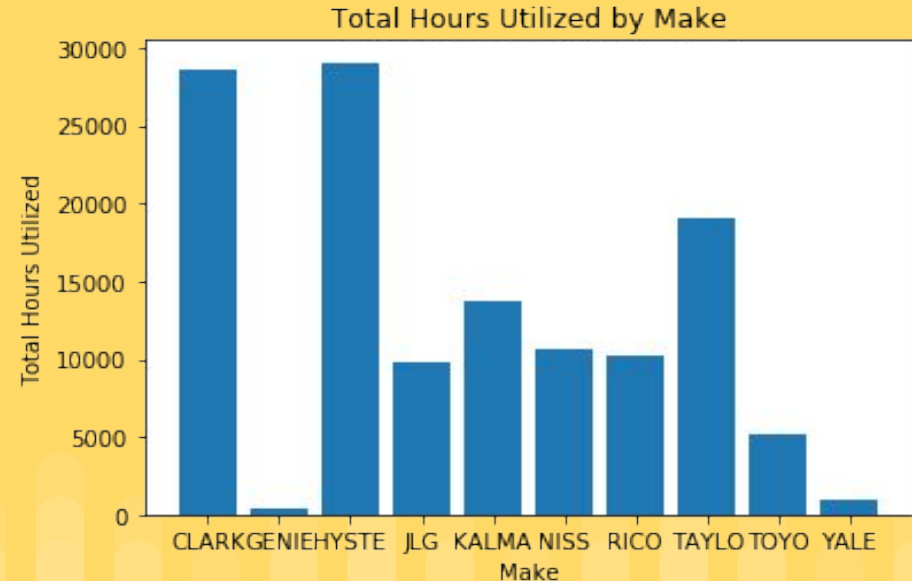
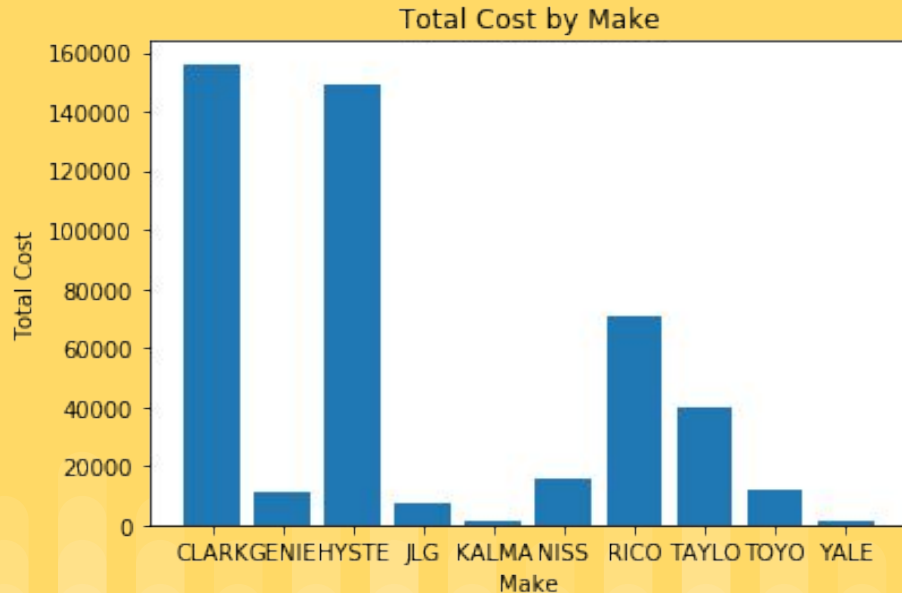
# Total Hours Utilized By Make

- Hours Utilized are an important variable in Cost Efficiency.
- Total hours utilized are a clear representation CLARK and HYTE were the two most used Makes.
  - CLARK and HYTE is trending to be top amongst the Makes.
- However, notice the GENIE make has extremely low hours utilized.



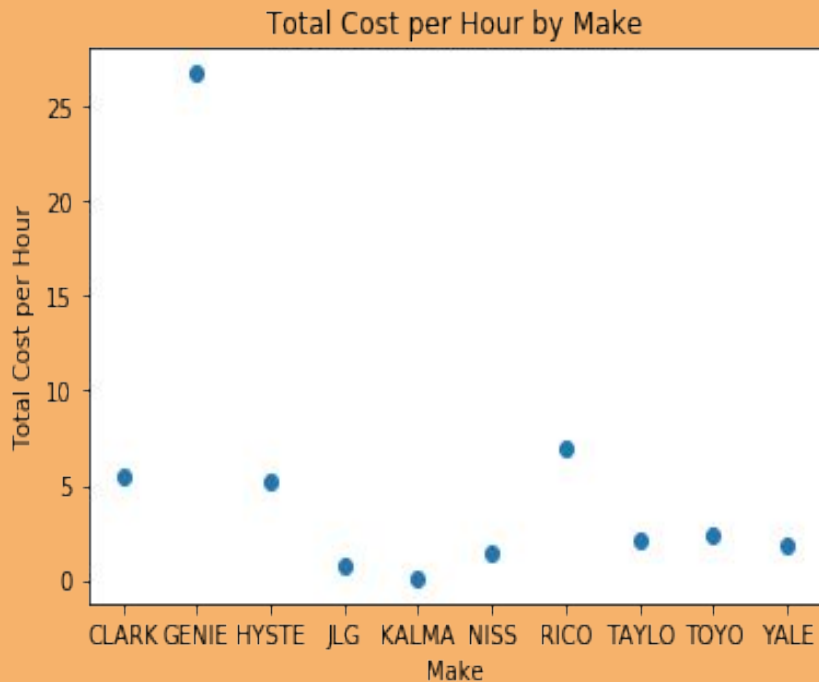
# CLARK and HYTE Trend

## Side By Side COST and HOURS UTILIZED Comparison





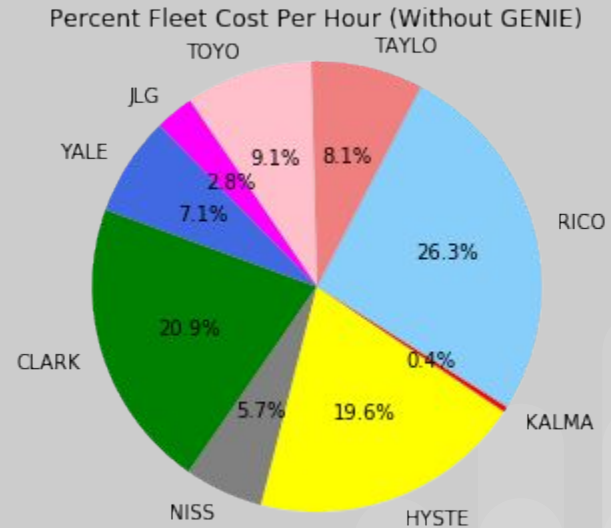
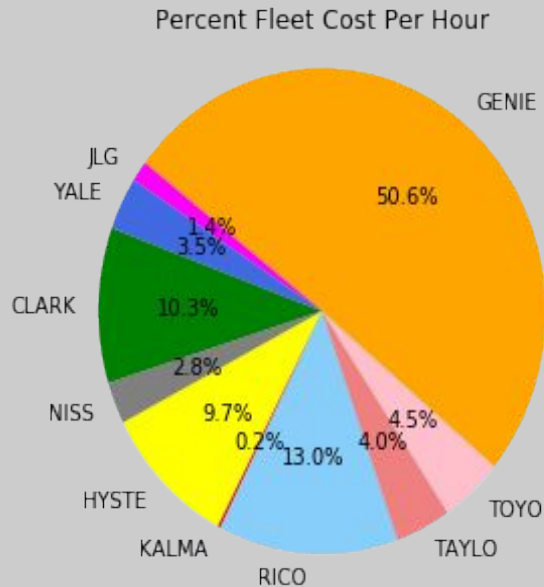
# Occasions of OUTLIERS in Data



- Given the scatter plot, GENIE surprisingly, although hinted in a previous slide, is the highest Cost per Hour by Make.
  - Even though GENIE has a low overall Total Cost, GENIE's extremely low Hours Utilized has skewed its Cost/Hour noticeably higher than other makes.
  - GENIE was clearly not utilized enough to offset initial costs.
- Outliers like this should normally be taken out of a dataset to give a consistent range of mode.

# Perspective of Individual Make Cost Per Hour

*Outlier (GENIE) removed only for individual charting to improve visualization.*





# Cost Per Hour Comparison

Make: Cost per Hour

CLARK: 5.471148

GENIE: 26.755201

HYSTE: 5.138567

JLG: 0.725855

KALMA: 0.100409

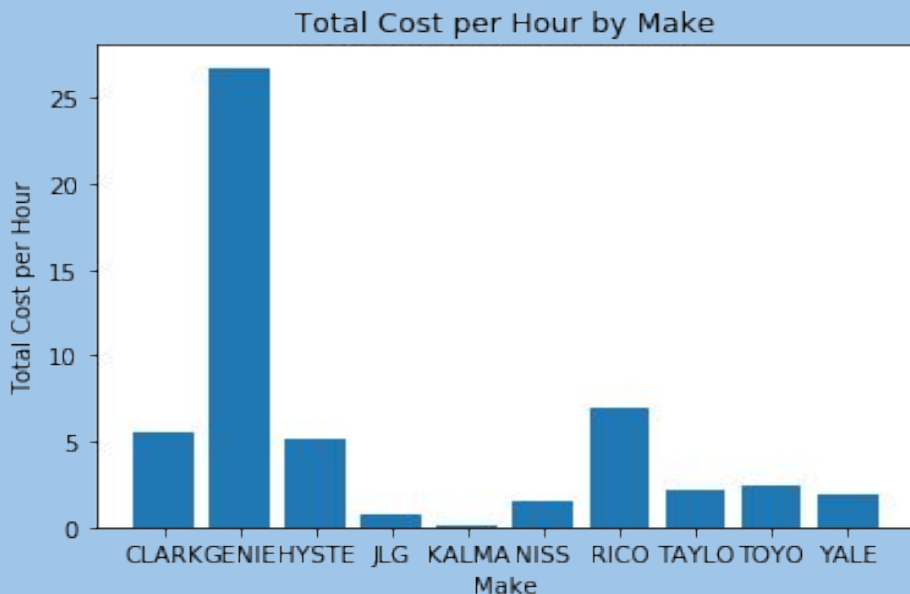
NISS: 1.484722

RICO: 6.894155

TAYLO: 2.107753

TOYO: 2.393147

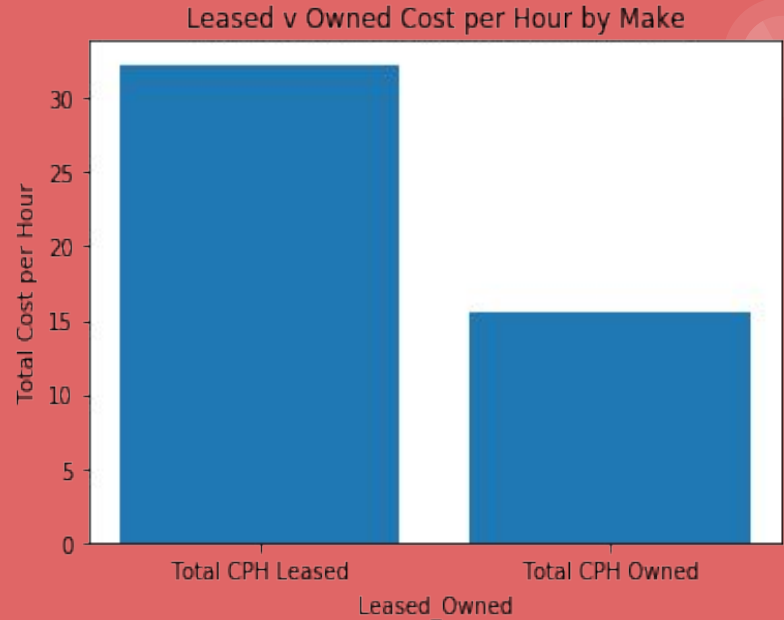
YALE: 1.862848



- Given the Data Frame and Bar Chart, CLARK and HYTE are a reliable trend in comparison.
- The two highest ranking are surpassed by RICO by a full dollar more per hour.
- With the individual Make data, further calculations can be made to give a Cost per Hour Comparison between Leased vs. Owned Makes.

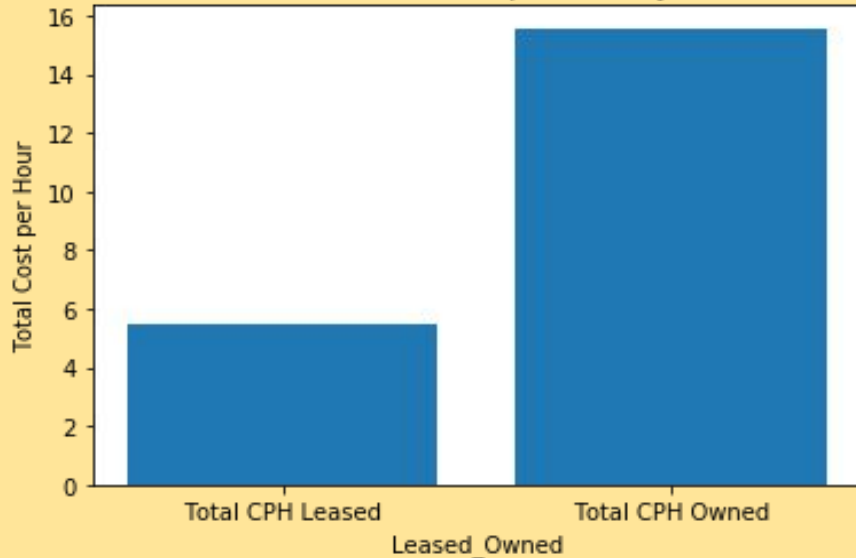
# Leased vs. Owned Make Comparison with Genie (Cost Per Hour)

	<u>Total CPH Leased</u>	<u>Total CPH Owned</u>
Cost per Hour	32.226349	15.568888



# Leased vs. Owned Make Comparison (cost per Hour)

Leased v Owned Cost per Hour by Make



	<u>Total CPH Leased</u>	<u>Total CPH Owned</u>
Cost per Hour	5.471148	15.568888



# CONCLUSION

The *MAGIC* of *Data Analytics!*

