Predicting Motor Vehicle Collisions in New York City

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```
#code below IS shown in final document
```

Abstract

Technological progress in the world has unarguably improved the quality of life for the average person in many ways. The age of the automobile has shaped the way in which work, play and live our lives. Roadways, buildings, cities and entire countries have been designed to accommodate motor vehicles. As automobile technology has advanced making cars faster and capable of more advanced maneuvers, so has our concern with the safety of these vehicles. Entire disciplines such as traffic management are devoted to optimizing numerous factors to ensure the safe and efficient movement of people and goods. As we move into the age of data, all stakeholders in the automobile industry must effectively collect and utilize the wealth of information available to better meet their goals if progress is to continue. In this project, we take the position of a law enforcement agency, the New York City Police Department, as they seek to best utilize their resources in the context of responding to traffic collisions in the city.

Background

At the end of 2017 in New York City, there were 1,923,041 cars registered to residents of the city. (https://nyc.streetsblog.org/2018/10/03/car-ownership-continues-to-rise-under-mayor-de-blasio/) This already-significant number does not include the heavy flow of vehicles of those who visit the city or are simply passing through. By contrast, the New York City Police Department (NYPD) budgets for a headcount of 35,822 uniformed officers (http://council.nyc.gov/budget/wp-content/uploads/sites/54/2017/03/056-NYPD.pdf - page 4), distributed across 77 police precincts (geographic divisions of the city). On-duty officers/traffic enforcement agents are allocated to each precinct to enforce traffic laws and handle emergency and administrative response to traffic incidents (such as collisions). NYC has been collecting traffic data, including specific data on vehicle collisions since 2014 to support "Vision Zero" , a traffic safety initiative which has the goal of eliminating traffic fatalities. (https://data.cityofnewyork.us/Public-Safety/Motor-Vehicle-Collisions-Crashes/h9gi-nx95/data)

Objective

The objective of our analysis is to develop a supervised, prediction model using Machine Learning techniques and the CRISP-DM framework (cite textbook) on the available collision data to predict whether there will be a collision in a specified police precinct at a specified time. The intent of predicting this data is to inform the NYPD's optimal assignment of limited officers and resources across the 77 police precincts.

Data Analysis

The data set that supports this analysis is sourced from the NYC Open Data project. The title of the data set is "Motor Vehicle Collisions – Crashes". It contains entries for every collision recorded within New York City limits by NYPD agents beginning July 1st, 2012 up to the present day. There are approximately 1.65 million entries in the data set.

Table 1: Data Dictionary - Motor Vehicle Collisions – Crashes

Feature	Feature.Description
COLLISION_ID	Unique record code generated by system
ACCIDENT_DATE	Occurrence date of collision
ACCIDENT_TIME	Occurrence time of collision
BOROUGH	Borough where collision occurred
ZIP CODE	Postal code of incident occurrence
LATITUDE	Latitude coordinate for Global Coordinate System, WGS 1984
LONGITUDE	Longitude coordinate for Global Coordinate System, WGS 1984
LOCATION	Latitude , Longitude pair
ON STREET NAME	Street on which the collision occurred
CROSS STREET NAME	Nearest cross street to the collision
OFF STREET NAME	Street address if known
NUMBER OF PERSONS INJURED	Number of persons injured
NUMBER OF PERSONS KILLED	Number of persons killed
NUMBER OF PEDESTRIANS INJURED	Number of pedestrians injured
NUMBER OF PEDESTRIANS KILLED	Number of pedestrians killed
NUMBER OF CYCLIST INJURED	Number of cyclists injured
NUMBER OF CYCLIST KILLED	Number of cyclists killed
NUMBER OF MOTORIST INJURED	Number of vehicle occupants injured
NUMBER OF MOTORIST KILLED	Number of vehicle occupants killed
CONTRIBUTING FACTOR VEHICLE 1	Factors contributing to the collision for designated vehicle
CONTRIBUTING FACTOR VEHICLE 2	Factors contributing to the collision for designated vehicle
CONTRIBUTING FACTOR VEHICLE 3	Factors contributing to the collision for designated vehicle
CONTRIBUTING FACTOR VEHICLE 4	Factors contributing to the collision for designated vehicle
CONTRIBUTING FACTOR VEHICLE 5	Factors contributing to the collision for designated vehicle
VEHICLE TYPE CODE 1	Type of vehicle based on the selected vehicle category
VEHICLE TYPE CODE 2	Type of vehicle based on the selected vehicle category
VEHICLE TYPE CODE 3	Type of vehicle based on the selected vehicle category
VEHICLE TYPE CODE 4	Type of vehicle based on the selected vehicle category
VEHICLE TYPE CODE 5	Type of vehicle based on the selected vehicle category

Data Dictionary

Data dictionary sourced from https://data.cityofnewyork.us/Public-Safety/Motor-Vehicle-Collisions-Crashes/h9gi-nx95/data - "MVCollisionsDataDictionary_20190813_ERD.xlsx".

Initial Data Exploration and Cleaning

[SUMMARY OF DATA INSERT TEXT]

CRASH.DATE	CRASH.TIME	BOROUGH	ZIP.CODE	LATITUDE	LONGITUDE
01/21/2014: 1161	16:00 : 24074	:499865	Min. :10000	Min. : 0.00	Min. :-201.36
11/15/2018: 1065	17:00 : 23613	BRONX :160097	1st Qu.:10304	1st Qu.:40.67	1st Qu.: -73.98
12/15/2017: 999	15:00 : 23171	BROOKLYN :355543	Median :11206	Median :40.72	Median : -73.93
05/19/2017: 974	18:00 : 21767	MANHATTAN :273153	Mean :10828	Mean :40.69	Mean : -73.87
01/18/2015: 961	14:00 : 21258	QUEENS :305510	3rd Qu.:11237	3rd Qu.:40.77	3rd Qu.: -73.87
02/03/2014: 960	13:00 : 19732	STATEN ISLAND: 49124	Max. :11697	Max. :43.34	Max. : 0.00
(Other) :1637172	(Other):1509677		NA's :500110	NA's :199425	NA's :199425

LOCATION	ON.STREET.NAME
: 199425	: 323553
POINT (0 0) : 1113	BROADWAY : 16258
POINT (-74.038086 40.608757) : 670	ATLANTIC AVENU
POINT (-73.9845292 40.6960346): 586	3 AVENUE : 11761
POINT (-73.98453 40.696033) : 574	NORTHERN BOUL
POINT (-73.91282 40.861862) : 545	BELT PARKWAY : 11
(Other) :1440379	(Other) :1254557

NUMBER.OF.PERSONS.INJURED	NUMBER.OF.PERSONS.KILLED	NUMBER.OF.PEDESTRIANS.INJURED	NUMBER.OF.PEDESTRIANS.KILLED
Min. : 0.0000	Min. :0.000000	Min. : 0.00000	Min. :0.000000
1st Qu.: 0.0000	1st Qu.:0.000000	1st Qu.: 0.00000	1st Qu.:0.000000
Median : 0.0000	Median :0.000000	Median : 0.00000	Median :0.000000
Mean : 0.2634	Mean :0.001174	Mean : 0.05092	Mean :0.000641
3rd Qu.: 0.0000	3rd Qu.:0.000000	3rd Qu.: 0.00000	3rd Qu.:0.000000
Max. :43.0000	Max. :8.000000	Max. :27.00000	Max. :6.000000
NA's :17	NA's :31		

NUMBER.OF.CYCLIST.INJURED	NUMBER.OF.CYCLIST.KILLED	NUMBER.OF.MOTORIST.INJURED	NUMBER.OF.MOTORIST.KILLED
Min. :0.00000	Min. :0.00e+00	Min. : 0.000	Min. :0.000000
1st Qu.:0.00000	1st Qu.:0.00e+00	1st Qu.: 0.000	1st Qu.:0.000000
Median :0.00000	Median :0.00e+00	Median : 0.000	Median :0.000000
Mean :0.02062	Mean :8.34e-05	Mean : 0.192	Mean :0.000452
3rd Qu.:0.00000	3rd Qu.:0.00e+00	3rd Qu.: 0.000	3rd Qu.:0.000000
Max. :4.00000	Max. :2.00e+00	Max. :43.000	Max. :5.000000

CONTRIBUTING.FACTOR.VEHICL
Unspecified :599544
Driver Inattention/Distraction:30838
Failure to Yield Right-of-Way : 94090
Following Too Closely : 82937
Backing Unsafely : 62951
Other Vehicular : 52108
(Other) :443281

CONTRIBUTING.FACTOR.VEHICLE.5	COLLISION_ID	VEHICLE.TYPE.CODE.1	VEHICLE.TYPE.CODE.2
:1637609	Min. : 22	PASSENGER VEHICLE :715236	PASSENGER VEHICLE :537550
Unspecified : 5361	1st Qu.:1038275	SPORT UTILITY / STATION WAGON :313500	:273620
Other Vehicular : 96	Median :3457776	Sedan :172288	SPORT UTILITY / STATION WAGON :237846
Following Too Closely : 51	Mean :2808228	Station Wagon/Sport Utility Vehicle:140852	Sedan :128269
Fatigued/Drowsy : 41	3rd Qu.:3868829	TAXI : 50670	Station Wagon/Sport Utility Vehicle:108877
Driver Inattention/Distraction: 40	Max. :4280357	VAN : 26540	(Other) :357127
(Other) : 94		(Other) :224206	NA's : 3

VEHICLE.TYPE.CODE.2	VEHICLE.TYPE.CODE.3	VEHICLE.TYPE.CODE.4	VEHICLE.TYPE.CODE.5
PASSENGER VEHICLE :537550	:1507965	:1593350	:1632527
:273620	PASSENGER VEHICLE : 63655	PASSENGER VEHICLE : 24743	PASSENGER VEHICLE : 5476
SPORT UTILITY / STATION WAGON :237846	SPORT UTILITY / STATION WAGON : 33161	SPORT UTILITY / STATION WAGON : 14375	SPORT UTILITY / STATION WAGON
Sedan :128269	Sedan : 11698	Sedan : 2598	Sedan : 668
Station Wagon/Sport Utility Vehicle:108877	Station Wagon/Sport Utility Vehicle: 9730	Station Wagon/Sport Utility Vehicle: 2102	Station Wagon/Sport Utility Vehicle: 5
(Other) :357127	UNKNOWN : 3285	TAXI : 1681	TAXI : 246
NA's : 3	(Other) : 13798	(Other) : 4443	(Other) : 689

Based on what we know about the data set from the specifications at NYC Open Data and the data dictionary, we have decided to perform some initial cleaning steps.

Our analytics problem is to predict whether there will be a collision at a specific time (time including a time of the day, day of the year and calendar year). In this context, we will first look at the "CRASH.DATE" graph. Thinking about the scheduling of police resource, we assume that this happens in advance, on a hour-by-hour and day-by-day basis. We assume that resources are not scheduled on a year-by-year basis due to uncertainty in staffing, budget, etc. We therefore examine the data to see whether we should include the year at all. Including the year would treat the data set as a time-series, years ranging from 2012-2020. Alternatively, we could drop the year and group all occurrences on the same day in the same bin, possibly enhancing our prediction.

To decide, we plot the dates and look for trends. If trends repeat annually, we will drop the year as this trend will be preserved when we combine. If the trend does not repeat annually (extends over the whole range of dates) then we will not combine year as we will lose this information when dropping year.

The vertical black lines in the "All Years" plot represent the start of each year. As you can see from the plot, there is a noticeable repeating trend in each year (between the black lines) with a decrease in collisions at the start of each year, followed by various other increase/decreases. As we are more interested in capturing this repeating annual trend than year-over-year changes, we will combine all data into a representation of one year. Additionally, we will drop years 2012 and 2020 (the first and last years in the data set) to avoid over/under-representing specific months in the combined-year data set. This leaves us with the "Years Combined" data set plotted below.

We use the following code to keep only data in 2013 onwards and in prior to 2020, as mentioned.

```
raw_crash_dates_df <- raw_crash_dates_df[raw_crash_dates_df$raw_crash_dates > "2013-01-01", ]
raw_crash_dates_df <- raw_crash_dates_df[raw_crash_dates_df$raw_crash_dates < "2020-01-01", ]
```

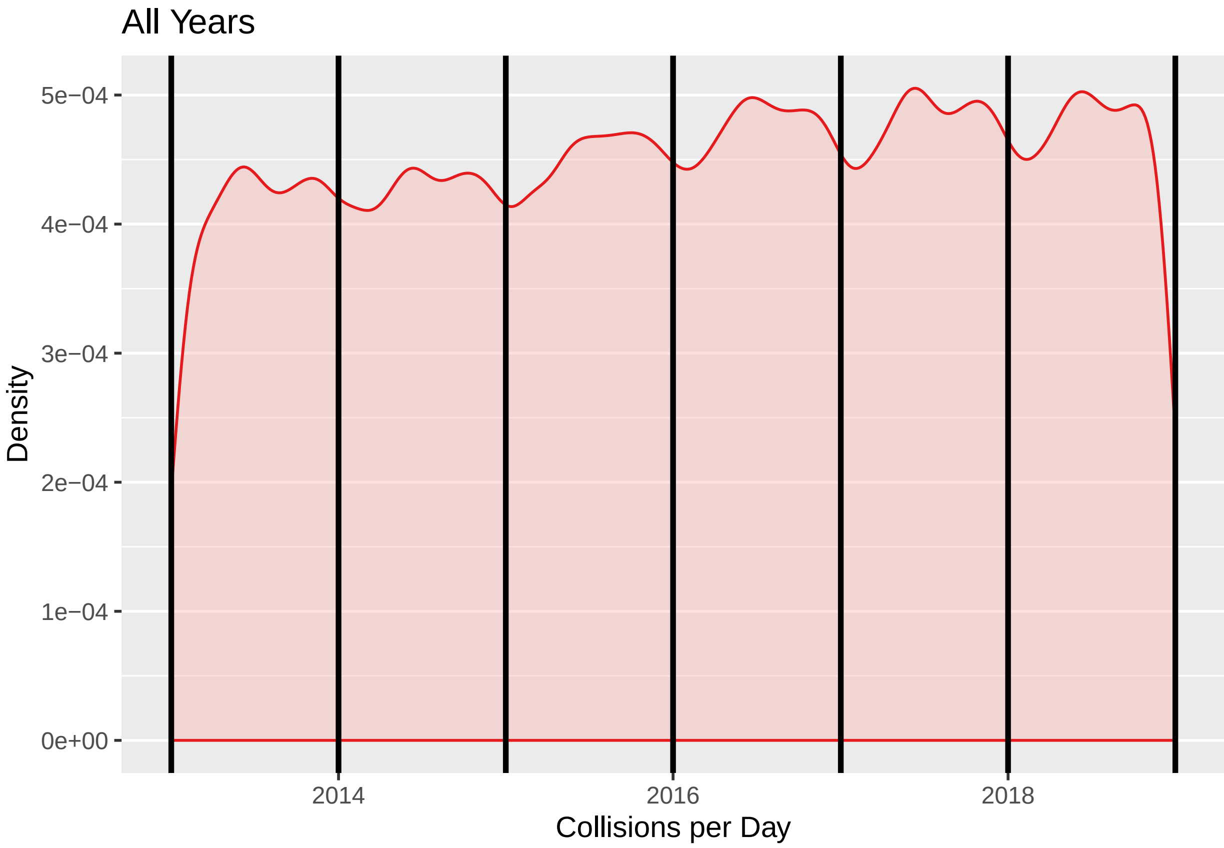


Figure 1: Collisions per Day - All Years

[INSERT WRITEUP ABOUT DATA CLEANING AND PREP HERE]

Cleaned Data Exploration

[TEXT ABOUT EXPLORING THE DATA]
#density plot

```
#crash_dates <- as.Date(raw_crashes_data$CRASH.DATE, "%m/%d/%Y")
#ggplot(raw_crashes_data, aes(x=CRASH.DATE))
```

Models

As we worked through the data set, we were unsure as to which supervised machine learning models would best suit our business needs. As such, we have run, evaluated and compared the following 6 models:

- Decision Tree
- Gradient Boosting
- K-Nearest Neighbor
- Logistic Regression
- Random Forest
- Regression Tree

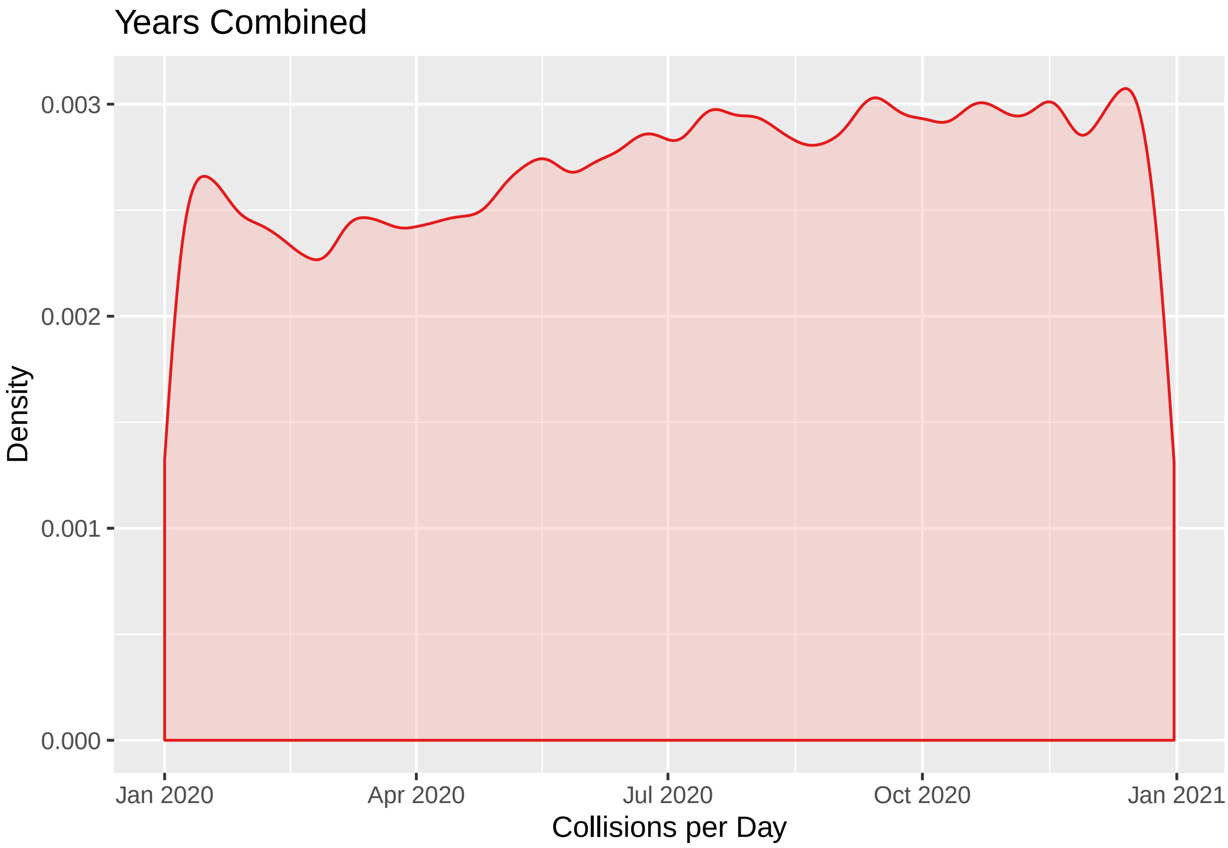


Figure 2: Collisions per Day - Years Combined

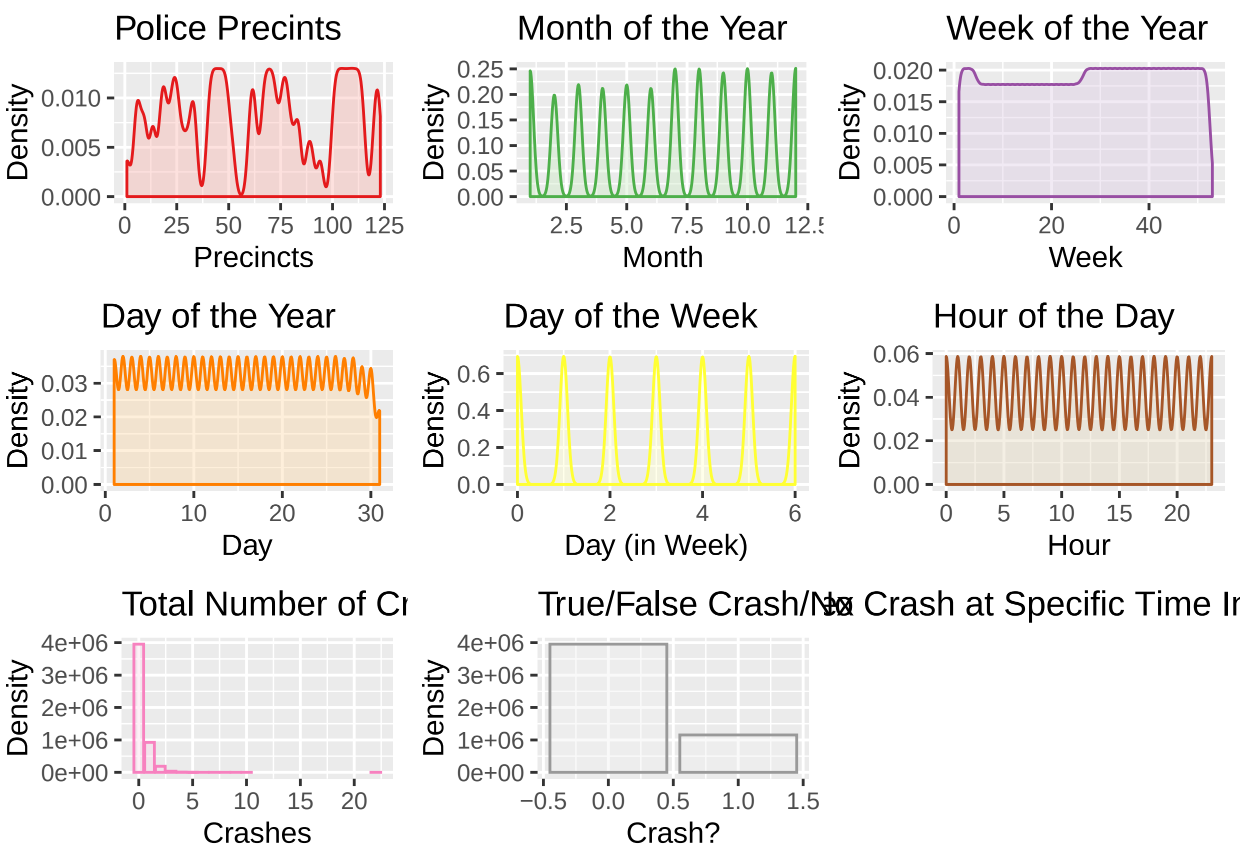


Figure 3: Plots of Selected Features

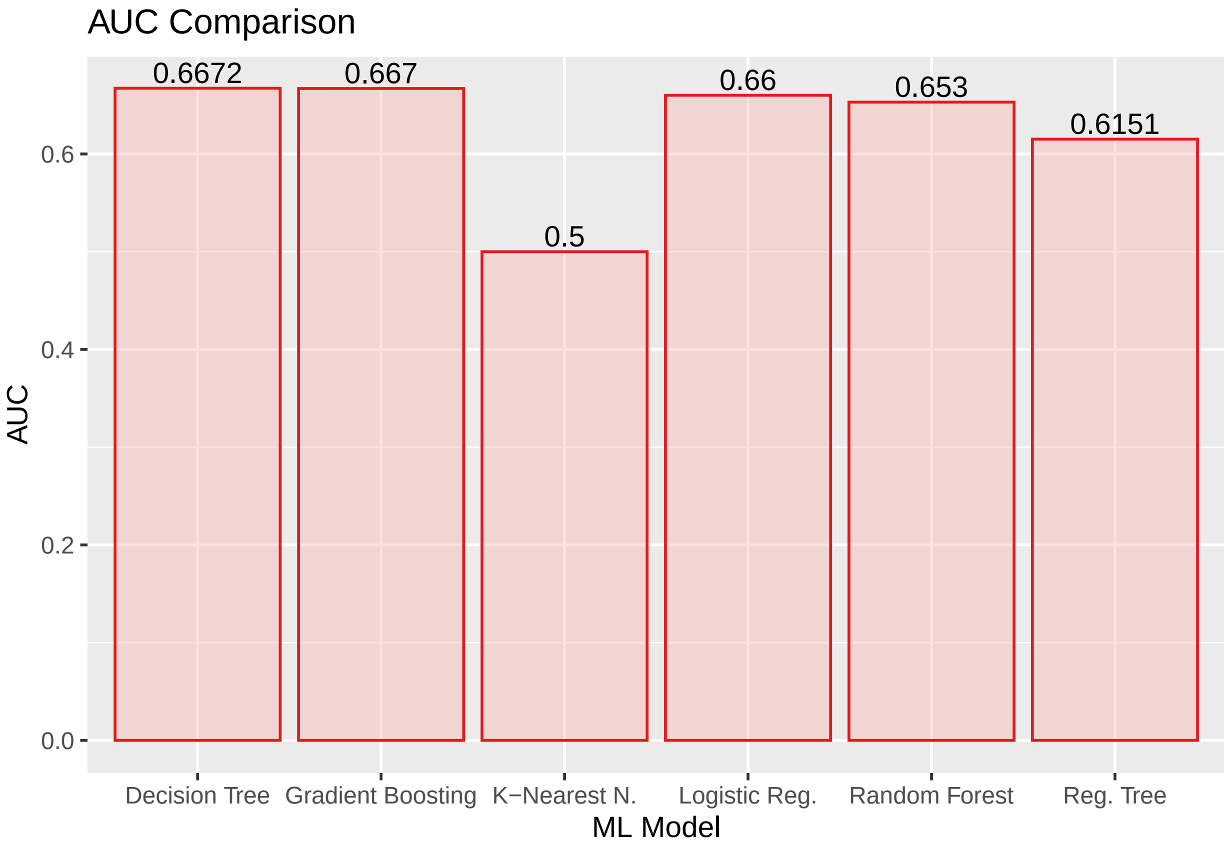


Figure 4: AUC Comparison

Evaluation

Document Style Attribution

This document was generated using a modified version of the "RJournal.sty" file provided by the The R Foundation at `https://journal.r-project.org/submissions.html`.

Inspiration and some sample code for the xtables and ggplot functionality has been reproduced from the example assignment 1 R Markdown file created by V2MSLabs (`https://github.com/v2msLabs/ML1000-1/blob/master/source/main.Rmd`).

The document can be regenerated in RStudio by Knitting the provided "R Markdown-Group 10-Assignment 1.Rmd" file with the provided "RJournal.sty" file in the same directory.

DEFAULT R MARKDOWN CODE BELOW

R Markdown

This is an R Markdown document. Markdown is a simple formatting syntax for authoring HTML, PDF, and MS Word documents. For more details on using R Markdown see `http://rmarkdown.rstudio.com`.

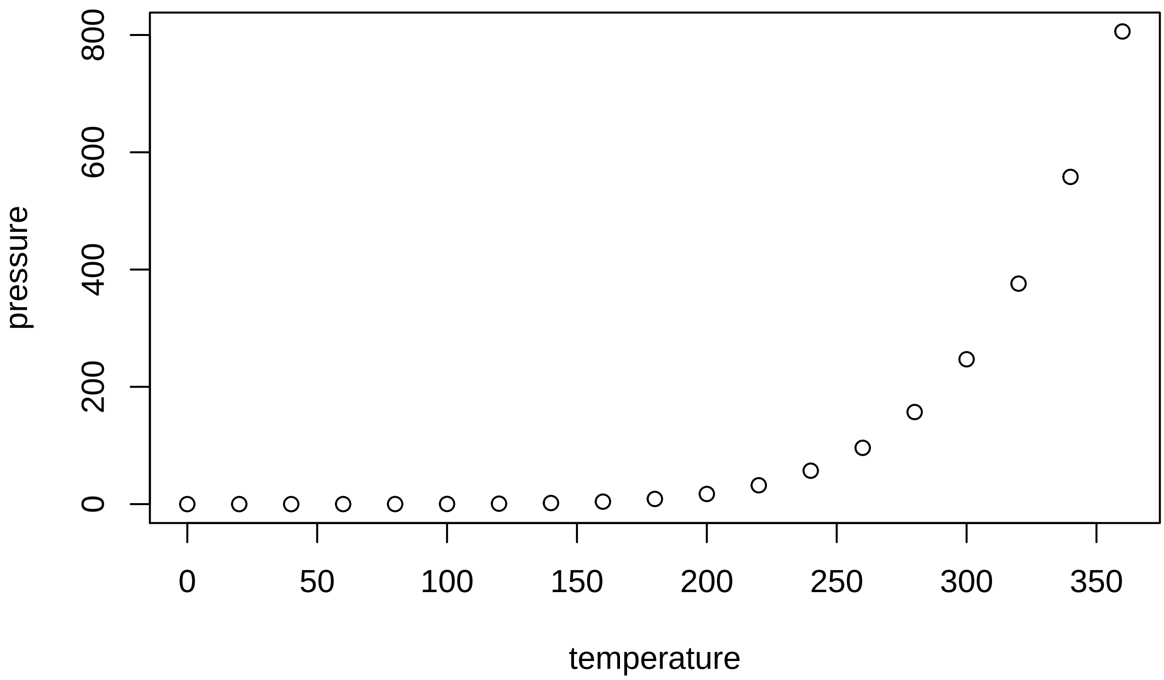
When you click the **Knit** button a document will be generated that includes both content as well as the output of any embedded R code chunks within the document. You can embed an R code chunk like this:

```
summary(cars)
```

```
#>      speed           dist       
#>  Min.   : 4.0   Min.   :  2.00  
#>  1st Qu.:12.0   1st Qu.: 26.00  
#>  Median :15.0   Median : 36.00  
#>  Mean   :15.4   Mean   : 42.98  
#>  3rd Qu.:19.0   3rd Qu.: 56.00  
#>  Max.   :25.0   Max.   :120.00  
```

Including Plots

You can also embed plots, for example:



Note that the `echo = FALSE` parameter was added to the code chunk to prevent printing of the R code that generated the plot.

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