Monte Carlo Simulation of Fuel Economy

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Executive Summary

In this post, I will explore EPA estimates for fuel economy values. Most specifically, I ask if one was to purchase a new car, what is the most likely per year improvement. In this post, we utilize a Monte-Carlo Simulation to get the average. Thus I show how veratile Monte-Carlo Simulations can be to analyze data that cannot create results deterministicaly or by other analyticial methods.

Introduction

Fuel economy is a very not well understood idea in the public mind (Turrentine & Kurani, 2007). The complexities of payback, initial cost and understanding of the different metrics, fuel economy (km/l, mpg) , fuel consumption (l/100 km) and carbon emissions (gCO2/km) are which used interchangeably, makes understanding for laypeople difficult. Thus, it is often difficult to quantify how well different cars perform over different time periods. In this post, I try to simplify the major shifts in fuel economy to quantify an average difference in fuel economy to try to get values for how much things change from year to year. To do this, I will utilize a Monte-Carlo Simulation to test various scenarios of car replacement and receive an average per year percent increase in efficiency. This value could help to predict when one should replace their vehicles.
Monte-Carlo Simulations are defined as “Any method which solves a problem by generating suitable random numbers and observing that fraction of the numbers obeying some property or properties. The method is useful for obtaining numerical solutions to problems which are too complicated to solve analytically.” (Weisstein, n.d.) In this case, we randomly select suitable car pairs and estimate the increase in fuel economy.

Methods

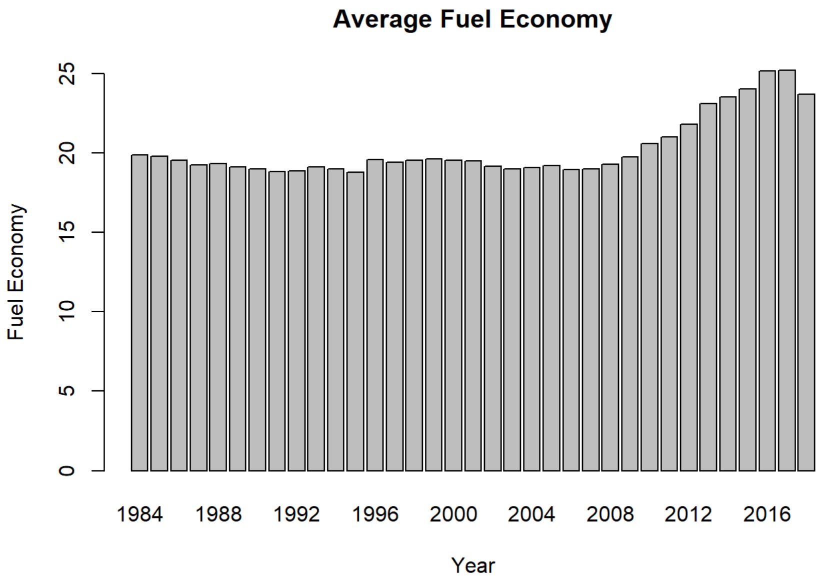
Our data was taken from the US EPA’s Dataset which can be found at fueleconomy.gov. We utilize only the combined fuel economy for one fuel in each of these vehicles. All code can be run after downloading this dataset and renaming to “raw_vehicles.csv” within the same document as the following code.

```r
library(readr)
library(dplyr)
library(ggplot2)
raw_vehicles <- read_csv("raw_vehicles.csv", col_types = cols(fuelType1 = col_factor(levels = c("Regular Gasoline"
, "Premium Gasoline", "Midgrade Gasoline", "Electricity", "Diesel"))))

gas<-filter(raw_vehicles, fuelType1 %in% c("Regular Gasoline","Premium Gasoline","Midgrade Gasoline"))
```

We can visualize the year by year average growth rate below. ##

```r
avgyearlyfuelecon<-raw_vehicles%>%group_by(year)%>%summarize(average=mean(comb08),count=n())
barplot(avgyearlyfuelecon$average,names=avgyearlyfuelecon$year,main="Average Fuel Economy",xlab = "Year", ylab="Fu
el Economy")
```



To create a more accuratly quantify learning rate of fuel economy, we utilize a Monte-Carlo Simulation to evaluate the learning rate of gasoline cars seperated by size-class. In this Monte-Carlo Simulation, each simuation will select two model years as well as a sedan class. Two cars of that class are selected, each corresponding to one of the selected years. The difference is then calculated and averaged over the difference of years. This average was then used to create our monte-carlo histogram.

```r
set.seed(1)
##number of simulations
sims=1000
##types of cars analysed
types<- c("Compact Cars","Large Cars", "Midsize Cars")
##accumulation of tests
tests<-NULL
##montecarlo simulation
for( i in 1:sims){
  #selection of years for analysis
  yearselect=sample(1984:2017,2)
  ##forces yers to be different
  while(yearselect[1]==yearselect[2]){
    yearselect=sample(1984:2018,2)}
  ##chooses car type for analysis
  cartype=sample(types,1)
  ##chooses car
  if( yearselect[1]<yearselect[2]){
      carselect1<-gas%>%filter(VClass==cartype)%>%filter(year==yearselect[1])
      carselect2<-gas%>%filter(VClass==cartype)%>%filter(year==yearselect[2])
  }
  else {
       carselect1<-gas%>%filter(VClass==cartype)%>%filter(year==yearselect[2])
      carselect2<-gas%>%filter(VClass==cartype)%>%filter(year==yearselect[1])
  }
  #gets fuel economy
  fe1<-sample(carselect1$comb08,1)
  fe2<-sample(carselect2$comb08,1)
  #calculates difference
  fe_improve=fe2-fe1
  fe_improve_perc=(fe2-fe1)/fe1
  feimp_year=fe_improve_perc/abs(yearselect[1]-yearselect[2])
  #saves values
  tests<-c(tests,feimp_year)
}
```

Results

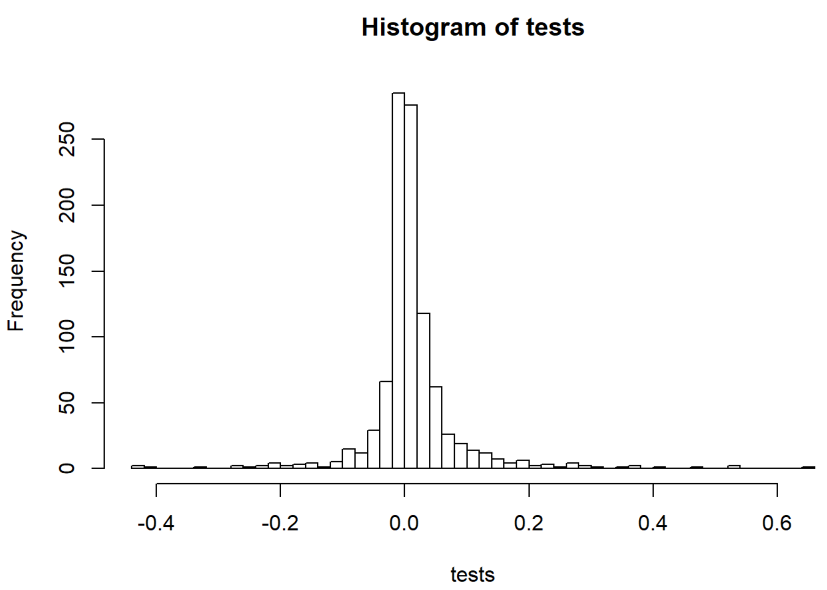
The summary of our monte-carlo test is shown below.

```r
summary(tests)
```

```
##       Min.    1st Qu.    Median      Mean    3rd Qu.      Max.
## -0.437500 -0.008387  0.005848  0.012826  0.025000  0.642857
```

We can also visualize this data in the histogram below:

```r
hist(tests,breaks=50)
```



This Monte-Carlo Simulation shows that on average, each year of vehicles being upgraded results in about a 1.2% increase of fuel efficiency. From the histogram, we can see thatmost values are concentrated around the 0% rate.

Conclusion

We can see that there is only a very minor increase in fuel economy from year to year over the past thirty years, based on our analysis. However there are many limitations to our study. First, it is based only on gasoline vehicles, with no distinction between gasoline fuel types. Furthermore, it assumes that all models have the same probability of being purchased. This of course is not the real world situation. Finally, it could be possible that values were more likely to be assessed at Major challenges exist in quantifying the fuel efficiency and fuel economy of vehicles. Quantifying the multitude of factors impacting these metrics is difficult as these can include a wide range of inputs such as road grade (Boriboonsomsin & Barth, 2010), pavement roughness(Louhghalam, Akbarian, & Ulm, 2015), air conditioning usage (Farrington & Rugh, 2000), driving style and traffic measures (Mierlo, Maggetto, Burgwal, & Gense, 2004). Furthermore, the various driving cycles have been shown to have significant effects (Joumard, André, Vidon, Tassel, & Pruvost, 2000). It is clear that many tests such as the European New European Driving Cycle (NEDC), the Japanese JC 08, and the United States Environmental Protection Agency FTP and HWFET all face criticism in their accuracy to real-world driving conditions (Bovee, Rizzoni, Midlam-Mohler, Yard, & Yatsko, 2015) (Marotta, Pavlovic, Ciuffo, Serra, & Fontaras, 2015) (Momenimovahed, Handford, Checkel, & Olfert, 2015). Real world collected data may be a much better predictor of values ,especially because the deterioration of fuel economy can be better measured. This work however is outside my scope. From this, we can say that for each year that one wishes to upgrade their car, on average they will save an increased .5% saved on fuel per year. As is clear from our analysis, MonteCarlo simulations help to cut through variability and more analitically complex questions.

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