Bass Model

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I choose Amazon Echo Speaker as the past look-alike Innovation of Sonos Era 300 Speaker.

My justification is as follows:

The Echo was a sensation when it arrived in 2014, with its pioneering artificial intelligence voice-controlled speaker technology that made it the ultimate cool device. Before Sonos launched their speaker in 2017 society had already got used to talking to gadgets, which meant that not having voice control was not an option for Sonos. It is likely that Sonos watched the Echo very closely and realized there was a growing need for voice-controlled assistants, subsequently directly incorporating this feature into their Era 300 speakers.

Sonos probably felt compelled to venture into the world of voice-controlled speakers because of the wide popularity of the Echo and also because they are known for making top-notch sound systems. The success recorded by the Echo has brought out a natural desire among people to converse with their devices, therefore prompting Sonos to give similar experience but with even more superior audio quality as usual. This enabled Sonos cash on what Echo had already done and make its system better like one improving an existing recipe while adding his/her own spices.

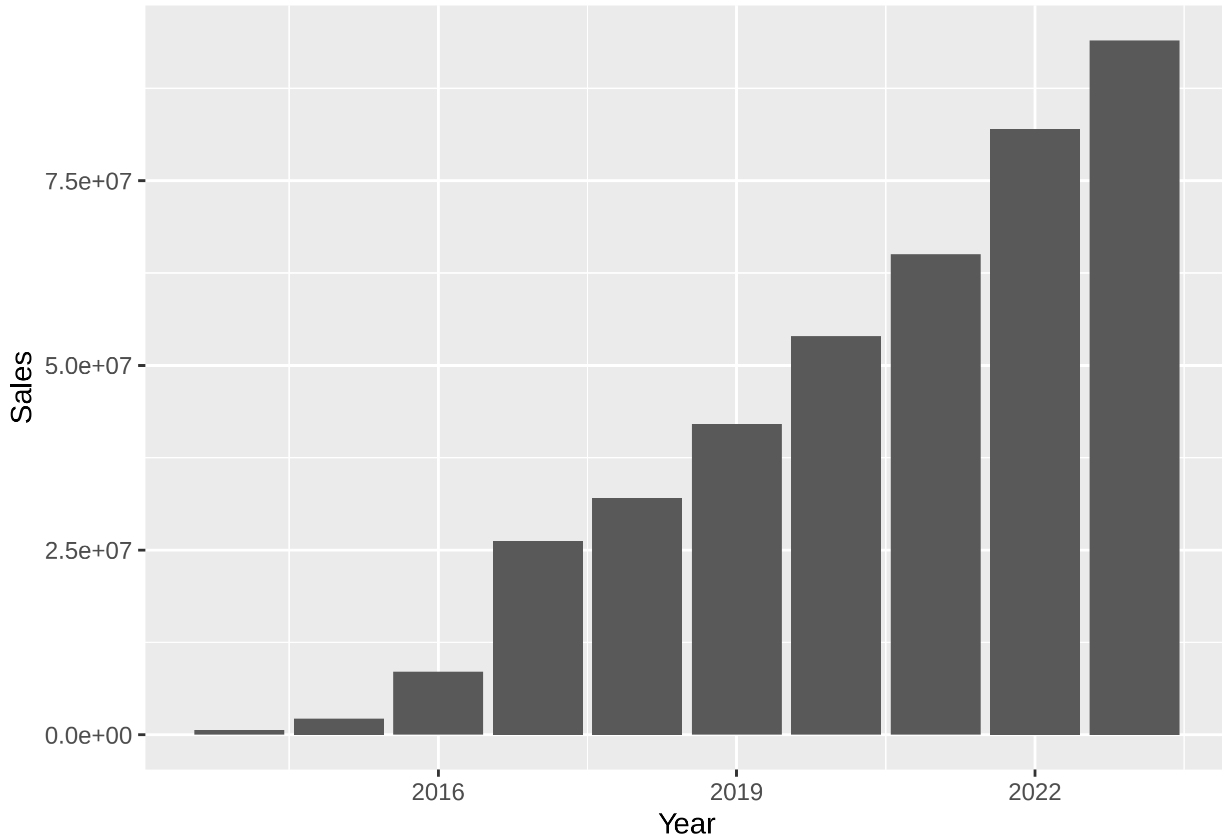
About the Data Time Series:

I chose this data as a perfect fit for estimating the bass model parameters and it contains a long range of years (2013-2023)

```r
library(ggplot2)
#read the data
echo_data <- read.csv('Echo_Sales.csv')
echo_data
```

```
##    Year    Sales  X X.1
## 1  2014   600000 NA  NA
## 2  2015  2200000 NA  NA
## 3  2016  8500000 NA  NA
## 4  2017 26200000 NA  NA
## 5  2018 32000000 NA  NA
## 6  2019 42000000 NA  NA
## 7  2020 53900000 NA  NA
## 8  2021 65000000 NA  NA
## 9  2022 82000000 NA  NA
## 10 2023 94000000 NA  NA
```

```r
#barplot of the data sales
ggplot(echo_data, aes(Year, Sales)) + geom_bar(stat = 'identity')
```



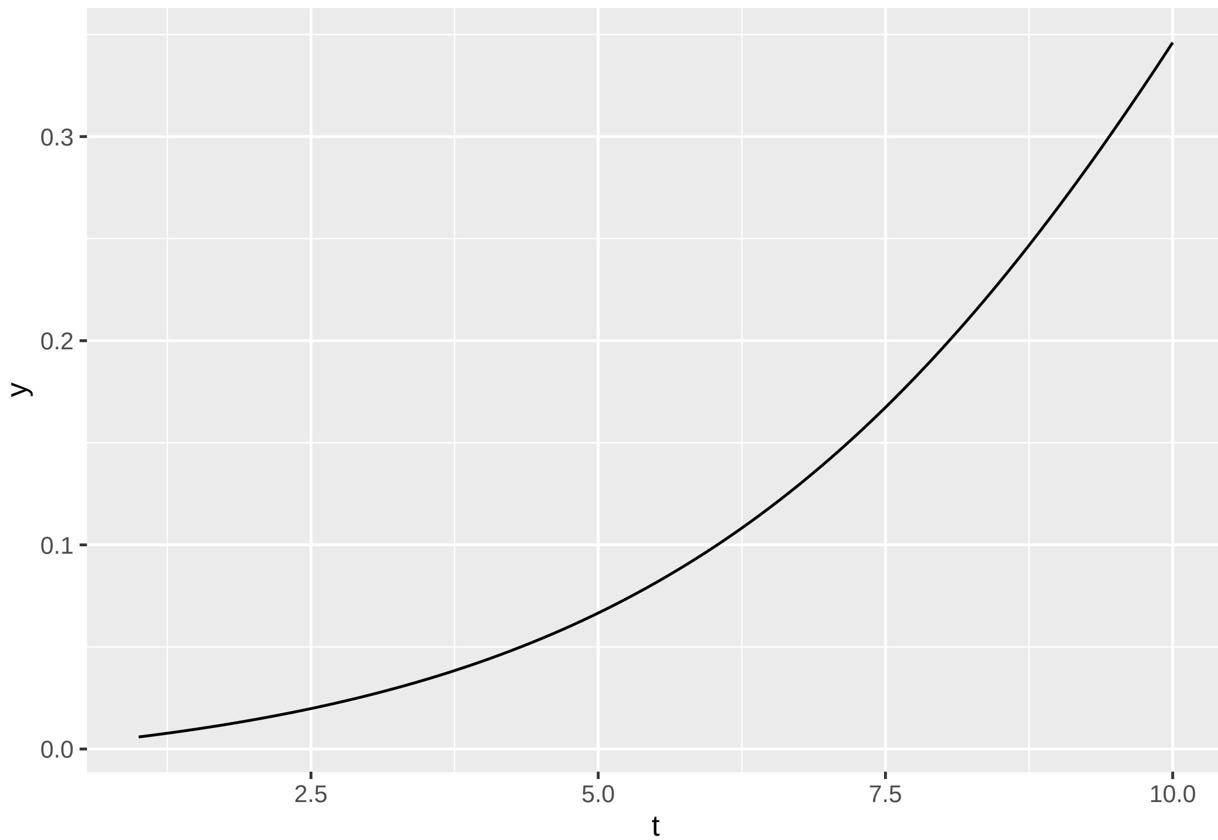

```
library(diffusion)
#using diffusion, estimate p, q and m of the current data
diff_m = diffusion(echo_data$Sales)
p = round(diff_m$w,4)[1]
q = round(diff_m$w,4)[2]
m = round(diff_m$w,4)[3]
diff_m
```

```
## bass model
##
## Parameters:
##                                  Estimate p-value
## p - Coefficient of innovation 4.900000e-03      NA
## q - Coefficient of imitation  3.668000e-01      NA
## m - Market potential          1.170835e+09      NA
##
## sigma: 4851130.4301
```

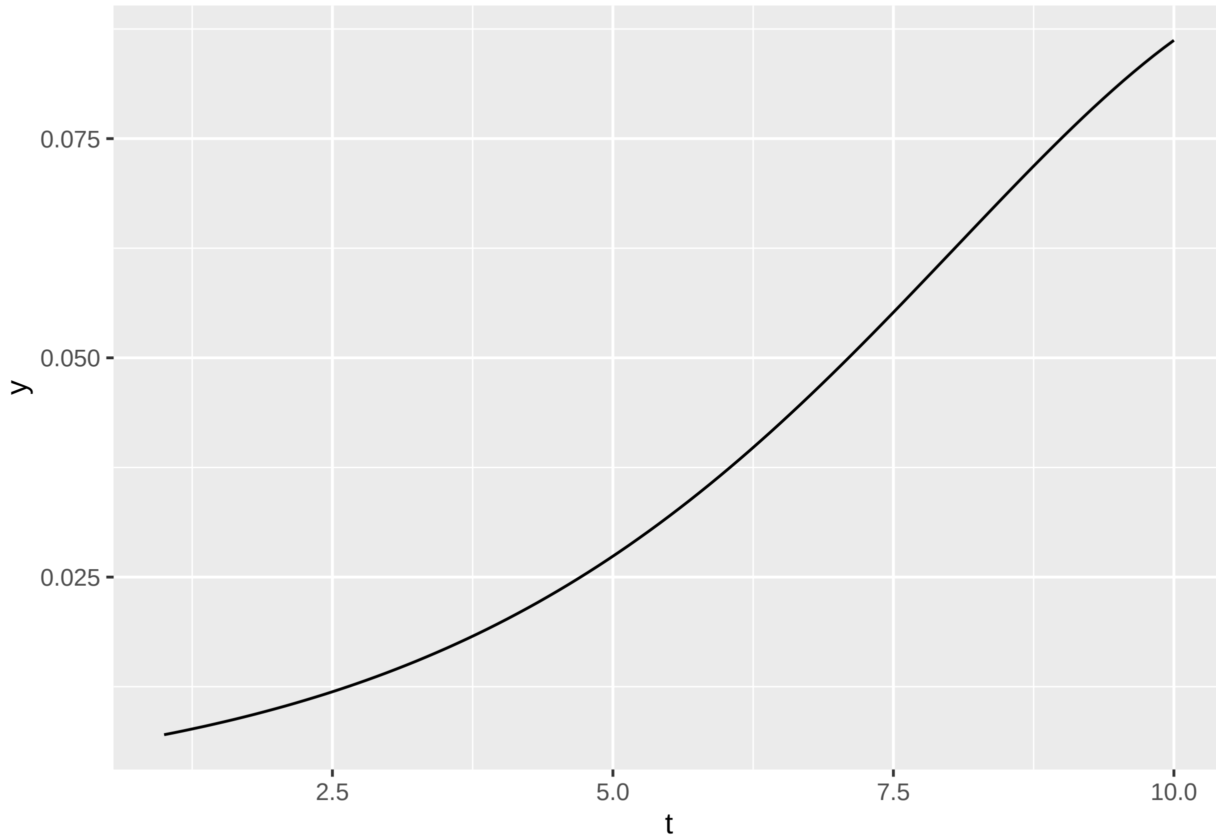
```
#divide into timelines from 1 to the size of our data
t <- 1:length(echo_data$Year)

#using bass mass function for current time
bass.f <- function(t,p,q) {
  ((p + q) ^ 2 / p) * exp(-(p + q) * t) / (1 + (q / p) * exp(-(p + q) * t)) ^ 2
}
```

```
#using cummulative function until the time included
bass.F <- function(t,p,q) {
  (1 - exp(-(p + q) * t)) / (1 + (q / p) * exp(-(p + q) * t))
}
```

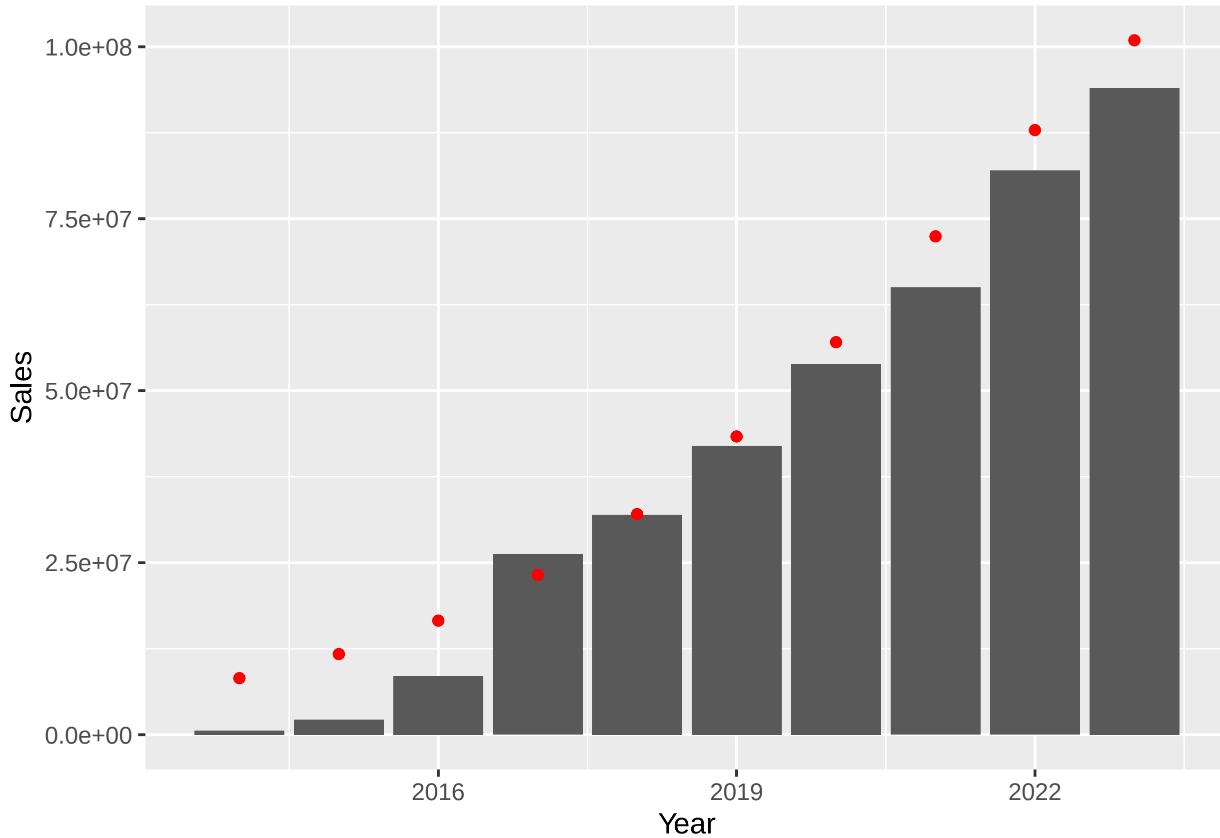
```
#plotting both cummulative and the current sales at moment t
ggplot(echo_data, aes(t)) +
  stat_function(fun = bass.F, args = c(p, q))
```




```
ggplot(echo_data, aes(t)) +
  stat_function(fun = bass.f, args = c(p, q))
```




```r
#predicting sales of new product using the estimated parameters
echo_data$sonos_predicted_sales = bass.f(t, p, q) * m
ggplot(data = echo_data, aes(Year, Sales)) +
  geom_bar(stat = 'identity') +
  geom_point(aes(Year, sonos_predicted_sales), color = 'red')
```




```
#getting the market of the past look-alike innovation
sum(echo_data$Sales)
```

```
## [1] 406400000
```

Estimating the market potential of the Sonos Era 300 Speaker using Fermi's logic:

Let's say that there are 8 billion people in the world. 40% prefer to have speakers at their houses. However, considering the fact that there are wide variety of options that some prefer budget speakers, that 40% drops down to 25%. Now there are people that would like to have the option of the voice assitant, hence 25% goes down to 10%, now some don't prefer wired speakers (not battery based), so it will be 3%. So the final count comes to 240million tops.

```
Innovators <- 0.025 * 240000000
Early_Adopters <- 0.135 * 240000000
Early_Majority <- 0.34 * 240000000
Late_Majority <- 0.34 * 240000000
Laggards <- 0.16 * 240000000

categories <- c("Innovators", "Early Adopters", "Early Majority", "Late Majority", "Laggards")
counts <- c(Innovators, Early_Adopters, Early_Majority, Late_Majority, Laggards)
population_data <- data.frame(Category = categories, Population_Count = counts)

print(population_data)
```

```
##          Category Population_Count
```

```
## 1      Innovators          6000000
## 2 Early Adopters         32400000
## 3 Early Majority         81600000
## 4  Late Majority         81600000
## 5       Laggards         38400000
```

Data: https://www.statista.com/statistics/1022701/worldwide-amazon-echo-unit-shipment/