

# Homework 1

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```
library(tidyverse)
```

```
## -- Attaching core tidyverse packages ----- tidyverse 2.0.0 --
## v dplyr      1.1.4      v readr      2.1.5
## v forcats    1.0.0      v stringr    1.5.1
## v ggplot2    3.5.1      v tibble     3.2.1
## v lubridate  1.9.3      v tidyr      1.3.1
## v purrr      1.0.2
## -- Conflicts ----- tidyverse_conflicts() --
## x dplyr::filter() masks stats::filter()
## x dplyr::lag()     masks stats::lag()
## i Use the conflicted package (<http://conflicted.r-lib.org/>) to force all conflicts to become errors
```

```
library(minpack.lm)
```

The innovation “Virtual Fauna” shares similarities with AR (Augmented Reality) due to their common focus on blending the physical and digital worlds. Virtual Fauna, like AR, utilizes technology to create interactive digital creatures that can inhabit real-world environments through devices like smartphones or AR glasses. Both innovations enhance user experiences by overlaying digital elements onto reality.

In terms of market impact, AR revolutionized industries like gaming (e.g., Pokémon GO) and retail (virtual try-ons), while Virtual Fauna can similarly impact entertainment, education, and wildlife simulation, offering immersive interactions with virtual animals.

```
data <- read.csv('Data.csv', stringsAsFactors = FALSE, sep = ";")
data$AR.Hardware <- as.numeric(data$AR.Hardware)
```

```
## Warning: NAs introduced by coercion
```

```
data$AR.Software <- as.numeric(data$AR.Software)
data$AR.Hardware[is.na(data$AR.Hardware)] <- 0
filtered_data <- data %>% filter(Year <= 2023) %>%
  select(Year, AR.Software, AR.Hardware)
filtered_data <- filtered_data %>%
  mutate(Total.AR.Adoption = AR.Software + AR.Hardware)
filtered_data
```

```
##   Year AR.Software AR.Hardware Total.AR.Adoption
## 1 2017      137.20         0.00          137.20
## 2 2018      143.50         0.00          143.50
```

```
## 3 2019      154.71      0.00      154.71
## 4 2020      172.96      9.05      182.01
## 5 2021      199.01     13.58     212.59
## 6 2022      230.94     21.92     252.86
## 7 2023      263.36     49.45     312.81
```

```
bass_model_cumulative <- function(t, p, q, M) {
  adoption <- M * (1 - exp(-(p + q) * t)) / (1 + (q / p) * exp(-(p + q) * t))
  return(adoption)
}

time_periods <- 1:nrow(filtered_data)
total_adoption <- filtered_data$Total.AR.Adoption

initial_guess <- c(p = 0.03, q = 0.38, M = max(total_adoption) * 2)

fit <- nlsLM(Total.AR.Adoption ~ bass_model_cumulative(time_periods, p, q, M),
  data = filtered_data, start = initial_guess)

params <- coef(fit)
p <- params['p']
q <- params['q']
M <- params['M']
```

```
cat("Estimated p (Coefficient of innovation):", p, "\n")
```

```
## Estimated p (Coefficient of innovation): 0.2200149
```

```
cat("Estimated q (Coefficient of imitation):", q, "\n")
```

```
## Estimated q (Coefficient of imitation): -0.2200872
```

```
cat("Estimated M (Market potential):", M, "\n")
```

```
## Estimated M (Market potential): 449.5019
```

```
future_years <- 1:(nrow(filtered_data) + 12)

predicted_cumulative_adoption <- bass_model_cumulative(future_years, p, q, M)
predicted_yearly_adoption <- c(0, diff(predicted_cumulative_adoption))

prediction_df <- data.frame(
  Year = 2020:(2020 + length(future_years) - 1),
  Cumulative_Adoption = predicted_cumulative_adoption,
  Yearly_Adoption = predicted_yearly_adoption
)

print(prediction_df)
```

```
##      Year Cumulative_Adoption Yearly_Adoption
```

## 1	2020	81.0598	0.000000
## 2	2021	137.3473	56.287534
## 3	2022	178.7132	41.365861
## 4	2023	210.3965	31.683294
## 5	2024	235.4406	25.044156
## 6	2025	255.7346	20.293927
## 7	2026	272.5127	16.778123
## 8	2027	286.6158	14.103124
## 9	2028	298.6364	12.020622
## 10	2029	309.0041	10.367666
## 11	2030	318.0378	9.033724
## 12	2031	325.9795	7.941666
## 13	2032	333.0158	7.036343
## 14	2033	339.2933	6.277479
## 15	2034	344.9284	5.635097
## 16	2035	350.0149	5.086520
## 17	2036	354.6293	4.614330
## 18	2037	358.8342	4.204975
## 19	2038	362.6820	3.847780

```

plot(prediction_df$Year, prediction_df$Cumulative_Adoption, type = "o", col = "blue",
      xlab = "Year", ylab = "Adoption", main = "Predicted Diffusion Path of AR Software + AR Hardware (B",
      ylim = range(c(prediction_df$Cumulative_Adoption, prediction_df$Yearly_Adoption)))

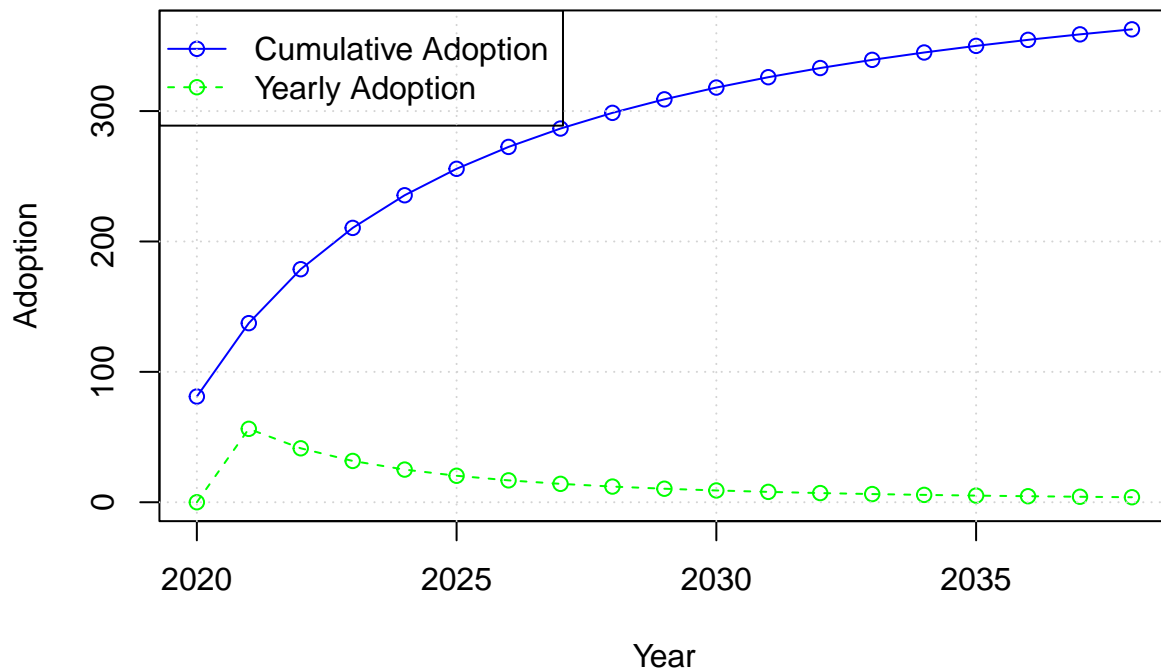
lines(prediction_df$Year, prediction_df$Yearly_Adoption, type = "o", col = "green", lty = 2)

legend("topleft", legend = c("Cumulative Adoption", "Yearly Adoption"), col = c("blue", "green"),
      lty = c(1, 2), pch = c(1, 1))

grid()

```

## Predicted Diffusion Path of AR Software + AR Hardware (Bass Mode



As my data is related to only Italy I decided to analyze the diffusion focusing on a country-specific analysis.

```
bass_model_cumulative <- function(t, p, q, M) {
  adoption <- M * (1 - exp(-(p + q) * t)) / (1 + (q / p) * exp(-(p + q) * t))
  return(adoption)
}
future_years <- 1:15

predicted_cumulative_adoption <- bass_model_cumulative(future_years, p, q, M)

predicted_yearly_adoption <- c(0, diff(predicted_cumulative_adoption))

adoption_df <- data.frame(
  Year = 2020:(2020 + length(future_years) - 1),
  Cumulative_Adoption = predicted_cumulative_adoption,
  Yearly_Adoption = predicted_yearly_adoption
)

print(adoption_df)
```

```
##   Year Cumulative_Adoption Yearly_Adoption
## 1  2020             81.0598         0.000000
## 2  2021            137.3473         56.287534
## 3  2022            178.7132         41.365861
## 4  2023            210.3965         31.683294
## 5  2024            235.4406         25.044156
```

## 6	2025	255.7346	20.293927
## 7	2026	272.5127	16.778123
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