MA

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```r
libs<-c('ggplot2','ggpubr','knitr','diffusion')
load_libraries<-function(libs){
new_libs <- libs[!(libs %in% installed.packages()[,"Package"])]
if(length(new_libs)>0) {install.packages(new_libs)}
lapply(libs, library, character.only = TRUE)
}
load_libraries(libs)
```

```
## [[1]]
## [1] "ggplot2"   "stats"     "graphics"  "grDevices" "utils"     "datasets"
## [7] "methods"   "base"
##
## [[2]]
## [1] "ggpubr"    "ggplot2"   "stats"     "graphics"  "grDevices" "utils"
## [7] "datasets"  "methods"   "base"
##
## [[3]]
##  [1] "knitr"     "ggpubr"    "ggplot2"   "stats"     "graphics"  "grDevices"
##  [7] "utils"     "datasets"  "methods"   "base"
##
## [[4]]
##  [1] "diffusion" "knitr"     "ggpubr"    "ggplot2"   "stats"     "graphics"
##  [7] "grDevices" "utils"     "datasets"  "methods"   "base"
```

```r
bass.f <- function(t,p,q){
((p+q)^2/p)*exp(-(p+q)*t)/
(1+(q/p)*exp(-(p+q)*t))^2
}
```

```r
bass.F <- function(t,p,q){
(1-exp(-(p+q)*t))/
(1+(q/p)*exp(-(p+q)*t))
}
```

I have chosen the robot vacuum cleaner innovation as it is a significant step toward automating and improving floor cleaning. The evolution of household chore automation can be seen in the progression from the simple vacuum cleaner to the robot vacuum cleaner. By mechanizing the cleaning process, the simple vacuum cleaner laid the foundation for the robot vacuum cleaner, which incorporates artificial intelligence and smart sensors. This transformation exemplifies the ongoing effort to improve efficiency and user experience, with the ultimate goal of relieving the burden of household chores and providing individuals with more time for other activities.

```r
library(readxl)
cleaner = read_excel('RVC Data.xlsx', col_names = TRUE)
cleaner
```

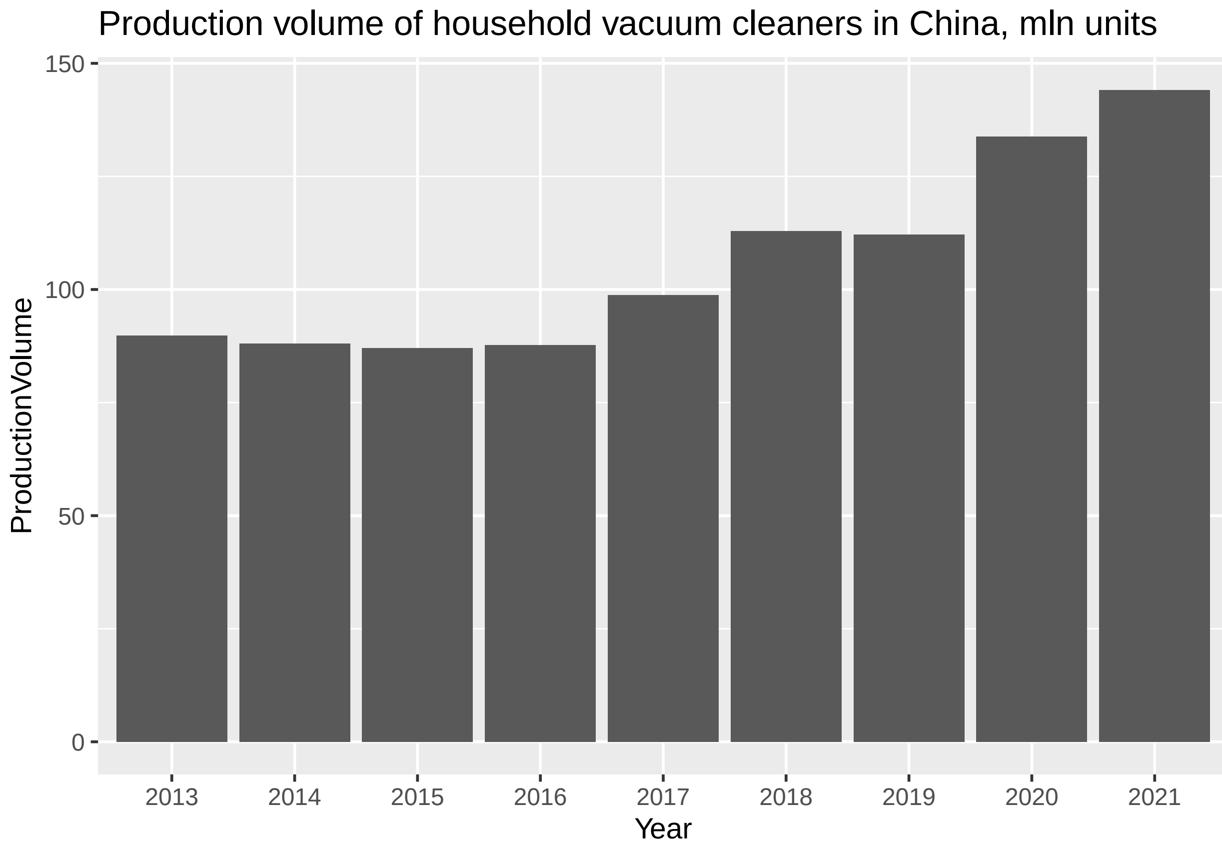
```
## # A tibble: 9 x 2
##   Year  ProductionVolume
##   <chr>            <dbl>
## 1 2013              89.8
## 2 2014              88
## 3 2015              87
## 4 2016              87.7
## 5 2017              98.8
## 6 2018             113.
## 7 2019             112.
## 8 2020             134.
## 9 2021             144.
```

source: https://www.statista.com/statistics/1365824/china-production-volume-of-household-vacuum-cleaners/

Using household vacuum cleaner production volume data in China from 2013 to 2021 for the Bass Model is highly relevant and provides critical insights for forecasting future adoption and diffusion patterns. The Bass Model is a well-known innovation diffusion model that is used to forecast the market adoption of new products or technologies. In this case, it can help forecast China's continued adoption and market penetration of household vacuum cleaners.

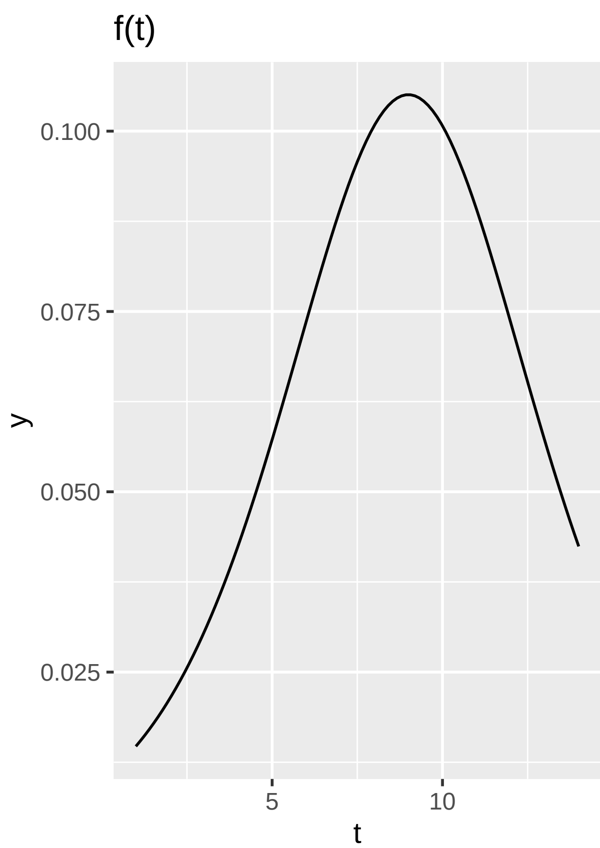
The historical production volume data for the specified time period enables a more in-depth understanding of the product's adoption curve in the Chinese market. The Bass Model is especially effective when historical data is available because it uses the cumulative adoption and innovation coefficients to estimate potential market size and the rate of new adopters. Using the Bass Model on this dataset, it is possible to forecast future adoption rates and better understand consumer acceptance dynamics and market saturation for household vacuum cleaners in China.

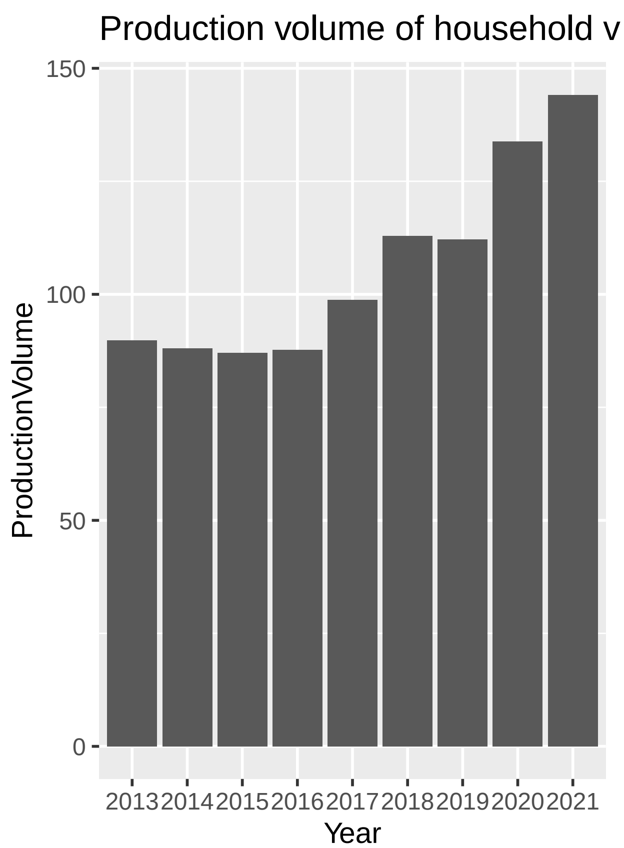
```r
ggplot(data = cleaner, aes(x = Year, y = ProductionVolume)) +
geom_bar(stat = 'identity') +
ggtitle('Production volume of household vacuum cleaners in China, mln units')
```




```r
time_ad = ggplot(data.frame(t = c(1:14)), aes(t)) +
stat_function(fun = bass.f, args = c(p=0.01, q=0.4)) +
labs(title = 'f(t)')

cl_production = ggplot(data = cleaner, aes(x = Year, y = ProductionVolume)) +
geom_bar(stat = 'identity') +
ggtitle('Production volume of household vacuum cleaners in China, mln units')
ggarrange(time_ad, cl_production)
```






```
ProductionVolume = cleaner$ProductionVolume
t = 1:length(ProductionVolume)
bass_m = nls(ProductionVolume ~ m*(((p+q)^2/p)*exp(-(p+q)*t))/
               (1+(q/p)*exp(-(p+q)*t))^2,
              start=c(list(m=sum(ProductionVolume),p=0.01,q=0.4)),
             control = list(maxiter =5000, tol=8))
```

```
summary(bass_m )
```

```
##
## Formula: ProductionVolume ~ m * (((p + q)^2/p) * exp(-(p + q) * t))/(1 +
##     (q/p) * exp(-(p + q) * t))^2
##
## Parameters:
##    Estimate Std. Error t value Pr(>|t|)
## m  954.3800  1505.9872   0.634    0.550
## p    0.0100     0.0149   0.671    0.527
## q    0.4000     0.5333   0.750    0.482
##
## Residual standard error: 62.89 on 6 degrees of freedom
##
## Number of iterations to convergence: 0
## Achieved convergence tolerance: 4.044
```

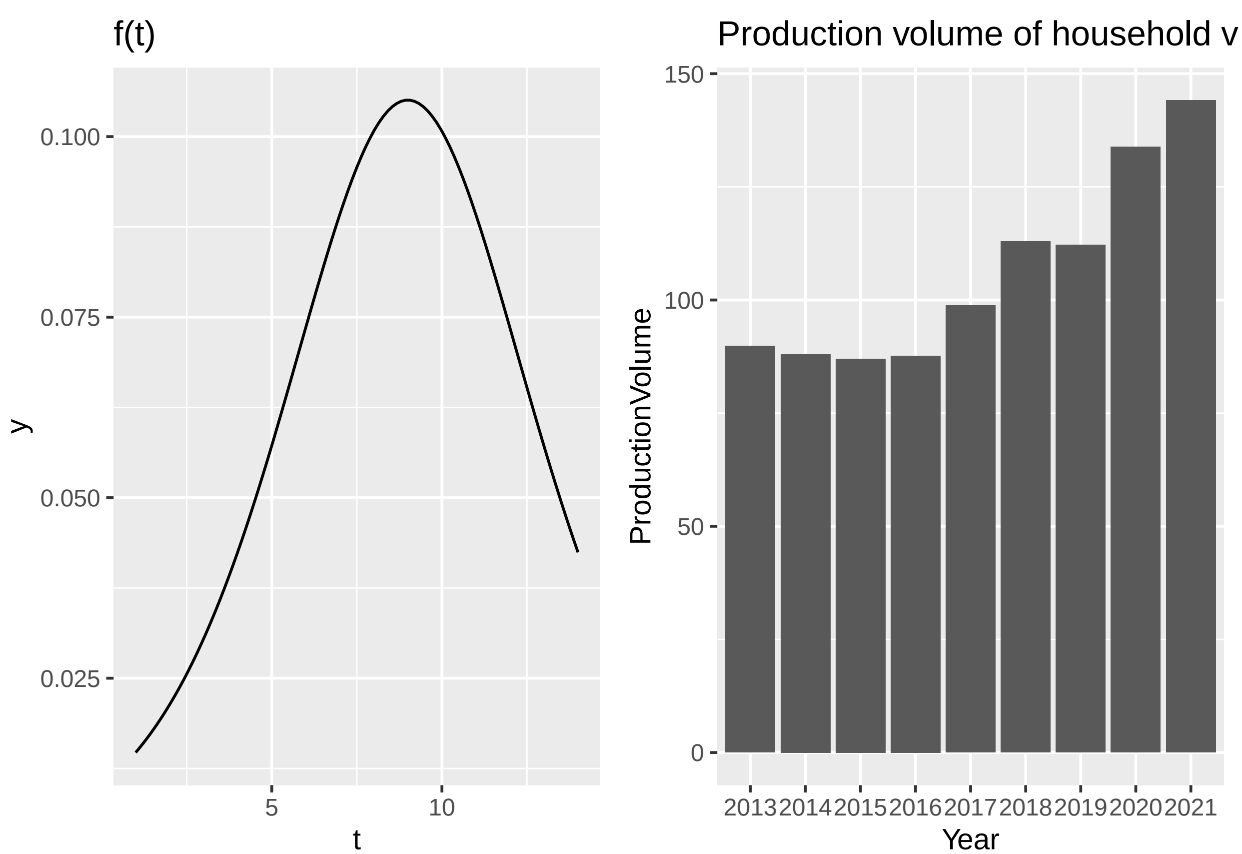
```r
p <- coef(bass_m)["p"]
p
```

```
##    p
## 0.01
```

```r
q <- coef(bass_m)["q"]
q
```

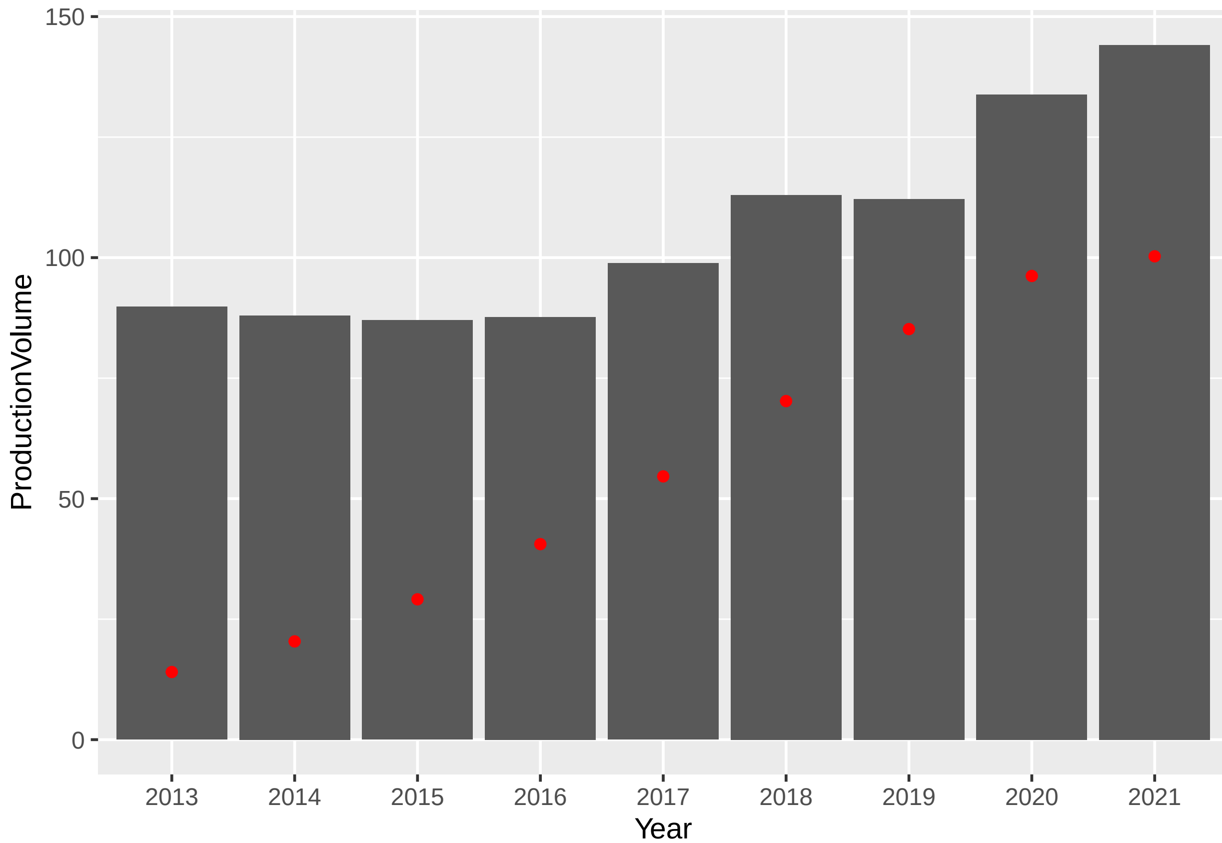
```
##   q
## 0.4
```

```r
time_ad = ggplot(data.frame(t = c(1:14)), aes(t)) +
stat_function(fun = bass.f, args = c(p=0.01, q=0.4)) +
labs(title = 'f(t)')
ggarrange(time_ad, cl_production)
```



Predicting sales | Method 1

```r
cleaner$pred_ProductionVolume = bass.f(1:9, p = 0.01, q = 0.4)*954.38
ggplot(data = cleaner, aes(x = Year, y = ProductionVolume)) +
geom_bar(stat = 'identity') +
geom_point(mapping = aes(x=Year, y=pred_ProductionVolume), color = 'red')
```



From this graph can seen that we have a very bad prediction.

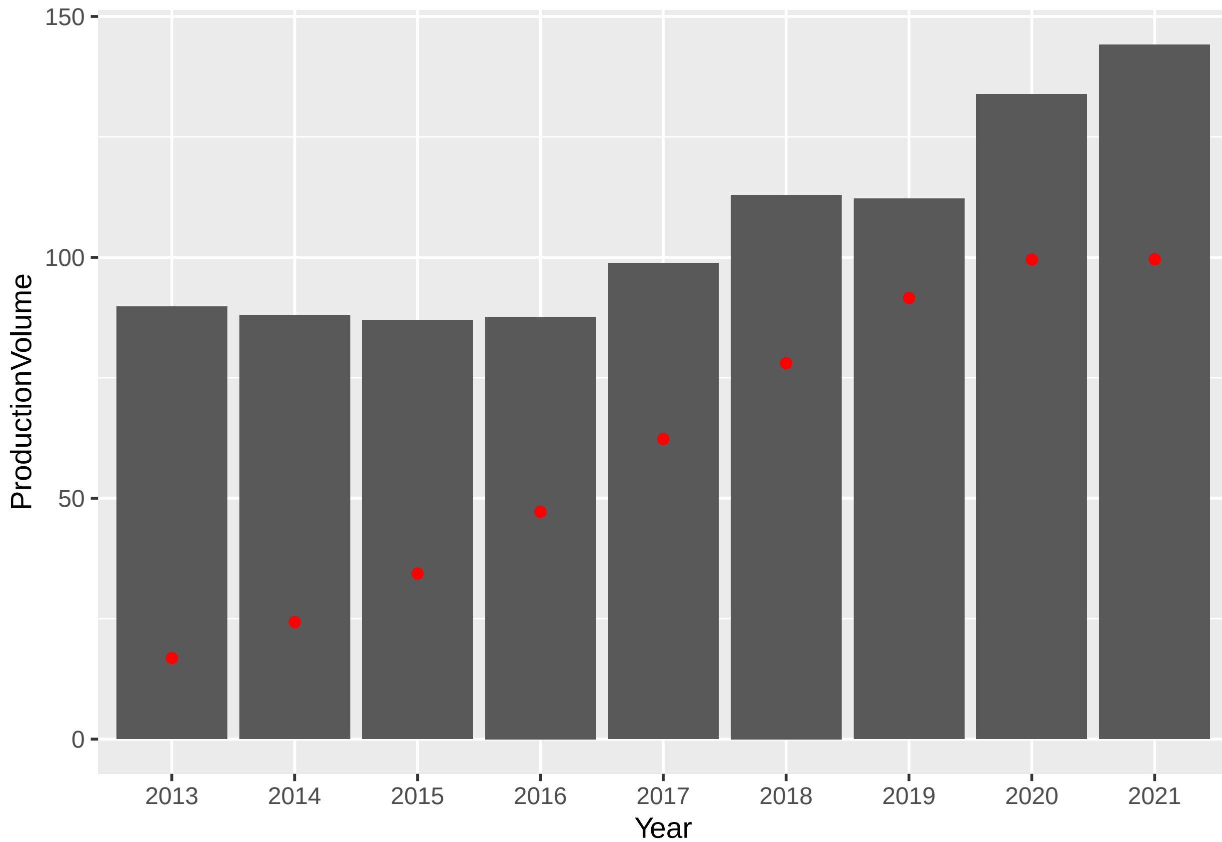
```
diff_m = diffusion(cleaner$pred_ProductionVolume)
p=round(diff_m$w,4)[1]
q=round(diff_m$w,4)[2]
m=round(diff_m$w,4)[3]
diff_m
```

```
## bass model
##
## Parameters:
##                                  Estimate p-value
## p - Coefficient of innovation      0.0121      NA
## q - Coefficient of imitation       0.3988      NA
## m - Market potential             950.8972      NA
##
## sigma: 0.0143
```

```
data.frame(Predicted=log(q/p)/(p+q),
Actual=which.max(cleaner$pred_ProductionVolume))
```

```
##   Predicted Actual
## q  8.506339      9
```

```r
cleaner$pred_ProductionVolume = bass.f(1:9, p = 0.0121 , q = 0.3988  )*950.8972
ggplot(data = cleaner, aes(x = Year, y = ProductionVolume)) +
geom_bar(stat = 'identity') +
geom_point(mapping = aes(x=Year, y=pred_ProductionVolume), color = 'red')
```



China produced 144 million vacuum cleaners in 2021, an increase of about 11 million vacuum cleaners from the year before. Some of the most well-known producers of home appliances in China include Midea, Haier, and Xiaomi. Source: https://www.statista.com/statistics/1365824/china-production-volume-of-household-vacuum-cleaners/ We can use Fermi's logic to estimate the number of adopters based on production volume: Assumption 1: Assume that every Chinese household purchases a new vacuum cleaner every five years. Assumption 2: According to World Bank data (source: https://www.worldbank.org/en/country/china/overview#3) , there were approximately 442 million households in China in 2021. Based on Assumption 1, approximately 88.4 million (442 million / 5) households are potential buyers of vacuum cleaners each year. Given 144 million units produced in 2021, the potential market share would be approximately 61% (88.4 million / 144 million * 100). Estimated number of adopters = Potential market share * Production volume 0.61 * 144 million (approximately) 87.84 million Based on the assumptions provided and Fermi's logic, the estimated number of household vacuum cleaner adopters in China in 2021 is 87.84 million.

```r
m <- 87840000
t <- c(1:9)
pred <- bass.f(t = t, p = p, q = q)*m
pred_df <- data.frame(t = t, pred = pred)
pred1 <- bass.F(t = t, p = p, q = q)
pred1_df <- data.frame(t = t, pred = pred1)
p1 <- ggplot(pred_df, aes(x = t, y = pred)) + geom_line() + ggtitle("Number of adoptions at time t")
p2<- ggplot(pred1_df, aes(x = t, y = pred1)) + geom_line() + ggtitle("Cummulative addoptions")
```

```
ggarrange(p1,p2)
```