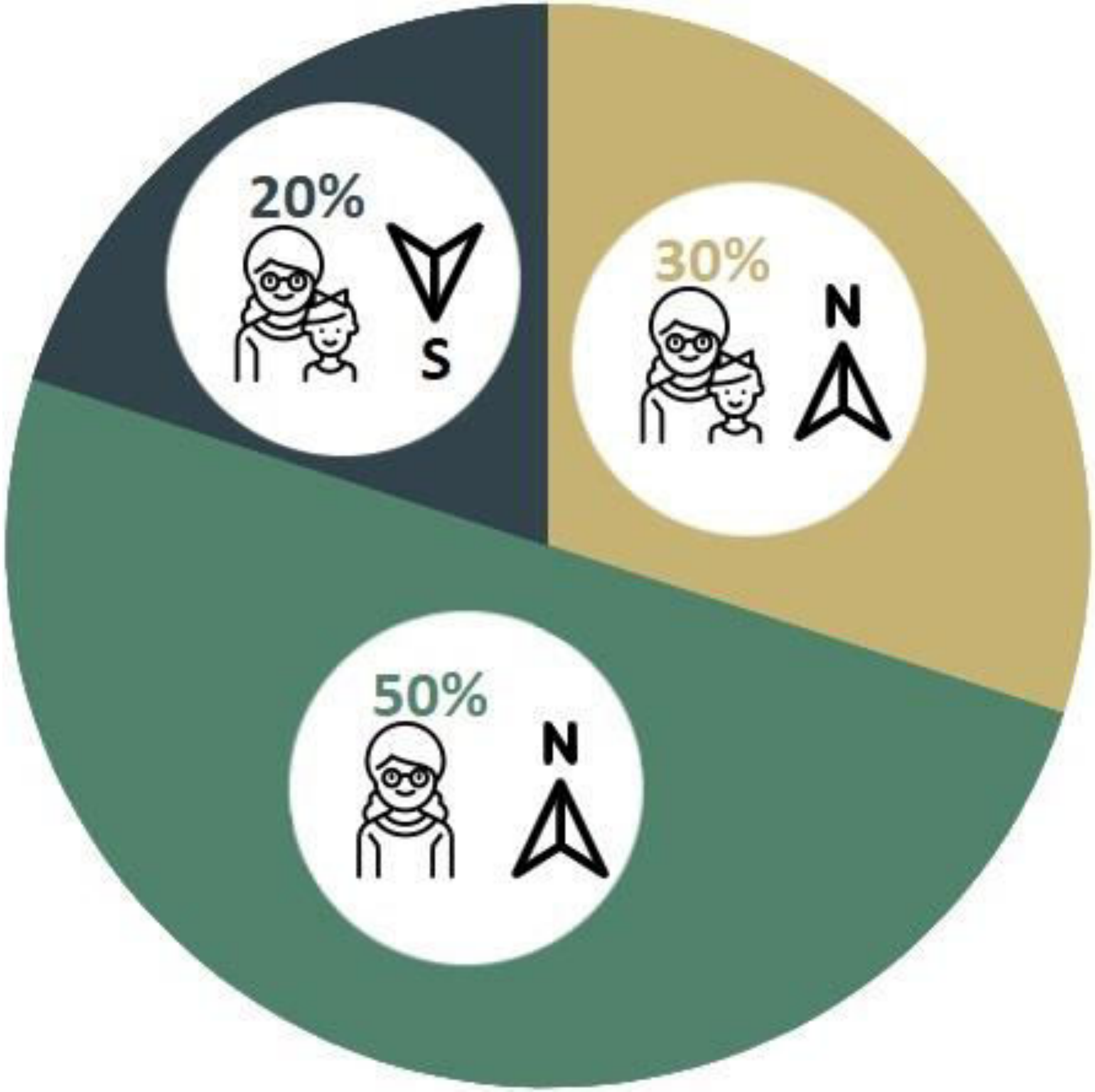
Data Intelligence Application

Pricing & Advertising

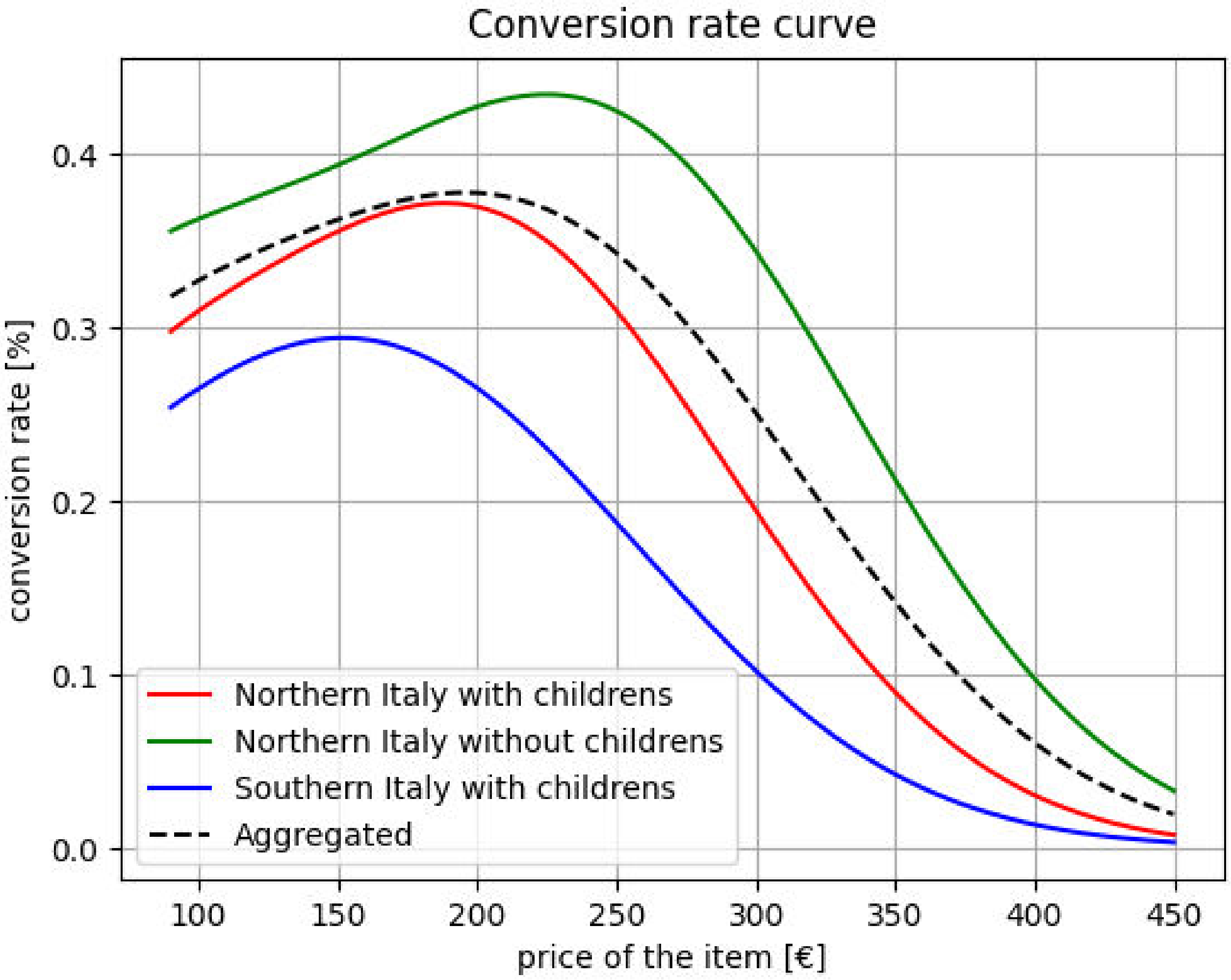
The Product

Louis Vuitton Scarf

The Users



The Curve



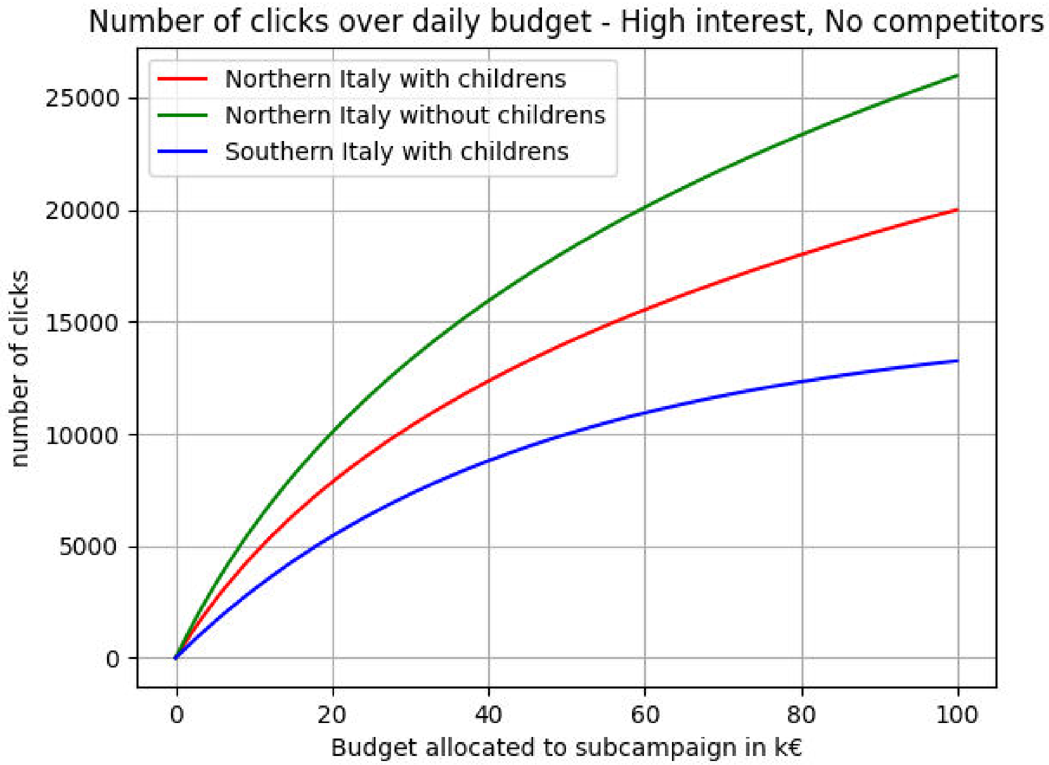
Conversion rate curve
conversion rate [%]
0.0
0.1
0.2
0.3
0.4
100
150
200
250
300
350
400
450
price of the item [€]
Northern Italy with childrens
Northern Italy without childrens
Southern Italy with childrens
Aggregated

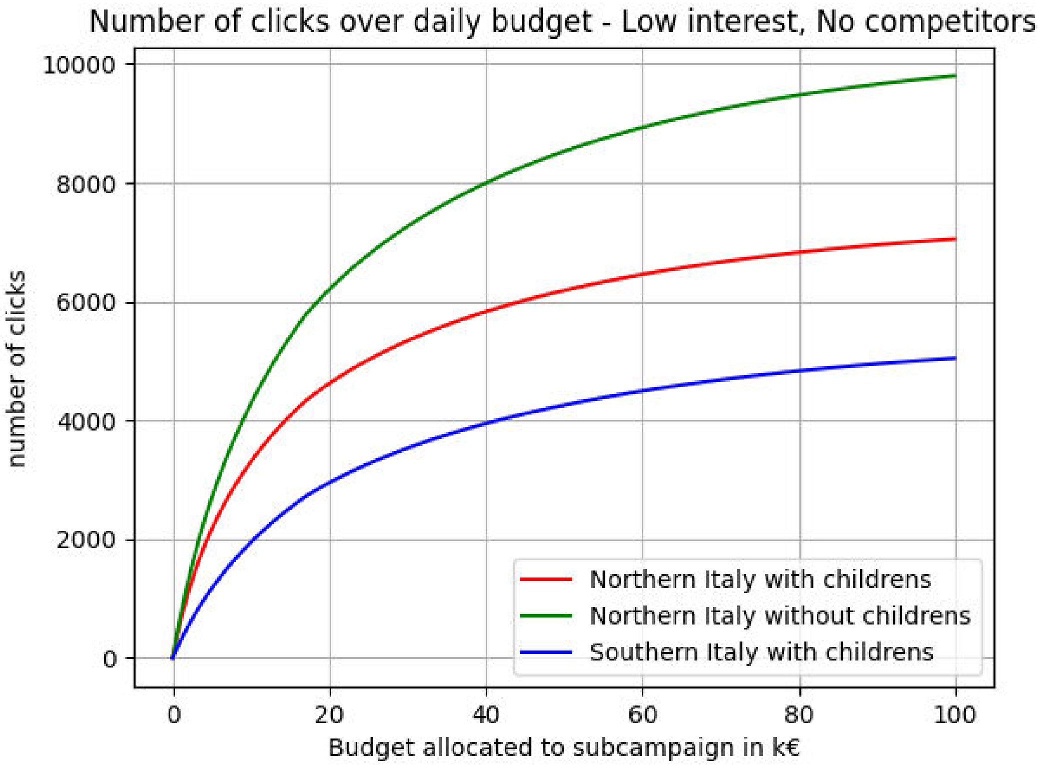
The Phases

louis vuitton scarf
100
75
50
25
6 mag 2015
6 nov 2016
6 mag 2018
6 nov 2019

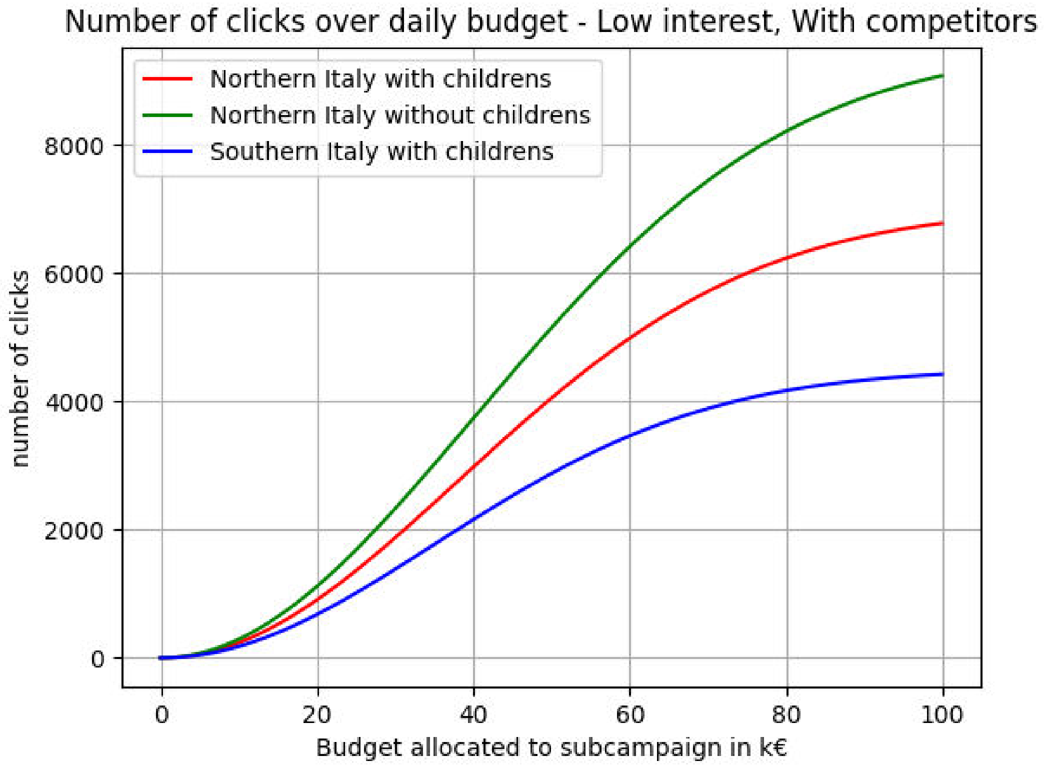
JAN
FEB
MAR
High Interest
No Competitors
APR
MAY
JUN
Low Interest
No Competitors
JUL
AUG
SEP
Low Interest
A New Competitor
Enters The Market
OCT
NOV
DEC
High Interest
With Competitors

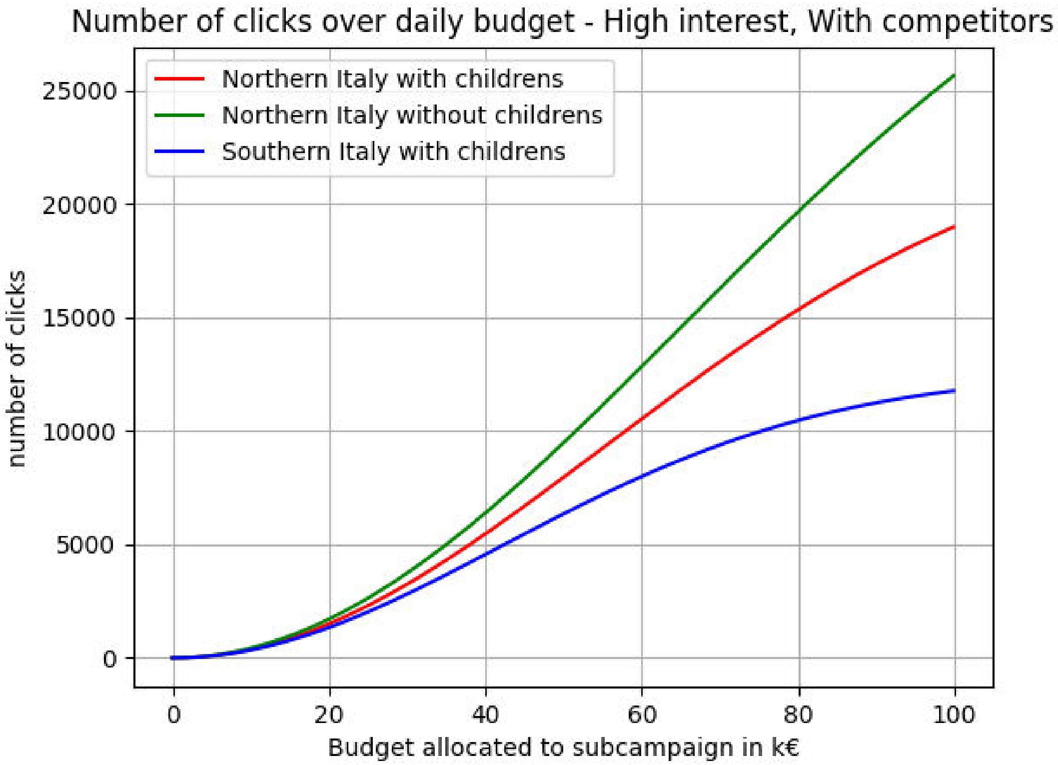
The Phases (1/2)





The Phases (2/2)





Budget Allocation

The first step of our project was focused on the budget allocation over the three subcampaigns and had as goal the maximization of the total number of clicks.

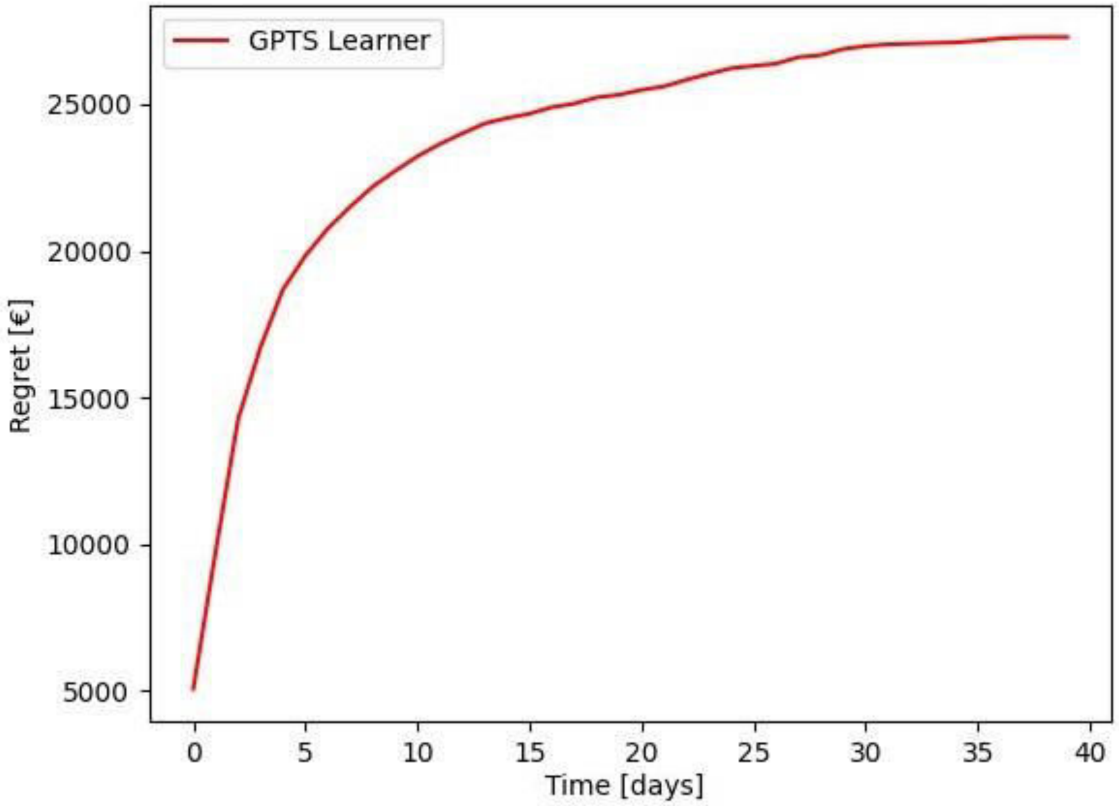
The graphs shows the results the we obtained considering just one phase and considering all the four phases.

The Algorithm (One Phase)

Algorithm 1 Gaussian Process CMAB

$J \leftarrow$ all classes of users
for $day \in T$ **do**
    for $j \in \{1, ..., J\}$ **do**
        $s \leftarrow$ Sample j-th GP-Learner
        Add s row to knapsack matrix
    end for
    Optimize knapsack matrix
    Play selected superarm
    Update GP-Learners model
end for

The Result (One Phase)



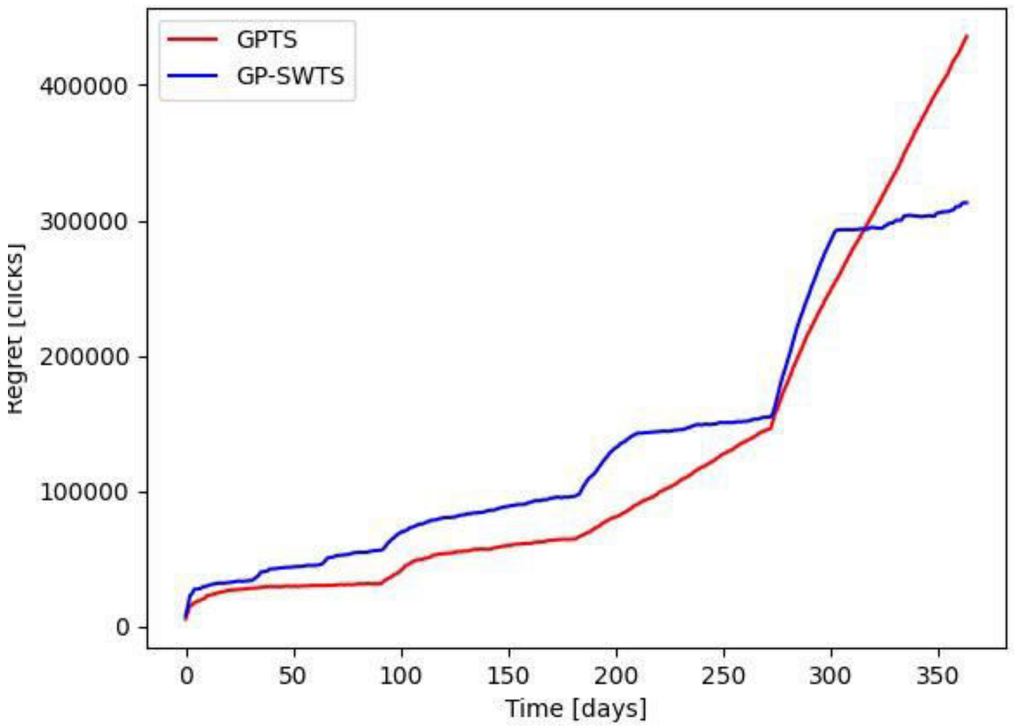
The Algorithm (Four Phases)

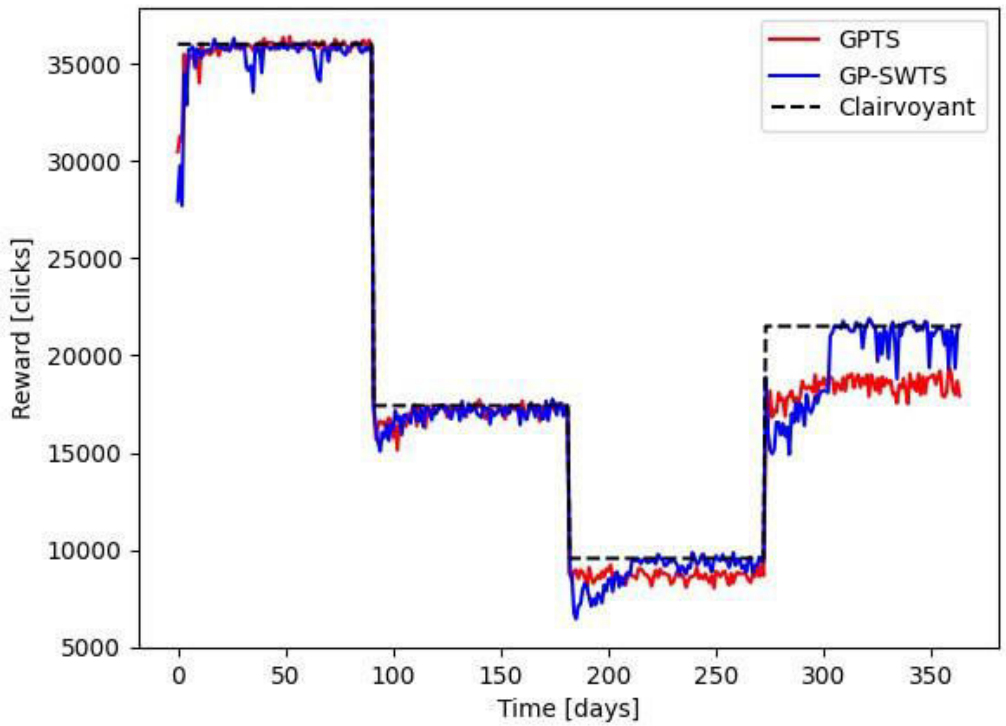
Algorithm 2 Gaussian Process CMAB

Input: τ sliding window size, J classes of users

for $day \in \{1, ..., T\}$ **do**
    for $j \in \{1, ..., J\}$ **do**
        Sample j-th GP-Learner(τ)
        Add row to knapsack matrix
    end for
    Optimize knapsack matrix
    Play selected superarm
    Update GP-Learners model(τ)
end for

The Results (Four Phases)





Price Learning

Next, we describe the learning algorithms that we used to maximize the number of purchases made by users that have reached our website by clicking on ads.

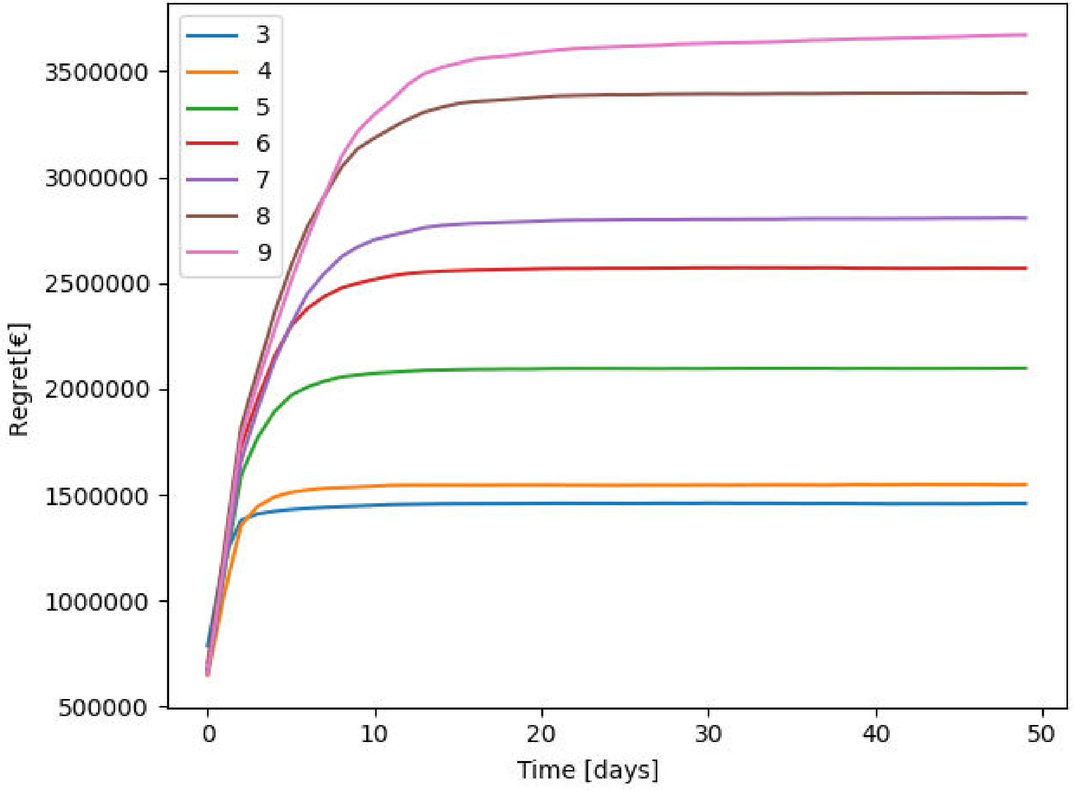
We first consider a normal setup followed by a context generation algorithm.

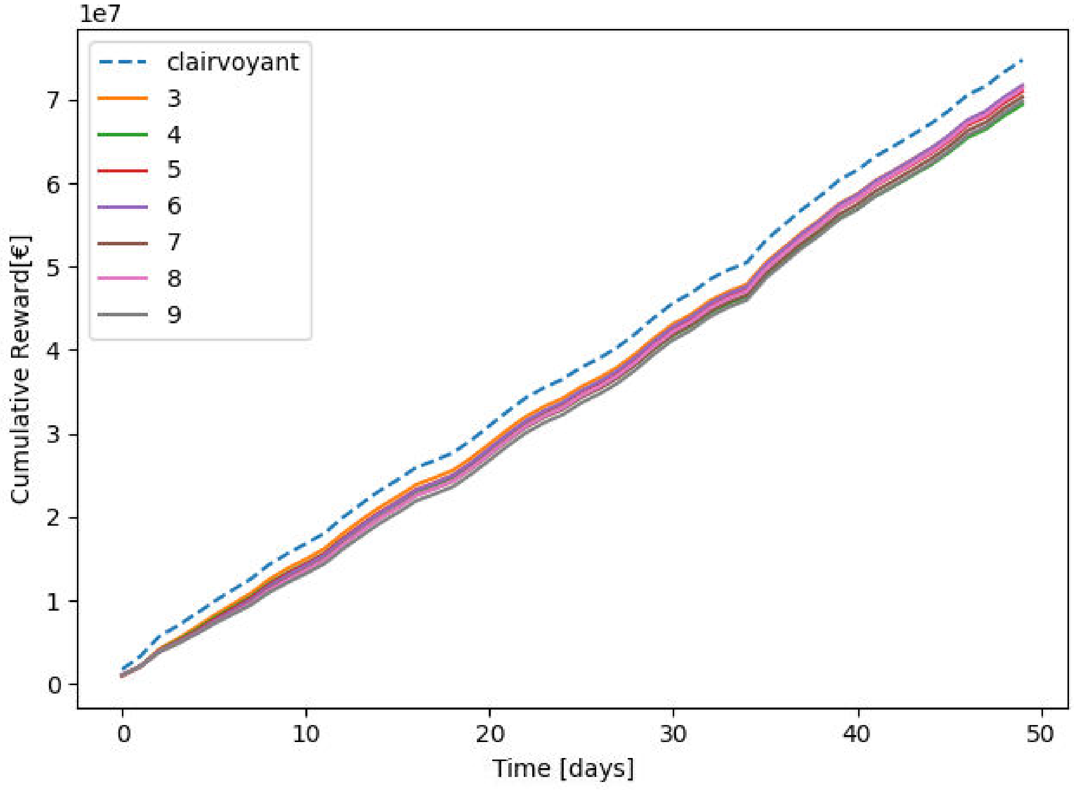
The Algorithm (No Context)

Algorithm 3 TS learners for pricing

```
J ← all classes of users
T ← 45 days
regret ←0
for day ∈ T do
    for j ∈ {1, ..., J} do
        price ←Draw a price from the j-th TS learner
        successes ←play the pulled arm
        failures ←clicks[j][day] - successes
        reward ←successes * price
        regret += optimum - reward
        TS[j].update(price, successes, failures)
    end for
end for
```

The Results (No Contexts)





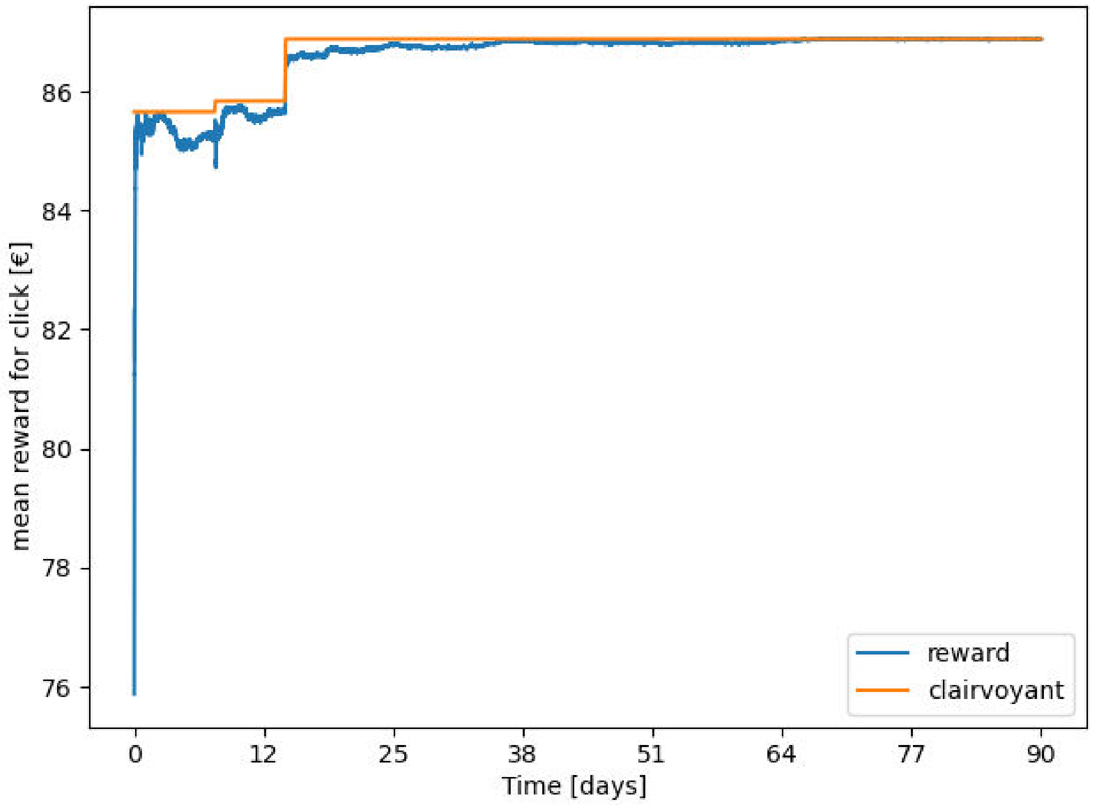
The Algorithm (With Context)

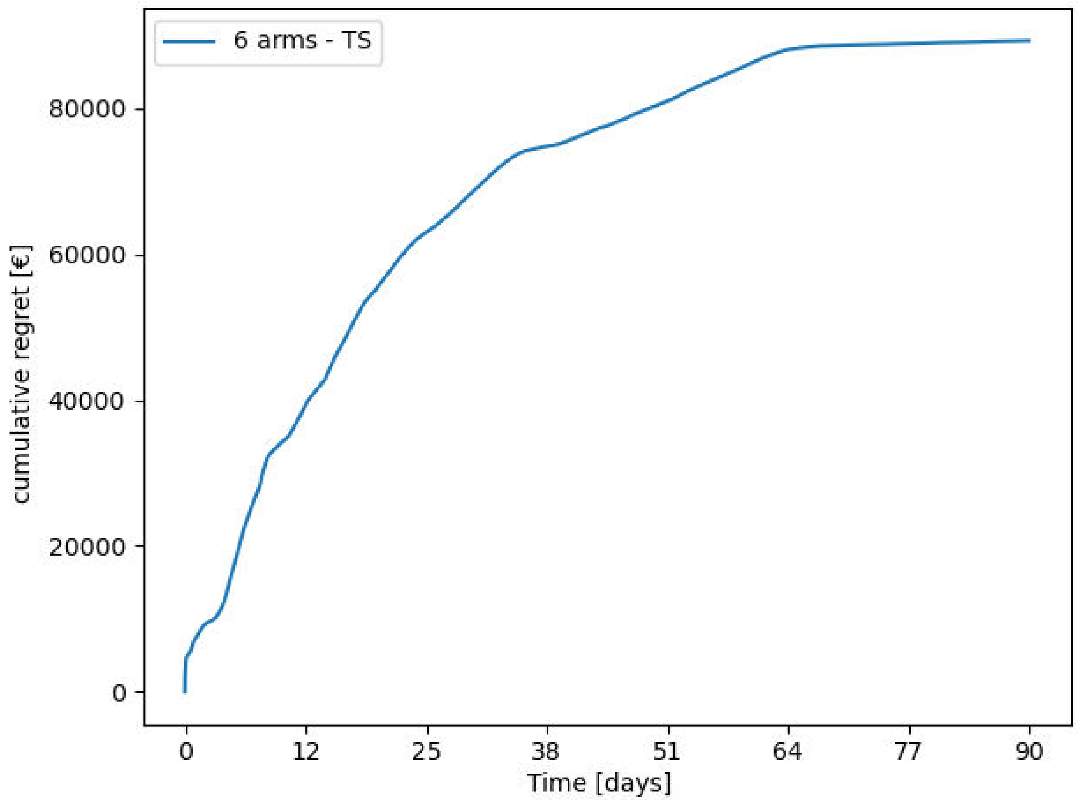
Algorithm 4 Context Generator Algorithm

Input: T : time span of the experiment, C : number of clicks per day

for $1 \leq t \leq T$ **do**
    for $1 \leq c \leq C$ **do**
        for $context \in Contexts$ **do**
            for $usertype \in context$ **do**
                $sort \leftarrow$ Draw the choice of the user from the binomial
                $successes \leftarrow$ Update the number of successes for that user and context
                $failures \leftarrow$ Update the number of failures for that user and context
            end for
            $reward \leftarrow$ Update the reward value for the day
        end for
        $rewards \leftarrow$ Append the reward value for the day
    end for
    if t mod 7 == 0 **then**
        for $context \in Contexts$ **do**
            for $usertype \in context$ **do**
                if split condition achieved **then**
                    $c1, c2 \leftarrow$ Perform the split
                end if
            end for
        end for
    end if
end for

The Results (With Contexts)





Optimization

After studing the budget allocation and the pricing scenario separately, we imagined the union of the two, used in a real application of the selling of our scarf.

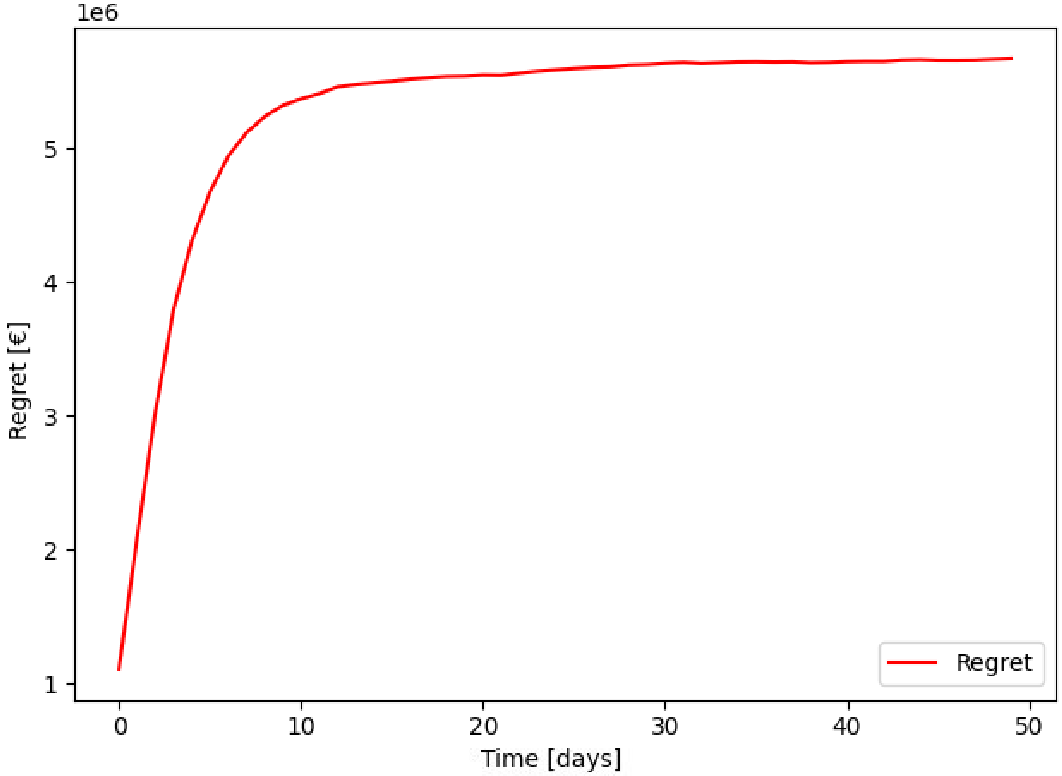
We first considered an environment without constraints, to later focus on a constrained variation.

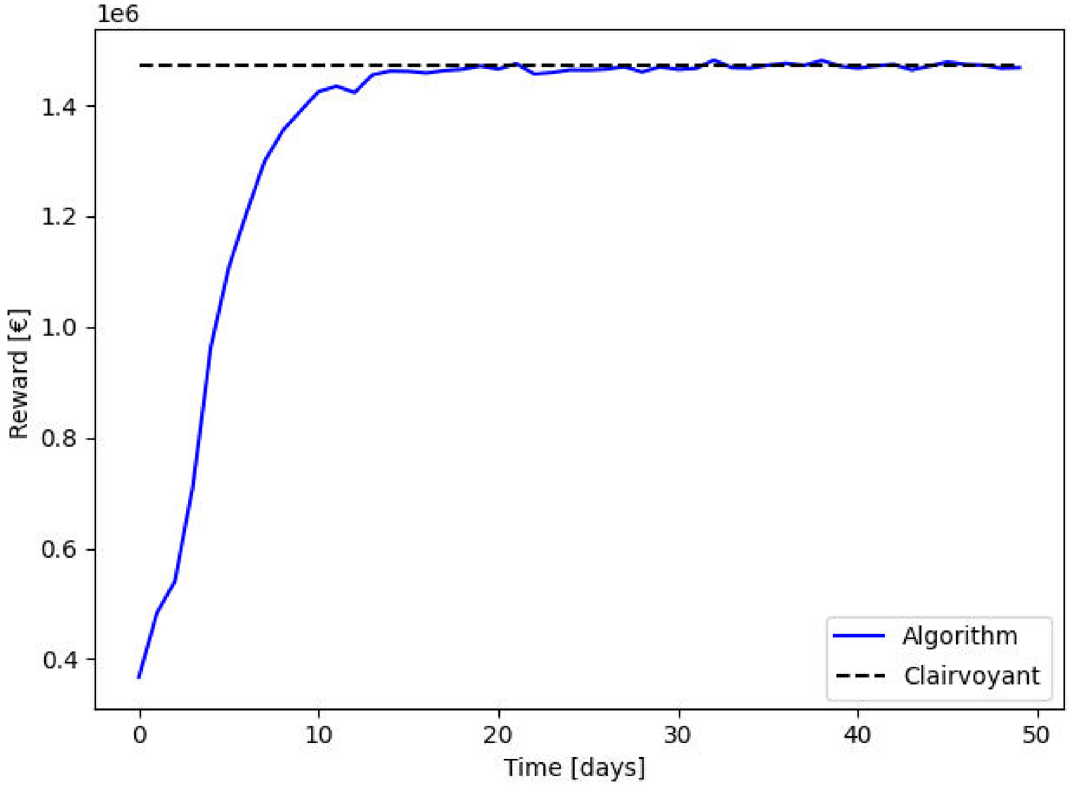
The Algorithm (No Costraints)

Algorithm 5 Optimization Algorithm

$J \leftarrow$ all classes of users
for $day \in T$ **do**
    for $j \in \{1, ..., J\}$ **do**
        $p \leftarrow$ Sample(j-th TS) // Price
        $a \leftarrow$ Get predicted conversion-rate given the pulled arm
        $c \leftarrow$ Sample(j-th GPTS) // Number of clicks
        $b \leftarrow$ Budget(j-th GPTS) // Budget spent
        $v \leftarrow \dfrac{p \cdot a \cdot c - b}{c}$ // Value per click
        Add row $v \cdot c$ to knapsack matrix
    end for
    $a \leftarrow$ Optimize knapsack matrix
    $rew \leftarrow$ Play selected superarm a
    Update GPTS-Learners model
    Update TS-Learners model
end for

The Results (No Constraints)



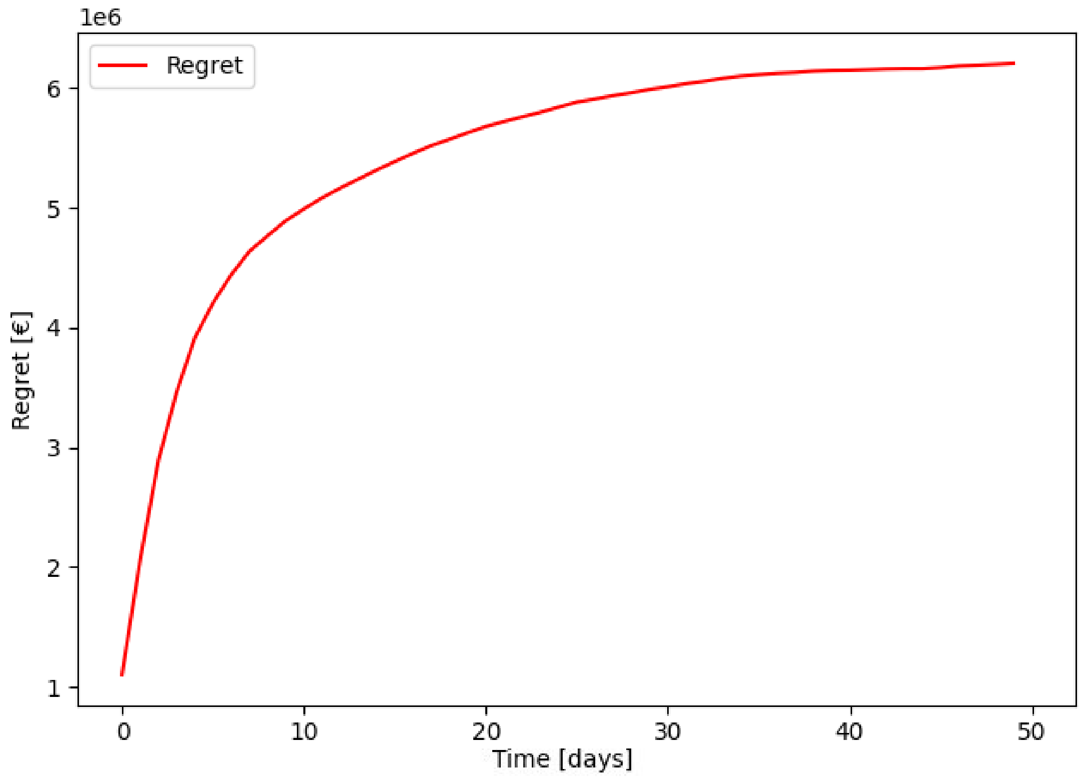


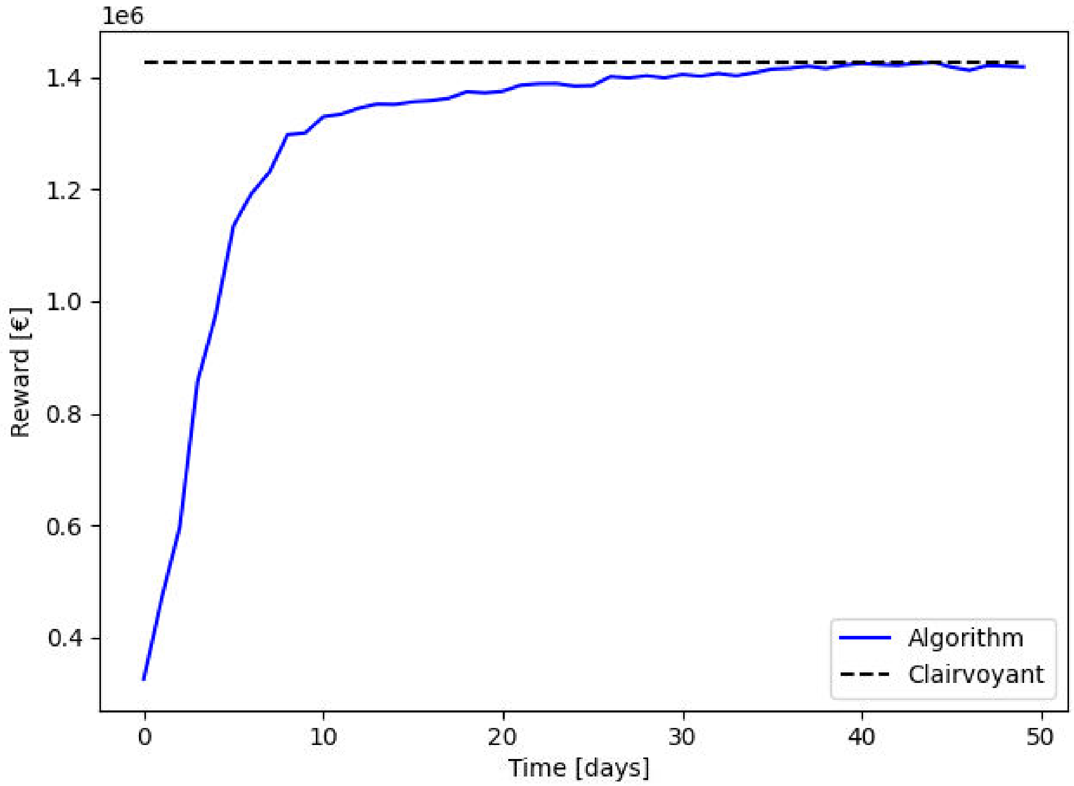
The Algorithm (With Costraints)

Algorithm 6 Budget and Pricing optimization with fixed price

for $1 \leq t \leq T$ **do**
$\theta \leftarrow$draw a sample from all TS Learners
for $p \in \theta$ **do**
$d_p \leftarrow demand(p)$
for $1 \leq c \leq C$ **do**
for $1 \leq b \leq |B|$ **do**
$clicks_{c,b} \leftarrow$Estimate clicks from GPTS learners
$vpc_{c,b} \leftarrow$Estimate values per click
end for
end for
$b_{best_p} \leftarrow$Use CMAB optimizer to get best budget allocation
$r_{exp_p} \leftarrow$Use CMAB optimizer to get expected revenues
end for
$r_{max} \leftarrow \max r_{exp}$
$(\bar{p}, \bar{b_c}) \leftarrow$Select best price and budgets associated with r_{max}
for $1 \leq c \leq C$ **do**
$(\bar{c}, \bar{b}, \bar{r}) \leftarrow$Test with env and get real clicks, buys and revenue
Update TS and GPTS learners
end for
end for

The Results (With Constraints)





Thanks
for your
attention!!