DATA INTELLIGENCE APPLICATIONS
PRICING & ADVERTISING

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ABSTRACT

The goal of the project is to model a scenario in which a seller exploits advertising tools in order to attract more and more users to its website, thus increasing the number of possible buyers.

The seller has to learn simultaneously the conversion rate and the number of users the advertising tools can attract.

In this report, we walk through the description of the specific scenario we have studied and the definition of the algorithm design choices we adopted in order to reach our goal. Then the achieved experimental results will be presented via some useful plots and a final conclusion summarizing the whole work.

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Chapter 1

Introduction: Scenario Setup

We have studied a possible real world scenario in which a seller wants to increase the number of possible buyers by exploiting advertising tools.

The product we have considered is a particular pair of shoes which has a production cost (without loss of generality we can assume that the production cost is null) and a sell price.

The analysed campaign consists of three sub-campaigns, each with a different ad to advertise the product and each targeting a different class of users. Each class is defined by the values of pre-defined features.

The feature space we have considered is characterized by two binary features:

- *Age<30* or *Age>30*
- *Profession* that can be either *student* or *worker*

So according to the values of the above described features, we can distinguish among the following classes of users:

- *Elagant*: a worker with age>30
- *Casual*: a student with age<30
- *Sport*: a worker with age<30

Chapter 2

Advertising: Clicks Maximization

2.1 Algorithm Design Choices and Results

This section deals with the description of the algorithm design choices we adopted and it also contains the most relevant reference to the code. For the description we will adopt the following structure: for each sub-section we will describe the actual scenario we are interested in by defining its goals and then we focus on how we have solved the problem and the results we have obtained.

Chapter 3

Advertising: Handling Abrupt Phases

Design a sliding-window combinatorial bandit algorithm for the case, instead, in which there are the three phases aforementioned. Plot the cumulative regret and compare it with the cumulative regret that a non-sliding-window algorithm would obtain.

Chapter 4

Pricing: Learning the Best Price

Design a learning algorithm for pricing when the users that will buy the product are those that have clicked on the ads. Assume that the allocation of the budget over the three subcampaigns is fixed and there is only one phase (make this assumption also in the next steps). Plot the cumulative regret.

4.1 Demand Curves

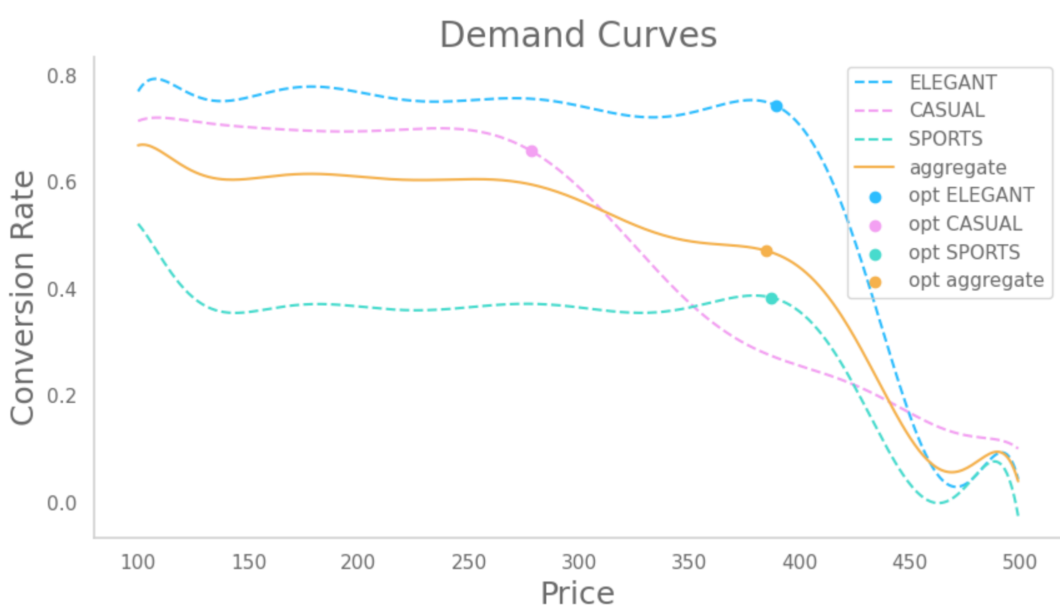


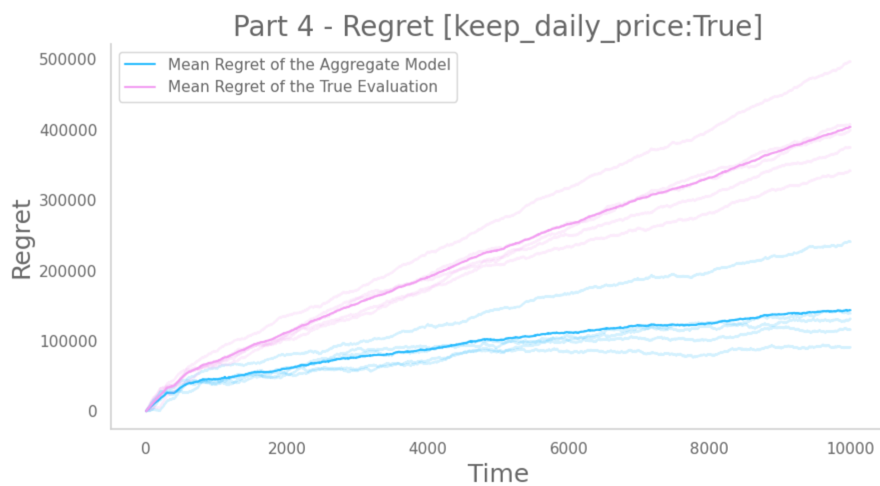
Figure 4.1: **Demand Curves**.
It used to show the probability (*conversion rate*) that a certain class, of customers, will buy or not the product w.r.t. a proposed price.
The dashed lines represent the demand curves of the corresponding classes: *blue* for the *Elegant* class; *pink* for the *Casual* class; and *light green* for the *Sports* class.
The *orange* curve is the mean between the others and it is used to study the *aggregate* model.
The points are displayed to show the optimal price w.r.t. the conversion rate: the area below them is maximum.

4.2 Environment

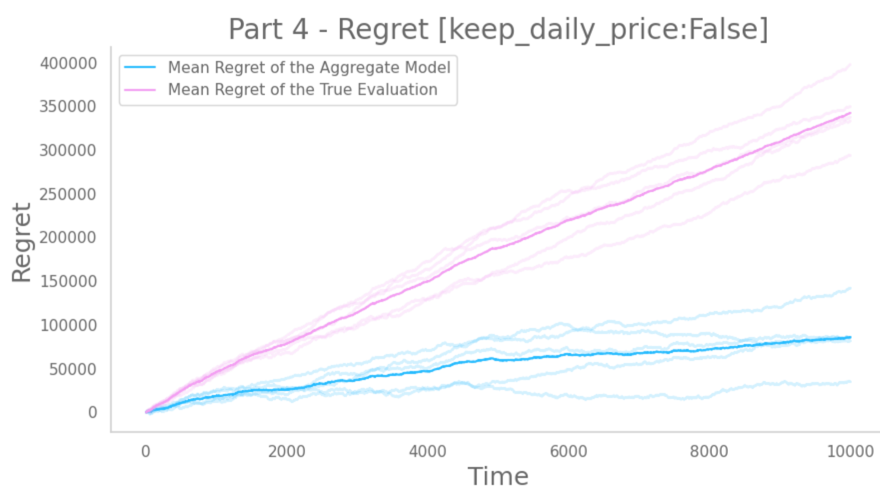
4.3 Learner Algorithm Selection

4.4 Experiments

4.5 Results



(a) Regret obtained proposing to the customers the same price for the entire day.



(b) Regret obtained proposing to the customers different prices for each visit. This method achieves better performances since the learner collects more data during the campaign.

Figure 4.2: Comparison between the regrets obtained after the campaign.
The **Mean Regret of the Aggregate Model** (colored in *blue*) is the regret computed keeping, as optimal, the area under the optimal point of the aggregate curve 4.1. In other words, both the learner and the clairvoyant don't know the class of the customers. This is an optimistic measure of the regret.
The **Mean Regret of the True Evaluation** (colored in *pink*) is the regret obtained computing the optimal value exploiting the original class of the customers.

Chapter 5

Pricing: Context Generation

Design and run a context generation algorithm for the pricing when the budget allocated to each single subcampaign is fixed. At the end of every week, use the collected data to generate contexts and then use these contexts for the following week. Plot the cumulative regret as time increases. In the next steps, do not use the generated contexts, but use all the data together.

Chapter 6

Adverting and Pricing: Combining the Algorithms

Design an optimization algorithm combining the allocation of budget and the pricing when the seller a priori knows that every subcampaign is associated with a different context and charges a different price for every context. Suggestion: the value per click to use in the knapsack-like problem depends on the pricing, that depends on the number of users of a specific class interested in buying the product. Notice that the two problems, namely, pricing and advertising, can be decomposed since each subcampaign targets a single class of users, thus allowing the computation of the value per click of a campaign only on the basis of the number of clicks generated by that subcampaign. Plot the cumulative regret when the algorithm learns both the conversion rate curves and the performance of the advertising subcampaigns.

Chapter 7

Advertising and Pricing: Fixed Prices

Do the same of Step 6 under the constraint that the seller charges a unique price to all the classes of users. Suggestion: for every possible price, fix this price and repeat the algorithm used in Step 6. Plot the cumulative regret when the algorithm learns both the conversion rate curves and the performance of the advertising subcampaigns.