# MARKDOWN OPTIMIZATION BASED ON SALES FORECASTING IN THE FASHION RETAIL SECTOR

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## INTRODUCTION

Penti is a Türkiye-based company and store chain founded in Istanbul in 1950, focusing on women's socks and underwear. It is Türkiye's leading sock brand with a market share of over 40%.

Penti has a very dynamic and variable planning process due to the sector it operates in. All processes in the fashion retail sector depend on customer behaviour. Since customer behaviour is difficult to predict and is directly affected by all social events, plans made at the beginning of the year cannot remain valid throughout the year.This project includes demand forecasting, sales forecasting and markdown optimization for Penti's underwear category.

## CURRENT SYSTEM

The forecasting and markdown optimization projects were realized for Penti's planning department. Penti's planning department is divided into two different processes: allocation planning and category planning. Penti divides its products into two groups: seasonal/fashion products and never out of stock (NOS) products. Fashion products are a group of products that are offered for sale at certain periods.NOS products are products that should never be out of stock, are suitable for daily use and are frequently preferred by everyone. These products are on sale in all seasons and customer demand is steady.

## PROBLEM DEFINITION

Penti targets the year-end profit margin at the beginning of the year and then carries out all allocation, budget planning and stock management to reach the targeted profit margin at the end of the year. The current forecasting models used by Penti are inadequate and superficial. In addition, they do not have any method to decide how much markdown will be applied to which product in which week in order to reach the desired profit margin. These deficiencies prevent Penti from reaching its targeted profit margin.

## METHODOLOGY

### DATA DESCRIPTION

The project focused on analyzing the 2017-2018 women's underwear sales data from Penti, divided into two categories: Fashion and Never out of Stock (NOS). Each category included two product groups: under-drawers and bras. The Fashion category had 11 under-drawers types and 5 bra types, while the NOS category had 9 under-drawers types and 7 bra types. The analysis included color specifications, weekly net unit sales, and markdown data.

To enhance accuracy, additional factors were incorporated: weekly averages of daily gold prices, net minimum wage, and dollar values; special days (Valentine's Day, Women's Day, Mother's Day, Eid al-Fitr, Eid al-Adha, New Year's Eve); direct and indirect campaigns; and weather data for Istanbul, Ankara, and Izmir. The special days and campaign data were gathered from social media accounts.

### DEMAND FORECASTING

The project involves analyzing Penti's women's underwear sales data from 2016, 2017, and 2018, with a focus on data from 2017 and 2018 due to inconsistencies in the 2016 data. The analysis includes input data sources (sales data from Penti and external sources), notebooks for data preprocessing, prediction, and model training, output data sources containing predictions, and registered models with the best-performing XGBoost models for Fashion and Never Out of Stock (NOS) products. Data preprocessing involved converting categorical variables using LabelEncoder, creating correlation matrices, identifying features (X) and target variables (Y), and normalizing the training data. Model parameters were optimized using GridSearchCV, and the datasets were tested using Decision Tree and XGBoost methods. Model performance was evaluated using metrics such as Mean Absolute Error, Mean Squared Error, Median Absolute Error, Explained Variance Score, and R² scores.

INPUTS
↓
DATASET PREPROCESSING
↓
SPLITTING DATASET INTO TRAIN AND TEST
↓
FEATURE SELECTION
↓
MODEL BUILDING (XGBOOST,DECISION TREE)
↓
PREDICTION (XGBOOST, DECISION TREE)

### SALES FORECASTING

The project aimed to predict weekly sales for Penti's women's underwear products by analyzing the relationship between weekly sales and markdown levels. Initially, product-based analysis failed to show a meaningful relationship between sales and markdown levels. Consequently, the analysis shifted to a category-based approach, examining 16 categories each for the Never Out of Stock (NOS) and Fashion product groups. The weekly sales coefficient, calculated by dividing each week's sales by the previous week's sales, was associated with markdown levels. Significant sales coefficients were found for 10 NOS categories and 9 Fashion categories. These coefficients were then used to adjust sales predictions based on markdown levels. Sales forecasts without markdowns were obtained from the demand forecasting model, while forecasts with markdowns were adjusted using the sales coefficients. This method created a weekly sales dataset for each markdown level for each product, which was used in the mathematical model.

### MATHEMATICAL MODEL

***Indices***

$i$ *Products*

$j$ *Weeks*

$l$ *Markdown levels*

***Parameters***

$H_{ij}$ *Holding cost of product i in week j*

$V_{ijl}$ *Number of sales of product i in week j when markdown is applied at level l*

$c_l$ *Price coefficient varying according to markdown level l*

$FP_i$ *Initial price of product i*

$FN_i$ *Initial stock quantity of product i*

***Decision Variables***

$X_{ijl}\begin{cases}1, & \text{If level } l \text{ md is applied to product } i \text{ in week } j\\ 0, & ow\end{cases}$

$P_{ij}$ *Sales price of product i in week j*

$S_{ij}$ *Number of sales of product i in week j*

$N_{ij}$ *Stock amount of product i at the beginning of week j*

***Objective Function***

$$Max\ Z = \sum_i \sum_j S_{ij}\left(FP_i \sum_l c_l X_{ijl}\right) - \sum_i \sum_j H_{ij} N_{ij} \quad (1)$$

*subject to*

| | | |
|---|---|---|
| $P_{i1} = FP_i$ | $\forall i$ | (2) |
| $N_{i1} = FN_i$ | $\forall i$ | (3) |
| $N_{ij} - S_{ij} = N_{i(j+1)}$ | $\forall i, j$ | (4) |
| $S_{ij} \geq V_{ijl} - M(1 - X_{ijl})$ | $\forall i, j, l$ | (5) |
| $S_{ij} \leq V_{ijl} + M(1 - X_{ijl})$ | $\forall i, j, l$ | (6) |
| $P_{ij} \geq c_l FP_i - M(1 - X_{ijl})$ | $\forall i, j, l$ | (7) |
| $P_{ij} \leq c_l FP_i + M(1 - X_{ijl})$ | $\forall i, j, l$ | (8) |
| $\sum_l X_{ijl} = 1$ | $\forall i, j$ | (9) |
| $S_{ij} \leq N_{ij}$ | $\forall i, j$ | (10) |
| $P_{ij} \geq 0$ | $\forall i, j$ | (11) |
| $S_{ij} \geq 0$ | $\forall i, j$ | (12) |
| $N_{ij} \geq 0$ | $\forall i, j$ | (13) |
| $X_{ijl} \in \{0,1\}$ | $\forall i, j, l$ | (14) |

Eq. (2) and (3) show each product's initial price and inventory. Eq. (4) is stock balance constraint. The estimated sales amount each week determines next week's stock. Sales quantity constraints shown in Eq. (5) and (6). Price calculation constraints shown in Eq. (7) and (8). The new prices of the products are calculated by multiplying the initial price and the markdown selected from the sales forecast. Eq. (9) ensures that a level 1 markdown is applied to each product in each week. Eq. (10) ensures that the sales quantity cannot exceed the stock quantity. Eq. (11), (12) and (13) are non-negativity constraints. Eq. (14) is binary constraint.

The stock of products in the NOS category is supported by additional stock. To ensure this in the model, the parameter $N'_{ij}$, which represents the additional stock of NOS products, was defined and added to Eq. (4). As a result, when the model was run for NOS products, the new stock balance constraint was shown with Eq. (15).

$$N'_{ij} + N_{ij} - S_{ij} = N_{i(j+1)} \qquad \forall i, j \qquad (15)$$

In this model, the multiplication of the binary and continuous decision variables in the objective function makes the model non-linear. Asghari et al. (2022) mentions that the product of binary and continuous variables is linearized by replacing it with a new variable subject to a new set of constraints.To linearize the bilinear term $S_{ij}X_{ijl}$ we replace it with the auxiliary variable $W_{ijl}$. Furthermore, the following constraint sets which are Eq. (16), (17), (18) and (19), also be imposed on the linear equivalent formulation, which force $W_{ijl}$ to take the value of $S_{ij}X_{ijl}$:

| | | |
|---|---|---|
| $W_{ijl} \leq S_{ij}$ | $\forall i, j$ | (16) |
| $W_{ijl} \leq M(X_{ijl})$ | $\forall i, j, l$ | (17) |
| $W_{ijl} \geq S_{ij} + M(X_{ijl} - 1)$ | $\forall i, j, l$ | (18) |
| $W_{ijl} \geq 0$ | $\forall i, j, l$ | (19) |

Linearized new objective function is shown Eq. (20):

$$Max\ Z = \sum_i \sum_j \sum_l c_l\, FP_i W_{ijl} - \sum_i \sum_j H_{ij} N_{ij} \qquad (20)$$

To show that linearization was applied correctly, the nonlinear and linearized version of the model was solved in both linear and nonlinear solvers in Gams. The results of the model run with a small dataset (5 product and 10 weeks) for each category are given in Table 2.

| | Nonlinear Model Result | Linearized Model Result |
|---|---|---|
| NOS | 42340 | 42505 |
| Fashion | 47830 | 48020 |

Following these results, the study continued with the linearized model. This model was run with different data and the results were analyzed in the Result section.

The code written in accordance with GAMS to analyze the Markdown optimization model was translated into Python code so that the company could access it more easily. Afterwards, a web-based platform was designed and interfaced to facilitate the company's uploading, processing and downloading of Excel files. The front end of the project is built using HTML, CSS and JavaScript. It creates a user-friendly interface where the company can upload different types of Excel files through a structured form layout. Optimization model results are returned as an Excel file. There are applied markdown levels, stock information, sales price information and total turnover information on different pages of the file.

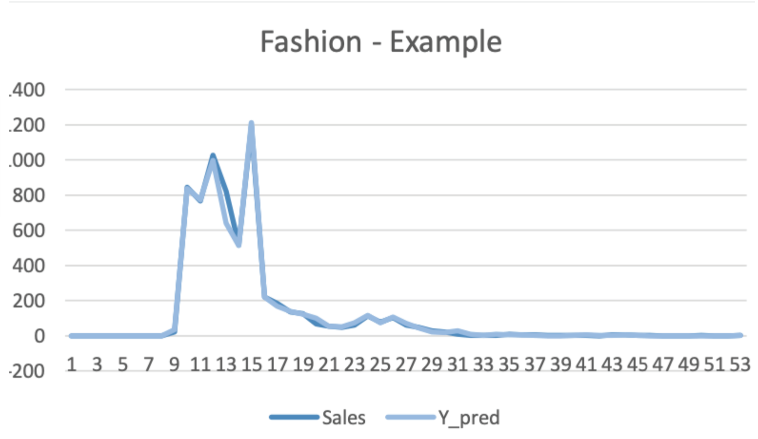
## RESULTS

**Demand Forecasting R² Score**

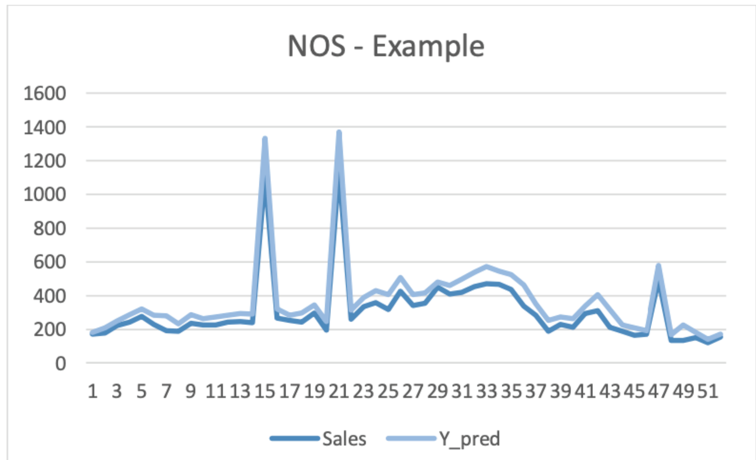
| Product | Method | Result (R² Score) |
|---|---|---|
| NOS | XGBoost | 0.93 |
| NOS | Decision Tree | 0.89 |
| Fashion | XGBoost | 0.72 |
| Fashion | Decision Tree | 0.43 |

**Comparison of Demand Forecasting Result and Real 2019 Data**

| Products Category | Forecast Results |
|---|---|
| Non-Wired Bra | 1.39% |
| Other Bra | 0.21% |
| Short Top | 0.00% |
| Lifting Bra | -1.15% |
| Minimizer Bra | 0.24% |
| Outlet Bra | 0.17% |
| Push Up Bra | -2.17% |




**Fashion and NOS Forecast Result Example**




The aim of the model is to maximize total turnover and minimize holding costs and as a result of the model, it was decided how much markdown would be applied to which product in which week. In the initial stock level analysis, the change in total turnover was observed by decreasing and increasing the initial stock levels, which were obtained with the forecasting results and used as input to the markdown optimization model, by 5%, 10% and 15%. In the comparison made for certain product groups for which Penti shared 2019 real sales data, a deviation of 10% was found as a result of the forecasting with XGBoost method, and this deviation value is less than the deviation values in the forecasting results used by Penti.

| Initial Stock Level Change | Turnover Change |
|---|---|
| -5% | -4.80% |
| 5% | 4.20% |
| -10% | -10.10% |
| 10% | 4.40% |
| **15%** | **4.70%** |

**Initial Inventory Analysis of Fashion and NOS Products**

| Initial Stock Level Change | Turnover Change |
|---|---|
| -5% | 0.60% |
| 5% | -0.50% |
| **-10%** | **1.20%** |
| 10% | -1.30% |
| 15% | -2.20% |

**Comparison of Result at Different Initial Stock Level**

| | Normal | 10.90% |
|---|---|---|
| Initial Stock Level | **-5%** | **11.50%** |
| | 5% | 10.00% |
| | 10% | 8.90% |
| | 15% | 7.80% |

When the total turnover value obtained as a result of the markdown optimization model is compared to the actual turnover value shared by Penti for certain product groups in 2019, an improvement of 10.9% was achieved. As a result of the initial stock level analysis, it was observed that the total turnover increased when the initial stock level decreased for NOS products, and the total turnover also increased when the initial stock level increased for fashion products. Finally, an interface was designed to make the project usable and sustainable for Penti.

INDUSTRIAL ENGINEERING

Penti