Analytics for an Online Retailer: Demand Forecasting and Price Optimization

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Online Retailing: Online Fashion Sample Sales Industry

- Offers extremely limited-time discounts (“flash sales”) on designer apparel & accessories
- Emerged in mid-2000s and has had nearly 50% annual growth in last 5 years
- Key players
  - Rue La La (US)
  - Gilt Groupe (US)
  - Markafoni (Turkish)
  - Trendyol (Turkish)
Snapshot of Rue La La’s Website

From the Reserve: Watches by Rolex & Cartier
CLOSING IN 2 DAYS, 19:47:42

Judith Ripka Jewelry & Watches
CLOSING IN 2 DAYS, 19:47:42

Check Off His List: Gift Ideas Under $100
CLOSING IN 2 DAYS, 19:47:42

Saucony Women
CLOSING IN 1 DAY, 19:47:42

Furs by Christian Dior & More: Picks by WGACA
CLOSING IN 1 DAY, 19:47:42

Saucony Men
CLOSING IN 1 DAY, 19:47:42
“Style”

Saucony "Triumph 10" Running Shoe
$130.00  $79.90

Saucony "Progrid Guide 6" Running Shoe
$110.00  $65.90

Saucony "Triumph 10" Running Shoe
$130.00  $79.90
“SKU”

Saucony "Progrid Guide 6" Running Shoe

$110.00  $65.90

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Quantity

1

ADD TO BAG

Sign up for Quick! Buy it. Never miss out on something you love.
Flash Sales Operations

- Merchants purchase items from designers
  - Designers ship items to warehouse*
    - Merchants decide when to sell items (create “event”)
      - During event, customers purchase items
        - Sell out of item?
          - Yes: First event that style is sold = “1st exposure”
          - No: End
*Sometimes designer will hold inventory
Video 1 Placeholder:

https://www.youtube.com/watch?v=ahOHAsECeIw&feature=youtu.be
Goal: Maximize expected revenue from 1st exposure styles

Demand Forecasting

Challenges:
- Predicting demand for items that have never been sold before
- Estimating lost sales

Techniques:
- Clustering
- Machine learning models for regression

Price Optimization

Challenges:
- Structure of demand forecast
- Demand of each style is dependent on price of competing styles → exponential # variables

Techniques:
- Novel reformulation of price optimization problem
- Creation of efficient algorithm to solve daily
Example Sales Curve for an Item that Doesn’t Sell Out

(sales < inventory)

\[ \text{demand} = \text{actual sales} \]
Example Sales Curve for an Item that Does Sell Out

\(sales = inventory\)

stock out 10 hours into event

demand = actual sales + estimated lost sales during period after stock out
Estimating Lost Sales

• Use data from items that did not stock out to predict lost sales of items that did stock out

• For each event length…
  – Aggregate hourly sales given set of characteristics, i.e. event start time of day
  – Create sales curve for each set of characteristics
    • Results in hundreds of sales curves
    • Use clustering to help further aggregate
Example Clustering Results: Demand Curves for 2-Day Events

8PM event with 100 units inventory sells out after 5 hours

Demand = \( \frac{100}{0.50} \) = 200 units
Forecasting Model: Explanatory Variables Included

Products
- Department
- Class
- Color Popularity
- Size Popularity
- Brand Type A/B
- Brand Popularity

Combination
- Price
- % Discount = (1 – Price / MSRP)
- # Concurrent Events in Department
- # Styles Sold in Same Subclass and Event (i.e. # Competing Styles)
- Relative Price of Competing Styles
- # Branded Events in Previous 12 Months

Events
- Year
- Month
- Week Day / Time
- Event Type
- Event Length

Each input is calculated for a unique \{style, event\} pair.
**Forecasting Model Approach**

- Separate data by department; for each department...
  - Randomly divide into training & testing data sets
  - Apply several machine learning techniques to training data
    - Linear regression
    - Power regression
    - Semi-logarithmic regression
    - **Regression trees**
  - Use cross-validation to choose best model
Regression Tree – Illustration

If condition is true, move left; otherwise, move right

Demand prediction
Approach

Goal: Maximize expected revenue from 1st exposure styles

Demand Forecasting

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Price Optimization

Challenges:
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Techniques:
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Complexity

• Three of the features used to predict demand are associated with pricing
  – Price
  – % Discount = \( \frac{1 - \text{Price}}{\text{MSRP}} \)
  – Relative Price of Competing Styles = \( \frac{\text{Price}}{\text{Avg. Price of Competing Styles}} \)

• Pricing must be optimized concurrently for all competing styles
Key Observation

- Demand depends only on *average* price of competing styles

- Let \( N = \# \) competing styles (to be priced concurrently), and let \( k = \) the sum of prices of all styles
  - Average price = \( \frac{k}{N} \)
  - Relative price of competing styles = \( \frac{price}{k/N} \)

- Finite set of possible prices
  - Prices must end in $4.90 or $9.90
  - Consists of lower bound, upper bound, and every increment of $5.00 between the bounds
  - Ex: \{ $24.90, $29.90, $34.90, $39.90 \}
Key Idea for Algorithm

- Formulate integer optimization problem for each value of $k$, $(IP_k)$

\[
\text{Maximize Revenue}
\]
\[
\text{s.t. } 1) \quad \text{Each style must be assigned exactly one price}
\]
\[
2) \quad \text{Sum of prices of all styles must } = k
\]

- Can show that optimal objective of $(IP_k)$ and its linear relaxation only differ by the revenue associated with a single style!
  - Independent of problem size

- Use this to develop efficient algorithm to solve on daily basis
IMPLEMENTATION & IMPACT
Pricing Decision Support Tool

Rue La La Enterprise Resource Planning System
- Products
- Transactions
- Events Planning
- Rue La La Database
- ETL Process
- Reports and Visualization
- Query / Drill Down Visualizer
- Ad hoc Reports
- Standard Reports
- Optimizer Database
- Optimal Price Recommendations
- LP Bound Algorithm
- Optimization Input
- LP_Solve API-based Optimizer

Retail Price Optimizer
- Statistics Tool - R
- Impending Event Data
- Regression Tree Prediction (Rscript)
- Inventory Information
- R Predictions
- Inventory-Constrained Demand Prediction
Video 2 Placeholder:
https://www.youtube.com/watch?v=lc4wV6O_YDA&feature=youtu.be
Live Tests

• Motivated by historical analysis
  – Suggests model recommended price increases will increase revenue by ~10% with little to no impact on demand
• Set lower bound on price = merchant suggested price
  – Model only recommends price increases (or no change)
• Identified ~1,300 event-subclass combinations where tool recommended price increases for at least one style
Live Tests

1,300 Event-Subclass Combinations

- Category A
  - Treatment (increase price)
  - Control (no change)

- Category B
  - Treatment (increase price)
  - Control (no change)

- Category C
  - Treatment (increase price)
  - Control (no change)

- Category D
  - Treatment (increase price)
  - Control (no change)

- Category E
  - Treatment (increase price)
  - Control (no change)

lowest price point

highest price point
Mann-Whitney / Wilcoxon Rank Sum Test

- Hypothesis test that assumes no particular distributional form on treatment or control groups
  - \( H_0 \): raising prices has no effect on sell-through
  - \( H_A \): raising prices decreases sell-through

- Idea of test
  - Combine sell-through data of treatment and control groups
  - Order data and assign rank to each observation
  - Sum ranks of all treatment group observations
  - If sum is too low, reject \( H_0 \)
Mann-Whitney / Wilcoxon Rank Sum Test

1,300 Event-Subclass Combinations

Category A
- Treatment (increase price)
- Control (no change)
- Rejects $H_0$ $\alpha = 1\%$

Category B
- Treatment (increase price)
- Control (no change)
- Does not reject $H_0$ $\alpha = 10\%$

Category C
- Treatment (increase price)
- Control (no change)
- Does not reject $H_0$ $\alpha = 20\%$

Category D
- Treatment (increase price)
- Control (no change)
- Does not reject $H_0$ $\alpha = 20\%$

Category E
- Treatment (increase price)
- Control (no change)
- Does not reject $H_0$ $\alpha = 20\%$
Visual Comparison

Comparison of Sell-Through: Treatment vs. Control Groups

- Category A
- Category B
- Category C
- Category D
- Category E

Sell-Through (% Inventory Sold)

Control
Treatment
Revenue Impact

- Treatment group’s increase in revenue, assuming demand is impacted by price increases as shown on previous slide
Video 3 Placeholder:

https://www.youtube.com/watch?v=AzJhAxkpkEU&feature=youtu.be
Conclusion

• Created and implemented pricing decision support tool that recommends prices for 1\textsuperscript{st} exposure styles
  – Used clustering to estimate lost sales
  – Built regression trees to predict demand
  – Developed efficient algorithm to solve multi-product price optimization problem

• Implementation of these analytics techniques shows expected increase in revenue of \(~10\%\) with little impact on demand
Our Team

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