On Product Pricing

Christian Setzkorn

2018/09/19
Talk Outline

- My Background, Shop Direct
- Motivation, Pricing Data (Challenges)
- Elasticity, Cross Elasticities, Pull Forward Effect
- Multi-Objective Optimisation
- (Competitor Impact Analysis)
My Background

University Of Liverpool – Computer Science (1999-2005)
- MSc Parallel And Scientific Computation
- PhD Machine Learning Using Multi-Objective Evolutionary Algorithms

NHS – Clinical Engineering (2004-2006)
- Applied Multi-Objective Evolutionary Algorithms To Cancer Data
- Implemented Databases And Websites For International Cancer Research

University Of Liverpool - NCZR (2006-2012)
- Applied Multi-Objective Evolutionary Algorithms To Zoonosis data
- Integrated And Exploited Data For Zoonosis Research
- Analysed Cattle Movement Data For Defra
- Implemented Databases And Websites For International Zoonosis Research
- Coauthored About 43 Papers Published In For Example Nature

Commercial Full Stack Software Developer (2012-2016)
- Modelled Heating Of Underground Cables Used For Smart Grids
- Implemented Databases, Websites And BI Solutions

Data Scientist – Shop Direct Data Intelligence (2016-Date)
- Pricing
- Data Integration
- Financial Modelling (Presence Value Modelling)
Shop Direct
Shop Direct Brands

- very.co.uk: 169K Products
- Littlewoods.ie: 111K Products
- Littlewoods.com: 152K Products
- SHOP DIRECT
- VE: Very Exclusive: 10K Products
Some Facts About Shop Direct

- £1.96bn Annual Sales (£1.39bn Very)
- UK’s Second Largest Pureplay Etailer
- 49+ Million Products Delivered Every Year
- 4.02 Million Customers
- 1.4 Million Website Visits Per Day On Average
- 1800+ Brands Sold
- CollectPlus To Deliver To 7,000 stores
Head Office - Speke Liverpool

• Head Office - Skyways House (Grade 2 Listed Former Aircraft Hangar)
• Distribution Centers: Shaw, Raven etc.
• Future Automated Warehouse East Midlands
• Office Dublin (Littlewoods Ireland) And London
Inside The Head Office In Speke
Nicole Scherzinger Visit Last Week

SHOP DIRECT
BEAUTY EVENT
WEDNESDAY 12TH SEPTEMBER, 11.30AM – 2.30PM

NICOLE SCHERZINGER
WILL BE HERE PROMOTING HER FRAGRANCE IN THE STREET!

Q&A AND PHOTO OPPORTUNITY FROM 11.45AM
Inside Our London Office
1st Year Anniversary Recently
Talk Outline

- My Background, Shop Direct
- **Motivation, Pricing Data (Issues)**
  - Elasticity, Cross Elasticities, Pull Forward Effect
  - Multi-Objective Optimisation
  - (Competitor Impact Analysis)
Motivation - Why Pricing?

Pricing is the lever with the highest and quickest impact on profit.

- Optimise Profit, Revenue
- Improve Price Perception
- Increase Market Share
- Allows Intelligent Bundling, Targeting And Recommending
- Control Stock
- Negotiate Costs

![Willingness To Pay Overbidding/Underbidding](chart.png)
Pricing Data Example – Price And Units Of Upright Dyson Hoover In 2016
Pricing Data Example – Price, Units And Stock Of Upright Dyson Hoover In 2016

[Graph showing pricing data with labels for units, price, and stock over time from 1/1/2016 to 12/1/2016.]
Promotion Data Of Upright Dyson Hoover In 2016

Units Depending On Promotions

Prices Depending On Promotions
Determine Promotions Automatically

30 days

30 days

95% Of Max

Price

Price Threshold
Television Example
Electronic Item Prices Usually Decline During Product’s Life Cycle
Data Issues - Customer Account Management System (CAM)
Price Data Extraction - For Old Data We Only Have Transactional Data
Price Only Known If Product Was Sold

Scheduled Processes To Create Pricing Data
Talk Outline

- My Background, Shop Direct
- Motivation, Pricing Data (Issues)
  - Elasticities, Cross Elasticities, Pull Forward Effect
  - Multi-Objective Optimisation
  - (Competitor Impact Analysis)
Price Elasticity is defined as the percentage change in quantity demanded due to a percentage change in price.

Elastic (E > 1)
- Price decrease increases total revenue
- Price increase decreases total revenue

<table>
<thead>
<tr>
<th>Product Examples</th>
<th>Examples</th>
</tr>
</thead>
<tbody>
<tr>
<td>More substitutable and more comparable</td>
<td>Furniture, large televisions, washing machines</td>
</tr>
<tr>
<td>High price items</td>
<td></td>
</tr>
</tbody>
</table>

Inelastic (E < 1)
- Price increase increases total revenue/margin

<table>
<thead>
<tr>
<th>Product Examples</th>
<th>Examples</th>
</tr>
</thead>
<tbody>
<tr>
<td>Fewer substitutes/necessities and less comparable</td>
<td>Petrol/diesel, Water (Insulin)</td>
</tr>
</tbody>
</table>

Arc or Mid-Point Formula

\[
|E_d| = \left(\frac{\frac{Q_2 - Q_1}{2}}{\frac{P_2 - P_1}{2}}\right) = \frac{\%\Delta Q}{\%\Delta P}
\]
Factors Affecting Price Elasticities

- Price Itself
- Customer Segments
- Time
  - E.g. Weather - Seasonality
  - Economy
- Availability Of Substitutional Products
- Products ‘Interactions’ - Internal and External
Estimating (Point) Elasticities Using Log Log Linear Regression Models

Log Demand = Intercept + Elasticity * Log Price
+ Dummies: Promos, Seasonality, Interactions … + ϵ

- Estimates percent change in demand for a percent change in price
- Example: Elasticity = -3 (elastic as abs(-3) = 3)
  - 1% price decrease => 3% demand increase
  - 1% price increase => 3% demand decrease
- Simple inferential shallow model that can be fitted fast
### Elasticity Results

Many Products Result In Invalid Models

Reasons: Too Few Price Changes/Sales, Short Product Life Cycles

<table>
<thead>
<tr>
<th>Brand</th>
<th>Valid</th>
<th>Invalid</th>
</tr>
</thead>
<tbody>
<tr>
<td>Very</td>
<td>27%</td>
<td>73%</td>
</tr>
<tr>
<td>Littlewoods</td>
<td>28%</td>
<td>72%</td>
</tr>
<tr>
<td>Littlewoods</td>
<td>15%</td>
<td>85%</td>
</tr>
</tbody>
</table>

#### Validity Definition
- E <= 0
- E >= -10
- P Values
- F Statistics
- R Squared

<table>
<thead>
<tr>
<th>Trading Department</th>
<th>Invalid</th>
<th>Valid</th>
</tr>
</thead>
<tbody>
<tr>
<td>CHILDRENSWEAR</td>
<td>70.14%</td>
<td>29.86%</td>
</tr>
<tr>
<td>ELECTRICAL</td>
<td>70.26%</td>
<td>29.74%</td>
</tr>
<tr>
<td>FOOTWEAR &amp; ACCESSORIES</td>
<td>79.48%</td>
<td>20.52%</td>
</tr>
<tr>
<td>FURNITURE &amp; HOMEWARE</td>
<td>57.20%</td>
<td>42.80%</td>
</tr>
<tr>
<td>MENSWEAR</td>
<td>82.55%</td>
<td>17.45%</td>
</tr>
<tr>
<td>SEASONAL</td>
<td>74.05%</td>
<td>25.95%</td>
</tr>
<tr>
<td>SPORTSWEAR</td>
<td>76.37%</td>
<td>23.63%</td>
</tr>
<tr>
<td>WOMENSWEAR</td>
<td>77.21%</td>
<td>22.79%</td>
</tr>
</tbody>
</table>

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From Data to Insights to Action
Escalation/Imputation Process To Provide Elasticities At Product Level And Other Trading Hierarchy Nodes

<table>
<thead>
<tr>
<th>Some Basic Statistics</th>
<th>Departments</th>
</tr>
</thead>
<tbody>
<tr>
<td>9 Departments</td>
<td>1. ELECTRICAL</td>
</tr>
<tr>
<td>82 Categories</td>
<td>2. VERY EXCLUSIVE</td>
</tr>
<tr>
<td>283 Sub Categories</td>
<td>3. WOMENSWEAR</td>
</tr>
<tr>
<td>1080 Ranges</td>
<td>4. FURNITURE &amp; HOMEWARE</td>
</tr>
<tr>
<td>169k Products (Very)</td>
<td>5. SPORTSWEAR</td>
</tr>
<tr>
<td>2500 Brands</td>
<td>6. CHILDRENSWEAR</td>
</tr>
<tr>
<td></td>
<td>7. SPORTS BRANDS</td>
</tr>
<tr>
<td></td>
<td>8. MENSWEAR</td>
</tr>
<tr>
<td></td>
<td>9. SEASONAL</td>
</tr>
</tbody>
</table>
### Elasticities At Department Level

<table>
<thead>
<tr>
<th>Trading Department</th>
<th>Inelastic</th>
<th>Elastic</th>
</tr>
</thead>
<tbody>
<tr>
<td>SPORTSWEAR</td>
<td>14.73%</td>
<td>85.27%</td>
</tr>
<tr>
<td>CHILDRENSWEAR</td>
<td>16.26%</td>
<td>83.74%</td>
</tr>
<tr>
<td>ELECTRICAL</td>
<td>17.99%</td>
<td>82.01%</td>
</tr>
<tr>
<td>MENSWEAR</td>
<td>23.42%</td>
<td>76.57%</td>
</tr>
<tr>
<td>SEASONAL</td>
<td>24.80%</td>
<td>75.20%</td>
</tr>
<tr>
<td>FOOTWEAR &amp; ACCESSORIES</td>
<td>30.26%</td>
<td>69.74%</td>
</tr>
<tr>
<td>WOMENSWEAR</td>
<td>35.56%</td>
<td>64.43%</td>
</tr>
<tr>
<td>FURNITURE &amp; HOMEWARE</td>
<td>69.12%</td>
<td>30.88%</td>
</tr>
</tbody>
</table>
## Brand Elasticities

<table>
<thead>
<tr>
<th>Brand</th>
<th>Inelastic</th>
<th>Elastic</th>
</tr>
</thead>
<tbody>
<tr>
<td>RIVER ISLAND</td>
<td>6%</td>
<td>93%</td>
</tr>
<tr>
<td>ADIDAS ORIGINALS</td>
<td>7%</td>
<td>93%</td>
</tr>
<tr>
<td>CLARKS</td>
<td>11%</td>
<td>89%</td>
</tr>
<tr>
<td>CONVERSE</td>
<td>12%</td>
<td>88%</td>
</tr>
<tr>
<td>SUPERDRY</td>
<td>15%</td>
<td>85%</td>
</tr>
<tr>
<td>LACOSTE</td>
<td>15%</td>
<td>85%</td>
</tr>
<tr>
<td>APPLE</td>
<td>15%</td>
<td>85%</td>
</tr>
<tr>
<td>V BY VERY</td>
<td>18%</td>
<td>82%</td>
</tr>
<tr>
<td>LADYBIRD</td>
<td>19%</td>
<td>81%</td>
</tr>
<tr>
<td>NIKE</td>
<td>19%</td>
<td>80%</td>
</tr>
<tr>
<td>ADIDAS</td>
<td>21%</td>
<td>79%</td>
</tr>
<tr>
<td>TED BAKER</td>
<td>24%</td>
<td>76%</td>
</tr>
<tr>
<td>CALVIN KLEIN</td>
<td>26%</td>
<td>74%</td>
</tr>
<tr>
<td>MISS SELFRIDGE</td>
<td>28%</td>
<td>72%</td>
</tr>
<tr>
<td>SOUTH</td>
<td>30%</td>
<td>70%</td>
</tr>
<tr>
<td>TOMMY HILFIGER</td>
<td>32%</td>
<td>68%</td>
</tr>
<tr>
<td>JOE BROWNS</td>
<td>37%</td>
<td>62%</td>
</tr>
</tbody>
</table>
Cross Elasticity (CE) Measures Responsiveness Of Demand For Product X Following Change In Price Of Product Y - Responsiveness Is Directional

Substitutional Products
Cannibalisation

Complimentary Products
Halo/Affinity Effect

Arc or Mid-Point Formula

Two goods that are substitutes have a positive cross elasticity of demand: as the price of good Y rises, the demand for good X rises

CE > 0

Two goods that complement each other show a negative cross elasticity of demand: as the price of good Y rises, the demand for good X falls

CE < 0

<table>
<thead>
<tr>
<th>Product Y</th>
<th>Product X</th>
</tr>
</thead>
<tbody>
<tr>
<td>Cola 1</td>
<td>Cola 2</td>
</tr>
<tr>
<td>Mobile 1</td>
<td>Mobile 2</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Product Y</th>
<th>Product X</th>
</tr>
</thead>
<tbody>
<tr>
<td>Hamburger Meat</td>
<td>Cheese</td>
</tr>
<tr>
<td>Television</td>
<td>Television Bracket</td>
</tr>
</tbody>
</table>

“If you don’t cannibalize yourself, someone else will.”

Steve Jobs
Internal Product Interaction Pairs
There Are Many Interaction Pairs – 140 Products => About 10000 Pairs

\[
\frac{n!}{r!(n-r)!} = \binom{n}{r}
\]

169K Products

Number Of Combinations

Used web session data to determine product pairs many people looked at in the same web session.
Internal Product Interaction Clusters
Internal Product Interaction Cluster
Potential Product Interaction Pairs

FOREST 6 x 8ft Double Door 2 Window Overlap Dip Treated Apex Shed with Optional Base and Assembly

FOREST 8x6 Pent Roof 2 Window Shed

FOREST 10 x 6ft Single Door 2 Window Overlap Dip Treated Pent Shed with Optional Assembly

FOREST Wooden Shed Base 8x6
Potential Product Interaction Pairs
Estimating Cross Elasticity Using Log Log Regression Models

\[
\text{Log Demand Product } X = \text{ Intercept} + \\
\text{Elasticity Product } Y \times \text{Log Price Product } Y + \\
\text{Cross Elasticity Product } X \times \text{Log Price Product } X + \\
\text{Dummies: Promos, Seasonality, Interactions} \ldots + \epsilon
\]

- **Cross Elasticity > 0**: Products Are **Supplementary** (Cannibalisation Effect)
- **Cross Elasticity < 0**: Products Are **Complimentary** (Halo Effect)

Cross Elasticity (CE) Measures Responsiveness Of Demand For Product X Following Change In Price Of Product Y
Product X and Y are substitutional/cannibalistic (parameter = 2.73). This means that if the price of product Y is increased by 1% the demand for product X would increase by 2.73%.
Product X and Y are complementary (parameter = -2.98). This means that if the price of product Y is decreased by 1% the demand for product X would increase by 2.98%.
Product X and Y are complementary (parameter = -1.94). This means that if the price of product Y is decreased by 1% the demand for product X would increase by 1.94%.
Pull Forward Effect
After Event/Intervention/Promotion There Is A Drop In Demand
Long Term Plan - Implement More Sophisticated Demand Prediction Models
Stop Focusing On Point Elasticities

Better Promotion
Marketing Data

Economic Data

Seasonality, Trends, Weather

Customer/Channel Segments

External Product Interactions
Competitor Product Prices

Internal Product Interactions
Internal Product Prices

Data Intelligence
From Data to Insights to Action
Talk Outline

- My Background, Shop Direct

- Motivation, Pricing Data (Issues)

- Elasticity, Cross Elasticities, Pull Forward Effect

  - Multi-Objective Optimisation

- (Competitor Impact Analysis)
Optimisation Using Demand Prediction Models
Trade-off Between Revenue And Profit
Exploit Demand Prediction Model And Use Multi-Objective Evolutionary Algorithm (MOEA) To Find Trade-Off Solutions For Several Objectives And Constraints

Objectives/Constraints:

- Maximise Revenue
- Maximise Profit
- Minimise Competitor Distance
- Minimise Price Point/Attractiveness Violations
- Supply/Stock
- Etc.
MSc Student Implemented POC Using Liger Whilst Collaborating With Sheffield University - Liger Implements Several MOEAs – We Used NSGA-II

Erin Knochenhauer

- MSc at the University of Leeds studying Consumer Analytics

Robin Purshouse

- Reader in Decision Modelling and Optimisation

Liger - An Open Source
Integrated Optimization Environment

- Liger is an open-source easy to use graphical programming environment developed for the car industry.
- Can integrate with other programming languages such as Matlab and Python.
- 3 Year project with Hartree to make more scalable using parallel processing.
- Utilised 2 versions of NSGA-II: crowding distance, partition-based selection
- Possible commercialization with Jaguar Land Rover and Ford to provide, for example, better user support.

http://codem.group.shef.ac.uk/index.php/liger
Min competitor price distance = | mean(competitor price$_{t-1}$) - price[0] |
Liger Output Showing Trade-Off Solutions
Academic Collaboration:

louise.utton@shopdirect.com

Technical Questions:

christian.setzkorn@shopdirect.com
csetzkorn@gmail.com
https://www.linkedin.com/in/christian-setzkorn-ph-d-367a893/

Any Questions (HOD Data Science):

rob.barham@shopdirect.com
Identification Of Products Affected By Competitor Pricing Using Two Way Interaction Regression

\[ \text{PostCreditUnits} = \text{Intercept} + \alpha \ast \text{QuarterDummy} + \beta \ast \text{RelativePricePerc} + \gamma \ast \text{QuarterDummy} \ast \text{RelativePricePerc} + \epsilon \]

- **QuarterDummy**
  - \( \text{QuarterDummy} = 0 \) for Quarter = 4, \( \text{QuarterDummy} = 1 \) for Quarter = 1 or 2 or 3

- **RelativePricePerc**
  - Relative percentage value based on minimum competitor price of:
    - Amazon, Tesco, Currys, ToysRUs, Smyths, John Lewis, Game, Argos, AO
  - Example: Shop Direct Price = 100, Minimum Competitor Price = 110 => -10
  - Example: Shop Direct Price = 120, Minimum Competitor Price = 100 => 20

- **Beta (\( \beta \))**: Effect of change of RelativePricePerc for quarter 4
  - Example: \( \beta = -3 \) => A 1% increase of the ShopDirect price (relative to the minimum competitor price) results in a drop of 3 units per day in the golden quarter (on average).

- **Valid Parameter**: Model’s and \( \beta \)’s p-value \( \leq 0.05 \) and \( \beta \geq -20 \) and \( \beta < 0 \) and adjusted R-squared \( \geq 0.2 \)
Results Of Two Way Interaction Regression
Fewer Products Than Expected Appear To Result In Valid Models
Thus Sensitive To Competitor Pricing

<table>
<thead>
<tr>
<th>Department</th>
<th>2017 Revenue Potentially Impacted By Competitor Pricing</th>
</tr>
</thead>
<tbody>
<tr>
<td>ELECTRICAL</td>
<td>2.35%</td>
</tr>
<tr>
<td>FURNITURE &amp; HOMEWARE</td>
<td>0.35%</td>
</tr>
<tr>
<td>SEASONAL</td>
<td>6.71%</td>
</tr>
</tbody>
</table>

Medium Threshold (Adjusted R-Squared): 0.5

<table>
<thead>
<tr>
<th>Department</th>
<th>2017 Revenue Potentially Impacted By Competitor Pricing</th>
</tr>
</thead>
<tbody>
<tr>
<td>ELECTRICAL</td>
<td>6.35%</td>
</tr>
<tr>
<td>FURNITURE &amp; HOMEWARE</td>
<td>6.89%</td>
</tr>
<tr>
<td>SEASONAL</td>
<td>24.03%</td>
</tr>
</tbody>
</table>

Medium Threshold (Adjusted R-Squared): 0.35

<table>
<thead>
<tr>
<th>Department</th>
<th>2017 Revenue Potentially Impacted By Competitor Pricing</th>
</tr>
</thead>
<tbody>
<tr>
<td>ELECTRICAL</td>
<td>15.42%</td>
</tr>
<tr>
<td>FURNITURE &amp; HOMEWARE</td>
<td>27.51%</td>
</tr>
<tr>
<td>SEASONAL</td>
<td>49.41%</td>
</tr>
</tbody>
</table>

Lowest Threshold (Adjusted R-Squared): 0.2

R-squared does not indicate whether a regression model is adequate. You can have a low R-squared value for a good model, or a high R-squared value for a model that does not fit the data.
Example Sensitive Product
The following summary statistics of 2017 time series data were used:

- Median Relative Percentage – percentage difference between minimum competitor and Shop Direct price
- Correlation - between minimum competitor and Shop Direct price
- Percentages Less Equal Zero – how often Shop Direct price is below minimum competitor price in 2017
- Shop Direct Volatility
- Minimum Competitor Volatility

- Used self-organising map clustering, hierarchical clustering and decisions trees to inform thresholds

- Given the output of these algorithms manual thresholds were defined, which divided the data into 6 segments/classes/clusters
Six By Six Node Self Organising Map Results
Bubble Plot Of Segmented Products Of ‘Free Standing Fridge’ Range

Bubble size = 2017 Revenue
Clusters With Plain English Description

- **Cluster 1:**
  - Almost always cheaper than minimum competitor

- **Cluster 2:**
  - Tightly tracks minimum competitor

- **Cluster 3:**
  - More expensive than minimum competitor and tracks minimum competitor

- **Cluster 4:**
  - More expensive than minimum competitor and does not track minimum competitor

- **Cluster 5:**
  - Much more expensive than minimum competitor most of the time and does not track minimum competitor
Example Cluster 1
Almost Always Cheaper Than Minimum Competitor
Not Sensitive Using Adjusted R-Squared Threshold 0.5 But Sensitive For 0.35
Example Cluster 2
Tightly Tracks Minimum Competitor

<table>
<thead>
<tr>
<th>Stock</th>
<th>Units+Price</th>
</tr>
</thead>
<tbody>
<tr>
<td>GrossDemandPostCredUnits</td>
<td>SeenNowFromPrice</td>
</tr>
<tr>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>10</td>
<td>10</td>
</tr>
<tr>
<td>20</td>
<td>20</td>
</tr>
<tr>
<td>30</td>
<td>30</td>
</tr>
<tr>
<td>40</td>
<td>40</td>
</tr>
<tr>
<td>50</td>
<td>50</td>
</tr>
<tr>
<td>60</td>
<td>60</td>
</tr>
<tr>
<td>70</td>
<td>70</td>
</tr>
<tr>
<td>80</td>
<td>80</td>
</tr>
</tbody>
</table>

Graph showing the relationship between stock and units + price over time.
Example Cluster 3
More Expensive Than Minimum Competitor And Tracks Minimum Competitor
Example Cluster 4
More expensive than minimum competitor and does not track minimum competitor
Example Cluster 5

Much more expensive than minimum competitor most of the time and does not track minimum competitor.
Questions

**Academic Collaboration:**

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**Technical Questions:**

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csetzkorn@gmail.com
https://www.linkedin.com/in/christian-setzkorn-ph-d-367a893/

**Any Questions (HOD Data Science):**

rob.barham@shopdirect.com
Abstract

Product pricing is the lever that has the highest and quickest impact on profit. It is also used to control revenue, price perception and market share. This talk introduces pricing concepts, techniques and algorithms being used in practice and challenges faced. Concepts discussed include: elasticity, halo, cannibalism and pull forward effects. We give a high level overview of basic statistical techniques used, such as, for example, log log and two way interaction regression. We also discuss techniques to determine interacting/similar products and the use of multi-objective evolutionary algorithms to optimise revenue, margin and competitor price distances.

Your talk will be about 30-45 minutes including questions from the audience.