Enhancing Retail Profitability through Data-Driven Decision Making: A Case Study on Price Elasticity and Discount Strategy Optimization at Dillard's

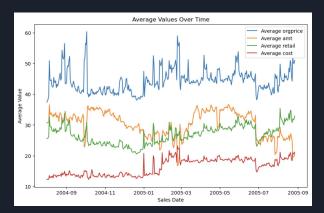
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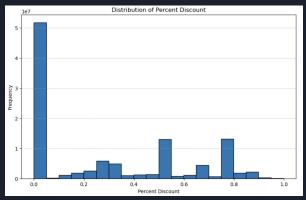
Overview

- Motivation & Problem Outline
- Business Case Proposal
- Model Specifications
- Findings
- Recommendations & ROI
- Conclusion and Outlook

Motivation & Problem Outline

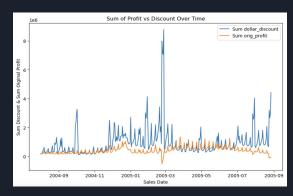
- Range of Discounting Strategy
 - > 0%-80%
 - ➤ Varies across stores, brands and items
 - > Varies in duration and relative time
 - ➤ 4.5% of SKU account for 50% of Revenue is our focus
- Potential Loss of Profit
 - ➤ No clear pattern in Optimizing Discounts
 - ➤ No consideration of customer preferences/habits
- Idea: Data-Driven Discount Strategy

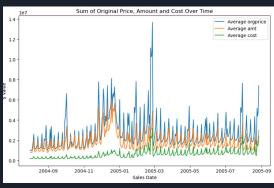


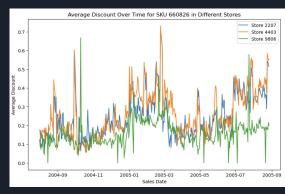


EDAs

- Mainly focus on SKU
- Examined sales data to reveal purchase trends, seasonal impacts, and pricing responsiveness
- Identified notable sales surges pre-Christmas and peak sales during holidays, along with a consistent pattern of elevated weekend sales









Business Case Proposal

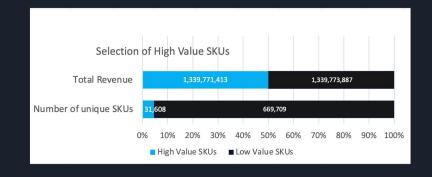
- Understand/Select our high-revenue Items
- Analyze Time Dependencies and Life-Span of Items
- Association Rule Mining to find buying patterns after product launch
- Price Elasticity Models to predict Demand based on Price
- Simulation of multiple Discount Strategies among Associated Items
- Identification of optimal Discount Approach to maximize Profits
- Dynamic Adjustment of Discount

Model Specifications - Basket

- Read in the transaction table and filter out the returns, and drop irrelevant columns of transaction table
- Read and store the SKST table and assign column names, drop irrelevant columns
- Calculate mean retail for SKU, merge the transaction and SKST tables, and then fill missing values in the tables
- Feature engineering on the saledate by extracting year, month, and day, and assigning day of week, and weekends
- Calculate **percent discount** and define final sale
- Return the final dataframe

	antecedents	consequents	antecedent support	consequent support	support	confidence	lift	leverage	conviction	zhangs_metric
33	(6480353, 6490353)	(6470353)	0.00124	0.00201	0.00113	0.911290	453.378270	0.001128	11.250069	0.999033
29	(6072521, 6032521)	(6062521)	0.00153	0.00236	0.00132	0.862745	365.569957	0.001316	7.268520	0.998793
28	(6062521, 6032521)	(6072521)	0.00155	0.00234	0.00132	0.851613	363.937138	0.001316	6.723361	0.998800
3	(4462521)	(4512521)	0.00135	0.00159	0.00114	0.844444	531.097135	0.001138	6.418350	0.999466
34	(6480353, 6470353)	(6490353)	0.00134	0.00204	0.00113	0.843284	413.374305	0.001127	6.367935	0.998919

	support	itemsets
206	0.00111	(6656135, 6706135)
207	0.00217	(6656135, 7596135)
208	0.00132	(6752521, 6742521)
209	0.00132	(6062521, 6072521, 6032521)
210	0.00113	(6480353, 6490353, 6470353)

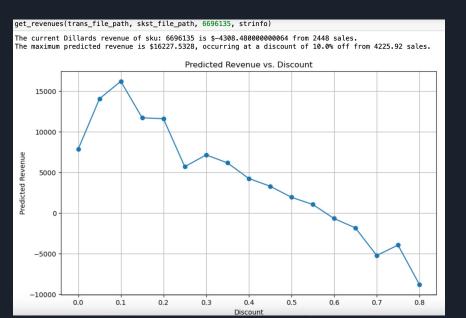


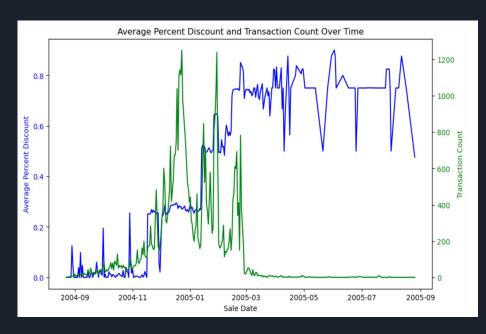
Model Specification - Price Elasticity

• In order to check on the revenues, we scraped the information from census data and get the average income and population based on state and zip code

	storeid	state	zip	population	median_earning
0	2	FL	33710	34462	41198
1	3	MO	63126	15362	55585
2	4	AR	72201	875	63063
3	7	TX	76137	59273	42936
4	9	ΑZ	85281	66878	30311
448	9808	ΑZ	85233	37651	53126
449	9812	LA	70006	15455	35704
450	9900	AR	72201	875	63063
451	9906	AR	72201	875	63063
452	9909	WY	82009	34509	53831

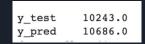
Price Elasticity





Model Results

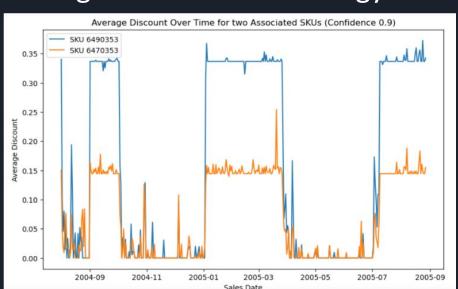
- Association results
 - Apriori Market Basket Algorithm (PrefixSpan)
 - Trained on 100.000 Baskets, relevant Items only:
 - ➤ 50% of Revenue Generators
 - ➤ Items with > 2 Prices
 - Items with known Launch-Date
 - Threshold: Lift > 30%, Support 0.001
 - Scalability given
- Random Forest Regressor
 - Predict the demand (number of sales)!
 - Result is much better
 - > MSE: 16.876349615975425
 - > R^2: 0.5256055000848339
 - Predicted v.s. actual number of sales in test data
- Simulating Discounts
 - For each item in the Association Rule:
 - Using Price Demand Model on individual item
 - > stimulate discounts from 0% to 80% with an interval of 5%
 - Predict demand for each discount
 - Calculate Profit (Price Cost) and Select Max



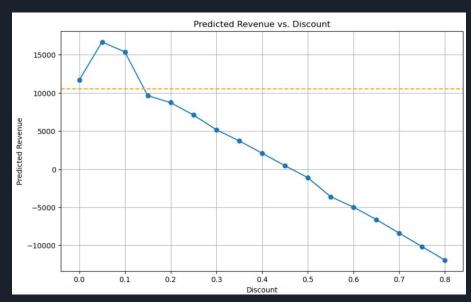
	support	itemsets		
209	0.00111	(6696135, 6656135)		

Example: Optimal Discount Strategy for Association Rule $6490353 \rightarrow 6470353$ (Confidence 0.70, Support 0.0218)

Original Discounts Strategy



Optimal Discount for sku 6470353:



With Optimal 5% Discount = 57.9% increase Increase in Profits!

Findings

- To Maximize profit, set sku 6696135 to 10% off and set sku 6656135 to 5% off
- More than \$20,000 Profit increase possible with Dynamic Pricing of
 2 Items
- · Downside: Considering individual items independently
- Future improvement: Field experiment of discount strategies on association rules (Which item to discount to increase overall sales)

Recommendations & ROI

- Immediate:
 - Keep Discounts for longer Period of time
 - Change Prices of targeted SKUs to confirm accuracy
- Long Term
 - Get more Data on Customer History
 - Improve Price Elasticity Model by adding more advanced features
 - Scale Models on all Data

ROI	\$\$\$
No. of high-revenue SKUs	24,431
Total Profit of high revenue SKUs	160,299,588.00
Percentage of Valuable Associations (Greater Confidence 0.2)	0.17
Total Profit of Association Rule SKU	27,250,929.96
50% (consequents) of Association Rule SKU	13,625,464.98
Potential Profit Increase through Model (Percentage)	0.12
Potential Profit with Model	15,260,520.78
Expected Net Profit Increase / Year	1,635,055.80
Cost	
AWS Environment Cost	1000000
Cloud Computing / Year Cost	100
3 FTE Data Scientist	450000
1 FTE Product Owner	400
Total	1450500

Conclusion & Outlook

- Action Needed Competitive Advantage (Benchmark)
- Synch with Marketing Team needed (Pricing)
- In Parallel: Controlled Case Study in 1 location (pick one)
- Decision Points

Thank you!