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

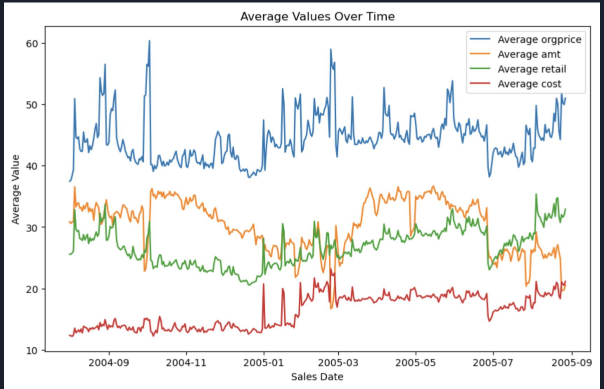
Jakob Kuemmerle, Lowan Li, Linda Liang, Yidan Wang

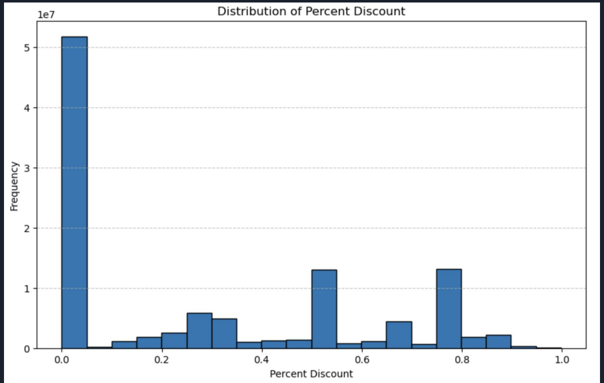
# Overview

- 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



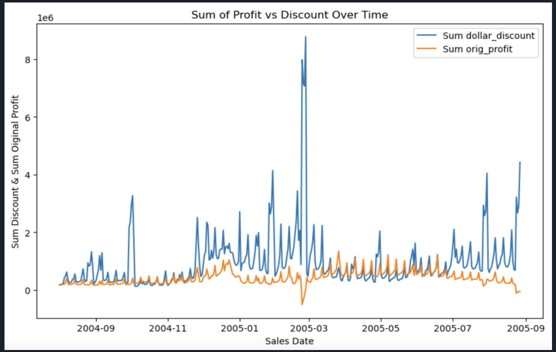



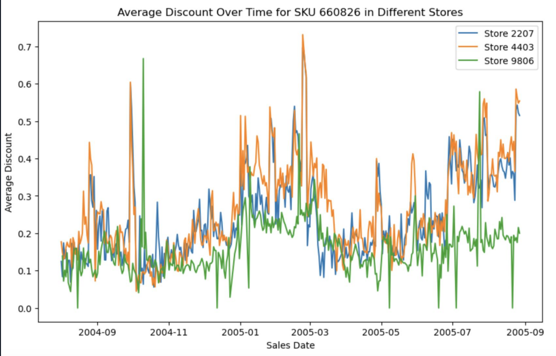
# EDAs

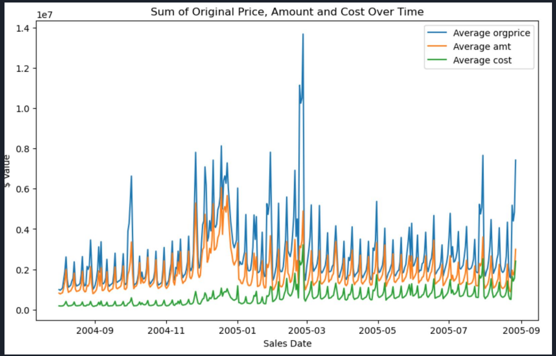
- Mainly focus on SKU

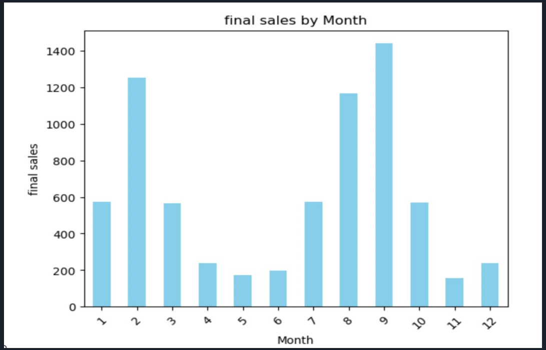
- Examined sales data to reveal purchase trends, seasonal impacts, and pricing responsiveness

- Identified notable sales surges pre-Christmas and peak sales during holidays, along with a consistent pattern of elevated weekend sales



# Business Case Proposal

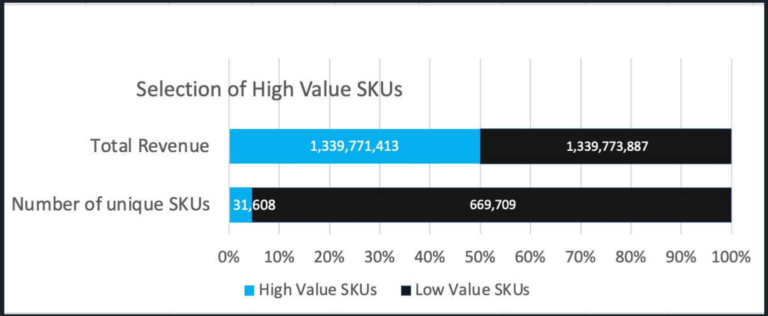
- Understand/Select our high-revenue Items
- Analyze Time Dependencies and Life-Span of Items
- Association Rule Mining to find buying patterns after product launch
- Price Elasticity Models to predict Demand based on Price
- Simulation of multiple Discount Strategies among Associated Items
- Identification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

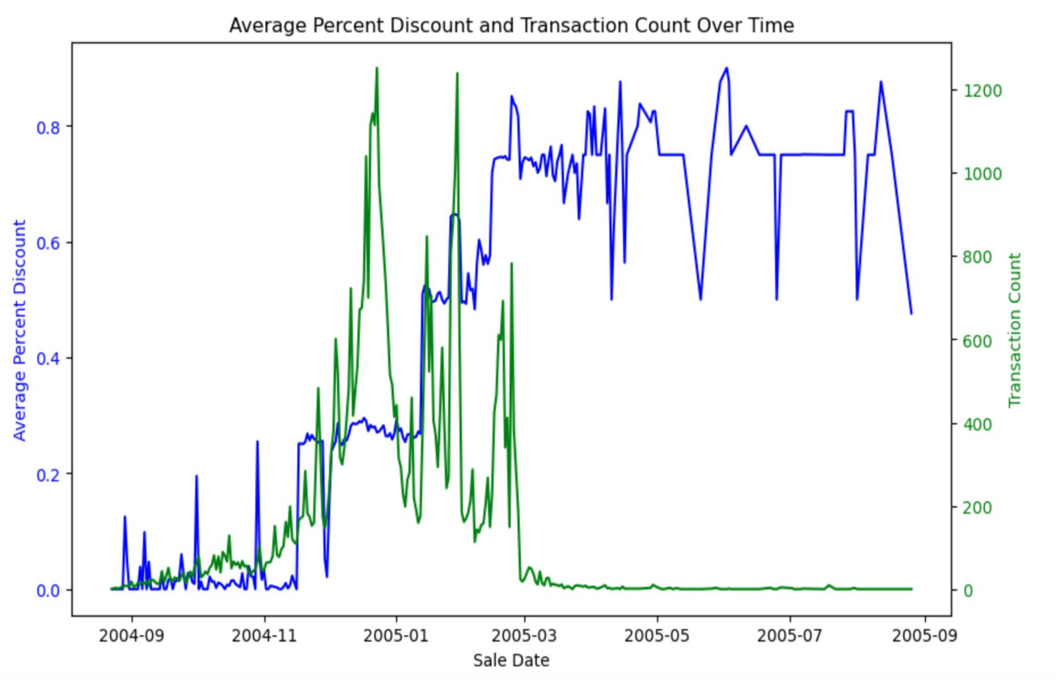


# Model Specification - Price Elasticity

- 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 | AZ | 85281 | 66878 | 30311 |
| .. | ... | ... | ... | ... | ... |
| 448 | 9808 | AZ | 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)I
  - 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

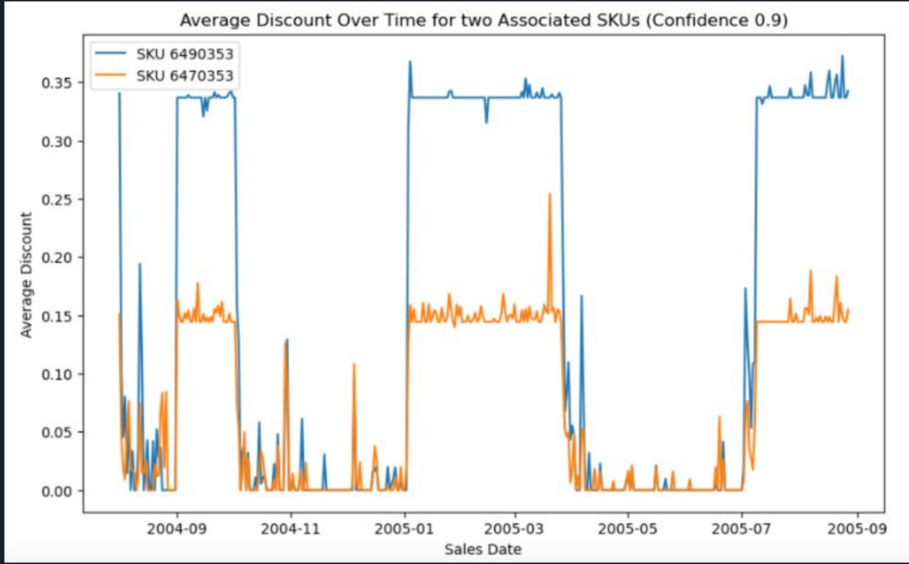
```
y_test     10243.0
y_pred     10686.0
```

| | support | itemsets |
|---|---|---|
| 209 | 0.00111 | (6696135, 6656135) |

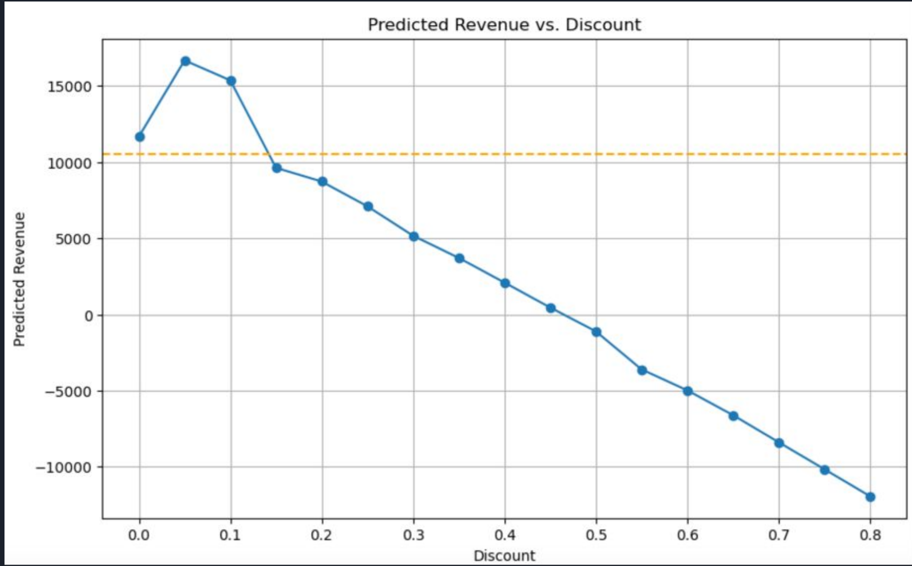
Basket example

# Example: Optimal Discount Strategy for Association Rule 6490353 → 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 6470353 to 5% off
- More than 50% Profit increase possible with Dynamic Pricing of 1 item
- 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

| A | B |
|---|---|
| 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 | 150000 |
| Total | 1600100 |

# 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!