Industry and Academic Collaborations

Management Science Department

Darla Moore School of Business, Operations and Supply Chain Program

July 2019

UNIVERSITY OF SOUTH CAROLINA
Darla Moore School of Business

Mark Ferguson, Department Chair

How Can Industry Work with Business Schools?

- Small Projects Within a Class (ad-hoc)
- Semester-Long Student Projects (typically formalized process)
- Sharing Data With Research Faculty For Specific Analysis
- Partnering With Research Faculty For Multi-Year Project (often involves cutting-edge methodologies)

UNIVERSITY OF SOUTH CAROLINA
Darla Moore School of Business

How Can Industry Work with Business Schools?

- Small Projects Within a Class (ad-hoc)
- Semester-Long Student Projects (typically formalized process)
- Sharing Data With Research Faculty For Specific Analysis
- Partnering With Research Faculty For Multi-Year Project (often involves cutting-edge methodologies)

UNIVERSITY OF SOUTH CAROLINA
Darla Moore School of Business

2006....
The distant past!

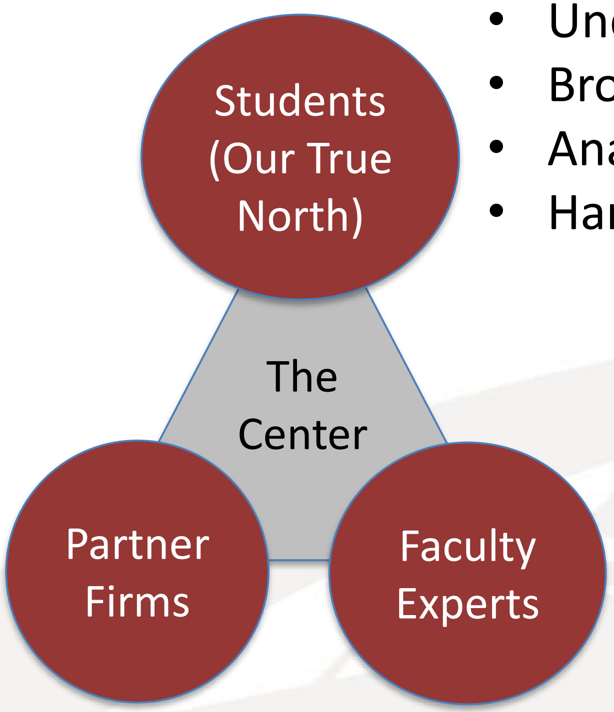
- Management Science Department
  - Several undergraduate programs but with few students
  - Job placement not a Key Performance Indicator
  - Little impact on the business community

Operations and Supply Chain: focused on creating job-ready professionals

- Teach the dual disciplines of Operations Management and Supply Chain Management
- Emphasis on Process Improvement
- Teach business students to think analytically and use industry-valued analytical tools
- Provide real (high stakes) work experience and industry level certifications for all students

UNIVERSITY OF SOUTH CAROLINA
Darla Moore School of Business

Academic-Industry Collaboration



Students

- Undergraduate & MBA
- Broad academic experiences
- Analytical
- Hard-working and career-focused

Faculty

- Unique: Can “teach” and “do”
- Practical immersion into industry
- Cutting-edge curriculum
- Capacity to lead 18-20 projects per semester
- Top-Ranked leadership in applied and scholarly research

Partner Firms

- Diversified by industry
- Prominent global and/or SC footprint
- Can identify, resource, and manage 2 Projects/year
- Advisory Board Membership
- Desire to hire students as interns and full-time employees

UNIVERSITY OF SOUTH CAROLINA
Darla Moore School of Business

Our 19 Industry Partners

Working with us to drive academic relevance and provide industry experience

Adidas
Atrium Health (CHS)
Continental Tire
Daimler Mercedes Benz
Textron
McLeod Health
Schneider Electric
Smith & Nephew
Trane-Ingersoll/Rand
UTC Aerospace Systems

BMW
Coca-Cola Bottling Co.
Cummins Engine/Turbo
Electrolux
Johnson & Johnson
Nephron Pharmaceutical
Siemens
Sonoco
UPS

UNIVERSITY OF SOUTH CAROLINA
Darla Moore School of Business

Undergraduate Student Project Example

- Adidas: https://www.youtube.com/watch?v=LnonxNrSC1g&feature=youtu.be

UNIVERSITY OF SOUTH CAROLINA
Darla Moore School of Business

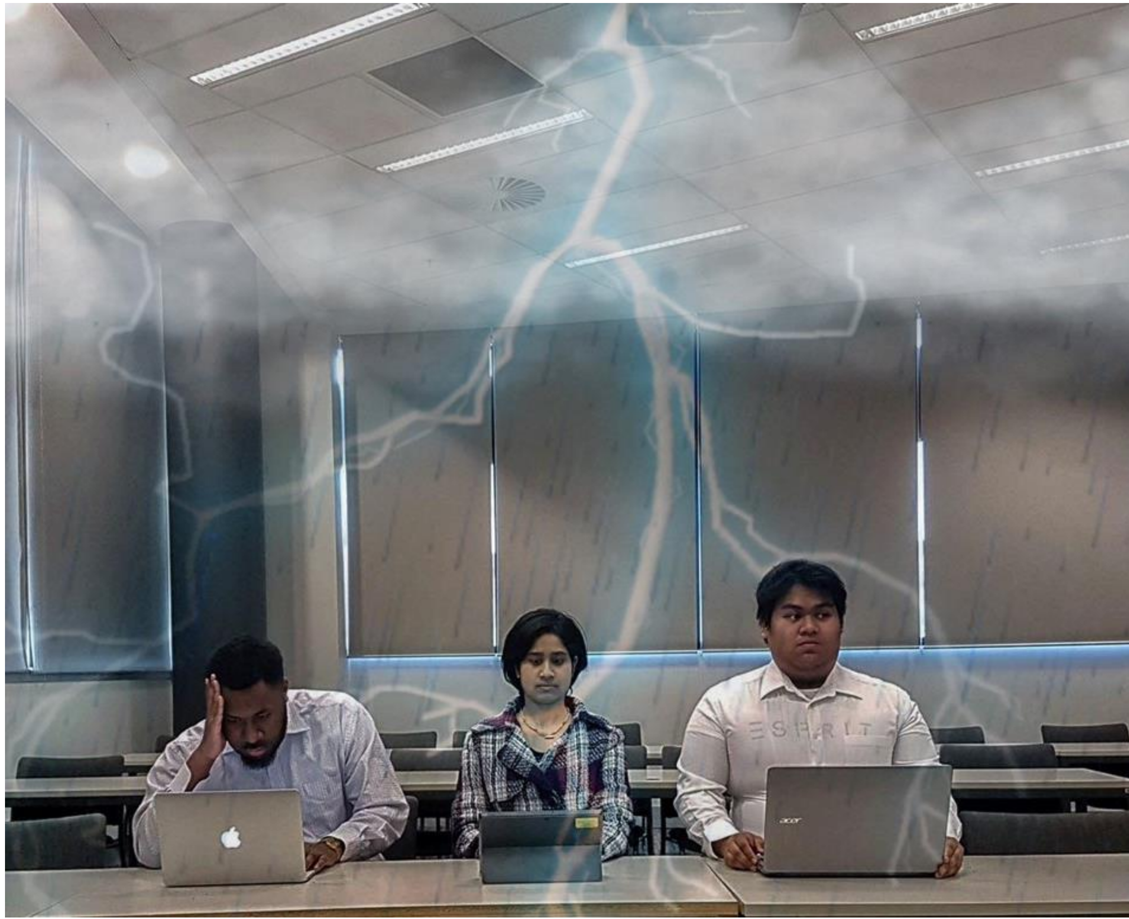
Student Industry projects by University of Auckland ISOM Department

Price Optimization at Red Cross Retail 2016

Optimization of Production Schedules at Douglas Pharmaceuticals

Inventory management at United Steel 2018

Inventory management at United Steel 2017



Warehouse optimization at T&G 2016

More of the recent projects …

- ASB Bank (Staff Training Recommendation system)
- ASB Bank (Online Customer Referral system)
- AsureQuality (Inventory Management process improvement)
- Beca (Asset Management Expert system)
- Computer Fanatics Ltd (vetlinkSQL Stock Management system)
- Datacom (Redevelopment of the Managed Asset Reconciliation system)
- DB Breweries (Reduction of packaging material losses in production process)
- Deloitte (CallPlus Public Data Explorer)
- Foodstuffs North Island
- Fonterra (Increasing warehouse efficiency)
- Hansen Technologies (Enterprise System data mining)
- Hansen Technologies (Social Media system development)
- Health Benefits Limited HBL (Developing decision criteria for non-critical clinical consumables inventory management)
- KPMG (Data Analytic Engine refinement)
- LSG Sky Chefs Auckland (Optimisation of warehouse processes)
- Mainfreight (Optimisation of inwards to outwards consignments process)
- OneNet (Measurement of Client Profitability)
- OneNet (Partnership Relationship Management system)
- OneNet (LiveVault Management and Business Intelligence tool)
- Orion Health (Synthetic Health Data Generator)
- PwC (Visualisation & CAATs Efficiency set)
- Ports of Auckland (Storeroom and Inventory Management process improvements)
- Tru-Test (Developing segmentation criteria to improve the Order Fulfilment process)
- Vista (Development of the Vista Usher Point system)
- Vista (Mobile Cinema Manager)

Join University of Auckland in 2020

Visit our 2019 project exhibition

- 26/09/2019 from 12:00 to 16:00

Get in touch

- Valery Pavlov v.pavlov@Auckland.ac.nz
- Koro Tawa k.tawa@Auckland.ac.nz

How Can Industry Work with Business Schools?

- Small Projects Within a Class (ad-hoc)
- Semester-Long Student Projects (typically formalized process)
- Sharing Data With Research Faculty For Specific Analysis
- Partnering With Research Faculty For Multi-Year Project (often involves cutting-edge methodologies)

UNIVERSITY OF SOUTH CAROLINA
Darla Moore School of Business

Retail Science

Estimating and Optimizing Promotional Displays: A Grocery Perspective

In collaboration with the University of South Carolina

Oracle Retail
October 2018

Promotional Displays

Major

End-of-aisle display

Lobby

and Minor

Island

Dump table

UNIVERSITY OF SOUTH CAROLINA

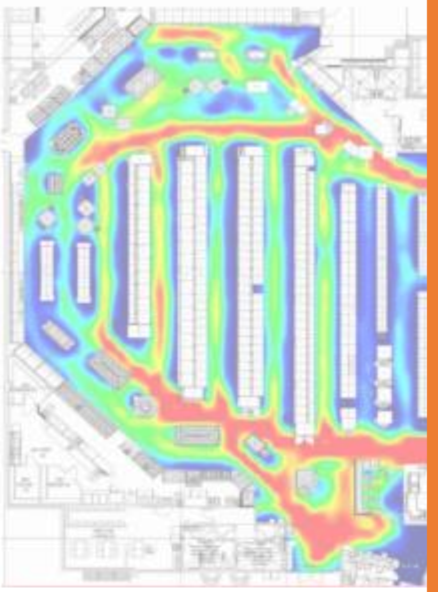
Promotional Displays

Courtesy of VideoMining's Grocery Shopper Insights

UNIVERSITY OF SOUTH CAROLINA

Promotional Displays

displayed product visibility



Courtesy of VideoMini

. Eric Bradlow

Promotional Displays

According to 2014 Mass Merchant survey (POPAI), 62% of purchases are unplanned.

62%

62% of purchases are unplanned, with shoppers not consulting any kind of pre-store media, such as television advertisements, store circulars, newspapers etc, to plan their trip.

How can retailers plan and schedule efficient assortments on limited promotional display

?

Proposed Methodology

1

Estimate Category Level Sales Lifts:

Beer vs Detergent

2

Solve for the Optimal Product Categories to put on Display

3

Estimate Subcategory Level Sales Lifts Within Chosen Categories:

Import and Craft

Proposed Methodology (Cont.)

4

Solve for the Optimal Product Subcategories to put on Display

5

Estimate Individual Product Level Sales Lifts Within Chosen Subcategories:

Heineken vs Fosters

6

Solve for the Optimal Products to put on Display

UNIVERSITY OF SOUTH CAROLINA

The vast majority of…

…commercial and academic research focus only on optimizing the center store shelf-space and product assortments.

Current Methodologies Used in Practice

- Using weekly nationwide planograms with a historically best-selling item to put on display (same across all stores, except some locations)
- Using past sales period to put the same items on display as last year
- Using the best-selling, most popular items of the current period

Problem Complexity

- 60,000-300,000s SKUs but, e.g., only 36 endcaps
- Sales lift not static; it is seasonal and diminishes over time
- Highest sales item does not mean highest profit
- An individual store has limited data on the sales lift of a particular SKU

Our Research Goals

1) Help a manager of a particular store estimate the relative lift of stocking a category, subcategory, and SKU on a promotional display space

2) Optimize the store's profit by choosing the most profitable products to stock on these display spaces on a weekly basis

UNIVERSITY OF SOUTH CAROLINA

Let's Focus on Beer

The Beer Dataset

- IRI Marketing Group Academic Dataset (Bronnenberg et al. 2008)
- Store-week-SKU level data
- 2011 (full 52 weeks)
- 50 US markets
- Originally 7.7M+ obs.
- 1258 grocery stores
- New England region approx. 500,000 obs.
- 6-, 12-, 18-, 24-pack purchases only
- 5 beer categories
  - 3,140 brands were assigned a beer category by using data from
    - Brewers Association (proprietary),
    - Department of Alcoholic Beverage Control (public), and
    - beeradvocate.com (public)

UNIVERSITY OF SOUTH CAROLINA

Table 2 New England Data Set Summary

Subcategory	Observations count	Total unit sales	Unique SKU count
Subpremium	35,653	149,554	59
Premium	80,699	720,379	75
Superpremium	70,830	332,791	85
Craft	116,008	632,439	352
Import	84,038	432,586	159
Hard Apple Cider*	6,165	27,567	17
Malt/Nonalcoholic*	20,680	73,889	21
Liquor-style*	21,275	74,548	29
Total	**435,348**	**2,443,75**	

*Other types of beer sold in New England but not considered in this analysis d e

A single store only has 10-20K observations whereas a national dataset has 40X more

Table 3 Single Store Sales Data

Subcategory	Observations count	Total unit sa	
Subpremium	1,050	6,110	
Premium	2,007	53,999	
Superpremium	1,947	21,233	
Craft	3,392	21,601	
Import	2,637	19,336	
Hard Apple Cider*	242	896	8
Malt/Nonalcoholic*	487	3,046	10
Liquor-style*	767	3,309	23
Total	**12,529**	**129,530**	**334**

UNIVERSITY OF SOUTH CAROLINA

Finding the Optimal Products from the Entire Store

- Typically, any merchandise from the entire store can go on a promotional display
- Selecting merchandise from across the entire store is difficult because the number of possible items can be quite large, resulting in unreasonable solution times
- Two approaches:
  - Limit the number of SKUs considered
  - Hierarchical approach

UNIVERSITY OF SOUTH CAROLINA

Estimating the Sales Lift from Placing a SKU on Display

There are many factors that effect weekly sales of a SKU that we control for but the display effect is the one of interest.

Week effect (seasonality)

Marketing mix effects (temporary price reduction, feature, advertising excluding promotional display)

Product effect

Discount effect

$$
\ln S_{ijt} = \overbrace{\delta_0}^{\text{Intercept}} + \overbrace{\sum_{z\in\mathbb{U}} \delta_{1z} Z_{jz} +}^{\text{SKU Effect}} \overbrace{\delta_2 D_{ijt}}^{\text{Display Effect}} + \overbrace{\delta_3 H_{ijt}}^{\text{Discount Effect}} + \overbrace{\sum_{t'=1}^{T} \delta_{4t'} W_{t't}}^{\text{Week Effect}} + \overbrace{\sum_{m\in\mathbb{M}} \delta_{5m} M_{ijmt}}^{\text{Marketing Mix Effect}} \qquad (1)
$$

$$
+ \overbrace{\sum_{z\in\mathbb{U}} \delta_{6z} \left(D_{ijt} Z_{jz}\right)}^{\text{Display-SKU Effect}} + \overbrace{\sum_{t'=1}^{T} \delta_{7t'} \left(D_{ijt} W_{t't}\right)}^{\text{Display-Week Effect}} + \overbrace{\sum_{a=1}^{C} \sum_{t'=1}^{T} \delta_{8at'} \left(A_{ja} W_{t't}\right)}^{\text{Subcategory-Week Effect}} + \overbrace{u_{i0}}^{\text{Random Store Effect}} + \overbrace{e_{ijt}}^{\text{Error Term}}
$$

SKU level sales

Interaction: display with SKUs

Interaction: display with weeks

Interaction: subcategories with weeks

Estimating the Sales Lift with Cross Effects

$$\ln S_{jti} = \overbrace{\delta_0}^{\text{Intercept}} + \overbrace{\sum_{z \in \mathbb{U}} \delta_{1z} Z_{jz}}^{\text{SKU Effect}} + \overbrace{\delta_2 D_{jti}}^{\text{Display Effect}} + \overbrace{\delta_3 H_{jti}}^{\text{Discount Effect}} + \overbrace{\sum_{t'=1}^{T} \delta_{4t'} W_{t't}}^{\text{Week Effect}} + \overbrace{\sum_{m \in \mathbb{M}} \delta_{5m} M_{jmti}}^{\text{Marketing Mix Effect}}$$
$$+ \overbrace{\sum_{z \in \mathbb{U}} \delta_{6z} (D_{jti} Z_{jz})}^{\text{Display-SKU Effect}} + \overbrace{\sum_{t'=1}^{T} \delta_{7t'} (D_{jti} W_{t't})}^{\text{Display-Week Effect}} + \overbrace{\sum_{a=1}^{C} \sum_{t'=1}^{T} \delta_{8at'} (A_{ja} W_{t't})}^{\text{Subcategory-Week Effect}}$$
$$+ \overbrace{\sum_{m \in \mathbb{M}} \sum_{g \in \mathbb{G}} \delta_{9gm} \sum_{j'=1/\{j\}}^{J} SIM_{jj'gti} M_{j'mti} (1 - M_{jmti})}^{\text{Cross-Marketing Mix Effects}} + \overbrace{\sum_{g \in \mathbb{G}} \delta_{10g} \sum_{j'=1/\{j\}}^{J} SIM_{jj'gti} D_{j'ti} (1 - D_{jti})}^{\text{Cross-Display Effect}}$$
$$+ \overbrace{u_{0i}}^{\text{Random Store Effect}} + \overbrace{e_{jti}}^{\text{Error Term}} \qquad (2)$$

Our model can also include cross-display effects – how does putting a SKU on display affect the sales of similar SKUs

Regression Results

Average estimated sales lift from putting a SKU on display is 32%

Table 5 Sales Response Function Estimates For Direct and Hierarchical Approaches

	Direct	Hierarchical				
ln(Unit sales)		Subcat 1	Subcat 2	Subcat 3	Subcat 4	Subcat 5
Constant	1.182***	1.131***	1.230***	1.230***	1.232***	1.233***
M_{ijmt}:						
Discount	0.009***	0.009***	0.009***	0.009***	0.009***	0.009***
Price Reduction	0. 078***	0.104***	0.100***	0.100***	0.085***	0.115***
Feature	0.255***	0.431***	0.395***	0.428***	0.369***	0.375***
D_{ijt}:						
Display	0.334***	0.550***	0.506***	0.563***	0.529***	0.514***
50 SKUs$^{\diamond}$ *	yes					
100 SKUs$^{\diamond}$ *		yes	yes	yes	yes	yes
W_{wt} *	yes	yes	yes	yes	yes	yes
$A_{ja}W_{wt}$ *	yes	yes	yes	yes	yes	yes
$D_{ijt}Z_{ja}$ *	yes	yes	yes	yes	yes	yes
$D_{ijt}W_{wt}$ *	yes	yes	yes	yes	yes	yes
Log-likelihood	-377684.44	-415376.56	-397513.84	-412373.84	-403605.81	-402306.93
AIC	756510.9	831755.1	796045.7	825761.7	808233.6	805633.9
BIC	762782.7	837258.1	801636.5	831330.5	813846.4	811235.7
Wald χ^2	189041.54***	89761.07***	134672.09***	97055.19***	118939.65***	122256.92***

**included in the model*

$^{\diamond}$ with a reference category of all 'other' existing SKUs

Incremental Display Profit

$$\Pi_{jti} = \underbrace{q_{jti}(l_{jti}-1)\pi_{jti}\Delta}^{\text{Self-effect profit}} + \underbrace{\sum_{j' \neq j} q_{j'ti}(CEL_{jj'i}-1)\pi_{j'ti}\Delta}^{\text{Cross-effect profit}}$$

Incremental display profit: additional profit from putting an item on display

Profit margin for product j plus any trade promotion

Base demand (at full price and no promotions) of product j

Ln(Base Demand)=Ln(Sales)-(Display Effects + Price Related Effects + Marketing Effects) from the model

Marginal lift for product j from being placed on promotional display

Ln(DisplayLift)=Sum of All Display Effects from model

Static Optimization for Endcap *d*

Select most profitable product *j's* for a given set of promotional display spaces *d* such that incremental profit is maximized

Incremental display profit for product j

Trade promotion from vendor

$$\max_{x_{jd}} \sum_{j \in \mathbb{U}, d \in i} (\Pi_j + o_{jt}) x_{jd}$$

$$\text{subject to} \quad \sum_{j \in \mathbb{U}} x_{jd} \le 1, \ \forall d,$$

$$\sum_{d \in i} x_{jd} \le 1, \ \forall j,$$

$$x_{jd} \in \{0, 1\}.$$

Display product j on endcap d

Only one product per endcap

UNIVERSITY OF SOUTH CAROLINA

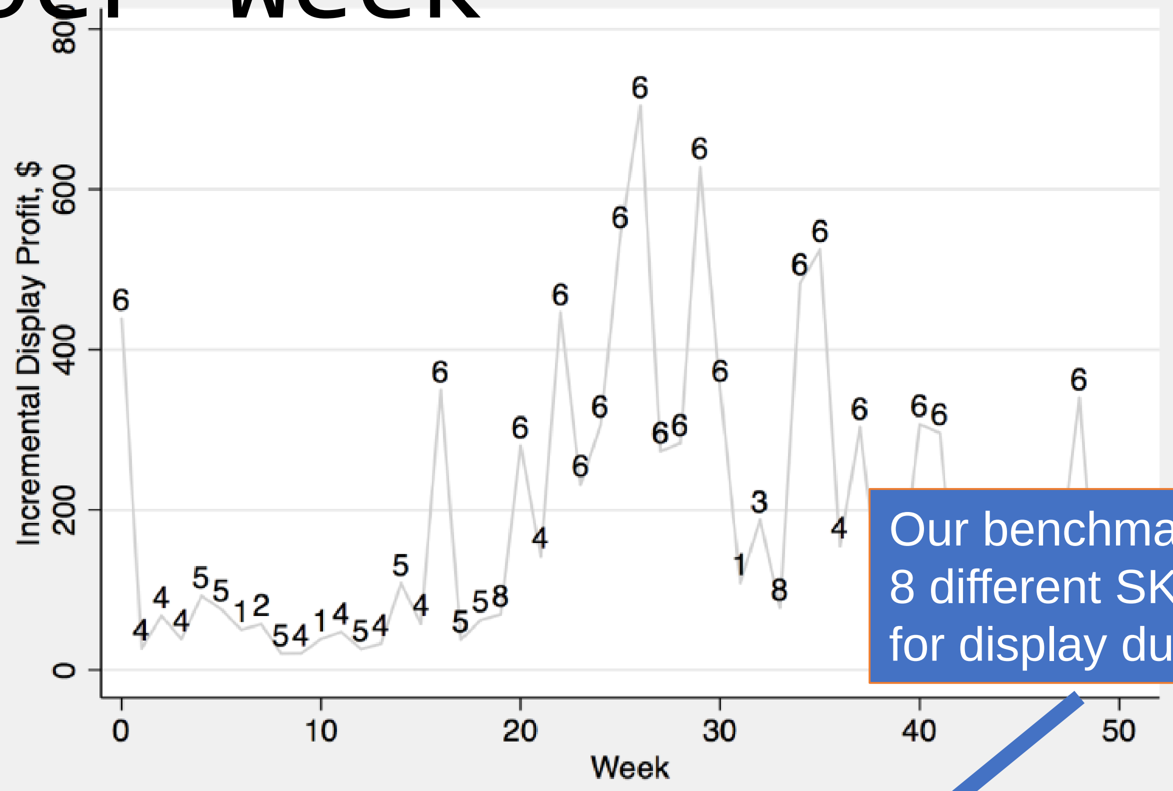
Benchmark: Choose the Highest Selling SKU for the Week

Table 9 Benchmark selection: Top selling SKUs annually, for Store i

Top	SKU	Annual unit sales
1	**Bud Light, bottle, 18-pack**	**5,822**
2	Bud Light, can, 18-pack	5,614
3	Miller Lite, can, 18-pack	4,166
4	Coors Light, can, 18-pack	3,560
5	Budweiser, can, 18-pack	3,315
6	Michelob Ultra, bottle, 18-pack	3,054
7	Miller Lite, bottle, 18-pack	3,025
8	Coors Light, bottle, 18-pack	2,956
9	Budweiser, bottle, 18-pack	2,815
10	Samuel Adams Seasonal, bottle, 12-pack	2,678

UNIVERSITY OF SOUTH CAROLINA

Benchmark: Just Pick the Highest Seller per Week



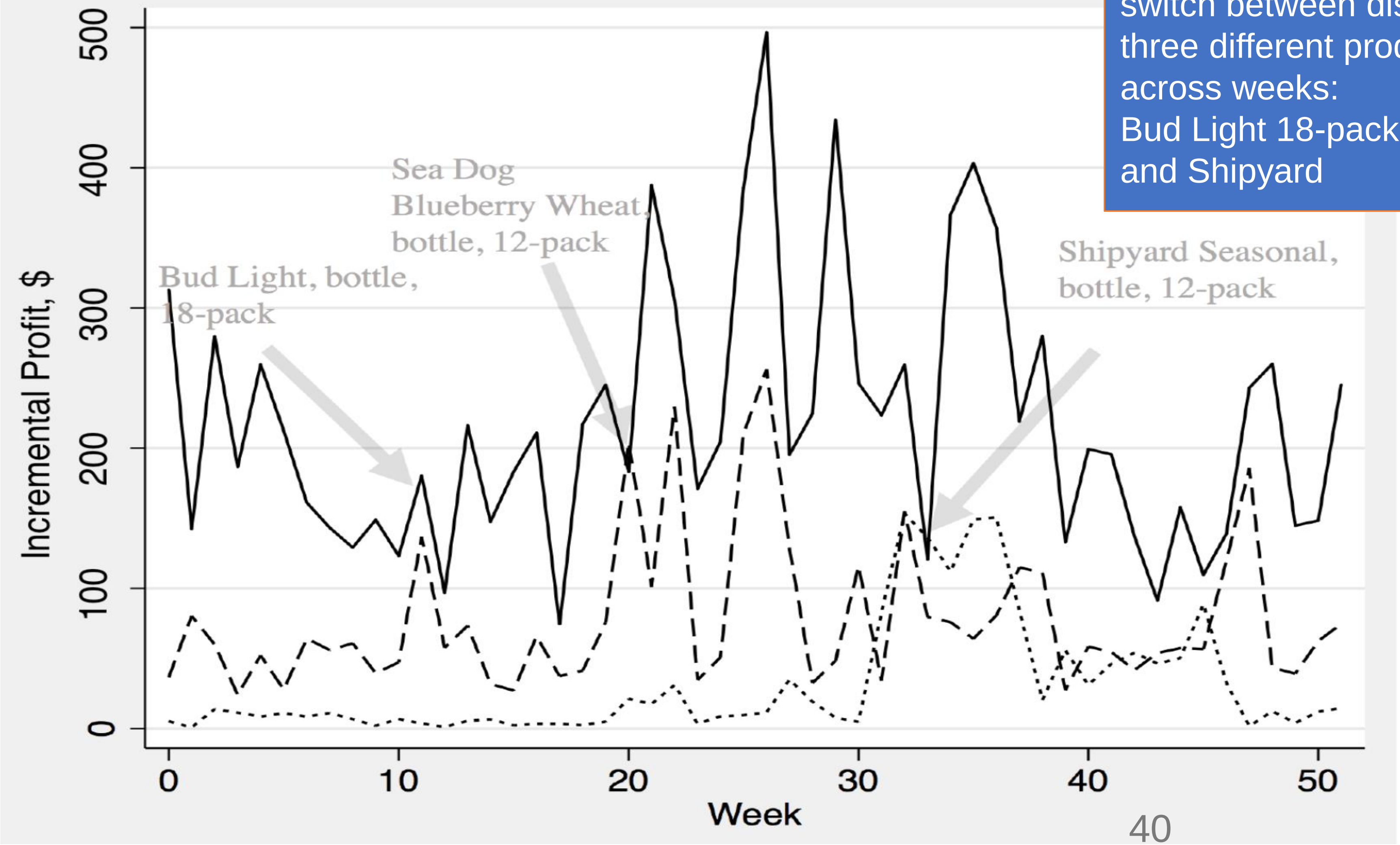
1: Michelob Ultra (bottle, 18-pack)
2: Miller High Life (bottle, 18-pack)
3: Shipyard Seasonal (bottle, 12-pack)
4: Bud Light (can, 18-pack)
5: Miller Lite (can, 18-pack)
6: Bud Light (bottle, 18-pack)
7: Samuel Adams Seasonal (bottle, 12-pack)
8: Coors Light (can, 18-pack)

Our benchmark results in 8 different SKUs chosen for display during a year.

Results: Hierarchical and Static Optimization

Weekly Incremental Profit Obtained under the Hiera

Our optimization says to switch between displaying three different products across weeks:
Bud Light 18-pack, Sea Dog and Shipyard



UNIVERSITY OF SOUTH CAROLINA

Comparison of Incremental Profits: Static Optimization

Direct	Hierarchical	Benchmark
Bud Light, bottle, 18-pack Shipyard Seasonal, bottle, 12-pack	Bud Light, bottle, 18-pack Budweiser, (bottle, 24-pack) Seadog, bottle, 12-pack	Bud Light, bottle, 18-pack Bud Light, can, 18-pack Miller Light, can, 18-pack Michelob Ultra, bottle, 18-pack Miller High Life, bottle, 18-pack Coors Light, can 18-pack Shipyard Seasonal, bottle, 12-pack Samuel Adams Seasonal, bottle, 12-pack
\$15,963.25	\$17,598.33	\$9,343.50

The Direct and Hierarchical provide similar profit lifts. Both are almost 2X the benchmark! (\$17.6K vs. \$9.3K)

UNIVERSITY OF SOUTH CAROLINA

Summary

- The Promotional Display problem is too important to leave to a store manager's intuition.
- An individual store, and even an individual chain, does not have the data to adequately solve this problem – need a large dataset.
- Applying data analytics to this problem offers significant profit improvement opportunities.