The Analytics of Pricing: From Theory to Practice

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MIT Sloan

June 10, 2017
Georgia Perakis

Born in Crete (Greece)!

- B.A. in Mathematics (NUA), M.Sc. in Applied Mathematics (Brown Univ.)
- PhD in Applied Math/Operations Research, Brown University
- Started teaching at Brown University as a PhD student
- At MIT since 1994, at Sloan since 1998. Teaching MBAs, EMBAs, MSc, PhDs
- Former Faculty Co-director LGO Program (LFM) (2009-2015)
- Group Head in Operations Management at MIT Sloan (2010-2017)
- **Incoming Faculty Director of EMBA** Program (2017-present)

- **Research:** Analytics / Optimization, Applications in pricing/retail, supply-chains, energy, transportation....

- **Projects:** **Retail:** Oracle, Inditex (Zara), IBM, J&J
  **Energy:** Nationalgrid, PG&E, **Transportation:** Thenamaris
Georgia Perakis


– Went to the White House in Fall 2000 (when Clinton was still president).
– Informs Fellow, Class 2016

– Why did I become an academic?

I enjoy learning and discovering new things.
I love working with students at MIT (PhD, Masters, Undergrad, MBA, EMBA).

I have graduated 19 PhD and ~40 Masters students so far.
Some of my students are now professors. (Columbia U, Wharton, UCLA, Michigan, Toronto, NYU) others are in industry (Finance, Consulting etc.).
My group includes: 8 PhDs, 4 Masters and 4 Undergraduate students.

My aspirations:
Educate the next generation of students in analytics.
Have an impact through analytics.
Bridge the gap between industry and academia
What is Analytics?

• An approach to solving problems that starts with **Data**, builds **Models** to arrive at **Decisions** that create **Value**

• **Analytics: Our Prophetic Science**
  Dean Schmittlein

• Undergraduate Major and Minor in Analytics
• New MBAn one year Masters
• New Certificate on Analytics for MBAs
Analytics Problems -- Process

• Determine what is the “important“ (first order) management / analytics problem to address

• What are the data needed and are available?

• Formulate/Solve the appropriate model (prediction, prescription)
When Analytics Meets Promotion Pricing

Lennart Baardman
Maxime Cohen
Tamar Cohen
Jeremy Kalas
Zachary Leung
Georgia Perakis

Steve Jeffreys
Kiran Panchamgamm
Tony Smith
Sajith Vijayan

MIT Sloan School of Management
Oracle
Promotions

Promotions are **temporary reduction in prices**

– 50 cents OFF Barilla sauce
– $1.70 OFF for 12 oz. coffee
Promotions

When and how deep to promote?

• In practice, need to decide the promotion decisions for many SKUs. When shall we use simultaneous promotions?

(250 items, 20 prices and 13 weeks \(\rightarrow\) \(~65,000\) decisions)

• Can retailers decide promotions as they wish?
Promotions

Promotions are **temporary reduction in prices**

– 50 cents OFF Barilla sauce
– $1.70 OFF for 12 oz. coffee

Retailers use promotions to:

• Increase **sales**
• Increase **traffic**
• Introduce **new items**
• Bolster **customer loyalty**
• **Price** discrimination
• **Competitive** Retaliation
Promotions in supermarkets -- Facts

- Almost half (42.8%) of U.S. supermarket purchases are sold on promotion (Nielsen, 2009)

- $7.66 billion in revenue in the U.S. in 2005 (C. Endicott and K. Wylie)

- “…, it’s stunning to see an additional 1.3 billion purchase decisions being influence by in-store promotions,” – T. Pirovano, Director at Nielsen, 2009
Retail pricing is a big business!

Pricing solution providers

![Logos of various pricing solution providers]
Promotion planning process

• The promotion planning process is complex and can be divided into four stages

How much discount should I give to the retailer? How much to require to pass through to the customer?

Out of all the offered vendor funds, which ones should I select?

Given the selection of vendor funds, what prices should I charge?

Given the selection of vendor funds and prices, what vehicles should I use?
Promotions

Sell the **right product**

At the **right time**

To the **right customer**

At the **right price**
Promotions and optimization

Set the ‘best’ selling prices throughout selling season (e.g., 13 weeks)
- carefully design the promotion planning
- obeying business rules

How to promote the
- right product,
- at the right time
- using the right price

Managing sales promotions for thousands of SKUs across many stores is a challenging problem

Current process is ad hoc (using experience and intuition)
Lots of money are left on the table
Business rules are important

• Prices have to be selected from a **price ladder**
  e.g., prices should end by 9 cents \{4.99, 4.79, 4.49, 4.39, 3.99\}

• **Limit** on the number of promotions per item, or per season
  e.g., can promote an item at most 3 times during the quarter

• Minimum time **separation** between promotions (called no-touch period)
  e.g., need to wait 3 weeks between successive promotions
More business rules

• Limit on how many items can be promoted per period

• Inter-item constraints
  - Cannot promote two items simultaneously
  - Must promote several items simultaneously
  - Items A and B need to have a price ordering (e.g., smaller size has to be cheaper than larger size)

Modeled with Integer Optimization
Retailer Faces Complex Business Problem ...

Promotion Planning

- Promotions lift
- Stockpiling
- Seasonality
- Cross-effects
- Vendor Deals
- Inter-item rules
- Limit on number of promotions
- Min time between consecutive promotions
Philosophy in Analytics Problems

• Build simple – practical – realistic model

• Model input easy to estimate directly from data

• Computationally efficient ("easy" and scalable)

• Leads to interesting insights

• Brings significant value to a retailer in practice
Data, Models and Decisions

Data $\rightarrow$ Models $\rightarrow$ Decisions

Prediction $\rightarrow$ Prescription
Promotion Planning Process

• Data in supermarkets
  Collection, aggregation, imputation, clustering

• Demand models
  Consumer behavior, cross-item effects, estimation from data

• Business rules
  Mathematical modeling to capture rules on promotions

• Promotion Optimization

• Profit impact – Out of Sample / Pilot
  3-18% improvement ($0.5M for a store with annual profits $10M)

• Implementation
Big supermarket chain-Tier-1 (annual Rev $1-5B)

Large data on customer transactions

Coffee category ~ 250 SKUs

32 brands
Private & non-private labels

Promotions information
18% of sales through promotions

Data filtering, aggregation
State of the Art in Industry

• Standard assumptions
  
  Monopolistic retailer, non-strategic shoppers, items are independent (or depend on a small number of other items)

  Parametric demand models
  
  1-4 years of historical data to estimate a few demand model parameters

• Every week

  Observe sales

  Implement promotions

  Demand learning

  Price recommendations that follow business rules

  Retailers review promotions
Dataset

• **113 weeks of data** from 2009 to 2011 from a large supermarket chain.

• Several stores (18 stores).

• Each observation contains **weekly brand-level data**:  
  – Week  
  – Store  
  – Brand/SKU  
  – Sales volume  
  – Price (actual prices)  
  – Past weeks prices  
  – Item features (size, flavor, etc.)
Training and Testing Sets

- Split the data into training (in sample) and testing (out of sample) sets
- First, we fit the models using the training set
- Second, we assess their performance on the test set
Price versus sales from data
Demand model -- Functional Forms

Linear model

\[ Sales = a - b \cdot Price \]

Captures price elasticity: \( b \) is usually positive (\( \uparrow Price \rightarrow \downarrow Sales \))

\[ a = 200 \]

When \( b \) increases, the product is more elastic, i.e., consumers are more sensitive to price changes.
Reference Price in Supermarkets
Stockpilling
Reference Price in Supermarkets
Stockpilling

= $10

$15
Anchoring Models in the Literature

Bounded Memory

- Adaptation-level theory (Helson, 1964)
  - The memory for prices is bounded
- Manohar et al. (1990), Rajendran and Tellis (1994)
  - (Used past 5 prices, and 3 prices respectively)

- Bounded Memory Model
  \[ d_t^{BM} = f_{BM}(p_t, p_{t-1}, \ldots, p_{t-M}) \]

Demand depends on current and \( M \) past weeks prices

\( M \) is the memory factor discovered from the data.
Initial prediction model

The *initial prediction model* includes all the independent variables we expect to have an influence on sales:

- Brand dummy variables
- Seasonality dummy
- Trend variable
- Price for each brand
- Past weeks price for each brand
Demand model -- Variables

\[ Sales_t = a + \beta \cdot I(brand) + \phi \cdot I(week_t) + Trend.t - \gamma^0 Price_t + \sum_{s=1}^{M} \gamma^s Price_{t-s} \]

- **Item seasonality and trend**
  Sales depend on time, e.g., ice-cream during summer, turkey for Thanksgiving etc.

- **Past prices and stockpiling behavior**
  \( M \) represents the memory of customers w.r.t past prices
  Promotions boost current sales but **may decrease future sales** (non-perishable products)
Sales data format

Example of a dataset for three brands: **Nescafe, Folgers, Maxwell House** over two weeks

<table>
<thead>
<tr>
<th>Brand</th>
<th>Week</th>
<th>Season</th>
<th>Price</th>
<th>Past Price</th>
<th>Sales</th>
</tr>
</thead>
<tbody>
<tr>
<td>Folgers</td>
<td>9</td>
<td>Winter</td>
<td>1</td>
<td>1</td>
<td>861</td>
</tr>
<tr>
<td>Nescafe</td>
<td>9</td>
<td>Winter</td>
<td>0.75</td>
<td>1</td>
<td>2259</td>
</tr>
<tr>
<td>Maxwell House</td>
<td>9</td>
<td>Winter</td>
<td>1</td>
<td>1</td>
<td>915</td>
</tr>
<tr>
<td>Folgers</td>
<td>10</td>
<td>Winter</td>
<td>1</td>
<td>1</td>
<td>823</td>
</tr>
<tr>
<td>Nescafe</td>
<td>10</td>
<td>Winter</td>
<td>1</td>
<td>0.75</td>
<td>754</td>
</tr>
<tr>
<td>Maxwell House</td>
<td>10</td>
<td>Winter</td>
<td>0.8</td>
<td>1</td>
<td>1993</td>
</tr>
</tbody>
</table>

\[
\text{Sales}_t = a + \beta \cdot I(brand) + \text{Trend}_t + \varphi \cdot I(\text{season}_t) - \gamma^0 \text{Price}_t + \gamma^1 \text{Price}_{t-1}
\]
Trimmed linear model

No insignificant variables

\[ Sales_t = a_0 + a + \sigma_t + Trend_t - b_0 Price_t + b_1 Price_{t-1} \]

<table>
<thead>
<tr>
<th>Variables</th>
<th>Estimate</th>
<th>Confidence Interval</th>
</tr>
</thead>
<tbody>
<tr>
<td>Intercept</td>
<td>5722.0364</td>
<td>[5129.7751, 6314.2978]</td>
</tr>
<tr>
<td>Trend</td>
<td>-2.0672</td>
<td>[-3.4325, -0.7018]</td>
</tr>
<tr>
<td>Price Brand</td>
<td>-5271.0429</td>
<td>[-5676.9521, -4865.1336]</td>
</tr>
<tr>
<td>1 Past Price Brand</td>
<td>478.5553</td>
<td>[78.9755, 878.1350]</td>
</tr>
</tbody>
</table>

OOS $R^2 = 0.9413$
# Understanding Demand

<table>
<thead>
<tr>
<th>Brand</th>
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<td>754</td>
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<td>10</td>
<td>Winter</td>
<td>0.80</td>
<td>1</td>
<td>1993</td>
</tr>
<tr>
<td>Folgers</td>
<td>11</td>
<td>Winter</td>
<td>1</td>
<td>1</td>
<td>?</td>
</tr>
<tr>
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<td>11</td>
<td>Winter</td>
<td>1</td>
<td>1</td>
<td>?</td>
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<td>11</td>
<td>Winter</td>
<td>1</td>
<td>0.80</td>
<td>?</td>
</tr>
</tbody>
</table>

\[
Sales_t = 5722.0364 - 2.0672*t - 5271.0429*Price_t + 478.5553*Price_{t-1}
\]

Prediction:
- Folgers: 907
- Nescafe: 907
- Maxwell House: 811
How Good is the Prediction?

Is this a good prediction?

\[
R^2 = 1 - \frac{\sum_{i=1}^{T} (y_i - \hat{y}_i)}{\sum_{i=1}^{T} (y_i - \bar{y})}
\]

\[
MAPE = \frac{1}{T} \sum_{i=1}^{T} \left| \frac{y_i - \hat{y}_i}{y_i} \right|
\]
Trimmed Linear Model OOS

We look at the model performance out-of-sample

\[ R^2 = 1 - \frac{\sum_{i=1}^{T} (y_i - \hat{y}_i)}{\sum_{i=1}^{T} (y_i - \bar{y})} \]

\[ MAPE = \frac{1}{T} \sum_{i=1}^{T} \left| \frac{y_i - \hat{y}}{y_i} \right| \]

<table>
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<tr>
<th>Performance statistic</th>
<th>Trim Model Out-of-sample</th>
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<tbody>
<tr>
<td>R squared</td>
<td>0.9413</td>
</tr>
<tr>
<td>MAPE</td>
<td>16.17%</td>
</tr>
</tbody>
</table>
Reference Price in Supermarkets

Extreme Experiences!
Reference Price in Supermarkets
Extreme Experiences!

=$10

$15
Anchoring Models - Peak-End

- Extreme experiences remain in our memory longer.

- “The requirement to report effect in real time could enhance the salience of the worst and the final moments” (Kahneman 1993)

- Peak-End Model with Bounded Memory

  \[ d_t^{PE} = f(\zeta_{t-1}, p_{t-1}) \]

  where \( \zeta_t = \min_{M<\tau<t} p_\tau \) (min price up to Memory)

\[
Sales_t = a + \beta \cdot I(brand) + Trend.t + \varphi \cdot I(season_t) - \gamma^0 Price_t + \gamma^1 Price_{t-1} + \gamma^{Peak} \min_{t-M<\tau<t} Price_\tau
\]
Trimmed Linear Model OOS

We compare the two models (bounded memory and bounded peak end) out-of-sample.

$$R^2 = 1 - \frac{\sum_{i=1}^{T} (y_i - \hat{y}_i)}{\sum_{i=1}^{T} (y_i - \bar{y})}$$

$$MAPE = \frac{1}{T} \sum_{i=1}^{T} \left| \frac{y_i - \hat{y}}{y_i} \right|$$

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Find Narratives in Data

Sales Quantity

Normalized Price
Demand Model -- Functional Forms

- **Linear model**

- **Non-linear models**
  Non-homogeneous effects (different price changes can have different impacts on sales)

Example:

**Log-log (power function)**

\[ \log(Sales) = a - b \cdot \log(Price) \]

Estimate the parameters **a** (market share/brand effect) and **b** (price elasticity) from data
Linear and log-log models

• Linear regression of **sales versus prices**

\[ sales_t = \alpha + \beta \cdot I(brand) + \phi \cdot I(week_t) + \delta \cdot t + \gamma^0 \cdot price_t \]

\[ \quad + \gamma^1 \cdot price_{t-1} + \ldots + \gamma^M \cdot price_{t-M} \]

• Linear regression of **logarithm of sales versus logarithm of prices** (Bdd Memory vs Peak-End)

\[ \log(sales_t) = \alpha + \beta \cdot I(brand) + \phi \cdot I(week_t) + \delta \cdot t + \gamma^0 \cdot \log(price_t) \]

\[ \quad + \gamma^1 \cdot \log(price_{t-1}) + \ldots + \gamma^M \cdot \log(price_{t-M}) \]

\[ \log(sales_t) = \alpha + \beta \cdot I(brand) + \phi \cdot I(week_t) + \delta \cdot t + \gamma^0 \cdot \log(price_t) \]

\[ \quad + \gamma^1 \cdot \log(price_{t-1}) + \gamma^2 \cdot \log(\min price_t) \]
Log-log vs Linear Bdd Memory Models

• Suggests that the log-log model performs better than the linear model with bounded memory

• Sales-price relationship is indeed non-linear

<table>
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<th>Performance statistic</th>
<th>Log-log Model Out-of-sample</th>
<th>Linear Model Out-of-sample</th>
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<tr>
<td>Bounded Memory $R^2$</td>
<td>0.9579</td>
<td>0.9411</td>
</tr>
<tr>
<td>Bounded Memory MAPE</td>
<td>11.11</td>
<td>16.09</td>
</tr>
</tbody>
</table>
Log-log Bdd Memory Forecast

80 weeks training
33 weeks testing

Out-of-sample
- **MAPE** = 11.11%
- **R²** = 0.9579

Memory $M = 2$
Log-log and Linear Models

Bdd Mem vs Bdd Mem Peak-End

- **log-log model** with peak end **performs better** than the linear as well as **bounded memory** models

- **Sales-price relationship** is indeed **non-linear**

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<td>16.17</td>
</tr>
<tr>
<td>Peak End $R^2$</td>
<td><strong>0.9606</strong></td>
<td>0.9413</td>
</tr>
<tr>
<td>Peak End MAPE</td>
<td><strong>11.04</strong></td>
<td>16.17</td>
</tr>
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</table>
GP, Log-log and Linear Models

- Suggests that the **GP model performs best** but...
- There are **tradeoffs:**
  - Black-box versus more transparent/interpretable model
  - ~0.52% improvement in MAPE. **Is it worth it?**

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<tr>
<td>Bounded Memory $R^2$</td>
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<td>0.9673</td>
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<tr>
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<td>16.17</td>
<td>10.54</td>
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<td>Peak End $R^2$</td>
<td><strong>0.9606</strong></td>
<td>0.9413</td>
<td>0.9744</td>
</tr>
<tr>
<td>Peak End MAPE</td>
<td><strong>11.04</strong></td>
<td>16.17</td>
<td>10.52</td>
</tr>
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Data, Models and Decisions

Data → Models → Decisions

Prediction

Prescription
Estimation → Optimization

• Recap about demand estimation

Data collection, aggregation, training/testing sets, demand models, estimate parameters, fit accuracy on the test set

• Next step is the optimization formulation

- Objective function?
- Decision variables?
- Constraints?

Assumptions

No inventory constraints so that demand = sales
Demand model estimated from data is an input
**Promotion Optimization Planning (POP)**

- **Finite horizon** $T = \text{quarter of 13 weeks}$ (time period=week)
- **Objective**: Maximize total profit
  
  Sum over all weeks $t$ in planning horizon:
  
  $$\sum_t (\text{demand over week } t) \times (\text{price}_t - \text{cost}_t)$$

- **Decision variables**: What price to set for the item in week $t$?

- **Constraints**: (business rules)
  - Prices must be chosen from the **price ladder**
  - **Limited number** $L$ of times retailer can promote the item
  - **No touch** constraints: two successive promotions are separated by at least $S$ weeks
  - **Inter-item** constraints
Solving the Optimization Problem

- Even for single item, the POP is **NP-hard** (Cohen, Gupta, Kalas, Perakis)
  - Objective is **neither concave nor convex**
  - Non-linear Integer Program
    - Non-linear solvers are slow and inaccurate
  - Enumeration is not tractable
- Need for a good approximation solution
Simple Solutions

• We formulated the POP problem with cross time, cross item effects and business rules

• BUT the problem is complex / hard to solve

• We come up with a simple approach that is mostly at least within 90% from optimal
Linear Optimization based approach

• We propose an approximation based on linearizing the objective

• Details are omitted and can be found online:

  The Impact of Optimization on Promotion Planning
  (Cohen, Leung, Panchamgam, Perakis, Smith)
  Patent Filed

• Allows us to solve the problem efficiently (for tens of thousands of items in a few minutes) and very close to optimal

• Can use solvers like Excel and hence accessible without licenses
Linear Optimization Approximation

**Key idea:** Approximate the true profit by the sum of the marginal contributions

Instead of accounting for promotions simultaneously, we compute the effect of each promotion separately (as if it was the only one)

If the number of promotions is small, or if the promotions are spaced out, the approximation is close to being optimal
Profit Impact

Optimal Prices - L=8

Current Practice

T=35 weeks

Running times: \( t \sim 0.05 \) [sec]

Translates to 12 sec per category per store for a Tier-1 Client
Pilot

• Demonstrate impact of optimizing promotions by *going live* with a large retailer
• Retailer agreed to use our model and pricing recommendations
• First: **Data analysis, data cleaning and Store Selection**

**Pilot design**

• Two stores (Store 1 and Store 2) – similar stores serving similar markets
• Two non-perishable products (A and B) - oil and chemicals category

<table>
<thead>
<tr>
<th></th>
<th>Store 1</th>
<th>Store 2</th>
</tr>
</thead>
<tbody>
<tr>
<td>Product A</td>
<td>Existing</td>
<td>Existing</td>
</tr>
<tr>
<td>Product B</td>
<td>Existing</td>
<td><strong>Our policy</strong></td>
</tr>
</tbody>
</table>

**Price recommendations (~10% improvement)**
Wrap-up

- Business Rules
- Time Dynamics
- Cross Item Effects

Promotion Optimization Model

Good/Simple Approximation Solution
Computationally Fast
With Theoretical Guarantees

Implementation + Pilot

3-18% Profit Improvement

Modeling

Optimization/Algorithm

Data and Impact in Practice

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Concrete Outcomes

– The Impact of Optimization on Promotion Planning
  (by M. Cohen, Leung, Panchamgam, Perakis, Smith) (Forthcoming in OR)

– Scheduling Promotion Vehicles to Boost Profits
  (by Baardman, M. Cohen, Panchamgam, Perakis, Segev) (Second Round MSc)

– An Efficient Algorithm for Dynamic Pricing using a Graphical Representation
  (by M. Cohen, Gupta, Kalas, Panchamgam, Perakis) (Submitted to OR)

– Optimizing Promotions for Multiple Items
  (by M. Cohen, Kalas, Panchamgam, Perakis) (to be submitted soon)

– The Role of Vendor Fund Selection in Promotion Planning
  (by Baardman, Panchamgam, Perakis) (to be submitted soon)

– Peak End Models and their Impact on Promotion Planning
  (by T. Cohen, Perakis) (to be submitted soon)

Three joint patents filed -- Pilot

Some Recognition

– First Prize: INFORMS Service Science Student Best Paper 2014

– First Prize: NEDSI Best Application of Theory Award  2015

– Finalists: INFORMS RM & Pricing Section Practice Award 2015

– First Prize INFORMS Service Science Best Paper Award 2016
Current Work

- **Personalizing** promotion recommendations.
- Predicting and targeting **influential customers**
- **Personalizing** bundle offerings and MD recommendations
- Learning **demand** for new products with **no/little data**.
Summary of Analytics Process

• Determine what is the “important“ management/analytics problem to address
• What are the data needed and available?
• Formulate the model (prediction, optimization)
  – May need to build a prediction model first to use in optimization (say through regression)
• Solve the problem (perhaps easy part)
• Analyze (get insight) the optimal solution to enhance managerial judgment. Get insights.
• Test out of sample and compare with current practice / perform a pilot.
• Articulate / communicate plan
• “Convince“ different stakeholders to implement
Collaboration in Analytics
MIT Sloan and Industry

• Focus on addressing an important problem for a company BUT with general academic implications.
• Close engagement with a company
• Access to data to inform problem specification and opportunity to test findings with company (pilot)
• Frequent meetings with company and MIT group to make sure we address the real issue
• Interwoven with educational mission of MIT Sloan (engagement of PhD, MSc and undergraduate students)
• Develop important frameworks/theory

• **Ideas made to matter!** Have an impact.
  Impact practice through analytics
The end!

Thank you!

Questions?