Enhancing Retail Assortment and Order Fulfillment with Big Data Decision Support

Matthew A. Lanham, CAP (lanham@vt.edu)
Doctoral Candidate
MatthewALanham.com

Ralph D. Badinelli, Ph.D. (ralphb@vt.edu)
Lenz Professor of Business
Department of Business Information Technology
VirginiaTech
Pamplin College of Business

Outline

Motivation – The Business Problem
- The Assortment Problem
- Assortment Decision Support

Motivation – The Analytical Problem
- Consumer Demand Parameter Estimation
- Assortment Optimization

Data
- Store, SKU, Consumer, Competitor Attributes
- Source - Internal/external
- Type - Structured/Unstructured
- Hierarchical parameters (i.e. budgets, shelf-space, growth intents, etc.)

Methodology/Approach Selection
- Classification (binary/multi-class) Techniques
- Forecasting Methods
- Textual Analysis
- Technology/Software
- Decision Model – Heuristics, DP, IP

Model Building
- Build and Assess Models
  - Traditional Fit Statistics
  - Business Performance Measures
- Business Analytics Approach to Combining Methodologies

Deployment/Research Contributions
- Score Models/New Forecasts
- Generate Store Assortments
- Review Analytical Solution & Problem Links
- New Hypotheses & Research Questions

Life Cycle Management/Business Benefits
- Track Model Quality
- Track and Evaluate Business Benefits
- Better Decision Support

Resources & References

The Assortment Problem

The Assortment Decision Entails:
- What, where, when, and how many products to offer?

Typical Objective:
- Determine which products to stock in a location in order to maximizes sales or profit while satisfying various constraints.

Importance:
- Considered to be the most important decisions faced by retailers because of the substantial impact the products carried, not carried, or not available have on sales and gross margin (Kök et al., 2015; Sauré & Zeevi, 2013).
- A retailer not providing what the consumers desires will lose market share
- Faster (real-time) and better assortment changes can create competitive advantages

Difficulty:
- Thousands of Products & Stores NP-hard Problem
- Understanding and modeling consumer purchase behavior adequately is the holy grail.

Research Focus Continues to Evolve:
- High-level: A process employed to find the optimal set of products to carry and amount of inventory to maintain of each product (Kök & Fisher, 2007).
- Specific: Making product decisions based on consumer choice behavior and substitution effects (A. H. Hübner & Kuhn, 2012).

Common Retail Example

Retail Example

- A category manager (a.k.a. Merchant) for a retailer will review their product category by removing SKUs that are not selling as expected and add SKUs that have higher potential to sell or are more profitable.
- Their objective is to maximize their categories sales

New Inventory Added

Unproductive Inventory Removed

- These decision-makers use various forecasts from ERP systems, custom internal decision-support tools, vendor suggestions, as well as any other information they believe is important to achieve their objective but really lack having a true assortment DSS.

Our Research:

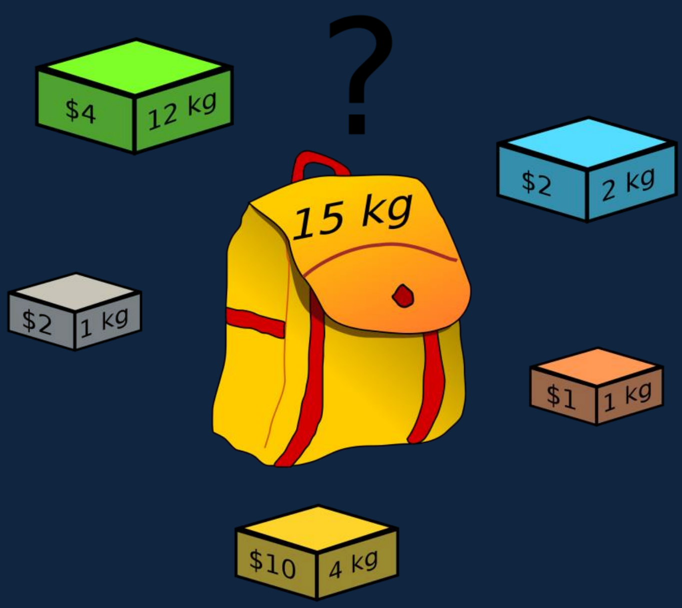
1) Estimating novel or improved product demand forecasts using machine learning algorithms (e.g. ensembles) and other data sources (e.g. product reviews)
2) Formulating a scalable store assortment recommendation optimization model using these forecasts as parameter inputs (e.g. an assortment DSS)

Assortment Decision = Knapsack Problem

Sketching out the Decisions, Constraints, and Objective

A category manager's problem is a variant of the classical knapsack problem

- **Constraint performance measures**: (*values passed down the decision hierarchy which would be used as parameters in an optimization model*)
  - Total allocated budget per category (or sub-category) ($)
    - Line review (investment) budget, In-stock budget
  - Category growth intents
  - Different shelf-space or dollars-invested per store
  - Vendor contractual obligations
- **Key performance indicators (KPIs):**
  - Increase sales ($)
  - Reduce non-working inventory (NWI) ($)
  - Maintain or increase conversion rate
  - Maintain acceptable margin levels
- **Decisions:**
  - What products to add (*or remove*)
  - When to add (*or remove*) the product
  - Where to add (*or remove*) the product
- **Potential Decisions (but typically fixed parameters):**
  - How many product units to stock (*decision from a replenishment model*)
  - What is the product price (*decision from a pricing model*)



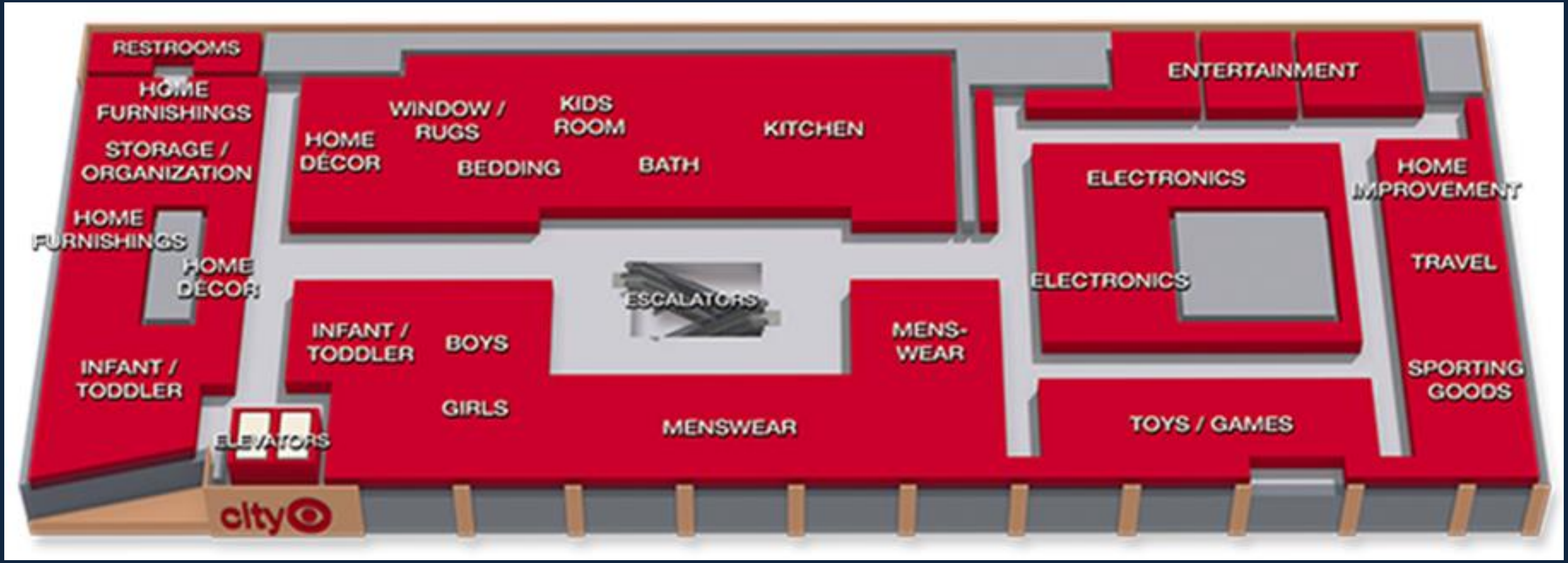
One Retail Store & Categories

The Literature

- Research has mostly focused on one assortment for a retailer, even though retailers will regularly have different assortments for different stores due to the differences in customer preference.
- It might be assumed that their solutions would then be implemented to each store individually (Kök, Fisher et al. 2015).

Positioning the Problem

- The store assortment problem could be formulated as a knapsack of various-sized knapsacks problem (for each retail store).



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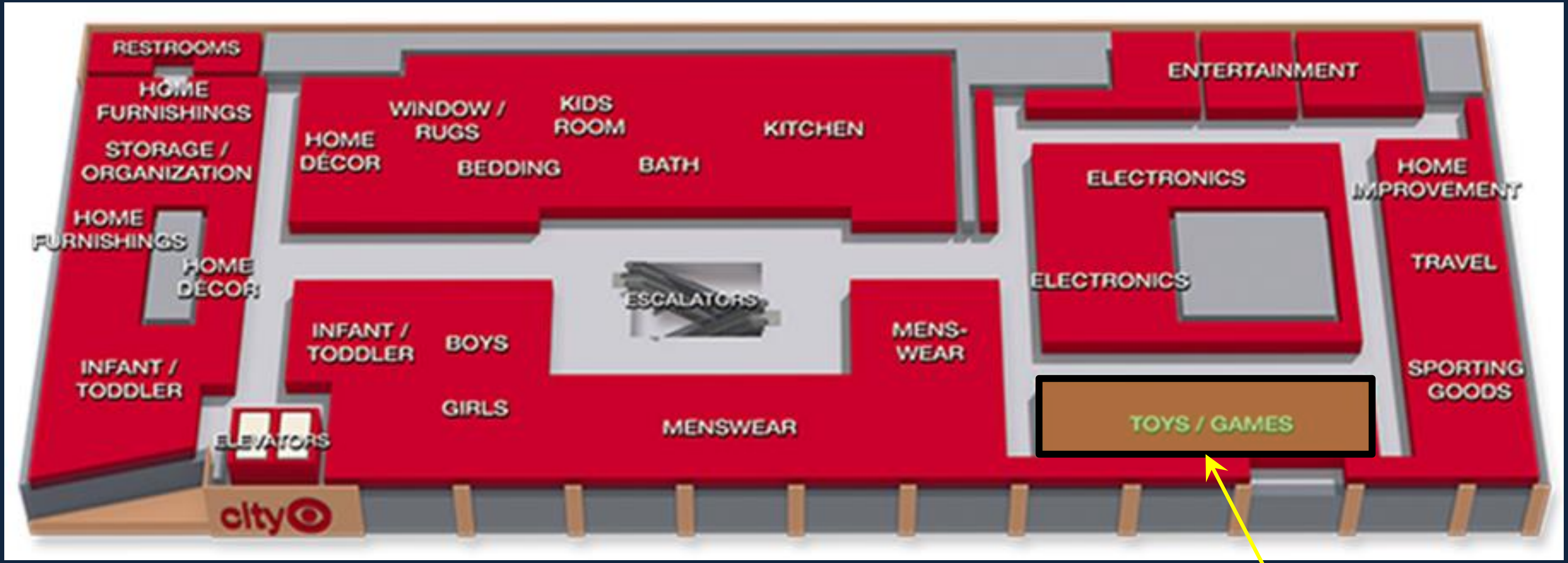

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Estimate, Formulate, Solve

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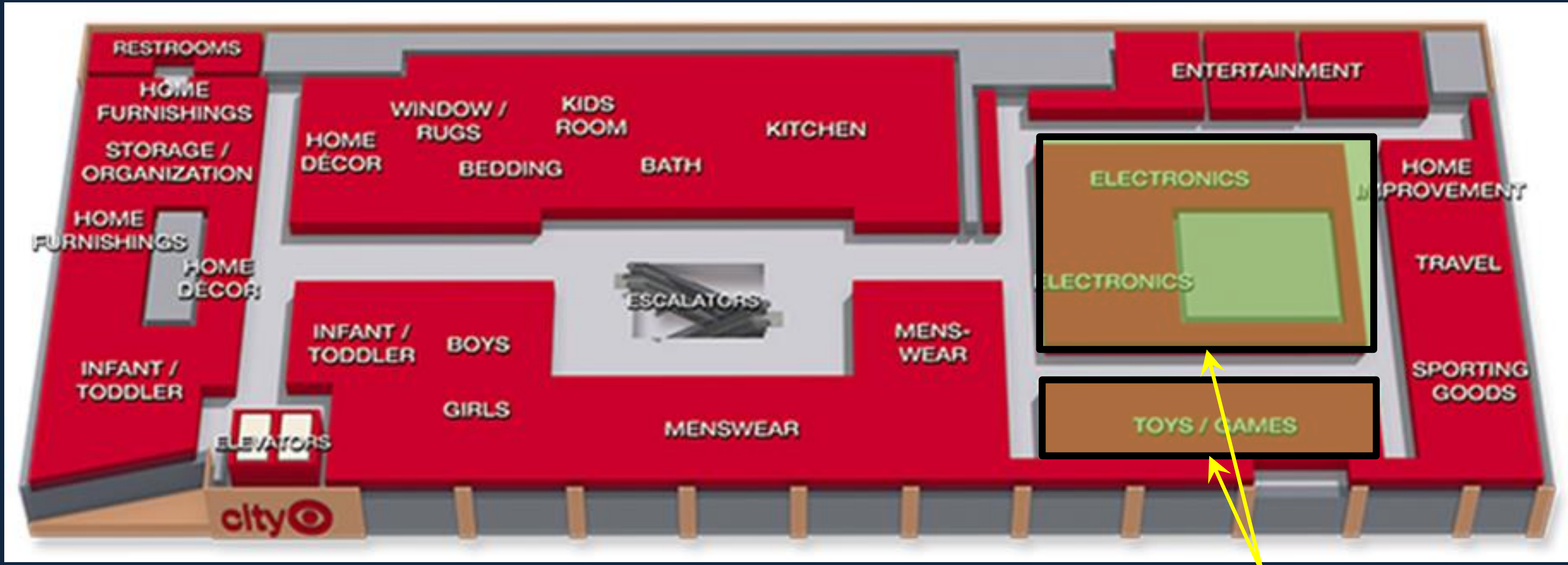

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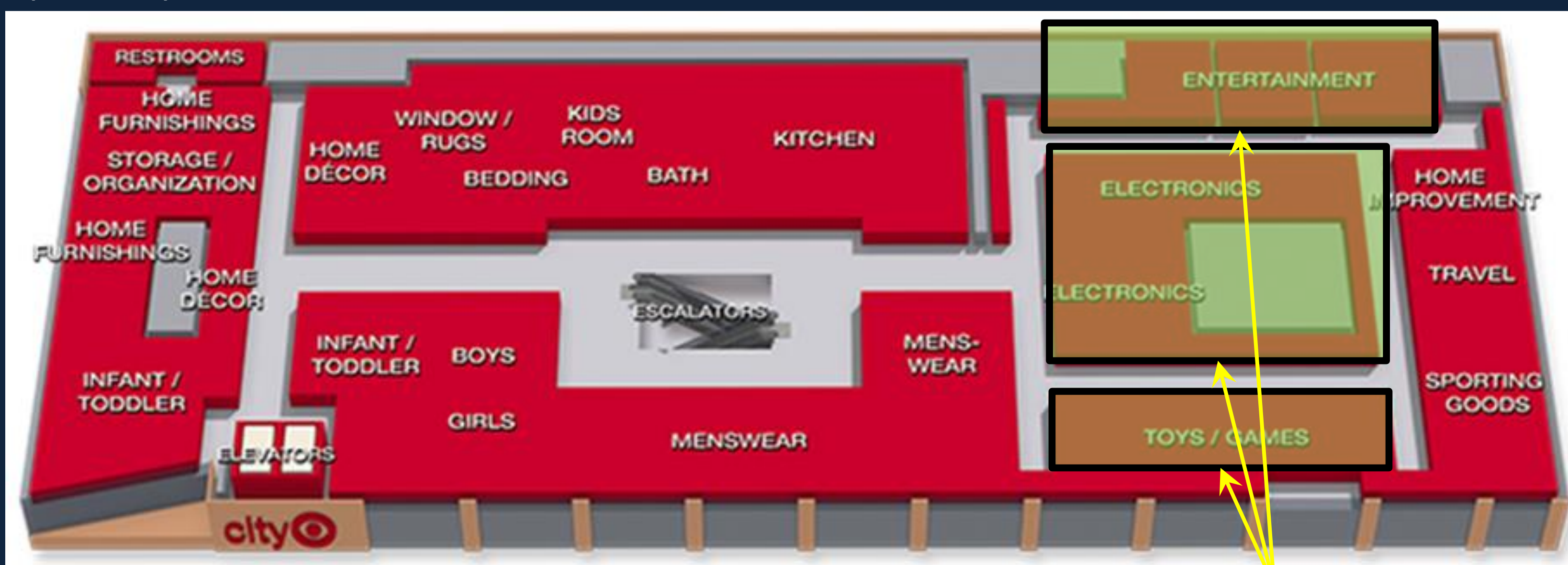

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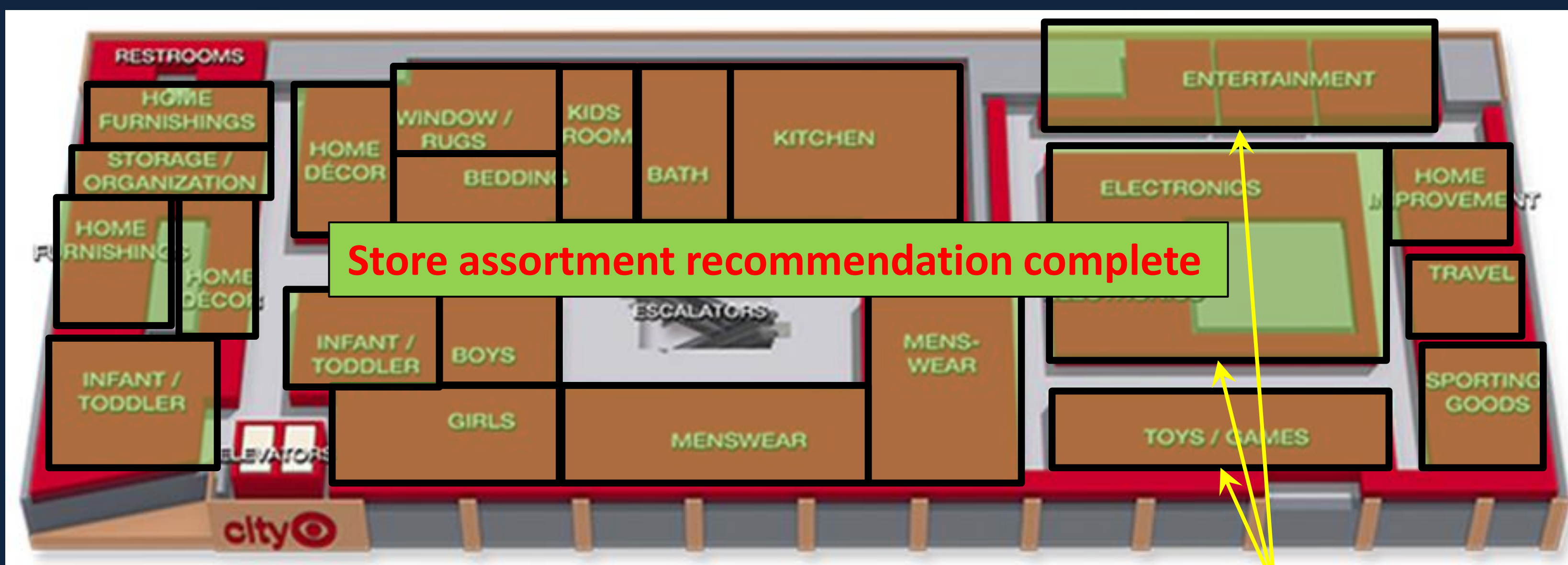

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Estimate, Formulate, Solve

Decision Making Hierarchy

Where do some of these parameters/constraints come from?

Category resource allocation is a fundamental component of **Category Management**.

Recommendations are empirically generated based on analyses that include the constraints defined up the hierarchy

Upper Management (CEO, CFO, SVP)

Strategic decisions
- Growth Strategy Decisions

Middle-Upper Management (Directors)

Operational decisions
- Product/Region Budget Allocation
- Allocated shelf-space or dollars-invested per store

Category Managers

Category decisions
- Line Review Decision
- Vendor contractual obligations
- Variety, brand, promotion strategy

Data Science Initiatives

Market Support

Assortment Support

Pricing Support

Assortment Modification

Five ways to modify an assortment

Inventory Adjustment Possibilities	Decision Maker	Time	By	Description
Line Review Plan	Category Manager	Once per year	Category	The primary category line review for the upcoming year
Periodic Review	Category Manager	Each period	Store per Week	The assortment is modified in smaller portions throughout the course of the year
Strategic Upgrades	Market Assessment	Each period	Store	Strategically add more volume of product based on competitor market share
Store Requests/Feedback	Market Assessment	Each week	Store	Store managers have relationships about their unique customer base and will request items that are not able to be captured from the predictive models
New Store Openings	Market Assessment	Varies	Store	Assortments initialized based on similar store demographics and characteristics with the goal of breaking-even as soon as possible

- All of these types of decisions necessitate a great understanding of consumer demand

Our Focus - The Line Review Plan

- The more we can improve in this area in the technical/model KPIs, the more a firm should realize an increase in the business KPIs (increased sales, reduced costs, acceptable margins, less "non-working inventory", etc.)

Predictive Modeling KPIs →  ← **Operational Business KPIs**

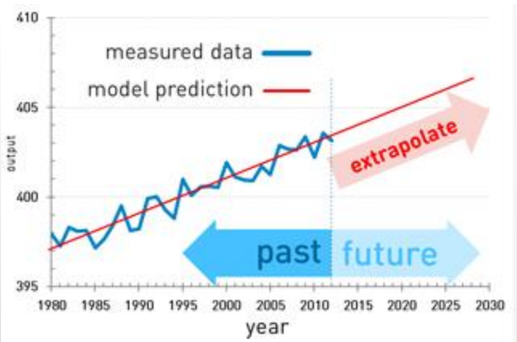
Business Analytics Domains

What is Analytics?

- *Refers to the skills, technologies, applications, and practices for continuous iterative exploration and investigation of past business performance to gain insight and* ***drive business planning*** (Wikipedia, 2014)."

Predictive Analytics

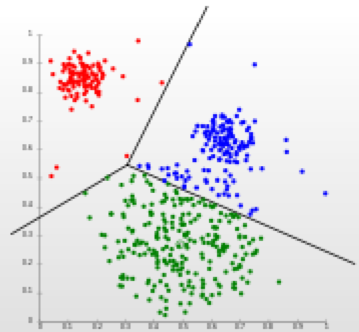
What will happen?



- Forecasting/Pattern recognition
- Classification
- Ensemble Modeling

Descriptive Analytics

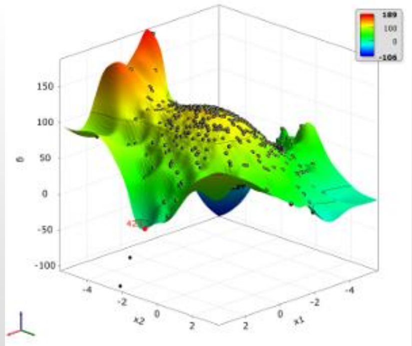
What has happened?



- Exploratory Data Analysis (EDA)
- Uni- and Multivariate Summaries
- Clustering - Segmentation - Profiling

Prescriptive Analytics

What is the best course of action?



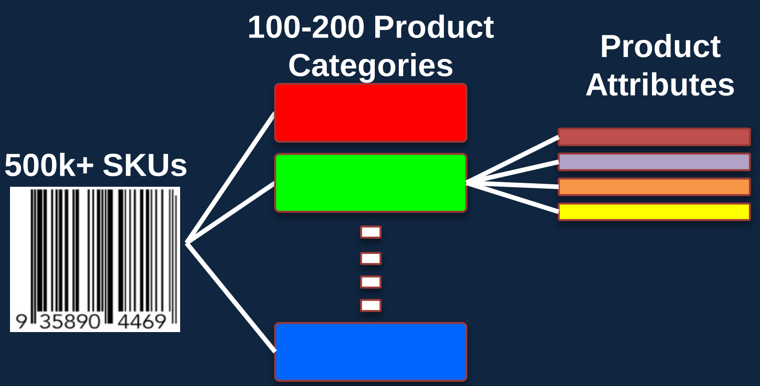
- Optimization/Heuristics
- Simulation
- Computational Stochastic Optimization

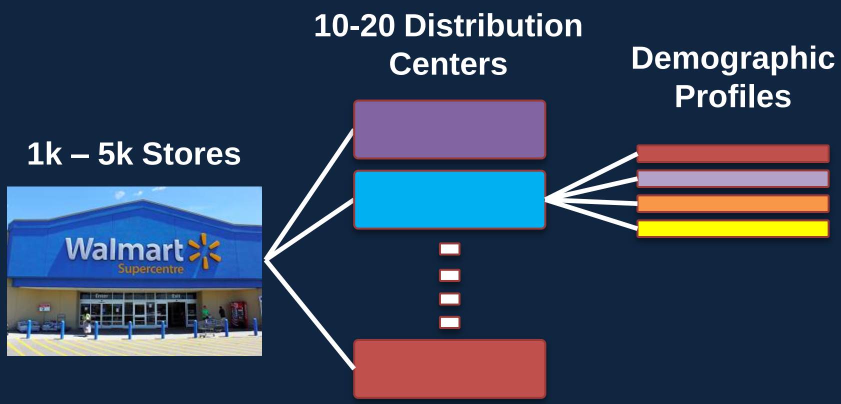
- To improve the assortment decision will require using techniques in all three domains

Assortment Complexity for Major Retailers

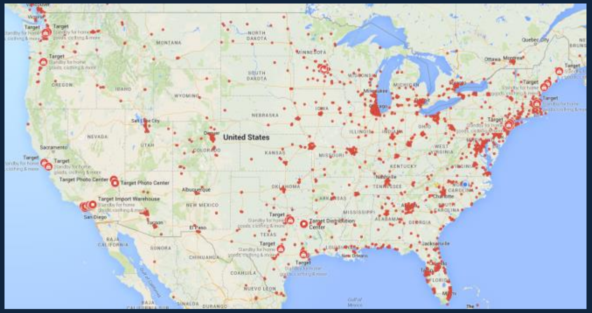
Store-SKU complexity

- The set of potential SKUs that a retailer may choose from can be 1,00,000+
- A traditional merchandise store (e.g. Big K) would carry approximately 16,000 unique stock-keeping units (SKUs) with an additional 6,000 seasonal products, depending on the time of year (Cox 2011).





- A chain retailer can have several thousands of stores. A few examples, Walmart has 5,187 stores in the U.S. alone (Walmart 2015), Target 2,155 (Target 2015), and J.C. Penny 1,060 (Wikipedia 2015).

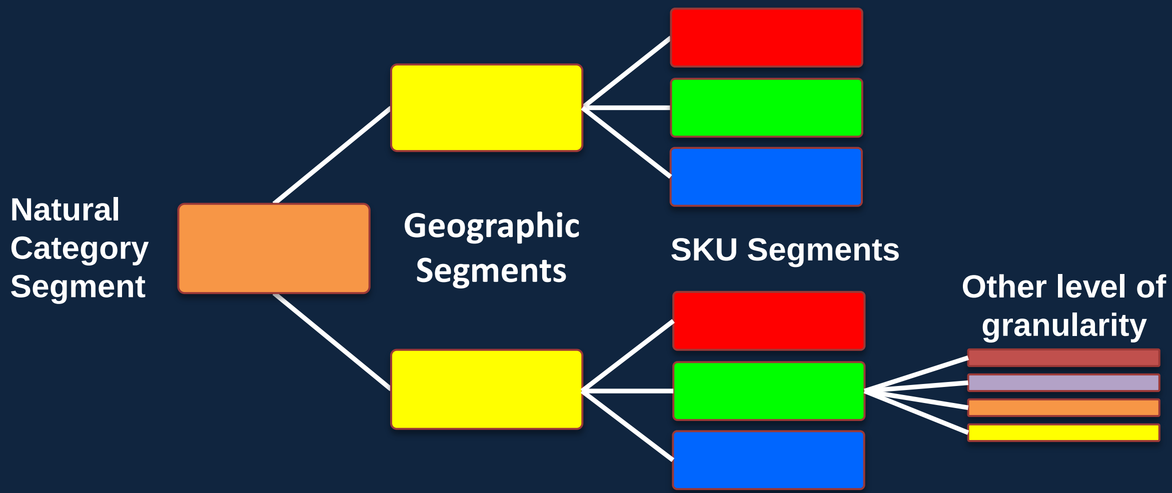


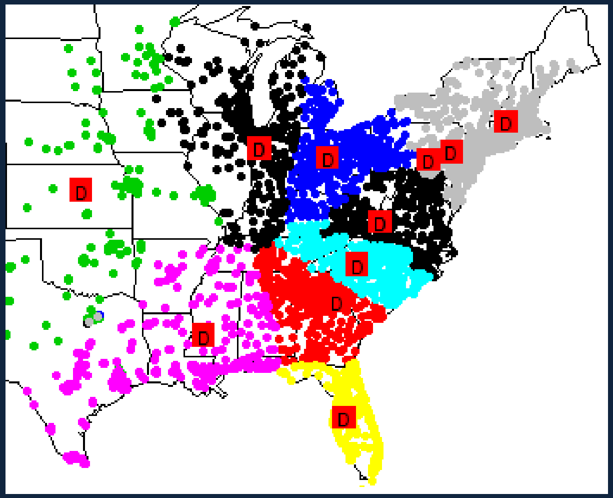
- How can we possibly model demand so that we know which SKUs to put in which stores?

Descriptive Analytics - Business Segmentation

Segmentation/Clustering

- It is common practice to segment your customers or product in some fashion (geography, planograms, categories, etc.) to increase the predictive accuracy of your predictive models



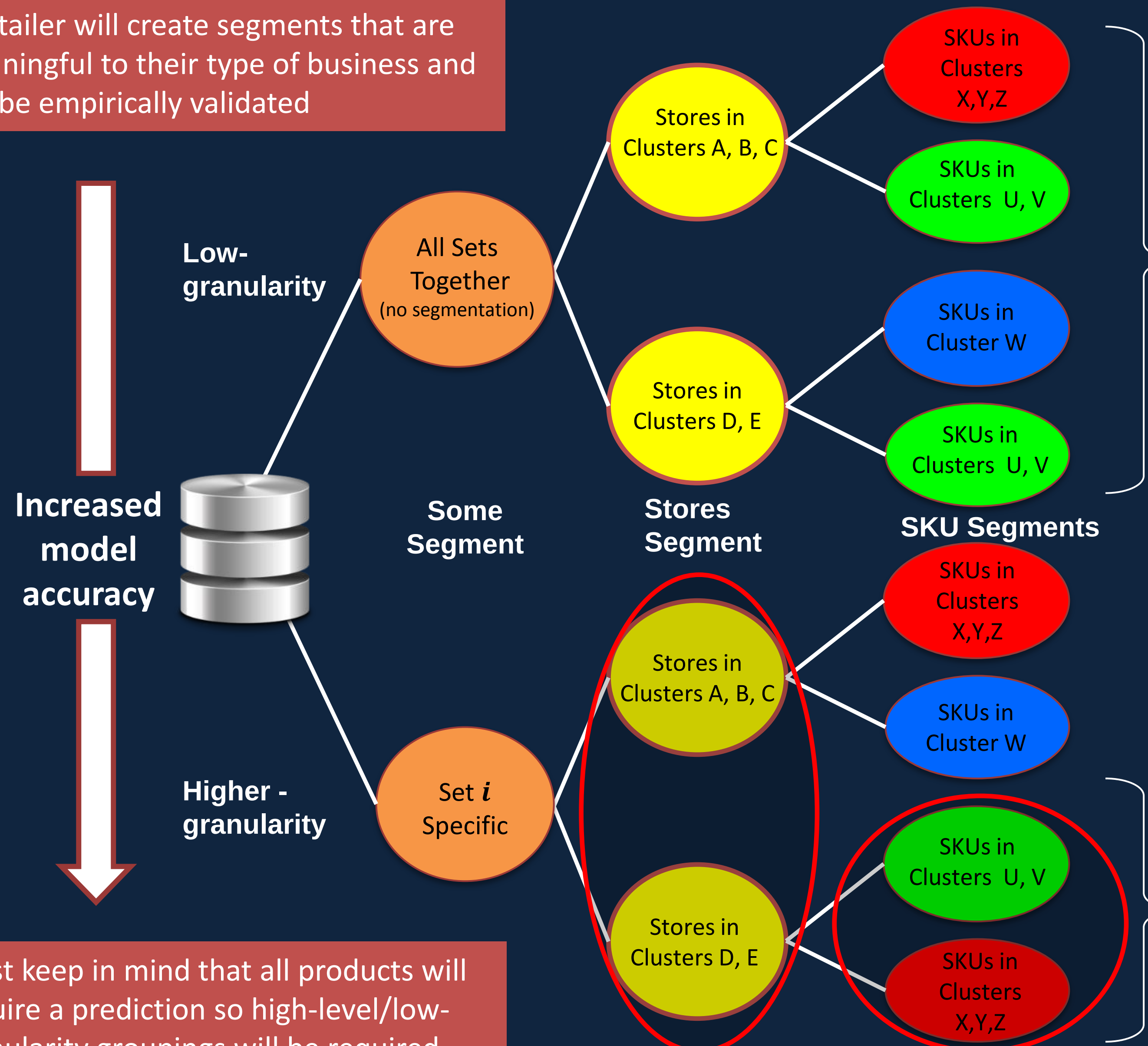


Modeling Art & Realities

- Some data clusters will have too few observations to train intelligent models
- Depending on the business, SKUs will sell at different rates for different time horizons
- The predictive ability of some model-type/data cluster will be better than others which can be taken advantage of
    1. To generate more accurate propensity estimates (I will provide an example of this shortly)
    2. To provide estimates for SKUs/Stores without sales history

A Generic Clustering Example

A retailer will create segments that are meaningful to their type of business and can be empirically validated



Lower predictive accuracy than higher-granularity models, but does provide a retailer a measure of demand

For set i, there may be too few observations to generate a model at this level of granularity, thus

1. Combing clusters may be required
2. Combing store clusters together may be required

Must keep in mind that all products will require a prediction so high-level/low-granularity groupings will be required

Predictive Analytics - Binary Classification

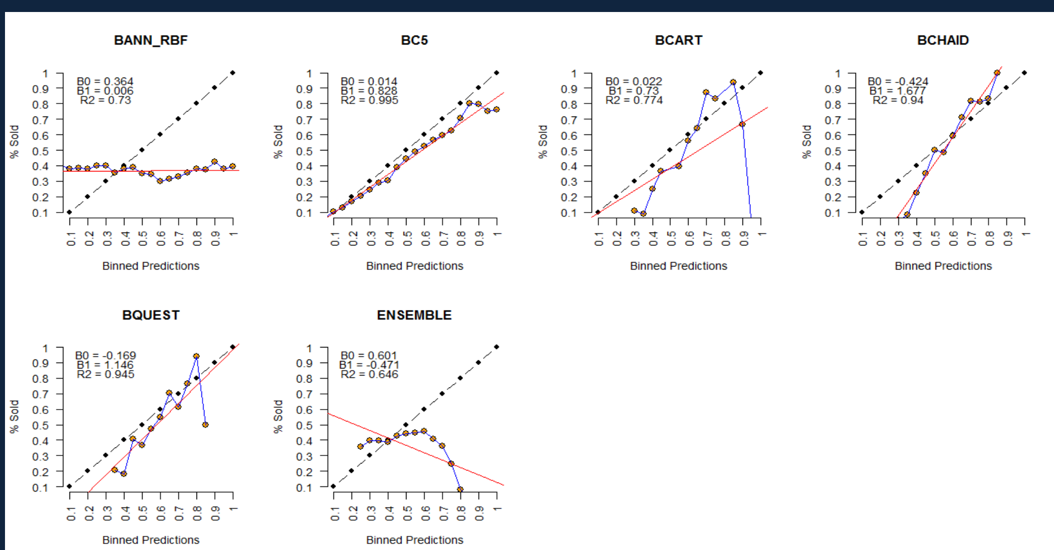
Predictive Analytics

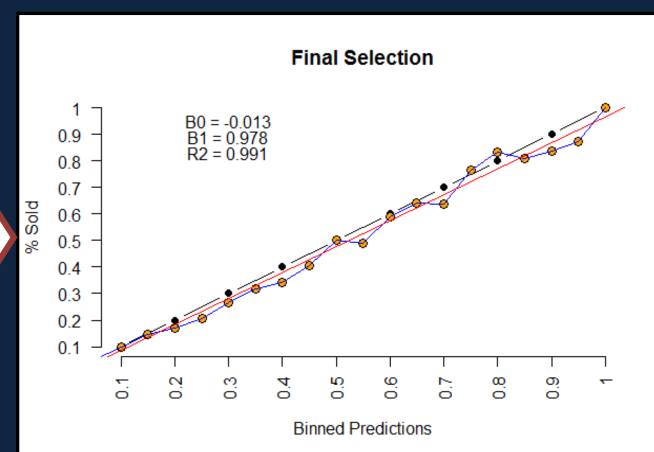
- the process of building a model that predicts some output or estimates some unknown parameter using statistical, machine learning/data mining, or pattern recognition techniques (M. Kuhn & Johnson, 2013).

Binary Classification

Objective 1: Determine the probability that SKU i will sell in store j

- This is not being performed in the academic literature for various reasons (type of retail business, product turn rates, etc.) but it can be effective
- We have found that if one is to use this approach selecting SKU propensity to sell measures based on traditional predictive model performance measures (e.g. ROC/AUC) is insufficient.





* More details to be presented at INFORMS Workshop on Data Mining and Analytics (Philadelphia, PA November 2015)

Multi-Class & Substitution Modeling

Objective 2: Estimate probability that SKU i will sell among its substitutable set S in store j

- Academic literature has primarily focused on these utility-based models to estimate substitution effects
  - Multinomial Logit Model (MNL)
  - Exogenous Demand (ED)
  - Locational-choice (LC)
  - Nested Logit (NL)
  - Bayesian Learning

Assumptions

- The set of potential products/classes is discrete; 1,..,N and class-specific (no-overlap)
- The features need not be statistically independent (but collinearity should be low)
- Independence of Irrelevant Alternatives (IIA) is a choice theory assumption stating that adding or removing different response categories does not affect the odds of the other response categories
- There is a substitute available in the set of products when a consumer's preferred product is not available in the set, N.

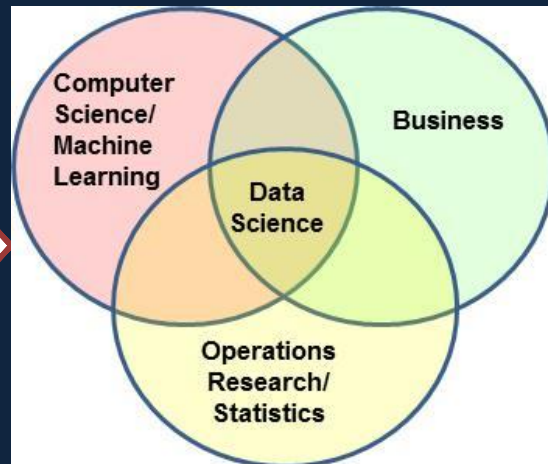
Requirements

- Need to know the set of substitutable products for each product (*work in progress*)

Big Data Analytics

What is Data Science/Big Data Analytics (BDA)?

- *"Data science involves extracting, creating, and processing data to turn it into business value* (Granville, 2014)"



Business Analytics Technologies

Hybrids

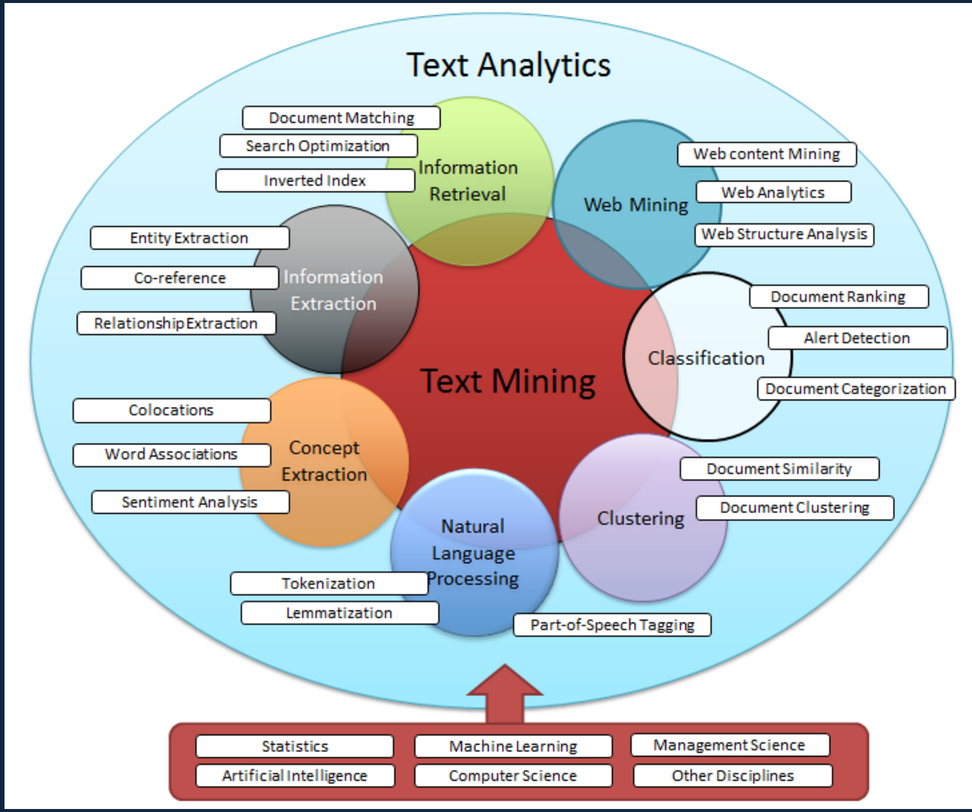
BDA Technologies

- Is there a business case for BDA in assortment planning?

Text Mining & Analytics

Text Analytics
- Text mining includes several techniques from the broader field of text analytics.

Idea
- Obtain and transform textual data into high-quality actionable information that can be used to support better decision-making.



Source: Modified from Practical Text Mining Figure I.1 (Elder, Hill et al. 2012)

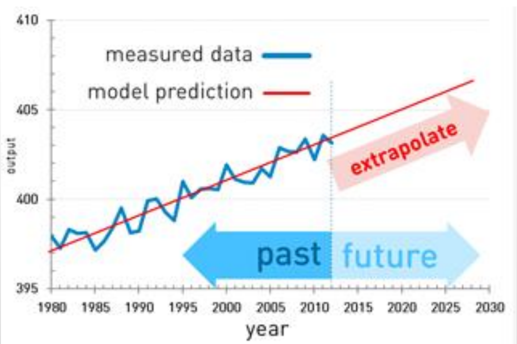
Bringing Business Analytics Full Circle

Business Analytics

- Once we obtain these clusters to generate predictive models, generate the predictive forecasts, our next step is to incorporate these forecasts as parameter inputs to an decision model

Predictive Analytics

What will happen?



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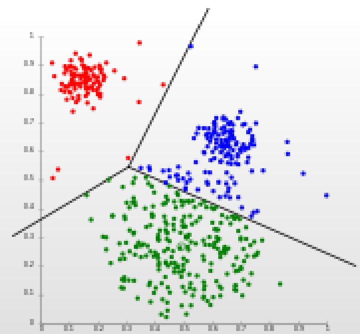

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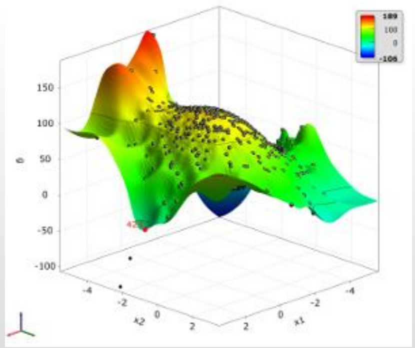

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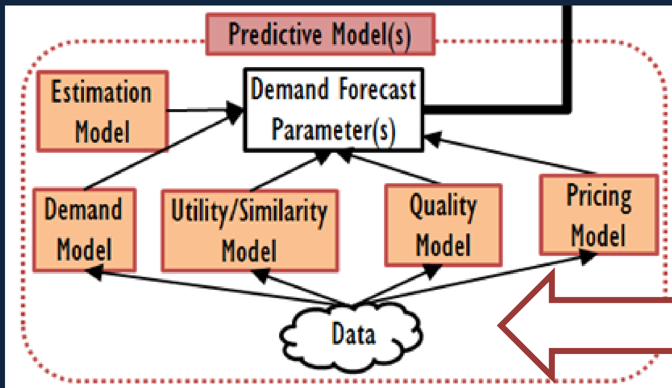
Thinking Like A Consumer

- Modeling consumer purchase behavior is difficult
- Certain attributes of a product, store, consumer, and experience may be measurable.

- Here we try to identify what a retailer does measure and work on discovering important relationships among these features
- Some claim that nearly "*95% of customers use a retailer's website and their competitors to research what they want to buy*."

A New Assortment Planning Approach

What data is available that could help us understand consumers preferences better?



Business Analytics

Typical internal retailer data

1. Transactions (TLOG) data
2. Loyalty cards
3. Warranties
4. Returns
5. Supplier provided metrics/forecasts
6. Industry reports

Big Data Analytics

Big Data external data not being utilized

1. Product reviews
2. Website clicks and views
3. Competitor websites
   - What is their assortment at location j?
   - What are their prices in zone z?
   - What is the perception of quality for their products for sku_{ij}?
4. Social engagement
   - Does Facebook/Twitter data provide any useful measures for the assortment decision?

Incorporate new "Big" data to strategically:

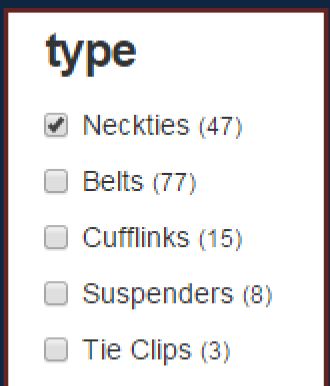
- Improve product understanding
- Price more intelligently
- Improve the assortment mix!!!

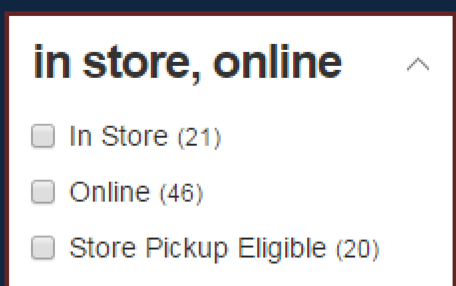
Product Reviews

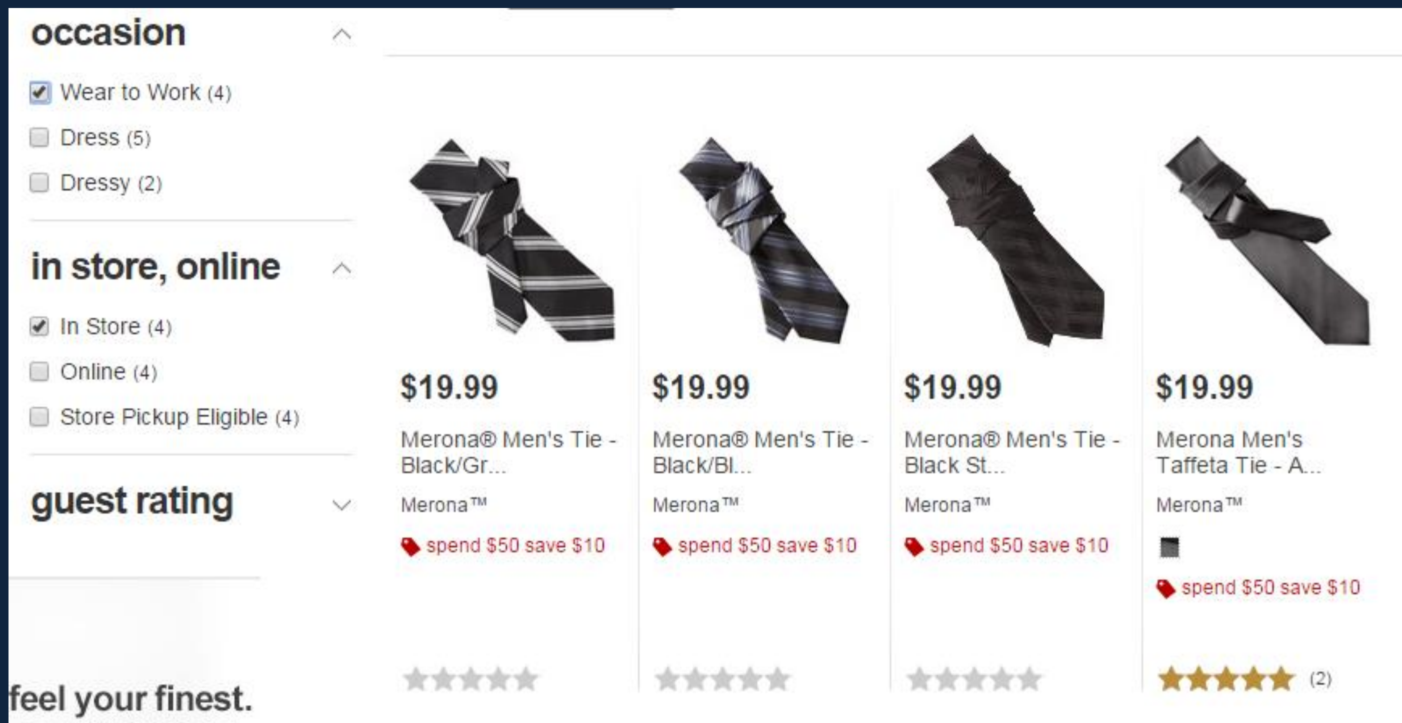
Breaking down product reviews

Say I am the Men's Accessories Category Manager

- The companies website shows they offer 47 neckties, 21 of them can be purchased within the store, and 46 online (98% of the entire category).
- If I'm seeking a new necktie that is work appropriate and can be purchased in-store, this reduces my purchase possibility set to four neckties. Notice one has a review.







- In this case the consumer would be price indifferent, but they might prefer the tie with the review because it has a 5-star rating

Product Review Example

- Consumer ratings provide overall ratings, as well as other characteristic ratings (e.g. quality, style, value).
- It has been shown that higher average product ratings lead to increased sales (Chevalier & Mayzlin, 2006; Luca, 2011). Furthermore, taking into consideration consumer demographics and product characteristics the effect on increased sales is modest (Zhu & Zhang, 2010).

- Previous authors have shown how social influences can modify a consumers initial beliefs about a product (Dellarocas & Narayan, 2006; Muchnik, Aral, & Taylor, 2013).
- Authors have suggested that divergence in product quality reviews could bias future reviewers assessments and influence future purchasing behavior (Dellarocas, Gao, & Narayan, 2010; Moe & Trusov, 2011).

Available Methodologies

Binary Classification Approaches

- Logistic Regression, Decision Trees, Neural Networks, etc.
- Goal: Propensity of a product to be purchased in a store

Multi-Class Classification Approaches

- Multinomial Logit Model (MNL), Nested Logit (NL), Locational-choice (LC), Exogenous Demand (ED)
- Goal: Propensity of a product to be purchased within a set of similar products within a store

Textual Analysis

- Sentiment scores, Likert ratings analysis
  - The majority of supervised learning approaches for sentiment analysis focus on sentence-level (Ding et al., 2008; Qu, Ifrim, & Weikum, 2010; Socher, Pennington, Huang, Ng, & Manning, 2011) and document-level (Nakagawa et al., 2010; Pang et al., 2002; Tan, Cheng, Wang, & Xu, 2009) classification.
- Goal 1: Estimate the influence on propensity to sell pre-post the existence of the product review
- Goal 2: Modify propensity measures posteriori for those products containing reviews

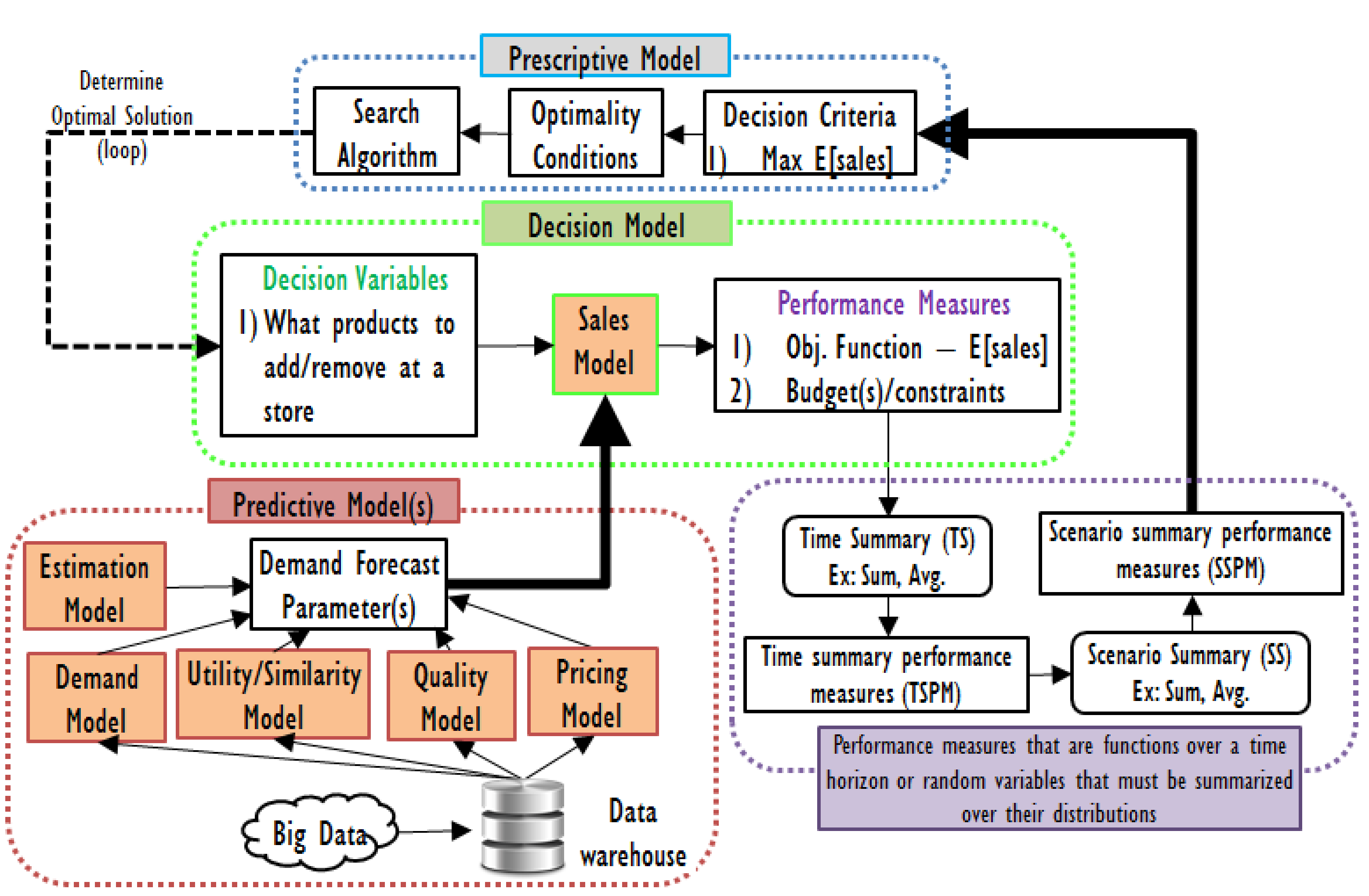
Decision Model Formulation

- Rules based assortment decision, Dynamic Programming (DP) formulation, integer programming (IP) model
- Goal 1: Generate an assortment for each category for each store
- Goal 2: Ability to simulate and perform sensitivity analysis in regard to expected sales for changes in parameter estimates

Complete Solution

Connecting the pieces

- Essentially such a solution would be solved for each category for every store to generate a customized assortment for every store



Deployment/Research Contributions

Demand Understanding

- How much can demand understanding be improved using big data?
- What advantages do binary-class models or substitution-based models have at identifying products that will truly sell if stocked?

Improved Decision Making

- Can the decision model be used as means of decision feedback to decision-makers up the decision hierarchy. DP provides a means to easily perform sensitivity analysis for any value.
  - Example: Reducing category growth X by 2% and increasing category Y by 2% will lead to an expected store sales increase of 4%
- What is the impact to the optimal assortment decision as we improve these demand parameters?
  - Example: Improving our predictive accuracy by 5% for category X will lead to a reduction of variation in expected sales for category X by 1%

Could this be the DSS that the field is looking for?

- Decision support systems (DSS) are in need for category planning because of the intensifying competitive nature of business due to their competitor's increased customer focus and improvement to operational competence (A. H. Hübner & Kuhn, 2012).

Life Cycle Mangement/ Business Contributions

An more empirical-based framework to supporting the assortment decision is in place

- The decision process has been outlined and the decision-support required/specified by decision-makers (e.g. category managers) allowing the data science team to incorporate other constraints or parameters over time instead of performing many ad-hoc analyses

Better Support up the Decision-making Hierarchy

- Certain predictive model parameters or external parameters up the decision-making hierarchy may be identified as having more impact on the objective function which might help more than category managers (e.g. Directors, VPs) improve their decision-making.

Benchmarking over time

- Forecasts can always be analyzed in the future to determine how well they performed. As forecasts improve the business should realize upward gains in their respective KPIs as well.

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