Using Machine Learning, Business Rules, and Optimization for Flash Sale Pricing

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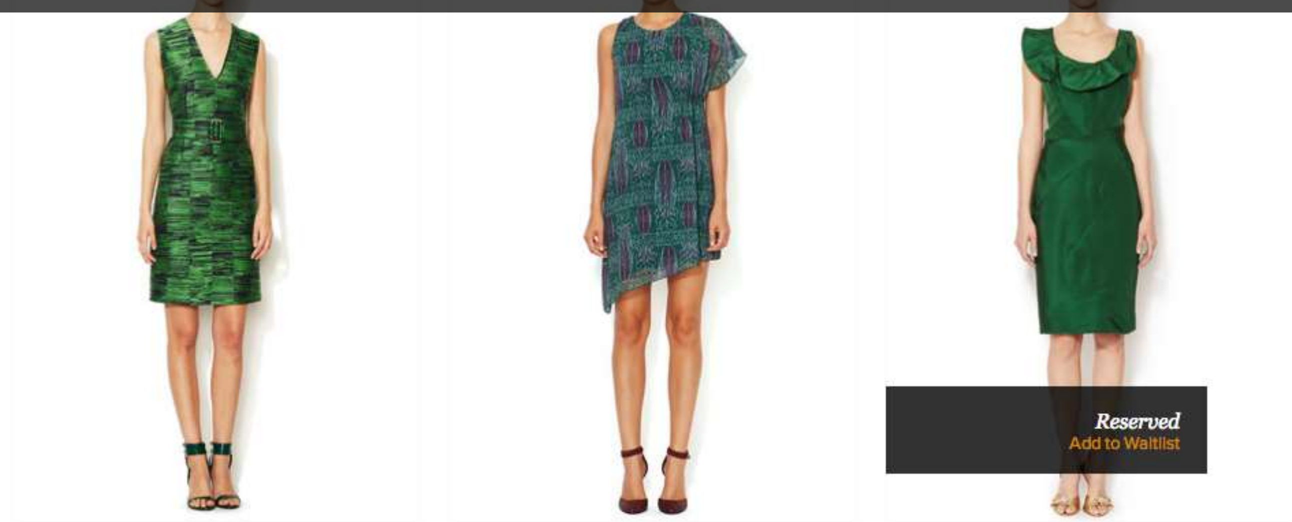


Building a Pricing System for an Online Retailer

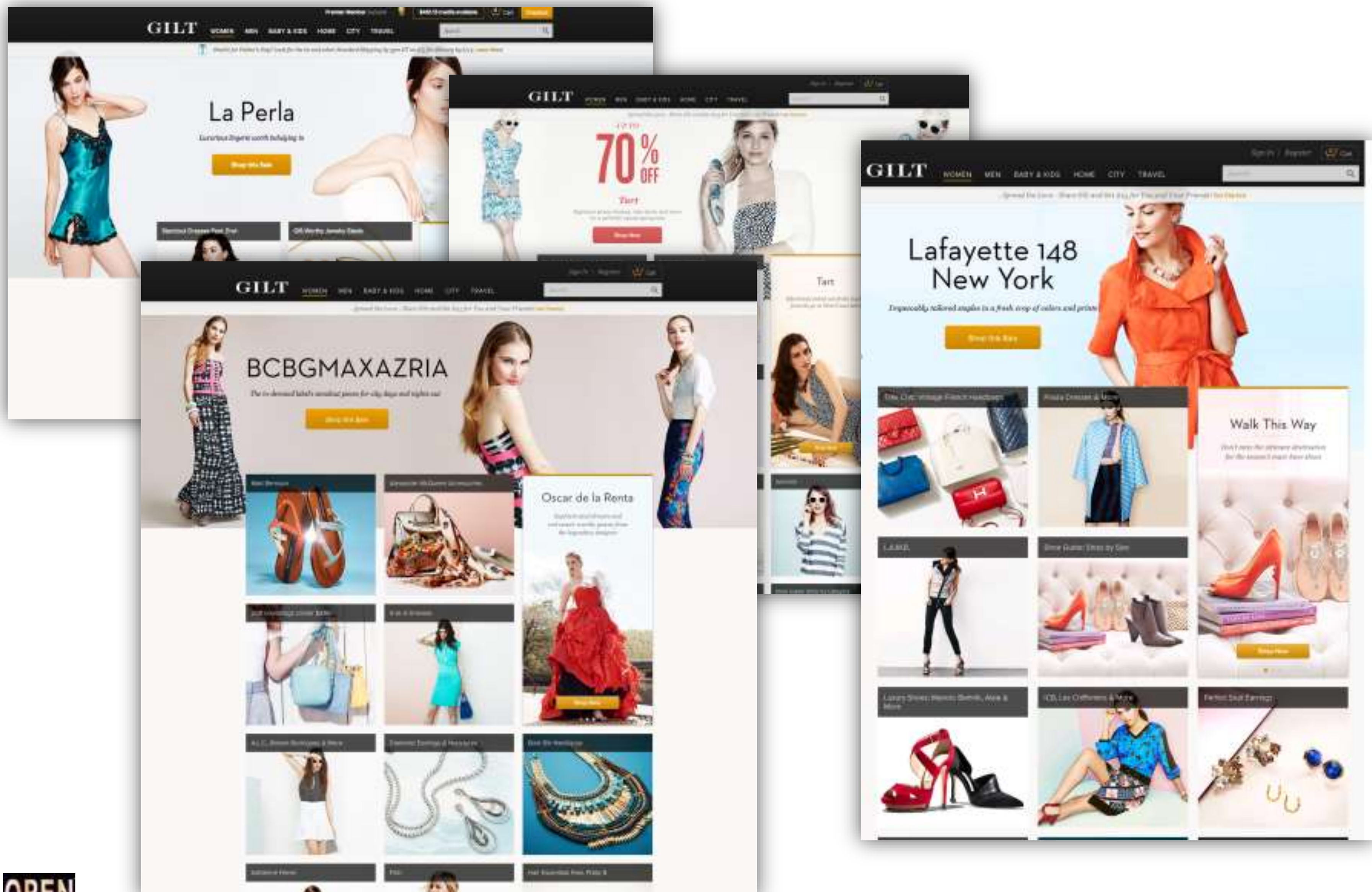
- GILT:
  - Online retailer selling curated collections of fashion products via flash sales
- Expected Functionality:
  - Utilize sales history to predict demand for ever-changing assortments of thousands of products
  - Collaborate with business domain experts to quickly generate optimal prices that can immediately go live on site

Applied Technology

- A combination of Machine Learning, Business Rules, and Multi-Objective Optimization:
  - Predictive Analytics
    - R, xgboost
  - Business Rules
    - OpenRules
  - Optimization
    - OpenRules/JSR-331 with various linear solvers

Before Gilt – sample sales

Gilt pioneered online “flash sales” in US



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LIFESTYLE MARKETING PLATFORM

Gilt is a members-only lifestyle destination and ecommerce site that provides insider access to today's top designer brands as well as exclusive local experiences.

GILT

Global Reach

9.7M+

active members

400

sales launch weekly

7K+

packages shipped daily

100

countries shipped to

1M+

active mobile app users*

50%

of revenue is generated via mobile purchases

1B+

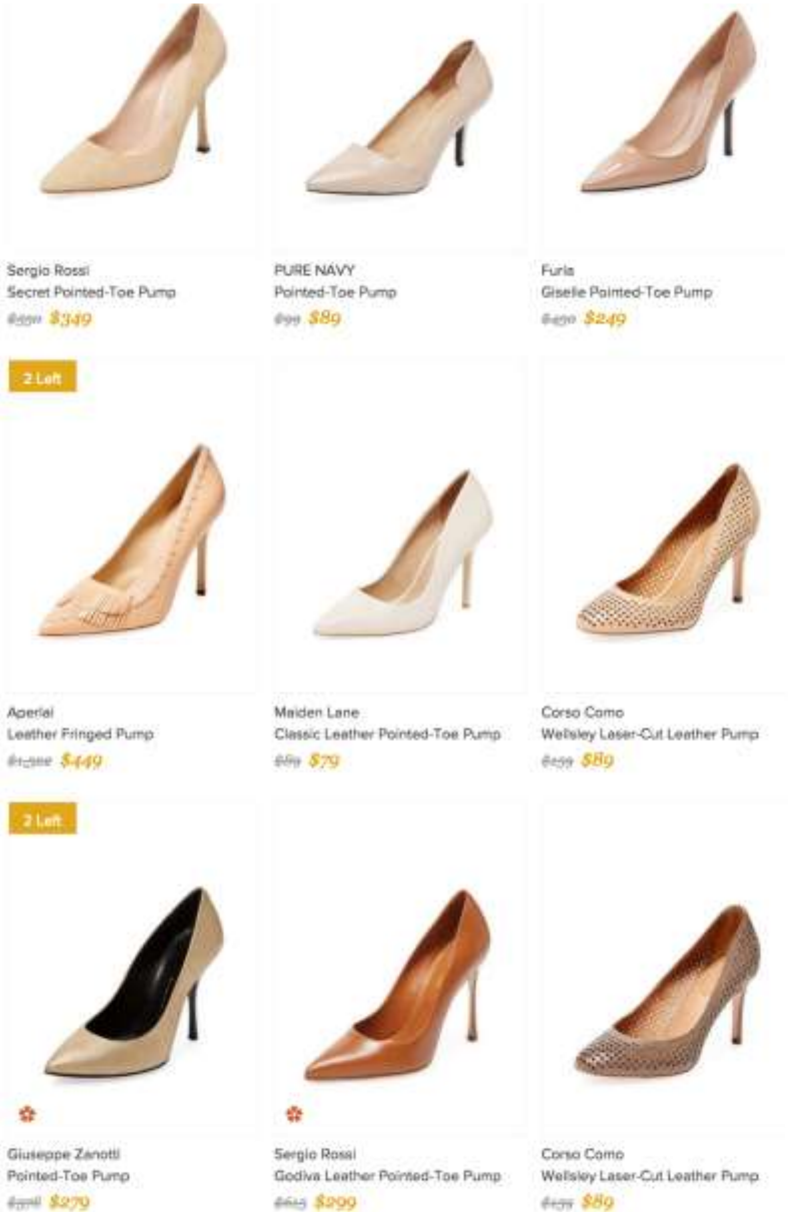
highest press impressions from a single partnership**

1.5M+

social media followers

*Gilt for iPhone, iPad & Android
**Michael Bastian x Hewlett-Packard

How to price thousands of items every day?



OBJECTIVES

- Predict demand for every product in a given sale for all possible prices
- Find the best combination of prices to satisfy business objectives (weighted mix of revenue, margin, sell-through, etc)
- Present price recommendations to business

How it's done

1. Data Prep
2. Demand Prediction
3. Price Optimization
4. Result validation

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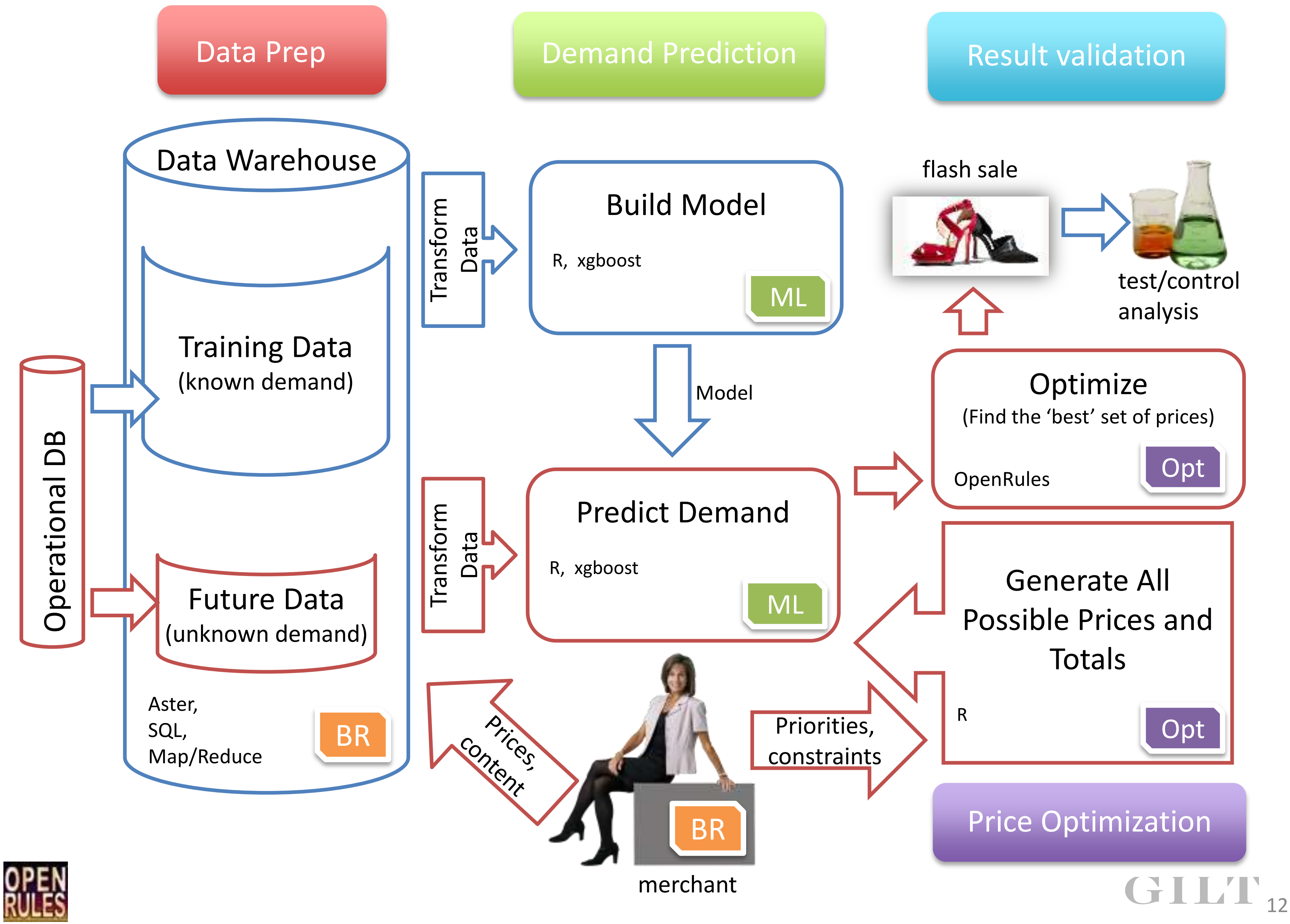
Data Prep
Demand Prediction
Result validation
Data Warehouse
Training Data
(known demand)
Future Data
(unknown demand)
Aster,
SQL,
Map/Reduce
BR
Operational DB
Transform Data
Transform Data
Build Model
R, xgboost
ML
Model
Predict Demand
R, xgboost
ML
flash sale
test/control analysis
Optimize
(Find the 'best' set of prices)
OpenRules
Opt
Generate All Possible Prices and Totals
R
Opt
Prices, content
Priorities, constraints
BR
merchant
Price Optimization
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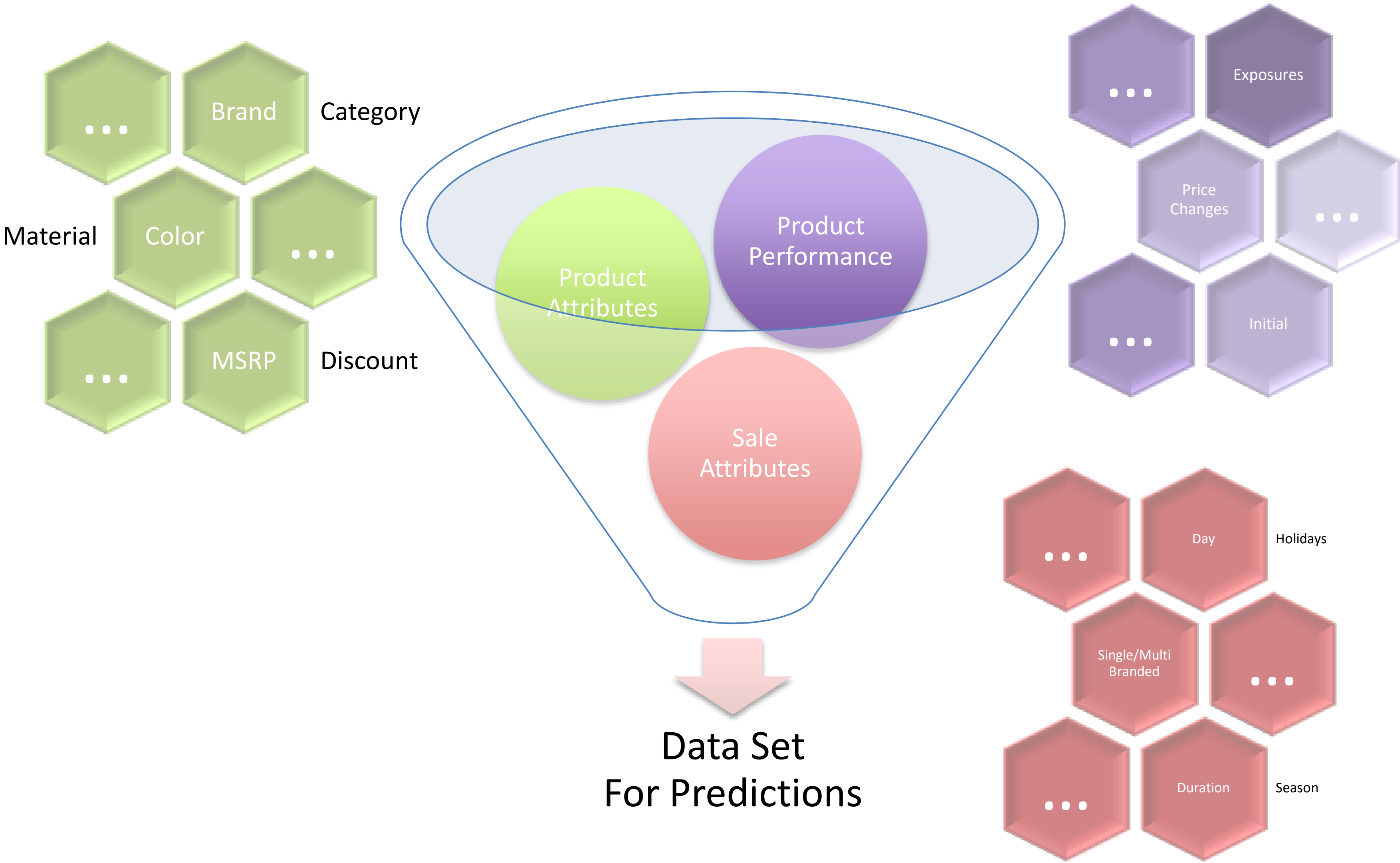
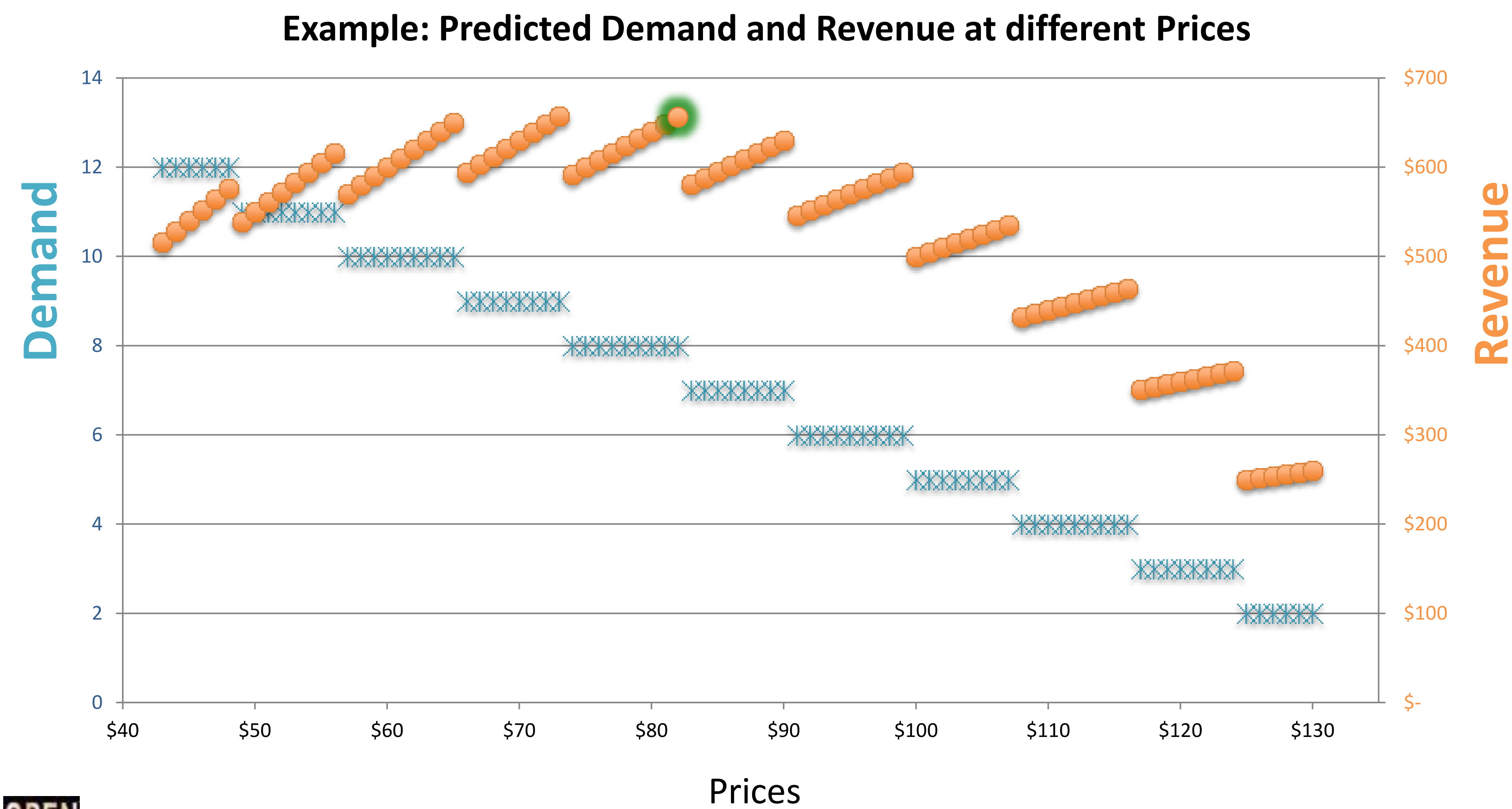
1. Data Preparation



2. Demand Prediction



3. Price Optimization

- Goals:
  - optimize per product and per sale
  - allow business user to set goals (revenue, sell-through, margin, or combination)
- Iterate quickly

Sample Rules

Minimal Number of Previous Exposures		Variable	<oper>	Value		
Is	0	**Minimum Discount from MSRP**	Is	20		Initial Sales
Is	0	**Percent Difference from Original Price**		40		
Is	0	**Minimal Margin Percent**		40		
Is	0	**Minimal Sell Through Percent**		20		
Is	1	**Minimum Discount from MSRP**	Is	20		Repeat Sales
Is	1	**Percent Difference from Original Price**		40		
Is	1	**Minimal Margin Percent**		30		
Is	1	**Minimal Sell Through Percent**		20		
Is	10	**Minimum Discount from MSRP**	Is	60		Exit Sales
Is	10	**Percent Difference from Original Price**		40		
Is	10	**Minimal Margin Percent**		5		
Is	10	**Minimal Sell Through Percent**		40		

Optimization Weights

	Variable	<oper>	Value
Gross Revenue Weight		Is	2
Gross Margin Weight			5
Gross Sell Through Weight			3

Sample Results For A Sale:

Target	Revenue	Margin	Sell-through
Max Revenue	$6,606	58%	23%
Max Margin	$4,289	67%	16%
Max Sell-through	$5,628	48%	24%

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Per sale optimization

Best predictors of demand (number of units sold):

- Number of units available
- Price, Discount, MSRP
- Item price relative to the prices of other items in the sale
- Product attributes, etc

Prediction changes:
Before: predict demand for all acceptable prices
Now: same as before but for all possible totals

Example

Prices: $2 or $4

Prices: $1 or $3

Price total: $3 - $7
- Apply constraints early
- Calculate all the totals

Item	Price	Total	Demand
Ball	***$2***	***$3***	***4***
Ball	$2	$4	4
Ball	***$2***	***$5***	***4***
Ball	$2	$6	3
Ball	$2	$7	3
Ball	$4	$3	2
Ball	$4	$4	2
Ball	***$4***	***$5***	***2***
Ball	$4	$6	2
Ball	***$4***	***$7***	***2***
Pen	***$1***	***$3***	***7***
Pen	$1	$4	7
Pen	***$1***	***$5***	***8***
Pen	$1	$6	8
Pen	$1	$7	8
Pen	$3	$3	1
Pen	$3	$4	1
Pen	***$3***	***$5***	***1***
Pen	$3	$6	1
Pen	***$3***	***$7***	***0***

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Multiple Knapsack Problem / Bin-packing problem

- All items must be priced
- Each item must have only one price
- Sum of all prices should equal to one and only one total

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Problem definition (MathProg)

```
set Look;
set Price := 1..10000;
set Total := 1..100000;

set Look_Price_Total within {l in Look, p in Price, t in Total};
param price  {(l,p,t) in Look_Price_Total}, >= 0, integer := p;
param demand {Look_Price_Total}, >= 0, integer;
param revenue{(l,p,t) in Look_Price_Total} := price[l,p,t] * demand[l,p,t];

param orig_price  {Look_Price_Total}, >= 0, integer, default 0;
param base_price  {Look_Price_Total}, >= 0, integer, default 0;
param msrp_price  {Look_Price_Total}, >= 0, integer, default 0;
param num_units_available {Look_Price_Total}, >= 0, integer, default 0;

set Unique_Total := setof{(l,p,t) in Look_Price_Total} t;

var Use {Look_Price_Total} binary;
var Use_Total {Unique_Total} binary;

maximize Revenue:    sum{(l,p,t) in Look_Price_Total} revenue[l,p,t] * Use[l,p,t];

s.t. one_of_each{l in Look}: sum{(l,p,t) in Look_Price_Total} Use[l,p,t] = 1;
s.t. single_total: sum{t in Unique_Total} Use_Total[t] = 1;
s.t. price_sum_is_total{t in Unique_Total}:
        sum{(l,p,t) in Look_Price_Total} price[l,p,t] * Use[l,p,t] = t * Use_Total[t];
```

```
set Look := Ball Pen;
param: Look_Price_Total: demand :=
Ball    2   3   4
Ball    2   4   4
Ball    2   5   4
Ball    2   6   3
Ball    2   7   3
Ball    4   3   2
Ball    4   4   2
Ball    4   5   2
Ball    4   6   2
Ball    4   7   2
Pen     1   3   7
Pen     1   4   7
Pen     1   5   8
Pen     1   6   8
Pen     1   7   8
Pen     3   3   1
Pen     3   4   1
Pen     3   5   1
Pen     3   6   1
Pen     3   7   0;
```

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Modeling and Solving Real-world Problems

- We modeled the problem using OpenRules and JSR-331 Standard
- Real optimization problems consist of hundreds of thousands records:
    - We used JSR-331 Constraint Solvers to validate the problem correctness. But actual problems were too large for constraint solvers
    - We tried various JSR-331 Linear Solvers (GLPK, LP-Solve, COIN suite, SCIP, and others)
    - None was able to solve large problems in a reasonable time or at all

How We Solved the Production Problem

- OpenRules was able to create a rules-based decision model that automatically splits one large problem into a set of smaller sub-problems (one for every individual total cost)
- While there may be thousands of sub-problems, JSR-331 Linear Solvers are able to quickly solve them
- Then OpenRules decision model analyzes all found solutions to come up with the optimal solution that satisfy a configurable combined objective – a maximal combination of Revenue, Margin, and Sell-Through
- Big advantage of this approach: it can be parallelized to solve even much larger problems!

Conclusion

- We applied a combination of Machine Learning, Business Rules, and Multi-Objective Optimization to solve a real-world operational problem – flash sale price optimization
- The pricing methodology and tools that support each of these 3 decision management techniques were readily available and quite powerful
- However, the production-level problems required a special ingenious approach to actually solve these problems

Questions?

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