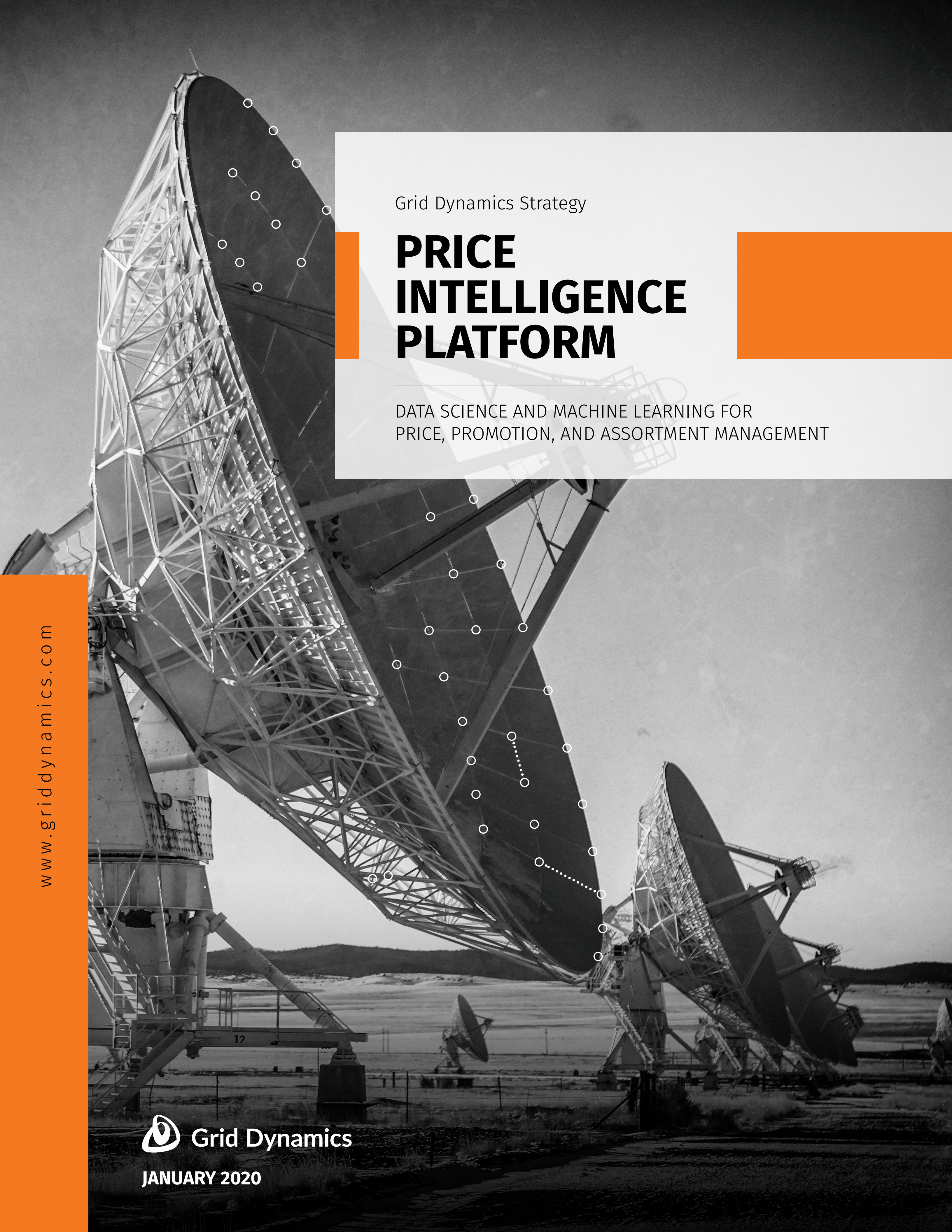


Grid Dynamics Strategy

PRICE INTELLIGENCE PLATFORM

DATA SCIENCE AND MACHINE LEARNING FOR
PRICE, PROMOTION, AND ASSORTMENT MANAGEMENT

www.griddynamics.com

Grid Dynamics

JANUARY 2020

Contents

About Grid Dynamics

Grid Dynamics is a data science and engineering services company that specializes in digital transformation through emerging technologies. We are an innovation partner to many tier-one retail, manufacturing, finance, media, and technology companies, specifically in areas related to data science and AI, including the following:

- Customer intelligence and deep personalization
- Algorithmic price management and optimization
- Natural language processing and search engines
- Visual search and image recognition
- Conversational agents and chatbots
- Data platforms and machine learning platforms

Grid Dynamics was founded in 2006 and is based in San Ramon, California with nine additional offices throughout the US and Europe. The company employs more than 1500 engineers and data scientists worldwide.

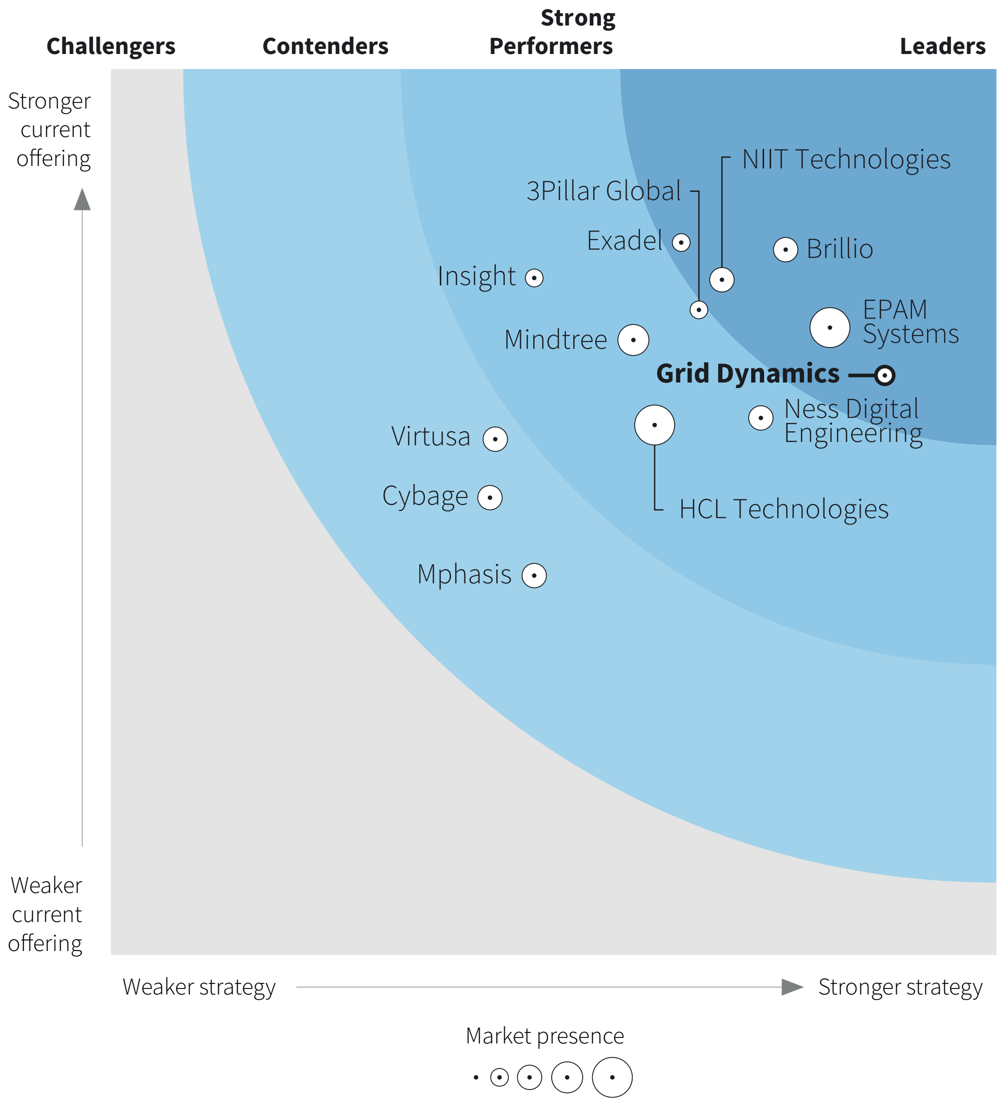
In 2019, Forrester named Grid Dynamics a leader among midsize agile development service providers.

Our Clients

About Grid Dynamics

The Forrester wave ™

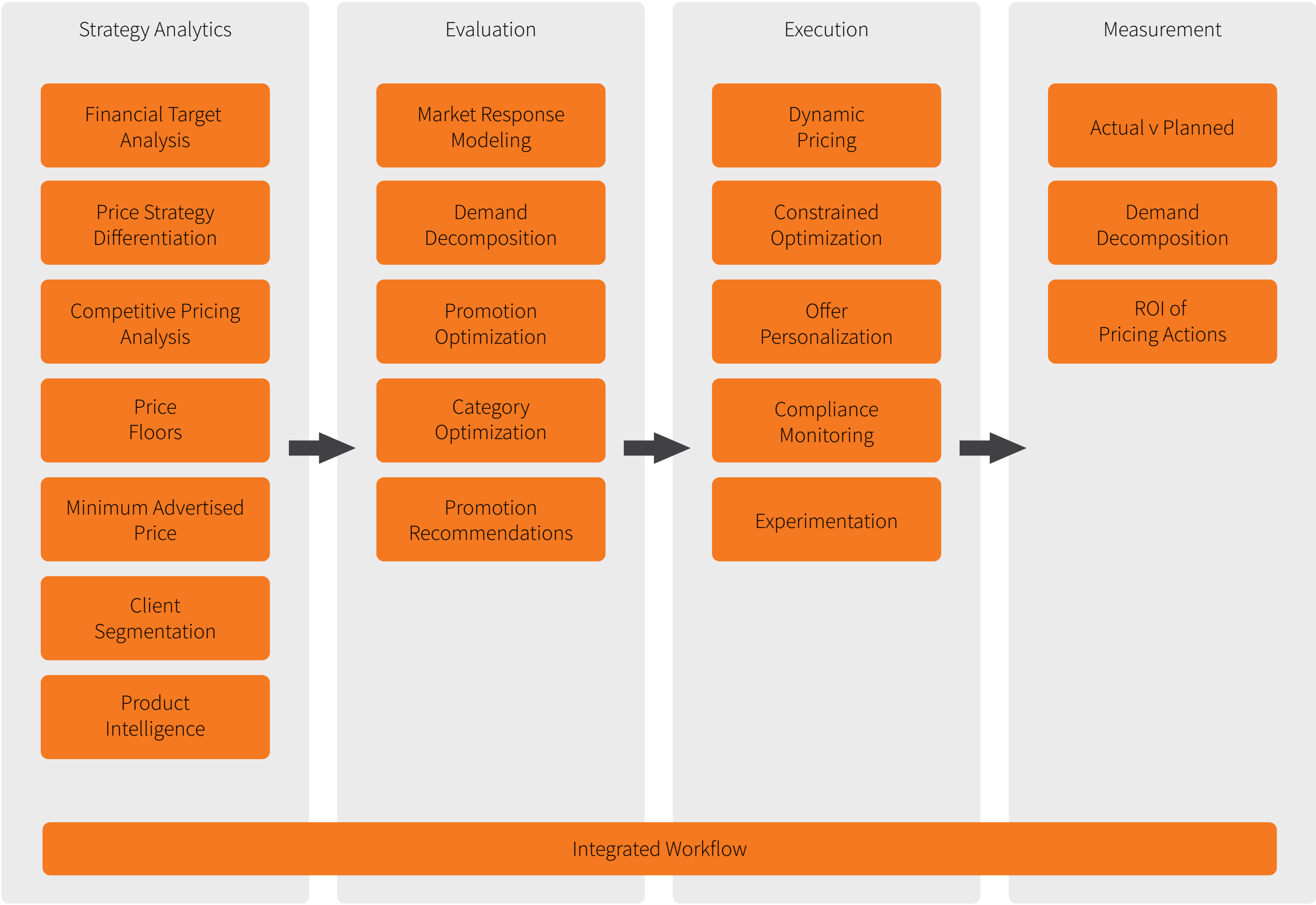
Midsize Agile Development Service Providers
Q2 2019



01

Solution Overview

Solution Capabilities
Process Perspective



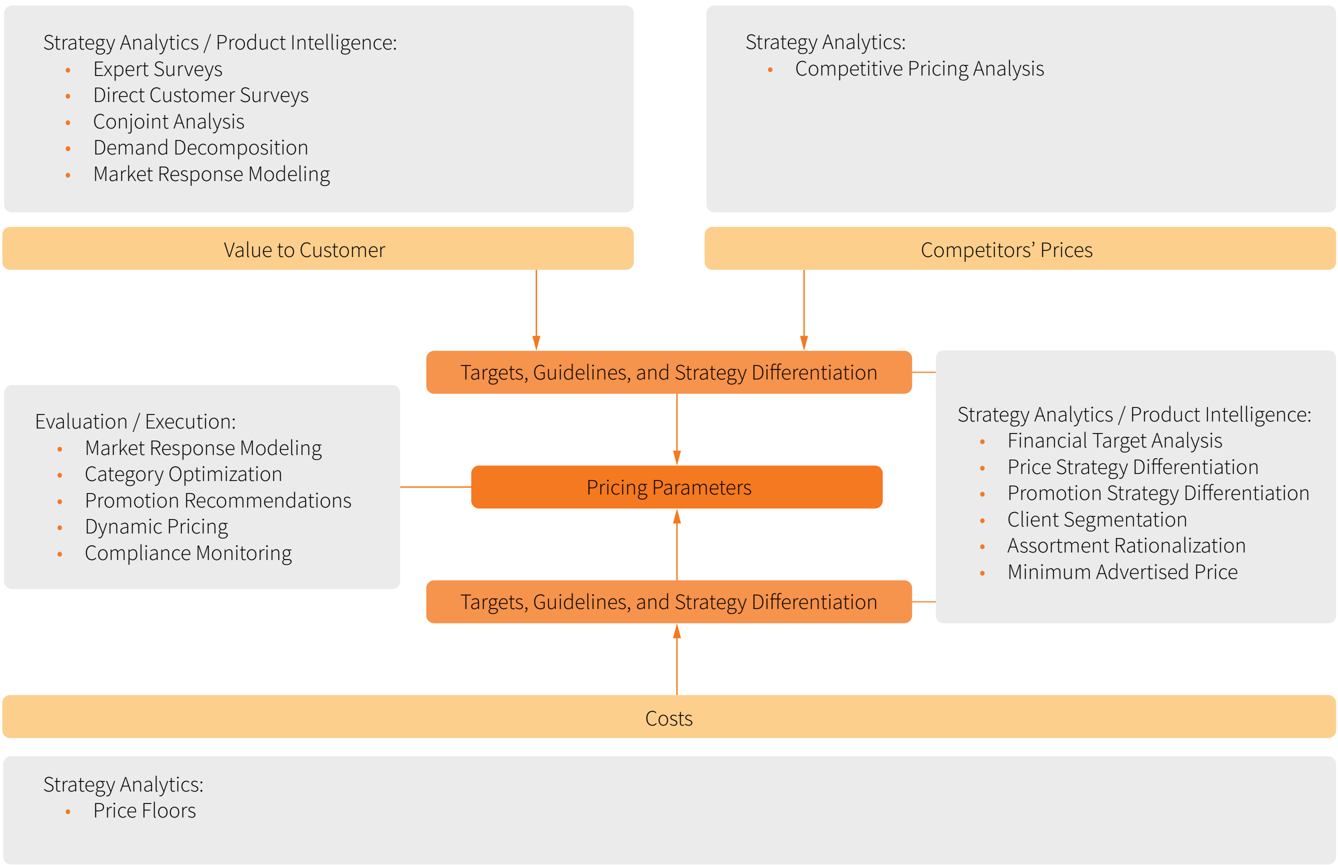
The platform provides analytical and automatic decision making capabilities for all stages of a price and promotion management life cycle:

- Strategy Analytics: Analytical capabilities that help assess longer-term risks and opportunities associated with pricing and assortment decisions, perform advanced analysis of the market and competitors' moves, conduct long-term planning, and set optimization guidelines for downstream processes and systems that make more tactical and shorter-term pricing decisions.
- Evaluation: Decision support systems and automatic decision making components that support what-if analysis and optimization of specific pricing and promotion scenarios.
- Execution: Components that automate and optimize dynamic and/or personalized pricing and promotion decisions in near real time.
- Measurement: Analytical capabilities and econometric and statistical models that help analyze and explain the observed outcomes of pricing changes and decisions.

The platform also provides analytical capabilities that support product design and life-cycle management decisions.

The above capabilities are integrated into a seamless workflow that allows business users to refer historical cases and insights, plan and evaluate new actions and changes, leverage automatic decision making and optimization, monitor execution, and deeply analyze results.

Solution Capabilities Economic Perspective



The price intelligence platform's business value becomes particularly clear when its capabilities are viewed through the lens of economic price determinants.

The main economic price determinants are costs, value to customer, and competition. These factors effectively define the lower and upper limits of prices:

- Costs: An analysis of costs is needed to establish consistent price floors across all channels. Price floors are based typically on variable unit costs (short-term limits) and fully loaded unit costs (long-term limits).
- Value to customer: The perceived value of a product determines the upper limit for the price. The platform provides several capabilities that help estimate the value through price-response modeling and deep analysis of the demand structure (demand decomposition). Methods such as conjoint analysis and expert surveys can be used to complement the analytics capabilities that the platform provides.
- Competition: Competitors' prices and price actions heavily influence price-setting logic and impose additional constraints. The platform addresses this aspect by providing advanced competitive pricing analytics.

The basic limits are refined further using decision support tools for financial target breakdown, price strategy differentiation, and strategic considerations such as brand positioning. These refinements are used as guidelines for fine-tuning and dynamic management of actual pricing parameters. Most of the capabilities that the platform provides are focused on data-driven refinements of pricing guidelines and automatic fine-tuning and optimization.

Solution Capabilities
Data Science Perspective

Data science and machine learning have many applications in price management and can contribute significantly toward better pricing decisions. Some of these applications, such as forecasting, are well-known and commonly used. At the same time, some less-obvious capabilities that machine learning offers, such as decomposition of observed metrics, often are overlooked, and such methods' potential is high.

The main uses for data science and machine learning techniques in the platform are outlined below, and more details are provided in the remainder of this paper.

Decision Support	Decision support tools often are created to analyze entities and processes in a space of certain metrics, such as profit or market share. Statistical analysis and machine learning help go beyond traditional metrics and measure complex properties of entities and processes that cannot be revealed through basic methods. For example, data science methods can be used to measure demand predictability or customer importance for products and categories, enabling insightful visualization and advanced analysis in the space of such metrics.
Decomposition	Observed sales and financial data are the bottom line for pricing actions, but the final numbers do not provide insights into the drivers and effects that contribute to such results. Econometric and machine learning models can decompose observed metrics into separate factors, such as cannibalization or competition, and measure their contributions to the final results. The same principles can be used not only to analyze historical data, but also to build insightful forecasts that quantify forecasted totals' individual components.
Forecasting	Evaluation and optimization of pricing decisions are based on the fundamental capability to forecast demand and profit as a function of discounts, product properties, competitors' prices, and other variables. This capability enables what-if analysis and automatic optimization of various pricing scenarios. This area is the most straightforward (but not the only) application of machine learning in price management.
Optimization	Forecasting capabilities usually are paired with optimization algorithms to search through possible pricing parameters' spaces and determine optimal values automatically. This process can be relatively straightforward in the optimization of individual actions or parameters, but complexity sharply increases when multiple actions (e.g., an entire category's promotion calendar) must be optimized.
Micro-decisioning	Digital channels provide dynamic pricing and personalization capabilities that cannot be leveraged efficiently without real-time decision automation components. Such components usually are implemented using propensity models that enable promotion personalization and active learning techniques that enable dynamic price optimization in rapidly changing environments.

02

Strategy Analytics

Pricing and marketing practitioners generally distinguish between three main approaches to pricing in consumer and industrial markets: cost-based; competition-based; and customer-value-based. In practice, price managers often combine these approaches and take into account the costs associated with a product, competitor pricing, market positioning, and consumers' price and value perception.

The strategy analytics part of the platform aims to provide price managers with advanced insights into all these areas and deliver the following business capabilities and benefits:

- Align pricing and promotion strategies with overall financial plans and targets, as well as assess associated risks.
- Break down high-level financial targets into specific promotion and assortment optimization tasks.
- Differentiate price and promotion strategies across product groups and categories based on customer and business value.
- Rationalize price and promotion decisions across clients based on their value.
- Analyze competitors' tactics and measure the efficiency of competitors' moves.
- Rationalize pricing and promotion decisions based on competitor analysis.
- Establish price floors for downstream processes and systems based on product value and costs.

Financial Target Analysis
Capabilities

Financial Target Analysis Module

Pricing, promotion, and assortment decisions can be better aligned with overall financial targets by analyzing and predicting trajectories of various entities (products, categories, business units, or stores) in the space of financial metrics. This analysis also helps identify risks and break down high-level targets into smaller tasks.

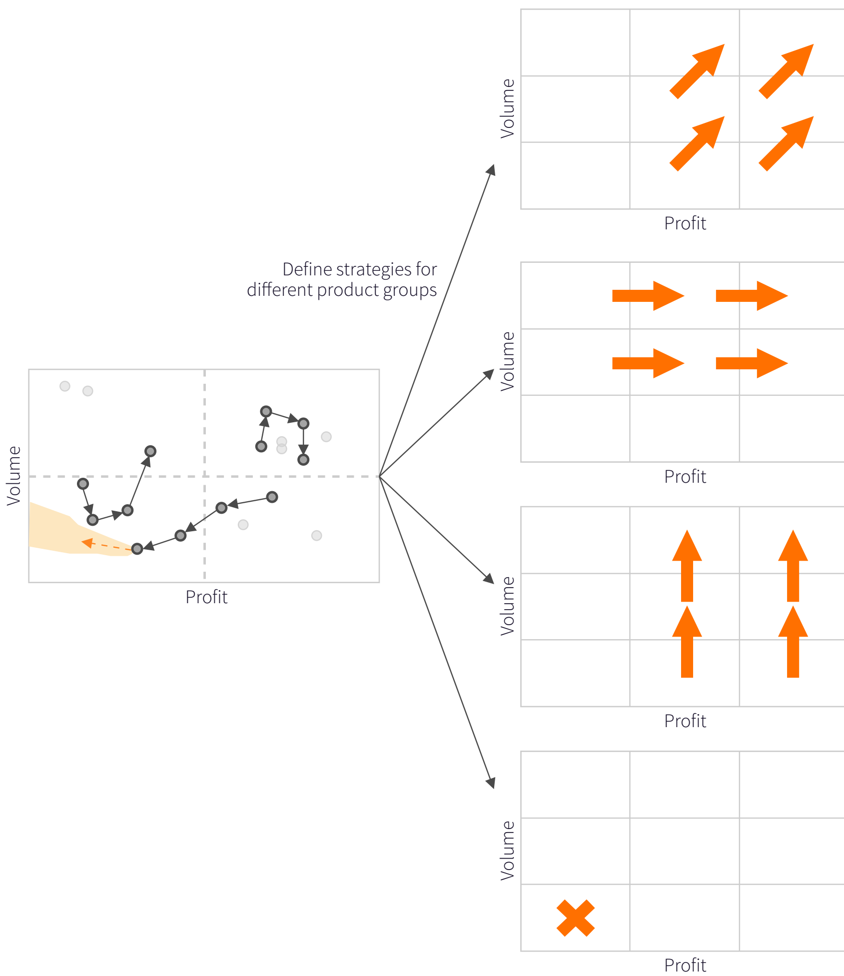
Business Use Cases

- Forecast the risks of not meeting financial targets.
- Analyze risks at different aggregation levels: products; categories; stores; and business units.
- Evaluate how risks can be mitigated using promotion, inventory, and assortment rationalization decisions.

How It Works

- Assortment and pricing decisions are supported by the analysis of product trajectories in the Volume x Profit space. Other possible dimensions include Market Share, Revenue, and Margin.
- Each product's trajectory reflects the product life cycle, from introduction to end of life.
- A product's trajectory is predicted with a regression model that uses the historical part of the trajectory, product attributes, and market-level data as inputs.
- Similar mapping can be done at the level of stores, categories, and business units to analyze their trajectories.

Financial Target Analysis
Usage



Profit and volume are both poised to grow (ideal case)

- Expanding market
- High-potential new product
- Fix prices that are too high: Volume increase overcompensates lower margin, delivering higher overall profit

Pursue rising profit and constant/declining volumes

Profit = Volume × (Price - Promo - Cost)

- Later phases of the product life cycle
- Fix prices that are below the optimal level: Price increase leads to volume decline, but higher margin offsets the decline, delivering higher overall profit
- Reduce costs by improving inventory and production decisions

Pursue growing volume/revenue/share and constant/decreasing profits

Revenue = Volume × (Price - Promo)

- Early stages of a market or product life cycle
- Optimize price and promo investments using market response, segmentation, and targeting models

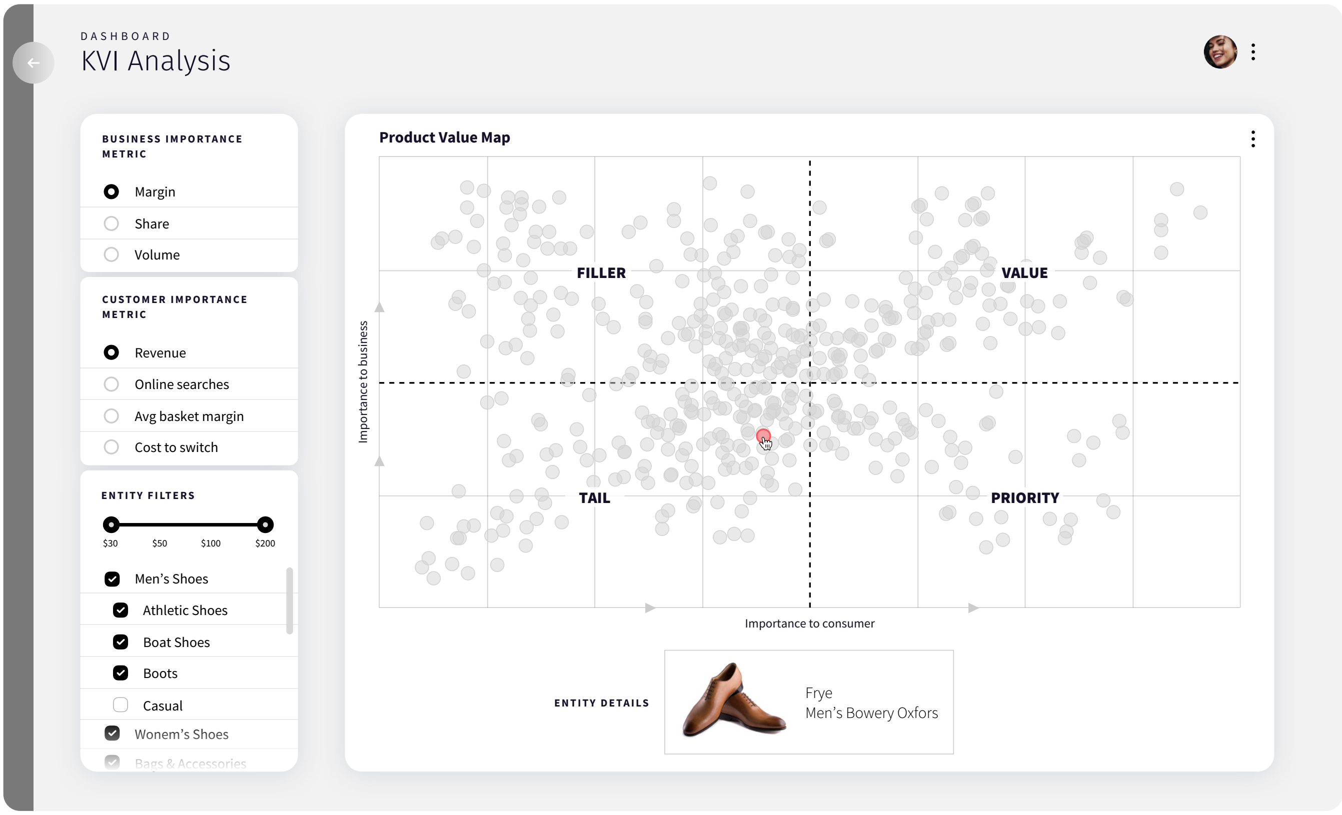
Profit and volume are both poised to decline

- Rationalize the assortment using assortment rationalization models

Usage Example

- The predicted product/category/store trajectories are compared with the enterprise's financial targets, gaps and risks are analyzed, and the results of the analysis inform strategies for different groups of products:
    - For certain products, one can pursue volume and growth goals (volume, revenue, market share, market dominance) through pricing, promotion, and marketing improvements. This is usually the case for products in the early stages of their life cycles and products with strong trajectories.
    - For certain products, one can pursue profitability goals (profit, margin, shareholder value) through promotion, cost, and assortment improvements. This is often the case for products in later phases of their life cycles.
    - Some products should be rationalized to mitigate risks and improve performance.
- High-level strategies are refined further and operationalized using downstream optimization models for pricing, promotions, and inventory management.

Price Strategy Differentiation Capabilities



KVI Analysis Module

Price and promotion strategies, as well as specific promotion levels and constraints, can be customized based on differences in consumer price and value perception, and the business importance of different products.

Business use cases

- Analyze the importance of products for business and clients/consumers.
- Differentiate price and promotion strategies based on product importance and price perception.
- Optimize in-store space allocation and safety stock levels based on product importance.

How it works

- Pricing strategies for various products and product groups can be differentiated based on analysis in the Importance-to-Business x Importance-to-Consumer space.
- Importance often is quantified in terms of revenue and margins, but additional metrics – such as number of online searches, number of shopping baskets, market share, and costs to switch between providers – can be used to measure product importance and consumer price perception. It is common to develop complex scores that combine multiple metrics.
- Importance metrics often are designed to identify the following groups of items:
    - Value-perception drivers (usually high-volume items)
    - Assortment-perception drivers (filler items)
    - Traffic drivers (high-volume items that drive incremental shopping trips)
    - Basket drivers (high-volume items that drive cross selling)

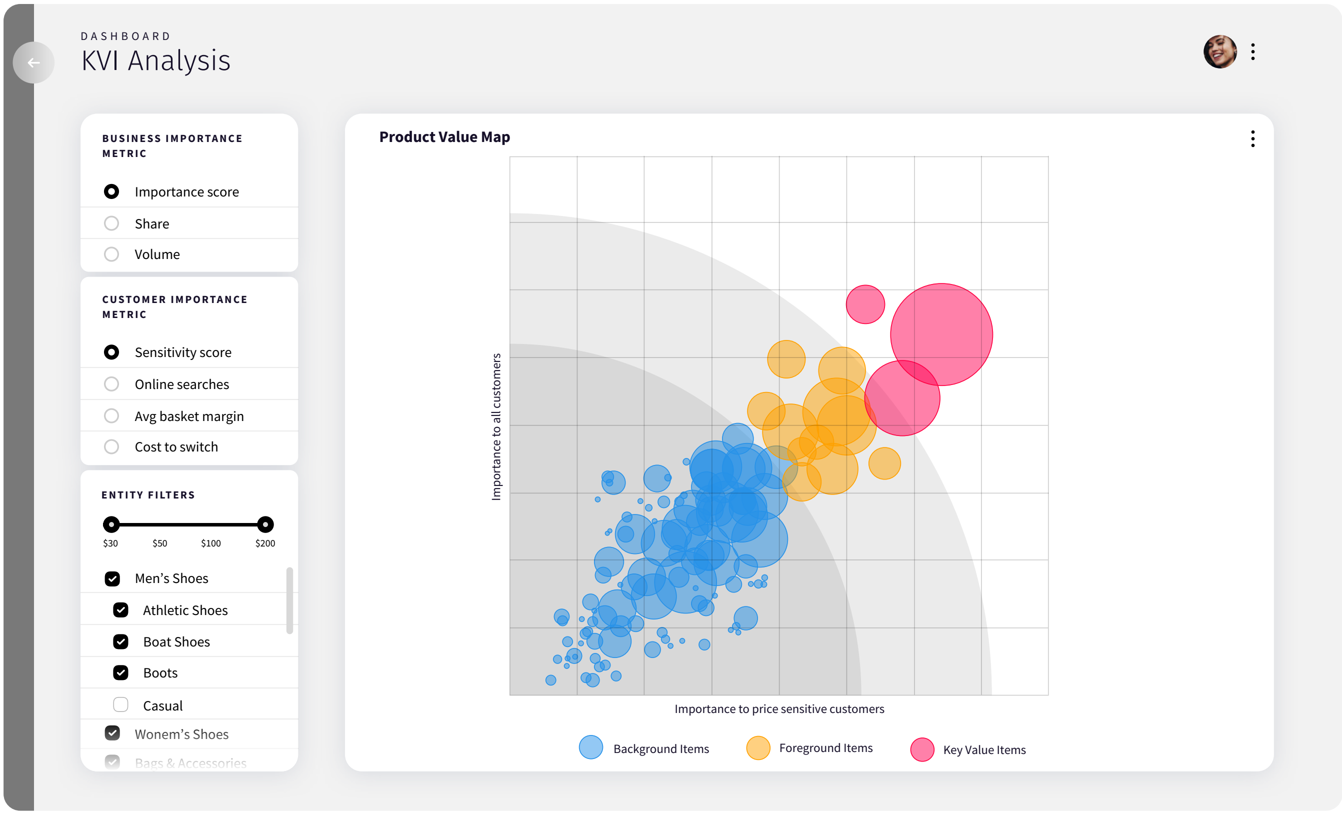
Price Strategy Differentiation
Usage

Product Value Map

Usage Example

- Value analysis helps differentiate price and promotion strategies from reference competitors' prices (match exactly, price higher or lower). The following example illustrates how several different strategies can be used depending on product value:
    - Key Value Items (KVIs): Items that drive high volume and are well-known to consumers can be priced mainly based on competitive pricing considerations.
    - Filler Items: Slow-moving items that complement the main assortment can be priced mainly based on internal economics (e.g., to maintain high margin).
    - Tail and Priority Items: Price segmentation and personalization can be used extensively for items that are highly important to consumers, but secondary to the business.
- The above analysis creates guidelines that are consumed by downstream price management systems and optimization models.
- A KVI analysis also can help optimize in-store space allocation and safety stock positions.

Price Strategy Differentiation
Advanced Capabilities



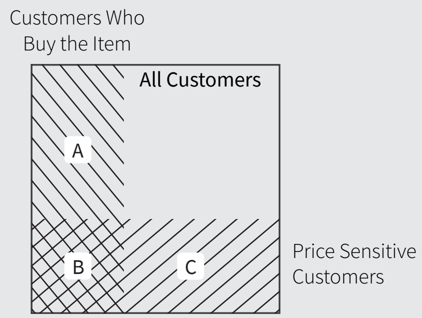
KVI Analysis Module

Although revenue and margin are useful metrics for product value and KVI analysis, these basic metrics are not perfect because they are not directly linked to price perception and sensitivity.

In practice, it is usually better to develop more advanced scores that incorporate several metrics and identify KVIs by ranking products according to these scores. For example, variants of the following algorithm are used commonly to identify KVIs in business verticals with frequently purchased items:

- Identify items that represent good value for the money (e.g., a 32 oz. yogurt product is a good value for the money, compared with a 6 oz. product).
- Identify price-sensitive customers who mostly buy bargain items.
- Score frequently purchased items using the following two metrics:
  - What percentage of price-sensitive customers buy the item?
  - What percentage of all customers who buy the item are price-sensitive?

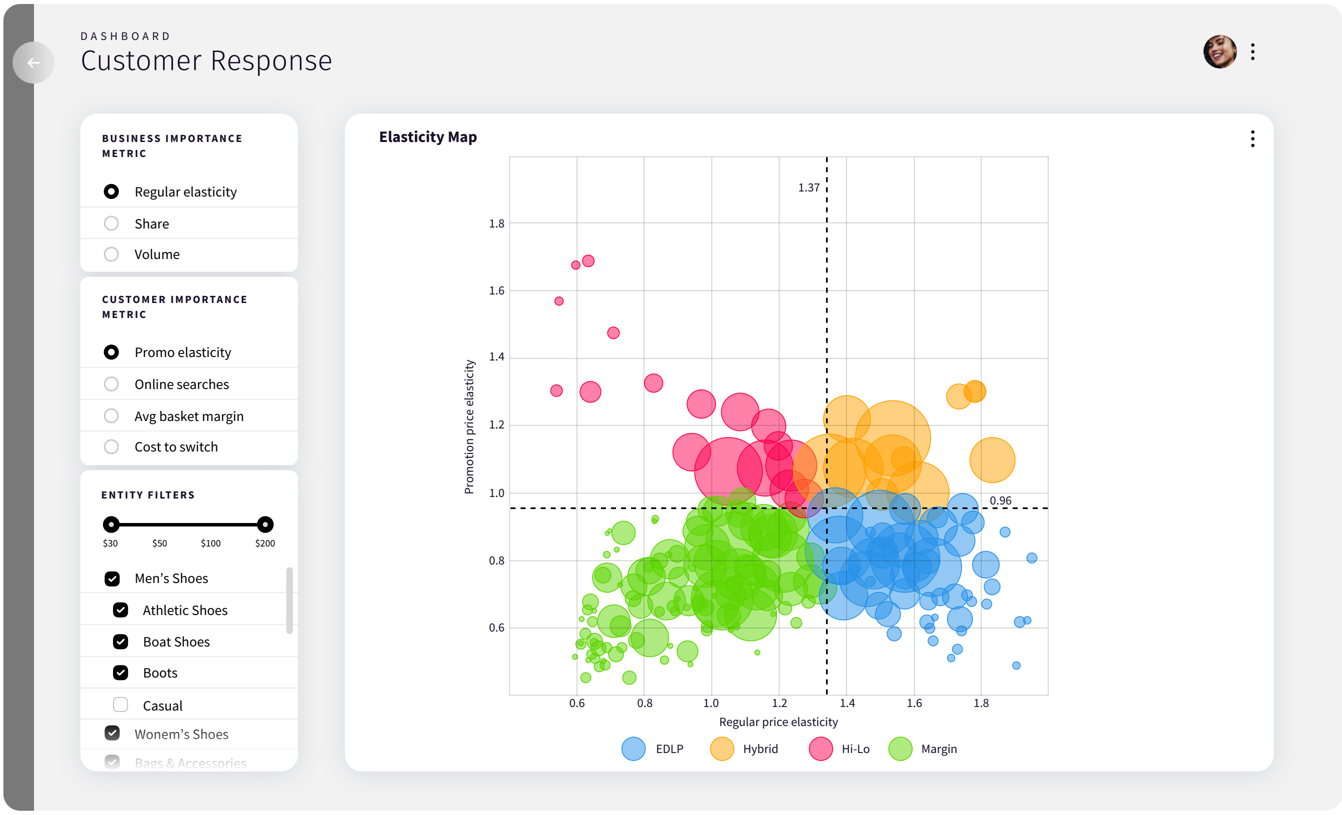
These two metrics generally provide a more convenient space for KVI analysis compared with basic financial metrics.



$$Score = \alpha \times B/(B + C) + \beta \times B/(A + B)$$

Price Strategy Differentiation

Advanced Capabilities



Customer Response Module

The KVI analysis mainly is focused on managing pricing decisions against reference competitors' prices. However, an analysis in the space of advanced metrics can help differentiate between other aspects of the pricing strategy.

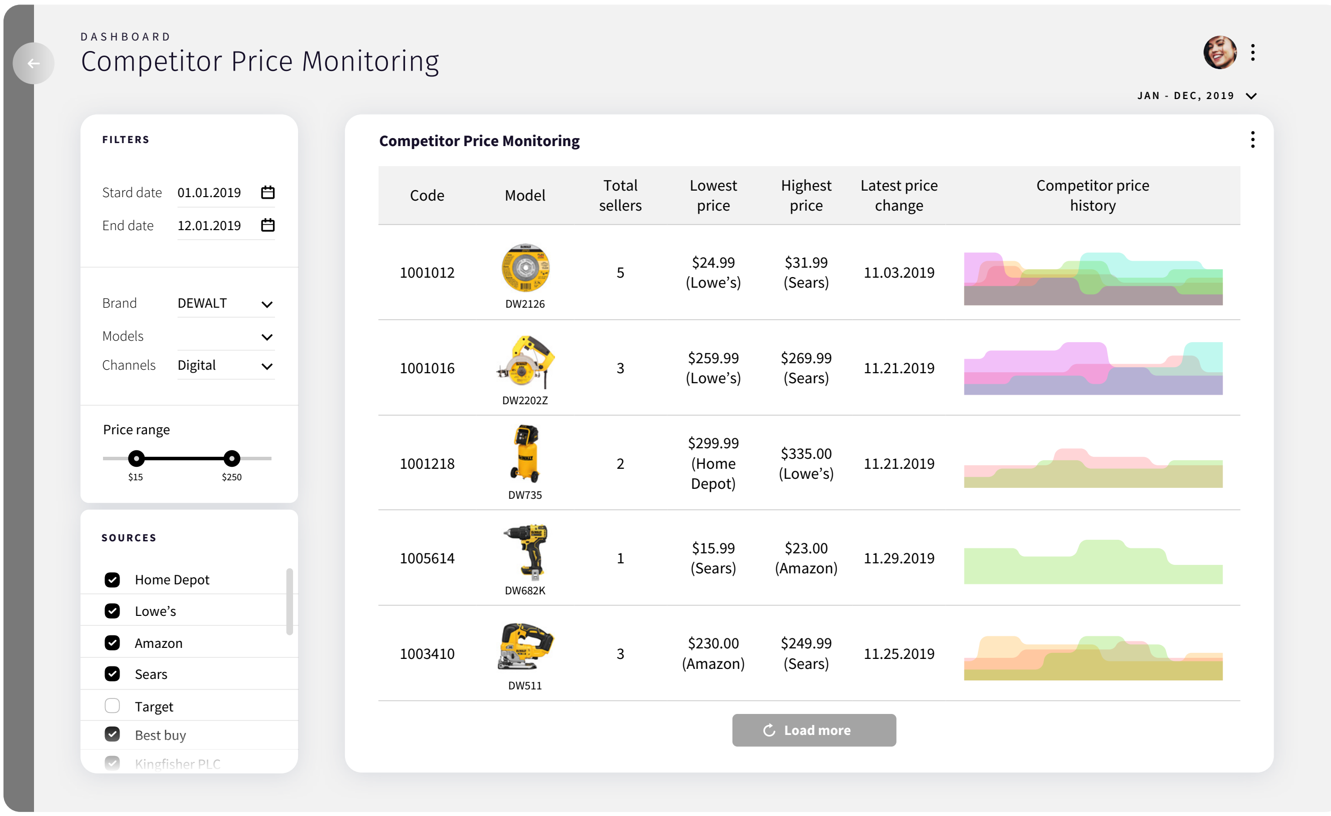
In many verticals, price managers must balance between competing based only on regular price and promoting products using special offers and discounts. These types of decisions can be supported by a statistical analysis that quantifies regular-price and promoted-price elasticities, so that products can be split into four pricing strategies:

- Everyday Low Price (EDLP): For products and categories with relatively low promoted-price elasticities, promotion dollars can be redirected to the regular price.
- Fewer, but deeper, discounts (Hi-Lo): Products that are more sensitive to promoted-price than regular-price changes.
- Hybrid: Products that are sensitive to both regular and promotion prices.
- Margin (Hi-No): Products with low sensitivity to both regular-price and promoted-price changes and can benefit from limits on promotion volume, as well as better price discipline.

In addition to the customer response analysis, the choice between EDLP and Hi-Lo strategies also can be supported by the following intelligence types:

- Market Share: Small brands generally will employ a high-low strategy to compete against stronger brands.
- Product Life Stage: The Hi-Lo strategy is advantageous for new products with high levels of innovation and strong marketing support, while EDLP generally is more suitable for mature products.
- Seasonality: Products with seasonal demand spikes are likely to benefit from the Hi-Lo strategy.

Competitive Pricing Analysis Capabilities



Competitor Price Monitoring Module

Market changes and competitors' moves are the key inputs of price and promotion management processes. It is critically important to have a complete up-to-date picture of the market and competition to make pricing decisions.

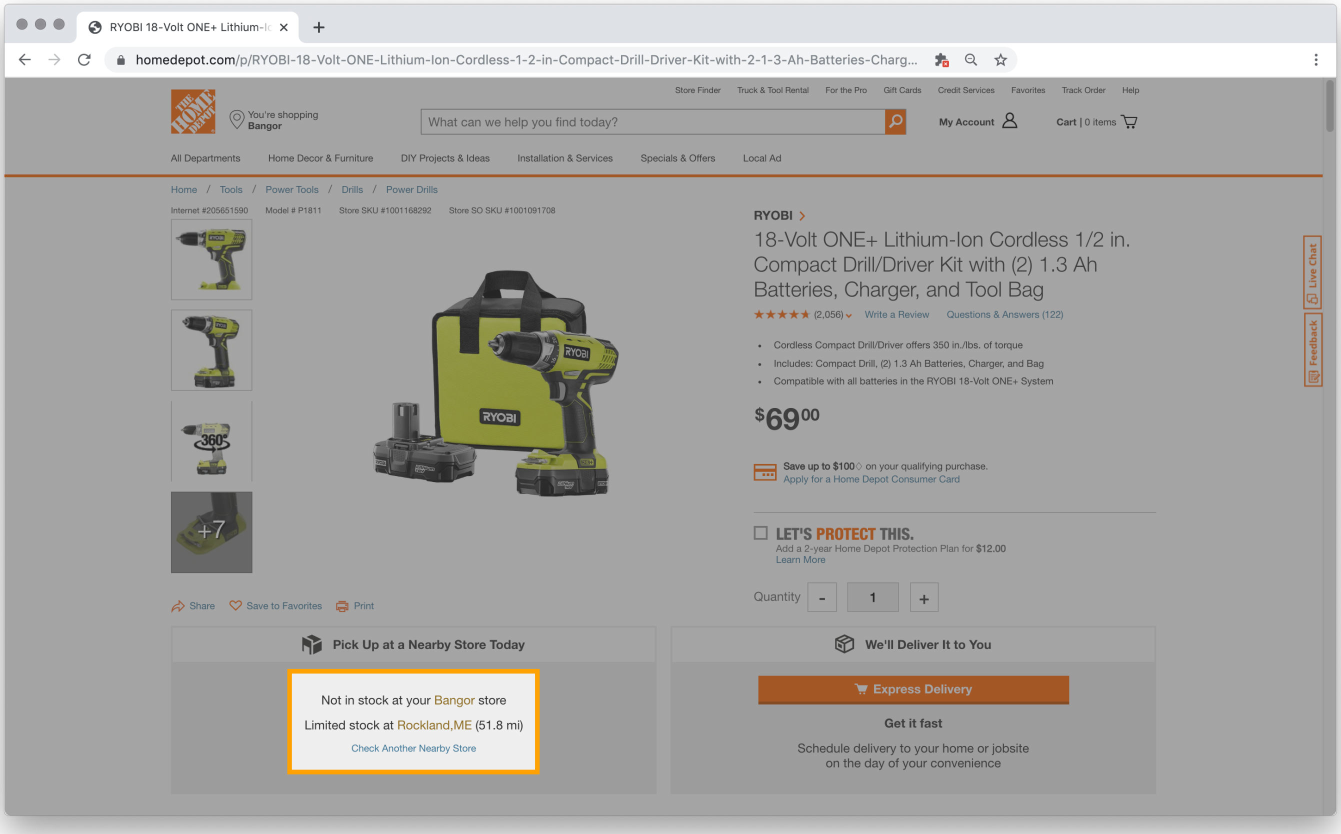
Business Use Cases

- Monitor competitive pricing and price changes.
- Create automatic pricing alerts.
- Enhance demand prediction and promotion optimization models with competitive pricing data.

How It Works

- Web crawlers are used to collect price, promotion, and inventory information across multiple sellers.
- Business users can view current and historical information and configure automatic pricing alerts.
- Collected data can be consumed through downstream promotion evaluation tools to account properly for competitors' pricing impacts and make more accurate forecasts.

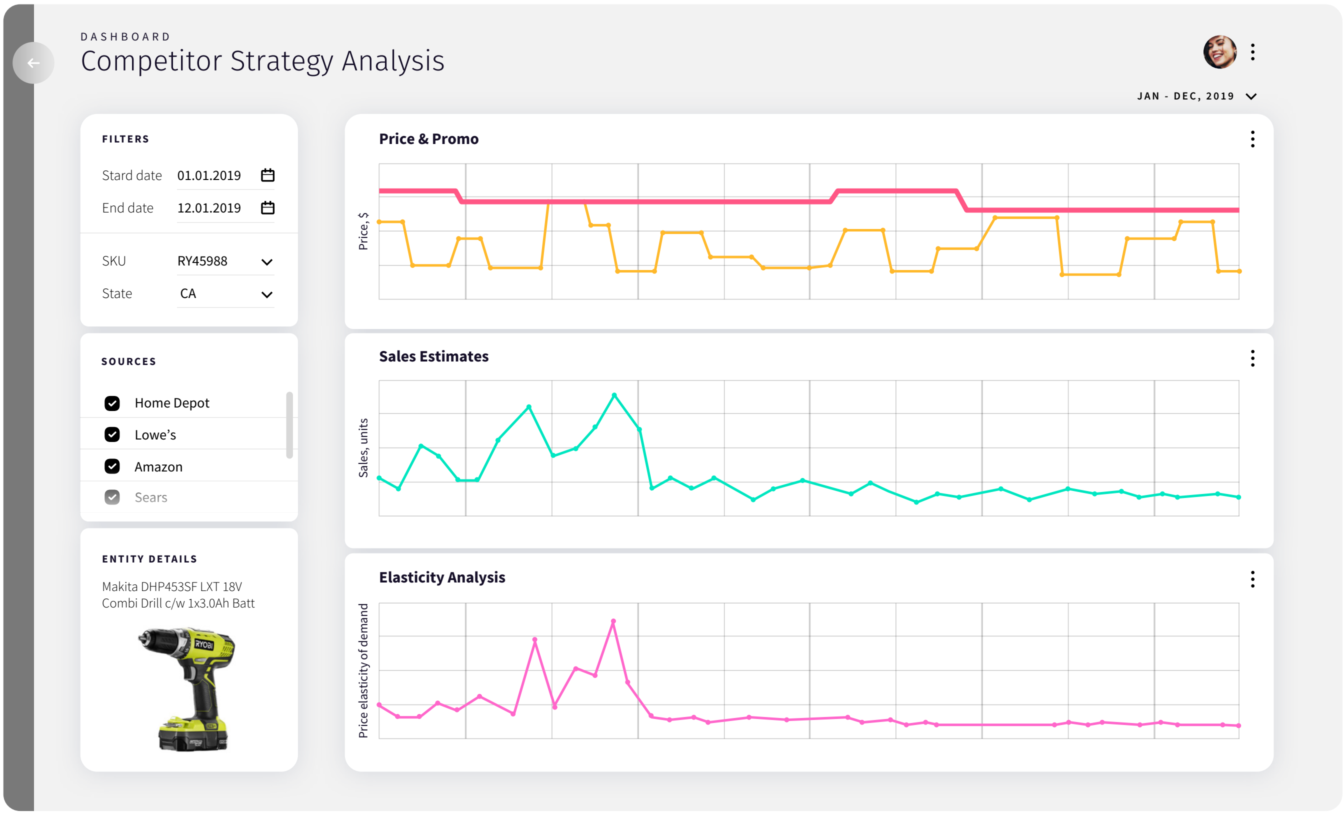
Competitive Pricing Analysis
Capabilities



Competitor price monitoring is merely a basic market analysis capability, and more advanced features can help get much deeper insights into competitors' strategies and market behavior.

Many retailers provide the ability to look up inventory in their physical stores online, as illustrated in the above screenshot. This information can be collected and compared with pricing data to get additional insights into market behavior.

Competitive Pricing Analysis Capabilities



Competitor Strategy Analysis Module

One of the main benefits of collecting comprehensive external data that include both pricing and inventory is that it enables advanced analysis of competitors' strategies. In particular, inventory and pricing data can be used to estimate the price elasticity of demand for competitors' products and measure the success of competitors' promotion campaigns.

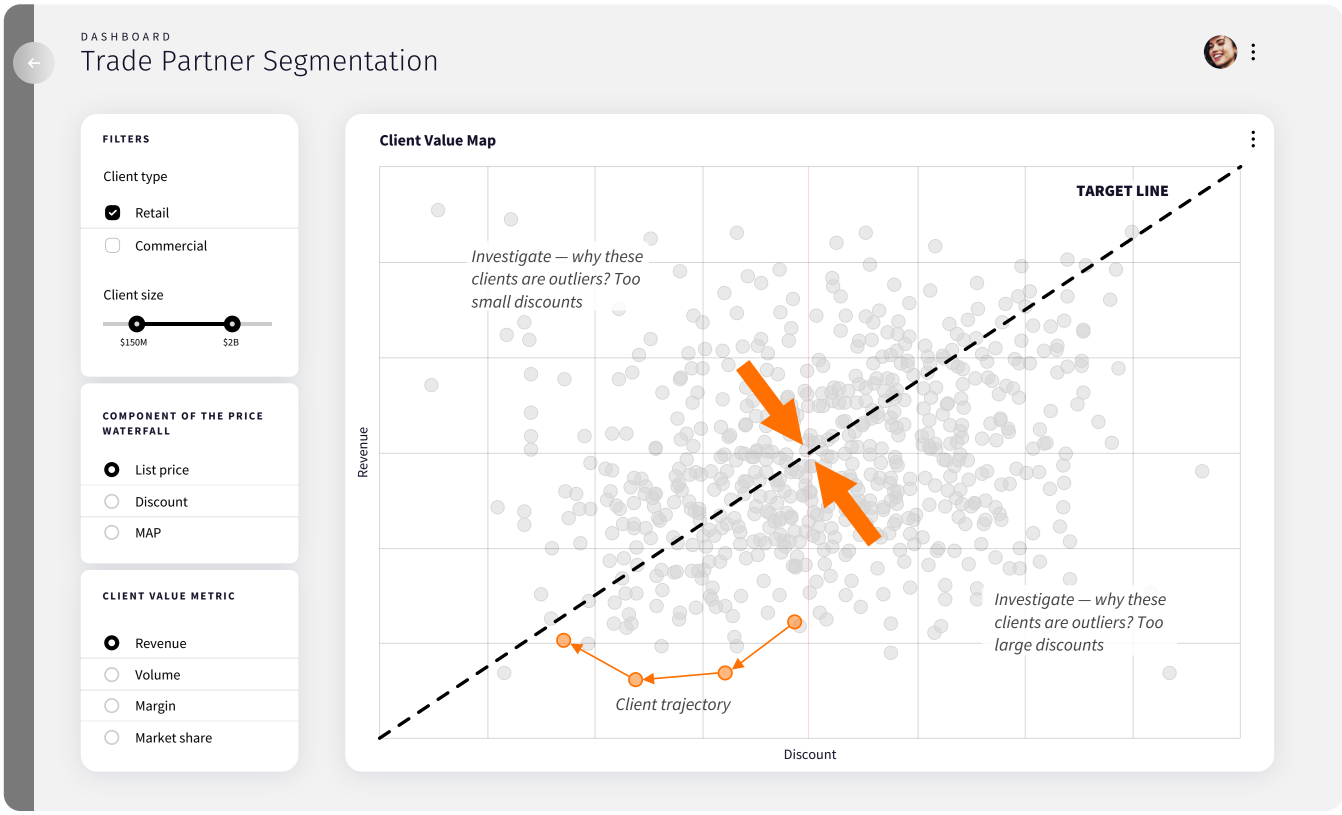
Business Use Cases

- Analyze patterns in competitors' promotion campaigns.
- Measure market response (price and promotion elasticities) for competitors' products.
- Measure the efficiency of competitors' promotion campaigns and corresponding sales volumes.

How It Works

- Pricing and inventory information collected through online channels is used to estimate sales volumes and the elasticity of demand.
- Price, sales, and elasticity time series are visualized to reveal patterns in competitors' behavior and analyze different actions' efficacy.

Segmentation of Retail Clients
Capabilities



Trade Partner Segmentation Module

Large manufacturers usually have multiple promotion managers, each of whom is responsible for his or her own subsets of categories and clients. Price and promotion decisions must be harmonized across all clients using guidelines that can be established and fine-tuned using analytics tools.

Business Use Cases

- Harmonize promotion decisions across all clients.
- Align promotion decisions with client value.
- Identify and rationalize outliers in promotion decisions.

How It Works

- Promotion decisions across retail clients can be rationalized in the Importance x Pricing space.
- Generally, discounts should be aligned with a client's importance (revenue share). Outliers should be analyzed and moved closer to the 45O target line.
- The rationalization process outputs a pricing/discount policy that is consumed by downstream systems for promotion fine-tuning (e.g., based on elasticity analysis).

Market Segmentation Capabilities

Market Segmentation Module

Market segmentation is a complex problem that can involve a wide range of analytics and execution capabilities. The market segmentation module helps define segments based on advanced behavioral characteristics quantified using statistical models. More advanced price differentiation capabilities are provided through offer personalization and dynamic pricing modules.

Business Use Cases

- Analyze behavioral characteristics such as promotion elasticity for different cohorting criteria, e.g., regions, channels, income, etc.
- Identify segmentation criteria for price differentiation based on behavioral characteristics.

How It Works

- Customer cohorts defined in terms of regions, channels, or demographic features are analyzed initially in terms of behavioral characteristics. Some of these characteristics are quantified using statistical and ML models.
- Cohorts with similar behavioral properties are grouped together into segments, and segments are defined in terms of stable and reachable characteristics and criteria, such as region, store/type, or channel.
- Pricing levels and strategies are differentiated based on segments.

03

Measurement

The ability to measure the return on investment (ROI) of pricing actions is critically important for any price management process or solution. Measurement has several dimensions of complexity that need to be addressed through the price intelligence platform.

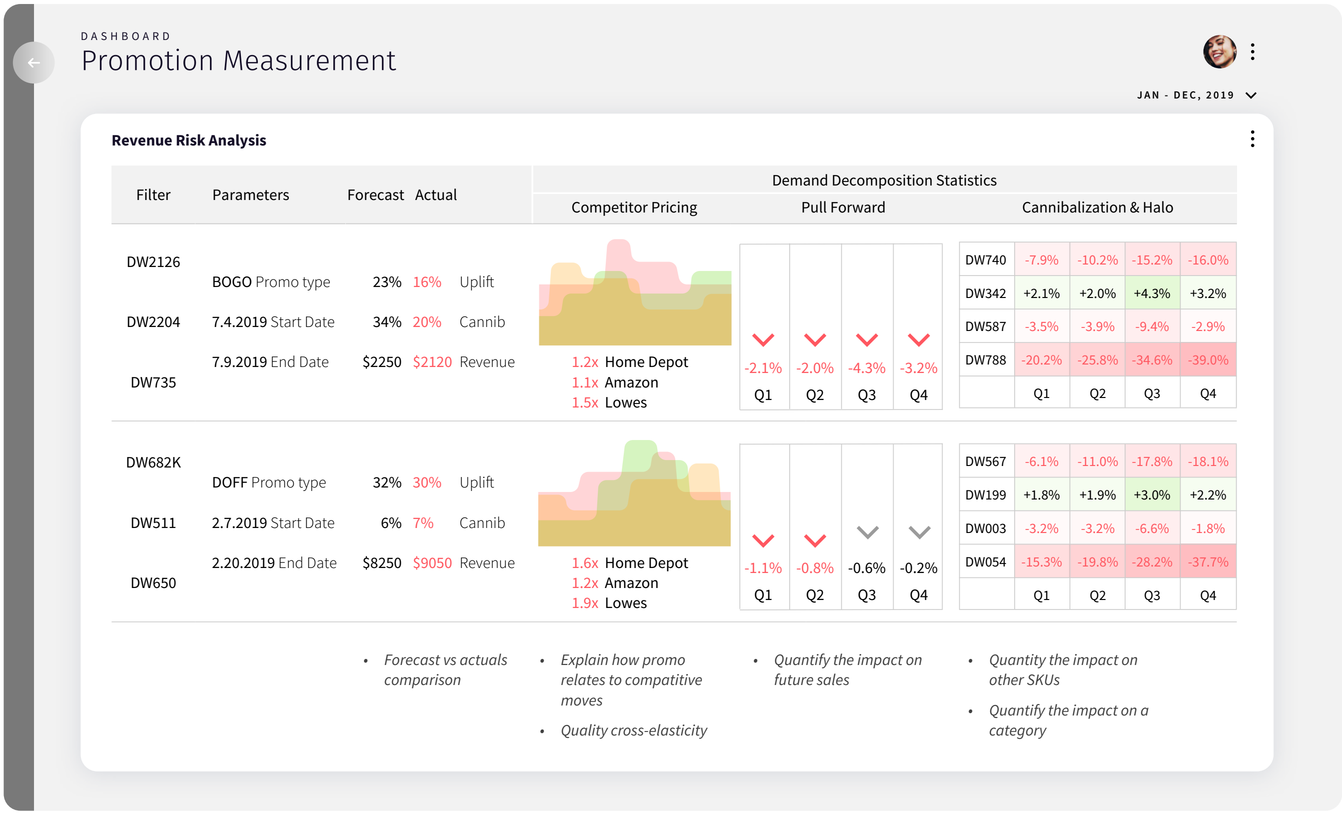
First, measurements usually serve different teams and purposes that require supporting different levels of aggregation and time scales:

- Operational: Near-real-time measurements for individual pricing actions, such as individual promotions.
- Strategic: Measurement and analysis of the long-term impact caused by pricing and product changes. The analysis of the demand redistribution caused by the launch of a new product is an example of a strategic measurement.
- Financial: An aggregated top-level view of the ROI from pricing actions.

Second, measurement tools should provide actionable insights into observed results to support the continuous improvement process. More specifically, the measurement part of the platform aims to deliver the following business capabilities and benefits:

- Continuously monitor pricing actions' outcomes to enable rapid response to market changes.
- Measure the true ROI of pricing actions (corrected for cannibalization and other negative effects).
- Explain what drives the difference between planned and actual results.
- Explain the internal structure of demand/revenue and quantify contributing factors and effects.

Demand Decomposition Capabilities



Promotion Measurement Module

Although basic promotion performance metrics are straightforward (e.g., incremental margins), it is generally hard to provide a comprehensive and insightful view of promotion performance that helps improve promotion decisions in the future. Creating such a view requires disentangling multiple overlapping processes and effects that can be achieved only by using advanced statistical modeling and machine learning.

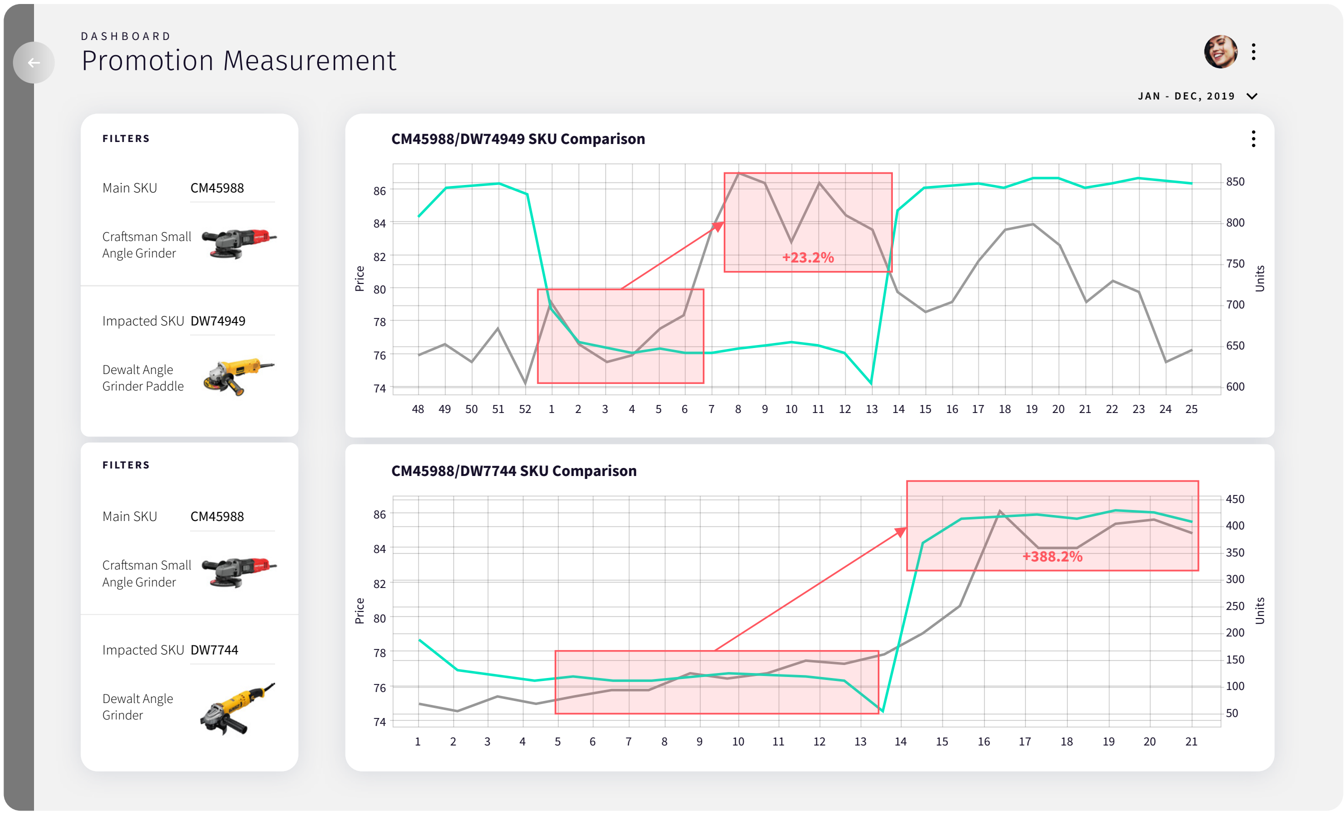
Business Use Cases

- Quantify competitor pricing's impact on a given product or promotion.
- Quantify a promotion's impact on future sales (magnitude of the pull-forward effect).
- Quantify a promotion's impact on similar or complementary products (magnitude of the cannibalization and halo effects).
- Quantify individual promotions' impact on total category sales.

How It Works

- Demand and revenue are decomposed into individual factors and effects using regression and econometric models.
- The decomposition results can be visualized in a user-friendly form to explain performance of a promotion and the difference between planned and actual results, as well as inform better promotion decisions in the future.
- A measurement dashboard that works in a descriptive mode is the basis for a promotion evaluation dashboard that provides similar functionality, but in a predictive mode.

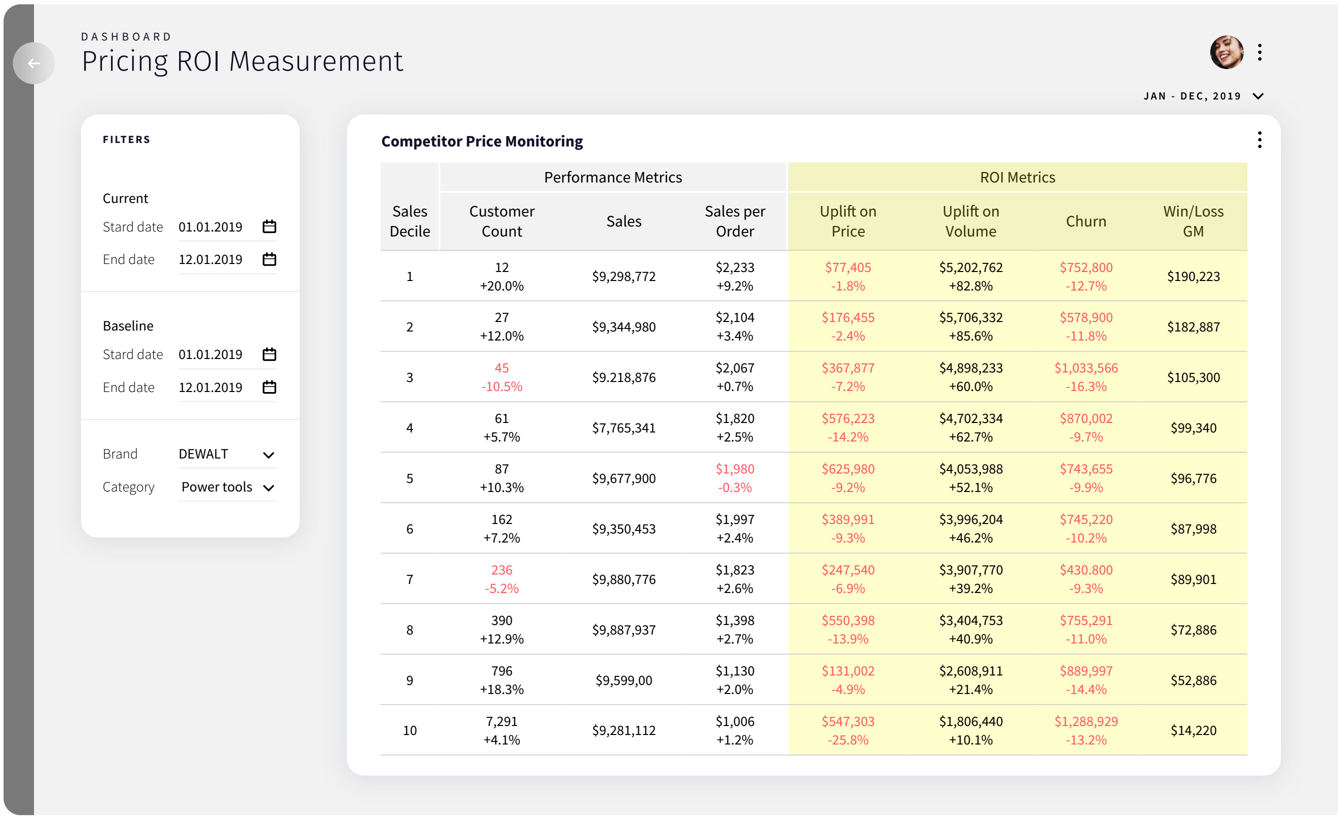
Demand Decomposition Capabilities



Business users can drill down into specific promotion cases and analyze cannibalization, halo, and pull-forward effects in more detail by comparing price and sales time series for various product combinations.

Machine learning models help identify related groups of products and time intervals, as well as quantify cross-impact effects.

Top-Down Pricing ROI Measurements Capabilities



	Performance Metrics			ROI Metrics			
Sales Decile	Customer Count	Sales	Sales per Order	Uplift on Price	Uplift on Volume	Churn	Win/Loss GM
1	12 +20.0%	$9,298,772	$2,233 +9.2%	$77,405 -1.8%	$5,202,762 +82.8%	$752,800 -12.7%	$190,223
2	27 +12.0%	$9,344,980	$2,104 +3.4%	$176,455 -2.4%	$5,706,332 +85.6%	$578,900 -11.8%	$182,887
3	45 -10.5%	$9.218,876	$2,067 +0.7%	$367,877 -7.2%	$4,898,233 +60.0%	$1,033,566 -16.3%	$105,300
4	61 +5.7%	$7,765,341	$1,820 +2.5%	$576,223 -14.2%	$4,702,334 +62.7%	$870,002 -9.7%	$99,340
5	87 +10.3%	$9,677,900	$1,980 -0.3%	$625,980 -9.2%	$4,053,988 +52.1%	$743,655 -9.9%	$96,776
6	162 +7.2%	$9,350,453	$1,997 +2.4%	$389,991 -9.3%	$3,996,204 +46.2%	$745,220 -10.2%	$87,998
7	236 -5.2%	$9,880,776	$1,823 +2.6%	$247,540 -6.9%	$3,907,770 +39.2%	$430.800 -9.3%	$89,901
8	390 +12.9%	$9,887,937	$1,398 +2.7%	$550,398 -13.9%	$3,404,753 +40.9%	$755,291 -11.0%	$72,886
9	796 +18.3%	$9,599,00	$1,130 +2.0%	$131,002 -4.9%	$2,608,911 +21.4%	$889,997 -14.4%	$52,886
10	7,291 +4.1%	$9,281,112	$1,006 +1.2%	$547,303 -25.8%	$1,806,440 +10.1%	$1,288,929 -13.2%	$14,220

Pricing ROI Measurement Module

Operational dashboards provide detailed insight into individual pricing actions' outcomes and quantify their ROI. This operational view is complemented by a top-down view with the financial metrics that quantify overall performance and ROI.

The exact design of ROI metrics is not trivial and should follow both industry best practices and the company's operational model. The following examples illustrate some industry best practices:

- The portion of revenue growth or loss attributable to a change in price:

  $$Uplift_{price} = (Price_{new} - Price_{baseline}) \times Volume_{new}$$

- The portion of revenue growth or loss attributable to a change in volume:

  $$Uplift_{volume} = (Volume_{new} - Volume_{baseline}) \times Price_{baseline}$$

- The portion of revenue growth or loss attributable to the net change in non-repeat sales:

  $$Products\ added = Products_{new} \setminus Products_{baseline}$$

  $$Products\ removed = Products_{baseline} \setminus Products_{new}$$

  $$Churn = Revenue\ of\ Products\ added - Revenue\ of\ Products\ removed$$

- Net positive or net negative effect of a pricing action on the unit:

  $$Win/Loss\ Gross\ Margin = (Volume_{new} - Volume_{baseline}) \times GM_{new} + (GM_{new} - GM_{baseline}) \times Volume_{baseline}$$

The above metrics can be computed for different aggregation levels, such as SKU, product, category, or business unit, as well as time periods. In particular, price in the first two formulas typically means the average selling price for the unit.

04

Evaluation

The platform's evaluation capabilities are focused on fine-tuning price and promotion parameters, accurate outcome forecasts, ROI of pricing actions, and automated optimization. Evaluation's principal goal and benefit are to provide formal (statistically and econometrically estimated) guarantees that pricing actions are near optimal and that no major gaps or miscalculations exist.

Evaluation capabilities can be provided at different aggregation levels (individual products, promotions, subcategories, or categories) and different levels of automation (predictive or prescriptive). Evaluation of individual entities, such as promotions, might require only forecasting (predictive) capabilities because the number of parameters is small, and promotion managers can do what-if analyses manually. Evaluation at higher aggregation levels, such as categories, involves many parameters and generally requires automatic optimization (prescriptive mode).

In this section, we focus on the following capabilities that the evaluation part of the platform provides:

- Estimate key performance indicators of a promotion for different parameters and execution scenarios.
- Explain how exactly the estimates are calculated and provide detailed diagnostics information.
- Jointly optimize a promotion calendar for a group or category of products, taking into account cross-effects.
- Automatically identify promotion opportunities and recommend new promotions.
- Automatically identify promotions that drive losses and recommend disabling them.

Market Response Modeling Capabilities

Promotion Evaluation Module

One of the most important steps in promotion management is the fine-tuning of promotion parameters. A proper choice of parameters helps maximize a promotion's impact, while an erroneous choice can elicit loss of profit. Promotion managers use the promotion evaluation tool to forecast market response to a promotion and fine-tune promotion parameters.

The market response on a promotion generally is a combination of multiple economic effects that must be quantified and analyzed both separately and jointly. For example, a promotion can deliver a profit boost for one product, but harm the overall category's profit due to cannibalization. It is important to account explicitly for such effects in evaluation models and tools.

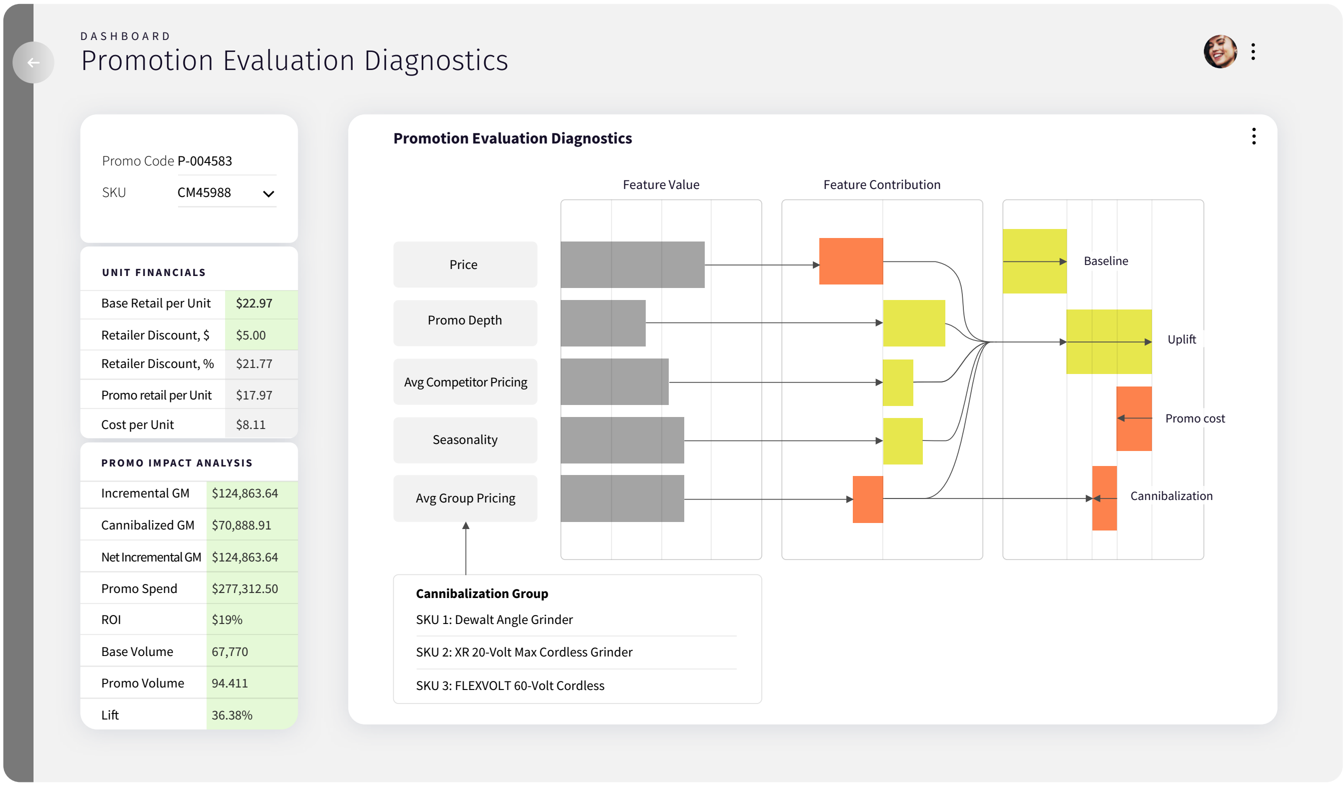
Business Use Cases

- Do a what-if analysis for different promotion parameters, such as start and end dates, promotion type, and depth.
- Quantify and analyze individual economic effects associated with a promotion, such as cannibalization, halo, and pull-forward.
- Predict key performance metrics of a promotion, such as volume, uplift, ROI, etc.

How It Works

- Evaluation functionality is based on the demand/profit forecasting model, which uses prices, discounts, product attributes, and other features as inputs.
- The forecasting model is combined with economic models that translate the forecast into other metrics, such as uplift and ROI.
- The best way to visualize some economic effects is through cumulative revenue/margin charts that highlight the tradeoff between short-term and long-term effects.

Market Response Modeling Capabilities



Promotion Evaluation Diagnostics Module

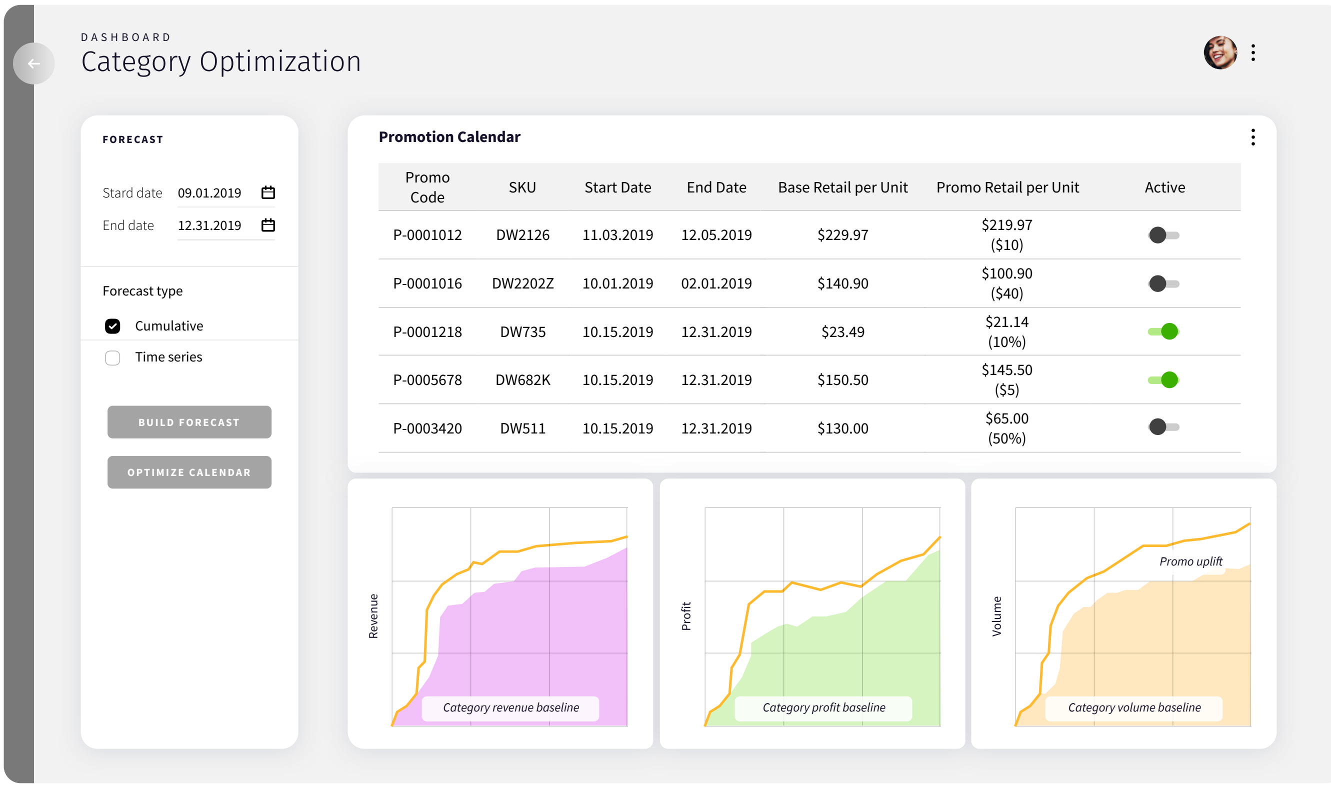
Promotion managers usually need to understand and quantify individual factors that drive demand, as well as understand how exactly these factors are accounted for in the promotion evaluation model.

If the model is a black box, it becomes challenging or impossible to use forecasts and promotion parameters that the model suggests if they do not match a promotion manager's intuition.

The tool provides detailed diagnostic reports that allow for understanding and troubleshooting the output that the prediction model produces. The diagnostic report includes the following details:

- Information about input features, e.g., lists of related and cannibalized products.
- Specific values of numerical and categorical features.
- Individual features' contribution (significance) coefficients.
- How input features are related to a promotion's individual performance indicators (uplift, cannibalization percentage, etc.)

Category Optimization Capabilities



Category Optimization Module

The promotion evaluation tools provide a way to fine-tune individual promotions, but promotions often are interdependent because of complex rules applied by a pricing engine (e.g., if a given shopping cart qualifies for multiple promotions, use one with the maximum discount) and cannibalization effects. These challenges are addressed by a category optimization tool that helps analyze and optimize a group of promotions jointly.

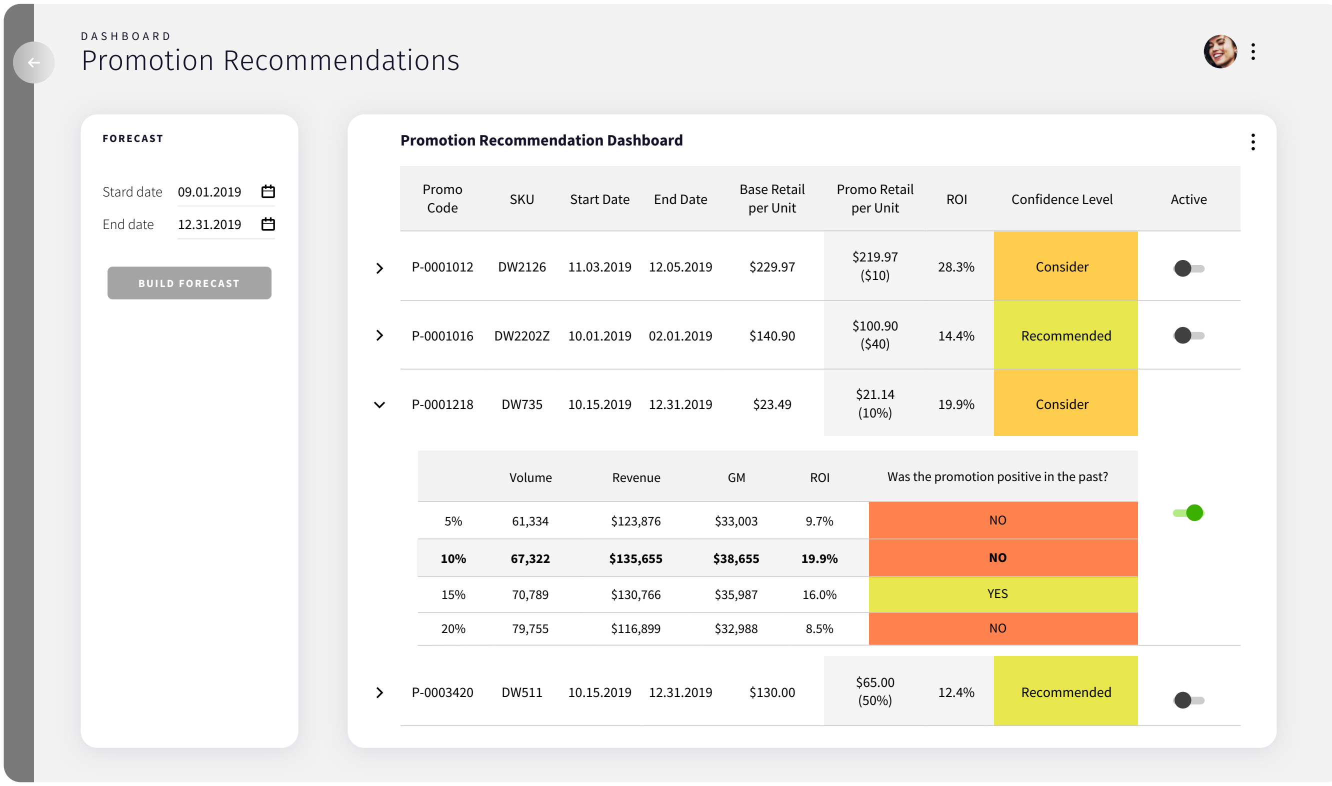
Business Use Cases

- Evaluate the overall performance of a promotion calendar for a category.
- Automatically optimize several promotions' parameters, taking into account cross-effects.

How It Works

- The demand-forecasting model provides a foundation for various optimization types, including category-level optimization.
- Promotion managers manually can evaluate different promotion combinations by turning individual promotions on and off.
- The system automatically can search for the optimal combination of promotions using combinatorial optimization algorithms.

Promotion Recommendations Capabilities



Promotion Recommendations Module

Promotion evaluation capabilities can be extended with a tool that searches for and suggests new promotion opportunities that are missed or overlooked in the manually created promotion calendar. This helps the promotion manager go beyond basic fine-tuning of historical promotion calendars and obtain some formal guarantees that the promotion calendar is nearly optimal.

Business Use Cases

- Identify gaps and new promotion opportunities in the manually created promotion calendar.
- Automatically generate near-optimal promotion recommendations (candidates) that cover gaps in the input calendar.

How It Works

- The promotion recommendation tool uses demand and profit forecasting models to evaluate possible promotion options.
- The tool uses combinatorial search algorithms to search efficiently through the space of possible promotion dates and other parameters.
- The system shows diagnostics information for each promotion recommendation to explain why a particular combination of parameters was selected and how the recommendation relates to historical cases.
- Once the recommendations are generated, the options are reviewed by promotion managers who can use other platform tools, such as category optimization, for fine-tuning purposes.

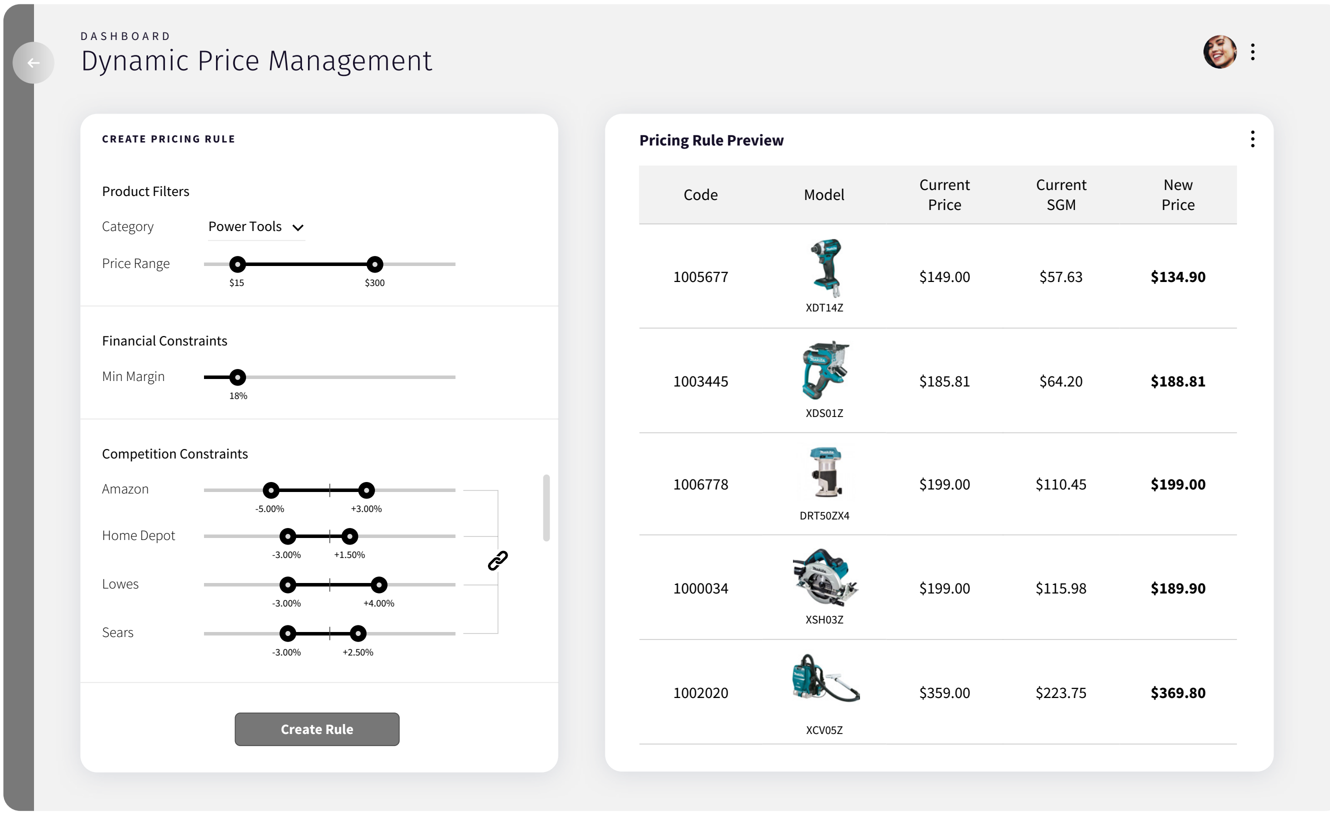
05

Execution

The platform's execution capabilities focus on near-real-time decision making that cannot be done in advance using strategy analytics and evaluation components. This type of decision making is needed for personalization and rapid response in dynamic environments. More specifically, execution capabilities include the following:

- Make dynamic (near-real-time) pricing and promotion decisions for channels that support dynamic pricing.
- Continuously re-optimize prices and promotions based on ongoing changes in inventory and demand.
- Personalize offers based on customer demographics and behavior.
- Monitor the execution of pricing actions and alert on exceptions.

Dynamic Pricing
Capabilities



Dynamic Price Management Module

Traditional price and promotion management processes heavily rely on historical data. New promotion calendars are created based on past best practices, targets are set based on year-over-year analyses, and demand forecasting models are designed using years of historical data. This approach is not necessarily perfect for channels that support dynamic pricing, and more specialized dynamic pricing capabilities can improve results.

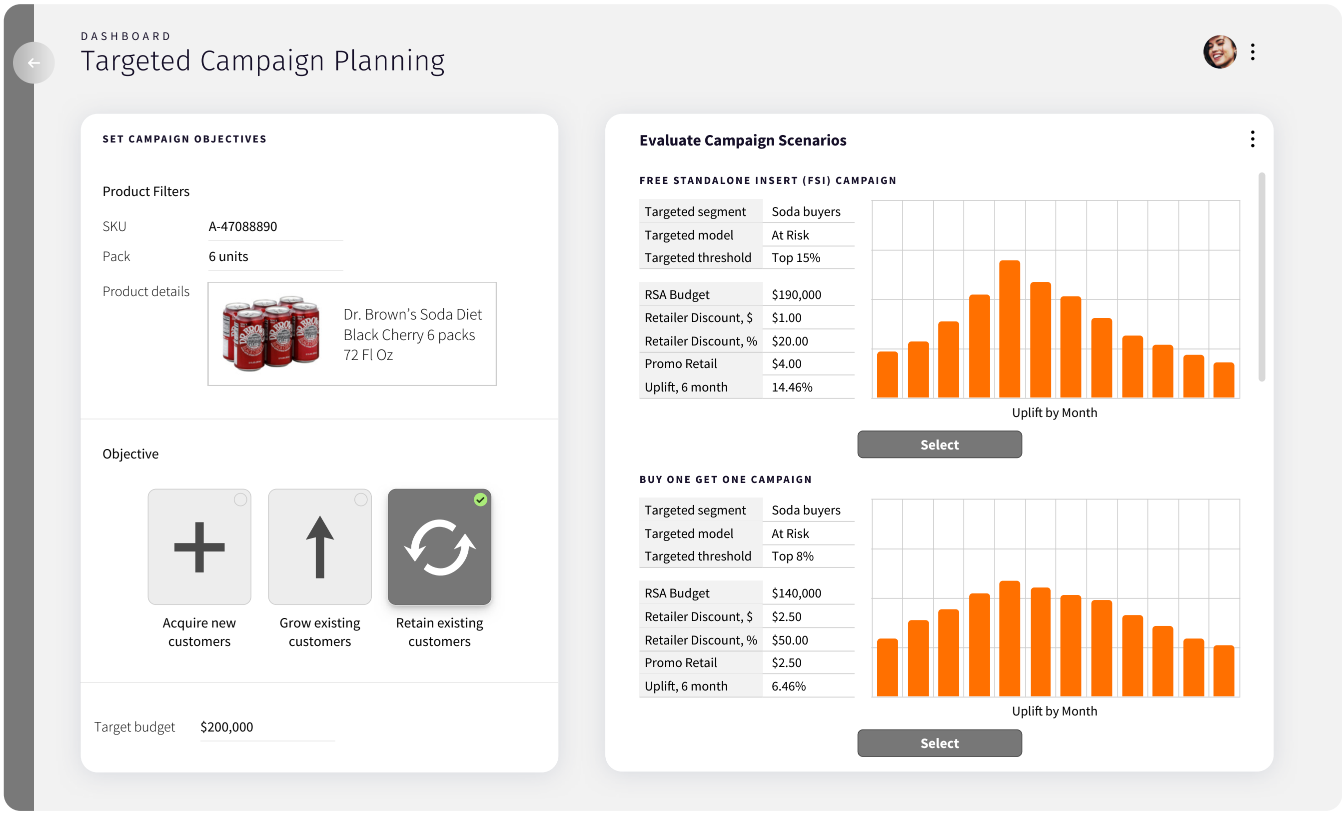
Business Use Cases

- Integrate with channels that provide dynamic pricing capabilities, such as Amazon.
- Adjust prices dynamically based on competitors' prices, financial targets, and price limits.
- Optimize prices dynamically based on ongoing transactions.
- Incorporate inventory and supply chain constraints (stock levels, lead times, etc.) into the optimization process.

How It Works

- The most basic implementation of dynamic pricing uses business rules to adjust prices and promotion based on competitor pricing and financial constraints and targets.
- The dynamic price engine analyzes ongoing transactions to rapidly re-estimate price-demand dependency and perform mathematical price optimization. This helps overcome traditional models' limitations in highly dynamic environments and scenarios with limited or no historical data (e.g., new product launches).
- The optimization process uses elements of reinforcement learning to incorporate inventory and supply chain constraints.

Offer Personalization Capabilities



Targeted Campaign Planning Module

The efficacy of B2C promotion campaigns can be improved using personalized offers, which help increase redemption and conversion rates, improve customer loyalty, and achieve more persistent and longer-term ROI improvements.

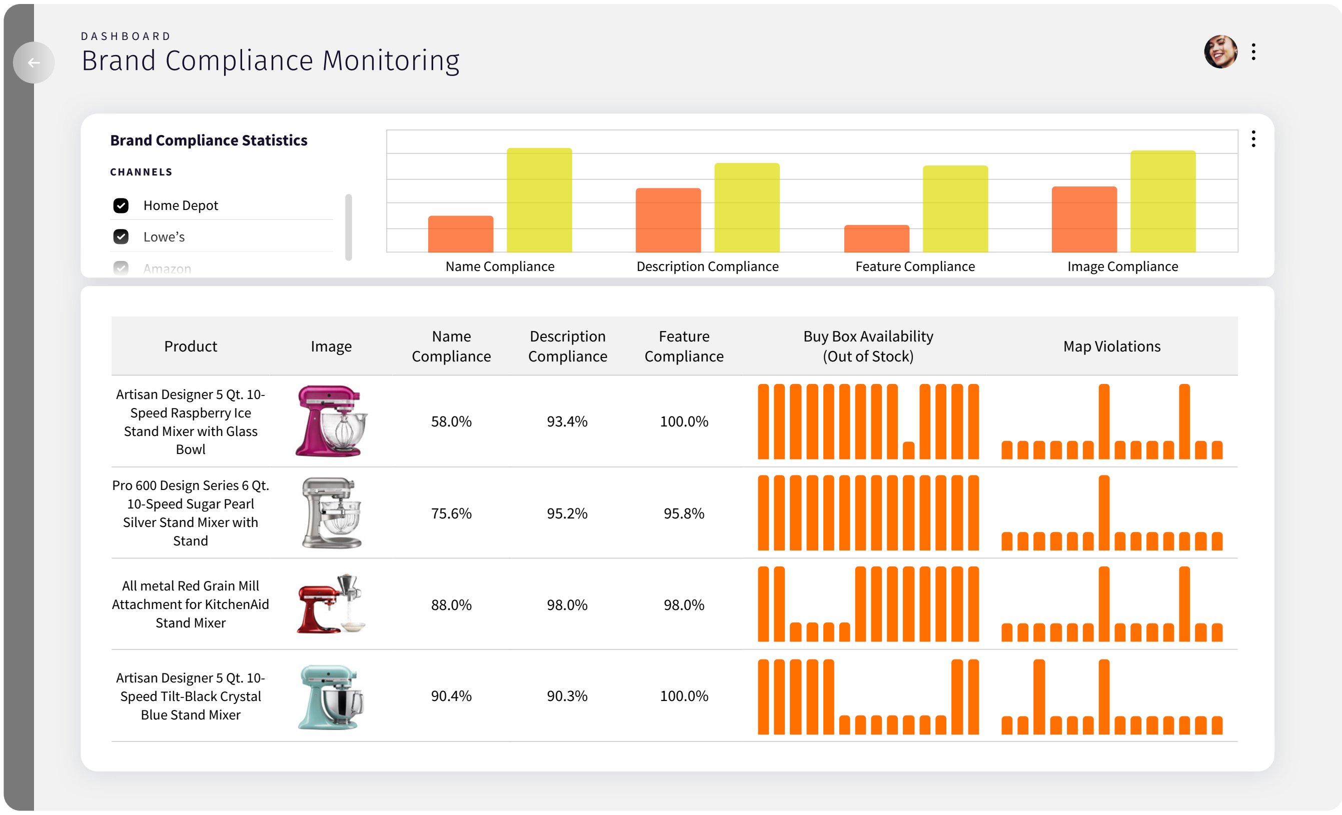
Business Use Cases

- Target customers with the highest expected probability of response.
- Optimize offer targeting based on business objectives, such as acquisition, growth, or retention.
- Forecast the performance of personalized promotion campaigns.
- Run personalized promotion campaigns across multiple channels, e.g., ecommerce, printed coupons, email, and mobile coupons.

How It Works

- The campaign planning tools support several types of campaigns (campaign templates) for each business objective.
- The system maintains and re-trains a set of targeting models for different business objectives and product categories.
- A campaign manager configures a product to be promoted and a business objective. The campaign-planning tools evaluate different campaign templates and targeting and promotion parameters using targeting and response models to recommend near-optimal campaign scenarios to the campaign manager.
- Once the campaign is fully configured, the targeting system can make targeting decisions with regard to individual customers (select the best offer) in real time.

Compliance Monitoring Capabilities



Brand Compliance Monitoring Module

Execution of pricing actions through third-party channels requires monitoring for compliance and consistency. The platform's monitoring capabilities include the following:

- Content compliance: Consistency of product names, descriptions, feature lists, and images.
- Availability: Monitoring of inventory levels and out-of-stock situations to reveal availability issues.
- MAP violations: Consistency of retail prices with minimum advertised price (MAP) policies to protect profit margins and brand positioning.

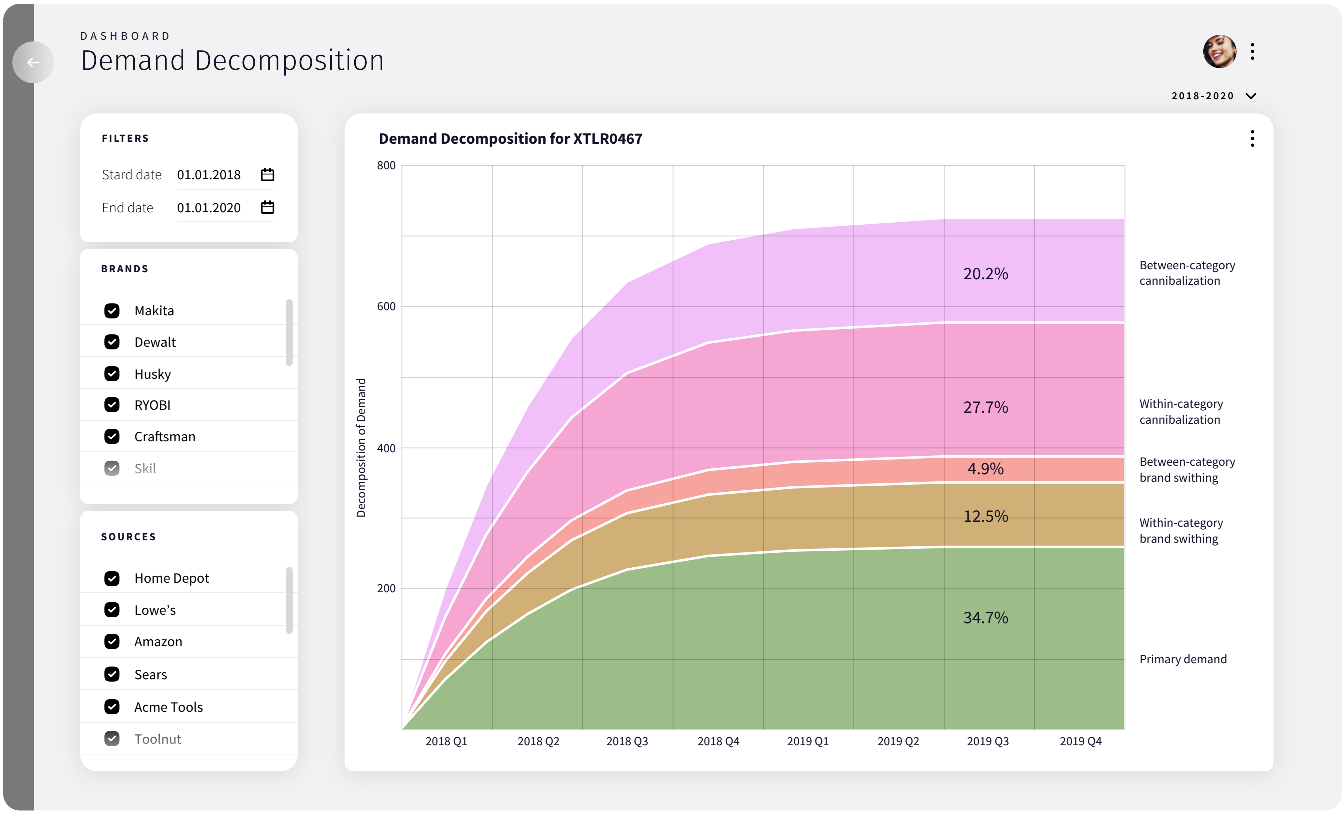
06

Product Intelligence

The product intelligence part of the platform extends strategy analytics capabilities with methods that focus on product success analysis, decision support for product design, and assortment optimization. Most of these capabilities require deep analysis of the demand's structure for multiple products, categories, and even brands, both short-term and long-term. In this section, we describe the following product intelligence capabilities:

- Evaluate the success of new product launches.
- Explain the structure of the demand for new products and its dynamics over time.
- Analyze halo and cannibalization dependencies between products for assortment rationalization.
- Analyze substitution dependencies between products for assortment rationalization.

Demand Decomposition for New Products
Capabilities



Demand Decomposition Module

The demand for a new product can come from various sources, including market growth (primary demand), cannibalization of the brand's other products, and drawing customers from competitors. To measure a new product's success level, observed demand needs to be decomposed, and each source's contribution needs to be quantified. This task can be accomplished using advanced econometric models that incorporate sales data series for multiple brands and products, and quantify dependencies between them.

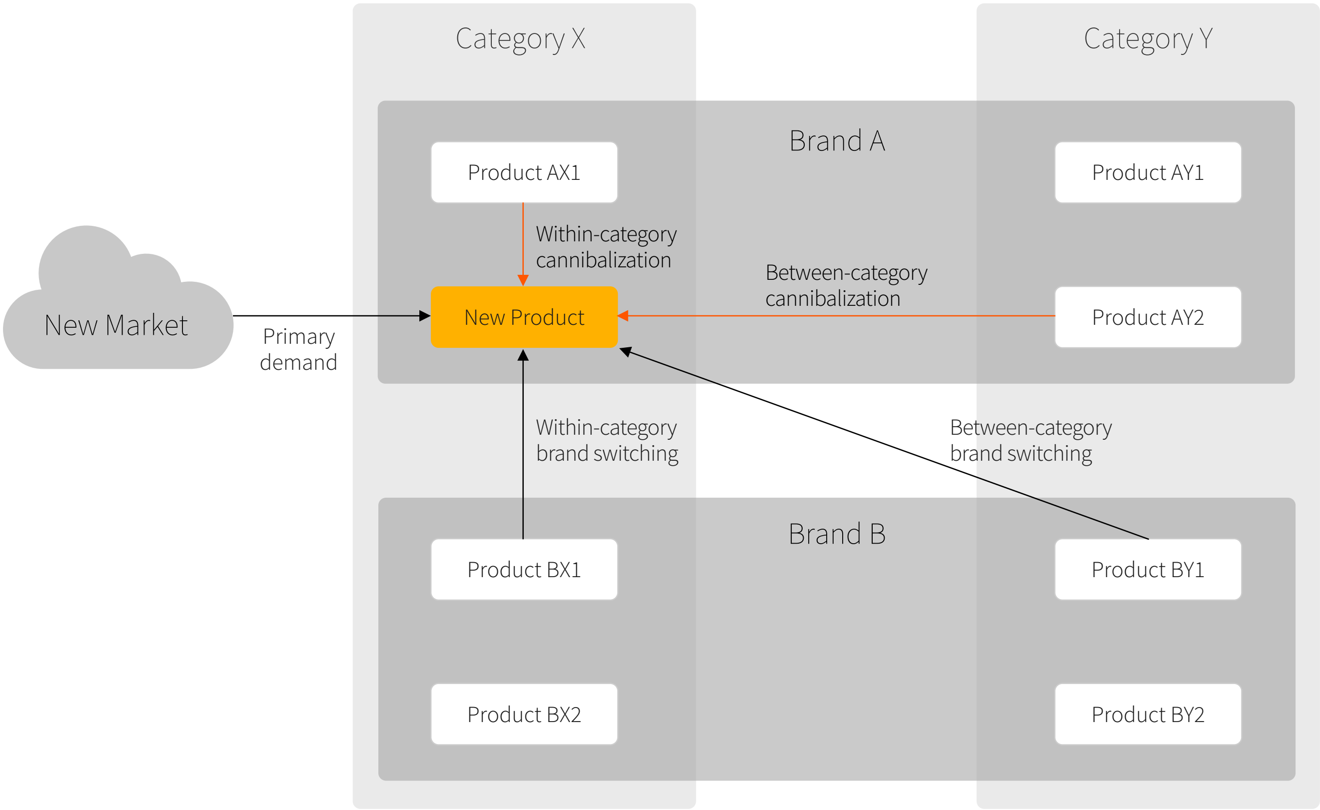
Business Use Cases

- Measure the success of a new product in terms of primary demand generation, drawing from competition and cannibalization.

How It Works

- Modern econometric methods, such as vector error-correction (VEC) models, allow for properly incorporating multiple signals, including sales data, for multiple products, brands, and categories, as well as marketing-mix data.
- The fitted model is analyzed to quantify the demand's composition and its dynamics over time.

Demand Decomposition for New Products
Usage



Usage Examples

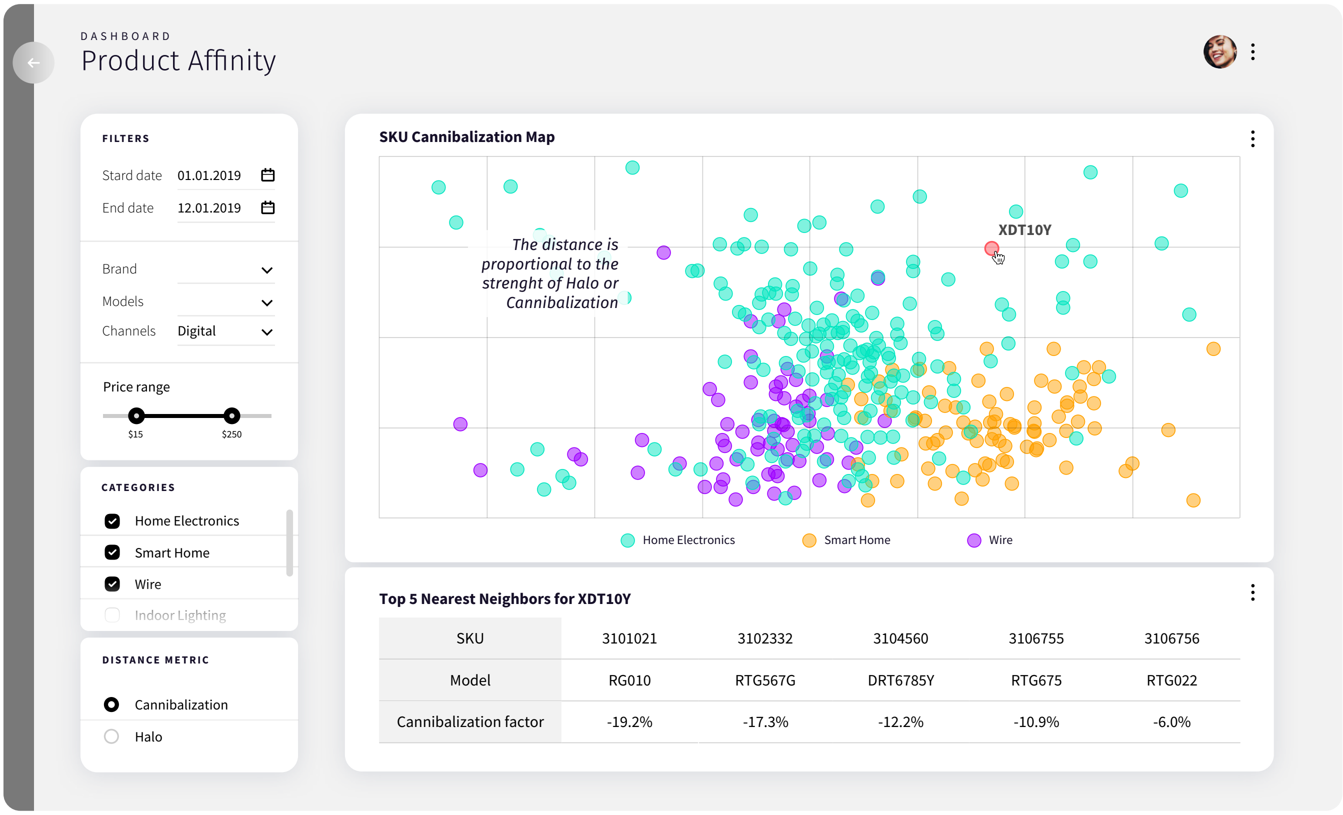
The demand for a new product generally can be decomposed into several components:

- Primary demand: Really new demand due to market expansion and attracting new customers.
- Within-category cannibalization: Sales cannibalization of a brand's other products within the category where the new product is introduced.
- Between-category cannibalization: Sales cannibalization of a brand's products in other categories. For example, cordless power tools cannibalize the demand for corded tools.
- Within-category brand switching: Demand drawn from competition within the category.
- Between-category brand switching: Demand drawn from competing products in other categories.

Brand-switching components can be decomposed further into subcomponents associated with individual brands.

The demand-decomposition model can be designed to quantify each of the above components (including the brand-level breakdown) and their dynamics over time.

Assortment Rationalization Capabilities



Product Affinity Module

Assortment and pricing decisions can be supported by analysis of cannibalization and halo dependencies across products. This analysis helps identify opportunities for assortment optimization (e.g., dense product clusters), as well as opportunities for new products (e.g., sparse areas).

Business Use Cases

- Analyze how sales are cannibalized across products.
- Analyze how price and promotion changes impact related products due to the halo effect.
- Rationalize assortment based on cannibalization and halo considerations.

How It Works

- Cannibalization and halo effects are quantified using the demand model.
- The distances between products in terms of halo/ cannibalization are projected onto a 2D plane for visualization and exploration.

07

Under the Hood: Machine Learning Models

Market Response Modeling
Econometrics

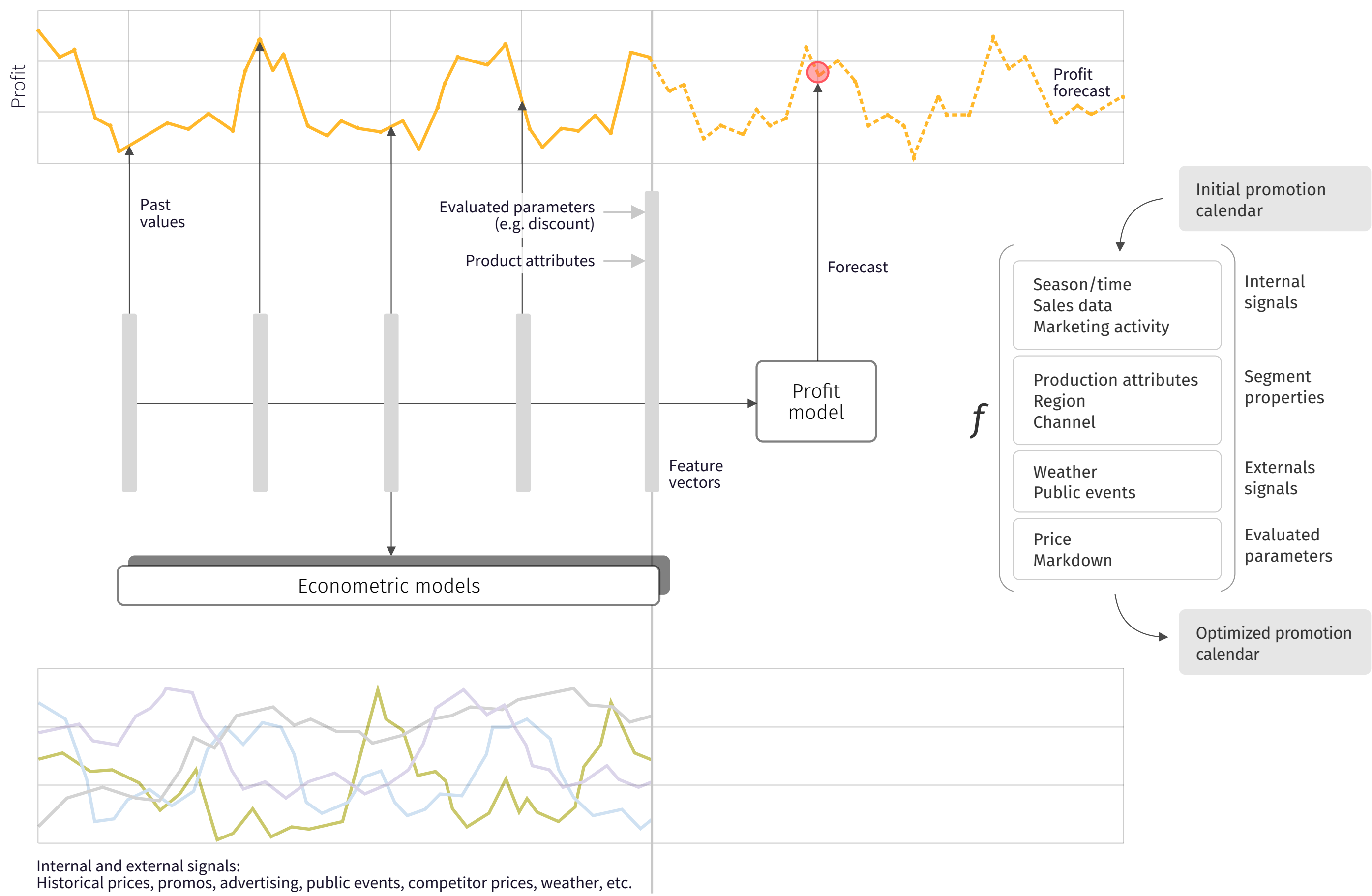
Demand modeling and forecasting are a fundamental capability that most price and promotion evaluation and optimization tools use.

Demand modeling generally requires quantifying a wide range of economic effects, such as:

- Own-item price elasticity: Dependency between a product's price and its sales. Price often includes several components – such as list price, discounts, and special offers – and elasticities are estimated separately for each of these components.
- Cannibalization: Dependency between the given product and its substitutes (other products in the same category or similar categories). A price increase on a given product can result in customers switching to the substitutes, decreasing sales of the product and increasing sales of substitutes.
- Halo: Dependency between the given product and complementary products. Sales of such complementary products can be boosted through promotion of a given product.
- Competitor price elasticity: Dependency between competitors' prices and a seller's own prices for the same or similar products.
- Pull forward: Dependency between current and future sales. Temporary promotions and price drops can incentivize customers to stockpile goods, which essentially draws from future sales (cannibalization in time).

These effects can be quantified separately using standalone econometric models, some of which require advanced feature engineering, e.g., cannibalization modeling often requires developing business rules or sub-models for initial grouping of products into small sets (cannibalization sets).

Market Response Modeling
Demand Forecasting



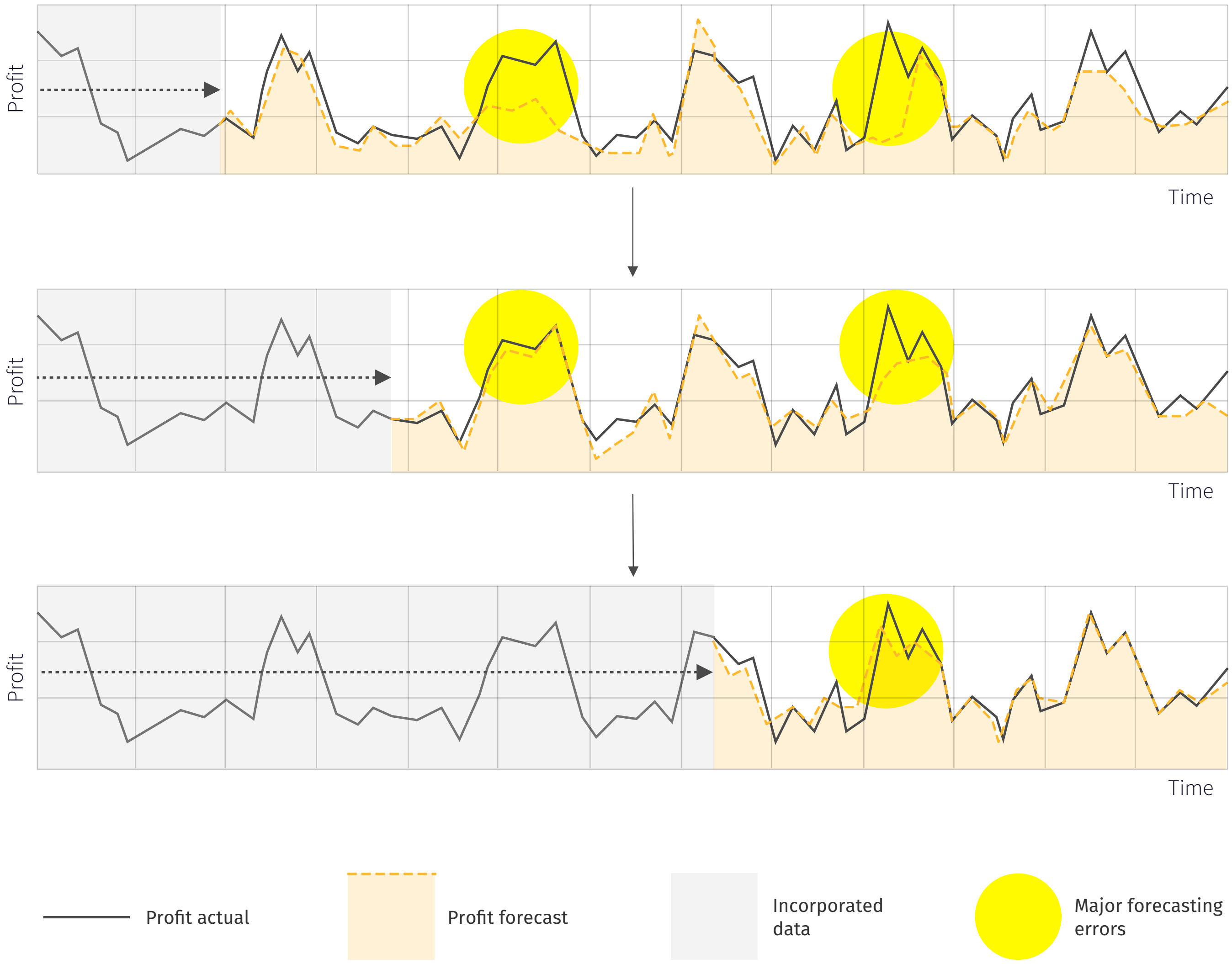
Besides basic price-related effects that econometric models capture, a demand model must account for other signals, including marketing-mix variables (e.g., advertising intensity, etc.), seasonality, public events, and macroeconomic metrics, among others.

In many cases, it is important to capture domain-specific signals. For example, demand for a sports videogame can be influenced significantly by sporting events, thereby requiring that the event be incorporated into the input feature set.

Internal and external signals, outputs, or econometric models, and historical demand data are usually used inputs to the second-level demand or profit model. This model often is created using higher-capacity methods (gradient-boosted decision trees, deep neural networks, or vector autoregressive models) to capture more complex patterns and dependencies.

Finally, demand usually is predicted for a certain segment (subset) of products, geographical regions, stores, or sales channels. It is quite common to build and train multiple segment-level models independently, i.e., one model per segment. However, this approach limits transfer learning across segments, as well as the ability to make forecasts for new segments (e.g., newly launched products). These limitations can be circumvented by building models that use segment properties instead of segment identities (e.g., making a forecast based on product type, color, size, etc.).

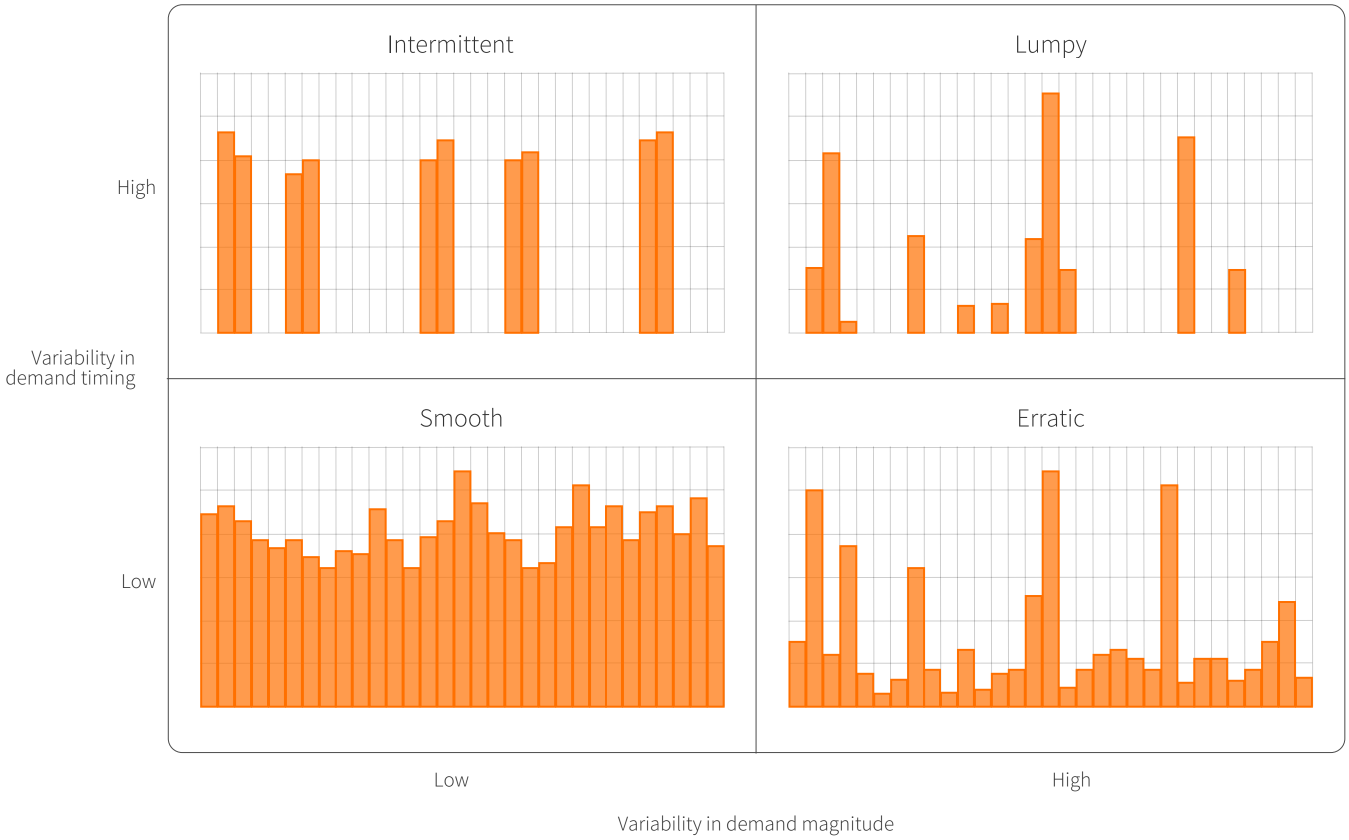
Market Response Modeling
Test Sales



In some environments, demand forecasting can be very challenging because of limited data. This is particularly common in wholesale and B2B environments in which a seller might have only aggregated weekly data without access to individual consumer transactions.

In environments with limited data availability, continuous incorporation of ongoing data and test sales are generally important. If it is not possible to make a highly accurate long-term forecast, the forecast's accuracy often can be improved, and major forecasting errors can be eliminated through continuous incorporation of ongoing data.

Market Response Modeling
Irregular Demand



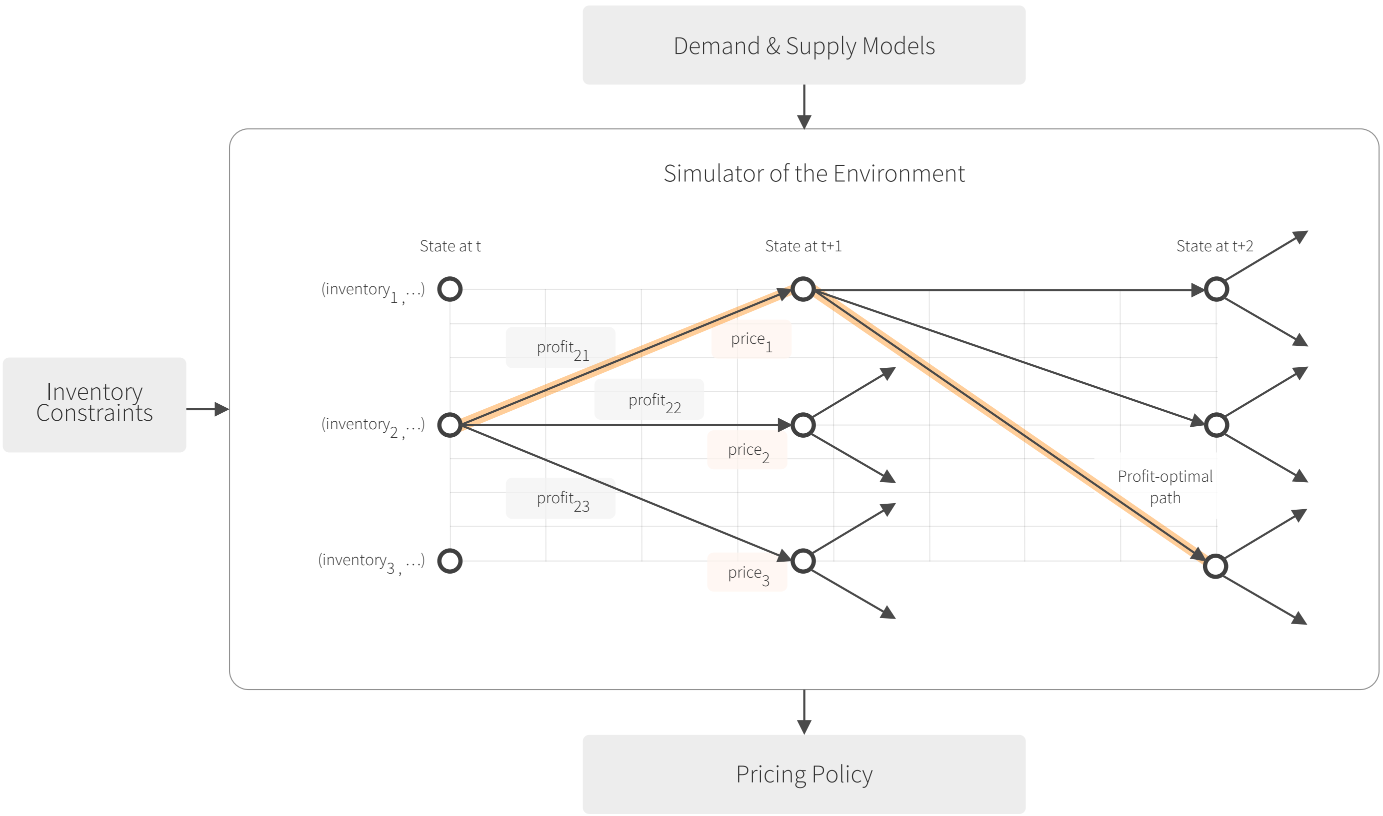
Depending on a specific use case, demand forecasting can be done at different aggregation levels: category; product; SKU; channel; region; or store. Selecting aggregation level is associated with the following trade-offs:

- Lower aggregation levels enable more granular decisions tailored to a specific segment, such as a region or channel.
- The lower the aggregation level, the higher the sparsity of data, which translates into a higher variance in the forecast and, ultimately, to lower-quality decisions.

In the latter case, the high variance in the forecast often stems from irregular demand patterns that are averaged out at high levels of aggregation, but become apparent at lower levels. For example, the demand for a slow-moving product at the level of a region or store can be highly irregular.

Irregularity is one of the major challenges in demand forecasting because performance of most forecasting methods degrades with sparse data. This problem can be alleviated by using specialized models for certain demand patterns, such as intermittent, lumpy, or erratic demand types. These models' outputs also can be used as inputs to downstream (generic) demand models to improve handling of irregularities and the forecast's overall accuracy.

Price Optimization
Long-Term Optimization With Constraints



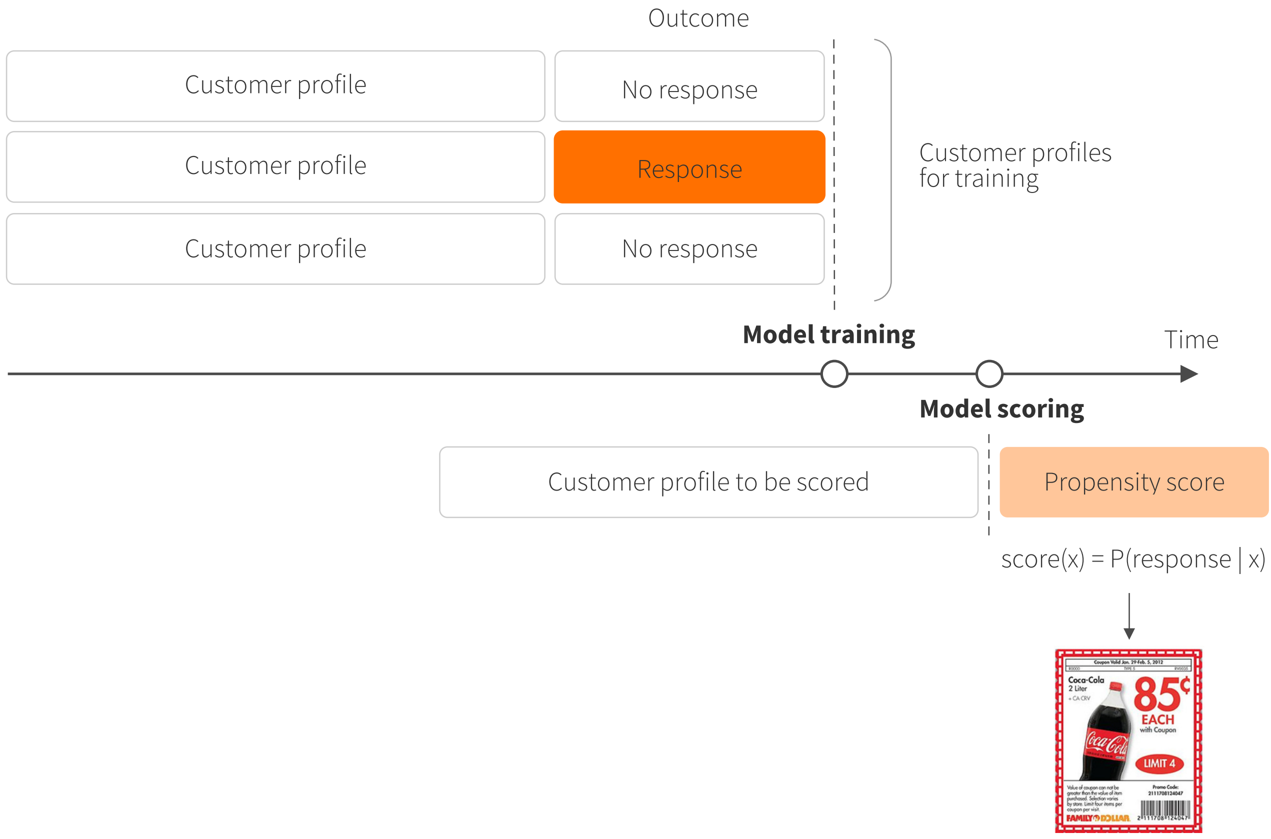
The price-optimization process generally focuses on the analysis of price-demand dependencies and on determining optimal price points based on that. However, practical price optimization cannot focus exclusively on demand and must be integrated with the supply chain and other enterprise processes. These processes usually impose additional constraints that must be incorporated into the price optimization algorithm. Examples of such constraints include:

- Inventory constraints: If price changes drive demand too high, items suddenly can be out of stock, leaving a fraction of the demand unfulfilled and corresponding revenues uncaptured. Some items can be replenished, but this process imposes its own constraints, such as lead time. Some items, such as seasonal apparel, cannot be replenished at all.
- Breakage constraints: Breakage refers to a situation in which some item variants (certain sizes, colors, etc.) are out of stock, while other variants remain in stock.
- Time constraints: Perishable products have limited shelf lives, and seasonal products need to be sold out or liquidated by the end of the season.

These considerations traditionally are incorporated into the price optimization problem using standard constraint-optimization methods, such as linear or integer programming.

An alternative approach is to use reinforcement learning methods and formulating the problem as a Markov decision process in which states correspond to stock levels and other constraints, and prices correspond to actions. Probabilistic demand and supply models then are used to do Monte Carlo simulations of various pricing scenarios in this environment and learn the optimal pricing policy. This approach provides more flexibility compared with traditional (declarative) constrained optimization methods and can be more easily combined with probabilistic demand models and online learning.

Offer Personalization
Targeting Models



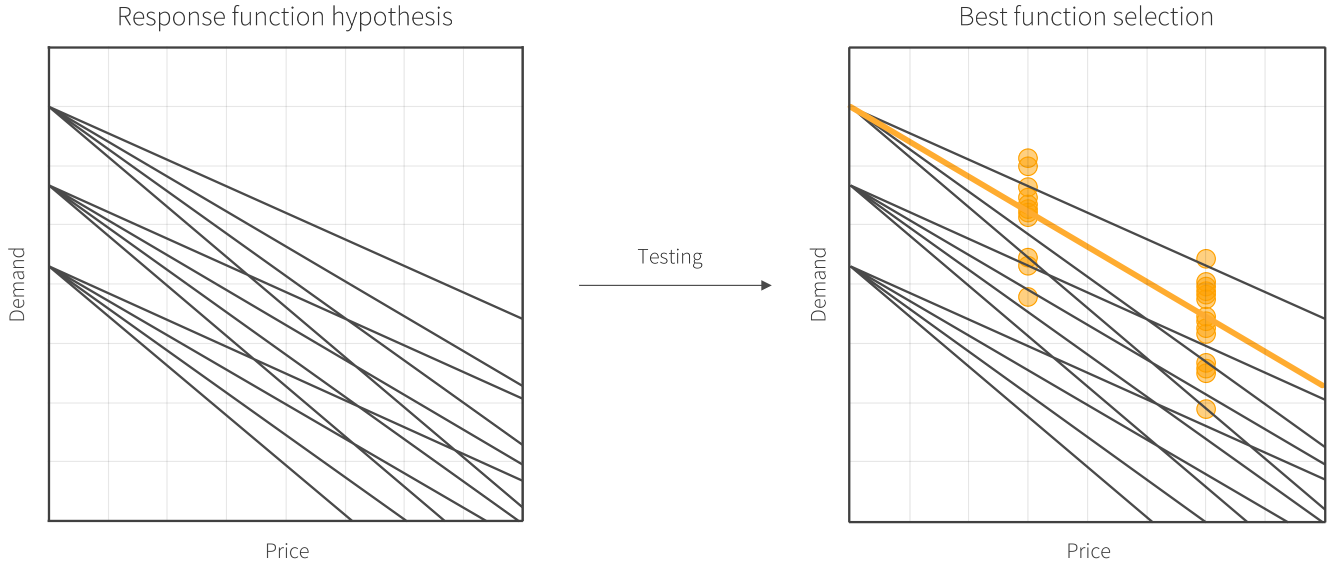
Offer targeting and personalization are a complex problem that generally requires creating multiple models for different types of decisions, including the following:

- Who: What is the optimal audience for a given offer, or alternatively, what is the best offer for a given customer?
- When: What is the optimal time to send an offer to a given customer?
- Where: What is the optimal channel for a given customer?
- How many: What is the optimal budget and outreach for a promotion campaign?

All these decisions can be supported or automated using machine learning methods. For example, offer targeting can be implemented using look-alike modeling, which is the most common targeting technique. The idea is to build classification models using profiles of customers who exhibited certain (desirable or undesirable) behaviors in the past. Offers then are personalized based on propensity scores that the models produce, i.e., probability of responding to certain offers or exhibiting certain behaviors.

Basic propensity scoring might not be optimal for campaigns or sequences of campaigns with multiple steps or offers. Such multi-step optimization can be codified as a Markov decision process and solved using reinforcement learning methods.

Dynamic Pricing Hypothesis Testing



Ecommerce channels allow for changing prices instantly based on market response and competitors' moves. On one hand, it represents a unique revenue optimization opportunity. On the other hand, it imposes unique implementation challenges:

- If the environment changes rapidly, historical data might not be relevant, and the optimization algorithm needs to explore the environment actively through experimentation, instantly collect the feedback data, and make price adjustments.
- Some business models, such as flash sales, require dynamic learning and optimization because a product can be on sale for only a few days, or even hours.
- Many sellers have business rules that limit the frequency of price changes to ensure good customer experiences. The optimization algorithm that actively explores price-demand dependency needs to operate efficiently under such constraints.

These challenges can be addressed through specialized dynamic pricing algorithms that optimize exploration-exploitation (learning-earning) time ratios and minimize the number of price changes.

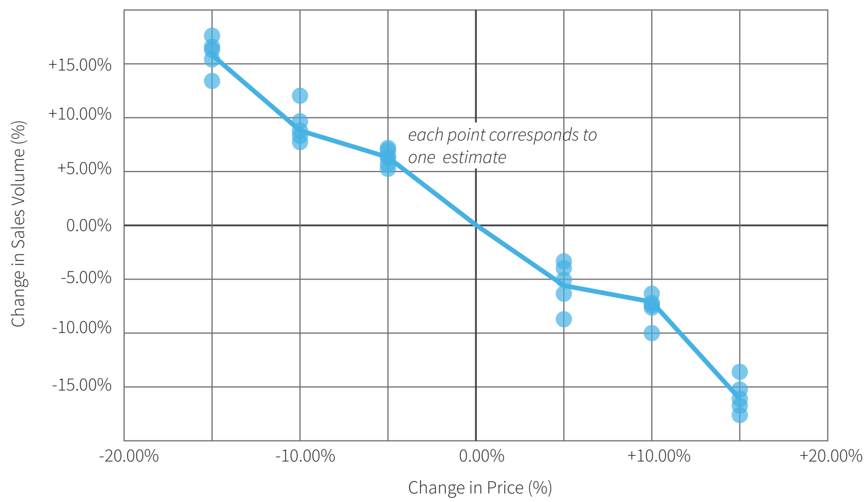
An example of a dynamic pricing algorithm is dynamic testing of price-demand function hypotheses. The algorithm first uses available historical data for a given or similar product to generate a set of price-demand functions that are likely for this product. Second, it conducts short experiments to collect several data points that help choose the best hypothesis. Finally, it optimizes the price based on the selected hypothesis. This process can be repeated to catch up with environmental changes. In practice, this approach is very efficient, even if only one experiment (one price change) is allowed under business rules.

08

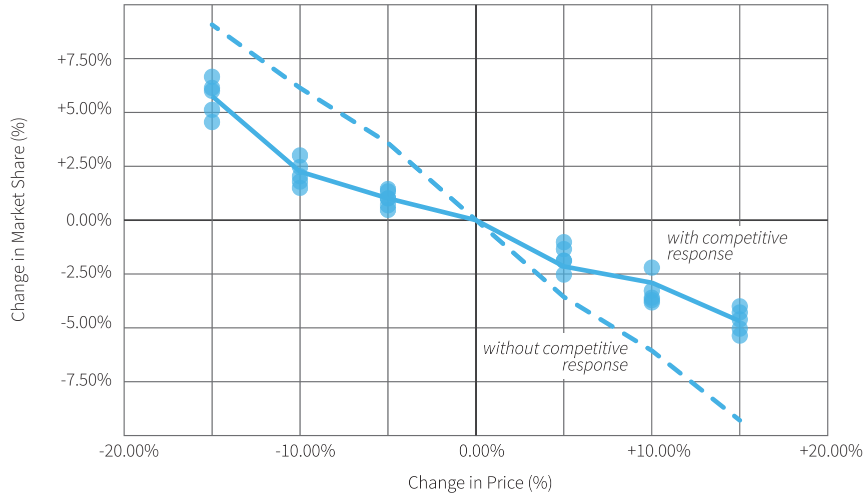
Under the Hood: Estimation Tools

Market Response
Expert Estimates and Corrections

Example of a price-demand curve estimated based on expert surveys



Example of a price-demand curve adjusted to account for competitive response



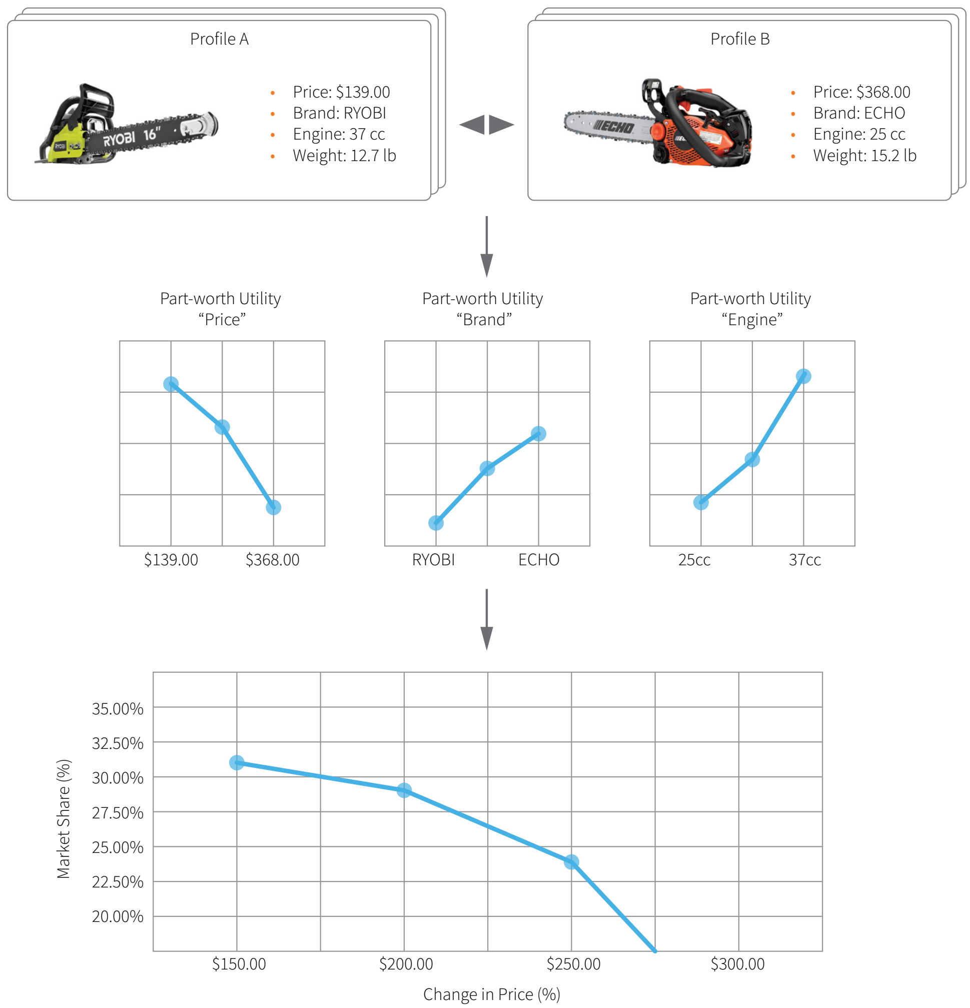
Market response modeling is fundamental for price optimization, and the platform provides advanced market response models that automatically can incorporate a wide range of factors, such as elasticities, competitors' prices, and cannibalization. However, the data-driven approach has certain limitations that need to be recognized and addressed using supporting techniques.

Examples of situations in which data analytics might need to be complemented with expert estimates and corrections include the following:

- Although it is normal to incorporate competitors' pricing into market response models, it can be challenging to forecast strategic competitors' responses to price increases and reductions.
- It is generally possible to forecast demand for new products in a data-driven way based on product features, but this approach is not applicable to innovative features and products.
- Long-term profit forecasting might need to incorporate a production experience curve (marginal costs tend to decrease with growing cumulative volume), market maturity, and product life cycle considerations.

One way to mitigate the above challenges is to incorporate expert estimates and corrections into the model. In some cases, the price-response curve is estimated fully based on expert surveys. In other cases, a statistically estimated curve is corrected to account for the anticipated competitive response or other factors.

Market Response
Conjoint Analysis



Expert surveys provide a relatively simple and inexpensive way to estimate market response when data-driven methods are insufficient. However, expert judgments sometimes fail to recognize true customer needs and priorities, and can fall short because of wrong assumptions. These limitations become particularly pronounced for new products and innovative features. In such cases, it is quite common to estimate market response based on customer surveys.

The most commonly used methodology for customer surveys is the conjoint analysis, which generally includes the following steps:

- A set of product attributes and attribute values (levels) are defined. For example, a gas chainsaw analysis can use attributes such as price, brand, bar length, and engine displacement.
- A customer panel is surveyed to do multiple paired comparisons of semi-randomly generated product profiles.
- Survey results are used to estimate the importance of individual attributes (part-worth utilities).
- Expected market shares of individual profiles are estimated based on their relative utilities. For example, the following normalization can be used to estimate the market share for a concrete model, i:

$$\text{Market share for } i = \frac{\text{Utility of model } i}{\text{Sum of all utilities of all models}}$$

The platform provides tools for efficient surveying, such as adaptive profile generation, as well as statistical processing of results. In practice, conjoint analysis methods have proved themselves to be efficient in producing accurate and actionable estimates that can be used in product design and price setting.

09

Solution Data Sheet

Reference Implementation Roadmap

The solution typically is developed in several phases. The two most commonly used approaches to start the program are:

- Discovery: The program can be started with a short discovery (analysis) phase to assess the environment and define the implementation roadmap. This approach generally is recommended for large enterprises with complex pricing processes, data, and technical ecosystems.
- Pilot: If a specific use case or a pain point already is identified, the program can be started with a pilot project that directly addresses the priority problem. This quickly helps demonstrate business value and ability to execute. In some cases, the pilot project can be executed in data-in-data-out mode to simplify integrations.

It is also quite common to start with a discovery phase, then proceed with a pilot project based on the priorities identified during the discovery.

The implementation of the core functionality usually starts with establishing measurement capabilities, then expands into more advanced analytical, evaluation, and process automation functions. The functionality developed for measurement purposes (descriptive analytics) often can be extended to support evaluation functions (predictive and prescriptive modes).

1 Discovery

Goals:

The discovery phase is focused on the assessment of the existing environment, identification of pain points and opportunities for improvement, ROI estimations, and development of the implementation roadmap.

Deliverables:

- Assessment of pricing capabilities: The overall strategic clarity, pricing intelligence, transaction price management, performance measurement, and organizational readiness.
- Business impact assessment: Immediate benefits, longer-term adoption benefits, and ROI calculations.
- Data assessment: Hands-on data exploration, gaps, and feasibility analysis.
- Implementation plan: Functional specification, roadmap, and resourcing plan for pilot projects and subsequent implementation phases.
- Technical design: Data processing and data science components, ML models, and user-facing applications.

Timeline:

- 2-3 weeks

2 Pilot Project

Goals:

The pilot project typically is focused on implementation and production validation of a specific use case. The main goals are to demonstrate the ability to deliver business value through new capabilities, validate assumptions about the environment, and improve the roadmap and estimates for subsequent phases.

Deliverables:

- Production-grade implementation of a priority use case or capability.
- Production evaluation and performance measurements.
- Analysis of performance measurements and improved ROI estimates.

Timeline:

- 6-8 weeks

Reference Implementation Roadmap

3

Strategy Analytics & Measurement

Goals:

One of the typical priorities is to establish measurement capabilities to track further improvements' impact and performance. Strategy analytics and measurement capabilities often are developed concurrently.

Deliverables:

- Data collection and data engineering pipelines that support measurement and analytics functions.
- Data science and modeling infrastructure needed for measurement and analysis.
- Statistical models for demand decomposition and other purposes.
- User-facing applications and dashboards.

Timeline:

- 12-16 weeks

4

Evaluation & Integrated Workflow

Goals:

Develop predictive and prescriptive capabilities for evaluation and execution of pricing actions. Integrate analytics, measurement, and evaluation stages into a seamless workflow.

Deliverables:

- Integrated operational workflow in which price managers can access historical cases, measurements, and evaluation tools seamlessly.
- Integrations with new execution systems and channels.
- Process improvements and fine-tuning of all capabilities based on the production experience.

Timeline:

- 12-16 weeks

Solution Summary
Features

ROI-Driven Approach
The solution emphasizes measuring pricing actions' true ROI, as well as planning such actions using accurate ROI estimates and models.

Compliance With the Industry Best Practices
The platform's functional capabilities are designed based on considerable experience with price management solutions and deep insight into industry best practices.

Deep Insight Using ML
The solution offers advanced analytics capabilities backed by statistical models that help to better understand the demand's structure and pricing actions' impact.

Advanced Decision Support and Decision Automation
The solution provides smart decision support tools backed by prescriptive and optimization models that help make near-optimal pricing decisions. Real-time and personalized decisions are automated using transactional components.

High Scalability
The solution is designed to support analysis and optimization of up to hundreds of thousands of products by using statistical analysis and a Big Data technology stack.

Seamless Workflow
The solution focuses on seamless integration of measurement, evaluation, and execution capabilities, so that price managers are provided with integrated environments and workflows.

Open Source Technology Stack
The solution can be implemented fully using open source frameworks and components, enabling deep customization and continuous innovation.

Cloud-Native Implementation
The solution can be deployed into a private or public cloud. In the latter case, it can take full advantage of native cloud services for data processing and machine learning.

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