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Born **Digital** . Born **Agile**

Power of
Data Analytics in Retail

WHY ARE RETAIL ENTERPRISES ADOPTING RETAIL ANALYTICS?

Analytic, AI/ML & Data Engineering have unleashed the next wave of digital disruption, and companies are focused on it. We already see real-life benefits from firms that adopted it, making it more urgent than ever for others to accelerate their digital transformations.

Adoption patterns illustrate a growing gap between digitized early Analytics adopters and others. Sectors at the top of one of the prominent analysts' Industry Digitization Index, such as Hi-Tech and telecom or financial services, are also leading adopters of AI. They also have the most aggressive AI investment intentions. Leaders' adoption is broad and deep: using multiple technologies across multiple functions, with deployment at the core of their business.

AI investment is growing fast, dominated by digital giants such as Google and Baidu. Globally, tech giants spent $20 billion to $30 billion on AI in 2016, with 90 percent spent on R&D and deployment and 10 percent on AI acquisitions. VC and PE financing, grants, and seed investments are expected to grow rapidly, albeit from a small base to a combined total of $6 billion to $9 billion. Machine learning, as an enabling technology, received the largest share of internal and external investment.

Early adopters are already creating competitive advantages, and the gap with the laggards looks set to grow. A successful program requires firms to address many elements of a digital and analytics transformation: identify the business case, set up the right data ecosystem, build or buy appropriate AI tools, and adapt workflow processes, capabilities, and culture.

HOW COMPANIES ARE ADOPTING AI?

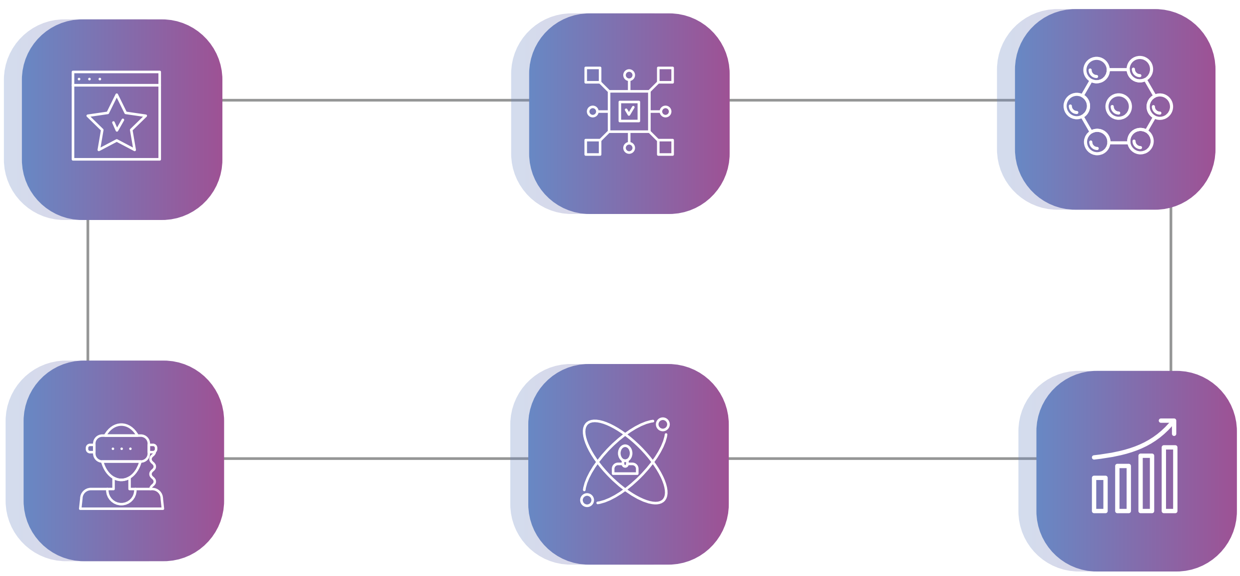
High AI Adoption	• Hi-Tech / Telecom • Automotive / Assembly • Financial Services
Medium AI Adoption	• Retail • Media / Entertainment • CPG
Low AI Adoption	• Education • Health Care • Travel / Tourism

SIX CHARACTERISTICS OF EARLY AI ADOPTERS

Digitally Mature

Larger Business

Adopt Multiple Technologies



Adopt AI in Core Activities

C-level Support for AI

Focus on Growth Over Savings

MAXIMIZE SALES, MINIMIZE INCURRED COSTS

Pervasive digitization of the path to purchase

An increasingly larger share of consumer's spends and activity will take place through digital channels.

Analytics is key to a better understanding of purchase and consumption occasions as well as tailoring channel experience.

Proliferation of customization and personalization

In a world where customized products and personalized, targeted marketing experiences win companies market share, technologies like digital commerce, additive manufacturing and artificial intelligence can give a company an edge by allowing it to create customized product offerings.

Continued resource shortages (Disruptions in product supply, such as the Ukraine War) and commodity price volatility

Analytics can fuel a better understanding of the resource market volatility and more efficient use of critical resources in the production process.

Unfulfilled economic recovery for core Retail segments (Greater Income Bifurcation, continued growth of dollar store, discount grocery store)

Analytics supports the shift to value by identifying key price points in the market, defining customer segments, developing new pricing strategies based on competitive intelligence and increasing efficiency in manufacturing and logistics to reduce costs.

Health, wellness, and responsibility as the new basis of brand loyalty (Continued growth of health & natural retailers)

Companies will experience greater pressure to better align offerings and activities with customer interests and values. Big Data and analytics help to better understand customer sentiment, preferences, and behavior. At the same time, data analytics enables supply chain visibility and identifies potential risks.

Assortment optimization

A growing number of SKUs, Limited physical shelf space, growing supply chain complexity, the "agony of choice" on the endless virtual shelves, and location-specific dynamics like developing a more highly analytical assortment management process that pays off, as the insights gained can lead to improvements across several areas. These improvements can significantly enhance financial performance.

Digital analytics optimizing products and portfolios

Social media posts and other unstructured text can reveal what matters most in product and service design. It helps

- Design the right product or service
- Manage product complexity and product offering

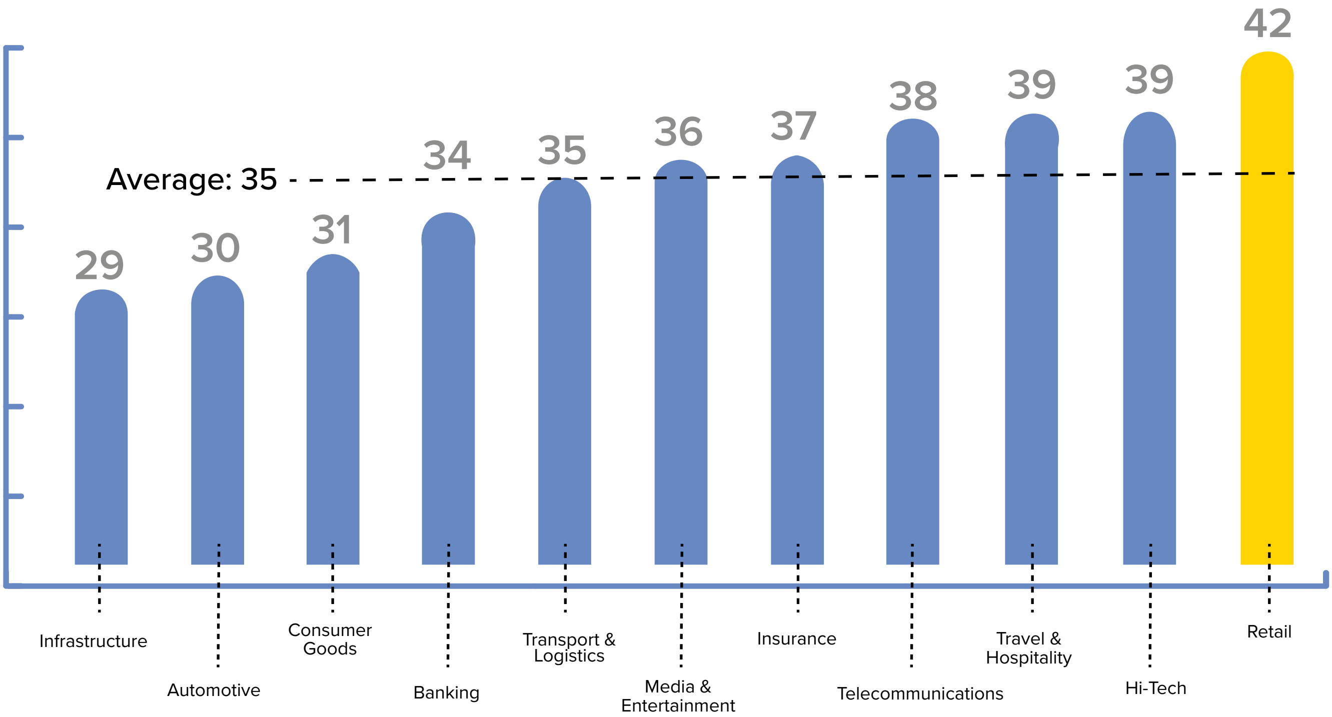
Advanced analytics identifies optimal combinations of pruning candidates.

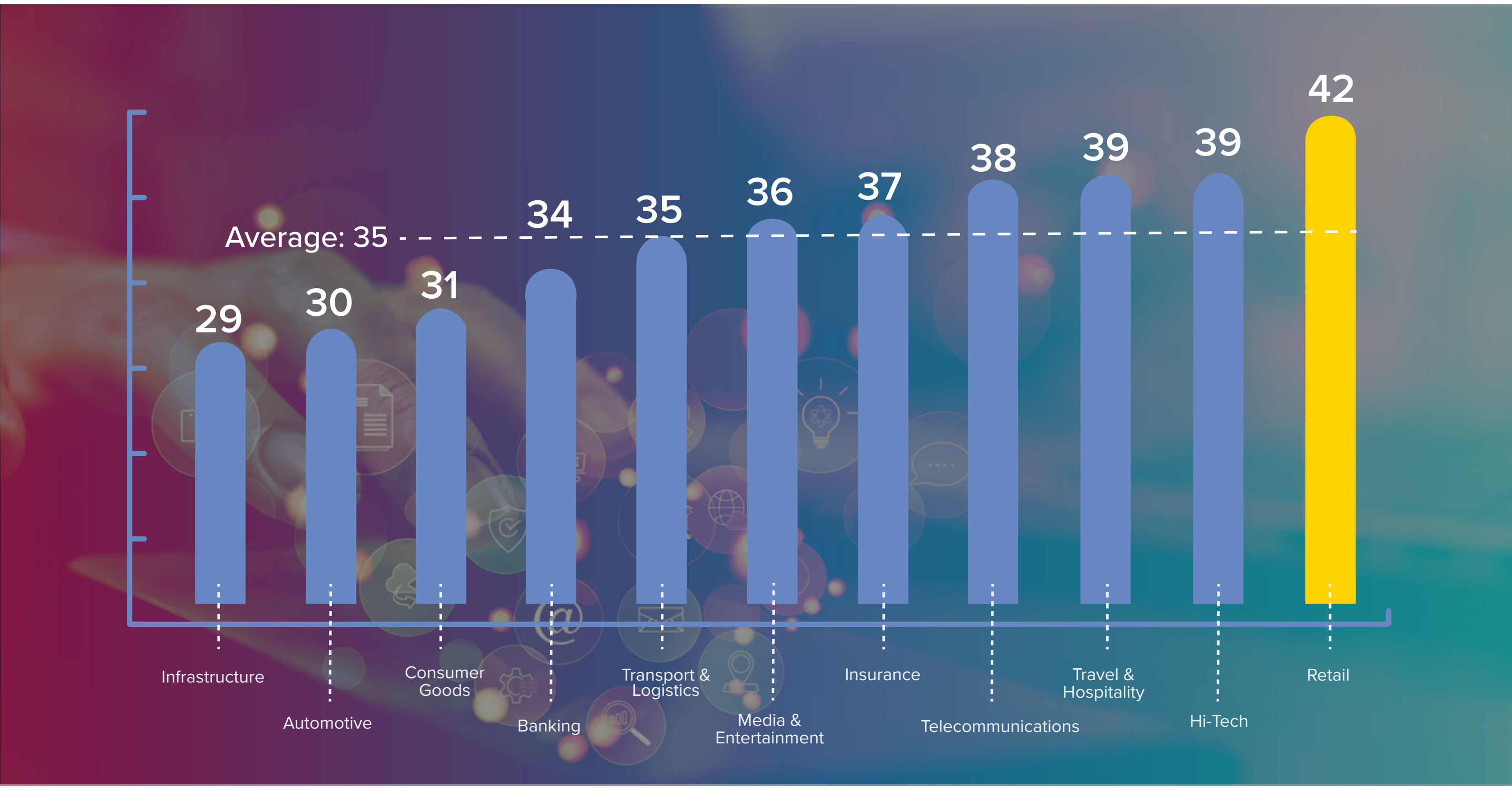
RETAIL IS DIGITALLY SAVVY, BUT IS IT ANALYTICALLY MATURE?

Sectors with more direct consumer connections, such as retail, have focused more on digital capabilities to enable an omnichannel consumer experience. This isn't surprising: most consumer goods companies have focused on established analytical areas (such as pricing) that require relatively little direct consumer data.

RETAIL IS AMONG THE MOST DIGITALLY MATURE INDUSTRIES

Distribution of digital quotient score by industry, global, points (100)




42
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31
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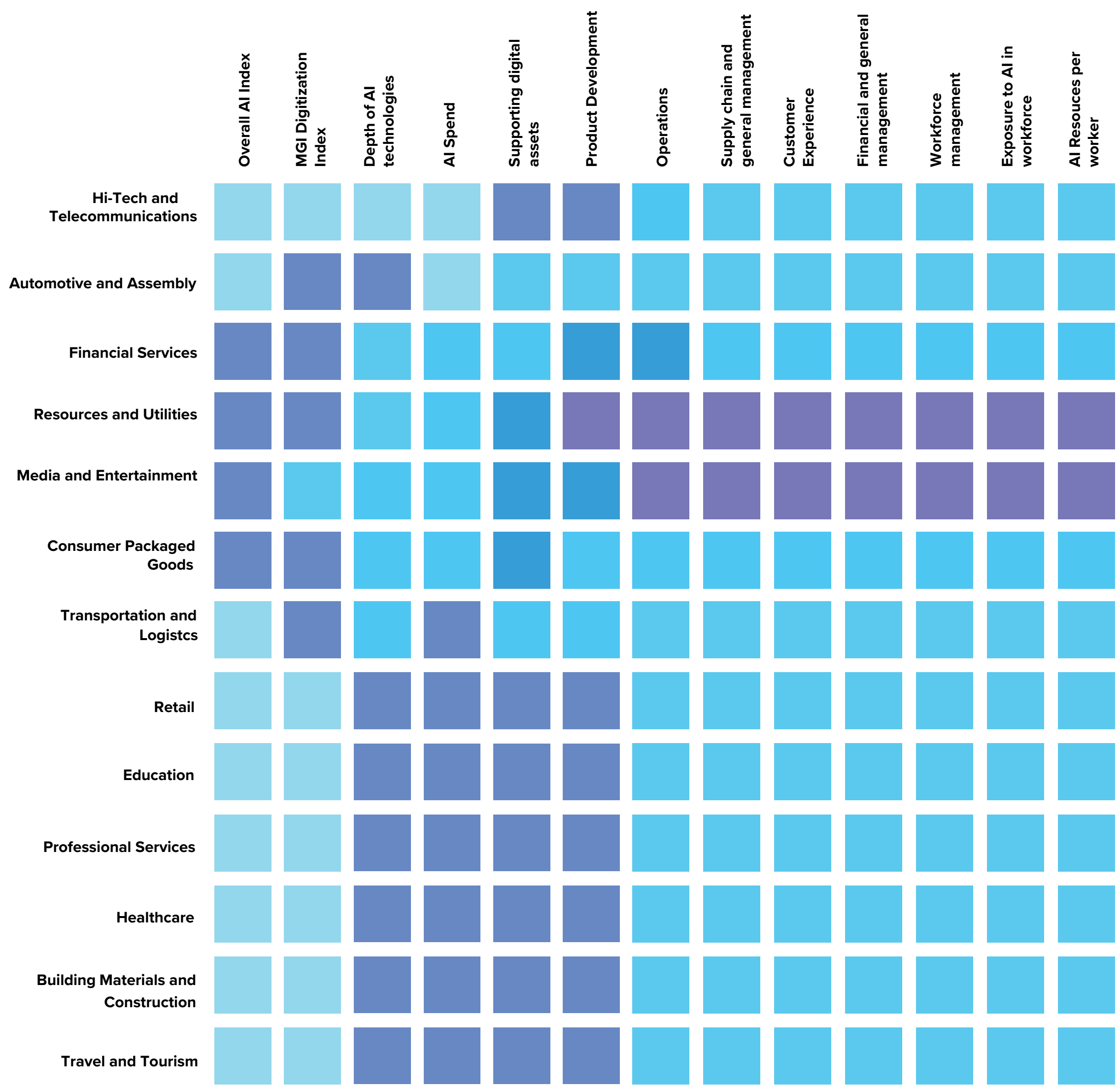
Average: 35
Infrastructure
Automotive
Consumer Goods
Banking
Transport & Logistics
Media & Entertainment
Insurance
Telecommunications
Travel & Hospitality
Hi-Tech
Retail


Overall AI Index
MGI Digitization Index
Depth of AI technologies
AI Spend
Supporting digital assets
Product Development
Operations
Supply chain and general management
Customer Experience
Financial and general management
Workforce management
Exposure to AI in workforce
AI Resouces per worker
Hi-Tech and Telecommunications
Automotive and Assembly
Financial Services
Resources and Utilities
Media and Entertainment
Consumer Packaged Goods
Transportation and Logistcs
Retail
Education
Professional Services
Healthcare
Building Materials and Construction
Travel and Tourism

SOURCING

- Automatic analysis of contract compliance
- Quantification of benefits from spend piling
- Cost modeling to identify cost drivers
- Guided Buying

PRODUCTION

- Quality Analysis
- Asset Analytics
- Statistical quality control & tolerance optimization capabilities
- Lot sizing & scheduling considering cost, inventory & capacity
- Scheduling of energy-intensive production

IN˜STORE CATEGORY MANAGEMENT

- Macro space allocation
- SKU listing or delisting
- Store clustering planogram (Position facing)
- Pricing (KVI, identification, price recommendation)
- Online or dynamic pricing
- Markdown optimization
- Promo (historic effectiveness, forecast, optimization)
- NLP on customer reviews to support for (de)listing decisions
- Automated Product comparison (NLP, computer vision)
- Geospatial Analytics

HUMAN CAPITAL & SUPPORTIVE FUNCTIONS

- People analytics (eg. hiring, chum)
- Sentiment analysis for customer service
- Automated Budgeting

MARKETING & CONSUMER ANALYTICS

- Personalized promotions
- E-commerce personalized content
- Marketing Mix Optimization (MROI)
- E-commerce improved product search
- Facial recognition for personalization
- Brand Analytics
- Credit Rating to define payment terms offered

SALES & POINT OF SALE

- Out-of-stock detention & prevention
- Shelf space optimization
- Fraud detection
- Product recommendation based on purchase history
- Return projection to calculate outstanding inventory

TRANSPORTATION & DISTRIBUTION

- Real-time routing & ramp allocation at warehouses
- Delivery scheduling
- Location Analysis
- Dynamic Routing

WAREHOUSING

- Picking zone / Warehouse space allocations
- Worker to picking zone allocation based on efficiency
- Stock relocation in high bay storage area
- Cost modeling
- Workforce Optimization

BUSINESS MANAGEMENT & SUPPORT

Workforce Analytics	Sustainability Analytics	Finance Analytics	Portfolio Analytics

Sales and Merchandising

4-5%

sales growth in categories reviewed

Digital and Omnichannel

15-25%

improvement in spend effectiveness

Marketing and Personalization

30%

digital sales growth

Operations and Supply chain

10-15%

reduction in inventory costs and improved sell-through, availability

People Analytics

50%

reduction in high-performing employee churn

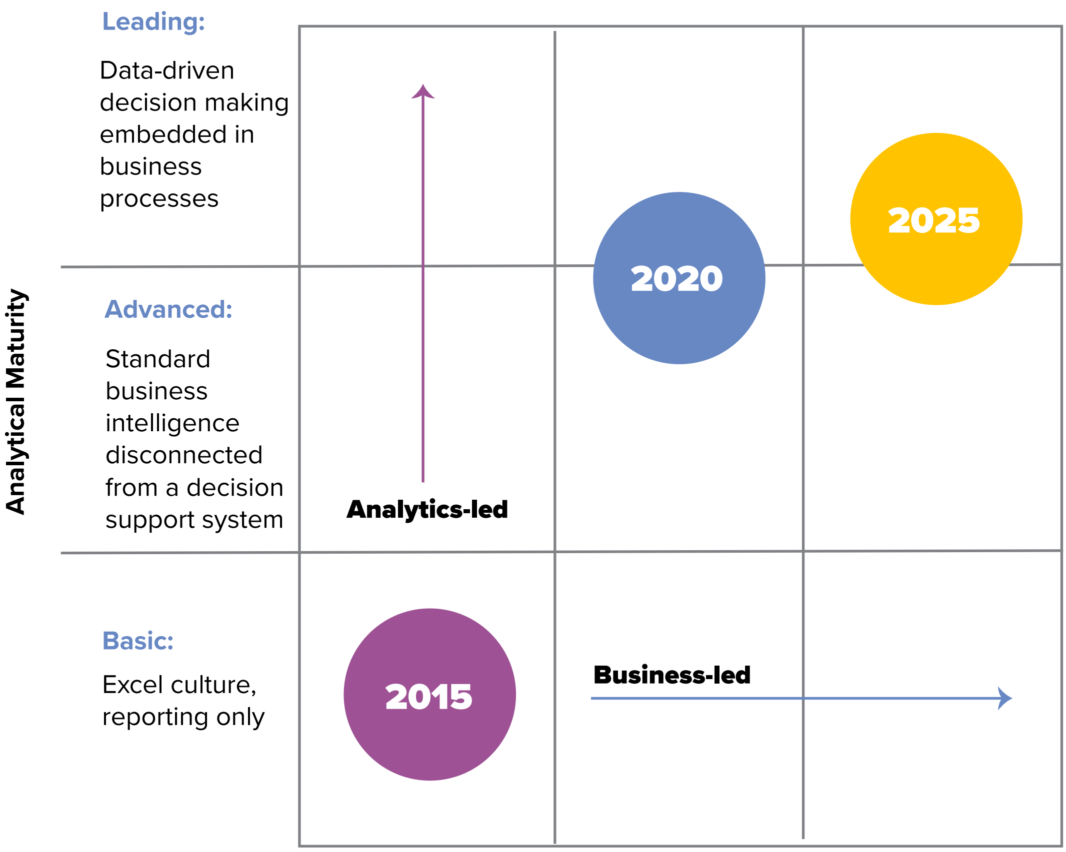
SYSTEMATIC DELISTING	STRATEGIC LISTING	SIMPLIFIED SUPPLY CHAIN	IMPROVED PROCUREMENT
Up to 0.5 pp of margin	2-4% of revenue	Up to 0.5 pp of	1-3% of procurement costs
Profit margin improvement from better product mix	Coverage of previously neglected	Coverage of previously neglected	

RETAILERS JOURNEY @ANALYTICS MATURITY

Capturing the value of advanced analytics depends even more on a retailer's organizational maturity than its analytical maturity.

Most of European grocery retailers are now embracing advanced analytics and investing in capturing its value. For example, in 2020, Ahold Delhaize announced the implementation of tools for assortment, pricing, and promotions across its European brands. Players such as ICA, Migros, and REWE have well-established analytics organizations, and several retailers have hired additional data scientists, including discounters Aldi and Lidl. Leaders in analytics have tackled most fundamental use cases, such as pricing, mass promotion, and assortment optimization. Now, they have increasingly turned their focus to pursuing new use cases along the value chain and improving the existing use cases—for example, using more granular, real-time data.

A strong analytics unit often drives these efforts, but the adoption of these use cases in the business varies. Organizational maturity, in many cases, is the main barrier to going beyond partial adoption and realizing analytics' full potential. Organizational maturity encompasses processes to technically embed and continually improve use cases, as well as constant change management with the users of the analytical insights—fostering understanding of analytics, ensuring it is embedded in daily processes, and measuring against new Key Performance Indicators (KPIs).



Analytics-led

- Build a small team of data scientists
- Assign a strong sponsor
- Identify and leverage quick wins to prove potential
- Systematize learning from data

Business-led

- Roll out analytics products across the business
- Create new processes based on insights
- Embed organizational change
- Strong representation at the board level (e.g., through a Chief Analytics Officer)

SOLUTION THEME

1. CATEGORY MANAGEMENT (ASSORTMENT OPTIMIZATION)

Finding and maintaining the optimal assortment of products to sell in stores has always been at the core of a retailer's commercial activity. Retailers who get the assortment right enjoy more sales, higher gross margins, leaner operations, and most importantly, more loyal customers.

Following are recent developments in the market that have make assortment optimization more important than ever.

A growing number of SKUs	• Large brands are continuously innovating and increasing the number of their SKUs. • While small brands may offer fewer individual SKUs, the number of small brands is rapidly increasing. • The number and share of private-label products are also growing briskly.	Increases Cost of Operation
Limited physical shelf space	• As the number of products is growing, shelf space is not. Opportunities to expand or reallocate shelf space between sections are limited to nonexistent. • Many new stores are opening in space-constrained, inner-city markets, exacerbating shelf space challenges.	Can pose the threat of losing customers due to stockout or the lack of the right product o˝erings
Growing supply chain complexity	• Even though the number of SKUs continues to grow, the supply chain becomes increasingly complex, compounding the need for thorough reviews of what should be listed or removed from the assortment.	Increases Cost of Operation
The "agony of choice" on the endless virtual shelves	• Even in e-commerce, where there is presumably infinite shelf space, retailers must manage assortment to hold customers' attention and control the costs of inventory and logistics.	• Can pose the threat of losing customers due to stockout or the lack of the right product offerings • Increases Cost of Operation
Location-specific dynamics	• Diversity is growing across each retailer's stores, with increasing variation in size and format. Location factors, such as traffic connection and neighborhood sociodemographics, mean that not all SKUs and categories perform similarly across all stores. • Assortment must, therefore, be optimized to the specifics of each store location. This optimization typically involves macro space allocation (how much space to dedicate to a specific category in each store) and localization (finding the optimal SKU mix for each store).	Can pose the threat of losing customers due to stockout or the lack of the right product offerings

Developing a more analytical assortment pays off, as the insights gained can lead to improvements across several areas. The following improvements can significantly enhance financial performance.

Systematic delisting

The ability to steer customers toward higher-margin products can contribute up to 0.5 of a percentage point to gross margins - a significant reduction in SKUs can be achieved without endangering sales levels.

Revenue increase through strategic listing

Retailers could realize an additional 2 to 4 percent increase in sales through a more customer-centric product portfolio.

Improved procurement conditions

Knowing a product's uniqueness—the likelihood that a customer will replace it with another—provides retailers with important information when deciding whether to delist a product or an entire brand. Not relying on a particular product or brand will give retailers more bargaining power with suppliers regarding their terms. This advantage can lower procurement costs by up to 3 percent.

Simplified supply chain

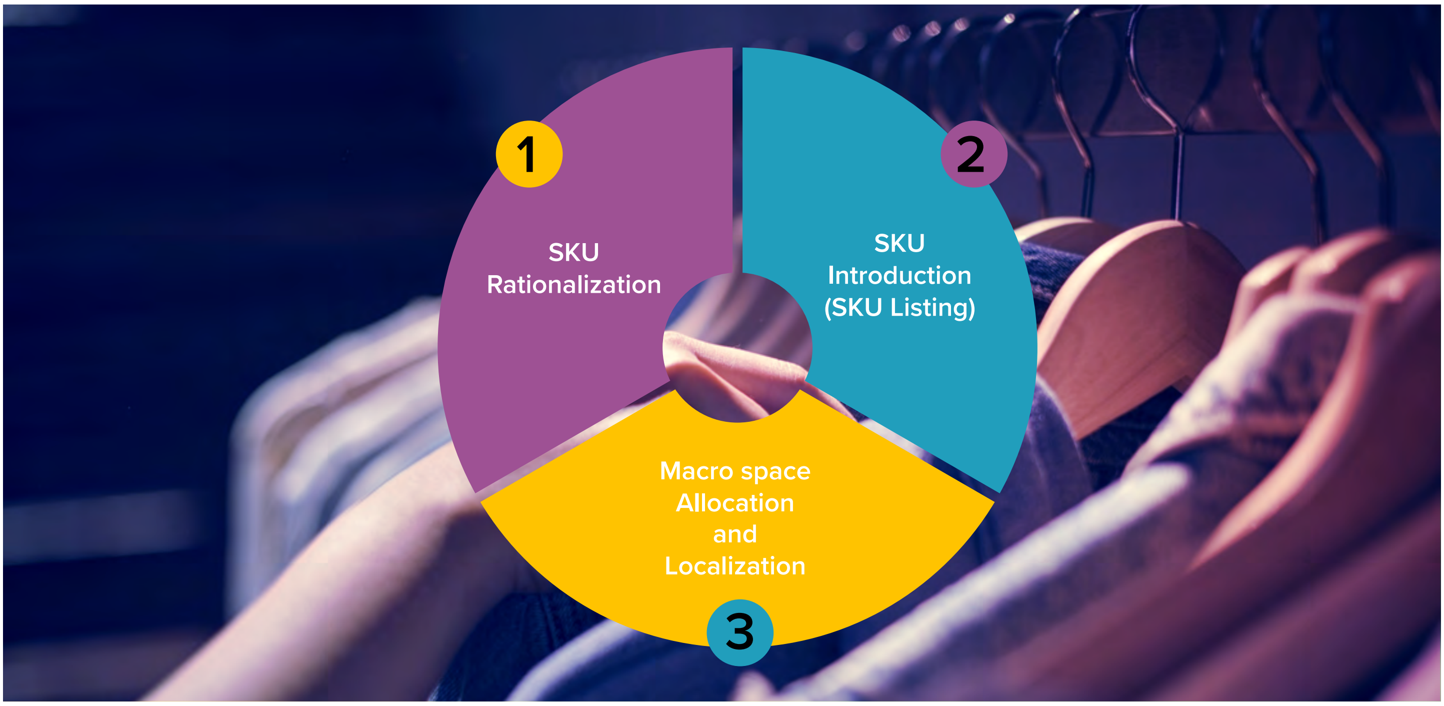
A margin improvement of up to 0.5 of a percentage point can come from a reduction of costs related to operations and supply chain, as well as—in situations where there is a high share of private-label products—product development.

CAPTURING VALUE FROM ASSORTMENT OPTIMIZATION THROUGH ADVANCED ANALYTICS

Significant improvement in financial performance and customer experience is possible through assortment optimization, but it requires a deep understanding of assortment performance beyond the superficial. For instance, strategic listing entails more than introducing every "hot" item to the market.

Similarly, smart delisting is more than cutting slow-moving items. Indeed, determining which SKUs to cut to make space for new ones requires not just a detailed, store-level look at financial performance but a deep understanding of customer purchasing behavior. For example, quantifying how unique an SKU is for the customer or identifying the customer needs that must be covered by the selection of products in the category.

Following Solution schemes would help retailers to capture value from assortment optimization.



A) SKU RATIONALIZATION: MANAGING MULTIDIMENSIONAL SKU-PERFORMANCE IN THE DELISTING PROCESS

What it does

A recommendation engine that suggests changes by item and links to category strategy (e.g., evaluates incremental sales by SKU, substitutability and transference, and consumer insights) – includes **SKU delisting (Store-specific SKU selection) to optimize the tail SKU spend management**.

Consideration

Whether an SKU is listed or delisted should not be based solely on simple financial measures such as total sales or rotation numbers. While traditional KPIs are essential, other dimensions should help determine the SKU's performance. The complete performance dimensions for an SKU include economic performance, uniqueness and value to the customer, cost to serve, and role in meeting the retailer's strategic objectives.

01

Economic performance (Total and local financial contribution)

Total product sales in isolation can be misleading because that number depends on how broadly the product was listed, including how many stores carried it and how many weeks it was on the shelf. Granular data points such as sales per week, per store or basket give retailers a more useful metric for a product's current and potential total economic performance.

02

Uniqueness (SKU substitutability and value to customers)

Similarly, traditional financial metrics can be misleading indicators of a product's value. Seemingly insignificant products, as measured by sales, can be so important to some customers that they would take all their retail shopping elsewhere if that product became unavailable in a store.

03

Cost to serve: SKU end-to-end cost

Because local supply chains can differ, operating costs to keep an SKU on the shelf can vary significantly across stores. A cost-to-serve analysis quantifies logistics costs at the level of both the SKU and the store and reveals end-to-end costs that extend financial considerations beyond gross margin to include operating costs for a fuller view of an SKU's profit contribution.

04

Strategic objectives: Beyond current performance

Not all retail success is directly or immediately reflected in current financial or operational KPIs. Strategic KPIs can be introduced at the SKU level, enabling retailers to take other objectives into account in their assortment decisions. One strategic objective may be to gain a higher share of organic, gluten-free, or regional products.

The ranking offers a convenient starting point for the category manager to decide which SKUs to keep and which to delist. The SKU rationalization process yields the best results when category managers combine science (analytics and KPI rankings) and art (experience and market knowledge from category managers).

KPI-BASED RANKING APPROACH

01 ECONOMIC PERFORMANCE

- Total sales per year across the whole network
- Sales per week per store: Performance when given shelf space
- Gross margin (including all supplier contributions)
- Basket-leverage: Average size of baskets containing this SKU

02 UNIQUENESS

- Walk rate: Share of units that will not reallocate to other SKUs in the category when the product is delisted
- Need-state density: Average number of SKUs per customer switching box the SKU is in

03 COST TO SERVE

- End-to-end logistics costs per SKU per store
- Wastage ratio: Share of SKUs thrown away
- Out-of-stock ratio: Share of time when product is out of stock

04 STRATEGIC OBJECTIVES

- Binary value for strategically important product attributes (regional, organic, vegetarian, vegan, etc.)
- Out performance of the product in a strategically important customer group, e.g. upper middle class, Generation Y

B) SKU INTRODUCTION SYSTEMATICALLY ASSESSING LISTING OPPORTUNITIES

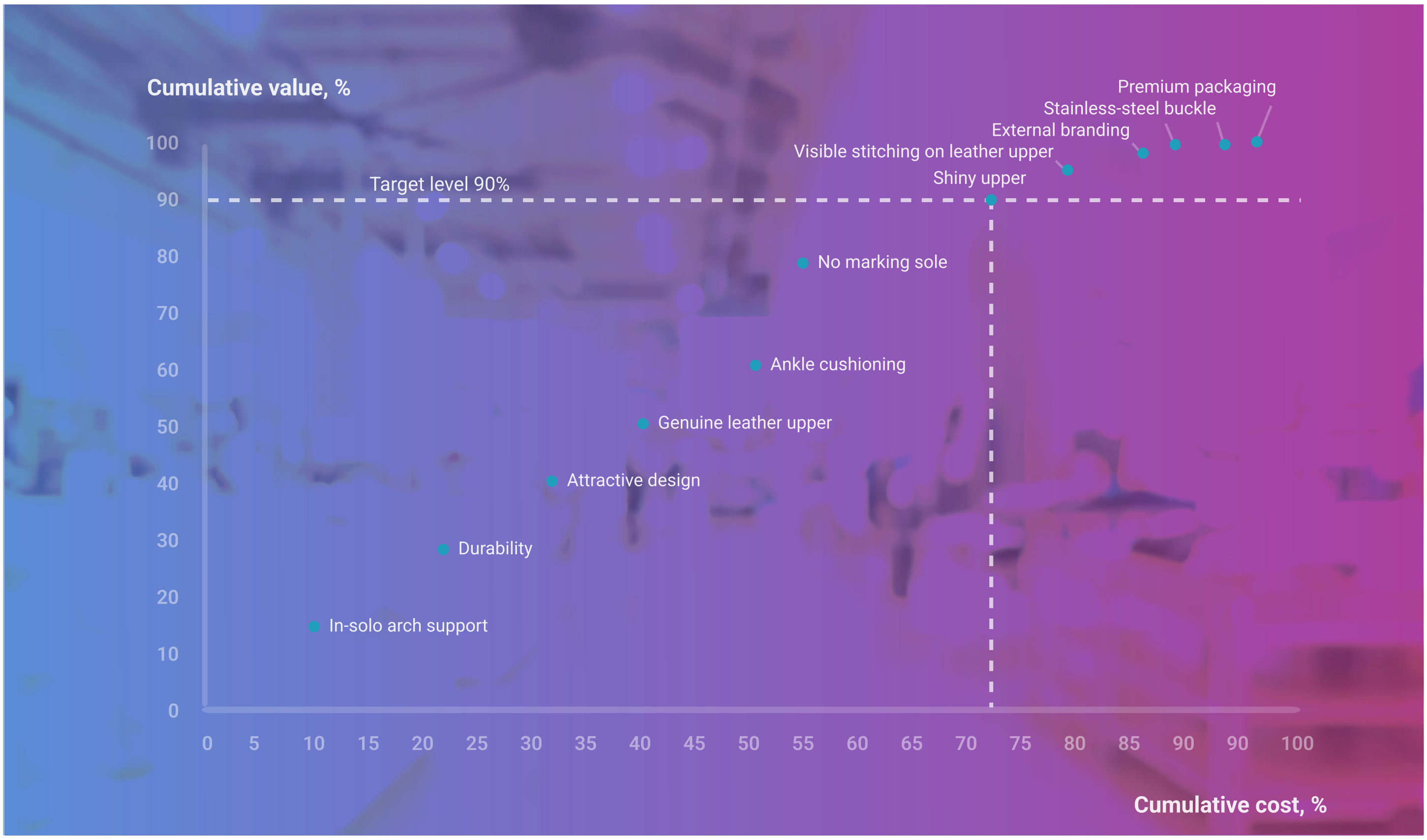
What it does

Delisting might reduce systemic assortment complexity or achieve higher average gross margins. Most delisting efforts, however, are also driven by the introduction of new SKUs. These SKU introductions typically fall into one of four categories:

- Extending distribution (listing an SKU in more stores within a retailer's network)
- Introducing a new private-label SKU
- Listing new branded products
- Listing new categories or introducing other offerings

Category managers can systematically evaluate the viability of these options using an advanced analytics-based approach that assesses the economic effect of an SKU's listing on the assortment's overall profitability.

An analytics-based approach can help the category manager to take the decision to introduce a new Department/Class/Subclass/ SKU such as below -
For ballet shoes, 6 features represented only 10% of customer value but 25% of the product cost.



So, new ballet shoes might not be the best decision to introduce a new SKU at this point in the enterprise.

C) MACRO SPACE ALLOCATION AND LOCALIZATION: ENSURING OPTIMAL SPACE ALLOCATION IN STORES

What it does

Because stores differ in size, traffic connection, and neighborhood socio-demographic characteristics, not all products will perform equally well across stores. **Therefore, it is important to have a flexible approach to determining how much store space to dedicate to which category (macro space allocation) and which SKUs to list in which store (localization).** Category managers can approach macro space allocation and localization using different levels of sophistication and regional differentiation.

Macro space relates to store layout, the location of departments or categories within the store, their associated fixtures and the planograms that are attached to them. Not to be confused with micro space that relates to the mix and positioning of the products defined in those planograms, or POGs as they are sometimes called.

Consideration

- In a basic model, space per store can be allocated across categories using the concept of “marginal profit contribution per category”: how much additional margin would an added meter of shelf space yield for a category. Space allocation across categories is then performed in an optimization process using the trade-off between different categories’ marginal profit contribution per additional meter of shelf space as a key metric.
- Focusing on localization provides a more sophisticated method to assess the optimal allocation of SKUs to individual stores.

First, determine which among a large set of micro-location factors best predicts a category’s economic performance.

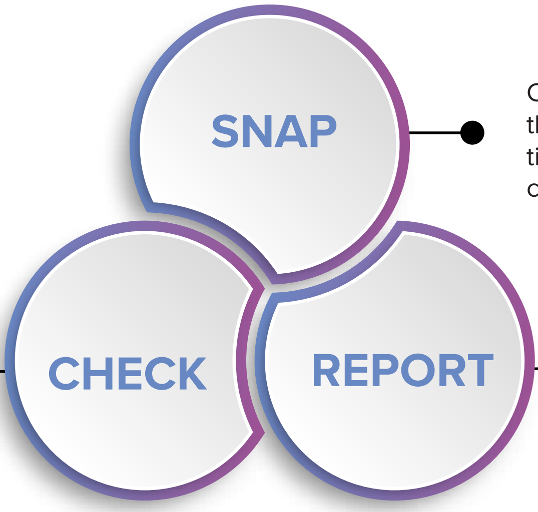
Then, build store clusters using similar micro-location factors and assess which well-performing SKUs in a smaller store cluster could be extended to the entire cluster or network.

WHAT WE HAVE BUILT SO FAR

PROPLAN – PRODUCT PLACEMENT AND PLANOGRAM COMPLIANCE SOLUTION

PROPLAN would the enable automation of product placement audits and planogram compliance audits for retailers by leveraging advanced image processing techniques.

TYPICAL PROCESS OF PLANOGRAM COMPLIANCE AUDIT



Capture a snapshot of the shelf at a specific time frame – e.g., at category reset

- Identify points of inconsistencies and report
- Gaps/ Empty Slots
- Understocked Items
- Over-stocked Items
- Misplaced Items

Analyze shelf compliance w.r.to reference planogram

2. CONNECTED STORE - GEOSPATIAL ANALYTICS IN OMNICHANNEL RETAIL

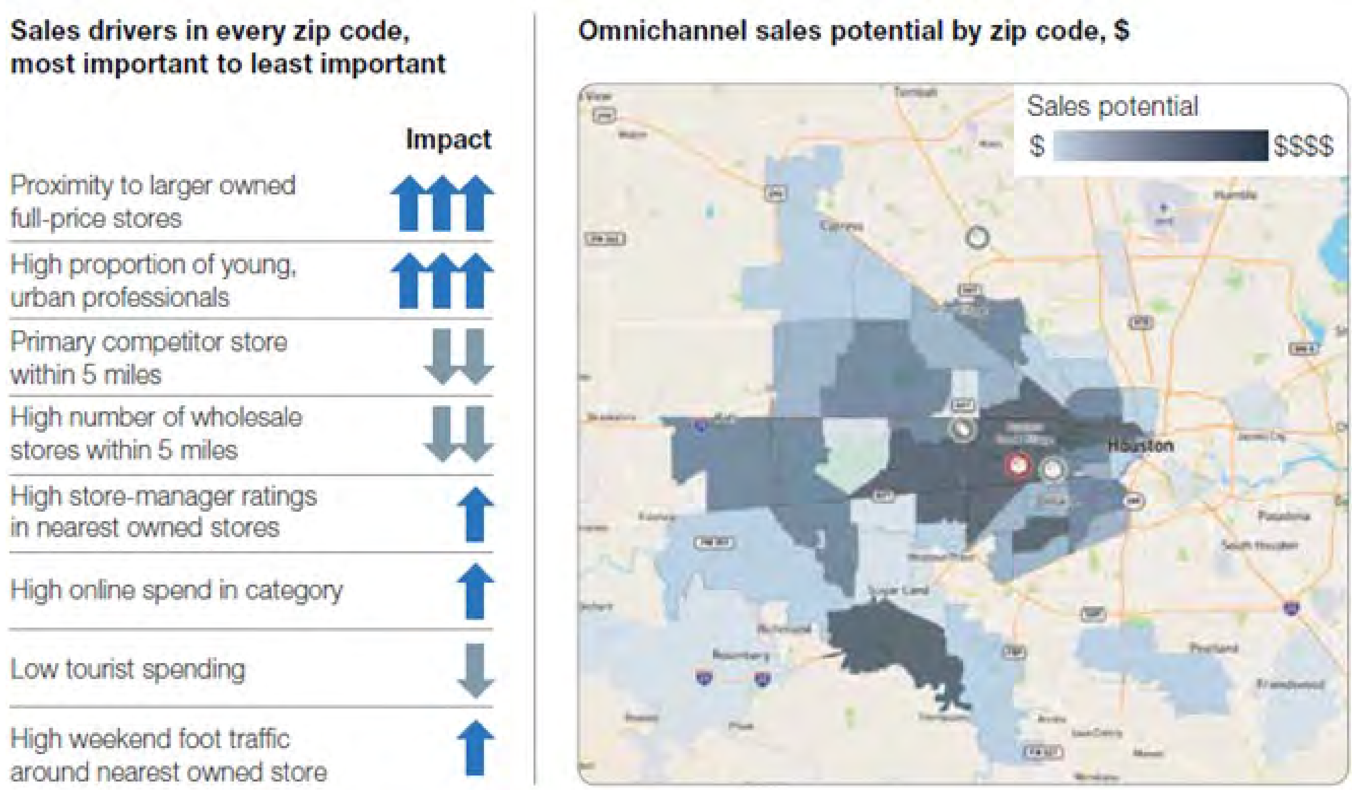
- The wave of store closures across the US retail sector continues. In 2017 alone, more than 7,000 stores went dark, unable to withstand consumers' rapid migration to e-commerce, the explosive growth of direct-to-consumer brands, and the glut of retail square footage in the heavily overstored US market. Retail space per capita in the United States is 15 to 20 times that of other major developed markets. Customer traffic at malls has been steadily decreasing. Margins are declining in almost every retail category. Given these trends, it's becoming harder to justify keeping expensive brick-and-mortar stores open if they don't meet sales expectations.

- Using advanced geospatial analytics, retailers can now quantify the true economic value of each of their stores across channels.

- Advances in data and analytics can help a retailer quantify both a store's halo effect (positive) and its cannibalization effect (negative)—in other words, how a store's existence influences the performance of the retailer's other sales channels. Retailers have long recognized that a store can have a halo effect, but it has traditionally been thought of in marketing terms—that is, a store can raise awareness of the retailer's brand, just like a billboard or a TV commercial. Viewed as such, the halo effect has been difficult to measure. However, in an omnichannel world, a store can do more than just raise awareness; it can drive sales through other channels, and vice versa.

Using geospatial machine learning, a retailer identified the factors that most affect a zip code's sales potential.

An analytical model can be built customized for the brand, leveraging both internal and external data using geospatial machine learning to identify the factors that have the greatest positive or negative effect on a zip code's total sales.



Based on these drivers, the model can predict the retailer's potential sales in each zip code and each store, and compare potential sales with actual sales. Then, using geospatial simulation to estimate each store's impact on wholesale and Online sales, a retailer can categorize stores into four groups based on sales potential and profitability.

The model can also isolate the unique factors that contribute to a strong e-commerce halo. It found that, in general, a store has a strong e-commerce halo if it is a larger store located in an area with a high proportion of young and urban professionals.

The retailer used these insights to identify which stores weren't living up to their sales and profit potential and which micro markets contained untapped growth opportunities.

3. Customer Analytics

In the increasingly customer-centric world, the ability to capture and use customer insights to shape products, solutions, and the buying experience is critically important. One of the analyst's reports shows that organizations that leverage customer behavioral insights outperform peers by 85% in sales growth and more than 25% in gross margin.

The customer of today is increasingly in control of their own path and a review of the end-to-end customer journey can help identify cut-in points for analytics opportunities.

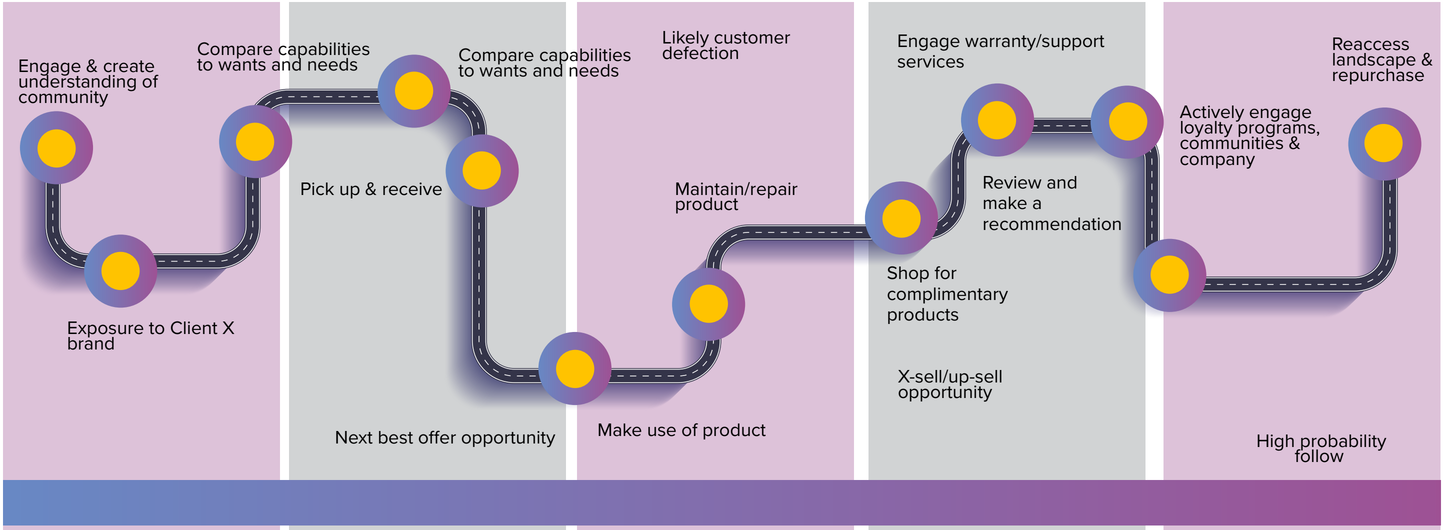
Pre-Purchase & Discovery
Awareness, consideration and evaluation

Purchase & Receipt
Purchase

Service & Maintenance
Experience

Ownership & Community
Advocacy

Repurchase
Loyalty



- See product/add
- Research product
- Visit stores/dealers
- Visit website
- Test product

- Interact w/sales staff
- Compare/negotiate price
- Financing
- Select / order /pick up product or service

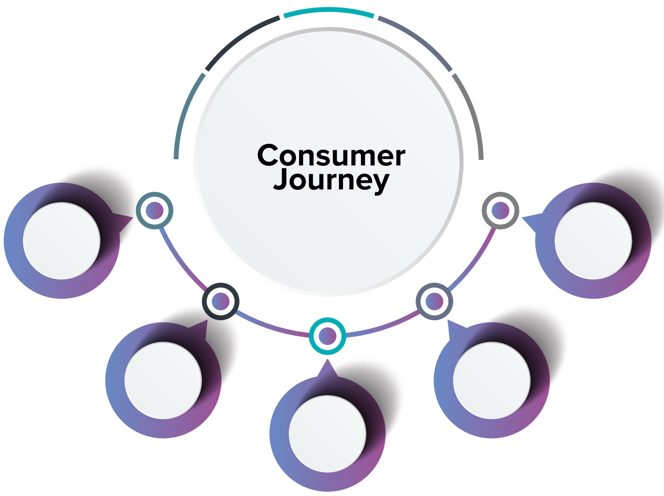
- Order parts
- Book appointments
- Drop off products
- Make payments
- Receive products

- Join community / loyalty program
- Receive / make comments
- Refer potential customers
- Shop for related products

- Evaluate product
- Engage loyalty program
- Research competitors
- Compare prices
- Visit stores / dealers

It has become important to get closer to customers and re-evaluate how the data about them is used. With the growing number of sources of data over the years - circumstantial data, situational data, behavioral data, etc. - ‘Big Data’ now presents endless opportunities to uncover patterns about the different types of customers and how they could be serviced in a more efficiently.

Customer experience can be supported by analytics at various points such as:



Pre-Purchase & Discovery

- Customer segmentation analysis
- Marketing ROI
- Customer portrait
- Customer growth

Ownership & Community

- Customer lifecycle engagement
- Social media analytics
- Experience gap identification
- Loyalty management

Purchase & Receipt

- Real-time interaction management
- Targeted promotions
- X-sell / up-sell
- Next best offer
- Product bundles

Service & Maintenence

- Cost to serve
- Customer lifetime value
- Customer sentiment analysis
- Prioritized product innovation

Repurchase

- Marketing mix optimization
- Promotion management
- Follow-on-sales
- Price setting

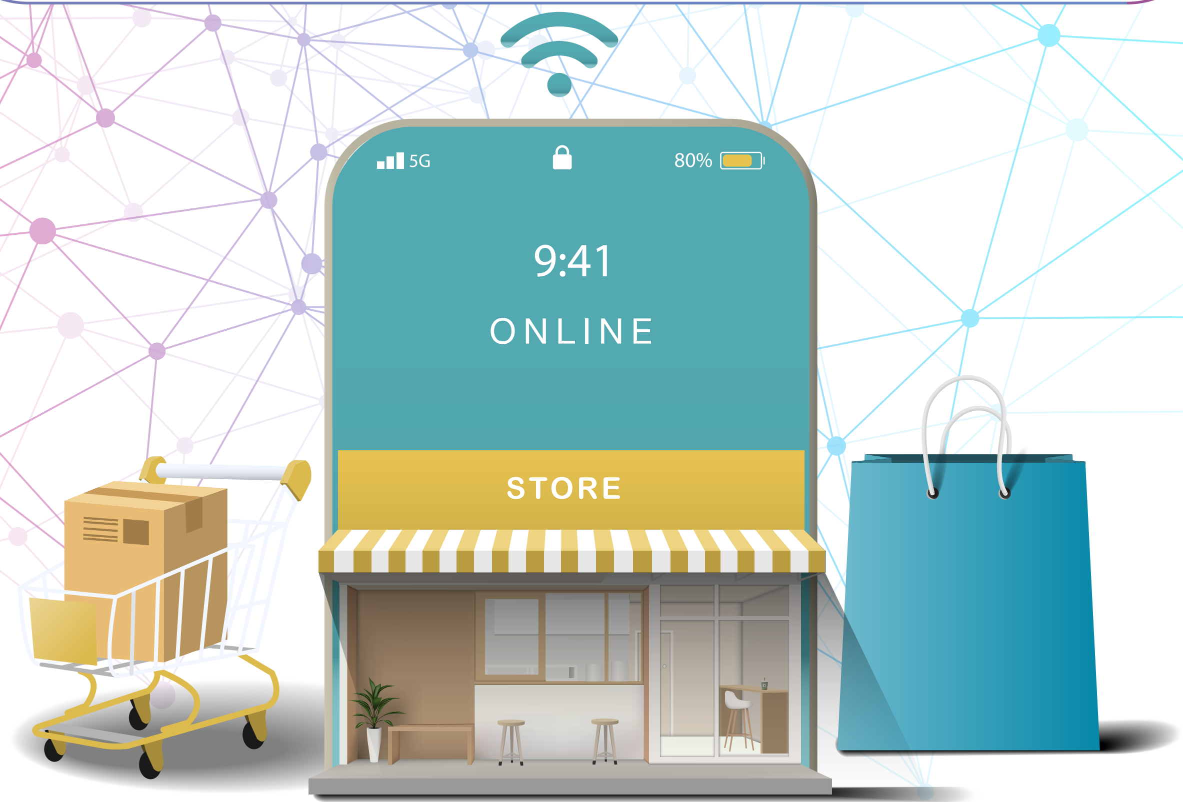
SOLUTION THEME

What it does

Customer segmentation is the practice of dividing a company's customers into groups that reflect similarity among customers in each group. The goal of segmenting customers is to decide how to relate to customers in each segment to maximize the value of each customer to the business.

Customer segmentation analysis is the process performed to discover insights that define specific segments of customers. Marketers and brands leverage this process to determine what campaigns, offers, or products to leverage when communicating with specific segments. A customer segmentation analysis allows marketers to identify discrete groups of customers with a high degree of accuracy based on demographic, behavioral and other indicators.

A retail brand looking to determine how to reactivate lapsed customers might create a segment of customers who purchased in the past and haven't purchased or browsed the e Commerce store in the past 30 days. It might then analyze that segment to understand what type of products these customers have bought in the past, their discount affinity and more. Using this information, the marketing team can determine the best campaign to reactivate these lapsed customers.



Consideration

a. Accurate customer segmentation involves tracking dynamic changes, and frequently updating new data. Some of the more common types are segmentation via cluster analysis, RFM segmentation, and longevity.

b. Customer Segmentation via Cluster Analysis

- The goal of cluster analysis in marketing is to accurately segment customers to achieve more effective customer marketing via personalization. A common cluster analysis method is a mathematical algorithm known as k-means cluster analysis.
- The following chart shows the results of a three-dimensional cluster analysis performed on the customer base of an e-commerce site. This analysis resulted in the discovery of four customer personas.
- Once the store's marketers have a clear view of the various customer personas, they can relate differently to each persona, with the marketing interactions most relevant to each persona's product preferences.

Customers	Days since last purchase	Number of Purchases (Past 12 Months)	Net Revenue (Past 12 Months)
High Spenders	9	4	$154
Mid Spenders	54	3	$121
Risk of churn	192	2	$70
Low Spenders	192	2	$4
3671	447	3	$87

c. Customer Segmentation via **RFM Analysis**

RFM analysis allows marketers to target specific clusters of customers with communications that are much more relevant for their behavior – and thus generate much higher rates of response, plus increased loyalty, and customer lifetime value.

Underlying the RFM segmentation technique is the idea that marketers can gain an extensive understanding of their customers by analyzing three quantifiable factors. These are:

01

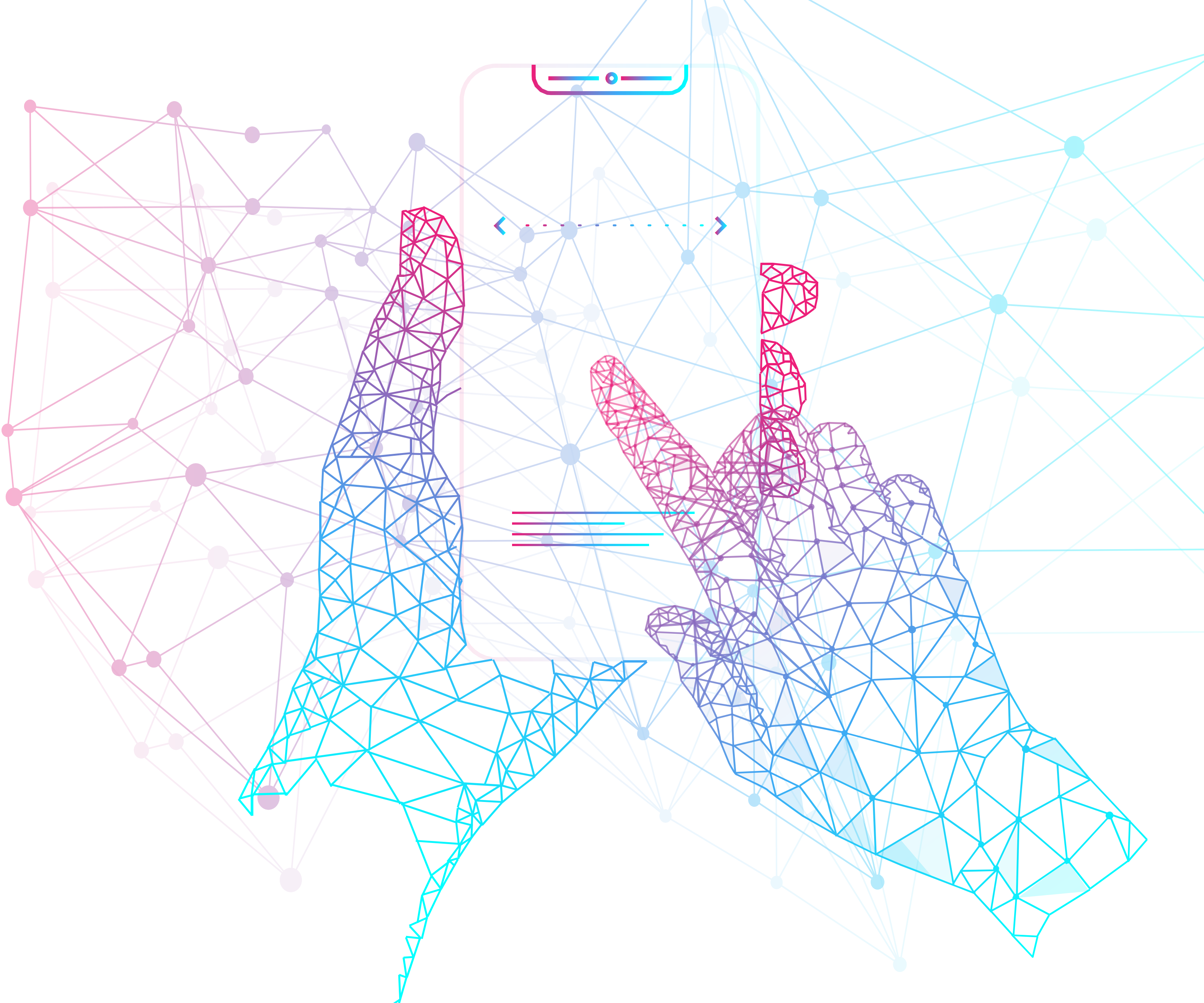
Recency
How much time has elapsed since a customer's last activity or transaction with the brand? Activity is usually a purchase, although variations are sometimes used, e.g., the last visit to a website or the use of a mobile app. In most cases, the more recently a customer has interacted or transacted with a brand the more likely that customer will be responsive to communications from the brand.

02

Frequency
How often has a customer transacted or interacted with the brand during a particular period? Clearly, customers with frequent activities are more engaged, and probably more loyal than customers who rarely do so. And one-time-only customers are in a class of their own.

03

Monetary
Also referred to as "monetary value," this factor reflects how much a customer has spent with the brand during a particular period. Big spenders should usually be treated differently than customers who spend little. Looking at monetary divided by frequency indicates the average purchase amount – an important secondary factor to consider when segmenting customers.



STEP 1

The first step in building an RFM model is to assign Recency, Frequency and Monetary values to each customer. The raw data for doing this should be readily available in the company's CRM or transactional databases.

STEP 2

Divide the customer list into tiered groups for each of the three dimensions (R, F and M), into four tiers for each dimension, such that each customer will be assigned to one tier in each dimension.

Recency	Frequency	Monetary
R-Tier-1 (most recent)	F-Tier-1 (most frequent)	M-Tier-1 (highest spend)
R-Tier-2	F-Tier-2	M-Tier-2
R-Tier-3	F-Tier-3	M-Tier-3
R-Tier-4 (last recent)	F-Tier-4 (only one transaction	M-Tier-4 (lowest spend)

This results in 64 distinct customer segments (4x4x4), into which customers will be segmented.

More sophisticated and less manual approaches, such as k-means cluster analysis, can be performed, resulting in groups of customers with more homogeneous characteristics.

Cluster	Cluster Size	Total Order Value	Number of Order days	Days Since
Top Tier Customers	3312	$2782	18	18
High Tier Customers	13005	$773	8	19
MidTier Customers	8931	$495	5	53
Mid Tier Customers	14415	$283	5	20
Low Tier Customers	24568	$123	2	97

STEP 3

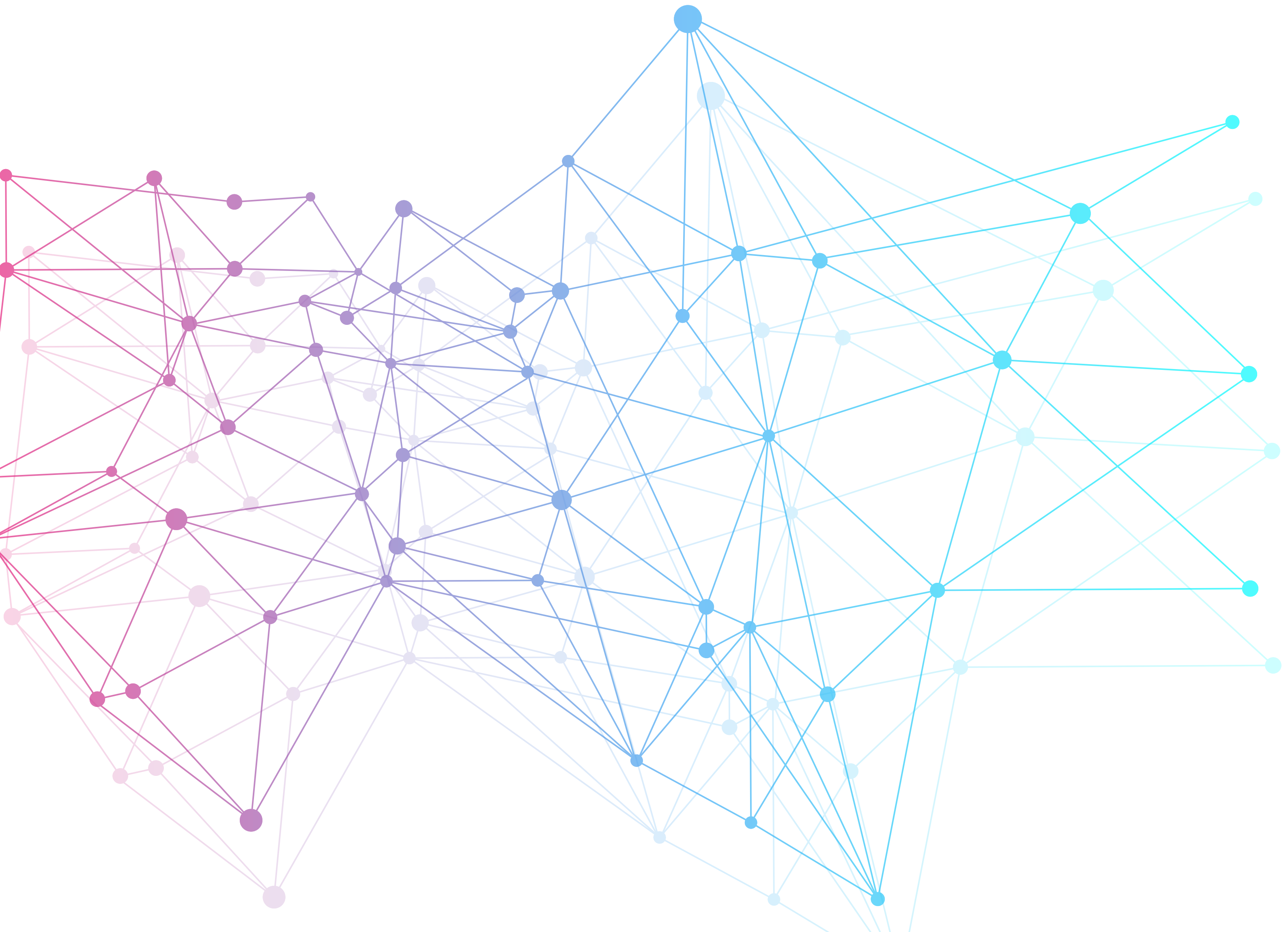
The third step is to select groups of customers to whom specific types of communications will be sent based on the RFM segments in which they appear.

Lowest-Spending Active Loyal Customers
This group consists of those customers in segments 1-1-3 and 1-1-4 (they transacted recently and do so often but spend the least).

Best Customers
This group consists of those customers who are found in R-Tier-1, F-Tier-1 and M-Tier-1, meaning that they transacted recently, do so often and spend more than other customers. A shortened notation for this segment is 1-1-1; we'll use this notation going forward.

High-Spending New Customers
This group consists of those customers in 1-4-1 and 1-4-2. These are customers who transacted only once, but very recently and they spent a lot.

Churned Best Customers
This segment consists of those customers in groups 4-1-1, 4-1-2, 4-2-1 and 4-2-2 (they transacted frequently and spent a lot, but it's been a long time since they've transacted).



CUSTOMER SENTIMENT ANALYSIS

What it does

- Customer sentiment analysis refers to the automated process of discovering and measuring how customers feel about your product, brand, or service.
- Unstructured textual data collected from online surveys, social media, support tickets, feedback forms, product reviews, forums, phone calls, emails, and chatbots. In machine learning, customer sentiment analysis is conducted through Natural Language Processing (NLP) that applies statistical and linguistic methods to extract positive, negative, and neutral sentiments directly from the text data. Essentially, it outputs two parameters:
  - Polarity - Indicates whether a sentiment is positive or negative,
  - Magnitude - Indicates the strength of that sentiment.
- It helps retailers to
  - improve customer service and hence customer experiences,
  - increase customer loyalty,
  - reduce churn rate,
  - upgrade products and services timely,
  - optimize marketing campaigns,
  - anticipate new trends and markets,
  - maintain our company's high reputation and increase profits.

Consideration

- Using a Supervised Machine Learning Model to predict sentiment
- Some industry-standard approaches:
  - using n-grams (combinations of words) instead of just single words to preserve the context,
  - excluding stop words,
  - limiting the size of vocabulary based on the upper or lower frequency values,
  - creating numeric extra features describing the length of each review or the number of punctuation marks (the latter can sometimes correlate with the magnitude of the sentiment),
  - excluding numbers, some characters, words of a certain length, or considering more complex word patterns,
  - applying stemming and lemmatization, i.e., reducing the words to their roots,
  - using more approaches for creating a vocabulary, e.g.Term Frequency - Inverse Document Frequency (TF-IDF) that accounts for how frequently a word occurs in a review with respect to the rest of the reviews, and
  - using some specialized libraries designed for sentiment analysis, such as TextBlob, SentiWordNet, VADER (Valence Aware Dictionary and Sentiment Reasoner).

4. MARKETING ANALYTICS - HYPER PERSONALIZATION

Customer and relevant advertising

Targeting customers with advertisements that are unique by either including relevant products or customer information.

Unique landing pages

Using cues on where customers are coming from past visits, geographic data and preferences to choose what is being presented.

Recommendation engines

Providing content, product, or service recommendations that are tailored to the individual customer's needs or wants.

Omnichannel customer

Using databases and AI technology to recognize and connect customers from both online and offline shopping channels.

Service chatbots

Using conversational AI technology that learns from customer behaviors and delivers personalized services that can answer specific questions and concerns in real time.

Dynamic pricing and offers

Changing the offer, promotion or price customers are served based on their propensity to convert.

Pre-populated applications

Using existing customer data with AI capability to pre-populate any documents, processes or applications that may be required.

Real-time product

Providing customers updates on the status of product shipments, promotions or refills based on their purchase history.

Loyalty programs

Using customer purchases, micro segmentation and geospatial data to send highly contextualized offers and messages.

CUSTOMER SENTIMENT ANALYSIS

What it does

- Dynamic pricing is a method used by business leaders, such as Amazon and Airbnb, to optimize their pricing strategy according to market and consumer data in order to attract more customers and increase profit. While traditional dynamic pricing algorithms use historical data to estimate the best prices, modern dynamic pricing algorithms leverage more data, as well as AI and machine learning capabilities, to better predict market trends and achieve dynamic pricing optimization.
- Dynamic pricing algorithms leverage
    - Historical data
    - Product prices
    - Production costs
    - Market trends
    - Customers' purchase behavior
- Modern algorithms may also include real-time data about competitors' prices and stocks collected from online websites.

Consideration

Dynamic pricing algorithms work by estimating the dependency of a price-on-demand in the following manner:

- Processing historical sales and price data, pricing points, and current market demand (e.g., data about wrapping paper during Christmas).
- Identifying significant parameters that the price depends on. For example, "school opening" is a parameter that affects stationery sales.
- Generating a mathematical model based on significant parameters.

MODELS OF DYNAMIC PRICING ALGORITHMS

BAYESIAN MODEL
In a Bayesian model, the user picks a prior value indicating the initial belief about the possible price. Then, whenever a new data point is entered into the algorithm, the initial belief shifts either higher or lower. This type of dynamic pricing model uses historical pricing data as the most important feature to decide on the final price, like a typical pricing algorithm.

REINFORCEMENT LEARNING MODEL
Reinforcement learning (RL) is a goal-directed dynamic pricing model that aims to achieve the highest rewards by learning from environmental data. An RL dynamic pricing model analyzes data regarding customers' demand, considering seasonality, competitor prices, and the uncertainty of the market, to achieve a revenue-optimal price.

DECISION TREE MODEL
Decision trees are classification machine learning models that output a tree-like model of decisions and their possible consequences, including the possibility of a certain outcome, resource costs, and utility. Decision tree dynamic pricing algorithms help businesses understand which parameters have the most effect on the prices and which of these price ranges predicts the highest revenues, and using this information, the algorithm predicts the best price range for each product.

HOW TO CHOOSE THE MOST SUITABLE DYNAMIC PRICING ALGORITHM?

To choose the best dynamic pricing algorithm, businesses need to consider an algorithm that should be able to provide prices that maximize revenue and profit.

Dynamic pricing algorithms are designed to ensure that prices adjust in real-time to dynamic market conditions, enabling businesses to capture maximum revenues and profits.

Minimize customer churn
An effective dynamic pricing algorithm should be able to analyze customer behavior and preferences to provide personalized prices that help reduce customer churn.

Compete with competitor prices and attract their customers
The algorithm should also be able to anticipate competitor prices and adjust your prices accordingly to stay competitive and attract customers.

Improves customer experience and maintains loyalty
Additionally, a dynamic pricing algorithm should be able to provide customers with personalized prices, discounts, and offers that improve their shopping experience and help build repeat business.

Aligns with business objectives
A good dynamic pricing algorithm ensures that price adjustments are always aligned with corporate goals. For instance, companies known for low prices should, therefore, define prices in their algorithm that are below the market average.

AUTHOR BIO

AMLAN SARKAR

Amlan Sarkar is a seasoned Consulting and Business Transformation professional specializing in Retail, Consumer Products and works as a Director of Domain Consulting group in the Retail & Consumer Goods vertical within Digital Business Services, at Happiest Minds Technologies.

He has 21+ years of industry experience driving major digital business transformation programs globally. He is passionate about merchandising & supply Chain in retail and use of digital tools and techniques to make businesses sustainable. He has worked with Tier 1 global retail clients in North America, Western Europe, Nordic, Asia Pacific and Middle East. Amlan is a Management graduate from Indian Institute of Management (Indore) and holds a Bachelor of Engineering (Chemical) from Jadavpur University, Kolkata.

About Happiest Minds

Happiest Minds Technologies Limited (NSE: HAPPSTMNDS), a Mindful IT Company, enables digital transformation for enterprises and technology providers by delivering seamless customer experiences, business efficiency and actionable insights. We do this by leveraging a spectrum of disruptive technologies such as: artificial intelligence, blockchain, cloud, digital process automation, internet of things, robotics/drones, security, virtual/augmented reality, etc. Positioned as 'Born Digital . Born Agile', our capabilities span digital solutions, infrastructure, product engineering and security. We deliver these services across industry sectors such as automotive, BFSI, consumer packaged goods, e-commerce, edutech, engineering R&D, hi-tech, manufacturing, retail and travel/transportation/hospitality.

A Great Place to Work-Certified™ company, Happiest Minds is headquartered in Bangalore, India with operations in the U.S., UK, Canada, Australia and Middle East.

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www.happiestminds.com

For Business
business@happiestminds.com