WHITE PAPER

SKU Rationalization

Category Managers are charged with the challenge of using limited space and cost to carry, display and promote the entire portfolio of products that the customers may need. Affine talks in detail about a holistic multi-level approach to decide which SKUs should be retained in your portfolio to ensure optimal returns…

Vineet Kumar | Co-Founder, Chief Solution Architect
Email: vineet.kumar@affineanalytics.com

Chavi Bhaskar | Data Science Project Manager
Email: chavi.bhaskar@affineanalytics.com

Harshit Gupta | Data Science & AI Consultant
Email: harshit.gupta@affineanalytics.com

Table of Contents

SKU Rationalization

1. Preface 03
2. Introduction 04
3. Solution Framework 05
    3.1. Affine's 360^o Approach 06
    3.2. Product Performance 07
    3.3. Cross-Product Interactions 09
        3.3.2. Demand Transference 10
    3.4. Level of Implementation 13
    3.5. Analytical Outcome 14
4. Implementation 15
    4.1. System Integration 17
    4.2. Communication & Training 18
    4.3. Collaborative Planning 19
    4.4. Systematic Testing & Measurement 20
5. Impact & Conclusion 21
    5.1. Impact 22
    5.2. Conclusion 23

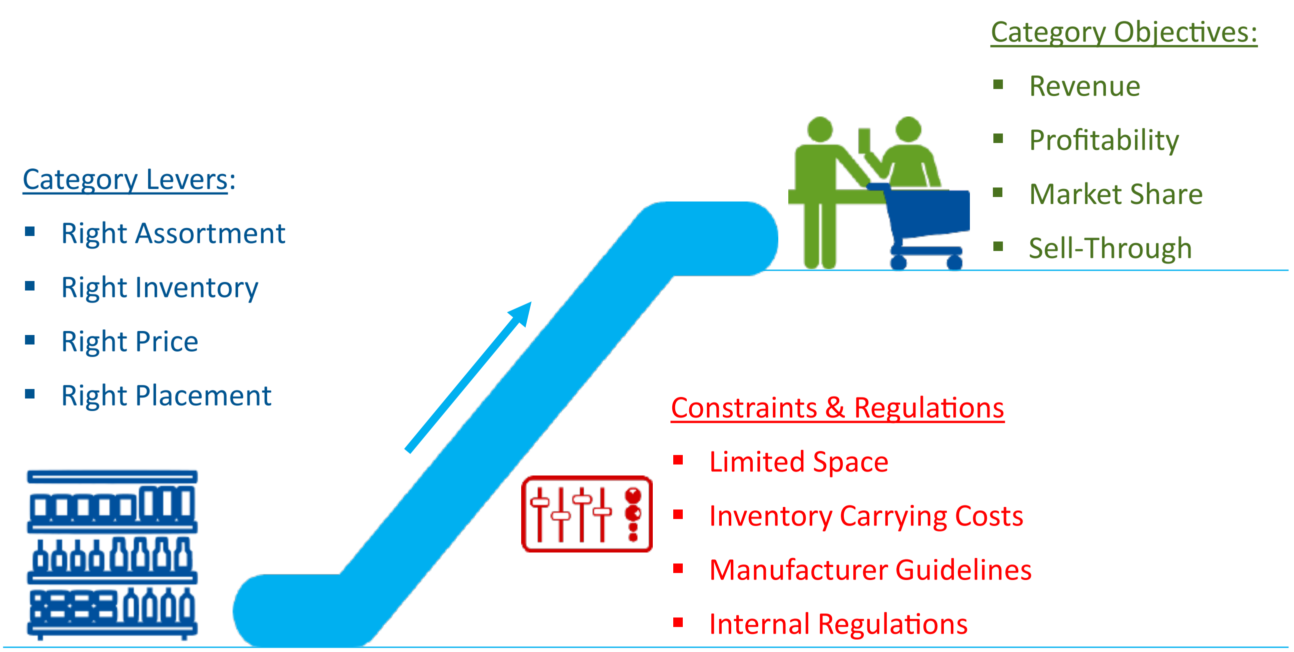
1. Preface

Levers Available to a Category Manager

Category Managers are critical for a Retailer achieving their category objectives – be it Revenue, Profitability, Sell-Through or Market Share.

The Category Manager must make the decision to carry the right SKUs in the right Volume placed in the right Shelf Space and promoted at the right Price. There are multiple infrastructural and regulatory restrictions that limit the flexibility of these decisions. Also, many environmental factors play a significant role in the success of the Category Plan.

<u>From Levers to Objectives…</u>



Environmental Factors:

- Store Location
- Demography
- Economic Factors
- Competition
- Seasonality
- Product Lifecycle
- Cross-Product Interactions – Halo, Affinity, Basket Size

2. Introduction

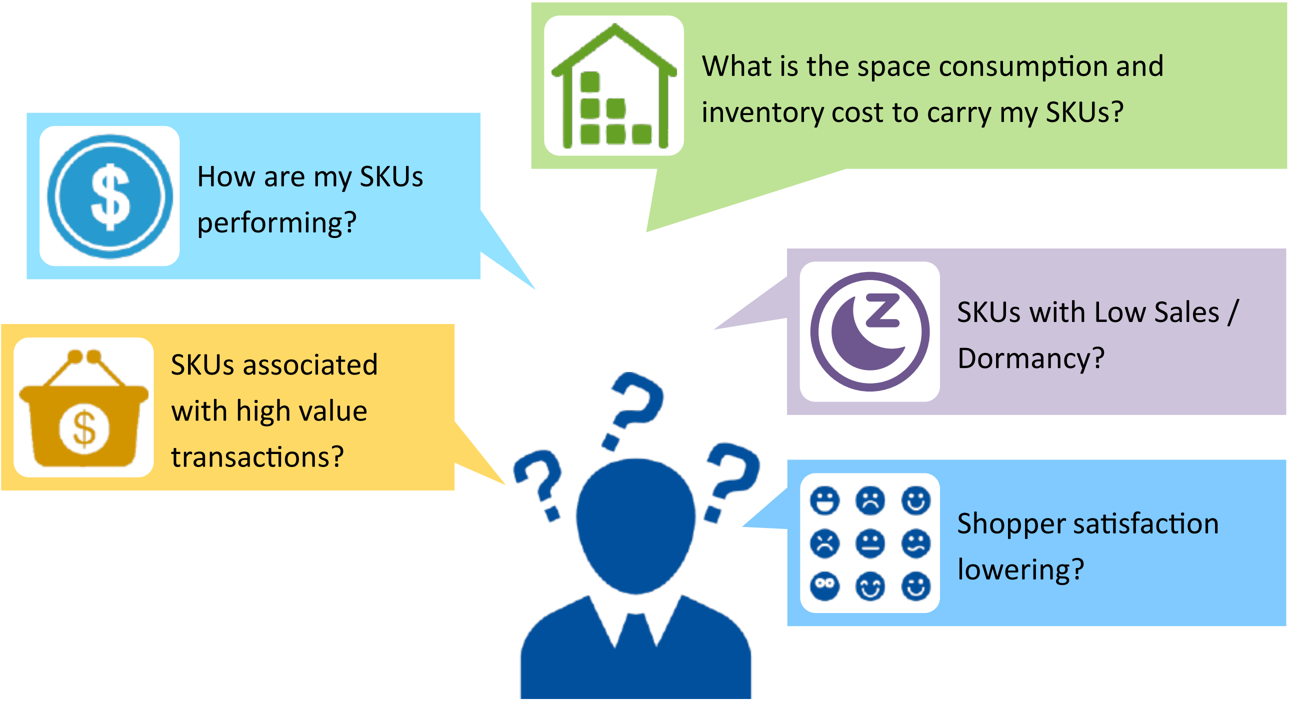
The Right Assortment Mix

The Right Assortment Mix is the foundational decision that must be made which will impact all other decisions down the line.

Assortment affects cost because it drives inventory decisions. Poorly conceived inefficient assortments raise inventory costs and waste valuable shelf space, one of the major assets of the retailer.

On the demand side, assortment is one of the two most powerful drivers of shopper satisfaction. Price being the other. Excellent assortments appeal to target shoppers by meeting their needs with the most preferred SKU. Poorly conceived assortments fail to satisfy shopper's needs resulting in slow inventory turns and in lower financial returns on inventory investment

<u>Key Concerns</u>



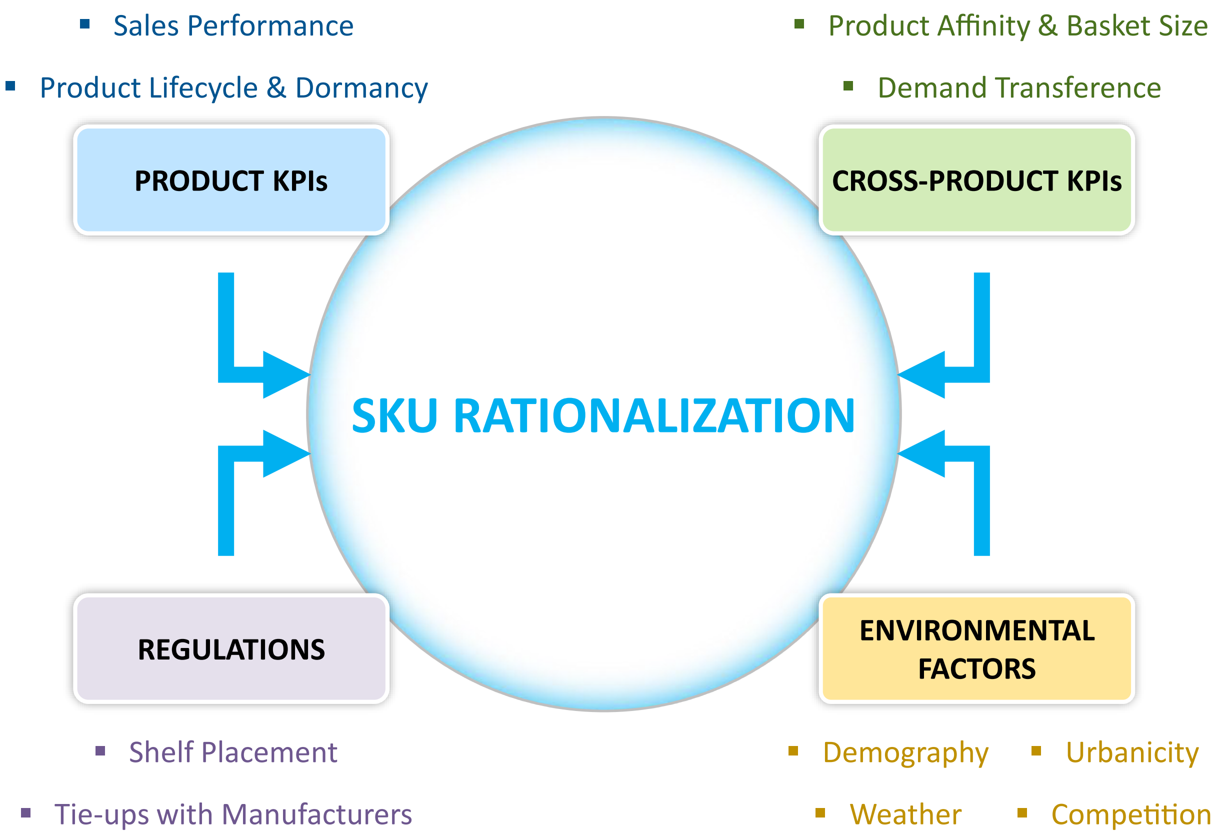
In this white paper, we have detailed how to arrive at the right assortment mix using SKU rationalization, while considering the multifarious constraints and influencing factors, to achieve the Category Objectives.

3. Solution Framework

3.1. Affine's 360⁰ Approach

Affine's SKU Rationalization approach comprises a series of meticulously sequenced analyses to determine the SKUs that need to dropped from the portfolio to achieve the Category Objectives without overstepping the regulations and being mindful of the environmental factors

<u>Factors influencing SKU Rationalization</u>



Although there are multiple solutions in the market that talk about these elements, there has never been a holistic approach that deals with the entire scenario.

Assortment Mix Strategy implementation should also be carefully planned, for ease and effectiveness. While each store's Assortment Mix can be individually assigned, it becomes difficult to implement and track. Assigning the same mix for the entire chain is also not advisable.

In this white paper we will describe the key analyses that are required for SKU rationalization and how Affine has combined them to deliver the 360⁰ approach.

We recommend using sequential elimination on the complete Product Portfolio to narrow down to the SKUs that must be removed from the shelves.

3.2. Product Performance

3.2.1. Sales Performance

Shortlisting Low-Performers for Removal

It is the obvious choice for a Category Manager to keep the SKUs that have high Sales Performance. Sales Performance is gauged differently by different retailers depending on the Category Objectives, type of products, company strategy and so on.

The illustration below depicts two commonly used and robust KPIs to gauge SKU Performance:

- Sales Contribution: % Contribution of the SKUs to Portfolio Revenue
- Sales Velocity: Units moved every week

SKUs shortlisted using poor sales performance are put through the next level of examination.

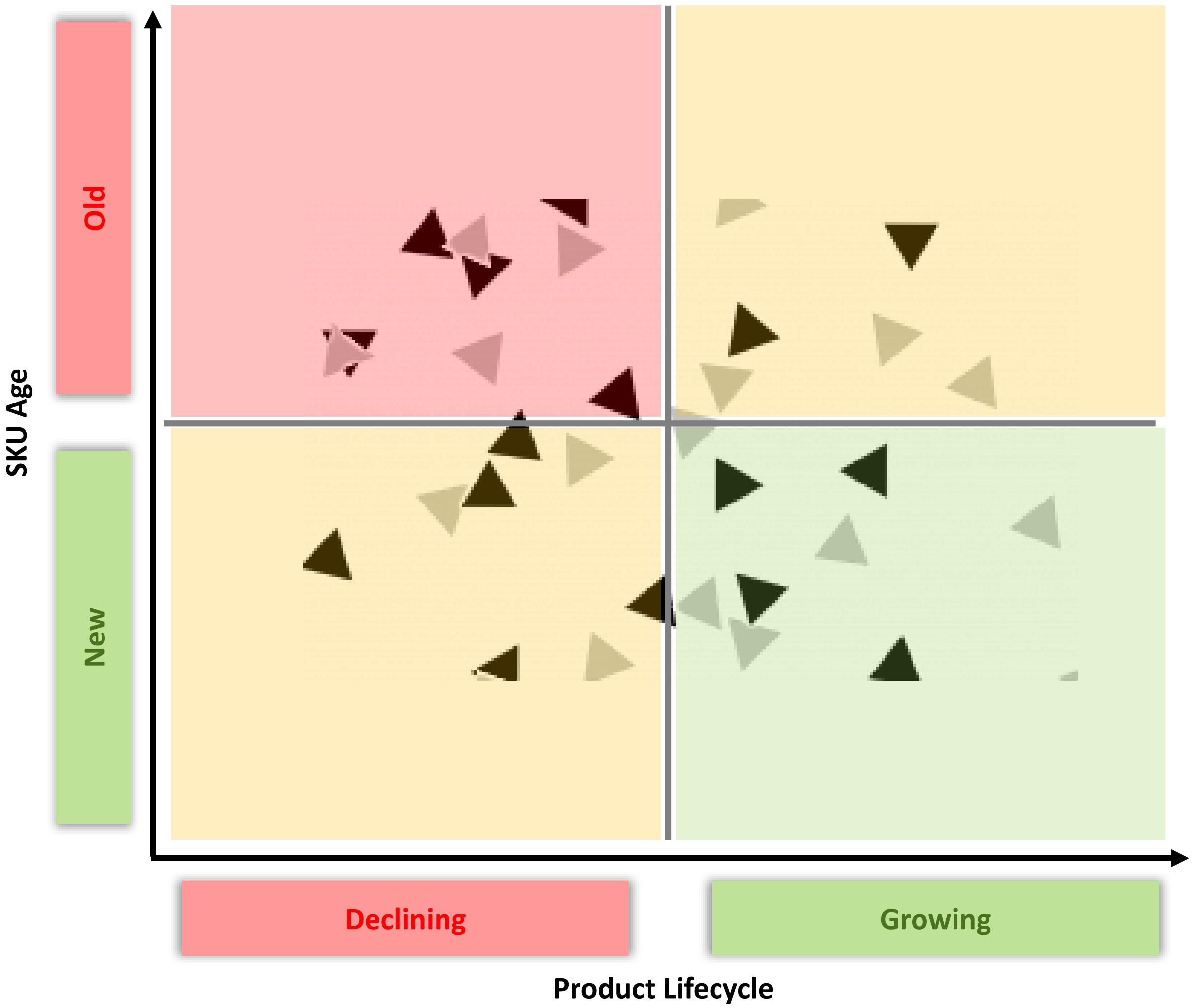
3.2. Product Performance

3.2.2. Dormancy & Product Lifecycle

Even with low sales performance, not all SKUs warrant being taken off the shelf. There could be SKUs that are recently launched or temporarily dormant which have low sales for now but could pick up in near future. The SKUs shortlisted for low sales performance are filtered based on age and sales growth of the SKUs.

Only the genuine low performer SKUs are the ones shortlisted as potential candidates to be taken off the shelf.

Checking Dormancy & Product Lifecycle



After the first two rounds of selection based on individual SKU performance, these SKUs will be scrutinized for cross-product interactions that would make them valuable to have at the store.

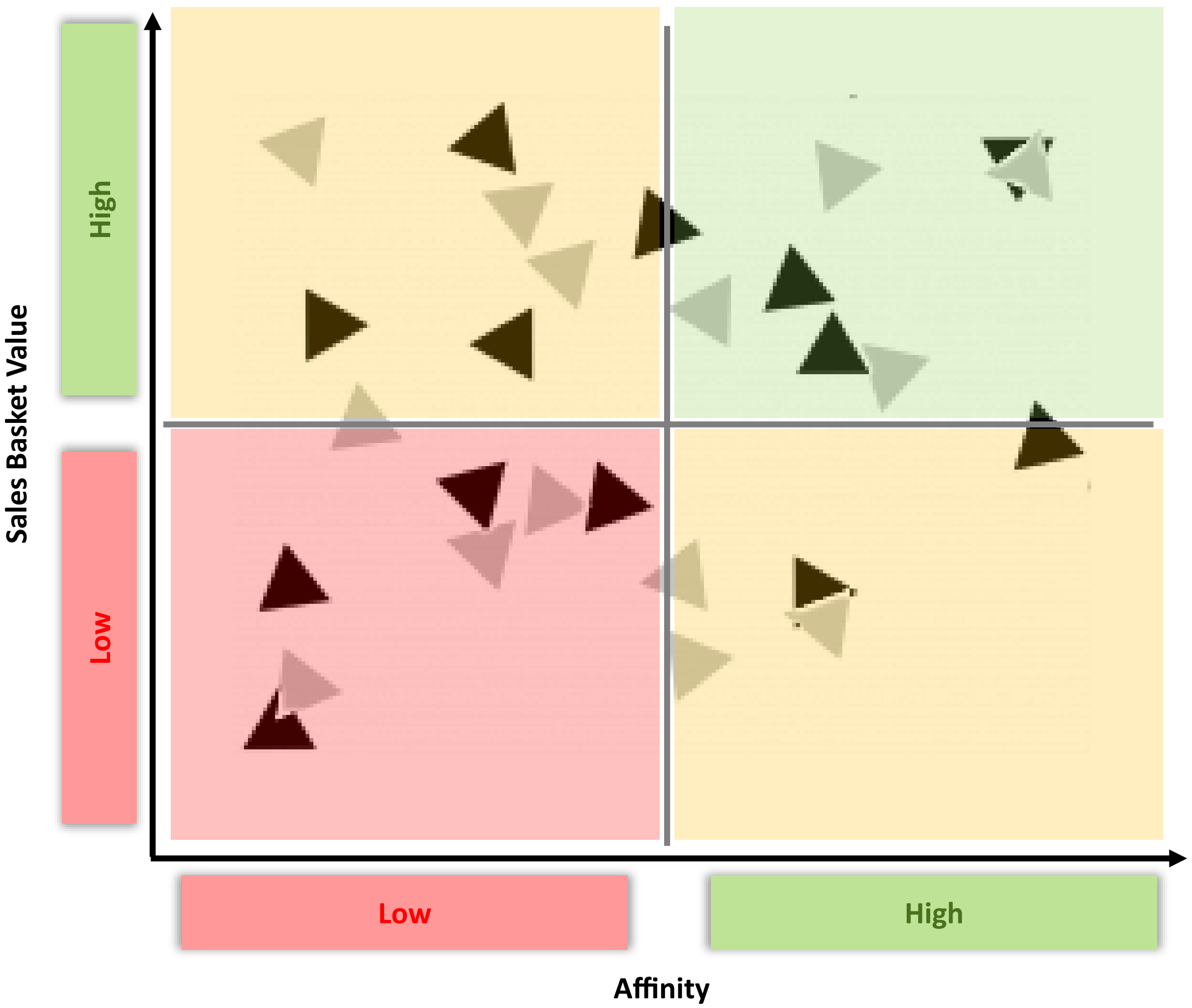
3.3. Cross-Product Interactions

3.3.1. Basket Size & Affinity

SKUs influence each other significantly. Removing an SKU will have a domino effect on sales of other products. Removing the low performer SKU could be what drives a high value customer away. There could also be SKUs which have high affinity with other SKUs

SKUs which appear in low value transaction baskets and having low affinity with high sales SKUs are chosen for the next stage of elimination

Basket Size & Affinity based Elimination



3.3. Cross-Product Interactions

3.3.2. Demand Transference

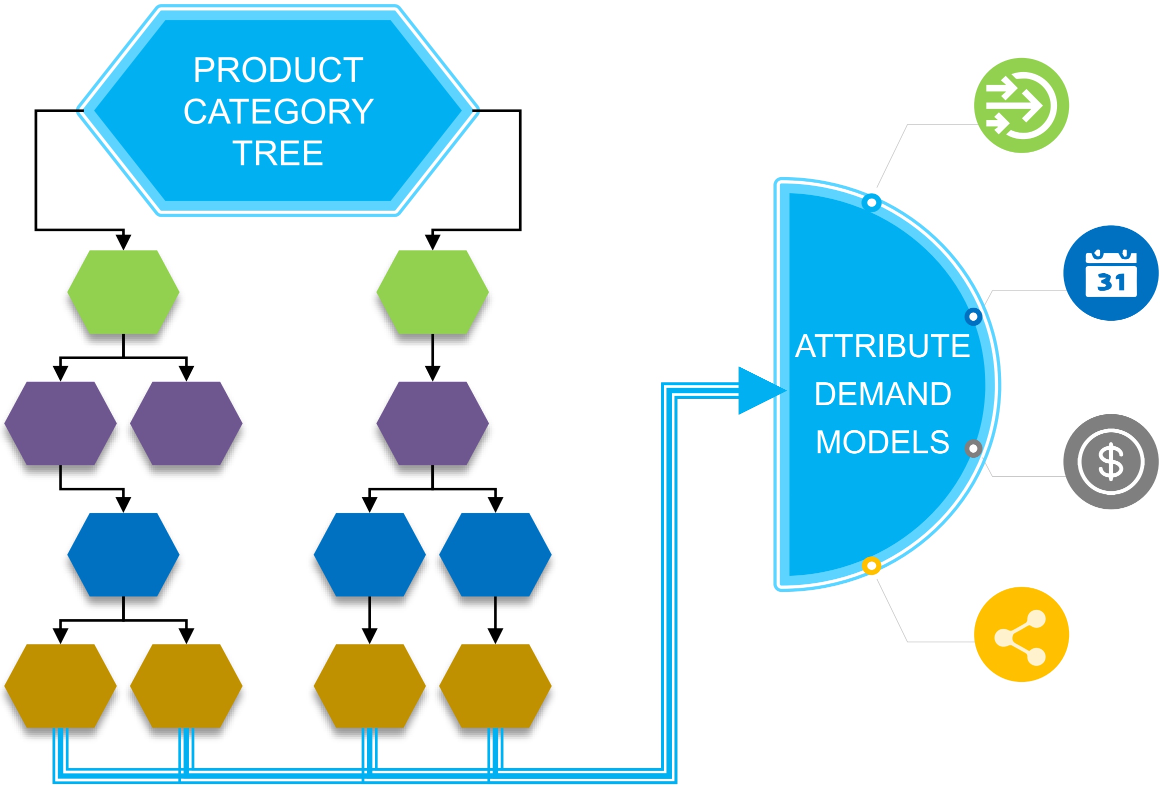
Phenomenon where an SKU is picked by the customer in the absence of a similar SKU is called Demand Transference. Since customers will have a higher preference of buying a similar product in case of non-availability of a product, demand transference can only occur within a group of products having high similarity.

To determine the demand transference, modern machine learning techniques can be used to determine which products are similar based on attributes and determine the precise demand transference index of each SKU to others.

A Product Category Tree (PCT) using decision tree techniques identifies cohorts of similar SKUs within the category. After PCT is created, Demand Transference Index is calculated, using an Attribute Demand Model, for the SKUs within each cohort.

Demand Transference

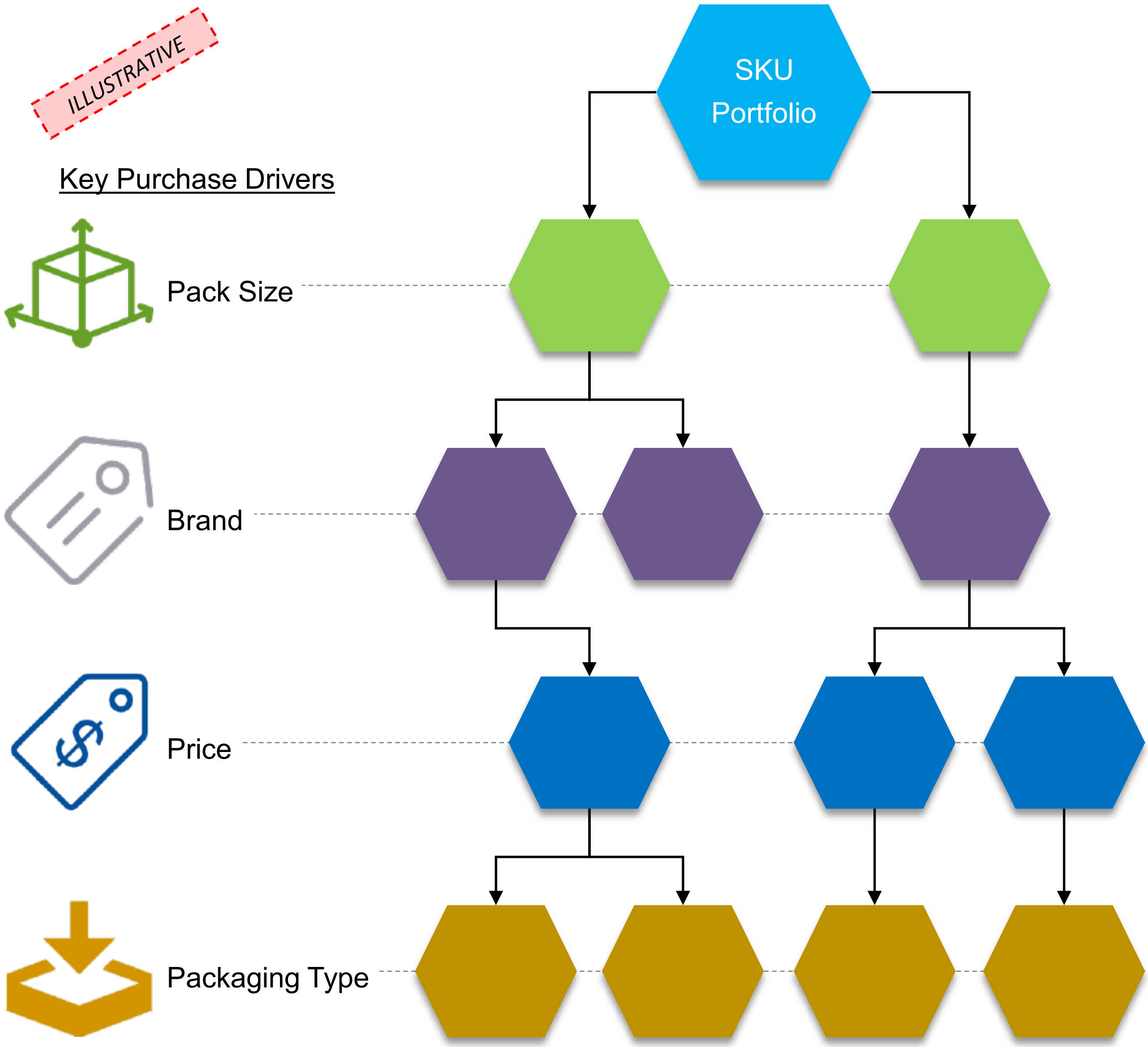
Product Category Tree (PCT) to Attribute Demand Model



3.3.2. Demand Transference – Product Category Tree

Decision Tree machine learning techniques can be used to build a Product Category Tree (PCT), to identify cohorts of similar SKUs. The key factors are picked by the decision tree technique from product attributes and varies from case to case.

Product Category Tree (PCT)



The final layer of nodes in the PCT can be said to have SKUs which are potentially substitutable for each other by a customer.

3.3.2. Demand Transference Index with Machine Learning

Attribute demand Modeling is done for each SKU to determine substitutivity by checking if stockouts of one SKU lead to lift in sales of another SKU in the PCT cohort. Models also needs to account for other Demand Drivers like Seasonality, Price Elasticity, Cannibalization, Affinity, Marketing, and so on.

Attribute Demand Modeling for Demand Transference Index (β_{SUB})

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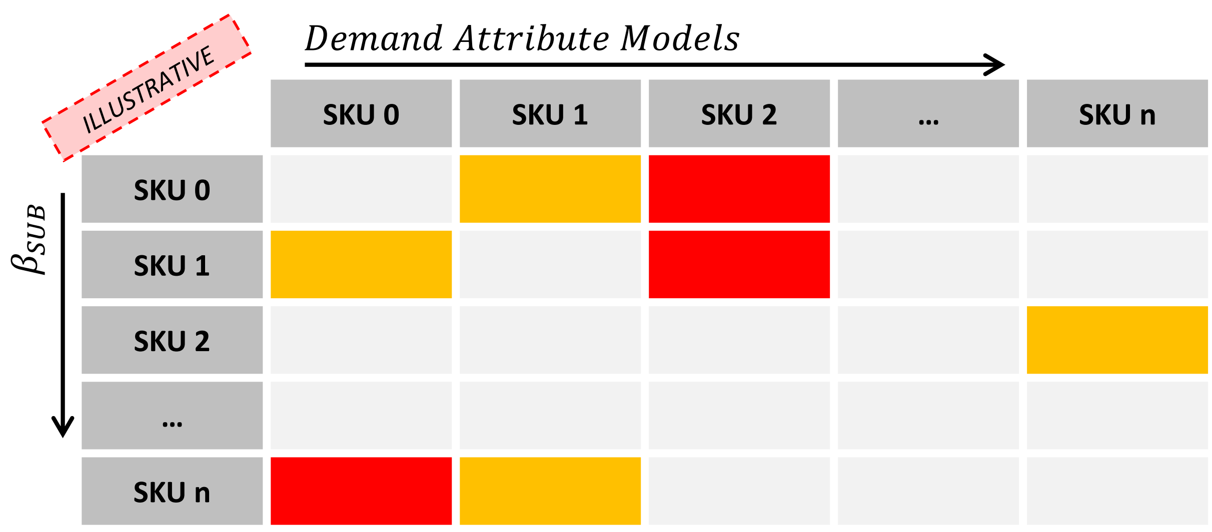
$$
\begin{aligned}
Demand_{SKU0} = & \sum_{k=1}^{n} \beta_{SUBk} \times STOCKOUT_{SKUk} && \text{Substitutivity} \\
& + \sum \beta_{SEASONALITY} \times Var_{SEASONALITY} && \text{Seasonality} \\
& + \beta_{PRICE\ ELASTICITY} \times PRICE_{SKU0} && \text{Price Elasticity} \\
& + \sum_{k=1}^{m} \beta_{CANNIBALk} \times PRICE_{SKUk} && \text{Cannibalization} \\
& + \ldots
\end{aligned}
$$

given n SKUs in the selected cohort

Demand Transference Index Grid



Final rationalization is decided by the Demand Transference Index Grid of the SKUs. The demand coming from a product removed from the assortment should be covered by another that remains on the shelf. In the above illustration, SKU 2's demand is seen to be transferred heavily on SKU 0 and SKU 1, making SKU 2 a candidate for removal from the portfolio.

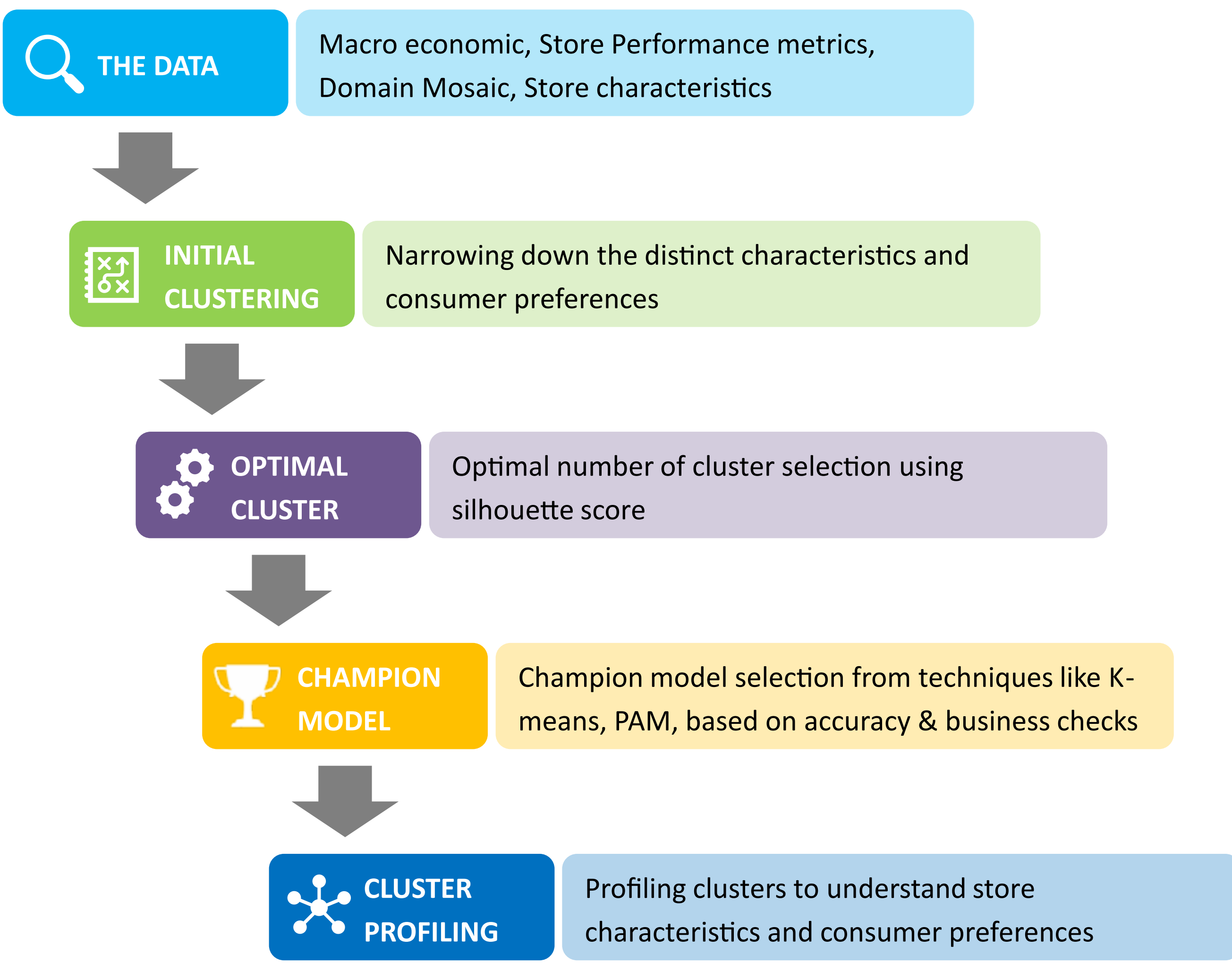
3.4. Level of Implementation

Store Clustering

No matter the strategy, implementation needs to be done at the right level. For a retail chain with hundreds or even thousands of stores, it is sub-optimal to apply the same strategy to all stores. And, it becomes complex for the Category Manager to customize and implement the strategy for each store.

Hence, clustering to find homogenous stores breaks the entire chain into manageable groups. The same strategy can be applied to stores in a cluster during implementation, since the stores will be more likely to have similar sales patterns.

<u>Store Clustering</u>

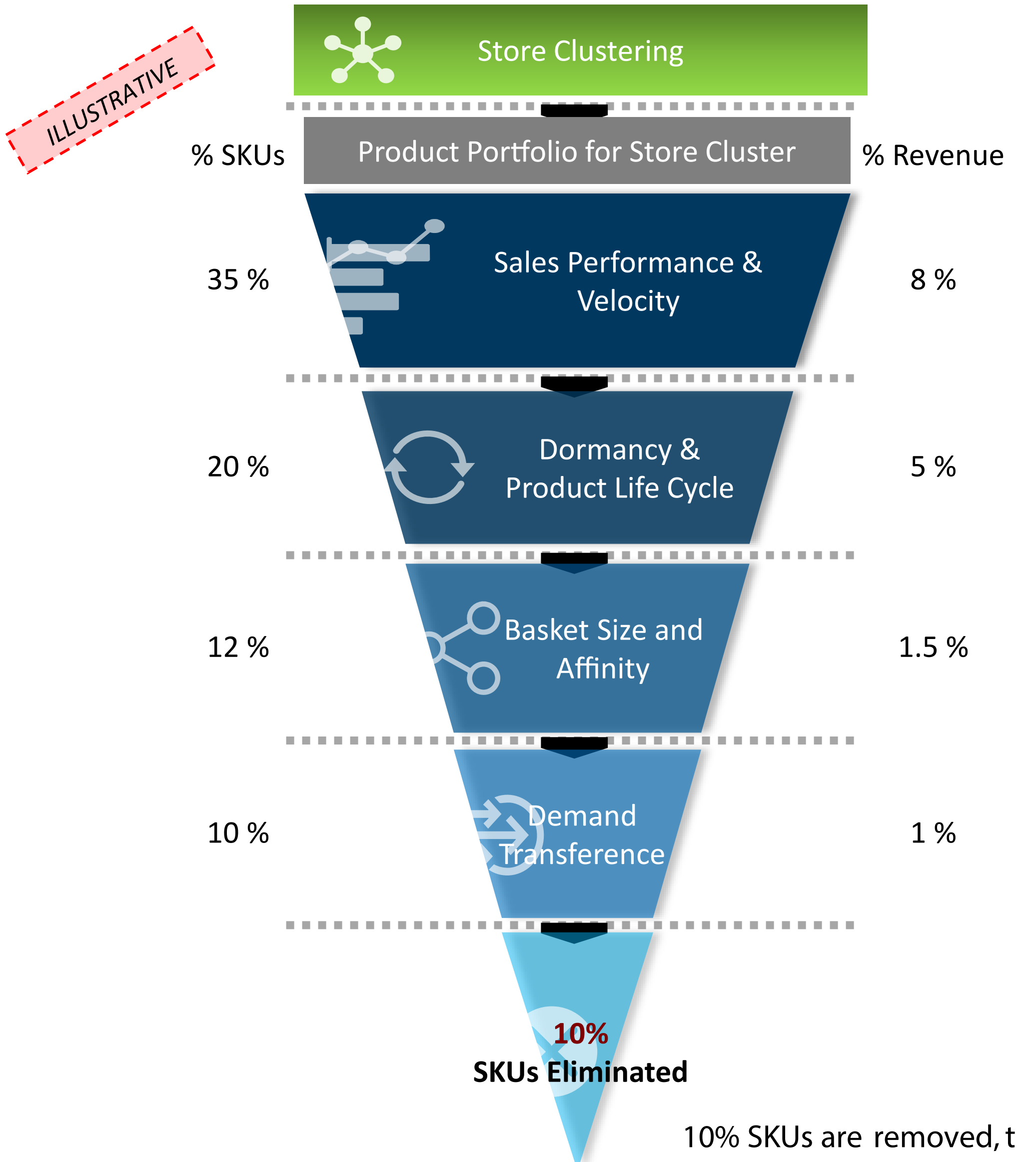


3.5. Analytical Outcome

The SKU Rationalization Funnel

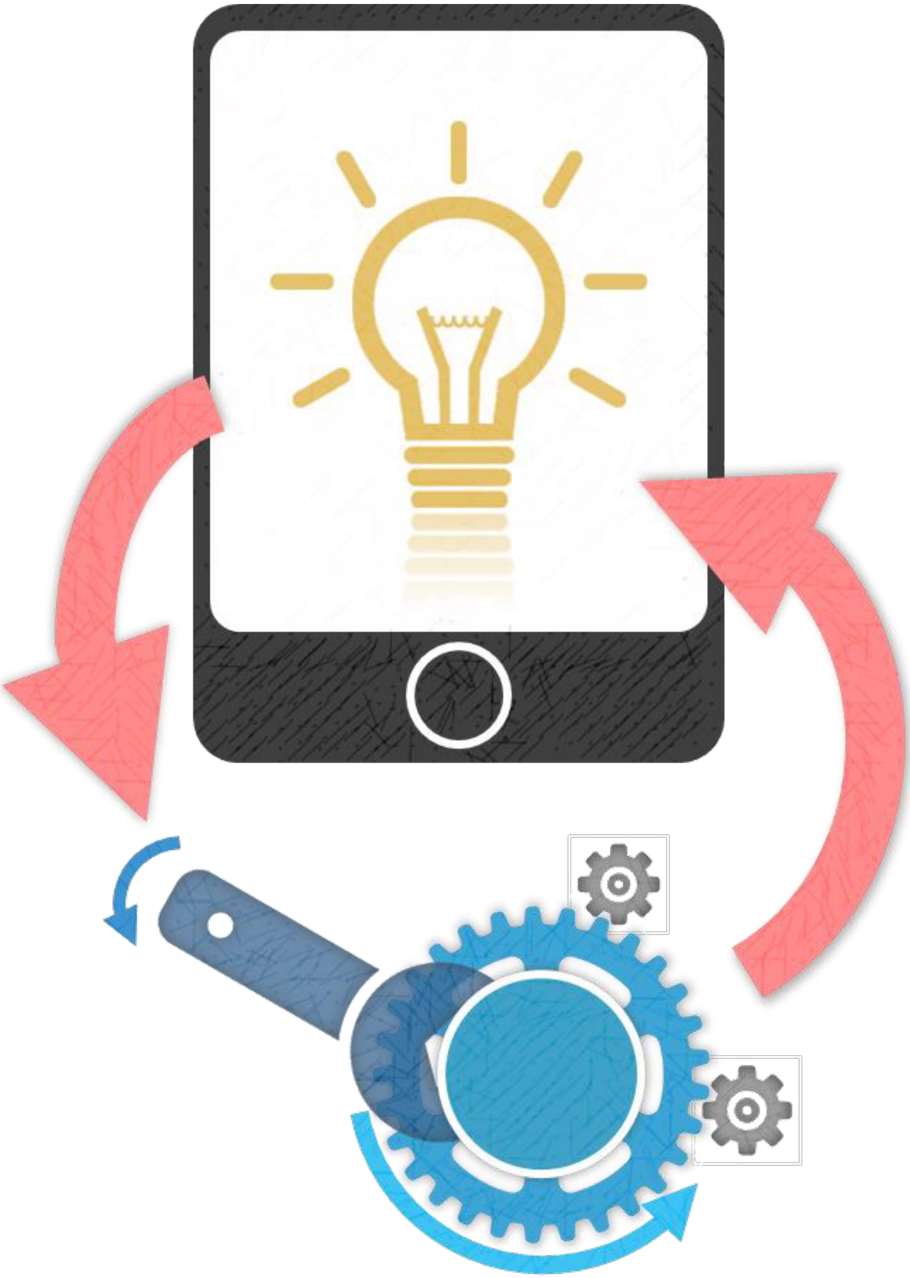
After implementing the SKU Rationalization funnel as described above, we observed results which meant removing roughly 10% SKUs from the portfolio, while impacting only 1% of the revenue. This is not considering that the removed SKUs will be replaced by better selling ones

SKU Rationalization Funnel



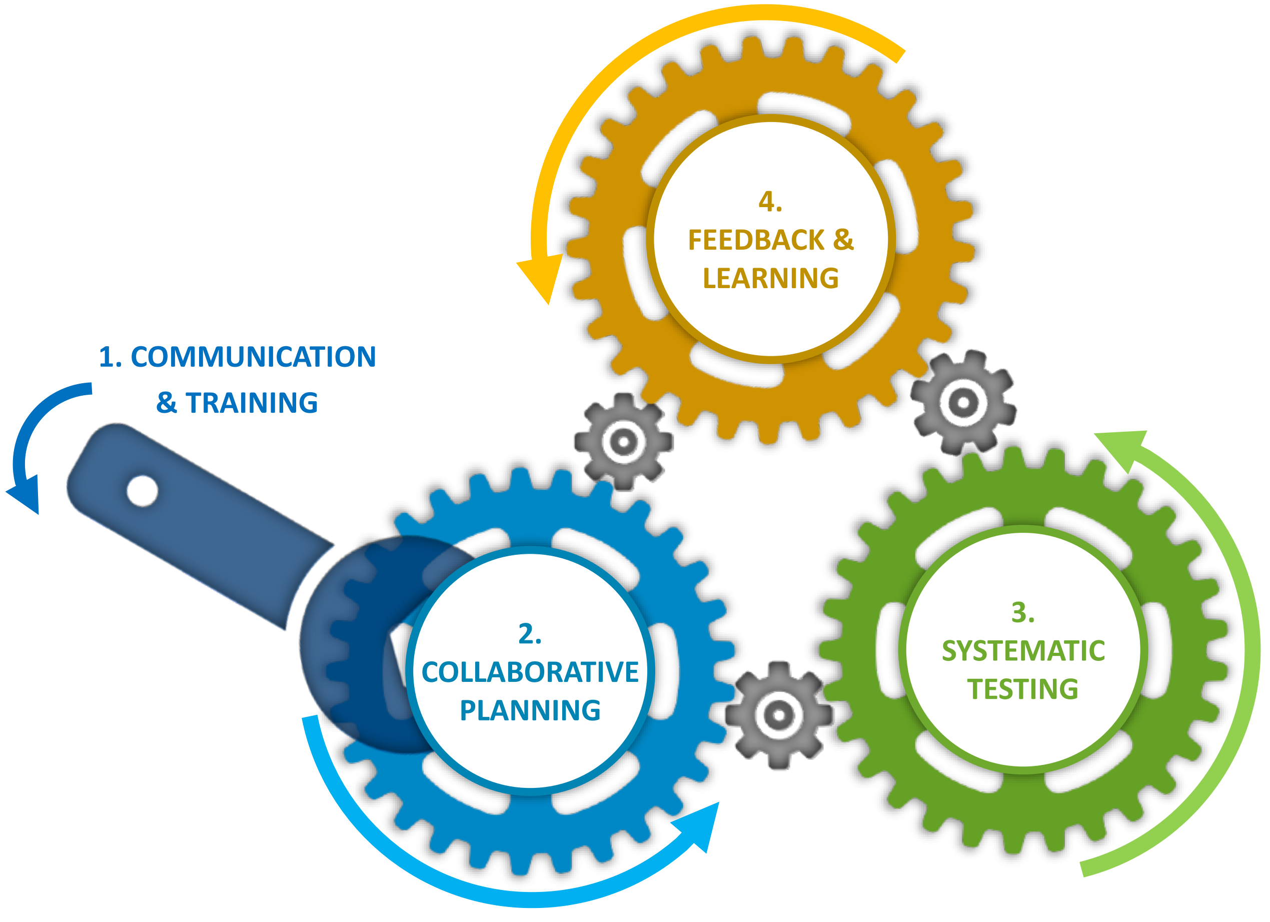
10% SKUs are removed, that contributed to 1% to the Overall $ Sales Value

4. Implementation



4. Implementation

Analytics-driven Decision Cycles



For any analytical information to have a transformational impact on business, it needs to be integrated into the business and implemented as the default process of making decisions. This is true for SKU rationalization as well.

System Integration and Implementation of the Assortment Mix Solution needs the buy-in and synergy of all stores and IT department. The solution provided should be easily understood and accessible, be flexible to account for market fluctuations, and should address concerns of various stakeholders where the solution trickles down to.

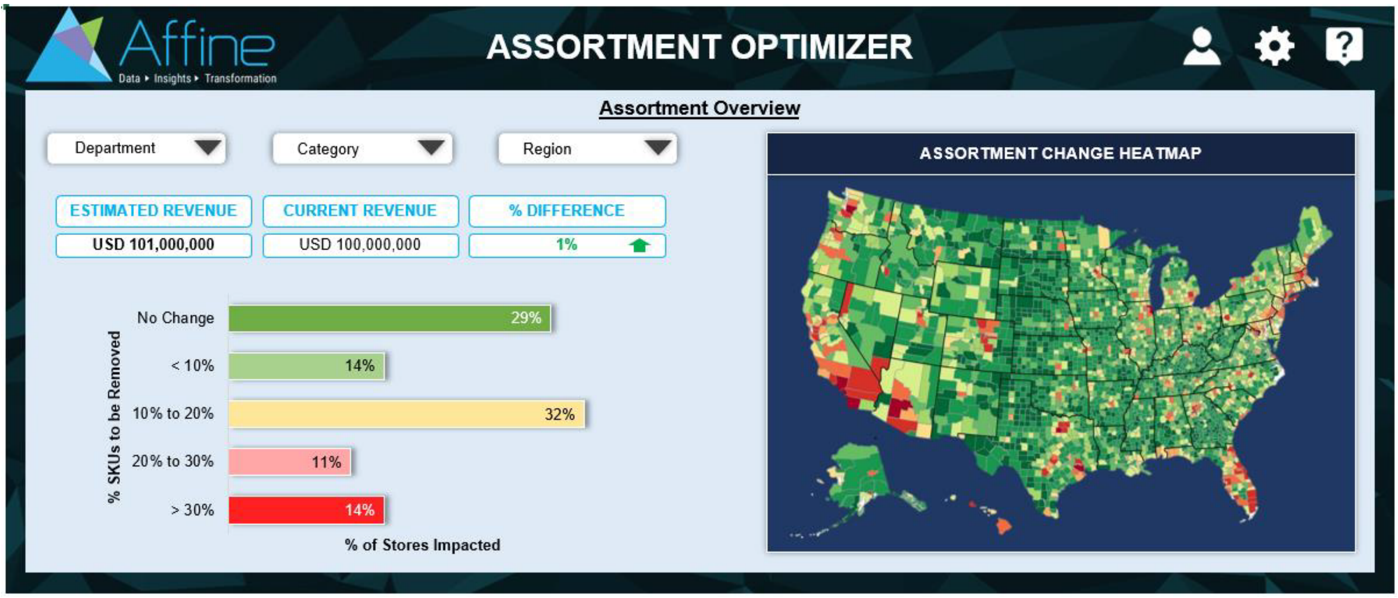
Any Analytical Solution serves the business best when the solution is collaboratively created, recommendations are systematically tested, and impact is scientifically measured and used to learn from in the next cycle. The business decision makers need to be trained on the process of training to carry out the analytics driven decision cycles.

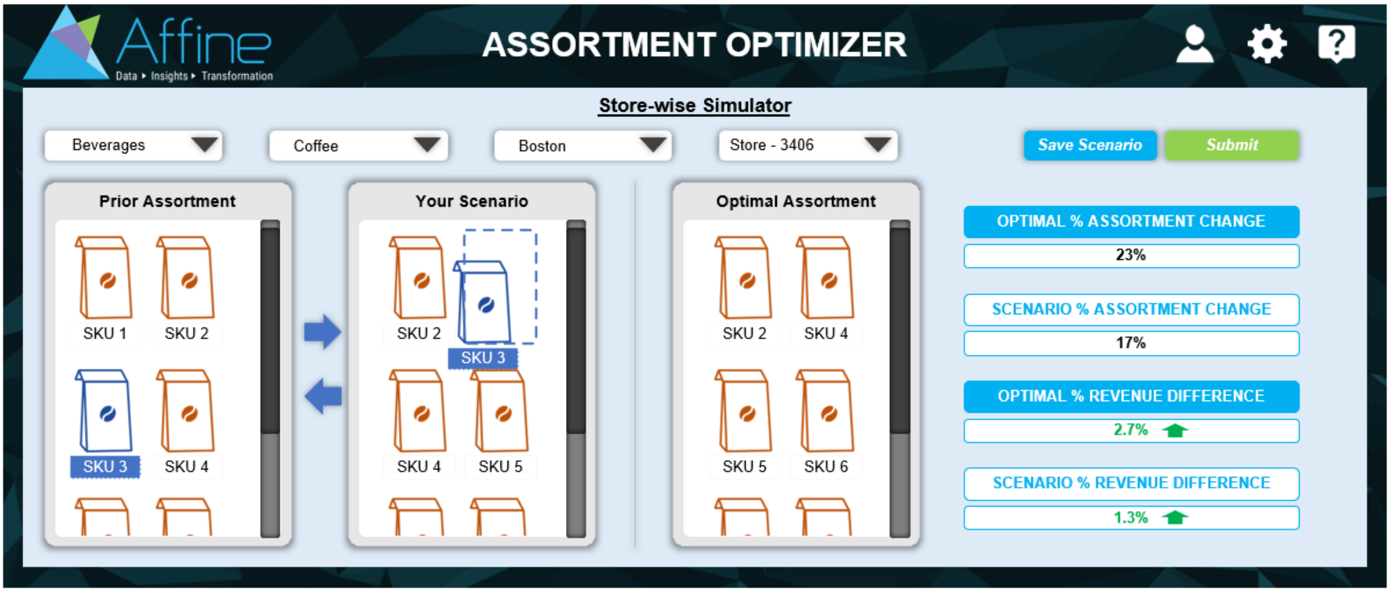
4.1. System Integration

Having an Integrated Analytics Solution means that Category Managers have the entire analysis at the tip of their fingers while being able to deploy the strategy directly into existing process.

To this end, we designed a web-based application as illustrated below. The application is designed so that the Category Manager and other stakeholders can easily collaborate, plan, simulate and apply the Assortment mix recommendation into the system for stores to follow.

Assortment Optimizer Web-based Application





4.2. Communication & Training

After developing the solution & the web app to implement assortment mix recommendations, we need to educate the retailer on how the entire solution works. The assortment mix tool needs multiple user roles like Admin, IT, Data Scientist, and most importantly Decision Makers. For the scope of this white paper, we will be talking about just the Decision Makers, usually the Category Managers.

Though, it is just the Category Manager that makes the decision on assortment mix, operationalizing the solution will require the buy-in from other business stakeholders and the store GMs. For business stake holders we recommend the following training regime:

- SKU Rationalization Concept Training and Results Interpretation for all stakeholders
- Assortment Optimization Tool Training for Decision Makers – Optimization, Simulation and Operationalizing

4.3. Collaborative Planning

The perpetual cycle of Analytics Driven Decision Making is kicked off by collaborative planning. Though the Category Manager is responsible for achieving Category Objectives, these goals are closely tied to the targets of store GMs and regional heads. The marketing and finance Departments need to support promotion of the new SKUs. Even the stand of external parties like manufacturers / distributors need to be considered before arriving at the optimal assortment mix.

The inputs from different stakeholders need to be fed into the web application as business rules so that the SKU rationalization funnel can handle exceptions and avoid failing regulations. Collaborative planning ensures fewer strategy rollbacks and conflicts of interest down the road.

4.4. Systematic Testing & Measurement

All assortment mixes should be considered tests. Their impact should be recorded, measured and studied. The returns from each strategy should become insights for both the business and the assortment optimization engine to learn and evolve. Continuous testing and learning will result in the analytics engine evolving to capture more details and deliver well-rounded insights & recommendations.

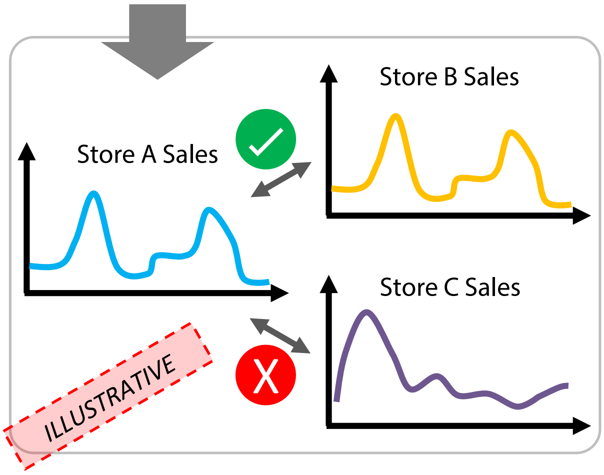
The scale of implementation determines the best format to test a strategy. For instance, if the solution is a pilot which has not been tested before, implement it for a few stores and compare performance to other similar stores. If the solution is applied at chain level, then comparing the sales for the test period to a different timeframe with similar seasonality and influencing factors would be the best approach

<u>Affine's Test & Control Store Selection Framework</u>

Ideal Test Store should have a profile resembling the entire chain. Ideal Control Store must not be a test store & must closely resemble the Test Store. Affine's Test & Control Store Selection utilize a Combination of Trend and Trait Matching to identify this resemblance.

Trend Matching

Sales / Volume patterns for the stores should be very similar to be considered a Match



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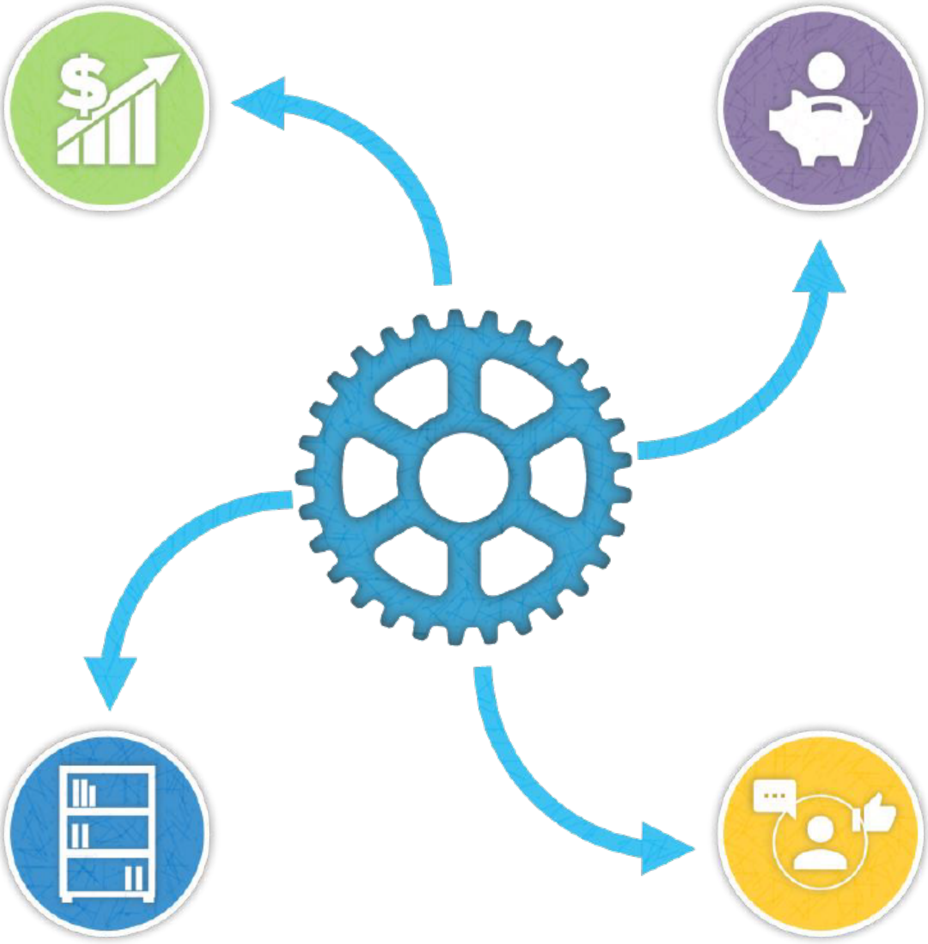
	Store A	Store B
Unemployment Rate	9.3%	9.25%
Median Income	$49,125	$48,750
% Caucasian	70.26%	72.35%
Competition (in 1 mile)	5	4

Traits for comparing stores are determined based on the Category for assortment mix, Category Objective, etc.

Traits Matching

5.5. Impact & Conclusion



5.1. Impact seen in Our Engagements

5% - 10%
Proven increase in Sales from space allocated to other SKUs

3% - 5%
In Operation Costs due to carrying fewer SKUs, due to less space & labor for stocking

Improved Customer Experience
Realized from CSAT surveys due to ease of finding things for customers

5.2. Conclusion

Category Managers at both brick & mortar and e-commerce retailers need to have an edge over competition. Affine's holistic integrated SKU Rationalization application is just the tool they need to optimize their assortment to reap the best rewards without losing customers. Equally critical to the holistic solution is the apt implementation of the solution.

Remember – For the SKU in your Portfolio "If it isn't a clear yes, then it's a clear no."