LatentView Analytics

Data Driven Intelligence to Identify High Net Worth Customers

October 2020

Harrods

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Agenda

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2 Solution Approach

2a Analyse & Understand Behavioral Patterns of High Net Worth Customers

2b Enhance Recommendations by Augmenting with External Data

2c Evaluate Performance using A/B Testing

3 Representative Case Studies

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Business Objective

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Business Objective

Business Objective:

Leverage analytics to identify Customers within Harrods database for whom assisted shopping intervention would be a success and lead to higher overall revenue.

Hypothesis:

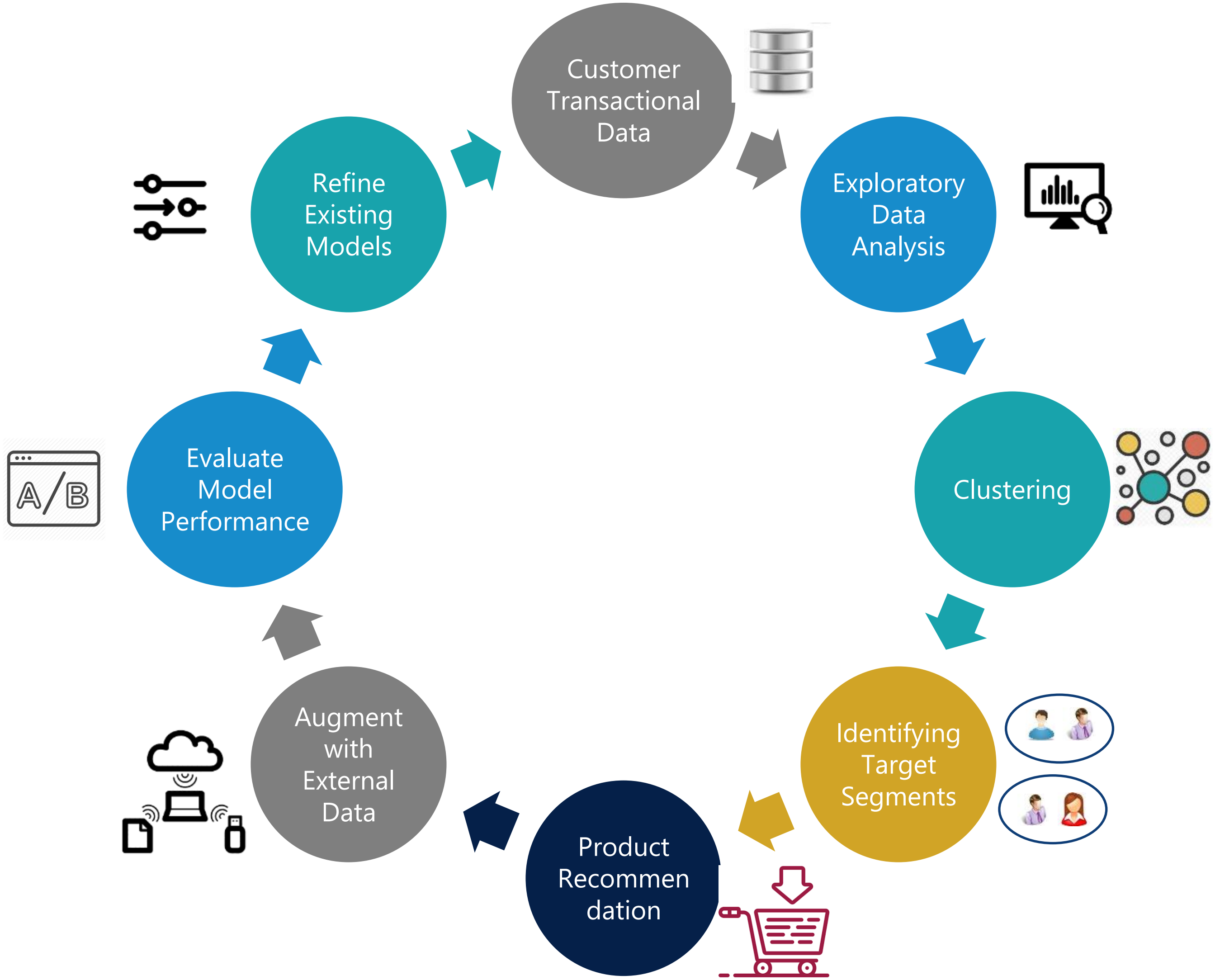
Customer data at Harrods can be mined to uncover patterns that signify wealth and propensity to higher spends. These patterns when uncovered can help identify the Customers who are of high value to Harrods.

This information can be further clubbed with other external and syndicated data to enhance model recommendations, thus providing avenues for hyper personalized experience to each of this individual Customer

Solution Approach

Data Mining Process Flow

The below illustration represents a typical Data mining Approach right from gathering Customer data to building model and fine tuning it based on performance



Solution Approach

Latentview recommends a three-step approach to fulfill Harrod's business objective

How to identify and engage High Net Worth Customers

1. Identify HNW Customers

Identify Customer groups or cluster and **build statistical models** for a market cluster combination

2. Enhance Recommendations

Augment the model results with **external and syndicated data** to enhance model recommendations

3. Evaluate performance

Run the analysis on a test market and **track the incremental benefits** through controlled experimentation (A/B tests)

Business Benefits:

- Understand Customer Characteristics, priorities & use it to drive cross sales for HNW customers using internal and external data
- Systematically develop data and analytics capabilities to improve personalization & enhance customer experience
- Achieve a more complete or unified view of the Customer in order to increase share of wallet for each customer
- Create relevant promotions & campaigns to help drive more sales volumes with HNW customers

Phase 1: Identify High Net Worth Customers

To determine the High Wealth Customers and their associated attributes and propensity to spend, we can apply algorithms to:

Mine key Customer behavioural patterns using exploratory data analysis & RFM techniques

Create cohorts of Customers through unsupervised / supervised learning & identify cohort characteristics

Build classification models to identify Customer behavioural patterns & propensity to buy

Exploratory Analysis

A Univariate, Bivariate & Multivariate analysis is done on the data to identify significant characteristics

Identify significant characteristics

Driver Analysis

RFM like techniques are used to identify features to understand spend, behavioral & purchase patterns which feeds as an input to form clusters

Identify key behavioral or spend drivers

Clustering

Create Customer cohorts / clusters based on identified spend patterns through rule-based approaches (or) clustering techniques like k-means

Identify homogenous customer segments

Feature Engineering

Engineer features identified from clusters to understand Customer behavioral patterns & propensity to spend

Input features to classification models

Identify Behavioral Patterns

Build classifiers & use techniques like market basket analysis using features extracted to understand customer behavioral patterns at a segment level

Identify Customer Behavioral Patterns

Propensity Model

Identify high net worth Customers & their potential lifetime value using propensity models

Identify HNW Customers & lifetime value

Exploratory Data Analysis

LatentView uses different analysis techniques detailed below to extract features for building propensity models:

Sample Data Snapshot

Customer Demographics
- House hold info
- Location
- Contact Details

Redemptions

Purchase History
- Frequency
- Transactions
- Monetary Value

Customer Location

Customer Household

Offers & Benefits

Partner Data

Customer Segments
- New
- Repeat
- Reactive

Customer Channel
- Online
- VIP
- In Store

Customer Activity

Analysis to understand Customer propensity to buy / cross sell

Customer Analysis
Analyze key patterns in data to determine customer characteristics using univariate, bivariate & multivariate analysis

Campaign Analysis
Campaign effectiveness can be studied and can help design better, productive & more desirable campaigns

Seasonal Analysis
Seasonal and timeline trends can be studied to understand the impact of holiday's and festivities on buying patterns

Geographical Analysis
Geographic information can assist in studying buying patterns across regions

Pricing Sensitivity Analysis
Understand customer sentiment with respect to pricing and discounts/offers on products

Customer Acquisition
Gain knowledge on the various sources of acquisition of members to understand the highly potential avenue

Market Basket Analysis
Understanding the baskets of specific individuals or groups. (Basket of a Single Mom/Teenager/Couple etc.)

Loyalty/Promotional data Analysis
Analyse segment level earns and avenues of redemptions to monitor the areas of interest

Channel Behaviour
Understand the behaviour of a customer across channels (In-store Vs Online, Members vs Non-Members)

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Exploratory Data Analysis – Methodology

Multivariate analysis is used to identify key patterns in the data which can act as features when we build the propensity model for the Customers. Hypothesis surrounding multivariate analysis can be relating to number of variables like: # of transactions, $ spent, gender, repeat vs one time buyer, member vs non member, time of purchase etc. Some sample illustrations are provided below:

Sample Hypothesis Validated

	Customer A ($ spends)	Customer B ($ spends)	Customer C ($ spends)	Customer D ($ spends)
Gucci	20k	2k	45k	-
Prada	45k	1k	-	30k
Local Brand 1	5k	7k	3k	-

Loyalty Customers who purchased only when wealth signifying brands

	Customer A (Festive $ spends)	Customer B (Festive $ spends)	Customer A (Yearly $ spends)	Customer B (Yearly $ spends)
Clothing	1k	5k	4k	20k
Jewelry	45k	2k	50k	8k
Food & Gift	2k	1k	8k	2k

Loyalty Customers, who are repeat buyers, only in festive seasons and only in specific categories

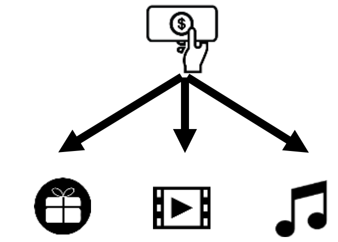
	Customer A ($ spends)	Customer B ($ spends)	Customer C ($ spends)	Customer D ($ spends)
Burberry Coat	1k	15k	1k	2k
Chloe Coat	1k	10k	1k	4k
Petit Coat	10k	-	1k	6k

Female Moms who are repeat customers and purchase baby products of specific wealth signifying brands

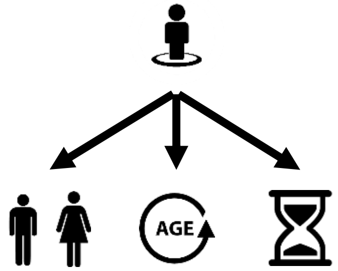
Clustering – Patterns to identify customers to conduct pilot tests

Understand key characteristics of the customer segments using Clustering approach

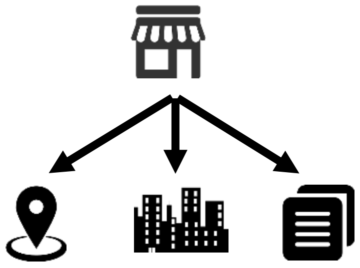
Data Collection



Transaction Data across each category

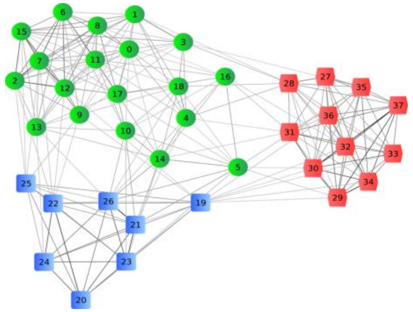


Customer Demographics data

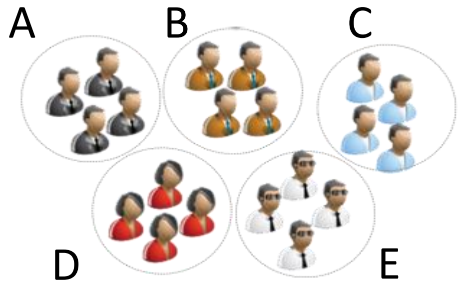


Store Demographics data

Clustering



Identify Characteristics of each cluster



Sample Cluster Characteristics

- Segment A – Loyalty customers with high propensity to buy
- Segment B – Festive shoppers with high festive season spends
- Segment C – Periodic Repeat customers via online channel
- Segment D – Customers who buy in specific outlets
- Segment E – Customers who buys fitness products

Deliverable 1: Drive Customer Propensity to buy providing right product recommendations

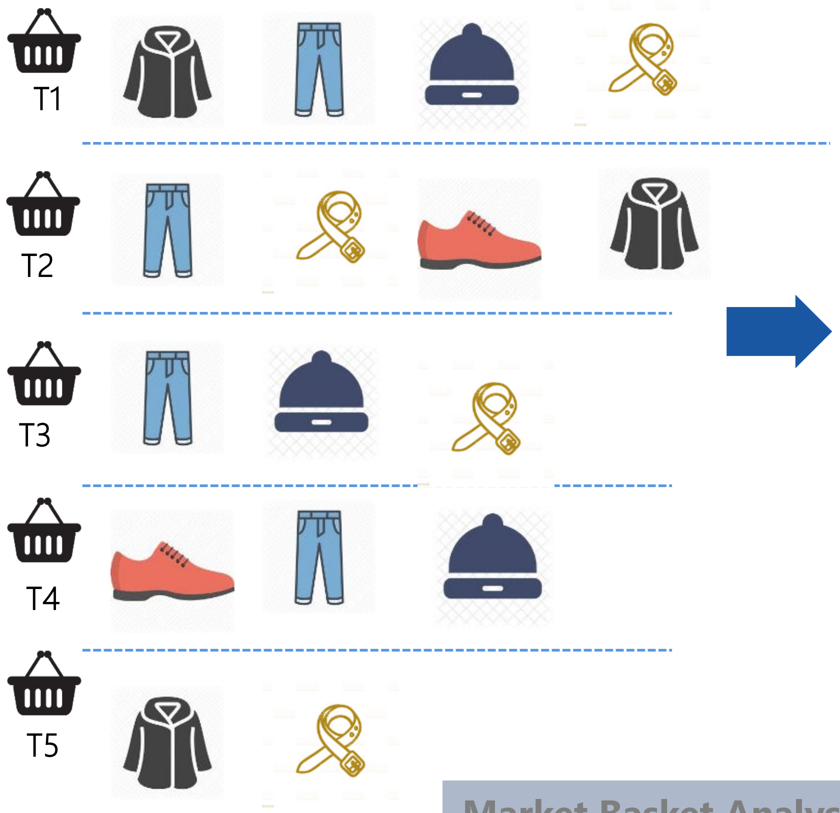
Assume segment X (**London Fashion Divas**), which contains female Harrod's loyalty Customers buying **leather coat & jeans**. Based on purchase patterns of customers in this segment, a marketing push to **cross sell beanie hats** is recommended

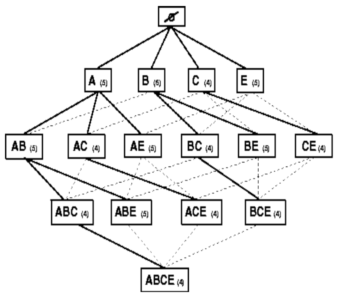
SEGMENT X (LONDON FASHION DIVAS)

TARGET Customer A -- Buys Leather Coat & Jeans

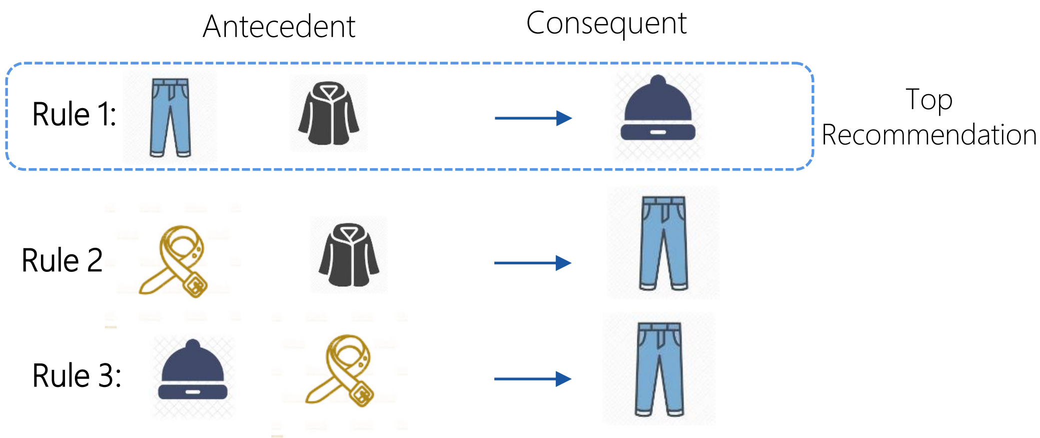
Transactions in a Segment

Items in basket





Use Apriori algorithm to generate set of products that are bought together



Top recommendations generated using Support, Confidence & Lift

Market Basket Analysis performed for all products bought by Customers in a segment. Select the product with highest likelihood to co-occur in the basket

Illustration: Product Recommendation across Customer segments

Assuming 4 Customer Segments, different products can be recommended to each of the Customers within these segments based on various factors such as Purchase pattern, Loyalty etc

London Fashion Divas

High interests in **Fashion & Style**

Items Bought Frequently :
- Chloe Belted Coat
- Burberry Scarf
- Gucci Shoulder Bag
- Gucci Belted Skirt

Items Recommended :
- Jeans
- Boots

New Moms

High interests in **Baby Products & Fitness**

Items Bought Frequently :
- Cybex Stroller
- Sleeping Bag
- Car Seat
- Outdoor Equipment

Items Recommended :
- Crib
- Car
- Yoga Mat

London Trekkers

High interests in **Adventure & Fitness**

Items Bought Frequently :
- Shoes
- Bag

Items Recommended :
- Tent
- Tools

Faithful Fiestas

High interests in **Festivals & Celebrations &** Loyalty Member

Items Bought Frequently :
- Champagne
- Christmas Trees

Items Recommended :
- Chocolate Hampers
- Glassware

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Deliverable 2: Projected Trade for HNW Customers using CLV modeling

Machine Learning based CLV models leverage and learn from customer data – their preferences, buying behavior etc. and predict with better precision compared with traditional CLV methods

	Churn Prediction	Sales Forecasting	CLV Calculation
Model Steps	Churn Prediction	Sales Forecasting	CLV Calculation
Model Description	Churn classification model using ML supervised algorithm such as Logistic Regression	Sales forecasting model based on historical data using ML supervised algorithm such as Linear Regression	Combining the results of previous two models and leveraging other important features to arrive at CLV metric
Illustrative Features Used	Demographic data, Geographic data, Psychographics data	Sales & Transactional data: Recency, Frequency, Monetary features	Outcome of two models and other attributes such as Profit Margin, Customer lifespan

Formulae

CLV = Function (Churn Prediction, Sales Forecasting, Profit Margin, Customer Lifespan)

Customer ID	Churn Propensity	Sales Forecast ('000 $)	Profit Margin	Potential CLV ('000 $)	Realized CLV ('000 $)	Pending CLV ('000 $)	CLV Category	Churn Classification
C1	48%	$41,16	10.45%	$224	$89	$134	Medium	Moderate
C2	80%	$15,70	15.76%	$49	$20	$30	Low	High
C3	41%	$26,04	29.40%	$452	$181	$271	High	Moderate
C4	35%	$35,70	6.30%	$146	$58	$88	Medium	Moderate
C5	46%	$22,18	12.65%	$152	$61	$91	Medium	Moderate
C6	12%	$19,70	18.50%	$321	$128	$192	High	Low

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Phase 2: Enhance Product recommendations using internal & external data

The modeling output can be further improved by enhancing the quality of data fed into the algorithm.
Phase 1: Leverage Internal Data
Phase 2: Augment with External Data

Phase 1

Leverage internal data

- Transactional Information
- Web Sessions
- Marketing Campaign data
- Agent Feedback Score(In store)

✓ Improved Cohort Performance
✓ Determine Customer LifeTime Value

ML / AI Services & Visualization

Phase 2

Augment with External data

- Partner Ecosystems (Credit Card, Brand, Real Estate)
- Demographic ,Economic ,Census Information
- Seasonality, Social Media

✓ Improved Modelling Accuracy
✓ Improved Customer Reach/Targeting

Potential External Data Sources

LatentView proposes to integrate a wide range of variables from variety of data sources listed below. These are indicative & prioritized in collaboration with Harrod's in the initial 2 weeks (discovery phase) based on **F**easibility, **A**pplicability, **C**omplexity & **C**ost.

Harrod 's Internal Data

Transactional:
- Sales information at channel, location, SKU granularity (daily, weekly, monthly timeframes)
- Product assortment

Web sessions:
- Web analytics – Visits, Sessions, Pages viewed etc.
- Website engagement information
- Panel data (if any)

Marketing Campaigns:
- Marketing campaigns / efforts (Instore, online)
- Promotions, offers, discounts, returns , seasonality

Agent Feedback (Store level):
- Agent feedback in store at a customer / product(if any)
- Product assortment feedback from agents

Syndicated Data

Partner Ecosystems:
- Credit card partnerships – Share of wallet
    - Purchasing power (Transactional)
    - Competitor purchase info (Transactional)
- Real estate / Property Data – Ex: Black Knight (US)
    - Housing units, Household size, type
- Brand Partnership – Procured from partner brands

Demographics:
- Nielsen / Acxiom – Customer Behaviour
    - Population, Median Age
    - Race distribution, Gender, Median wage etc.
    - Psychographic data

Seasonality Data – Weather:
- Temperature, Wind, Humidity, Precipitation, Cloud, Frost/dew/snow indicators

External Data

Economic Indicators:
- UK Data Service, World Bank etc
    - Macro Indicators – House prices, Oil prices etc.
    - # Business Establishments
    - Sales, Annual Payroll, # Employees on payroll
    - Stock indices

Census Data – Zip / Pin Code:
- Census bureau, - # Population, Age, Distribution
- #Households, # Average Households Size

Social Media:
- Customer's social profiles, handles, activity
- # Brand mentions

Location (GIS) Data:
- Customer neighborhood, #Events in Neighborhood

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Illustrations: Enhance Recommendations

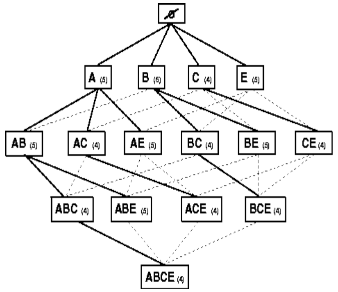
Augmenting data quality with external inputs will enhance recommendations provided by the model across categories & brands. An illustration can be seen below.

Internal Data

Transactions in a Segment

Items in basket

T1 C1



Top Recommendation

Antecedent

Consequent

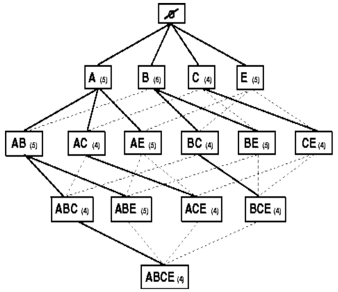
Rule 1:

Prada, Gucci

Illustration : Augment with Partner Data (Credit Card Spends)

Credit Card Transactions for Customer C1

	$ Spent	Brands Purchased	Discount offered
Harrods	10k	Prada, Gucci	5%
Farfetch	25k	Prada, Gucci	30%



Top Recommendation

New Recommendation

Antecedent

Consequent

Rule 1:

20% discount

Prada, Gucci

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Step 3: Evaluate performance using A/B testing

Model performance can be evaluated using A/B tests on product categories, stores / segments for the business to do live tests & see if each event does lead to higher trade in that segment (or) with that Customer.

Marketing

Share data with store executives

Campaign Planning

- Budget and Target Revenue
- Schedule of Campaigns
- Store identification
- Segment identification
- Category identification

Experiment Design

- Frequency & duration
- Channel(s) of contact
- Eligible population
- Offers / promotions

Target Identification

- Target User selection
- Control user selection

Execution

- Target customers through chosen channel
- Record offer and response data

Track Measurement

- Analyze campaign response rates and sales volume

Assess Model Performance through statistical testing

Refine Models based on Performance

# Sales	Pre-Campaign	Post Campaign
Target	A	B
Control	X	Y

Incremental Lift [B/Y] / [A/X] - 1

Incremental lift is calculated by comparing the ratio of Target : Control across the post campaign over pre campaign periods

Significance Testing

In Significance Testing, i.e. Hypothesis Testing, we try to develop an idea of our own or confront previously held beliefs about whether launched campaign was/was not significant to the output of the process.

Equivalence Testing

Equivalence tests assess whether there is a practical difference in means of Target and Control Group post-campaign.

Representative Case Studies

Identifying Potential Annual Members using Segmentation

Leading Home Appliances and Repair Services Provider

The Problem: Our client did not have a scientific way to target the trial members who have the characteristics of becoming the annual members

Business Objective

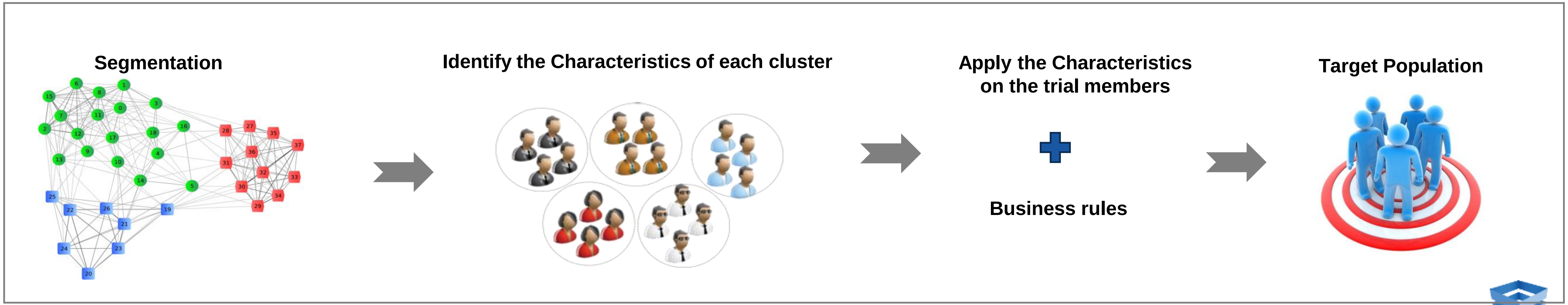
- To identify the trial members who have the more likelihood of taking the Annual Membership

LatentView Solution

- Understanding the transaction behaviour of Annual Members who were trial before taking up Annual Membership
- Segmentation of Trial and Annual Members on the basis of Transaction Behaviour
- Applying the Business Rules (e.g VIP, Savings amount and Recent order) and targeting with appropriate messaging

Business Benefits

- Segmentation of members leading to reduction of target trial members (55 K to 3 K)
- A better targeting strategy with reduction in Annual Membership price from $39 to $19



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Improving Customer Experience using Site Analytics

Leading American E-Commerce Retailer

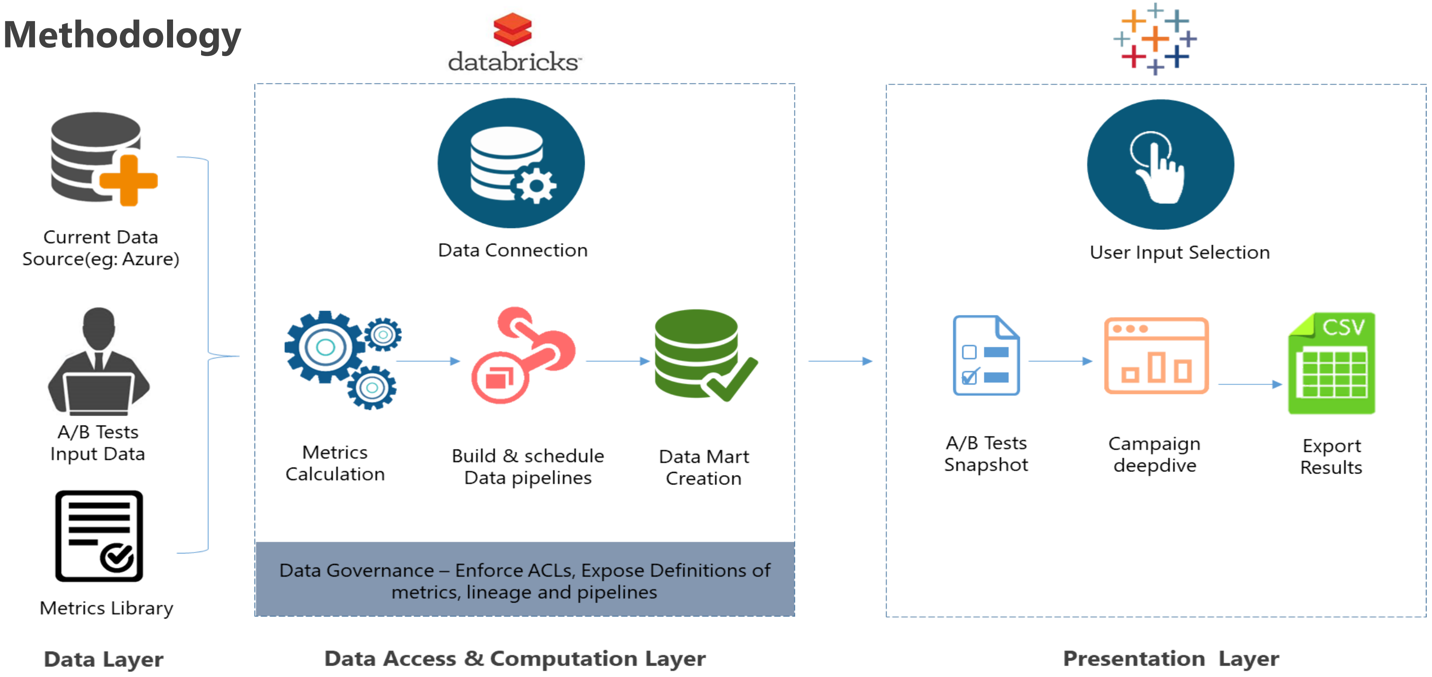
The Problem: Lack of a comprehensive measurement platform of site-wide A/B testing activities led to time consuming and manual efforts involved in tracking & improving customer experience

The "Before" State
- Client ran multiple A/B testing methods to determine the product positioning, placement, messaging, color of various web elements.
- There was no single platform to keep a tab on all the experiments. As a result, each business unit had their own resources to track their testing measurements.

LatentView Solution
- Built a one stop visualization platform to track and measure the site-wide A/B testing experiments using Tableau.
- Derived useful business metrics such as Lift %, Lift Trends calculation across all the dimensions such as OS, Browser, Marketing channels etc.

The "After" State
- Centralized all A/B testing experiments at scale and reduced manual tracking efforts.
- Applied Bayesian approach to call out early variant winners with 60% improvement.
- Deployed the A/B testing measurement platform to the executive team to classify the experiments as positive, neutral and negative.

Methodology



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Maximize Business Value using Optimization and Personalization

US Based Retail Corporation

The Problem: Identify the right communication to be placed at the right slot on the right channel for a given customer/customer segment that maximizes both the marketing and merchandising goals

The "Before" State

Offers on the web page and email based on ad-hoc customer segmentation and random placement of the same on the web-page/email.

Challenges

- Millions of customers across segments
- 100s of webpages & 100s of Email Layouts
- 1.7M+ SKUs with 1K+ Offers every week
- Each BU with different objective to maximize
- Experimentation set up not consistent with the goal

LatentView Solution

- Identify key-metric by BU to maximize by customer segment
- Unified segmentation logic that is consistent across Bus
- Optimization algorithm that recommends the right offer by slots factoring in the business rules to maximize the chosen metric by BU
- Continuous experimentation to evaluate the efficacy and improve from feedback

Universal set of marketing and merchandising offers

Estimate

Choose the top offers with the highest:

- Propensity to click
- Purchase conversion
- Value generated

Optimize

Display offers to:

- Maximize propensity to click/convert by customer
- Based on Page / email composition constraints
- Business rules

Experiment

- Test new offers, creatives, layouts
- Evaluate impact of optimization
- Analyze and refine

DYNAMIC PERSONALIZED OFFERS

Evaluate performance using A/B testing

50+A/B Testing Experts

15+ A/B Testing Projects

Across 5 Industries

1500+ Person Hours

Client	Business Objective	Platform/Technology Used	LatentView's Involvement
Largest Payment gateway	Improve Customer and Merchant account acquisitions and engagement on the website	• PXP/ELMO • Tealeaf	Involved in end to end experimentation life cycle management involving ideation, design, execution, analytics and feedback for future experiments.
Leading Airlines company	To optimize the web page design by understanding user behavior patterns in order to improve user engagement	• Google Analytics • Spotfire • Google BigQuery	Started in 2013. Since then Latentview is continuously provided support by giving insights on the A/B testing using an analytical approach
Leading baby food nutirition company	To decrease enrolment form drop-off by experimenting with the number of fields on the registration form.	• Google Analytics • Optimizely	Generated insights on both the original and variant designs. The experiment outcome led to a higher conversion rate for the business.

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Thank You

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