Customer propensity to purchase

Customer propensity to purchase refers to the likelihood or probability of a customer making a purchase. It is a vital metric in marketing and sales strategies, aiming to predict consumer behaviour.

Types of Customer Propensity:

a. Behavioural Propensity: Based on past actions and purchasing behaviour.
b. Predictive Propensity: Utilizes data analysis and predictive modelling to forecast future purchases.
c. Attitudinal Propensity: Focuses on customer attitudes, opinions, and preferences toward products or brands.
d. Demographic Propensity: Considers factors like age, gender, income, etc., in predicting purchasing behaviour.
e. Contextual Propensity: Takes into account situational factors influencing purchase decisions.

Factors Influencing Customer Propensity:

a. Historical Purchase Data: Previous buying patterns and frequency.
b. Customer Interactions: Engagement through various touchpoints like social media, emails, or customer service.
c. Market Trends: External factors affecting consumer behaviour.
d. Psychographic Information: Lifestyle, values, interests affecting purchase decisions.
e. Technological Advancements: AI, machine learning used in predictive analytics.

Methods for Analysing Customer Propensity:

a. Data Mining: Extracting patterns from large datasets to predict future behaviour.
b. Machine Learning Algorithms: Utilizing algorithms to predict buying patterns based on historical data.
c. Customer Surveys: Gathering direct feedback to understand preferences and buying intentions.
d. Segmentation Analysis: Grouping customers based on similarities to predict behaviour within segments.

Use Cases and Applications:

a. Targeted Marketing: Tailoring campaigns to specific customer segments likely to make purchases.
b. Customer Retention: Identifying at-risk customers to prevent churn.
c. Product Recommendations: Suggesting products based on predicted preferences.
d. Inventory Management: Forecasting demand to optimize stock levels.

Using Machine Learning to Predict Customers' Next Purchase Day

1. **Data Collection, Preparation, and Wrangling:**
   - Gather historical transactional data including purchase dates, customer IDs, and item bought. Clean and pre-process the data, ensuring consistency and removing anomalies.

2. **Feature Engineering:**
   - Use RFM segmentation method:
     - Recency (time since last purchase)
     - Frequency (number of purchases)
     - Monetary value/revenue (total spend)
   - Additional features might include seasonality, average purchase interval, or customer demographics.

3. **Selecting and building a Machine Learning model (followed by model evaluation):**
   - Choose a suitable machine-learning model:
     - Regression Models: Predict the number of days until the next purchase.
     - Survival Analysis: Model time until the next purchase event.
     - Recurrent Neural Networks (RNNs) or LSTM: Handle sequential data for time-based predictions.

4. **Prediction and Implementation:**
   - Use the trained model to predict the next purchase day for customers in real-time.
   - Integrate these predictions into business strategies for targeted marketing campaigns, personalized recommendations, or inventory management.

5. **Continuous Improvement:**
   - Refine the model based on new data and evolving customer behaviour.

Determine a propensity score using a machine-learning-generated predictive model

Propensity score refers to the probability of an individual unit (like a person, a business, etc.) being exposed to a particular treatment or intervention given a set of observed covariates (predictor variables). It is commonly used in observational studies, especially when attempting to estimate causal effects.

Purpose:

It helps balance and reduce bias when comparing treatment effects in observational studies, particularly in situations where random assignment to treatment groups is not feasible (unlike in randomized controlled trials).

Calculation:

The propensity score is derived from a logistic regression model predicting the probability of receiving a treatment based on a set of observed covariates or predictors.

Usage:

Once the propensity scores are calculated for each individual in the study, researchers can use various methods to match or control for these scores. Common methods include matching individuals with similar propensity scores (propensity score matching), stratifying by propensity score, or using the propensity score as a covariate in subsequent analyses.

Benefits:

Reduces selection bias by creating more comparable treatment and control groups, which makes it easier to estimate the treatment effect accurately. Helps in addressing confounding variables, increasing the validity of observational studies.

Limitations:

Requires assumptions (like no unmeasured confounding) for accurate estimation. The quality of propensity score analysis heavily depends on the quality and relevance of the covariates used in the model.

Propensity Score Estimation Methods:

a. Logistic Regression: Predicts the probability of treatment assignment based on observed covariates.
b. Probit Model: Similar to logistic regression, but uses a different functional form to estimate propensity scores.
c. Machine Learning Algorithms: Techniques like decision trees, random forests, or gradient boosting to estimate propensity scores when dealing with complex data patterns.

Propensity Score Adjustment Methods:

a. Propensity Score Matching: Matches treated and control units with similar propensity scores, creating comparable groups.

b. Stratification: Divides the dataset into strata based on propensity scores, reducing bias within each stratum.
c. Inverse Probability Weighting (IPW): Assigns weights to each observation based on the inverse of its propensity score, balancing treated and untreated groups.

Sensitivity Analysis:

a. Rosenbaum Bounds: Examines the potential impact of unmeasured confounding on estimated treatment effects.
b. Multivariate Sensitivity Analysis: Evaluates the robustness of results to various assumptions and potential biases.

Extensions and Advanced Methods:

a. Propensity Score Calibration: Adjusts estimated propensity scores to better match the observed proportion of treated and untreated units.
b. Covariate Balancing Propensity Score (CBPS): Estimates propensity scores while simultaneously optimizing balance across covariates.
c. Bayesian Propensity Score Methods: Incorporates Bayesian frameworks in propensity score estimation and adjustment.

Matched Sampling Techniques:

a. Nearest Neighbour Matching: Matches treated and control units with the closest propensity scores.
b. Kernel Matching: Assigns weights to observations based on the similarity of their propensity scores.
c. Mahalanobis Distance Matching: Matches based on a measure of distance accounting for covariance among covariates.

Example of a machine learning predictive model used to determine propensity score:

https://experienceleague.adobe.com/docs/experience-platform/query/use-cases/propensity-score.html?lang=en#:~:text=A%20target%20column%20must%20be,indicator%20of%20a%20customer%20purchase

Use Cases

Personalization goes a long way when it comes to customer engagement, company growth, and brand loyalty. Different businesses, especially those using the subscription model, try to tailor the right services and/or products to the right people to gain the most value. Although the path of personalization is often rocky, propensity modelling is one of the ways to make it smoother. Here are a few real-life examples of how propensity modelling is used.

Barack Obama re-election campaign: Voters segmentation

During Barack Obama's 2012 re-election campaign, a team of data scientists was hired to build propensity-to-convert models. The task was to predict which undecided voters could be encouraged to vote for democrats and which type of political campaign contact such as a door knock, call, flyer, etc., would work best for each voter. The use of Big Data predictive analytics contributed to the Obama re-election win.

US flower delivery company: Enabling faster and greater ROI

As a company operating in the floral industry, The Bouqs. Co needs to master demand forecasting to perform well despite seasonality. The company invested in the development of event propensity models that relied on data about customers using its subscription and special events scheduling services. As a result, the company managed to pinpoint the most valuable audiences and provided them with personalized offers to drive greater ROI.

Scandinavian Airlines: Personalized communication with customers

Scandinavian Airlines (SAS) leverages machine learning and predictive analytics to calculate a customer’s propensity to book a flight ticket. Armed with this data, they can provide timely offers for customers who are more willing to buy a flight and avoid having empty seats.

Vodafone: Customer churn risks identification

Vodafone is the second-largest mobile operator in Ukraine providing services to more than 23 million users. The company was looking for a way to reduce customer churn rate and improve their targeting with a final goal to outpace their top competitor. The company called on SAS Customer Intelligence, which leverages artificial intelligence opportunities, to build more accurate propensity models and make better decisions. With the help of outputs provided by ML-powered propensity modelling, marketers at Vodafone Ukraine managed to form accurate customer segments and determine which products perfectly match the next-best offers. The strategy resulted in the 30 percent customer churn reduction, increasing incremental revenue by 2 percent.

Case Study: Acxiom

Acxiom is a customer intelligence company that offers data-driven insights to marketers for personalized advertising campaigns.

Acxiom's journey in building a scalable machine learning infrastructure using Amazon SageMaker is an intricate saga of evolution, challenges, and triumphs. Their transition from an on-premise setup to a Cloud-based architecture was fueled by the need to handle an immense workload of building and scoring 5,000 audience propensity models, generating a staggering 3 trillion inferences. This shift aimed to address challenges of capacity limitations, prolonged processing times, and impeded critical business activities due to resource constraints.

The core challenges with the on-premise setup were manifold. The infrastructure was confined by hardware limitations, leading to extended processing times of 11 to 15 days, hindering timely delivery of fresh data to clients. As the models were re-scored monthly, the Hadoop cluster's shared nature and full capacity operation caused constant disruptions to other crucial business activities. Moreover, the spike in resource demand during the scoring process required either a substantial increase in on-premise hardware capacity or a shift to a more scalable cloud-based solution.

Acxiom's solution involved stringent criteria for their Cloud-based platform. They aimed to score all 5,000 models within a day, seeking seamlessness, high reliability (>99%), and an automated platform for end-to-end machine learning processes. Their evaluation led them to Amazon SageMaker due to its robust ML workflows, scalability, security features, and pay-as-you-go model, eliminating licensing constraints.

The process begins with robust feature engineering, a pivotal step in constructing informative features from raw data. Acxiom employs meticulous data balancing techniques, addressing imbalanced data classes, followed by feature selection and hyperparameter optimization. These steps are crucial for refining models and ensuring their accuracy and relevance. Leveraging tools like TensorFlow, SKLM, and SAS, Acxiom fine-tunes its models, optimizing their predictive capabilities to decipher audience behaviour.

Their initial version, DaVinci v1.0, comprised separate training and inference pipelines. The training pipeline incorporated feature engineering, data balancing, model building, hyperparameter optimization, and model evaluation. However, the inference pipeline encountered various challenges during full load tests. Excessive IO operations, writing large volumes of intermediate data, and throttling issues significantly affected performance.

Learning from these challenges, they redesigned their pipeline for DaVinci v2.0, addressing fundamental issues. They partitioned S3 prefixes, diversified instances, implemented job control layers, and optimized payload and concurrency. They transitioned from SageMaker batch transform to SageMaker processing to manage processing, inferencing, and post-processing more efficiently. Though this transition necessitated adjustments to containers, it substantially enhanced reliability and performance.

The performance improvements from DaVinci v1.0 to v2.0 were impressive: a 73% reduction in inference time, 60% cost reduction, 98% decrease in S3 API requests, and a 25% boost in CPU utilization. These enhancements enabled the processing of trillions of inferences within the SLA, marking a significant success.

Key takeaways from their journey include conducting proof of concepts for multiple design patterns, leveraging AWS services through thorough testing, engaging AWS well-architected review sessions to validate designs, considering account-level service quotas, implementing job control layers, and testing at full scale in the development phase.

Acxiom's transition from a constrained on-premise setup to a fully scalable Cloud-based infrastructure illustrates the intricate and demanding nature of managing large-scale machine learning pipelines. Their journey underscores the iterative nature of problem solving in complex systems, emphasizing the criticality of optimizing processes, leveraging appropriate technologies, and iteratively refining solutions to achieve optimal performance and scalability.

1. **Tools and Technologies:**
    - DaVinci Platform
    - Amazon SageMaker
    - AWS Glue
    - Airflow
    - TensorFlow
    - SKLM
    - SAS
    - TLS 1.2 encryption
    - AWS Batch Transform
    - SageMaker Processing

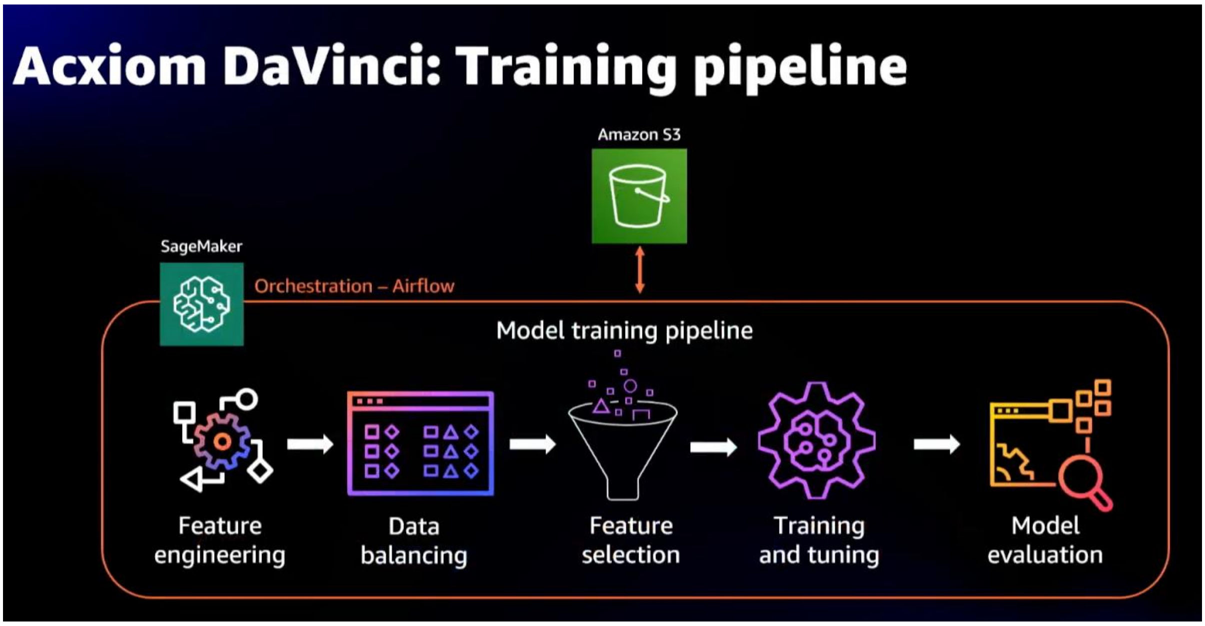
2. **Statistical Numbers and Improvements (DaVinci 1.0 to 2.0):**
    - Inference time reduction: 73%
    - Cost reduction: 60%
    - S3 requests reduction: 98%
    - CPU utilization boost: 25%

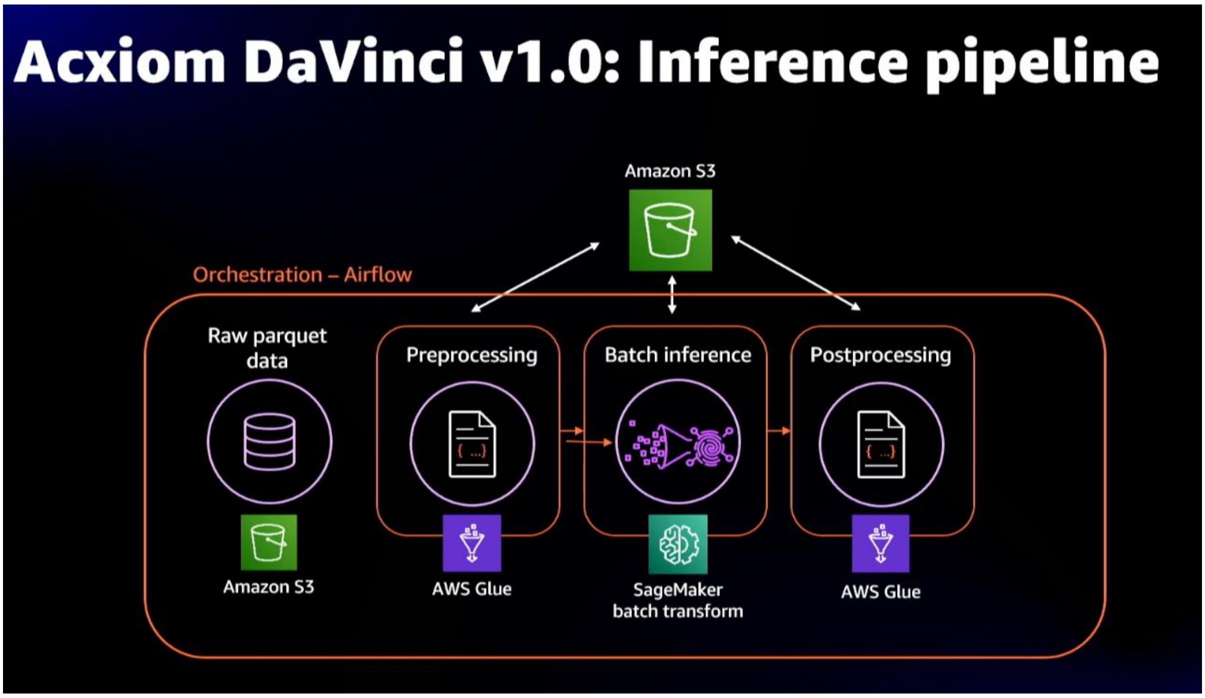
3. **Processes and Techniques:**
    - Feature Engineering
    - Data Balancing Techniques
    - Feature Selection
    - Hyperparameter Optimization
    - Secure Data Transit Strategies
    - S3 Prefixing for Throughput Optimization
    - Memory Management
    - Instance Diversity Optimization
    - Payload Optimization
    - Job Control Layer Implementation
    - AWS Service Quotas Management

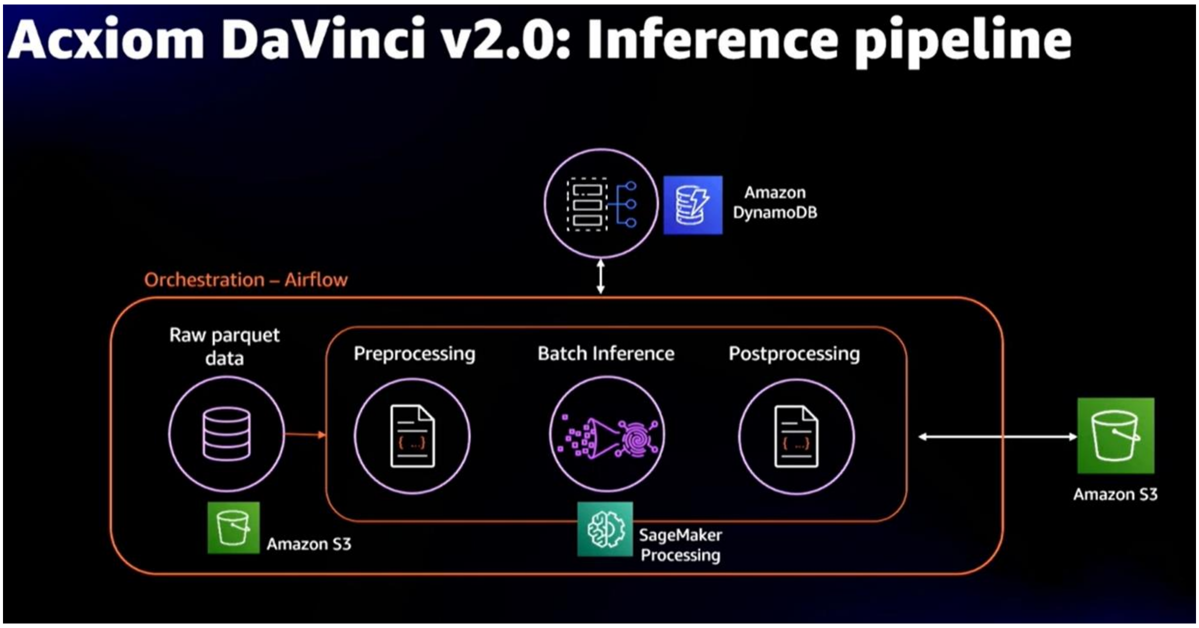
4. **Business Use Case Examples:**

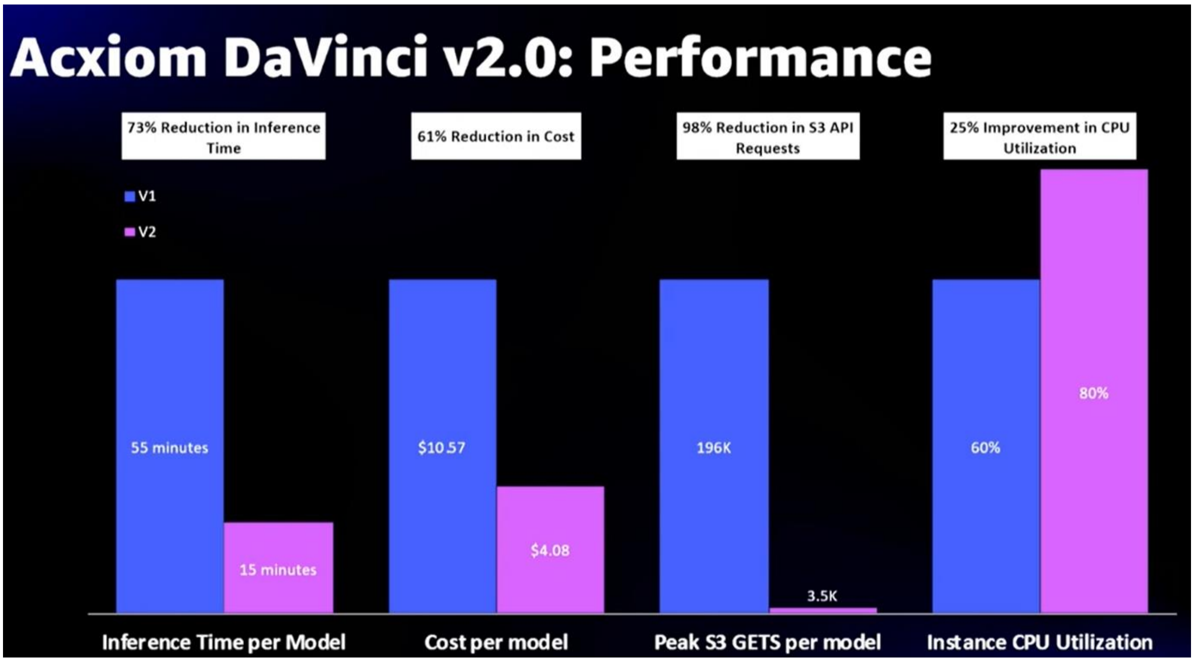
- Audience Propensity Analysis
- Predictive Modeling for Marketing Strategies
- To identify brand affinity
- To identify preferred products
- To measure campaign performance

Use of Machine Learning in Acxiom DaVinci models, training and inference pipelines:






Acxiom DaVinci v2.0: Inference pipeline
Amazon DynamoDB
Orchestration – Airflow
Raw parquet data
Preprocessing
Batch Inference
Postprocessing
Amazon S3
SageMaker Processing
Amazon S3


Acxiom DaVinci v2.0: Performance
73% Reduction in Inference Time
61% Reduction in Cost
98% Reduction in S3 API Requests
25% Improvement in CPU Utilization
V1
V2
55 minutes
15 minutes
$10.57
$4.08
196K
3.5K
60%
80%
Inference Time per Model
Cost per model
Peak S3 GETS per model
Instance CPU Utilization