Machine Learning & Predictive Analytics Report

Adventure Work

Objective: Add Predictive Intelligence to Analytics

The Machine Learning phasemovedour analytics capability from descriptive reporting to forward-looking decision intelligence. Primaryobjectivesincluded: forecastingrevenue,predictingcustomerchurn, and identifying products with high return risk. These initiatives were selected to directly improve financial planning, customer retention, and margin protection.

Across the program we prioritized interpretable models, measurable business KPIs, and operationalizable outputs (probabilities, scores, and actionable feature insights). The result: analytics that inform decisions rather than only explain past performance.

Revenue Forecasting Model

Model & Data

Model: **LinearRegression**.Datapreparation aggregated historical revenue to a monthly cadence (Year, Month → Revenue). The model used temporal predictors (year and month) to capture trend and seasonality while remaining interpretable for finance partners.

Evaluation

Primary metric: **MAE (Mean Absolute Error)**. The model captured seasonality and delivered stable month-ahead accuracy for planning.

Business Value

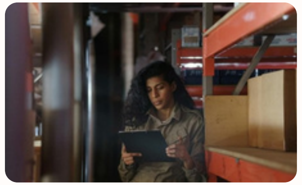
Enablesbudgeting, inventory readiness for peak months, and reduction of forecasting uncertainty—improving capital allocation.

Revenue Trend Analysis

Visualizationof monthly revenue revealedearly-yeargrowth, mid-period fluctuations, and consistent seasonal demand windows. These patterns guided the selection of month-based features for forecasting and informed marketing and inventory timing.

Peak Windows

Identified predictable high-demand months to prioritize promotions and inventory replenishment.



Mid-Period Fluctuations

Irregular dips highlighted distribution and supply vulnerabilities to address for smoother fulfillment.

Customer Churn Prediction

Model: **Random Forest Classifier**. Churn was defined as RecencyDays > 90. Features: total revenue per customer, order quantity, and recency. Outputs included churn probability scores, a classification report, and feature importance rankings for stakeholder review.

The classifier produced probabilistic outputs enabling prioritized outreach and budgeted retention interventions rather than binary yes/no lists.

Churn Model Insights

Key Drivers

RecencyDays is the strongest predictor. Low-revenue and low-frequency customers show elevated churn probability—clear segments for targeted programs.

Business Impact

Early identification of at-risk customers enables targeted campaigns, improving Customer Lifetime Value and reducing revenue leakage from avoidable churn.

Prioritize interventions for customers with high-probability scores and moderate revenue first—highest ROI.

Customer Behavior Visualization

Visual analytics complemented the churn model: churn distribution counts, revenue vs. recency scatter plots, and segmentation to flag high-value but high-risk customers. These visuals made model outputs actionable for marketing and CRM teams.

Segmentation

Clear separation of loyal, at-risk, and churned cohorts for prioritization.

Prioritization

Targeted retention budgets focused on customers with high revenue and elevated churn probability.

High Return Risk Product Identification

Return risk logic flagged SKUs with negative profit contribution as high risk. This rule-based approach was complemented by exploratory checks for quality issues, seasonality of returns, and abnormal return rates by vendor.

Business Meaning

- Detects margin-eroding products
- Signals pricing or quality issues
- Feeds procurement and product-quality teams

Operational Actions

Recommend immediate review of flagged SKUs, temporary delisting, or vendor remediation to stop repeated losses.

Top Customer & Category Analysis

We produced rankedlists of toprevenue-generatingcustomers anda category-wise revenue & profit breakdown. This analysis identifies where marketing and account management should concentrate efforts and where product investments will likely yield the strongest returns.

Top Customers

High-touch engagement plans for top accounts to secure renewals and upsells.

Category Performance

Shift investment toward high-margin categories and rationalize low-margin assortments.

Predictive Examples Implemented

Implemented practical examples: month-ahead revenue forecasts (including a 2018 Q1 sample), churn probability for incoming customers, and risk scores for products. These examples validated the models end-to-end and demonstrated deployment-ready outputs for downstream systems (CRM, ERP, planning).

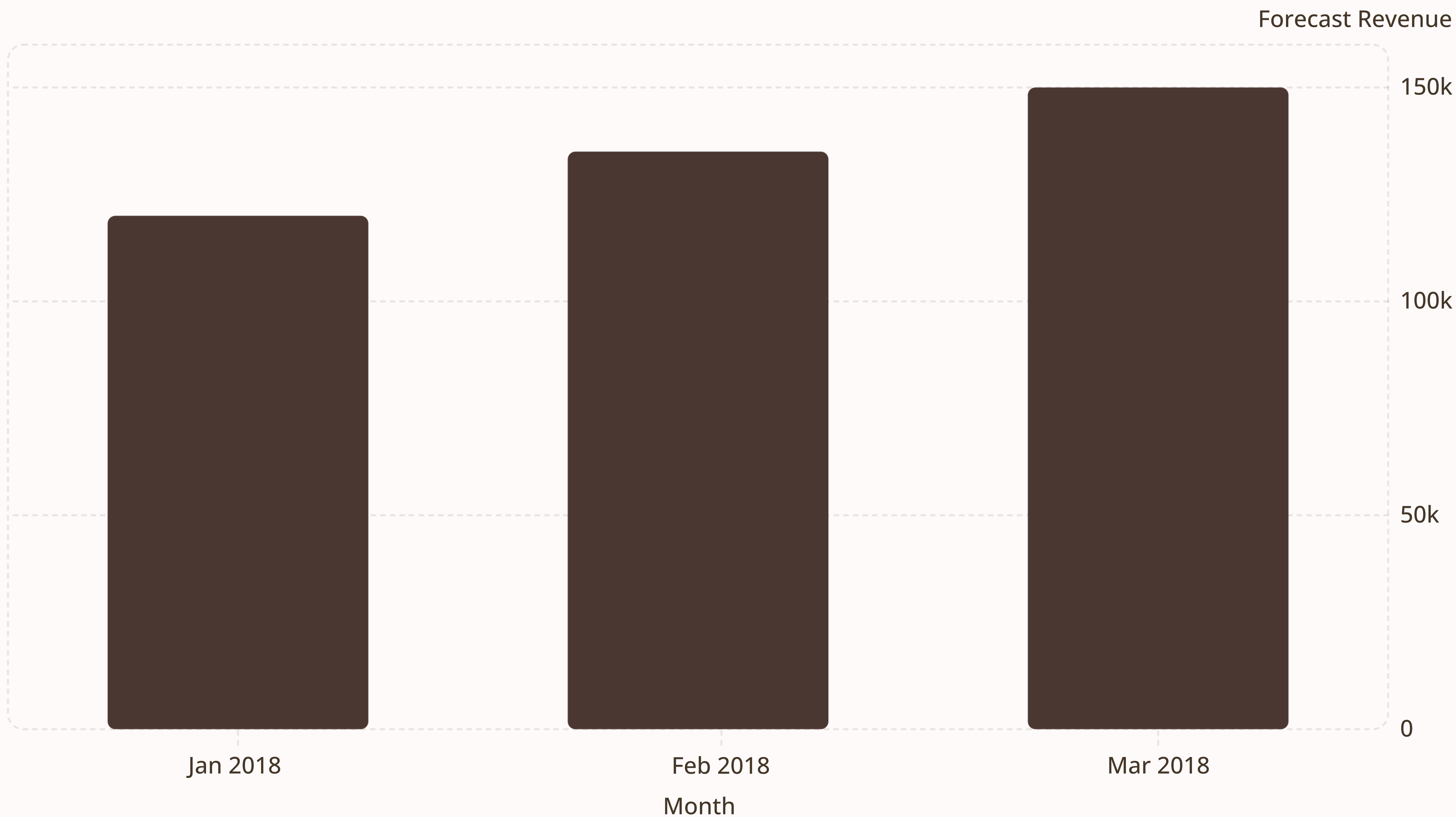


Chart: sample month-level forecasts used in financial planning exercises.

Overall Predictive Transformation

Integrating machine learning produced tangible strategic benefits: improved revenue forecasting for better financial planning, probabilistic churn predictions enabling prioritized retention, and return-risk detection protecting margins. Combined customer and category intelligence supports smarter capital allocation and marketing focus.

Next Steps

- Operationalize scores into CRM and planning systems
- Establish monitoring & retraining cadence
- Run controlled retention experiments to measure lift

KPIs to Track

- MAE for forecast accuracy
- Churn lift and retention ROI
- Reduction in loss from flagged SKUs

Color palette applied for emphasis: #835E54 (primary), #C9907C, #B3BDB5. Recommend executive review to prioritize operational deployment.