Customer Churn in retail chain

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Scope of the Presentation

1) Understand Customer Churn
2) Need of Data Driven Approach for Tackling Customer Churn
3) Role of Machine Learning in Reducing Customer Churn
4) Machine Learning canvas for Retail Customer Churn
5) Costs and Considerations
6) Conclusion

Understanding Churn

- Percentage of lost customers compared to the total number of customers during that period.
- Customer Churn Rate = (churned customers / total customers at the start of period) x 100
- Revenue Churn Rate = (churned revenue / total revenue at start of period) x 100
- Example: Let’s say we have two worth $500, two worth $400, two worth $300, two worth $200, and two worth $100 that sum up to $3000

Customer Churn in Retail: Need of Data-Driven Approach

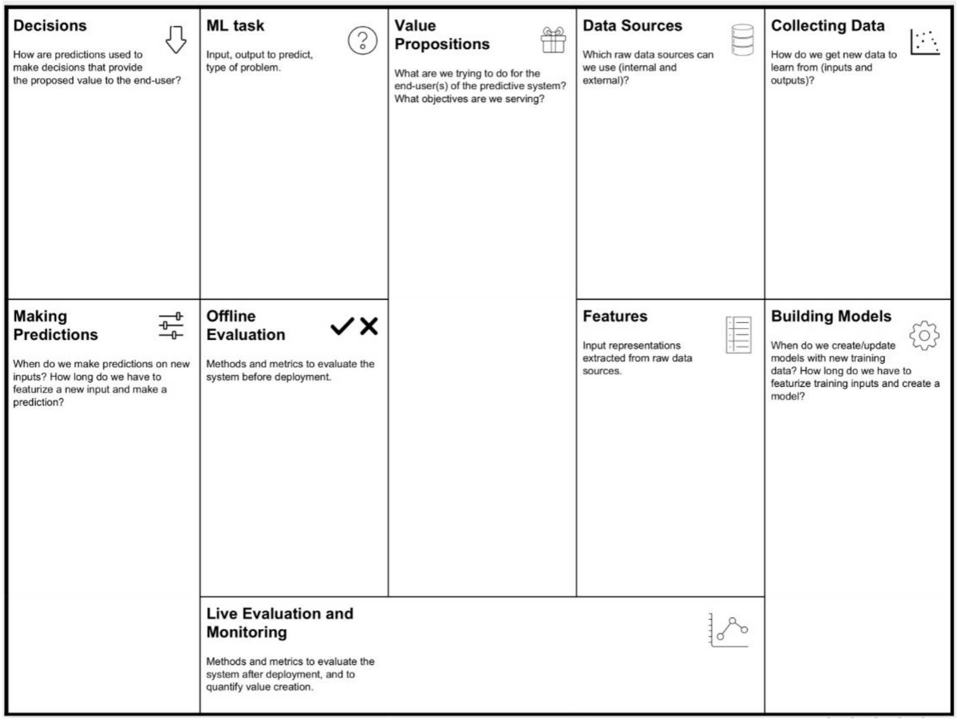
- Customer churn, the loss of customers to competitors, is a critical challenge in the retail industry.
- According to (Zarema P), Companies lose $1.6 trillion due to customer churn.
- Retaining existing customers is significantly more cost-effective than acquiring new ones,
- Implementing a data-driven approach to predict and prevent churn is essential for:
    - Maintaining profitability and sustainable growth
    - Reducing revenue loss
    - Reducing Higher customer acquisition costs
    - Maintaining brand reputation

Machine Learning: The Game-Changer

We can leverage the power of Machine Learning to predict customer churn with remarkable accuracy.

- Identify at-risk customers
- Implement targeted strategies to retain them
- Improve customer segmentation

Machine Learning Canvas: Our Blueprint for Success



- Decisions
- Machine Learning Task
- Value Propositions
- Data Sources
- Data Collection
- Making Predictions
- Offline Evaluation
- Features
- Building Models
- Model Monitoring

How are ML predictions used to take decisions?

Our ML model will predict the probability of a customer churning within a specific timeframe (e.g., next 3 months). This information will be used to:

- Target marketing campaigns
- Customer service interventions
- Product and service optimization
- Pricing strategies

Data Sources

- **Internal Sources**
    - **Customer loyalty program**: Valuable data on purchase history, product preferences, and redemption behavior.
    - **Point-of-sale (POS) systems**: Comprehensive transaction data from our physical stores.
    - **Website analytics:** Data on online browsing behavior, product views, abandoned carts, etc.
    - **Social media monitoring**: Insights into customer sentiments and preferences.
    - **CRM systems:** Customer interaction data, support tickets, communication history, etc.
- **External data sources:**
    - Customer feedback and reviews from social media
    - Third-party APIs for market trends
    - Geo-socio-demographic data from census information

Features Extracted from Input Data

Example features extracted from input data:

- **Purchase frequency:** How often does the customer make purchases?
- **Average transaction value:** How much does the customer typically spend per purchase?
- **Product category preferences:** What types of products does the customer buy most frequently?
- **Customer demographics:** Age, gender, location, income level, etc.
- **Customer feedback:** Reviews, ratings, and online interactions.
- **Marketing campaign engagement:** How does the customer respond to marketing campaigns and promotions?

Machine Learning Task

Input:

Customer data including: Transaction data, Customer demographics, Customer feedback, Marketing and promotion data etc..,

Output:

The probability of a customer churning within a specific timeframe.

Value Proposition

- **Reduced customer acquisition costs:** Attract fewer new customers and focus on retaining existing ones.
- **Increased customer lifetime value:** Strengthen customer loyalty, leading to repeated purchases and increased revenue.
- **Improved customer segmentation:** Identify distinct customer groups with varying churn risks and tailor strategies accordingly.
- Reduces revenue loss from churned customers
- Enables proactive retention efforts and targeted incentives
- Enhances overall business profitability and growth

Technical and Business Metrics to Evaluate Model

- Business Metrics
  - **Churn Rate:** Percentage of customers lost over a specific period
  - **Customer Lifetime Value (CLV)**: Predicted revenue from a customer over time
  - **Retention Rate**: Percentage of customers retained after a given period
  - **Net Promoter Score (NPS):** Measure of customer loyalty and satisfaction
  - **Return on Investment (ROI):** Financial returns from retention efforts
  - **Decile analysis**
- Technical Metrics
  - Accuracy
  - F1-Score
  - Precision
  - Recall
  - ROC Curve

Live Evaluation of Model

Models perwill be continuously monitored in real-time to identify any potential issues or biases. This will involve tracking key metrics, analyzing model predictions, and making adjustments as needed.

When to Update Model?

Model will be updated periodically (e.g., quarterly or semi-annually) to ensure its accuracy and effectiveness. This will involve retraining the model with new data and evaluating its performance.

Implementation Costs and Considerations

- **Data Infrastructure:** Cloud storage, data warehousing, and processing capabilities
- **Analytics Tools:** Machine learning platforms, data visualization software, and predictive modeling tools
- **Personnel:** Data scientists, analysts, and IT specialists for model development and maintenance
- **Integration:** Costs associated with integrating the model into existing systems
- **Training:** Employee training on new tools and processes
- **Ongoing Maintenance:** Regular updates, model refinement, and system upgrades

Conclusion: The Future of Customer Retention in Retail

Implementing a data-driven churn prediction strategy is crucial for the future of retail. By leveraging advanced analytics and machine learning, businesses can proactively identify at-risk customers and implement targeted retention strategies. This approach not only reduces customer churn but also enhances overall customer satisfaction and loyalty. The long-term benefits include increased customer lifetime value, improved operational efficiency, and a competitive edge in the market. As retail continues to evolve, those who embrace these predictive technologies will be better positioned to thrive in an increasingly data-centric landscape.

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