Guide to *Predicting Churn* Using AutoAI

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What is

customer churn?

Customer churn - a metric that likely keeps business leaders up at night - refers to the rate at which customers stop doing business with a company or stop using its products or services. It is a critical metric for businesses, as losing customers can have a significant impact on revenue and profitability. Churn can occur for various reasons, including dissatisfaction with the product or service, competitive offers, changes in customer needs or circumstances, or poor customer experience.

Churn has a direct impact on revenue and profitability, and is thus an important metric that companies track and focus on reducing. For example, a 4% reduction in churn can generate an extra revenue of $11,150 over six months, in a specific example in the SaaS space.

What are the

types of churn?

Churn is defined differently for different types of businesses.

Subscription churn

Subscription churn refers to the rate at which customers or subscribers stop doing business with a subscription-based entity, often measured as a percentage of accounts that cancel or choose not to renew their subscriptions. This impacts the Monthly Recurring Revenue (MRR) and overall health of the business. Services like Netflix, YouTube, news publication subscriptions, telecom plans, and many SaaS offerings fall in this category.

E-commerce or retail churn

Here, churn describes the number of customers who stop buying from an online or store front over a predetermined period. An example of churn here would be customers who have earlier been making purchases on Amazon but have not made any purchases in say three months.

Factors influencing subscription churn include attracting the wrong customers, failed payments, and poor customer service. E-commerce churn can be influenced by similar factors such as wrong product-customer fit, lack of engagement, and higher prices compared to other sellers.

Churn is also classified based on the way in which the dropoff occurs:

Voluntary churn

This is when customers actively choose to end their relationship with a company. It can result from factors such as dissatisfaction with the product or service, better offers from competitors, or changing needs or priorities.

Involuntary churn

Involuntary churn happens when customers are forced to stop using a company's products or services due to factors beyond their control. For example, it can occur when a customer moves to a location where the company doesn't operate or encounters billing or administrative issues.

Understanding the types of churn is crucial for businesses to identify the underlying causes and develop strategies to reduce churn rates. The types that are most critical to track and reduce are voluntary as these are a direct indicator of customer satisfaction. Inadvertent churn can also be tracked to reduce attrition to technical or administrative reasons. By proactively addressing the reasons behind churn, companies can work towards improving customer retention and long-term success.

Why is churn prediction

a critical problem to solve?

For any business, a satisfied and stable customer base that continues to grow is an excellent indicator of success. High rates of churn indicate that something is breaking down in the process, and driving customers away. Monitoring churn rates, therefore, is essential ongoing activity. If any variation from the average is observed, this must be studied further to understand the cause and address it to stem the customer attrition.

Acceptable churn rates vary by business type and industry - for example, for B2C SaaS businesses that offer self-serve solutions, a 'good' monthly churn rate is estimated to be between 2 and 8%.

Retaining customers

Accurate churn prediction allows businesses to identify customers who are likely to churn in the future. By accurately predicting churn, companies can proactively implement targeted retention strategies to prevent customer attrition, thereby increasing customer retention rates and preserving revenue streams.

Cost savings

Acquiring new customers is typically more expensive than retaining existing ones. By accurately predicting churn, businesses can allocate their resources more efficiently by focusing on retaining at-risk customers. This approach helps reduce customer acquisition costs and maximize the return on investment (ROI) in customer retention efforts.

Improving customer satisfaction

Churn prediction enables companies to understand the underlying reasons behind customer attrition. By identifying patterns and factors leading to churn, businesses can address customer pain points, improve their products or services, and enhance the overall customer experience. This leads to increased customer satisfaction and loyalty.

Strategic decision-making

Accurate churn prediction provides valuable insights into customer behavior, preferences, and market dynamics. This information empowers businesses to make data-driven decisions and develop effective strategies for product development, pricing, customer engagement, and marketing. It enables businesses to stay ahead of the competition and adapt their offerings to meet customer needs, ultimately driving growth and profitability.

Using

AI & ML for churn prediction

AI and ML can be effectively used for churn prediction to identify customers who are likely to cancel a subscription or stop doing business with a company. Machine learning algorithms, a subset of AI, are particularly useful in this regard as they can analyze large amounts of data and identify patterns that may not be immediately apparent to human analysts.

What are some

current techniques used for churn detection?

There are several current techniques used for churn detection that businesses employ to identify customers who are at risk of churning. These are a combination of traditional analysis methods and strategies that incorporate AI and ML techniques. AI and ML can take the predictive capabilities of traditional techniques and augment them with increased accuracy and processing power.

Here are some common techniques:

Predictive modeling

This technique utilizes historical customer data to build predictive models that can forecast future churn. The data includes details about their behavior, usage patterns, and previous interactions with the company. Machine learning algorithms, such as logistic regression, decision trees, random forests, or neural networks, are commonly employed to analyze customer behavior patterns and identify indicators of potential churn.

Customer segmentation

Businesses segment their customer base into different groups based on various characteristics, such as demographics, behavior, usage patterns, or purchasing history. By analyzing each segment separately, companies can identify high-risk groups with a higher likelihood of churn and implement targeted retention strategies.

Customer behavior analysis

This technique involves monitoring and analyzing customer interactions, behaviors, and engagement with the company's products or services. By tracking metrics like customer activity, frequency of usage, purchase history, or customer support interactions, businesses can detect early warning signs of dissatisfaction or reduced engagement that may lead to churn.

Sentiment analysis

Sentiment analysis involves analyzing customer feedback, such as reviews, surveys, social media posts, or customer support interactions, to assess customer sentiment towards the company. By identifying negative sentiment or indicators of dissatisfaction, businesses can take proactive measures to address customer concerns and mitigate churn risk.

Propensity modeling

Propensity modeling is used to determine the likelihood of a customer taking a specific action, such as churning. By considering various factors like customer demographics, historical behavior, transactional data, and other relevant variables, businesses can calculate the propensity of a customer to churn and take appropriate actions to retain them.

Real-time monitoring

This technique involves monitoring customer activities and behaviors in real-time. By leveraging technologies like event streaming, data analytics, and machine learning algorithms, businesses can detect immediate churn signals or anomalies, allowing for timely intervention and personalized retention efforts.

The effectiveness of these churn detection techniques varies depending on the industry, business model, and available data. Companies often combine multiple approaches to gain a comprehensive understanding of customer churn and devise targeted strategies to retain customers.

What are the

challenges of using AI & ML for churn prediction?

Data quality and availability

Churn detection relies on accurate and comprehensive data about customer interactions, behaviors, and historical records. However, businesses often face challenges related to data quality, inconsistencies, missing values, or limited access to relevant data sources. Poor data quality can undermine the effectiveness of churn prediction models and lead to inaccurate results.

Imbalanced data

Churn events are generally infrequent compared to non-churn events, resulting in imbalanced datasets. This class imbalance can affect the performance of churn detection models, as they may become biased towards the majority class (non-churn). It becomes crucial to handle this imbalance appropriately to avoid misclassifying or overlooking churn cases.

Feature selection and dimensionality

Churn detection involves selecting relevant features or variables from a potentially large pool of available data. The process of feature selection becomes challenging as it requires identifying the most informative features that have a significant impact on churn prediction. Additionally, high-dimensional datasets can introduce computational complexity and increase the risk of overfitting.

Dynamic customer behavior

Customer behavior and preferences can change over time, making it challenging to capture evolving patterns accurately. The dynamic nature of customer behavior requires continuous monitoring, updating of churn prediction models, and adapting retention strategies accordingly.

Interpretability and explainability

While machine learning models offer powerful prediction capabilities, they often lack interpretability. Understanding and explaining the factors contributing to churn can be challenging, particularly with complex models like neural networks. Interpretable models are important for businesses to gain insights into the reasons behind churn and take appropriate actions.

External factors and context

Churn is influenced by various external factors and contextual information that extend beyond customer data. Economic conditions, market trends, competitor activities, or changes in industry regulations can impact customer behavior and churn rates. Incorporating such external factors into churn detection models can be complex but essential for accurate predictions.

Addressing these challenges requires a combination of robust data management, feature engineering techniques, model validation strategies, and expertise. Overcoming these obstacles enhances the effectiveness of churn detection efforts and enables businesses to implement targeted retention strategies, optimize customer relationships, and drive long-term success.

Using AutoAI to

solve the churn prediction problem

AI and ML are powerful tools in solving the problem of churn but, as discussed above, there are practical challenges to overcome in creating the most effective AI models for this use case.

AutoAI, which offers the capability to automate the entire lifecycle of AI development, is an efficient way of taking advantage of the benefits of AI and surmounting many of the challenges the life cycle poses. In AutoAI, automation includes all the tasks beginning with data preparation, feature engineering, model selection, hyperparameter tuning, and model deployment, to data app or dashboard creation to showcase the results. AutoAI does what otherwise would need a team of specialized data scientists and other professional resources, and does it faster and more efficiently.

(Learn more about AutoAI here)

Simplifying the process of AI development and deployment offers many advantages to businesses looking to better understand their churn patterns and develop strategies to address it.

Automated Model Building

AutoAI automates the end-to-end process of model building, including data preprocessing, feature selection, algorithm selection, hyperparameter tuning, and model evaluation. It eliminates the need for manual trial and error, saving time and effort in developing an effective churn prediction model.

Efficient Use of Resources

AutoAI optimizes the use of computational resources by automatically exploring various algorithms and hyperparameter combinations. It performs extensive model search and selection techniques, such as grid search or random search, to find the best-performing model within the given constraints. This leads to improved efficiency and resource utilization.

Enhanced Accuracy

AutoAI leverages sophisticated algorithms and ensemble techniques to create high-performing churn prediction models. It can automatically try out multiple algorithms and combine their predictions to achieve superior accuracy compared to traditional manual approaches. With this, a business can accurately predict the likelihood that a customer will churn.

Reduced Bias and Variance

AutoAI helps reduce bias and variance in churn prediction models by applying techniques such as cross-validation and regularization. These techniques address overfitting and underfitting issues, leading to more reliable and robust models.

Scalability and Adaptability

AutoAI frameworks are designed to handle large datasets and can scale to accommodate high volumes of customer data. They can adapt to different industries, business domains, and churn prediction use cases, making them suitable for a wide range of applications.

Interpretability and Transparency

AutoAI tools incorporate model interpretability features, providing insights into the factors that contribute to churn predictions. This helps businesses understand the underlying reasons behind customer churn, enabling them to take targeted actions to mitigate it.

Democratization of Data Science

AutoAI democratizes churn prediction by making the process accessible to users with limited data science expertise. It empowers business analysts, subject matter experts, and non-technical stakeholders to participate in the model development process and gain valuable insights from churn predictions.

AutoAI simplifies and accelerates the churn prediction process, leading to more accurate and efficient models. It enables businesses to leverage advanced machine learning techniques without the need for extensive data science knowledge or manual experimentation.

What are the types of

data needed to use AutoAI for churn prediction?

To build an accurate model using AutoAI to predict churn, historical data of different types is required.

Customer Profile Data

Regardless of the variety of the churn, customer profile information is essential. This includes customer demographic information such as age, gender, location, occupation, and other relevant attributes. It provides insights into the characteristics of customers who churn and helps identify any patterns based on customer demographics.

Behavioral Data

Behavioral intent data encompasses customers' interactions and activities with a product or service. This data may include frequency of usage, engagement levels, browsing history, feature adoption, login patterns, and session durations. A decrease in user activity or engagement could signal potential churn.

Survey Responses

Conducting customer surveys to gather feedback and gauge satisfaction levels can be a direct source of customer intent. Responses indicating dissatisfaction or an inclination to switch to a competitor may signal potential churn.

Product or platform usage and support data can also be used to build an overall understanding of the customer base.

Usage or Engagement Data

This dataset tracks customer interaction and engagement with the service. It includes metrics such as login frequency, session durations, feature usage, content consumption, or any other relevant user actions. Usage data helps identify customer behavior patterns that may indicate churn risk, such as declining engagement levels.

Customer Support Interactions

This dataset captures information from sources such as a CRM or Customer support system and includes customer support interactions, including customer service calls, chat transcripts, support ticket details, or email communication. Analyzing customer support data can provide insights into customer satisfaction, complaints, or issues that may contribute to churn.

Labeled data, which helps train a model to recognize churn, is also used.

Labeled historical data

Churn prediction datasets include a labeled target variable indicating whether a customer has churned or not. These labels are typically derived from historical data, such as customers who canceled their subscription, did not renew a contract, or discontinued using the product or service.

Subscription Churn

These are some of the data types that can be used to calculate churn for subscription businesses:

Subscription Details

This dataset contains information related to the subscription plans chosen by customers, such as subscription type, duration, start date, renewal date, pricing, and any plan changes or upgrades. It helps understand how different subscription features or pricing structures impact churn rates.

Billing and Payment Data

This dataset includes information on billing cycles, payment methods, payment history, invoice amounts, and any payment-related issues or delays. Analyzing billing and payment data can help identify patterns that may influence churn, such as customers experiencing payment difficulties or inconsistencies.

Churn Labels

Churn prediction models require labeled data indicating whether a customer has churned or not. The churn labels dataset should include historical records of customers who have canceled their subscription or discontinued using the service. These labels are used as the target variable for training the churn prediction model.

Time-Related Data

Time-related data is important to understand the temporal aspect of churn. It includes timestamps of various events, such as subscription start and end dates, payment dates, customer interactions, or plan changes. Time-related data helps capture customer behavior trends, seasonality, or changes in churn patterns over time.

E-commerce churn

These are some of the data types that can be used to calculate churn for e-commerce businesses:

Transactional Data

Transactional data captures the historical interactions between customers and the business. It includes details of purchases, subscription plans, usage patterns, transaction dates, and monetary values. Analyzing transactional data can help identify indicators of churn, such as decreasing purchase frequency or declining usage.

Customer Interaction Data

This dataset captures various forms of customer interactions with the business, such as customer service calls, emails, live chats, or social media interactions. It provides valuable insights into customer sentiment, complaints, inquiries, and overall engagement. Analyzing customer interactions can help identify potential triggers or patterns leading to churn.

Customer Satisfaction Surveys

Surveys or feedback data collected from customers can provide direct insights into customer satisfaction levels, preferences, and potential churn drivers. Analyzing survey responses can help identify specific pain points, areas for improvement, and factors influencing customer churn.

What are the steps in

using AutoAI for churn prediction?

With AutoAI, the steps in the AI lifecycle are reduced to a few clicks. A user - business or technical - can carry out the following functions to produce a model that can predict customer churn accurately.

01

Data Preparation

Gather and preprocess the churn dataset. This involves cleaning the data, handling missing values, transforming variables if needed, and ensuring the dataset is in a suitable format for analysis.

02

Data Exploration

Explore the churn dataset to gain a better understanding of the variables and their relationships. Identify any patterns, correlations, or potential outliers that may influence churn.

03

Feature Engineering

Create relevant features or derive new variables from the existing churn dataset. Feature engineering can involve aggregating customer behavior, creating time-based features, or incorporating external data sources to enhance predictive power. Some examples of features include products seen or purchased, categories of products, total amount spent.

04

Model Training

Use AutoAI to automatically build churn prediction models using the prepared datasets. The AutoAI framework will perform algorithm selection, hyperparameter tuning, and model evaluation using different techniques like cross-validation or holdout validation. This step typically involves extensive computation and exploration of various model configurations.

05

Model Evaluation

Assess the performance of the generated churn prediction models. Evaluate the models based on appropriate metrics such as accuracy, precision, recall, F1-score, or receiver operating characteristic (ROC) curve. Consider factors like interpretability, computational requirements, and business constraints when selecting the final model.

06

Model Deployment

Deploy the selected churn prediction model into a production environment where it can be used to make real-time predictions. Ensure that the model is integrated into the existing business systems or workflows for seamless churn monitoring and decision-making.

07

Model Consumption Through Data Apps

Access the insights generated by the model in the form of interactive dashboards and data apps. Business users can refer to the dashboards to monitor the metrics that are critical to their operations, like the churn rate, customer lifetime value, and others.

08

Monitoring and Maintenance

Continuously monitor the churn prediction model's performance in the production environment. Track the model's accuracy, recalibrate if necessary, and retrain periodically with new data to maintain its predictive power. Regularly evaluate the model's effectiveness and make adjustments as needed.

Throughout the process, it is important to collaborate with subject matter experts and stakeholders to interpret the results, validate the model's predictions, and align the churn prediction process with the business objectives.

What metrics showcase the

impact of AutoAI for churn?

Once an AutoAI solution is implemented for churn prediction, the first and most direct metric is the monthly or annual churn rate. Other metrics that will also be impacted over time with a successful churn prediction model and can be configured on a dashboard or data app are:

Customer Retention

Reducing churn directly improves customer retention rates. Retaining existing customers is more cost-effective than acquiring new ones. By reducing churn, businesses can maintain a larger customer base and foster long-term customer relationships.

Customer Lifetime Value (CLV)

CLV represents the total value a customer generates over their entire relationship with a business. By reducing churn, customers stay with the company for a longer duration, resulting in a higher CLV. Increasing CLV allows businesses to maximize the return on their marketing and acquisition investments.

Customer Acquisition Costs (CAC)

Reducing churn reduces the need to spend significant resources on acquiring new customers. As the existing customer base remains stable, businesses can allocate their marketing and sales budgets more efficiently, potentially lowering CAC. This leads to improved profitability and a higher return on investment (ROI).

Revenue and Sales

All of these in some way impact the overall revenue and can lead to increased sales. Retaining customers means they continue to make purchases or utilize services, generating consistent revenue streams. Additionally, satisfied customers are more likely to spend more and make additional purchases, contributing to higher sales figures.

Some qualitative metrics that can be studied and will be positively impacted over time by reduced churn are:

Customer Satisfaction and Loyalty

Decreasing churn implies that customers are satisfied with the products or services provided. Satisfied customers are more likely to become loyal advocates who refer others, provide positive reviews, and contribute to positive word-of-mouth marketing. Improved customer satisfaction and loyalty can enhance the brand reputation and attract new customers.

Brand Image and Trust

A high churn rate can negatively impact a company's brand image and reputation. By reducing churn, businesses demonstrate their commitment to customer satisfaction and loyalty. This helps build trust among existing and potential customers, enhancing the brand's image and credibility.

Operational Efficiency

Churn reduction can improve operational efficiency by reducing the resources needed to address customer churn. Businesses can allocate fewer resources to customer retention efforts and focus more on delivering value-added services, product development, or customer acquisition strategies.

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