Predict & Prevent Customer Churn



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# Abstract

Purpose of the project is to study customer’s behavior and data to predict and possibly prevent customer churn using data science techniques. Customer churn occurs when customers or subscribers stop doing business with a company or service. Also known as customer attrition or turnover, it is a critical metric due to the cost savings for a company to retain a customer in comparison to acquiring new ones. Awareness about customer churn helps an organization define customer retention processes, project goal success rates and identify strategies for improvement.

# Author Keywords

Customer churn, Retention, Attrition, Prediction, Logistic Regression, Classification, Data Science, Machine Learning, EDA, feature engineering, data cleansing, bias, outlier, training, validation, test, feature scaling, data skew, balancing, modeling, KNN, SVM, decision tree, K-fold, parameter tuning, correlation, NLP, Stemming, Lemmatization, TF-IDF, Sentiment Analysis, Report, Dashboard, Business Intelligence, CRISP-DM.

# ACM Classification Keywords

1. Computing methodologies~Artificial intelligence;500
2. Computing methodologies~Machine learning~Machine learning approaches~Classification and regression trees;500
3. Computing methodologies~Machine learning~Learning paradigms~Supervised learning~Supervised learning by classification;500
4. Computing methodologies~Artificial intelligence~Natural language processing~Information extraction;300
5. Computing methodologies~Machine learning~Machine learning algorithms~Feature selection;100

# Introduction

One of the key aspects of a successful business model is how to establish and maintain a loyal customer base. If a company can keep their customers in a subscription-based revenue system, they can maintain a strong financial foundation and increase their return on investments. The cost savings can then be used to adopt better product technology and to create a more diverse marketing strategy to provide better support & decrease customer churn. Through a stable customer base, the company can establish a strong customer review system and increase the likelihood of customer referrals as a source of increased product subscriptions & acquire new customers. Major reasons for customer attrition include bad quality product, the low cost for customers to switch to competitors, and bad customer service. Companies should take advantage of their data resources, apply data analytics & data science techniques to discover insights that can help predict & prevent customer churn. Next we have discussed few such approaches utilizing data science.

*Figure 2 – SVM*

*Figure 1 – Logistic Regression*

# Data Science Approach – Predict Churn

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To predict customer churn, we will apply data science techniques & core principles of CRISP-DM (*See Figure 1*) as follows:

*Figure 3 – KNN*

1. **Business Understanding**: Conduct sessions to understand the problem, discuss possible causes, and understand known impacts.
2. **Data Acquisition**: Identify & source relevant data i.e. considered, rewards & offer used, surveys, online reviews, complaints etc.
3. **EDA (Exploratory data analysis)**: Clean data & identify valuable attributes as features. **Data cleansing** involves null value handling, duplicate removal, standardization & formatting. **Feature engineering** involves visualizing data using histograms, pie charts, correlation matrix, & scatterplots to identify relevant features, understand trends, & **bias** within the data.

*Figure 4 – Decision Trees*

1. **Data Preparation**: Split data into **training** (50%), **validation** (20%) & **test** (30%) sets.

Apply **feature scaling** to normalize data to identify any **outliers** or **redundant values** that may **skew** the data & analysis. This in turn may require data **balancing**, to keep sample consistent with the larger data set.

1. **Modeling**: Fit & train the model. As this is prediction (classification) problem **logistic regression** (Fig -1), **KNN** (K nearest neighbors – Fig 3), **SVM** (Support Vector Machine – Fig 2), **decision trees** (Fig - 4) algorithms are considered.Predict from each model.
2. **Evaluation**: Prediction results from each model are evaluated using **confusion matrix** & measures like **accuracy score**, **F1 score**, **precision score** & a **recall score**. Based on evaluation result best model is chosen. If none gives preferred results model **parameter tuning** is tried and model combinations can be tried and re-evaluated. **K-fold cross validation** is applied to select only effective features. Model selected is recreated with chosen features to run light when deployed.
3. **Deploy**: Model inputs & outputs are integrated with data processing workflow & deployed in prod.

# Data Science Approach – Sentiments, Tweets & Complaints

Companies run customer surveys to understand what customer thinks about their products & services. Customer feedback usually answers to series of predefined questions & free form text, which are then explored using Natural

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Language Processing **(NLP)**. Preprocessing removes stop words, applies, **stemming**, **lemmatization**, & **TF-IDF**(Term Frequency-Inverse Document Frequency) to convert words into matrix of numbers. Series of binary classification models can then be used to classify text

*Figure 5– Topic Modeling*

positive, negative, neutral (See Fig 6,7). Each word is a feature with weight for these models which can be varied to achieve desired results. Similarly, tweets can also be analyzed to understand feedback & complaint texts (call transcripts) can be analyzed to understand complaint reasons & uncover product issues. Topic modeling can be considered here to discover words frequently mentioned with respect certain contexts (See Figure 5).

# Business Inteligence – Presenting Insights

*Figure 6 – Sentiment Word Cloud*

Outputs from above data science applications are integrated with customer & other base data and dashboards are created for business executives, to understand customer behavior, attrition reasons, other attributes trend over time for churning customers.

# Customer Churn Prevention

Outputs from data science applications and BI insights are integrated with marketing processes & sales screens to provide real time customer insights, early warnings, and custom guidance for retention. In addition, custom offers and campaigns can be run for the purpose as well.

*Figure 7 – Sentiment Analysis*

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# What is the deliverable for this project?

1. Pre-trained (supervised) model to predict customer churn.
2. NLP (Natural Language Processing) model to understand customer sentiment overall and for each product (positive, negative, neutral).

*Figure 8 – Executive Dashboard*

1. Process integration with marketing & sales screens to provide real time customer insights, early warnings, and custom guidance for retention.
2. Executive dashboards to understand customer behavior and attributes trend over time for churning customers.
3. Executive dashboards to analyze customer churn reasons (i.e. product issues, bad customer service, bad onboarding, budding competition, etc.) and predict trends over time for customer churn.

*Figure 9 – Integration with sales*

# Conclusion

It’s cheaper: 70% of companies say that it is cheaper to retain existing customers than to acquire new ones, while others have suggested that cost of acquiring new customers can be as much as seven time.

Its faster: Again, it’s often much easier to sell to an existing customer than it is to sell to a new one. This is because all barriers to purchase have already been overcome. Existing customers may just need a slight nudge to increase your share of their wallet, and this will speed up your sales process.

It better positions your business: One of the best things about high levels of customer retention is that you’re able to build a more nuanced view of who your customers really are.

Retention = Acquisition: Customer loyalty is priceless and can even result in further customer acquisition for your company. After all, word of mouth advertising is not only free, but possible one of the most credible forms of advertising.

Closing thoughts: Marketers don’t tend to focus on customer retention enough because loyalty and engagement are often not seen as strictly “measurable”, but this doesn’t mean they aren’t important. Customer acquisition is critical in the early stages of a start-up business, but once you’ve built a customer base, as soon as you’ve got one customer, retention should be on your mind. The more customers you have, the more important retention is.

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