Customer Churn Management Using Predictive Modeling – A Machine Learning Approach

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Abstract

Customers are an essential part of any business; all businesses require to retain their customers especially if they offer subscription services. By the use of churn modeling, we can optimize this process and ensure that businesses of all sizes can be more comfortable as far as customer retention is concerned. This paper majorly analyzes how churn modeling is done, the formula used to calculate a churn rate, and the types of churn used in the ecosystem.

Keywords. : Machine Learning, Computer Engineering, Customer and Churn.

Introduction

Companies that are in subscription-based services depend highly on their customers to improve their revenue. This could also be enhanced by acquiring new customers. However, the most important thing for these companies is customer retention. They need to make sure they do not lose the customers they have gained over the years. Customers may be lost entirely to competitors or lost partially as they stop using the services they used to subscribe to. Customer behavior can be used to understand when they are likely to stop using a service or are likely to switch to a competitor. This is what we call churning.

Machine learning has opened a new opportunity for businesses of all scales. Prediction is a key factor in any sector of our lives and businesses are no exception by any means. They need to be aware of how customers are likely to behave in the future and be able to plan for the same. Profit depends on how many customers are acquired and the level of retention of these customers hence creating the need to know what is likely to cause them to leave. This is the problem that churn customer prediction is trying to solve.

In this paper, we will look deeply into churn modeling implementation for all business sizes. How can we ensure that businesses with few resources can acquire these prediction models in America? How do we use the churn model to increase customer retention both locally and internationally? We aim to understand American customer behavior. Churn uses previous customer data in making predictions and deciding whether the customer will churn or not. Only two outcomes are expected at the end of a prediction exercise. With this information, we will be able to know how we can retain our customers. We can tell which services to improve on based on how many customers want to churn from the service. This will help us retain more customers and ensure business prosperity.

Literature review

Subscription-based services are affected by every customer who leaves (CAMPBELL, 2021). This is because these customers are at the center of their revenue. Customer retention should then be at the core of any of these businesses (CAMPBELL, 2021). Churn will then help us know when customers are likely to stop using these services (Patel, 2021). Big Data is currently gaining foot into the world of businesses and churn uses big data to model customer behavior to predict when these customers are likely to stop using our services.

Churn rate is an important factor when it comes to implementing churn model. We need to calculate the churn rate and use it in the churn algorithm. To calculate this rate, we need to know the number of customers who stopped using a service within a given period and the customers currently using the service, we will then divide the former by the latter to determine our churn rate (What is Customer Churn Modeling? Why is it valuable? - KDnuggets, 2021).

In the beginning, only big corporates used churn modeling (Patel, 2021). However, by the use of APIs many prediction services have been built and these services have helped businesses of all services subscribe to the churn model and enabled them to grow exponentially. It is quite easy to perform tasks that can help us do overall customer retention, however individual customer retention is not only difficult but also expensive (Patel, 2021). Individual attention to customers is expensive both on time and the cost that businesses will incur when they are dealing with each customer. This creates a need for a solution that will not only be cheap but also be fast and efficient (Patel, 2021). We can develop customized solutions for each customer based on their experience and likelihood to churn from a service.

Customers are diverse in their behavior. The behavior of a customer affects which services they decide to use or churn. It is key that businesses understand this customer behavior and create a model that will help identify each customer experience.

Distribution Analysis of Churn and Non-Churn Customers

As part of the Exploratory Data Analysis process, in the following step we analyzed the distributions of other variables for the Leaving (Churn) and Remaining (Non Churn) customers. This is extremely useful! It provides an insight into the data, identifying if the data contains outliers or if the dataset is unbalanced. We can now start to formulate hypotheses. Categorical data, such as gender or nationality, appears in a pie chart. On the other hand, numerical data such as credit score or balance is shown as a bar chart.

```
import pandas as pd
import seaborn as sns#visualization
import plotly.offline as py#visualization
py.init_notebook_mode(connected=True)#visualization
import plotly.graph_objs as go#visualization
import plotly.tools as tls#visualization
import plotly.figure_factory as ff#visualization
import matplotlib.pyplot as plt
import matplotlib as mpl
mpl.style.use('ggplot')
churn     = df[df["Exited"] == 1]
not_churn = df[df["Exited"] == 0]

def plot_pie(column) :

    trace1 = go.Pie(values  = churn[column].value_counts().values.tolist(),
                    labels  = churn[column].value_counts().keys().tolist(),
                    hoverinfo = "label+percent+name",
```

```
                domain  = dict(x = [0,.48]),
                name    = "Churn",
                marker  = dict(line = dict(width = 2,
                                           color = "rgb(243,243,243)")
                              ),
                hole    = .6
               )
    trace2 = go.Pie(values  = not_churn[column].value_counts().values.tolist(),
                labels  = not_churn[column].value_counts().keys().tolist(),
                hoverinfo = "label+percent+name",
                marker  = dict(line = dict(width = 2,
                                           color = "rgb(243,243,243)")
                              ),
                domain  = dict(x = [.52,1]),
                hole    = .6,
                name    = "Non churn"
               )


    layout = go.Layout(dict(title = column + " distribution in customer attrition ",
                        plot_bgcolor  = "rgb(243,243,243)",
                        paper_bgcolor = "rgb(243,243,243)",
                        annotations = [dict(text = "Churn",
                                            font = dict(size = 13),
                                            showarrow = False,
                                            x = .15, y = .5),
                                       dict(text = "Non churn",
                                            font = dict(size = 13),
                                            showarrow = False,
                                            x = .88,y = .5
                                           )
                                      ]
                       )
                  )
    data = [trace2,trace1]
    fig  = go.Figure(data = data,layout = layout)
    py.iplot(fig)


#function  for histogram for customer attrition types
def histogram(column) :
    trace1 = go.Histogram(x  = churn[column],
                      histnorm= "percent",
                      name = "Churn",
                      marker = dict(line = dict(width = .5,
                                                color = "black"
                                                )
                                   ),
                     opacity = .9
                     )

    trace2 = go.Histogram(x  = not_churn[column],
                      histnorm = "percent",
                      name = "Non churn",
                      marker = dict(line = dict(width = .5,
                                              color = "black"
                                             )
```

```
                        ),
                    opacity = .9
                   )

    data = [trace2,trace1]
    layout = go.Layout(dict(title =column + " distribution in customer attrition ",
                            plot_bgcolor  = "rgb(243,243,243)",
                            paper_bgcolor = "rgb(243,243,243)",
                            xaxis = dict(gridcolor = 'rgb(255, 255, 255)',
                                         title = column,
                                         zerolinewidth=1,
                                         ticklen=5,
                                         gridwidth=2
                                        ),
                            yaxis = dict(gridcolor = 'rgb(255, 255, 255)',
                                         title = "percent",
                                         zerolinewidth=1,
                                         ticklen=5,
                                         gridwidth=2
                                        ),
                           )
                      )
    fig  = go.Figure(data=data,layout=layout)

    py.iplot(fig)

#function  for scatter plot matrix  for numerical columns in data
def scatter_matrix(df)  :

    df  = df.sort_values(by = "Exited" ,ascending = False)
    classes = df["Exited"].unique().tolist()
    classes

    class_code  = {classes[k] : k for k in range(2)}
    class_code

    color_vals = [class_code[cl] for cl in df["Exited"]]
    color_vals

    pl_colorscale = "Portland"

    pl_colorscale

    text = [df.loc[k,"Exited"] for k in range(len(df))]
    text

    trace = go.Splom(dimensions = [dict(label  = "Tenure",
                                        values = df["Tenure"]),
                                   dict(label  = 'Balance',
                                        values = df['Balance']),
                                   dict(label  = 'EstimatedSalary',
                                        values = df['EstimatedSalary'])],
                     text = text,
                     marker = dict(color = color_vals,
                                   colorscale = pl_colorscale,
                                   size = 3,
                                   showscale = False,
```

```
                          line = dict(width = .1,
                                      color='rgb(230,230,230)'
                                     )
                          )
               )
    axis = dict(showline  = True,
                zeroline  = False,
                gridcolor = "#fff",
                ticklen   = 4
               )

    layout = go.Layout(dict(title  =
                        "Scatter plot matrix for Numerical columns for customer attrition",
                        autosize = False,
                        height = 800,
                        width  = 800,
                        dragmode = "select",
                        hovermode = "closest",
                        plot_bgcolor  = 'rgba(240,240,240, 0.95)',
                        xaxis1 = dict(axis),
                        yaxis1 = dict(axis),
                        xaxis2 = dict(axis),
                        yaxis2 = dict(axis),
                        xaxis3 = dict(axis),
                        yaxis3 = dict(axis),
                       )
                  )
    data   = [trace]
    fig = go.Figure(data = data,layout = layout )
    py.iplot(fig)


cat_cols = ["Geography", "Gender", "NumOfProducts","HasCrCard", "IsActiveMember"]
num_cols = ["Age", "Balance", "EstimatedSalary","CreditScore","Tenure"]
#for all categorical columns plot pie
for i in cat_cols :
    plot_pie(i)

#for all categorical columns plot histogram
for i in num_cols :
    histogram(i)
```

Use cases of churn model

Churn model has several use cases. It can be applied in a variety of fields. In this sub-topic, we will state use cases previously identified by other writers. Churn can be implemented using machine learning (What is Customer Churn Modeling? Why is it valuable? - KDnuggets, 2021). We use machine learning and historical data to calculate the probability that a user is going to stop using a service. According to (What is Customer Churn Modeling? Why is it valuable? - KDnuggets, 2021), some of the use cases of churn include but are not limited to the following.

For long-term use we can compute the impact of product features, this helps us understand why customers churn our services. This helps in developing a long-term customer retention strategy. For immediate benefit, we develop risk scores that help us determine which clients are likely to leave. Using these scores, we can develop a tailor-made customer retention strategy. This is key in retaining customers that we currently have. This use case has a link with the first use case in that, we can use the previously generated model when creating these risk scores.

We can use the probability of churn for our clients when developing a retention strategy. Based on which services a client is likely to churn, we can develop campaigns for these customers about upcoming new features and products. By use of call centers, we can have live information of when customers are likely to stop using a service. This information and data can then be used to develop models that will be used to determine customers' future behavior. The call centers can also be used to drive campaigns to customers on upcoming services. We can drive campaign strategies to customers who are more likely to quiet than others

According to (How Churn Prediction Can Improve Your Business - Baremetrics, 2021), churn can be used in many kinds of businesses but is more relevant in subscription-based fields. These services can include membership services such as gym membership, football seasonal tickets, movie tickets, and so on. It also states that churn is more useful in software-based products and services. (How Churn Prediction Can Improve Your Business - Baremetrics, 2021) shows us that churn is more useful for SaaS providers. (How Churn Prediction Can Improve Your Business - Baremetrics, 2021) also states that to determine customers' lifetime value, we can use churn. This lifetime value places companies in a better position in making decisions for the future. According to (How Churn Prediction Can Improve Your Business - Baremetrics, 2021), churn can be used in many areas but it is important to focus on the following areas.

Customer Outreach
Customer Service
Value to the customer.

Customer outreach

Reaching out to customers helps us determine the future churn. Even though it does not have a direct impact on the business, it is a key factor in forecasting the future. We can improve the outreach to help us determine which customers are detractors and passive. This information can then be used to turn these clients into promoters. Tailor-made services can be created for each of the customers that make them stay and even subscribe to new services.

Improving customer service

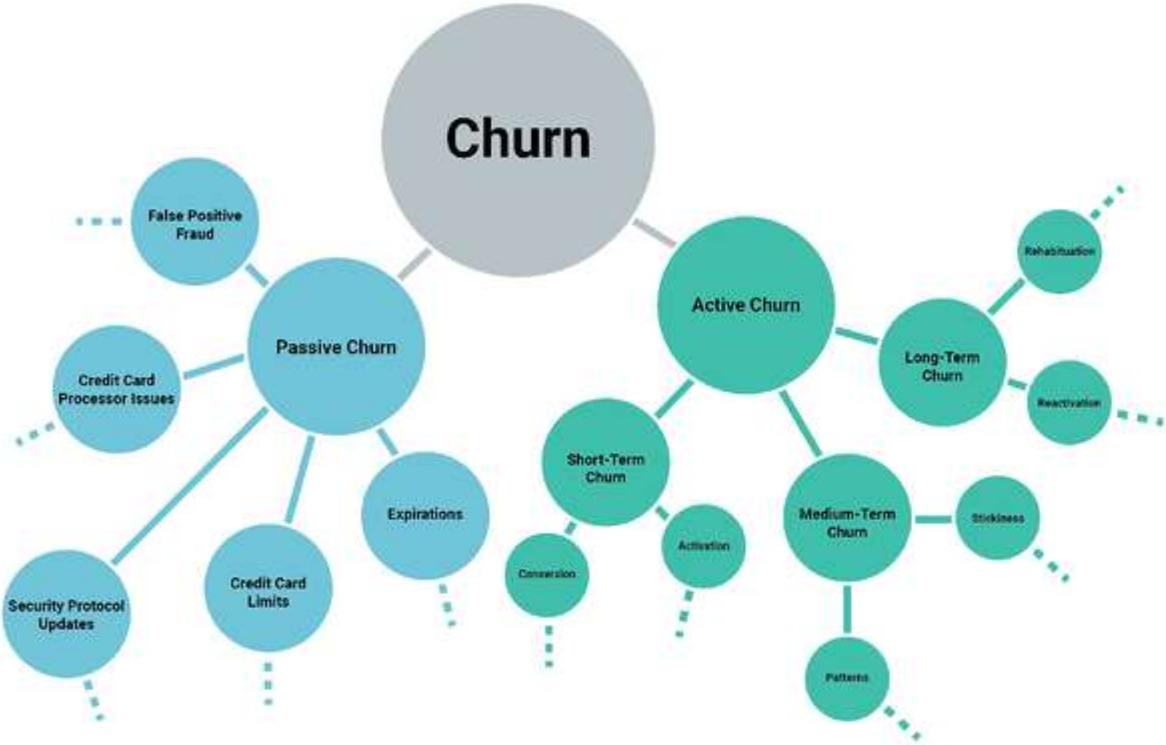
We use the churn feedback to improve our services. This helps us reduce the number of customers who are likely to churn hence reducing the churn rate. This has a positive impact on our revenues. (Murphy, 2021) states that a churn rate of between 0.42% - 0.58% should be acceptable. Churn rates below these ranges should be considered red flags by businesses and businesses should jump into action.

Types of churn

The major types of churn are voluntary churn and involuntary churn. Voluntary churn is where a customer voluntarily quits a service or switches to a service provided by a competitor while on the other hand, involuntary churn is where a customer has no control over quitting, this can include, failure to pay, change of location, and many more (Krull, 2021). While businesses can control voluntary churn and mitigate the number of customers they are losing. It is extremely out of their hands to influence involuntary churn.

(CAMPBELL, 2021) says that to combat voluntary churn we need to understand how to better satisfy our customers. Customers are the pillar of business and it's key that we learn best how to treat them and manage what they need. (CAMPBELL, 2021) also states that involuntary or delinquent churn is the most common type of churn. He goes ahead stating that this type of churn is easily avoided compared to voluntary churn. This type of churn can be avoided by doing analysis and fixing areas that lead to customers churning. An example can be where customers have a problem with the billing and are forced to stop purchasing. If the business billing process is made easier, about 80% of the sales lost due to failing or complex billing process can be regained. Some cases require businesses to be better equipped. An example would be where a customer is leaving to a new area, if the company knows prior about this they can put a campaign that would inform the client about the services the business is offering in the region they are moving into

Churn can also be divided into several categories as shown below. This is a more high-level view of churn.



Causes of customer churn

Customers can churn because of several reasons. We will look at the most common reasons why customers churn. (It, 2021) lists the following reasons as the major reasons why customers churn.

Poor customer service
Little value
Poor communication with customers
Lack of brand loyalty

Poor customer service.

(It, 2021) states that customers tend to stop subscribing to company products because of the treatment they get from the business. The problem is these customers do share their experiences with other customers and this leads to adverse effects to the business. Customers must be made to feel part and parcel of the business. Their feedback is taken seriously and into account. (It, 2021) points out that customers want to feel engaged and appreciated.

Little Value

Even though it is not the leading reason for customers leaving, it should not be equated with price (It, 2021). Value also varies from one customer to another, this entirely because of the varying customer taste. It is key to know what each customer likes and how to present these in value for them. Customers often prefer value over price, this can be seen as more and more clients are willing to pay much more money to receive better services as opposed to cheaper services.

Poor Communication

According to (It, 2021), communication has many variants. There are cases where too much is sent to customers to the extent that they feel bothered. This mostly leads to them disengaging in the communication platform. Sometimes businesses send irrelevant communication to a customer. Other businesses on the other hand do not communicate as frequently as they should with their customers. All these factors need to be analyzed for a business to come up with a better communication strategy.

Lack of loyalty brand

Customers can sometimes decide which products to subscribe to based on prices. According to (It, 2021), this mostly occurs when customers view products being provided by two competing parties as of the same value and hence can easily swap them.

Calculating churn rate

The following mathematical implementation can be used to calculate the churn rate. This is according to (How Churn Prediction Can Improve Your Business - Baremetrics, 2021).

Churn Rate = (Subscribers at the beginning of the month – Subscribers that remain at end of the month) / Subscribers at the beginning of the month

Let's assume we had the following data.
1500 Subscribers at the beginning of the month
1300 subscribers at the end of the month

Churn rate = (1500-1300)/1500 = 0.133
Subscribers gained during the month are not used when calculating churn. These customers will be used when calculating churn for the next month.

This churn formula can be used to calculate the churn rate for any particular period. Most companies however calculate churn rate monthly. According to (How Churn Prediction Can Improve Your Business - Baremetrics, 2021), forecasting future churn rates is more complex than calculating churn rates of the past. We can however use NPS (Net Promoter Score) when calculating future churn rates. (How Churn Prediction Can Improve Your Business - Baremetrics, 2021) outlines the following steps as critical when performing an NPS survey.

Steps for NPS survey

<u>Step 1</u>
Perform a campaign with the following two main questions.
Ask customers how likely they are to recommend the services you provide to the people you know
The reason as to why they gave the score
<u>Step 2</u>
We will then differentiate our subscribers into the following categories.
Promoters: They give the highest score
Passives: Gives an average score
Detractors: Give the lowest score

<u>Step 3</u>
The values obtained from the scores above can then be used to calculate NPS. When computing NPS we also use the previous history of NPS for us not to have a vague picture of NPS. (Promoter, 2021) came up with the following conclusions on NPS.
About 50% of the detractors are highly likely to churn within three months of the survey.
On the other hand, 40% of the passives are highly likely to stop using the services within six months.

Challenges in building churn model

(WIRE, 2021) states that one of the major challenges when building a churn model is the lack of a single approach as a solution. This leaves businesses with but few options to choose from.
(3 Major Challenges Enterprises Face in Building an Effective Churn Model | Quantzig, 2019), outlines three major challenges when building a churn model.

Lack of single solution
Feature and exploratory analysis
Validating churn model

Lack of a single solution

No single model can be used in multiple cases, businesses hence are needed to test several models until they acquire one that meets their needs. Machine learning is used to analyze huge data sets and conclude about a certain scenario.

Feature exploratory analysis

(3 Major Challenges Enterprises Face in Building an Effective Churn Model | Quantzig, 2019) states that one of the problems is skills. It is difficult to find skilled individuals that can build a good churn model for a business. Small businesses also have small data set which if used can give a false positive or negative about churn. To have a good churn model, large amounts of data are needed.

Validating models

Optimization and validation of data sets is an important part of building an accurate churn analysis model. This is more so because churn is used to predict future occurrences and this highly influences how decisions are made by major shareholders. This creates a need for businesses to ensure that the churn models are validated before they can be put to production.

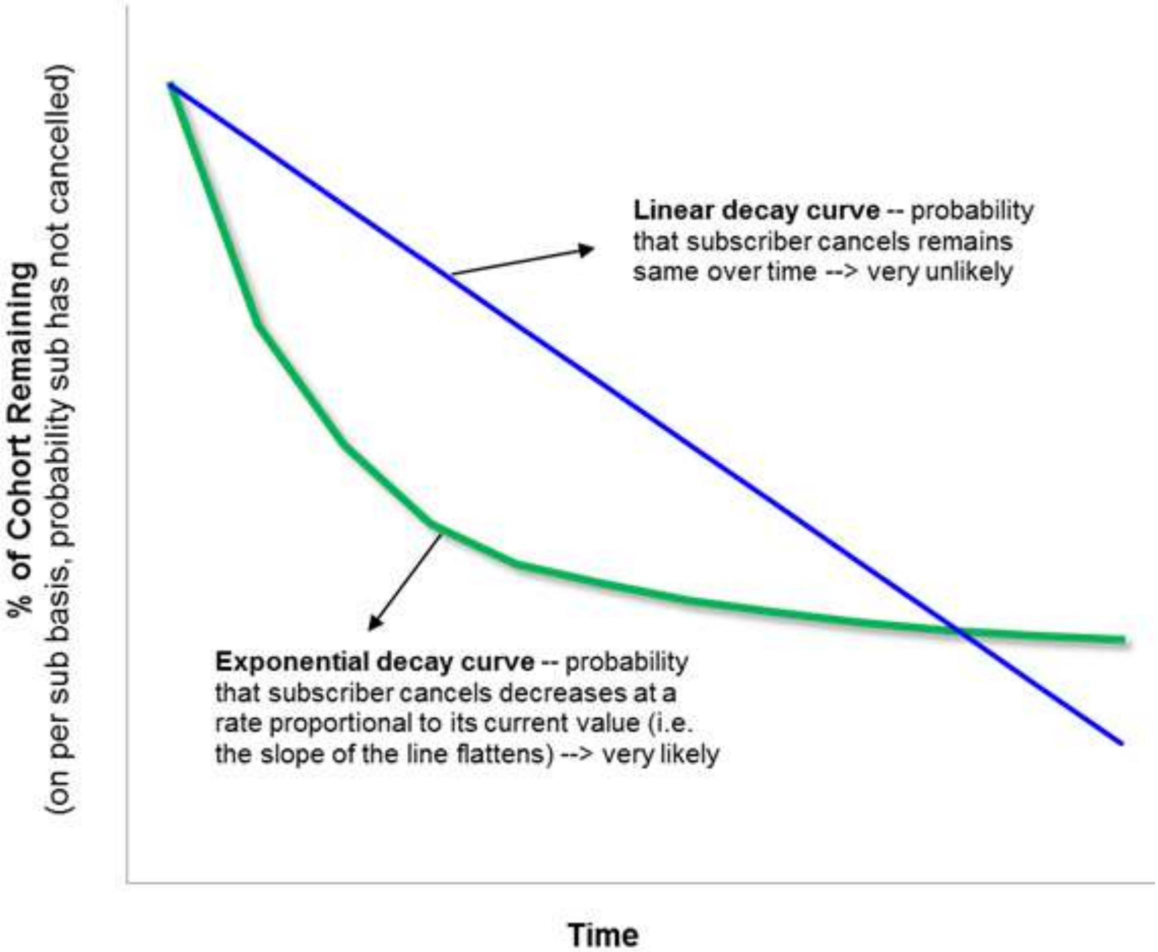
Limitations of churn model

Churn model has its limitations too. Sometimes businesses misuse churn. (DeRamus, 2021) state the following as some of the limitations of churn.

Sensitivity to absolute cancels
Dependency on size of businesses
Misused when calculating lifetime value

Sensitivity to absolute cancels

Churn is so sensitive to fluctuations (DeRamus, 2021).

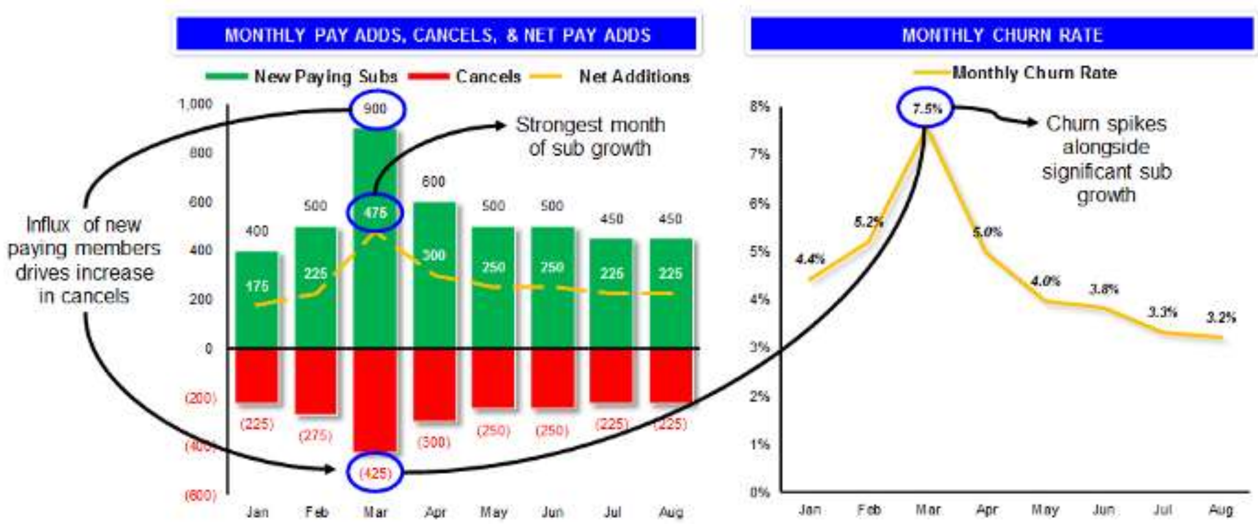


Dependency on size of business

Churn highly depends on the growth of customers (DeRamus, 2021). This according to (DeRamus, 2021) leads to the following problems.

Comparing churn just for individual company

Comparing churn on an industrial basis.



Applications of churn models in the American market

Churn models can be applied in many fields in the American market. Some of them include:

Improving customer satisfaction for small businesses

Improving election turnout

Improving work conditions

Understanding the international market
Improving on products and services

Improving customer satisfaction for small businesses

We can use churn to improve customer satisfaction for small businesses. Software is becoming diversified and being sold more as a service than before when the software was hosted by its users. This is good news for small businesses as they will not need to purchase the equipment's needed to run these models. These models can be hosted by providers in a cloud environment where consumers can access them at a cheaper price. These businesses can pay for the services on a usage basis.

As we have solved how we would make the churn acquisition cheaper, we need to know the benefits of the churn model to these businesses. With churn, these businesses can know which products or services they need to improve on. By improving on these services, they have a higher chance of retaining their customers. This in turn increases revenue.

Improving election turnout

Churn models can also be used to determine why the population that does not vote doesn't do so. We can perform a survey that helps us understand why this population is not concerned about voting, after understanding the data set we can develop tailor-made campaigns for them to try to entice them to vote.

Improving work conditions

An improved work condition means that we retain our best employees. Although churn is more focused on customer satisfaction, customers are a key component of any business too. We need to ensure that the American market retains the best employees in the world. By retaining the best employees the American market will produce the best services and products and hence have a better share of the global market.

Understanding the international market

The global market is a key aspect to look at in this century, we need to ensure that we understand how different populations behave. By understanding the global market, we can optimize and produce different products for different collaborations. It is increasingly easier to understand the global market as there is a lot of data that can be used to create models now.

Conclusion

Every business needs customers to stay in business, with predictive churn modeling this process is made much easier. Businesses can now mitigate the effects of losing customers by simulating how easily these customers can leave, without a doubt, we see that churn modeling using machine learning is not only more effective and cheaper, it has also tremendously changed how businesses operate.

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