Analytics Vidhya

Guide On Customer Churn: Don't Just Predict, Prevent it!

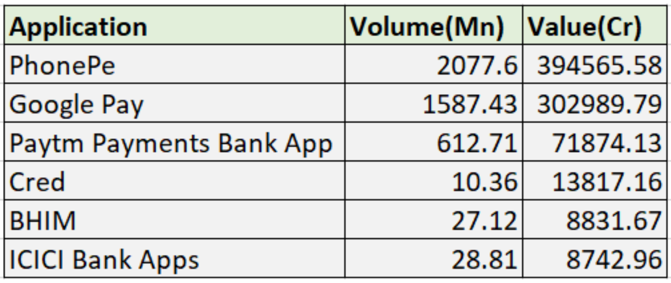
BEGINNER CLASSIFICATION DATA VISUALIZATION DEEP LEARNING GUIDE PYTHON

This article was published as a part of the Data Science Blogathon.

Introduction

Phonepe, Google Pay (Tez) are ubiquitous names in the Indian payment ecosystem and the top two players in the area. According to Phonepe pulse report, it has133 million monthly active users as of July'21. For the Q3-21 quarter, the total transactions were 526.8 Cr and total transaction of 9 Lakh Cr and an average transaction value of Rs1,751. Another payment major who recently launched its IPO of Rs 18300 Cr is Paytm, a huge player, a unicorn, like its counterpart Phonepe. It has 337M registered customers 21.8M merchants, and in FY21, its GMV was Rs 4 Trillion, of which revenue was 28.02 B. All this has been made possible by three major changes 1. NPCI-UPI, 2. Smartphone penetration and 3. High-speed internet. The pilot launch UPI project was on 11th April 2016 by Dr Raghuram G Rajan, then Governor, RBI at Mumbai. Banks started uploading their UPI enabled Apps on the Google Play store from 25th August 2016 onwards.

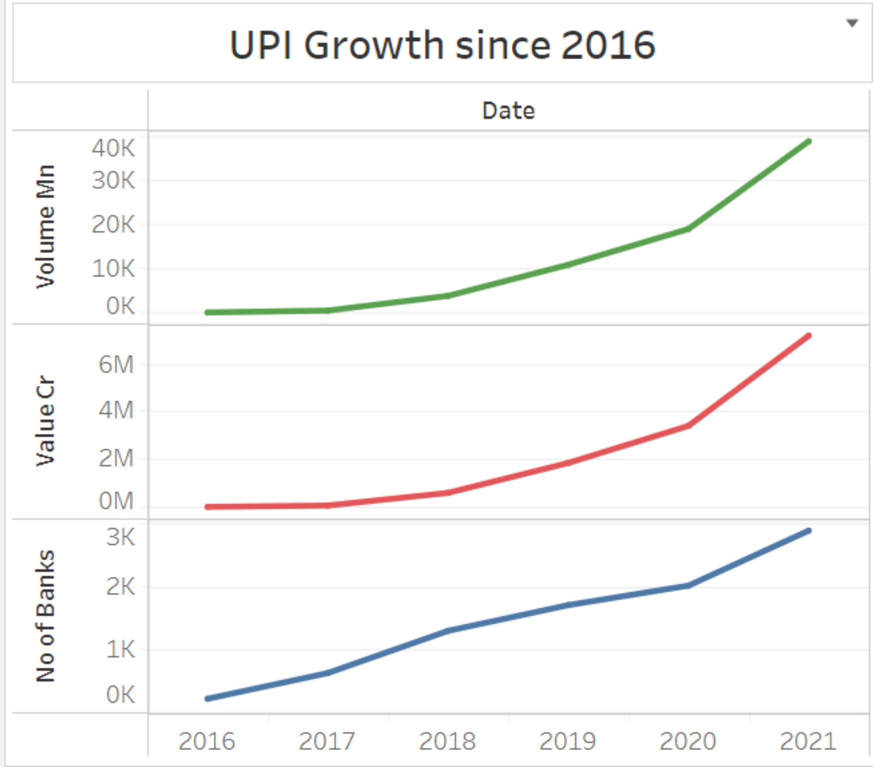
In the last quarter(Dec-21), the top 5 UPI applications based on volume are:



Application	Volume(Mn)	Value(Cr)
PhonePe	2077.6	394565.58
Google Pay	1587.43	302989.79
Paytm Payments Bank App	612.71	71874.13
Cred	10.36	13817.16
BHIM	27.12	8831.67
ICICI Bank Apps	28.81	8742.96

https://www.npci.org.in/what-we-do/upi/upi-ecosystem-statistics

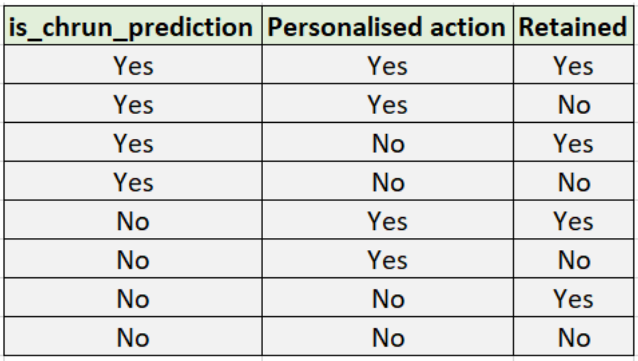
UPI has seen phenomenal growth since 2016 – from 2M transactions in 2016 to over 4500M transactions in 2021. All this data is readily available on the NPCI website.



https://www.npci.org.in/what-we-do/upi/upi-ecosystem-statistics

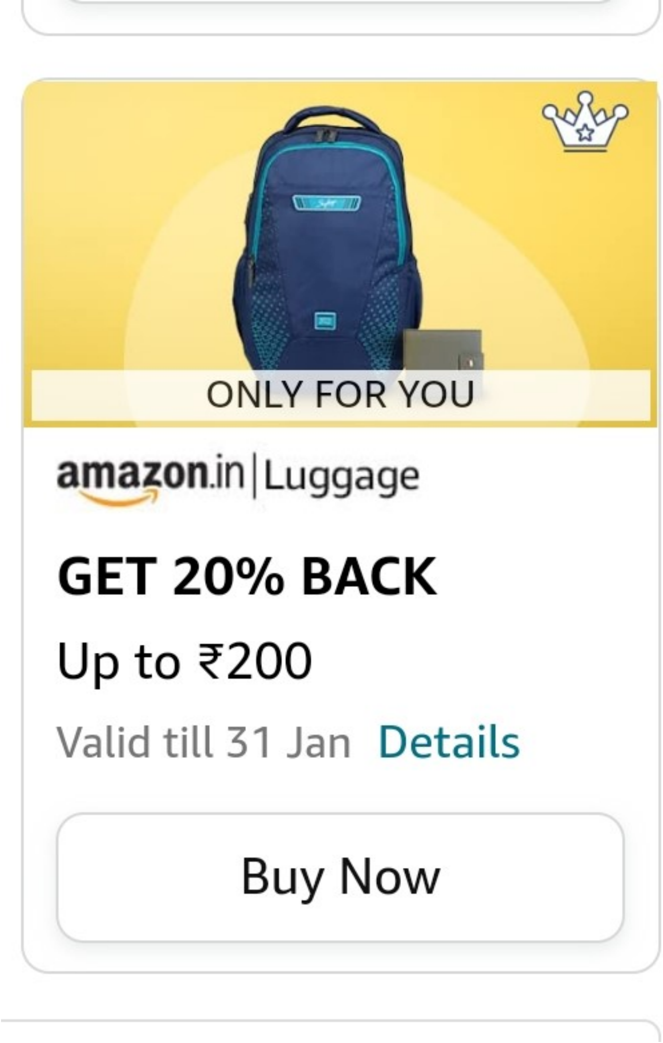
The backbone of this growth has been adoption in Tier1 and 2/3 cities, customer retention efforts, faster transaction (some with 2 seconds), exploiting new areas of growth(Cred as successfully done with credit cards). Data science has played its part in this growth, be it customer churn modelling, pricing models, growth models, fraud detection models, optimization models, risk analysis etc.

This article explores the world of customer churn prediction and recommendation. Just predicting churn has little value; the actions that need to be taken to arrest that churn personalize those actions and derive value; this is a major part that many churn prediction articles do not focus on. The below image depicts the complexity that comes after churn prediction. There are eight possible combinations in a simplistic view; the model predicts a customer is going to churn in the next six months(depending on how the model is trained), personalised coupon(refer to Amazon pay coupon below) or promotion is sent, the user retains, this adds value, the opposite of this is even with retention efforts the user churns, and customers are lost causes. While churn prediction models cannot differentiate between these users, the Uplift modelling technique helps identify these use cases and target only customers who provide an uplift.



is_chrun_prediction	Personalised action	Retained
Yes	Yes	Yes
Yes	Yes	No
Yes	No	Yes
Yes	No	No
No	Yes	Yes
No	Yes	No
No	No	Yes
No	No	No

screenshot



Personalized Recommendation – Amazon Pay

Table of Content

Problem Statement

Customer segmentation to reduce churn, churn prediction, and recommendation to arrest churn are the three board areas that modern B2C firms tackle using data science. A few firms are exploring uplift modelling and means to save costs. Uplift models can predict if a customer churns and is given an action, which customers have a high probability of retention, and only those customers will be targeted. Finding the right segment to target when there are millions of active customers is a tedious task and a resource-intensive, cost-intensive activity; uplift modelling can help mitigate the risks of targeting customers who aren't going to buy. Thus reducing irritating marketing messages and notifications.

This article will focus on

1. Customer segmentation with an eye for retention.
2. Churn prediction
3. Recommendation to reduce churn and increase retention.

Explore Dataset

Data can be downloaded here.

The dataset has 18 columns:

1. device user's – device brand (Categorical)
2. first_payment_amount – user's first payment amount(Numeric)
3. age – user's age(Numeric or categorical?)
4. city – user's city(Categorical)
5. number_of_cards – #of cards user owns
6. payments_initiated – #of payments initiated by user
7. payments_failed – #of payments failed
8. payments_completed – #of payments completed
9. payments_completed_amount_first_7days – amt of payment completed in first 7 days of joining
10. reward_purchase_count_first_7days – #of rewards claimed in first 7 days
11. coins_redeemed_first_7days – coins redeemed in first 7 days

12. is_referral – is user a referred user
13. visits_feature_1 – #of visits made by user to product feature 1
14. visits_feature_2 – #of visits made by user to product feature 2
15. given_permission_1 – has user given permission 1
16. given_permission_2 – has user given permission 2
17. user_id – user identifier
18. is_churned – whether user churned

Data Pre-Processing

Apart from a few variables – device, age, city, is_referral, all NA's can be filled with 0.

df_chrun.fillna(0, inplace = True)

Percentage of NULL values for rewards_puchase_count_first_7days is very high @ 22%. One option is to leave this column and proceed with the analysis.

City variable has 5% NULL; the city is important as it provides geographical information that can serve as a proxy for income elasticity of the customer or basically serve as a proxy for internet penetration etc. Cities can be Tiered into 3 to 5 and used as a categorical variable; hence fixing NULL's here serves an important purpose.

```
@staticmethod def missing_percentage(df_insurance_train, other_dict = {}): ''' input is a dataframe returns :
the percentage of missing values ''' missing_df = df_insurance_train.isnull().sum().reset_index()
missing_df["total"] = len(df_insurance_train) missing_df.columns = ["features", "null_count", "total"]
missing_df["missing_percent"] = round(missing_df["null_count"]/missing_df.total*100, 2)
missing_df.sort_values("missing_percent", ascending = False, inplace = True) print(missing_df.to_markdown())
return missing_df
```

Should age be used as a continuous variable or as a bucket?

Exploratory Data Analysis

Simplifying data questions to business questions and vice versa-

1. Which users have higher retention – organic or inorganic?
2. What effect do devices have on churn? Is it an important variable?
3. Does first payment play an important role in retaining users?
4. Do inorganic users download the app for monetary benefit, or do they intend to use it?
5. Can higher payment/conversion translate to retention?
6. What is the impact of age on customer churn? Is it is linear relationship quadratic?
7. What is the impact of rewards and discoverability?

Tableau has been used for EDA.

<u>Which users have higher retention – organic or inorganic?</u>

1. Referred users have to engage more with rewards/notifications to avoid higher churn.
2. 35% of referred users churned compared to 25% of organic, switch to more engaging referrals, such as staggered coupons based on payments to keep them hooked.

% Users churned vs retained (screenshot)

# Users based on referrals (*screenshot*)

Legend used :

- Blue – Not Churned
- Orange – Churned

<u>What effect do devices have on churn? Is it an important variable?</u>

1. High-end device users have churned less as compared to budget phone users.
2. Churned users have half the bills paid and amount transacted compared to retained. Incentivize or push to double the # of payments and amount paid in the first seven days to reduce churn.

% Churned vs Retained users based on devices (screenshot)

# of payments and amount paid based on churned vs retained(screenshot)

Does first payment play an important role in retaining users?

1. Users need to be nudged to complete the first payment, ensuring retention.
2. Referred users amount paid is 50% less compared to organic users.
3. Ensure more than four payments to reduce churn.

The total amount paid and % of total users of 0 First payment vs greater than 0 users(screenshot)

Do inorganic users download the app for monetary benefit, or do they intend to use it?

1. Referred users with 0 First payment churned higher than organic users.
2. Nudge referred users to make immediate first payment – Mobile recharge, electricity bill etc.

Total users and % of total users of 0 First payment – Organic vs Referral (screenshot)

Can higher payment/conversion translate to retention?

1. The payment failure did not have a significant impact on churn.
2. Churn was reduced drastically when users transacted more than once.

% users based on total # of payments and impact of payment failure on churn(screenshot)

What is the impact of age on customer churn? Is it is linear relationship quadratic?

1. Users below 20 are low to create an impact churn 33% faster than the rest.
2. Above 40 users churn faster than the rest. This further can be explored based on feature use and rewards.

Distribution of churn based on user age(screenshot)

What is the impact of rewards and discoverability?

1. Churned users have redeemed on average lower # of coins.
2. Retained users have purchased higher amounts of rewards using coins.
3. Retained users have redeemed more than 150% of coins and bought 33% higher rewards than churned users.

Averaged coins redeemed and rewards bought has a great influence on churn(screenshot)

Summary of EDA

- 35% of referred users churned compared to 25% of organic, switch to more engaging referrals, such as staggered coupons based on payments to keep them hooked.
- Referred users amount paid is 50% less compared to organic users.
- High-end device users have churned less as compared to budget phone users.

- Churned users have half the bills paid and amount transacted compared to retained. Incentivize or push to double the # of payments and amount paid in the first seven days to reduce churn.
- Users need to be nudged to complete the first payment, ensuring retention.
- Ensure more than four payments to reduce churn.
- Referred users with 0 First payment churned higher than organic users.
- Nudge referred users to make immediate first payment – Mobile recharge, electricity bill etc.
- Users below 20 are low to create an impact churn 33% faster than the rest.
- Above 40 users churn faster than the rest.
- Retained users have redeemed more than 150% of coins and bought 33% higher rewards than churned users.

Data Visualization

Tableau is easy to use and versatile, and anyone without an analytics or BI background can create awesome visualizations with some guidance and practice. Follow this tutorial on Tableau for beginners. It provides complete details on how to download tableau public, use it for basic plots, and build dashboards.

An online version of the EDA is uploaded on Tableau public; curious viewers can play around to find insights.

Clustering Using Heuristics

When time is of the essence, business leaders tend to use heuristics based on their experience, domain knowledge, and depth of expertise; it is easy to segment based on a few rules or set of rules. This approach is quick and easy to explain. Business leaders tend to value explainability more while making strategic decisions, and this approach

Code

```
## Final Segments df_chrun["segment"] = np.where(((df_chrun.is_churned == 1) & (df_chrun.first_payment_amount
== 0 | df_chrun.first_payment_amount.isna() )) ,"chrun_no_first_payment", np.where(((df_chrun.is_churned ==
1) & (df_chrun.first_payment_amount > 0) & (df_chrun.is_referral == False) ) ,"chrun_first_payment_n0_refer",
np.where(((df_chrun.is_churned == 0) & ((df_chrun.payments_completed >2) | (df_chrun.first_payment_amount ==
0 | df_chrun.first_payment_amount.isna() ))) ,"no_chrun_no_first_payment_payment_2",
np.where(((df_chrun.is_churned == 0) & (df_chrun.first_payment_amount >0 ) & (df_chrun.payments_completed ==
1 ) & (df_chrun.is_referral == True)) ,"no_chrun_first_payment_only_payment_referral",
np.where(((df_chrun.is_churned == 1) & (df_chrun.first_payment_amount > 0) & (df_chrun.is_referral == True))
,"chrun_first_payment_refer", np.where(((df_chrun.is_churned == 0) &
((df_chrun.reward_purchase_count_first_7days == 0) | (df_chrun.reward_purchase_count_first_7days.isna()) |
(df_chrun.coins_redeemed_first_7days == 0) | (df_chrun.coins_redeemed_first_7days.isna())))
,"no_chrun_first_payment_no_coins_rewards", np.where(((df_chrun.is_churned == 0) &
(df_chrun.first_payment_amount > 0) & ((df_chrun.visits_feature_1 == 0 | df_chrun.visits_feature_1.isnull())
& (df_chrun.visits_feature_2 == 0 | df_chrun.visits_feature_2.isnull())) &
((df_chrun.reward_purchase_count_first_7days > 0) | (df_chrun.coins_redeemed_first_7days > 0)))
,"no_chrun_first_paymen_coins_rewards_no_feature", "no_chrun_first_paymen_coins_rewards_good_feature")))))))
```

screenshot

Clustering using Kmeans

Kmeans is the goto clustering algorithm for its ease of understanding. Kmeans considers continuous variables only; hence categorical features have been dropped. Steps involved in K-means clustering.

Code

```
import matplotlib.pyplot as plt # from kneed import KneeLocator from sklearn.datasets import make_blobs from
sklearn.cluster import KMeans from sklearn.metrics import silhouette_score from sklearn.preprocessing import
StandardScaler df_chrun = Utils.load_data(churn_data_loc) cols_to_consider =
["first_payment_amount","age","number_of_cards","payments_initiated","payments_failed","payments_completed","payments_
df_chrun.fillna(0, inplace = True ) df_chrun.replace(0, 0.9 ,inplace = True ) thresh =
df_chrun.quantile([.25,.75, 0.95]) display(thresh) df_chrun = df_chrun.clip(upper=thresh.loc[.95],axis=1)
df_chrun = df_chrun[cols_to_consider].apply(pd.to_numeric) df_chrun = np.log(df_chrun) scaler =
StandardScaler() scaled_features = scaler.fit_transform(df_chrun) kmeans = KMeans( init="random",
n_clusters=7, n_init=10, max_iter=300, random_state=42 ) kmeans.fit(scaled_features) kmeans_kwargs = {
"init": "random", "n_init": 10, "max_iter": 300, "random_state": 42, } # A list holds the SSE values for each
k sse = [] for k in range(1, 11): kmeans = KMeans(n_clusters=k, **kmeans_kwargs) kmeans.fit(scaled_features)
sse.append(kmeans.inertia_) plt.style.use("fivethirtyeight") plt.plot(range(1, 11), sse) plt.xticks(range(1,
11)) plt.xlabel("Number of Clusters") plt.ylabel("SSE") plt.show() predict=kmeans.predict(scaled_features)
df_chrun['segment_new'] = pd.Series(predict, index=df_chrun.index)
```

Kmeans elbow curve(screenshot)

The elbow curve shows the # of clusters that can go upto 11 or 12, but clusters need to be worthwhile, so in this article, eight has been chosen as the optimum cluster.

Some issues faced with K-means clustering:

1. Large # of 0;s
2. How to deal with categorical features.
3. How to cap outlier based on thresholds.

Clustering Using Deep Learning

Autoencoders are used to learn feature representation; it forces the network to create a compressed version of input data. The compressed data is passed as an input to find the optimal value of k. WCSS – the within-cluster sum of squares plot of simple means, and autoencoder-means justify the use of autoencoders.

https://wiki.pathmind.com/deep-autoencoder

Code:

```
df_fintec =
pd.read_csv("https://raw.githubusercontent.com/chrisdmell/Project_DataScience/working_branch/07_cred/Analytics%20Assi
cols_basic_model = ['number_of_cards', 'payments_initiated', 'payments_failed', 'payments_completed',
'payments_completed_amount_first_7days', 'reward_purchase_count_first_7days', 'coins_redeemed_first_7days',
'is_referral', 'visits_feature_1', 'visits_feature_2', 'given_permission_1', 'given_permission_2']
df_fintec_LR = df_fintec[cols_basic_model] df_fintec_LR["is_referral"] =
df_fintec_LR["is_referral"].astype(int) df_fintec_LR.fillna(0, inplace = True) oh_cols =
["is_referral","given_permission_1","given_permission_2"] df_fintec_LR.drop(columns = oh_cols, inplace =
True) #KMEANS# scaler = StandardScaler() creditcard_df_scaled = scaler.fit_transform(df_fintec_LR)
display(creditcard_df_scaled.shape) score_1 = [] range_values = range(1, 20) for i in range_values: kmeans =
KMeans(n_clusters = i) kmeans.fit(creditcard_df_scaled) score_1.append(kmeans.inertia_) #AUTOENCODERS#
input_df = Input( shape = (len(creditcard_df_scaled[0]), )) x = Dense(7, activation = 'relu')(input_df) x =
Dense(500, activation = 'relu', kernel_initializer='glorot_uniform')(x) x = Dense(500, activation = 'relu',
kernel_initializer='glorot_uniform')(x) x = Dense(2000, activation = 'relu',
kernel_initializer='glorot_uniform')(x) encoded = Dense(10, activation = 'relu',
kernel_initializer='glorot_uniform')(x) x = Dense(2000, activation = 'relu',
kernel_initializer='glorot_uniform')(encoded) x = Dense(500, activation = 'relu',
kernel_initializer='glorot_uniform')(x) decoded = Dense(len(creditcard_df_scaled[0]),
kernel_initializer='glorot_uniform')(x) autoencoder = Model(input_df, decoded) encoder = Model(input_df,
encoded) autoencoder.compile(optimizer = 'adam', loss = 'mean_squared_error')
display(creditcard_df_scaled.shape) autoencoder.fit(creditcard_df_scaled, creditcard_df_scaled, batch_size=
120, epochs = 25, verbose = 1) autoencoder.summary() pred = encoder.predict(creditcard_df_scaled)
display(pred.shape) score_2 = [] range_values = range(1, 20) for i in range_values: kmeans =
KMeans(n_clusters = i) kmeans.fit(pred) score_2.append(kmeans.inertia_) #PLOT WCSS# plt.plot(score_1, 'bx-',
color = 'r', label = 'Original Data') plt.plot(score_2, 'bx-', color = 'b', label = 'Compressed Data')
plt.legend()
```

Comparing the WCSS between kmeans vs autoencoder-k-means, it’s clear that WCSS is lower using deep learning compressed data. So wrapping the data with an autoencoder layer provides an alternate way to scale data.

screenshot

Customer Churn Prediction Using Machine Learning Models

Tree-based models perform well for classification; a catboost classifier has been used in this case to build a binary classifier model. Ideally, improving recall(model churn/actual churn) would better retention. As churn data is usually imbalanced, evaluating just based accuracy could lead to wrong marketing strategies.

Actual	**Prediction**	**Action**
Churned	Churned	Incentivize
Churned	Not Churned	Customer churns – opportunity lost
Not Churned	Churned	Loss of capital through incentivization
Not Churned	Not Churned	Stay as is

Code:

```
X_train, X_test, y_train, y_test = train_test_split(df_fintec_LR, df_fintec[["is_churned"]],random_state =
70, test_size=0.30) scaler = StandardScaler() scaler.fit(X_train) X_train_Scaled = scaler.transform(X_train)
X_test_Scaled = scaler.transform(X_test) X, y =X_train_Scaled ,y_train # define model model =
CatBoostClassifier(verbose= False, loss_function='Logloss') # define evaluation cv =
RepeatedKFold(n_splits=10, n_repeats=3, random_state=1) # define search space space = dict()
space['max_depth'] = [3,4,5] space['n_estimators'] = [100,200,300] space['learning_rate'] =
[0.001,0.002,0.003,0.01] # define search search = GridSearchCV(model, space, scoring='accuracy', n_jobs=-1,
cv=cv) # execute search result = search.fit(X, y) # summarize result print('Best Score: %s' %
result.best_score_) print('Best Hyperparameters: %s' % result.best_params_) file_name = "cat_cls.pkl" # save
pickle.dump(search, open(file_name, "wb"))
```

Customer Churn Prediction using Deep Learning Models

Deep learning model

Code:

```
X = X_train_Scaled Y = y encoder = preprocessing.LabelEncoder() encoder.fit(Y) encoded_Y =
encoder.transform(Y) # baseline model model = Sequential() model.add(Dense(12, input_dim=12,
activation='relu')) model.add(Dense(1, activation='sigmoid')) # Compile model
model.compile(loss='binary_crossentropy', optimizer='adam', metrics=['accuracy']) display(model.summary())
history = model.fit(X, encoded_Y, batch_size=50, epochs=10, verbose=1) y_pred_cb =
search.predict(X_test_Scaled) y_pred_dl = model.predict(X_test_Scaled) y_pred_dl_f = [1 if x > 0.5 else 0 for
lis in list(y_pred_dl) for x in lis ]
```

Model Evaluation

Consider a re-engagement email campaign that says something like, “We noticed you might be leaving us. Please don’t!” You’d likely want to ensure that the precision for this email was high. In other words, you would want to minimize the number of happy users who see this email and instead have this email almost exclusively hit users in danger of churning.

On the other hand, consider an email that you want to send more broadly to your user base – it may be an offer to receive Rs50 off the next purchase. You’d be less concerned with users who are not in danger of churning receiving this marketing message. Ideally, though, you would want anyone who might churn to see the email. In this case, you would want your recall to be higher than your precision.

Retention Strategy and Recommendation

Recommendation based on EDA:

	Recommendation	Adoption and Evaluation
Rewards	1. Increases reward coins for the first bill paid. 2. Engage referral users with higher rewards. 3. Identify users segmentation basis rewards(cashback, vouchers etc.) and target effectively.	1. Decrease in 0 first payment and increase in retention post 1st bill paid. 2. Increase in 2+ payments in first seven days
Strategy	1. Competitor analysis and match competitor rewards. 2. Strengthen referral onboarding. 3. Track user journey and take action on exit point: user segmentation and targeting. 4. SMS/Email campaigns 5. Be more than just a bill payment app. Worked well for Paytm.	1. Consistent recurring bill payments. 2. Increase in frequency and recency metric. 3. Increased App activity post campaigns.
Features	1. Personalization and in-app messages 2. Include local biller – Descoms, QR pay @stores, Fastag 3. Multiple payment options – Pay later, credit cards, UPI. 4. Reduce payment failure.	1. Increase app usage activity. 2. Increase in Tier 2 cities adoption. 3. Increase in in-app card storage 4. Increase in successful payments
Discoverability	1. Easy discoverability of critical features such as vouchers, coupon offers bank offers. 2. App updates and pushes notifications to enhance users notifications.	1. Regular app updates 2. Increase in new feature engagement.

Advantages and drawbacks of segmentation techniques used:

Heuristic	1. Leverage business knowledge to identify cohesive user groups. 2. Rule-based method. 3. Easy to understand segment characteristics. 4. Susceptible to analyst bias.

	5. Quick and easy implementation.
Statistical Model	1. Use statistical techniques and identify similar groups based on user data. 2. A scientific approach rooted in data. 3. Additional effort to understand segments characteristics. 4. Devoid of analyst bias. 5. Involves an overall data-centric approach from preprocessing to modelling.

Properties of segments based on heuristics:

Segment 1	Segment 2	Segment 3	Segment 4
1. Churned user. 2. First payment amount > 0 3. Organic user.	1. Churned user 2. First payment amount > 0 3. Referred user.	1. 0 First payment 2. Churned user.	1. Retained user. 2. First payment made. 3. Aware of coins and rewards 4. Aware of features
Segment 5	Segment 6	Segment 7	Segment 8
1. Retained user 2. Aware of rewards and coins 3. Not aware of features	1. Retained user. 2. Lower coins usage and unaware of rewards 3. Healthy first payment amount	1. Retained user. 2. Referred user only. 3. Only one payment was made.	1. High values users. 2. More than two payments. 3. Occupied with rewards and features.

Recommendation for segments based on heuristics :

1	2	3	4
1. Churned user. 2. Increase coins and reward discoverability	1. Churned user 2. Push to complete recurring payments after the first payment.	1. 0 First payment, so nudge to make payment as soon as an app is installed. 2. Help discover coins and rewards. 3. Churned user.	1. Retained user. 2. Keep them occupied with rewards and regular notifications, updates 3. Star user
5	6	7	8
1. Increase new feature discoverability 2. Retained user	1. Retained user. 2. Nudge to use coins and rewards. 3. Nudge to finish two or more payments	1. Retained user. 2. Referral users with one payment, lure with bonus coupons 3. Keep occupied through features	1. Best Segment, High values users. 2. Keep them occupied with rewards and regular notifications updates.

Readers are encouraged to replicate properties and recommendations for Kmeans clusters as well.

Abbreviations used for Customer Churn

1. MAU – monthly active users.
2. Users vs Customers – Users and customers can be used interchangeably; typically, a user is anyone who browses through the platform, a customer is someone who transacts.
3. GMV – Gross merchandising value.
4. NPCI UPI – national payments corporation – unified payment interface

Useful Resources and References

Data science can be broadly divided into business solution-centric and technology-centric divisions. The below resources will immensely help a business solution-centric data science enthusiast expand their knowledge.

1. The Complete Guide to Checking Account Churn Prediction in BFSI Domain

2. Phonepe pulse report.
3. How do I interpret odds ratios in logistic regression?
4. NPCI statistics.
5. Paytm IPO Opens: Should you buy or not? Here's expert advice
6. How PayPal Uses Real-time Graph Database and Graph Analysis to Fight Fraud
7. A Complete Guide To Tableau For Beginners in Data Visualization
8. Tableau – Bill Pay App – churn analysis EDA.
9. Deep Clustering for Financial Market Segmentation.
10. Credit Card Customer Clustering with Autoencoder and K-means.
11. K-means: Why minimizing WCSS is maximizing Distance between clusters?
12. Neural Network: For Binary Classification, use 1 or 2 output neurons?

End Notes on Customer Churn

Churn/Retention/CLV models are the bread and butter of every business out there. Understanding churn can help frame appropriate marketing strategies for long-term retention and revenue growth.

Hope you liked my article on customer churn.

Good luck! Here's my Linkedin profile if you want to connect with me or want to help improve the article. Feel free to ping me on Topmate/Mentro; you can drop me a message with your query. I'll be happy to be connected. Check out my other articles on data science and analytics here.

The media shown in this article is not owned by Analytics Vidhya and are used at the Author's discretion.

Article Url - https://www.analyticsvidhya.com/blog/2022/02/guide-on-customer-churn-dont-just-predict-prevent-it/

Chrisx10 Dmello

Data scientist! Extensively using data mining, data processing algorithms, visualization, statistics and predictive modelling to solve challenging business problems and generate insights.