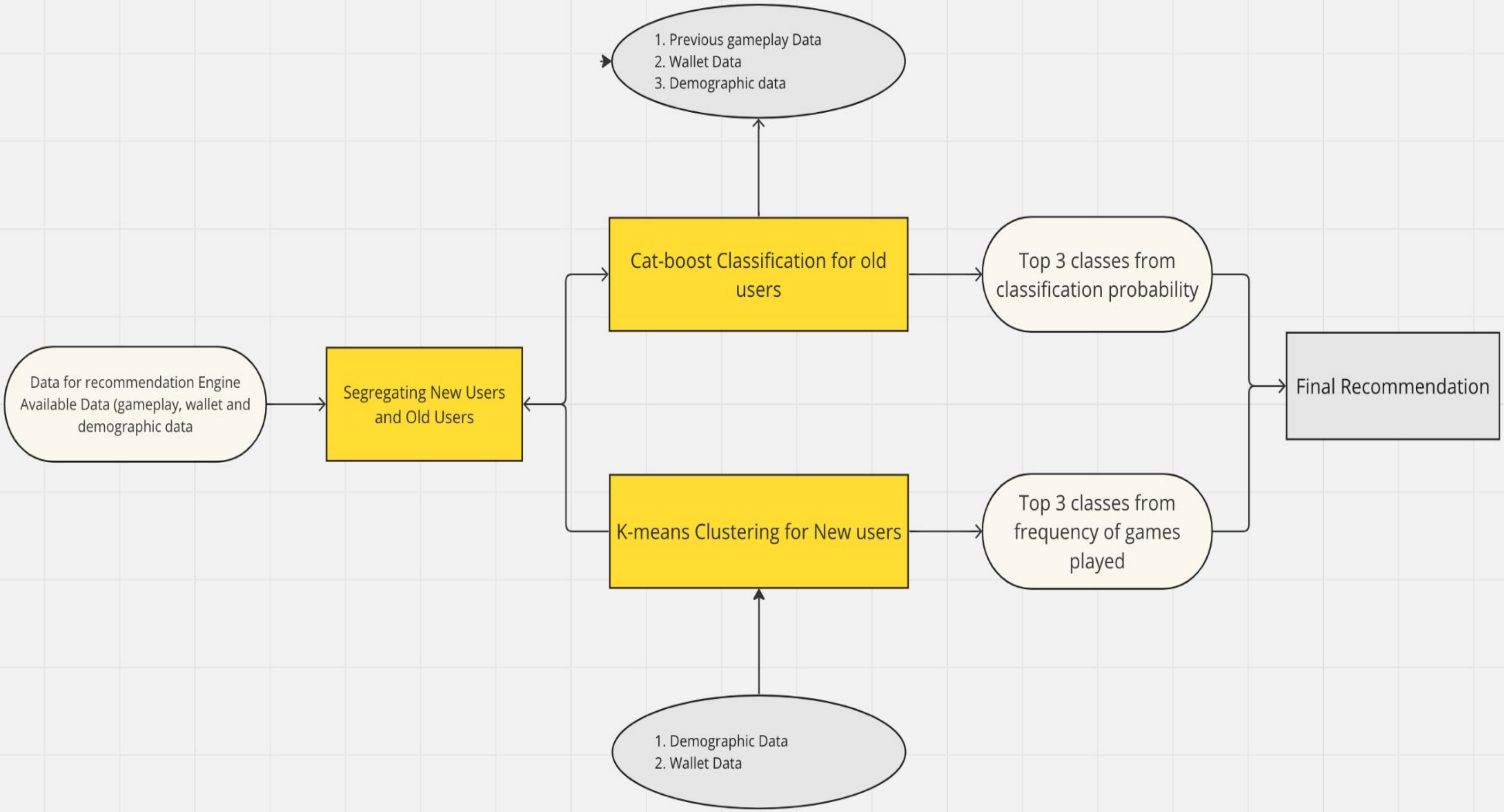
GAME RECOMMENDATION

Rakesh Bobbati

DATA INSIGHTS

- Tournament types are well distinguished with the price points and number of players
- User choices of tournaments and entry fee:
  - Only 46% users stick to single tournament type, 13 % play 2 types and ~9% for each 3 and 4 game types
  - 35% users play more than 3 tournament types out of 4 tournament types
  - 59% play tournament A , D is played by 30% , 9% play C and 2% play B
- Good Correlation in Entry Fee and Number of Games played, at earlier stages people play less fees games
- Good Correlation in Wallet Balance and Number of Games played.
- Users like to play 2 player games, 60% users play 2 player games and 4 player games
- Discrepancy in tournament Game Timing. Removed major outliers.
- Users like to play the tournaments they just previously played and won.



1. Previous gameplay Data
2. Wallet Data
3. Demographic data
Cat-boost Classification for old users
Top 3 classes from classification probability
Data for recommendation Engine Available Data (gameplay, wallet and demographic data
Segregating New Users and Old Users
Final Recommendation
K-means Clustering for New users
Top 3 classes from frequency of games played
1. Demographic Data
2. Wallet Data

Recommendation Solution by Segregation of users

Old User: Idea is to show recommended tournaments based on historical data

This problem fits into a classification problem of Tournament type and combined with payments.

- Used most recent information and historical cumulative data for better recommendation.
- Used recent and cumulative information of tournament, wallet info to create features for the classification models.
- Also used demographic data to create features
- Reason for using Cat-Boost Model
    - Cat-boost is very good with categorical features as it handles then well.
    - No need to create encodings for categorical data, taken care by the model itself
    - More explainability for predictions with supporting libraries like shapely.
    - Can use GPU for faster Training.
    - Tried Random Forest and balanced RF but catboost gave better results

New User: Idea is to increase the adoption, show users which is most engaging

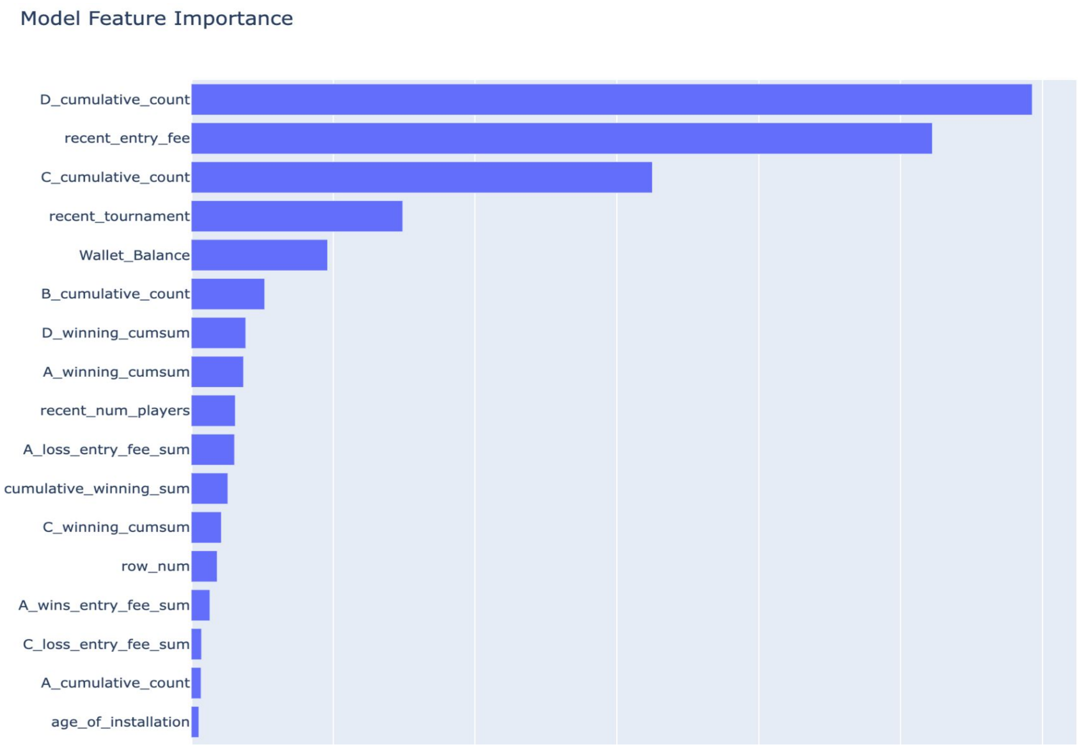
As we do not have any data of the initial user, I used demographic and wallet info to show in order of games played by similar users.

- Created Clusters based on demographic and device information along with wallet info for some cases.
- Sort the tournaments played in the order frequency, show the tournaments in order of decreasing frequency along with pricing mostly users tend to play low entry fee games and in tournament A i.e – A->D->C->B

Features Engineering for Old Users

- Used Gameplay data along with Wallet balance and Demographic details which includes device details
    - Tournament wise wins and losses cumulative entry fee amount and their respective counts
    - Total amount spent cumulative game by game
    - Frequency of tournaments played cumulative. Total Games played count
    - App installation Age
    - Most recent Entry Fee.
    - Most recent Tournament type
    - Wallet Balance just before playing the Game
    - Game timing and number of players in previous game.

Feature Importance Scores from Model and output




```
clf_catboost.predict_proba(X_test.iloc[:1,:])

array([[9.98735294e-01, 5.63155595e-04, 7.14578588e-07, 7.35569542e-08,
        2.81416623e-06, 9.49195024e-08, 1.80814899e-06, 1.45300650e-06,
        1.50785057e-07, 1.24048577e-07, 7.48593699e-05, 5.41419139e-05,
        2.88059176e-07, 5.06609452e-06, 3.14908678e-06, 8.42708962e-07,
        1.35734899e-05, 5.42396308e-04]])

clf_catboost.classes_

array(['A_1.0', 'A_10.0', 'A_100.0', 'A_1000.0', 'A_25.0', 'A_250.0',
       'A_35.0', 'A_50.0', 'A_500.0', 'A_5000.0', 'B_10.0', 'C_10.0',
       'C_100.0', 'C_25.0', 'C_35.0', 'C_50.0', 'D_15.0', 'D_5.0'],
      dtype=object)

class_prob = np.argsort(clf_catboost.predict_proba(X_test.iloc[:1,:])[0])[::-1][:3]

clf_catboost.classes_[class_prob]

array(['A_1.0', 'A_10.0', 'D_5.0'], dtype=object)
```

Accuracy Of the Model

	precision	recall	f1-score	support
A_1.0	0.99	1.00	1.00	13746
A_10.0	0.99	0.98	0.98	4948
A_100.0	0.95	0.93	0.94	824
A_1000.0	0.96	0.81	0.88	53
A_25.0	0.91	0.94	0.92	2087
A_250.0	0.96	0.92	0.94	285
A_35.0	0.64	0.46	0.54	179
A_50.0	0.93	0.89	0.91	885
A_500.0	0.97	0.84	0.90	104
A_5000.0	1.00	0.50	0.67	4
B_10.0	0.99	1.00	1.00	779
C_10.0	0.93	1.00	0.96	1973
C_100.0	0.96	0.89	0.92	475
C_25.0	0.60	0.14	0.22	111
C_35.0	0.84	0.90	0.87	542
C_50.0	0.84	0.78	0.81	291
D_15.0	0.94	0.81	0.87	442
D_5.0	0.98	1.00	0.99	3396
accuracy			0.97	31124
macro avg	0.91	0.82	0.85	31124
weighted avg	0.97	0.97	0.97	31124

Features Engineering for New Users

- Used Demographic details which includes device details and Wallet Info
  - Demographic details for location , device and connection are frequency encoded along with wallet balance
  - K-means Clustering is used, hyperparameter tuned with elbow method for WCSS
  - WCSS is the sum of the squared distance between each point and the centroid in a cluster.
  - Most Frequently played games are recommended for the respective clusters.

Game_category	A_1.0	A_10.0	A_100.0	A_25.0	A_250.0	A_35.0	A_50.0	B_10.0	C_10.0	C_100.0	C_25.0	C_35.0	D_15.0	D_5.0
0	152.0	18.0	1.0	NaN	NaN	17.0	1.0	NaN	4.0	NaN	2.0	NaN	NaN	13.0
1	1511.0	166.0	NaN	3.0	NaN	160.0	4.0	4.0	37.0	NaN	39.0	1.0	NaN	81.0
2	113.0	25.0	NaN	NaN	NaN	25.0	NaN	NaN	7.0	1.0	NaN	NaN	NaN	5.0
3	398.0	55.0	NaN	1.0	NaN	47.0	1.0	NaN	11.0	NaN	4.0	NaN	NaN	43.0
4	749.0	60.0	4.0	3.0	1.0	31.0	NaN	2.0	11.0	NaN	3.0	NaN	NaN	32.0
5	195.0	10.0	NaN	NaN	NaN	1.0	NaN	NaN	NaN	NaN	NaN	NaN	NaN	6.0
6	340.0	42.0	NaN	NaN	NaN	25.0	1.0	1.0	8.0	NaN	6.0	NaN	NaN	24.0
7	75.0	24.0	NaN	NaN	NaN	15.0	NaN	NaN	7.0	NaN	1.0	NaN	NaN	4.0
8	1018.0	132.0	3.0	2.0	NaN	47.0	3.0	1.0	28.0	1.0	19.0	NaN	1.0	72.0
9	299.0	39.0	NaN	NaN	NaN	16.0	2.0	1.0	8.0	NaN	1.0	1.0	1.0	27.0

Accuracy of the model using MRR

Metric:

MRR: Mean Reciprocal Rank :

$$MRR = \frac{1}{|U_{all}|}\sum_{u=1}^{|U_{all}|} RR(u)$$

$$RR(u) = \sum_{i \leq L} \frac{relevance_i}{rank_i}$$

where $RR(u)$ is the reciprocal rank of a user u, and it is defined by the sum of relevance score of top L items weighted by reciprocal rank. MRR is simply the mean of all users in the test dataset.

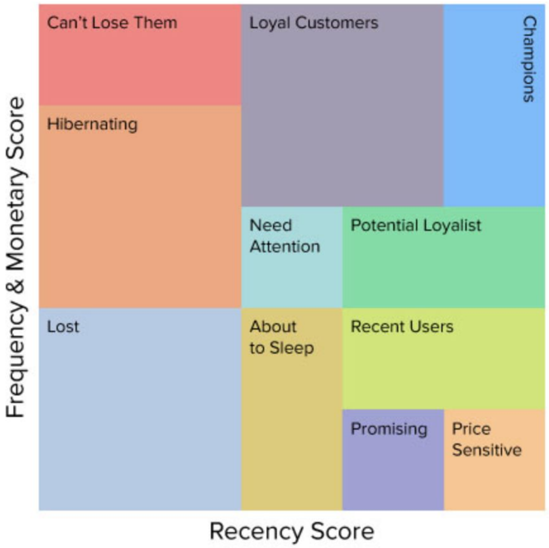
1. Made a custom evaluation dataset as the evaluation dataset provided does not have any subset information from gameplay data. A total of 5448 users data is taken for evaluation.
2. MRR value for predicted results is : 0.83 = [((4170/5448)/1) + ((635/5448)/2) + ((133/5448)/3)] (close to 1 better)
3. ~76% users choose first option followed by ~12% second and ~2.5% third options. Rest did not choose any recommendations.
4. **Overall 90.6% users played out of the 3 recommendation products**

Also tried NDCG (Normalized Discounted Cumulative Gain) But usually observed most frequently MRR is used for recommender systems.

Improvements Scope

- Hyperparameter Tuning of the models and better balancing the dataset.
- When New tournaments come , we need to retrain the models. Also we can try collaborative filtering.
- We can Use the information from next slide to handle specific customer type so that we can improve their experience and also can possibly gain revenue by customizing our recommendation.

Repeat Users ||RFM Reference || CLM Segmentation



Label	Characteristics
Champions	Ones who have bought recently, do frequent purchase & spend heavily. They also do word of mouth marketing for brands & hence needed to be treated with utmost care.
Potential Loyalists	These are high spending customers who need more attention from the company to become loyal to the brand.
Recent users	Recent users have started purchasing recently & hence marketing strategy needs to be planned carefully to prevent their drop out.
Can't loose them	This category is a high spending category but prone to risk from competitors & hence need continuous attention.
Needs attention	These customers are the ones who are thinking of stopping the usage of the brand which might be due to internal or external factors. Hence, they need very personalized attention & messages to prevent attrition.
Loyal customers	This category needs to be offered what they are being offered currently & risk of losing them is minimal.
Price sensitive	Price sensitive customers need offers of discount & low prices. They are least loyal & hence discount & sale campaigns should be targeted towards them.
About to sleep	These are on the verge of being lost & hence needs high & immediate attention.
Hibernating	These are current customers who have not made any purchase in the recent past & need to be induced for shopping else they might be lost forever.
Lost customers	This category is very difficult to bring back & minimal efforts should be channeled towards them. Instead companies can understand from their experiences about areas to improve on.

Thank You