

How can we increase revenue from Catch the Pink Flamingo?

Michel Truyenque

Context

- Catch the Pink Flamingo
 - Multi user game
 - Team oriented
 - In game purchases
 - Collects info while users are gaming.

Objective

Catch as many Pink Flamingos as possible by following the missions provided by real-time prompts in the game and cover the map provided for each level.



Catch the Pink Flamingo game, is a multiuser and team oriented game where users can purchase items while gaming.

The objective is to catch as many pink flamingos as possible by following the missions provided by real-time prompts in the game and cover the map provided for each level.

All information about user gaming, purchases and interactions/chats with their teammates are collected for further analysis in order to trace strategies to increase the total revenue for the game.

Problem Statement

How can we use the following data sets to understand options for increasing revenue from game players?



flamingo-data

files containing simulated game data and log data.



combined-data

files containing few aggregations from flamingo-data.



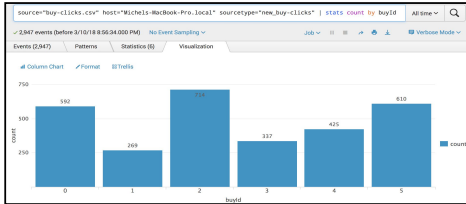
chat-data

files containing simulated chat data.

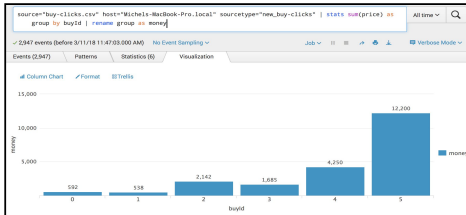
Here we present a little description of the data sets we have for our analysis. Most of the data is a simulated data that contains gaming data as clicks, purchases, aggregations (as average_price purchased per session), and also a set of tables that describe chat interactions between teammates.

Data Exploration Overview

How many times item is purchased



Money for each item



- While items 2 and 5 are the most purchased, the biggest revenue comes from item 5. We may analyse our price strategy for item 2 in order to capitalize its popularity.
- In terms of revenue, even with good number of purchases. There are items with poor revenue numbers.
- Top buying users seem to be in *iphone* platform.

Rank	User Id	Platform	Hit-Ratio (%)
1	2229	iphone	11.59
2	12	iphone	13.06
3	471	iphone	14.50

In our first exploration of data that represent item purchase history we can discover some interesting information.

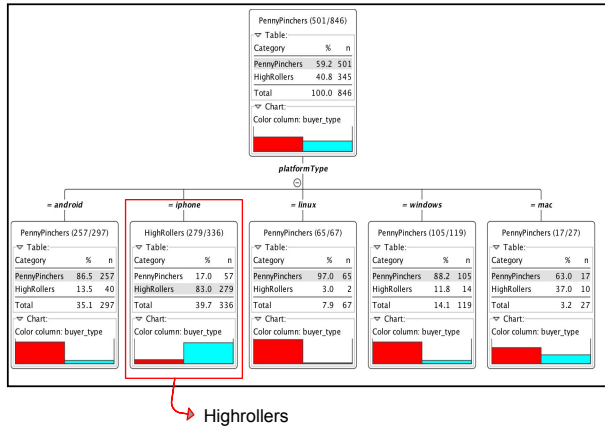
While items 2 and 5 are the most purchased in numbers, it is interesting to observe that biggest revenue comes basically only from item 5. It would be interesting to analyze the case of item 2 and see why, besides its reasonable high number of purchases, it is not translated to good revenue numbers.

Maybe we can review our price strategy in order to capitalize money with popular items.

Top buying user are mostly concentrated in iphone platform.

What have we learned from classification?

Decision Tree of our model



- New categorical attribute "user_category" created based in avg purchase per user session.
 - PennyPinchers :] -∞ ... 5.0]
 - HighRollers :] 5.0 ... ∞ [
- HighRollers are mainly concentrated in *iphone* platform.
- Overall accuracy of the model is **88.496%**

Confusion Matrix - 2:1:1 - Scorer			
File	Hitite		
user_type	Prediction...	PennyPinchers	HighRollers
PennyPinchers		308	27
HighRollers		38	192
Total			
		346	219
		Total	
		565	
		Correct classified: 500	
		Wrong classified: 65	
		Accuracy: 88.496 %	
		Error: 11.504 %	
		Cohen's kappa (κ) 0.76	

A new categorical attribute was created to enable the analysis of players broken into 2 categories (HighRollers and PennyPinchers).

The categorical attribute was based on average purchase price per session per user. According to the resulting model, we infer that user_category is highly affected by the type of platform the user is gaming.

PennyPinchers are highly correlated to users that use android, linux, windows and mac platforms. While HighRollers category is highly correlated to Iphone platform users.

Certainly there are a set of game features in iphone platform that makes users to be attracted more to the game and purchase more products as they advance in the game levels.

What have we learned from clustering?

Decided to cluster in 2 sets

Cluster #	Cluster Center
1	array([-0.81771878, -0.37749641, -0.4354828])
2	array([0.84528233, 0.39022101, 0.45016199])

➡ Low spending users (LS)

➡ High spending users (HS)

Attribute	Rationale for Selection
Total ads clicks per user	According this attribute, we can compare users based on total amount of ads clicks they made. It captures users ads clicks behavior for all ads categories.
Total game clicks per user	According this attribute, we can compare users also based on total amount of game clicks they made in all interaction with the game. It captures user game clicks behavior for all time users interacted with the game.
Total revenue per user	According this attribute, we can capture total sum of money spent by users in all categories.

- **Cluster 1** : players have a low number of game clicks, which translate in less often ads clicking behavior reducing the revenue we have per user in this group.
- **Cluster 2**: players have a high number of game clicks. Potentially translate into a more often ads clicking behavior increasing the revenue.

Clustering our training set into two clusters allowed us to identify two big user groups.

As expected they have big differences on all values and we could infer that the amount of revenue per user is directly influenced by the amount of clicks (on game and ads). Also we can see that low values in game clicking normally influence to low values in ads clicking. High number of game_clicks normally influence into high values on ads clicking.

Cluster 1: is different from the other, as players in this group have a low number of game clicks, which translate in less often ads clicking behavior reducing the revenue we have per user in this group.

Cluster 2: is different from the other, as players in this group have a high number of game clicks. As we can see, it potentially translate into a more often ads clicking behavior increasing the revenue we have per each user in this group.

Graph Chat Analysis

Chattiest Users

"User"	"NumChats"
394	115
2067	111
1087	109
209	109
554	107
999	105
516	105
1627	105
461	104
668	104

Chattiest Teams

"Team"	"NumChatSessions"
82	1324
185	1036
112	957
18	844
194	836
129	814
52	788
136	783
146	746
81	736

Teams of Chatties

"User"	"Team"	"NumChats"
394	63	115
2067	7	111
209	7	109
1087	77	109
554	181	107
516	7	105
1627	7	105
999	52	105
461	104	104
668	89	104

1. Who are the top 10 chattiest users?
2. What are the top 10 chattiest teams?
3. Any chattiest user belong to chattiest team?
4. How active are groups of users?
Cluster coefficient

Most Active Users (based on Cluster Coefficients)

User ID	Coefficient
209	0.9523
554	0.9047
1087	0.8

We have created a graph model based on the ChatItems and ChatSessions users have participated in their gaming history.

In order to calculate the top 10 chattiest users, we analyzed the number of ChatItems each user has created.

For the top 10 chattiest teams, we analyzed all the ChatItems that belong to chat sessions of an specific team. As noticed we can observe one chattiest user that also belongs to one of the top chattiest teams (user 999).

The cluster coefficient is an interesting indicator of how active a group of users are. It would help us to create specific marketing strategies/ads for most active user groups.

Recommendations

1. Offer some promotions/rewards to high concentration of PennyPinchers on linux, windows, android and mac platforms.
2. Increase the number of products offered in iphone platform.
3. Offer a kind on incentive for iphone users who recommend the game to friends in same iphone platform.
4. Engage “Low spending users” to spend more time gaming.
5. Increase prices of ads shown to “high spending users”.
6. Provide more purchase items to “high spending users”.

1. As there is a high concentration of PennyPinchers on linux, windows, android and mac platforms. We can offer some promotions/rewards for these specific platforms in order to increase the game engagement and purchases.

2. For Iphone users, we could increase the number of products offered in this platform.

3. As Iphone platform is a high revenue platform, we can open a kind of incentive and rewards for iphone users who recommend the game to friends using an Iphone platform as well.

4. Engage “low spending users” to spend more time gaming. As revenue is highly affected by the amount of game clicks user does during the game. We can provide some fixed pay packages or promotions that encourage them to increasing the time in gaming. Thus, we potentially increase the number of game clicks and also the number of ads-clicks user does, increasing our revenue.

5. Increase prices of ads shown to “high spending users”

As we get paid for showing ads, we could increase our revenue by building a price mechanism that would increase ads fees when shown to frequent clickers. As we have users clicking profile we can charge more to ads shown to top x% users, for instance.

6. Provide more purchase items to “high spending users”

We can diversify and also increase the purchase items offer to frequent clickers, so we potentially increase our revenue with additional products.