KKBox: Business Impacts of Plan

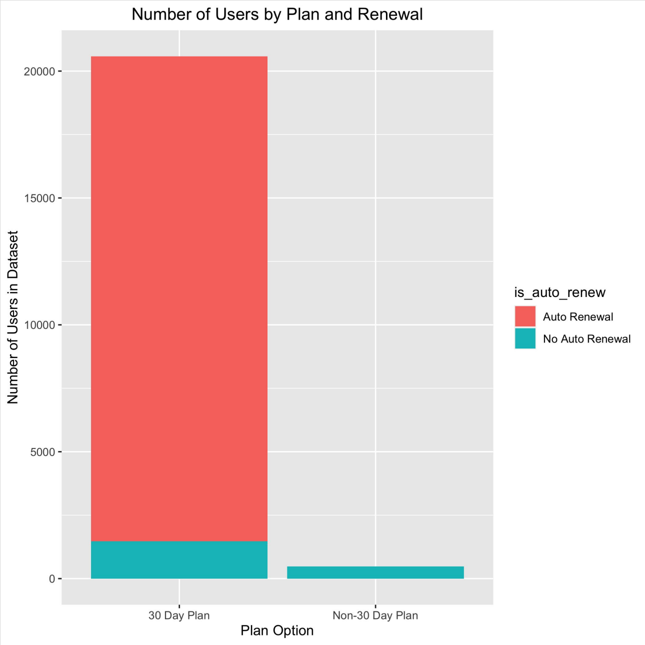
NYCDSA Hackathon October 2020

Pause for Names James

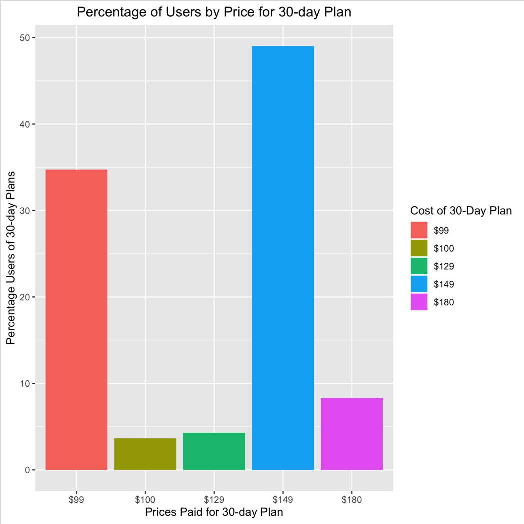
Overview

- For this project we were tasked with designing a marketing strategy for KKBox, a streaming music service, and were given four datasets describing user demographics, transaction history, listening history, and churn rate.
- We will discuss today:
  - How we isolated the most important users,
  - How churn impacts revenue,
  - Two potential marketing plans, and
  - The differences between user segments
  - Future improvements to the data set

- The right graph shows that the vast majority of users are on 30-day plans, and the vast majority of those users have auto-renew.
- This group accounts for nearly 96% of all users we had data for, therefore, we isolated our research to only 30-day auto-renew users.



- We further isolated the users by price of plan, shown on the left - 98 percent of users have one of 5 pricing options out of many more.
- Two of these plans are $99 and $100, so we categorized them as low-tier plans.
- One plan is $129, so it is our mid-tier plan.
- The last two plans are $149 and $180, so they make up the high-tier plans.



This bar plot shows the amount of churn among users in each plan.

Our low-tier plans have the least amount of churn while our high-tier plans have the most churn.

However, both the number of customers in a plan and the amount of churn for that plan influence the monetary value of that plan.

Marketing Strategies

Because of this, we have suggested two marketing strategies - one that minimizes churn, and one that maximizes revenue.

Marketing Strategies

Churn appears to be directly related to the price of plans given this dataset, so our recommendation to reduce churn is to lower prices, since churn increases as plan price increases.

To figure out how to maximize revenue, we looked at the annual value of a single user for each of our five plans, shown on the graph here. First we made the assumptions that a user would remain a member for 12 months continuously and on the same plan. For example, on the $99 plan, a user would be worth $99 the first month. The next month, however, due to churn, that user would only be worth $97.

By breaking down the numbers, we were able to find that high-tier plans, the blue and green lines, net about $345 more annually than low tier plans, despite the variations in user quantity and in amount of churn per plan.

Sign up Patterns are distinct between plans

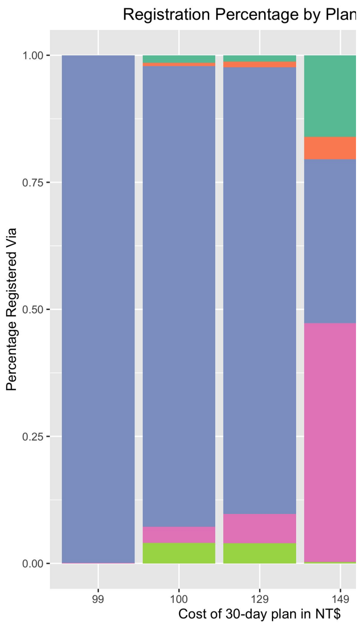
User interaction seems to weakly increase with price paid:

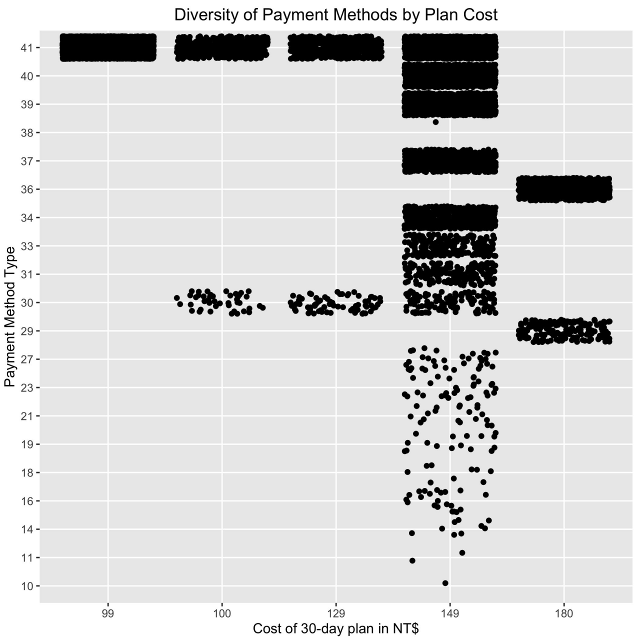
Registration = age and duration
Payment = duration and city

kkBox seems to be proud of its many avenues of service, TV, device, computer, smart speakers:

without knowing more about what these values stand for it is difficult to suggest a strategy.

The channel differentiation into more lucrative users could help expand user growth and revenues by driving consumers toward this category. City is also diverse too.





Literature Review

An sociological based method was developed to classify music service users into 7 ‘personas’.

Persona	Description
Active Curator	
Music Epicurean	
Guided Listener	
Music Recluse	
Non-believer	
Wanderer	
Addict	

Separately, Spotify identified 3 metrics to classify users (to better sell ads):

Discovery: finding new music

Diversity: range of music

Tilt: how actively streaming is curated

Future Improvements - Additional Data

- Time of usage
  - when are users on the app? (commute, gym, weekend party)
  - Improved “session” data - replace singular date with start datetime and end datetime
    - Some listening times extend over 24 hours
  - From literature we know users have strong daily listening patterns.
- Interactivity (how active are users in the app and what features do they use?)
  - Likes, Dislikes, Adds to playlist, Shares, Downloads, Follows (artist, user, playlist)
- Music categorization (what kind of music is popular on the platform?)
  - Genre
  - Discovery method: (Personal playlist, Curated playlist, Album, Artist page, Via search)
- Device data - how are users accessing the platform?
  - (by session vs registration)
  - Activations by device (android, iphone, pc, smart watch, etc.)

Future Improvements - Additional Questions and How to Answer

Q: When are users on the app? (Morning Commute, At the Gym, Weekend Party)
A: Date -> Session Start (Datetime) and Session End (Datetime)

Q: What do users like to listen to?
A: Seconds listening -> split by genre (Rock, Hip-hop, K-pop, etc.)

Q: How are users accessing the app?
A: Device - device used for each session (PC, iPhone, Android, etc.)

Q: How are users discovering music?
A: “Referral” - (Home Page, Album, Artist, Personal Playlist, Curated Playlist, via Search)

Q: How are users interacting with the app?
A: Likes, Dislikes, Downloads, Adds to Playlist, Follows (artists, playlists, users), Shares