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Faculty of Engineering  
Department of Computer Science

ICOM6044 Data Science for Business  
Instructor: Professor Alan Montgomery

Group Written Assignment 2  
Freemium Case

By

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**High Note**

To: Lisa Peschke, Director of Marketing  
From: Daniel Lee, Jacky Ng, Joseph Kwan, and Christy Chan  
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Subject: Recommendation on High Note “Freemium” services

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**A. Background**

Our team has completed analysing the data of our subscribers and now we have a clearer picture about the characteristics of our free and premium users. In this memo, we would like to share our findings and provide recommendations on how we could increase our paid premium user base in longer run.

**B. Differences Between Free vs Premium Subscribers**

The data that we pulled out covers the demographic information, social network characteristics and behavioural level data of High Note’s subscribers [Refer to Appendix 1 for the detailed list of variables included]. In total, we have over 1.2m of free users and 37k of premium users. There are few key differences that we observe among these two groups of users. In terms of network of friends, premium subscribers have 2.6 times more friends than free users. They also have over 4.7 times more friends who are also subscribed to premium plans. On the other hand, premium users in general show more interactivity with us. Compared to our free subscribers, they are known to create more playlists (2.7 times more) and more loved tracks (3.3 times more). They are also significantly more engaged in writing posts on our Q&A forum (5.1 times more) and using shouts (4.8 times more). [Appendix 2]

**C. Data Insights based on Modelling**

Next, we apply logistic regression to look for the characteristics of users who have switched from being free to premium subscribers in current period. Our logistic regression model helps

predict whether a free user will pay for our services. Some metrics indicate that our model predicts whether a user will become a premium subscriber reliably. The details of those metrics are presented in [Appendix 3].

We find that a user is more likely to go from “free to fee” if he is a friend of a premium subscriber<sup>1</sup>. Our model predicts that for every premium subscriber a free user is friend with, he is 40% more likely to pay for our services<sup>2</sup>. We think a free user is motivated to convert when a friend impresses him with the privileges of a premium subscriber.

We also discover that a user who makes many playlists is more likely to go from “free to fee”. Our model predicts that a free user is 22% more likely to pay for our services for every playlist he makes<sup>3</sup>. We believe the more playlists a user makes, the more affection he has towards music, and the more likely he pays for preventing advertisements from disrupting his enjoyment of music.

A user who loves many tracks is more likely to convert to a premium subscriber. As some pieces of music are offered to premium subscribers only, a free user might not be able to listen to all pieces in the track he loves. This unmet desire motivates the user to pay for our subscription to listen to whole of his favourite track.

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<sup>1</sup> The odds ratio represents the probability of becoming a premium subscriber to the probability of remaining as a free user. The larger the impact of a variable on the odds ratio, the more important the variable is in converting a free user to a premium subscriber. The variable `subscriber_friend_cnt` represents the number of friends who are premium subscribers. Its coefficient in our logistic regression model is 0.39206. The exponent of this coefficient (1.48003) indicates that if a free user becomes friend with a premium subscriber, the odds ratio increases by 48% (1-1.48003). A change of this variable raises the odds ratio rises by the highest percentage. The number of friends who are premium subscribers is the most important variable. Please refer to Appendix 4 for comparison with other variables.

<sup>2</sup> This percentage is approximated by the coefficient of `subscriber_friend_cnt` (0.39206).

<sup>3</sup> This percentage is approximated by the coefficient of `playlists` (0.21530).

## **D. Recommendations**

To attract and retain premium subscriptions, the following recommendations are suggested in two perspectives – feature improvements and marketing programs. The recommendations of feature improvements are based on three key variables (subscriber friends, playlists and loved tracks) identified from our analysis of the existing user pool.

### **Feature Improvements**

#### **1. Optimize Friend Recommendation Engine**

It is found that the conversion to premium service is positively correlated with the number of premium subscriber friends. We could adjust our algorithm to the friend recommendation engine by suggesting more premium friends with similar taste in music to the free users. If they could successfully make a connection, premium users could make a peer influence on their friends in the hope of converting them from free to fee.

#### **2. Optimize Play List Function**

Another finding is that the more playlists a user creates or has, the higher chance a user converts from free to paid subscription in which it implies our existing playlist function could increase our platform stickiness. If we want to convert more “free to fee”, we should focus on enhancing the playlist function further. From the customer’s perspective, the playlist function could be improved by facilitating the customisation of the playlist such as adding music with a list of recommended songs instead of the manual search and dropping music from the playlist only with a few clicks, making the user interface of the platform more user friendly. From our company's perspective, we could continue to expand our machine learning team to optimize the playlist module such as building playlists for the users based on their preferences in order to retain the users on our platform and eventually convert into paid users.

### **3. Enhance Loved Tracks Function**

According to our findings, a user has more loved tracks in his account, he will probably convert to the premium account. It implies the users are more engaged compared to those with lesser loved songs. We could optimise this function along with the recommendation engine by recommending songs like their loved song with the collaborative filtering model which analyses other High Note users who have similar loved songs. Apart from loved songs, a dislike tracks function could be developed in order to add a new parameter into our recommendation engine so that we could more precisely sort out what our users really love.

All these enhanced functionalities could increase users' stickiness on our platform as they will be only listening to their favourite songs and music in the future. If they want to listen to them uninterruptedly and ubiquitously, chances to convert from free to premium will be higher.

To attract more premium subscribers, we shall not only consider converting free users, but should also leverage the word-of-mouth (WOM) power of existing premium subscribers. Nielsen once reported that 92% of consumers believe suggestions from friends and families more than other advertising means<sup>4</sup>. There are two types of WOM - organic or amplified for WOM tactics consideration.

### **4. Differentiate Free and Premium Features**

To boost organic WOM, it is suggested to create unique and upgrade features for premium users so they become our natural fans to recommend their close friends or family members in subscribing premium plans. Differentiation of free or premium plan is more than crucial. Given

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<sup>4</sup> <https://www.forbes.com/sites/kimberlywhitler/2014/07/17/why-word-of-mouth-marketing-is-the-most-important-social-media/?sh=590d8b8254a8>

our premium users are already quite addicted to creating posts and shouts (respective mean values are about 5 times larger than free users), we can consider enhancing the user interface and offering exclusive functions on these 2 features, e.g. customization flexibility, encrypted posts, special emoji. New unique features such as playlists for simultaneous update among selected friends in premium subscribers' group, automatic translation of lyrics with premium users' preferred language can be explored.

## **Marketing Programs**

### **1. Offer 1-month Free Trial for Free Users**

As discussed, one of the key findings on our model is that there is a positive correlation between the probability of converting from free to premium and the number of premium friends a user has. In order to convert free users into paid users at first, we may consider offering a month of free premium service for the free users to experience our extended services and get used to it such as uninterrupted and ubiquitous music streaming service on multiple devices. At the same time, we could also attract more new users to expand our user base by providing a free trial given the general free to paid conversion rate is between 2%-4%.<sup>5</sup>

### **2. Design Social Media Campaigns**

To accelerate WOM impact, the concept of amplified WOM comes in. Social media campaigns can be designed in a game or challenge context. For example, invite premium subscribers quoting their top reasons of being High Note premium subscribers and tagging their premium subscriber friends in Facebook or Instagram to continue the game without repeating any previously mentioned reasons. We can reward all participated premium subscribers with

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<sup>5</sup> <https://neliosoftware.com/blog/how-to-increase-payment-customers-in-a-freemium-model/?nab=1>

chances to win a lottery of exclusive concert tickets. The amplified WOM impact is expected to draw high traffic in social media platform and attract more people joining our premium plan. It can also re-emphasize the benefits of High Note to existing premium subscribers and reduce attrition rate.

### **3. Set Up Referral Program**

Moreover, referral program could be set up to provide monetary incentives for premium subscribers to recommend High Note. For example, offering premium subscribers one-month premium fee rebate when a new customer registers account with their designated referral code. The more customers they refer, the longer the premium fee rebate period. While the existing premium users are being rewarded, new premium customers are potentially being generated. It is expected that our offer would raise the number of premium subscribers significantly.

## **Appendix 1**

List of available variables of our subscribers:

<b>Variable</b>	<b>Definition</b>
Age	
Male	Gender (Male = 1; Female = 0)
# of Friends	Number of friends
# of Subscriber Friends	Number of friends who are premium subscribers
Avg Friend Age	Average age of friends
Avg Friend Male	Average proportion of friends that are male
# Friend Country	Number of countries that user's friends are from
Song Listened	Number of songs listened in current period
Playlists	Number of playlists made in current period
Posts	Number of forum posts created in current period
Shouts	Number of shouts received from other users in current period
Loved Tracks	Number of tracks loved in current period
Tenure	Number of months the user been on the site
Good Country	US, UK, Germany = 1; Other countries = 0

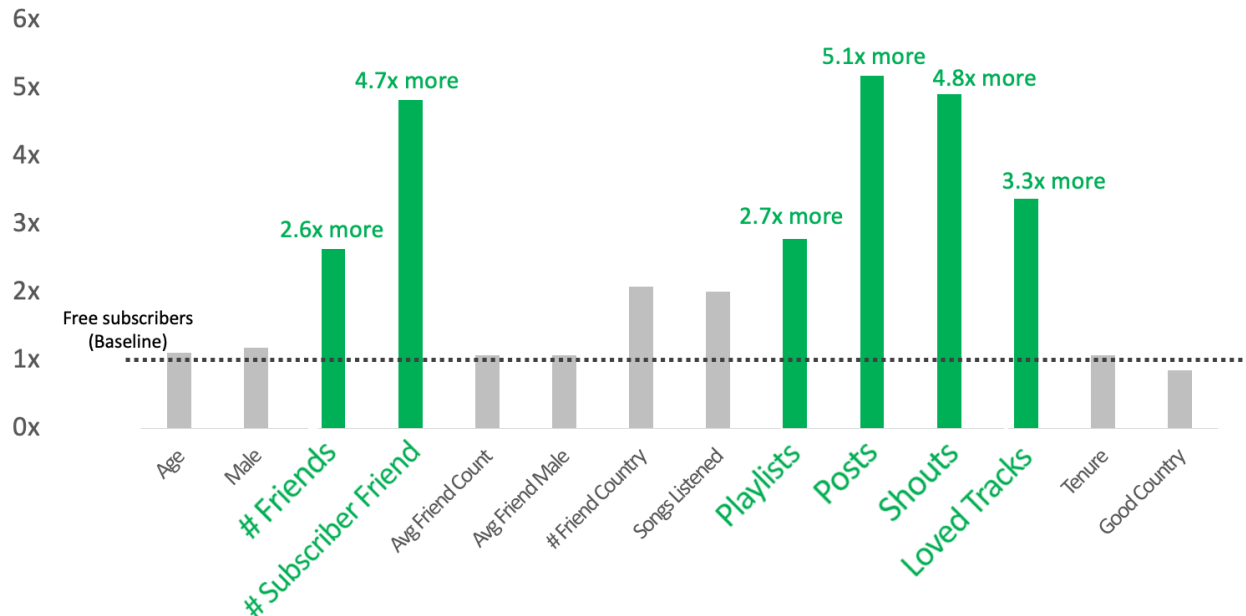
Remarks: There are missing values in Age, Gender and Shouts because some users do not provide these information with us upon their sign ups. In our analysis, we have replaced all missing values using the mean of that particular variable to make sure these records are not missed out.



## Appendix 2

Compared to Free users, Premium subscribers have more **friends** and more **subscriber friends**. They also create more **playlists**, **posts**, **shouts** and **loved tracks**.

Premium vs Free subscribers (x no. of times):



Variable mean by Free vs Premium subscribers:

Variable	Free subscribers	Premium subscribers
Age	24.2	26.2
Male	0.6	0.72
# Friends	11.2	28.83
# Subscriber Friend	0.3	1.28
Avg Friend Count	24.5	25.83
Avg Friend Male	0.6	0.66
# Friend Country	2.6	5.34
Songs Listened	12,019	23,630
Playlists	0.5	1.34
Posts	2.6	13.36
Shouts	17.5	84.35
Loved Tracks	67.5	223.57
Tenure	39.4	41.3
Good Country	0.4	0.31
<b>Total subscribers</b>	<b>1,214,303</b>	<b>37,161</b>

### **Appendix 3**

#### Confusion Matrix and Metrics to Evaluate Predictive Ability

Prediction	Actual	
	Free users	Premium subscribers
Free users	32,427	1,283
Premium subscribers	8,105	1,653

Above confusion matrix summarises the predictions from our model and the actual results of a validation dataset. The variable adopter is 1 if the user switches from being free to premium subscriber in current period. Otherwise, its value is 0. We use the mean of adopter (0.07) as the cut-off of the confusion matrix. In other words, if our model predicts that the probability a user will become a premium subscriber is larger than 0.07, we classify that user as a premium subscriber.

The accuracy of our model is 78.40%<sup>6</sup>. The true positive rate is 56.30%<sup>7</sup>. The precision is 16.94%<sup>8</sup>.

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<sup>6</sup> Accuracy = (True positives + True negatives) / (Positives + Negatives) = (1,653 + 32,427) / [(1,283 + 1,653) + (32,427 + 8,105)] = 78.40%

<sup>7</sup> True positive rate = True positives / (True positives + False negatives) = 1,653 / (1,653 + 8,105) = 56.30%

<sup>8</sup> Precision = True positives / (True positives + False positives) = 1,653 / (1,653 + 8,105) = 16.94%

## Appendix 4

### List of Characteristics of Users who Go from “Free to Fee”

Variable	Estimate	Importance	Users are more likely to go "from free to fee" if they...
subscriber_friend_cnt	▲ 0.39	2.49	are friends of premium subscribers
playlists	▲ 0.22	0.36	make many playlists
lovedTracks	▲ 0.00	0.32	love many tracks
male	▲ 0.45	0.24	are male
songsListened	▲ 0.00	0.23	listen to many songs
age	▲ 0.03	0.20	are mature adults
friend_country_cnt	▲ 0.02	0.12	have friends from different countries
avg_friend_age	▲ 0.02	0.12	have friends who are mature
friend_cnt	▲ 0.00	0.11	have many friends
good_country	▼ -0.25	0.11	are not from US, UK or Germany