Marketing Analytics: Homework 4

Group Members: Spriha Gupta; Jasmine Kaur; Daniel Lesser; Joseph Standerfer

To: Lisa Peschke

From: Group 2

**Subject: Recommendations for Freemium user conversion** 

Converting free users to premium users is one of the most certain ways to improve

profitability and longevity for the High Note platform. Low conversion rates are typical of

freemium models, with even the biggest players like LinkedIn, Pandora and Dropbox having

subscriber rates in the low single digits. High Note has a 6.7% adoption rate based on the most

recent data, which appears to be above the industry average. This may make it challenging to

raise the adoption rate further. Regardless, the remainder of this memo outlines what types of

users are more likely to be non-subscribers, how we might convert those users, and how we might

attract premium users to the platform.

The first step to better understand the user base of High Note is to review some basic

descriptive statistics about users who take advantage of the free platform vs. those who

subscribe. Based on figures 1 and 2, we can see that subscribers are typically slightly older than

free users and more likely to be male. These users use the platform more to get value out of their

subscription. From a music perspective, they listen and favorite more songs on average. From a

social media perspective, they have more friends on the platform and have five times more posts

and shouts. One similarity of note is the tenure on the platform: both free and premium users have

similar account ages. Thus, we should not count on length of time of the platform as being a natural

driver towards subscription.

Just based on these descriptive statistics, there are multiple potential opportunities for us to focus on. Males in their late 20s tend to be adopters. We also know that subscribers are greater users of the social media functionality of the platform. While it is not yet clear if this is a causal relationship, if we incentivize these users to post, shout, and connect over the app, this may drive deeper user engagement with the platform and lead to an increase in subscriptions.

One way to promote social engagement on the platform could be providing a free one-month premium subscription to users. The additional features (enhanced interface and recommended playlists) and the absence of advertisements would likely prompt users to spend more time on the site during their trial period. We suspect that these higher usage rates would in turn drive more social interaction, which has historically been the case with premium subscribers. Ideally, at the end of the subscription period, users will now find more value in the site because of the social networks that they've developed. That, along their experience of using the premium site features ad free, may just tip these users from "free to fee".

The primary risk we see in this proposal would be a temporary loss of ad revenue from those who take advantage of the promotion. This should not be a major concern as ads account for a small portion of the company's revenue. We used a logistic regression model to provide a good starting point for identifying the users who should be targeted by this marketing program.

Several forward stepwise regressions models with varying features and interaction terms were tested out in this study. When selecting a regression model, we felt that it was inappropriate to use accuracy as our primary performance metric because of the large class imbalance. To illustrate this concern, if we were to use a model that predicts all users to be non-subscribers, it would achieve a 93% accuracy purely due to the fact non-subscribers outnumber subscribers 93 to

7. Instead we focused on the each of the model's false positive rate – the ratio the model's incorrect subscriber predictions to the total number of non-subscribers. By keeping this metric low we ensure that the highest proportion of non-adopters are identified correctly by the model.

The model indicates that males have an odds ratio of 3 to 2, implying that they are more likely to buy a premium subscription. Since we want to focus on those who are not inherently more likely to subscribe, our focus will be females in their early 20s. One way to target this group would be to use promotional subscriptions to build up their social networks within the platform. Alternatively, we could offer bundles with other products that appeal to them, such as spa or coffee discounts.

Another large non-subscriber group to target would be users from the U.S., U.K. and Germany. Users within these three countries have a low subscription odds ratio of 3 to 4 when compared the rest of the world. One way to differentiate countries would be to license more popular music within these countries, particularly local artists.

Other than the 'one-month free trial' strategy proposed above, we can also offer reduced annual subscriptions if users opt to try the premium version within a defined time-frame. Such techniques have been shown to work in increasing paid subscribers. "Limited-time offers help the goal of always having news -- it keeps a brand in the forefront of the consumers' minds," says Mary Chapman, director-product innovation at research firm Technomic. The sense of urgency created by such offers leads to a 'call for action'. Additionally, we can use second degree price discrimination and offer discounted group or family plans to attract them, as this would leverage the peer network effect.

Descriptive statistic	s by	group						
group: 0				- d	min		222.00	
200	vars	n 31178	mean		min	max	range	
age male			24.21	6.77		79	71 1	
		37847	0.62	0.49		1	_	
friend_cnt		60140	11.16	41.53		3921	3921	
subscriber_friend_cnt		60140	0.27	1.89		309	309	
avg_friend_age		47878	24.50	5.72		79	71	
avg_friend_male		50785	0.63	0.36		1		
friend_country_cnt		60140	2.62	4.67		119	119	
songsListened			12019.41			1000000		
playlists		60140	0.49	1.54		261	261	
posts		60140	2.63	47.14		5644	5644	
shouts		59122	17.52	119.87		8694	8694	
lovedTracks	12	60140	67.53	229.04		12522	12522	0.93
tenure	13	60125	39.39	19.27	0	108	108	0.08
good_country	14	37696	0.37	0.48	0	1	1	0.00
group: 1								
group. I	vars	n	mean	sd	min	max	range	se
age		2677	26.20	7.11	8	78	70	0.14
male		3147	0.72	0.45	0	1	1	0.01
friend_cnt		4327	28.83	108.10	0	5089	5089	1.64
subscriber_friend_cnt		4327	1.28	5.39	ő	287	287	0.08
avg_friend_age		3621	25.83	5.66	12	70	58	0.09
avg_friend_age		3761	0.66	0.28	0	1	1	0.00
friend_country_cnt		4327	5.34	8.11	ŏ	136	136	0.12
songsListened			25654.79			1000000		
playlists		4327	1.34	29.63	0	1943	1943	0.45
		4327	13.36	126.29	0	5176	5176	1.92
posts shouts		4171	84.35	1159.43	0	65872	65872	
								17.95
lovedTracks		4327	223.57	798.85	0	44005	44005	12.14
tenure		4324	41.30	19.67	0	108	108	0.30
good_country	14	3179	0.31	0.46	0	1	1	0.01

Figure 1: Free users vs. Subscribers, raw non-imputed data

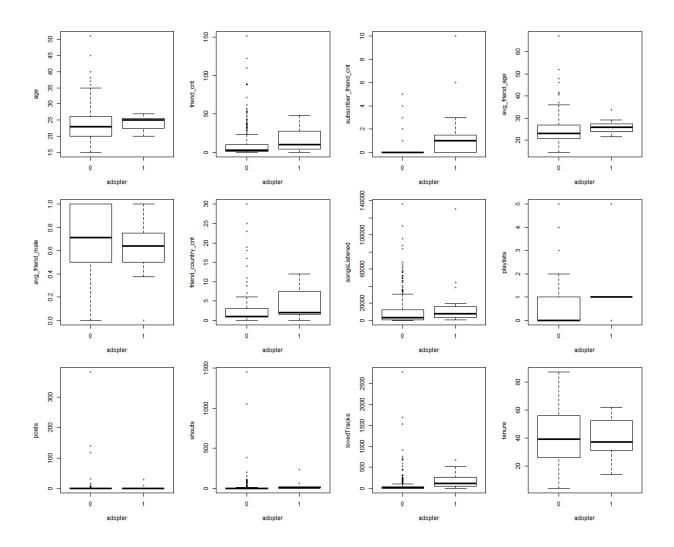


Figure 2: Boxplot of free users vs. premium users

## Coefficients:

```
Estimate Std. Error z value Pr(>|z|)
(Intercept)
                     -4.354e+00 9.029e-02 -48.226 < 2e-16 ***
lovedTracks
                                                    < 2e-16 ***
                      7.287e-04 4.973e-05
                                            14.653
songsListened
                      7.632e-06 4.881e-07 15.635 < 2e-16 ***
subscriber_friend_cnt
                                             7.991 1.33e-15 ***
                      8.873e-02 1.110e-02
age
                      2.223e-02 3.084e-03
                                             7.207 5.71e-13 ***
male
                      4.484e-01 4.424e-02 10.136 < 2e-16 ***
                     -3.870e-01 4.271e-02 -9.060 < 2e-16 ***
good_country
avg_friend_age
                      2.476e-02 3.213e-03
                                             7.704 1.32e-14 ***
friend_country_cnt
                      4.616e-02 4.255e-03 10.847 < 2e-16 ***
friend_cnt
                     -4.111e-03 5.543e-04 -7.416 1.21e-13 ***
playlists
                      6.206e-02 1.206e-02
                                             5.147 2.65e-07 ***
Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

Figure 3: Logistic Regression model with 10 steps

Actual			True Negative Rate	99.07277	
		0	1	False Positive Rate	0.927232
Predicted	0	9830	672	Accuracy	92.82764
	1	92	58	True Positive Rate	7.945205
				False Negative Rate	92.05479
				Precision	38.66667

Figure 4: Evaluation metrics

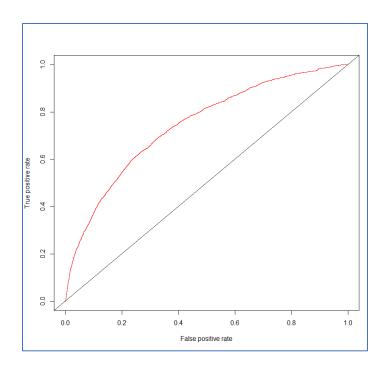


Figure 5: ROC curve