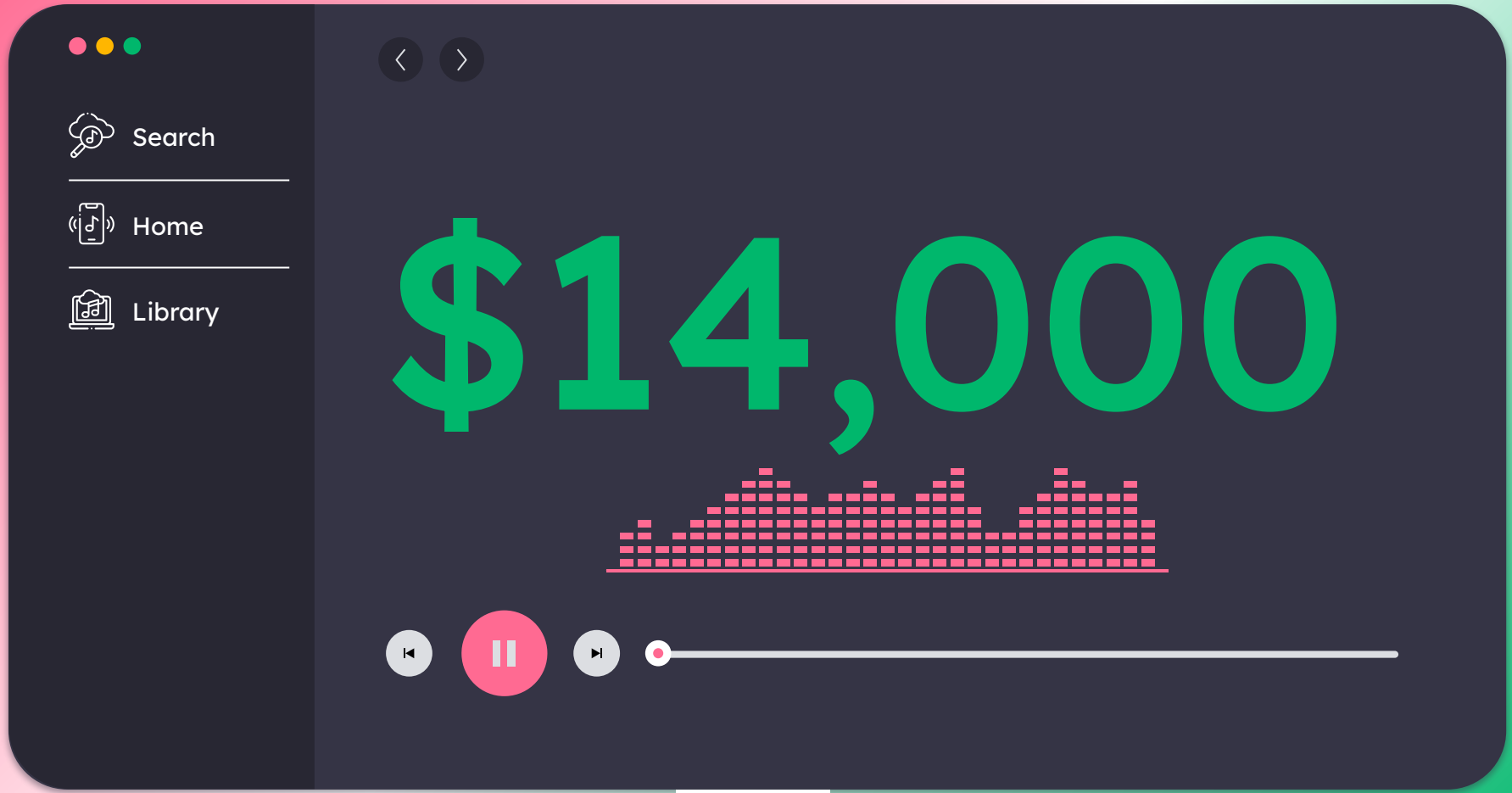

How much profit do you think we are losing every year from users wandering off from our platform?
HighNote
music online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$14,000


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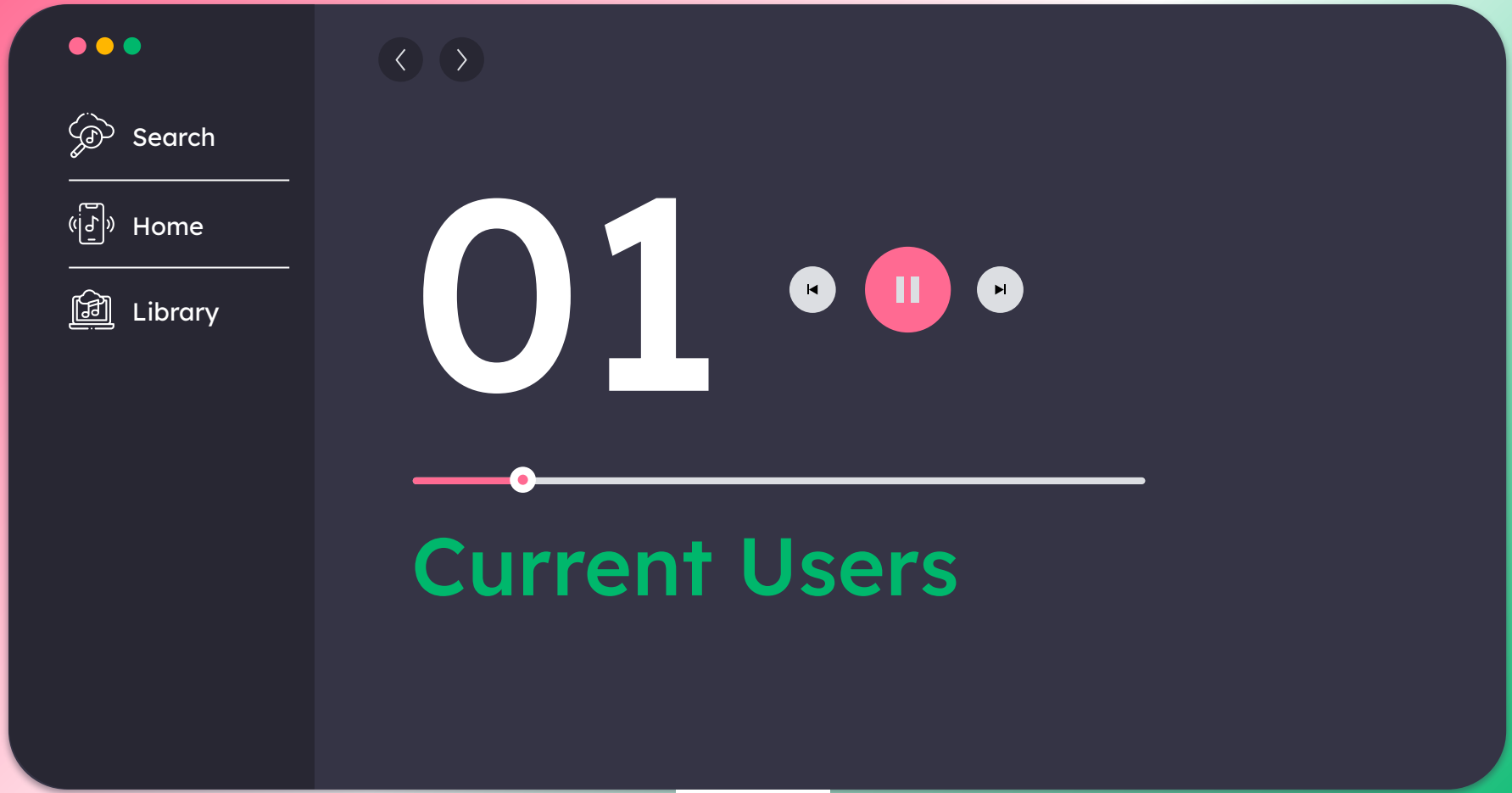
Orchestrating
Engagement for
High Note
Cecilia Zhang, Clarissa Gunawan, Kelly Hong,
Sylvanne Braganza, Yukta Butala

What should HN do to ensure user retention?

Product Improvements

Promotions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01
Current Users

What are the main differences between current adopters and non-adopters?

1. Demographics

Findings

Adopters:

1. Are generally **older**
2. Mostly **male**

Insights

Adopters are more **financially established** and **males**

What are the main differences between current adopters and non-adopters?

2. User Listening Behaviour

Findings

Adopters:

1. Listen to **2x more songs**
2. Have **3x more playlists**
3. Have **3x more loved tracks**

Insights

Adopters enjoy listening to music much more than non-adopters

What are the main differences between current adopters and non-adopters?

3. User Interactions

Findings

Adopters:

1. Create **5x more posts**
2. Create **5x more shouts**

Insights

Adopters are **more social** than non-adopters

What are the main differences between current adopters and non-adopters?

4. Network Circle

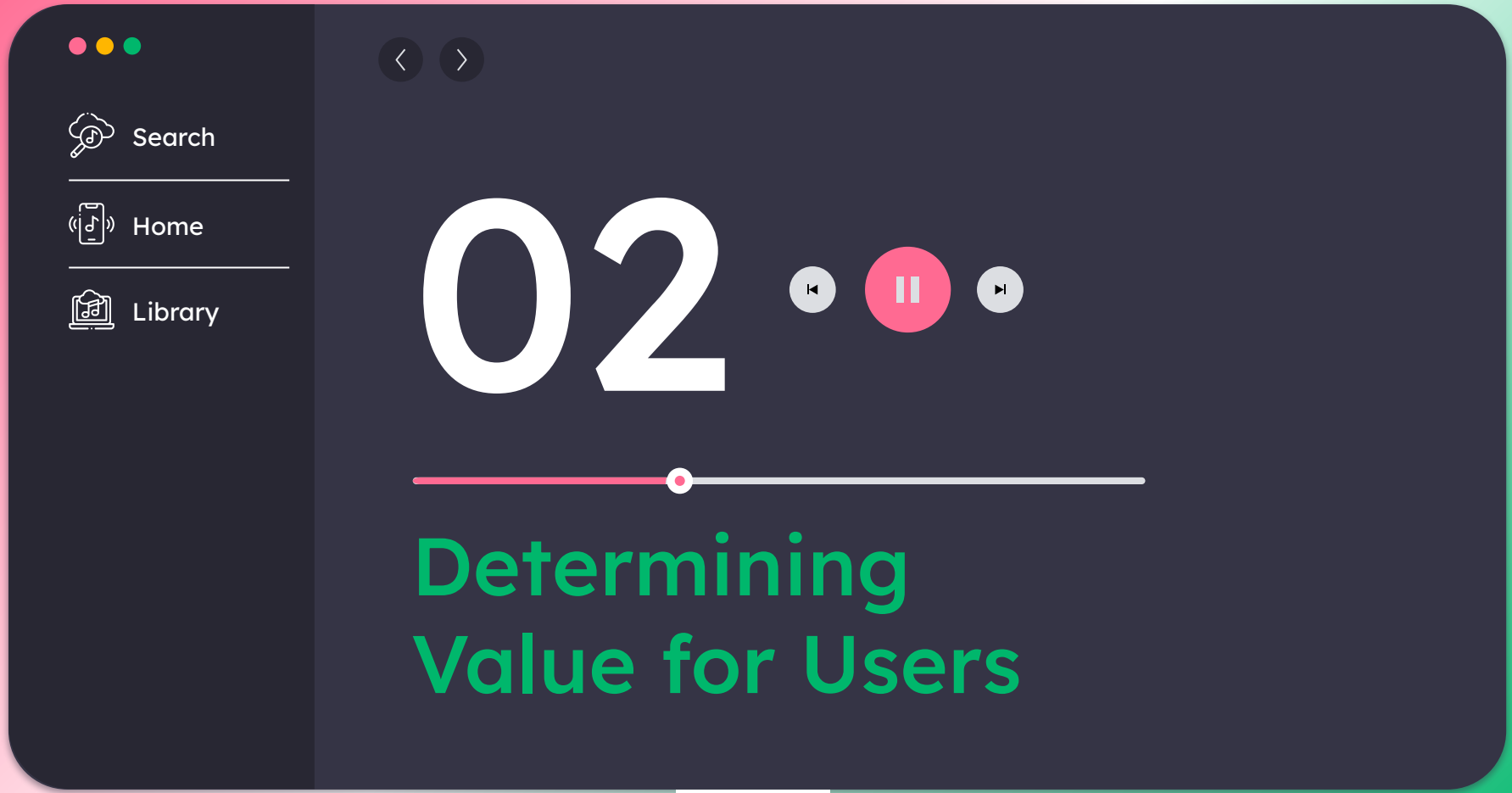
Findings

Adopters:

1. Have **2.5x more friends**
2. Have **5x more adopter friends**
3. Have more **diverse friends**

Insights

People are likely to **become adopters if their friends are adopters**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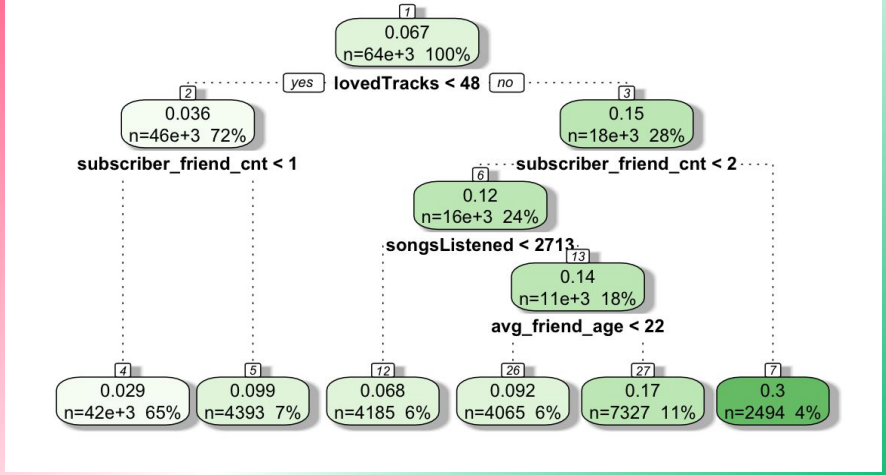
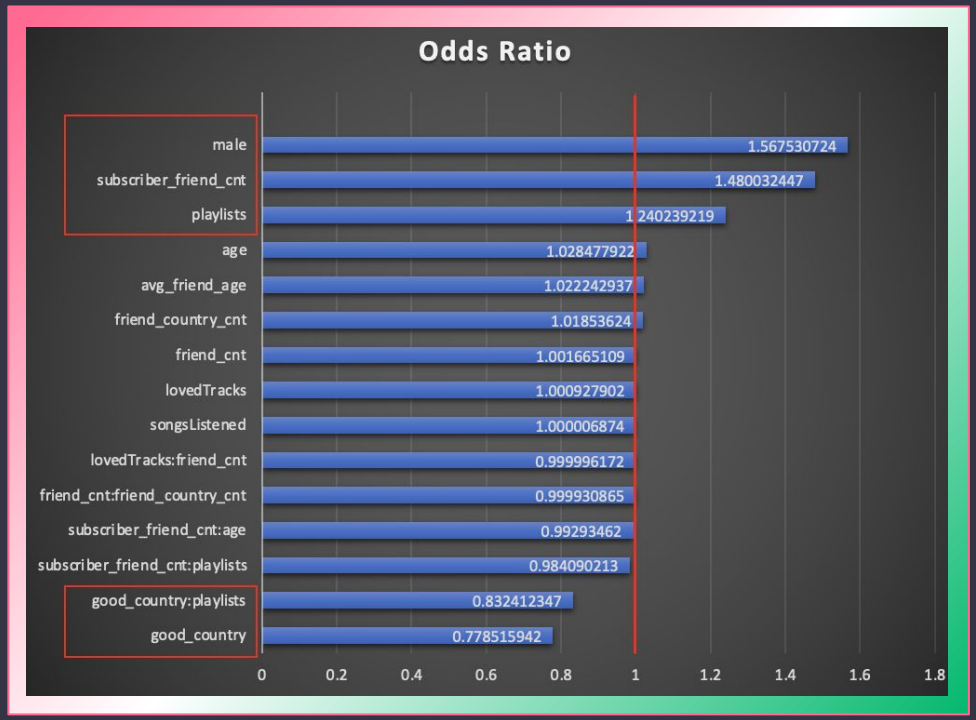
02
Determining
Value for Users

Decision Tree Findings



Logistic Regression Interpretation



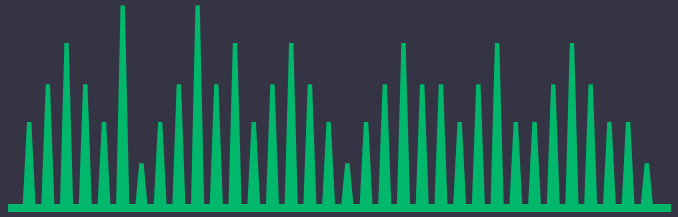
Logistic Regression Simulation

rn	Estimate	userdata	userdata - mean	score	rn
(Intercept)	-4.555650582	1	0	-2.7920749	(Intercept)
lovedTracks	0.000927472	78.0015822	0	0	# of lovedTracks
songsListened	6.87E-06	12934.6135	0	0.00E+00	# of songsListened
subscriber_friend_cnt	0.392064011	0.67339879	0.336699397	0.13200772	# of friends that subscribe
age	0.028079964	48.7488637	24.37443187	6.84E-01	age
male	0.449501594	1	0.376322643	0.16915763	male (1 is male, 0 is female)
good_country	-0.25036581	0.36692536	0	0.00E+00	good_country (1 is US, UK, or Germany)
playlists	0.21530428	1	0.4550235	0.09796851	# of playlists
friend_cnt	0.001663724	12.3498069	0	0.00E+00	# of friends
friend_country_cnt	0.018366538	2.80228644	0	0	# of diff countries friends are from
avg_friend_age	0.021999171	24.5945253	0	0.00E+00	avg age of friends
subscriber_friend_cnt:age	-0.007090458	8.78296001	0	0	subscriber_friend_cnt:age (interaction)
good_country:playlists	-0.183427352	0.19594076	0	0.00E+00	good_country:playlists (interaction)
subscriber_friend_cnt:playlists	-0.016037707	0.39525649	0	0	subscriber_friend_cnt:playlists (interaction)
lovedTracks:friend_cnt	-3.83E-06	3532.89365	0	0.00E+00	lovedTracks:friend_cnt (interaction)
friend_cnt:friend_country_cnt	-6.91E-05	215.958072	0	0	friend_cnt:friend_country_cnt (interaction)
			score=	-1.7085079	
			prob=	15.34%	

for a user with above average sub friend count, age, playlists, and male and simulation data mean for everything else

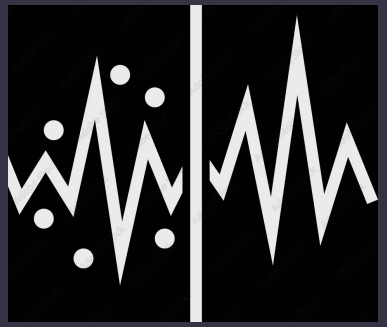
Why did we choose Logistic Regression?

Based on the characteristics of our data



Ex) Age, Tenure etc.

Better at handling continuous data



Real life Data

Better at handling data with noise

Why did we choose Logistic Regression?

Logistic Regression showed better performance scores

Compared Performance scores between Logistic Regression and Decision Tree

Decision Tree : 0.736

<

Logistic Regression : 0.745

Why did we choose Logistic Regression?

Logistic Regression shows better Performance Scores

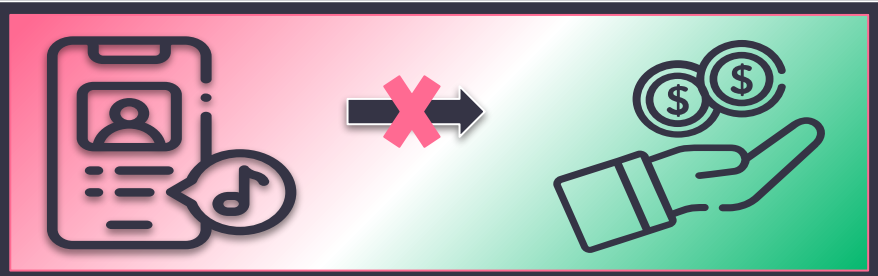
Measures	Decision Tree		Logistic Regression	
Accuracy	0.84		**0.91**	9% Higher
Predicted Adopters among Actual Adopters	**0.44**	>	0.18	
★ Actual Adopters among Predicted Adopters	0.20	<	**0.29**	

Better Resource Allocation & Positive Customer Experience

Why did we choose Logistic Regression?

Logistic Regression shows better Performance Scores

Measures	Decision Tree	Logistic Regression	
Accurate Prediction of Non-Adopters	0.87	0.97	11% Higher
Practicality of the prediction	2.9	3.2	

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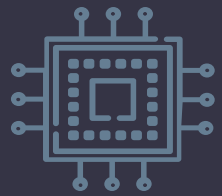
03
Focusing
Recommendations

How do we drive up subscriptions?

Target customer segments with a promotional offer



Data matrix from logistic regression

Weighted with coefficients

Customer Clusters

How do we drive up subscriptions?

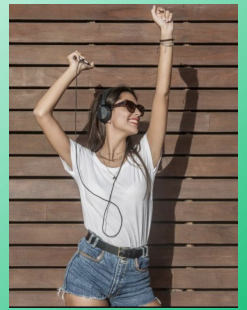
Target customer segments with a promotional offer

Engaged Veterans

Passive Patrons

Discerning Listeners

Casual Explorers



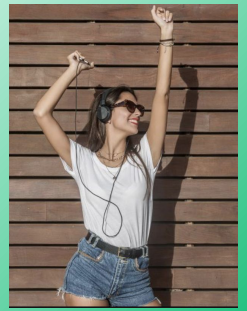
Energetic Trendsetters

How do we drive up subscriptions?

Target customer segments with a promotional offer

Engaged Veterans

Discerning Listeners



Energetic Trendsetters

How do we drive up subscriptions?

Target customer segments with a promotional offer

3-month subscription promotional offer

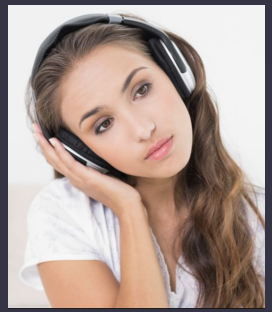
$2,000

With advanced marketing

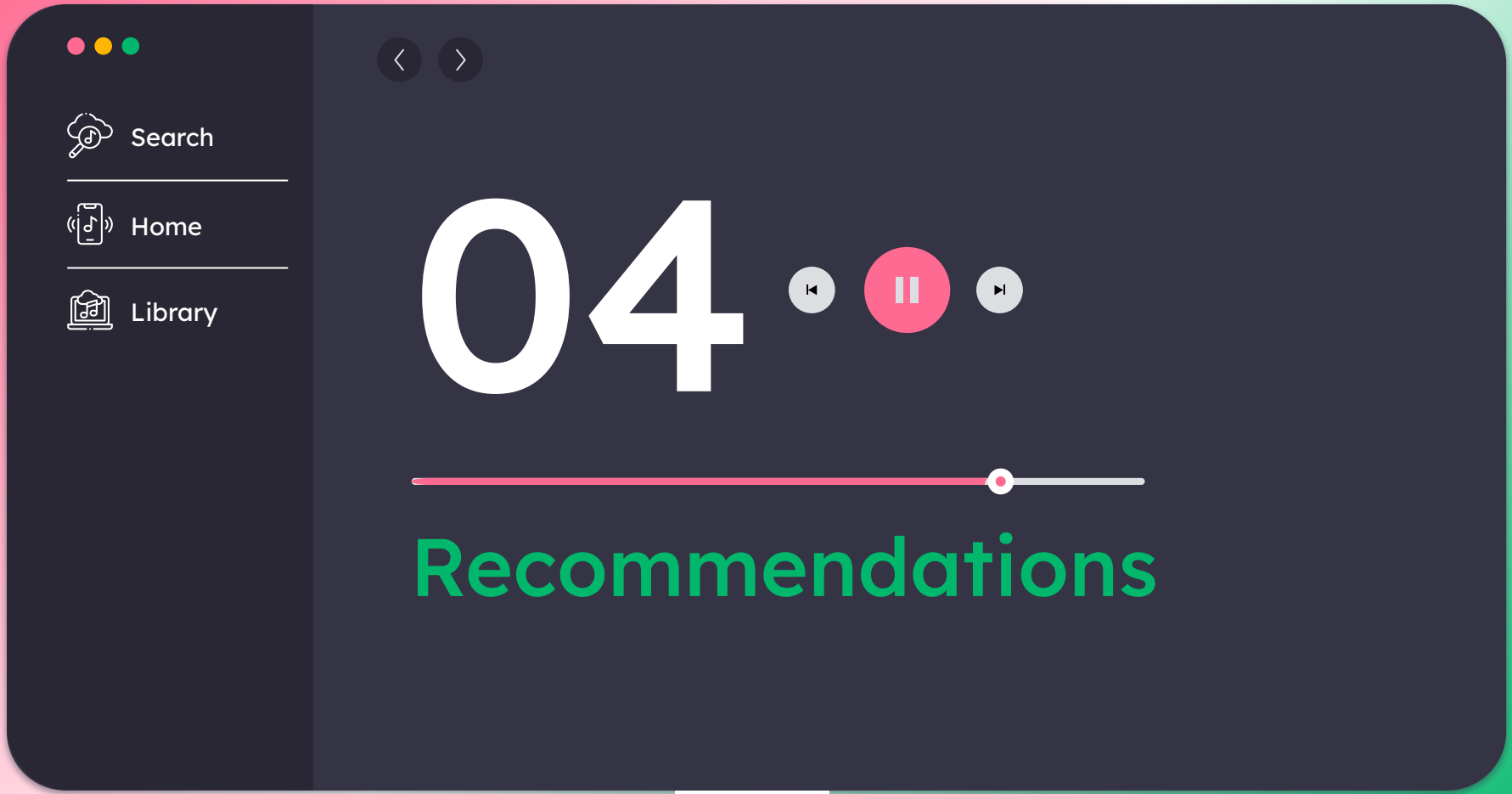
$14,000

How do we drive up subscriptions?

Target customer segments with a promotional offer



Casual Explorers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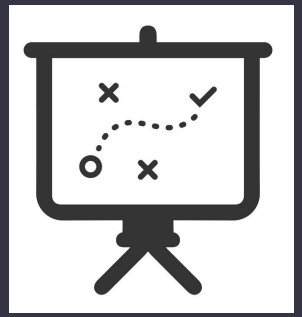
04
Recommendations

Why should you trust our Analysis?



Strategic Methodology

Quantitative Analysis

Qualitative Justification

How to keep our users engaged?

Virtual Listening Party

User Generated Content

Live Concert Streaming

Discussion Board + Artist Interactions

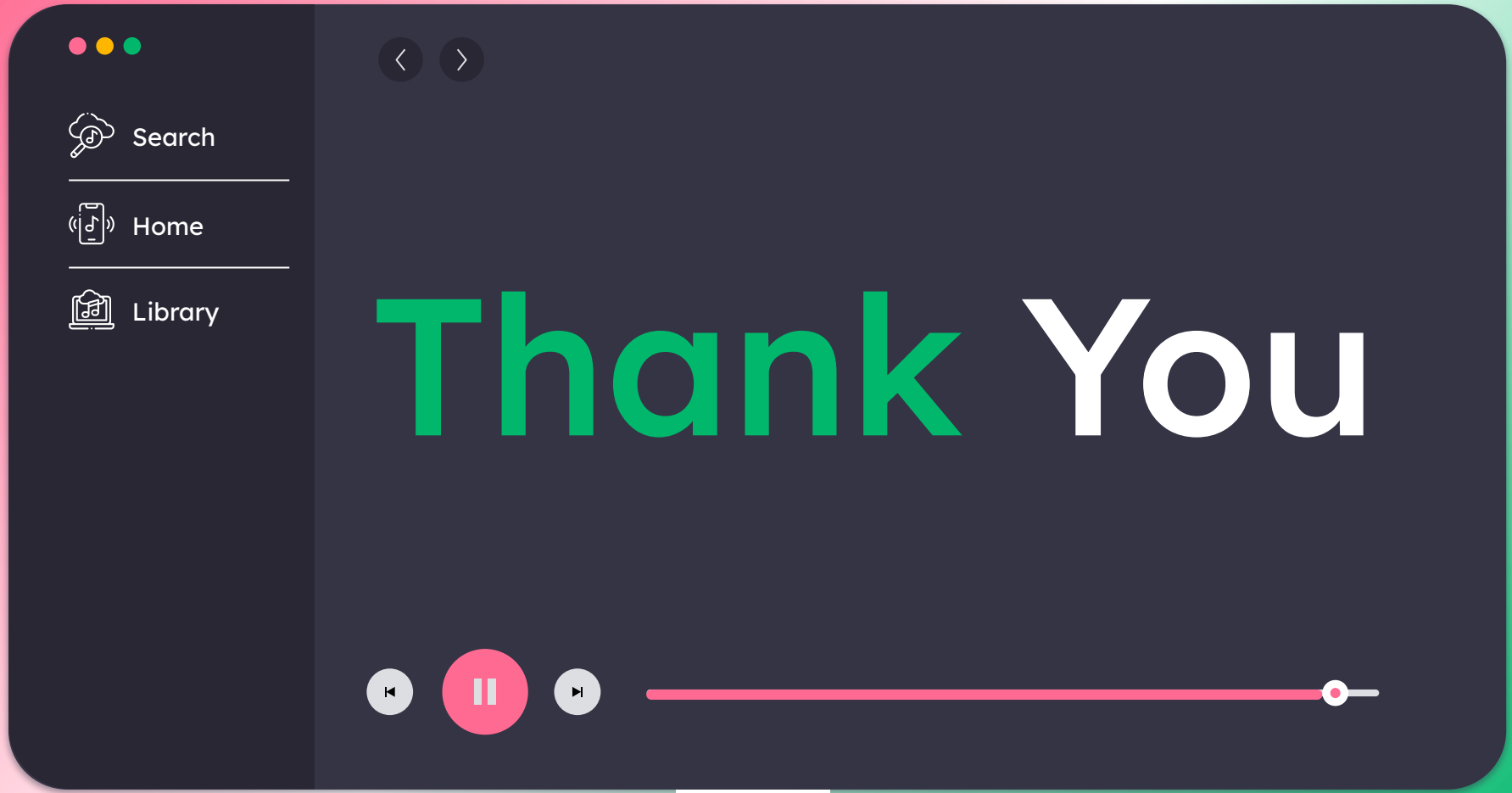
What should HN do to ensure user retention?

Product Improvements

1. Improve **song recommendation**
2. Expand **song selection**
3. Encourage user **engagement**

Promotions

1. Free **3-month premium plans**
2. **Yearly discounts** on premium plans
3. Friend **referral** program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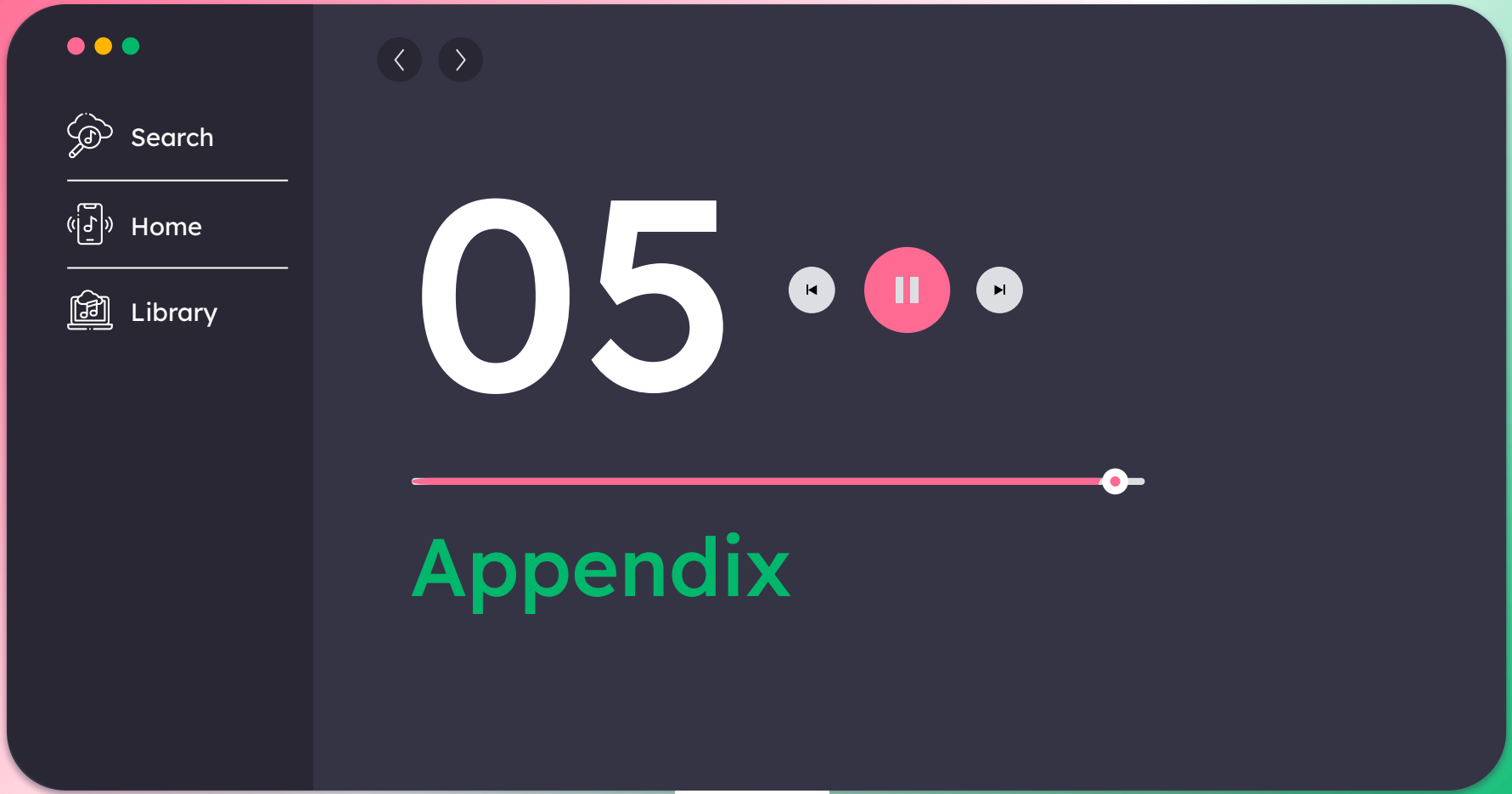
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Appendix

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1.1

group: 0

	vars	n	mean	sd	min	max	range	se
age	1	60140	24.29	4.88	8	79	71	0.02
age_Missing	2	60140	0.48	0.50	0	1	1	0.00
male	3	60140	0.62	0.39	0	1	1	0.00
male_Missing	4	60140	0.37	0.48	0	1	1	0.00
friend_cnt	5	60140	11.16	41.53	0	3921	3921	0.17
subscriber_friend_cnt	6	60140	0.27	1.89	0	309	309	0.01
avg_friend_age	7	60140	24.52	5.10	8	79	71	0.02
avg_friend_age_Missing	8	60140	0.20	0.40	0	1	1	0.00
avg_friend_male	9	60140	0.63	0.33	0	1	1	0.00
avg_friend_male_Missing	10	60140	0.16	0.36	0	1	1	0.00
friend_country_cnt	11	60140	2.62	4.67	0	119	119	0.02
songsListened	12	60140	12019.41	23629.51	0	1000000	1000000	96.35
playlists	13	60140	0.49	1.54	0	261	261	0.01
posts	14	60140	2.63	47.14	0	5644	5644	0.19
shouts	15	60140	17.58	118.85	0	8694	8694	0.48
shouts_Missing	16	60140	0.02	0.13	0	1	1	0.00
lovedTracks	17	60140	67.53	229.04	0	12522	12522	0.93
tenure	18	60140	39.39	19.27	0	108	108	0.08
good_country	19	60140	0.37	0.38	0	1	1	0.00
good_country_Missing	20	60140	0.37	0.48	0	1	1	0.00

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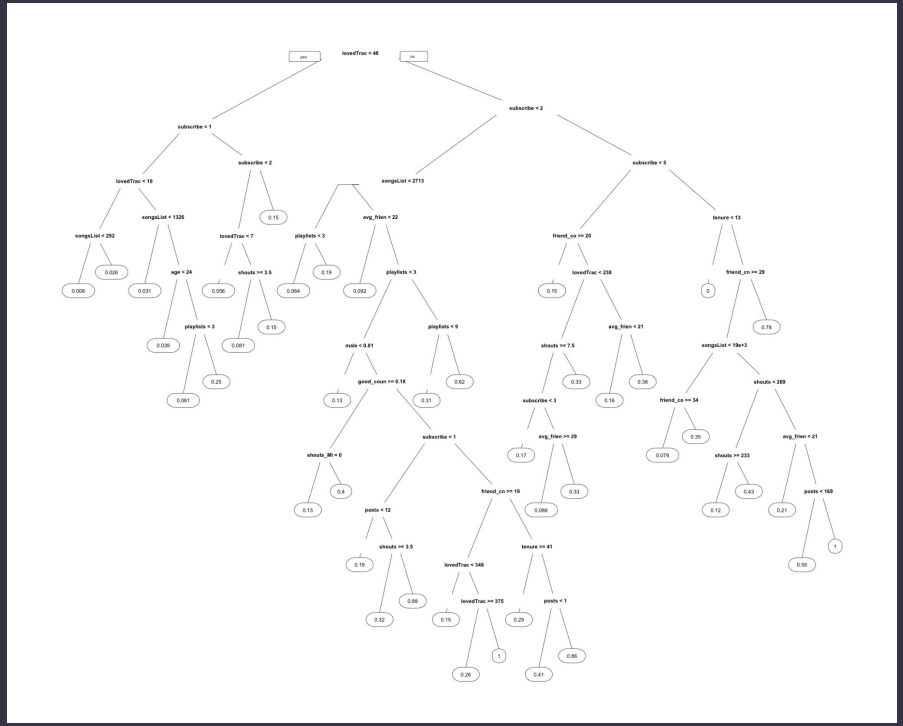
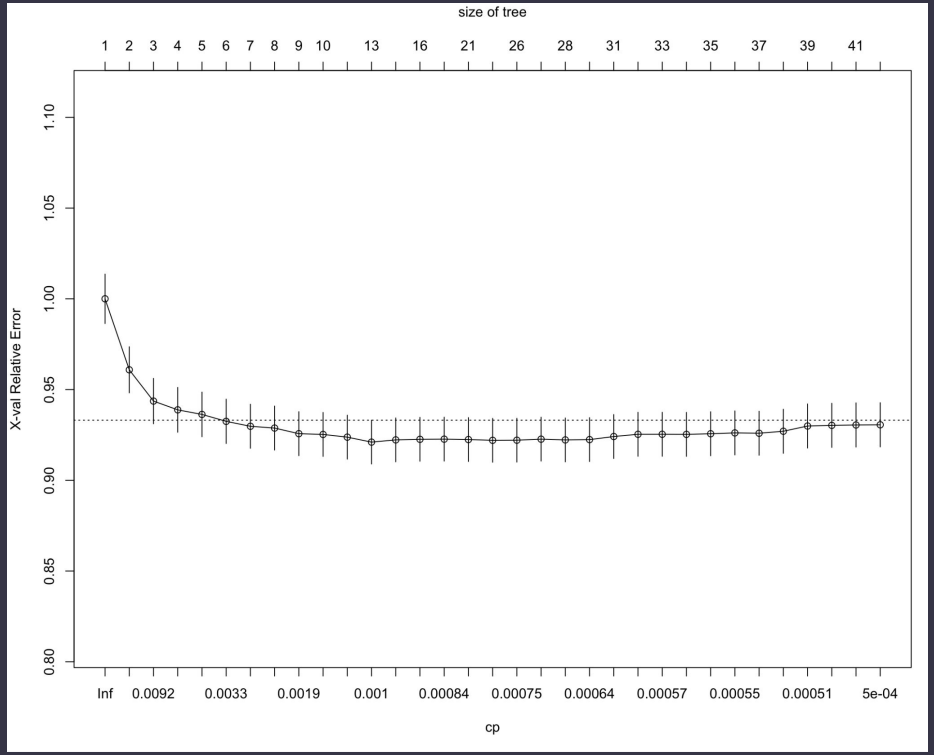
1.2

```
group: 1
                      vars    n     mean       sd min     max   range    se
age                      1 4327    25.51     5.66   8      78      70  0.09
age_Missing              2 4327     0.38     0.49   0       1       1  0.01
male                     3 4327     0.70     0.38   0       1       1  0.01
male_Missing             4 4327     0.27     0.45   0       1       1  0.01
friend_cnt               5 4327    28.83   108.10   0    5089    5089  1.64
subscriber_friend_cnt    6 4327     1.28     5.39   0     287     287  0.08
avg_friend_age           7 4327    25.63     5.19  12      70      58  0.08
avg_friend_age_Missing   8 4327     0.16     0.37   0       1       1  0.01
avg_friend_male          9 4327     0.65     0.26   0       1       1  0.00
avg_friend_male_Missing 10 4327     0.13     0.34   0       1       1  0.01
friend_country_cnt      11 4327     5.34     8.11   0     136     136  0.12
songsListened           12 4327 25654.79 41737.56   0 1000000 1000000 634.50
playlists               13 4327     1.34    29.63   0    1943    1943  0.45
posts                   14 4327    13.36   126.29   0    5176    5176  1.92
shouts                  15 4327    82.06  1138.39   0   65872   65872 17.31
shouts_Missing          16 4327     0.04     0.19   0       1       1  0.00
lovedTracks             17 4327   223.57   798.85   0   44005   44005 12.14
```

2.1 Decision Tree

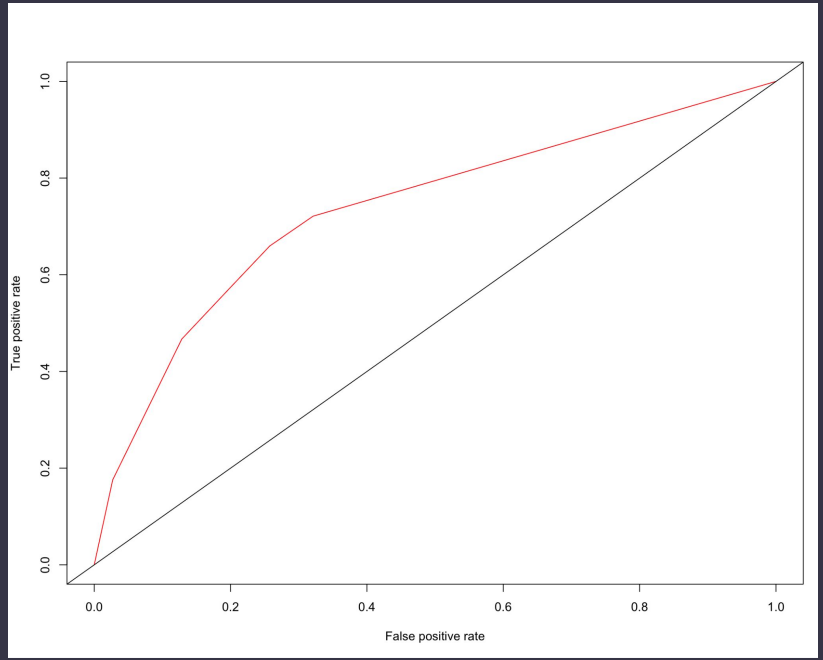


2.1 Decision Tree



2.1 Decision Tree

```
$confmatrix
          trueclass
predclass     0     1
        0 27723  1429
        1  2215   727

$accuracy
[1] 0.8864585

$truepos
[1] 0.3371985

$precision
[1] 0.2471108

$trueneg
[1] 0.9260138

$lift
[1] 3.09086
```



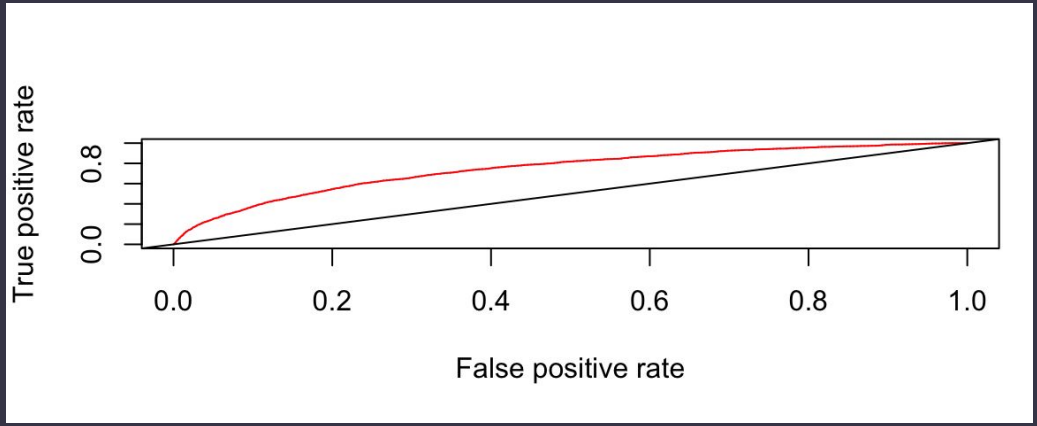
2.2 Logistic Regression

```
Call:
glm(formula = adopter ~ lovedTracks + songsListened + subscriber_friend_cnt +
    age + male + good_country + playlists + friend_cnt + friend_country_cnt +
    avg_friend_age + subscriber_friend_cnt:age + good_country:playlists +
    subscriber_friend_cnt:playlists + lovedTracks:friend_cnt +
    friend_cnt:friend_country_cnt, family = "binomial", data = rfreemium[trainsample,
    crvarlist])

Coefficients:
                                  Estimate Std. Error z value Pr(>|z|)
(Intercept)                     -4.556e+00  9.228e-02 -49.366  < 2e-16 ***
lovedTracks                      9.275e-04  5.750e-05  16.130  < 2e-16 ***
songsListened                    6.874e-06  4.936e-07  13.925  < 2e-16 ***
subscriber_friend_cnt            3.921e-01  3.306e-02  11.861  < 2e-16 ***
age                              2.808e-02  3.166e-03   8.868  < 2e-16 ***
male                             4.495e-01  4.440e-02  10.125  < 2e-16 ***
good_country                    -2.504e-01  4.522e-02  -5.536 3.09e-08 ***
playlists                        2.153e-01  1.874e-02  11.489  < 2e-16 ***
friend_cnt                       1.664e-03  7.974e-04   2.086   0.0369 *
friend_country_cnt               1.837e-02  4.405e-03   4.169 3.05e-05 ***
avg_friend_age                   2.200e-02  3.266e-03   6.736 1.63e-11 ***
subscriber_friend_cnt:age       -7.090e-03  1.003e-03  -7.069 1.56e-12 ***
good_country:playlists          -1.834e-01  1.977e-02  -9.277  < 2e-16 ***
subscriber_friend_cnt:playlists -1.604e-02  1.872e-03  -8.569  < 2e-16 ***
lovedTracks:friend_cnt          -3.828e-06  5.340e-07  -7.169 7.58e-13 ***
friend_cnt:friend_country_cnt   -6.914e-05  8.544e-06  -8.092 5.87e-16 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1
```

2.2 Logistic Regression

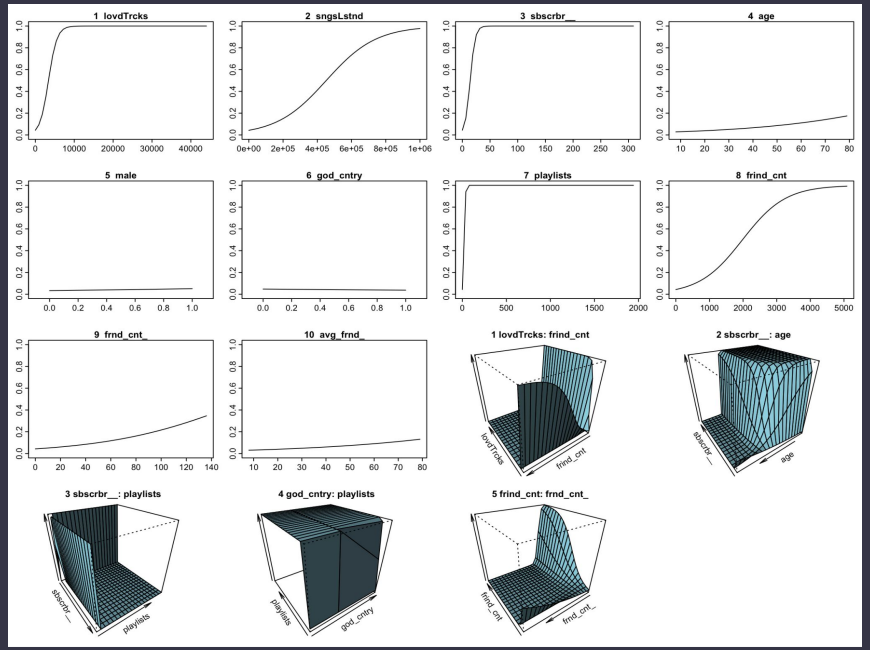
rn	Estimate	Std. Error	z value	Pr(>|z|)	meandata	sddata	userdata	X1		score		userdata - mean	score	rn
(Intercept)	-4.555650582	0.092283348	-49.36590076	0	1	0		1		-4.55565058		0	-2.7920749	(Intercept)
lovedTracks	0.000927472	5.75E-05	16.13012315	1.57E-58	78.0015822	305.4294013		348		0.32276013		269.9984178	0.25041587	# of lovedTracks
songsListened	6.87E-06	4.94E-07	13.92524673	4.45E-44	12934.6135	25483.66318		8414		0.057838328		-4520.613492	-3.11E-02	# of songsListened
subscriber_friend_cnt	0.392064011	0.033055649	11.86072662	1.89E-32	0.3366994	2.31357166		1		0.392064011		0.663300603	0.2600563	# of friends that subscribe
age	0.028079964	0.003166307	8.868364702	7.42E-19	24.3744319	4.942647433		24.3868581		0.684782087		0.012426205	3.49E-04	age
male	0.449501594	0.044397076	10.12457647	4.30E-24	0.62367736	0.38628242		0		0		-0.623677357	-0.280344	male (1 is male, 0 is female)
good_country	-0.25036581	0.045224474	-5.536068997	3.09E-08	0.36692536	0.383664806		1		-0.25036581		0.633074643	-1.59E-01	good_country (1 is US, UK, or Germany)
playlists	0.21530428	0.018740093	11.48896554	1.50E-30	0.5449765	7.822435253		1		0.21530428		0.4550235	0.09796851	# of playlists
friend_cnt	0.001663724	0.000797435	2.086345037	0.03694738	12.3498069	49.11935009		20		0.033274478		7.650193122	1.27E-02	# of friends
friend_country_cnt	0.018366538	0.004404993	4.169481428	3.05E-05	2.80228644	5.022880578		14		0.257131527		11.19771356	0.20566323	# of diff countries friends are from
avg_friend_age	0.021999171	0.003265971	6.735875111	1.63E-11	24.5945253	5.118339921		30.2857143		0.666260609		5.69118903	1.25E-01	avg age of friends
subscriber_friend_cnt:age	-0.007090458	0.001003048	-7.068909697	1.56E-12	8.78296001	82.50322883		24.3868581		-0.172914		15.60389806	-0.1106388	subscriber_friend_cnt:age (interaction)
good_country:playlists	-0.183427352	0.019772516	-9.276884622	1.75E-20	0.19594076	1.339113632		1		-0.18342735		0.804059236	-1.47E-01	good_country:playlists (interaction)
subscriber_friend_cnt:playlists	-0.016037707	0.001871609	-8.568941451	1.04E-17	0.39525649	10.43271842		1		-0.01603771		0.604743512	-0.0096987	subscriber_friend_cnt:playlists (interaction)
lovedTracks:friend_cnt	-3.83E-06	5.34E-07	-7.168607616	7.58E-13	3532.89365	61910.93897		6960		-0.0266452		3427.106349	-1.31E-02	lovedTracks:friend_cnt (interaction)
friend_cnt:friend_country_cnt	-6.91E-05	8.54E-06	-8.092023552	5.87E-16	215.958072	4106.724774		280		-0.01935858		64.04192843	-0.0044277	friend_cnt:friend_country_cnt (interaction)
									score=	-2.59498378		score=	-2.5949838	
									prob=	6.95%		prob=	6.95%	

2.2 Logistic Regression



2.2 Logistic Regression

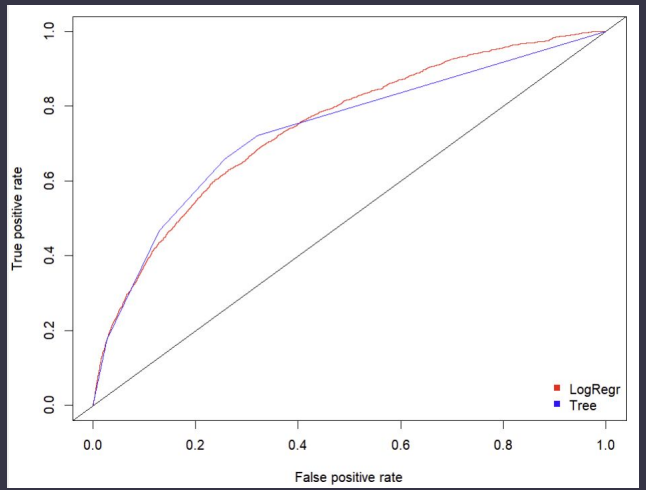
Predicted Probabilities of User Adoption



Variable Values

Why did we choose Logistic Regression?

Logistic Regression showed better ROC-AUC scores



Compared ROC - AUC scores between Logistic Regression and Decision Tree

Decision Tree : 0.7358563

Logistic Regression : 0.7446576

Why did we choose Logistic Regression?

Comparing the Confusion Matrix

Measures	Decision Tree	Logistic Regression
Accuracy	0.8377769	0.9131618
True Positive Rate	0.4438356	0.1780822
Precision	0.1968408	0.2857143

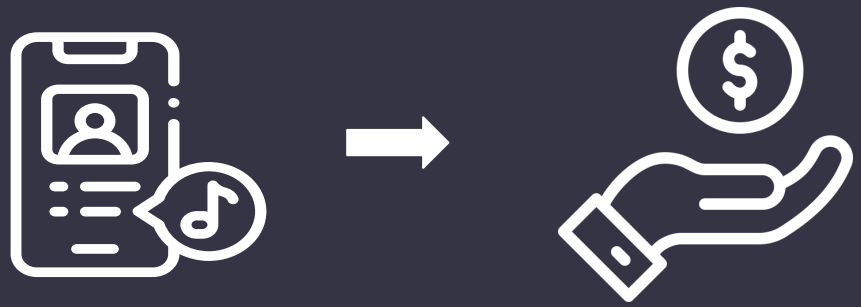
Trade-Off between TPR and Trustworthiness

⇒ Focus our resources at the right customers

Why did we choose Logistic Regression?

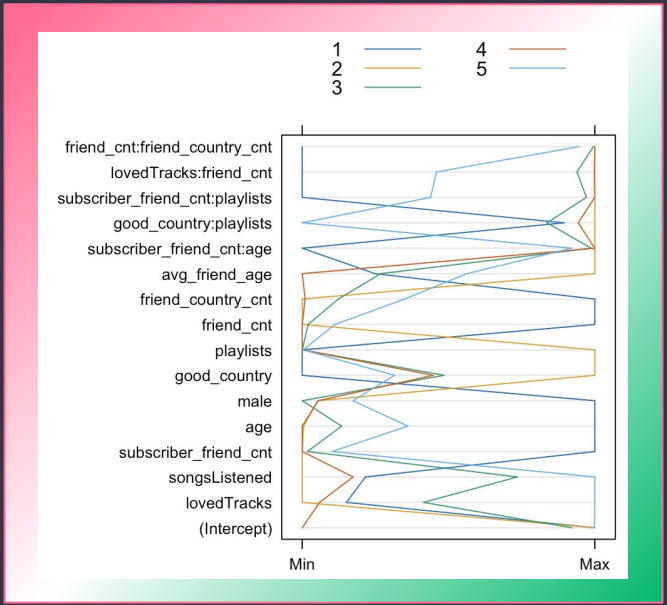
Comparing the Confusion Matrix

Measures	Decision Tree	Logistic Regression
True Negative	0.8667607	0.9672445
Lift (Practicality of the prediction)	2.872258	3.175697



How do we drive up subscriptions?

Target customer segments with a promotional offer



Who to give the promotional offer to

The Engaged Veterans	Engaged veterans with a high number of friends and a strong sense of loyalty. Predominantly male and older, they are active users and are connected to many premium subscribers.
The Passive Patrons	Passive users with older friends from diverse international backgrounds and extensive social networks. Predominantly male. They exhibit lower engagement metrics such as songs listened and loved tracks, indicating a more passive usage pattern.
The Discerning Listeners	Discerning listeners who prioritize quality content. Predominantly female. They enjoy immersive experiences and curated content, exhibiting a discerning approach to content creation and curation, focusing on quality over quantity.
The Casual Explorers	Casual explorers who enjoy the platform at their own pace, occasionally discovering new content. Predominantly female. With a balanced representation across demographics, they appreciate the platform's diverse offerings but may not be deeply involved.
The Energetic Trendsetters	Energetic trendsetters who lead the way in discovering and sharing new content. Predominantly female. Active users. Highly engaged across age groups, they embrace the platform's social aspects and contribute to its dynamic community.

Profitability

	Projected revenue (yearly)	Cost	Projected profit (yearly)
10% adoption rate	10%*($3*3,317*12) = 11,941.2	$1*3,317*3 = 9,951	**$1,990.2**
20% adoption rate (with recommendations)	20%*($3*3,317*12) = 23.882.4	$1*3,317*3 = 9,951	**$13,931.4**