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Marketing Campaign Optimization with Predictive Modeling

Group 9
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Problem Statement

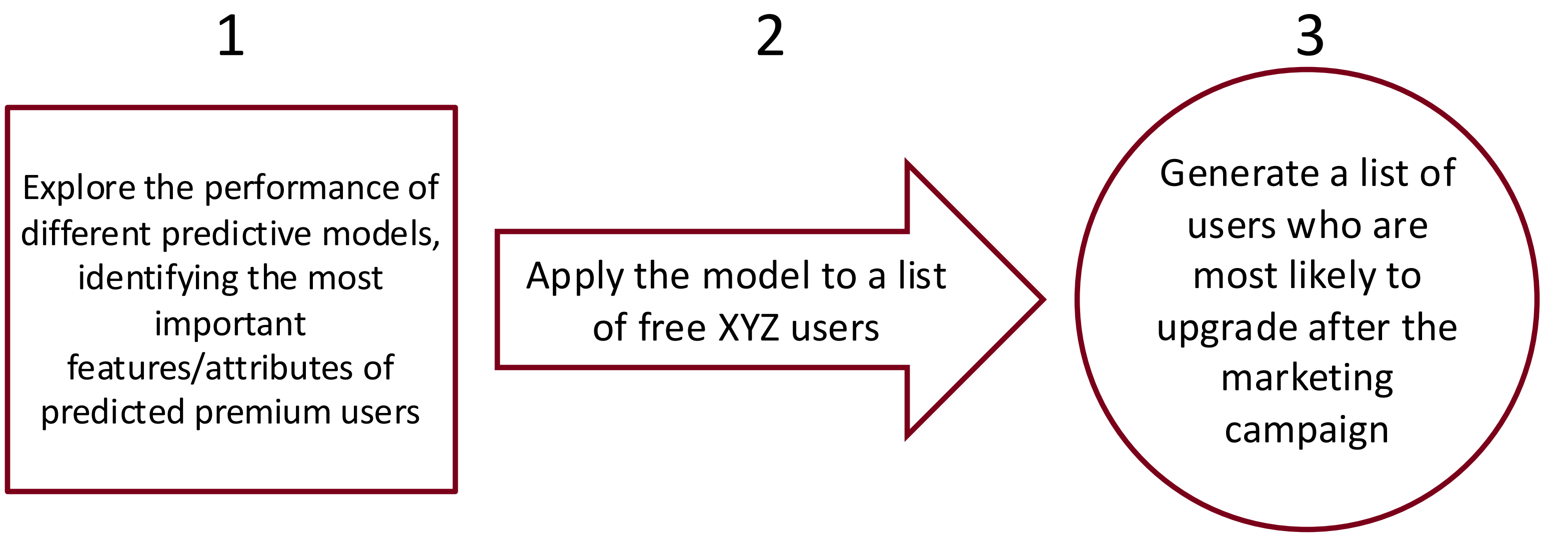
- XYZ's main goal is to **maximize revenue** by:
  - Increasing their number of premium subscribers
  - Minimizing marketing cost

- **Business Challenge:**
  - XYZ's current marketing strategy is to randomly target current free users and hope they convert to premium subscribers.
  - Unfortunately, the previous marketing campaign had a success rate of 3.7%, an inefficient use of resources.

- **Our Solution:** A predictive model that identifies potential adopters more efficiently.
  - Marketing campaigns are expensive and ideally, you want to target only individuals who have the highest probability of upgrading to premium.
  - By creating a predictive model, we can identify those individuals and only market to them, thereby saving money and time.

Predictive Modeling Process

- Using the results from the previous marketing campaign, we have constructed a **<u>predictive model</u>** that highlights which of XYZs free users are most likely to subscribe to the premium version.
- We would then use our model to predict and target the people who are most likely to upgrade.



Predictive Model Impact

Let's assume marketing to a new user costs $1 and each premium user yields $60/year in revenue

Campaign **without** a predictive model:

- Total User Count: 41,540
- Users who upgraded: 1,540

Campaign Conversion Rate **without** a predictive model:

1,540 / 41,540 = **3%**

Cost to acquire new premium user:

$41,540 / 1,540 = **$27**

Net revenue per premium user after 1 year:

$60 - $27 = **$33**

Campaign **with** a predictive model:

- Total "Targeted" Count: 1912
- Users who upgraded: 180

Campaign Conversion Rate **with** a predictive model:

180 / 1912 = **9%**

Cost to acquire new premium user:

$1912 / 180 = **$10.6**

Net revenue per premium users after 1 year:

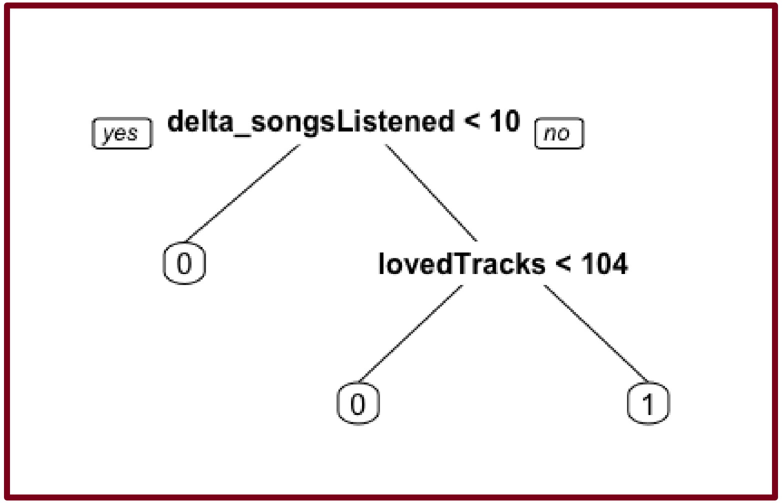
$60 - $10.6 = **$49.4**

Using a predictive model would:

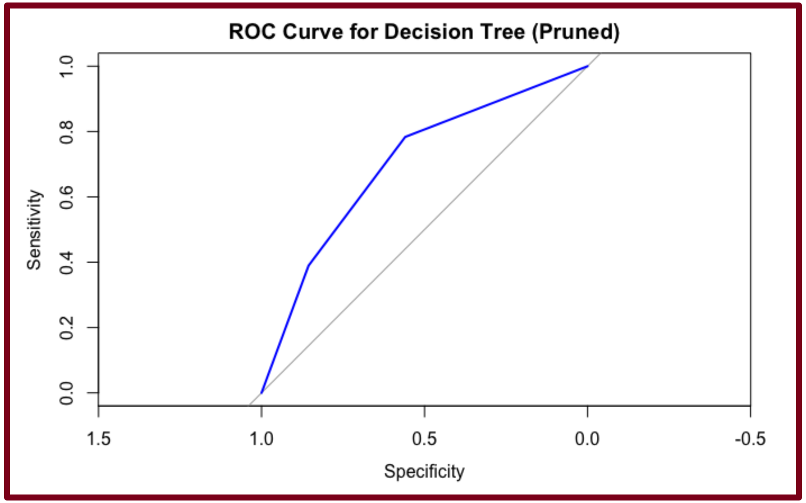
1. Lower XYZ's cost to acquire each premium user by 60.7%
2. Increase conversion rate by 6%

Main Takeaways | Decision Tree w/ 2 Features

- Adopter's Trend:
  - Users that **increased the numbers of songs they listened to by at least 10** in the 3 months leading up to the marketing campaign **and also "liked" at least 105 songs** were most likely to upgrade their membership to a premium subscription.



Visualized Decision Tree



ROC Curve

(ROC curve evaluates the effectiveness of a model in distinguishing between adopters vs. non-adopters)

Model Selection

- What types of predictive model were explored?
  - Decision Tree
  - k-NN
  - Naïve
  - Random Forest
  - Logistic Regression

- How do we decide on which model to use?
  - **AUC score***
    - A measure of how well a model can distinguish between customers who are likely to upgrade and those who are not.

- Model Selection Conclusion
  - Considering **interpretability**, **simplicity** and **efficiency**, we selected **Decision Tree.**

Feature Selection

- What is feature selection, and why do we need it?
  - It selects only the best/most predictive features
  - It minimizes overfitting and noise; and it's more computationally efficient

- What was our process?
  - First, used Filter Approach to rank all 25 features based on information gain*
    - Information Gain helps us determine which features are most informative about whether a user will upgrade.
  - Second, used Forward Selection to incrementally add each of the features to the model
    - The results of each combination (k1, k1+k2, k1+k2+k3, … k1+…+k25) were evaluated based on AUC score

- Feature Selection Conclusion
  - We noted minimal improvement beyond the first 2 features ("lovedTracks", "delta_songsListened").
    - "lovedTracks" is the total number of different songs that the user “liked”
    - "delta_songsListened" is the change in the number of songs a user listened to over the 3-month period before the marketing campaign

Benchmarking Comparison with All Models

Model	Positive Class Precision	F1	AUC
Naïve Bayes	0.0375	0.0720	0.5134
Naïve Bayes w/ Feature Selection	0.0514	0.0938	0.5319
k-NN, k = 5	0.0387	0.0683	0.5752
K-NN, k = 5 w/ Feature Selection	0.0652	0.1157	0.6255
Decision Tree	**0.1121**	**0.1697**	**0.7098**
Decision Tree w/ Feature Selection	**0.0941**	**0.1516**	**0.7007**

- Final Model Conclusion
  - To balance performance and complexity, we opted for a Decision Tree with feature selection, using only the top 2 most important features - "lovedTracks" and "delta_songsListened".

Thank you