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Customer Churn Prediction in a Leading Music App

1. Overview

Customer churn prevention is a **critical challenge** in subscription-based services, particularly in the **music streaming industry**. Companies that effectively **analyze customer behavior** can proactively **identify potential churners**, enabling them to implement **retention strategies** that **reduce customer attrition** and **boost long-term growth**.

The **leading music app** under study operates on a **freemium model**, where users can either **listen to music for free** with ads or **subscribe to a premium plan** for an ad-free experience. Understanding **why users leave the platform** is essential for **improving customer engagement** and maintaining a **loyal user base**.

To achieve this, we perform:

- **Exploratory Data Analysis (EDA)** to extract insights from user interactions.
- **Feature Engineering** to identify key predictors of churn.
- **Machine Learning Modeling** using **logistic regression, random forest, gradient boosting, and decision tree classifiers** to predict churn.
- **Model Evaluation & Tuning** to ensure the most accurate predictions using **F1-score and accuracy** metrics.

2. Metrics for Evaluation

The classification models are evaluated using **F1-score** and **accuracy**. Given that **customer churn is an imbalanced problem** (with fewer users churning than staying), the **F1-score** is prioritized.

Why F1-Score?

- Accuracy can be misleading when classes are imbalanced.
- F1-score balances **precision and recall**, making it a **better metric** for predicting churn.

The goal is to identify **which features have the strongest correlation with churn** and how these insights can drive **business strategies**.

3. Dataset Overview

The dataset consists of **user event logs**, where every user interaction—such as **playing a song, adding a song to a playlist, giving a thumbs-up, or upgrading/downgrading a subscription**—is recorded.

Key Features in the Dataset:

- **User ID** – Unique identifier for each user.
- **Session Activity** – Number of sessions, session duration, total songs played.
- **Page Events** – User interactions like "Next Song," "Thumbs Up," "Add to Playlist."
- **Device Information** – Operating system (Windows, Mac, iPhone, Android).
- **Subscription Status** – Free or Paid user level.
- **Churn Indicator** – Whether the user canceled their subscription.

These event logs allow us to **track user engagement** and determine **patterns leading to churn**.

4. Exploratory Data Analysis (EDA)

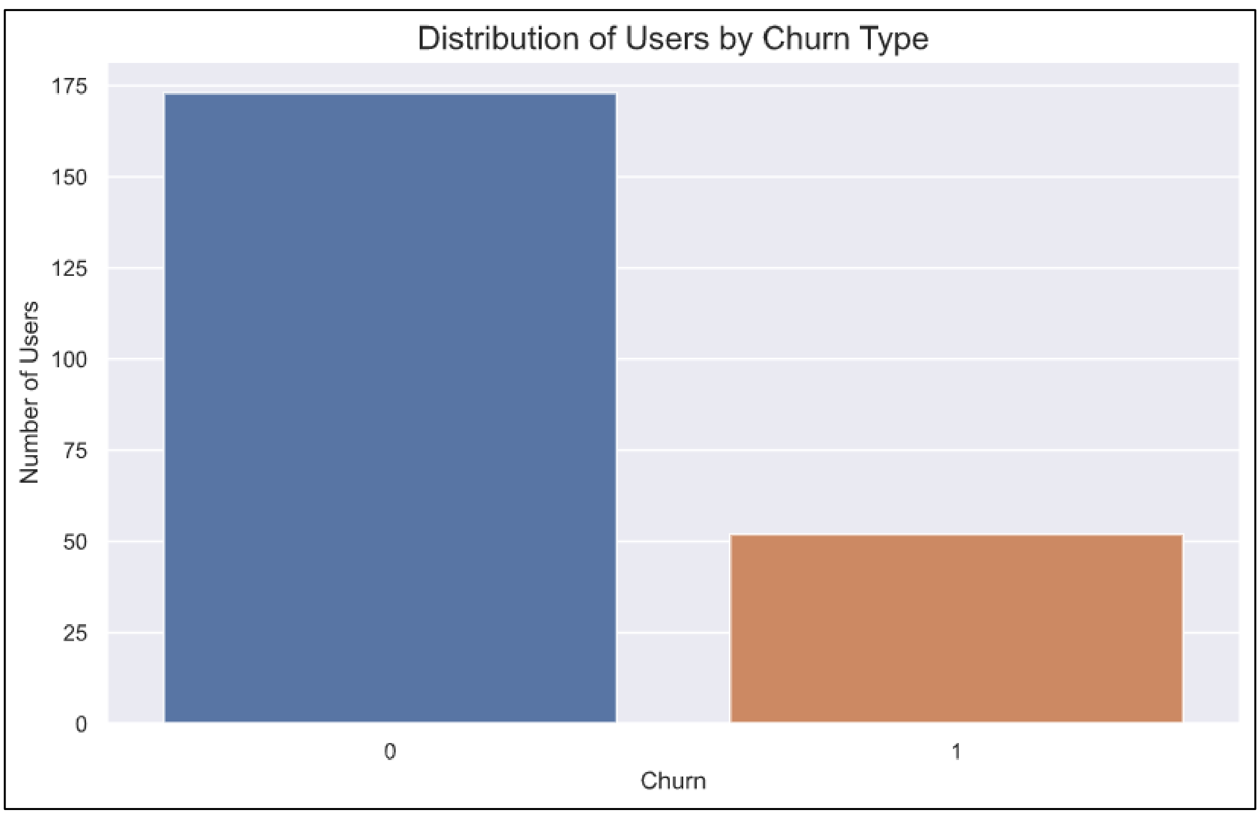
4.1 Understanding Churn Behavior

The churn label is created by identifying users who **confirmed subscription cancellations**. Once we define churned users, we explore **how their behavior differs** from non-churned users.

4.2 EDA and its Key Insights

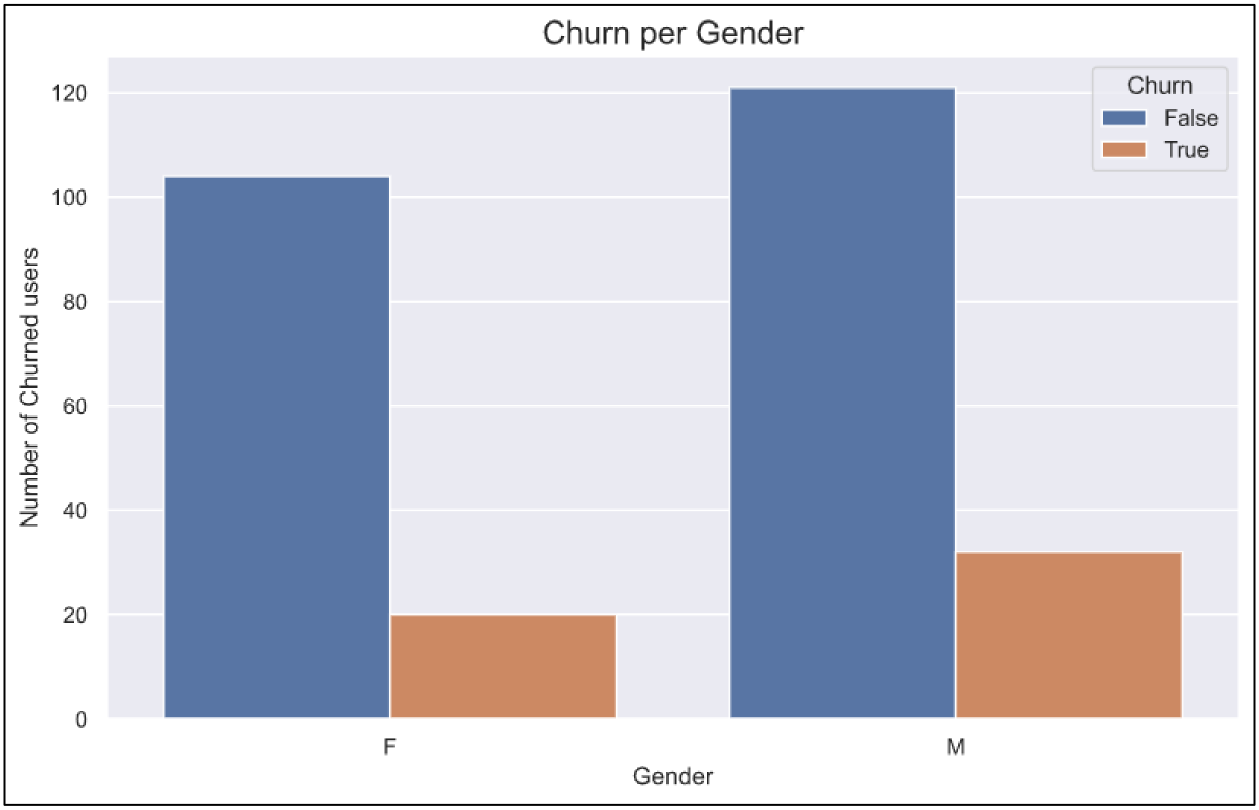
A few business questions are explored are as follows:

Q1) What is the churn rate of MusicApp?



The above figure shows out of 225 total users, 52 users were identified to be churned; this is approximately 24% of the universe.

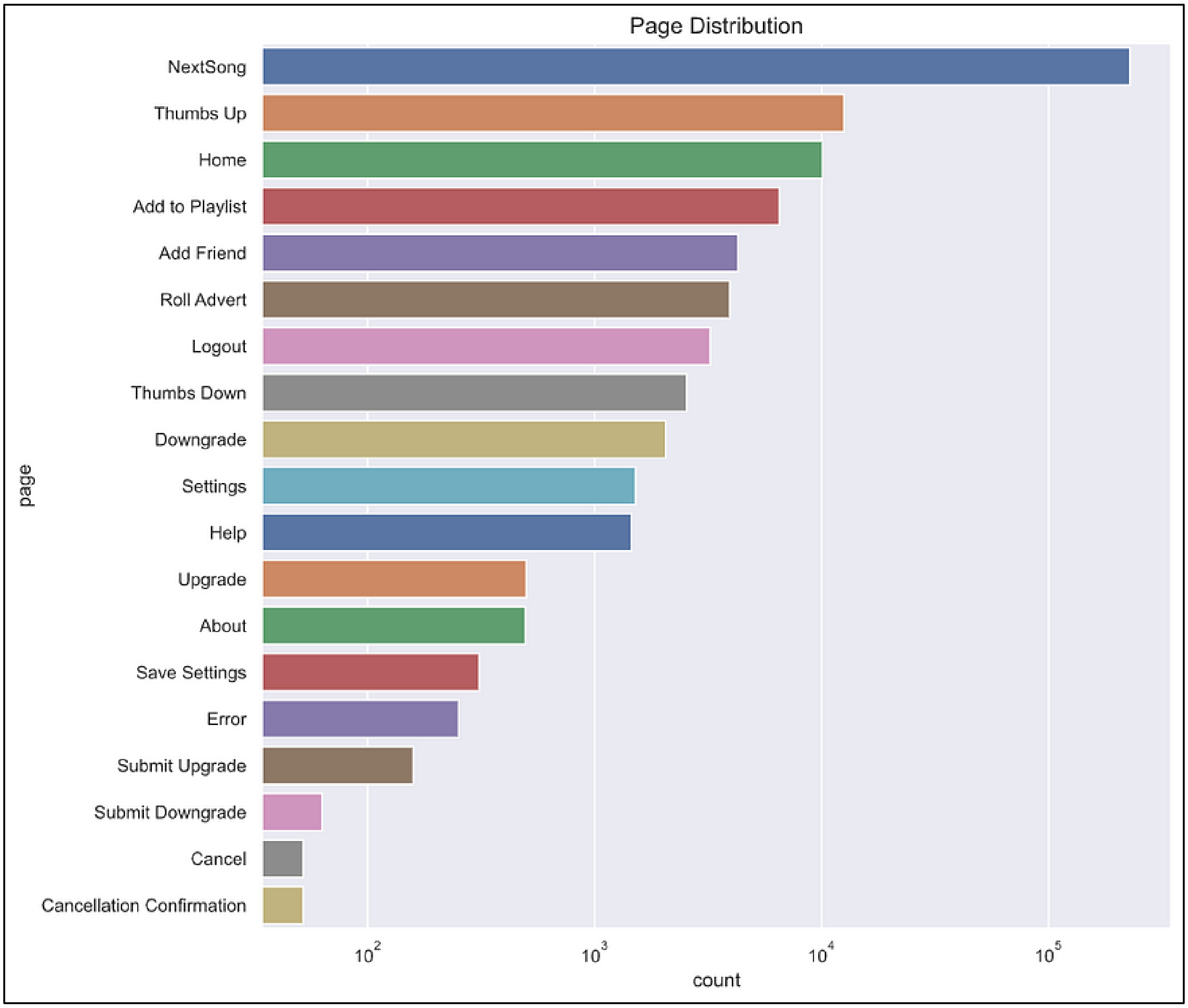
Q2) Does the type of gender affect churn rate?



The figure above illustrates churn per gender. We have more male users (~54% male, ~46% female) in our dataset so it's no surprise that we'd have more male users who churn. The churn rate for males is quite higher than females (26% vs 19%).

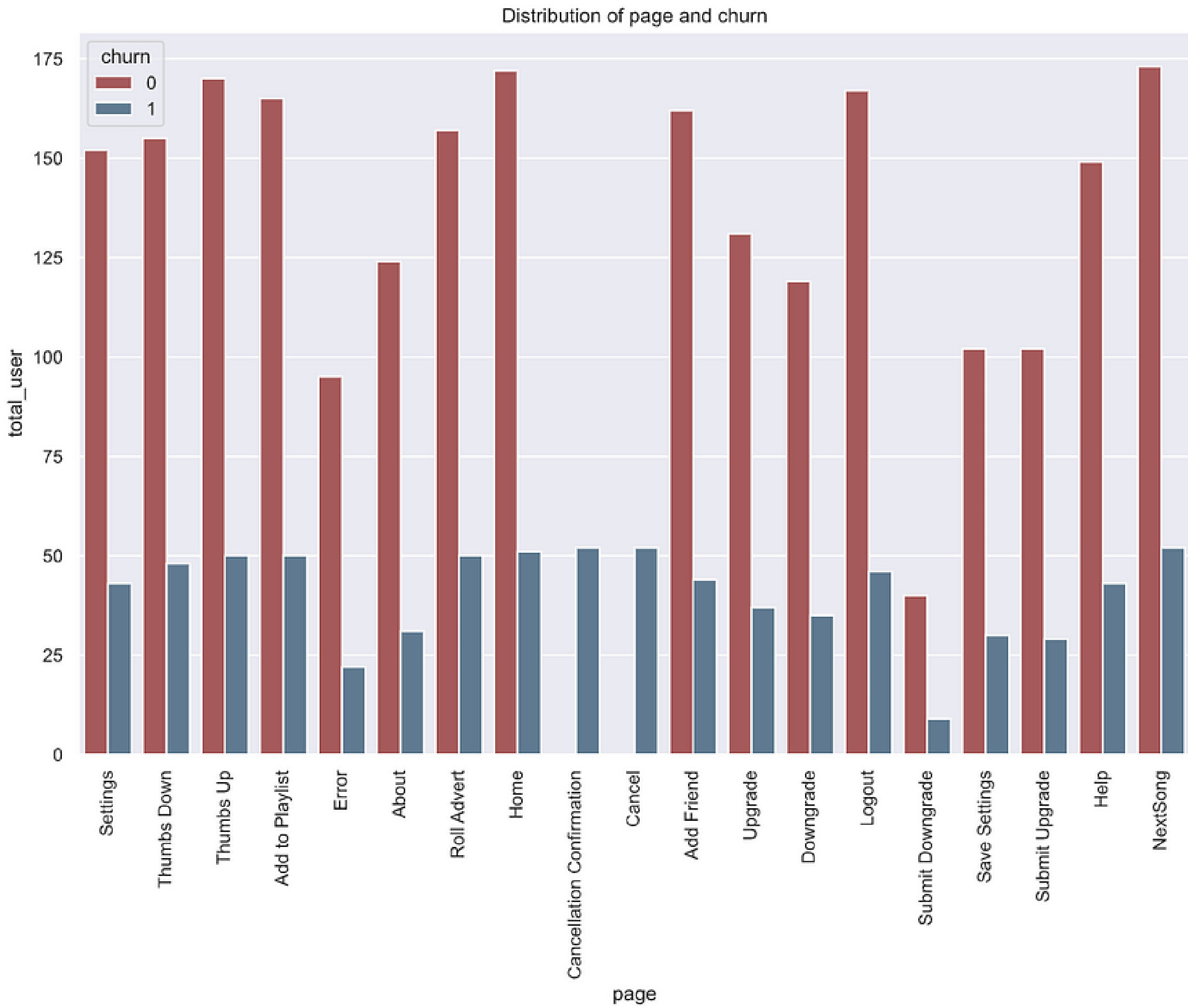
Q3) What is the page distribution for user activity?

Many users visit 'Next Song' page which is beneficial for the music streaming business. 'Thumbs Up' is another important factor that suggests users like the songs played and enjoy the app. 'Home' may indicate constant user activity with the app.



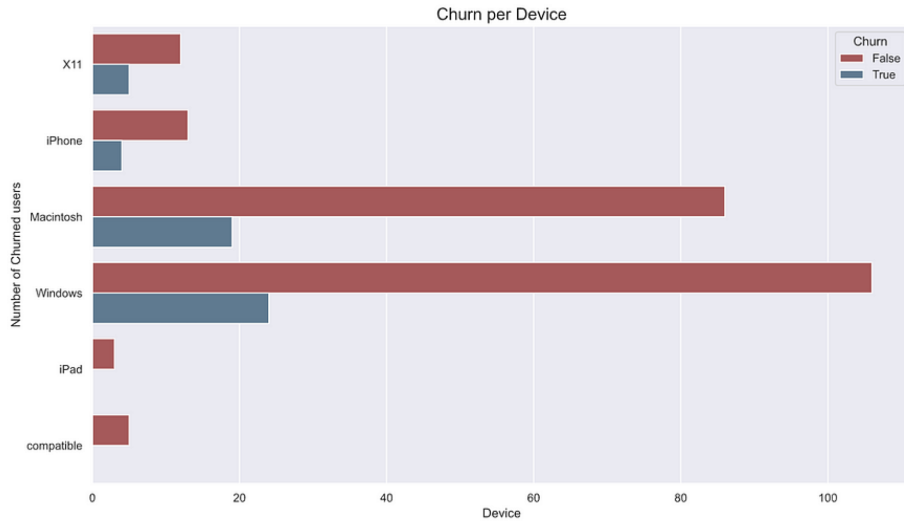
Q4) What is the page distribution for churn?

Next, we'll explore the distribution of page and churn users. Pages such as 'Next Song', 'Thumbs Up', 'Add Friend', and 'Add to Playlist' have a higher proportion of non-churn users. Finding the number of users visit these pages may determine if the users are likely to churn or not.



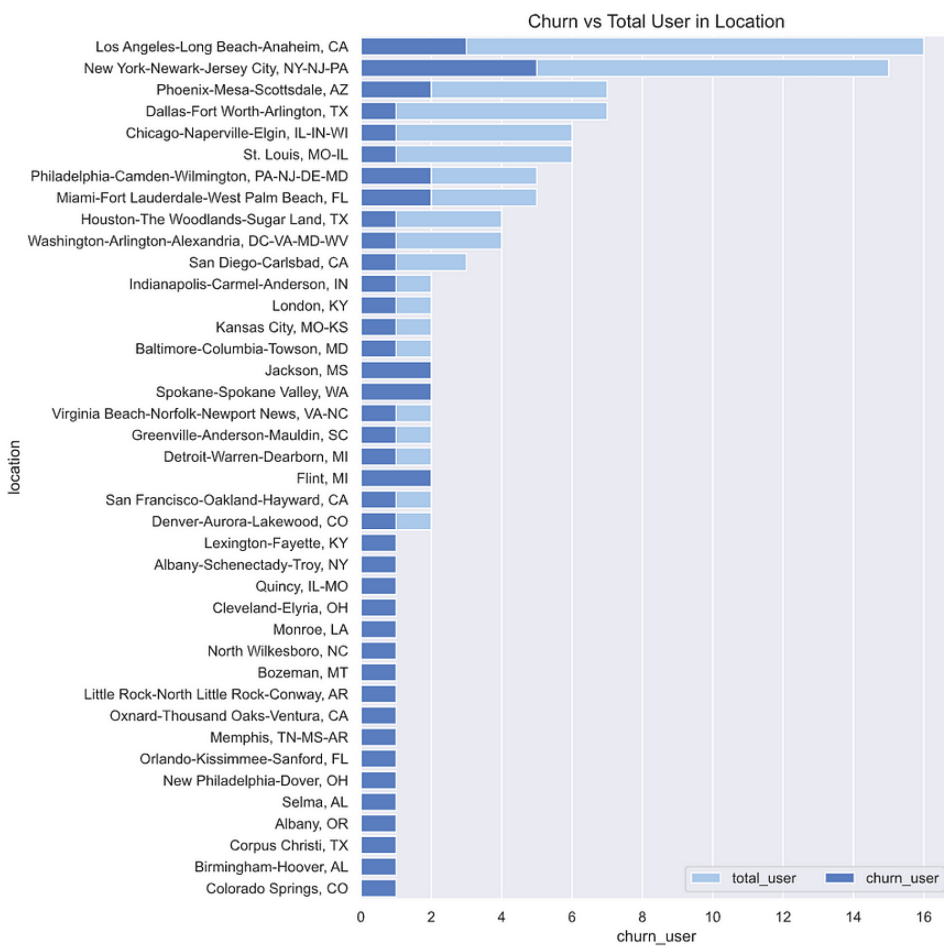
Q5) Does the type of user device influence the churn rate?

The majority of users use Windows or Mac to access the service, which also have the highest customer churn. The churn rate for Windows users is 18.5% which is slightly higher than Mac sitting at 18.1%. Devices such as X11 and iPhone have a much lower user base resulting in lower churn amount.

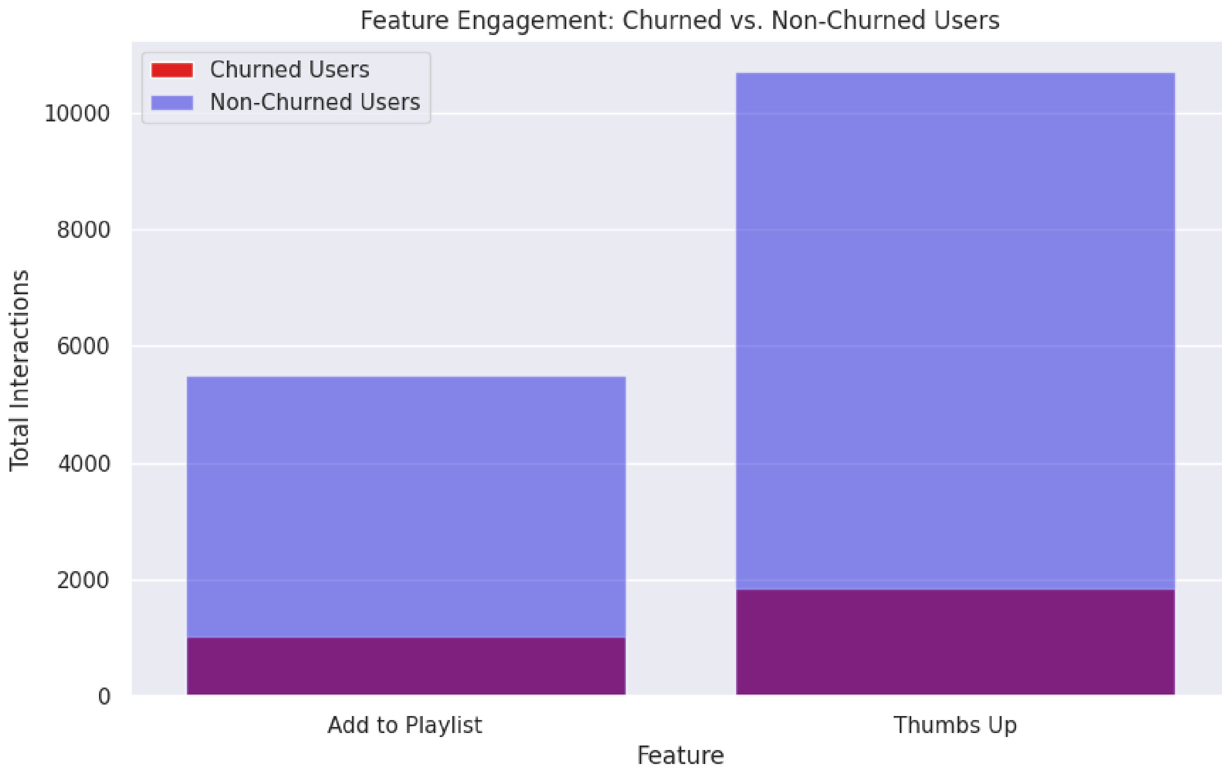


Q6) Does user location affect the churn rate?

The locations with the highest total users and churn users are in 'Los Angelos-Long Beach-Anaheim, CA', 'New York-Newark-Jersey City, NY-NJ-PA', and 'Phoenix-Mesa-Scottsdale, AZ'. User locations are scattered widely and are rather sparse in almost all locations.



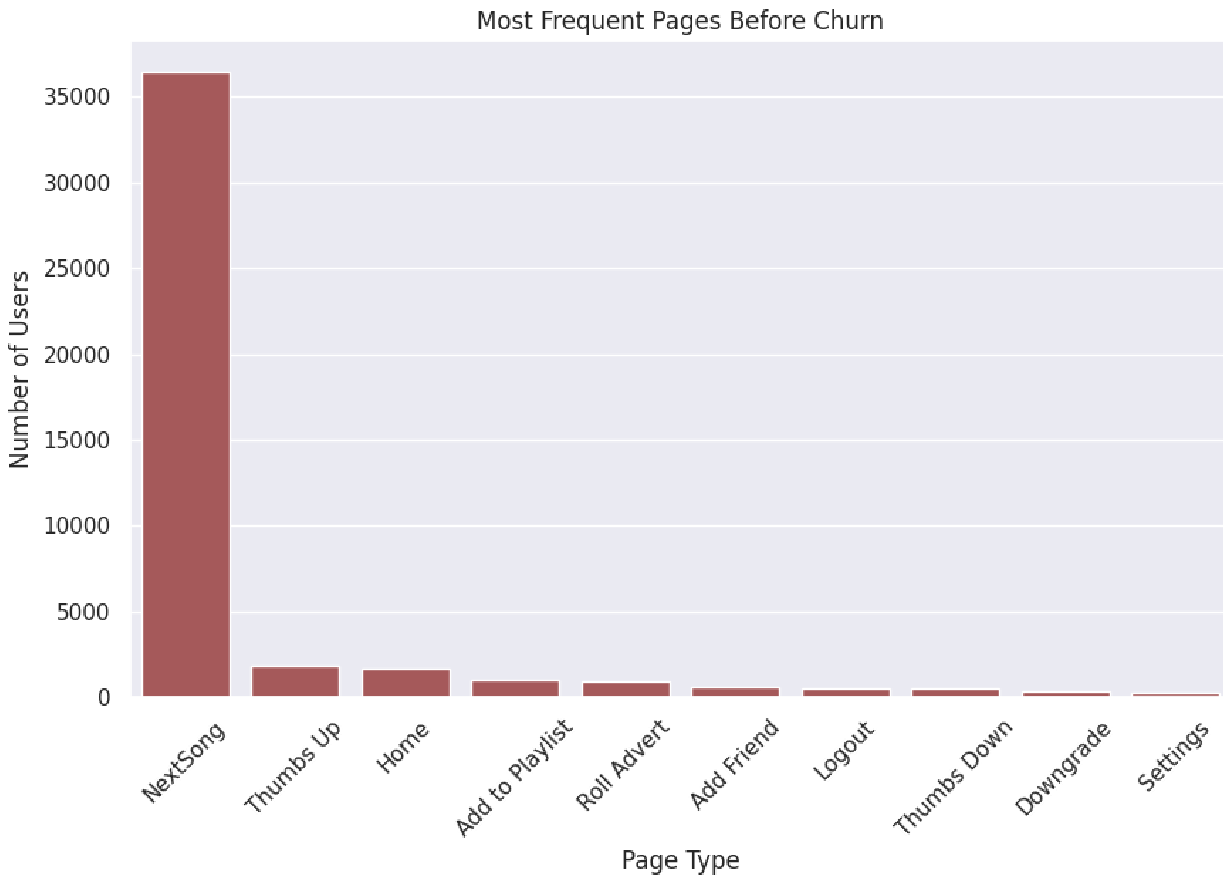
Q7) Do churned users engage differently with core features?



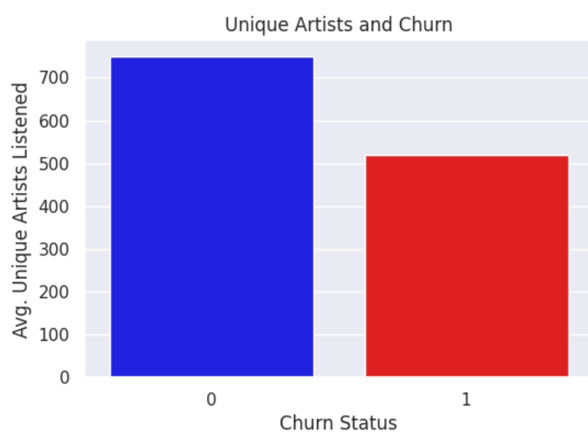
The graph shows that non-churned users engage significantly more with features like "Thumbs Up" and "Add to Playlist" compared to churned users. Thumbs Up is the most frequently used feature, suggesting it plays a key role in user engagement. Churned users have noticeably lower interaction counts, indicating that reduced feature engagement may be an early sign of churn. Encouraging users to interact more with these features—through recommendations or incentives—could help improve retention and reduce churn rates.

Q8) Which pages do users visit most frequently before they churn?

The graph shows that **"Next Song"** is by far the most frequent page visited before users churn, indicating that churned users may be skipping through content rather than engaging deeply. Other interactions like **"Thumbs Up," "Home," and "Add to Playlist"** appear much less frequently, suggesting that churned users engage less with features that indicate satisfaction. The presence of **"Logout," "Downgrade," and "Thumbs Down"** further supports the idea that these users may already be disengaged before leaving. This suggests that **early detection of high skip rates and lower engagement with positive interactions could help predict and prevent churn**.

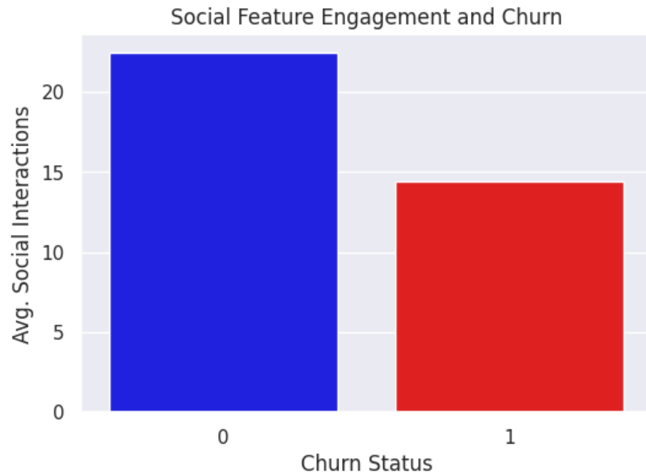


Q9) Do churned users listen to fewer unique artists compared to non-churned users?



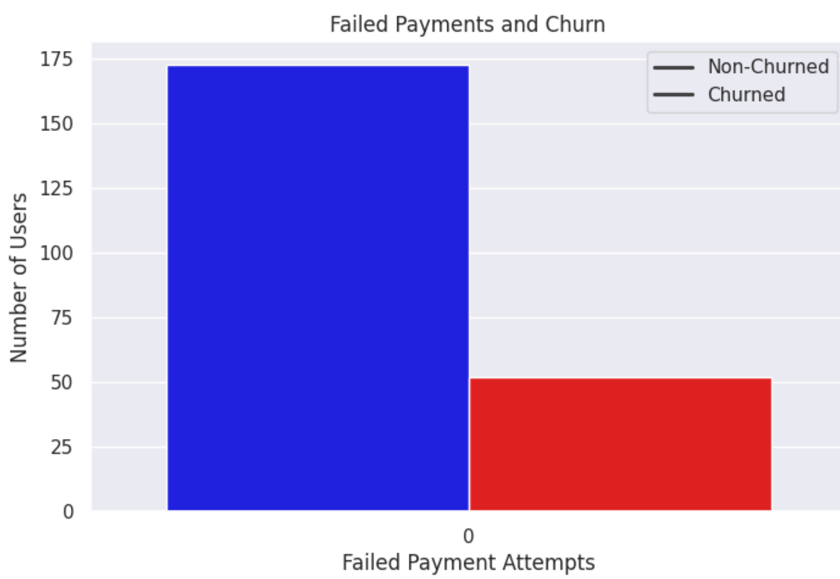
The graph shows that non-churned users (0) listen to a significantly higher number of unique artists compared to churned users (1). This suggests that users who explore a wider variety of music tend to stay engaged with the platform, while those who listen to fewer artists may lose interest and eventually churn. Encouraging music discovery through personalized recommendations or curated playlists could help increase engagement and reduce churn rates.

Q10) Do churned users interact less with social features like "Add Friend" or "Share"?



The graph shows that non-churned users (0) have significantly higher social interactions compared to churned users (1). This suggests that users who engage more with social features, such as adding friends or sharing content, are more likely to stay on the platform. Lower social engagement among churned users indicates that fostering community interactions could help improve user retention and reduce churn.

Q11) Are users with failed payments more likely to churn?



The graph shows that users with failed payment attempts are more likely to churn, as the number of churned users (red) is significantly lower than non-churned users (blue). This suggests that payment failures are a strong indicator of potential churn, possibly due to financial issues or dissatisfaction with the service. Implementing reminders, flexible payment options, or retry mechanisms could help retain users who experience failed payments.

Overall Churn Rate: ~24% of users churn.
Gender & Churn: Males churn at **26%**, while females churn at **19%**.
Page Activity:

- "Next Song" and "Thumbs Up" have **higher engagement from non-churn users**.
- "Add to Playlist" and "Home" indicate **consistent app engagement**.
  Device Usage & Churn:
- **Windows users churn the most (18.5%)**, slightly higher than Mac users (18.1%).
- X11 and iPhone users show **lower churn rates** due to smaller user bases.
  Location & Churn:
- Highest churn observed in **Los Angeles, New York, and Phoenix**—indicating urban churn patterns.

These insights **inform retention strategies**, such as **targeted promotions for high-risk locations and user segments**.

5. Feature Engineering

From our analysis, we engineered **10 key features** that **hypothetically influence churn**:

Feature	**Description**	**Type**
Gender	Male/Female	Binary
Churn	Subscription cancellation indicator	Binary
User Level	Free/Paid	Binary
Total Length of Songs Played	Total listening duration	Float
Avg Session Duration	Average time spent per session	Float
Page Interactions	"Thumbs Up", "Add to Playlist", "Home", etc.	Integer
Time Since Registration	Days since user signup	Integer
Total Sessions	Number of unique sessions	Integer

Total Songs Played	Total count of played songs	Integer
Device Type	Windows, Mac, iPhone, Android, etc.	Categorical

The dataset is then **split into 70% training and 30% testing**.

6. Model Building & Evaluation

Since this is a **classification problem (churn vs. non-churn)**, we experiment with:

- **Logistic Regression**
- **Random Forest**
- **Gradient Boosting**
- **Decision Tree Classifier**

The exploratory analysis revealed common trends and features that hypothetically influenced churn rates, and the features selected for modeling were proven to be significant factors in predicting churn rate as all the important models have performed very well. The f1 score of 0.9915 for gradient boosting and 0.9871 for random forest respectively. The f1 score is the key evaluation metric in selecting the best model as it results in low false positive and false negative values thereby reducing business costs. It also provides equal weightage to both precision and recall values and is robust measure in comparison to other metrics.

Model Performance Metrics

Model	F1-Score	Accuracy
Gradient Boosting	**0.9915**	**Highest**
Random Forest	0.9871	
Logistic Regression	0.9558	
Decision Tree	0.9523	

- **Gradient Boosting performed best, achieving an F1-score of 0.9915.**
- **Random Forest was the second-best model, achieving an F1-score of 0.9871.**

7. Hyperparameter Tuning & Model Improvement

Since **Gradient Boosting and Random Forest performed best**, we performed **hyperparameter tuning** to improve performance:

Model	Tuned Parameters
Gradient Boosting	maxDepth [2, 4, 6, 8, 10]
Random Forest	impurity ['entropy', 'gini'], maxDepth [2, 4, 6, 8]
Logistic Regression	regParam [0.1, 0.01], fitIntercept [True, False]
Decision Tree	impurity ['entropy', 'gini'], maxDepth [2, 4, 6, 8]

After hyperparameter tuning, model performance improved slightly (~0.001% in F1-score).

8. Feature Importance Analysis

The most important features influencing churn prediction are:
1) **Page Settings**
2) **Home Page Visits**
3) **Thumbs Up Count**
4) **Total Time Spent**
5) **Error Page Visits**

These **high-impact features** help explain **why users churn**, providing actionable insights for **business decisions**.

9. Conclusion & Business Recommendations

9.1 Key Takeaways

- Gradient Boosting is the best predictive model with an **F1-score of 0.9915**.
- Feature importance analysis helps identify user behaviors contributing to churn.
- Males, Windows users, and users from high-churn cities need special attention.

9.2 Business Recommendations

1. Target High-Risk Segments with Personalized Offers

- Users on Windows devices and in high-churn locations (e.g., Los Angeles, New York) should receive geo-targeted promotions and exclusive discounts to improve retention.
- Implement behavior-based incentives, such as early access to features or loyalty rewards, for users who engage less frequently.

2. Enhance Engagement with Churn-Prone Users

- Encourage users to engage more with playlists and likes by offering personalized recommendations and AI-driven playlist suggestions.
- Use push notifications and email reminders to re-engage users who show declining activity, highlighting missed interactions or new content.

3. Optimize User Experience Through A/B Testing

- Conduct experiments on UI layouts, onboarding experiences, and pricing models to determine what keeps users engaged.
- Test subscription incentives (e.g., limited-time discounts, premium trials) to assess their impact on long-term retention.

4. Reduce Churn Due to Payment Failures

- Introduce automated payment retries, flexible billing dates, and alternative payment methods to prevent unnecessary churn.
- Send reminders and proactive support notifications for upcoming renewals and failed transactions, ensuring users don’t churn due to billing issues.

5. Leverage Social Engagement to Improve Retention

- Strengthen community-driven features like collaborative playlists, friend suggestions, and music sharing to increase user stickiness.
- Use gamification strategies (e.g., badges, milestones) to reward users for social engagement, encouraging them to stay active on the platform.

10. Future Work

There are a couple of potential improvements in future:

- **Collect more user data**

We can create various metrics such as — number of times user logged in by month, number of times user upgraded or downgraded their services, and add demographic information to improve the accuracy of model prediction.

- **The XGBoost and LightGBM models could be good supervised learning approaches to try here. Another way is to perform A/B testing to select which action to take.**
- Build a Recommendation Engine.

By collecting additional data as mentioned above, building a recommendation engine using collaborative filtering where we could identify user similarity between other users based on the type of songs/artists/genres they enjoy, and provide personalized recommendations regarding songs/artists they may like to improve user experience with the app.