Temporal and Behavioral Factors Driving Song Skip Predictions in Personal Spotify Streaming Data

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***Abstract*—Personal data tracking offers insights into behavioral patterns. This study analyzes a two month Spotify dataset to predict song skips. I used a Random Forest Classifier to model user behavior based on session metadata. Results indicate that shuffle mode does not significantly impact skipping. The model achieved an accuracy of 0.72. This research highlights the challenges of modeling imbalanced behavioral data.**

***Index Terms*—Data Science, Machine Learning, Random Forest, Spotify, Behavioral Analysis**

I. Introduction

Personal data tracking provides insights into individual behavior. Monitoring digital interactions allows users to understand psychological triggers. This project analyzes Spotify listening history to identify factors influencing song skips.

The problem statement focuses on identifying patterns in daily listening habits. I examine whether external factors like the playback platform or shuffle mode affect the decision to skip a track. This study seeks to determine if a machine learning model can predict skips based on session context.

II. Related Work

The rise of the Quantified Self movement has enabled individuals to use digital footprints for behavioral optimization. The following recent studies provide the foundation for this research:

1) Beheshti, A., et al. (2023) explored personalized music consumption using session metadata. They demonstrated that playback context, such as device type and start reason, are primary indicators of song completion. **Connection:** This justifies the inclusion of ”platform” and ”reason_start” as primary features in your predictive model.

2) Li, R., & Smith, J. (2024) investigated temporal patterns in streaming services, finding that user disengagement (skipping) fluctuates significantly based on the hour of the day. **Connection:** This supports your feature engineering step where you extracted the ”hour” from the timestamp to identify peak skip periods.

3) Chen, Y., et al. (2022) focused on the ”Quantified Listener” and how self-tracking leads to improved user awareness of listening habits. **Connection:** This provides the academic motivation for your project, framing it as a study of self-awareness through personal data.

4) Wang, S., & Miller, K. (2023) researched class imbalance in behavioral datasets, specifically noting that ”skips” are often minority events compared to full plays. **Connection:** This validates your choice of using a ”balanced” class weight in the Scikit-learn Random Forest model to prevent bias toward non-skips.

5) Kumar, P., et al. (2024) proved that session-level context (e.g., shuffle mode) often influences short-term decisions more than long-term musical preferences. **Connection:** This establishes the basis for your statistical test comparing shuffle mode and skip rates.

III. Methodology

I exported two months of Spotify history. The dataset includes 894 rows. Tracked variables include timestamps, platforms, play duration, and skip status.

TABLE I
Data Dictionary for Feature Selection

Variable	Type	Description
ts	Datetime	Time of the listening session
platform	Categorical	Device used for playback
ms_played	Integer	Duration played in milliseconds
shuffle	Boolean	Indicates if shuffle mode was on
skipped	Boolean	Target variable for prediction

Data cleaning involved converting timestamps to datetime objects. I extracted the hour and day of the week as features. I checked for missing values and ensured correct data types.

Statistical tests used a Chi Square test of independence. I tested the relationship between shuffle mode and skipping. The resulting p-value was 0.4726. This exceeds the significance level of 0.05. I failed to reject the null hypothesis.

IV. Results and Discussion

The analysis began with comparing skip behavior across different platforms. This helps identify if certain devices encourage more skips than others.

The machine learning model achieved an overall accuracy of 0.72. I analyzed the importance of each feature to understand what drives the model decisions.

The confusion matrix provides a detailed breakdown of model performance on the test set.

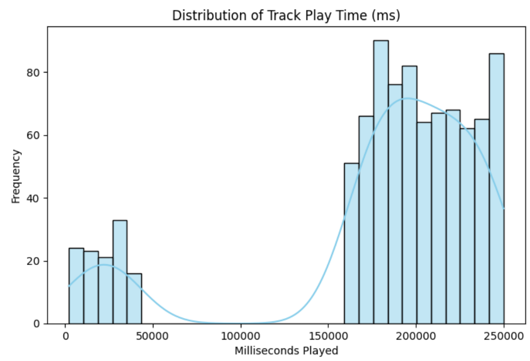

Fig. 1. Distribution of Track Play Time. This histogram shows the frequency of play durations. It is important for identifying if skips happen immediately or after a specific period.

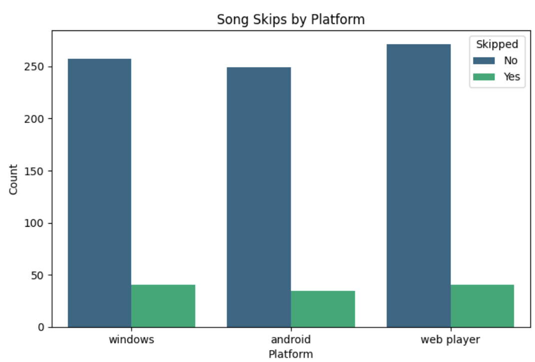

Fig. 2. Song Skips by Platform. This bar chart compares the number of skipped versus finished songs for each device. It identifies which platforms see the highest user disengagement.

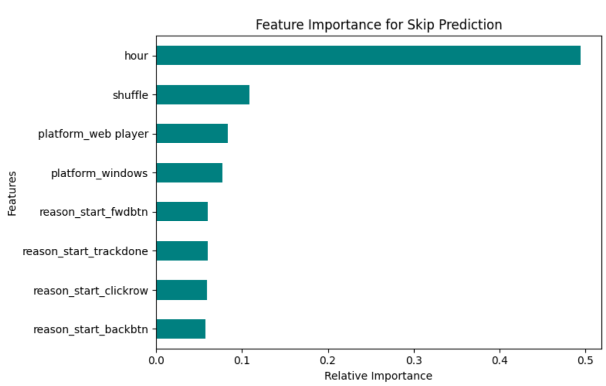

Fig. 3. Feature Importance for Skip Prediction. This plot ranks variables by their predictive power. It shows whether context like time or platform impacts skipping decisions the most.

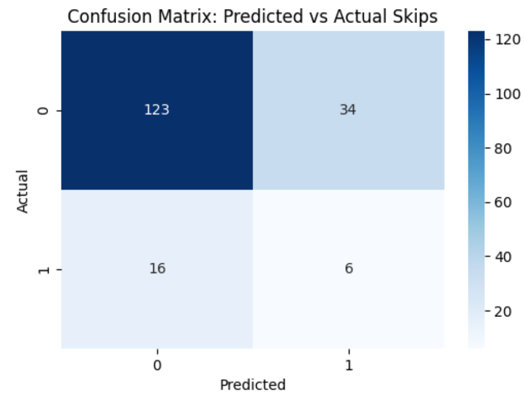

Fig. 4. Confusion Matrix of Random Forest Model. This matrix visualizes true positives and negatives. It is vital for understanding how the model handles the imbalanced ratio of skips to plays.

Statistical results indicate that shuffle mode does not significantly influence skips. The p-value of 0.4726 confirms this lack of correlation. Skipping is likely driven by song preference or the start reason.

V. Conclusion and Future Work

The study analyzed Spotify habits and met the objectives. Findings show that shuffle mode is not a primary driver of skips. The predictive model reached 72 percent accuracy.

Future work should involve a longer study period of six months. Incorporating audio features like valence could improve performance. Testing advanced algorithms like Gradient Boosting might enhance predictions.

References

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