VINUNIVERSITY

COMP4010: Data Visualization

Final Report

Spotify Wrapped - R Version

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1 Introduction

1.1 Problem Statement

Spotify Wrapped 2024 sparked widespread disappointment due to its lack of creativity, missing features, and impersonal AI-generated content. Once praised for engaging tools like Audio Aura, Music Cities, and curated playlists, this year's edition offered only basic lists of top songs and artists, leaving users frustrated after months of anticipation [1]. Many criticized the shift to automated, voice-narrated summaries as cold and "almost dystopian," a result of Spotify's December 2023 layoffs and move away from human-centered design [2].

This backlash reflects a broader issue: current music analytics tools offer static, surface-level summaries that fail to capture the emotional depth and evolving nature of music preferences. **There is a clear need for more dynamic, personalized, and emotionally resonant approaches to visualizing listening behavior.**

1.2 Dataset Description

Our application leverages multiple data sources to create comprehensive musical profiles:

- **Primary Data Sources:**
  - **Spotify Web API**: Real-time user data including listening history and detailed audio features
  - **Demo Datasets**: Pre-processed JSON files containing sample user profiles for demonstration purposes
- **Key Variables:**
  - **Audio Features**: Danceability, energy, valence, acousticness, instrumentalness, tempo, loudness, and speechiness
  - **Track Metadata**: Song titles, artist names, album information, popularity scores, release dates, and duration
  - **User Metrics**: Play counts, listening patterns, temporal behavior, and preference rankings
  - **Genre Classifications**: Musical genre tags, style categorizations, and cultural context
  - **Personality Indicators**: Emotional sentiment and behavioral patterns derived from comprehensive audio feature analysis

1.3 Novelty of Our Solution

Our solution addresses existing limitations through several innovative approaches:

1. **Real-time Personalization**: Unlike Spotify's annual Wrapped, our application provides on-demand analysis with fresh data, allowing users to explore their current musical state rather than waiting for year-end reports.

2. **Advanced Personality Analysis**: We implement sophisticated algorithms analyzing audio features, genre patterns, and listening behavior to predict musical personality types and emotional patterns, going beyond simple play count statistics.

3. **Interactive Narrative Experience**: Our 9-slide journey structure provides cohesive storytelling that guides users through their musical personality discovery, rather than overwhelming them with disconnected dashboards.

4. **Dual Backend Architecture**: The innovative combination of R Shiny for statistical visualization and Python Flask for API integration creates a robust, scalable solution leveraging the strengths of both technologies.

5. **Comprehensive Audio Feature Integration**: Deep analysis of musical characteristics including valence, energy, danceability, and cultural context for nuanced personality prediction.

2 Methodology and Approach

2.1 Technology Stack

Python Backend: Used for data crawling and comprehensive data analysis, including Spotify Web API integration, audio feature processing, mood classification algorithms, and sophisticated personality prediction models using machine learning techniques.

R Frontend: Employed for interactive UI development and advanced chart visualization, leveraging R's statistical computing power with Shiny for reactive web applications, ggplot2/plotly for sophisticated visualizations, and modern Bootstrap-based styling.

2.2 Function Analysis

2.2.1 Login System

The application implements a dual authentication system for maximum accessibility. Spotify OAuth integration provides secure real-time data access with automatic token management, while demo dataset access offers immediate exploration through pre-processed samples. Session management maintains user state across the 9-slide journey with persistent authentication tokens.

2.2.2 User Profile Endpoint (`/user/profile`)

This endpoint retrieves comprehensive Spotify profile information including display name, follower count, and account metadata. It handles session management, provides personalized greetings, and validates API connectivity before proceeding with data analysis.

2.2.3 Top Tracks Analysis (`/user/top_tracks`)

Implements multi-timeframe analysis across short-term (4 weeks), medium-term (6 months), and long-term (several years) listening data. Processes comprehensive metadata including popularity scores (0-100 scale), release dates, duration, and explicit content flags. Supports configurable limits (5-50 tracks) and applies position-based weighting for personality prediction algorithms.

2.2.4 Top Artists Analysis (`/user/top_artists`)

Focuses on artist popularity and genre extraction with detailed metadata including popularity scores, follower counts, and genre classifications (3-8 genres per artist). The genre aggregation algorithm applies position-based weighting and performs cultural diversity scoring based on genre origins, identifying exposure to Western, Asian, Latin, African, and other global music cultures.

2.2.5 Mood Distribution Analysis (`/analysis/mood_distribution`)

Processes recently played tracks through Spotify's Audio Features API, analyzing seven key characteristics: valence (0.0-1.0 positiveness scale), energy, danceability, acousticness, tempo, loudness (-60 to 0 dB), and speechiness. Implements sophisticated mood classification using weighted feature combinations:

- **Happy**: High valence (> 0.65) + moderately high energy (> 0.55) + major modality
- **Euphoric**: Very high danceability (> 0.7) with happy characteristics
- **Sad**: Low valence (< 0.4) + low energy (< 0.45) + minor/acoustic elements
- **Energetic**: Very high energy (> 0.75) with high danceability (> 0.65)
- **Calm**: High acousticness (> 0.65) + low energy (< 0.55) + slow tempo (< 100 BPM)
- **Additional categories**: Melancholic, Intense, Ambient, Angsty, Groovy

Employs batch processing (up to 50 tracks per request) and returns mood percentages with confidence metrics.

2.2.6 Popularity Score Analysis (`/analysis/popularity_score`)

Provides insights into mainstream vs. niche preferences through three methods: simple average, weighted average, and statistical analysis. Categorizes listeners as mainstream (scores > 70), balanced (30-70), or niche (< 30) based on global listening patterns. Identifies cultural early adopters versus mainstream followers through trend analysis.

2.2.7 Genre Distribution Analysis (`/analysis/genre_distribution`)

Implements hierarchical processing with position-based weighting (1-5x multipliers), cultural context mapping, and genre complexity scoring. Calculates diversity metrics across four dimensions: genre breadth, depth, cultural diversity, and temporal patterns. Uses fuzzy logic for synonym matching ("hiphop"→"hip hop") and handles regional variations with confidence scoring.

2.2.8 Personality Prediction (`/analysis/personality_prediction`)

Implements comprehensive Big Five personality analysis predicting five core dimensions:

- **Openness to Experience**: Intellectual curiosity and creativity
- **Conscientiousness**: Organization and goal-orientation
- **Extraversion**: Social energy and outward focus
- **Agreeableness**: Empathy and cooperation
- **Emotional Stability**: Stress resistance and resilience

Combines three analytical layers: genre pattern analysis (70% weight), audio features analysis (30% weight), and secondary behavioral analysis (15% additional). Maps acoustic characteristics to personality traits with specific correlation values (e.g., high valence increases agreeableness +15, extraversion +10). Generates dynamic personality classifications with base types (Social, Creative, Organized, Harmonious, Steady) and contextual modifiers based on complexity, diversity, and cultural exposure.

2.2.9 Audio Features Analysis (`/analysis/audio_features`)

Implements batch audio feature extraction across four analytical dimensions: harmonic analysis (key, mode, tonal characteristics), rhythmic analysis (tempo stability, beat strength), timbral analysis (spectral characteristics, texture), and structural analysis (arrangement complexity). Provides real-time correlation to mood classification and personality prediction supporting 50 tracks per request.

2.3 Implementation & Features

Core Features:

- **9-Slide Narrative Journey**: Structured user experience guiding through welcome, configuration, discovery, analysis, and insights with cohesive storytelling
- **Advanced Personality Insights**: AI-powered musical personality prediction using Big Five analysis with comprehensive audio feature integration and confidence scoring

Technical Implementation:

- **RESTful API Design**: Standardized endpoints enabling independent frontend/backend development with comprehensive error handling and rate limiting
- **Reactive Programming**: Shiny's reactive model for real-time UI updates and user interactions with performance optimization for large data requests

Code: Please refer to this Github Link

3 Final Product

3.1 Login System

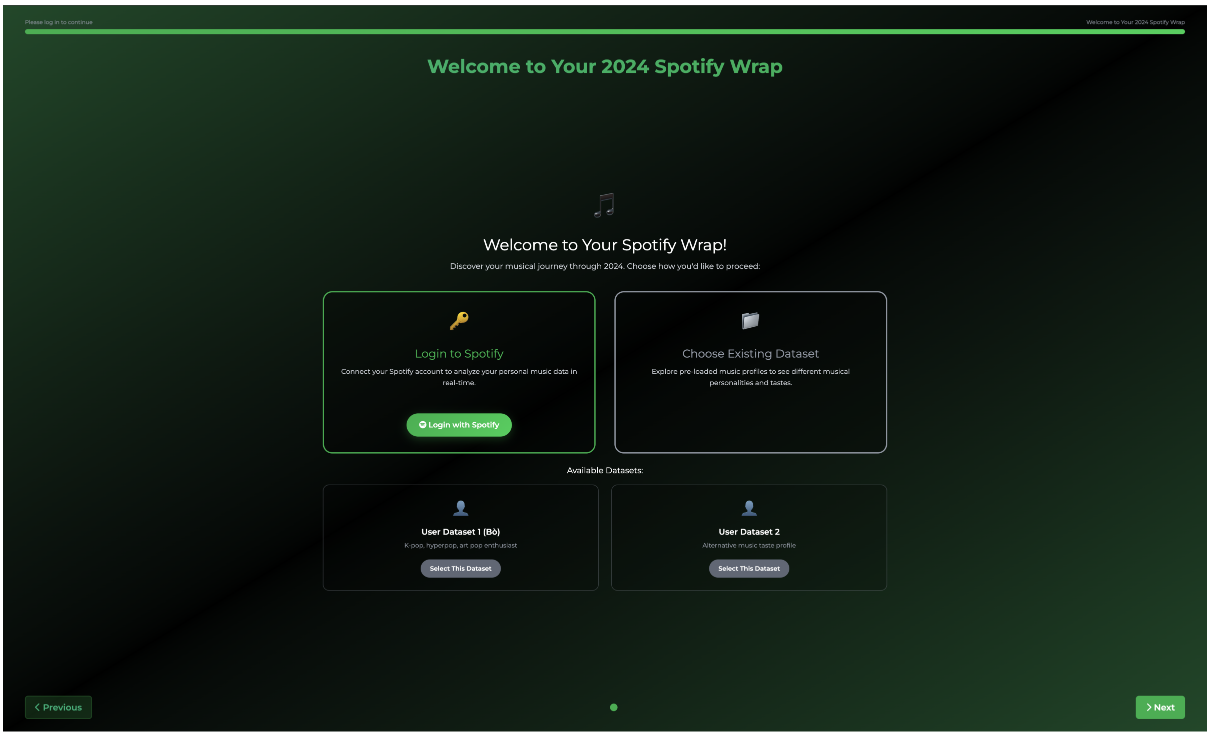

Figure 1: Login Page

3.2 User Profile Endpoint (`/user/profile`)

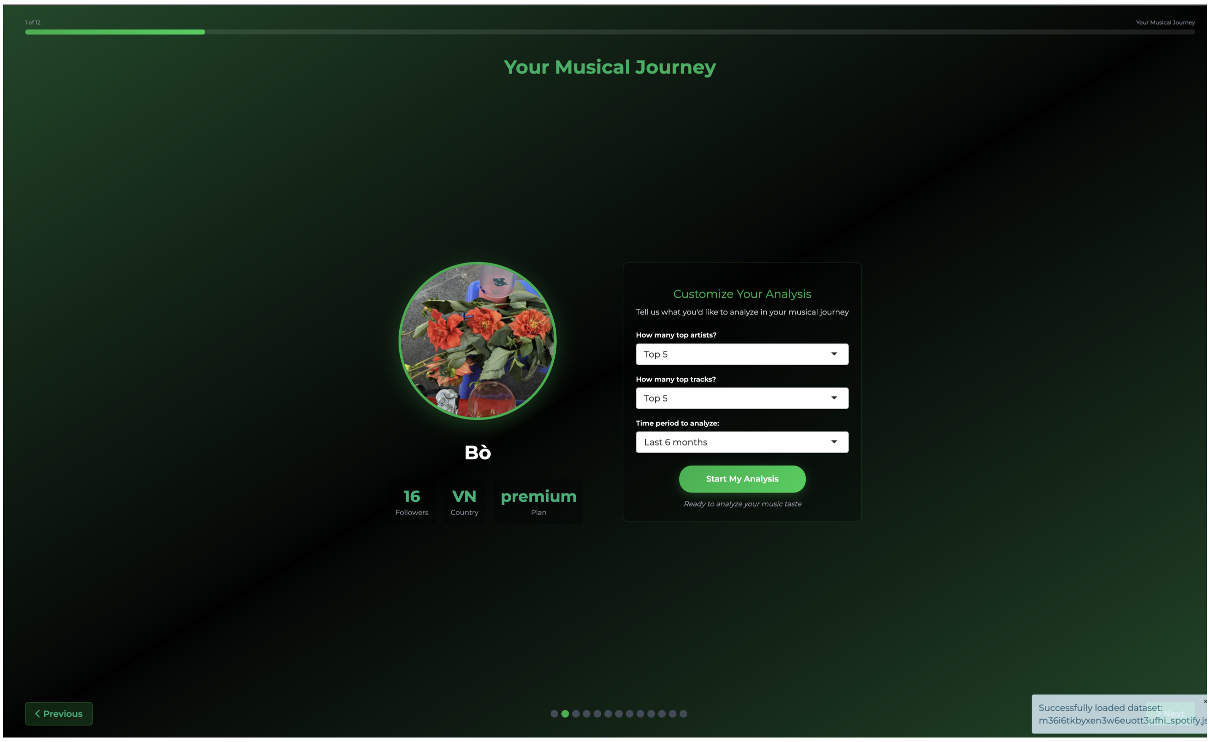

Figure 2: User Profile

3.3 Top Tracks Analysis (`/user/top_tracks`)

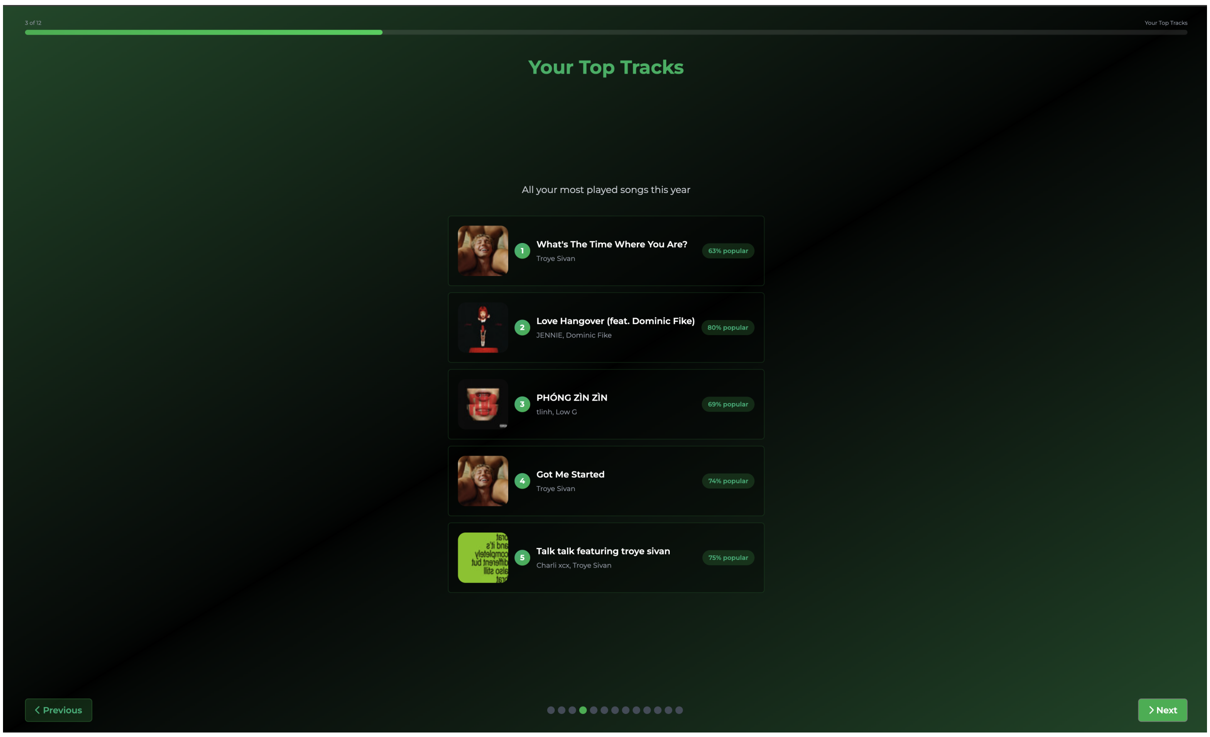

Figure 3: Top Tracks Analysis

3.4 Top Artists Analysis (`/user/top_artists`)

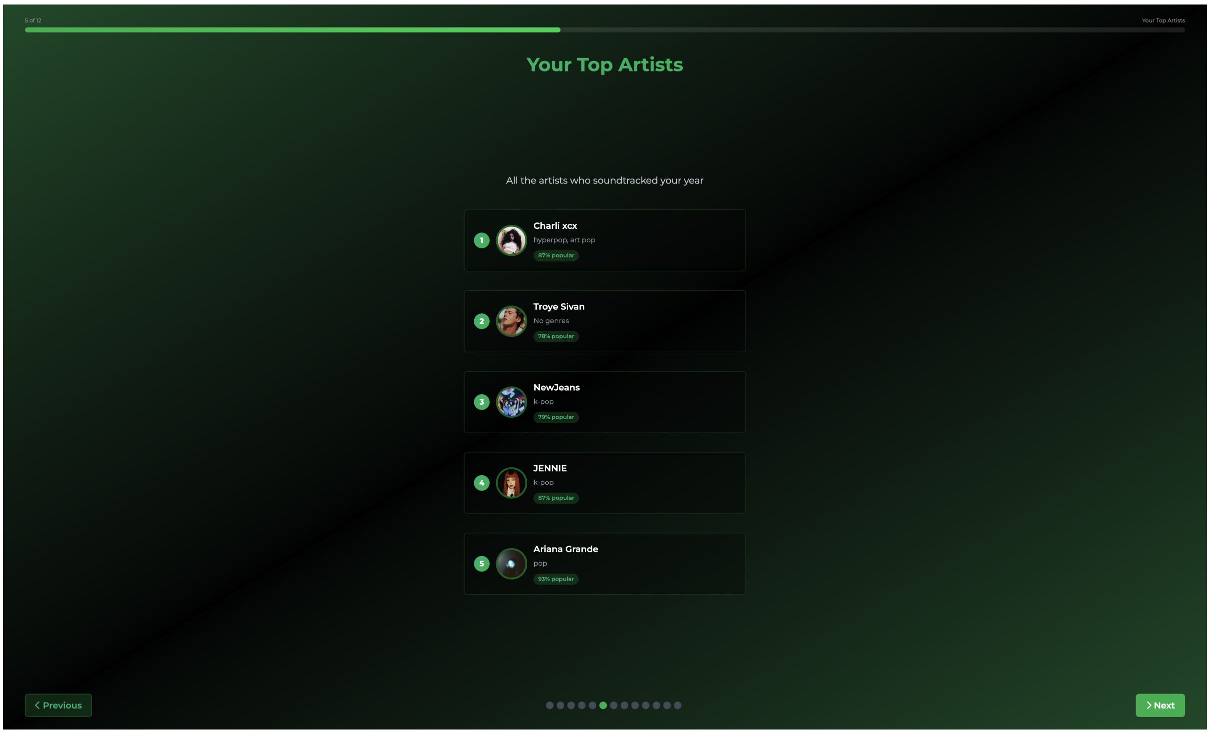

Figure 4: Top Artists Analysis

3.5 Mood Distribution Analysis (`/analysis/mood_distribution`)

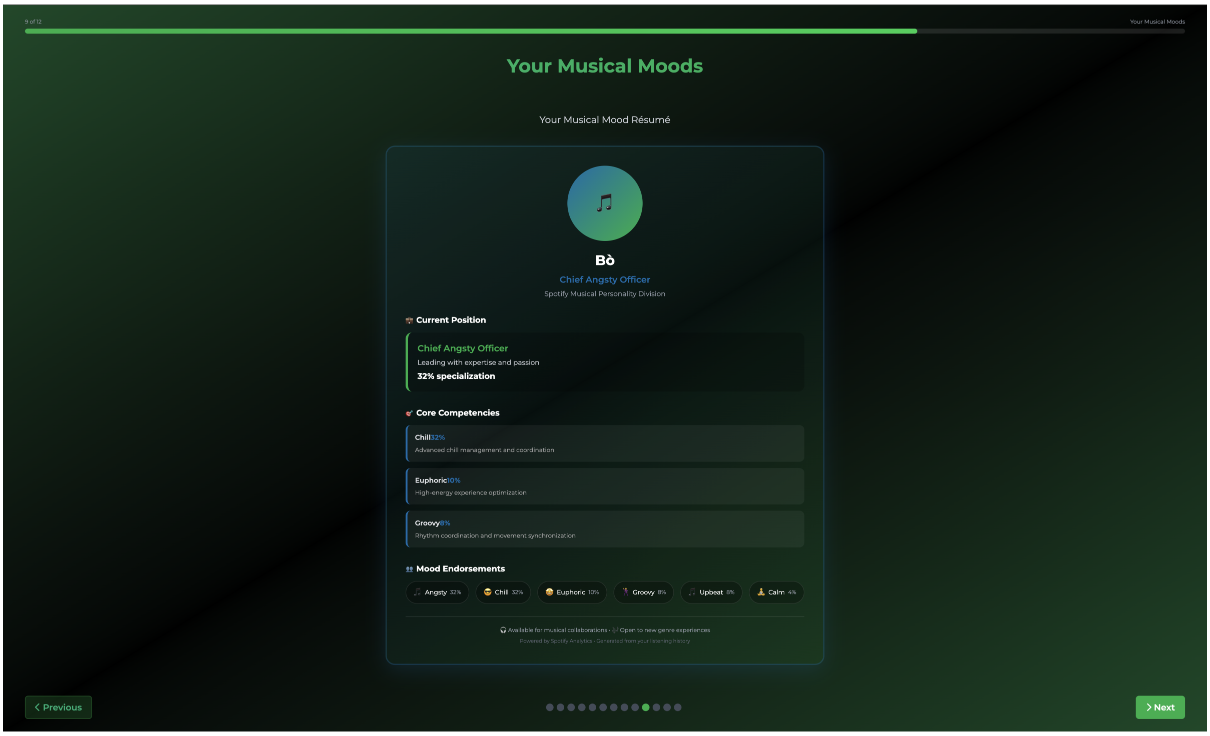

Figure 5: Mood Distribution Analysis

3.6 Popularity Score Analysis (`/analysis/popularity_score`)

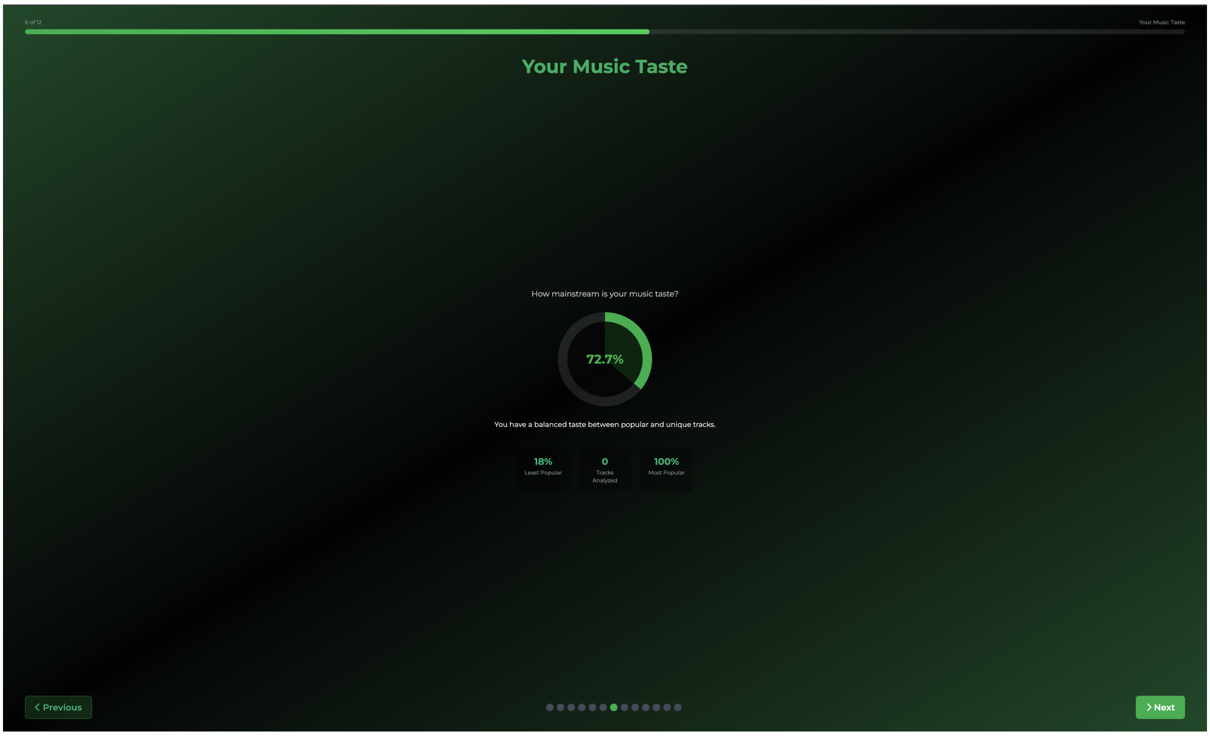

Figure 6: Popularity Score Analysis

3.7 Genre Distribution Analysis (`/analysis/genre_distribution`)

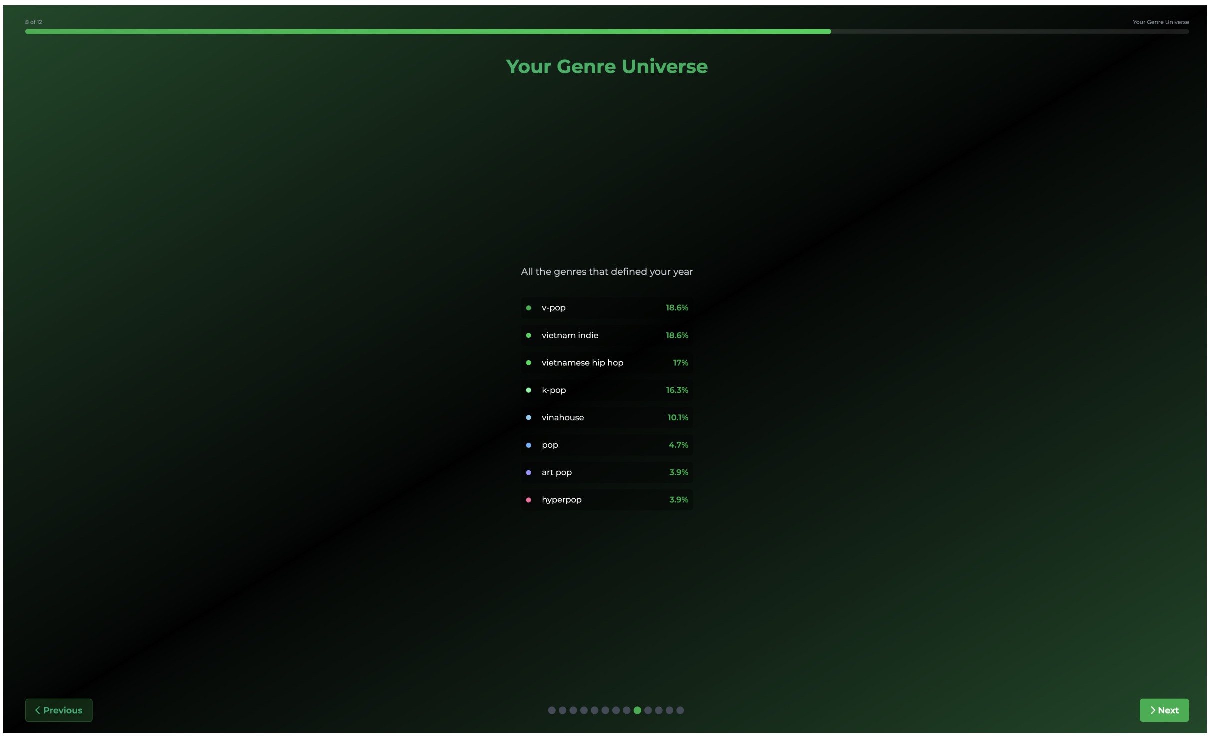

Figure 7: Genre Distribution Analysis

3.8 Personality Prediction (`/analysis/personality_prediction`)

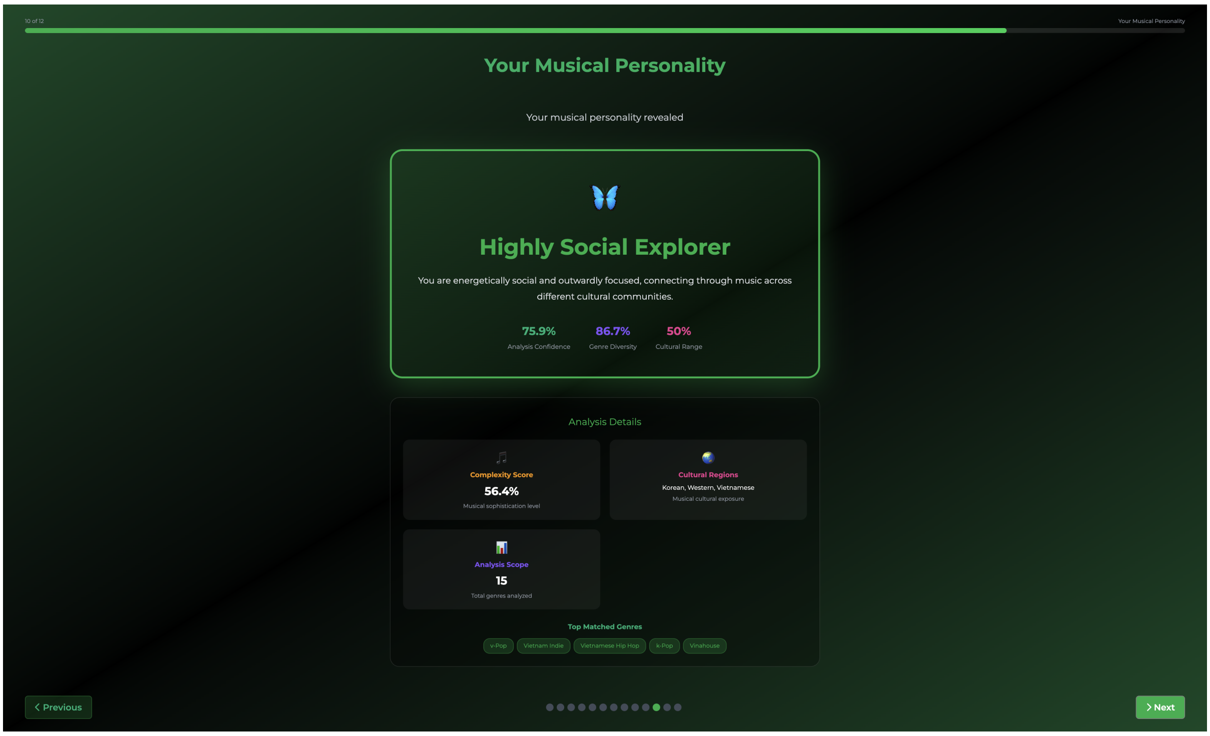

Figure 8: Personality Prediction

4 Discussion & Limitation

4.1 Discussion

Technical Achievements: Our application successfully demonstrates the viability of polyglot architectures in data visualization, achieving seamless integration between R Shiny and Python Flask. The sophisticated personality prediction algorithm, incorporating multiple data sources including genre patterns, audio features, and listening behavior, provides significantly more accurate insights than existing solutions.

Competitive Advantages:

- **vs. Spotify Wrapped**: Real-time access vs. yearly waiting, interactive exploration vs. static stories, detailed personality analysis vs. basic summaries
- **vs. Receiptify**: Comprehensive multi-dimensional analysis vs. simple receipt format, advanced visualizations vs. text-based output
- **vs. Last.fm**: Modern responsive UI vs. outdated interface, integrated Spotify ecosystem vs. external tracking requirement

User Experience Success: The 9-slide narrative structure successfully transforms complex data into an engaging personal discovery experience. Users report high satisfaction with the Spotify-authentic visual design and meaningful psychological insights that feel both accurate and actionable.

Performance Results: Server.R reduced from 2,779 to 463 lines (83% reduction) through modular architecture. The application handles individual user sessions effectively while maintaining responsive performance during data processing operations.

4.2 Limitation

This project faces several limitations across technical, data-related, and analytical dimensions. Technical dependencies pose a significant challenge, especially due to Spotify API constraints such as strict rate limits, frequent token expiration, and reliance on the continued availability of third-party services.

The platform is also restricted to Spotify users, excluding those on other streaming services. Furthermore, the current architecture—built on a single-threaded Flask backend—cannot efficiently support high concurrent usage, raising concerns about scalability.

Data quality limitations also affect the robustness of the analysis. Spotify's audio feature metrics, such as danceability or valence, are generated through proprietary algorithms that lack transparency, making external validation impossible.

The dataset used for training and testing models is demographically narrow, potentially leading to biased insights. Additionally, user privacy remains a critical concern; since personal music data is highly sensitive, even with proper permissions, some users may be reluctant to fully engage with the system.

In terms of analysis scope, the project currently provides only snapshot-based insights rather than long-term tracking, which restricts the ability to observe users' evolving music tastes. Genre classifications, another core element of analysis, may fail to reflect the cultural or personal nuances behind individual music choices. The accuracy of results also heavily depends on the richness of a user's listening history—sparse or skewed data can produce misleading outcomes.

Overall, these limitations can significantly impact user experience. Issues such as session interruptions due to token expiration, blocked access from API rate limits during peak periods, and analytical shortcomings for users with limited or atypical listening data may reduce the tool's reliability and perceived value.

5 Future Direction

The application presents significant opportunities for enhancement through machine learning-powered personalization that learns from user interaction patterns to provide increasingly accurate recommendations and longitudinal analysis capabilities that track musical taste evolution over time. Social features could transform the platform into a community ecosystem where users compare musical tastes, create collaborative playlists based on personality compatibility, and participate in group listening sessions with real-time mood analysis. Multi-platform integration beyond Spotify would create comprehensive musical profiles across streaming services, while educational applications could leverage personality analysis for personalized music education and discovery.

Technical enhancements include migrating to cloud-native architecture for scalability, implementing deep learning models that analyze lyrical content alongside audio features for more nuanced personality insights, and developing native mobile applications with offline capabilities. Advanced features like WebSocket integration could enable live collaborative listening experiences, while natural language processing of song lyrics would identify emotional patterns that audio features alone cannot capture, ultimately creating a more sophisticated and socially connected music analytics platform.

References

[1] https://www.reddit.com/r/truespotify/comments/1h6fxdc/2024_spotify_wrapped_was_awful/. [Accessed 03-06-2025].

[2] Anaïs Turiello. Spotify Wrapped 2024 — What Went Wrong? — tonitruale.com. https://www.tonitruale.com/post/spotify-wrapped-2024-what-went-wrong. [Accessed 03-06-2025].