The Power of Suggestion: Do Recommender Systems Change Our Musical Preferences?

Research Proposal Presentation Transcript

I. Introduction

a. Hello, my name is Rob Mennell and I'm a Computer Science MSc candidate. The title of this research proposal is *The Power of Suggestion: Do Recommender Systems Change our Musical Preferences?*

II. Research Problem

a. This proposed research seeks to determine if the usage of music recommender systems, or MRS, affect users' musical preferences.

b. This builds upon a previous literature review that suggested that MRS may affect musical preferences of users because they limit the variety of music played (Mennell, 2023).

c. This review notes that despite mass adoption of MRS and daily use by hundreds of millions of users, research in this field is relatively underdeveloped when compared to similar recommender system phenomena in social media, politics, and consumer behaviour (Mennell, 2023).

III. Significance

a. This is significant since the impact of recommender systems on primarily extrinsic reward systems – making decisions based on external factors, such as survival – is well documented and often forms the basis of MRS studies (Karayanni & Nelken, 2022; Reiss, 2012).
b. While not unanimous, a significant body of literature suggest that humans interpret music information differently than information related to external factors (Crooke, 2016; Sachs et al., 2016; Schmidhuber, 2010).
c. Music preference is dictated by the intrinsic reward system, which drives human behaviour according to internal emotional motivations (Gold et al., 2019; Rentfrow et al., 2011).
d. Theories highlighting differences between intrinsic and extrinsic motivation have existed for millennia, famously annotated by Aristotle and Darwin and continuously studied in modern science (Gold et al., 2019; Reiss, 2004).

IV. Research Aims and Objectives

a. The purpose of this proposed research is to mitigate current gaps in the field by 1) performing foundational experiments with music information and 2) collecting user preference data without using a rating system prone to bias, and 3) accurately determining that causation can be established between MRS use and preference change (Mennell, 2023).

b. The ultimate goal is to help technologists, users, and researchers realise the nuance and complexities of human-machine relationships.

V. Trends in Existing Literature

a. The presiding theory in existing recommender system literature suggests that recommender systems expose users to an increasingly homogeneous body of information, and in turn, users are only able to build preferences based on the limited information curated to them (Mennell, 2023).
b. Continued research following the literature review found that this notion is reinforced in the study of music preference formation, with exposure commonly noted as a primary factor for music preference development (Zajonc, 2006).
c. This is largely attributed to the nature of recommender services, which are generally variations of matching algorithms (Helberger et al., 2018).

VI. Prominent Works

a. MRS-specific literature builds upon this foundation, with three prominent studies examining the impact of MRS on user preference (Mennell, 2023).
    i. Adomavicius et al.’s 2021 study, *Effects of Personalized and Aggregate Top-N Recommendation Lists on User Preference Ratings*, examined how MRS suggestions affected user preference ratings using a numerical rating scale.

ii. Porcaro et al.'s 2021 review, *Diversity by Design in Music Recommender Systems*, posits that MRS user preferences are artificially constrained because MRS are inherently designed to resist heterogeneous music suggestions.

iii. Schedl et al.'s 2018 study, *Current challenges and visions in music recommender systems research*, studied methods for calculating diversity within MRS, measuring user preferences, and suggested including social, historical, and psychological factors to improve MRS diversity and accuracy.

VII. Limitations and Gaps in Current Literature

a. Existing literature presents well justified solutions, with two noted limitations.

i. Though an increasing number of studies have examined the correlation between recommender systems and user preferences, few have exclusively used music information (Porcaro et al., 2021).

ii. Those that have used music information have measured changes in results through a numerical rating scheme in which users rate their own preferences (Adomavicius et al., 2021). However, this method has been found to produce biased results (Hadaway & Marler, 2005).

b. Thus, two primary gaps exist within current literature:

i. First, research has yet to prove that recommender systems affect intrinsic decisions in the same manner as extrinsic decisions. This requires foundational experimentation with music data.

ii. Second, changes in music preference have yet to be measured without using subject-provided data

VIII. Research Design and Methodology

a. The aim of this research is to measure recommender system influence specifically using music information, to collect user data without inducing bias, and to determine if observed changes in preferences may be attributed to MRS usage.

b. The research methodology is to conduct a field experiment with a test group and a control group to compare MRS and non-MRS performance, respectively, whilst using passive collection and analysis techniques to mitigate result bias or interference (Paluck & Cialdini, 2014).

c. Playback data will be analysed quantitatively to compare subject listening habits before and after sustained MRS usage and compared to a control group.

d. This study has three main objectives.

IX. Objective 1: Conduct Experiments with Music Information

a. The first objective is to conduct experiments using music information.

b. This requires access to a music library or platform containing a representatively diverse sample and quantity of music.

c. The platform will support capturing each user's playback history and musical interaction, such as skipping or repeating songs.

d. The platform will allow activation and deactivation of MRS for specific groups of users according to data collection schedules.

e. Ideally, partnering with an established music platform may help minimise both cost and uncontrolled variables.

X. Objective 2: Collect User Data Without Bias

a. The second objective is to collect user preference data without inducing bias.

b. This can be accomplished by using passive collection techniques that do not require cognitive input from the observed users, as this may impact the results (Hadaway & Marler, 2005; Paluck & Cialdini, 2014).

c. Instead of asking users to rate their own preferences, user preferences will be inferred by capturing their music playing activity during the baseline phase of the experiment.

d. This will produce a profile for each user with three levels of granularity to allow greater examination of results. This baseline will capture listening activity by songs, by artists, and genres.

e. The baseline for both the test and control groups will be captured in Phase I.

f. During Phase II, the test group will have MRS functions enabled whilst continuing to use the platform. The control group will continue using the music platform without MRS functions.

g. During Phase III, MRS functions will be disabled for the test group, and listening activity will be recorded for both groups without MRS functionality. This will produce an updated profile for each user.

XI. Objective 3: Attribute Changes to MRS Exposure

a. The third objective is to attribute observed changes in music preference to MRS usage.

b. This can be accomplished by assessing and mitigating some of the variables that affect musical preferences, especially on a temporary basis (Cuadrado-García et al., 2022; Ferrer et al., 2013).

c. Experiments have observed seasonal, psychological, social, economic, and political factors affect musical preferences (Park et al., 2019; Pettijohn et al., 2010).

d. Though most of these factors are difficult to isolate, and thus, not practically mitigable, seasonal patterns are predictable.

e. Since most seasonal patterns occur in annual cycles, this also represents the optimum duration for each phase of the experiment (Park et al., 2019).

f. Further, phases of the experiment should be conducted consecutively to prevent other factors from influencing results (Paluck & Cialdini, 2014).

XII. Post-Experiment Quantitative Analysis

a. After the conclusion of the phased experiment, baseline user profiles will be compared against post-intervention profiles for each group to determine the average change in preferences (*Δp*) for the test group and the control group.

b. Baseline and post-intervention profiles will be quantitatively analysed according to the number of plays per song, artist, and genre, as a percentage of total songs played.

c. If the average preference change for the test group (*tΔp*) is meaningfully higher or lower than the control group (*cΔp*), it may be reasonably inferred that MRS affect user preferences..

d. Otherwise, it will be evident that MRS exposure is not significant to preference formation.

XIII. Timeline

a. The recommended timeline for this study incorporates six months for planning, partnerships, and technology development. This is necessary to obtain access to a suitable music platform, configure data collection and MRS functions, and recruit subjects.

b. A six-week pilot program will provide sufficient throughput to test the platform and collection systems, whilst giving researchers the ability to preview data and refine analytical techniques.

c. A planned two-month break between the conclusion of the pilot and the beginning of the full experiment will allow the research team to address issues found during the pilot.

d. The full study will occur over three years, with one year allocated per phase to normalise seasonal variations.

e. Finally, six months is allocated for analysis of collected data, synthesis of findings, and report publication.

XIV. Research Considerations and Risks

a. This research design attempts to measure intrinsic preferences, and thus, is subject to many variables beyond the control of this experiment (Paluck & Cialdini, 2014). This can be mitigated by attracting a large sample size (Roy et al., 2016).

b. Study participants may contaminate the results of this study in many ways, such as using an MRS-enabled platform, allowing other users to use the study platform, or using the platform for purposes other than personal enjoyment. This may be mitigated by explaining the rationale and importance of the study and asking participants to agree to refrain from such activities prior to observation.

c. The classification of music of genres is an evolving field of study varying greatly between researchers (Cuadrado-García et al., 2022; Vlegels & Lievens, 2017), and thus, associations between songs, artists, and genres may be inconsistent with data sets outside of this study. However, comparing the same genres between baseline and post-intervention preference profiles for each user should minimise variance.

d. The three-year duration of this experiment may also lead to significant participant attrition (Paluck & Cialdini, 2014). Retention may be incentivised by virtue of having free access to the music platform, particularly if partnered with an established streaming music service. A large sample size would also help mitigate the effects of participant attrition (Roy et al., 2016).

e. Due to the duration of this experiment, a pilot study may be useful to test user interaction with the platform, refine data collection methods, and preview results.

XV. Ethical Considerations and Risks

a. Though the proposed research does not deal with excessive amounts of overly personal information, there are still ethical concerns.

b. Prospective study subjects should be warned that this experiment may affect their musical preferences. However, because MRS are already prevalent (Mennell, 2023), it is likely that many subjects have already been exposed to MRS effects. Thus, additional potential exposure is highly unlikely cause harm.

c. This study will collect anonymised data about each user's interaction with the music platform, subject to General Data Protection Regulation (GDPR) standards (European Union, 2016). As such, subjects will be required to consent to data collection prior to participation (GDPR EU, 2023).

d. Collected data will be restricted to a randomly generated identification number and music playback information for each subject, presenting minimal risk to subjects.

e. Based on the minimal amount of anonymised data collected over the course of this study, and negligible amount of harm that could be inflicted upon subjects, the risk assessment for this study is assessed to be very low (Paluck & Cialdini, 2014).

XVI. Study Artefacts and Follow-on Research

a. This study will culminate with a report describing the observed difference in preference change (Δp) between the test and control groups.

b. Raw anonymised data collected through the course of this experiment will also be shared to enable future research.

c. The synthesised data consisting of anonymised initial and post-intervention profiles will also be shared to allow researchers to further examine or reproduce these findings.

d. This study also presents opportunities for future research.

    i. Subsequent analysis of this data set may reveal if MRS have varying effects according to musical genre, season, or over time.

    ii. Understanding the impact of recommender systems on music preferences, leveraging the intrinsic reward system, may also provide useful insights to other intrinsic human-machine interactions.

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