Spotify + Last.fm Tag-Based Music Recommender

Logistic regression baseline + Streamlit demo

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Background

Overview of the Project

Goal	• Train a model on Nathan's Spotify listening history (likes and dislikes) • Get features for tracks using LastFM tags • Outputs song recommendations not in user's library
Motivation	• Streaming services' recommendation algorithm is often repetitive • Wanted to see how a basic model competes when the features are chosen well
Why LastFM?	• Originally wanted to use Spotify API to train and predict • Tags signify genre, mood, location, era, etc. • Act as a proxy for musical features + users make their own
Broader Question	• Can simple tag patterns understand individual taste well enough to recommend new songs?

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Setting up Code

Making our Dictionary

Positive examples

- Pull Nathan's top tracks and saved tracks from Spotify
- Assign weights: 2 for top tracks, 1 for saved-only tracks
- Fetch top tags using Last.fm (for the tracks + artists)
- Aggregate tags into a weighted user_tag_counts profile that reflects Nathan's listening habits.

Negative examples

- Using the positive examples, expand dictionary
- For tags that never appear in listening history, find top tracks, artists and similar tags
- Remove tracks that overlap: same artist or tag as positive example
- Remaining tracks become negative examples (weight = 0)

Preprocessing and Training the Model

Turning tags into feature vectors

- Clean each tag string into a list
- Use CountVectorizer with our custom tag splitter
- Build a binary bag-of-tags matrix:
  - One column per tag in the dictionary
  - 1 = track has that tag; 0 = it doesn't
- Attach the label, giving us a full feature matrix ready for modeling.

Training + Tuning

- Fit a logistic regression model on the tag vectors
- Split the data into train/dev/test sets to avoid overfitting
- Tune regularization parameter C → pick value that gives the best F1 on the dev set
- Refit on train+dev with the chosen C, then evaluate once on the test set
- Save the final model and vectorizer so we can score new tracks later.

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Demo

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Limitations

Model is trained on one user's listening history only

Tags from Last.fm are noisy, inconsistent, and sometimes non-musical

Positive labels are implicit ("liked" = saved or top tracks); no explicit user feedback

Negative labels rely on tag-based filtering, which may not reflect true dislikes

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Future Direction

How can we improve our model?

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More Data & More Users

More users and more listening history would improve the model's generalization

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Better Negative Sampling

Use skips or explicit dislike signals instead of relying only on tag differences.

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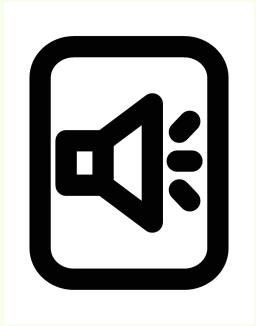

Add Audio Features

Combine tags with Spotify audio metrics (tempo, energy, bass) for more nuanced output

How can we improve our model?

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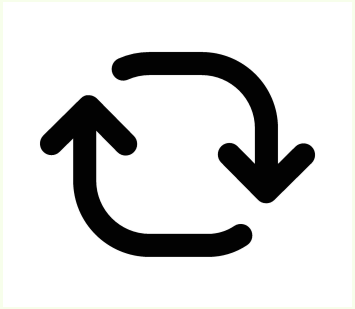

Interactive Feedback Loop

Let users to rate the recommendations so the model adapts over time

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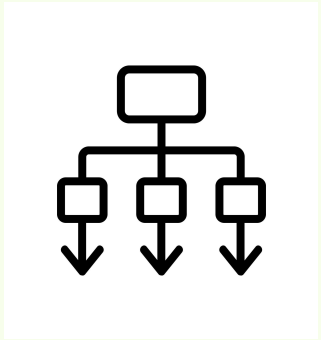

Stronger models

Experiment with linear SVMs, tree-based models, or neural net to better capture tag interactions

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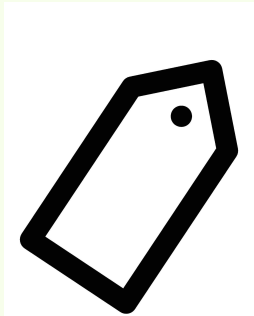

Improve Tag Normalization

Clean and merge redundant tags (hip hop vs. hip-hop) so the model has less noisy data

References

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THANK YOU!

Questions?