Music Recommendation System

Enhancing User Experience

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The Context:

- In today's digital world, users spent considerable amount of time on the internet. For the music platforms, it means providing best experience. We achieve this by keeping users engaged. This helps platform grow to achieve their revenue expectations.

The Objective:

- Recommendation system help provide better engagement with users. If we can recommend new songs that users will enjoy, it provides added value apart from users listening to their usual favorite songs. This is a win win situation for users and platform providers.

The Key Questions:

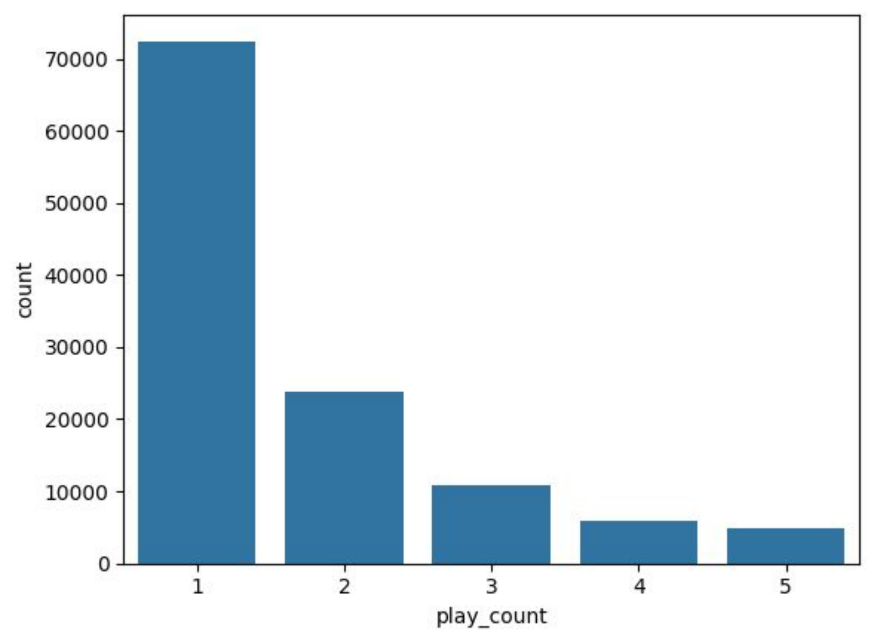
- Can we recommend top 10 songs for users on their likes? Can we achieve a reliable recommendation system where users will look forward to next recommended songs on their devices?

The Problem Formulation:

- Data science helps in answering above questions. It helps understand the existing data. We can take relevant records from the data and build different models available, we then compare to find the best possible solution for our goal.

Unsurprising hurdle of imbalanced data!

From millions of play count and songs dataset, 120k records selected with play count 1 to 5 then we see this imbalance. 60% of records belong to one class!



Solving the imbalanced data hurdle.

Why is it a problem?

- The models might become biased towards the majority class, neglecting the important but rarer minority class.
- In our case, model will not learn much about records with play count 3 to 5. We want recommend these songs!

What is the solution?

- Oversampling the minority class records with SMOTE (Synthetic Minority Oversampling Technique) algorithm.
- The new synthetic sample is similar to the original minority class point but not identical. New variations while staying within the existing data distribution of the minority class.

How did we implement for our case?

- To minimize overfitting problem, we did not match minority class record count to majority class. Whilst adding synthetic data, trying to maintain the structure of minority class. Therefore each minority class count was proportionately increased.
- Oversampling was implemented only on training set of original data and not test set. It means we can test this model with real world data without any bias.

Testing different models with original and oversampled data.

Please see the metrics comparison chart for details in Appendix A.

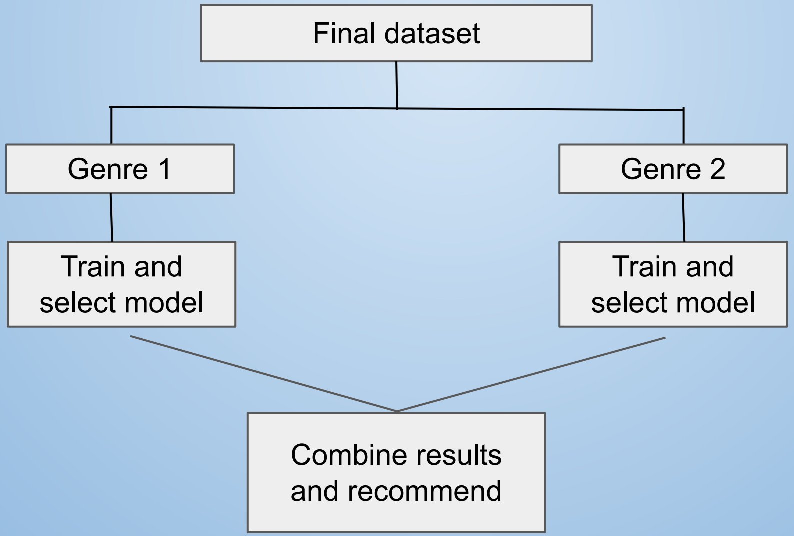
Key Insights:

- Root Mean Square Error remained undesirably high in all models indicating data sparsity.
- Precision was lower around 0.4 in all models.
- Recall was doing well with best score of 0.73 with oversampled SVD Optimized model.
- Obviously F_1 score was hovering around 0.5.
- Testing different models was memory and CPU-time consuming. Session crashed several times.

Proposal for solution

- SVD optimized with SMOTE oversampled data model. With recall of 0.73 means out of all the relevant songs model identified 73% from K number of recommendations.
- Popularity based and content based results can be implemented as separate portlets or sections within user UI.

Further exploration:



Appendix A

Model	Baseline	Optimized	SMOTE-Baseline	SMOTE-Optimized
User User Similarity-Based Collaborative Filtering	RMSE: 1.0878 Precision: 0.396 Recall: 0.692 F_1 score: 0.504	RMSE: 1.0596 Precision: 0.414 Recall: 0.623 F_1 score: 0.497	RMSE: 1.0885 Precision: 0.396 Recall: 0.695 F_1 score: 0.505	RMSE: 1.0599 Precision: 0.413 Recall: 0.624 F_1 score: 0.497
Item Item Similarity-based collaborative filtering	RMSE: 1.0394 Precision: 0.307 Recall: 0.562 F_1 score: 0.397	RMSE: 1.0409 Precision: 0.329 Recall: 0.596 F_1 score: 0.424	RMSE: 1.0394 Precision: 0.311 Recall: 0.569 F_1 score: 0.402	RMSE: 1.0429 Precision: 0.342 Recall: 0.573 F_1 score: 0.428
Model Based Collaborative Filtering - Matrix Factorization	RMSE: 1.0252 Precision: 0.41 Recall: 0.633 F_1 score: 0.498	RMSE: 1.0141 Precision: 0.415 Recall: 0.635 F_1 score: 0.502	RMSE: 1.0348 Precision: 0.409 Recall: 0.698 F_1 score: 0.516	RMSE: 1.0225 Precision: 0.406 Recall: **0.732** F_1 score: 0.522
Cluster Based Recommendation System	RMSE: 1.0487 Precision: 0.397 Recall: 0.582 F_1 score: 0.472	RMSE: 1.0487 Precision: 0.396 Recall: 0.592 F_1 score: 0.475	RMSE: 1.0404 Precision: 0.383 Recall: 0.517 F_1 score: 0.44	RMSE: 1.0429 Precision: 0.383 Recall: 0.527 F_1 score: 0.444

Thank You!