

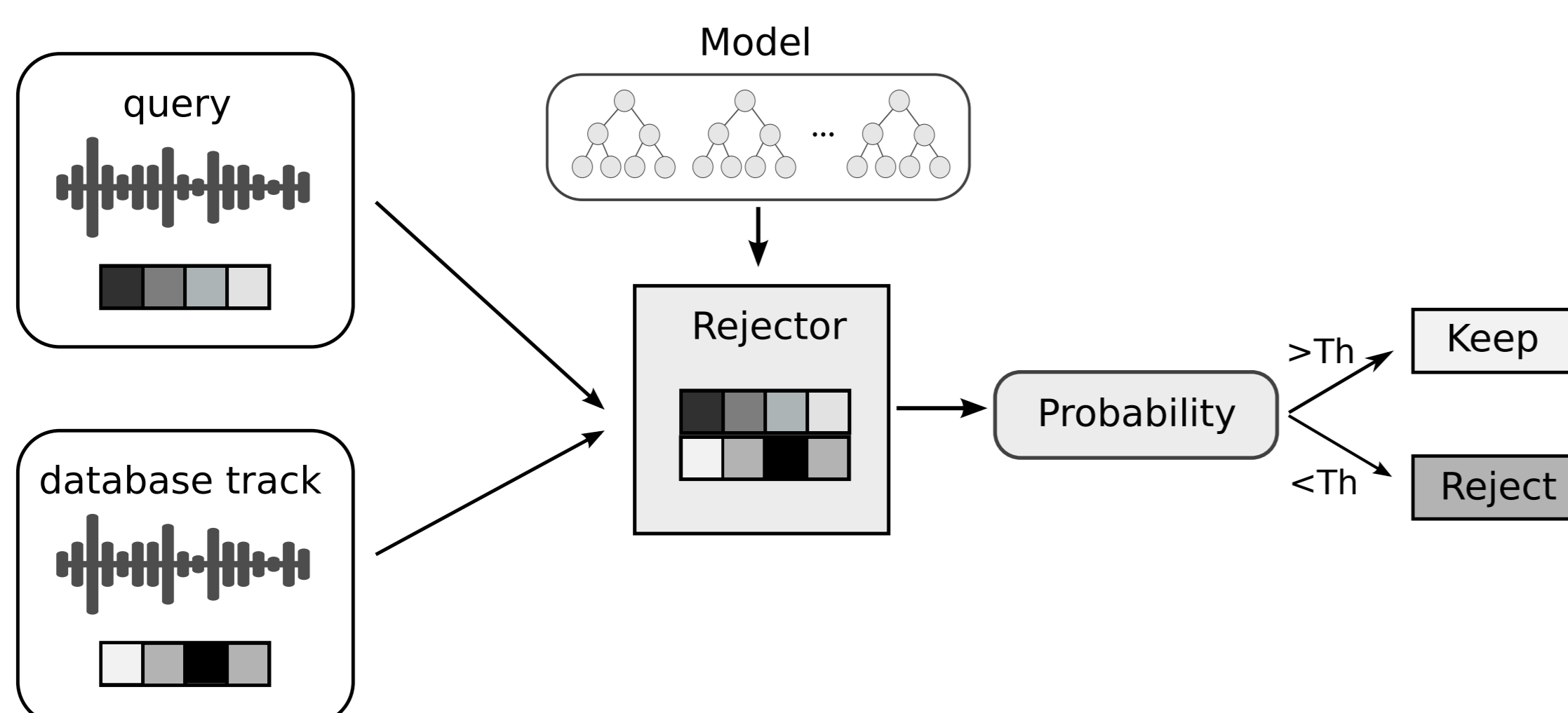
Abstract

We evaluate a set of methods for combining features for cover song identification. We create multiple classifiers based on global tempo, duration, loudness, beats and chroma average features. We evaluate combination rules for merging these single classifiers into a composite classifier. We further obtain two higher level classifiers based on chroma features. For combining the chroma-based classifiers with the composite classifier based on global features, we use rank aggregation methods. We evaluate performance with the Second Hand Songs dataset (SHSD). Each combination rule outperforms single methods in terms of the total number of identified queries. Experiments with rank aggregation methods show an increase of up to 24 % of the number of identified queries, compared to single classifiers.

1. Approach Overview

We design several classifiers, called **rejectors**, based on different features to take into account **multiple sources of musical information**.

We design low-dimensional rejectors based on *tempo*, *duration*, *loudness*, *beats* and *average chroma features* using **random forests** to output a **probability of similarity** between a query and a track of the database.



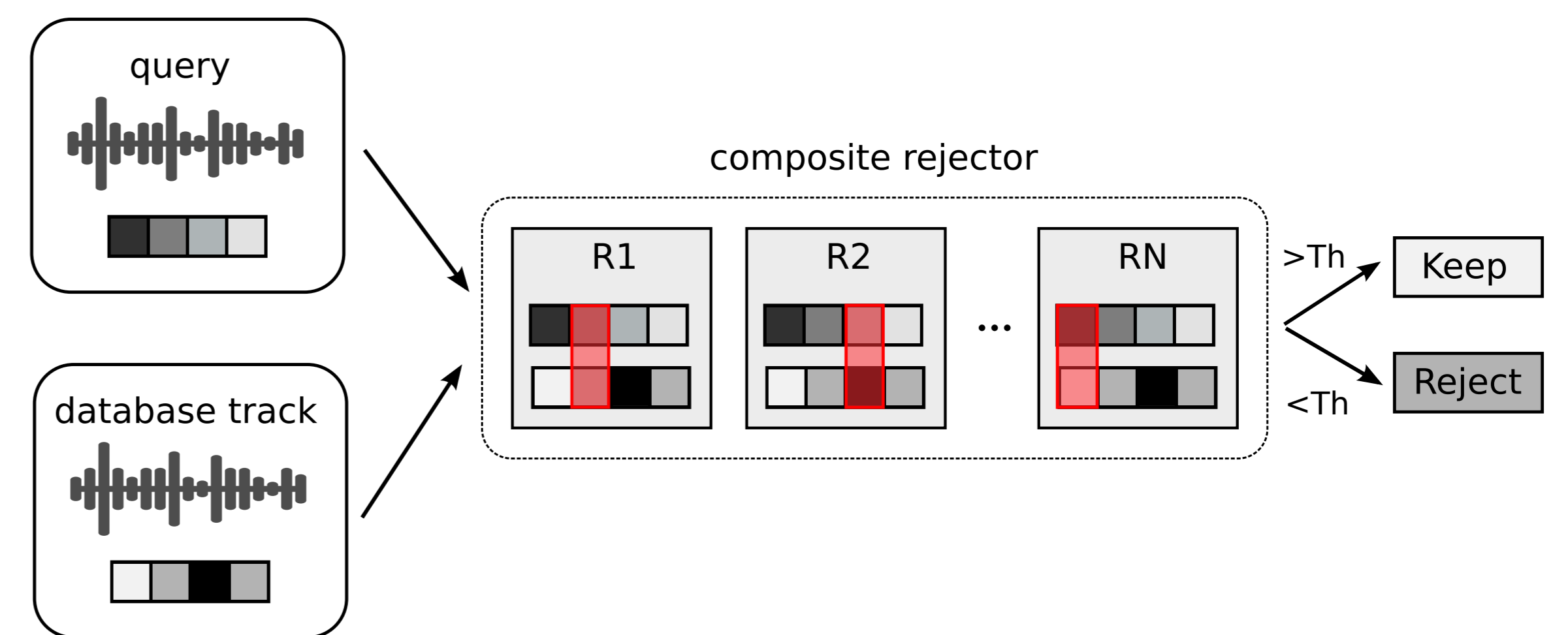
We then **combine** these rejectors to build a more robust **composite rejector** using state-of-the-art probabilistic fusion rules.

Two rejectors based on **chroma sequences** are added to account for **harmonic** and **temporal** information.

- **Quantization Rejector**: A track is represented as a histogram of codewords, determined by a K-Means clustering of **beat-synchronous chroma features**. Distance between tracks is computed as the **cosine similarity** between normalized histograms.
- **Cross Correlation Rejector (XCORR)**: Comparing songs is performed by cross-correlating entire beat-synchronous chroma matrices. Final distance is taken as the reciprocal of the peak value of the cross-correlated function.

2. Fusion of Probabilistic Rejectors

As the low-dimensional rejectors return probabilities, we use standard **probabilistic fusion rules** such as the *product*, *sum* and *median* rules.

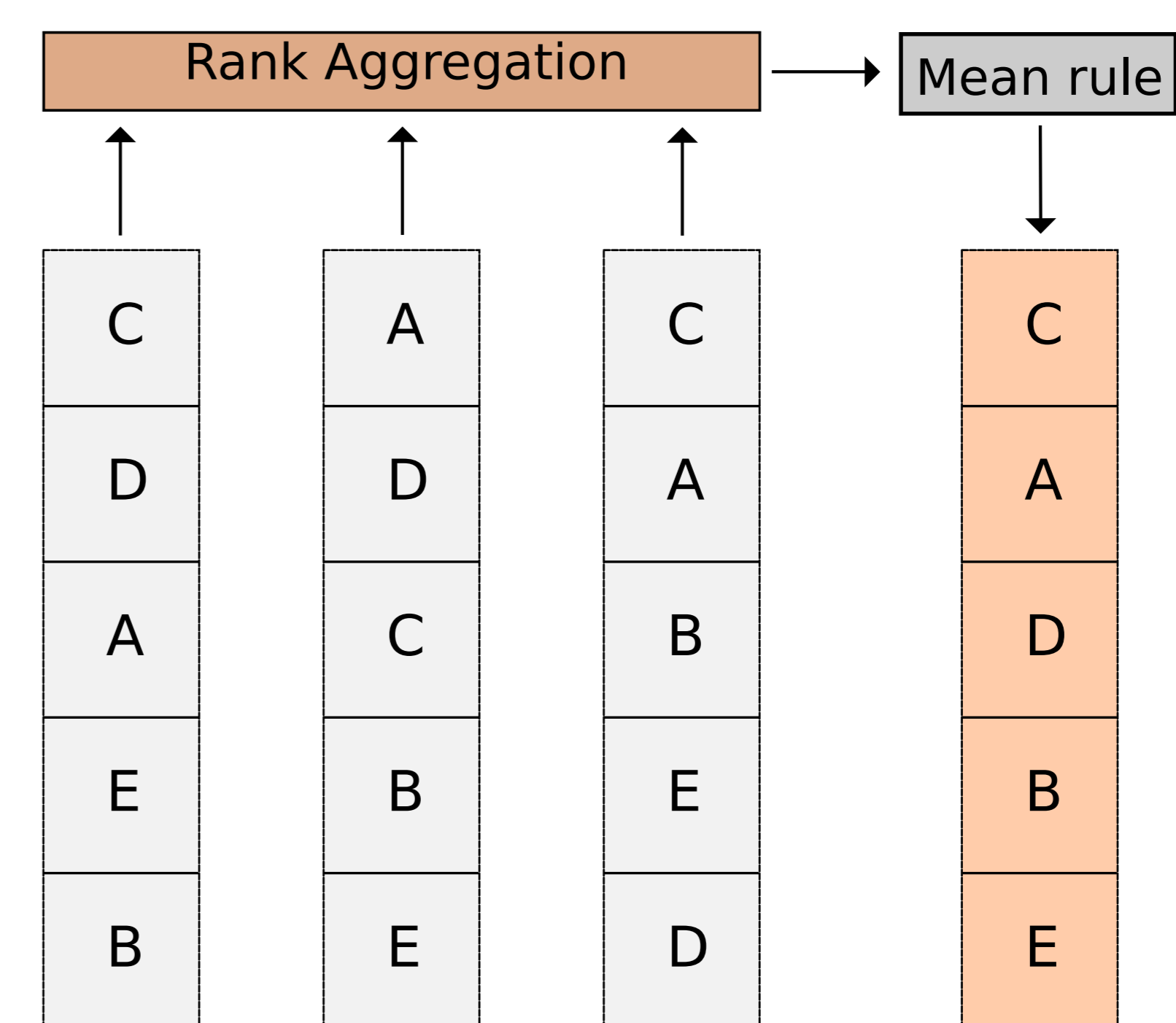


The **median rule** produces best results with an improvement of **63%**, **44%** and **16%** of the number of tracks identified as cover songs in the top-10, 100 and 1000.

In terms of Mean Rank (MR) and Mean Reciprocal Rank (MRR), the composite rejector improves the scores by **24.9%** and **63.2%** respectively.

3. Rank Aggregation

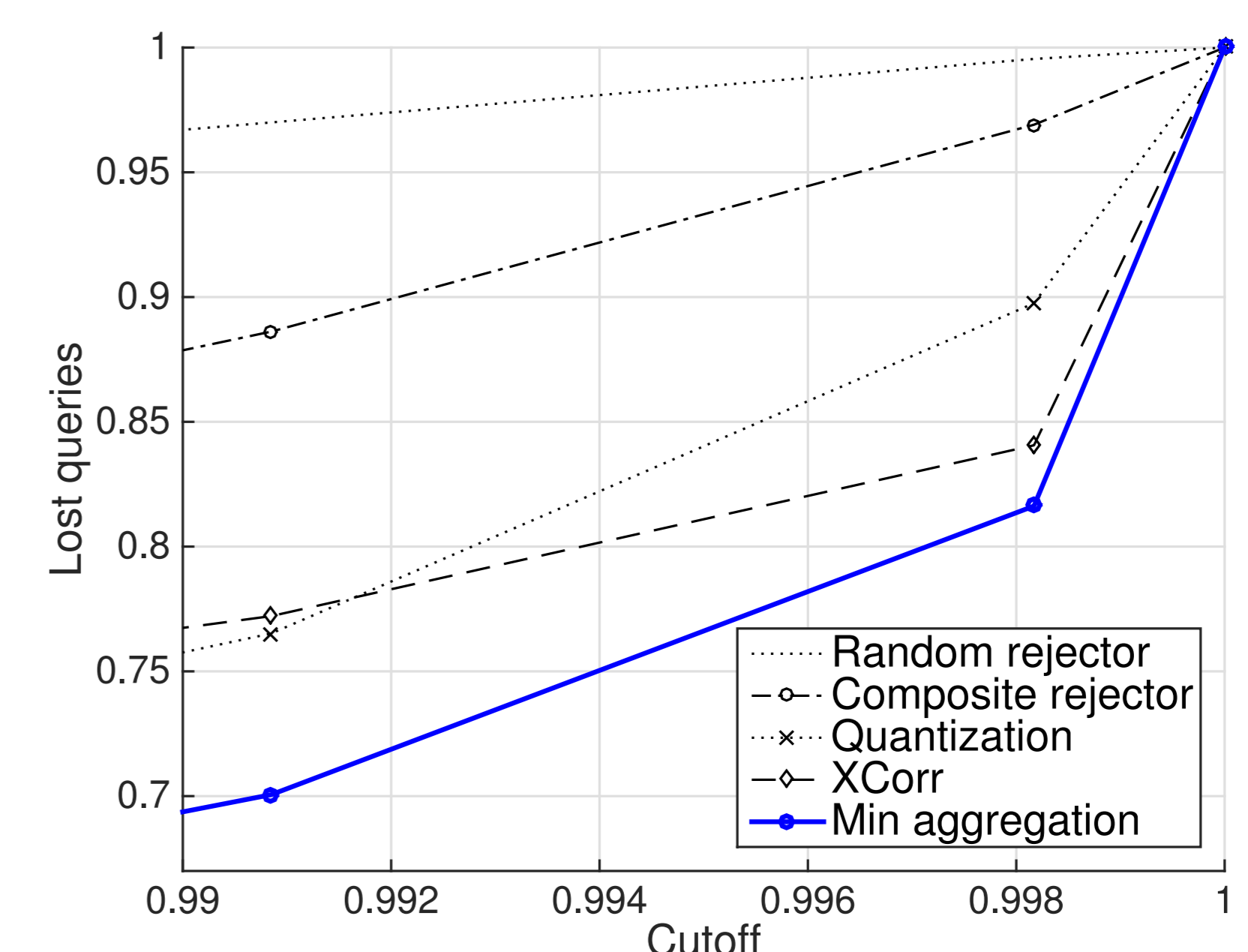
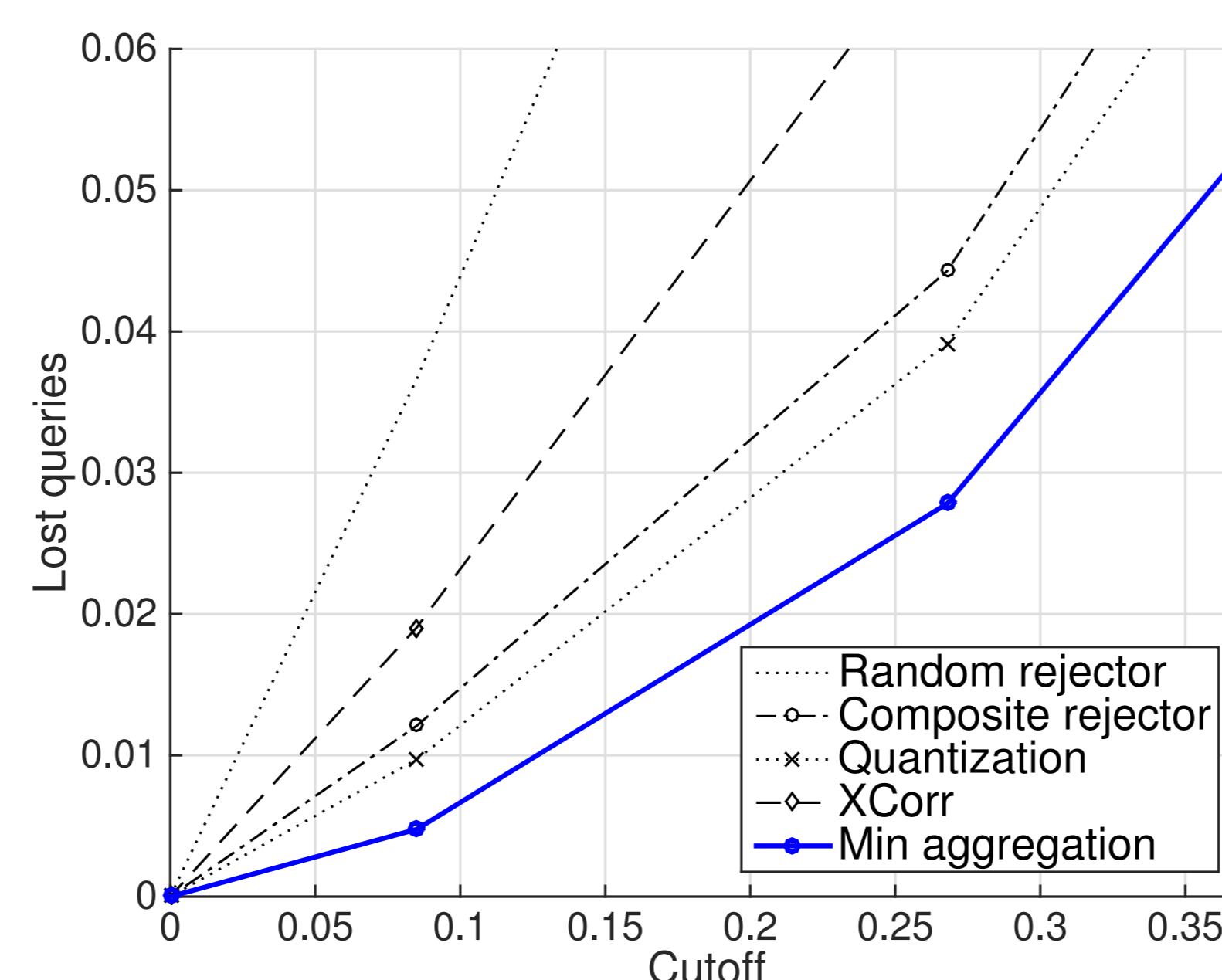
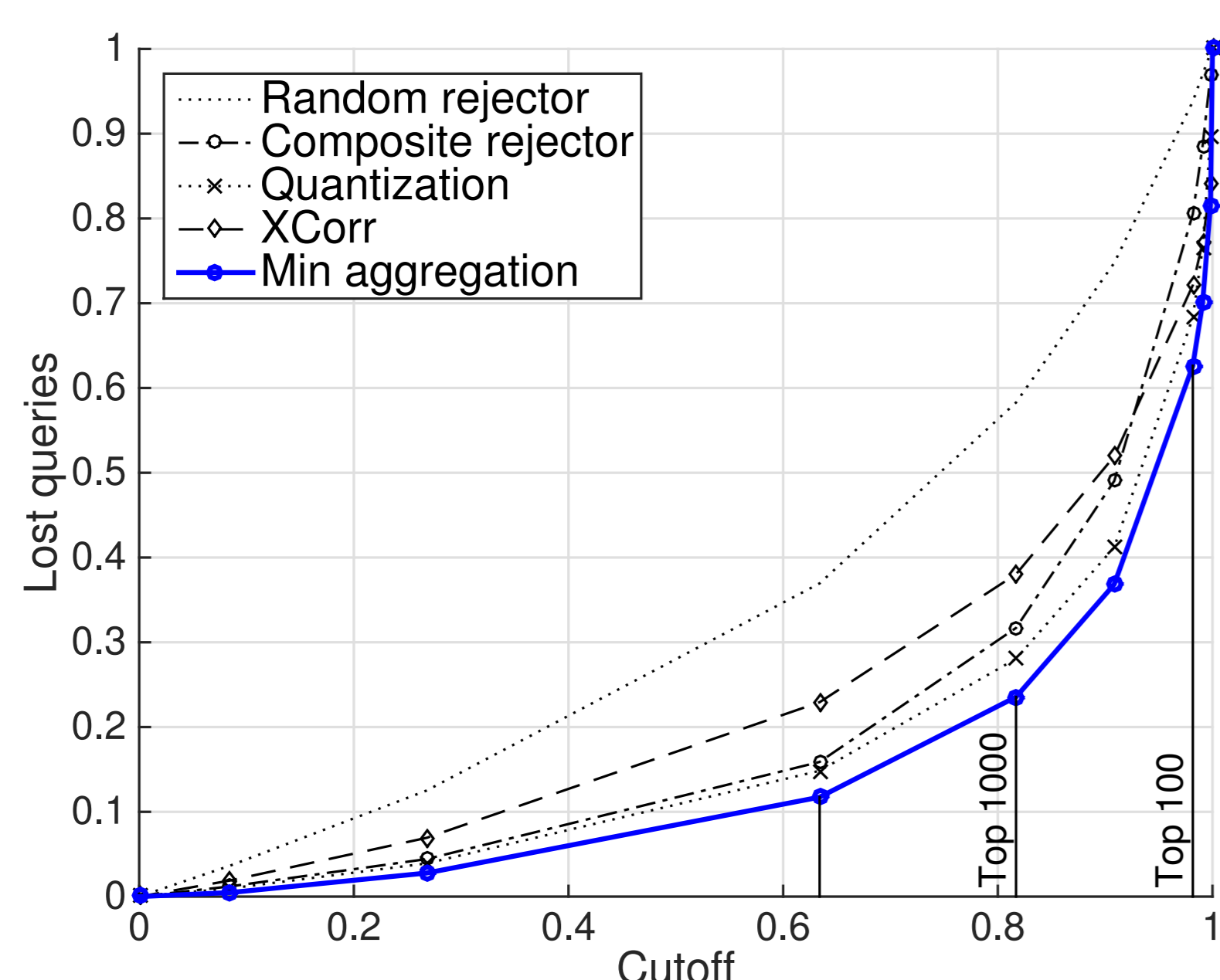
To **merge** rejectors producing different kinds of outputs (probability, cosine similarity, peak of the cross-correlation), we use **rank aggregation**, specifically three rules: **minimum rank**, **mean rank** and **median rank**.



Each rejector compares queries to the database and returns a permutation of the database. Rank aggregation methods combine the permutations obtained by each method to produce the final list.

4. Evaluation and results

The system is evaluated with the **Second Hand Songs Dataset**. Results are reported on a Test Set containing 30% of the SHSD samples (5,464 queries). Each aggregation rule outperforms single rejectors. Best results for the top-10 returned tracks are obtained with the **minimum rule** with an improvement of **15.2%** compared to the cross-correlation rejector. Best results for the top-100 and top-1000 are achieved with the mean rule with improvements of **23.5%** and **7.19%**.



5. Conclusion

We evaluated multiple techniques for combining distances and features for cover song identification. Results show that combining single rejectors based on global features improves the performance compared to single classifiers. As rejectors return values on different scales, we used rank aggregation techniques to combine them at the rank level. We evaluated several aggregation rules. Our method shows that aggregating multiple classifiers does increase the number of identified tracks.

