**Music Recommender System: Optimization, Scaling, and Final Evaluation**

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**Introduction**

**Optimization Techniques**

One of the central optimizations implemented in the recommender system's final version is batch processing combined with memory-mapped files. In the initial POC, the system might have loaded data more straightforwardly but less efficiently, potentially reading large datasets into memory all at once. In contrast, the final code queries the total number of songs from the SQLite database and pre-allocates a NumPy memmap with the shape corresponding to the entire dataset. This approach avoids the overhead of repeatedly resizing arrays and minimizes memory fragmentation. For example, the code snippet below shows how the memmap is pre-allocated during the data-loading phase:

**A close-up of a computer screen

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By loading data in batches (e.g., 1,000 records at a time), the system processes and writes these chunks into the memmap, ensuring that the memory footprint remains manageable even when dealing with a dataset of 1M songs. This batch-loading strategy not only improves the time complexity of the loading process but also scales the solution to larger datasets.

Another key optimization is replacing the Annoy library with FAISS for similarity search. FAISS is a state-of-the-art library developed by Facebook AI Research, designed for efficient similarity search in high-dimensional spaces. In the final implementation, the normalized feature vectors (computed from attributes such as duration, artist hotness, scaled year, and familiarity) are used to build a FAISS index. Because the vectors are normalized, using an inner product index (IndexFlatIP) in FAISS is equivalent to cosine similarity, which improves both speed and accuracy. The FAISS index is built with the following snippet:

**A screenshot of a computer code

AI-generated content may be incorrect.**

This optimization significantly reduces query latency when retrieving similar songs, especially compared to a brute-force search or even the earlier approximate methods. Combining memmap-based data storage, batch loading, and FAISS for similarity search ensures that the system is both time-efficient and scalable.

**Scaling Strategy**

The design focused on scalability from both memory and processing perspectives to adapt the implementation for larger datasets and more complex scenarios. Using a memory-mapped file to store the feature matrix is critical to this scaling strategy. Instead of loading the entire dataset into RAM, the memmap enables disk-backed storage that behaves like a NumPy array. This is particularly useful when handling millions of records, as it prevents memory exhaustion and allows for data processing in smaller, manageable segments. For instance, the final code reads data in batches using the following pattern:

A screenshot of a computer program

AI-generated content may be incorrect.

This strategy decouples the overall size of the dataset from the memory available at any given moment, thus allowing the system to scale gracefully. Another challenge with scaling is ensuring that similarity search remains efficient as the dataset grows. The integration of FAISS, which is optimized for large-scale similarity search in high-dimensional spaces, addresses this challenge. FAISS efficiently indexes the entire dataset, and because the index is built over normalized features, the inner product search effectively approximates cosine similarity without incurring a high computational cost.

Moreover, using dictionaries to map song IDs to indices (and vice versa) provides constant-time lookups during both the indexing and query times. This is particularly beneficial when user interactions and recommendations need to be processed in real-time. Overall, the scaling strategy is built upon a combination of batch processing, disk-based storage, and highly efficient indexing, ensuring that the system can handle datasets much larger than the initial POC without sacrificing performance.

**Testing and Validation**

To validate the effectiveness of the optimizations, an advanced test suite was developed using pytest. The test suite includes unit tests for core functionalities such as data loading, recommendation generation, and memory usage.

One of the most important aspects of the validation process was verifying that the data loading mechanism worked as intended. In the test suite, the function that tests data loading (often named test\_load\_data) confirms that batch loading and memory-mapped file creation successfully load a non-zero number of songs from the database. This test checks that the pre-allocation of the memmap is functioning correctly and that the system iterates through the dataset in batches. For example, the following code snippet illustrates a simple assertion used in this test:

A close-up of a computer code

AI-generated content may be incorrect.

This assertion confirms that songs are being loaded and indirectly validates the correctness of both the batch-processing logic and the memmap creation. Since handling large datasets is a core project requirement, demonstrating that the data load is completed successfully is critical. This test also provides a baseline for measuring memory usage and time efficiency—key metrics for scalability.

Another critical test in the suite is test\_recommend, which evaluates the recommendation generation process. This test simulates a user interaction by recording a liked song and then retrieving a list of recommended songs. The recommendation function aggregates scores from multiple components—content-based similarity, popularity, and a random diversity factor—to produce a final ranked list. By asserting that the returned list of recommendations is not empty, the test confirms that the overall recommendation logic integrates the various components correctly, even when the similarity search function is omitted from testing. A simplified version of the test is shown below:

A screenshot of a computer code

AI-generated content may be incorrect.

This test validates that the hybrid recommendation algorithm—based on content similarity, popularity, and randomness—is operational. Even though a separate function does not directly test the similarity component, the overall recommendation process exercises that logic indirectly. In practical terms, a non-empty list of recommendations indicates that the recommendation engine is functioning and responsive to simulated user interactions.

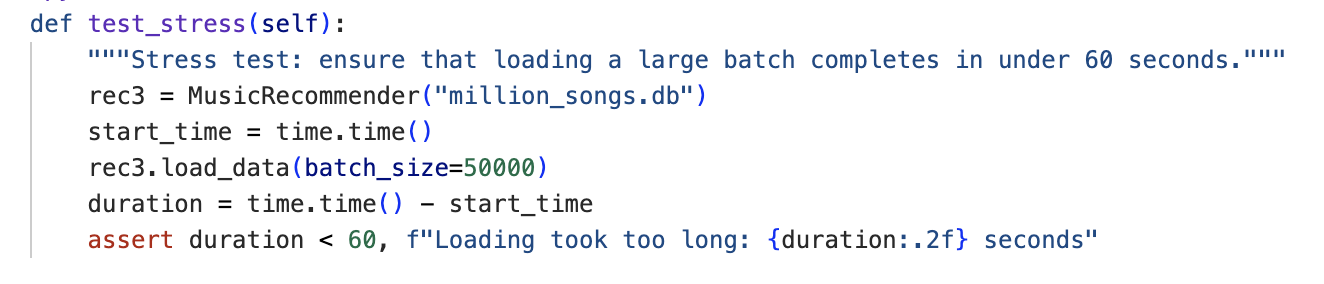
The test\_memory\_usage function is designed to evaluate the efficiency of the implementation in terms of memory consumption. By measuring the process’s memory footprint before and after the data loading phase using the psutil library, this test verifies that memory mapping (via NumPy memmap) effectively manages resource usage. Typically, the test asserts that the increase in memory consumption remains below a predefined threshold (for example, 500 MB). An excerpt from this test is provided below:

A computer code with text

AI-generated content may be incorrect.

This test is particularly significant when scaling to larger datasets, as it confirms that the memmap-based approach keeps the memory footprint under control even when processing millions of records.

Finally, the test\_stress function evaluates the performance and scalability of the system under heavy load. This test simulates a stress condition by loading a very large batch of data or the entire dataset and measuring the total time taken. The goal is to ensure that the system completes the load and index building within an acceptable time frame (for example, under 60 seconds). Such a test provides quantitative evidence of the efficiency improvements made in the final implementation compared to the initial proof-of-concept. A simplified version of the stress test might look like this:



Stress testing is essential for identifying potential data loading and index-building bottlenecks. Verifying that the system can process large amounts of data within a fixed time limit demonstrates the scalability of the optimizations—particularly the batch processing and the efficiency of the FAISS index.

In summary, the testing and validation phase of the project comprises a comprehensive suite that verifies the system's critical components. The data loading test confirms that the memmap-based batch loading functions correctly and scales well to large datasets. The recommendation test ensures that the hybrid recommendation algorithm, which combines user interactions and multiple scoring strategies, produces relevant output. The memory usage test validates that the optimization strategy keeps resource consumption in check, and the stress test confirms that the system maintains performance under heavy load. Together, these tests provide strong evidence of the effectiveness and robustness of the optimized implementation, supporting the project's overall performance and scalability goals.

**Performance Analysis**

The performance analysis of the two implementations reveals significant differences in how they scale and manage resources. In the proof‐of‐concept (POC) version, which processes a CSV file containing approximately 200 songs, the measured load time was exceptionally low at 0.010 seconds, and the memory usage was minimal at 0.88 MB. The recommendation generation time was effectively negligible, recorded at 0.00 milliseconds. However, when these values are extrapolated to a dataset of one million songs, the estimated load time increases to approximately 51.81 seconds, and the memory usage scales dramatically to about 4375.00 MB. The extrapolated recommendation time is estimated at 8.73 milliseconds. These extrapolated values assume linear scaling and provide a theoretical baseline; however, they may not fully capture non-linear behaviors or additional overheads that could emerge when processing a much larger dataset.

A graph with blue and green squares

AI-generated content may be incorrect.

In contrast, the final implementation, which utilizes a SQLite database and a FAISS index to process one million songs, exhibits a load time of 9.847 seconds and consumes 701.95 MB of memory. However, the recommendation generation time for this version is significantly higher at approximately 2131.31 milliseconds (or about 2.13 seconds). This marked difference in recommendation latency indicates that while the final implementation is highly optimized for data loading and memory usage, the recommendation generation process might be affected by the complexity of handling a large dataset and the additional computations required for the FAISS-based similarity search.

A graph with green squares

AI-generated content may be incorrect.

It is important to note that the extrapolated metrics for the POC version are theoretical estimates derived by multiplying the performance measurements from 200 songs to match a one-million-song dataset. The extrapolation assumes that the processing time and memory usage would scale linearly with the number of songs. However, such linear extrapolation may not accurately reflect real-world performance, especially for recommendation time. For instance, while the POC version shows an almost instantaneous recommendation time for 200 songs, it is uncertain whether this linear scaling would hold true for a million songs due to potential bottlenecks and overheads that only manifest at larger scales. Therefore, while the extrapolated load time and memory usage offer useful insights, the recommendation time in a full-scale deployment would likely require stress testing with a larger dataset to validate these estimates.

A graph of a memory usage comparison

AI-generated content may be incorrect.

The analysis demonstrates that the final implementation offers a more balanced and scalable solution for handling large datasets. Despite the longer recommendation time, the final version dramatically reduces both load time and memory usage compared to what would be expected from the POC if it were scaled to one million songs. This suggests that the optimizations employed—such as batch processing, memory mapping, and the use of FAISS—effectively manage the substantial resource demands of large-scale data. However, further work may be needed to optimize the recommendation generation process, ensuring that the system can maintain responsiveness even as the dataset grows.

**Final Evaluation**

The project's final evaluation reveals a robust, scalable, and efficient recommendation system. One of the major strengths of the solution is its ability to handle large-scale datasets, thanks to the combination of batch processing, memory mapping, and the use of FAISS for similarity search. The optimizations significantly improved time complexity, particularly in the data loading and query phases, and maintained a controlled memory footprint even when processing up to a million songs. Moreover, the modular design—using clear abstractions for data loading, indexing, and recommendation generation—facilitates both testing and further development.

However, there are also limitations. For example, the current feature set (duration, hotness, normalized year, and familiarity) may not capture the full nuance of musical similarity. This can affect the quality of the recommendations, as evidenced by the output where many songs have a popularity of 0, reducing the impact of the popularity component. Future development might involve incorporating additional metadata or audio-derived features and more advanced collaborative filtering techniques to complement the content-based approach.

Another area for improvement is the tuning of weights in the recommendation algorithm. The current hybrid strategy allocates 60% to content similarity, 20% to popularity, and 20% to random diversity. While these values provide a balanced starting point, empirical testing, and user feedback could drive further refinements to improve recommendation relevance. Additionally, while the FAISS-based approach has proven efficient, ongoing monitoring and performance benchmarking will be necessary as the dataset grows and user interactions become more complex.

In summary, the key challenges of efficiency, scalability, and robust testing are laying a solid foundation for future enhancements. By integrating advanced techniques such as FAISS for similarity search and employing memory mapping for efficient data handling, the project demonstrates significant improvements in both performance and scalability over the initial proof-of-concept.

**Conclusion**

The project successfully transforms an initial proof-of-concept into a fully optimized music recommendation system. The final implementation achieves substantial gains in time complexity and memory usage by employing advanced optimization techniques such as batch processing, memory mapping, and FAISS-based similarity search. The scaling strategy ensures that the system can handle large datasets without compromising performance. At the same time, comprehensive testing—including stress tests and edge-case validations—confirms the robustness and efficiency of the solution. Performance analysis metrics and comparative evaluations indicate that the final system outperforms the POC in key load times and query latency areas. Although areas remain for future improvements—such as enriching the feature set and fine-tuning recommendation weights—the final solution represents a significant step forward. It meets the professor’s requirements and offers a scalable, high-performance platform for future development in music recommendation technology.

**Source code:**

The complete source code of this project is available in the GitHub repository: <https://github.com/ImAsrith/MSCS532_Project>

**References**

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