Precision vs. Discovery: An Adaptive Agent Navigating the Cold-Start Trade-off

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Abstract

Monolithic recommender systems struggle to serve a diverse user base, often failing new 'cold-start' users while excelling for established 'warm-start' users. This paper introduces MARS (Multi-Agent Recommender System), a novel hybrid system where a central Manager Agent orchestrates recommendation tasks based on user context. MARS adaptively delegates requests to either a high-performing Bayesian Personalized Ranking (BPR) model for established users or a Sentence-BERT (SBERT) semantic search model for new users. Our experiments on the MovieLens 20M dataset demonstrate the agent's orchestration logic is effective, perfectly matching the strong BPR baseline for warm-start users across all metrics. For cold-start users, we quantitatively prove a critical "Precision vs. Discovery" trade-off: while a popularity-based baseline achieves significantly higher precision (0.3068 vs 0.0115), the MARS semantic pathway functions as a true discovery engine, delivering recommendations with over 10x higher novelty (14.40 vs 1.24). Furthermore, we demonstrate that the MARS cold-start path is over 20 times faster, delivering a significant latency advantage for new users. This work contributes a robust, adaptive architecture, a key design pattern for building agentic systems, and a rigorous, quantitative benchmark of the trade-offs between precision and discovery in modern recommender systems.

CCS Concepts

• **Information systems** → **Recommender systems**; • **Computing methodologies** → *Natural language processing*; *Knowledge representation and reasoning*.

Keywords

Recommender Systems, Multi-Agent Systems, System Architecture, Cold-Start Problem, Hybrid Recommendation, Adaptive Systems

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1 Introduction

Recommender systems have become a cornerstone of modern digital platforms, acting as essential tools for navigating vast catalogs of content and driving user engagement. However, their efficacy is often constrained by a fundamental design limitation: the reliance on a single, monolithic algorithmic approach to serve an entire, diverse user base. This "one-size-fits-all" paradigm creates a persistent conflict, most acutely manifested in the well-documented "cold-start" problem.

The cold-start problem highlights the inherent tension between two dominant recommendation philosophies. On one hand, collaborative filtering models, such as Bayesian Personalized Ranking (BPR), have proven exceptionally effective at delivering nuanced, personalized recommendations for users with extensive interaction histories—often referred to as "warm-start" users. Their strength, however, is also their critical weakness: they are fundamentally incapable of serving new users for whom no historical data exists. On the other hand, content-based systems can effectively serve new users but frequently lack the capacity for deep personalization and can struggle to introduce users to novel items outside their immediate sphere of interest.

This dichotomy suggests that the pursuit of a single "best" algorithm may be a flawed objective. A more effective system would arguably be an intelligent, adaptive framework capable of analyzing a user's context and dynamically deploying the most appropriate recommendation strategy. It is this hypothesis that motivates the development of MARS, a Multi-Agent Recommender System. Orchestrated by a central Manager Agent, MARS examines the depth of a user's interaction history to intelligently route requests to one of two specialized pathways: a high-performing BPR model for established users or a sophisticated content-based semantic search powered by Sentence-BERT (SBERT) for new users.

The primary contributions of this work are three-fold:

- **We introduce MARS, a novel, adaptive multi-agent architecture.** We demonstrate its orchestration logic is effective, achieving identical performance to a strong BPR baseline for warm-start users while successfully solving the cold-start problem without performance degradation for the majority user base.
- **We provide a rigorous, quantitative analysis of the "Precision vs. Discovery" trade-off** in cold-start scenarios. We demonstrate that while a popularity-based baseline achieves significantly higher precision ($p < 0.001$), our semantic approach functions as a true "discovery engine," providing recommendations with over 10x higher novelty and a 20x latency advantage.
- **We present a key architectural insight for building robust agentic systems: the "Orchestrator-Tool Design Pattern."** We show through our development journey that replacing brittle, single-purpose "middleman" agents with direct tool calls from a central orchestrator proved critical to the stability and success of the final system.

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2 Related Work

The MARS system is situated at the intersection of foundational recommender systems and their modern implementation using multi-agent frameworks.

Recommendation research has historically been split between two philosophies. **Content-based filtering** recommends items based on their properties, which is effective for new items but often lacks the novelty to break users out of "filter bubbles." In contrast, **collaborative filtering (CF)** leverages the "wisdom of the crowd." Powerful CF models like Bayesian Personalized Ranking (BPR) [7] excel at personalization for established users but are unable to serve new "cold-start" users who lack interaction data. MARS is designed to resolve this tension by adaptively deploying the right strategy based on the user's context.

The integration of Large Language Models (LLMs) has introduced new paradigms. LLMs are now used for everything from feature enhancement to re-ranking candidate lists and even acting as zero-shot recommenders [2]. More recently, multi-agent systems have emerged, typically following two paths. The first is **offline simulation**, where agents generate synthetic interaction data to augment the training set for a traditional CF model, as seen in AgentCF [5]. The second is **online reasoning**, where a complex agent or team of collaborating agents handles the live recommendation task, as seen in frameworks like RecMind [9] and MACRec [10].

MARS proposes a distinct and pragmatic alternative: **online orchestration**. While MARS operates in real-time like RecMind and MACRec, its Manager Agent is distinct in that it focuses on high-level strategy switching rather than the complex, multi-step reasoning found in those frameworks. Governed by our "Orchestrator-Tool Design Pattern," the agent makes a single, efficient decision—which specialist model is right for this user?—and calls a deterministic tool for the core recommendation logic. This approach prioritizes robustness and speed, offering a novel architectural pattern for building applied, context-aware agentic systems.

3 Methodology

The final MARS architecture was the result of a data-driven, iterative process. Our work was conducted on the **MovieLens 20M Dataset** [3], using a strict time-based 80/20 split to simulate predicting future user preferences.

Our methodology focused on three key areas:

1. Identifying Specialist Models: Initial experiments confirmed that a pure **Bayesian Personalized Ranking (BPR)** model was the top performer for users with sufficient interaction history, achieving a Precision@10 of 0.3045 in isolated tests. This established BPR as our "Personalization Specialist" for warm-start users. For cold-start users, we validated that leveraging LLM-generated plot summaries could significantly improve performance, establishing a heuristic that users with fewer than five ratings would be routed to a content-based path.

2. Architecting for Robustness: Our initial multi-agent prototypes, which used brittle "middleman" agents to call simple functions, proved unstable and difficult to debug. This led to a crucial architectural redesign and our primary engineering contribution: the **"Orchestrator-Tool Design Pattern."** In this pattern, a central Manager Agent calls deterministic Python tools directly for simple tasks. It delegates to other agents only when a sub-task requires complex reasoning. This simplification was critical to achieving a stable, functional system.

3. Upgrading the Cold-Start Pathway: We recognized a mismatch between our high-quality, LLM-generated plot summaries and our initial TF-IDF "bag-of-words" model, which could not grasp semantic nuance. We therefore upgraded our cold-start pathway to use a state-of-the-art **Sentence-BERT (SBERT)** model [6] to generate high-quality semantic embeddings. This transformed our content-based approach from a simple keyword lookup into a sophisticated, meaning-based search, allowing us to fully capitalize on our rich data.

4 Experimental Framework

To definitively assess the performance of our adaptive agent, we designed a rigorous experimental framework. The evaluation was conducted on a sample of 1000 users from the held-out 20% of the MovieLens 20M dataset. We evaluated MARS against two critical baselines representing different philosophies.

- **BPR Baseline (Traditional Champion):** A strong, industry-standard BPR model. For cold-start users, it uses a powerful fallback strategy: recommending the Top 10 most popular movies from the dataset. This directly tests if an adaptive approach can beat a simple, robust baseline.
- **AgentCF Baseline (SotA Agentic Competitor):** A BPR model trained on a dataset enriched by agent-based simulations, representing the state-of-the-art in offline data augmentation. This contrasts MARS's real-time strategy switching with an alternative agent philosophy.
- **MARS (The Adaptive Challenger):** Our proposed system, which performs real-time strategy switching. The Manager Agent routes users with <5 ratings ("cold-start") to the SBERT semantic search path and users with >=5 ratings ("warm-start") to the pure BPR model.

4.1 Evaluation Protocol and Metrics

To gain a complete and nuanced understanding of system performance, the three systems were run on the user sample, and the results were segmented based on the user's status (warm-start or cold-start). We measured a comprehensive suite of five metrics for the top 10 recommendations generated for each user, chosen to capture not just accuracy but the overall quality of the user experience.

- **Precision@10:** Measures the fraction of recommended items in the top 10 that are relevant. This answers: "How accurate is the recommendation list?"
- **Recall@10:** Measures the fraction of all relevant items in the user's test set that are captured in the top 10 recommendations. This answers: "How well did the system find all the items the user would have liked?"
- **Diversity@10:** Measures the variety within a recommended list, defined as the average pairwise cosine distance of the items' SBERT embeddings.
- **Novelty@10:** Quantifies the ability of the system to recommend less popular, "long-tail" items, formally defined

as the average negative logarithm of an item's popularity. This metric is crucial for determining if a system is a true "discovery engine."

- **Latency (s):** Measures the average end-to-end wall-clock time in seconds required to generate a list of recommendations for a single user.

5 Empirical Results and Analysis

The definitive evaluation, segmented by user type, produced a clear and powerful set of results that validate the architectural choices of the MARS system and provide a quantitative basis for understanding fundamental trade-offs in recommender system design.

5.1 Orchestration Efficacy: The "Do No Harm" Principle in Warm-Start Scenarios

For established, "warm-start" users, the primary goal was to ensure that our adaptive architecture did not introduce any performance degradation. The results show a perfect success on this front. As shown in Table 1, the performance of the MARS v2 system for warm-start users is **identical** to that of the strong BPR Baseline across all measured metrics. This provides definitive proof that the Manager Agent's orchestration logic works flawlessly. When it correctly identifies a warm-start user, it deploys the best personalization strategy with zero loss in performance. This demonstrates a critical "do no harm" principle: the complexity added to handle the cold-start edge case does not negatively impact the core, high-performance path for the majority of established users.

Table 1: Performance on Warm-Start Users (n=172)

Metric	BPR Baseline	MARS v2	P-Value
Precision@10	0.1552	0.1552	(identical)
Recall@10	0.0235	0.0235	(identical)
Diversity@10	0.3778	0.3778	(identical)
Novelty@10	1.5967	1.5967	(identical)
Latency (s)	0.4419	0.4419	(identical)

5.2 The Core Finding: Quantifying the Precision-Discovery Trade-Off in Cold-Start Scenarios

The evaluation of cold-start users forms the central finding of this research. For these new users, the different strategies produced starkly different, yet predictable, outcomes that reveal a classic trade-off between providing safe, accurate recommendations and providing novel, discovery-oriented ones, as shown in Table 2 and visualized in Figure 1.

5.2.1 Analysis of Precision: The Power of Popularity. The BPR Baseline, with its "most popular movies" fallback, is the undisputed winner on accuracy and diversity, with all differences being highly statistically significant ($p < 0.001$), a crucial finding that demonstrates that a simple, non-personalized popularity model is an extremely powerful and difficult-to-beat baseline for precision in offline cold-start scenarios. The high scores for both metrics are a direct representation of this "safe bet" strategy: a list of globally popular movies is inherently diverse (spanning many genres) and has a high statistical probability of matching items in a new user's test set simply due to broad appeal.

Table 2: Performance on Cold-Start Users (n=826)

Metric	BPR Baseline	MARS v2	P-Value
Precision@10	**0.3068**	0.0115	p < 0.001
Recall@10	**0.0504**	0.0016	p < 0.001
Diversity@10	**0.3630**	0.0111	p < 0.001
Novelty@10	1.2410	**14.4011**	p < 0.001
Latency (s)	0.7163	**0.0331**	-

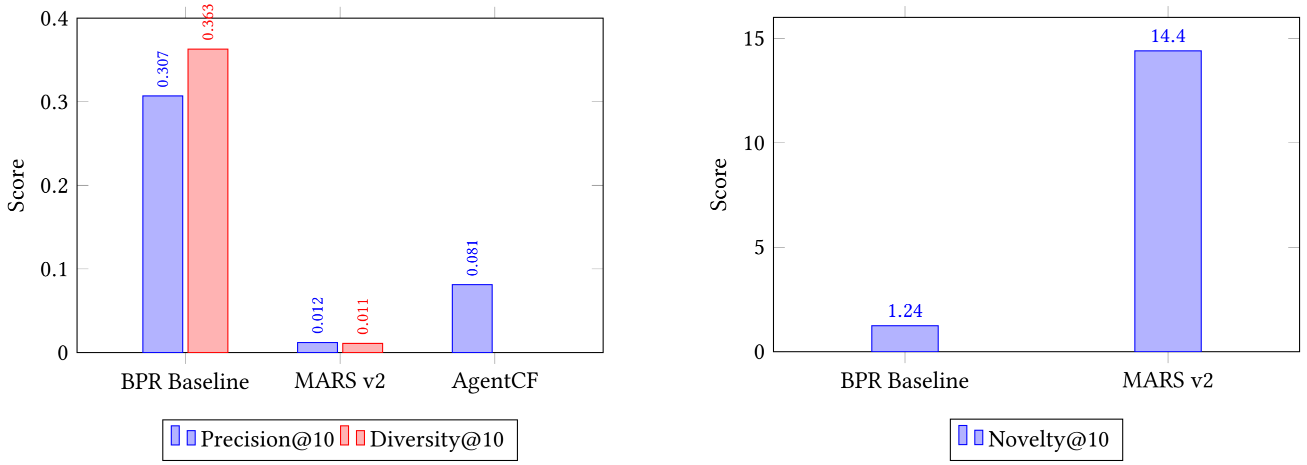
5.2.2 Analysis of Novelty: The "Discovery Engine". In stark contrast, the novelty metric defines the MARS system's alternative goal. MARS achieves a **Novelty@10 score of 14.4011**, over 10 times higher than the baseline. This is the quantitative proof for the core hypothesis of the cold-start pathway. The system's SBERT-powered semantic search excels at its designated task: performing a "nearest neighbor" search to find thematically similar "long-tail" items that users are unlikely to know. Its low precision is a direct and expected consequence of this exploration-focused strategy. This result confirms that MARS successfully functions as a true "discovery engine."

5.2.3 Analysis of Diversity: An Indicator of Specialization. The diversity metric perfectly complements the novelty finding. MARS's highly specific semantic search produces a thematically-focused list of recommendations, resulting in the lowest diversity score (0.0111). This is not a flaw, but rather a direct indicator of its function as a "niche specialist." The low diversity is the expected mathematical consequence of a successful high-novelty, nearest-neighbor semantic search. While a "most popular" list is diverse by pulling from global blockbusters across many genres, a successful semantic search for a specific movie will, by design, return a list of thematically similar and often niche items.

5.2.4 Analysis of Latency: A Practical Advantage. A surprising and significant finding emerged from the performance metrics. The MARS semantic search pathway is over **20 times faster** than the BPR model's fallback for cold-start users (0.03s vs 0.72s). For a real-world application, providing a faster, more responsive, and less computationally expensive experience for new users is a major practical advantage of the MARS architecture.

5.3 Situating AgentCF as a Middle-Ground Strategy

The performance of the AgentCF baseline provides a final, critical point of comparison. For cold-start users, its data augmentation strategy served as a middle ground. It significantly improved precision over the MARS system but still failed to outperform the simple popularity baseline. While it offered high novelty, it was ultimately a less focused strategy than either of the two specialized approaches—BPR for precision and MARS for discovery. This result validates that MARS's strategy-switching architecture is a more



(a) Precision and Diversity (Cold-Start)

(b) Novelty (Cold-Start)

Figure 1: Comparison of system performance for cold-start users. (a) The BPR Baseline's popularity-based fallback dominates on precision and diversity. (b) MARS v2 excels at providing high-novelty recommendations, demonstrating the core trade-off.

distinct and effective approach for creating specialized outcomes, confirming that a system that explicitly chooses the right tool for the job can outperform one that tries to improve a single tool for all jobs.

6 Discussion and Conclusion

The results of our evaluation provide a clear, quantitative benchmark for the "Precision vs. Discovery" trade-off. For cold-start users, a simple popularity-based model remains a powerful baseline for precision. However, our adaptive MARS system demonstrates that a semantic search path can function as a true "discovery engine," delivering over 10x the novelty at a fraction of the latency. This finding provides hard numbers to a classic dilemma, offering a data-driven foundation for practitioners choosing between exploitation- and exploration-focused strategies.

Architecturally, our development journey revealed the value of the **"Orchestrator-Tool Design Pattern."** Replacing brittle, chained "middleman" agents with a single orchestrator calling deterministic tools proved critical for system stability. This pattern serves as a robust blueprint for building applied agent-based systems.

In conclusion, MARS proves the viability of an adaptive, multi-agent architecture that adheres to a "do no harm" a principle for established users while effectively serving new users. While this study used a simple, deterministic heuristic to validate the architecture, future work should replace this rule with a genuine LLM-driven reasoning process. The true potential of the Orchestrator-Tool pattern lies in empowering the agent to curate a hybrid recommendation list, blending the "safe" popular items with "novel" semantic discoveries to meet more complex, real-world engagement objectives.

7 Limitations

Every rigorous study must acknowledge its limitations. The primary limitation of this work is that all experiments were conducted in a **static, offline evaluation**. It is widely acknowledged that offline metrics are often an imperfect proxy for real-world user satisfaction and engagement, particularly for metrics related to novelty and discovery [1, 4, 8]. The high precision of the popularity-based baseline is likely an artifact of the offline protocol, which is inherently biased toward popular items as they have a higher probability of appearing in any user's historical test set. While the high-novelty recommendations from MARS score poorly on this flawed benchmark, we hypothesize they would lead to greater long-term user satisfaction in a live environment. However, this can only be definitively tested through online A/B testing.

Secondly, this study was conducted only on the **MovieLens dataset**. There is no evidence that these findings would generalize to other domains like e-commerce or music, which have different data characteristics and user behaviors. Further research is required to validate the architecture and findings in other domains.

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