Improving LLM-Based Recommender Systems with User-Controllable Profiles

Stanisław Woźniak
stanislaw.wozniak@pwr.edu.pl

Jacek Duszenko
jacek.duszenko@pwr.edu.pl

Jan Kocoń
jan.kocon@pwr.edu.pl

Przemysław Kazienko
przemyslaw.kazienko@pwr.edu.pl

Department of Artificial Intelligence, Wroclaw University of Science and Technology

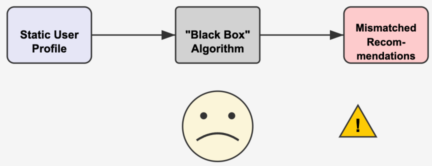
Introduction

- Human-centered recommender systems represent a pivotal shift
- Current models often fail to incorporate:
  - Users' evolving goals
  - Diverse preferences
  - Contextual nuances
- Our contribution: A novel framework for **controllable**, **explainable**, and **adaptable** recommender systems
- Key innovation: User-controllable profiles in natural language

Motivation

Current Limitations

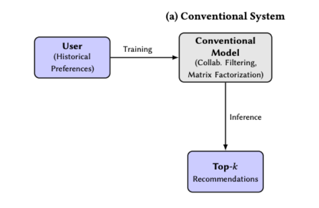
- ”Black box” recommendations lack transparency
- Limited user agency in shaping recommendation context
- Difficulty adapting to short-term preference shifts



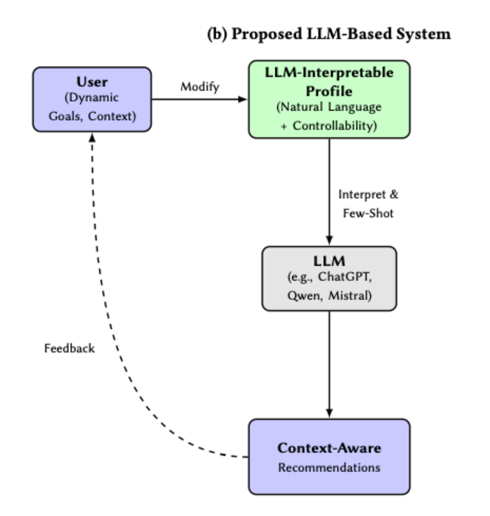
Opportunities

- Natural language representation improves explainability
- Context-aware recommendations adapt to user goals

Method



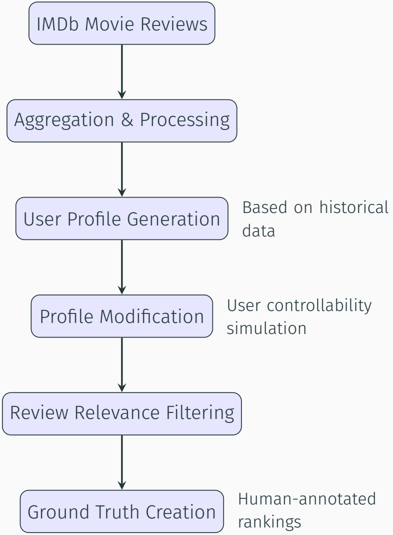
Conventional RS



Refined context-aware RS

Dataset

- Custom dataset for evaluating controllable recommendation
- Sources:
  - Movie reviews from IMDb
  - LLM-generated user profiles
  - Human-annotated ground truth
- Key features:
  - Original and modified user profiles
  - Relevance-filtered review examples
  - 50 users with comprehensive data



Wrocław University of Science and Technology

Research Questions:

1. How does in-context user representation impact RS performance?
2. Does controllability increase RS performance?
3. How does complex in-context user representation perform in a controllable environment?

Feature	LLM-based RS method		
	User profiles	Few-shots	Profiles + Few-shots
Size in the prompt	short	long	long
Ease of control by the user	easy	moderate	moderate
Ease of fine-tuning	moderate	easy	moderate
Increase size in time	$O(1)$	$O(n)$	$O(n)$
Inter-user aggregation	difficult	easy	moderate

Results - RQ #1: User Representation Impact

Model	FS^{10}	P_O	$P_O + FS^{10}$	$FS^{10} + P_O$
Mistral 7B	0.4136	0.6123	0.5499	0.5186
LLaMA3.1 8B	0.5580	0.6145	0.5369	**0.6238**
Mixtral 8x7B	0.5664	**0.6224**	0.5662	0.6020
LLaMA3.3 70B	**0.6061**	0.6165	**0.6040**	0.6043
Qwen2.5 72B	0.5758	0.6018	0.6039	0.5936
Mixtral 8x22B	0.2924	0.5829	0.3122	0.5032
GPT-4o	**0.6322**	**0.6419**	**0.6446**	**0.6449**

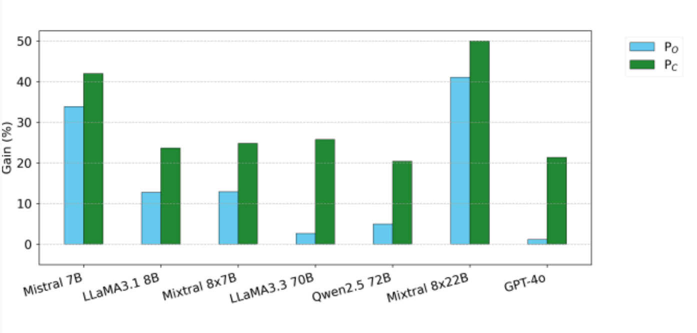
NDCG@10

FS10: Few-shot with 10 samples
P_O: Original user profile
P_O+FS10: Profile first, then samples
FS10+P_O: Samples first, then profile

Conclusion

Textual user profiles are superior to few-shot historical data, providing more effective preference representation.

Results - RQ #2: Controllability Impact



Gain (%)

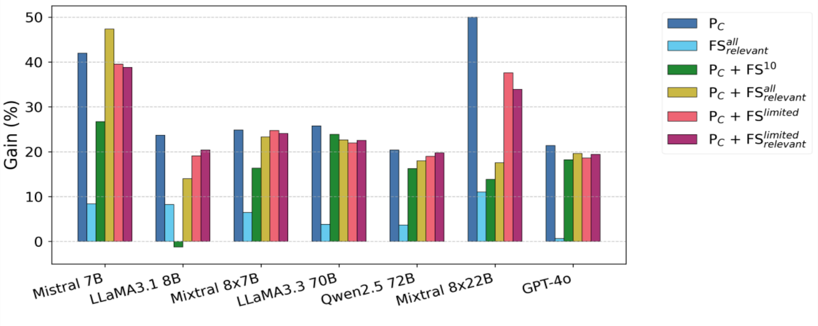
P_O: Original user profile

P_C: User-controlled profile

Conclusion

User controllability significantly enhances recommendation quality across all models, highlighting the critical role of user agency in recommendation systems.

Results - RQ #3: Complex User Representation Environment



Conclusion

Textual controlled profiles provide more accurate information than historical samples. Quality filtering and limiting sample quantity prevents misleading the model.

Conclusions

Wrocław University of Science and Technology

- **Textual profiles outperform few-shot approaches** for representing user preferences in LLM-based recommender systems
- **User controllability** significantly enhances recommendation quality:
  - Up to 50% performance improvement across diverse LLM architectures
  - Empowers users to refine preferences based on evolving goals
- **Combined approaches** must carefully consider:
  - Relevance filtering to prevent misleading the model
  - Sample quantity to optimize performance
  - Information ordering for maximum effectiveness
- **Future directions:**
  - Fine-tuning LLM-based recommendation systems
  - Continual adaptation through reinforcement learning