TAAI 2024

Proposal of Modeling Personal Values Using Large Language Models for Extracting Mentions of Item Attributes and Polarity from Review Texts

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GitHub repo is here!

Background

Challenges in recommender systems face the following issues:
cold-start problem / sparsity problem

Personal Value-based User Modeling

- Estimate users' particular interests in item`s attributes
- Users' personal values are reflected in the priority of item's attributes when evaluating items
- Rating Matching Rate (RMrate) is an indicator that quantifies personal values.

$$RMrate(u,j) = \frac{O(u,j)}{O(u,j) + Q(u,j)}$$

$O(u,j)$ / $Q(u,j)$: The number of times the evaluation polarity of attribute j matches / mismatches the overall evaluation polarity of user u

- RMrate requires explicitly collected attribute evaluations

→ Can not be applied to some platforms

- User-written review texts strongly reflect preferences

→ Resource for extracting contain extractable attribute evaluations

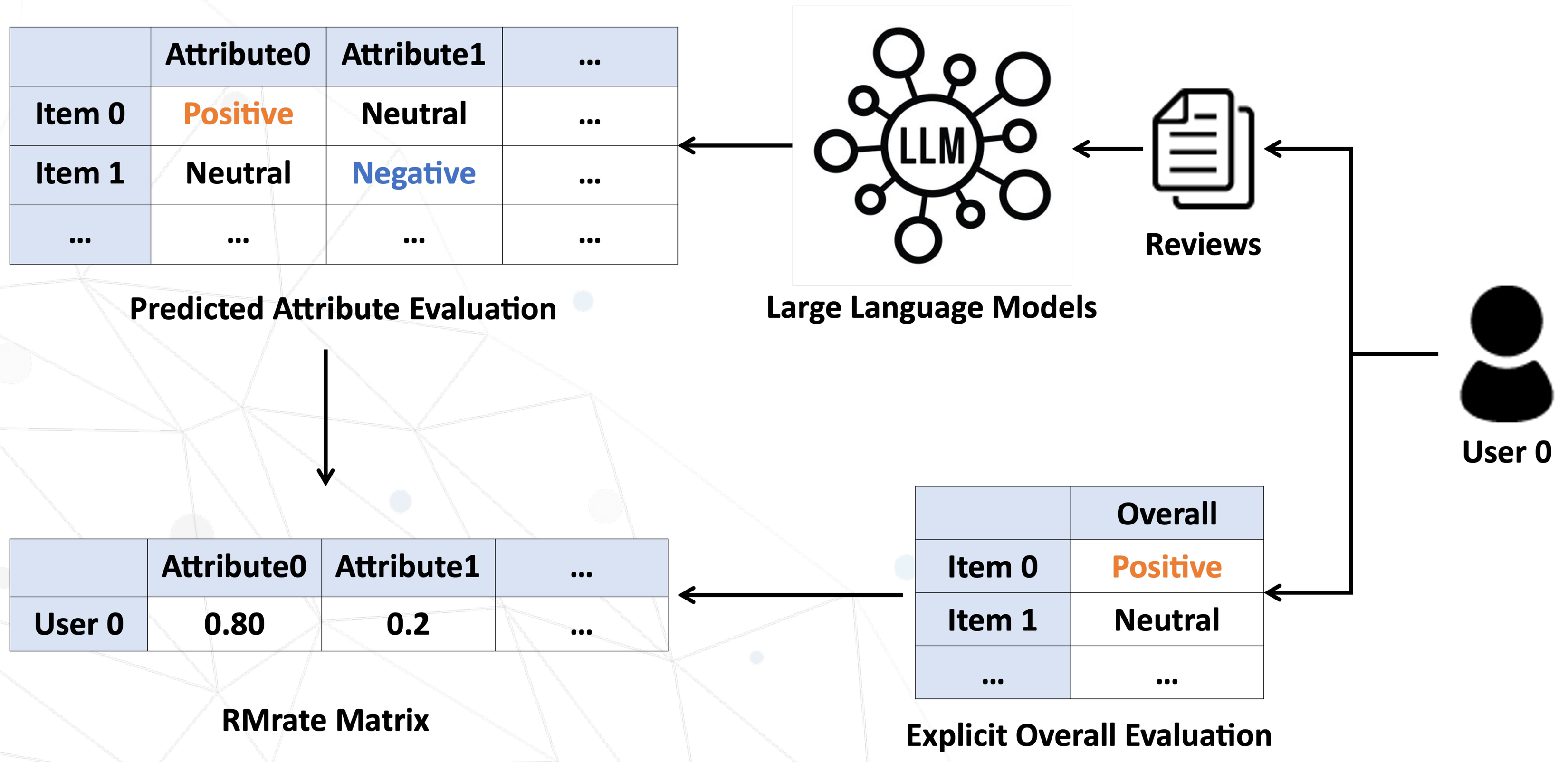
Research Purpose

Construct a personal value-based user modeling by extracting attributes from review texts using LLMs

Methods

Two main components:

1. **Sentiment Extraction Module using LLM:**
   Using LLM prompting to extract polarity of item attribute polarity from review texts
2. **Recommendation Module:**
   Calculating RMrates based on extracted attribute polarities and explicitly given overall item evaluations.



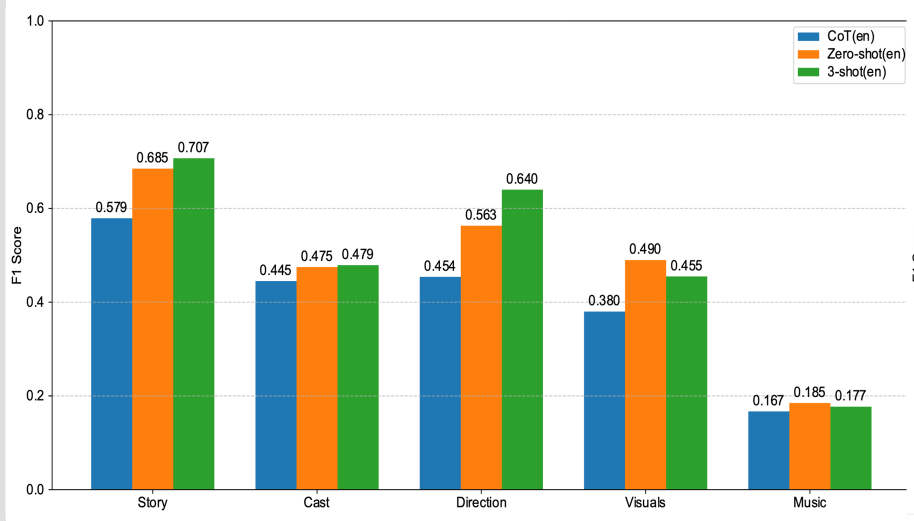
Experiments: Settings

- **Dataset:** Yahoo! Movie Reviews (ja)
- **LLM used:** GPT-3.5-turbo-1106
- **Prompt type** (Both English and Japanese versions):
  Zero-shot / Few-shot (3-shot) / Chain-of-Thoughts
- **Ground truth datasets:**
  - Explicit Evaluations
  - Manual Annotations

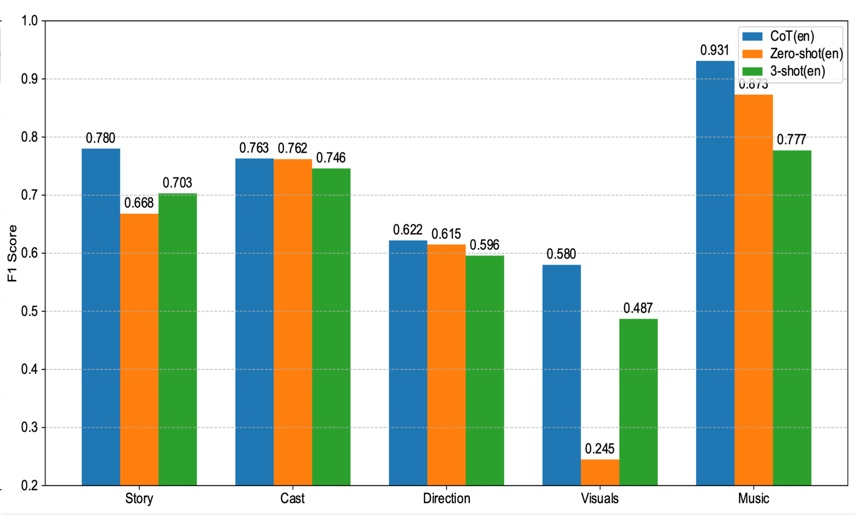
Experiments: Results

Accuracy of attribute polarity extraction

- **Explicit attribute ratings as ground truth:**
  - Low F1 scores regardless of method
  - The reasoning provided through CoT is reasonable
  - When there is a discrepancy between the sentiment expressed in the review text and the explicit attribute evaluations
  - Inconsistency between review text polarity and attribute evaluations
- **Manually annotation as ground truth:**
  - CoT (en) tends to show the high performance
  - Attribute clearly mentioned in reviews, extraction accuracy is comparable to manually annotated
  - Hard to predict reviews with vague writing or implicit attributes



F1-score when using explicit attribute s polarity as the correct answer



F1-score when using manually annotated s polarity as the correct answer

Recommendation Accuracy

- ECFPV: Explicit Collaborative Filtering employing Personal Values
  → achieved best score
- ICFPV: Implicit Collaborative Filtering employing Personal Values
  → achieved comparable score to ECFPV

	Precision@5	Recall@5	F1@5	RMSE
KNN-pearson	0.273	0.146	0.191	**1.057**
KNN-cosine	0.555	0.234	0.330	1.066
ECFPV	**0.618**	**0.270**	**0.376**	1.058
ICFPV(Zero-shot)	**0.603**	0.258	0.361	1.063
ICFPV(Few-shot)	**0.588**	0.252	0.352	1.071

Conclusion / Key Findings

- The proposed method successfully extracted polarity from review texts using LLMs, with recommendation accuracy comparable to systems using explicit evaluations
- Demonstrates potential for model construction in scenarios without explicit attribute evaluations

Future Works

- Challenge: Extracting attributes from vague reviews without explicit mentions
- Issue: LLM inference time limits large dataset processing
- Potential Solution: Use of OSS LLMs (Llama, Gemma, etc.)

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