

Item Response Theory for NLP

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<https://eacl2024irt.github.io/>

Conclusion, Recent Work, and Future Directions

Concluding Remarks and Summary

1. Learned about IRT models
2. How to implement IRT models and/or use py-irt
3. Showed ways to apply IRT to specific NLP problems
 - 3.1 Annotation Error
 - 3.2 Evaluation
 - 3.3 Training
4. Classical IRT is a starting point, but the range of IRT methods is much larger

1. Classical IRT is a starting point, but the range of IRT methods is much larger
2. Future Directions
 - 2.1 LLMs?
 - 2.2 Multidimensional IRT and Big Benchmarks?
 - 2.3 Predictability?

Join our IRT in NLP Google group! [TODO-link](#)

Recent Work

Do great minds think alike? Investigating Human-AI Complementarity for Question Answering

- Skill/difficulty should be multidimensional, but making it work is difficult (Rodriguez et al., 2022)
- Idea: use BERT-informed embeddings to inform multidim difficulty, etc.
- Compare different proficiencies of humans versus models
- Gor et al. (2024) made it work!

Do great minds think alike? Investigating Human-AI Complementarity for Question Answering

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Abstract

This study examines question-answering (QA) abilities across human and AI agents. Our framework CAIMIRA addresses limitations in traditional item response theory, by incorporating multidimensional analysis, identifiability, and content awareness, enabling nuanced comparison of QA agents. Analyzing responses from ~ 30 AI systems and 155 humans over thousands of questions, we identify distinct knowledge domains and reasoning skills where these agents demonstrate differential proficiencies. Humans outperform AI systems in scientific reasoning and understanding nuanced language, while large-scale LLMs like GPT-4 and LLAMA-2-70B excel in retrieving specific factual information. The study identifies key areas for future QA tasks and model development, emphasizing the importance of semantic understanding and scientific reasoning in creating more effective and discriminating benchmarks.

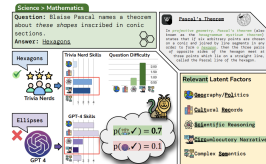


Figure 1: Response Correctness prediction using Agent skills and Question difficulty over relevant latent factors. We list the five latent factors that CAIMIRA discovers, and highlight the relevant ones (green), which contribute to estimating whether an agent will respond to the example question correctly. The agent skills over these relevant factors are highlighted in red boxes.

tion answering, particularly with the new panoply

1. Understanding Dataset Difficulty with \mathcal{V} -Usable Information (Ethayarajh et al., 2022)
2. IRT in Recommender System Benchmarking (Liu et al., 2023)

References

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