

AI Report

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This paper proposes CoFiGR, a coarse-to-fine generative recommendation framework to address semantic - 2/16/2026

This paper proposes CoFiGR, a coarse-to-fine generative recommendation framework to address semantic misalignment and optimization instability in LLM-based generative recommendation tasks. CoFiGR introduces BiReSID, which maps items and users into a unified discrete space that combines textual semantic information with collaborative filtering signals, aligning them with the LLM's latent space via multi-task continual pre-training. Subsequently, the CPPO strategy is applied to progressively expand the optimization scope from coarse category levels to fine item levels. Experimental results demonstrate that CoFiGR achieves superior performance compared to existing baselines across various benchmark datasets and a large-scale industrial dataset.

The proposed framework introduces a novel coarse-to-fine hierarchical design that jointly aligns item, user, and interaction objectives.

The paper proposes BiReSID, a unique tokenization strategy that embeds both users and items into a unified semantic space.

The effectiveness of the proposed method is validated on a massive industrial dataset comprising two weeks of interactions from ten million online users.

The paper positions CPPO as a core contribution for preference alignment. However, the justification for the CPPO design is unconvincing. The reward function is defined solely based on the exact match between the predicted tokens and the ground truth. This is intrinsically identical to the goal of Cross-Entropy Loss in Supervised Learning. Since the reward is merely checking for token correctness, it is unclear why a complex RL framework like PPO is necessary over standard Maximum Likelihood Estimation. The methodology would be more rigorous if the authors could provide theoretical or empirical justification for why Curriculum-based Supervised Fine-Tuning is insufficient for this task. Evidence demonstrating the distinct advantages of PPO over MLE in this context is needed to justify the added design complexity.

Although the paper claims practical effectiveness on a large-scale industrial dataset, it lacks evaluation of inference latency and computational efficiency. Given that the model employs autoregressive generation with a beam search width of 20, the inference cost is expected to be higher than traditional embedding-based baselines. The absence of specific metrics such as latency weakens the argument for the framework's real-world deployability in production environments.

The proposed BiReSID represents users as a dynamic multiset of actions, implying that the discrete user identifier potentially changes with every new interaction. However, there is no clarification of the inference mechanism for handling these updates. If the system requires re-encoding and re-quantizing the user representation via RQ-VAE for every interaction, it would yield computational overhead. Furthermore, it is unclear whether these frequent ID shifts might affect the stability of the learned user embeddings during inference.

The RQ-VAE to map continuous embeddings into discrete BiReSIDs inevitably introduces information loss. It would be helpful to include an analysis of metrics like the collision rate or the reconstruction error to further validate the quantization process. Given the paper's emphasis on fine-grained alignment, investigating whether the discrete codes preserve sufficient granularity to distinguish between semantically similar items would strengthen the claims. Specifically, high collision rates could potentially lead to ambiguity in the generation process, limiting the model's ability to provide precise recommendations.

● Sentences that are likely AI-generated.

FAQs

What is GPTZero?

GPTZero is the leading AI detector for checking whether a document was written by a large language model such as ChatGPT. GPTZero detects AI on sentence, paragraph, and document level. Our model was trained on a large, diverse corpus of human-written and AI-generated text with support for English, Spanish, French, German, and other languages. To date, GPTZero has served over 10 million users around the world, and works with over 100 organizations in education, hiring, publishing, legal, and more.

When should I use GPTZero?

Our users have seen the use of AI-generated text proliferate into education, certification, hiring and recruitment, social writing platforms, disinformation, and beyond. We've created GPTZero as a tool to highlight the possible use of AI in writing text. In particular, we focus on classifying AI use in prose. Overall, our classifier is intended to be used to flag situations in which a conversation can be started (for example, between educators and students) to drive further inquiry and spread awareness of the risks of using AI in written work.

Does GPTZero only detect ChatGPT outputs?

No, GPTZero works robustly across a range of AI language models, including but not limited to ChatGPT, GPT-5, GPT-4, GPT-3, Gemini, Claude, and AI services based on those models.

What are the limitations of the classifier?

The nature of AI-generated content is changing constantly. As such, these results should not be used to punish students. We recommend educators to use our behind-the-scene [Writing Reports](#) as part of a holistic assessment of student work. There always exist edge cases with both instances where AI is classified as human, and human is classified as AI. Instead, we recommend educators take approaches that give students the opportunity to demonstrate their understanding in a controlled environment and craft assignments that cannot be solved with AI. Our classifier is not trained to identify AI-generated text after it has been heavily modified after generation (although we estimate this is a minority of the uses for AI-generation at the moment). Currently, our classifier can sometimes flag other machine-generated or highly procedural text as AI-generated, and as such, should be used on more descriptive portions of text.

I'm an educator who has found AI-generated text by my students. What do I do?

Firstly, at GPTZero, we don't believe that any AI detector is perfect. There always exist edge cases with both instances where AI is classified as human, and human is classified as AI. Nonetheless, we recommend that educators can do the following when they get a positive detection: Ask students to demonstrate their understanding in a controlled environment, whether that is through an in-person assessment, or through an editor that can track their edit history (for instance, using our [Writing Reports](#) through Google Docs). Check out our list of [several recommendations](#) on types of assignments that are difficult to solve with AI.

Ask the student if they can produce artifacts of their writing process, whether it is drafts, revision histories, or brainstorming notes. For example, if the editor they used to write the text has an edit history (such as Google Docs), and it was typed out with several edits over a reasonable period of time, it is likely the student work is authentic. You can use GPTZero's Writing Reports to replay the student's writing process, and view signals that indicate the authenticity of the work.

See if there is a history of AI-generated text in the student's work. We recommend looking for a long-term pattern of AI use, as opposed to a single instance, in order to determine whether the student is using AI.