T5-graph learning-driven models have made remarkable progress in the field of recommendation . but their performance in the reviewer recommendation task may suffer from a false negative issue . this study proposes an unsupervised Pseudo Neg-Label strategy to enhance graph contrastive learning (GCL) RevGNN outperforms all baselines across four metrics; further analyses confirm the effectiveness of each component in RevGNN .

Bart-RevGNN: Negative Sampling Enhanced Contrastive Graph Learning for Academic Reviewer Recommendation. Acquiring reviewers for academic submissions is a challenging recommendation scenario. RevGNN utilizes a two-stage encoder structure that encodes both scientific knowledge and behavior using Pseudo Neg-Label to approximate review preference. Extensive experiments on three real-world datasets demonstrate that RevGnn outperforms all baselines across four metrics. The study aims to tackle the ambiguous nature of unobserved interactions in academic reviewer recommendations. Also, detailed further analyses confirm the effectiveness of each component in RevGNC. The authors propose an unsupervised Pseudogene-Label strategy to enhance graph contrastive learning (GCL) for recommending reviewers for Academic submissions, which we call RevG Cohn. The researchers also propose a new type of algorithm to enhance GCL for academic reviewer recommendation, which they call RevC Cohn.

Gemini -RevGNN addresses the false negative issue in academic reviewer recommendation by introducing Pseudo Neg-Label, which enhances graph contrastive learning (GCL) by approximating review preferences. RevGNN employs a two-stage encoder to capture scientific knowledge and reviewer behavior. Experiments on real-world datasets show that RevGNN outperforms baselines across multiple metrics, proving the effectiveness of its components in improving recommendation accuracy.

Gpt-4-The research paper introduces RevGNN, a novel graph neural network model designed to enhance the process of recommending academic reviewers by addressing the challenges associated with the traditional graph learning models. Traditional models often misinterpret unobserved interactions (where no explicit reviewer-submission relationship is recorded) as negative instances, which is problematic due to the nature of the anonymous academic review process. This process frequently results in many unobserved interactions that are not truly negative but are merely unrecorded due to the lack of exposure between reviewers and submissions.

RevGNN tackles this issue by implementing an innovative unsupervised Pseudo Neg-Label strategy within a graph contrastive learning framework. This strategy is crucial for distinguishing between genuine negative interactions and those unobserved due to other reasons, such as the anonymity of the review process. By refining the understanding and labeling of these interactions, RevGNN aims to more accurately model and predict suitable reviewer-submission matches.

The architecture of RevGNN comprises a two-stage encoder that effectively captures and integrates both scientific knowledge and behavioral data to approximate reviewers' preferences more accurately. This dual-approach allows RevGNN to leverage comprehensive features of potential reviewers, enhancing the recommendation process.

The effectiveness of RevGNN has been rigorously tested through extensive experiments on three real-world datasets. The results from these tests show that RevGNN consistently outperforms existing baseline models across four different performance metrics. Further detailed analyses of each component of RevGNN confirm that the model's superior performance can be attributed to its innovative approach to handling unobserved interactions and its robust learning architecture.

Overall, RevGNN represents a significant advancement in the field of academic reviewer recommendation, offering a more reliable and effective tool for matching reviewers with academic submissions, thereby potentially improving the peer review process in academic publications.

Gpt-3-The study "RevGNN: Negative Sampling Enhanced Contrastive Graph Learning for Academic Reviewer Recommendation" addresses the challenge of acquiring reviewers for academic submissions. While graph learning-driven models have shown progress in recommendation systems, they often struggle with false negatives in academic reviewer recommendations due to the assumption that unobserved edges represent negative samples. The anonymous review process further complicates this issue by limiting interactions between reviewers and submissions. To overcome this challenge, the study introduces RevGNN, which employs an unsupervised Pseudo Neg-Label strategy to enhance graph contrastive learning. RevGNN utilizes a two-stage encoder structure to encode scientific knowledge and behavior, approximating review preferences. Experimental results on real-world datasets demonstrate that RevGNN outperforms existing baselines across multiple metrics. The study's detailed analyses validate the effectiveness of each component in RevGNN, highlighting its potential to improve academic reviewer recommendation systems. By addressing the ambiguity of unobserved interactions and leveraging negative sampling techniques, RevGNN offers a promising solution to enhance the accuracy and efficiency of reviewer recommendations in academic settings.