Supplementary Material

Anonymous Author(s)

1 Details of Public Datasets

To construct user-news interaction sequences for our study, we leveraged four publicly available datasets: GossipCop [10], Pheme [1], MCFEND [3], and CED [4]. These datasets provide both user-news interaction histories and news authenticity labels, making them well-suited for evaluating systems that recommend reliable news aligned with user interests.

GossipCop and Pheme are English datasets. GossipCop primarily focuses on fact-checked celebrity and entertainment news, accompanied by user interactions such as comments and shares. On the other hand, Pheme specializes in multi-event rumors sourced from social media, providing temporal user-news interactions as well as authenticity labels distinguishing between real and fake news.

MCFEND and CED are Chinese datasets. MCFEND aggregates news from a variety of sources, including social media, messaging platforms, and conventional news outlets. The dataset, fact-checked by 14 international agencies, also includes chronological user interaction data. CED is designed for early rumor detection and contains temporal interaction data alongside labels for real and fake news.

By organizing user interactions in chronological order, we constructed user reading sequences that incorporate both real and fake news. This approach enables a more realistic and comprehensive evaluation of news recommendation systems.

2 Baselines

NRMS [14] leverages a multi-head self-attention mechanism to learn user preferences based on their historical news interactions. The model first uses an attention-based encoder to extract news semantic representations from textual headlines. By aggregating these representations across a user's click history using the multi-head self-attention network, NRMS captures the diversity of user interests and achieves personalized news recommendations.

MINER [2] proposes a multilevel interactive framework to align user preferences with news content. The model integrates micro-level semantic feature extraction with macro-level preference modeling through bidirectional attention. This hierarchical design constructs fine-grained user profiles by uncovering latent relationships between users and items, resulting in improved recommendation performance.

CAUM [8] introduces a context-aware user modeling framework for sequential news recommendation. It leverages the temporal order and contextual dependencies of users' historical clicks by employing a self-attention network. By dynamically weighting the importance of past interactions, CAUM effectively captures evolving user interests and adapts to behavioral changes in news consumption.

FUM [7] focuses on fine-grained user modeling to address the diverse and heterogeneous nature of news content. It divides user interests into multiple sub-spaces based on themes or semantic aspects and builds detailed user profiles. By encoding these sub-interests, FUM enables precise and highly personalized news recommendations, particularly in scenarios with rich content diversity.

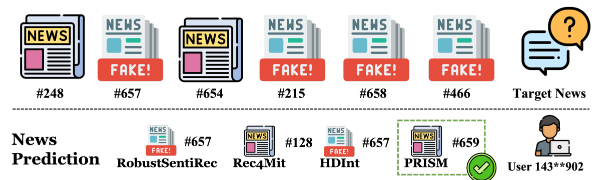

Figure 1: Case Study: A Challenging Scene Observed

RobustSentiRec [9] incorporates sentiment information and robust optimization into the recommendation process. It extracts emotional attributes from news headlines to emphasize the role of sentiment alignment in recommendations. By addressing the impact of noisy data, RobustSentiRec enhances recommendation accuracy, especially in sentiment-driven scenarios.

Rec4Mit [12] integrates fake news suppression with recommendation tasks. It trains a classifier to distinguish authentic and fake news items, and incorporates a Top-K filtering mechanism to exclude fake news from the final recommendation list. By explicitly combining news authenticity detection with traditional recommendation, Rec4Mit aims to mitigate the spread of disinformation while maintaining recommendation relevance.

HDInt [11] proposes a disentanglement-based framework for hierarchical modeling of news content and authenticity. The model separates semantic and authenticity features through a carefully designed architecture and aligns them via a cross-feature mechanism. Additionally, it uses a multi-task learning framework to jointly optimize for both news recommendation and fake news detection. HDInt excels at balancing recommendation diversity and credibility.

3 Implement Details

We utilized PyTorch [5], scikit-learn [6], and Transformers [13] to implement PRISM. For the extraction of news embeddings, we utilized "bert-base-uncased" for the English dataset and "bert-base-chinese" for the Chinese dataset. All experiments were conducted on an RTX 3090. Different learning rates and parameters were applied to the Chinese and English datasets, with specific settings detailed in Table.1

Table 1: Specific Hyperparameter Settings for Experiments.

Hyperparameter	English Dataset	Chinese Dataset
optimizer	Adam	Adam
classifier learning rate	4e-4	5e-4
diffusion learning rate	2e-4	5e-5
λ_{OT}	0.8	0.8
λ_c	0.4	0.4
λ_r	0.5	0.5
λ_{rec}	0.5	0.6

4 Details of Case Study

In the case study, as illustrated in Figure.1, we observed that over 50% of the news in a user's interaction sequence were fake news.

Post Id	News Title
#248	Backlash Has Brought More 'Bullies Out'
#657	Minnie Driver, Alyssa Milano Call Out Matt Damon For "Tone Deaf" Comments About Sexual Assault
#654	Naya Rivera refiles for divorce after domestic battery arrest
#215	All the times Caitlyn Jenner has shaded the Kardashians and they've shaded her right back
#658	Iggy Azalea Blasts Nick Young After Accidental Dinner Reunion
#466	Justin Bieber and Selena Gomez fly to Seattle for sweets
#128	How Star Wars: The Last Jedi Says Goodbye to Carrie Fisher
#659	'The Office' Revival Reportedly in the Works at NBC

Figure 2: Title of news in our case study.

Upon examining the recommendation results of various models, we found that all models except PRISM failed to recommend accurately. We selected the results of RobustSentiRec, Rec4Mit, and HDInt for comparison, as they are representative. It can be seen that both RobustSentiRec and HDInt recommended fake news, while Rec4Mit, although it recommended real news, did not recommend the target news. The titles of the news items in the user interaction sequence and those predicted by the models are shown in Figure.2. It is evident that in this challenging scenario, PRISM maintained robust performance.

References

[1] Elena Kochkina, Maria Liakata, and Arkaitz Zubiaga. 2018. All-in-one: Multi-task Learning for Rumour Verification. In *Proceedings of the 27th International Conference on Computational Linguistics, COLING 2018, Santa Fe, New Mexico, USA, August 20-26, 2018*, Emily M. Bender, Leon Derczynski, and Pierre Isabelle (Eds.). Association for Computational Linguistics, 3402–3413. https://aclanthology.org/C18-1288/

[2] Jian Li, Jieming Zhu, Qiwei Bi, Guohao Cai, Lifeng Shang, Zhenhua Dong, Xin Jiang, and Qun Liu. 2022. MINER: Multi-Interest Matching Network for News Recommendation. In *Findings of the Association for Computational Linguistics: ACL 2022*, Smaranda Muresan, Preslav Nakov, and Aline Villavicencio (Eds.). Association for Computational Linguistics, Dublin, Ireland, 343–352. https://doi.org/10.18653/v1/2022.findings-acl.29

[3] Yupeng Li, Haorui He, Jin Bai, and Dacheng Wen. 2024. MCFEND: A Multi-source Benchmark Dataset for Chinese Fake News Detection. In *Proceedings of the ACM on Web Conference 2024, WWW 2024, Singapore, May 13-17, 2024*, Tat-Seng Chua, Chong-Wah Ngo, Ravi Kumar, Hady W. Lauw, and Roy Ka-Wei Lee (Eds.). ACM, 4018–4027. https://doi.org/10.1145/3589334.3645385

[4] Zhiyuan Liu, Le Zhang, Cunchao Tu, and Maosong Sun. 2015. Statistical and semantic analysis of rumors in Chinese social media. *Scientia Sinica Informationis* 45, 12 (2015), 1536.

[5] Adam Paszke, Sam Gross, Soumith Chintala, Gregory Chanan, Edward Yang, Zachary DeVito, Zeming Lin, Alban Desmaison, Luca Antiga, and Adam Lerer. 2017. Automatic differentiation in pytorch. (2017).

[6] Fabian Pedregosa, Gaël Varoquaux, Alexandre Gramfort, Vincent Michel, Bertrand Thirion, Olivier Grisel, Mathieu Blondel, Peter Prettenhofer, Ron Weiss, Vincent Dubourg, et al. 2011. Scikit-learn: Machine learning in Python. *the Journal of machine Learning research* 12 (2011), 2825–2830.

[7] Tao Qi, Fangzhao Wu, Chuhan Wu, and Yongfeng Huang. 2022. FUM: Fine-grained and Fast User Modeling for News Recommendation. In *SIGIR '22: The 45th International ACM SIGIR Conference on Research and Development in Information Retrieval, Madrid, Spain, July 11 - 15, 2022*, Enrique Amigó, Pablo Castells, Julio Gonzalo, Ben Carterette, J. Shane Culpepper, and Gabriella Kazai (Eds.). ACM, 1974–1978. https://doi.org/10.1145/3477495.3531790

[8] Tao Qi, Fangzhao Wu, Chuhan Wu, and Yongfeng Huang. 2022. News Recommendation with Candidate-aware User Modeling. In *Proceedings of the 45th International ACM SIGIR Conference on Research and Development in Information Retrieval* (Madrid, Spain) *(SIGIR '22)*. Association for Computing Machinery, New York, NY, USA, 1917–1921. https://doi.org/10.1145/3477495.3531778

[9] Mete Sertkan, Sophia Althammer, Sebastian Hofstätter, and Julia Neidhardt. 2022. Diversifying Sentiments in News Recommendation. In *Proceedings of the Perspectives on the Evaluation of Recommender Systems Workshop 2022 co-located with the 16th ACM Conference on Recommender Systems (RecSys 2022)*.

[10] Kai Shu, Deepak Mahudeswaran, Suhang Wang, Dongwon Lee, and Huan Liu. 2018. FakeNewsNet: A Data Repository with News Content, Social Context and Dynamic Information for Studying Fake News on Social Media. *arXiv preprint arXiv:1809.01286* (2018).

[11] Shoujin Wang, Wentao Wang, Xiuzhen Zhang, Yan Wang, Huan Liu, and Fang Chen. 2024. A Hierarchical and Disentangling Interest Learning Framework for Unbiased and True News Recommendation. In *Proceedings of the 30th ACM SIGKDD Conference on Knowledge Discovery and Data Mining, KDD 2024, Barcelona, Spain, August 25-29, 2024*, Ricardo Baeza-Yates and Francesco Bonchi (Eds.). ACM, 3200–3211. https://doi.org/10.1145/3637528.3671944

[12] Shoujin Wang, Xiaofei Xu, Xiuzhen Zhang, Yan Wang, and Wenzhuo Song. 2022. Veracity-aware and Event-driven Personalized News Recommendation for Fake News Mitigation. In *Proceedings of the ACM Web Conference 2022* (Virtual Event, Lyon, France) *(WWW '22)*. Association for Computing Machinery, New York, NY, USA, 3673–3684. https://doi.org/10.1145/3485447.3512263

[13] Thomas Wolf, Lysandre Debut, Victor Sanh, Julien Chaumond, Clement Delangue, Anthony Moi, Pierric Cistac, Tim Rault, Rémi Louf, Morgan Funtowicz, et al. 2020. Transformers: State-of-the-art natural language processing. In *Proceedings of the 2020 conference on empirical methods in natural language processing: system demonstrations*. 38–45.

[14] Chuhan Wu, Fangzhao Wu, Suyu Ge, Tao Qi, Yongfeng Huang, and Xing Xie. 2019. Neural News Recommendation with Multi-Head Self-Attention. In *Proceedings of the 2019 Conference on Empirical Methods in Natural Language Processing and the 9th International Joint Conference on Natural Language Processing (EMNLP-IJCNLP)*, Kentaro Inui, Jing Jiang, Vincent Ng, and Xiaojun Wan (Eds.). Association for Computational Linguistics, Hong Kong, China, 6389–6394. https://doi.org/10.18653/v1/D19-1671