the effectiveness of all experts. (2) Among these experts, FINet contributes more to Item DT, while SimNet and IGNet contribute more to Box CTR. It confirms that the semantic relevance and information gain are more essential factors for guiding users to conduct extended readings, while the general feature interactions capture other useful information for predicting dwell time of items. (3) The multi-critic attention also helps to learn a better R3S model. We replace M3oE with an average pooling for feature aggregation from different experts. It implies that the combination of multiple experts should be carefully customized with M3oE in R3S.

Table 5: Ablation tests for R3S.

Ablation version	Item AUC	Box AUC
R3S	**0.7419**	**0.8101**
– Feature interaction network	0.7336	0.8057
– Similarity network	0.7367	0.8040
– Information gain network	0.7371	0.8037
– Multi-critic attention	0.7348	0.8038

6 CONCLUSION AND FUTURE WORK

In this work, we propose a novel task named recommendation suggestion for relevant items, and design R3S for real-time relevant box insertion. R3S consists of an Item recommender and a Box trigger, which uses an M3oE strategy to jointly combine multi-aspect factors including feature interaction, semantic relevance and information gain. The improvements in offline and online evaluations verify the effectiveness of R3S in relevant recommendation.

In the future, we will utilize more types of feature interactions between seed and target items, and conduct more sophisticated models to model the semantic relevance and information gain. We will also explore the joint training of recommendation suggestion and overall recommendation to better model delay costs. Other feedback mechanisms and product forms of recommendation suggestion should be investigated to further improve user's activeness in recommendation. We will also explore the possibility of applying R3S (or its M3oE, SimNet, IGNet modules) to other tasks.

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