For instance, users that have watched videos related to *The Great Wall* may also be interested in *Monument* or other ancient Chinese buildings like *Forbidden city*. Besides, users interested in history or tour are also willing to seek information of *Qin Dynasty* (when *The Great Wall* was built) or *Tourism inventory*. These nearest tags reflect not only semantic similarities on tags, but also user preferences and videos. We also conduct a quantitative analysis on 100 randomly-sampled top-frequent tags with human annotators, which shows that the percentage of diversified tag (the tag that has at least 3 tags belonging to different categories in top 5 nearest tags) is 89%.

Table 5: Examples of target tags with nearest tags.

Tag	Nearest tags
The Great Wall	Monument; World Cultural Heritage; Forbidden city; Qin Dynasty; Tourism inventory
Michelin star restaurant	Michelin chef; French red wine; Gourmet show; Spain Seafood Risotto; Japanese food
New energy vehicle	Hydrogen powered vehicle; Fuel consumption; Bao- jun; 4-wheel drive; Foreign car

5.7.2 Personalized Tag Ranking. Table 6 gives a real dynamic tag case for different users. User1 is a fan of N Jia (an actor) and loves variety shows (e.g., Go Champion!). User2 is crazy about basketball and its superstars like Jordan and O'Neal. User3 is simply interested in funny videos with no preferences in specific actors or stars. GraphTR well captures these user preferences and explicitly shows different personalized tags to highlights different contents. Hence, all users are attracted and willing to click tags and watch this video.

Table 6: Tag ranking results for different users.

Video title	Shaquille O'Neal performs his Dream shake and N Jia imitates the movement comically.
User1 tags	N Jia; Go Champion!; Variety show in China
User2 tags	Shaquille O'Neal; Basketball; Variety show
User3 tags	Imitation; Funny moment; Variety show

6 CONCLUSION AND FUTURE WORK

In this paper, we highlight the tag ranking in tag-enhanced video recommendation. We propose a novel GraphTR, which creatively uses a new HFIN model to combine transformer, GraphSAGE and FM for node aggregation on heterogeneous networks. GraphTR utilizes rich information in video-related behaviors and profiles to learn user preferences on tags. Both online and offline evaluations confirm the significant improvements in tag and video related metrics. GraphTR has been deployed on a real-world tag-enhanced video recommendation system in WeChat Top Stories.

In future, more interactions like social relations and tag-related behaviors could be considered in network construction. Weighted edges could also be used in our network. Moreover, we will design more sophisticated NRL models and online ranking models with supervised learning to improve the performances, and enhance the user nodes with more sophisticated representations.

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