HieRec: Hierarchical User Interest Modeling for Personalized News Recommendation

Tao Qi[1], Fangzhao Wu[2], Chuhan Wu[1], Peiru Yang[1], Yu Yang[2],

Xing Xie[2], Yongfeng Huang[1]

[1]Department of Electronic Engineering & BNRist, Tsinghua University, Beijing 100084, China

[2]Microsoft Research Asia, Beijing 100080, China

taoqi.qt@gmail.com

Personalized News Recommendation

- Online news platforms become popular for people to read news
- News recommendation is important for online news platforms

Personalized News Recommendation

- User interest modeling is the core task of news recommendation
- Most existing methods encode user interest via a single embedding
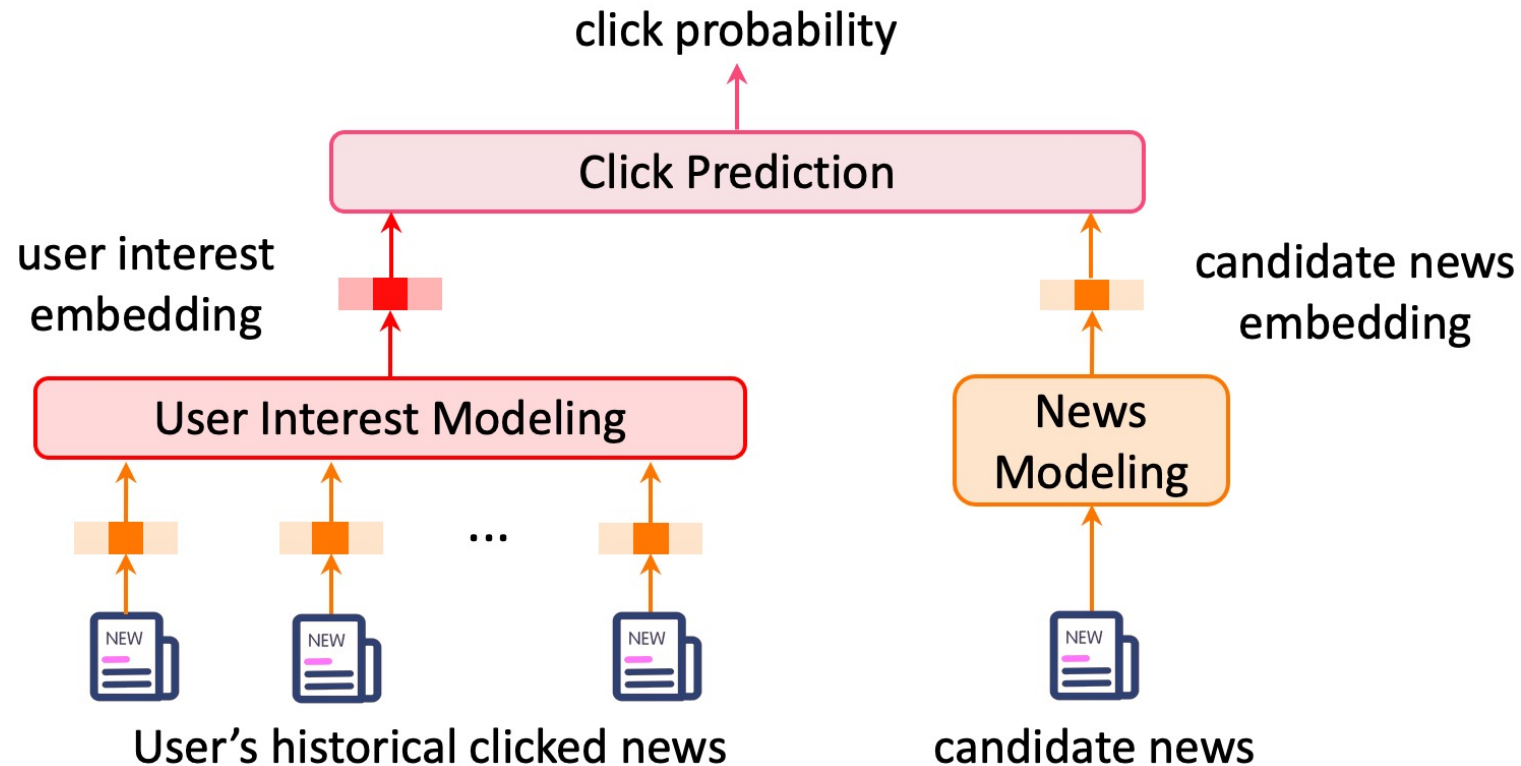
Framework of mainstream methods

Challenge

- User interest is usually diverse and multi-grained
  - A single embedding is difficult to effectively model user interest in different aspects and granularities

ID	Click	Topic	Subtopic	Title
1	✓	Movies	Celebrity	Ben Affleck breaks silence after "slip" in sobriety.
2	✓	Sports	Football	Myles Garrett suspended indefinitely by the NFL.
3	✓	Sports	Football	Jaguars veteran cornerback Josh Robinson retires suddenly.
4	✗	Sports	Basketball	Trey Lyles off to a good start with Spurs.
5	✗	Sports	Golf	Can an amateur win again on the PGA Tour?
6	✓	Finance	Stocks	3M is a dog of the Dow -- and it may not get better in 2020.
7	✓	Finance	Taxes	New Trump tax documents show major inconsistencies.
8	✓	Health	Fitness	This guy lost 30 pounds and gained a rock-hard pack.
9	✗	Lifestyle	Food	Candy Corn has tired to the Metro East.

Historical click and non-click behaviors of an example user.

HieRec

- Overall framework
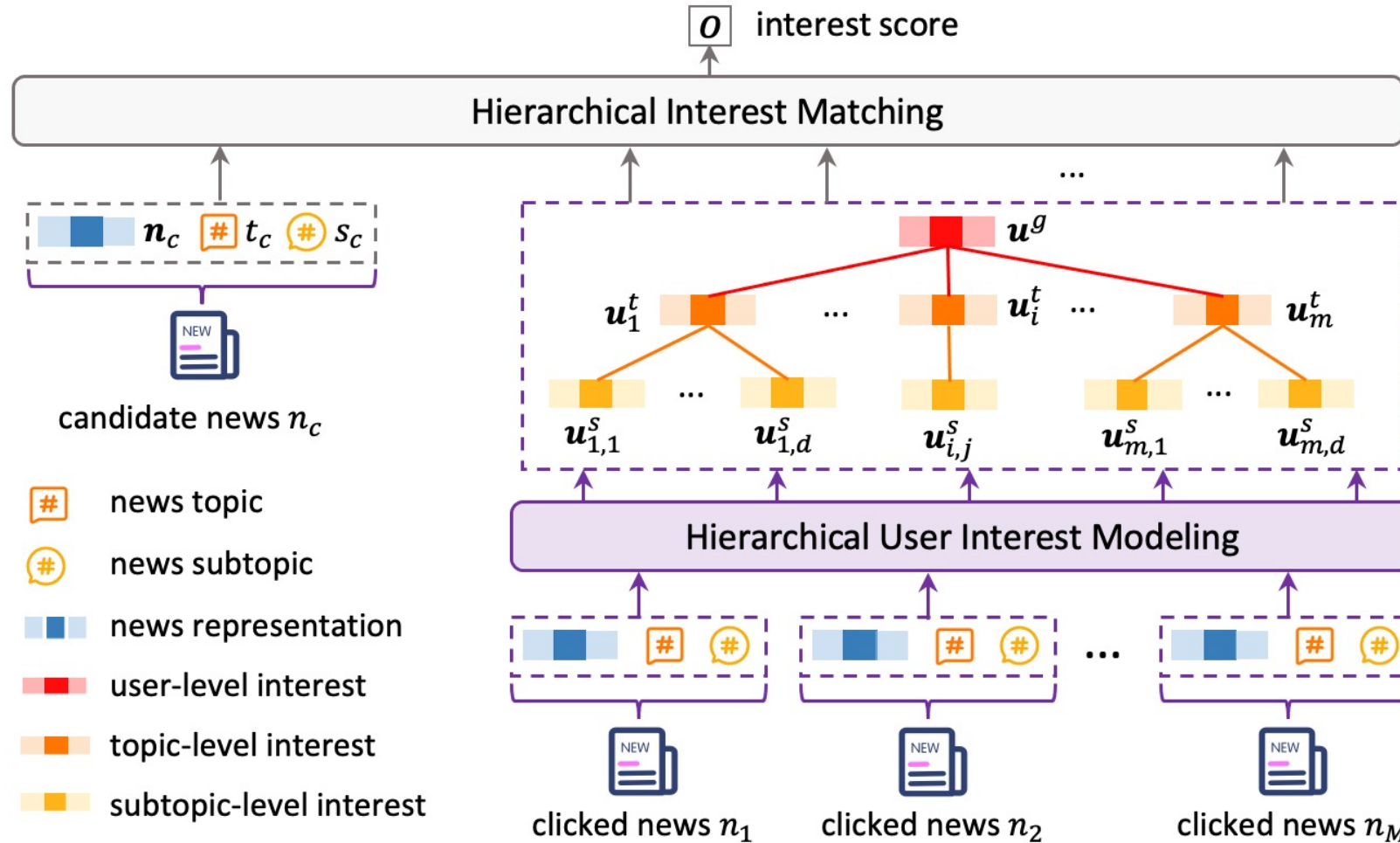
Hierarchical User Interest Modeling

- Learn hierarchical user interest representation to model diverse and multi-grained user interest

Hierarchical User Interest Modeling

- Learn hierarchical user interest representation to model diverse and multi-grained user interest

Hierarchical User Interest Modeling

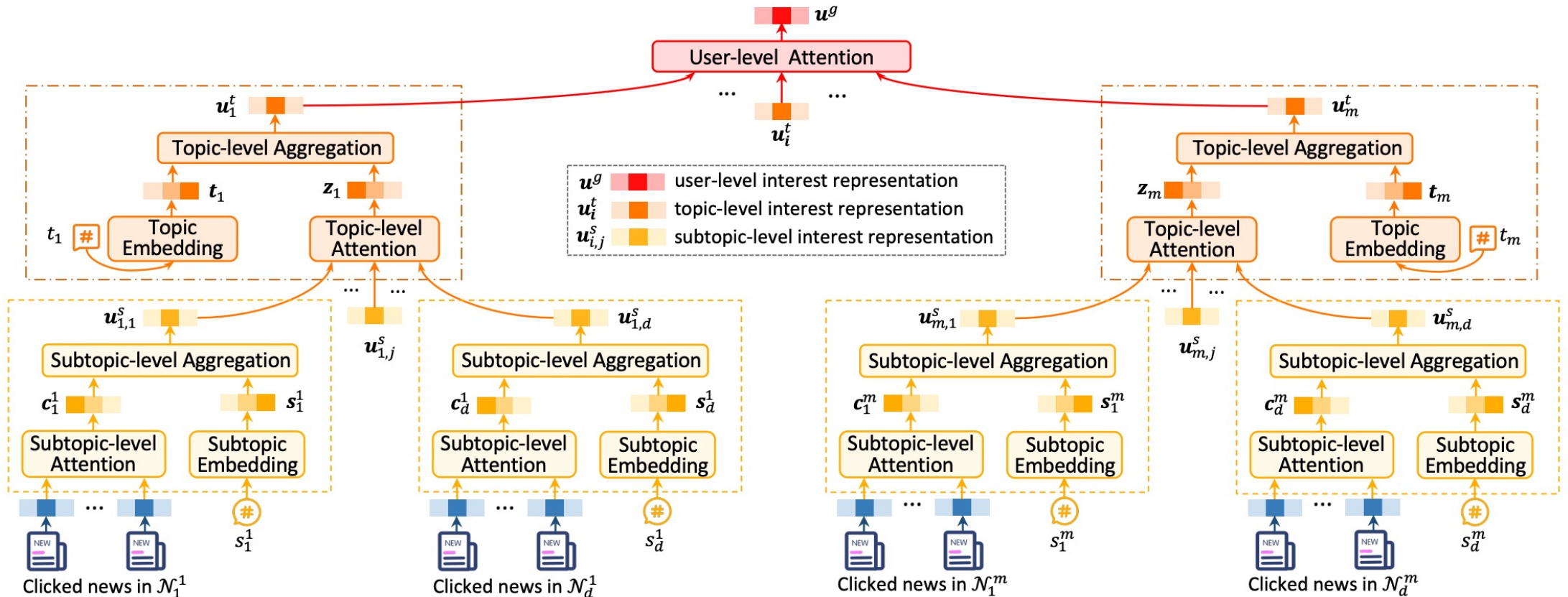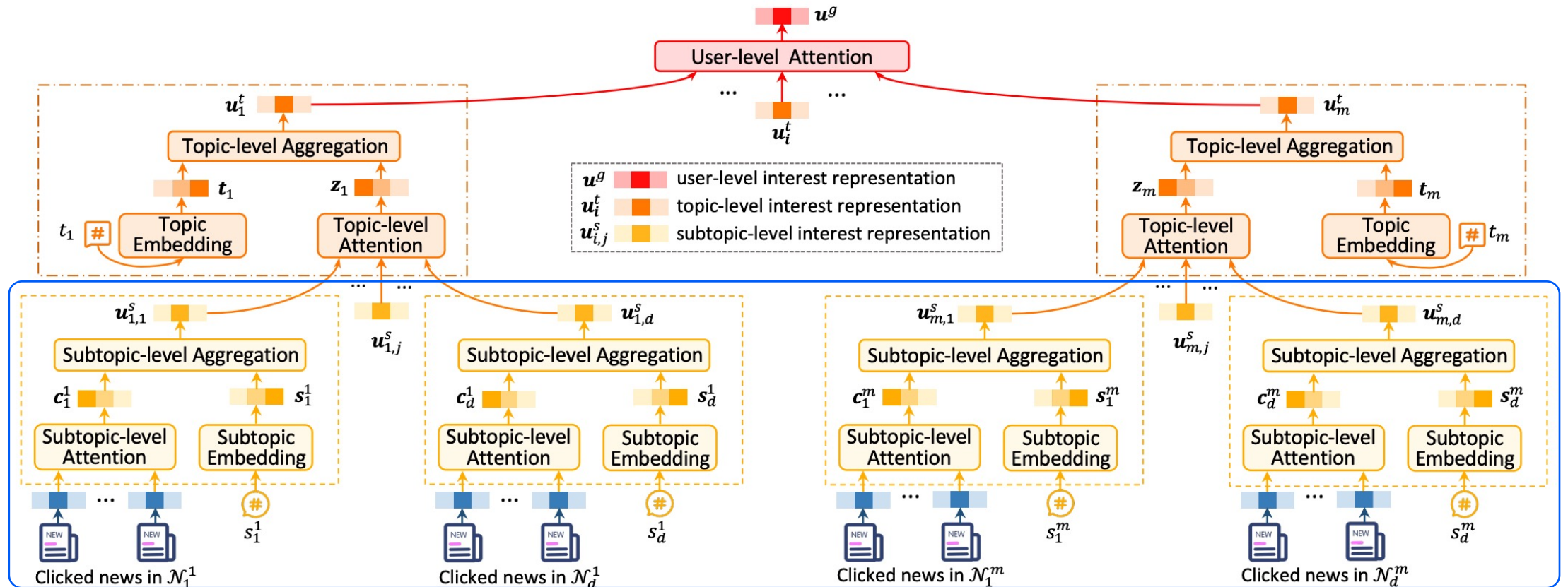- Learn hierarchical user interest representation to model diverse and multi-grained user interest

Hierarchical User Interest Modeling

- Learn hierarchical user interest representation to model diverse and multi-grained user interest
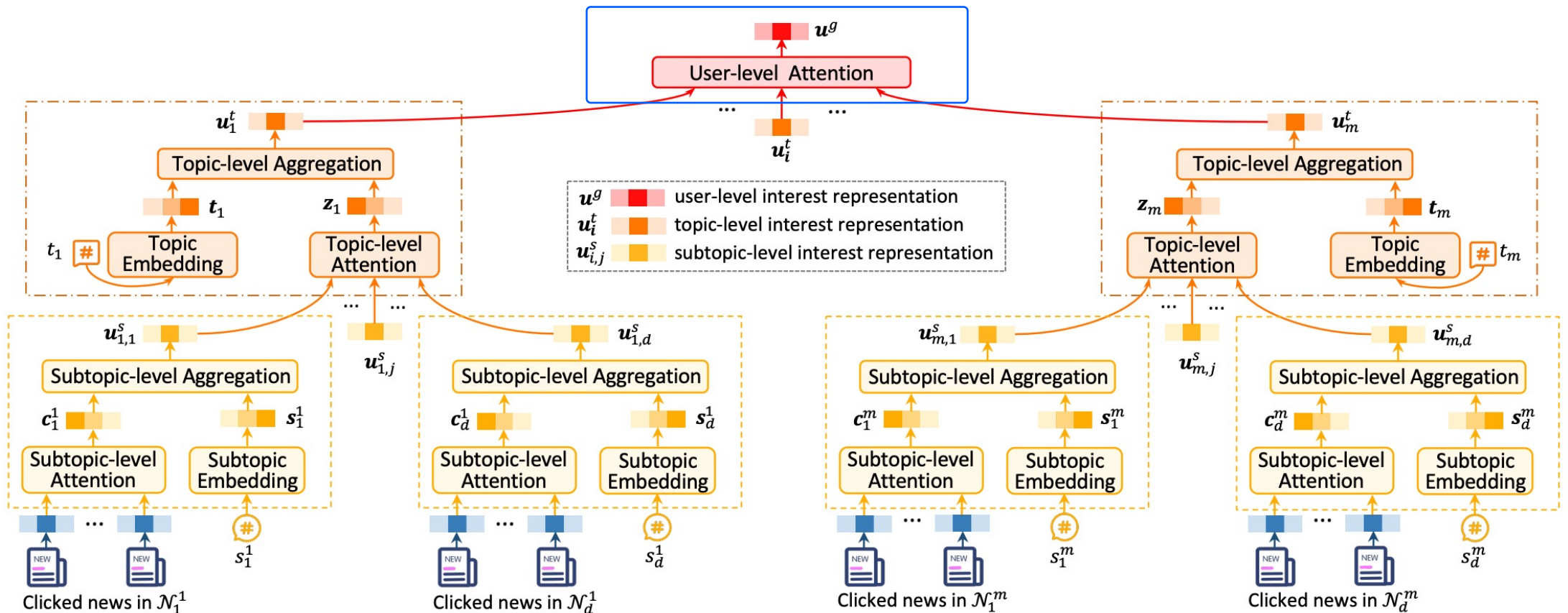
Hierarchical Interest Matching

- Match candidate news and user from different interest granularities
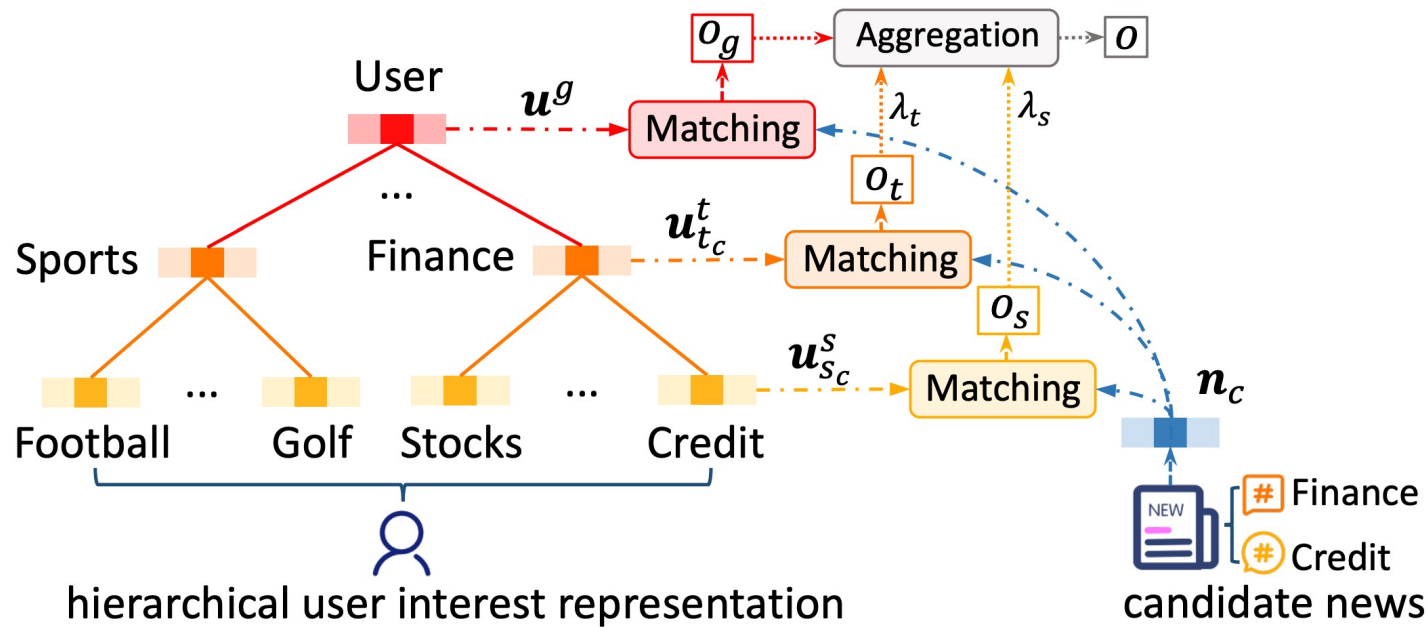
- Subtopic-level: $o_s = \boldsymbol{n}_c^T \cdot \boldsymbol{u}_{s_c}^t$
- Topic-level: $o_t = \boldsymbol{n}_c^T \cdot \boldsymbol{u}_{t_c}^t$
- User-level: $o_g = \boldsymbol{n}_c^T \cdot \boldsymbol{u}^g$
- Overall interest score:

$$o = \lambda_t o_t + \lambda_s o_s + (1 - \lambda_t - \lambda_s) o_g$$

News Encoder

- Learn news representation from both news texts and entities
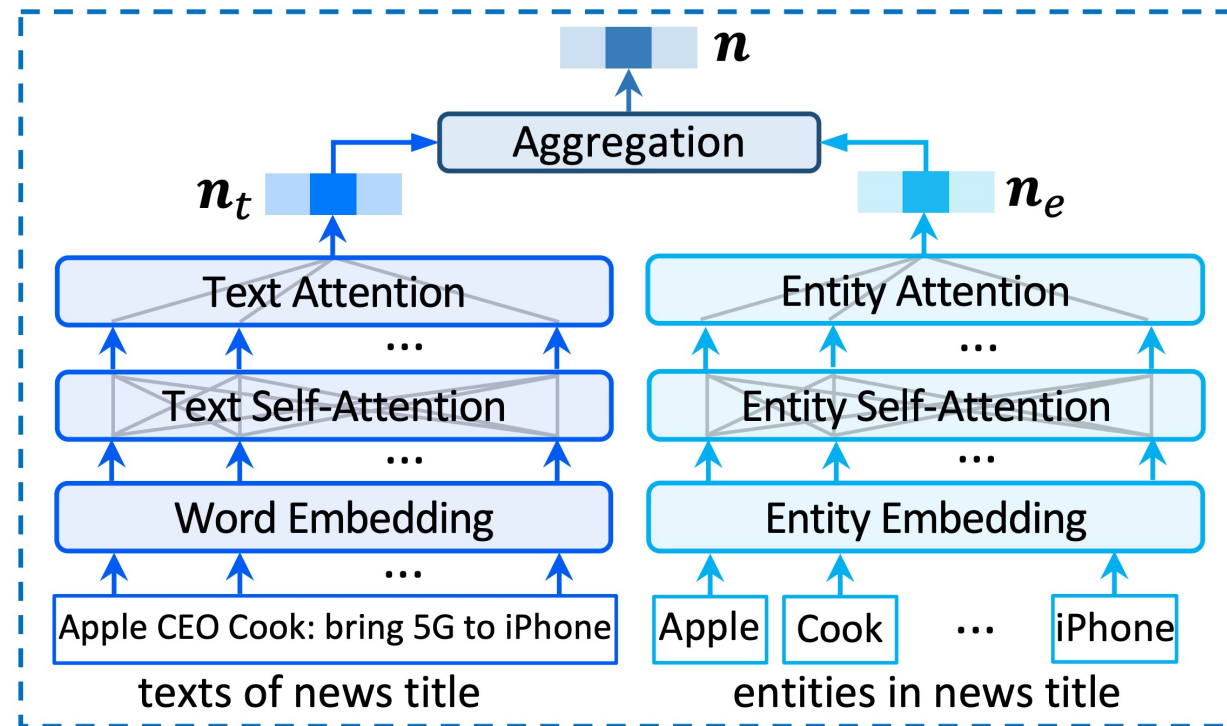
Datasets

- MIND:
  - A public news recommendation dataset based on Microsoft News
  - Constructed by user logs from 2019.10.19 to 2019.11.15 (6 weeks)
- Feeds:
  - A private news recommendation dataset
  - Constructed by user logs on a news feeds in Microsoft
  - Constructed by user logs from 2020.01.23 to 2020.04.23 (13 weeks)

	# News	# Topics	# Subtopics	# Users	# Clicks
MIND	65,238	18	270	94,057	347,727
Feeds	1,126,508	28	-	50,605	473,697

Performance Comparison

	MIND				Feeds			
	AUC	MRR	nDCG@5	nDCG@10	AUC	MRR	nDCG@5	nDCG@10
EBNR	61.62±0.15	28.07±0.18	30.55±0.22	37.07±0.21	63.48±0.32	28.01±0.18	32.05±0.23	37.64±0.22
DKN	63.99±0.23	28.95±0.08	31.73±0.14	38.38±0.17	62.94±0.22	28.05±0.26	32.15±0.34	37.68±0.36
DAN	64.68±0.13	29.78±0.13	32.63±0.21	39.27±0.15	62.67±0.49	27.75±0.34	31.74±0.44	37.42±0.43
NAML	64.30±0.30	29.81±0.17	32.64±0.24	39.11±0.20	64.48±0.24	28.99±0.13	33.37±0.16	38.90±0.18
NPA	64.28±0.53	29.64±0.33	32.28±0.37	38.93±0.39	64.02±0.63	28.71±0.39	33.01±0.50	38.55±0.47
LSTUR	65.68±0.35	30.44±0.39	33.49±0.45	39.95±0.39	65.01±0.13	29.28±0.06	33.74±0.09	39.16±0.11
NRMS	65.43±0.15	30.74±0.18	33.13±0.17	39.66±0.15	65.27±0.19	29.40±0.15	33.89±0.16	39.34±0.15
KRED	65.89±0.31	30.80±0.32	33.78±0.27	40.23±0.26	65.51±0.11	29.57±0.06	34.04±0.06	39.60±0.05
GNewsRec	65.91±0.21	30.50±0.21	33.56±0.21	40.13±0.18	65.23±0.16	29.36±0.11	33.87±0.13	39.44±0.12
FIM	64.65±0.14	29.70±0.17	32.51±0.25	39.30±0.16	65.41±0.23	29.57±0.18	34.08±0.25	39.56±0.23
HieRec	**67.95**±0.14	**32.87**±0.08	**36.36**±0.07	**42.53**±0.10	**66.23**±0.10	**29.82**±0.11	**34.42**±0.13	**39.94**±0.13

Effectiveness in User Modeling

|	AUC	MRR	nDCG@5	nDCG@10
NAML	65.81±0.27	30.89±0.21	34.16±0.30	40.55±0.24
DKN	66.03±0.27	31.17±0.25	34.47±0.33	40.85±0.29
EBNR	65.90±0.27	30.86±0.21	34.14±0.30	40.58±0.24
LSTUR	66.02±0.14	31.16±0.15	34.37±0.15	40.83±0.12
GNewsRec	66.16±0.14	31.19±0.05	34.40±0.09	40.82±0.10
NRMS	66.04±0.21	31.20±0.19	34.53±0.22	40.89±0.18
HieRec	**67.95**±0.14	**32.87**±0.08	**36.36**±0.07	**42.53**±0.10

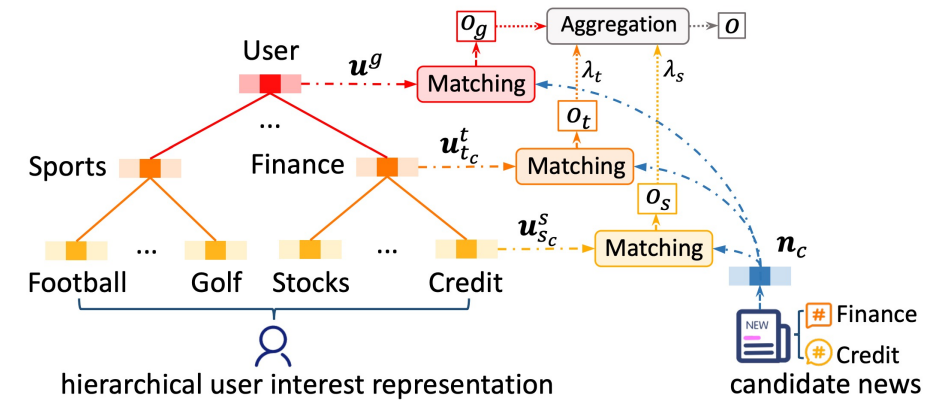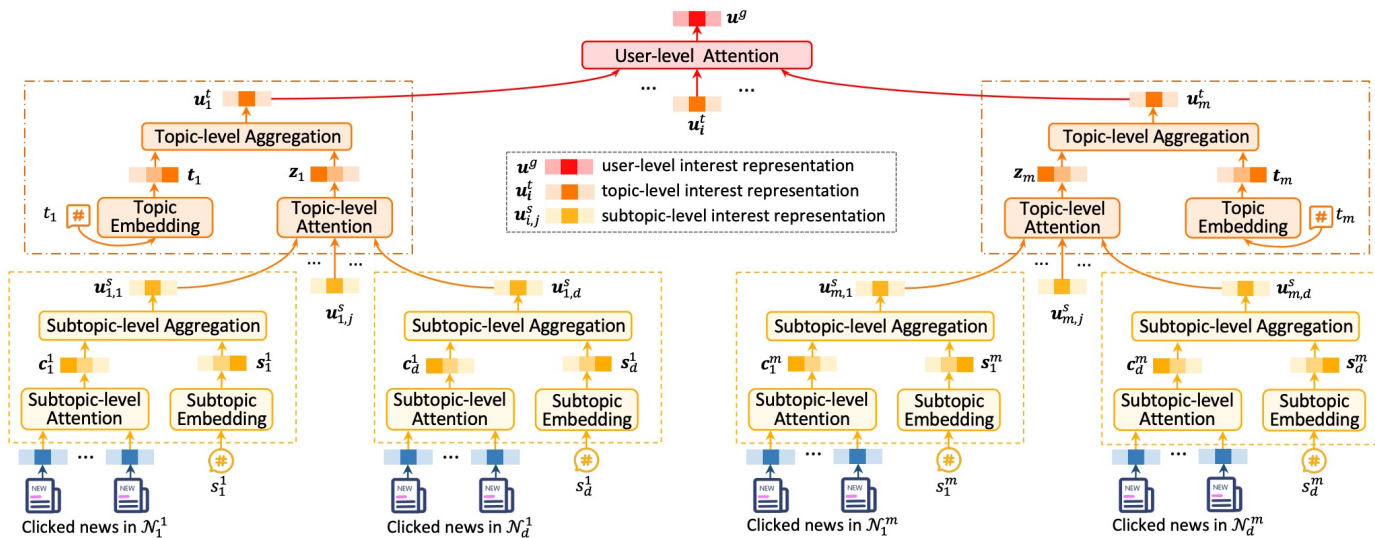# Performance on News Recall
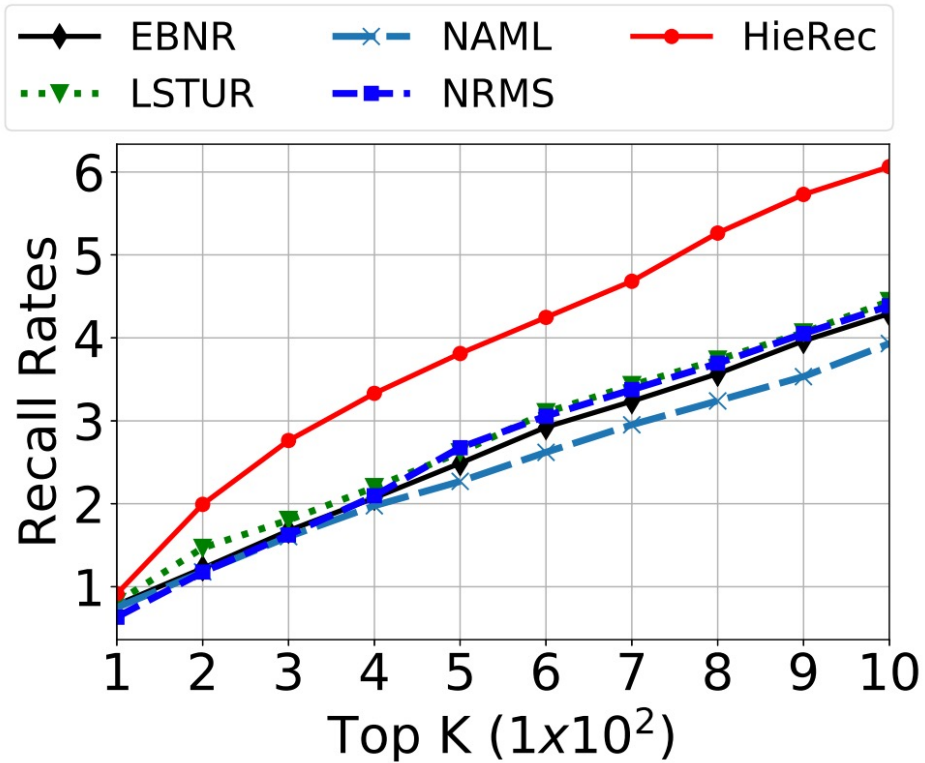
Recall rates
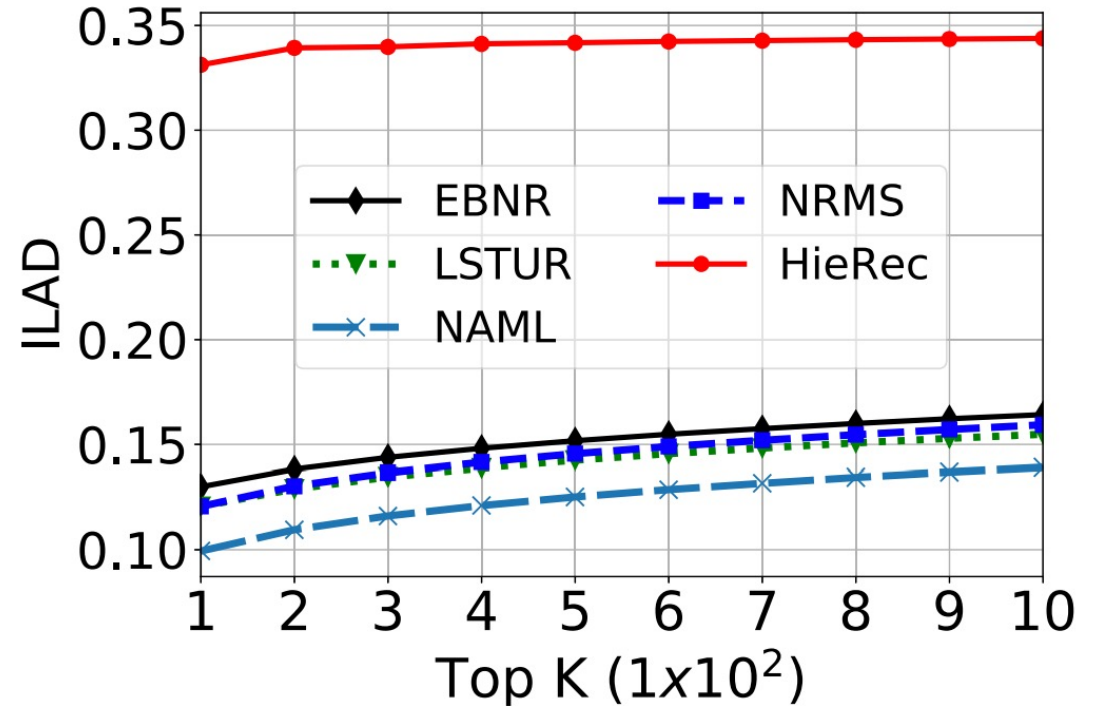
Recall diversity

Ablation study
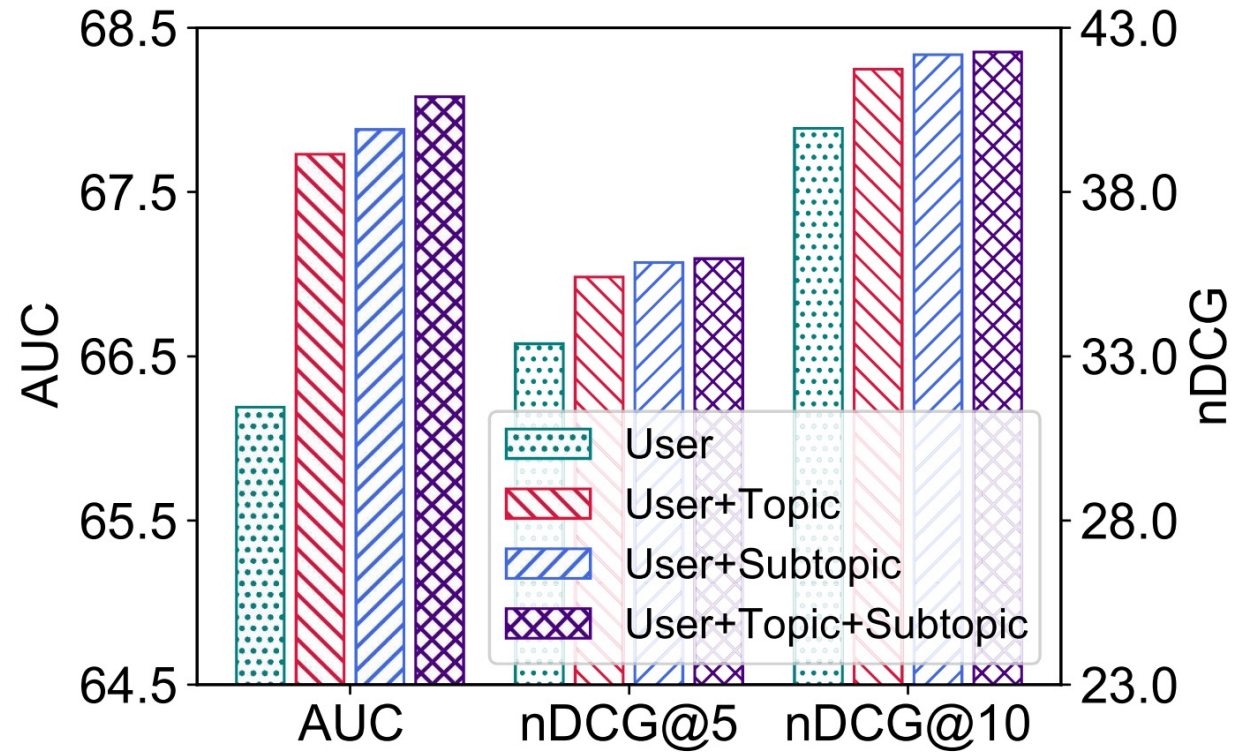
Conclusion

- A HieRec model for news recommendation which can model diverse and multi-grained user interest in news
  - Hierarchical user interest modeling framework
  - Hierarchical user interest matching framework

- Improve accuracy and diversity of news recommendation

Tao Qi

taoqi.qt@gmail.com