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Personalized News Recommendation with Knowledge-aware Interactive Matching

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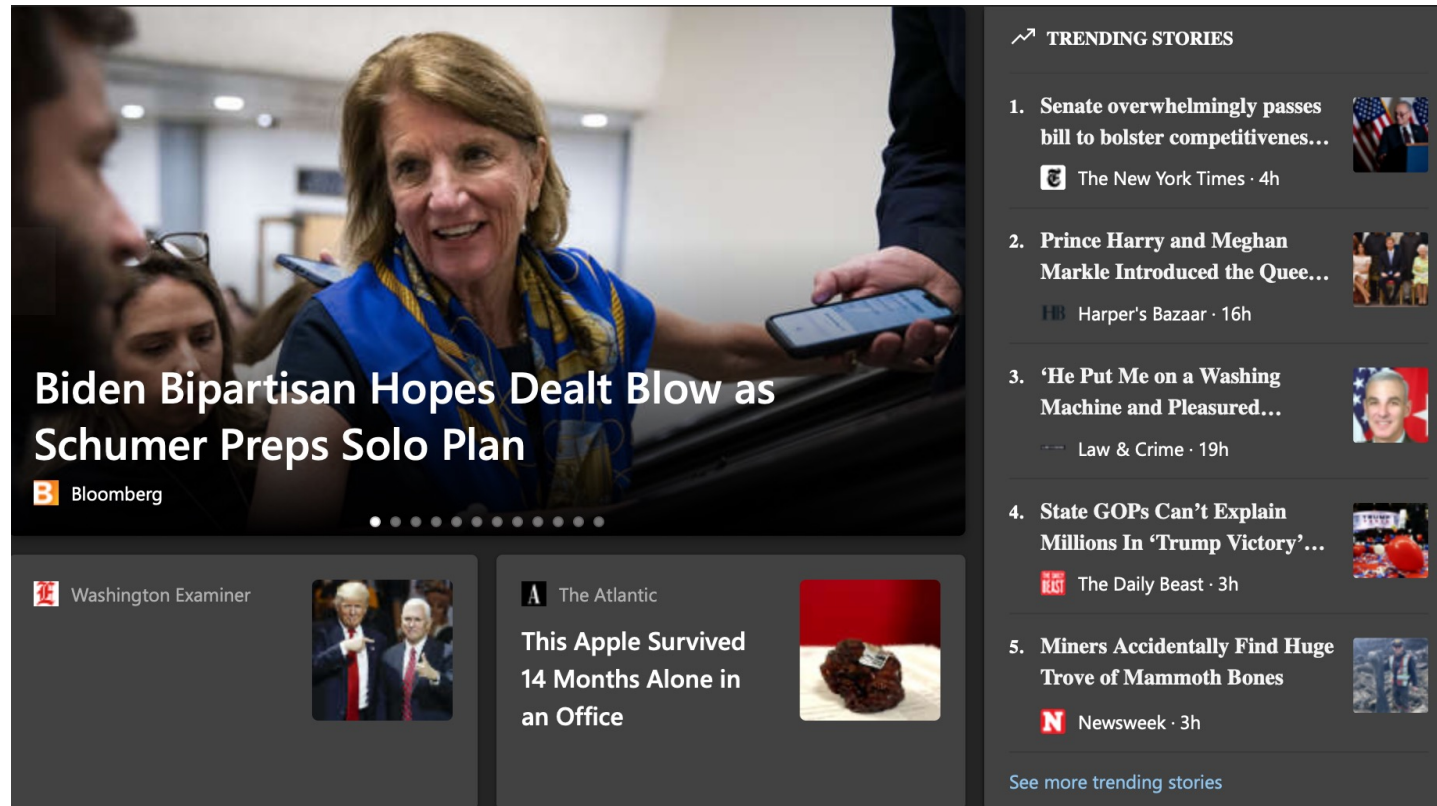
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Personalized News Recommendation

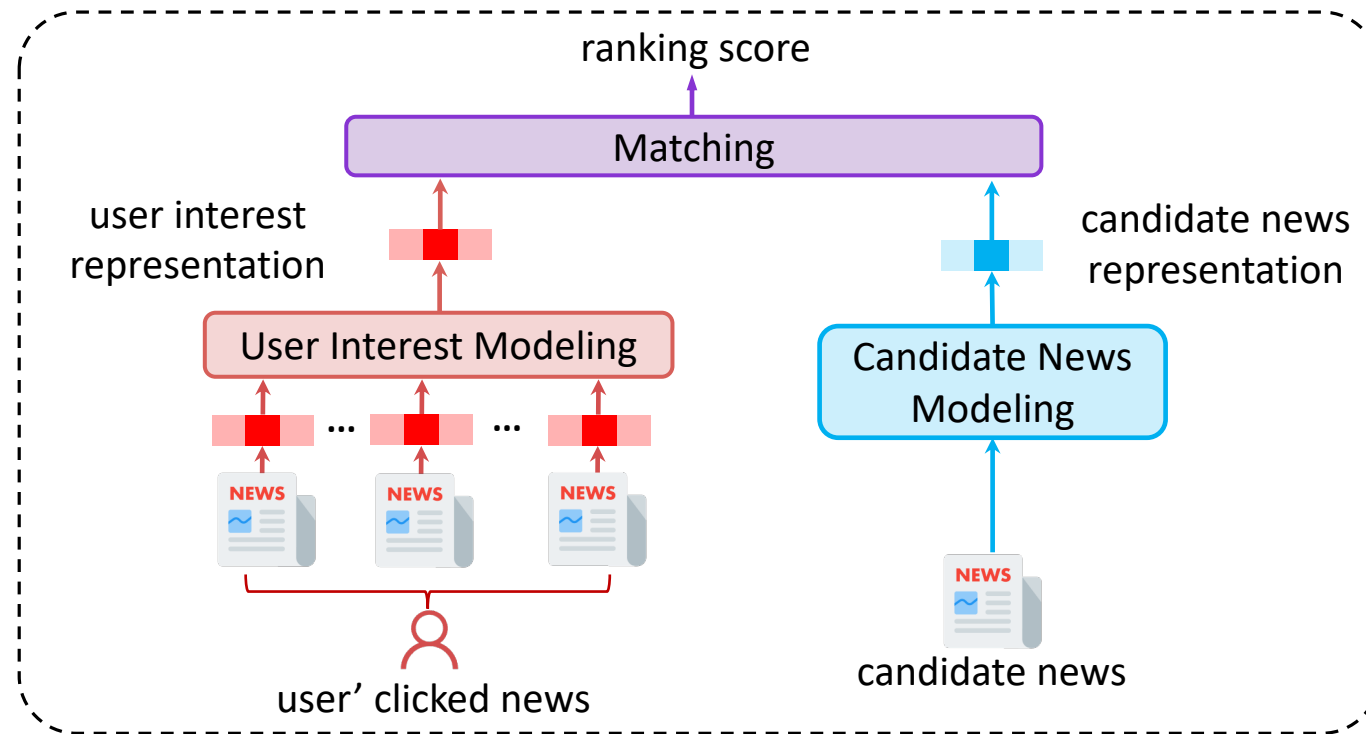
- Important for improving user experience on online news platforms
 - e.g., Microsoft News, Apple News, and Google News



The screenshot displays a news recommendation interface. The main article features a photo of a woman in a blue vest and a yellow scarf, with the headline "Biden Bipartisan Hopes Deal Blow as Schumer Preps Solo Plan" and the Bloomberg logo. Below this are three smaller article recommendations: "Washington Examiner" with a photo of two men, "The Atlantic" with the headline "This Apple Survived 14 Months Alone in an Office" and a photo of an apple, and "The Daily Beast" with a photo of a red object. To the right, a "TRENDING STORIES" section lists five items: 1. "Senate overwhelmingly passes bill to bolster competitiveness..." from The New York Times (4h); 2. "Prince Harry and Meghan Markle Introduced the Queen..." from Harper's Bazaar (16h); 3. "'He Put Me on a Washing Machine and Pleasured..." from Law & Crime (19h); 4. "State GOPs Can't Explain Millions In 'Trump Victory'..." from The Daily Beast (3h); 5. "Miners Accidentally Find Huge Trove of Mammoth Bones" from Newsweek (3h). A "See more trending stories" link is at the bottom.

Personalized News Recommendation

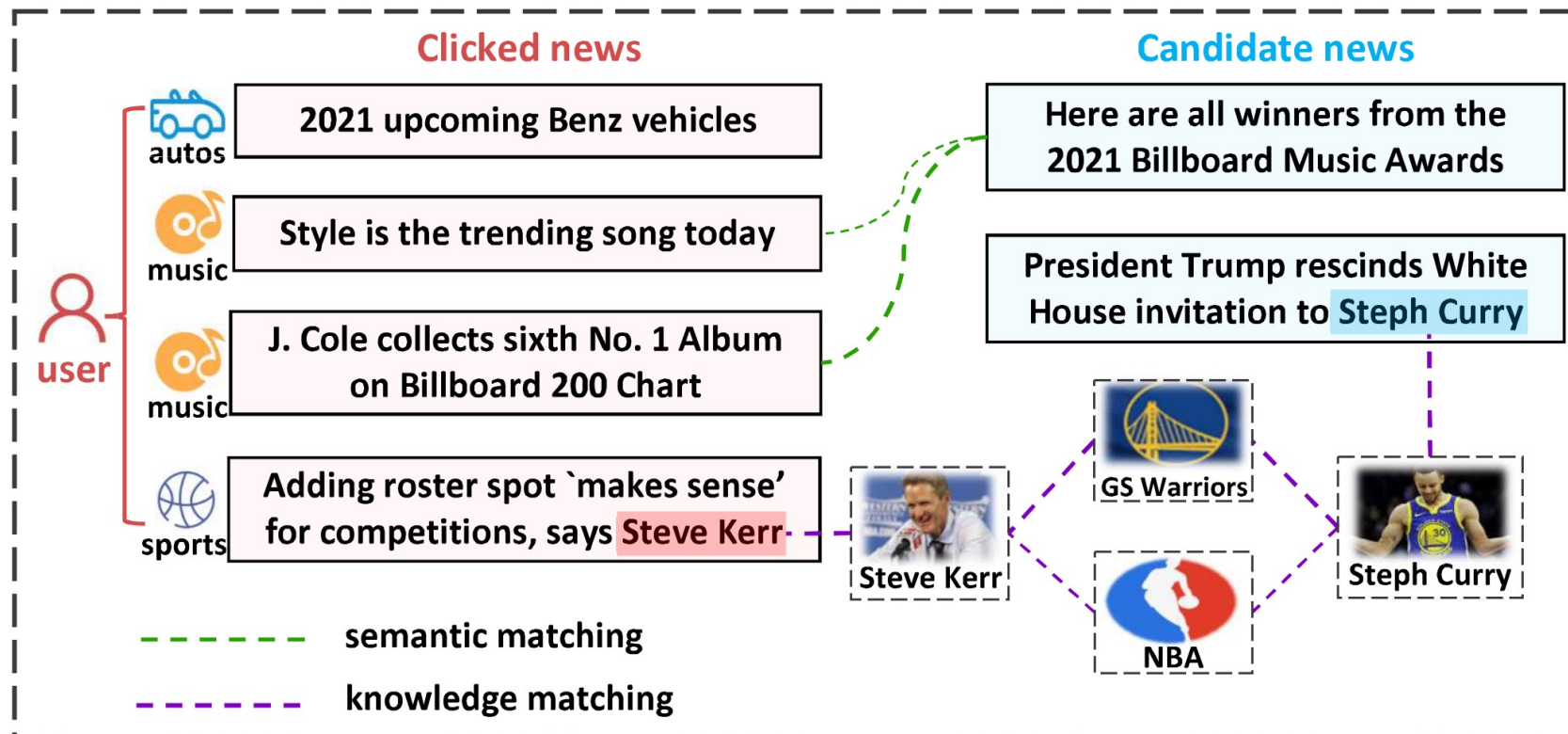
- Interest matching is the core task of personalized news recommendation
- Most existing methods model user interests and candidate news independently
 - e.g., NAML, NRMS, LSTUR



Mainstream Personalized News Recommendation Methods

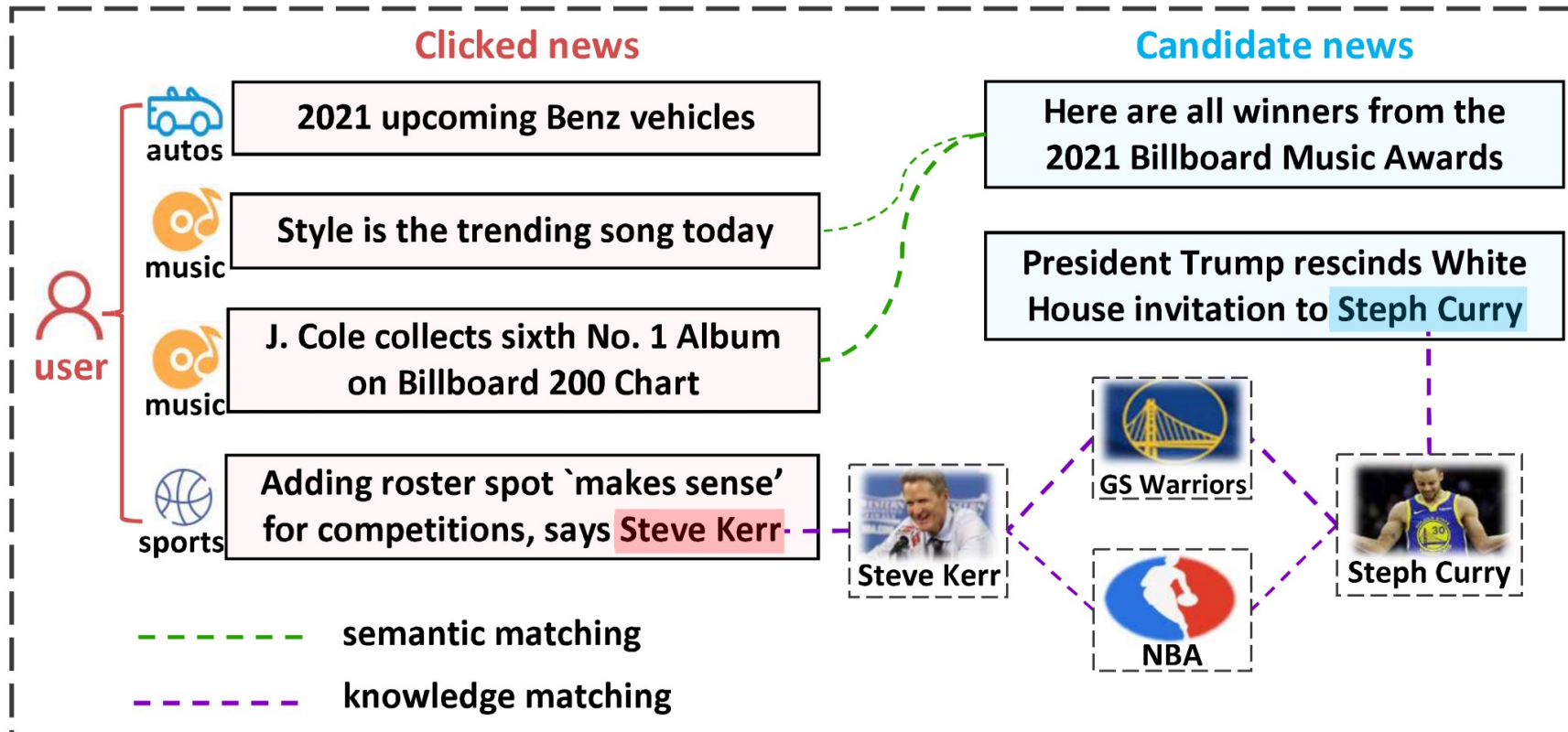
Challenges

- User interests are usually very diverse
- Candidate news may cover multiple entities and aspects
- Independent modeling of them is not optimal for interest matching



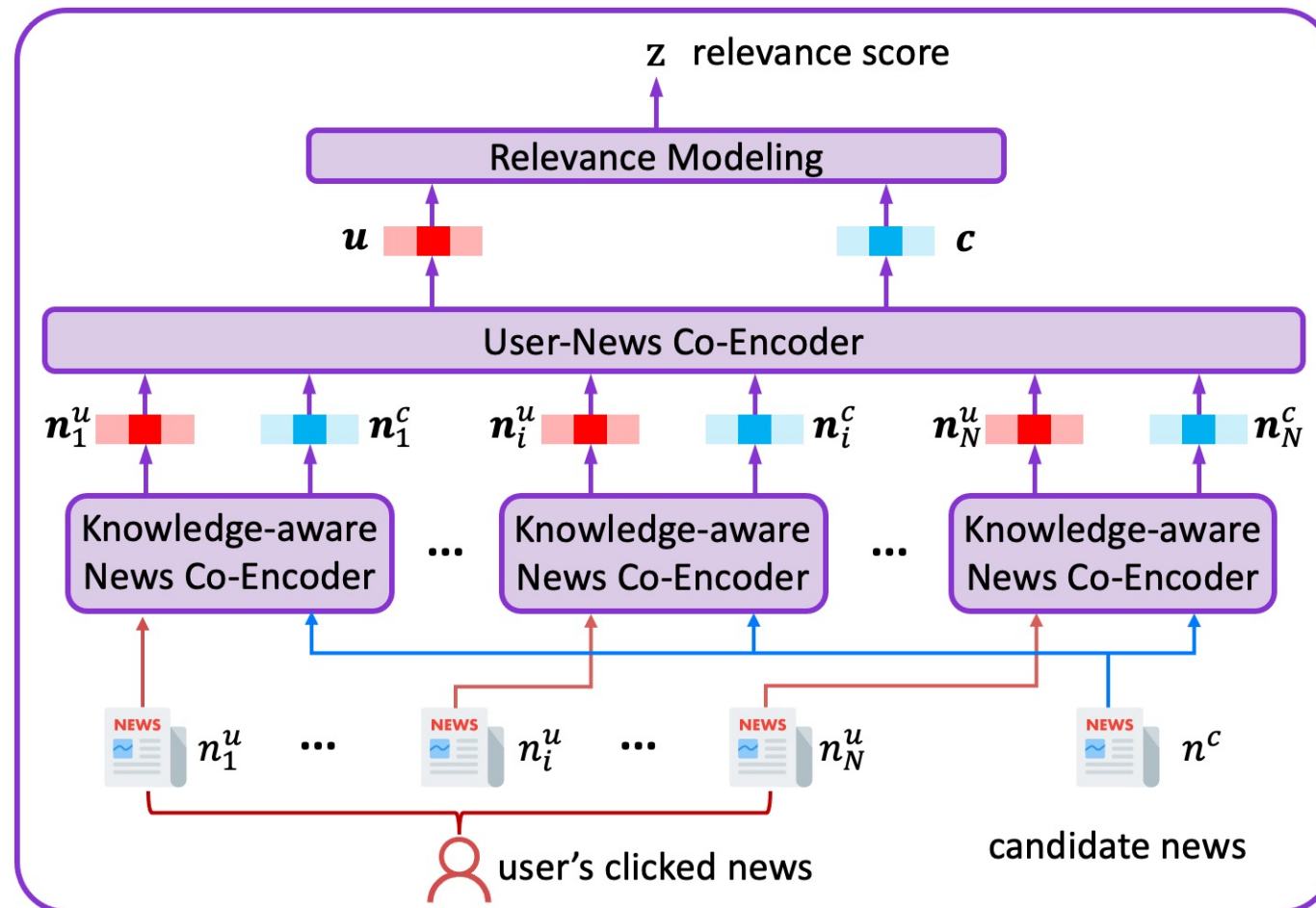
Motivation

- Model user interests and candidate news interactively
- Matching of clicked news and candidate news is helpful for interest matching
 - Knowledge-level matching, semantic-level matching



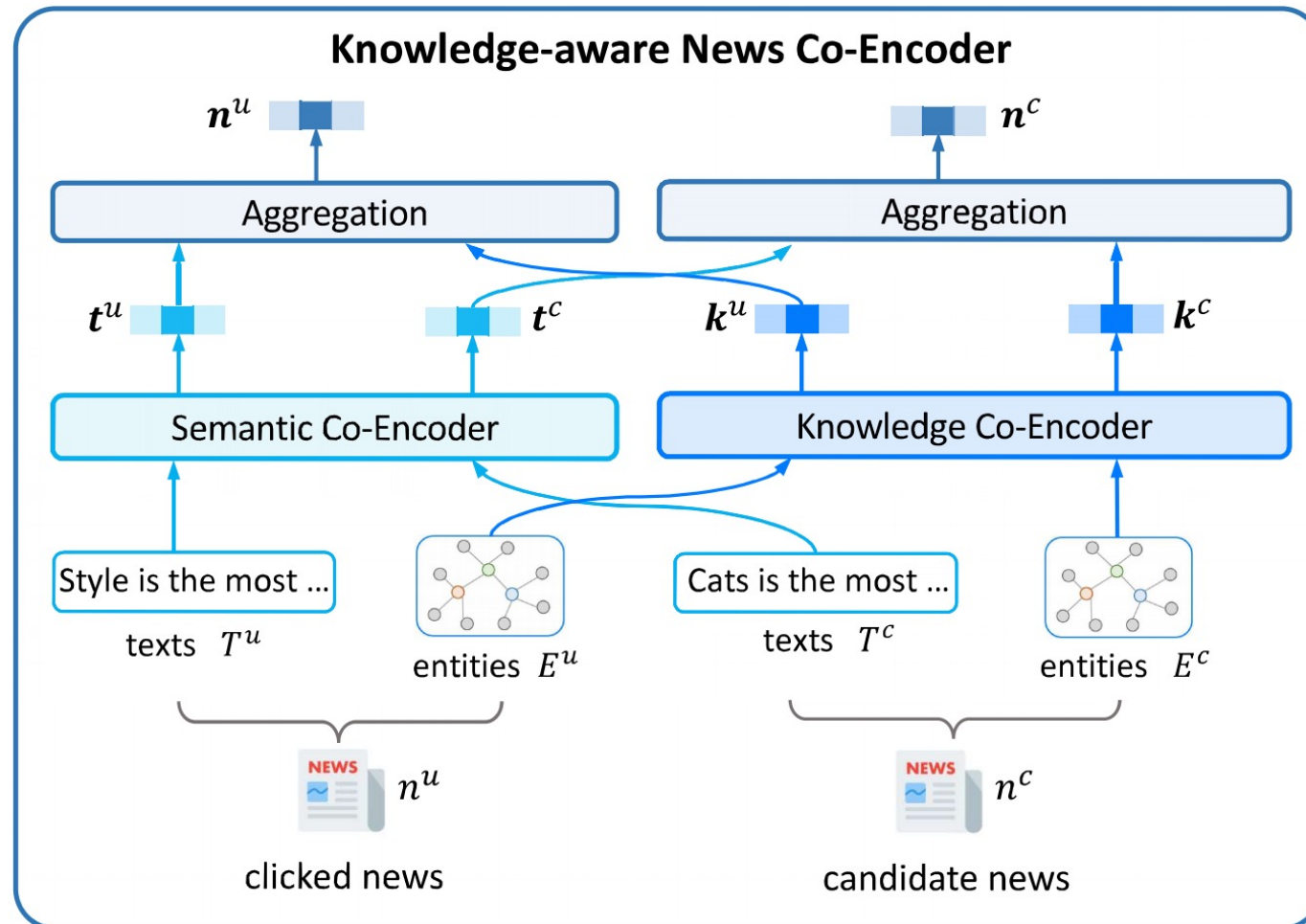
Knowledge-aware Interactive Matching: KIM

- Personalized news recommendation with knowledge-aware interactive matching



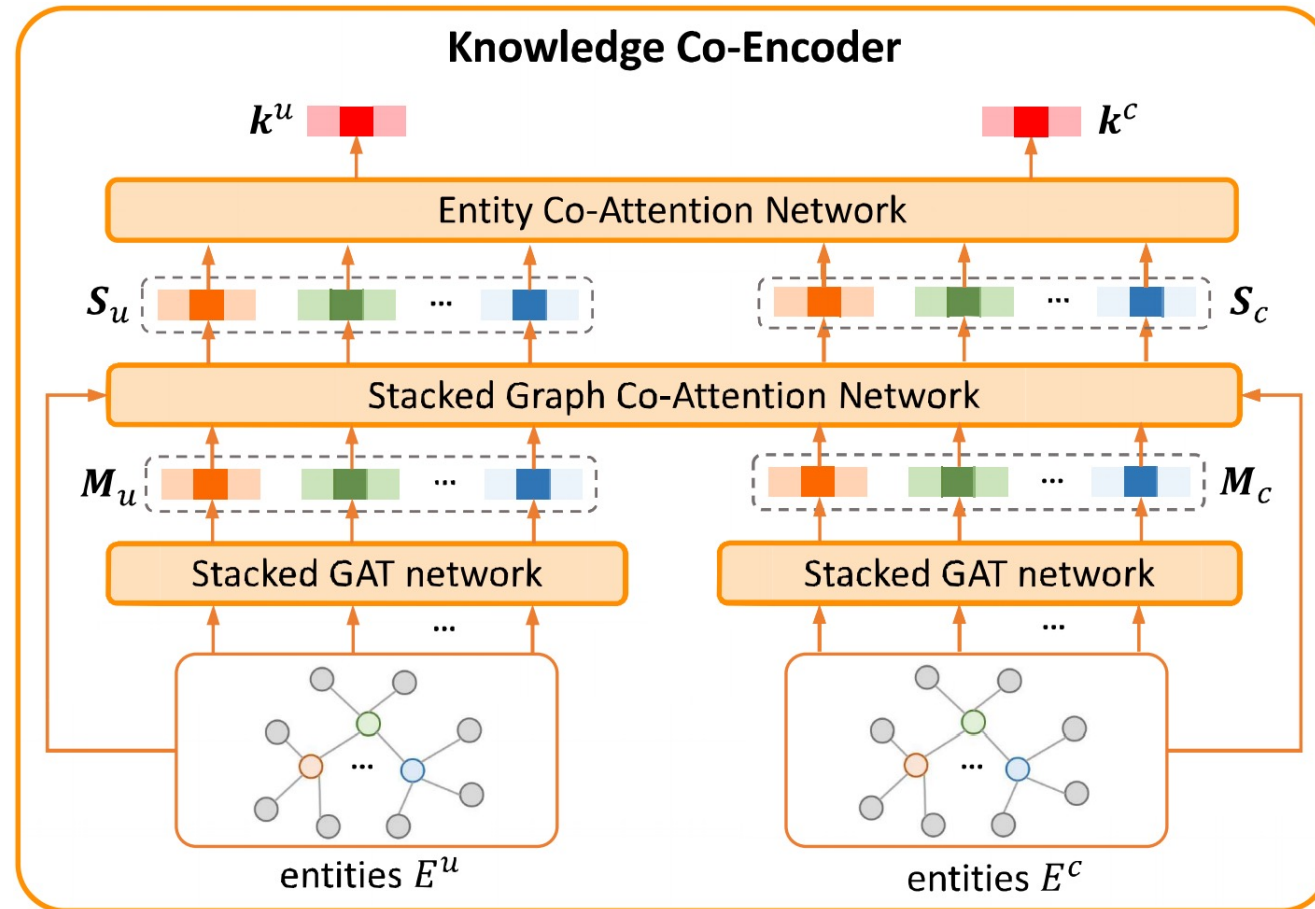
Knowledge-aware News Co-Encoder

- Interactively model clicked news and candidate news



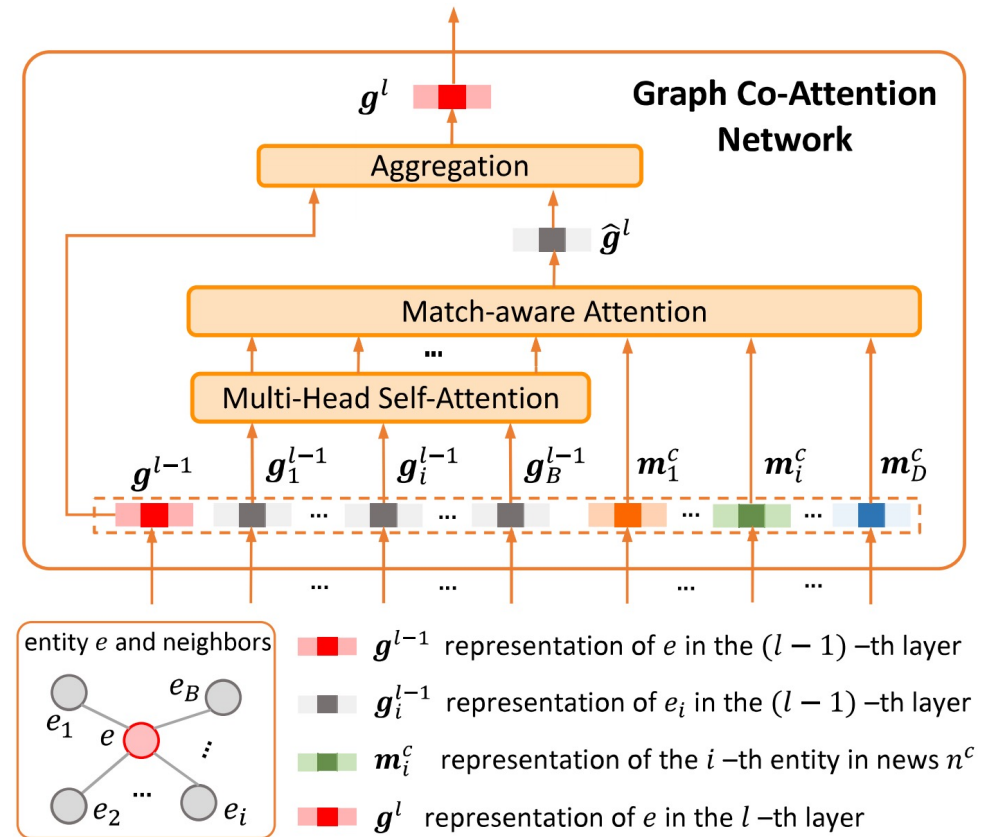
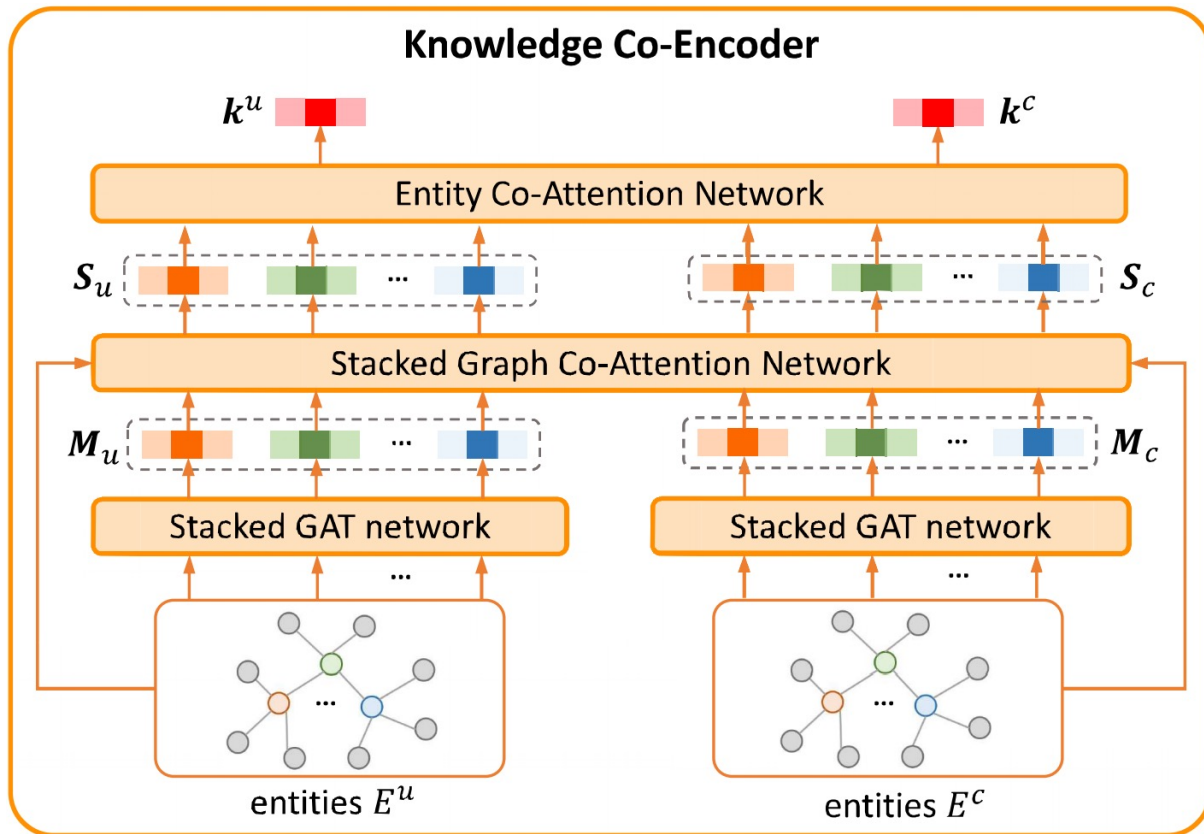
Knowledge Co-Encoder

- Interactively model knowledge relatedness of clicked news and candidate news



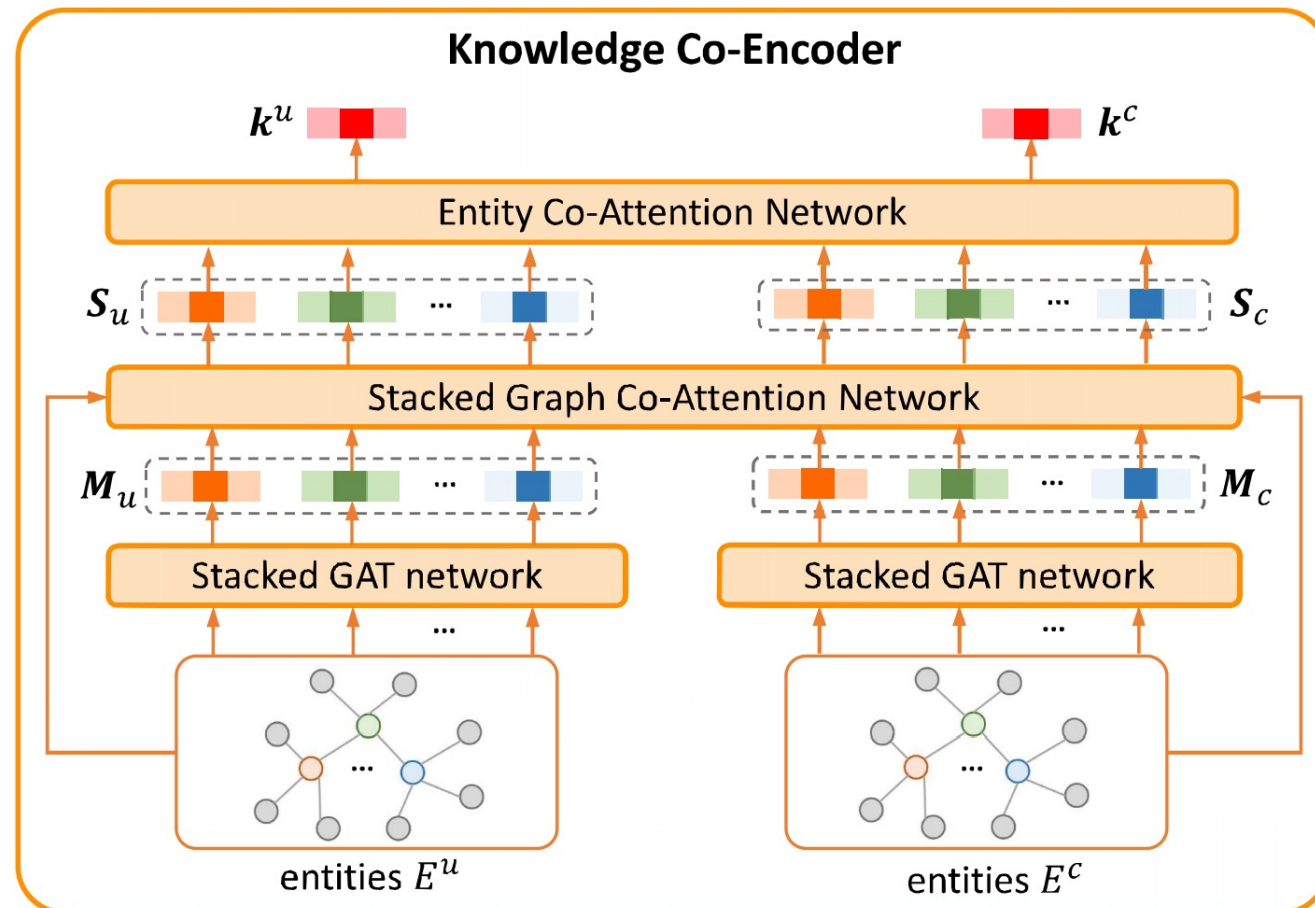
Knowledge Co-Encoder

- Stacked Graph Co-Attention Network
 - Interactively model entities in clicked news and candidate news



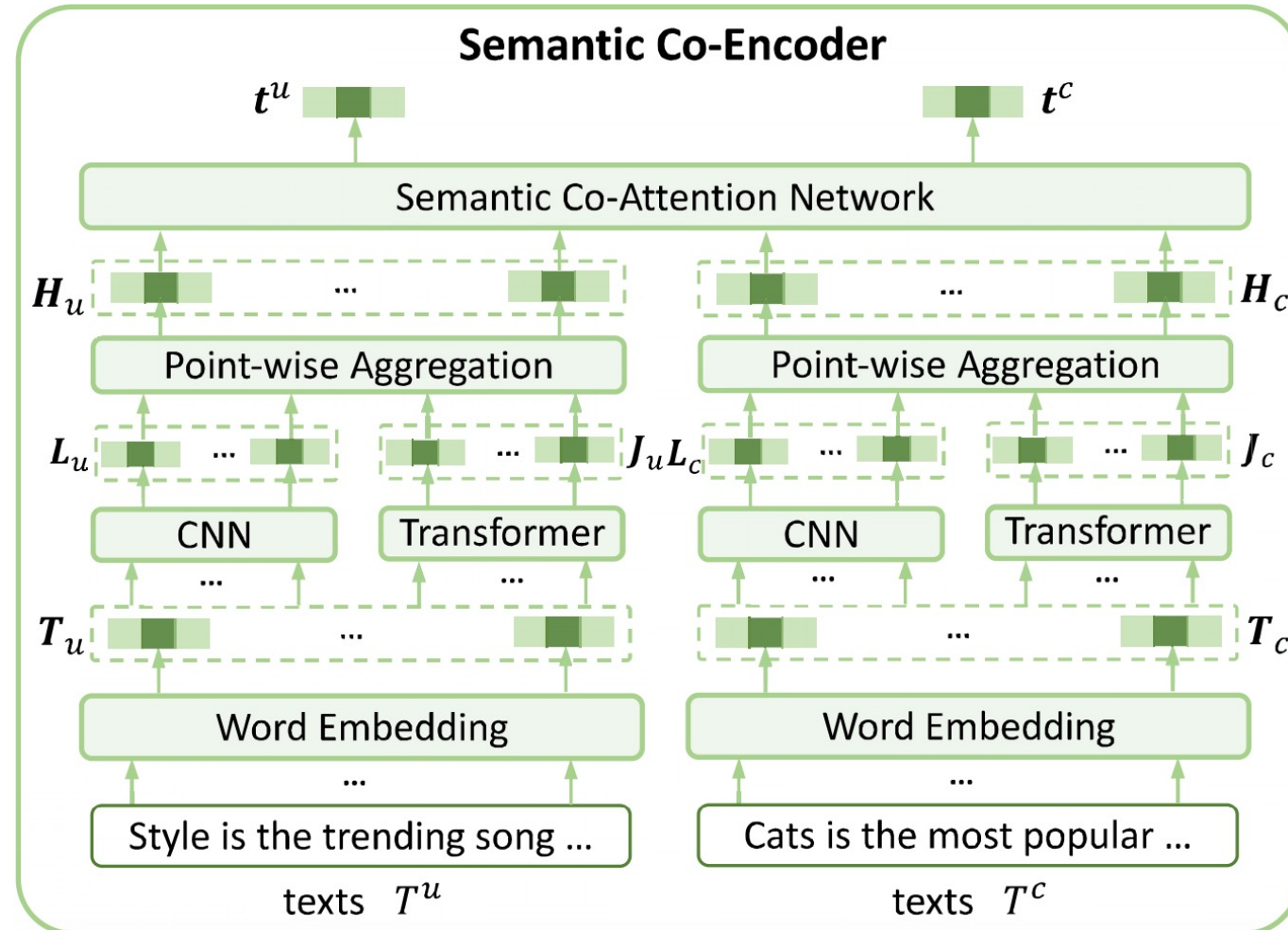
Knowledge Co-Encoder

- Entity Co-Attention Network
 - Model relatedness of entities in clicked news and candidate news



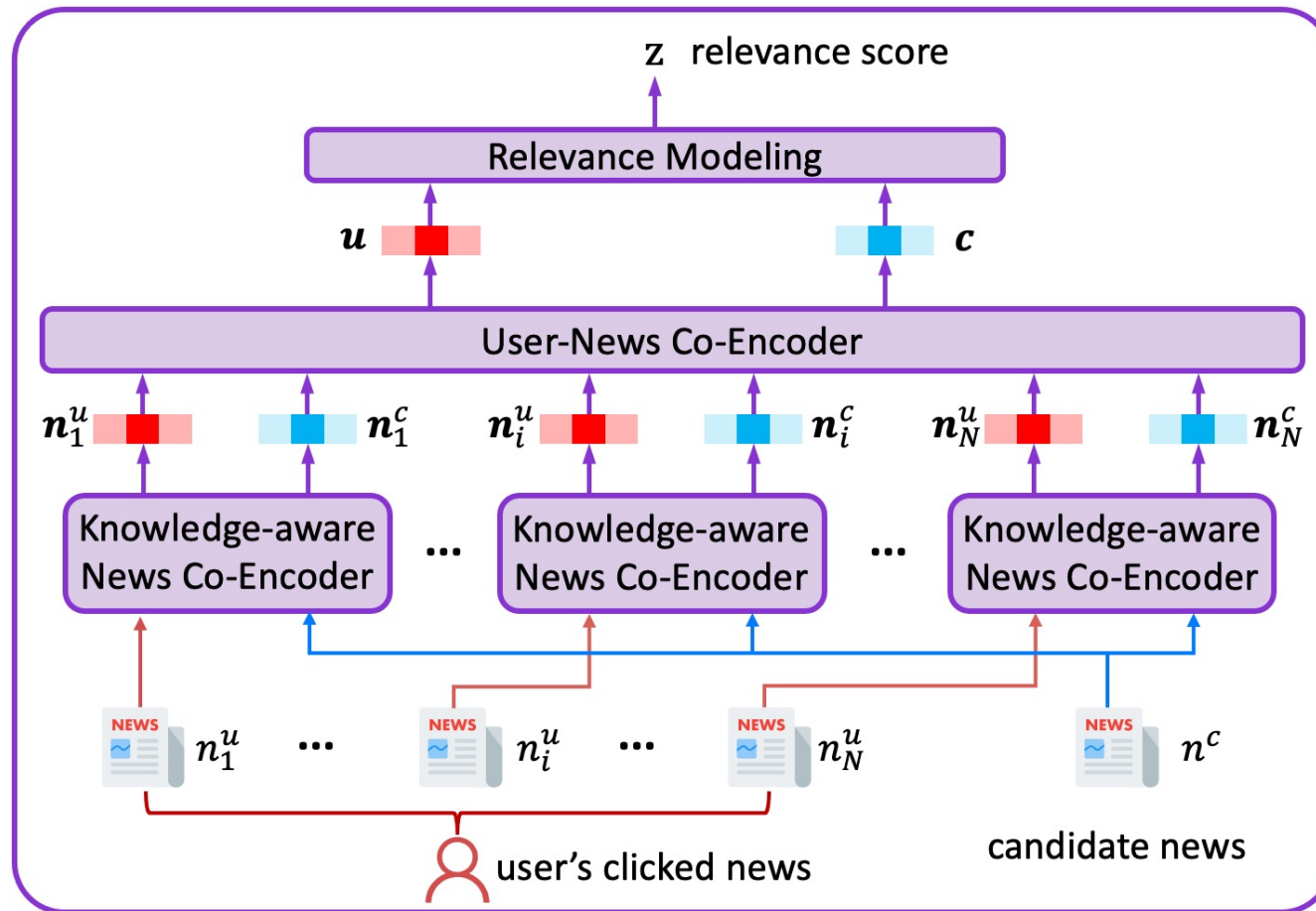
Semantic Co-Encoder

- Interactively model semantic relatedness of clicked news and candidate news



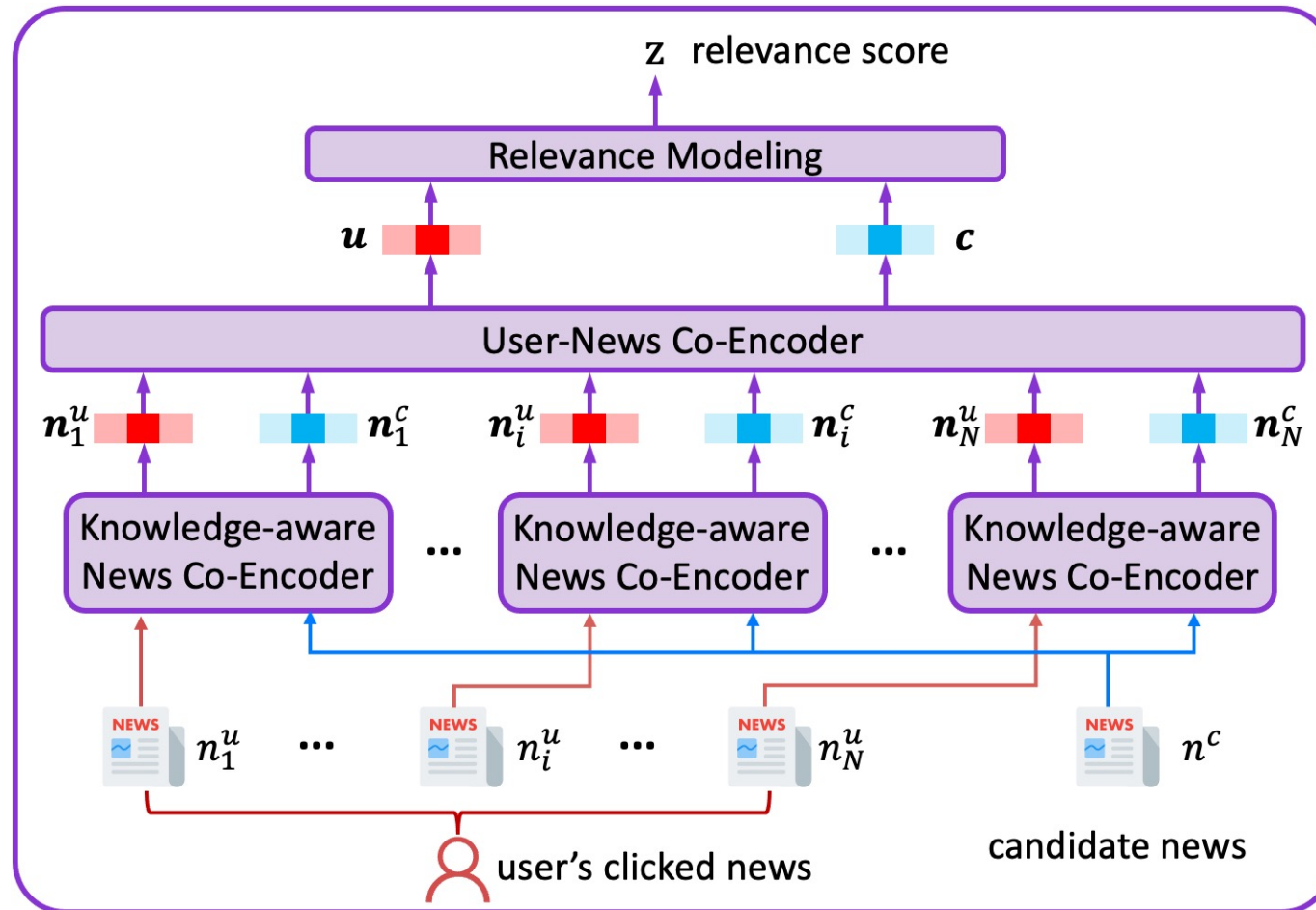
User-News Co-Encoder

- Learn candidate news-aware user interest representation
- Learn user-aware candidate news representation



Interest Matching

- Model user interest in candidate news
 - $z = \mathbf{u} \cdot \mathbf{c}$



Datasets

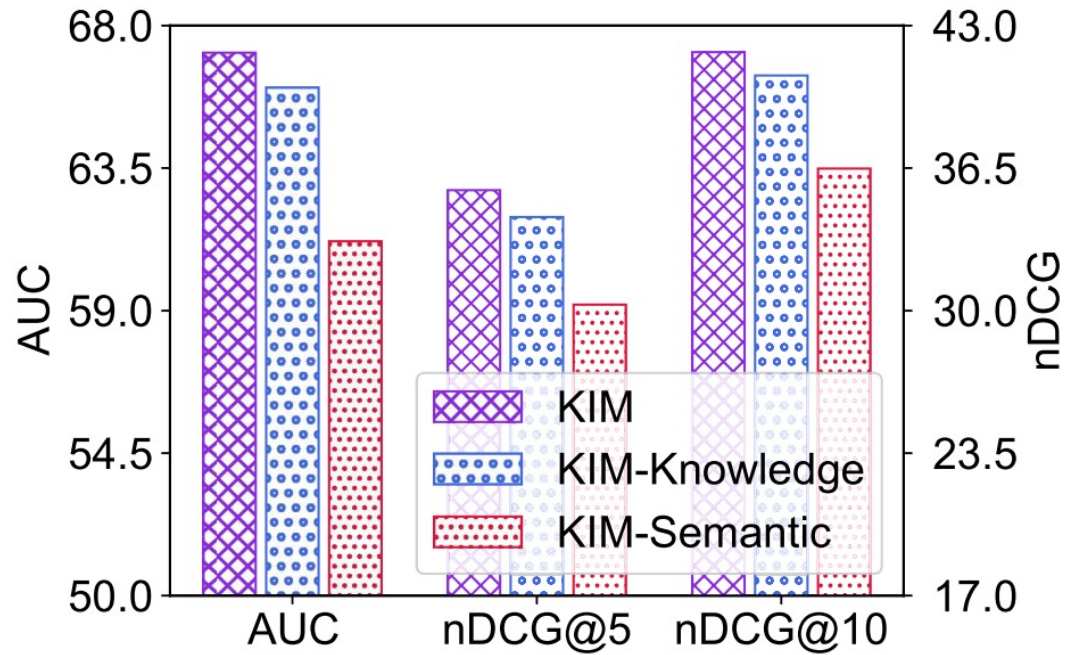
- MIND:
 - Based on user logs on Microsoft News
 - Collect user logs from 10.19 to 11.15, 2019
 - Using user logs in the last week for evaluation
 - Entities in news are extracted and linked to WikiData
- Feeds:
 - Based on user logs on a commercial news feeds in Microsoft
 - Collect user logs from 1.23 to 4.23, 2020
 - Using user logs in the last three weeks for evaluation
 - Entities in news are extracted and linked to WikiData

Performance Evaluation

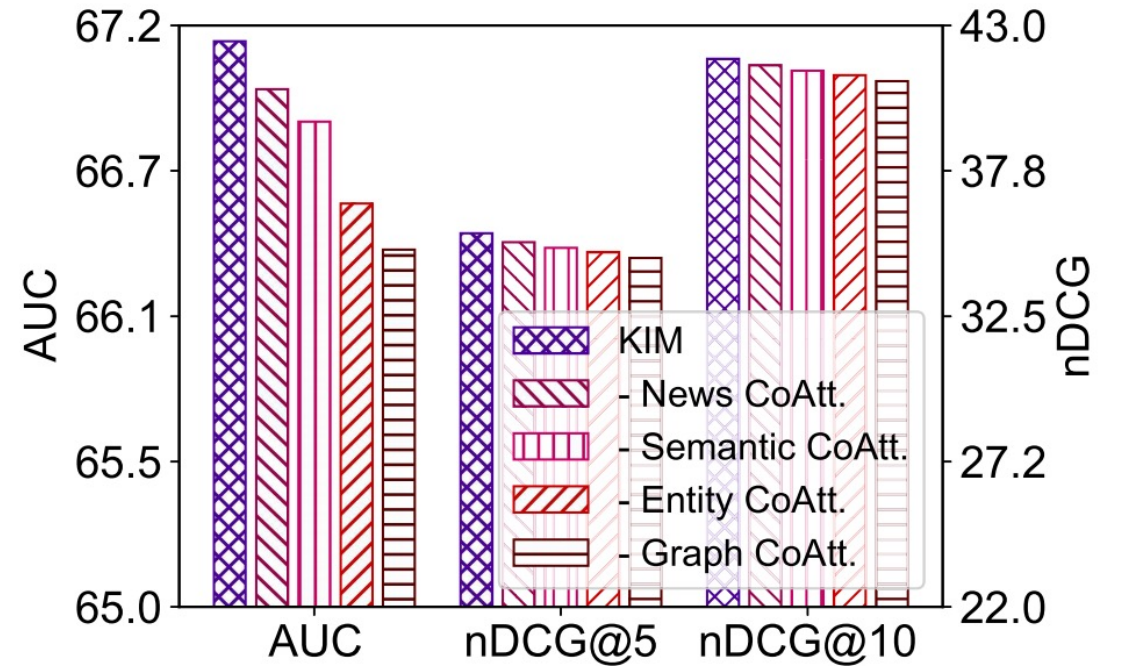
	<i>MIND</i>				<i>Feeds</i>			
	AUC	MRR	nDCG@5	nDCG@10	AUC	MRR	nDCG@5	nDCG@10
EBNR	61.28±0.27	27.77±0.21	30.10±0.28	36.75±0.24	63.44±0.39	27.97±0.25	32.01±0.32	37.57±0.35
DKN	64.08±0.12	29.06±0.16	31.82±0.11	38.52±0.14	62.91±0.26	28.08±0.20	32.20±0.24	37.75±0.22
DAN	65.14±0.16	30.04±0.20	32.98±0.22	39.52±0.19	62.65±0.49	27.79±0.32	31.79±0.40	37.37±0.39
NAML	64.21±0.20	29.71±0.13	32.51±0.20	39.00±0.12	64.24±0.38	28.81±0.21	33.06±0.28	38.52±0.29
NPA	63.71±0.27	29.84±0.12	32.40±0.19	39.02±0.20	63.69±0.75	28.51±0.47	32.74±0.64	38.27±0.62
LSTUR	65.51±0.29	30.22±0.31	33.26±0.38	39.76±0.34	64.66±0.33	29.04±0.26	33.44±0.32	38.82±0.30
NRMS	65.36±0.21	30.02±0.11	33.11±0.15	39.61±0.14	65.15±0.13	29.29±0.12	33.78±0.13	39.24±0.13
FIM	64.46±0.22	29.52±0.26	32.26±0.24	39.08±0.27	65.67±0.20	29.83±0.24	34.51±0.31	39.97±0.25
KRED	65.61±0.35	30.63±0.27	33.80±0.24	40.23±0.27	65.47±0.07	29.59±0.04	34.15±0.05	39.69±0.05
KIM	67.13±0.29	32.08±0.24	35.49±0.34	41.79±0.28	66.45±0.13	30.27±0.09	35.04±0.09	40.43±0.12

KIM significantly outperforms other baseline methods

Ablation Study

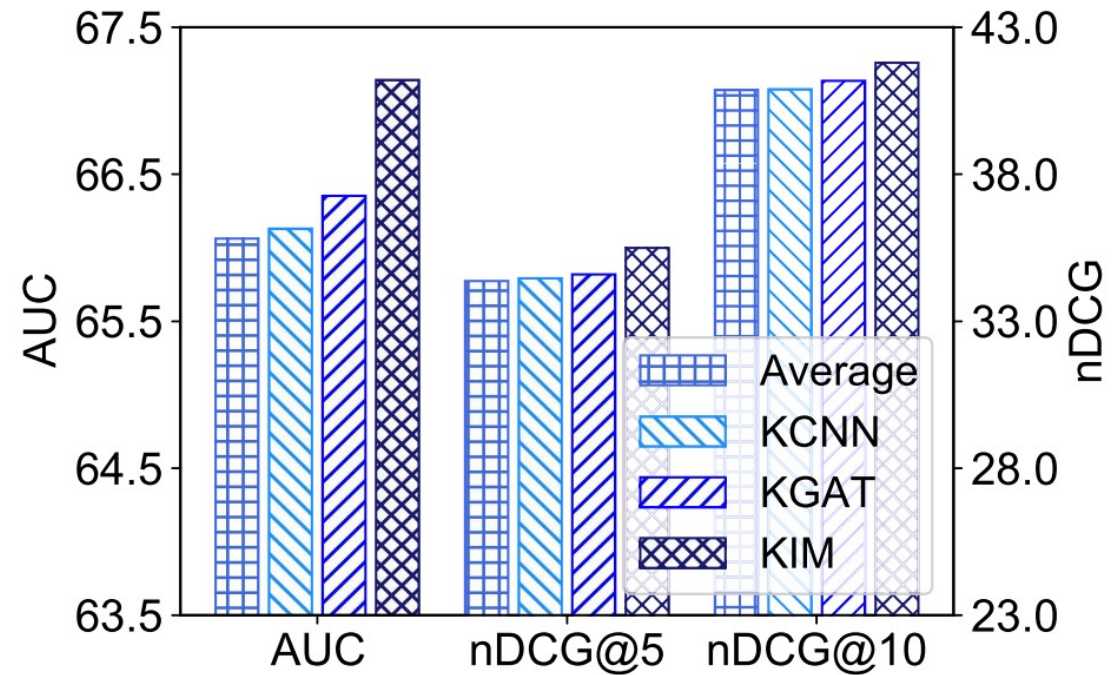


Both knowledge and semantic matching are useful for the interest matching



All co-attention networks in KIM are useful for interest matching

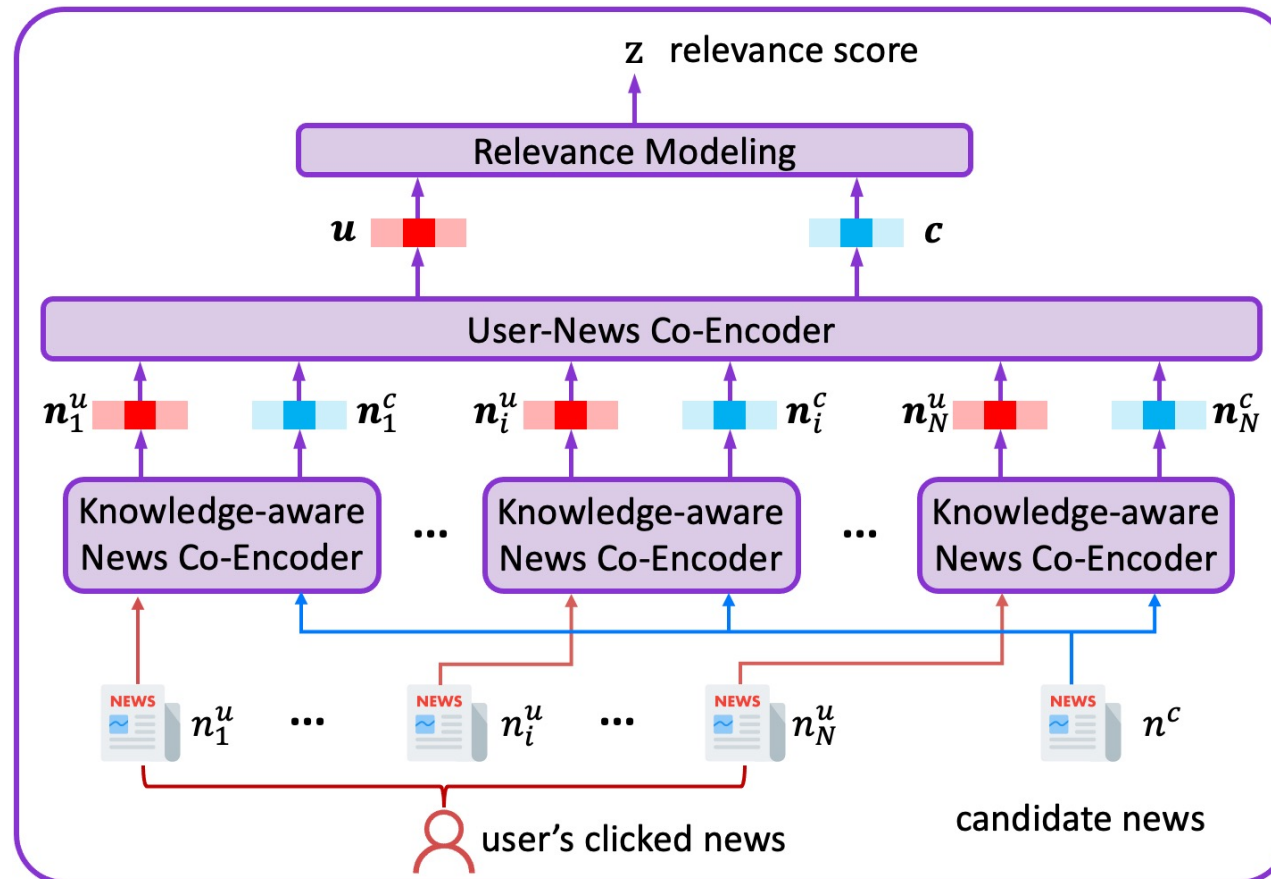
Knowledge Modeling



KIM is effective in knowledge modeling

Conclusion

- News recommendation with knowledge-aware interactive matching
 - Knowledge co-encoder, semantic co-encoder
 - User-news co-encoder



*Thank
you*



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