PP-Rec: News Recommendation with Personalized User Interest and Time-aware News Popularity

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Outline

Motivation

1. **Personalized news recommendation methods are usually based on**
    a. the matching between news content
    b. user interest inferred from historical behaviors.

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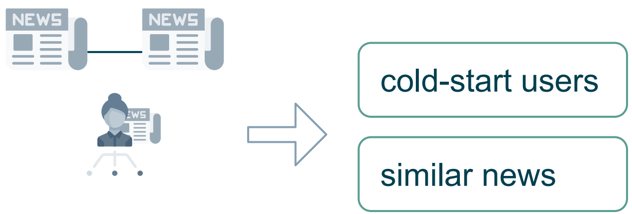
        i. have difficulties in making accurate recommendations to **cold-start users**.
        ii. tend to recommend **similar news** with those users have read.



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      i. have difficulties in making accurate recommendations to **cold-start users**.
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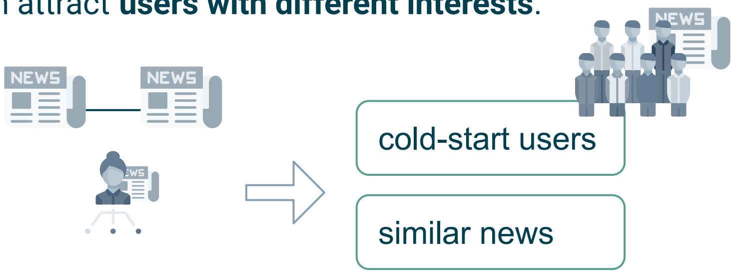
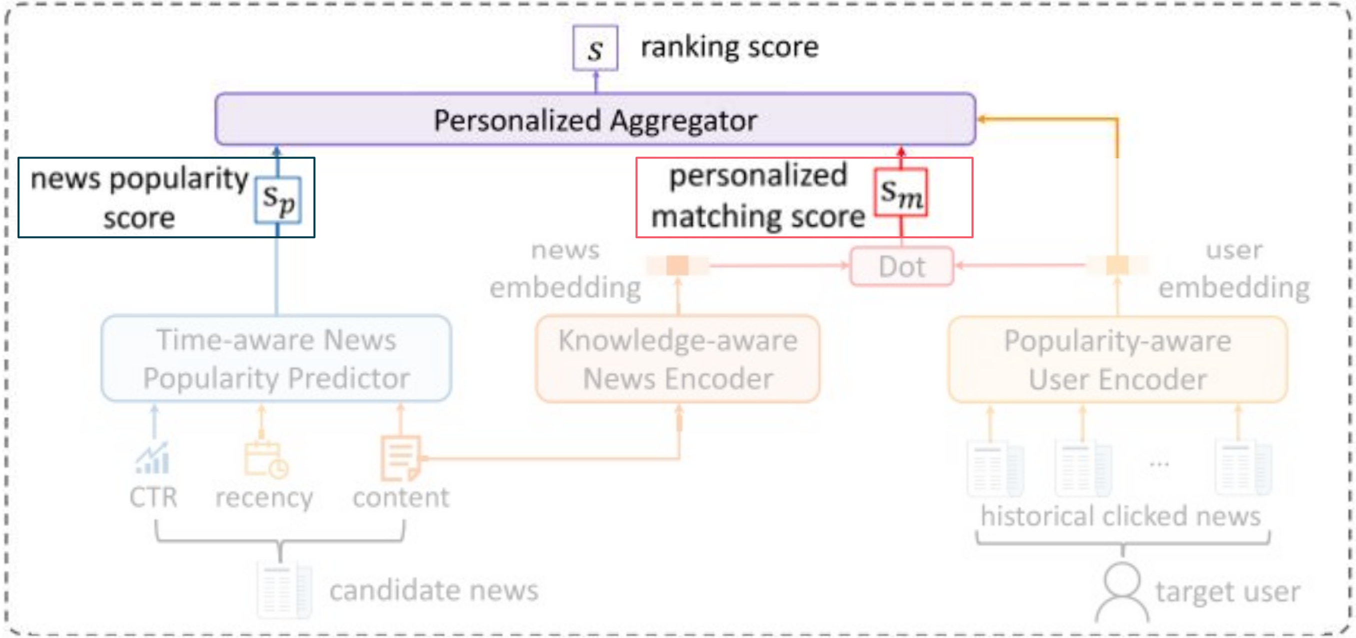
3. **Solution: Popular News**
      i. usually contain important information and can attract **users with different interests**.
      ii. are usually **diverse in content and topic**.

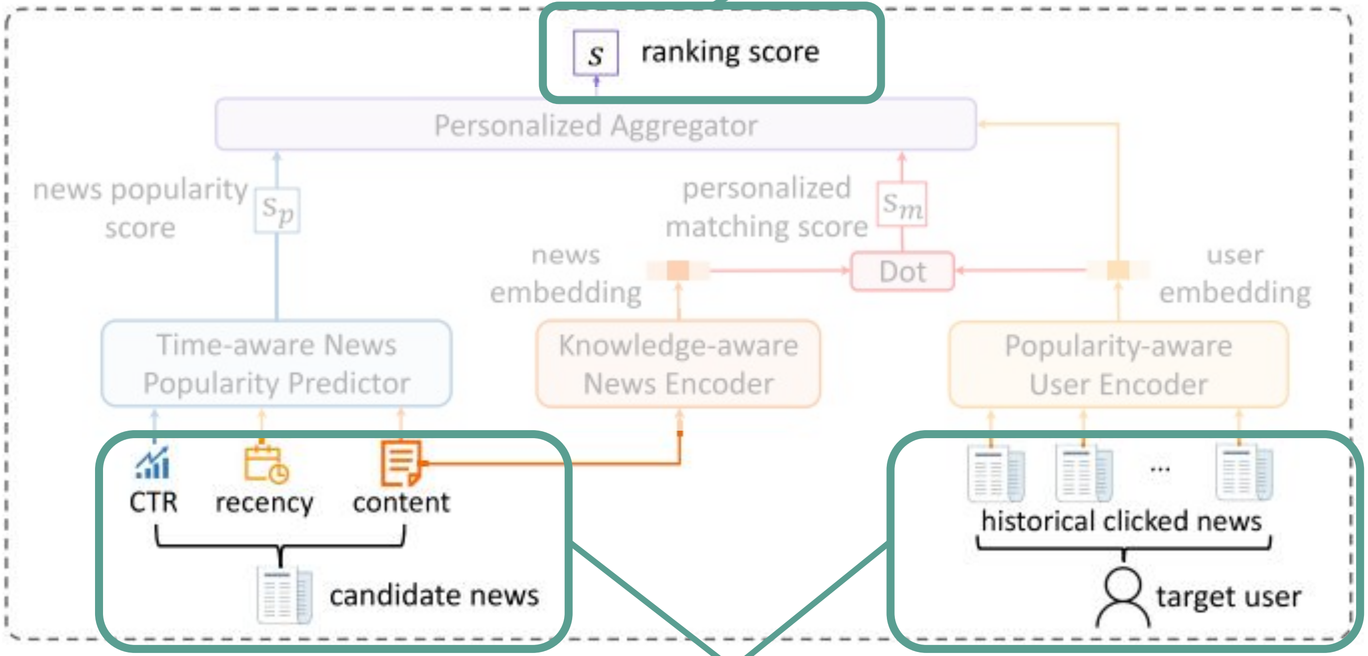


Framework of PP-Rec



Input/Output

Output



Input

Outline

1 Introduction

2 Method

3 Experiment

4 Conclusion

- Framework of PP-Rec
- News Popularity Score
  - Time-aware News Popularity Predictor
- Personalized matching score
  - Knowledge-aware News Encoder
  - Popularity-aware User Encoder

Framework of PP-Rec

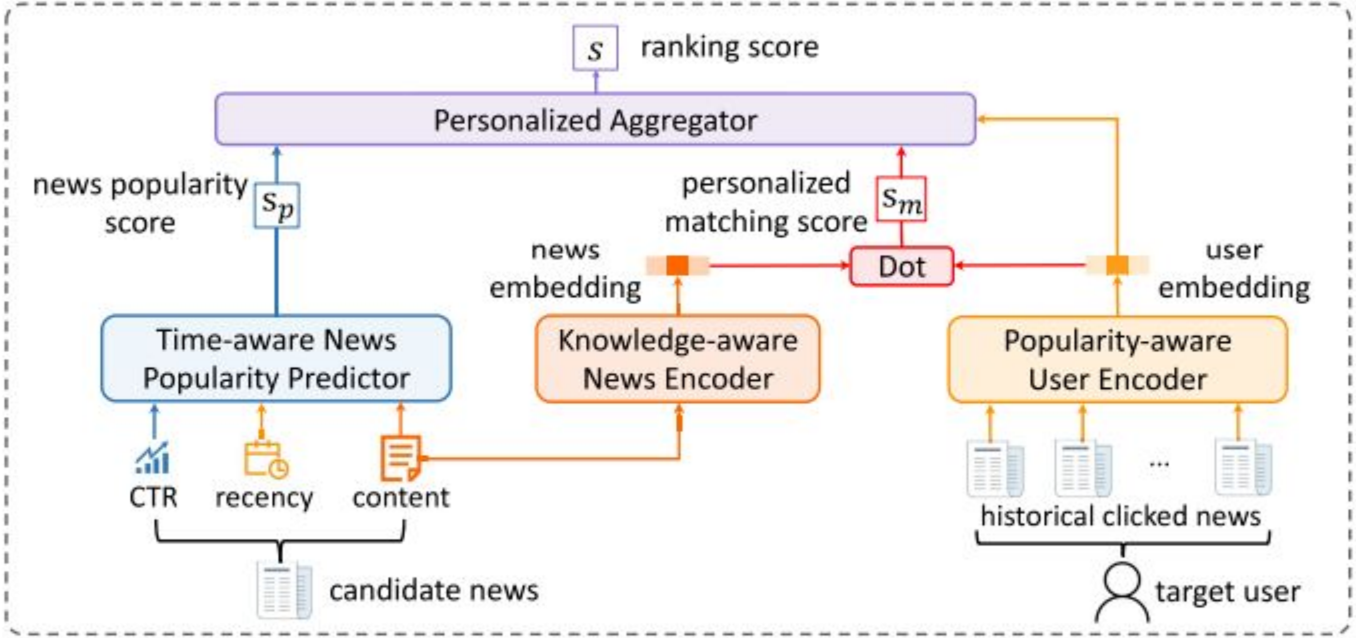
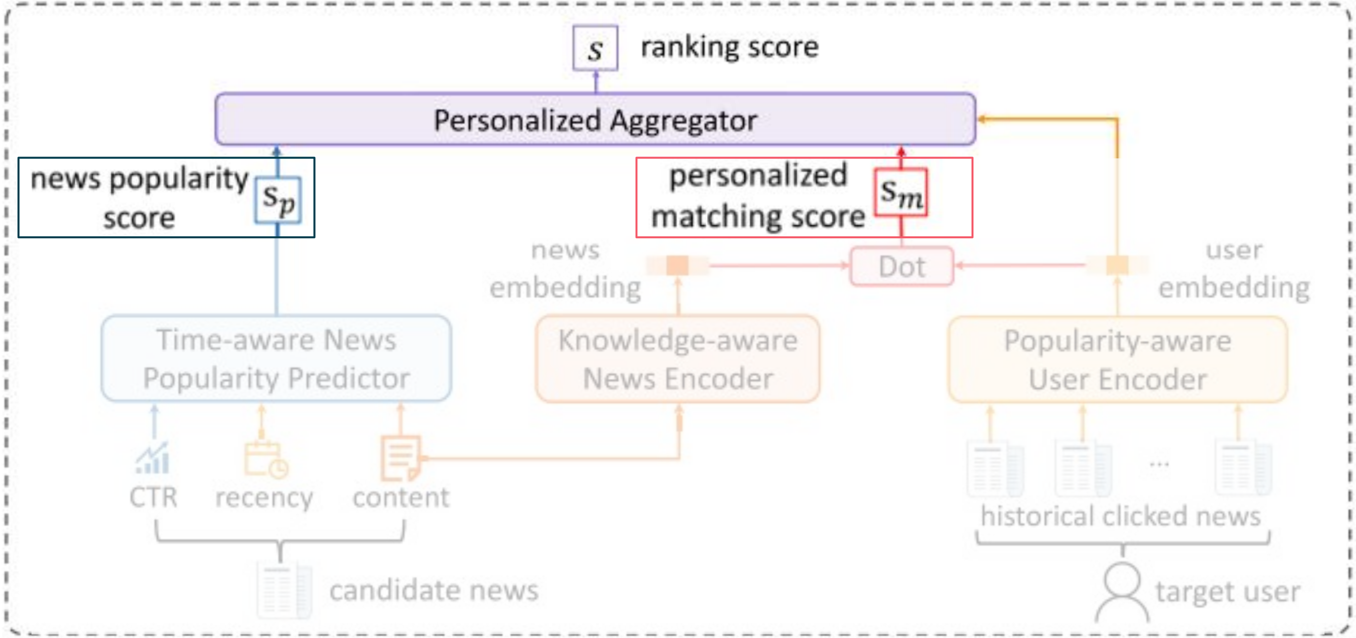


Figure 2: The overall framework of *PP-Rec*.

Framework of PP-Rec



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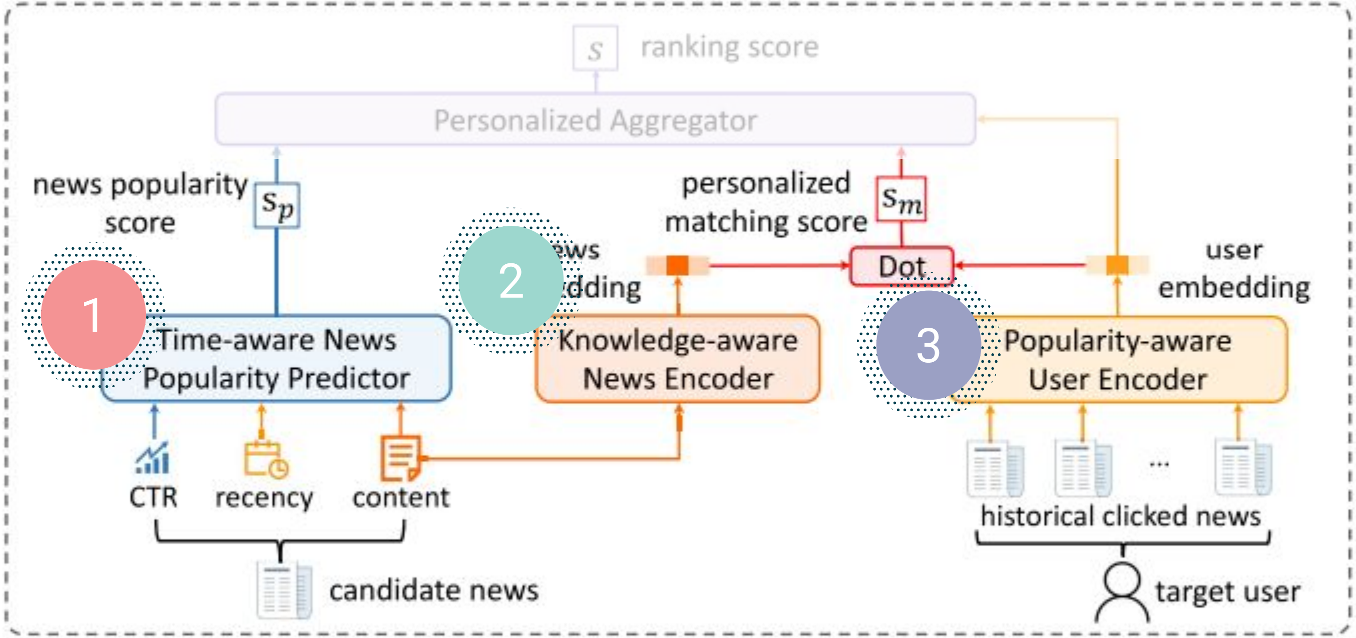

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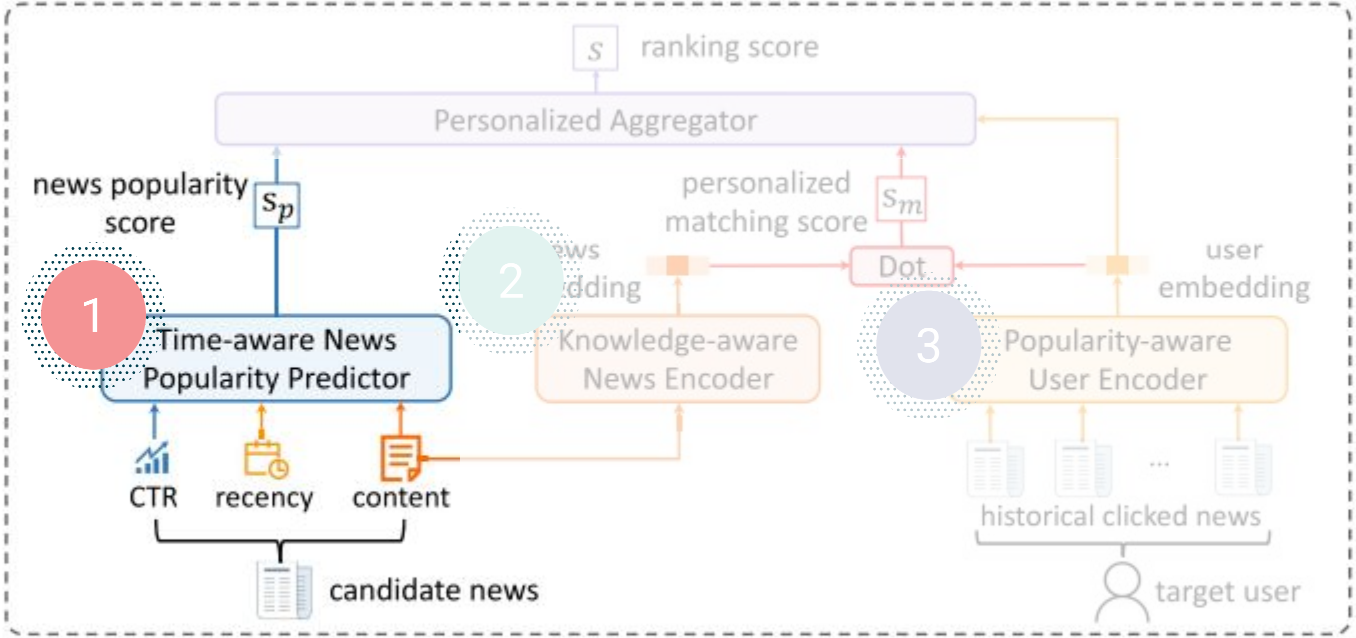
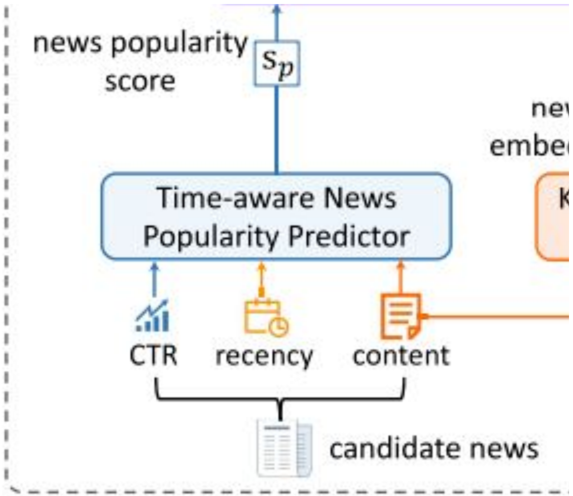
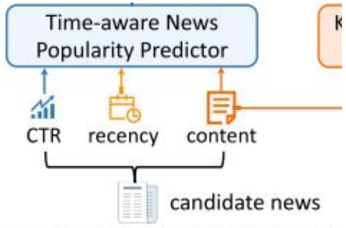


News Popularity Score



1. **Purpose:**
   a. predict time-aware news popularity (Sp)
2. **Based on**
   a. news content
   b. recency
   c. near real-time CTR information.

Reasons for Choosing These Elements



1. **near real-time CTR(Click-Through Rate)**
    - Popularity of a news article usually dynamically changes.
    - Using recent t hours (Ct)

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   - The duration between the publish time and the prediction time.

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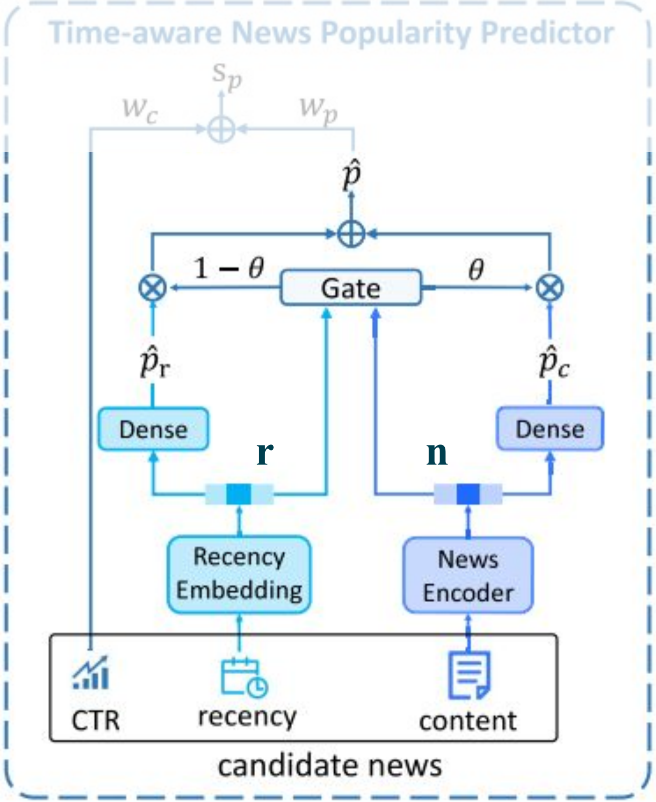
2. **recency**
    - News content is time-independent and cannot capture the dynamic change of news popularity.
    - The duration between the publish time and the prediction time.
3. **news content**
    - CTR needs to accumulate sufficient user interactions
    - News content is very informative for predicting news popularity(e.g. earthquakes)

Time-aware News Popularity Predictor



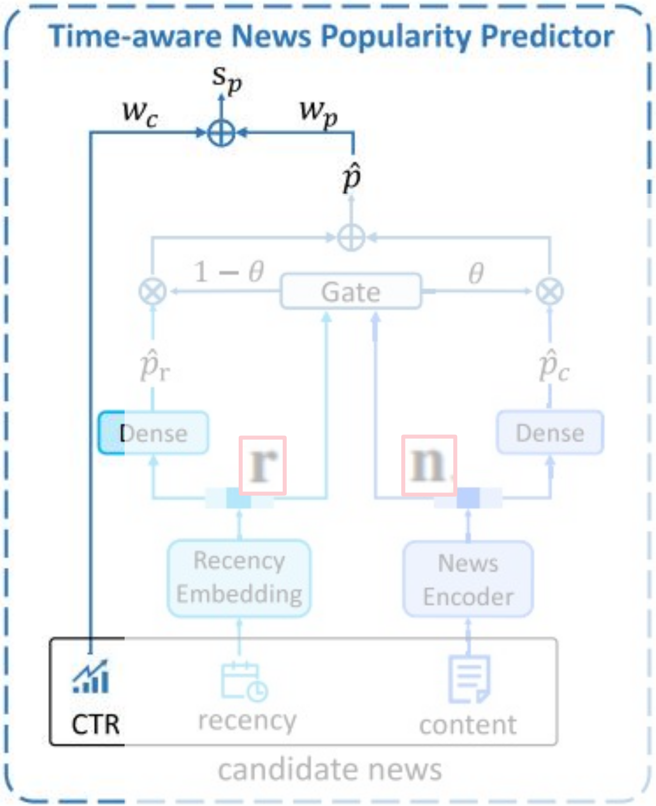
1. $\hat{p}_c$ **: content-based news popularity**
   - content embedding ($\mathbf{n}$)
2. $\hat{p}_r$ **: recency-aware content-based news popularity**
   - recency embedding ($\mathbf{r}$)
3. $\hat{p}$ **: time-aware content-based news popularity**

$$\hat{p} = \theta \cdot \hat{p}_c + (1-\theta) \cdot \hat{p}_r, \ \theta = \sigma(\mathbf{W}^p \cdot [\mathbf{n}, \mathbf{r}] + \mathbf{b}^p), \quad (1)$$

where $\theta \in (0, 1)$ means the content-specific gate

1

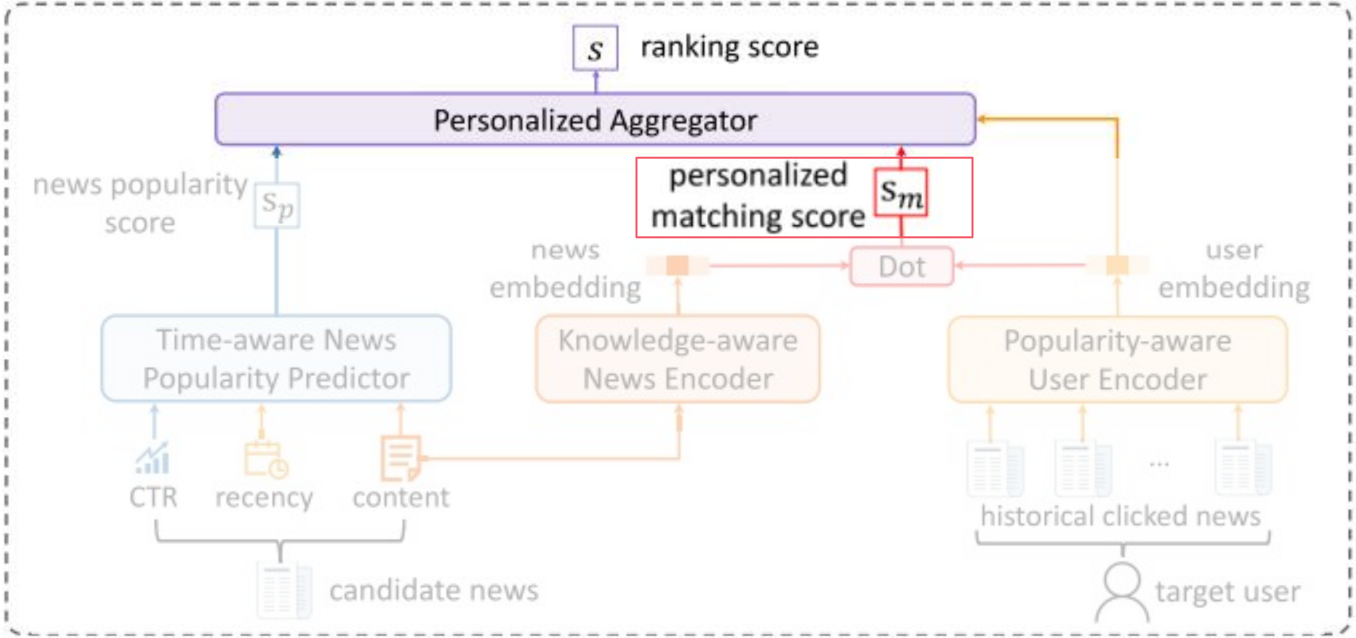
Time-aware News Popularity Predictor



1. c_t : CTR based popularity
2. $\hat{p}$: time-aware content-based news popularity
3. s_p : time-aware news popularity

$$s_p = w_c \cdot c_t + w_p \cdot \hat{p},$$

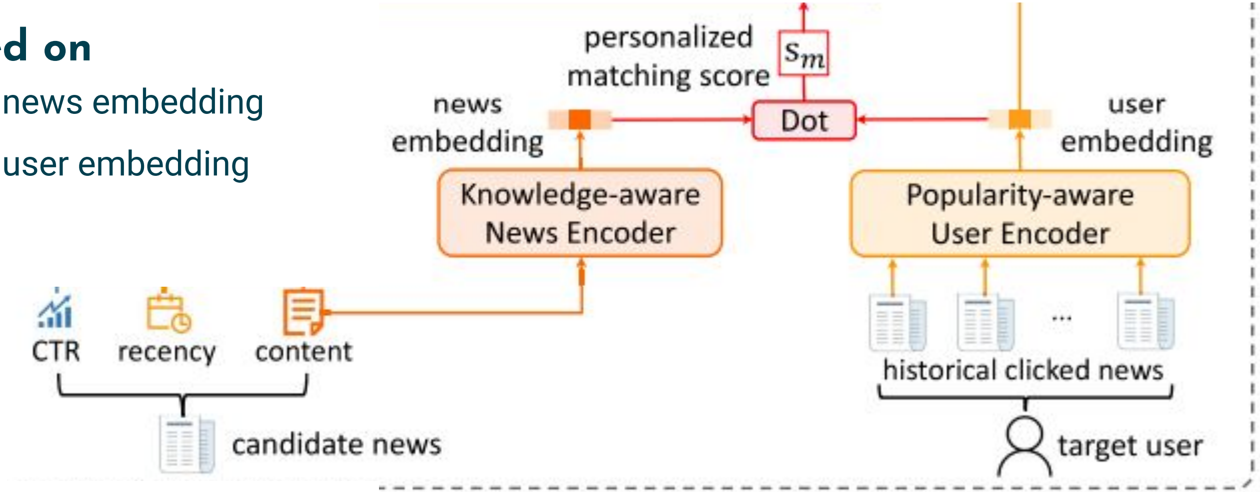
Framework of PP-Rec



Personalized matching score

1. **Purpose**
    - measure the user's personal interest in the content of candidate news

2. **Based on**
    - news embedding
    - user embedding



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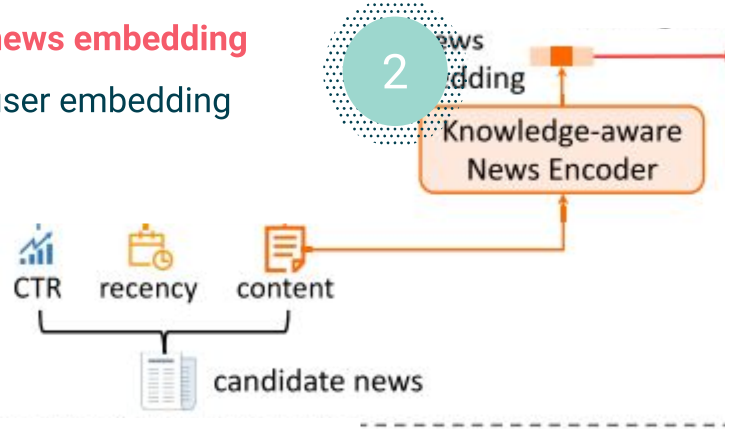
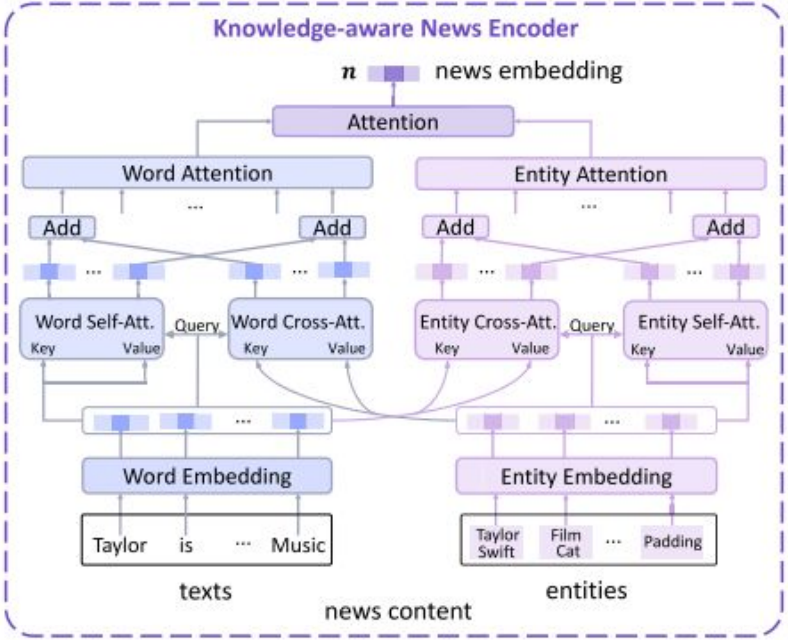


Knowledge-aware News Encoder

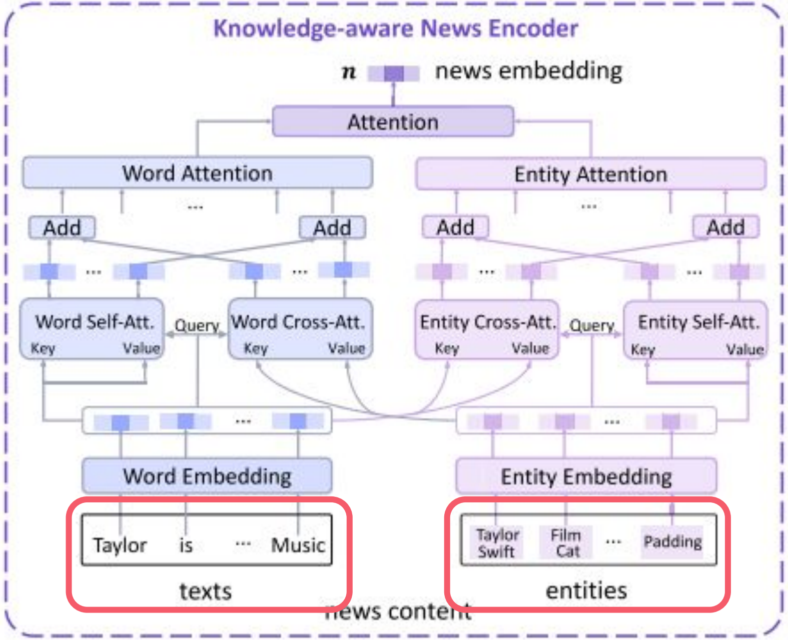
1. Purpose

- learn news representation($\mathbf{n}$) from both <u>text</u> and <u>entities</u> in news title.



Knowledge-aware News Encoder

1. **Purpose**
   - learn news representation(**n**) from both text and entities in news title.
2. **Based on**
   - texts
   - entities



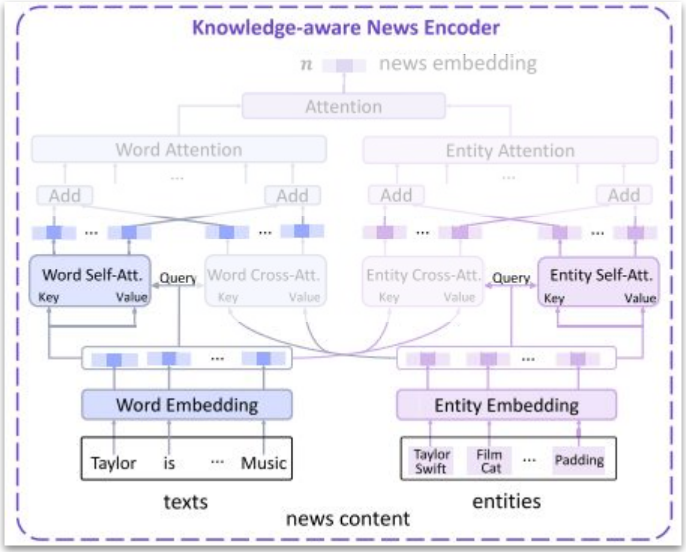
Scenario(1) relatedness

...MAC...Apple....

...MAC...Lancome....

MHSA

1. **Multi-Head Self-Attention**
2. **Propose**
   - learn entity/word representations by capturing their relatedness



Scenario(2) Textual Contexts

"Why do MAC need an ARM CPU?"

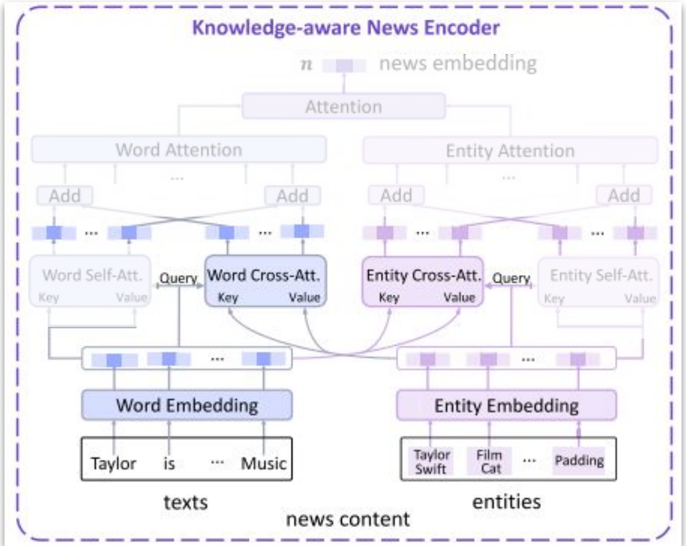
"MAC cosmetics expands AR try-on"

Computer

Cosmetic

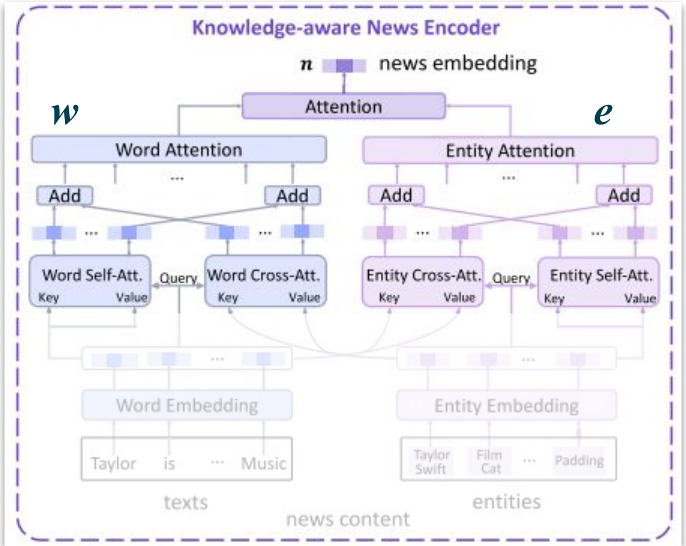
MHCA

1. **Multi-Head Cross-Attention**
2. **Propose**
   - learn entity/word representations from the textual contexts

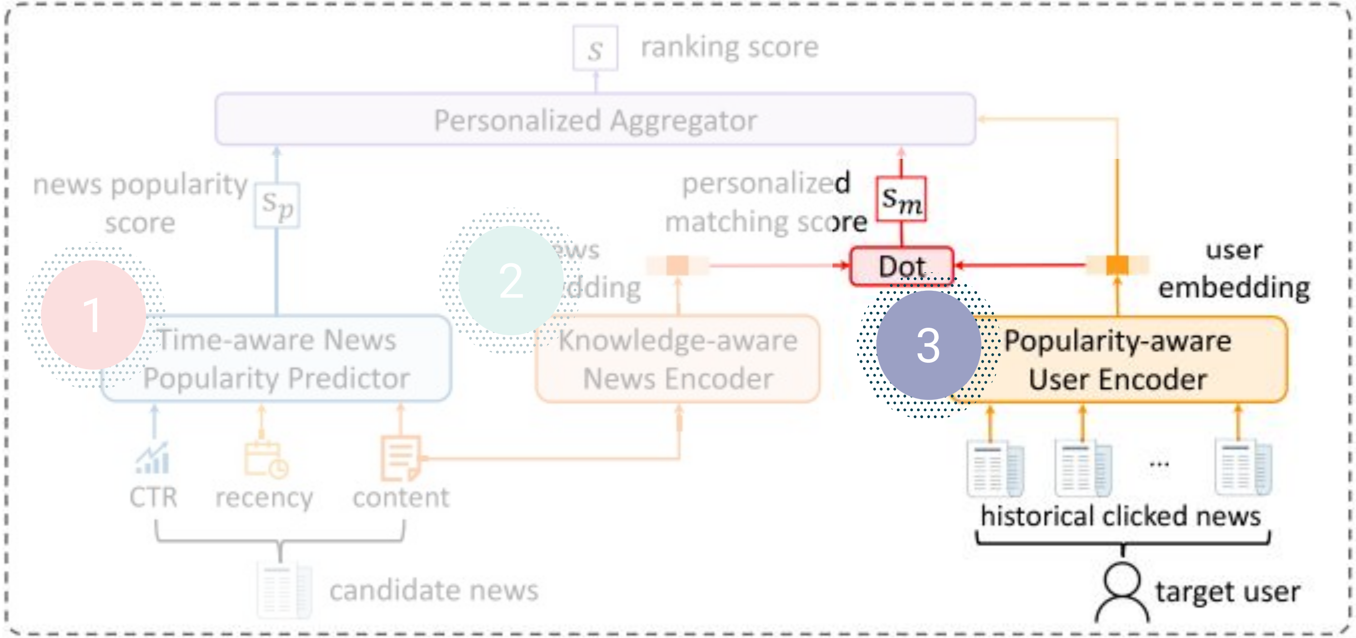


News embedding

1. **entity-based news representation** e
    - Entity Attention
2. **word-based news representation** w
    - Word Attention
3. **news representation** n



Framework of PP-Rec



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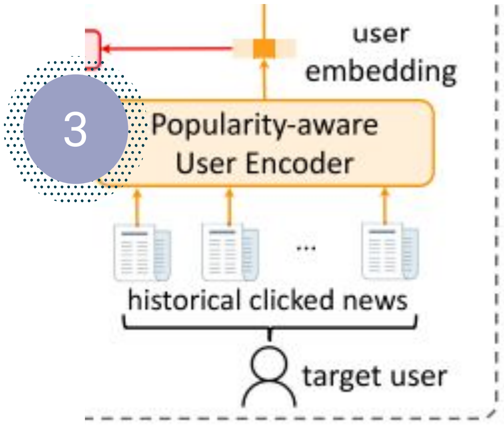
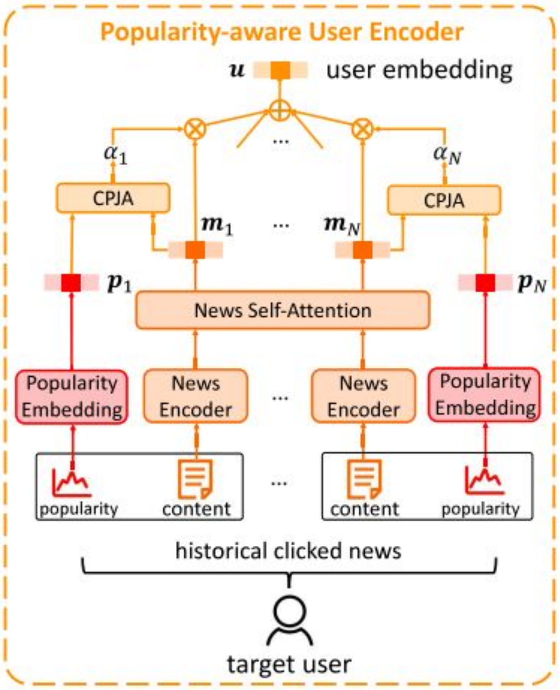


Popularity-aware User Encoder

1. **Purpose**
   - Measure user interest model.

2. **Based on**
   - content of user clicked news .
   - popularity of user clicked news.



Reasons for Choosing These Elements

1. **"Justin Timberlake unveils the song"**
    - User likes the songs of "Justin Timberlake".

2. **"House of Representatives impeaches President Trump"**
    - It is popular and contains breaking information.

Reasons for Choosing These Elements

1. **"Justin Timberlake unveils the song"** user interest
   - User likes the songs of "Justin Timberlake".

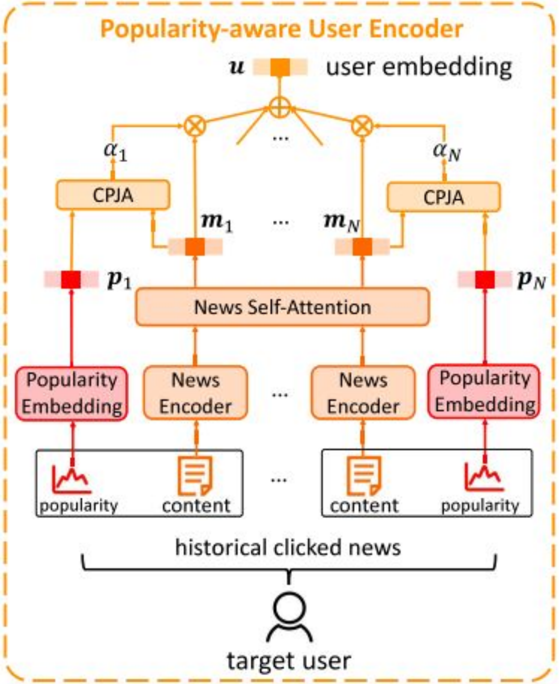
2. **"House of Representatives impeaches President Trump"** popular
   - It is popular and contains breaking information.

- **Eliminating the popularity bias in user behaviors can help more accurately.**

Popularity-aware User Encoder

1. **content-popularity joint attention network(CPJA)**
    - alleviate popularity bias
    - select important clicked news for user interest modeling
2. **$\mathbf{p}_i$: popularity embedding**
3. **$\mathbf{m}_i$: news representation**
4. **α_i : attention weight**

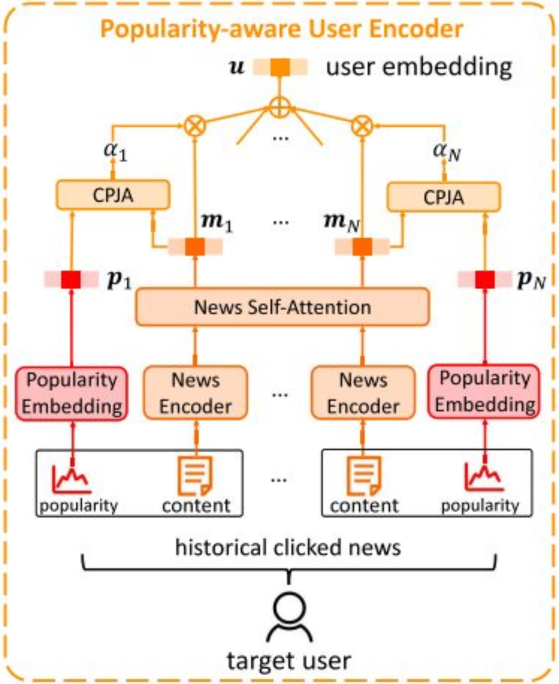
$$\alpha_i = \frac{\exp(\mathbf{q}^T \cdot \tanh(\mathbf{W}^u \cdot [\mathbf{m}_i, \mathbf{p}_i]))}{\sum_{j=1}^{N} \exp(\mathbf{q}^T \cdot \tanh(\mathbf{W}^u \cdot [\mathbf{m}_j, \mathbf{p}_j]))}, \quad (2)$$



Popularity-aware User Encoder

5. user interest embedding

$$\mathbf{u} = \sum_{i=1}^{N} \alpha_i \cdot \mathbf{m}_i.$$



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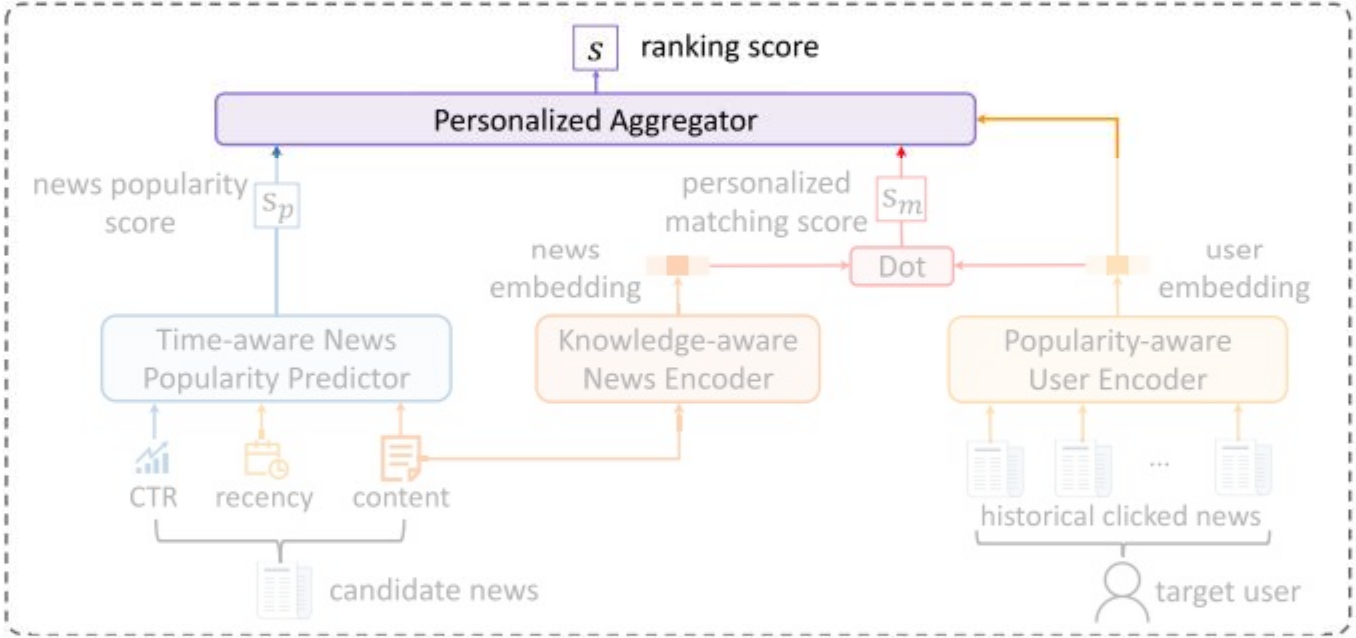
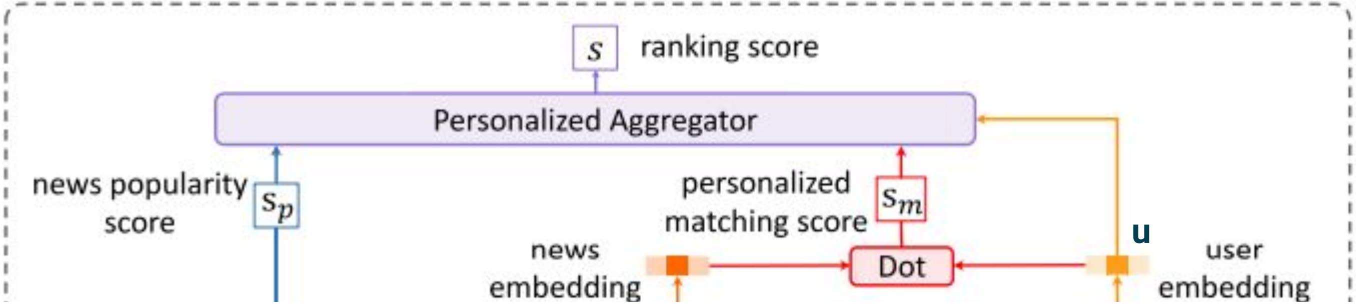


News Ranking Score



$$s = (1 - \eta) \cdot s_m + \eta \cdot s_p, \qquad (3)$$

- s : ranking score
- η : user representation u via a dense network with sigmoid activation.

Loss Function

1. **BPR pairwise loss**
   - Bayesian Personalized Ranking

$$\mathcal{L} = -\frac{1}{|\mathcal{D}|}\sum_{i=1}^{|\mathcal{D}|}\log(\sigma(s_i^p - s_i^n)), \qquad (4)$$

Loss Function

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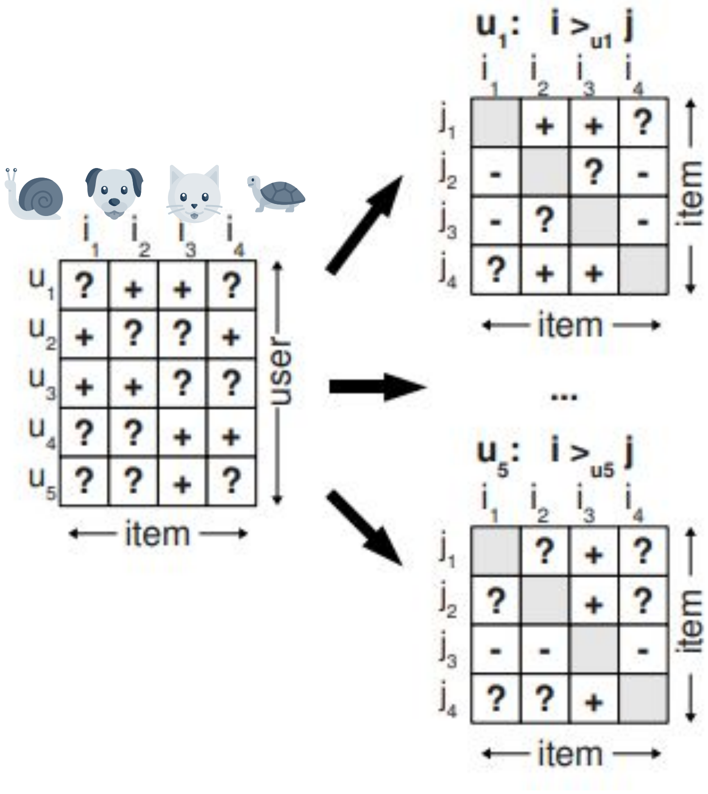

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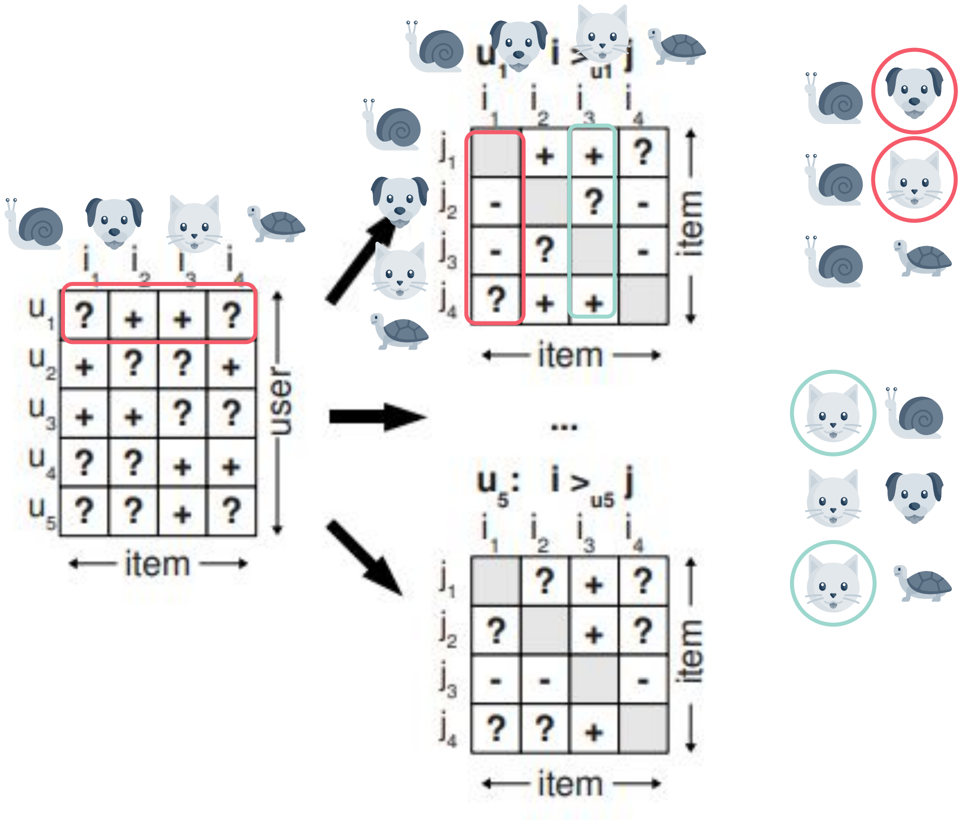

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Outline

1 Introduction

2 Method

3 **Experiment**

- Dataset
- Performance Evaluation
- Ablation Study
- Case Study

4 Conclusion

Dataset

- **MSN**
  - Microsoft News website
  - 2019/10/19 - 2019/4 /23
- **Feeds**
  - commercial news feeds in Microsoft
  - 2020/1/23 - 2020/4/23

	# News	# Users	# Impressions	# Clicks
MSN	161,013	490,522	1,100,000	1,675,084
Feeds	4,117,562	98,866	1,100,000	2,384,976

Performance Evaluation

Methods	*MSN*				*Feeds*			
	AUC	**MRR**	**nDCG@5**	**nDCG@10**	**AUC**	**MRR**	**nDCG@5**	**nDCG@10**
ViewNum	54.12±0.00	24.95±0.00	26.07±0.00	31.56±0.00	58.99±0.00	23.71±0.00	26.83±0.00	32.38±0.00
RecentPop	55.67±0.00	28.72±0.00	30.45±0.00	36.62±0.00	56.27±0.00	24.93±0.00	28.37±0.00	33.89±0.00
SCENE	57.89±0.02	27.41±0.01	28.81±0.02	34.36±0.03	60.82±0.03	27.29±0.03	31.25±0.02	36.56±0.03
CTR	65.72±0.00	30.50±0.00	32.79±0.00	38.68±0.00	66.40±0.00	30.29±0.00	35.53±0.00	40.72±0.00
EBNR	63.90±0.20	30.13±0.12	32.25±0.14	38.05±0.14	64.88±0.04	28.91±0.03	33.29±0.03	38.87±0.02
DKN	64.16±0.19	30.63±0.10	32.98±0.12	38.66±0.11	66.30±0.11	30.25±0.06	35.01±0.07	40.55±0.06
NAML	66.06±0.17	32.10±0.10	34.73±0.11	40.43±0.11	67.50±0.09	31.07±0.08	36.08±0.10	41.61±0.10
NPA	65.83±0.20	31.70±0.09	34.24±0.10	39.96±0.10	67.25±0.10	30.80±0.05	35.72±0.07	41.25±0.07
NRMS	66.34±0.16	32.00±0.08	34.68±0.09	40.39±0.09	68.10±0.05	31.47±0.03	36.61±0.03	42.12±0.03
LSTUR	66.69±0.16	32.12±0.05	34.76±0.05	40.51±0.04	67.43±0.16	30.95±0.11	35.92±0.16	41.45±0.14
KRED	66.54±0.17	31.97±0.14	34.65±0.14	40.38±0.14	67.67±0.18	31.16±0.13	36.19±0.16	41.72±0.16
PP-Rec	**71.05**±0.09	**39.34**±0.08	**44.01**±0.13	**50.46**±0.20	**72.11**±0.21	**32.42**±0.12	**38.13**±0.08	**43.50**±0.13

popularity-based news recommendations

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Popularity-based News Recommendations

- **ViewNum**
    - use number of news view
- **RecentPop**
    - use number of news view in recent time
- **SCENE**
    - use view frequency
    - adjusting the ranking of news with same topics based on their popularity
- **CTR**
    - use news CTR

Personalized News Recommendations

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KRED	66.54±0.17	31.97±0.14	34.65±0.14	40.38±0.14	67.67±0.18	31.16±0.13	36.19±0.16	41.72±0.16
PP-Rec	**71.05**±0.09	**39.34**±0.08	**44.01**±0.13	**50.46**±0.20	**72.11**±0.21	**32.42**±0.12	**38.13**±0.08	**43.50**±0.13

Personalized News Recommendations

- **EBNR**
  - GRU network to learn user representations
- **DKN**
  - knowledge-aware CNN network
- **NAML**
  - attention network
  - from news title, body and category
- **NPA**
  - attention networks
- **NRMS**
  - multi-head self-attention networks
- **LSTUR**
  - GRU network to learn short-term interests
  - user ID to learn longterm interests
- **KRED**
  - knowledge graph attention network

	# News	# Users	# Impressions	# Clicks
MSN	161,013	490,522	1,100,000	1,675,084
Feeds	4,117,562	98,866	1,100,000	2,384,976

Methods	*MSN*				*Feeds*			
	AUC	**MRR**	**nDCG@5**	**nDCG@10**	**AUC**	**MRR**	**nDCG@5**	**nDCG@10**
ViewNum	54.12±0.00	24.95±0.00	26.07±0.00	31.56±0.00	58.99±0.00	23.71±0.00	26.83±0.00	32.38±0.00
RecentPop	55.67±0.00	28.72±0.00	30.45±0.00	36.62±0.00	56.27±0.00	24.93±0.00	28.37±0.00	33.89±0.00
SCENE	57.89±0.02	27.41±0.01	28.81±0.02	34.36±0.03	60.82±0.03	27.29±0.03	31.25±0.02	36.56±0.03
CTR	65.72±0.00	30.50±0.00	32.79±0.00	38.68±0.00	66.40±0.00	30.29±0.00	35.53±0.00	40.72±0.00
EBNR	63.90±0.20	30.13±0.12	32.25±0.14	38.05±0.14	64.88±0.04	28.91±0.03	33.29±0.03	38.87±0.02
DKN	64.16±0.19	30.63±0.10	32.98±0.12	38.66±0.11	66.30±0.11	30.25±0.06	35.01±0.07	40.55±0.06
NAML	66.06±0.17	32.10±0.10	34.73±0.11	40.43±0.11	67.50±0.09	31.07±0.08	36.08±0.10	41.61±0.10
NPA	65.83±0.20	31.70±0.09	34.24±0.10	39.96±0.10	67.25±0.10	30.80±0.05	35.72±0.07	41.25±0.07
NRMS	66.34±0.16	32.00±0.08	34.68±0.09	40.39±0.09	68.10±0.05	31.47±0.03	36.61±0.03	42.12±0.03
LSTUR	66.69±0.16	32.12±0.05	34.76±0.05	40.51±0.04	67.43±0.16	30.95±0.11	35.92±0.16	41.45±0.14
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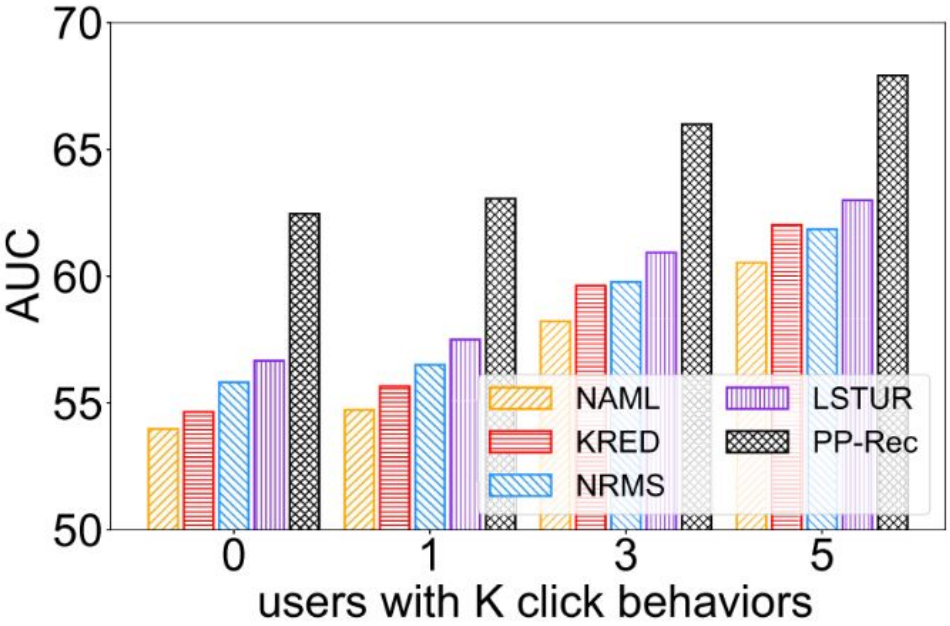
Performance Evaluation

- **popularity-based news recommendations**
  - cannot recommended personalized interests news
- **personalized news recommendations**
  - ignore the popularity of each news leading to <u>bias</u> in user interests.

Performance on Cold-Start Users

- **Choose methods which is good performs in Evaluation.**
- **all of them is <u>personalized news recommendations</u>**
- **K = 0, 1, 3, 5**
- **Dataset: MSN**



Diversity Evaluation (ILAD)

- **Intra-list average diversity**
- ***Sij***
  - the similarity between recommendation i and j
- ***U***
  - the set of all users

$$ILAD = \underset{u \in U}{\text{mean}} \underset{i,j \in R_u, i \neq j}{\text{mean}} (1 - \boldsymbol{S}_{i,j})$$

user A's Top 3 news recommendation similarity			
i j	1	2	3
1	-	0.3	0.1
2	0.3	-	0.9
3	0.1	0.9	-

Diversity Evaluation (ILAD)

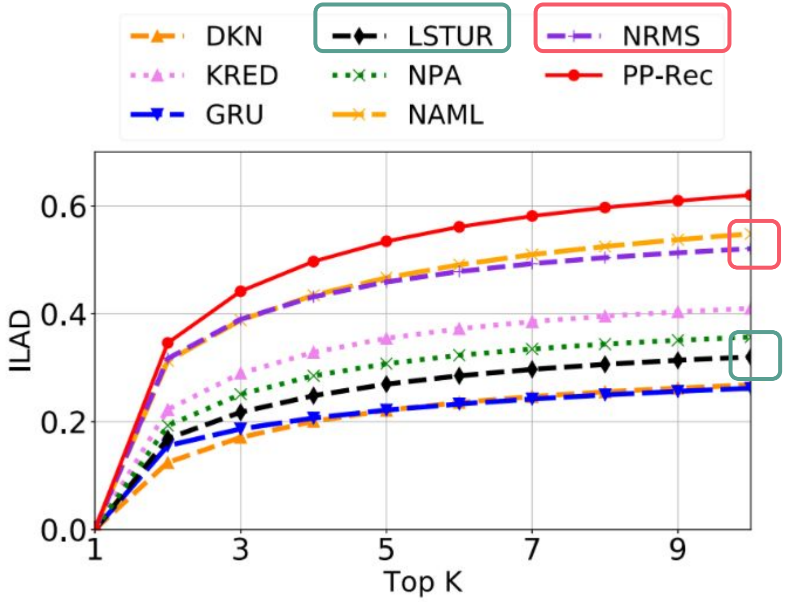


Figure 7: Intra-list average distance of news recommended by different methods.

Diversity Evaluation (New Topic Ratio)

- **Topic similarity between**
  - recommended news
  - users' historical clicked news

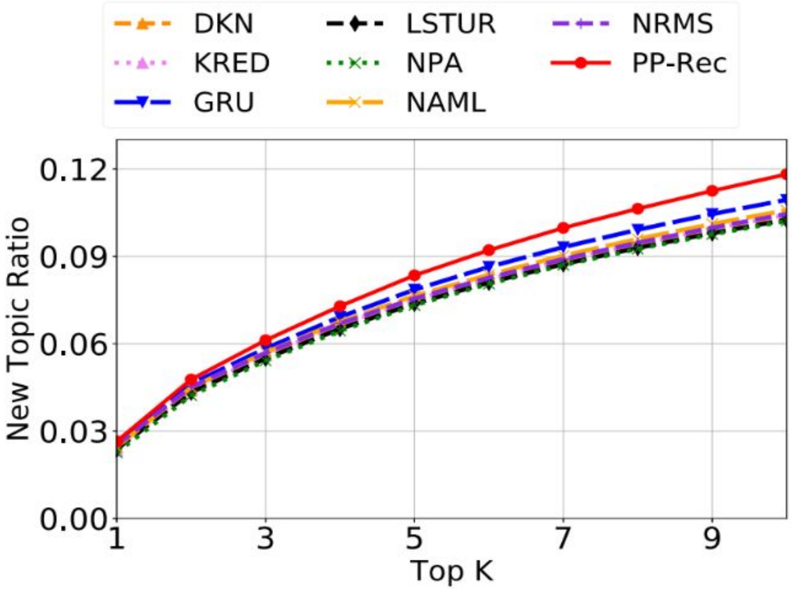


Figure 8: New topic ratio of news recommended by different methods.

Ablation Study

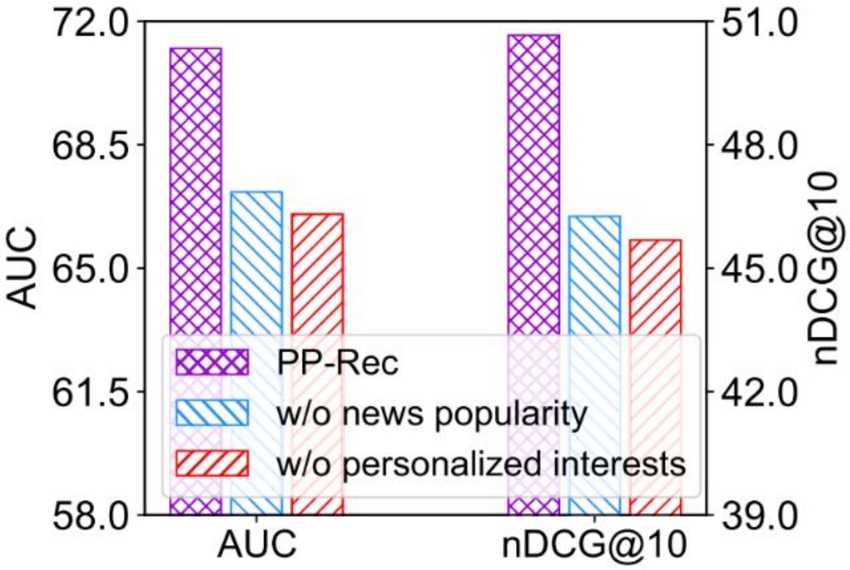
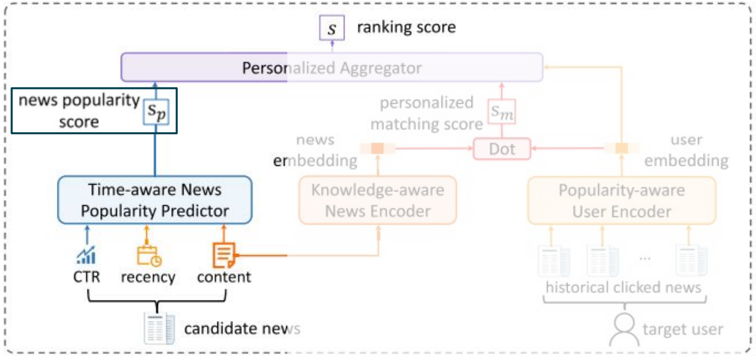
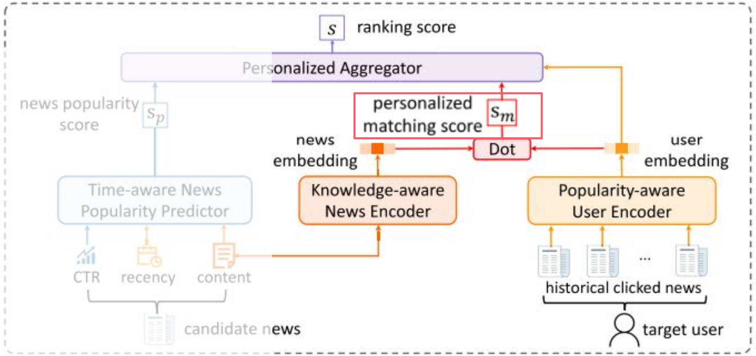


Figure 9: Effectiveness of personalized matching score and news popularity score.





Ablation Study

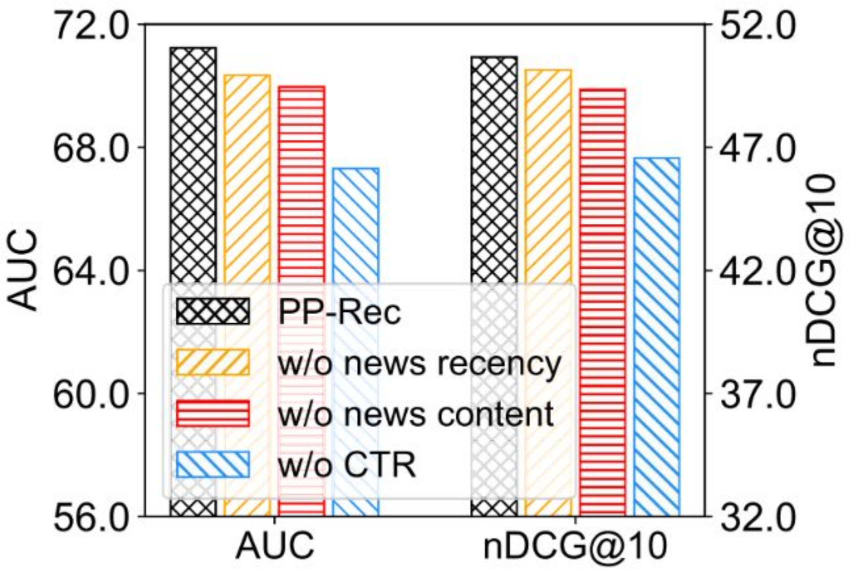
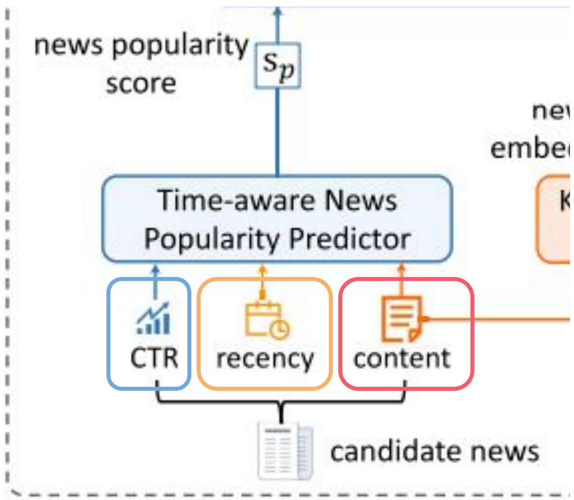
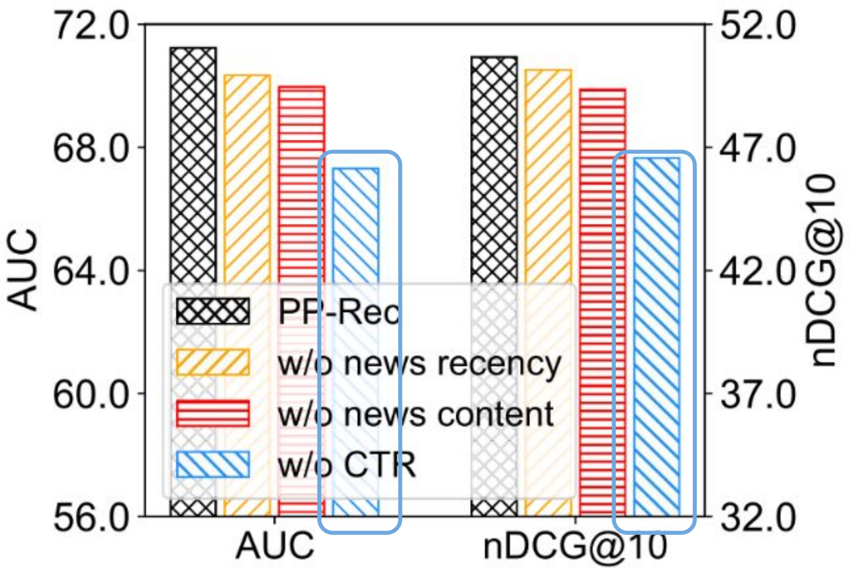


Figure 10: Effectiveness of different information used for news popularity prediction.



Ablation Study



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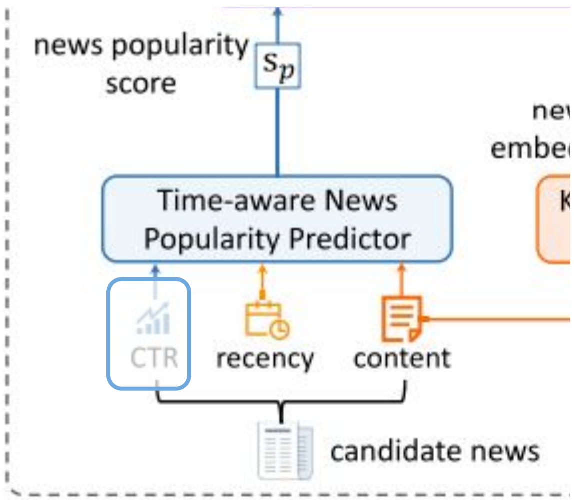
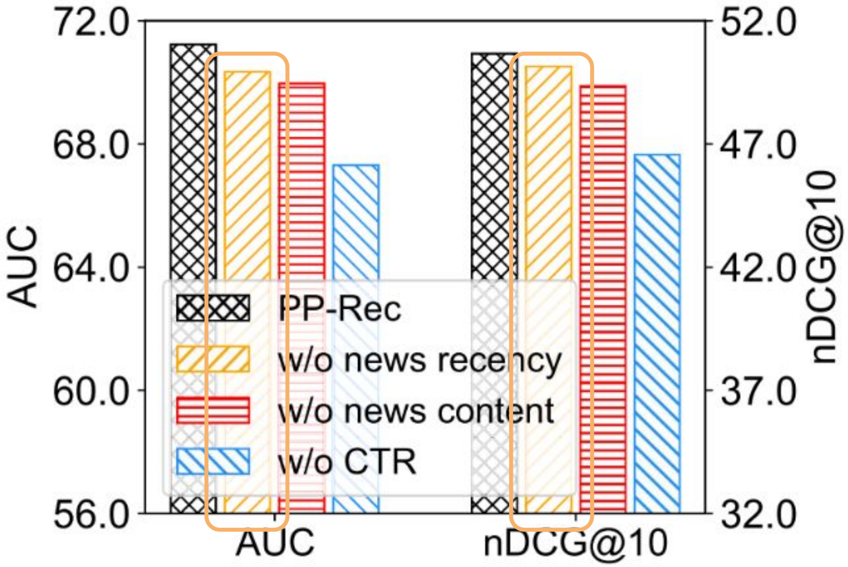


Ablation Study



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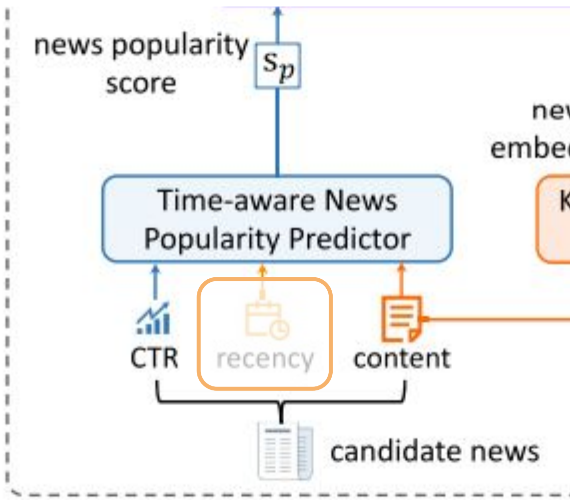


Case Study (with LSTUR)

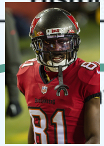
Historical clicked news of the user
Title
Frustrated Antonio Brown has active morning on twitter.
Tom Brady: When it comes to the future, my focus is on this season.
Odell Beckham Jr. trolled Steelers coach Mike Tomlin with yawn celebration.

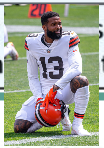
Top recommendations from PP-Rec	
Title	Popularity
For grandfather charged in girl's cruise ship death, video could be key.	0.156
Patriots-Ravens part II seems inevitable.	0.016
Jared Goff regression: Here's exactly what's gone wrong for rams.	0.031

Top recommendations from LSTUR	
Title	Popularity
Jared Goff regression: Here's exactly what's gone wrong for rams.	0.031
Bill Belichick irritated with questions about Antonio brown.	0.036
Patriots-Ravens part II seems inevitable.	0.016

Figure 11: Top news recommended by *PP-Rec* and *LSTUR*. The clicked news are in red and bold.

Case Study (with LSTUR)





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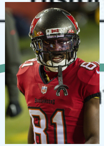
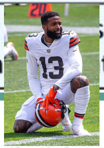
Football

Case Study (with LSTUR)

Historical clicked news of the user
Title
 ted Antonio Brown has active morning on twitter.
Tom Brady: When it comes to the f  my focus is on this season.
Odell Beckham Jr. trolled  coach Mike Tomlin with yawn tion.

Top recommendations from PP-Rec	
Title	
For grandfather charged in girl's cru ship death, video could be key.	
Patriots-Ravens part II seems inevita	
Jared Goff regression: Here's exactly what's gone wrong for rams.	0.031

Top recommendations from LSTUR	
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Jared Goff regression: Here's exactly what's gone wrong for rams.	0.031
Bill Belichick irritated with questions about Antonio brown.	0.036
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Figure 11: Top news recommended by *PP-Rec* and *LSTUR*. The clicked news are in red and bold.

Football

Case Study (with LSTUR)

Historical clicked news of the user	Top recommendations from PP-Rec		Top recommendations from LSTUR	
Title	Title	Popularity	Title	Popularity
Frustrated Antonio Brown has active morning on twitter.	**For grandfather charged in girl's cruise ship death, video could be key.**	0.156	**Jared Goff regression: Here's exactly what's gone wrong for rams.**	0.031
Tom Brady: When it comes to the future, my focus is on this season.	Patriots-Ravens part II seems inevitable.	0.016	Bill Belichick irritated with questions about Antonio brown.	0.036
Odell Beckham Jr. trolled Steelers coach Mike Tomlin with yawn celebration.	**Jared Goff regression: Here's exactly what's gone wrong for rams.**	0.031	Patriots-Ravens part II seems inevitable.	0.016

Figure 11: Top news recommended by *PP-Rec* and *LSTUR*. ... d.

Popularity

Outline

Conclusion

- **Propose a new news recommendation method named PP-Rec**
  - deal with cold-start and diversity problems
  - consider both the personal interest of users and the popularity of candidate news.
- **Propose a unified model to predict time-aware news popularity**
- **Propose a knowledge-aware news encoder**
  - to generate news content embeddings from news texts and entities.
- **Propose a popularity-aware user encoder**
  - to generate user interest embeddings from the content and popularity of clicked news.