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# Uni-FedRec: A Unified Privacy-Preserving News Recommendation Framework for Model Training and Online Serving

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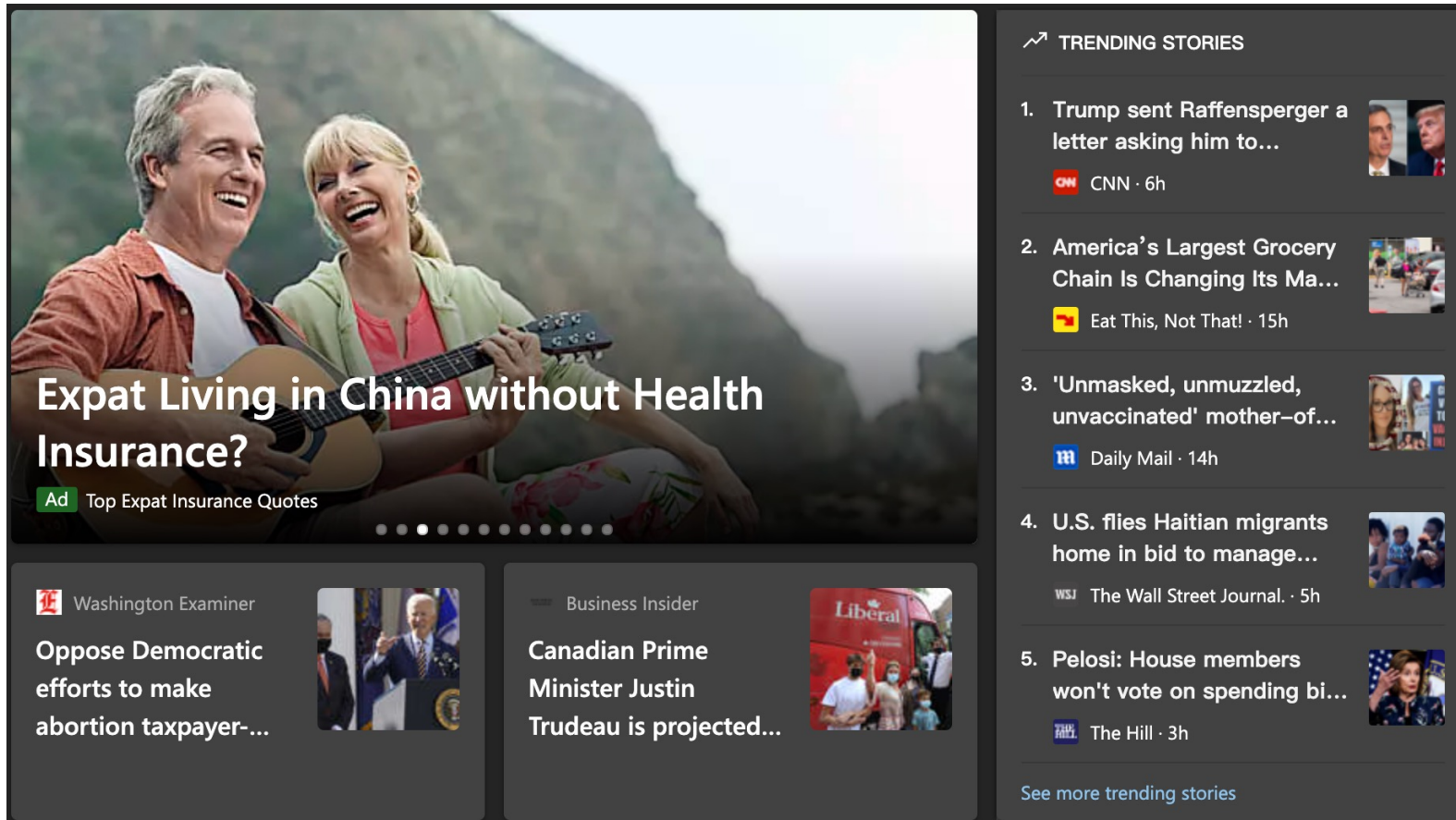
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# News Recommendation

- Online news platforms become popular for people to read news
- News recommendation is critical for improving user experience



The screenshot displays a news recommendation interface. At the top, a large featured article titled "Expat Living in China without Health Insurance?" is shown with a photo of a smiling couple. Below the title, it is marked as an advertisement with the text "Ad Top Expat Insurance Quotes".

To the right, a "TRENDING STORIES" section lists five items:

1. Trump sent Raffensperger a letter asking him to... (CNN · 6h)
2. America's Largest Grocery Chain Is Changing Its Ma... (Eat This, Not That! · 15h)
3. 'Unmasked, unmuzzled, unvaccinated' mother-of... (Daily Mail · 14h)
4. U.S. flies Haitian migrants home in bid to manage... (The Wall Street Journal · 5h)
5. Pelosi: House members won't vote on spending bi... (The Hill · 3h)

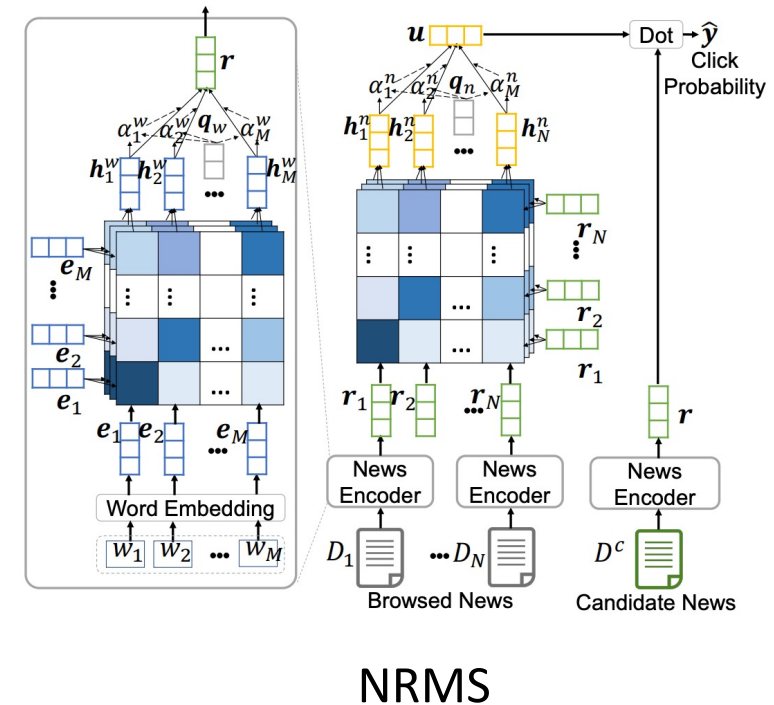
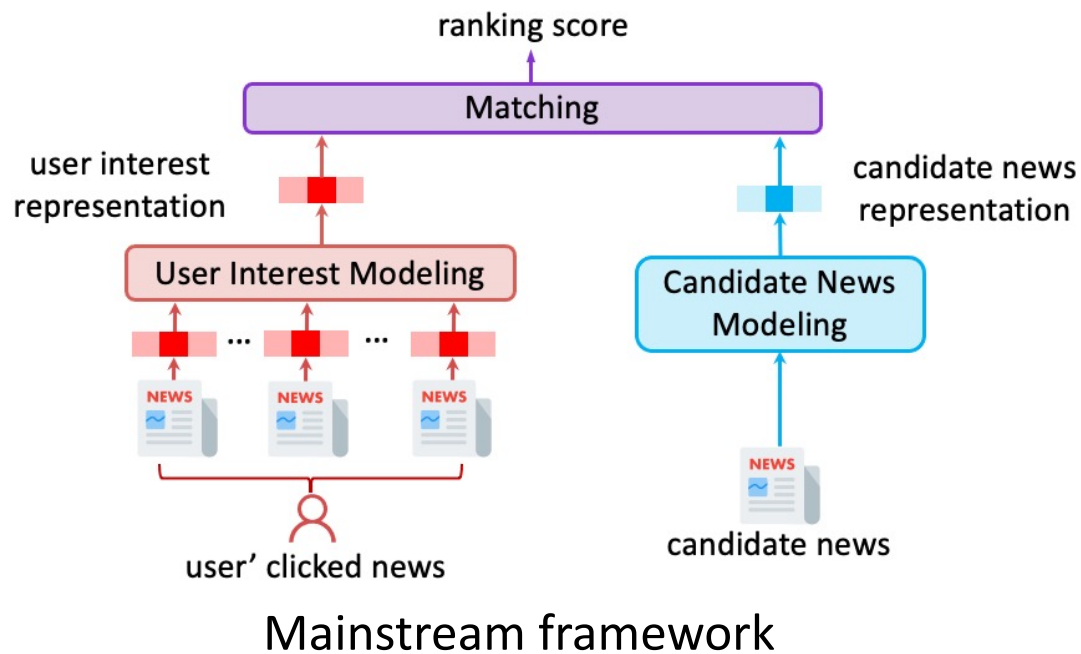
At the bottom, two more news items are visible:

- Washington Examiner: Oppose Democratic efforts to make abortion taxpayer...
- Business Insider: Canadian Prime Minister Justin Trudeau is projected...

A link "See more trending stories" is located at the bottom right of the trending stories section.

# News Recommendation Methods

- Most existing methods rely on centralized storage of user data to train models and serve users

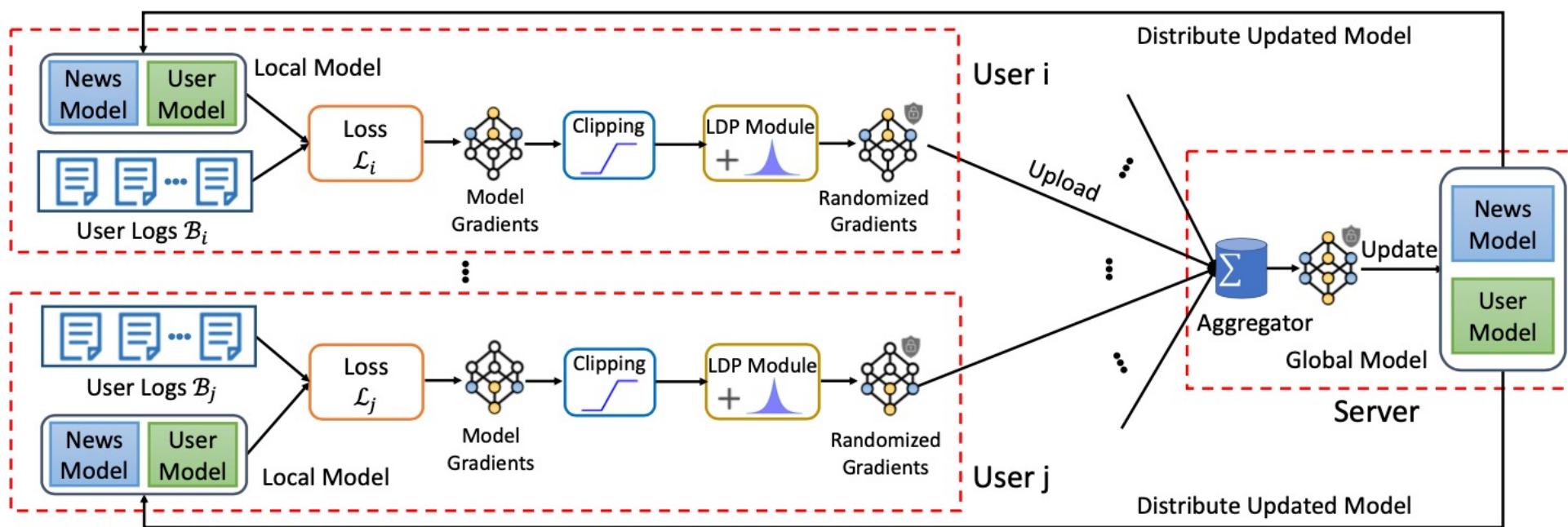


- **Challenges**

- Centralized storage of user data may arouse privacy concerns and risks
- Application of these methods may violate some privacy regulations

# Privacy-Preserving Recommender Systems

- Most existing methods focus on training a recommend model for ranking candidate items (e.g. news) in a privacy-preserving way

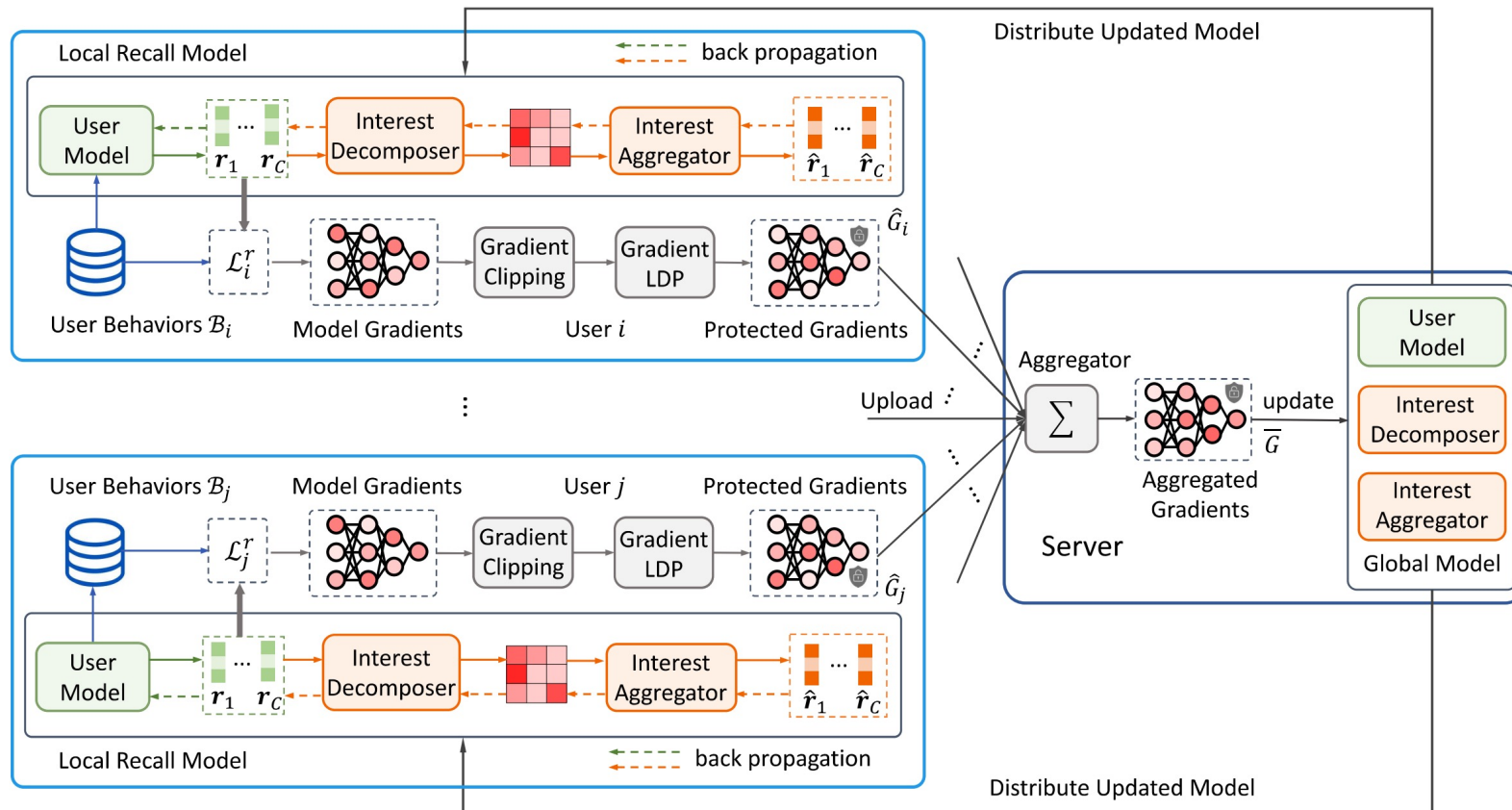


- **Challenges**

- How to generate candidate news and serve users with decentralized user data in a privacy-preserving way remains an open problem

# Uni-FedRec

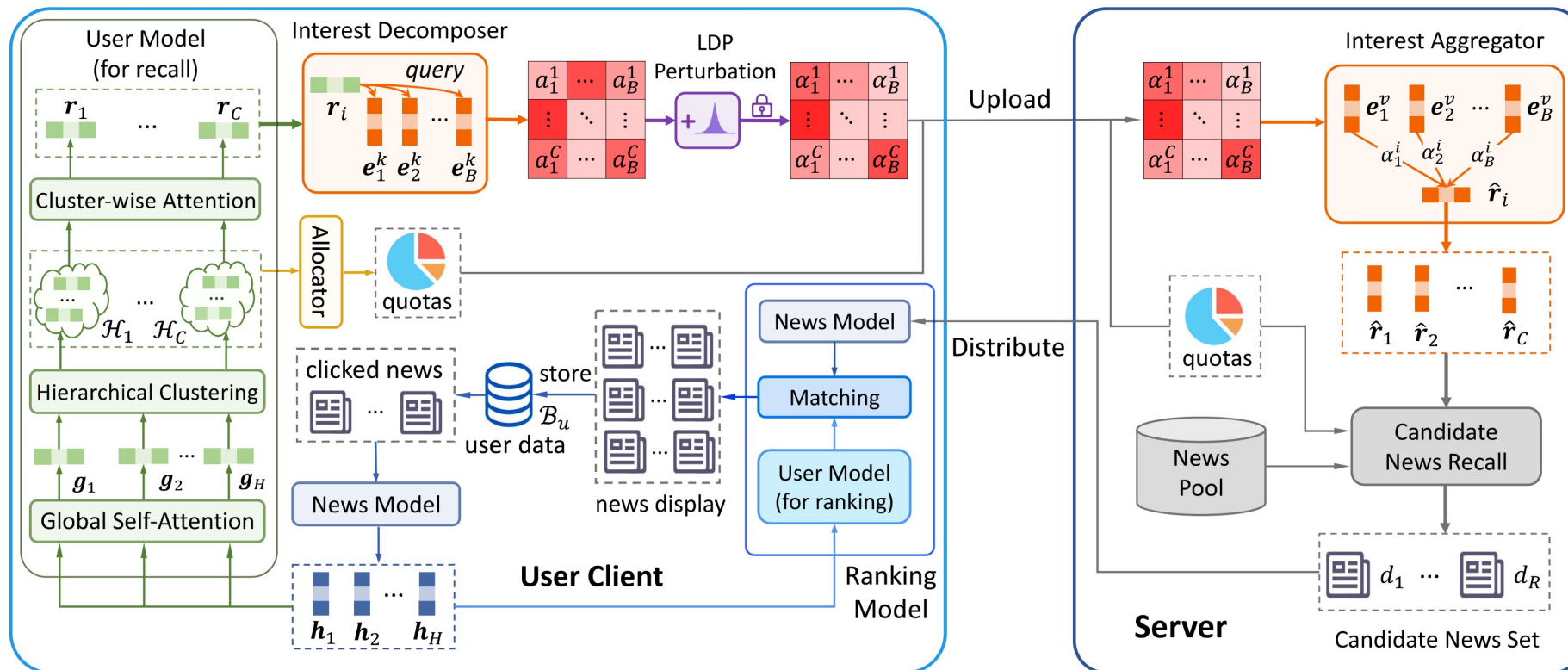
- A unified privacy-preserving news recommendation framework for both model training and online serving



The framework of Uni-FedRec for privacy-preserving model training

# Uni-FedRec

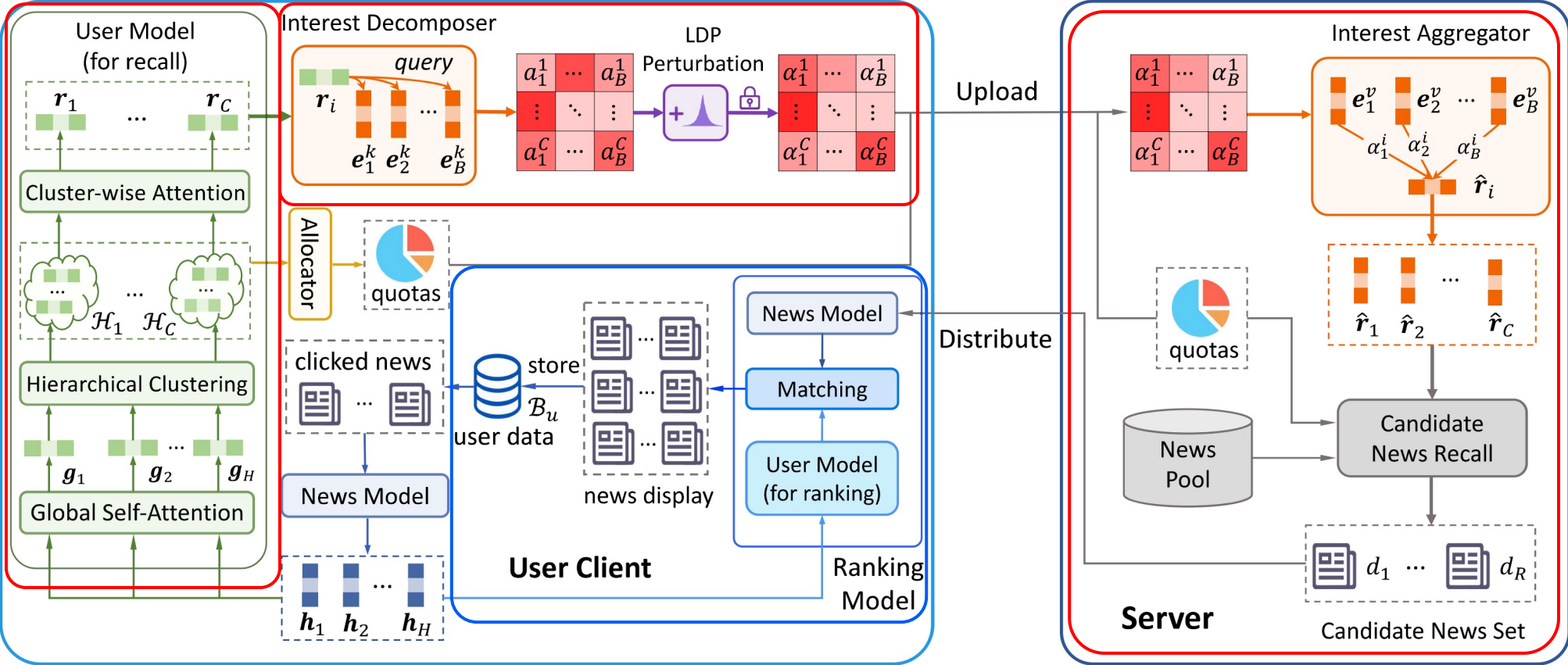
- A unified privacy-preserving news recommendation framework for both model training and online serving



The framework of Uni-FedRec for privacy-preserving online serving

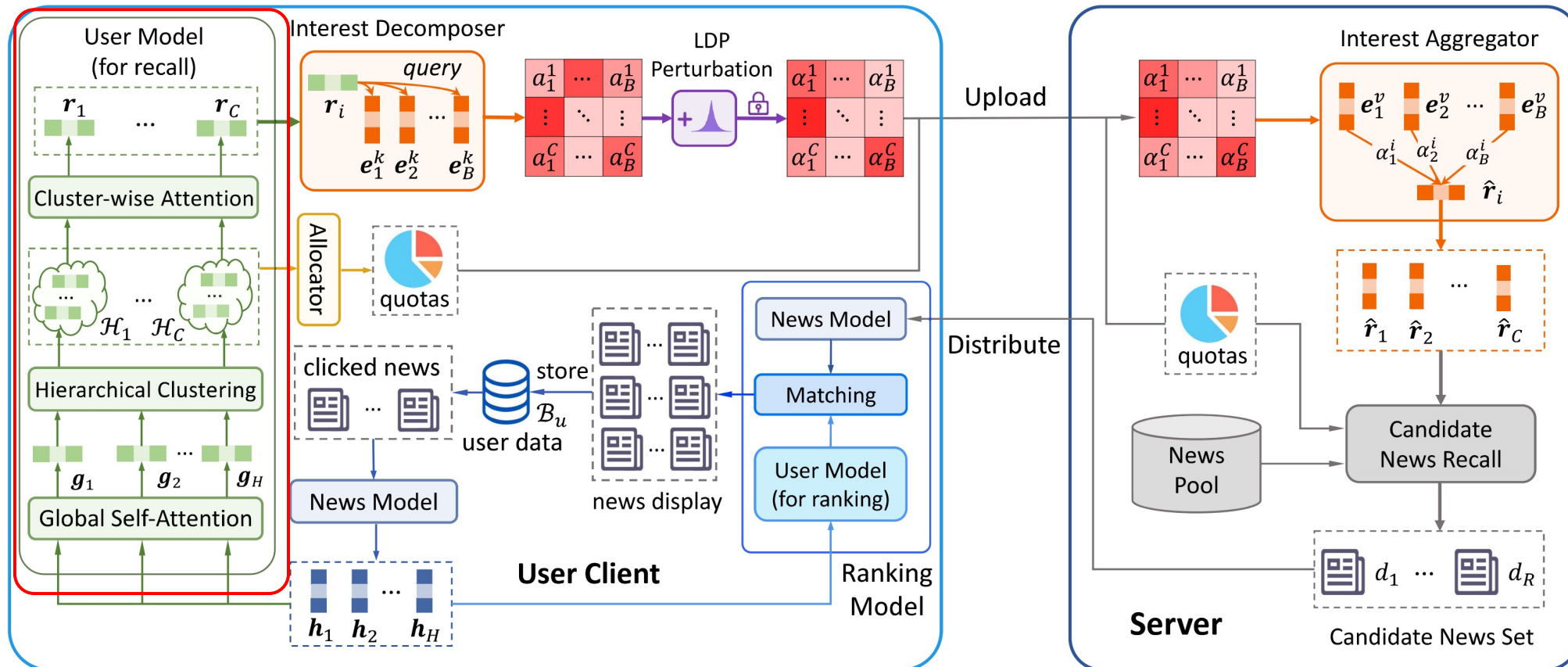
# Uni-FedRec: Privacy-Preserving Online Serving

- Recommend news according to user interest with decentralized user data
  - Privacy-preserving news recall framework; Local news ranking framework



# User Model for News Recall

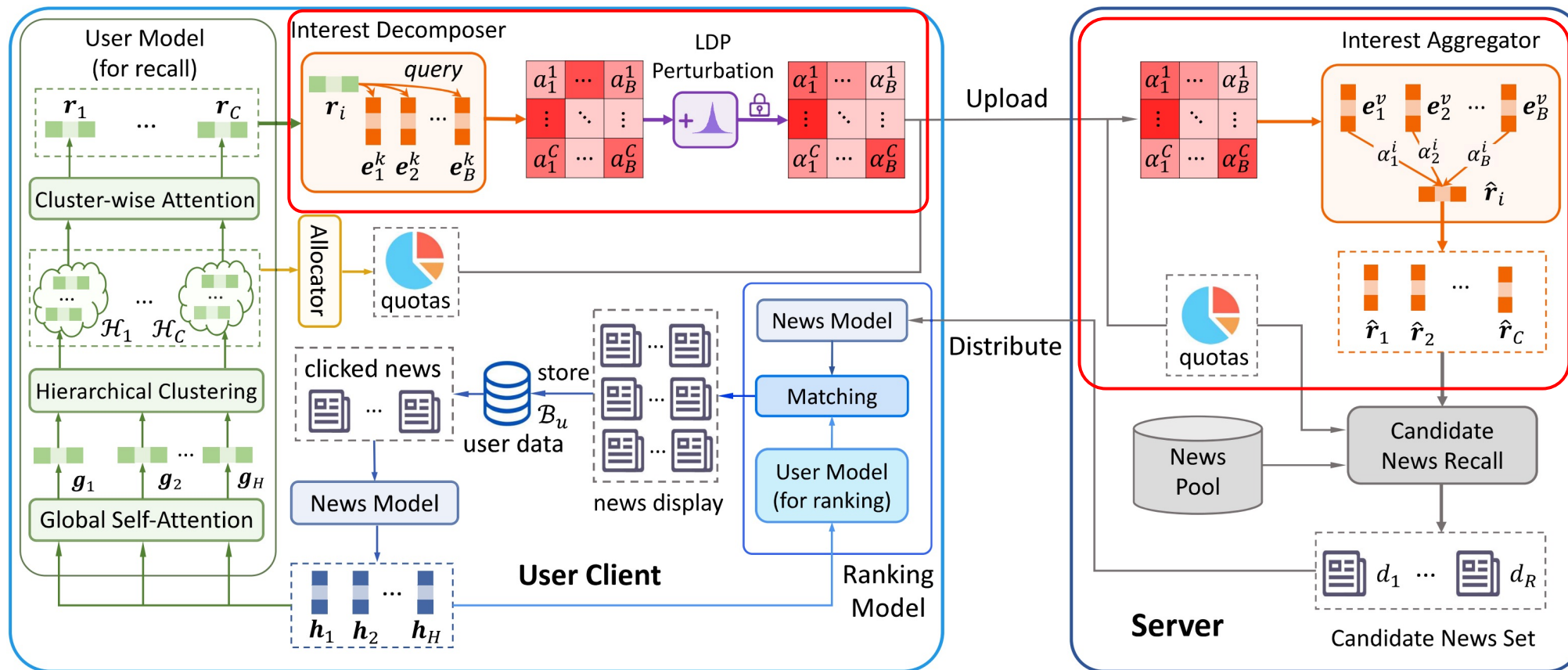
- Users usually have multiple interest
- Learn multiple representation to model diverse user interest





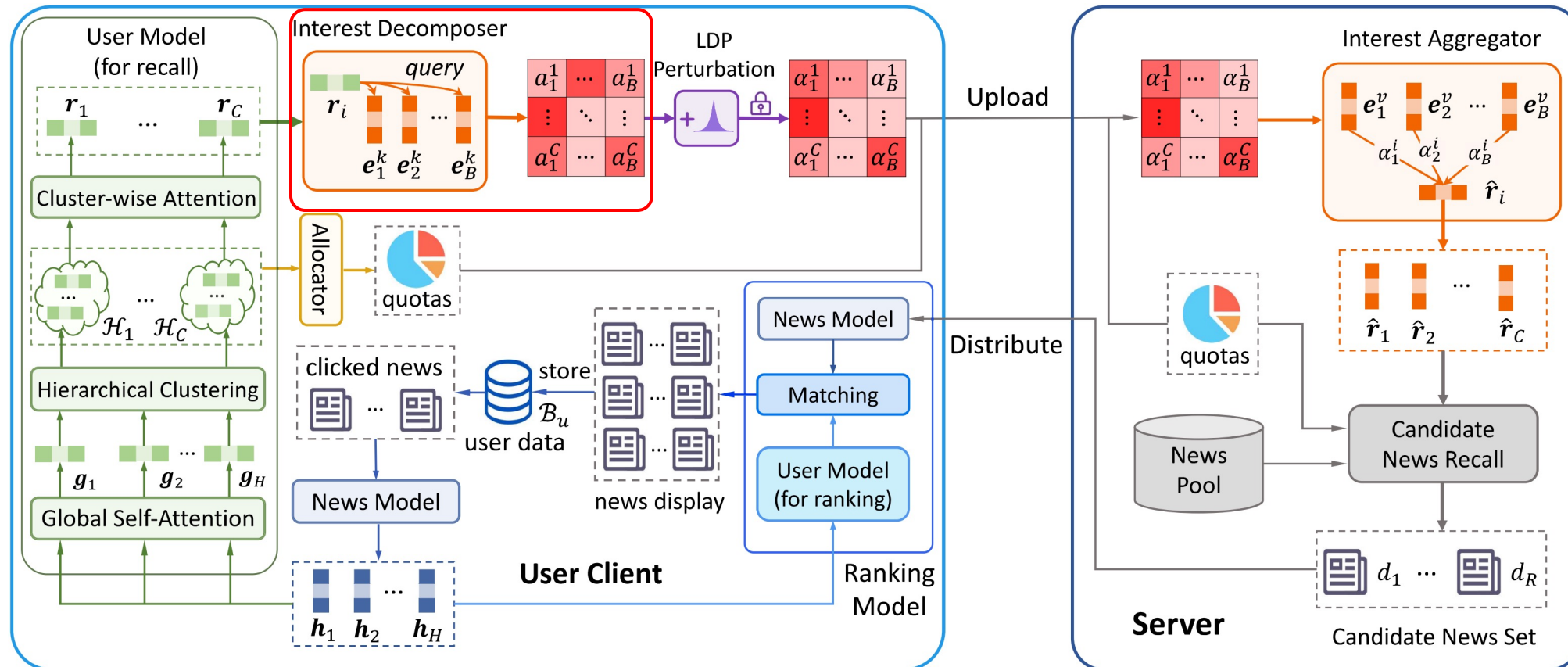
# Interest Decomposer-Aggregator Framework

- Synthesize interest representations via basic interest embeddings



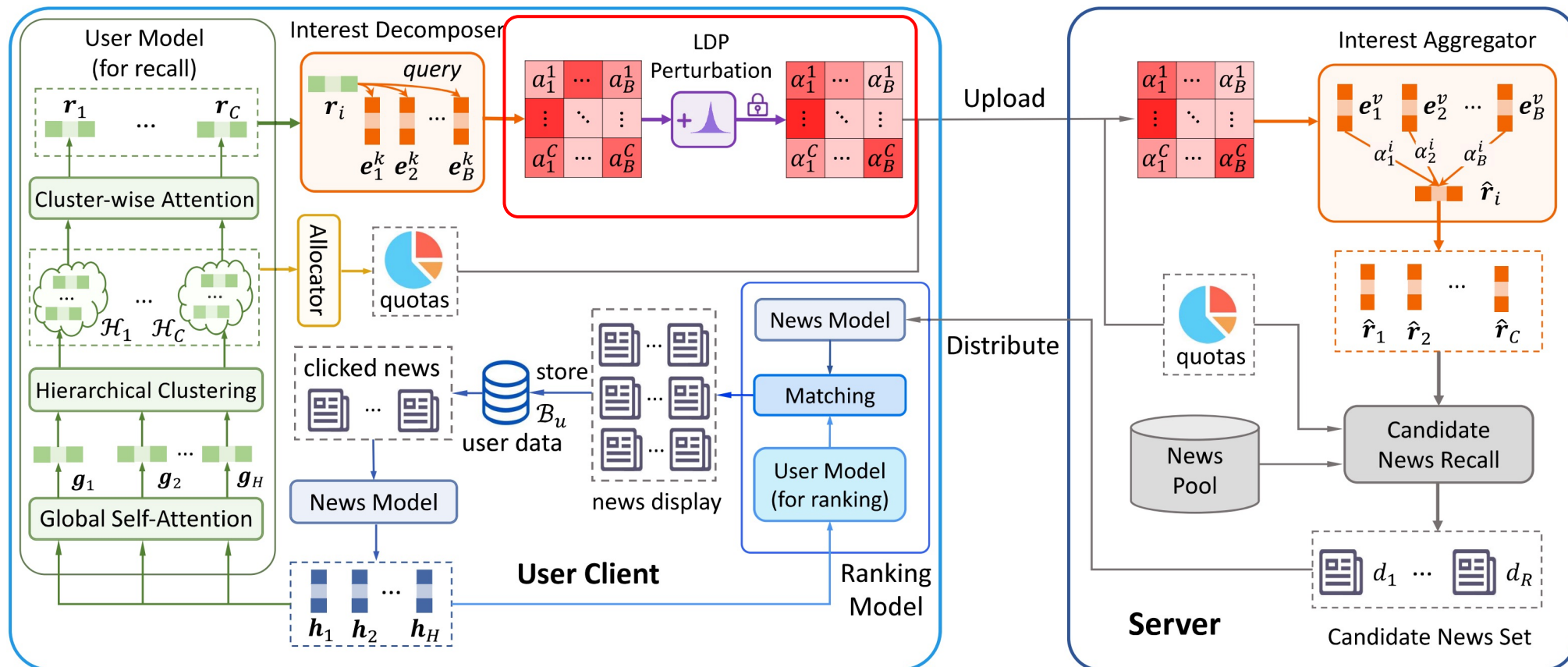
# Interest Decomposer-Aggregator Framework

- Synthesize interest representations via basic interest embeddings
- Interest decomposer:  $a_j^i = \mathbf{r}_i \cdot \mathbf{e}_j^k$ ,  $j = 1, 2, \dots, B$



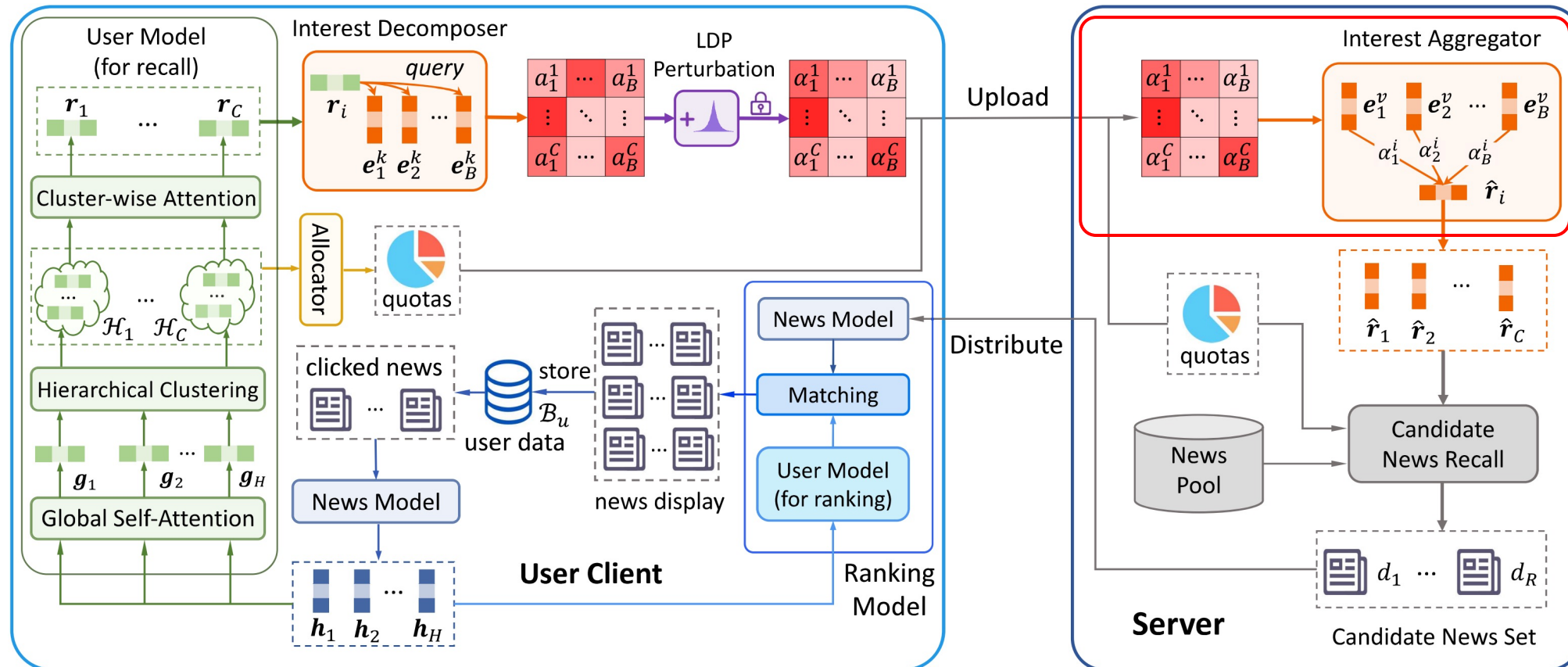
# Interest Decomposer-Aggregator Framework

- Synthesize interest representations via basic interest embeddings with noise
- Perturbation noise:  $\hat{a}_j^i = f_\delta(a_j^i) + n_I, n_I \sim La(0, \lambda_I)$



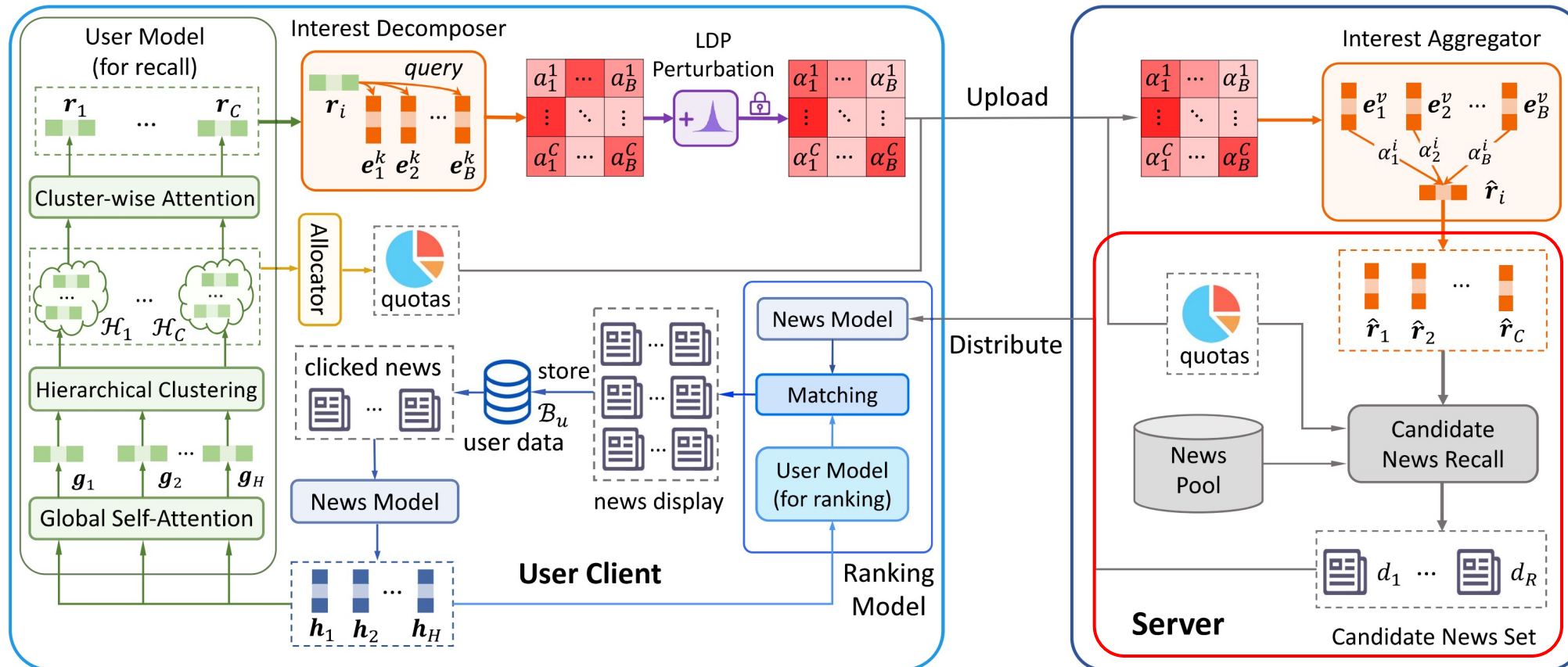
# Interest Decomposer-Aggregator Framework

- Synthesize interest representations via basic interest embeddings with noise
- Interest aggregator:  $\hat{r}_i = \sum_{j=1}^B \alpha_j^i e_j^v$



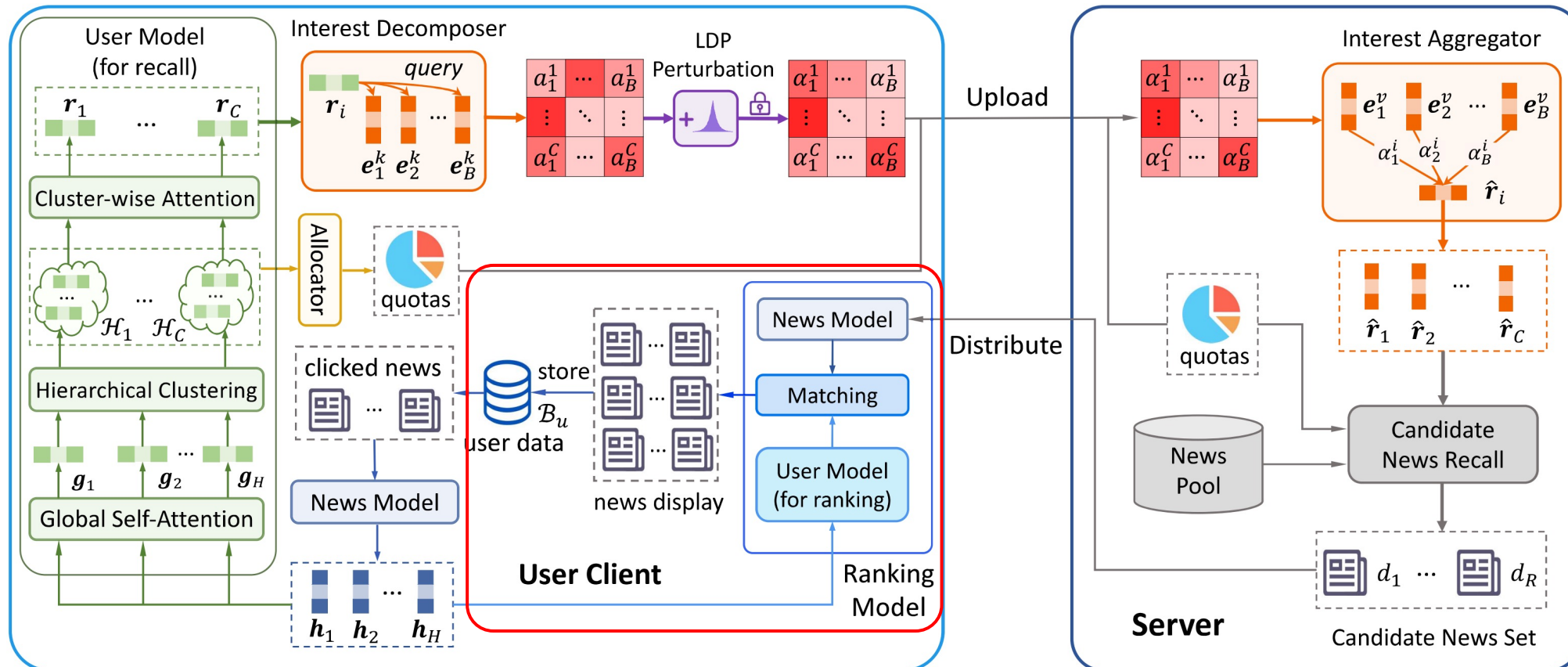
# Multi-Channel News Recall

- Recall news according to different user interest representations
- Integrate candidate news generated by different channels



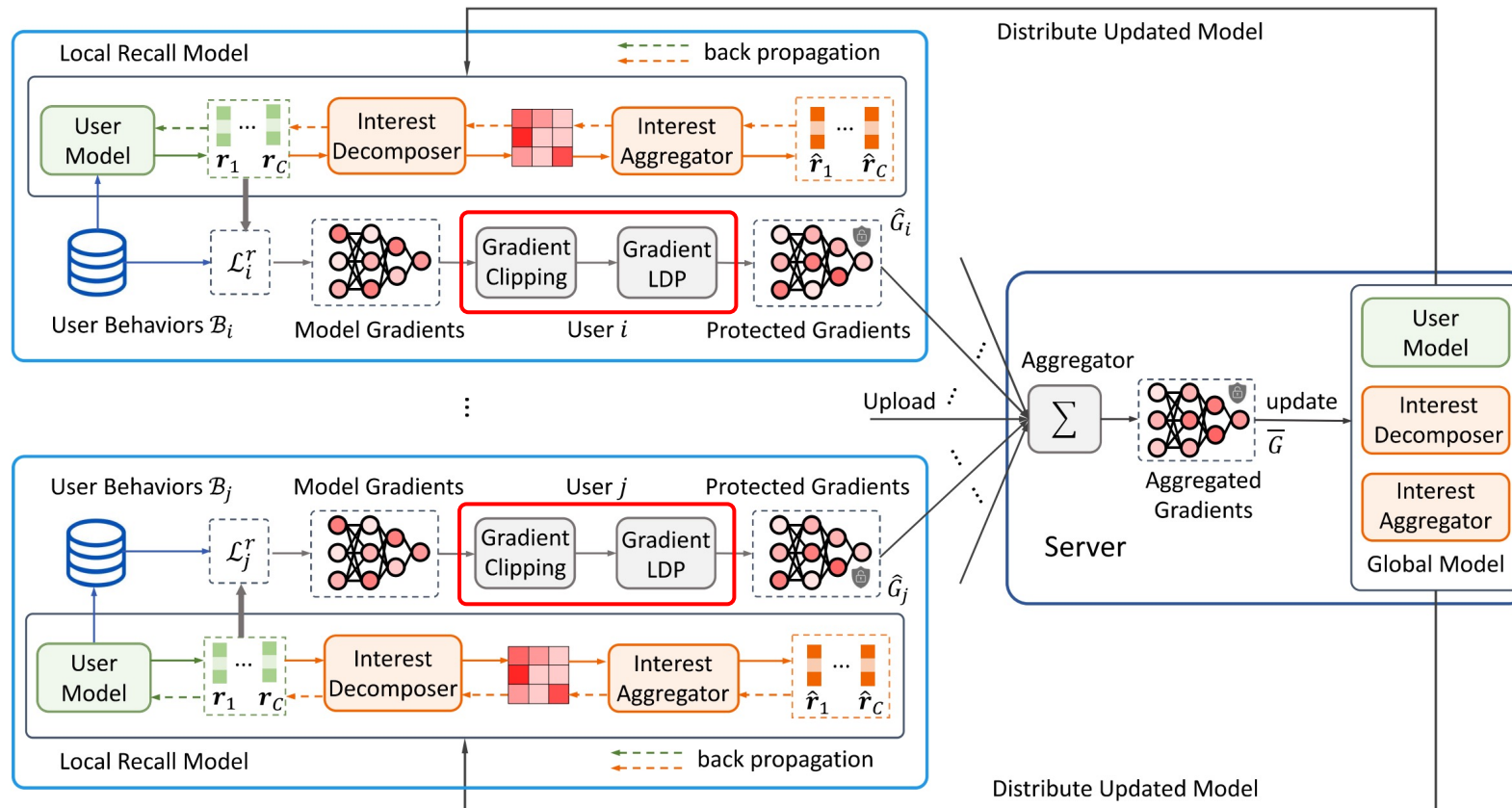
# Local News Ranking

- Locally rank candidate news in the user client via existing personalized news ranking methods



# Privacy-Preserving Model Training

- Privacy-preserving model training with federated learning
- Protect uploaded gradients with LDP:  $\hat{G}_u = f_\theta(G_u) + n_g, n_g \sim La(0, \lambda_g)$



# 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)
- NewsFeeds:
  - Constructed by user logs on a news feeds app in Microsoft
  - Constructed by user logs from 2020.01.23 to 2020.04.23 (13 weeks)

	# News	# Users	# Clicks	# Impressions
<i>MIND</i>	161,013	1,000,000	24,155,470	15,777,377
<i>NewsFeeds</i>	120,219	20,000	112,927	48,923



# News Recall Performance Comparison

	MIND				NewsFeeds			
	R@100	R@200	R@300	R@400	R@100	R@200	R@300	R@400
YoutubeNet	1.50±0.03	2.43±0.08	3.34±0.08	3.96±0.13	0.60±0.02	0.92±0.01	1.17±0.01	1.45±0.02
HUITA	1.69±0.06	2.67±0.04	3.37±0.06	3.97±0.06	0.60±0.01	0.91±0.01	1.18±0.03	1.45±0.01
EBNR	2.31±0.17	3.72±0.13	4.69±0.17	5.61±0.17	0.64±0.03	0.96±0.05	1.28±0.06	1.55±0.06
SASRec	2.22±0.05	3.51±0.07	4.54±0.07	5.38±0.07	0.62±0.06	0.96±0.01	1.20±0.06	1.49±0.05
PinnerSage	1.22±0.14	1.85±0.28	2.69±0.23	3.53±0.20	0.59±0.01	0.93±0.01	1.15±0.01	1.45±0.02
Octopus	1.26±0.03	1.93±0.07	2.74±0.06	3.55±0.06	0.60±0.02	0.92±0.02	1.17±0.02	1.44±0.03
Uni-FedRec	<b>2.95±0.11</b>	<b>4.13±0.12</b>	<b>5.13±0.12</b>	<b>5.99±0.11</b>	<b>0.80±0.08</b>	<b>1.14±0.10</b>	<b>1.60±0.12</b>	<b>2.03±0.12</b>

News recall performance of different methods.  
**Higher** recall rates means **better** performance.

# Privacy Protection Performance Comparison

	MIND				NewsFeeds			
	R@100	R@200	R@300	R@400	R@100	R@200	R@300	R@400
YoutubeNet	12.29	15.91	18.48	20.64	29.43	31.22	32.46	33.47
HUITA	13.44	16.11	17.98	19.49	29.51	31.24	32.44	33.39
EBNR	5.49	8.27	10.30	12.05	11.35	13.08	14.14	14.86
SASRec	6.00	8.71	10.81	12.52	7.78	9.18	10.16	11.03
PinnerSage	16.91	21.35	24.48	27.18	29.43	31.10	32.32	33.38
Octopus	17.04	21.62	24.72	27.31	29.45	31.15	32.36	33.38
Uni-FedRec	<b>0.55</b>	<b>1.14</b>	<b>1.69</b>	<b>2.22</b>	<b>0.23</b>	<b>0.54</b>	<b>0.83</b>	<b>1.08</b>

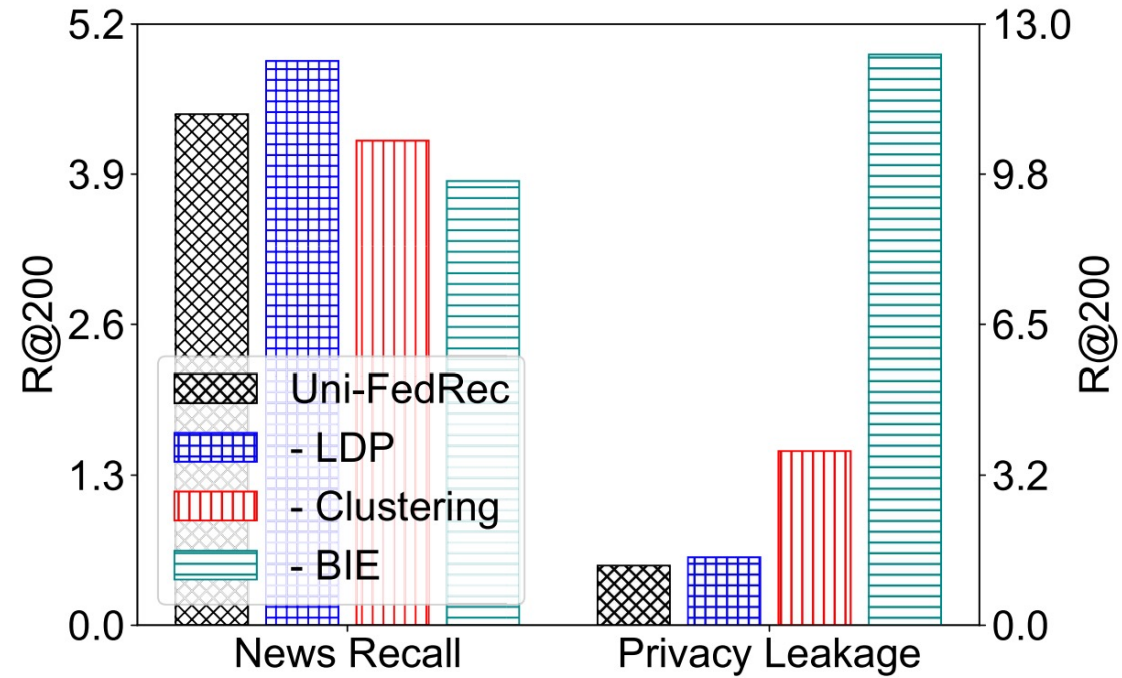
Privacy protection ability is measured by rates of user's historical clicked news recalled from the news pool. **Lower** recall rates means **better** privacy protection performance.

# Recommendation Performance

	FedRec	LSTUR	NRMS	NAML
YoutubeNet	70.65	68.53	68.79	65.93
HUITA	70.48	68.76	70.48	68.76
EBNR	75.56	73.82	75.01	70.89
SASRec	75.07	72.51	73.35	70.51
PinnerSage	69.26	68.96	67.28	66.09
Octopus	69.76	69.12	67.11	65.75
Uni-FedRec	<b>79.26</b>	<b>77.31</b>	<b>78.91</b>	<b>75.40</b>

Recommendation performance (AUC) of different methods, where rows and columns are different recall and ranking methods, respectively.

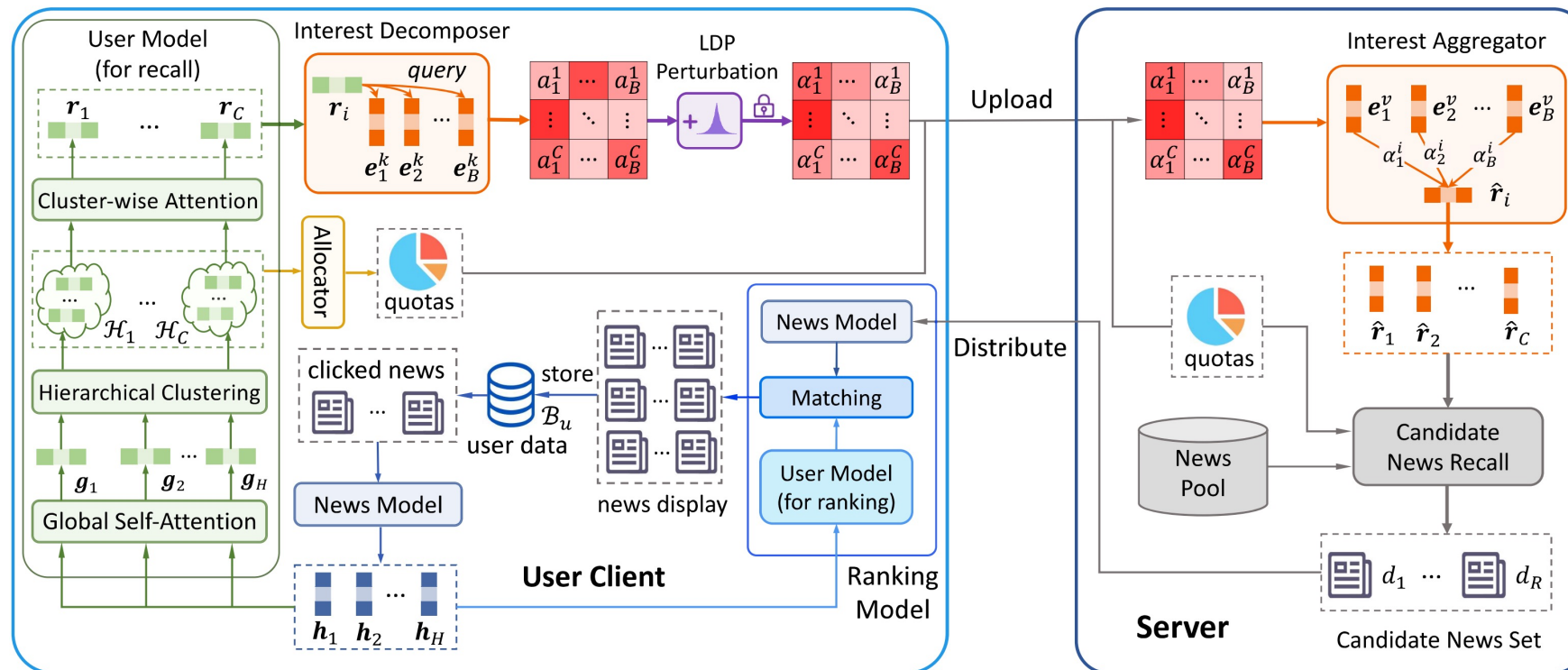
# Ablation Study on Uni-FedRec



Effectiveness of different modules in recall performance and privacy protection

# Conclusion

- Propose a unified privacy-preserving news recommendation framework for both online serving and model training
- Propose a privacy-preserving recall model which can compressively model user interest and protect user privacy



*Thank  
you*



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