ProFairRec: Provider Fairness-aware News Recommendation

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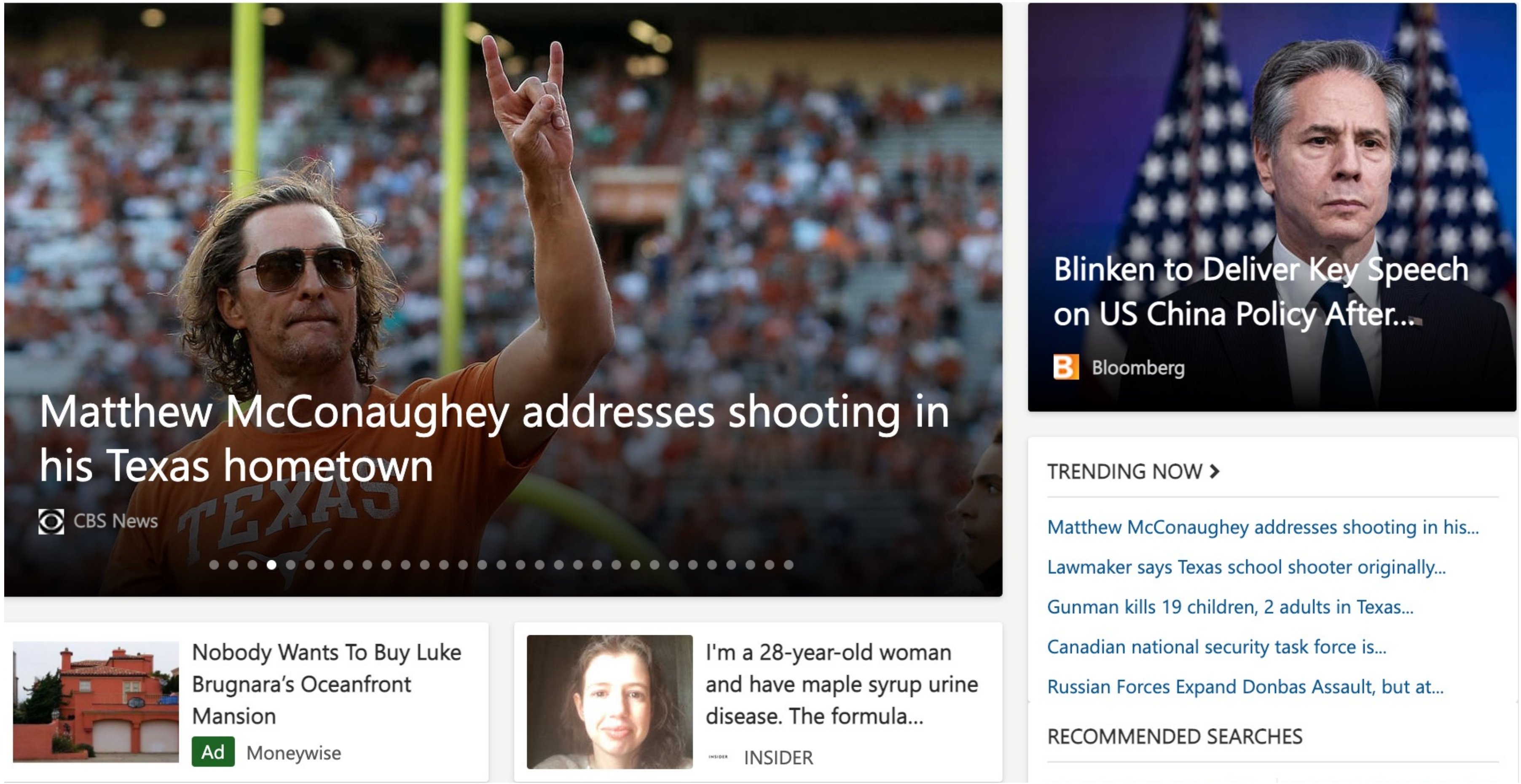
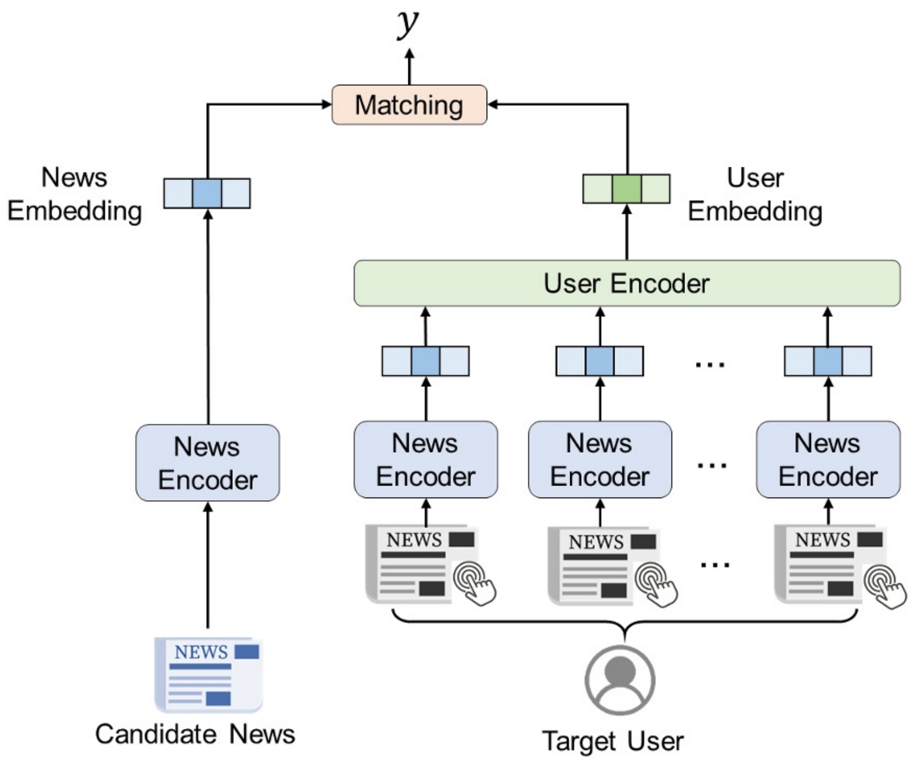
News Recommendation

- News recommendation is important for people to obtain information

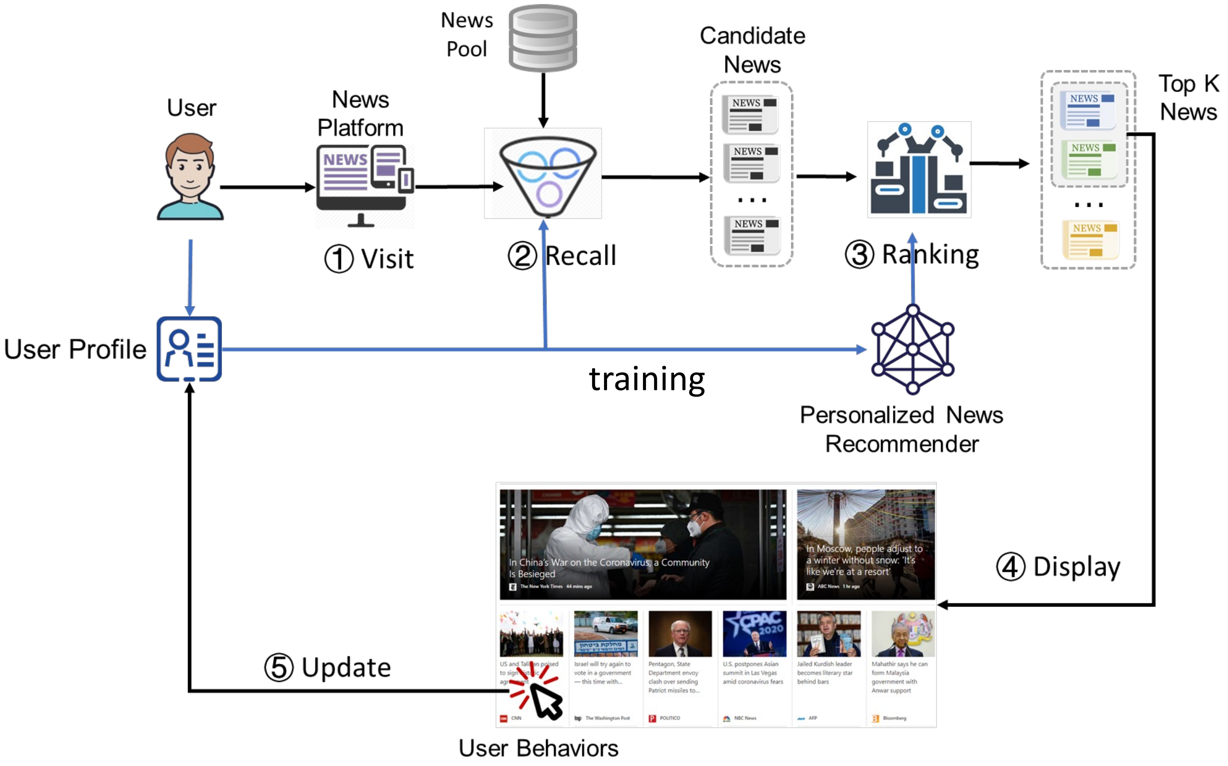


News Recommendation Methods

- Existing news recommendation methods usually learn models from user behavior data (e.g., click data)



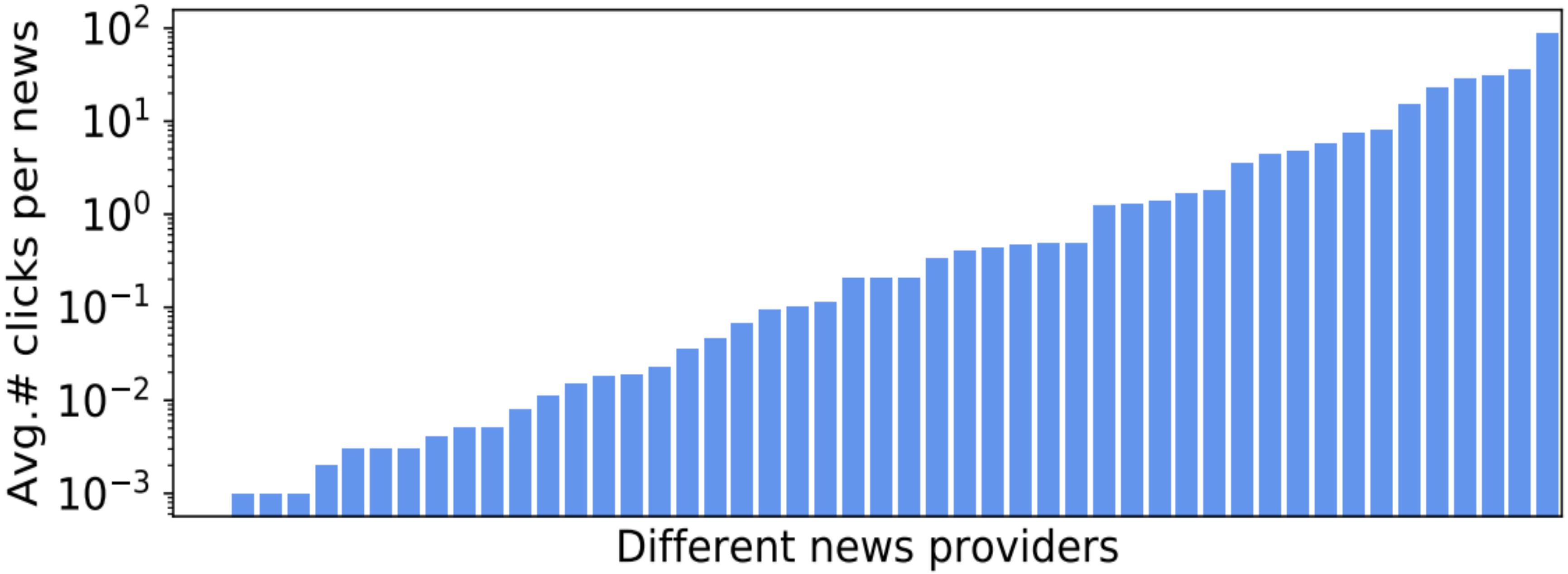
Mainstream news recommendation models.



Framework of news recommendation.

Provider Biases in News Recommendation

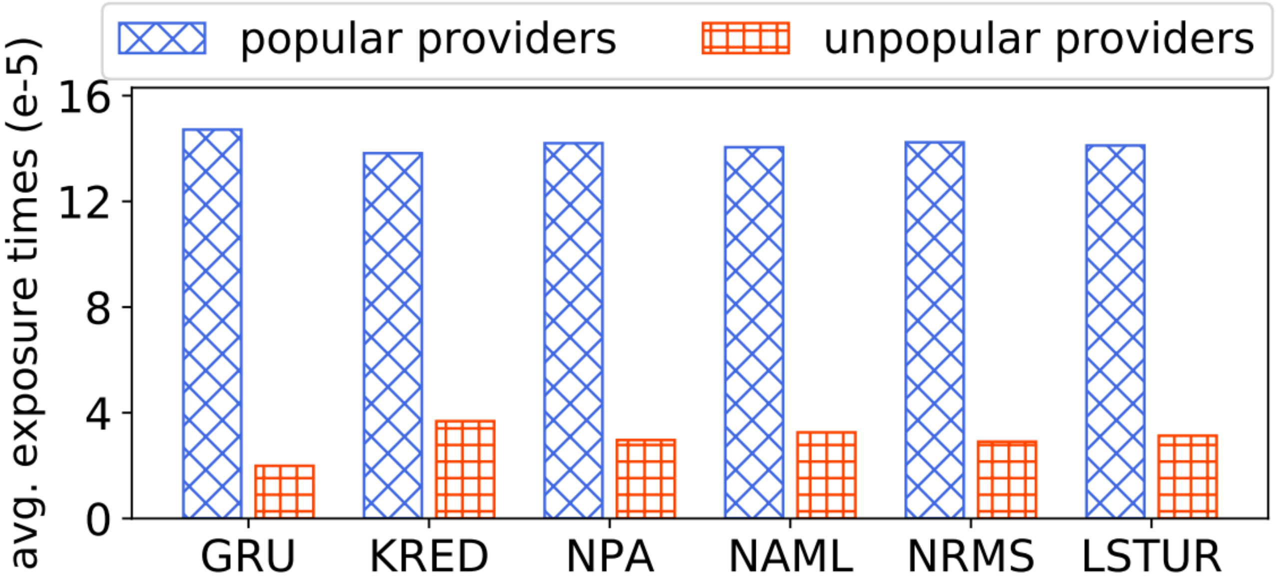
- User reading behaviors on different news providers are usually biased



Average #clicks per news from different providers on MIND.

Provider Biases in News Recommendation

- News recommendation models can capture provider bias from data



Average exposure number of popular & unpopular providers

- Challenges
  - Most of the existing news recommendation methods do not consider provider fairness
  - Biased model may hurt the diversity of news sources and perspectives

Provider Fairness-aware Recommendation

- Many provider fairness-aware methods are usually based on re-ranking
  - e.g., OFAiR, FairRec, TFROM

$$MMR(u,v,R,S) \triangleq \arg\max_{v \in R \setminus S} [\lambda(rec(v,u) - (1-\lambda)\sum_{v' \in S} sim(v,v')]$$

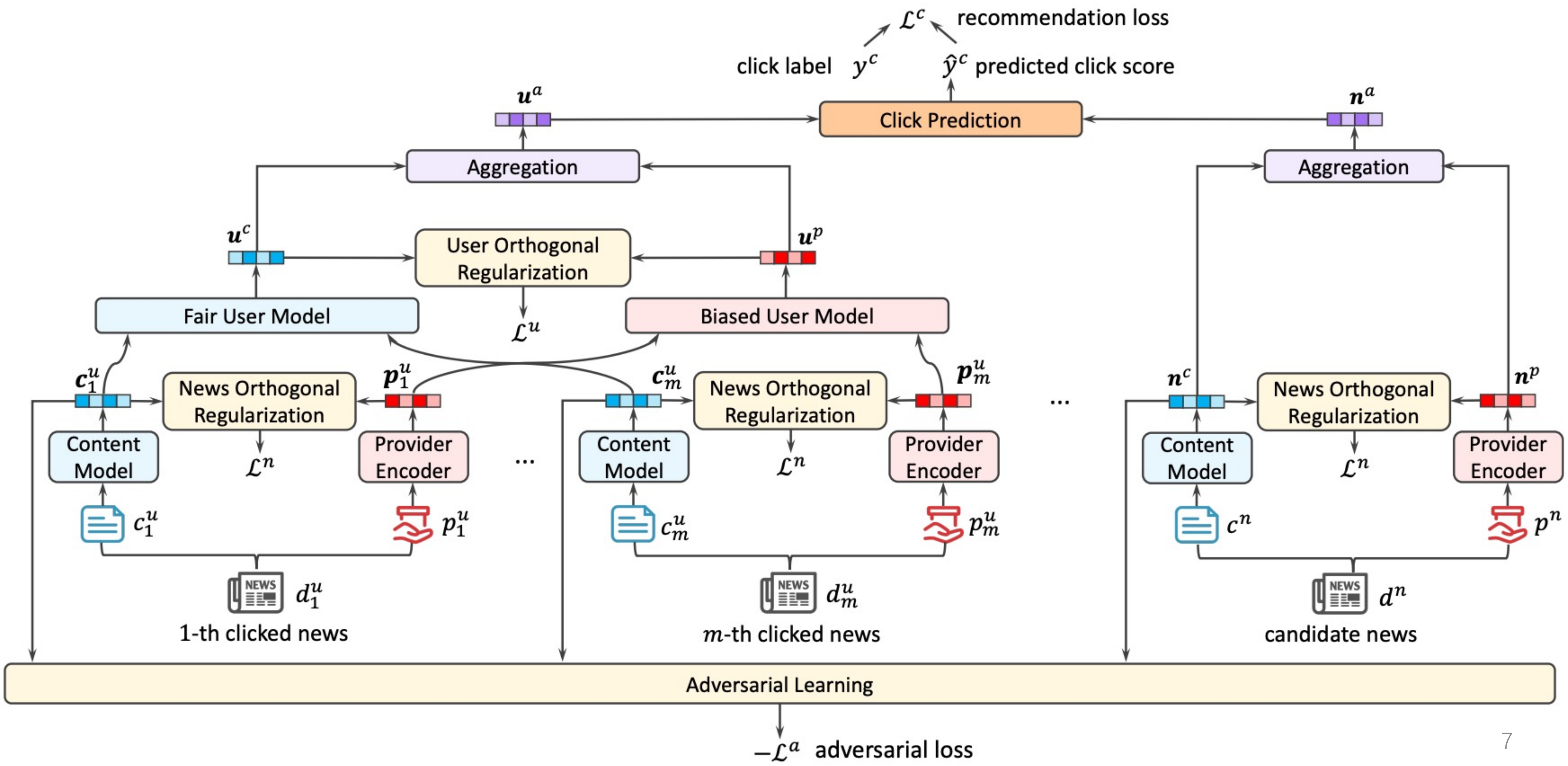
$$xQuAD(u,v,R,S) \triangleq \arg\max_{v \in R \setminus S} [\lambda(rec(v,u) + (1-\lambda)\max_{v' \in S} \mathbb{1}_{\vec{v} \cap \vec{v}' = \emptyset}],$$

1: Initialize allocation $\mathcal{B} = (B_1, \ldots, B_m)$ with $B_i \leftarrow \emptyset$ for each customer $i \in [m]$.
2: Initiate $x \leftarrow m$.
3: Initiate round $r \leftarrow 0$.
4: **while** true **do**
5:     Set $r \leftarrow r + 1$.
6:     **for** $i = 1$ to m **do**
7:         Set $p \in \arg\max_{p' \in F_{\sigma(i)}:(S_p \neq 0)} V_{\sigma(i)}(p')$
8:         **if** $p == \emptyset$ **then**
9:             Set $x = i - 1$ only if $i \neq 1$.
10:             **go to** Step 22.
11:         **end if**
12:         Update $B_{\sigma(i)} \leftarrow B_{\sigma(i)} \cup p$.
13:         Update $F_{\sigma(i)} \leftarrow F_{\sigma(i)} \setminus p$.
14:         Update $S_p \leftarrow S_p - 1$.
15:         Update $T \leftarrow T - 1$.
16:         **if** $T == 0$ **then**
17:             $x = i$.
18:             **go to** Step 22.
19:         **end if**
20:     **end for**
21: **end while**
22: Return $\mathcal{B} = (B_1, \ldots, B_m)$, $F = (F_1, \ldots, F_m)$ and index x.

- Challenges
  - Manually designed re-ranking rules may be sup-optimal for achieving an effective trade-off between performance and fairness

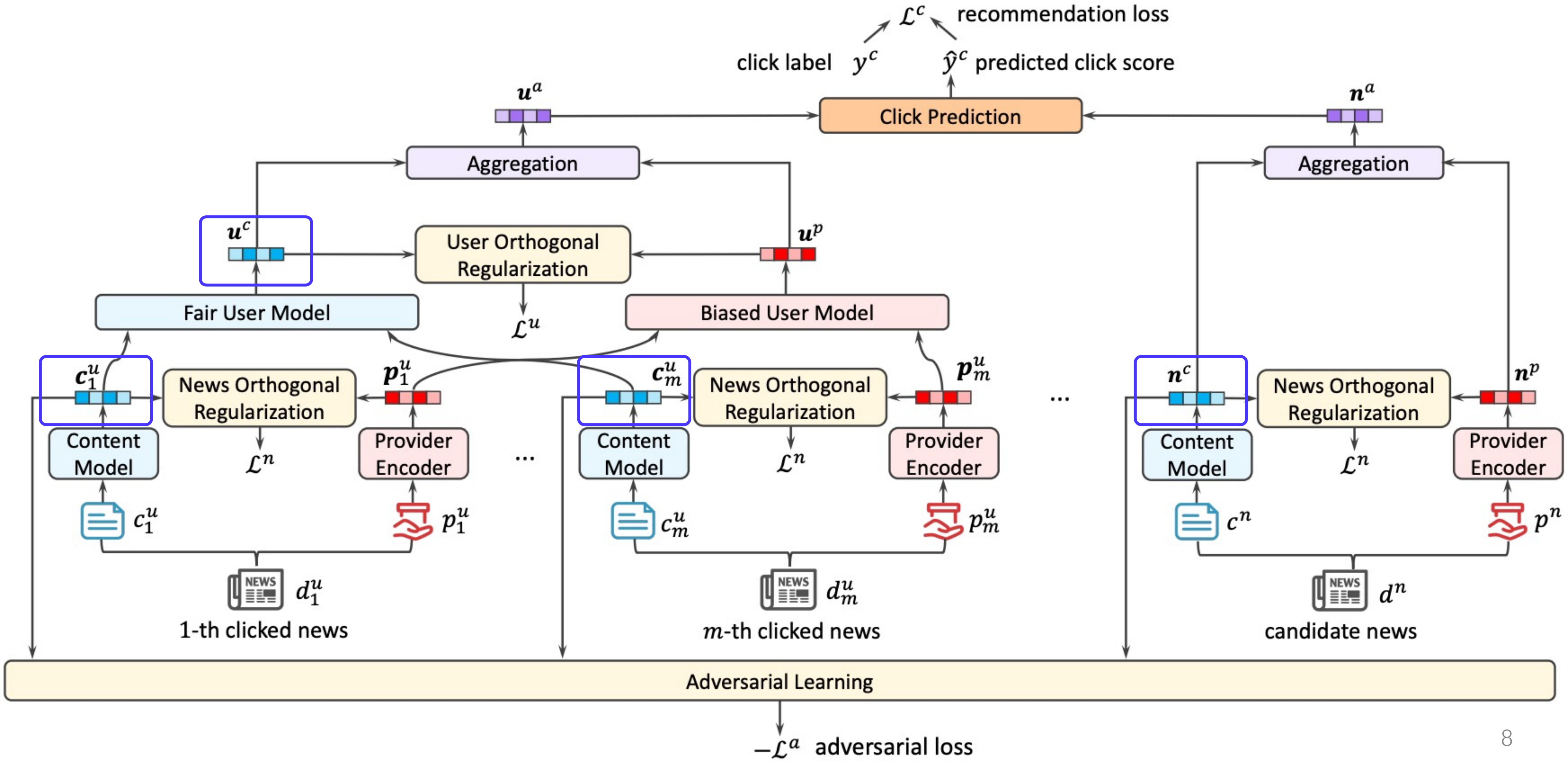
ProFairRec: Overall Framework

- Improve fairness of recommendation models learned from biased data



ProFairRec: Overall Framework

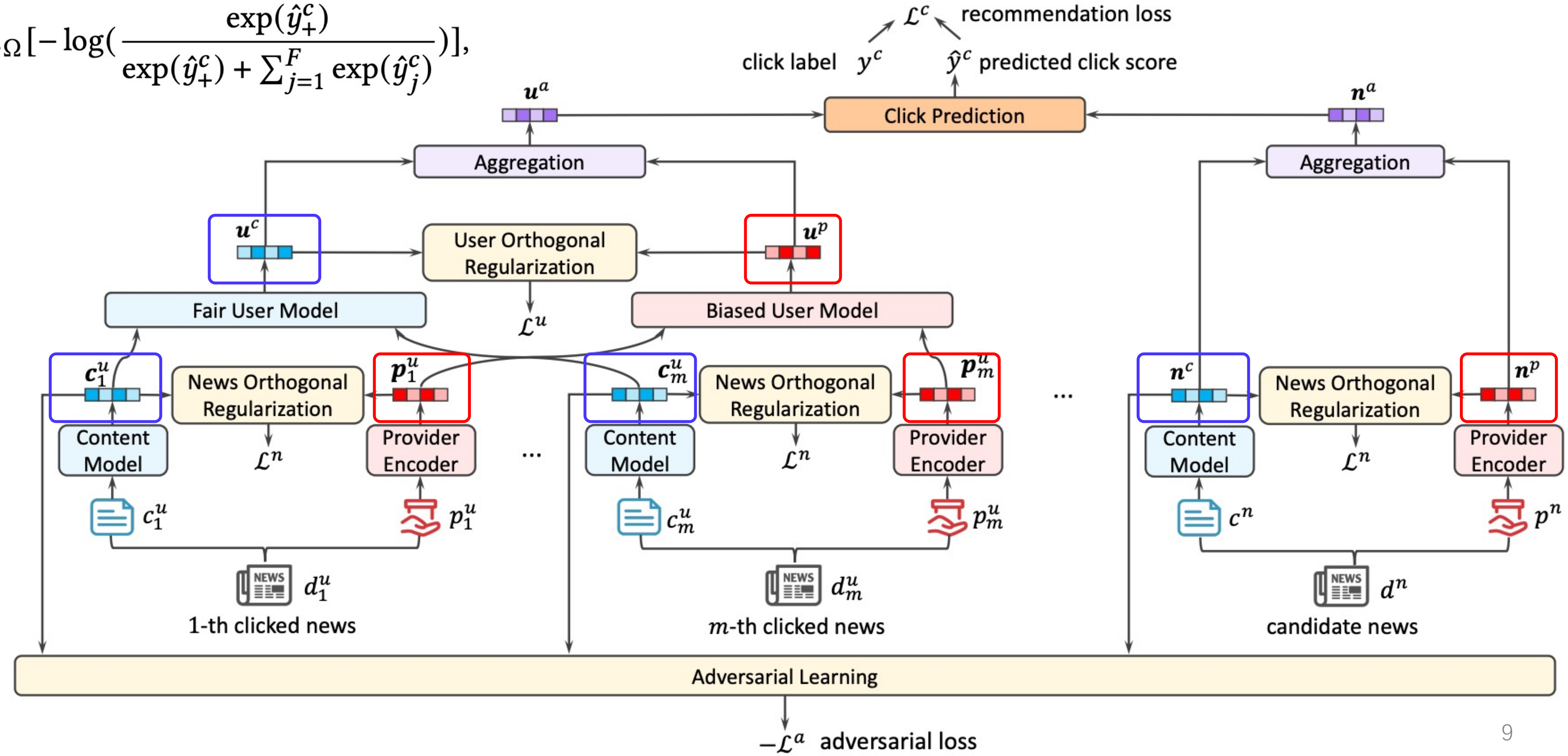
- Learn fair representations for news and user to achieve provider fairness



ProFairRec: Fair Model Training

- Learning fair representations for news and user to achieve provider fairness

$$\mathcal{L}^c = \mathbb{E}_{x\sim\Omega}[-\log(\frac{\exp(\hat{y}^c_+)}{\exp(\hat{y}^c_+) + \sum_{j=1}^{F} \exp(\hat{y}^c_j)})],$$



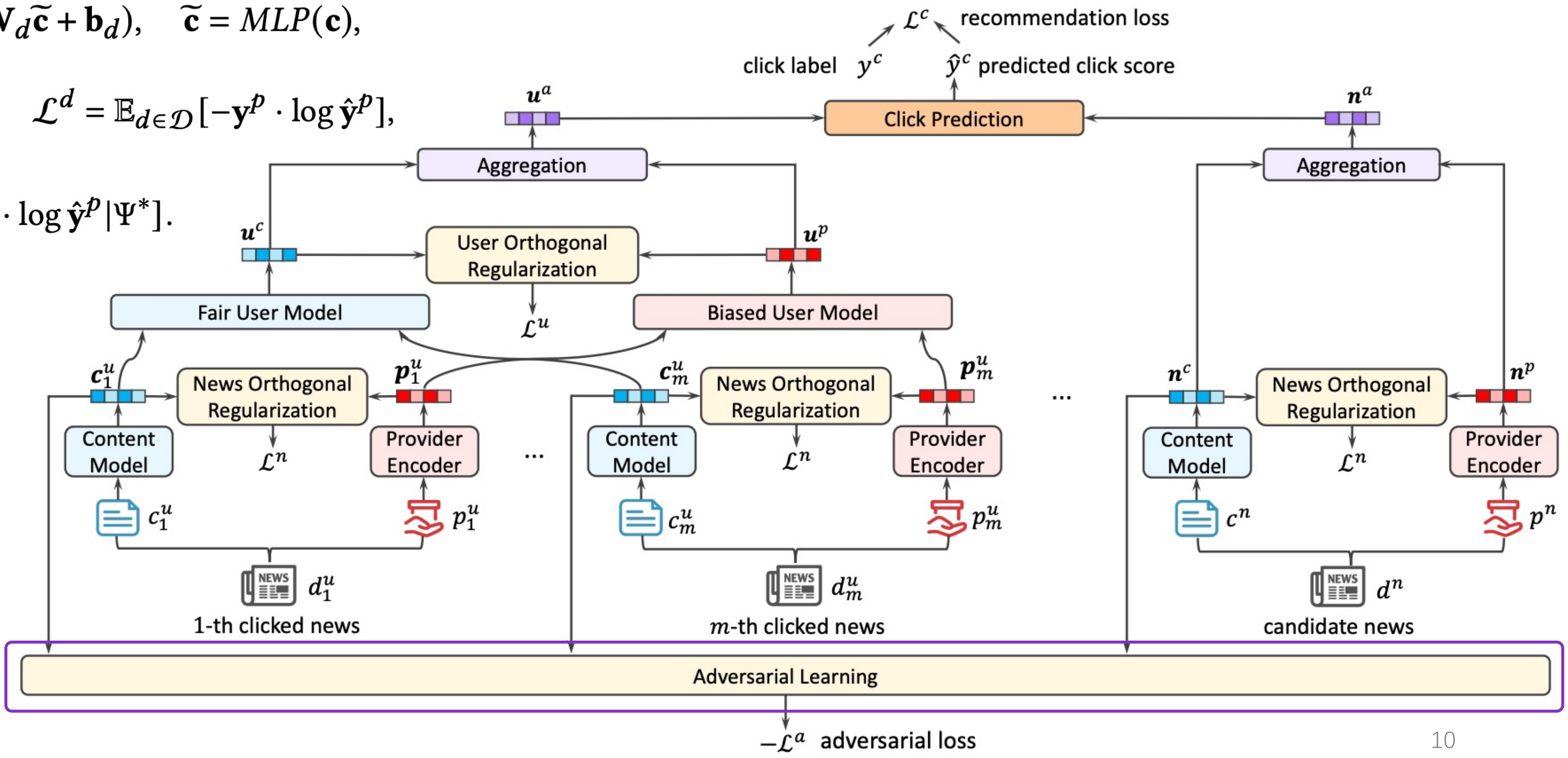
ProFairRec: Fair Model Training

- Adversarial learning: prevent fair representations from encoding provider bias

$$\hat{\mathbf{y}}^p = softmax(\mathbf{W}_d\widetilde{\mathbf{c}} + \mathbf{b}_d), \quad \widetilde{\mathbf{c}} = MLP(\mathbf{c}),$$

$$\Psi^* = \arg\min_{\Psi} \mathcal{L}^d, \quad \mathcal{L}^d = \mathbb{E}_{d\in\mathcal{D}}[-\mathbf{y}^p \cdot \log \hat{\mathbf{y}}^p],$$

$$\mathcal{L}^a = \mathbb{E}_{d\in\mathcal{D}}[-\mathbf{y}^p \cdot \log \hat{\mathbf{y}}^p | \Psi^*].$$



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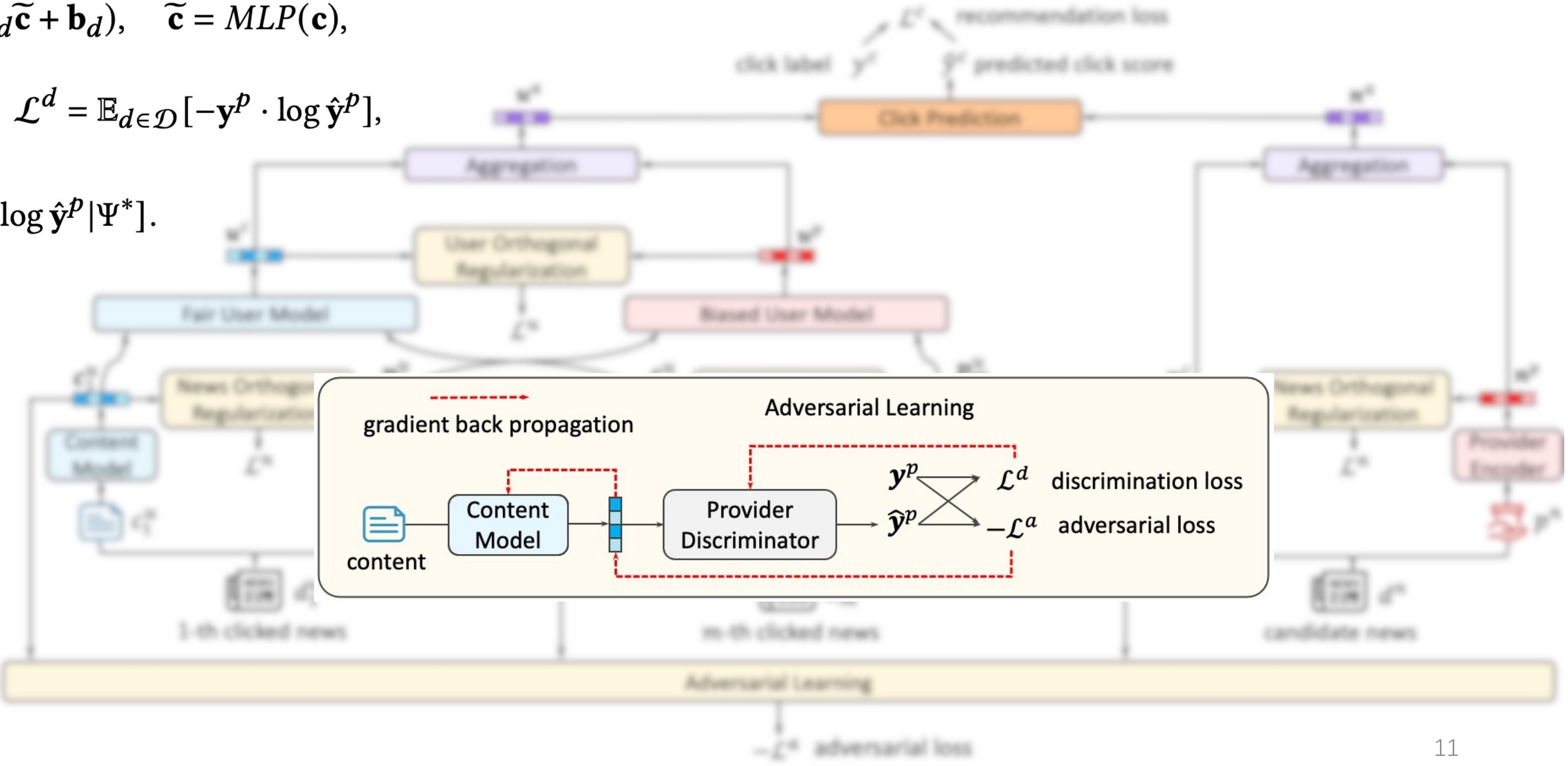
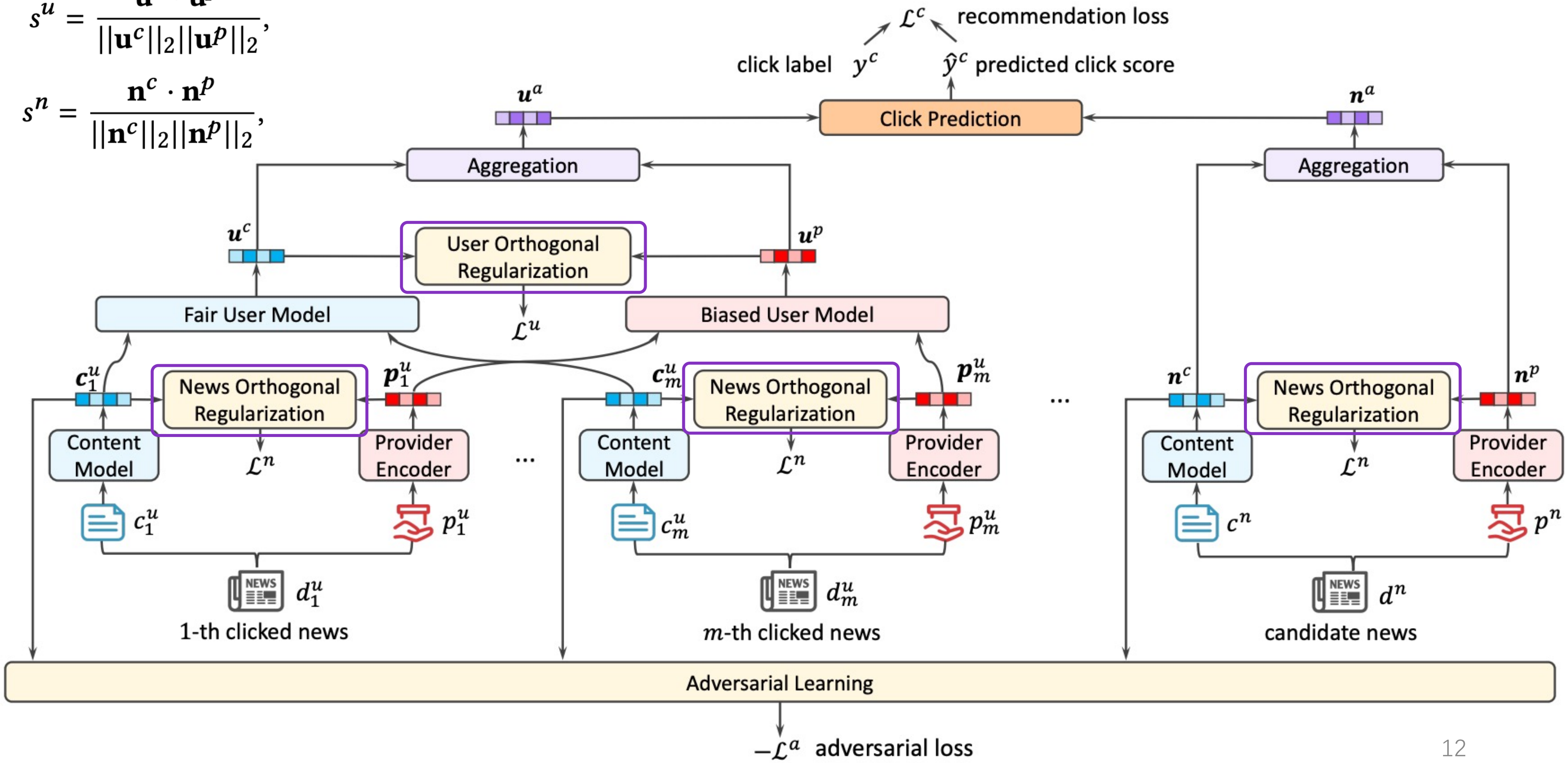


ProFairRec: Fair Model Training

- Regularization enforces the orthogonality of fair and biased representations

$$\mathcal{L}^u = \mathbb{E}_{u \in \mathcal{U}}[|s^u|], \quad s^u = \frac{\mathbf{u}^c \cdot \mathbf{u}^p}{||\mathbf{u}^c||_2 ||\mathbf{u}^p||_2},$$

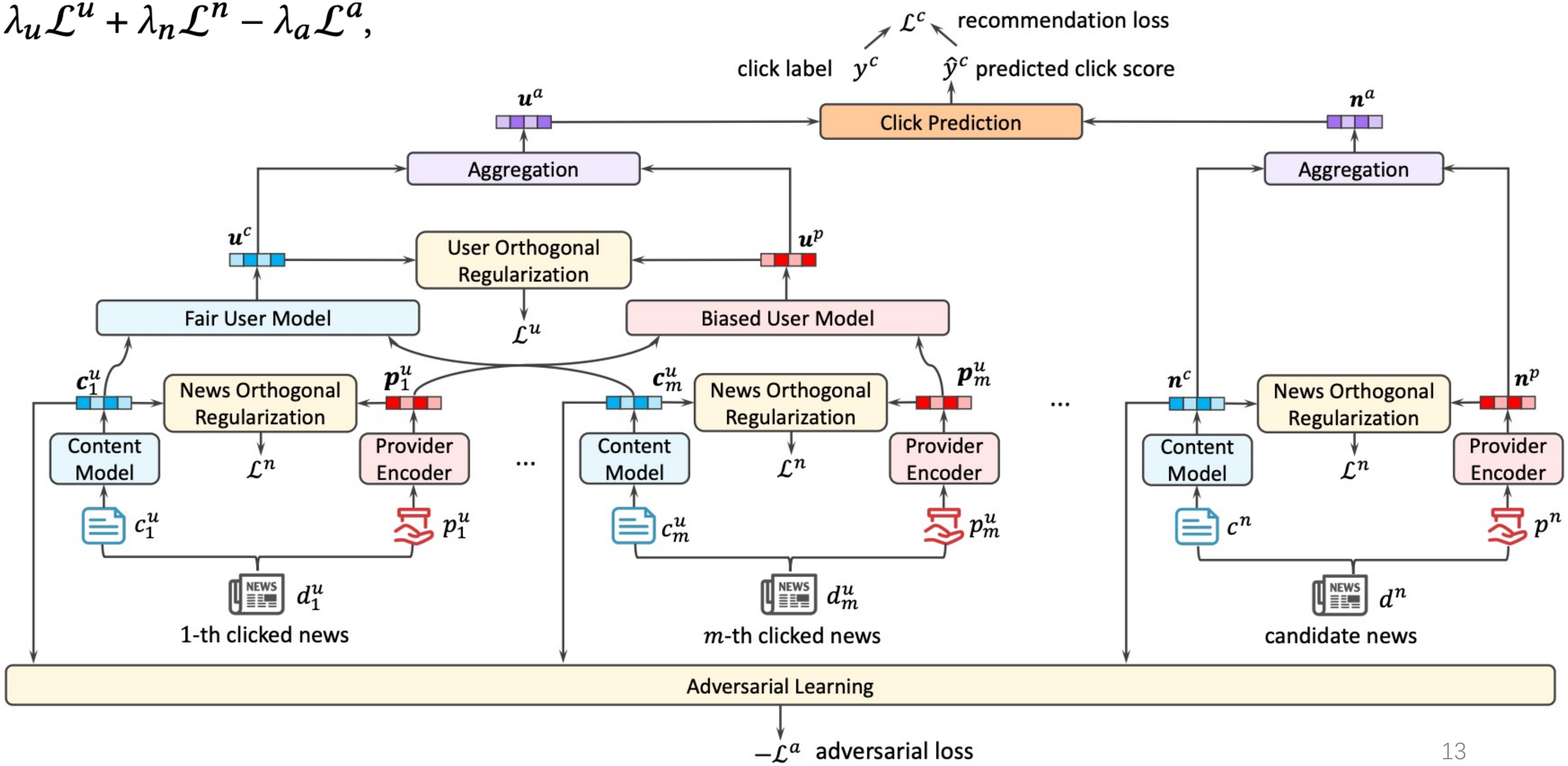
$$\mathcal{L}^n = \mathbb{E}_{d \in \mathcal{D}}[|s^n|], \quad s^n = \frac{\mathbf{n}^c \cdot \mathbf{n}^p}{||\mathbf{n}^c||_2 ||\mathbf{n}^p||_2},$$



ProFairRec: Fair Model Training

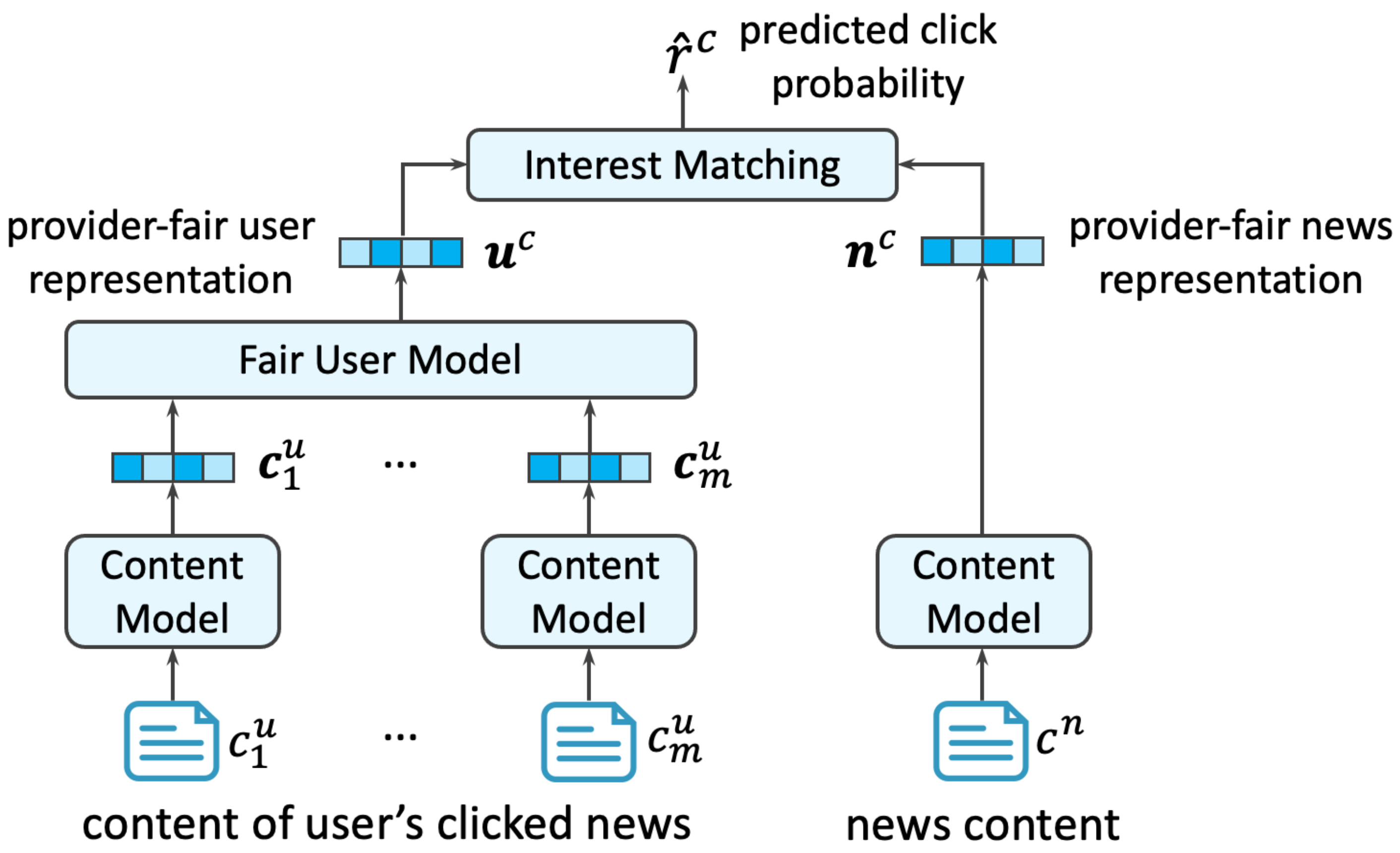
- The overall training objective for learning fair news recommendation models

$$\mathcal{L} = \lambda_c \mathcal{L}^c + \lambda_u \mathcal{L}^u + \lambda_n \mathcal{L}^n - \lambda_a \mathcal{L}^a,$$



ProFairRec: Fair News Recommendation

- Only match provider-fair news and user representations to improve provider fairness in news recommendation



Experimental Dataset and Settings

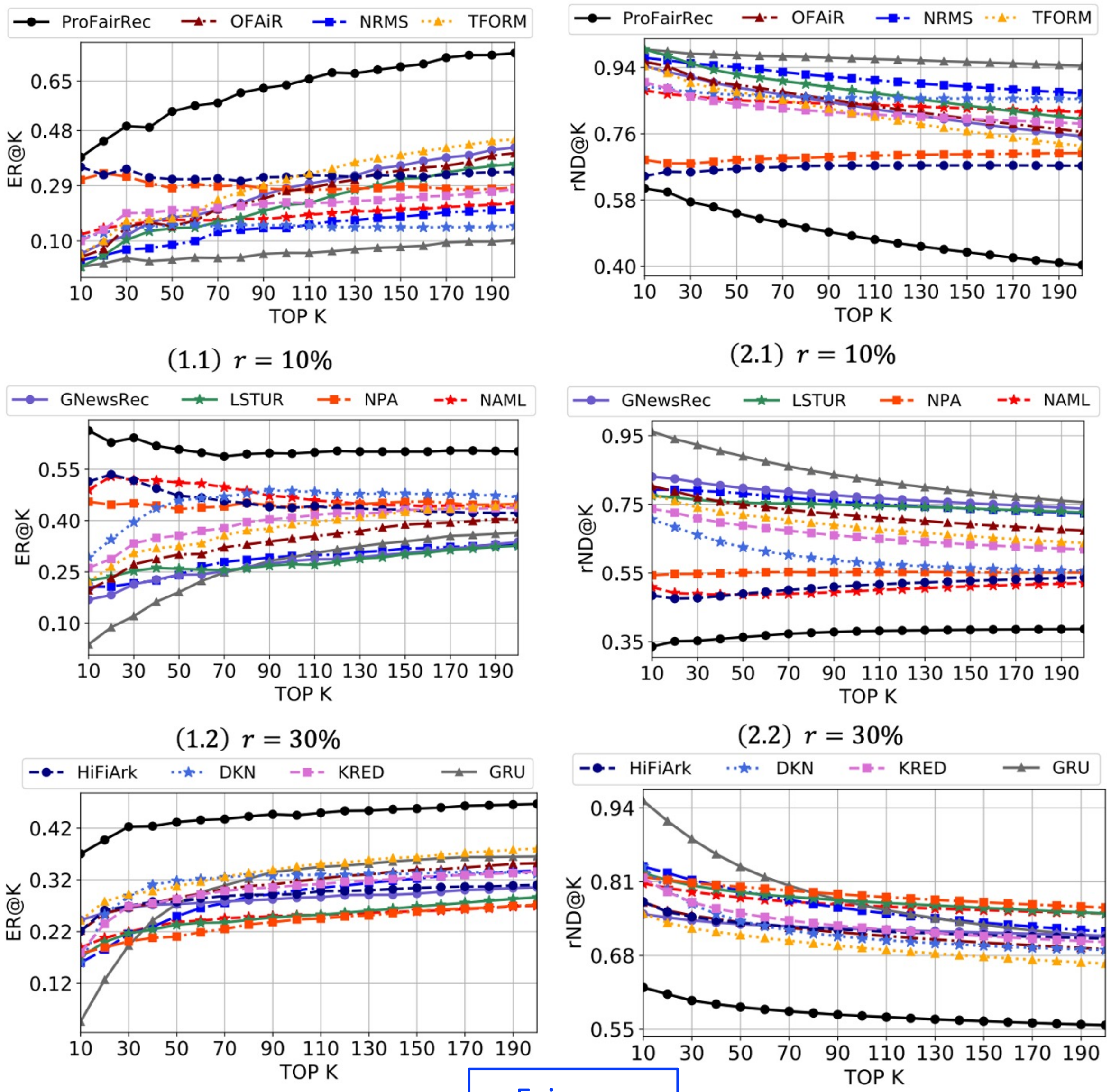
- Dataset: MIND

# News	130,379	# Providers	1,705
# Users	1,000,000	# Impressions	4,979,946
# Clicks	7,583,733	# Non-clicks	183,124,199
Avg. # words in news titles			11.78

- Recommendation metric: AUC, MRR, nDCG@10
- Partition providers into two groups based on popularity
- Fairness metric: measuring the unfairness of exposure opportunities

$$ER@K = \frac{\mathbb{E}_{u\in\mathcal{U}}[|\mathcal{R}_K^u \cap \mathcal{D}^+|/|\mathcal{D}^+|]}{\mathbb{E}_{u\in\mathcal{U}}[|\mathcal{R}_K^u \cap \mathcal{D}^-|/|\mathcal{D}^-|]}, \qquad rND@K = \frac{1}{Z}\mathbb{E}_{u\in\mathcal{U}}[\sum_{n=10,20,\ldots}^{K} \frac{1}{log_2 n}|\frac{|\mathcal{R}_n^u \cap \mathcal{D}^+|}{n} - \frac{|\mathcal{D}^+|}{|\mathcal{D}|}|]$$

Performance and Fairness



(1.1) $r = 10\%$ (2.1) $r = 10\%$

(1.2) $r = 30\%$ (2.2) $r = 30\%$

(1.3) $r = 50\%$ (2.3) $r = 50\%$

Fairness

	AUC	MRR	nDCG@10
GRU	66.50±0.04	32.06±0.04	40.45±0.02
DKN	66.70±0.15	32.41±0.11	40.88±0.12
HiFiArk	67.49±0.19	33.04±0.15	41.57±0.15
NAML	67.22±0.20	33.01±0.10	41.54±0.12
NPA	67.13±0.07	32.90±0.07	41.45±0.07
KRED	67.55±0.11	33.27±0.05	41.83±0.05
GNewsRec	68.41±0.10	33.59±0.10	42.24±0.11
LSTUR	68.35±0.10	33.48±0.10	42.16±0.09
NRMS	68.08±0.13	33.43±0.09	42.07±0.10
OFAiR	67.46±0.17	33.08±0.14	41.62±0.17
TFORM	67.53±0.16	33.12±0.13	41.63±0.16
ProFairRec	67.64±0.10	33.08±0.05	41.67±0.07

Performance

Generalization of ProFairRec

Fairness

	ER@10	ER@30	ER@50	rND@10	rND@30	rND@50
NAML	0.1646±0.0080	0.2099±0.0107	0.2236±0.0102	0.8316±0.0082	0.8130±0.0077	0.8022±0.0077
+ProFairRec	**0.2644**±0.0329	**0.2721**±0.0229	**0.2822**±0.0255	**0.7303**±0.0332	**0.7271**±0.0261	**0.7232**±0.0230
KRED	0.1518±0.0399	0.2271±0.0349	0.2572±0.0321	0.8447±0.0407	0.8138±0.0379	0.7940±0.0356
+ProFairRec	**0.2223**±0.0777	**0.2627**±0.0649	**0.2918**±0.0596	**0.7730**±0.0788	**0.7565**±0.0734	**0.7425**±0.0699
NPA	0.1503±0.0358	0.1894±0.0203	0.2086±0.0220	0.8462±0.0364	0.8301±0.0298	0.8189±0.0276
+ProFairRec	**0.2444**±0.0382	**0.2499**±0.0361	**0.2584**±0.0332	**0.7506**±0.0388	**0.7483**±0.0373	**0.7452**±0.0358
NRMS	0.1237±0.0243	0.1991±0.0213	0.2378±0.0195	0.8734±0.0248	0.8423±0.0225	0.8202±0.0212
+ProFairRec	**0.3644**±0.0847	**0.3941**±0.0689	**0.4156**±0.0658	**0.6295**±0.0854	**0.6174**±0.0779	**0.6071**±0.0738
LSTUR	0.1583±0.0206	0.2086±0.0292	0.2254±0.0326	0.8381±0.0210	0.8174±0.0232	0.8050±0.0257
+ProFairRec	**0.3765**±0.1067	**0.4491**±0.0791	**0.4865**±0.0663	**0.6174**±0.1070	**0.5879**±0.0952	**0.5668**±0.0869

Performance

	AUC	MRR	nDCG@10
NAML	67.22±0.20	33.01±0.10	41.54±0.12
+ProFairRec	67.13±0.08	32.86±0.09	41.38±0.09
KRED	67.55±0.11	33.27±0.05	41.83±0.05
+ProFairRec	67.51±0.19	33.11±0.16	41.71±0.16
NPA	67.13±0.07	32.90±0.07	41.45±0.07
+ProFairRec	67.13±0.03	32.86±0.05	41.39±0.05
NRMS	68.08±0.13	33.43±0.09	42.07±0.10
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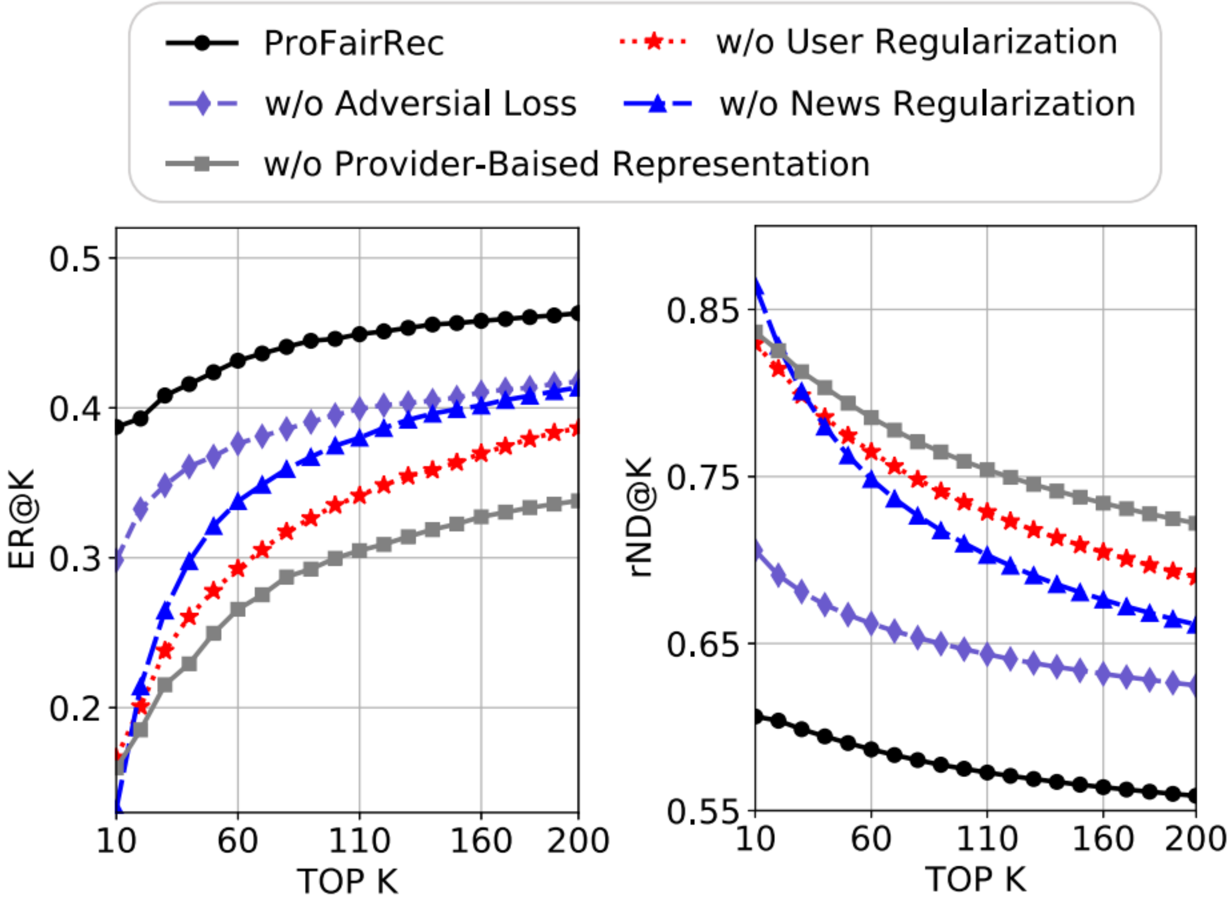
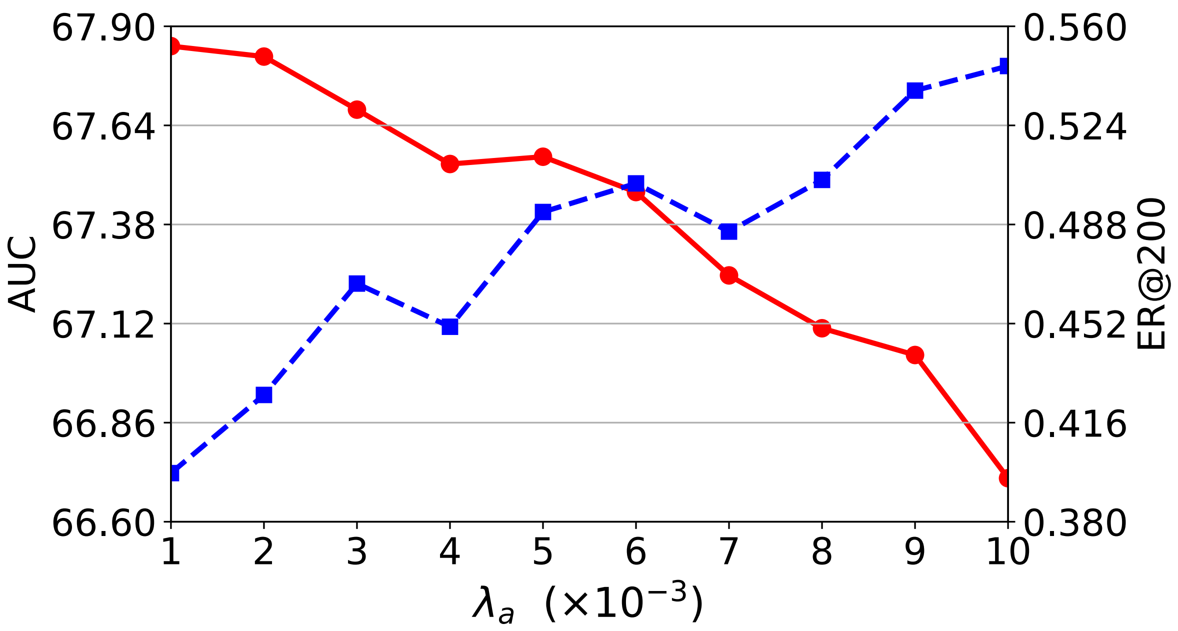
Ablation Study on ProFairRec



Ablation study on ProFairRec.

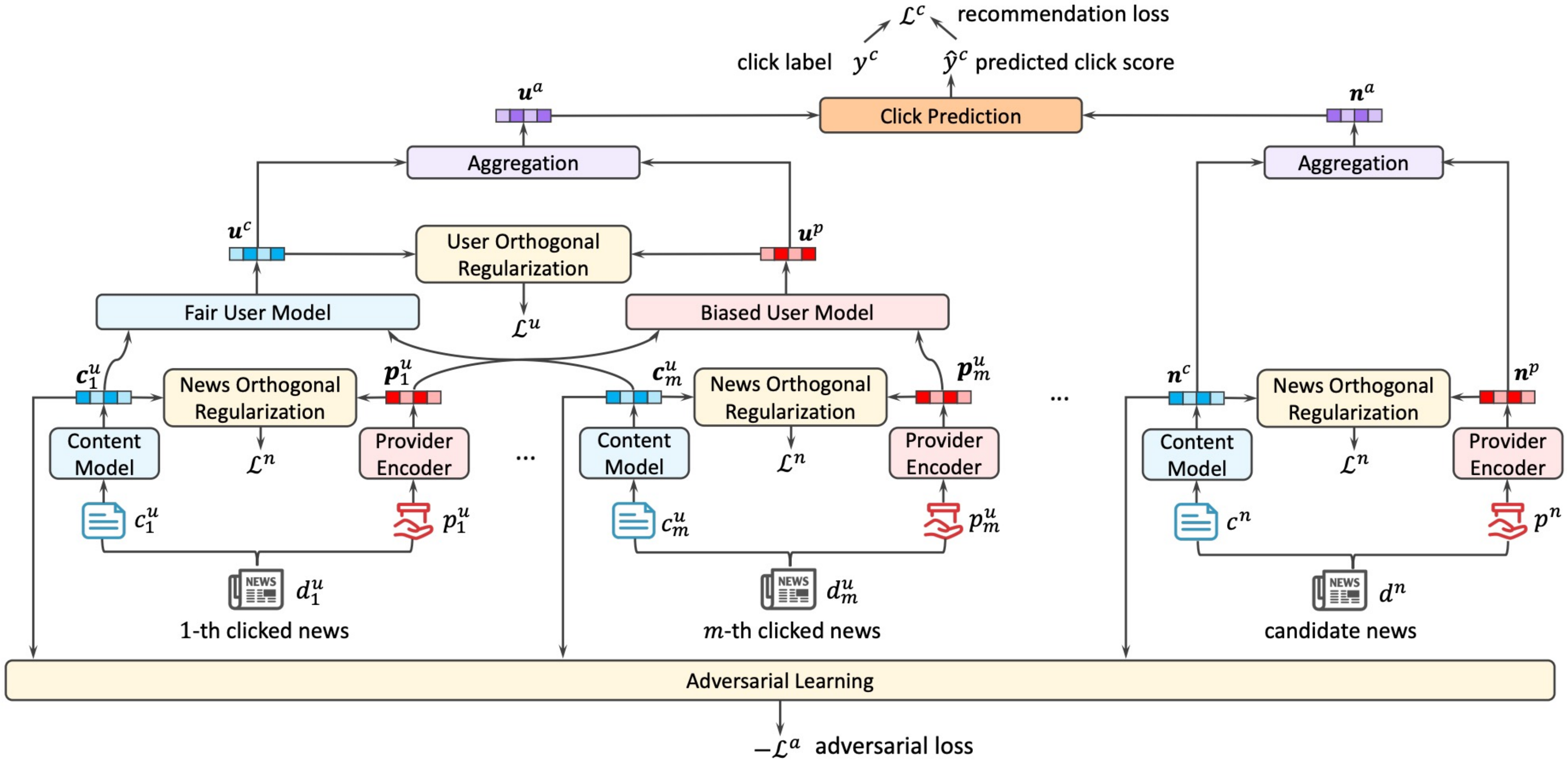
Influence of Adversarial Learning



Trade-off between recommendation performance and fairness

Conclusion

- We are the first to to study the provider fairness problem in news recommendation
- We propose a unified framework to learn provider-fair news representations and user representations from biased data.



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