Untargeted Attack Against Federated Recommendation Systems via Poisonous Item Embeddings and the Defense

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Introduction

- Recommender systems are widely used to alleviate the information overload problem.
- Most existing recommender systems are trained on **centralized user data**.
  - Risk of data leakage.
  - Privacy concerns.
- Privacy regulations (e.g., GDPR, CCPA) make it more difficult to collect user data for centralized model training.

Introduction

- **Federated learning (FL)** enables multiple clients to collaboratively learn a global model without sharing their local data.
- Several studies have applied FL to train privacy-preserving **federated recommendation (FedRec)** systems.
- Unfortunately, FL is known to be vulnerable to **poisoning attacks**.
  - **Targeted Attack**
    - Increase the exposure rate of certain target items.
  - **Untargeted Attack**
    - Degrade the overall performance of the FedRec system.
    - Also known as the denial-of-service attack.
    - Continuously disrupt the user experience → Severe losses of customers and revenue.

Introduction

- **Challenges**
  - The attack method must be effective even with a small fraction of malicious clients.
  - The attacker can only access a small set of data stored on the malicious clients.
  - The attack needs to manipulate the model output on arbitrary inputs.
  - Many recommenders are naturally robust to malicious perturbation to a certain degree.

- In this work
  - **ClusterAttack**: an effective and covert untargeted model poisoning attack method.
  - **UNION**: a general uniformity-based defense mechanism.

Preliminaries

Federated Recommendation Systems

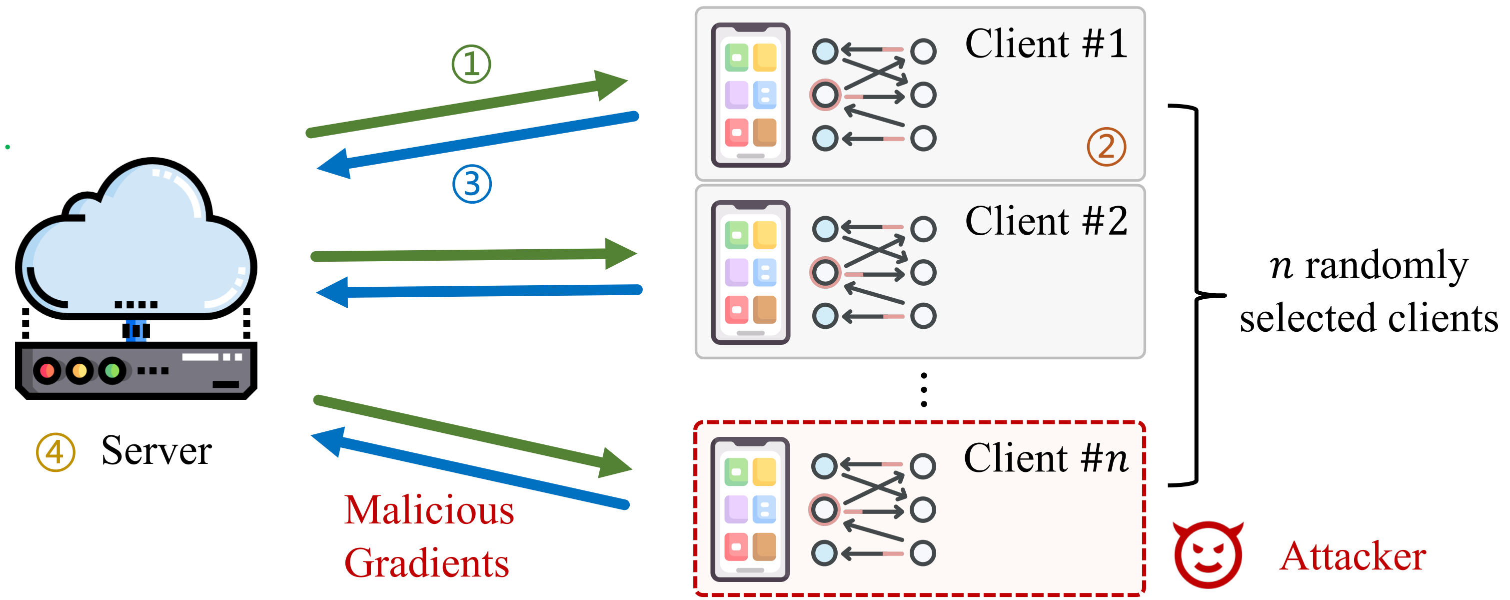
- The parameters of the recommendation model $\boldsymbol{\Theta} = [\boldsymbol{\Theta}_{\text{item}}; \boldsymbol{\Theta}_{\text{user}}; \boldsymbol{\Theta}_{\text{pred}}]$.
- Standard FL procedure

① Distribute global model $[\boldsymbol{\Theta}_{\text{item}}; \boldsymbol{\Theta}_{\text{pred}}]$.

② Compute local gradients $\mathbf{g} = [\mathbf{g}_{\text{item}}; \mathbf{g}_{\text{user}}; \mathbf{g}_{\text{pred}}]$.

③ Upload $[\mathbf{g}_{\text{item}}; \mathbf{g}_{\text{pred}}]$ and update local $\boldsymbol{\Theta}_{\text{user}}$ with $\mathbf{g}_{\text{user}}$.

④ Aggregate and update global model.



Threat Model

- $m\%$ (typically small, e.g., 1%) of clients are controlled by the attacker.
- The attacker knows the training code, local model, and user data of malicious clients.
- The attacker cannot access the data or gradients of other benign clients.

Methodology

- **ClusterAttack**
  - The recommendation model generally predicts the ranking score based on the user embedding and the item embedding.
  - Upload malicious gradients that converge item embeddings into several dense clusters.

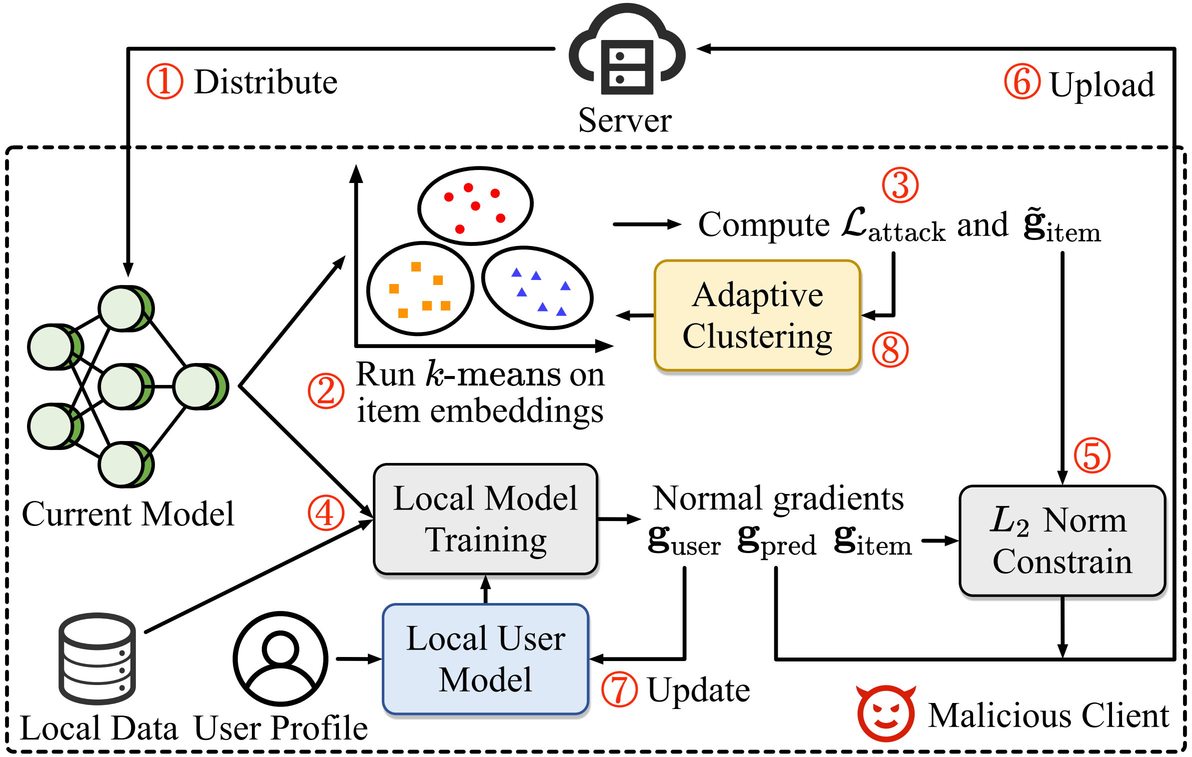


Figure 1: The procedure of ClusterAttack.

Methodology

ClusterAttack

- Apply k-means to split the item embeddings $\{\boldsymbol{v}_i\}_{i=1}^{M}$ into K clusters $\{C_i\}_{i=1}^{K}$ with centroids $\{\boldsymbol{c}_i\}_{i=1}^{K}$.
- Compute the within-cluster variance and the malicious gradient.

$$\mathcal{L}_{attack} = \sum_{i=1}^{K} \sum_{\boldsymbol{v}_j \in C_i} \left\| \boldsymbol{v}_j - \boldsymbol{c}_i \right\|_2^2 \qquad \tilde{\mathbf{g}}_{\boldsymbol{v}_i} = \frac{\partial \mathcal{L}_{attack}}{\partial \boldsymbol{v}_i}$$

- **Gradient clipping**
  - Compute the normal gradient of each malicious client.
  - Calculate the mean μ and standard deviation σ of the L_2 norms of all normal item embedding gradients.

$$b_i^{(j)} = \mu + \lambda_i^{(j)} \sigma, \ \lambda_i^{(j)} \in [0,3] \qquad \hat{\mathbf{g}}_{\boldsymbol{v}_i}^{(j)} = \frac{\tilde{\mathbf{g}}_{\boldsymbol{v}_i}}{\max(1, \left\|\tilde{\mathbf{g}}_{\boldsymbol{v}_i}\right\|_2 / b_i^{(j)})}$$

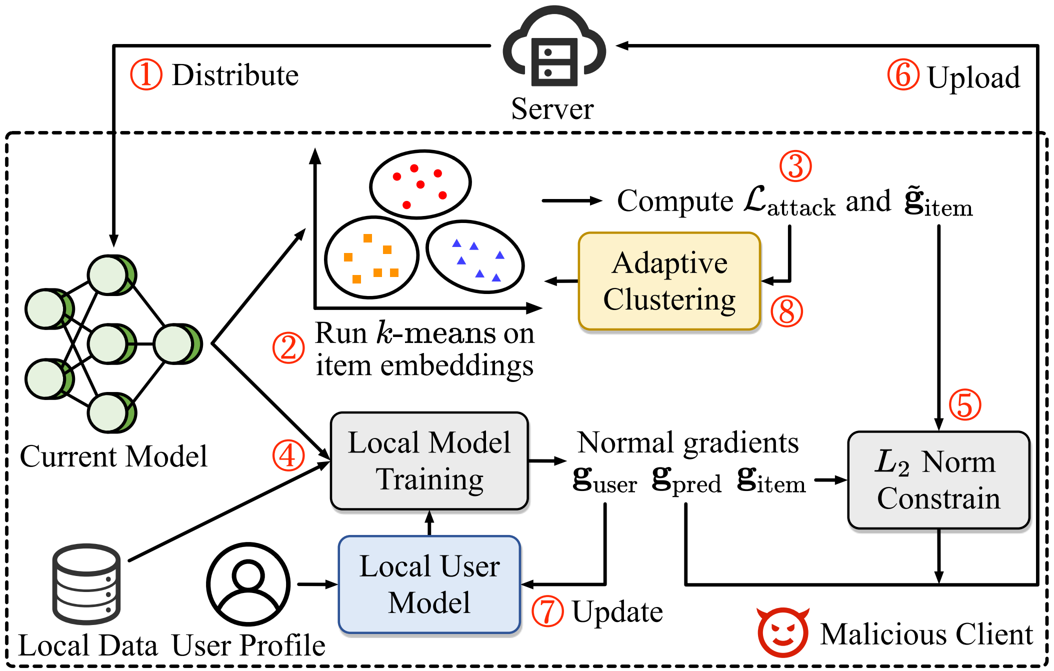


Figure 1: The procedure of ClusterAttack.

Methodology

ClusterAttack

Adaptive clustering

- Adjust the number of clusters K after each round of attack.
- Use the change of $\mathcal{L}_{attack}$ as the feedback.
- $\mathcal{L}_{attack}$ keeps increasing → $\mathcal{L}_{attack}$ cannot converge well.
- $\mathcal{L}_{attack}$ keeps decreasing → decrease K for stronger attack.

Algorithm 1: Adaptive Clustering

Input: Number of clusters K, range of number of clusters $[K_{\text{min}}, K_{\text{max}}]$, threshold R, and decay rate β.

Init: Set $\tilde{\mathcal{L}}^{(0)}_{\text{attack}}, n_{\text{inc}}, n_{\text{dec}}$ and t as 0.

// Repeat after each round of attack

$t \leftarrow t + 1$;

Calculate $\mathcal{L}^{(t)}_{\text{attack}}$ with Equation (2);

$\tilde{\mathcal{L}}^{(t)}_{\text{attack}} \leftarrow \beta \cdot \tilde{\mathcal{L}}^{(t-1)}_{\text{attack}} + (1-\beta) \cdot \mathcal{L}^{(t)}_{\text{attack}}$;

$\hat{\mathcal{L}}^{(t)}_{\text{attack}} \leftarrow \tilde{\mathcal{L}}^{(t)}_{\text{attack}} / \left(1-\beta^t\right)$;

if $\hat{\mathcal{L}}^{(t)}_{\text{attack}} > \hat{\mathcal{L}}^{(t-1)}_{\text{attack}}$ **then** $n_{\text{inc}} \leftarrow n_{\text{inc}} + 1$;

else $n_{dec} \leftarrow n_{\text{dec}} + 1$;

if $n_{\text{inc}} - n_{\text{dec}} \geqslant R$ **then**

  $K \leftarrow \min\left(\left\lfloor K + \sqrt{K_{\text{max}} - K}\right\rfloor, K_{\text{max}}\right)$;

  Reset $n_{\text{inc}}, n_{\text{dec}}$ and t as 0;

end if

if $n_{\text{dec}} - n_{\text{inc}} \geqslant R$ **then**

  $K \leftarrow \max\left(\left\lfloor K - \sqrt{K - K_{\text{min}}}\right\rfloor, K_{\text{min}}\right)$;

  Reset $n_{\text{inc}}, n_{\text{dec}}$ and t as 0;

end if

Methodology

UNION Mechanism

Client Side

- Train the local recommendation model with an **additional contrastive learning task**.
- Denote the item set interacted by the user as $\mathcal{V}_u = \{v_i\}_{i=1}^{L}$ and the entire item set as $\mathcal{V}$.
- For each $v_i \in \mathcal{V}_u$, randomly select another positive item $v_i^+ \in \mathcal{V}_u$ and P negative items $\{v_i^-\}_{i=1}^{P} \subseteq \mathcal{V} \backslash \mathcal{V}_u$.

$$\mathcal{L}_{\mathrm{cl}} = -\sum_{i=1}^{L} \log \frac{e^{f(v_i)^{\mathrm{T}} f(v_i^+)}}{e^{f(v_i)^{\mathrm{T}} f(v_i^+)} + \sum_{j=1}^{P} e^{f(v_i)^{\mathrm{T}} f(v_i^-)}} \qquad \mathcal{L} = \mathcal{L}_{\mathrm{rec}} + \alpha \mathcal{L}_{\mathrm{cl}}$$

- $\mathcal{L}_{\mathrm{cl}}$ can regularize the item embeddings toward a uniform distribution in the space [1] while training with the recommendation task (opposite to the goal of ClusterAttack).

[1] Wang et al. Understanding Contrastive Representation Learning through Alignment and Uniformity on the Hypersphere. In *ICML*. 2020.

Methodology

- UNION Mechanism
  - **Server Side**
    - Estimate the uniformity of updated item embeddings for each received gradient.

$$d_i = \mathbb{E}_{x,y \overset{\text{i.i.d}}{\sim} p_{\text{data}}} \|f(x) - f(y)\|_2^2$$

    - Use the **Gap Statistics algorithm** [2] to estimate the number of clusters in $\{d_i\}_{i=1}^n$.
    - If the algorithm estimates that there is more than one cluster, we apply k-means to split $\{d_i\}_{i=1}^n$ into two clusters and remove all the gradients belonging to the minor one.
  - **Note**
    - UNION is a general mechanism that aims to preserve the distribution of item embeddings.
    - It can be combined with existing Byzantine-robust FL methods (e.g., MultiKrum, NormBound) to provide more comprehensive protection for FedRec systems.

[2] Tibshirani et al. Estimating the Number of Clusters in a Data Set via the Gap Statistic. *Journal of the Royal Statistical Society: Series B (Statistical Methodology)*. 2001.

Experiments

- **Datasets**
  - MovieLens-1M
  - Gowalla
- **Base Recommendation Model**
  - MF
  - SASRec
- **Metrics**
  - Hit Ratio (HR)
  - Normalized Discounted Cumulative Gain (NDCG)
  - Only calculated on benign clients using the all-ranking protocol.

Dataset	#Users	#Items	#Actions	Avg. length	Density
ML-1M	6,040	3,706	1,000,209	165.6	4.47%
Gowalla	29,858	40,981	1,585,043	53.1	0.13%

Table 2: Detailed statistics of the two datasets.

Experiments

Attack Performance with No Defense

Model	Attack Method	ML-1M		Gowalla	
		HR@5	NDCG@5	HR@5	NDCG@5
MF	No Attack	0.03549 (-)	0.02226(-)	0.02523 (-)	0.01697 (-)
	LabelFlip	0.03561 (-0.34%)	0.02238 (-0.54%)	0.02541 (-0.71%)	0.01711 (-0.82%)
	FedAttack	0.03358 (5.38%)	0.02118 (4.85%)	0.02371 (6.02%)	0.01585 (6.60%)
	Gaussian	0.03555 (-0.17%)	0.02224 (0.09%)	0.02528 (-0.20%)	0.01701 (-0.24%)
	LIE	0.03259 (8.17%)	0.02062 (7.37%)	0.02316 (8.20%)	0.01571 (7.42%)
	Fang	0.03038 (14.40%)	0.01897 (14.78%)	0.02131 (15.54%)	0.01448 (14.67%)
	ClusterAttack	**0.02451 (30.94%)**	**0.01545 (30.59%)**	**0.01664 (34.05%)**	**0.01117 (34.18%)**
SASRec	No Attack	0.10810 (-)	0.07053 (-)	0.03251 (-)	0.02217 (-)
	LabelFlip	0.10857 (-0.43%)	0.07071 (-0.26%)	0.03270 (-0.58%)	0.02222 (-0.23%)
	FedAttack	0.10013 (7.37%)	0.06572 (6.82%)	0.03054 (6.06%)	0.02087 (5.86%)
	Gaussian	0.10769 (0.38%)	0.07055 (-0.03%)	0.03226 (0.77%)	0.02222 (-0.23%)
	LIE	0.09677 (10.48%)	0.06281 (10.95%)	0.03008 (7.47%)	0.02021 (8.84%)
	Fang	0.08964 (17.08%)	0.05909 (16.22%)	0.02797 (13.96%)	0.01883 (15.07%)
	ClusterAttack	**0.06547 (39.44%)**	**0.04130 (41.44%)**	**0.02223 (31.62%)**	**0.01544 (30.36%)**

Table 1: Model performance under different untargeted attack methods with no defense. The percentages in parentheses indicate the relative performance degradation compared with the no-attack scenario.

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Experiments

Attack Performance under Defense (Left five groups)

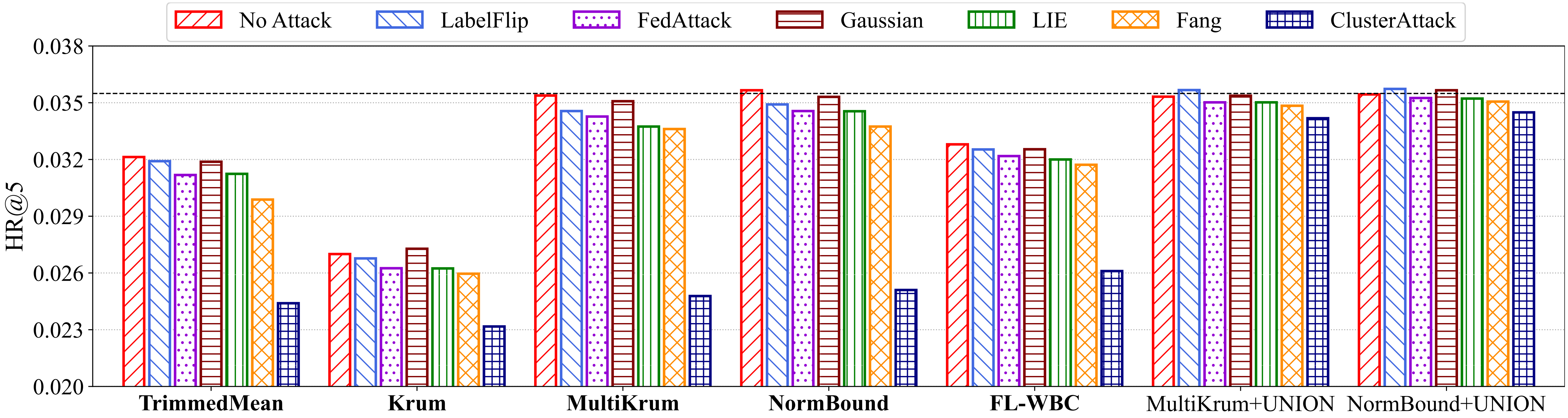

Figure 2: Model performance under different untargeted attack methods with different defense mechanisms. The black dashed line represents the model performance without any attack or defense.

Experiments

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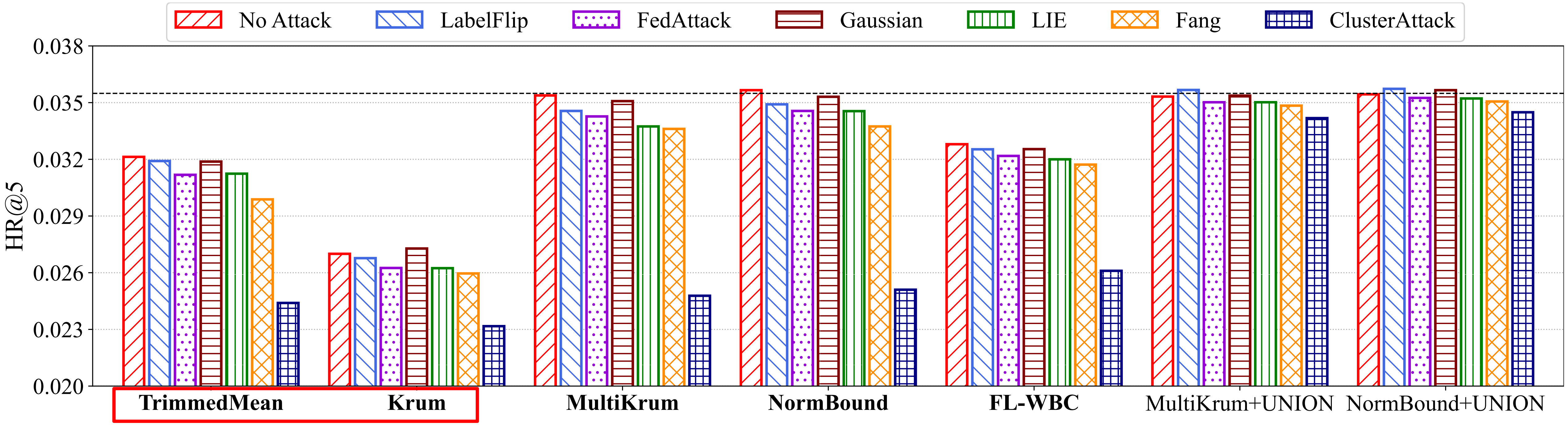

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Experiments

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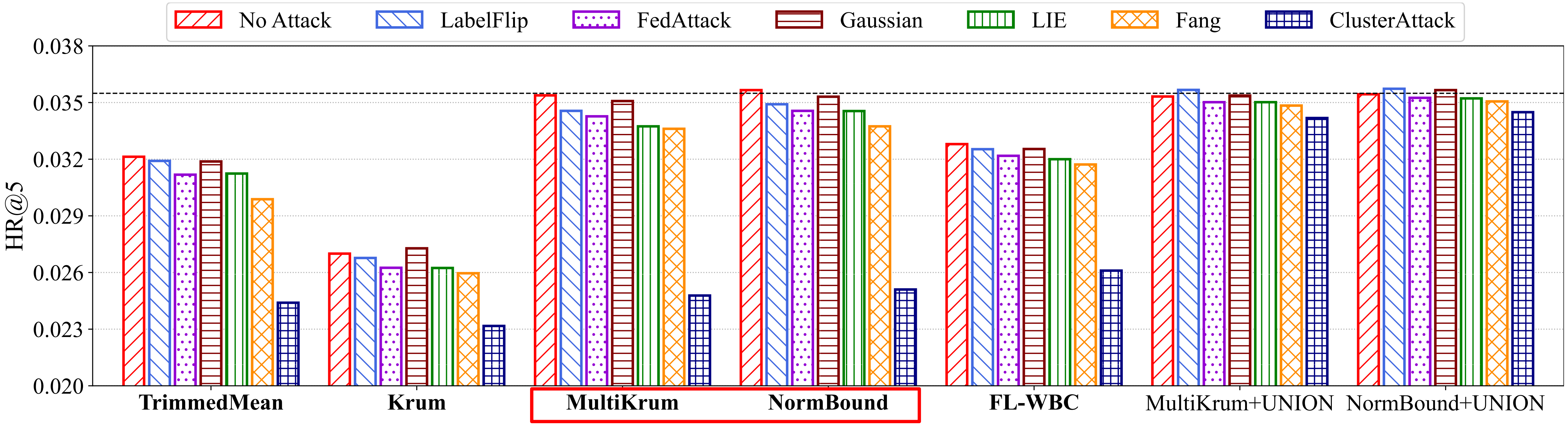

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Experiments

Defense Performance (Right two groups)

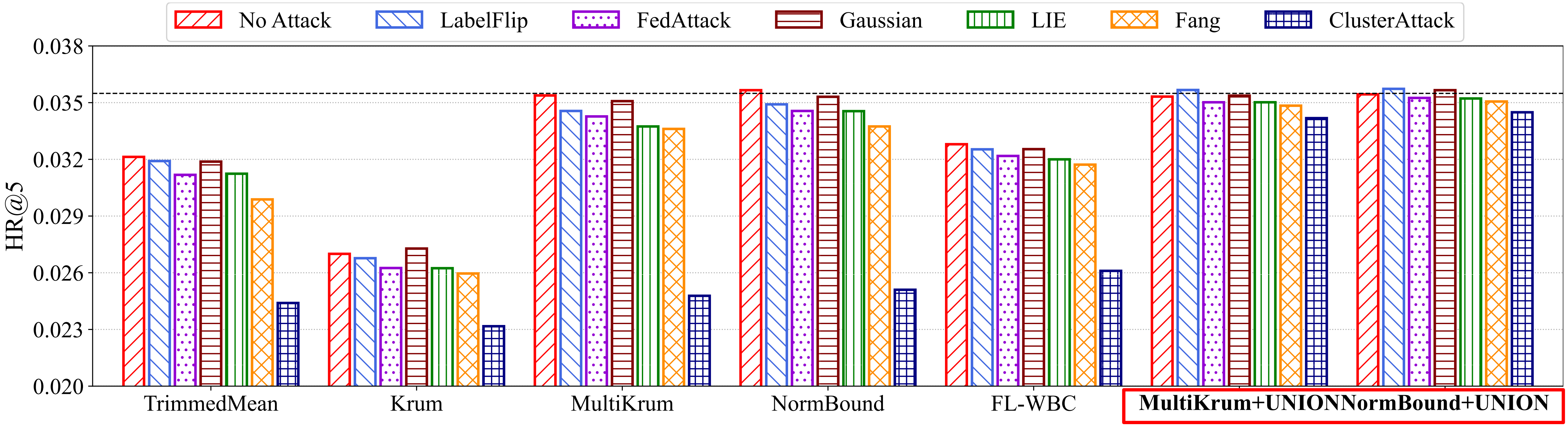

Figure 2: Model performance under different untargeted attack methods with different defense mechanisms. The black dashed line represents the model performance without any attack or defense.

Experiments

- **Can the attacker evade UNION?**
  - $\mathcal{L}'_{attack} = \mathcal{L}_{attack} + \alpha \cdot \mathcal{L}_{cl}$
  - The extra contrastive learning task weakens the attack effect of ClusterAttack.

Defense Method	Attack Method	HR@5
MultiKrum+UNION	ClusterAttack	0.03378 (4.82%)
	ClusterAttack+CL	0.03525 (0.68%)
NormBound+UNION	ClusterAttack	0.03449 (2.82%)
	ClusterAttack+CL	0.03566 (-0.48%)

Table 3: Attack performance of ClusterAttack+CL.

Experiments

Impact of Adaptive Clustering

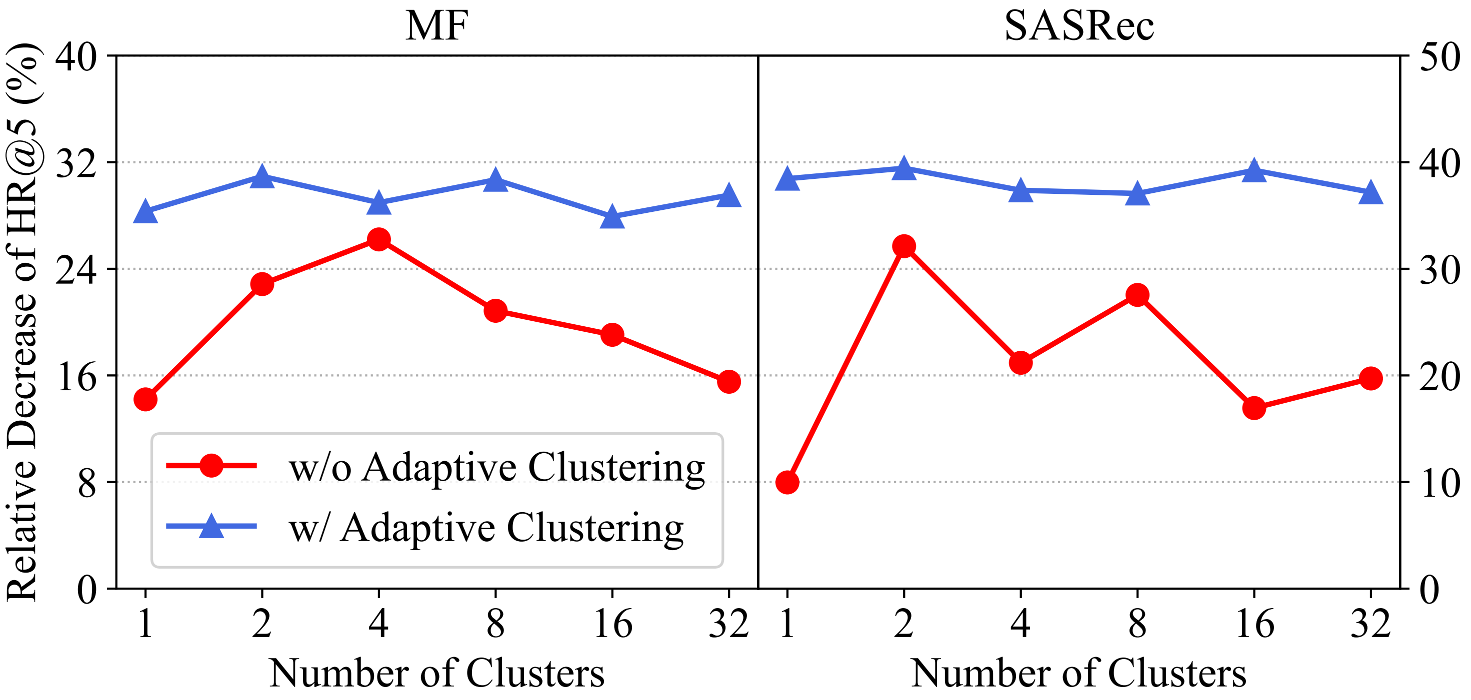

Figure 3: Impact of adaptive clustering.

Experiments

Gradients and Uniformity Analysis

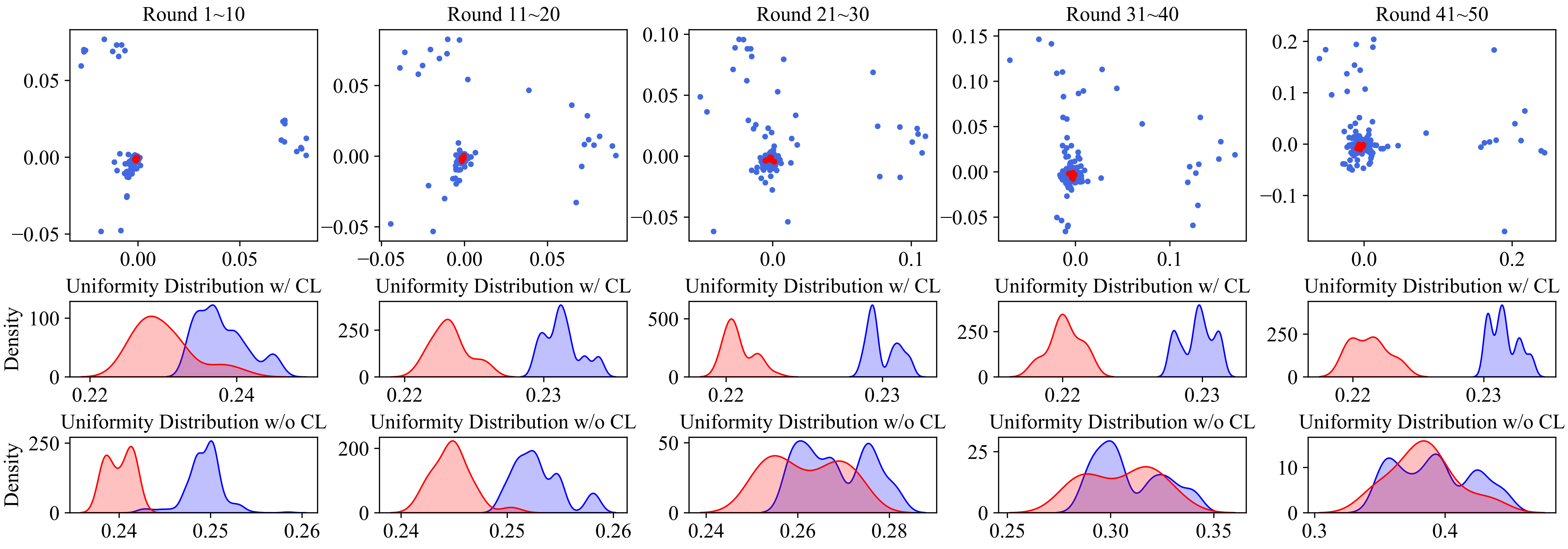

Figure 4: Visualization of the uploaded gradients and the uniformity distribution in different rounds of model training. The blue color and red color denote benign clients and malicious clients, respectively.

Conclusion

- ClusterAttack
  - Uploads malicious gradients that converge the item embeddings into dense clusters.
  - Reveals the security risk of FedRec systems even with existing defense methods.
- UNION
  - Preserves the distribution of item embeddings with an additional contrastive learning task.
  - Combines with existing Byzantine-robust FL methods to better protect the FedRec system from potential untargeted attacks in the real world.
- Extensive experiments validate the effectiveness of our attack and defense methods.

Paper

Code

Thanks For Your Attention