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Federated Learning of User verification Models Without Sharing Embeddings

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Outline

- Background & Motivation
- FedUV method design
- Implementation
- Results
- Conclusion

Background & Motivation

- User verification models have multiple forms of modalities
- Face, voice, fingerprint
- Used on mobile devices for unlocking or specific services

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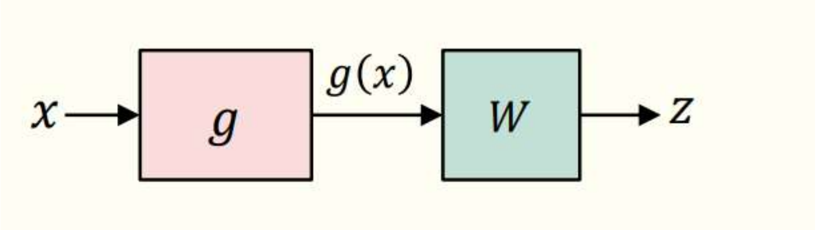
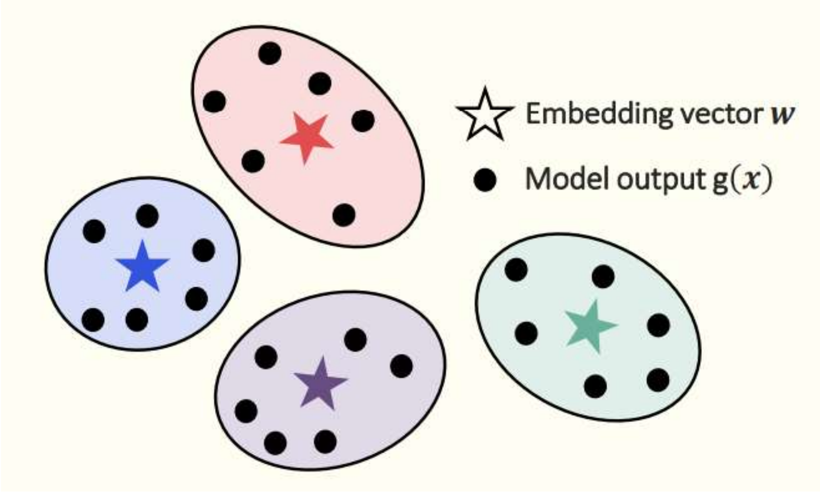
Background & Motivation

- User verification models: embedding-based classifier
- The embedding of data should be close to its user and away from other users





Background & Motivation

- How to train UV model: calculating loss function

  1) positive loss: minimize distance of g(x) to embedding vector of corresponding user

  2) negative loss: maximize distance of other users

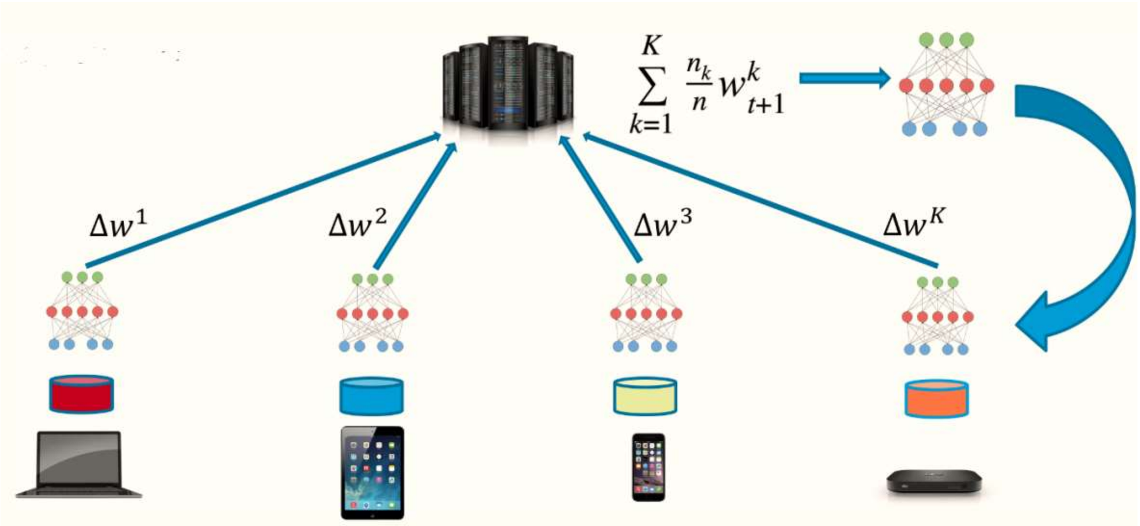
$$\ell = l_{\text{pos}} + \lambda l_{\text{neg}}$$

$$l_{\text{pos}} = d(g(x), w_y)$$

$$l_{\text{neg}} = -\min_{u \neq y} d(g(x), w_u)$$

Background & Motivation

- What we need: data for training and embedding vector
- Data collection encounters privacy issue
- Solution: Federated learning



Background & Motivation

- Embedding vector cannot be shared with other users
- Hence, cannot calculate negative loss
- Training with only positive loss will collapse all embeddings

$$\ell = l_{\text{pos}} + \cancel{\lambda l_{\text{neg}}}$$

FedUV method design

- Contribution: User verification without sharing the embedding vectors
- Comparable performance with existing approaches
- Using Error-correcting codes (ECC) as secret vectors

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FedUV method design

- Definition of loss function
- Let W be a set of c vectors, v_u be the secret vector for user u
- Try to make the negative loss be negligible

- Original loss function: $\ell(x, y; g, w) = d(g(x), w_y) - \lambda \min_{u \neq y} d(g(x), w_u)$
- **FedUV** loss function: $\ell(x, y; g, w) = d(g(x), W^T v_y) - \lambda \min_{u \neq y} d(g(x), W^T v_u)$

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FedUV method design

$$\begin{cases} \ell_{\text{pos}} = \max(0, 1 - \frac{1}{c} v_y^T W g_\theta(x)), \\ \ell_{\text{neg}} = \max_{u \neq y} \frac{1}{c} v_u^T W g_\theta(x). \end{cases}$$

Lemma 1. *Assume* $\|W g_\theta(x)\| = \sqrt{c}$ *and* $v_y \in \{-1, 1\}^c$. *For* ℓ_{pos} *defined in (4), we have* $\ell_{\text{pos}} = 0$ *if and only if* $W g_\theta(x) = v_y$.

Proof. Let $z = W g_\theta(x)$. The term $\ell_{\text{pos}} = 0$ is equivalent to $\frac{1}{c} v_y^T z \geq 1$. We have $\frac{1}{c} v_y^T z \leq \frac{1}{c} \|v_y\| \|z\| = 1$ and the equality holds if and only if $z = \alpha v_y, \forall \alpha > 0$. Since $\|z\| = \|v_y\| = \sqrt{c}$, then $\alpha = 1$ and, hence, we have $\ell_{\text{pos}} = 0$ if and only if $z = v_y$.

FedUV method design

- Error correcting codes (ECCs)
- Techniques that enable restoring sequences from noise
- Designed to maximize the minimum Hamming distance between distinct codewords

FedUV method design

Theorem 1. *Assume* $\|Wg_\theta(x)\| = \sqrt{c}$ *and* $v_y \in \{-1, 1\}^c$. *Assume* v_u*'s are chosen from ECC codewords. For* ℓ_{pos} *and* ℓ_{neg} *defined in (4), minimizing* ℓ_{pos} *also minimizes* ℓ_{neg}.

Proof. Since $v_u \in \{-1, 1\}^c$, the Hamming distance between v_{u_1} and v_{u_2} is defined as

$$\begin{aligned}\Delta_{u_1,u_2} &= \frac{1}{4}\|v_{u_1} - v_{u_2}\|^2 \\ &= \frac{1}{4}(\|v_{u_1}\|^2 + \|v_{u_2}\|^2 - 2v_{u_1}^T v_{u_2}) \\ &= \frac{c}{2}(1 - \frac{1}{c}v_{u_1}^T v_{u_2}).\end{aligned}$$

FedUV method design

- To wrap it up
- According to lemma 1:

$$\ell_{\text{neg}} = \max_{u \neq y} \frac{1}{c} v_u^T v_y$$

- According to Theorem 1:
- ECCs minimize: $\max_{u_1 \neq u_2} \frac{1}{c} v_{u_1}^T v_{u_2}$

- Negative loss is at its minimum when:

1) Positive loss = 0
2) v_u are chosen from ECC codewords

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FedUV method design

- What we established: minimizing positive loss also minimizes negative loss
- Hence, no need to calculate negative loss
- Next: how to construct the secret codewords?

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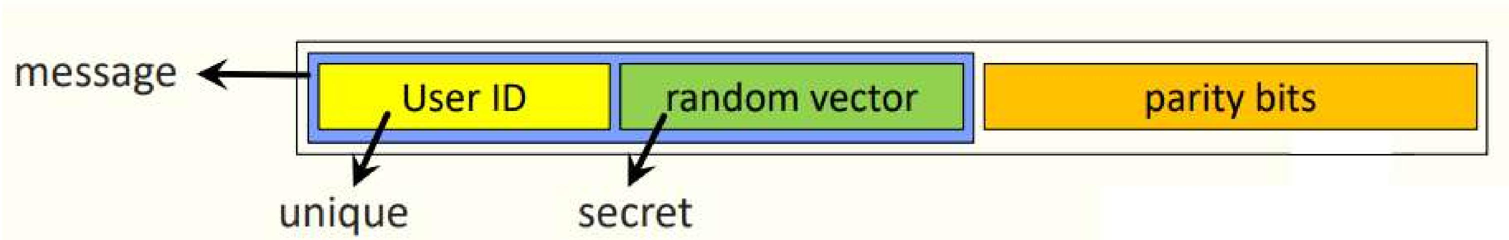
FedUV method design

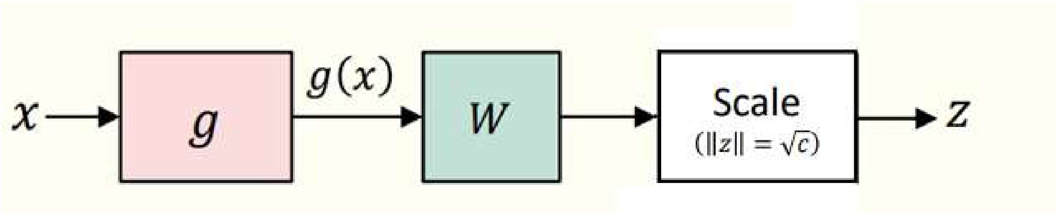
- Structure of secret codewords

1) Unique binary vector representing user ID
2) Random binary vector chosen by the user



FedUV method design

- Model structure of FedUV



- Loss function: $\ell_{\text{pos}} = \max(0, 1 - \frac{1}{c} v_y^T \sigma(W g_\theta(x)))$

- Verification: $\frac{1}{c} v_y^T \sigma(W g_\theta(x')) \underset{\texttt{reject}}{\overset{\texttt{accept}}{\gtrless}} \tau,$

Implementation

- Datasets

  VoxCeleb: text-independent speaker identification

  CelebA: over 20000 facial images for training

  MNIST-UV: handwriting identification
- Setting

  1000 users, BCH coding for generating codeword
- Baseline

  softmax, FedAwS

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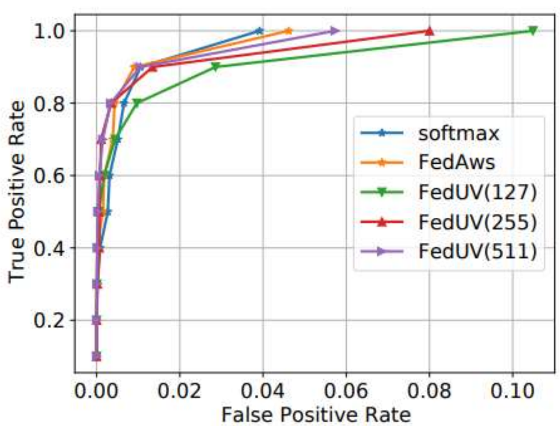
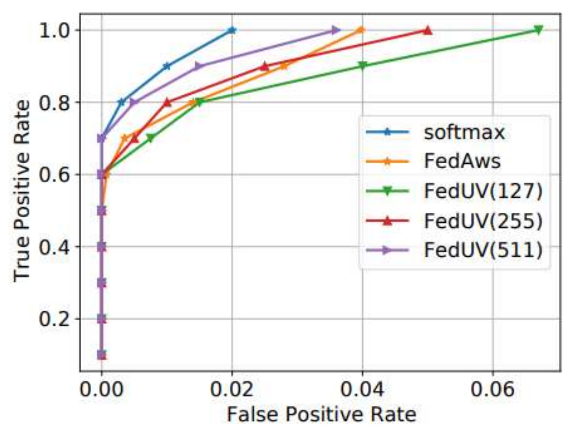
Results

- Verification performance

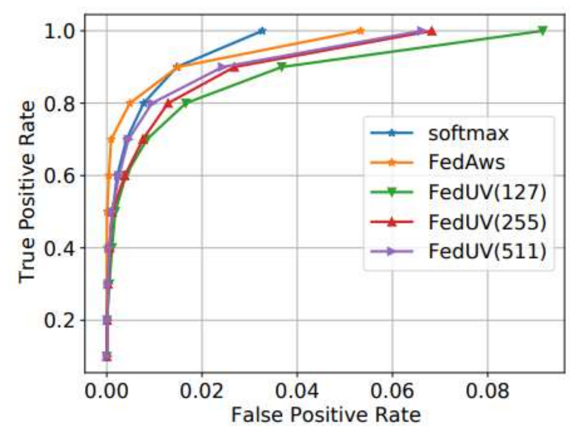
VoxCeleb dataset



CelebA dataset

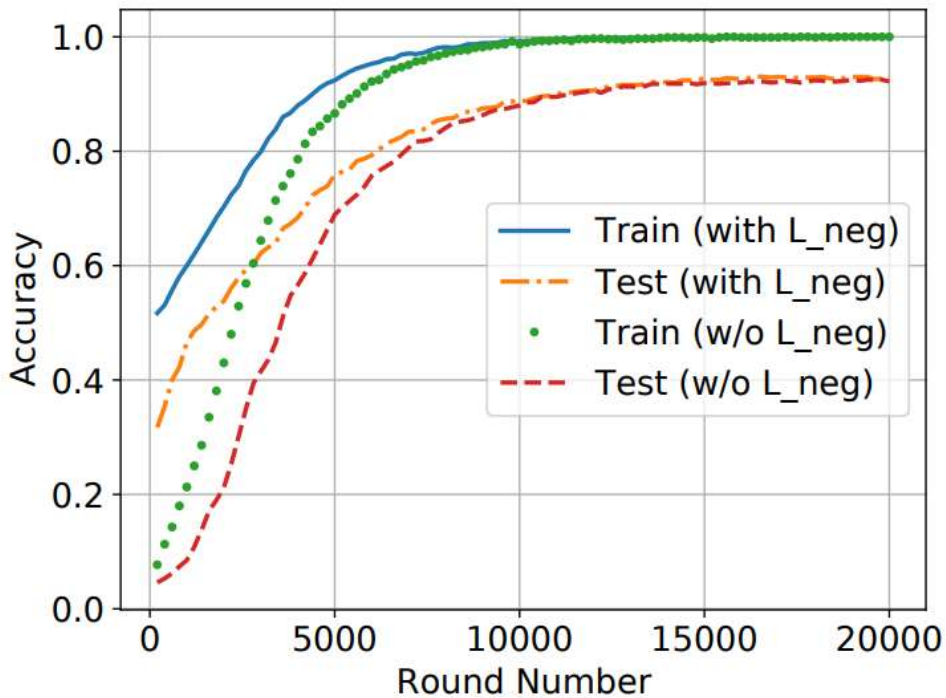


MNIST-UV dataset



Results

- Performance with or without negative loss



Conclusion

- FedUV: framework for training user verification models in FL setup
- Perform the training without sharing embeddings
- On par with existing approaches
- Showing results from variety of modalities

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