

# UniID: Spoofing Face Authentication By Universal Identity

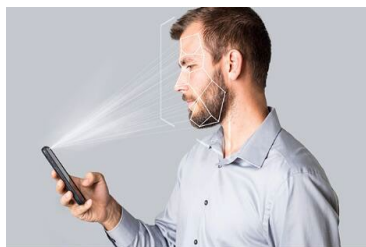
Zhihao Wu<sup>1</sup>, Yushi Cheng<sup>\*1, 2</sup>, Shibo Zhang<sup>1</sup>, Xiaoyu Ji<sup>\*1</sup>, Wenyuan Xu<sup>1</sup>

<sup>1</sup> Ubiquitous System Security Lab (USSLAB), Zhejiang University

<sup>2</sup> ZJU-UIUC Institute, Zhejiang University

{zhihaowu, yushicheng, zhsb, xji, wyxu}@zju.edu.cn

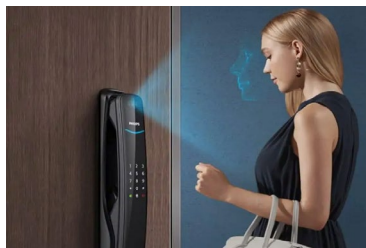
# Face Authentication Systems are everywhere!



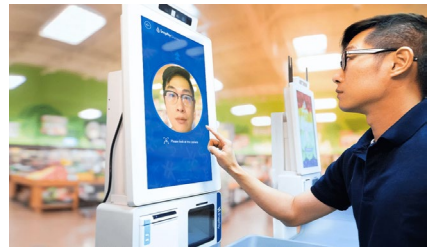
Smart Phone Unlock



Access Control



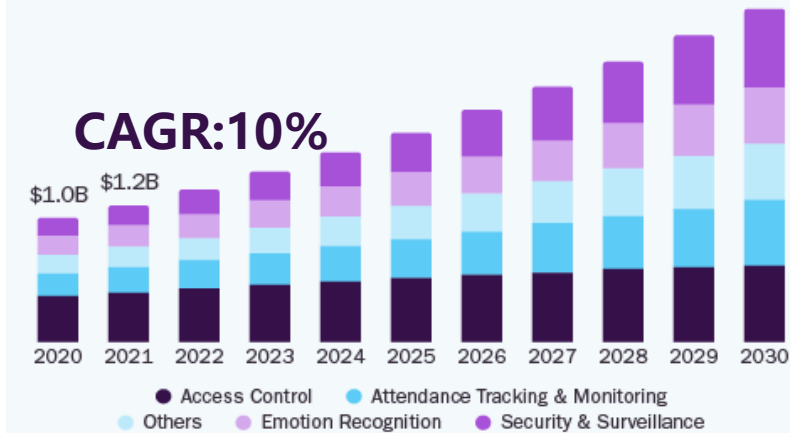
Home Unlock



Financial Payments

## U.S. Facial Recognition Market

Size, by Application, 2020 - 2030 (USD Billion)



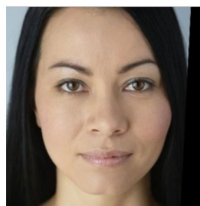
Source: Grandviewresearch

*Are face authentication systems secure?*

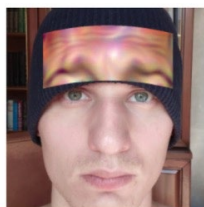
# Spoofing Face Authentication Systems

## □ *Adversarial Attacks*

Target



Attacker



Adv-Glass

Adv-Hat

Adv-Makeup

# Spoofing Face Authentication Systems

## ❑ *Adversarial Attacks*



## *Properties :*

- ❑ Specially designed (1v1)
- ❑ One-time effective
- ❑ Easily detectable

***Not practical and stealthy enough in the real-world***

# Spooing Face Authentication Systems

## □ Adversarial Attacks

**Can we spoof the face authentication  
*without any camouflage*  
when recognizing?**

Target



Attacker



Adv-Glass

Adv-Hat

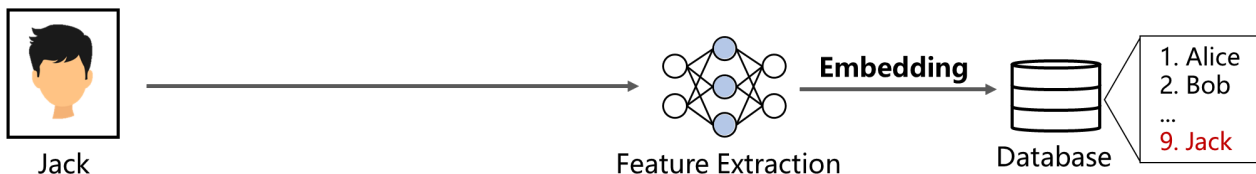
Adv-Makeup

□ Easily detectable

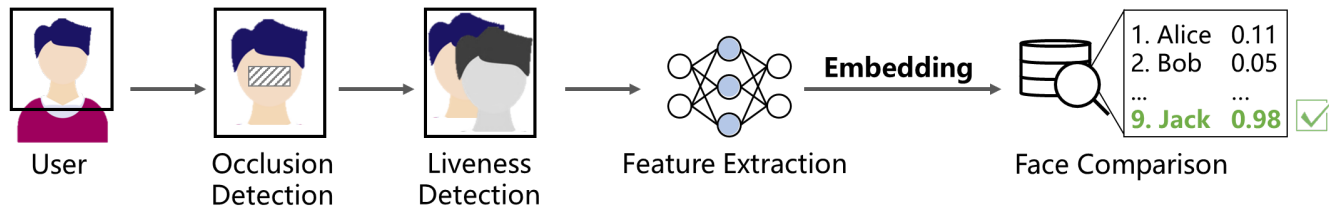
*Not practical and stealthy enough in the real-world*

# Face authentication system

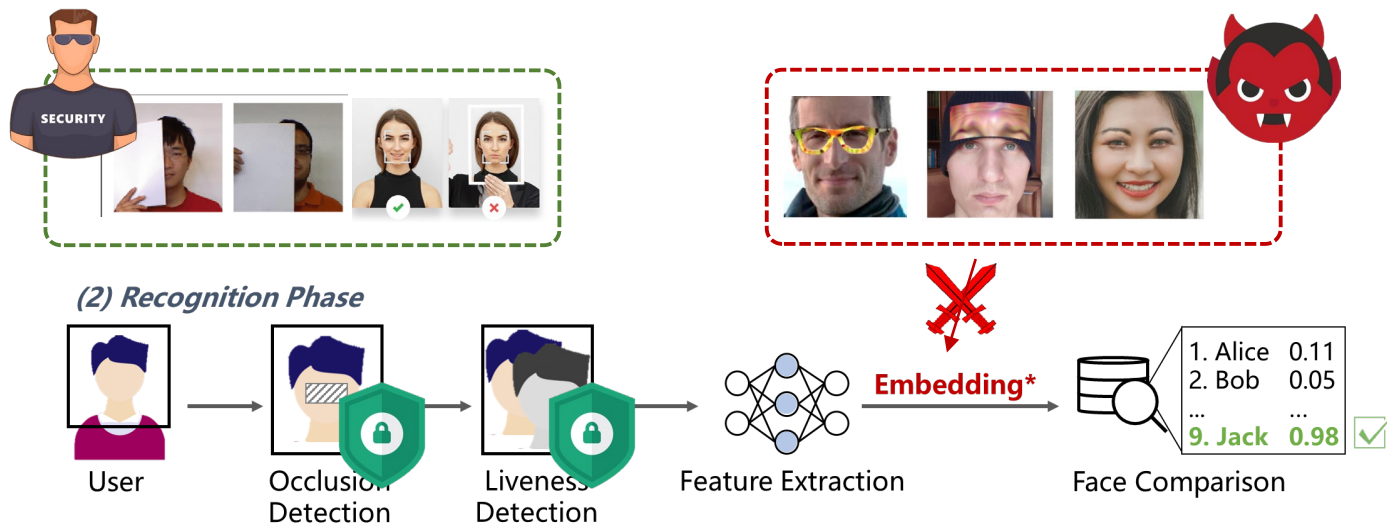
## (1) Enrollment Phase



## (2) Recognition Phase

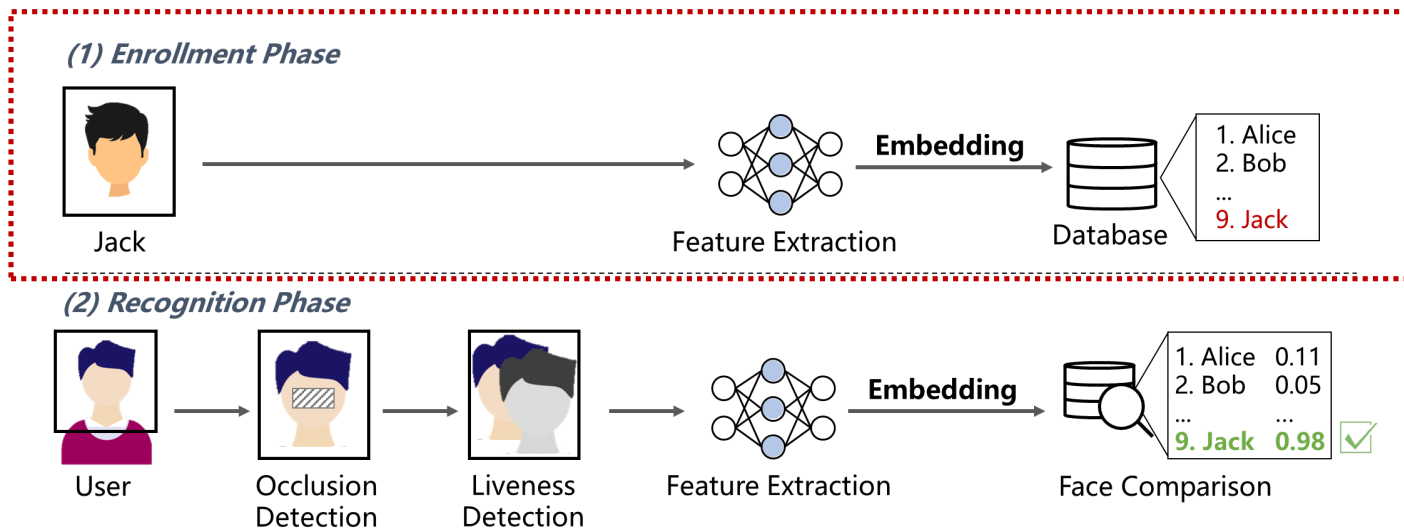


# Existing attacks and defenses



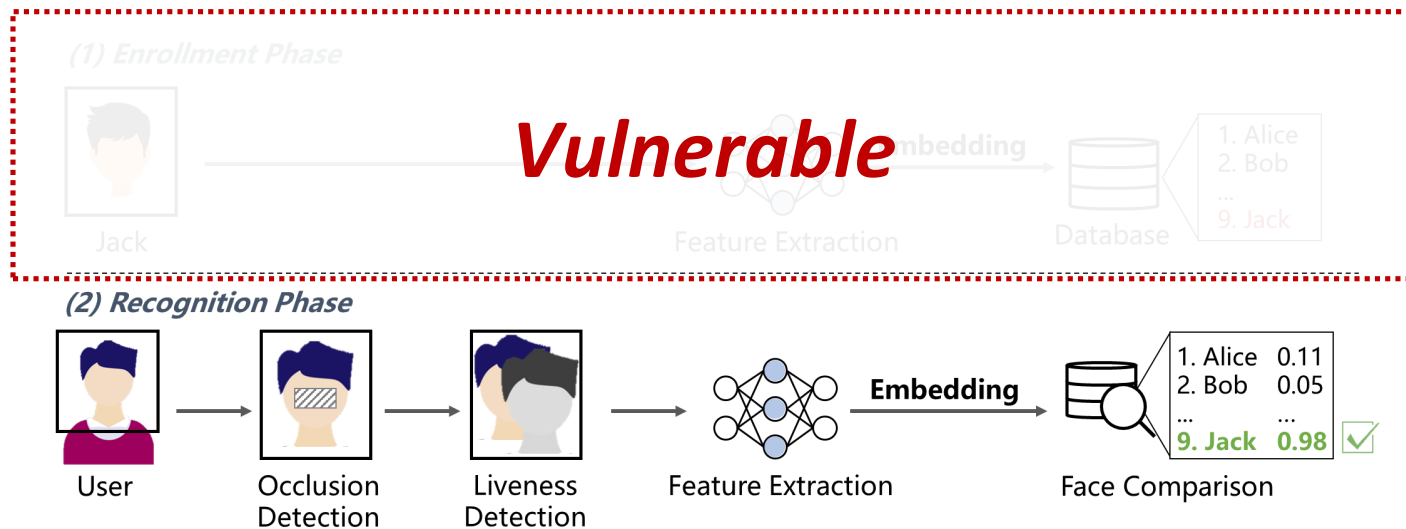
***Spoof attacks through recognition phase become difficult!***

# The enrollment phase is **overlooked!**



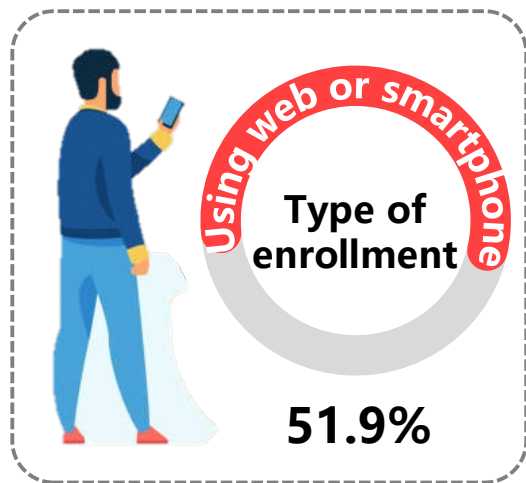


# The enrollment phase is **overlooked!**



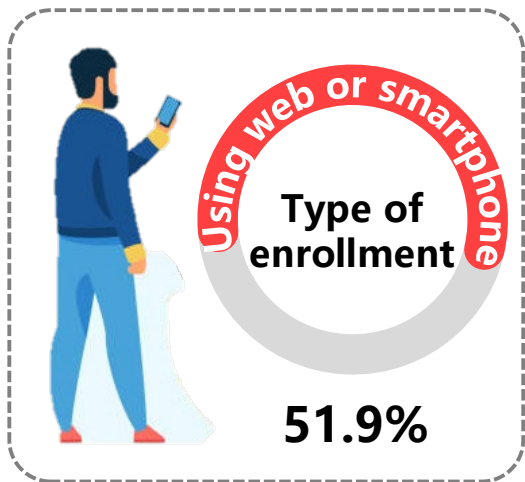
# Vulnerabilities in the enrollment phase

## Self-uploading



# Vulnerabilities in the enrollment phase

## Self-uploading

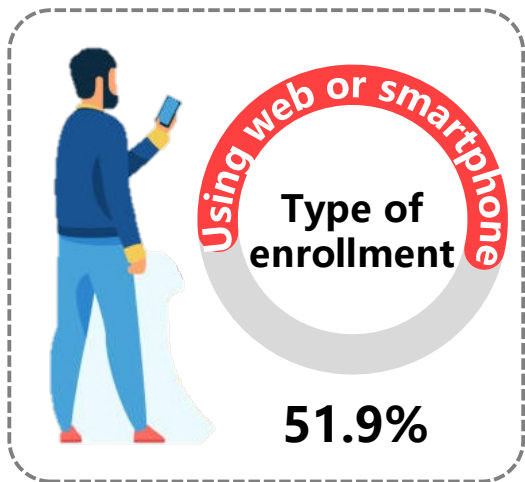


## Unsupervised



# Vulnerabilities in the enrollment phase

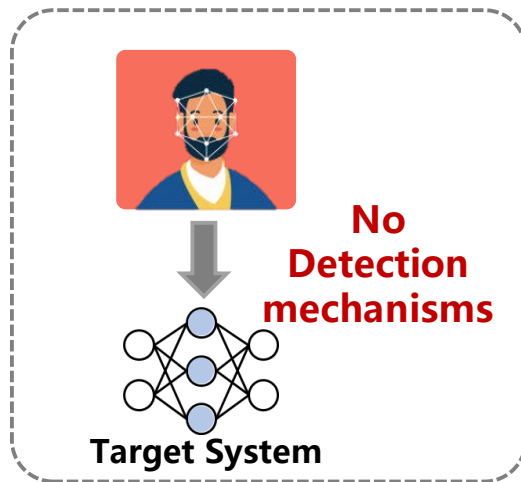
## Self-uploading



## Unsupervised

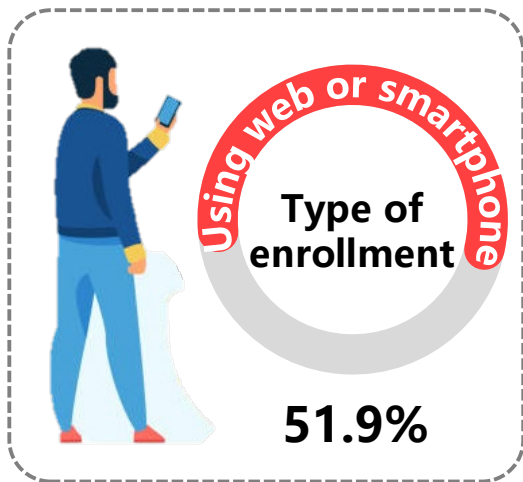


## Unchecked



# Vulnerabilities in the enrollment phase

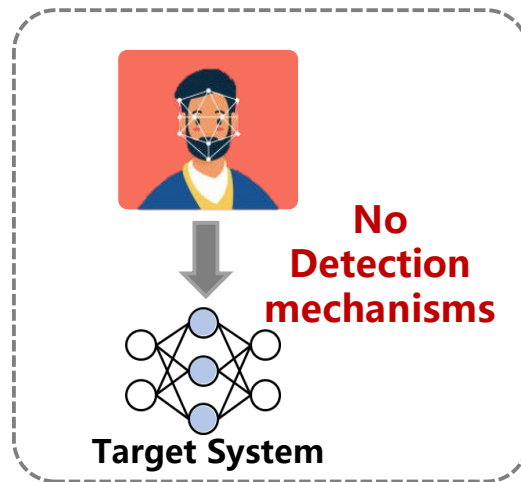
## Self-uploading



## Unsupervised

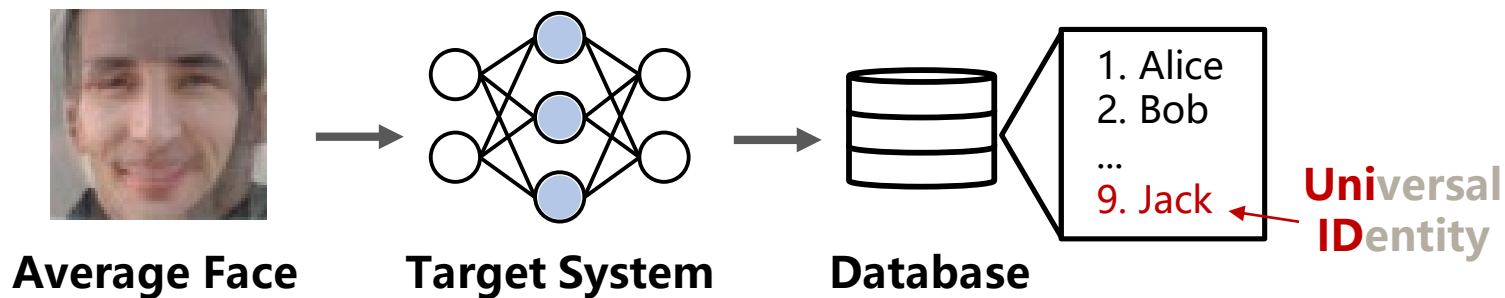


## Unchecked

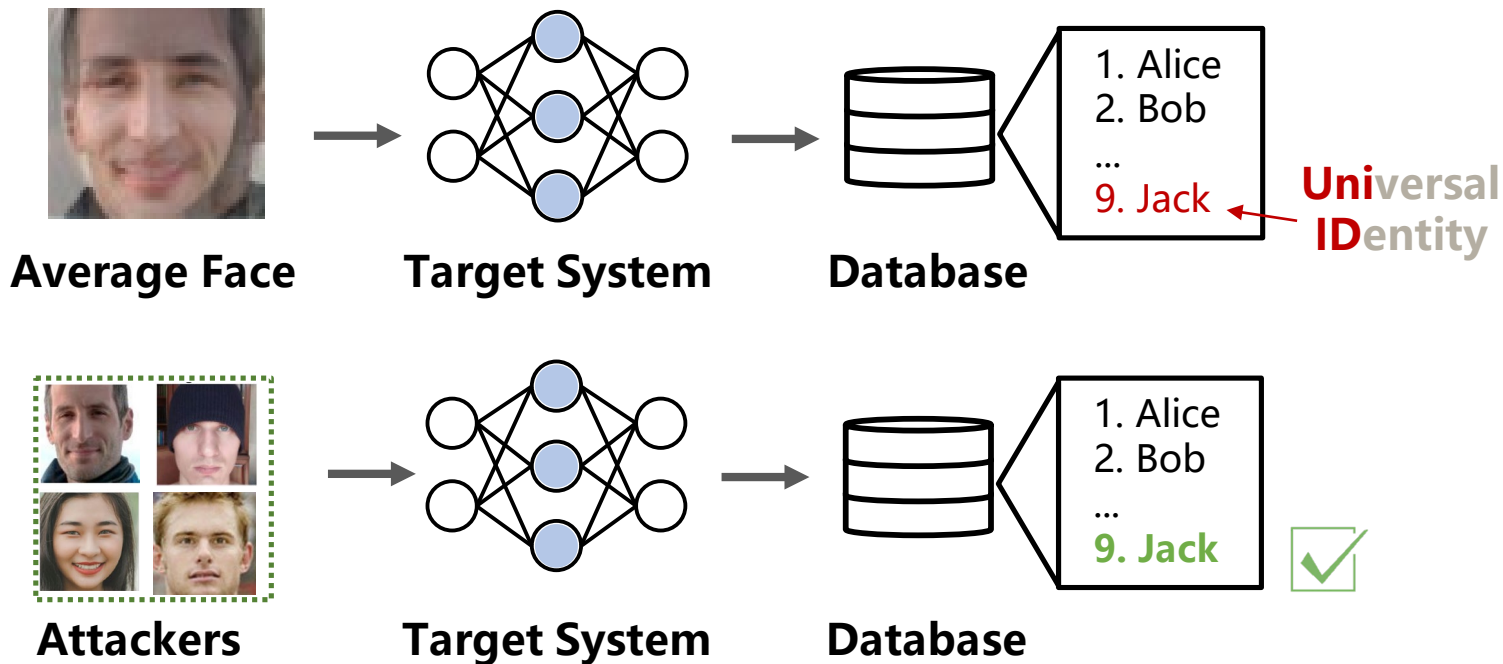


*The enrollment phase can be **a new entry point** for spoofing attacks!*

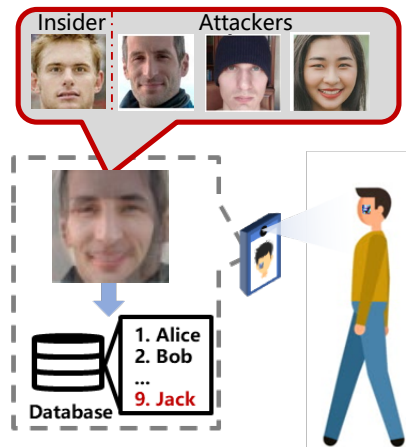
# Our basic idea



# Our basic idea



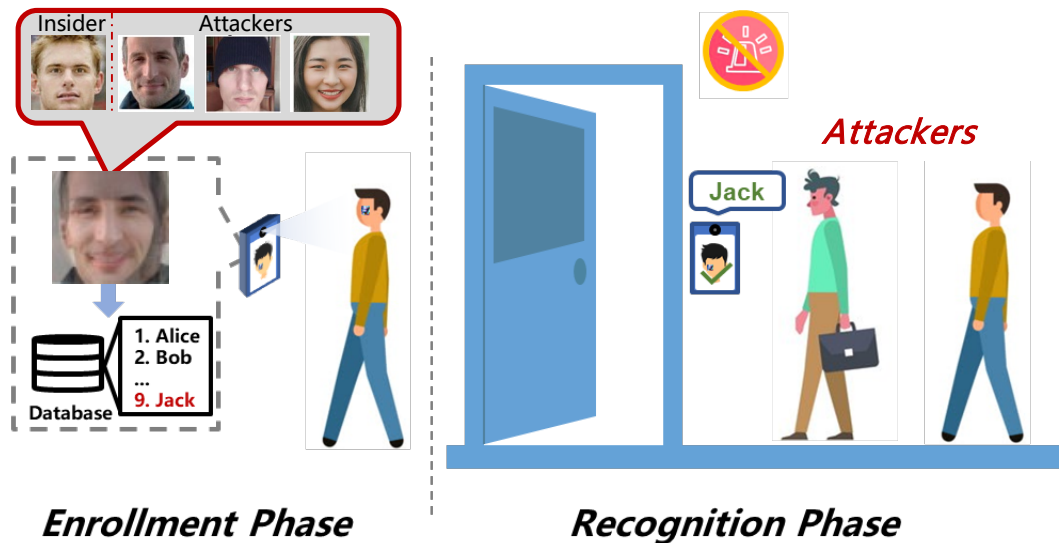
# What UniID can do?



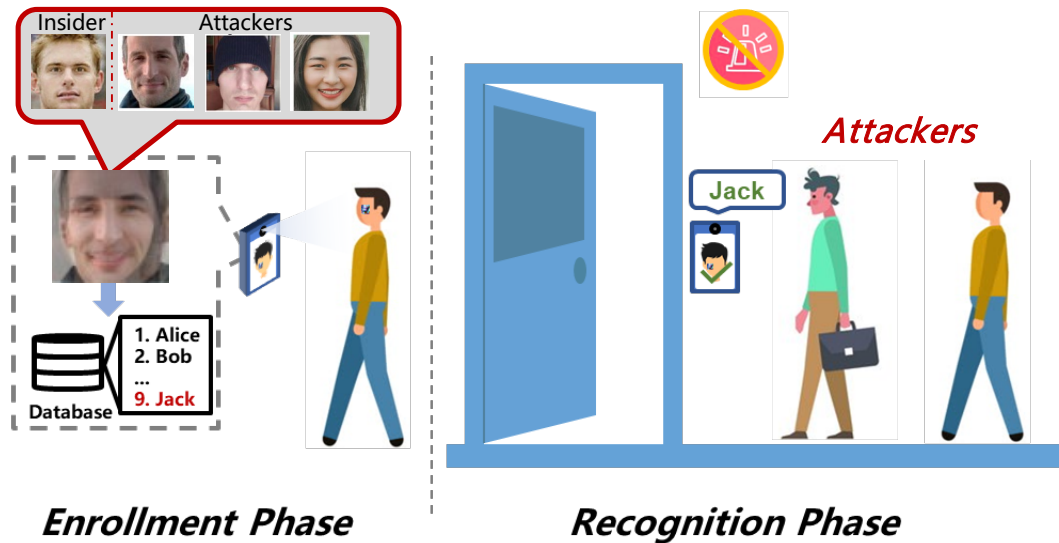
***Enrollment Phase***



# What UniID can do?



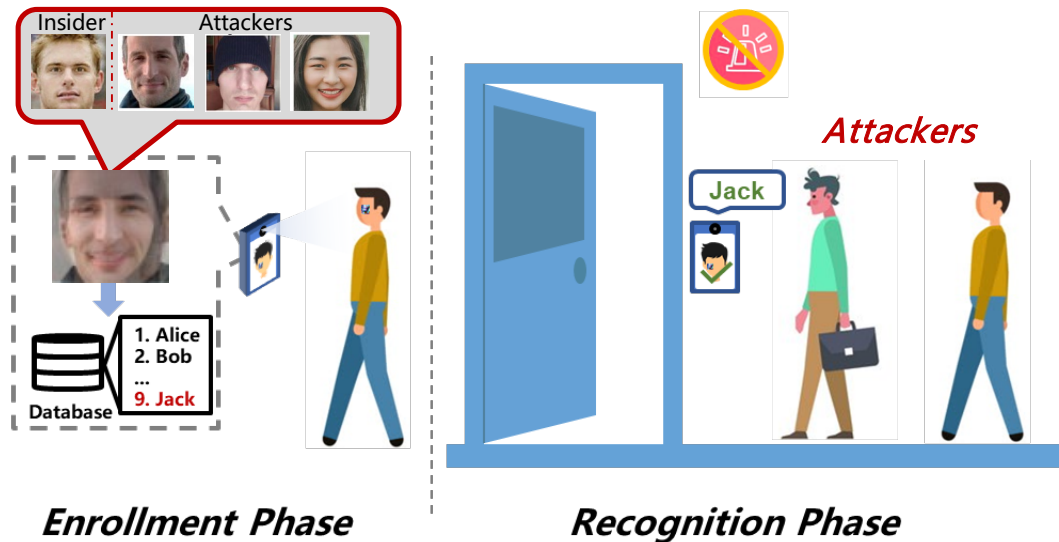
# What UniID can do?



## Capabilities :

- ❑ Multiple attackers
- ❑ Inconspicuous

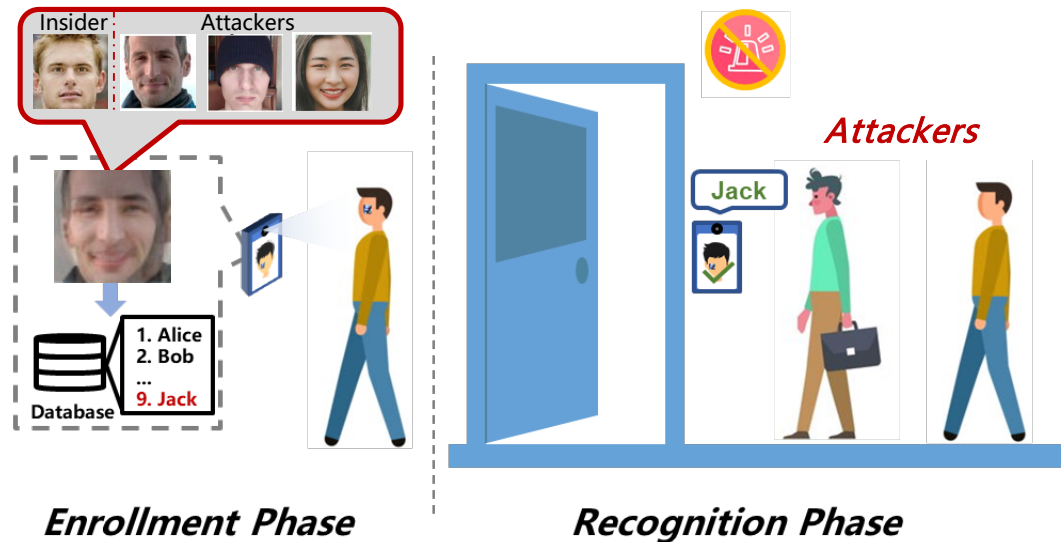
# What UniID can do?



## Capabilities :

- ❑ Multiple attackers
- ❑ Inconspicuous
- ❑ One-time enrollment, unlimited-times spoofing

# What UniID can do?

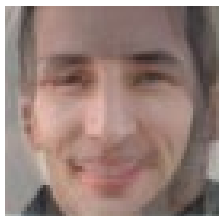


## Capabilities :

- ❑ Multiple attackers
- ❑ Inconspicuous
- ❑ One-time enrollment, unlimited-times spoofing

*Injecting UniID sounds intuitive, but not trivial.*

# How to achieve UniID...

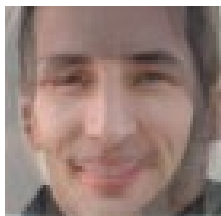


**Average Face**

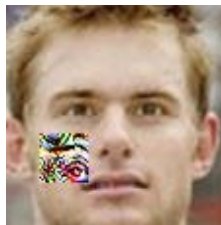
## ***Facts :***

- ***Attackers have no permission to access the database***
- ***Average face doesn't exist in real life***

# How to achieve UniID...



Average Face



Insider

## ***Facts :***

- ***Attackers have no permission to access the database***
- ***Average face doesn't exist in real life***

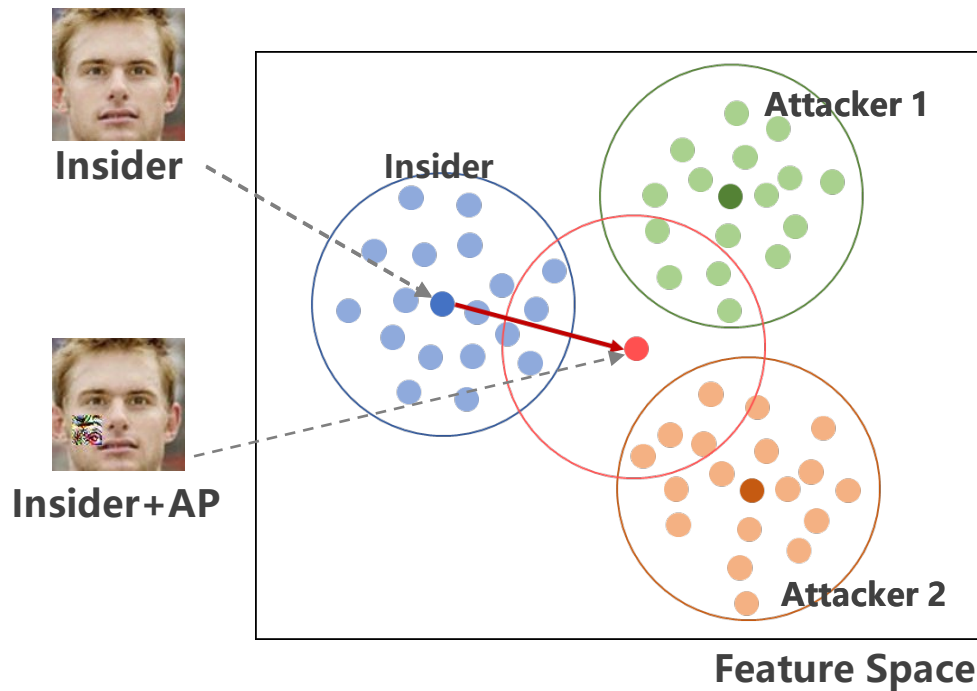
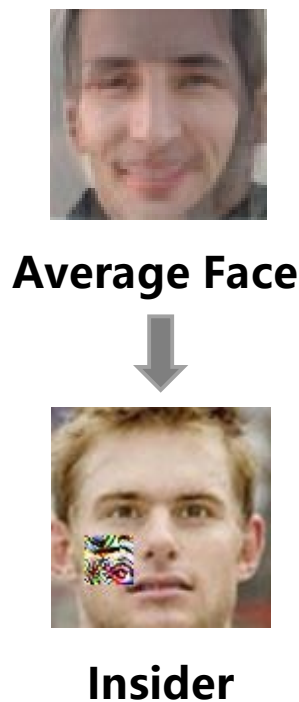
## ***Our method:***

- ***Try to find an “average face” at the feature level***

# How to achieve UniID...



# How to achieve UniID...





# UniID still has challenges...

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***C1: For a specific insider, selecting attackers is important***

# UniID still has challenges...

***C1: For a specific insider, selecting attackers is important***



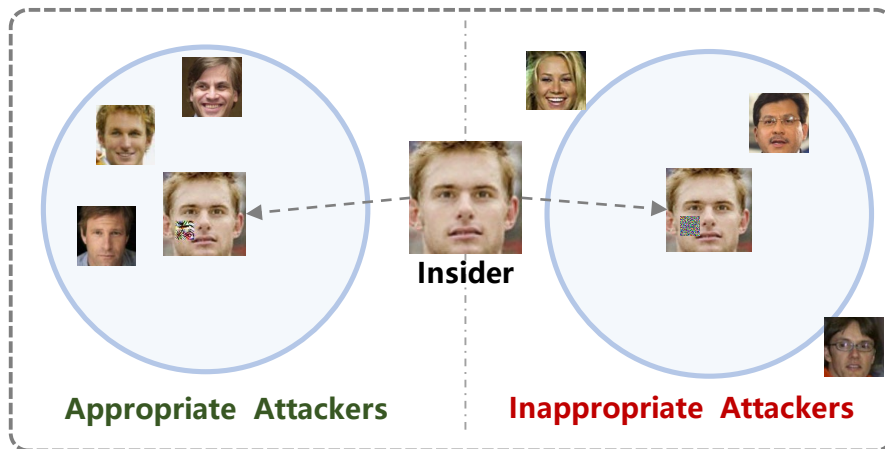
***The choice of insider is restricted!***

# UniID still has challenges...

***C1: For a specific insider, selecting attackers is important***



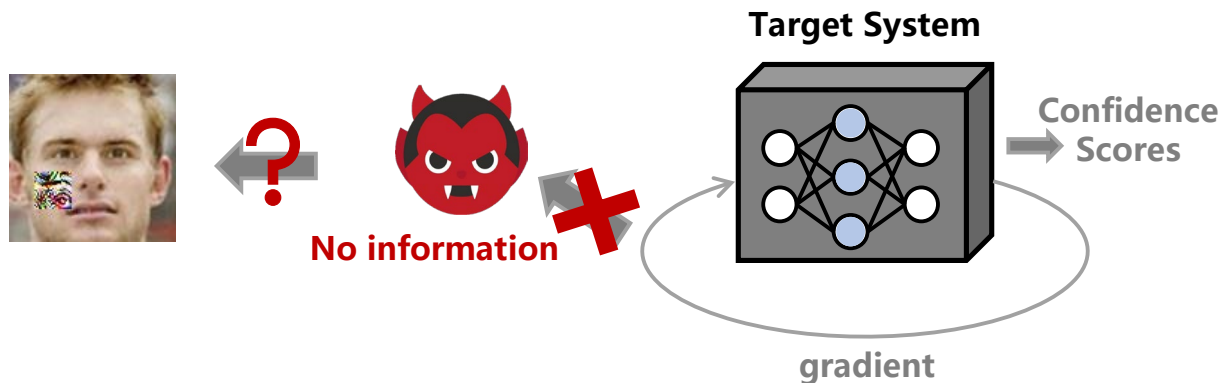
***The choice of insider is restricted!***



- **Q1: How to determine the appropriate attackers?**
- Q2: How to address the black-box setting?
- Q3: How to increase its physical robustness in real life?

# UniID still has challenges...

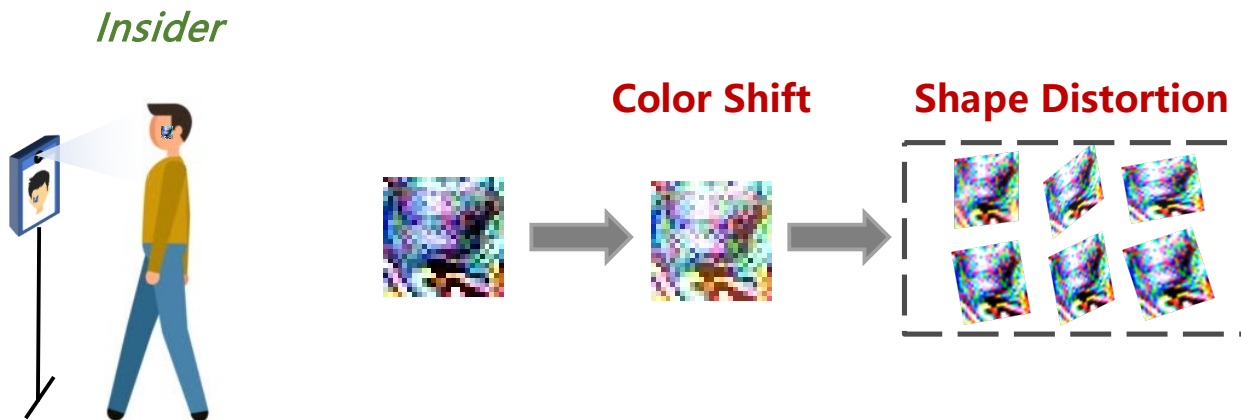
*C2: Real-world face authentication systems are fully black-box settings*



- **Q1: How to determine the appropriate attackers?**
- **Q2: How to optimize the adversarial patch under the black-box setting?**
- *Q3: How to increase its physical robustness in real life?*

# UniID still has challenges...

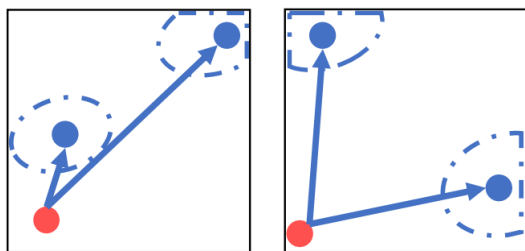
***C3: The insider need to take photos on-site to upload his enrollment image***



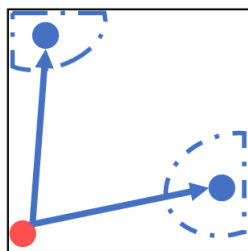
- ***Q1: How to determine the appropriate attackers?***
- ***Q2: How to optimize the adversarial patch under the black-box setting?***
- ***Q3: How to increase its physical robustness in real life?***

# Q1 -> Attacker Selection

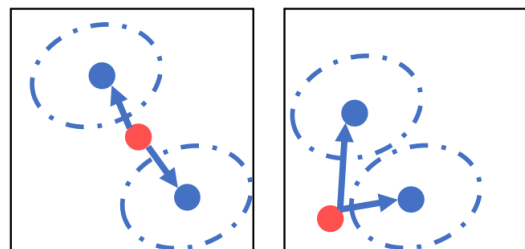
## □ *Multi-attackers Analysis:*



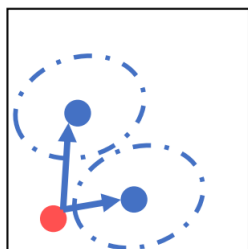
(a)



(b)



(c)

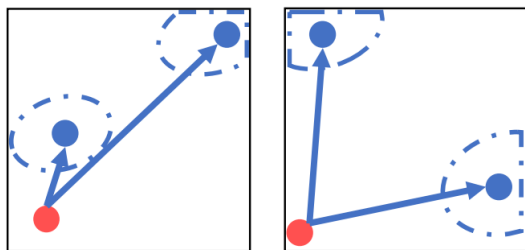


(d)

● Insider ● Attacker

# Q1 -> Attacker Selection

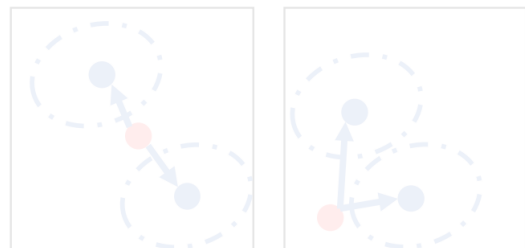
## □ *Multi-attackers Analysis:*



(a)

(b)

- **Case a & b:**  
The attackers are too far away from the insider



(c)

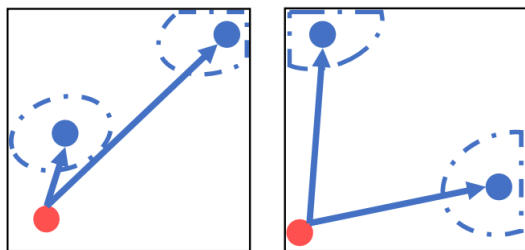
(d)

● Insider ● Attacker



# Q1 -> Attacker Selection

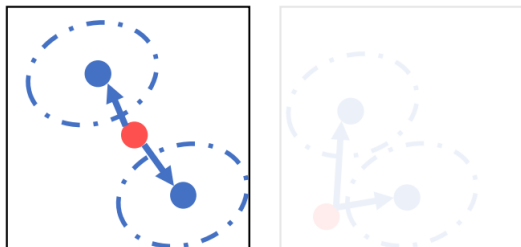
## □ *Multi-attackers Analysis:*



(a)

(b)

- **Case a & b:**  
The attackers are too far away from the insider
- **Case c:**  
The attackers are located on either side of the insider



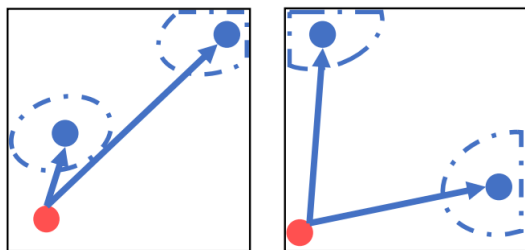
(c)

(d)

● Insider ● Attacker

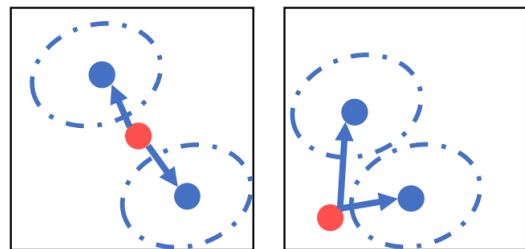
# Q1 -> Attacker Selection

## □ *Multi-attackers Analysis:*



(a)

(b)



(c)

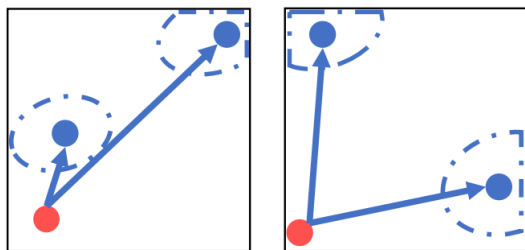
(d)

● Insider ● Attacker

- **Case a & b:**  
The attackers are too far away from the insider
- **Case c:**  
The attackers are located on either side of the insider
- **Case d:**  
The attackers and the insider are as close to each other as possible

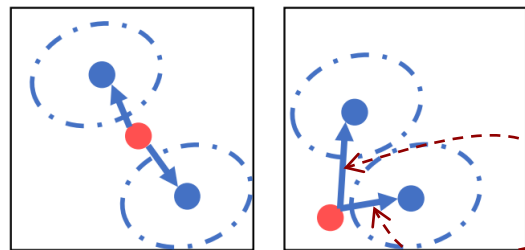
# Q1 -> Attacker Selection

## Attacker Combination Choosing:



(a)

(b)



(c)

(d)

● Insider ● Attacker

- **Case a & b:**  
The attackers are too far away from the insider
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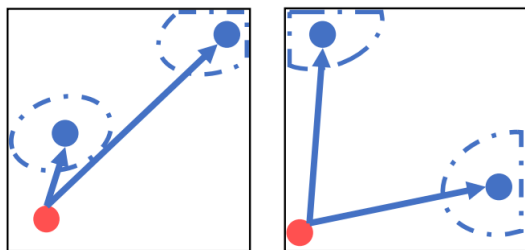
*Similarity Metric*

*Aggregation Metric*

$$Sim(V, A) = \frac{1}{N} \sum_{i=1}^N \frac{f(V) \cdot f(A_i)}{|f(V)| \times |f(A_i)|}$$

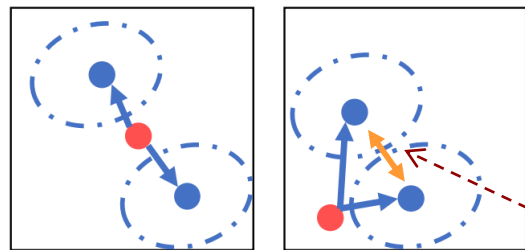
# Q1 -> Attacker Selection

## Attacker Combination Choosing:



(a)

(b)



(c)

(d)

● Insider

● Attacker

### ➤ Case a & b:

The attackers are too far away from the insider

### ➤ Case c:

The attackers are located on either side of the insider

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The attackers and the insider are as close to each other as possible

### Similarity Metric

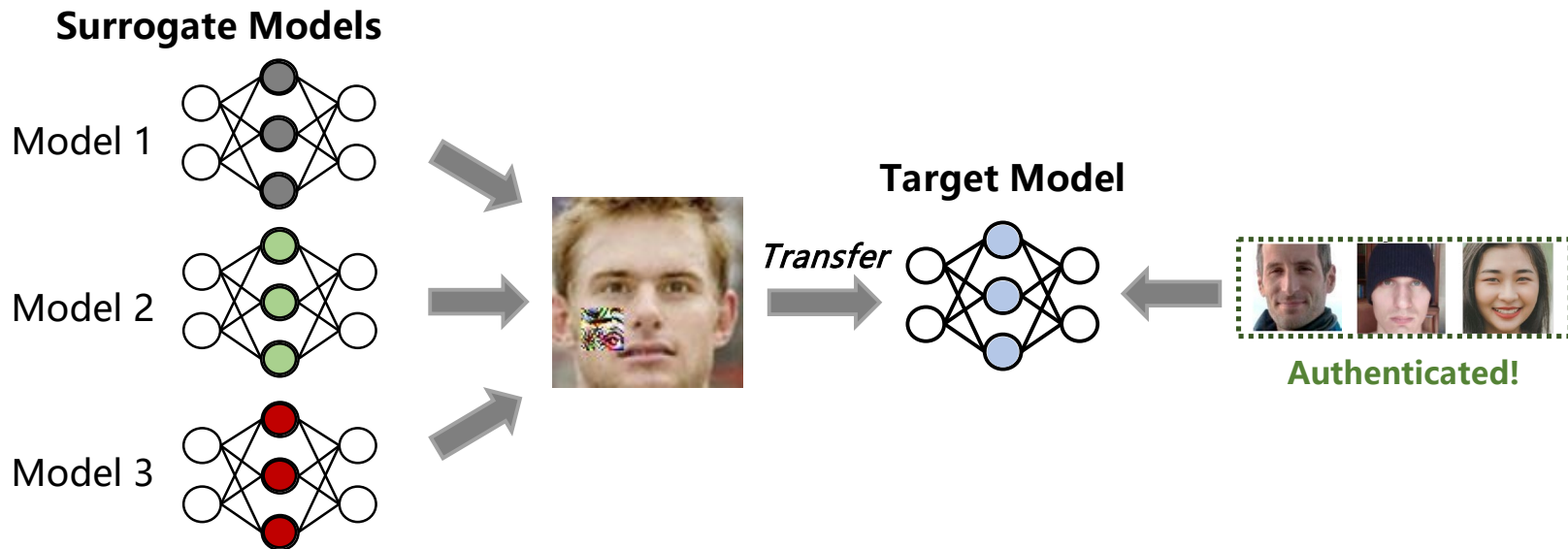
$$Sim(V, A) = \frac{1}{N} \sum_{i=1}^N \frac{f(V) \cdot f(A_i)}{|f(V)| \times |f(A_i)|}$$

### Aggregation Metric

$$Agg(V, A) = \frac{1}{N^2} \sum_{i=1}^N \sum_{j=1}^N \frac{f(A_j) \cdot f(A_i)}{|f(A_j)| \times |f(A_i)|}$$

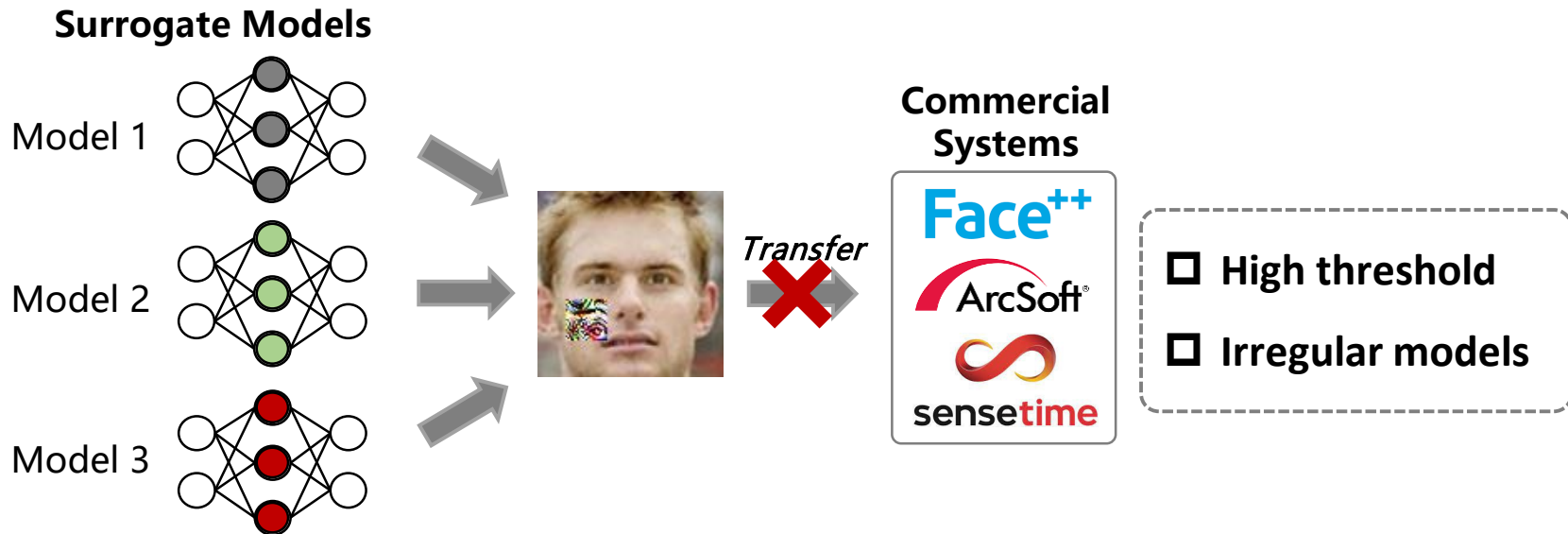
# Q2 -> Black-box Transfer

□ *A straightforward method: Assembled-models*



# Q2 -> Black-box Transfer

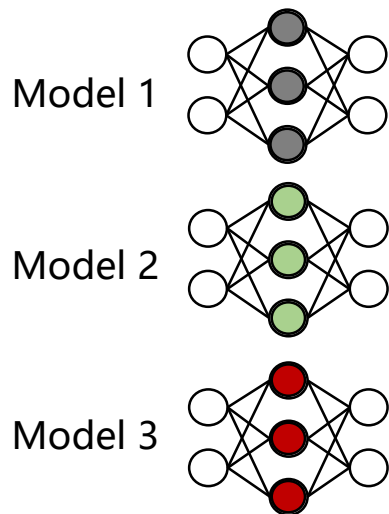
- ❑ *The transferability is insufficient when targeting commercial systems*



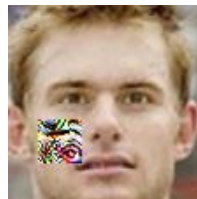
# Q2 -> Black-box Transfer

□ Reason: Imbalanced gradients

## Surrogate Models



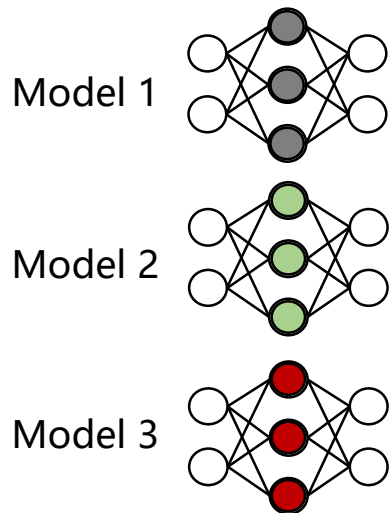
$$\frac{1}{N} \sum_{i=1}^N Model_i$$



# Q2 -> Black-box Transfer

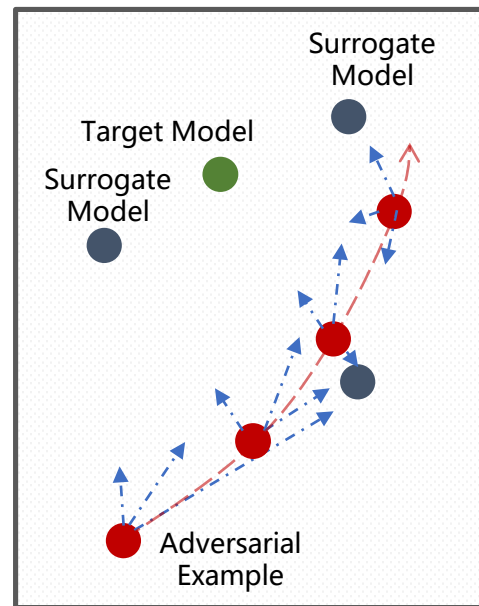
□ *Gradient imbalance reduces effectiveness*

## Surrogate Models



$$\frac{1}{N} \sum_{i=1}^N Model_i$$

## Optimization Process



Gradient Direction

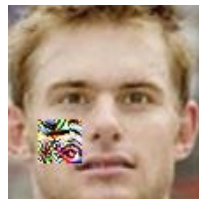
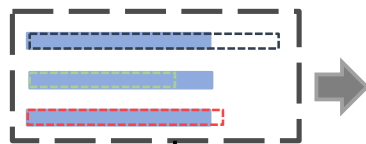
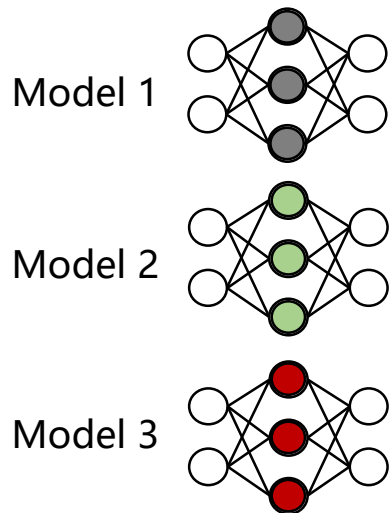
Optimization Direction



# Q2 -> Black-box Transfer

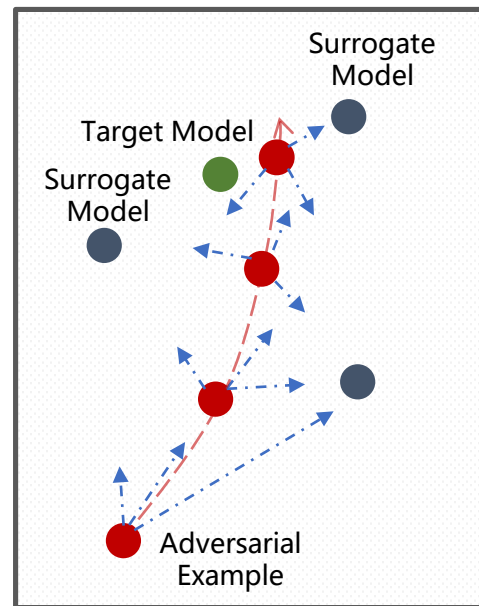
## □ *Agent Model Balance*

### Surrogate Models



$$\frac{1}{N} \sum_{i=1}^N \text{LeakyReLU}(\text{Model}_i)$$

### Optimization Process

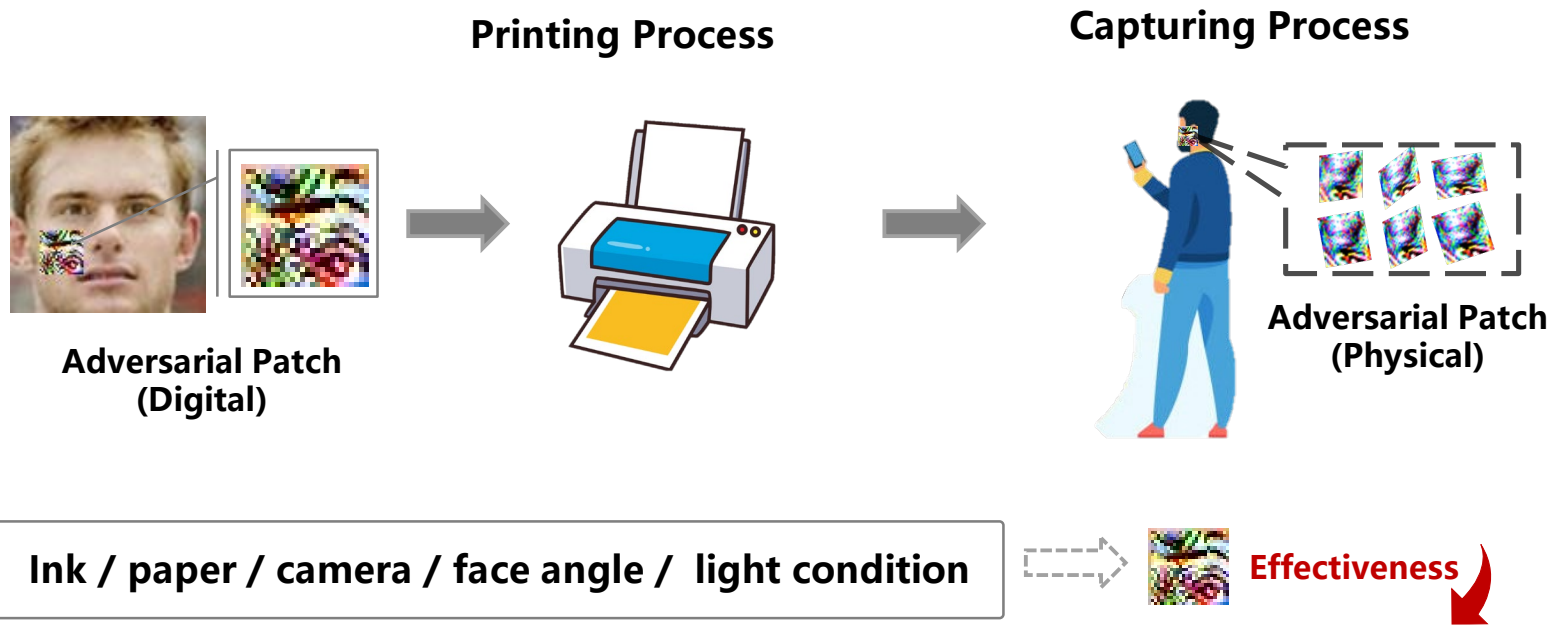


Gradient Direction

Optimization Direction

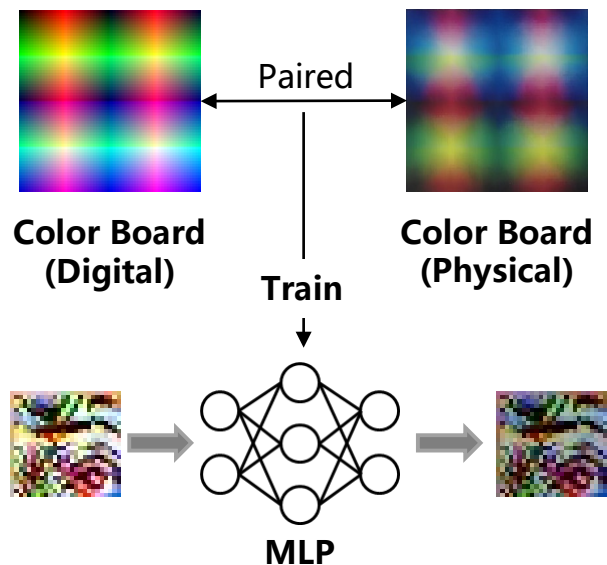
# Q3 -> Physical Implementation

- *The printing-capturing process is a non-linear function*



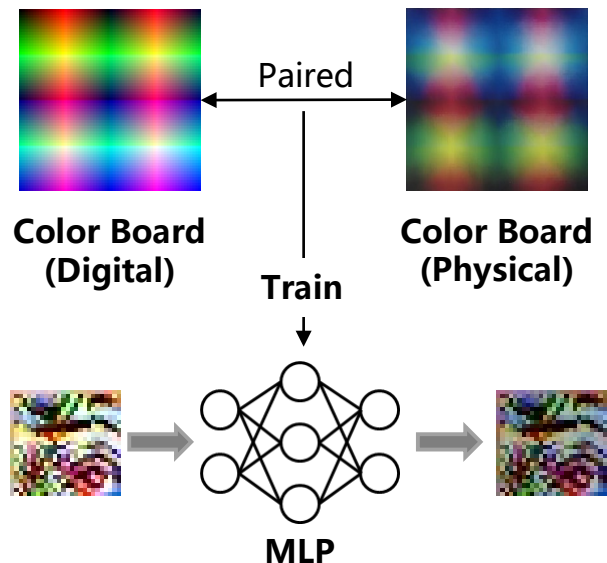
# Q3 -> Physical Implementation

## □ *Color-shift Calibration:*



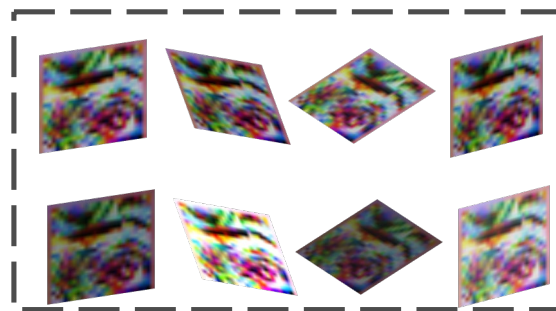
# Q3 -> Physical Implementation

## □ Color-shift Calibration:



## □ Shape-distortion Calibration:

- Expectation of Transformation (EoT)



- Position
- Scaling
- Rotation
- Affine
- Brightness

Transform Distribution

$$\delta^* = \arg \min_{\delta} \mathbb{E}_{t \sim T} [\mathcal{L}[f(V, \mathbb{A}, t(\delta)), f(\mathbb{A})]]$$

***The adversarial patch will be calibrated at each step of the optimization.***

# Evaluation

## □ *Simulation Evaluation*

- *Overall Performance*
- *Impact of patch factors*
- *Impact of threshold settings*

## □ *Real-world Evaluation*

- *Overall Performance*
- *Impact of light conditions*
- *Impact of camera settings*

# Simulation Evaluation

## □ Overall Performance :

- **Datasets: 100 users in LFW & CelebA**
- **Target models: FaceNet, Mobile-FaceNet, ArcFace-18/50, MagFace-18/50, Face++, ArcSoft**

Table 1: Overall Performance in White-box Models

| Target Models | Number of Attackers |     |     |     |     |
|---------------|---------------------|-----|-----|-----|-----|
|               | 1                   | 2   | 3   | ... | 7   |
| FaceNet       | 99%                 | 92% | 81% | ... | 24% |
| M-FN          | 98%                 | 80% | 57% | ... | 8%  |
| Arc-18        | 100%                | 99% | 92% | ... | 46% |
| Arc-50        | 99%                 | 83% | 53% | ... | 1%  |
| Mag-18        | 100%                | 99% | 92% | ... | 53% |
| Mag-50        | 98%                 | 81% | 43% | ... | 2%  |

- ASR: The attack success rate

## Under white-box setting

- **ASR: 100% in 3-Users Scenario**  
(1 Insider + 2 Attckers)
- **Can Extend to 8-Users Scenario**

# Simulation Evaluation

## ❑ Overall Performance :

- **Target models: FaceNet, Mobile-FaceNet, ArcFace-18/50, MagFace-18/50, Face++, ArcSoft**
- **Datasets: 100 users in LFW & CelebA**

Table 2: Overall Performance in Black-box Models

| Target Models | Number of Attackers |     |     |
|---------------|---------------------|-----|-----|
|               | 1                   | 2   | 3   |
| Arc-18        | 95%                 | 79% | 45% |
| Mag-18        | 98%                 | 71% | 36% |
| Mag-50        | 95%                 | 62% | 20% |
| Face++        | 81%                 | 45% | 20% |
| ArcSoft       | 86%                 | 27% | 12% |

- ASR: The attack success rate

## Under Black-box setting

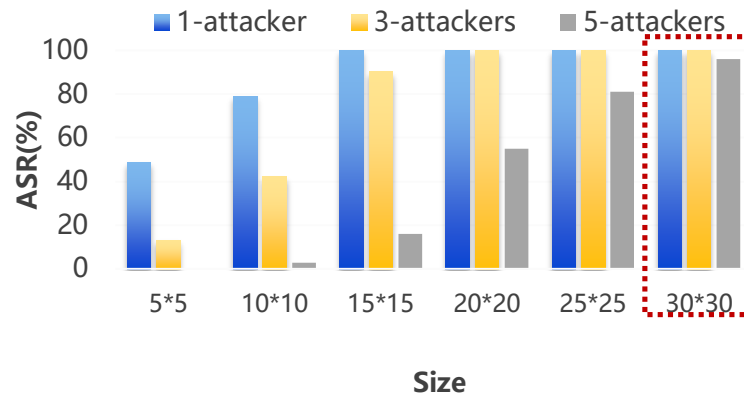
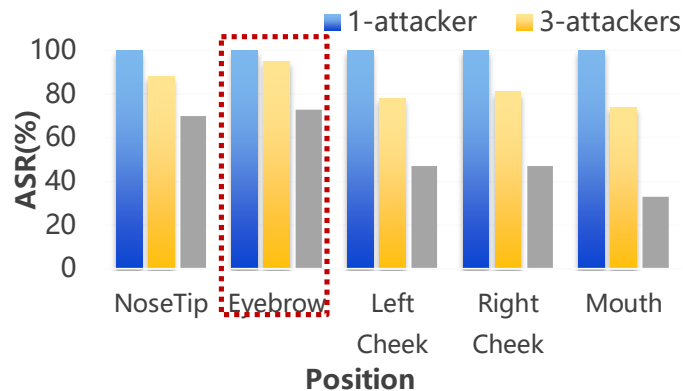
- **ASR: 91% in 2-Users Scenario**  
(1 Insider + 1 Attckers)
- **ASR: 57% in 3-Users Scenario**  
(1 Insider + 2 Attckers)

# Evaluation – simulation attack

## □ *Attack Effectiveness:*

### ➤ *Patch Position*

### ➤ *Patch Size*



**UniID is better to deploy in the eyebrow region with 30\*30 size (7% of face)**

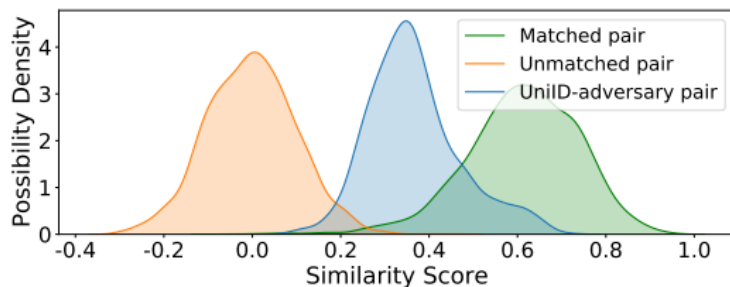


# Evaluation – simulation attack

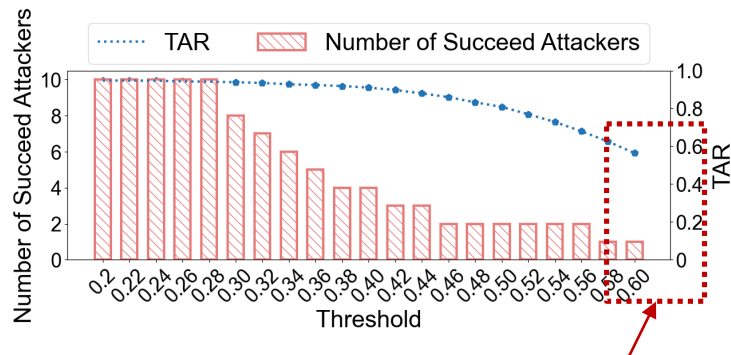
## □ Attack Effectiveness:

### ➤ Threshold Setting

The distribution of similarity scores



Impact of different thresholds



40% of legitimate users are unable to authenticate

**Merely increasing the threshold cannot simply block our attack**

# Real-world Evaluation

## □ Overall Performance

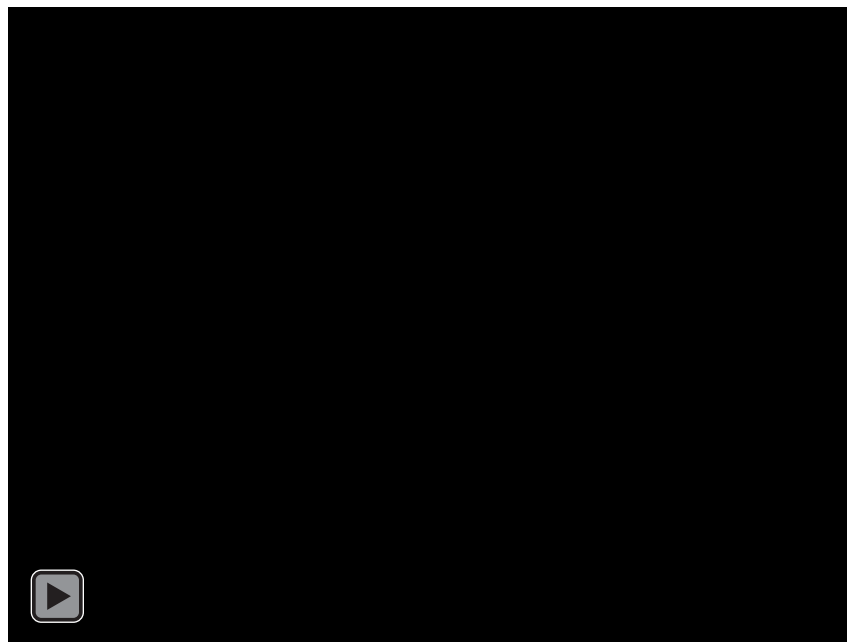
➤ **Target system: Face++ & ArcSoft**

➤ **Datasets: 20 volunteers**

Table 3: Overall Performance of UniID in Real World

| Metric | Target System | Number of Attackers |       |
|--------|---------------|---------------------|-------|
|        |               | 1                   | 2     |
| ASR    | Face++        | 87%                 | 41%   |
|        | ArcSoft       | 86%                 | 47%   |
| F_succ | Face++        | 84.3%               | 71.1% |
|        | ArcSoft       | 86.5%               | 61.5% |

- ASR: The attack success rate
- F\_succ: The attack success rate in consecutive frames

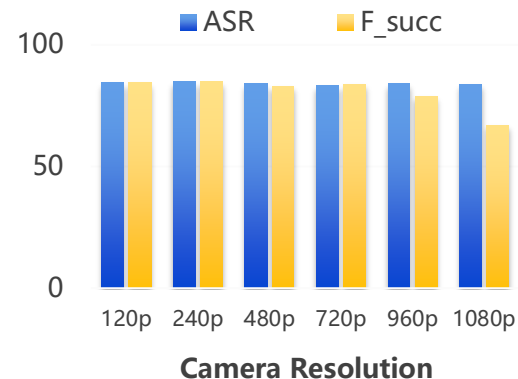
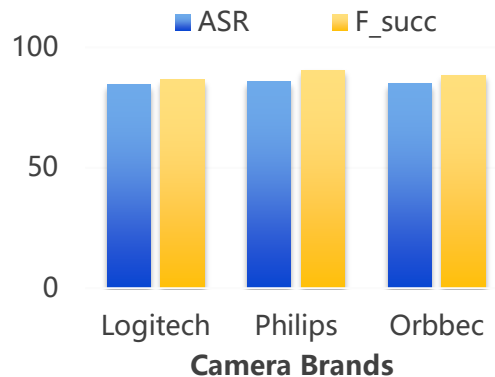
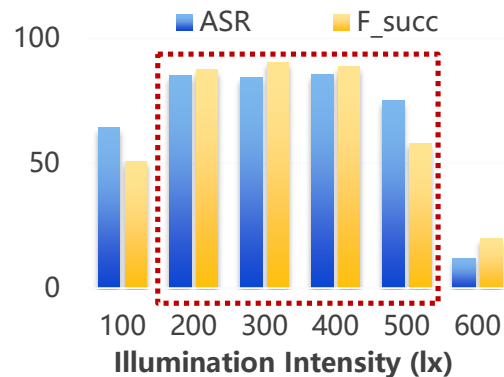


# Real-world Evaluation

## ▣ *Attack Effectiveness*

➤ *Light Conditions*

➤ *Cameras settings*



**UniID is robust to various cameras in most light conditions**

# Discussion and Countermeasures

## □ **Goal :**

- Offering **a systematic analysis** of face authentication security
- urging service providers to **focus on security issues across all phases** of the workflow to make face authentication systems more secure

## □ **Countermeasures:**

- *Enhancing the ability to distinguish different identities*
- *Detecting adversarial examples at both the enrollment and recognition phases*
- *Using assembled models to increase the attack difficulty*

# Conclusion

- ❑ We **identify the vulnerability** in the face enrollment phase that enables multiple attackers to be successfully authenticated **without any disguise**.
- ❑ We design **UniID** that make the legitimate user register a universal identity into the database, thus achieving the spoofing attack.
- ❑ This vulnerability exists in other authentication systems that require an enrollment process.

# UniID: Spoofing Face Authentication by Universal Identity



Paper and demo website:

<https://github.com/USSLab/UniID>

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