# FACESEC:

# A Fine-Grained Robustness Evaluation Framework for Face Recognition Systems

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# **DL-Based Face Recognition in Daily Life**



(Source: www.businessinsider.com)
Homeland security



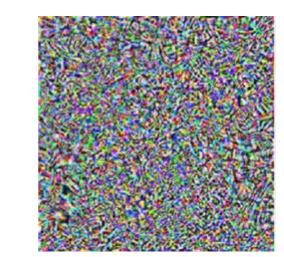
#### (Source: www.nec.com) Financial services



(Source: www.apple.com)

# **DL Models Are Not Robust**







"Pig"

#### Small adversarial noise

(Goodfellow et al., ICLR'14)

"Airliner"

### DL models are inherently vulnerable to adversarial examples

# Face Recognition Systems Are Not Secure







"Bob"

Adversarial eyeglass frame

"Alice"

(Sharif et al., CCS'16)

### Adversarial examples can be realizable in physical space

# Face Recognition Systems Are Not Secure

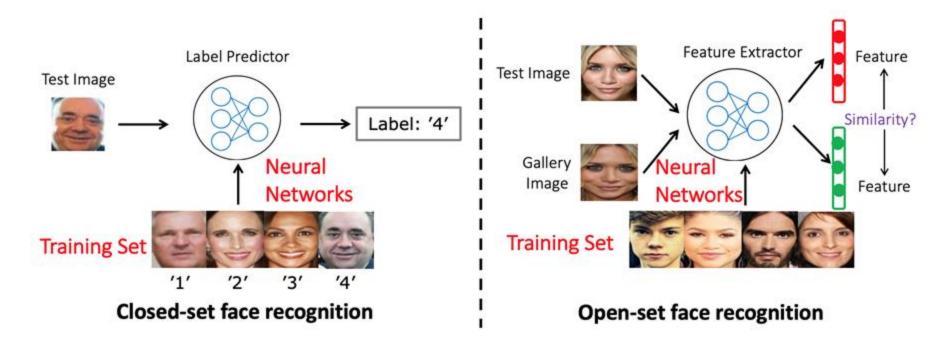


(Source: www.faception.com)

(Source: www. en.wikipedia.org)

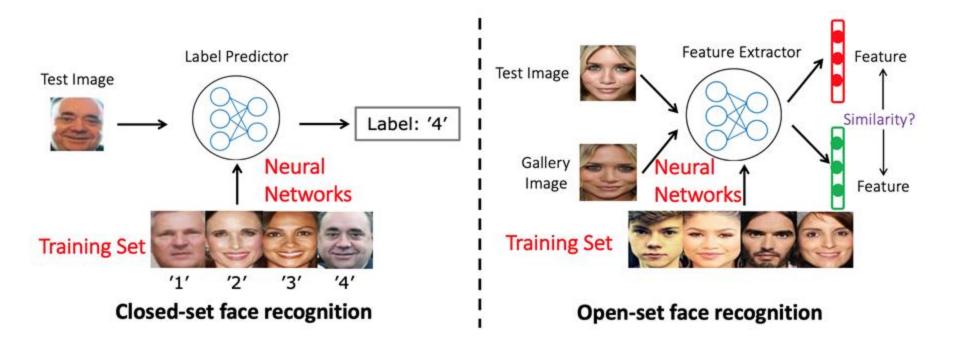
# It is critical to evaluate robustness of face recognition systems in adversarial settings

# **Robustness Evaluation Is Challenging**



- Lack of understanding which *individual* or *combination* of components is vulnerable to adversarial examples
  - Different training sets and neural architectures result in different performance and robustness
  - Existing approaches: only use **white-box** or **black-box** attack for evaluation

# **Robustness Evaluation Is Challenging**



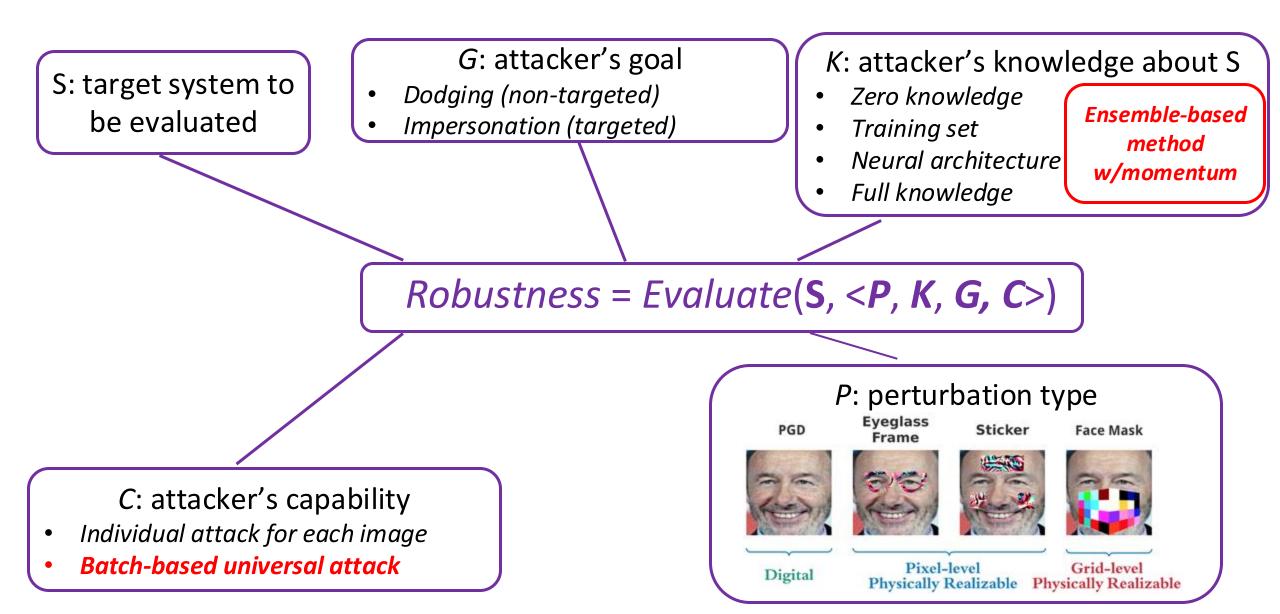
- Lack of understanding *different levels of robustness* corresponding to different types of attacks
  - Attackers vary by perturbation types, goals, knowledge, and capabilities
  - Existing approaches: only use **a specific type** of attack (e.g., digital attack)

# **Robustness Evaluation Is Challenging**

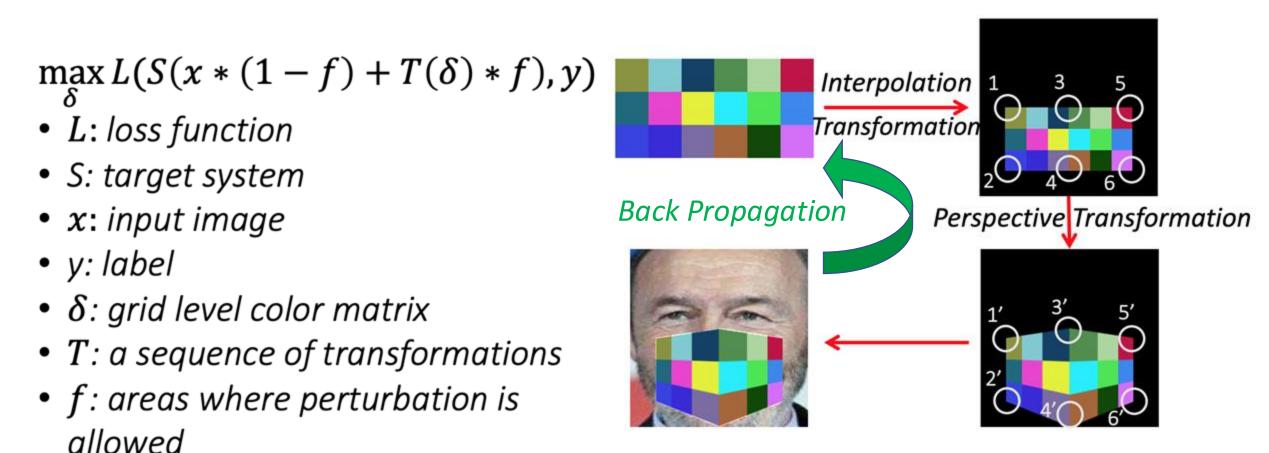


- Lack of understanding *different levels of risks* corresponding to different types of attacks
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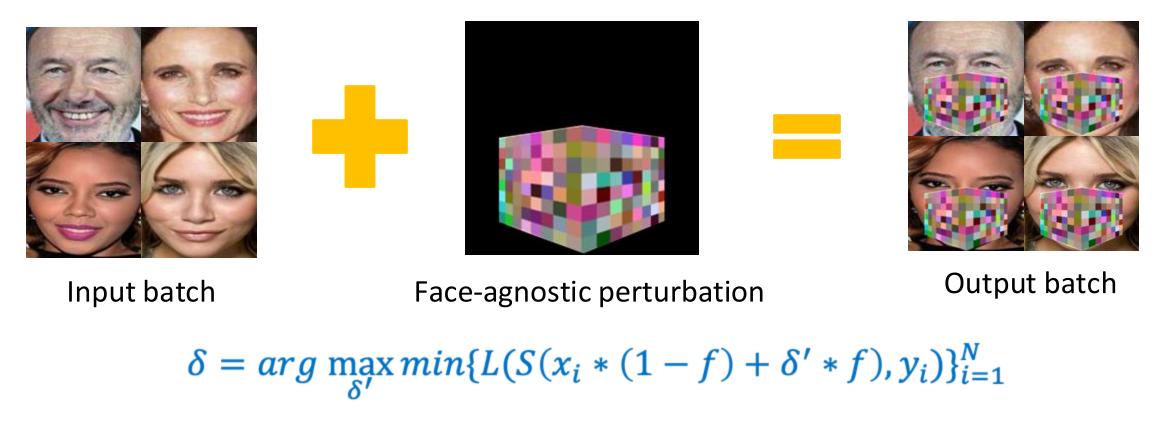
## FaceSec - Framework



# FaceSec – Face Mask Attack



## FaceSec – Universal Attack



### A general approach that works for both digital and physically realizable attacks

## **Experimental Results**

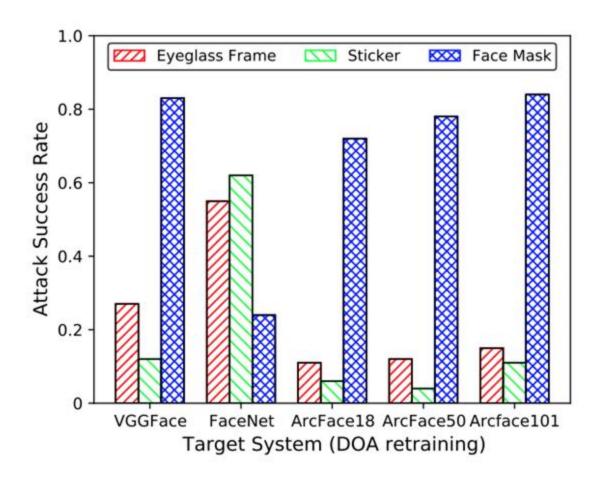
### Attack Success Rate of Dodging Face Mask Attacks

Target System	Attacker's System Knowledge			
	Zero knowledge	Training set	Neural architecture	Full knowledge
VGGFace	0.26	0.32	0.63	1.00
FaceNet	0.30	0.42	0.83	1.00
ArcFace18	0.27	0.33	0.71	1.00
ArcFace50	0.29	0.36	0.67	0.99
ArcFace101	0.26	0.36	0.54	0.99

Accurate knowledge of neural architecture is significantly more important than training data in black-box attacks

# **Experimental Results**

### Dodging Attacks VS. SOTA Defense



- 1. Adversarial robustness highly depends on both the nature of perturbation and the neural architecture
- 2. Adversarial robustness against one type of perturbation may not be generalized to other types

# Conclusion

- FACESEC is the first that supports to evaluate the risks of different components of face recognition systems from multiple dimensions and under various adversarial settings
- □ FACESEC can work for both *closed-set* and *open-set* systems
- Our systematic and comprehensive evaluations demonstrate that FACESEC can greatly help understand the robustness of face recognition systems

# Thank you!

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