

Rethinking Deep Neural Network Ownership Verification: Embedding Passports to Defeat Ambiguity Attacks

Lixin Fan¹, Kam Woh Ng^{1,2}, Chee Seng Chan²

¹WeBank AI Lab, Shenzhen, China

²Center of Image and Signal Processing, University of Malaya,
Kuala Lumpur, Malaysia

{ lixinfan@webank.com ; jinhewu@webank.com ; cs.chan@um.edu.my }

Rethinking Deep Neural Network Ownership Verification: Embedding Passports to Defeat Ambiguity Attacks

Paper: <http://papers.nips.cc/paper/8719-rethinking-deep-neural-network-ownership-verification-embedding-passports-to-defeat-ambiguity-attacks>

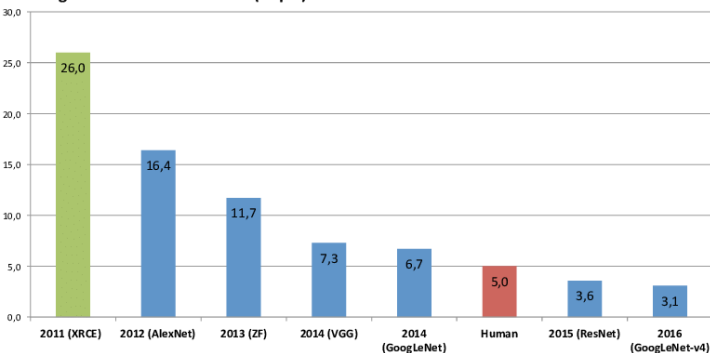
Arxiv: <https://arxiv.org/abs/1909.07830>

Github Page: <https://kamwoh.github.io/DeepIPR>

Machine Learning as a Service (MLaaS)

- More and more **business models and services** using Deep Neural Network (DNN)

ImageNet Classification Error (Top 5)



How Marketers Use Machine Learning



\$1
BILLION

the amount Netflix saved from the use of machine learning algorithm



15
MINUTES

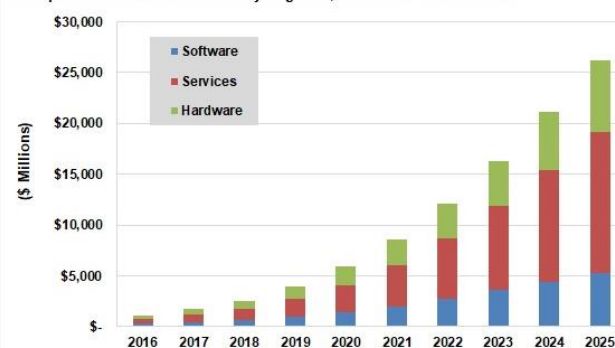
Amazon's ship time after it started using machine learning



87%

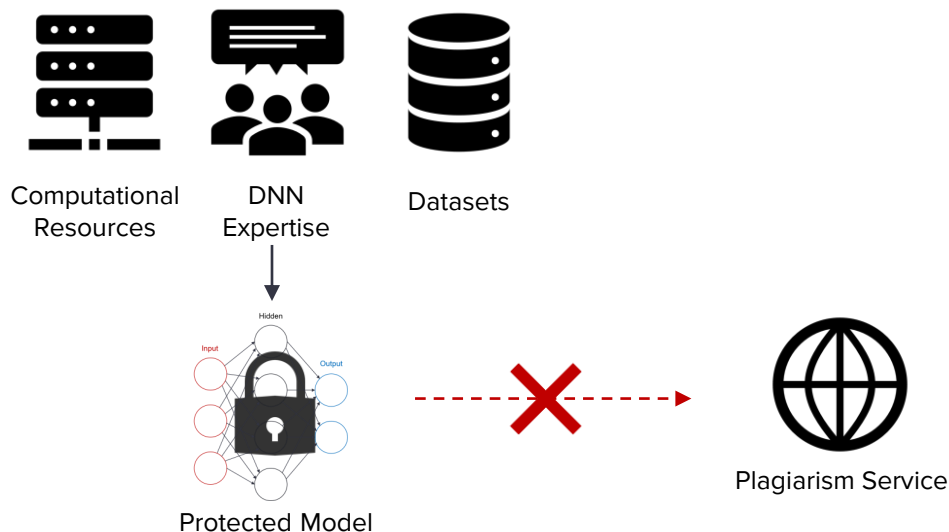
of companies who use AI plan to use them in sales forecasting and email marketing

Computer Vision Total Revenue by Segment, World Markets: 2016-2025



Protection on DNN model is needed!

- Companies **invested a lot** to create powerful models
- They are **easily copied** and used by plagiarizers.
- We **need a protection** on DNN **from being illegally copied, distributed and abused.**



How do we protect DNN?

Conventional DNN watermarking methods

1. Feature based approach

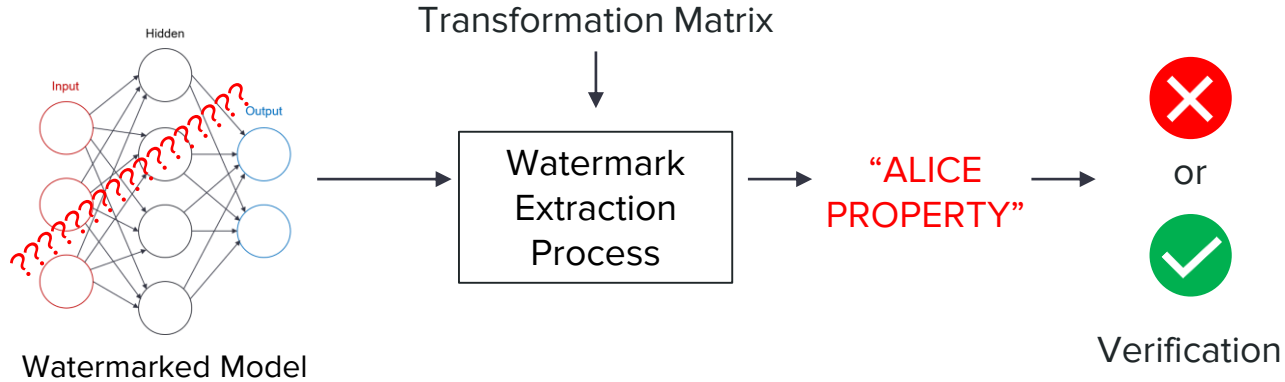
- Y. Uchida, Y. Nagai, S. Sakazawa, and S. Satoh, **“Embedding watermarks into deep neural networks”**
- B. D. Rouhani, H. Chen, and F. Koushanfar, **“Deepsigns: A generic watermarking framework for IP protection of deep learning models”**

2. Trigger-set based approach

- Yossi Adi, Carsten Baum, Moustapha Cisse, Benny Pinkas, and Joseph Keshet. **“Turning Your Weakness Into a Strength: Watermarking Deep Neural Networks by Backdooring”**
- Jialong Zhang, Zhongshu Gu, Jiyong Jang, Hui Wu, Marc Ph. Stoecklin, Heqing Huang, and Ian Molloy. **“Protecting Intellectual Property of Deep Neural Networks with Watermarking”**

Feature-based approach

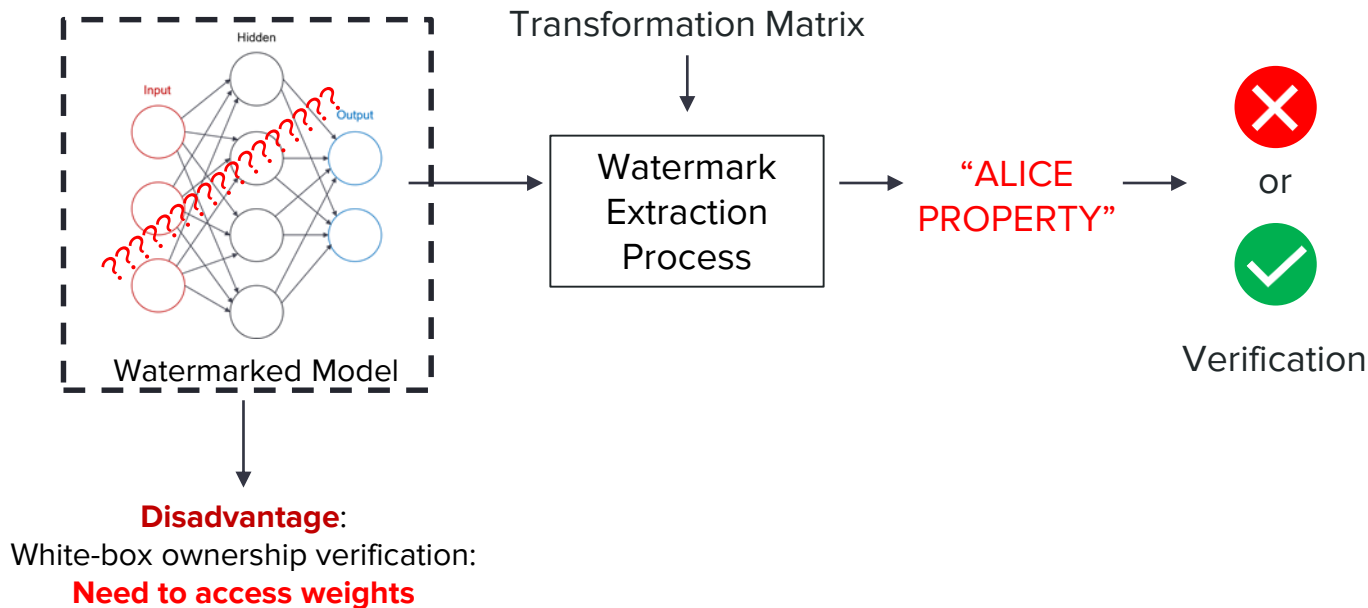
Feature based watermark detection



**Embedding process is identical

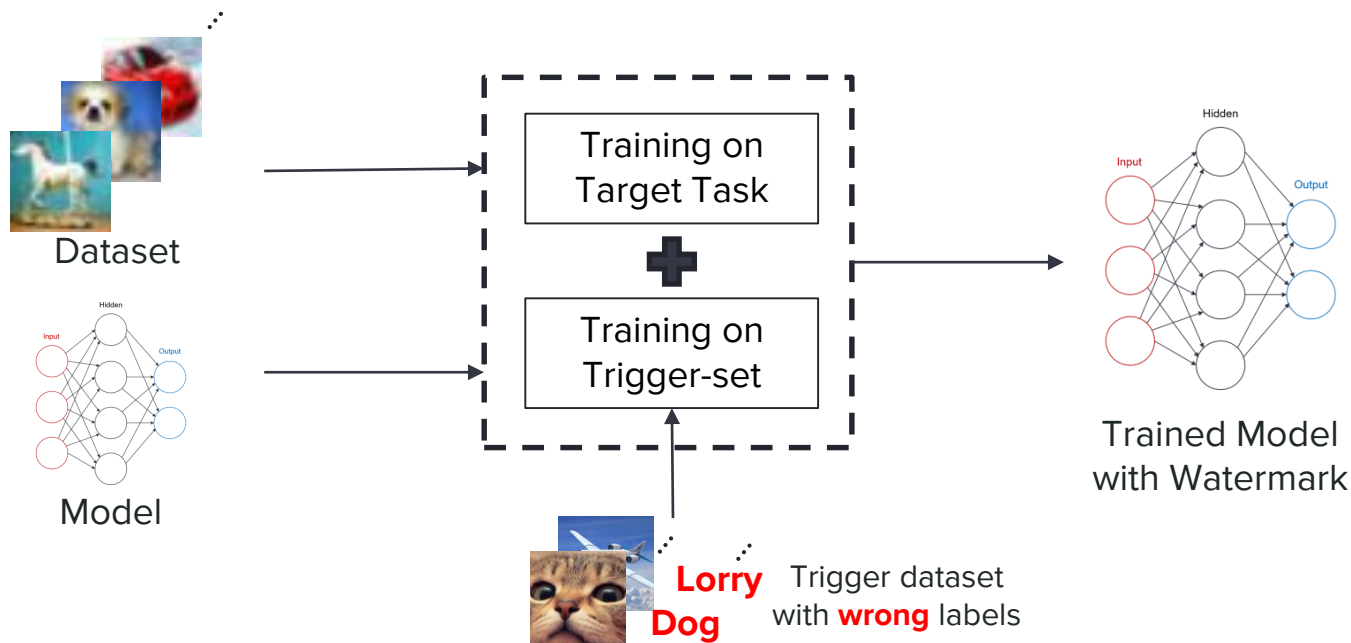
Feature-based approach

Feature based watermark detection



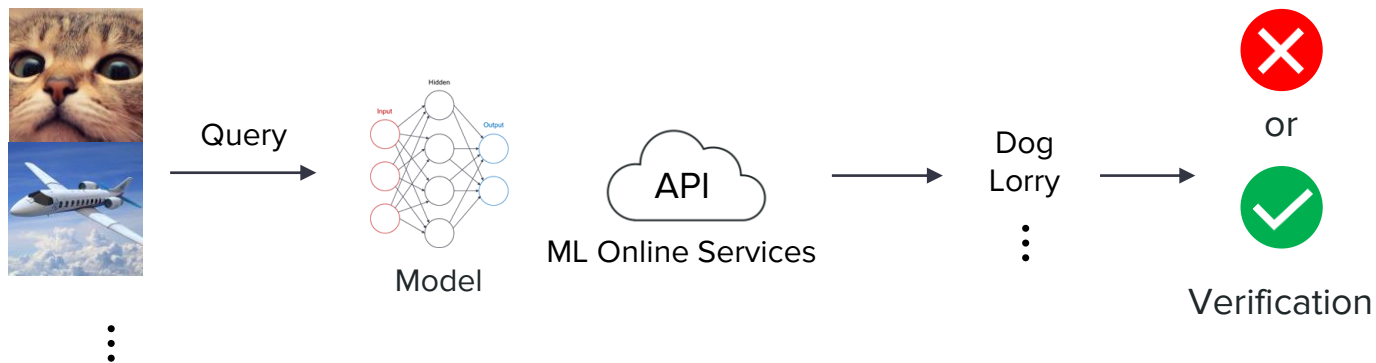
Trigger-set based approach

Trigger-set based watermark embedding



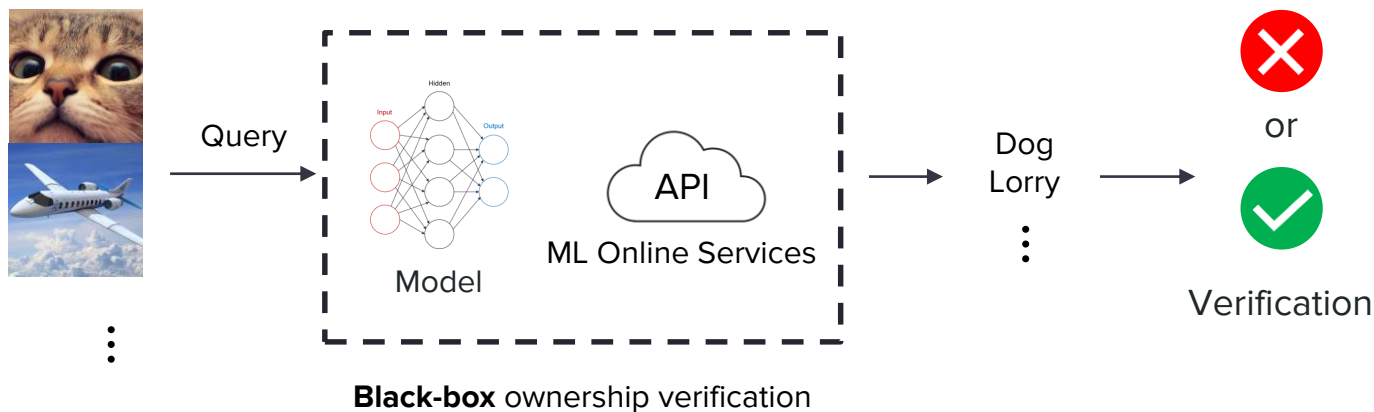
Trigger-set based approach

Trigger-set based watermark detection

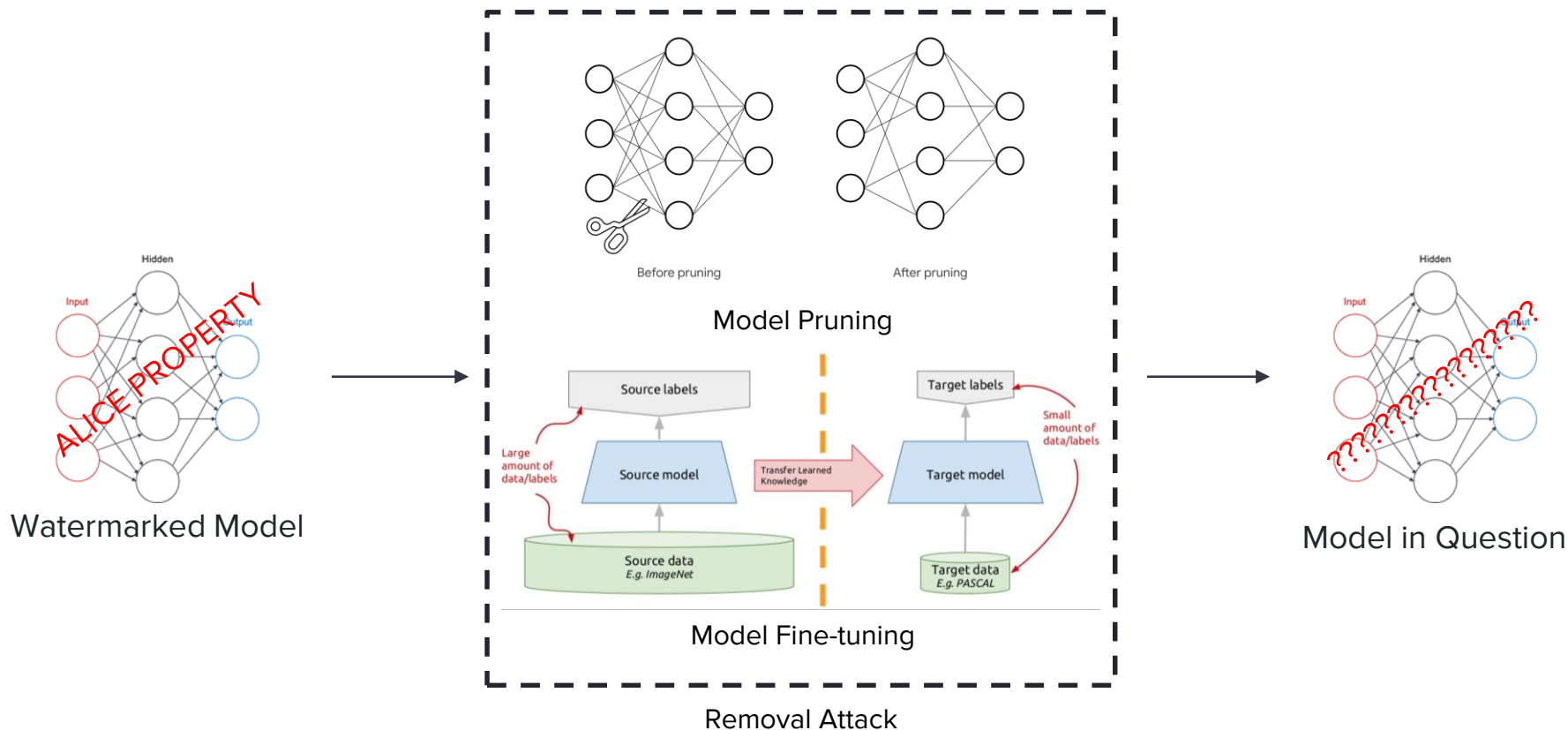


Trigger-set based approach

Trigger-set based watermark detection



Possible attacks to Ownership Protection

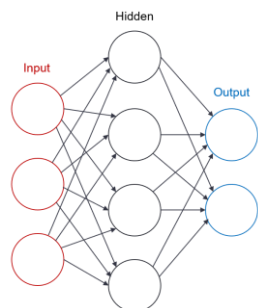


Effectiveness of Removal Attacks

- Watermark embedded in AlexNet for CIFAR10 classification

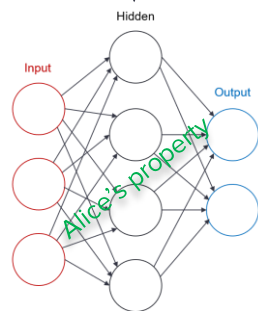
Removal Attacks	Feature based watermarking [1] (White-box)	Trigger-set based watermarking [2] (Black-box)
Model Pruning	Strong (100% watermark detected with 65% pruning rate)	Strong (100% watermark detected with 70% pruning rate)
Fine-tuning (CIFAR10 → CIFAR100)	Strong (100% watermark detected after fine-tuning)	Weak (25% watermark detected after fine-tuning)

What is Ambiguity Attack



Alice trained a
DNN model

embeds watermark



Detection

Alice's
property

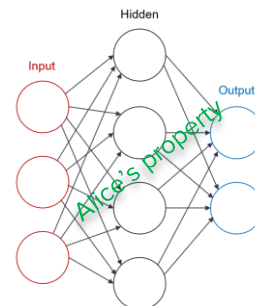


Judge confused due to
two different watermarks are
being detected from the model



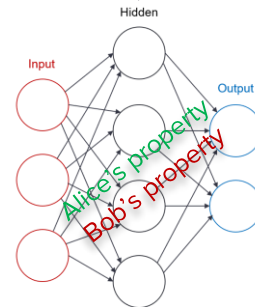
Bob stole Alice's
model

embeds
fake watermark



Detection

Bob's
property



Effectiveness of Ambiguity Attack

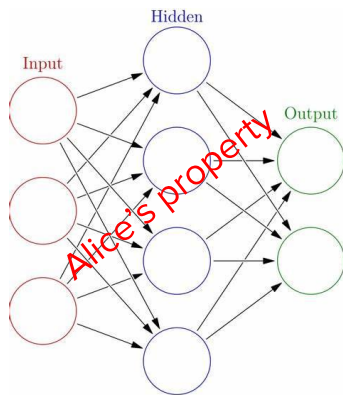
- Watermark embedded in AlexNet for CIFAR10 classification

Watermark approach	Real Watermark	Fake Watermark
Feature based (White-box)	100% watermark detected	100% watermark detected
Trigger-set based (Black-box)	100% watermark detected	100% watermark detected

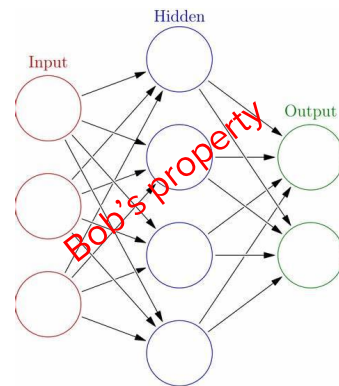
Watermark detection rate for both **real** and **fake** watermarks

How to deal with **ambiguity** attack?

Current Situation

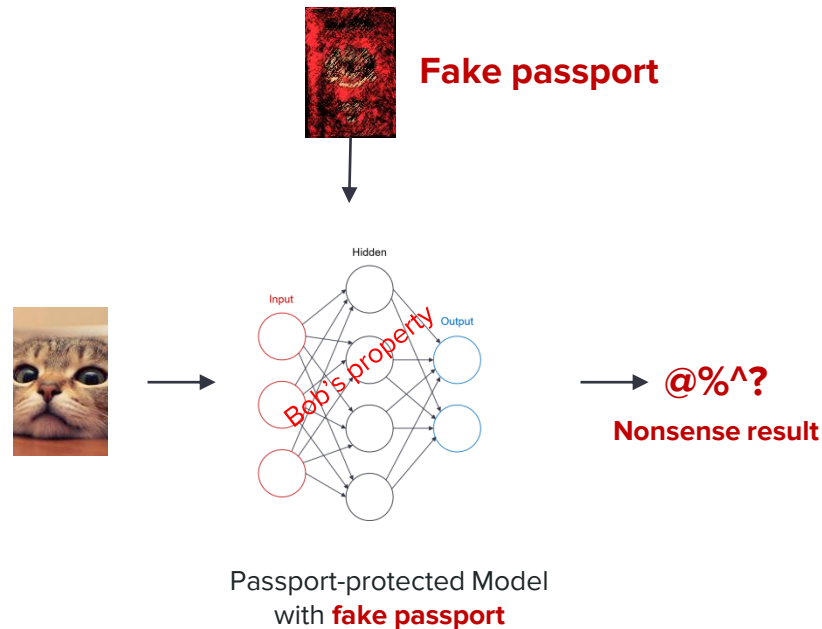
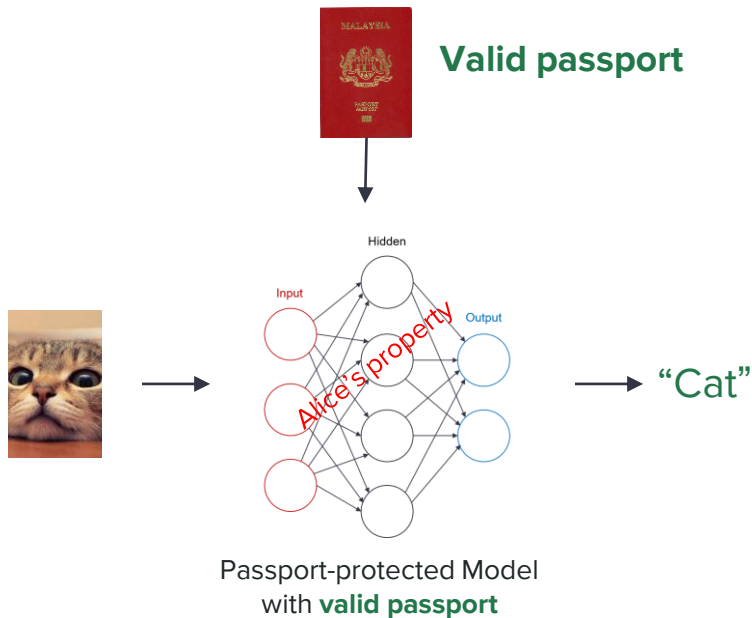


Passport-protected Model
with original watermark



Copied Model
with fake watermark

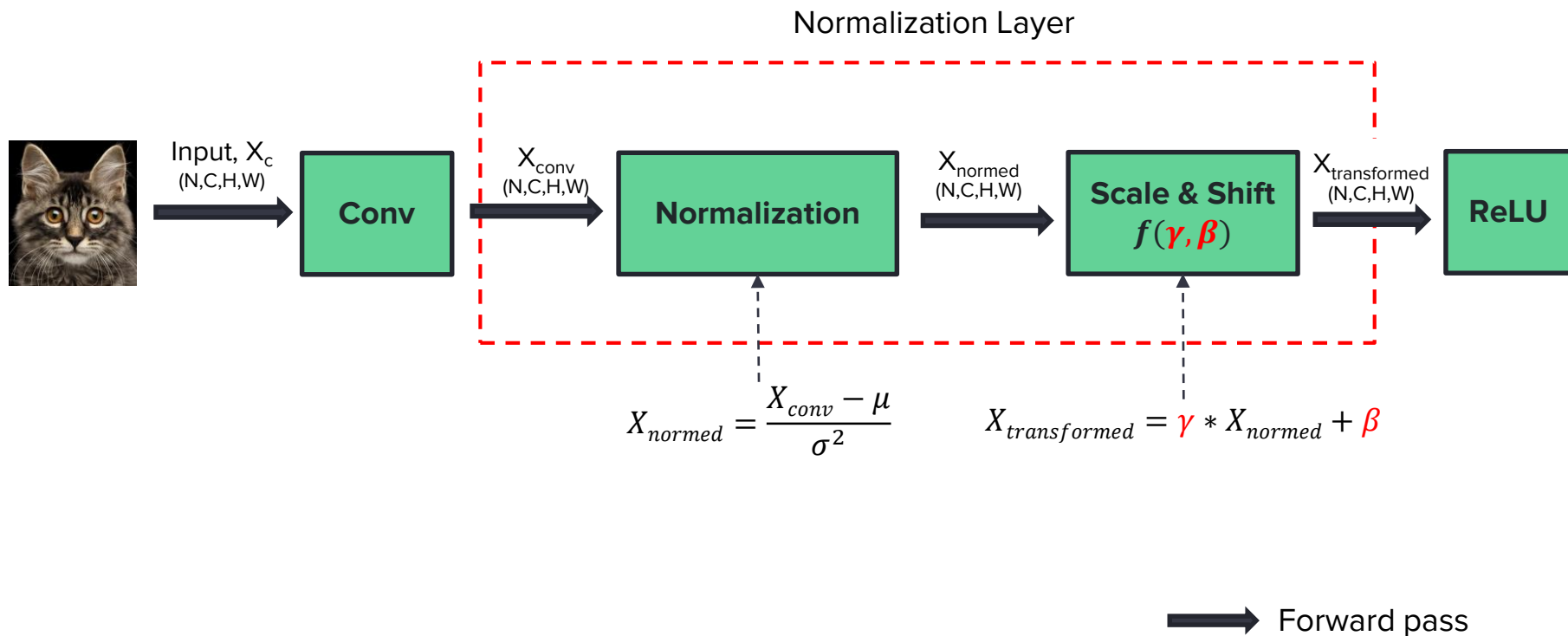
Proposed Solution



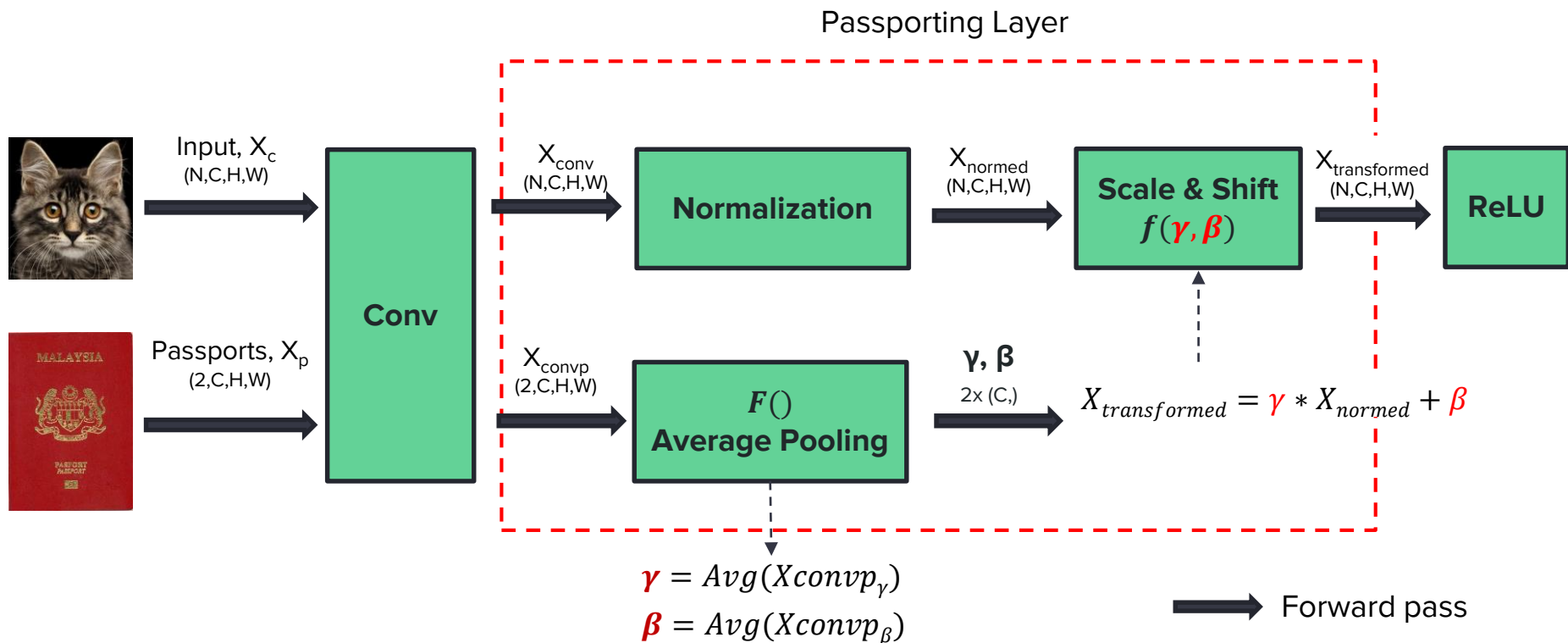
Aim:

- Model cannot function without valid passport

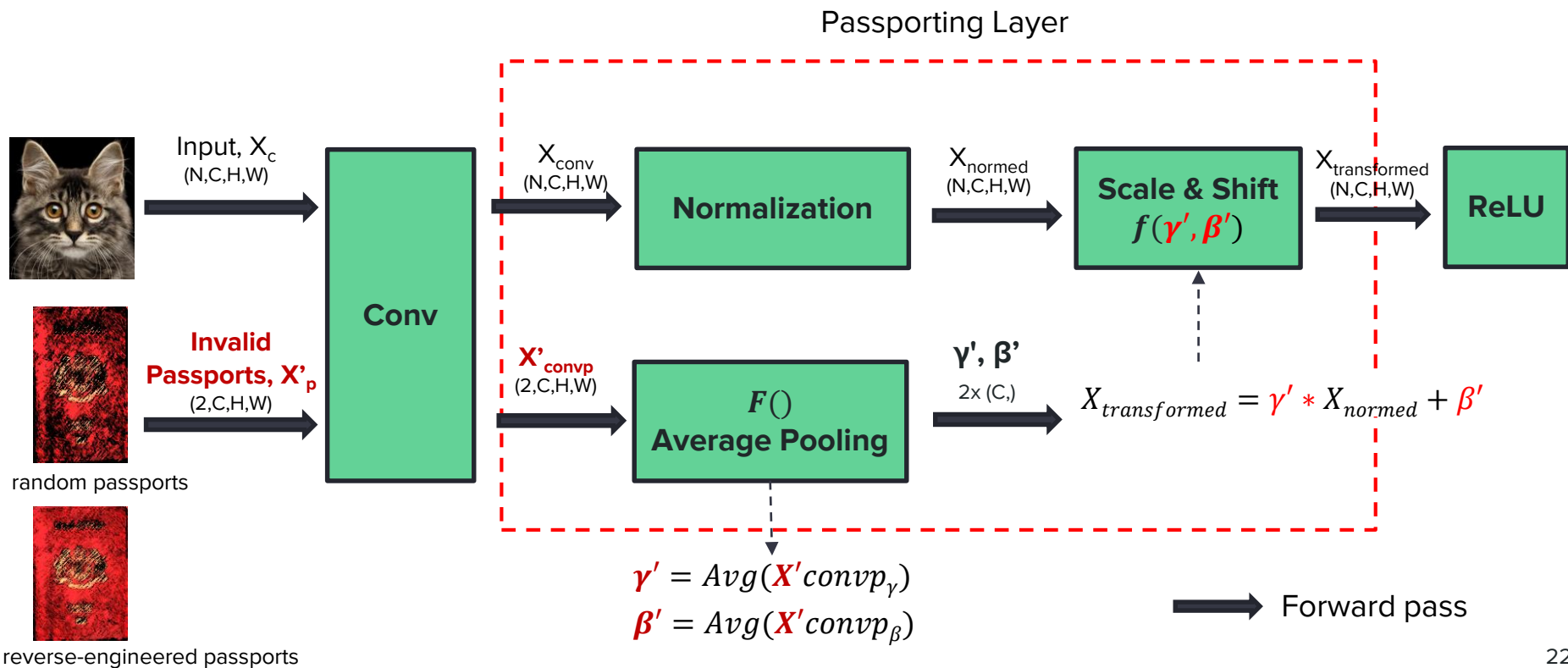
Conventional Convolution Layer



Passporting Layer





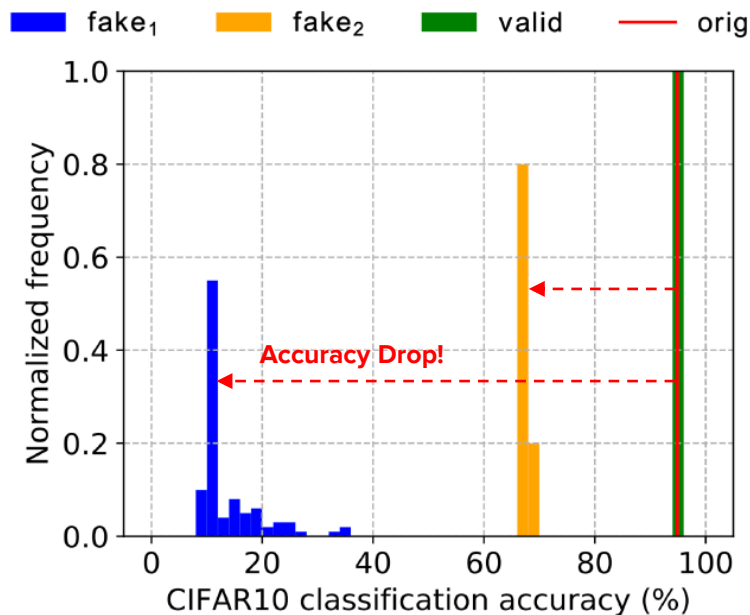
Passporting Layer



Effectiveness of Passport Protection

Result of Invalid passports

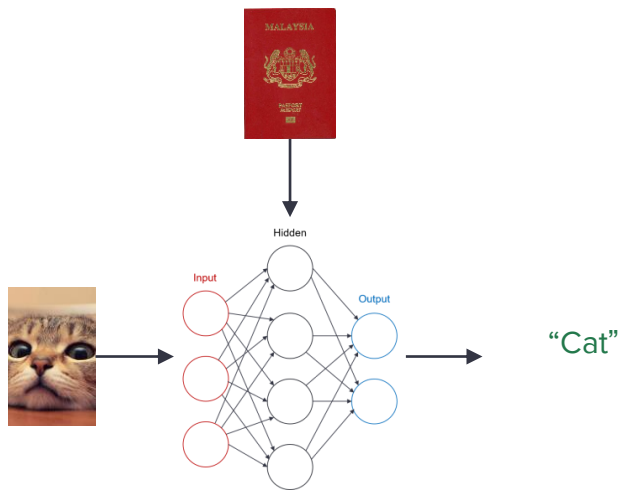
Ambiguity attack	Effect
Fake ₁ (random passports) 	Random guessing (at max 35%)
Fake ₂ (reverse-engineered passports) 	Performance deteriorated (at max 70%)



Example of ResNet_p-18 performance on CIFAR10 when performing different ambiguity attacks (fake₁ & fake₂)

Ownership Verification with Passports (Scheme 1)

Training & Inference



Passport is distributed with the trained DNN model

Model ownership is verified by **passports, performance and signature**

Verification type:

- **White-box**

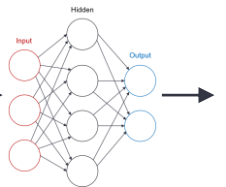
Disadvantage:

1. **Need to distribute the passports**
2. **Extra inference time**

Ownership Verification with Passports (Scheme 2)

Inference

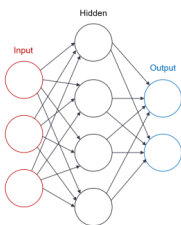
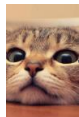
Public



“Cat”

Verification

Private



“Cat”

Private passport is embedded but not distributed

Verification type:

- **White-box**

Advantage:

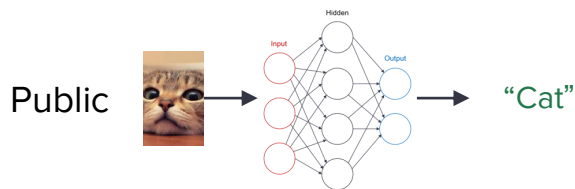
1. **No need to distribute the passports**
2. **No extra inference time**

Disadvantage:

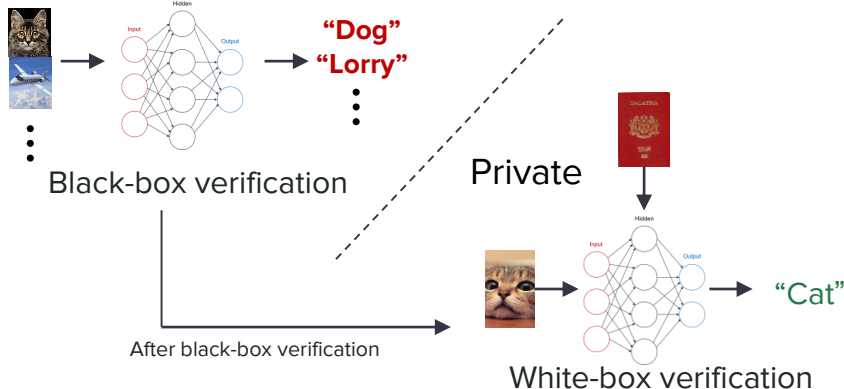
- **Still a white-box verification**

Ownership Verification with Passports (Scheme 3)

Inference



Verification



Both the private passport and trigger set are embedded but not distributed

Black-box model ownership is verified by **query API calls**

Verification type:

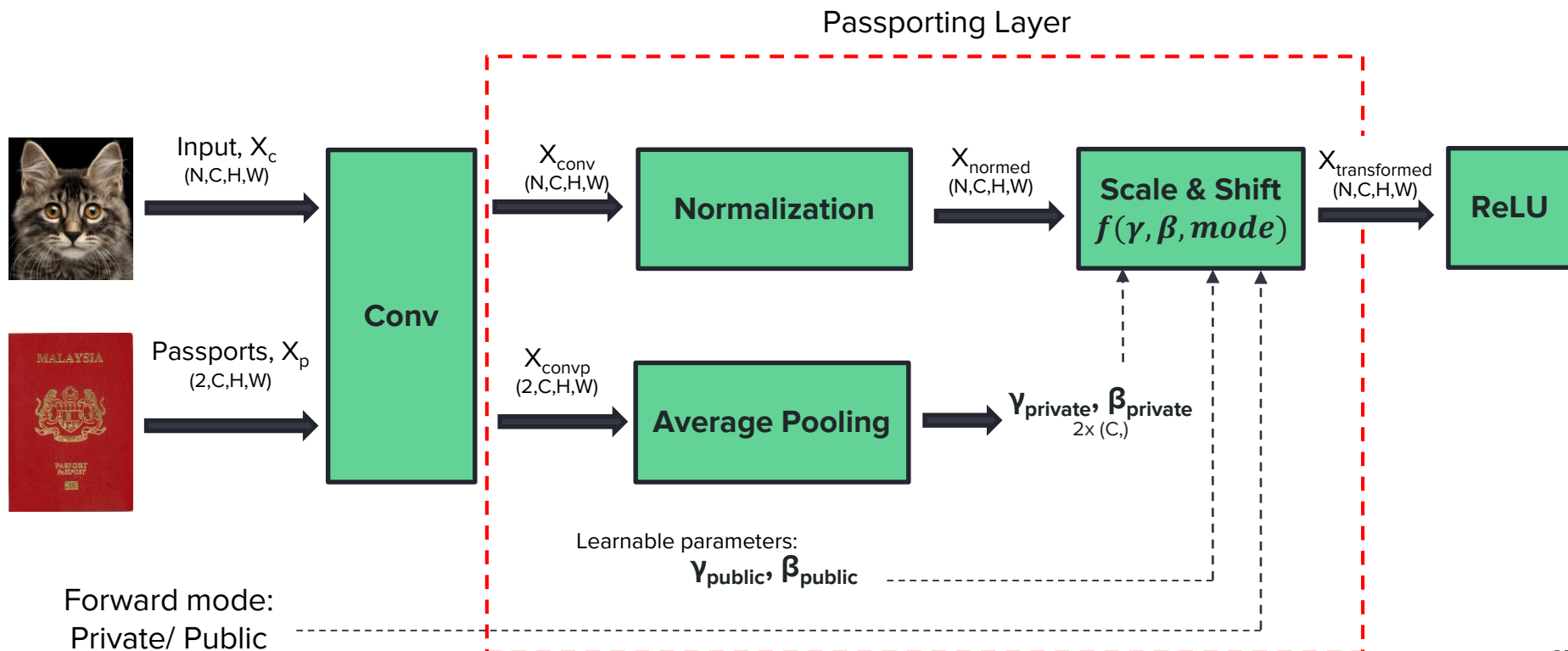
1. **Black-box**
2. **White-box**

Disadvantages of Scheme 1 & 2 Solved:

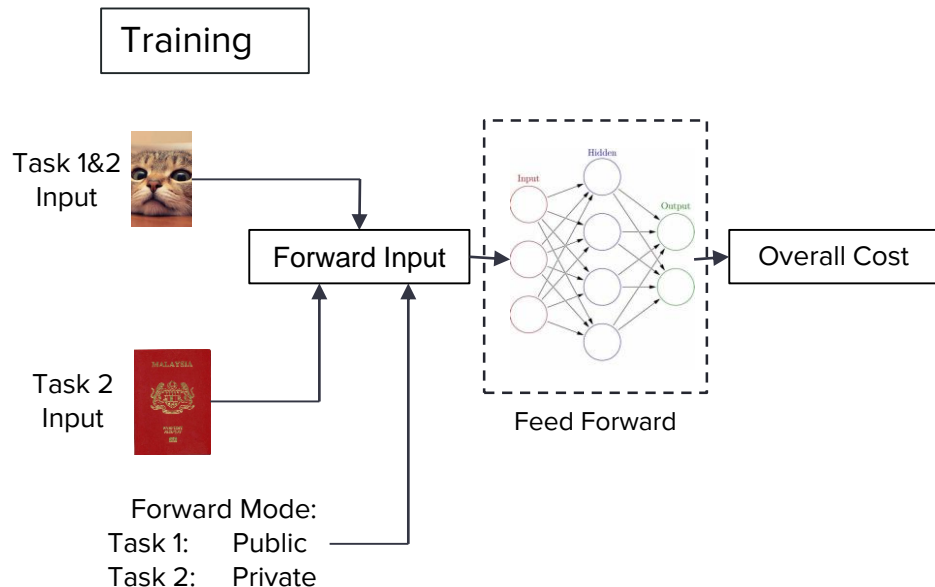
1. **No need to distribute the passports**
2. **No extra inference time**
3. **Able to have an initial suspect through black-box verification**

Passporting Layer (Scheme 2 & 3)

➡ Forward pass



Training on Scheme 2 & 3



Multi-task training:

Simultaneously minimizing following cost functions:

Scheme 2

Task 1: Cross Entropy (Public)

Task 2: Cross Entropy + Sign Loss (Private)

Overall Cost: $L = L_{\text{Task 1}} + L_{\text{Task 2}}$

Scheme 3

Task 1: Cross Entropy (Public)

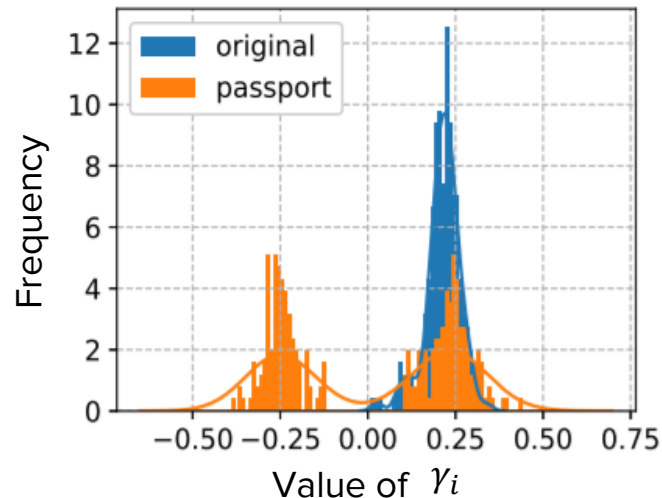
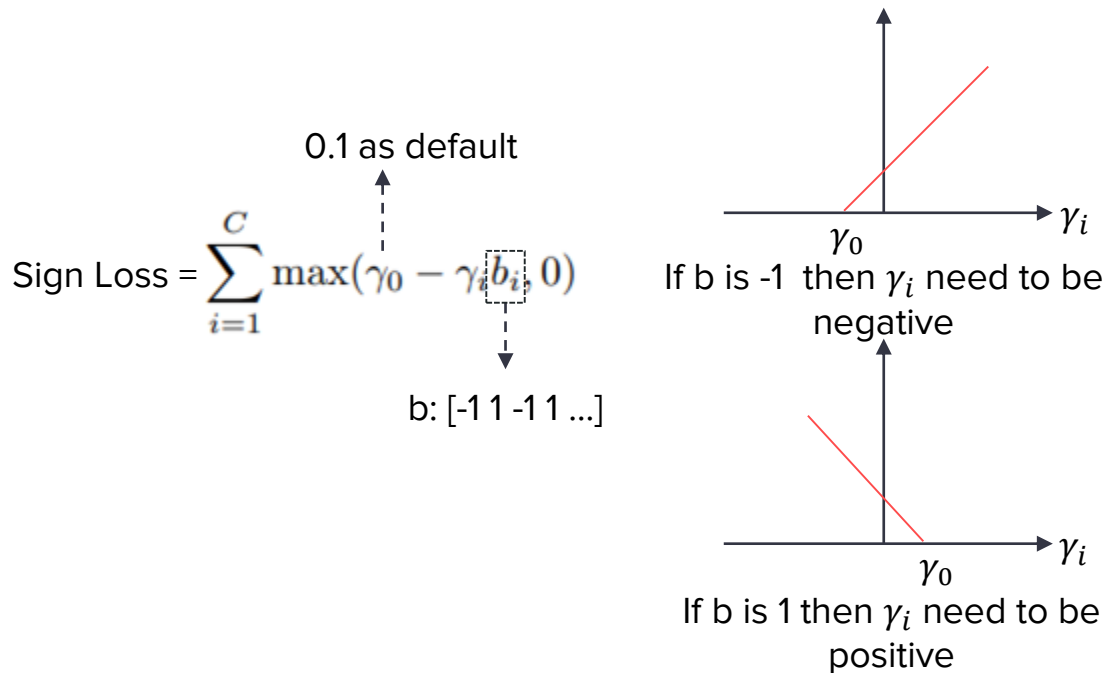
Task 2: Cross Entropy + Sign Loss (Private)

Task 3: Trigger-set Embedding Loss (Public + Private)

Overall Cost : $L = L_{\text{Task 1}} + L_{\text{Task 2}} + L_{\text{Task 3}}$

Embedding Binary Signatures by Sign of Scale Factors

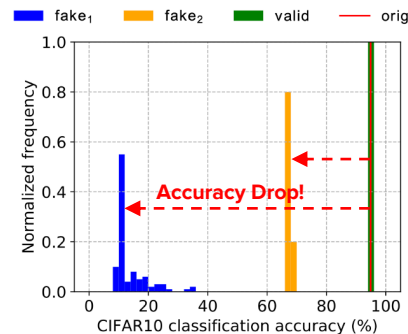
- **Enforce scale factor** to take **either positive or negative signs** as designated
 - Using hinge-loss like of regularization: **Sign-Loss**
 - **64 channels can embed 8 bytes signature**



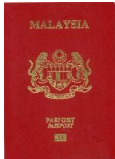


Summary of Ambiguity Attacks

Summarized result done on: AlexNet & ResNet18

Datasets: CIFAR10 & CIFAR100



Ambiguity Attacks		Inference Phase	Verification Phase
	Fake ₁ , Random Passport	<ul style="list-style-type: none"> - Random Guessing - Useless Model 	- Useless Infringement
	Fake ₂ , Reverse-Engineered Passport	<ul style="list-style-type: none"> - Deteriorated Performance - Useless Model 	- Useless Infringement
	Fake ₃ , Copied Passport	<ul style="list-style-type: none"> - Performance Detained - Signature Detected 	- Ownership Verified

Summary of Ownership Verification Schemes

	Scheme 1	Scheme 2	Scheme 3
Need to distribute passport	Yes	No	No
Inference time	Up to 10%** more time	No extra time	No extra time
Training time	Up to 30%** more time	Up to 150%** more time	Up to 150%** more time
Black or White box Verification	White	White	Black & White

**Time increases are linearly depending on complexity of the network architecture

Take Home message

- **Protection on DNN** is urgently needed!
- **Existing** watermarking approaches are **vulnerable to ambiguity attack**
- **Passport-based approach** provided better protection in terms of **robustness against removal attack and ambiguity attack**
- **Passport-protected DNN model** will **only perform well if and only if a valid passport is used**, else the performance will be significantly deteriorated

References

- [1] Yusuke Uchida, Yuki Nagai, Shigeyuki Sakazawa, and Shin'ichi Satoh. Embedding watermarks into deep neural networks. In Proceedings of the 2017 ACM on International Conference on Multimedia Retrieval, pages 269–277, 2017.
- [2] Y Adi, C Baum, M Cisse, B Pinkas, and J Keshet. Turning your weakness into a strength: Watermarking deep neural networks by backdooring. In 27th USENIX Security Symposium (USENIX), 2018.
- [3] Jialong Zhang, Zhongshu Gu, Jiyong Jang, Hui Wu, Marc Ph Stoecklin, Heqing Huang, and Ian Molloy. Protecting intellectual property of deep neural networks with watermarking. In Proceedings of the 2018 on Asia Conference on Computer and Communications Security (ASIACCS), pages 159–172, 2018.

