Incremental Learning for Mobile Encrypted Traffic Classification

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Closed-world mobile encrypted classification

- Classify encrypted traffic into its belonging application

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- Classify encrypted traffic into its belonging application

Open-world mobile encrypted classification

- Breaks the closed-world assumption

Closed-world mobile encrypted classification

- Classify encrypted traffic into its belonging application

Open-world mobile encrypted classification

- Breaks the closed-world assumption
- Deal with the unseen applications

Closed-world Encrypted Traffic Classification

Mobile Encrypted Traffic

Classifier

Existing Applications

Existing state-of-the-art methods		
SoB [1]	91.22% TPR	0.08% FPR
MaMPF [2]	96.40% TPR	0.20% FPR
FS-Net [3]	99.14% TPR	0.05% FPR
MAAF [4]	98.69% Acc	98.64% F1

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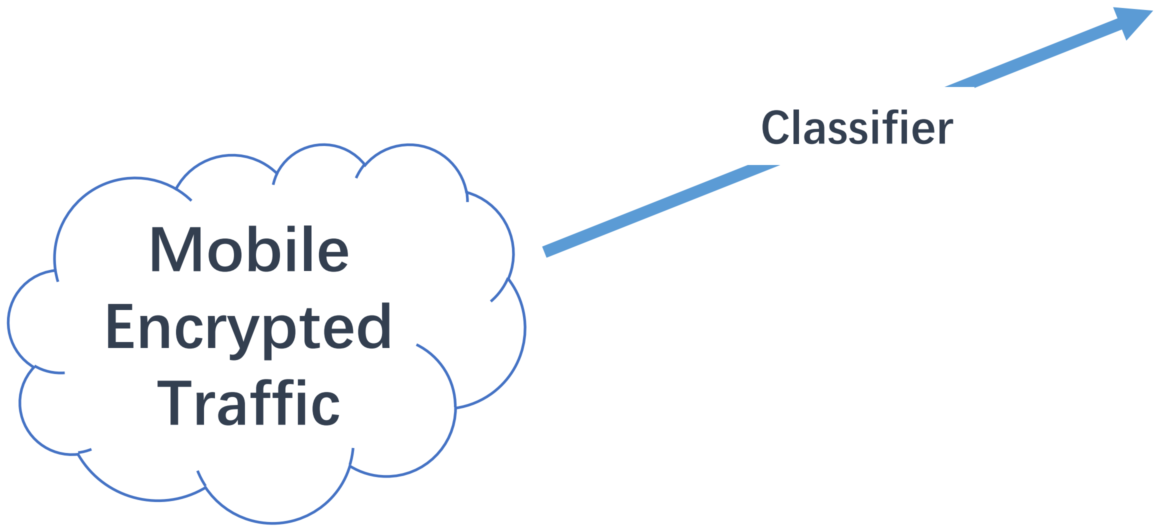
Closed-world Encrypted Traffic Classification



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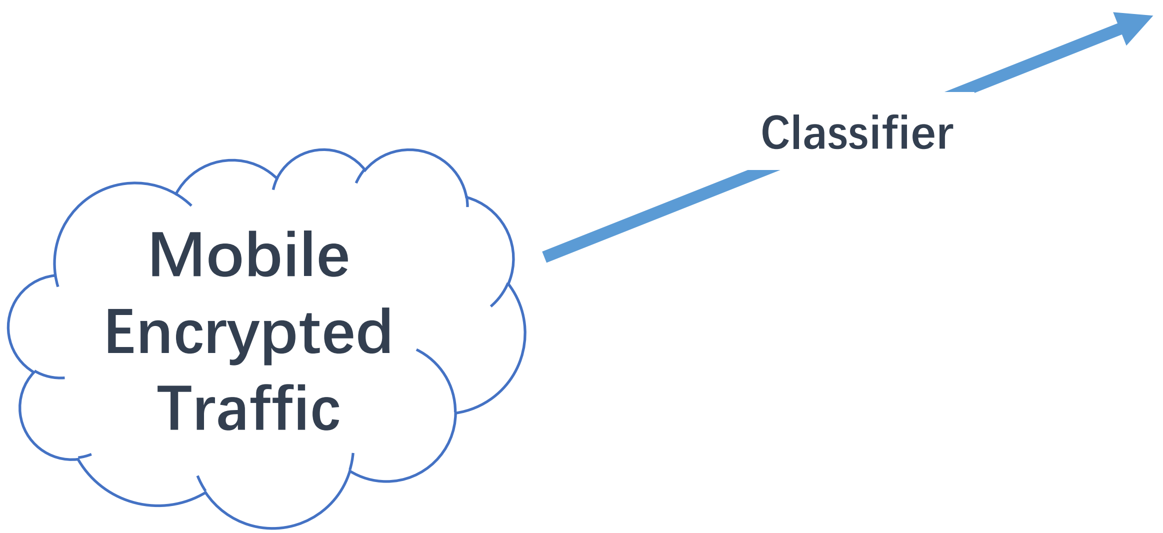

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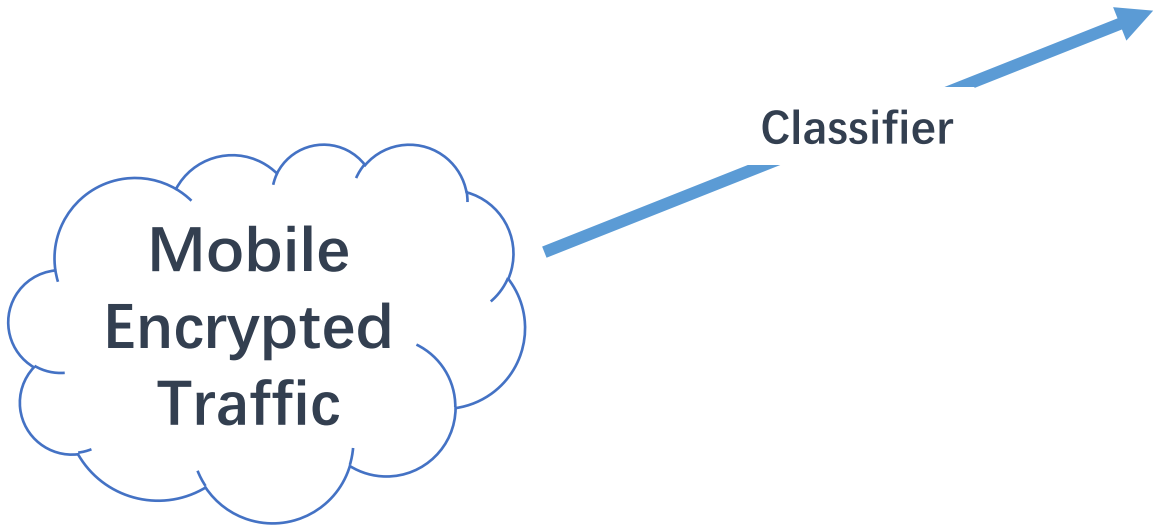

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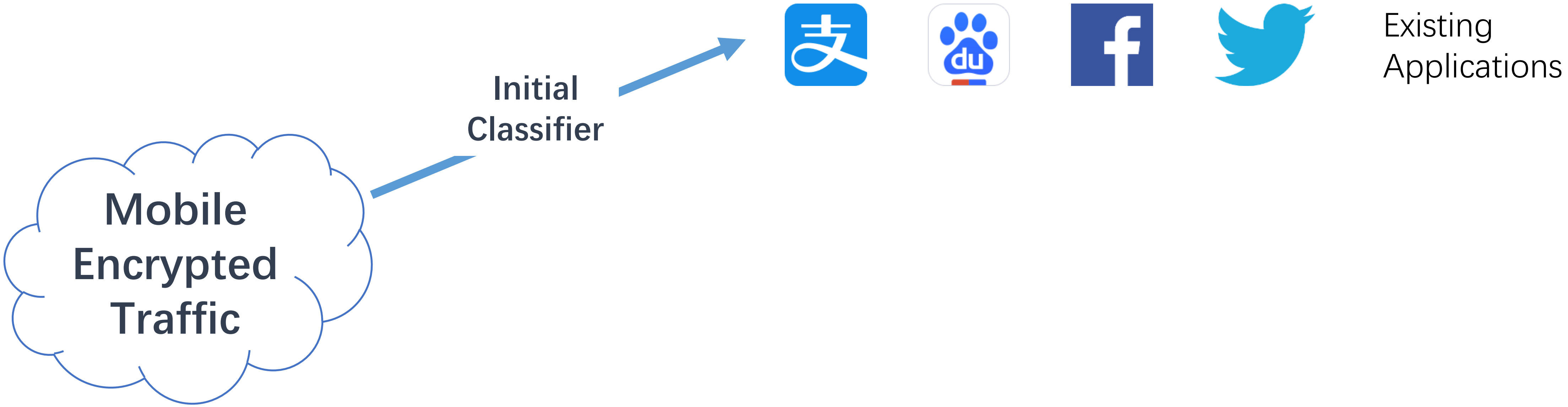

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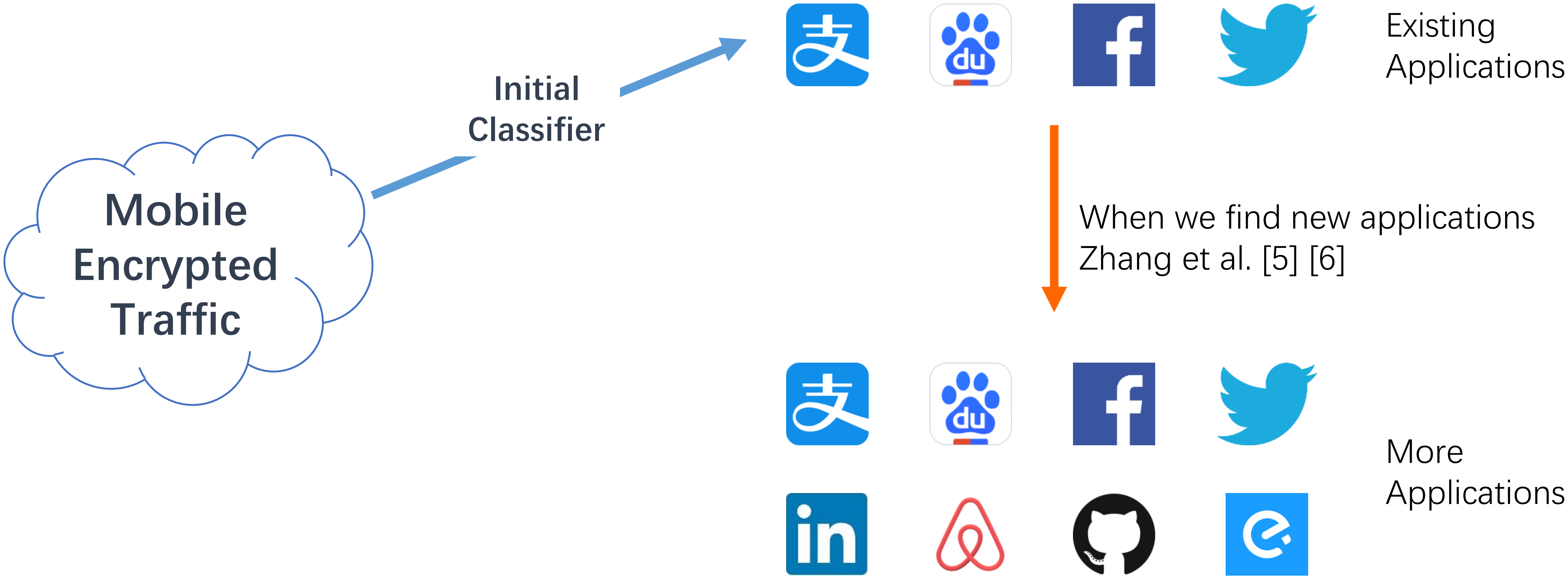

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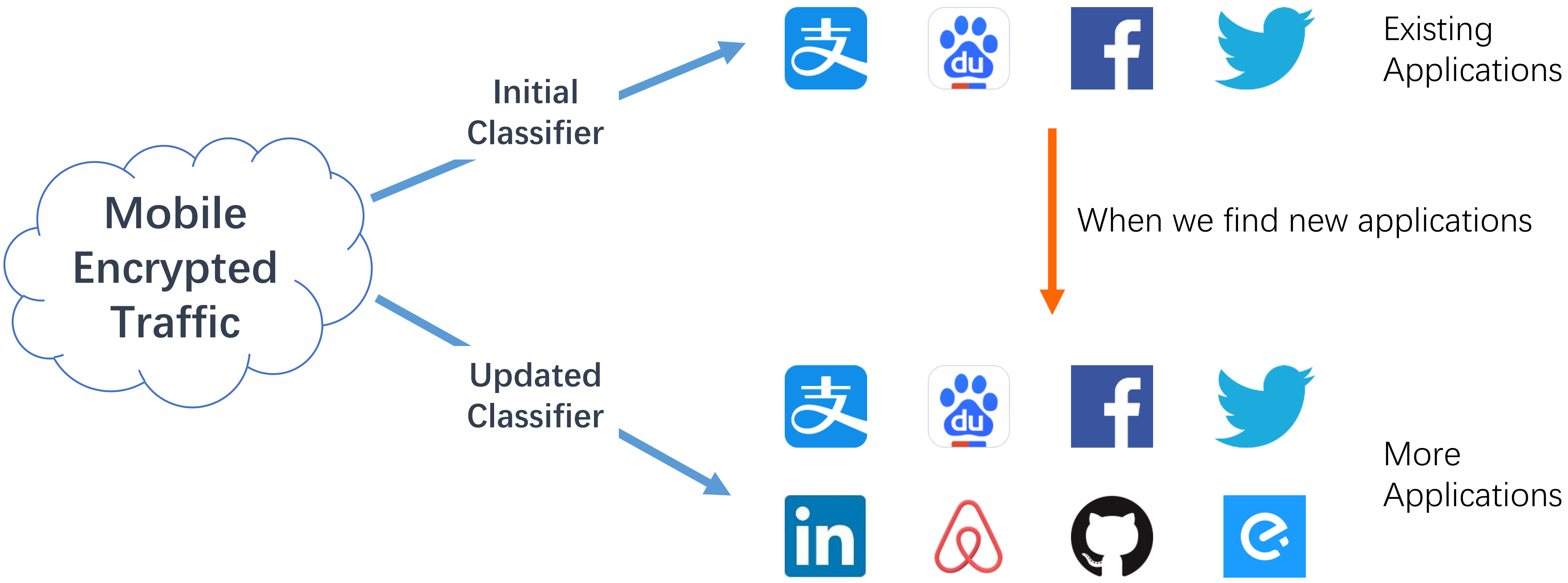

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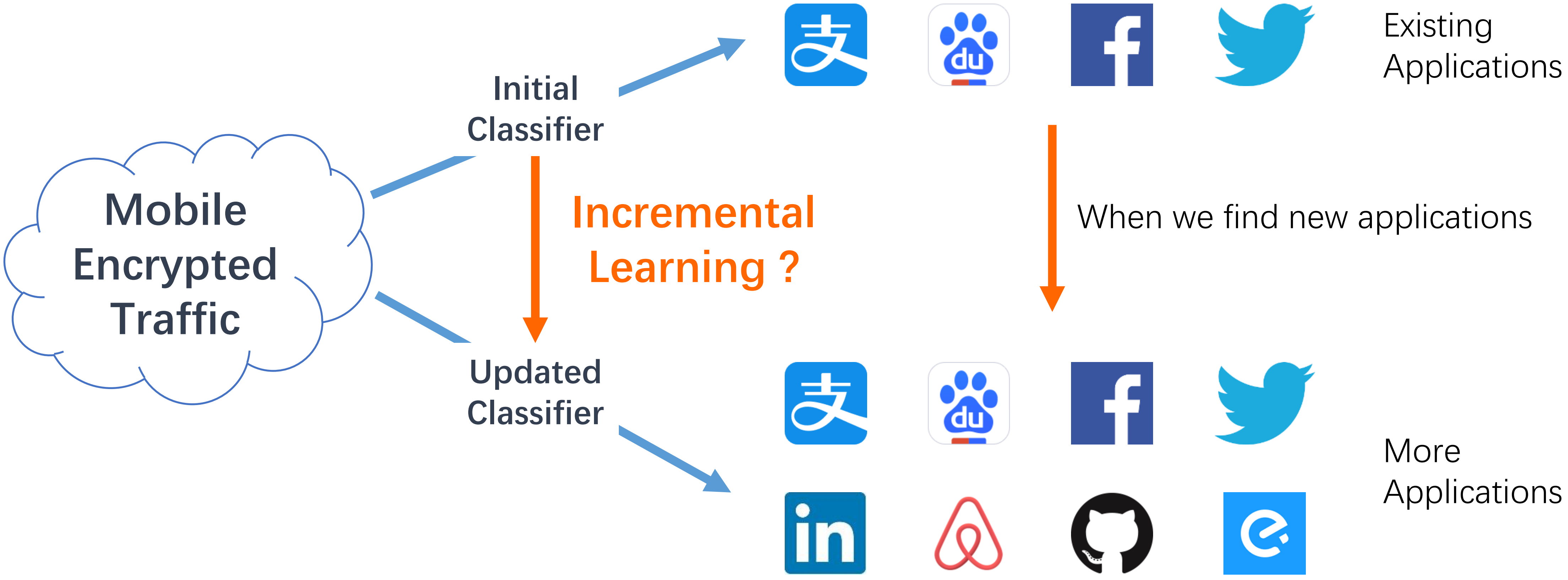

Naive Incremental Learning Methods

1. Retraining the updated classifier from scratch
   - Considerable training time and effort
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    - Considerable training time and effort
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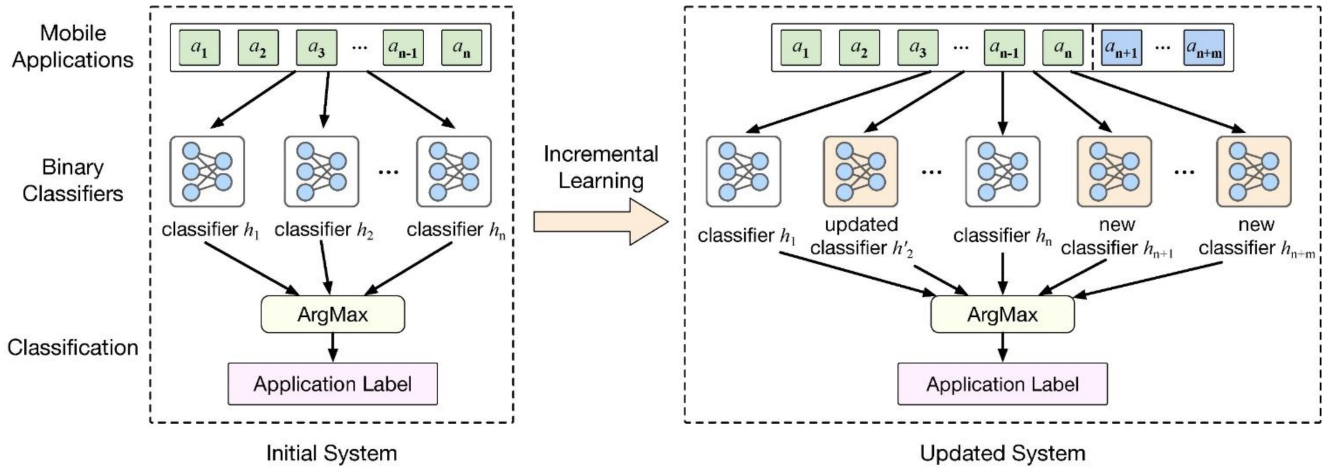
2. Fine-tuning the existing classifier
    - catastrophic forgetting problem

Incremental Learning based on (OvR) Strategy



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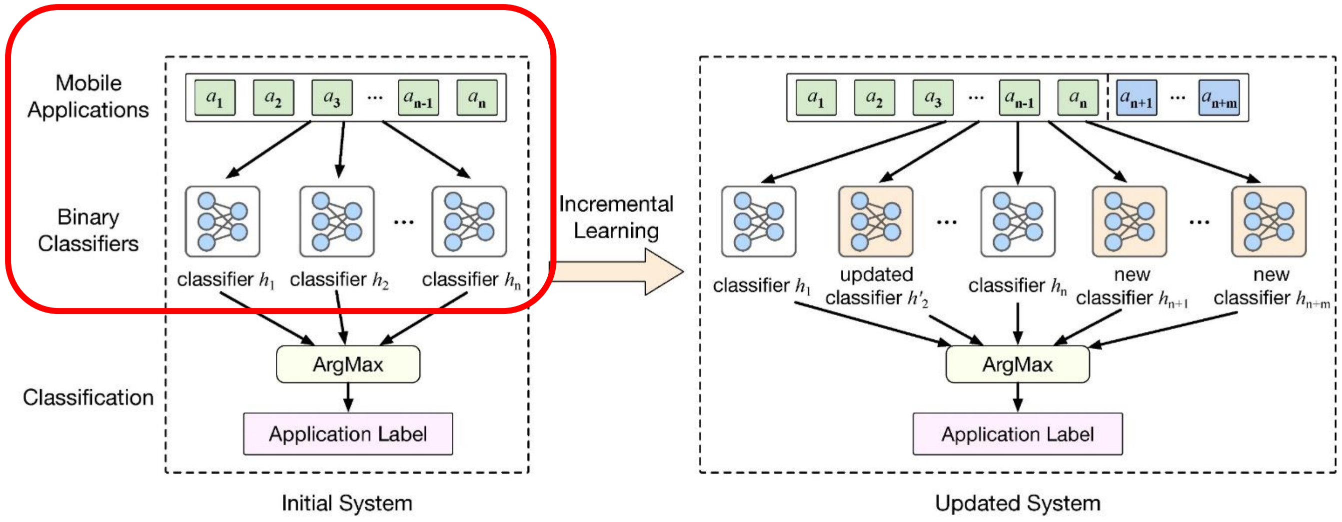

One vs Rest Strategy

- n binary classifiers. The classifier h_i correspond to i^{th} mobile application.

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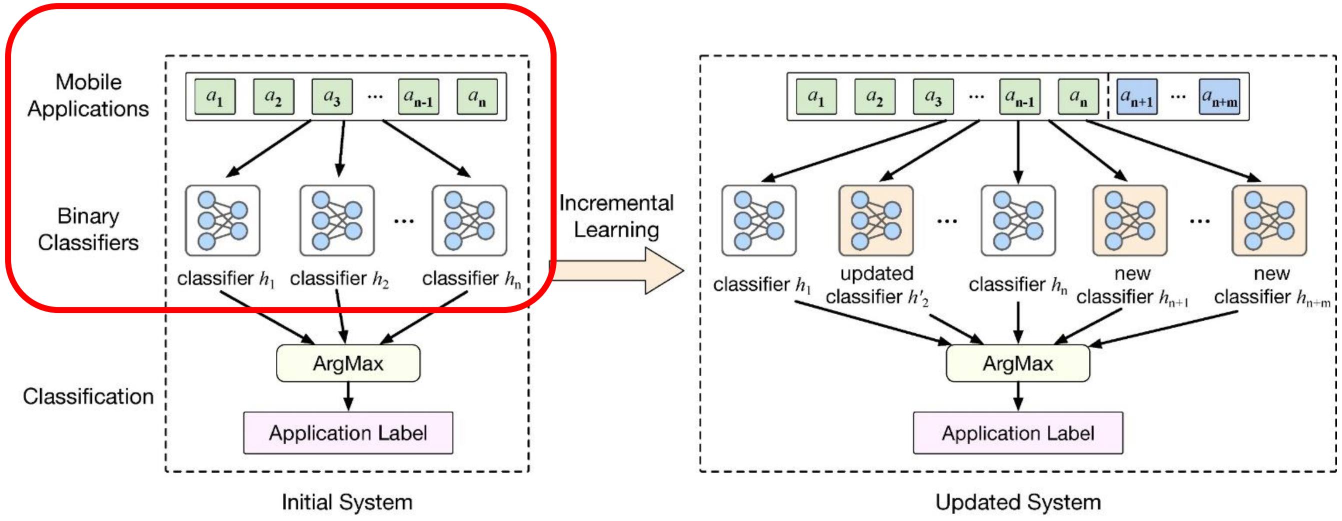

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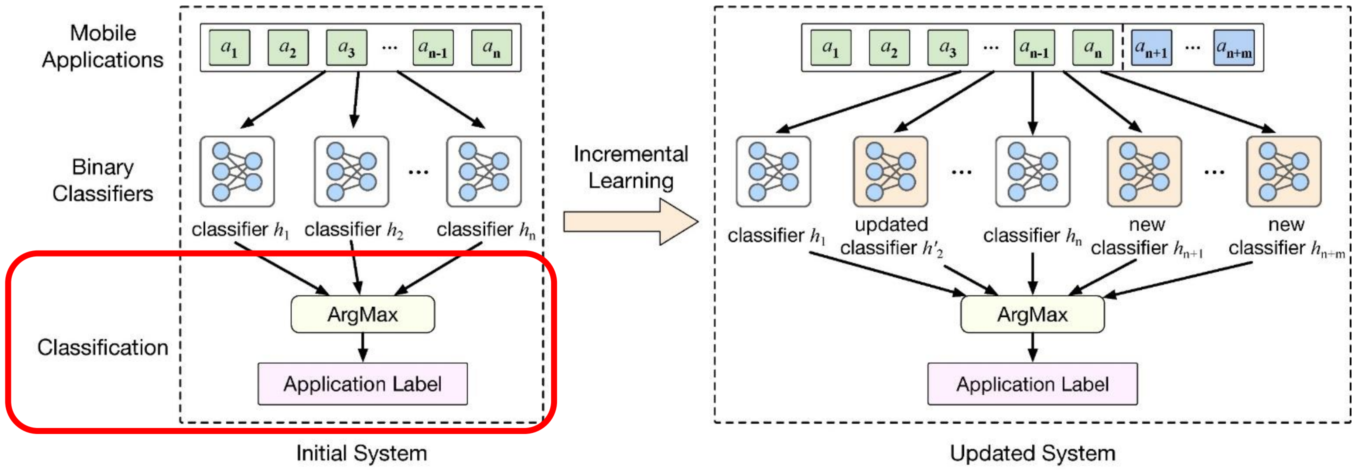

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- The system integrates all binary classifiers to make classification.

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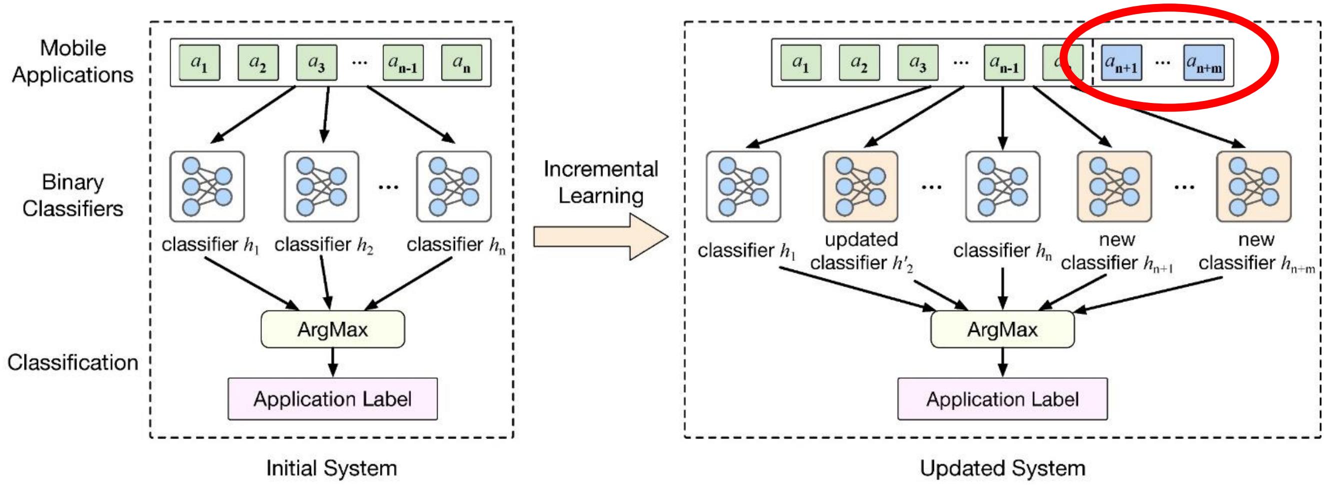

Incremental Learning

- Collect the dataset of new applications.

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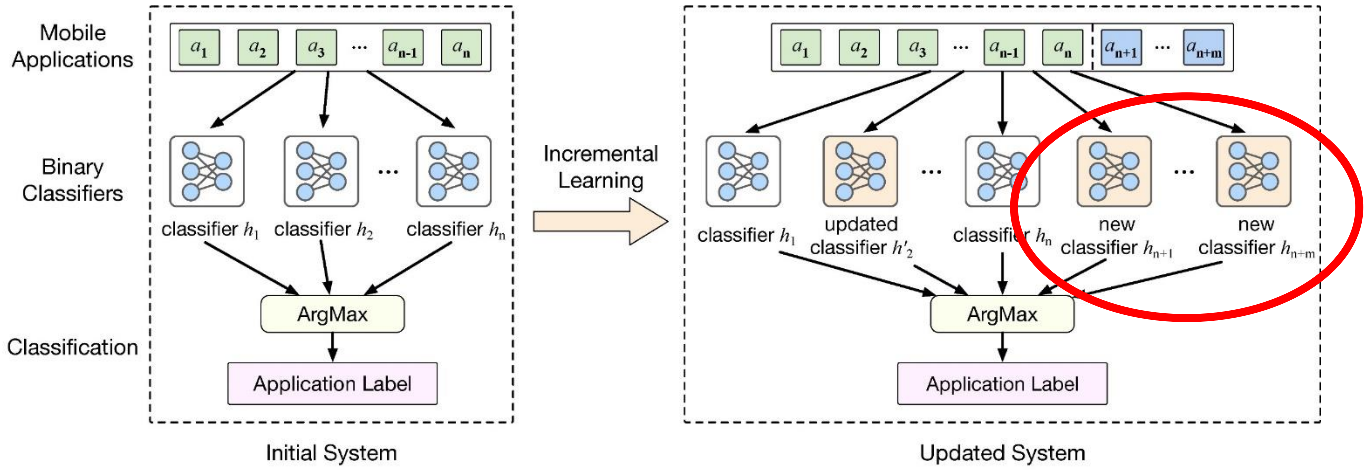

Incremental Learning

- Collect the dataset of new applications.
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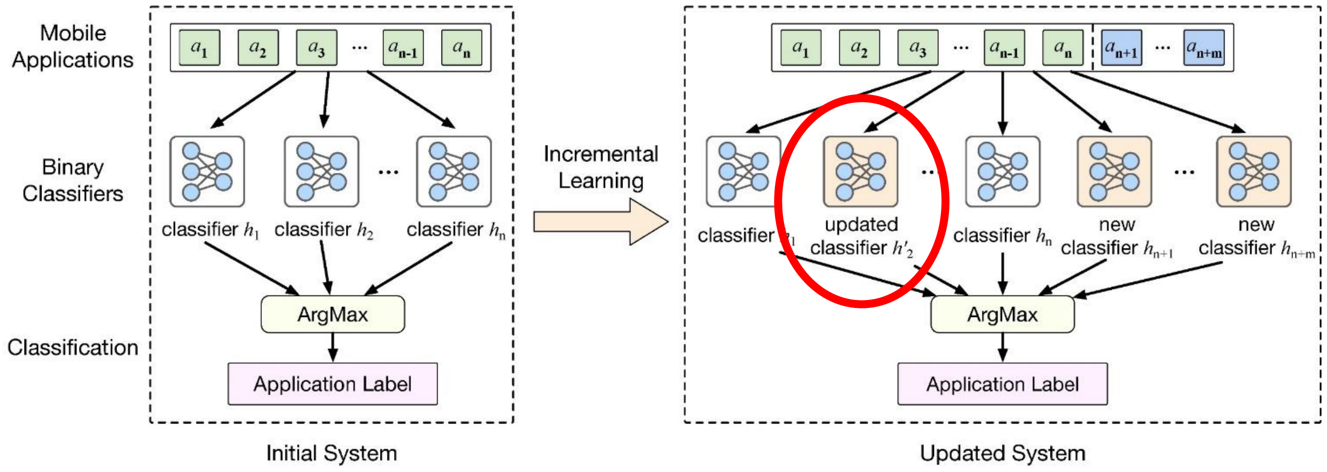
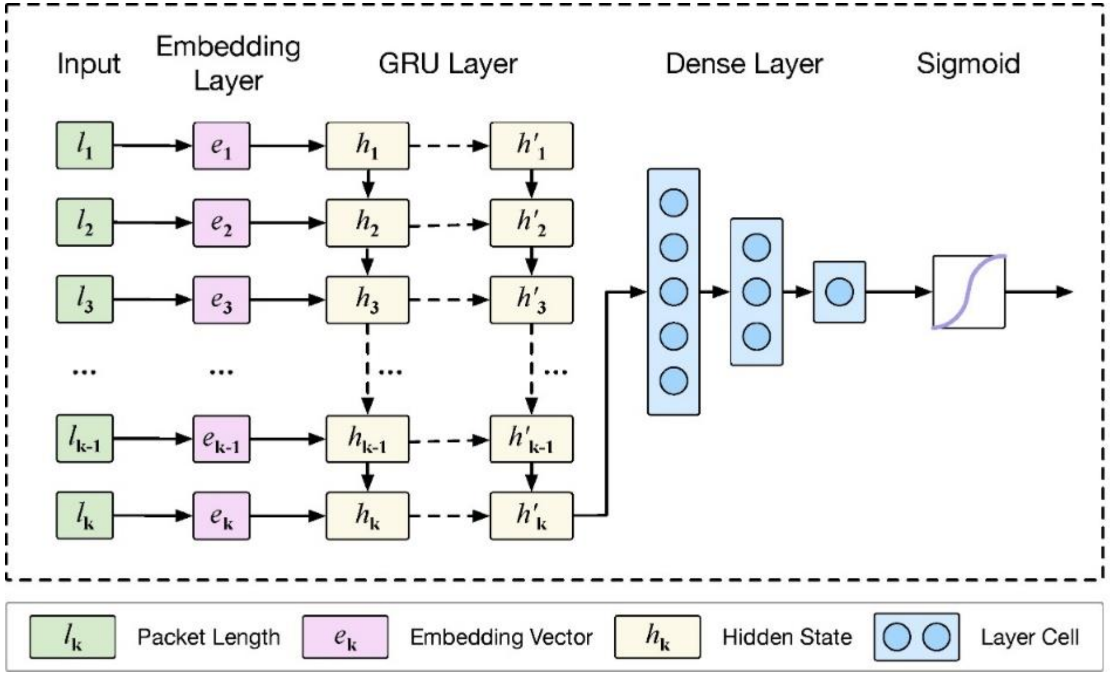


Incremental Learning

- Collect the dataset of new applications.
- Build extra new binary classifiers for the new applications.
- Retrain the outdated classifier that accept more than the retraining threshold τ of the new applications' traffic

Binary Classifier

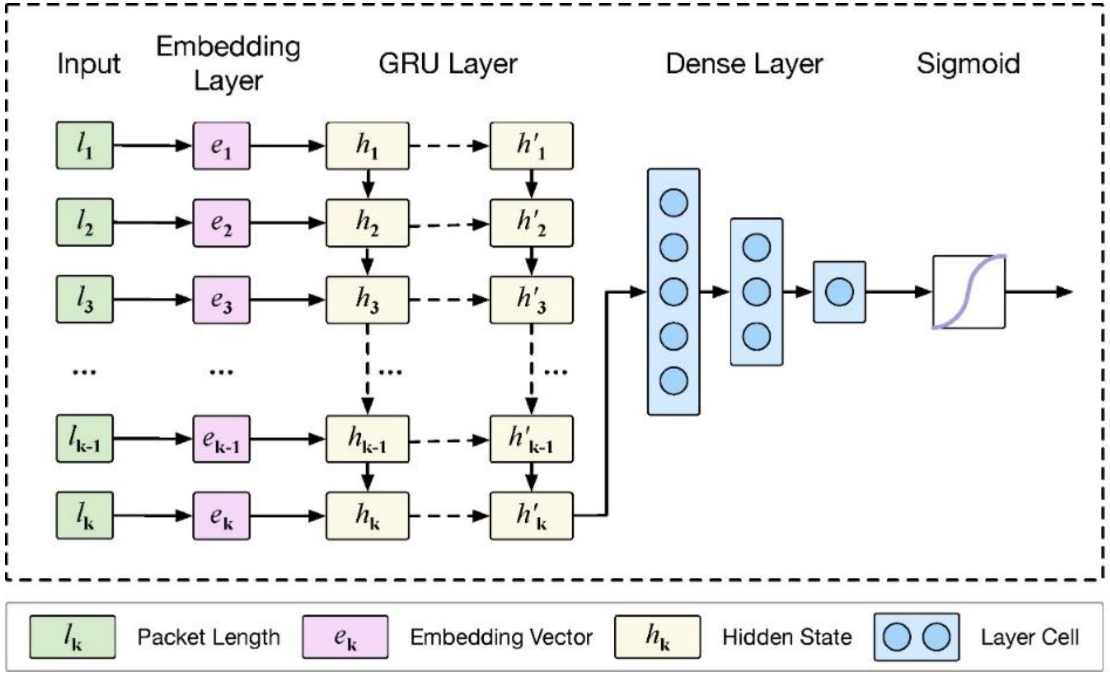
1. A neural network-based Implementation.



Neural Binary Classification Network

Binary Classifier

1. A neural network-based Implementation.
2. Take the first k packet lengths of flows as classifier input.



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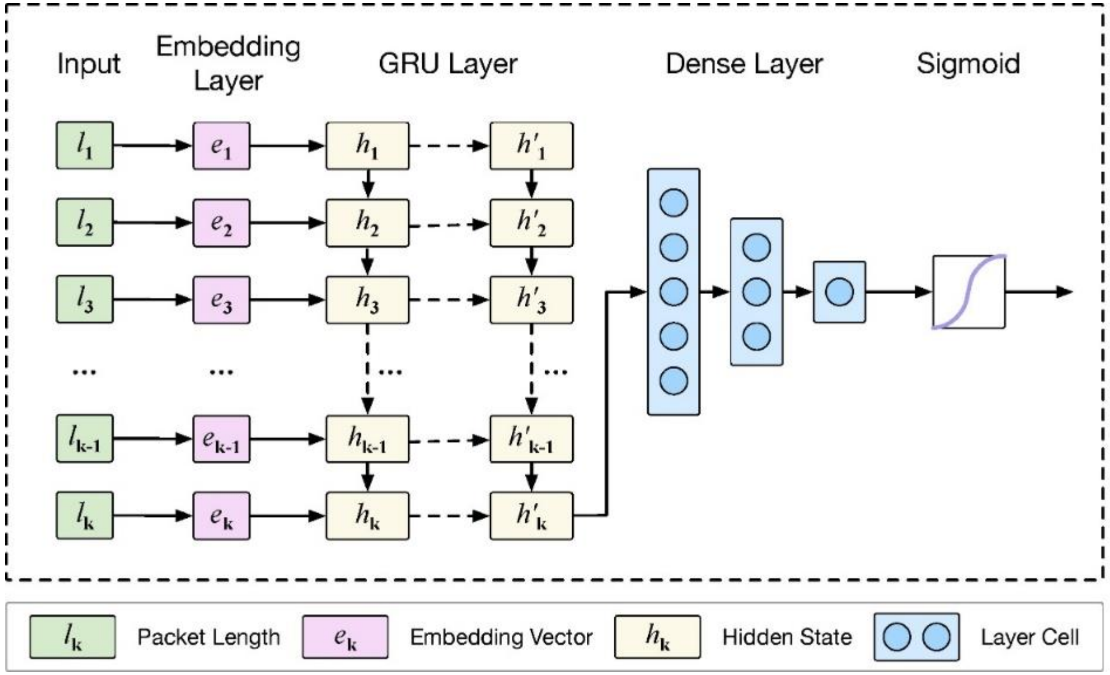

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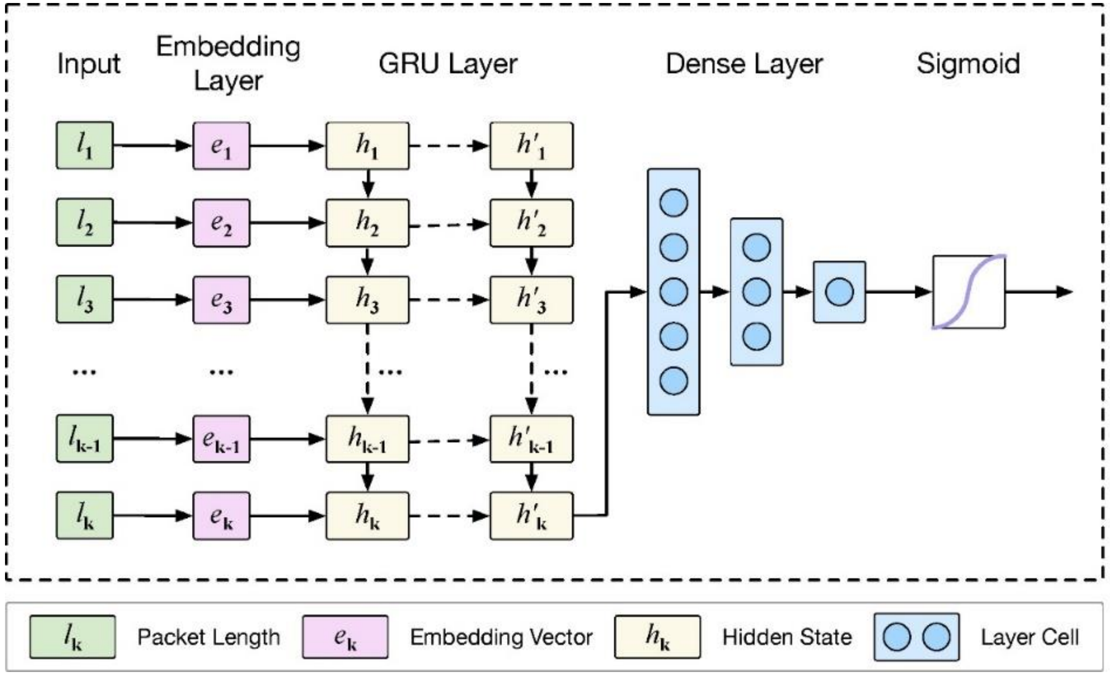
4. Adopt a sigmoid function to normalize classification probability ∈ (0-1).



Neural Binary Classification Network

Sample Selection

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3. Sequentially selects samples that keeps its vector average nearest to the original vector average.

Evaluation Dataset

- A manually collected dataset provided by MAAF [1].
- 77,278 real-world encrypted flows of 16 popular mobile applications.

TABLE II
THE STATISTIC OF 16 APPLICATION TRACESETS

Developer	Application	Manually Collected Traceset				
		Flows	Packets	Domain	Cert	Both[1]
Alibaba	Alipay	5201	315234	16.4%	96.3%	97.3%
	Taobao[2]	3231	291348	93.9%	96.8%	99.4%
	AMap[2]	3624	114513	91.7%	98.8%	99.4%
Baidu	Baidu Search	4732	181971	52.5%	90.3%	94.3%
	Baidu Map[2]	5544	215920	40.0%	89.2%	93.8%
Facebook	Facebook	4148	526289	46.3%	82.2%	87.4%
	Instagram	4379	343809	27.0%	5.8%	31.8%
Twitter	Twitter	4463	167166	45.6%	89.7%	93.9%
Sina	Weibo	3817	127057	95.4%	95.2%	99.6%
Airbnb	Airbnb	5843	875837	76.0%	67.7%	82.2%
Linkedin	Linkedin	4203	160614	91.4%	91.8%	98.5%
Evernote	Evernote	7504	202557	98.4%	48.1%	98.5%
Blued	Blued	4833	478467	73.4%	55.6%	73.8%
Ele	Ele	6740	99193	98.9%	98.5%	99.9%
Github	Github	4431	151355	98.6%	96.4%	98.8%
Yirendai	Yirendai	4585	61356	98.1%	97.5%	99.2%
Total		77278	4312686	71.7%	79.9%	90.7%

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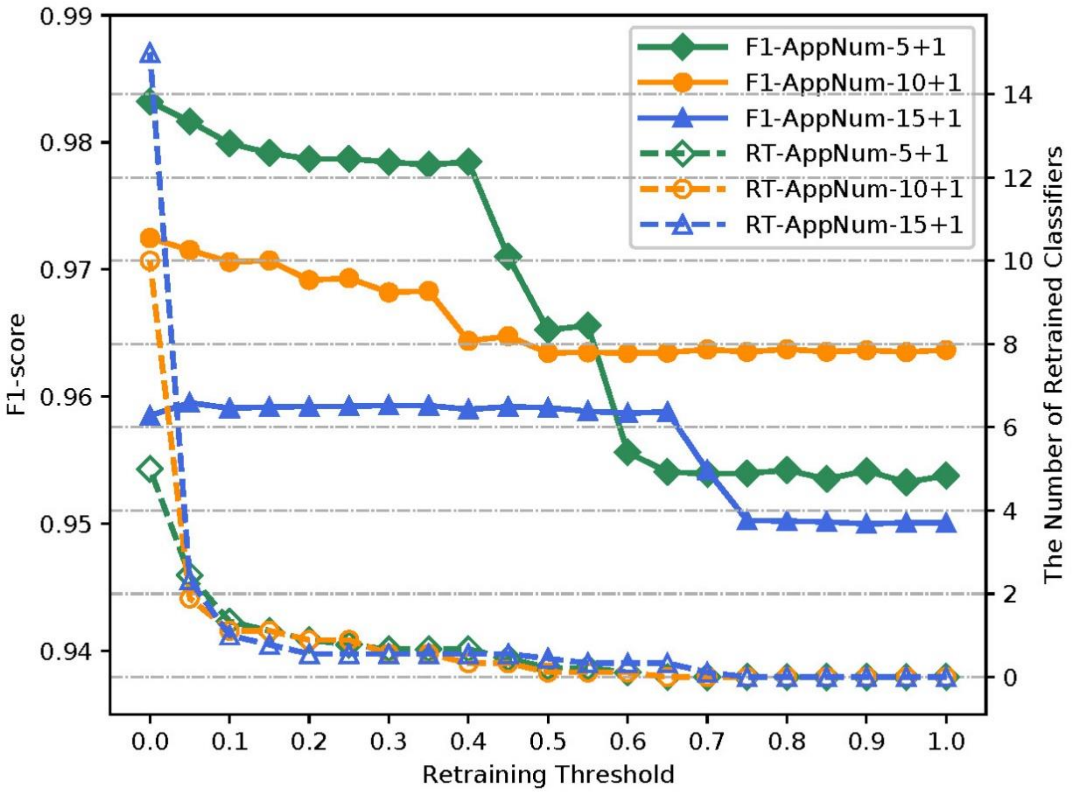
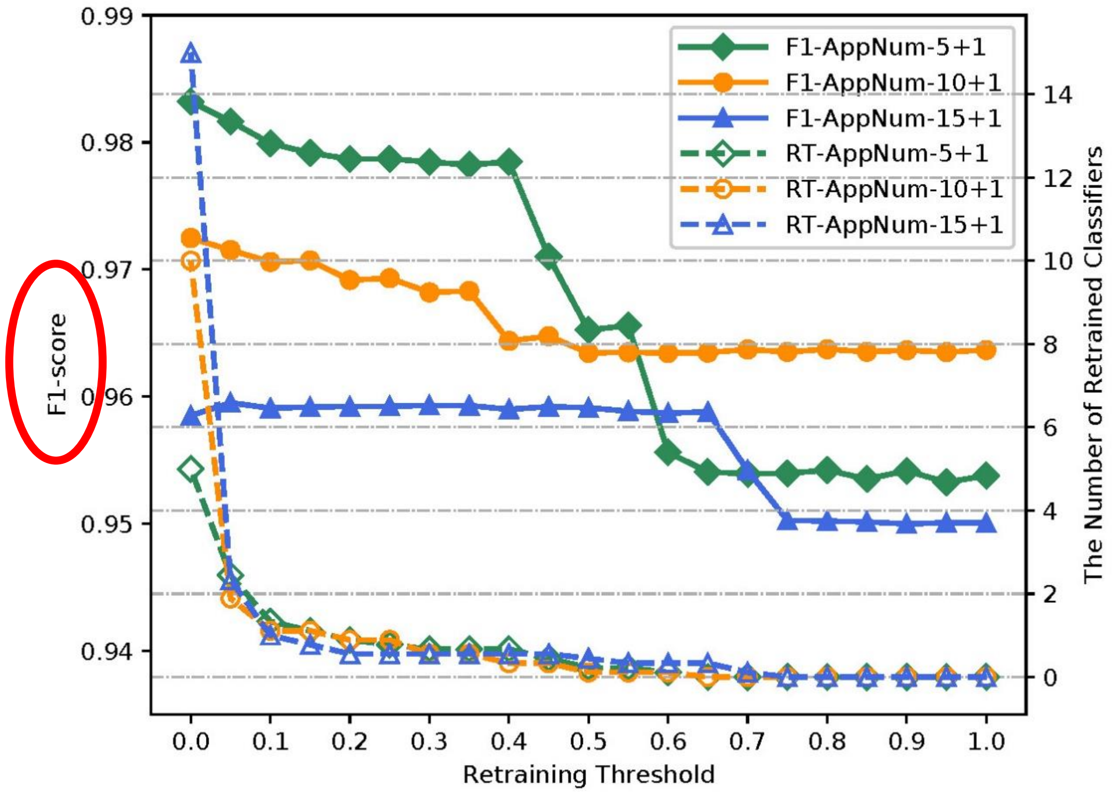
Analysis of the Retraining Threshold



Performance Evaluation on Different Retraining Thresholds

Analysis of the Retraining Threshold

- Both the F1-scores and the number of retrained classifiers declines with the retraining threshold.



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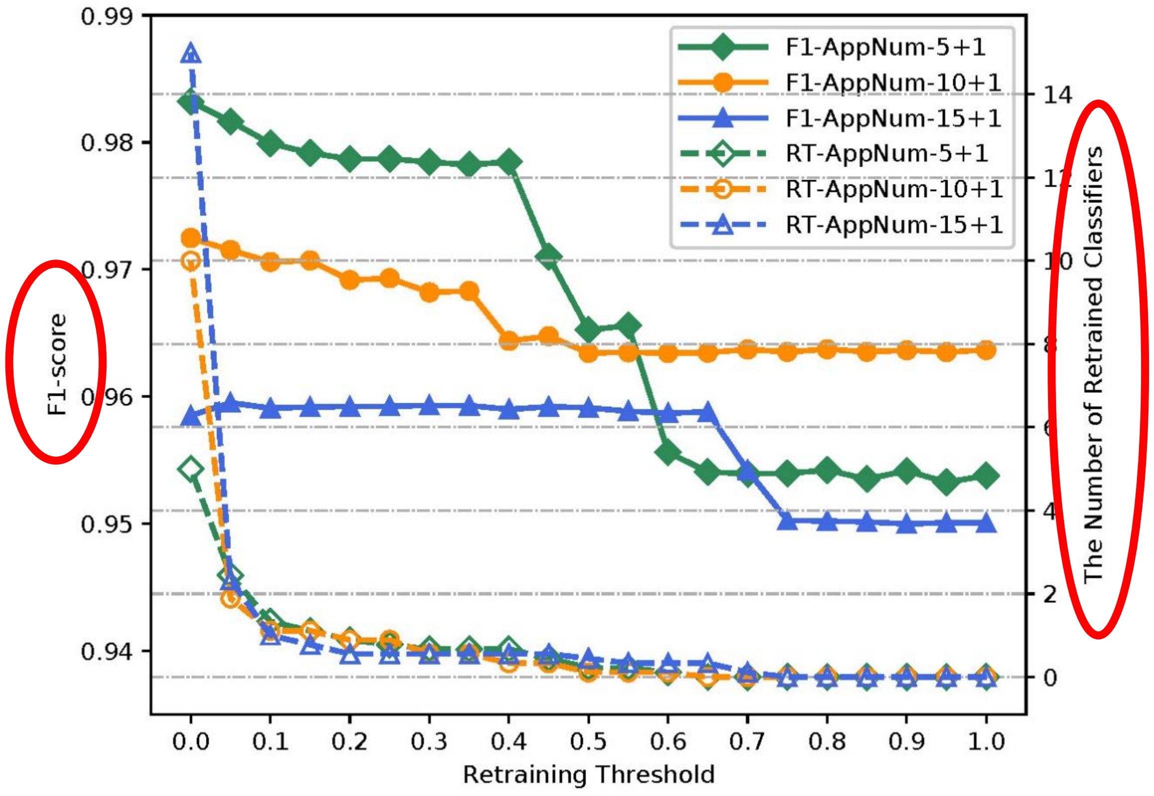

Performance Evaluation on Different Retraining Thresholds

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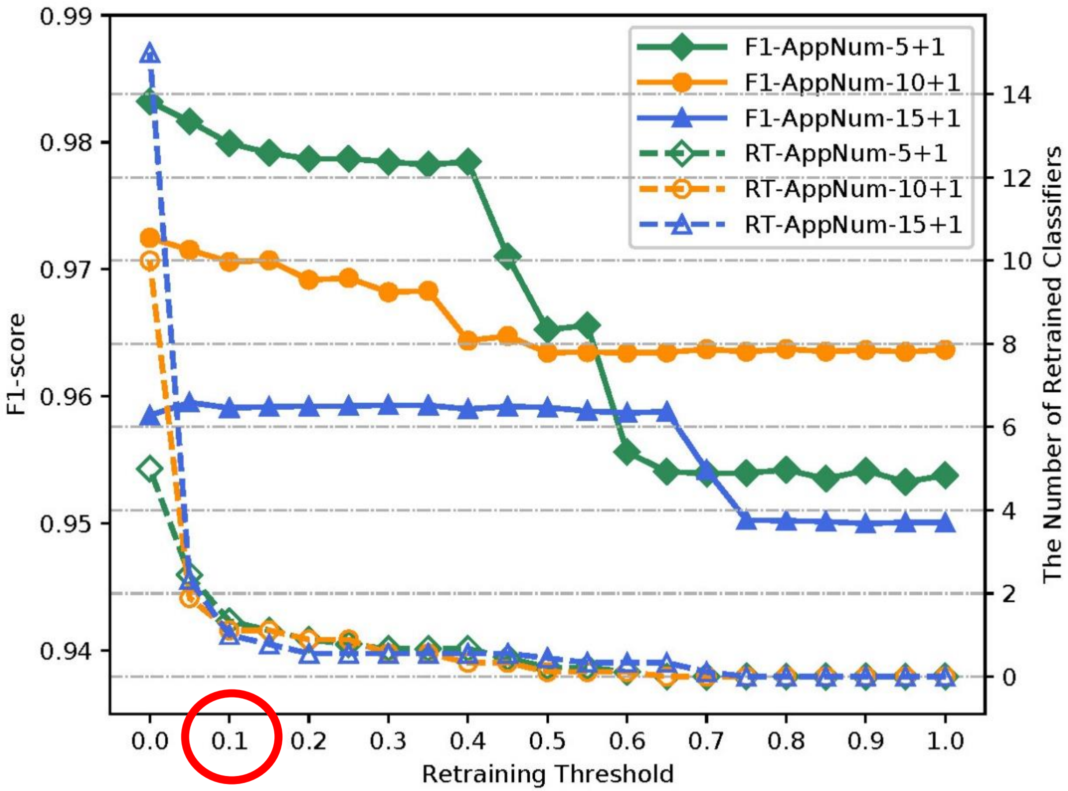
- Both the F1-scores and the number of retrained classifiers declines with the retraining threshold.
- When the retraining threshold increases from 0 to 0.1, the number of retrained classifiers decreases sharply while the classifier only loses a little F1-scores.



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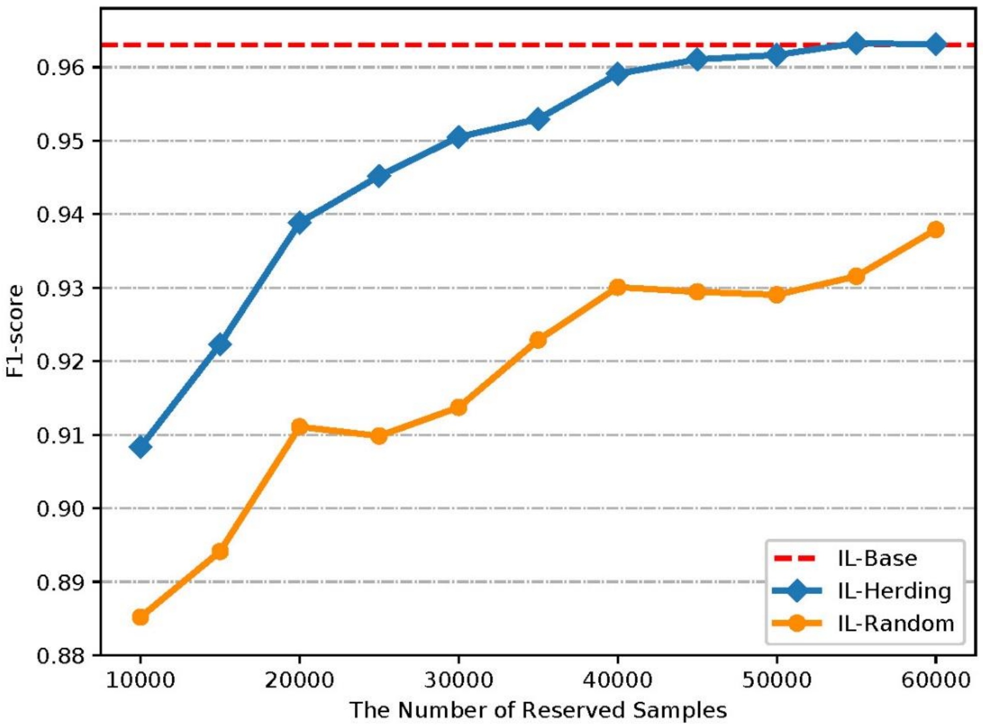
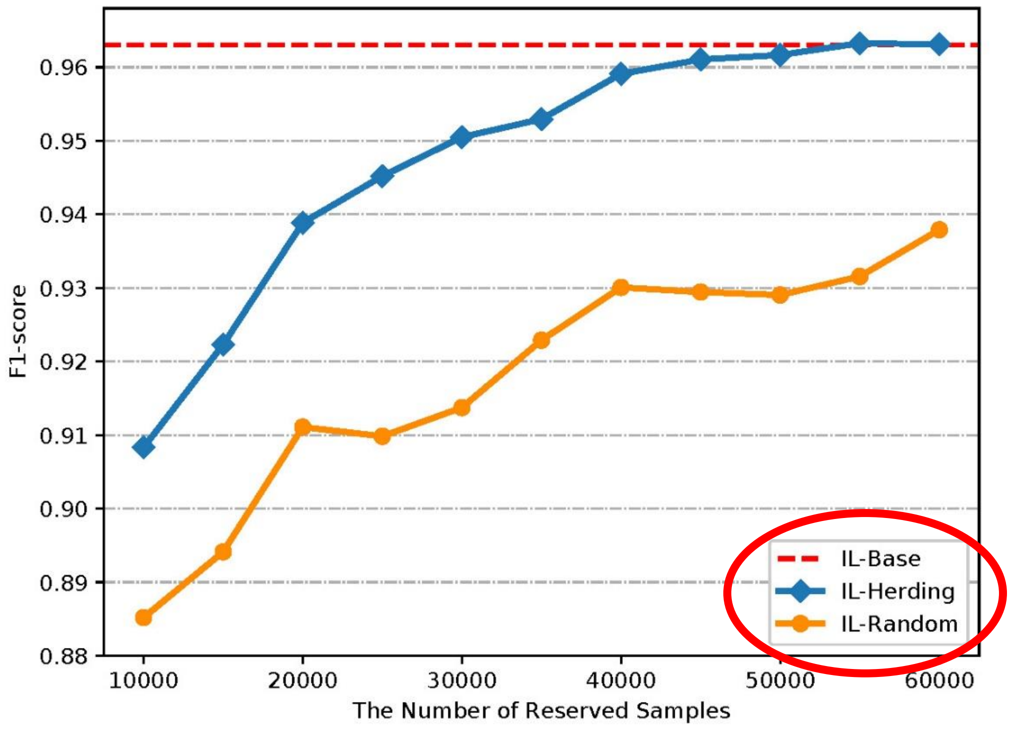


Comparison Results on Different Sample Numbers

Analysis of the Sample Selection



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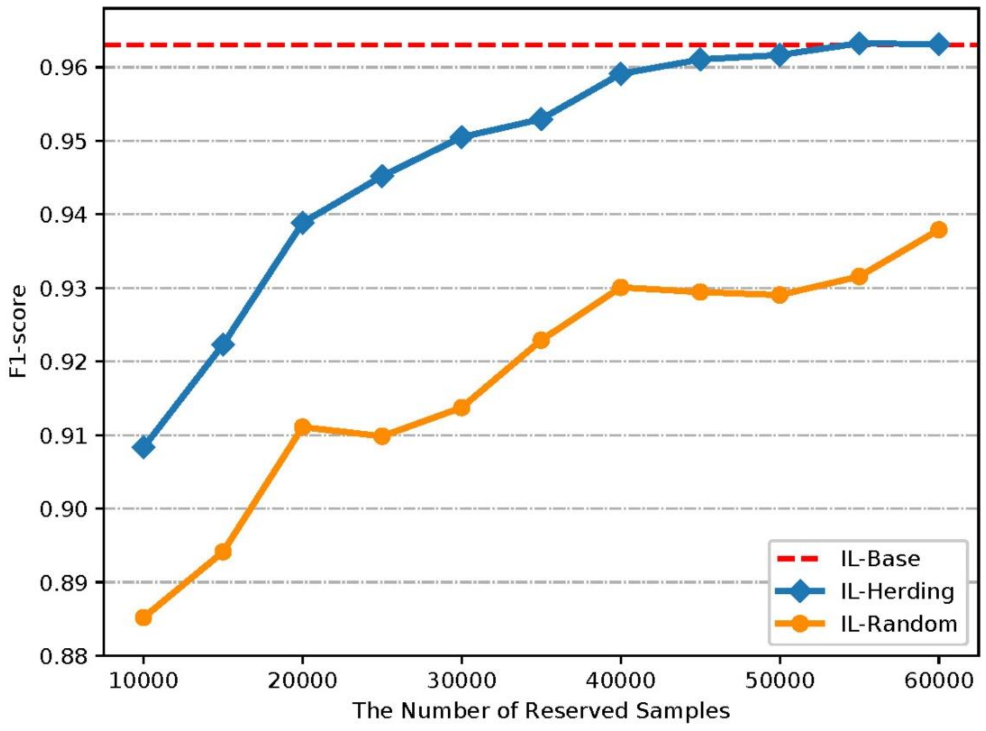
- The F1-score of both IL-Herding and IL-Random increases.



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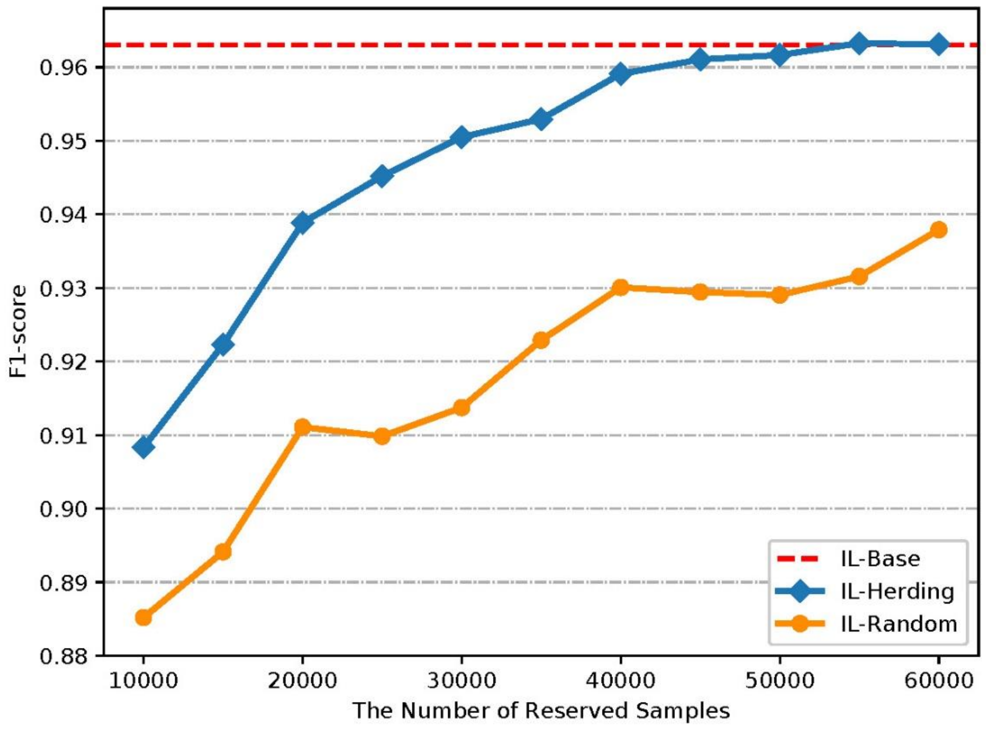
- The IL-Herding gradually approaches IL-Base with the enrichment of reserved samples.



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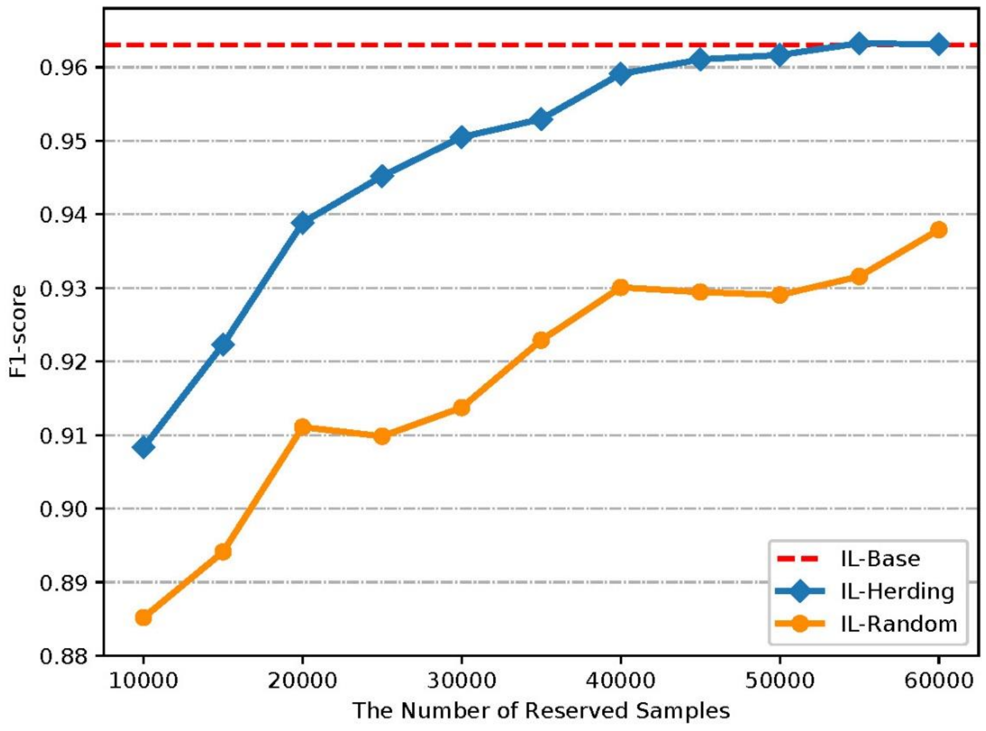

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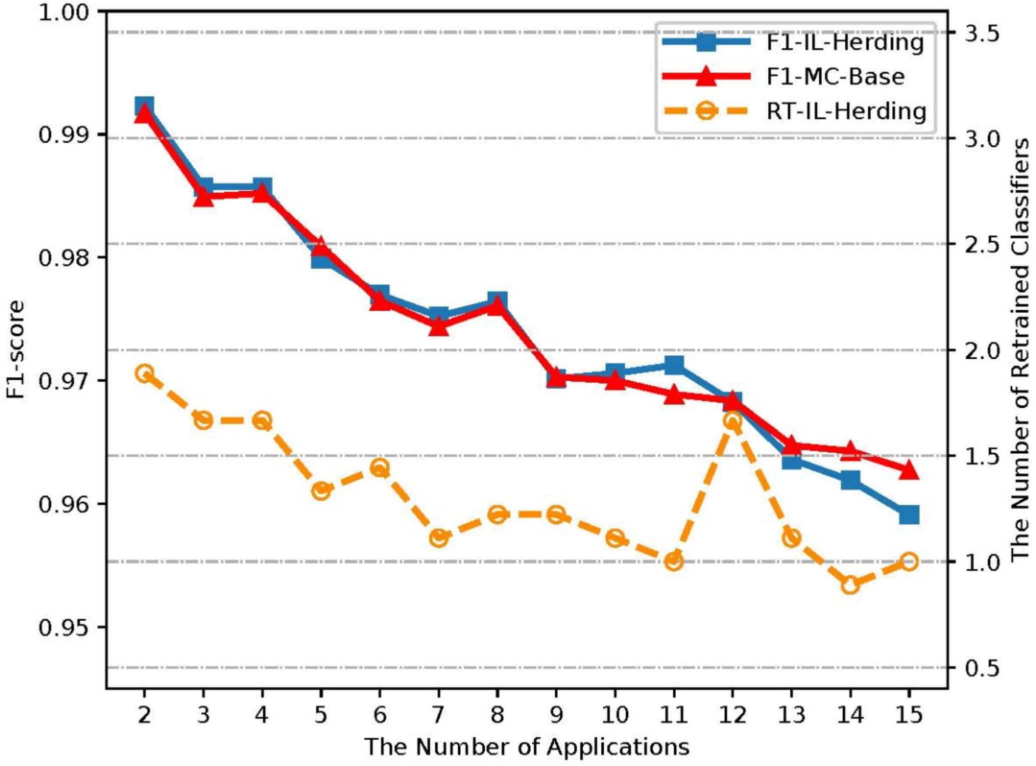

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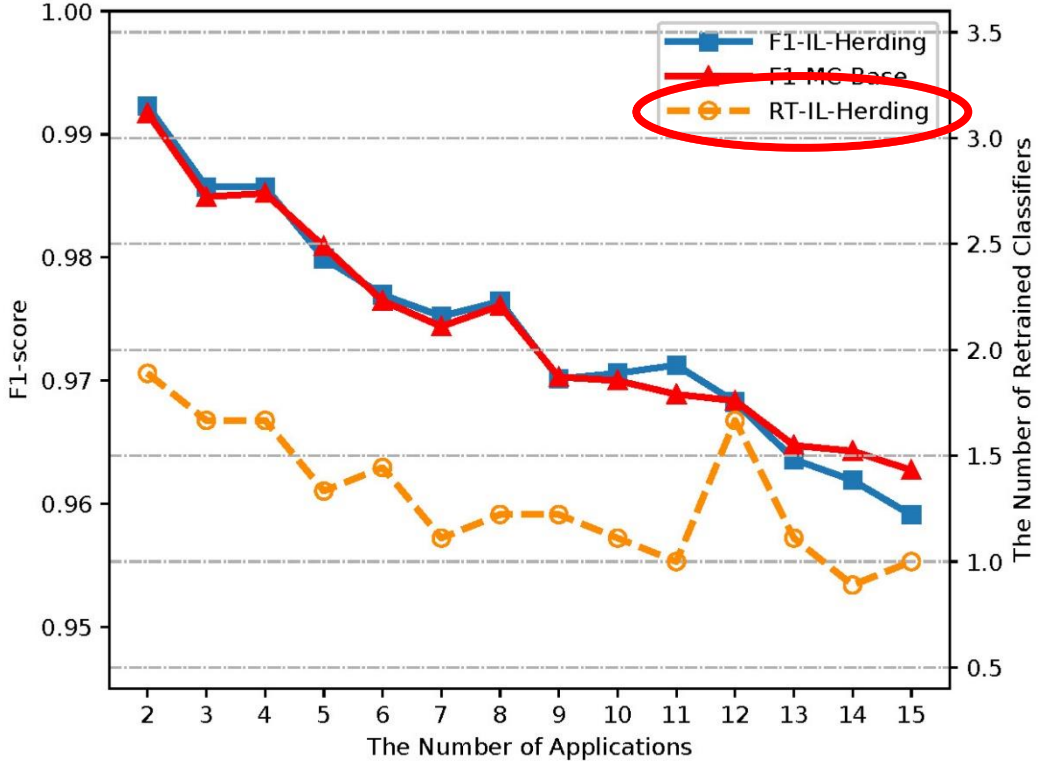

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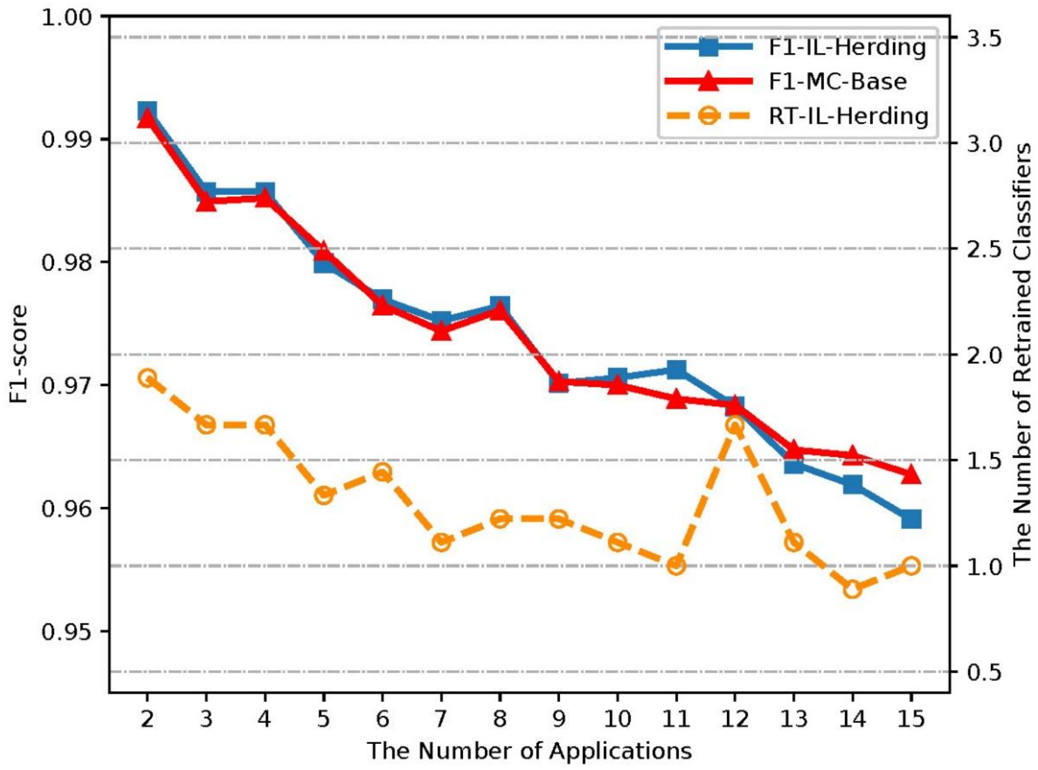

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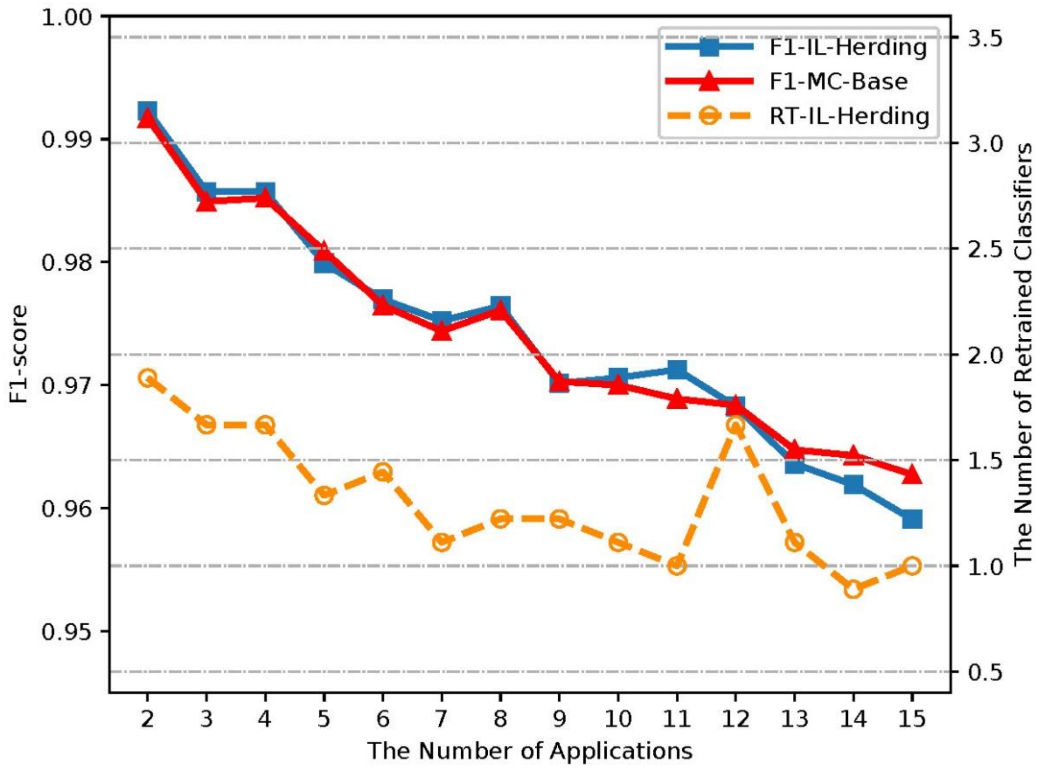
- The number of retrained classifiers generally declines from 2.0 to 1.0 with the increase in the number of applications.



Comparison Results on Different Numbers of Applications

- For more details, please contact chenyige@iie.ac.cn
- Questions & Answers