

An Input-Agnostic Hierarchical Deep Learning Framework for Traffic Fingerprinting

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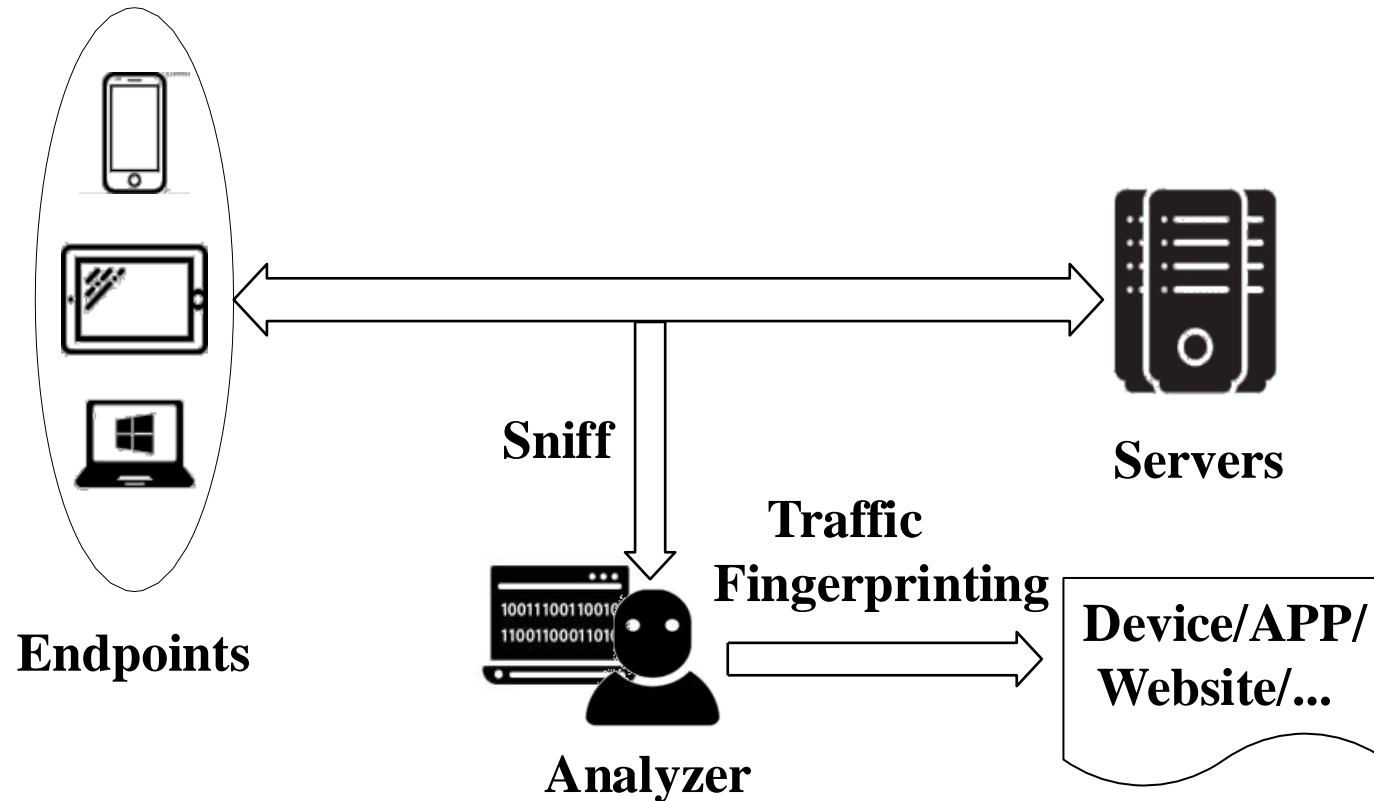
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Outline

- **Background and Problem Description**
- System Design
- Evaluation
- Conclusions

Background and Problem Description



Related work

Website Fingerprinting

Shen et al. [ACM ARES, 2019]

Di Martino et al. [IEEE ICC, 2019]

Application Fingerprinting

App-Net [INFOCOM WKSHPs, 2020]

FOAP [USENIX Security, 2022]

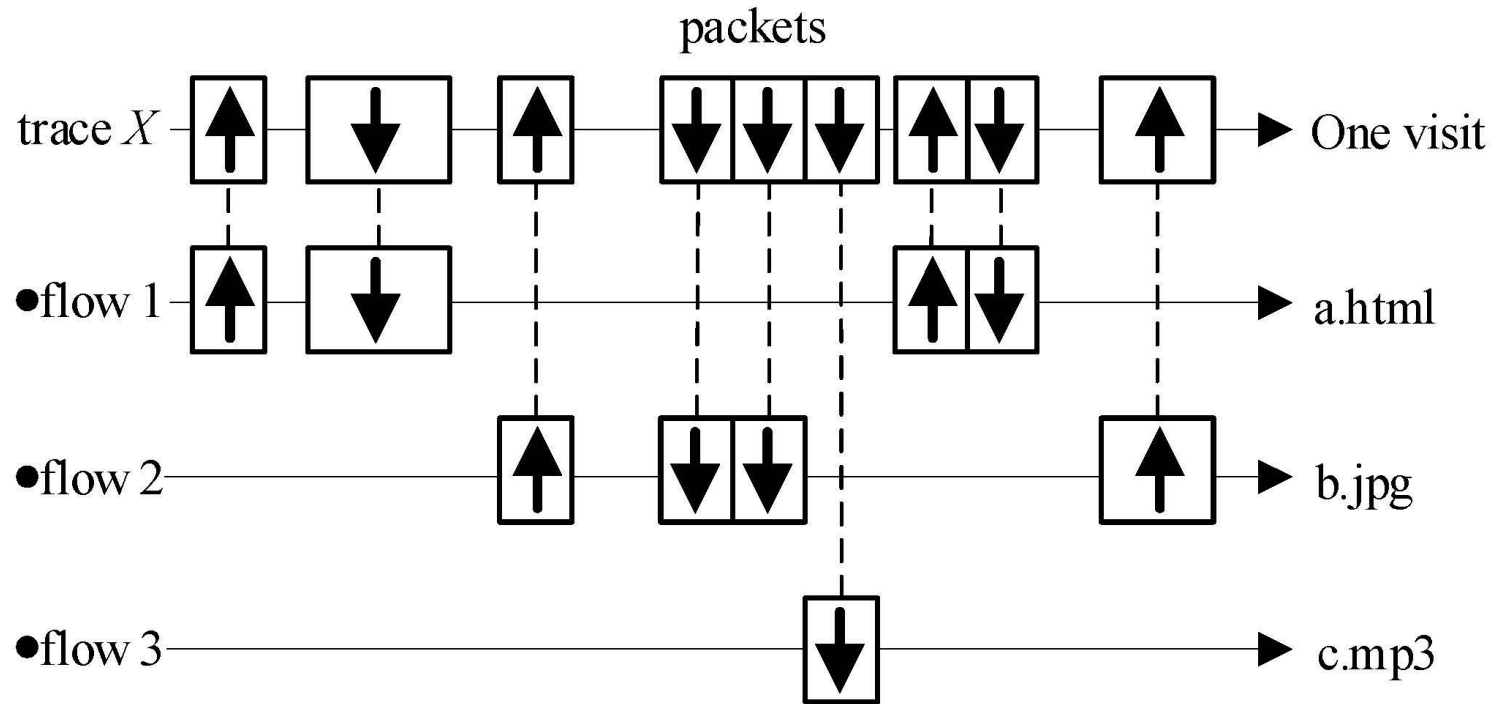
Internet of Things Fingerprinting

Ma et al. [IEEE INFOCOM, 2020]

IoTFinder [EuroS&P, 2020]

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Motivation



Related work

Feature-based traffic fingerprinting
k-fingerprinting [USENIX Security, 2016]
Shafiq et al. [The Journal of Supercomputing, 2019]

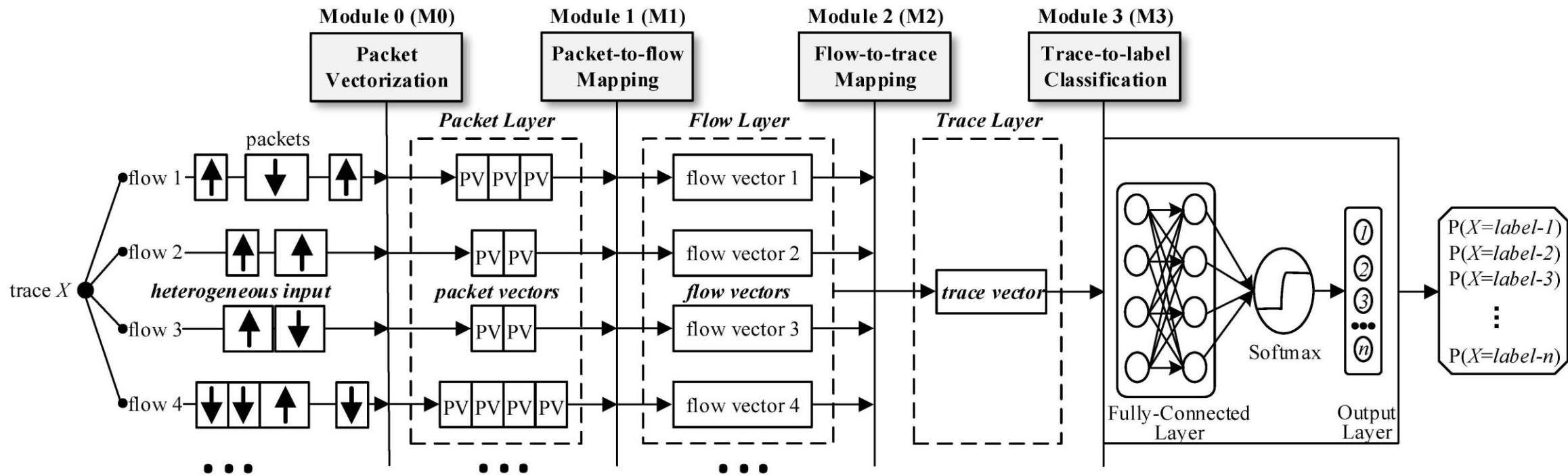
Deep learning-based traffic fingerprinting
Deep fingerprinting [ACM CCS, 2018]
Var-cnn [PETS, 2019]
SHAME [ACM WPES, 2021]

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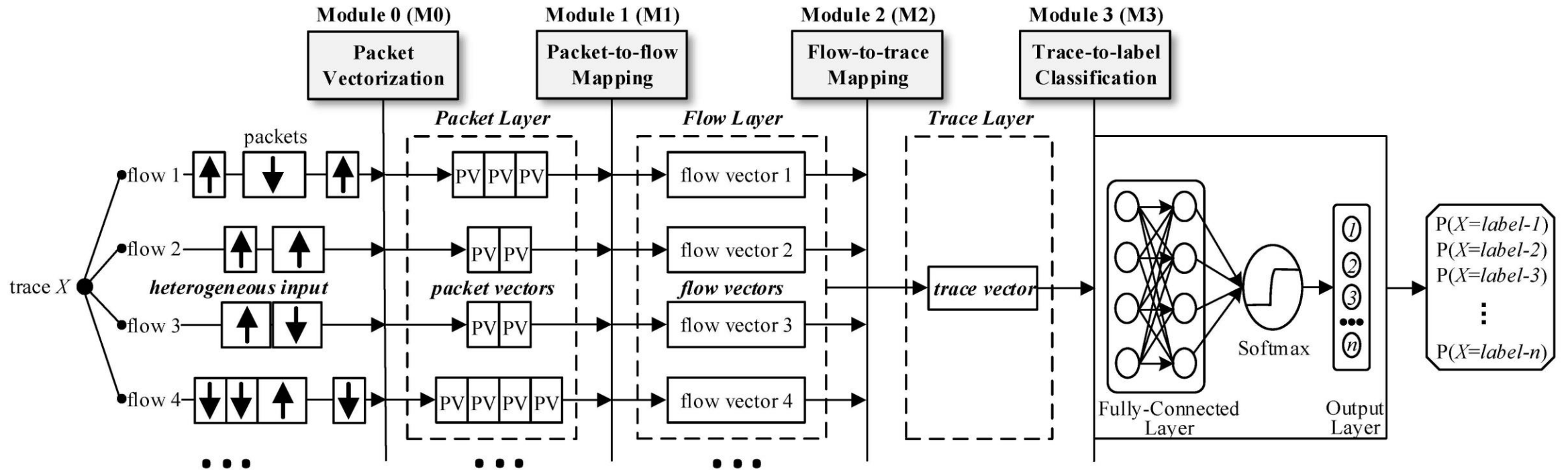
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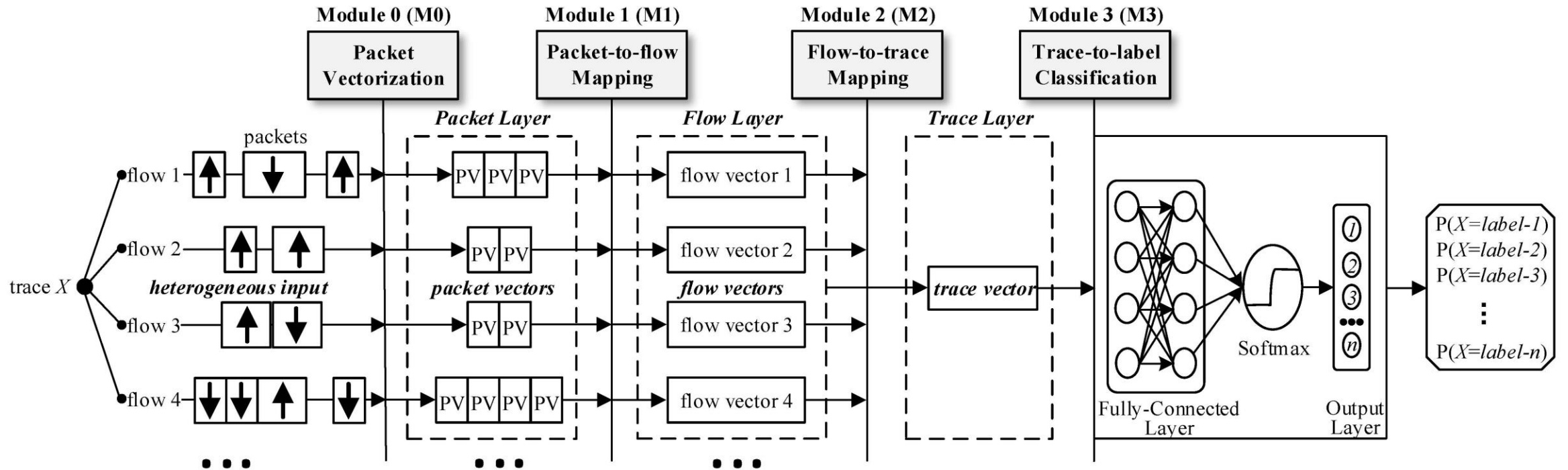
System Design



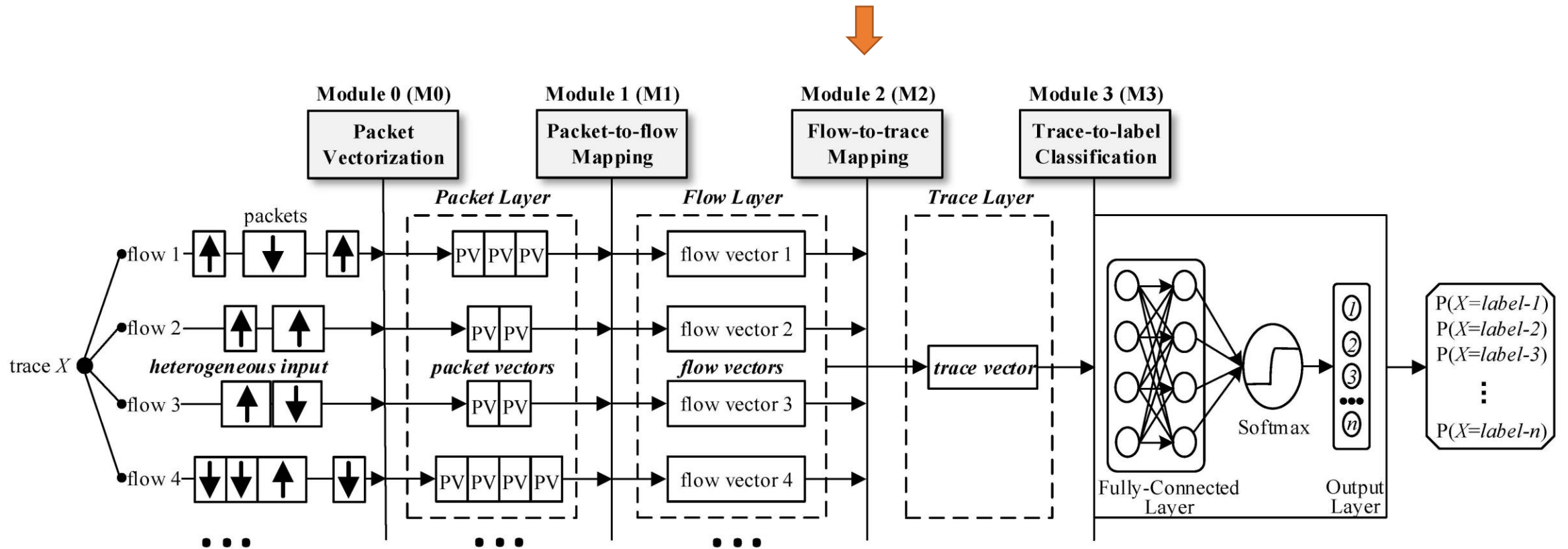
System Design



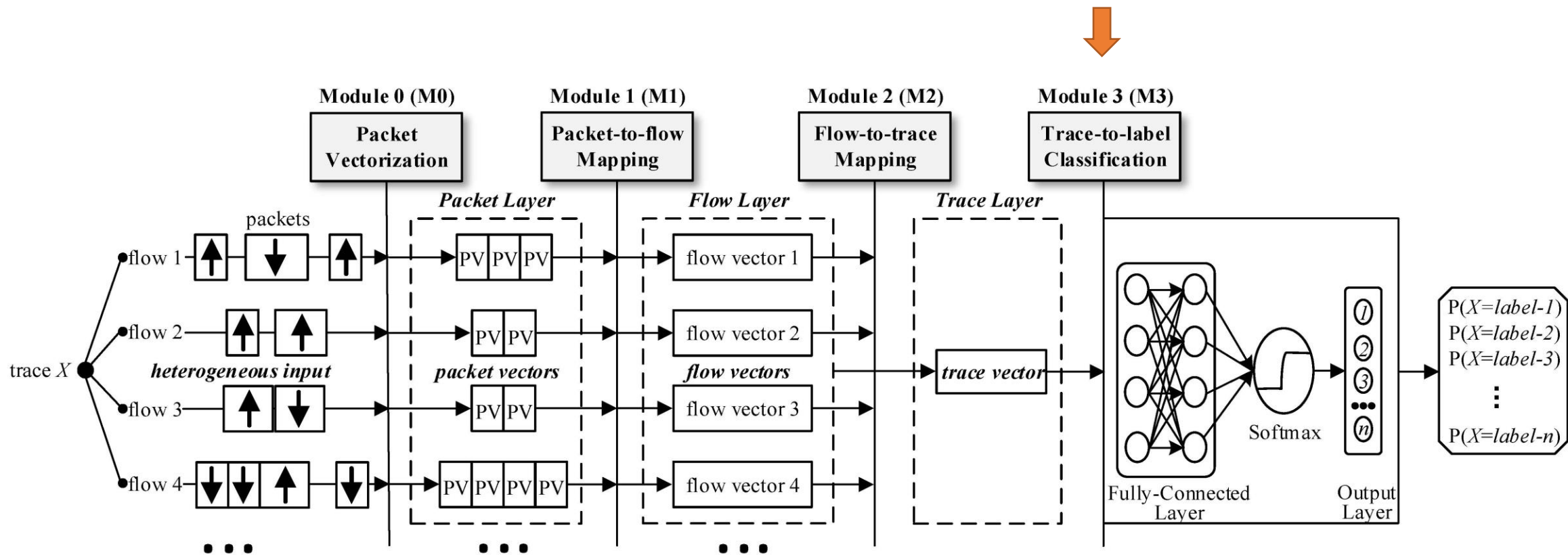
System Design



System Design



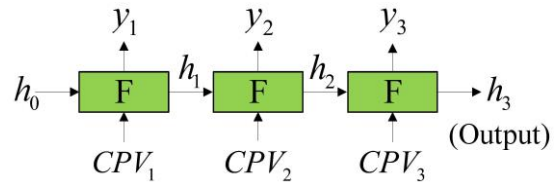
System Design



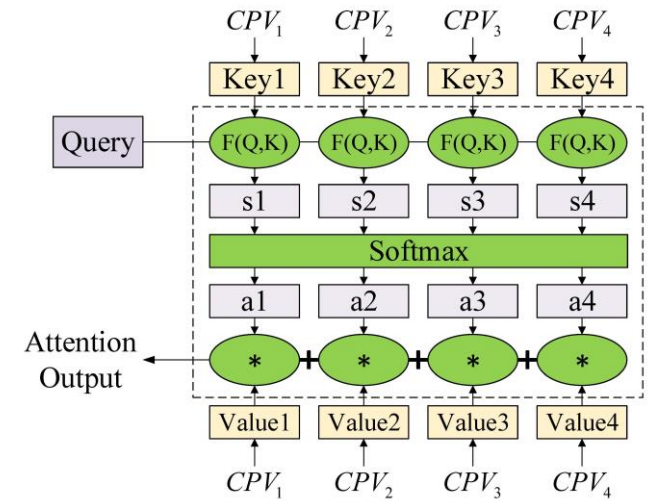
System Design

NN Structure in Packet-to-flow (M1) Mapping and Flow-to-trace (M2) Mapping

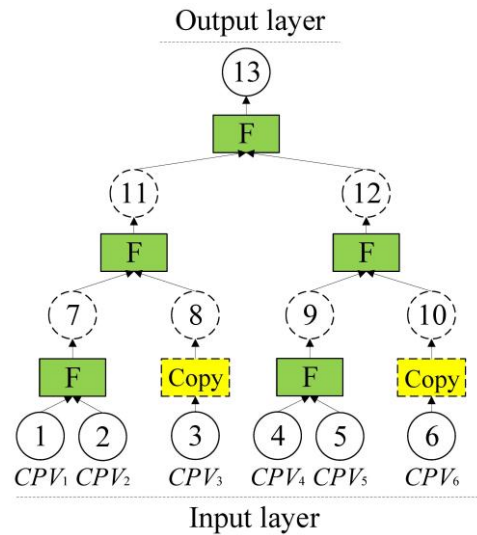
(1) Chain-structured



(3) Attention-structured



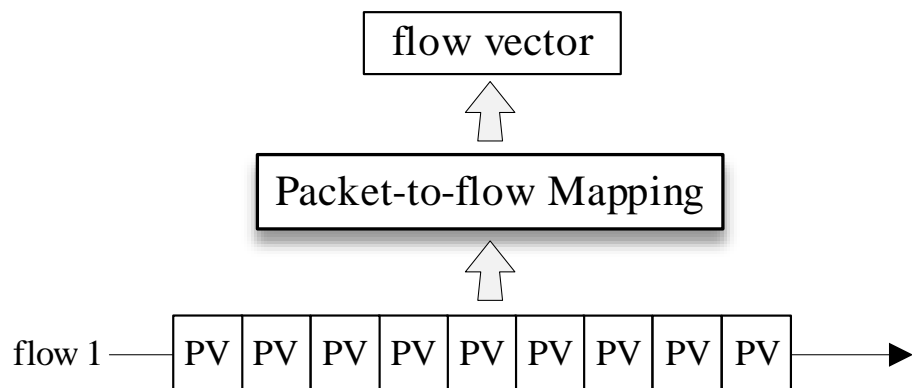
(2) Tree-structured



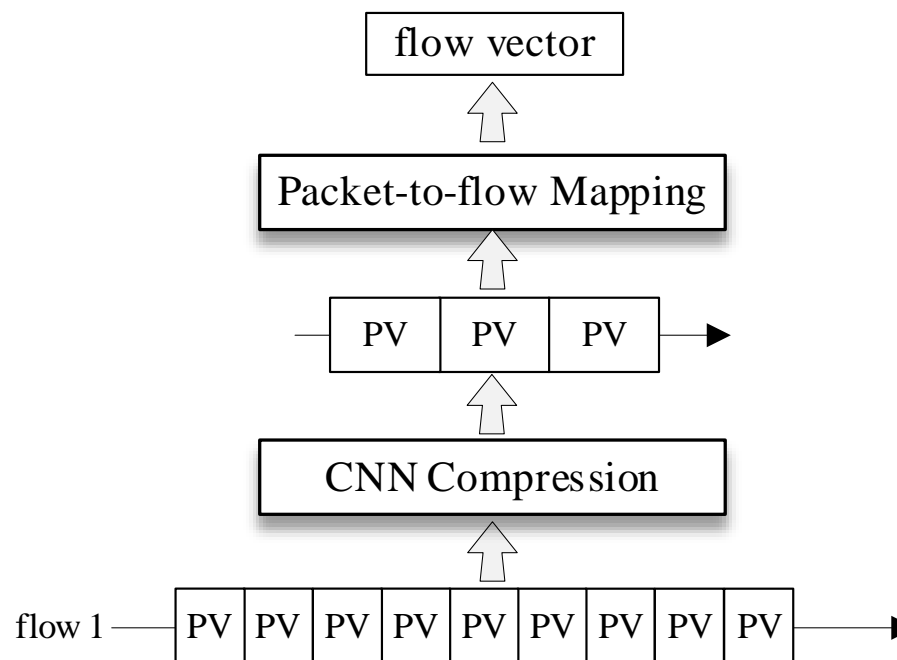
(4) Hybrid (uses multiple neural network structures)

System Design

Use CNN Compression to Speed up Training



(a) Without CNN Compression



(b) With CNN Compression

System Design

Techniques to Handle Overfitting

- ❑ Early Stopping
- ❑ Weight Decay
- ❑ Dropout
- ❑ Batch Normalization
- ❑ Auxiliary Loss
- ❑ Data Enhancement

System Design

Techniques to Handle Overfitting

- ❑ Early Stopping
- ❑ Weight Decay
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- ❑ Batch Normalization
- ❑ Auxiliary Loss
- ❑ Data Enhancement

The diagram illustrates the decomposition of a total loss function. A blue arrow points from the 'Auxiliary Loss' item in the list to the first term of the equation. The equation is presented in a box and then split into two parts, each with a downward arrow pointing to a label.

$$\text{Loss} = \text{CrossEntropy}(P, \mathcal{L}) + \frac{1}{N} \sum_{i=1}^N \text{CrossEntropy}(P'_i, \mathcal{L})$$

Trace Classification loss

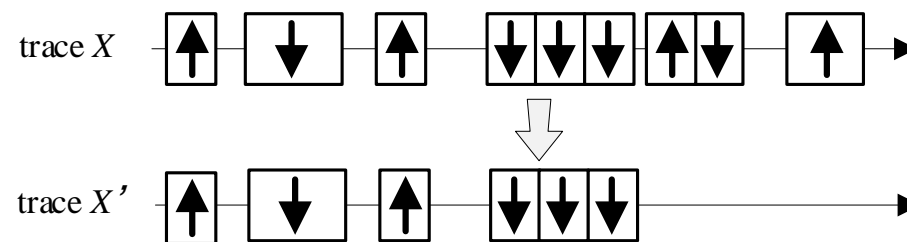
Flow Classification loss

System Design

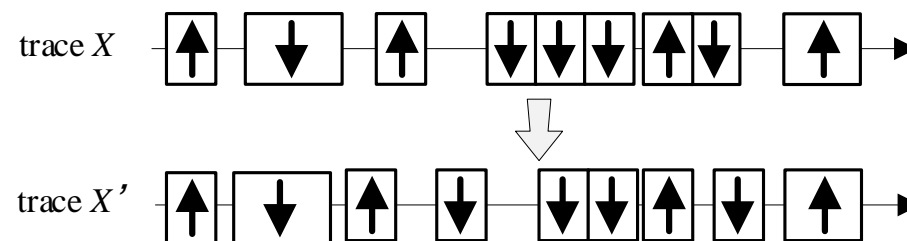
Techniques to Handle Overfitting

- ❑ Early Stopping
- ❑ Weight Decay
- ❑ Dropout
- ❑ Batch Normalization
- ❑ Auxiliary Loss
- ❑ Data Enhancement

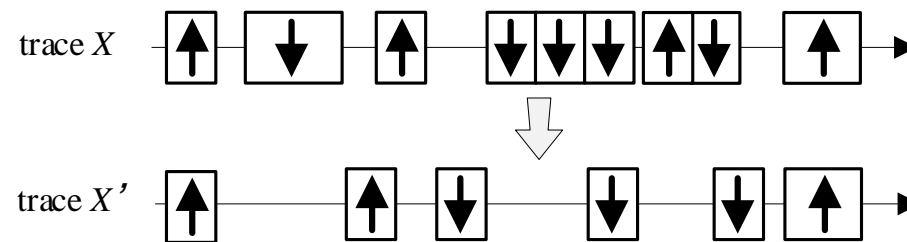
Cropping



Noising



Dropping



System Design

Techniques to Handle Overfitting

- ❑ Early Stopping
- ❑ Weight Decay
- ❑ Dropout
- ❑ Batch Normalization
- ❑ Auxiliary Loss
- ❑ Data Enhancement
- ❑ **Hybrid**

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Evaluation

Performance comparison with the SOTA methods.

Dataset	Our F1-score	SOTA method	SOTA F1-score
UAV [4]	0.928 (± 0.023)	K-Means +RF [4]	0.957
SWF	0.996 (± 0.003)	RF+LCS [43]	0.982
KWF	0.977 (± 0.009)	PSC+ET [44]	0.974
IDI [30]	0.940 (± 0.040)	RF [45]	0.91
ISD [31]	0.984 (± 0.022)	CCR-ELM [46]	0.961

Datasets

- User Activities (UAV)
- IoT Device Identification (IDI)
- Intrusion Detection (ISD)
- Keyword Searching (KWS)
- Shadowsocks Website Fingerprinting (SWF)

◆ Our method effectively fingerprint traffic across multiple tasks.

Evaluation

Macro F1-scores using different neural network structures

M1 module	UAV [4]	SWF	KWS	IDI [30]	ISD [31]
Attention	0.925 (± 0.019)	0.995 (± 0.004)	0.977 (± 0.010)	0.968 (± 0.024)	0.990 (± 0.010)
Chain	0.922 (± 0.029)	0.992 (± 0.006)	0.979 (± 0.014)	0.954 (± 0.033)	0.995 (± 0.008)
Tree	0.923 (± 0.023)	0.993 (± 0.001)	0.976 (± 0.010)	0.937 (± 0.037)	0.986 (± 0.014)
Hybrid	0.920 (± 0.025)	0.993 (± 0.003)	0.974 (± 0.020)	0.940 (± 0.040)	0.997 (± 0.005)

M2 module	UAV [4]	SWF	KWS	IDI [30]	ISD [31]
Attention	0.912 (± 0.031)	0.991 (± 0.003)	0.979 (± 0.009)	0.924 (± 0.055)	0.992 (± 0.008)
Chain	0.920 (± 0.027)	0.994 (± 0.004)	0.950 (± 0.014)	0.963 (± 0.030)	0.982 (± 0.022)
Tree	0.907 (± 0.027)	0.987 (± 0.006)	0.806 (± 0.039)	0.848 (± 0.041)	0.992 (± 0.012)
Hybrid	0.920 (± 0.025)	0.993 (± 0.003)	0.974 (± 0.020)	0.940 (± 0.040)	0.997 (± 0.005)

◆ Hybrid structures should be adopted for stable Macro F1-scores.

Evaluation

**Macro F1-scores using different solutions to handle overfitting.
H-* removes method * from the hybrid solution.**

Solutions		UAV [4]	SWF	KWS	IDI [30]	ISD [31]
No Handling		0.918 (± 0.027)	0.956 (± 0.025)	0.204 (± 0.275)	0.721 (± 0.137)	0.998 (± 0.005)
Pure	ES	0.913 (± 0.034)	0.953 (± 0.024)	0.203 (± 0.275)	0.723 (± 0.134)	0.995 (± 0.010)
	WD	0.922 (± 0.022)	0.945 (± 0.027)	0.391 (± 0.391)	0.720 (± 0.066)	0.998 (± 0.005)
	DO	0.922 (± 0.024)	0.736 (± 0.161)	0.052 (± 0.132)	0.277 (± 0.105)	0.994 (± 0.008)
	BN	0.922 (± 0.021)	0.994 (± 0.003)	0.970 (± 0.011)	0.859 (± 0.211)	0.992 (± 0.011)
	AL	0.919 (± 0.023)	0.990 (± 0.005)	0.869 (± 0.010)	0.833 (± 0.070)	0.992 (± 0.008)
	DE	0.921 (± 0.022)	0.980 (± 0.016)	0.140 (± 0.261)	0.789 (± 0.071)	0.995 (± 0.010)
Hy-brid	H-ES	0.932 (± 0.023)	0.996 (± 0.002)	0.820 (± 0.076)	0.940 (± 0.049)	0.998 (± 0.005)
	H-WD	0.918 (± 0.026)	0.995 (± 0.004)	0.974 (± 0.007)	0.933 (± 0.037)	0.989 (± 0.016)
	H-BN	0.917 (± 0.024)	0.991 (± 0.008)	0.872 (± 0.033)	0.848 (± 0.080)	0.994 (± 0.008)
	H-AL	0.916 (± 0.021)	0.993 (± 0.003)	0.970 (± 0.015)	0.944 (± 0.040)	0.995 (± 0.007)
	H-DE	0.924 (± 0.024)	0.996 (± 0.004)	0.973 (± 0.005)	0.958 (± 0.026)	0.990 (± 0.011)
	H	0.928 (± 0.023)	0.996 (± 0.003)	0.977 (± 0.009)	0.935 (± 0.041)	0.998 (± 0.004)

◆ Hybrid solutions should be adopted for high Macro F1-scores.

Evaluation

Macro F1-scores when confronted with hierarchy unawareness deep learning methods

Method	UAV [4]	SWF	KWS	IDI [30]	ISD [31]
HA-1.1	0.835 (\pm 0.024)	0.964 (\pm 0.012)	0.388 (\pm 0.365)	0.816 (\pm 0.072)	0.811 (\pm 0.057)
HA-1.2	0.906 (\pm 0.022)	0.966 (\pm 0.013)	0.927 (\pm 0.021)	0.840 (\pm 0.112)	0.914 (\pm 0.063)
HA-2	0.556 (\pm 0.025)	0.800 (\pm 0.022)	0.204 (\pm 0.012)	0.749 (\pm 0.018)	0.872 (\pm 0.029)
Ours	0.928 (\pm 0.023)	0.996 (\pm 0.003)	0.977 (\pm 0.009)	0.940 (\pm 0.040)	0.997 (\pm 0.005)

- HA-1.1: Treat a trace consisting of multiple flows as a sample, **without** distinguishing between flows.
- HA-1.2: Treat a trace consisting of multiple flows as a sample, **with** distinguishing between flows.
- HA-2: Treat each flow of a trace as a sample, and classifying it into different trace labels.

◆ Hierarchy awareness is important.

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Conclusions

- ◆ We take the first step to designing an input-agnostic hierarchical deep learning framework to seamlessly land deep learning onto traffic fingerprinting.
- ◆ Our framework successfully applies in various fingerprinting tasks where SOTA methods rely on handcrafted features and deep learning is not easily applicable.
- ◆ We proposed techniques to handle overfitting and analyzed real-world factors that affect performance.
- ◆ Code available at https://github.com/shashadehuajiang/trace_classifier

Thank you!

Feel free to contact with any questions:

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