You Are What You Broadcast: Identification of Mobile and IoT Devices from (Public) WiFi

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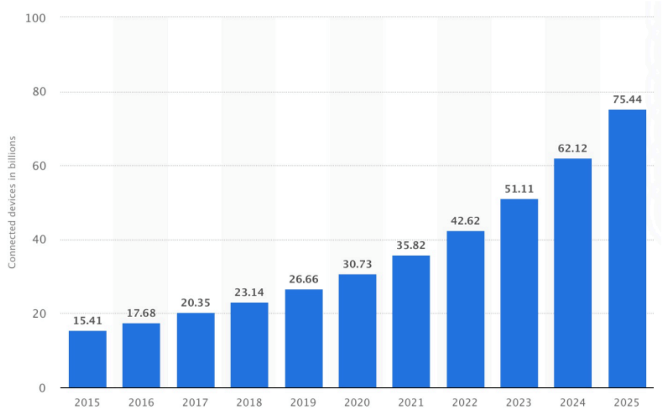
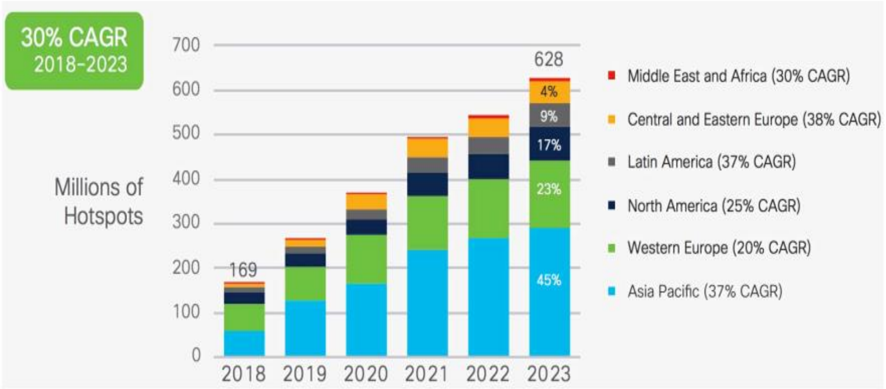
Background





Ubiquitous Connectivity

Public WiFi Hotspots

Security & Privacy?

Device Identification: Why?

Device identification in communication and computing	Network measurement Cyber situational awareness
Device management	Malicious device discovery

Task 1: Device Identification

When a mobile/IoT device connects to a WiFi network, we want to know that it is.

To identify the **manufacturer, type, model** of mobile devices using public information.

Task 2: Malicious Device Detection

When a **malicious** device connects to a WiFi network, we want an alert.

To detect the **abnormal** devices, whose BC/MC traffic deviates from benign patterns.

OWL: Overhearing on WiFi for Device Identification

Core Idea: Use Features from Broadcast/Multicast Packets

When a device is connected to a wireless network, it sends out broadcast or multicast packets: DHCP, mDNS, SSDP, etc

Use these packets to fingerprint devices.

Device Identification: Data Collection

Open Public WiFi

Public WiFi with Captive Portals

Encrypted WiFi

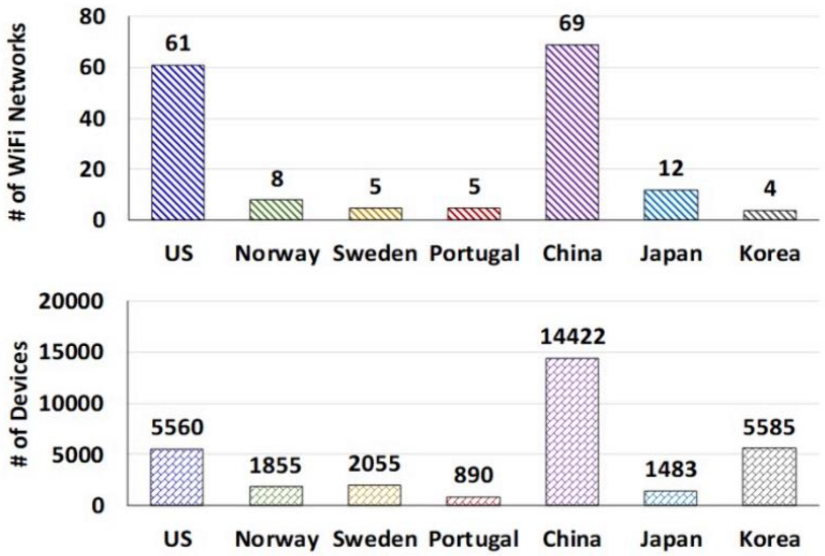
Device Identification: Data Collection

7 Countries: US, Norway, Sweden, Portugal, China, Japan, Korea

Collected Broadcast/Multicast traffic from 176 WiFi Networks, 12 networks disabled BC/MC traffic

Locations: coffee shops, restaurants, retail stores, airports, hotels, corporate guest networks, universities, authors' own homes

BC/MC packets from 31,850 unique devices



Device Identification: Data Collection

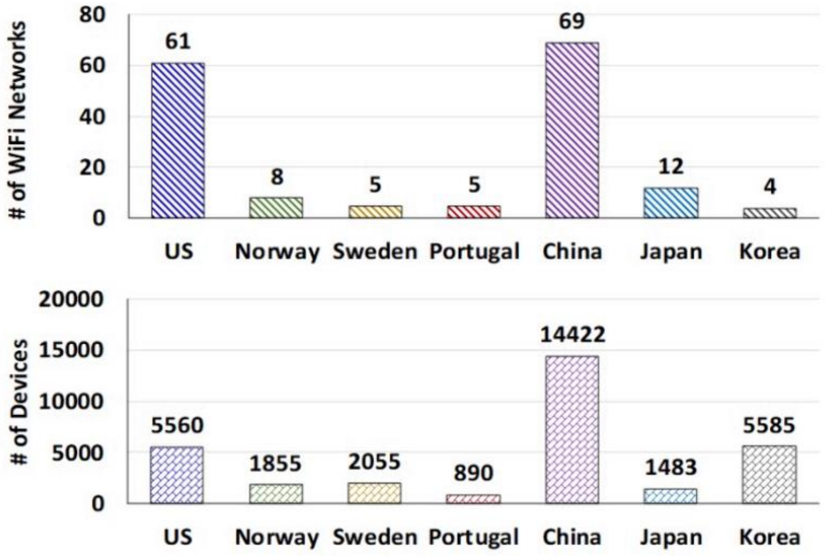
We collected data through a completely passive approach.

We did not turn on promiscuous mode: we were the legitimate and intended receivers of these BC/MC packets. NO unicast traffic.

No violation of Terms and Conditions to our best knowledge.

Post-processing to remove any potential personal identifier.

Discussed with two Institutional Review Boards.



Device Identification: Data Collection

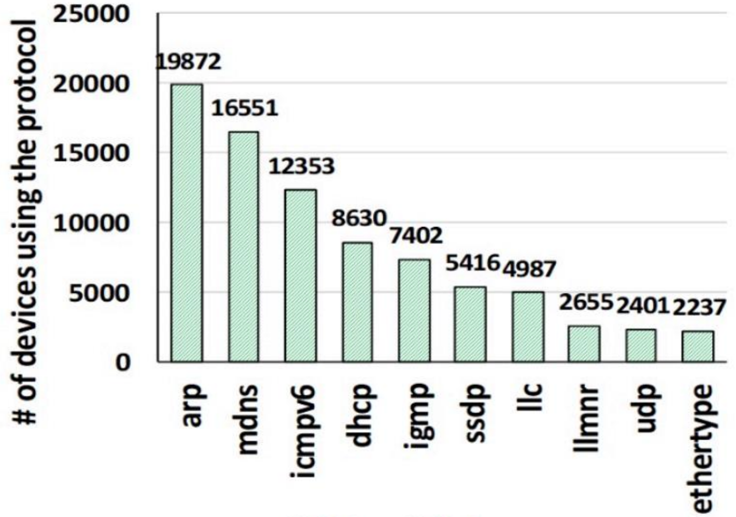
275 different BC/MC protocols were identified in our data

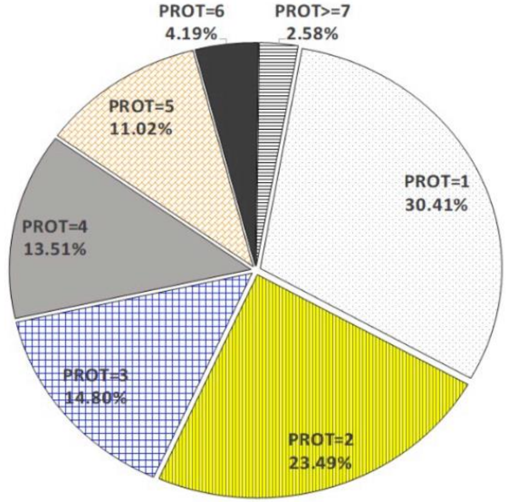
51.9% of the devices use mDNS. Several other application-layer protocols are also widely used.

69% of the devices use more than two protocols

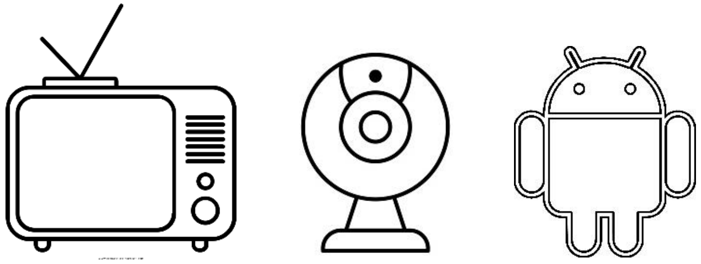
Popularity of protocols appear to be relatively consistent across countries, with a few small exceptions

Some (proprietary) protocols were only discovered from one manufacturer/type/model of devices, e.g., KINK in Samsung TVs



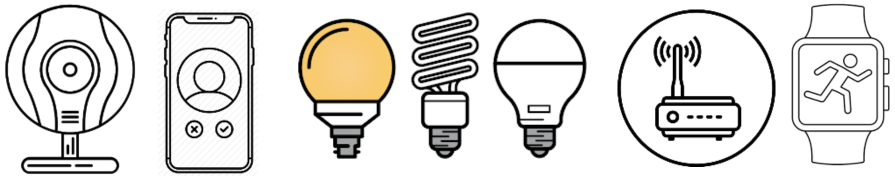


Device Identification: Data Collection



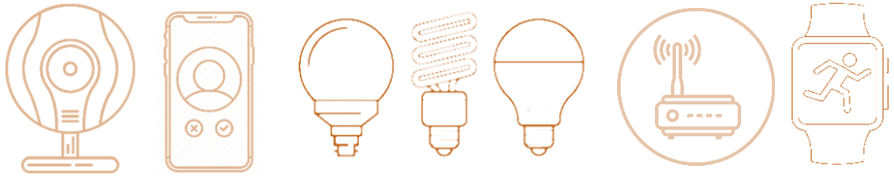
The ground truth dataset

- The identity of each device is physically verified
- **423 devices** with {manufacturer, type, model} labels
- E.g., {D-link, camera, dcs-930lb}



The annotated dataset

- Labeled by annotators based on human-readable content
- **4064 devices** with {manufacturer, type, model} labels
- **6519 devices** with {manufacturer, type} labels
- **15895 devices** with only {manufacturer} label



The sanitized dataset

- Removed all human interpretable textual features from the annotated dataset.
- MAC prefixes are also removed.

Device Identification: Feature Extraction

Identifiers. MAC prefix, HostName in DHCP, etc.

- ✓ Informative, unique
- × not always available, may be tampered

Main Features. Key-value pairs, pseudo natural language features

- × Not unique identifiers
- ✓ Robust, available, provide good discriminatory power

Auxiliary Features. SSDP notify → URL → device description file

- ✓ Include identifiers (device names)
- × Need to actively retrieve the file, not always available

Table 3.2 Examples of data fields that may contain identifiers

priority	Protocol	Fields
1	–	MAC prefix
2	DHCP	Option12 (HostName)
3	DHCP	Option60 (VendorClass)
4	DHCP	Option77 (ModuleName)
5	DHCPv6	Option39 (ClientFQDN)
6	MDNS	answer names in response messages
7	SSDP.MSEARCH	user-agent
8	SSDP.MSEARCH	X-AV-Client-Info
9	LLMNR	query name
10	BROWSER	query name
11	NBNS	query name
12	UDP	device name

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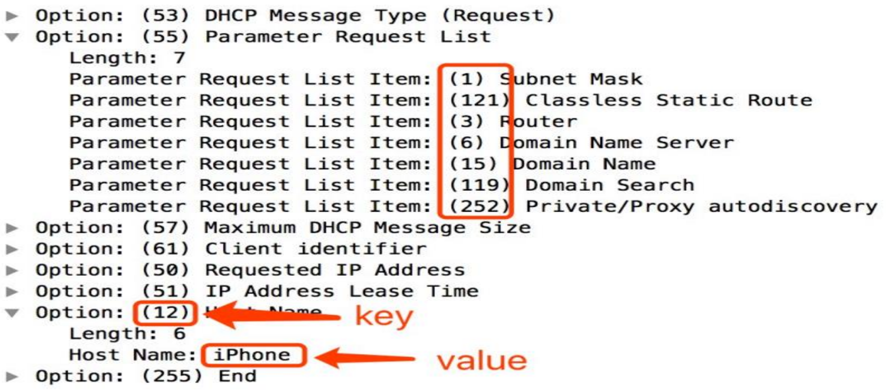

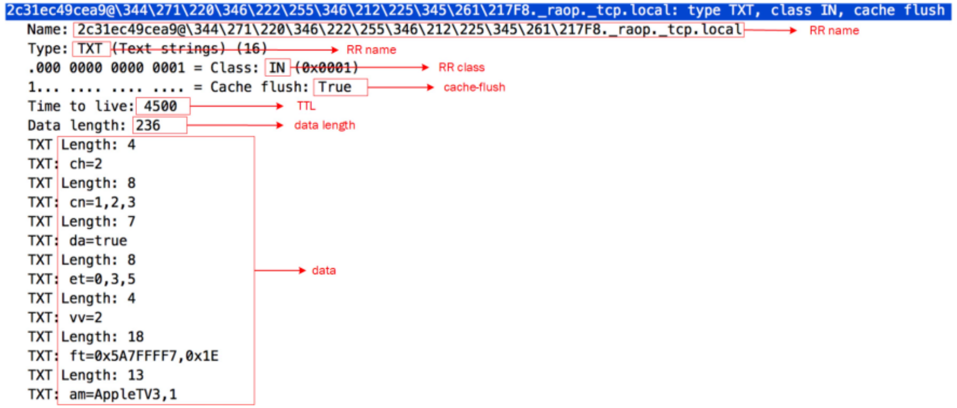

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Auxiliary Features. SSDP notify → URL → device description file

- ✓ Include identifiers (device names)
- × Need to actively retrieve the file, only used in evaluation


```
▼<root xmlns="urn:schemas-upnp-org:device-1-0">
   <script/>
  ▼<specVersion>
     <major>1</major>
     <minor>0</minor>
   </specVersion>
  ▼<device>
     <UDN>uuid:3f2c04b9-6d19-4d3f-b4a2-fd1f0cf1eec8</UDN>
     <friendlyName>DELL-PC: dell:</friendlyName>
     <deviceType>urn:schemas-upnp-org:device:MediaServer:1</deviceType>
     <manufacturer>Microsoft Corporation</manufacturer>
     <manufacturerURL>http://www.microsoft.com</manufacturerURL>
```

Device Identification: Feature Extraction

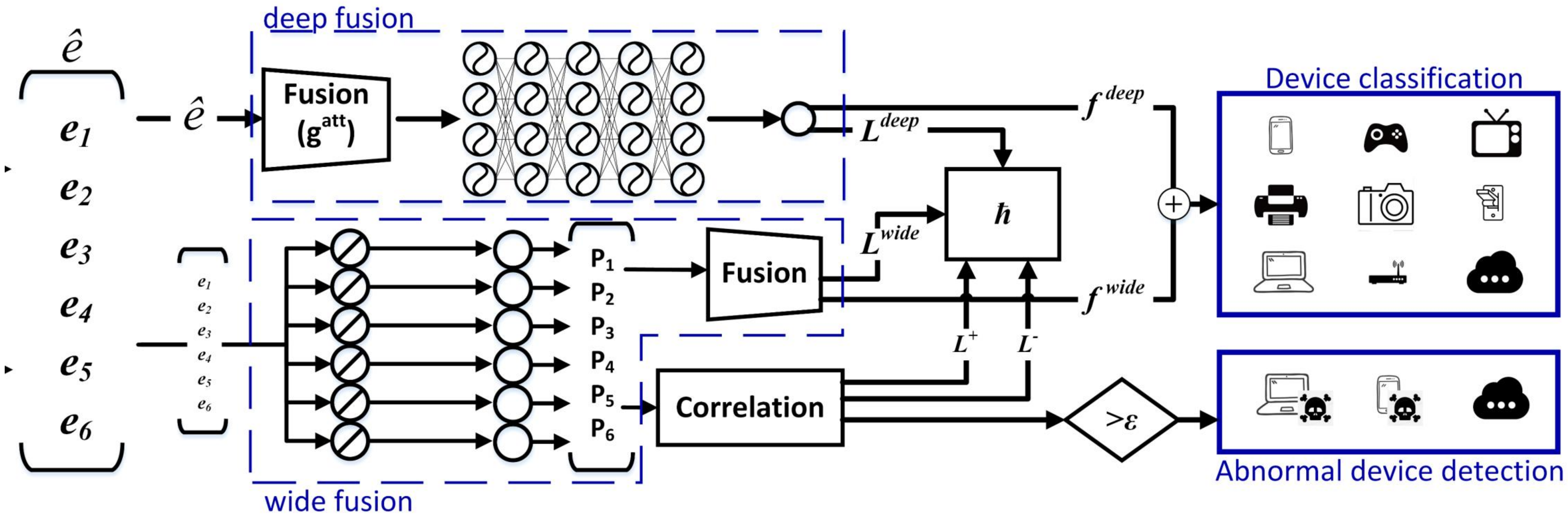
Each protocol generates an independent set of features

Features from different protocols complement each other

Not all protocols are available in all devices

Multi-view Classification

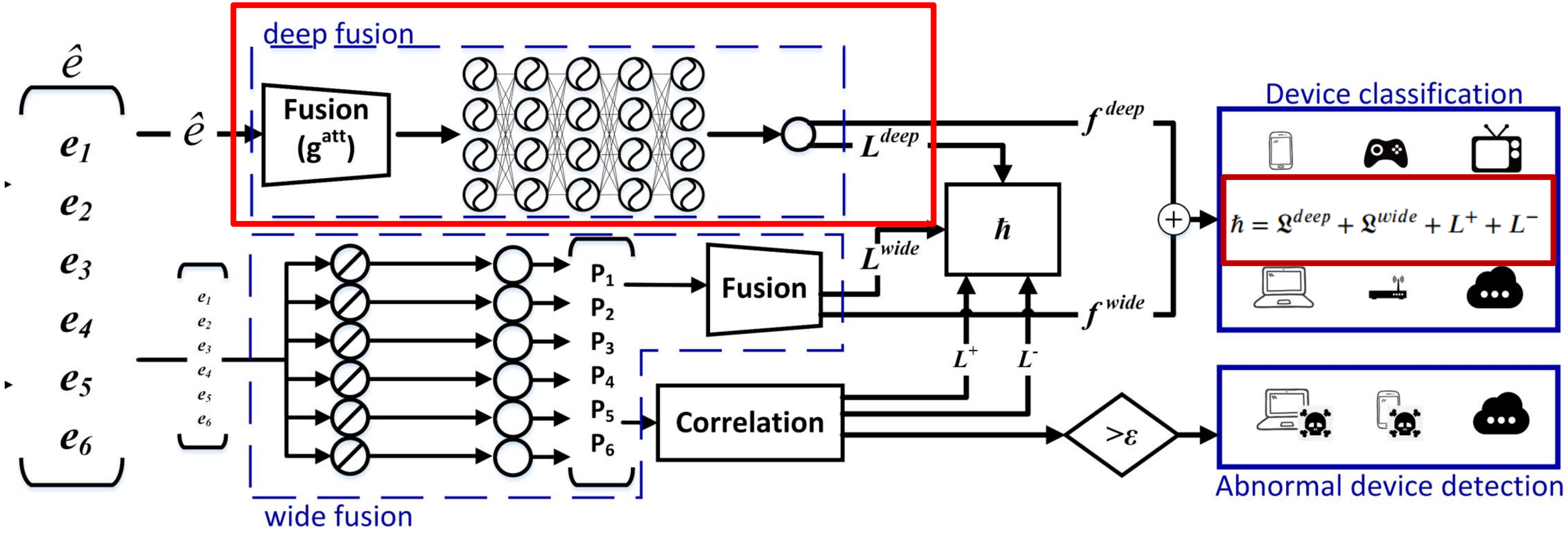
Device Identification: Multi-view Wide and Deep Learning



The deep component: early fusion; maximize the generalization performance

The wide component: late fusion; improve the memorization of label-view interaction

Device Identification: Multi-view Wide and Deep Learning



- $\mathcal{L}^{deep}$: best classification performance for device labels under input features
- $\mathcal{L}^{wide}$: to optimize classification performance on each view
- $\mathcal{L}^{+}$: view consistency: to maximize view agreement for benign samples
- $\mathcal{L}^{+}$: to maximize the view inconsistency for malicious devices

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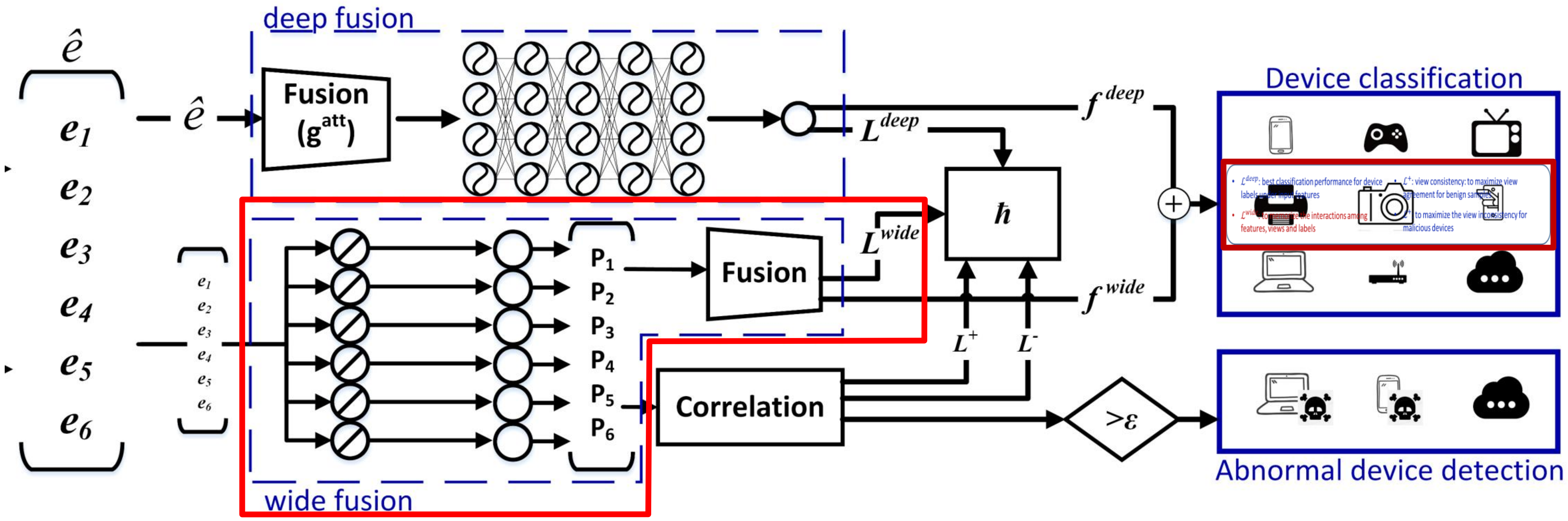

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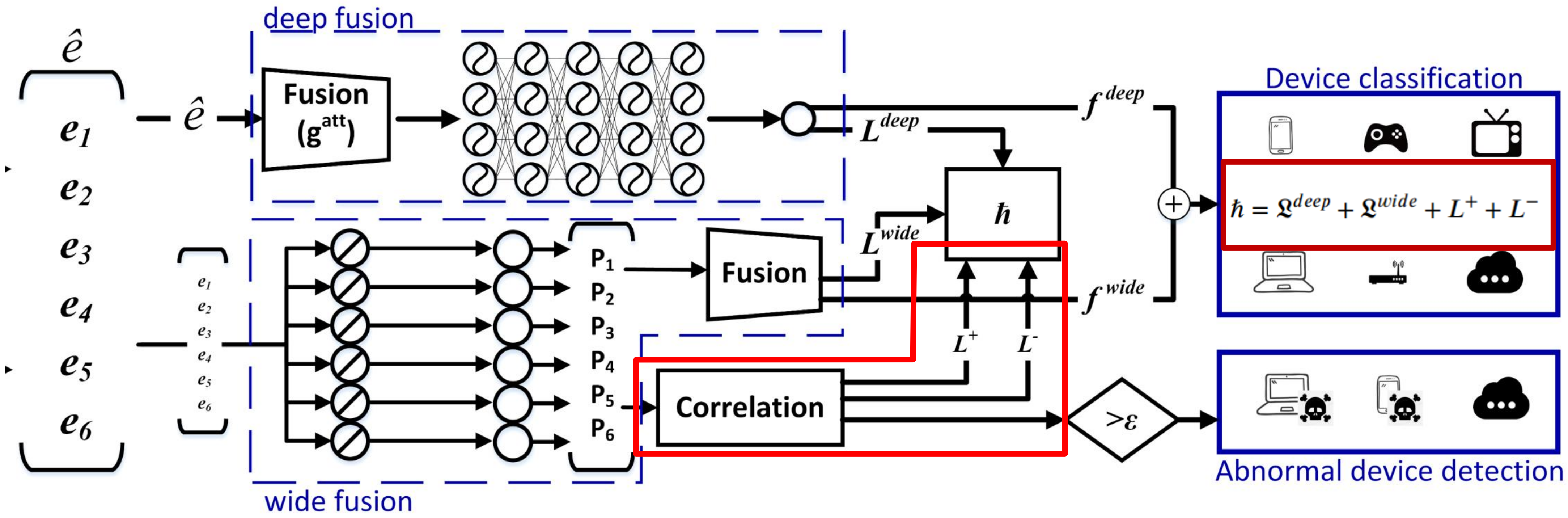

- $\mathcal{L}^{deep}$: best classification performance for device labels under input features
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- $\mathcal{L}^{+}$: view consistency: to maximize view agreement for benign samples
- $\mathcal{L}^{-}$: to maximize the view inconsistency for known malicious devices

Device Identification: Experiments

Coverage: the fraction of all devices that OWL could generate a label for.

$$C = |\{\text{labeled devices}\}| / |\{\text{all devices}\}|$$

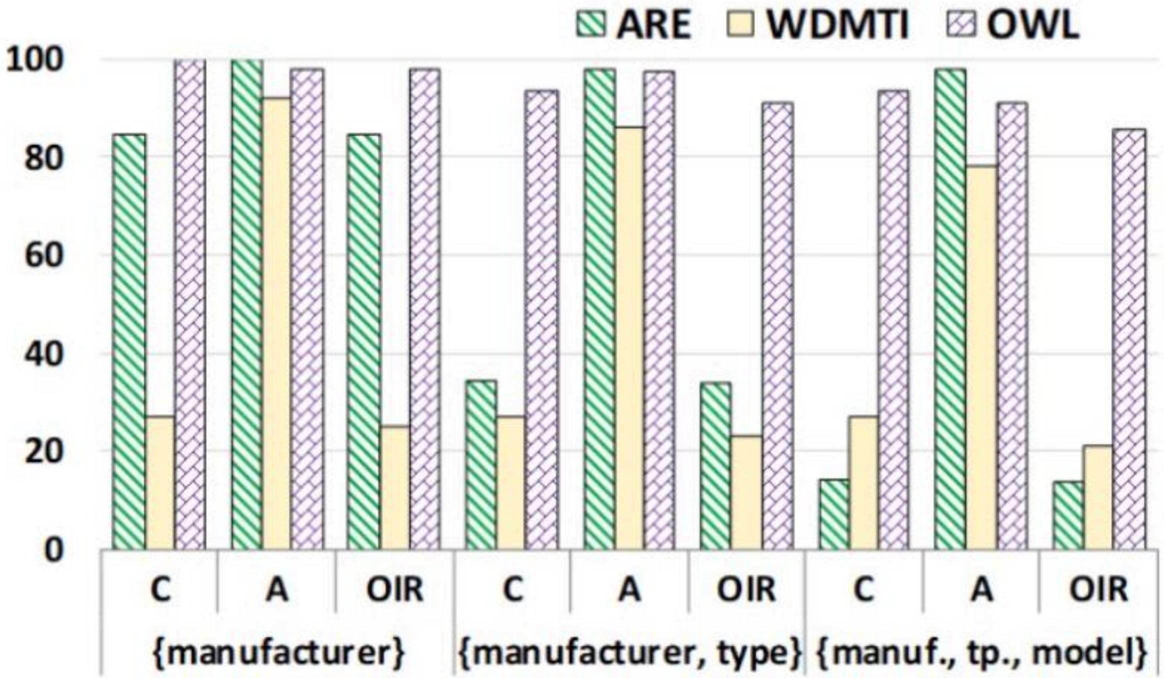
Accuracy: the fraction of labeled devices that are correctly labeled

$$A = \frac{|\{\text{correctly labeled devices}\}|}{|\{\text{labeled devices}\}|}$$

Overall Identification Rate: the faction of all devices that are correctly labeled.

$$OIR = \frac{|\{\text{correctly labeled devices}\}|}{|\{\text{all devices}\}|} = C \times A$$

Device Identification: Experiments



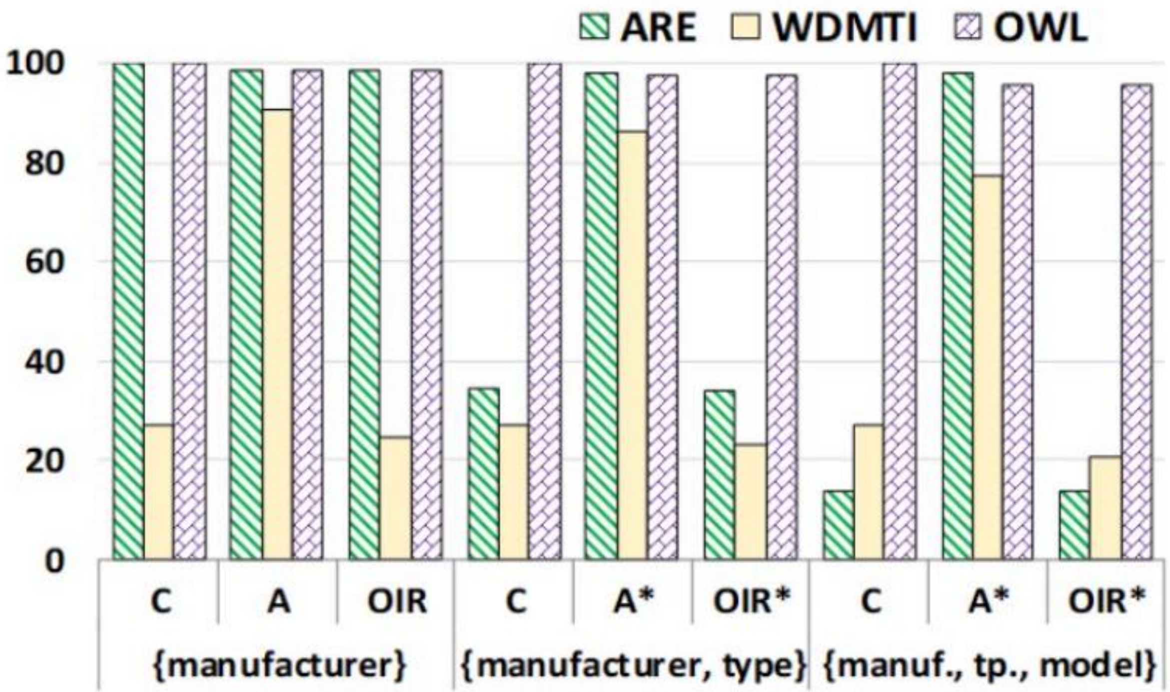
Performance on Ground truth Data

- OWL provides the best overall performance (OIR) at all granularity levels.
- OWL's coverage is consistently the highest.
- At finer granularity, OWL significantly outperforms both ARE and WDMTI in OIR.
- ARE has the best accuracy but limited coverage, especially at fine granularity levels.
- WDMTI's coverage is always limited.

[ARE] Xuan Feng, Qiang Li, Haining Wang, and Limin Sun. Acquisitional rule-based engine for discovering internet-of-things devices. In *USENIX Security*, 2018.

[WDMTI] Lingjing Yu, Tao Liu, Zhaoyu Zhou, Yujia Zhu, Qingyun Liu, and Jianlong Tan. WDMTI: Wireless Device Manufacturer and Type Identification using Hierarchical Dirichlet Process. In *IEEE MASS*, 2018.

Device Identification: Experiments



Performance on Annotated Data

- Again, OWL provides the best overall performance (OIR) at all granularity levels.
- Accuracy (A*) and OIR (OIR*) was only evaluated on partial data in {M, T} and {M, T, M} categories.
- A* and OIR* represent the upper-bound of the actual A and OIR.
- OIR* in the range of [0.95, 0.98]

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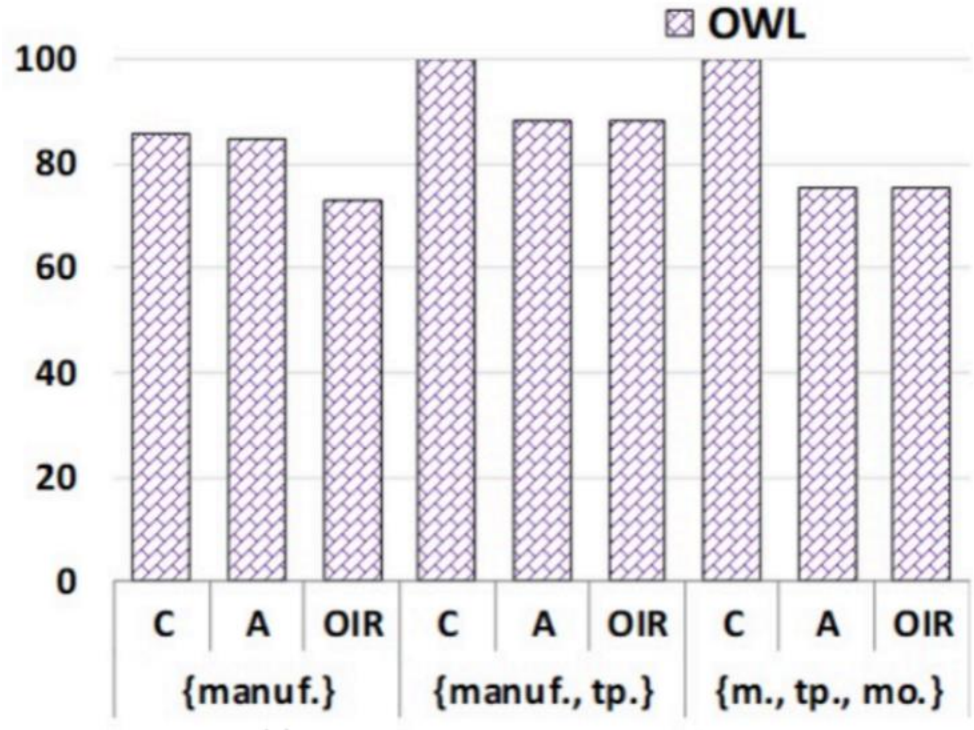
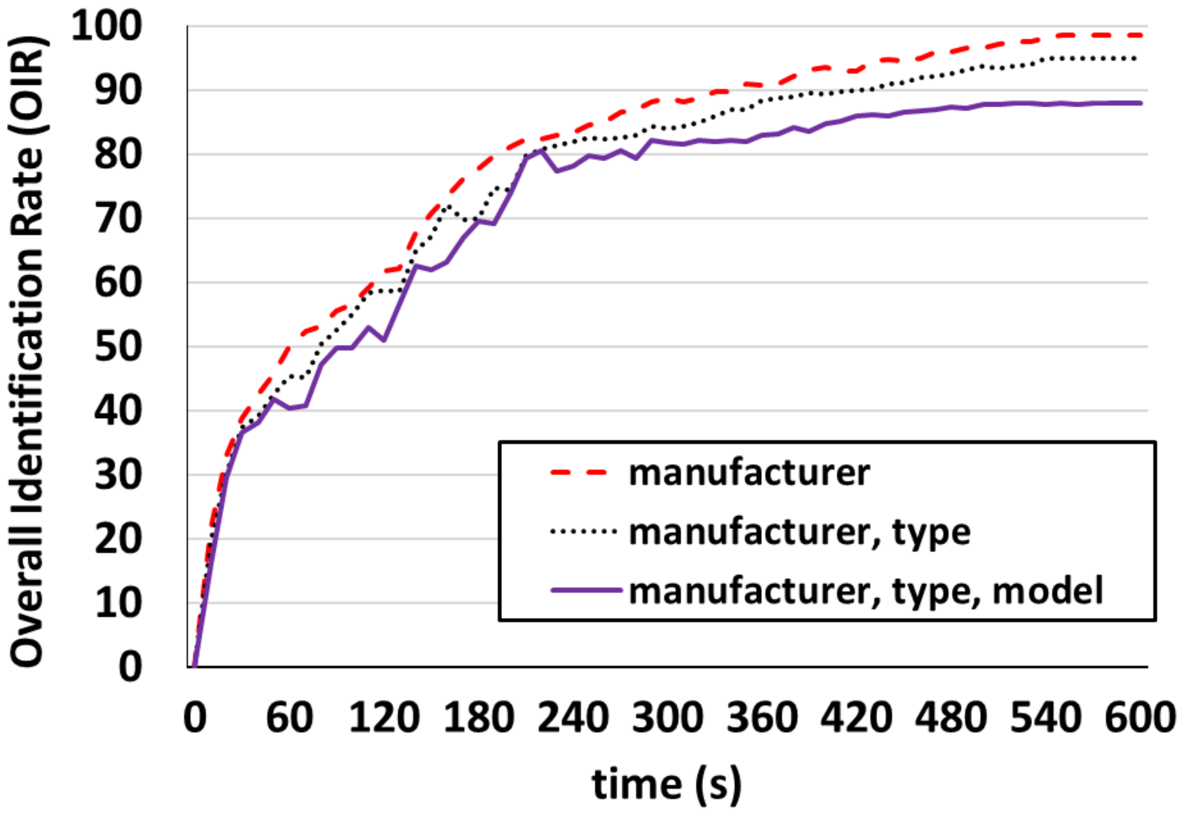
Device Identification: Experiments



Performance on Sanitized Data

- All human-interpretable contents are removed from annotated dataset.
- This is to evaluate OWL's performance in extreme conditions.
- A and OIR represent the lower-bound of the actual A and OIR.
- OWL's OIR is still high, in the range of [0.75, 0.88].

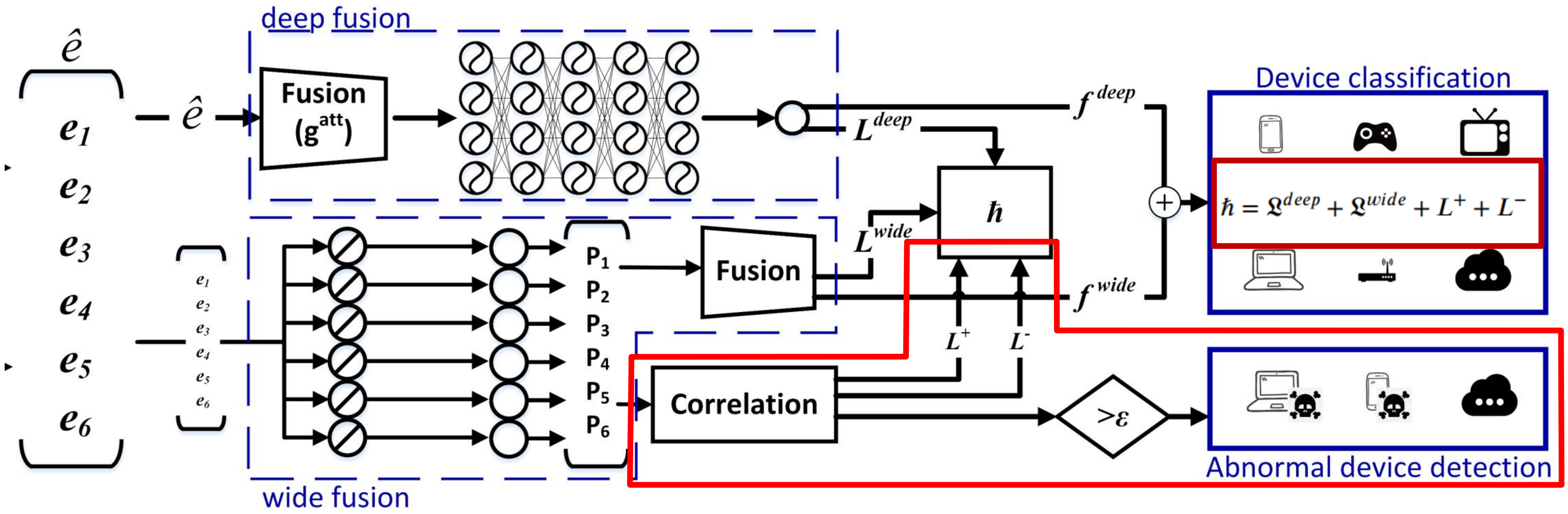
Device Identification: Experiments



Detection Speed

- When all the features are available, It only takes mini-seconds for a trained MvWDL model to classify a new device
- However, packets/features come to OWL slowly in real world settings.
- OWL was connected to the network at t_0, and started to see packets on the network.
- OIR increased rapidly for approximately 240 seconds, when OIR reached 80%.
- OIR peaked in about 500 seconds.

Malicious Device Detection: Approach



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Malicious Device Detection: Case Study

mDNS view

other views

Xiaomi,TV,4	Leshi,TV,x55	Leshi,TV,x65s
Gaoshengda,TV	Funshion,TV	Chuangwei,TV
Hisense,TV,vidaa	PPTV,TV	Changhong,TV,43s1
whaley,TV,w50j	MTN,TV	Changhong,TV,LED50
Rflink,TV	Nebula,TV	Tianmao,Magiccast,m18

Spoofed Apple TV (31 devices)

- **mDNS view: AppleTV, high confidence**
- **Other views: not AppleTV, high confidence**
- Labels: not AppleTV, some in ground truth dataset
- AirPlay: Apple's proprietary protocol suite for multimedia streaming over WiFi
- mDNS packets of these devices were similar to AppleTV, so that others may AirPlay on them
- They were all connected to a corporation named Lebo (or HappyCast)

Malicious Device Detection: Case Study

DHCP view

other views

Fake DHCP Server and Gateway (1 device)

- **DHCP view: router, high confidence**
- **Other views (mDNS, SSDP): Microsoft Surface**
- The device sent DHCP Offer and DHCP ACK messages to inform other devices the gateway of the network is itself.
- MAC prefix: Microsoft
- Explanation: Microsoft surface book spoofed a gateway to lure others to connect through it.
- Some devices were tricked (DHCP request)
- Simulated this attack in the lab

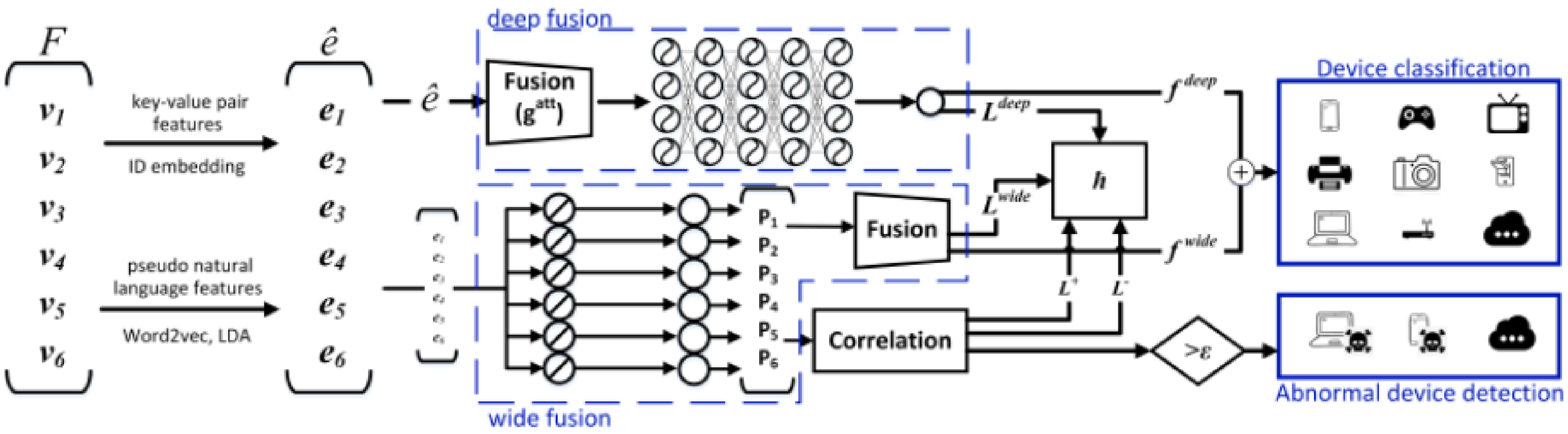
Malicious Device Detection: Case Study

(Hidden) Camera Detection

- Hidden cameras are often considered as sensitive or malicious devices that infringe users’ privacy.
- Existing solutions: traffic analysis
- Cannot detect cameras that are not actively transmitting (in stand-by)
- Attackers and record/store now and send later
- Cameras are still online, they send out BC/MC packets and they can be detected by OWL
- OWL achieved 100% accuracy in detecting cameras at {manufacturer, type} granularity

OWL: Overhearing on WiFi for Device Identification

OWL



MvWDL

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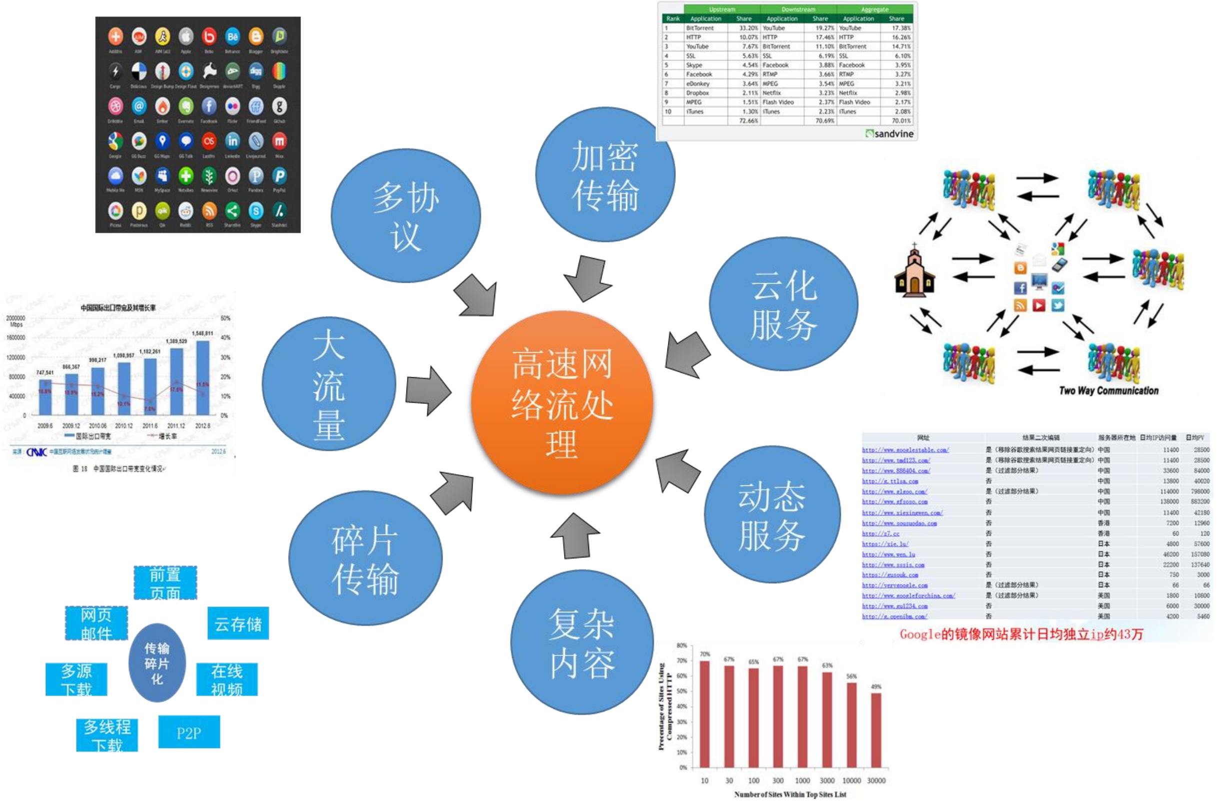
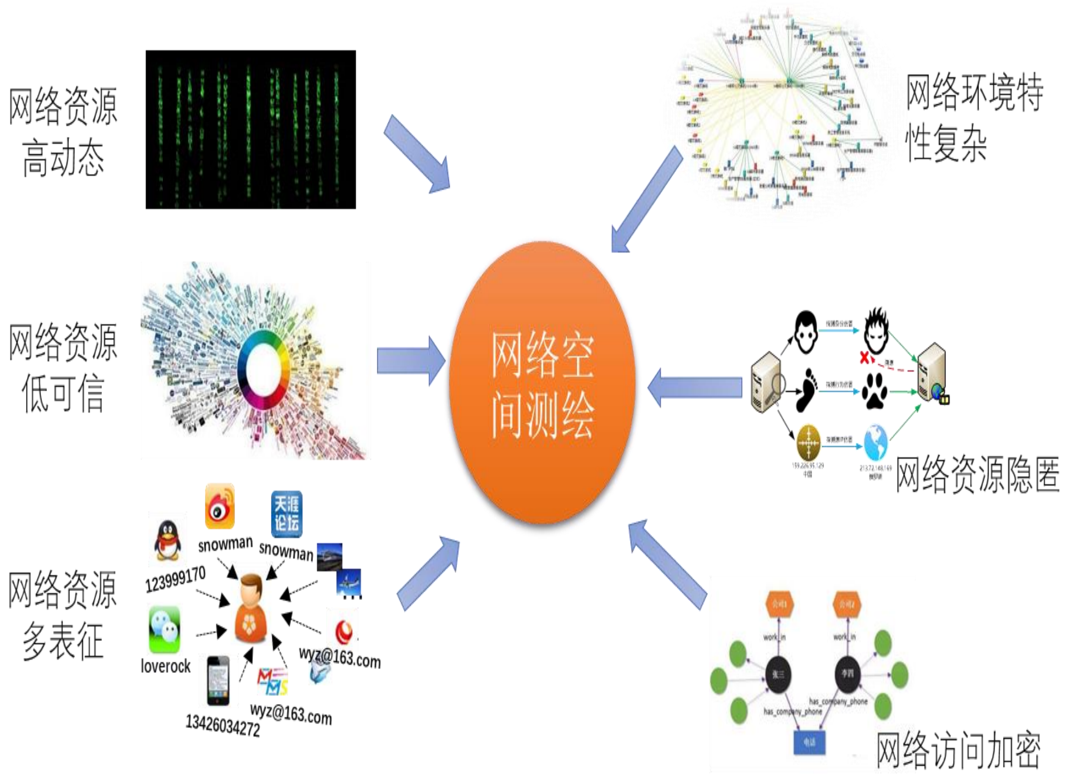
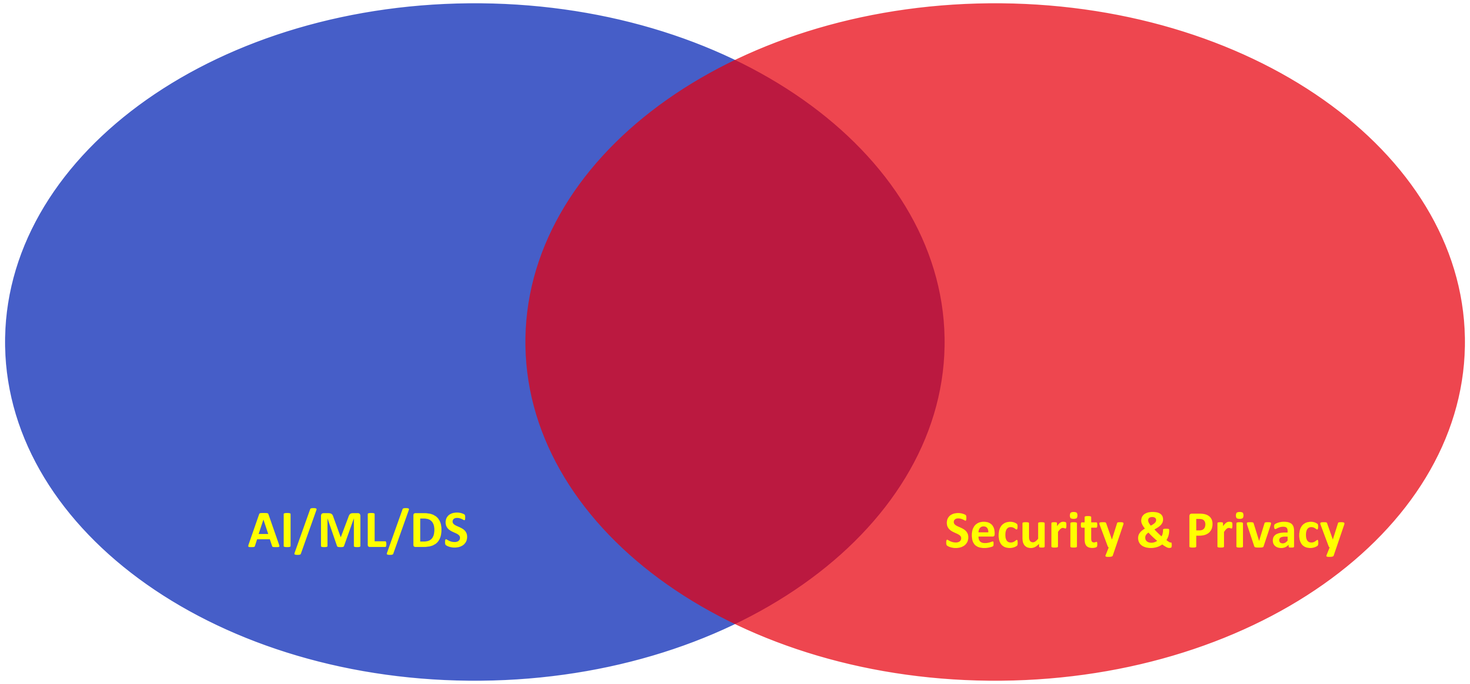




The InfoSec Group at KU



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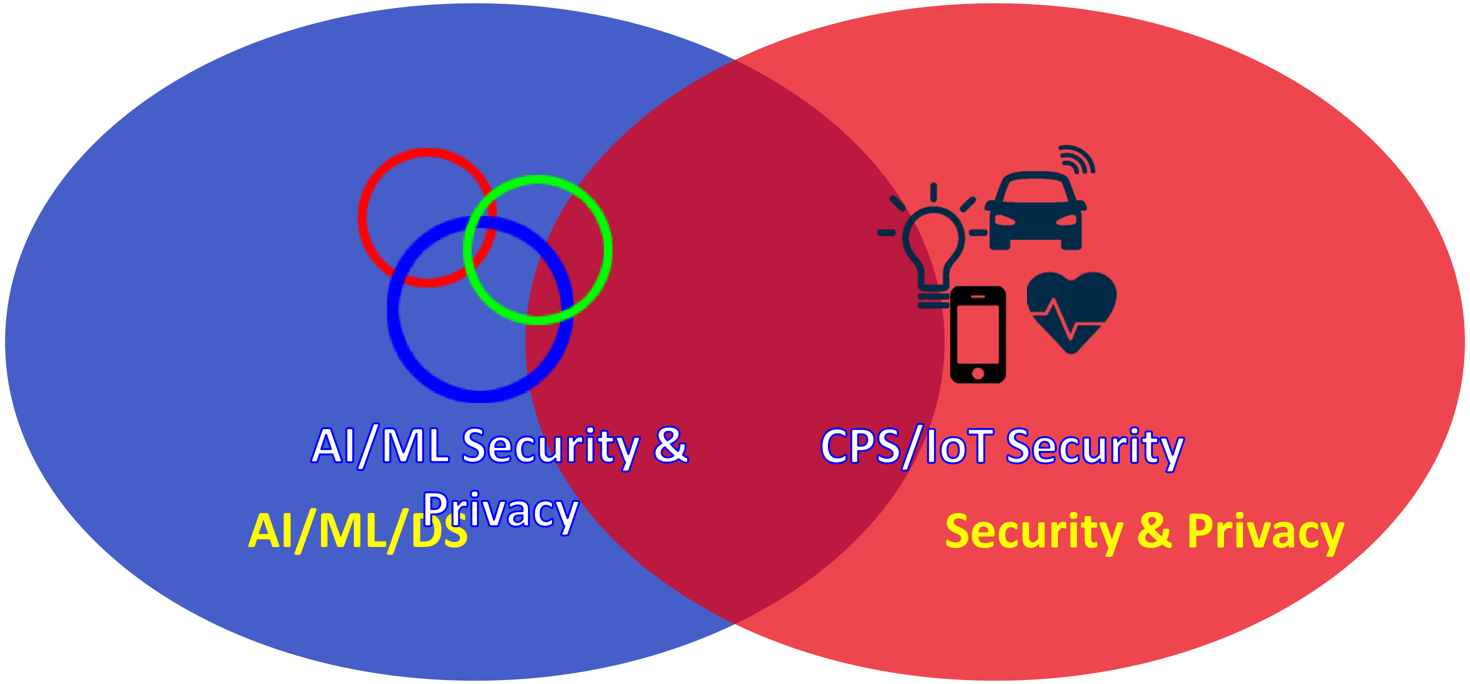

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Thanks for listening！ Q&A

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