Northeastern

MAC ID Spoofing-Resistant Radio Fingerprinting

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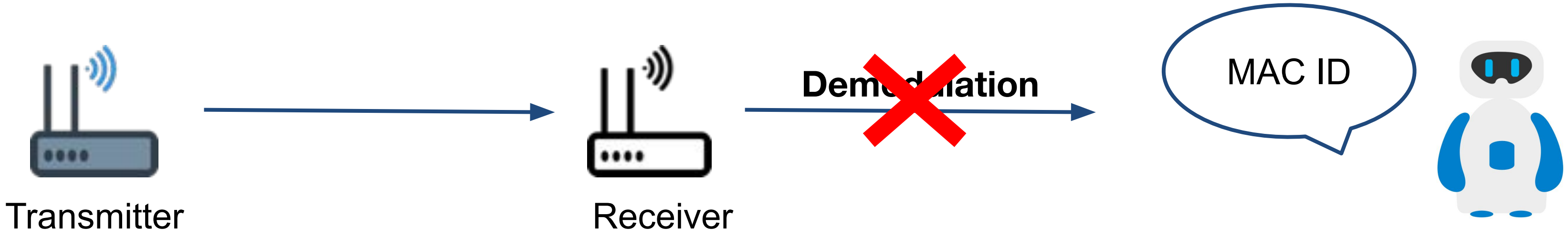
Jennifer Dy, Kaushik Chowdhury, and Stratis Ioannidis

Radio Fingerprinting

- Detecting **transmission source** of signals is a key security mechanism



! Demodulation:

- protocol-specific
- limits ability of detection over new packet frame structures, channel bandwidths, modulation choices, and coding schemes

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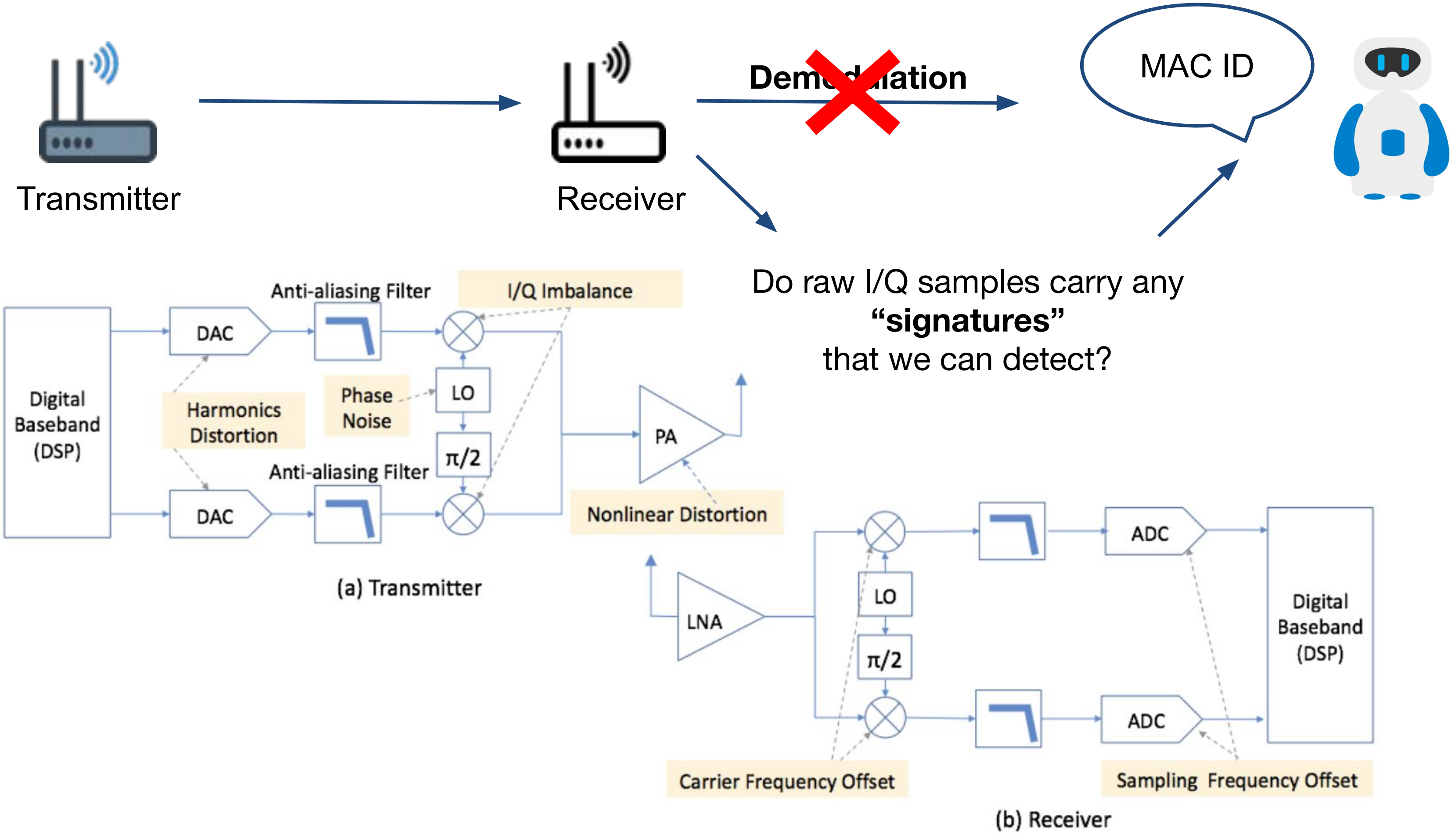

Do raw I/Q samples carry any **"signatures"** that we can detect?

(a) Transmitter

(b) Receiver

Radio Fingerprinting

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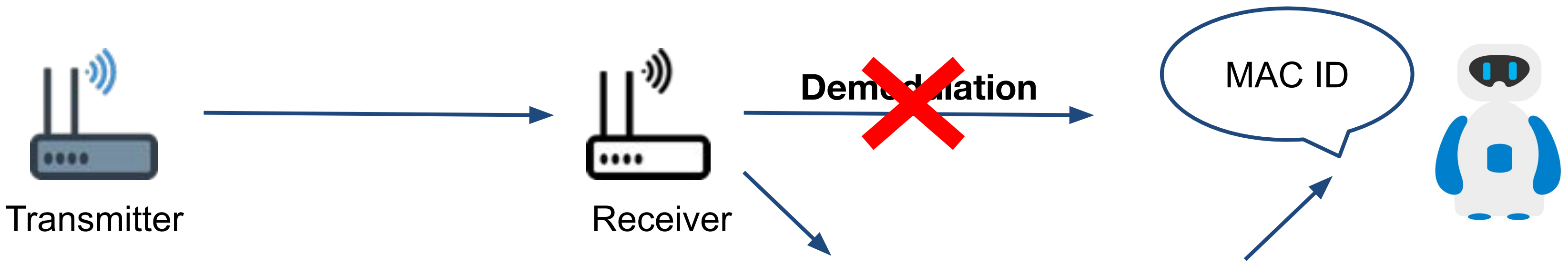

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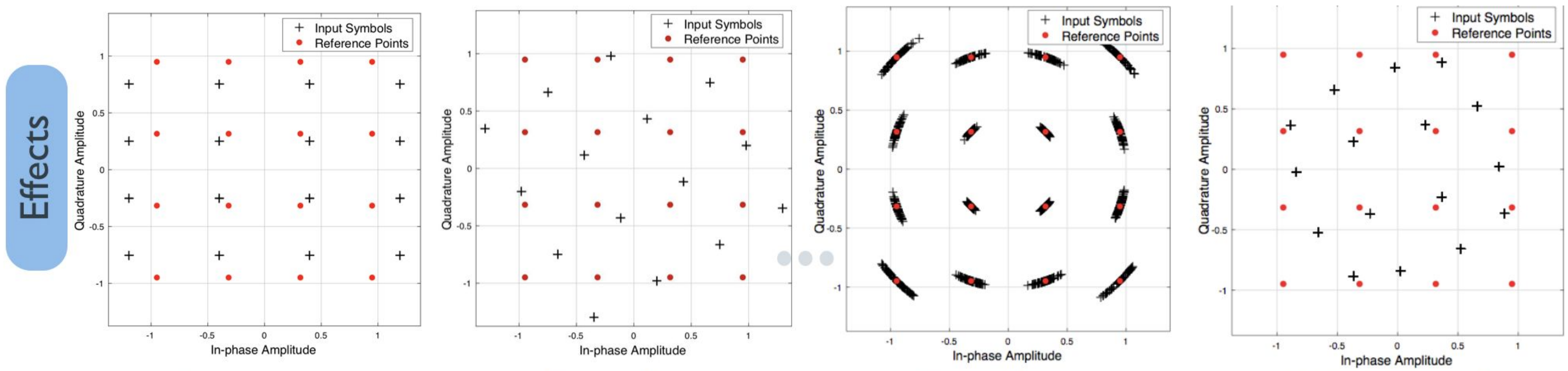

IQ Imbalance

Phase offset

Phase Noise

AM/PM Distortions

*K. Sankhe, M. Belgiovine,F. Zhou, S. Riyaz, S. Ioannidis, and K. R. Chowdhury, "ORACLE: Optimized Radio clAssification through Convolutional neuraL nEtworks,” IEEE INFOCOM 2019, Paris, France, May. 2019

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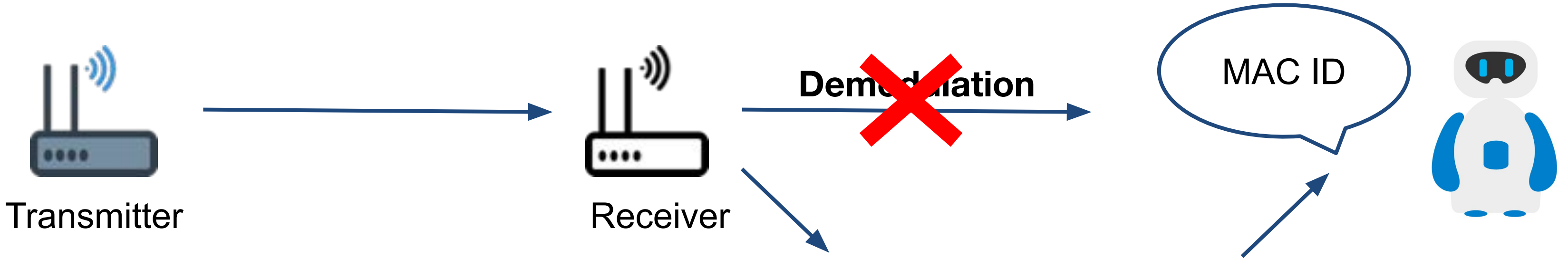

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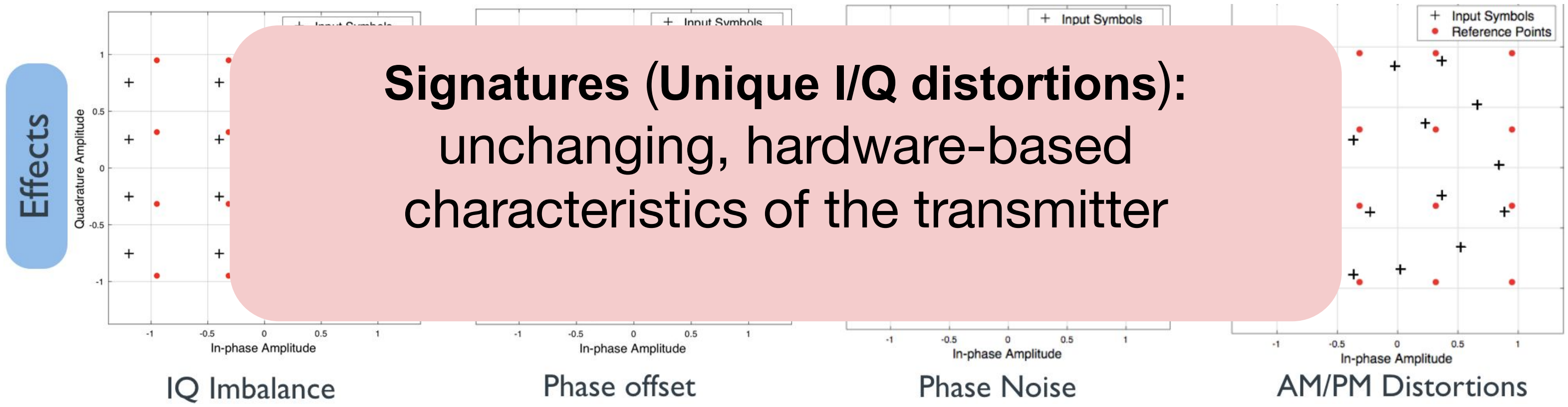

Signatures (Unique I/Q distortions):
unchanging, hardware-based
characteristics of the transmitter

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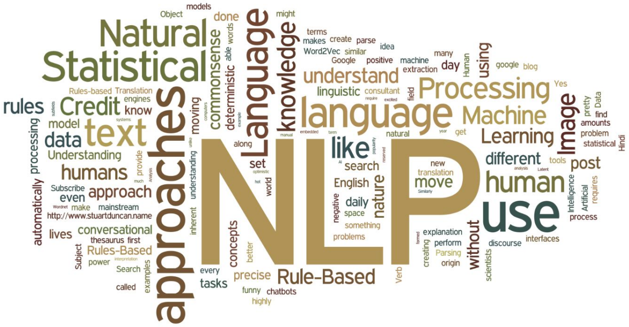
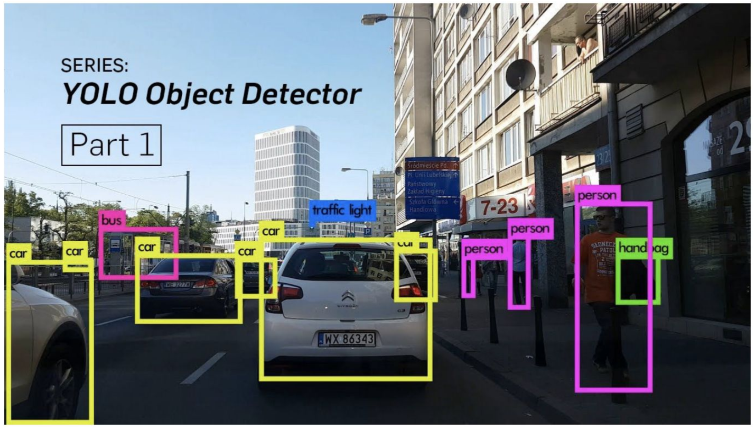
Radio Fingerprinting

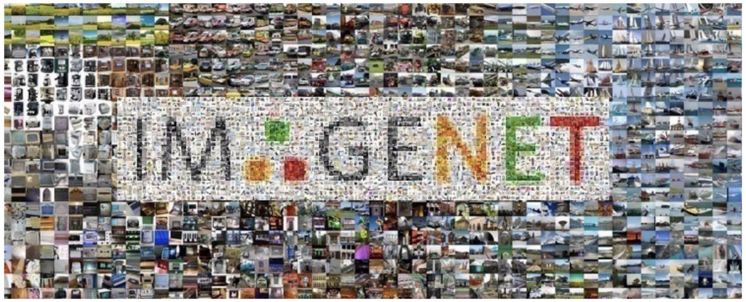
- Need for CNNs:
  - End-to-End feature interpreters -> protocol-independent

Radio Fingerprinting

- Need for CNNs:
  - End-to-End feature interpreters -> protocol-independent
  - Demonstrated performance record on numerous inference problems across application domains







upper right: NLP
lower right ImageNet
left: Object Detection

Challenges

- Features extracted by deep models cannot be easily interpreted!!!

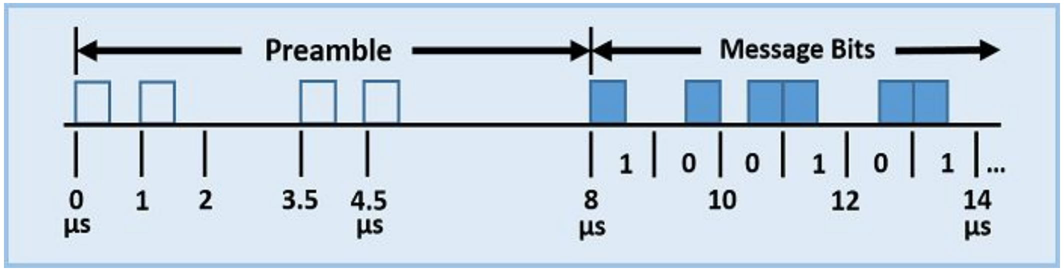
Indeed learns
unique **I/Q distortions**

OR

Simply picking up
artifacts present in the data

- Unfortunately, almost all transmissions contain a strongly discriminative artifact, **the identity of the transmitting device**, which is often included in a transmitted packet

ADS-B



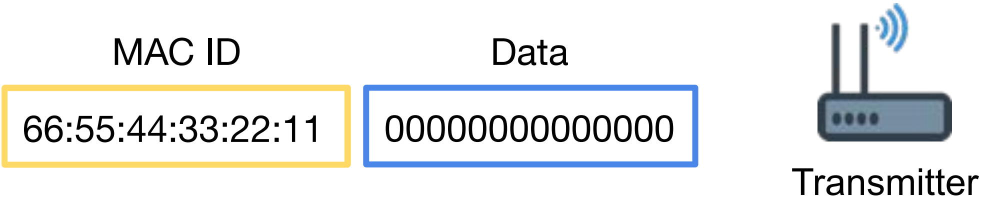
Source: https://www.mathworks.com/help/examples/xilinxzynqbasedradio_product/win64/zynqRadioHWSWADSBAD9361AD9364SL_ModeS_PPM.png

Challenges

- Features extracted by deep models cannot be easily interpreted!!!

Indeed learns unique **I/Q distortions** **OR** Simply picking up **artifacts** present in the data

- If latter…



Our Contributions

❏ Slicing technique

— makes the classifier **resistant** to learning **MAC IDs** as features

❏ Experiments on WiFi and ADS-B demonstrate slicing helps

— **100 %** -> **bitwise identical** transmissions by 19 devices

— **99.7%** -> **MAC ID** in the test set are shuffled

Overview

❑ Framework

❑ Experiments on WiFi protocol

❑ Experiments on ADS-B protocol

Overview

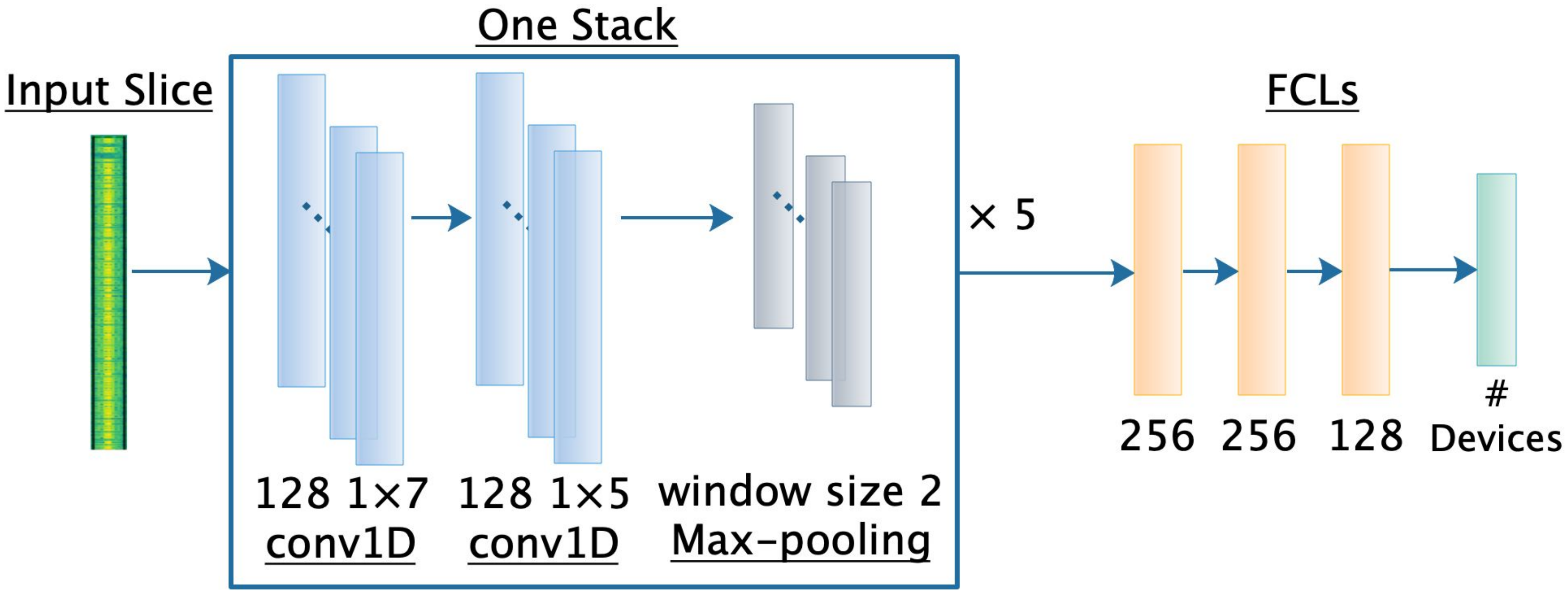
❑ Methodology

❑ Experiments on WiFi protocol

❑ Experiments on ADS-B protocol

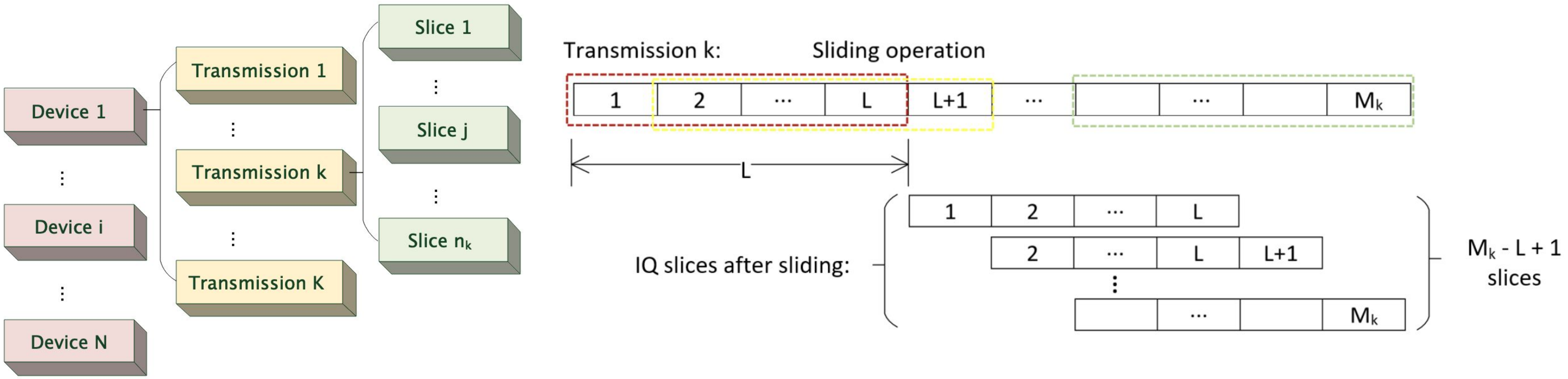
Methodology: Architecture

- CNN Architecture



Methodology: Slicing

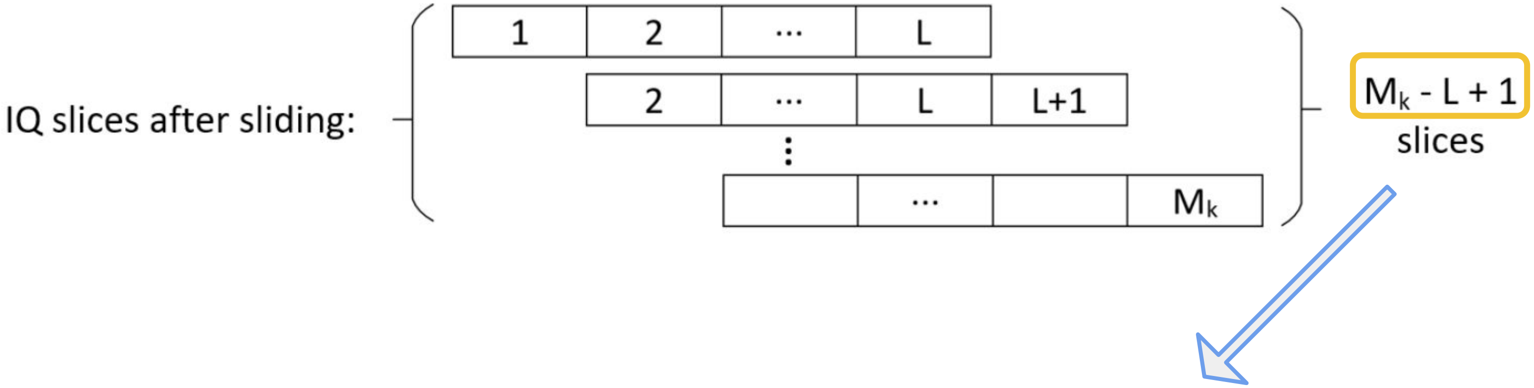
- Slicing [Riyaz et al]



*Riyaz, K. Sankhe, S. Ioannidis, and K. Chowdhury, “Deep learning convolutional neural networks for radio identification,” IEEE Communications Magazine, vol. 56, no. 9, pp. 146–152, 2018.

Methodology: Slicing

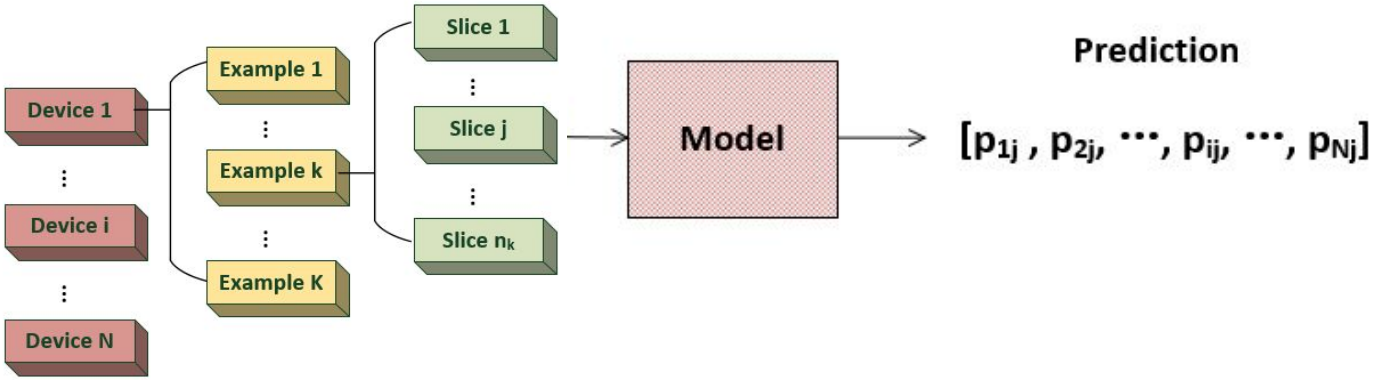
- Randomized slicing:



- For each transmission k, we sample $\boxed{n_k = \frac{M_k - L + 1}{L} \cdot \kappa}$ slices uniformly at random from all generated slices

Methodology: Testing

- We evaluate per-slice accuracy on test set
- We also evaluate per-transmission accuracy
  - Suppose there are N devices, and transmission k has n_k slices
  - p_{ij} is the probability of slice j classified as belonging to device i
    - Sum of probability over all slices: $\boxed{\hat{y} = \arg\max_i \sum_{j=1}^{n_k} p_{ij}}$



Methodology

- Advantages of randomized slicing:
  - satisfies the requirement of fixed-size input for CNNs
  - improves classifier’s ability to learn shift-invariant features
  - reduces computations during training

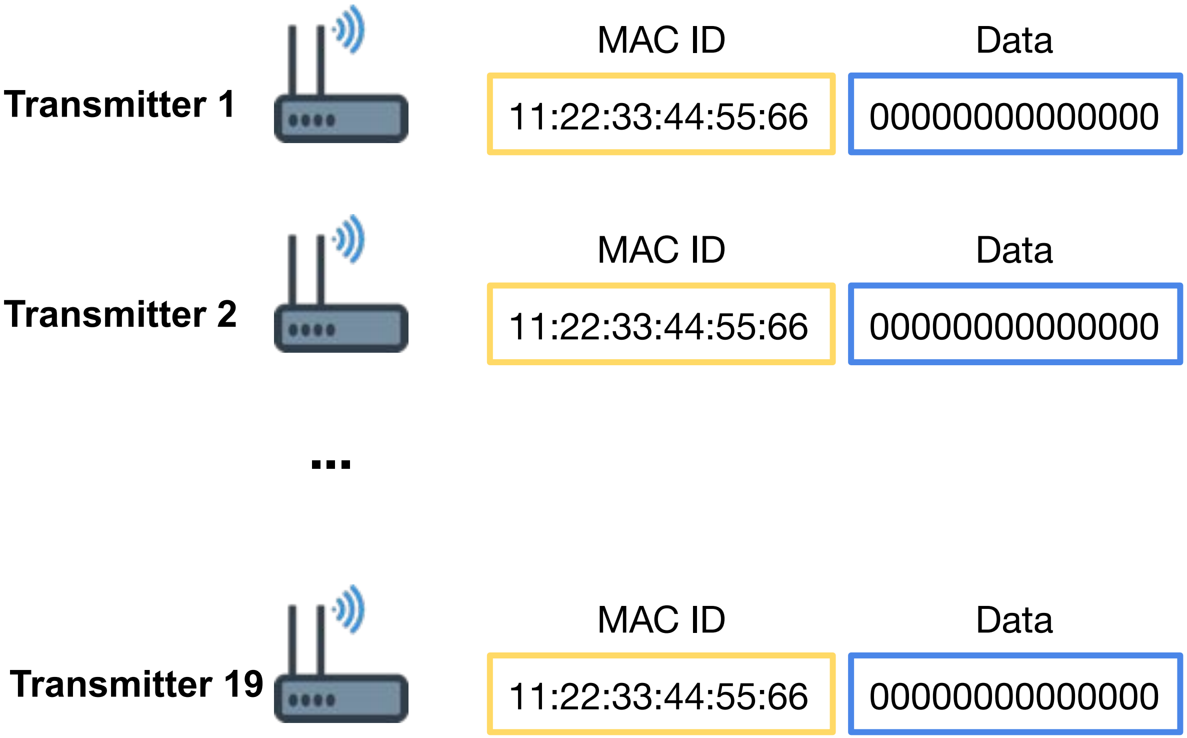
Overview

- ❑ Methodology
- ❑ Experiments on WiFi protocol
- ❑ Experiments on ADS-B protocol

Experiments on WiFi protocol

- Datasets:
  - Bitwise Identical WiFi:

    Bitwise identical WiFi transmissions by 19 devices.



Transmitter 1

MAC ID

11:22:33:44:55:66

Data

00000000000000

Transmitter 2

MAC ID

11:22:33:44:55:66

Data

00000000000000

...

Transmitter 19

MAC ID

11:22:33:44:55:66

Data

00000000000000

Experiments on WiFi protocol

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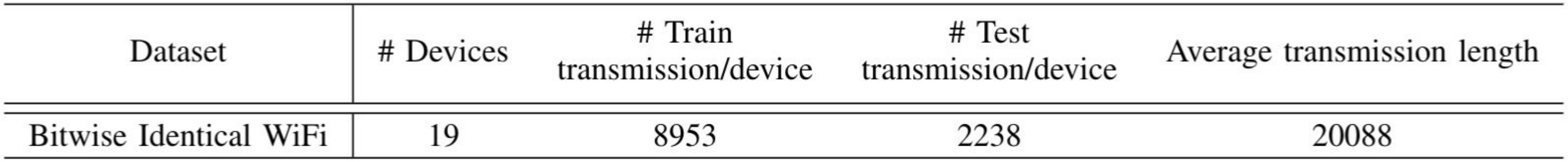
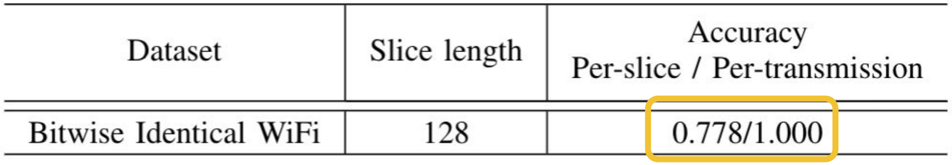
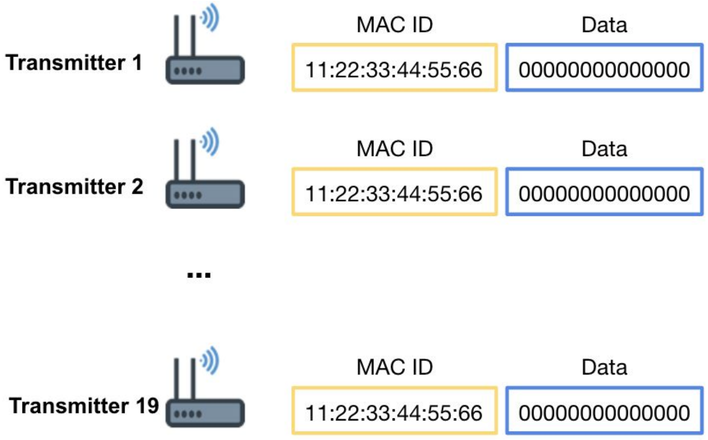


Dataset	# Devices	# Train transmission/device	# Test transmission/device	Average transmission length
Bitwise Identical WiFi	19	8953	2238	20088

- Results:



Dataset	Slice length	Accuracy Per-slice / Per-transmission
Bitwise Identical WiFi	128	0.778/1.000



Experiments on WiFi protocol

- Datasets:
  - Scrambled MAC WiFi:

    MAC IDs are randomly permuted among the signals in the test set.

	Training Set		Test Set	
	MAC ID	Data	MAC ID	Data
Transmitter 1	11:11:11	asdlkn2p	22:22:22	2ejrnlfddf
	11:11:11	23oidfkjn	33:33:33	dfaldkflkd
Transmitter 2	22:22:22	130df093	33:33:33	huhuhuhu
	22:22:22	2odfoiejo	11:11:11	omomom
Transmitter 3	33:33:33	asasasas	33:33:33	qdfqfqdq
	33:33:33	vcvcvcvc	11:11:11	bhbhbhb

Experiments on WiFi protocol

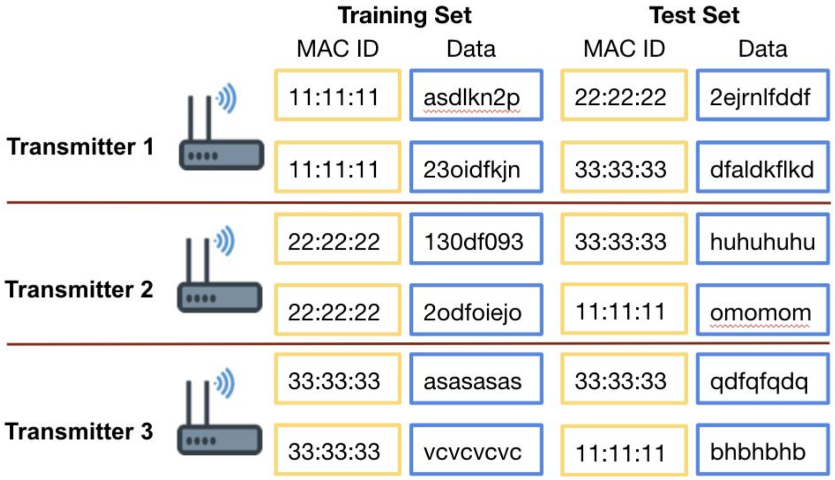
- Datasets:
  - Scrambled MAC WiFi:

    MAC IDs are randomly permuted among the signals in the test set.

Dataset	# Devices	# Train transmission/device	# Test transmission/device	Average transmission length
Scrambled MAC WiFi	100	1000	1000	45183

- Results:

Dataset	Slice length	Accuracy Per-slice / Per-transmission
Scrambled MAC WiFi	1024	0.972/0.997



	Training Set		Test Set	
	MAC ID	Data	MAC ID	Data
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	11:11:11	23oidfkjn	33:33:33	dfaldkflkd
Transmitter 2	22:22:22	130df093	33:33:33	huhuhuhu
	22:22:22	2odfoiejo	11:11:11	omomom
Transmitter 3	33:33:33	asasasas	33:33:33	qdfqfqdq
	33:33:33	vcvcvcvc	11:11:11	bhbhbhb

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- ❑ Methodology
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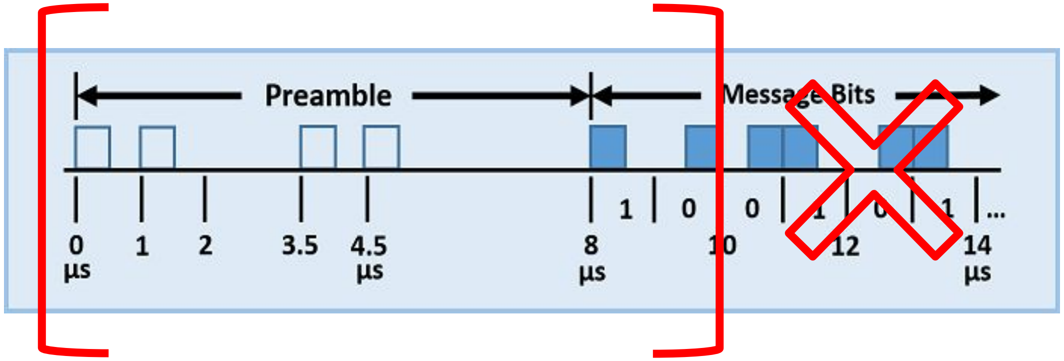
- ❑ Experiments on ADS-B protocol

Experiments on ADS-B protocol

- Datasets:

Dataset	# Devices	# Train transmission/device	# Test transmission/device	Average transmission length
ADS-B	50	141	55	9519



Crop

Experiments on ADS-B protocol

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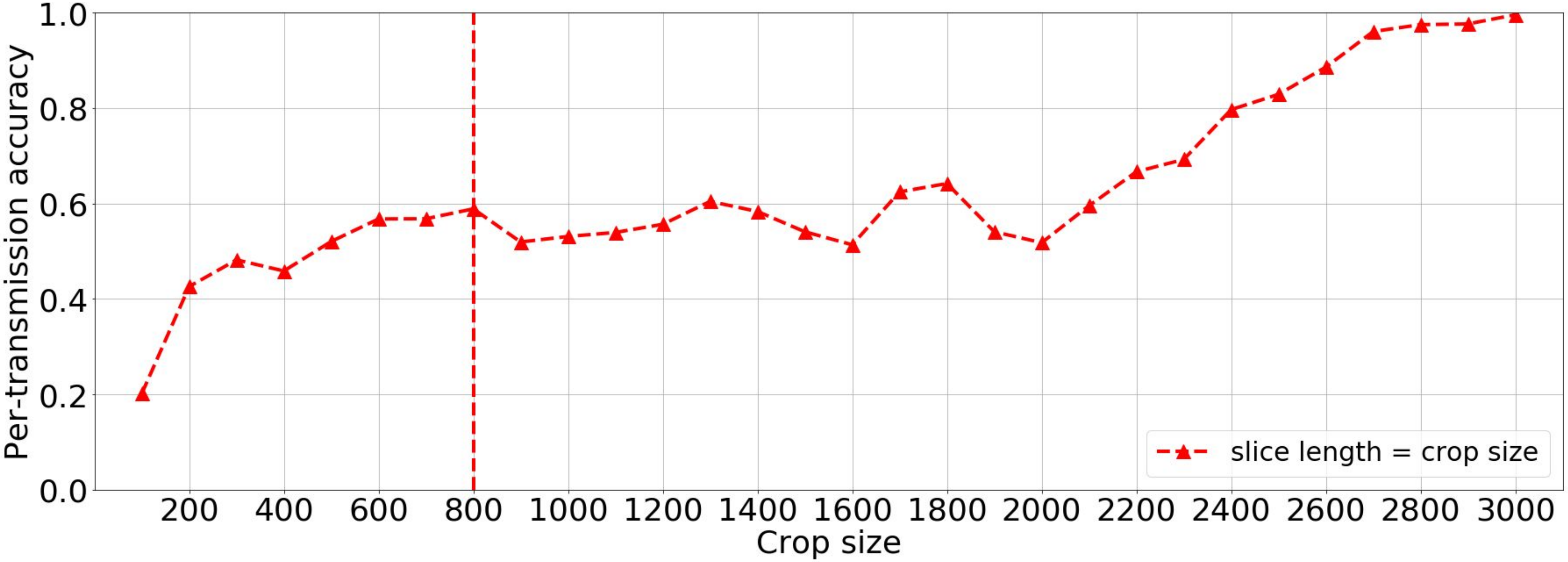

Fig. Test Accuracy without Slicing

Experiments on ADS-B protocol

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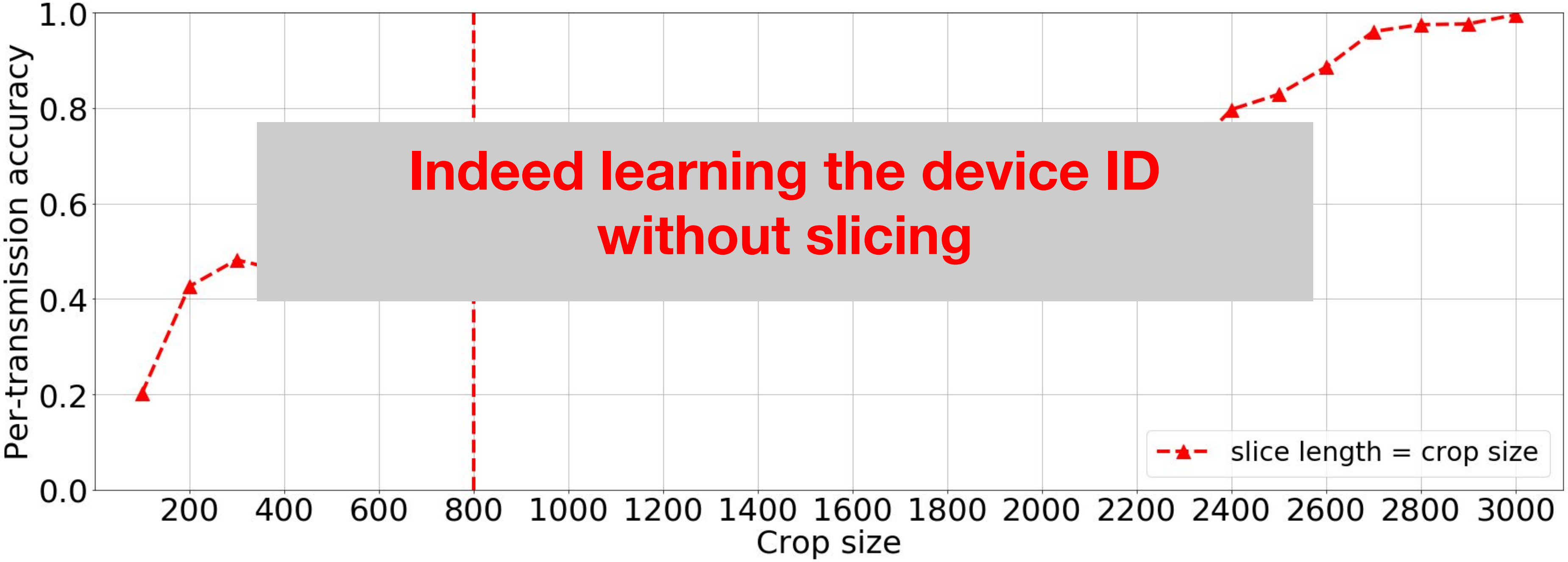

Indeed learning the device ID without slicing

Fig. Test Accuracy without Slicing

Experiments on ADS-B protocol

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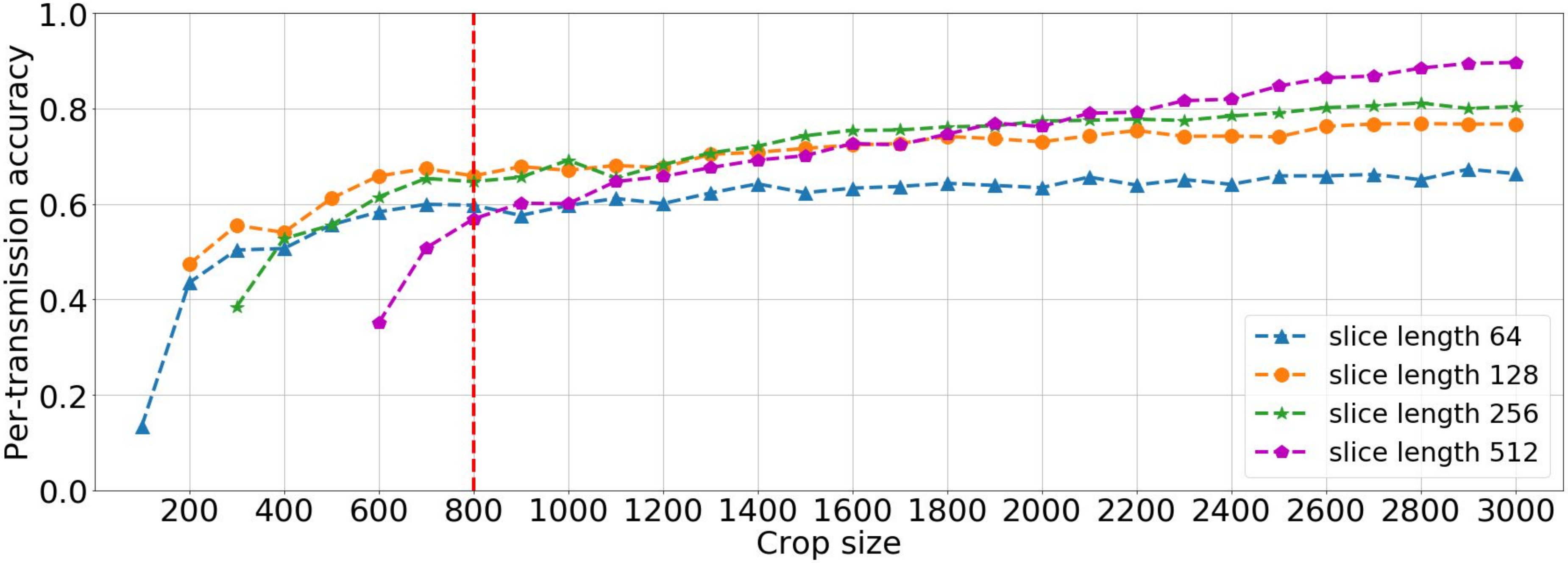

Fig. Test Accuracy with Slicing

Summary & Future Directions

❑ Classifying transmission slices
- enhances **shift-invariance**
- MAC ID spoofing-resistant
- experiments on WiFi and ADS-B protocols.

❑ We are working on...
- classification over >10K transmitters
- beating channel variations

рахмат
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謝謝
ngiyabonga
شكراً جزيلاً
Баярлалаа
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