

# Synchronization and Deep Learning: Experiences Learned from Dataset Creation

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# Summary

- 1 Context
- 2 Dataset Generation
- 3 Learning and Classifying
- 4 The Problem, The Analysis and The Solution
- 5 Results
- 6 Conclusion

# Context

## PhD work of Cyrille Morin

- Main topic: on Deep Learning for radio
- Specific work: transmitter identification through radio fingerprinting
- Two objectives:
  - Construct a “good” dataset with Cognitive Radio Testbed (FIT/CorteXlab)
  - Test Deep Learning Convolutional Neural Network (CNN) models to fingerprint

## Disclaimer!!

- Deep Learning for Radio  $\Rightarrow$  Not the holy grail!
- Choose your problems:
  - Many problems in communications have well behaved closed form solutions  
 $\Rightarrow$  no need for DL
  - Some problems are too difficult to model, or models are too complex or current tools are not adaptive  
 $\Rightarrow$  DL may help

# Transmitter Fingerprinting with Deep Learning

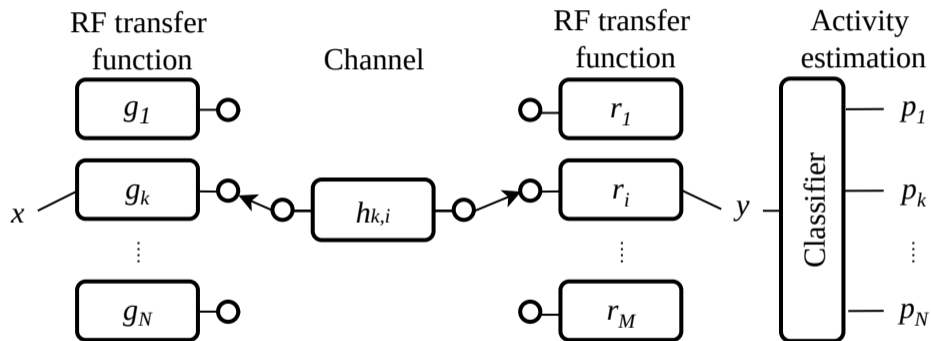
## What is radio fingerprinting?

- Using the radio unique characteristics of the transmitters to tell them apart
- Radio's version of recognising the "voice" of familiar people on the phone
- Achieve radio identification in spite of the ID fields of packets!

## Why do radio fingerprinting?

- IoT/small packet context
  - IoT based sensor networks: payload is of the same order of size as headers
  - High cost of header w.r.t. payload (energy and medium access)
  - Potential gains with TX identification based on radio fingerprinting
- Security/privacy context
  - Make ID spoofing harder :)
  - Enable ID-field validation :)
  - Track individual radios even if address is randomised :(





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### Base band

- Implementations of digital filters
- processing delays, jitter
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### Radio Frequency

- RF filter characteristics, RF amplifiers
- Local oscillator frequency offset, jitter, noise
- ...

## (Identifiable) Radio Characteristics

### From Prior art

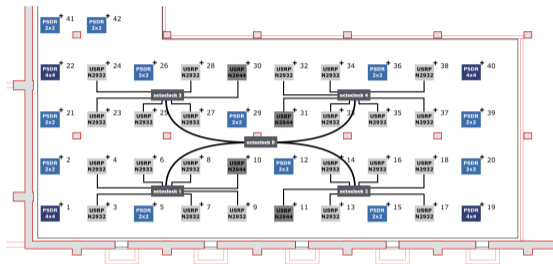
- Channel effects [**Xiao2009**] [**Xiao2009a**]
  - Channel effects dominate over RF signature
  - Identification is restricted to propagation features: not robust
- Power amplifier characteristics [**Sankhe2018**] and [**Wong2018**] [**Hanna2018**]
  - Artificially manipulate the TX signals to exploit different characteristics
  - Easy to impersonate
- Local oscillator imperfections [**Hanna2018**]

# Objectives

## The task at hand

- Identify 21 transmitters using an IoT like signal (USRP N2932 - *equiv. N210 with SBX*)
- Use only raw IQ samples
- No channel equalization
- Produce a correctly labelled dataset devoid of channel bias (as much as we can)
- Test learning and generalisation ability

# FIT/CorteXlab



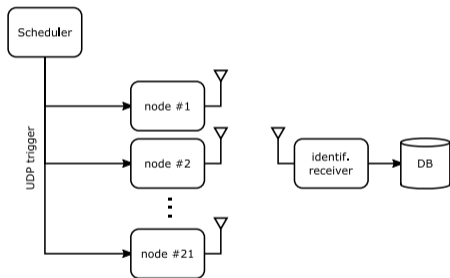
## Characteristics

- Total of 42 radio nodes among USRPs N2932 and N2944R, PicoSDRs 2x2 and 4x4, Octoclocks for synchronization (USRPs only)
- Fully electromagnetically isolated and semi-anechoised experimentation room (at least 60 dB of isolation)
- Robots for radio mobility
- Remote access operation, 100% automated experiment deployment

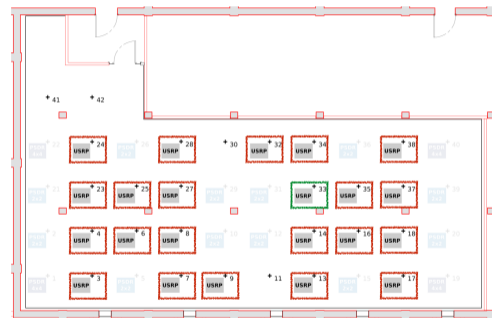
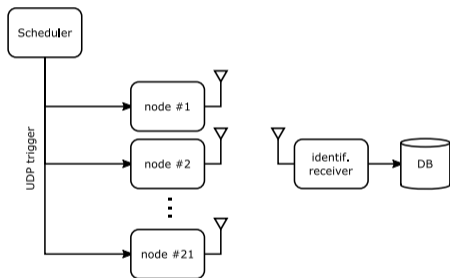
# Dataset Generation



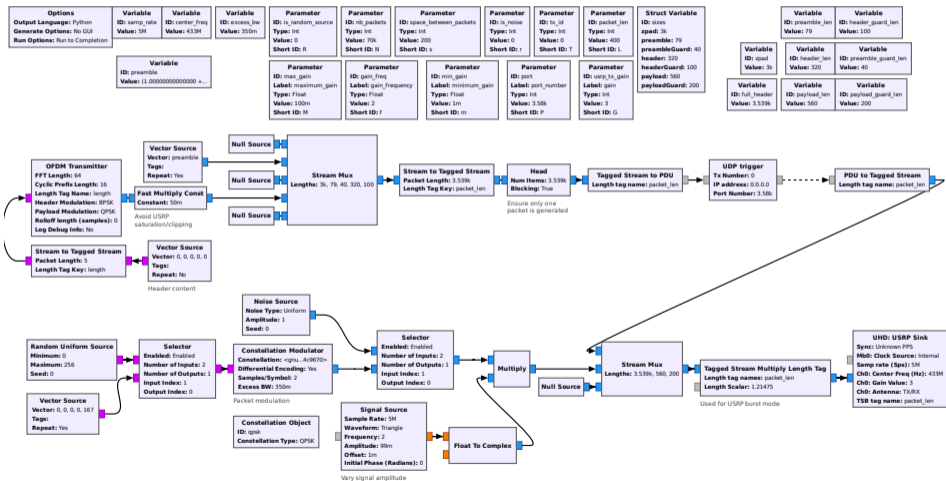
# Overall structure



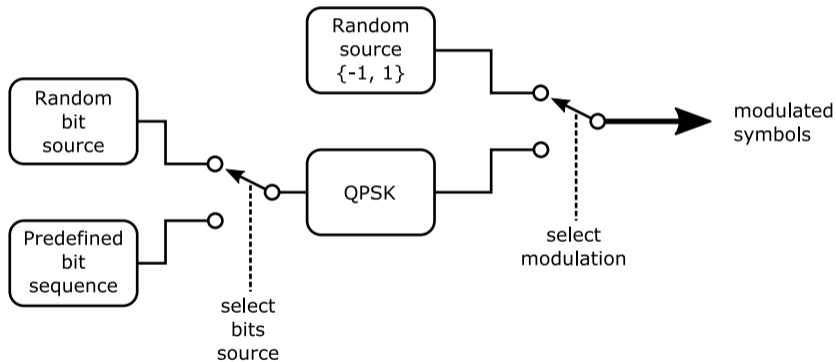
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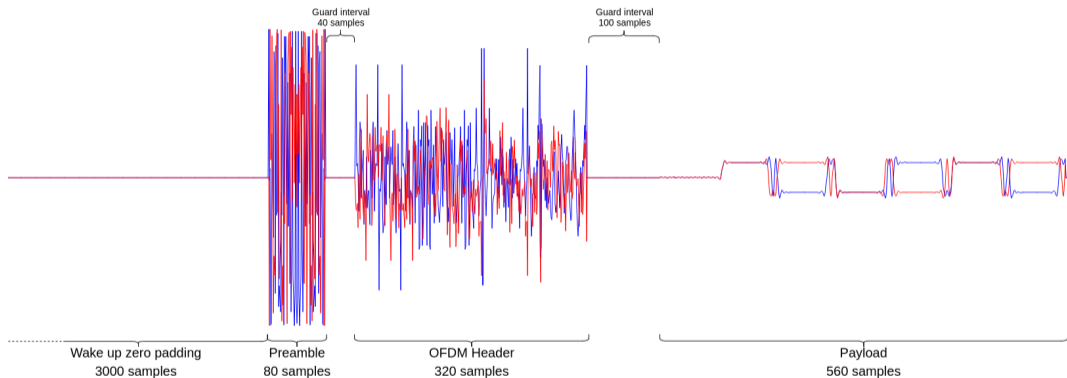
# Transmission



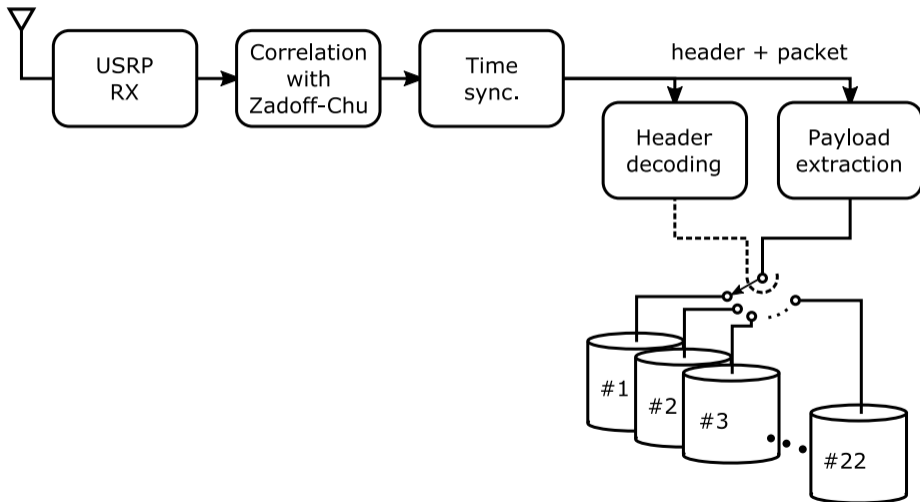
## Payload selection



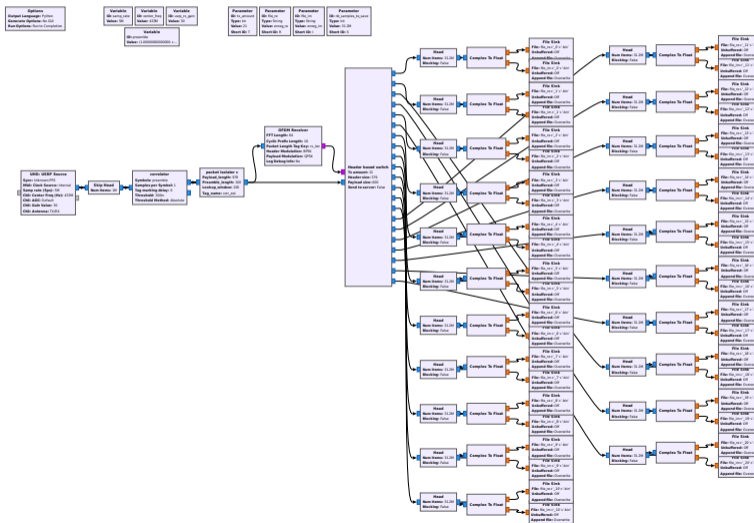
# Frame



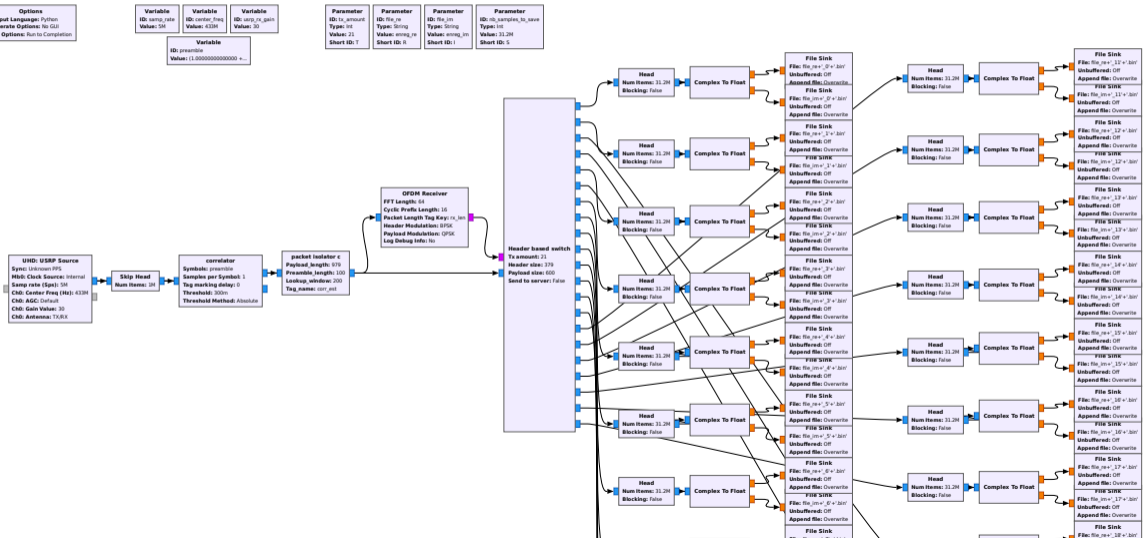
## Reception and Labeling (Simplified)



## Reception and Labeling



# Reception and Labeling (zoom)





# Learning and Classifying

# Classification

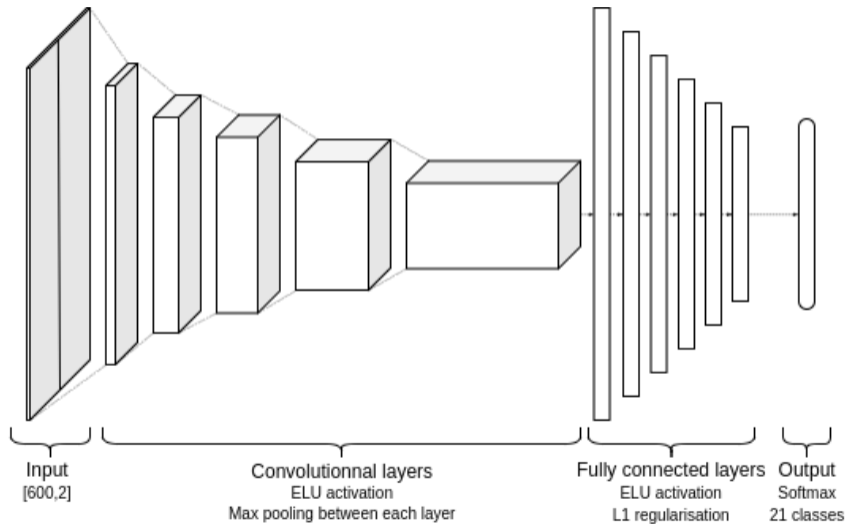
## Classifier and data

- Gold standard classifiers for fingerprinting: Convolutional Neural Networks (CNN)
- Used mainly for image recognition, due to its feature extraction capabilities
- Raw packet (600 samples) is used to construct an “image”
- Complex samples  $\Rightarrow$ 
  - Real part is encoded in first column
  - Imag part is encoded in second column
  - Rows are each sample of the packet
- $2 \times N_{\text{samples}}$  “image”

## Data handling

- $50000 \times 21 = 1050000$  examples in one dataset
- Dataset examples split in 70% training, 10% validation and 20% test sets

# Neural network architecture

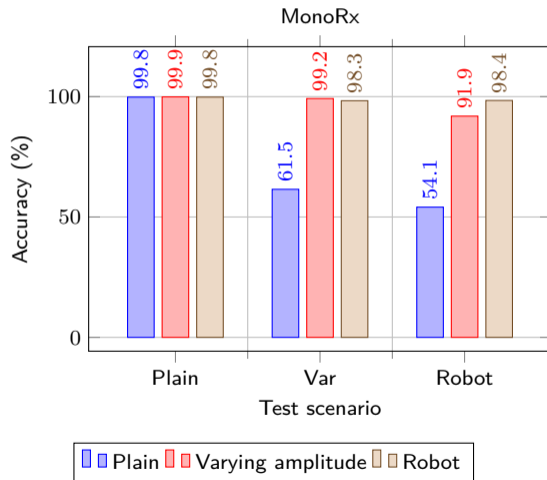


## Training and testing process

### Training process

- Offline - on a GPU server connected to FIT/CorteXlab
- 128 examples per batch
- More than 30 training epochs

# Generalisation capabilities



Moving to multi-RX: three months of misery...

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## Problem

- Multi-RX datasets gave very poor performance!

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SingleRX tests, but this time done over more RXs

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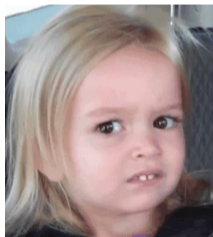
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- Exchange USRP devices that do not generalise  $\Rightarrow$  some replacements work, some others don't
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## Facts

- Before starting the MultiRX tests the octoclocks were installed
- We turned on "external reference clock" on the basis of "it can not hurt to be synchronized"

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Disable "external reference clock" and repeat the generalisation tests ⇒

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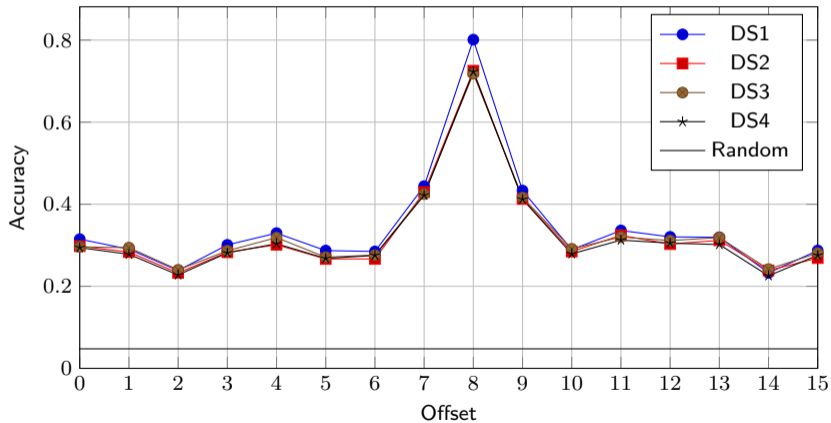
## Final explanation

- The signal used to train is always sampled at the same rate (2 samples/syms) at the RX, but with:
  - A random initial sampling time for each transmission for unsynchronised nodes
  - A fixed and *constant* initial sampling time for each transmission for synchronized nodes
- Which essentially means:
  - A random initial sampling time for each transmission  
⇒ CNN learns to "ignore" sampling differences
  - A fixed and constant initial sampling time for each transmission  
⇒ CNN learns one sampling and can not generalise to another sampling time

Let's dig deeper...

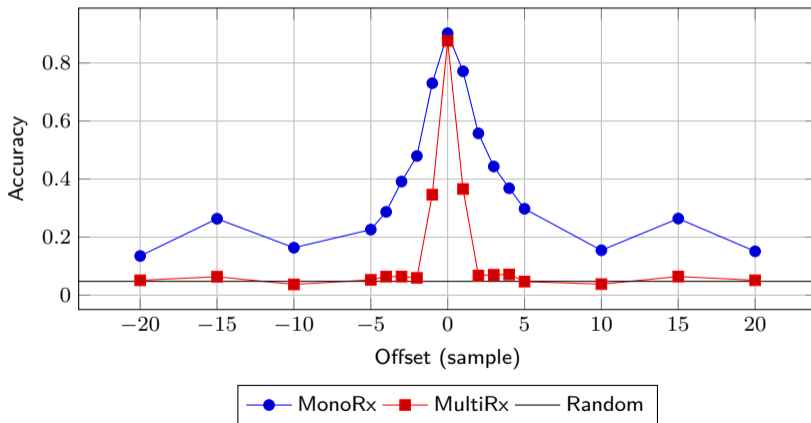
# Sample time synchronisation

Accuracy over sampling time offset (upsampling  $\times 8$ )



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Accuracy over sample synchronisation offset (upsampling  $\times 8$ )



Synced radio	Tx	Both	Rx	None
Tx	81.2%	34.5%	19.2%	38.3%
Both	54.4%	45.6%	38.2%	38.2%
Rx	21.1%	28.5%	80.2%	22.3%
None	41.3%	43.8%	34.6%	81.1%

**Table:** Accuracy of networks trained on one synchronisation possibility and tested on the others

# Conclusion

## Takeaways

- Creating datasets for training DL for radio (or anything else) can be hard
- Seemingly innocuous parameters and settings can completely derail your DL system
- Datasets with raw I-Q samples: always check your clock source on UHD
  - Using PPS to synchronise time is probably OK
  - Using the 10 MHz REF signal to synchronise clock references should be carefully studied in your specific case
- Keep a logbook of important changes to your platforms if you're changing them while experimenting

## If you want to explore further

- Full paper is online at: <https://hal.inria.fr/hal-03117090/>
- Datasets online at: <https://wiki.cortexlab.fr/doku.php?id=tx-id>
- FIT/CorteXlab wiki page: <https://wiki.cortexlab.fr>
- Next publication on this is coming soon...