Leveraging Machine Learning for Spectrum Sharing in Wireless Networks

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Leveraging Machine Learning for Spectrum Sharing in Wireless Networks

- Motivation for spectrum sharing
- Challenges for spectrum sharing

Leveraging Machine Learning for Spectrum Sharing in Wireless Networks

- Motivation for spectrum sharing
- Challenges for spectrum sharing

- Three examples from the literature
- Open challenges and conclusions

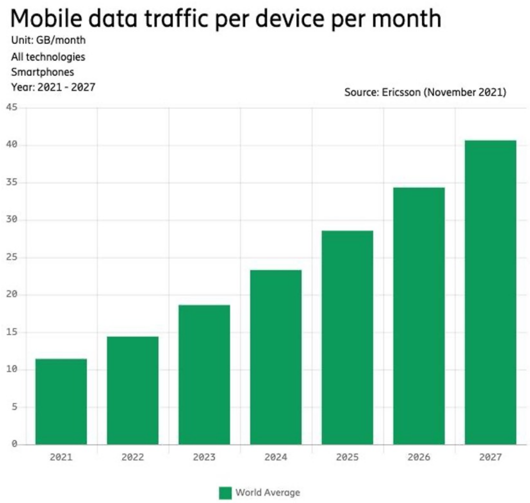
Sharing is caring ….

More environment-friendly, cost-effective, …

Sharing is caring ….

And also needed for higher spectrum utilization efficiency!

Sharing is needed for meeting the wireless demand

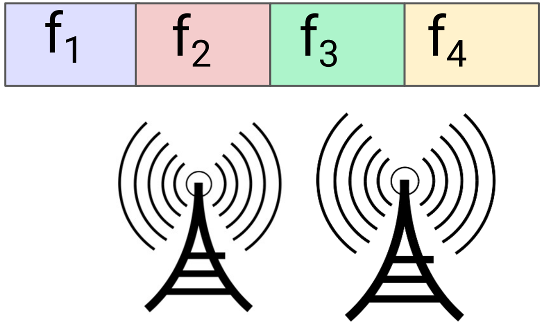


Source: https://www.ericsson.com/en/reports-and-papers/mobility-report/mobility-visualizer

And also needed for higher spectrum utilization efficiency!

Today's approach: static spectrum management

nearly a century old!

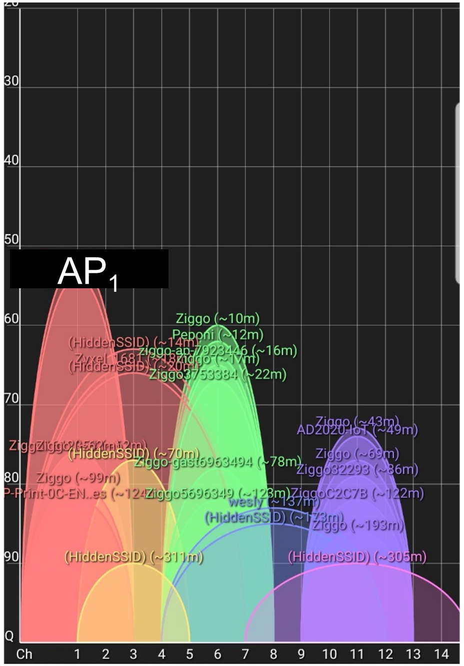


- Licensed bands:
  - isolate wireless systems by assigning them to different frequencies
  - long terms, wide regions (country-wide)
  - guarantee of interference-free communication
  - not adaptive to the dynamics of supply and demand, unnecessarily creating *spectrum scarcity*

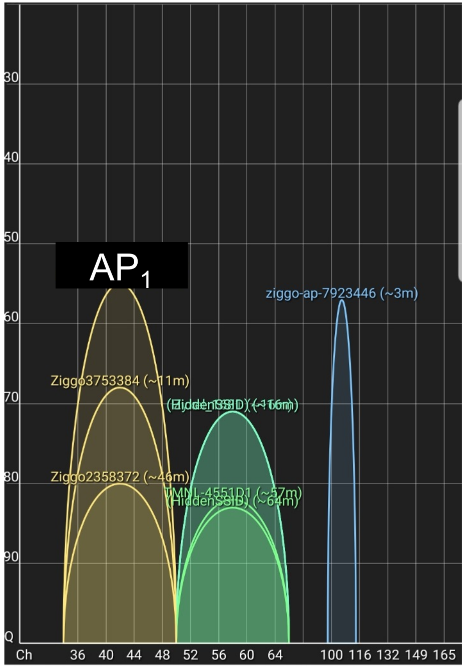
https://www.darpa.mil/program/spectrum-collaboration-challenge

A success story: Wi-Fi

2.4 GHz



5 GHz



2.4 GHz (ISM)

5 GHz (UNII)

6 GHz

60 GHz

Spectrum sharing works for Wi-Fi!

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If it works for Wi-Fi, what is the challenge in sharing spectrum?

If it works for Wi-Fi, what is the challenge in sharing spectrum?

- growing complexity in hardware, access technologies, configurations
- unlike Wi-Fi, traditional cellular networks are not designed to operate in spectrum-sharing mode
- heterogeneity of networks (e.g., power asymmetry, no communication*/coordination among networks)
- *fair/peaceful* coexistence for different traffic types (e.g., URLLC, eMBB)

- Verónica Toro-Betancur, Suzan Bayhan, Piotr Gawlowicz, Mario Di Francesco, *CTC-CEM: Low-Latency Cross-Technology Channel Establishment with Multiple Nodes*, IEEE WoWMoM 2020
- Piotr Gawlowicz, Anatolij Zubow, Suzan Bayhan, Adam Wolisz, *Punched Cards over the Air: CTC Between LTE-U/LAA and WiFi*, IEEE WoWMoM 2020
- Piotr Gawlowicz, Anatolij Zubow, Suzan Bayhan, *Demo: Cross-Technology Communication between LTE-U/LAA and WiFi*, IEEE INFOCOM 2020
- Anatolij Zubow, Piotr Gawłowicz, Suzan Bayhan, *Deep Learning for Cross-Technology Communication Design*, arxiv, 2019

Challenges

Spectrum opportunity discovery

Spectrum access & mobility

- Accurately identifying the state of the spectrum by spectrum sensing: *how*, *when*, *where* to perform sensing and decide on the spectrum state
- Selecting the best transmission parameters for *peaceful* and *fair* coexistence, e.g., proactive approaches predicting the channel conditions
- Identifying the spectrum misuse for regulatory enforcement

(How) can ML help?

(How) can ML help?

- When model-driven approaches
  - fall short of reflecting accurately the physical processes
  - have prohibitive run-time complexity: usually NP-hard problems

- ML: can capture complex interactions between different layers, growing complexity of technologies (e.g., Wi-Fi, LTE, NB-IoT, 5G-NR), patterns in spectrum usage, channel characteristics

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(How) can ML help?

- RL for trial and error: spectrum access and accumulated reward
- CNNs for image analysis: spectrum measurement in 2D is considered as an image
- RNNs for time-series forecasting problems: spectrum occupancy as sequential data

- IEEE Comsoc's Best Readings in Machine Learning in Communications: https://mlc.committees.comsoc.org/research-library
- IEEE Comsoc Cognitive Networks Technical Committee https://cn.committees.comsoc.org/

ML approaches in the spectrum sharing context

- Example-1: Spectrum awareness
- Example-2: Multiple transmitter localization
- Example-3: Modulation classification at the edge

Regulatory bodies and network operators need spectrum awareness

- to understand its utilization level and usage patterns, and improve efficiency accordingly
  - Spatio-temporal characteristics of the spectrum usage (short and long-term)

- for misuse identification and spectrum enforcement
  - Who uses the spectrum? Authorized transmitters or misuse of the spectrum?
    - Advances in both reconfigurable hardware and spectrum usage policies make it easy to misuse spectrum without authorization
    - Transmissions at unexpected power levels, misconfigured devices
  - Fair coexistence or not?

Real-time analysis and prediction

Long-term trends

Near-real-time identification

Non-real-time big data analysis

DNNs for spectrum anomaly detection

- Manual diagnosis following customer complaints and operational failure logs

Scaling Deep Learning Models for Spectrum Anomaly Detection

Zhijing Li+, Zhujun Xiao, Bolun Wang+, Ben Y. Zhao and Haitao Zheng
University of Chicago, +University of California, Santa Barbara

ABSTRACT

Spectrum management in cellular networks is a challenging task that will only increase in difficulty as complexity grows in hardware, configurations, and new access technology (*e.g.* LTE for IoT devices). Wireless providers need robust and flexible tools to monitor and detect faults and misbehavior in physical spectrum usage, and to deploy them at scale. In this paper, we explore the design of such a system by building deep neural network (DNN) models[1] to capture spectrum usage patterns and use them as baselines to detect spectrum usage anomalies resulting from faults and misuse. Using detailed LTE spectrum measurements, we show that the key challenge facing this design is model scalability, *i.e.* how to train and deploy DNN models at a large number of static and mobile observers located throughout the network. We address this challenge by building context-agnostic models for spectrum usage and applying transfer learning to minimize training time and dataset constraints. The end result is a practical DNN model that can be easily

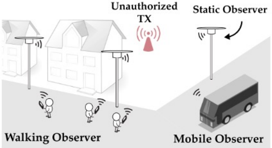

Figure 1: Spectrum anomaly detection by multiple observers.

leakage from cable plants and connectors. For example, interference from a misconfigured amplifier led to persistent quality-of-service issues for a tier 1 service provider [39].

These problems will grow in severity and scale in the near future. Advances in both reconfigurable hardware and spectrum usage policies make it easy to misuse spectrum without authorization. There is already evidence of these misuse attacks in China,

Li, Zhijing, et al. *Scaling Deep Learning Models for Spectrum Anomaly Detection.* ACM MobiHoc 2019. Code: https://github.com/0x10cxR1/spectrum_anomaly_detection/ Figures on the following slides are from the paper.

DNNs for spectrum anomaly detection

- Manual diagnosis following customer complaints and operational failure logs

- **Proposal**: Use sensors scattered in the network and use the identified patterns via DNNs as baselines to detect spectrum usage anomalies resulting from faults and misuse: **on-the-spot identification of an anomaly**

- **Challenge:** Location of the sensor, mobility profile, time are relevant. But, training at each location, at each LTE cell and band: not scalable!

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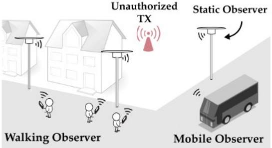
Edge!



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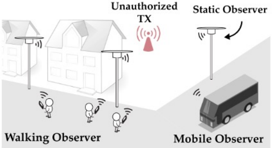

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Edge!

Solution: Context-agnostic models for spectrum usage and applying transfer learning to minimize training time and dataset constraints

Approach: Training

Given past time-frequency spectrum raw data for *x time units (in the absence of anomalies)*

Mixture of static and mobile users' data (in the same cell)

DNN model training (LSTM/autoencoder)

Next *y time units* of the spectrum data

RMSE between the **ground truth signal** and LSTM model **prediction values**

Approach: Detection

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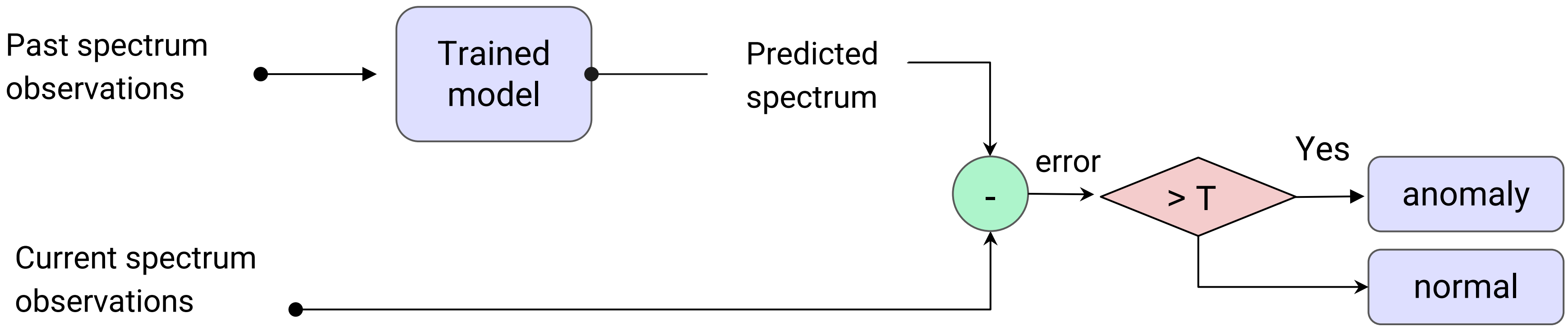


If divergence from the prediction above some threshold T: Anomaly

Does removing context-awareness decrease the accuracy of DNNs (false alarms and correct detection)?

Scalable DNN: *context-agnostic* and transfer learning

- Data: 3 LTE MNOs in U.S January-March and June 2018
- USRP N210 devices, sensing on 5 MHz bandwidth of each LTE band
- Static, walking, driving
- Large university campus and downtown
- Day and night
- Controlled misuse scenario: unauthorized transmitters and observers within 50m of the misuser
- LSTM and deep autoencoder as DNN models

- Accuracy of models trained on data collected by a static observer when used by another static observer at a different location and another mobile observer in the same cell

- Accuracy of using Cell-A’s model in Cell-B (with and without transfer learning)

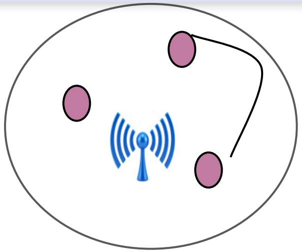
- Accuracy of using band-1’s model in band-2

Key take-away:

- For scalable, accurate identification of spectrum anomalies at the edge, context-agnostic DNNs (LSTM and deep autoencoders) with transfer learning can help.

3 key findings:

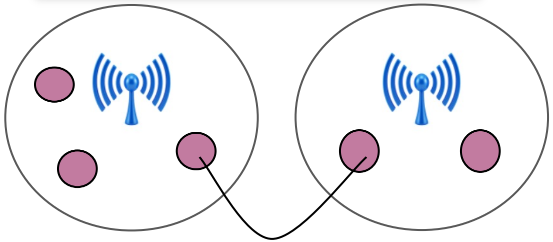
Within a single LTE cell



A unified model for an LTE cell

Comparison with other approaches (e.g., rule-based, Kalman Filter), DNN outperforms!

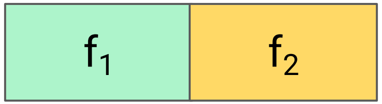
Across LTE cells



Transfer learning needed for other cells

Small training data at the target cell: training data reduction by 288x compared to training from scratch

Across different frequency bands



Transfer learning needed for other spectrum bands (frequency, UL/DL) but more changes in the transfer phase

DL to UL transfer is challenging

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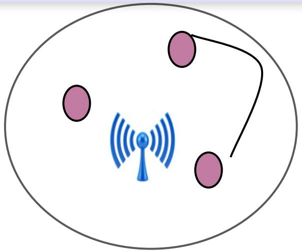

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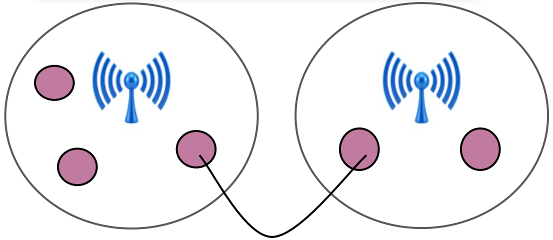
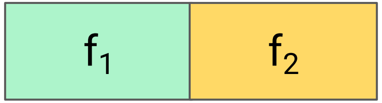


Across different frequency bands

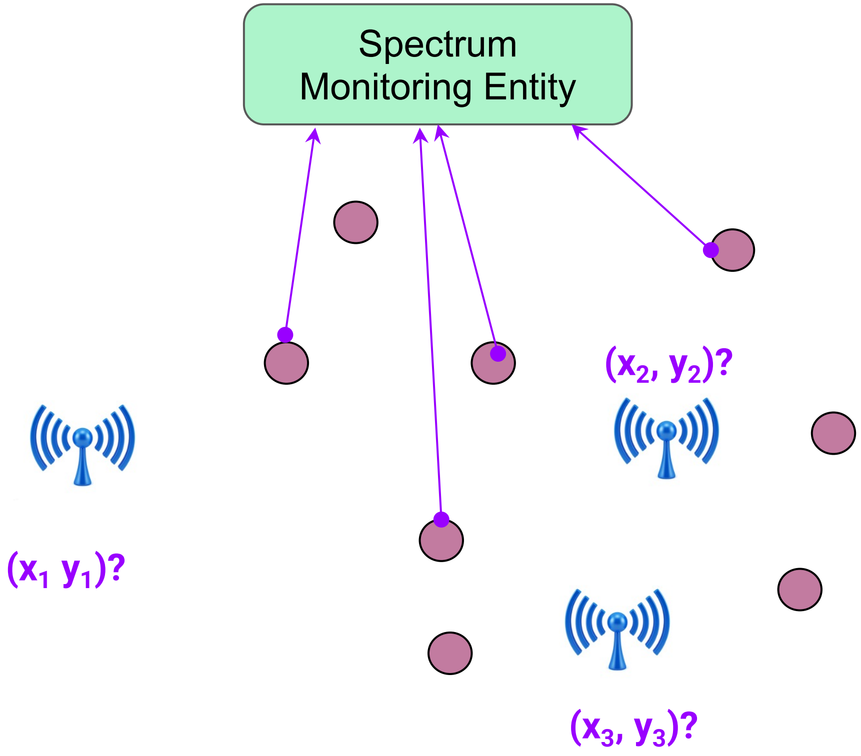


Please see the details in the paper: Li, Zhijing, et al. *Scaling Deep Learning Models for Spectrum Anomaly Detection.* ACM MobiHoc 2019. Code: https://github.com/0x10cxR1/spectrum_anomaly_detection/

ML approaches in the spectrum sharing context

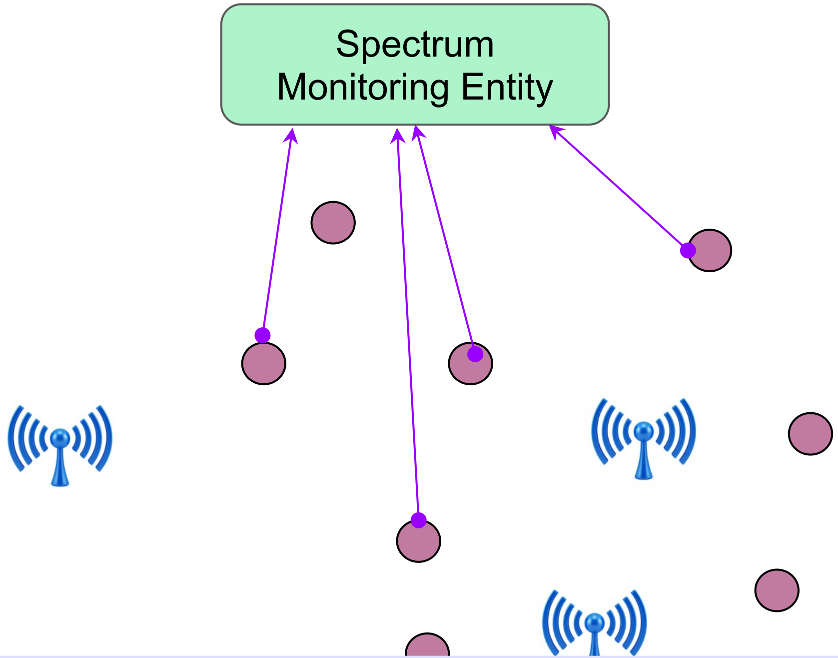
- Spectrum awareness
- Multiple transmitter localization
- Modulation classification at the edge

Problem: Multiple transmitter localization (MTL)



- Goal: Identify the locations (x, y) of transmitters
- Regulatory body: Legitimate or illegitimate transmitter, security threats on shared spectrum bands (selfish transmitters, jammers etc.)
- Mobile network operator: Any misuser or better strategizing for spectrum sharing

Problem: Multiple transmitter localization (MTL)



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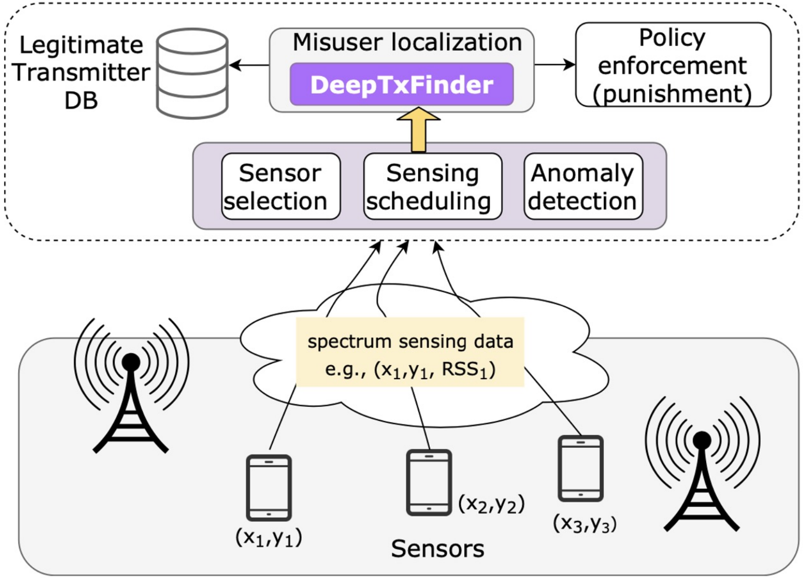
- Mobile network operator: Any

Challenge: Multiple transmitters, multiple transmission power levels, channel variations! The sensors receive a sum of the signals.

DeepTxFinder*: CNNs for MTL

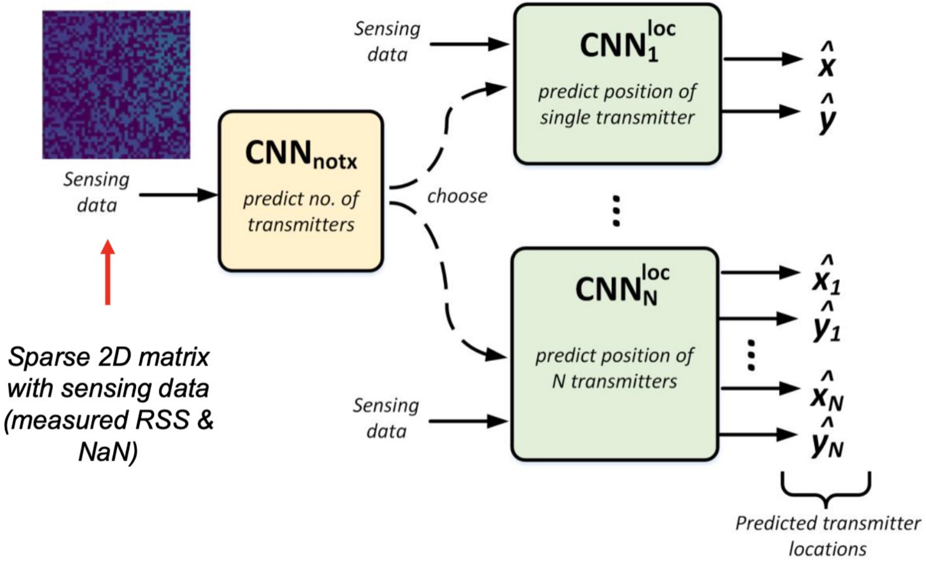
- Unknown number of transmitters
- Two transmitters closely located can be identified
- Scalability via tile-based operation
- Goal: low false alarm rate for avoiding waste of expert time

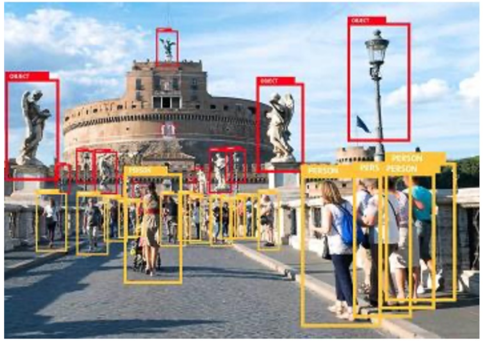


*Zubow, A., Bayhan, S., Gawłowicz, P., & Dressler, F. Deeptxfinder: Multiple transmitter localization by deep learning in crowdsourced spectrum sensing. IEEE ICCCN, 2020 (invited paper)

Two-step CNN approach

- Step-1: CNN detects the number of transmitters
- Step-2: CNN estimates actual 2D locations of *that* many transmitters





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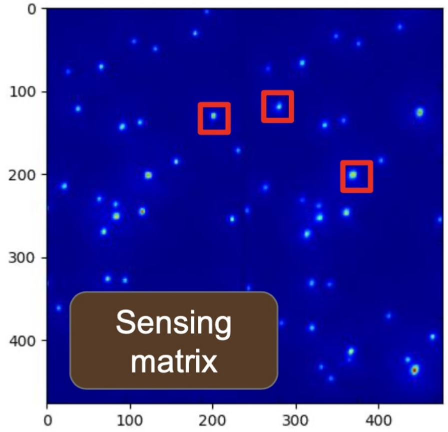

Scalability is a challenge: tiling-based approach

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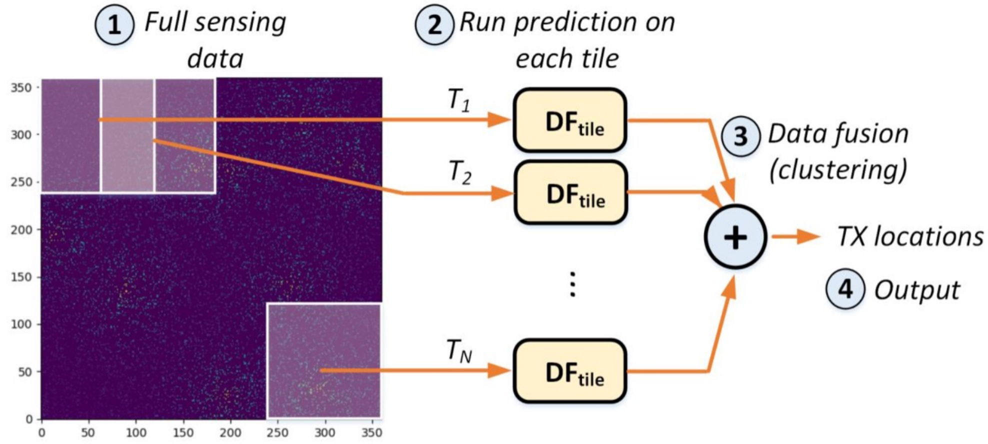
- Area of interest is divided into smaller uniform tiles,
- Run prediction on each tile
- Fuse the individual predictions from multiple tiles using majority voting to derive the final set of predicted locations



Performance assessment

- Model training
  - On artificial data generated by the simulator, simple pathloss model

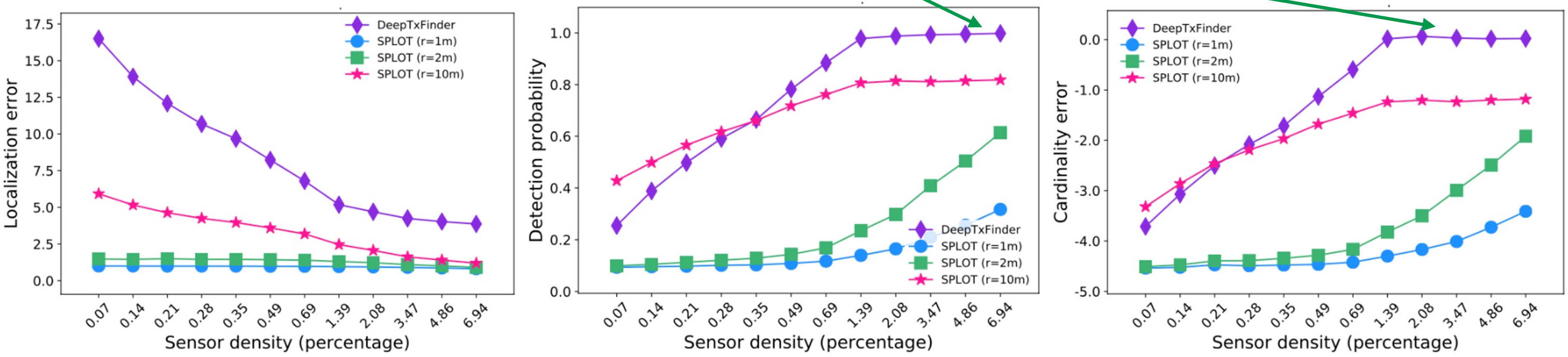
- Metrics:
  - Localization error, cardinality error, detection probability, false alarm, execution time
- Baseline: SPLOT*
  - Breaks down multiple-transmitter-localization to several single-transmitter localization problems
  - Three variants with different threshold value *r* used for finding the local maximas
- Scenarios:
  - S1 = no shadowing & known Ptx,
  - S2 = shadowing & known Ptx
  - S3 = shadowing & unknown Ptx

- Impact of sensor density
- Impact of field size on execution time

* M. Khaledi, et al., Simultaneous power-based localization of transmitters for crowdsourced spectrum monitoring, ACM MobiCom 2017 [SPLOT]

Key take-away

- Even under sparse sensor deployment, transmitter locations can be identified
- DeepTxFinder identifies all transmitters, but with lower location inaccuracy!



(a) Localization error. (b) Detection probability. (c) Cardinality error.

Figure 5. Scenario I: Performance comparison of SPLOT and DeepTxFinder under no shadowing and constant TX power.

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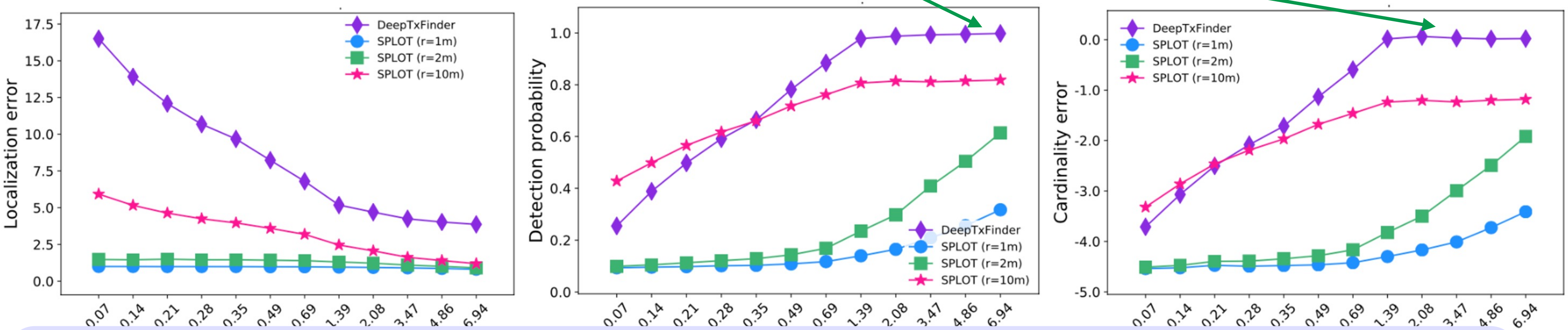

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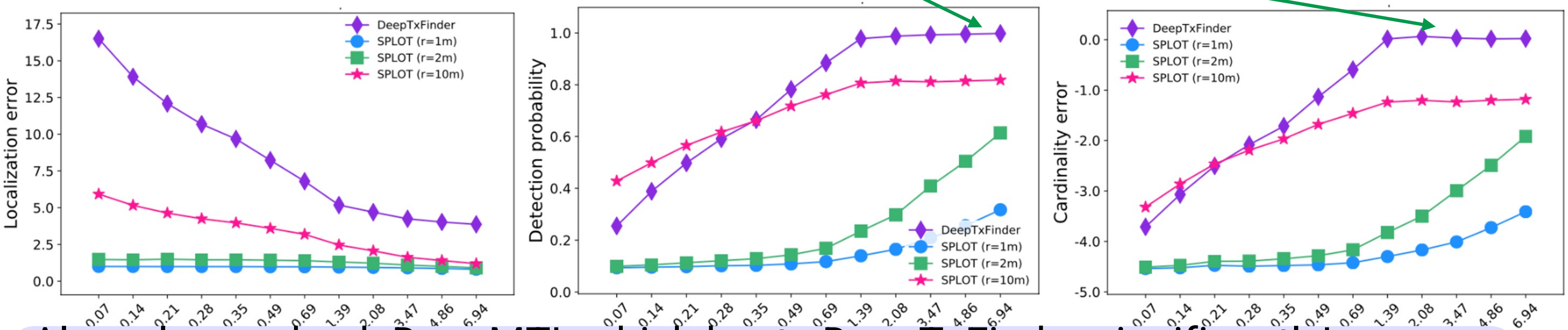

Also, please check DeepMTL which beats DeepTxFinder significantly!

DeepMTL: C. Zhan, M. Ghaderibaneh, P. Sahu and H. Gupta, DeepMTL: Deep Learning Based Multiple Transmitter Localization, IEEE WoWMoM 2021
https://github.com/caitaozhan/deeplearning-localization

(How) can edge AI help?

(How) can edge AI help?

(mobile device interested in transmitting in the uplink or a small base station with limited computation capacity than the core network)

(How) can edge AI help?

- Need for edge spectrum analytics
  - For timely exploitation of the spectrum, otherwise, spectrum opportunities might get lost
  - Lower traffic load (saving from data transmission to the fusion center), lower energy consumption
  - Less privacy/security risks

(How) can edge AI help?

- FPGA based implementations, e.g., [Restuccia and Melodia, INFOCOM 19]
- Federated learning, e.g., [Chakraborty et al., COMSNETS 20]
- Compressed ML models, e.g., [Soltani et al., DySpan19]

- F. Restuccia & T. Melodia, Big data goes small: Real-time spectrum-driven embedded wireless networking through DL in the RF loop, IEEE INFOCOM 2019
- S. Chakraborty, M. Hesham, D. Saha. Learning from Peers at the Wireless Edge. IEEE COMSNETS, 2020.
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Modulation classification at the edge

- Identifying modulation type can help to understand which technologies coexist/compete in this band, e.g., Wi-Fi, U-LTE, 5G NR-U
- Classification problem: 24 modulation schemes
- Existing schemes: low accuracy in low SNR regime and not designed to work at the edge
- Proposal:
  - different CNN models for low, moderate, high SNR regimes
  - Training on GPU and compressing/running it on smartphones
  - Step-1: identify SNR regime
  - Step-2: run the corresponding CNN

Wi-Fi: BPSK, QPSK, 16QAM, 64 QAM, 256 QAM

LTE: QPSK, 16QAM, 64QAM

5G: QPSK, 64QAM, 256QAM

Soltani, N., Sankhe, K., Ioannidis, S., Jaisinghani, D., & Chowdhury, K. Spectrum awareness at the edge: Modulation classification using smartphones. IEEE DySPAN 2019

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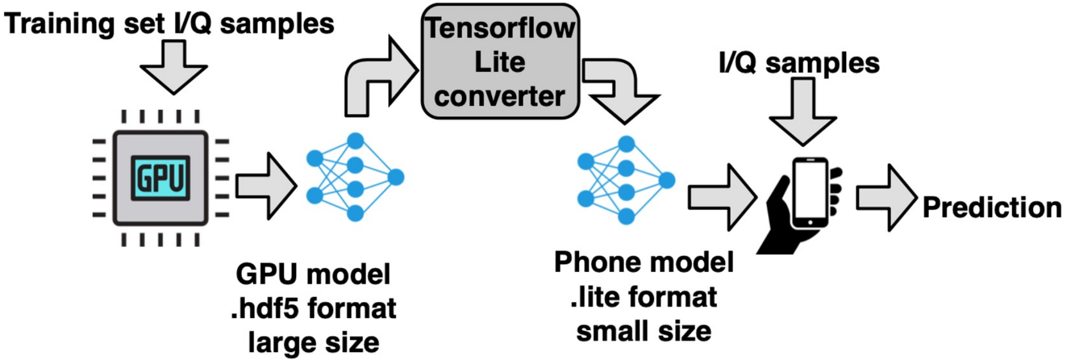

Training on the GPU

<I/Q, SNR, Modulation>

Compress the model for edge device

Classification at the edge

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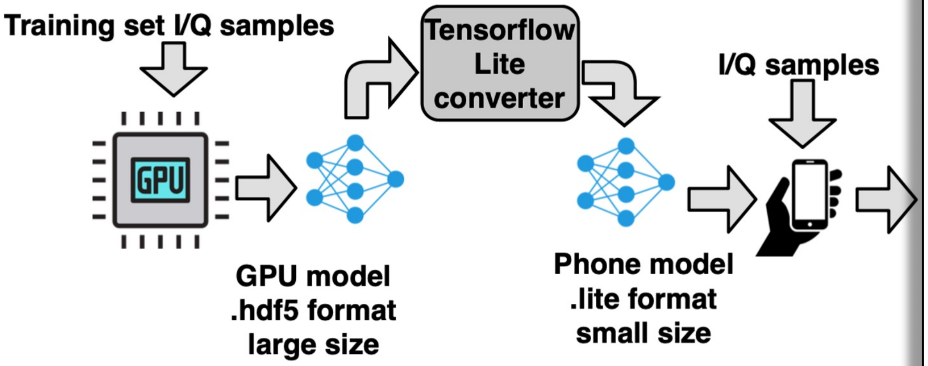

Tested on three smartphones

Classification accuracy:

- No noticeable performance difference between GPU and smartphone

Classification time:

- Significant boost in classification time in the smartphones for single I/Q sequence!
- GPU underutilized

Memory usage:

- ⅓ memory with TensorFlow Lite

Training on the GPU

NVIDIA Tesla V100 with 640 Tensor Cores and 100 teraFLOPS

Compress the model for edge device

Classification at the edge

(i) MSM8917 Quad-core 1.4 GHz (ii) 1.2 GHz (iii) Quad-core Cortex-A7, MT6753 8-core 1.7 GHz

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Some open questions/challenges

- Scalability (training overhead): MIMO, directional transmissions, more dynamic spectrum usage
- Higher frequencies require directional transmission: an opportunity for sharing in the spatial/angular domain, but might increase complexity of sensing and beamforming for spectrum awareness
- Energy efficiency, overhead in spectrum usage for centralized models
- Interpretability of ML-based sharing solutions: acceptance by the operators
- Access to data, availability of real-world data

* Tommy van der Vorst et al, Managing AI use in telecom infrastructures Advice to the supervisory body on establishing risk-based AI supervision, 2019

Key takeaways

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- Spectrum needs to be shared *dynamically, regulatory bodies in favour of sharing*
- *Model based approaches:*
    - may not capture accurately the essence of the physical processes due to complex interactions among protocol layers, complexity of the hardware, increasing diversity of access technologies, configurations
    - *too complex (NP-hard problems) requiring accurate knowledge on, e.g., CSI, leading to high signalling/coordination overhead*
- Many ML--based proposals, but:
    - Training challenge, scalability
    - Data availability: spectrum statistics, transmitter locations
    - Needs more analysis on energy efficiency and overhead leading to more spectrum usage
    - Interpretability
- Hybrid solutions* combining ML and model-based solutions can also be promising!

* Ghauch, H., Shokri-Ghadikolaei, H., Fodor, G., Fischione, C., & Skoglund, M. (2020). ML for Spectrum Sharing in Millimeter-Wave Cellular Networks. Machine Learning for Future Wireless Communications, 45-62.

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Thank you!

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