Leveraging Machine Learning for Spectrum Sharing in Wireless Networks

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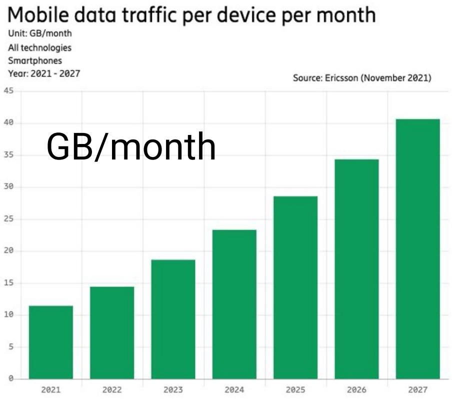
Invited session: Approaches and Methods for Monitoring and Management of Edge Computing Systems and Networks

Spectrum sharing for higher spectrum usage efficiency

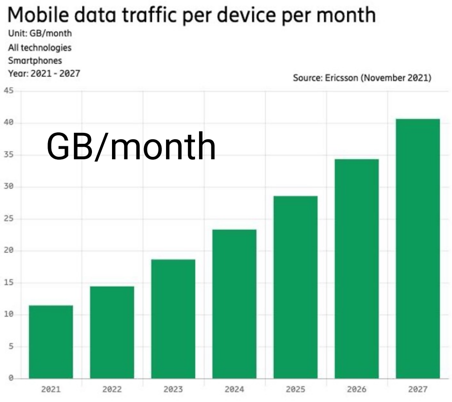
- Wireless connectivity as a basic need
- Emerging services with high capacity requirements



World average

Spectrum sharing for higher spectrum usage efficiency

- Wireless connectivity as a basic need
- Emerging services with high capacity requirements
- Static spectrum management
    - 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*



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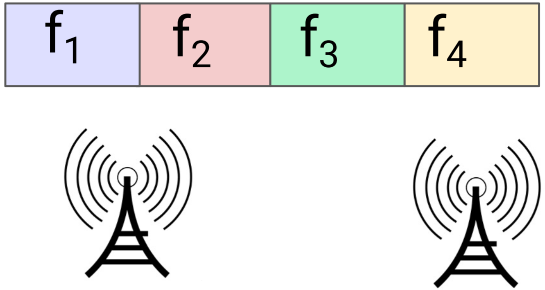
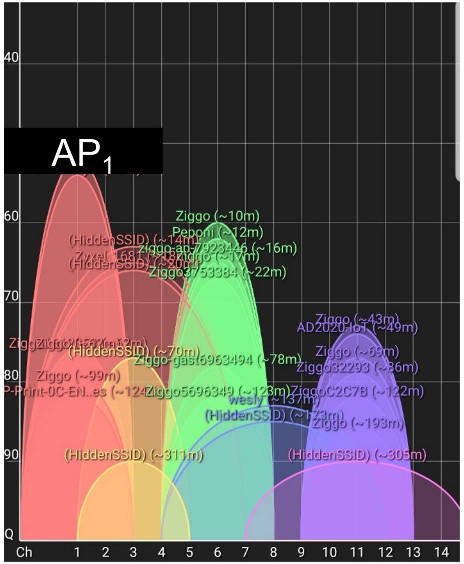
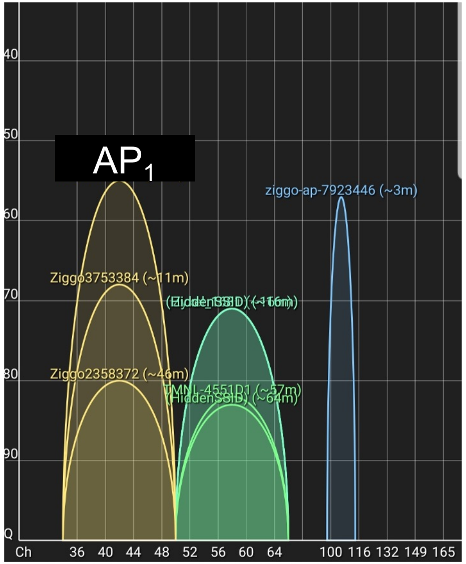


A success story: Wi-Fi

2.4 GHz



5 GHz



6 GHz

60 GHz

M. Parvini et al., “A Comprehensive Survey of Spectrum Sharing Schemes from a Standardization and Implementation Perspective,” 2022 https://arxiv.org/pdf/2203.11125.pdf

Spectrum sharing challenges

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- Growing complexity
  - hardware, access technologies, configurations
- Heterogeneity of networks
  - unlike Wi-Fi, traditional cellular networks are not designed to operate in spectrum-sharing mode
  - power asymmetry or different levels of robustness to interference
  - no communication/coordination among networks
- Metrics for assessing coexistence
  - throughput-oriented fairness metric
  - for different traffic types (e.g., URLLC, eMBB)
- Flexibility bringing spectrum security problems
  - Unauthorized or misconfigured transmission in the spectrum

- 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
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Spectrum sharing challenges

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Identify the spectrum opportunities

Coexistence challenge

Spectrum anomalies/misuse

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(How) can ML help?

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Design and Analysis of Communication Systems

- 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

(How) can ML help?

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- Edge spectrum analytics
  - For timely exploitation of the spectrum
  - Lower traffic load (saving from data transmission to the fusion/decision center), lower energy consumption
  - Less privacy/security risks

Literature on ML-based spectrum sharing and awareness

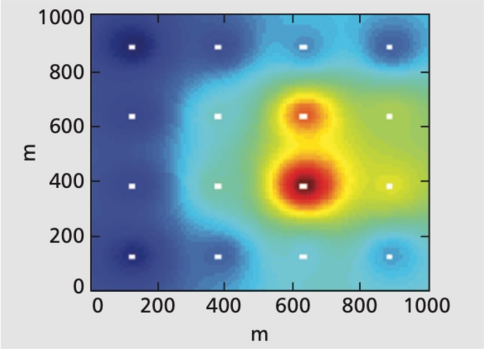
- Step-1: Spectrum state identification
- Step-2: Spectrum access and peaceful coexistence
- Step-3: Spectrum anomaly detection

- 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/

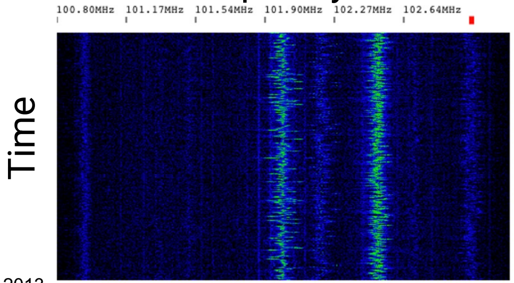
Step-1: ML-based spectrum state identification

- Regulatory bodies and network operators need to understand spatio-temporal characteristics of the spectrum usage and improve efficiency accordingly
    - Real-time, non-real-time analysis of short-term or long-term trends
- Is the spectrum idle or occupied? When will the spectrum be idle/busy?
- Which other networks are there in the neighborhood?

Spatial occupancy

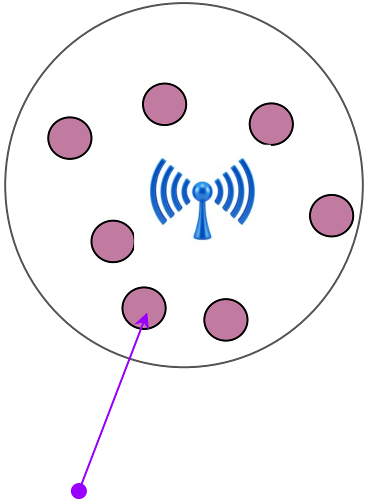


Frequency



- K.M. Thilina, K,W. Choi, N. Saquib, E. Hossain, *Machine learning techniques for cooperative spectrum sensing in cognitive radio networks.* IEEE JSAC 2013.
- S.Rajendran, W. Meert, D. Giustiniano, V. Lenders, S. Pollin, S. *Deep learning models for wireless signal classification with distributed low-cost spectrum sensors*, IEEE TCCN 2018.
- N. Soltani, N., K. Sankhe, S. Ioannidis, D. Jaisinghani, K. Chowdhury, *Spectrum awareness at the edge: Modulation classification using smartphones*. IEEE DySPAN 2019
- J. Gao, X. Yi, C.Zhong, X. Chen, Z. Zhang, *Deep learning for spectrum sensing*. IEEE Wireless Communications Letters, 2019.
- Y.Zeng, V. Chandrasekaran, S. Banerjee, D. Giustiniano, *A framework for analyzing spectrum characteristics in large spatio-temporal scales*, ACM Mobicom 2019
- X. Liu, Q. Sun, W. Lu, C. Wu, and H. Ding, *Big-Data-Based Intelligent Spectrum Sensing for Heterogeneous Spectrum Communications in 5G*, IEEE Wirel. Comms. 2020.
- K. Tekbıyık, Ö. Akbunar, A. R. Ekti, A. Görçin, G. K. Kurt and K. A. Qaraqe, *Spectrum Sensing and Signal Identification With Deep Learning Based on Spectral Correlation Function*, IEEE TVT 2021.

Step-1: Is the spectrum idle or occupied?: a classification problem



Sensing node(s): Vector of energy levels at each sensing node

- **Goal:** Low false alarms, high detection accuracy, low cost in time/energy/bandwidth
- Traditionally:
  - If measured energy level < Energy Detection threshold, then *idle*
  - If collaborative sensing, fusion of individual results, e.g., AND/OR/Majority
- ML:
  - Feature vector: measured energy level at each sensor
  - Classifier's output: idle or busy
  - Training
    - Unsupervised: K-means clustering and Gaussian mixture model (GMM)
    - Supervised learning, e.g., support vector machine (SVM) and K-nearest neighbor (KNN)
- **Performance:** training time, the classification delay, and the ROC curve, the effect of the number of the sensing devices

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Step-1: Spectrum state prediction with DNNs

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

DNN model training (LSTM/autoencoder)

Next *y time units* of the spectrum data

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

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

Step-1: 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 (e.g., 24 modulation schemes)
- Goal: high accuracy, robustness to different SNR regimes, low complexity to be able to run at the edge

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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- Proposal by Soltani et al.:
    - Step-1: identify SNR regime (low, moderate, high SNR regimes)
    - Step-2: run the corresponding CNN for identification
    - Training on GPU and compressing/running it on smartphones

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

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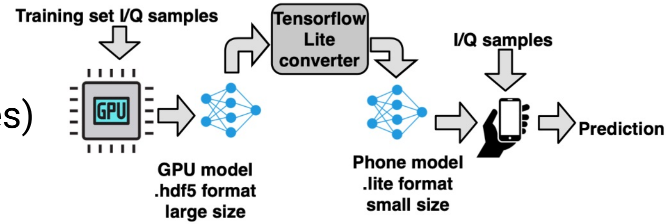

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Step-2: Spectrum access and peaceful coexistence

- Reinforcement learning based schemes:
  - Expected reward of each action-state pair
  - Spectrum access and accumulated reward

- Autoencoders to design cross-technology channels
  - Networks can communicate with each other directly via cross-technology-channels
  - How to create a signal that can be decoded both at the intended in-technology receiver and cross-tech receiver?

- Han, M., Khairy, S., Cai, L. X., Cheng, Y., & Zhang, R., Reinforcement learning for efficient and fair coexistence between LTE-LAA and Wi-Fi. IEEE TVT 2020
- Yu, Y., Wang, T., & Liew, S. C., Deep-reinforcement learning multiple access for heterogeneous wireless networks. IEEE JSAC, 2019
- Mosleh, S., Ma, Y., Rezac, J. D., & Coder, J. B. Dynamic spectrum access with reinforcement learning for unlicensed access in 5G and beyond. IEEE VTC2020-Spring
- Anatolij Zubow, Piotr Gawłowicz, Suzan Bayhan, Deep Learning for Cross-Technology Communication Design, arxiv, 2019
- https://mlc.committees.comsoc.org/tag/autoencoders/

Step-3: Spectrum anomaly detection

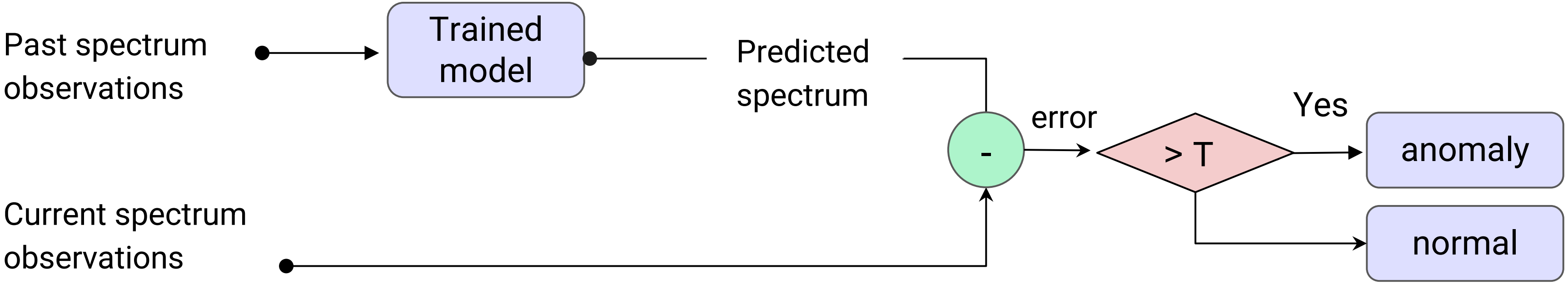
- Advances in both reconfigurable hardware and spectrum usage policies make it easy to misuse spectrum without authorization
  - Transmissions at unexpected power levels, out of band transmission, misconfigured devices, unexpected patterns
  - Authorized transmitters or misuse of the spectrum? Where are the transmitters?
  - Fair coexistence or not?

- Manual diagnosis following customer complaints and operational failure logs

- ML-based
  - Anomaly detection (supervised and unsupervised approaches)
  - Transmitter localization

- Li, Zhijing, et al. *Scaling Deep Learning Models for Spectrum Anomaly Detection.* ACM MobiHoc 2019. Code: https://github.com/0x10cxR1/spectrum_anomaly_detection/
- S. Rajendran, W. Meert, V. Lenders, S. Pollin, *SAIFE: Unsupervised Wireless Spectrum Anomaly Detection with Interpretable Features,* IEEE DySPAN 2018 & TCCN 2019
- S. Rajendran, V. Lenders, W. Meert and S. Pollin, Crowdsourced Wireless Spectrum Anomaly Detection, IEEE TCCN, 2020
- https://socrates.networks.imdea.org

Supervised Approach: Detection



If divergence from the prediction above some threshold T: Anomaly

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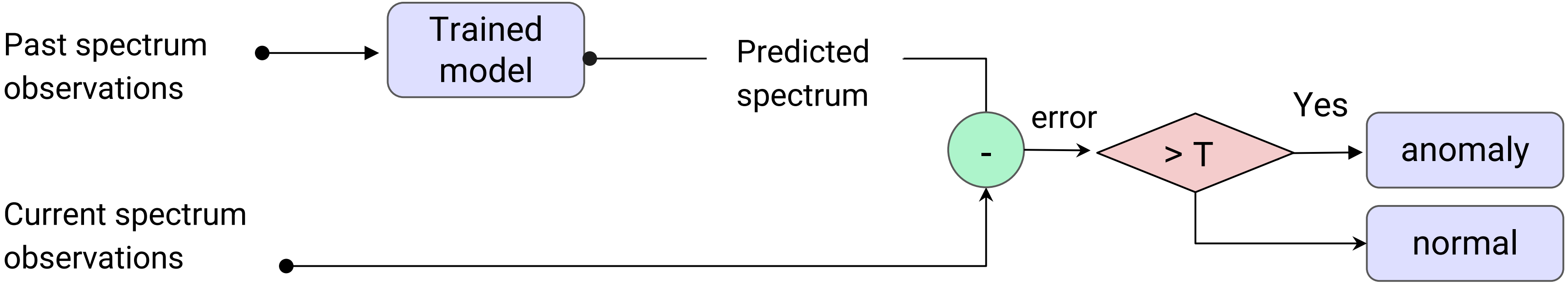

If divergence from the prediction above some threshold T: Anomaly

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

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

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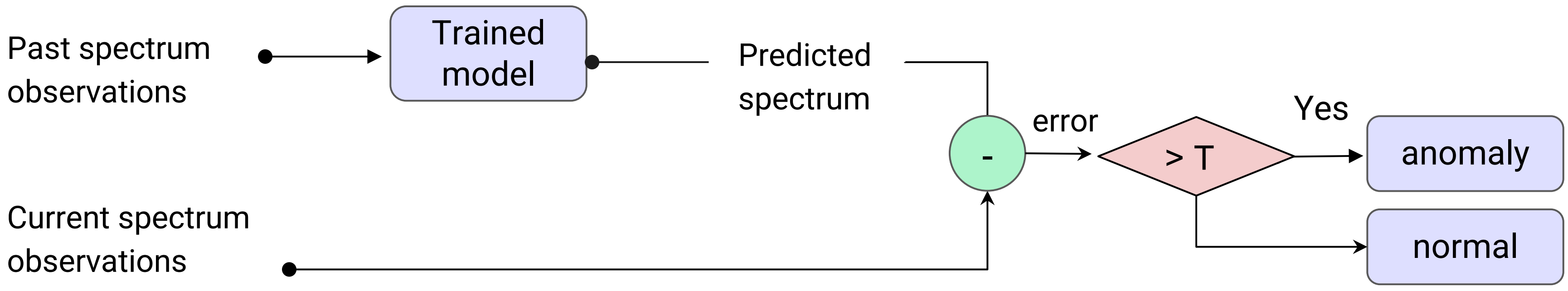
Supervised Approach: Detection

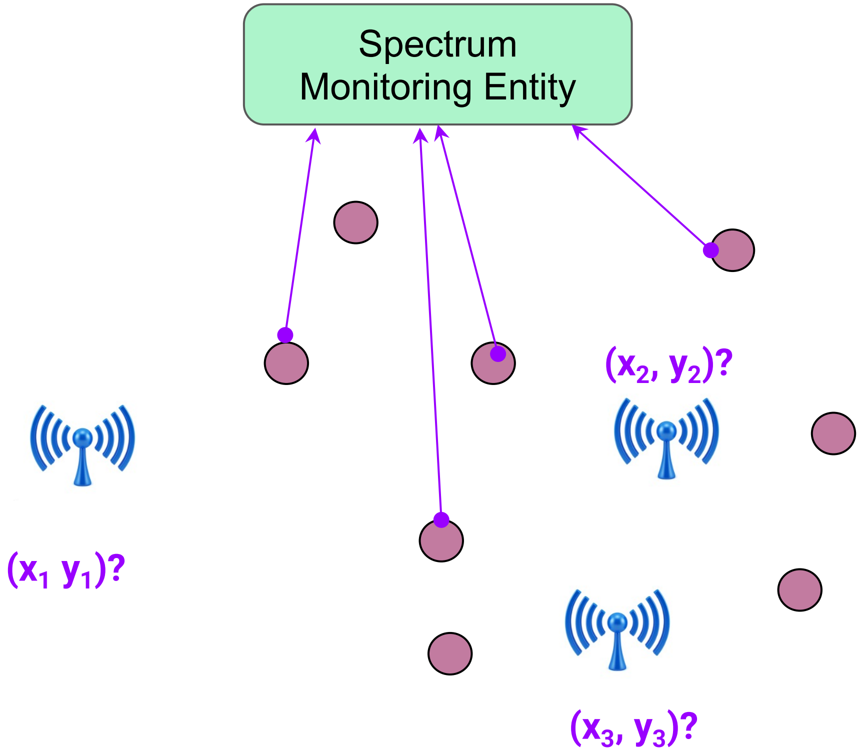


If divergence from the prediction above some threshold T: Anomaly

Does removing context-awareness decrease the accuracy of DNNs (false alarms and correct detection)? → *Yes, but Transfer Learning can help to some extent.*

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

Step-3: Multiple transmitter localization



- Goal: Identify the locations (x, y) of transmitters with high location accuracy and low false alarm rate for avoiding waste of expert time
- Challenge: Multiple transmitters, multiple transmission power levels, channel variations! The sensors receive a sum of the signals.
- CNNs for transmitter localization

- A. Zubow, S. Bayhan, P. Gawłowicz, F. Dressler, Deeptxfinder: Multiple transmitter localization by deep learning in crowdsourced spectrum sensing. IEEE ICCCN, 2020
- C. Zhan, M. Ghaderibaneh, P. Sahu and H. Gupta, DeepMTL: Deep Learning Based Multiple Transmitter Localization, IEEE WoWMoM 2021
- Zhan, H. Gupta, A. Bhattacharya, M. Ghaderibaneh, Efficient localization of multiple intruders for shared spectrum system, IPSN 2020.
- Debashri, et al. Detection of Rogue RF Transmitters using Generative Adversarial Nets, IEEE WCNC 2019.

DeepTxFinder: Two-step CNN approach

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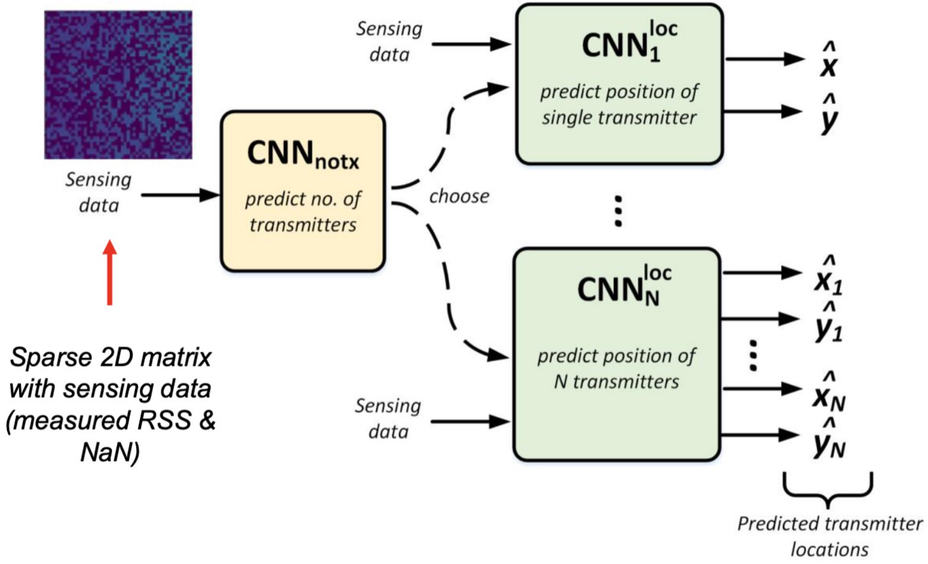
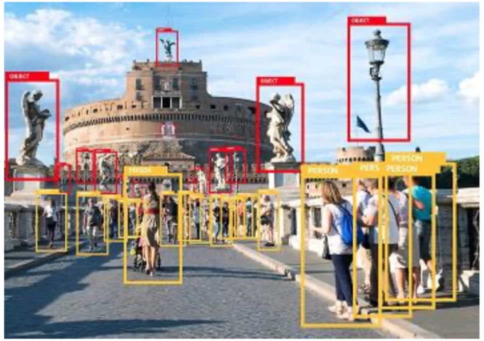
- Step-1: CNN detects the number of transmitters
- Step-2: CNN estimates actual 2D locations of *that* many transmitters





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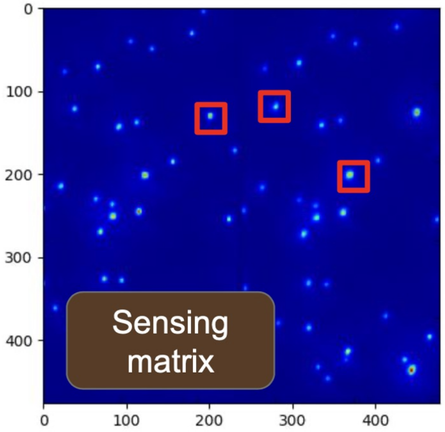

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Some open questions/challenges

- Scalability (training overhead):
  - MIMO, directional transmissions at higher frequencies, more dynamic spectrum usage
  - Difficulty of anomaly detection in a dynamic environment

- Overheads:
  - Energy efficiency (training cost)
  - Spectrum usage overhead for centralized models

- Interpretability of ML-based sharing solutions
  - acceptance by the operators

- Availability of real-world data and access to this data
  - Challenge for researchers

* 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
  - Needs more analysis on energy efficiency and overhead leading to more spectrum usage
  - Interpretability
  - Data availability: spectrum statistics, transmitter location

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