DeepTxFinder: Multiple Transmitter Localization by Deep Learning in Crowdsourced Spectrum Sensing

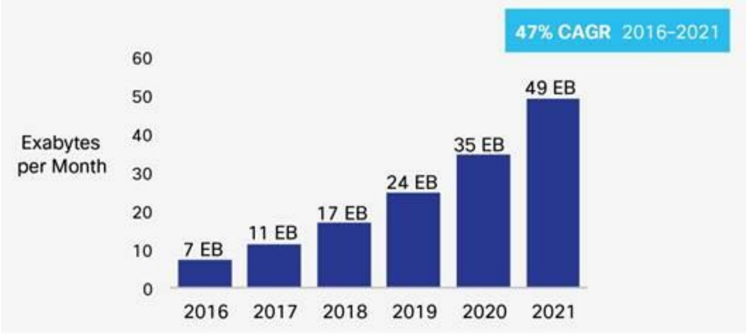
Anatolij Zubow, Suzan Bayhan, Piotr Gawłowicz, Falko Dressler

---

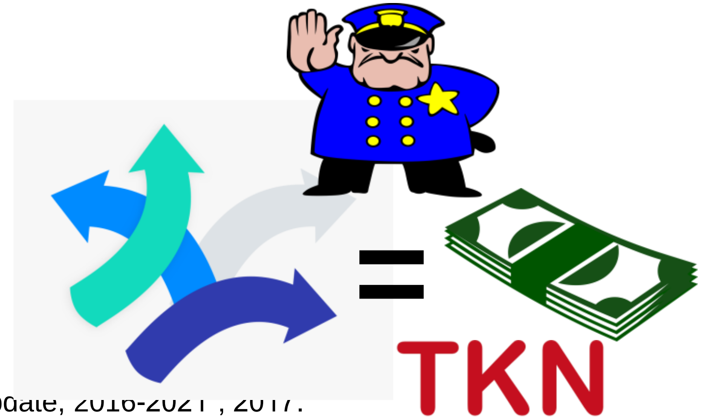
IEEE ICCCN 2020, USA

Technische Universität Berlin

Motivation



- Massive growth of wireless data traffic [1]
- Trend towards ultra-dense networks
- Radio spectrum becomes the bottleneck
- Wide deployment of flexible software defined radios (SDR)
- **Idea**: more flexible usage of radio spectrum in time, space, and frequency dimensions → increase in spectral efficiency
- **Problem**:
  - Flexibility in spectrum allocation comes with **cost** of increased complexity of **spectrum monitoring** by enforcement authorities



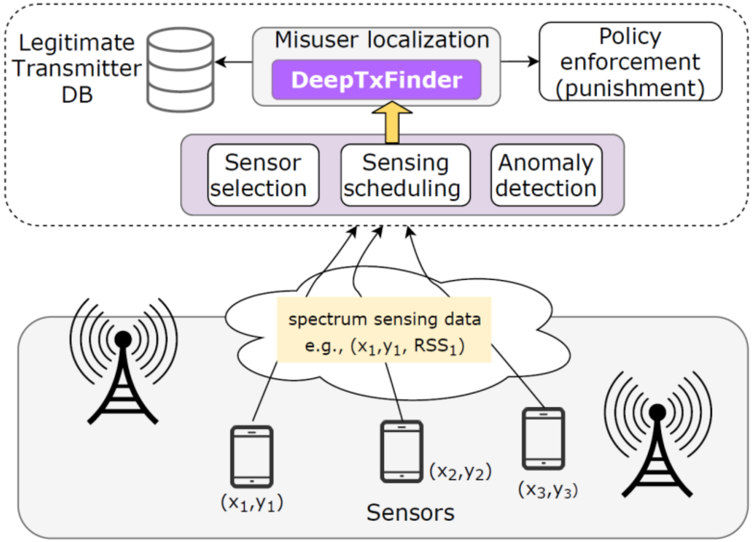
[1] “Cisco Visual Networking Index: Global Mobile Data Traffic Forecast Update, 2016-2021”, 2017.

Problem Statement

- **Identifying the unauthorized transmitters** is at interest of **spectrum enforcement authorities** to ensure that spectrum is used as intended by the legitimate users.

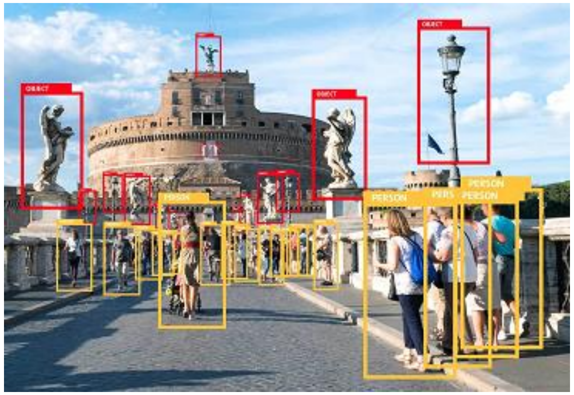
- **But**, a scalable, efficient, and highly-accurate solution is needed.

- **System model**:
  - Crowdsourced spectrum sensing,
  - COTS sensing devices reporting their measured total Received Signal Strength (RSS) values to central entity,
  - Information is centrally fused & analyzed for localization of unknown number of transmitters.



Proposed system model

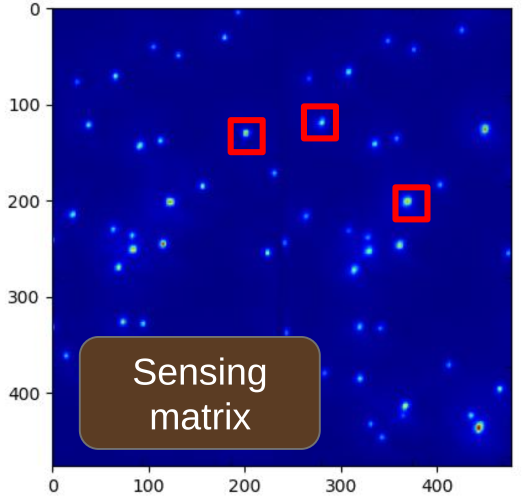
Proposed Approach - DeepTxFinder



- We leverage **deep learning** to identify & localize transmitters → similar to image recognition

≈

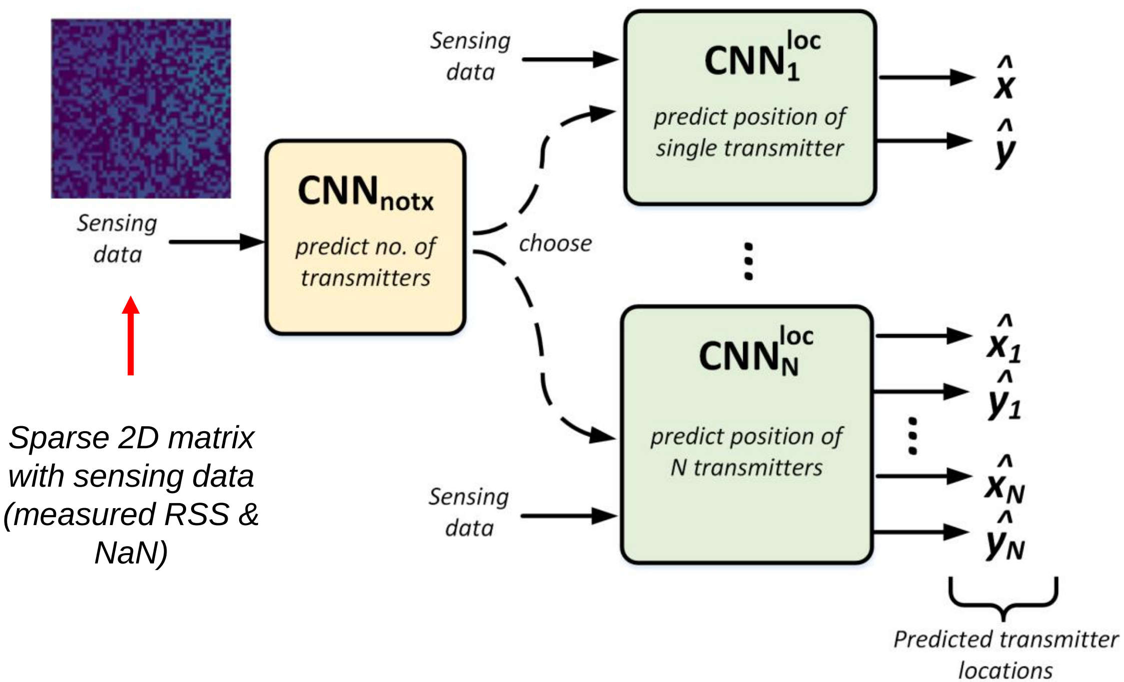
- But not so easy as we have many **sources of uncertainty** in the operation environment, i.e.:
  - Number of transmitters,
  - Transmission power levels,
  - Insufficient space separation between transmitters,
  - Channel conditions (e.g., level of Shadowing)



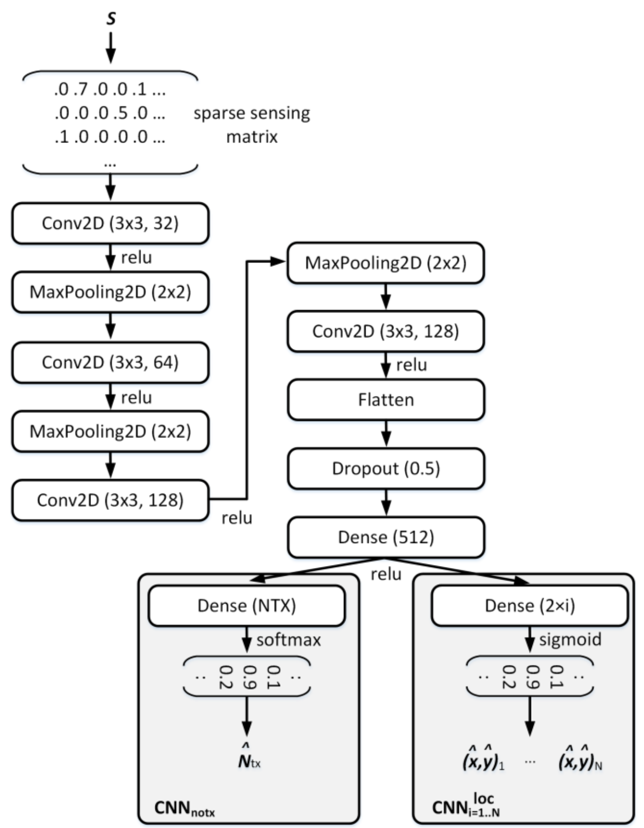
- **Scalable solution**: tiling-based approach reduces computational complexity

DeepTxFinder Architecture

- **Two step approach**:
  - First CNN is used to detect the number of transmitters
  - Second CNN estimates actual 2D locations of that many transmitters

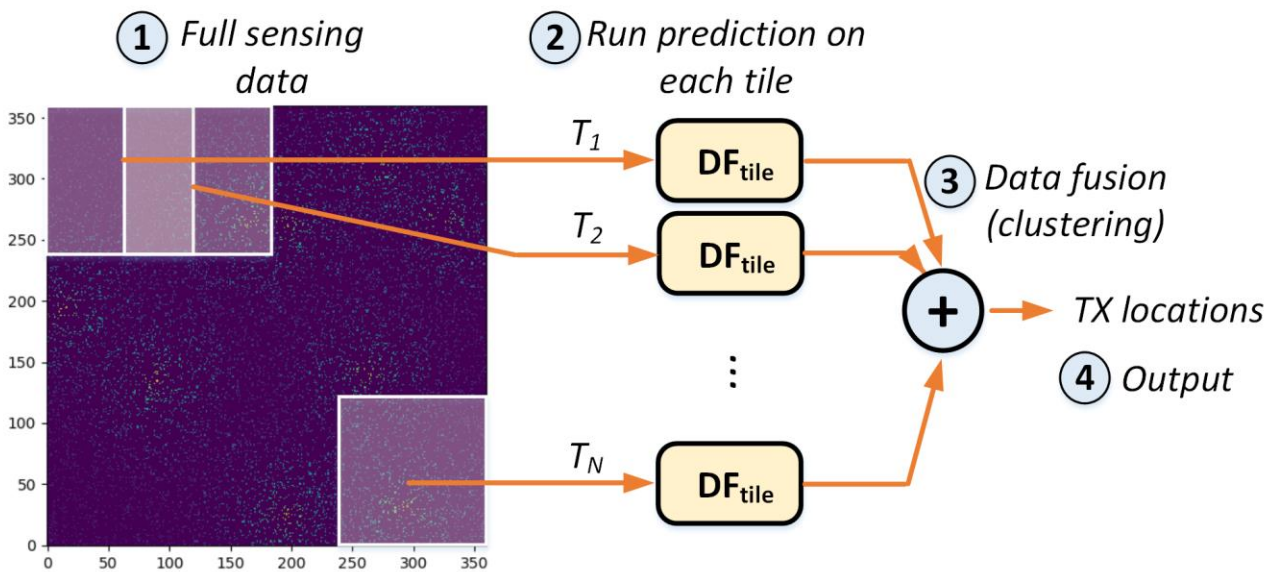


Sparse 2D matrix with sensing data (measured RSS & NaN)



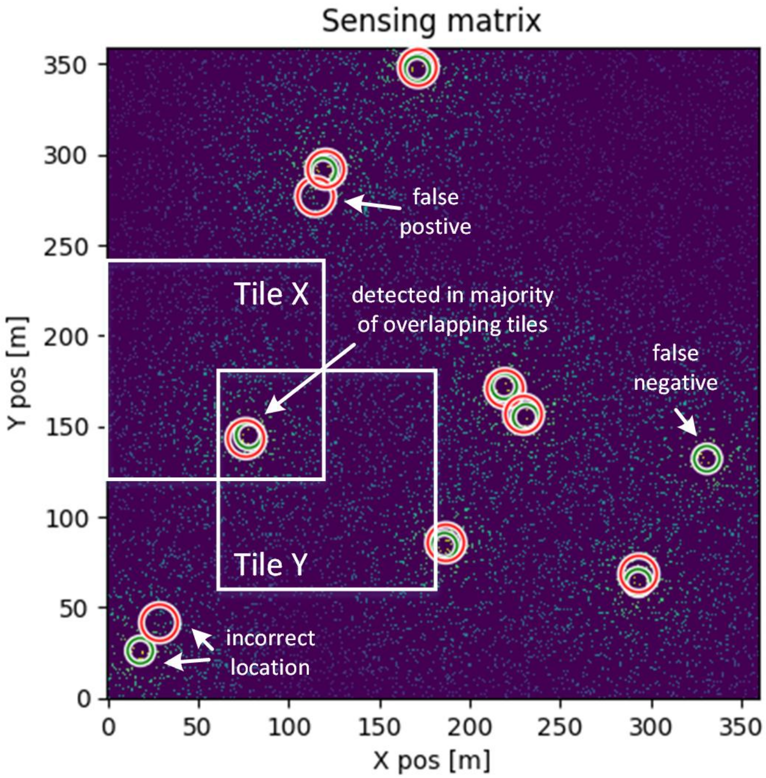
DeepTxFinder Architecture (II)

- **Tiling-based approach** to achieve scalability:
  - 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 final set of predicted locations



DeepTxFinder Architecture (II)

- Example output of prediction in **large environments**:



Performance Analysis

- Custom system-level simulator:
  - Python using ML libraries (TF, Keras)
  - 900 MHz, Keenan-Motley pathloss, spatially-correlated Shadowing

- Model training
  - 10^5 samples: 70% for training 30% for testing (validation)

- Baseline: **SPLOT**, 2017 [1]
  - Breaks down multiple-transmitter-localization to several single-transmitter-localization problems
  - Three variants with different threshold value *r* used for finding the local maximas

- Metrics:
  - Localization error, cardinality error, detection probability, false alarm, exec. time

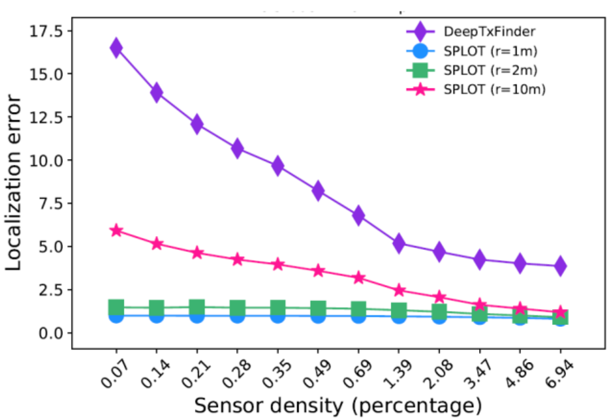
[1] M. Khaledi et al.: "Simultaneous Power-Based Localizationof Transmitters forCrowdsourced SpectrumMonitoring", MobiCom, 2017

Performance Analysis (II)

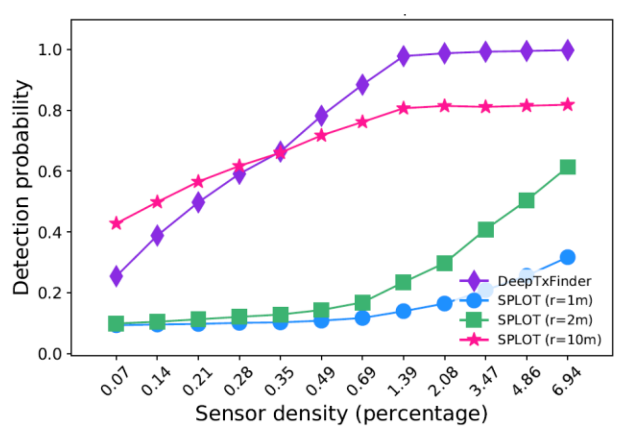
- Investigated scenarios:
  - **S1 = no shadowing & known Ptx**:
    - Simplest case where the channel pathloss is fully deterministic, i.e., depends exclusively on the distance (no Shadowing)
    - Transmitter power is constant & known for all transmitters
  - **S2 = shadowing & known Ptx**:
    - More realistic case where the signal propagation experiences shadowing (where σ= 5 dB)
    - Transmitter power is constant & known for all transmitters
  - **S3 = shadowing & unknown Ptx**:
    - Most challenging case: channel with shadowing (with σ = 5 dB) and the transmitter power is variable, i.e., random between 0-10 dBm

Results

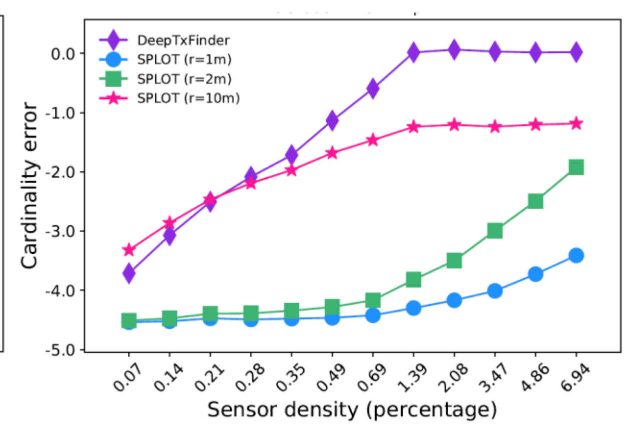
- **Scenario I**: no shadowing and constant (known) TX power
  - sparse sensing is feasible: both schemes converge to acceptable localization errors (few meters) with only 1–2% sensor density
  - SPLOT with r=10 offers best performance



(a) Localization error.



(b) Detection probability.



(c) Cardinality error.

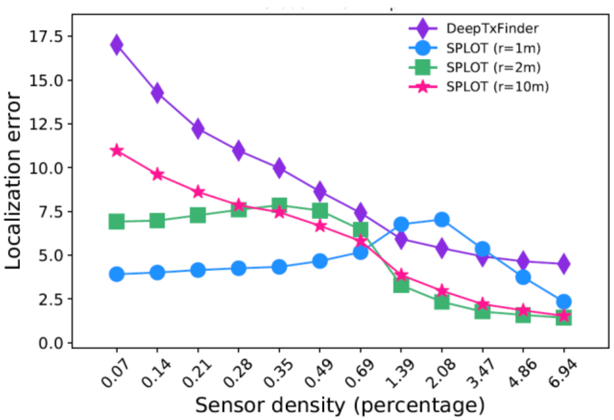
SPLOT:

DeepTXF:

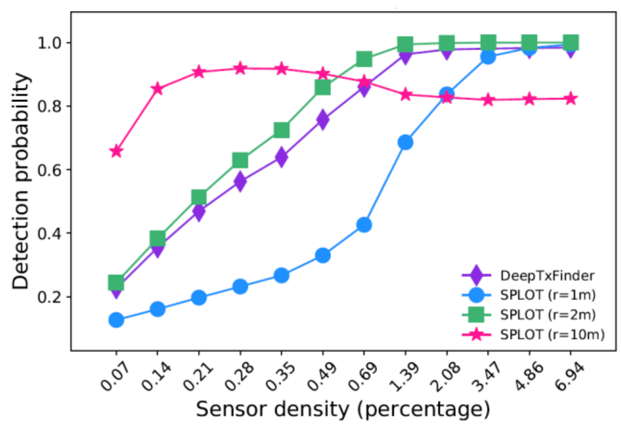
DeepTXF:

Results (II)

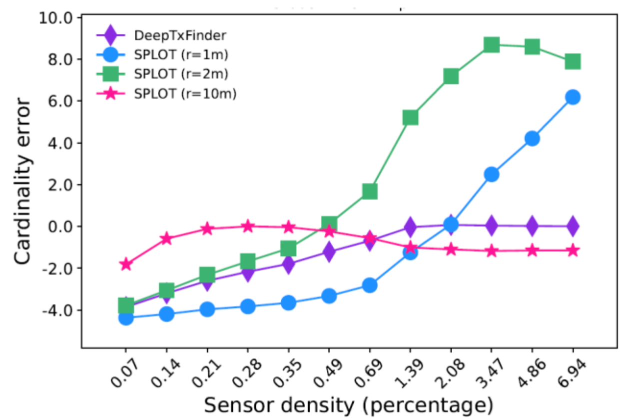
- **Scenario II**: shadowing and constant (known) TX power
  - SPLOT: higher localization error but also higher detection probability
  - perf. of DeepTxFinder remains same showing its robustness against different environment conditions → feasibility in wide range of settings



(a) Localization error.



(b) Detection probability.



(c) Cardinality error.

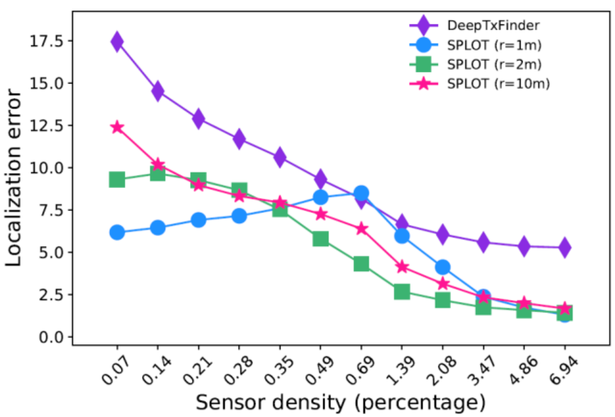
SPLOT: 🙂

SPLOT+ DeepTXF: 🙂

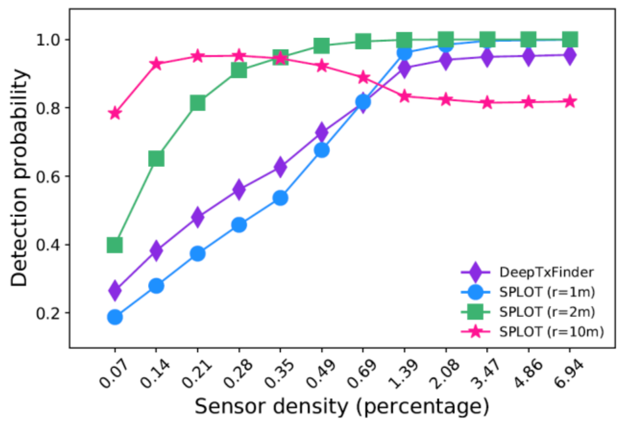
SPLOT+ DeepTXF: 🙂

Results (III)

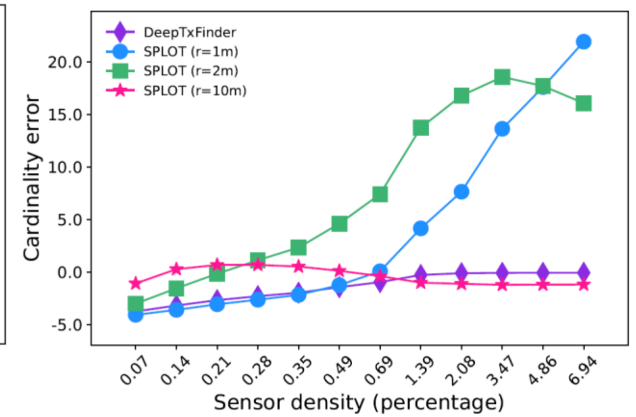
- **Scenario III**: shadowing and variable (unknown) TX power
  - DeepTxFinder maintains a lower detection probability if the transmitter power is randomly distributed between 0–10 dBm: converges to 90%



(a) Localization error.



(b) Detection probability.



(c) Cardinality error.

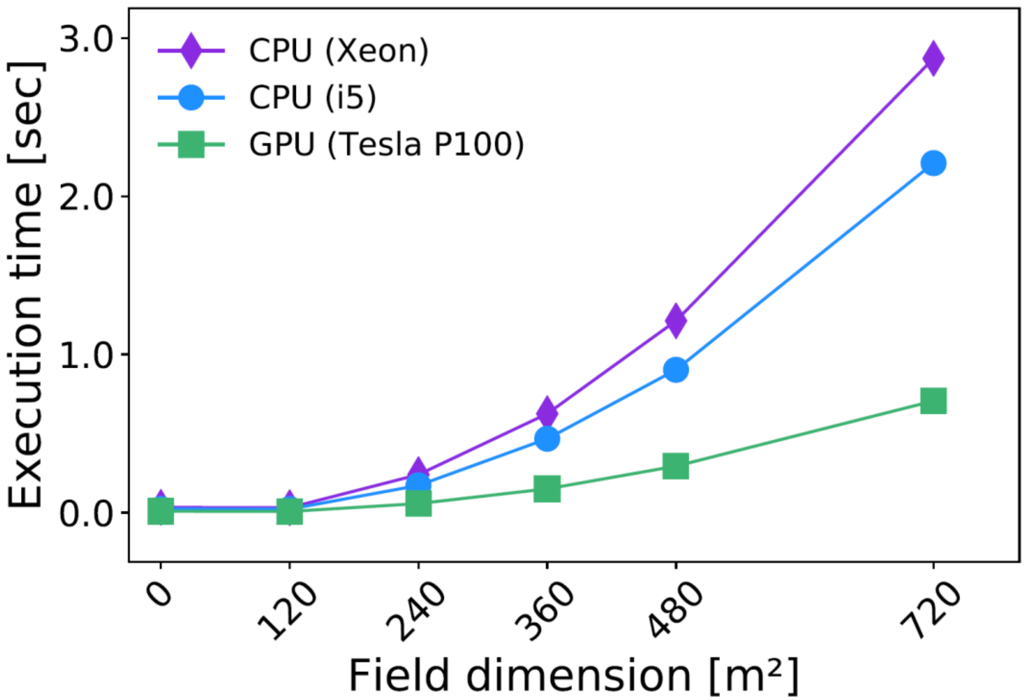
SPLOT+ DeepTXF: 

SPLOT+ DeepTXF: 

SPLOT+ DeepTXF: 

Results (IV)

- Execution performance DeepTxFinder
  - for different field sizes on state-of-the-art machines
  - speedup with GPU is clearly visible



Conclusions

- Increase in flexibility of spectrum usage → need for **identifying the sources of transmissions** & localizing them to prevent illegitimate spectrum use
- Crowdsensing the spectrum is promising but requires **scalable solutions**
- Focus is on transmitter localization under **sparse spectrum sensing**
- **DeepTxFinder** uses **deep learning** to localize unknown number of transmitters:
  - Robust to uncertainty in TX power & channel propagation (Shadowing)
  - Provides high detection accuracy even under sparse sensing: ≈ 1–2% sensor density is sufficient
  - Low false alarm rate → essential to avoid waste of expert labor (e.g., officers at the regulatory body)