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Machine Learning for Decentralized and Flying Radio Devices

European Research Council

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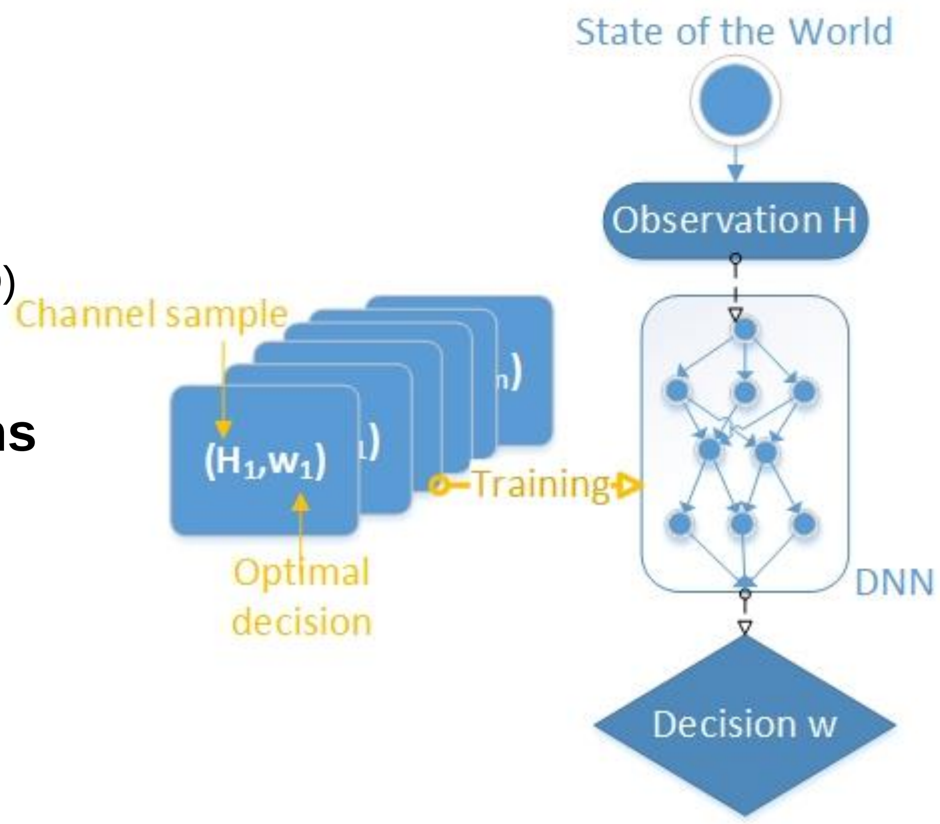
Prof. David Gesbert
EURECOM – Sophia Antipolis, France

EURECOM - Sophia Antipolis

- Sophia Antipolis: One of Europe's largest technology parks
- EURECOM is a ICT-oriented lab and English-speaking graduate school
- Co-owned by IMT Paris, TUM, Chalmers, Politecnico Torino, CTU Prag, NTNU, Aalto, etc. (15 academic/industrial shareholders)

AI For Wireless

- **Why?**
  - **Robustness wrt model uncertainties**
  - **Ability to make use of large measurement data sets**
  - **Efficient implementations**
- **PHY applications**
  - Modulation detection
  - Error correcting code (decoding)
  - Beam search (hybrid massive MIMO)
  - Etc.
- **LINK/Network level applications**
  - Traffic classification
  - Predictive resource allocation
  - SDN optimization
  - Etc.
- **QoE enhancement**
  - User-machine interction



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AI For Wireless: New perspectives

- **Autonomous radio devices**
  - Dealing with measurements uncertainties
  - Dealing with decentralized decision scenarios

- *Case 1: Team DNN for cooperative decentralized communications*
- *Case 2: Machine learning for optimal placement of flying relays*

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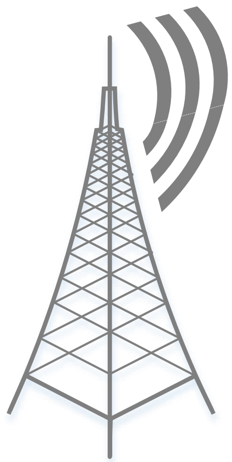
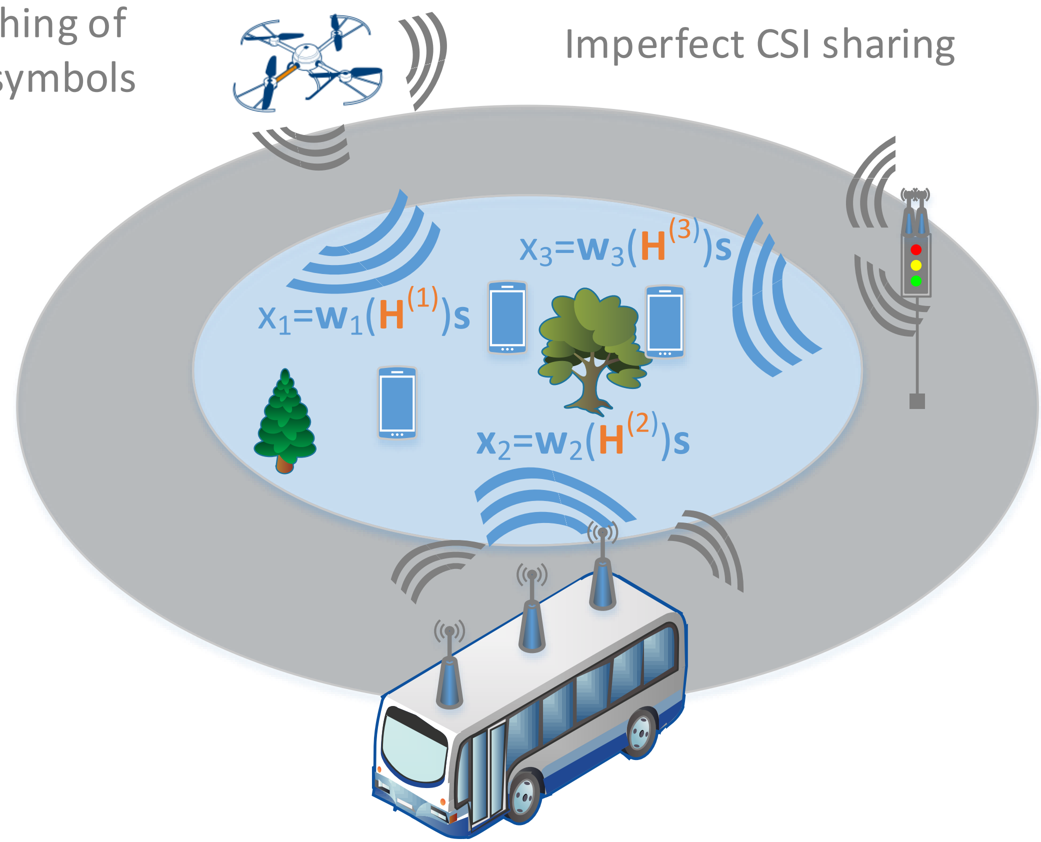
Team Learning for decentralized wireless networks

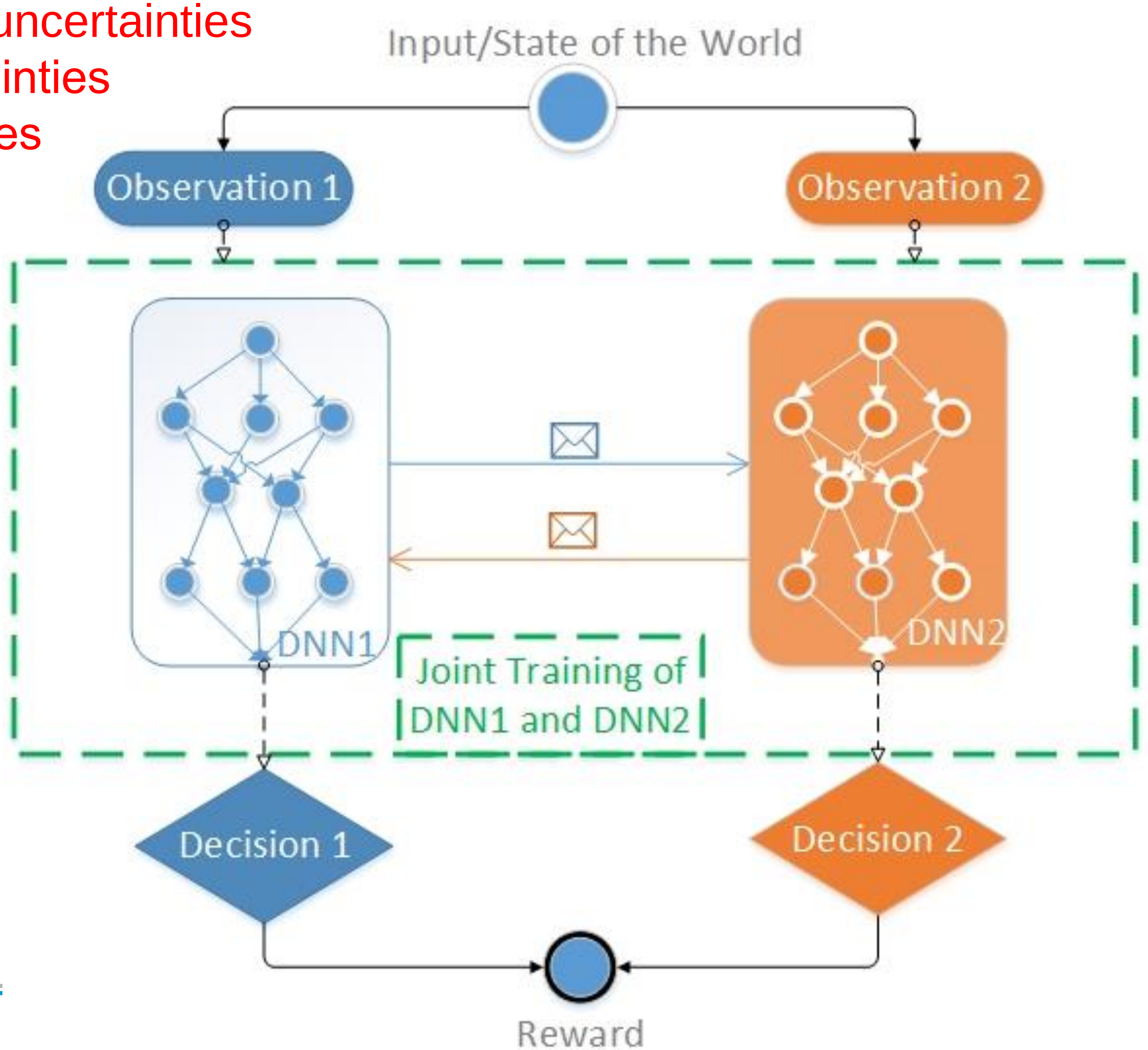




- Collaboration/Coordination
  - Pilot allocation
  - power control
  - beam alignment
  - resource allocation
  - Caching
- Decentralized/heterogeneous setting
  - Lack of efficient backhaul
  - Observations are noisy, local
  - Need for robust decision, predict decisions of others!

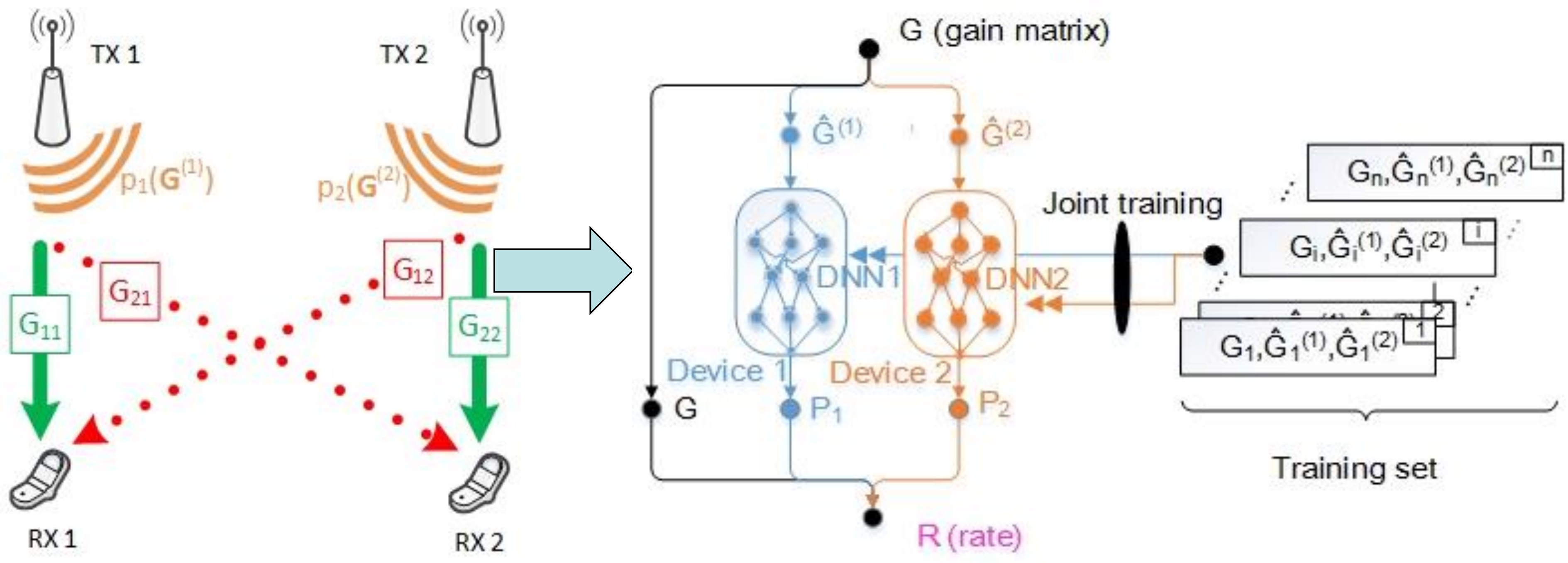
Introducing *Team DNNs*

Goal 1: Learning to collaborate/coordinate
Goal 2: Learning to deal with uncertainties
-> one's own uncertainties
-> other's uncertainties



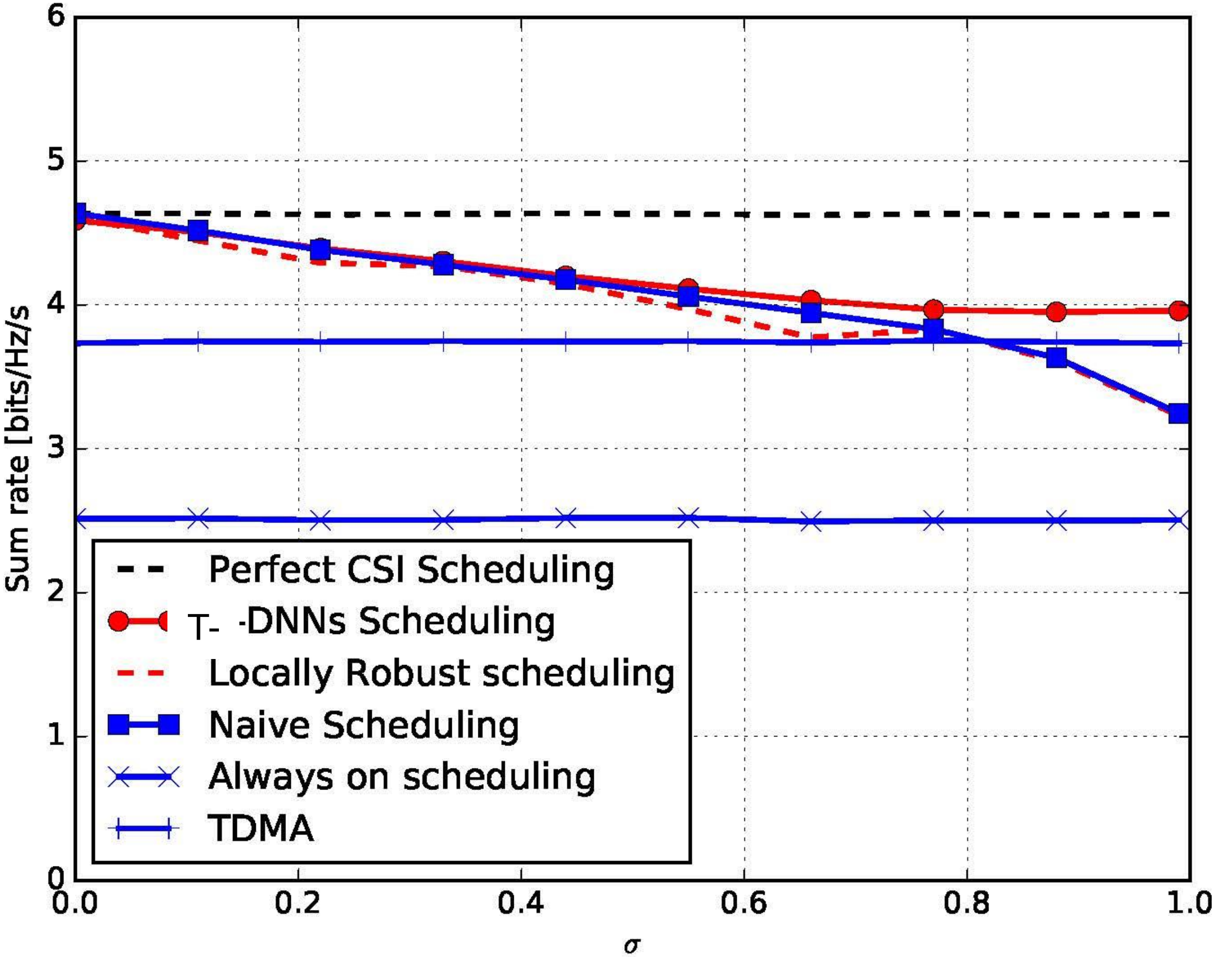
Team DNN example: Power Control under arbitrary noisy feedback

- Decentralized power control to maximize total throughput
- Each TX observes gain feedback with arbitrary observation noise
- Each TX needs to make instantaneous power control decision



(de Kerret & Gesbert2018,Arxiv)

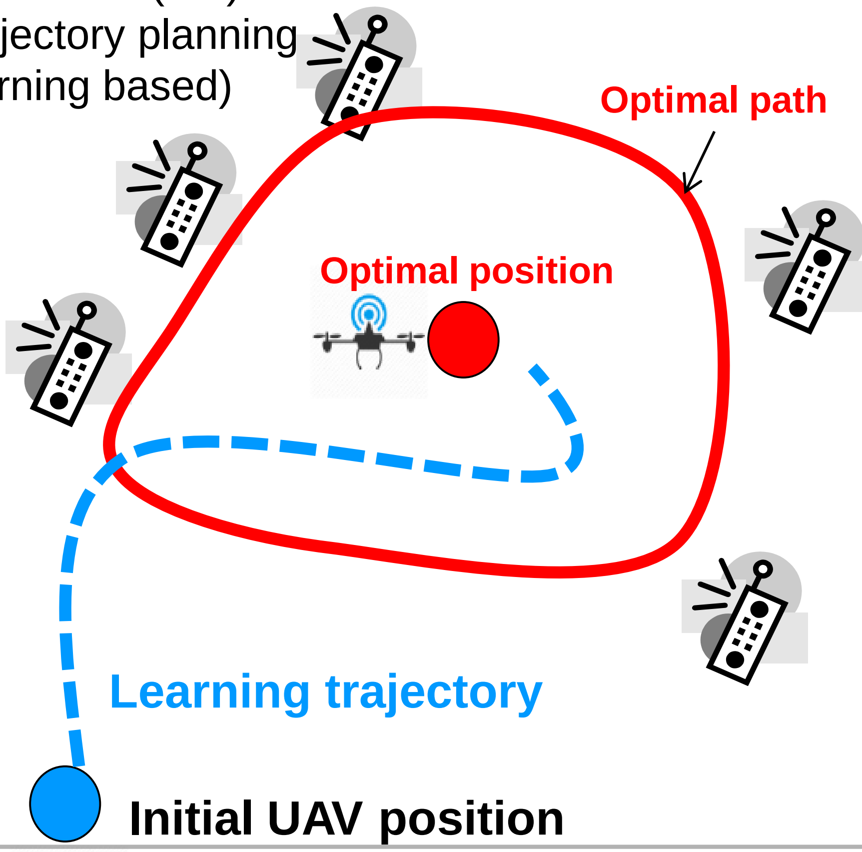
Illustration of Team DNN behavior



Feedback Uncertainties

UAV-aided wireless networks

- UAVs provide connectivity where and when it matters
- Dramatically improves propagation statistics
- Many possible scenarios
  - *Data scenario*: broadband access vs data collection (IoT)
  - *Placement scenario*: static placement vs. trajectory planning
  - *Optimization scenario*: Offline vs. online (learning based)

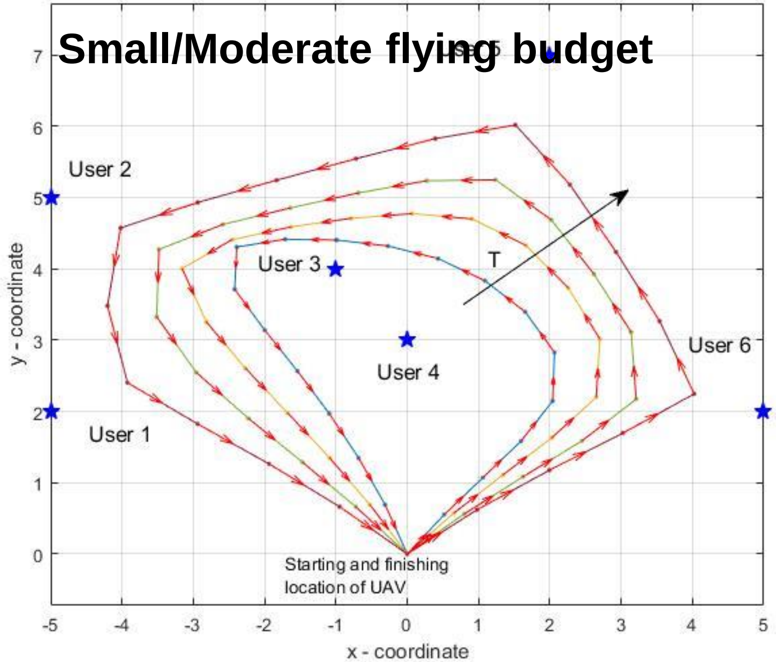


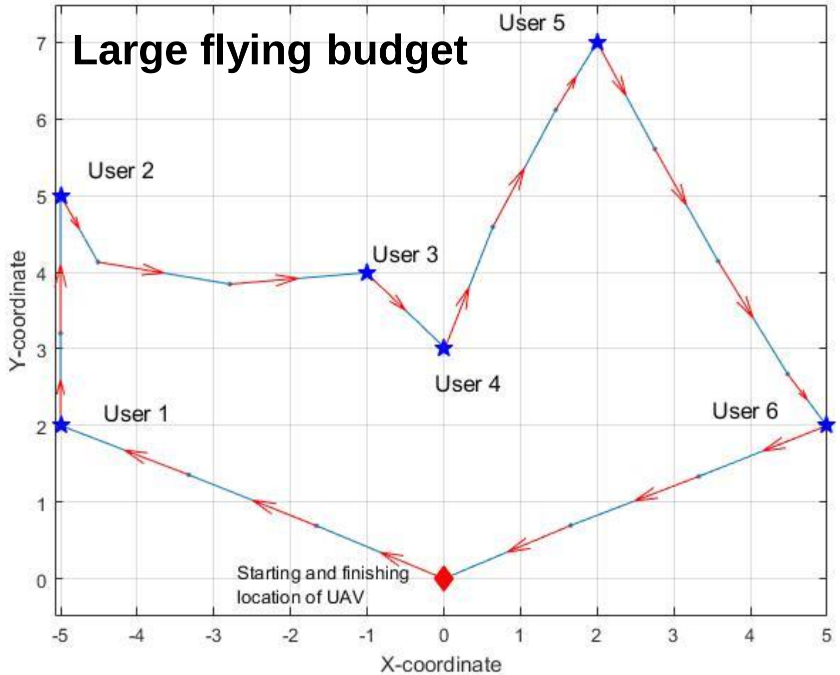
Offline path planning

$$\max_{x(t),y(t)} \; min\left\{\int_{t=0}^{T} R_1(t)dt\,,\int_{t=0}^{T} R_2(t)dt \ldots,\int_{t=0}^{T} R_K(t)dt\right\}$$ **(Max-min rate)**

Subject to $\sqrt{\dot{x}(t)^2+\dot{y}(t)^2} \leq V\,, t \in [0,T]$ **(Velocity Constraint)**

$$x(0)=x_o, y(0)=y_o,\; x(T)=x_F, y(T)=y_F$$ **(Start and end location)**

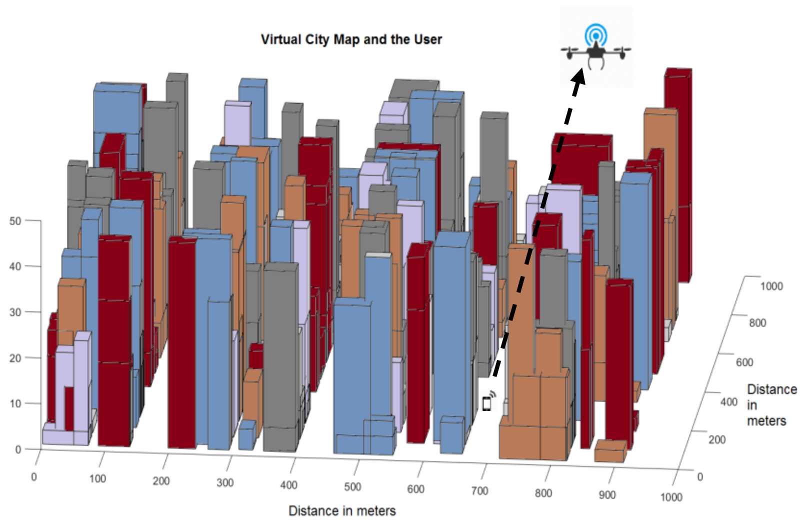




[1] R.Gangula, D.Gesbert, et.al "Trajectory Optimization for Mobile Access Point" Accepted in Asilomar 2017.
[2]A. T. Klesh, P. T. Kabamba, and A. R. Girard, "Path planning for cooperative time-optimal information collection," in American Control Conference, June 2008, pp. 1991–1996.
[3] Q. Wu, Y. Zeng, and R. Zhang, "Joint Trajectory and Communication Design for UAV-Enabled Multiple Access," , Apr. 2017.

Learning-based positioning

Training Data Collection (RSSI, traffic,) → Radio Map Reconstruction → Automatic Drone Position Computation → Autonomous Drone Navigation



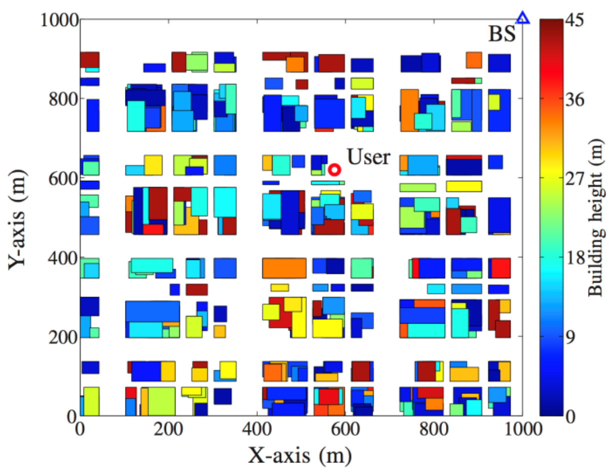
New approach: Simultaneous Learning and Positioning (SLAP)

Key idea: Learn positioning through radio map reconstruction

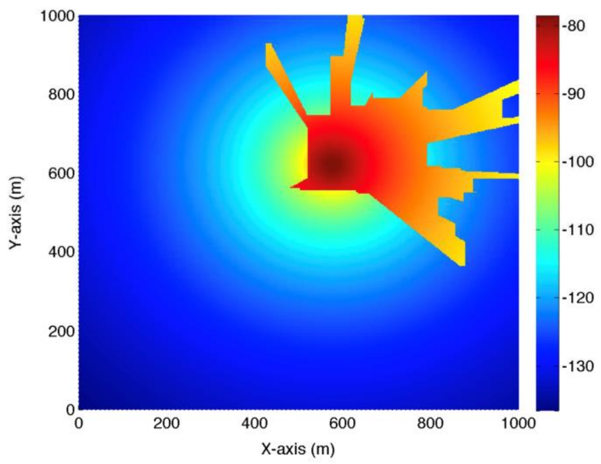
Map-based positioning

Suitable for micro-UAV (low altitude) high accuracy positioning:

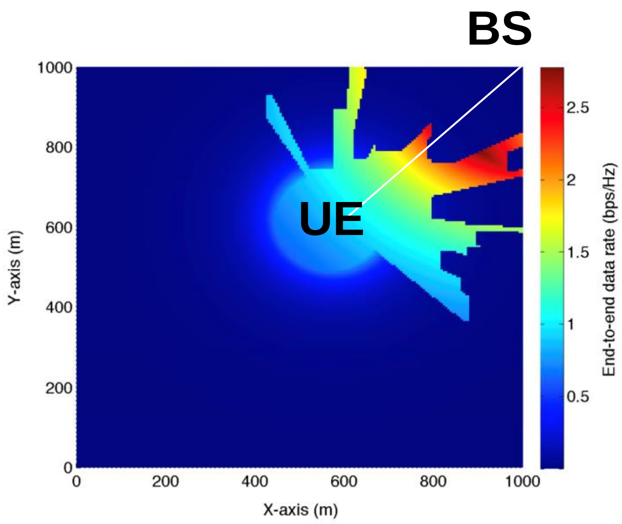
1) **UAV Learns LoS opportunities from above, with guarantees.**
2) **Use limited drone training locations only (flying time is costly!)**



Top view city map



UAV-user radio map



End-to-end capacity map

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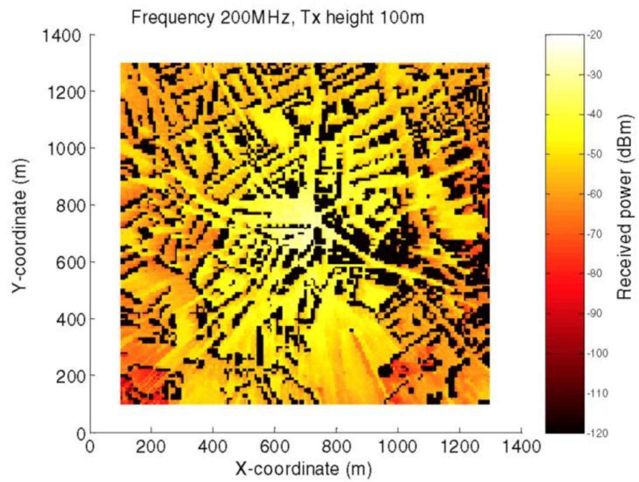
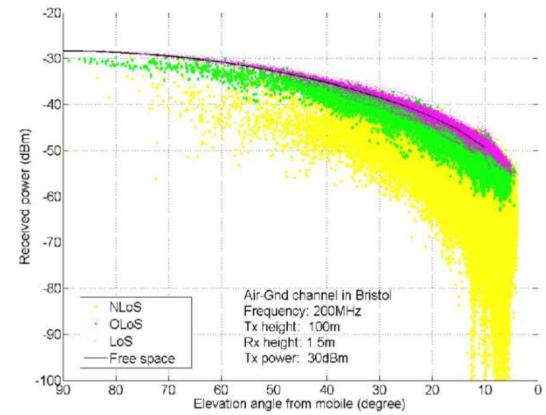
Learning Segmented Channel Models

Received power map UAV 100 meter above center of Bristol





Proposed Model: Ray-tracing with **Segmented Approximation**

- Classical log-distance model

$$10\log_{10}\left(g_{\mathrm{U}}(\mathbf{x})\right) = 10\log_{10}(\beta) - 10\alpha\log_{10}\left(\|\mathbf{x}-\mathbf{x}_{\mathrm{U}}\|\right) + \boxed{\xi}$$

Shadowing (e.g., LOS/NLOS), reflection, and diffraction, etc.

$$\xi_k + \tilde{\xi}_k$$

Ignore small residual

- Segmented propagation model: K segments

$$g_{\mathrm{U}}(\mathbf{x}) = \sum_k g_k(\mathbf{x})\mathbb{I}\{(\mathbf{x},\mathbf{x}_{\mathrm{U}}) \in \mathcal{D}_k\}$$

$$10\log_{10}\left(g_k(\mathbf{x})\right) = 10\log_{10}(\beta_k) - 10\alpha_k\log_{10}\left(\|\mathbf{x}-\mathbf{x}_{\mathrm{U}}\|\right)$$

Captured by classification to propagation segments, e.g., LOS/NLOS

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Kernel-based Radio Map Reconstruction

Given a position x, find a set of points from training data set $\{\mathbf{x}^{(m)}\}$

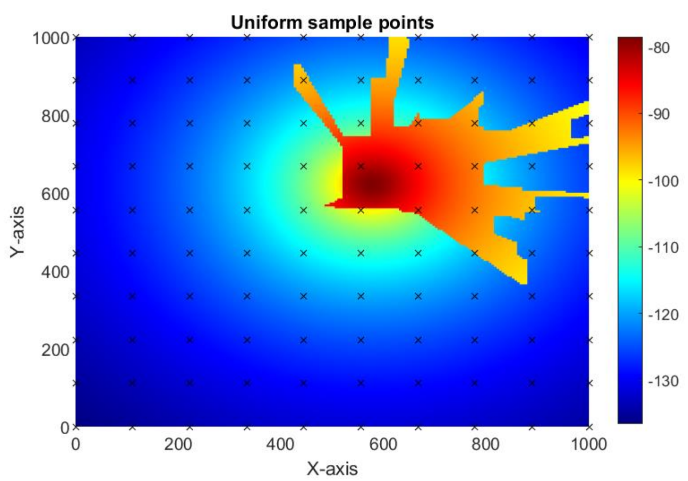
$$\mathcal{N}(\mathbf{x}) \triangleq \arg\min_{\mathcal{S}\subseteq\{1,2,\ldots,N\},|\mathcal{S}|=M} \sum_{m\in\mathcal{S}} \|\mathbf{x}-\mathbf{x}^{(m)}\|$$

Estimate segment labels through: $\hat{\mathbf{z}}(\mathbf{x}) = \mu \sum_{m\in\mathcal{N}(\mathbf{x})} \mathcal{K}(\mathbf{x},\mathbf{x}^{(m)})\bar{\mathbf{z}}^{(m)}$

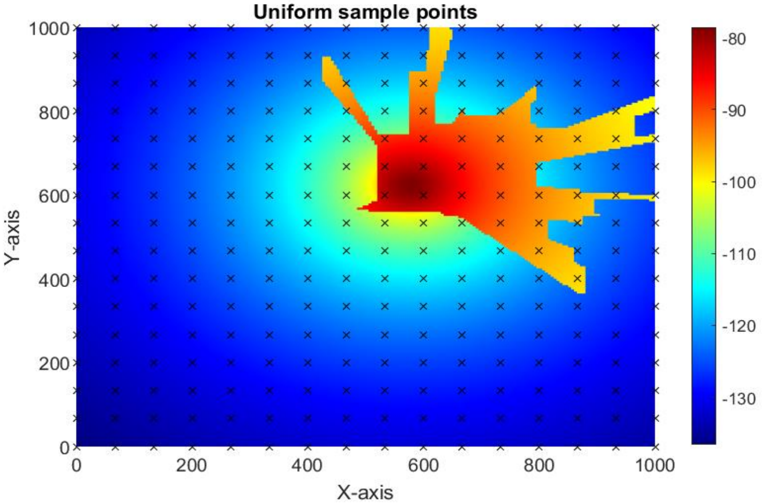
using the kernel function $\mathcal{K}(\mathbf{x},\mathbf{x}^{(m)}) = \exp\left\{-\|\mathbf{x}-\mathbf{x}^{(m)}\|^2/s\right\}$

Soft SNR reconstruction

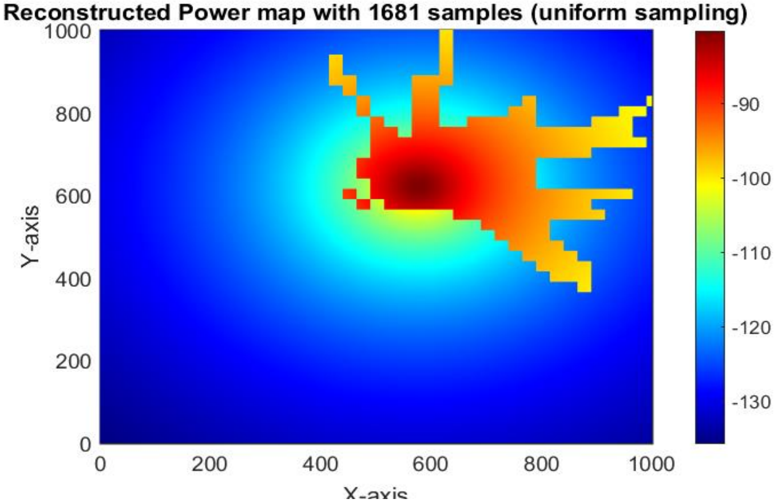
$$\hat{\gamma}_{\mathrm{S}}(\mathbf{x}) = \sum_{k=1}^{K} \left(\beta_k - 10\alpha_k \log_{10} d(\mathbf{x})\right) \hat{z}_k(\mathbf{x})$$

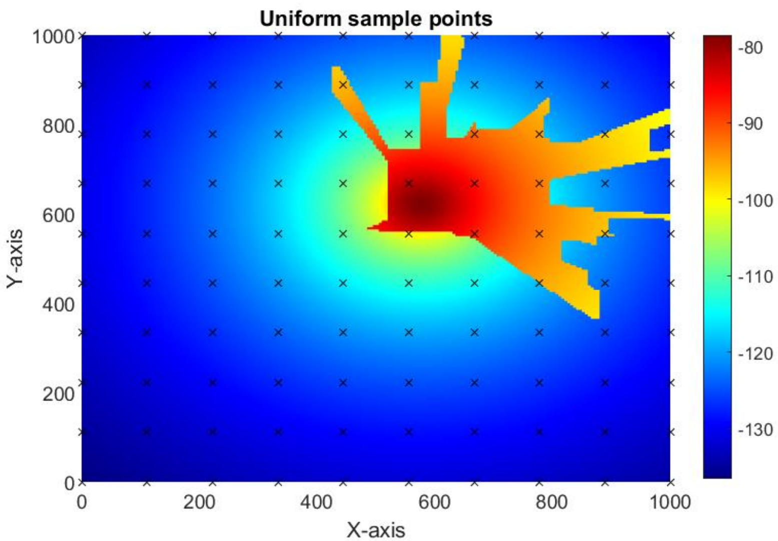


Radio map reconstruction

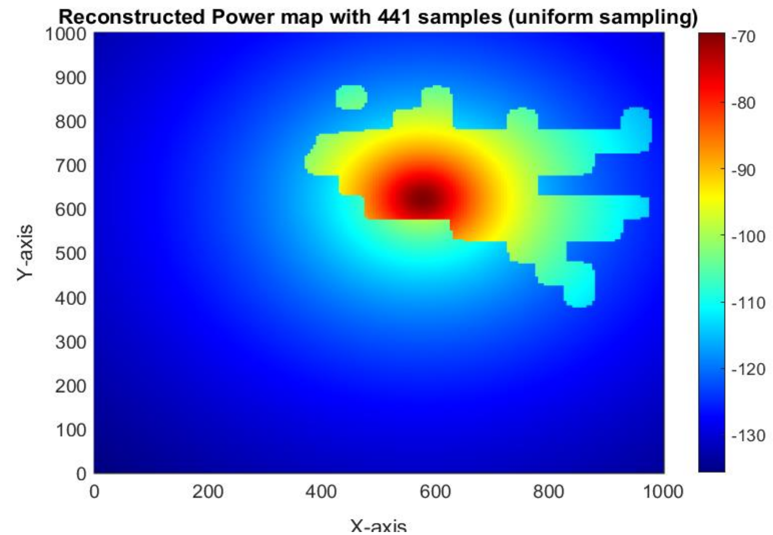


Dense Training



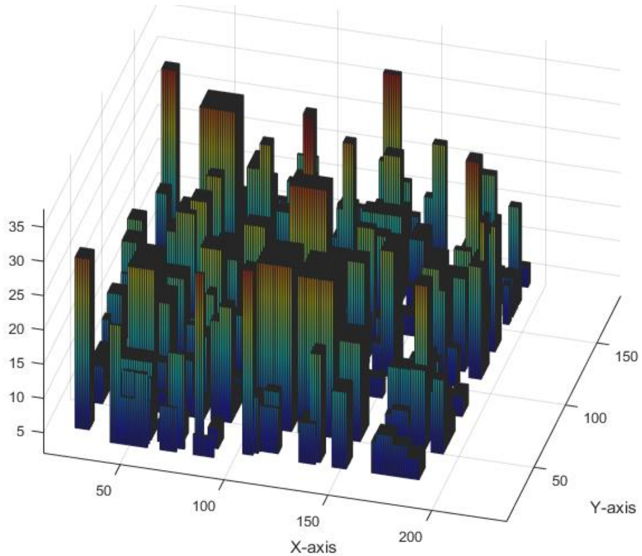


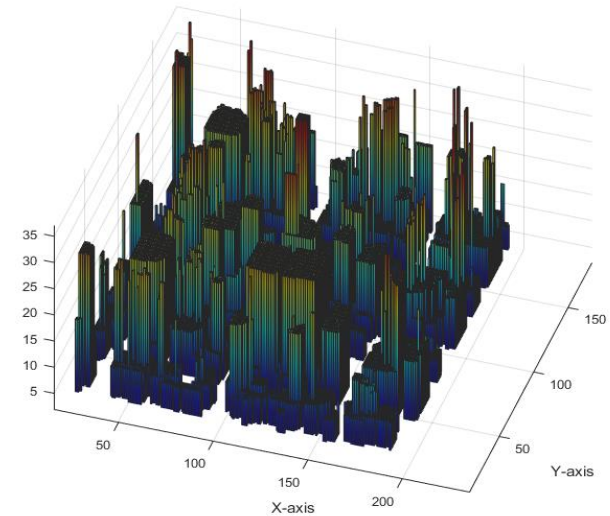
Sparse Training



Role of 3D maps?

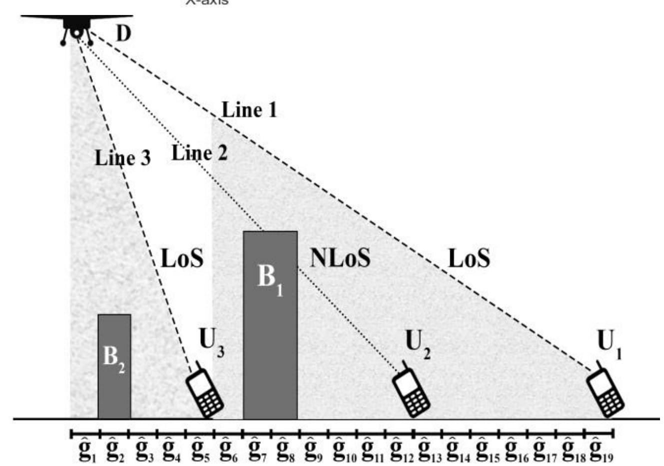
Machine Learning for 3D map reconstruction





Proposed concept:

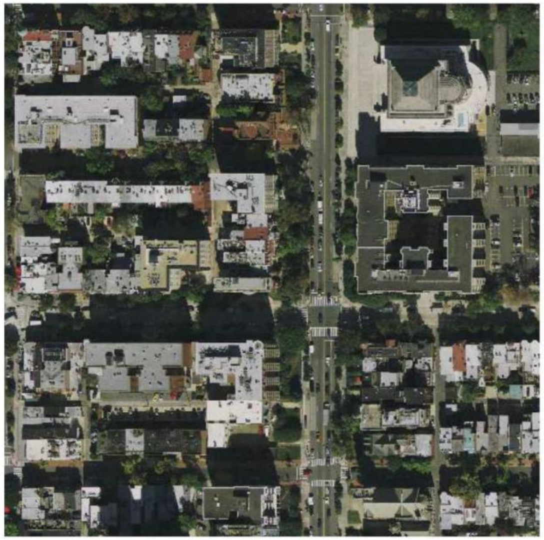
1- Learn propagation parameters using previous EM algorithr
2- Soft-classify users into LoS/NLoS
3- Reconstruct 3D map from “radio shadow” data



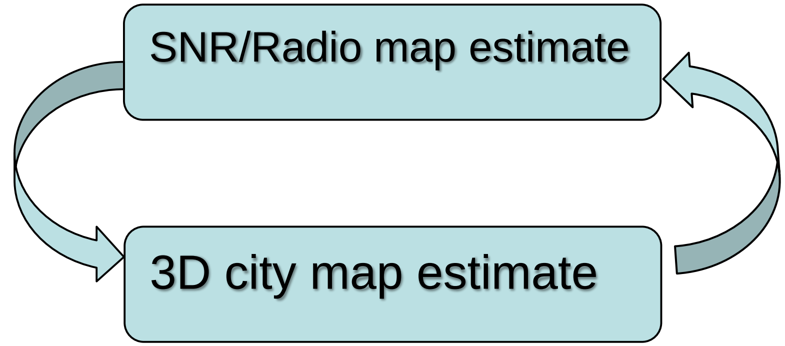
Connections with
-**3D Imaging with WiFi** [Y. Mostofi et al. @ UCSB]
-**GPS based 3D imaging** [Madhow et al @ UCSB]

[Esrafilian, Gesbert, Globecom 2017]

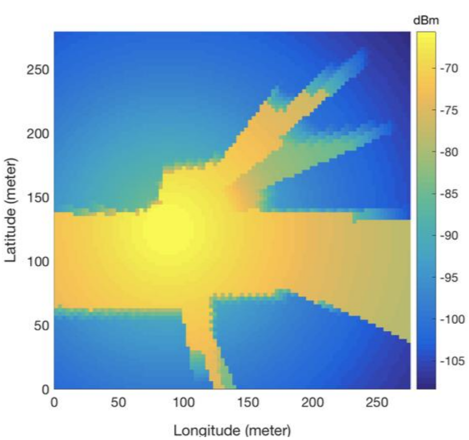
Joint 3D and radio map reconstruction



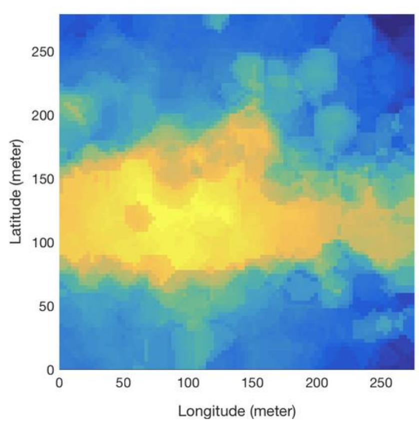
An orthoimagery of an area at center Washington DC, USA



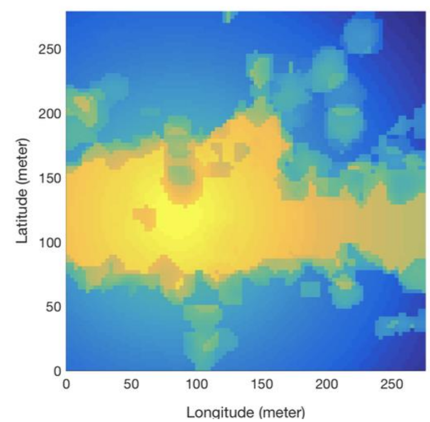
Radio map reconstruction



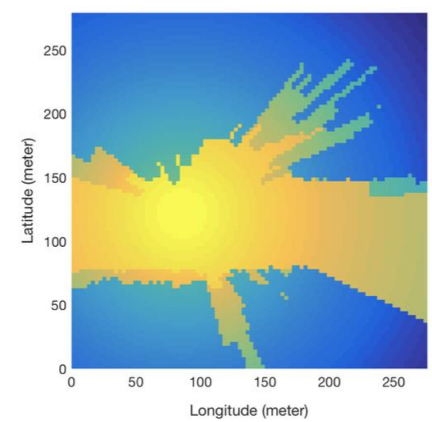
(a) True radio map



(b) KNN



(c) Direct reconstruction [8]



Joint approach

[Chen, Esrafilian, Gesbert, Mitra, Robotics, Science and Systems, MIT, 2017]

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- **Live video demo**
- **Please contact David G to watch it again!**