MACHINE LEARNING FOR WIRELESS COMMUNICATIONS AND NETWORKING:
MOTIVATIONS, CASE STUDIES, AND OPEN PROBLEMS

IEEE Communications Society **Kingston/CA & Denver Chapters**

Shiwen Mao
Auburn University, Auburn, AL, USA
http://www.eng.auburn.edu/~szm0001/

Joint work with: Chao Yang, Ticao Zhang, and Xuyu Wang

AUBURN UNIVERSITY
Electrical and Computer Engineering

In This Talk

- **The evolution towards 6G**
- Motivating examples of machine learning (ML) for Wireless
- Three case studies
- Challenges and thoughts

Evolution of Wireless Technology

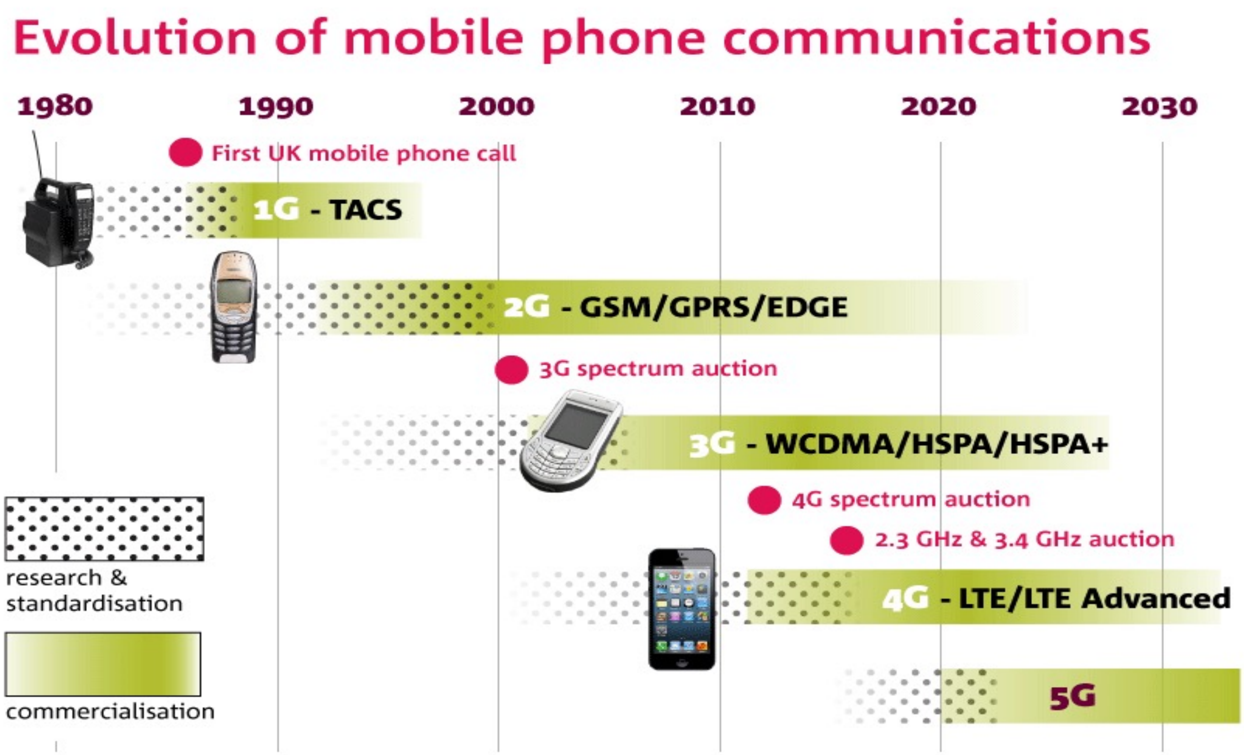
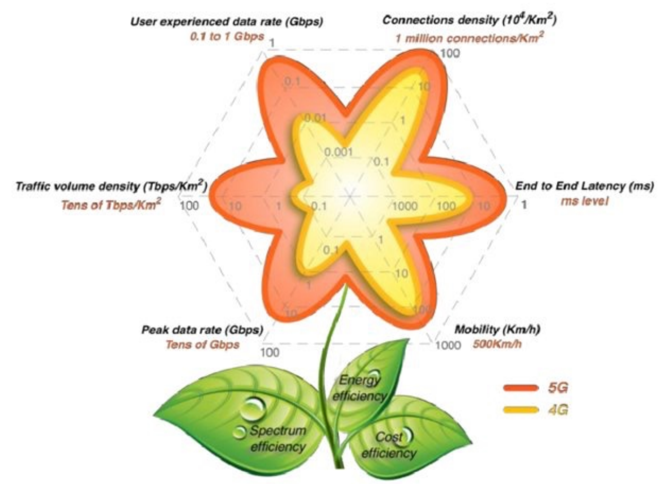


Image Source: http://tutorvoice.com/index.php/2015/10/11/generations-of-wireless-communication-technology/

$\mathcal{G}$ = Generation

- **Generation**: defined by new, fundamental, disruptive technology, a paradigm shift, for most devices (e.g., cellphones).
- 1G to 4G: each defined by its unique, key technology
- 5G is different:
  - Technology's view: Full duplex, cognitive radio, SDN/NFV, non-orthogonal multiple access (NOMA), small cells/HetNet, massive MIMO, mmWave communications; **OR**: spectrum expansion, spectrum efficiency enhancement, network densification
  - Standardization's perspective: Enhanced Mobile Broadband (eMBB), URLLC (Ultra Reliable Low Latency Communications), mMTC (massive Machine Type Communications)
- How about 6G?
  - Spectrum, Terahertz communications, light (VLC, FSO), blockchain, satellite, under water, VR/AR, …, intelligence
  - *AI is disruptive*: ML vs. model based; but seems highly suitable for wireless systems, which are historically based on probabilistic models



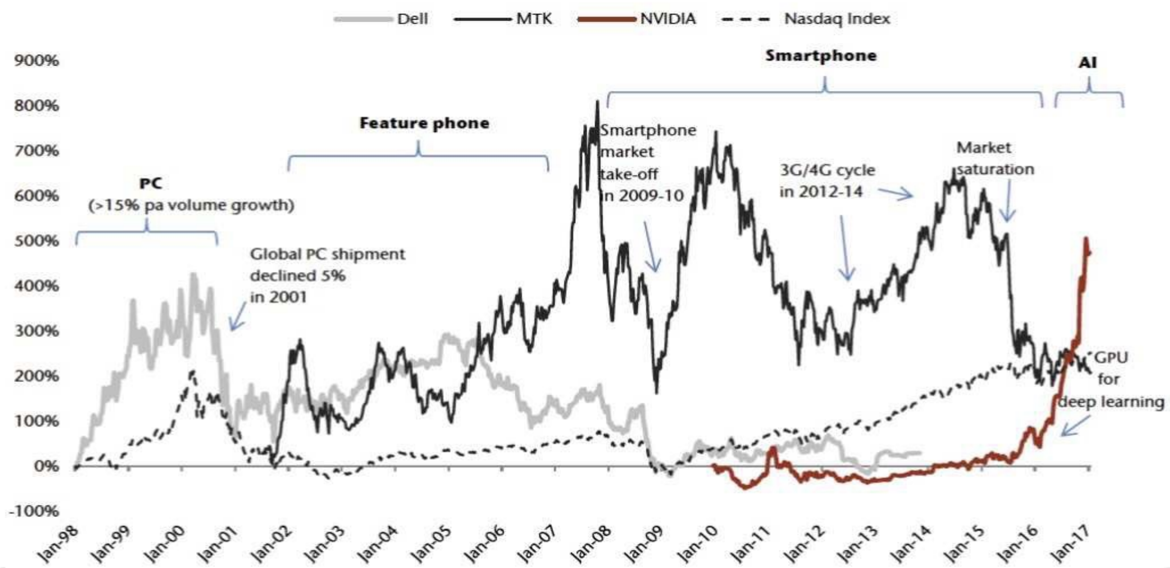
AUBURN UNIVERSITY
Electrical and Computer Engineering

Evolution of Hardware Platform

Machine Learning in the Market

Technology cycle - from *PC*, to *smartphone*, to ***artificial intelligence?***

***"Pure Play"* Share Price Performance**



Source: Bloomberg, Jefferies

6

AUBURN UNIVERSITY
Electrical and Computer Engineering

Time is Right

- Success in other fields: natural langrage processing, image recognition, gaming, …
- Epic events (good advertisement):
  - IBM Deep Blue vs. World Chess Champion Garry Kasparov (1997)
  - IBM's DeepQA project: quiz show Jeopardy! against legendary champions Brad Rutter and Ken Jennings, and won the first place prize of $1 million (2011)
  - Google DeepMind's AlphaGo/AlphaGo Zero: beat Ke Jie, the world No.1 ranked *Go* player (2017)
  - Facebook/CMU’s Pluribus: beat 15 of the world’s top poker players (2019)
  - Dr. Fill, Champion of the 43rd Annual American Crossword Puzzle Tournament (2021)
- Technology is ready:
  - Availability of: Data, Computing, and open-source Platforms
  - Smartphones and GPUs: more powerful than the computer used for moon landing/space shuttles
  - Network size increasing, heterogeneous, and more complex: hard to model, hard to solve
  - Wireless designs: historically based on probabilistic models (e.g., traffic, channel, interference, …), and are fault tolerant

AI, ML and Deep Learning

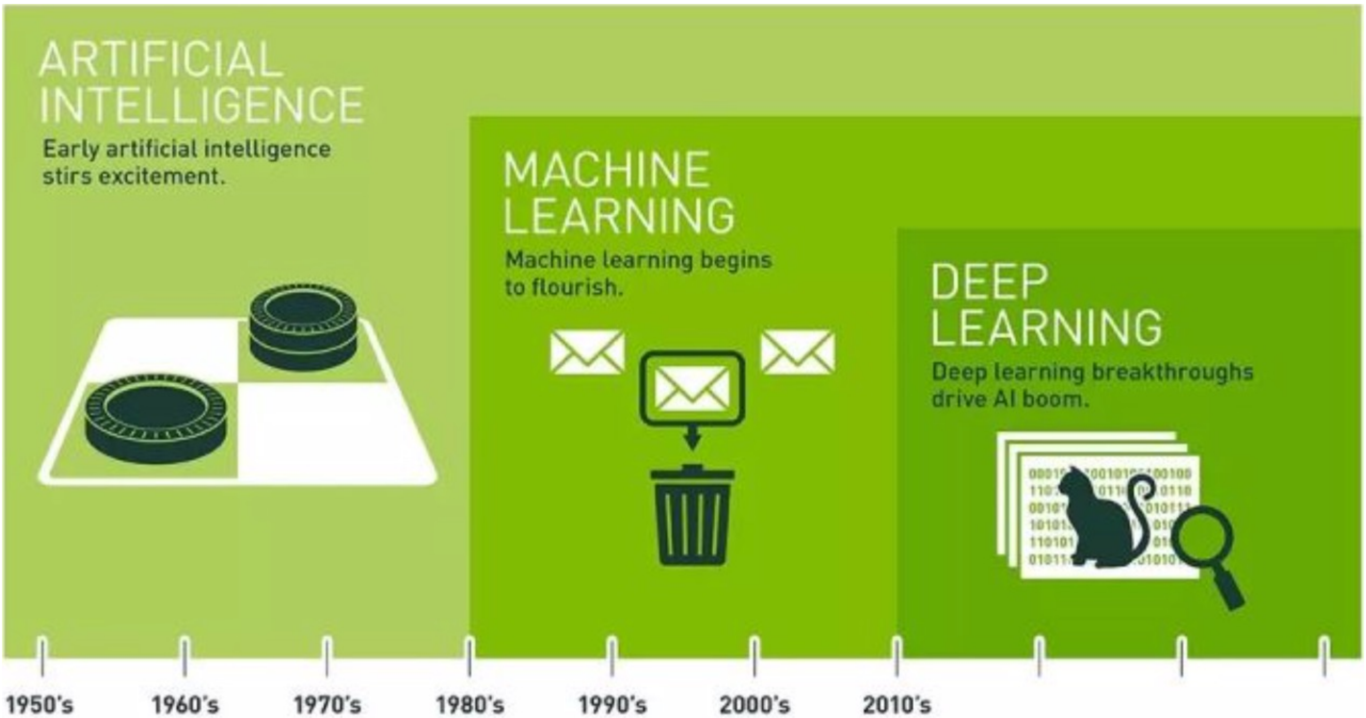


Image source: https://zhuanlan.zhihu.com/p/43435006

AI, ML and Deep Learning (Cont'd)

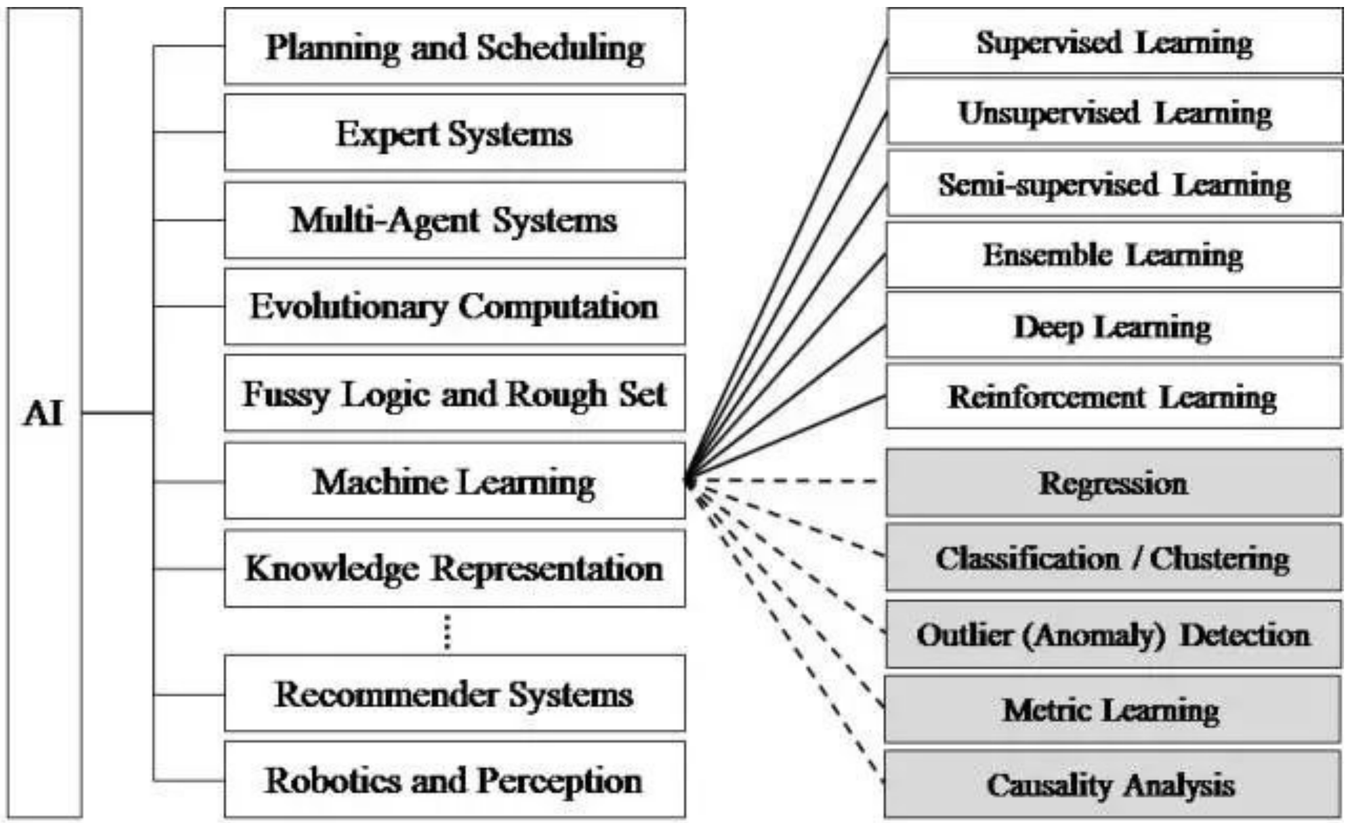


Image source: https://www.zhihu.com/question/57770020

Existing Work on ML for Communications

- Best Readings in Machine Learning in Communications
  - https://www.comsoc.org/publications/best-readings/machine-learning-communications
- Surveys
  - F. O. Olowononi, D. B. Rawat and C. Liu, "Resilient machine learning for networked cyber physical systems: A survey for machine learning security to securing machine learning for CPS," *IEEE Communications Surveys & Tutorials*, vol. 23, no. 1, pp. 524-552, Firstquarter 2021
  - M. Chen, U. Challita, W. Saad, C. Yin, and M. Debbah, "Artificial neural networks-based machine learning for wireless networks: A tutorial," *IEEE Communications Surveys & Tutorials*, vol. 21, no. 4, pp. 3039-3071, Fourthquarter 2019
  - Y. Sun, M. Peng, Y. Zhou, Y. Huang, and S. Mao, “Application of machine learning in wireless networks: Key technologies and open issues,” *IEEE Communications Surveys and Tutorials*, vol.21, no.4, pp.3072-3108, Fourth Quarter 2019
  - …
- Problems that have been explored
  - Signal detection
  - Channel encoding and decoding
  - Channel estimation, prediction, and compression
  - End-to-end communications
  - Resource allocation
  - Selected topics: localization, signal classification, full duplex, etc.
  - ….

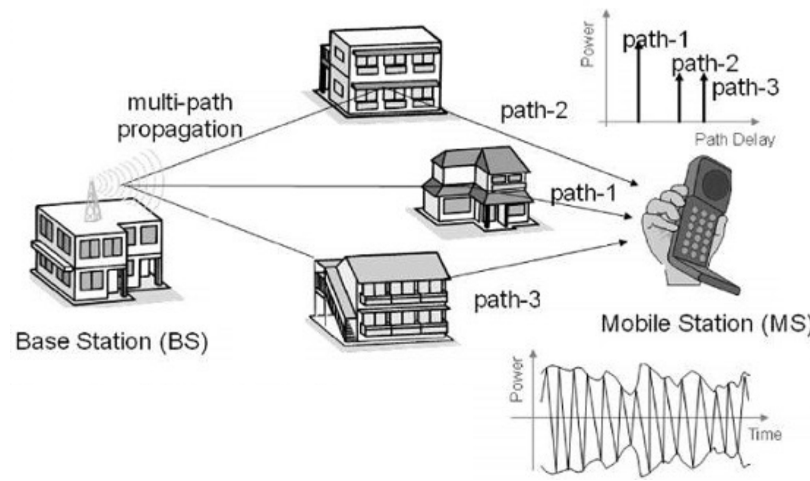
AUBURN UNIVERSITY
Electrical and Computer Engineering

In This Talk

- The evolution towards 6G
- **Motivating examples of ML for Wireless**
- Case studies
- Challenges and thoughts

Wireless Channel Modeling

- Parametric models:
  - Free-space model, two-way ground model
  - Rayleigh, Rician, Lognormal
- Empirical models:
  - Okumura/Hata Model: based on experimental data collected around Tokyo, Japan, by curve fitting and adding correction factors for specific conditions
  - …
- Ray tracing: for know environments using a simulator



- Channel estimation:
  - Complex channel function represented by basis expansion models: $\mathbf{h}(n;l) = \sum_{m=1}^{M} \mathbf{h}_m(l) u_m(n)$
  - A regression problem

AUBURN UNIVERSITY
Electrical and Computer Engineering

Image source: https://www.tutorialspoint.com/cdma/cdma_fading.htm

Wireless Systems Are Getting More Complex

- Considers:
  - Local execution, and offloading (to which BS)
  - CPU frequency tuning
  - Energy harvesting
  - Mobility/handover
- Control knobs (c^j, e^j):
  - c^j: offloading or local execution
  - e^j: energy allocation

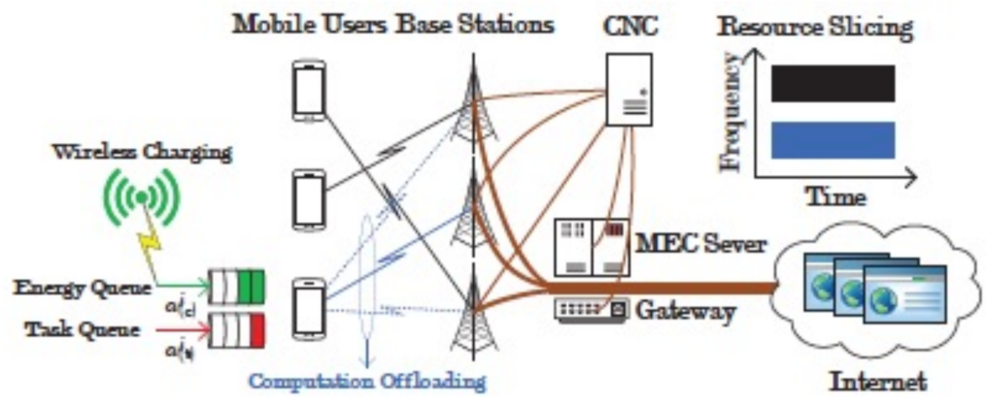


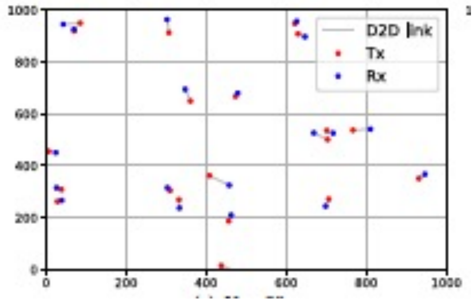
Fig. 1. Illustration of mobile-edge computing (MEC) in a virtualized radio access network, where the devices of mobile users are wireless charging enabled, the radio resource is sliced between conventional communication services (the links in black color) and MEC services (the links in blue color), and a centralized network controller (CNC) is responsible for all control plane decisions over the network.

Traditional analytical methods may not be capable of handling such complex problems

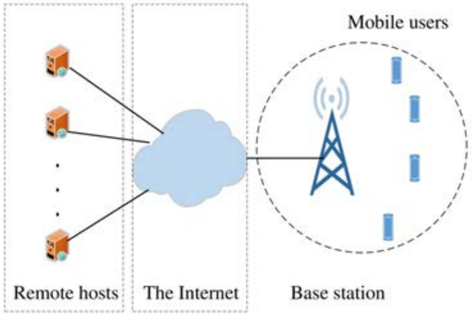
X. Chen, H. Zhang, C. Wu, S. Mao, Y. Ji, and M. Bennis, "Optimized computation offloading performance in virtual edge computing systems via deep reinforcement learning," *IEEE Internet of Things Journal*, vol.6, no.3, pp.4005-4018, June 2019.

Distributed Algorithms

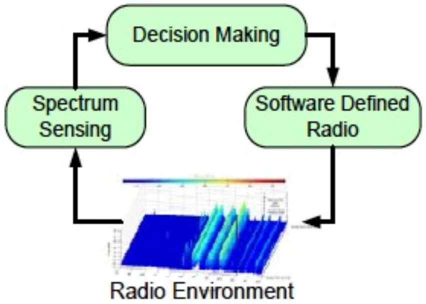
- Distributed power control:



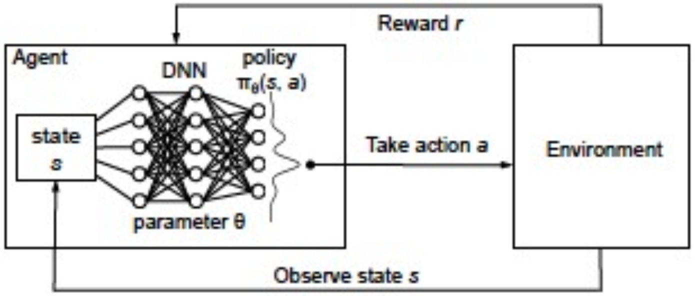
- End-to-end congestion control



- Cognitive radios



- Deep reinforcement learning



K. Xiao, S. Mao, and J.K. Tugnait, "TCP-Drinc: Smart congestion control based on deep reinforcement learning," *IEEE Access Journal*, Special Section on Artificial Intelligence and Cognitive Computing for Communications and Networks, vol.7, no.1, pp.11892-11904, Jan. 2019.

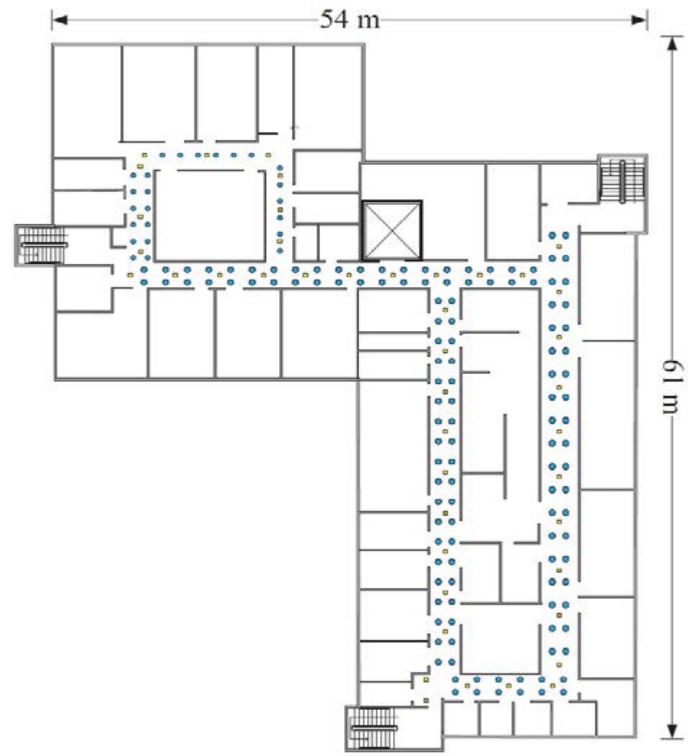
Image source: http://people.csail.mit.edu/hongzi/content/publications/DeepRM-HotNets16.pdf

Indoor Localization: Fingerprinting

- Training locations: war-driving to collect measurements at the training locations

- Compare new measurements from an unknown location with stored fingerprints to find the best match

A classification problem

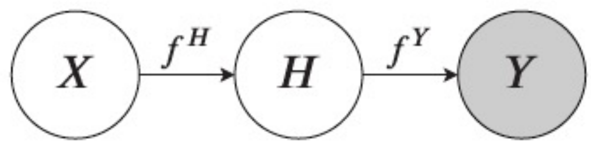


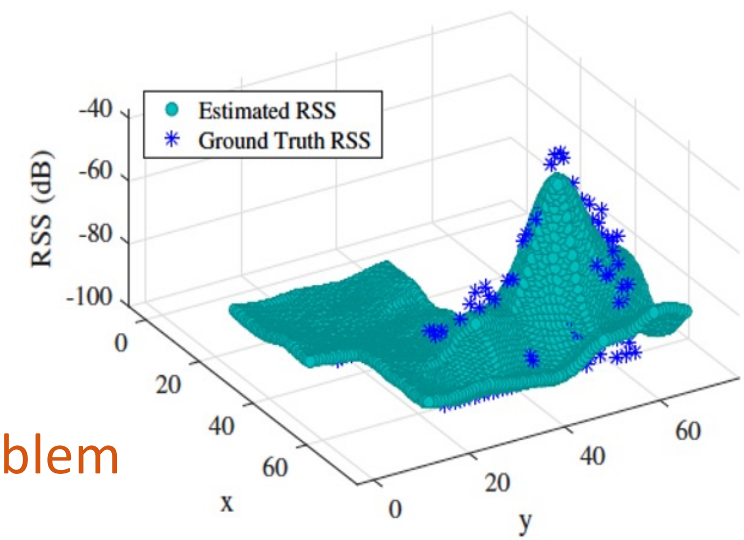
X. Wang, X. Wang, and S. Mao, “Indoor fingerprinting with bimodal CSI tensors: A deep residual sharing learning approach,” *IEEE Internet of Things Journal*, vol.8, no.6, pp.4498-4513, Mar. 2021.
X. Wang, L. Gao*, S. Mao, and Santosh Pandey, “CSI-based fingerprinting for indoor localization: A deep learning approach,” *IEEE Transactions on Vehicular Technology*, vol.66, no.1, pp.763-776, Jan. 2017.

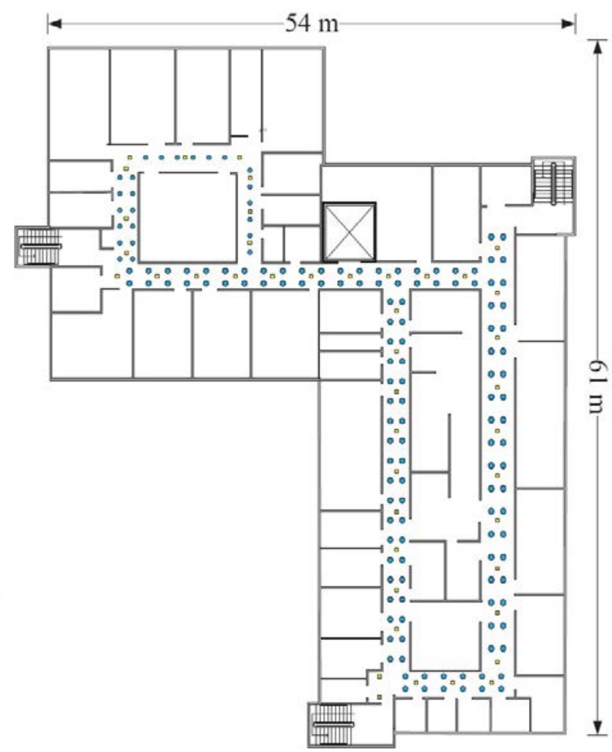
Indoor Localization: Radio Map Construction

- Construct a radio map with discrete training data
- Use the radio map for location estimation
- Deep Gaussian process

A regression problem







X. Wang*, X. Wang*, S. Mao, J. Zhang, S. CG Periaswamy, and J. Patton, "Indoor radio map construction and localization with deep Gaussian Processes," *IEEE Internet of Things Journal*, vol.7, no.11, pp. 11238-11249, Nov. 2020.

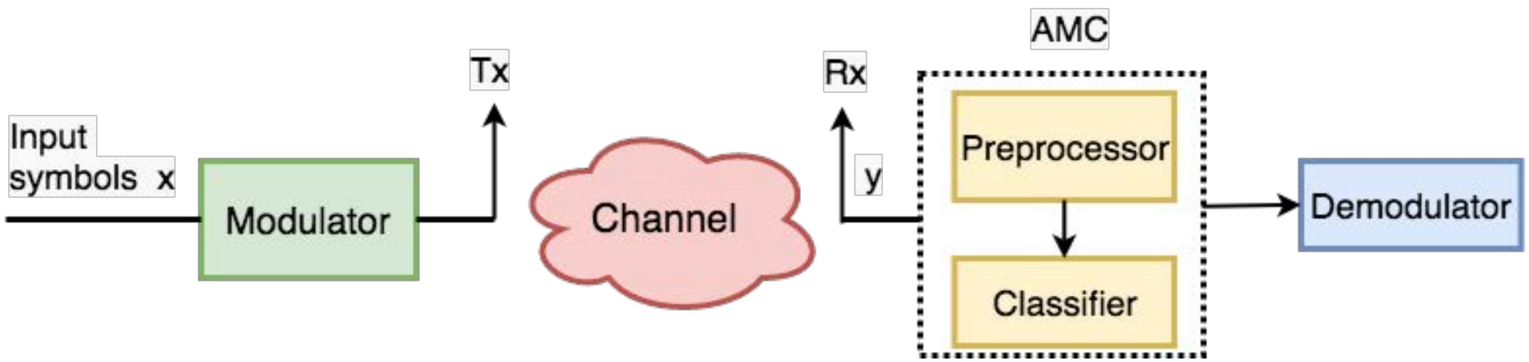
In This Talk

- The evolution towards 6G
- Motivating examples of ML for Wireless
- **Case studies**
  - **Automatic Modulation Classification**
  - Energy efficiency maximization
  - 3D human skeleton tracking
- Challenges and thoughts

AUBURN UNIVERSITY
Electrical and Computer Engineering

Automatic Modulation Classification (AMC)

- An essential component of cognitive radio (CR) to detect the nearby emitters, avoid radio inference, and improve spectrum efficiency
- Classify the modulation types of received signals without a priori information of the signal and channel; an important step between signal detection and demodulation
- Applications: spectrum sensing and access, spectrum anomaly detection, classification security, and transmitter identification



M. Patel, X. Wang, and S. Mao, "Data augmentation with Conditional GAN for automatic modulation classification," in *Proc. 2020 ACM Workshop on Wireless Security and Machine Learning* (WiseML 2020), in conjunction with ACM WiSec 2020, Linz, Austria, July 2020, pp.31-36.

Related Work

Likelihood-based:

- Bayesian estimation for modulation classification assuming prior information such as channel and noise models
- High computational complexity and are not suited for highly dynamic environments

Feature-based:

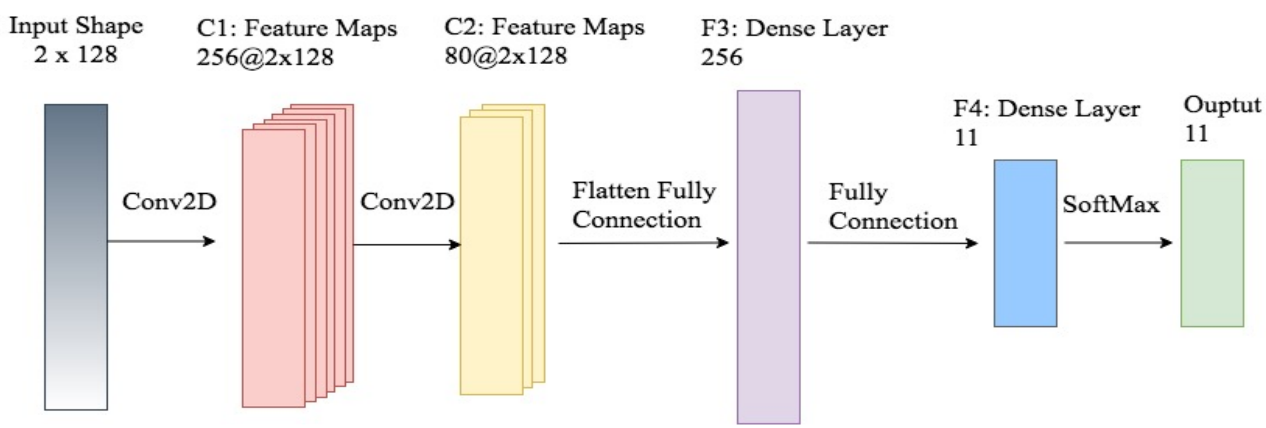
- Handcrafted features (i.e., cumulant, and maximum power spectral density) for classifying modulations
- Requires reliable features and manual selection

Deep Learning-based:

- Without assuming prior information such as channel models.
- Convolutional neural network (CNN), recurrent neural networks (RNN), and fusion methods are proposed
- A massive amount of training samples are required and the performance hinges upon the quality of the samples

System Model

- Dataset [1]
  - RadioML2016.10A dataset: synthetic samples with 11 different modulations, including 8PSK, AM-DSB, AM-SSB, BPSK, CPFSK, GFSK, PAM4, QAM16, QAM64, QPSK, and WBFM
  - 220,000 samples; 20,000 samples for each modulation type
  - Sampled at 20 different SNR levels (from -20dB to 18dB), with 1,000 samples for each SNR level
  - Each radio signal sample consists of 128 consecutive I/Q data units
- CNN model [1]



[1] T. J O'Shea, J. Corgan, and C. Clancy, "Convolutional radio modulation recognition networks," In *Proc. 2016 Int. Conf. Engineering Appl. Neural Netw.*, Aberdeen, Scotland, 213–226, 2016.

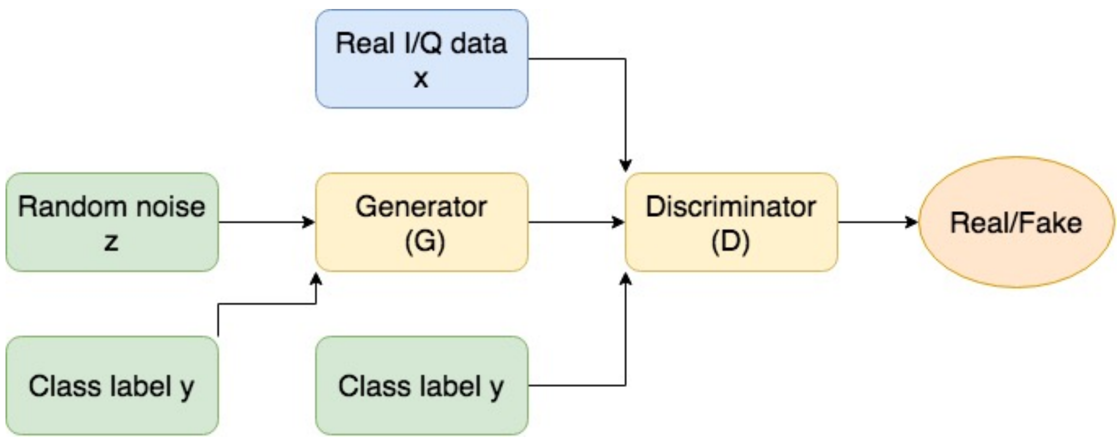
Data Augmentation: CGAN Model

Generative adversarial network (GAN): a generative machine learning model

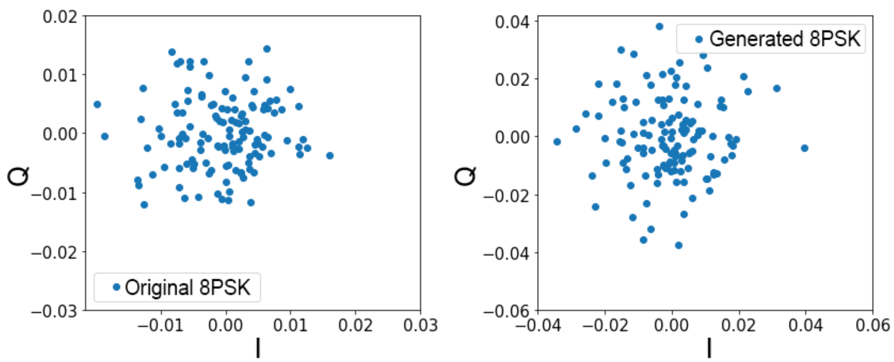
- A generative model G: generate samples from random noise z
- A discriminative model D: distinguish generated samples from training samples
- Unsupervised learning, and thus *cannot generate labeled data*

Conditional GAN (CGAN): both G and D are conditioned on auxiliary information, i.e., class label y, that act as an extension to the latent space z to generate and discriminate synthesized data

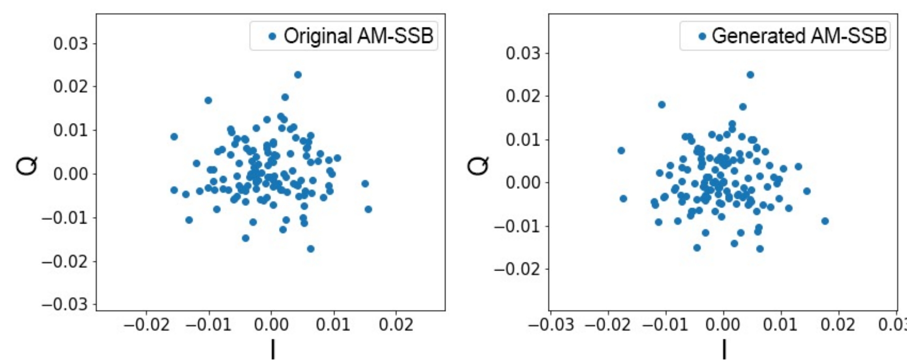
- Adding class labels y can control the output and guide the generator G to figure out what to generate



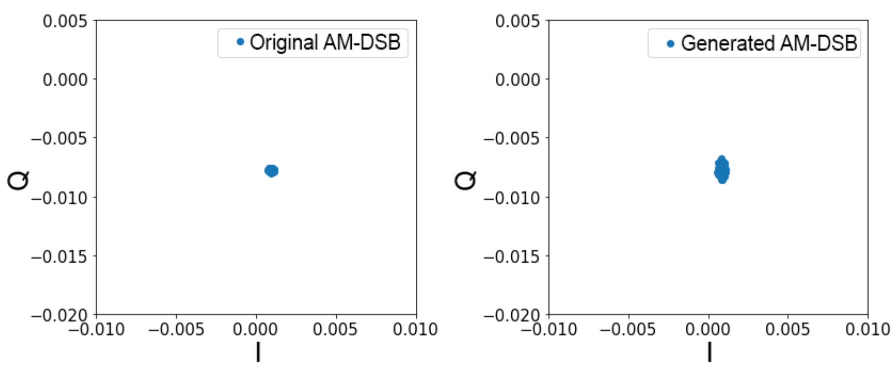
Experiment Results (Original vs. Synthesized Data)



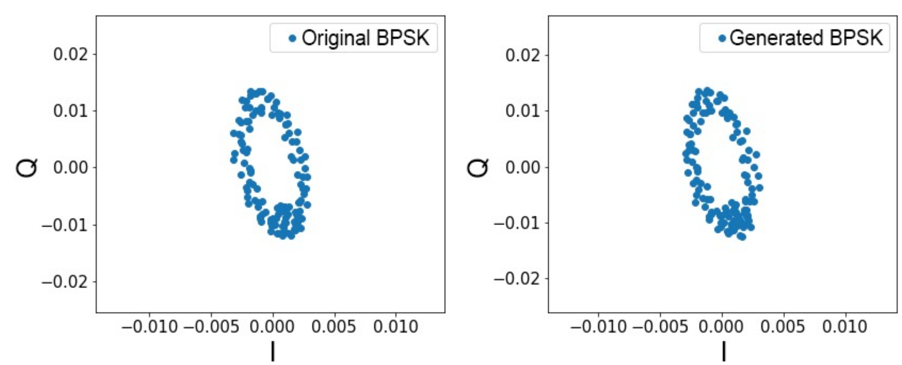
8PSK (SNR=16dB): (left) original data; (right) synthesized data.



AM-SSB (SNR=16dB): (left) original data; (right) synthesized data.

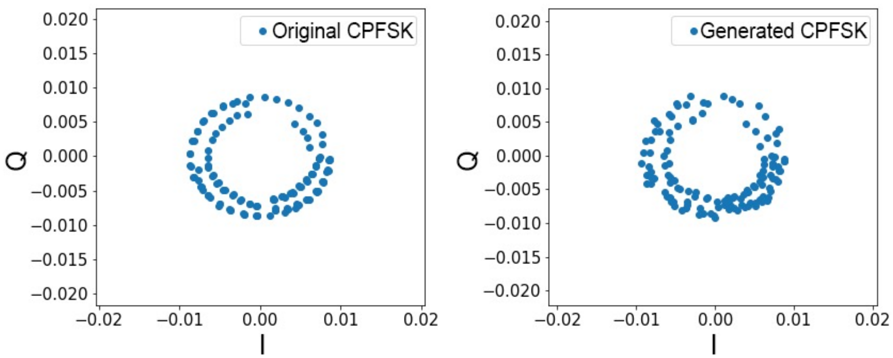


AM-DSB (SNR=16dB): (left) original data; (right) synthesized data.

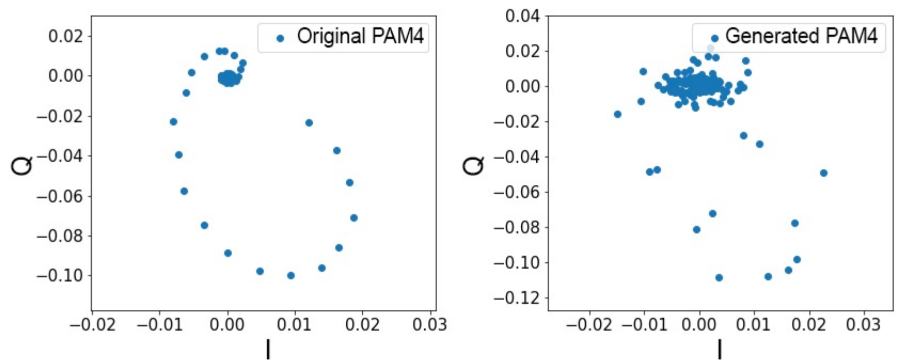


BPSK (SNR=16dB): (left) original data; (right) synthesized data.

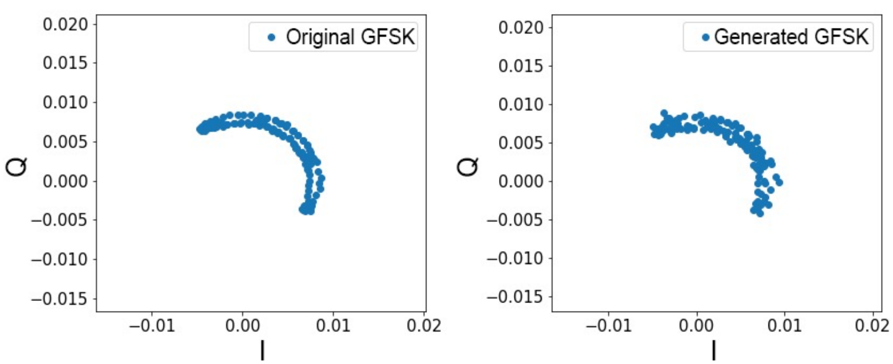
Experiment Results (Original vs. Synthesized Data, Cont'd)



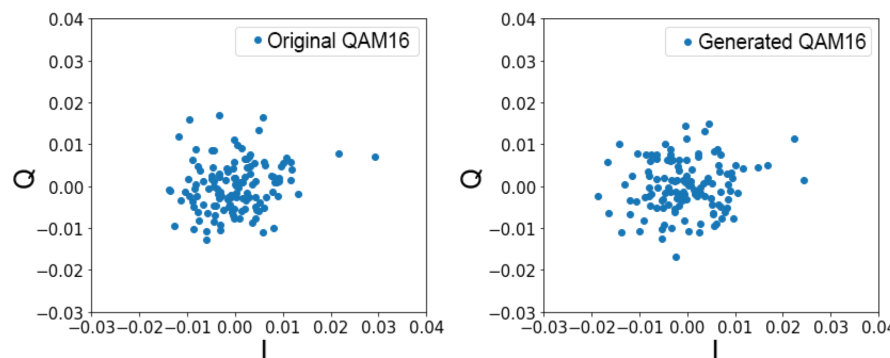
CPFSK (SNR=16dB): (left) original data; (right) synthesized data.



PAM4 (SNR=16dB): (left) original data; (right) synthesized data.

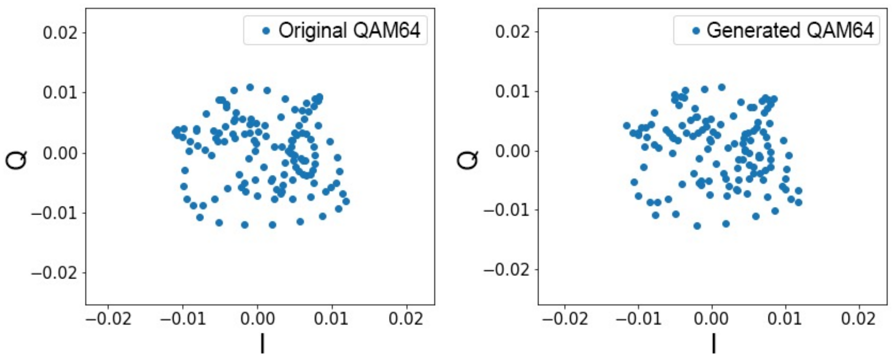


GFSK (SNR=16dB): (left) original data; (right) synthesized data.

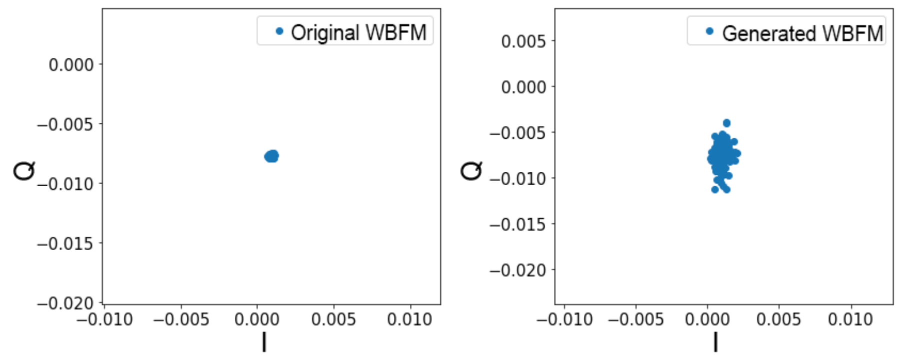


QAM16 (SNR=16dB): (left) original data; (right) synthesized data.

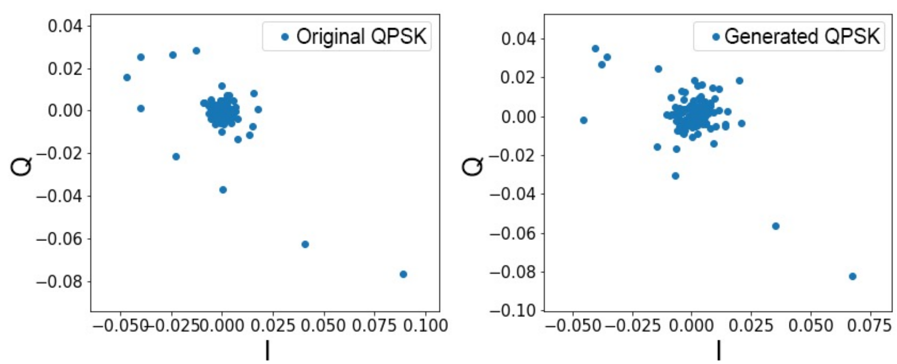
Experiment Results (Original vs. Synthesized Data, Cont'd)



QAM64 (SNR=16dB): (left) original data; (right) synthesized data.



WBFM (SNR=16dB): (left) original data; (right) synthesized data.

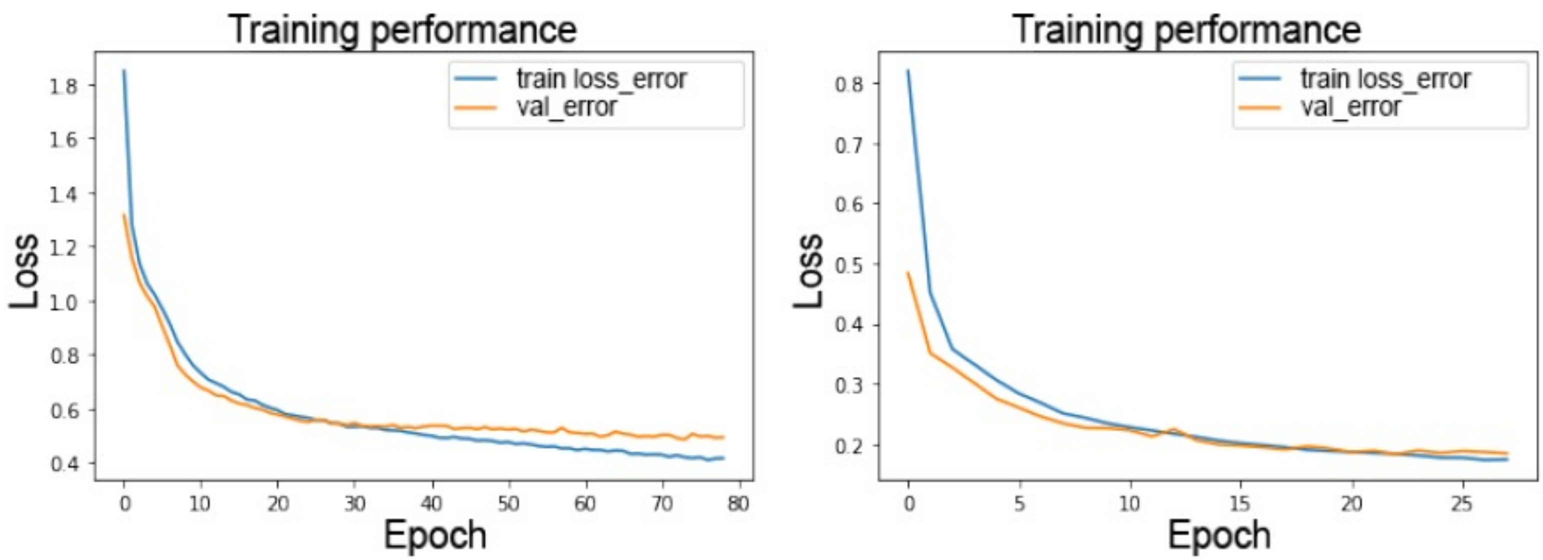


QPSK (SNR=16dB): (left) original data; (right) synthesized data.

AUBURN UNIVERSITY
Electrical and Computer Engineering

Training and Validation Errors

CNN training can greatly benefit from the CGAN augmented data to achieve fast convergence and a smaller training loss



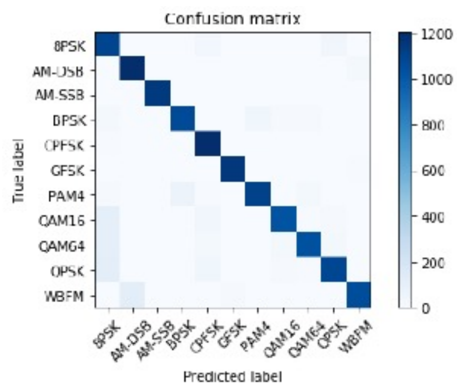
(a) 1000 synthesized samples. **(b) 5000 synthesized samples.**

Training performance when SNR=16 dB with (a) 1000 and (b) 5000 synthesized samples.

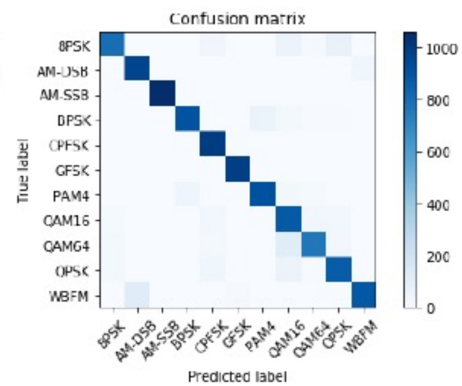
Confusion Matrices

Confusion matrices for modulation classification when SNR = 16dB with different amount of synthesized data

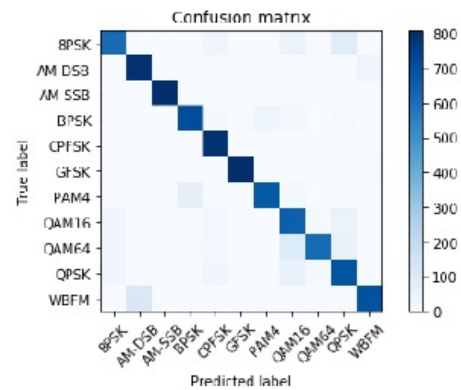
Synthesized data helps



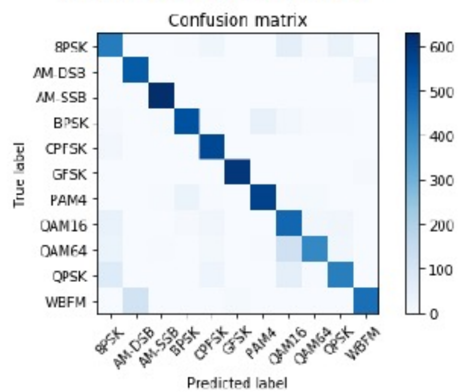
(a) 5000 synthesized samples.



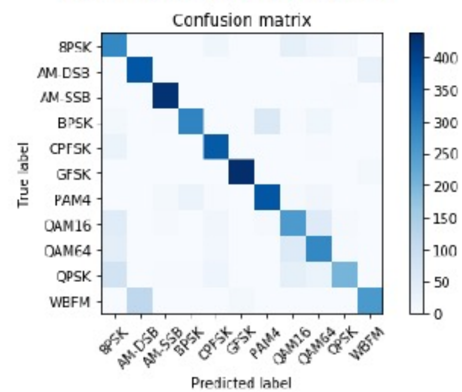
(b) 4000 synthesized samples.



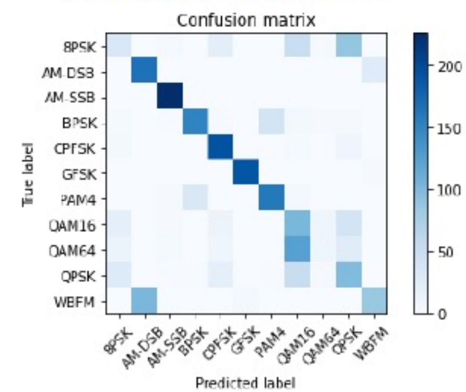
(c) 3000 synthesized samples.



(d) 2000 synthesized samples.



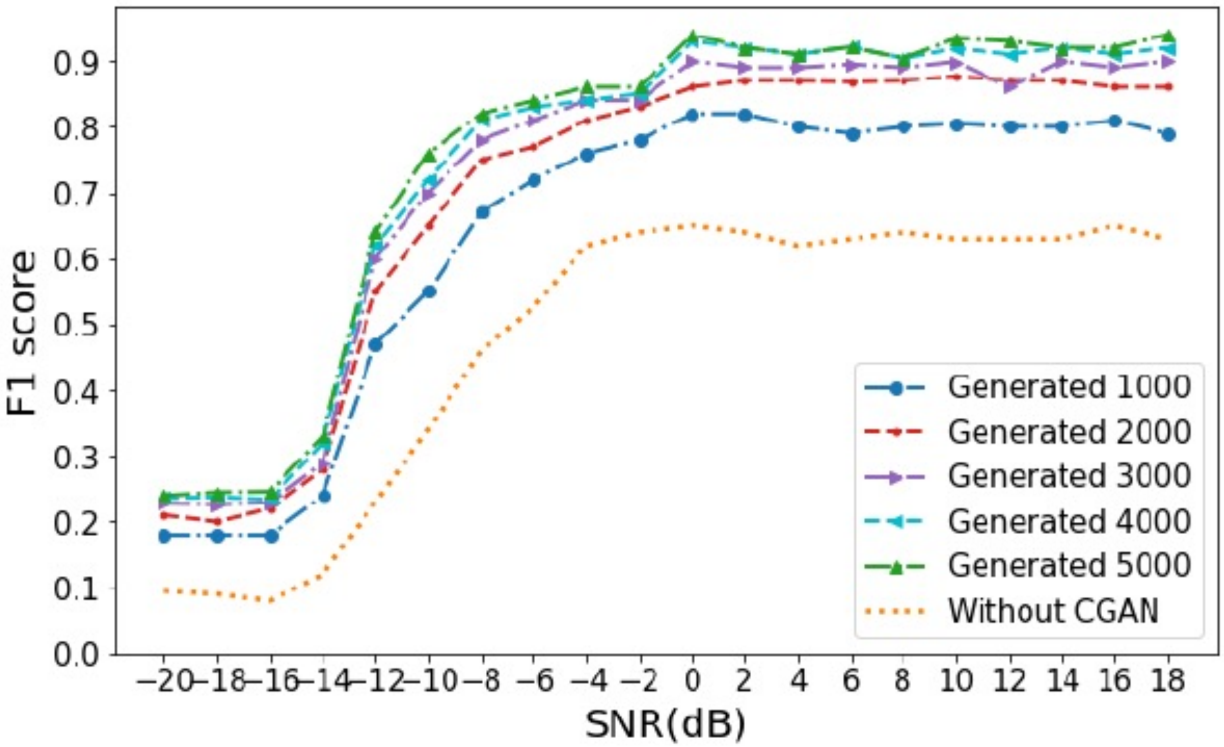
(e) 1000 synthesized samples.



(f) Without CGAN.

Classification Accuracy

16% to 25% gain in F1 score



Classification accuracy with different amount of augmented data

AUBURN UNIVERSITY
Electrical and Computer Engineering

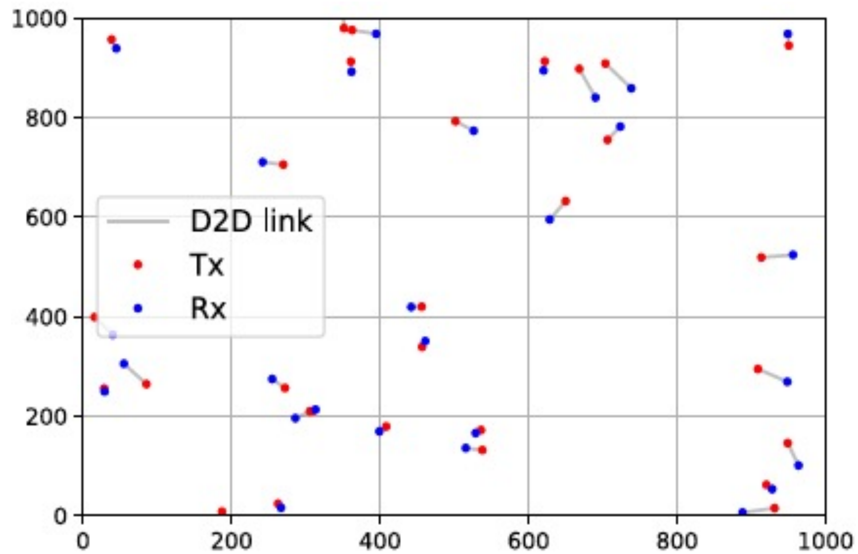
In This Talk

- The evolution towards 6G
- Motivating examples of ML for Wireless
- **Case studies**
  - Automatic Modulation Classification
  - **Energy efficiency maximization**
  - 3D human skeleton tracking
- Challenges and thoughts

Energy Efficiency Maximization

- The energy efficiency maximization problem:

$$(\mathrm{P1}) \quad \max_{p_i} \quad \eta_{\mathrm{EE}}(\mathbf{p}) = \frac{R(\mathbf{p})}{P(\mathbf{p})}$$
$$\text{s.t.} \quad p_i \in [0, p_{\max}]$$



- Fractional format, conventional convex optimization theory does not apply
- NP-hard problem [1,2]; a global optimal incurs an exponentially growing complexity [2]
- Duality theory and fractional programming [3] can provide suboptimal solutions

[1] A. Zappone, E. Bjornson, L. Sanguinetti, and E. Jorswieck, "Globally optimal energy-efficient power control and receiver design in wireless networks," *IEEE Trans. Signal Process.*, vol. 65, pp.2844–2859, June 2017.
[2] A. Zappone, L. Sanguinetti, G. Bacci, E. Jorswieck, and M. Debbah, "Energy-efficient power control: A look at 5G wireless technologies," *IEEE Trans. Signal Process.*, vol. 64, no. 7, pp.1668–1683, Apr. 2016.
[3] C. Isheden, Z. Chong, E. Jorswieck, and G. Fettweis, "Framework for link-level energy efficiency optimization with informed transmitter," *IEEE Trans. Wireless Commun.*, vol. 11, no. 8, pp.2946–2957, Aug. 2012.

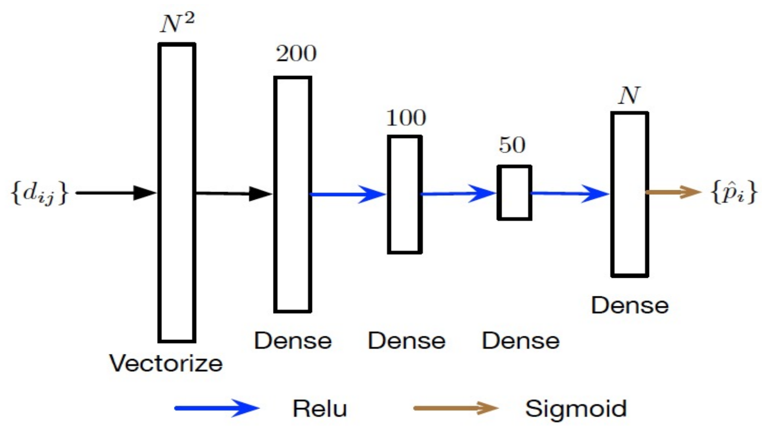
Approximation Algorithms

- Branch-and-bound and Reformulation-Linearization Technique (RLT) [1]: high complexity
- *Successive pseudo-convex approximation* (SPCA) algorithm [2,3]
  - To approximate the objective function with functions that have specific properties (e.g., convexity)
    - Expand the nonconvex sum rate function in the numerator with a first-order Taylor series, which is positive concave
  - The objective function is approximated by a pseudo concave function, which ensures that the original problem and the approximated problem shares the same sets of stationary points
  - Search the stationary points of the approximation problem. Pseudo concavity ensures that the resulted stationary points are global optimal for the approximated problem …
  - which is a suboptimal solution to the original problem
  - But at high computation cost

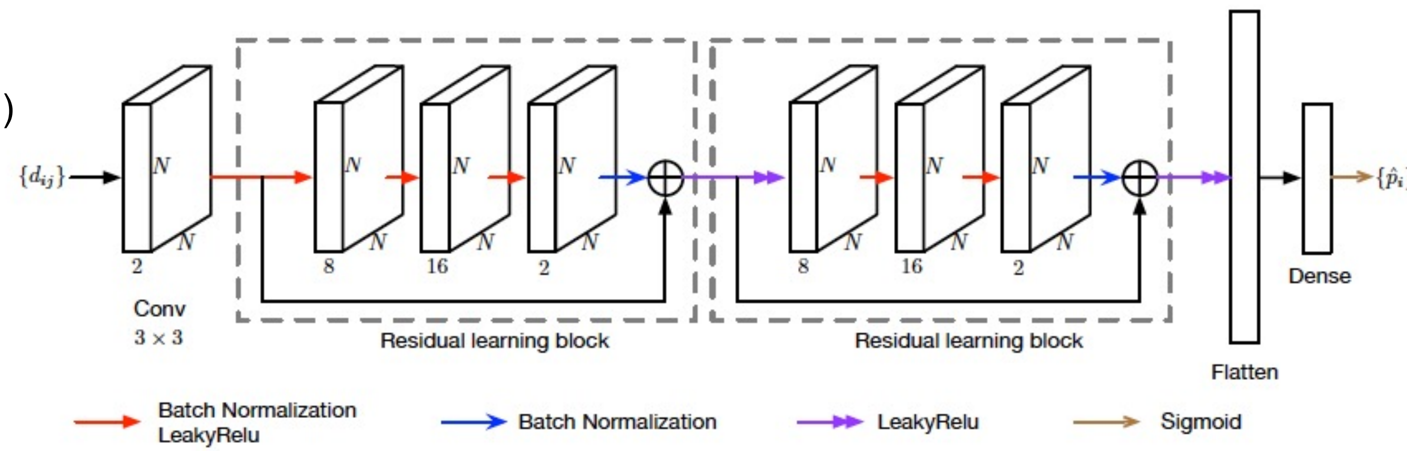
[1] S. Kompella, S. Mao, Y. T. Hou, and H. D. Sherali, "On path selection and rate allocation for video in wireless mesh networks," *IEEE/ACM Transactions on Networking*, vol.17, no.1, pp.212-224, Feb. 2009.
[2] Y. Yang and M. Pesavento, "A unified successive pseudoconvex approximation framework," *IEEE Trans. Signal Process.*, vol. 65, no. 13, pp.3313–3328, July 2017.
[3] T. Zhang and S. Mao, "Energy-efficient power control in wireless networks with spatial deep neural networks," *IEEE Transactions on Cognitive Communications and Networking*, vol.6, no.1, pp.111-124, Mar. 2020. DOI: 10.1109/TCCN.2019.2945774.

Deep Learning Models

DNN



PowerNet
(CNN based)



Evaluation

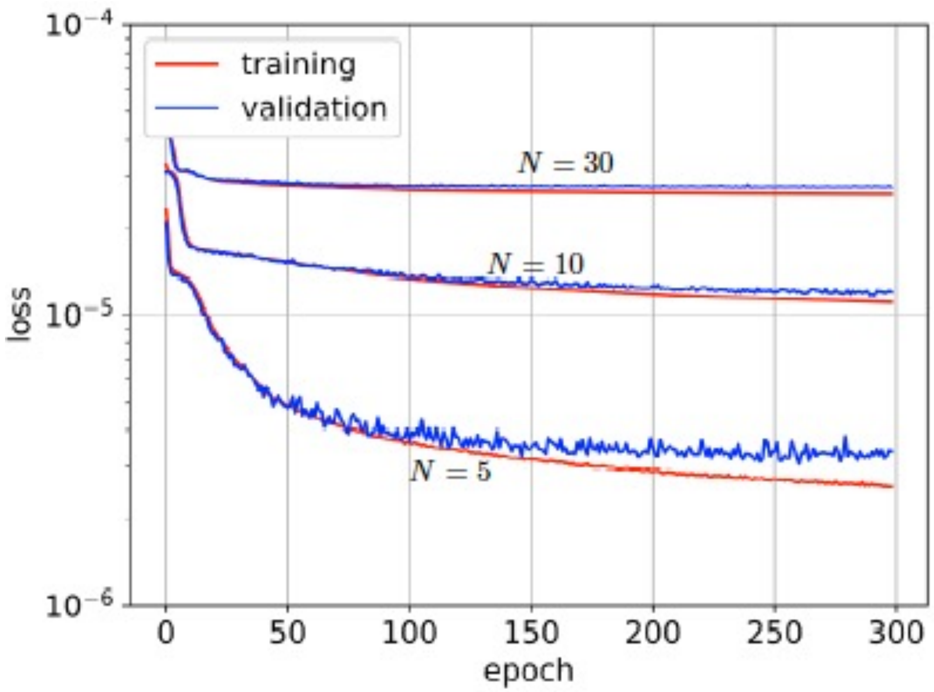
- Generate random locations $\{d_{ij}\}$, use the SPCA algorithm to compute the power allocation $\{p_i\}$
- Repeat, to generate a training dataset

- The DNN and PowerNet models, taking input $\{d_{ij}\}$ and label $\{p_i\}$, will be trained to minimize the loss function:

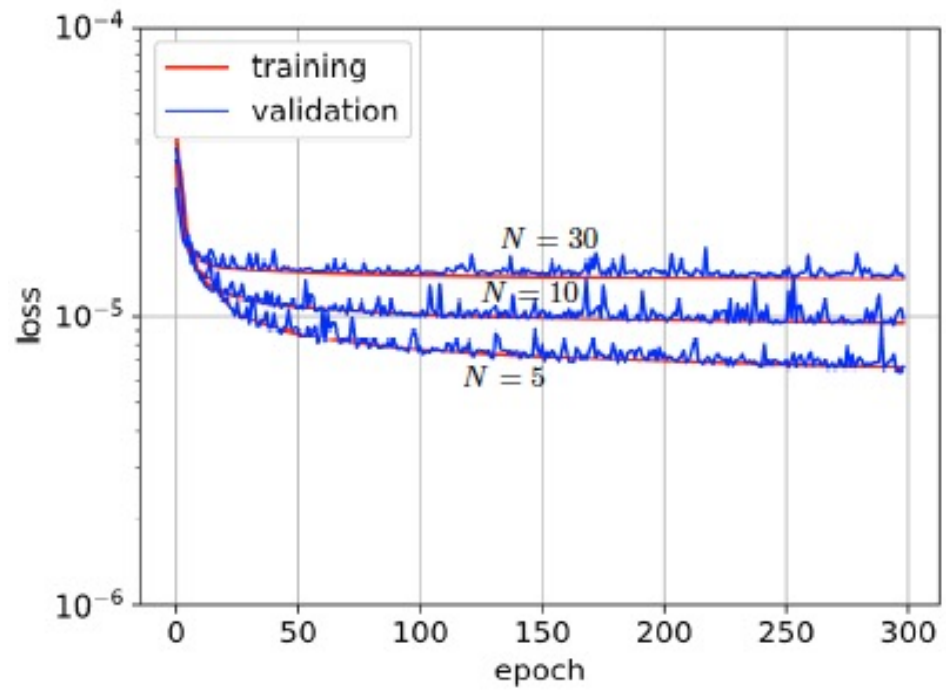
$$\mathcal{L} = \mathbb{E}[(p_i - \hat{p}_i)^2]$$

- Compare the ML derived EE with SPCA computed EE

Training Process

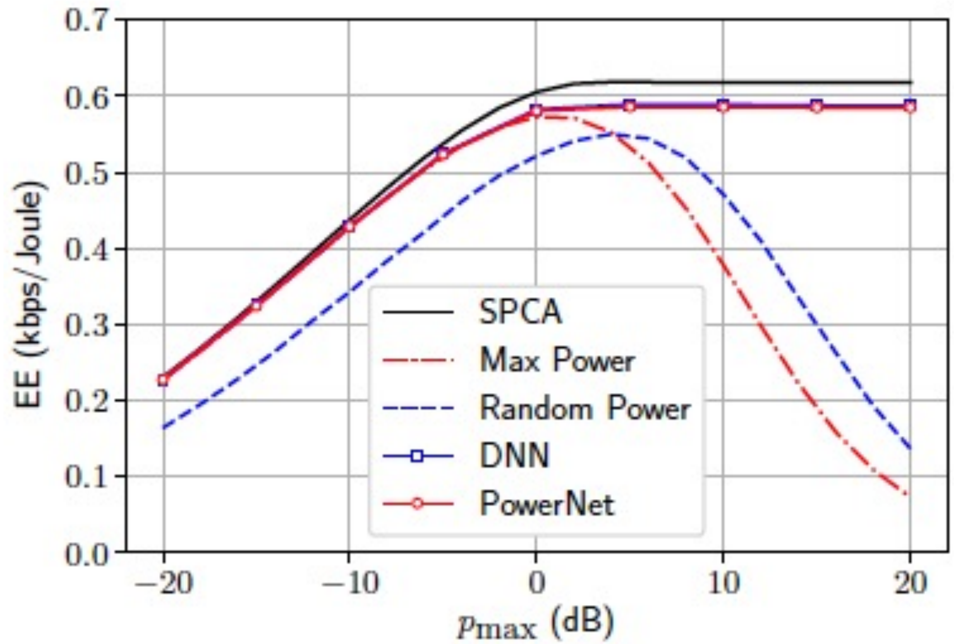


DNN

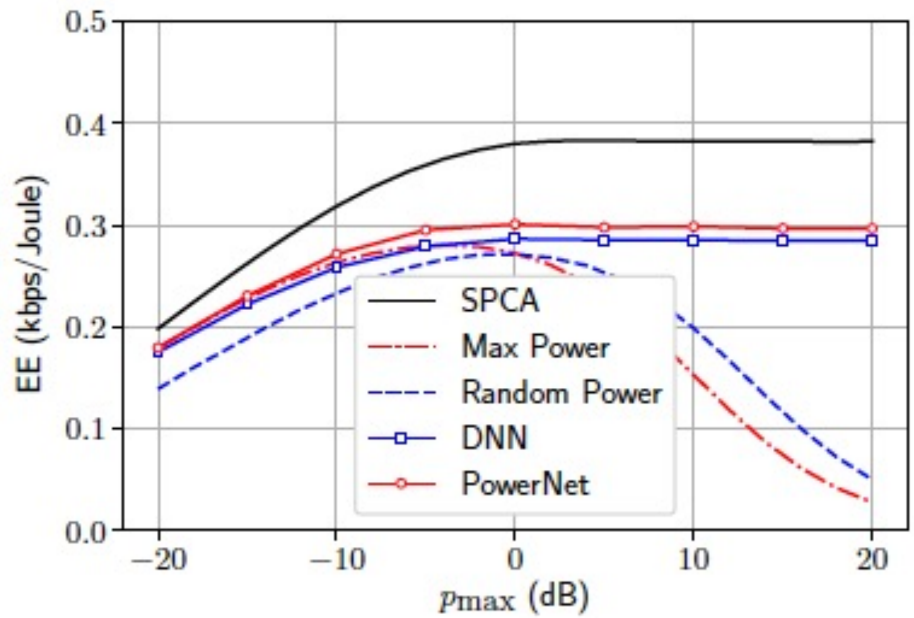


PowerNet

EE Results Under Fast Fading Channels



5 nodes



30 Nodes

Simulation Results: EE

TABLE III
AVERAGED EE (KBPS/JOULE) FOR DIFFERENT TYPES OF FADING CHANNELS

N	Methods	Path loss		Shadowing		Fast fading	
		EE (kbps/Joule)	Percentage	EE (kbps/Joule)	Percentage	EE (kbps/Joule)	Percentage
5	DNN	0.6683	99.10%	0.6340	96.16%	0.5872	95.38%
	PowerNet	**0.6636**	**98.40%**	**0.6306**	**95.63%**	**0.5849**	**95.01%**
	SPCA	0.6744	100%	0.6594	100%	0.6157	100%
10	DNN	0.5577	95.69%	0.5136	91.10%	0.4796	90.12%
	PowerNet	**0.5518**	**94.69%**	**0.5087**	**90.24%**	**0.4757**	**89.39%**
	SPCA	0.5828	100%	0.5637	100%	0.5322	100%
20	DNN	0.4203	88.90%	0.3775	82.50%	0.3556	81.26%
	PowerNet	**0.4346**	**91.93%**	**0.3862**	**84.40%**	**0.3630**	**82.96%**
	SPCA	0.4728	100%	0.4576	100%	0.4356	100%
30	DNN	0.3378	83.46%	0.2984	75.76%	0.2822	74.27%
	PowerNet	**0.3603**	**89.09%**	**0.3158**	**80.18%**	**0.2973**	**78.22%**
	SPCA	0.4048	100%	0.3939	100%	0.3800	100%

Simulation Results: Execution Time

TABLE IV
COMPUTATIONAL TIME COMPARISON

N	Methods	CPU time (ms)	percentage	GPU time (ms)	percentage
5	DNN	0.022	0.17%	0.025	0.33%
	PowerNet	0.091	0.69%	0.109	1.44%
	SPCA	13.268	100%	7.546	100%
10	DNN	0.008	0.07%	0.026	0.32%
	PowerNet	0.160	1.43%	0.107	1.33%
	SPCA	11.159	100%	8.066	100%
20	DNN	0.012	0.09%	0.026	0.27%
	PowerNet	0.483	3.75%	0.115	1.20%
	SPCA	12.887	100%	9.549	100%
30	DNN	0.019	0.11%	0.029	0.25%
	PowerNet	1.107	6.10%	0.131	1.14%
	SPCA	18.161	100%	11.541	100%

AUBURN UNIVERSITY
Electrical and Computer Engineering

In This Talk

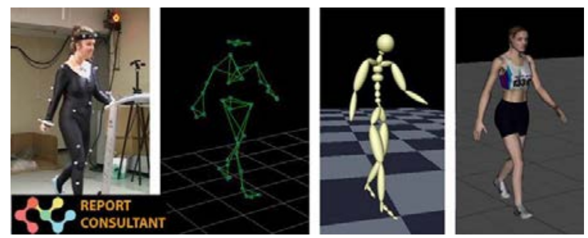
- The evolution towards 6G
- Motivating examples of ML for Wireless
- **Case studies**
  - Automatic Modulation Classification
  - Energy efficiency maximization
  - **3D human skeleton tracking**
- Challenges and thoughts

Human Skeleton Reconstruction and Pose Tracking

Human pose tracking becomes an important topic in *human-computer interaction* (HCI)

- Activity Recognition
  1) Full-body sign language reading (e.g., traffic police hand signals, aircraft ground handling)
  2) Fall detection of elders
  3) Surveillance for security
- Motion capture and augmented reality
- Somatosensory games

Camera-based: privacy concerns



https://medium.com/@victoriamazo/3d-human-pose-estimation-ce1259979306

https://www.ubisoft.com/en-us/game/just-dance/2021

https://www.openpr.com/news/1345254/3d-motion-capture-market-witness-a-consistent-growth-in-the-forecast-years-with-the-key-vendors-phoenix-technologies-codamotion-solutions-vicon-motion-analysis-corporation-optitrack.html

RF Sensing Based Related Works

Wi-Fi based:

1. 2D pose estimation for multiple people [1], and 3D pose generation [2]
2. Contact-free pose estimation, and wide range detection.
3. Low-cost hardware

Sensitive to the interference from environment

Radar based:

1. Frequency-Modulated Continuous Wave (FMCW) radar-based system [1]
2. High accuracy and more robust to the environmental interference than Wi-Fi based systems

Require expensive and complicated hardware

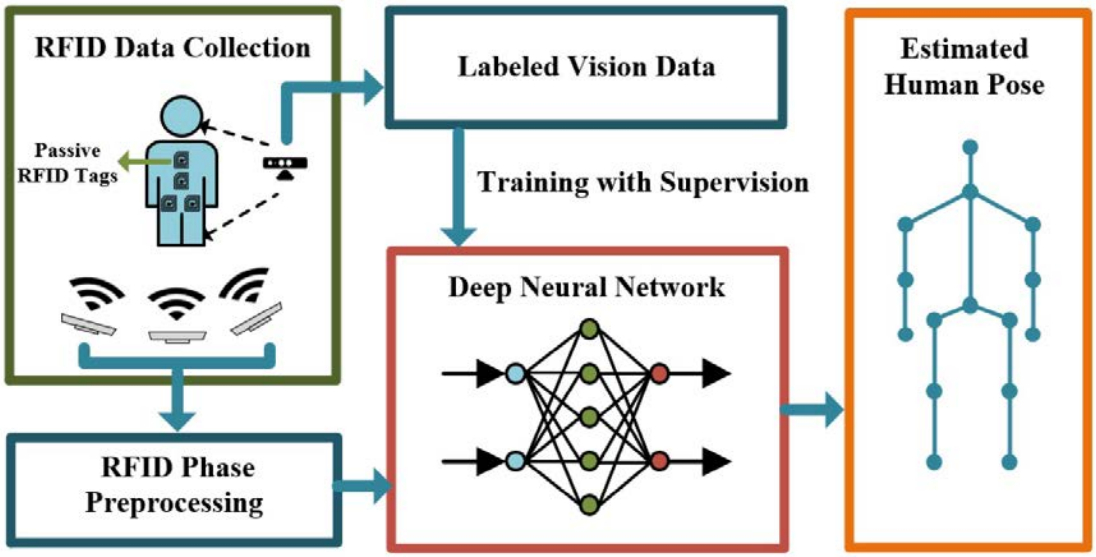
RFID based:

1. RF-Kinect based on RF hologram technique [4], and 3D limbs movement tracking with RFID array [5]
2. Good performance for single limb tracking

Not suitable for the full body skeleton reconstruction

[1] *F. Wang, S. Zhou, S. Panev, J. Han, and D. Huang, "Person-in-WiFi: Fine-grained person perception using WiFi," in Proc. IEEE ICCV 2019, Seoul, Republic of Korea, Oct. 2019, pp. 5452–5461.*
[2] *W. Jiang, H. Xue, C. Miao, S. Wang, S. Lin, C. Tian, S. Murali, H. Hu, Z. Sun, and L. Su, "Towards 3D human pose construction using WiFi," in Proc. ACM MobiCom'20, London, UK, Sept. 2020, pp. 1–14.*
[3] *M. Zhao, T. Li, M. Abu Alsheikh, Y. Tian, H. Zhao, A. Torralba, and D. Katabi, "Through-wall human pose estimation using radio signals," in Proc. IEEE CVPR 2018, Salt Lake City, UT, June 2018, pp. 7356–7365.*
[4] *C. Wang, J. Liu, Y. Chen, L. Xie, H. B. Liu, and S. Lu, "RF-Kinect: A wearable RFID-based approach towards 3D body movement tracking," Proc. ACM Int., Mobile, Wearable Ubiquitous Technol., vol. 2, no. 1, Mar. 2018.*
[5] *H. Jin, Z. Yang, S. Kumar, and J. I. Hong, "Towards wearable everyday body-frame tracking using passive RFIDs," Proc. ACM Interactive, Mobile, Wearable Ubiquitous Technol., vol. 1, no. 4, pp. 1–23, Dec. 2018.*

RFID-Pose/Meta-Pose System Overview



RFID Data Collection
- Kinect Data collection
- RFID Data collection

RFID Data Preprocessing
- Phase calibration
- Downsampling and synchronization
- RFID Data imputation

Skeleton Reconstruction
- Deep neural network
- Vision-aided training

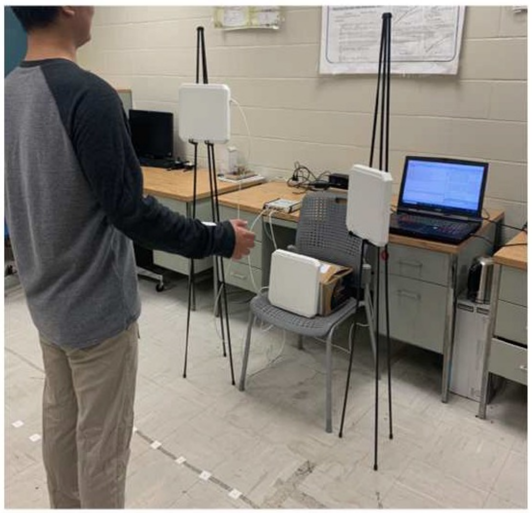
C. Yang, X. Wang, and S. Mao, "RFID-Pose: Vision-aided 3D human pose estimation with RFID," *IEEE Transactions on Reliability*, to appear. DOI: 10.1109/TR.2020.3030952.

C. Yang, X. Wang, and S. Mao, "RFID based 3D human pose tracking: A subject generalization approach," *Elsevier/KeAi Digital Communications and Networks*, Special Issue on Edge computation and intelligence, to appear.

C. Yang, S. Wang, and S. Mao, "Subject-adaptive skeleton tracking with RFID," invited paper, in *Proc. The 16th IEEE International Conference on Mobility, Sensing and Networking* (MSN 2020), Tokyo, Japan, Dec. 2020, pp.599-606.

C. Yang, L. Wang, X. Wang, and S. Mao, "Meta-Pose: Environment-adaptive human skeleton tracking with RFID," under review.

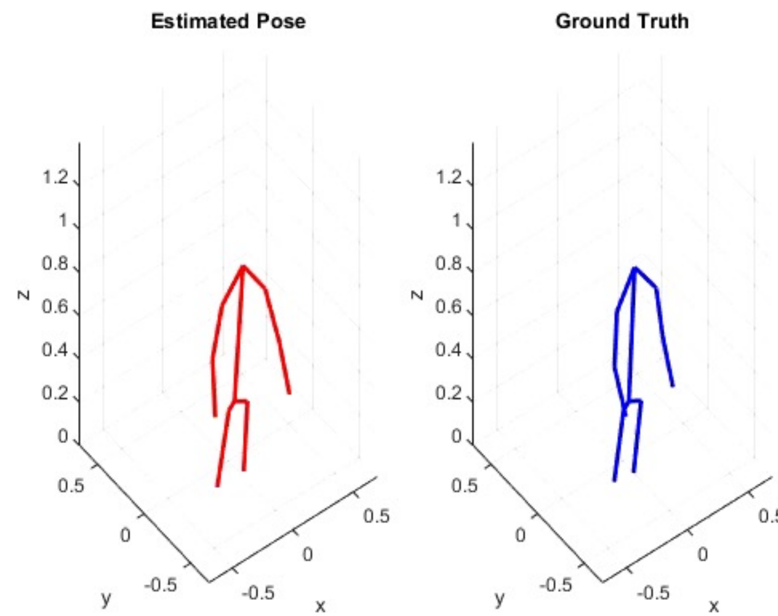
RFID-Pose: Vision-aided 3D Human Pose Estimation



Standing Still

Walking

Pose tracking experiments



Pose estimation when the subject is walking

C. Yang, X. Wang, and S. Mao, "RFID-Pose: Vision-aided 3D human pose estimation with RFID," *IEEE Transactions on Reliability*, to appear. DOI: 10.1109/TR.2020.3030952.

AUBURN UNIVERSITY
Electrical and Computer Engineering

Adapt to Different Data Domains

The same motion generates very different RF data when sampled in different environments

Developing 3D human pose estimation techniques adaptive to the environment has become a great challenge for RF based techniques

To analyze the influence from the environment, the RF data sampled from a different environment is considered as a different data domain

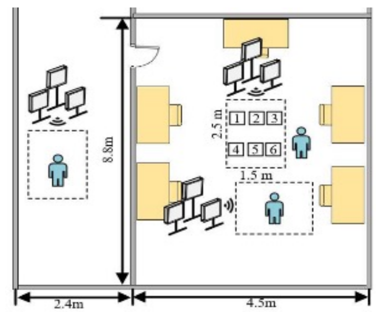
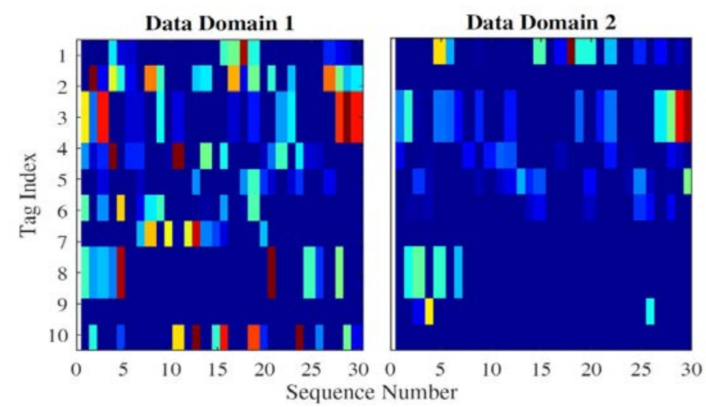


TABLE IV
PERFORMANCE EVALUATION FOR DIFFERENT STANDING POSITIONS

Position Index	*Estimation Error*
Position 1 (Trained)	4.53cm
Position 2 (Trained)	3.82cm
Position 3 (Trained)	4.75cm
Position 4 (Untrained)	8.38cm
Position 5 (Untrained)	5.71cm
Position 6 (Untrained)	9.14cm

Different deployment environments and standing positions

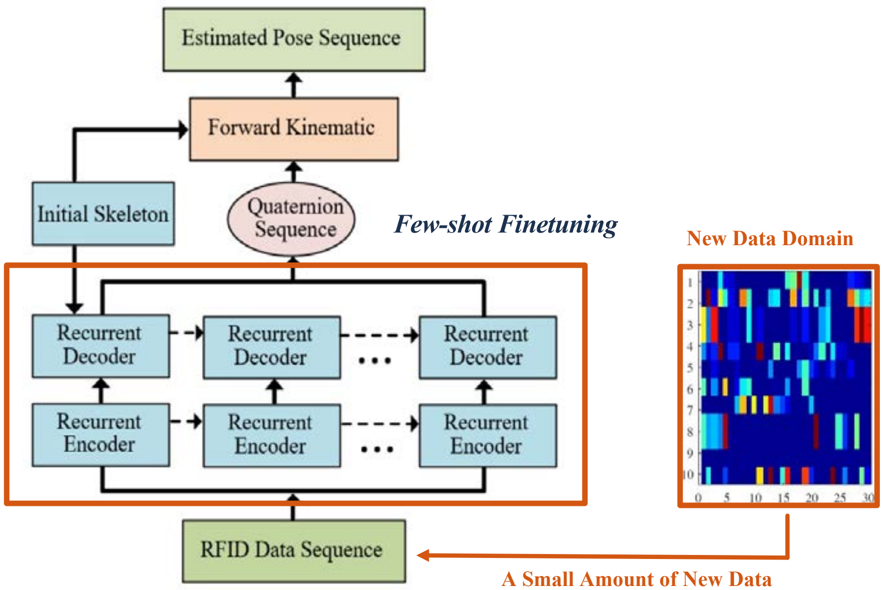


RFID phase collected in two different domains for the same motion

AUBURN UNIVERSITY
Electrical and Computer Engineering

Meta-Learning Based Solution

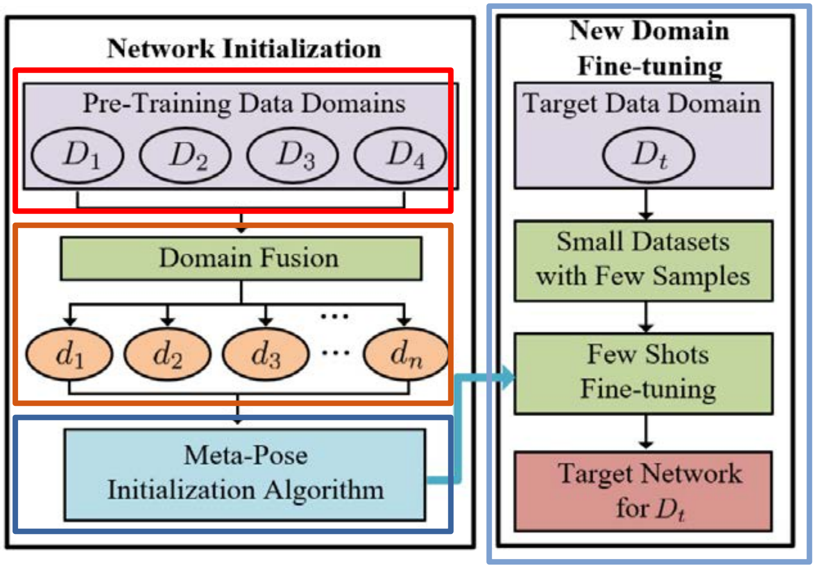
Structure of the deep learning model



- Meta learning [1]:
  - To learn the learning algorithm itself, i.e., learning to learn
  - To train a general model that can generalize across different tasks or datasets
  - Learn and adapt quickly from few-shot of examples, and be able to keep adjusting as more data coming in
- The network parameters should first be well initialized in the pretraining phase
- The network will be fine-tuned for a new data domain with only a few additional samples

[1] C. Finn, P. Abbeel, and S. Levine, "Model-agnostic meta-learning for fast adaptation of deep networks," *arXiv preprint arXiv:1703.03400*, July 2017.

Meta-Pose Framework Overview



Training framework of the proposed Meta-Pose system

The deep learning model is pretrained with data from four known data domains

A domain fusion algorithm is adopted to produce more data domains

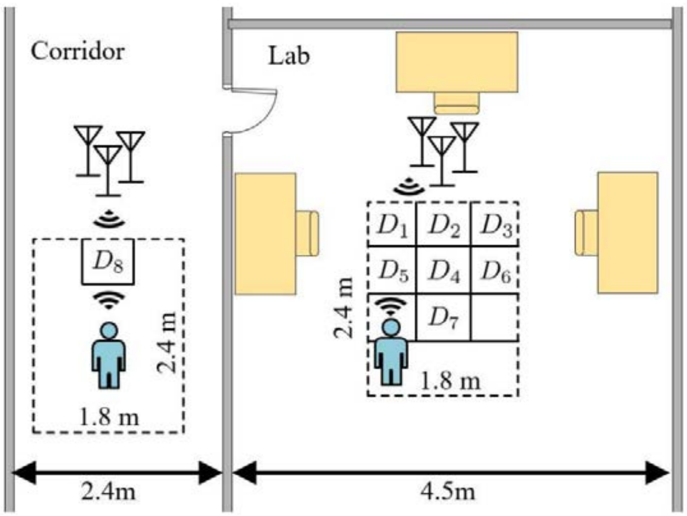
The training variables are updated recursively by the Reptile meta-learning algorithm

When transferring to a new data domain, we only need to collect very few examples to fine-tune the generalized network

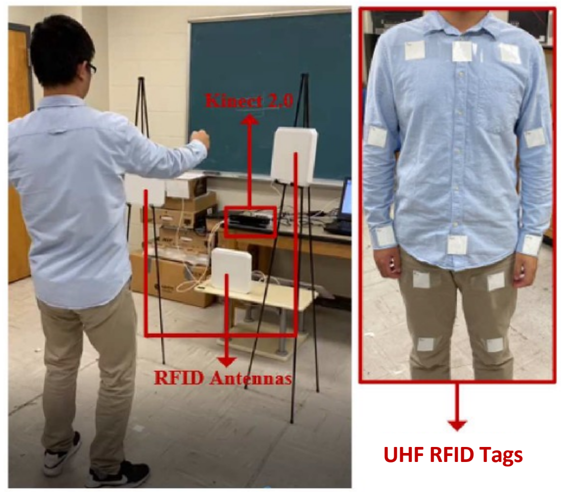
C. Yang, L. Wang, X. Wang, and S. Mao, "Meta-Pose: Environment-adaptive human skeleton tracking with RFID," under review.

AUBURN UNIVERSITY
Electrical and Computer Engineering

Implementation and Evaluation



Data domains used in the experiments



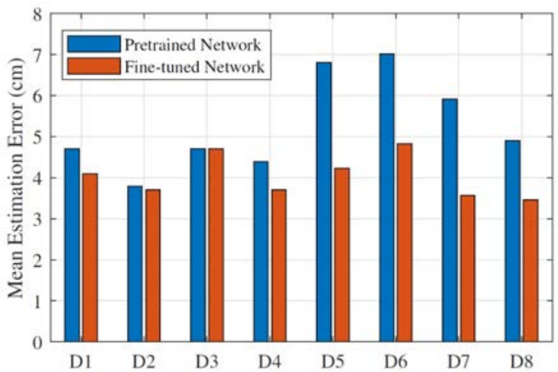
Hardware configuration of Meta-Pose

Seven data domains are sampled in the computer lab, and the 8th domain is sampled in an empty corridor

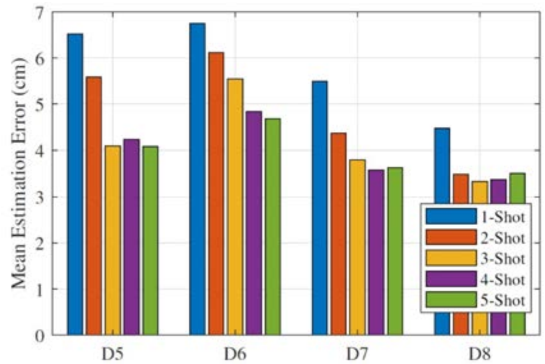
- D1 to D4 are used for pretraining
- D5 to D8 are considered as new data domains for validation

Five subjects participate in the experiments

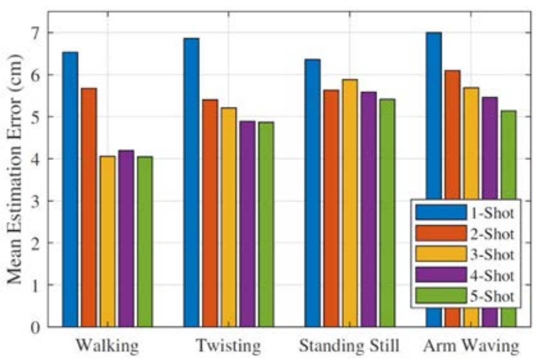
Experimental Results and Analysis



Overall performance in terms of mean estimation error in the eight different data domains



Fine-tuning performance of different activities with different shots of new data in new data domain D5



Fine-tuning performance of different new data domains with different shots of new data

Average error comparison with the baseline method RFID-Pose

Domain Index	*RFID-Pose*	*Meta-Pose*
D_5	6.72cm	3.72cm
D_6	7.62cm	4.32cm
D_7	5.46cm	3.51cm
D_8	4.62cm	4.11cm
D_{all}	6.27cm	3.97cm

One shot of data in Meta-Pose is defined as consecutive data samples within 6 seconds

With few-shot finetuning, the mean error for all the new data domains is 3.98cm, which is very similar to that of the pretrained data domains

4-shot fine-tuning is sufficient; the minimum error 4.04cm is achieved by walking

Mean error of RFID-Pose for all the new data domains is 6.27cm, while that for Meta-Pose is only 3.97cm (a 36.68% reduction)

In This Talk

- The evolution towards 6G
- Motivating examples of ML for Wireless
- Case studies
- **Challenges and thoughts**

AUBURN UNIVERSITY
Electrical and Computer Engineering

Challenges and Thoughts

- Platform, dataset, benchmark
- Need high quality (labeled) data:
  - *How many cats do you need to recognize a cat* (sample complexity)?
- The ML performance will be as good as your training data
  - Inconsistency between the training dataset and real deployment
- Sparse noisy data → Data augmentation, data imputation (in time, space)

Challenges and Thoughts (cont'd)

- Although communications systems are based on probabilistic models, we do need to guarantee the worst-case performance in many cases ➔ robustness
  - Incorporate models into the ML model
- Many applications are in real-time: e.g., autonomous driving ➔ fast convergence, few-shot learning
- Dynamic environment ➔ need to retrain the models ➔ generalization
  - Transfer learning
  - Meta-learning, few-shot learning, …

Challenges and Thoughts (cont'd)

- Reproducible results
- AI/ML for wireless and wireless for AI/ML
- Can ML/AI bring about new theory and breakthroughs in wireless communications and networking, as traditional models did?
- Explainable ML: need to know why it works or why it does not work
- Distributed ML/federated learning for resource constrained mobile devices and privacy
- The wireline network may need to be redesigned: the new bottleneck?
- Application, application, application!
  - Technologies that did not fly: need killer apps

AUBURN UNIVERSITY
Electrical and Computer Engineering

Conclusions

- 5G gets real, 6G is on the horizon
- Intelligence: likely to be a key component and common theme of the new generation
- Advances in AI/ML algorithms, data, computing, and platforms: ready for wireless communications and networking
- Shared our experience of applying ML to solving several wireless problems
- Many challenges and interesting problems remain

This work is supported in part by the National Science Foundation (NSF) under Grants ECCS-1923163, ECCS-1923717, and CNS-2107190, and through the Wireless Engineering Research and Education Center (WEREC) at Auburn University.

For more information: http://www.eng.auburn.edu/~szm0001/

AUBURN UNIVERSITY
Electrical and Computer Engineering