
AI for Communications and (Bio) Signal Processing and Communications for AI

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Associate Professor

AI and Signal Processing Group (AISP)

Communication Electronics and Signal Processing Lab (CommLab)

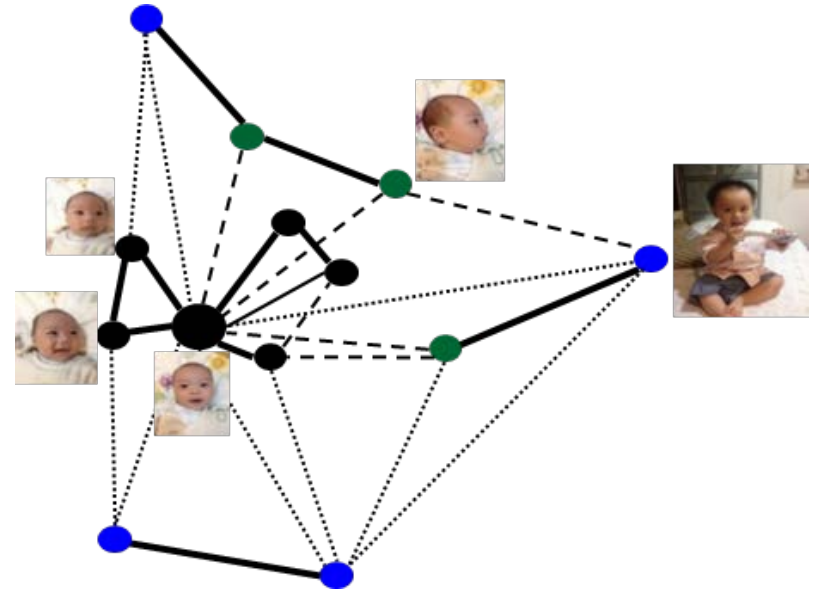
Institute of Electronics

National Yang Ming Chiao Tung University



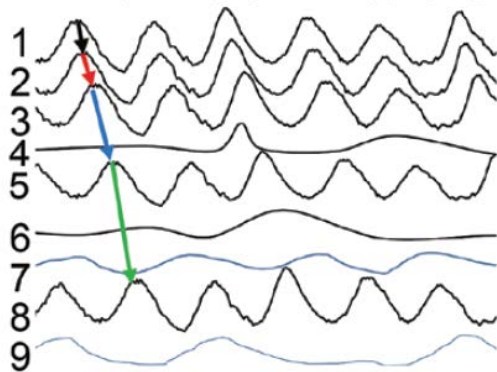
AISP Group

- Research focuses on
 - **Learning (causal nonlinear) data model using time-varying graphs (online graph learning)**
 - Identify rotational drivers of atrial fibrillation in the heart though cardiac mapping
 - Identify channel and/or interference graph for transceiver design
 - Service chain graph embedding for virtual network function
 - **6G: Model-based DNN design for intelligent reflective surface (IRS)**
 - Channel estimation
 - Beamformer design
 - Aerial IRS positioning
 - **Federated learning for communications using generative AI model**
 - Channel estimation
 - Beamformer design
 - Medical image generation
- Summer internship **abroad** for Ph.D. candidates are strongly encouraged (possible for outstanding M.S. students)
 - M.S. and 1st-year Ph.D. students encouraged to apply for the industrial Ph.D. program (教育部產學博計畫)
- Group members: 6 M.S., 1 U.G.
- Graduates work at **Google** (Taipei and Mountain View), **Qualcomm** (San Diego), **Amobee** (Hsinchu), **Realtek** (Hsinchu), **Umbo Computer Vision**, Netapp (Los Angeles)

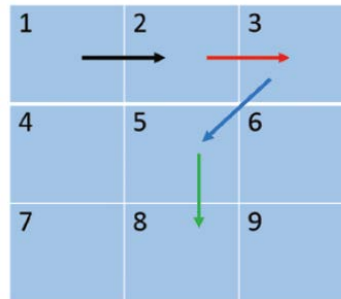


Identification of Rotational Drivers (RDs) for Atrial Fibrillation

Intracardiac electrogram (iEGM)



Granger causality vector map



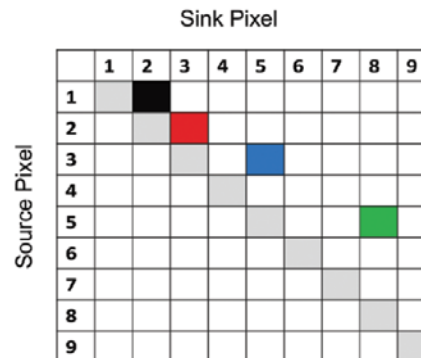
Possible solutions:

- Using linear and nonlinear vector autoregressive model to overcome spatial resolution problem
- Online solution to track the transient behavior of iEGM (RDs)

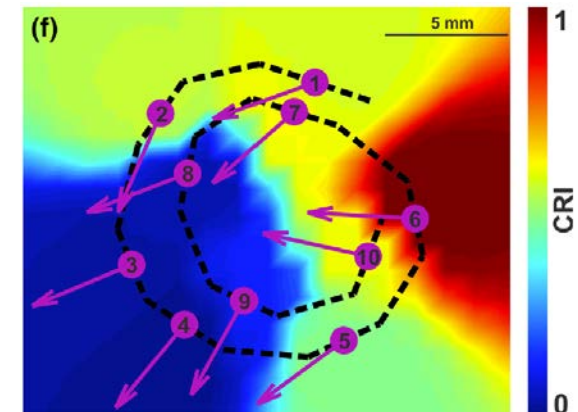
Challenges:

- Low spatiotemporal resolution of the mapping
 - Lead to false positive RDs
- Variability in the iEGM signals causes RDs to exhibit a winding and transient behavior

Causality pairing index



RD that causes atrial fibrillation



M. Rodrigo *et al.*, "Identification of dominant excitation patterns and sources of atrial fibrillation by causality analysis," *Annals of Biomedical Engineering*, Feb. 2016.

B.S Handa *et al.*, "Granger causality-based analysis for classification of fibrillation mechanisms and localization of rotational drivers," *Circulation: Arrhythmia and Electrophysiology*, pp. 258- 273, Mar. 2023.



Why Learn the Non-Euclidean Distance?

Node classification problem

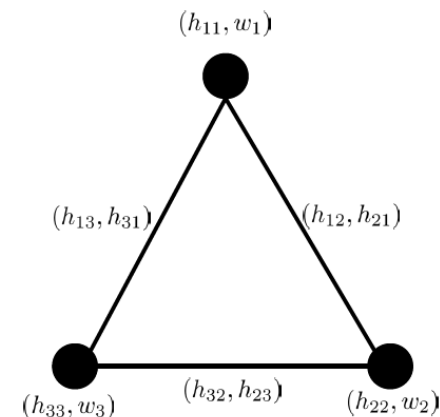
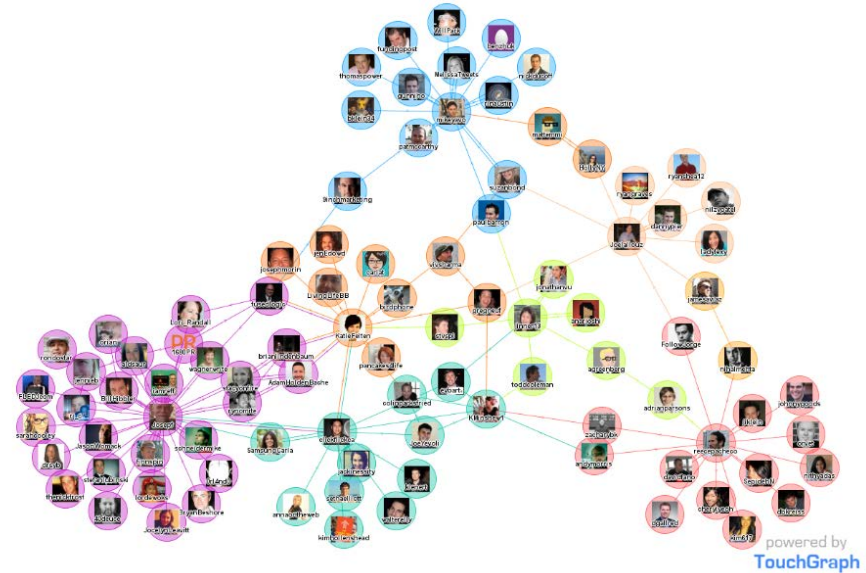
- **Applications:** Community discovery (e.g. Netflix, Pinterest) and offer targeted recommendations to different groups (prediction)

Graph classification problem

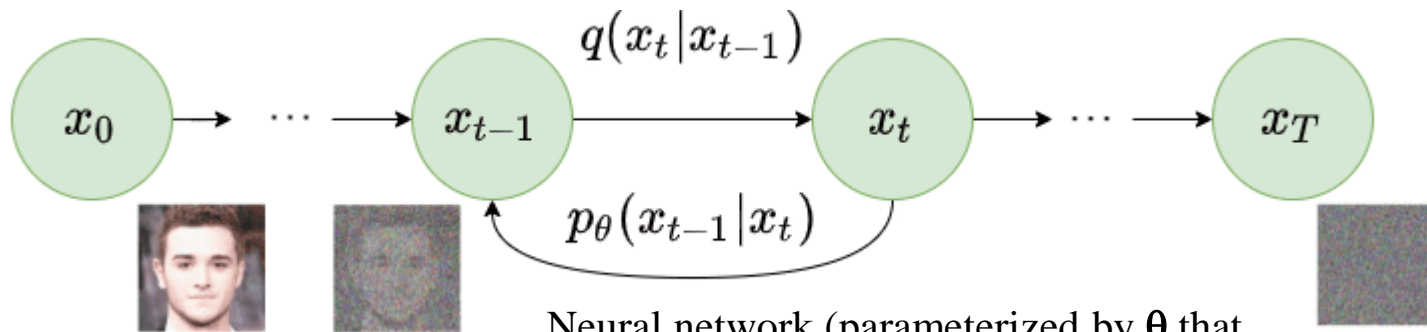
- **Application:** Compare brain graphs across different subjects that have labels (e.g. Alzheimer's disease) may identify if the subject without label may have Alzheimer's

Node regression

- **Application:** Building an interference graph and identifying the power needed for transmission in a multi-transmitter and multi-receiver environment

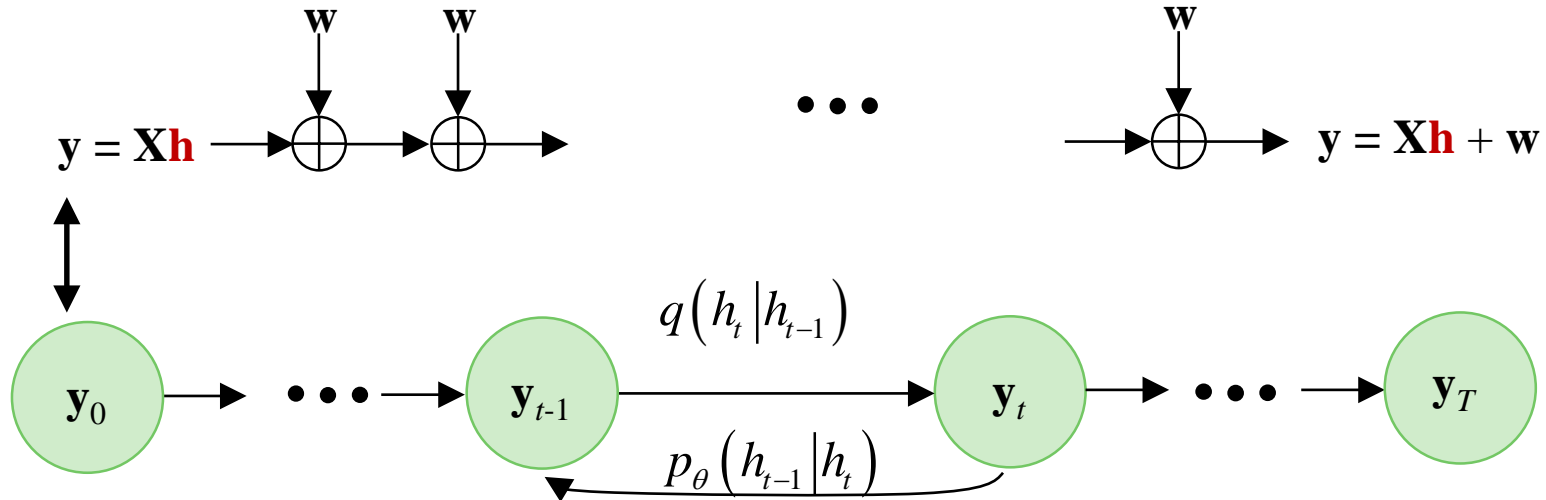


Diffusion Probability Models (Generative AI models) for Communications



Neural network (parameterized by θ that tries to capture the probability distribution of the noise added at each encoding/diffusion step

Diffusion Probability Models (Generative AI models) for Communications



$$\Rightarrow \hat{\mathbf{h}} = (\mathbf{X}^H \mathbf{X})^{-1} \mathbf{X}^H \mathbf{y}$$

What models to use? **Why?**

MISO signal recovery?

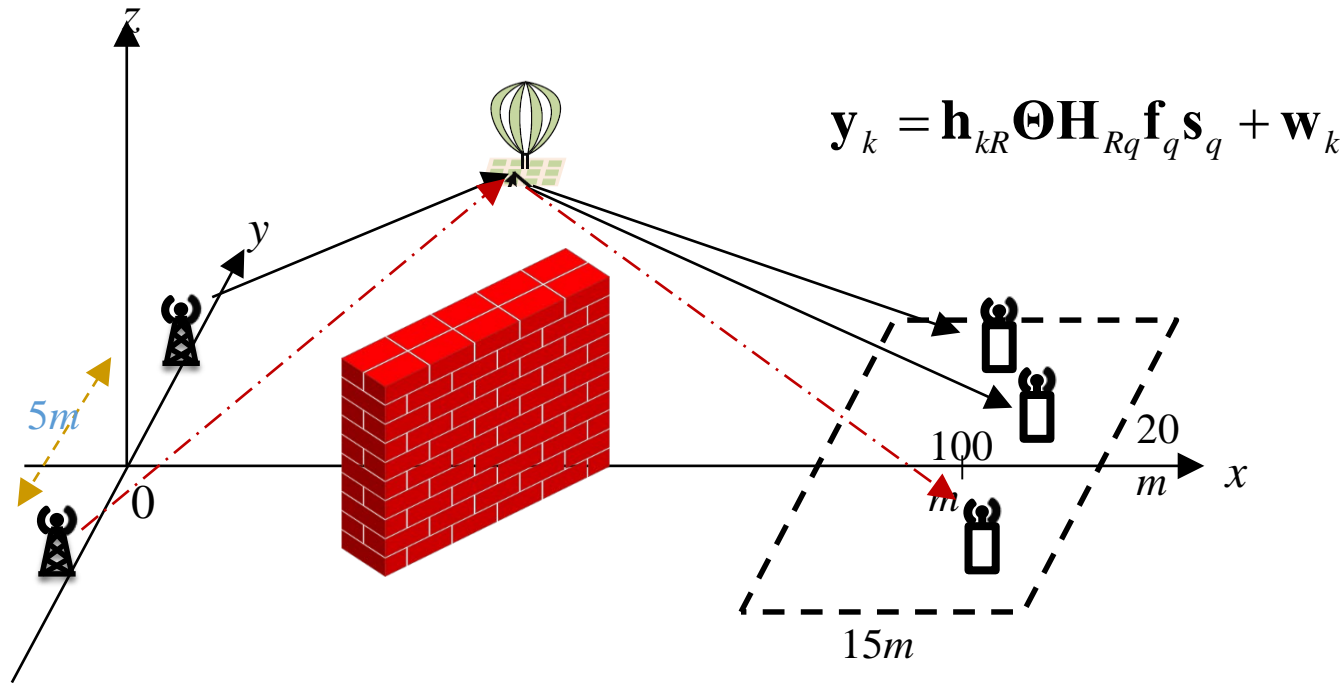
- Needs to deal with **multiplicative** noise: $\mathbf{y} = \mathbf{H}\mathbf{x} + \mathbf{w}$

MIMO Precoding? $\mathbf{Y} = \mathbf{H}\mathbf{F}\mathbf{X} + \mathbf{W}$

For more complicated systems and problems?



Aerial Intelligent Reflective Surface Systems (AIRS)

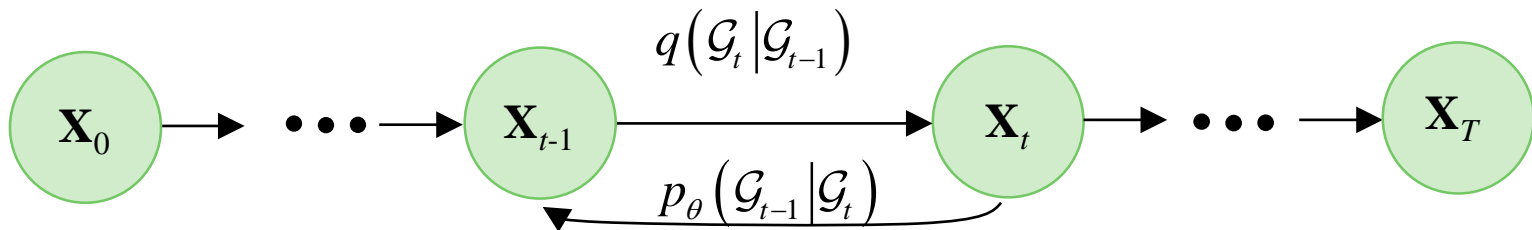


A.M. Huroon, Y.-C. Huang, **C.C. Fung** and L.-C. Wang, “Generalized Bender’s Decomposition (GBD) for reconfigurable intelligent surface-assisted transmission strategy problem”, *Proc of the IEEE VTS Asia Pacific Wireless Communications Symposium (VTS-APWCS)*, Seoul, Korea, Aug. 2022.

T. Chao, *Joint Beamforming Design in IRS-Assisted MISO Systems*, M.S. Thesis, National Yang Ming Chiao Tung University, Aug. 2021. (Adviser: **C.C. Fung**)



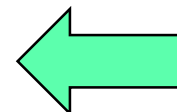
Diffusion Probability Models (Generative AI models) for Graph Learning



How to deal with generative function \mathcal{F} ?

How to exploit generative AI in an online setting?

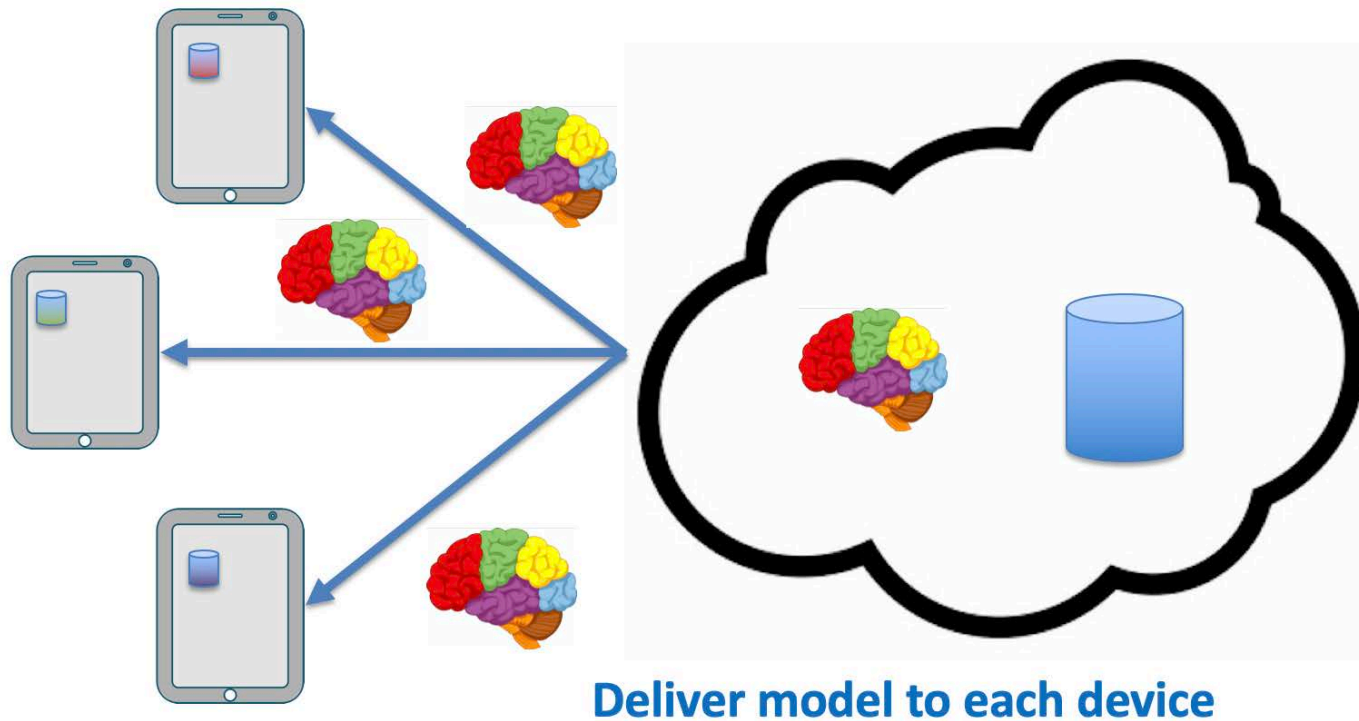
Z.-Y. Wu, *Online Graph Learning Via Proximal Newton Method*, M.S. Thesis, National Yang Ming Chiao Tung University, Sep. 2022. (Adviser: **C.C. Fung**)



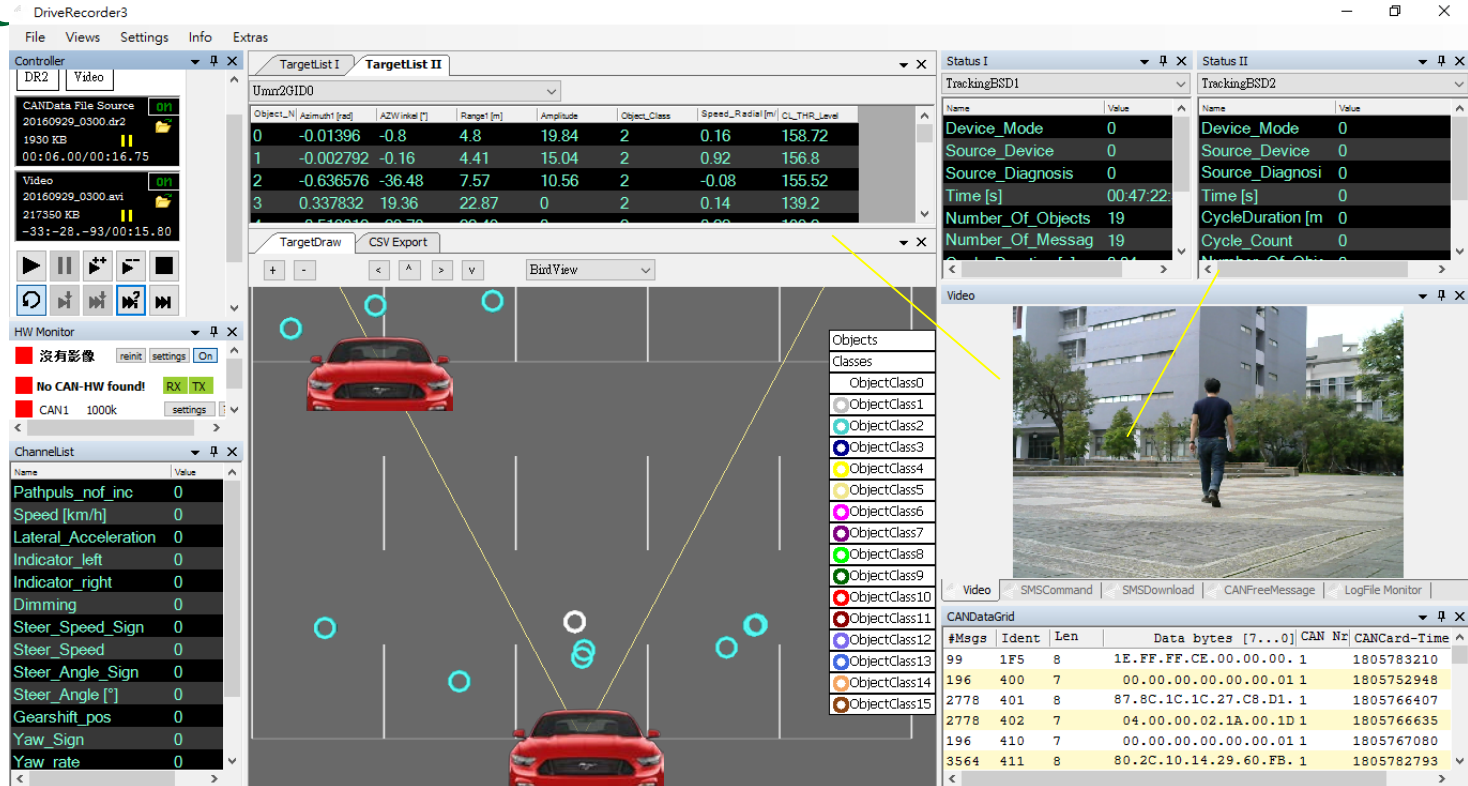
Why Not GAN?

Communications for AI

- GAN (Generative Adversarial Network) has been known to suffer from statistical heterogeneity (nonIID data) between agents
- Is DPM robust to system heterogeneous (network asynchronicity)?



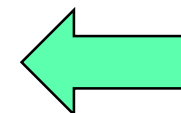
Comm for AI Application: 3D mmWave Radars



M. Servetnyk and C.C. Fung, “Distributed dual averaging based data clustering,” *IEEE Trans. on Big Data*, vol. 9(1), pp. 372-379, Jan./Feb. 2023.

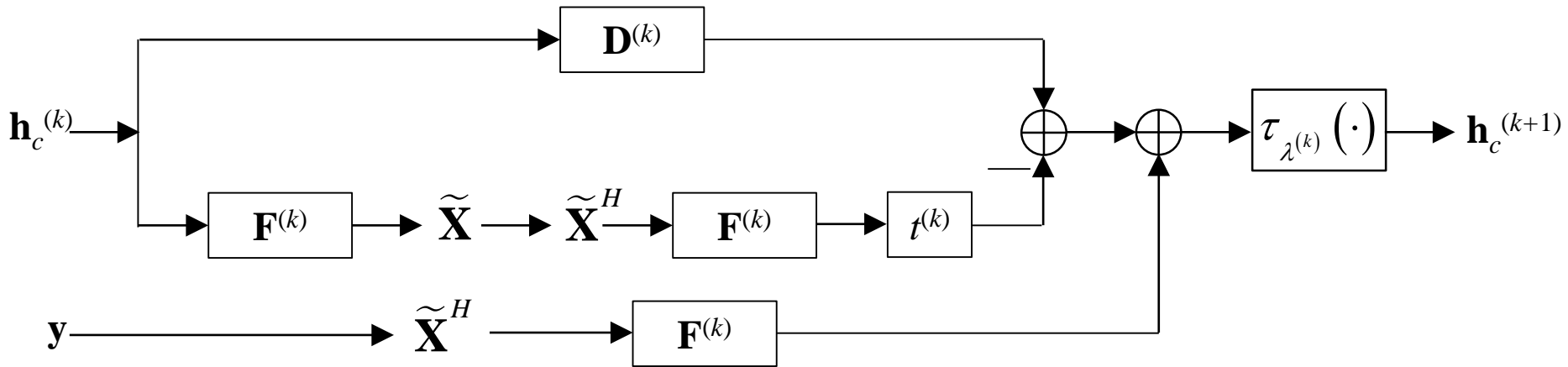
M. Servetnyk, C.C. Fung, and Z. Han, “Unsupervised federated learning for unbalanced data,” *Proc. of the IEEE Global Communications Conference*, Taipei, Taiwan, Dec. 2020.

C.-N. Chan and C.C. Fung, “RFCM for data association and multitarget tracking using 3D radar,” *Proc. of the IEEE Intl. Conf. on Speech, Acoustics and Signal Processing*, Calgary, AB, Canada, Apr. 2018.



Explainable Model-Driven Neural Network for Communications

Algorithm Unrolling for MIMO Channel Estimation



Single layer of the ISTA-LS-Net.

$$\hat{\mathbf{h}}_c = \arg \min_{\mathbf{h}_c} \left\| \mathbf{y} - \tilde{\mathbf{X}} \tilde{\mathbf{U}} \mathbf{h}_c \right\|_2^2 + \lambda \left\| \mathbf{h}_c \right\|_1 = f(\mathbf{h}_c) + g(\mathbf{h}_c)$$

$$\mathbf{h}_c^{(k+1)} = \tau_{\lambda^{(k)}} \left[\left(\mathbf{I}_{n_T n_R} - t^{(k)} \mathbf{F}^{(k)H} \tilde{\mathbf{X}}^H \tilde{\mathbf{X}} \mathbf{F}^{(k)} \right) \mathbf{h}_c^{(k)} + t^{(k)} \mathbf{F}^{(k)H} \tilde{\mathbf{X}}^H \mathbf{y} \right]$$

Learnable parameters: $t^{(k)}, \lambda^{(k)}, \mathbf{F}^{(k)}, \mathbf{D}^{(k)}$

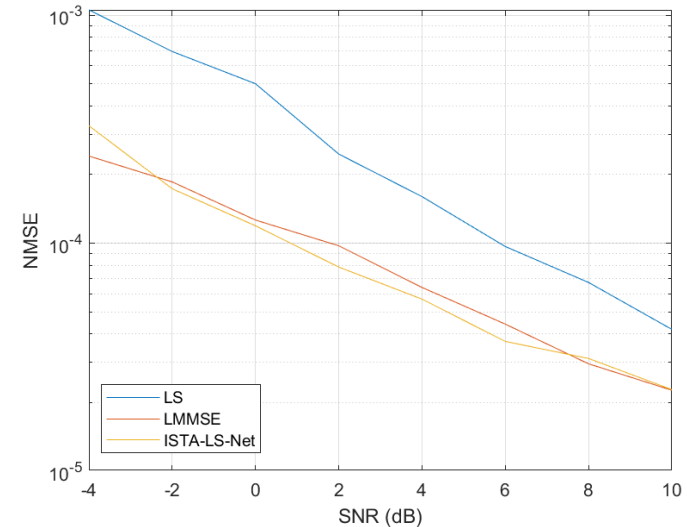
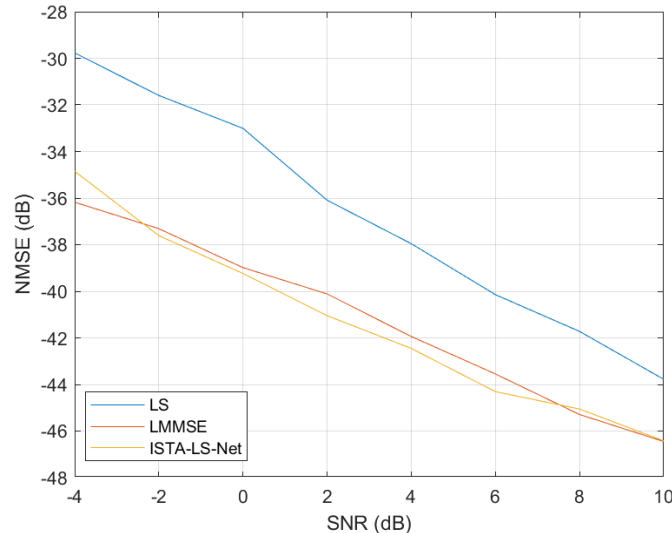
$\mathbf{D}^{(k)}$ has different configurations

Can be made into a CNN to reduce # of trainable parameters

C.C. Fung, D. Ivakhnenov and N. Toephiniytham, "Model-driven neural networks based MIMO channel estimator via eigenmode representation," *Presented at the IEEE Communication Theory Workshop*, Hualien, Taiwan, Jul. 2023.



Explainable Model-Driven Neural Network for Communications



- Learnable parameters: $\mathbf{t}^{(k)}, \mathbf{F}^{(k)}, \mathbf{D}^{(k)}$
- 10 layers
- ~830K parameters
- $\lambda^k = 0.5$
- Will the CNN version (with less trainable parameters) perform better?
- Improve estimation performance by increasing layers and adjusting dropouts?

C.C. Fung, D. Ivakhnenov and N. Toephiniytham, "Model-driven neural networks based MIMO channel estimator via eigenmode representation," *Presented at the IEEE Communication Theory Workshop, Hualien, Taiwan, Jul. 2023.*



What skills are required/learned to be successful?

- Good in mathematics and programming
 - Linear algebra, optimization, statistics, Matlab+Python/Julia
- Willingness and courage to explore and learn new (cross-disciplinary) subjects
- Ingenuity
- Be vocal, especially with your adviser

THEN MY GROUP IS FOR YOU!!!

Stop by and talk to me (ED 639)!

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or Google “Carrson Fung”





