GNU Radio
THE FREE & OPEN SOFTWARE RADIO ECOSYSTEM

GNU Radio Conference 2018

DeepSig

Advances in Machine Learning for Sensing and Communications Systems

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About DeepSig

Embracing data in signal processing

Who we are

- Software product focused venture backed start-up ~2 years old
  - Core team that has been heavily involved in GNU Radio, VOLK, USRP, and many software radio applications over past decade
  - Leveraging deep learning at the physical layer to bring about orders of magnitude improvement in how RF sensing and communications systems and algorithms are built
- First major research of its kind in end-to-end learned baseband capabilities and first commercial product offerings of their kind
  - Embracing data-centric design of algorithms which scales to optimize for complexity and rich representations of the world
  - Leveraging same core technology which has made leaps in performance possible in computer vision and natural language
- Rapidly growing interest in the area and future use of technology in a range of communications systems

Open Source, Real World, Validation First

- GNU Radio and Software Radio provide the perfect entry point into radio machine learning
  - Measurement, simulation, and iteration central to research and application of ML to radio
- DeepSig hosted RadioML.org resources have helped many get started in the field
  - GNU Radio based signal simulator
  - GNU Radio TensorFlow Integration (gr-tf)
  - Open Emitter Recognition datasets
  - Python notebooks with simple examples
  - Open Source Involvement /w SigMF & others
- **New 24-class Over the Air modrec dataset available!**
  - Available today on http://radioml.org
  - Additional details in IEEE JSTSP paper: "**Over the Air deep learning based radio signal recognition**"

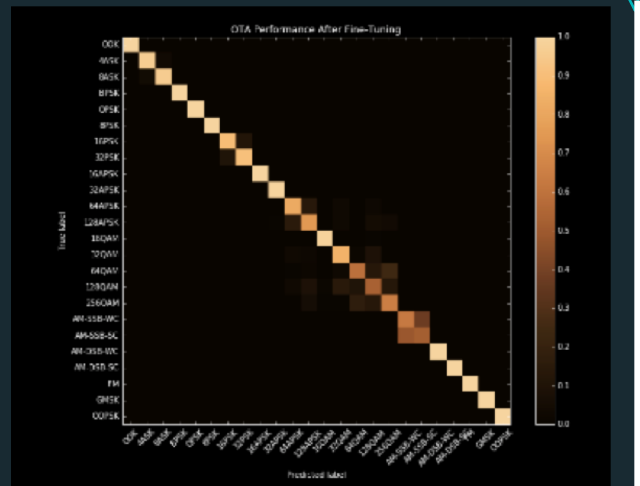
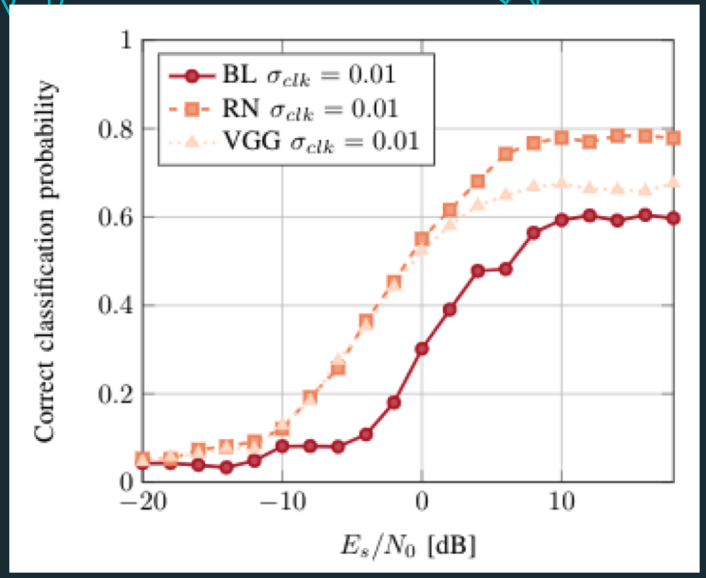
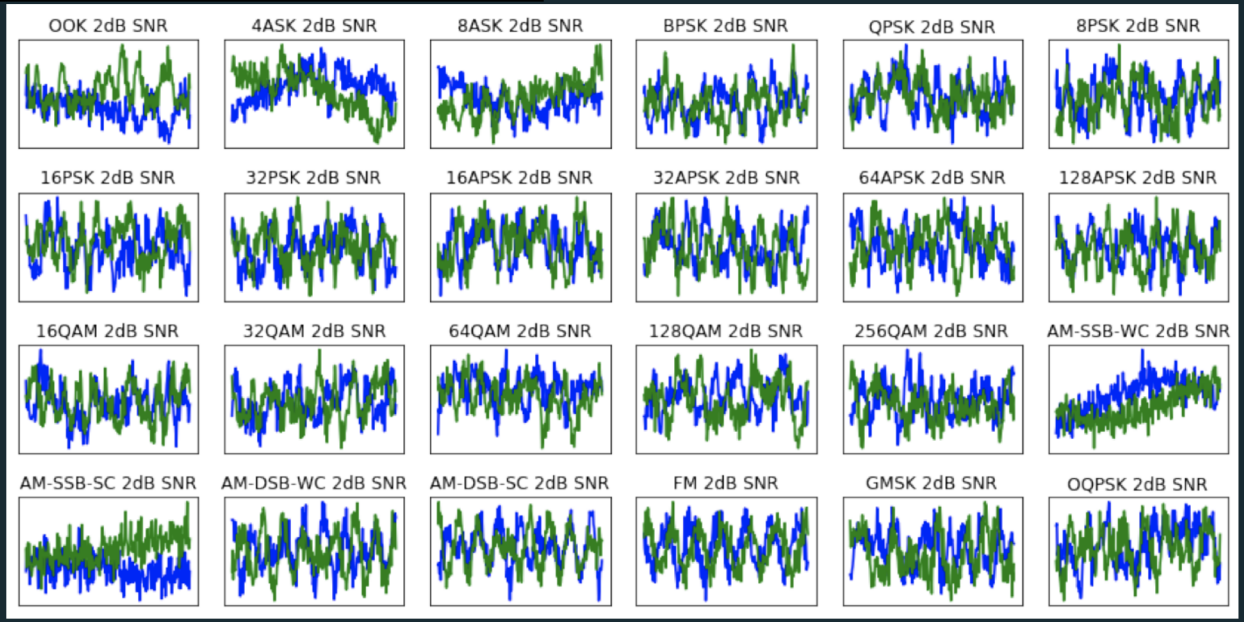
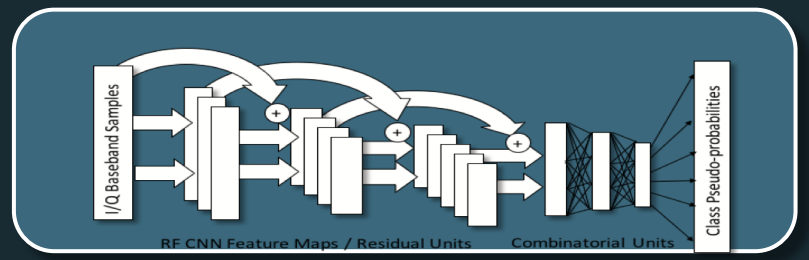


Fig. 22. 24-modulation confusion matrix for ResNet trained on synthetic $\sigma_{clk} = 0.0001$ and tested on OTA examples with SNR $\sim$ 10 dB (after fine-tuning)



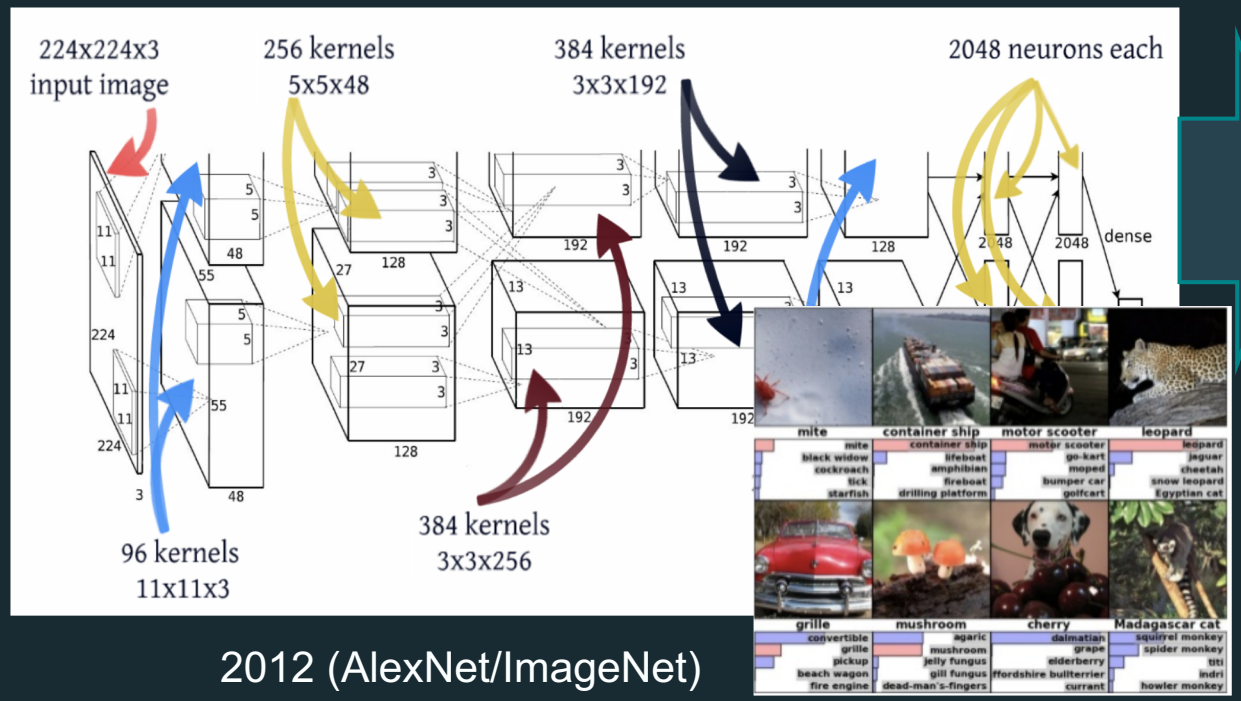




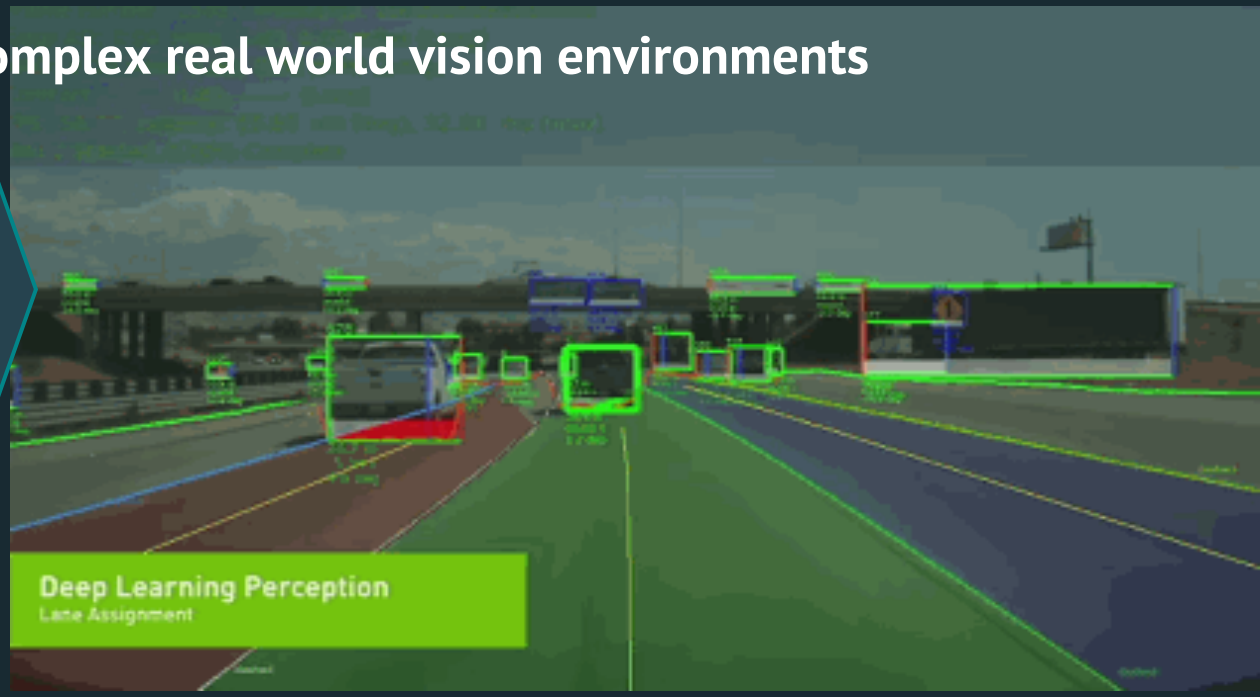
End-to-end DL Computer Vision Systems that Scale

- True end-to-end system learning on complex tasks is actually pretty new
  - First widely successful end-to-end learning approach in computer vision
    - AlexNet in 2012 -- things have moved astoundingly fast in vision since then
  - Learn direct from pixel level data performing probability regression!
    - **End-to-end feature learning from data for a compact end-objective.**
  - No longer reliant on hand engineered/expert features or decision criterion for best performance

Advancing from simple image problems. to complex real world vision environments



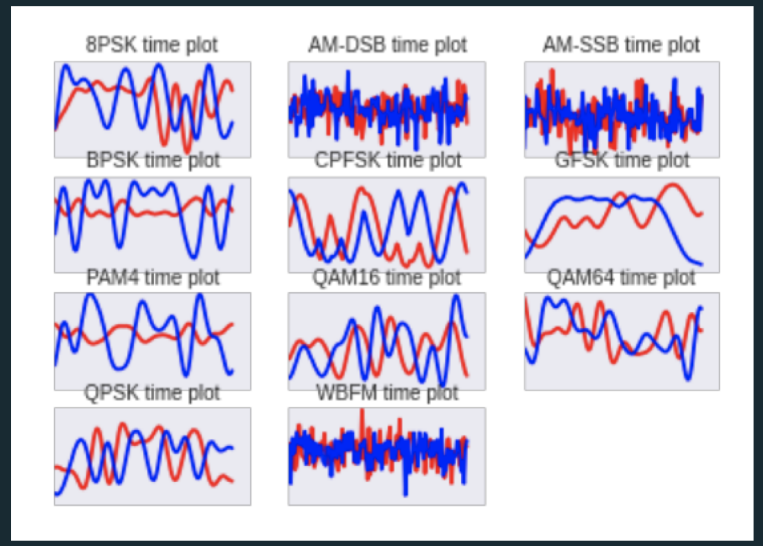
2012 (AlexNet/ImageNet)

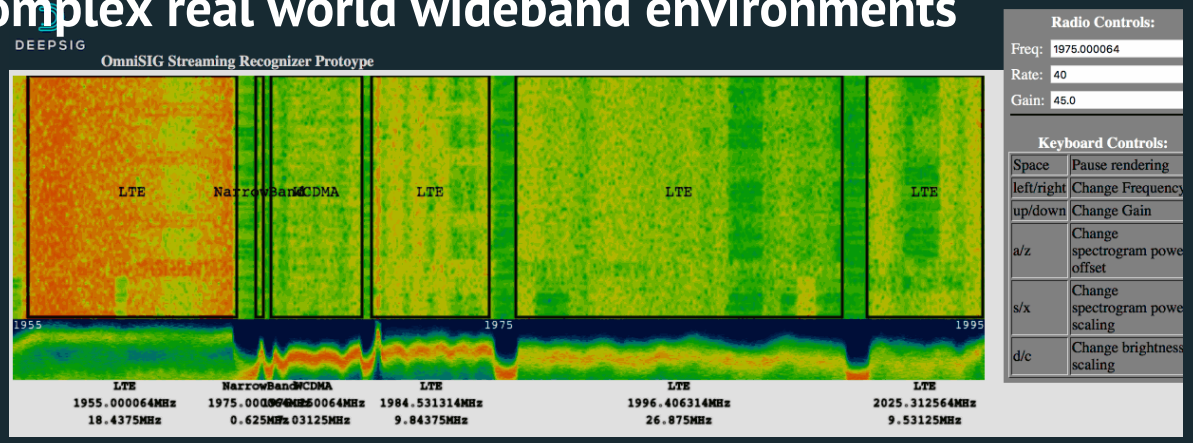


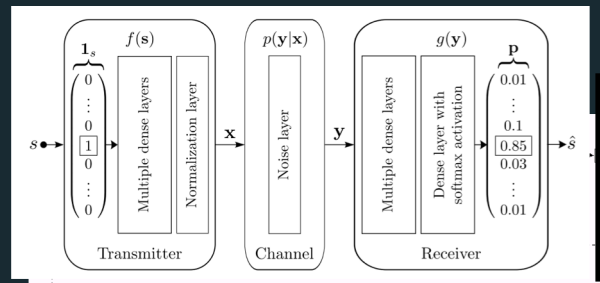
2018 (nVidia)

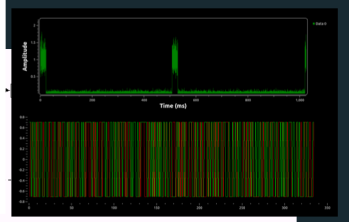
Scaling Radio Machine Learning to Real Data

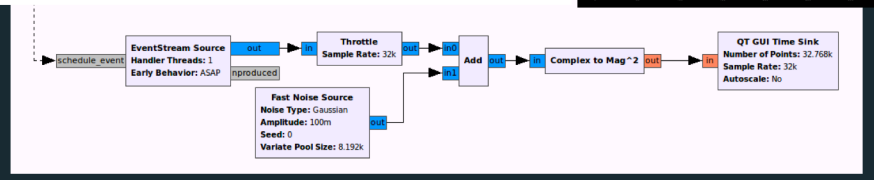
Advancing from simple toy emitter models to complex real world wideband environments

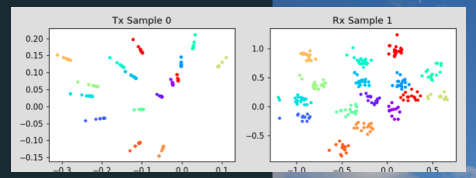


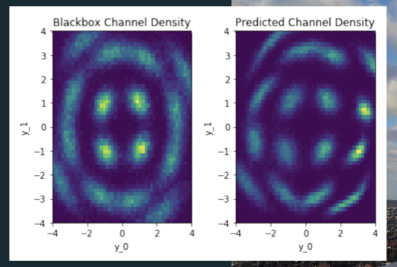


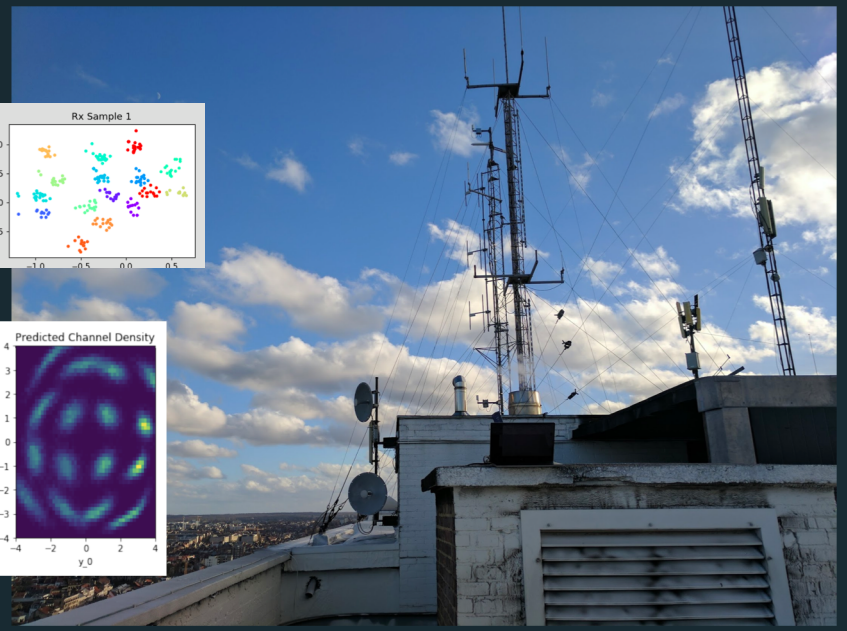






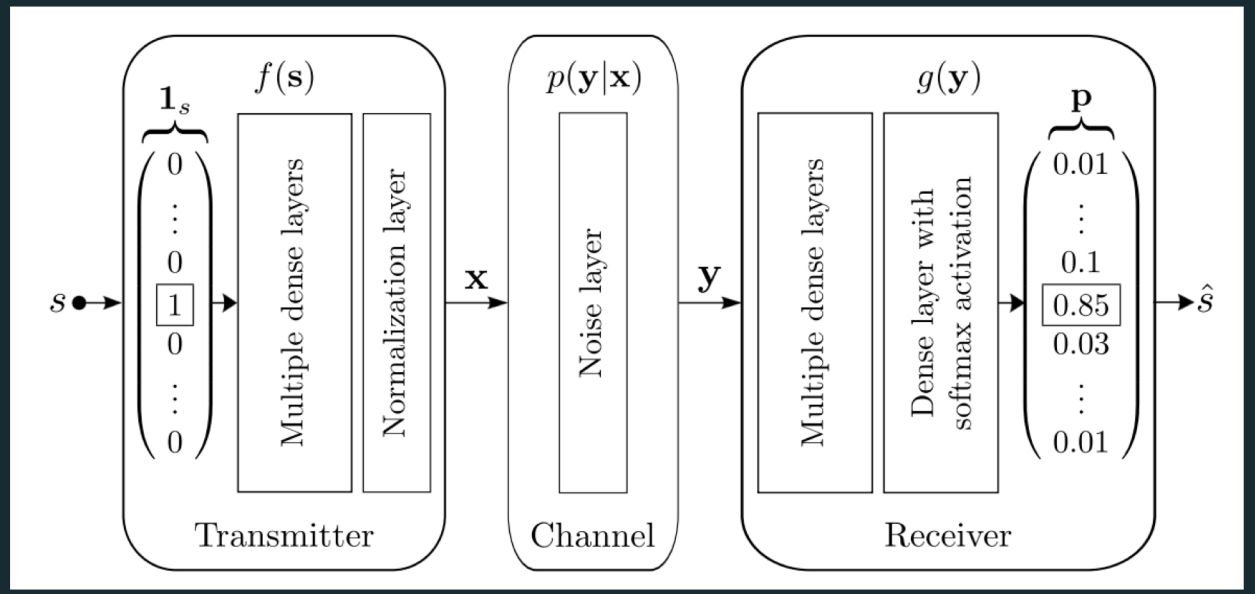


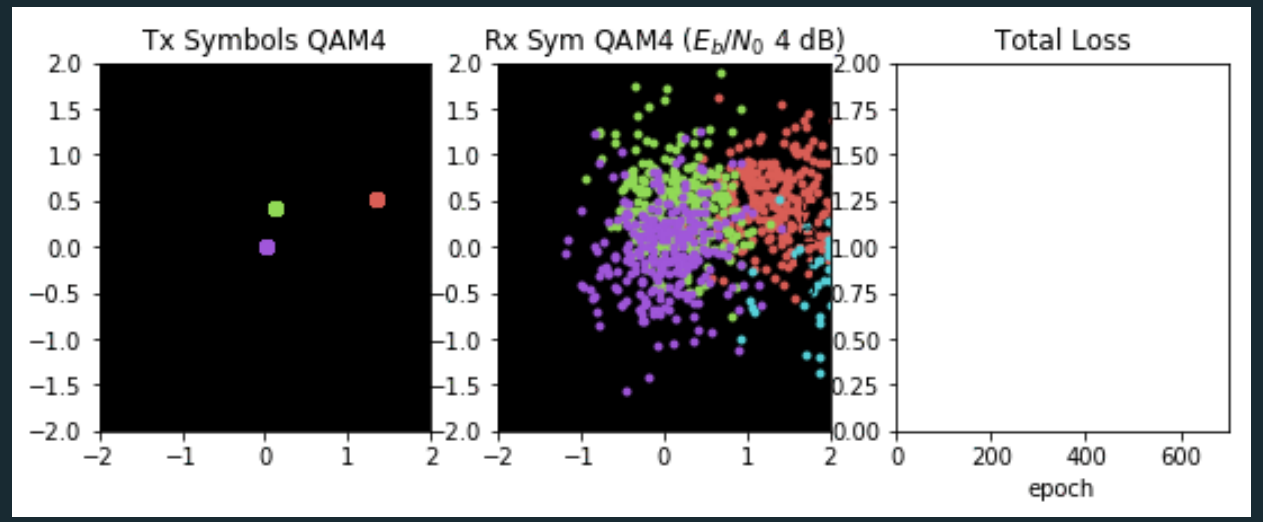




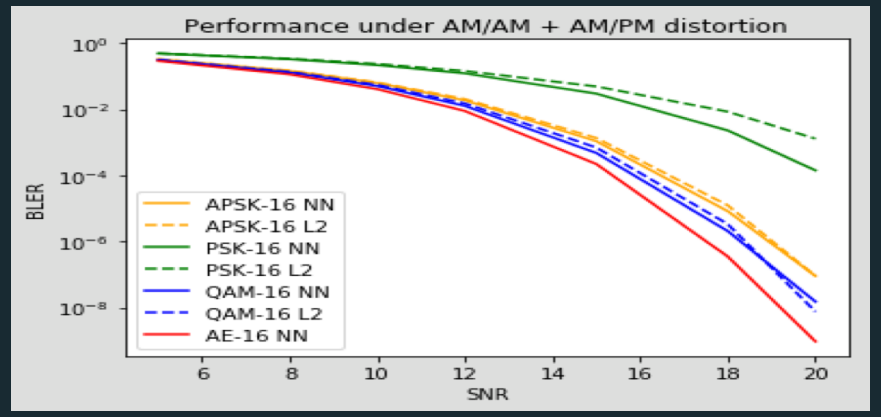
Advancing from overly simplified channel models to rich expression of real world effects

Learning Communications Systems: Basic Approach



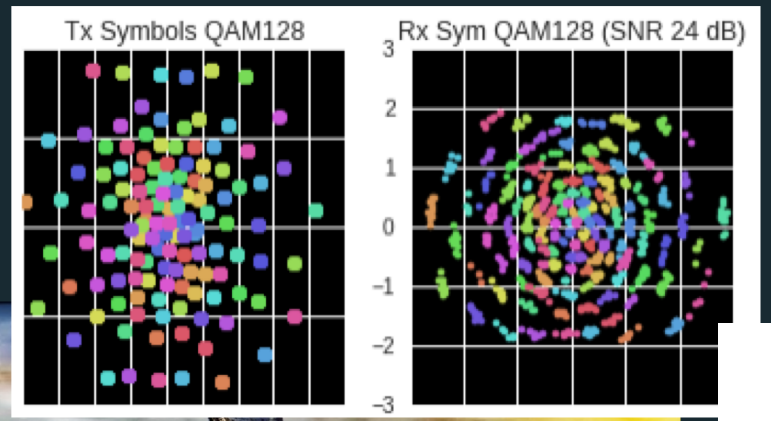


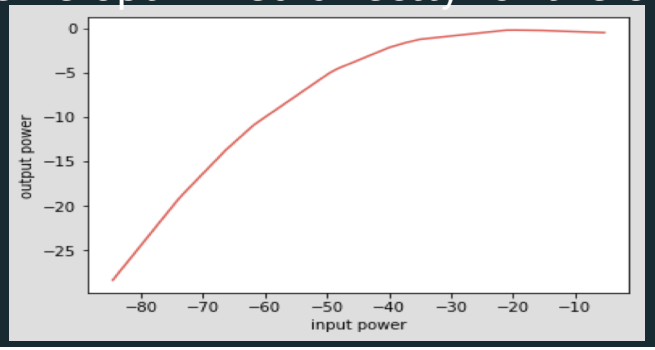
- Autoencoder approach to communications
  - Can learn novel modulation and coding schemes which optimize directly for channel effects
  - Minimize bit errors using cross-entropy or other similar performance driven loss functions
- Originally focused on having a differentiable analytic model for the channel
  - Numerous additional ways to apply partial approach to existing standards and

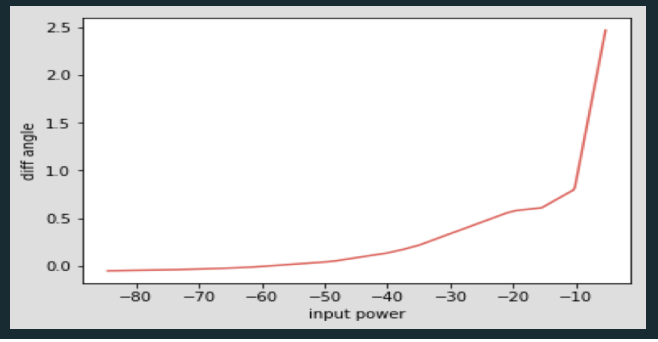


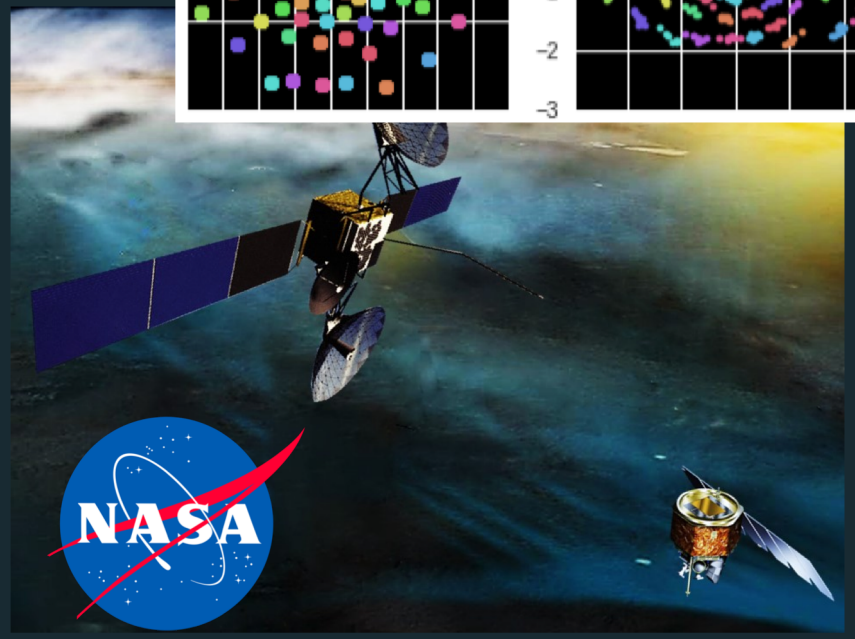
Learning Communications Systems: NASA TDRS

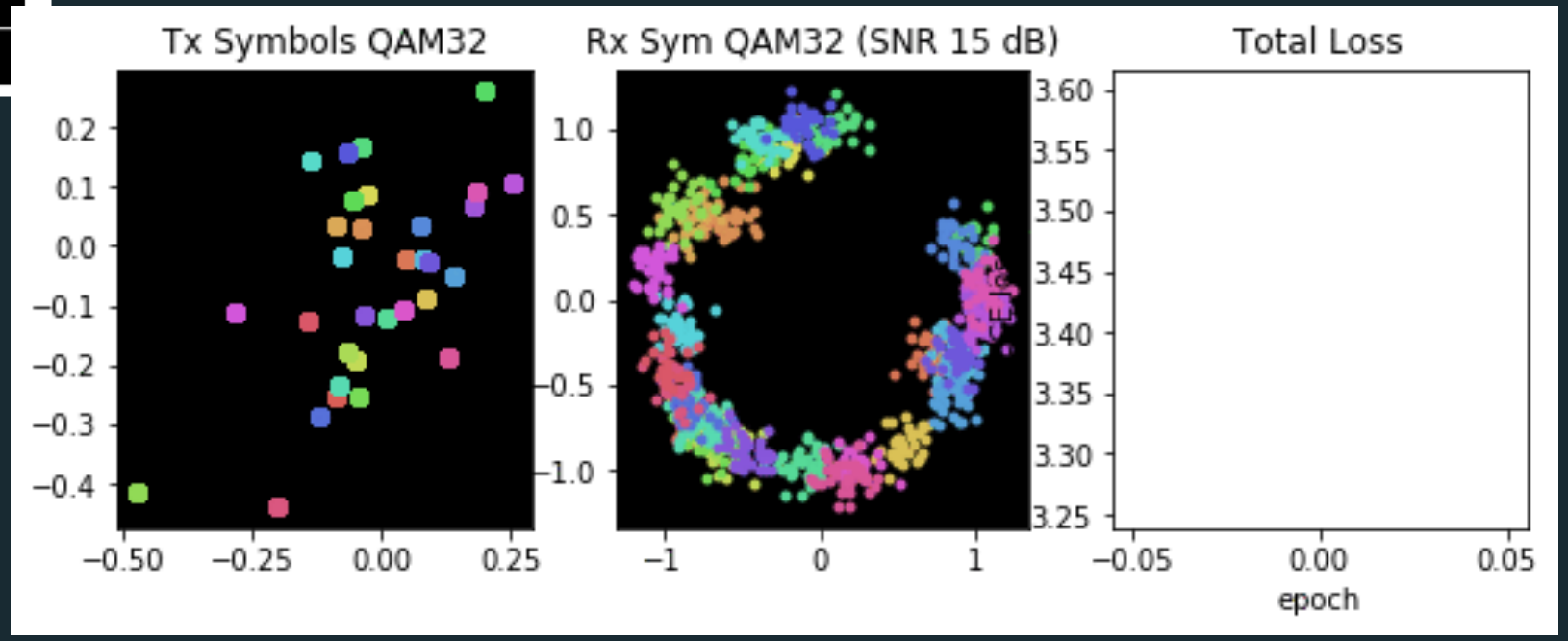
- Approach can scale to many real world systems with many harsh impairments and non-linearities
  - Study effort with NASA looking at compression region on TDRS TWT amplifiers
  - Instead of pre-distortion, we learn a scheme optimized directly for the channel, shown below



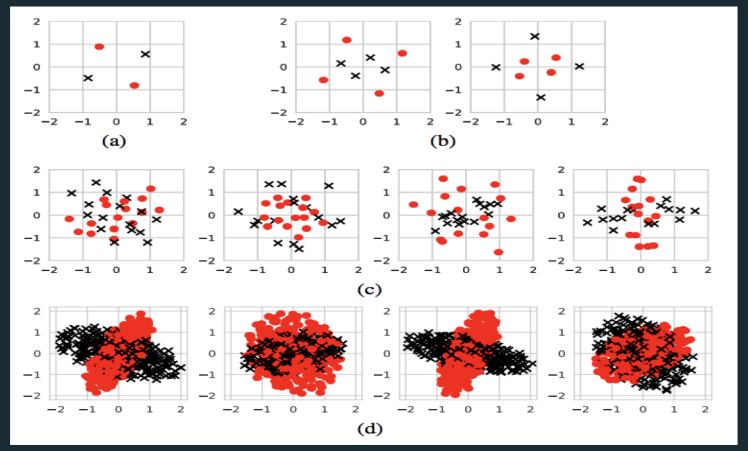


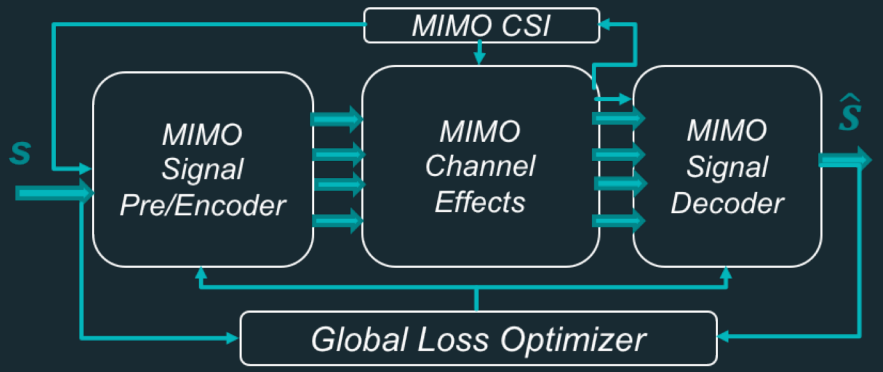






Learning Communications Systems: Scaling Applications





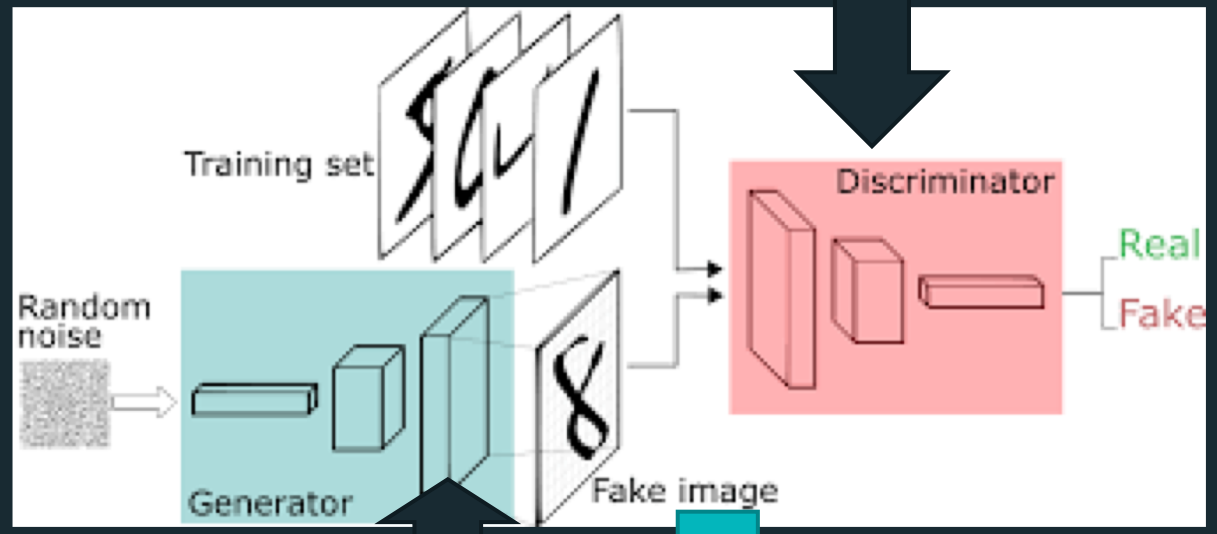
- Satellite Communications
- Mobile & Backhaul Radios
- Dense Urban Wireless
- MIMO 5G+ Cellular / WiFi Enhancements
- Resilient Comms & Denied Environments

- Adversarial learning, measurement and modeling allow for unique solutions to a range of systems
  - Can achieve resilience to hardware failures, malicious emitters, radar systems, adversarial tactics
  - Optimization of dense low-cost, many-antenna, many-user radio systems key req for 5G+

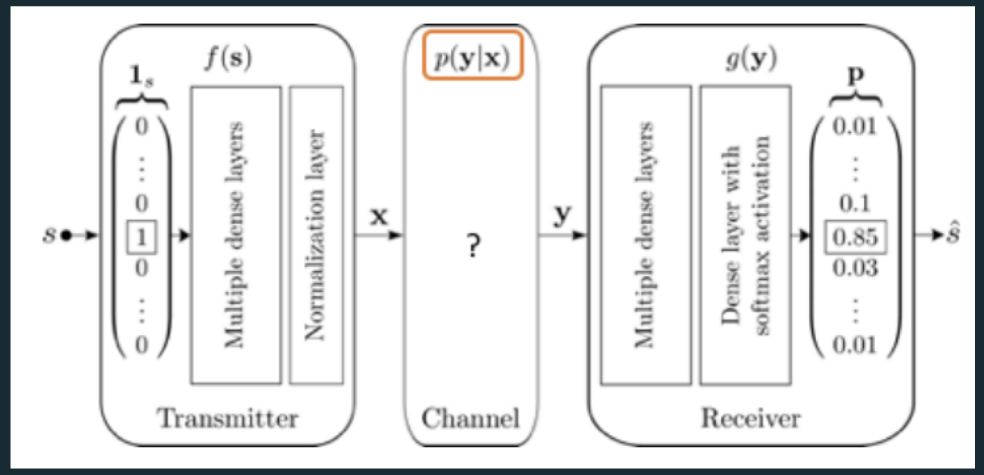
Brief GAN Introduction

- Introduced by Ian Goodfellow ~2014
  - Allow generator and discriminator to compete to enhance the performance of each.
  - Fully differentiable model leveraging known examples and random generator
- Apply this to unknown channel problem (below)
  - Combine generative RF models with discriminative RF models in an adversarial way to improve both

$$\nabla_{\theta_d} \frac{1}{m} \sum_{i=1}^{m} \left[\log D\left(\boldsymbol{x}^{(i)}\right) + \log\left(1 - D\left(G\left(\boldsymbol{z}^{(i)}\right)\right)\right) \right]$$

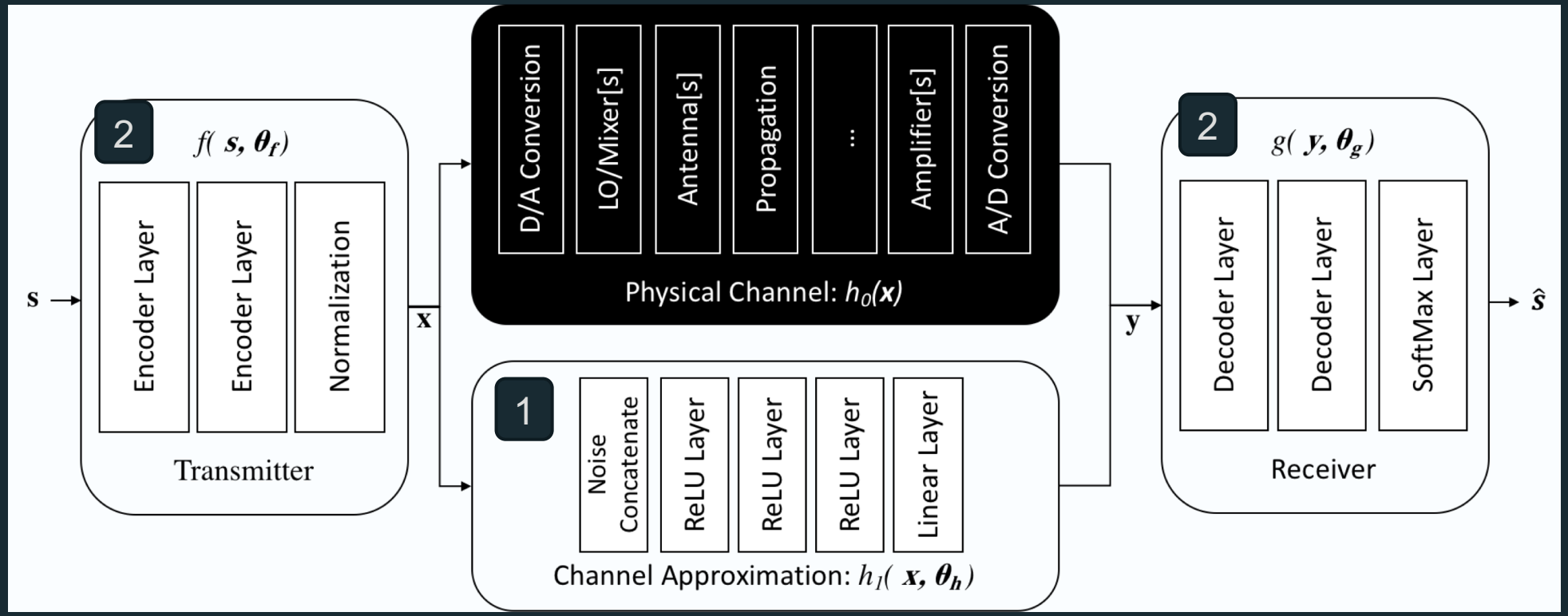


$$\nabla_{\theta_g} \frac{1}{m} \sum_{i=1}^{m} \log\left(1 - D\left(G\left(\boldsymbol{z}^{(i)}\right)\right)\right)$$



GAN Based Autoencoder Training

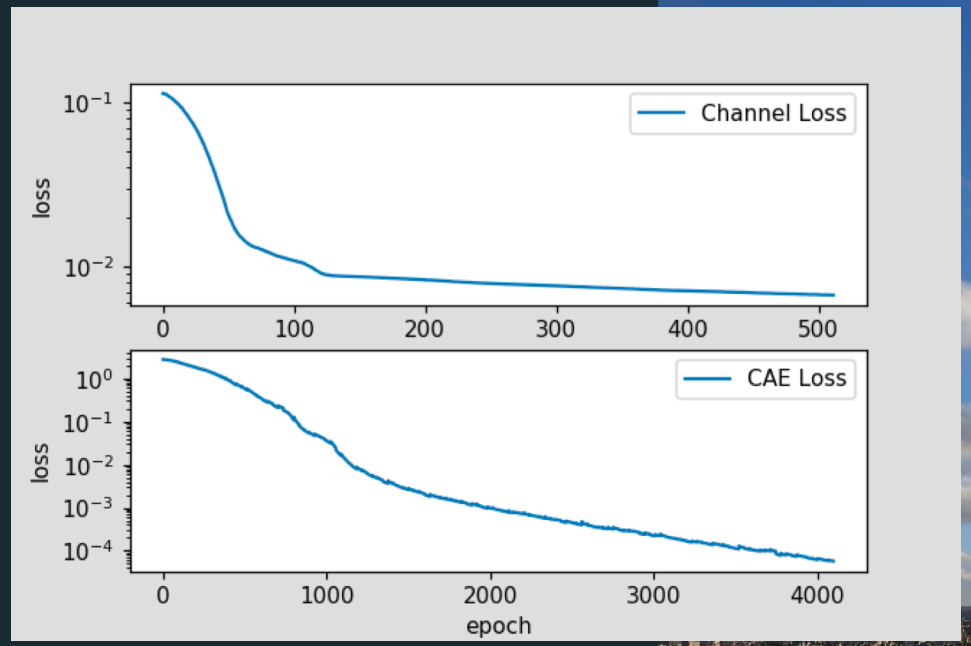
- In many cases we may not have an accurate analytic channel model
  - But still want to optimize the performance of some real world system we can measure
  - Need a closed form channel approximation to perform end-to-end optimization!
- Use adversarial autoencoder network configuration to jointly:
  - (1) Approximate the channel response model from measurement ($h(x, \theta)$)
  - (2) Optimize encoding and decoding to minimize BER for the channel response. ($f(s, \theta), g(y, \theta)$)

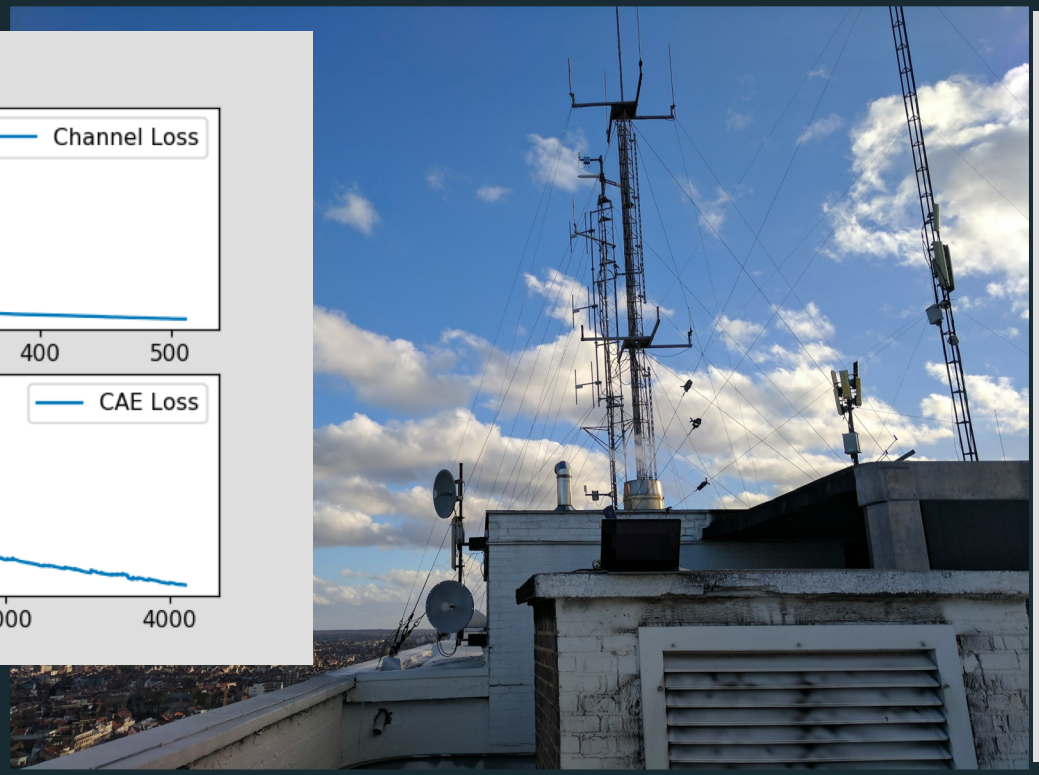


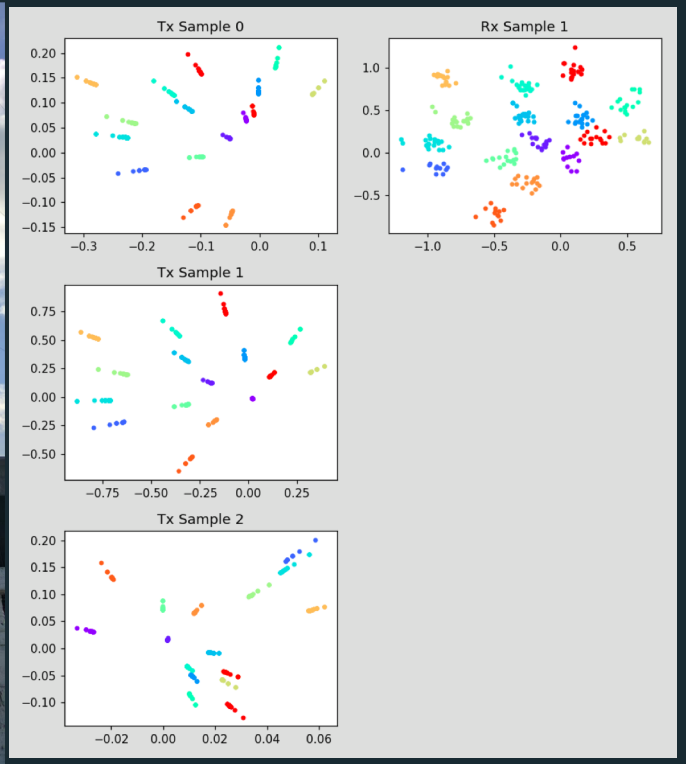
- Procedure
- 1. update θ_h according to MSE Loss of channel response
- 2. update θ_f, θ_g according to CCE loss of autoencoder reconstruction

Channel GAN Convergence OTA

- We can evaluate this over the air using a USRP radio as our black-box channel model
- Both channel loss and reconstruction loss decrease during OTA optimization approach
- Encoding 4 bits per symbol results in a non-standard looking 16-QAM constellation learned over the air only from channel measurement
  - Stable but unsynchronized (misaligned) timing in this example



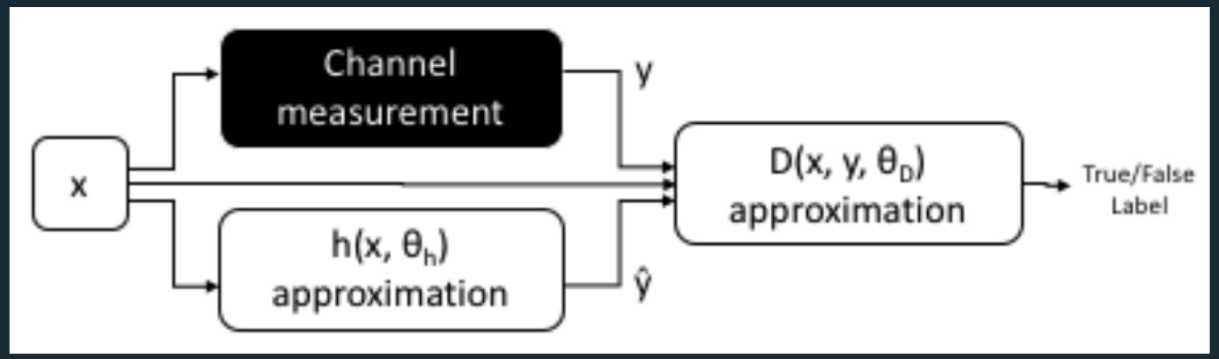


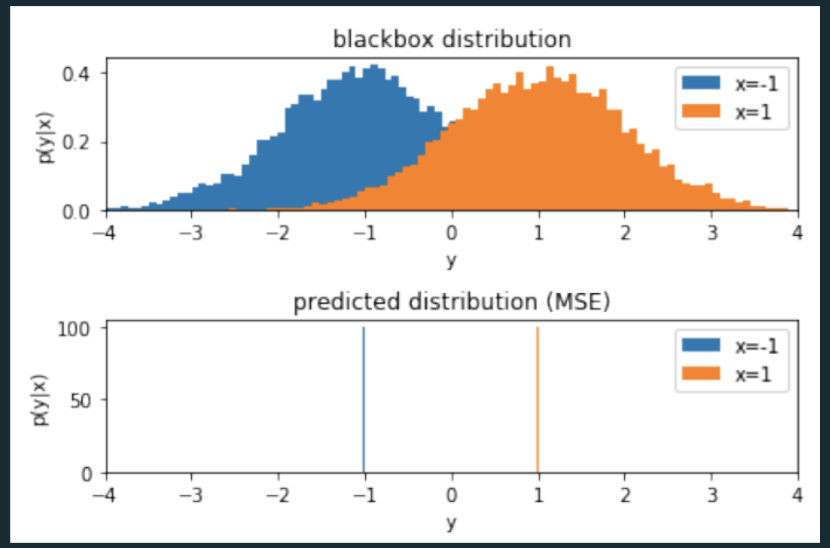


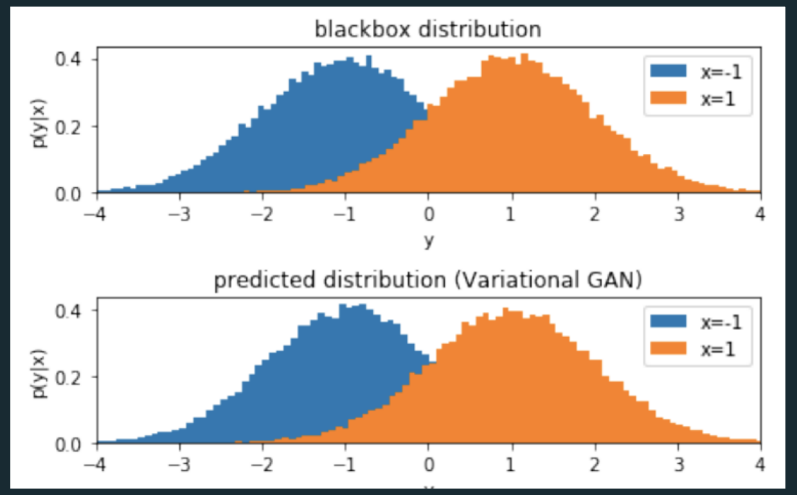
Enhancing GAN Channel Approximations

- Results were not as clean as we had hoped –
  - Loss metric: MSE only approximates only mean of conditional distribution
- Need to consider learning full distribution in order to accurately approximate cluster variance and other stochastic effects of the channel!
  - To accomplish this, we introduce a secondary GAN for channel approximation
  - Optimize conditional, variational channel approximation network & Channel Discriminator network

- 1. update D according to CCE min Loss
- 2. update H according to CCE max Loss
- 3. Update encoder and decoder according to min CCE BER error





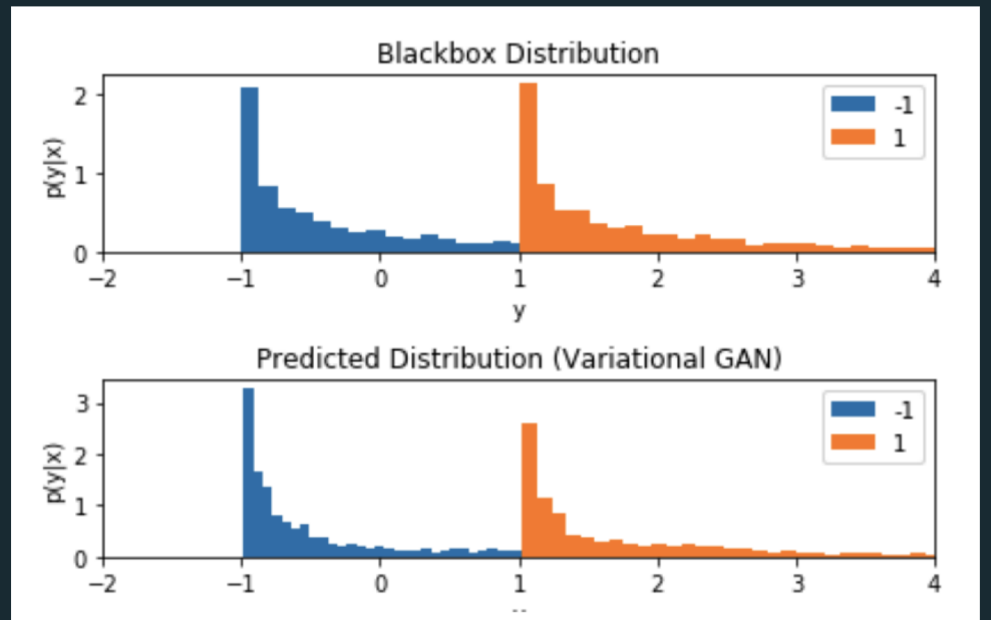


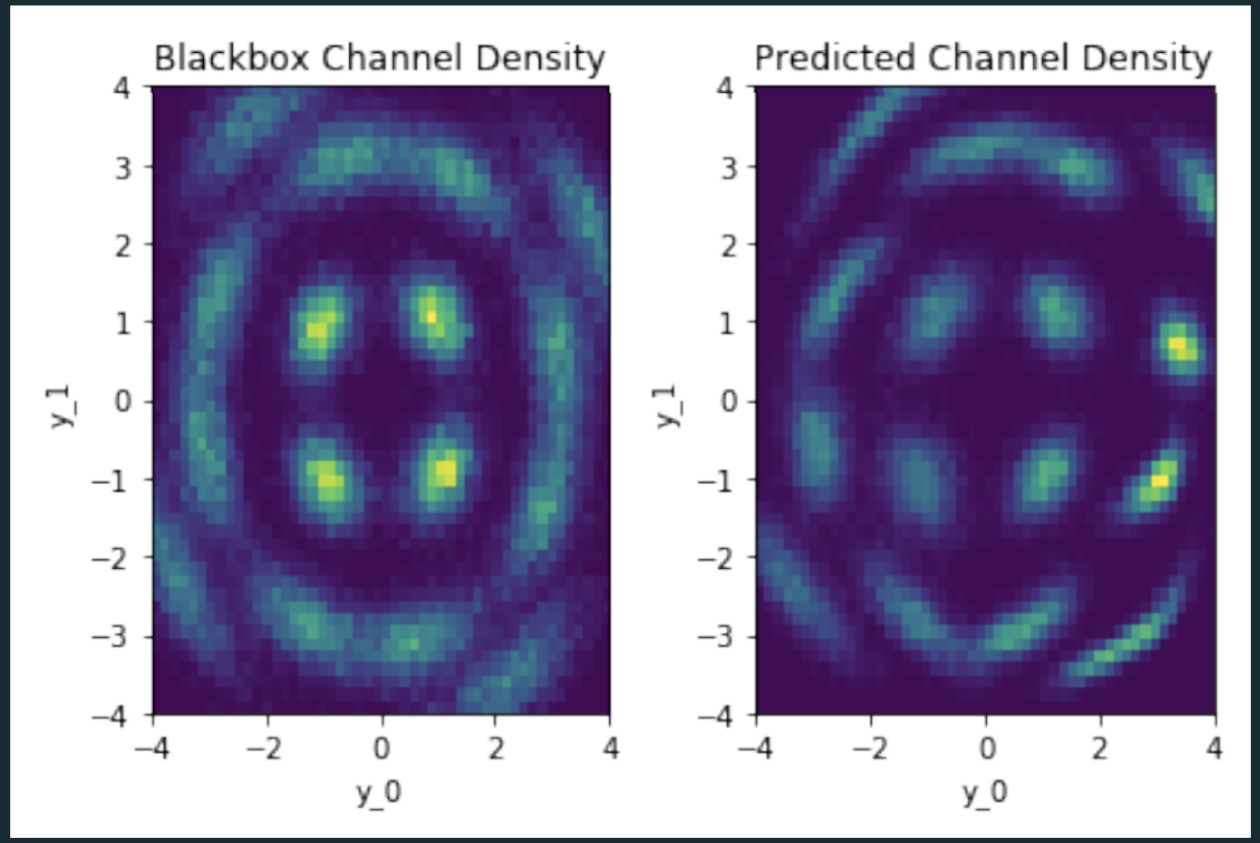
Enhancing GAN Channel Approximations

- Approach scales to non-gaussian distributions and multi-dim signal spaces
  - I/Q domain 16-QAM shown with non-linear distortion and phase noise
  - Captures conditional distribution quite accurately and compactly
- Can also leverage more stable Wasserstein GAN optimization metrics
  - Leads to better stochastic channel models and learned constellation modes

$$\nabla_{\theta_D} \frac{1}{N} \sum_{i=0}^{N} [(D(x_i, y_i, \theta_D)) - D(x_i, h(x_i, \theta_h), \theta_D)]$$

$$\nabla_{\theta_h} \frac{1}{N} \sum_{i=0}^{N} D(x_i, h(x_i, \theta_h), \theta_D)$$





Low Latency, Wideband, Generalized Sensing

- OmniSIG efforts provide an entirely new approach to RF sensing and identification
  - Achieves extremely low latencies which are 100x faster than many older methods
  - Numerous applications in spectrum monitoring, security, mapping, behavior analysis, and others

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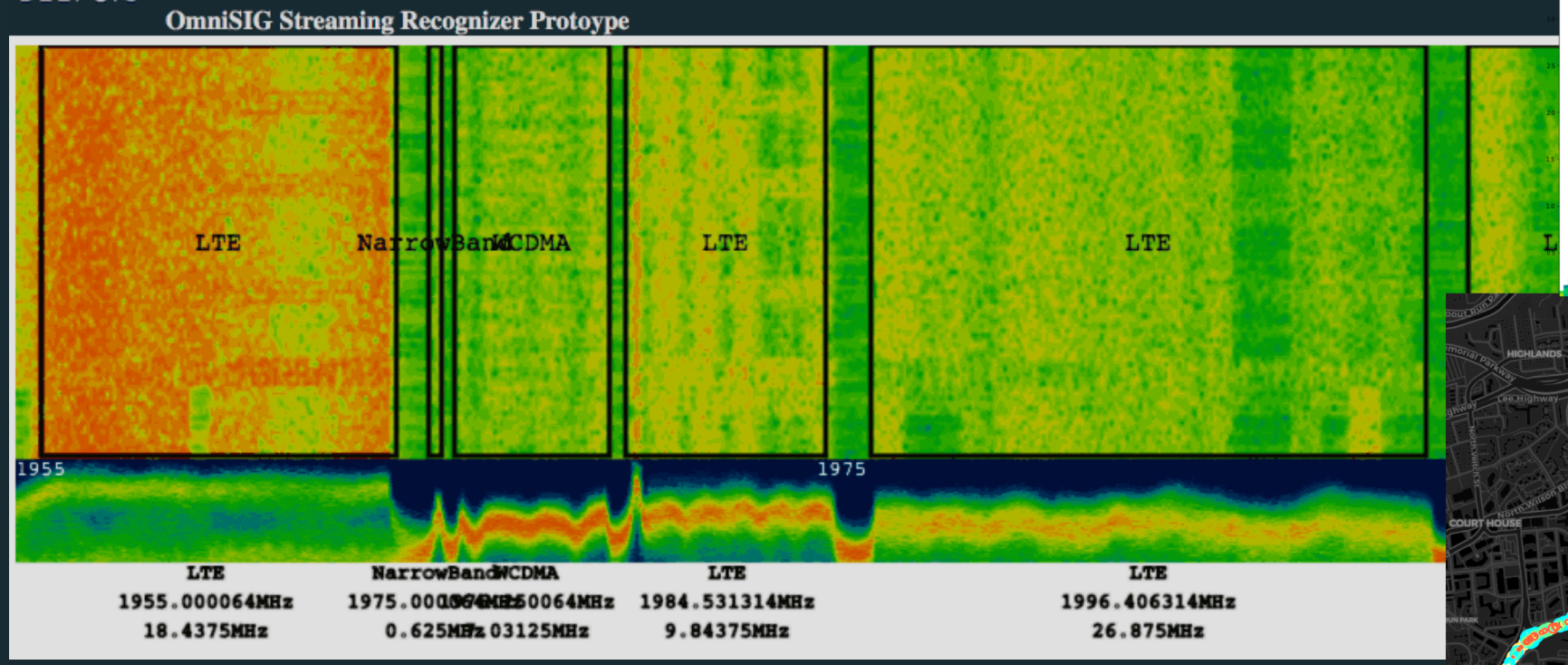
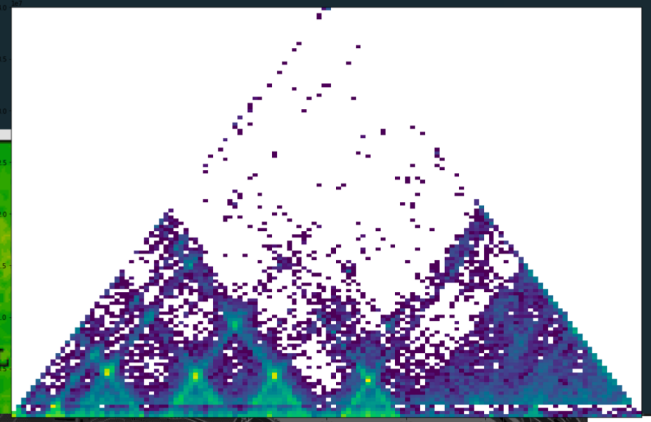
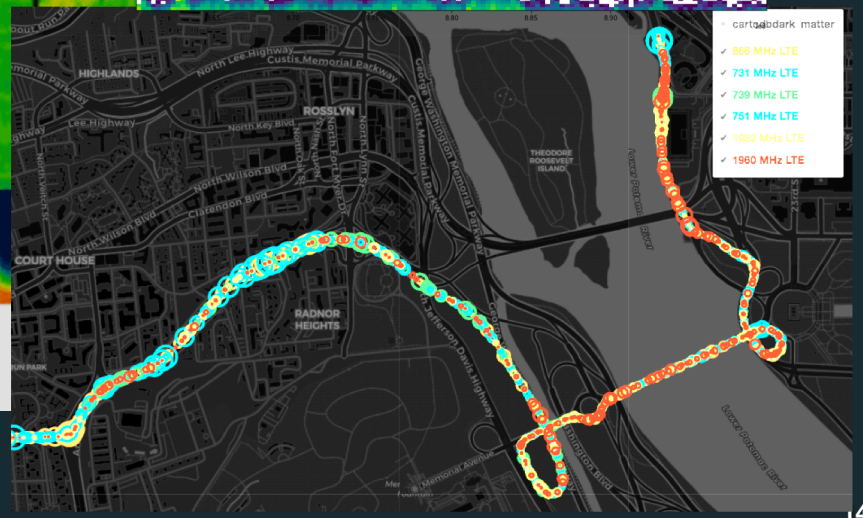
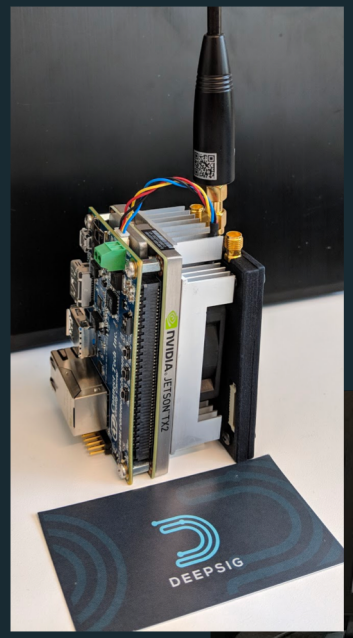


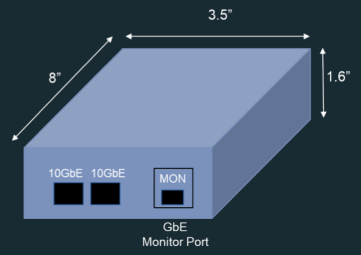


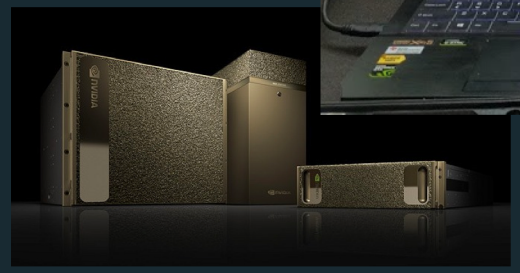


Scaling Model Deployment

- SDR Deployment range widely
  - Low power edge sensors
  - Datacenter class ground stations
  - Everything in between
- Luckily this is the case in computer vision world as well –
  - Deep learning models can be efficiently deployed and scaled across a wide range of hardware targets
  - Vision processing is driving an economy of scale for NN processors which the radio community should embrace!
- Our capabilities shown scaling smartphone/embedded to desktop/server class devices
  - Models remain largely unchanged







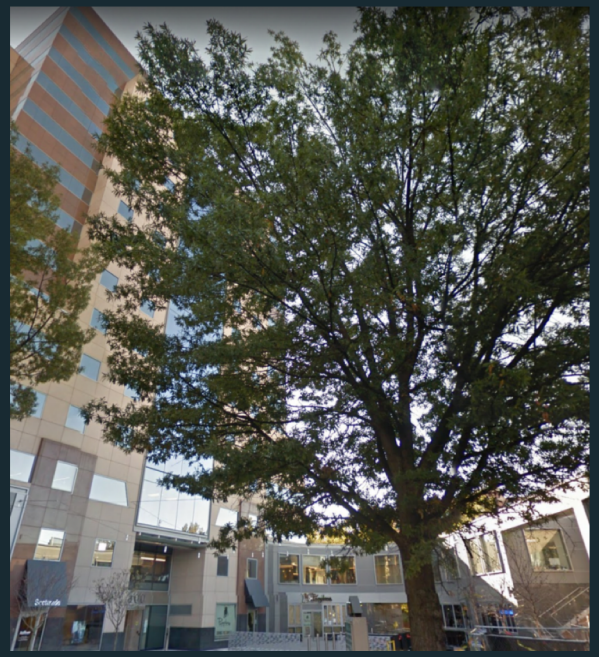
In Summary

- **Machine learning is rapidly advancing physical layer radio processing**
  - Offers numerous new avenues to complement existing methods
  - Allows capabilities to be more rapidly updated and adapted
  - Exploits more information than we can traditionally handle
  - Offers orders of magnitude improvement in some cases
  - Methods and research are still accelerating and here for the long haul

- **Good data and software radio infrastructure is critical to enabling this**
  - **GNU Radio** will play a central role here in measurement and simulation
  - **GNU Radio** also provides a powerful deployment tool for many uses
  - Efforts like **SigMF** will help capabilities scale

- Thanks for listening!

Thanks!



Come chat with us!

Demos running and additional info available in our booth

DeepSig Inc. Arlington, VA

Hiring ML/DSP/Software/embedded!

https://deepsig.io