

# Deepmod: An Over-the-Air Trainable Machine Modem for Resilient Communications

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U.S. DEPARTMENT OF  
**ENERGY**

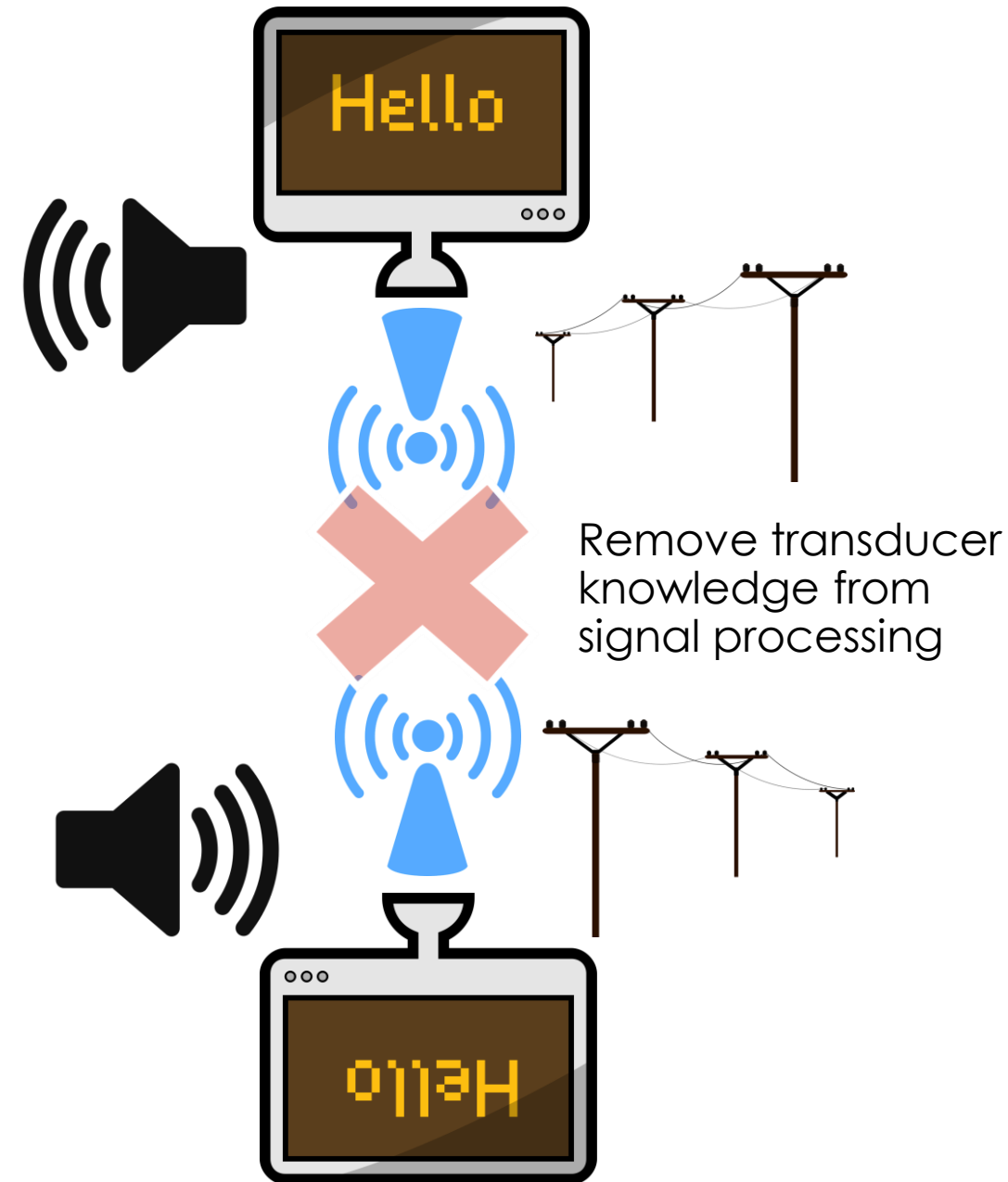
# Specific Goal: Security

## Definition of Security [44 U.S.C., Sec. 3542]

- **Confidentiality:** “Preserving authorized restrictions on information access and disclosure, including means for protecting personal privacy and proprietary information....”
- **Integrity:** “Guarding against improper information modification or destruction, and includes ensuring information non-repudiation and authenticity....”
- **Availability:** “Ensuring timely and reliable access to and use of information....”

## Deepmod

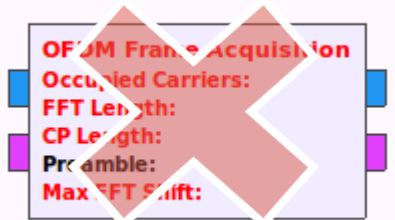
“... by generating, on-the-fly, viable physical layer modem protocols, using deep learning, in a variety of media or channel conditions.”



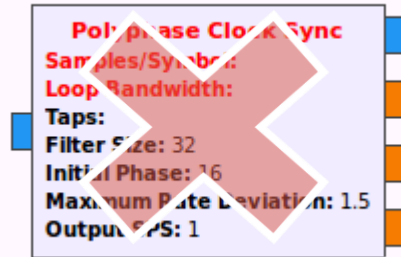
# Pie-in-the-Sky Goal: Throw Out 75 Years of Digital Comms

Figure out: How much of traditional PHY can Deepmod actually learn?

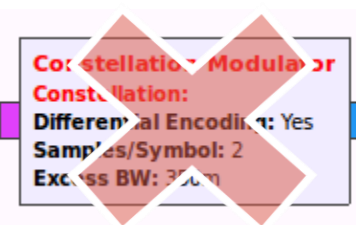
## Frame Synchronization



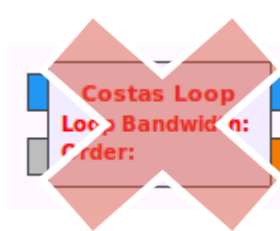
## Timing Synchronization



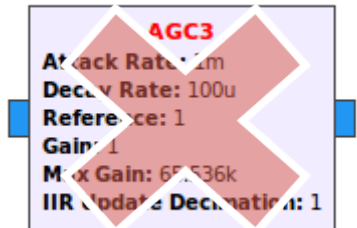
## Digital Modulation



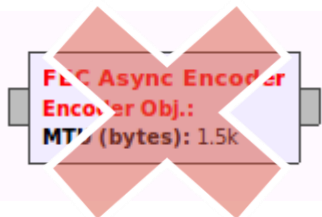
## Phase Correction



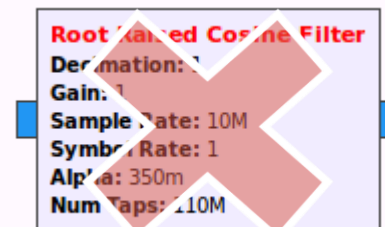
## Automatic Gain Control



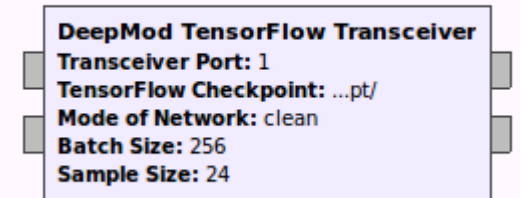
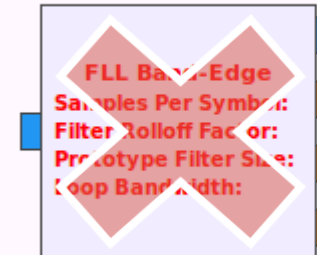
## Error Correction



## Matched Filtering



## CFO Correction



We want to replace **all** signal processing blocks with a single learner

# Recent Work on “Machine Modems”

- “Machine speak: Left to their own devices, computers can figure it out,” <https://www.ornl.gov/news/machine-speak-left-their-own-devices-computers-can-figure-it-out>
- “Machine Learning Modems: How ML Will Change How We Specify And Design Next Generation Communication Systems, ” (www.comsoc.org)
- T. J. O’Shea and J. Hoydis, “An introduction to machine learning communications systems,” ArXiv e-prints, Feb. 2017.
- T. OShea and J. Hoydis, “An introduction to deep learning for the physical layer,” *IEEE Transactions on Cognitive Communications and Networking*, vol. 3, no. 4, pp. 563–575, Dec 2017.
- S. Drner, S. Cammerer, J. Hoydis, and S. t. Brink, “Deep learning based communication over the air,” *IEEE Journal of Selected Topics in Signal Processing*, vol. 12, no. 1, pp. 132–143, Feb 2018.
- ECE 7970: Statistical Learning, Fall 2015, Class Project

# A Note on Vocabulary

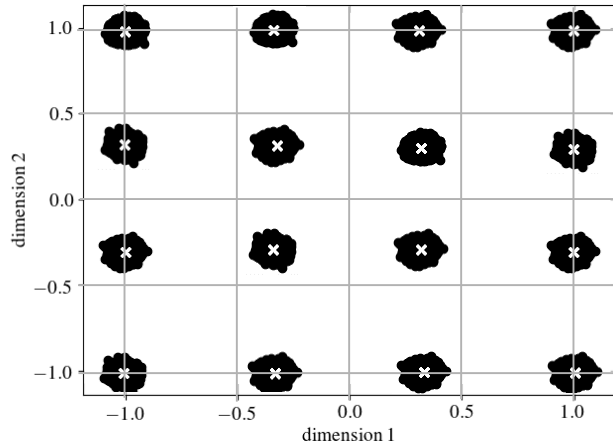
Some ambiguity between comms and ML communities

- **Network:** The communication network in question
- **Graph:** The “brain” of the neural network
- **Sample:** This is what comes out of, or into, your USRP
- **Example:** This is what goes into your machine learner
- **Spectral Efficiency:** We'll call it bits-per-sample. In traditional comms you have samples-per-symbol, bits-per-symbol,  $r=1/2$  FEC, etc. With Deepmod you have number of classes (bits-per-class) and samples-per-example. Both lead to the same definition of spectral efficiency.

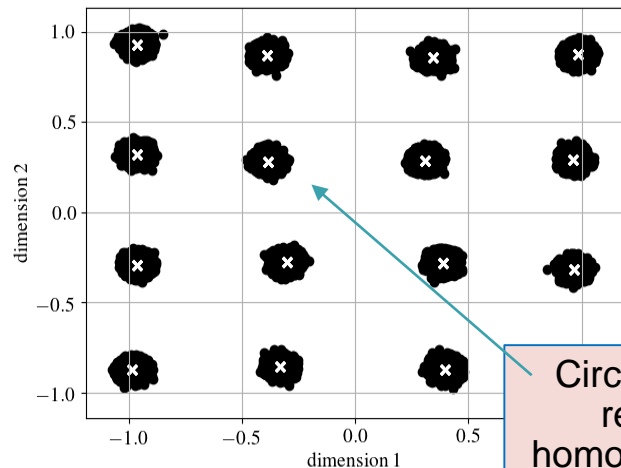
# How Resiliency? A Toy Example

## 1) Homogeneous noise channel

Human Invented 16-QAM



Machine Invented 16-QAM

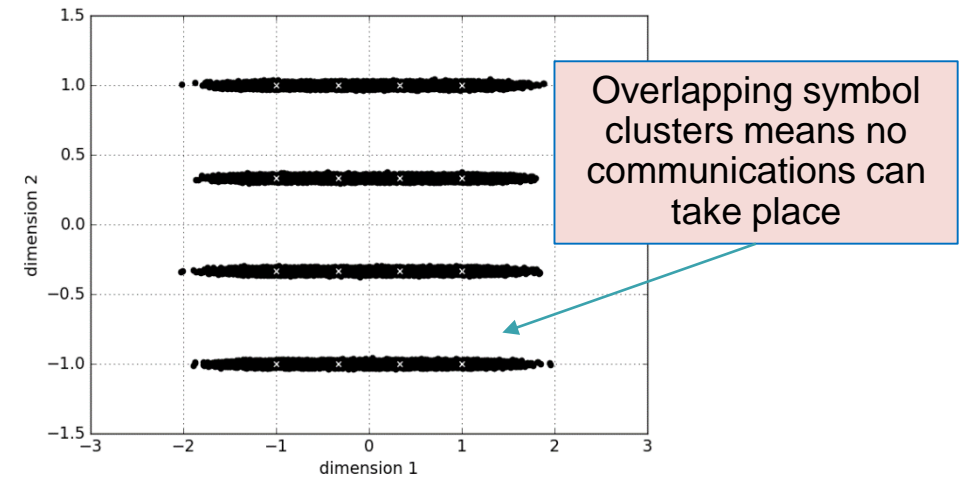


Circular clusters  
result from  
homogenous noise

- Human coded information flow goes to zero when the channel changes drastically.
- The machine is able to “learn” around the attack and maintain identical flow.  
**The machine discovers latent communications.**
- Sure, a human could invent 8x2-QAM but we don't want to wait two-years for hardware upgrades.

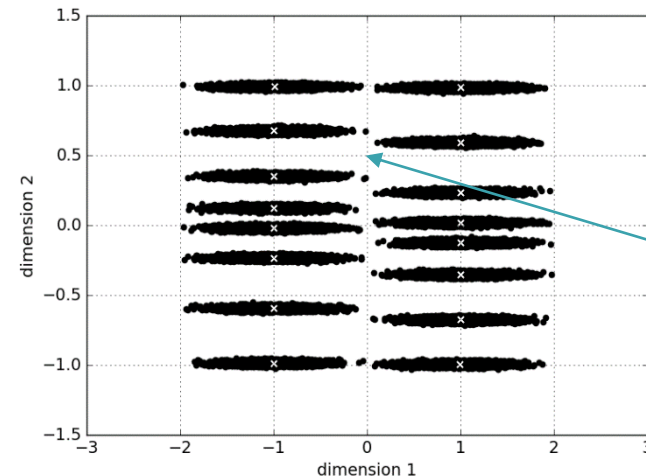
## 2) Heterogeneous noise channel

Human Invented 16-QAM



Overlapping symbol  
clusters means no  
communications can  
take place

Machine Invented 8x2-QAM



No overlap. Symbol  
centers rearranged  
around  
heterogenous noise



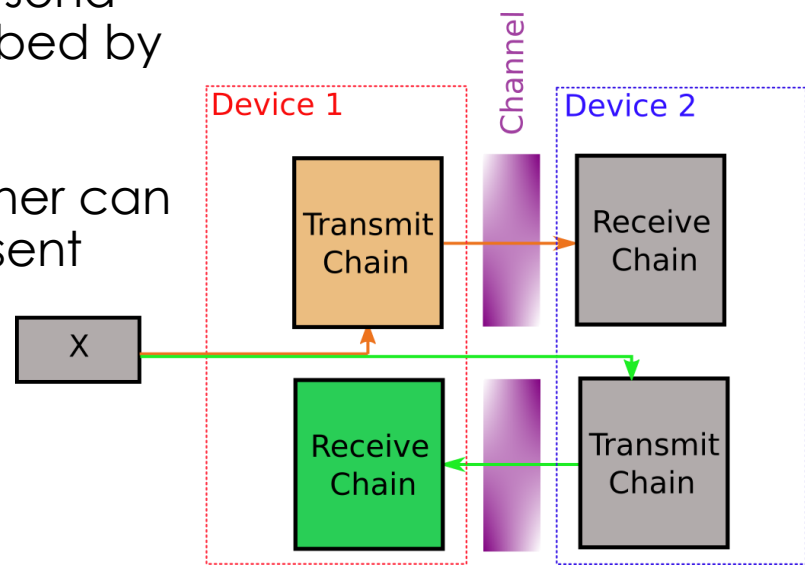
# A Real Example: Over-the-Air Training with Autoencoders

Autoencoders are a classic first approach to unsupervised learning.

1. Encoder (transmit chain) converts classes to samples.
2. Decoder (receive chain) converts samples to class estimates.

Transmit chain is trained to send message that is least disturbed by channel

- Trivial loss function
- Doesn't ensure partner can understand what is sent



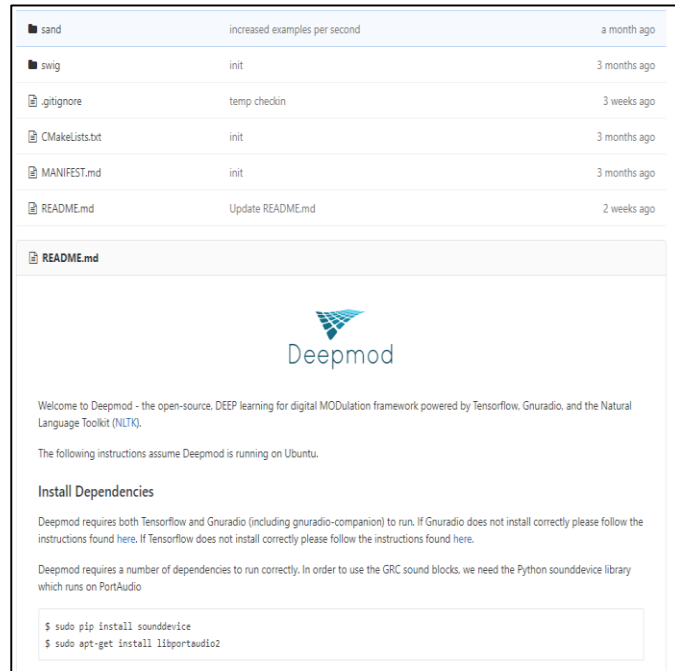
Receive chain is trained to decode from known sequence

No backpropagation is allowed through the wireless channel!

**Result:** Better than just inventing constellations but not much learning on transmit side

# Deepmod: Acoustic Channel with Autoencoder

## Step 1) Make Fancy GIT Repo



## Step 2) Make Fancy Hardware



## Step 3) Demo “Machine Speak”

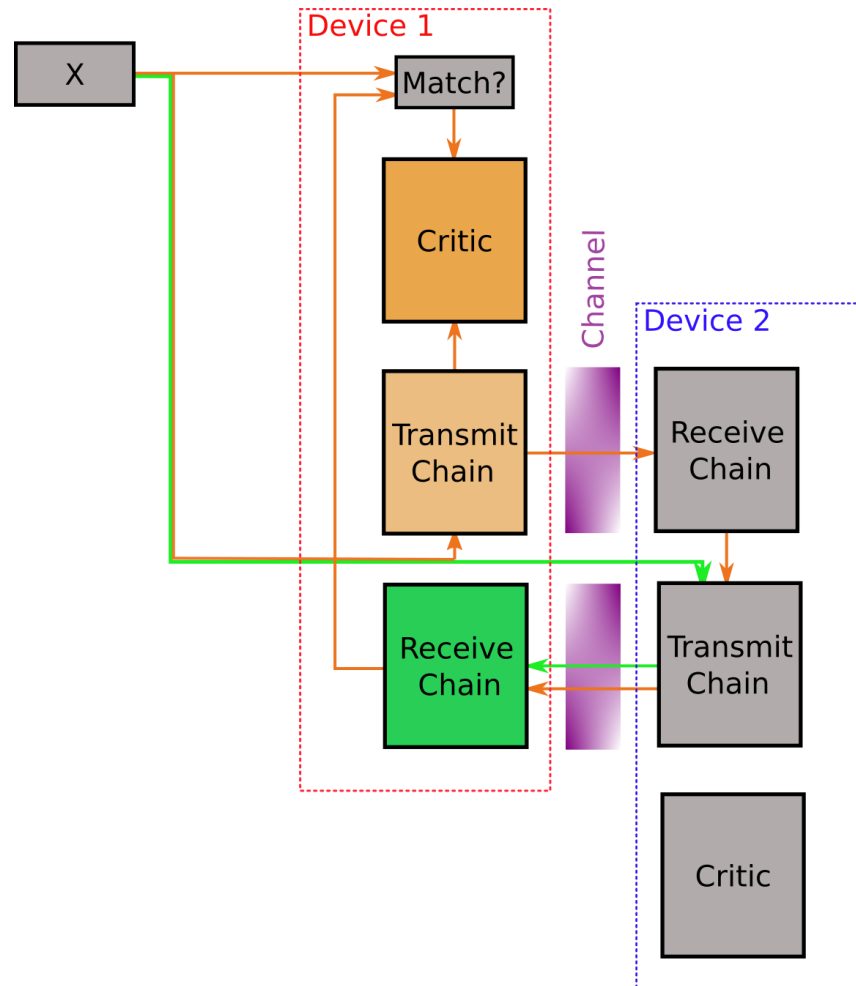
- Deep convolutional neural network autoencoder
- Single transducer rig (soundcard, microphone, speaker)
- GNU Radio, TensorFlow, Natural Language Toolkit
- Classes are English phonemes
- Listen as computers communicate via chat terminal



# Over-the-Air Adversarial Training

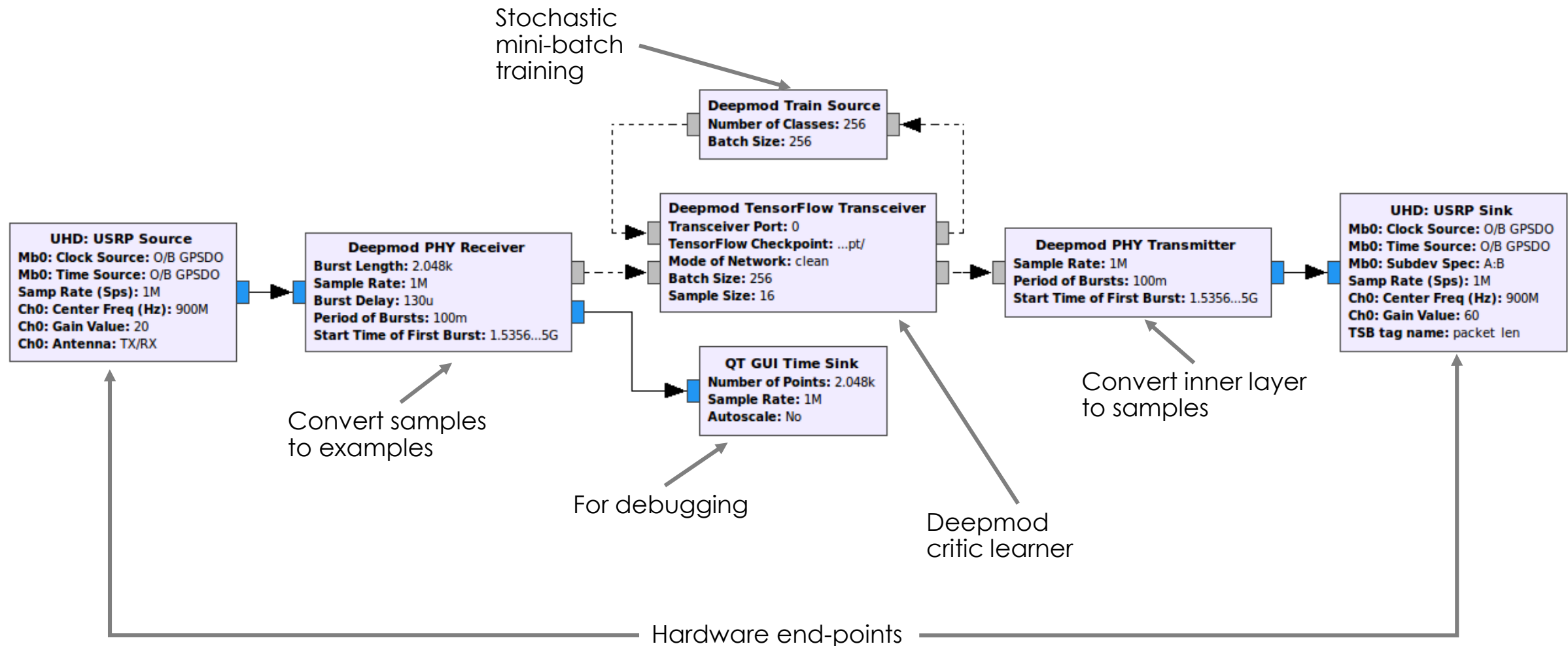
We need a method for the transmit chain to learn as well

1. Stochastic mini-batches. 256 “classes” or 8 bits per class
2. Device 1 converts classes to samples and transmits
3. Device 2 replies with what is heard not what is known
4. Device 1 separates correctly decoded classes from incorrect
5. Transmit chain (encoder) is updated to optimize understandable classes



Receive chain is still trained in same manner


# Obligatory GNU Radio Companion Screenshot



# Deepmod: RF Channel

Step 1) Add a whole lot of gnuradio and tensorflow code to the repo

Name	Last commit	Last update
apps	init	7 months ago
cmake	init	7 months ago
docs	almost ready for powerline	a week ago
examples	jammer	a week ago
grc	jammer	a week ago
include/deepmod	init	7 months ago
lib	init	7 months ago
python	jammer	a week ago
sand	rf dm	3 months ago
swig	init	7 months ago
.gitignore	prepping for branch	4 months ago
CMakeLists.txt	init	7 months ago
MANIFEST.md	init	7 months ago
README.md	Update README.md	5 months ago
ber.npy	about to branch gps	3 weeks ago



Welcome to Deepmod - the open-source, DEEP learning for digital MODulation framework powered by Tensorflow, Gnuradio, and the Natural Language Toolkit (NLTK).

Step 2) Plug into a different set of transducers (USRPs in this case)

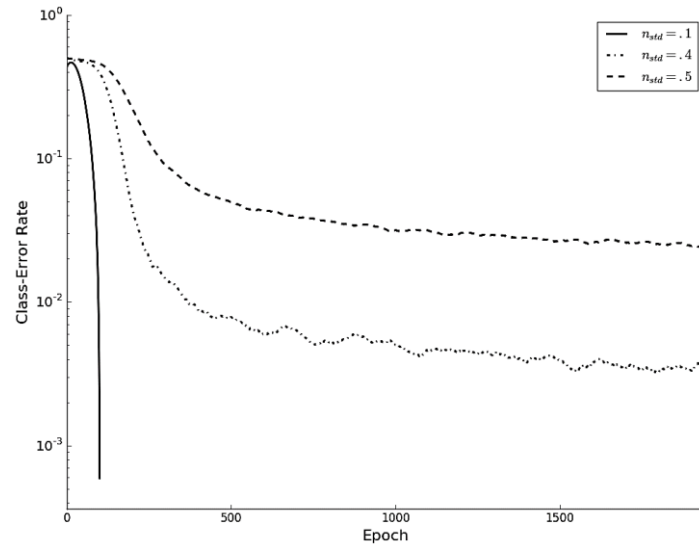


## Step 3) Demo Deepmod

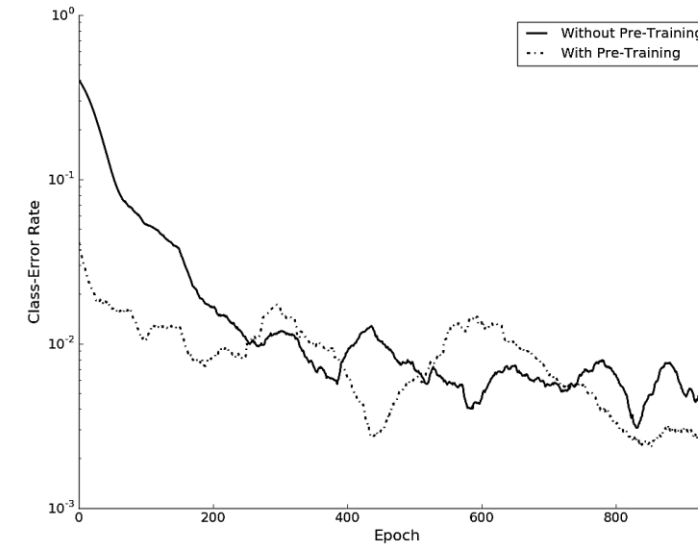
- Sample rate = 1 Msps
- Center frequency = 900 MHz
- SNR adjusted to match simulation
- 256 classes, 16 (real) samples, **1 bit per sample**
- **0 signal processing blocks**
- High rate communications

# Simulated vs. Over-the-Air

Simulated class error rate vs. training epoch



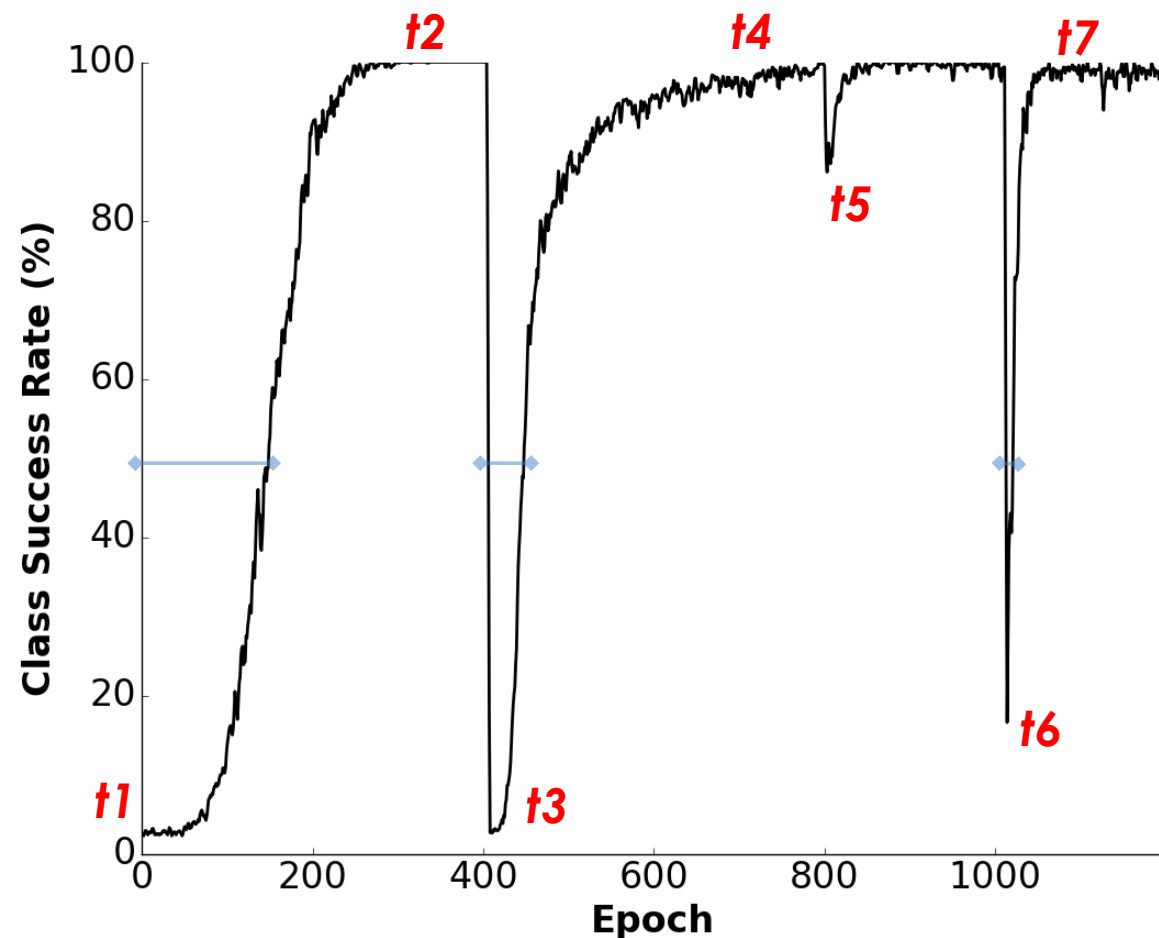
Over-the-air class error rate vs. training epoch and graph initialization



- Current Deepmod achieves realistic spectral efficiency (1 bit per sample)
- At acoustic rates also achieves good throughput
- At RF rates Deepmod is **throttled due to TensorFlow bottleneck**
- Need to get Deepmod closer to traditional PHY layer throughputs\*

\* Inference is MUCH faster than training fortunately

# Resiliency to Extreme Channel Changes



**t1:** Two Deepmod enabled radios are powered on

**t2:** Radios converge to a viable communications protocol

**t3:** Narrowband jammer is engaged; performance bottoms out

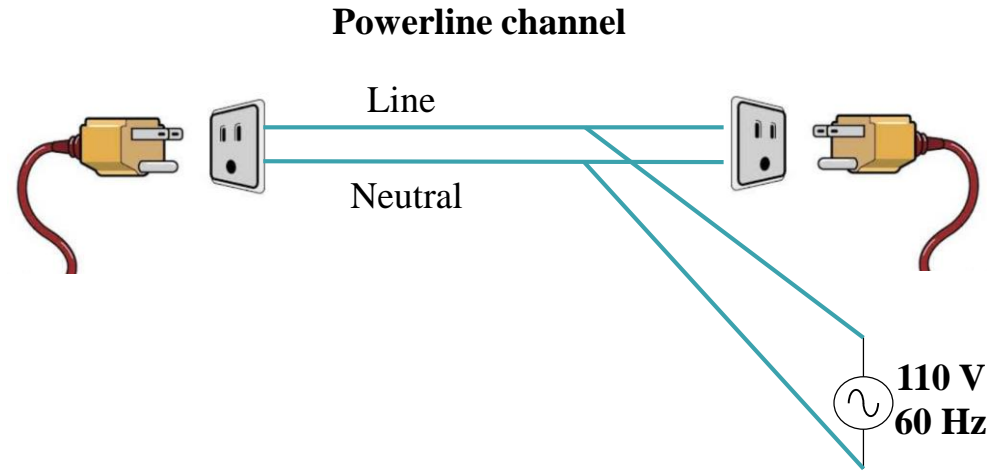
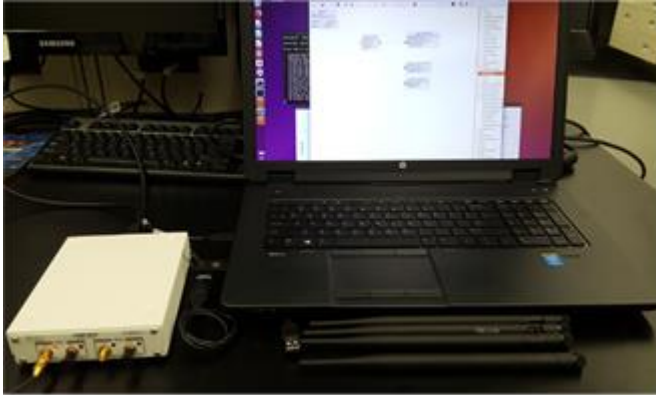
**t4:** Deepmod recovers by “learning” new jammed channel

**t5:** Jammer is turned off confusing Deepmod temporarily

**t6:** Jammer is turned back on

**t7:** Deepmod recovers quickly; retained knowledge of both “on” and “off” jammer states

# Deepmod: Powerline Communications (in progress)



**Signal down-converted from 75 MHz carrier**



**High-Pass, 60 Hz Isolation Filter w/Plug-in Shielded Enclosure**

- Powerline channel is extremely noisy and difficult to model all possibilities. Every channel is different.
- Perfect environment for a learnable PHY layer!
- However, Deepmod isn't magic; it won't increase your SNR or range. Still need some signal to make it across channel.



# Deepmod Didn't Learn Everything We Had Hoped

Remember, we wanted to replace **all** signal processing blocks with a single learner

## Frame Synchronization

OFDM Frame Acquisition  
Occupied Carriers:  
FFT Length:  
CP Length:  
Preamble:  
Max FFT Shift:

## Timing Synchronization

Polyphase Clock Sync  
Samples/Symbol:  
Loop Bandwidth:  
Taps:  
Filter Size: 32  
Initial Phase: 16  
Maximum Rate Deviation: 1.5  
Output SPS: 1

## Digital Modulation

Constellation Modulator  
Constellation:  
Differential Encoding: Yes  
Samples/Symbol: 2  
Excess BW: 300m

## Phase Correction

Costas Loop  
Loop Bandwidth:  
Order:



## Automatic Gain Control

AGC3  
Attack Rate: 10m  
Decay Rate: 100u  
Reference: 1  
Gain: 1  
Max Gain: 65536k  
IIR Update Decay: 1

## Error Correction

FEC Async Encoder  
Encoder Obj.:  
MTU (bytes): 1.5k

## Matched Filtering

Root-raised Cosine Filter  
Derivation:  
Gain: 1  
Sample Rate: 10M  
Symbol Rate: 1  
Alpha: 350m  
Num Taps: 110M

## CFO Correction

FLL Back-Edge  
Samples Per Symbol:  
Filter Rolloff Factor:  
Prototype Filter Size:  
Loop Bandwidth:

DeepMod TensorFlow Transceiver  
Transceiver Port: 1  
TensorFlow Checkpoint: ...pt/  
Mode of Network: clean  
Batch Size: 256  
Sample Size: 24

Don't give up yet!

# A Quick Note on Frame (Example) Synchronization

We tried a little bit of everything...

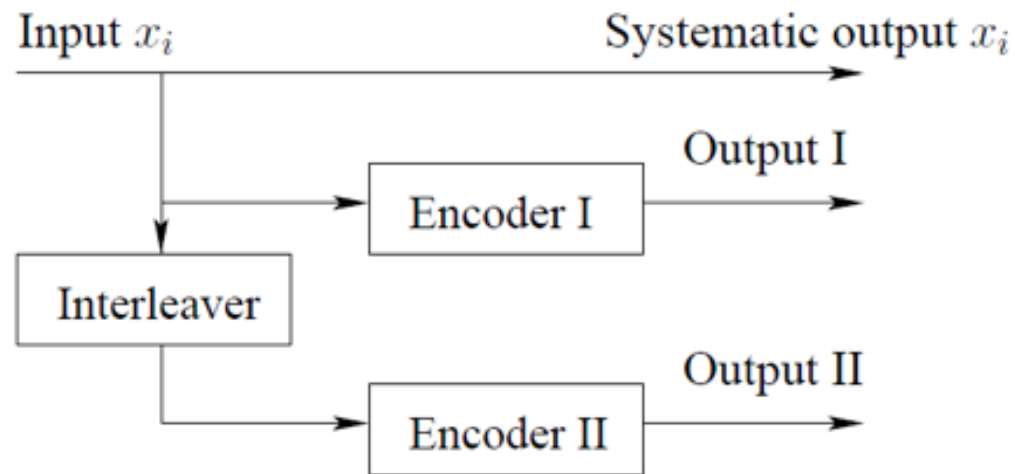
- **Continuous Tone-Coded Squelch System** (CTCSS) – only listen when a prearranged tone was present. Used in the original acoustic demo.
- **Energy Detection** – classic double-sliding window for packet edge detections.
- **Preamble** – this felt like “cheating” since it assumes a rudimentary “language” before training.
- **GPS** – only listen to channel in certain time slots. Okay to be off by a sample or two; Deepmod can work around that.
- **Machine Learner** – is where we are headed. Will probably need to be its own machine at the front end of Deepmod.

# Moving from CNN to Recurrent Neural Network (RNN)

“Ordinary neural networks including CNNs don’t perform well in cases where sequence of data is important”

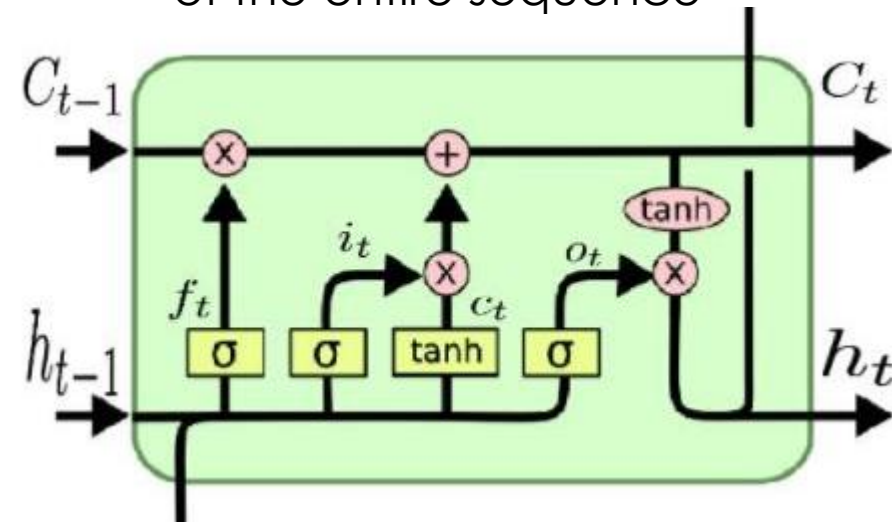
## Turbo Code

Output samples are functions of all input samples



## LSTM Cell

All classification is a function of the entire sequence



In comms, sequence of data is important. Deepmod is currently a CNN. Maybe we need it to be an RNN?

# Conclusions and Future Work

## What We Did

- Deepmod can generate a new PHY protocol on-the-fly when:
  - The channel is severely distorted
  - The channel medium is completely altered
- Deepmod can learn what you make it capable of learning

## What We Want to Do

- Move away from Deepmod CNN critic toward RNN critic
- Need high spectral efficiency AND high throughput
- Powerline comms, underwater comms, deep-space comms: whatever medium you can stick two transducers into

