



DeepSig

Pioneering Deep Learning for Wireless

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DEEPSIG

Universal Approximation

Let $\varphi(\cdot)$ be a nonconstant, **bounded**, and **monotonically-increasing continuous** function. Let I_m denote the m -dimensional **unit hypercube** $[0, 1]^m$. The space of continuous functions on I_m is denoted by $C(I_m)$. Then, given any $\varepsilon > 0$ and any function $f \in C(I_m)$, there exist an integer N , real constants $v_i, b_i \in \mathbb{R}$ and real vectors $w_i \in \mathbb{R}^m$, where $i = 1, \dots, N$, such that we may define:

$$F(x) = \sum_{i=1}^N v_i \varphi(w_i^T x + b_i)$$

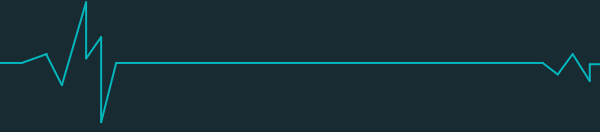
as an approximate realization of the function f where f is independent of φ ; that is,

$$|F(x) - f(x)| < \varepsilon$$

for all $x \in I_m$. In other words, functions of the form $F(x)$ are **dense** in $C(I_m)$.



Universal Approximation



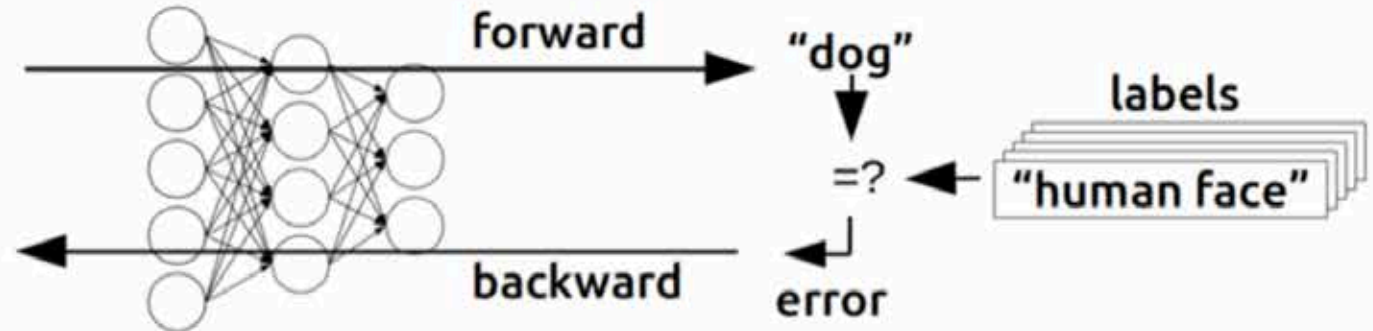
“The theorem thus states that simple neural networks can *represent* a wide variety of interesting functions when given appropriate parameters; however, it does not touch upon the algorithmic learnability of those parameters.”

https://en.wikipedia.org/wiki/Universal_approximation_theorem



Machine Learning

Training



Inference

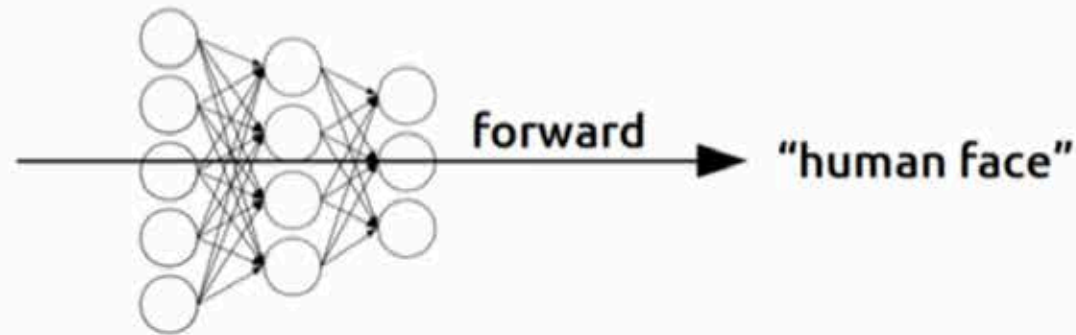
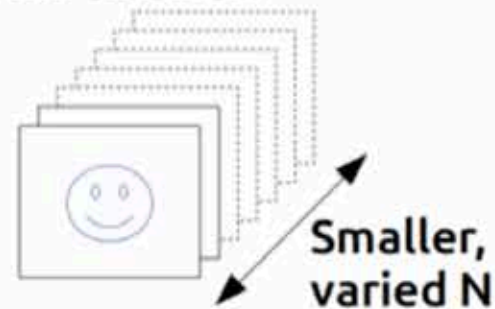


Figure 1: Deep learning training compared to inference. In training, many inputs, often in large batches, are used to train a deep neural network. In inference, the trained network is used to discover information within new inputs that are fed through the network in smaller batches.

Machine Learning for RF



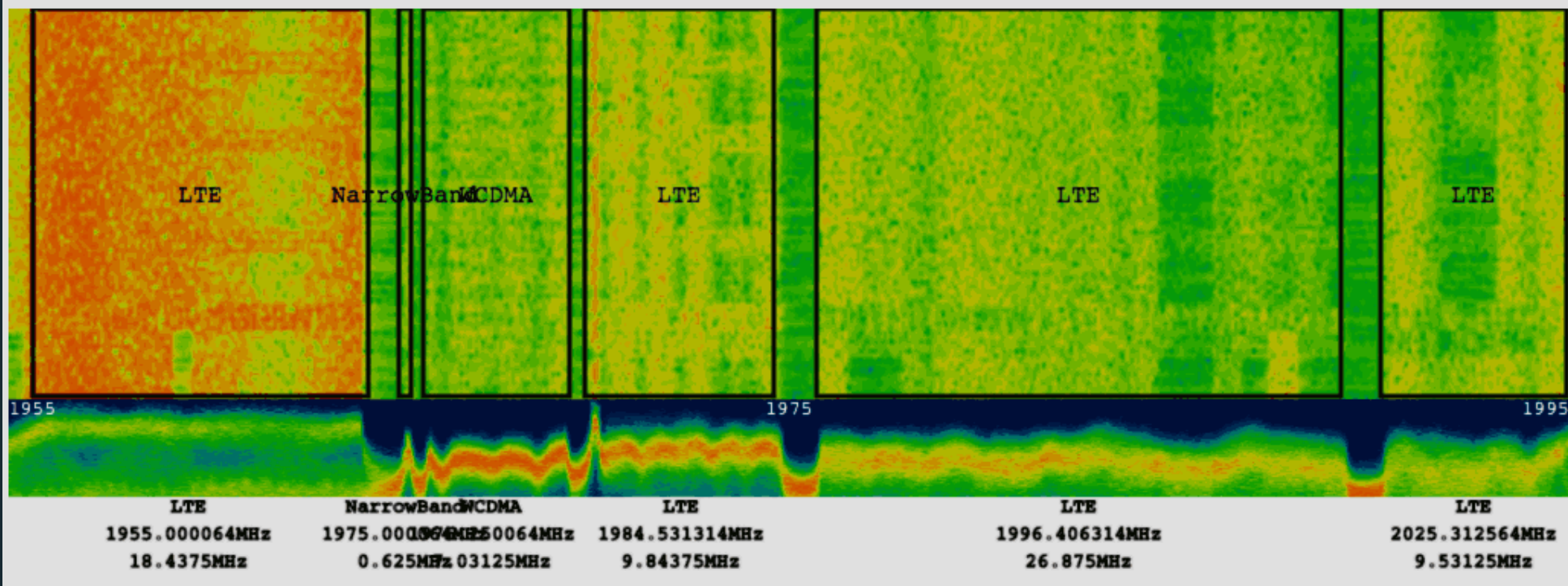
- Replacing signal processing with machine learning
 - Applying the concept of [Software 2.0](#) to RF systems
- In all deep learning applications, the data is the key.
 - [“...in the future your data is your company’s source code.”](#) – J. Huang, NVIDIA CEO
- Two primary product areas: sensing and *learned* physical layers



Data for Sensing



OmniSIG Streaming Recognizer Prototype



Radio Controls:

Freq: 1975.000064

Rate: 40

Gain: 45.0

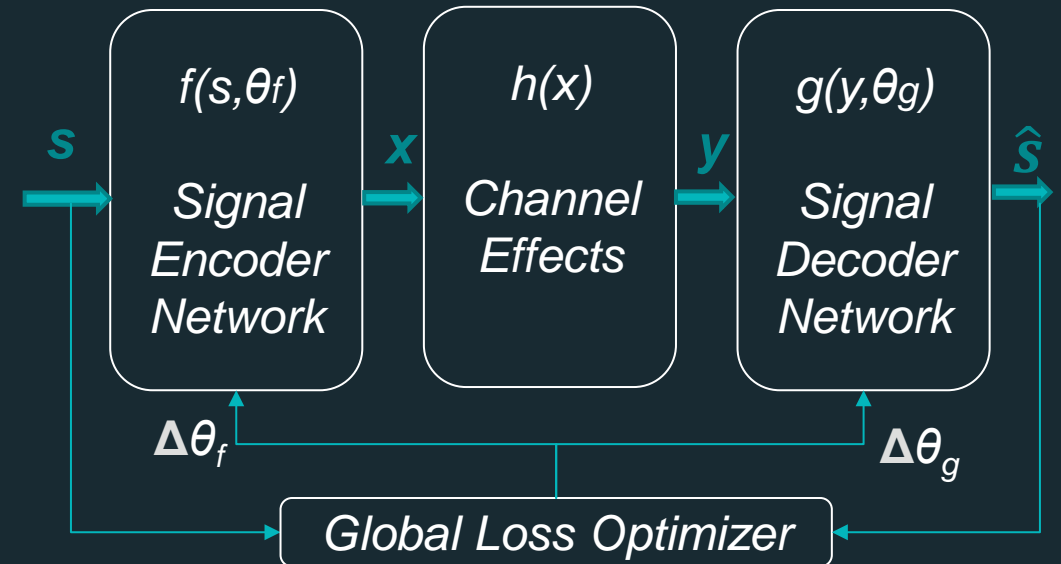
Keyboard Controls:

Space	Pause rendering
left/right	Change Frequency
up/down	Change Gain
a/z	Change spectrogram power offset
s/x	Change spectrogram power scaling
d/c	Change brightness scaling

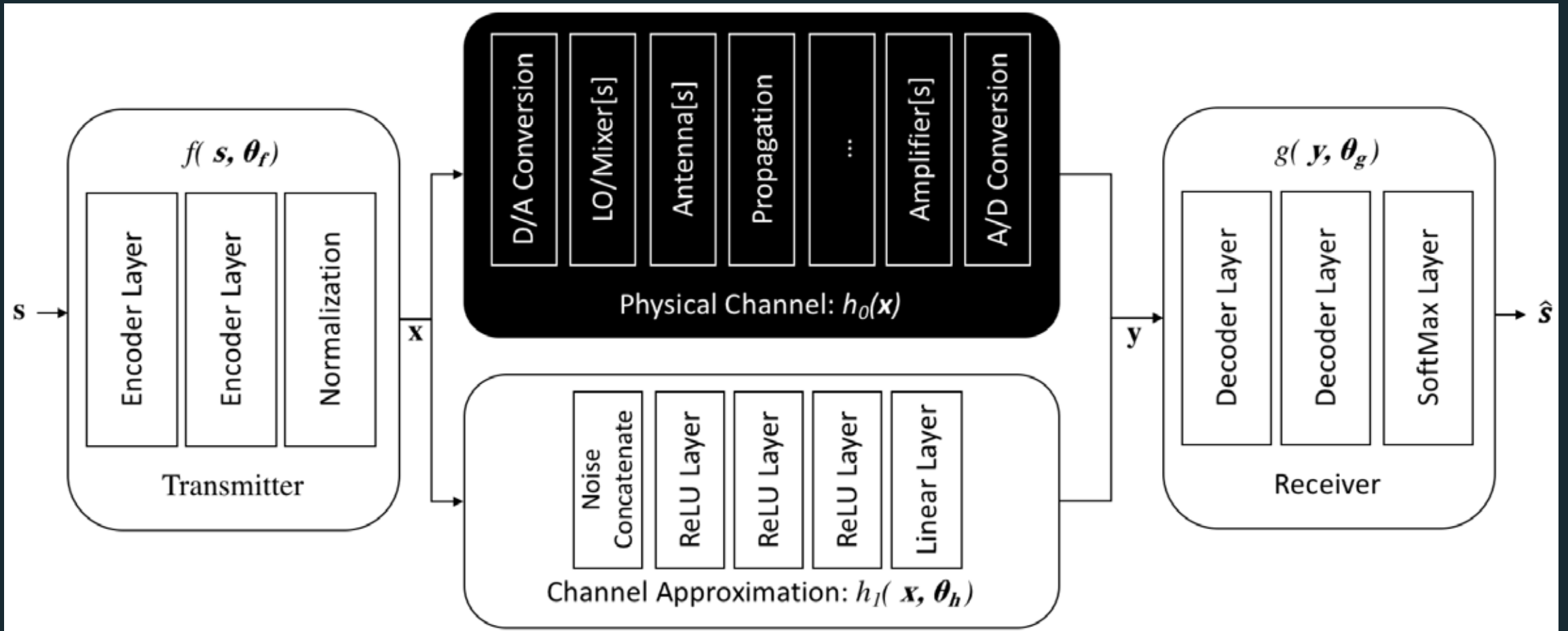


Learned Physical Layers

- Creating a *learned physical layer* means training over a channel or channel model.
- One of our techniques is *learning* a channel model on which to train a PHY.
- Put differently, we use Deep Learning to approximate channel models.
 - The machines outperform us.



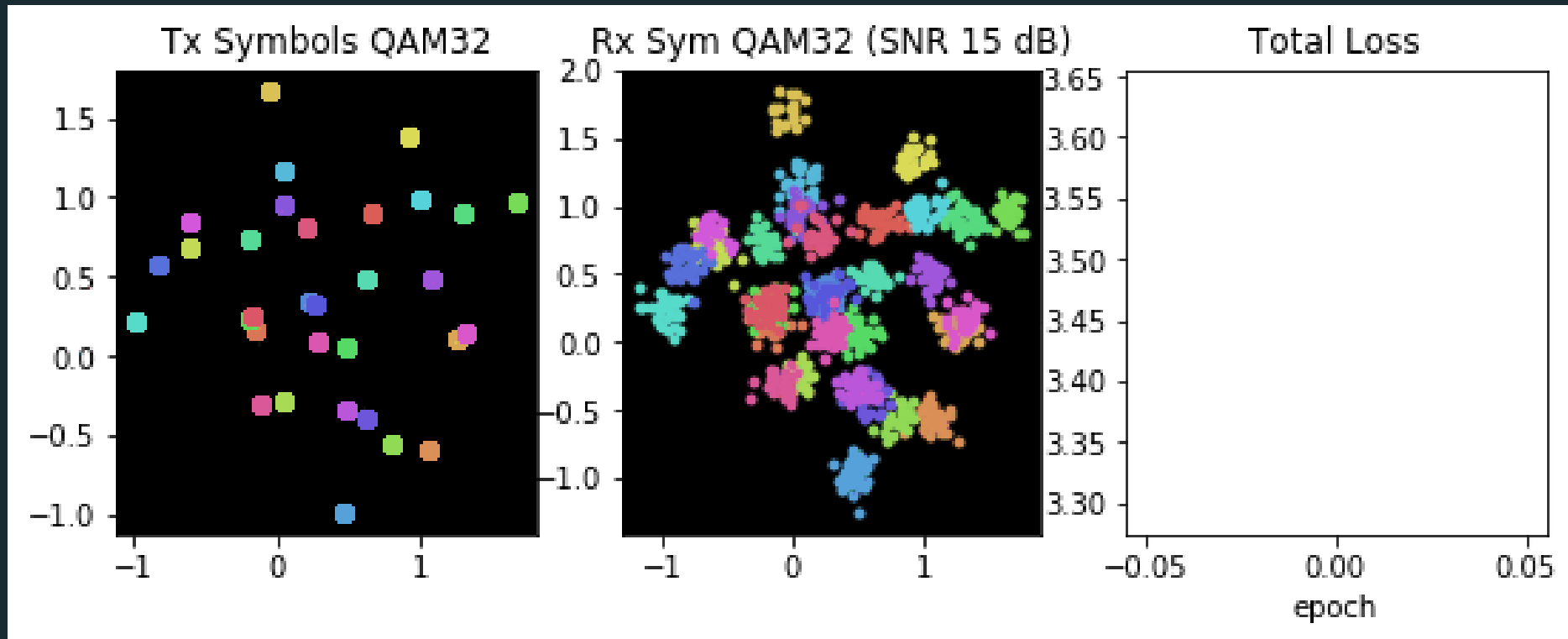
Learned Channel Models



Training over Simple Channel Models



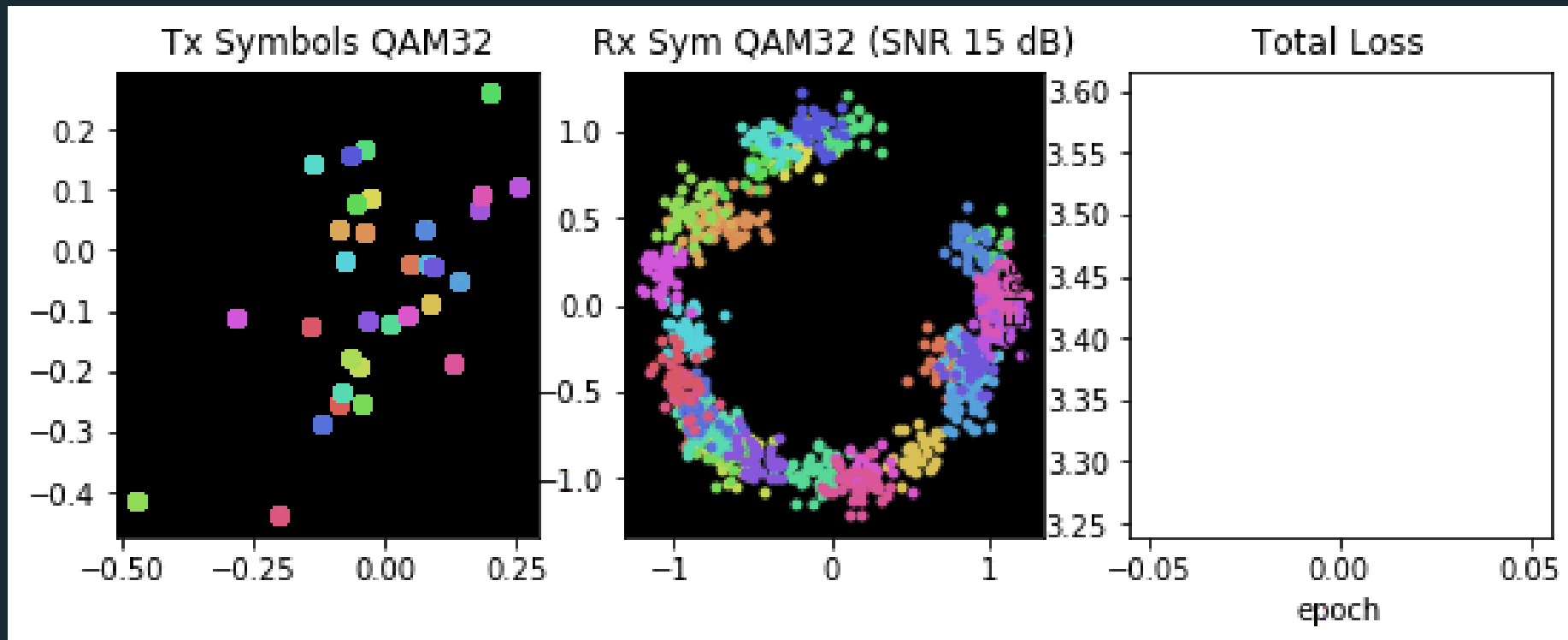
Training a simple 32-QAM autoencoder for an AWGN channel



Training over Insane Channel Models



Training a 32-QAM system over harsh TDRSS TWTA non-linearities



(Ballmer voice) Data, Data, Data!

- We are using the Signal Metadata Format (SigMF) for everything
 - <https://sigmf.org>
 - Disclaimer: I'm the lead developer of SigMF, but I'm totally not biased.
 - Specification for describing recordings of digital samples with JSON
- Based on our experience thus far, *real data*TM is critical
 - Actually making useful datasets with *real data*TM turns out to be rather difficult
 - We are collecting, processing, and labeling live captures