



The Future of Radio Learning Efficient Signal Processing Systems



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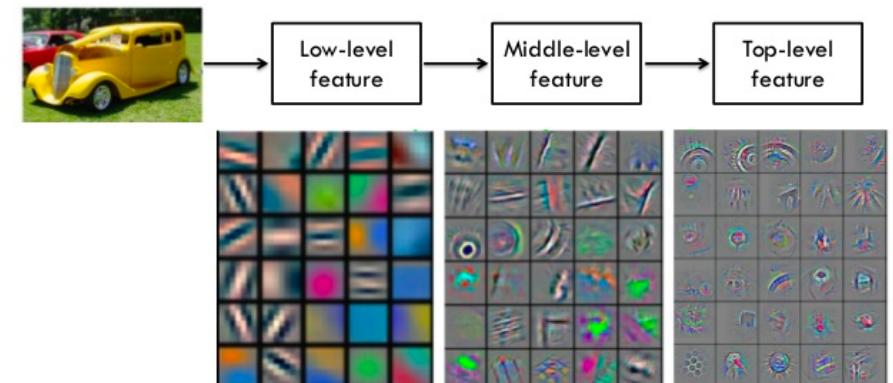
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Deep Learning Trends

- Large Neural Networks are Disrupting Signal Processing
- Bigger change than most people realize
 - Feature Learning
 - End-to-end learning
 - Widely applicable to many domains
- Feature engineering is becoming irrelevant
 - Expert transforms unnecessary to achieve state of the art performance
 - Engineered features created barriers to learning anyway
 - Engineered algorithms created work in optimizing disparate algorithms
 - Just embrace everything as a dense multiply accumulate with some arbitrary set of weights



Hierarchy of trained representations



Feature visualization of convolutional net trained on ImageNet from [Zeiler & Fergus 2013]

- Things that aren't that exciting anymore
 - Computer Vision (Object Recognition)
 - Self driving cars (Tesla, Comma.ai, etc)
 - Voice Recognition (Siri / Google Assistant)
- It's clear deep learning can (has) destroy the state of the art in these fields
 - Custom silicon can drastically bring down power costs of these networks
 - Apple "Bionic" processor, Google TPU, etc
 - These ships are already sailing wholesale

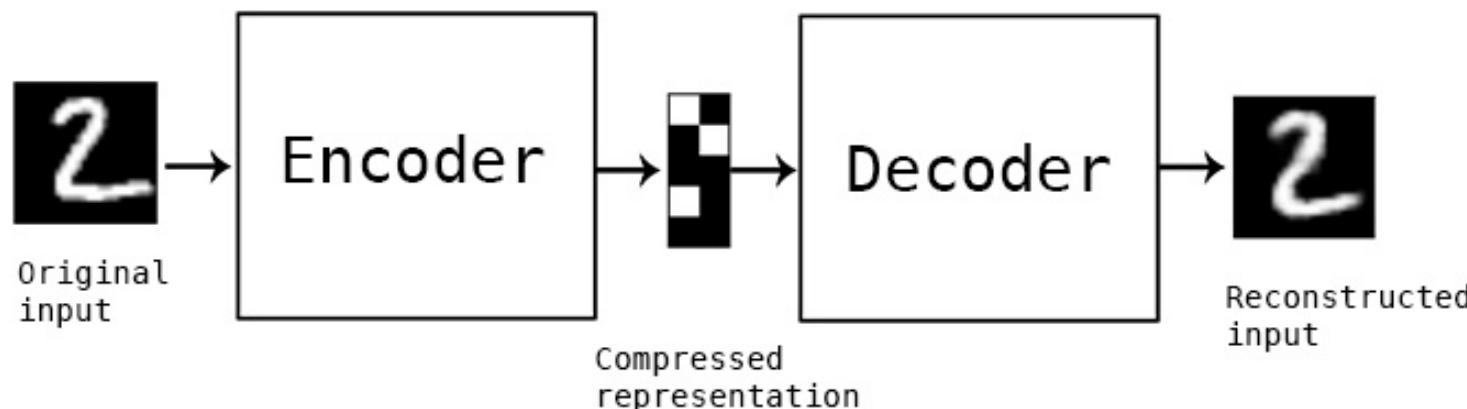


- Probably every signal processing algorithm on earth could be reconsidered/improved

- Especially learned representations ...

$$\phi : \mathcal{X} \rightarrow \mathcal{F} \quad \psi : \mathcal{F} \rightarrow \mathcal{X}$$

- Simple construct of the autoencoder
 - Learns entirely new representations of information
 - Based on reconstruction loss or other loss functions



$$\phi, \psi = \arg \min_{\phi, \psi} \|X - (\psi \circ \phi)X\|^2$$

Minimize encoder and decoder loss

Only for relevant distribution of X!

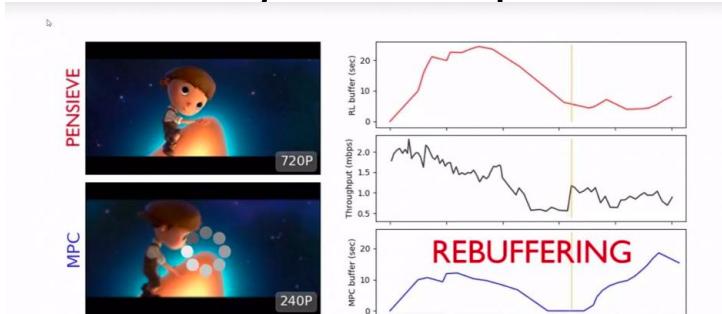
What's interesting ... and coming next...

- **Image Compression Schemes**

- Context aware compression: both 0.08 bits/pixel
- New JPEG Standards

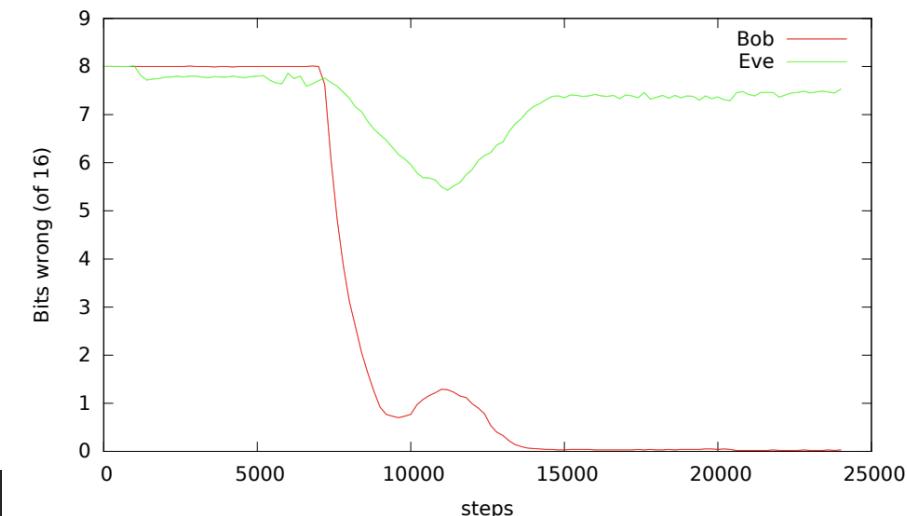
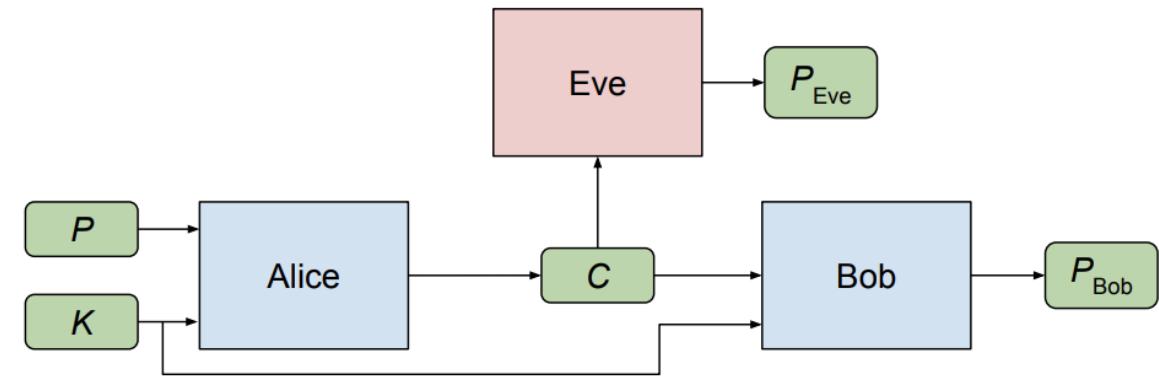


- **Video Compression**
 - Netflix / MIT adoption now



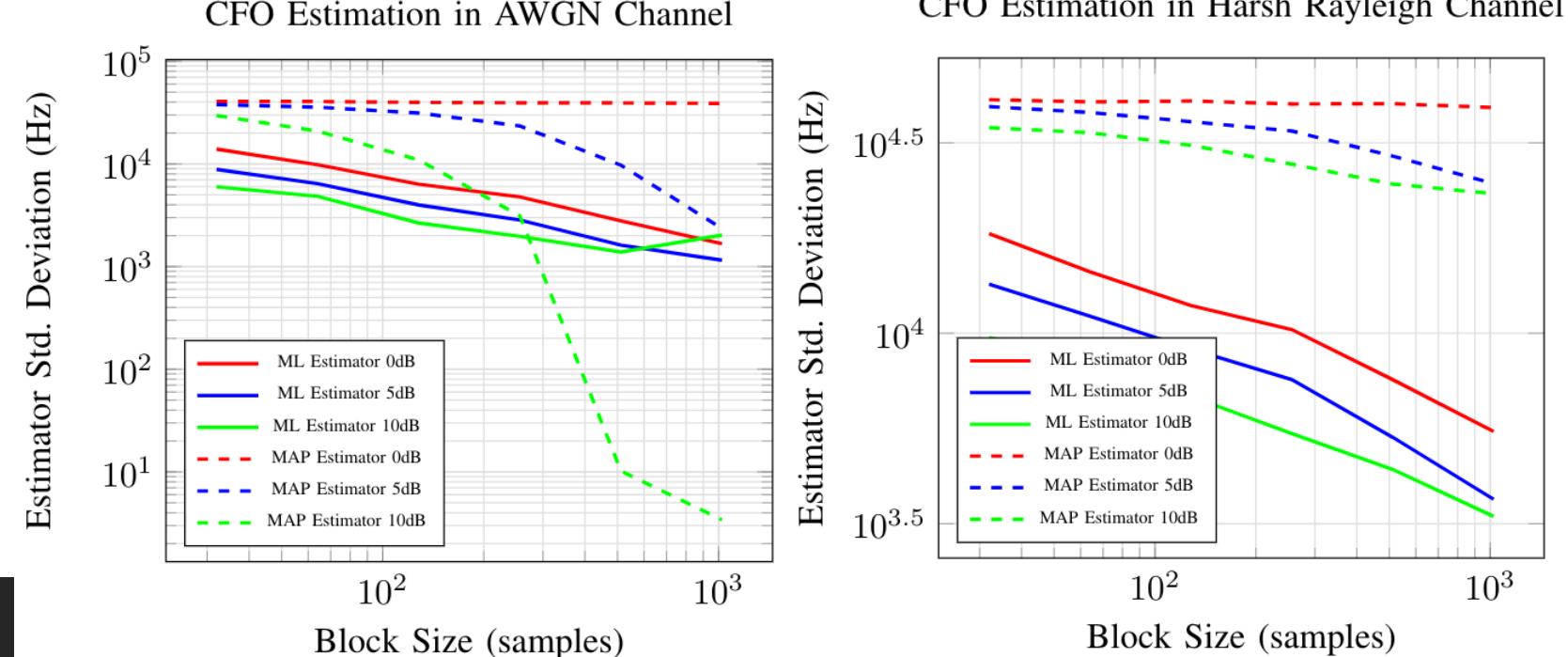
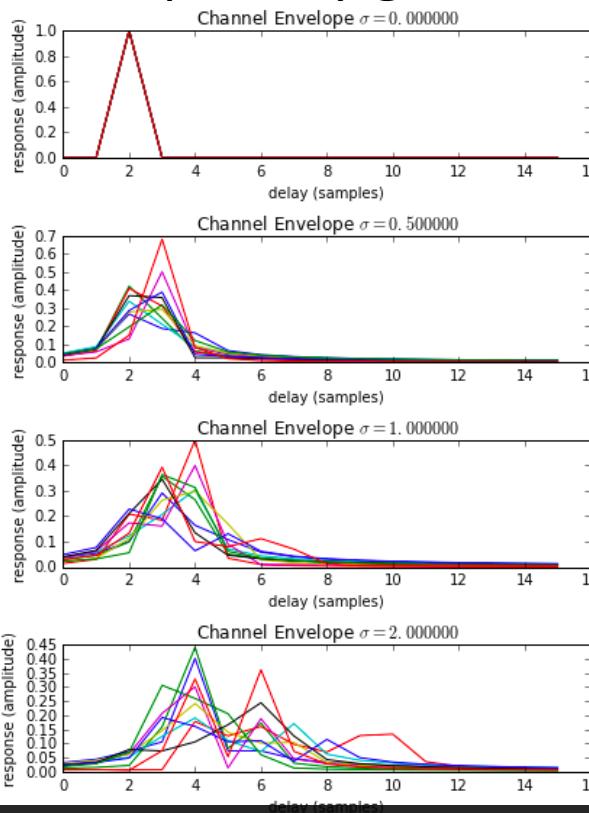
- **Encryption**

- Simply a min/max reconstruction optimization



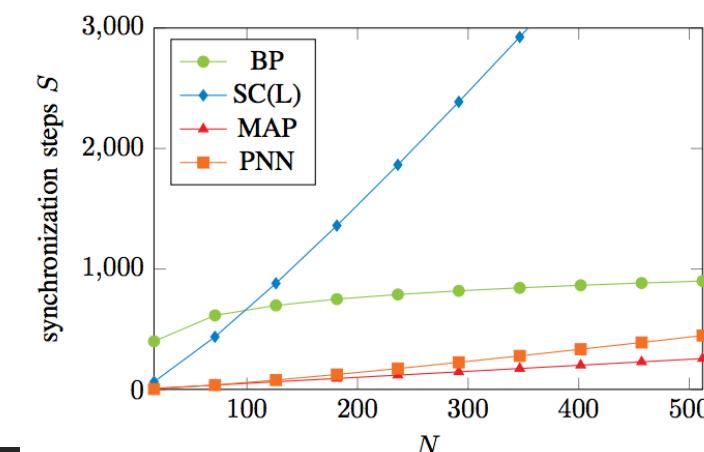
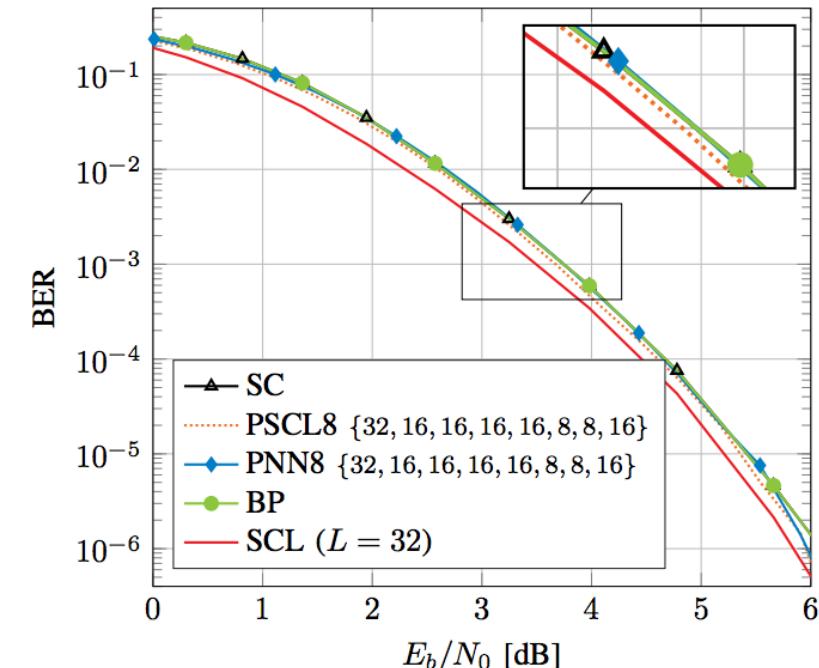
Better Estimators under impaired channels

- Re-consider estimators and representations
 - In the context of actual distribution information
 - Better estimation under impairments!
 - Especially good for short-time windows



Efficient Approximate Decoders

- Learning decoders for ‘near optimal’ error correction codes! (Partitioning to scale)
 - FEC decoding / detection currently the #1 power consuming operation in radio baseband devices
 - Work from Cammerer, Gruber, Hoydis, ten Brink (University of Stuttgart / Nokia-Bell Labs)
 - Shows near-optimal polar code decoding performance with partitioned neural networks at lower complexity than successive cancellation or Belief Propagation!
- Potentially a major advance in error correction
 - Learn approximate decoders on code-word sets
 - Low latency one-shot decoding at higher efficiency
- “Scaling Deep Learning-based Decoding of Polar Codes via Partitioning” <https://arxiv.org/abs/1702.06901>



Rethink Approach to Communications

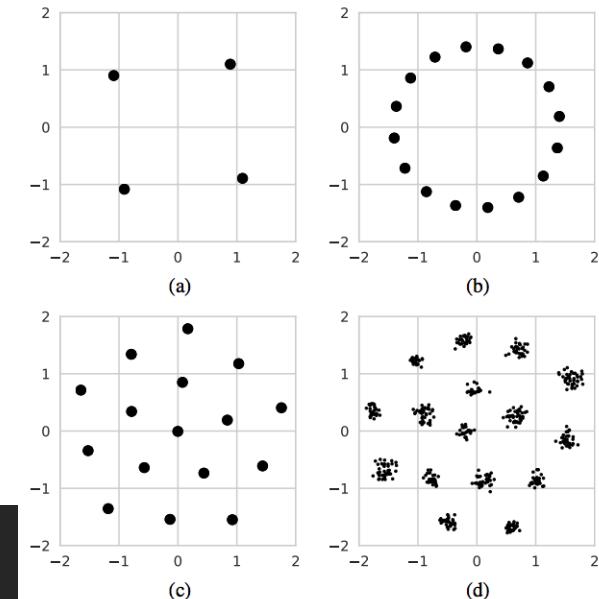
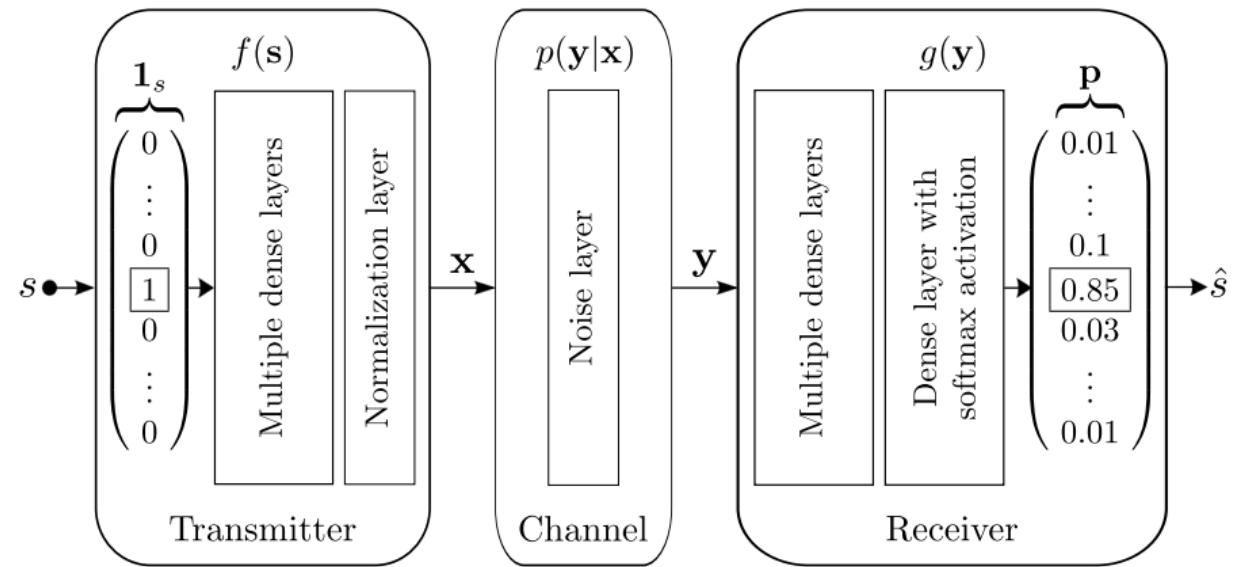
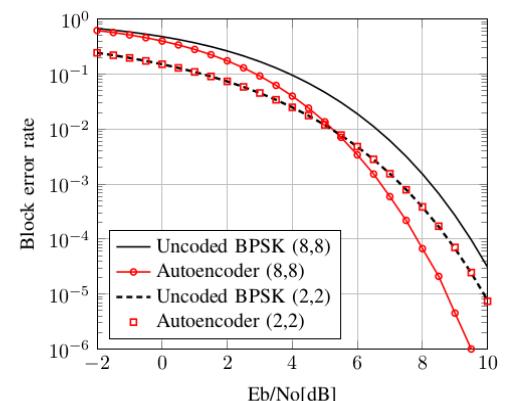
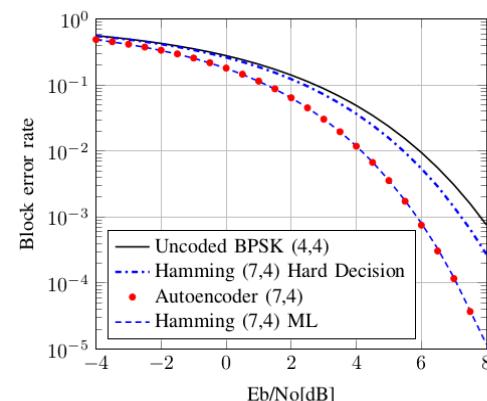
“Reproducing at one point either exactly or approximately a message selected at another point”

- C. E. Shannon, “A mathematical theory of communication,” 1948

- All communication systems need to do is optimize for reconstruction loss

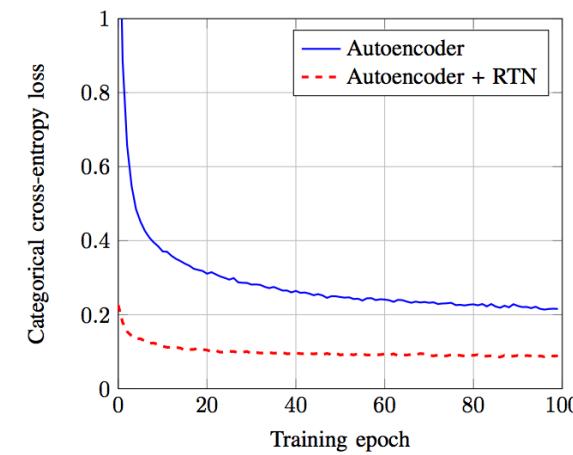
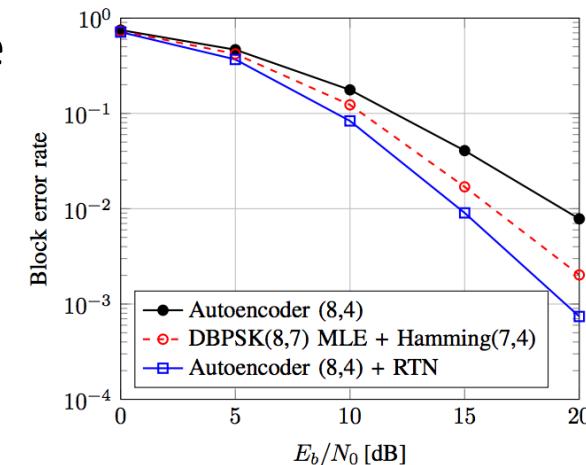
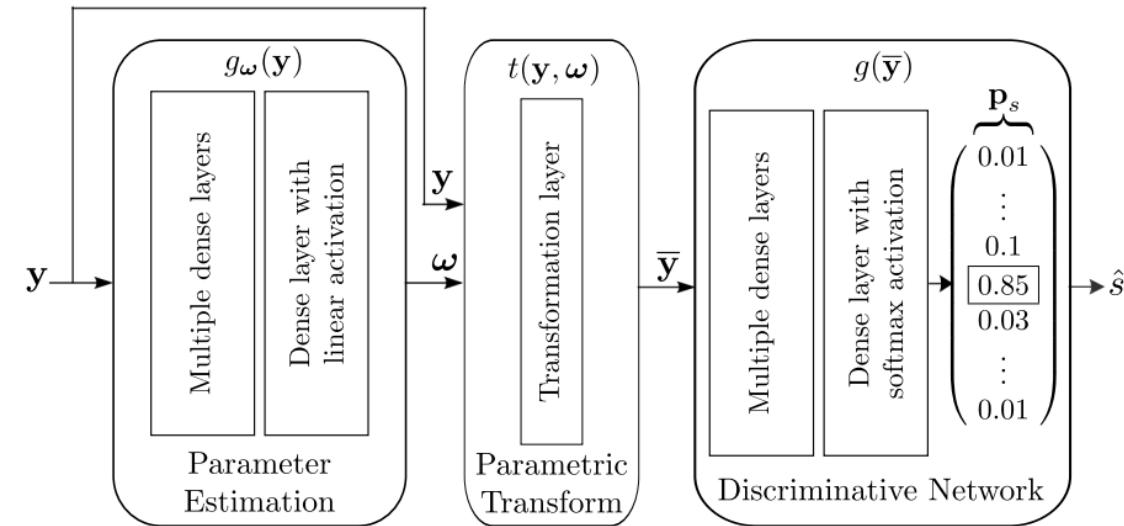
- Everything else is a secondary sub-task
- Lets not get hung up on minutia

- This actually works really well
 - Matches coded modulation baselines immediately



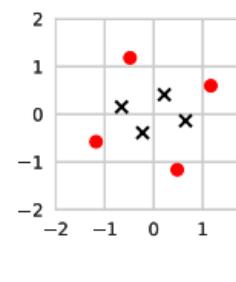
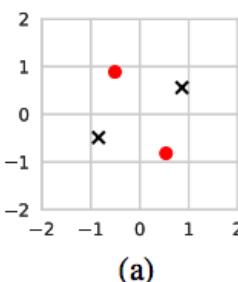
Radio Methods for Saliency

- How can we reduce the search space?
 - Leverage things we know about propagation physics?
- Introduce domain aware attention mechanisms in the right way –
 - Decomposition of receiver
 - Learned estimation modules (Attention model)
 - Expert transformation modules to match physical world propagation models/effects
 - Learned demapping/representation modules
 - Joint learning of encoder/modulator, synchronizer, decoder/demodulator, and over the air representation
 - Lower complexity learning problem
 - Converges faster, less overfitting
 - Only imparts propagation medium expert knowledge (things we can't change)
 - Learn everything else end-to-end

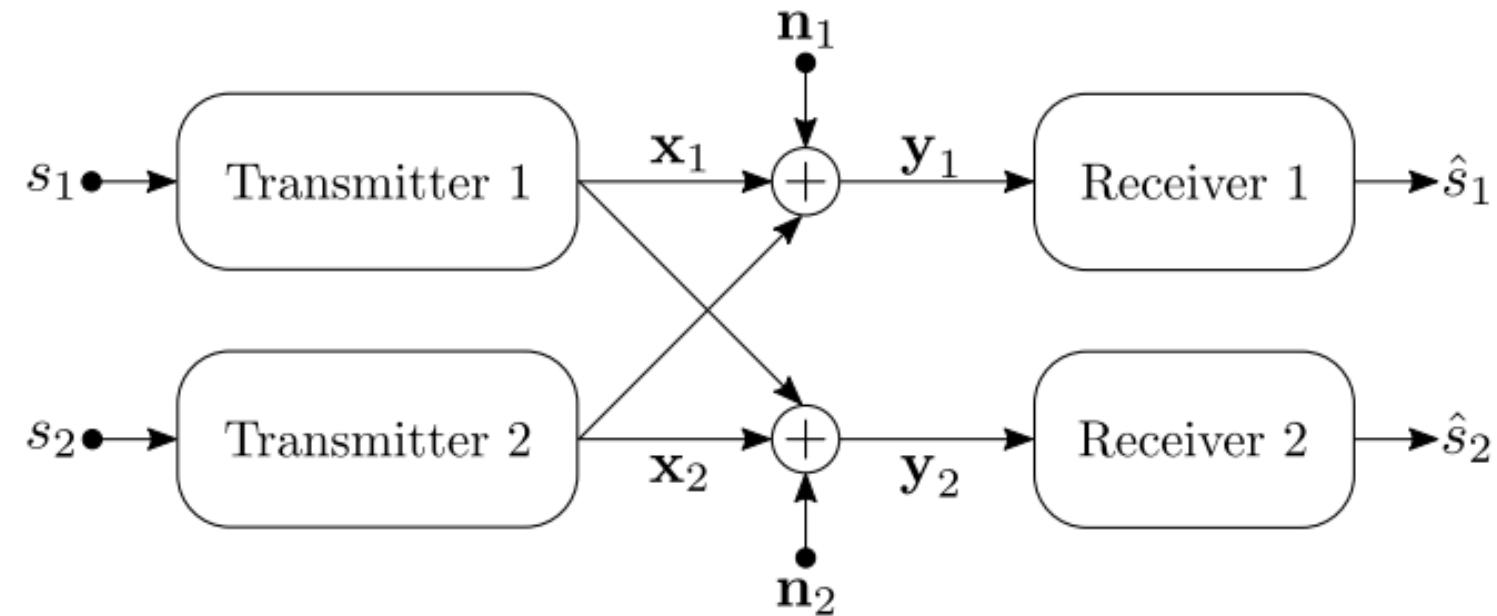


What if we have to share the channel?

- Can easily extend this method to multi-access channel
 - Learn a better solution than orthogonality
 - Same basic principals
 - Comes up with immediately interpretable results



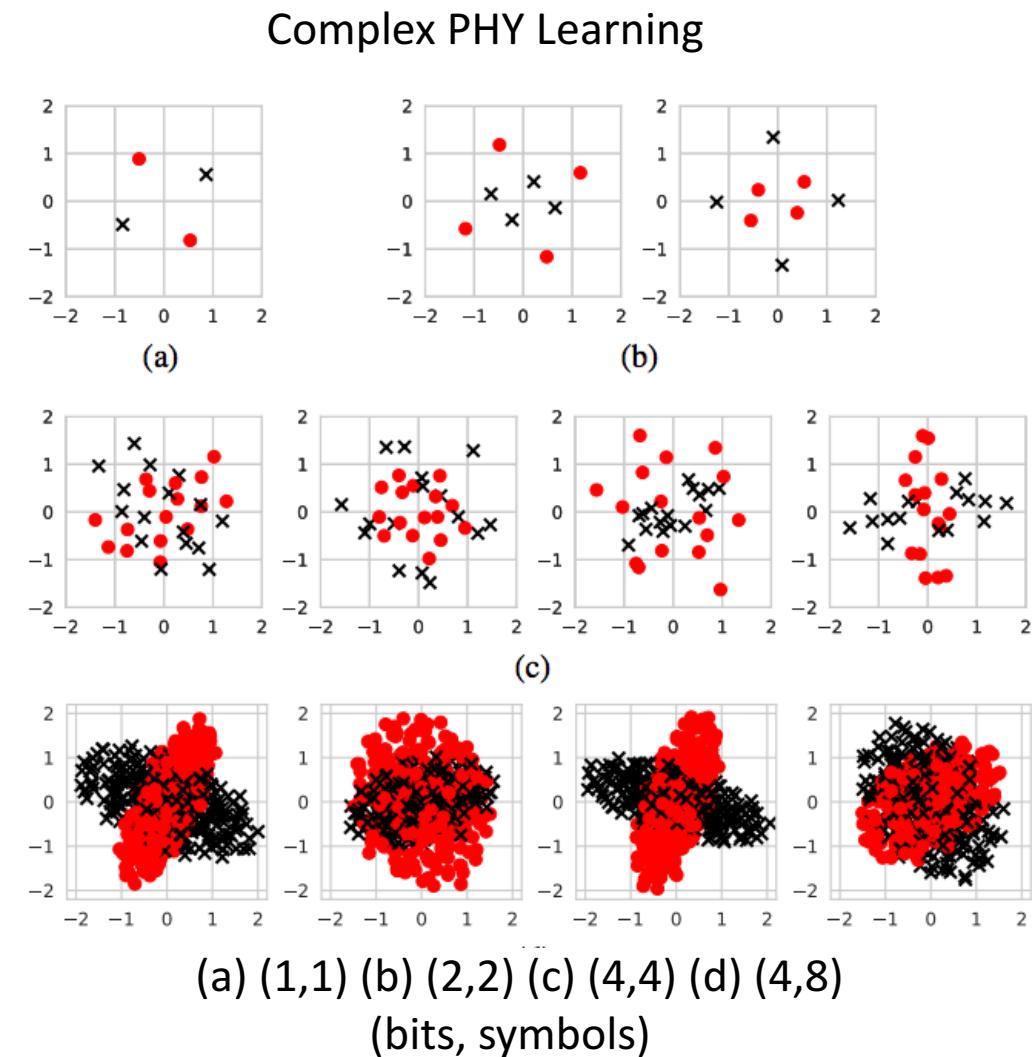
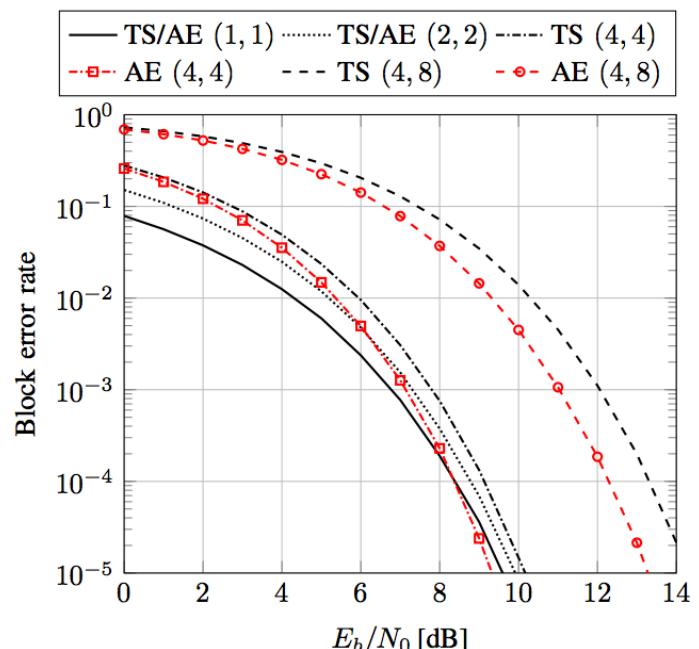
(a) (1,1) (b) (2,2)
(bits, symbols)



Synthesizing Complex Multi-user PHYs



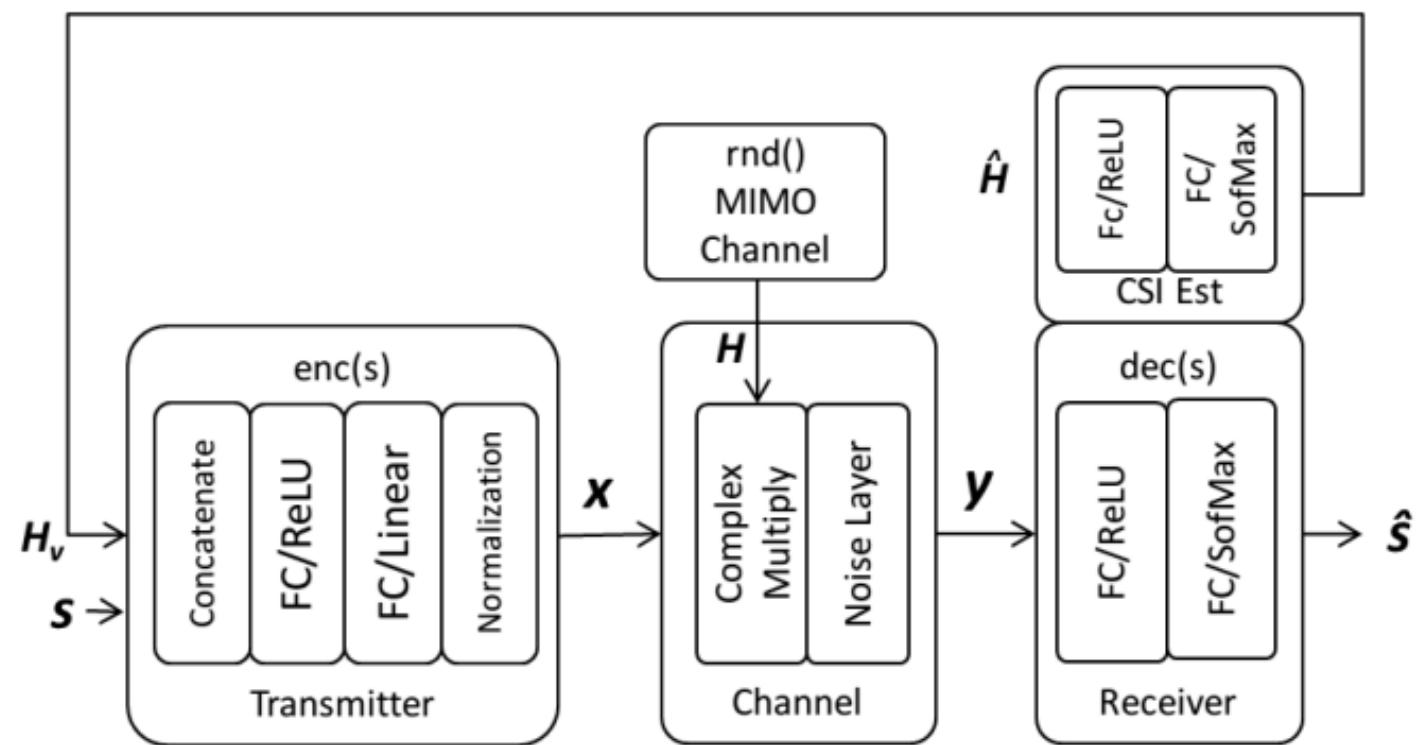
- Comparison with existing methods
 - Compare the multi-user access channel
 - Orthogonal (Time-slicing (TS)) vs learned method
 - Learns new never before seen PHY scheme
 - Infinite number of possible waveforms!
 - In this case pseudo-orthogonal superposition code



Synthesizing Complex Multi-Antenna PHYs



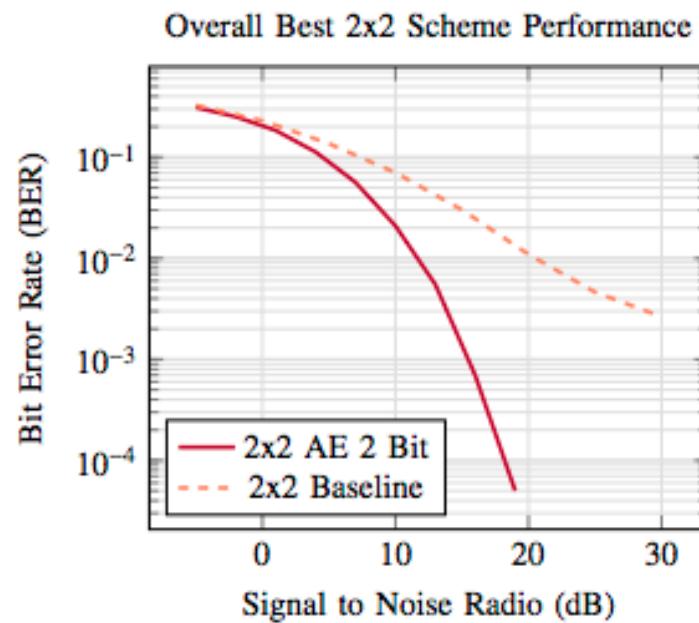
- Extend this technique to multi-antenna
 - Same basic principals
 - Complex MIMO channel effects
- Incorporate CSI feedback
- Entirely new MIMO scheme



Synthesizing Complex Multi-Antenna PHYs



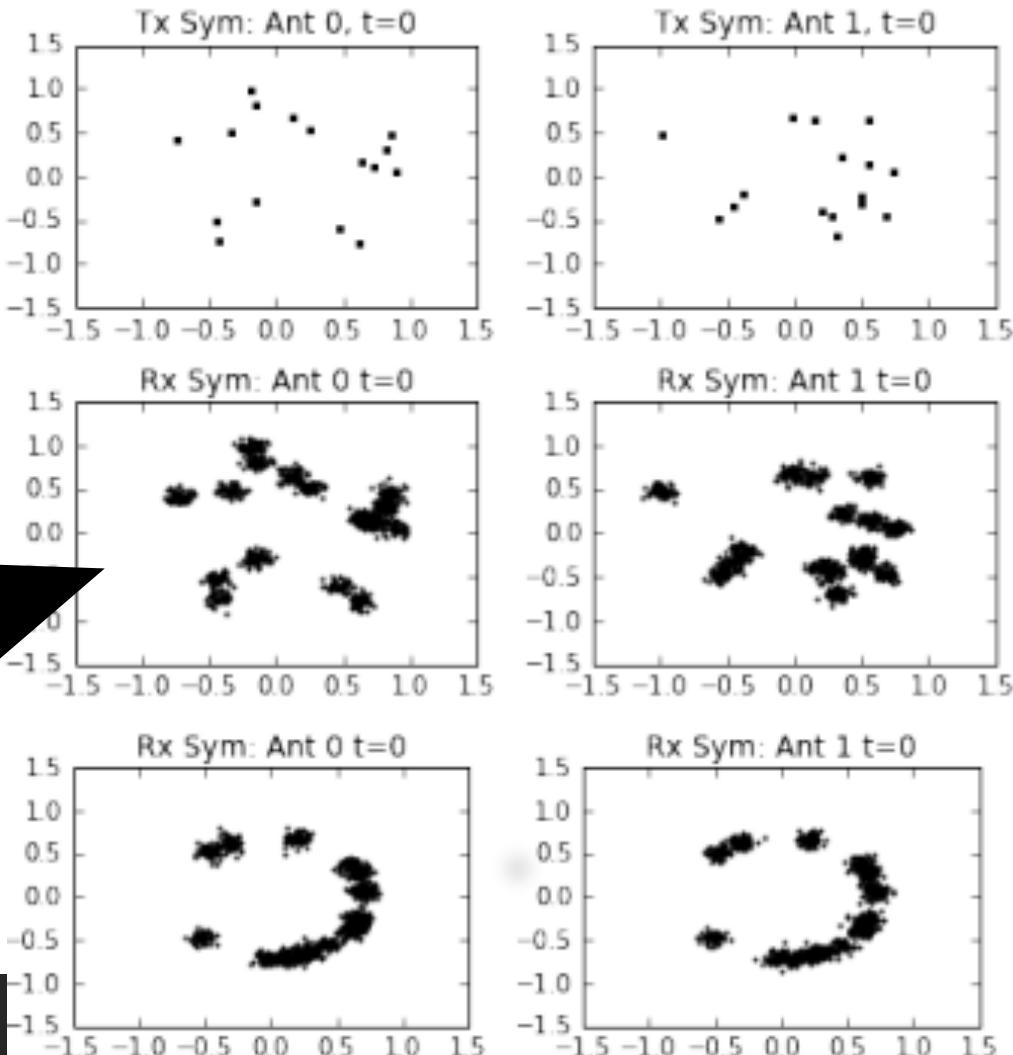
- Can learn incredibly complex joint solutions
 - Soft joint-modulation-coding schemes
 - Outperform current baselines (zero forcing MIMO)
- Enormous potential for distributed wireless
 - MIMO system performance
 - Secrecy and privacy



Learned 2x2 Constellations

1. Transmitted
2. Diag Rx
3. Uniform Rx

Complex MIMO PHY Learning
Non-standard MIMO QAM Modes



Thanks! Questions?

ML Driven RF Systems are coming FAST
Come and work with us / talk to us!

Next generation radio sensing and communications systems



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Enabling Research
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