Imperial College London

Learn to Communicate - Communicate to Learn

David Burth Kurka

Information Processing and Communications Lab
Department of Electrical and Electronic Engineering
Imperial College London, London UK

d.kurka@imperial.ac.uk

Information Processing and Communications Laboratory

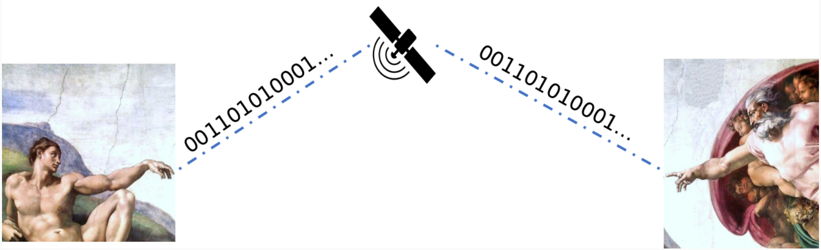
- Part of Intelligent Systems and Networks Group: dedicated to machine learning for robotics, networking, machine vision, multi-agents systems, neural processing, etc.

Future Autonomous Systems

- Intelligence is the key for future autonomous systems ...
- ...and so is communication
- Our goal is to push the boundaries of **communications** using **intelligence**, and to develop better intelligence with more efficient **communications**.

Tactile Internet

- *"Internet network that combines ultra low latency with extremely high availability, reliability and security"* (ITU)
- Next generation Internet of Things: human-machine and machine-machine interaction: haptic interaction with visual feedback
- Augmented reality (AR), virtual reality (VR), automation, robotics, remote education, telepresence, ...
- 1ms round trip delay?



IPC-Lab - Selected Projects

- ## Deep Joint Source-Channel Coding

  Bourtsoulatze, Kurka and Gunduz, **Deep joint source-channel coding for wireless image transmission**, sub. to IEEE Trans. on Cognitive Comm. and Networking, 2018.
  D. B. Kurka, D. Gunduz, **Successive Refinement of Images with Deep Joint Source-Channel Coding**, submitted to SPAWC, Cannes, France, 2019.

- ## Distributed Computation

  E. Ozfatura, D. Gunduz and S. Ulukus, **Speeding up distributed gradient descent by utilizing non-persistent stragglers**, submitted to SysML, Stanford, CA, Mar. 2019.
  M. Mohammadi Amiri and D. Gunduz, **Distributed uncoded computation**, sub. to IEEE Trans. on Signal Processing, 2018.
  M. Mohammadi Amiri and D. Gunduz, **Machine learning at the wireless edge: Distributed stochastic gradient descent over-the-air**, Jan. 2019.

- ## Adversarial ML for Secure Communications

  M. Z. Hameed, A. Gyorgy and D. Gunduz, **Communication without Interception: Defense against Deep-Learning-based Modulation Detection**. SPAWC, Cannes, France, 2019.

- ## Hypothesis Testing Over Noisy Channels

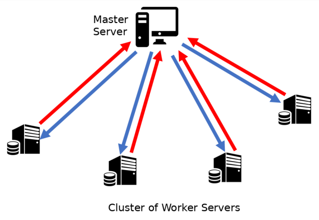
  S. Sreekumar and D. Gunduz, **Distributed hypothesis testing over discrete memoryless channels**, sub. IEEE Transactions on Information Theory, 2018.

- ## Privacy Aware Learning

  G. Giaconi, D. Gunduz and H. V. Poor, **Privacy-aware smart metering: progress and challenges**, IEEE Signal Processing Magazine, to appear.

- ## Deep RL for Wireless Resource Optimization

  Faqir, Kerrigan and Gunduz, **Joint optimization of transmission and propulsion in aerial communication networks**, IEEE Conf. on Decision and Control, 2017.

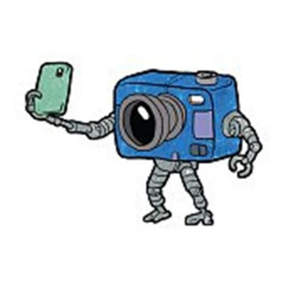


Learn to Communicate

Deep Joint Source Channel Coding

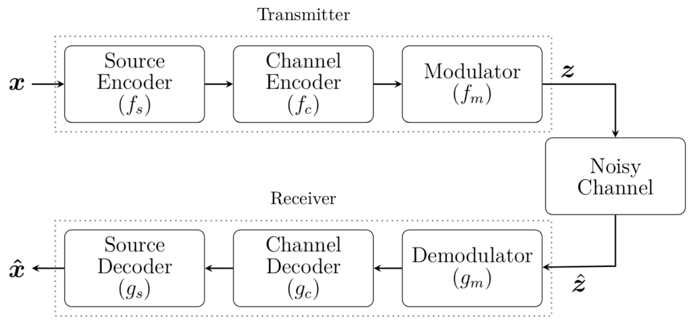
Motivation

- Increasing applications involving transmission and consumption of images in human-human, human-machine (e.g. AR, VR, telepresence) and machine-machine (e.g. pattern recognition, automation) interactions
- Particularly, how to deal with image/video transmission under extreme low latency, small bandwith and energy constraints?



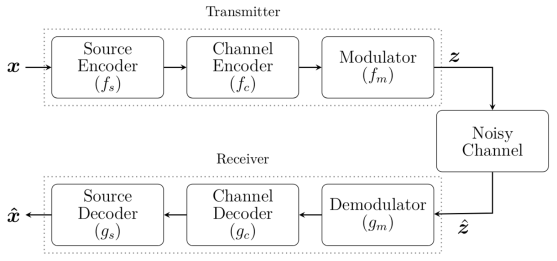
Wireless Image Transmission

How information is transmitted over a noisy channel?



- Shannon's Separation Theorem: First compress underlying source into bits; Then, transmit bits over noisy channel reliably
- Highly efficient compression algorithms (e.g. JPEG, JPEG2000, WebP) and near-optimal channel codes (LDPC, Turbo codes) approach theoretical limits

Wireless Image Transmission

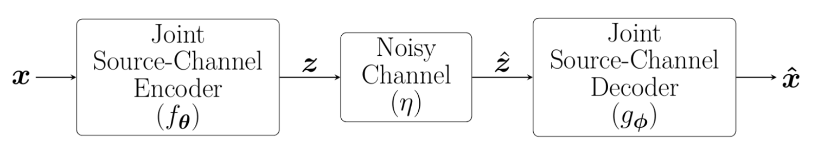


Challenges brought by modern requirements:

- Optimally holds only for infinite blocklength and complexity
- Design assumes a specific channel quality, being vulnerable to changes, variations or non-ergodic channels
- No separation theorem for multi-user networks: when broadcasting to many users, target the worst one

Proposed System - Joint Source Channel Coding

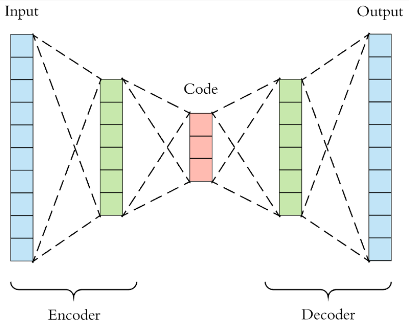
Can we learn to do better?



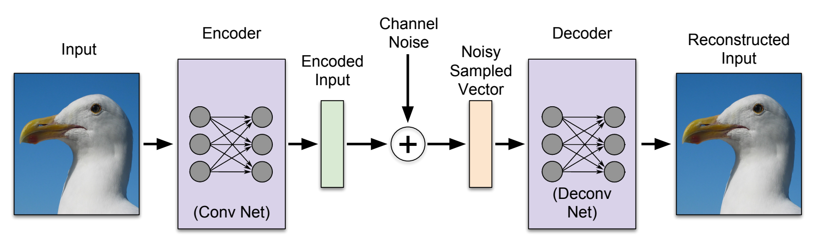
- Can we learn a direct mapping from pixel values to channel input symbols?
- Can this optimal mapping be learned directly from data, without the need of prior models?

Autoencoders

- Unsupervised learning: two neural networks trained together
- Similarities to digital communication systems
- Successfully applied in compression; design of channel code; blind channel equalization; etc.

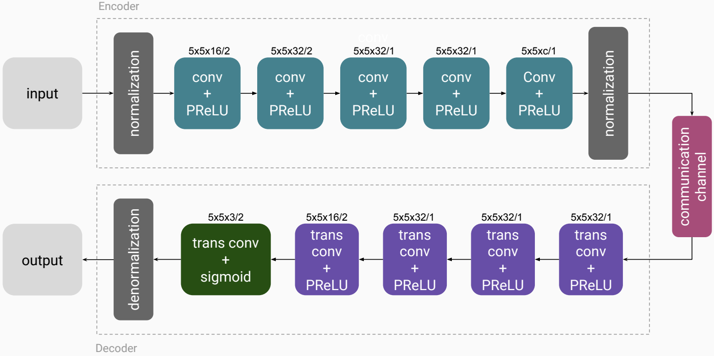


Proposed Model - Deep JSCC



- Noisy channel added as non-trainable layer
- Directly mapping to channel: no bits conversion, speeding up the process and exploiting channel coding compression
- Coherent mapping: similar content stay close to each other

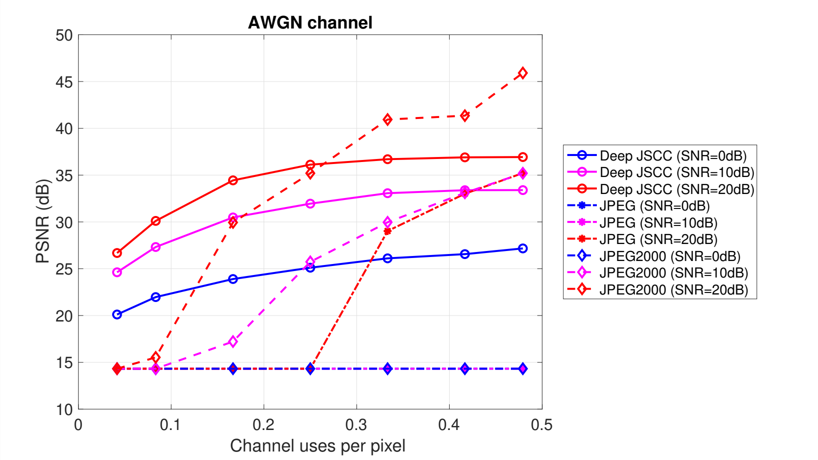
Proposed Model - Deep JSCC



- Low-delay: bandwidth compression
- Low-energy: average power constraint

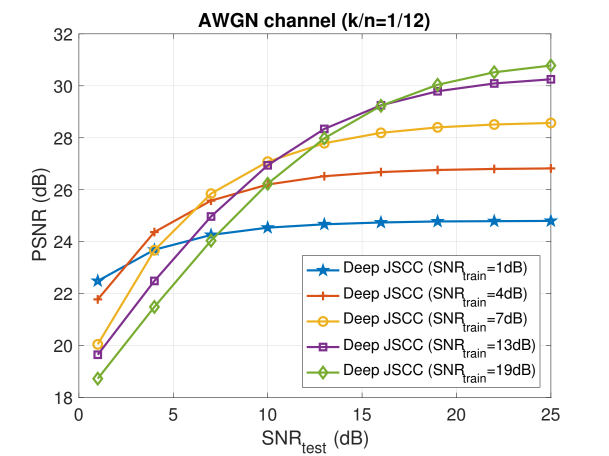
E. Bourtsoulatze, D. Burth Kurka and D. Gunduz, **Deep joint source-channel coding for wireless image transmission**, revised, IEEE Trans. on Cognitive Comm. and Networking, 2018.

AWGN Channel - Performance by Bandwidth



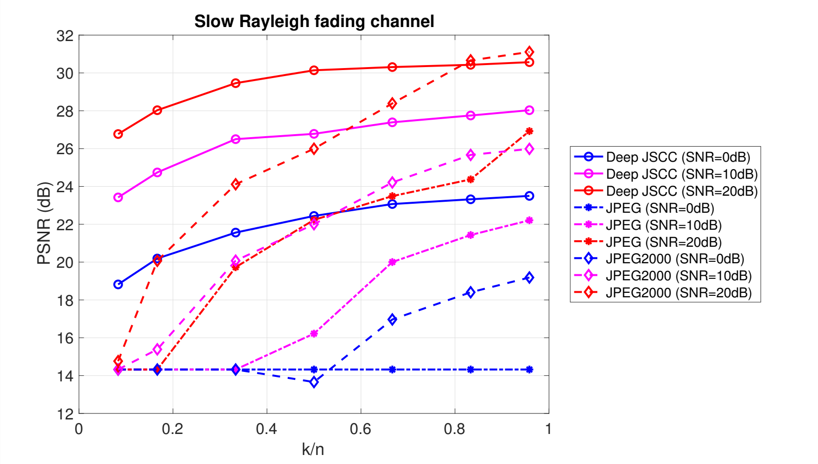
- Significant improvement to separation-based digital transmission for low SNR and low channel bandwidth

AWGN Channel - Performance by Channel SNR



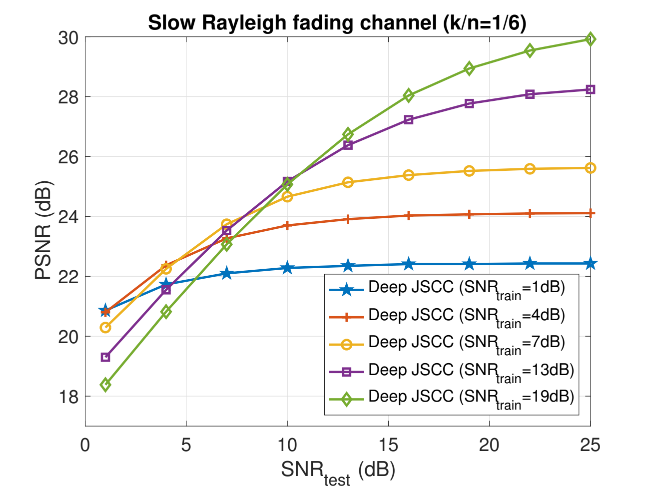
- Optimise for one SNR, deploy to different channel conditions
- Not affected by the “cliff effect”: graceful degradation
- More like analog communications than digital!

Rayleigh Fading Channel - Performance by Bandwidth



- Time-varying channel or multiple receivers scenarios
- Significantly outperforms separation-based digital communication at all SNR and channel bandwidth values

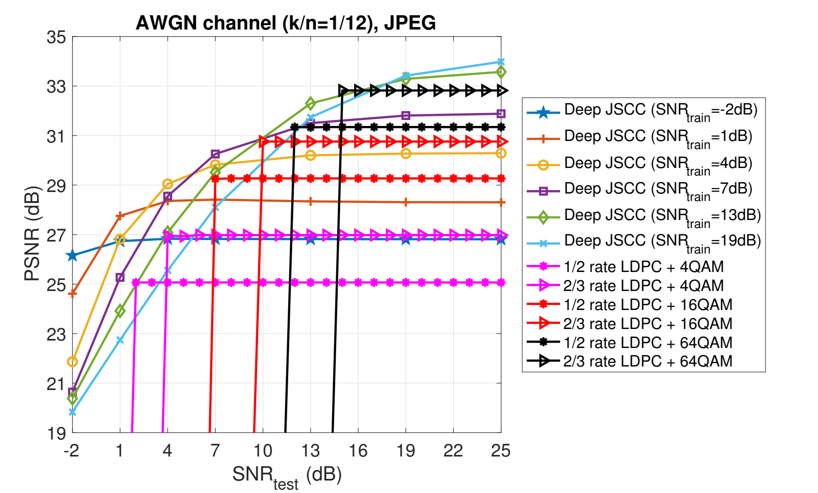
rayleigh fading channel - performance by channel snr



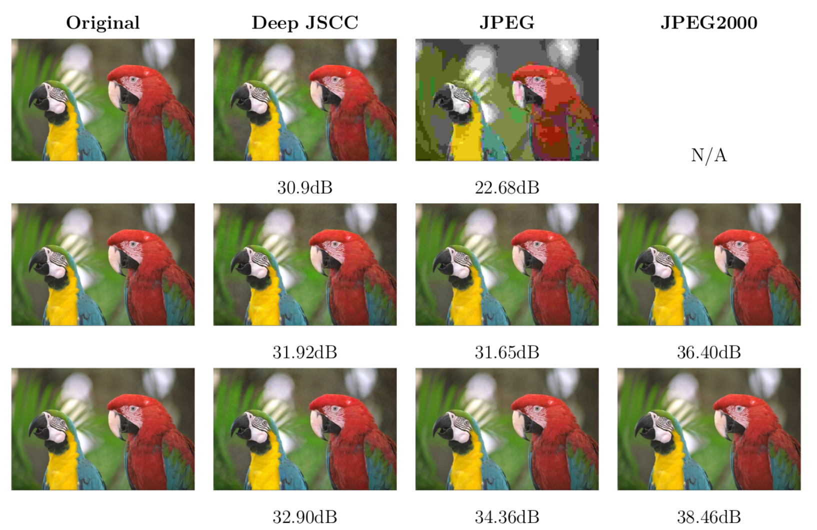
- no pilot signal or explicit channel estimation!

Larger Natural Images

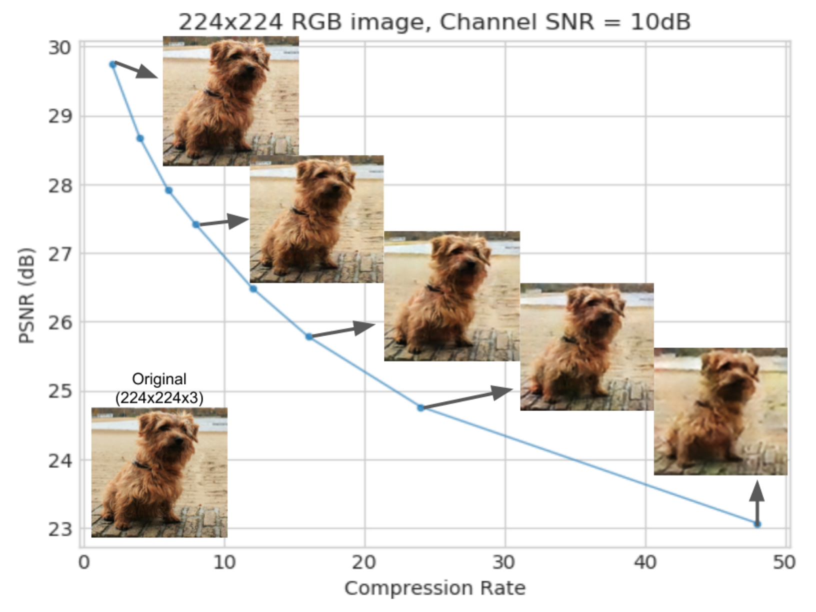
- Train on ImageNet, test with Kodak dataset (24 images of size 768×512)



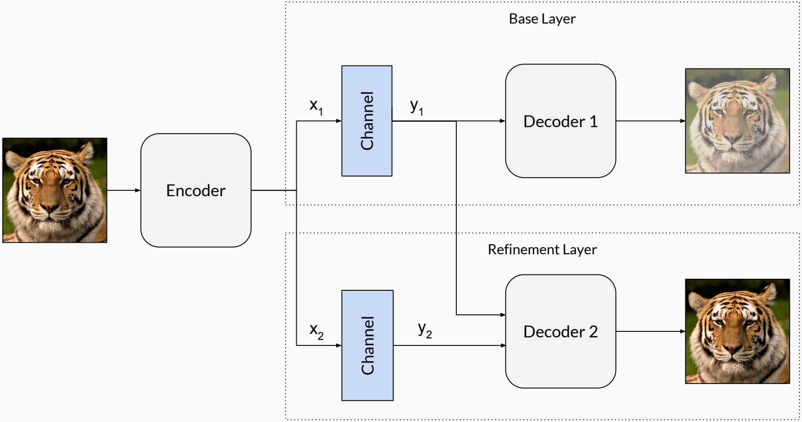
Larger Natural Images (Kodak)



Quality vs Compression Rate

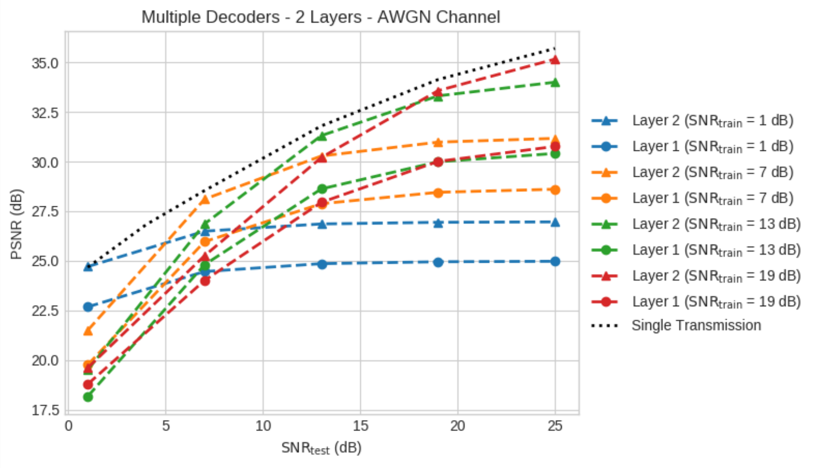


Deep Wireless Successive Refinement



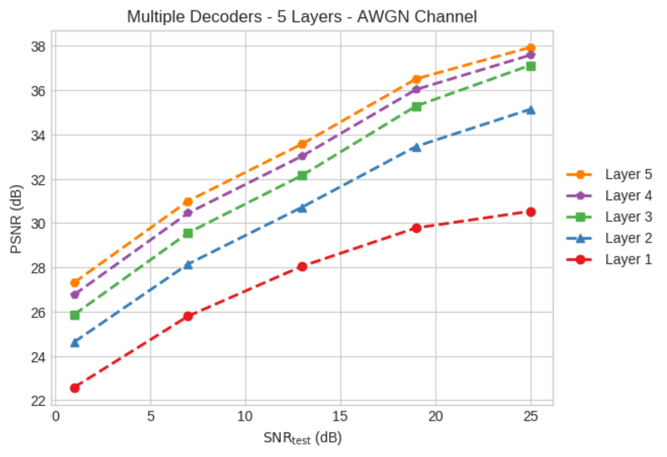
D. B. Kurka, D. Gunduz, **Successive Refinement of Images with Deep Joint Source-Channel Coding**, submitted to IEEE International Workshop on Signal Processing Advances in Wireless Communications (SPAWC), Cannes, France, 2019.

2 Layer Deep JSCC



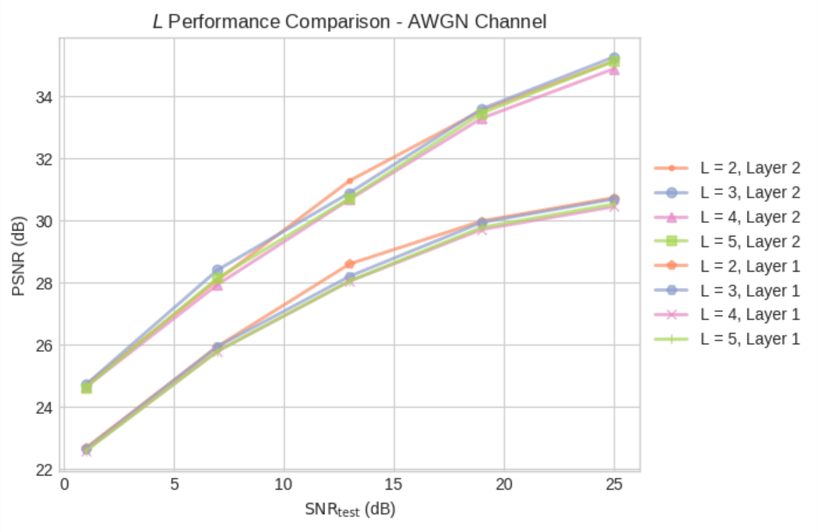
- Keep the same properties of single transmission (graceful degradation, analog behaviour)
- Small loss due to generalisation

5 Layer Deep JSCC



- Keep the same properties of single transmission (graceful degradation, analog behaviour)
- Small loss due to generalisation

Effect of adding additional layers



- the addition of extra layers has small impact on previous layers

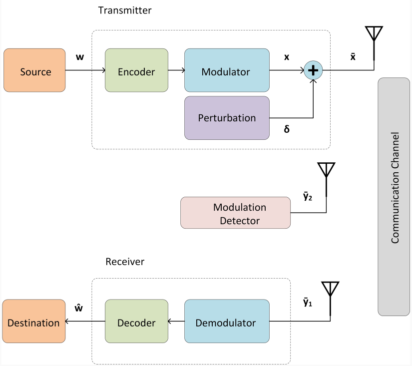
Summary so far...

- Novel deep JSCC architecture for image transmission over wireless channels under low latency, bandwidth and energy
- Proposed model outperforms state-of-the-art separation-based transmission schemes, especially for limited channel bandwidth and SNR
- Absence of cliff effect and graceful degradation of the reconstruction quality with channel SNR
- Ability to communicate without explicit channel estimation

Related research from Imperial IPC-Lab

Adversarial ML for Secure Communications

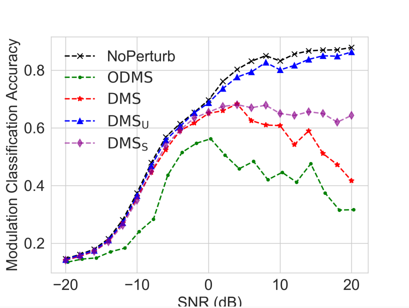
- Secure communication by preventing intruder form detecting the modulation scheme
- Small perturbations so that intruder is unable to identify modulation; receiver decodes message with acceptable BER (without knowing about the modifications)
- Use adversarial learning to solve trade-off



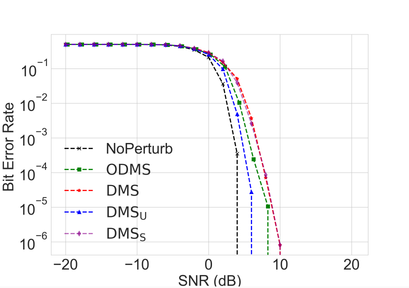
M. Z. Hameed, A. Gyorgy and D. Gunduz, **Communication without Interception: Defense against Deep-Learning-based Modulation Detection**. SPAWC, Cannes, France, 2019.

Adversarial ML for Secure Communications - Results

Modulation Classification Accuracy Intruder

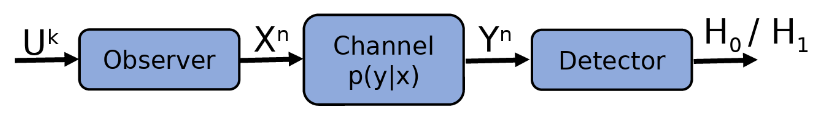


BER of legitimate Receiver



Hypothesis Testing Over Noisy Channels

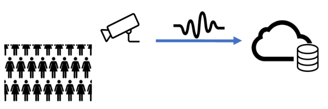
- Distributed statistical inference problems in which data needs to be communicated to a remote decision maker.
  (e.g. Sensor networks, cloud computing, machine learning...)



$$H_0 : U^k \sim \prod_{i-1}^{k} P_U \qquad H_1 : U^k \sim \prod_{i-1}^{k} Q_U$$

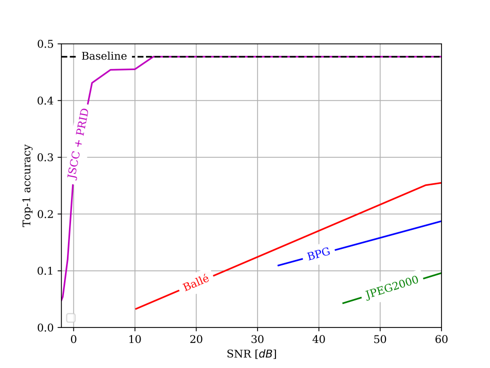
S. Sreekumar, D. Gunduz, **Hypothesis testing over a noisy channel**, IEEE ISIT, 2019.
S. Sreekumar and D. Gunduz, **Distributed hypothesis testing over discrete memoryless channels**, revised, IEEE Transactions on Information Theory.
S Sreekumar, A Cohen, D Gunduz, **Distributed hypothesis testing with a privacy constraint**, Submitted.

Person re-identification over noisy channels



Standard approach:

- Transmit images to the cloud
- Determine features most relevant for reidentification over image database
- Most of image's elements are useless for reId



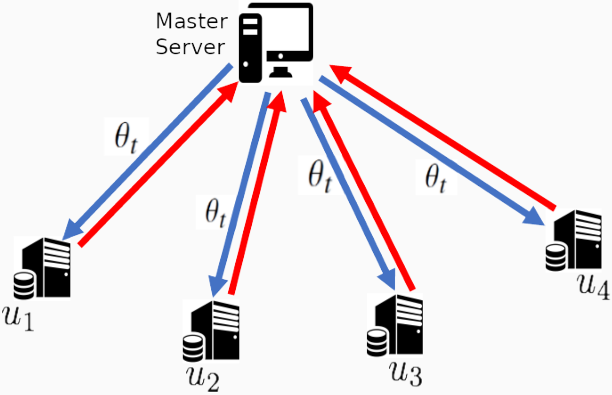
Communicate to Learn

Distributed Computation Learning

- Terms like petabytes, exabytes and zettabytes are replacing megabytes, gigabytes and terabytes
- Handling such data volumes in a single machine is neither efficient nor possible DeepMind's AlphaGo ran on 1920 CPUs and 280 GPUs
- In IoT, users or devices may not want to, or cannot have the bandwidth/ energy to share their data with cloud. Alternative is distributed / federated learning

Distributed Learning Framework

$$F(\theta) = \frac{1}{M}\sum_{m=1}^{M} f(\theta, \mathcal{U}_m) \qquad\qquad \theta_{t+1} = \theta_t - \eta_t \frac{1}{M}\sum_{m=1}^{M} \nabla f(\theta_t, \mathcal{U}_m)$$



Distributed Linear Regression

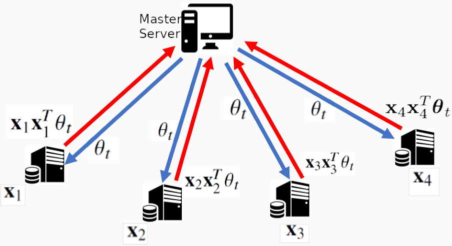
- N labeled data points $(\mathrm{x_1}, y_1), \dots (\mathrm{x_n}, y_n)$
- Minimize mean squared error:

$$L(\theta) = \frac{1}{2}\sum_{i=1}^{N}(y_i - \mathrm{x}_i^T\theta)^2$$

- Gradient descent:

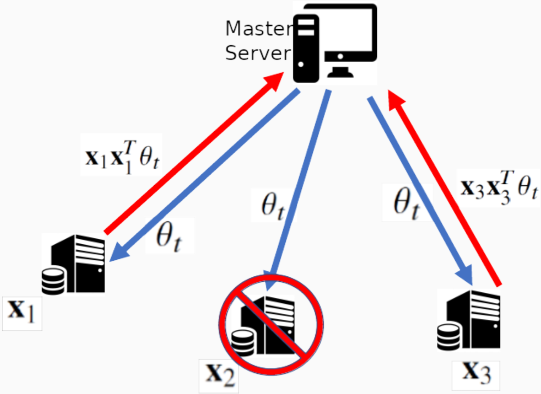
$$\nabla_\theta L(\theta) = \mathrm{X}^T\mathrm{X}\theta_t - \mathrm{X}^T\mathrm{y}$$

$$\mathrm{X}^T\mathrm{X}\theta_t = \sum_{i=1}^{N}\mathrm{x}^T\mathrm{x_1}^T\theta_t$$



This can be distributed!

Straggling Servers



Treat system as a packet erasure communication channel, in which transmitted data packets are randomly erased.

J. Chen, R. Monga, S. Bengio, and R. Jozefowicz. **Revisiting distributed synchronous SGD**. In Int'l Conf. on Learning Representations (ICLR), Workshop Track, 2016.

Dealing with Straggling Servers

- Gradient Coding

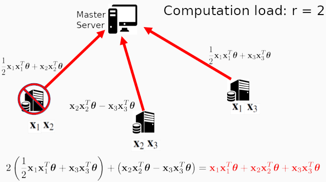
  R. Tandon, Q. Lei, A. G. Dimakis, and N. Karampatziakis, **Gradient coding**, arXiv preprint: arXiv:1612.03301, 2016.

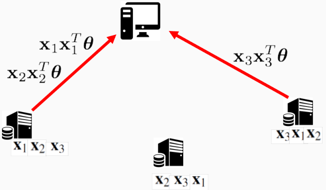
- Multi-message Distributed Computing (non-persistent stragglers)

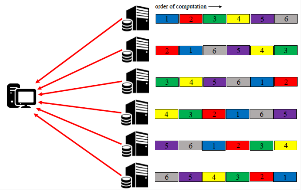
  E. Ozfatura, D. Gunduz and S. Ulukus, **Speeding up distributed gradient descent by utilizing non-persistent stragglers**, submitted to SysML, Stanford, CA, Mar. 2019.

- Multi-message Uncoded Computation

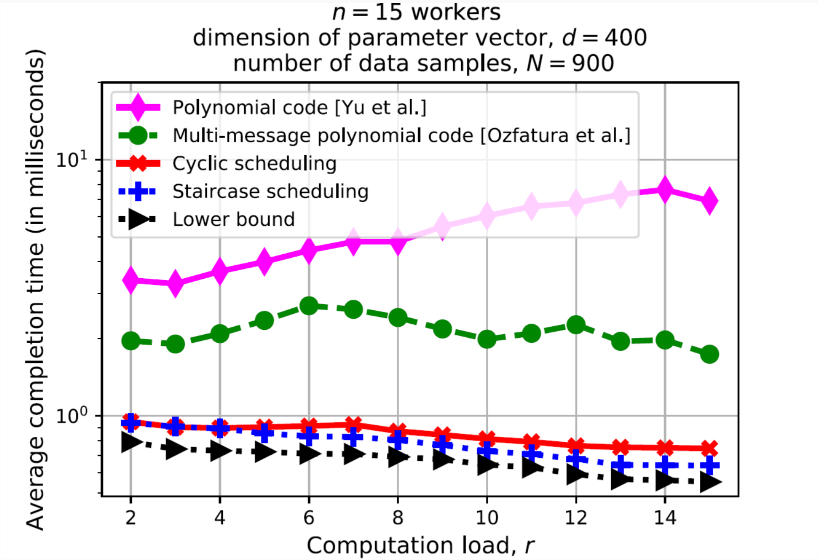
  M. Mohammadi Amiri and D. Gunduz, **Distributed uncoded computation**, submitted to IEEE Trans. on Signal Processing, 2018.





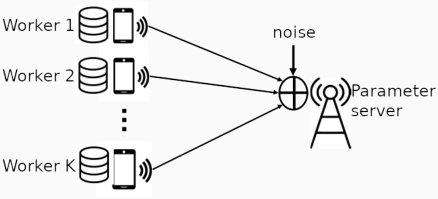


Straggling Servers



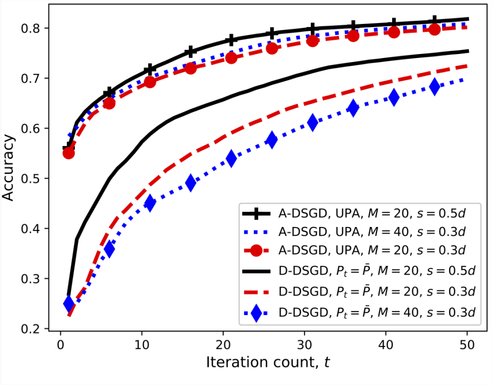
Wireless Edge Learning

- Wireless devices with own data
- a parameter server (PS) enables learning
- Devices (workers) connected to PS through wireles links: bandlimited multiple access channel (MAC)
- Digital approach: separate learning an communications
- Analog approach: let channel do gradient averaging



M. Mohammadi Amiri and D. Gunduz, **Machine learning at the wireless edge: Distributed stochastic gradient descent over-the-air**, Jan. 2019.

Wireless Edge Learning - accuracy vs iteration



- Distributed MNIST classification (single layer with 10 neurons)
- Parameter vector size $d = 28 \times 28 \times 10 + 10 = 7850$
- d: dimension of parameter vector
- s: symbols per iteration
- M: number of devices (i.e., workers)

Conclusion

Conclusions

- Machine Learning (ML) can improve communication networks, and learning also requires efficient communications
- ML brings along many new problems for communications researchers

Some other problems we look into, not mentioned in this talk:

- Deep RL for wireless resource optimization
- GANs for channel modeling
- Privacy-aware learning

Further References and Acknowledgements

Feel free to contact me at:

- d.kurka@imperial.ac.uk

To retrieve all papers mentioned in this presentation:

- **https://www.imperial.ac.uk/information-processing-and-communications-lab/**
- "**Deniz Gunduz**" on Google Scholar

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Thank you!