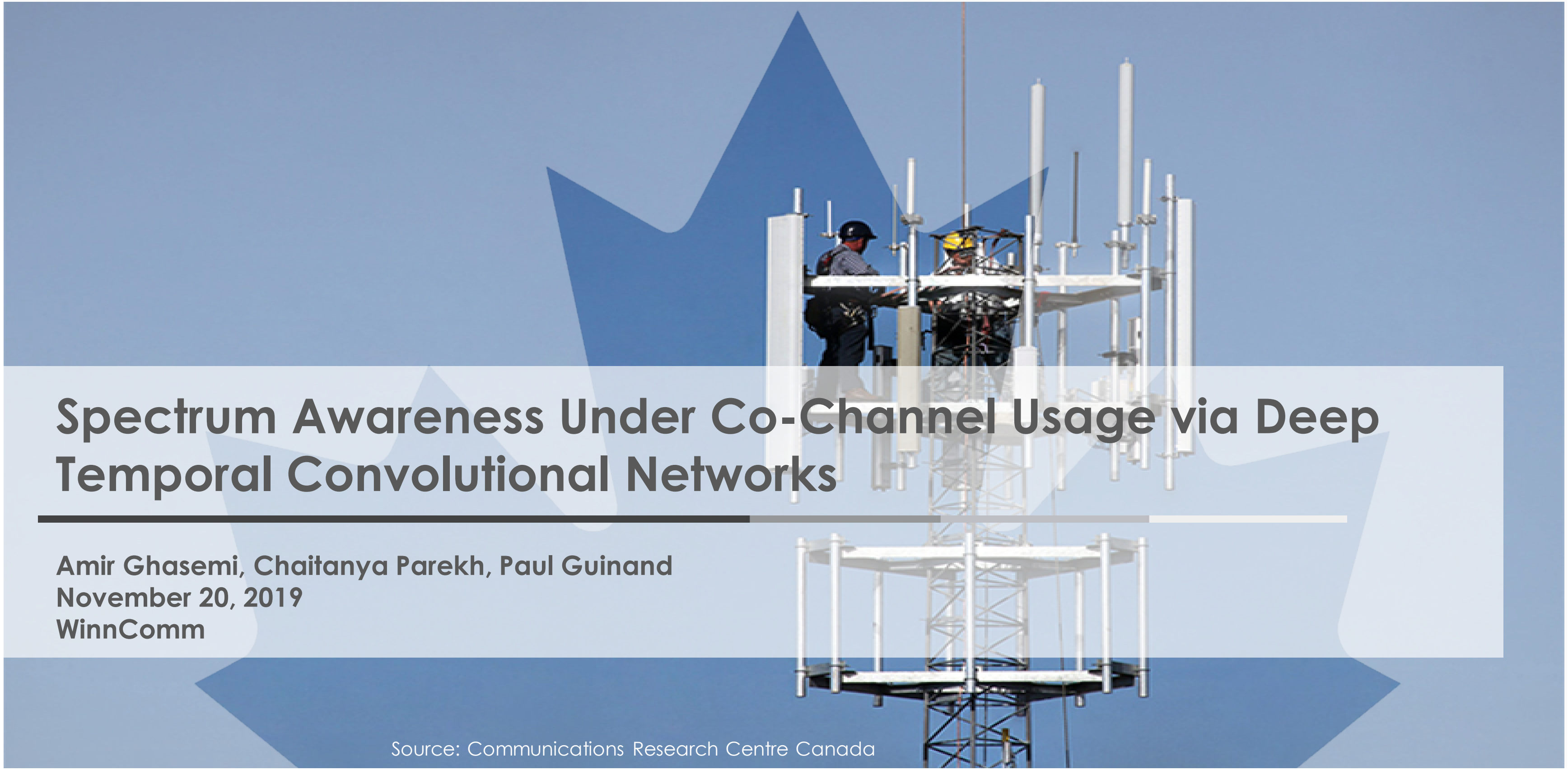

Spectrum Awareness Under Co-Channel Usage via Deep Temporal Convolutional Networks

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November 20, 2019
WinnComm

Source: Communications Research Centre Canada

Overview

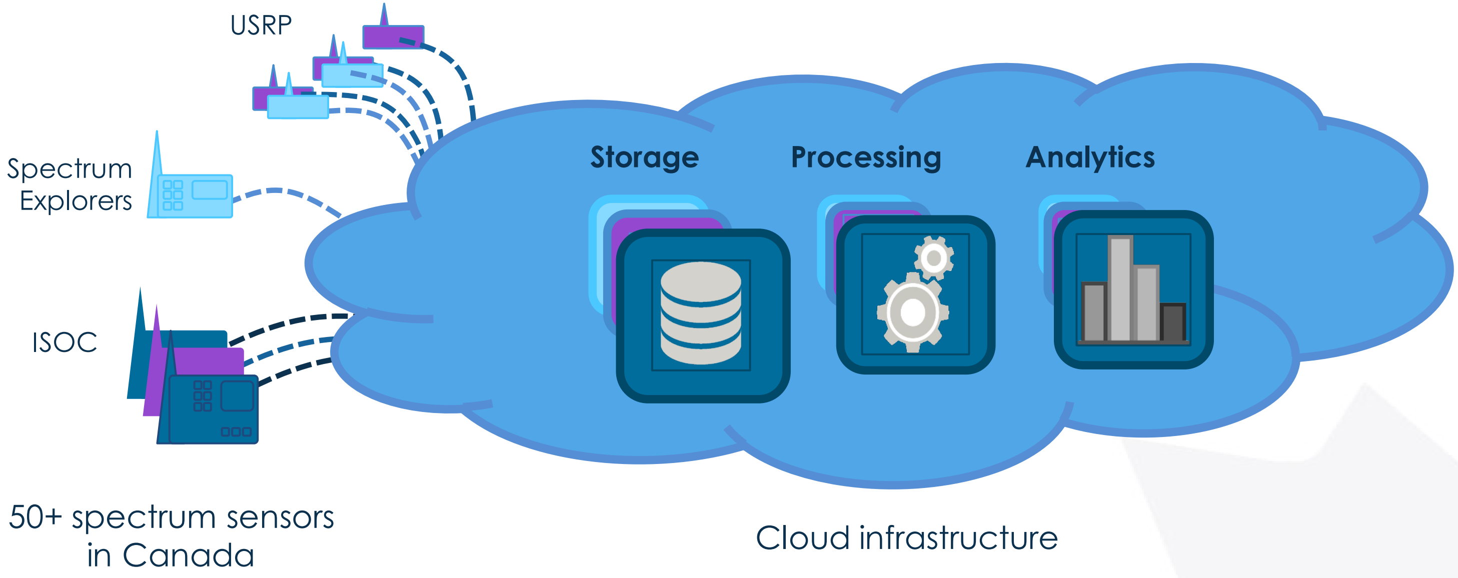
- Motivation
- Background
- Proposed Scheme
- Performance Analysis
- Summary and Future Work

Communications Research Centre Canada (CRC)

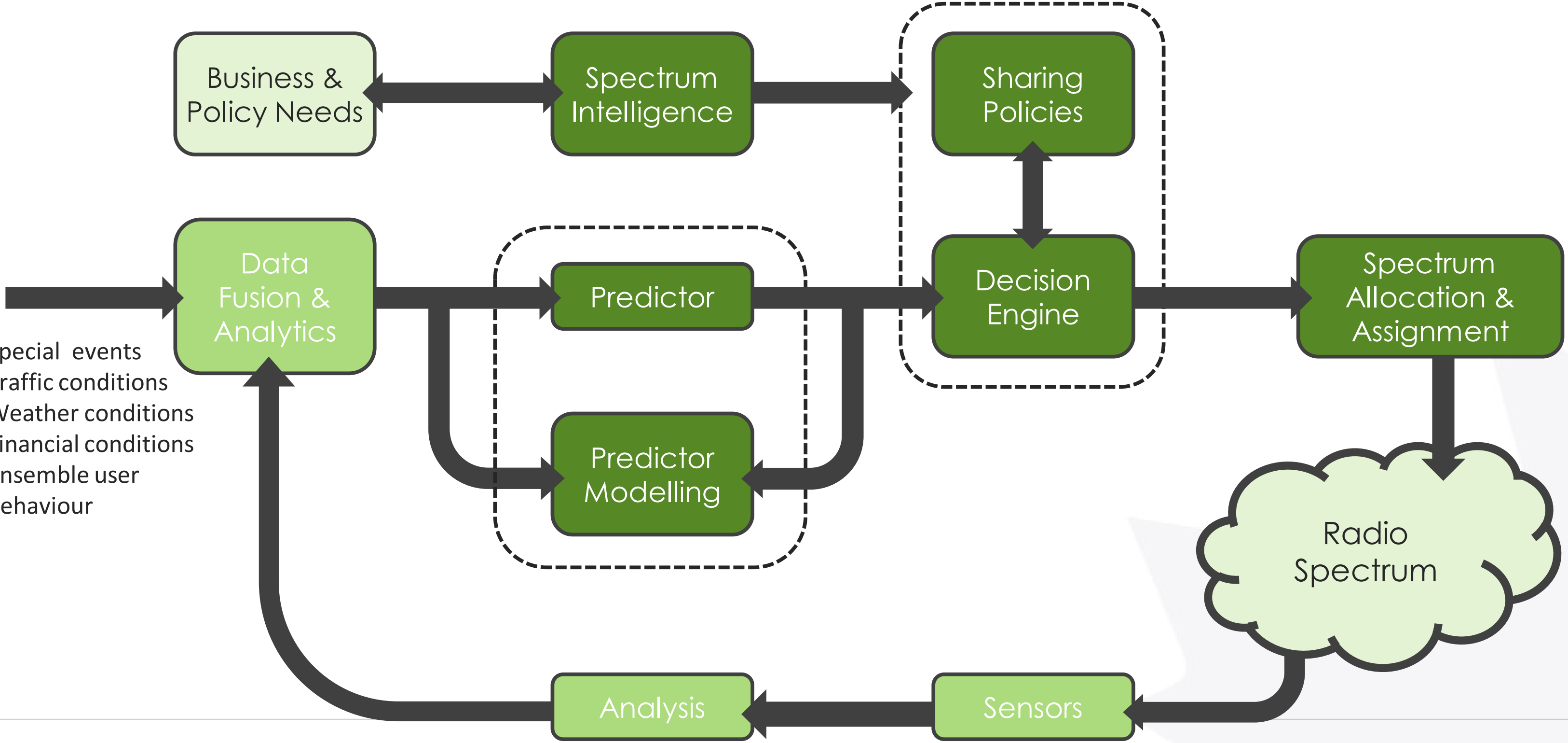
Government of Canada's primary R&D lab for advanced telecommunications

Spectrum Environment Awareness

Providing ‘just-in-time’ spectrum knowledge



Making Better Use of Spectrum



- Special events
- Traffic conditions
- Weather conditions
- Financial conditions
- Ensemble user behaviour

Motivation

- Spectrum sharing is expected to be the norm in some bands
- Spectrum awareness is a key enabler for sharing to ensure fairness, regulatory compliance, and avoid harmful interference
- Sensing at low signal-to-noise-ratio (SNR) and co-channel interference is critical esp. for protection of incumbent services

Background – Modulation Classification

- Traditionally relying on domain experts and carefully-crafted features
  - Auto-correlation and spectral correlation functions, cyclo-stationarity
  - Statistical properties of amplitude and phase

- Features are derived and fed into conventional classifiers (small neural nets, decision trees, SVMs, …)

Background

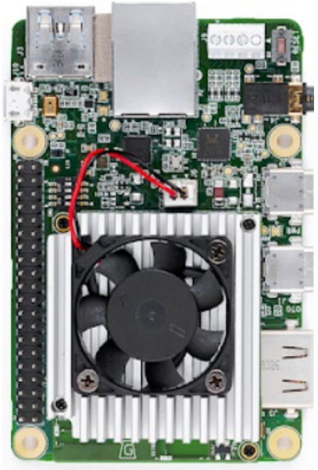
- Feature detectors require (often complex) analytical derivations for different combinations of signal, interference, channel, and noise

- Not scalable

- Can we instead learn to detect co-channel modulations directly from the raw data?

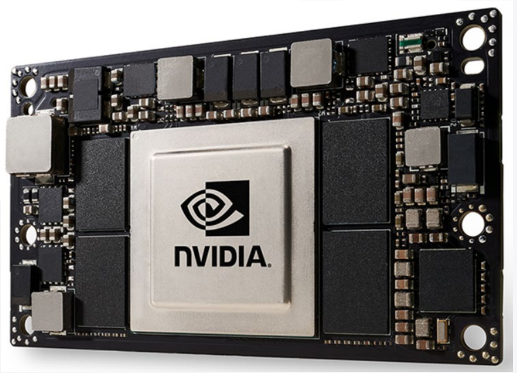
Why Deep Learning

- Deep learning (DL) proven effective in processing raw image and speech without hand-crafted features



- DL is now available at the edge

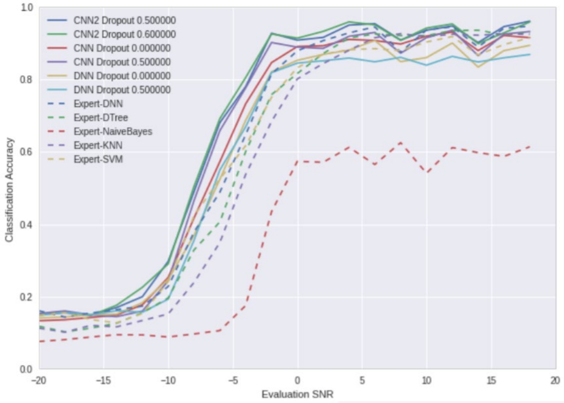
- Trained models can be adjusted quickly for slightly different situations (transfer learning)



DL-Based Modulation Classification

- Raw baseband I/Q samples can be used directly to identify the modulation using deep CNNs[1]

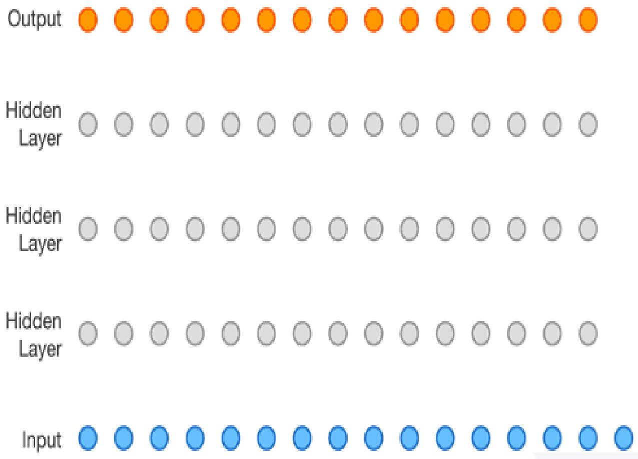
- Variations based convolutional LSTM improved performance further[2]



1. T. J. O'Shea, J. Corgan, T. C. Clancy, "Convolutional Radio Modulation Recognition Networks," 2016, https://arxiv.org/pdf/1602.04105
2. N. E. West, T. J. O'Shea, "Deep Architectures for Modulation Recognition," in Proc. IEEE DySPAN 2017

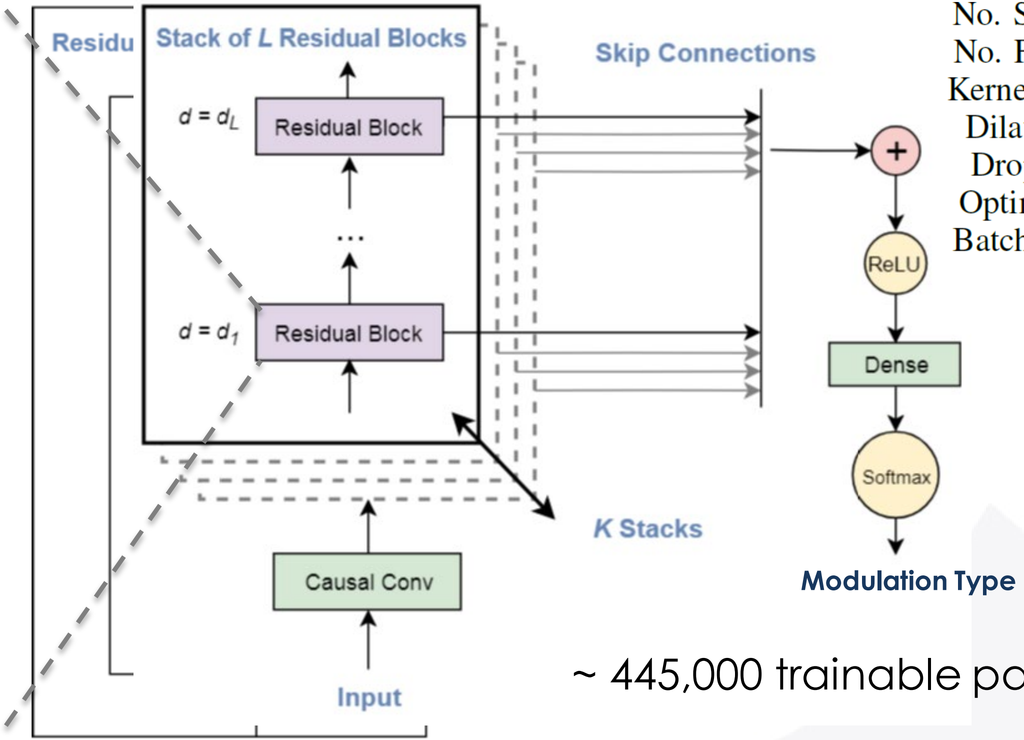
Temporal Convolutional Networks (TCN)*

- Inspired by WaveNet architecture originally proposed by Google DeepMind
- Fully convolutional auto-regressive network using 1-dimensional causal convolution filters
- Dilated convolutions enable using longer training sequences
- Residual and skip connections enable training very deep architectures



* S. Bai, J. Z. Kolter, V. Koltun, "An Empirical Evaluation of Generic Convolutional and Recurrent Networks for Sequence Modeling," available online: https://arxiv.org/abs/1803.01271, April 2018.

TCN Architecture



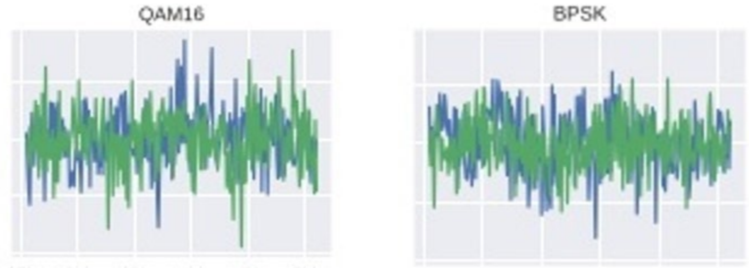
No. Stacks	3
No. Filters	64
Kernel Size	8
Dilations	2, 4, 16, 256
Dropout	0.5
Optimizer	Adam
Batch Size	300

~ 445,000 trainable parameters

Dataset and Scenarios

- Created by extending the publicly available RadioML 2016.10 dataset* for co-channel signals scenario
- Raw I/Q vectors of length 128 and 1024 samples, generated with GNU Radio

- **Single Signal**:
  - 8 digital modulations: GFSK, CPFSK, BPSK, PAM4, QPSK, 8PSK, 16QAM, 64QAM
  - SNR levels ranging from -20 to 18dB in steps of 2dB
  - 5000 vectors per SNR (total of 100k examples per modulation)



* http://deepsig.io/datasets/

Dataset and Scenarios

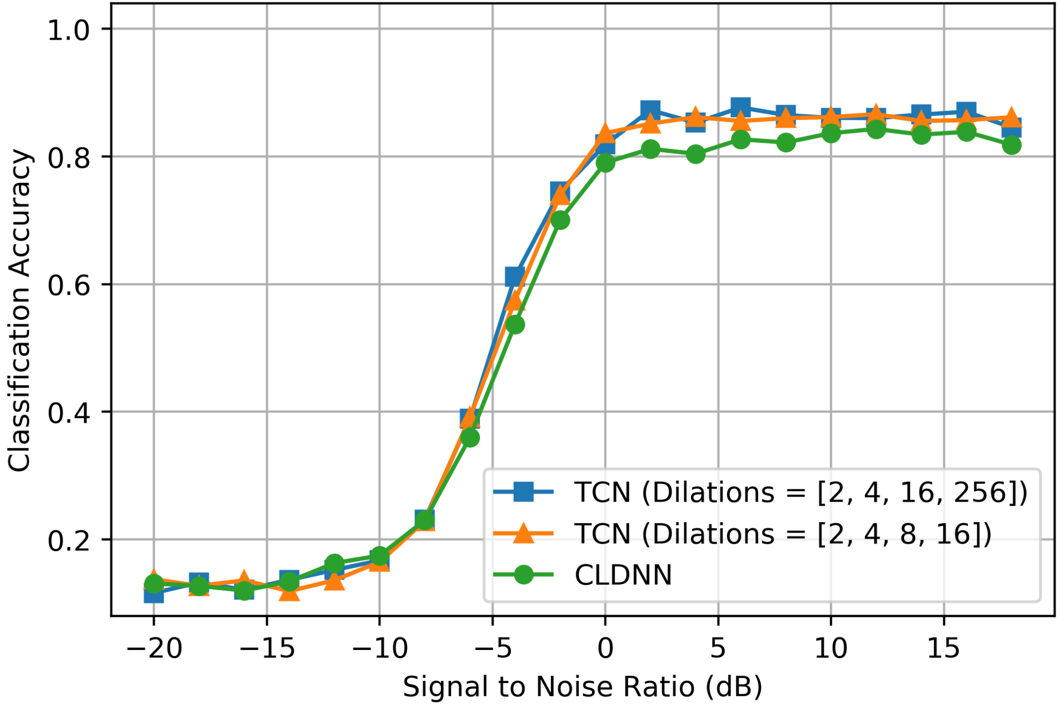
- **Interference Signal**:
  - Modulation of desired signal known and fixed
  - Need to identify the modulation of a potential interferer
  - Of particular interest in spectrum regulation e.g. to identify unauthorized use of a channel licensed to a specific user
  - SNR fixed at 10dB, five SIR levels (-10,-5,0,5,10 dB)
  - Second signal added with random phase (uniformly distributed between 0 and 2π).
  - 4000 vectors per SIR (20k examples per class)
- **Mixed Signal:**
  - 29 Classes: All pairwise combinations of 7 digital modulations (21 classes), single signal (7 classes), noise only (1 class)
  - Second signal added with random phase (uniformly distributed between 0 and 2π)
  - Four SNR levels (-18,-6,6,18 dB) and five SIR levels (-10,-5,0,5,10 dB)
  - 4000 vectors per SIR/SNR combination (100k I/Q vectors per class)

Performance Analysis

- Dataset is split 80%/10%/10% for training, validation, and final testing with early stopping of 10 epochs to avoid over-fitting

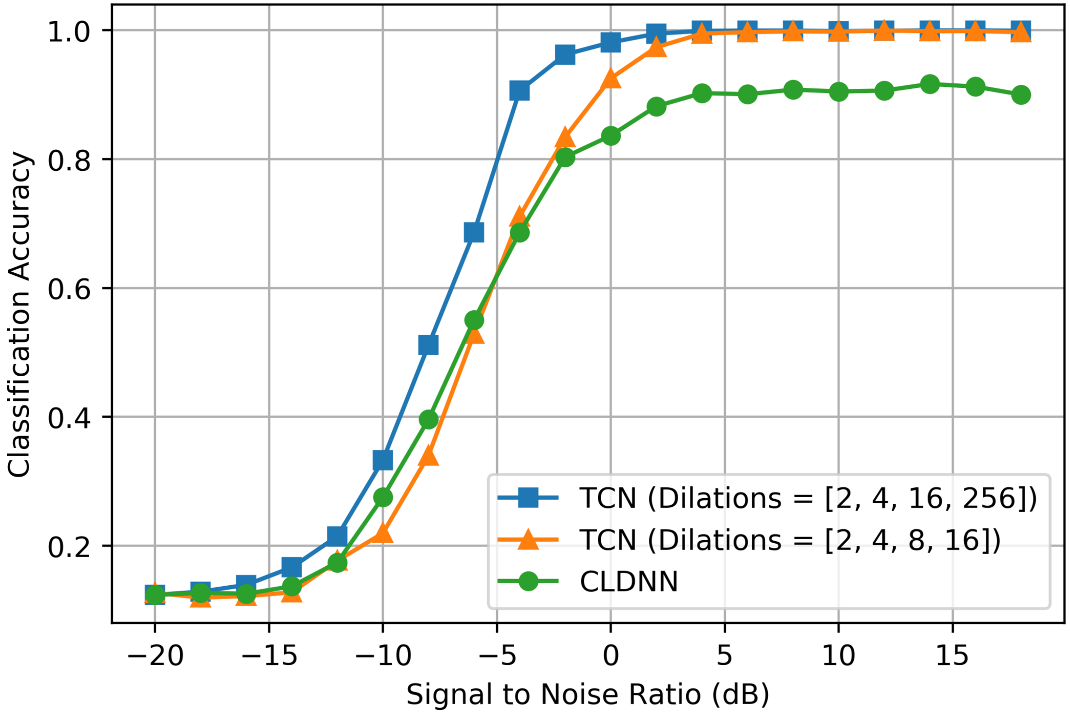
- Network is trained using Keras with Tensorflow backend on a Tesla V100 GPU with categorical cross-entropy loss function

Performance Analysis – Single Signal



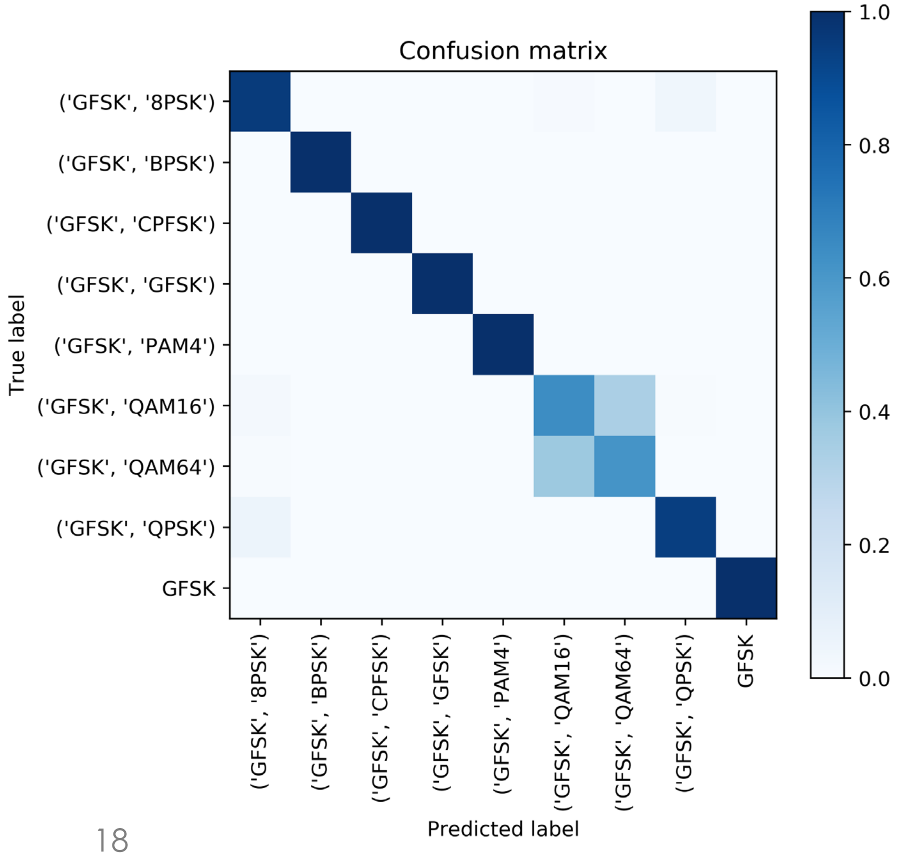
- Short-duration dataset (128-sample I/Q vectors)
- SNR levels ranging from -20 to 18dB in steps of 2dB
- 5000 vectors per SNR (total of 100k examples per modulation)

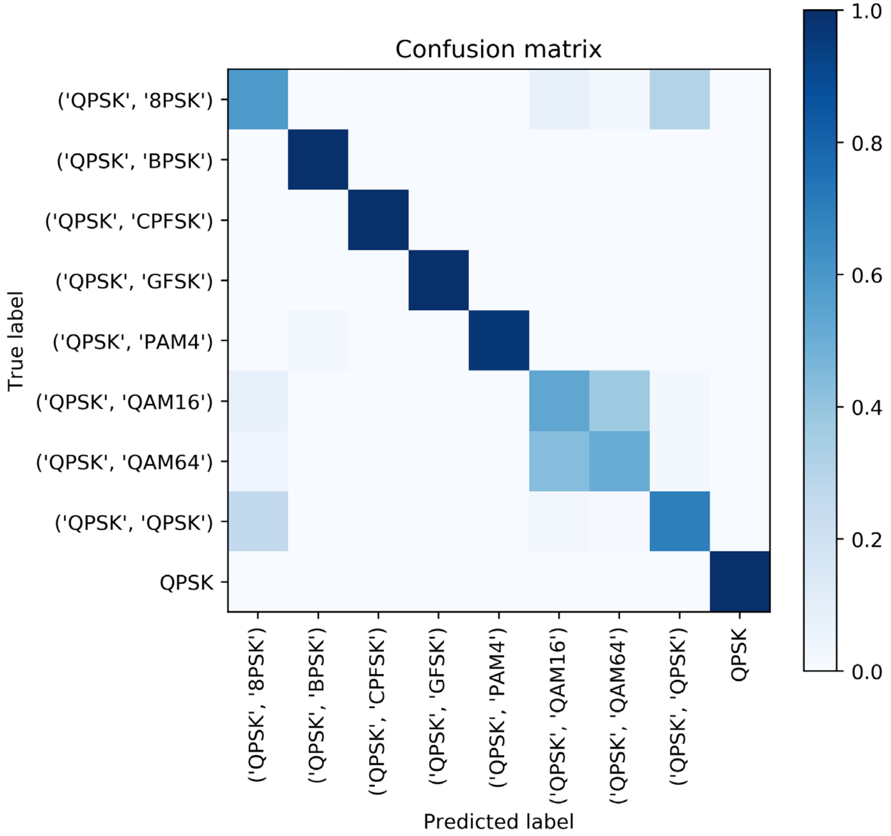
Performance Analysis – Single Signal



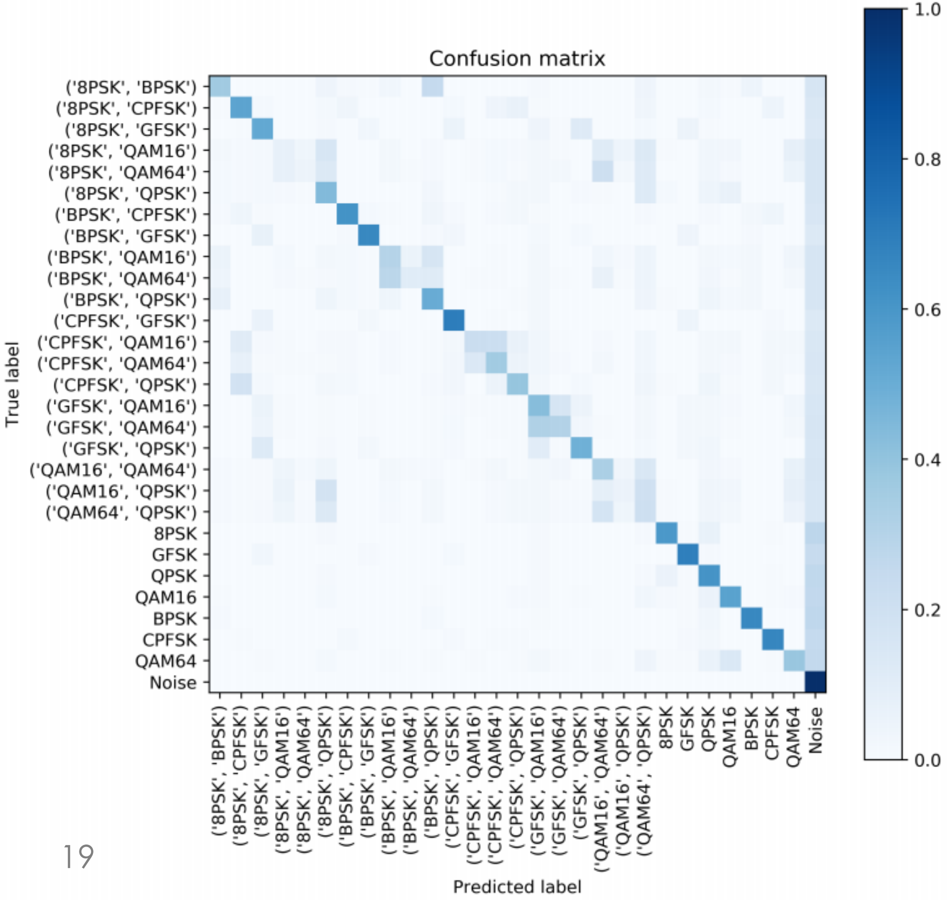
- Long-duration dataset (1024-sample I/Q vectors)

Performance Analysis – Interference Classifier



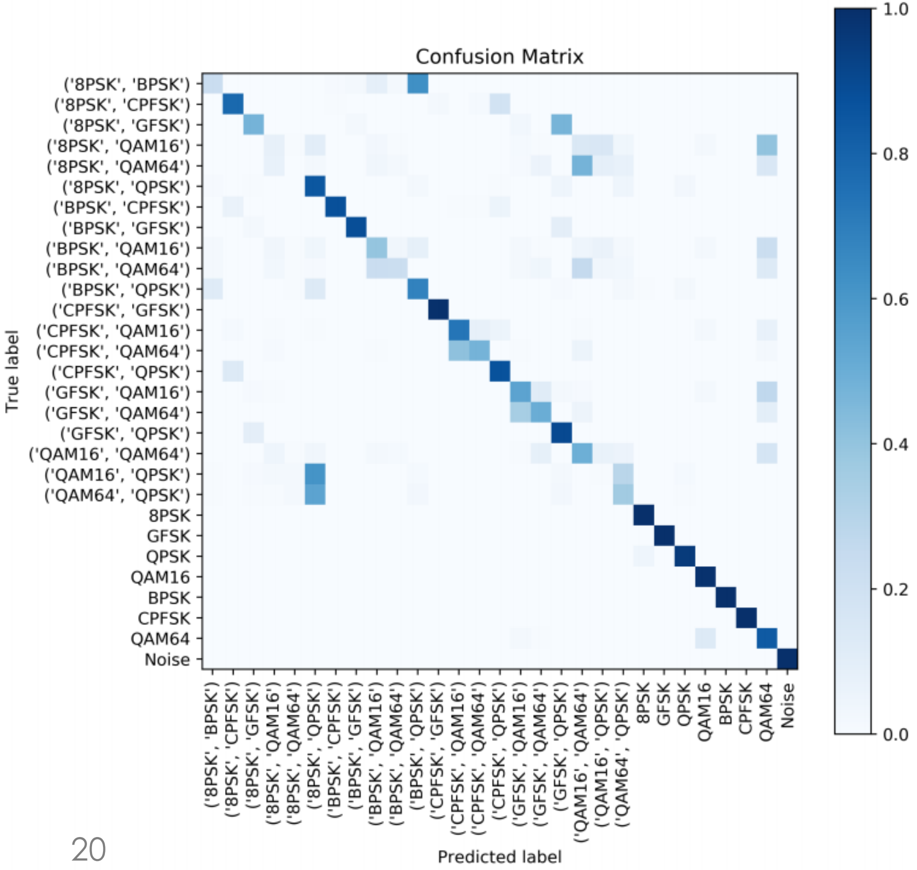


Performance Analysis – Mixed Signals



Confusion matrix for mixed-signal classification across the full SNR and SIR range

Performance Analysis – Mixed Signals

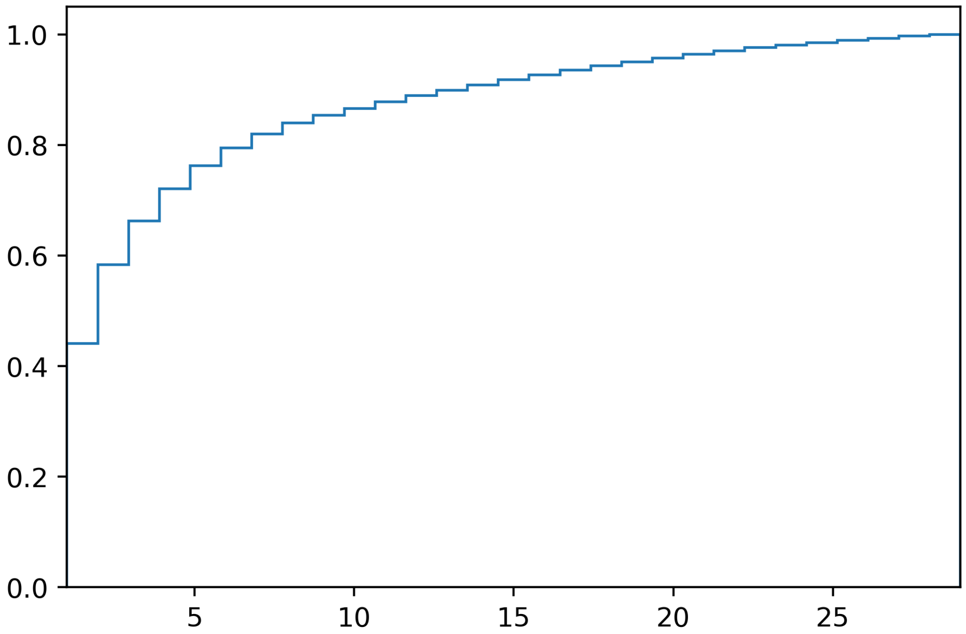


Confusion matrix for mixed-signal classification:

SNR = 18dB

SIR = -10dB

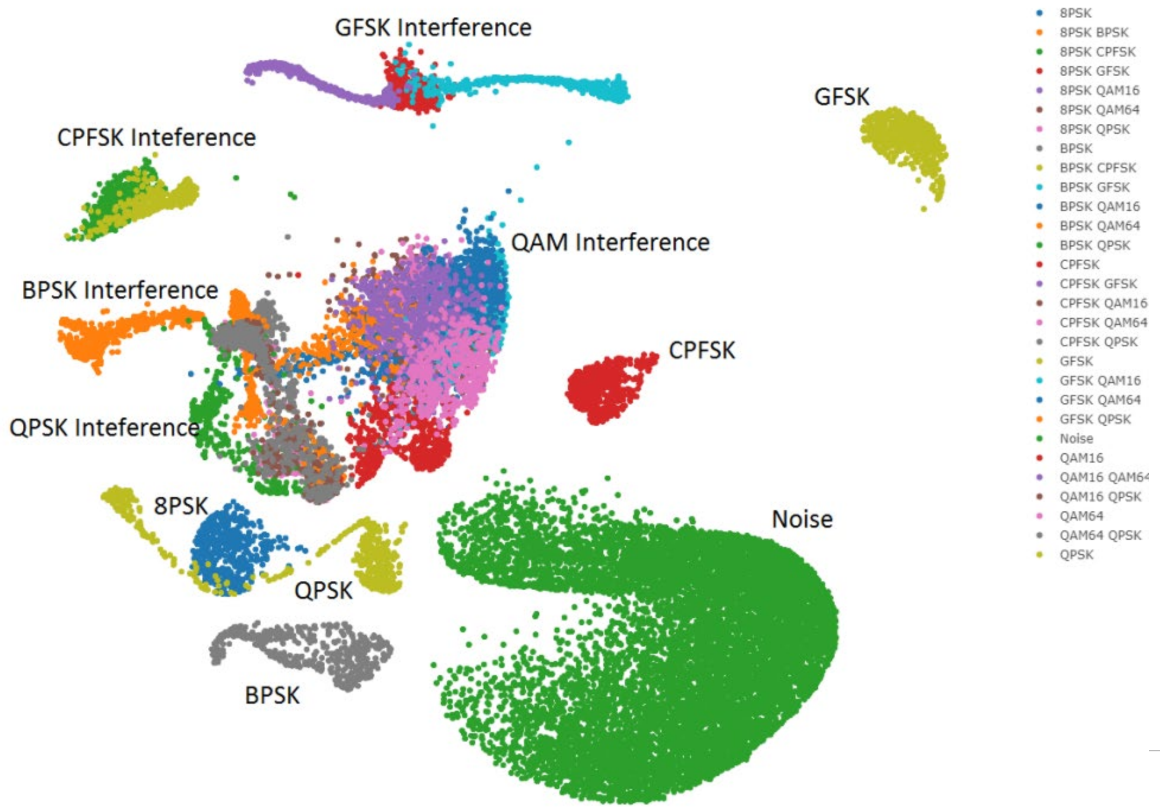
Performance Analysis – Mixed Signals



- Top-1 accuracy: 43%
- Top-5 accuracy: 75%

Probability distribution of true label’s rank among the predicted labels

Peeking into the Classifier



Summary

- Spectrum awareness is becoming increasingly important to users and regulators
- Data-driven approaches to sensing are model-agnostic and not limited by analytical complexities
- Deep learning can successfully learn signal features with little to no pre-processing
- Key challenge is to synthesize/collect representative training data

Further Work

- Model interpretation
- Robustness to channel impairments
- Over-the-air experiments