Radio Spectrum Analytics

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Radio Spectrum Analytics

Making sense from and understanding what is going on in the radio spectrum

- **Unauthorized spectrum uses:** malicious or accidental
- **Unused spectrum** licensed or assigned that may be under-utilized
- **Spectrum Measurement** of usage efficiency, user types, propagation models, allocation efficiency and other enablers for optimization

Challenge boils down to

- Consuming **large amounts of unlabeled radio signals**
- Labeling and digesting important events and actions into **concise intelligible information** for operators, enforcement, policy makers, and researchers

Generalized Spectrum Analytic Process

- Signal Detection
    - Which spectrum lies vacant, which spectrum is occupied
- Signal Identification
    - What kinds of signals are occupying which bits of spectrum
- Signal Localization
    - Where are the emitters spatially that are occupying our spectrum
- Signal Measurement and Metrics
    - How fully utilized are existing radio access networks
    - What does the propagation environment look like in the real world
- Other specialized tasks

Changing Requirements in Spectrum Analytics

Monitoring More Critical: As dynamic assignment and security concerns

Software Defined Modems: Dynamic Waveform Behaviors

- **Flexible Radio Frontends**: Wide Many-Band Capabilities
- **New and Shared Spectrum**: Opening up as allowed by regulators
- **Increasing standards complexity**: expensive DSP implementations for specialized algorithms, optimization on low SWaP hardware, etc

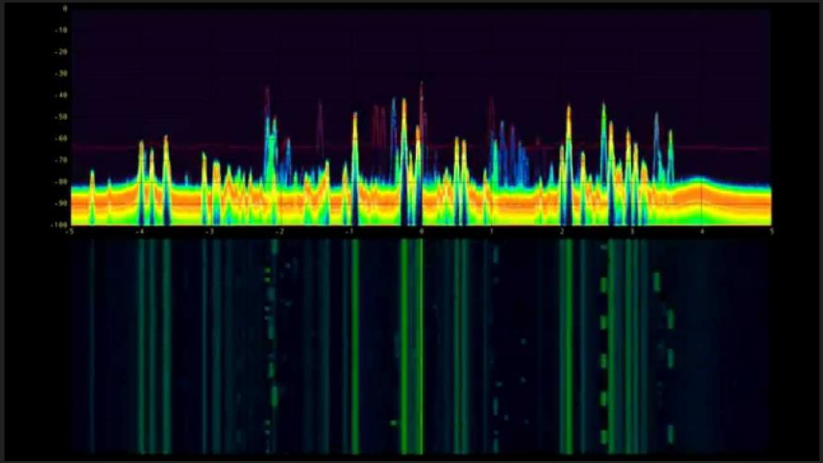
Result: Difficulty relying on highly constrained expert systems!

Potential Solution: Radio analytic systems which **learn to find, identify, and summarize** important events rather than relying on manual methods or specialized expert systems.

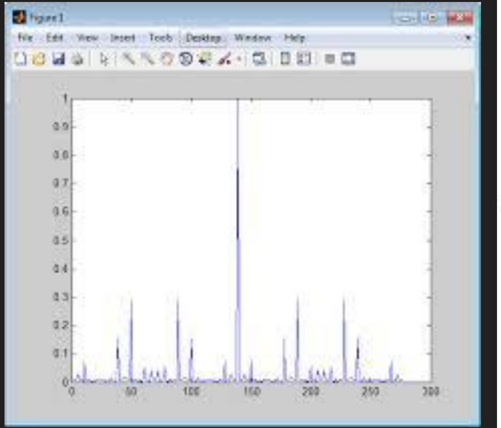
Traditional Methods

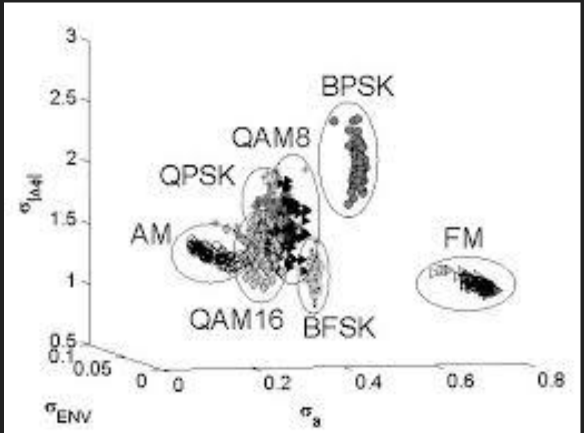
Signal Detection

- Energy based methods: Power Spectrum Density, Spectrogram, Wavelet methods, ...
- Specialized Methods: Signal Specific Detectors
    - Matched filters, correlations, expert-feature based detectors
- Wide band dwelling vs scanning systems
- Manual inspection of interferers
- Automated methods based on energy



Traditional Methods





http://tinyurl.com/zpxve6l

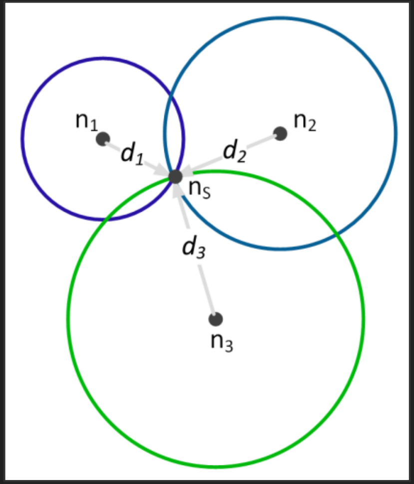
Signal Identification

- Expert modulation-feature based methods
  - Moment based methods (known properties of modulations)
  - Wavelet based signatures (known shapes of modulation spectrum occupancy)
  - Cyclic features of the modulation (known peaks in the autocorrelation)
- Expert specific-signal based methods
  - Preamble correlation / expert synchronizers (LTE PSS, SSS / Zadoff Chu)
  - WiMAX / WiFi -- Delay conjugate multiplies / Schmidl & Cox type methods
  - Many others …
- All relatively labor intensive to implement, lack generality to numerous other types of signals

Traditional Methods

Signal Localization Methods

- Mobile-subscriber reported location information
- Tower/cell/sector localization information
- Spatial observations of power, propagation delay, doppler offsets



Signal Measurement and Analytics

- Base-station provided coverage and CQI statistics
- Highly specialized signal-specific demodulation, diagnostic client devices, etc
  - Resource Block allocation percent, traffic types, UEs associated, ...

System Deployment & Analysis Models

Range of System Deployment Methods

- Spectrum Analyser Recordings → Offline MATLAB manual analysis
- Deployed sensors:
  - Remote minimal - occasional remote IQ collection & maybe PSD plots (fixed/mobile)
  - Remote processing - detection and feature based identification, compute requirements
  - Cloud RAN style Radio backhaul, streaming IQ, bandwidth requirements - no compute
  - Remote storage - significant storage requirements
  - Realization of algorithms in Dense Neural Networks in high level language all map easily to concurrent, energy efficient dense matrix algebra, i.e. Keras/TensorFlow/Cuda

Analysis Types

- Offline IQ file analysis (all manual)
- Online detection / energy plotting
- Online recognition / identification -- metadata backhaul
- Online detection, identification, localization -- metadata backhaul
- Richer learning systems, online feature extraction, adaptation, learning, summarization

Lots of these techniques can be improved ...

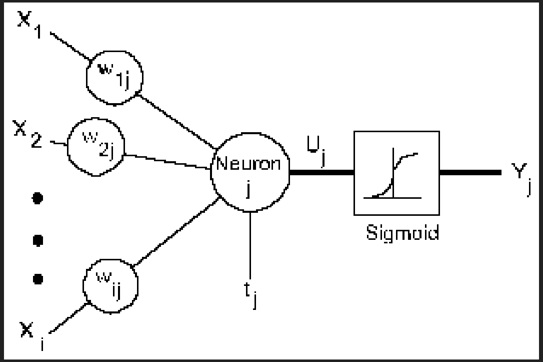
Machine learning holds potential for many of these tasks

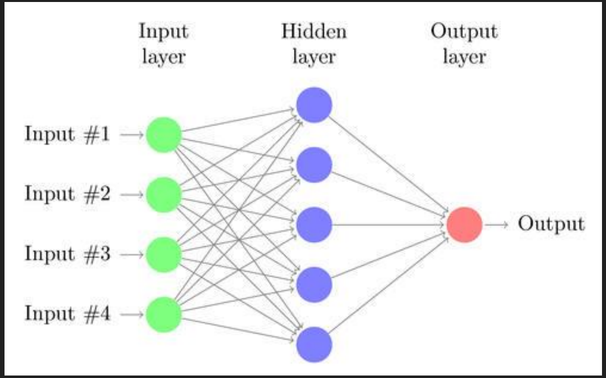
Let's explore this by:

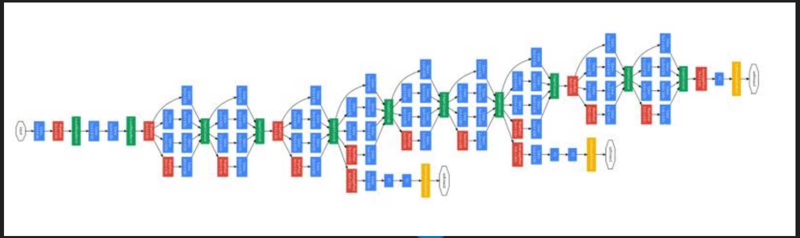
- Reviewing recent ML advances, causes, capabilities
- Identifying areas for enhancement of existing tasks
- Demonstrating efficacy and improvement in this area
- Maturing and vetting realistic benchmarks for these tasks

Brief (NN) Machine Learning Background

- Deep neural networks: resurgence in recent time and state of the art on many tasks
  - Network of layers of neurons with inputs, weight vectors, activation functions (sigmoid, ReLU, linear, etc), outputs
  - Trained based on backpropagation of loss gradient with respect to network weights (Wij -= delta*dL/dWij)
  - Loss can be categorical cross-entropy, mean squared error regression, or many other tasks --
  - Scales to very large tasks, datasets, representations
  - Somewhat “model free”: General DNN can learn many tasks and representation without expert knowledge
  - Architecture does affect performance -- but can also be learned







Selected Recent advances in Machine Learning

Rapidly growing area principally focused in Computer Vision, Natural Language, Voice Recognition, Question Answering, Information Retrieval

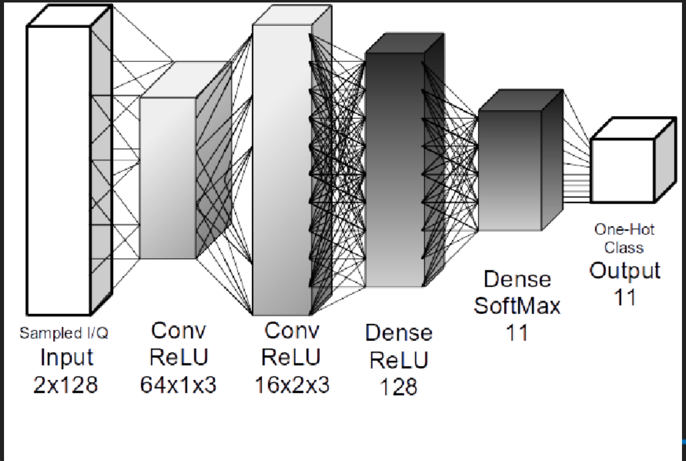
Way too many advances to list here, but some key advances in the deep neural network area in recent years include

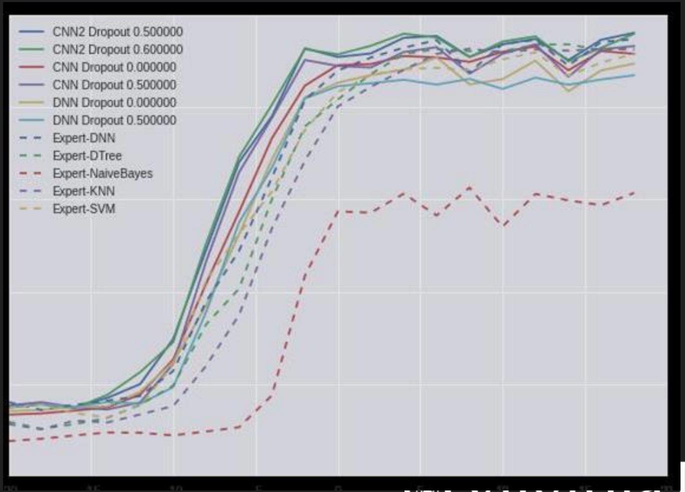
- **Gradient Descent Methods:** Async-SGD, Momentum: RMSProp, Adam
- **Regularization Methods:** Dropout, Dropconnect, Noise Injection
- **Computational Methods**: Concurrent Architectures (GPUs and high level languages)
- **Framework Methods**: Auto-differentiation, Modularization of Components
- **Dataset Availability**: Large well-characterized tasks and benchmark datasets
- **End-to-end learning:** Objective based whole system learning
- **Attention Models**: Learning parametric transforms to canonicalize examples
- **Adversarial Models**: Training with learning adversarial components

ML Driven Signal Identification

Focus on data driven methods, feature learning, minimization of expert knowledge which limits generality -- Supervised learning of deep conv-net

Initial results show sensitivity improvements, less data needed, ability to generalize, significantly lower computational complexity, no expert knowledge or feature design used in classifier design.





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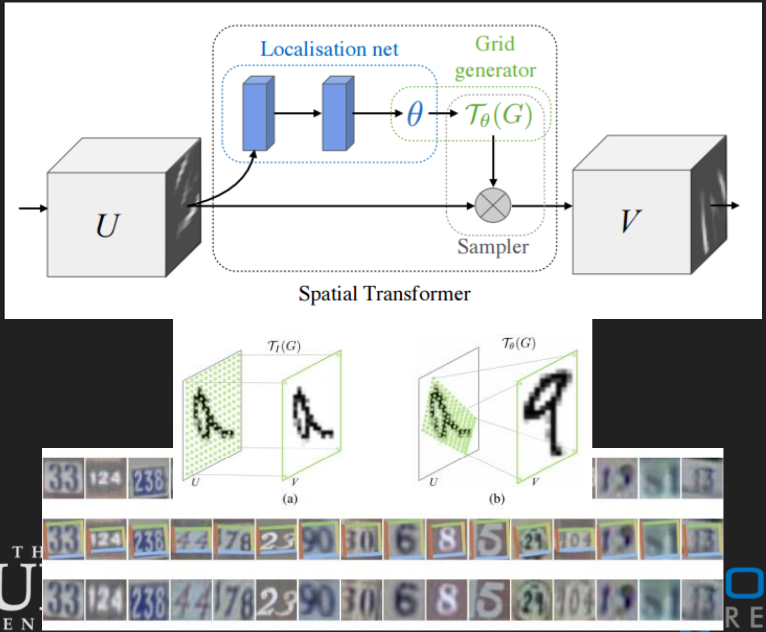
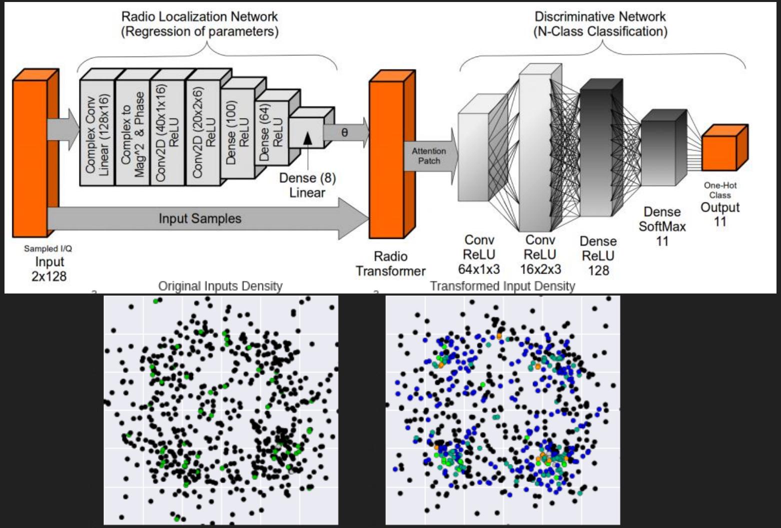
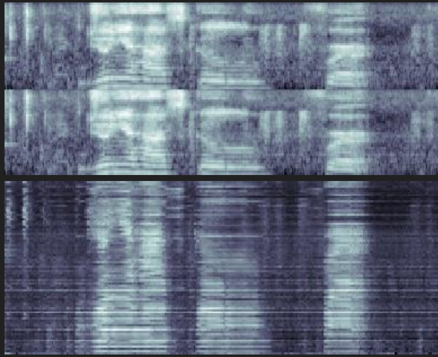
ML Driven Signal Reception

- Learning attention models, highly successful in image canonicalization (for example in street view). Also some success so far in canonicalization of RF
- Ultimately learn to synchronize and discern high layer effects on carriers





Saineth [15] end-to-end voice model



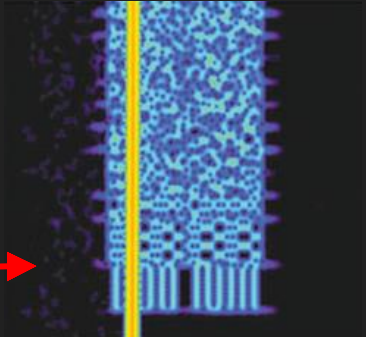
ML Driven Anomaly Det. & Summarization

- Sequence learning for signal behavior learning beyond modulation ID
  - Learning end-to-end representation
  - Protocol and temporal behavior recognition
  - Anomalous PHY and MAC layer event detection
- RNN Based sequence models have been wildly successful in natural language embedding and translation

Image to N.L. Sequence Tasks

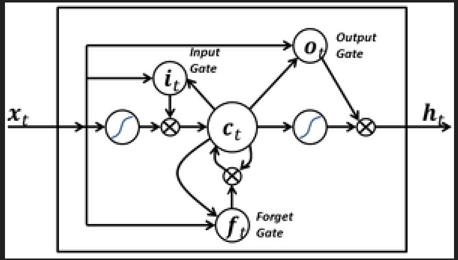
'a man with a uniform standing next to a stop sign'

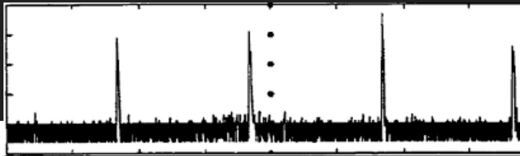
'a group of people on a skateboard'



'A powerful tone is on top of the OFDM carrier'

RNN/LSTM Sequence model anomaly detection methods





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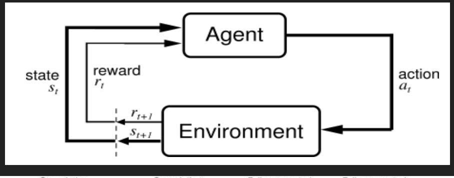
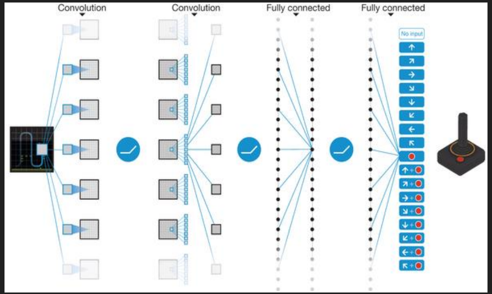
ML/RL Driven Methods

- Focus on learning of active control systems: Google Deepmind has really been pioneering this field
- Atari and AlphaGo accomplishments
- Google datacenter power savings 15-40%

https://deepmind.com/blog





DeepQ Network Methods (DQN)

$$Q^*(s,a) = \mathbb{E}_{s' \sim \mathcal{E}}\left[r + \gamma \max_{a'} Q^*(s',a') \middle| s,a \right]$$

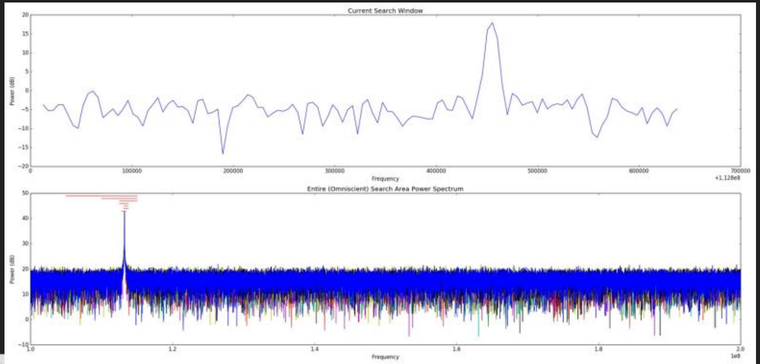
Policy-Gradient Methods

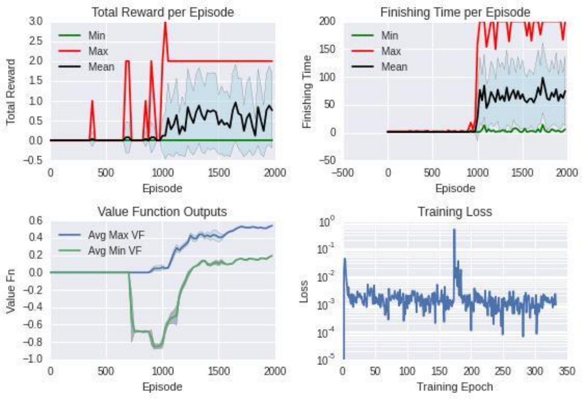
$$\nabla_\theta \leftarrow \frac{1}{N}\sum_{j=1}^{N}\sum_{t=1}^{H_j}\left(\nabla_\theta \log \pi_\theta(s_{j,t}, a_{j,t})\right)\sum_{k=t+1}^{H_j} R(s_{j,k})$$

Asynchronous DQN/PG Methods: (Asynchronous Actor Advantage Critic [**A3C**]) -- current state of the art.

ML/RL Driven Signal Detection & Control

- Formulate radio sensing and network control problems as active environmental simulations which can iterate very quickly.
- Define objectives: detection accuracy, detection time, false detection rate
- Learn to find and localize tones within a wide-band scanning radio scenario
- Put RL directly in charge of radio control & detection, iterate learning policy
- Leverage **A3C & RL** to develop effective end-to-end search & control policy





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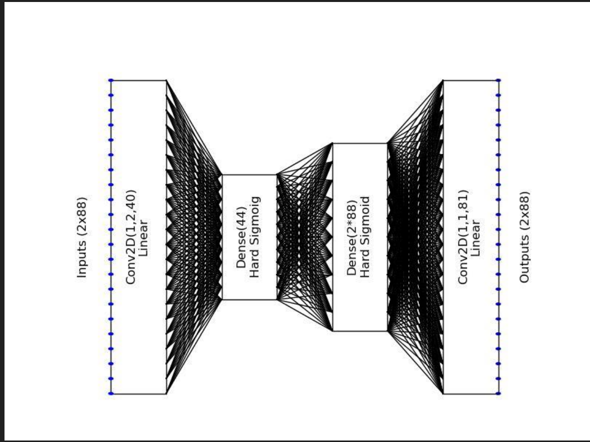
ML Driven Signal Localization

- Learning regression tasks for localization
- Significant potential for ML driven localization methods
  - Channel sounding methods in dense urban/indoor environments
  - Regression tasks of location estimates from channel effects
  - Classification of legitimate emitter locations
  - Richer models that adapt to environment vs simplistic closed form analytic line of sight eqns
- Numerous possibilities in this area yet to be explored
- Will see more work in this area in coming years

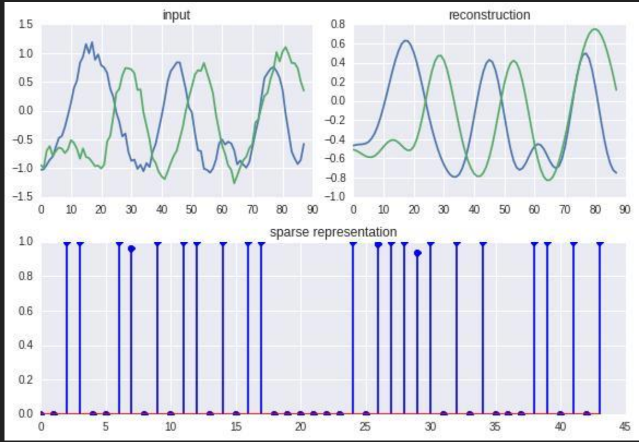
ML Driven Radio Signal Compression

Domain aware learned compression algorithms hold potential to significantly improve Cloud RAN capacity for Carriers and for Sensors

Unsupervised methods for sparse representation learning of radio signals!



- Binary Representation
  - Cpx 32 bits
  - 2*128*64 → 44 bits
  - 16384/44 = 372x
- Dynamic Range @20dB
  - Cpx 4 bits
  - 2*88*4 → 44 bits
  - 704/44 = 16x



Potential Early ML Impacts in Spectrum Analytics

Ability to generalize, learn good features, make sense of LARGE and unlabeled but structured radio datasets autonomously!

Reduce backhaul and storage requirements by rapidly consuming, efficiently representing and summarizing spectrum streams

Reduce expert knowledge and implementation cost & difficulty in generating low SWaP, high performance sensing algorithms through learning from data

Improve portability across heterogeneous infrastructure using efficient tensor ML frameworks. Reduce impact of special, optimized, platform code.

Learn features and control systems in highly complex systems of systems that work better than hand crafted features, logic, and heuristics!

Improve Autonomy and allow humans to interact with higher level information!

Thanks

Questions? Research collaboration Interest?

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