Machine Learning for RAN: Delusion or Salvation?

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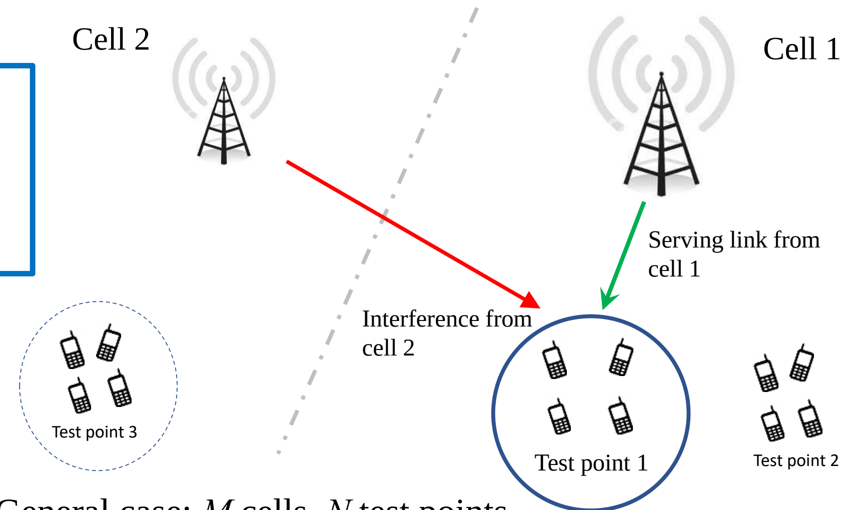
Why ML for Communications (=MLC)?

- **Entry points for ML-based improvements**
  1. high complexity (bad models)
  2. inefficient computation (limited resources)
  3. slow convergence (low latency applications)

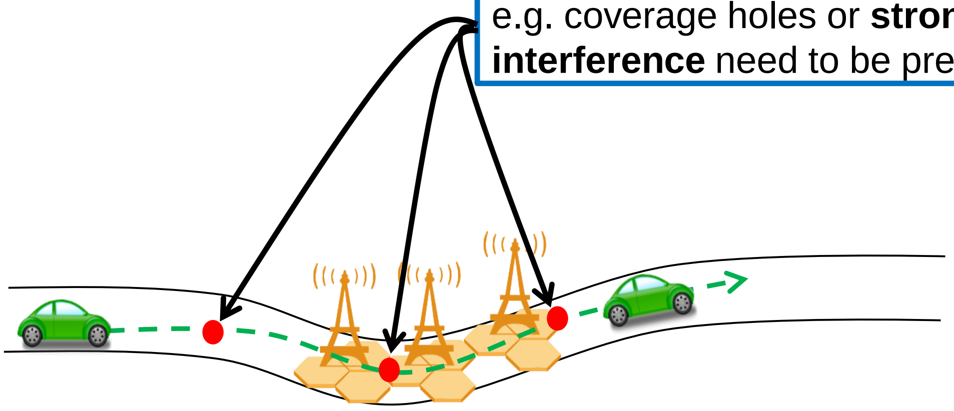
- **Potential benefits**
  1. enable to cope with increased complexity
  2. enhance efficiency
  3. facilitate cognitive network management
  4. **provide robust predictions**

Load Learning

Problem
What are users' rates as a function of the **load at each base station?**



General case: M cells, N test points



e.g. coverage holes or **strong inter-cell interference** need to be predicted

Reliable **rate-load mapping estimates/predictions** are key to reliable QoS predictions

- R. L. G. Cavalcante, Y. Shen, S. Stańczak, "Elementary Properties of Positive Concave Mappings with Applications to Network Planning and Optimization," IEEE Trans. Signal Processing, vol. 64, no. 7, pp. 1774-1783, April 2016

Performance Improvement due to Predicitons

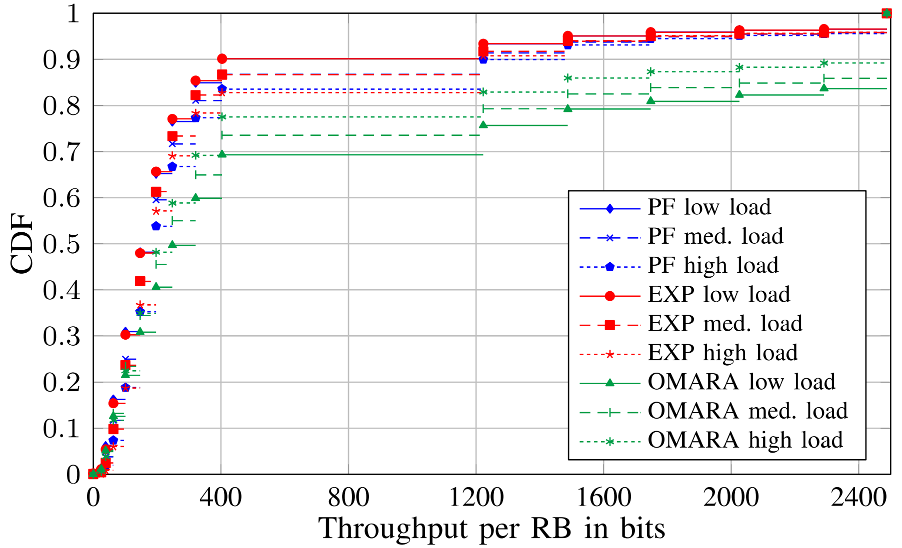


Fig. 3. CDF of the throughput per allocated RB

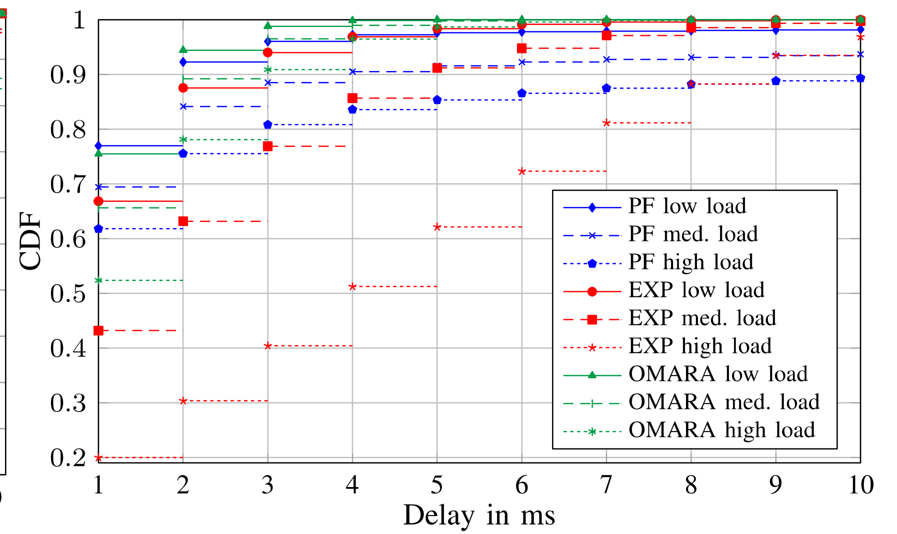


Fig. 4. DC packet delay CDF for successfully transmitted packets

- D. Külzer, S. Stańczak, M. Botsov, "Novel QoS Control Framework for Automotive Safety-Related and Infotainment Servcies," submitted, Nov. 2019

Classic vs. ML Approach (inspired by David Wipf)

Problem

Find a load vector x^* given users' rates θ and network configuration

Classic approach (model-driven)

- Modeling $f_\theta(x)$
- Simplification: $\hat{f}_\theta(x)$
- Human-designed algoirthm

  input: θ

  while <some condition is met>

  $x^{(n+1)} = T(x^{(n)})$; end

  output: $\hat{x} = x^*$

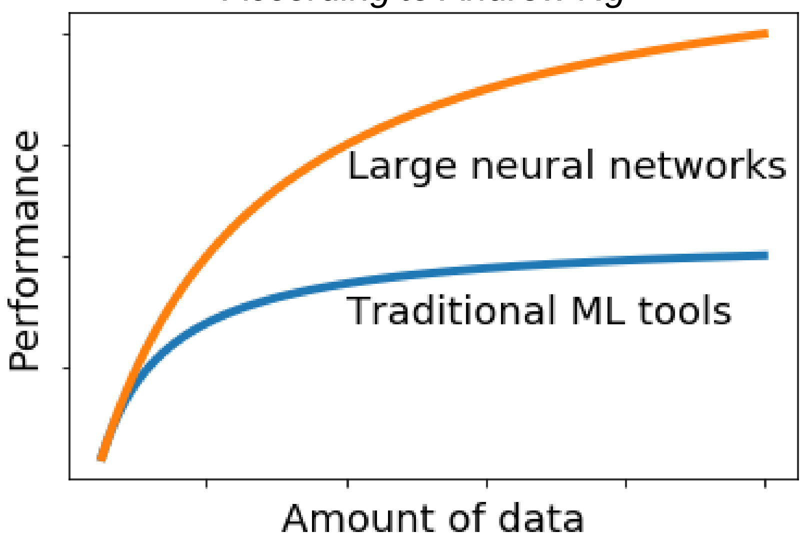
ML approach (data-driven)

- Choose a function set $\{g_\omega\}_{\omega \in \Omega}$
- Learn ω offline (e.g. from data)
- $\hat{x} = g_\omega(\theta) \approx x^*$

➔ **ML is much more than neural networks!**

Which Tools for MLC?

According to Andrew Ng



Key issues:

- Energy efficiency neglected
- Domain knowledge ignored
  ➔ Function properties not preserved
- Choice of performance metrics
- Amount of training data

Lower layers (PHY/MAC)	Higher layers
Collection of training data is limited • Fast time-varying channels and interference • **Short stationarity interval (V2X: 10-40ms)** • Distributed data • Limitations on computational power/energy	Huge datasets are available but • Incomplete data (missing measurements for long periods) • Erroneous data (e.g. software bugs) • Misaligned data (different times) • Time series (i.i.d. unrealistic)

Load Learning (cont.)

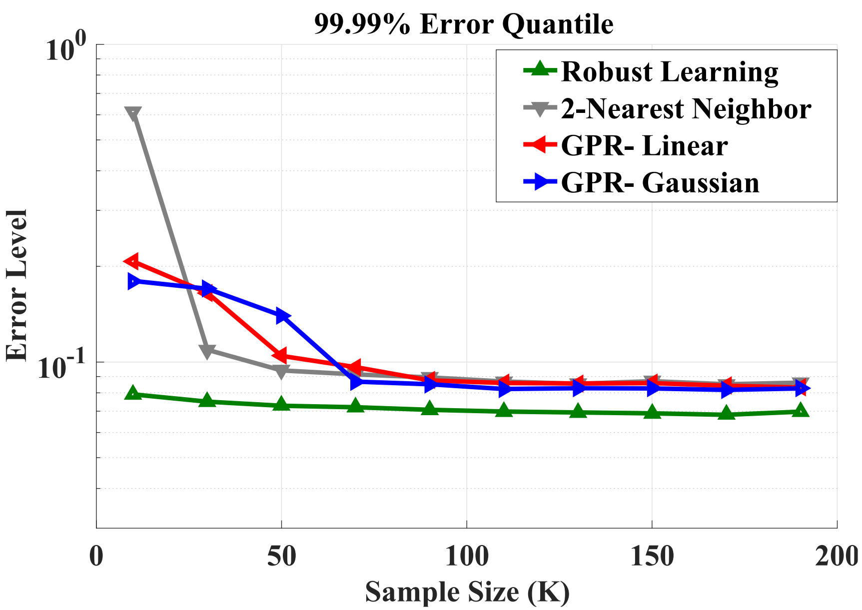
Challenge: The rate-load mapping (RLM) is highly dynamic and nonlinear owing to interference
➔ **training must be short**
➔ **important properties must be preserved**

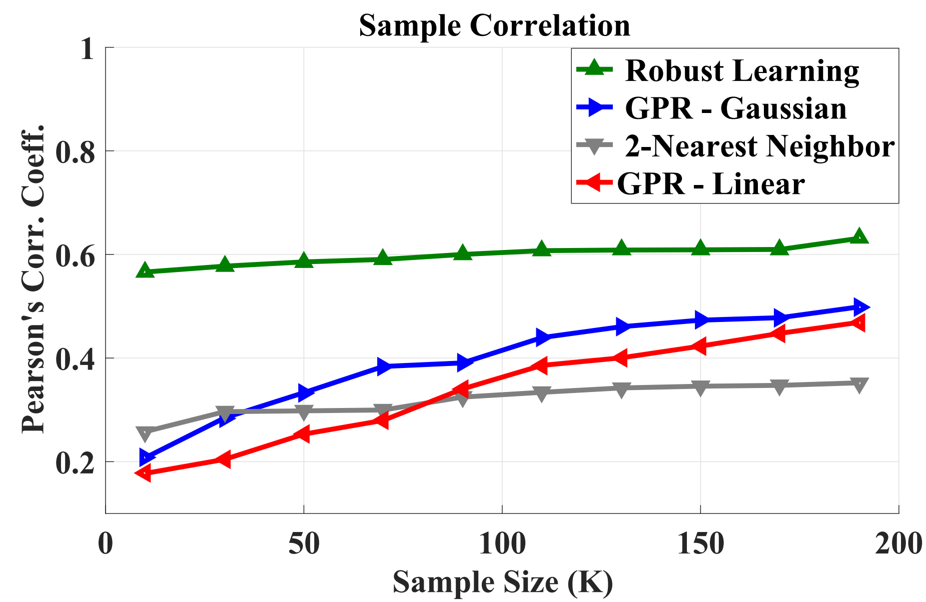
- Model-based approaches require too much a priori information
  But we should not ignore models

- The RLM has a rich structure (e.g., **monotonicity and Lipschitz**)
  They are hard to exploit in typical machine learning tools

Robust Online Load Learning

Hybrid-driven robust methods under uncertainty (e.g., few training samples)





- D. A. Awan, R. L. G. Cavalcante, and S. Stańczak, "A robust machine learning method for cell-load approximation in wireless networks," in Proc. IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP), 2018

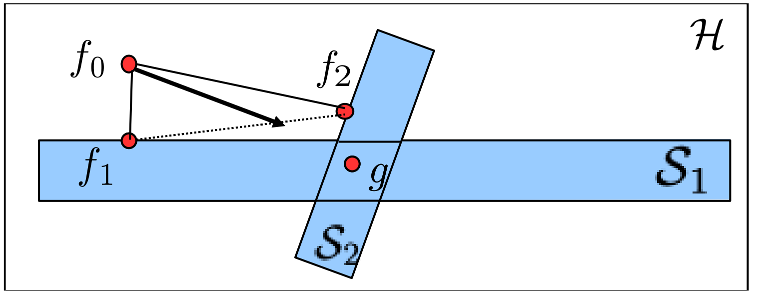
Demands on MLC

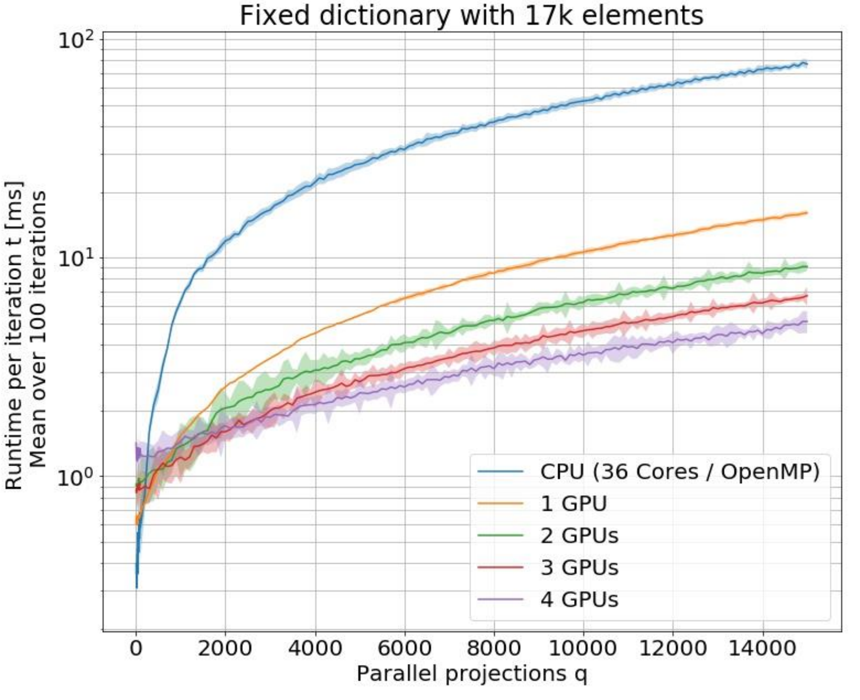
- ***Robust online*** ML with good tracking capabilities
  ➔ ML with small (uncertain) data sets
- Exploit ***domain knowledge*** (e.g. models, correlations, AoA)
  ➔ Hybrid-driven ML approaches (e.g. use production data)
  ➔ Learn features that change slowly over frequency, time...
  ➔ Preserve important function properties
- ***Distributed learning*** under communication constraints
  ➔ New functional architectures for Big Data analytics
- Low-complexity, ***low-latency implementation***
  ➔ New algorithms, massive parallelization

Learning in (Reproducing Kernel) Hilbert Spaces

Use projection methods in RKHS:

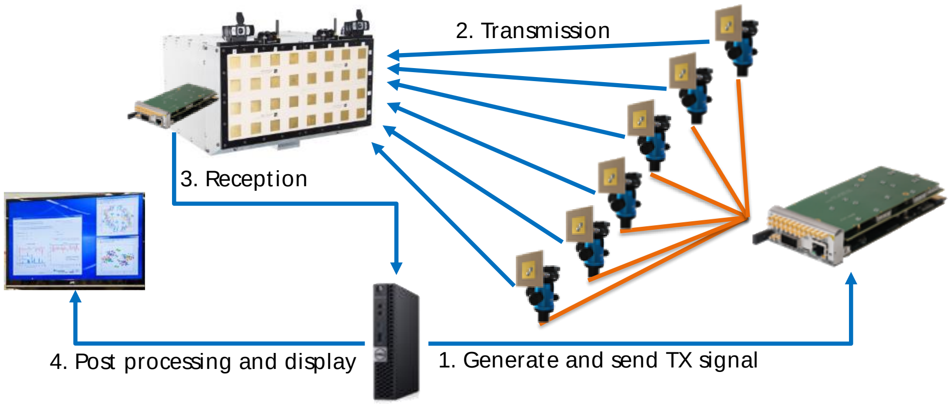
- ➔ Easy to exploit side information
- ➔ Initial fast speed
- ➔ Low complexity
- ➔ Convergence guarantees
- ➔ Massive parallelization via APSM for **fast learning on GPUs**

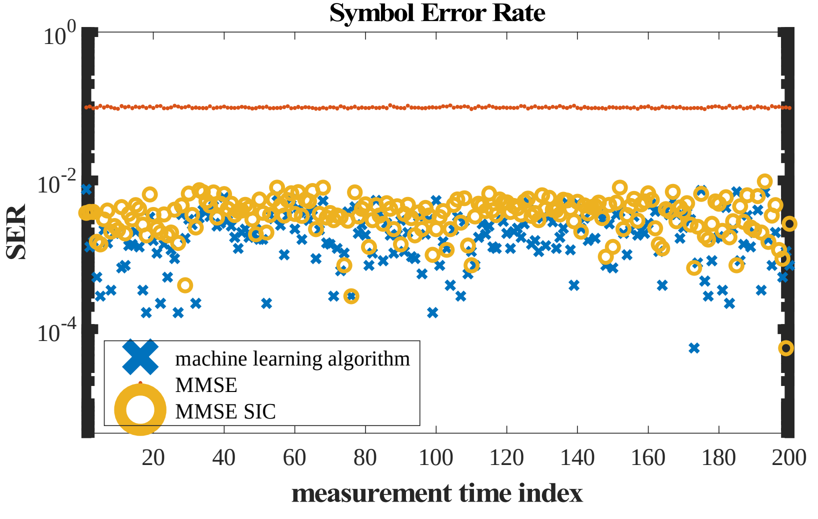


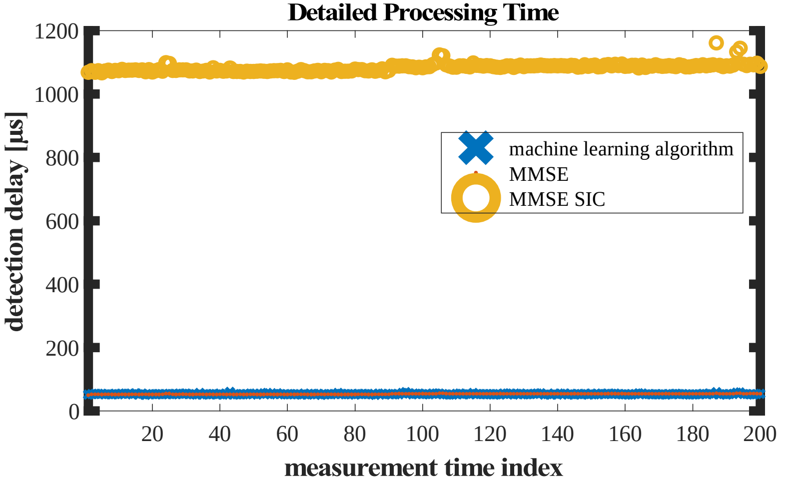


- I. Yamada and N. Ogura, "Adaptive projected subgradient method for asymptotic minimization of sequence of nonnegative convex functions," Numerical Functional Analysis and Optimization, vol. 25, no. 7/8, pp. 593–617, 2004.

Learning-based Reception for 5G NOMA







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- D. A. Awan, R.L.G. Cavalcante, M. Yukawa, and S. Stanczak. Adaptive Learning for Symbol Detection: A Reproducing Kernel Hilbert Space Approach. Wiley, 2019. to appear.
- M. Mehlhose et.al., “Machine Learning-Based Adaptive Receive Filtering: Proof-of-Concept on an SDR Platform” submitted Oct. 2019

Can we design better neural networks?

Sparsity in Communication Systems

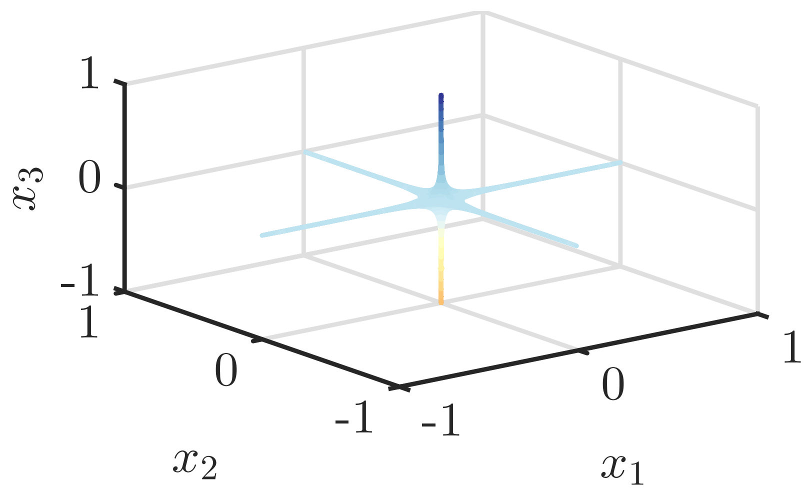
- Sparsity in the data (soft sparsity)
- Sparsity in the channel (soft sparsity)
- Sparsity in the user activity (hard sparsity)
- Sparsity in the network flow (hard sparsity)

We aren't likely to get a 1000X improvement in compute with the traditional, pure hardware improvements, or even better software and communication to put more chips together. It will need co-design of algorithms and compute e.g. can we create a model with a 1000X more parameters, but using only 10X more compute? I believe sparse models that address this issue and systems that can take advantage of these constraints will make a big difference.

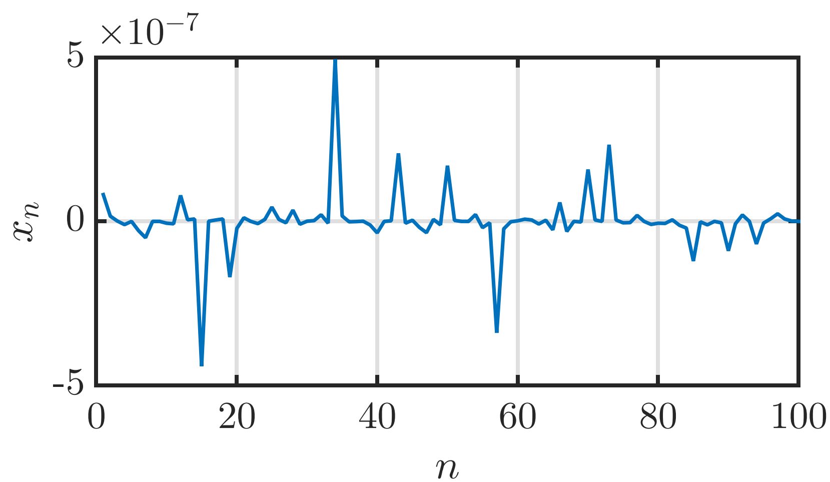
Rajat Monga, Google Brain, Lead Developer of TensorFlow

Sparsity in Communication Systems

- We can use $\mathcal{B}_p$-balls to model sparse signals $\mathcal{B}_p = \{\mathbf{x} : \sum_{i=1}^{N} |x_i|^{p_i} \leq 1\}$



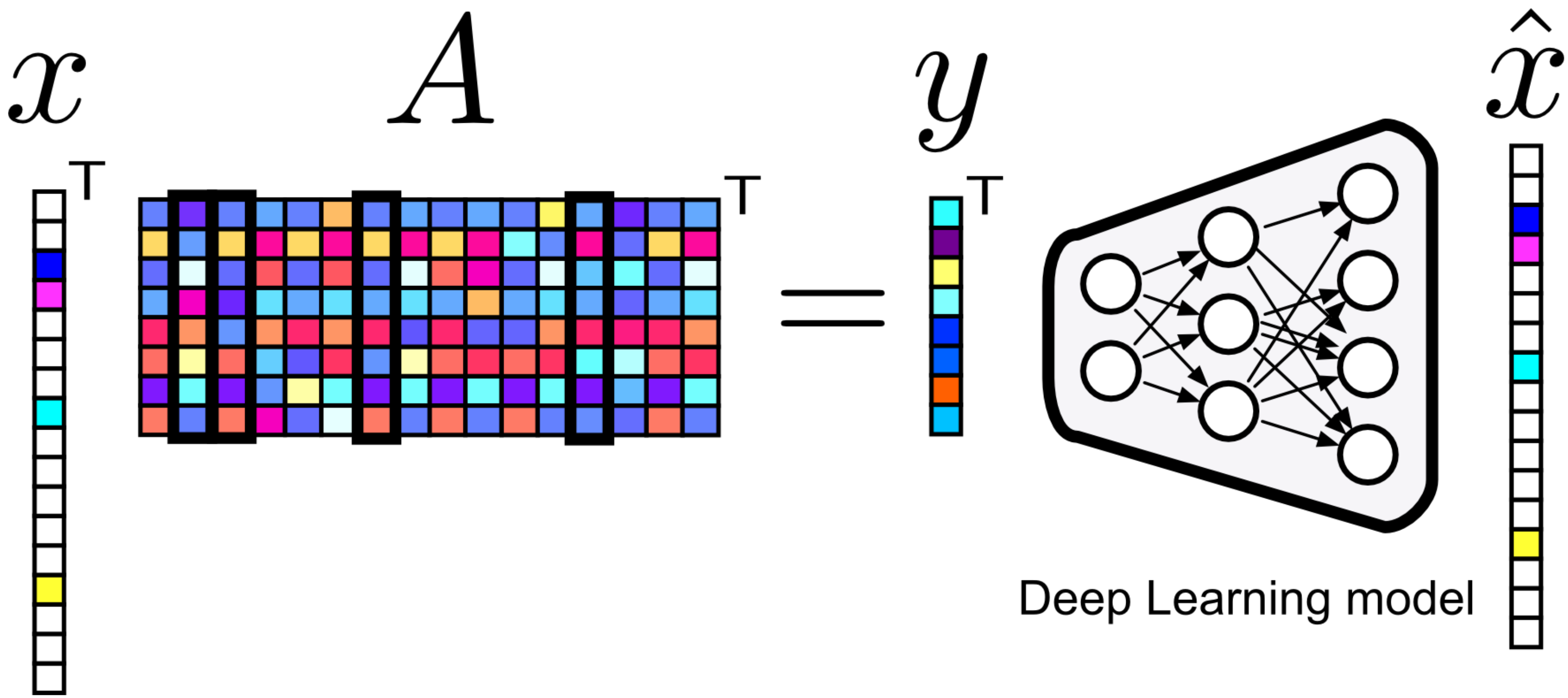
(a) $\mathcal{B}_{\boldsymbol{p}}$ for $\boldsymbol{p} = 0.25 \cdot \mathbf{1}$, $N = 3$



(b) realization of $p_{\mathbf{x}}$ for $\boldsymbol{p} = 0.25 \cdot \mathbf{1}$, $N = 100$

- S. Limmer and S. Stanczak, "Towards optimal nonlinearities for sparse recovery using higher-order statistics," 2016 IEEE 26th International Workshop on Machine Learning for Signal Processing (MLSP), Vietri sul Mare, 2016, pp. 1-6.

Sparse Recovery via a Deep Neural Network

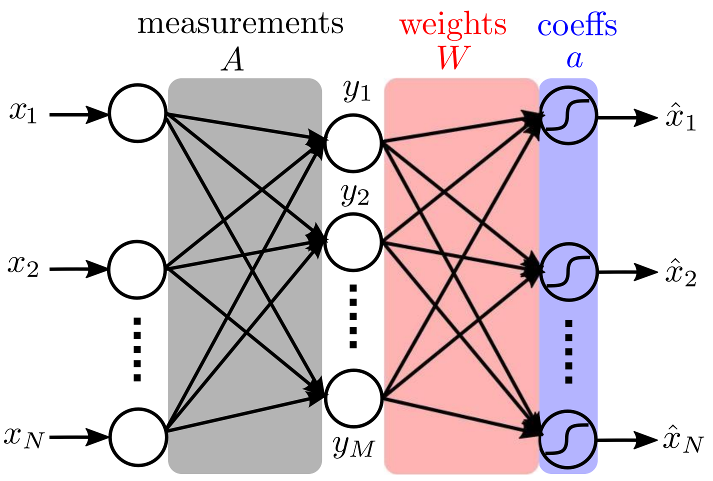


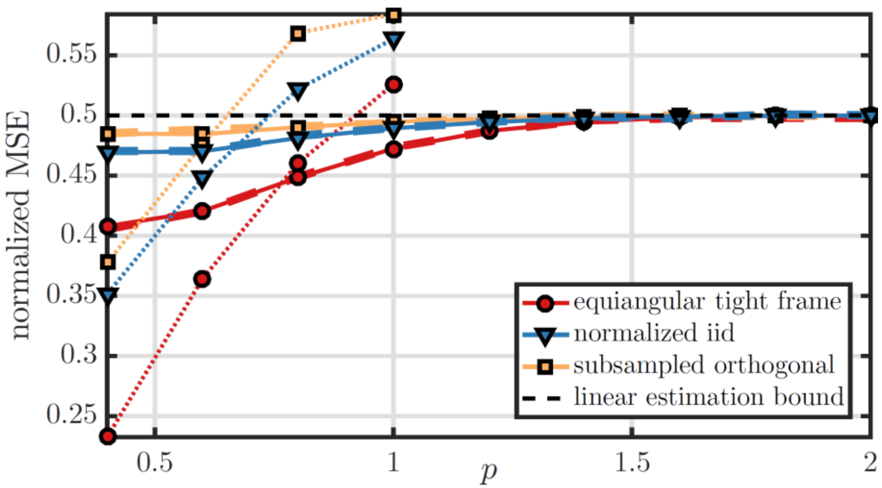
- CS methods are ***not*** suitable for low-latency applications
- Training must be short
  ➔ **Design** a good DNN for sparse recovery

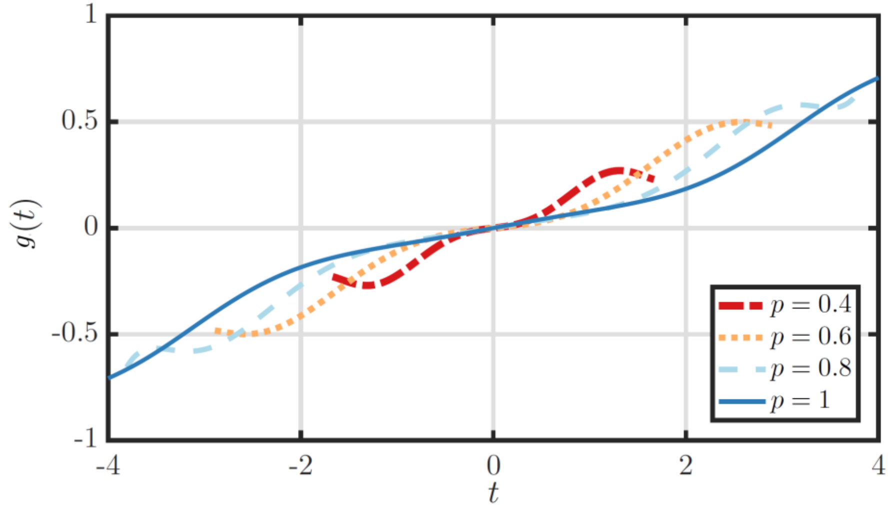
Optimization for MMSE Recovery

$\boldsymbol{A} \in \mathbb{R}^{3\times 6}$, activation σ with polynomial degree 9

- proposed (solid/dashed): linear estimator $+\epsilon \rightarrow$ online feasible
- LASSO (dotted): many iterations $\rightarrow$ online infeasible







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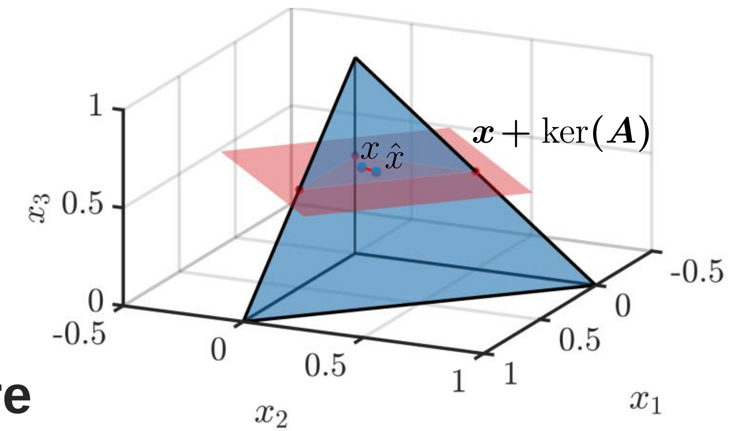
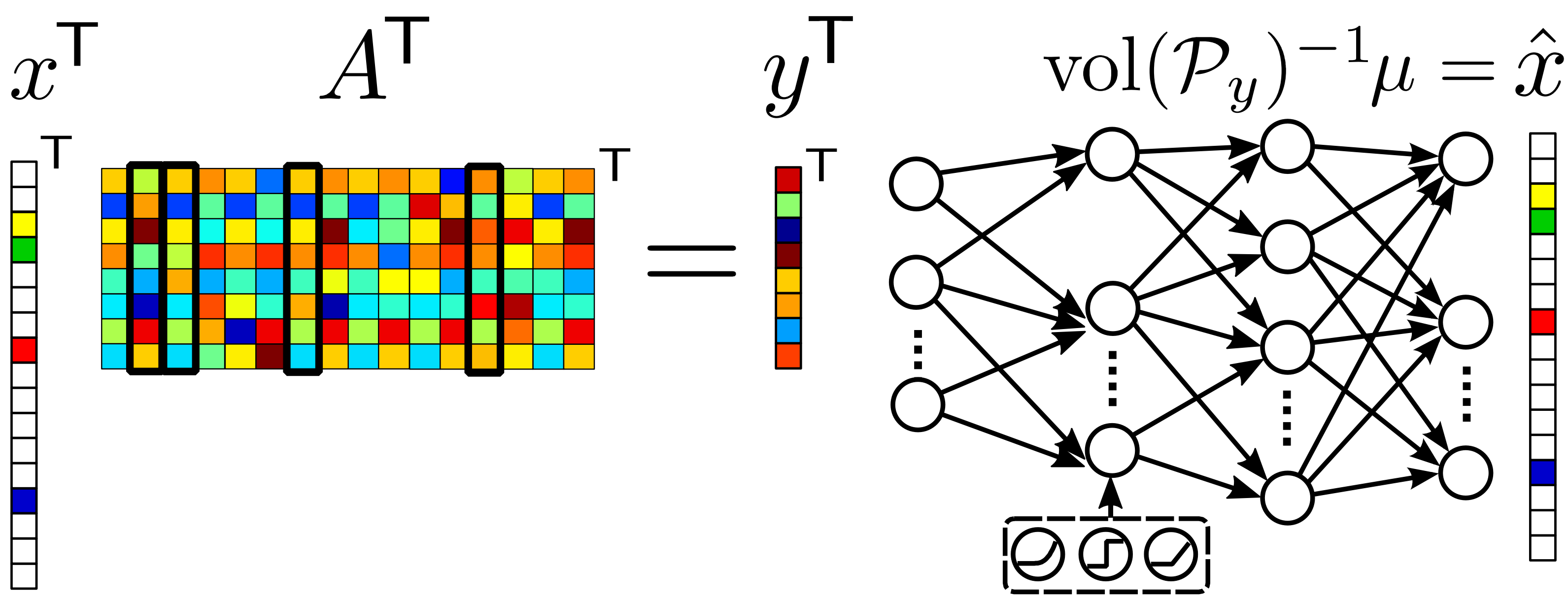
Designing DNNs via Laplace Techniques

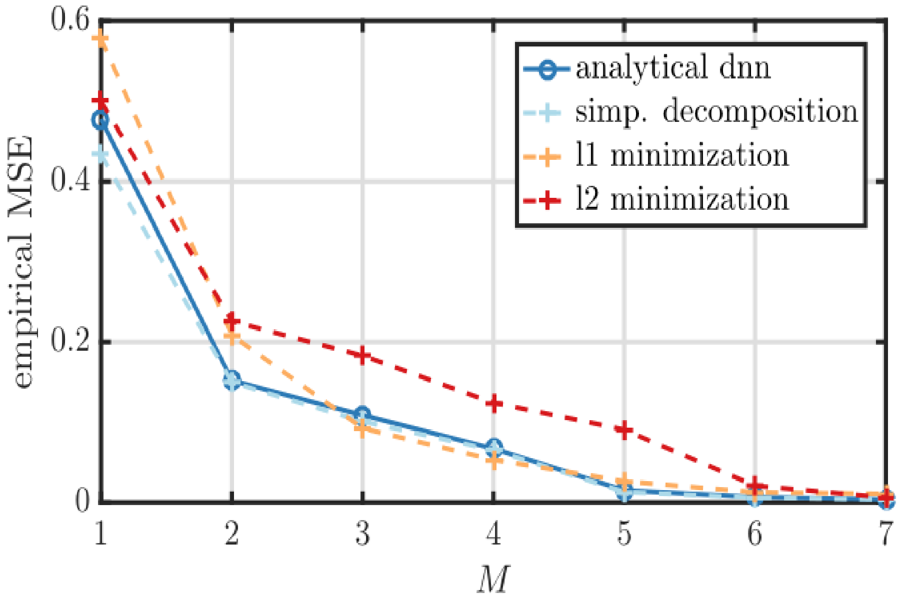
- Input uniformly distributed on
$$\mathcal{B}_1 = \{\mathbf{x} \geq 0 : \sum_{i=1}^{N} x_i \leq 1\}$$
- The conditional MMSE estimator is a polytope centroid under certain conditions.
  ➔ Volume and moment computation
- **Implementable using the DL architecture**

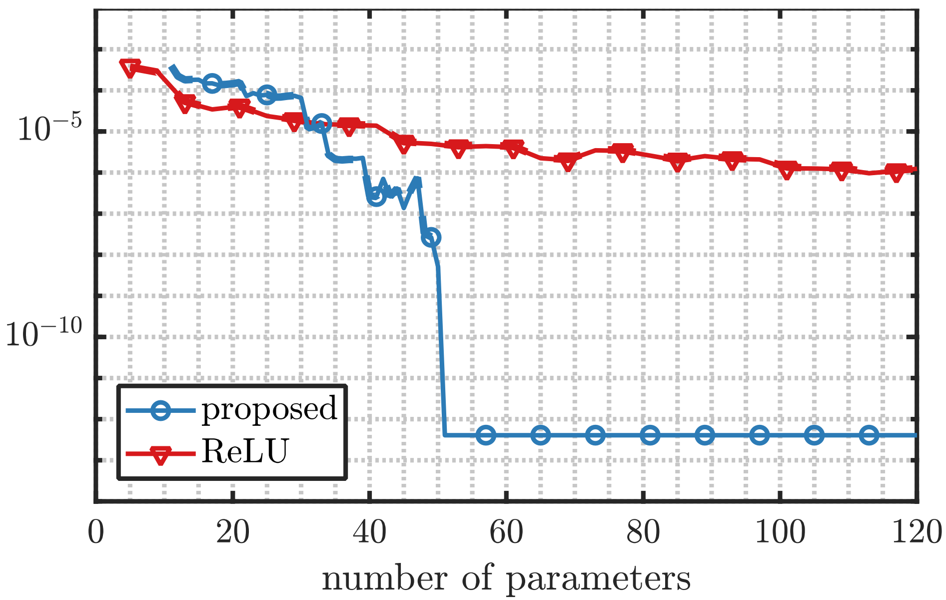




Numerical Experiments with Training

Real data





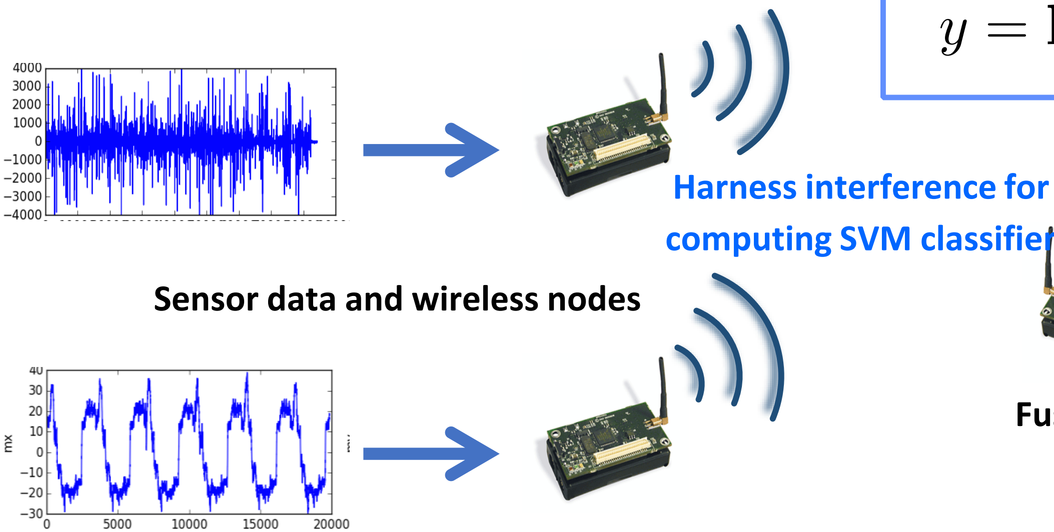
- S. Limmer and S. Stanczak, “A neural architecture for Bayesian compressive sensing via Laplace techniques“, IEEE Trans. On Signal Processing, Nov. 2018

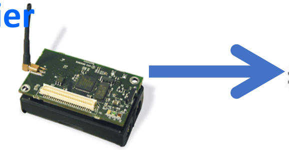
Take-away Message

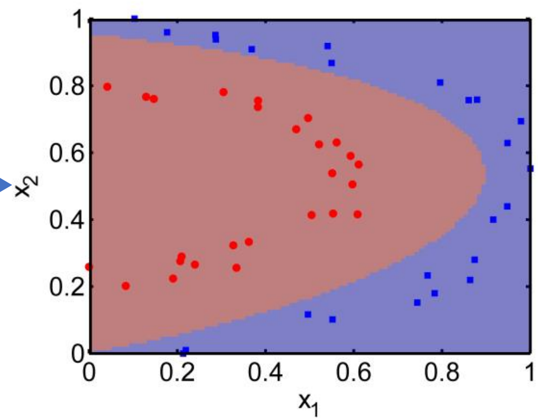
- ML/AI might be a “salvation” for industrial communication
- But there is a strong need for robust online ML methods
  → Exploit domain knowledge: Hybrid-driven distributed ML
  → Learn feature insensitive to frequency bands, phases …
- No time and data for extensive training of DNN
  → Design good NN architectures for a given task

Exploiting „Interference“ for Learning

$$y = \mathbf{h}^T \mathbf{x} + n \Rightarrow \psi\left(\sum_{k=1}^{K} \phi(x_k)\right)$$







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