Machine learning for non-linear signal processing in communications

Workshop on Neuromorphic High-Speed Communications (NeuCoS), December 9, 2021

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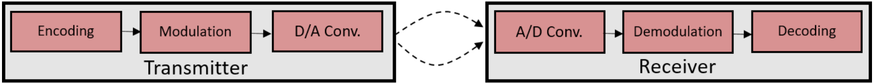
EINDHOVEN UNIVERSITY OF TECHNOLOGY

Machine Learning & Communications: An Unlikely Alliance?



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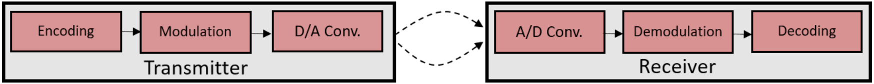

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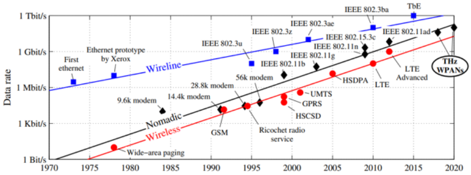

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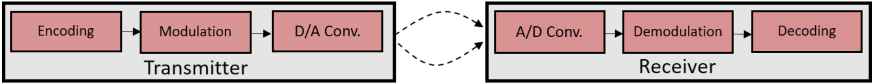

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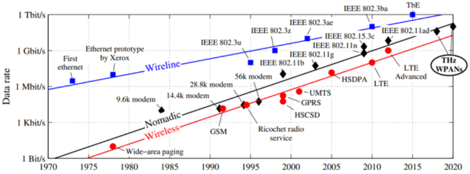

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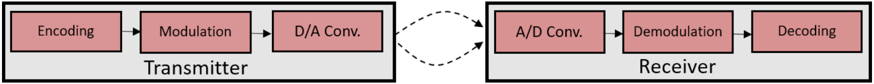

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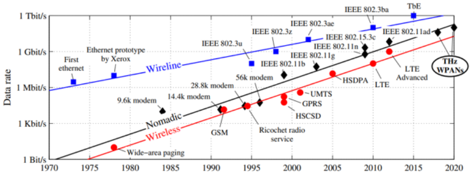

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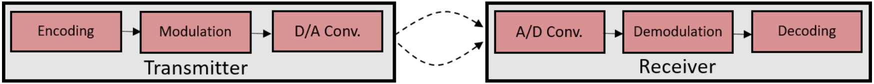

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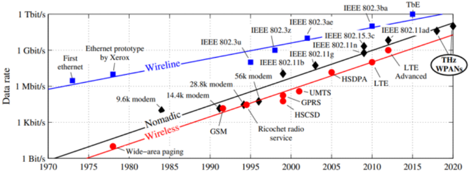

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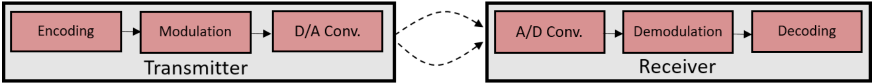

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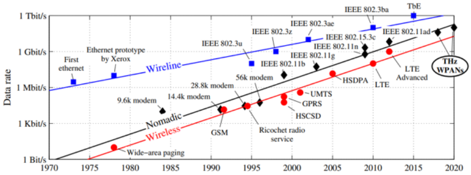

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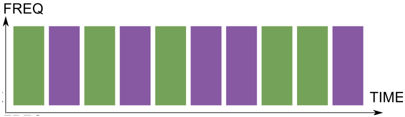
Outline

1. **"Black-box" Neural Networks**
   - Self-interference cancellation in full-duplex radios
   - Digital pre-distortion of power amplifier non-linearities

2. **Model-Based Neural Networks**
   - Deep unfolding for self-interference cancellation in full-duplex radios

Bi-directional Wireless Communications



Time-division duplexing (TDD)

Wasted time resources: switching interval

Frequency-division duplexing (FDD)

Wasted frequency resources: guard bands

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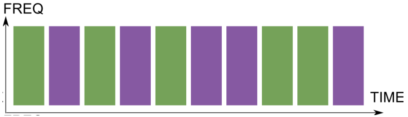

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In-Band Full-duplex (IBFD)

Up to twice the throughput wrt TDD & FDD!

No additional bandwidth

No wasted time or frequency resources

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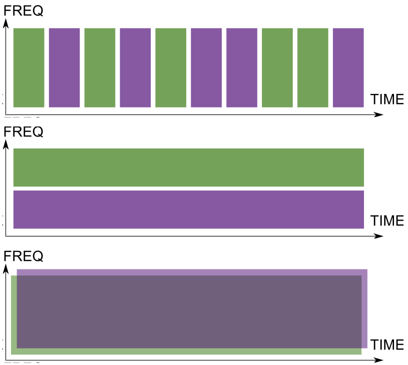
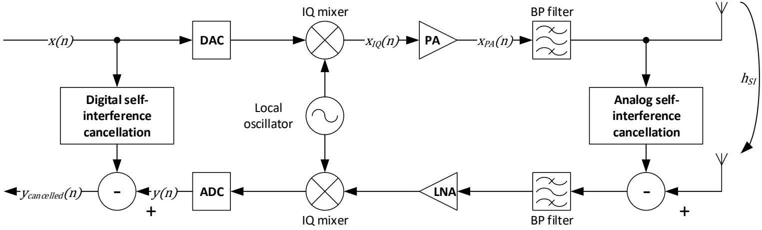


Fundamental Challenge

Self-interference is much stronger than the desired signal!

Self-Interference Cancellation in Full-Duplex Radios

- **In principle**, cancellation is easy since digital transmitted signal is known!
- **In practice**, the digital signal does not tell the whole story.



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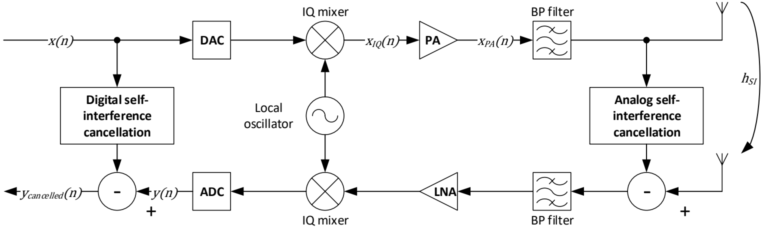

- **Three-stage** cancellation process:
  1. Passive analog cancellation
  2. Active analog cancellation
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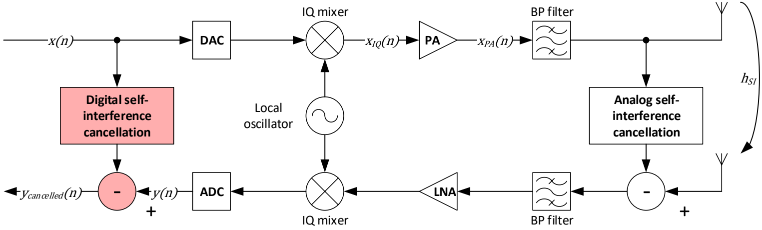

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Our focus: digital SI cancellation

Strong **non-linear** component effects need to be taken into account!

Self-Interference Cancellation Using a Polynomial Model

- Main transceiver non-linearities:
  1. **Power Amplifier:** Odd harmonics (even harmonics lie out of band when filtered)
  2. **Mixer:** IQ imbalance

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$$y[n] = \sum_{\substack{p=1,\\ p \text{ odd}}}^{P} \sum_{q=0}^{p} \sum_{l=0}^{L-1} h_{p,q}[l] \underbrace{x[n-l]^{q} x^{*}[n-l]^{p-q}}_{\text{basis functions}}$$

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Alternative Approach

Use a **neural network** to reproduce the SI non-linearities.

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Self-Interference Cancellation Using Neural Networks

- **Focus separately** on linear and non-linear SI: $y[n] = \underbrace{y_{\text{lin}}[n]}_{\text{easy!}} + \underbrace{y_{\text{nl}}[n]}_{\text{hard!}}$

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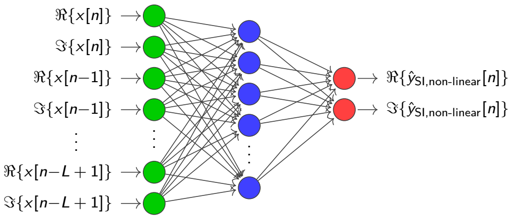

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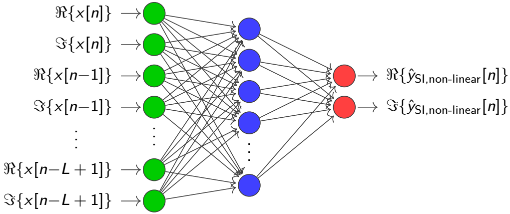

Identical SI cancellation with **significantly lower complexity** than the polynomial model!

Self-Interference Cancellation Performance

- **Dataset:** measured 20 MHz OFDM signal, sampled at 80 MHz
- **Performance evaluation:** $C_{\text{dB}} = 10\log_{10}\left(\frac{\sum_n |y[n]|^2}{\sum_n |y[n]-\hat{y}[n]|^2}\right)$

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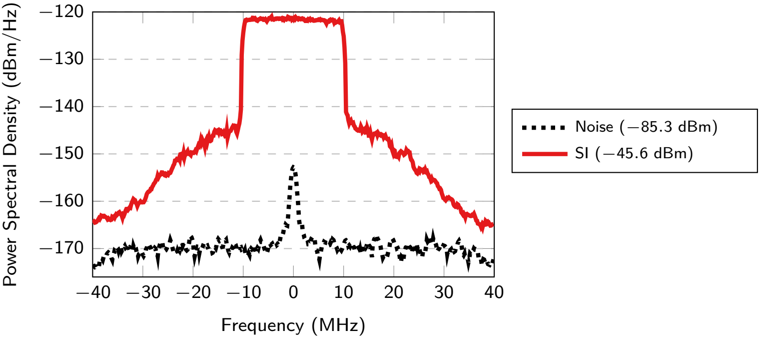

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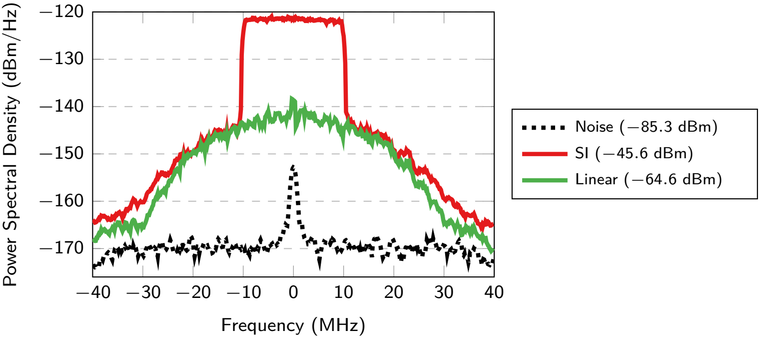

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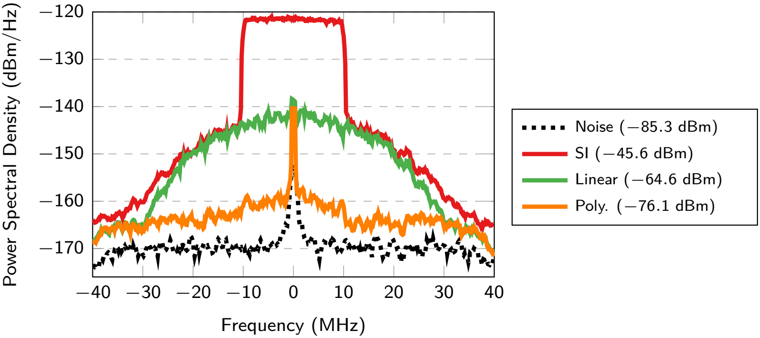

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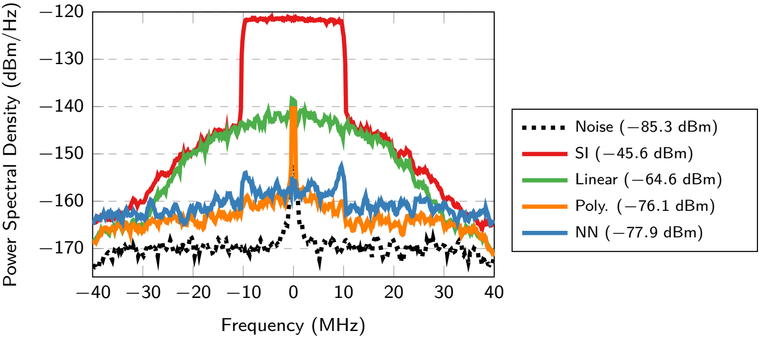

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Self-Interference Cancellation Complexity

	Polynomial	NN
Cancellation (dB)	30.5	32.3
Real Additions	418	82 (**−80%**)
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How do these gains translate into hardware?

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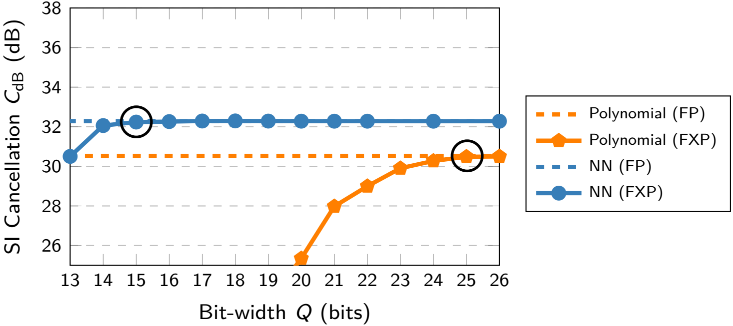

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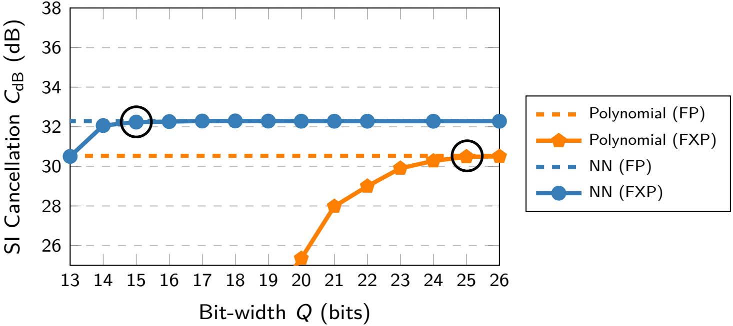

ASIC Implementation (28nm FD-SOI, typical corners, at 0.9 V, 25 °C)

	Polynomial	NN
Throughput (MS/s)	80	80
Area (mm^2)	0.18	0.02 (**−89%**)
Power (mW)	84.1	11.0 (**−87%**)

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- Xilinx System Generator
- Zynq UltraScale+ RFSoC ZCU1285

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NN models may be **less sensitive to low oversampling!**

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Model-Based Neural Networks via Deep Unfolding

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Deep Unfolding [Hershey et al., 2014]

"[...] given a model-based approach that requires an iterative inference method, we unfold the iterations into a layer-wise structure analogous to a neural network"

1. J. R. Hershey, J. Le Roux, F. Weninger, "Deep unfolding: Model-based inspiration of novel deep architectures," arXiv:1409.2574, Nov. 2014

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Large number of applications in communications & signal processing!

Examples:

1. Deep unfolding for self-interference cancellation in full-duplex radios

1. J. R. Hershey, J. Le Roux, F. Weninger, "Deep unfolding: Model-based inspiration of novel deep architectures," arXiv:1409.2574, Nov. 2014
2. A. Balatsoukas-Stimming and C. Studer, "Deep unfolding for communications: A survey and some new directions," IEEE Workshop on Signal Processing Systems (SiPS), Oct. 2019
3. V. Monga, Y. Li, Y. C. Eldar, "Algorithm unrolling: Interpretable, efficient deep learning for signal and image processing," IEEE Signal Processing Magazine, Mar. 2021

Deep Unfolding for Self-Interference Cancellation

- **Concept:** unfold the non-linear equations and train using backpropagation

$$y[n] = \sum_{l=0}^{L-1} \sum_{\substack{p=1,\\ p \text{ odd}}}^{P} h_p[l] (\underbrace{K_1 x[n-l] + K_2 x^*[n-l]}_{x_{\mathrm{IQ}}[n-l]}) | (\underbrace{K_1 x[n-l] + K_2 x^*[n-l]}_{x_{\mathrm{IQ}}[n-l]}) |^{p-1}$$

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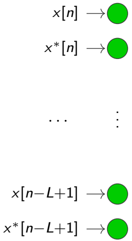

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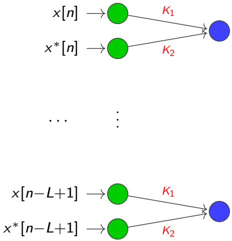

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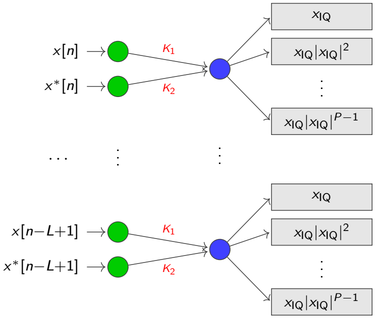

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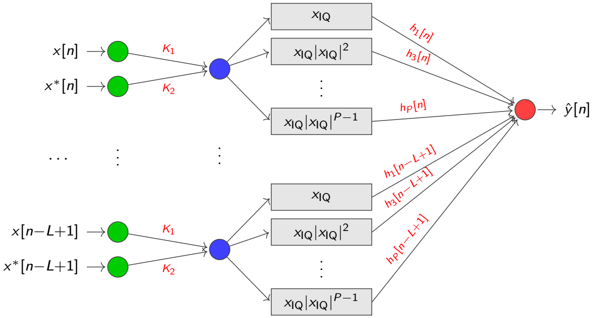

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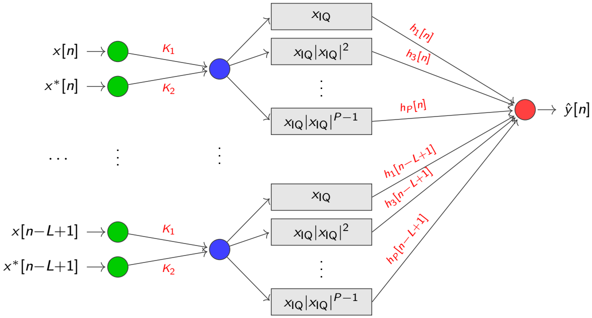

- **Goal:** $\left\{\hat{h}_p[l], \hat{K}_1, \hat{K}_2\right\} = \arg \min_{\{h_p[l], K_1, K_2\}} \frac{1}{N} \sum_{i=1}^{N} |y[n] - \hat{y}[n]|^2$

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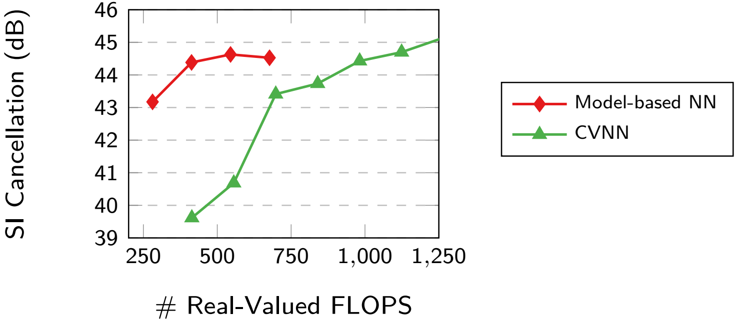
Deep Unfolding for Self-Interference Cancellation - Results



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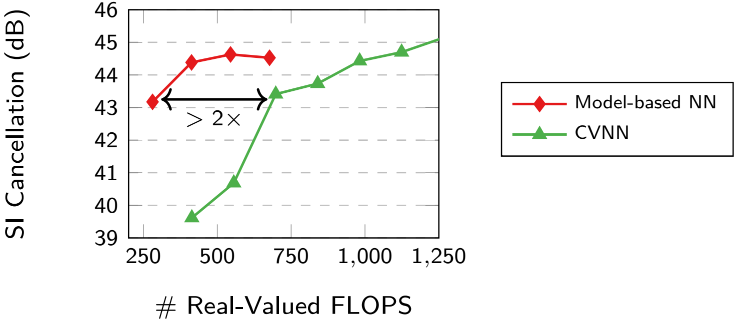

- More than **2x lower complexity** than black-box NNs for the same performance!

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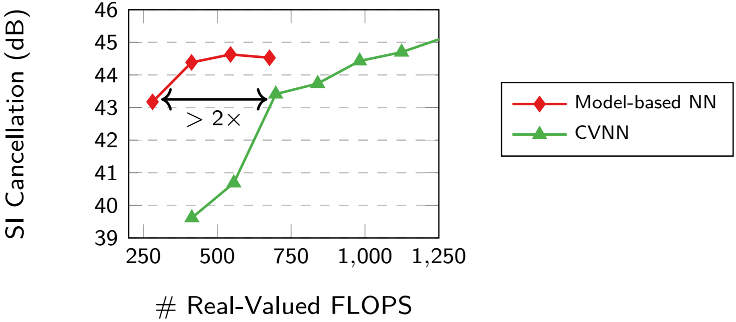

- More than **2x lower complexity** than black-box NNs for the same performance!
- Can be used verbatim in many other applications, such as DPD.

Conclusions

Main take-away messages:

1. Neural networks are particularly well-suited for **non-linear signal processing**.
2. Deep unfolding is an elegant way to obtain **compact and efficient model-based neural networks** for communications & signal processing.

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Questions?