PHYSIC-INFORMED MACHINE LEARNING TECHNIQUES FOR EMC PROBLEMS

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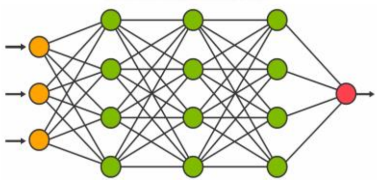
Vrije Universiteit Brussel (VUB)

EMC Forum, Sønderborg, 29 – 30 June 2026

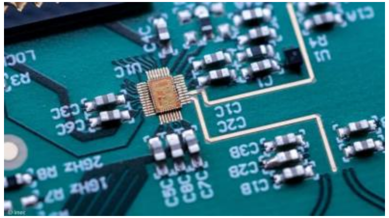
ELEC MM2IC RESEARCH GROUP

- Focus on
  - Design, modeling, experimental characterization of complex RF/mmWave systems

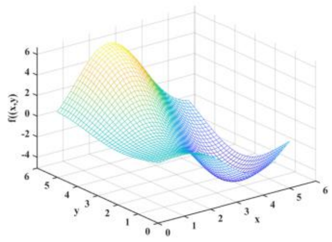


Data-driven modelling
System identification
Machine learning

Characterization
Data/feature engineering



RF system characterization and modelling



Model-based design of electronic components

EXAMPLE OF APPLICATION

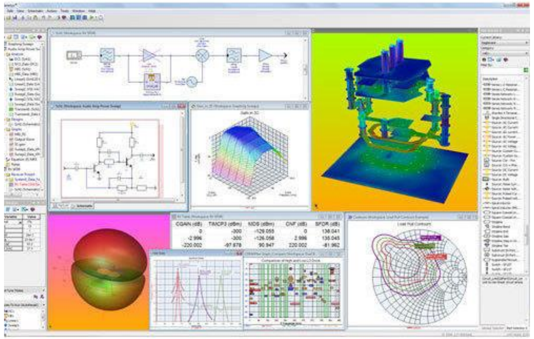
- Heterogeneous integration of nonlinear, thermal & EM-simulations, design
  - Integrate power amplifier and antenna design
  - Realization and measurements up to D-band

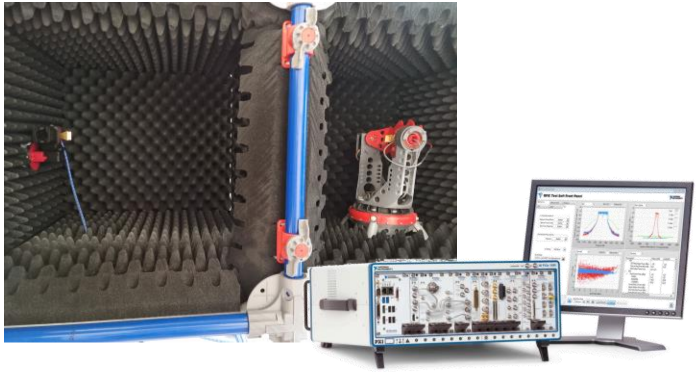
METHODOLOGY

Combine different simulation domains

- electromagnetic simulations
- electronic SPICE simulations
- device physics / TCAD simulations
- thermal simulations

Data from simulations and instrumentations





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- Team
  - Prof. Gerd Vandersteen
    - Design
  - Prof. Dries Peumans
    - Measurements

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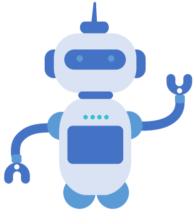
    - Measurements
  - Profs. John Lataire and Domenico Spina
    - System identification and macromodeling

INTRODUCTION

- EMC, SI and PI are crucial for modern circuits
  - Complex systems under several physical effects
  - Must be robust to interferences and be integrated with other components (digital)

- New production technologies, increased complexity and high operational frequencies bring new challenges to EMC/SI/PI design!

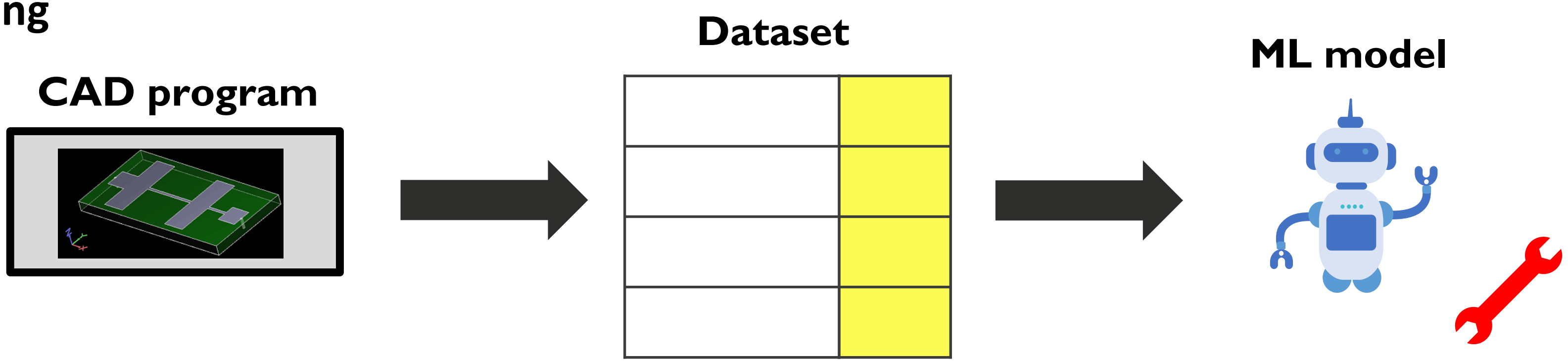
- What is the role of Machine Learning (ML)?



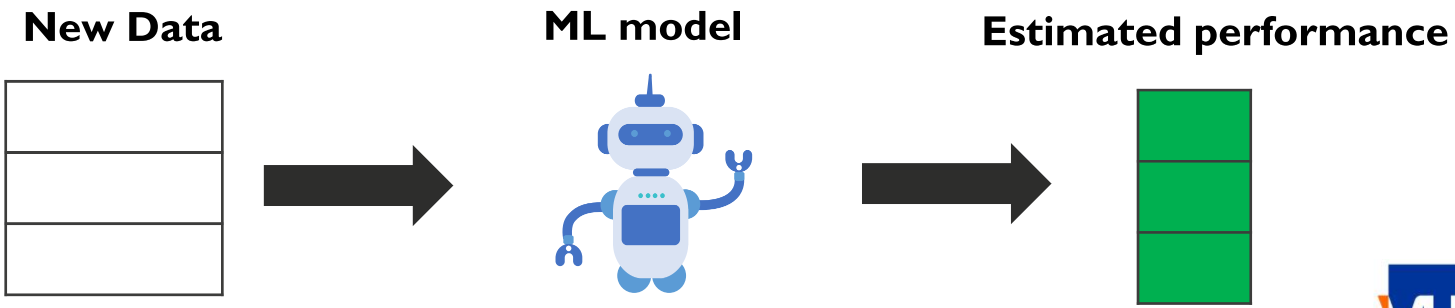
- What is ML?
  - ML is a set of methodologies in artificial intelligence (AI)
    - Mathematical techniques able to learn information from a set of data
    - Supervised ML

MACHINE LEARNING FOR ELECTRICAL ENGINEERING

1. **Training**



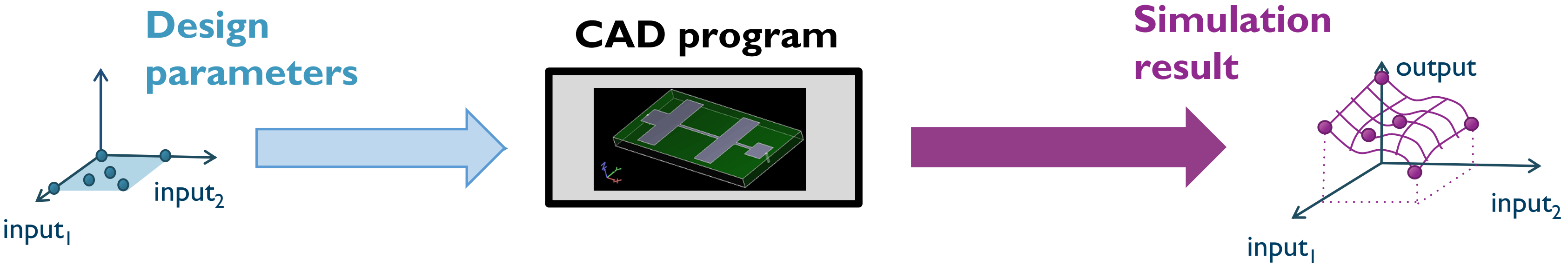
2. **Application**



- What is ML?
  - ML is a set of methodologies in artificial intelligence (AI)
    - Mathematical techniques able to learn information from a set of data
    - Supervised ML
- How can ML be applied to EMC, SI & PI?
  - Let's see an example

Design Process

1. Design an analog device/circuit in a simulation program (CAD)
2. Define design parameters
3. Tune value of design parameters until desired performance are reached



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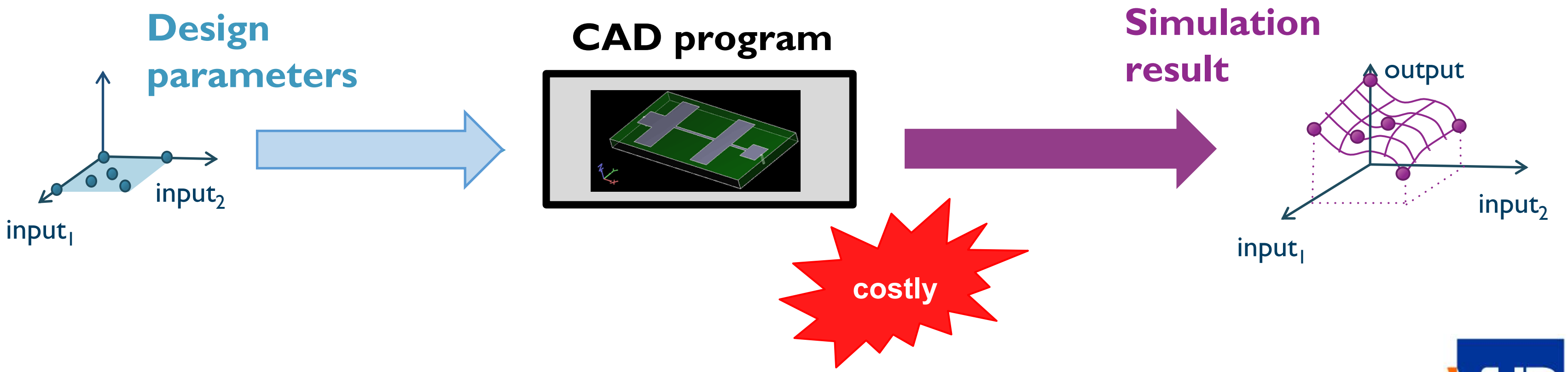

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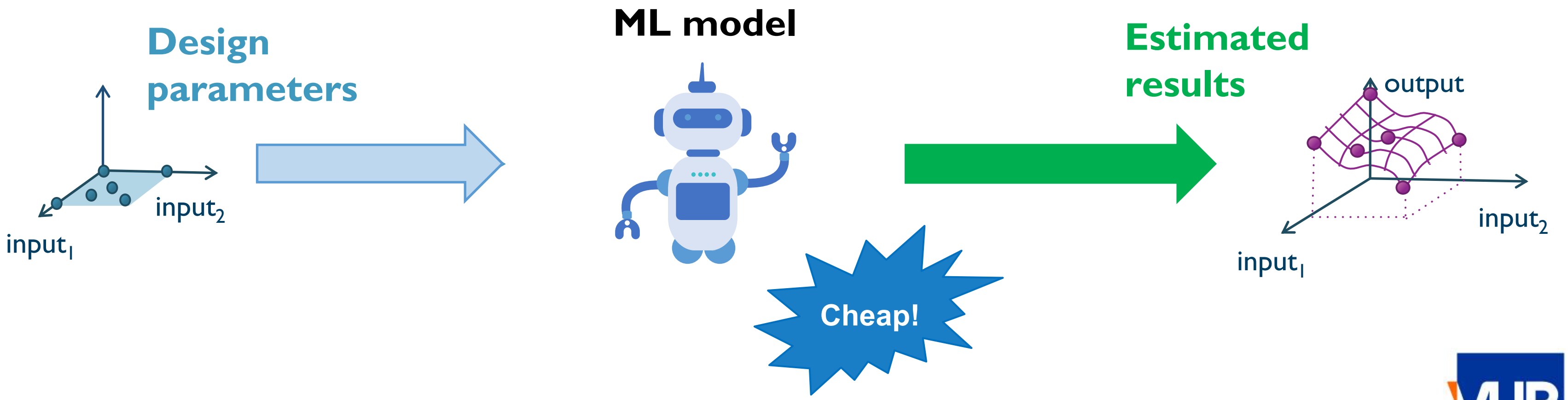

MACHINE LEARNING FOR ELECTRICAL ENGINEERING

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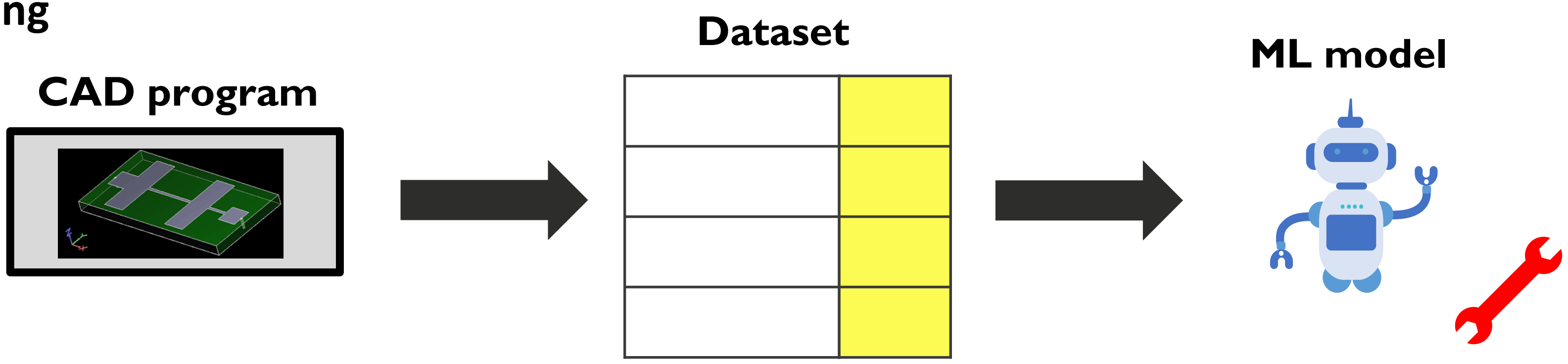

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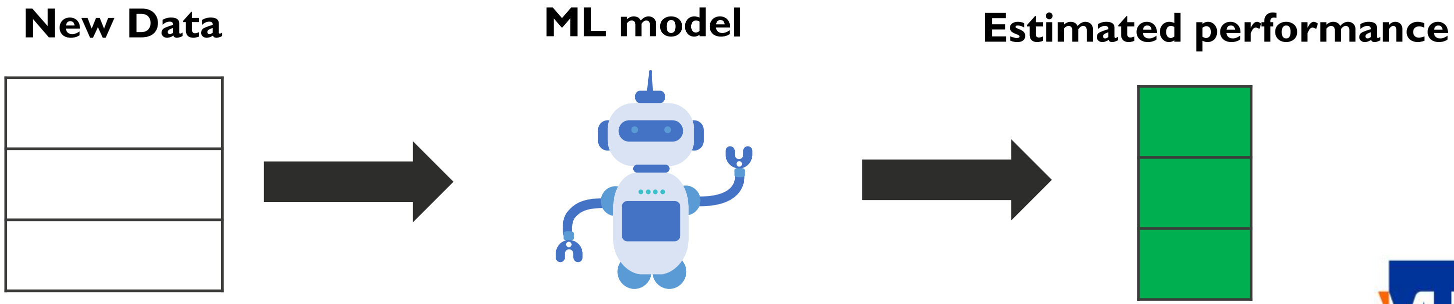

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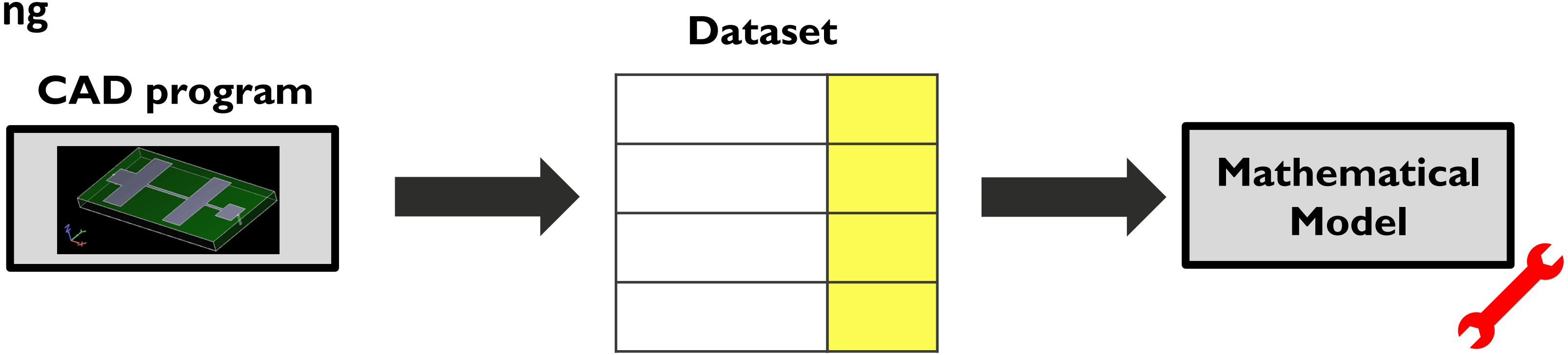

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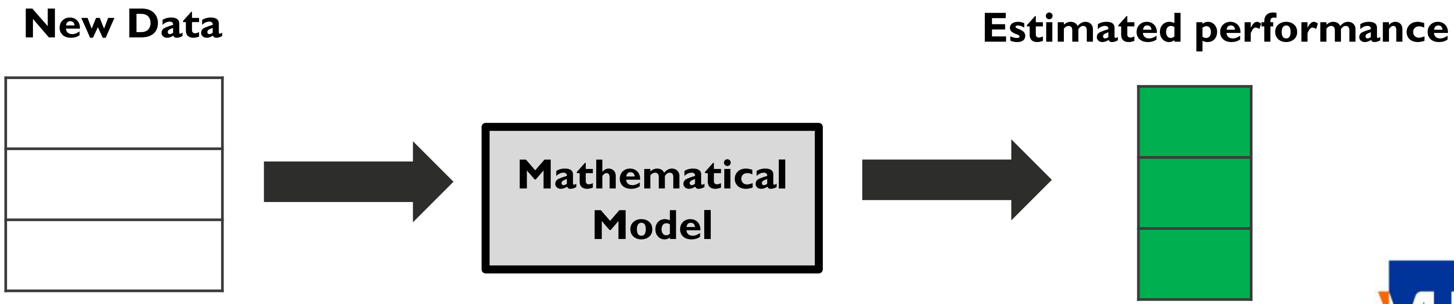

MACHINE LEARNING FOR ELECTRICAL ENGINEERING

- Macromodel (Surrogate model, Behavioral model): low-complexity model describing the I/O behaviour of the system under study
  - Vector Fitting
  - Response Surface Modeling

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- **Properties**
  - Able to describe complex systems
    - Resonance, nonlinear effects, crosstalk, ….

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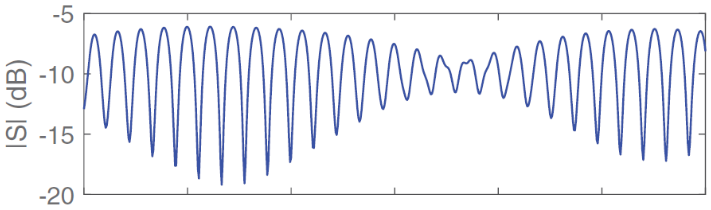
  - Accurate estimation
  - Generalize well to unseen data

  - Able to handle large amount of data or design parameters

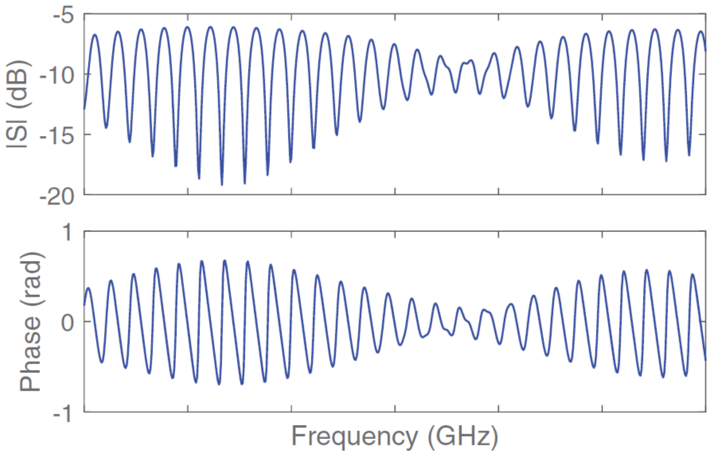
- **Examples of ML applications in electrical engineering**
  - Scattering parameters modeling [Akinwande24]
  - Transfer function extrapolation [Guo23, Zhou26]
  - Inverse problems [Karahan24]
  - SI & PI analysis on PCB: [Hillebrecht25]
  - Generative design for analog IC [Noori25, De Haseleer25]
  - Broadband Interconnect modeling: [Garbuglia23, Yihune26]
  - Eye diagram optimization: [Lee25]

- Challenges
  - Model highly correlated elements



- Frequency samples close to each other

- Challenges
  - Model highly correlated elements



- Frequency samples close to each other
- Magnitude and phase

- Challenges
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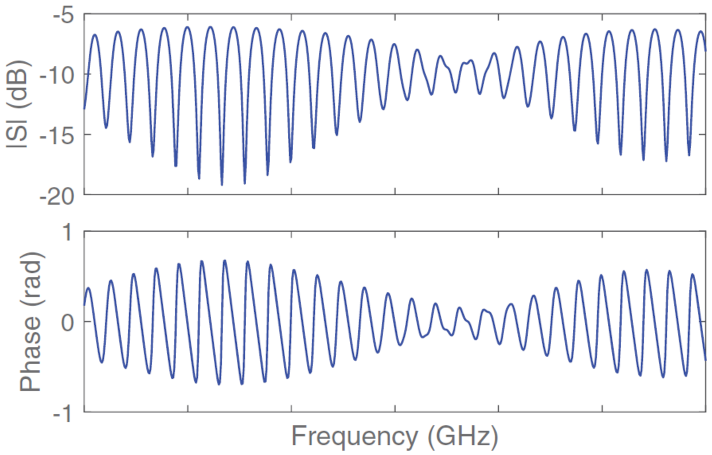
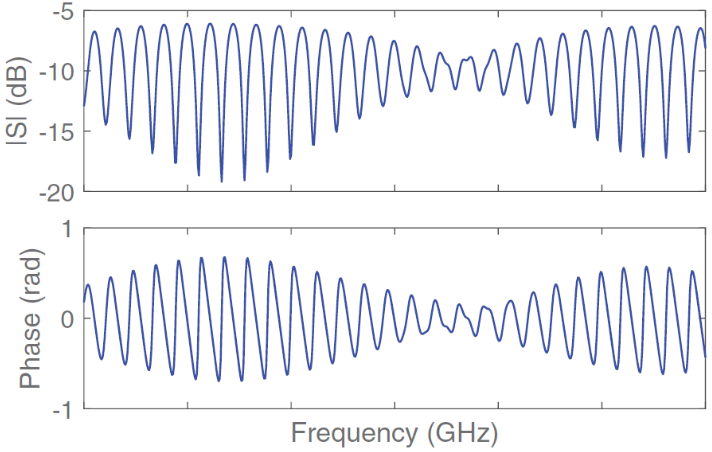
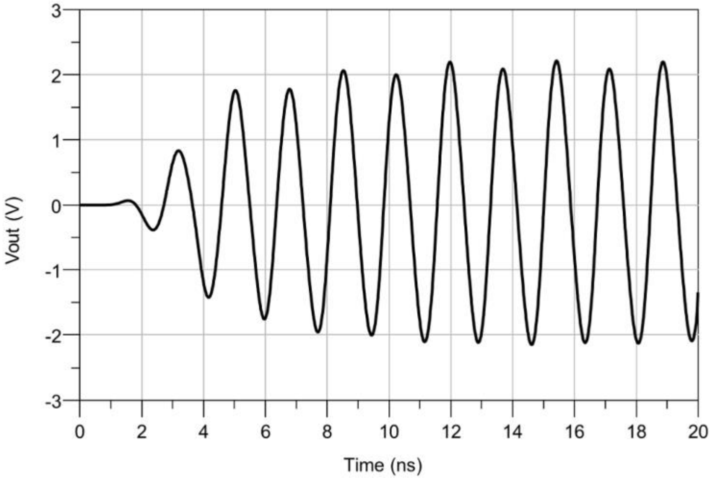


- Frequency samples close to each other
- Magnitude and phase
- Different element of scattering matrix

- Challenges
  - Model highly correlated elements
  - Analyze behaviour of DUT in frequency and time



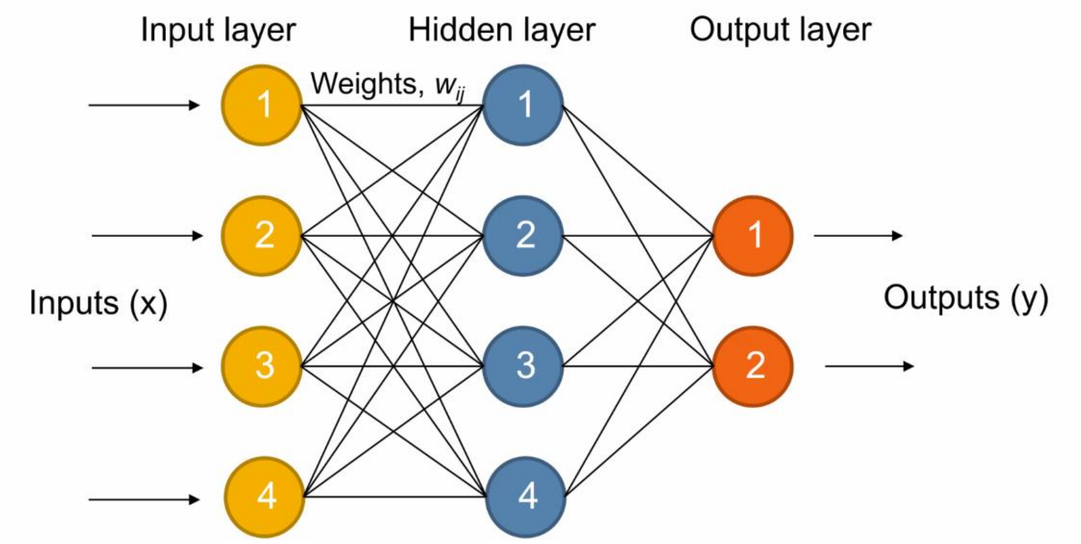


PHYSICS-INFORMED MACHINE LEARNING

- Merging domain-expertise with ML fundamental!
  - Physics-informed ML

- Two examples
  - Neural Networks
  - Gaussian Process

- Neural Network: overview



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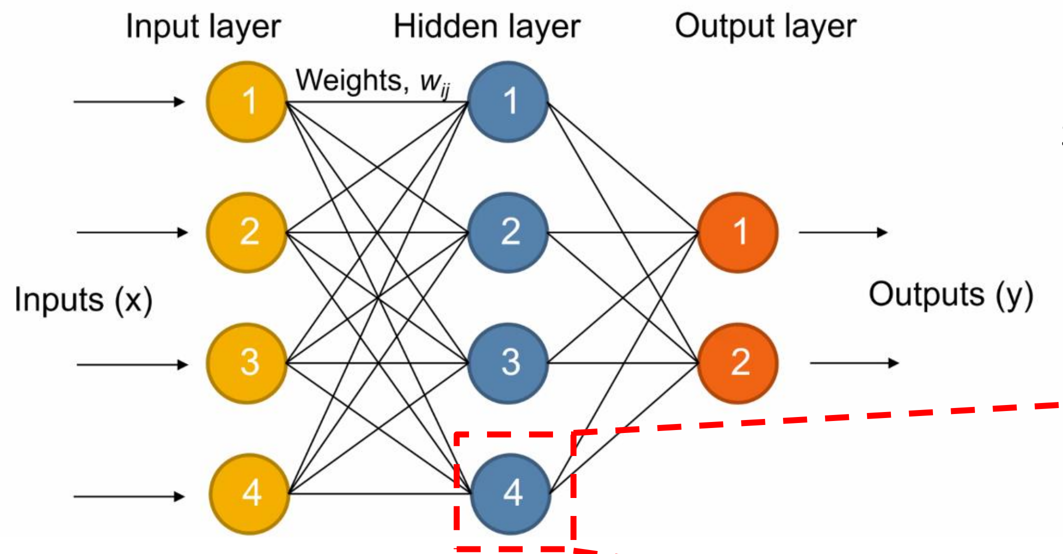
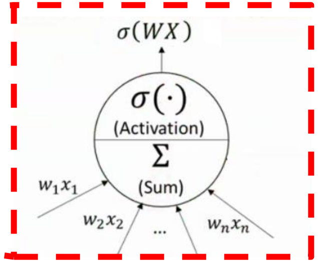


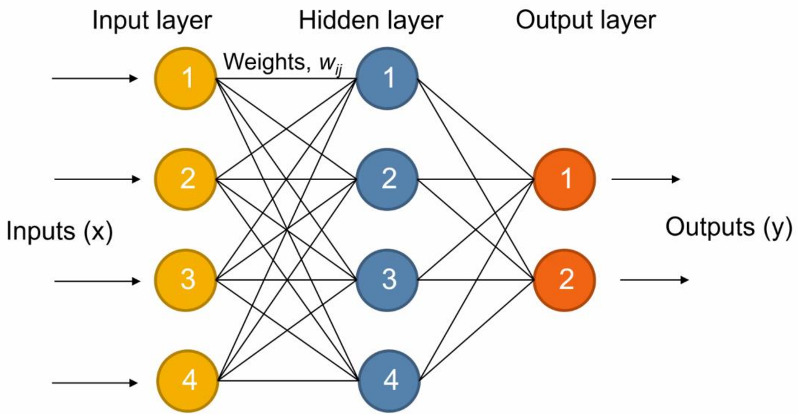
Single Neuron

- Input X
- Create a weighted sum
- Pass through non-linear activation function (Introduces nonlinearity and bounds output)



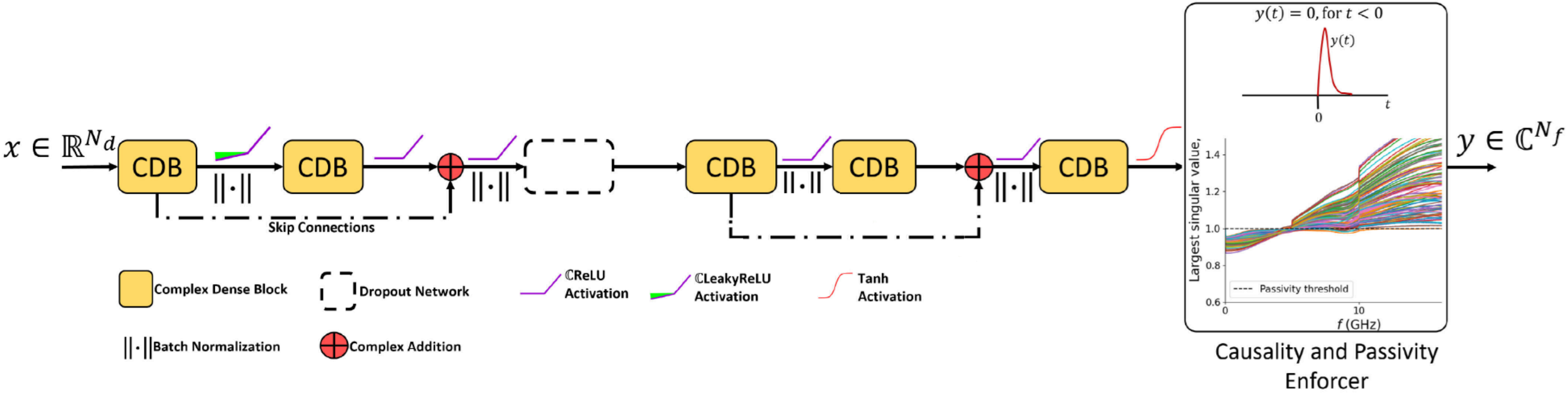
PHYSICS-INFORMED MACHINE LEARNING

- Neural Network: How to train?
  - User has to decide architecture
    - Number of hidden layers
    - Size each hidden layer
    - Activation function
  - Purpose training
    - Find optimal value of hyperparameters
      - Weights and parameters $\sigma(\bullet)$
    - Number of hyperparameters can influence the size of training dataset
  - How?
    - Calculating gradients of suitable error measure (cost function) w.r.t. hyperparameters
    - Using gradients to find hyperparameters' value → minimum of cost function



PHYSICS-INFORMED MACHINE LEARNING

- **Complex NN for Scattering parameters modeling**
  - Input: design parameters
  - Output: complex S-parameters



[Akinwande24]

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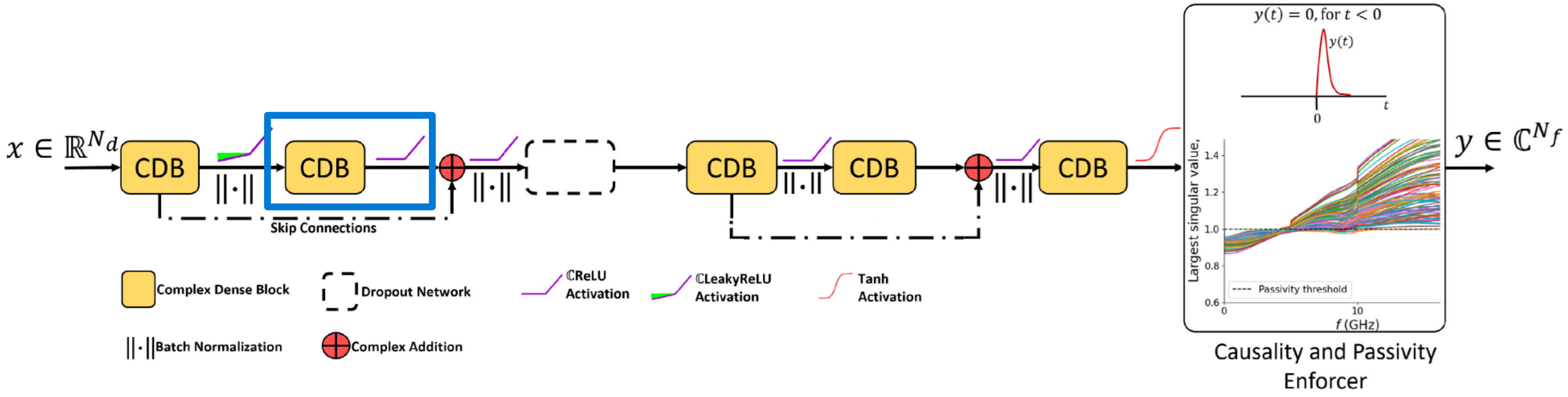

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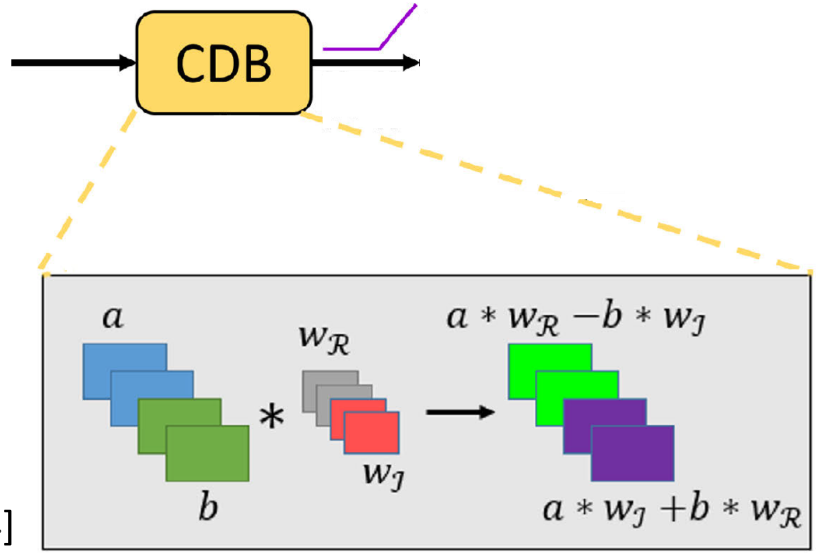
COMPLEX NEURAL NETWORKS

- **Complex dense block (CBD)**
  - Let's define $z = a + jb$
  - CBD computes $w * z = (a * \Re(w) - b * \Im(w)) + j(a * \Im(w) + b * \Re(w))$



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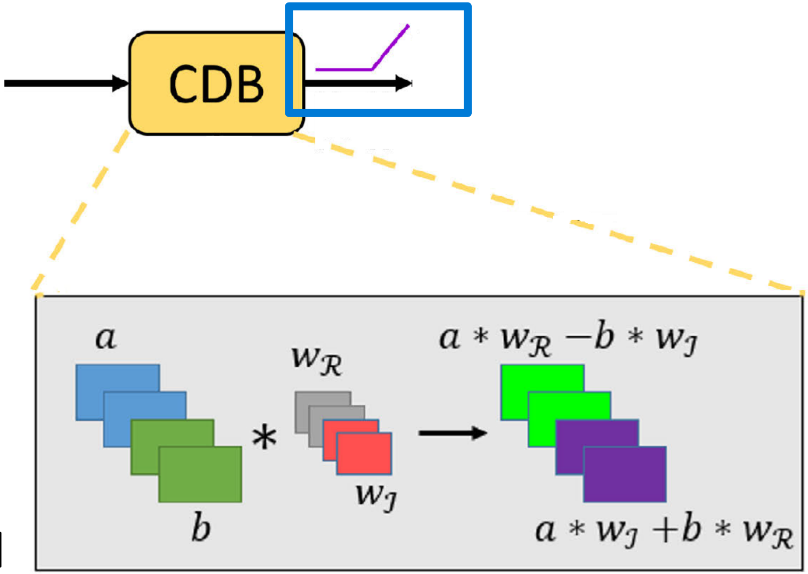

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- **Nonlinear complex activation function**

$$\tanh(z) = \frac{e^z - e^{-z}}{e^z + e^{-z}}$$

$$\mathbb{C}\mathrm{ReLU}(z) = \mathrm{ReLU}(a) + j\mathrm{ReLU}(b)$$

$$\mathbb{C}\mathrm{LeakyReLU}(z) = \mathrm{LeakyReLU}(a) + j\mathrm{LeakyReLU}(b)$$

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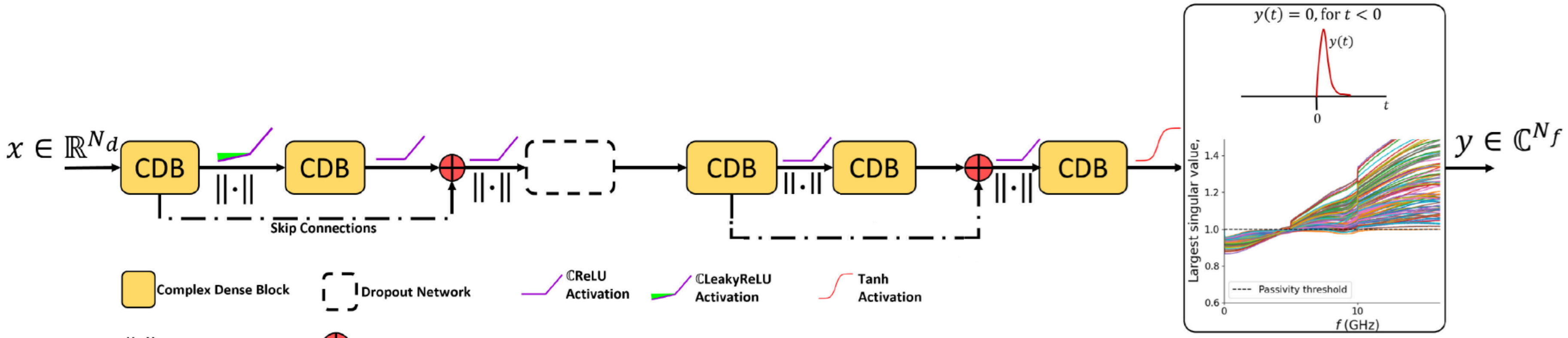

Causality and Passivity Enforcer

[Akinwande24]

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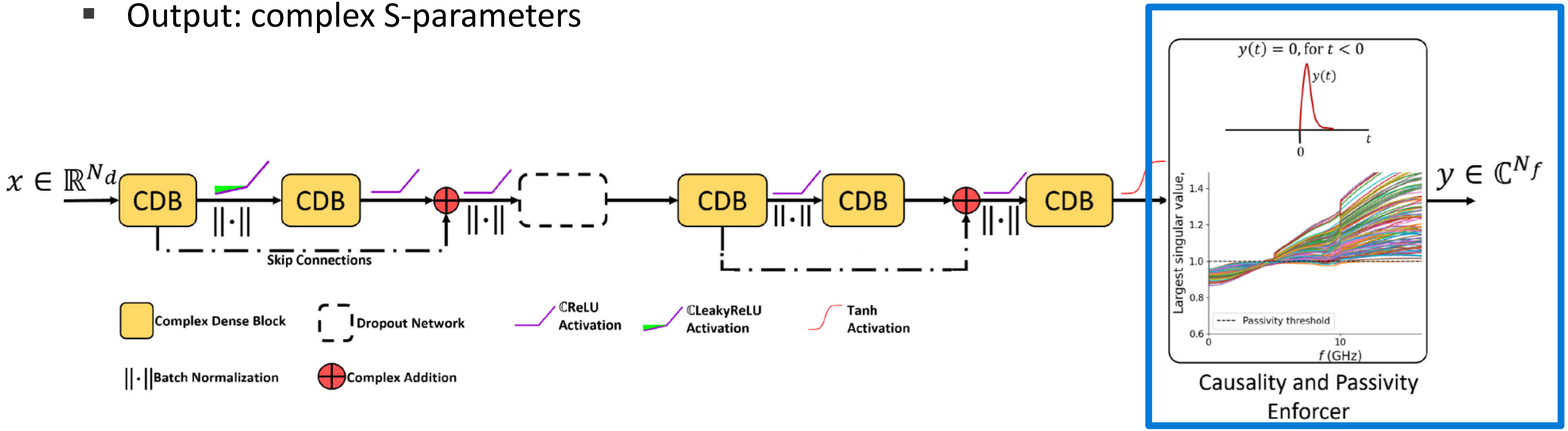


[Akinwande24]

PHYSICS-INFORMED MACHINE LEARNING

- **Causality**
  - Preserved
- **Passivity Assessment**
  - SVD to estimate singular values (sv) of S-parameters: max(sv(f)) <1
  - Approximated via efficient upper bound
- **Passivity Enforcement**
  - Filtering computed S-param via minimum-phase filter
  - Serves as causality enforcement

- **Realization minimum-phase filter**

for $i : f_i \in B$ **do**

Calculate an upper bound for the largest singular value $\hat{\sigma}_1(f_i)$

Implement minimum-phase filter as:

$$\Sigma(f_i) = |\Sigma(f_i)| e^{j\phi(f_i)} \quad \Rightarrow \quad |\Sigma(f_i)| = \begin{cases} \frac{1}{\hat{\sigma}_1(f_i)}, & \text{for } \hat{\sigma}_1(f_i) > 1 \\ 1, & \text{for } \hat{\sigma}_1(f_i) \leq 1 \end{cases},$$

$$\phi(f_i) = \mathscr{H}\{\log|\Sigma(f_i)|\}.$$

/* $\mathscr{H}\{\cdot\}$ is the Hilbert transform computed via FFT */

Enforce passivity as: $S_P(f_i) = \tilde{S}(f_i) \odot \Sigma(f_i)$.

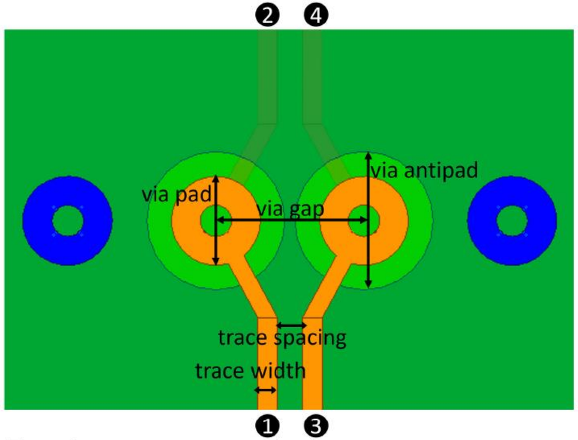
Adapted from [Akinwande24]

PHYSICS-INFORMED MACHINE LEARNING

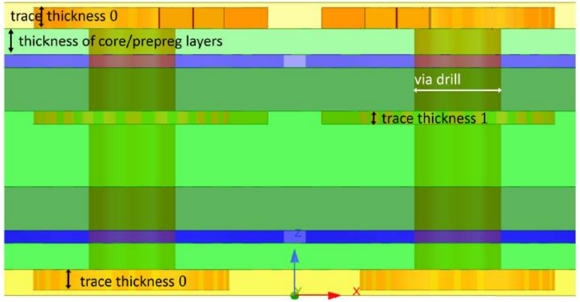
Example: five layer through – hole vias

- Four port device
- Sparam [0.02 – 20] GHz via HFFS
- 9 Design parameters, Train/Test samples = 900/100

Parameter		Unit	Min	Max
Trace spacing (first layer)	t_{s1}	mil	3.5	20
Trace thickness (first layer)	t_{t1}	mil	0.6	1.55
Trace width (first layer)	t_{w1}	mil	2.5	12
Trace spacing (third layer)	t_{s3}	mil	3.5	20
Trace thickness (third layer)	t_{t3}	mil	0.6	1.55
Trace width (third layer)	t_{w3}	mil	2.5	12
Anti-pad diameter	d_a	mil	22	28
Drill diameter	d_d	mil	8	10
Pad diameter	d_p	mil	16	20



Top view

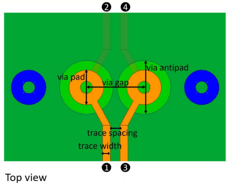


Cross section

[Akinwande24]

PHYSICS-INFORMED MACHINE LEARNING

- **Example: five layer through – hole vias**
  - Mean absolute error over test set: S11 = 0,133 dB, S12 = 0,036 dB



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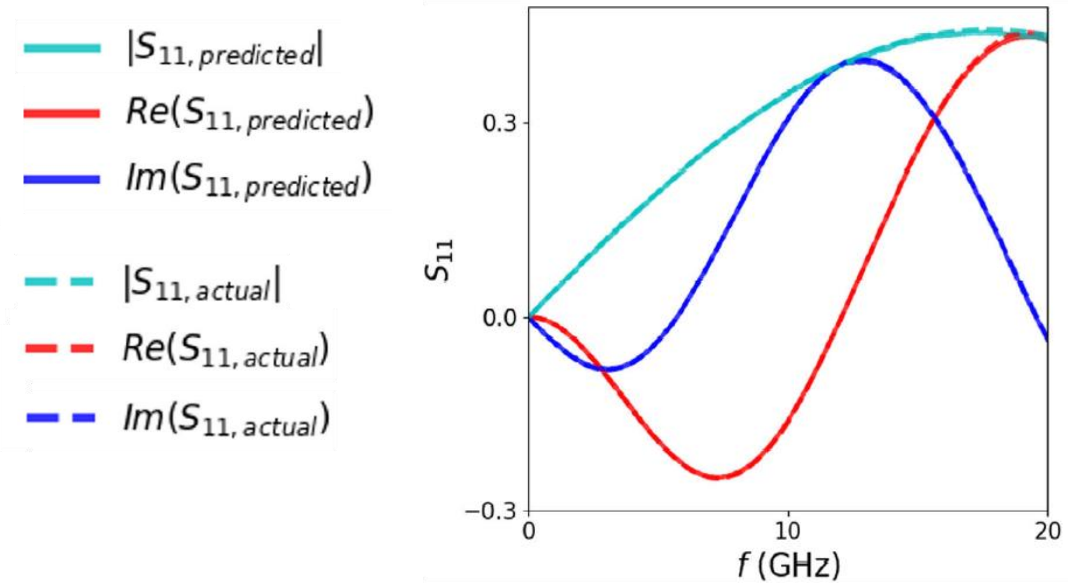

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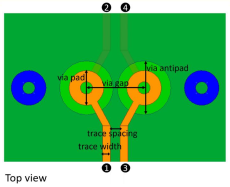
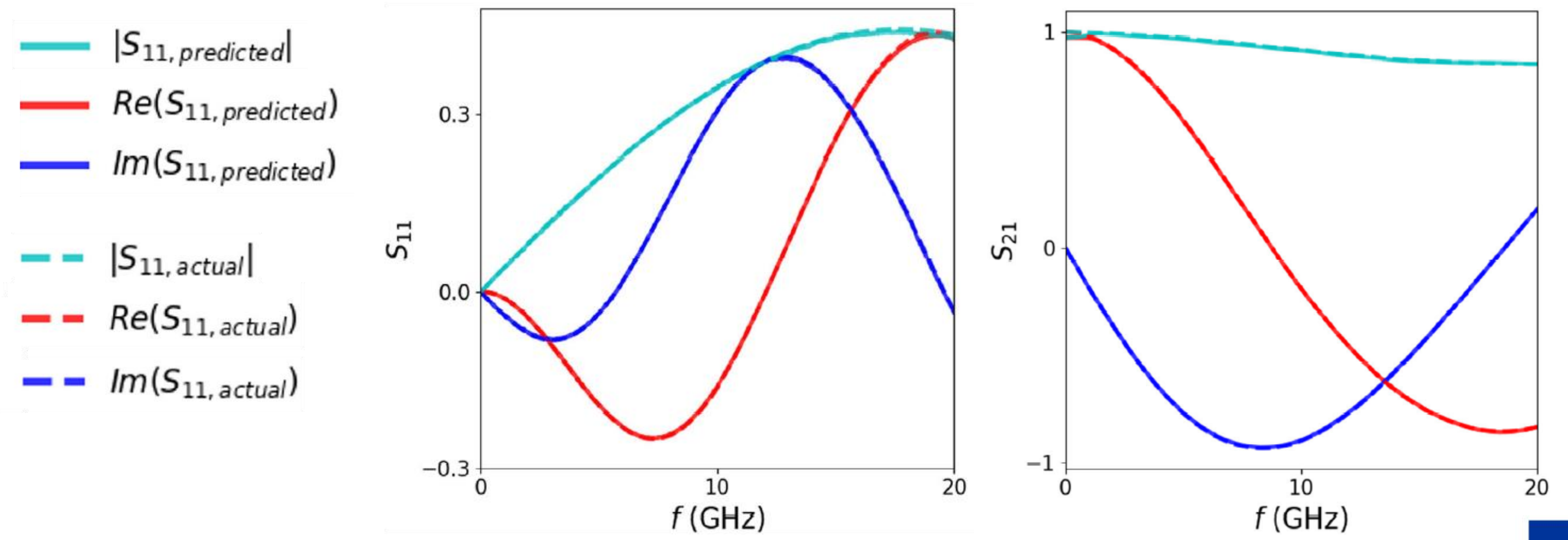




- **Gaussian Process (GP)**

  = **Distribution over functions**

  = Generalization of Gaussian distribution

  - Fully characterized by **mean** and **covariance** function

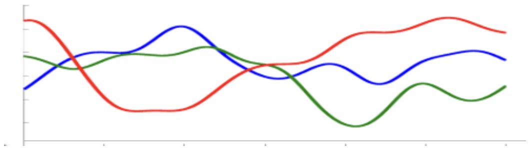
$$GP\left(m(x),k(x,x')\right)$$

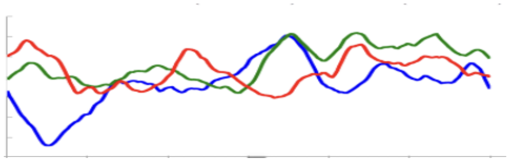
mean function *covariance function*

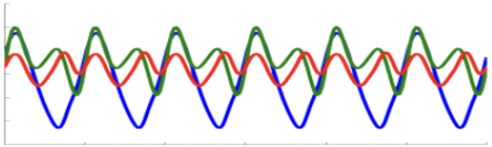
kernel choice

- **Examples** of **covariance** function

Squared Exponential	Matérn	Periodic
$k(x,x')=\beta\exp\left(-\frac{1}{2}\sum_{d=1}^{D}\left(\frac{x_d-x'_d}{l_d}\right)^2\right)$	$k(x,x')=\frac{2^{1-\nu}}{\Gamma(\nu)}\left(\frac{\sqrt{2\nu}\lVert x-x'\rVert}{l}\right)^{\nu}K_{\nu}\left(\frac{\sqrt{2\nu}\lVert x-x'\rVert}{l}\right)$	$k(x,x')=\exp\left(-\frac{2\sin^2(0.5(x-x'))}{l^2}\right)$







- Choosing the *'optimal'* **covariance** function
  - User choice

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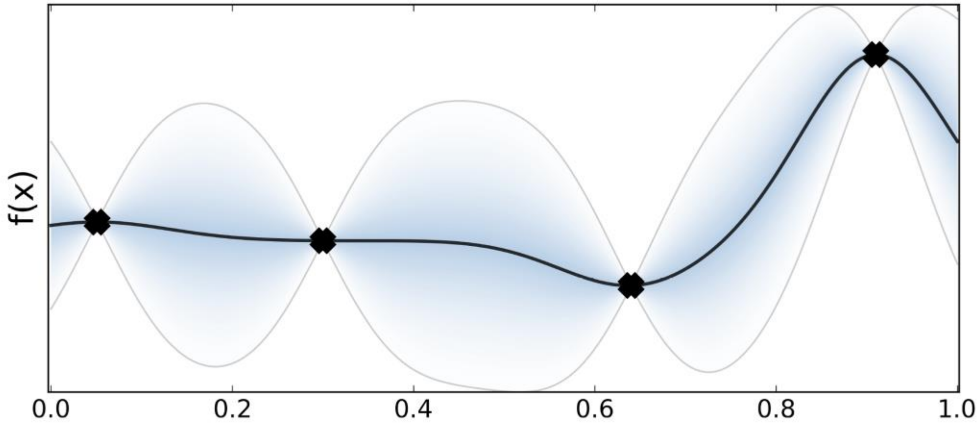
hyperparameters

- Choosing the *'optimal'* **covariance** function
  - User choice
- Selecting the *'optimal'* **hyperparameters**
  - **data-driven** approach, during **training** phase (MLE)

PHYSICS-INFORMED MACHINE LEARNING

- Once the **covariance** matrix is chosen…
  - **Bayesian inference** → **model prediction** & **uncertainty**



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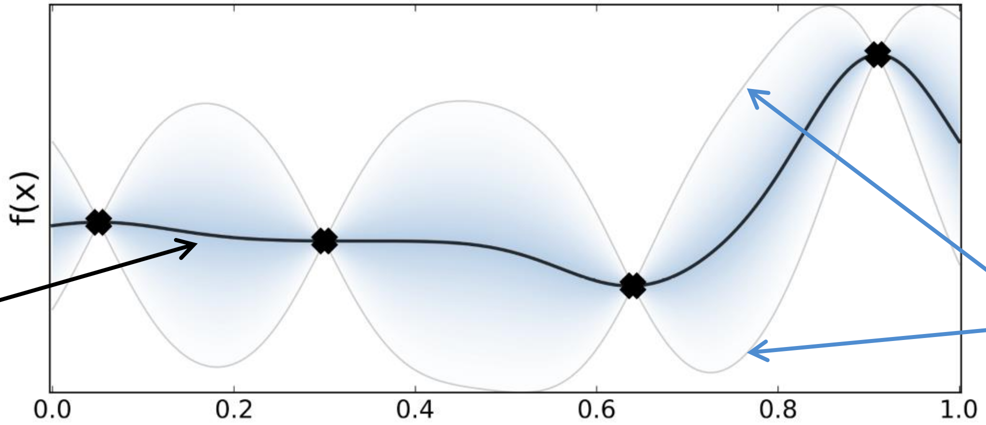
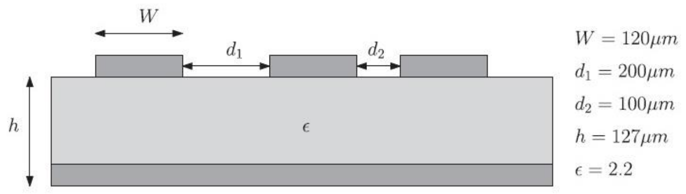
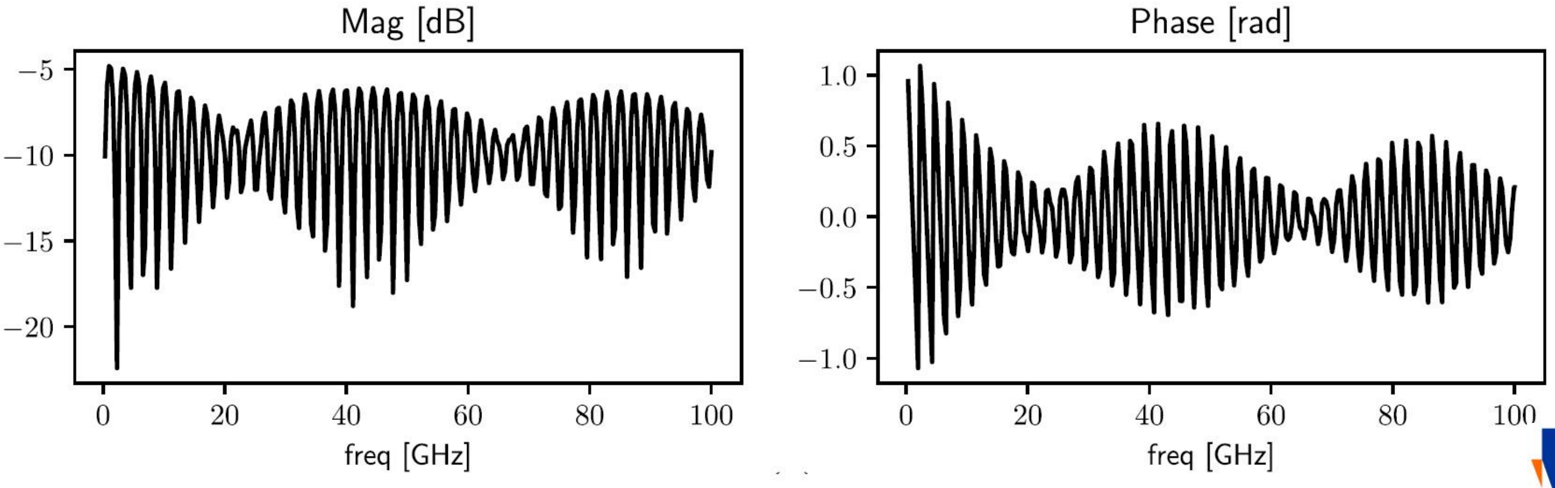


prediction

uncertainty

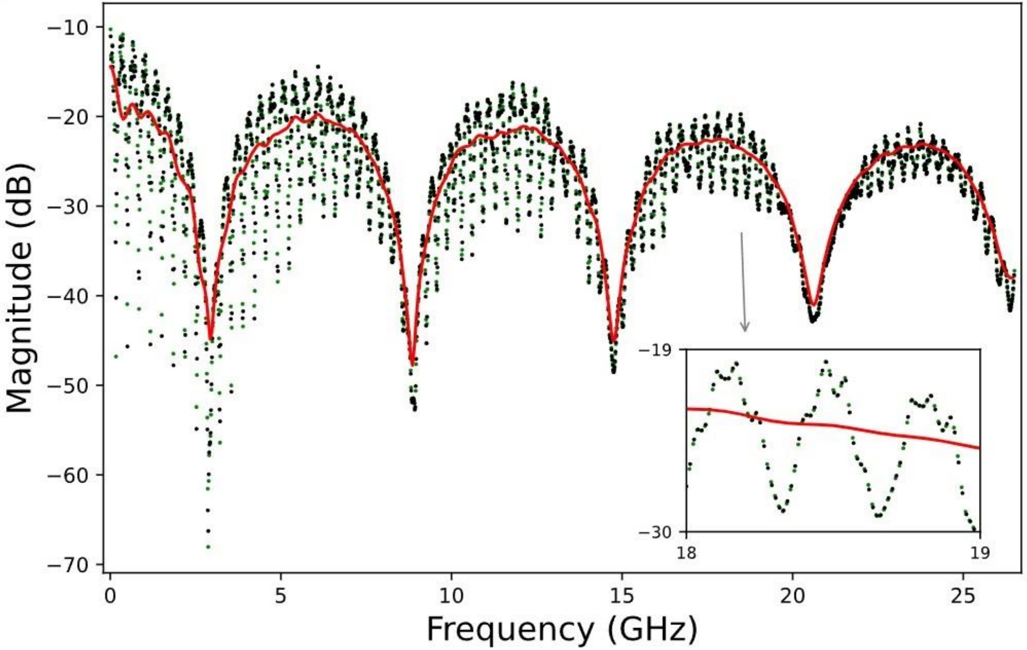
- Interconnect modeling
  - Crucial for EMC and Si
  - Dynamic behavior as bandwidth increases





[Garbuglia23]

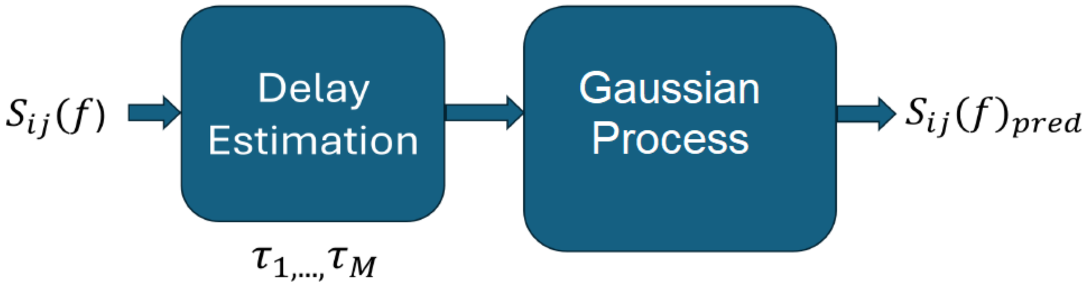
- Accurate modeling challenging
  - S-parameter data
  - Gaussian Process model



PHYSICS-INFORMED MACHINE LEARNING

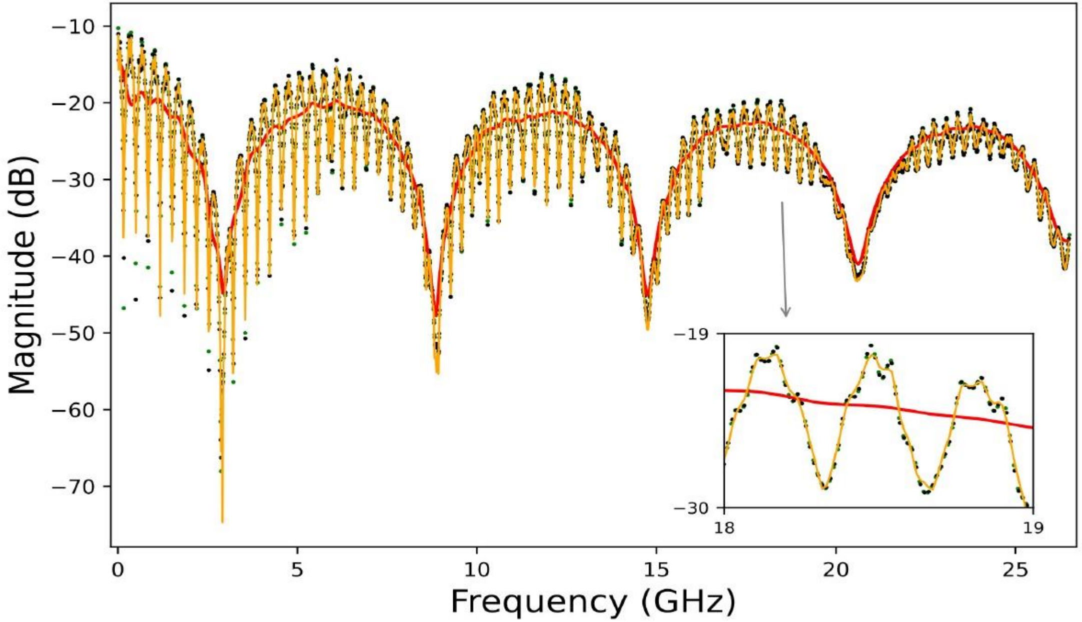
- Interconnect modeling
  - Crucial for EMC and Si
  - Dynamic behavior as bandwidth increases

- Solution
  - Integrating propagation delays into the ML model



PHYSICS-INFORMED MACHINE LEARNING

- Accurate modeling challenging
  - S-parameter data
  - Gaussian Process model
  - Delay-based Gaussian Process



[Yihune25]

CONCLUSIONS

- **Can ML bring a revolution in EMC/SI/PI design?** **YES**

- What is needed
  - Include physic-based knowledge in ML
  - Comprehensive approach
    - ML for system- circuit- and device-level
  - Human-in-the-loop
    - Easy to use, interpretable results

Cooperation between academia and industry is fundamental!

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