Fundamentals of machine learning methodologies for the design of modern RF and microwave systems

Domenico Spina

IDLAB, IMEC RESEARCH GROUP AT GHENT UNIVERSITY

TUTORIAL ORGANIZATION

- Introduction
- Machine Learning for Electrical Engineering
  - Neural Networks
- Data–Efficient Machine Learning
  - Bayesian Optimization
- Conclusions

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PROBLEMS IN ANALOG DESIGN

- Designing high-frequency analog circuits is a challenging task
  - Complex systems under several physical effects
  - Must be robust to external interferences and be integrated with other components (i.e. digital)
  - Computer Aided Simulations (CAD) can be computationally expensive

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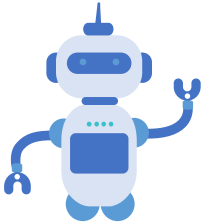
- Machine Learning (ML) promises to
  - Increase level of automation and efficiency design process



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- What is ML?
  - ML is a set of methodologies in artificial intelligence (AI)
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MACHINE LEARNING FOR ELECTRICAL ENGINEERING

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    - Mathematical techniques able to learn information from a set of data
    - Supervised ML
- How can ML help in analog circuit design?
  - Let's see an example

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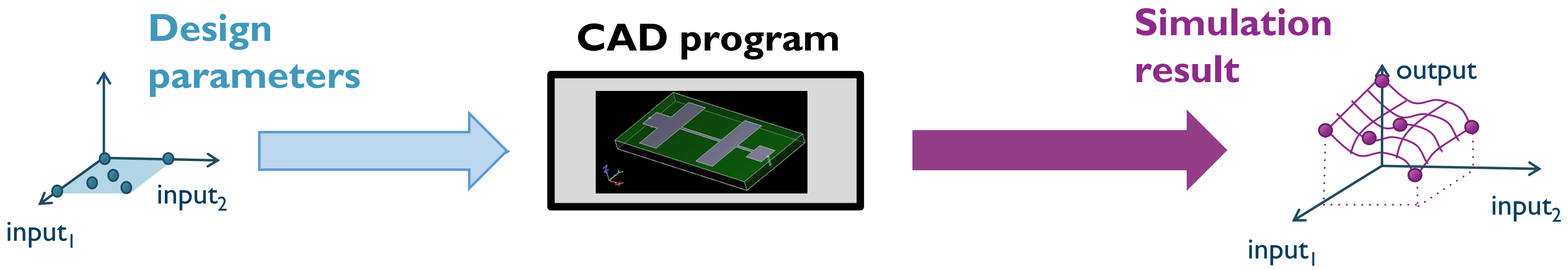
MACHINE LEARNING FOR ELECTRICAL ENGINEERING

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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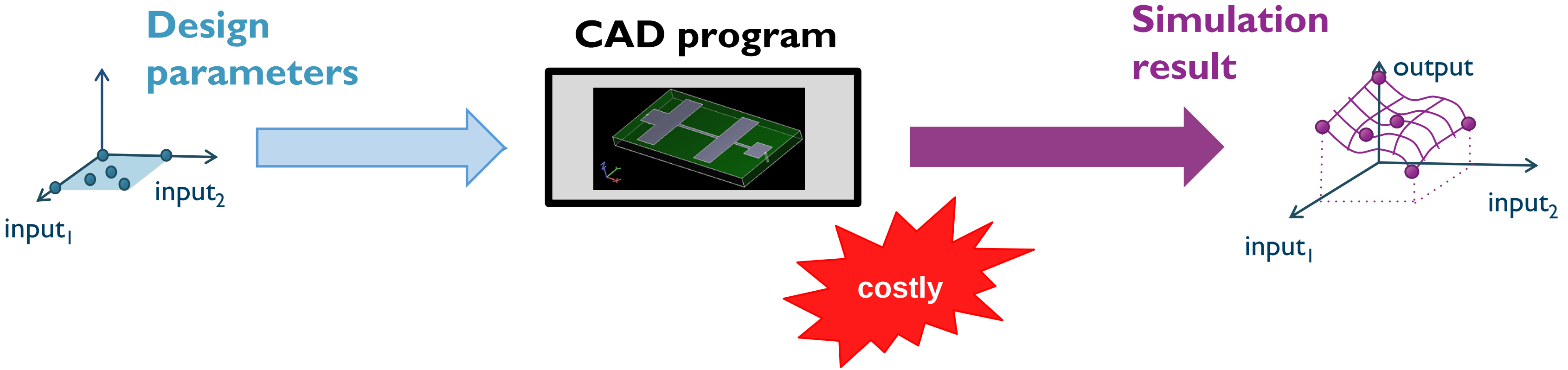

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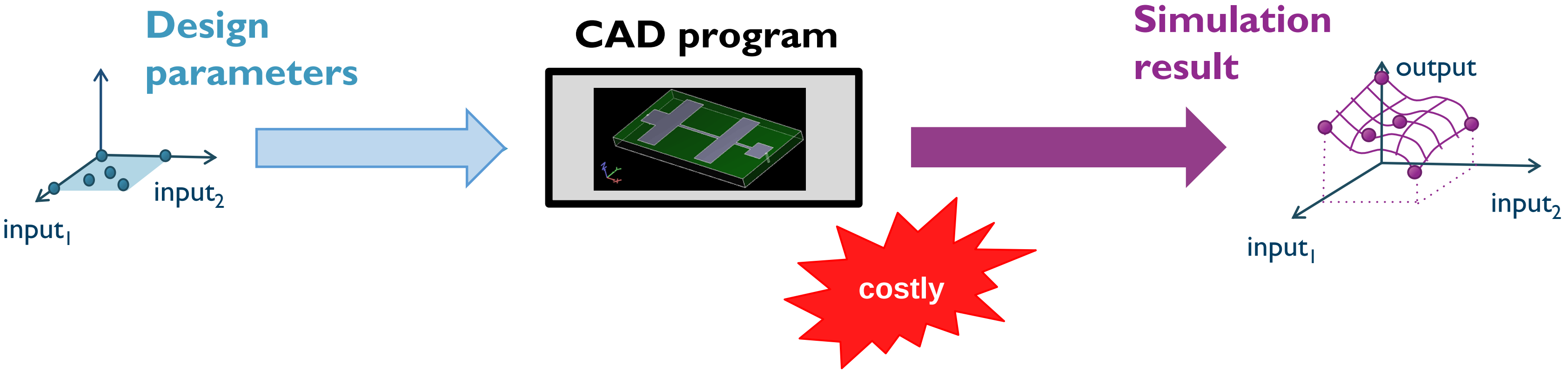

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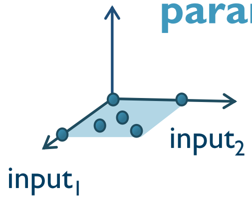
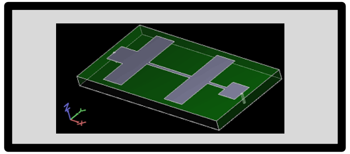
MACHINE LEARNING FOR ELECTRICAL ENGINEERING

Design parameters

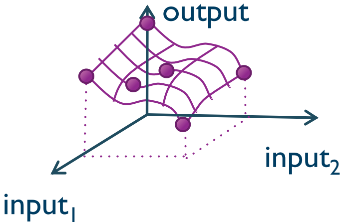


$$\left(x_1^1, x_2^1, x_3^1, \ldots x_N^1\right)$$

CAD program



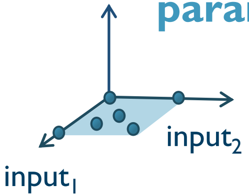
Simulation result



$$y^1$$

MACHINE LEARNING FOR ELECTRICAL ENGINEERING

Design parameters



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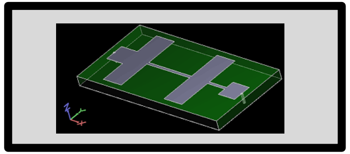

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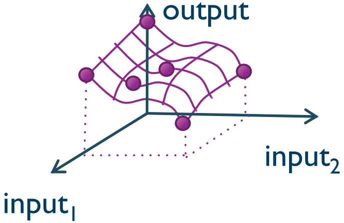

$$\left(x_1^1, x_2^1, x_3^1, \ldots x_N^1\right) \qquad y^1$$

$$\left(x_1^2, x_2^2, x_3^2, \ldots x_N^2\right) \qquad y^2$$

MACHINE LEARNING FOR ELECTRICAL ENGINEERING

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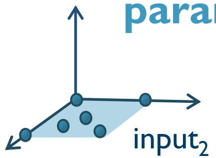
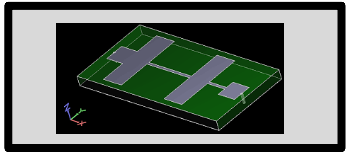


CAD program



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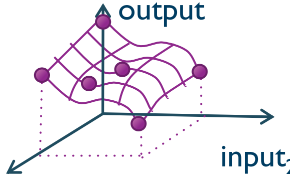

$\left(x_1^1, x_2^1, x_3^1, \ldots x_N^1\right)$
$\left(x_1^2, x_2^2, x_3^2, \ldots x_N^2\right)$
$\vdots$
$\left(x_1^M, x_2^M, x_3^M, \ldots x_N^M\right)$

y^1
y^2
$\vdots$
y^M

- **Dataset**
  - Samples of design parameters and corresponding values

$\left(x_1^1, x_2^1, x_3^1, \ldots x_N^1\right)$	y^1
$\left(x_1^2, x_2^2, x_3^2, \ldots x_N^2\right)$	y^2
$\vdots$	$\vdots$
$\left(x_1^M, x_2^M, x_3^M, \ldots x_N^M\right)$	y^M

Ready for ML!

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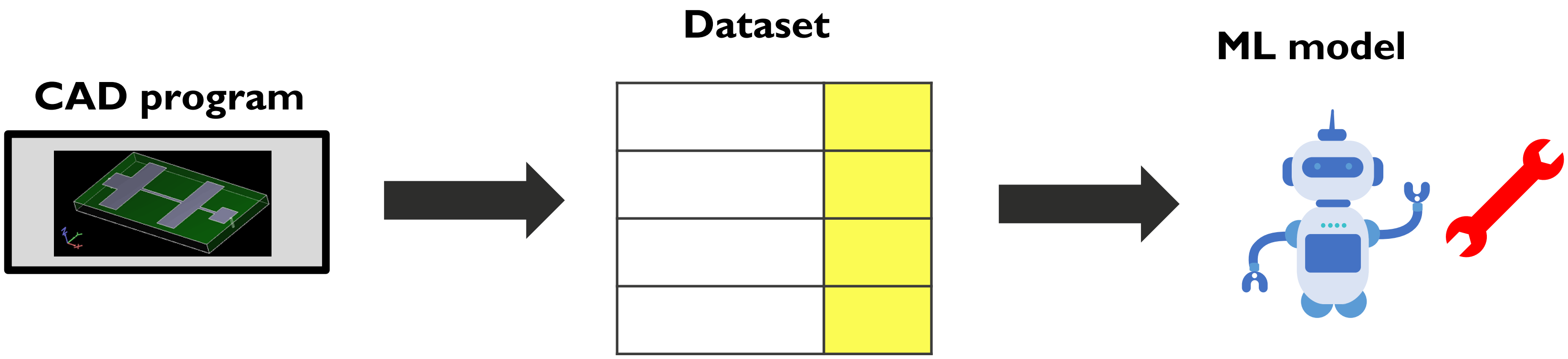
1. Training

- Goal: tune model to learn relation between design parameters and performance metric



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MACHINE LEARNING FOR ELECTRICAL ENGINEERING

1. **Training**
   - ML does not return explicit analytical expression between design parameters and performance

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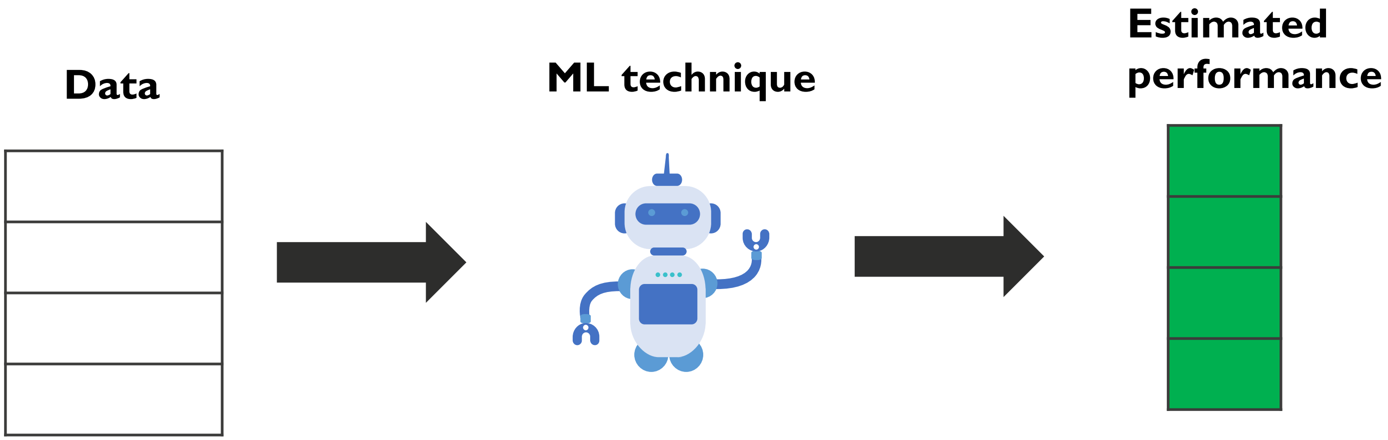
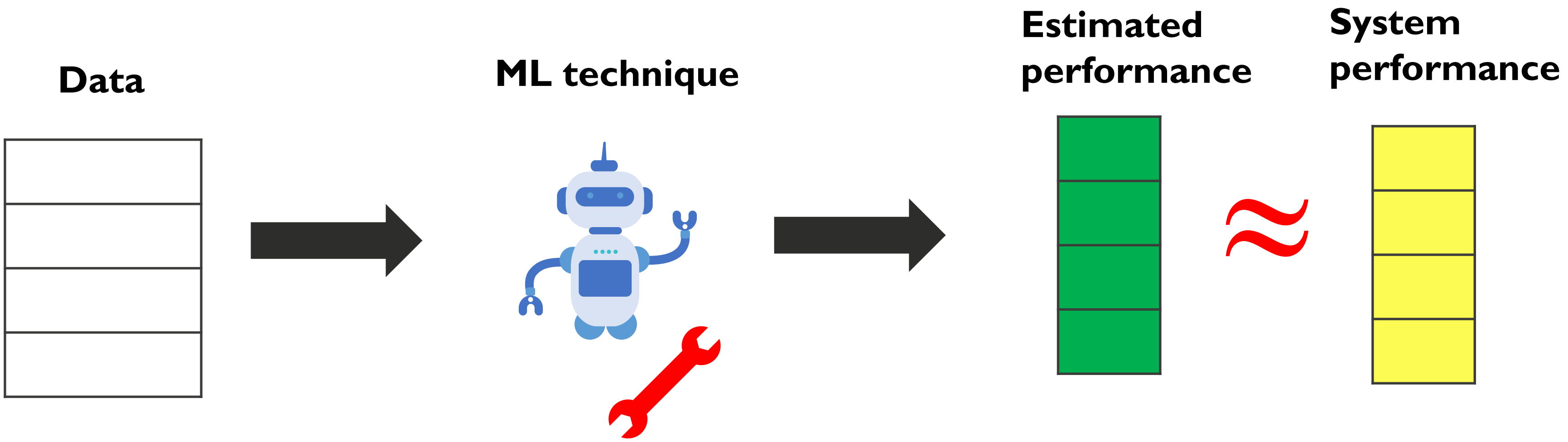


MACHINE LEARNING FOR ELECTRICAL ENGINEERING

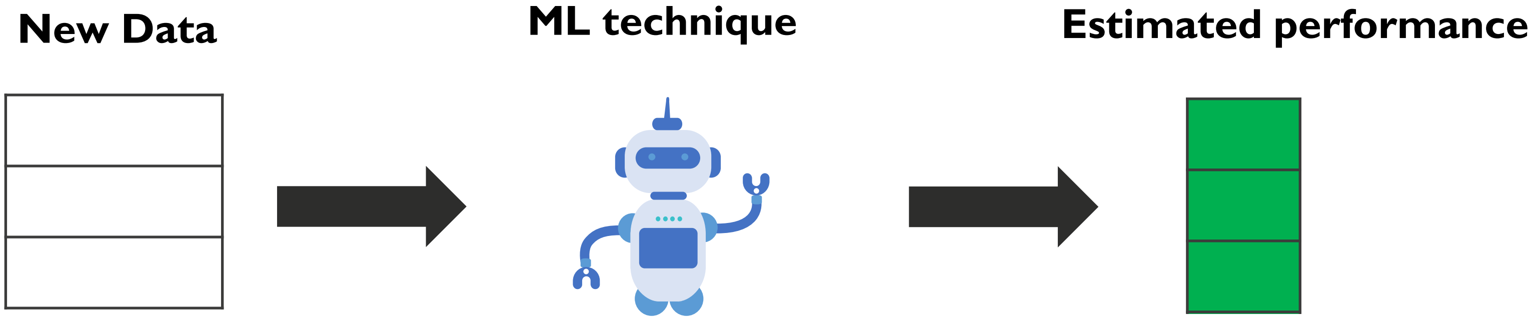
1. **Training**
   - ML does not return explicit analytical expression between design parameters and performance
   - ML model is able to estimate performance value w.r.t. design parameters
   - Tune model parameters until predictions are accurate



MACHINE LEARNING FOR ELECTRICAL ENGINEERING

2. Application

- Feed new values of design parameters to ML model
- Model predicts performance of the system



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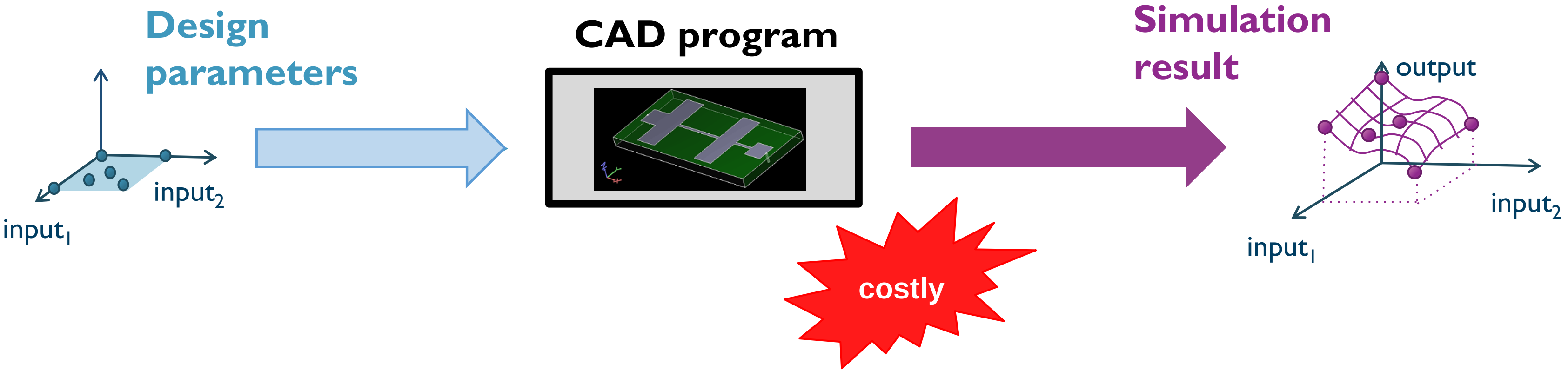

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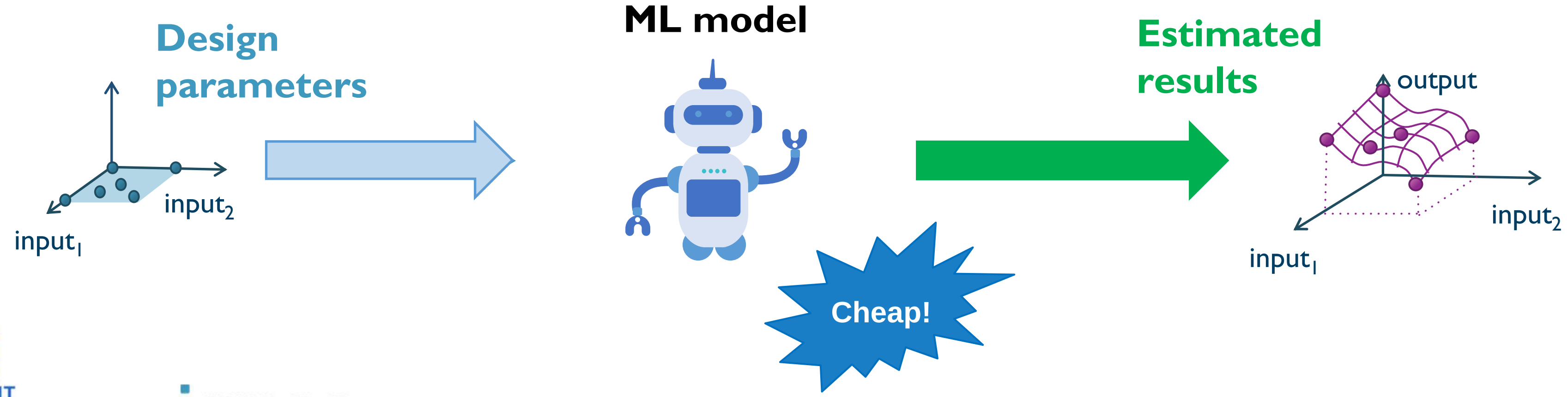

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MACHINE LEARNING FOR ELECTRICAL ENGINEERING

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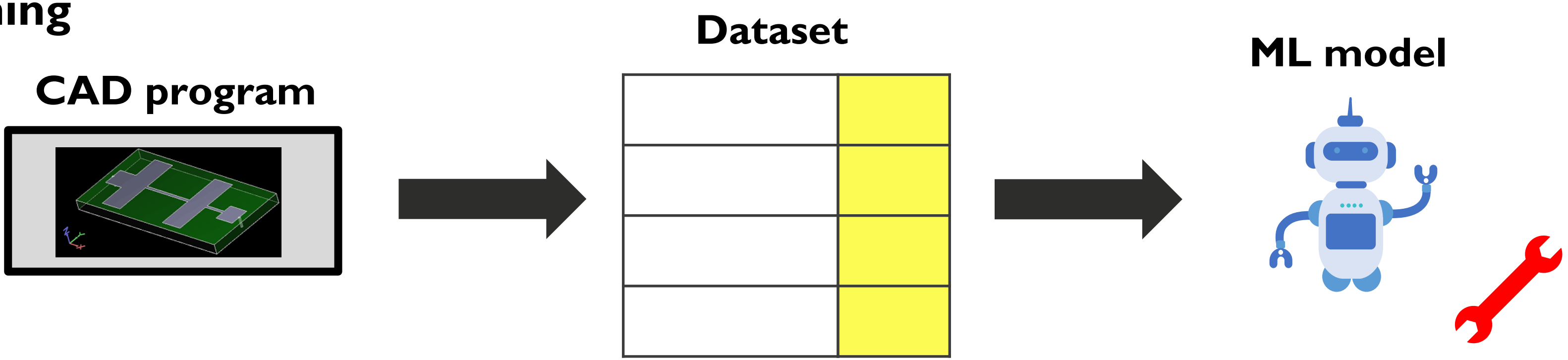
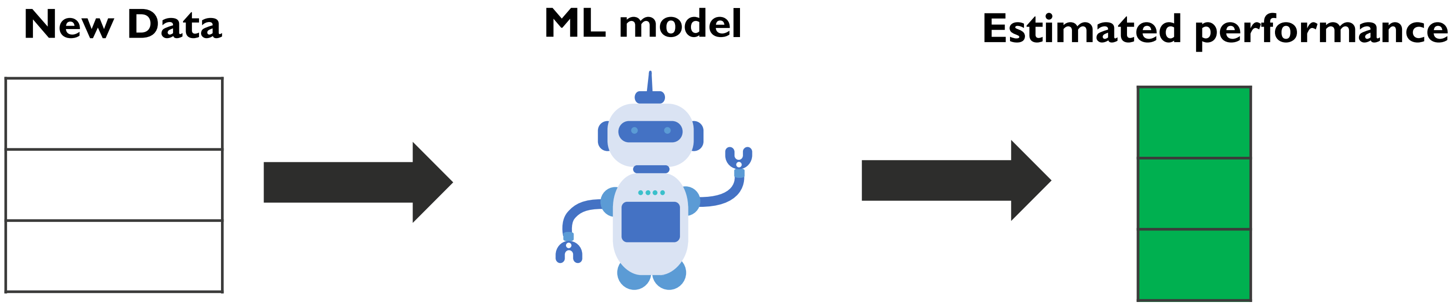


2. **Application**



MACHINE LEARNING FOR ELECTRICAL ENGINEERING

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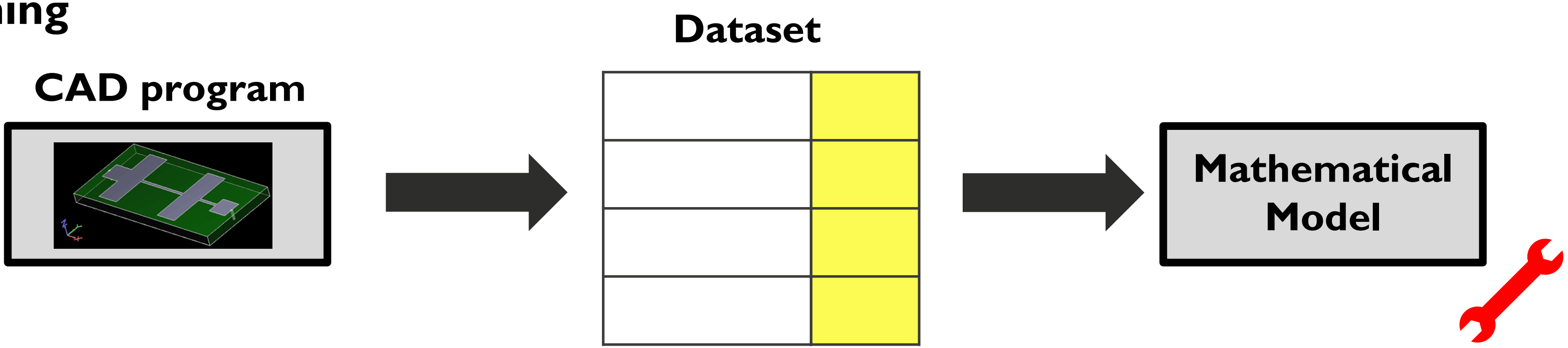

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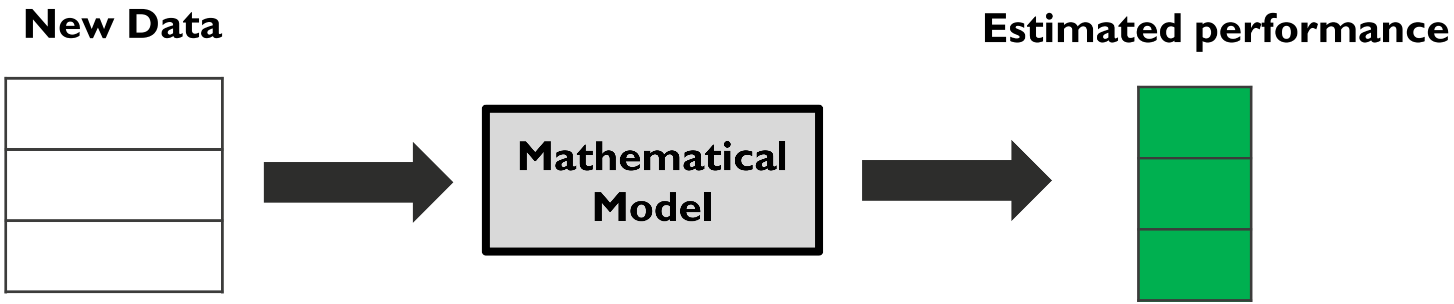

MACHINE LEARNING FOR ELECTRICAL ENGINEERING

- 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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MACHINE LEARNING FOR ELECTRICAL ENGINEERING

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

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- **Properties**
  - Able to describe complex systems
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  - Able to handle large amount of data or design parameters

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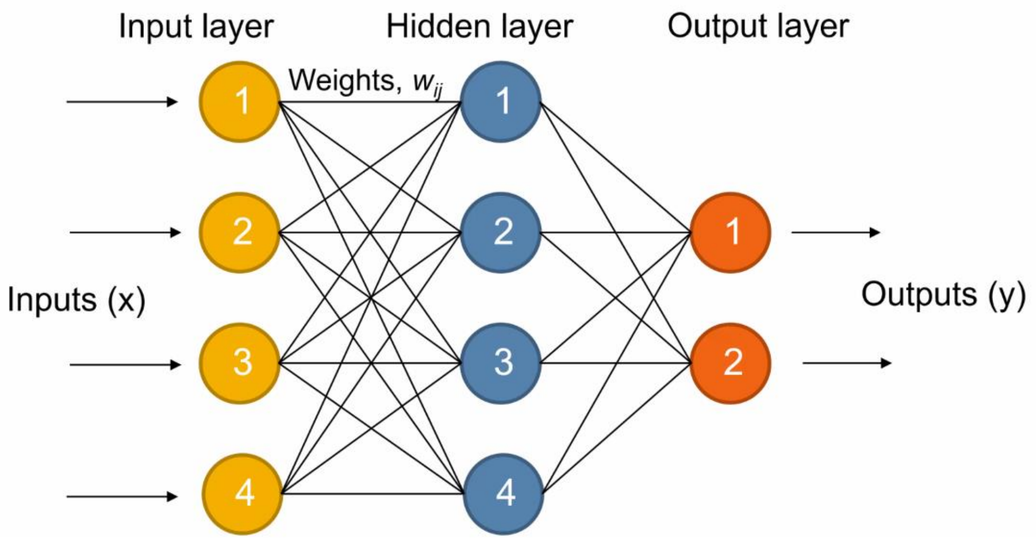
NEURAL NETWORKS

- Neural Network: overview



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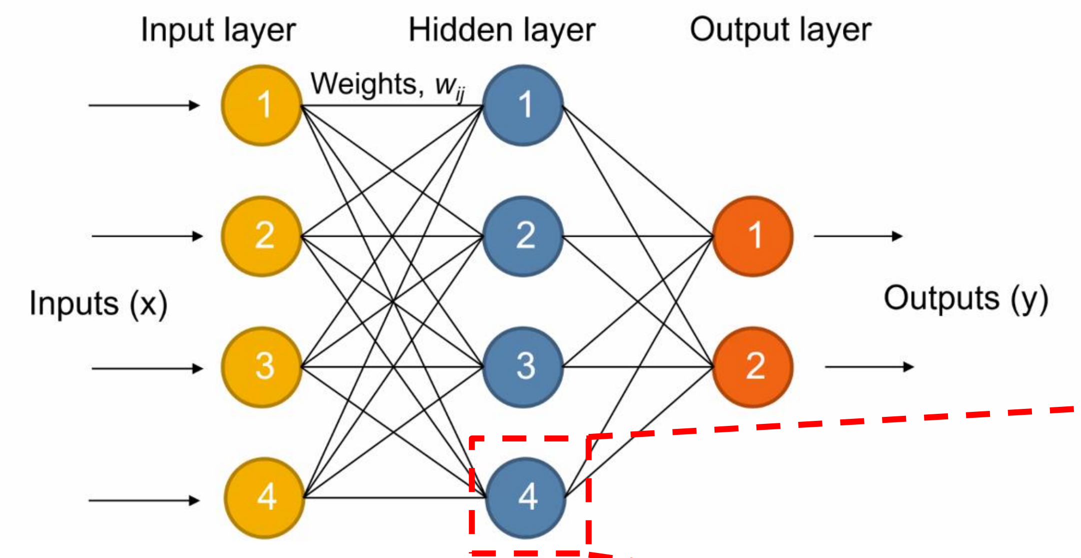
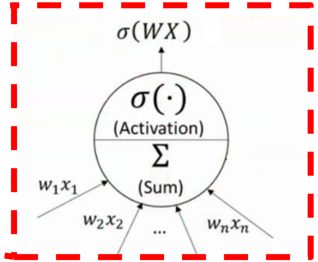


Single Neuron

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



NEURAL NETWORKS

- Neural Network: How to train?
  - User has to decide architecture
    - Number of hidden layers
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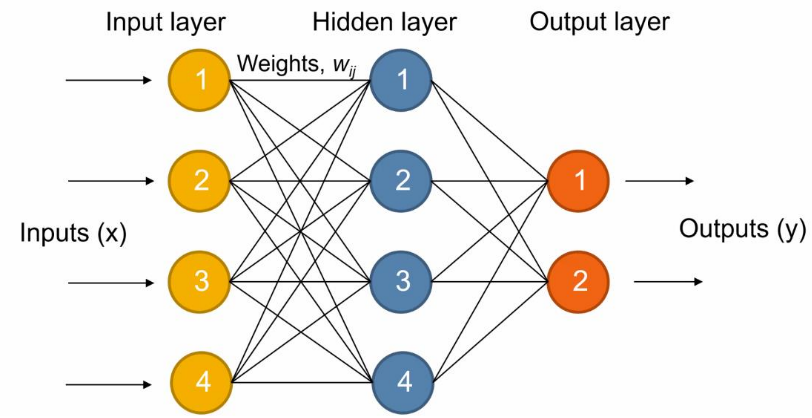
    - Activation function



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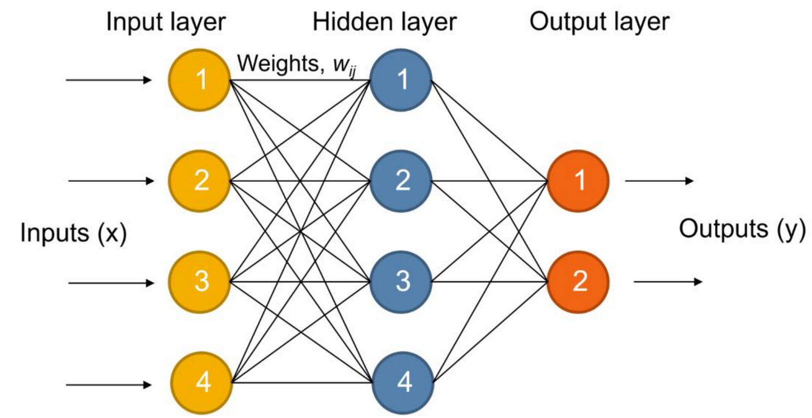

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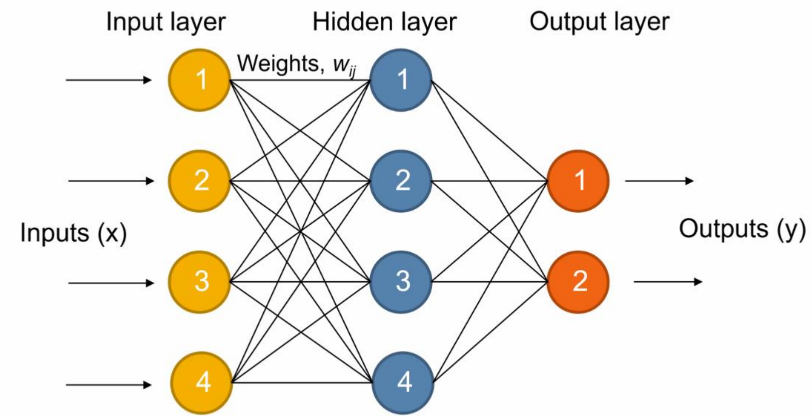
    - Number of hyperparameters can influence the size of training dataset



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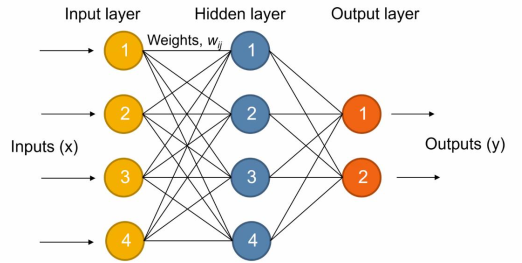
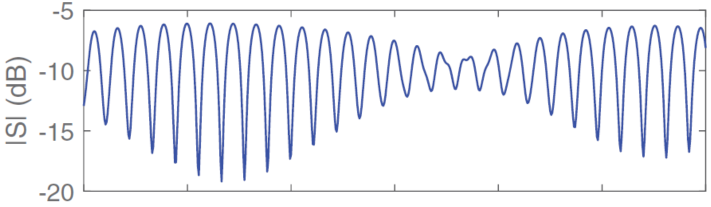
NEURAL NETWORKS

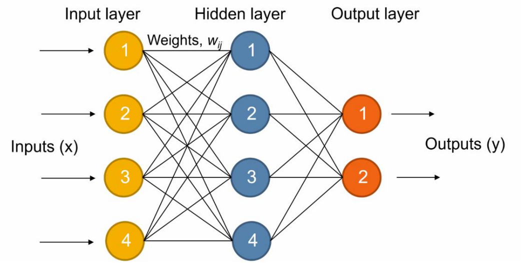
- Neural Network in electrical engineering
  - Model highly correlated elements





- Frequency samples close to each other

NEURAL NETWORKS



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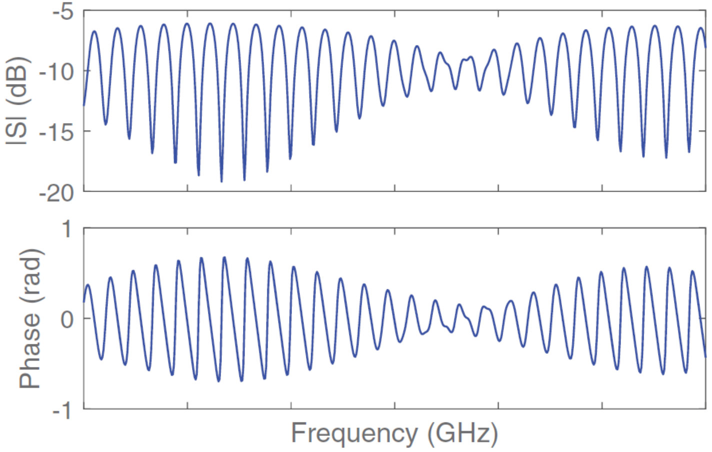
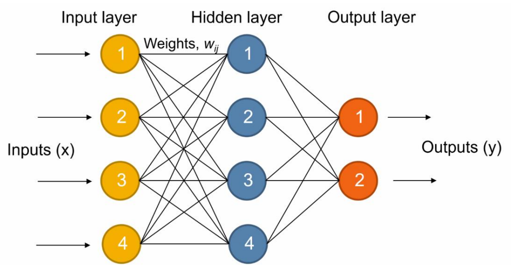


- Frequency samples close to each other
- Magnitude and phase

NEURAL NETWORKS



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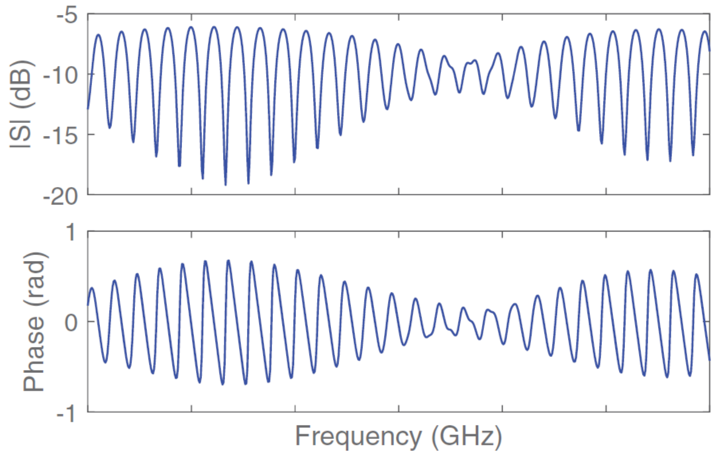
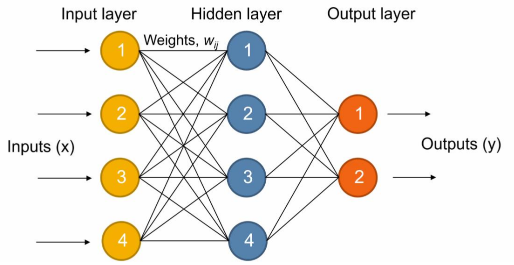


- Frequency samples close to each other
- Magnitude and phase
- Different element of scattering matrix

NEURAL NETWORKS



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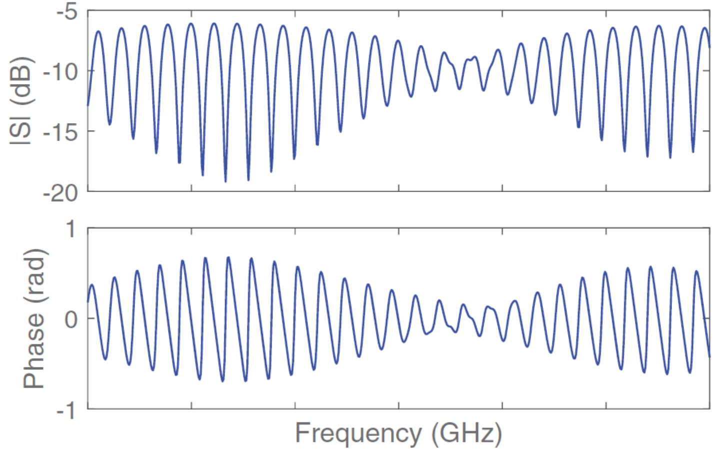

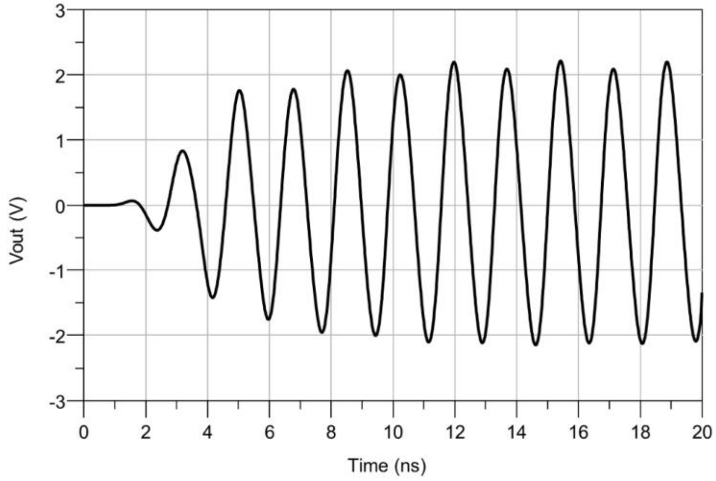

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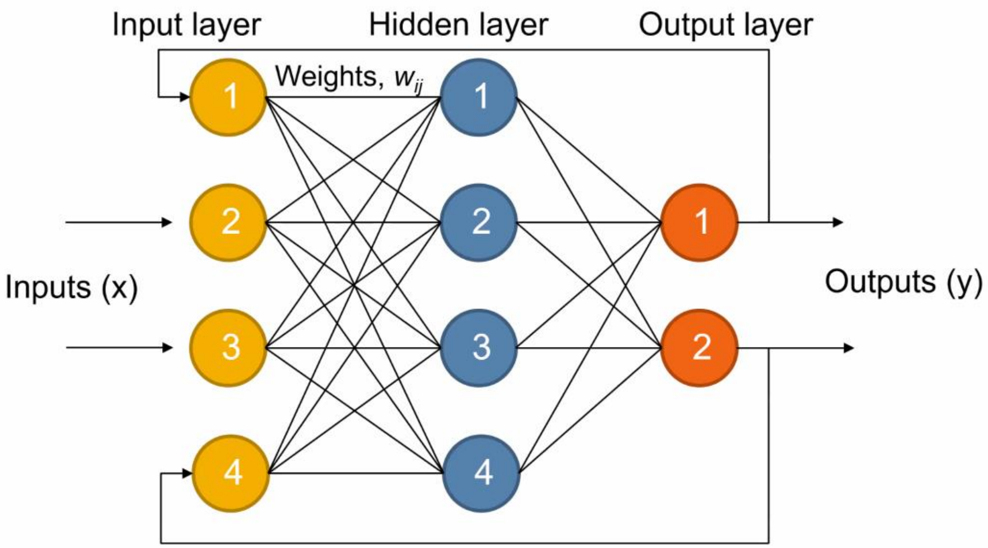
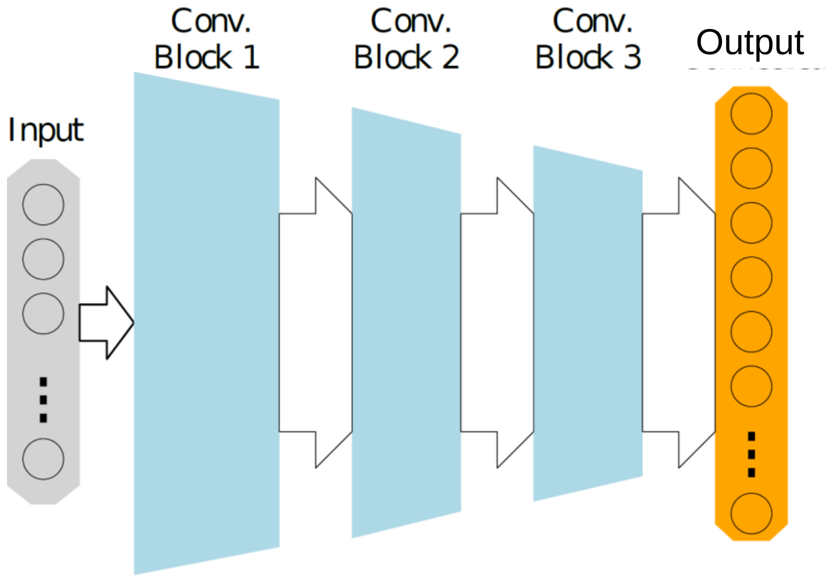
NEURAL NETWORKS

- Recurrent Neural Network
  - Output depends on previous state



NEURAL NETWORKS

- Convolutional Neural Network
  - Convolutional layers in neural networks aim to learn local patterns from the input



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NEURAL NETWORKS

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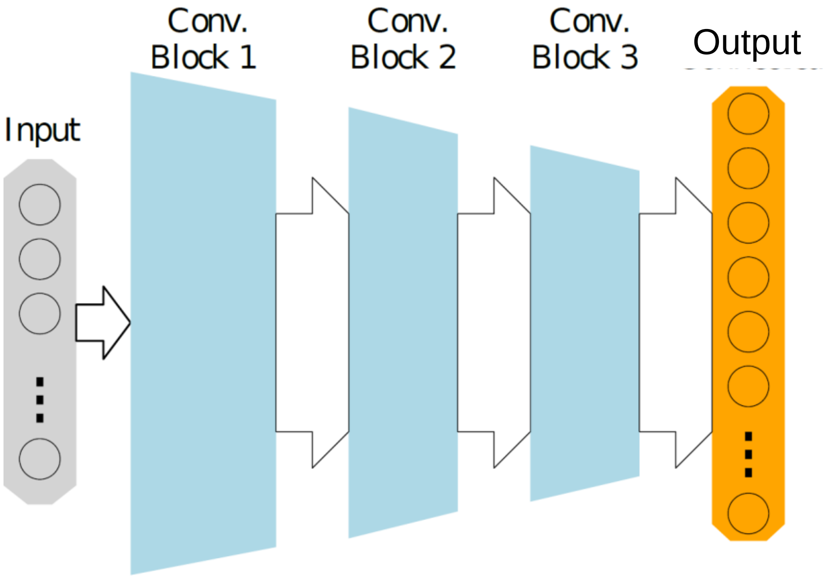
  - Convolutional layers in neural networks aim to learn local patterns from the input
  - When modeling frequency responses, this corresponds to searching for patterns such as resonances, ripples and flat regions in small frequency bands



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NEURAL NETWORKS

- **Examples of NNs applications in analog design**
  - Scattering parameters modeling [Jin19, Torun20]
  - Transfer function extrapolation [Bhatti22]
  - Inverse problems [Xiao21, Wu22]
  - Power amplifier design [Wang20]
  - Power delivery network design [Schierholz22]
  - Active antenna design [Brihuega20]

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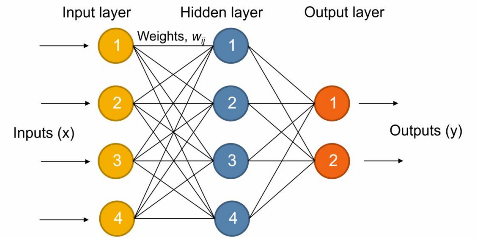
NEURAL NETWORKS

- **Scattering parameters modeling via NN: linear and passive systems**
  - First challenge: Output dimensionality >> Input dimensionality

Design parameters

Output



Complex valued matrix

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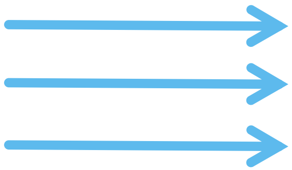

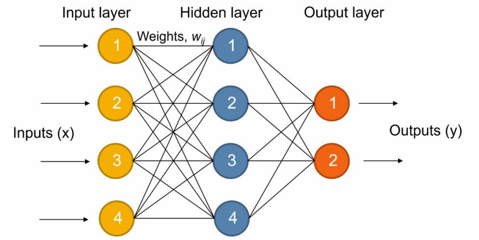

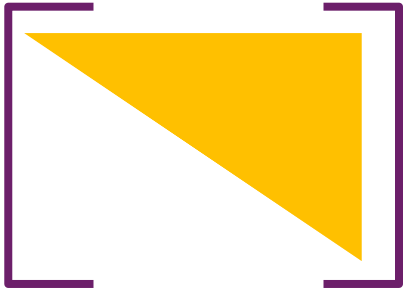

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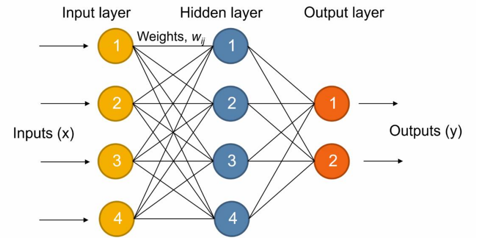
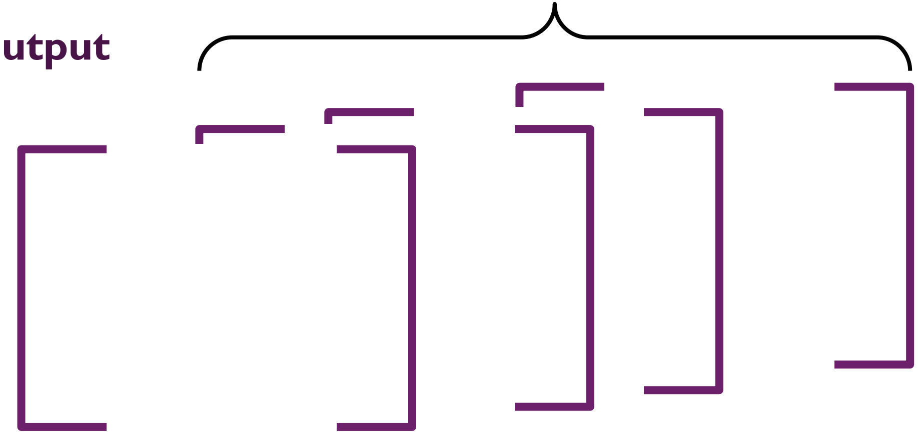


Output

Frequency



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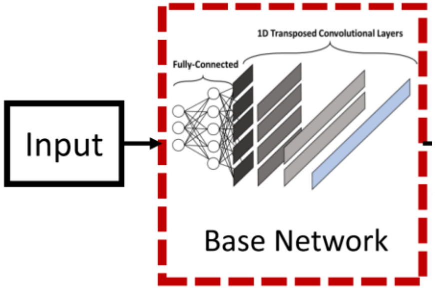
NEURAL NETWORKS

- **Scattering parameters modeling via NN: linear and passive systems**



Variation of CNN

[Torun20]

NEURAL NETWORKS

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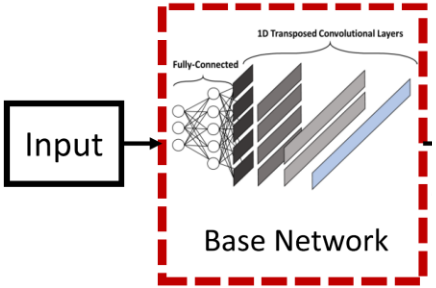

Variation of CNN

We need
1. To reduce modeling complexity
   - Input << Output
2. To enforce physical properties

[Torun20]

NEURAL NETWORKS

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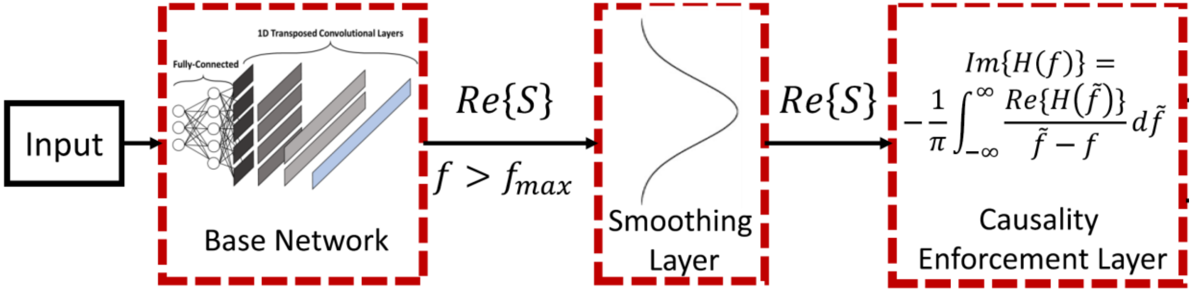

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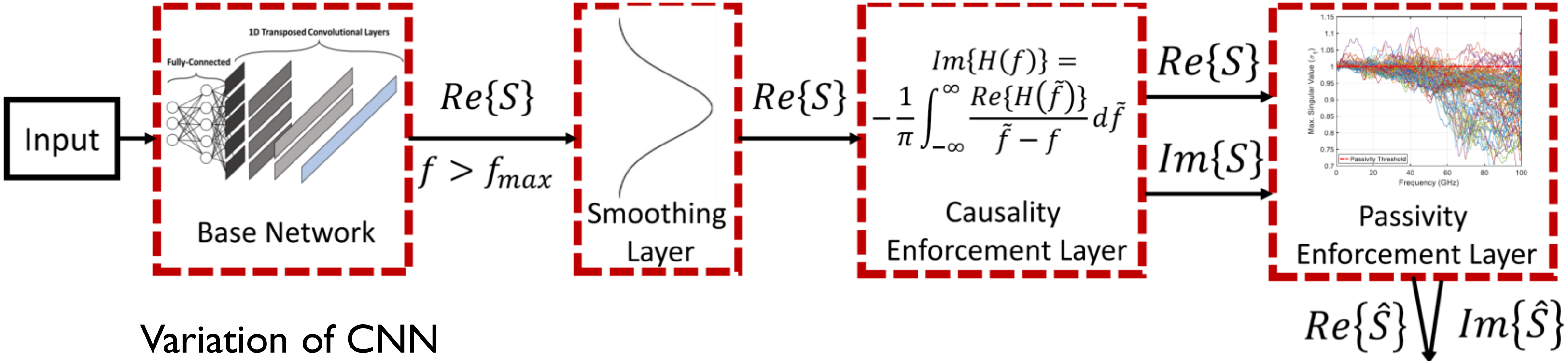
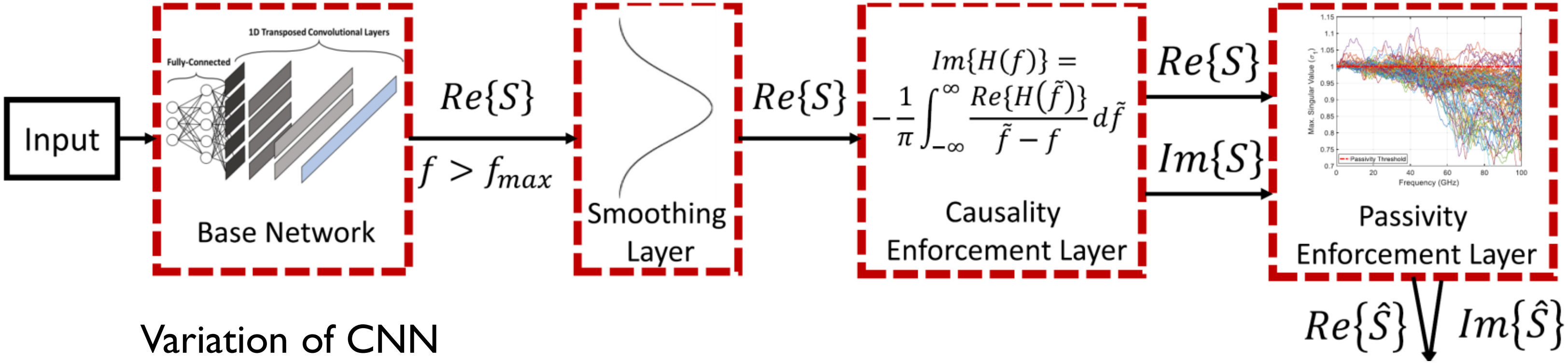


Variation of CNN

[Torun20]

NEURAL NETWORKS

- **Scattering parameters modeling via NN: linear and passive systems**
  - Merging domain-expertise with ML fundamental!



Variation of CNN

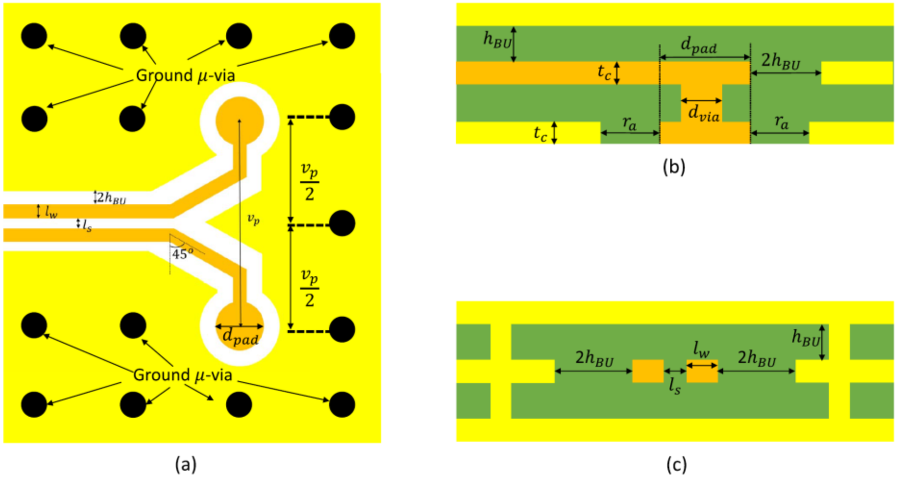
[Torun20]

NEURAL NETWORKS

- **Example: differential stripline pair**

- Four port device
- Sparam [0.1 - 100] GHz via HFFS
- 8 Design parameters

Parameter		Unit	Min	Max
Line Width	l_w	μm	15	75
Pair Spacing	l_s	μm	30	60
μ-via Diameter	d_{via}	μm	30	70
μ-via Pad Diameter	d_{pad}	μm	31	140
μ-via Antipad Radius	r_a	μm	50	500
Via Pitch	v_p	μm	300	1200
Copper Thickness	t_c	μm	10	20
BU Layer Thickness	h_{BU}	μm	20	35



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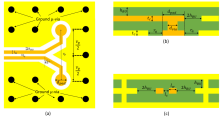
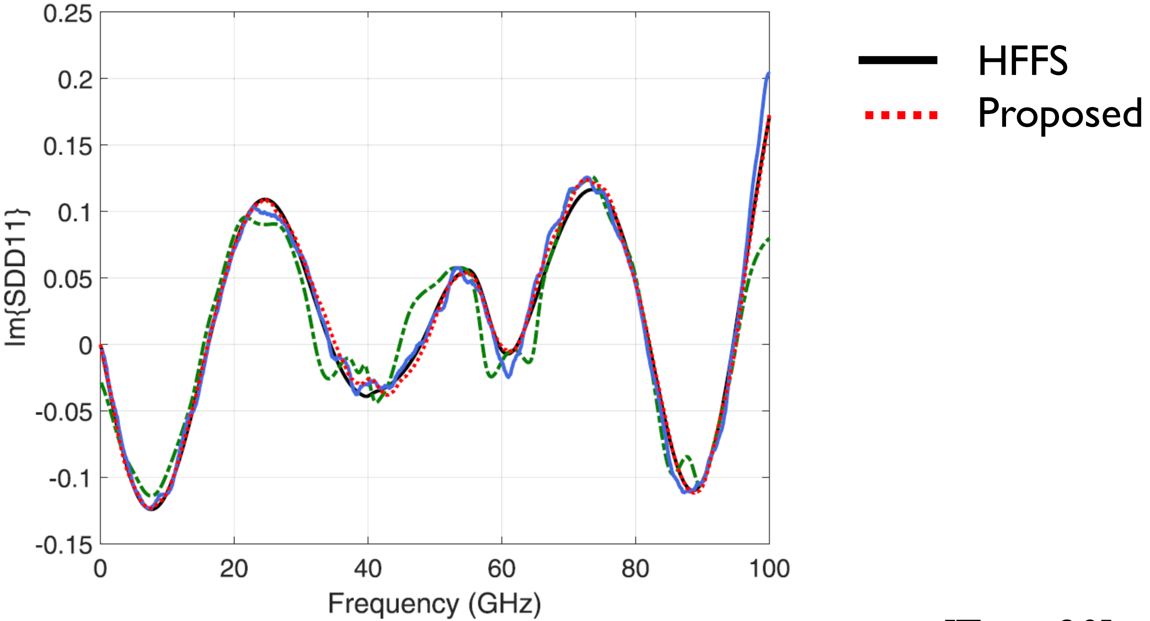


- Training on 750 samples
- Validation on 190 samples



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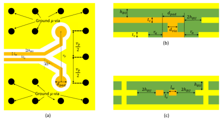

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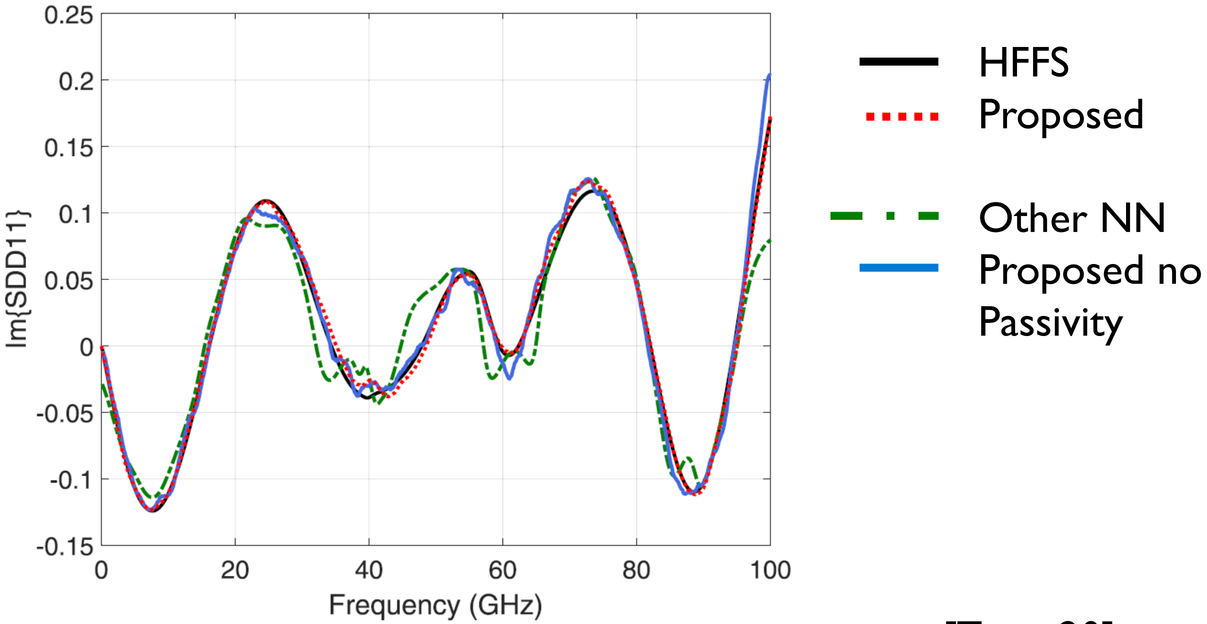

[Torun20]

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NEURAL NETWORKS

- **Examples of NNs applications in EE**
  - Scattering parameters modeling [Jin19, Torun20]
  - Transfer function extrapolation [Bhatti22]
  - Inverse problems [Xiao21, Wu22]
  - Power amplifier design [Wang20]
  - Power delivery network design [Schierholz22]
  - Active antenna design [Brihuega20]

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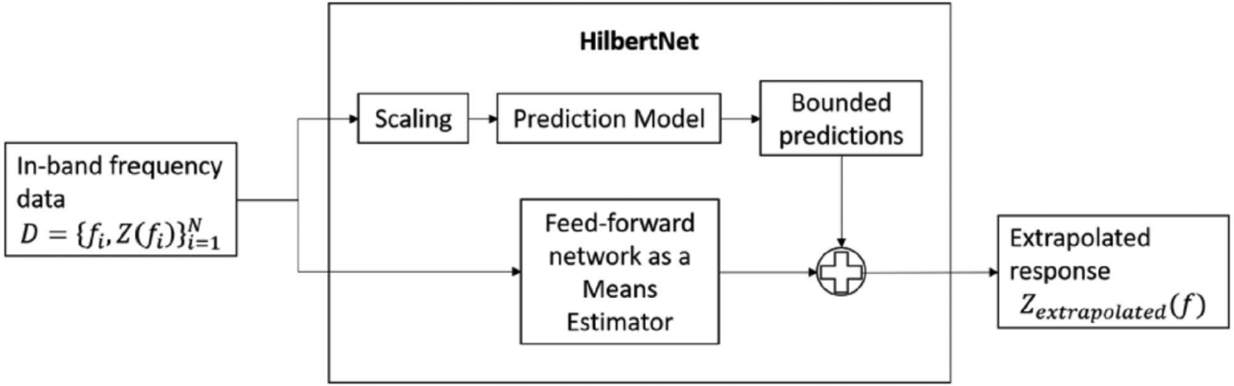
NEURAL NETWORKS

- **Transfer function extrapolation via NN**
  - 2-phases process



[Bhatti22]

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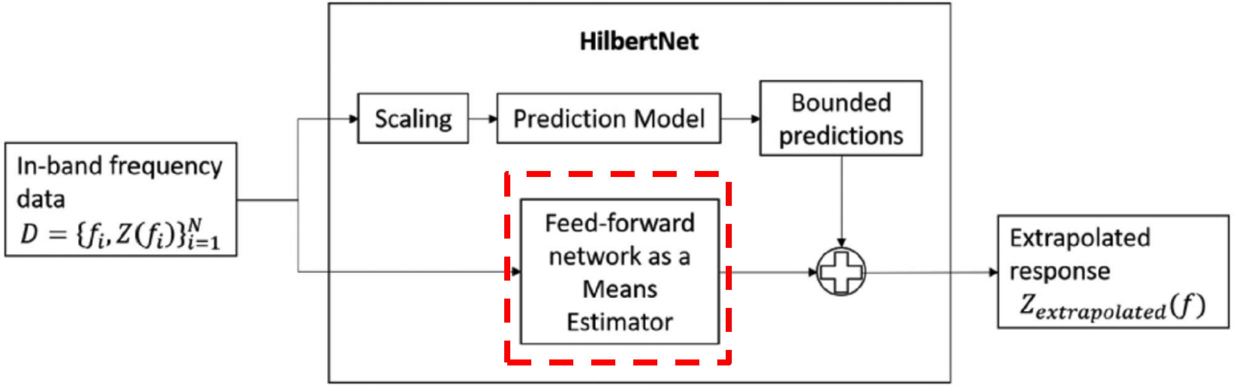
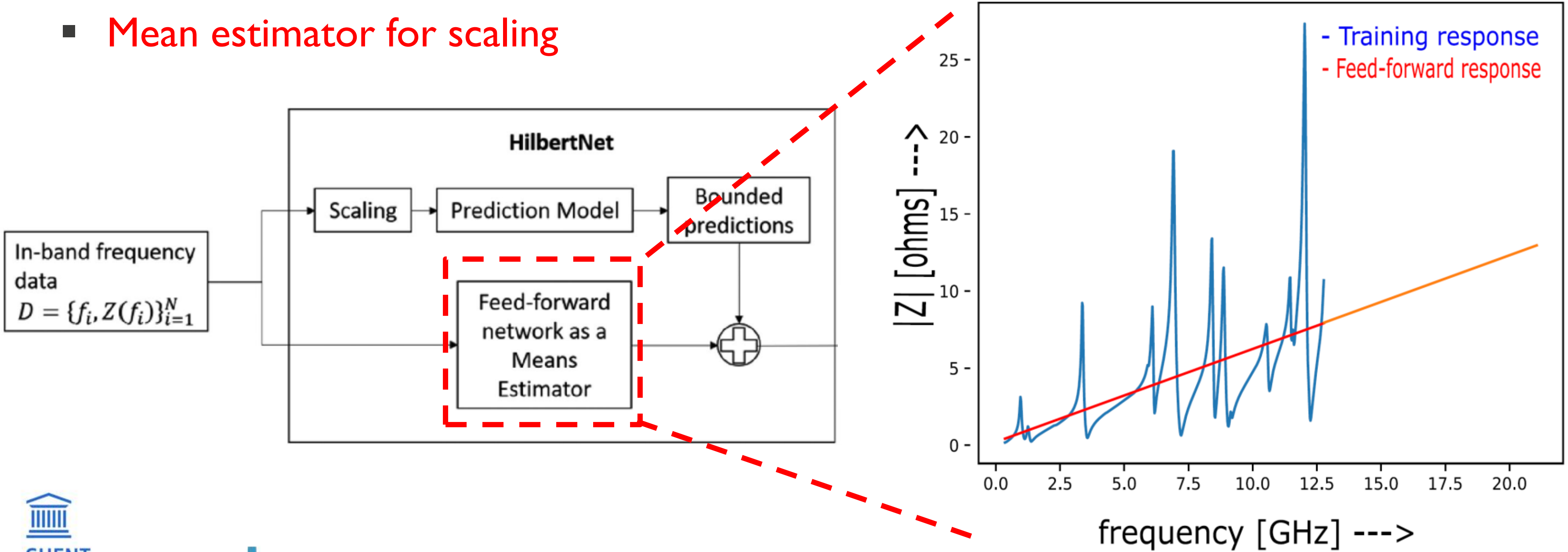


[Bhatti22]

NEURAL NETWORKS

- **Transfer function extrapolation via NN**
  - 2-phases process
  - Mean estimator for scaling



[Bhatti22]

NEURAL NETWORKS

- **Transfer function extrapolation via NN**
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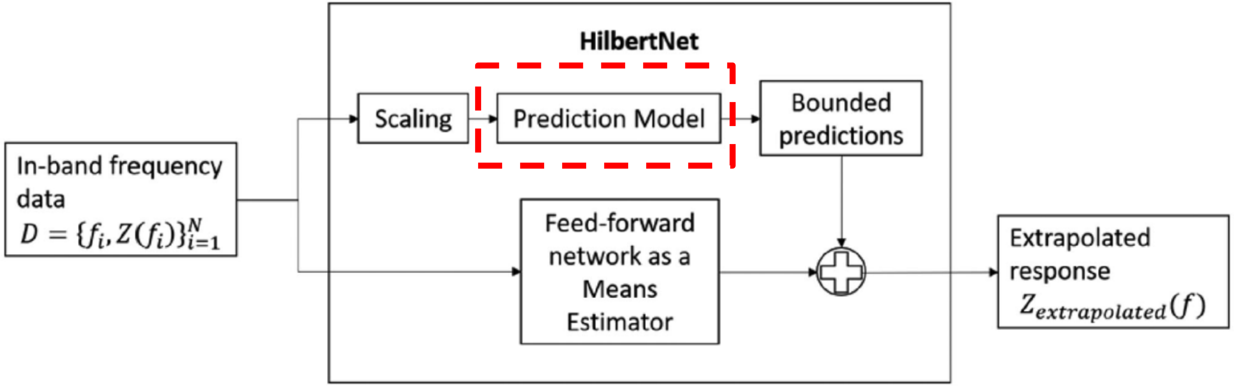

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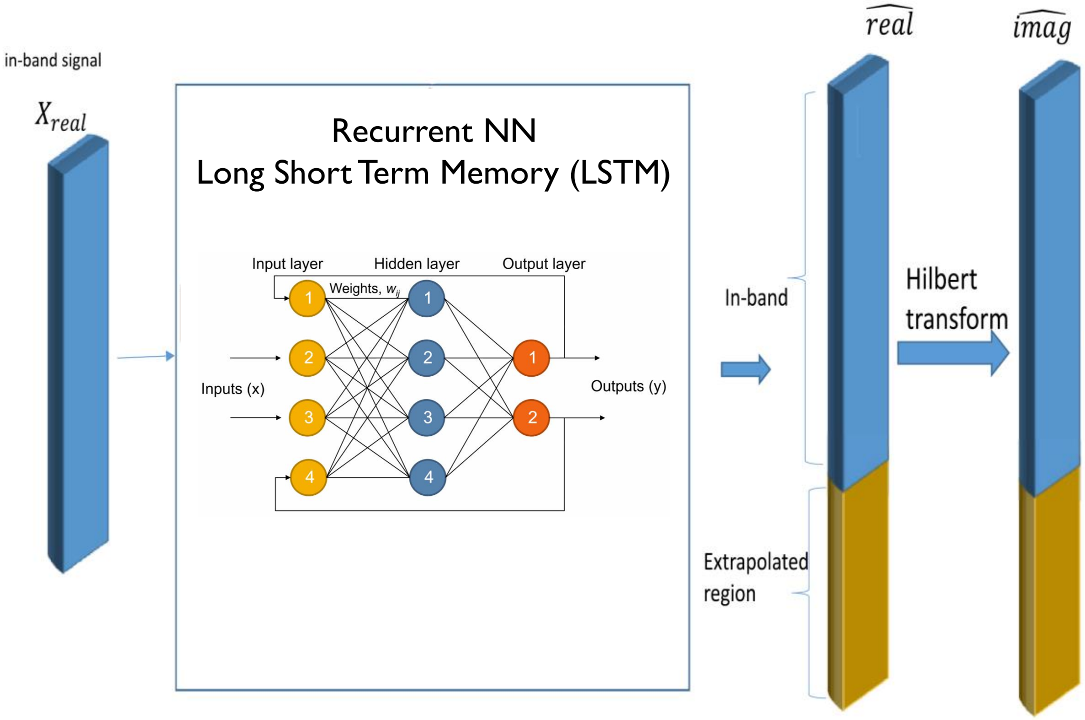

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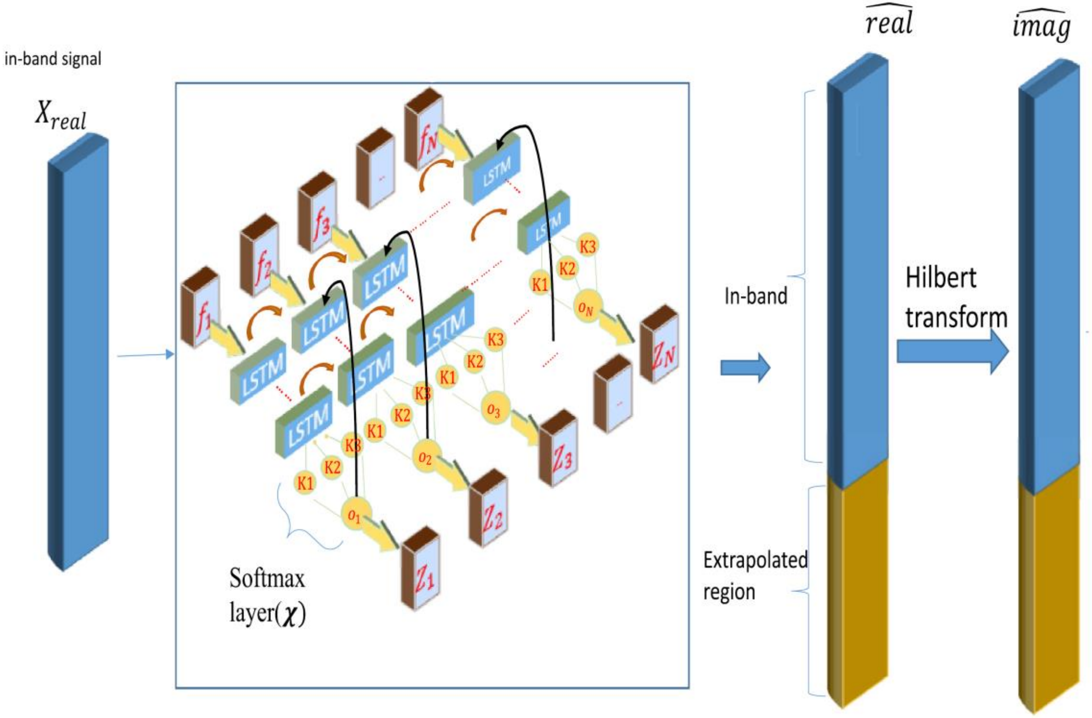
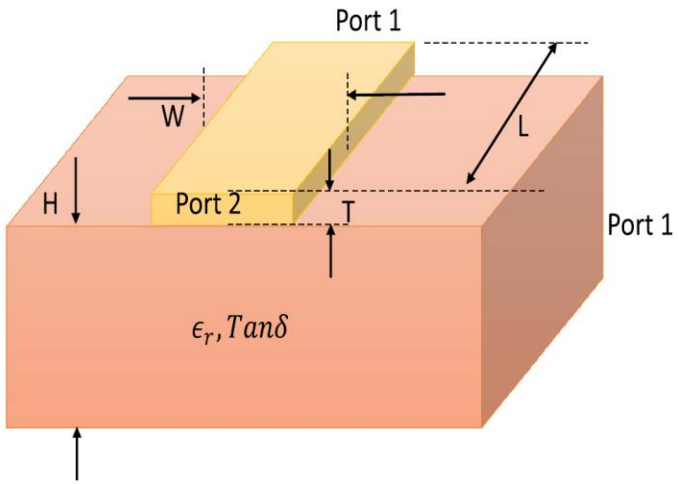


[Bhatti22]

NEURAL NETWORKS

- **Example: microstrip**

- Two port device
- Modeling: Sparam [0 - 25] GHz
  - 750 samples
- Extrapolation: Sparam [25 - 50] GHz
  - 750 samples



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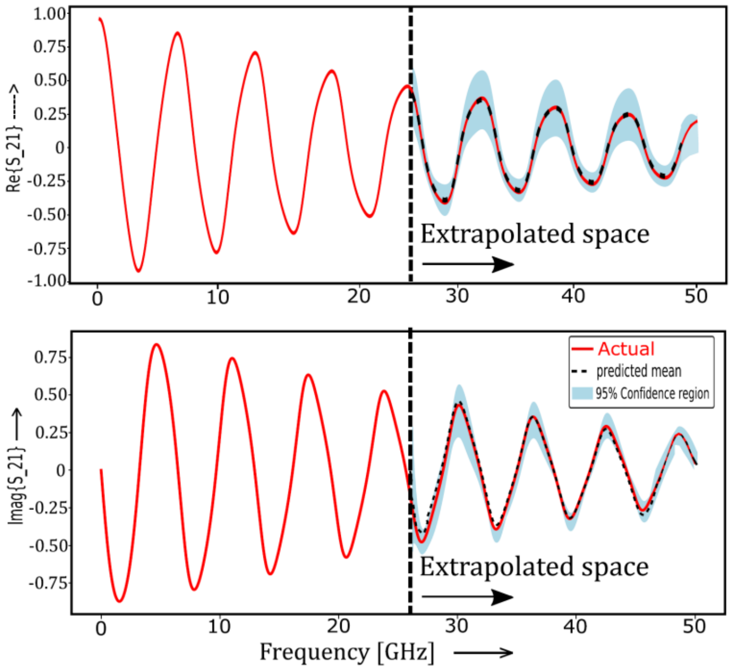
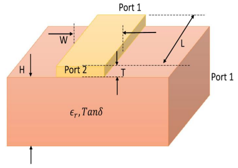
[Bhatti22]

NEURAL NETWORKS

- **Example: microstrip**
  - Results S21

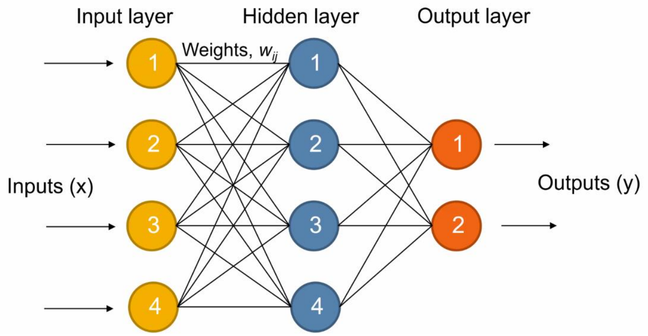




[Bhatti22]

NEURAL NETWORKS

- Challenges
  - Size training data influences complexity NN architecture
  - Increase automation in building NN model



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TUTORIAL ORGANIZATION

- Introduction
- Machine Learning for Electrical Engineering
  - Neural Networks
- Data–Efficient Machine Learning
  - Bayesian Optimization
- Conclusions

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DATA-EFFICIENT ML

- **Problem**
  - Simulations are expensive → High cost of generating a dataset

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DATA-EFFICIENT ML

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- **Goal Data–efficient ML**
  - Minimize number of simulations to build dataset→ Efficiency

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DATA-EFFICIENT ML

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DATA-EFFICIENT ML

- **Problem**
  - Simulations are expensive → High cost of generating a dataset
- **Goal Data–efficient ML**
  - Minimize number of simulations to build dataset→ Efficiency
  - Maximize the information → Accuracy
- **Solution**
  - Iteratively acquire new data in order to maximize information
  - Adapt ML model predictions according to new data

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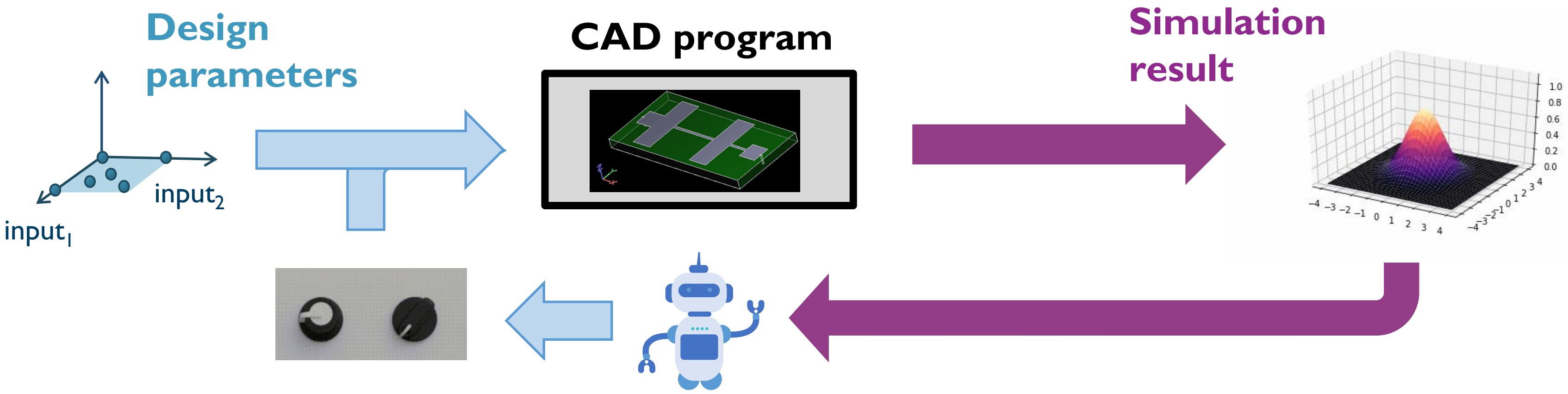
DATA-EFFICIENT ML

- **Data–efficient ML**



DATA-EFFICIENT ML

- **Data–efficient ML**
  - General framework applicable to a large range of design activities
  - Focus: optimization problems
    - Bayesian optimization (BO)

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BAYESIAN OPTIMIZATION

- Global optimization problem
  - Given $f : \mathrm{X} \rightarrow \mathbb{R}$ where $\mathrm{X} \in \mathbb{R}^D$

$$x_M = \arg\max_{x \in \mathrm{X}} f(x) \qquad \text{or} \qquad x_M = \arg\min_{x \in \mathrm{X}} f(x)$$

- Properties
  - "Black box": unknown and multimodal
  - Expensive
  - Noisy (possibly)

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BAYESIAN OPTIMIZATION

Initial samples

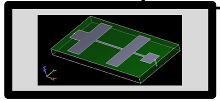
$$x^N = [x_i]_{i=1}^N$$

Performance evaluation

$$f(x^N)$$

costly

N is small



CAD program

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BAYESIAN OPTIMIZATION

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New sample

$$x_{i+1} \rightarrow x^{N+1}$$

Sampling Strategy

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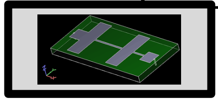


CAD program

Model update

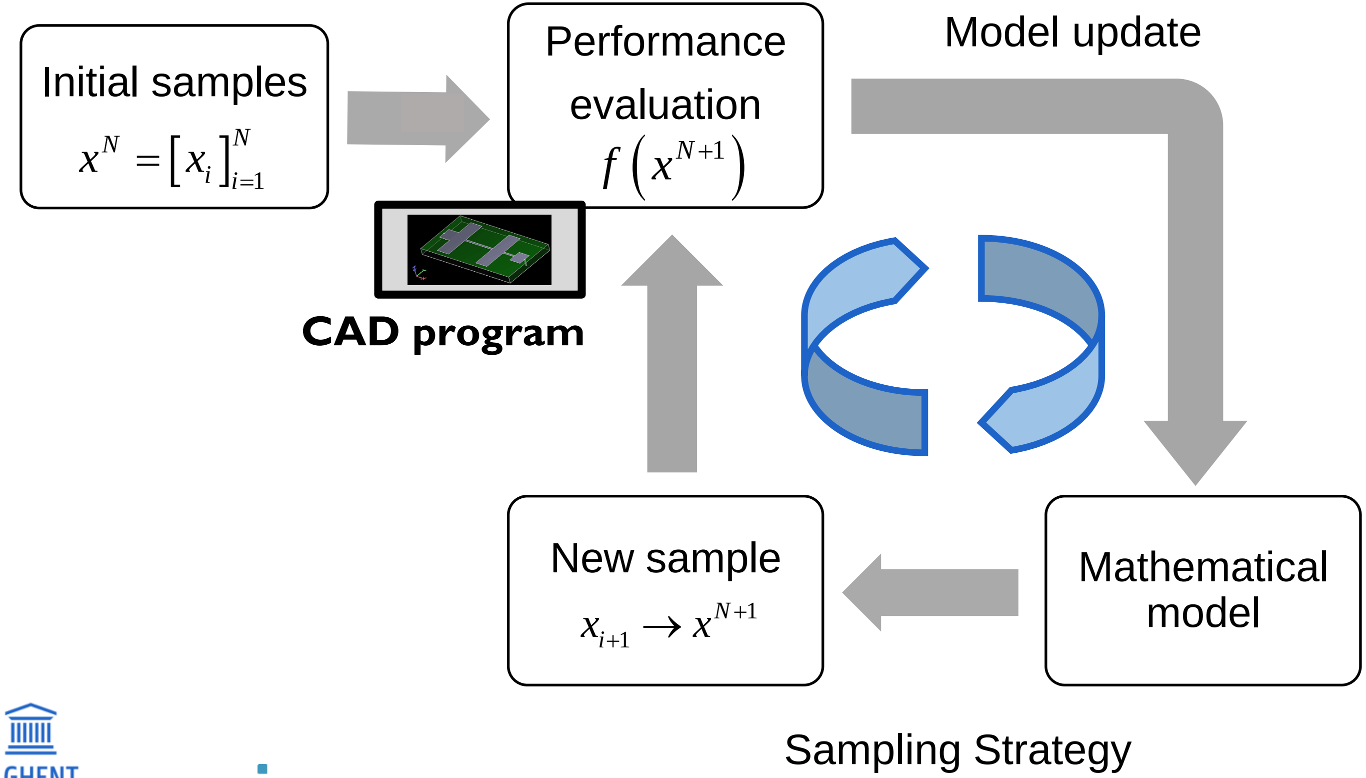
Mathematical model

New sample

$x_{i+1} \rightarrow x^{N+1}$

Sampling Strategy

BAYESIAN OPTIMIZATION



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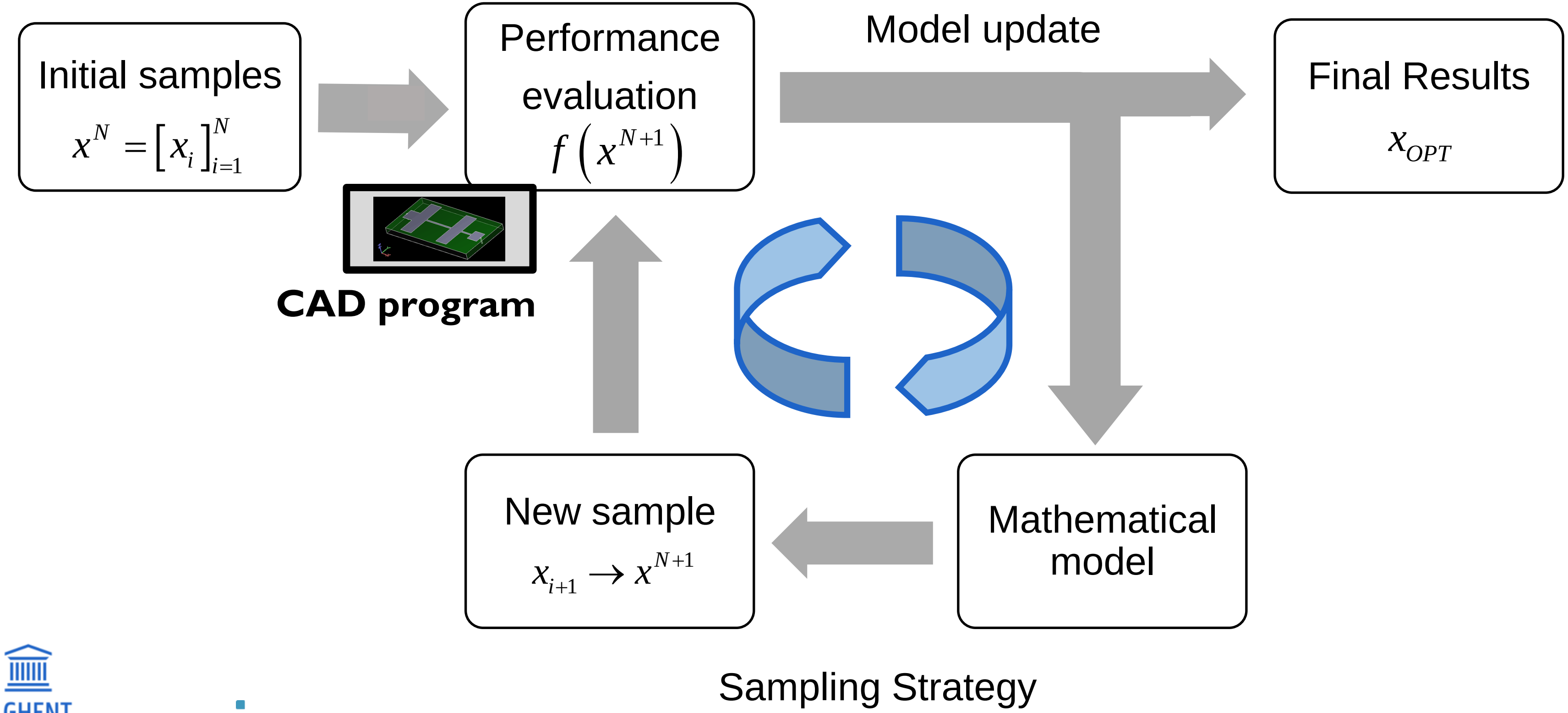

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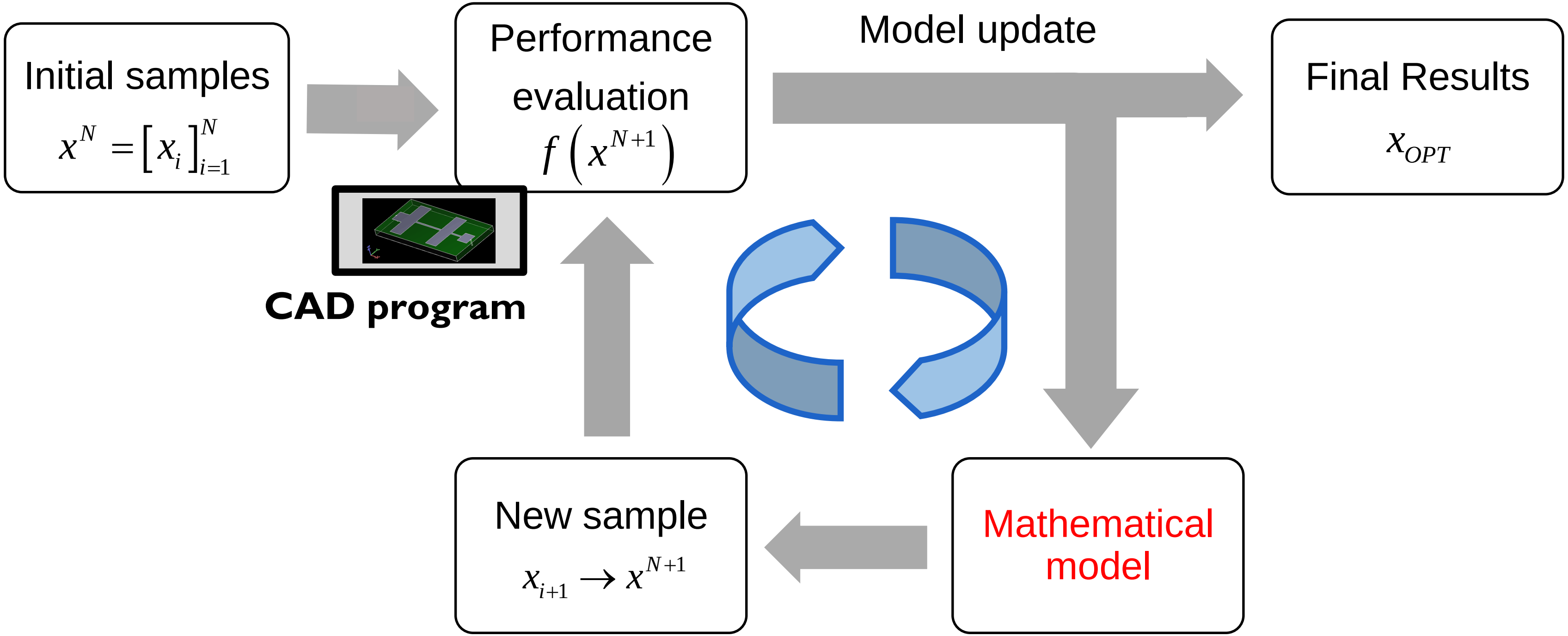

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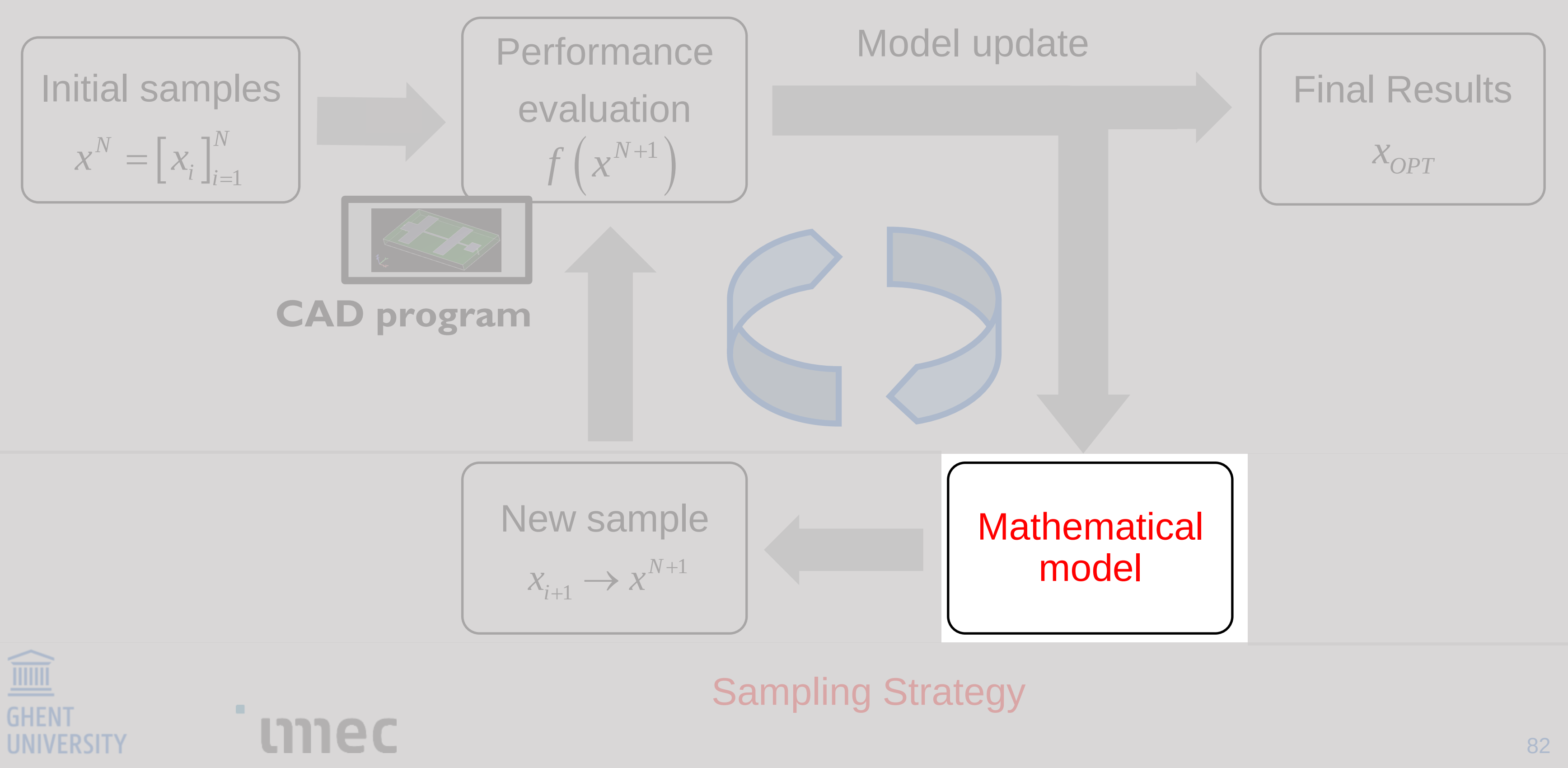

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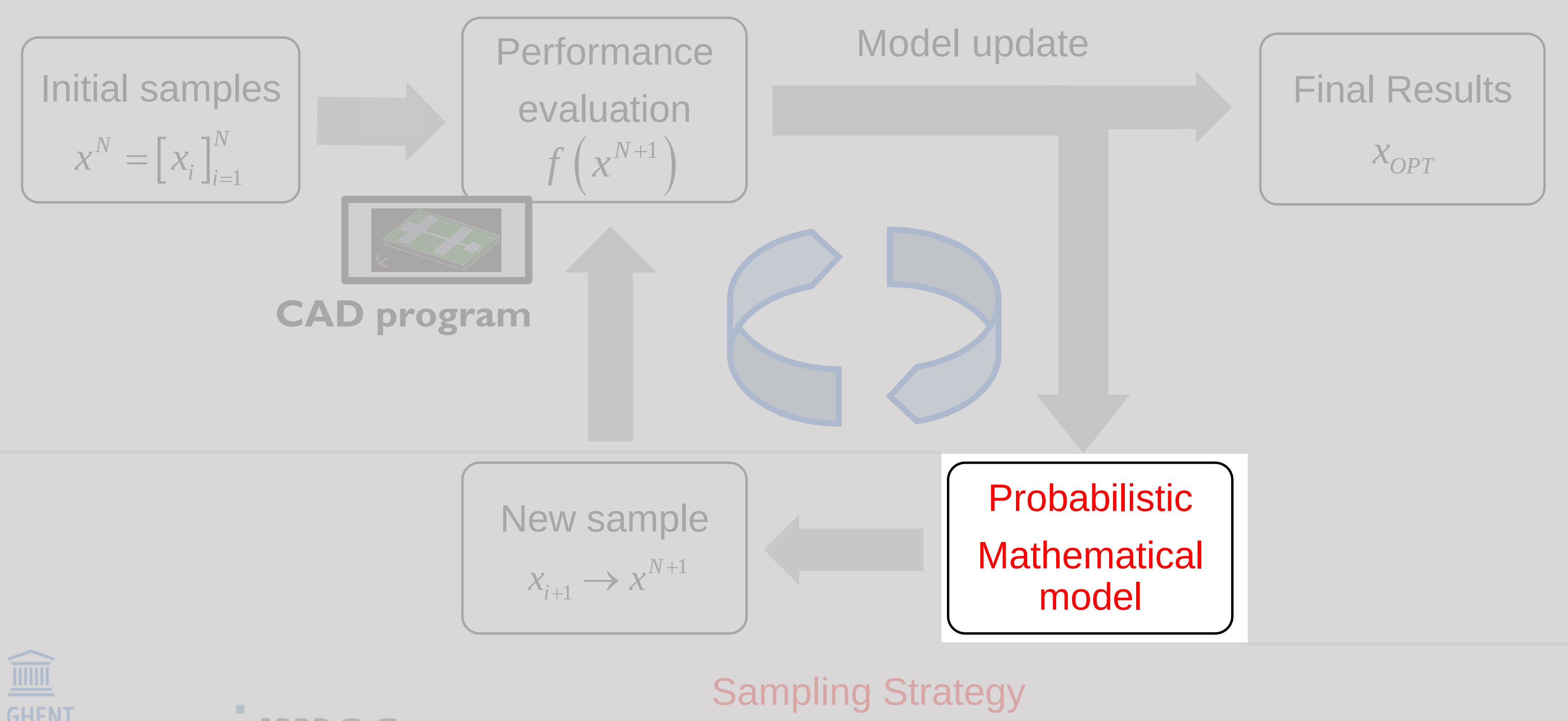
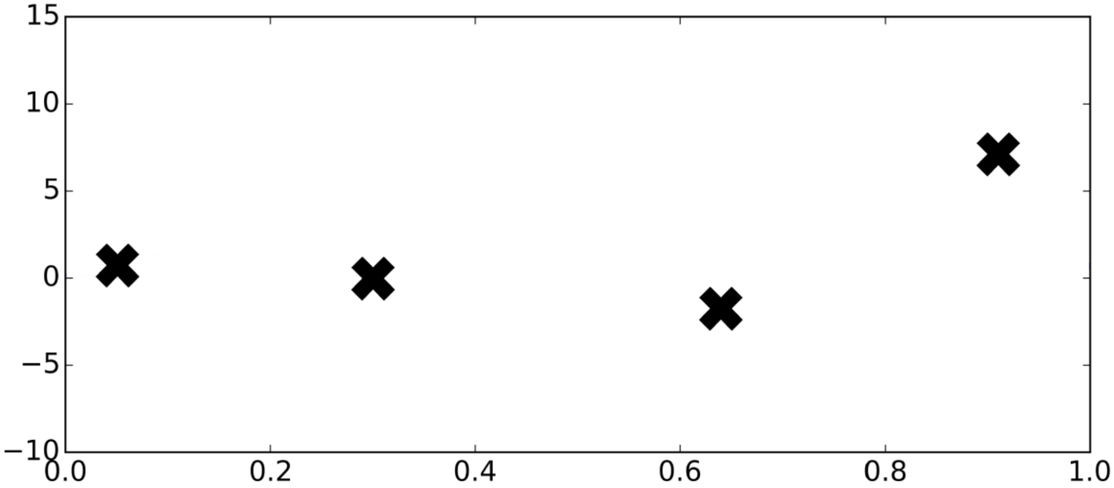


BAYESIAN OPTIMIZATION

- Example: find minimum of 1D function



[Gonzàlez17]

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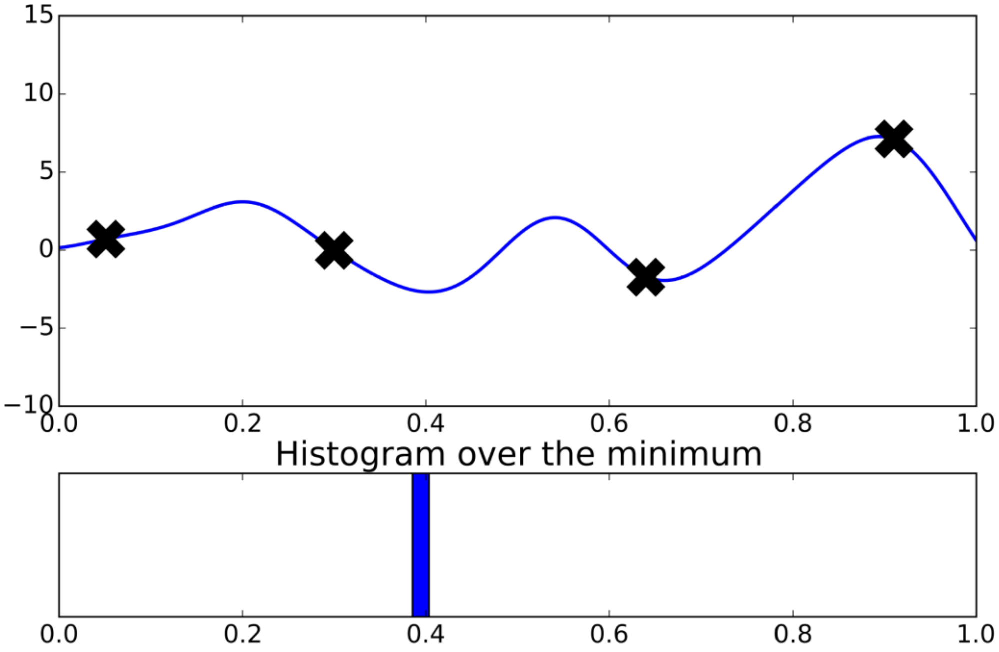

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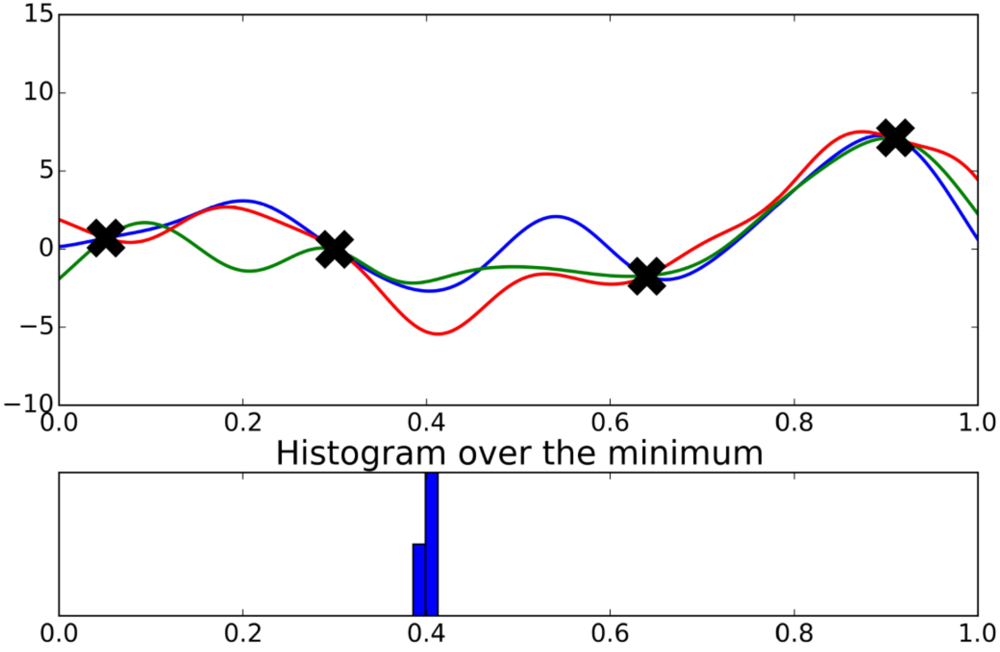

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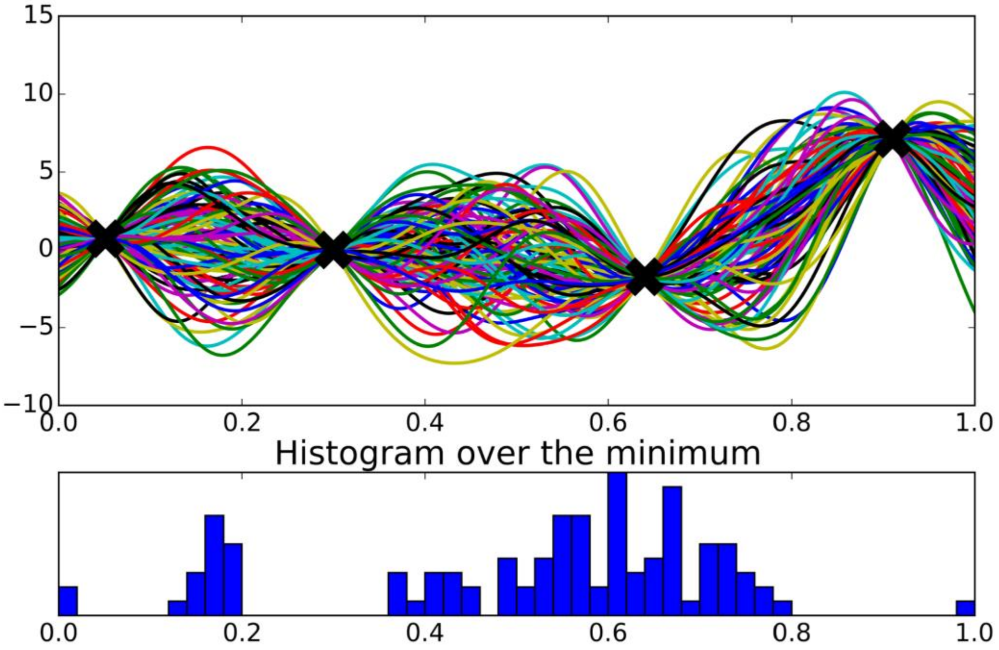

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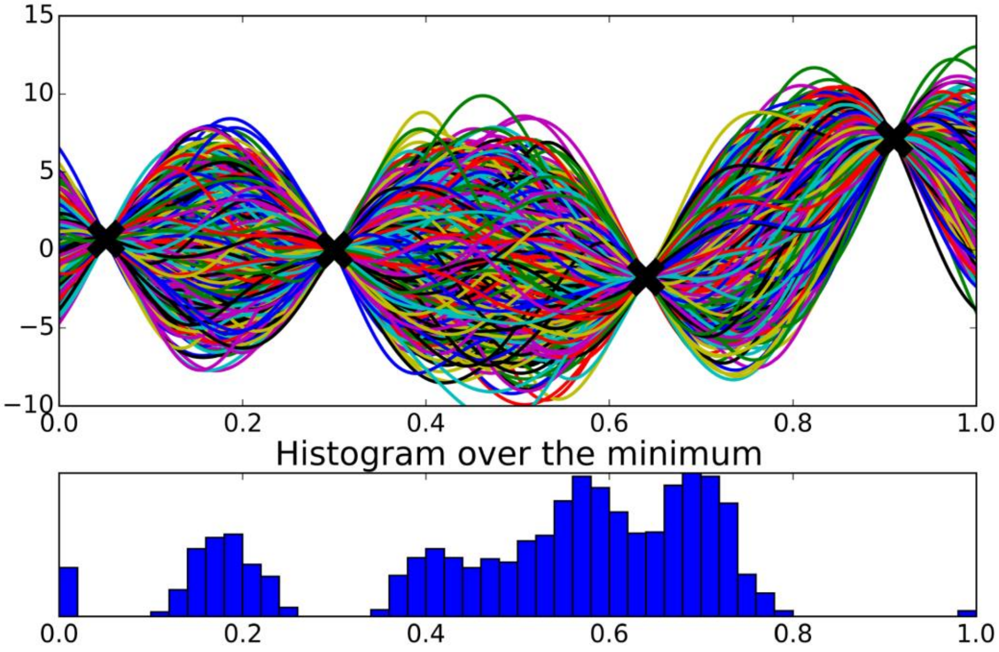

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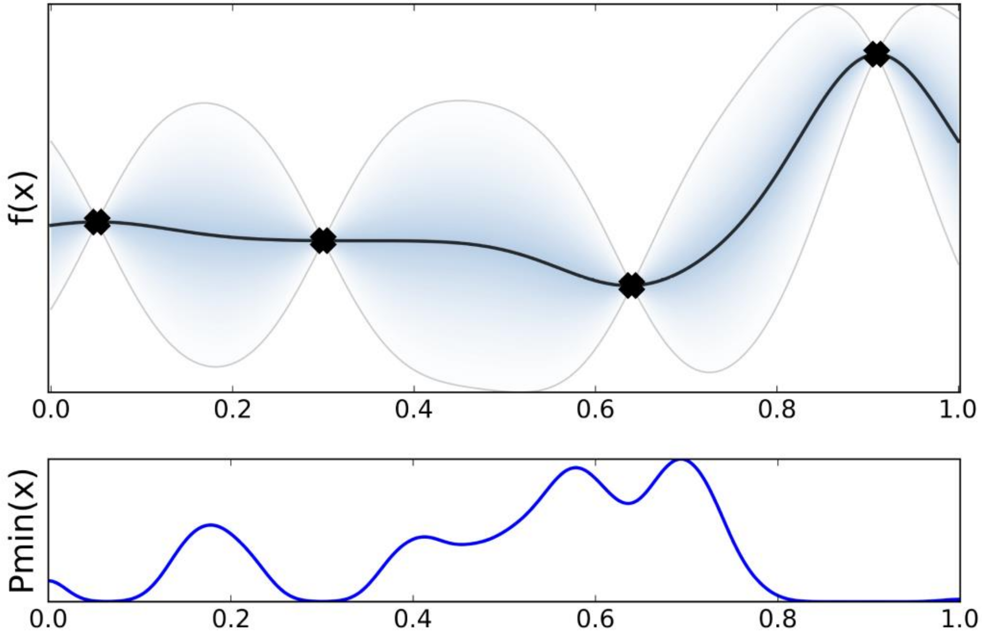

[Gonzàlez17]

BAYESIAN OPTIMIZATION

- **Distribution over functions**
  - Gaussian process (GP)
    - Generalization of Gaussian distribution
    - Fully characterized by mean and covariance function

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

Mean function   Covariance function

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Mean function Covariance function

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BAYESIAN OPTIMIZATION

- **Example of Covariance functions**

Squared exponential

$$k(x,x') = \beta \exp\left(-\frac{1}{2}\sum_{d=1}^{D}\left(\frac{x_d - x'_d}{l_d}\right)^2\right)$$

Matern

$$k(x,x') = \frac{2^{1-\nu}}{\Gamma(\nu)}\left(\frac{\sqrt{2\nu}\,\|x-x'\|}{l}\right)^{\nu} K_{\nu}\left(\frac{\sqrt{2\nu}\,\|x-x'\|}{l}\right)$$

Periodic

$$k(x,x') = \exp\left(-\frac{2\sin^2\left(0.5\left(x-x'\right)\right)}{l^2}\right)$$

- Choosing the correct covariance function for our problem
  - User choice

BAYESIAN OPTIMIZATION

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Hyperparameters

- Choosing the correct covariance function for our problem
  - User choice
- Estimating the value of the hyperparameters
  - Training phase

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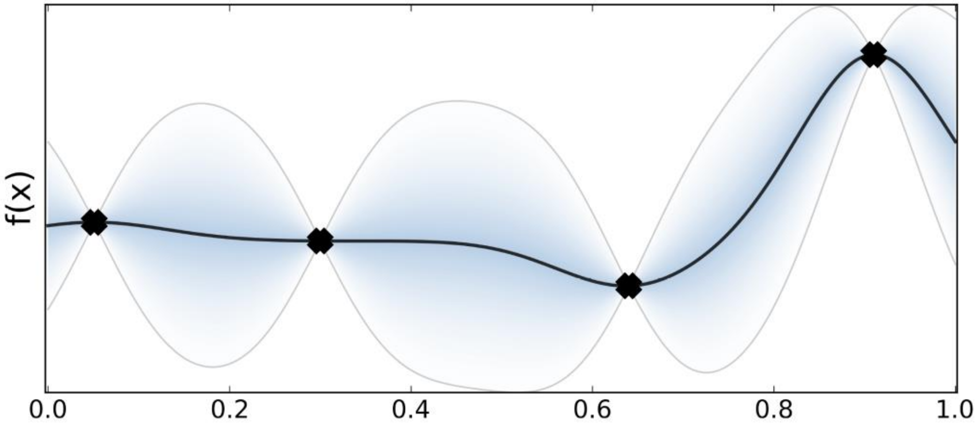
BAYESIAN OPTIMIZATION

- **Once the Covariance matrix is chosen**
  - Bayesian inference gives analytical expression for model prediction and uncertainty



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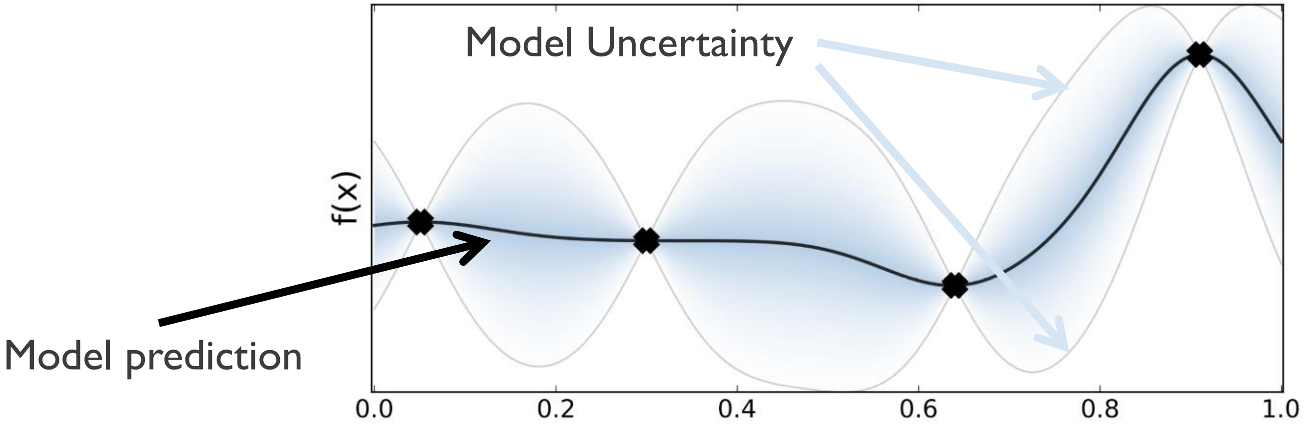

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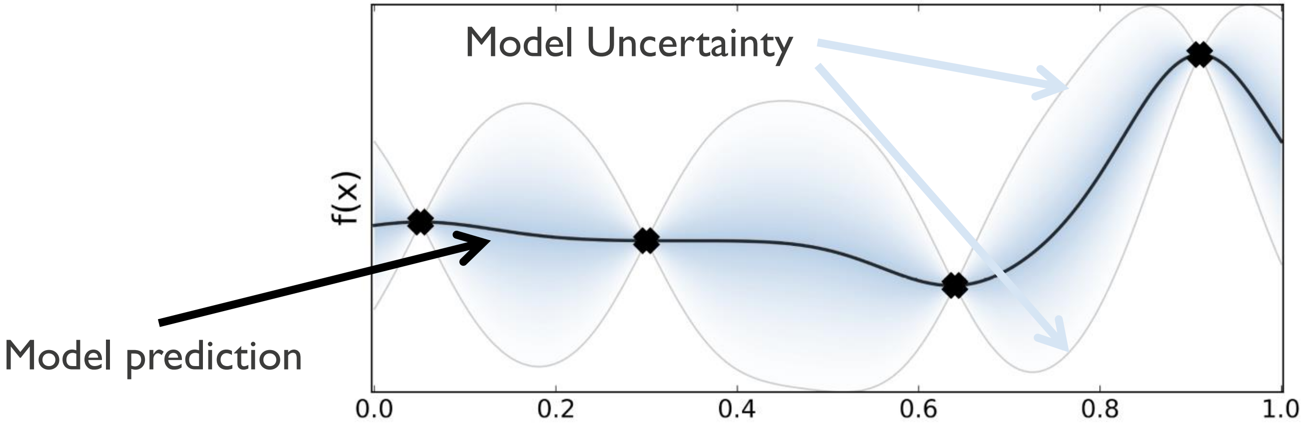

  - How to use it to determine new point to sample?

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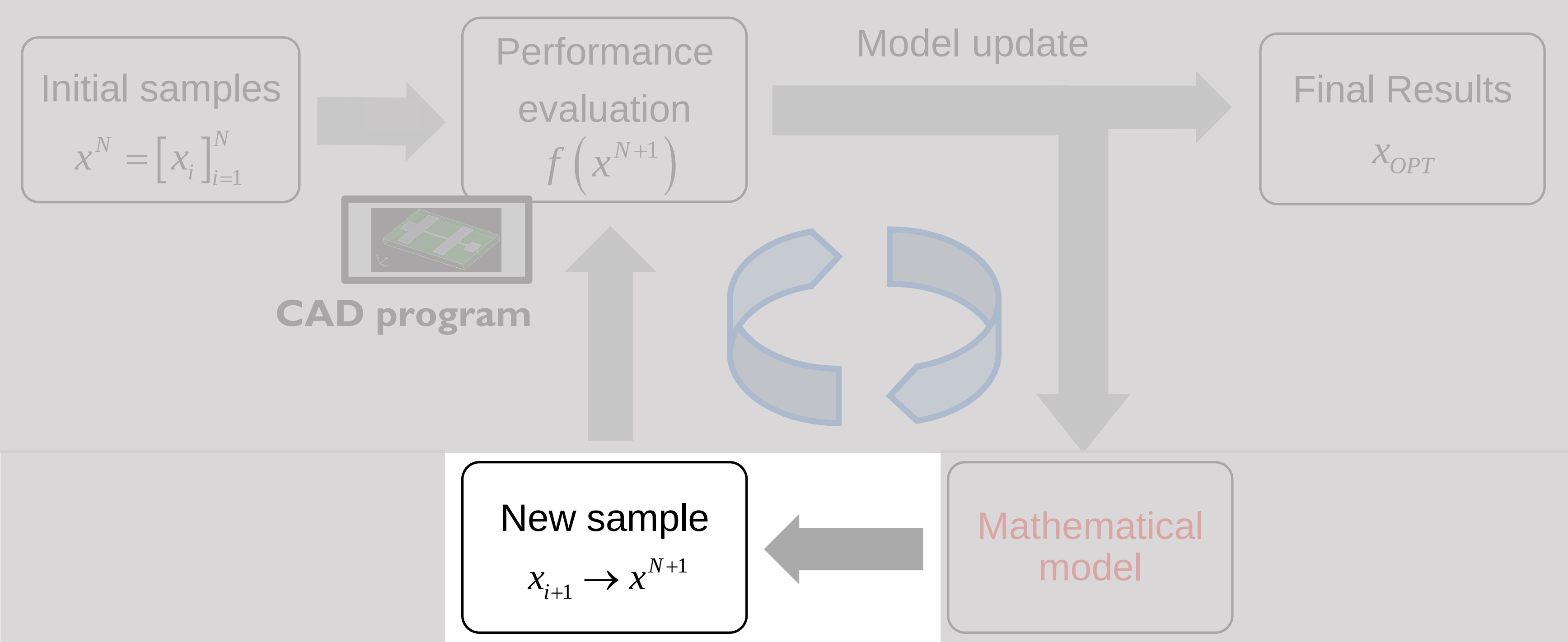
BAYESIAN OPTIMIZATION



Sampling Strategy

BAYESIAN OPTIMIZATION

- Acquisition function (AF)
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    - Example Probability of Improvement

Model's prediction

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Normal cumulative distribution function (CDF)

Model's Uncertainty

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Normal cumulative distribution function (CDF)

Model's Uncertainty

- Goal:
  - The design point maximizing AF's value is the best candidate to be chosen as next sample

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BAYESIAN OPTIMIZATION

- Using AF require to solve an optimization problem at every iteration!
  - AQ is fast to evaluate, its gradient are (typically) available

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  - AQ is fast to evaluate, its gradient are (typically) available

- BO in a nutshell
  - Strategy to transform an unsolvable global optimization problem

$$x_M = \arg\max_{x \in \mathrm{X}} f(x) \qquad \text{or} \qquad x_M = \arg\min_{x \in \mathrm{X}} f(x)$$

  - In a series of optimization problems that are easy to solve

$$x_{i+1} = \arg\max_{x \in \mathrm{X}} \alpha(x)$$

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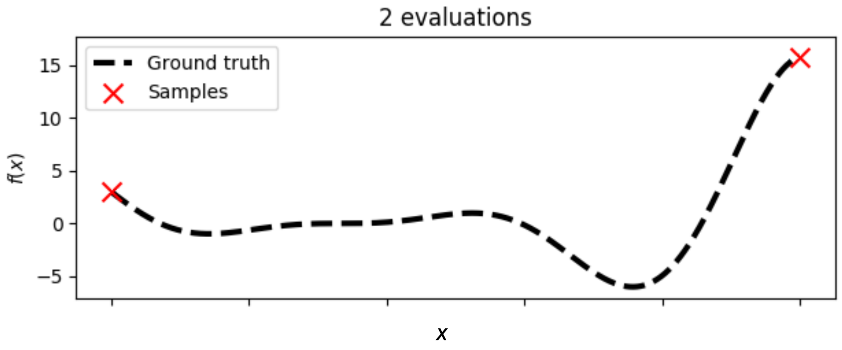
BAYESIAN OPTIMIZATION

- Example: find minimum 1D function



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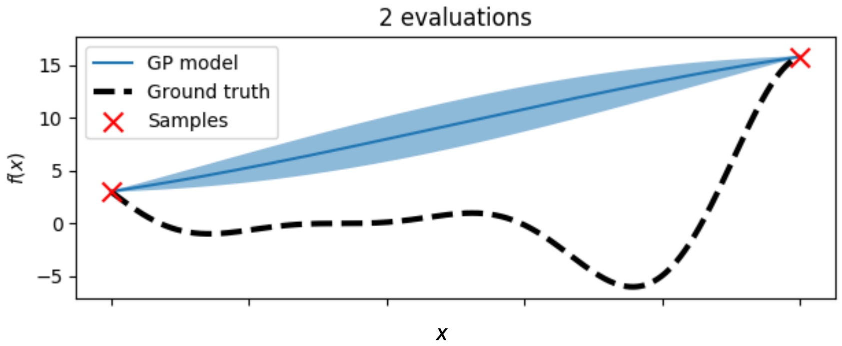

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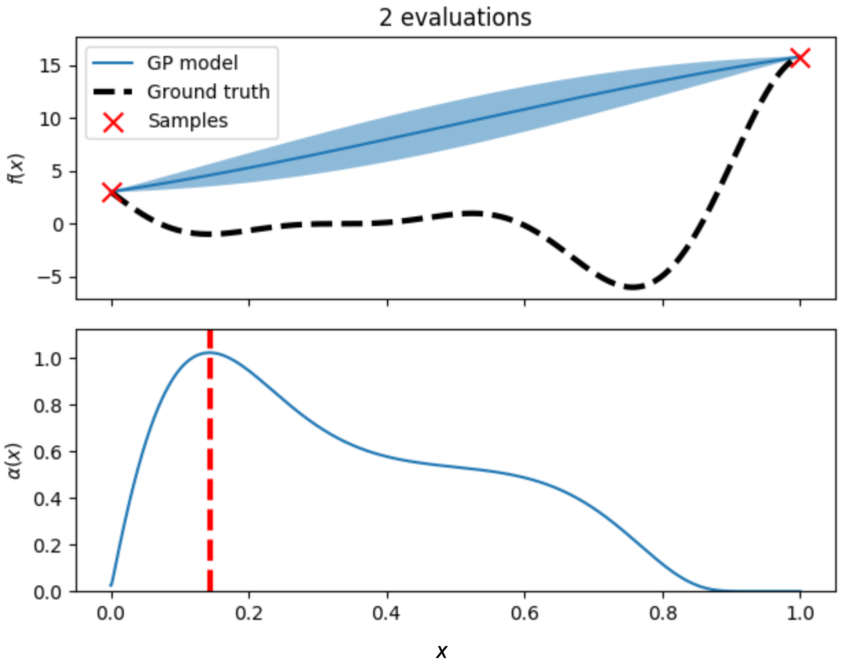

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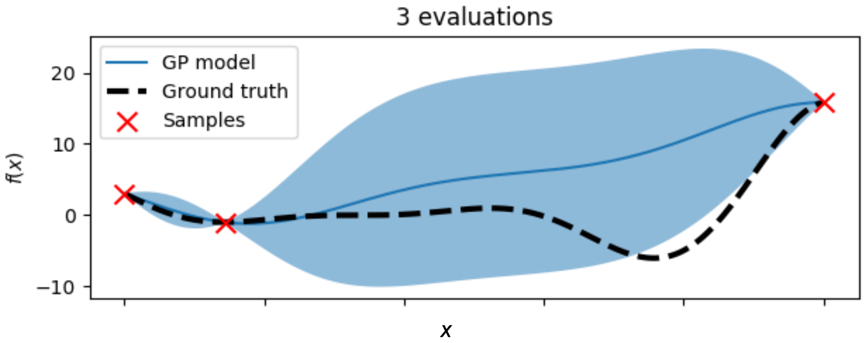

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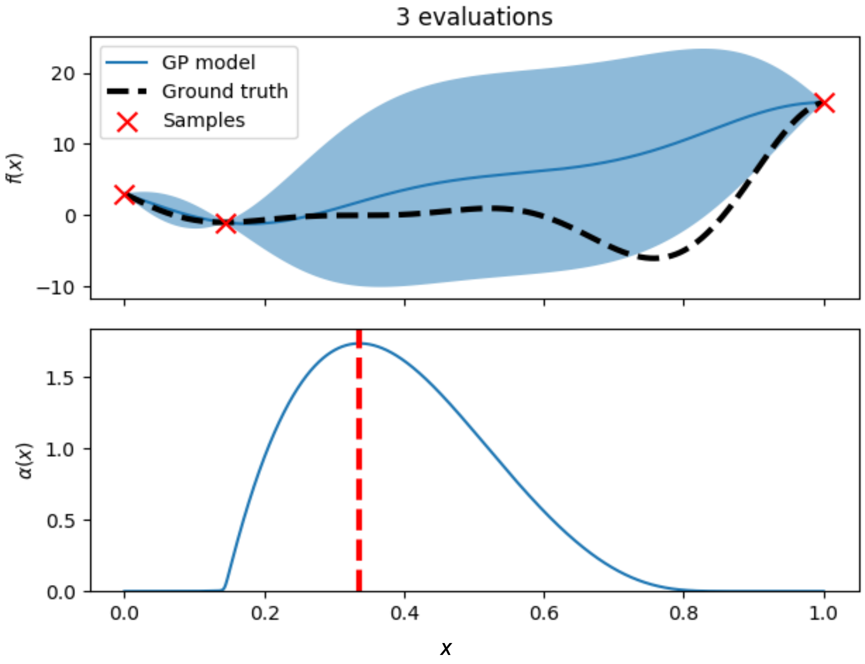
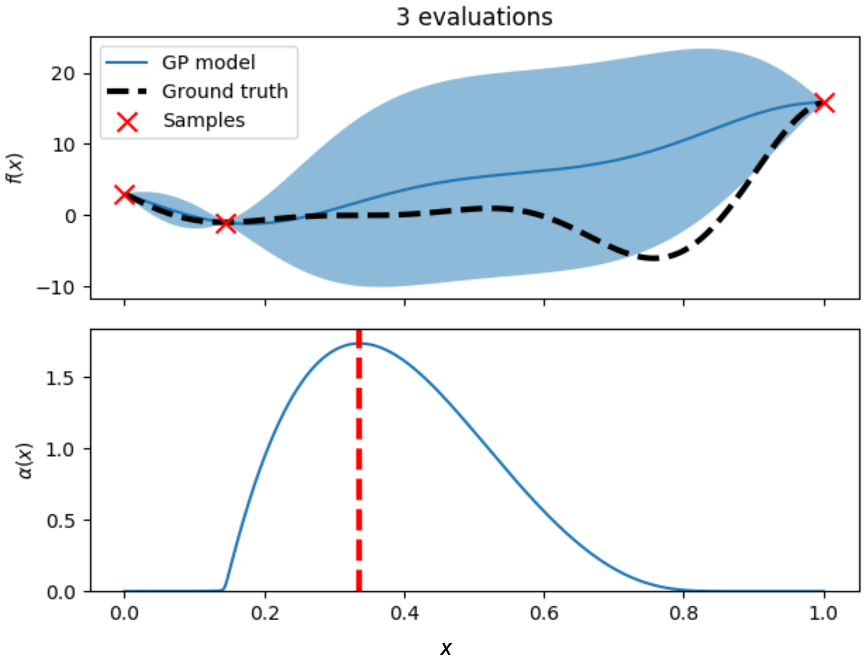


BAYESIAN OPTIMIZATION

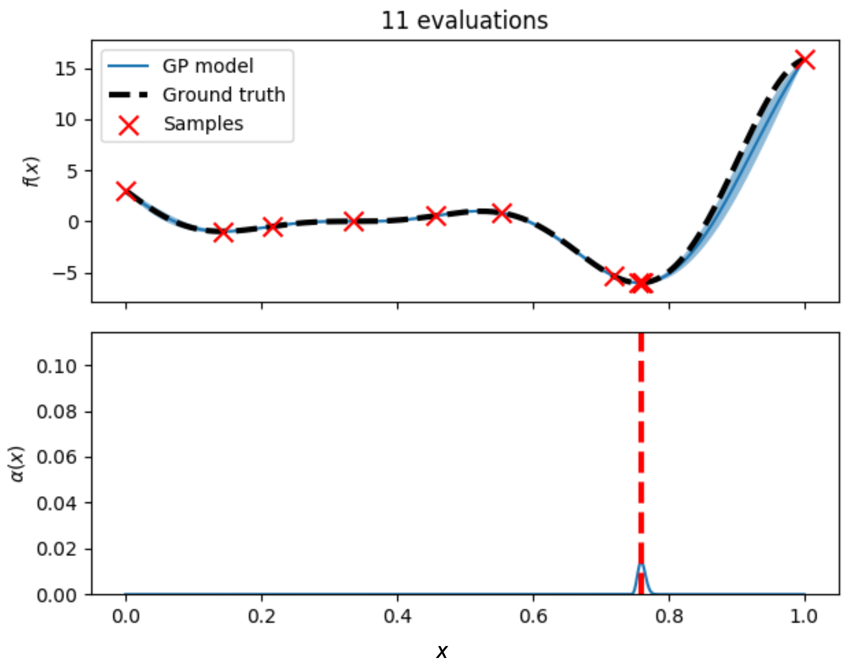
- Example: find minimum 1D function

Continue Until ….



BAYESIAN OPTIMIZATION

- Example: find minimum 1D function



BAYESIAN OPTIMIZATION

- Several AFs exist
  - Probability of Improvement (Kushner 1964)
  - Expected Improvement (Mockus 1978)
  - GP Upper confidence bound (Srinivas et al. 2010)
- Impossible to know a-priori which one is more suited to the problem at hand
  - User choice

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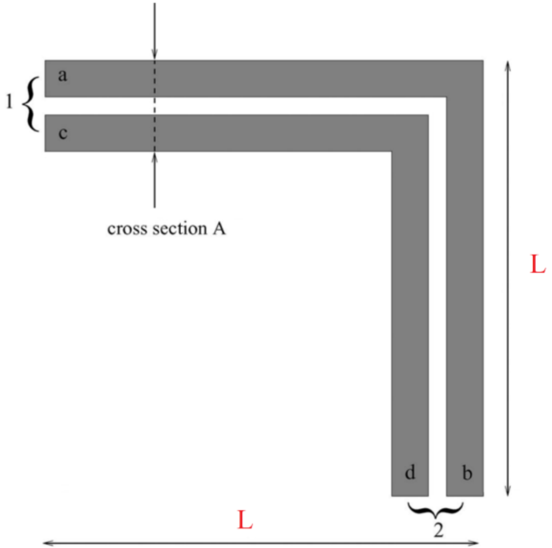
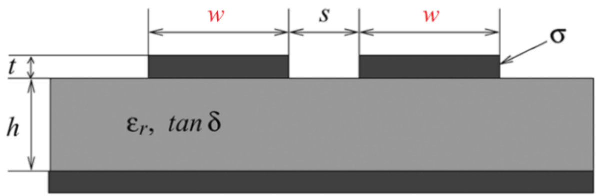
BAYESIAN OPTIMIZATION

- **Example: Optimization Bended Interconnection**
  - 2 design parameters





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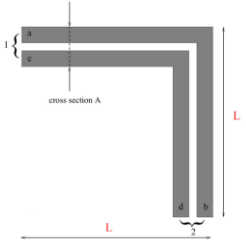
BAYESIAN OPTIMIZATION



- **Example: Optimization Bended Interconnection**
  - 2 design parameters
    - Width ϵ [0.5 – 2.1] mm
    - Length ϵ [45 - 55] mm

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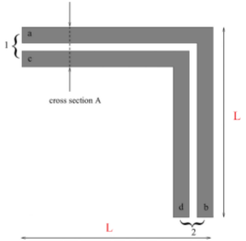
BAYESIAN OPTIMIZATION



- **Example: Optimization Bended Interconnection**
  - 2 design parameters
    - Width ϵ [0.5 – 2.1] mm
    - Length ϵ [45 - 55] mm
  - Sparam ϵ [0 - 6] GHz simulated in Advanced Design System (ADS)

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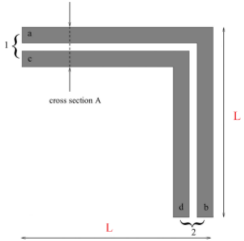
BAYESIAN OPTIMIZATION



- **Example: Optimization Bended Interconnection**
  - 2 design parameters
    - Width ϵ [0.5 – 2.1] mm
    - Length ϵ [45 - 55] mm
  - Sparam ϵ [0 - 6] GHz simulated in Advanced Design System (ADS)
  - Goal: minimize differential to common mode conversion

$$\mathrm{T}_{\mathrm{DMCM}} = \left(\int_{0GHz}^{6GHz} \left(\left| S_{cd11}(f) \right|^2 + \left| S_{cd21}(f) \right|^2 \right)^{1/2} df \right)^{1/2}$$

Elements of the modal S-parameters matrix

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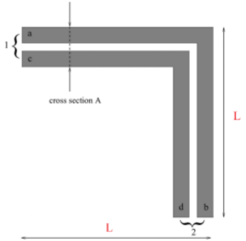
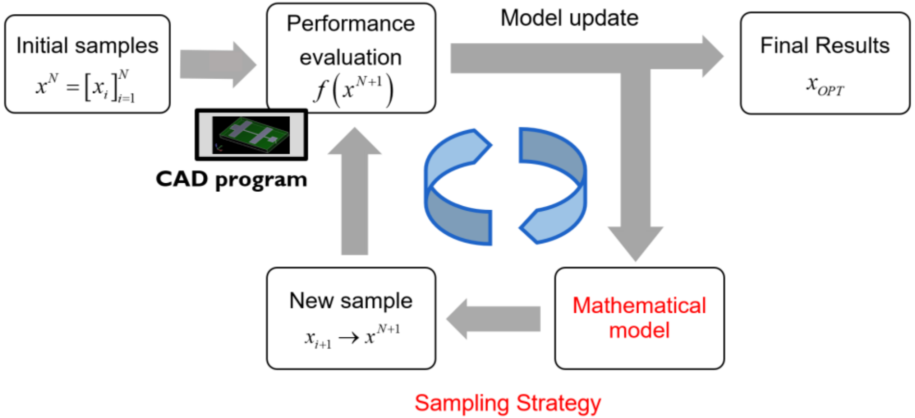
BAYESIAN OPTIMIZATION

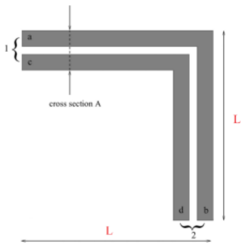
- **Example: Optimization Bended Interconnection**

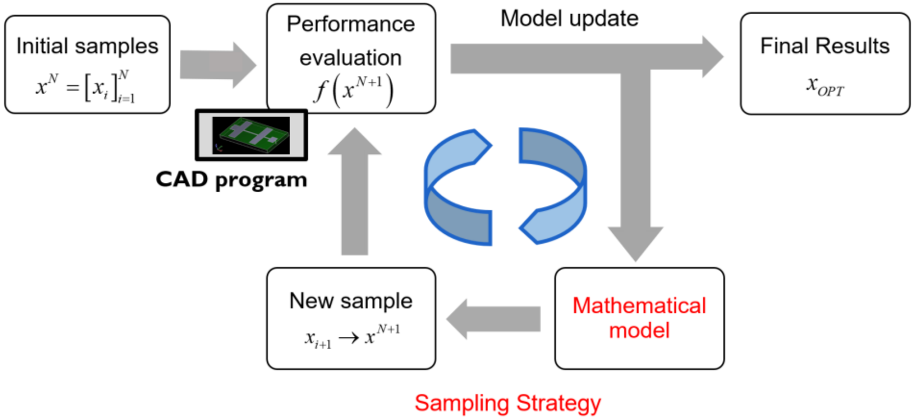




BAYESIAN OPTIMIZATION

- **Example: Optimization Bended Interconnection**
  - GP model building
    - Covariance function: Matern 3/2
      - Able to model a wide class of functions (non-differentiable ones)





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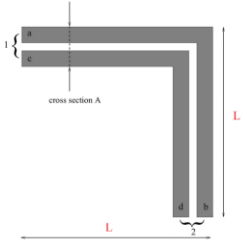
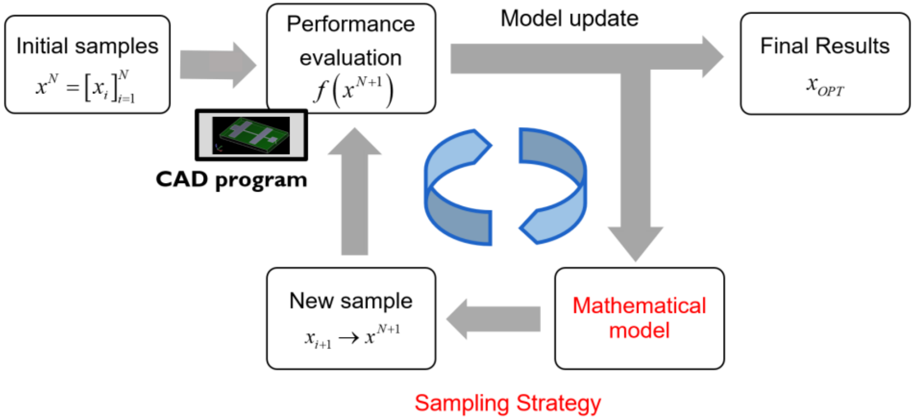
BAYESIAN OPTIMIZATION



- **Example: Optimization Bended Interconnection**
  - GP model building
    - Covariance function: Matern 3/2
      - Able to model a wide class of functions (non-differentiable ones)
  - Acquisition function
    - Expected Improvement
      - Among "standard" options



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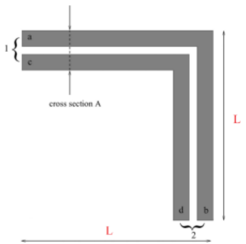
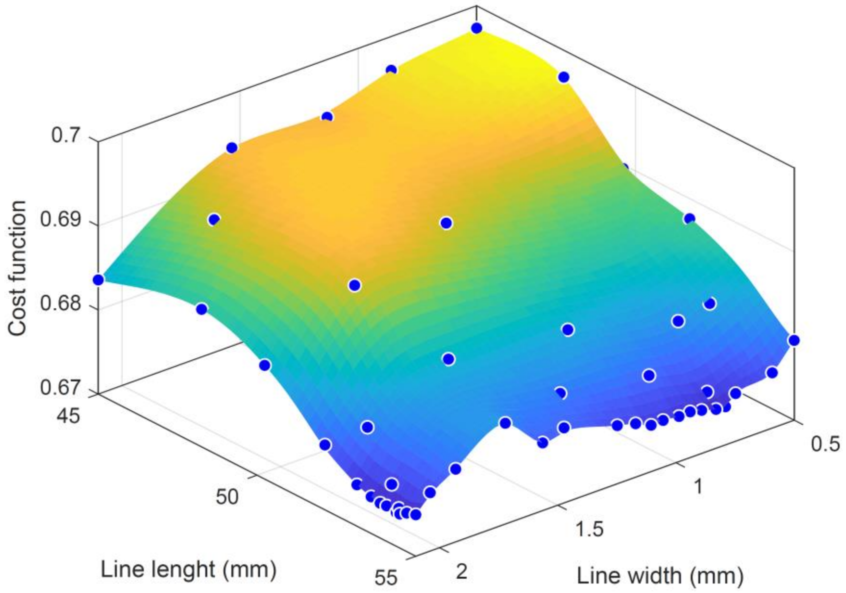
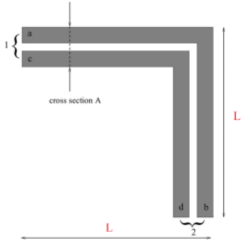
BAYESIAN OPTIMIZATION

- **Example: Optimization Bended Interconnection**
  - Optimization Results





BAYESIAN OPTIMIZATION



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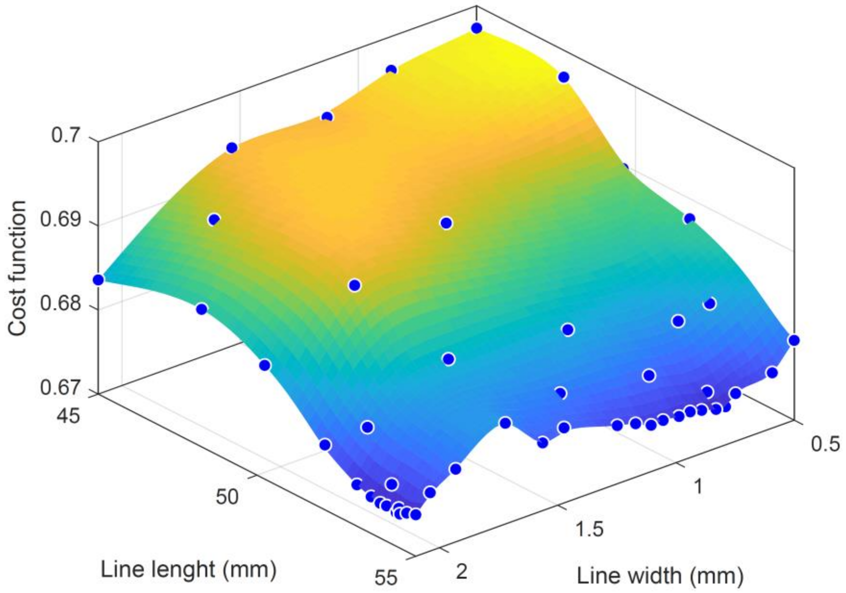
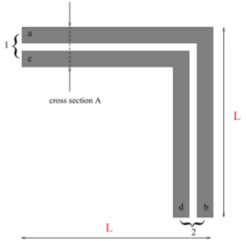
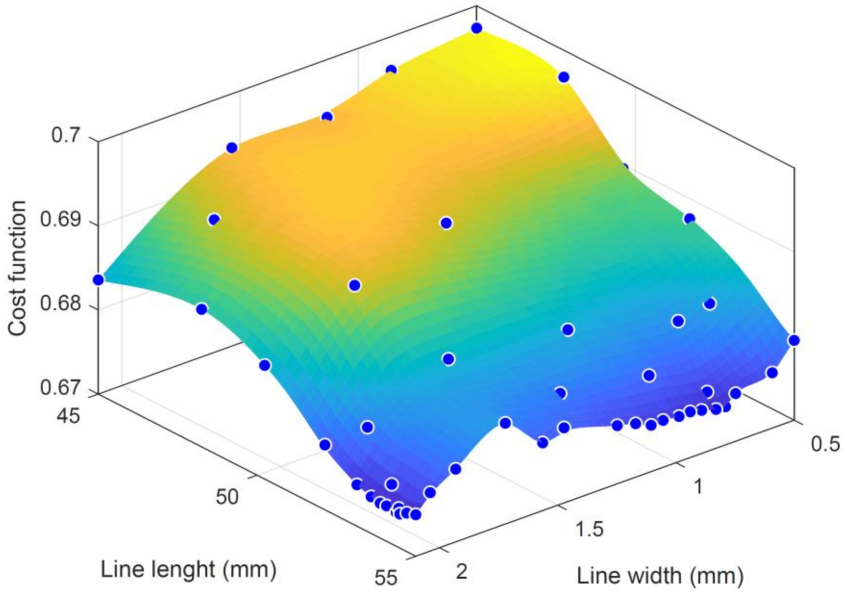


Design parameters	Min Objective function	Number of iterations
w=2.094 mm L=54.398 mm	0.6739	50

BAYESIAN OPTIMIZATION

- **Example: Optimization Bended Interconnection**
  - Optimization Results





Design parameters	Min Objective function	Number of iterations
w=2.094 mm L=54.398 mm	0.6739	50

Computational Time	
S-parameters simulations (ADS)	86 min 35.82 s (103.92 s per sample)
Bayesian Optimization	58.58 s
Total	87 min 34.4 s

BAYESIAN OPTIMIZATION

- **BO Advanced properties**
  - Constraints
    - Can be added by modifying AF
  - Multi-objective formulation
  - High-dimensional problems
    - Partitioning strategies design space

BAYESIAN OPTIMIZATION

- **Examples of BO applications in EE**
  - Antenna Design: [Wang20]
  - Microwave Filters optimization: [Jacobs14], [Garbuglia22]
  - High-speed channel optimization: [Kim21]
  - Eye Diagram worst case analysis: [Dolatsara21]
  - Power Amplifiers Optimization: [Guo22], [Knudde18]
  - Analog circuit layout optimization: [Touloupas22]

BAYESIAN OPTIMIZATION

- **BO Challenges**
  - Flexible problem formulation for analog engineering application
  - Automated model building
  - High-dimensional problems

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TUTORIAL ORGANIZATION

- Introduction
- Machine Learning for EE
  - Neural Networks
- Data–Efficient Machine Learning
  - Bayesian Optimization
- Conclusions

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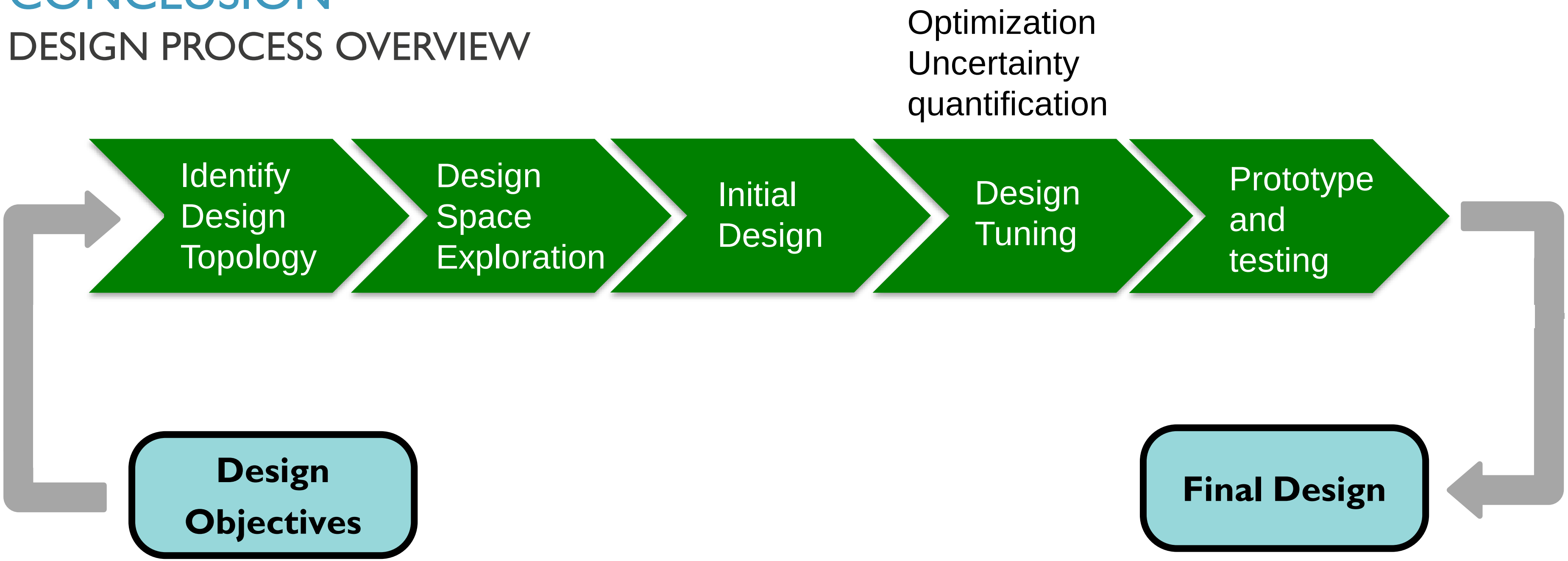
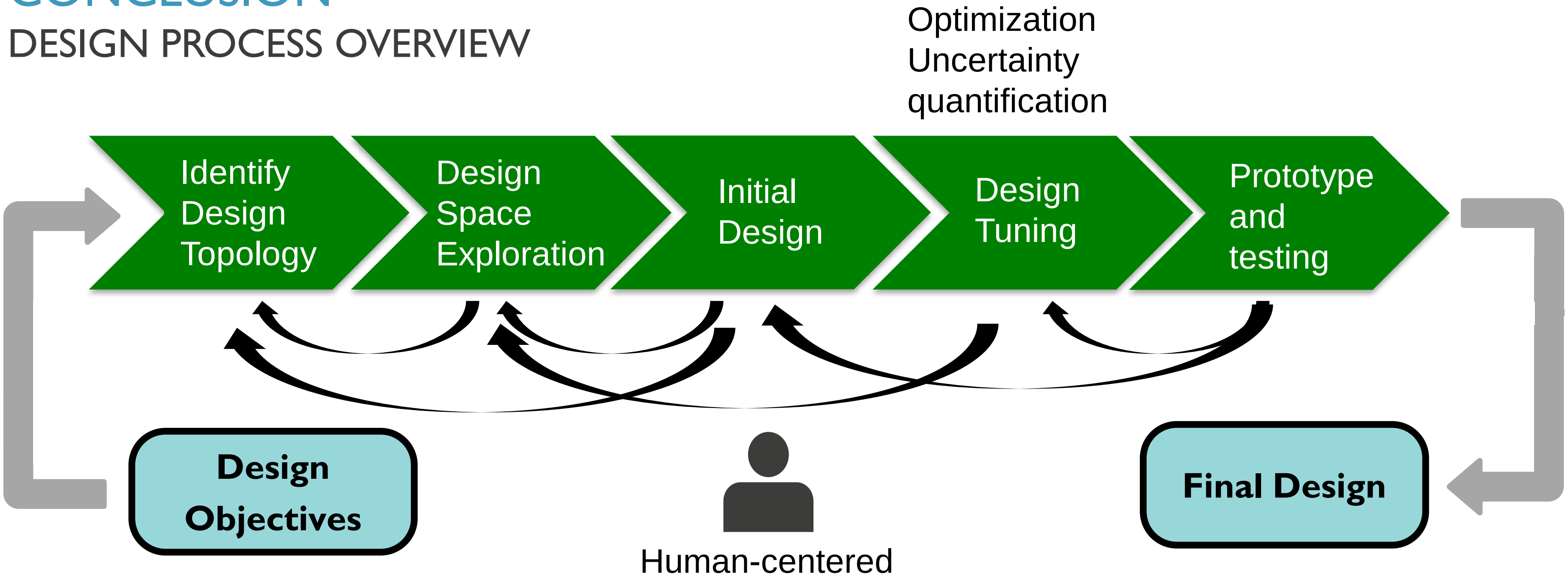
CONCLUSION

DESIGN PROCESS OVERVIEW

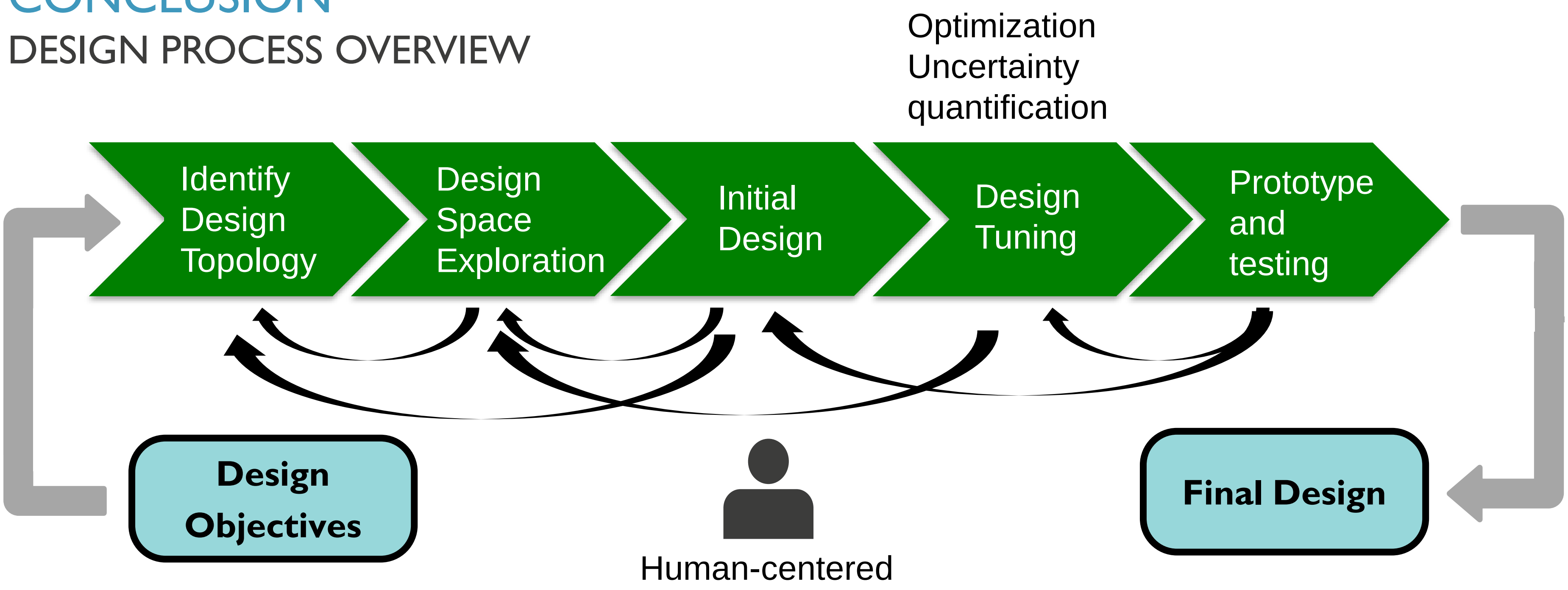


CONCLUSION

DESIGN PROCESS OVERVIEW



CONCLUSION
DESIGN PROCESS OVERVIEW



- ML promises to increase level of automation and efficiency design process

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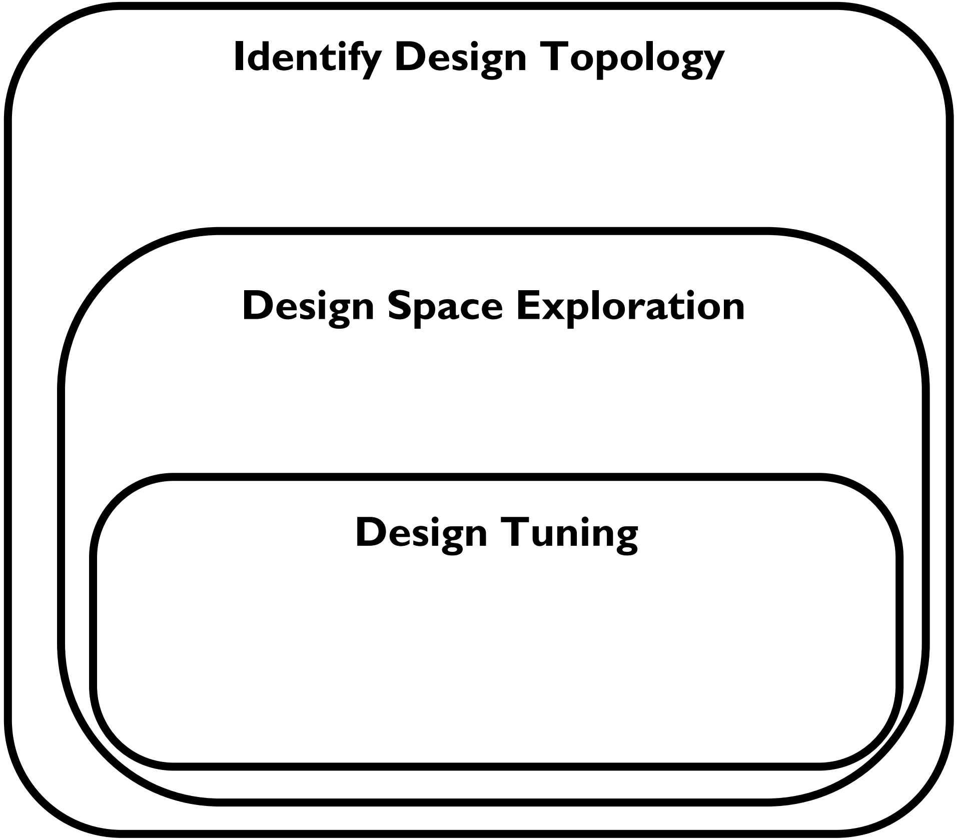
CONCLUSION
DESIGN PROCESS OVERVIEW



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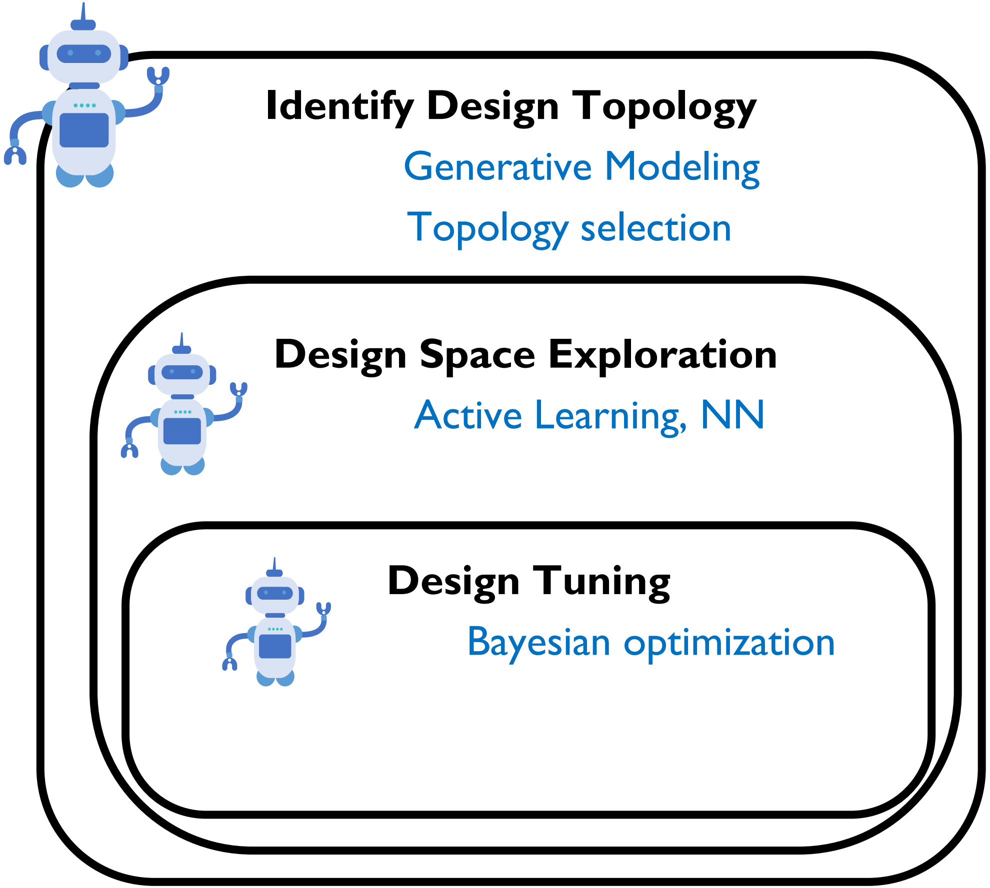
DESIGN PROCESS OVERVIEW



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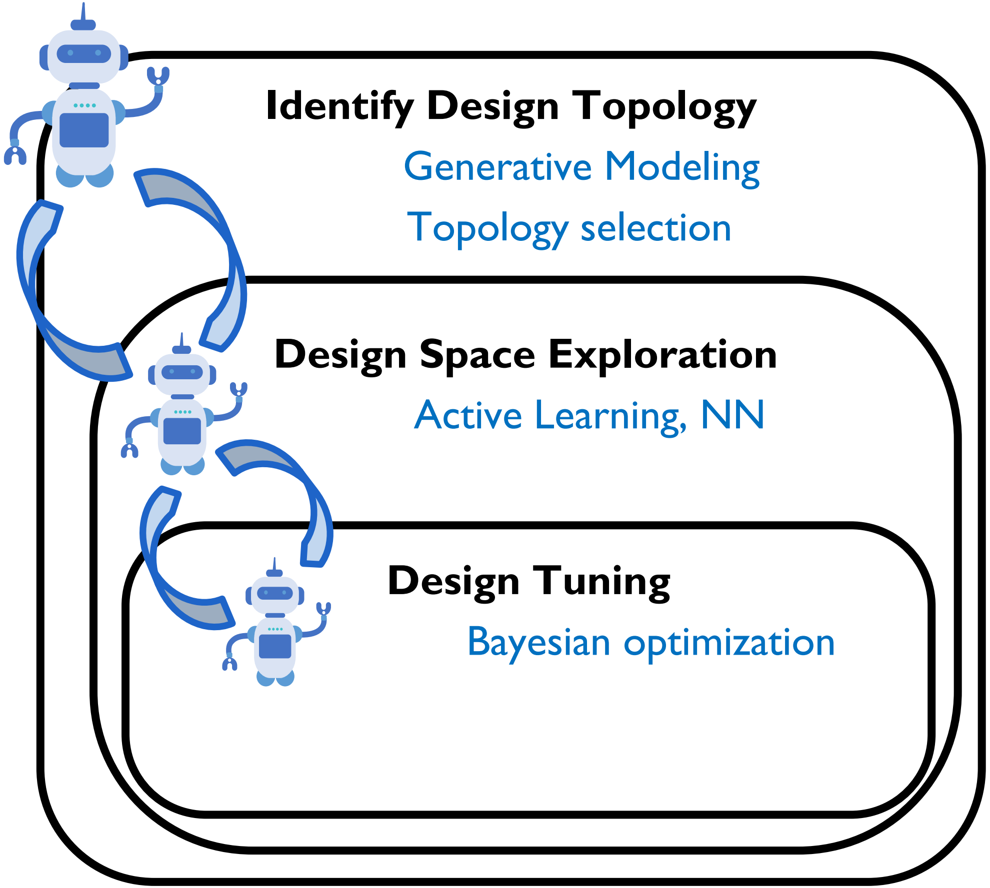

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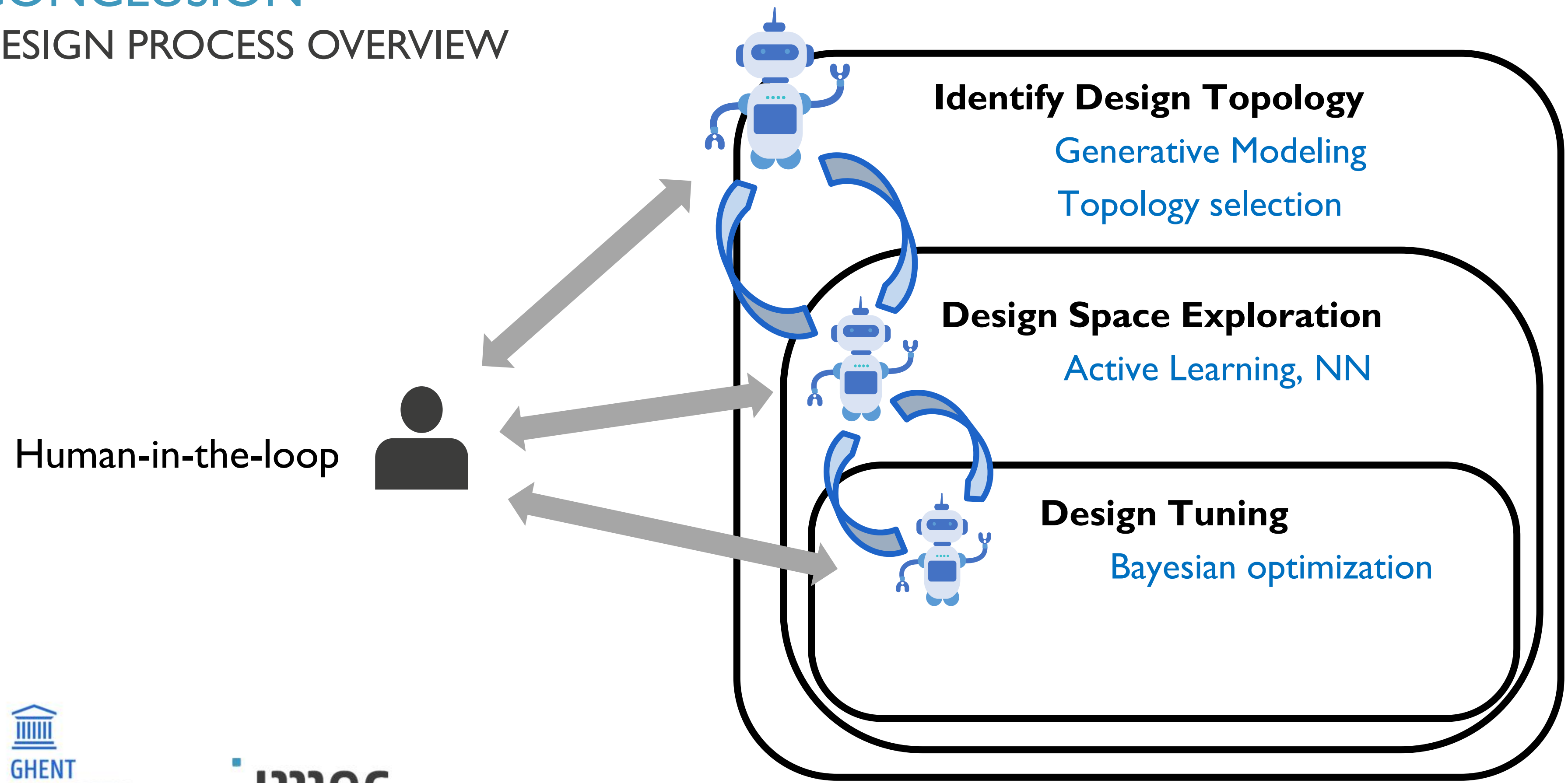

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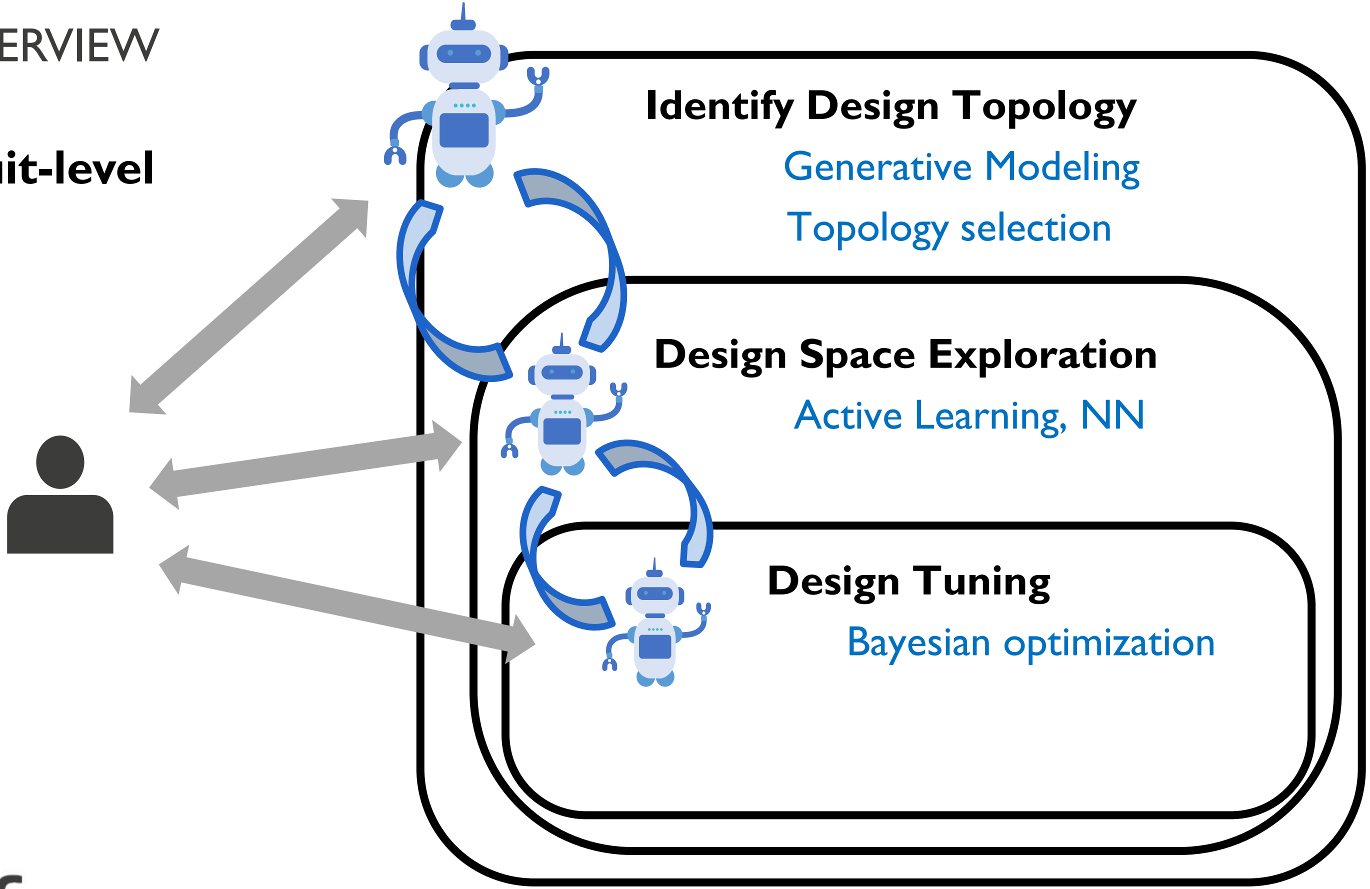
CONCLUSION

DESIGN PROCESS OVERVIEW

- **Device- and Circuit-level**

Human-in-the-loop



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Thanks for your attention!

Questions?

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