Evaluation of Generative Modeling techniques for frequency responses

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Outline

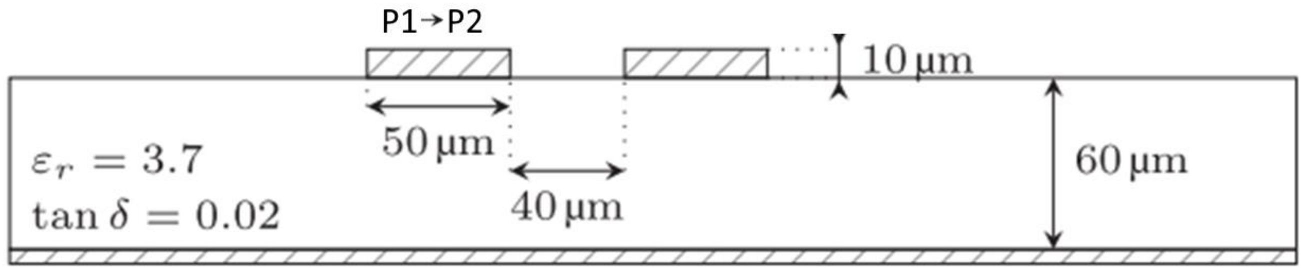
- Introduction
- Methodology
- Results
- Conclusion

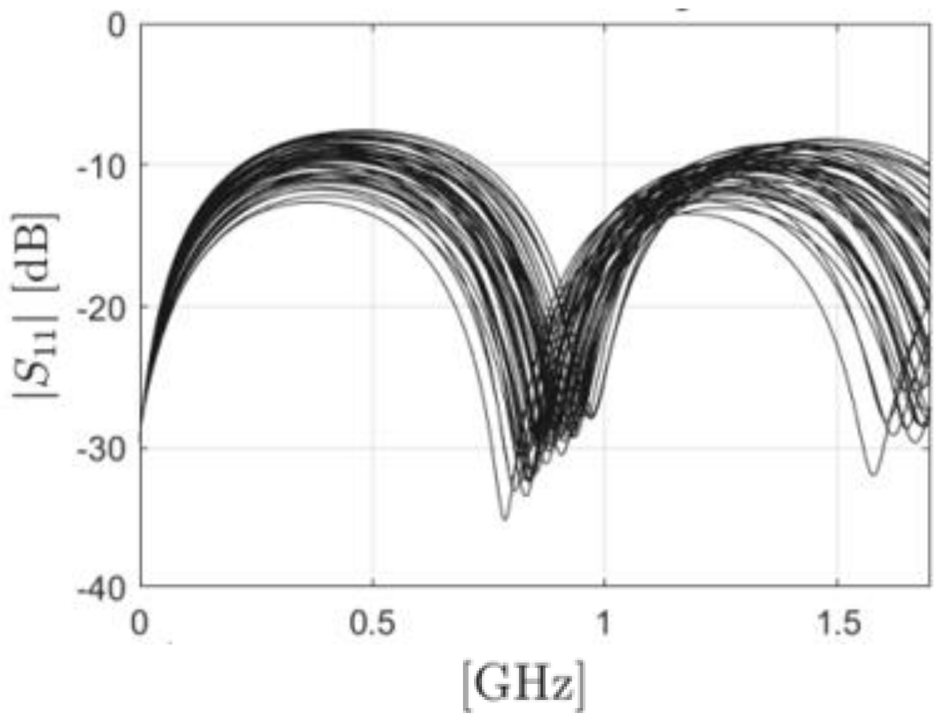
Introduction

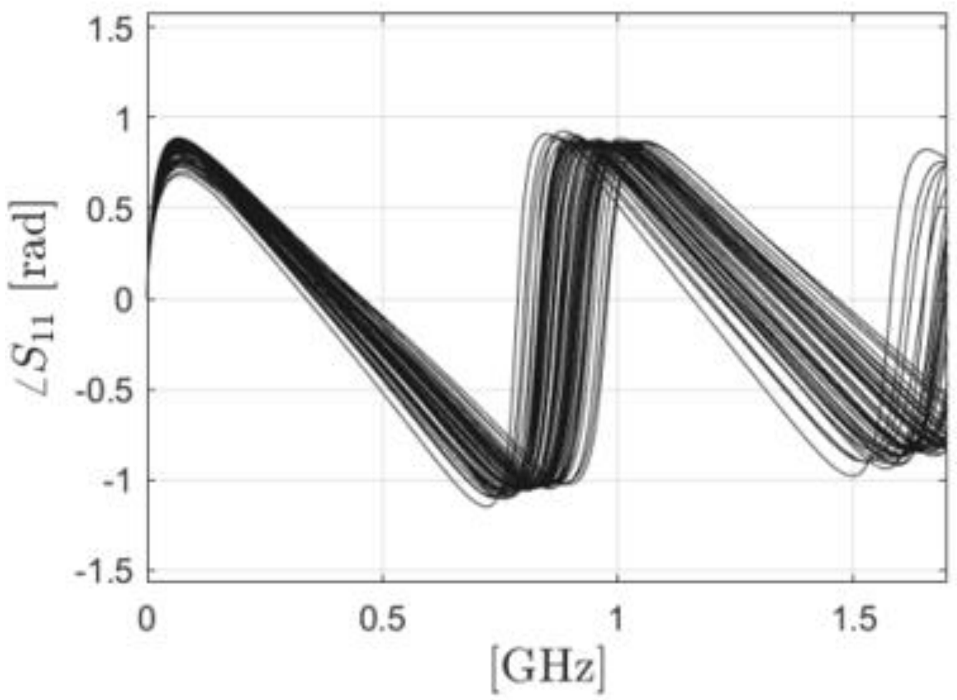
Introduction

- Performance of modern RF and Microwave circuits is largely affected by manufacturing tolerances
- A device frequency response is usually subject to **high variability** with respect to **design parameters**

  →Uncertainty quantification is often required







Introduction

- Uncertainty quantification requires many statistical samples, i.e. frequency responses, which are expensive to obtain

  → Use of **Generative Modeling** techniques

- The *idea* behind **Generative Modeling**

  1) Simulate or measure few frequency responses (training instances)
  2) Train a model to produce new responses, according to a **statistical distribution that matches the original one**
  3) Generate many new responses for uncertainty quantification

Methodology

Methodology

- **In this work:**
  - Two generative algorithms:

    Gaussian Process-Latent Variable Model (**GP-LVM**)

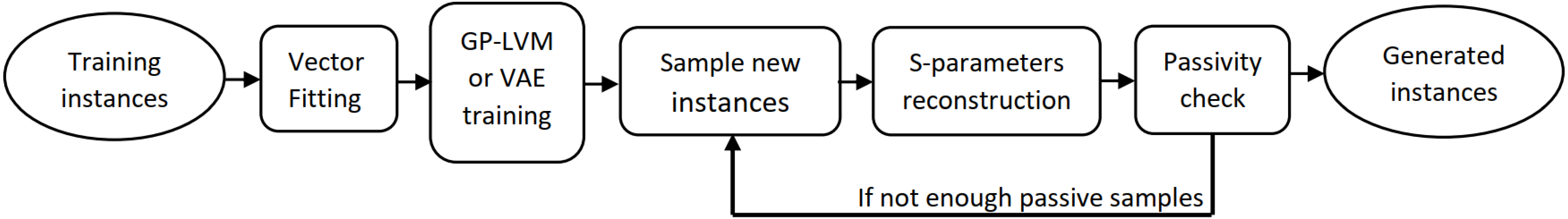
    Variational Autoencoder (**VAE**)
  - Both algorithms adopt a generative framework based on Vector Fitting (**VF**) [1]

- **Advantages**

  1. Black-box approach
  2. No knowledge of the number of varying parameter or their distribution
  3. Stability and reciprocity of frequency responses guaranteed by VF characterization

Methodology

— Proposed Modeling Framework [1]



— Steps

1. Training data are converted from S-parameters to rational coefficients via VF
2. The generative model (GP-LVM or VAE) is trained on the rational coefficients
3. New rational instances are generated by the model
4. Rational instances are reconverted in S-parameters
5. Non-passive instances are discarded

Vector Fitting

- Converts S-parameters responses $\boldsymbol{S}(s)$ into a rational model [2]

$$\boldsymbol{S}(s) = \sum_{i=0}^{D} \frac{\boldsymbol{r}_i}{s - a_i} + \boldsymbol{r}_0$$

$\boldsymbol{r}_i$: $residues$

a_i: $poles, common\ to\ all\ instance$

s: $complex\ frequency\ variable$

- **Only residues** $\boldsymbol{r}_i$ are fed into the GP-LVM or VAE
- S-parameters are reconstructed by evaluating the rational model at the desired frequency s

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Generative Models

- Generative models reproduce the distribution of observed residues data $p(Y)$, given a distribution of latent variables $p(X)$
  - X variables encode the sources of variability, without an explicit relation to the design parameters

- $p(Y)$ is obtained by marginalizing

$$p(Y, X) = p(Y|X)p(X)$$

- $p(X)$ is Gaussian by assumption in both GP-LVM and VAE:

$$p(X) = N(\boldsymbol{O}, \boldsymbol{I})$$

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Gaussian Process-Latent Variable Model

- The GP-LVM [3] maps the latent space to the observed space using Gaussian Processes (GPs), modeling the likelihood $p(Y|X)$

$$p(Y|X) = \prod_{d=1}^{D} N(y_d|0, \Sigma),$$

$\Sigma: chosen\ kernel\ matrix$

$y_d: observations\ \ of\ the\ d^{th}\ residue$

- A **new instance** of residues Y^* is generated by drawing a sample X^* from $p(X)$ and evaluating the corresponding GPs output

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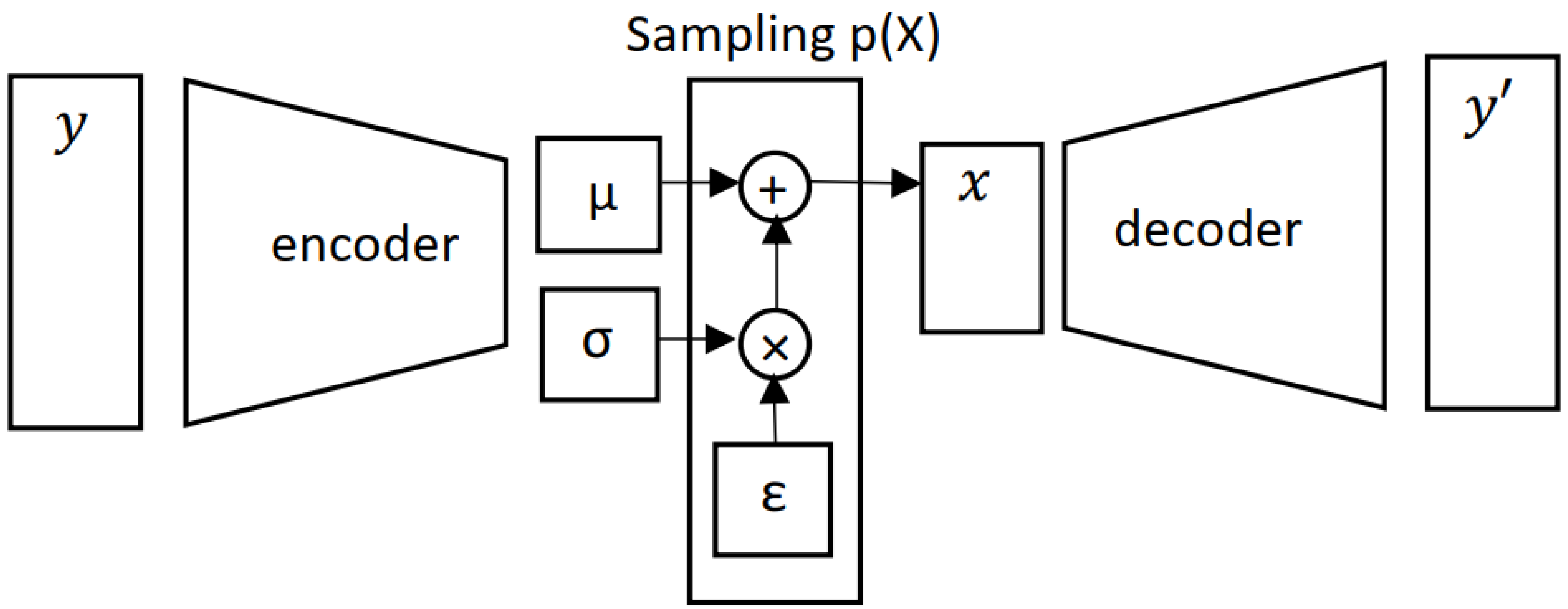
Variational Autoencoder

- The VAE [4] learns $p(Y|X)$ likelihood and $p(X|Y)$ posterior at the same time, by maximizing a variational lower bound
- It maps the latent space to the observed space using a neural architecture:



- Like in GP-LVM, a new instance of residues Y^* is **generated** by drawing a sample X^* from $p(X)$ and evaluating the output of the decoder network

Accuracy Metric

– **Cramer-Von-Mises** statistics [5] is employed:

- It compares
  1. the original distribution from a **validation set** of responses
  2. the distribution of a set of generated responses

- The two sets can have different cardinality
- It provides a dissimilarity score (**CM-score**) across the frequency range
- **Lower** CM-score means **higher** accuracy of the model

Results

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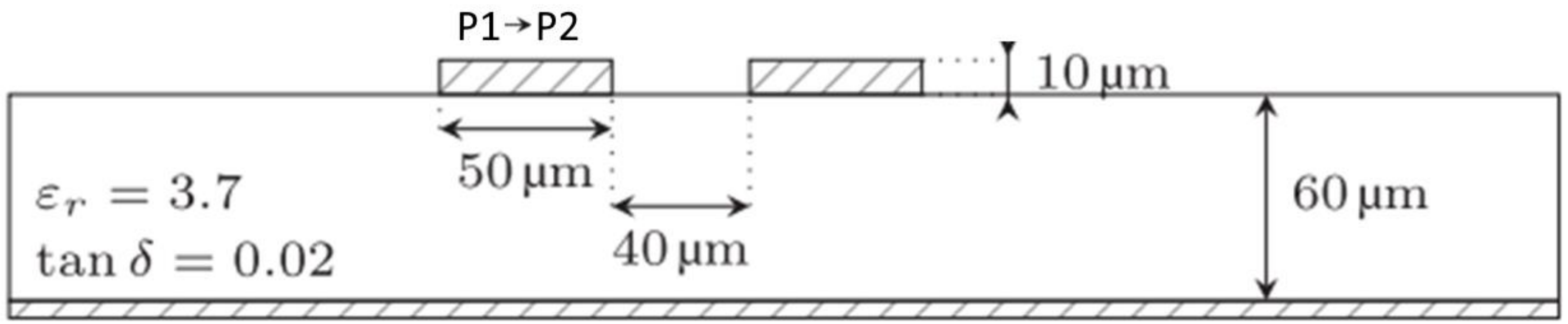
Example 1: Microstrip coupled transmission lines

— Settings:

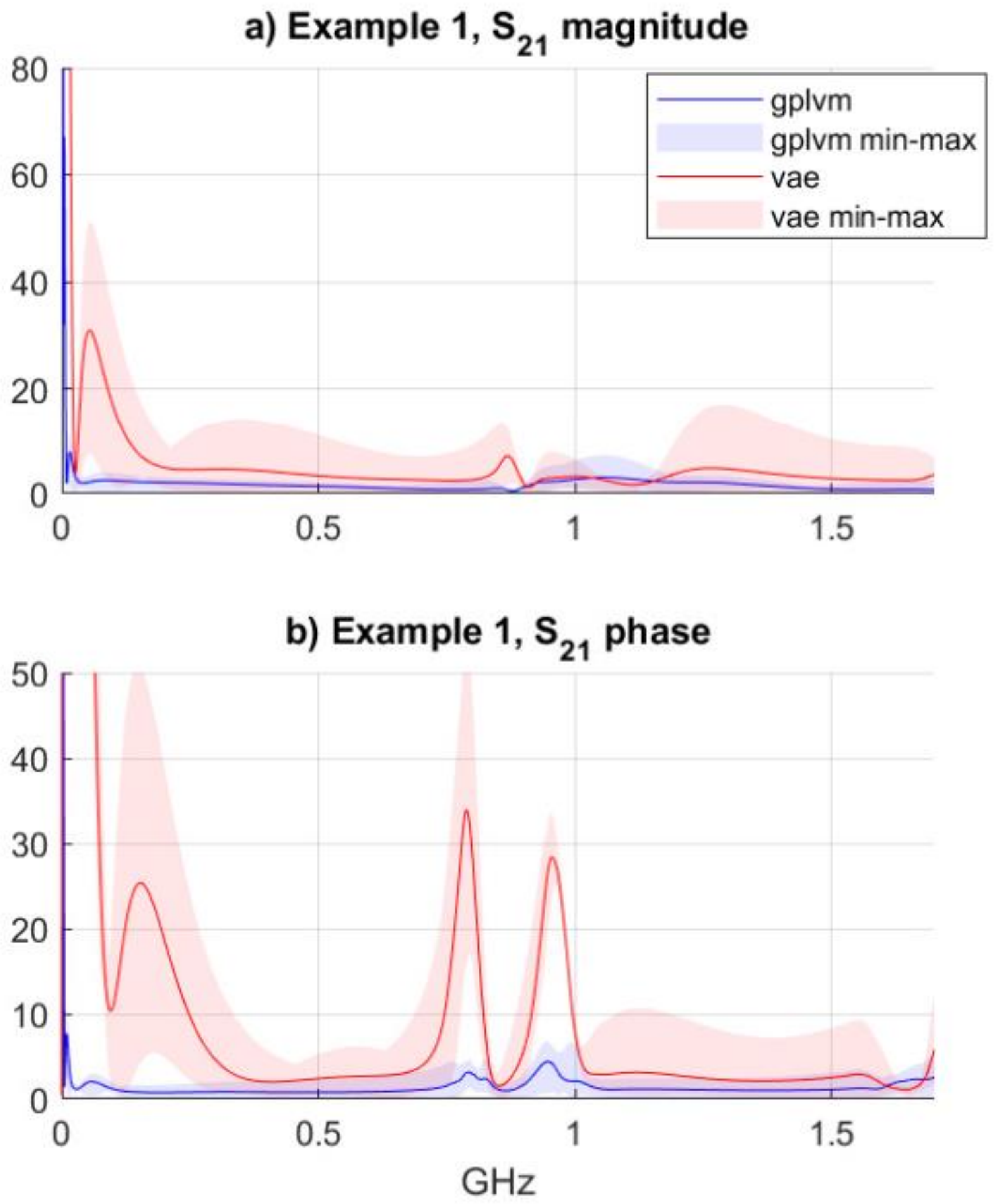
- 5 design parameters, 2 ports, range [0-1.8] GHz
- 10% standard deviation from nominal value
- **50** training instances



— Results:

- High accuracy for both GP-LVM and VAE
- GP-LVM more accurate on average

Avg. CM score



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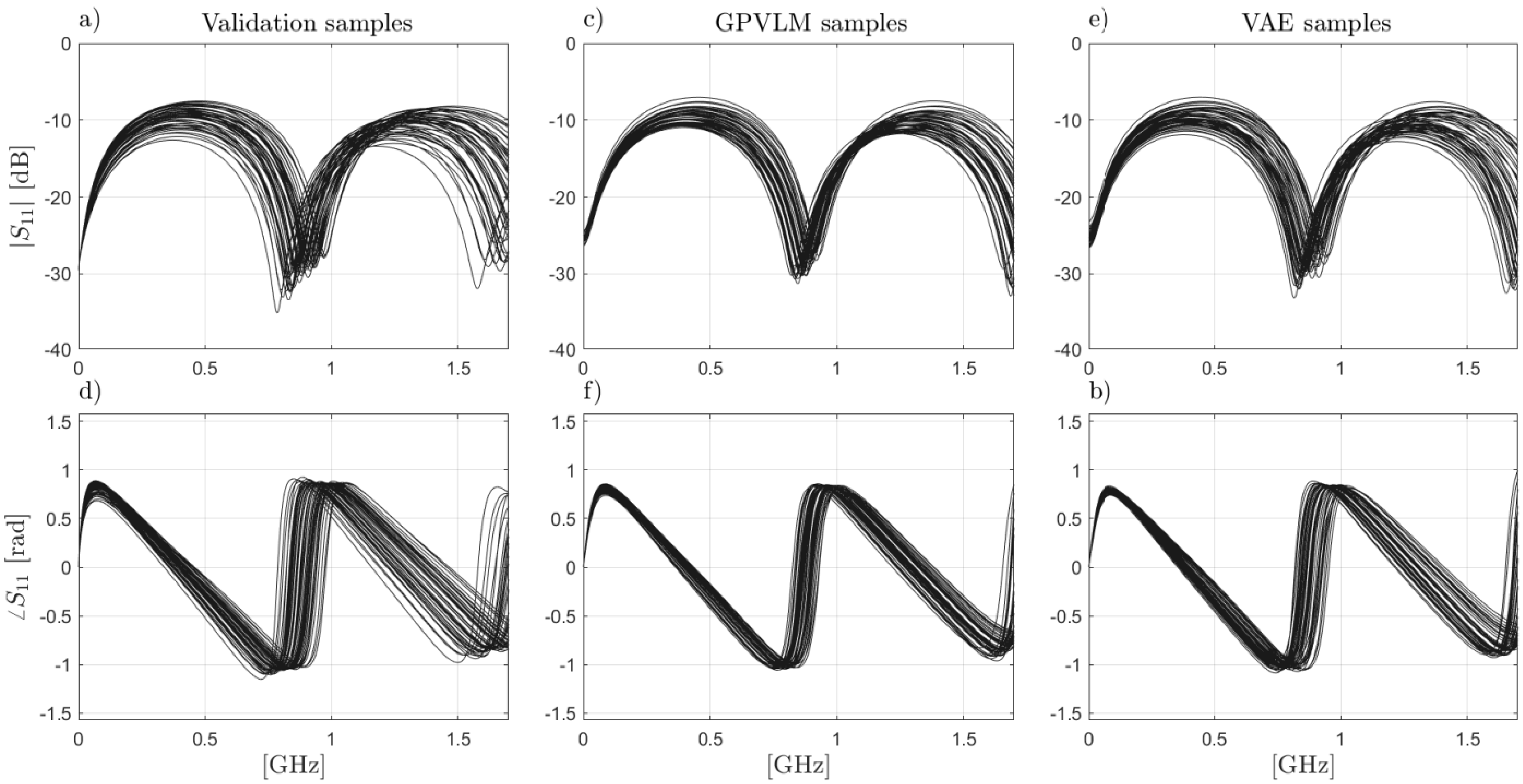
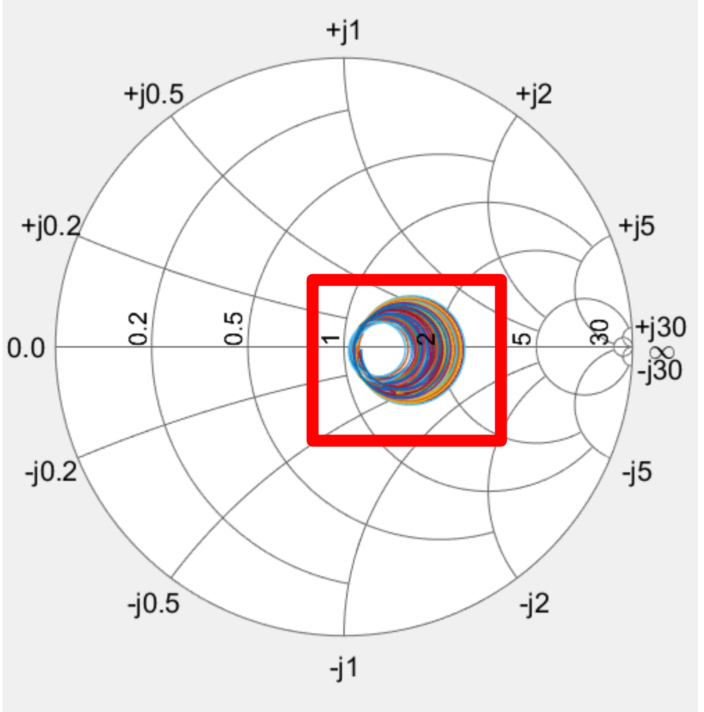
Example 1: Generated Distributions

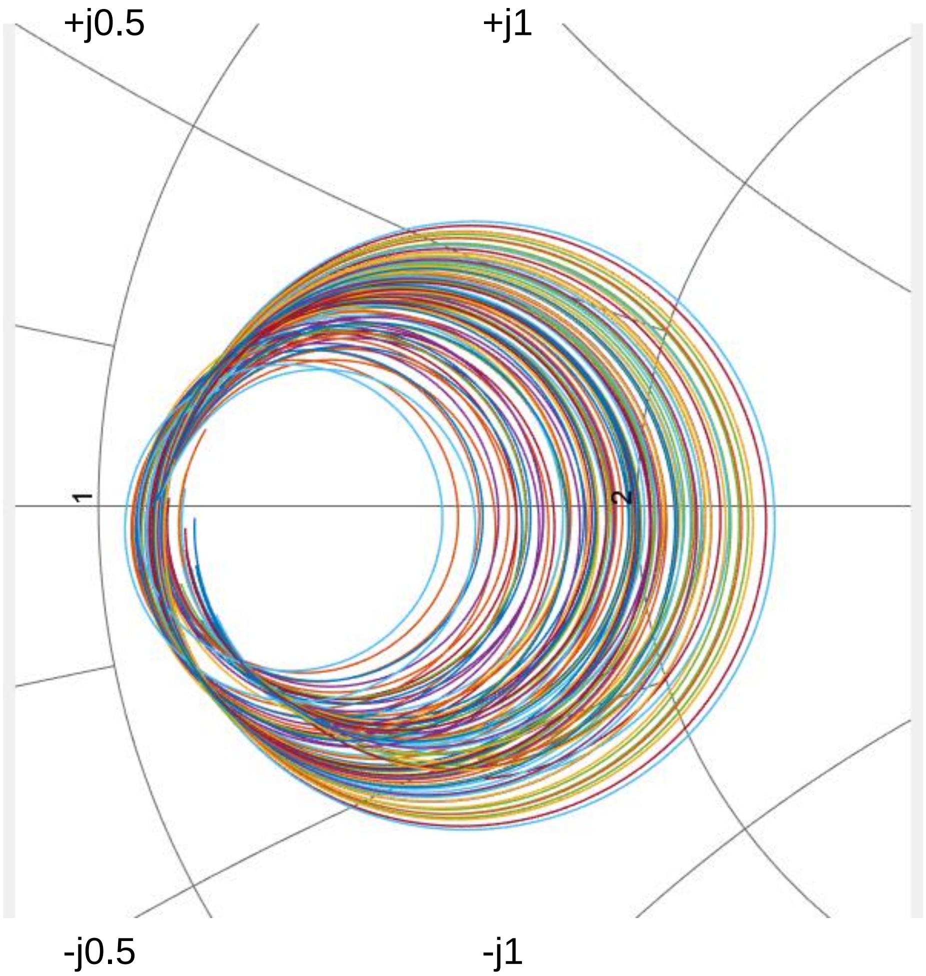


Example 1: Microstrip coupled transmission lines

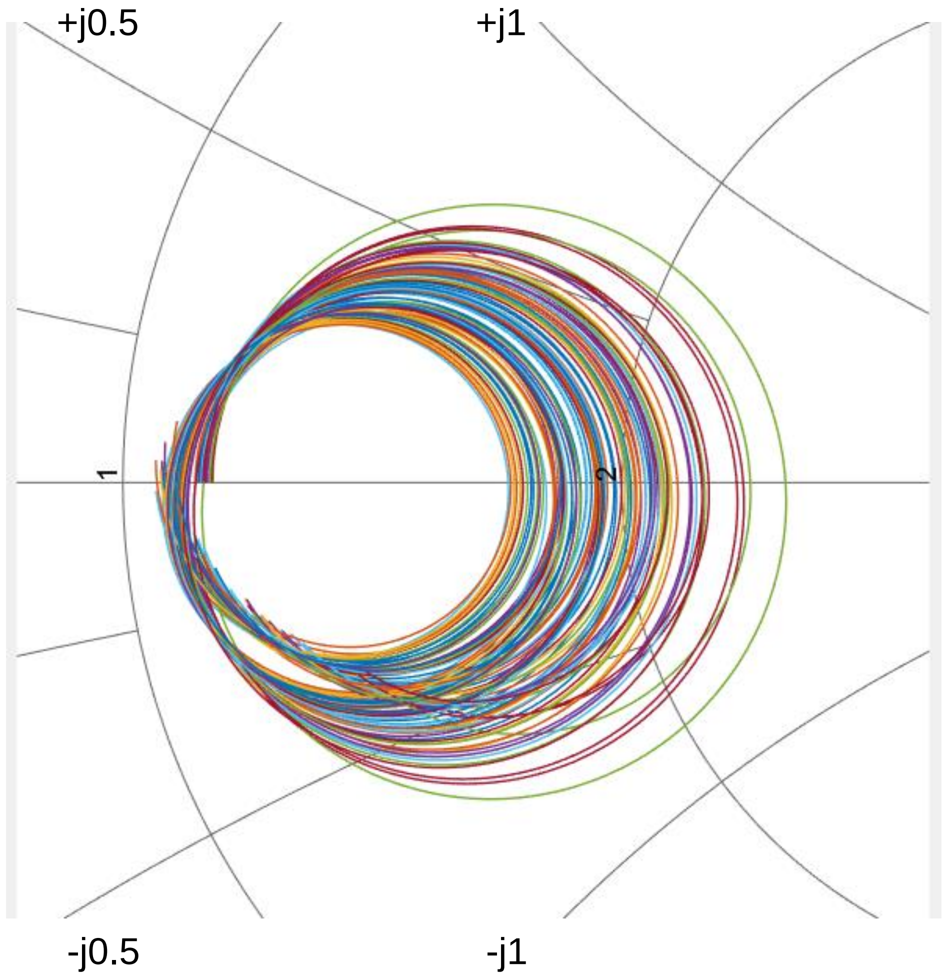


S_{11} Smith Chart (detail), for 50 frequency responses

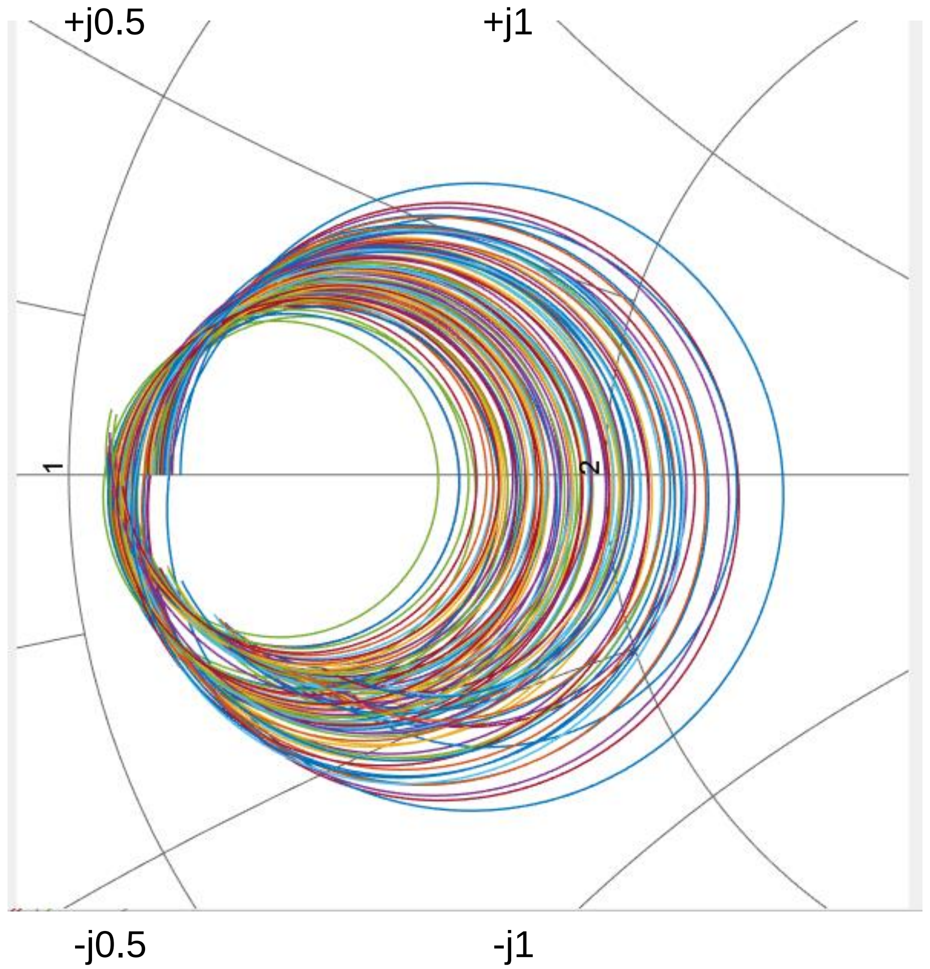
Training responses



GPLVM generated responses



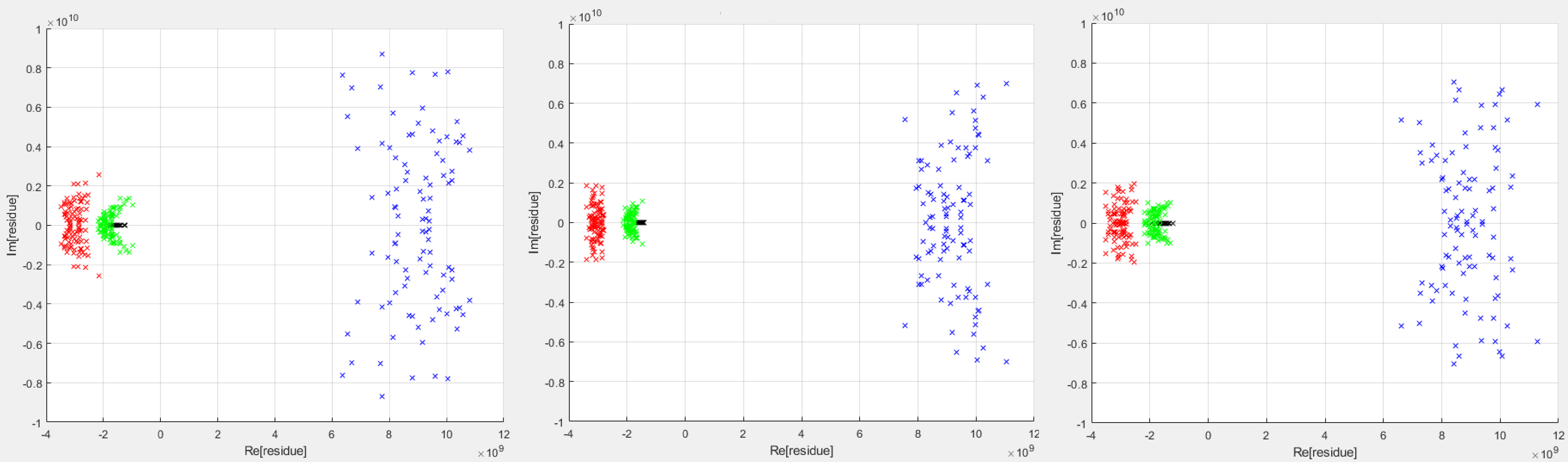
VAE generated responses



Example 1: Microstrip coupled transmission lines

S_{11} residues pairs in the complex plane, for 50 frequency responses

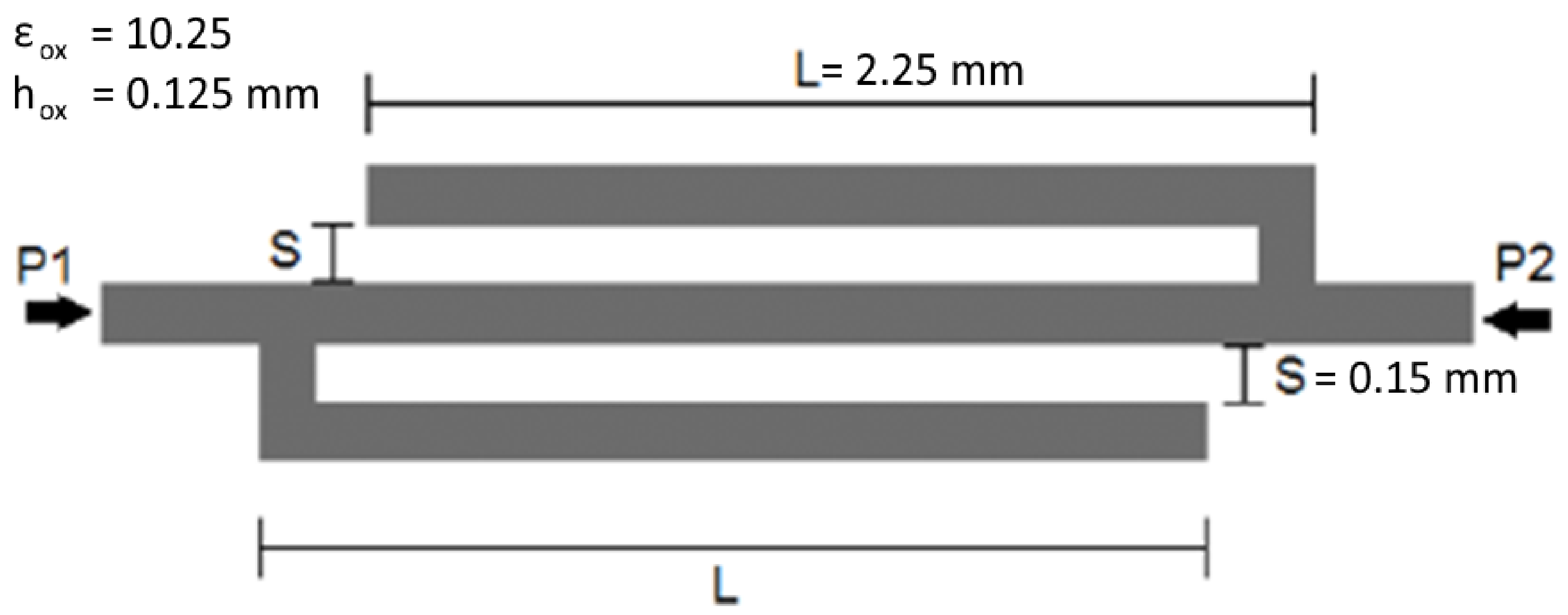
Training responses | GPLVM generated responses | VAE generated responses



Example 2: Microstrip stop-band filter

— Settings:

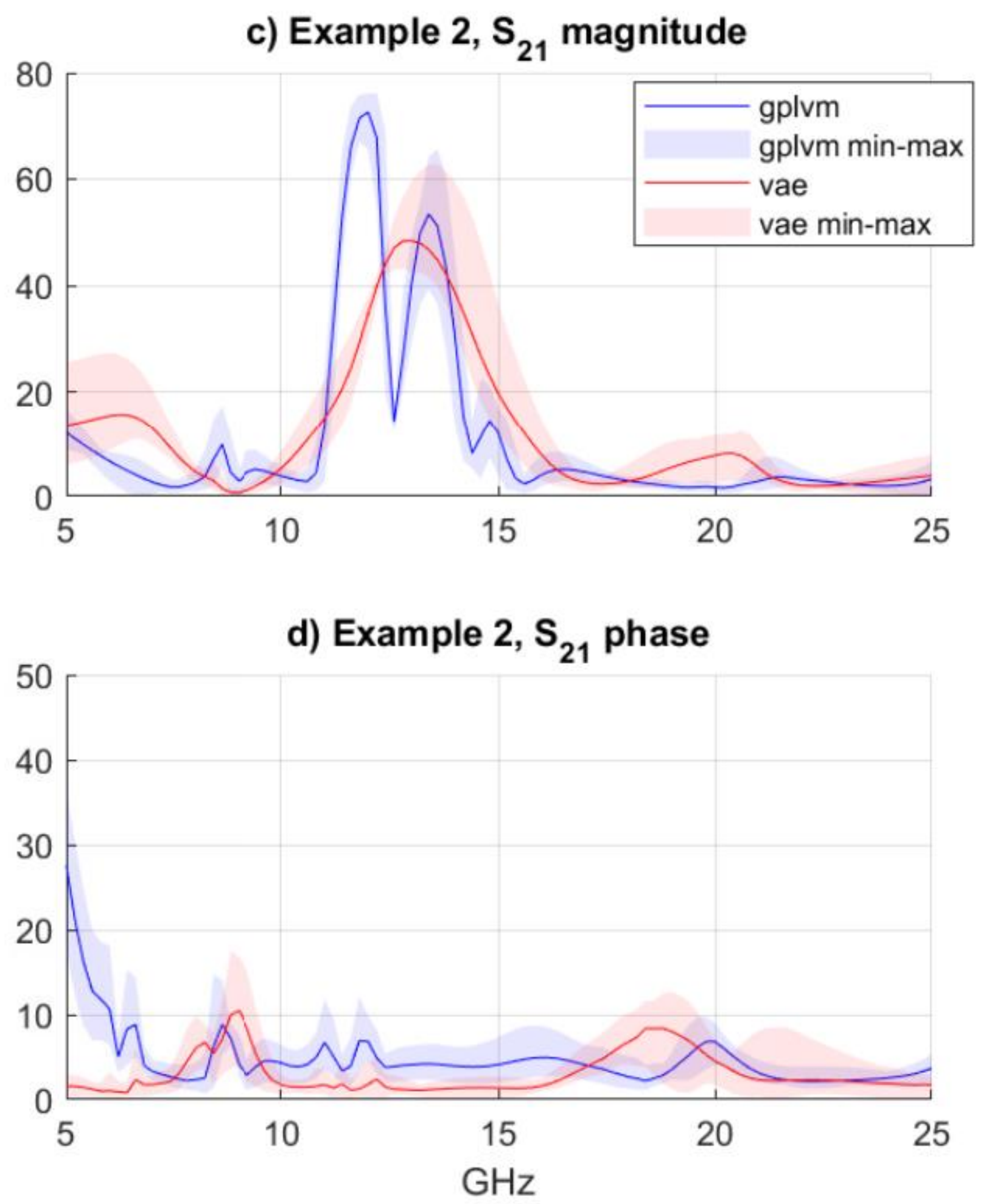
- 4 design parameters, 2 ports, range: [5-25 GHz]
- 5% standard deviation from nominal value
- **100** training instances



— Results:

- wide-band and highly variable frequency response:
  → lower accuracy than in Example 1
- VAE more accurate on average

Avg. CM score



Conclusions

Conclusions

- The VF-based generative modeling framework can produce many frequency responses from a small set of data

- Two generative models, the GP-LVM and the VAE are tested on two application examples

- Both models show adequate performance and can reduce the computational load for uncertainty quantification purposes

References

[1] De Ridder, S. Deschrijver, D. Manfredi, P. Dhaene, T. Vande Ginste, D. Generation of Stochastic Interconnect Responses via Gaussian Process Latent Variable Models. *IEEE Trans. Electromagn. Compat.* **2018**, *61*, 582–585

[2] Gustavsen, B. Semlyen, A. Rational approximation of frequency domain responses by vector fitting. *IEEE Trans. Power Del.* **1999**, *14*, 1052–1061.

[3] Titsias, M. Lawrence, N. D. Bayesian Gaussian process latent variable model. *Proc. 13th Int. Conf. Artif. Intell. Statist.* **2010**, 844-851.[Online]

[4] Ma, X. Raginsky, M. Cangellaris, A.C. A Machine Learning Methodology for Inferring Network S-parameters in the Presence of Variability. *Proc. IEEE 22nd Workshop Signal Power Integr. (SPI), Brest, France* **2018**.

[5] Anderson, T.W. On the distribution of the two-sample Cramer-von Mises criterion *Ann. Math. Statist.* **1962**, *33*, 1148–1159

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