FACULTY OF ENGINEERING AND ARCHITECTURE

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23RD IEEE WORKSHOP ON SIGNAL AND POWER INTEGRITY

A BAYESIAN APPROACH TO ADAPTIVE FREQUENCY SAMPLING

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GHENT UNIVERSITY

Overview

MOTIVATON

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The need for adaptive frequency sampling

- Characterization of devices through **simulations** is **essential** to design
- Simulation at every frequency often too **expensive**
- Need a **broadband characterization** with few simulations

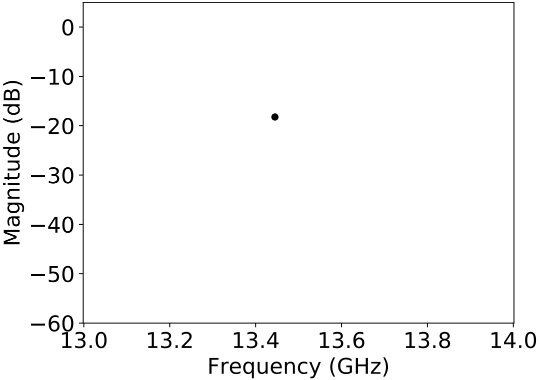
Adaptive Frequency Sampling

Sequential strategy

Classic approach: **sweep** over frequency range

Adaptive frequency sampling (**AFS**): Sequentially simulate at **one frequency at a time**.

support points $\rightarrow$ one or several macromodels $\rightarrow$ new simulation.



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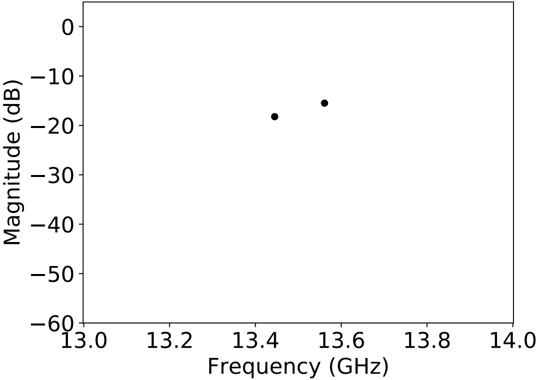

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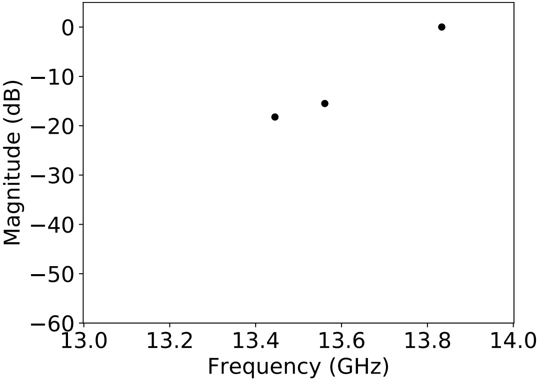

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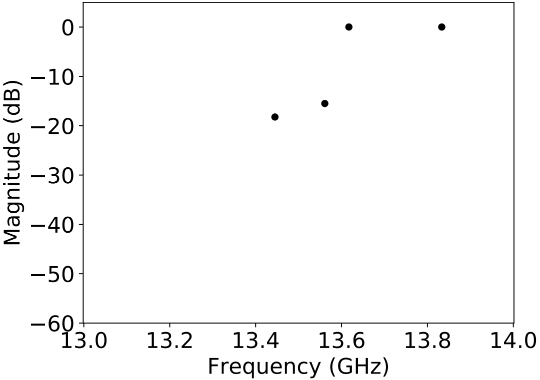

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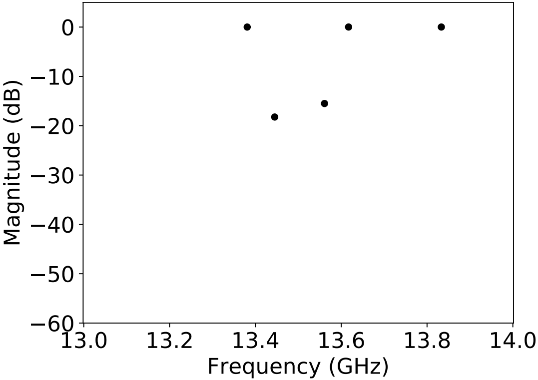

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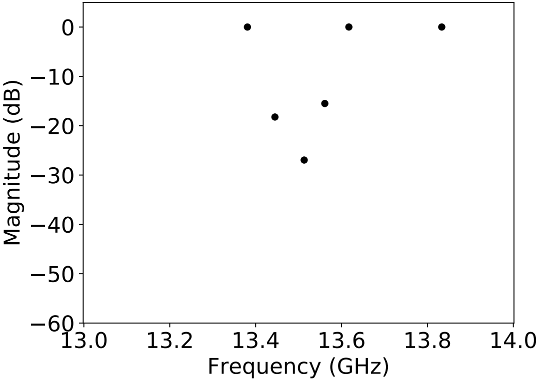

Adaptive Frequency Sampling

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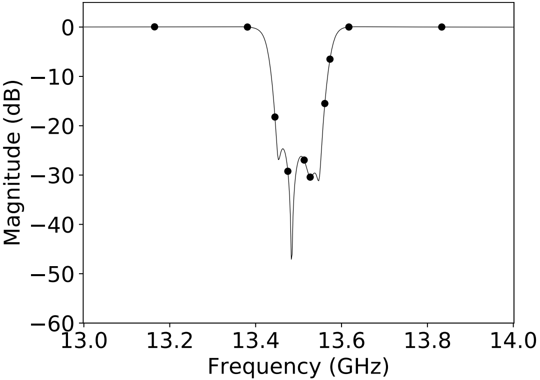

Linear Bayesian Vector Fitting

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Classic Vector Fitting

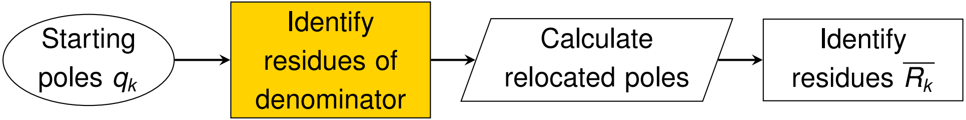
Goal of VF: modeling transfer function (e.g. S-parameters)

Approximate the **transfer function** with a **rational pole/residue model**

$$\overline{F}(s) \approx \sum_{k=1}^{K} \frac{\overline{R_k}}{s - a_k} + \overline{D} + s\overline{E}$$

$\rightarrow$ Nonlinear problem due to a_k.

Classic Vector Fitting



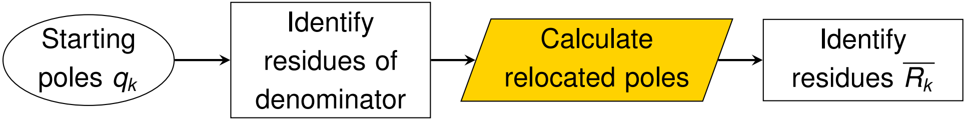
Rewrite as

$$\overline{F}(s) = \frac{\overline{p}(s)}{\sigma(s)} = \frac{\sum_{k=1}^{K} \frac{\overline{r}_k}{s-q_k} + \overline{d} + s\overline{e}}{\sum_{k=1}^{K} \frac{\widehat{r}_k}{s-q_k} + \widehat{d}}$$

Solve $\sigma(s)\overline{F}(s) = \overline{p}(s)$ for $\widehat{r}_k$ and $\widehat{d}$.

linear regression

CLASSIC VECTOR FITTING



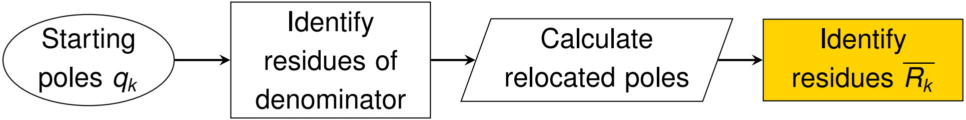
$$\overline{F}(s) = \frac{\overline{p}(s)}{\sigma(s)} = \frac{\sum_{k=1}^{K} \frac{\overline{r}_k}{s-q_k} + \overline{d} + s\overline{e}}{\sum_{k=1}^{K} \frac{\widehat{r}_k}{s-q_k} + \widehat{d}}$$

Zeros of $\sigma(s)$ = poles of $\overline{F}(s)$.

(nonlinear) eigenvalue problem

$\rightarrow$ relocated poles a_k

Classic Vector Fitting

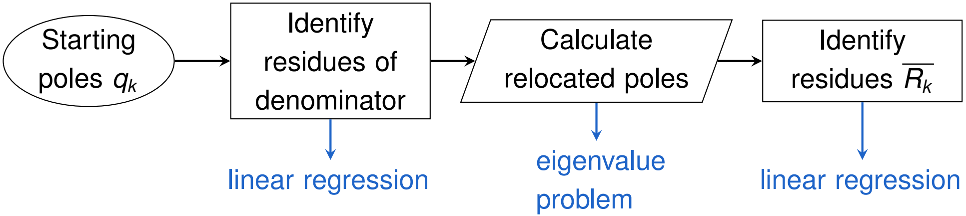


$$\overline{F}(s) = \sum_{k=1}^{K} \frac{\overline{R_k}}{s - a_k} + \overline{D} + s\overline{E}$$

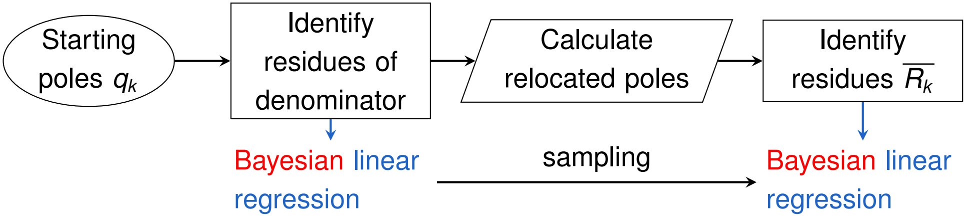
Identify $\overline{R_k}$, $\overline{D}$ and $\overline{E}$.

linear regression

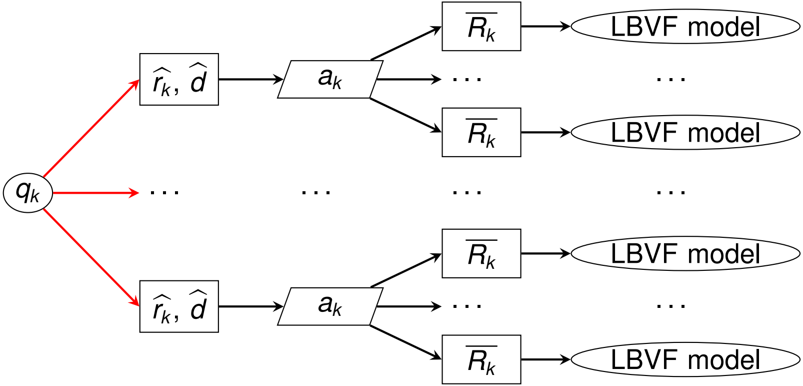
Classic Vector Fitting



LINEAR BAYESIAN VECTOR FITTING

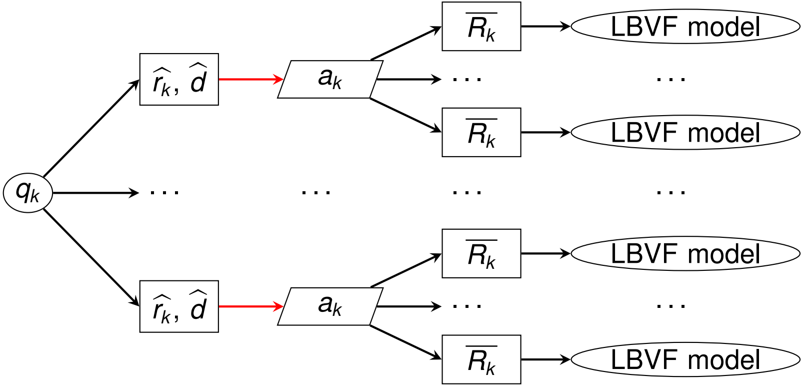


Linear Bayesian Vector Fitting



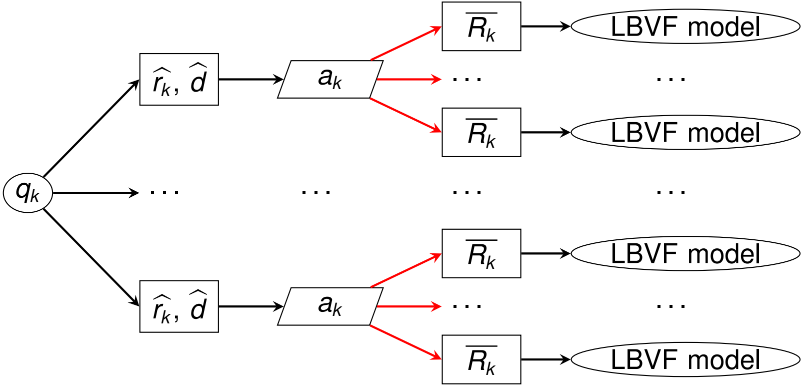
Sampling denominator residues

Linear Bayesian Vector Fitting



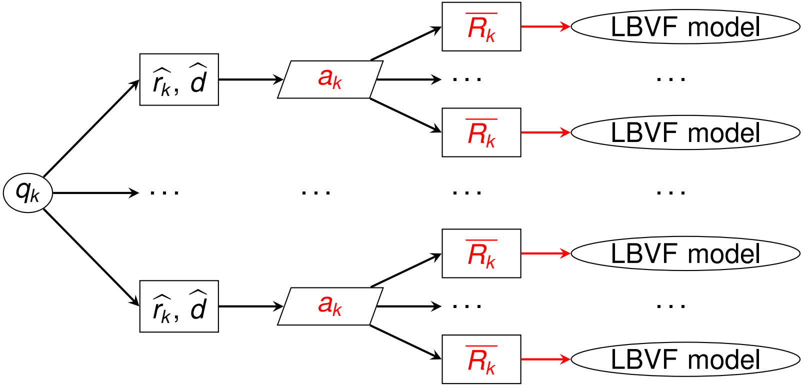
Calculating relocated poles

Linear Bayesian Vector Fitting



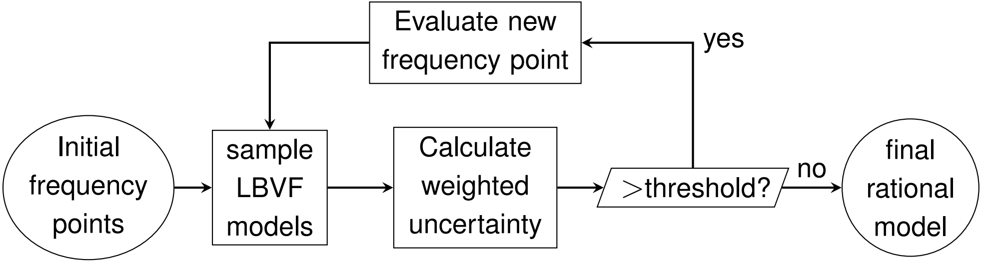
Sampling residues

Linear Bayesian Vector Fitting

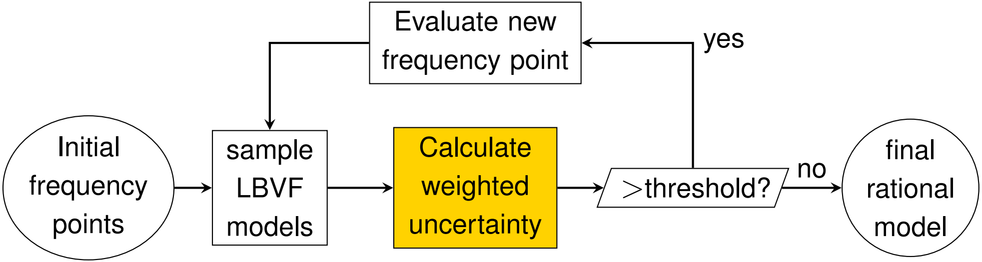


LBVF models

AFS with Linear Bayesian Vector Fitting



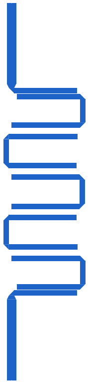
AFS with Linear Bayesian Vector Fitting

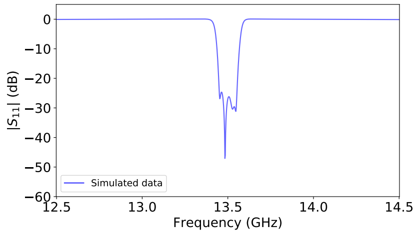


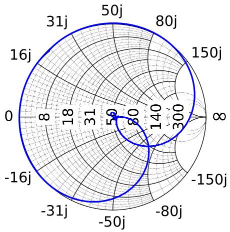
- samples from LBVF models of different orders
- weighted standard deviation using marginal likelihood as weights
- Gaussian penalties at already evaluated points

Example

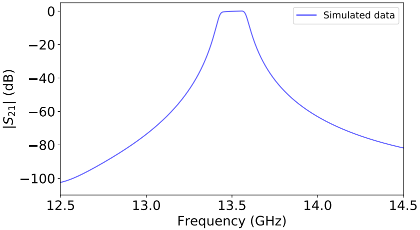
Hairpin filter

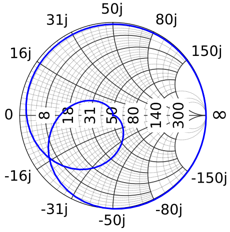






S_{11}

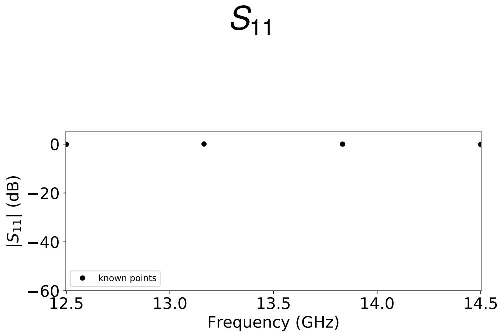


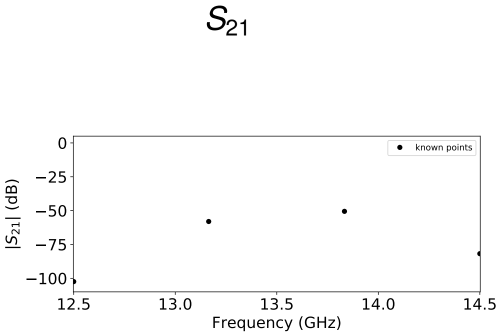


S_{21}

HAIRPIN FILTER

4 INITIAL POINTS





Hairpin filter

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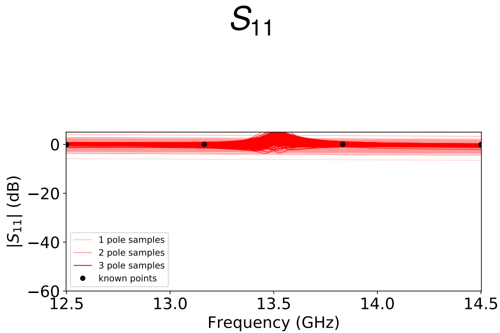

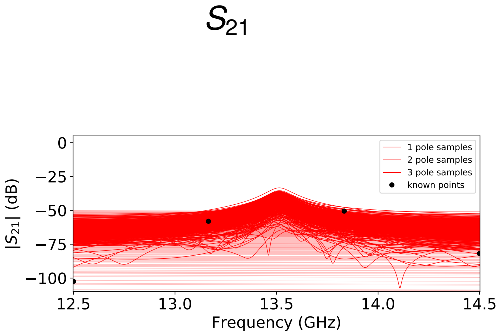

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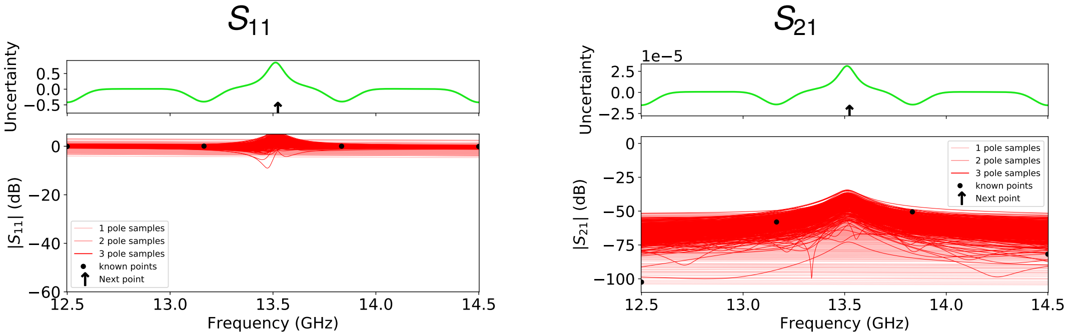
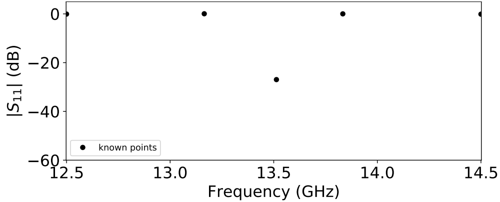


Hairpin filter

5 points

S_{11}



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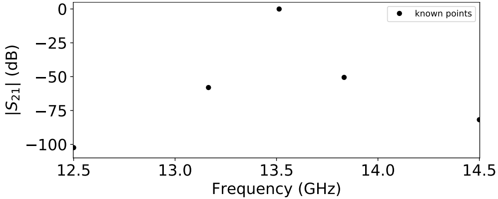

Hairpin filter

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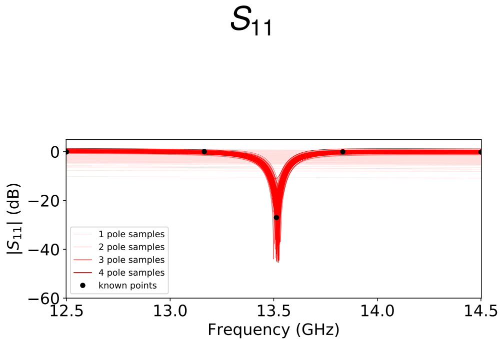

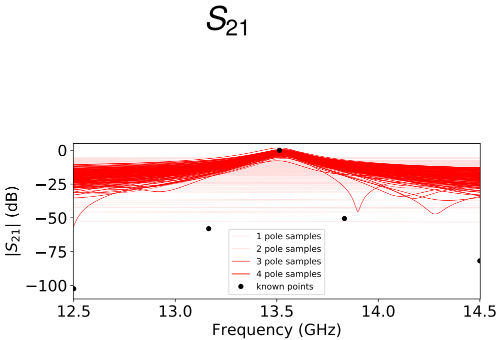

Hairpin filter

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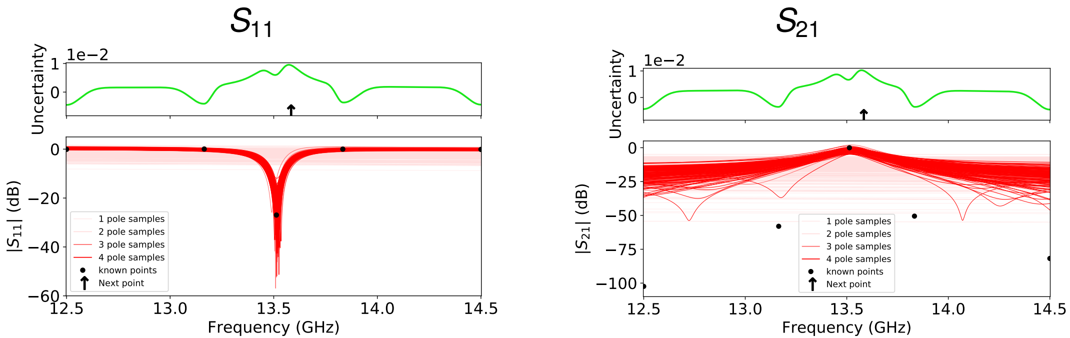
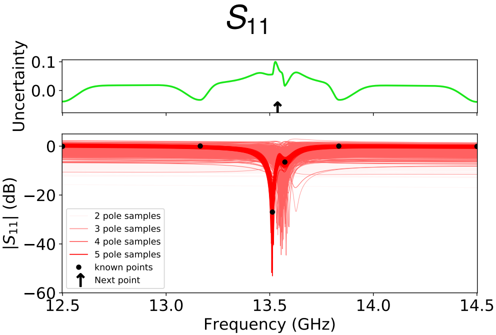
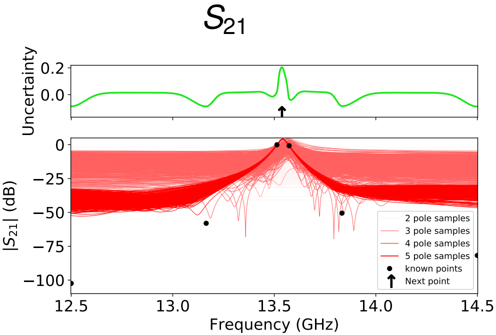


Hairpin filter

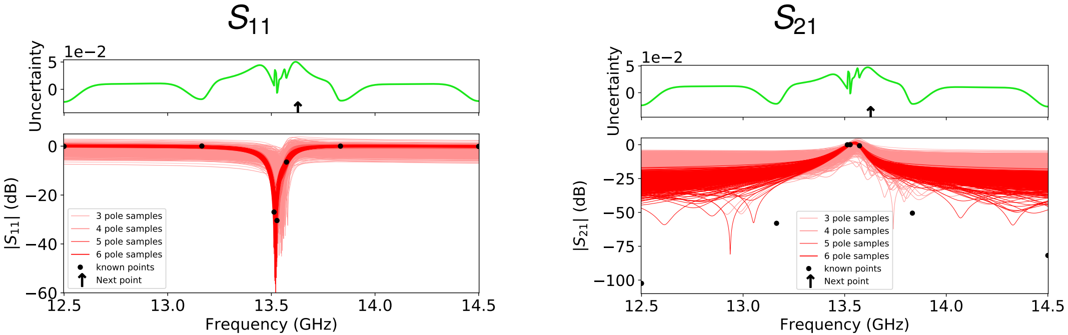
6 points





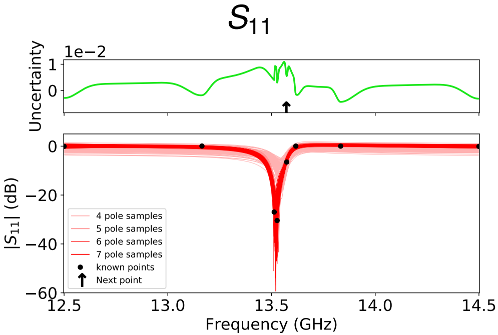
Hairpin filter

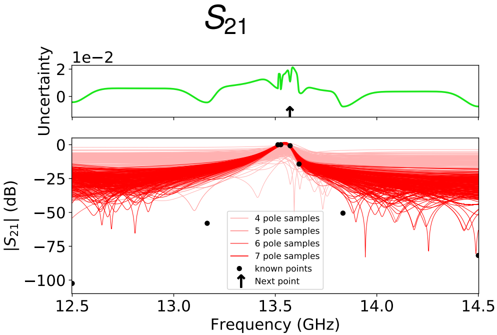
7 points



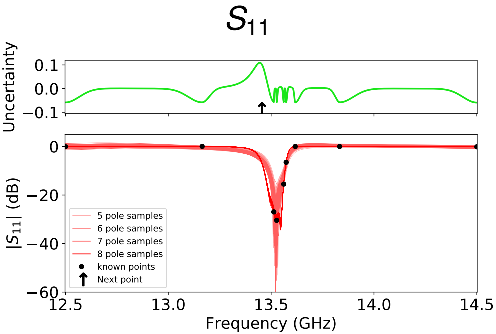
HAIRPIN FILTER

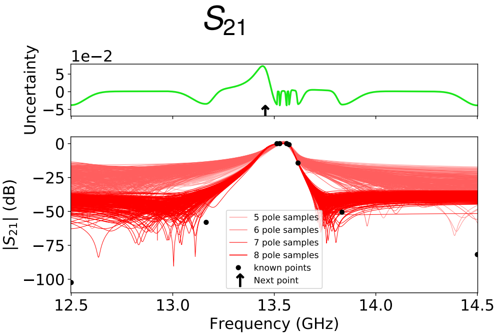
8 POINTS



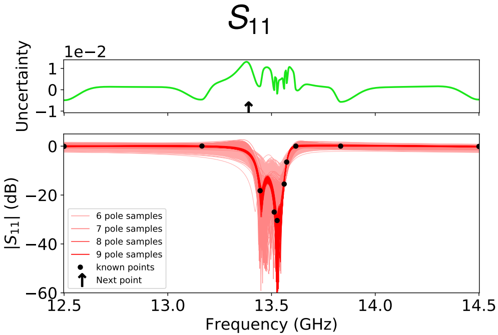


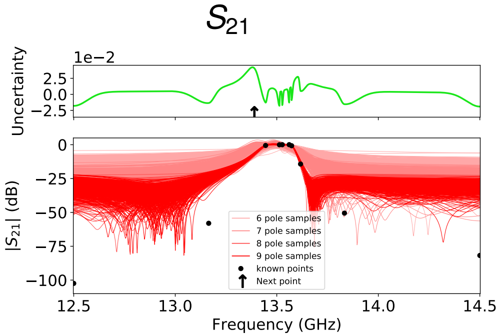
HAIRPIN FILTER
9 POINTS



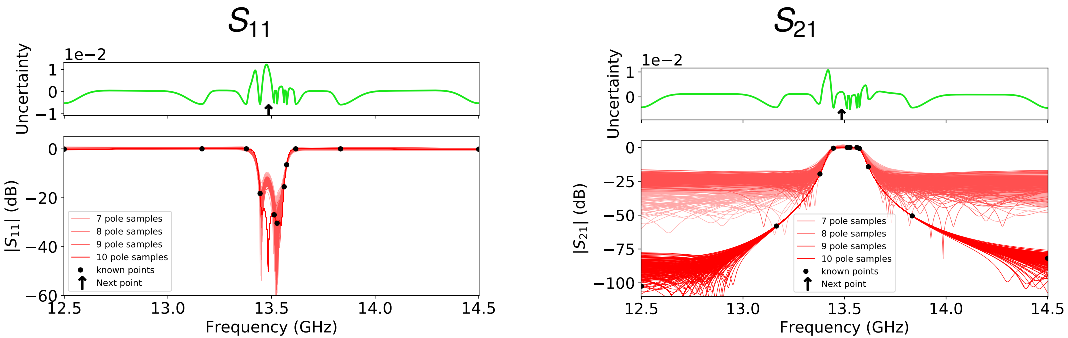


Hairpin filter
10 points

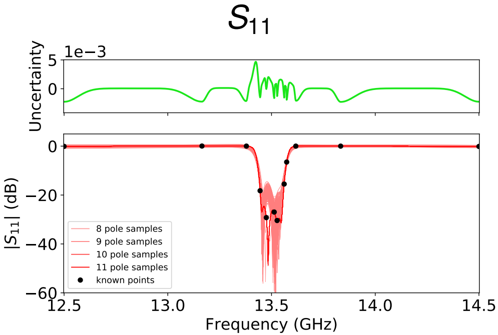


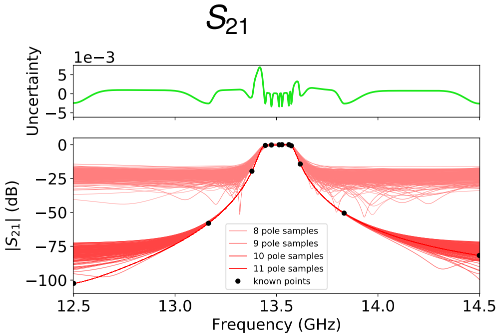


HAIRPIN FILTER
11 POINTS



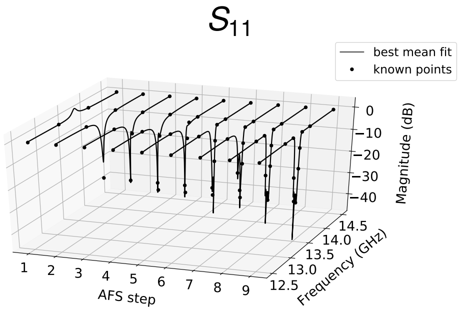
HAIRPIN FILTER
12 POINTS

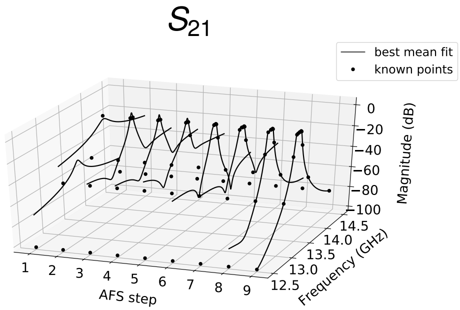




HAIRPIN FILTER

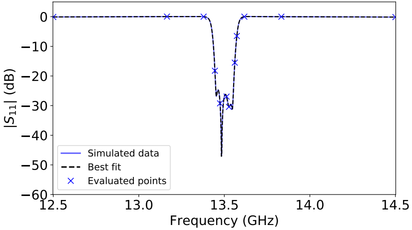
BEST MEAN FIT AT EACH STEP

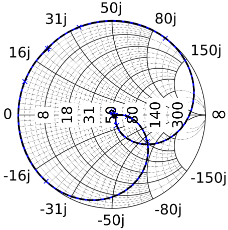




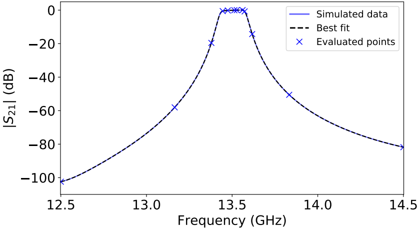
Hairpin filter

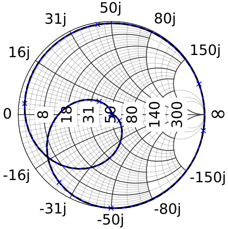
Final mean fit





S_{11}





S_{21}

SUMMARY

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SUMMARY

- LBVF is a next-generation stochastic modeling framework based on Vector Fitting.
- It provides a useful measure of model uncertainty.
- Key advantages:
  - provides model uncertainty in a principled and statistically sound manner
  - can handle noisy (non-deterministic) data

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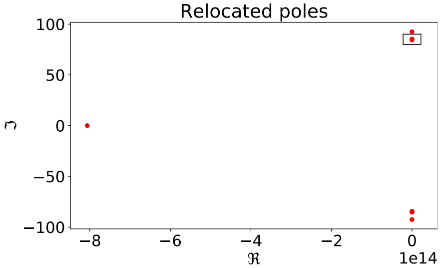
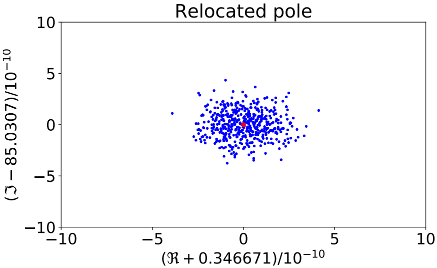
Hairpin filter

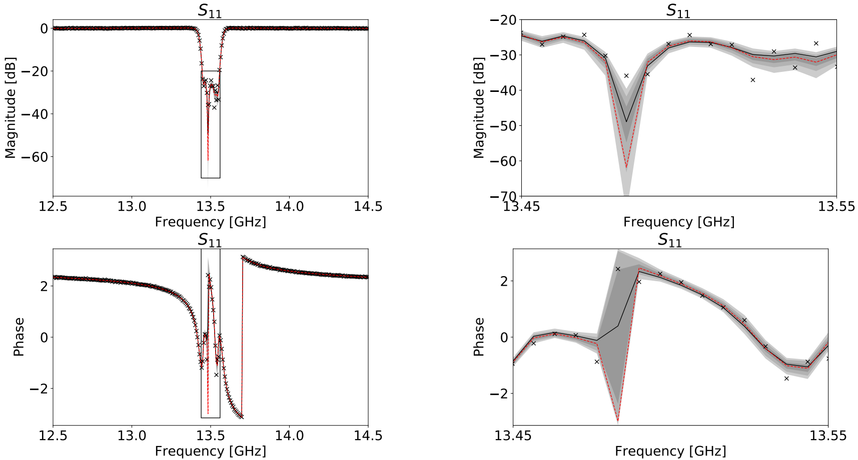
Uncertainty Quantification with Gaussian noise



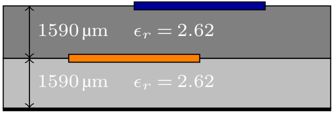


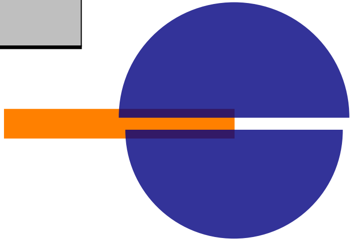
HAIRPIN FILTER

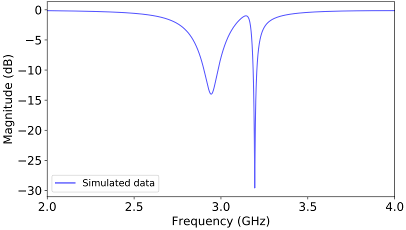
UNCERTAINTY QUANTIFICATION WITH GAUSSIAN NOISE

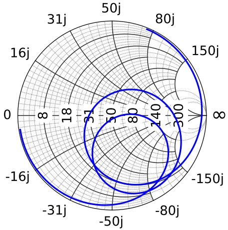


Double semi-circular patch antenna



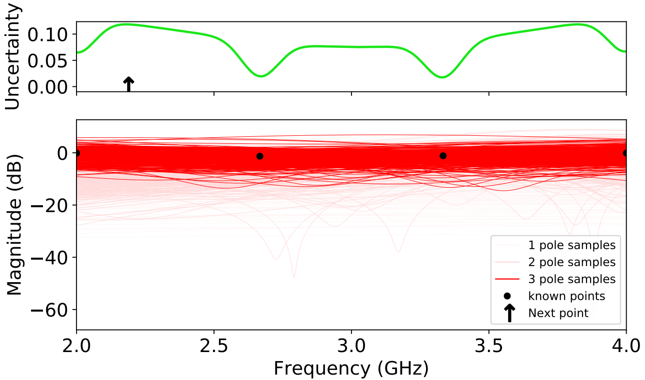




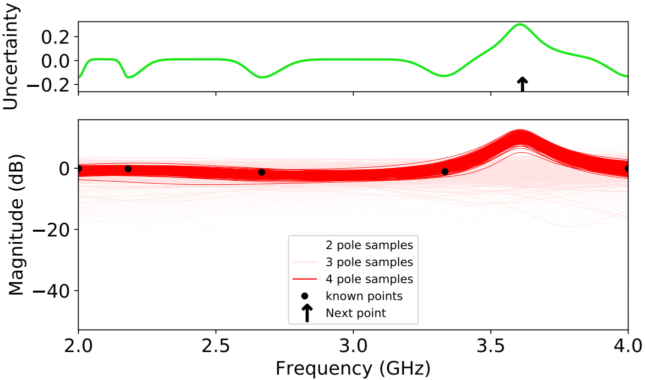


Double semi-circular patch antenna

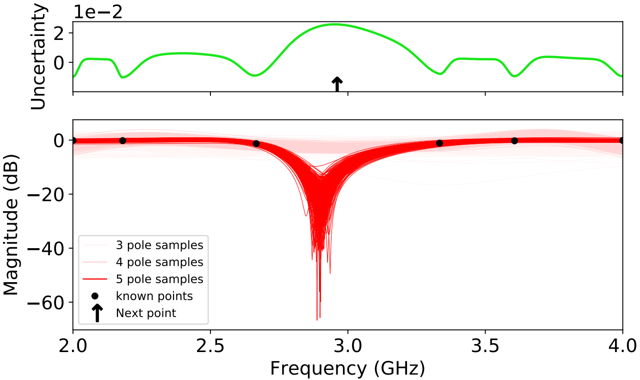
AFS



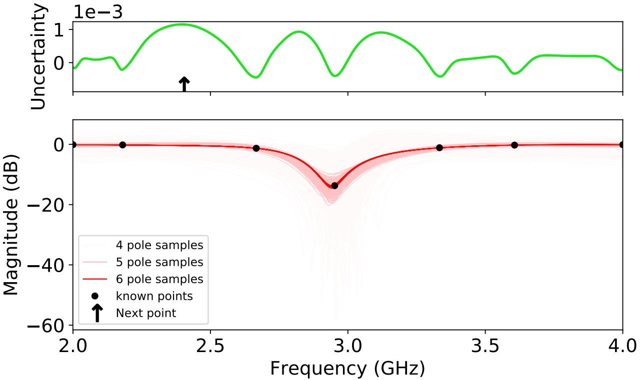
Double semi-circular patch antenna
AFS



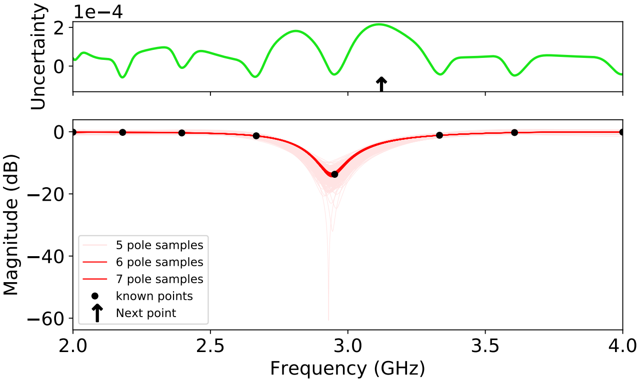
Double semi-circular patch antenna
AFS



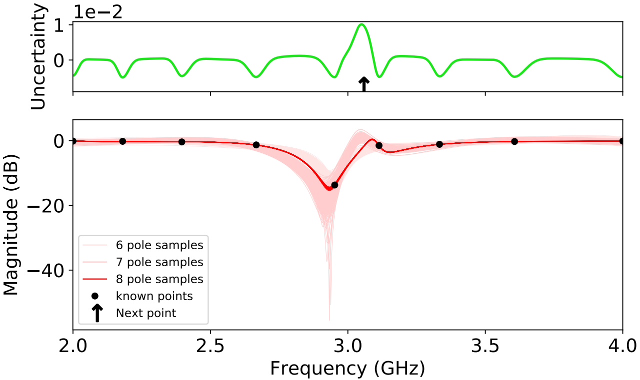
DOUBLE SEMI-CIRCULAR PATCH ANTENNA
AFS



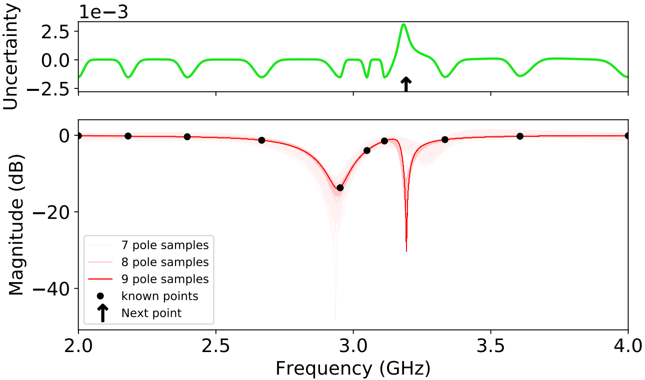
Double semi-circular patch antenna
AFS



DOUBLE SEMI-CIRCULAR PATCH ANTENNA
AFS

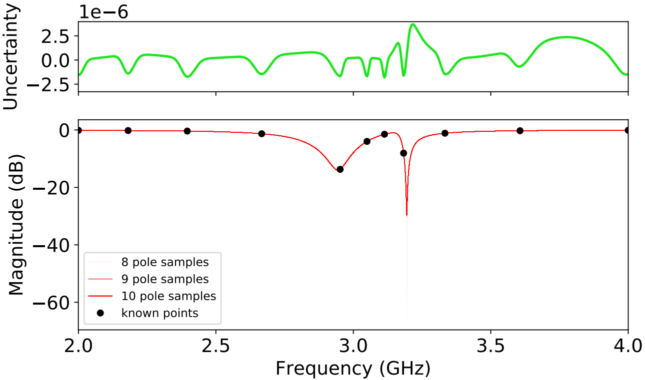


DOUBLE SEMI-CIRCULAR PATCH ANTENNA
AFS



Double semi-circular patch antenna

AFS



DOUBLE SEMI-CIRCULAR PATCH ANTENNA
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