Machine Learning Applications for Simulation and Modeling of 56 and 112 Gb SerDes Systems

This session was presented as part of the
DesignCon 2019 Conference and Expo

For more information on the event, please go to DesignCon.com

SPEAKER

Alex Manukovsky

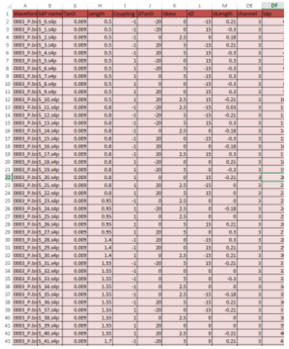
Technical lead of the Signal & Power Integrity, Intel

Alex.manukovsky@intel.com

Alex Manukovsky is a technical lead of the Signal & Power Integrity team at Intel Networking Division, responsible for the development of indoor link simulator for high speed serial links, combining both traditional methods of frequency and time domain simulation along with machine learning capabilities.

Machine Learning in a nutshell

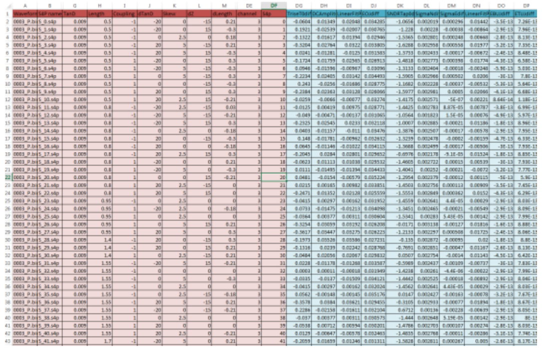
Factors
Training Set



Behavioral Model

My System

Responses
Training Set



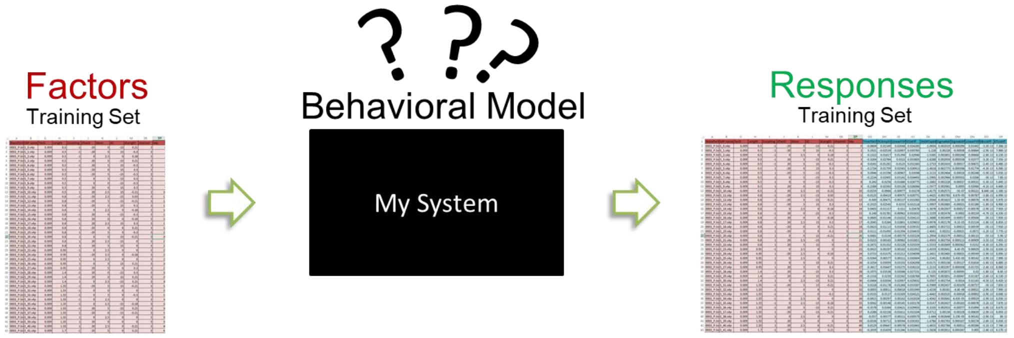
Features selection and ranking

From this initial dataset we build a set of features that satisfies the following requirements:

1. The selected features are highly correlated to the response.
2. The selected features are highly independent from each other.
3. The feature set has a high coverage of the variation in the response.

Principle Component Analysis (PCA) is often used to generate a feature set for building a model

We use the Minimum Redundancy Maximum Relevance (MRMR) algorithm to select a feature set for the prediction model from the initial dataset



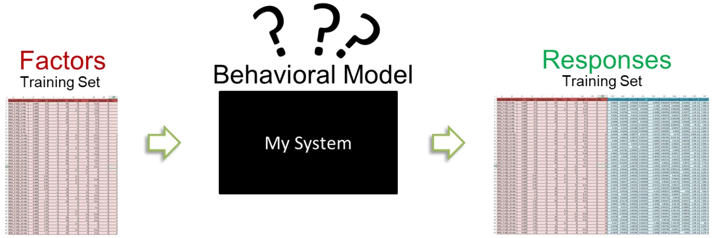
Models building methods used in this work

The main prediction algorithms:

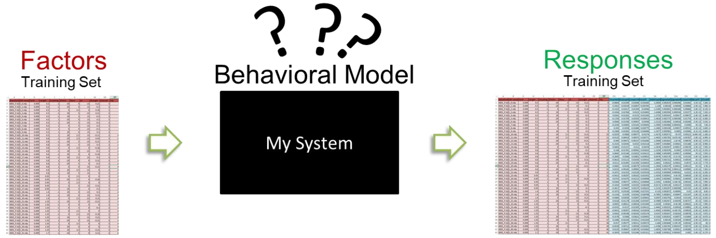
1. Random Forest (RF and CARET_RF) [7]
2. Boosted Trees (BT) [8,9]
3. Generalized Linear Models (GLM) [10]
4. Neural Networks (NNET, NEURALNET, CARET_NNET) [12,13]
5. Support Vector Machines (SVM) [11]
   A. Linear Kernels (SVML)
   B. Radial Kernels (SVMR)
   C. Best tuned SVM model chosen thru cross-validation (SVMB)

Random Forest and Boosted trees
are the most accurate on most of the problem instances that we have encountered

GLM and SVM
are good at predicting values outside the range of the values set seen in the training data



Ensembles



No best algorithm for all problems

Ensemble methods usually work better than the individual predictors

Ensemble prediction is a weighted average of the predictions of individual algorithms

Ensemble 1: Weighted average of individual algorithms' predicted values per sample, weights are pre-defined by the user.

Ensemble 2: Weighted average of individual algorithms' predicted probabilities per sample, weights are pre-defined by the user.

Ensemble 3: Weighted average of individual algorithms' predicted values per sample, weights are equal to the accuracy of the respective model on the validation set.

Ensemble 4: Weighted average of individual algorithms' predicted probabilities per sample, weights are equal to the accuracy of the respective model on the validation set.

Ensemble 5: Simply selects the best performing individual prediction model based on its accuracy on the validation set.

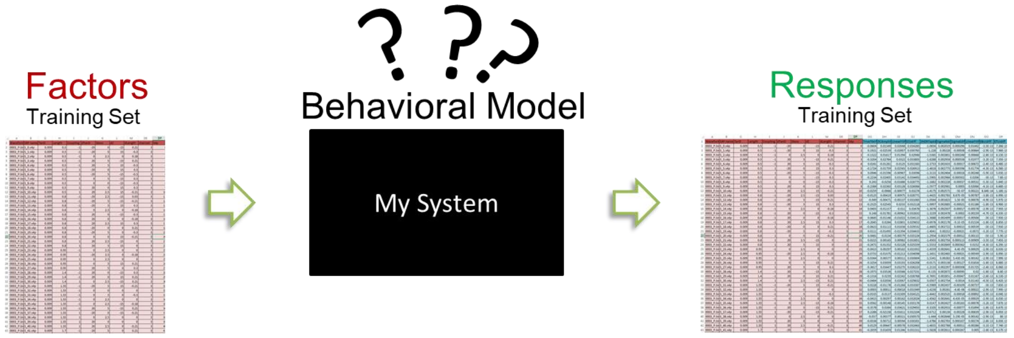
Features selection and ranking

From this initial dataset we build a set of features that satisfies the following requirements:

1. The selected features are highly correlated to the response.
2. The selected features are highly independent from each other.
3. The feature set has a high coverage of the variation in the response.

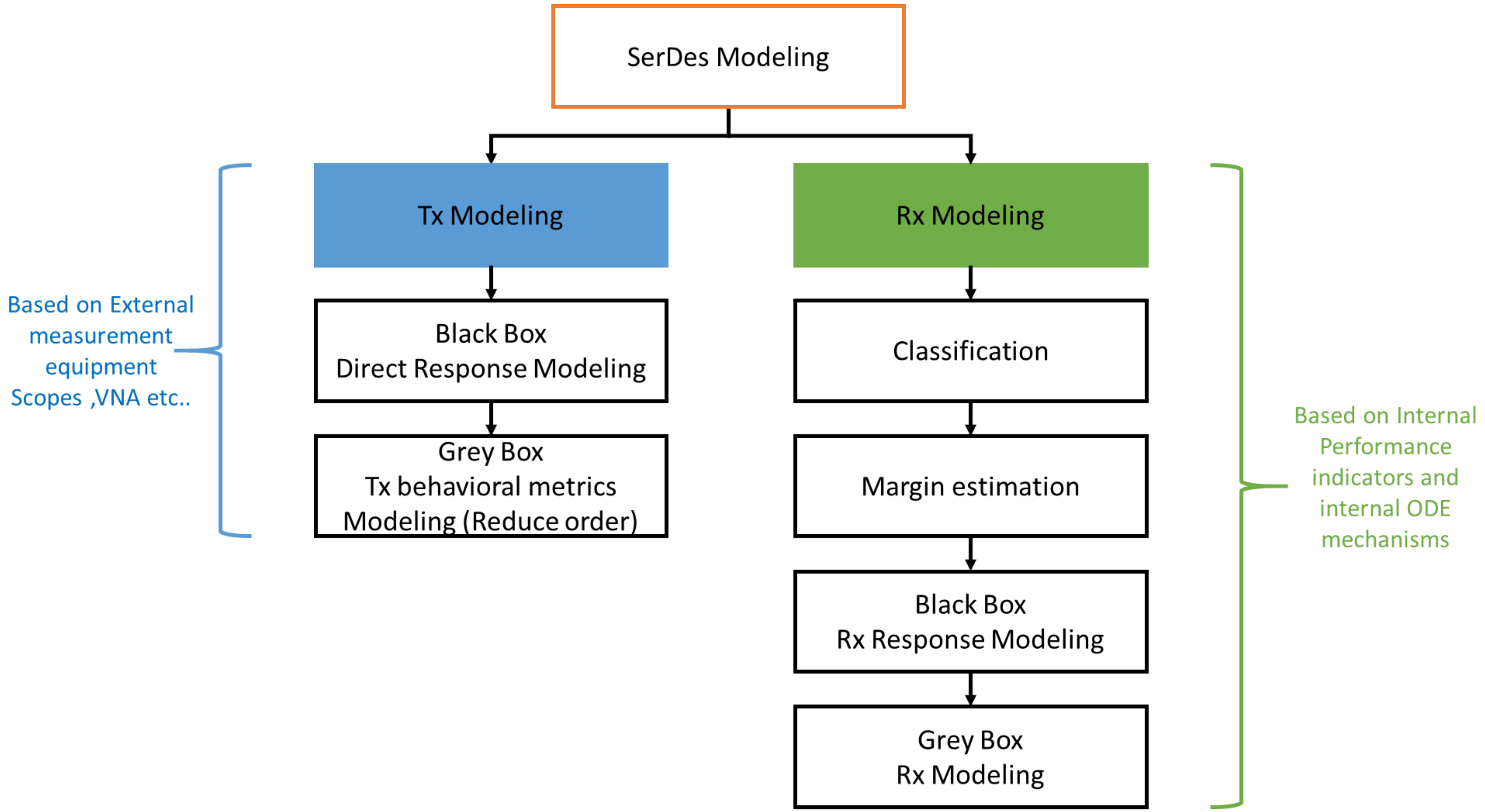
Principle Component Analysis (PCA) is often used to generate a feature set for building a model

We use the Minimum Redundancy Maximum Relevance (MRMR) algorithm to select a feature set for the prediction model from the initial dataset



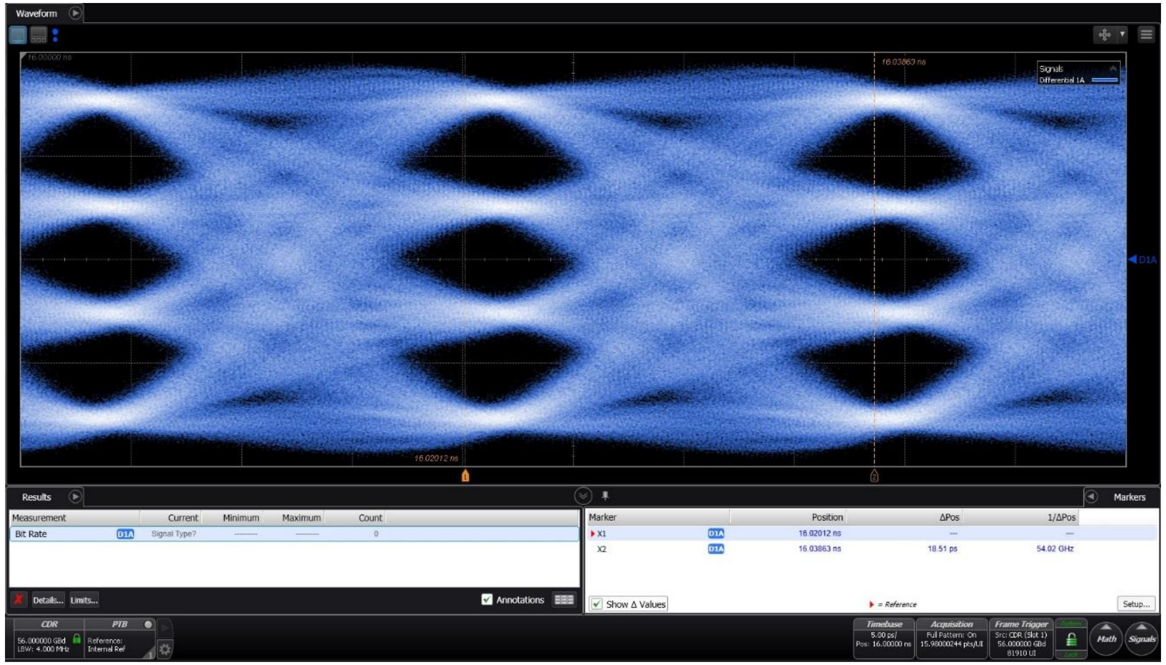
ML Technics For SerDes Systems In Practice

Measurement Based Modeling

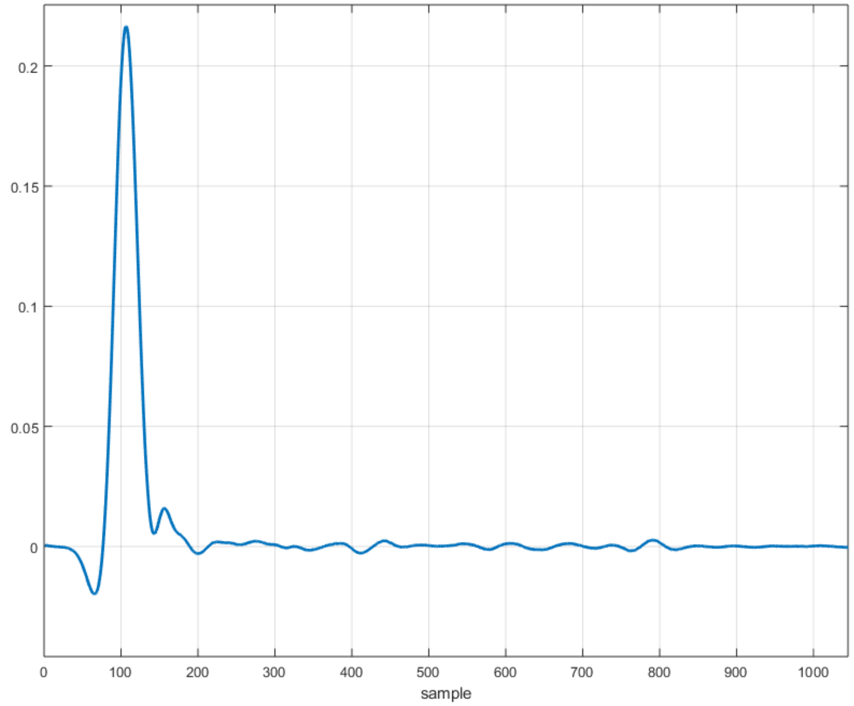


The modeling challenges in going for 112 GB

Waveform Measurement



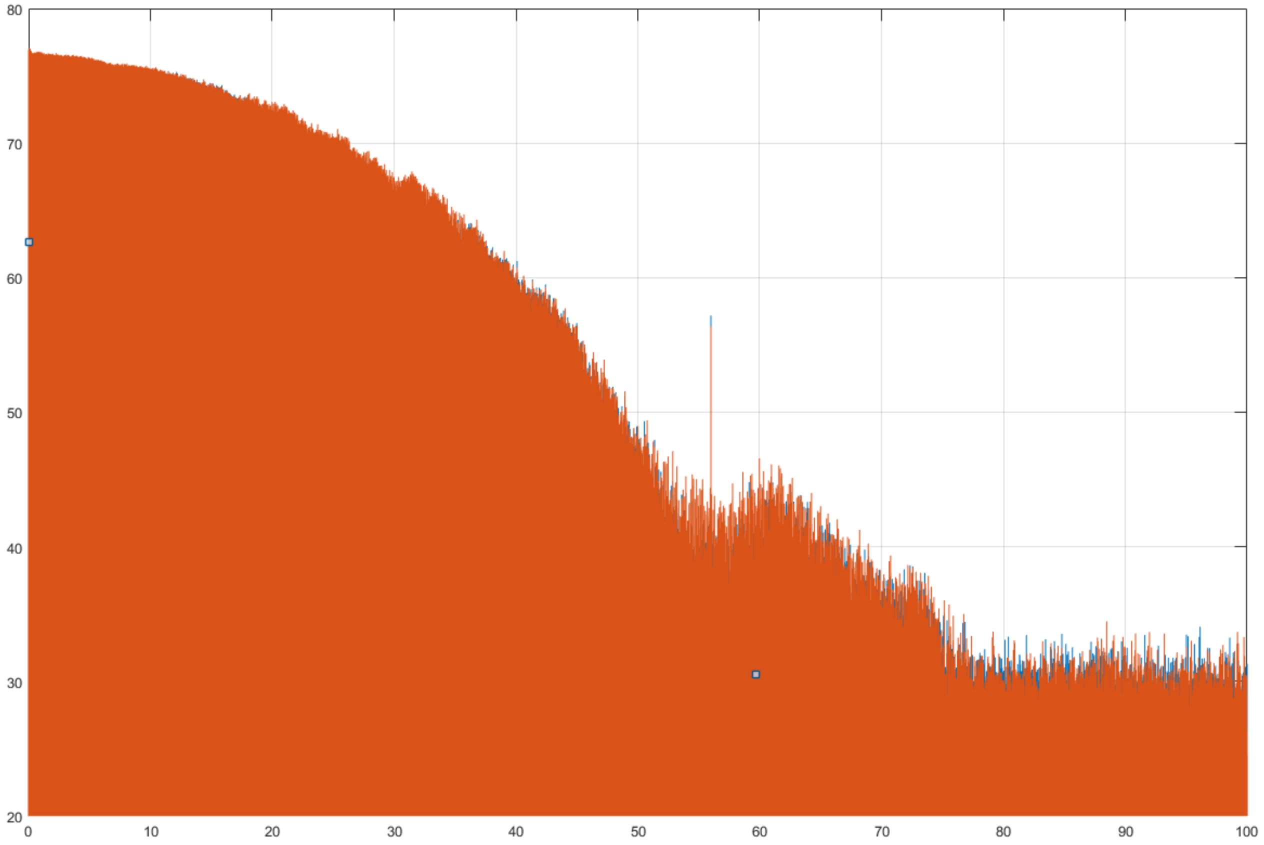
Pulse response



The modeling challenges in going for 112 GB

Waveforms Spectrum

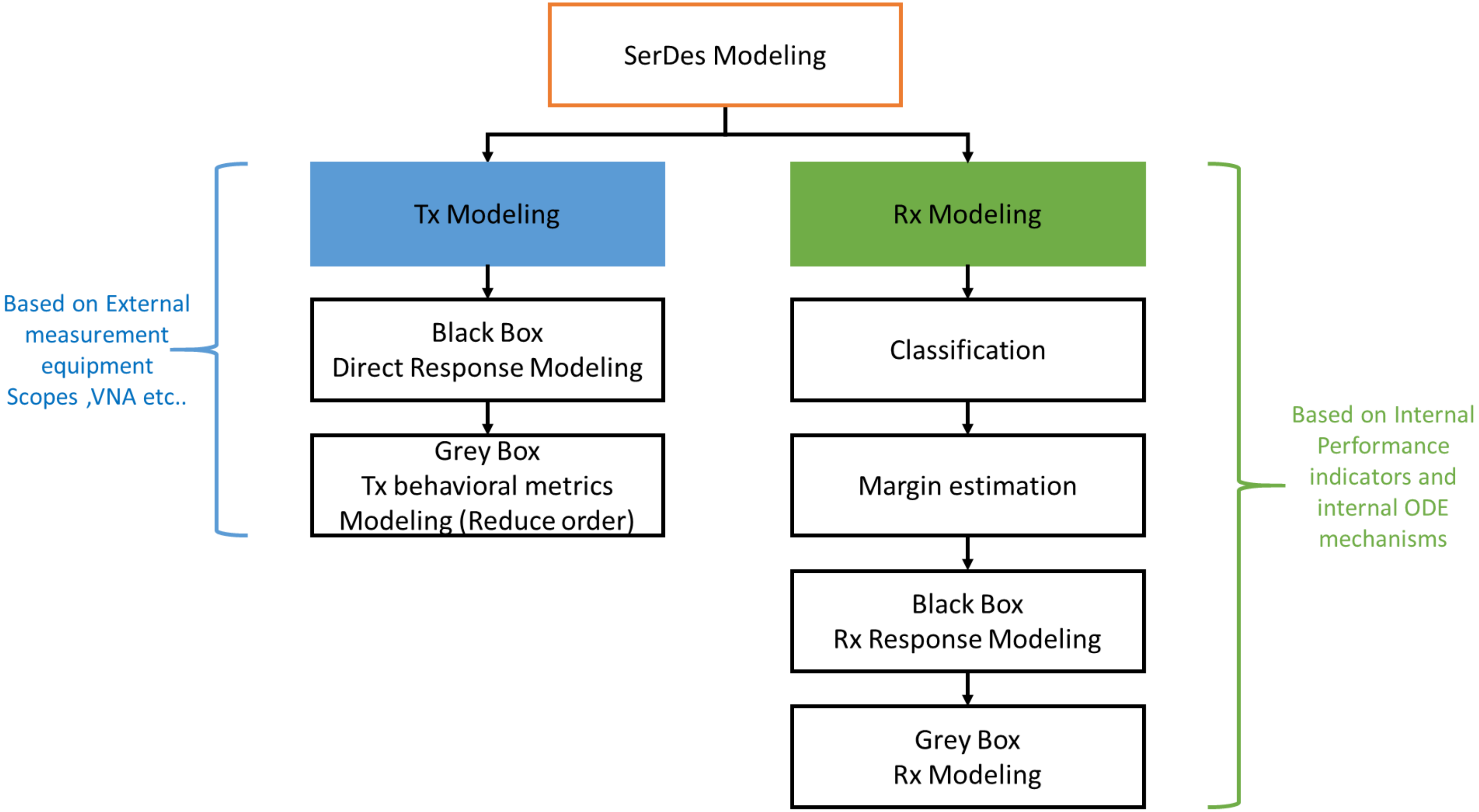
[dB]



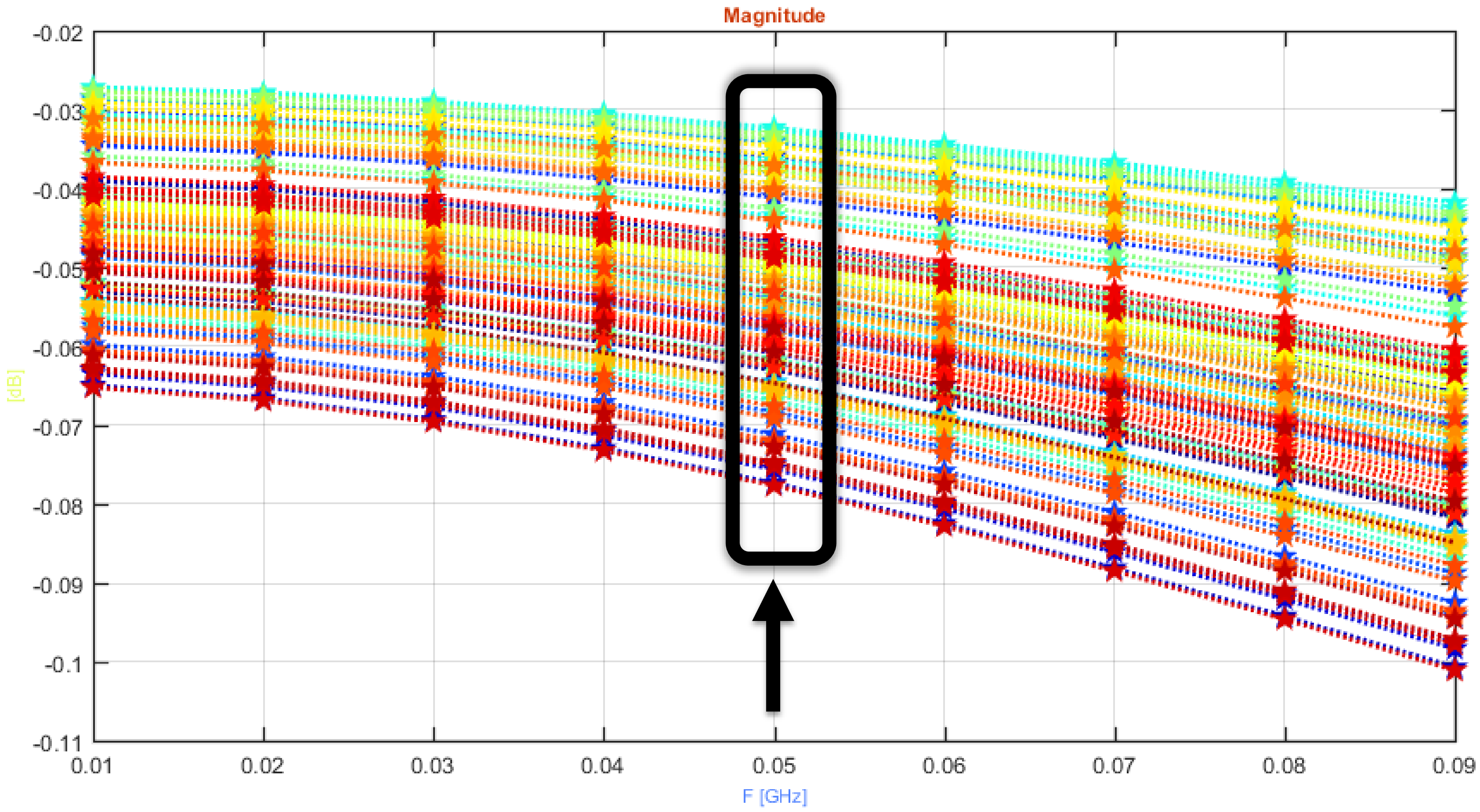
f [GHz]

ML Technics For SerDes Systems In Practice

Measurement Based Modeling



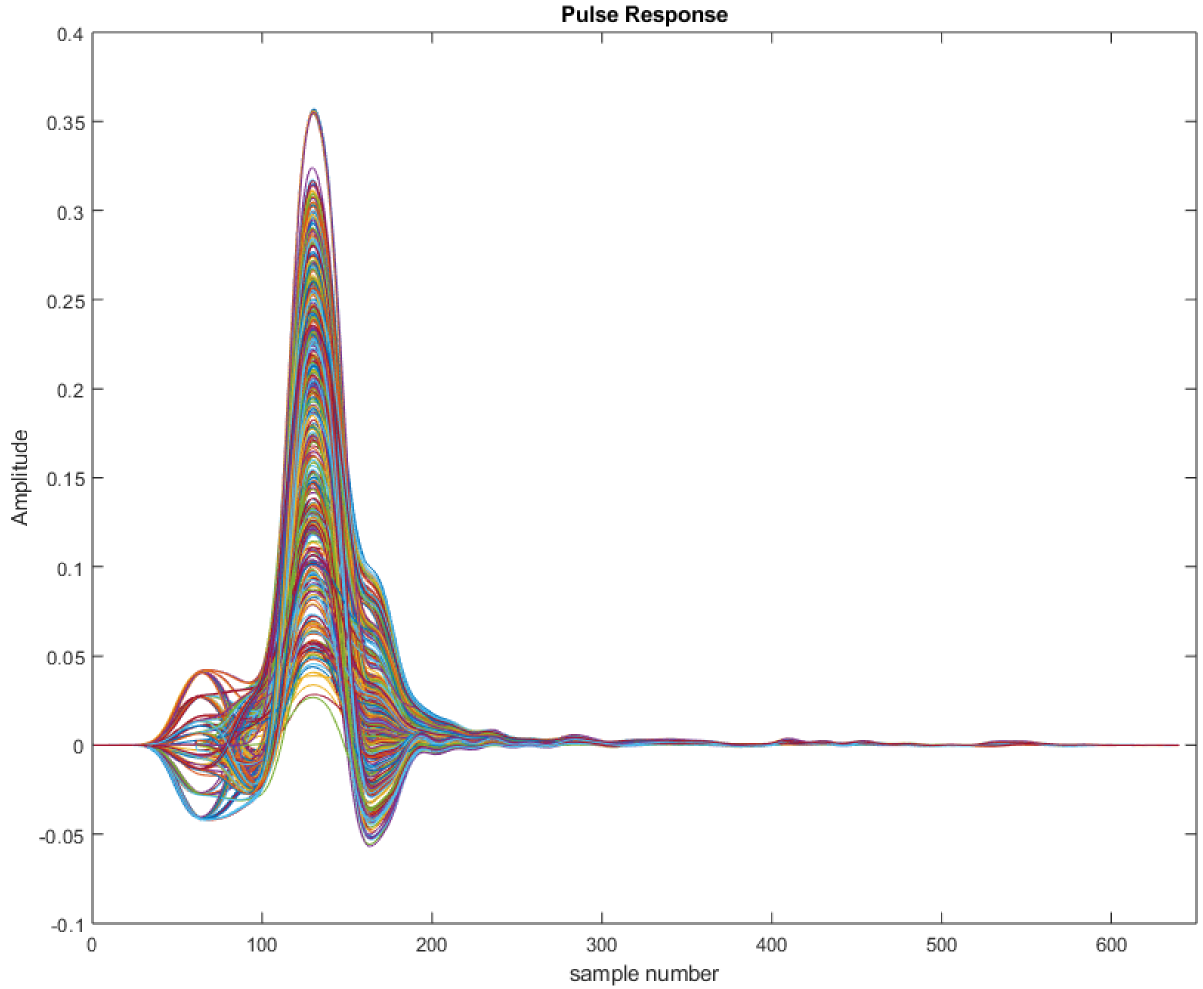
Tx modeling - the Black box approach



Tx Equalization, PVT and pulse response

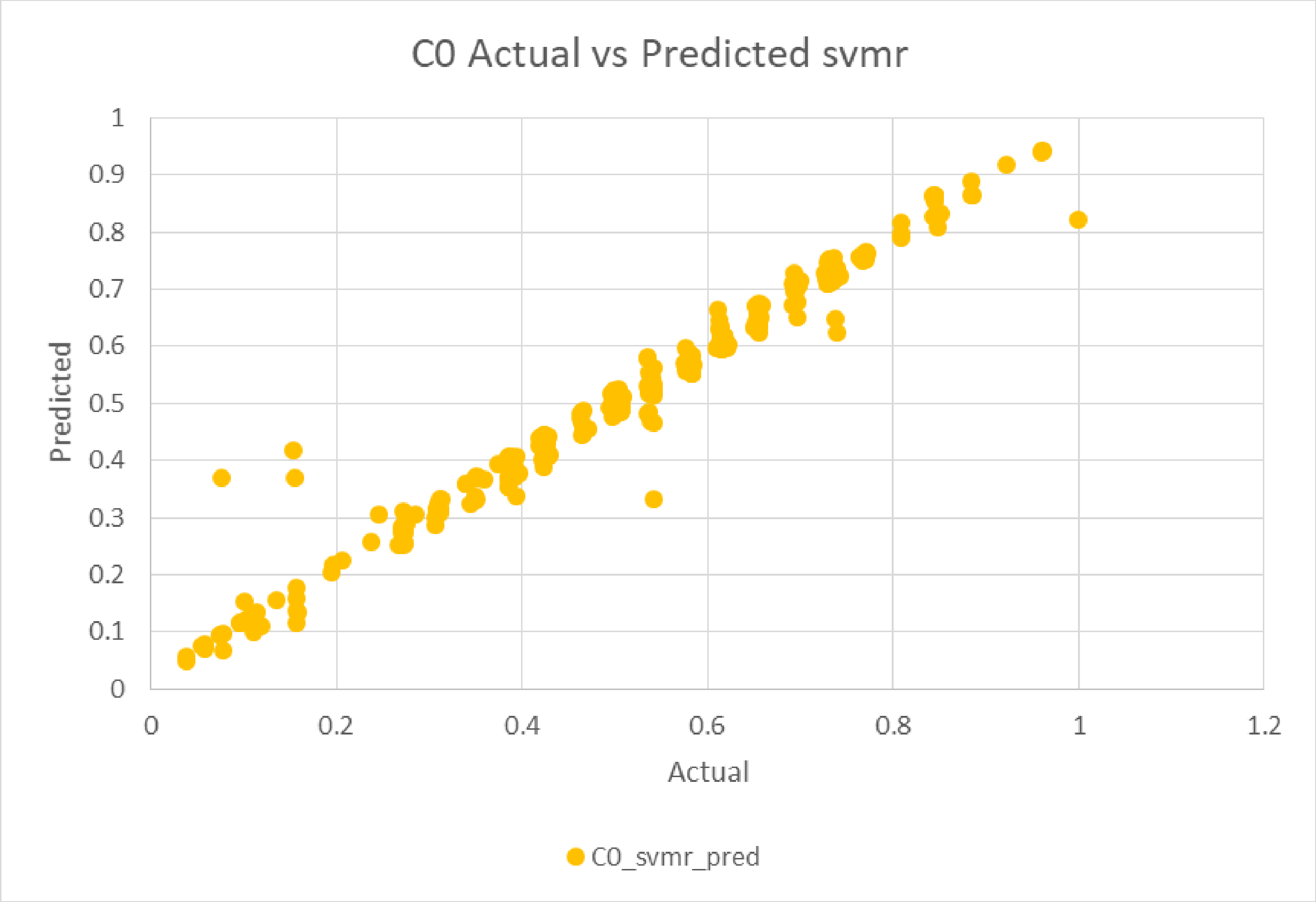
Training Set Challenge

Model generation relies on a sufficient training set of the input parameters along with its corresponding output response to train the model in the learning process



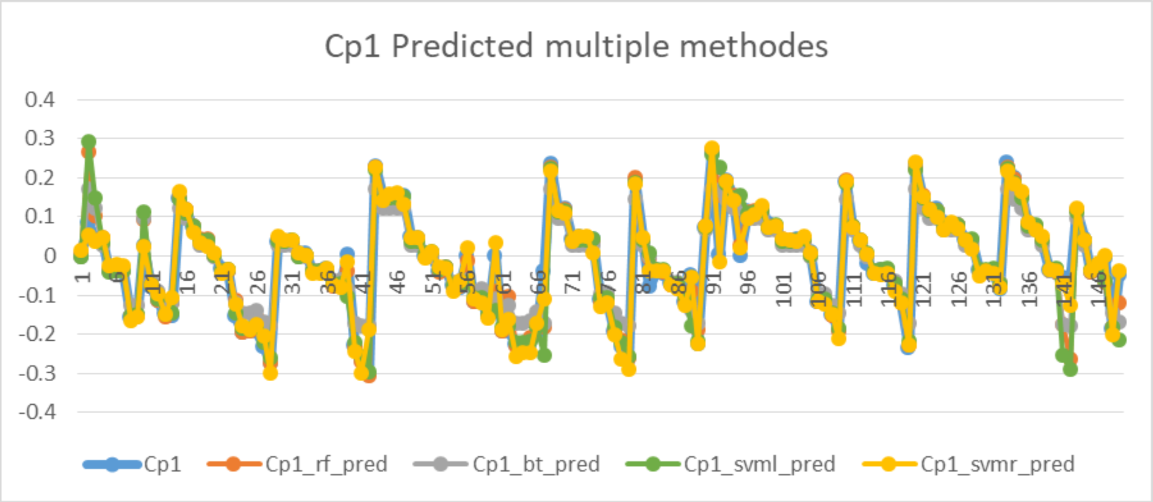
Grey Box Tx model - reduced order model

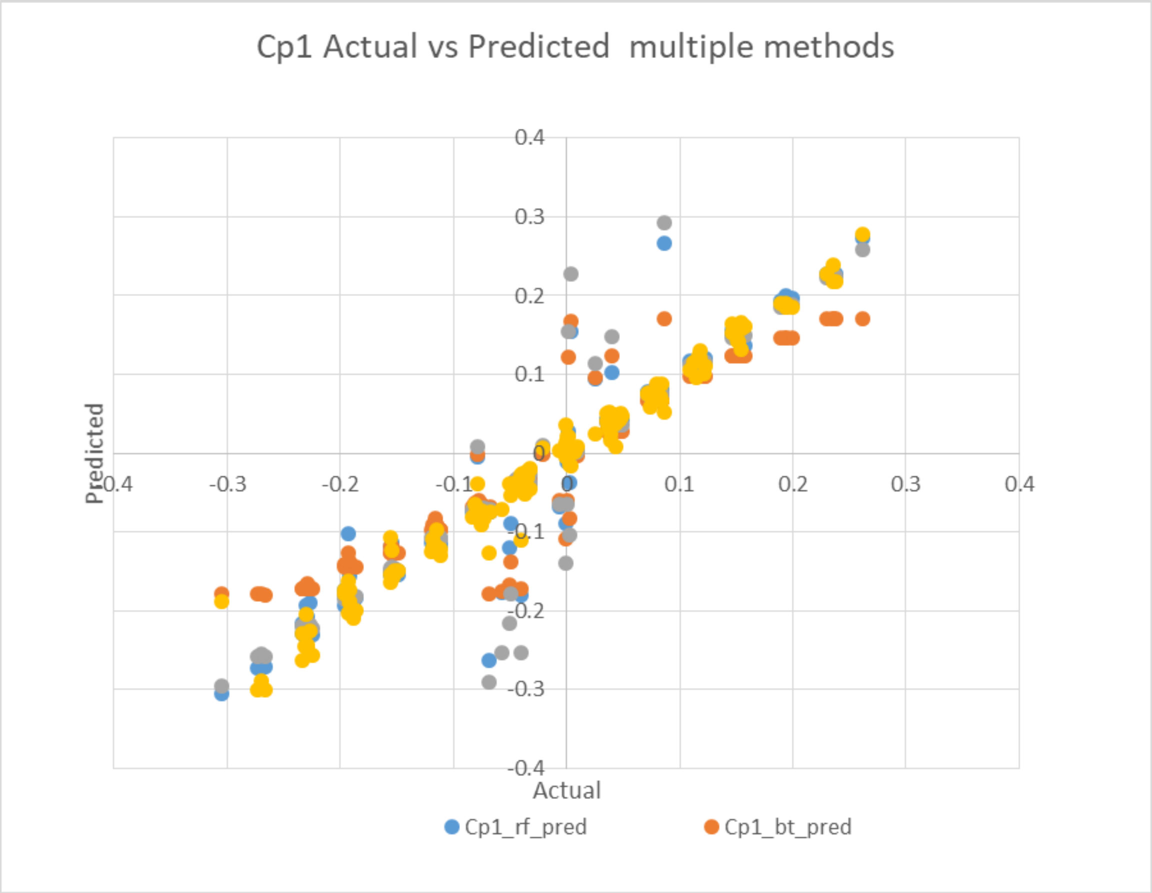
FFE main tap height



Grey Box Tx model - reduced order model

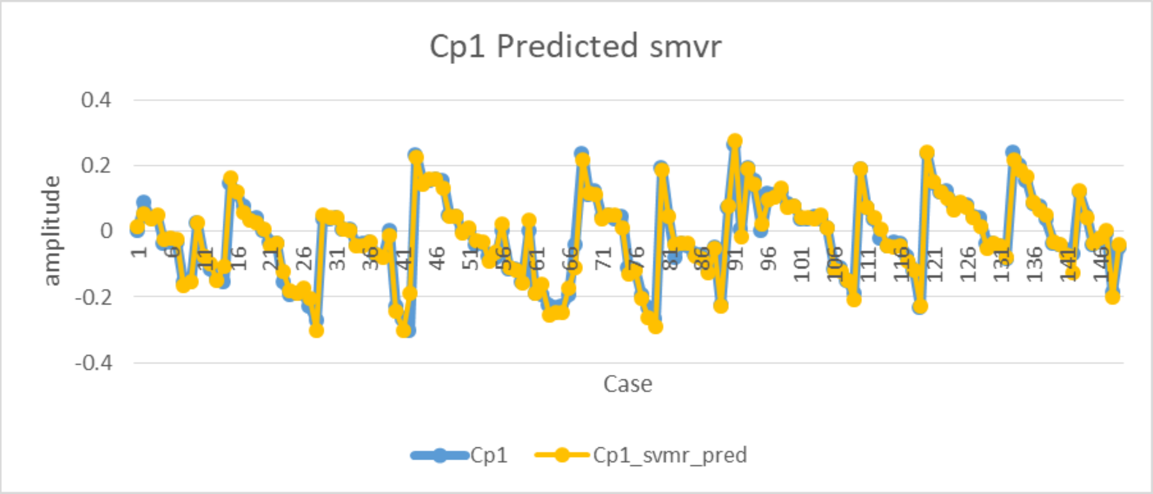
FFE pre1 tap height

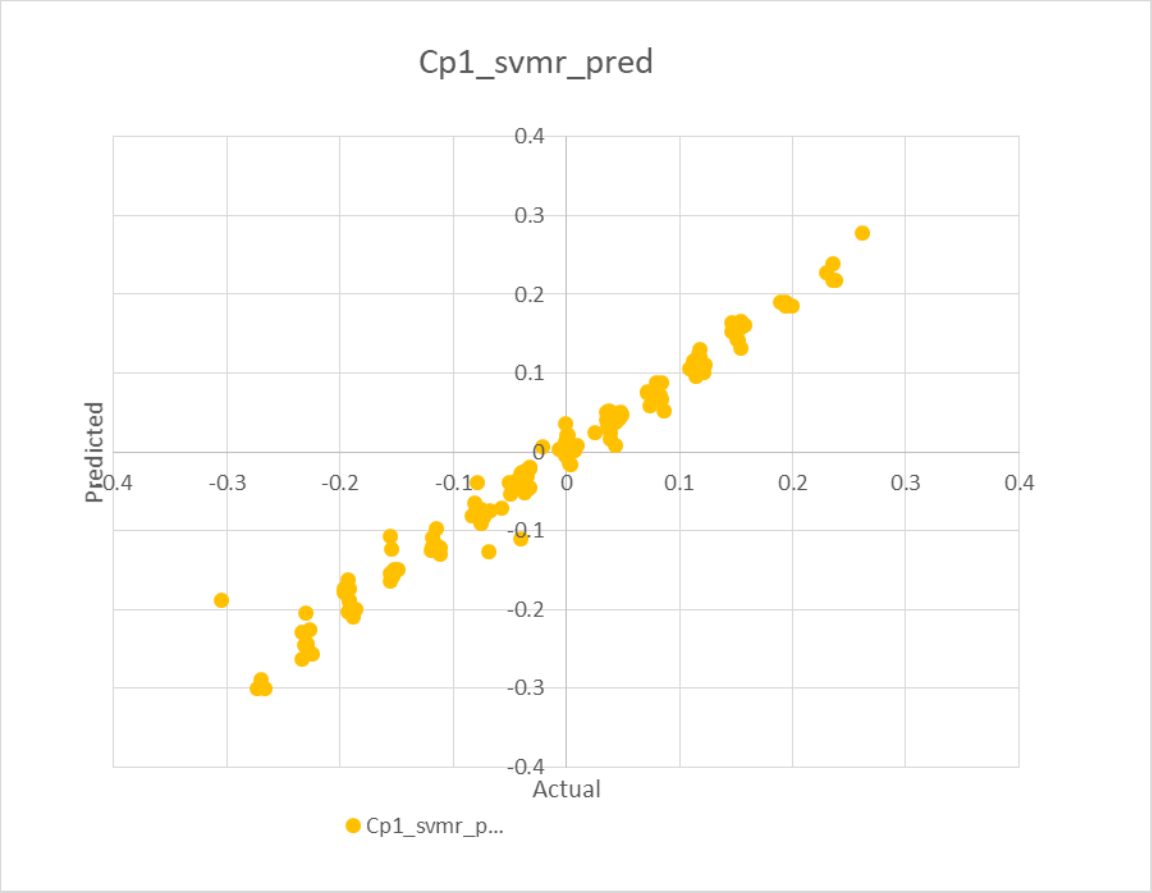




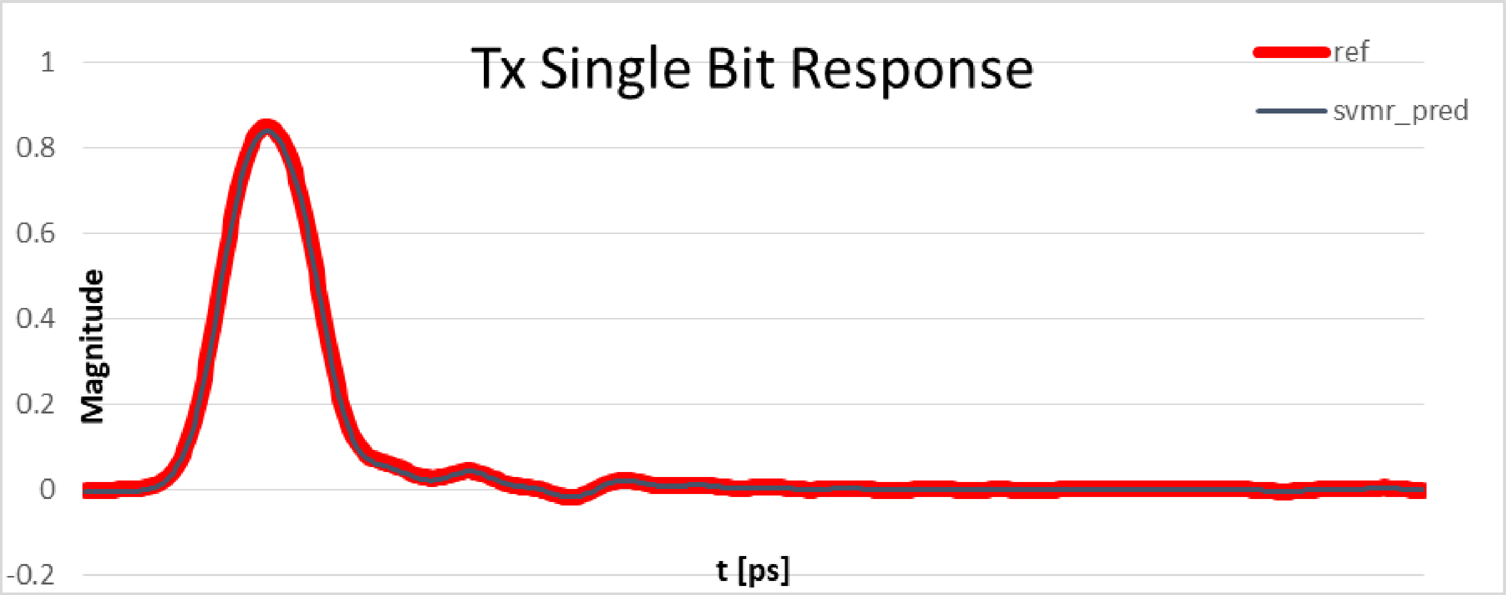
Grey Box Tx model - reduced order model

FFE pre1 tap height





Predicted Vs Measured



Rx System Classification for handling complexity

Eye margin Prediction from intra-die variation parameters (IDVs) measured on the silicon.

- The dataset contains over 10K IDV features
- The dataset contains 82 samples
- Margin values <= 30 are treated as failing
- There are 10 samples with failing margins
- There are 72 with passing margins.
- We use 75% of the samples for training and validation and 25% for testing.
- 10 features selected by MRMR

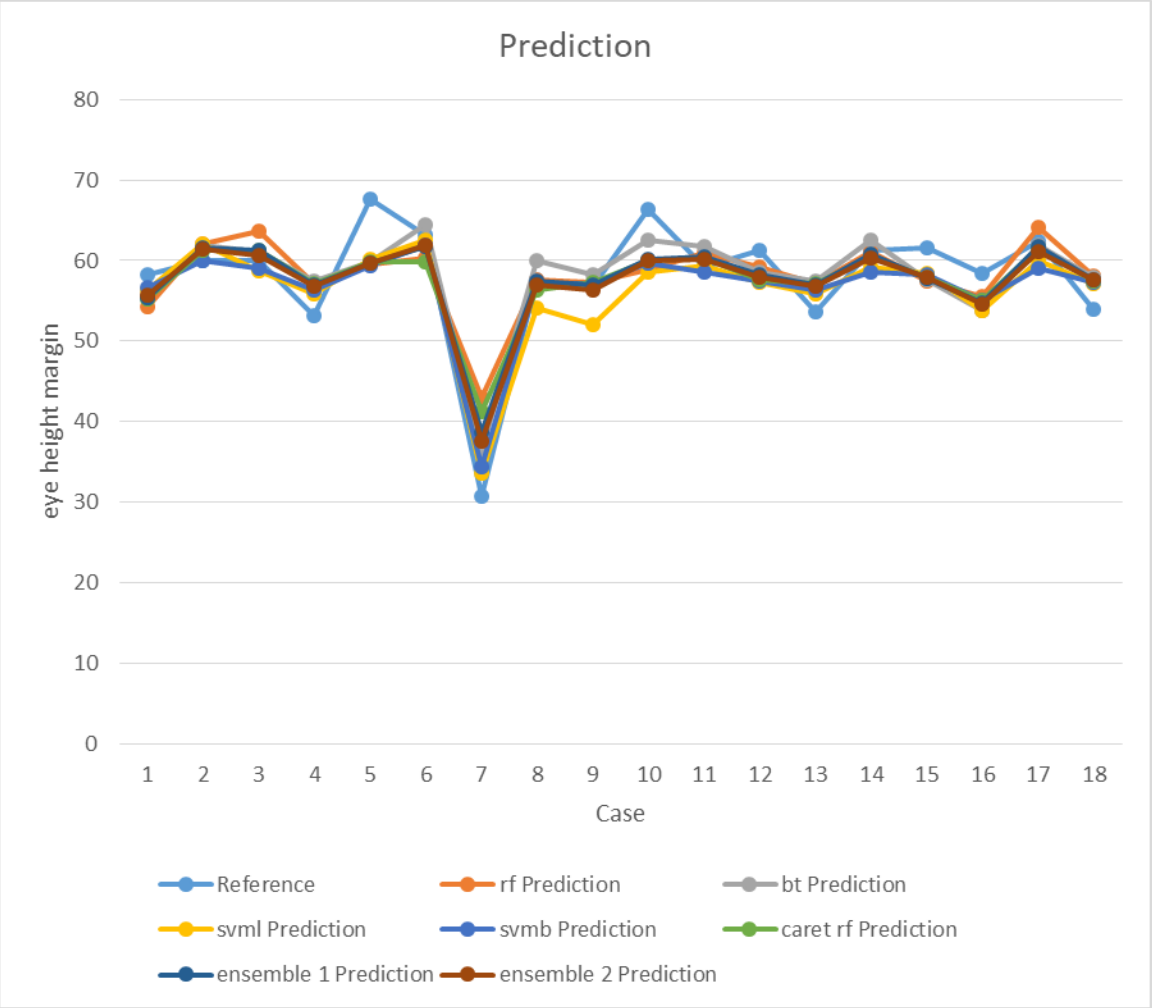
Reference	rf prediction	bt prediction	caret rf prediction	ensemble 1 prediction	ensemble 2 prediction	ensemble 3 prediction	ensemble 4 prediction	ensemble 5 prediction
1	1	1	1	1	1	1	1	1
1	1	1	1	1	1	1	1	1
1	1	1	1	1	1	1	1	1
1	1	1	1	1	1	1	1	1
1	1	1	1	1	1	1	1	1
1	1	1	1	1	1	1	1	1
1	1	1	1	1	1	1	1	1
1	1	1	1	1	1	1	1	1
1	1	1	1	1	1	1	1	1
1	1	1	1	1	1	1	1	1
1	1	1	1	1	1	1	1	1
1	1	1	1	1	1	1	1	1
1	0	1	1	1	1	1	1	1
0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0
1	1	1	1	1	1	1	1	1
1	1	1	1	1	1	1	1	1
1	1	1	1	1	1	1	1	1
1	1	1	1	1	1	1	1	1
1	1	1	1	1	1	1	1	1

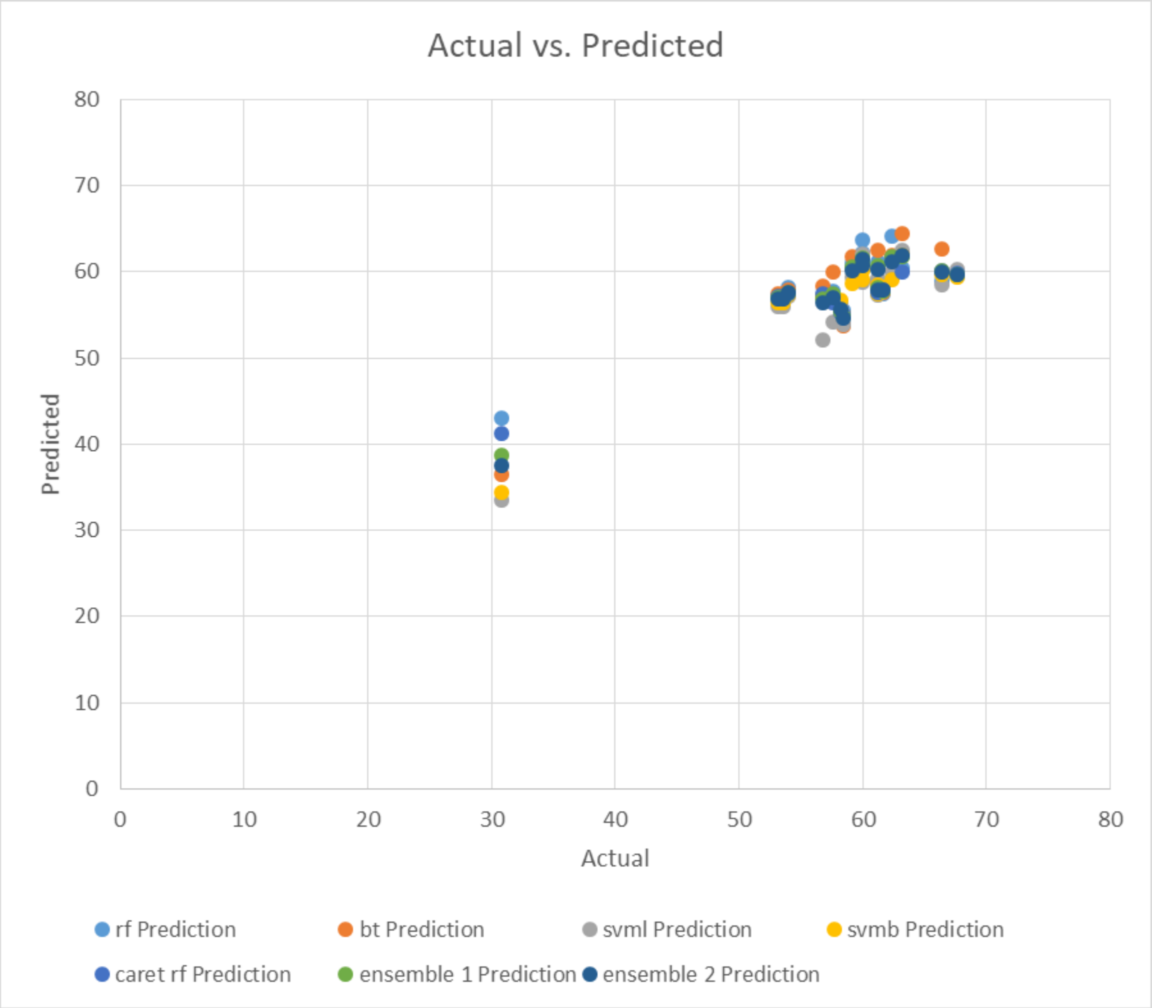
Confidence in system classification prediction

Ensemble methods provide more confidence in system classification prediction end are more reliable in those tasks.

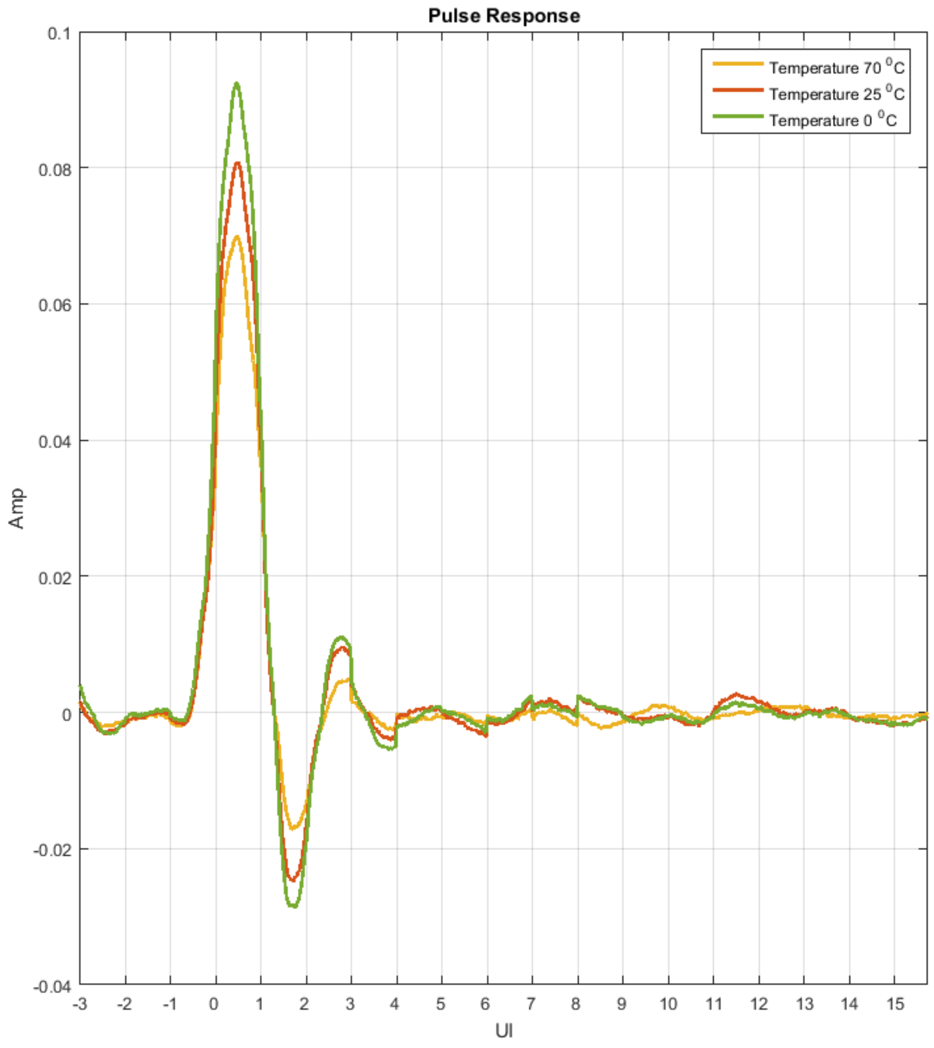
	rf probability	bt probability	caret rf probability	ensemble 1 confidence	ensemble 2 confidence	ensemble 3 confidence	ensemble 4 confidence	ensemble 5 confidence
	1	0.97374761	1	1	0.9825	1	0.9816	0.9475
	1	0.97374761	1	1	0.9825	1	0.9816	0.9475
	1	0.97374761	1	1	0.9825	1	0.9816	0.9475
	1	0.97374761	1	1	0.9825	1	0.9816	0.9475
	0.6095	0.92310814	0.797	1	0.5531	1	0.571	0.8462
	1	0.9739796	0.9955	1	0.9797	1	0.9786	0.948
	1	0.97374761	1	1	0.9825	1	0.9816	0.9475
	1	0.97374761	1	1	0.9825	1	0.9816	0.9475
	0.9135	0.9062373	0.878	1	0.7985	1	0.797	0.8125
	0.796	0.8186425	0.7295	1	0.5628	1	0.5612	0.6373
	1	0.97374761	1	1	0.9825	1	0.9816	0.9475
	0.871	0.88729168	0.854	1	0.7415	1	0.7415	0.7746
	0.499	0.74736983	0.5615	0.3333	0.2052	0.4047	0.2163	0.4947
	0.2255	0.38427917	0.1825	1	0.4718	1	0.4677	0.2314
	0.176	0.27547331	0.219	1	0.553	1	0.5479	0.4491
	0.4745	0.41914411	0.364	1	0.1616	1	0.1675	0.1617
	0.839	0.89275134	0.8235	1	0.7035	1	0.7049	0.7855
	0.884	0.87615631	0.843	1	0.7354	1	0.7337	0.7523
	1	0.97374761	1	1	0.9825	1	0.9816	0.9475
	1	0.97374761	1	1	0.9825	1	0.9816	0.9475
	1	0.97374761	1	1	0.9825	1	0.9816	0.9475
Total Score	0.8232381	0.84961473	0.82130952	0.9682524	0.7757667	0.9716524	0.7763476	0.77944286

Performance Prediction – Margin Estimation

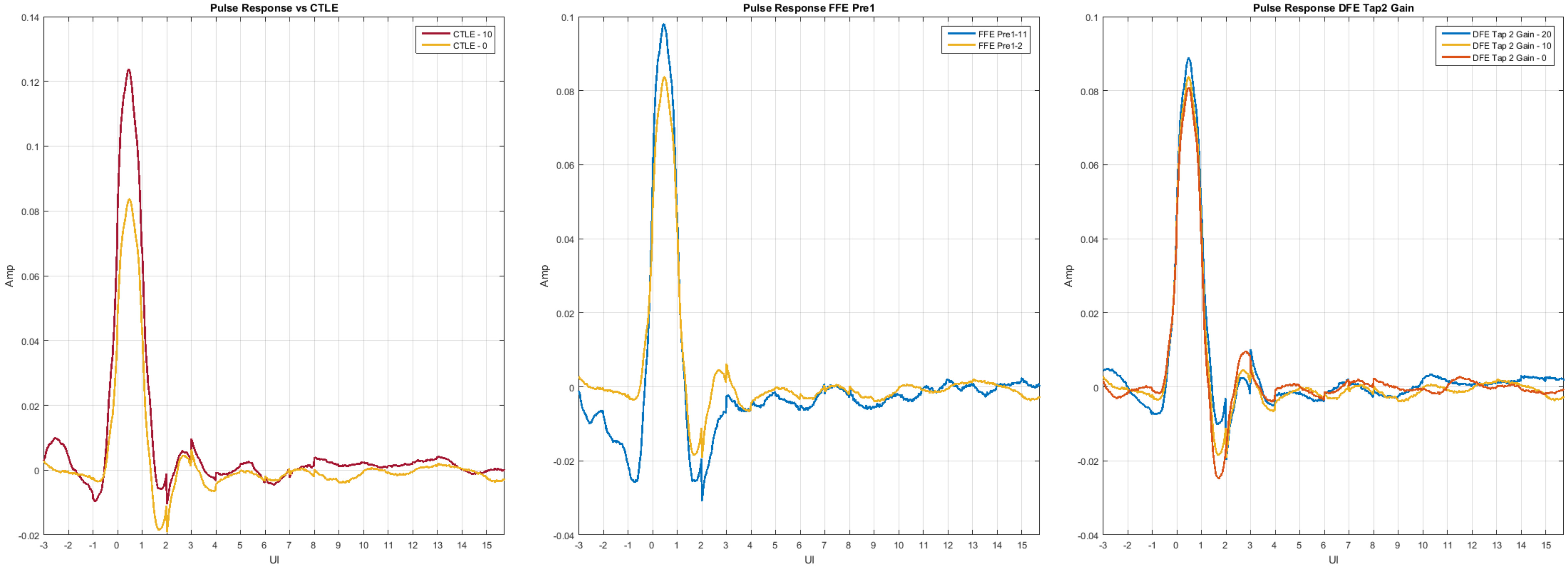




PVT Modeling



Modeling aspects of CTLE, FFE and DFE



Thank you!

QUESTIONS?