Cross Validation for Metamodels

Outline

- Recall: Cross-Validation
- What are metamodels
- Metamodels example
- Why is it important?
- Code example

Quick cross validation recap

- K-fold cross validation
 - Test data is already put aside
 - K blocks of data
 - Rotate the validation block

- Increase usage of the data
- Decrease splitting bias
- Train an ensemble of models



Other possible methods

- Naïve and fast cross-validation
- Leave-one-out cross-validation
- Fast leave-one-out cross-validation of a linear model
- Corrected leave-one-out
- K-fold cross-validation
- Fast K-Fold cross-validation of a linear model

Metamodels

What is a **model**?

A model is an abstraction of phenomena in the real world

$$y = f(\mathbf{x})$$

What is a **metamodel**?

• The idea is to find a proper approximation that is accurate, cheap and fast to evaluate.

$$\hat{y}(\mathbf{x}) \approx y(\mathbf{x})$$

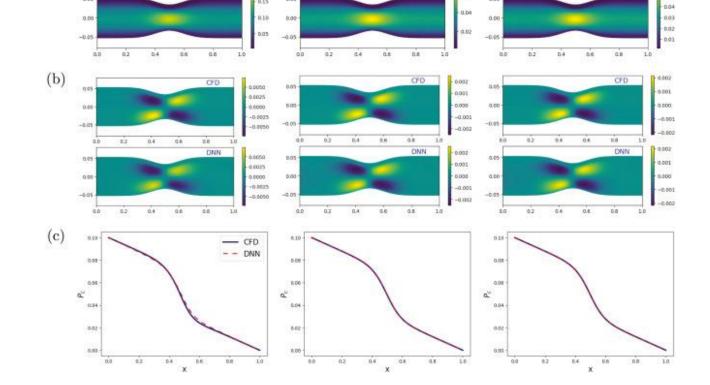
How to construct such model?

- 1. **Definition of Design Space:** select design variables and bounds of the design space
- 2. Experimental Design: perform a design of experiments (DOE) to select a set of sampling points
- **3. Models Evaluation:** evaluating the true model or simulation at each of the sampled points
- **4. Metamodels Creation:** by using any available procedure, like: PRS, Polynomial Response Surface, RBF, KRG, NN, SVR, etc.
- 5. Metamodel Validation: error metric or cross validation

Example of Metamodels

(a)

- LabelFree-DNN-Surrogate
 - Simulation-free, physicsconstrained deep learning. A surrogate for the CFD model.
- DL model gives quick solutions for fluid flow problems without the grid-based computations of CFD.
- Embedding the governing eq. (Navier-Stokes) and boundary/initial conditions into the loss function of DNN.
- Loss function: ensure the model's prediction satisfy the Navier-Stokes eq.

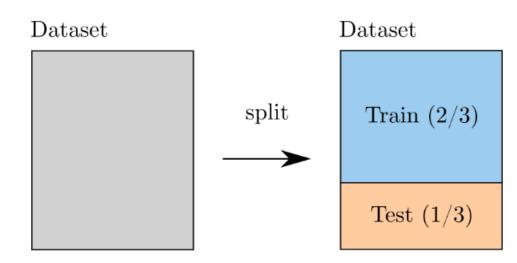


0.10

DNN

Validation in context of metamodel

- In ordinary validation of a metamodel, we hold some observations from the sample and train the model on the remaining observations.
- Then, we test the metamodel against the held-out observations.



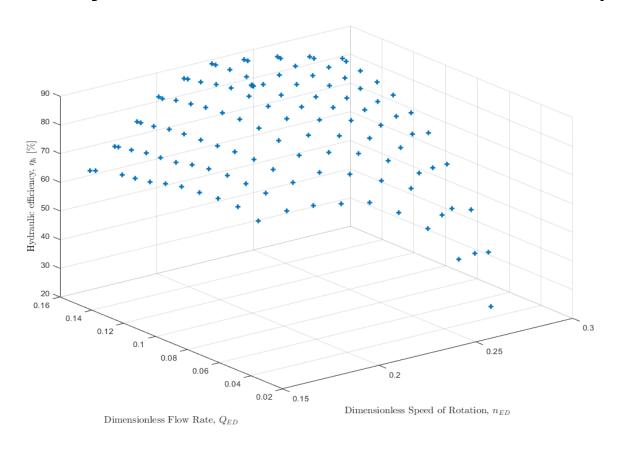
Source:

https://openturns.github.io/openturns/latest/user_m anual/response_surface/_generated/openturns.Meta ModelValidation.html

Importance of Cross-Validation for Metamodels

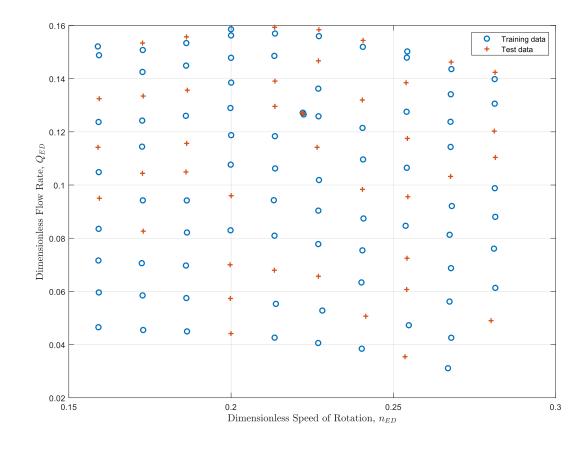
- Accuracy estimation
- Overfitting prevention
- Model selection
- Hyperparameter tuning
- Error and uncertainty quantification
- Efficient use of limited data

- Want a model for efficiency
- Collected efficiency measurements of a reversible pump-turbine



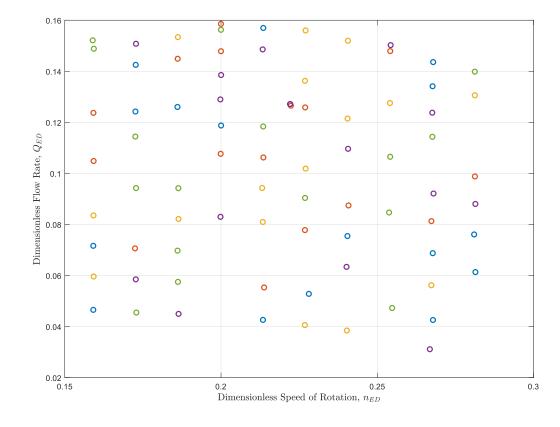
Divided into training set and test set

```
%% Divide Data into Training and Test Sets
% Define number of bins to ensure domain coverage
numBins = 8;
% Determine bin edges for nED and QED to distribute data evenly
[~, edges_nED] = histcounts(nED, numBins);
[~, edges_QED] = histcounts(QED, numBins);
% Initialize training and test index lists
trainIndices = [];
testIndices = [];
% Loop over each bin in nED and QED to proportionally split data
for i = 1:numBins
   binIndices nED = find(nED >= edges nED(i) & nED < edges nED(i+1));
        binIndices QED = find(QED >= edges QED(j) & QED < edges QED(j+1));</pre>
        % Find indices in both current nED and QED bins
        binIndices = intersect(binIndices nED, binIndices QED);
        numBinData = length(binIndices);
        % Split data in bin if there are values present
        if numBinData > 0
            numTrainBin = round(2 * numBinData / 3);
            shuffledBinIndices = binIndices(randperm(numBinData));
           % Assign data points to training and test sets
           trainIndices = [trainIndices; shuffledBinIndices(1:numTrainBin)];
            testIndices = [testIndices; shuffledBinIndices(numTrainBin+1:end)];
% Separate training and test data using determined indices
nED train = nED(trainIndices);
QED train = QED(trainIndices);
eta train = eta(trainIndices);
nED_test = nED(testIndices);
QED_test = QED(testIndices);
eta_test = eta(testIndices);
```



- Did a 5-fold cross validation of the training data
- Training RMSE: 0.5624

```
%% 5-Fold Cross-Validation on Training Set
% Combine training data into a matrix for partitioning
trainData = [nED train, QED train, eta train];
% Create 5-fold cross-validation partition
cv = cvpartition(size(trainData, 1), 'KFold', 5);
validationErrors = zeros(cv.NumTestSets, 1); % Array for errors
figure()
hold on
% Iterate over each fold to train and validate
for i = 1:cv.NumTestSets
    trainIdx = cv.training(i);
    testIdx = cv.test(i);
    % Extract training and validation sets for this fold
    nED train fold = nED train(trainIdx);
    QED train_fold = QED_train(trainIdx);
    eta_train_fold = eta_train(trainIdx);
    nED val fold = nED train(testIdx);
    QED val fold = QED train(testIdx);
    eta_val_fold = eta_train(testIdx);
    % Train a Gaussian Process model on the fold's training set
    cvmodel = fitrgp([nED train fold, QED train fold], eta train fold);
    % Predict on the validation set and calculate validation error
    eta_pred = predict(cvmodel, [nED_val_fold, QED_val_fold]);
    validationErrors(i) = mean(sqrt((eta val fold - eta pred).^2));  % RMSE
    % Plot the validation data points for visual validation
    plot(nED val fold, QED val fold, 'o', 'LineWidth', 1.5)
```



- Tested the model against the test data
- Test RMSE: 0.3541

```
%% Fit Model on Training Set and Predict on Test Set
% Fit the Gaussian Process model on the full training data
model = fitrgp([nED_train, QED_train], eta_train);

% Predict eta values on the test set and compute error
eta_model_pred = predict(model, [nED_test, QED_test]);
averageModelError = mean(sqrt((eta_test - eta_model_pred).^2));
```

