

Class 4- Machine Learning concepts

Part I

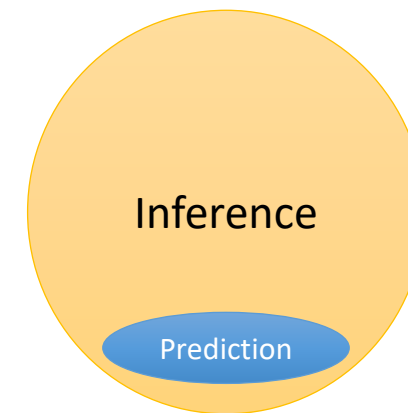
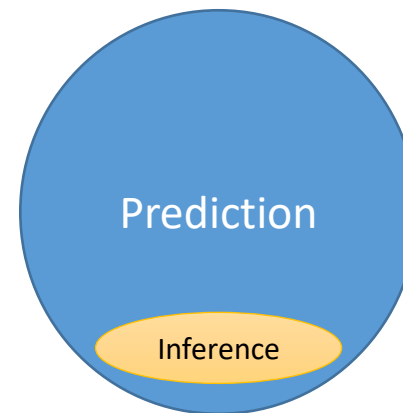




Motivation

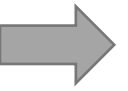
Machine learning fundamental concepts:

- Inference and prediction
- Part I: The Model
 - Parameters and hyperparameters
 - Parametric vs nonparametric ML models
- Part II: Evaluation metrics
- Part III: Bias-Variance tradeoff
- Part IV: Resampling methods
- Part V: scaling the features
- Part VI: How do machines learn?
- Part VII: Solvers/learners (GD, SGD, Adagrad, Adam, ...)



Part I

The Model



The Model

$$y = f(X, \theta) + \epsilon = f(X_1, X_2, \dots, X_m, \theta_1, \theta_2, \dots, \theta_k) + \epsilon$$

y : response, dependent variables, output, **Target**

X : predictors, independent variables, input, **Features**

θ : estimates, specifications, **Parameters**

✓ It is all about estimating f by \hat{f} for two purposes:

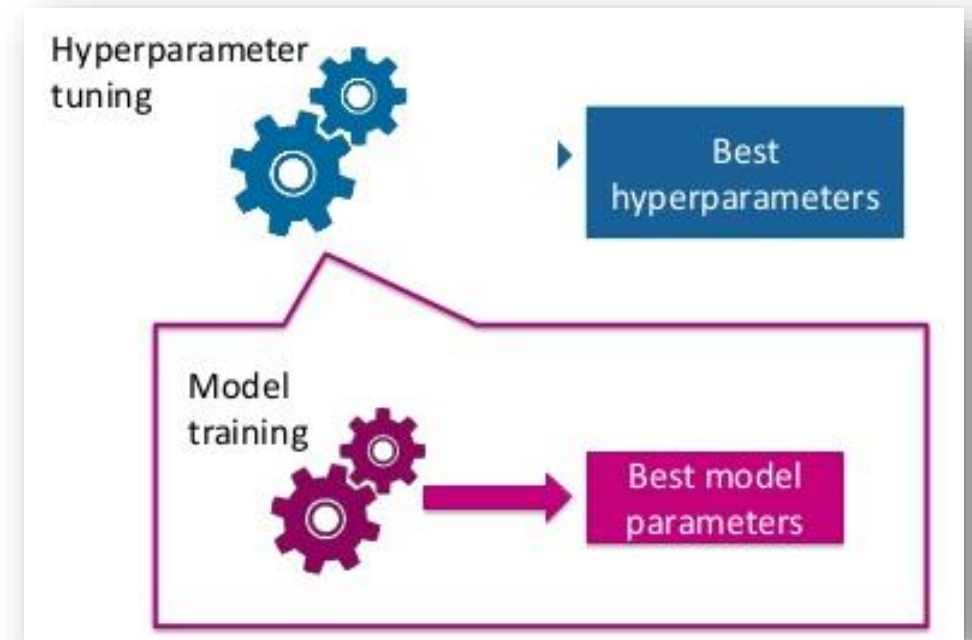
- 1) Inference (interpretable ML)
- 2) Prediction

Parameters and Hyperparameters

$$y = f(X, \theta) + \epsilon = f(X_1, X_2, \dots, X_m, \theta_1, \theta_2, \dots, \theta_k) + \epsilon$$

Model **parameters** are estimated from data automatically and model **hyperparameters** are set manually (prior to training the model) and are used in processes to help estimate model parameters.

Example?





Parametric Vs. Nonparametric models

$$y = f(X, \theta) + \epsilon$$

The true relationship, $f(X)$ is **unknown** and the goal is to see which ML algorithm is better at **approximating** it. An algorithm learns/estimates $f(X)$ from training data.

$f(X)$ is **assumed**. Examples:
Linear regression, GLM,
logistic regression, simple
Neural networks,



	Pros 	Cons 
Parametric algorithms	Simpler Easier to understand and to interpret Faster Very fast to fit your data Less data Require "few" data to yield good perf.	Limited complexity Because of the specified form, parametric algorithms are more suited for "simple" problems where you can guess the structure in the data

Part II

Evaluation Metrics

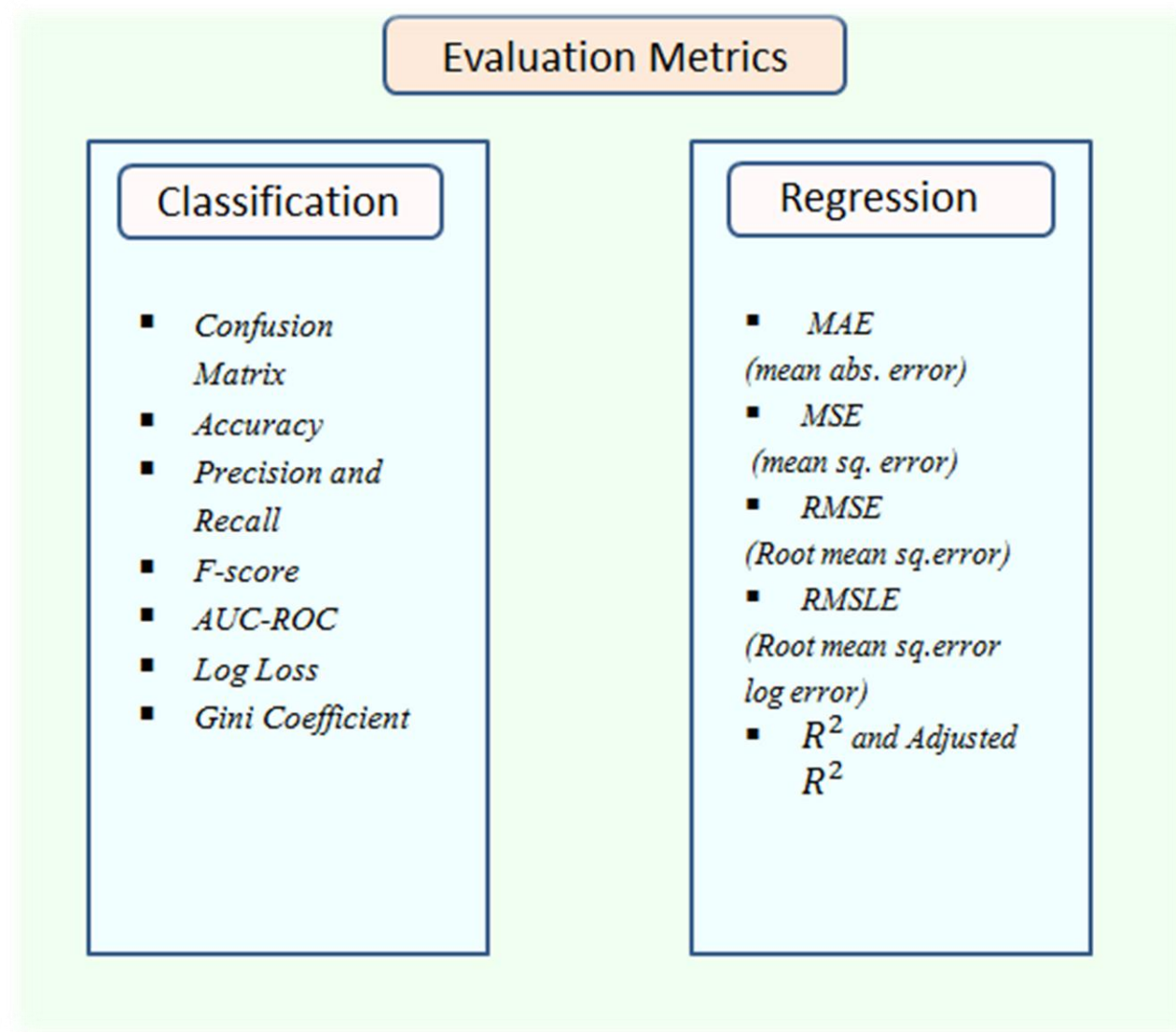


Evaluation metrics

In general, we want to compare how close are the predictions to the actual numbers in the **test set**.

This is typically assessed using

- MSE for **quantitative** response
- Misclassification rate for **qualitative** response



Part III

Bias-Variance Tradeoff



ML relative to statistical learning algorithms

- Advantages

- Ability to uncover complex interactions
- Process massive amount of data quickly
- Capture non-linear relationships
- Predict structural changes between features and target

- Disadvantages

- Can produce overly complex models
- Difficult to interpret
- Sensitive to noise
- Can overfit!

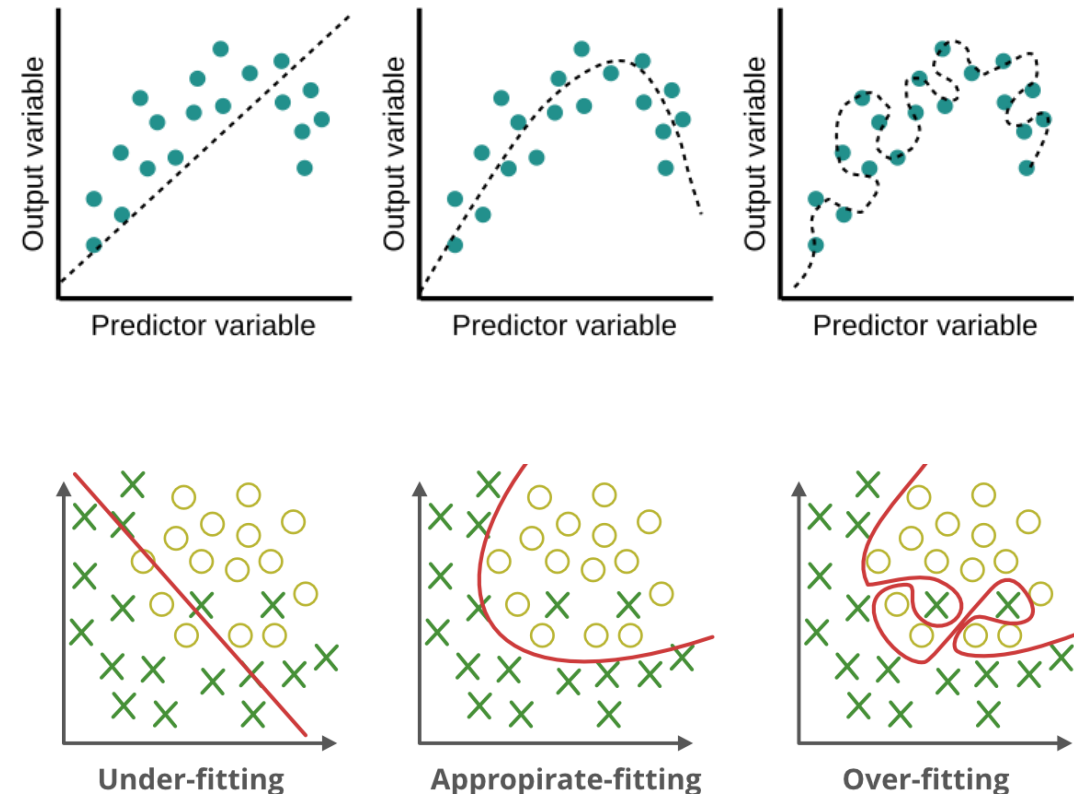
	Statistical Learning	Machine Learning
Focus	Hypothesis testing & interpretability	Predictive accuracy
Driver	Math, theory, hypothesis	Fitting data
Data size	Any reasonable set	Big data
Data type	Structured	Structured, unstructured, semi-structured
Dimensions / scalability	Mostly low dimensional data	High dimensional data
Model choice	Parameter significance & in-sample goodness of fit	Cross-validation of predictive accuracy on partitions of data
Interpretability	High	Low
Strength	Understand causal relationship & behavior	Prediction (forecasting and nowcasting)

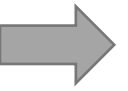


Overfitting

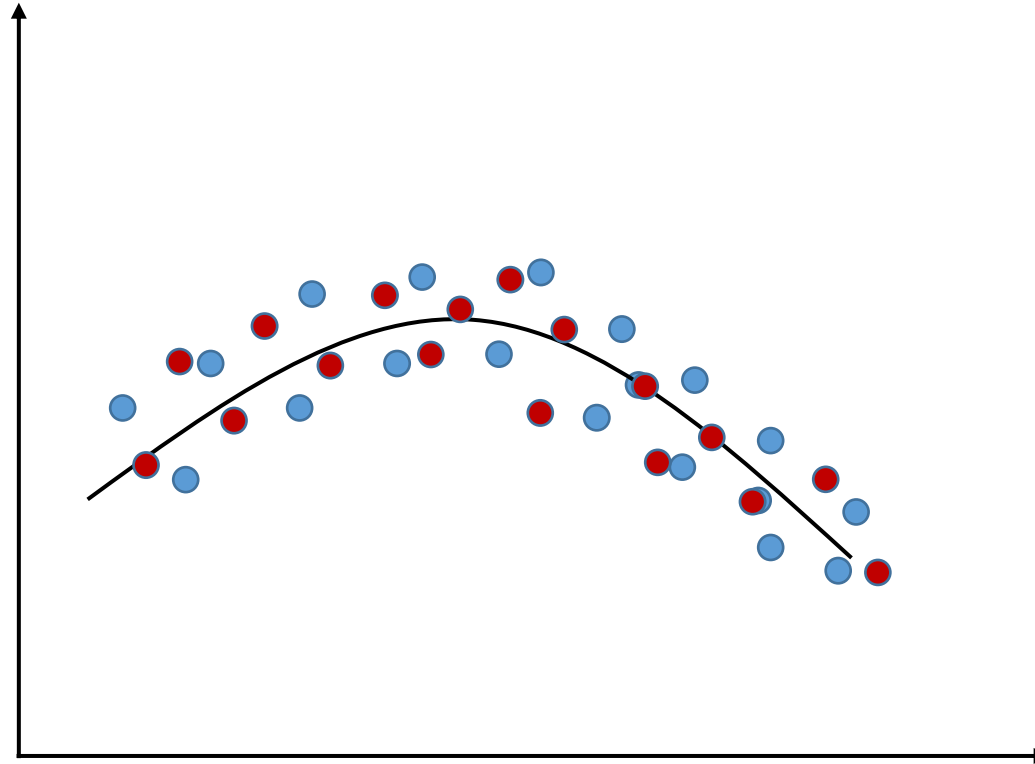
Overfitting happens when the fitted algorithm does **not generalize** well to new data:

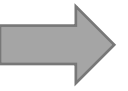
- The model fits the training data **too** well while not predicts well in the new data
- The model **fits the noise** (ϵ) in training data (finds a pattern that does not exist)
- The algorithm has simply **memorized** the data, rather than **learned** from it!
- The model is too **complex**!



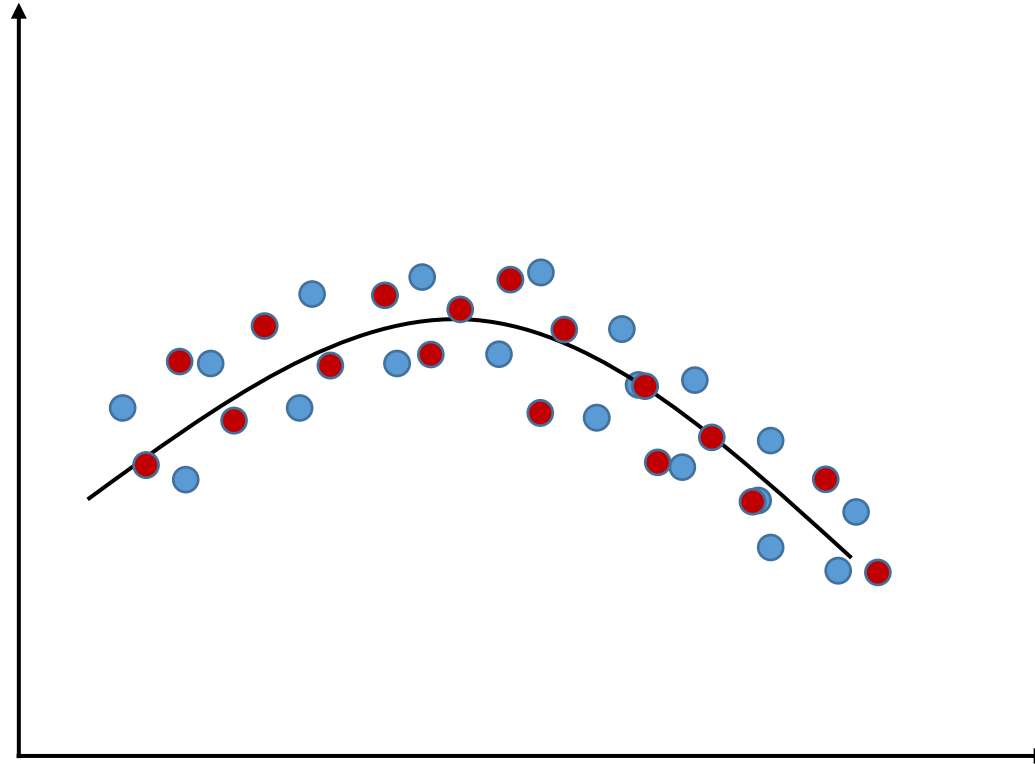


Model Bias & Model Variance in machine learning





Model Bias & Model Variance in machine learning



→ MSE decomposition

The **bias-variance** tradeoff is one of the core concepts in supervised learning.



Assume that the data is generated by a simple model!

$$y_i = f(\mathbf{x}_i) + \epsilon_i, \quad \mathbb{E}[\epsilon] = 0, \quad \mathbb{V}[\epsilon] = \sigma^2$$

The estimated model yields

$$\hat{y}_i = \hat{f}(X_i)$$

Let us decompose the mean squared error (**MSE**):

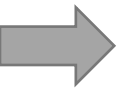
$$\begin{aligned} \mathbb{E}[\hat{\epsilon}^2] &= \mathbb{E}[(y - \hat{f}(\mathbf{x}))^2] = \mathbb{E}[(f(\mathbf{x}) + \epsilon - \hat{f}(\mathbf{x}))^2] \quad \dots = \underbrace{\mathbb{V}[\hat{f}(\mathbf{x})]}_{\text{variance of model}} + \underbrace{\mathbb{E}[(f(\mathbf{x}) - \hat{f}(\mathbf{x}))^2]}_{\text{squared bias}} + \sigma^2 \\ &= \underbrace{\mathbb{E}[(f(\mathbf{x}) - \hat{f}(\mathbf{x}))^2]}_{\text{total quadratic error}} + \underbrace{\mathbb{E}[\epsilon^2]}_{\text{irreducible error}} \end{aligned}$$

→ MSE decomposition

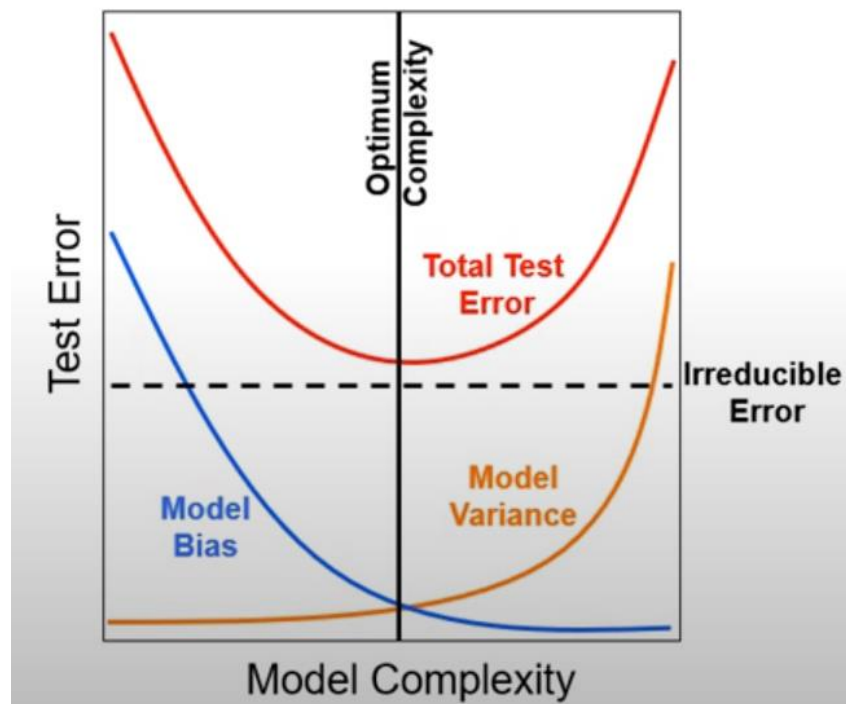
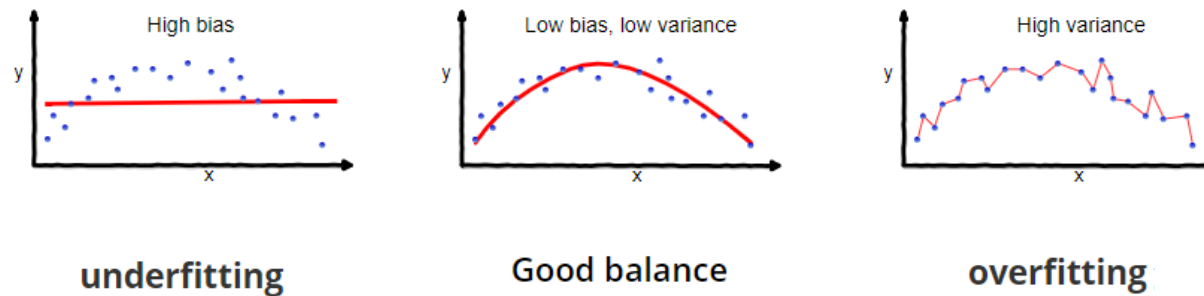
$$MSE = \text{model variance} + \text{model bias} + \text{irreducible error}$$

- 1) **Model variance** is the variance if we had estimated the model with a different **training set**
 - 2) **Model bias** is the error due to using an approximate model (model is too simple)
 - 3) **Irreducible error** is due to missing variables and limited samples. Can't be fixed with modeling
- The goal is to minimize the sum of **model variance** and **model bias**.
 - This is known as the bias-variance tradeoff because reducing one often leads to increasing the other.
 - Choosing the flexibility (complexity) of $\hat{f}(X)$, will amount to bias-variance tradeoff.



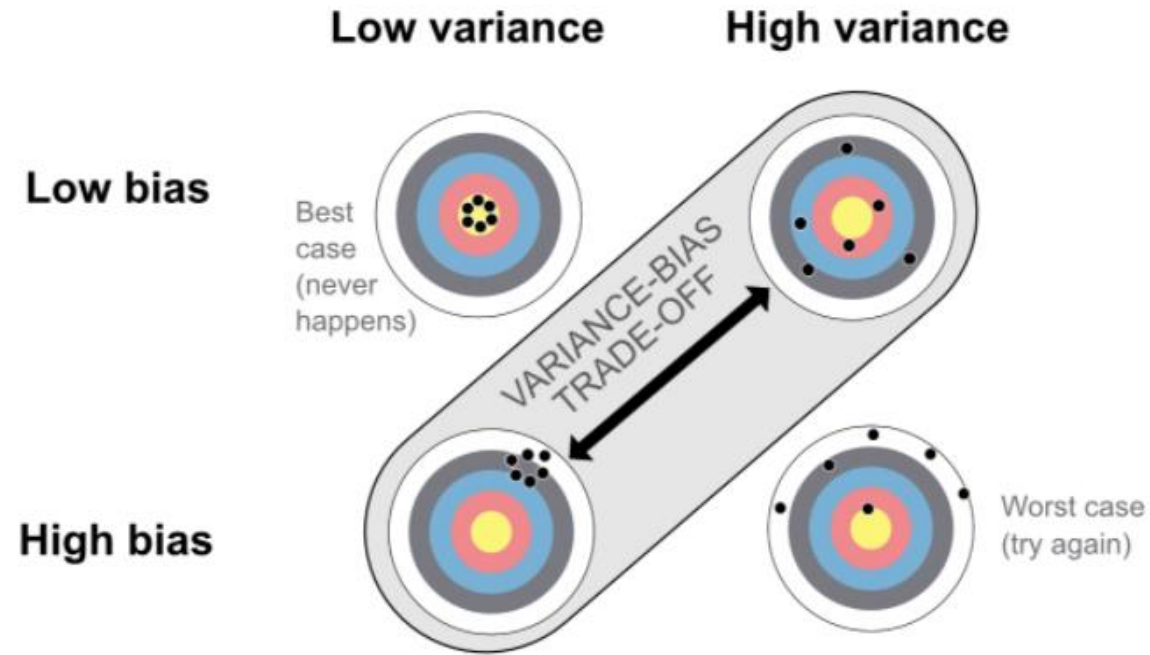


Representations of the bias-variance tradeoff





Other representations of the bias-variance tradeoff



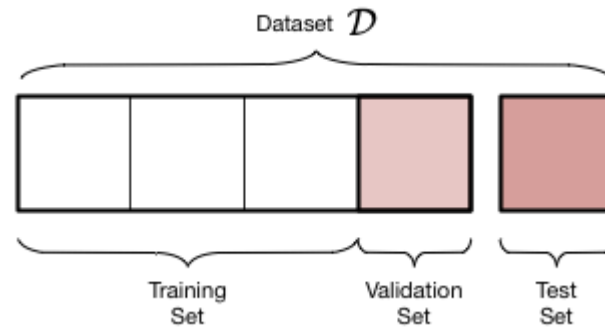
Part IV

Resampling methods

→ Partitioning of the dataset

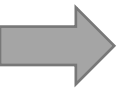
The data set is typically divided into three non-overlapping samples:

- 1) **Training set** used to train the model
- 2) **Validation set** for validating and tuning the model
- 3) **Test set (holdout set)** for testing the model's ability to predict well on new data



To be valid and useful, any supervised machine learning model **must** generalize well beyond the training data.

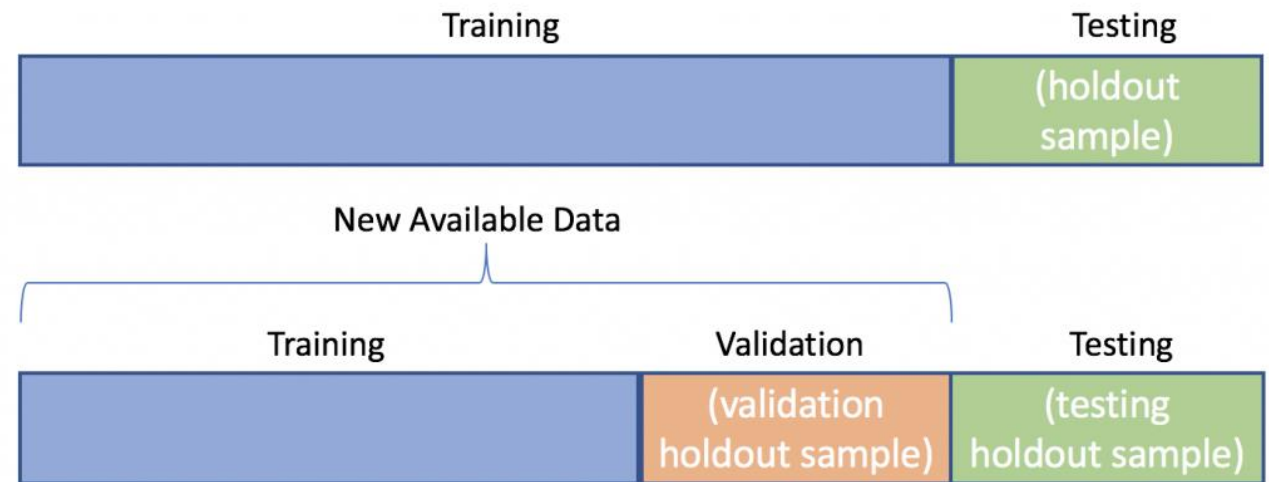
Large dataset is needed! But what if we don't have it?



Resampling methods

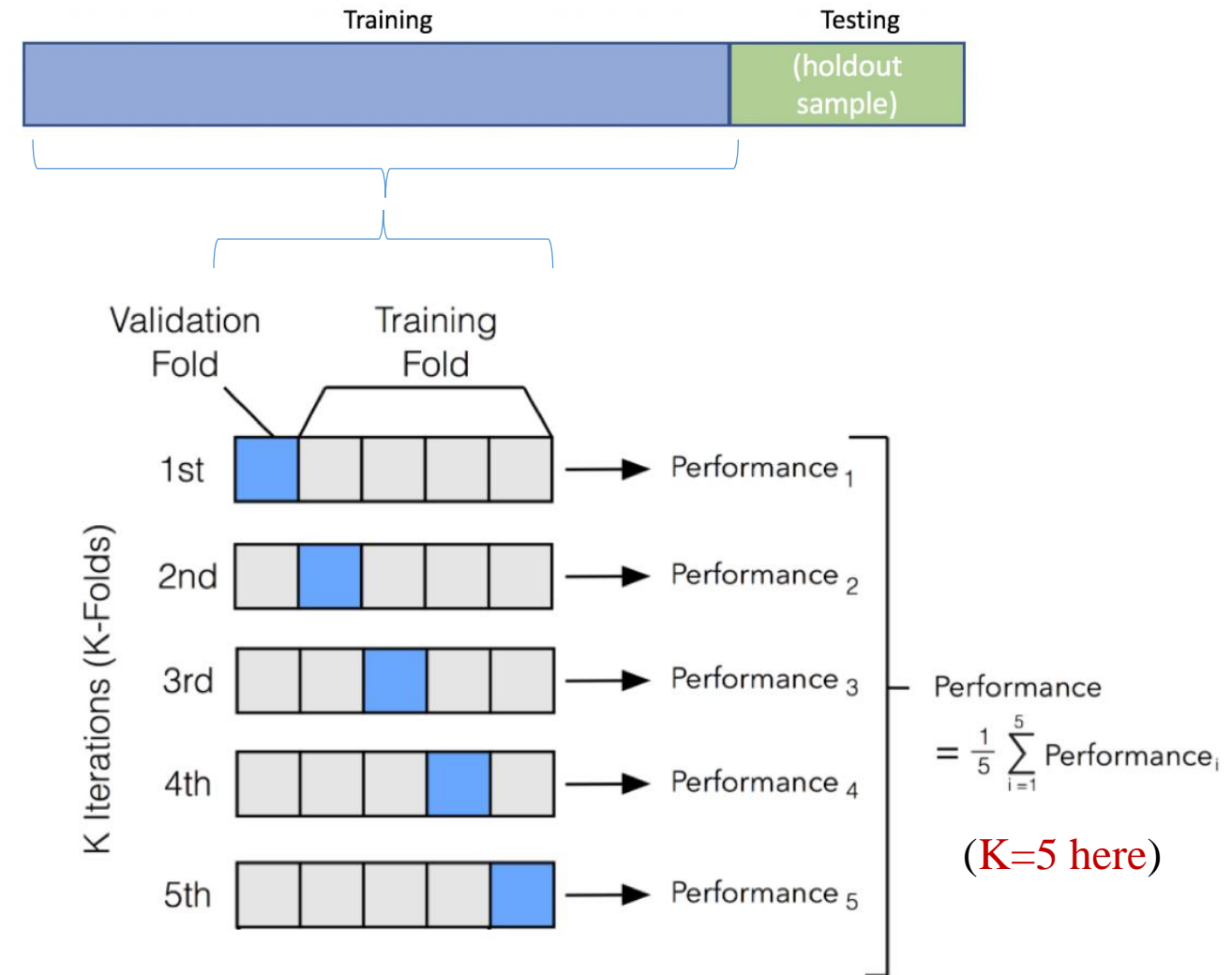
Cross validation

- Sometimes we cannot afford to split the data in three because the algorithm may **not learn** anything from a **small training dataset**!
- **Small validation set** is also problematic because we cannot tune the hyperparameters properly!
- Solution: combining the training and validation sets!
- The goal is to obtain additional information about the fitted model!
For example, to provide **estimates of test set prediction errors**.



→ K-fold Cross Validation

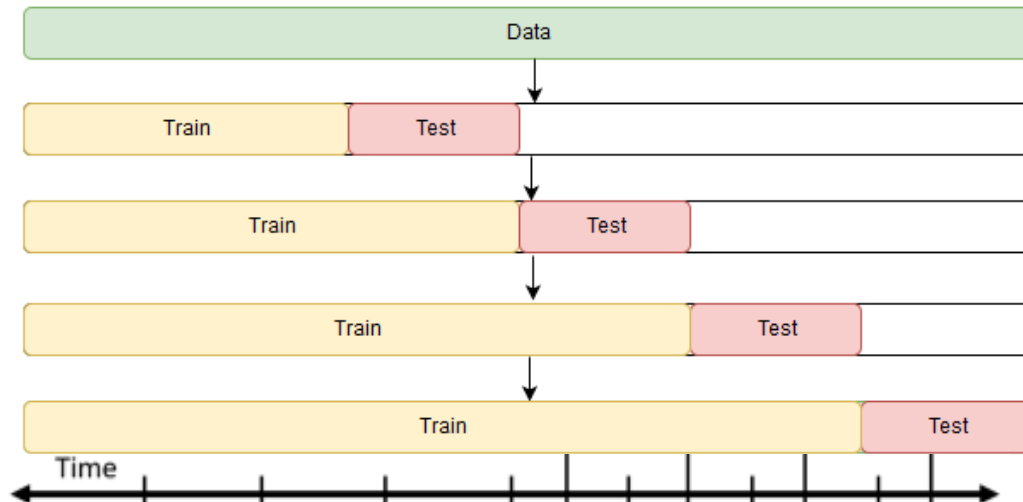
- 1) Divide the training data into K roughly equal-sized non-overlapping groups. Leave out k^{th} fold and fit the model to the other $k - 1$ folds. Finally, obtain predictions for the left-out k^{th} fold.
- 2) Performance can be any of the evaluation metrics for regression or classification models. For example, MSE, accuracy, ...
- 3) This is done in turn for each part $k = 1, 2, \dots, K$, and then the results are combined.
 - Leave one out CV (LOOCV): if there is only 1 observation in each fold.



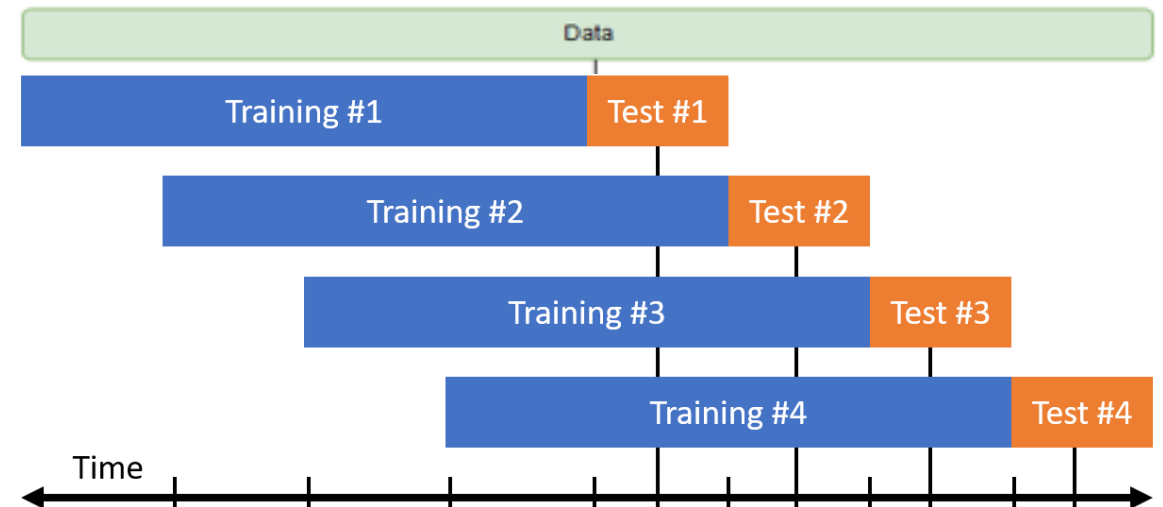
Time Series Cross Validation

With time series data, we **cannot shuffle** the data! We also need to **avoid look-ahead bias**!

Walk forward cross validation
Expanding windows



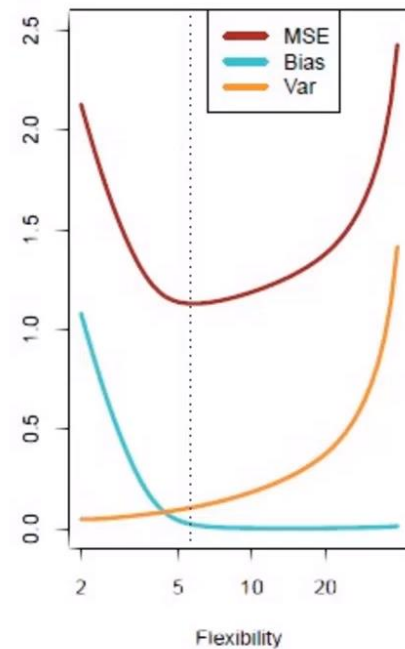
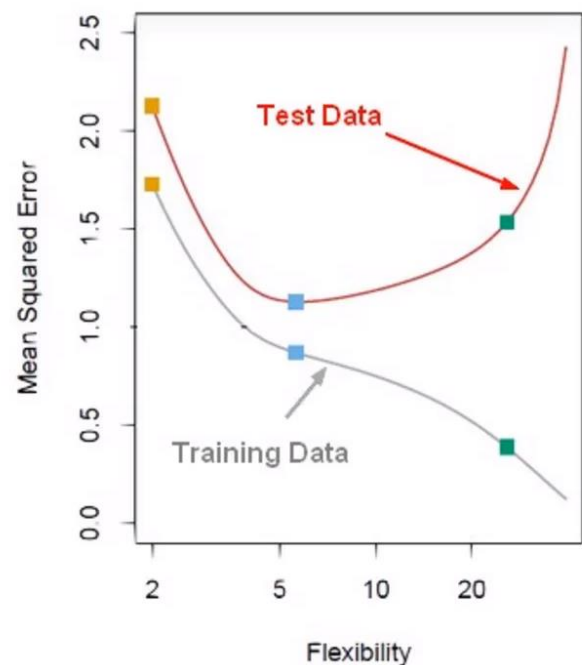
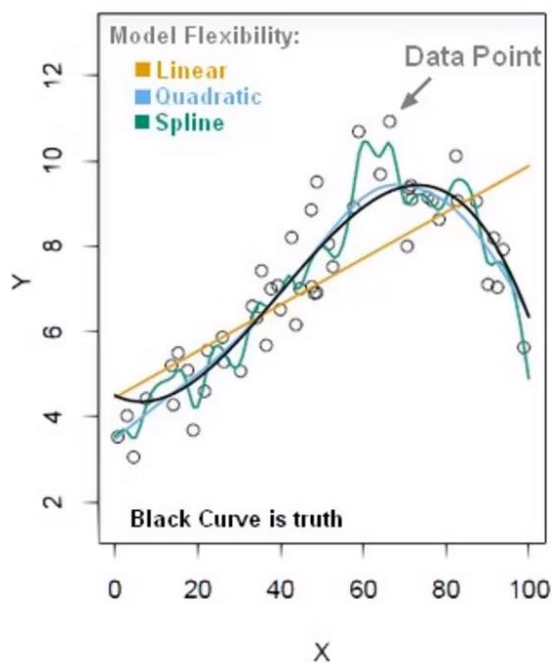
Walk forward cross validation
Rolling windows



➔ Mitigate overfitting

The main techniques used to mitigate overfitting risk in a model construction are:

- 1) Complexity reduction (regularization)
- 2) Cross validation (estimate the test error)



➔ Question of the day!



