Introduction to Machine Learning

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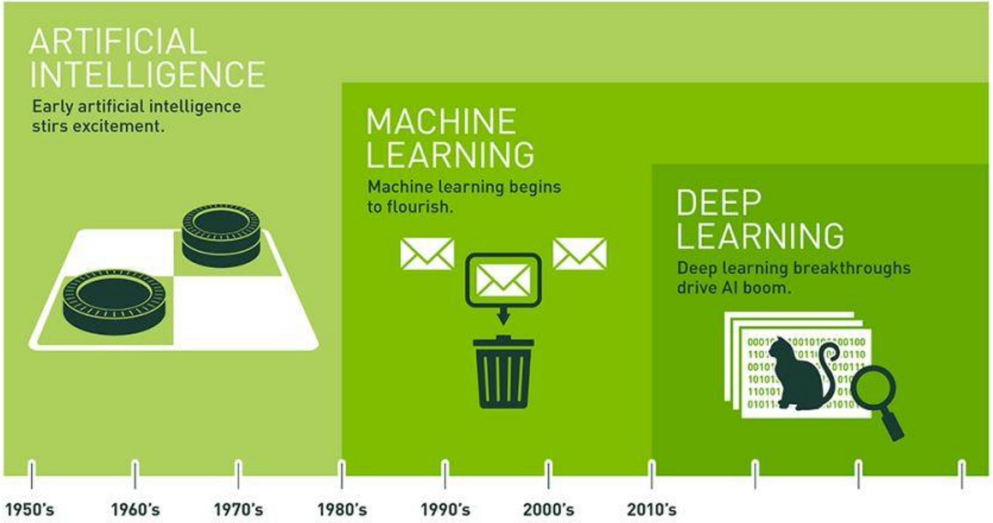
DESAY SV automotive

Confidential

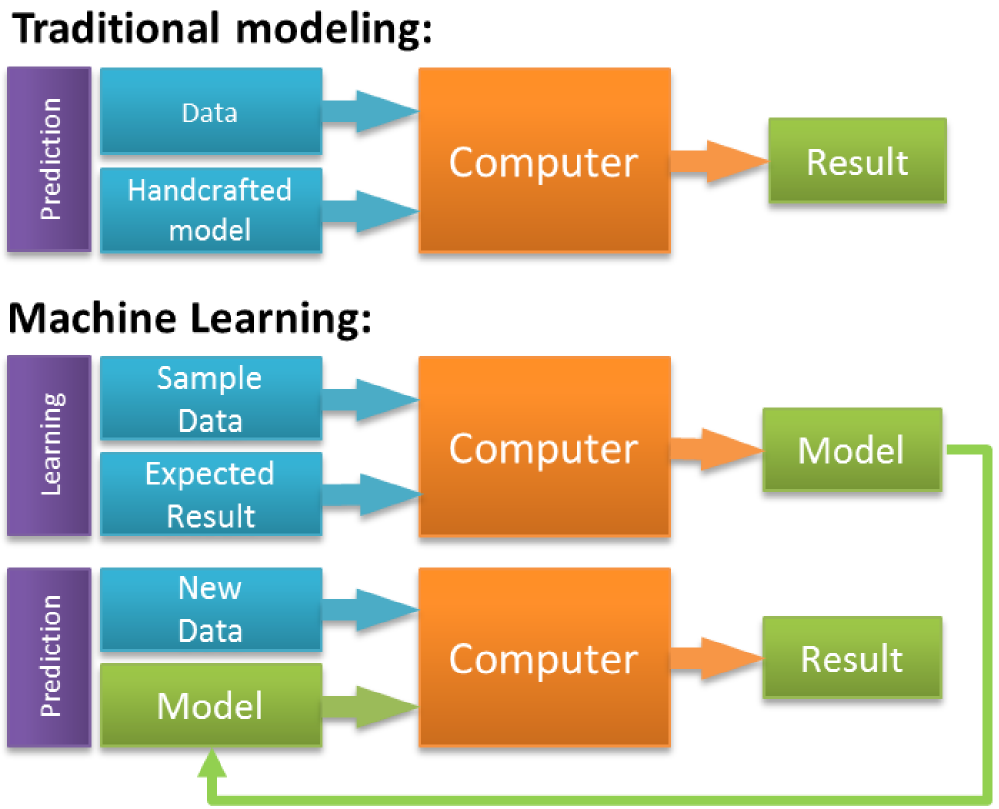
What is Machine Learning

- Branch of Artificial Intelligence
- Learn from data
- Make predictions or decisions



Since an early flush of optimism in the 1950s, smaller subsets of artificial intelligence – first machine learning, then deep learning, a subset of machine learning – have created ever larger disruptions.

Structure of Machine Learning



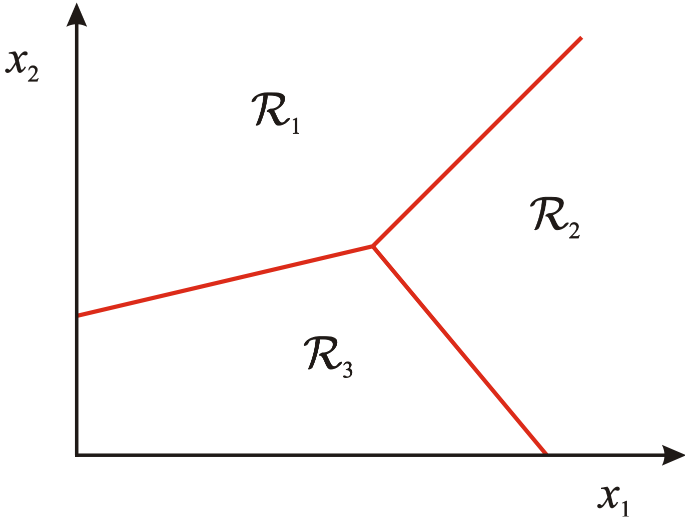
Categories of Machine Learning

Machine Learning Problems

	Supervised Learning	*Unsupervised Learning*
Discrete	classification or categorization	clustering
Continuous	regression	dimensionality reduction

Classification

- Assign input vector to one of two or more classes
- Any decision rule divides input space into *decision regions* separated by *decision boundaries*



Examples:

Spam email filtering:

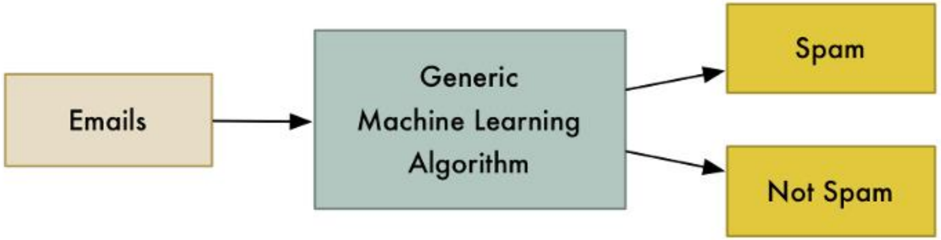


Image recognition:

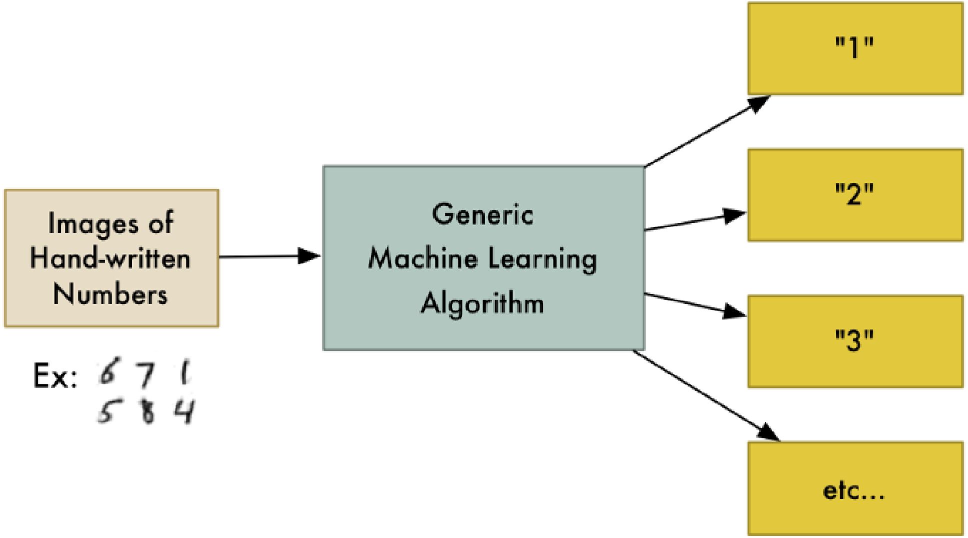


Image recognition

- Apply a prediction function to a feature representation of the image to get the desired output:

F() = “apple”

F() = “tomato”

F() = “cow”

Image recognition

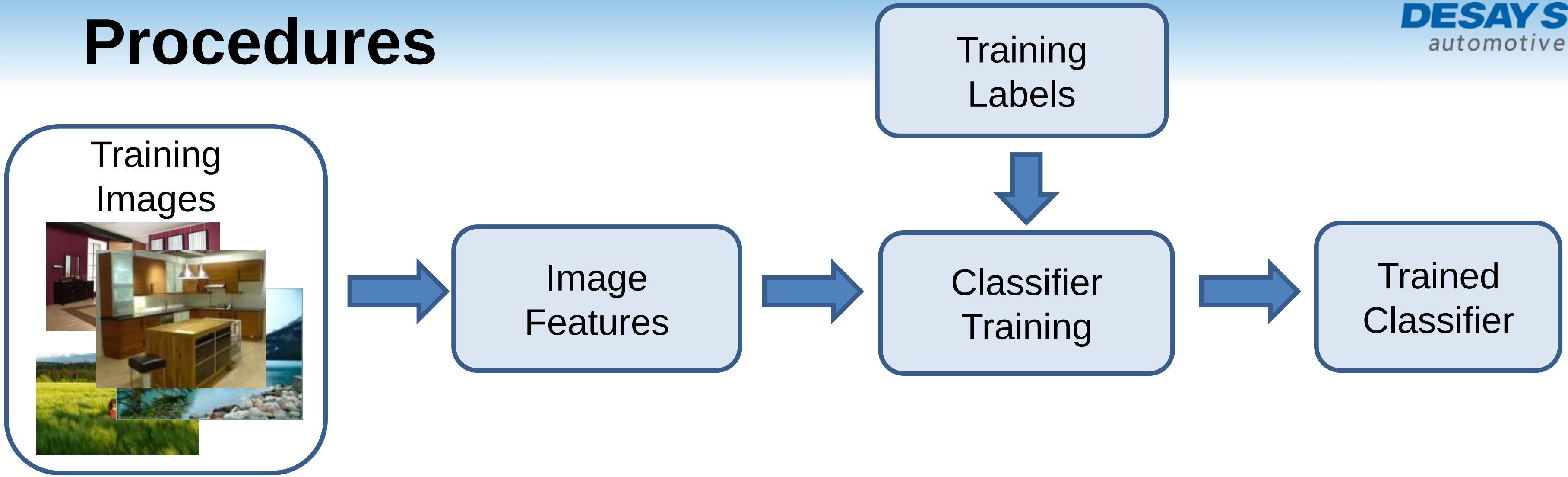
$$y = F(\mathbf{x})$$

Output Prediction function Image feature

Training:
Given a *training set* of labeled examples $\{(\mathbf{x}_1,y_1), \ldots, (\mathbf{x}_N,y_N)\}$, estimate the prediction function F by minimizing the prediction error on the training set

Testing:
Apply F to a test *example* $\mathbf{x}$ and output the predicted value $y = F(\mathbf{x})$

Procedures


Training Labels
Training Images
Image Features
Classifier Training
Trained Classifier

Procedures

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Training Labels

Training Images

Image Features

Classifier Training

Trained Classifier

Test Image

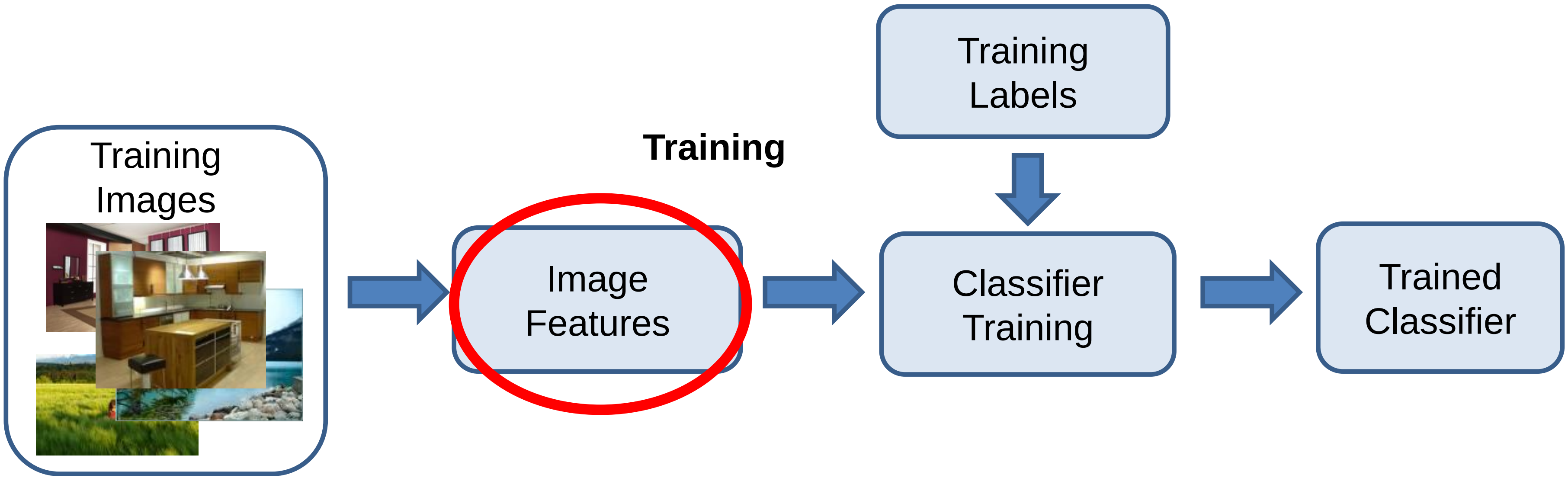
Image Features

Trained Classifier

Prediction

Outdoor

Image Features

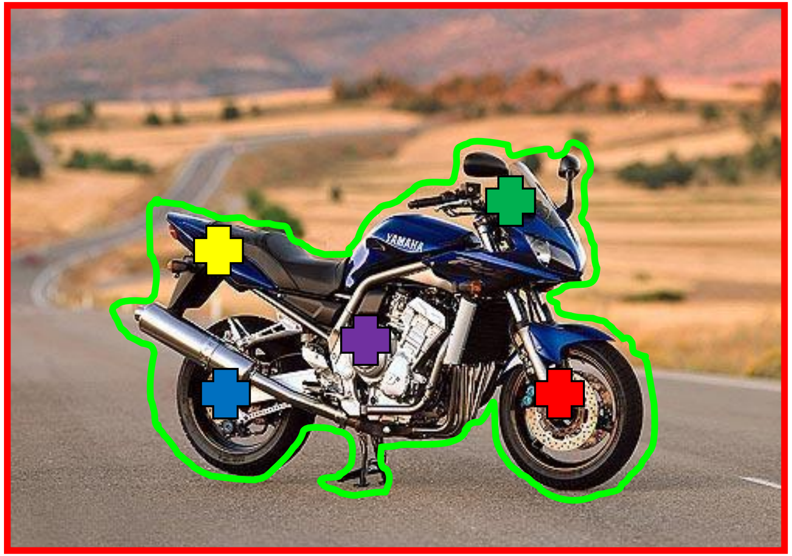


General Principles of Representation

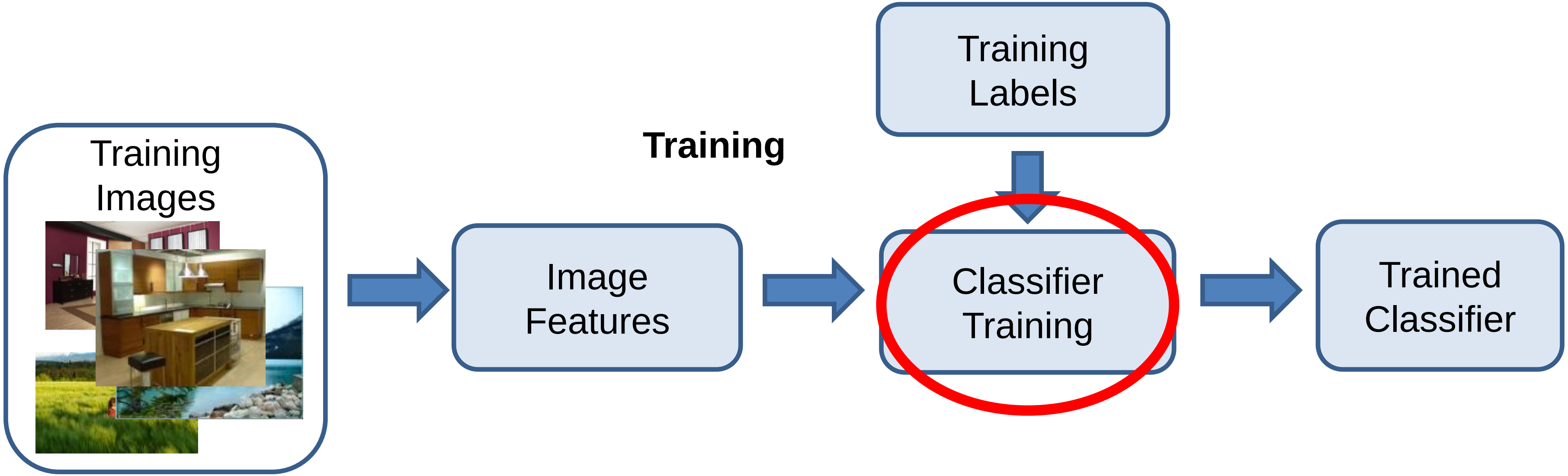
- **Coverage**
Ensure that all relevant info is captured

- **Concision**
Minimize number of features without sacrificing coverage

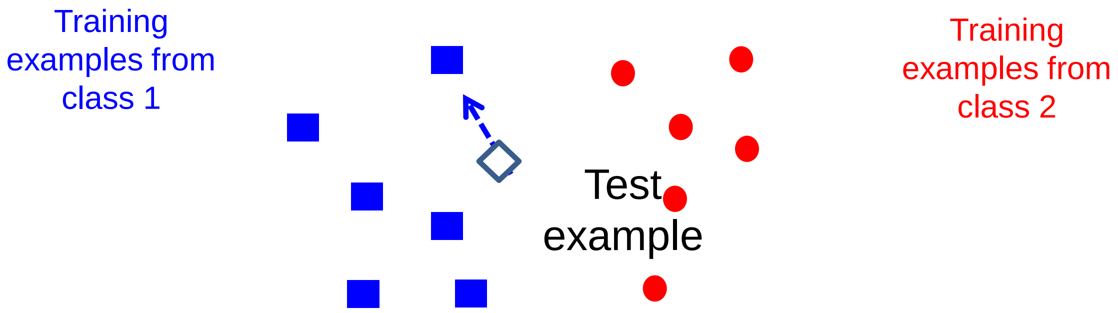
- **Directness**
Ideal features are independently useful for prediction



Classifiers

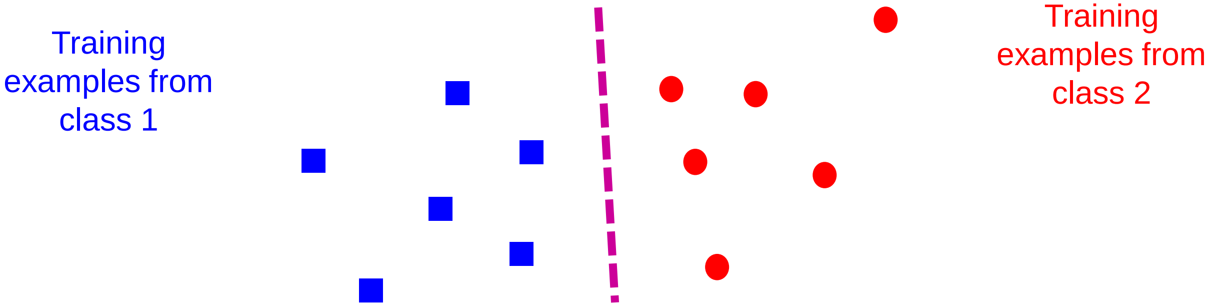


Classifiers: Nearest neighbor



- F(**x**) is label of the training example nearest to **x**
- All we need is a distance function for our inputs
- No training required!

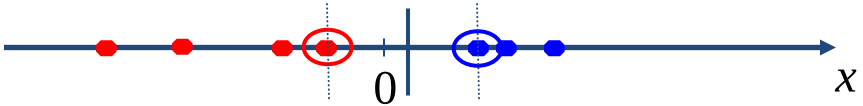
Classifiers: Linear SVM



- There is a *linear function* to separate the classes:
- $F(\mathbf{x}) = \mathrm{sgn}(\mathbf{w} \cdot \mathbf{x} + b)$

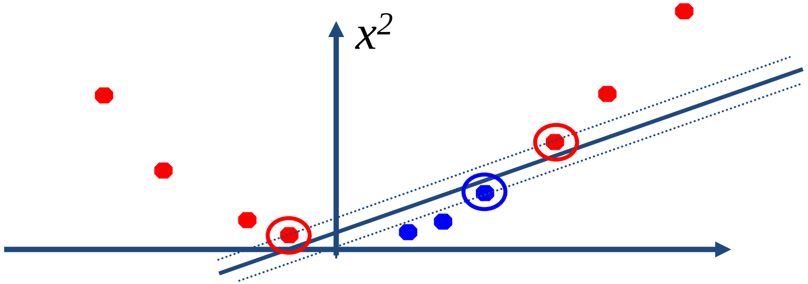
Classifiers: Nonlinear SVM

- Datasets that are linearly separable work out great:



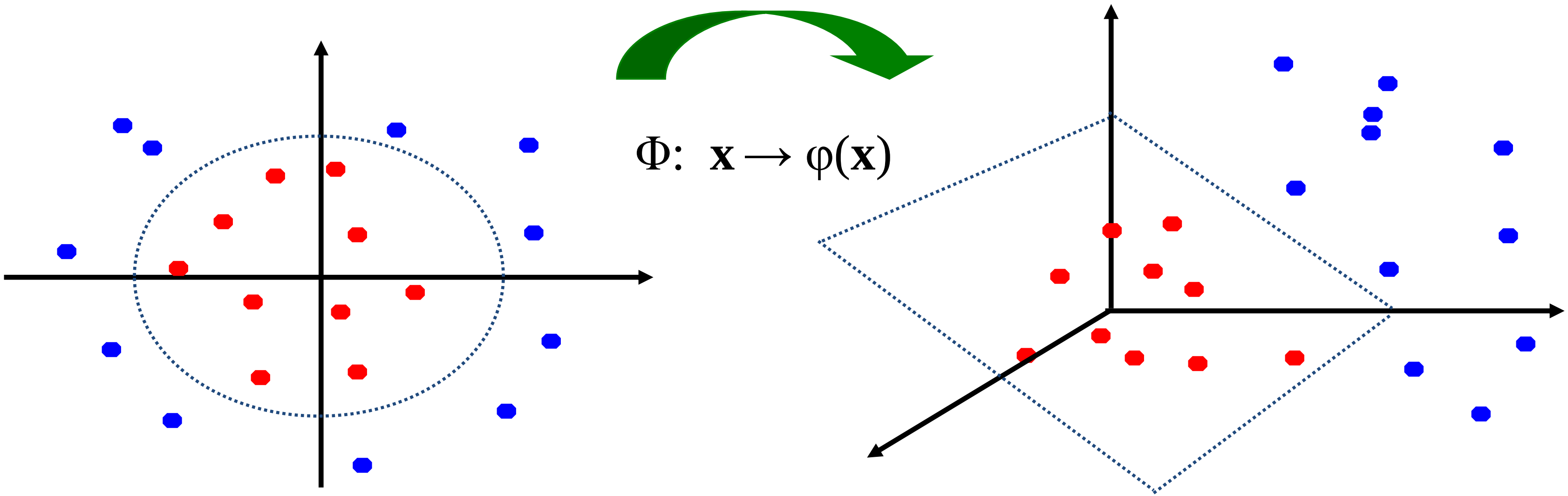
- But what if the dataset is just too hard?

- We can map it to a higher-dimensional space:

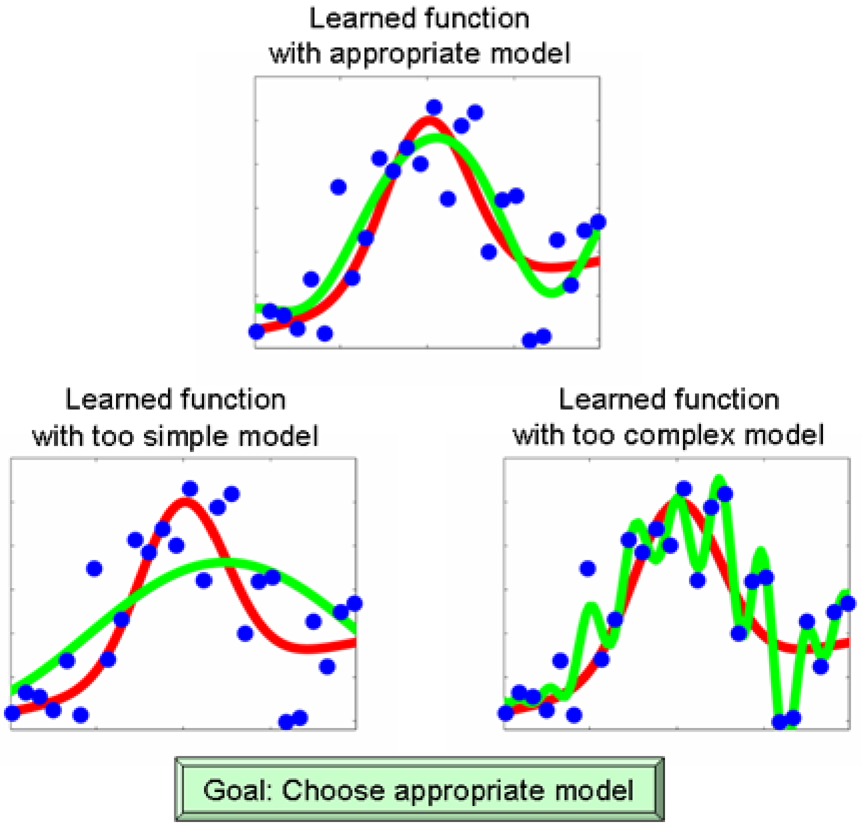


Classifiers: Nonlinear SVM

General idea: the original input space can always be mapped to some higher-dimensional feature space where the training set is separable:



Model Selection



Generalization error

$$\text{Error} = \text{Noise}^2 + \text{Bias}^2 + \text{Variance}$$

Noise²: Unavoidable error

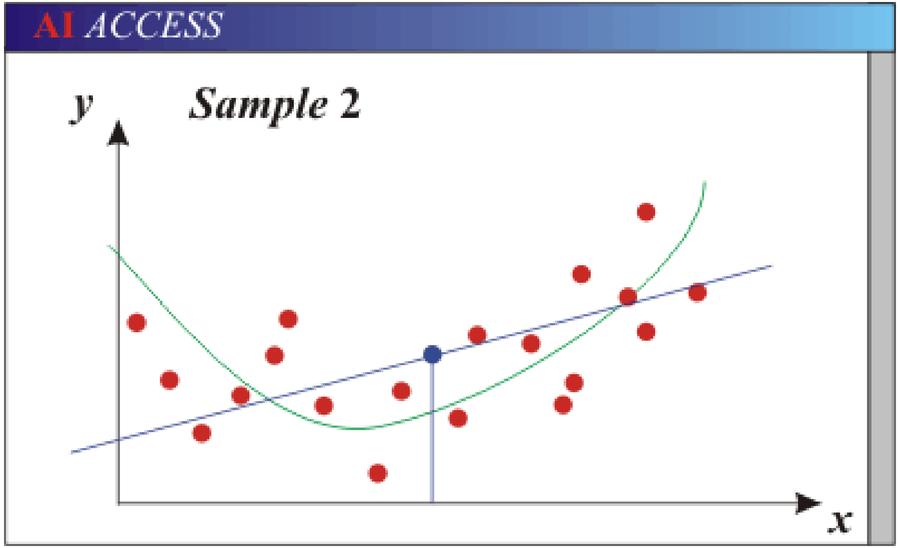
Bias²: Error due to inaccurate assumptions/simplifications made by the model

Variance: Error due to variance of training samples

Under Fitting

Model is too “simple” to represent all the relevant class characteristics:

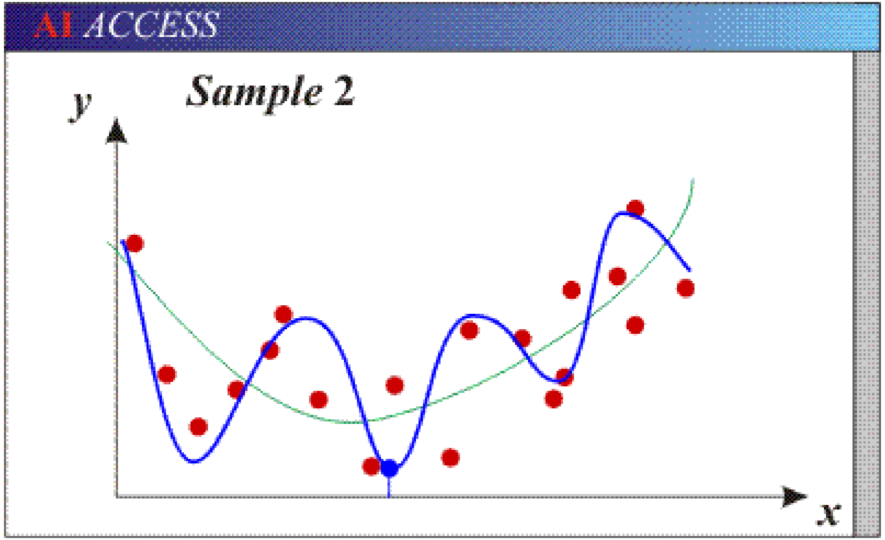
- High bias and low variance
- High training error and high test error
- Not enough flexibility



Over Fitting

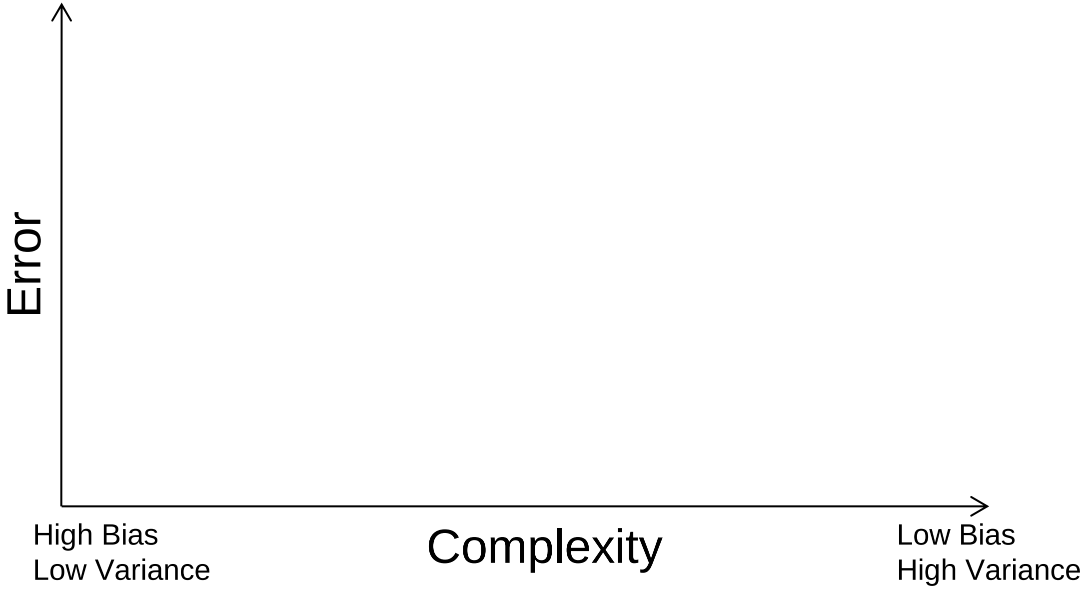
Model is too “complex” and fits irrelevant characteristics (noise) in the data:

- Low bias and high variance
- Low training error and high test error
- Too much sensitivity to the sample



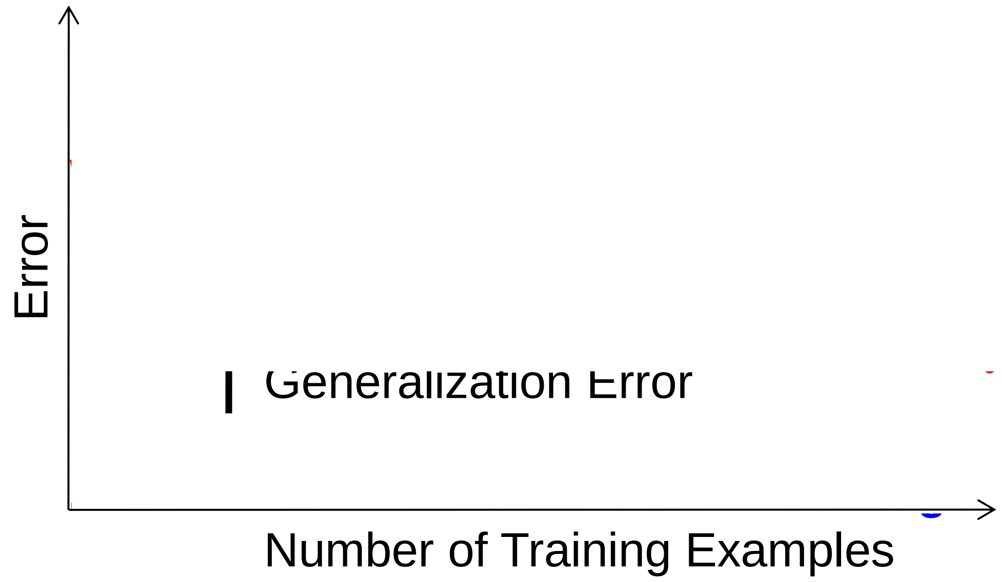
Bias-Variance Trade-off

Underfitting **Overfitting**



Bias-Variance Trade-off

Fixed prediction model



The perfect classification algorithm

Objective function

- Encode the right loss for the problem

Parameterization

- Makes assumptions that fit the problem

Training algorithm

- Find parameters that maximize objective on training set

Inference algorithm

- Solve for objective function in evaluation

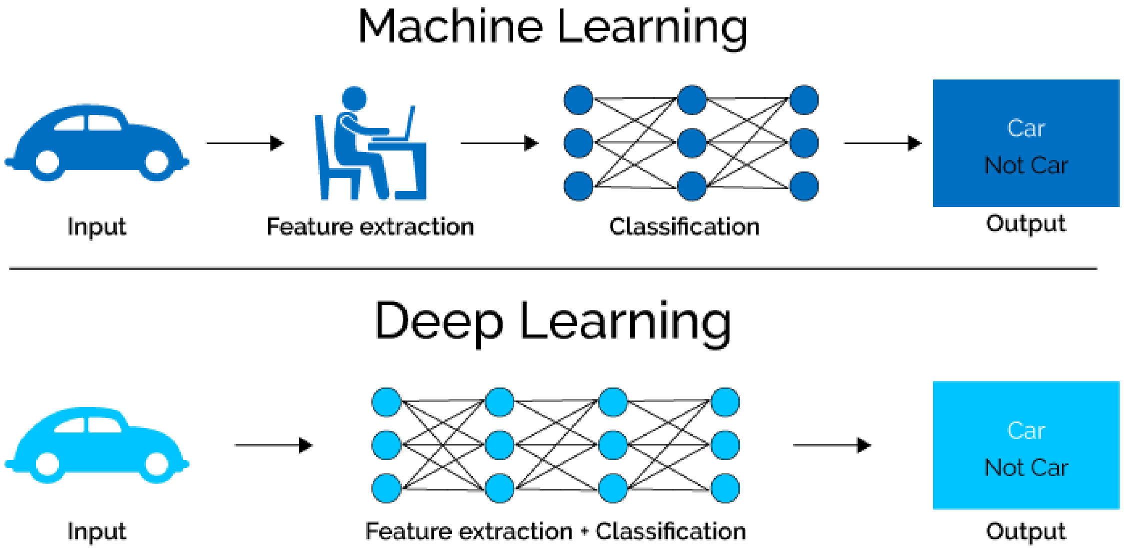
More about classifiers

- Machine learning algorithms are tools, not dogmas.
- Try simple classifiers first.
- Better to have smart features and simple classifiers than simple features and smart classifiers.
- Use increasingly powerful classifiers with more training data (bias-variance tradeoff).

Different types of classifiers

- SVM, Adaboost, …
- Neural Networks

Deep learning



Thank You !