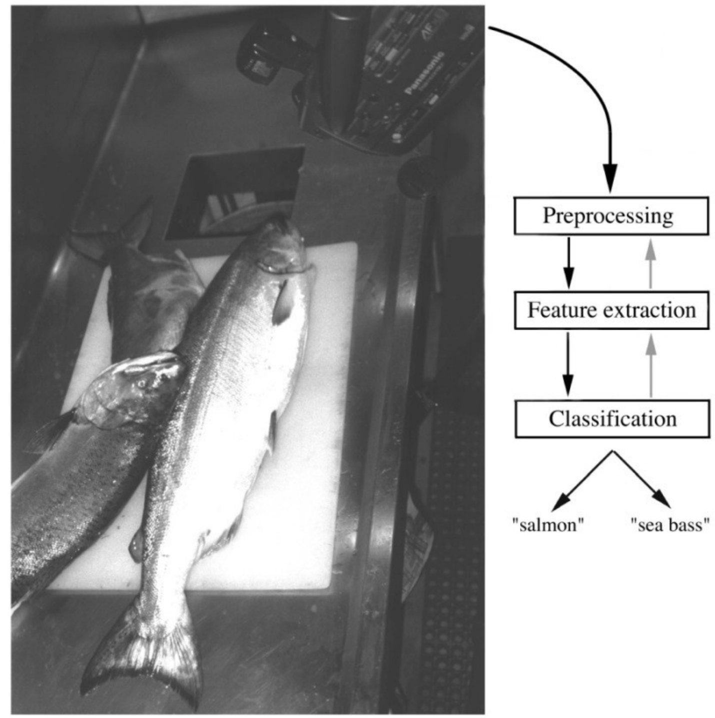
Complexity of PR – An Example

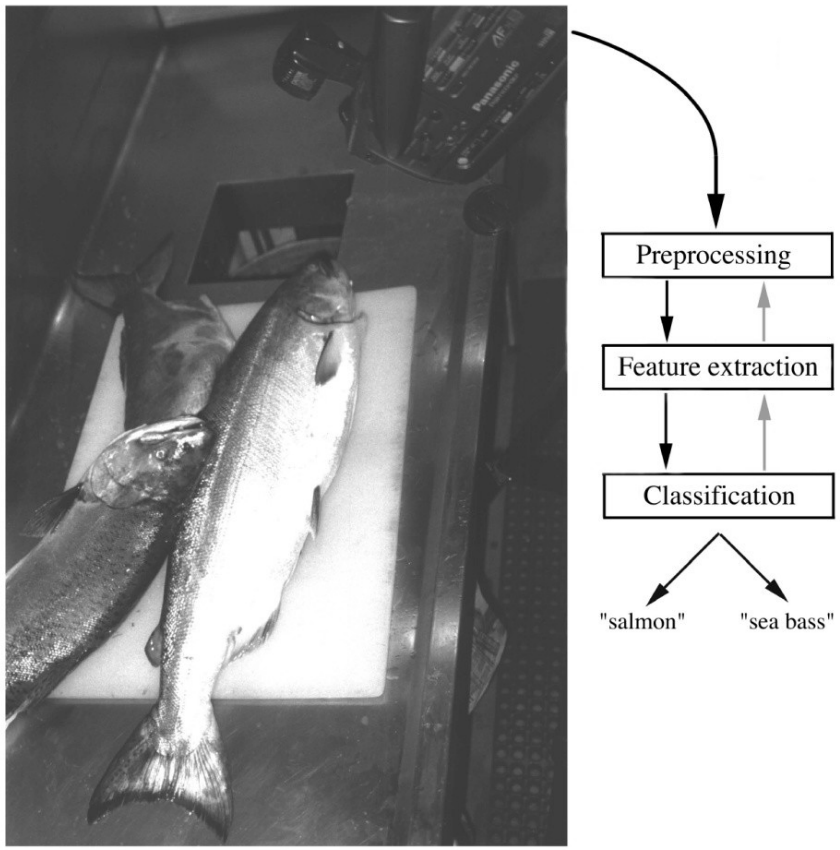
Problem: Sorting incoming fish on a conveyor belt.

Assumption: Two kind of fish:

(1) sea bass
(2) salmon



Pre-processing Step



Example

(1) Image enhancement

(2) Separate touching or occluding fish

(3) Find the boundary of each fish

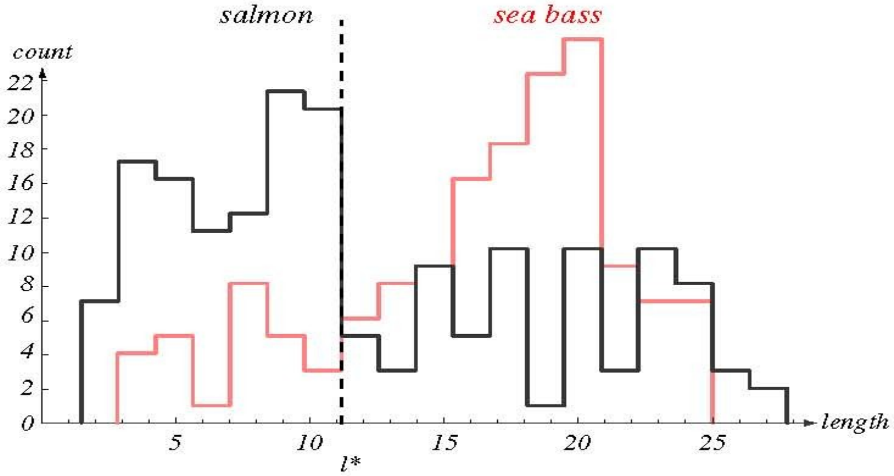
Feature Extraction

- Assume a fisherman told us that a sea bass is generally longer than a salmon.

- We can use length as a feature and decide between sea bass and salmon according to a threshold on length.

- How should we choose the threshold?

“Length” Histograms

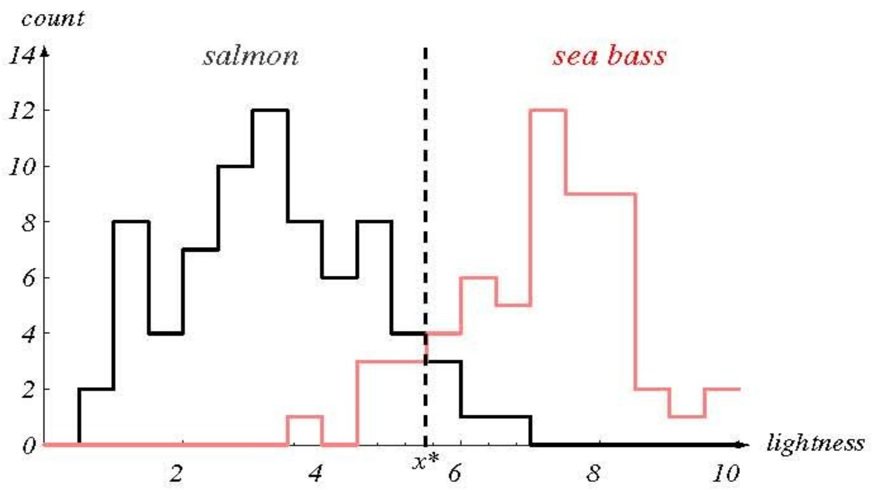


threshold *l**

- Even though sea bass is longer than salmon on the average, there are many examples of fish where this observation does not hold.

"Average Lightness" Histograms

- Consider a different feature such as "average lightness"



threshold *x**

- It seems easier to choose the threshold x^* but we still cannot make a perfect decision.

Multiple Features

- To improve recognition accuracy, we might have to use more than one features at a time.
  - Single features might not yield the best performance.
  - Using combinations of features might yield better performance.

$$\begin{bmatrix} x_1 \\ x_2 \end{bmatrix}$$

- x_1: length
- x_2: lightness

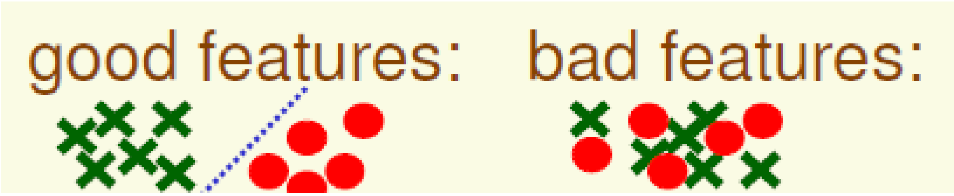
- How many features should we choose?

How Many Features?

- Does adding more features always improve performance?
  - It might be difficult and computationally expensive to extract certain features.
  - Correlated features might not improve performance.
  - "Curse" of dimensionality.

Feature Extraction

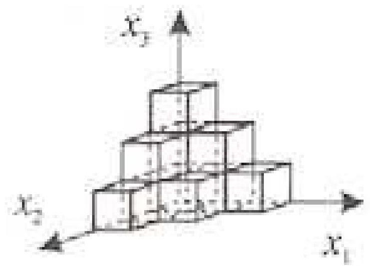
- How to choose a good set of features?
  - Discriminative features



  - Invariant features (e.g., translation, rotation and scale)
- Are there ways to automatically learn which features are best ?

Curse of Dimensionality

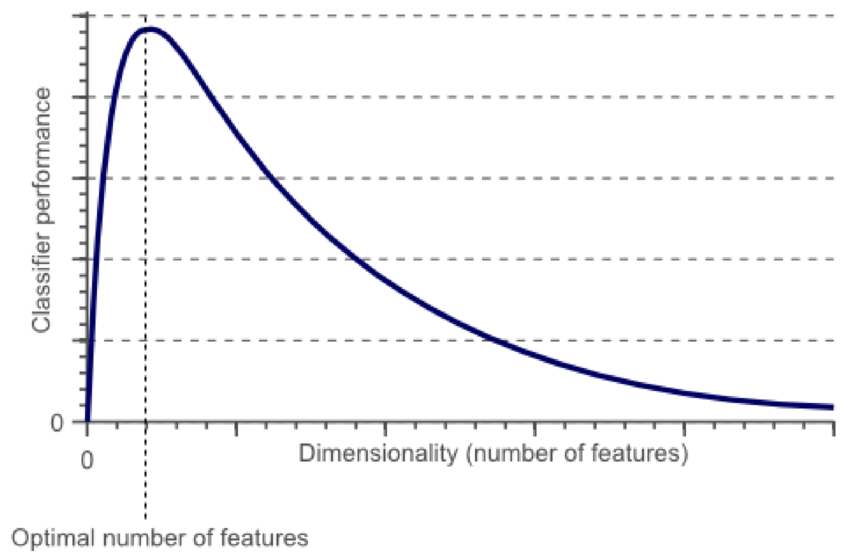
- Adding too many features can, paradoxically, lead to a worsening of performance.
  - Divide each of the input features into a number of intervals, so that the value of a feature can be specified approximately by saying in which interval it lies.



  - If each input feature is divided into **M** divisions, then the total number of cells is $\mathbf{M}^d$ (***d*:** # of features).
  - Since each cell must contain at least one point, the number of training data grows exponentially with ***d***.

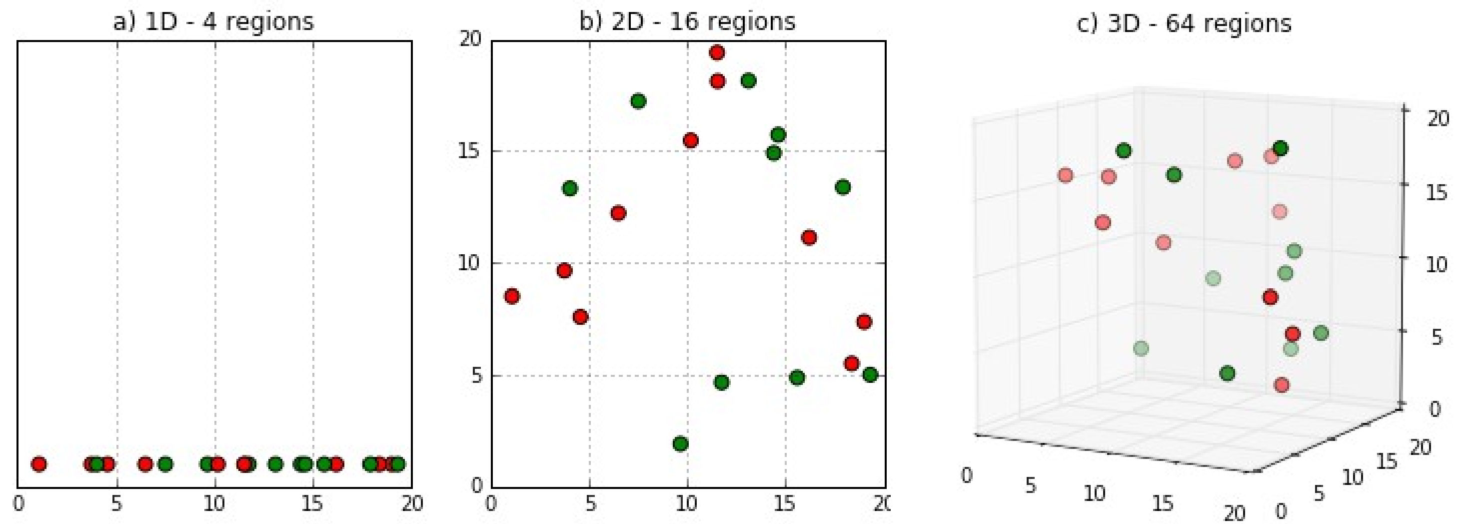
Curse of Dimensionality-definition

- As the number of features or dimensions grows, **the amount of data we need to generalize accurately grows exponentially."**
- In applied maths, COD refers to the **problem caused by the exponential increase in volume associated with adding extra dimensions to a mathematical space.**



Curse of Dimensionality-(contd)

- Fig. 1 (a) shows 10 data points in one dimension i.e. there is only one feature in the data set. It can be easily represented on a line with only 10 values, x=1, 2, 3... 10.



Curse of Dimensionality-(contd)

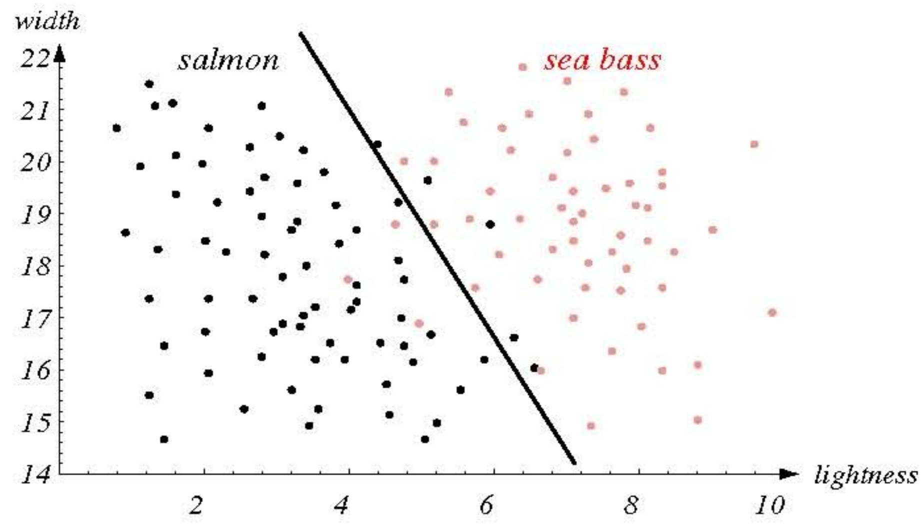
- But if we add one more feature, same data will be represented in 2 dimensions (Fig.1 (b)) causing increase in dimension space to 10*10 =100.
- And again if we add 3rd feature, dimension space will increase to 10*10*10 = 1000. As dimensions grows, dimensions space increases exponentially.
- 10^1 = 10
- 10^2 = 100
- 10^3 = 1000 and so on…

Missing Features

- Certain features might be missing (e.g., due to occlusion).
- How should we train the classifier with missing features ?
- How should the classifier make the best decision with missing features ?

Classification

- Partition the *feature space* into two regions by finding the decision boundary that minimizes the error.



- How shou ndary?

Main Classification Approaches

***x**: input vector (pattern)*

↓

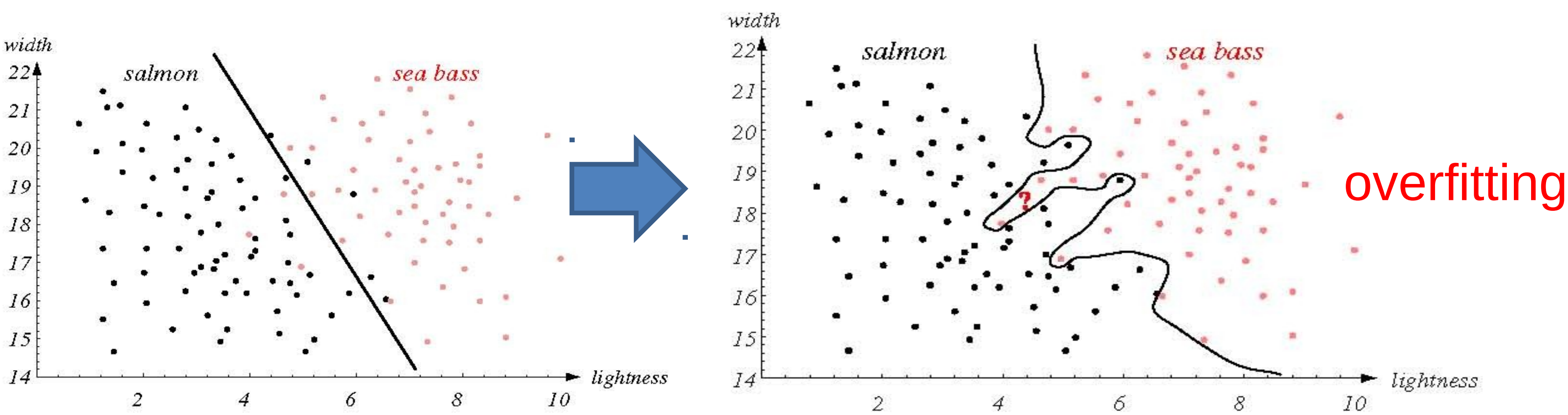
***y**: class label (class)*

- *Generative*
  - Model the joint probability, p(x, y)
  - Make predictions by using Bayes rules to calculate p(ylx)
  - Pick the most likely label y

- *Discriminative*
  - Estimate p(ylx) directly (e.g., learn a direct map from inputs x to the class labels y)
  - Pick the most likely label y

Complexity

- We can get perfect classification performance on the training data by choosing complex models.
- Complex models are tuned to the particular training samples, rather than on the characteristics of the true model.

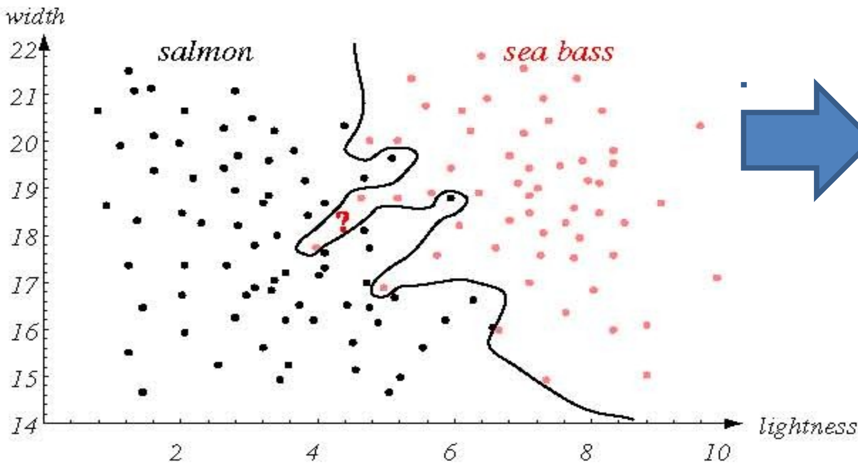


How well can the model generalize to unknown samples?

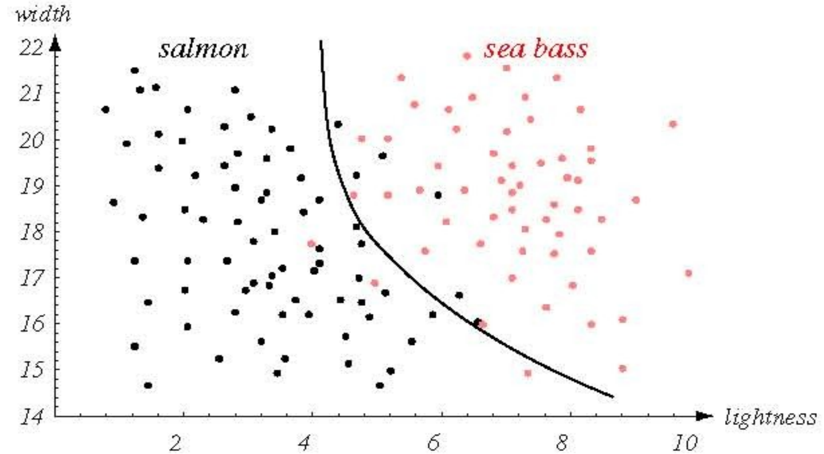
Generalization

- Generalization is defined as the ability of a classifier to produce correct results on novel patterns.
- How can we improve generalization performance ?
  - More training examples (i.e., better model estimates).
  - Simpler models usually yield better performance.

complex model



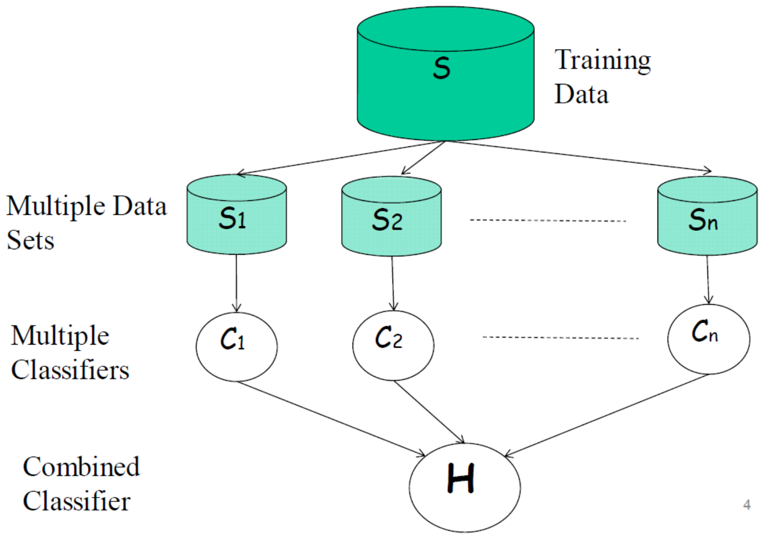
simpler model



Ensembles of Classifiers

- Performance can be improved using a "pool" of classifiers.

- How should we build and combine different classifiers ?



Would it be possible to build a "general purpose" PR system?

- Humans have the ability to switch rapidly and seamlessly between different pattern recognition tasks.
- It is very difficult to design a system that is capable of performing a variety of classification tasks.
  - Different decision tasks may require different features.
  - Different features might yield different solutions.
  - Different tradeoffs exist for different tasks.