CSC 480/580 Principles of Machine Learning

02 Limits of Learning

Chicheng Zhang

Department of Computer Science

THE UNIVERSITY OF ARIZONA

Motivation

- Supervised learning is a general & useful framework

- Understand when supervised learning will and will not work

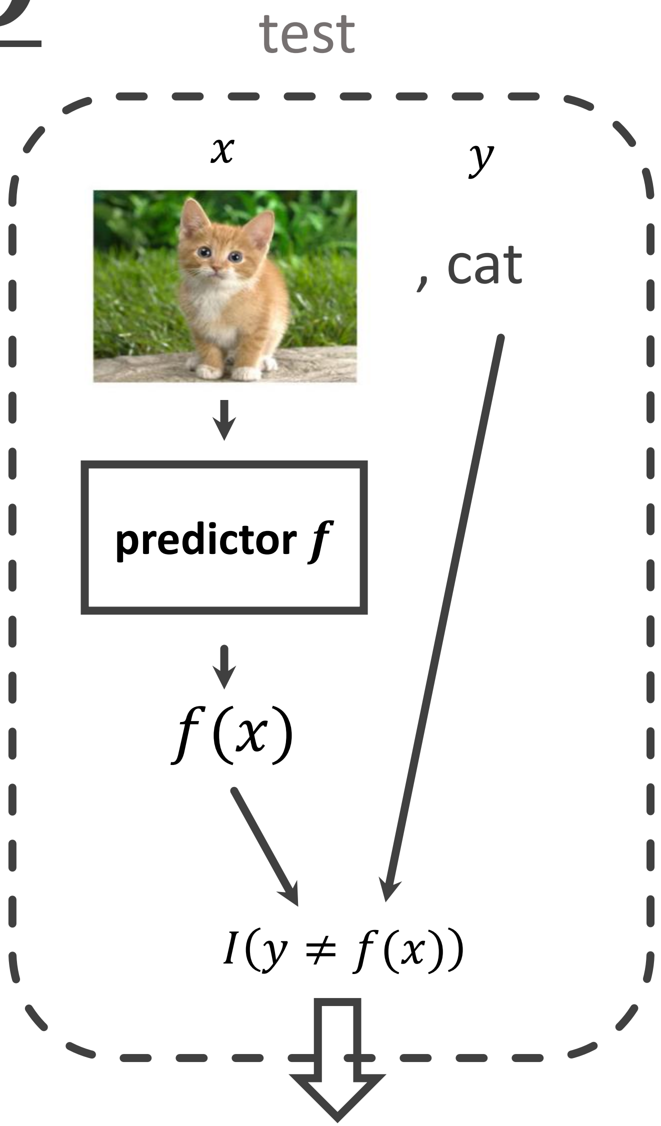
Optimal classification with **known $\boldsymbol{D}$**

- Suppose: $I(A) = 1$ *if A happens, and = 0 otherwise*
  - Binary classification, 0-1 loss $\ell(y, \hat{y}) = I(y \neq \hat{y})$
  - D is *known:* for every (x, y), $P_D(x, y)$ is known to us

- What is the f that has the smallest *generalization error*

  $L_D(f) = \mathrm{E}_{(x,y)\sim D} I(y \neq f(x))$?

- Note (alternative expression) : $L_D(f) = P_{(x,y)\sim D}\ (y \neq f(x))$



Generalization error: $L_D(f)$ = $\mathrm{E}_{(x,y)\sim D} I(y \neq f(x))$

Simple case: discrete domain $\mathcal{X}$

$P_D(x,y)$	$x=1$	$x=2$	$x=3$
$y=-1$	0.2	0.2	0.15
$y=+1$	0.1	0.3	0.05

Which classifier is better?

- $f_1(1)=-1, f_1(2)=-1, f_1(3)=-1 \quad \Rightarrow \quad L_D(f_1)=0.1+0.3+0.05$
- $f_2(1)=-1, f_2(2)=+1, f_2(3)=-1 \quad \Rightarrow \quad L_D(f_2)=0.1+0.2+0.05$

Is this the best classifier? Why?

- For any x, should choose y that has higher value of $P_D(x,y)$
- $f^*(1)=-1, f^*(2)=+1, f^*(3)=-1$

Bayes optimal classifier

Theorem f_{BO} achieves the smallest generalization error among all classifiers.

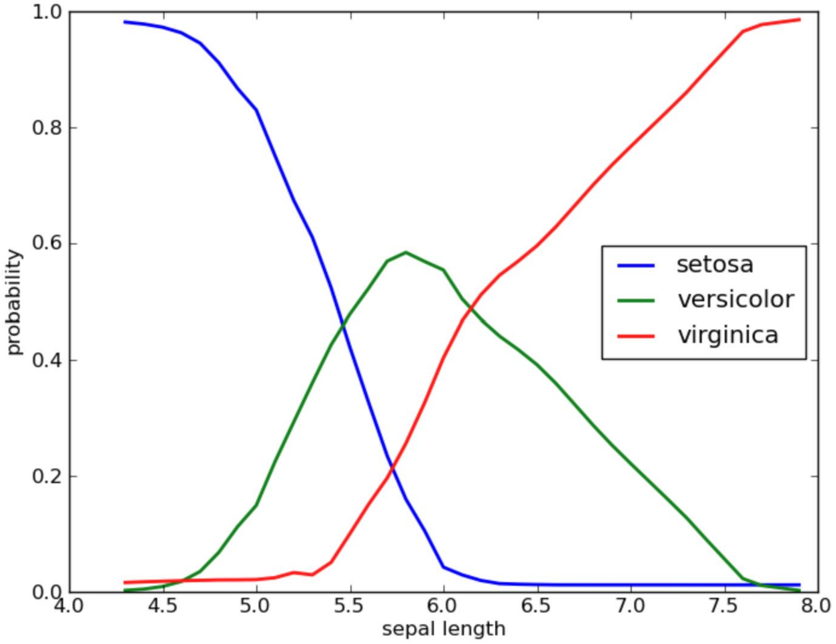
$$f_{BO}(x) = \arg\max_{y \in \mathcal{Y}} P_D(X = x, Y = y) = \arg\max_{y \in \mathcal{Y}} P_D(Y = y \,|X = x)\,, \forall x \in \mathcal{X}$$

Example Iris dataset classification:

Iris Setosa

Iris Versicolor

Iris Virginica



Proof of theorem

Step 1 consider accuracy,

- $A_D(f) = 1 - L_D(f) = P_D\big(Y = f(X)\big) = \sum_x P_D\big(X = x, Y = f(x)\big)$
- Suffices to show f_{BO} has the highest accuracy

Step 2 comparison,

$$A_D(f_{BO}) - A_D(f) = \sum_x P_D\big(X = x, Y = f_{BO}(x)\big) - P_D\big(X = x, Y = f(x)\big) \geq 0$$

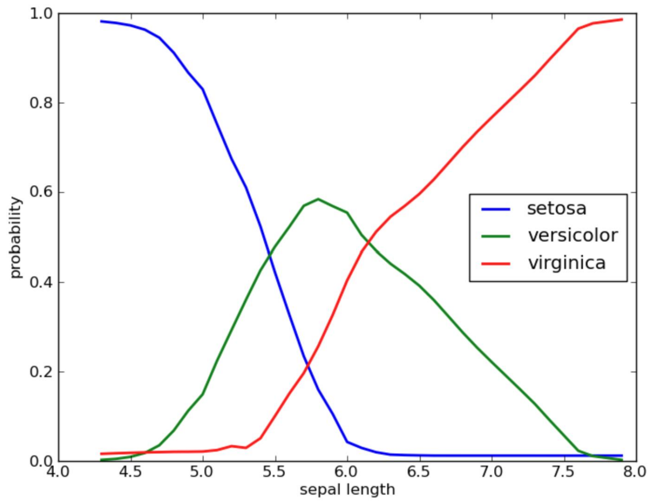
$$\boxed{f_{BO}(x) = \arg\max_{y \in \mathcal{Y}} P_D(X = x, Y = y)}$$

Remarks

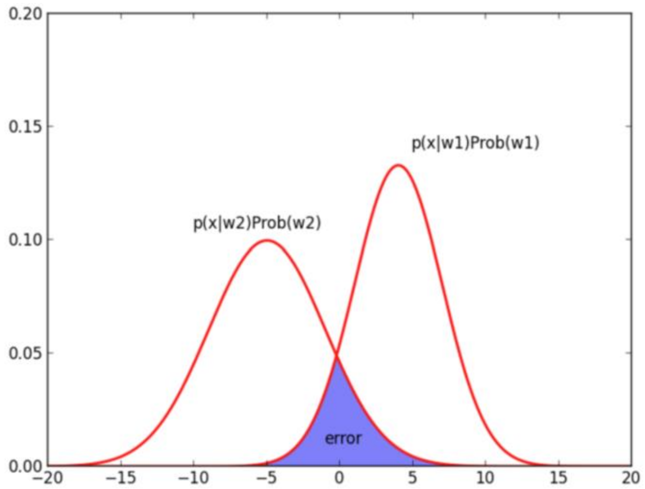
- Similar reasoning can be used to prove the theorem with continuous domain $\mathcal{X}$ (sum -> integral)
- This just shows deterministic classifier, can be extended to show BO is 0-1 optimal for all classifiers

Bayes error rate: alternative form

$$
\begin{aligned}
L_D(f_{BD}) &= P_D\big(Y \neq f_{BD}(X)\big) \\
&= \textstyle\sum_x P_D(Y \neq f_{BD}(x) \mid X = x)\, P_D(X = x) \\
&= \textstyle\sum_x (1 - P_D(Y = f_{BD}(x) \mid X = x))\, P_D(X = x) \\
&= \textstyle\sum_x \left(1 - \max_y P_D(Y = y \mid X = x)\right) P_D(X = x) \\
&= \mathrm{E}\left[1 - \max_y P_D(Y = y \mid X)\right]
\end{aligned}
$$



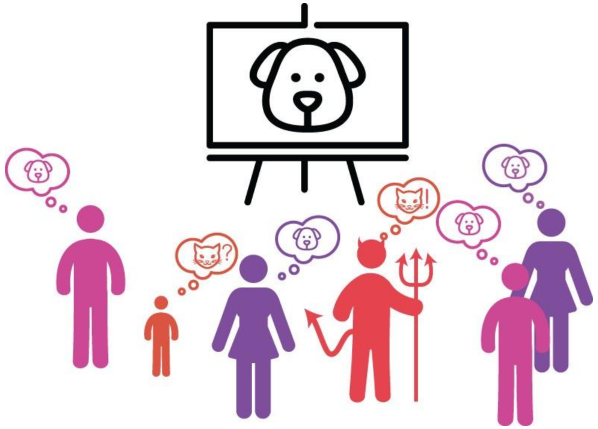
- Special case: binary classification
  - $L_D(f_{BD}) = \sum_x P_D(Y \neq f_{BD}(x), X = x)$
    $= \sum_x \min(\, P_D(Y = +1, X = x)\,, P_D(Y = -1, X = x))$

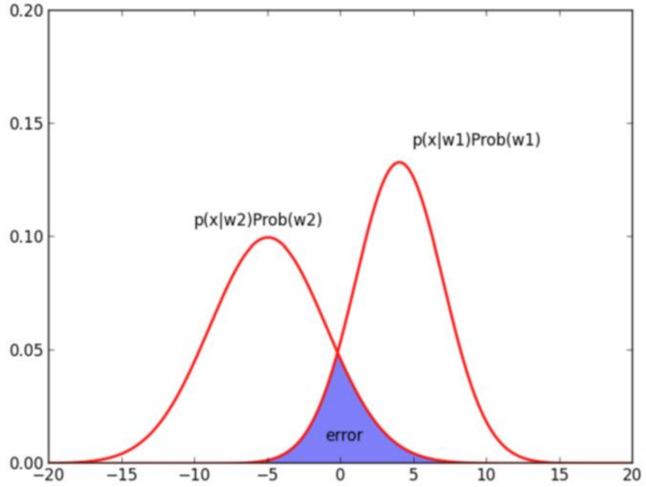


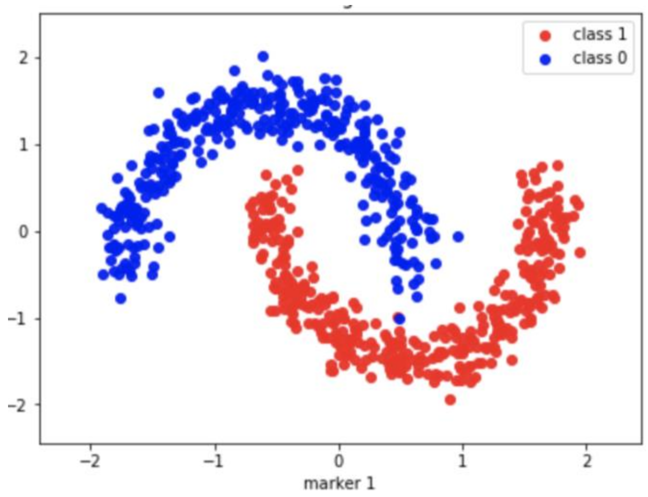
When is the Bayes error rate nonzero?

$$L_D(f_{BO}) = \sum_x \min(\, P_D(Y = +1, X = x)\,, P_D(Y = -1, X = x))$$

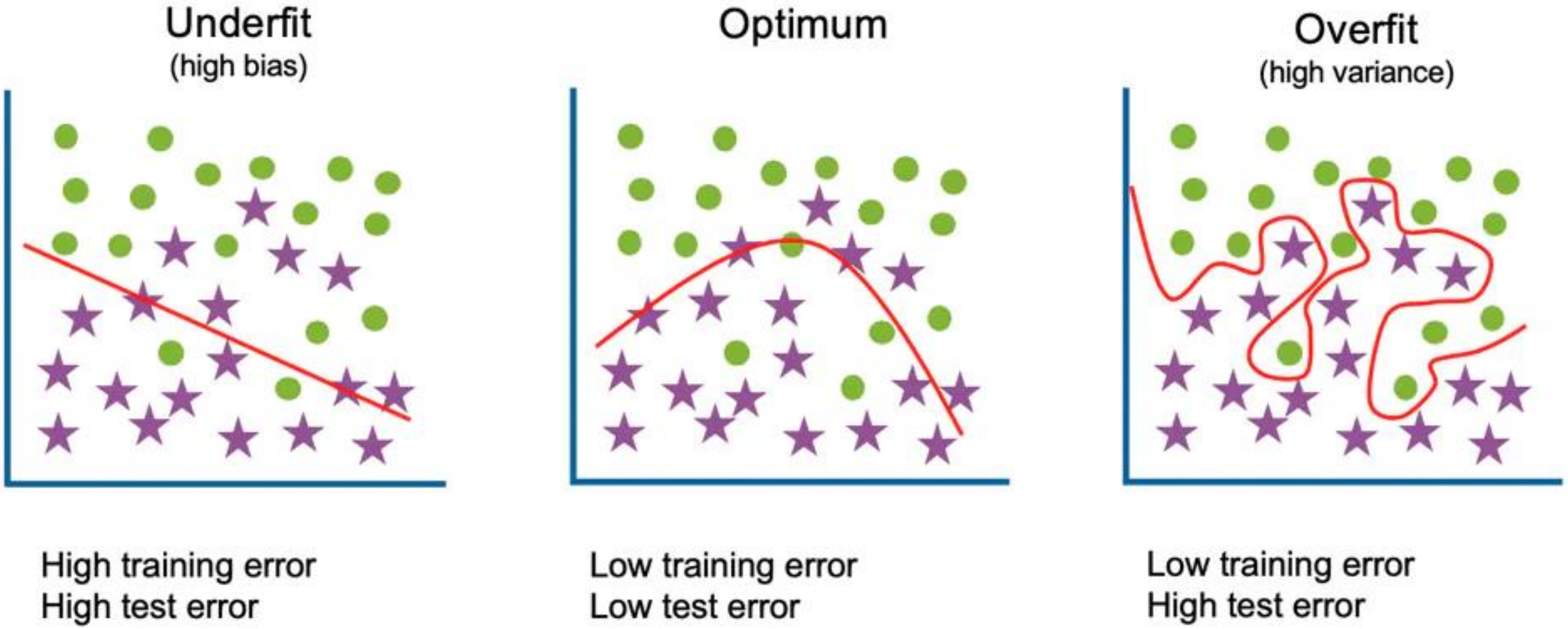
- Limited feature representation
- Noise in the training data
  - Feature noise
  - Label noise – e.g. typo transcribing reviews
  - Sensor failure
  - Typo in reviews for sentiment classification
- May not have a single “correct” label







Overfitting vs Underfitting

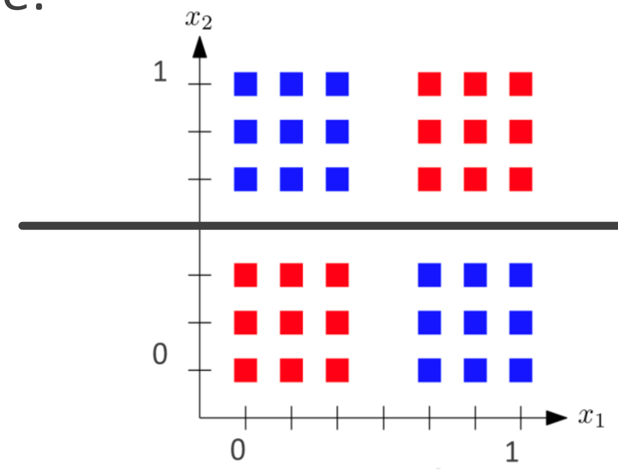


Source: ibm.com

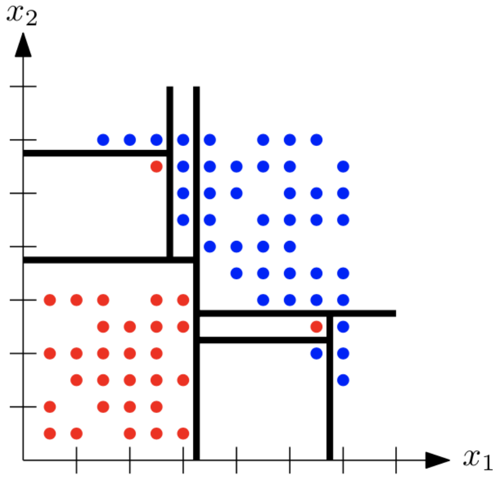
Overfitting vs Underfitting

- Q: should I train a shallow or deep decision tree?

- Shallow tree:



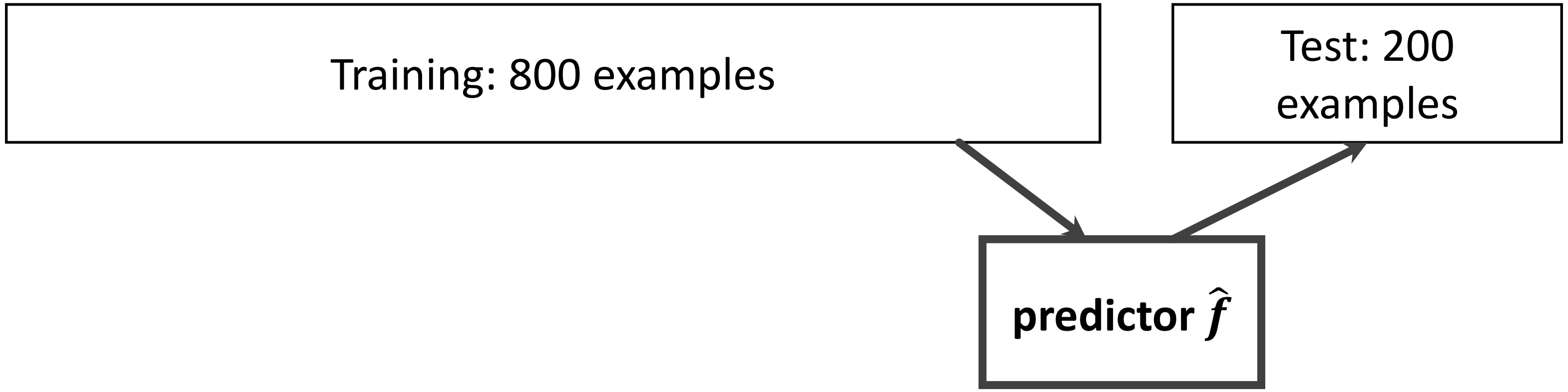
Deep tree:



- Underfitting: have the opportunity to learn something but didn’t
- Overfitting: pay too much attention to idiosyncrasies to training data, and do not generalize well
- A model that neither overfits nor underfits is expected to do best

Unbiased model evaluation using test data

- Your boss says: I will allow your recommendation system to run on our website only if the error is <= 10%!
- How to prove it?
- Idea: reserve some data as test data for evaluating predictors

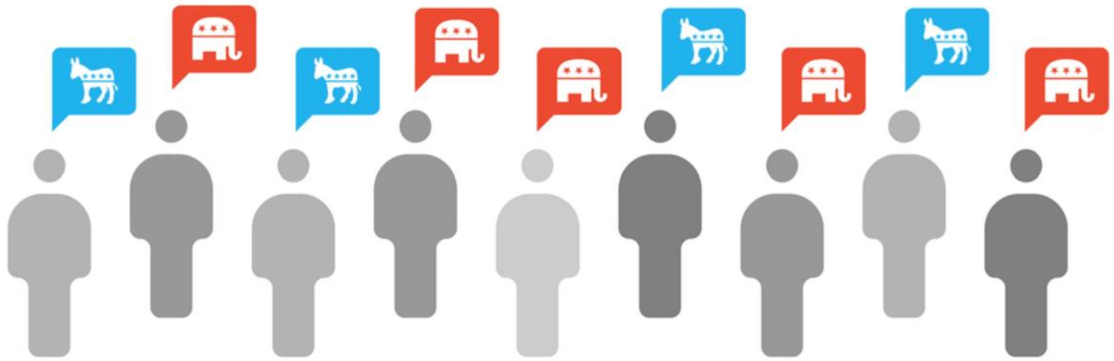


- $L_{\text{test}}(\hat{f}) = \frac{1}{|S_{\text{test}}|} \sum_{(x,y) \in S_{\text{test}}} I(y \neq \hat{f}(x))$
- Law of large numbers $\Rightarrow L_{\text{test}}(\hat{f}) \to L_D(\hat{f})$

Law of large numbers (LLN)

- Suppose $v_1, \ldots, v_n$ are IID (independent & identically distributed) random variables, the sample average $\bar{v} = \frac{1}{n}\sum_{i=1}^{n} v_i$ converges to $\mathrm{E}[v_1]$ as $n \to \infty$

- Useful in e.g. election poll
- Foundation of statistics



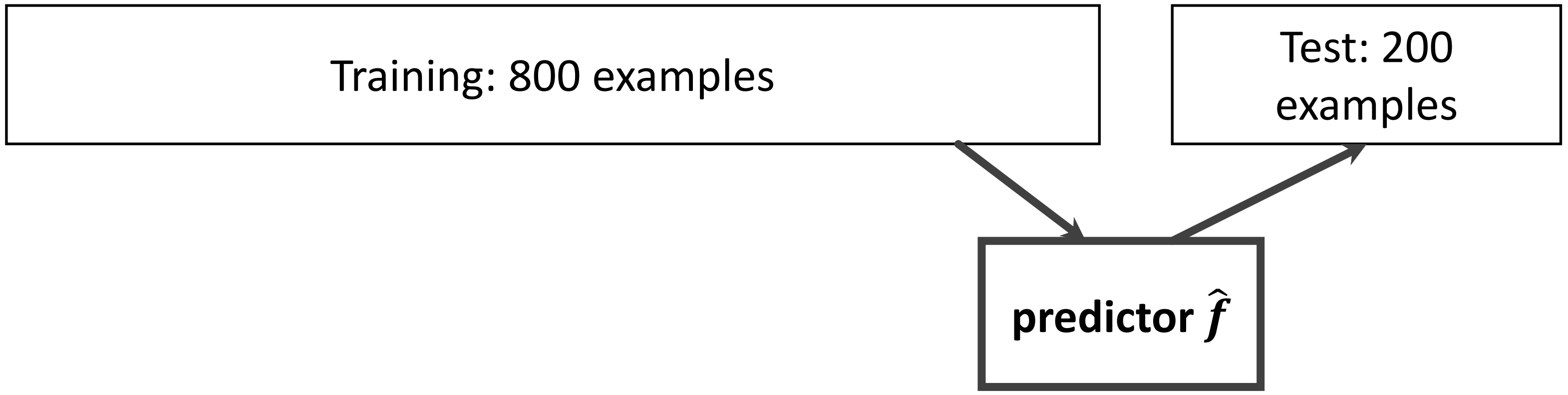
- Can we apply LLN to conclude that
- $L_{\text{train}}(\hat{f}) = \frac{1}{|S_{\text{train}}|}\sum_{(x,y)\in S_{\text{train}}} I\big(y \neq \hat{f}(x)\big) \to L_D(\hat{f})$ as $|S_{\text{train}}| \to \infty$?

Training: 800 examples

Test: 200 examples

predictor $\hat{f}$

Never touch your test data!



- More precisely: test data should only be used **once**, only for final evaluation
- If $\hat{f}$ depends on test examples, $L_{\text{test}}(\hat{f})$ may no longer estimate $L_D(\hat{f})$ accurately
- Be mindful about indirect dependence as well:
  - adaptive data analysis – choose a new learning algorithm, after seeing that the previous algorithm produces a high-test-error model

Case Study: MNIST Dataset

All publications use standard train/test split

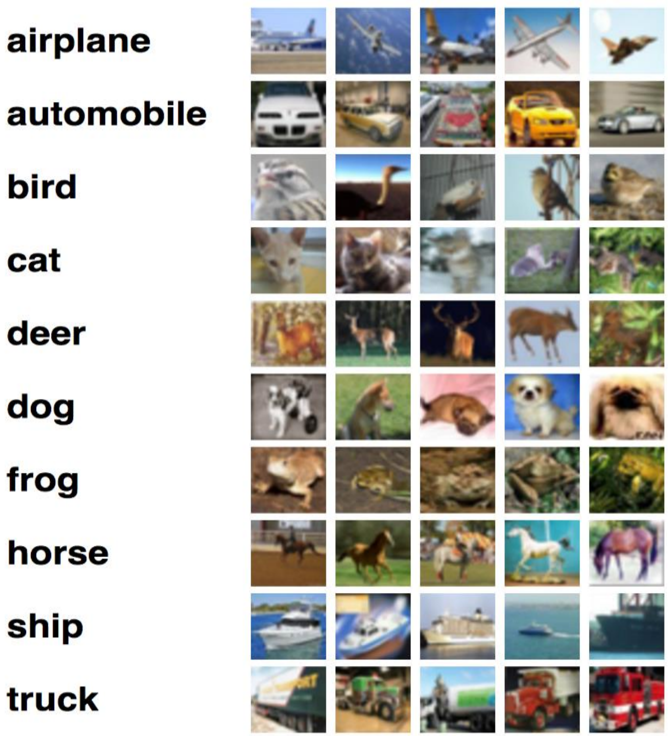
Hundreds of publications compare to each other

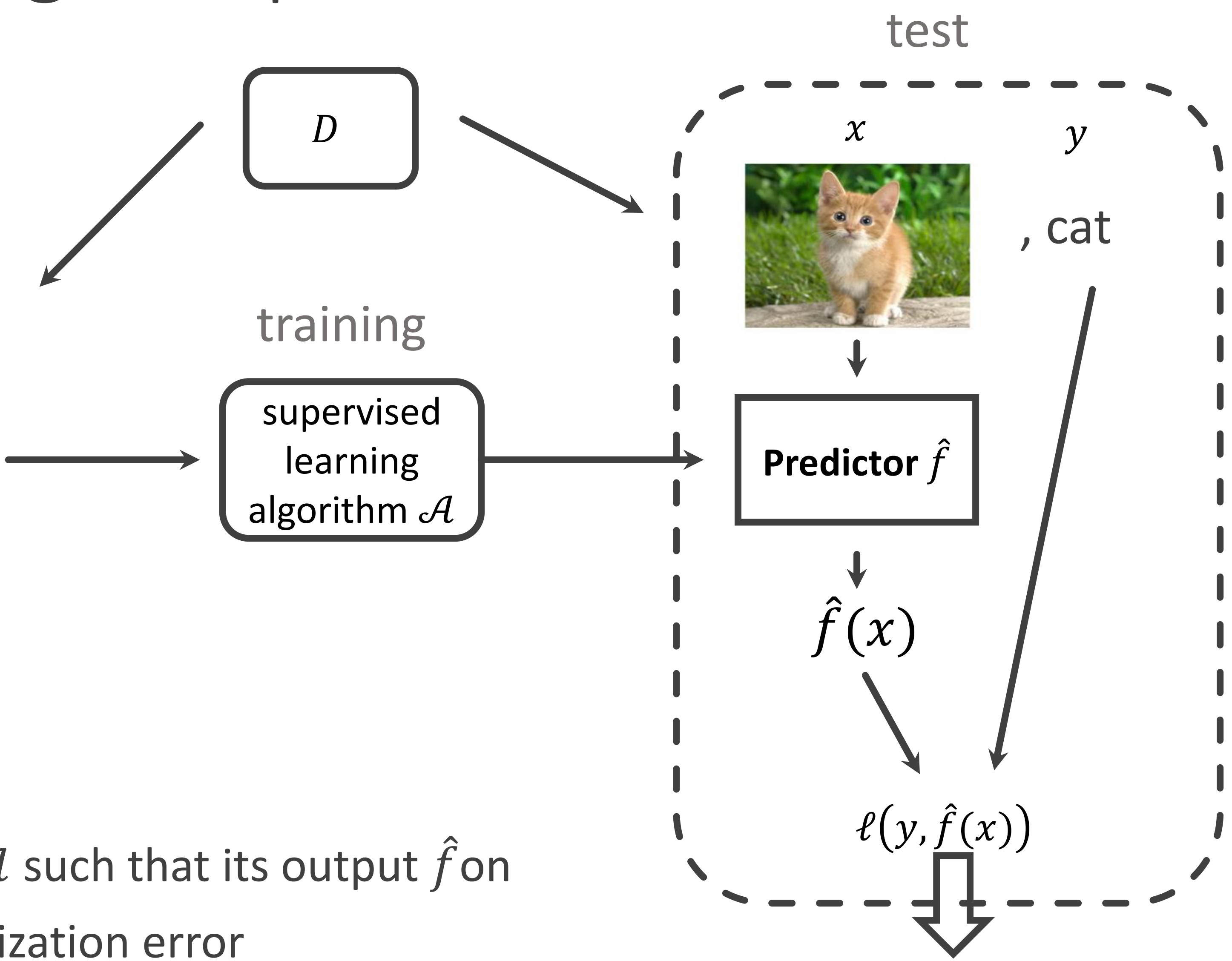
Type	Classifier	Distortion	Preprocessing	Error rate (%)
Linear classifier	Pairwise linear classifier	None	Deskewing	7.6[10]
Decision stream with Extremely randomized trees	Single model (depth > 400 levels)	None	None	2.7[28]
K-Nearest Neighbors	K-NN with rigid transformations	None	None	0.96[29]
K-Nearest Neighbors	K-NN with non-linear deformation (P2DHMDM)	None	Shiftable edges	0.52[30]
Boosted Stumps	Product of stumps on Haar features	None	Haar features	0.87[31]
Non-linear classifier	40 PCA + quadratic classifier	None	None	3.3[10]
Random Forest	Fast Unified Random Forests for Survival, Regression, and Classification (RF-SRC)[32]	None	Simple statistical pixel importance	2.8[33]
Support-vector machine (SVM)	Virtual SVM, deg-9 poly, 2-pixel jittered	None	Deskewing	0.56[34]
Deep neural network (DNN)	2-layer 784-800-10	None	None	1.6[35]
Deep neural network	2-layer 784-800-10	Elastic distortions	None	0.7[35]
Deep neural network	6-layer 784-2500-2000-1500-1000-500-10	Elastic distortions	None	0.35[36]
Convolutional neural network (CNN)	6-layer 784-40-80-500-1000-2000-10	None	Expansion of the training data	0.31[37]
Convolutional neural network	6-layer 784-50-100-500-1000-10-10	None	Expansion of the training data	0.27[38]
Convolutional neural network (CNN)	13-layer 64-128(5x)-256(3x)-512-2048-256-256-10	None	None	0.25[22]
Convolutional neural network	Committee of 35 CNNs, 1-20-P-40-P-150-10	Elastic distortions	Width normalizations	0.23[17]
Convolutional neural network	Committee of 5 CNNs, 6-layer 784-50-100-500-1000-10-10	None	Expansion of the training data	0.21[24][25]
Random Multimodel Deep Learning (RMDL)	10 NN-10 RNN - 10 CNN	None	None	0.18[27]
Convolutional neural network	Committee of 20 CNNS with Squeeze-and-Excitation Networks[39]	None	Data augmentation	0.17[40]
Convolutional neural network	Ensemble of 3 CNNs with varying kernel sizes	None	Data augmentation consisting of rotation and translation	0.09[41]

What's the problem with this?

Supervised learning setup

training data S



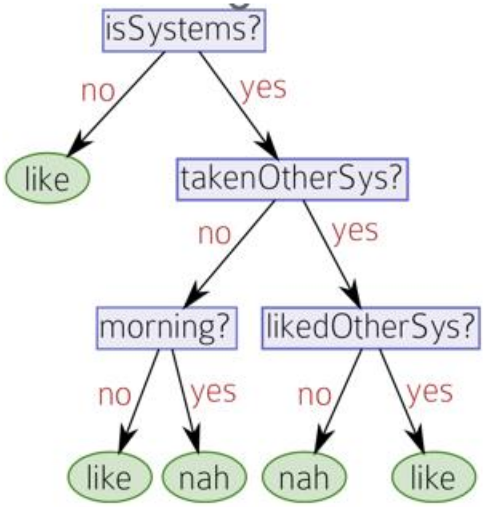


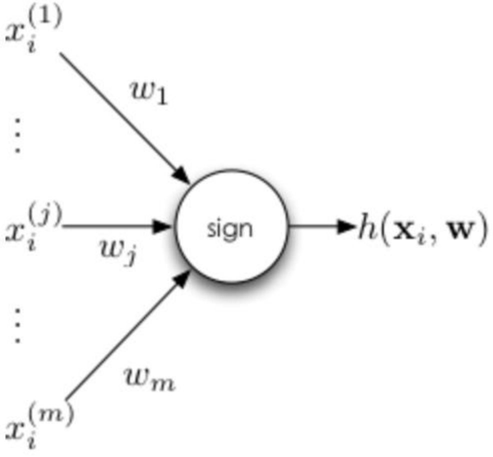
- Goal: design learning algorithm $\mathcal{A}$ such that its output $\hat{f}$ on iid training data S has low generalization error

Generalization error: $L_D(\hat{f}) = \mathrm{E}_{(x,y)\sim D}\, \ell(y, \hat{f}(x))$

Terminologies

- Model: the predictor $\hat{f}$
  - Often from a model class $\mathcal{F}$,
  - e.g. $\mathcal{F}$ = {decision trees}, {linear classifiers}



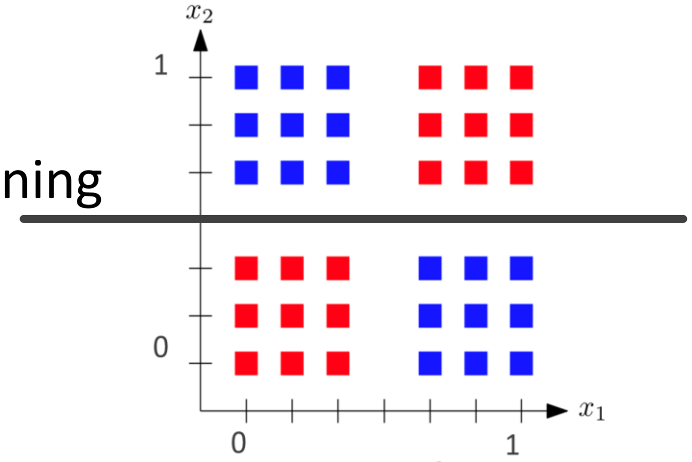


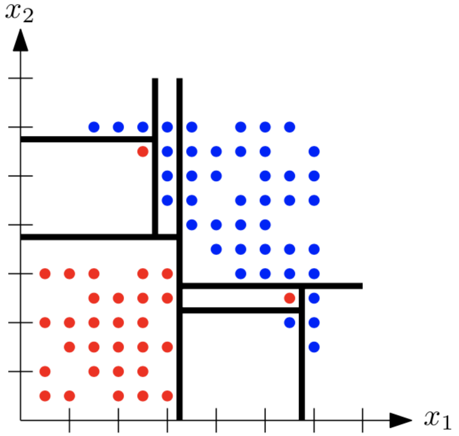
- Parameter: specifics of $\hat{f}$
  - E.g. for decision tree $\hat{f}$: tree structure, questions in nodes, labels in leaves
  - For linear classifier: linear coefficients

- Hyperparameter: specifics of learning algorithm $\mathcal{A}$
  - E.g. in DecisionTreeTrain, constrain to output tree of depth $\leq h$
  - Tuning hyperparameters often results in {over, under}-fitting

Hyperparameter tuning using validation set

- E.g. in decision tree training, how to choose tree depth $h \in \{1, \dots, H\}$?



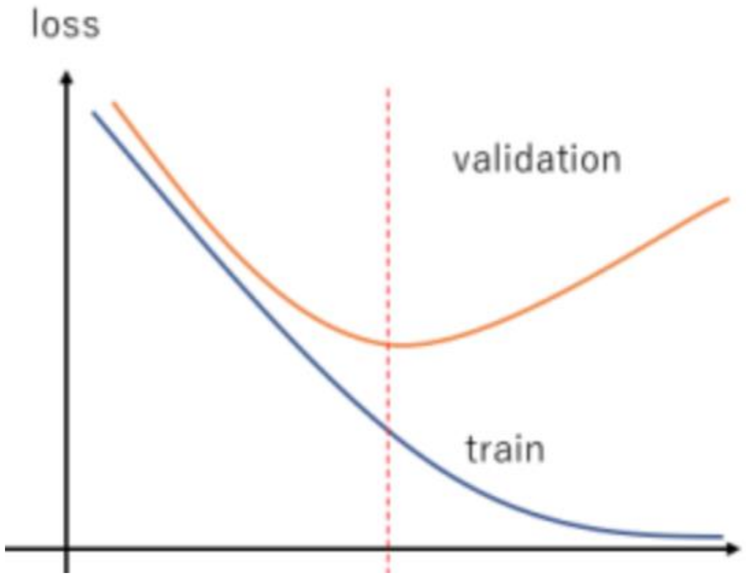


- For each hyperparameter $h \in \{1, \dots, H\}$:
  - Train Tree_h using DecisionTreeTrain by constraining the tree depth to be h
- Choose one from $\mathrm{Tree}_1, \dots, \mathrm{Tree}_H$
- Idea 1: choose Tree_h that minimizes training error
- Idea 2: choose Tree_h that minimizes test error
- Idea 3: further split training set to training set and validation set (development/hold-out set), (1) train Tree_h's using the (new) training set; (2) choose Tree_h that minimizes validation error

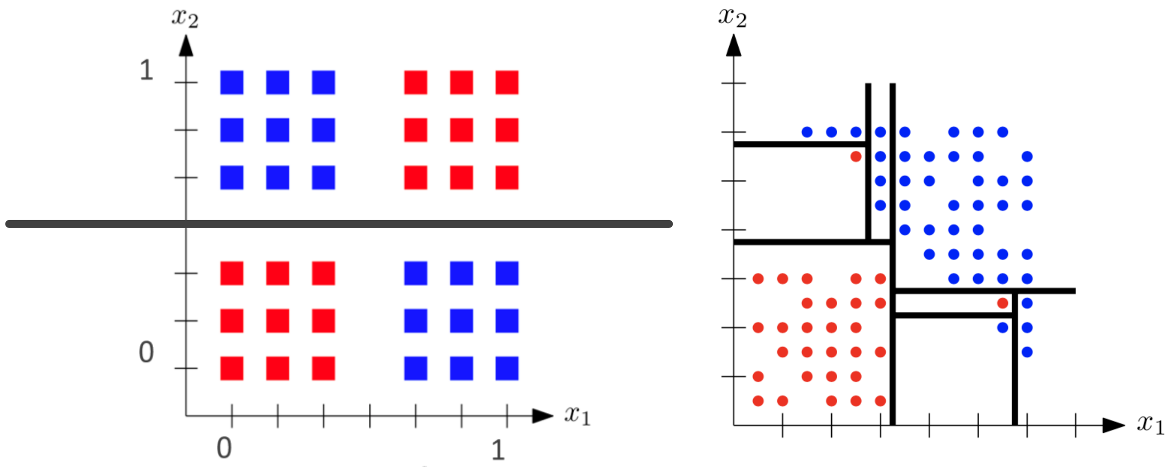
Training: 700 examples	Val:100 examples	Test: 200 examples

Hyperparameter tuning using validation set

- E.g. in decision tree training, how to choose tree depth $h \in \{1, \dots, H\}$?



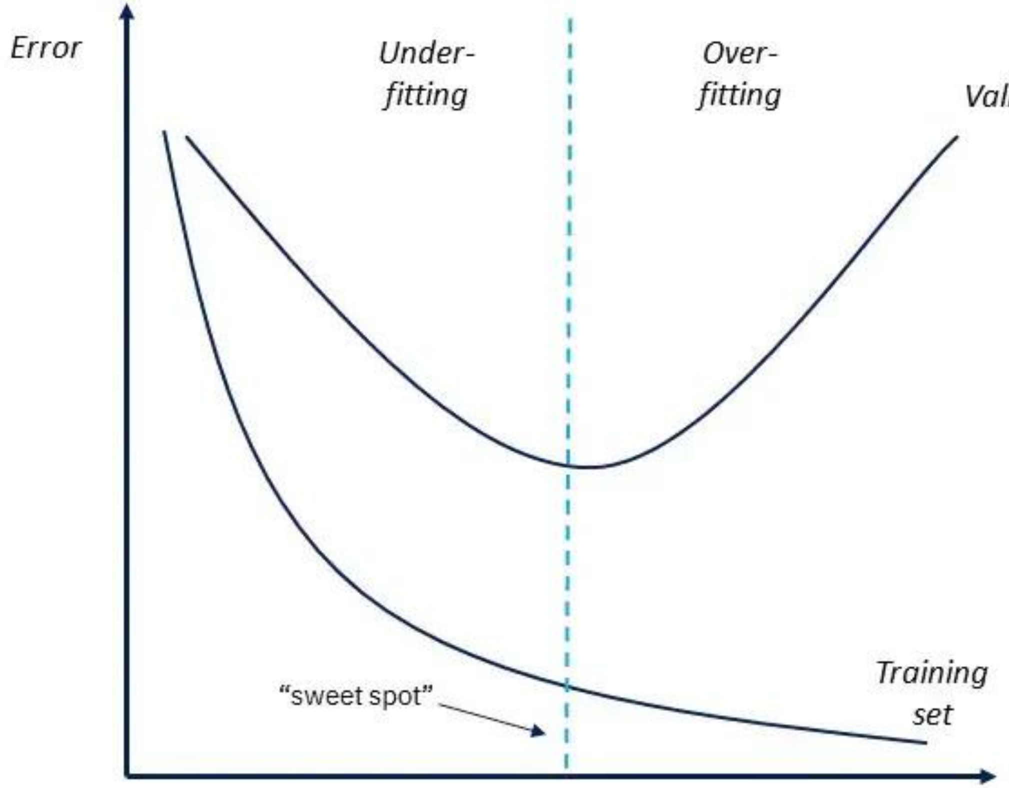
hyperparameter



- Law of large numbers => Validation error closely approximates generalization error (& test error)

Overfitting vs Underfitting

Underfitting: performs poorly on *both* training and validation…



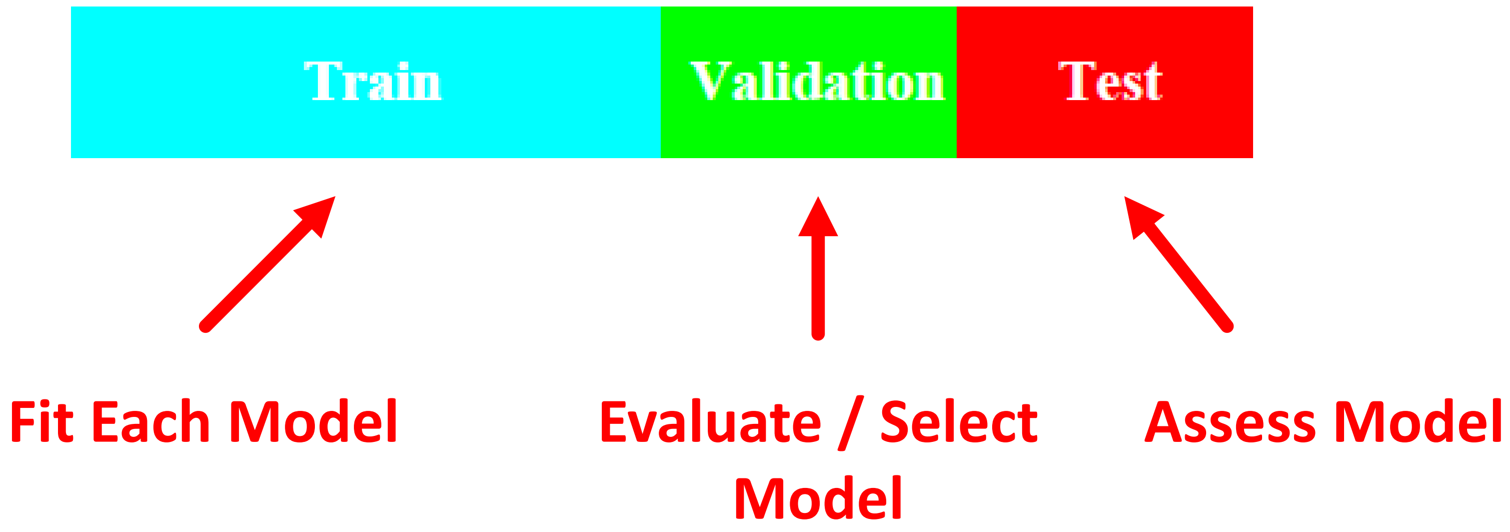
Source: ibm.com

hyperparameter

…overfitting: performs well on training but not on validation

Model Selection / Assessment

Partition your data into Train-Validation-Test sets

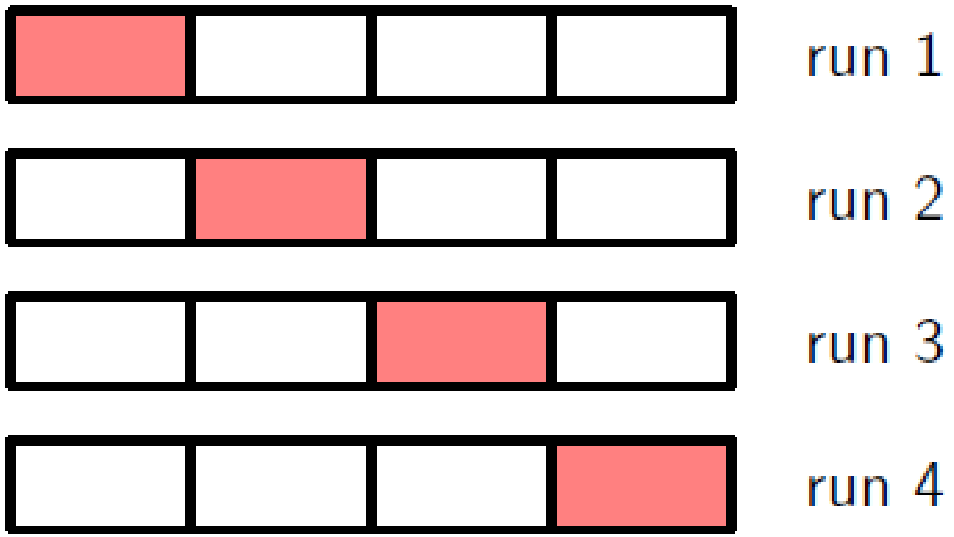


- Ideally, Test set is kept in a "vault" and only peek at it once model is selected
- Training-Validation-Test splits work if you have enough data ("data rich")
- As a general rule 50% Training, 25% Validation, 25% Test (very loose rule)

Source: Hastie, Tibishrani, Freidman

Hyperparameter tuning: cross-validation

Main idea: reuse data by splitting the training / validation data in multiple ways



N-fold Cross Validation: Partition training data into N "chunks" and for each run select one chunk to be validation data

For each run, fit to training data (N-1 chunks) and measure accuracy on validation set. Average model error across all runs.

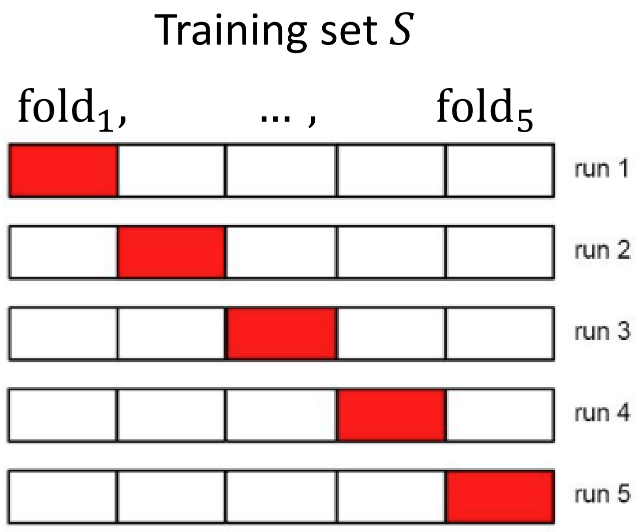
Drawback Need a lot of training data to partition.

Source: Bishop, C. PRML

Cross-validation: formal description

- For hyperparameter $h \in \{1, \dots, H\}$
  - For $k \in \{1, \dots, K\}$
    - train $\hat{f}_k^h$ with $S \setminus \mathrm{fold}_k$
    - measure error rate $e_{h,k}$ of $\hat{f}_k^h$ on fold_k
  - Compute the average error of the above: $\widehat{\mathrm{err}}_h = \frac{1}{K} \sum_{k=1}^{K} e_{h,k}$
- Choose $\hat{h} = \arg\min_h \widehat{\mathrm{err}}_h$
- Train $\hat{f}$ using S (all the training points) with hyperparameter $\hat{h}$

- $k = |S|$: leave one out cross validation (LOOCV)



Inductive bias

- What classification problem is class A vs. class B?
  - Birds vs. Non-birds
  - Flying animals vs. non-flying animals

- **<u>Inductive bias</u>**: in the absence of data that narrow down the target concept, what type of solutions are we likely to prefer?

- What is the inductive bias of learning shallow decision trees?

An example real-world machine learning pipeline

- Any step can go wrong
  - E.g. data collection, data representation
- Debugging pipeline: run *oracle experiments*
  - Assuming all lower-level tasks are perfectly done, is this step achieving what we want?
- General suggestions:
  - Build the stupidest thing that could possibly work
  - Decide whether / where to fix it

1	real world goal	increase revenue
2	real world mechanism	better ad display
3	learning problem	classify click-through
4	data collection	interaction w/ current system
5	collected data	query, ad, click
6	data representation	bow^2, $\pm$ click
7	select model family	decision trees, depth 20
8	select training data	subset from april'16
9	train model & hyperparams	final decision tree
10	predict on test data	subset from may'16
11	evaluate error	zero/one loss for $\pm$ click
12	deploy!	(hope we achieve our goal)

Next lecture (1/23)

- Geometric view of supervised learning; nearest neighbor methods

- Assigned reading: CIML Chap. 3 (Geometry and Nearest Neighbors)

- HW1

Simple case: discrete domain $\mathcal{X}$

$P_D(x,y)$	$x=1$	$x=2$	$x=3$
$y=-1$	0.2	0.2	0.15
$y=+1$	0.1	0.3	0.05

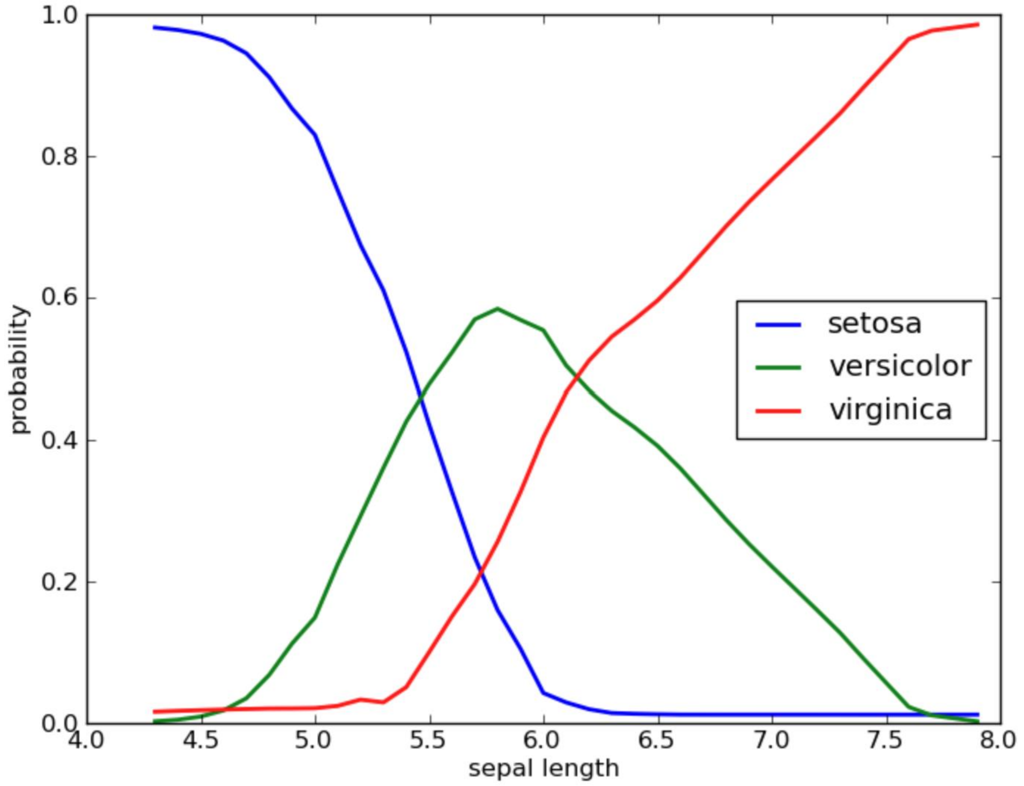
Which classifier is better?

- $f_1(1)=-1, f_1(2)=-1, f_1(3)=-1 \quad \Rightarrow \quad L_D(f_1)=0.1+0.3+0.05$
- $f_2(1)=-1, f_2(2)=+1, f_2(3)=-1 \quad \Rightarrow \quad L_D(f_2)=0.1+0.2+0.05$

- What is the best classifier?
- For any x, should choose y that has higher value of $P_D(x,y)$
- $f^*(1)=-1, f^*(2)=+1, f^*(3)=-1$

Bayes optimal classifier

- $f_{BO}(x) = \arg\max_{y \in \mathcal{Y}} P_D(X = x, Y = y) = \arg\max_{y \in \mathcal{Y}} P_D(Y = y \,|X = x)\,, \forall x \in \mathcal{X}$
- Theorem: f_{BO} achieves the smallest error rate among all functions.
- Bayes error rate: $L_D(f_{BO})$



Proof of theorem

- Step 1: consider accuracy:
  - $A_D(f) = 1 - L_D(f) = P_D\big(Y = f(X)\big) = \sum_x P_D\big(X = x, Y = f(x)\big)$
  - Suffices to show f_{BO} has the highest accuracy

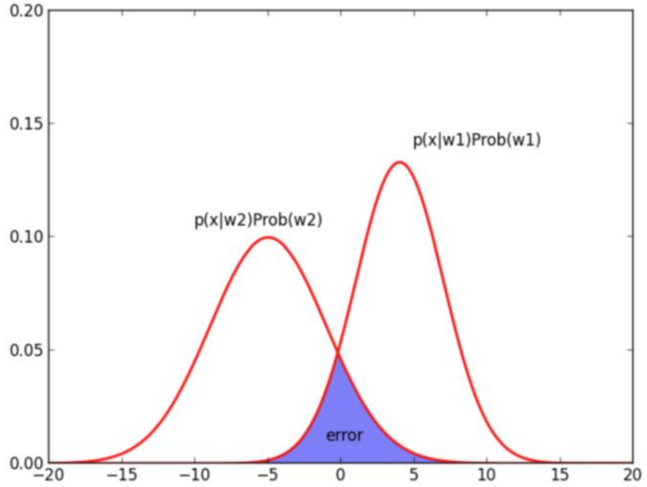
- Step 2: comparison:

$$A_D(f_{BO}) - A_D(f) = \sum_x P_D\big(X = x, Y = f_{BO}(x)\big) - P_D\big(X = x, Y = f(x)\big) \geq 0$$

$$\boxed{f_{BO}(x) = \arg\max_{y \in \mathcal{Y}} P_D(X = x, Y = y)}$$

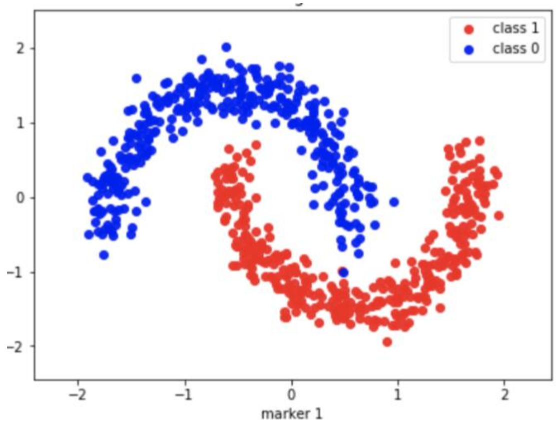
- Remark: similar reasoning can be used to prove the theorem with continuous domain $\mathcal{X}$ (sum -> integral)

When is the Bayes error rate nonzero?



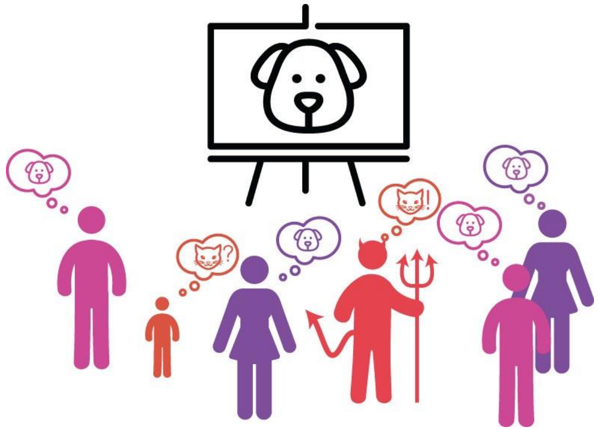
- $L_D(f_{BO}) = \sum_x \min(\, P_D(Y=+1, X=x)\,, P_D(Y=-1, X=x))$

- Limited feature representation



- feature noise
  - Sensor failure
  - Typo in reviews for sentiment classification

- label noise
  - Crowdsourcing settings



Class Participation

- Asking review questions on Piazza (3pts)
  - Every week, I will ask two of you to post questions (related to the past week's material) on Piazza
  - 3 questions per student

- Other in-class / Piazza discussions (e.g. asking/answering in-class questions; Piazza Q&As)

- Extra credit: Catching errors in the CIML book
  - Post on Piazza; we'll discuss and confirm together, and hopefully send these back to the author
  - 1pt for every error found