Generalization, Model Selection, and Validation

Machine Learning- CS-433
30 Sep 2025
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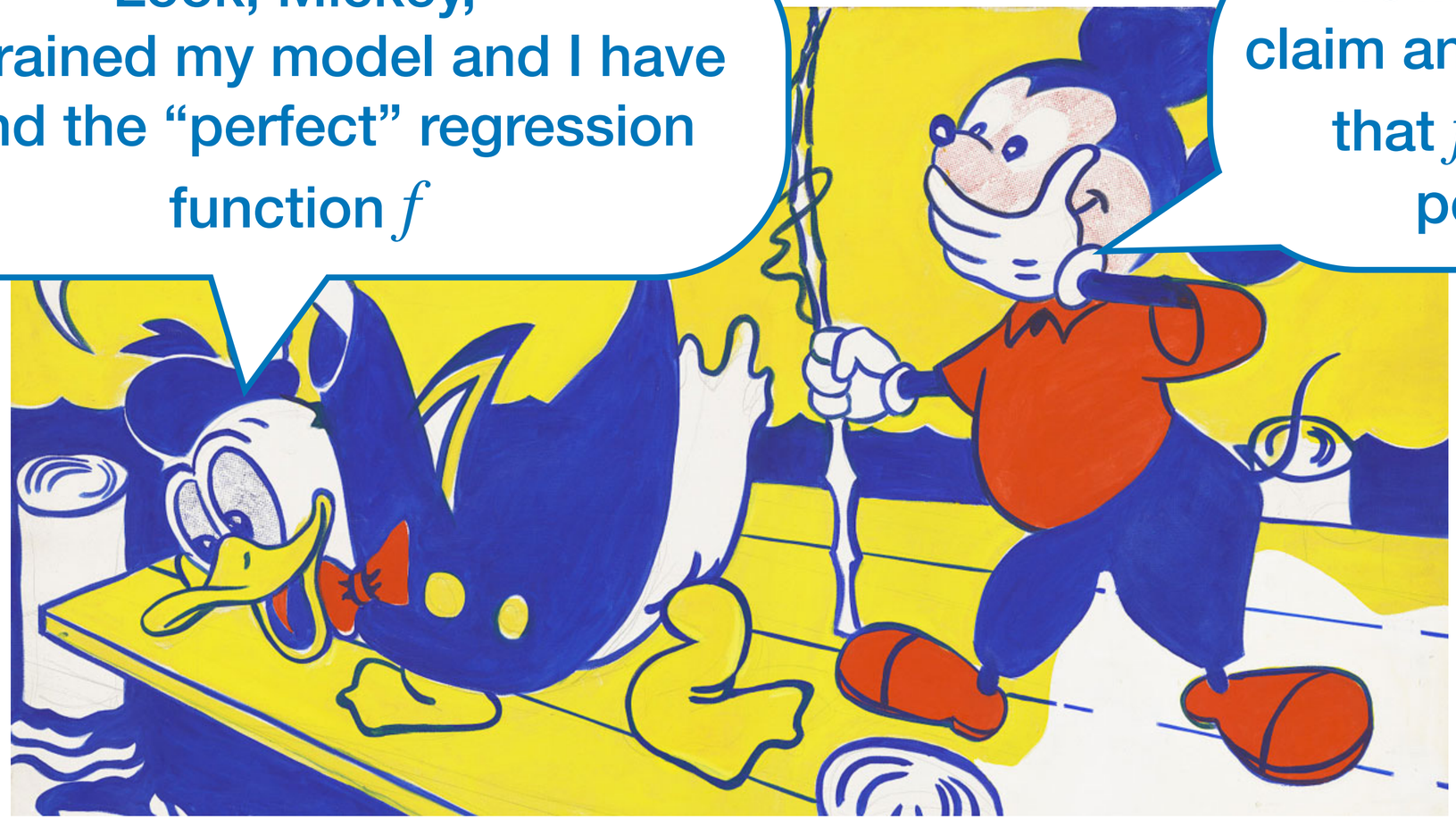
(Slide credit: Martin Jaggi & Nicolas Flammarion)

EPFL

Generalization, validation?

Look, Mickey,
I've trained my model and I have found the "perfect" regression function f

How can I verify this claim and have confidence that f will have good performance?



What is the model selection problem?

- Ridge regression: $w_\lambda = \arg\min_w \frac{1}{2N}\sum_{n=1}^{N}(y_n - x_n^\top w)^2 + \lambda\|w\|_2^2$

  Hyperparameter

  - λ can be tuned to control the model complexity (to reduce overfitting)
  - In practice: $(\lambda_1, \cdots, \lambda_k) \longrightarrow$ Algorithm $\longrightarrow (w_1, \cdots, w_k)$
  - Which λ should we use?

- Polynomial feature expansion: $(x_{(1)}, x_{(2)}) \xrightarrow{\phi} (x_{(1)}, x_{(2)}, x_{(1)}^2 + x_{(2)}^2)$

  $(x_{(1)}, x_{(2)}, 5x_{(1)}^2 + 2x_{(2)}^2, x_{(2)}^3 + 2x_{(1)})$

  - Enrich the model complexity, by augmenting the feature vector x.
  - Here the degree d is the hyperparameter

We are facing the same problem: **how do we choose these hyperparameters?**

Model selection for neural networks

Algorithms?

SGD
Adam
Which step-size?
Which batch-size?
Which momentum?

Architectures?

FullyConnected
ConvNet
ResNet
Transformer
Which width?
Which depth?
Batch normalization?

Regularizations?

Weight decay?
Early stopping?
Data augmentations?

Probabilistic Setup

Data Model:

Unknown distribution $\mathscr{D}$ with range $\mathscr{X} \times \mathscr{Y}$
We see a dataset S of independent samples from $\mathscr{D}$:

$$S = \{(x_n, y_n)\}_{n=1}^{N} \sim \mathscr{D} \quad \text{i.i.d.}$$

Learning Algorithm:

$$\mathscr{A}(S) = f_S$$

Input Output

Ridge regression: gradient descent or least-squares estimator

Can add a subscript $f_{S,\lambda}$ to indicate the hyper parameter dependency

Generalization Error: how accurate is f at predicting?

We compute the ***expected error*** over all samples drawn from distribution $\mathscr{D}$:

$$L_{\mathscr{D}}(f) = \mathbb{E}_{(x,y)\sim\mathscr{D}}[\ell(y, f(x))]$$

where $\ell(\,\cdot\,,\cdot\,)$ is the loss function

- Ex: $\ell(y, y') = \frac{1}{2}(y - y')^2$, logistic loss, hinge loss

The quantity $L_{\mathscr{D}}(f)$ has many names: **True / Expected / Generalization** — **Risk / Error / Loss**

This is the quantity we are fundamentally interested in

Problem: $\mathscr{D}$ is unknown

Empirical Error: what we can compute

We can approximate the true error by **averaging the loss function over the dataset**

$$L_S(f) = \frac{1}{|S|} \sum_{(x_n, y_n) \in S} \ell(y_n, f(x_n)) \, .$$

Also called: **empirical risk/error/loss**

⚠ The samples are random thus $L_S(f)$ is a random variable

It is an unbiased estimator of the true error

Law of large number: $L_S(f) \underset{|S| \to \infty}{\to} L_{\mathcal{D}}(f)$ but fluctuations!

Generalization gap: $|L_{\mathcal{D}}(f) - L_S(f)|$

law of large numbers = if we use a large enough amount of data then the average expected value of them is the same as the one of the whole distribution of data

using that we say that the loss is the expected value of the predictions made by our model, which is equal to the sum of the probability of each sample of our dataset happening in the world times our prediction

Training error: what we are minimizing

⚠ the prediction function f_S is itself a function of the data S

When the model has been trained on the same data it is applied to, the empirical error is called the ***training error:***

$$L_S(f_S) = \frac{1}{|S|} \sum_{(x_n, y_n) \in S} \ell(y_n, f_S(x_n))$$

This is the objective function you are minimizing to find the predictor

It might not be representative of the error we see on “fresh” samples

The reason that $L_S(f_S)$ might not be close to $L_{\mathcal{D}}(f_S)$ is overfitting

Splitting the data

Problem: Validating model on the same data we trained it on
Fix: **Split the data** into an independent *training and test set:*

$$S = S_{\text{train}} \cup S_{\text{test}}$$

1. We **learn** the function $f_{S_{\text{train}}}$ using the **train set**
2. We **validate** it computing the error on the **test set**

$$L_{S_{\text{test}}}(f_{S_{\text{train}}}) = \frac{1}{|S_{\text{test}}|} \sum_{(y_n, x_n) \in S_{\text{test}}} \ell(y_n, f_{S_{\text{train}}}(x_n))$$

➡ Since S_{test} and S_{train} are independent: $L_{S_{\text{test}}}(f_{S_{\text{train}}}) \approx L_{\mathcal{D}}(f_{S_{\text{train}}})$

⚠ We have less data both for the learning and the validation tasks (tradeoff)

Generalization gap:
How far is the test from the true error?

Claim: given a model f and a test set $S_{\text{test}} \sim \mathscr{D}$ i.i.d. (not used to learn f) and a loss $\ell(\cdot, \cdot) \in [a, b]$:

$$\mathbb{P}\left[\left| \underbrace{L_{\mathscr{D}}(f) - L_{S_{\text{test}}}(f)}_{\text{Generalization Gap}} \right| \geq \sqrt{\frac{(b-a)^2 \ln(2/\delta)}{2\,|S_{\text{test}}|}} \right] \leq \delta$$

The error decreases as $\mathcal{O}(1/\sqrt{|S_{\text{test}}|})$ with the number of test points

High probability bound: δ is only in the $\ln$

➡ The more data points we have, the more confident we are that the empirical loss we measure is close to the true loss

Why do you care?

- Given a predictor f and a dataset S you can control the expected risk:

$$\mathbb{P}\Bigg(\underbrace{L_{\mathscr{D}}(f)}_{\text{not computable}} \geq \underbrace{L_{S_{test}}(f)}_{\text{Computable}} + \underbrace{\sqrt{\frac{(a-b)^2 \ln(2/\delta)}{2\,|S_{test}|}}}_{\text{deviation}} \Bigg) \leq \delta$$

- Given a dataset S
  1. Split: $S = S_{\text{train}} \cup S_{\text{test}}$
  2. Train: $\mathscr{A}(S_{\text{train}}) = f_{S_{\text{train}}}$
  3. Use:

$$\mathbb{P}\left(L_{\mathscr{D}}(f_{S_{\text{train}}}) \geq L_{S_{\text{test}}}(f_{S_{\text{train}}}) + \sqrt{\frac{(a-b)^2 \ln(2/\delta)}{2\,|S_{test}|}} \right) \leq \delta$$

➡We can obtain a probabilistic upper bound on the expected risk

The proof relies only on concentration inequalities

Since $(x_n, y_n) \in S_{\text{test}}$ are chosen independently, the associated losses $\Theta_n = \ell(y_n, f(x_n)) \in [a, b]$ given a fixed model f, are also i.i.d. random variables

Empirical loss: $\frac{1}{N}\sum_{n=1}^{N} \Theta_n = \frac{1}{N}\sum_{n=1}^{N} \ell(y_n, f(x_n)) = L_{S_{\text{test}}}(f)$

True loss: $\mathbb{E}[\Theta_n] = \mathbb{E}[\ell(y_n, f(x_n))] = L_{\mathcal{D}}(f)$

What is the chance that the empirical loss $L_{S_{\text{test}}}(f)$ deviates from the true loss by more than a given constant?

➡ classically addressed using **concentration inequalities**

Hoeffding inequality: a simple concentration bound

Claim: Let $\Theta_1, \ldots, \Theta_N$ be a sequence of i.i.d. random variables with mean $\mathbb{E}[\Theta]$ and range $[a, b]$

$$\mathbb{P}\left[\left|\frac{1}{N}\sum_{n=1}^{N}\Theta_n - \mathbb{E}[\Theta]\right| \geq \varepsilon\right] \leq 2e^{-2N\varepsilon^2/(b-a)^2} \text{ for any } \varepsilon \geq 0$$

Concentration bound: the empirical mean is concentrated around its mean

A. Use it with $\Theta_n = \ell(y_n, f(x_n))$

B. Equating $\delta = 2e^{-2|S_{\text{test}}|\varepsilon^2/(b-a)^2}$ we get $\varepsilon = \sqrt{\frac{(b-a)^2 \ln(2/\delta)}{2|S_{\text{test}}|}}$ □

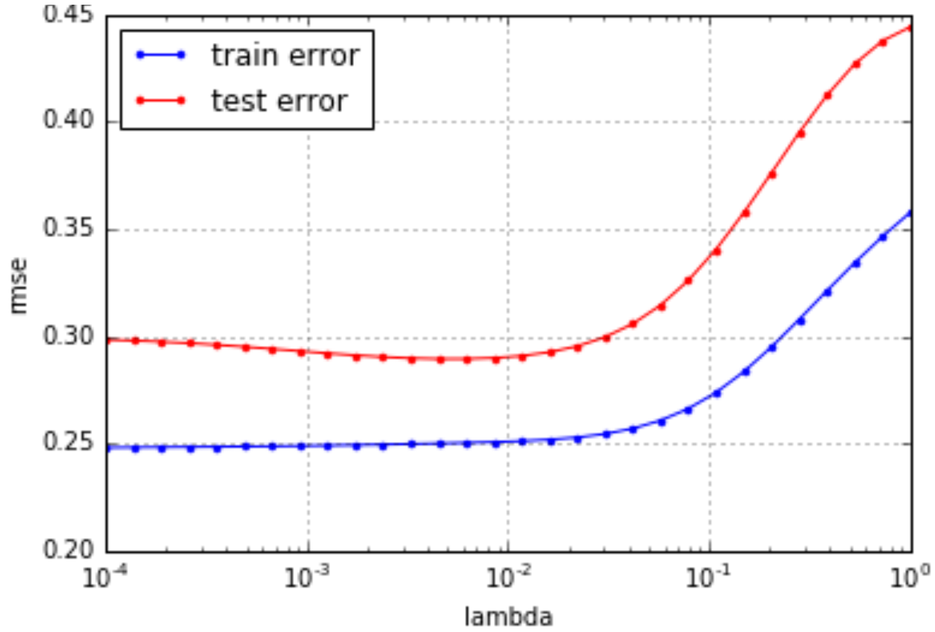
Model Selection: pick the best model

Goal: select the hyperparameters of our model (λ for ex. in ridge regression)
We have a set of candidate values $\{\lambda_k\}_{k=1}^{K}$. Which one should we choose?

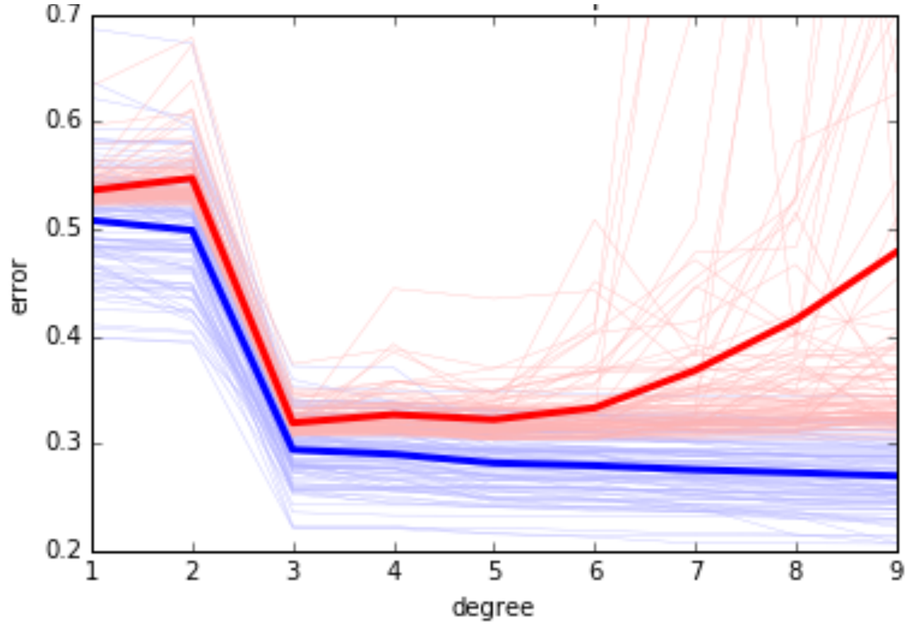
1. Split the data into $S = S_{\text{train}} \cup S_{\text{test}}$, generated independently from $\mathscr{D}$
2. Run the learning algorithm K times on the same training set S_{train} to compute the K prediction functions $f_{S_{\text{train}},\lambda_k}$
3. For each prediction function, compute the test error $L_{S_{\text{test}}}(f_{S_{\text{train}},\lambda_k})$

We then choose the value of the parameter λ giving the smallest test error

Examples



Ridge regression



Degree in case of a polynomial feature expansion

Does model selection work?

Two questions:

- How do we know that the best function $f_{S_{\text{train}},\lambda}$ is a good approximation of the best model within our function class?

- How do we know that $L_{S_{\text{test}}}(f_{S_{\text{train}},\lambda_k}) \approx L_{\mathcal{D}}(f_{S_{\text{train}},\lambda_k})$?

  We have discussed it for a single model
  What about several models?
  I.e., what is the justification that the min is actually good?

How far is each of the K test errors $L_{S_{\text{test}}}(f_k)$ from the true $L_{\mathcal{D}}(f_k)$?

Claim: we can bound the maximum deviation for all K candidates, by

$$\mathbb{P}\left[\max_k \left| L_{\mathcal{D}}(f_k) - L_{S_{\text{test}}}(f_k) \right| \geq \sqrt{\frac{(b-a)^2 \ln(2K/\delta)}{2\,|S_{\text{test}}|}} \right] \leq \delta$$

- The error decreases as $\mathcal{O}(1/\sqrt{|S_{\text{test}}|})$ with the number test points
- When testing K hyper-parameters, the error only goes up by $\sqrt{\ln(K)}$

➡So we can test many different models without incurring a large penalty

- It can be extended to infinitely many models

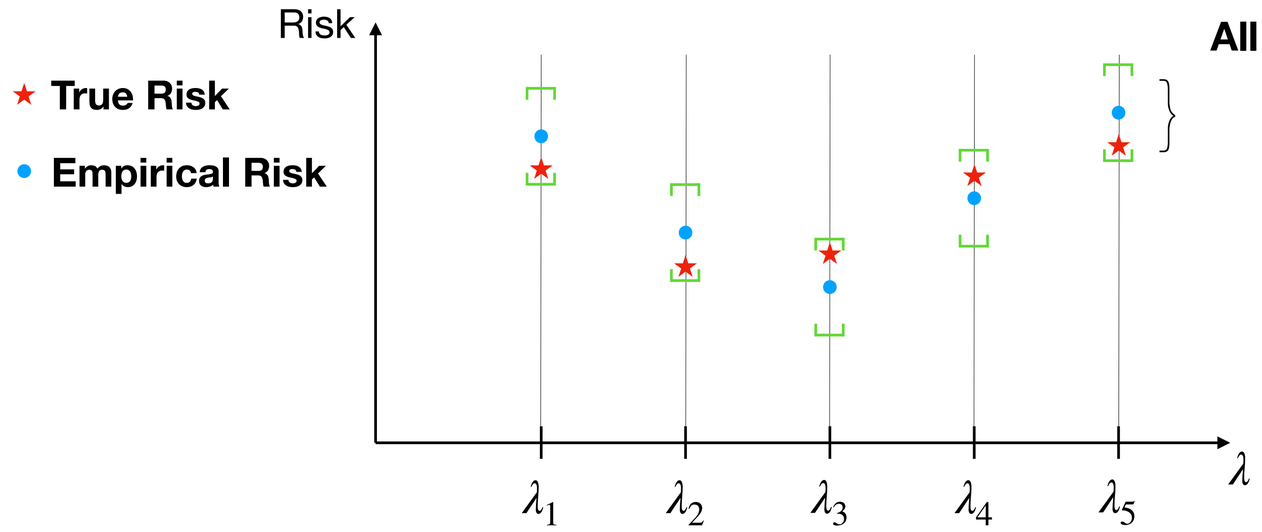
Proof: A simple union bound

The proof of this statement follows the proof of the special case $K = 1$

$$\begin{aligned}
\mathbb{P}\left[\ \max_k \left| L_{\mathscr{D}}(f_k) - L_{S_{\text{test}}}(f_k) \right| \geq \varepsilon \right] &= \mathbb{P}\left[\ \cup_k \left\{ \left| L_{\mathscr{D}}(f_k) - L_{S_{\text{test}}}(f_k) \right| \geq \varepsilon \right\} \right] \\
&\leq \sum_k \mathbb{P}\left[\left| L_{\mathscr{D}}(f_k) - L_{S_{\text{test}}}(f_k) \right| \geq \varepsilon \right] \\
&\leq 2Ke^{-2N\varepsilon^2/(b-a)^2}
\end{aligned}$$

Hence, equating $\delta = 2Ke^{-2N\varepsilon^2/(b-a)^2}$, we get $\varepsilon = \sqrt{\frac{(b-a)^2 \ln(2K/\delta)}{2N}}$ as stated

If we choose the “best” function according to the empirical risk then its true risk is not too far away from the true risk of the optimal choice



All the widths are the same

$$2\sqrt{\frac{(b-a)^2 \ln(2K/\delta)}{2\,|S_{\text{test}}|}}$$

Let $k^* = \text{argmin}_k L_{\mathcal{D}}(f_k)$ and $\hat{k} = \text{argmin}_k L_{S_{\text{test}}}(f_k)$ then

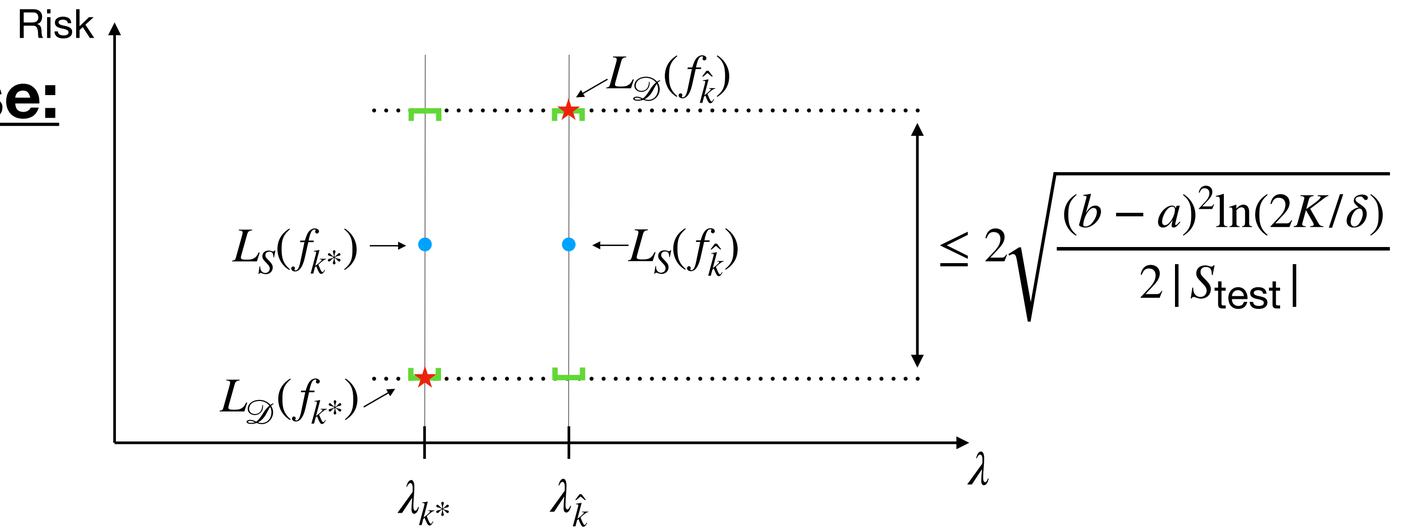
$$\mathbb{P}\left[\; L_{\mathcal{D}}(f_{\hat{k}}) \geq L_{\mathcal{D}}(f_{k^*}) + 2\sqrt{\frac{(b-a)^2 \ln(2K/\delta)}{2\,|S_{\text{test}}|}} \;\right] \leq \delta$$

Function with the smallest empirical risk

Function with the smallest true risk

If we choose the “best” function according to the empirical risk then its true risk is not too far away from the true risk of the optimal choice

Worst case:



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Function with the smallest empirical risk

Function with the smallest true risk

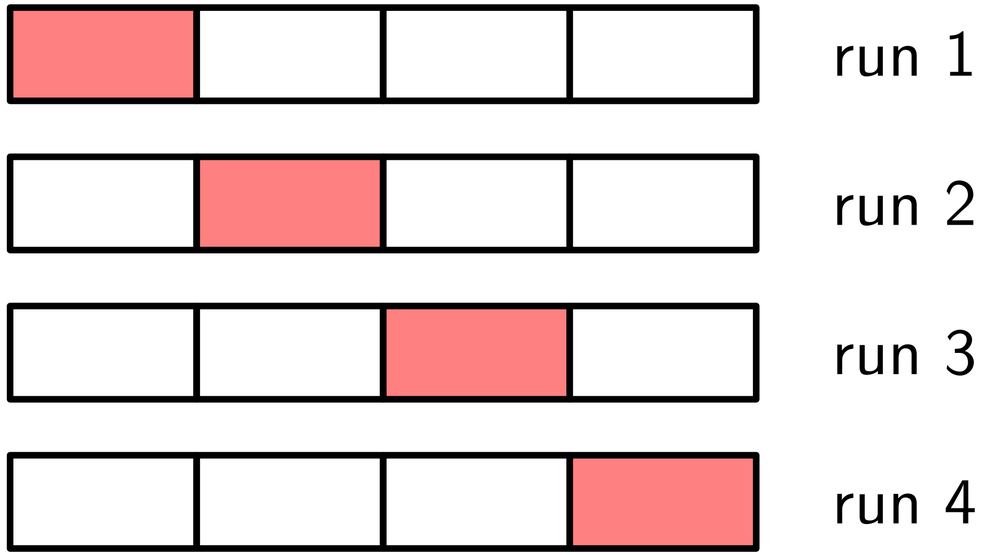
Cross-Validation

- Splitting the data once into two parts (one for training and one for testing) is not the most efficient way to use the data

- Cross-validation is a better way

M-fold Cross-Validation*

1. Randomly partition the data into M groups
2. Train M times. Each time leave out exactly one of the M groups for testing and use the remaining $M-1$ groups for training.
3. Average the M results



- We have used all data for training, and all data for testing, and used each data point the same number of times
- Cross-validation returns an estimate of the *generalization-error* and its variance

* Usually called “K-fold”, but that would clash with K as used before (# values tried for hyperparam)…

Do we still have some time?

Hoeffding's inequality:

Let $\Theta_1, \ldots, \Theta_N$ be a sequence of i.i.d. random variables with mean $\mathbb{E}[\Theta]$ and range $[a, b]$. Then, for any $\varepsilon > 0$

$$\mathbb{P}\left[\left|\frac{1}{N}\sum_{n=1}^{N}\Theta_n - \mathbb{E}[\Theta]\right| \geq \varepsilon\right] \leq 2e^{-2N\varepsilon^2/(b-a)^2}$$

Proof (I)

- We equivalently assume that $\mathbb{E}[\Theta] = 0$ and that $\Theta_n \in [a, b]$
- We will only show that

$$\mathbb{P}\left\{ \frac{1}{N} \sum_{n=1}^{N} \Theta_n \geq \varepsilon \right\} \leq e^{-2N\varepsilon^2/(b-a)^2}$$

This, together with the equivalent bound

$$\mathbb{P}\left\{ \frac{1}{N} \sum_{n=1}^{N} \Theta_n \leq -\varepsilon \right\} \leq e^{-2N\varepsilon^2/(b-a)^2}$$

will prove the claim

Proof (II)

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For any $s \geq 0$, $\mathbb{P}\left\{ \frac{1}{N} \sum_{n=1}^{N} \Theta_n \geq \varepsilon \right\} = \mathbb{P}\left\{ s\frac{1}{N} \sum_{n=1}^{N} \Theta_n \geq s\varepsilon \right\}$

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$$= \prod_{n=1}^{N} \mathbb{E}[e^{\frac{s\Theta_n}{N}}]e^{-s\varepsilon} \qquad \text{(the r.v } \Theta_n \text{ are independent)}$$

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$$\leq e^{s^2(b-a)^2/(8N)}e^{-s\varepsilon} \qquad \text{(Hoeffding lemma)}$$

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Hoeffding lemma

For any random variable X, with $\mathbb{E}[X] = 0$ and $X \in [a, b]$ we have

$$\mathbb{E}[e^{sX}] \leq e^{\frac{1}{8}s^2(b-a)^2} \text{ for any } s \geq 0$$

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Proof outline:

Consider the convex function $s \mapsto e^{sx}$. In the range $[a, b]$ it is upper bounded by the chord

$$e^{sx} \leq \frac{x-a}{b-a}e^{sb} + \frac{b-x}{b-a}e^{sa}$$

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$$e^{sx} \leq \frac{x-a}{b-a}e^{sb} + \frac{b-x}{b-a}e^{sa}$$

Taking the expectation and recalling that $\mathbb{E}[X] = 0$, we get

$$\mathbb{E}[e^{sX}] \leq \frac{b}{b-a}e^{sa} - \frac{a}{b-a}e^{sb} \leq e^{s^2(b-a)^2/8}$$