

Validation and Model Selection

A new look at E_{out}

Validation is a new cure for overfitting

$$E_{out} = E_{in} + \underbrace{\text{overfit penalty}}$$

VC bounds this using a complexity error bar for \mathcal{H}

Regularization estimates this through a heuristic complexity penalty for g

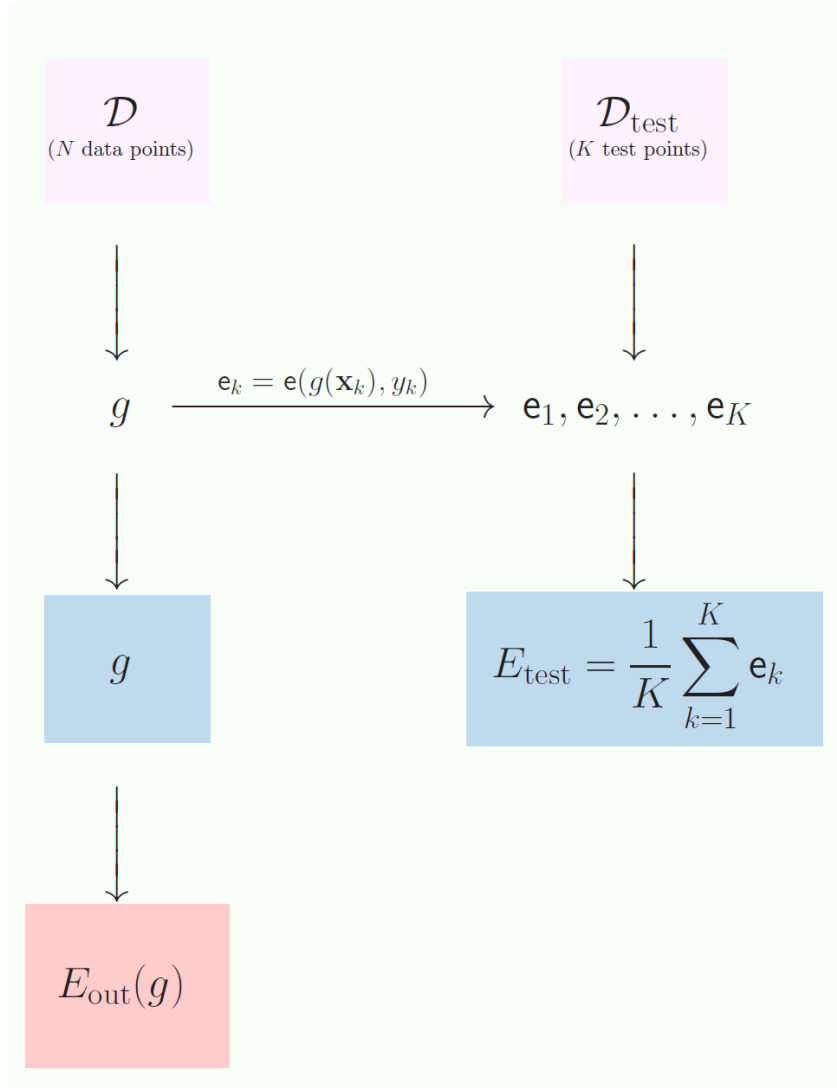
Validation is a direct estimation to E_{out}

$$\underbrace{E_{out}} = E_{in} + \text{overfit penalty}$$

validation estimates this directly

This is a similar estimation to given by the Test Set

E_{test} is an unbiased estimate of E_{out}



e_1, \dots, e_K are *independent*

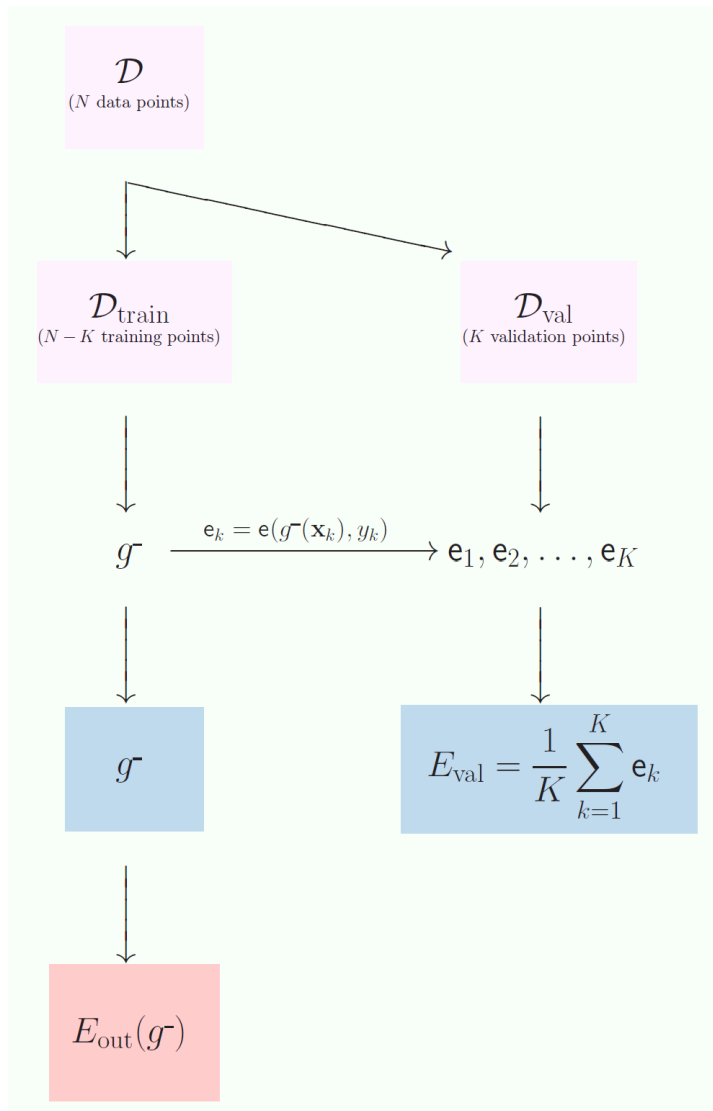
$$\begin{aligned}\text{Var}[E_{\text{test}}] &= \frac{1}{K^2} \sum_{k=1}^K \text{Var}[e_k] \\ &= \frac{1}{K} \text{Var}[e]\end{aligned}$$

decreases like $\frac{1}{K}$
bigger $K \implies$ more reliable E_{test} .

E_{test} is an estimate for $E_{\text{out}}(g)$

$$\begin{aligned}\mathbb{E}_{\mathcal{D}_{\text{test}}}[e_k] &= E_{\text{out}}(g) \\ \mathbb{E}[E_{\text{test}}] &= \frac{1}{K} \sum_{k=1}^K \mathbb{E}[e_k] \\ &= \frac{1}{K} \sum_{k=1}^K E_{\text{out}}(g) = E_{\text{out}}(g)\end{aligned}$$

The Validation Set



1. Remove K points from \mathcal{D}

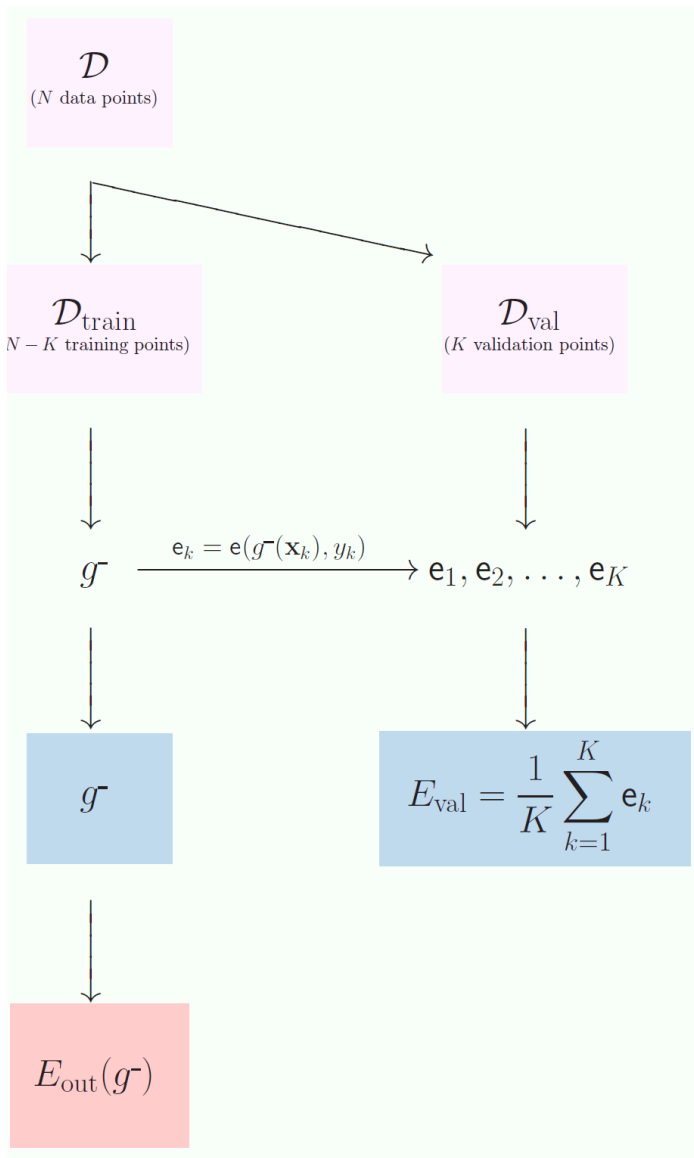
$$\mathcal{D} = \mathcal{D}_{\text{train}} \cup \mathcal{D}_{\text{val}}.$$

2. Learn using $\mathcal{D}_{\text{train}} \longrightarrow g^-$.

3. Test g^- on $\mathcal{D}_{\text{val}} \longrightarrow E_{\text{val}}$.

4. Use error E_{val} to estimate $E_{\text{out}}(g^-)$.

The Validation Set



E_{val} is an estimate for $E_{\text{out}}(\bar{g})$

$$\mathbb{E}_{\mathcal{D}_{\text{val}}}[\mathbf{e}_k] = E_{\text{out}}(\bar{g})$$

$$\begin{aligned} \mathbb{E}[E_{\text{test}}] &= \frac{1}{K} \sum_{k=1}^K \mathbb{E}[\mathbf{e}_k] \\ &= \frac{1}{K} \sum_{k=1}^K E_{\text{out}}(\bar{g}) = E_{\text{out}}(\bar{g}) \end{aligned}$$

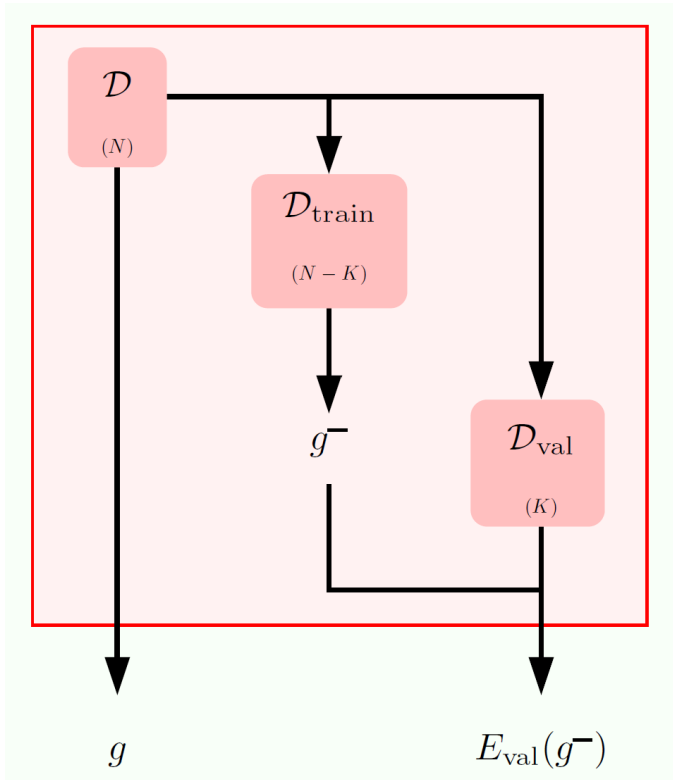
$\mathbf{e}_1, \dots, \mathbf{e}_K$ are *independent*

$$\text{Var}[E_{\text{val}}] = \frac{1}{K^2} \sum_{k=1}^K \text{Var}[\mathbf{e}_k]$$

$$= \frac{1}{K} \text{Var}[e(\bar{g})]$$

decreases like $\frac{1}{K}$
depends on \bar{g} , not \mathcal{H}
bigger $K \Rightarrow$ more reliable E_{val} ?

How relate K with our goals ?



Primary goal: output the best hypothesis trained on all data.

Secondary goal: estimate $E_{\text{out}}(g)$ using $E_{\text{val}}(g^-)$

Let's focus on the **Secondary Goal**:

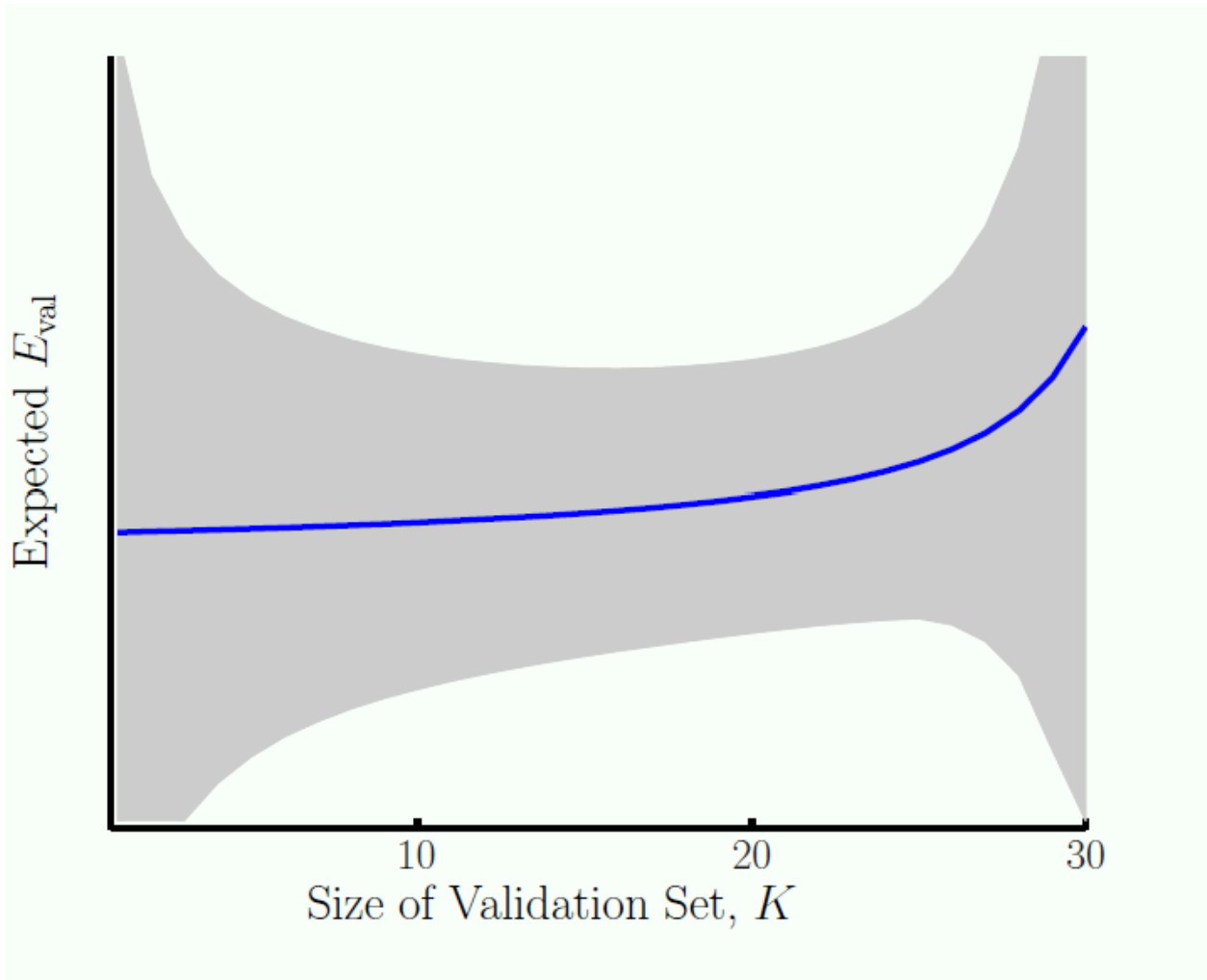
$$E_{\text{out}}(g) \leq E_{\text{out}}(g^-) \leq E_{\text{val}}(g^-) + \mathcal{O}\left(\frac{1}{\sqrt{K}}\right)$$

Hoeffding bound
Learning curves

Primary goal: Once we have a good estimation for E_{out} all samples can be used for training.

Clearly the estimation for E_{out} will be pessimistic respect to performance of our best hypothesis.

Choosing K



This picture, associated to a simple model, shows the price to pay to put out K points to estimate E_{val}

Rule of thumb: $K^* = \frac{N}{5}$

The bias from validation

Now $E_{val}(g_{m^*}^-)$ is not an unbiased estimator for $E_{out}(g_{m^*}^-)$

$E_{val}(g_{m^*}^-)$ will be an optimistic estimator

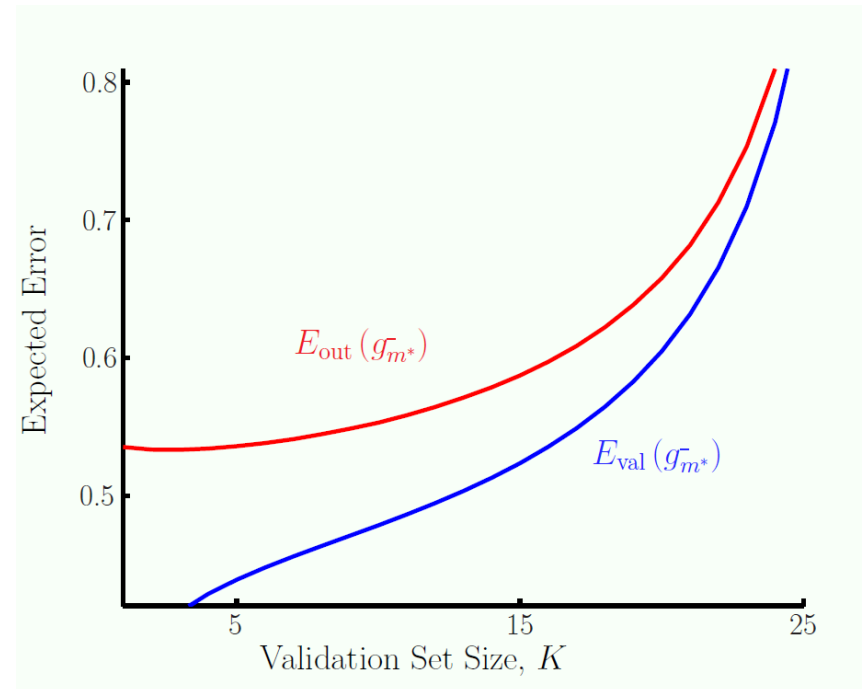
..... because we choose one of the M finalist with the minimum error

How good is the generalization error for this entire process of model selection using validation ?

According to the Hoeffding's inequality for finite hypothesis

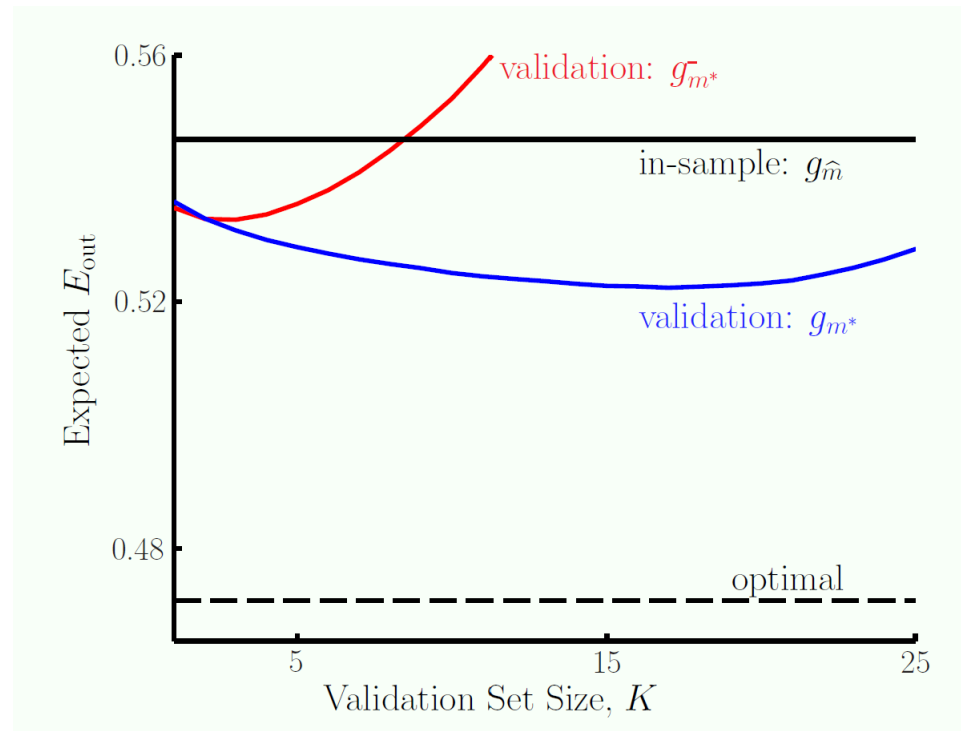
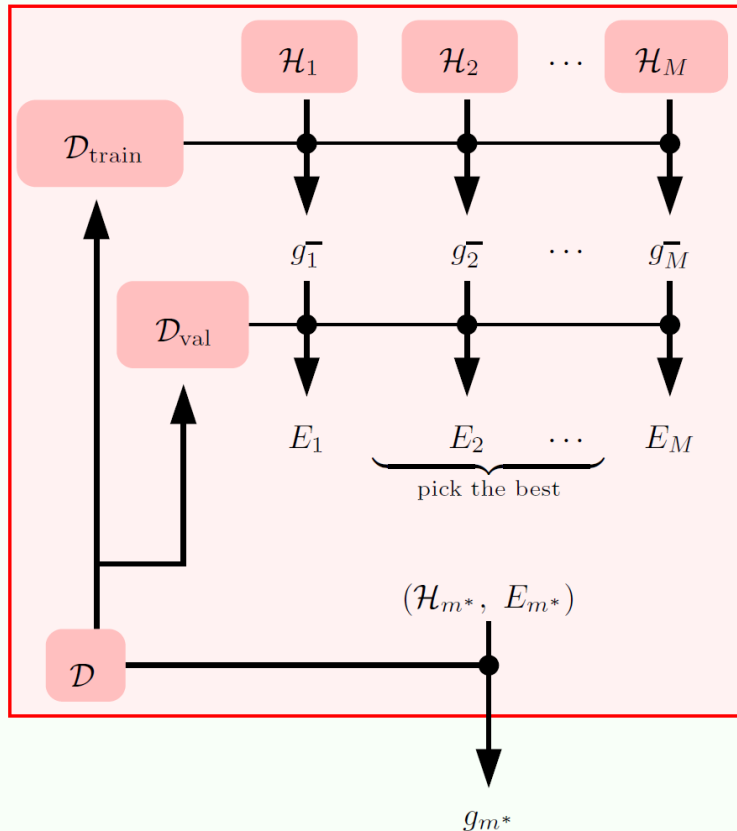
$$E_{out}(g_{m^*}^-) \leq E_{val}(g_{m^*}^-) + \mathcal{O}\left(\sqrt{\frac{\ln M}{K}}\right)$$

$$E_{out}(g_m^*) \leq E_{out}(g_{m^*}^-) \leq E_{val}(g_{m^*}^-) + \mathcal{O}\left(\sqrt{\frac{\ln M}{K}}\right)$$



Example of optimistic bias of the validation error when using a validation set for the model selected. (see the book)

Comparing E_{in} and E_{val} for Model Selection



Curves for model selection from two hypothesis using validation set

It can be appreciated how the use of validation for model selection provides in general the hypothesis with the minimum expected out-of-sample error

An exception appears when the validation set is very small

The Dilemma when choosing K

Validation relies on the following chain of reasoning:

$$E_{out}(g) \approx E_{out}(g^-) \approx E_{val}(g^-)$$

Small K Large K

What to do ?

Taking K small we get a very good agreement between the two estimates of the out-of-sample error BUT in this case the validation error although still unbiased will have a very large variance.

Solution: Let's fix K=1 and use **CROSS-VALIDATION**

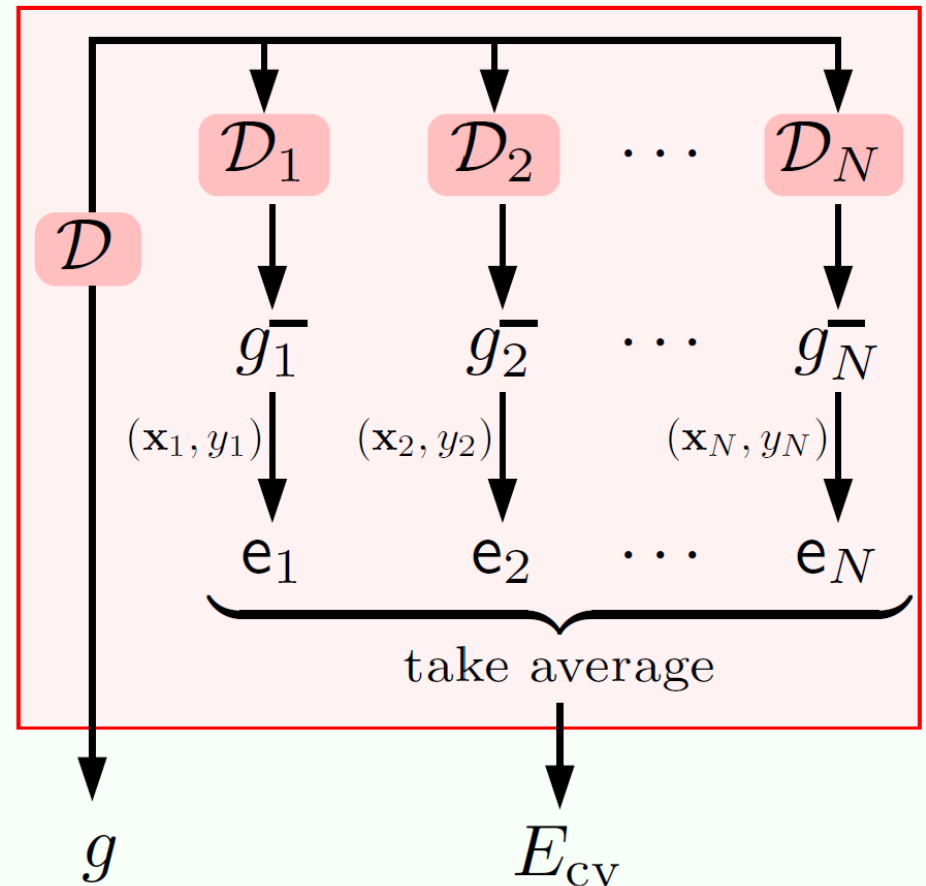
CROSS-VALIDATION estimates the validation error as an average of validation errors

Leave-One-Out

Let fix $K=1$ and compute N different models using a validation set with a single element

$$E_{cv} = \frac{1}{N} \sum_{i=1}^N E_{val}(g_i^-)$$

Result: E_{cv} is an unbiased estimate of $\bar{E}_{out}(N - 1)$.



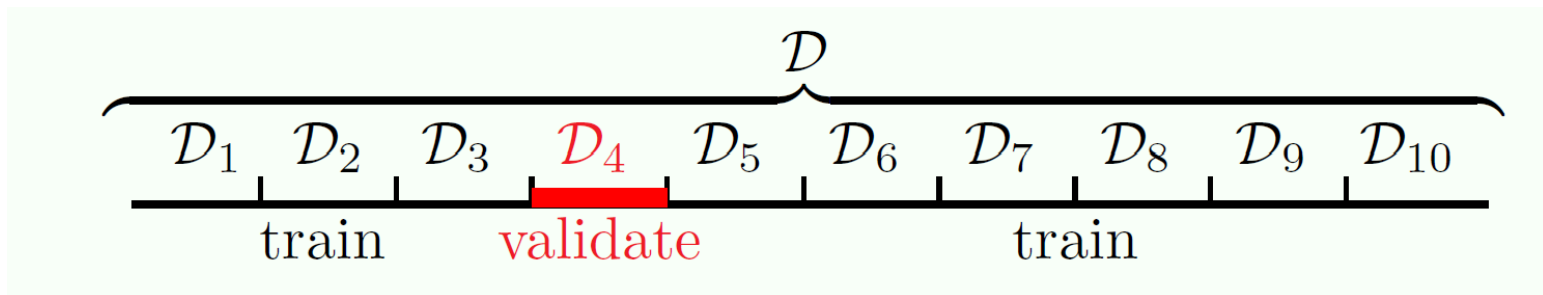
According to the learning curves $E_{out}(g) \leq E_{cv}(g)$

BUT how stable is the estimation using $K=1$?: **GOOD ENOUGH !!** (experimental result)

Cross-Validation is computationally intensive

N epochs of learning each of size N-1

- A general alternative is V-fold Cross-Validation ($V \in [5, 10]$)



- For linear regression is possible to compute analitically this error

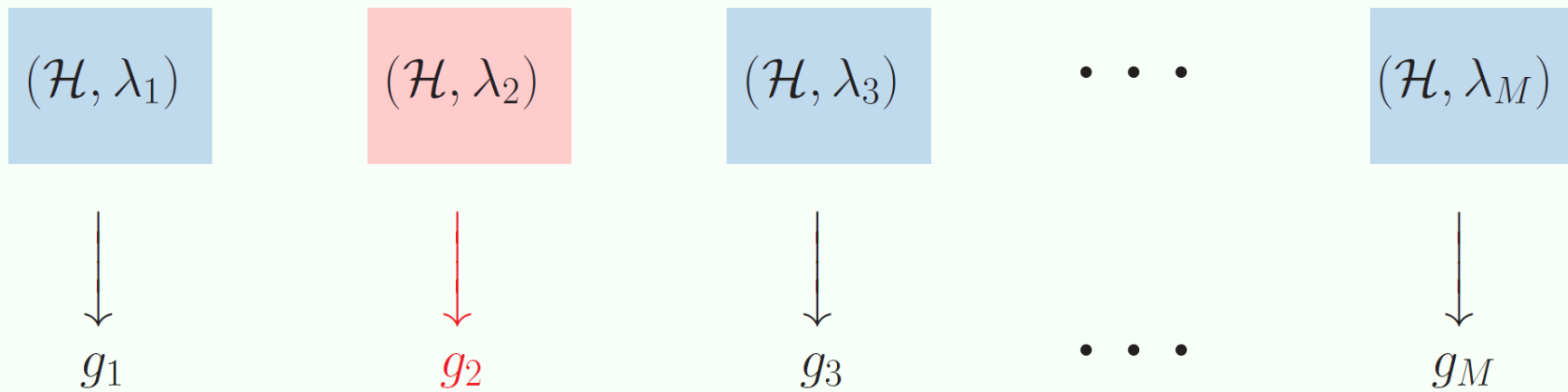
$$\mathbf{w}_{\text{reg}} = (Z^T Z + \lambda I)^{-1} Z^T \mathbf{y}$$
$$E_{\text{cv}} = \frac{1}{N} \sum_{n=1}^N \left(\frac{y_n - \hat{y}_n}{1 - H_{nn}(\lambda)} \right)^2$$

$$H(\lambda) = Z(Z^T Z + \lambda I)^{-1} Z^T$$

Application to selecting λ

What regularization parameter to use? : $\lambda_1, \lambda_2, \dots, \lambda_M$

This is an special case of *model selection* over M models

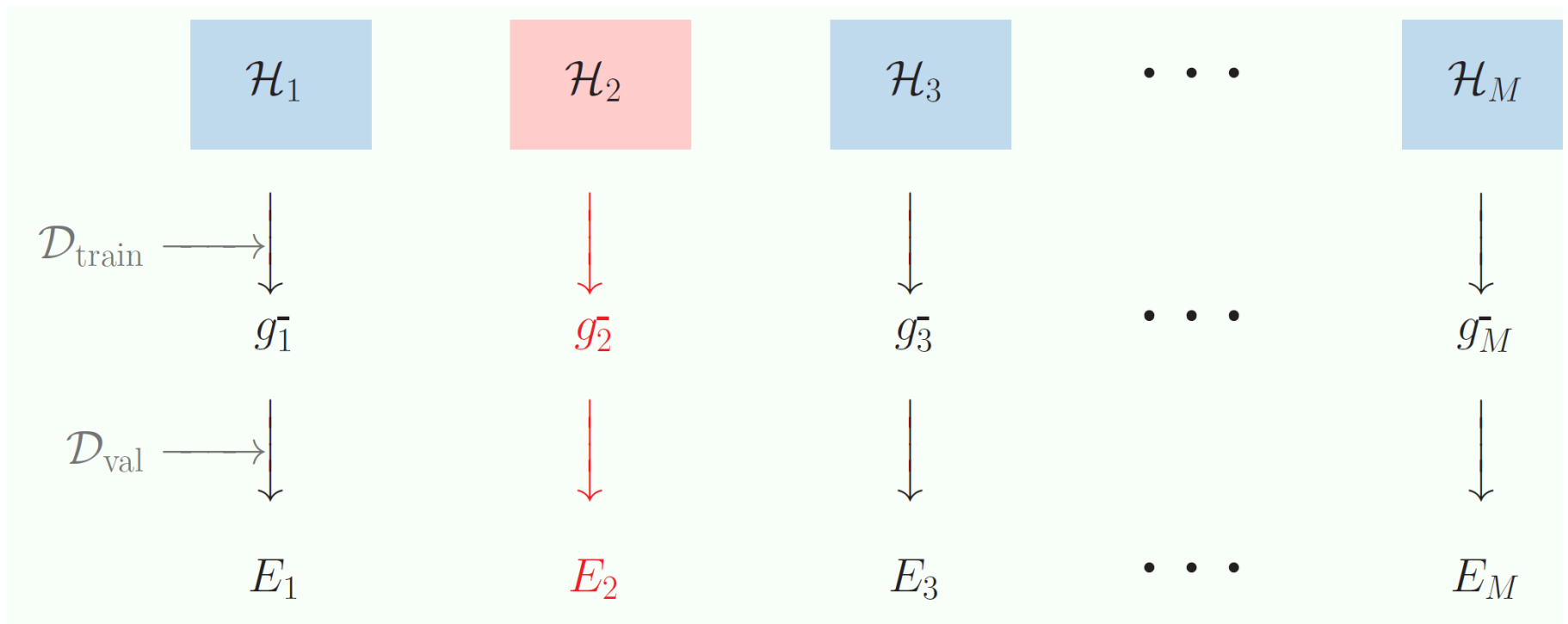


Picking a model amount to choosing the optimal λ

Model Selection

The most important use of Validation

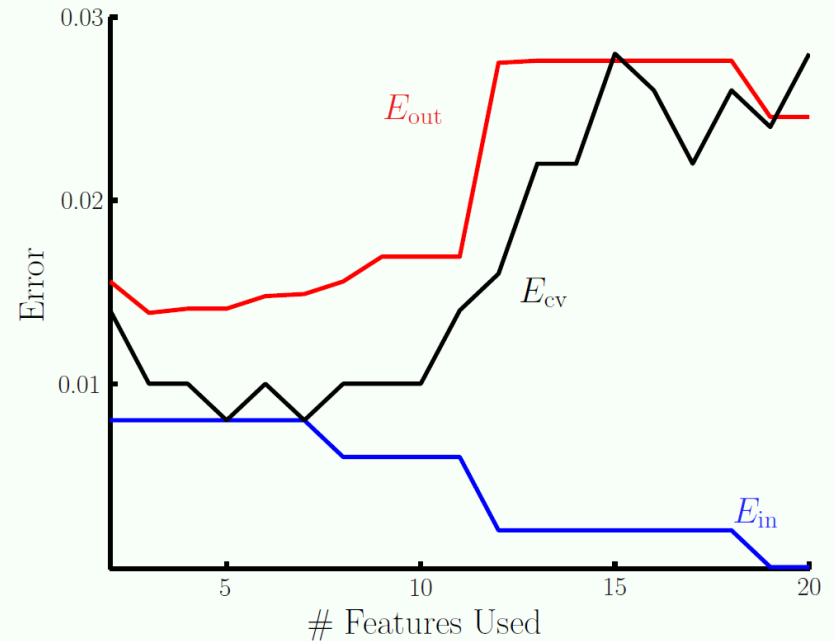
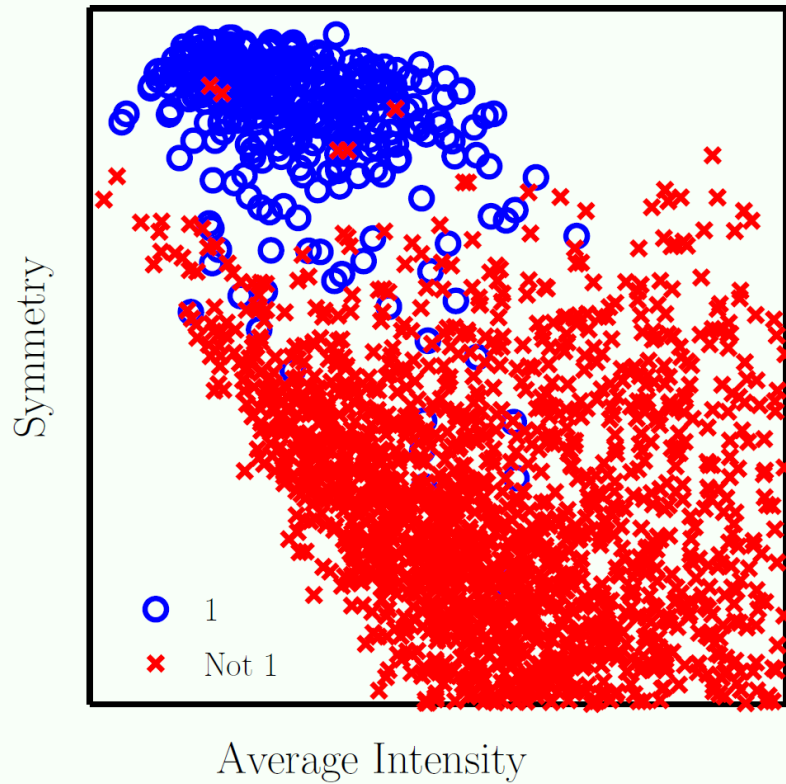
Pick the model with the minimum validation error: $g_{m^*}^-$



Summary of Results

- **Noise** (stochastic o deterministic) affects learning adversely, leading to overfitting
- **Regularization** helps to prevent overfitting by constraining the model, reducing the impact of the noise, while still giving us flexibility to fit the data.
- **Validation** and **Cross-Validation** are useful techniques for estimating E_{out} . One important use of validation is model selection, in particular to estimate the amount of regularization to use.

Example: digit classification

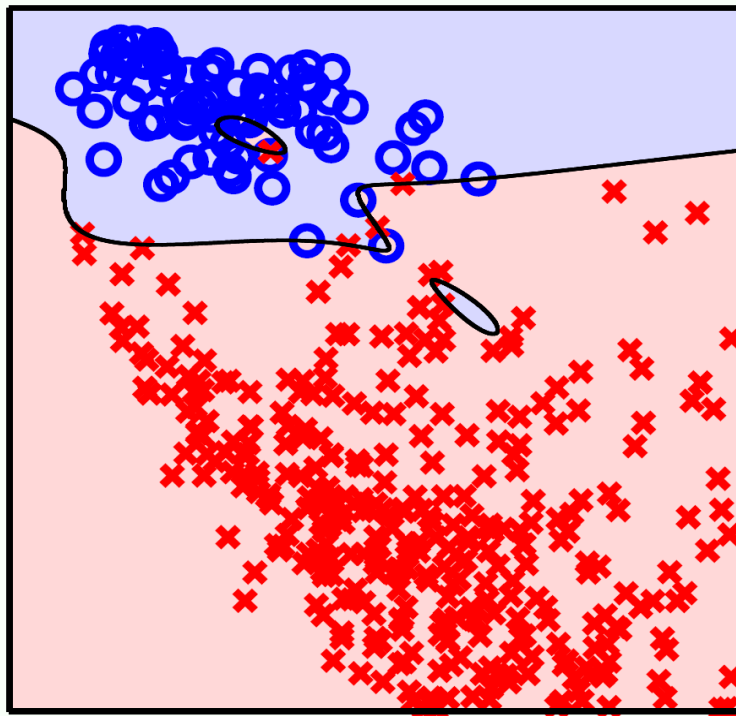


$$\mathbf{x} = (1, x_1, x_2)$$

$$\mathbf{z} = (1, x_1, x_2, x_1^2, x_1x_2, x_2^2, x_1^3, x_1^2x_2, x_1x_2^2, x_2^3, \dots, x_1^5, x_1^4x_2, x_1^3x_2^2, x_1^2x_2^3, x_1x_2^4, x_2^5)$$

5th order polynomial transform \rightarrow 20 dimensional non linear feature space

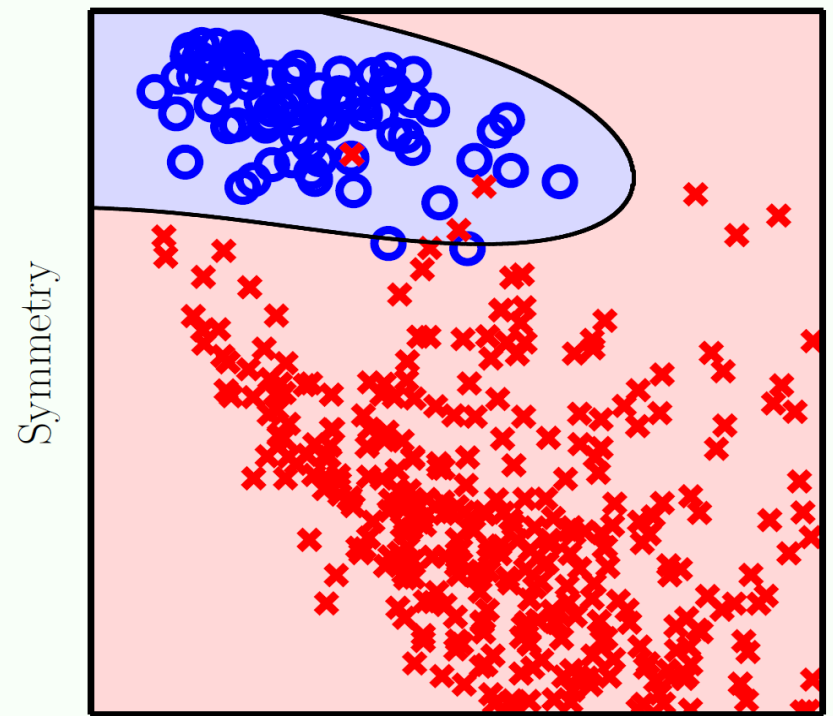
Example: digit classification



Average Intensity

no validation (20 features)

$$E_{\text{in}} = 0\%$$
$$E_{\text{out}} = 2.5\%$$



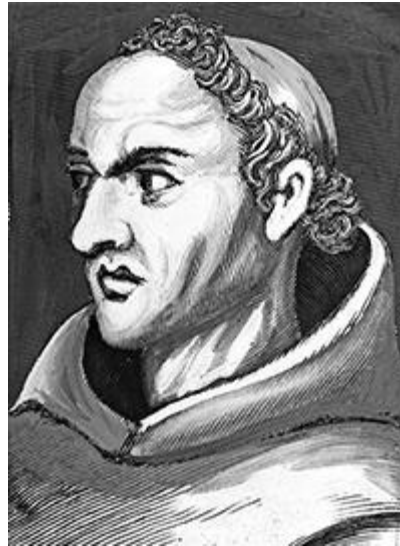
Average Intensity

cross validation (6 features)

$$E_{\text{in}} = 0.8\%$$
$$E_{\text{out}} = 1.5\%$$

Three Learning Principles

Occam's razor

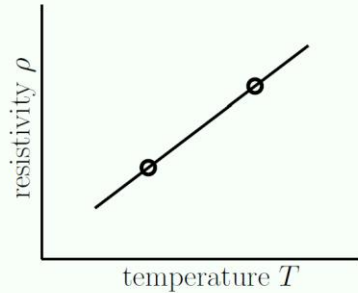


Entities should not be multiplied beyond necessity “Occam’s razor”
principle attributed to William of Occam c. 1280–1349

We should seek simpler models over complex ones and optimize the tradeoff between model complexity and the accuracy of model’s description of the training data

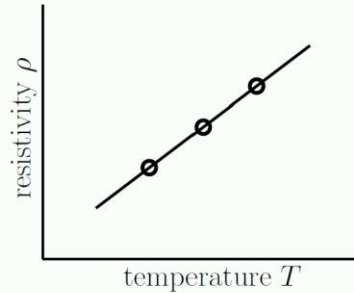
Scientific Experiment

Scientist 1



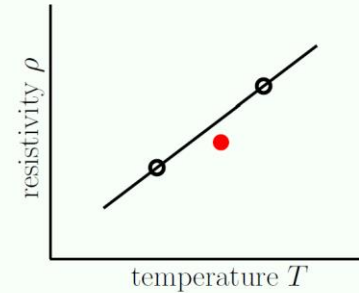
no evidence

Scientist 2



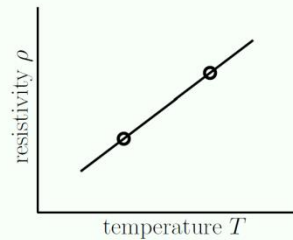
Very convincing

Scientist 3



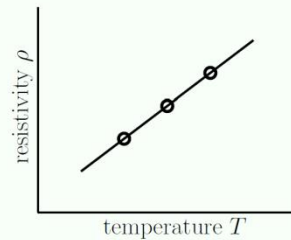
some evidence?

Scientist 1



no evidence

Scientist 2



very convincing

Axiom of Non-Falsifiability.

If an experiment has no chance of falsifying a hypothesis, then the result of that experiment provides no evidence one way or the other for the hypothesis.

Sampling Bias in Learning

If the data is sampled in a biased way, learning will produce a similarly biased outcome.

. . . or, make sure the training and test distributions are the same.

You cannot draw a sample from one distribution and make claims about another distribution

Example.1: Consider the data set of customer loan from a Bank. ¿where is the bias when used to build a rule for new credit appointment ?

Example.2: Consider the data set of historical values of the current trading companies to select companies in which to invest ¿where is the bias?

Data Snooping

If a data set has affected any step in the learning process, it cannot be fully trusted in assessing the outcome.

- ... or, estimate performance with a completely uncontaminated test set
- ... and, **choose \mathcal{H} before** looking at the data

Example : Consider a 8 years data set of the daily changes USD/EURO. We want predict UP/DOWN.

Before fitting a model:

- 1.- We normalize the fully data set.
- 2.- We separate the last two years from the data set as Test Set.
- 3.- We fit a model
- 4.- The fitted model works very well on the data set,
- 5.- But when used with new data the prediction error was very high,
is there any rational explanation ?

Data Snooping is a Subtle Happy Hell

- The data looks linear, so I will use a linear model, and it worked.
 - If the data were different and didn't look linear, would you do something different?
- Try linear, it fails; try circles it works.
 - If you torture the data enough, it will confess.
- Try linear, it works; so I don't need to try circles.
 - Would you have tried circles if the data were different?
- Read papers, see what others did on the data. Modify and improve on that.
 - If the data were different, would that modify what others did and hence what you did?
 - the data snooping can happen all at once or sequentially by different people
- Input normalization: normalize the data, now set aside the test set.
 - Since the test set was involved in the normalization, wouldn't your g change if the test set changed?