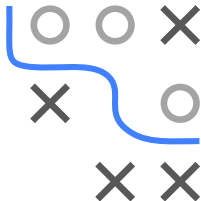


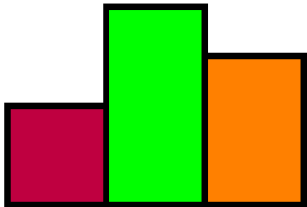
Introduction to Machine Learning

Evaluation: Generalization Error



Learning goals

- Understand the goal of performance estimation
- Know the formal definition of generalization error as a statistical estimator of future performance
- Understand the difference between GE for a model and GE for a learner.
- Understand the difference between outer and inner loss



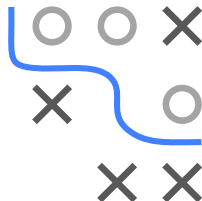
PERFORMANCE ESTIMATION

- For a trained model, we want to know its future **performance**.
- Training works by ERM on $\mathcal{D}_{\text{train}}$ (inducer, loss, risk minimization):

$$\mathcal{I} : \mathbb{D} \times \mathbf{\Lambda} \rightarrow \mathcal{H}, \quad (\mathcal{D}, \lambda) \mapsto \hat{f}_{\mathcal{D}, \lambda}.$$

$$\min_{\theta \in \Theta} \sum_{i=1}^n L\left(y^{(i)}, f\left(\mathbf{x}^{(i)} \mid \theta\right)\right)$$

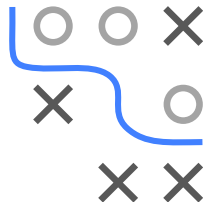
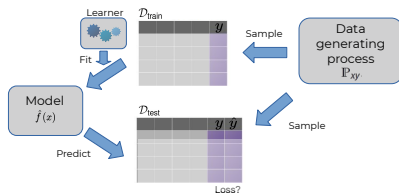
- Due to effects like overfitting, we cannot simply use this **training error** to gauge our model, this is likely optimistically biased. (more on this later!)
- We want: the true expected loss, a.k.a. **generalization error**.
- To reliably estimate it, we need independent, unseen **test data**.
- This simply simulates the application of the model in reality.



GE FOR A FIXED MODEL

- GE for a fixed model: $\text{GE}(\hat{f}, L) := \mathbb{E} \left[L(y, \hat{f}(\mathbf{x})) \right]$
Expectation over a single, random test point $(\mathbf{x}, y) \sim \mathbb{P}_{xy}$.
- Estimator, **if a dedicated test set is available** (size m)

$$\widehat{\text{GE}}(\hat{f}, L) := \frac{1}{m} \sum_{(\mathbf{x}, y) \in \mathcal{D}_{\text{test}}} \left[L(y, \hat{f}(\mathbf{x})) \right]$$



NB: Very often, no dedicated test-set is available, and what we describe here is not same as hold-out splitting (see later).

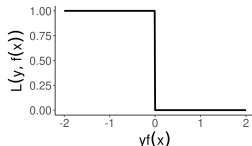
INNER VS OUTER LOSS

- Sometimes, we would like to evaluate our learner with a different loss L or metric ρ .
- Nomenclature: ERM and **inner loss**; evaluation and **outer loss**.
- Different losses, if computationally advantageous to deviate from outer loss of application; e.g., optimization faster with inner L2 or maybe no implementation for outer loss exists.



Example: Linear binary classifier / Logistic regression.

- Outside: We often want to eval with "nr of misclassified examples", so 0-1 loss.
- Problem: 0-1 neither differentiable nor continuous. Hence: Inner loss = binomial. (0-1 actually NP hard).
- For evaluation, differentiability is not required.



SET-BASED PERFORMANCE METRICS

- Metric ρ measures quality of predictions as scalar on one test set.

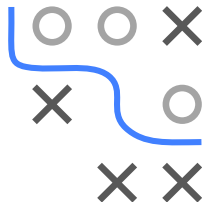
$$\rho : \bigcup_{m \in \mathbb{N}} (\mathcal{Y}^m \times \mathbb{R}^{m \times g}) \rightarrow \mathbb{R}, \quad (\mathbf{y}, \mathbf{F}) \mapsto \rho(\mathbf{y}, \mathbf{F}).$$

- Needed as some metrics are not observation-based losses but defined on sets, e.g. AUC or metrics in survival analysis.
- For test data of size m , \mathbf{F} is prediction matrix

$$\mathbf{F} = \begin{bmatrix} \hat{f}(\mathbf{x}^{(1)}) \\ \dots \\ \hat{f}(\mathbf{x}^{(m)}) \end{bmatrix} \in \mathbb{R}^{m \times g}$$

- Point-wise loss L can easily be extended to a ρ_L :

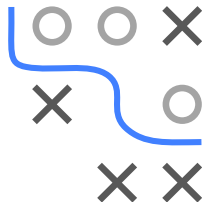
$$\rho_L(\mathbf{y}, \mathbf{F}) = \frac{1}{m} \sum_{i=1}^m L(y^{(i)}, \mathbf{F}^{(i)}) \quad \left(= \frac{1}{m} \sum_{i=1}^m L(y^{(i)}, \hat{f}(\mathbf{x}^{(i)})) \right).$$



MODEL GE VS. LEARNER GE

To clear up a major point of confusion (or totally confuse you):

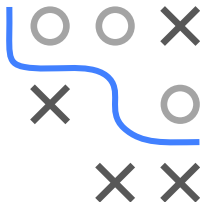
- In ML we frequently face a weird situation.
- We are usually given a single data set, and at the end of our model fitting (and evaluation and selection) process, we will likely fit one model on exactly that complete data set.
- We only trust in unseen-test-error estimation – but have no data left for that final model.
- So in the construction of any practical estimator we cannot really use that final model!
- Hence, we will now evaluate the next best thing: The inducer, and the quality of a model produced when fitted on (nearly) the same number of points!



GENERALIZATION ERROR FOR INDUCER

$$\text{GE}(\mathcal{I}, \lambda, n_{\text{train}}, \rho) := \lim_{n_{\text{test}} \rightarrow \infty} \mathbb{E} [\rho(\mathbf{y}, \mathbf{F}_{\mathcal{D}_{\text{test}}, \mathcal{I}(\mathcal{D}_{\text{train}}, \lambda)})]$$

- Quality of models when fitted with \mathcal{I}_λ on n_{train} points from \mathbb{P}_{xy} .
- Expectation **both** over $\mathcal{D}_{\text{train}}$ and $\mathcal{D}_{\text{test}}$, sampled independently.
- This is estimated by all following **resampling** procedures.
- NB: All of the models produced during that phase of evaluation are only intermediate results.



GENERALIZATION ERROR FOR INDUCER

$$\text{GE}(\mathcal{I}, \boldsymbol{\lambda}, n_{\text{train}}, \rho) := \lim_{n_{\text{test}} \rightarrow \infty} \mathbb{E} [\rho(\mathbf{y}, \mathbf{F}_{\mathcal{D}_{\text{test}}, (\mathcal{I}(\mathcal{D}_{\text{train}}, \boldsymbol{\lambda}))})]$$

- We can already see a potential source of pessimistic bias in our estimator: While we would like to estimate a GE with $n_{\text{train}} = |\mathcal{D}|$, the size of the complete data set, in practice we can only do this for strictly smaller values, so that test data is left to work with.
- For pointwise losses ρ_L :

$$\text{GE}(\mathcal{I}, \boldsymbol{\lambda}, n_{\text{train}}, \rho_L) := \mathbb{E} [L(y, \mathcal{I}(\mathcal{D}_{\text{train}}, \boldsymbol{\lambda})(\mathbf{x}))]$$

Expectation **both** over $\mathcal{D}_{\text{train}}$ and (\mathbf{x}, y) independently from \mathbb{P}_{xy} .

- Retcon for GE of model: GE of learner, conditional on $\mathcal{D}_{\text{train}}$

$$\text{GE}(\hat{f}, L) := \text{GE}(\mathcal{I}, \boldsymbol{\lambda}, n_{\text{train}}, \rho_L | \mathcal{D}_{\text{train}})$$

if $\hat{f} = \mathcal{I}(\mathcal{D}_{\text{train}}, \boldsymbol{\lambda})$ and $n_{\text{train}} = |\mathcal{D}_{\text{train}}|$.

