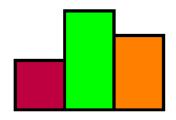
Introduction to Machine Learning

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**.
- ullet Training works by ERM on \mathcal{D}_{train} (inducer, loss, risk minimization):

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

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

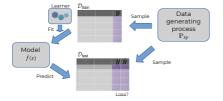
- Due to effects like overfitting, we cannot simply use this training error to gauge our model, this is likely optimistically biased. (more on this later!)
- We want: the true expected loss, a.k.a. generalization error.
- To reliably estimate it, we need independent, unseen **test data**.
- This simply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



GE FOR A FIXED MODEL

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

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

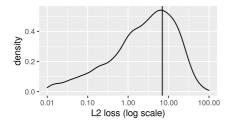


NB: Very often, no dedicated test-set is available, and what we describe here is not same as hold-out splitting (see later).



EXAMPLE: TEST LOSS AS RANDOM VARIABLE

- For a fixed model and dedicated i.i.d. test set, we can easily approximate the complete test loss distribution $L(y, \hat{f}(\mathbf{x}))$.
- LM on mlbench::friedman1 test problem
- With $n_{\rm train} = 500$ we create a fixed model
- We feed 5000 fresh test points to model
- And plot the pointwise L2 loss.



- The result is a unimodal distribution with long tails.
- Mean and one standard deviation to either side are highlighted in grey.

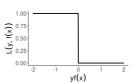


INNER VS OUTER LOSS

- 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 misclassifed 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

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

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

- 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*, **F** is prediction matrix

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

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

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



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

$$ext{GE}(\mathcal{I}, oldsymbol{\lambda}, \emph{n}_{ ext{train}},
ho) := \lim_{n_{ ext{test}} o \infty} \mathbb{E}\left[
ho\left(oldsymbol{y}, oldsymbol{F}_{\mathcal{D}_{ ext{test}}, \mathcal{I}(\mathcal{D}_{ ext{train}}, oldsymbol{\lambda})}
ight)
ight]$$

- Quality of models when fitted with \mathcal{I}_{λ} on n_{train} points from \mathbb{P}_{xy} .
- Expectation **both** over \mathcal{D}_{train} and \mathcal{D}_{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

$$\mathrm{GE}(\mathcal{I}, oldsymbol{\lambda}, \emph{n}_{\mathrm{train}},
ho) := \lim_{\emph{n}_{\mathrm{test}} o \infty} \mathbb{E}\left[
ho\left(oldsymbol{y}, oldsymbol{F}_{\mathcal{D}_{\mathrm{test}}, (\mathcal{I}(\mathcal{D}_{\mathrm{train}}, oldsymbol{\lambda})}
ight)
ight]$$

- 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 :

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

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

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

$$\operatorname{GE}\left(\hat{\pmb{ au}}, \pmb{L}
ight) := \operatorname{GE}(\mathcal{I}, \pmb{\lambda}, \pmb{n_{ ext{train}}},
ho_{\pmb{L}} | \mathcal{D}_{\mathsf{train}})$$

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

