EE-559 – Deep learning

2.4. Proper evaluation protocols

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Learning algorithms, in particular deep-learning ones, require the tuning of many meta-parameters.

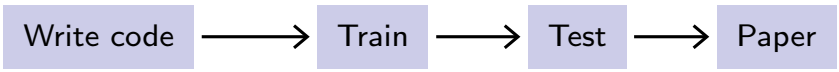
These parameters have a strong impact on the performance, resulting in a "meta" over-fitting through experiments.

We must be extra careful with performance estimation.

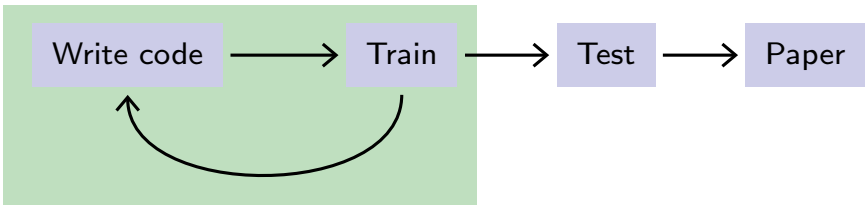
Running 100 times the same experiment on MNIST, with randomized weights, we get:

Worst	Median	Best
1.3%	1.0%	0.82%

The ideal development cycle is

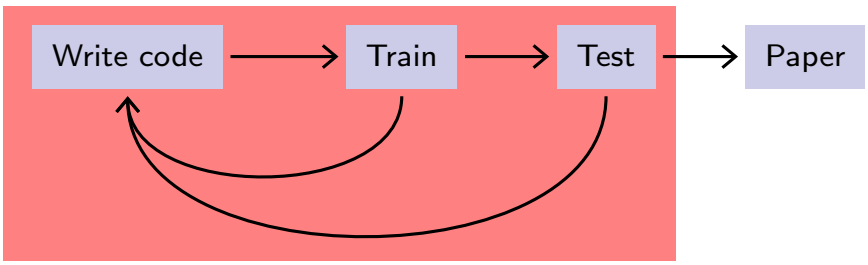


or in practice something like

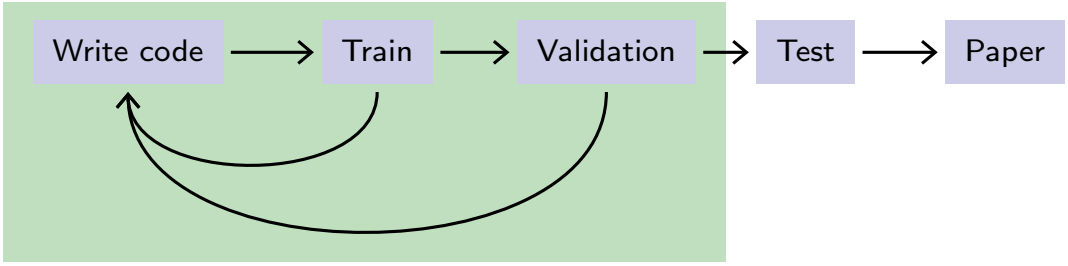


There may be over-fitting, but it does not bias the final performance evaluation.

Unfortunately, it often looks like



⚠ This should be avoided at all costs. The standard strategy is to have a separate validation set for the tuning.

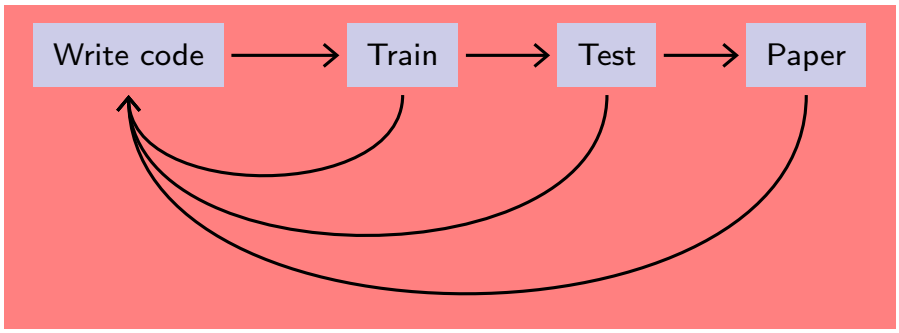


When data is scarce, one can use cross-validation: average through multiple random splits of the data in a train and a validation sets.

There is no unbiased estimator of the variance of cross-validation valid under all distributions (Bengio and Grandvalet, 2004).

Some data-sets (MNIST!) have been used by thousands of researchers, over millions of experiments, in hundreds of papers.

The global overall process looks more like



"Cheating" in machine learning, from bad to "are you kidding?":

- "Early evaluation stopping",
- meta-parameter (over-)tuning,
- data-set selection,
- algorithm data-set specific clauses,
- seed selection.

Top-tier conferences are demanding regarding experiments, and are biased against "complicated" pipelines.

The community pushes toward accessible implementations, reference data-sets, leader boards, and constant upgrades of benchmarks.

References

Y. Bengio and Y. Grandvalet. No unbiased estimator of the variance of k-fold cross-validation. *Journal of Machine Learning Research (JMLR)*, 5:1089–1105, 2004.