EE-559 – Deep learning

2.4. Proper evaluation protocols

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https://fleuret.org/ee559/

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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

Write code $\longrightarrow$ Train

The ideal development cycle is

Write code $\longrightarrow$ Train $\longrightarrow$ Test

The ideal development cycle is

Write code $\longrightarrow$ Train $\longrightarrow$ Test $\longrightarrow$ Paper

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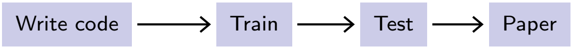
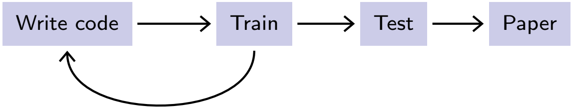


or in practice something like



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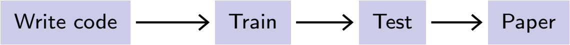

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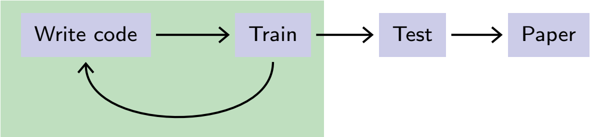
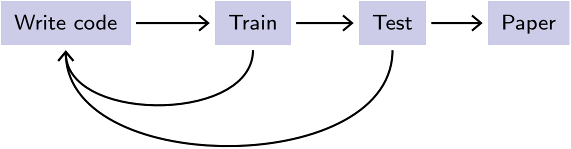


There may be over-fitting, but it does not bias the final performance evaluation.

Unfortunately, it often looks like

$$\begin{tikzcd} \text{Write code} \arrow[r] & \text{Train} \arrow[l, bend left] \arrow[r] & \text{Test} \arrow[r] & \text{Paper} \end{tikzcd}$$

Unfortunately, it often looks like



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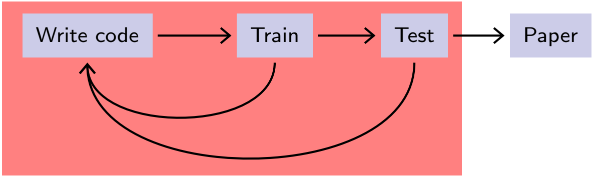

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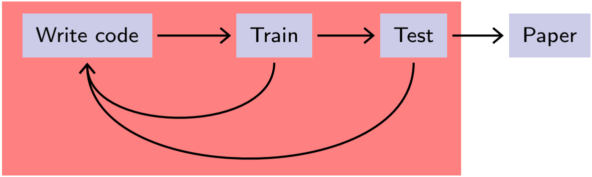

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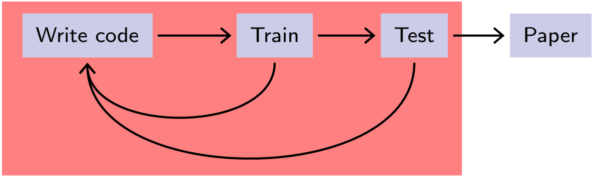

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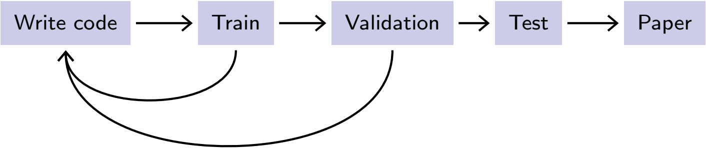

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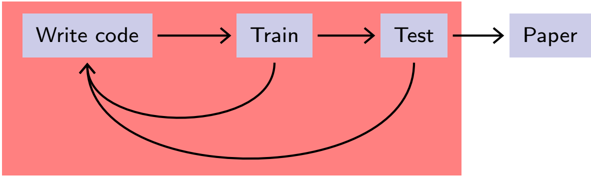

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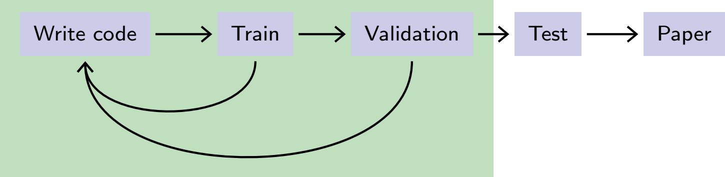

When data is scarce, one can use cross-validation: average through multiple random splits of the data in a train and a validation sets.

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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.

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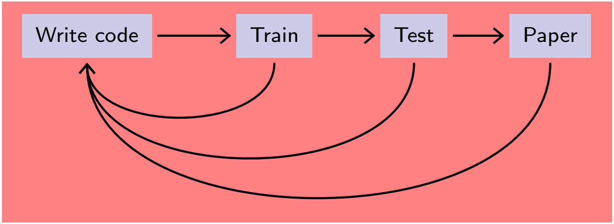
The global overall process looks more like



"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.

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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.

The end

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.