

EE-559 – Deep learning

2.4. Proper evaluation protocols

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<https://fleuret.org/ee559/>

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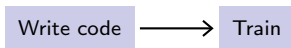
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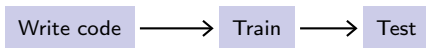
Running 100 times the same experiment on MNIST, with randomized weights, we get:

Worst	Median	Best
1.3%	1.0%	0.82%

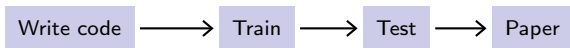
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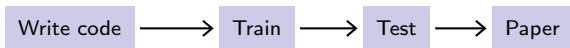
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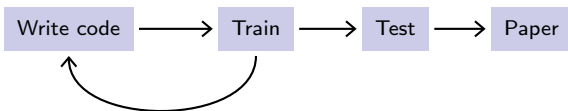
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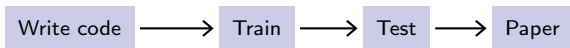
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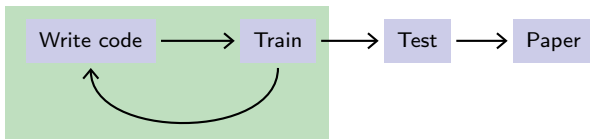
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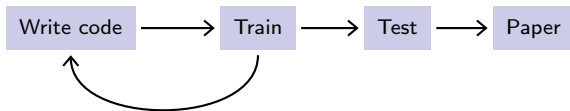


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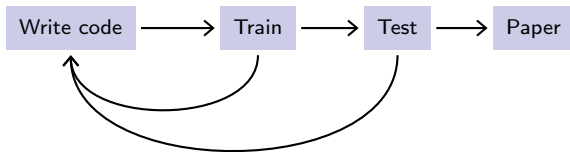


There may be over-fitting, but it does not bias the final performance evaluation.

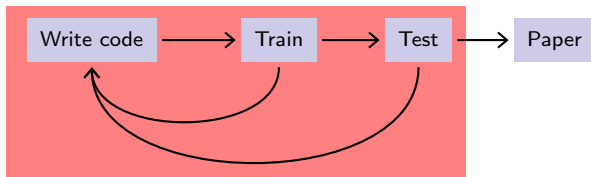
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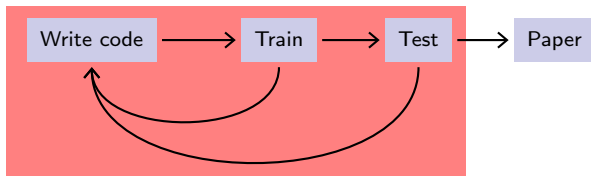
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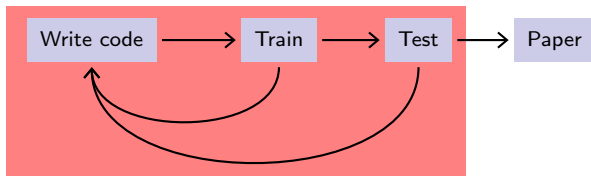


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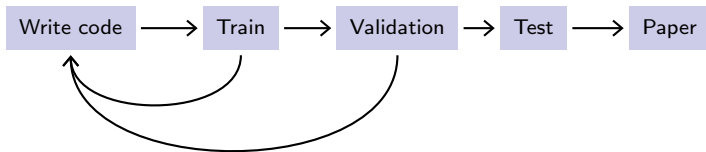


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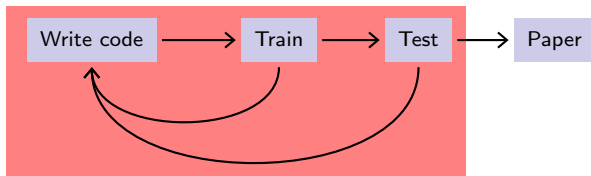
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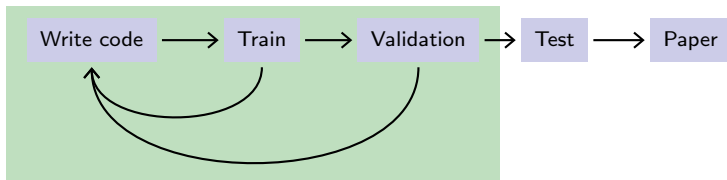
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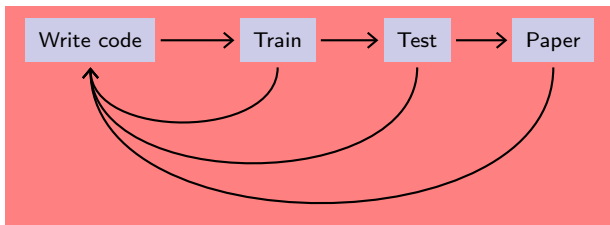
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There is no unbiased estimator of the variance of cross-validation valid under all distributions (Bengio and Grandvalet, 2004).

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The global overall process looks more like



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- “Early evaluation stopping” ,
- meta-parameter (over-)tuning,
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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.