# Deep learning

## 2.4. Proper evaluation protocols

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

| Worst | Median | Best |
|---|---|---|
| 1.3% | 1.0% | 0.82% |

The ideal development cycle is

Write code $\longrightarrow$ Train

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or in practice something like

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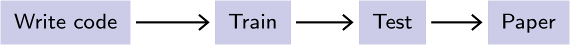


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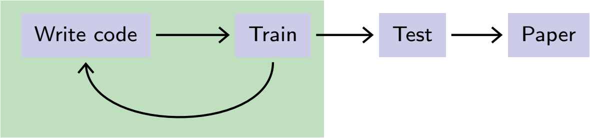


There may be over-fitting, but it does not bias the final performance evaluation.

Unfortunately, it often looks like

$$
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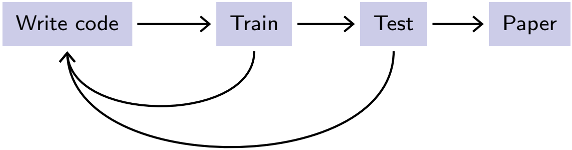

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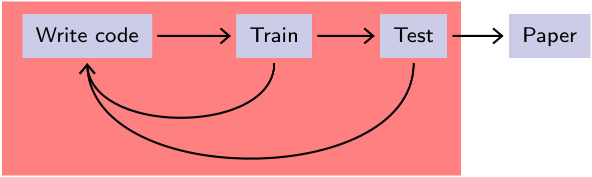

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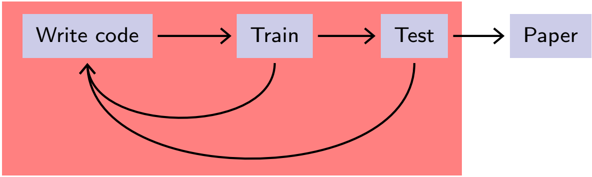


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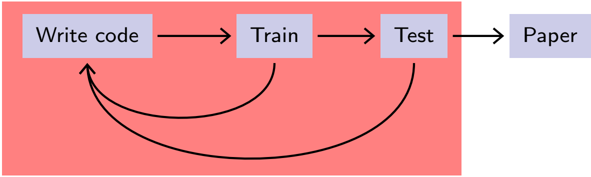


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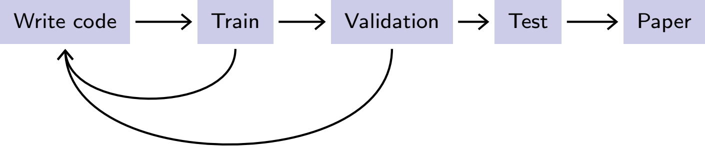

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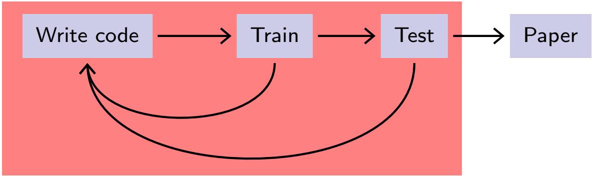


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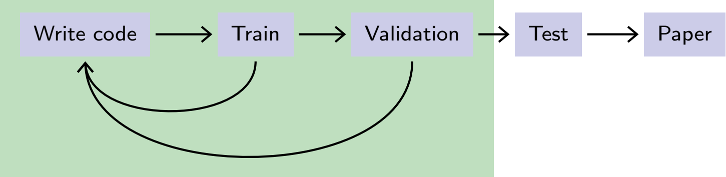

When data is scarce, one can use cross-validation: average through multiple random splits of the data in a train and a validation sets.

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

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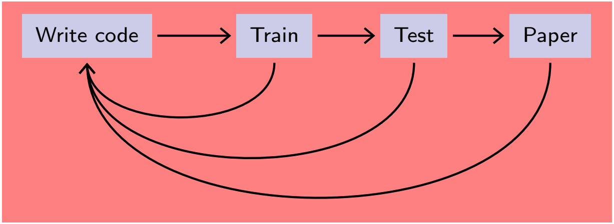
The global overall process looks more like



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

- "Early evaluation stopping",
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- algorithm data-set specific clauses,
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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.