Deep learning

2.4. Proper evaluation protocols

François Fleuret
https://fleuret.org/dlc/
Learning algorithms, in particular deep-learning ones, require the tuning of many meta-parameters.
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.
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.
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 MNIST experiment, with randomized weights, we get:

<table>
<thead>
<tr>
<th></th>
<th>Worst</th>
<th>Median</th>
<th>Best</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>1.3%</td>
<td>1.0%</td>
<td>0.82%</td>
</tr>
</tbody>
</table>
The ideal development cycle is

Write code $\rightarrow$ Train
The ideal development cycle is

Write code → Train → Test
The ideal development cycle is

Write code → Train → Test → Paper
The ideal development cycle is

Write code → Train → Test → Paper

or in practice something like

Write code → Train → Test → Paper

There may be over-fitting, but it does not bias the final performance evaluation.
The ideal development cycle is

![Diagram of the development cycle: Write code → Train → Test → Paper]

or in practice something like

![Diagram of the practical development cycle: Write code → Train → Test → Paper]

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

Write code → Train → Test → Paper

This should be avoided at all costs. The standard strategy is to have a separate validation set for the tuning.
Unfortunately, it often looks like
Unfortunately, it often looks like

![Diagram showing the process of writing code, training, testing, and publishing a paper. The diagram includes arrows from 'Write code' to 'Train', from 'Train' to 'Test', and from 'Test' to 'Paper'.]
Unfortunately, it often looks like

![Diagram](image)

This should be avoided at all costs. The standard strategy is to have a separate validation set for the tuning.
Unfortunately, it often looks like

![Diagram](image.png)

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

![Diagram](image.png)
Unfortunately, it often looks like

Write code → Train → Test → Paper

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

Write code → Train → Validation → Test → Paper
When data is scarce, one can use cross-validation: average through multiple random splits of the data in a train and a validation sets.
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.
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.
“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.
The end