EE-559 – Deep learning

2.4. Proper evaluation protocols

François Fleuret
https://fleuret.org/ee559/
Feb 26, 2020
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 → Train
The ideal development cycle is

Write code → Train → Test
The ideal development cycle is

Write code → Train → Test → Paper

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

Write code $\rightarrow$ Train $\rightarrow$ Test $\rightarrow$ Paper

or in practice something like

Write code $\rightarrow$ Train $\rightarrow$ Test $\rightarrow$ Paper

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

![Diagram: Write code → Train → Test → Paper]

or in practice something like

![Diagram: 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

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

Write code → Train → Test → Paper
Unfortunately, it often looks like

![Diagram showing sequence: 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

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

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.
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

```
Write code → Train → Test → Paper
```

François Fleuret
“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
References