9.1. Looking at parameters

François Fleuret
https://fleuret.org/dlc/
Nov 29, 2020
Understanding what is happening in a deep architectures after training is complex and the tools we have at our disposal are limited.

In the case of convolutional feed-forward networks, we can look at

- the network’s parameters, filters as images,
- internal activations on a single sample as images,
- derivatives of the response(s) wrt the input,
- maximum-response synthetic samples,
- adversarial samples.

We can also look at distributions of activations on a population of samples at different stages in a model.
Hidden units of a perceptron
Given a one-hidden layer fully connected network $\mathbb{R}^2 \rightarrow \mathbb{R}^2$

\[
\begin{align*}
\text{nb\_hidden} & = 20 \\
\text{model} & = \text{nn.Sequential}(
    \text{nn.Linear}(2, \text{nb\_hidden}), \\
    \text{nn.ReLU}(), \\
    \text{nn.Linear}(\text{nb\_hidden}, 2)
)
\end{align*}
\]
Given a one-hidden layer fully connected network $\mathbb{R}^2 \rightarrow \mathbb{R}^2$

```python
nb_hidden = 20

model = nn.Sequential(
    nn.Linear(2, nb_hidden),
    nn.ReLU(),
    nn.Linear(nb_hidden, 2)
)
```

we can visit the parameters $(w, b)$ of each hidden units with

```python
for k in range(model[0].weight.size(0)):
    w = model[0].weight[k]
    b = model[0].bias[k]
```

and draw for each the line

$$\{ x : w \cdot x + b = 0 \}.$$
Given a one-hidden layer fully connected network $\mathbb{R}^2 \rightarrow \mathbb{R}^2$

\[
nb\_hidden = 20
\]

\[
model = nn.Sequential(
    nn.Linear(2, nb\_hidden),
    nn.ReLU(),
    nn.Linear(nb\_hidden, 2)
)
\]

we can visit the parameters $(w, b)$ of each hidden units with

\[
\text{for } k \text{ in range(model[0].weight.size(0))}:
    \begin{align*}
    w &= model[0].weight[k] \\
    b &= model[0].bias[k]
    \end{align*}
\]

and draw for each the line

\[
\{ x : w \cdot x + b = 0 \}.
\]

During training, these separations get organized so that their combination partitions properly the signal space.
Iteration 1
Iteration 4
Iteration 7
Iteration 10
Iteration 16
Iteration 34
Iteration 77
Iteration 100
Iteration 703
Iteration 1407
Iteration 2789
Iteration 9999
Iteration 1
Iteration 4
Iteration 7
Iteration 10
Iteration 16
Iteration 34
Iteration 100
Iteration 272
Iteration 556
Iteration 2222
Iteration 9999
Convnet filters
A similar analysis is complicated to conduct with real-life networks given the high dimension of the signal.

The simplest approach for convnets consists of looking at the filters as images.

While it is quite reasonable in the first layer, since the filters are indeed consistent with the image input, it is far less so in the subsequent layers.
LeNet’s first convolutional layer (1 $\rightarrow$ 32), all filters
LeNet’s second convolutional layer \((32 \rightarrow 64)\), first 32 filters out of 64
AlexNet’s first convolutional layer ($3 \rightarrow 64$), first 20 filters out of 64
AlexNet’s first convolutional layer \((3 \rightarrow 64)\), first 20 filters out of 64

or as RGB images
AlexNet’s second convolutional layer ($64 \rightarrow 192$). First 15 channels (out of 64) of the first 20 filters (out of 192).
The end