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Note. code examples `torch.nn`.

Let $f: \mathbb{X} \longrightarrow \mathbb{Y}$ be a function we want to learn from observations $\mathscr{D} \in \mathbb{X} \times \mathbb{Y}$

x	$y \simeq f(x)$
x_1	y_1
$\vdots$	$\vdots$
x_n	y_n

The function f can be learned from (noisy) observations $\mathscr{D}$ by optimization if

1. we have a suitably expressive function class $\mathscr{F} := \{f(x;\theta) | \theta \in \Theta\}$ such that $f(x) \simeq f(x;\theta^\star)$ for some parameter (vector) $\theta^\star$ and some quality criterion "$\simeq$".
2. we have a practicable algorithm $A: (\mathscr{D}, \mathscr{F}, \mathscr{H}) \longrightarrow \theta^\star$.

$\longrightarrow$ rich model class, quality criterion and practical inference algorithm $\longleftarrow$

rich model class. (deep) feedforward neural networks

quality criterion. low *test* error: empirical risk minimization + regularization

learning algorithm. descent along gradients calculated by backpropagation

Feedforward neural networks became useful function approximators with concurrent, often interdependent improvements in

- expressivity (depth, conv/pool layers)
- regularization (dropout, early stopping, explicit cost penalties…)
- inference speed/stability (activations, gradient rules, backpropagation…).

networks. graphical expression of function composition

feedforward. no cycles – network is a DAG

neural. each node calculates $h_i = g(x^\top W_{:,i} + c_i)$. The linear combination followed by nonlinear threshold/saturation function resembles a *very* stylized neuron

deep. more layers facilitate training of very expressive networks

`torch.nn.[Conv2d|Linear|Dropout2d|...]`,
`torch.nn.functional.[max_pool2d,|relu|...]`

Note: $H = g(XW + c)$ batch matrix multiplication $\rightarrow$ leverage GPU acceleration

`torch.[.cuda].Tensor`, `a_tensor.to_device(<dev>)`

As our functions are parameterised, we turn this into an optimisation problem:

$$\theta^\star = \text{argmin}_\theta \text{cost}(f(x;\theta), y)$$

Two terms contribute to the cost:

i. loss: penalizes bad predictions, i.e. some idea of *training error*

ii. regularization: penalizes complex f, leading to *generalization error*

→ this is the difference between pure optimization (fit = minimize training error) and a machine *learning* algorithm.

`torch.nn.*loss`

- Find how the cost J depends on each of the parameters θ_i

  $\rightarrow$ *find* gradients, (reverse) differentiation $\rightarrow$ backpropagation

- and adjust the parameters to minimize it

  $\rightarrow$ *use* gradients, learning rule

$$\theta^{[k]} = \theta^{[k-1]} - \eta \nabla_\theta J(\theta), \qquad \eta \in \mathbb{R}^+$$

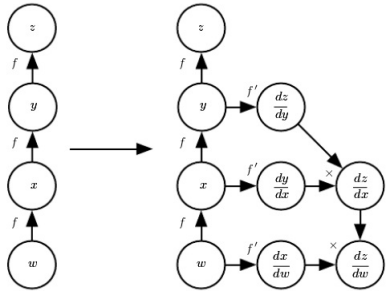
- only local minima – but some of these surprisinly useful in NNs
- since J usually additive on samples, i.e. $J = J_i$ we can perform gradient updates with fixed batch size $\ll$ dataset size $\rightarrow$ *minibatches* (uniform sampling)
- Adadelta, Adagrad, Adam, momentum, RMSprop…

`torch.optim.*`

- gradient descent may need or benefit from learning rate adaptation

`torch.optim.lr_scheduler.*`

Where do the gradients come from?




```
torch.Tensor(..., require_grad=True)
```

```
a_tensor.backward()
```

```
torch.autograd.
```

- dynamic computation graphs vs. declaration/execution phases
- distributed, multimachine training → `torch.distributed`
- C++ model serving → tensorflow.serving
- checkpointing → `torch.utils.checkpoint`
- monitoring / debugging / optimizing → tensorflow.tensorboard
- model porting (to production / other frameworks) → ONNX
- fast forward mode embedded / mobile → tensorflow lite

Alternatives

- caffe 2 (production, mobile) → PyTorch 1.0
- tensorflow: docs, community, tensorboard, serving, lite
- keras (tf, cntk, theano): prototyping, spark,
- mxnet: language agnostic
- cntk: spark, azure