Deep learning

1.4. Tensor basics and linear regression

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https://fleuret.org/dlc/
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- A 0d tensor is a scalar,
- A 1d tensor is a vector (e.g. a sound sample),
- A 2d tensor is a matrix (e.g. a grayscale image),
- A 3d tensor can be seen as a vector of identically sized matrix (e.g. a multi-channel image),
- A 4d tensor can be seen as a matrix of identically sized matrices, or a sequence of 3d tensors (e.g. a sequence of multi-channel images),
- etc.
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**Manipulating data through this constrained structure allows to use CPUs and GPUs at [near] peak performance.**
The “dimension” of a vector in linear algebra is its number of coefficients, while the “dimension” of a tensor is the number of indices to specify one of its coefficients.

E.g. an element of $\mathbb{R}^3$ is a three-dimension vector, but a one-dimension tensor.
PyTorch’s main features are:

- Efficient tensor operations on CPU/GPU,
- automatic on-the-fly differentiation (autograd),
- optimizers,
- data I/O.

"Efficient tensor operations" encompass both standard linear algebra and, as we will see later, deep-learning specific operations (convolution, pooling, etc.). A key specificity of PyTorch is the central role of autograd to compute derivatives of anything! We will come back to this.
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A key specificity of PyTorch is the central role of autograd to compute derivatives of *anything*! We will come back to this.
```python
>>> x = torch.empty(2, 5)
>>> x.size()
torch.Size([2, 5])
>>> x.fill_(1.125)
tensor([[ 1.1250,  1.1250,  1.1250,  1.1250,  1.1250],
        [ 1.1250,  1.1250,  1.1250,  1.1250,  1.1250]])
>>> x.mean()
tensor(1.1250)
>>> x.std()
tensor(0.)
>>> x.sum()
tensor(11.2500)
>>> x.sum().item()
11.25
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In-place operations are suffixed with an underscore, and a 0d tensor can be converted back to a Python scalar with `item()`.
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\begin{itemize}
  \item \textbf{Reading a coefficient returns a 0d tensor.}
\end{itemize}

>>> x = torch.tensor([[11., 12., 13.], [21., 22., 23.]])
>>> x[1, 2]
tensor(23.)
PyTorch provides operators for component-wise and vector/matrix operations.

```python
>>> x = torch.tensor([ 10., 20., 30.])
>>> y = torch.tensor([ 11., 21., 31.])
>>> x + y
  tensor([ 21., 41., 61.])
>>> x * y
  tensor([ 110., 420., 930.])
>>> x**2
  tensor([ 100., 400., 900.])
>>> m = torch.tensor([[ 0., 0., 3. ],
                     [ 0., 2., 0. ],
                     [ 1., 0., 0. ]])
>>> m.mv(x)
  tensor([ 90., 40., 10.])
>>> m @ x
  tensor([ 90., 40., 10.])
```
And as in NumPy, the : symbol defines a range of values for an index and allows to slice tensors.

```python
>>> import torch
>>> x = torch.randint(10, (2, 4))
>>> x
tensor([[8, 7, 6, 6],
        [5, 0, 4, 8]])
>>> x[0]
tensor([8, 7, 6, 6])
>>> x[0, :]
tensor([8, 7, 6, 6])
>>> x[:, 0]
tensor([8, 5])
>>> x[:, 1:3] = -1
>>> x
tensor([[ 8, -1, -1, 6],
        [ 5, -1, -1, 8]])
```
PyTorch provides interfacing to standard linear operations, such as linear system solving or eigen-decomposition.

```python
>>> y = torch.randn(3)
>>> y
tensor([ 1.3663, -0.5444, -1.7488])
>>> m = torch.randn(3, 3)
>>> q = torch.linalg.lstsq(m, y).solution
>>> m@q
```
```
tensor([ 1.3663, -0.5444, -1.7488])
```
Example: linear regression
Given a list of points

\[(x_n, y_n) \in \mathbb{R} \times \mathbb{R}, \ n = 1, \ldots, N,\]

can we find the affine function

\[f(x; a, b) = ax + b\]

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\arg\min_{a, b} \frac{1}{N} \sum_{n=1}^{N} \left( ax_n + b - y_n \right)^2.
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\]

Such a model would allow to predict the \( y \) associated to a new \( x \), simply by calculating \( f(x; a, b) \).
bash> cat systolic-blood-pressure-vs-age.dat
39   144
47   220
45   138
47   145
65   162
46   142
67   170
42   124
67   158
42   124
67   158
56   154
64   162
56   150
59   140
34   110
42   128
/.../
\begin{align*}
\begin{pmatrix}
x_1 & y_1 \\
x_2 & y_2 \\
\vdots & \vdots \\
x_N & y_N \\
\end{pmatrix} & \quad \text{data} \in \mathbb{R}^{N \times 2} \\
\begin{pmatrix}
x_1 & 1.0 \\
x_2 & 1.0 \\
\vdots & \vdots \\
x_N & 1.0 \\
\end{pmatrix} & \quad \alpha \in \mathbb{R}^{2 \times 1} \\
\begin{pmatrix}
y_1 \\
y_2 \\
\vdots \\
y_N \\
\end{pmatrix} & \quad y \in \mathbb{R}^{N \times 1}
\end{align*}

\begin{align*}
\text{import } & \text{ torch, numpy} \\
\text{data } & \text{ = torch.tensor(numpy.loadtxt('systolic-blood-pressure-vs-age.dat'))} \\
\text{nb_samples } & \text{ = data.size(0)} \\
\text{x, y } & \text{ = torch.empty(nb_samples, 2), torch.empty(nb_samples, 1)} \\
\text{x[:, 0] } & \text{ = data[:, 0]} \\
\text{x[:, 1] } & \text{ = 1} \\
\text{y[:, 0] } & \text{ = data[:, 1]} \\
\text{alpha } & \text{ = torch.linalg.lstsq(x, y).solution} \\
\text{a, b } & \text{ = alpha[0, 0].item(), alpha[1, 0].item()}
\end{align*}
import torch, numpy

data = torch.tensor(numpy.loadtxt('systolic-blood-pressure-vs-age.dat'))

nb_samples = data.size(0)

x, y = torch.empty(nb_samples, 2), torch.empty(nb_samples, 1)

x[:, 0] = data[:, 0]
x[:, 1] = 1

y[:, 0] = data[:, 1]

alpha = torch.linalg.lstsq(x, y).solution

a, b = alpha[0, 0].item(), alpha[1, 0].item()
The end