EE-559 – Deep learning

1.4. Tensor basics and linear regression

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- 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 matrix, or a sequence of 3d tensors (*e.g.* a sequence of multi-channel images),
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Compounded data structures can represent more diverse data types.

PyTorch is a Python library built on top of Torch's THNN computational backend.

Its main features are:

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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.

```
>>> 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]])
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>>> x.std()
tensor(0.)
>>> x.sum()
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>>> x.sum().item()
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Reading a coefficient also generates a 0d tensor.

```
>>> x = torch.tensor([[11., 12., 13.], [21., 22., 23.]])
>>> x[1, 2]
tensor(23.)
```

PyTorch provides operators for component-wise and vector/matrix operations.

```
>>> 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.

```
>>> x = torch.empty(2, 4).random_(10)
>>> x
tensor([[ 8.,  3.,  3.,  4.],
        [ 7.,  0.,  6.,  4.]])
>>> x[0]
tensor([ 8.,  3.,  3.,  4.])
>>> x[0,:]
tensor([ 8.,  3.,  3.,  4.])
>>> x[:,0]
tensor([ 8.,  7.])
>>> x[:,1:3] = -1
>>> x
tensor([[ 8., -1., -1.,  4.],
        [ 7., -1., -1.,  4.]])
```

PyTorch provides interfacing to standard linear operations, such as linear system solving or Eigen-decomposition.

```
>>> y = torch.empty(3).normal_()
>>> y
tensor([ 0.0477,  0.8834, -1.5996])
>>> m = torch.empty(3, 3).normal_()
>>> q, _ = torch.gels(y, m)
>>> torch.mm(m, q)
tensor([[ 0.0477],
        [ 0.8834],
        [-1.5996]])
```

Example: linear regression

Given a list of points

$$(x_n, y_n) \in \mathbb{R} \times \mathbb{R}, \; n = 1, \dots, N,$$

can we find the "best line"

$$f(x; a, b) = ax + b$$

going "through the points"

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$$\underset{a,b}{\operatorname{argmin}} \frac{1}{N} \sum_{n=1}^{N} \Big(\underbrace{a x_n + b}_{f(x_n; a, b)} - y_n \Big)^2.$$

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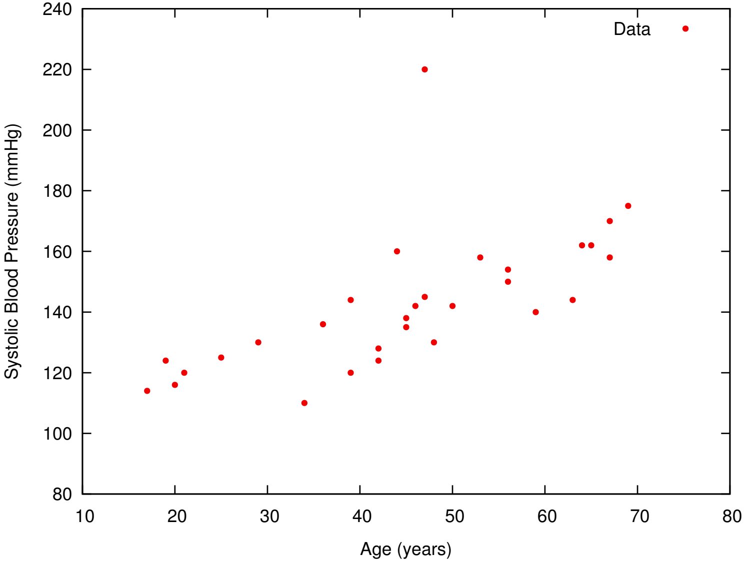
Such a model would allow to predict the y associated to a new x, simply by calculating $f(x; a, b)$.

```
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
56  154
64  162
56  150
59  140
34  110
42  128
/.../
```


Data
Systolic Blood Pressure (mmHg)
240
220
200
180
160
140
120
100
80
10
20
30
40
50
60
70
80
Age (years)

$$\underbrace{\begin{pmatrix} x_1 & y_1 \\ x_2 & y_2 \\ \vdots & \vdots \\ x_N & y_N \end{pmatrix}}_{\text{data} \in \mathbb{R}^{N \times 2}}$$

$$\underbrace{\begin{pmatrix} x_1 & 1.0 \\ x_2 & 1.0 \\ \vdots & \vdots \\ x_N & 1.0 \end{pmatrix}}_{x \in \mathbb{R}^{N \times 2}} \underbrace{\begin{pmatrix} a \\ b \end{pmatrix}}_{\alpha \in \mathbb{R}^{2 \times 1}} \simeq \underbrace{\begin{pmatrix} y_1 \\ y_2 \\ \vdots \\ y_N \end{pmatrix}}_{y \in \mathbb{R}^{N \times 1}}$$

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```
import torch, numpy

data = torch.tensor(numpy.loadtxt('systolic-blood-pressure-vs-age.dat'))
nb_samples = data.size(0)

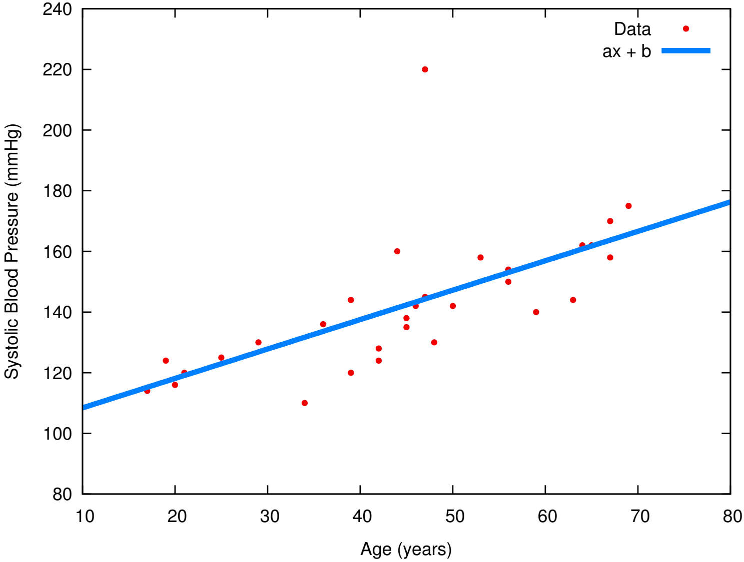
x, y = torch.empty(nb_samples, 2), torch.empty(nb_samples, 1)

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

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

alpha, _ = torch.gels(y, x)

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



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ax + b
Systolic Blood Pressure (mmHg)
Age (years)
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The end