

Basics of Tensors and Simple Example

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① Generalized matrix

Tensor

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- ② Finite table of data

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- ③ Indexed along discrete dimensions

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- ④ 3D tensor \rightarrow vector of identically sized matrices (e.g. RGB image)
- ⑤ 4D tensor \rightarrow matrix of identically sized matrices or a sequence of 3D tensors (e.g. sequence of RGB images)

Tensor

1D TENSOR/
VECTOR



2D TENSOR /
MATRIX



3D TENSOR/
CUBE

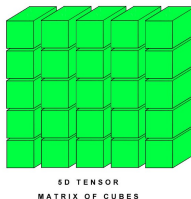
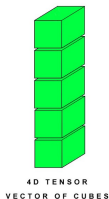
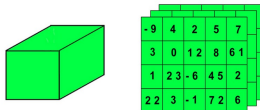


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- 1
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 - Internal states and parameters of the model

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 - Encoding signals (e.g. text, speech, image, etc.)
 - Internal states and parameters of the model
- ② Operating on data through this constrained structure allows CPUs and GPUs to operate at their near peak performance.

PyTorch's main features

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 - Variety of optimizers (e.g. SGD, Adam, etc.); Hassle-free to apply
- ④ Data i/o
 - Load a data sample or datasets, etc.

Tensor Basics

► Colab Notebook: Tensor basics

Example: Linear Regression

Linear Regression

- ① Given a set of data points $(x_n, y_n) \in \mathcal{R} \times \mathcal{R}, n = 1, 2, \dots N$

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Linear Regression

- ① Given a set of data points $(x_n, y_n) \in \mathcal{R} \times \mathcal{R}, n = 1, 2, \dots, N$
- ② Finding the best line that fits the data, $f(x; a, b) = ax + b$
- ③ i.e., minimizes the mean squared error (MSE),

$$\arg \min_{a,b} \frac{1}{N} \sum_{i=1}^N (ax_n + b - y_n)^2$$

Linear Regression

$$① \quad a = \frac{\sum_{i=1}^N (x_i - \bar{x})(y_i - \bar{y})}{\sum_{i=1}^N (x_i - \bar{x})^2}$$

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$$\textcircled{2} \quad b = \bar{y} - a\bar{x}$$

Linear Regression

► Colab Notebook: Linear Regression

Tensors can be

- `torch.float16`, `torch.float32`, `torch.float64`
- `torch.uint8`
- `torch.int8`, `torch.int16`, `torch.int32`, `torch.int64`

Tensors can be

- Located either in CPU or in GPU
- Operations are performed only by that device in whose memory the tensor is stored