



Machine Learning: Elements of **Linear Algebra**

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Introduction to Machine Learning

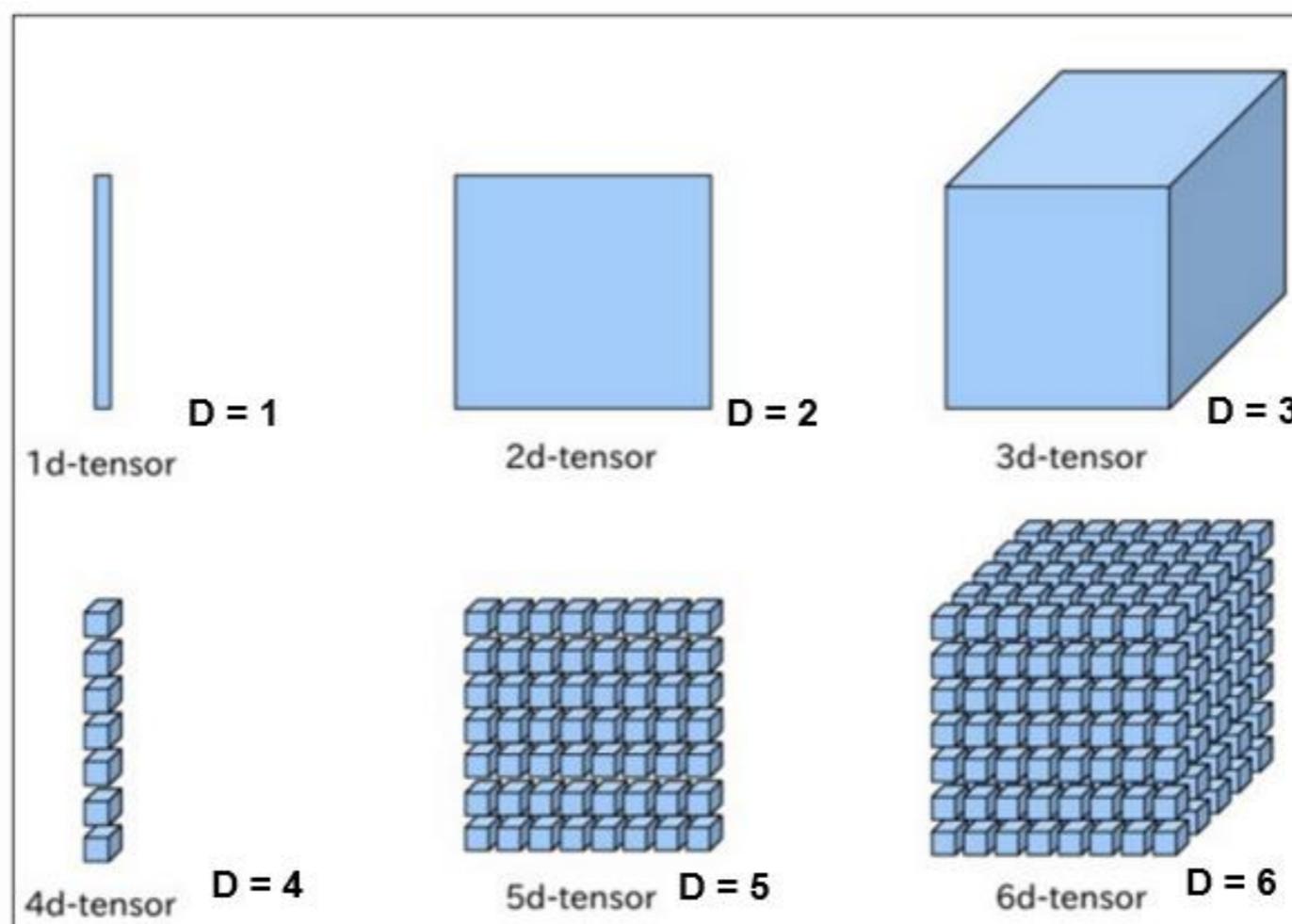
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So, Again, What are Tensors?

```
import numpy as np
```

- A building block of linear algebra
- A mathematical formalism for a multi-dimensional collection / object – houses items, notably numbers / values
 - In Python, there are often called arrays or n-dimensional arrays (*ndarrays*)



Transposing/manipulation in NumPy

$$(\mathbf{A}^T)_{i,j} = A_{j,i}$$

$$\mathbf{x} = [x_1, \dots, x_n]^T$$

Table 2-12. Summary of NumPy Functions for Array Operations

Function	Description
<code>np.transpose</code> , <code>np.ndarray.transpose</code> , <code>np.ndarray.T</code>	Transpose (reverse axes) an array.
<code>np.fliplr</code> / <code>np.flipud</code>	Reverse the elements in each row/column.
<code>np.rot90</code>	Rotate the elements along the first two axes by 90 degrees.
<code>np.sort</code> , <code>np.ndarray.sort</code>	Sort an array's elements along a specified axis (which defaults to the last axis of the array). The <code>np.ndarray</code> method <code>sort</code> performs the sorting in place, modifying the input array.

$$A = \begin{bmatrix} A_{1,1} & A_{1,2} \\ A_{2,1} & A_{2,2} \\ A_{3,1} & A_{3,2} \end{bmatrix} \Rightarrow A^T = \begin{bmatrix} A_{1,1} & A_{2,1} & A_{3,1} \\ A_{1,2} & A_{2,2} & A_{3,2} \end{bmatrix}$$

Hadamard Product

- Multiply each $A(i, j)$ to each corresponding $B(i, j)$
- Element-wise multiplication

0.5	-0.7
-0.69	1.8

 \odot

0.5	-0.7
-0.69	1.8

 =

$.5 * .5 = .25$	$-.7 * .7 = .49$
$-.69 * -.69 = .4761$	$1.8 * 1.8 = 3.24$

Elementwise Functions

- Applied to each element (i, j) of matrix/vector argument
 - Could be $\cos(\cdot)$, $\sin(\cdot)$, $\tanh(\cdot)$, etc. (the “.” means argument)
- *Identity*: $\phi(\mathbf{v}) = \mathbf{v}$
- *Logistic Sigmoid*: $\phi(\mathbf{v}) = \sigma(\mathbf{v}) = \frac{1}{1+e^{-\mathbf{v}}}$
- *Softmax*: $\phi(\mathbf{v}) = \frac{\exp(\mathbf{v})}{\sum_{c=1}^C \exp(\mathbf{v}_c)}$ $\mathbf{v} \in \mathbb{R}^C$
- *Linear Rectifier*: $\phi(\mathbf{v}) = \max(0, \mathbf{v})$

$$\varphi \left(\begin{array}{|c|c|} \hline 1.0 & -1.4 \\ \hline -0.69 & 1.8 \\ \hline \end{array} \right) = \begin{array}{|c|c|} \hline \varphi(1.0) = 1 & \varphi(-1.4) = 0 \\ \hline \varphi(-0.69) = 0 & \varphi(1.8) = 1.8 \\ \hline \end{array}$$

Elementwise Operators

Table 2-6. Operators for Elementwise Arithmetic Operation on NumPy Arrays

Operator	Operation
<code>+, +=</code>	Addition
<code>-, -=</code>	Subtraction
<code>*, *=</code>	Multiplication
<code>/, /=</code>	Division
<code>//, //=</code>	Integer division
<code>** , **=</code>	Exponentiation

Vectorization and Broadcasting

Adding a 3x3 matrix to a 1x3 row vector:

11	12	13		1	2	3		12	14	16
21	22	23	+	1	2	3	=	22	24	26
31	32	33		1	2	3		32	34	36

Adding a 3x3 matrix to a 3x1 column vector:

11	12	13		1	1	1		12	13	14
21	22	23	+	2	2	2	=	23	24	25
31	32	33		3	3	3		34	35	36

True elements

Broadcasted elements

- **Vectorization**: store numerical data in arrays to use batch operations (applied to all values in array)

- Avoids explicit loops
- Makes code easier to maintain / more concise, better performance
- Binary op well-defined if two arguments are same shape

Broadcasting: effective array expansion

- Array + scalar – scalar distributed (& op applied) to each element in array
- Unequal shape arrays – if smaller array can be broadcasted to larger array (**rule**: if array axes on 1-on-1 basis have same length or length of 1)
 - If an array has fewer axes, dummy axes are padded on until dimensions of arrays agree

Elementwise / Broadcasted Mathematics

- Addition “+” (+)

$$C = A+B \Rightarrow C_{i,j} = A_{i,j} + B_{i,j}$$

0.5	-0.7
-0.69	1.8

 +

0.5	0.7
-0.69	1.8

 =

.5 + .5 = 1.0	-.7 - .7 = -0.0
-.69 - .69 = -1.38	1.8 + 1.8 = 3.6

- Subtraction “-” (-)

- Multiplication (Hadamard product) “*” (⊙)

0.5	-0.7
-0.69	1.8

 ⊙

0.5	0.7
-0.69	1.8

 =

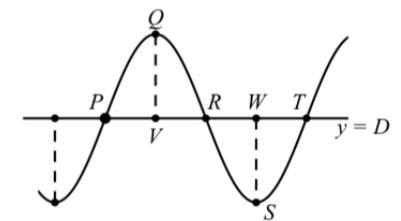
.5 * .5 = .25	-.7 * .7 = -.49
-.69 * -.69 = .4761	1.8 * 1.8 = 3.24

- Division “/” (/)

Elementwise Functions (Vectorized Operators)

Table 2-7. Selection of NumPy Functions for Elementwise Elementary Mathematical Functions

NumPy Function	Description
<code>np.cos</code> , <code>np.sin</code> , <code>np.tan</code>	Trigonometric functions
<code>np.arccos</code> , <code>np.arcsin</code> , <code>np.arctan</code>	Inverse trigonometric functions
<code>np.cosh</code> , <code>np.sinh</code> , <code>np.tanh</code>	Hyperbolic trigonometric functions
<code>np.arccosh</code> , <code>np.arcsinh</code> , <code>np.arctanh</code>	Inverse hyperbolic trigonometric functions
<code>np.sqrt</code>	Square root
<code>np.exp</code>	Exponential
<code>np.log</code> , <code>np.log2</code> , <code>np.log10</code>	Logarithms of base e, 2, and 10, respectively



Sinusoid function

- NumPy contains many vectorized functions – elementwise evaluation of basic mathematical functions (over tensors)
 - Take in tensor/ndarray, return tensor/ndarray of same shape as input (though not necessarily of same type)

Table 2-8. Summary of NumPy Functions for Elementwise Mathematical Operations

NumPy Function	Description
<code>np.add</code> , <code>np.subtract</code> , <code>np.multiply</code> , <code>np.divide</code>	Addition, subtraction, multiplication, and division of two NumPy arrays
<code>np.power</code>	Raises first input argument to the power of the second input argument (applied elementwise)
<code>np.remainder</code>	The remainder of the division
<code>np.reciprocal</code>	The reciprocal (inverse) of each element
<code>np.real</code> , <code>np.imag</code> , <code>np.conj</code>	The real part, imaginary part, and the complex conjugate of the elements in the input arrays
<code>np.sign</code> , <code>np.abs</code>	The sign and the absolute value
<code>np.floor</code> , <code>np.ceil</code> , <code>np rint</code>	Converts to integer values
<code>np.round</code>	Rounds to a given number of decimals

- Elementwise functions can be single or multi-argument
- Can use the `np.vectorize` to convert some custom functions to those that operate on tensors/ndarrays

QUESTIONS?

Deep robots!

Deep questions?!

