# Foundations for Machine Learning 

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Slides 06 Convolution
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## Reference

> Jon Kleinberg and Éva Tardos. Algorithm Design. Pearson Education / Addison-Wesley, 2006.
> Mauro Caresta. The Meaning of the Convolution.

## 1D CONVOLUTION: THE CONTINUOUS CASE

## The meaning of the Convolution

$>$ The convolution of two functions $x(t)$ and $h(t)$ is defined as:

$$
f(t)=(x * h)(t)=\int_{-\infty}^{\infty} x(u) h(t-u) d u
$$

$>$ To understand the meaning of the convolution we break it down into the following steps:

1) $x$ and $h$ are given as function of a dummy variable $u$.
2) Get the mirror of the function $h: h(u) \rightarrow h(-u)$.
3) Add an offset $t$ which allows $h(t-u)$ to slide along the $u$ axis in the right direction, as $t$ increases.
4) The value at a fixed $t_{1}$ is given by the area of the curve resulted by the product of the two functions $x(u)$ and $h\left(t_{1}-u\right)$ i.e.

$$
f\left(t_{1}\right)=\int_{-\infty}^{\infty} x(u) h\left(t_{1}-u\right) d u
$$

## Example

$>$ The following example is the convolution of two identical window-shape functions. Note that in this case $h(-u)=h(u)$.



Exercise:

## Find the

convolution
of the following two functions:
$x(t)$ and
 $h(t)$.


## Properties of Convolution

> Commutative: $x^{*} h=h^{*} x$

$$
\int_{-\infty}^{+\infty} x(u) h(t-u) d u=\int_{-\infty}^{+\infty} h(w) x(t-w) d w
$$

Proof: By the substitution $w=t-u$.
$>$ Associative: $f$ * $\left(g^{*} h\right)=\left(f^{*} g\right)$ * $h$
(With the assumption that all convolution integral exist.)
$>$ Distributive: $f *(g+h)=f * g+f * h$

## CONVOLUTION: THE DISCRETE CASE

## The Convolution of Two Vectors

$>$ Given two vectors $a=\left(a_{0}, a_{1}, \ldots, a_{n-1}\right)$ and $b=\left(b_{0}, b_{1}, \ldots, b_{n-1}\right)$ of length $n$, the convolution of $a$ and $b$ is $a$ vector $c=a * b$ with $2 n-1$ components, where component $k$ is defined as

$$
c_{k}=\sum_{(i, j): i+j=k} a_{i} b_{j}=\sum_{i=0}^{k} a_{i} b_{k-i}
$$

$>$ In other words,

$$
a^{*} b=\left(a_{0} b_{0}, a_{0} b_{1}+a_{1} b_{0}, a_{0} b_{2}+a_{1} b_{1}+a_{2} b_{0}, \ldots, a_{n-1} b_{n-1}\right)
$$

$>$ Another way to think about the convolution is to picture an $n \times n$ table whose ( $i, j$ ) entry is $a_{i} b_{j}$, like this:

$$
\begin{array}{ccccc}
a_{0} b_{0} & a_{0} b_{1} & \ldots & a_{0} b_{n-2} & a_{0} b_{n-1} \\
a_{1} b_{0} & a_{1} b_{1} & \ldots & a_{1} b_{n-2} & a_{1} b_{n-1} \\
\hline a_{2} b_{0} & a_{2} b_{1} & \ldots & a_{2} b_{n-2} & a_{2} b_{n-1} \\
\ldots & \ldots & \ldots & \ldots & \ldots \\
a_{n-1} b_{0} & a_{n-1} b_{1} & \ldots & a_{n-1} b_{n-2} & a_{n-1} b_{n-1}
\end{array}
$$

and then compute the components of the convolution vector by summing along the diagonals, as shown.

## Example

$$
\begin{aligned}
> & a=(1,2,2) \\
> & b=(2,5,4) \\
>c=a * b= & \left(a_{0} b_{0}\right. \\
& a_{0} b_{1}+a_{1} b_{0} \\
& a_{0} b_{2}+a_{1} b_{1}+a_{2} b_{0} \\
& a_{1} b_{2}+a_{2} b_{1} \\
& \left.a_{2} b_{2}\right) \\
= & (2,9,18,18,8)
\end{aligned}
$$

## Exercise

$>$ Compute the convolution of $a=(2,1,2,3)$ and $b=(4,3,2,-1)$.

## General Case

$>$ The convolution can be easily generalized to vectors of different lengths, $a=\left(a_{0}, a_{1}, \ldots, a_{m-1}\right)$ and $b=\left(b_{0}, b_{1}, \ldots, b_{n-1}\right)$.
$>$ In this more general case, $c=a * b$ is defined to be a vector with $m+n-1$ components, where component $k$ is equal

$$
c_{k}=\sum_{\substack{(i, j): i+j=k \\ i<m, j<n}} a_{i} b_{j}=\sum_{i=0}^{k} a_{i} b_{k-i}
$$

$>$ Like in the continuous case, the discrete convolution of two vectors $a=\left(a_{0}, a_{1}, \ldots, a_{m-1}\right)$ and $b=\left(b_{0}, b_{1}, \ldots, b_{n-1}\right)$ can be interpreted as follows:

1. Write the vector $b$ in reverse: $b^{\prime}=\left(b_{n-1}, b_{n-2}, \ldots, b_{0}\right)$.
2. Slide $b^{\prime}$ into successive positions relative to vector a for each successive value of the convolution, by summing products of the corresponding values of the two vectors.

$$
\begin{aligned}
& a_{0} a_{1} a_{2} a_{3} \cdots a_{m-1} \\
& b_{n-1} \cdots b_{3} b_{2} b_{1} b_{0} \\
& a_{0} a_{1} a_{2} a_{3} \cdots a_{m-1} \\
& b_{n-1} \cdots b_{3} b_{2} b_{1} b_{0} \\
& a_{0} a_{1} a_{2} a_{3} \cdots a_{m-1} \\
& b_{n-1} \cdots b_{3} b_{2} b_{1} b_{0} \\
& a_{0} a_{1} a_{2} a_{3} \cdots a_{m-1} \\
& b_{n-1} \cdots b_{3} b_{2} b_{1} b_{0} \\
& \left\{\begin{array}{l}
\left\{\begin{array}{l}
c_{0}=a_{0} b_{0} \\
c_{1}=\left(a_{0} b_{1}+a_{1} b_{0}\right) \\
c_{2}=\left(a_{0} b_{2}+a_{1} b_{1}+a_{2} b_{0}\right) \\
\vdots \\
c_{m+n-2}=a_{m-1} b_{n-1}
\end{array}, ~ \$ ~\right.
\end{array}\right.
\end{aligned}
$$

## convolution as matrix multiplication

> Toeplitz matrix or diagonal-constant matrix is a matrix in which each descending diagonal from left to right is constant.

- Example: $\left[\begin{array}{lllll}a & b & c & d & e \\ e & a & b & c & d \\ f & e & a & b & c \\ g & f & e & a & b\end{array}\right]$
> The convolution operation can be expressed as a matrix multiplication, where one of the inputs is converted into a Toeplitz matrix.
$>$ For example, the convolution of $a=(a 0, a 1, a 2, a 3)$ and $b=(b 0$, b1, b2) can be formulated as:

$$
c=a * b=\left[\begin{array}{ccc}
a 0 & 0 & 0 \\
a 1 & a 0 & 0 \\
a 2 & a 1 & a 0 \\
a 3 & a 2 & a 1 \\
0 & a 3 & a 2 \\
0 & 0 & a 3
\end{array}\right]\left[\begin{array}{l}
b 0 \\
b 1 \\
b 2
\end{array}\right]
$$

> In general,
$\overbrace{\left[\begin{array}{ccccc}a_{1} & 0 & \cdots & 0 & 0 \\ a_{2} & a_{1} & \cdots & \vdots & \vdots \\ a_{3} & a_{2} & \cdots & 0 & 0 \\ \vdots & a_{3} & \cdots & a_{1} & 0 \\ a_{m-1} & \vdots & \cdots & a_{2} & a_{1} \\ a_{m} & a_{m-1} & \vdots & \vdots & a_{2} \\ 0 & a_{m} & \cdots & a_{m-2} & \vdots \\ 0 & 0 & \cdots & a_{m-1} & a_{m-2} \\ \vdots & \vdots & \vdots & a_{m} & a_{m-1} \\ 0 & 0 & 0 & \cdots & a_{m}\end{array}\right]}^{\left[\begin{array}{c}b_{1} \\ b_{2} \\ b_{3} \\ \vdots \\ b_{n}\end{array}\right]}$

## Exercise

$>$ Compute the convolution of $a=(2,2,3,3,4)$ and b $=(1,1,2)$ using:

1. the sliding method
2. matrix multiplication
3. polynomial multiplication

## Applications

$>$ Image/Signal Smoothing.
> String Matching.
> Convolutional Neural Networks.
$>$ Etc.

## Implementation in Python 3 (part 1)

\# -*- coding: utf-8 -*-

II II II
Created on Sat Jul 7 20:17:15 2018

Version 1:
Compute the convolution of two sequences $a$ and $b$ given as lists of numbers, using the convolution formula directly
@author: L Y Stefanus

II III

## Implementation in Python 3 (part 1)

$$
\begin{aligned}
& \operatorname{def} \operatorname{convo1}(a, b): \\
& n a=\operatorname{len}(a) \\
& n b=\operatorname{len}(b) \\
& n c=n a+n b-1 \\
& c=[0]^{*} n c \\
& a=a+[0]^{*}(n c-n a) \\
& b=b+[0]^{*}(n c-n b)
\end{aligned}
$$

for $k$ in range( $n c$ ):

$$
\begin{aligned}
& \text { for } i \text { in range }(k+1): \\
& \qquad c[k]=c[k]+a[i] * b[k-i]
\end{aligned}
$$

return c

## Implementation in Python 3 (part 2)

\# -*_ coding: utf-8 -*_
\|I \| \|

Created on Sat Jul 7 21:19:13 2018
\# version 2:
Compute the convolution of two sequences $a$ and $b$ given as lists of numbers, using the multiplication of Toeplitz matrix of a and matrix of $b$
@author: L Y Stefanus
"" "

## Implementation in Python 3 (part 2)

```
import numpy as np
from scipy import linalg
def convo2(a,b):
    h = np.array(a)
    padding = np.zeros(len(b) - 1, h.dtype)
    first_col = np.r_[h, padding]
    first_row = np.r_[h[0], padding]
    T = linalg.toeplitz(first_col, first_row)
    H = np.mat(T)
    g = np.mat(b).T
    hasil = H*g
    return hasil.T.tolist()[0]
```


## Implementation in Python 3

$$
\begin{aligned}
& \ggg a=[1,2,2] \\
& \ggg b=[2,5,4] \\
& \ggg c=\operatorname{convo}(a, b) \\
& \ggg \operatorname{print}(c) \\
& {[2,9,18,18,8]} \\
& \ggg \\
& \ggg a=[2,2,3,3,4] \\
& \ggg b=[1,1,2] \\
& \ggg c=\operatorname{convo} 2(a, b) \\
& \ggg \operatorname{print}(c) \\
& {[2,4,9,10,13,10,8]} \\
& \ggg
\end{aligned}
$$

