Fast 1D Convolution CML Algorithms summary

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- Convolution Algorithms
- Linear Convolutions
- Winograd Linear Convolution
- Cyclic Convolutions
- 1D FFT
- Winograd Cyclic Convolution
- Nested convolutions
- Block convolutions
- Applications

• Convolutional neural networks.



Convolution Algorithms

- Machine learning
 - Fast implementation of 1D/2D/3D convolutions in
 - Convolutional Neural Networks (CNNs).
- Fast implementation of 1D digital filters
 - 1D signal filtering (e.g., audio/music, ECG, EEG)
 - 1D Signal feature calculation
 - Fast implementation of 1D correlation
 - 1D template matching
 - Time-of-flight (distance) calculation (e.g., sonar)





Convolution Algorithms

- Fast implementation of 2D/3D convolutions:
 - Image/video filtering
 - Image/video feature calculation:
 - Gabor filters
 - Spatiotemporal feature calculation
 - Fast implementation of 2D correlation:
 - Template matching
 - Correlation tracking.

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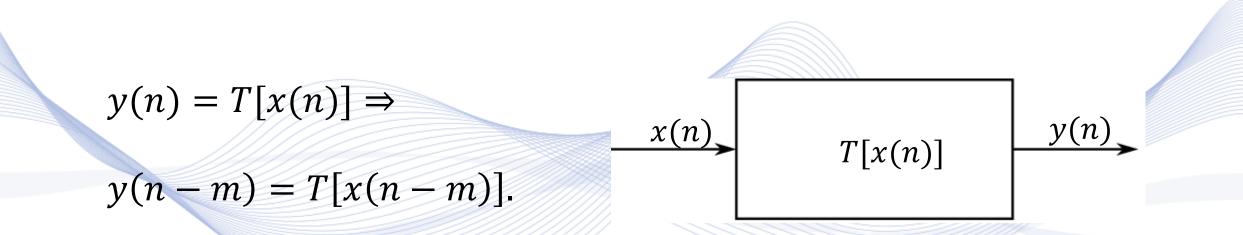
• Convolutional neural networks.



• Linearity:

$$T[ax_1 + bx_2] = aT[x_1] + bT[x_2].$$

• Shift-Invariance:



LSI system convolution : y(n) = h(n) * x(n).

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The one-dimensional (linear) convolution of:

• an input signal *x* of length *L* and

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 a convolution kernel h (filter mask, finite impulse response) of length M is defined as:

$$y(n) = h(n) * x(n) \triangleq \sum_{i=0}^{M-1} h(i)x(n-i).$$

• For a convolution kernel centered around 0 and M = 2v + 1, convolution takes the form:

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$$y(n) = h(n) * x(n) = \sum_{i=-v}^{v} h(i)x(n-i).$$



Vectorial convolution input/output, kernel representation:

- $\mathbf{x} = [x(0), ..., x(L-1)]^T$: input vector.
- $\mathbf{h} = [h(0), ..., h(M-1)]^T$: filter corfficient vector.
- $\mathbf{y} = [y(0), ..., y(N-1)]^T$: output vector, with N = L + M 1.
- 1D linear convolution between two discrete signals x, h can be expressed as the matrix-vector product:

 $\mathbf{y} = \mathbf{H}\mathbf{x},$

where **H** is a $N \times L$ matrix.





• **H** : a $N \times L$ band matrix of the form:

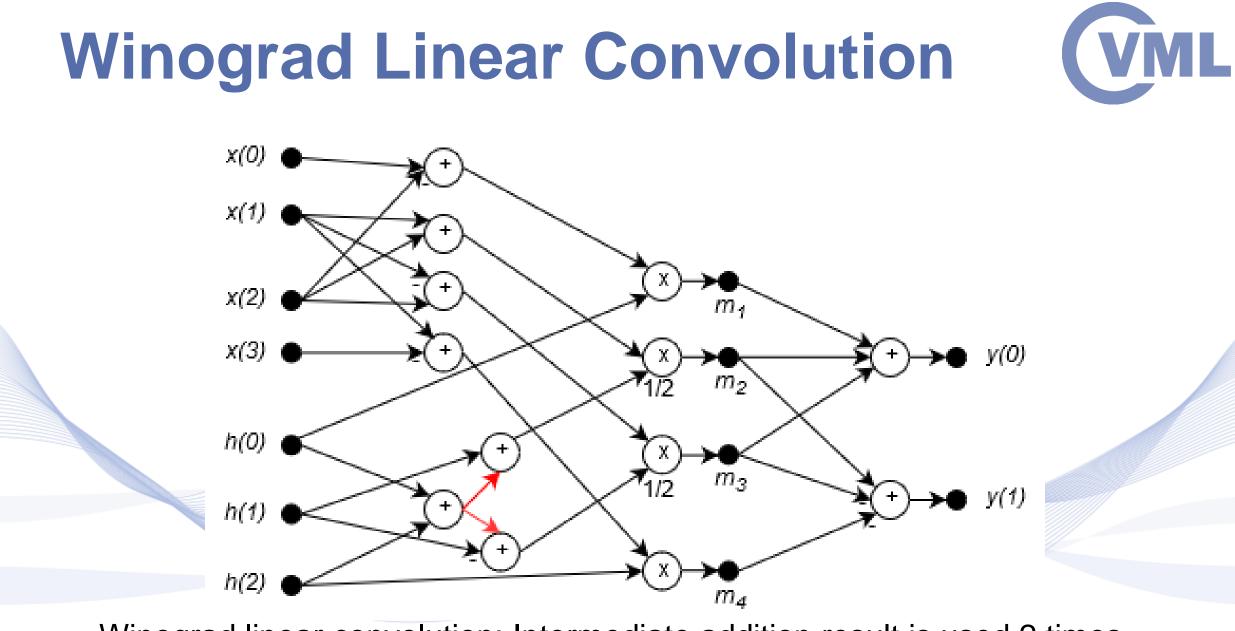
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$$\mathbf{H} = \begin{bmatrix} h(0) & 0 & \cdots & 0 \\ h(1) & h(0) & \cdots & \cdots \\ \cdots & \cdots & \cdots & 0 \\ h(M-1) & h(M-2) & \cdots & 0 \\ 0 & h(M-1) & \cdots & 0 \\ \cdots & \cdots & \cdots & \cdots \\ 0 & 0 & \cdots & h(M-1) \end{bmatrix}.$$

- Alternative matrix notation: y = Xh, where X is an N $\times M$ matrix.
- Fast calculation of the product y = Hx using BLAS/cuBLAS.

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Winograd linear convolution: Intermediate addition result is used 2 times.

Winograd Linear Convolution

- **VML**
- Winograd linear convolution algorithm requires m + r 1 multiplications, m and r: lengths of y and h, respectively.
- General form of optimal Winograd linear convolution algorithms:

 $\mathbf{y} = \mathbf{A}^T[(\mathbf{H}\mathbf{h}) \otimes (\mathbf{B}^T\mathbf{x})],$

- \otimes indicates element-wise m + r 1 multiplications.
- x, h, y: input signal, filter coefficient and output signal vectors.



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Cyclic 1D convolution



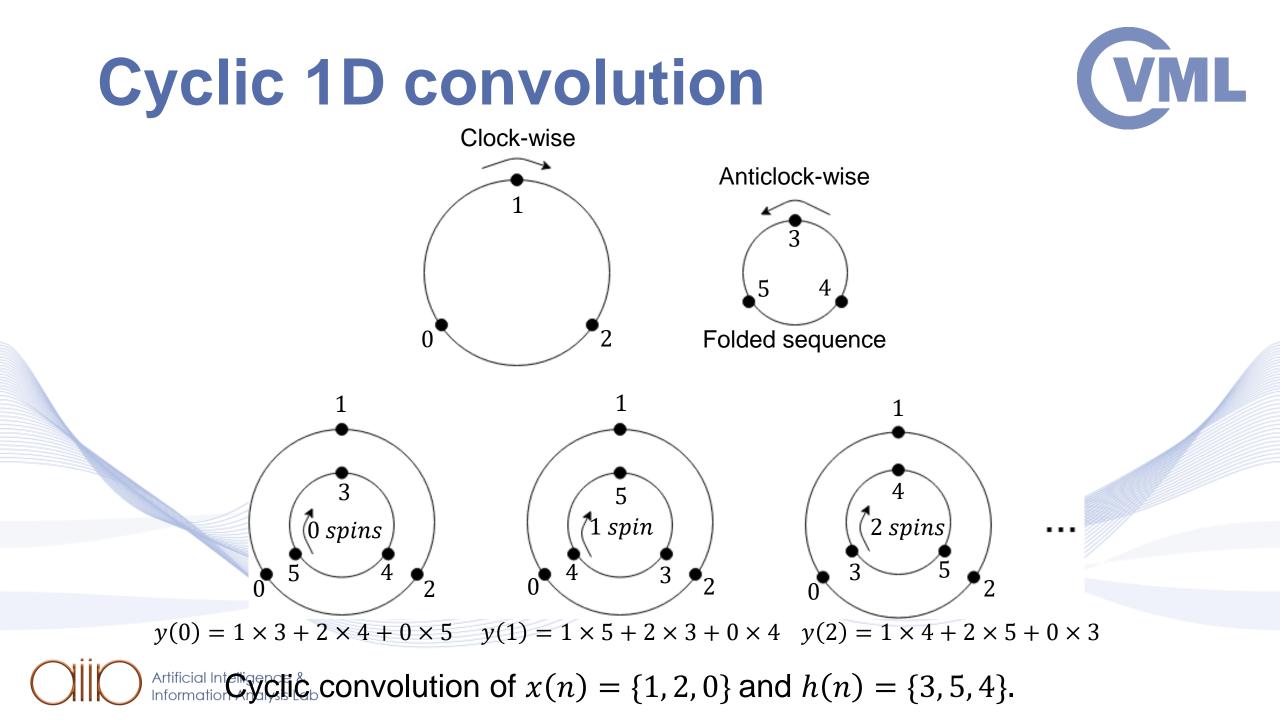
• One-dimensional cyclic convolution of length N :

$$y(k) = x(k) \circledast h(k) = \sum_{i=0}^{N-1} h(i)x(((k-i)_N)),$$

(k)_N = k mod N.

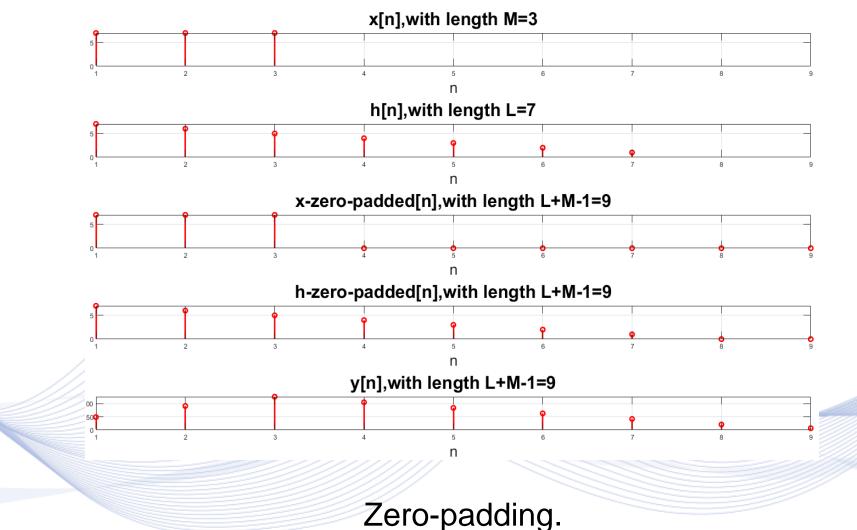
- It is of no use in modeling linear systems.
- Important use: Embedding linear convolution in a fast cyclic convolution $y(n) = x(n) \circledast h(n)$ of length $N \ge L + M 1$ and then performing a cyclic convolution of length *N*.

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Cyclic 1D convolution



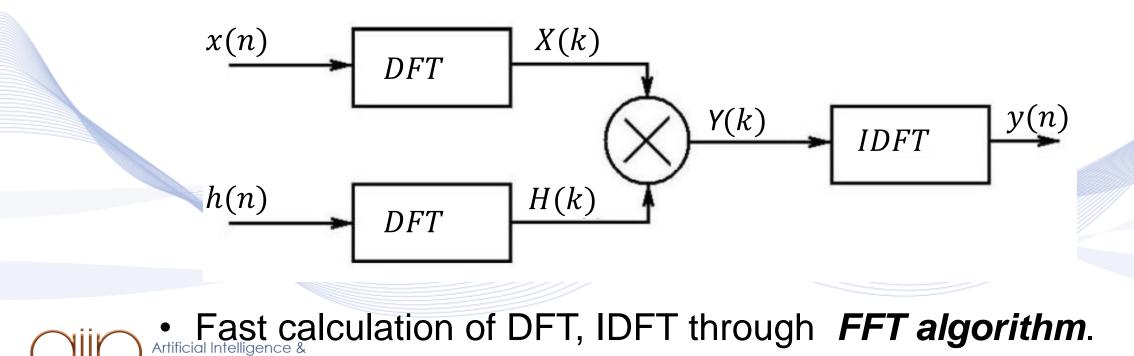


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Cyclic 1D convolution



• Cyclic convolution calculation using 1D **Discrete Fourier Transform** (**DFT**): $y = IDFT(DFT(x) \otimes DFT(h)).$



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1D FFT



- There are various *Fast Fourier Transform* (*FFT*) algorithms to speed up the calculation of DFT.
- The best known is the radix-2 decimation-in-time (DIT) Fast Fourier Transform (FFT) (Cooley-Tuckey).
- DFT of a sequence x(n) of length N (n = 0, ..., N 1):

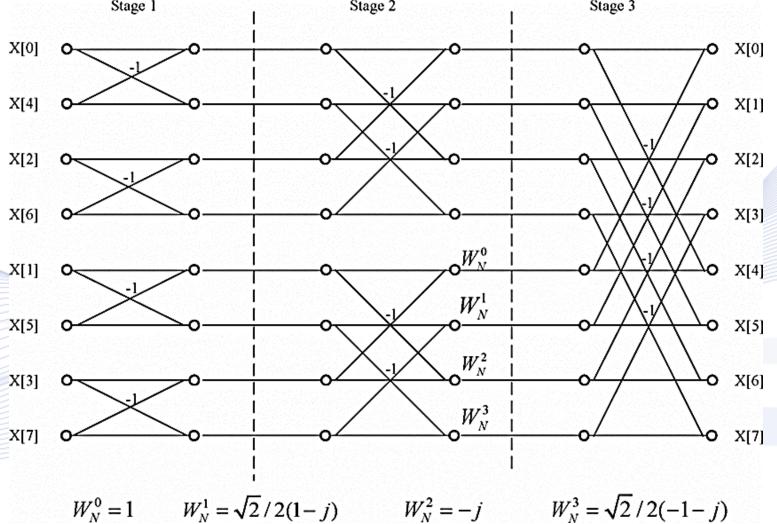
$$X(k) = \sum_{n=0}^{N-1} x(n) e^{-\frac{2\pi i}{N}nk}, \quad k = 0, ..., N-1.$$

• N-th complex root of unity: $W_N^n = e^{-\frac{2\pi i}{N}n}$, n = 0, ..., N - 1.



1D FFT

- radix-2 FFT breaks a length-N DFT into many size-2 DFTs called "butterfly" operations.
- There are log_2N FFT stages.





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 \mathcal{Z} transform of a discrete signal x(n) having domain [0, ..., N - 1] is given by:

$$X(z) = \sum_{n=0}^{N-1} x(n) z^{-n}.$$

The domain of Z transform is the complex plane, since z is a complex number.

Convolution property of the Z transform (polynomial product X(z)H(z)):

 $y(n) = x(n) * h(n) \Leftrightarrow Y(z) = X(z)H(z).$

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Polynomial product form of the 1D cyclic convolution:

$$y(k) = x(k) \circledast h(k) = \sum_{i=0}^{N-1} h(i)x((k-i)_N),$$

where: $(k)_N = k \mod N$.

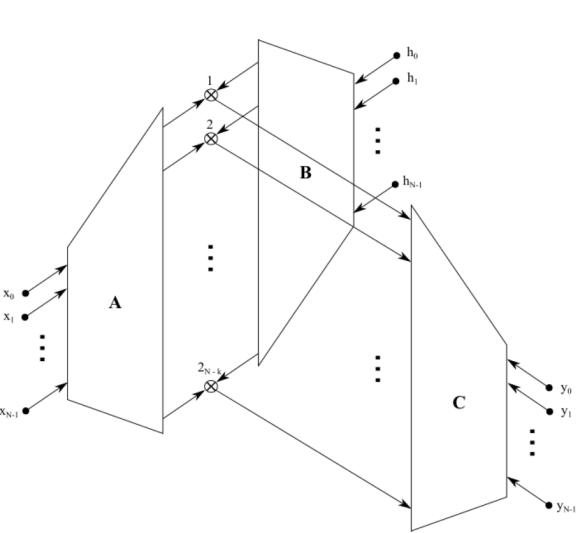
 $y(k) = x(k) \circledast h(k) < = > Y(z) = X(z)H(z) \mod z^N - 1.$



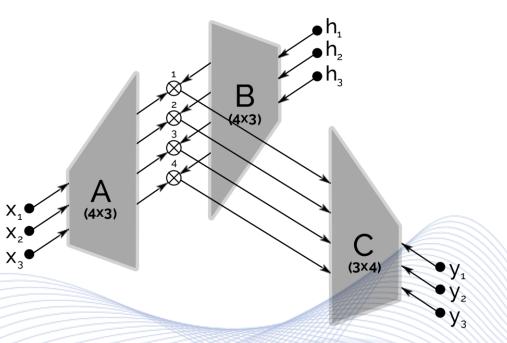


- Winograd convolution algorithms or fast filtering algorithms: $\mathbf{y} = \mathbf{C}(\mathbf{Ax} \otimes \mathbf{Bh}).$
- They require only 2N v multiplications in their middle vector product, thus having minimal complexity.
- v: number of cyclotomic polynomial factors of polynomial $z^N 1$ over the rational numbers Q.



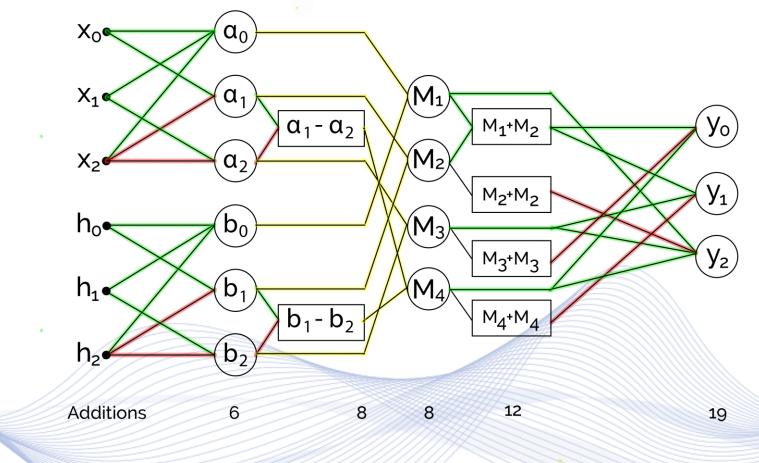






Block diagram of Winograd Cyclic convolution Algorithm for N = 3.





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Block diagram of Winograd Cyclic convolution Algorithm for N = 3.

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Multiplications

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Winograd Cyclic Convolution algorithm can be equivalently expressed as:

 $\mathbf{y} = \mathbf{R}\mathbf{B}^T(\mathbf{A}\mathbf{x}\otimes\mathbf{C}^T\mathbf{R}\mathbf{h}).$

- Matrices A, B typically have elements 0, +1, -1.
- Multiplications C^TRh, RB^Ty' are done only by additions/subtractions.
- **R** is an $N \times N$ permutation matrix.
- $\mathbf{C}^T \mathbf{R} \mathbf{h}$ can be precomputed.





- Winograd algorithm works on small blocks of the input signal.
- The input block and filter are transformed.
- The outputs of the transform are multiplied together in an element-wise fashion.
- The result is transformed back to obtain the outputs of the convolution.
- GEneral Matrix Multiplication (GEMM) BLAS or cuBLAS routines can be used.



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Nested convolutions



- Winograd algorithms exist for relatively short convolution lengths, e.g.: N = 3, 5, 7.
- Use of efficient short-length convolution algorithms iteratively to build long convolutions.
- Does not achieve minimal multiplication complexity.
- Good balance between multiplications and additions. Decomposition of 1D convolution into a 2D convolution:
 - 1D convolution of length: $N = N_1 N_2$
 - with N_1, N_2 co-prime integers, $(N_1, N_2) = 1$
 - results into a 2D $N_1 \times N_2$ convolution.

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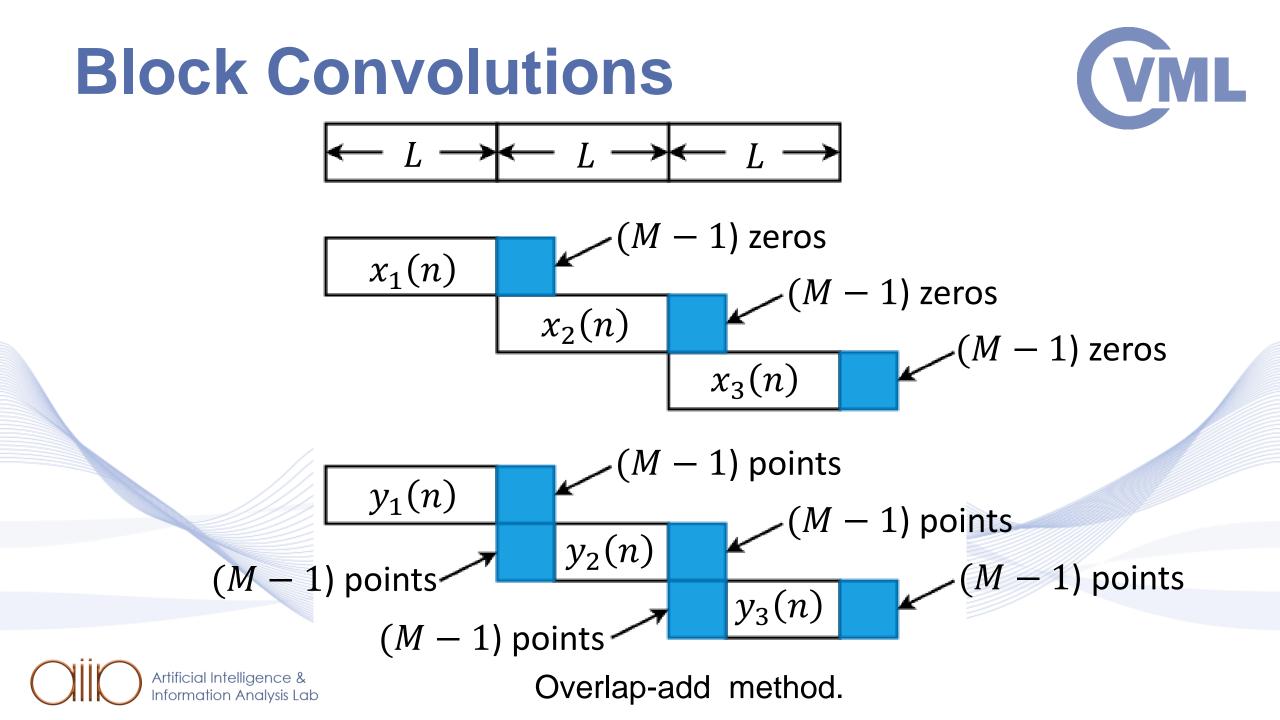
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Block Convolutions



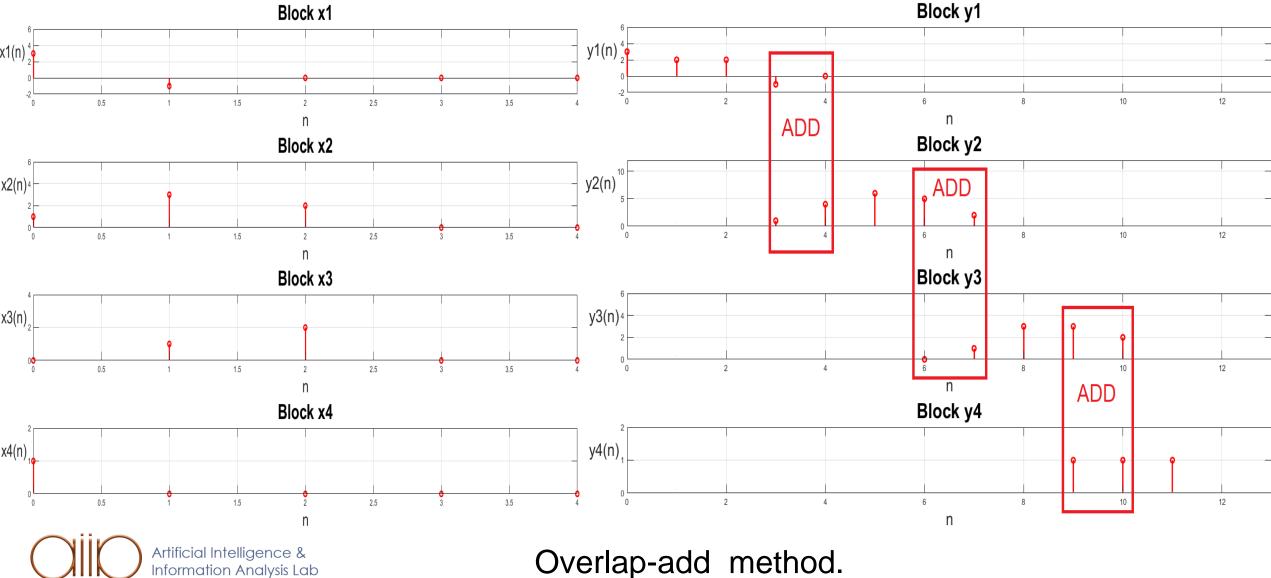
- Input signal x(n) is split in overlapping/non-overlapping blocks.
- Blocks are convolved independently.
- Great parallelism is achieved.
 - Two block-based convolution methods:
- Overlap-add method
- Overlap-save method.





Block Convolutions

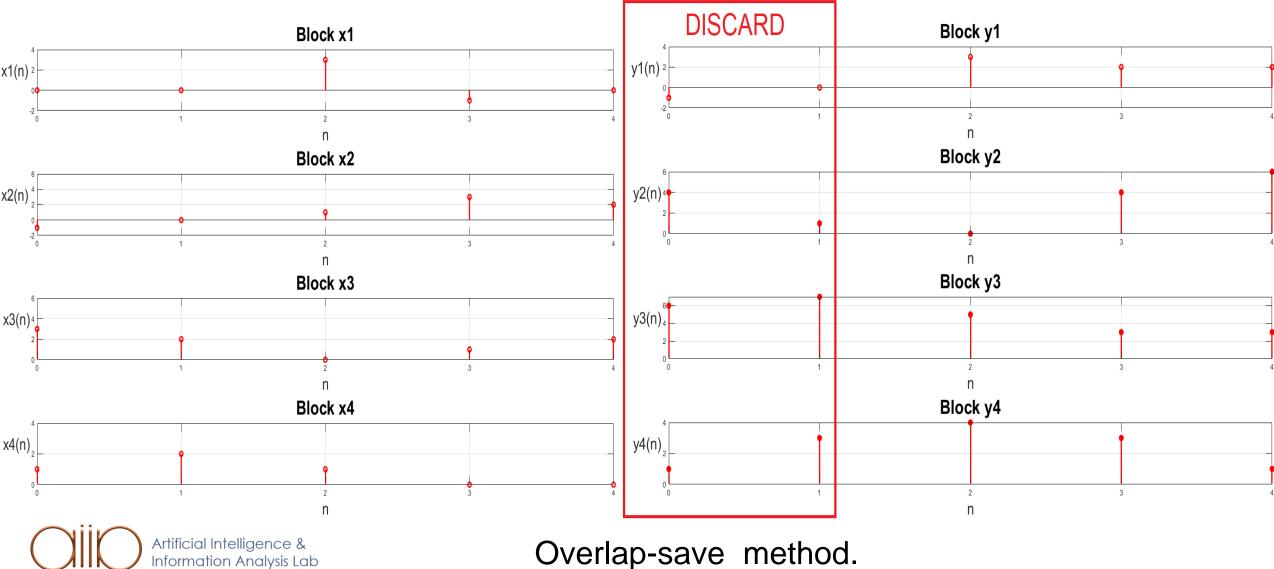




Block Convolutions Input signal blocks >(M-1) zeros(M-1) point overlap (M-1) point overlap **Output signal blocks** Discard (M-1) points \nearrow Artificial Intelligence & Overlap-save method. Information Analysis Lab

Block Convolutions





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Applications



- Convolutional neural networks
- Signal processing
 - Signal filtering
 - Signal restoration
 - Signal deconvolution
- Signal analysis
 - Time delay estimation
 - Distance calculation (e.g., sonar)
 - 1D template matching

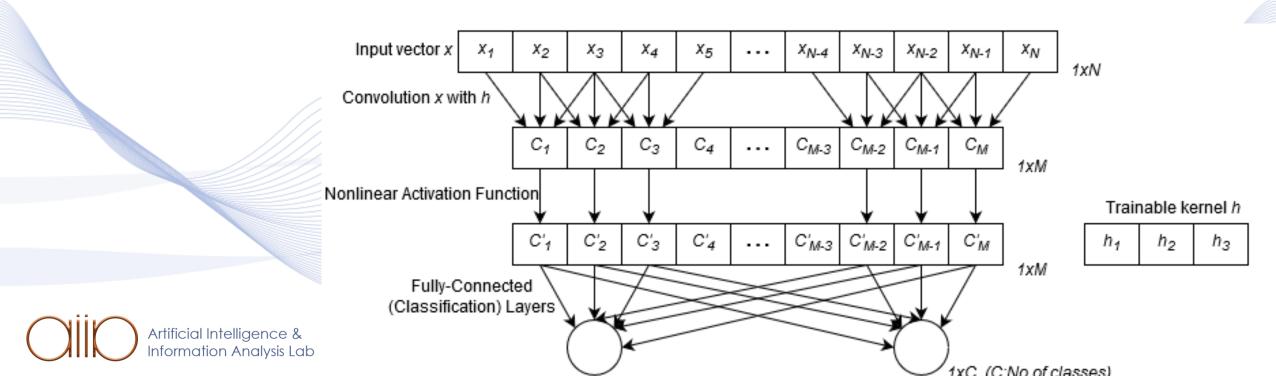
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Applications



Convolutional Neural Network (CNN) two step architecture:

- First layers with sparse NN connections: convolutions.
- Fully connected final layers.
- Need for fast convolution calculations.



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