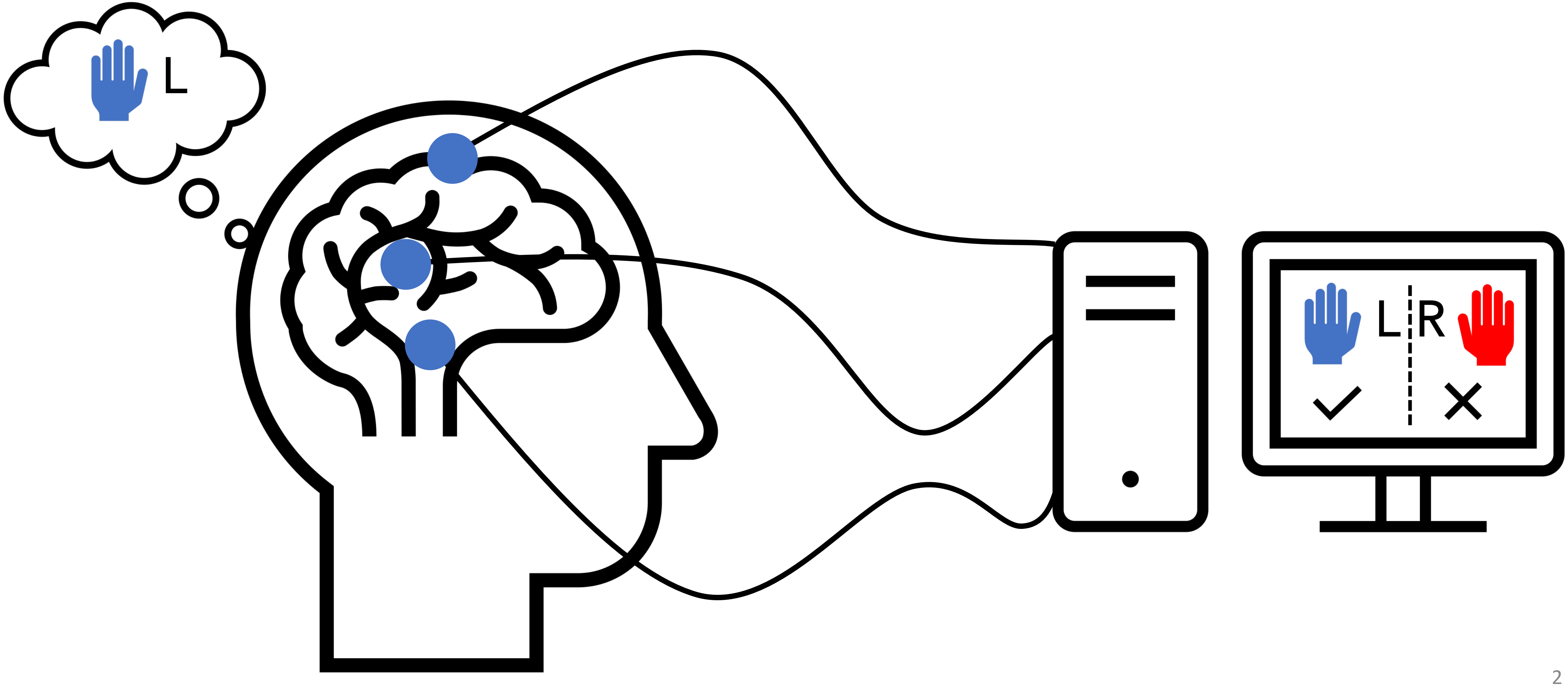
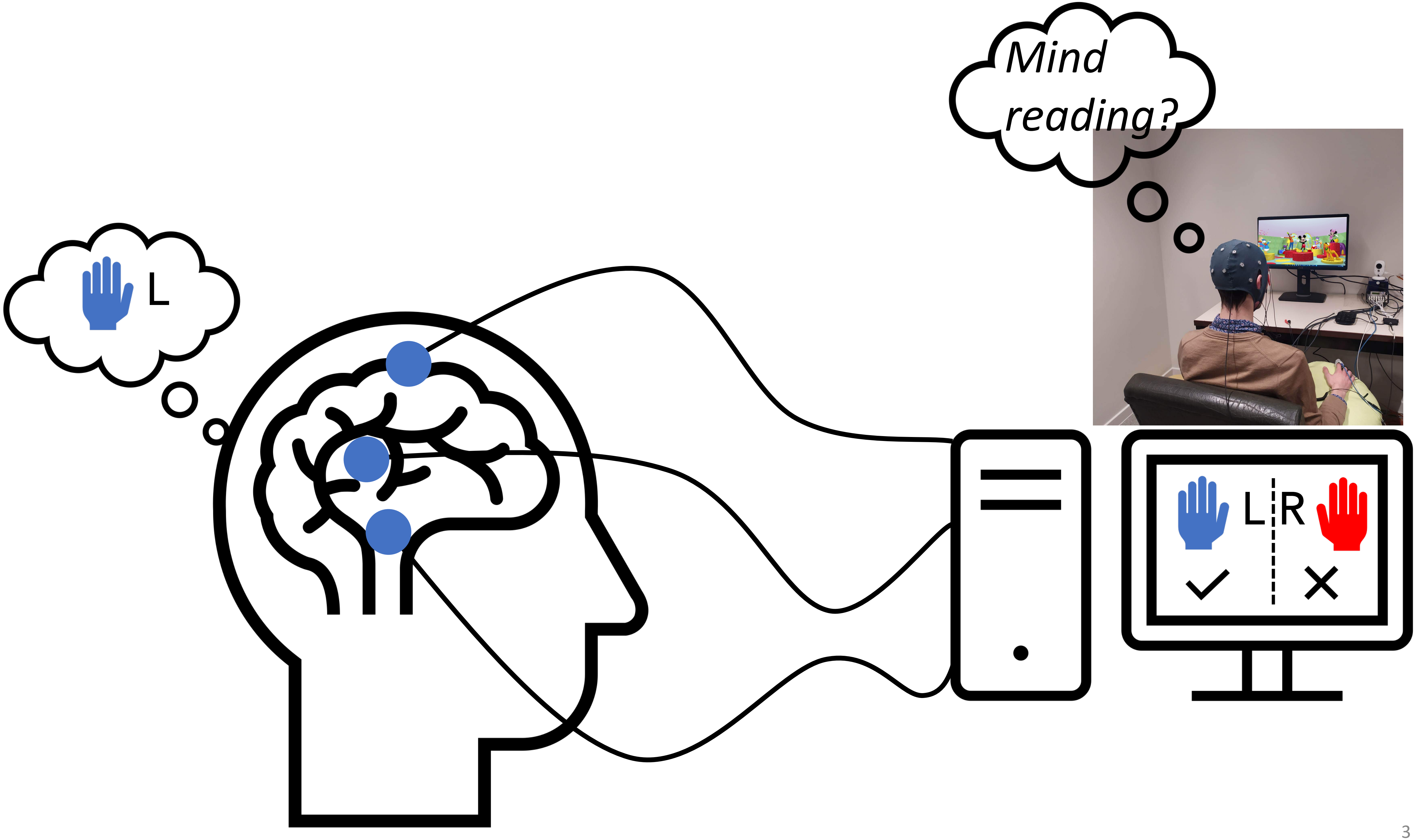
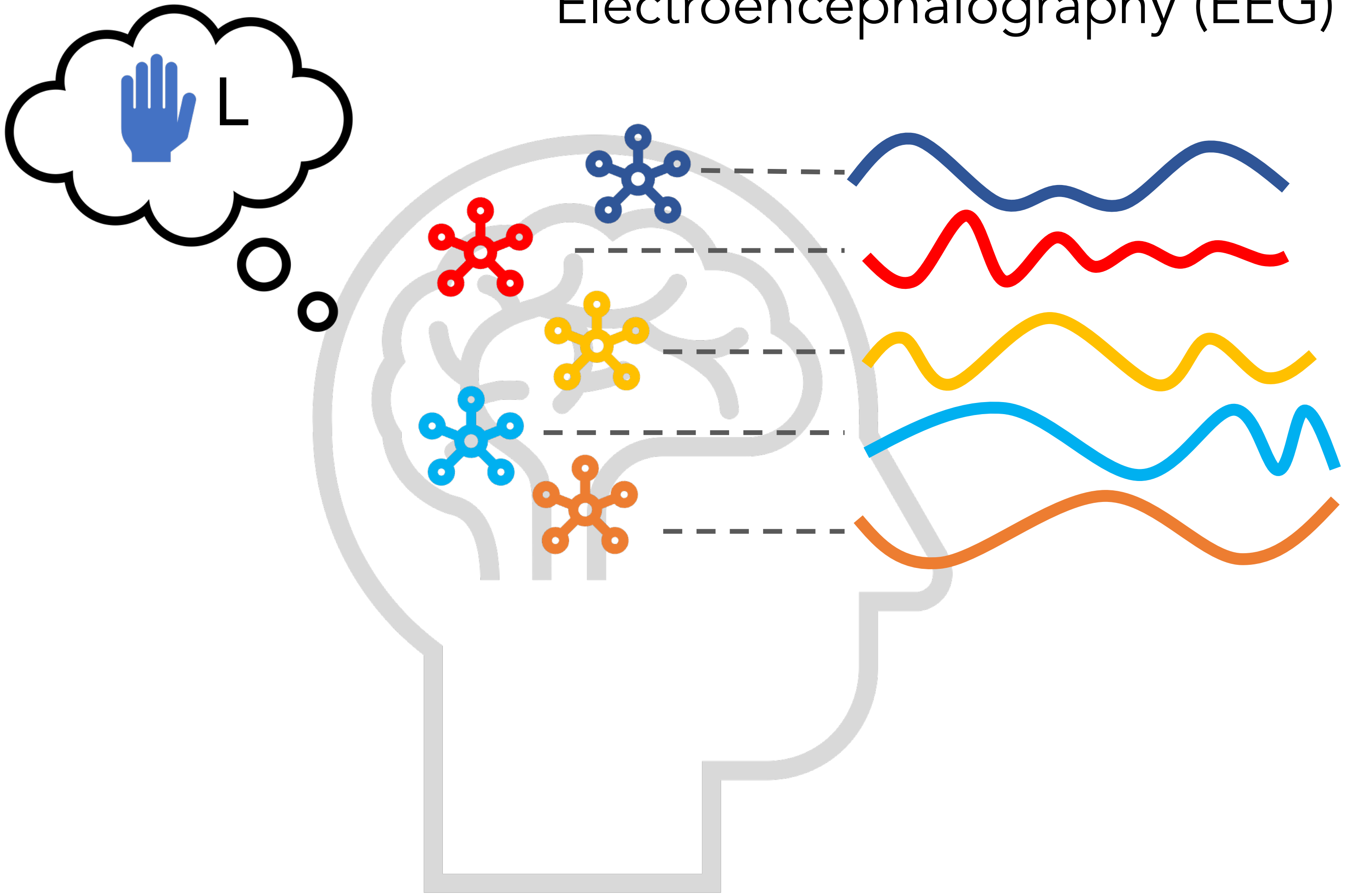
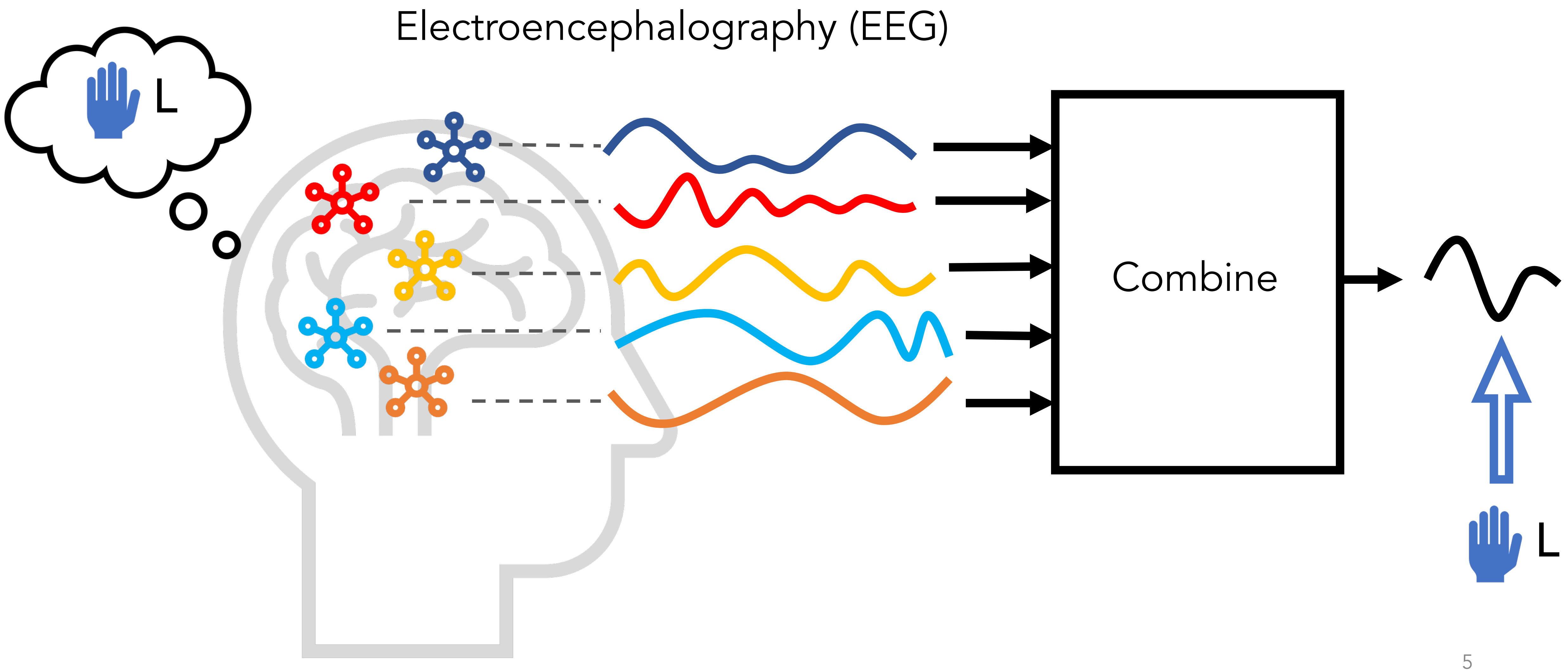

L
L
R



Mind reading?
L
L
R

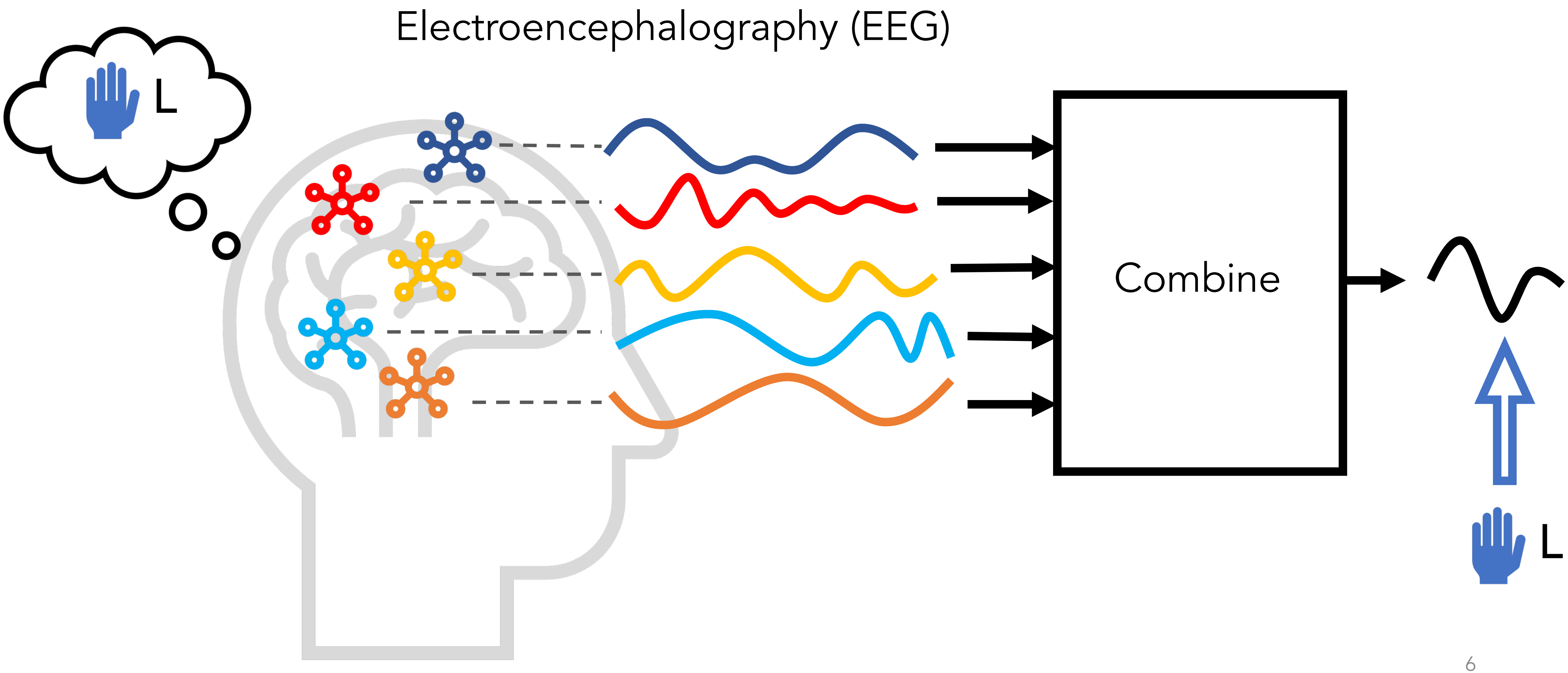
Electroencephalography (EEG)

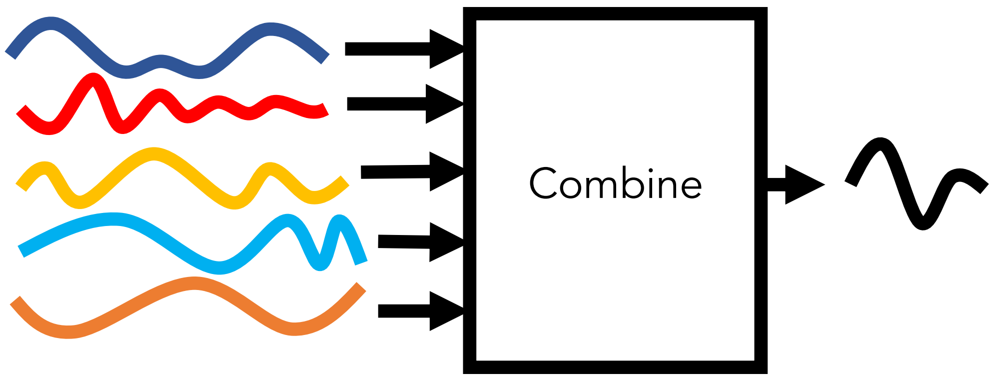




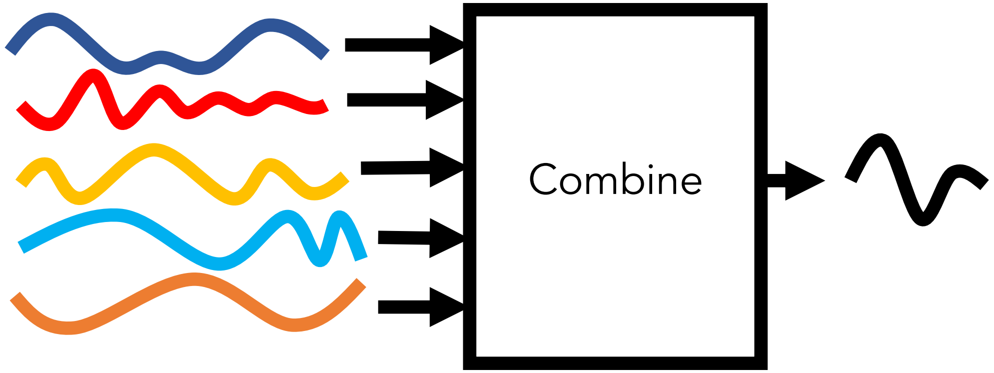
L
Electroencephalography (EEG)
Combine
L

Motor imagery



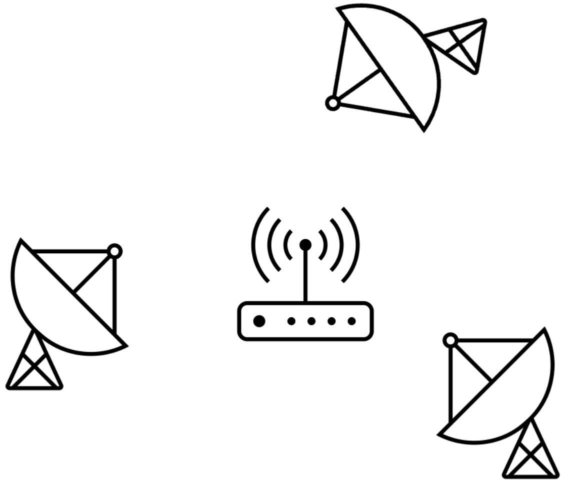


Seizure detection

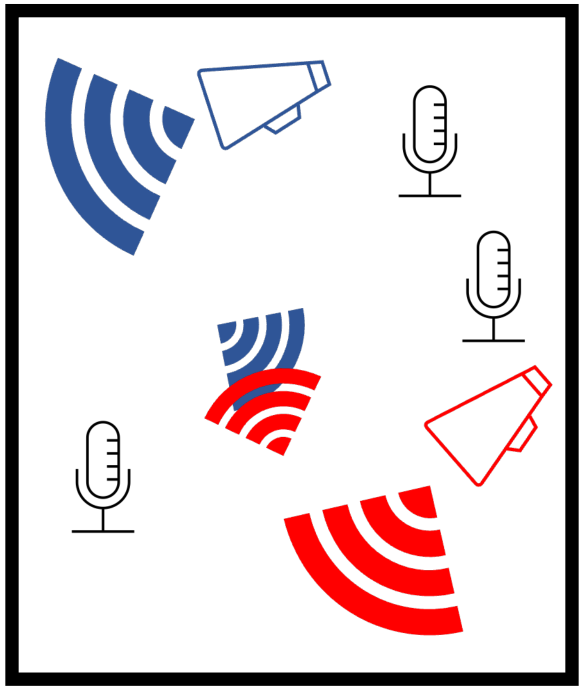


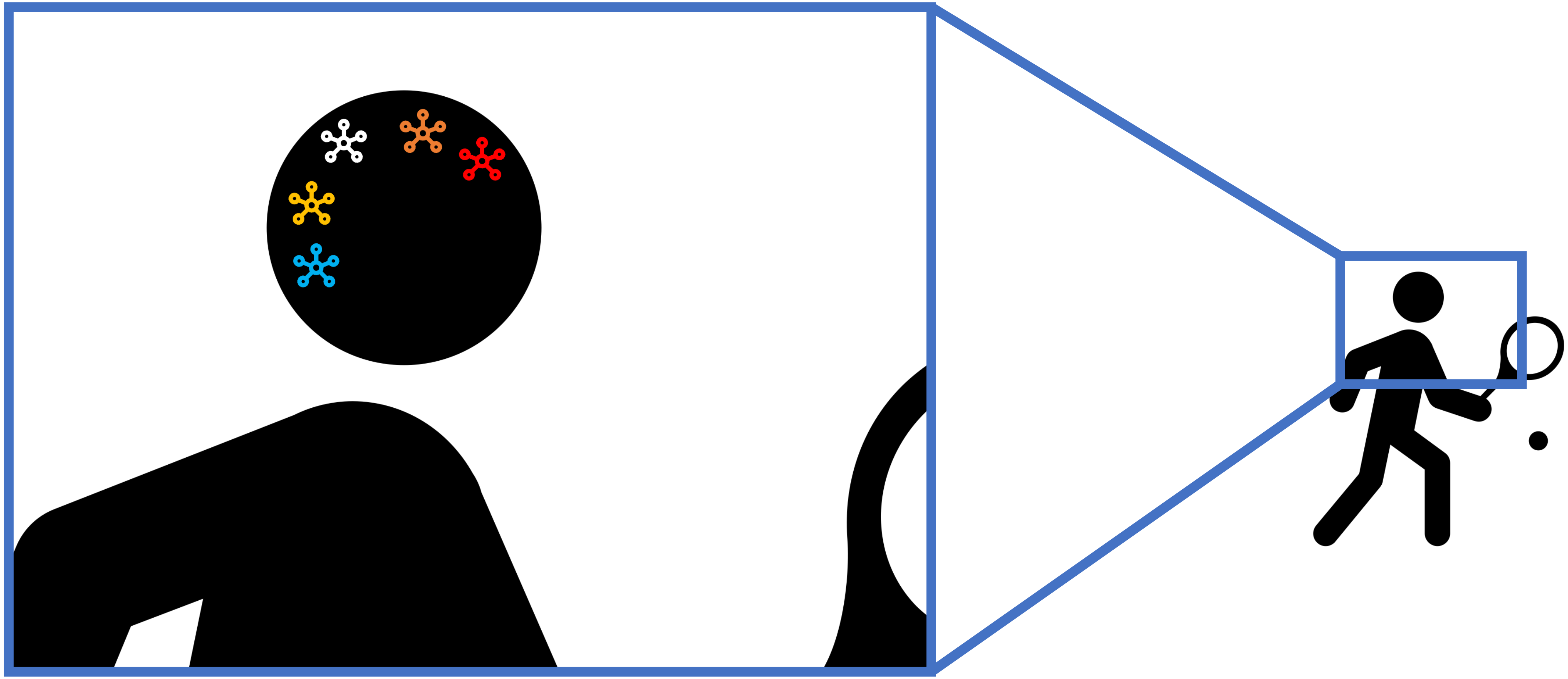
Seizure detection

Source localization



Source separation





Distributed Spatial Filtering in Wireless Sensor Networks

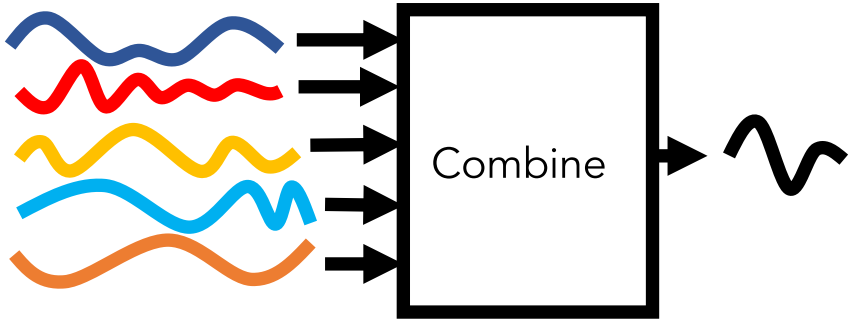
Cem Ates Musluoglu

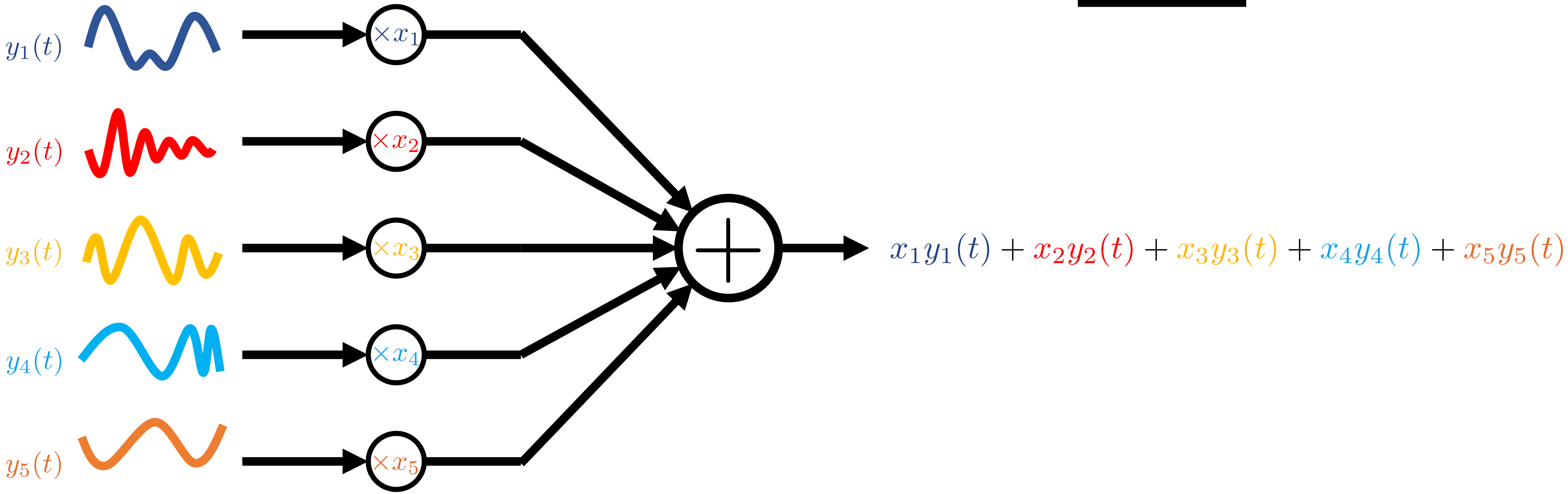
Supervisor: Prof. dr. ir. Alexander Bertrand

STADIUS
Center for Dynamical Systems, Signal Processing and Data Analytics

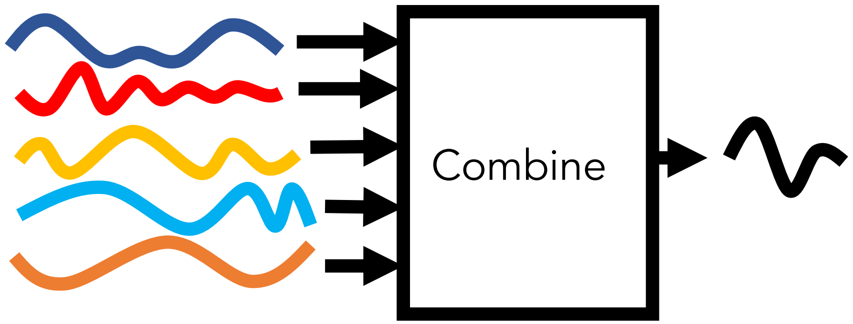
KU LEUVEN

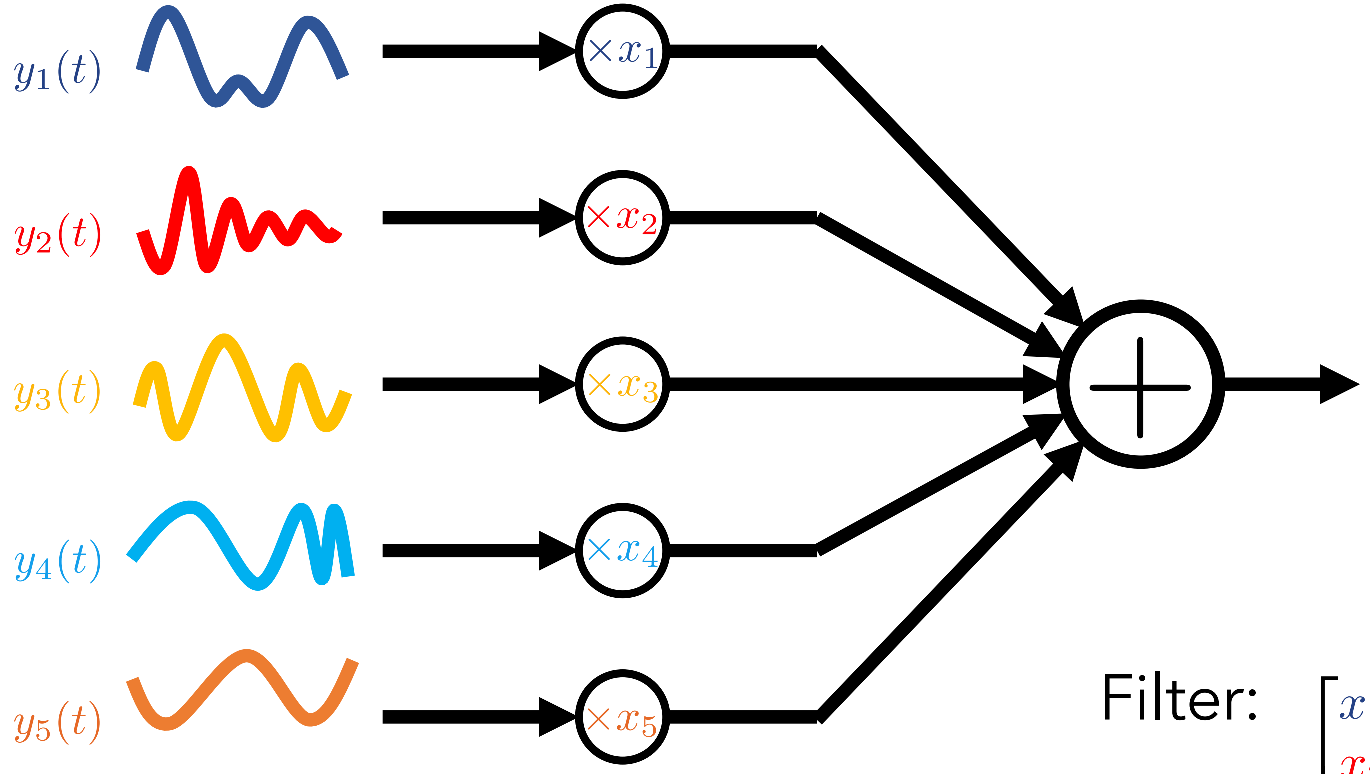
Spatial filtering





Spatial filtering





$$x_1 y_1(t) + x_2 y_2(t) + x_3 y_3(t) + x_4 y_4(t) + x_5 y_5(t)$$
$$= \mathbf{x}^T \mathbf{y}(t)$$

Filter: $\mathbf{x} = \begin{bmatrix} x_1 \\ x_2 \\ x_3 \\ x_4 \\ x_5 \end{bmatrix}$

Signal / data: $\mathbf{y}(t) = \begin{bmatrix} y_1(t) \\ y_2(t) \\ y_3(t) \\ y_4(t) \\ y_5(t) \end{bmatrix}$

Choosing the right filter

Choose the best possible!

Choosing the right filter

Choose the best possible!

Best?

Different for each task

Choosing the right filter

Choose the best possible!

Best?

Different for each task

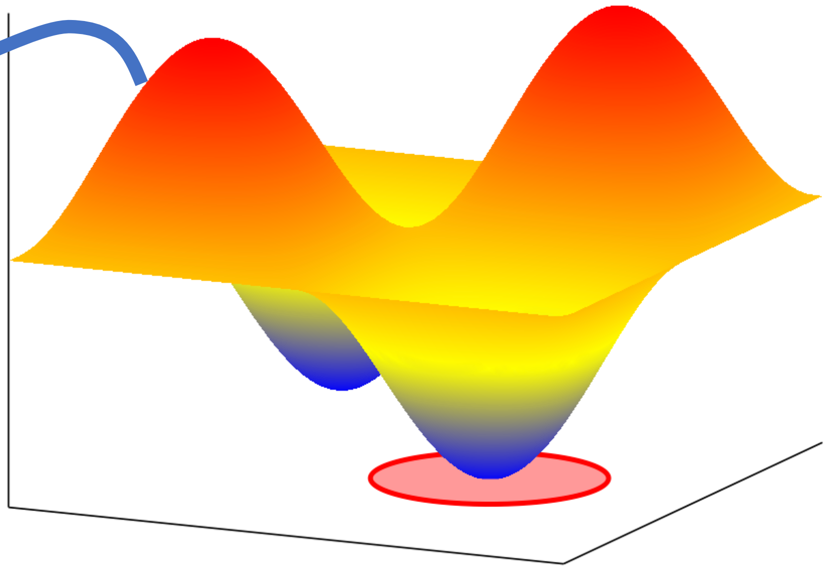
Tasks: What are we aiming to do?

MMSE, PCA, LCMV, GEVD, TRO, CCA,…

Tasks: Optimization problems

$$\underset{\mathbf{x}}{\text{minimize}}\ f(\mathbf{x})$$

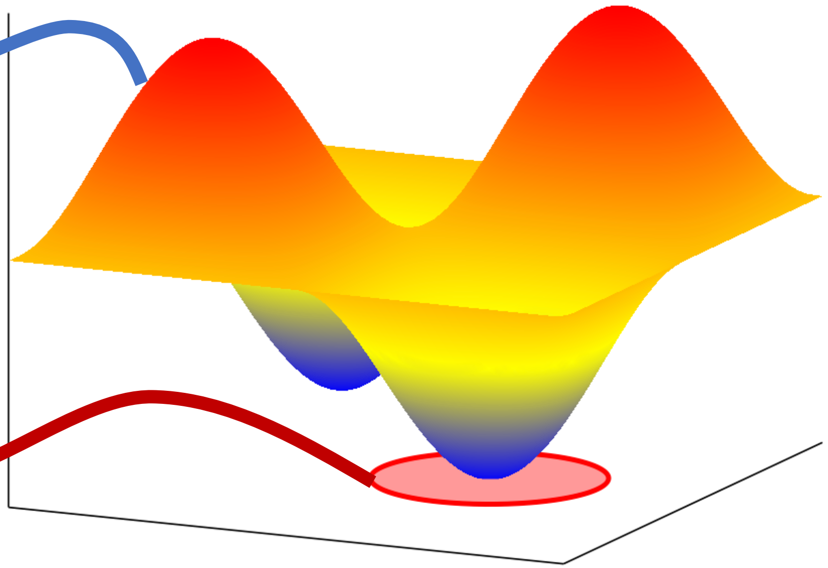
$$\text{subject to } \mathbf{x} \in \mathcal{S}$$



Tasks: Optimization problems

$$\underset{\mathbf{x}}{\text{minimize}} \; f(\mathbf{x})$$

$$\text{subject to } \mathbf{x} \in \mathcal{S}$$

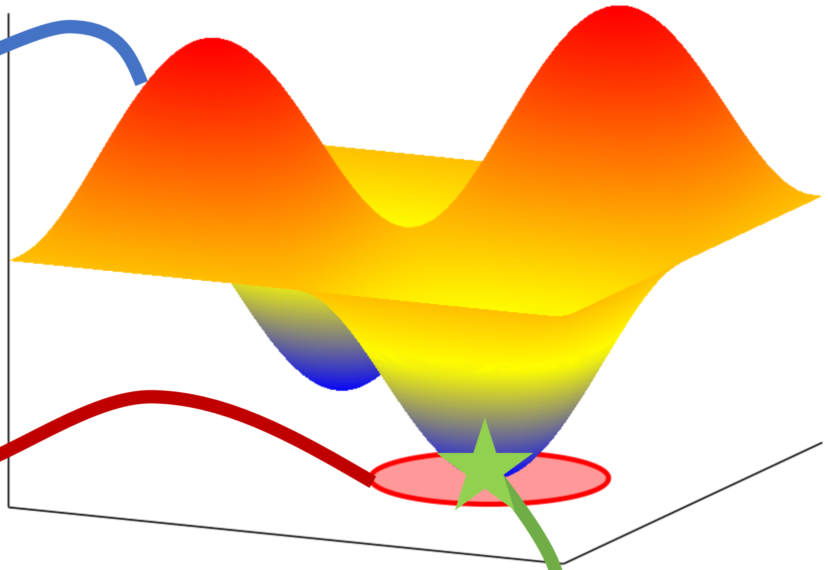


$$\mathbf{x} \in \mathcal{S} \;\Rightarrow\; \begin{cases} g(\mathbf{x}) = 0 \\ h(\mathbf{x}) \leq 0 \end{cases}$$

Tasks: Optimization problems

$$\underset{\mathbf{x}}{\text{minimize}} \; f(\mathbf{x})$$

$$\text{subject to } \mathbf{x} \in \mathcal{S}$$



$\mathbf{x}^*$

$$\mathbf{x} \in \mathcal{S} \;\Rightarrow\; \begin{cases} g(\mathbf{x}) = 0 \\ h(\mathbf{x}) \leq 0 \end{cases}$$

Spatial filtering tasks

$\mathbf{x}^T\mathbf{y}(t)$: Main quantity of interest

$$\Downarrow$$

$$f(\mathbf{x}^T\mathbf{y}(t))$$

Spatial filtering tasks

$\mathbf{x}^T\mathbf{y}(t)$: Main quantity of interest

$$\Downarrow$$

$$f(\mathbf{x}^T\mathbf{y}(t))$$

$$\Downarrow$$

$\mathbf{x}^*$: Depends on the data

Spatial filtering tasks

$\mathbf{x}^T\mathbf{y}(t)$: Main quantity of interest

$$\Downarrow$$

$$f(\mathbf{x}^T\mathbf{y}(t))$$

$\mathbf{x}^*$: Depends on the data $\Rightarrow$ Contains uncertainty

Spatial filtering tasks

$\mathbf{x}^T \mathbf{y}(t)$: Main quantity of interest

$\Downarrow$

$f(\mathbf{x}^T \mathbf{y}(t))$

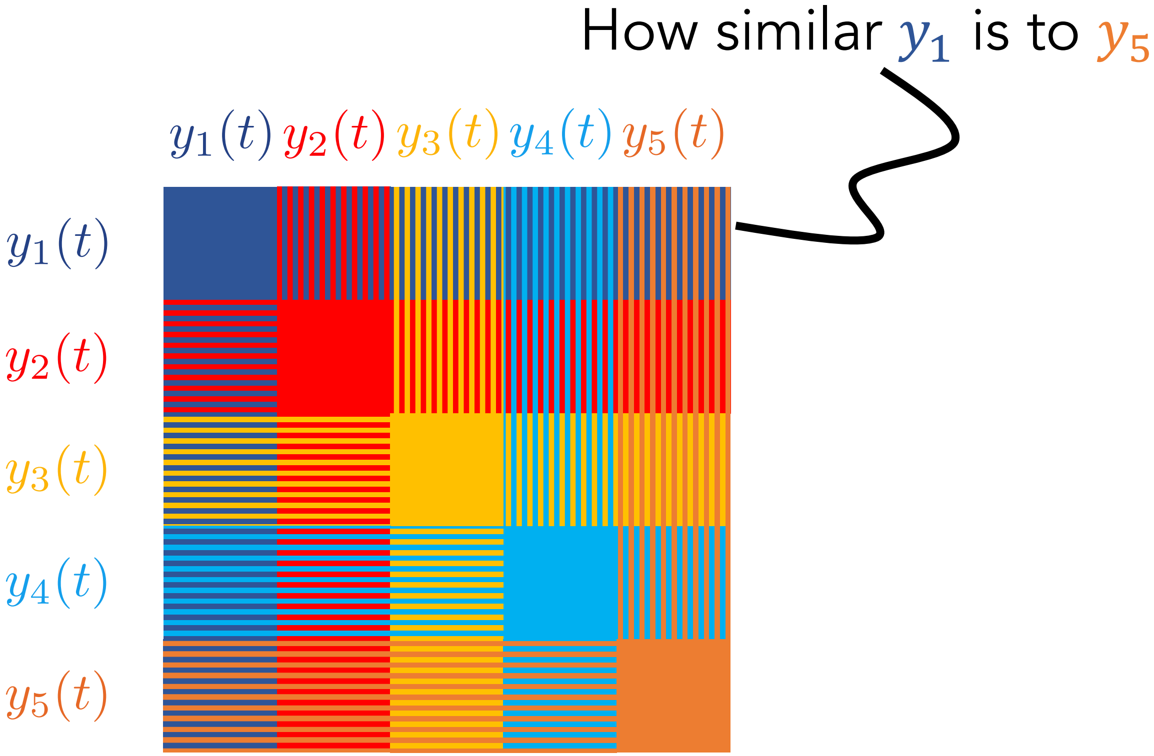
$\mathbf{x}^*$: Depends on the data $\Longrightarrow$ Contains uncertainty

Use averages: $\mathbb{E}[\cdot]$

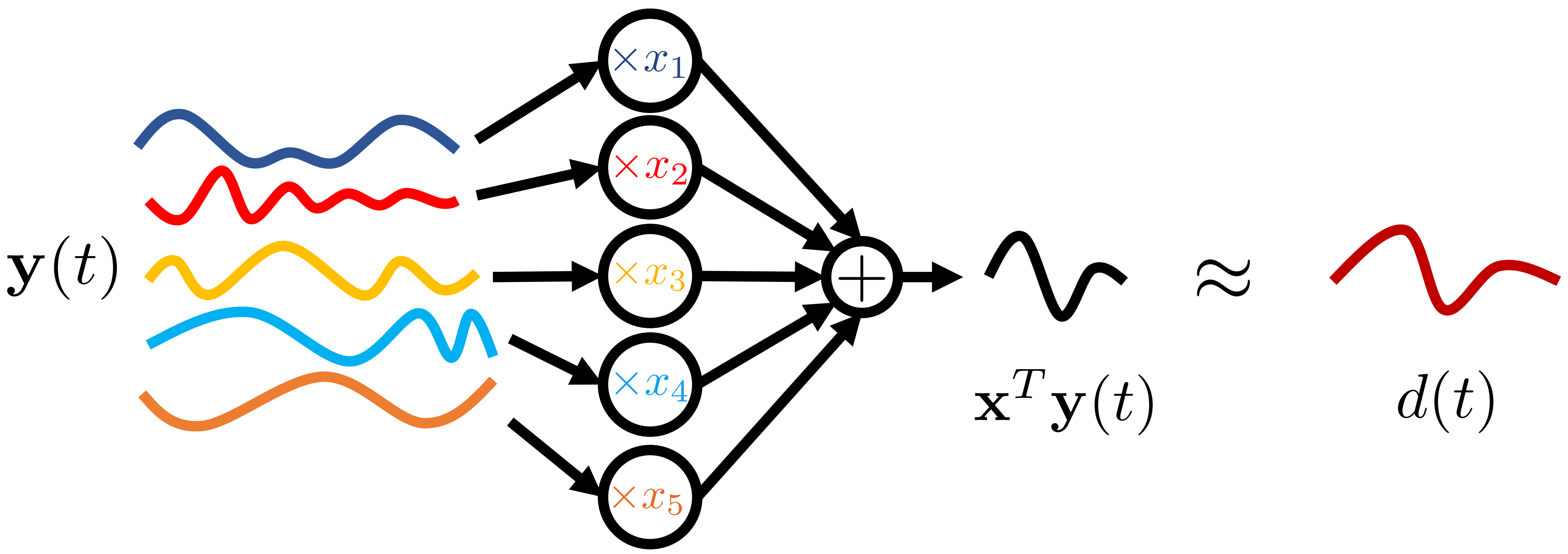
Covariance matrix

$$\boxed{R_{\mathbf{yy}} = \mathbb{E}[\mathbf{y}(t)\mathbf{y}^T(t)]}$$

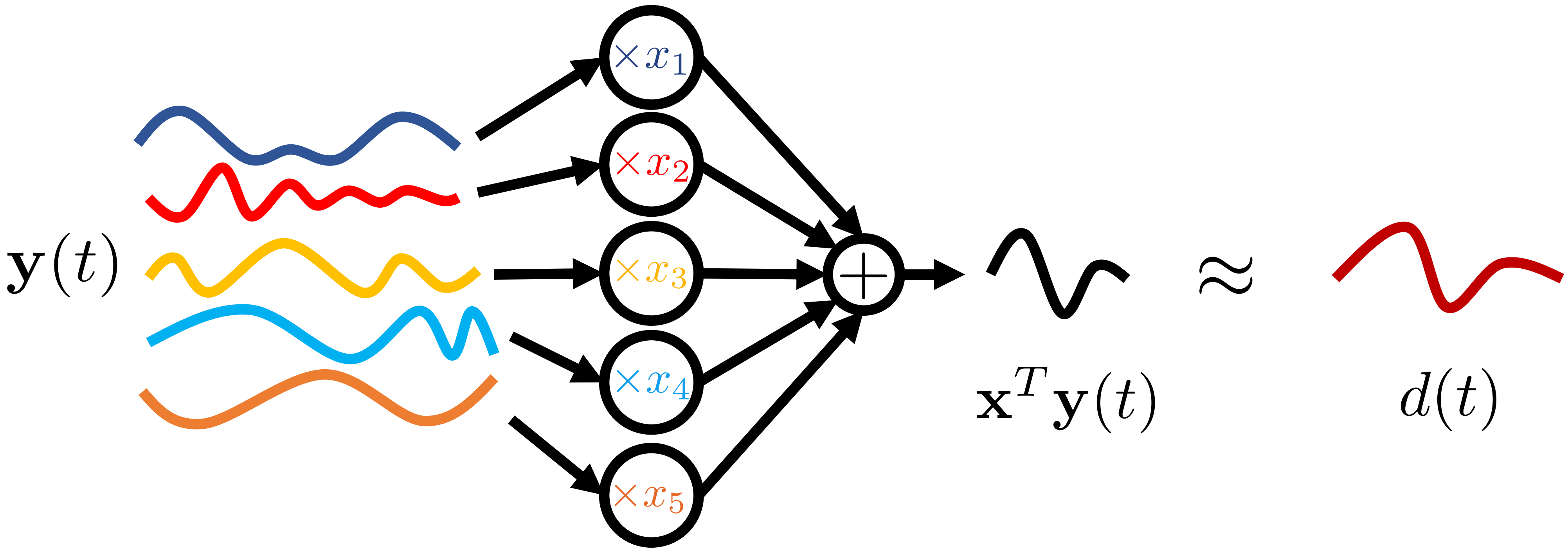
$$\mathbf{y}(t) = \begin{bmatrix} y_1(t) \\ y_2(t) \\ y_3(t) \\ y_4(t) \\ y_5(t) \end{bmatrix}$$



MMSE: "$\mathbf{x}^T\mathbf{y}(t)$ closest to $d(t)$ *on average*"



MMSE: "$\mathbf{x}^T\mathbf{y}(t)$ closest to $d(t)$ *on average*"



$$\min_{\mathbf{x}} \mathbb{E}[|d(t) - \mathbf{x}^T\mathbf{y}(t)|^2]$$

$$\mathbf{x}^* = R_{\mathbf{yy}}^{-1}\mathbf{r}_{\mathbf{y}d}$$

Cannot compute $\mathbb{E}[\cdot]$ in practice

Solution: Use sample averages

Collect: $\{\mathbf{y}(0), \mathbf{y}(1), \ldots, \mathbf{y}(N-1)\}$

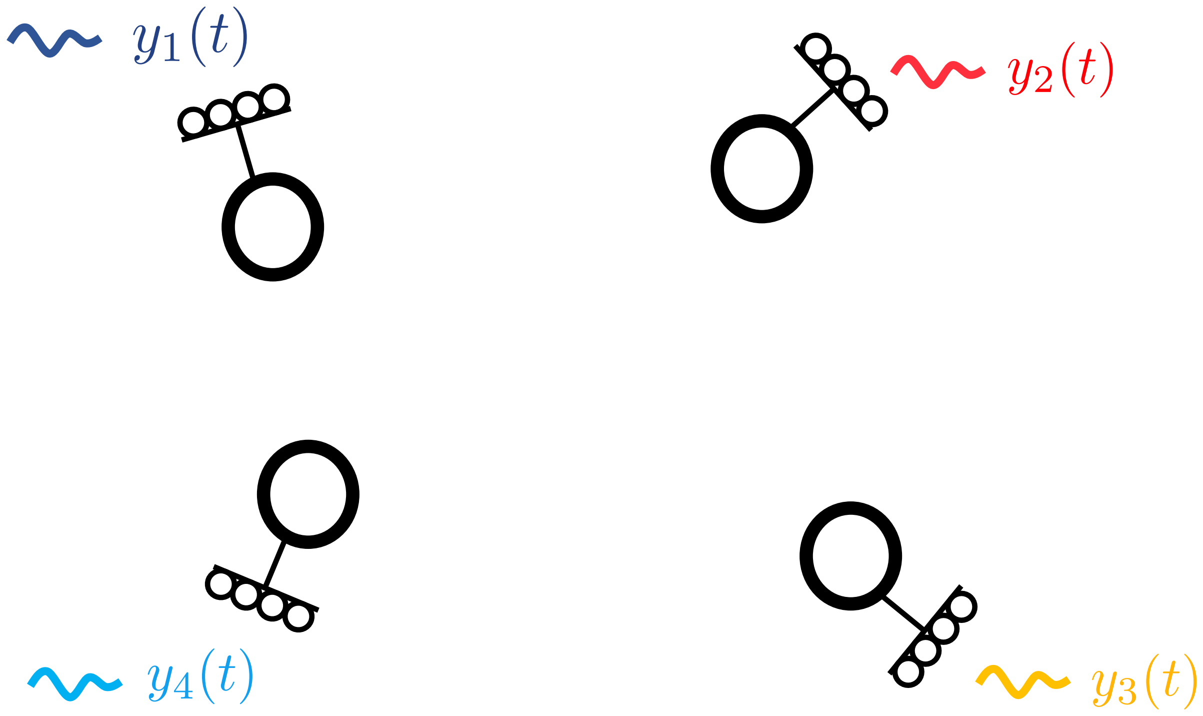
Replace: $R_{\mathbf{yy}} = \mathbb{E}[\mathbf{y}(t)\mathbf{y}^T(t)] \approx \frac{1}{N}\sum_{\tau=0}^{N-1} \mathbf{y}(\tau)\mathbf{y}^T(\tau)$

Spatial filtering tasks

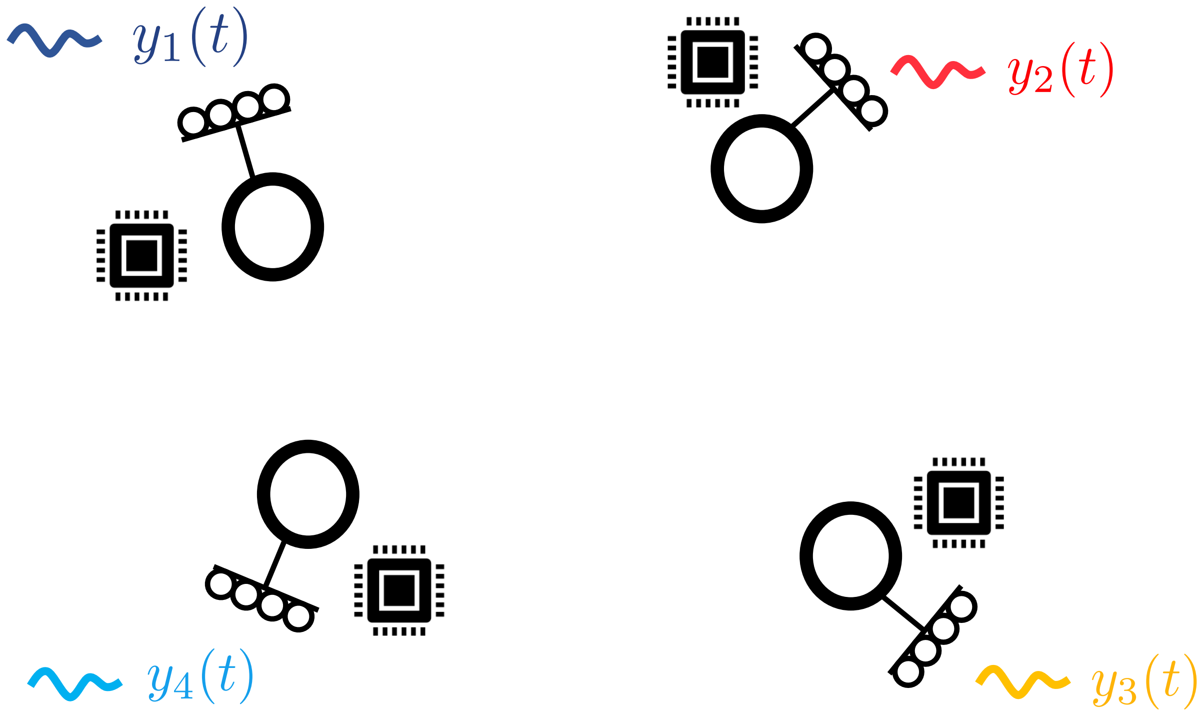
$$\underset{\mathbf{x}}{\text{minimize}} \; f(\mathbf{x}^T \mathbf{y}(t))$$

$$\text{subject to } \mathbf{x} \in \mathcal{S}$$

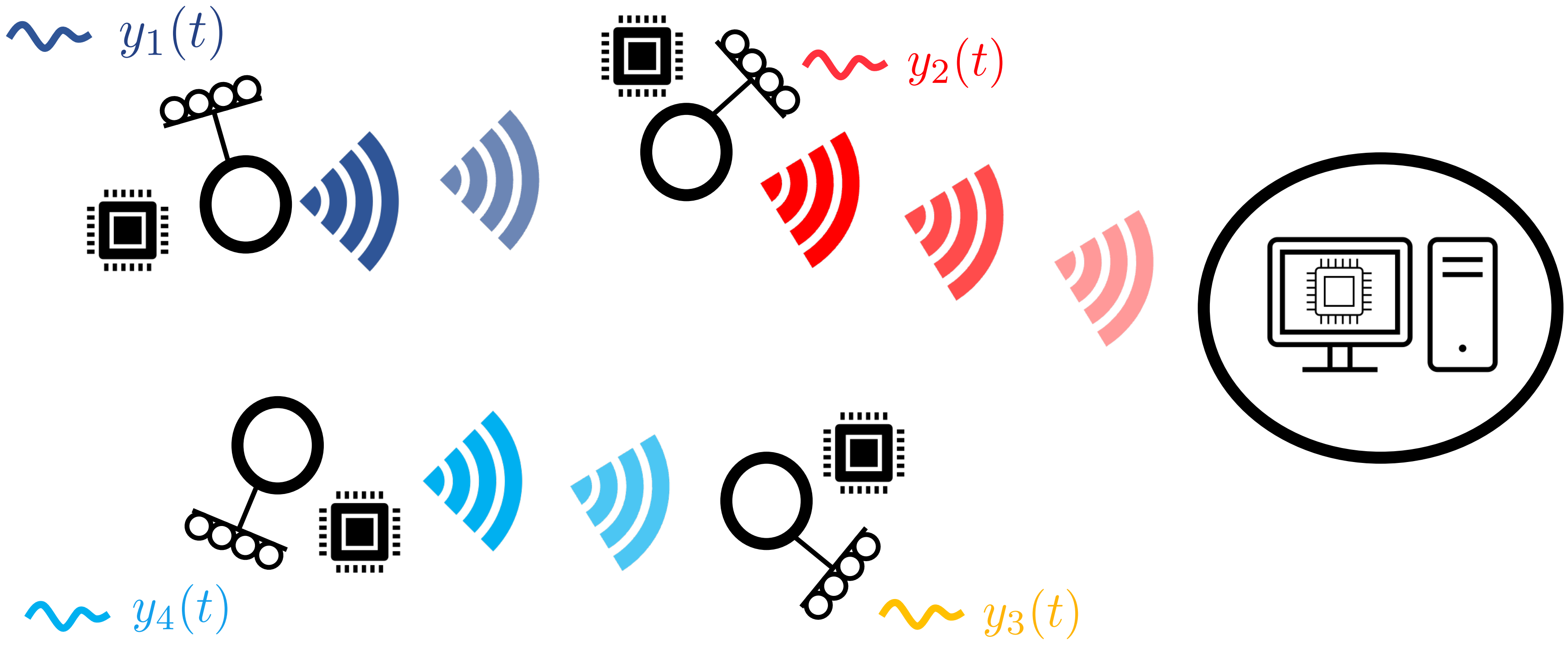
Wireless sensor networks (WSNs)



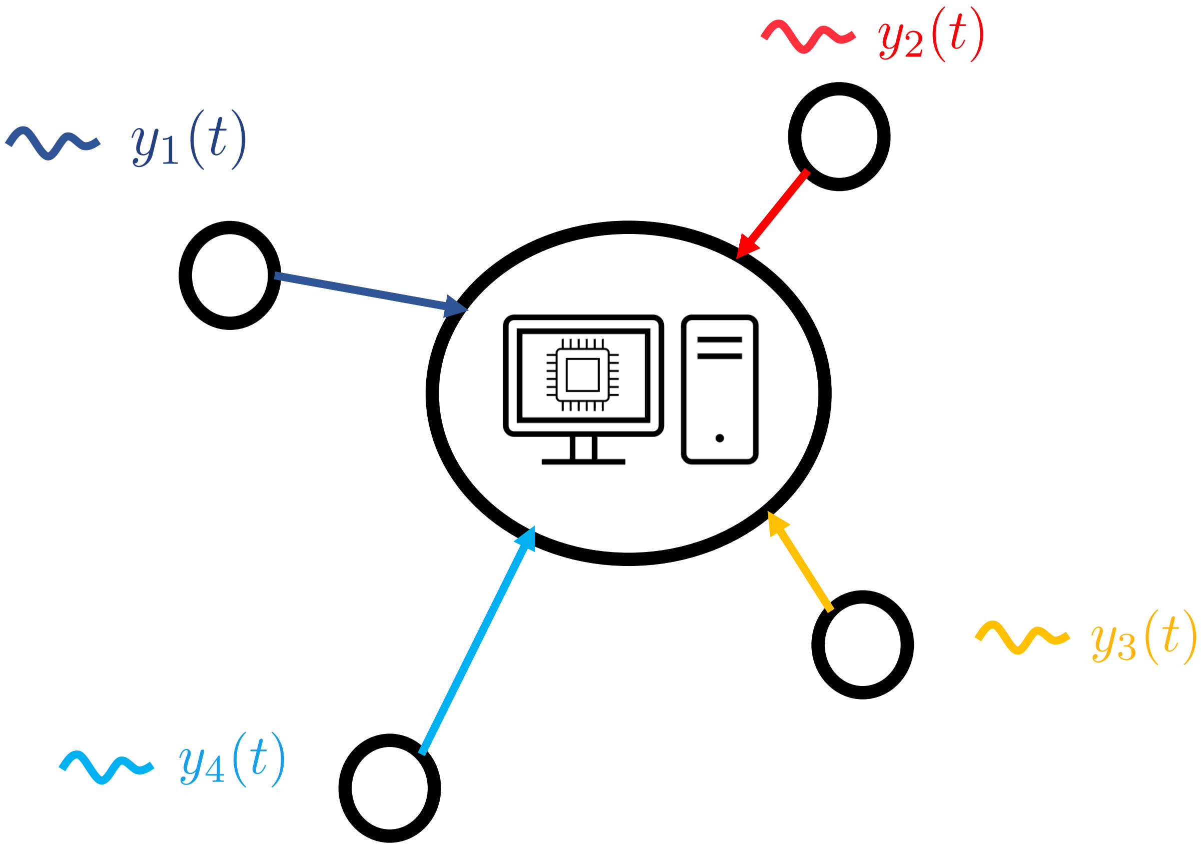
Wireless sensor networks (WSNs)



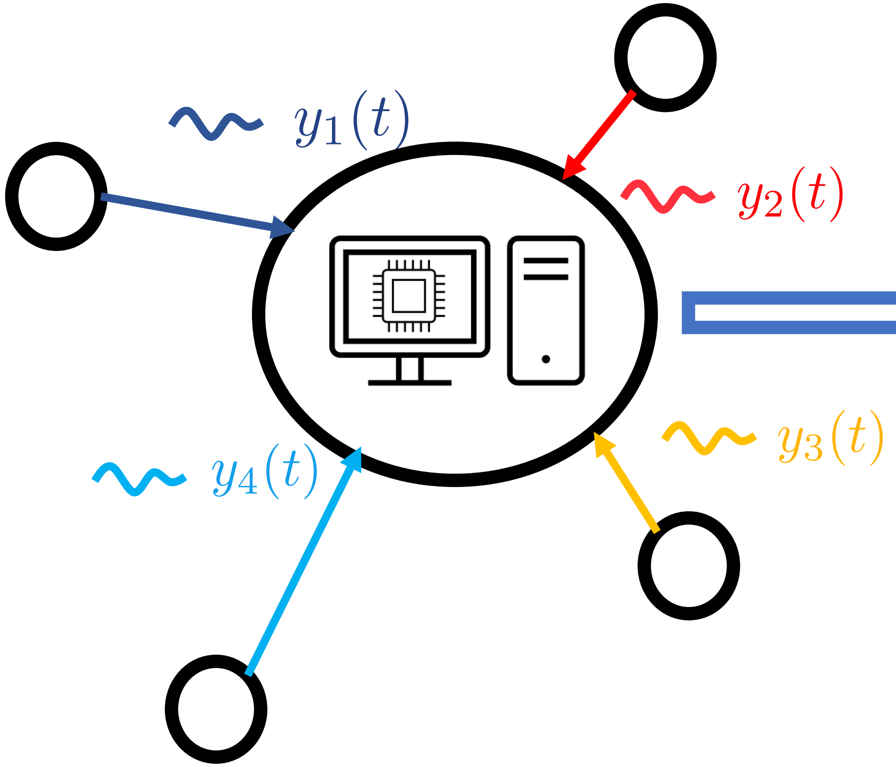
Wireless sensor networks (WSNs)



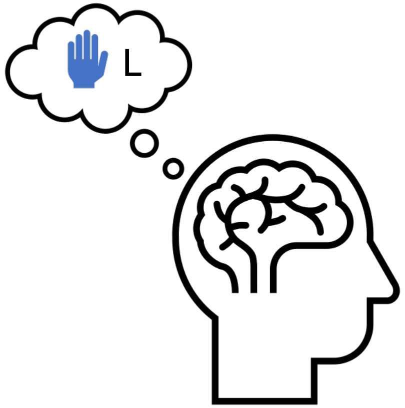
Centralized solution

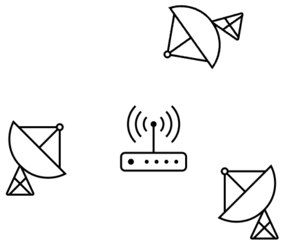


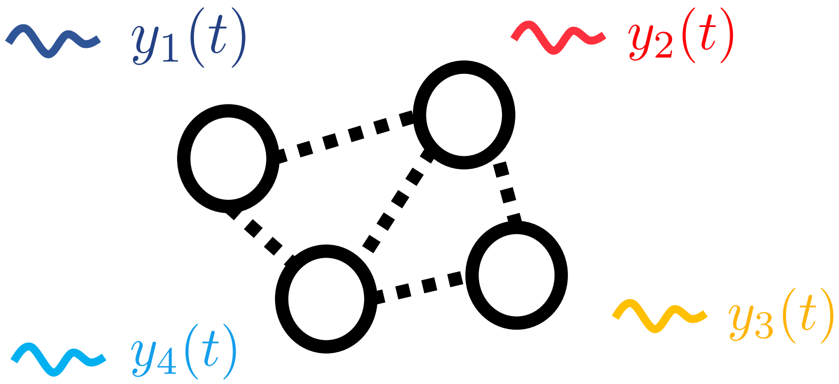
Centralized solution



$\Longrightarrow$ Solve
$$\min_{\mathbf{x}} \; f(\mathbf{x}^T \mathbf{y}(t)) \quad \text{s. t. } \mathbf{x} \in \mathcal{S}$$
$\Longrightarrow$ $\mathbf{x}^*$





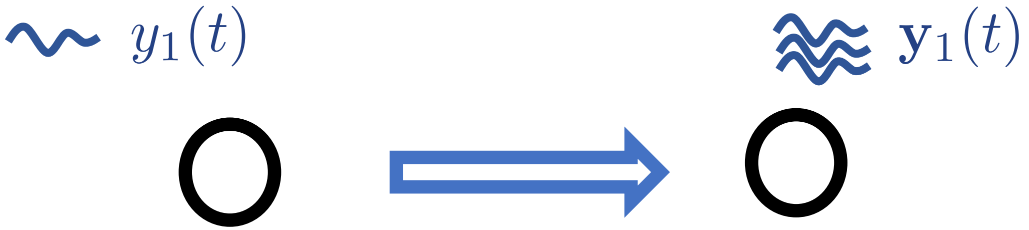


Limited bandwidth

Limited energy resources

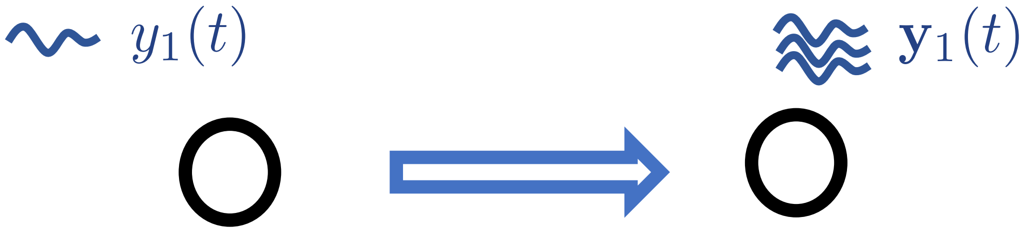
Issues with centralized solution

Bandwidth

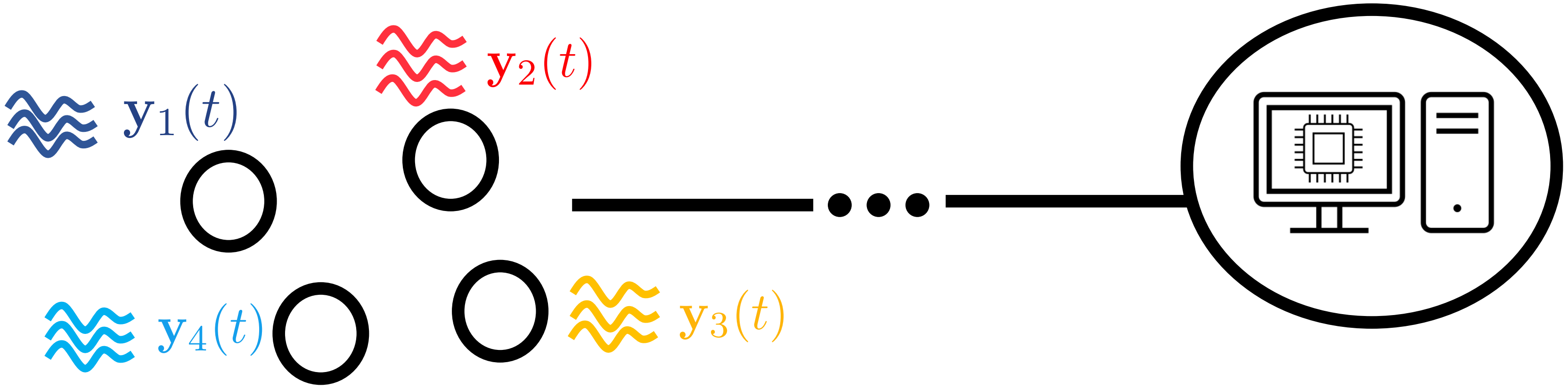


Issues with centralized solution

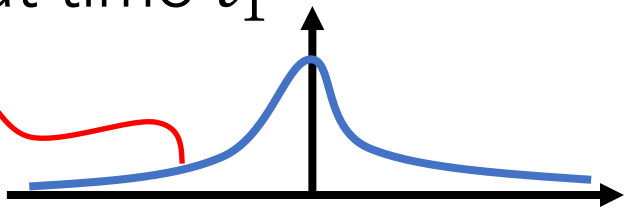
Bandwidth



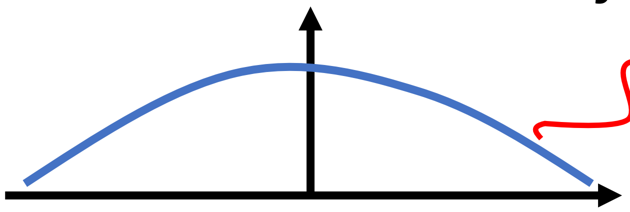
Energy



Uncertainty on $\boldsymbol{y}$ at time t_1

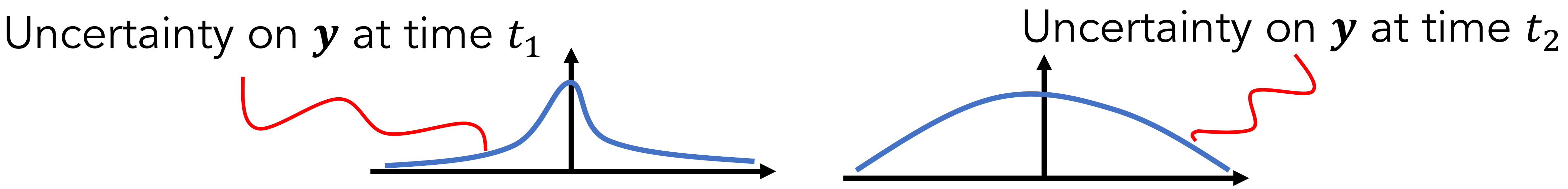


Uncertainty on $\boldsymbol{y}$ at time t_2



$$R_{\mathbf{yy}}(t_1) \neq R_{\mathbf{yy}}(t_2)$$

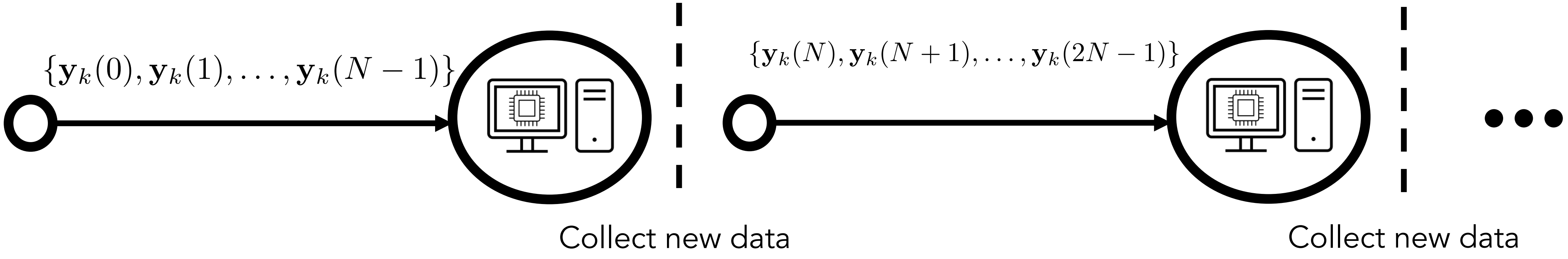
$$\mathbf{x}^*(t_1) \neq \mathbf{x}^*(t_2)$$



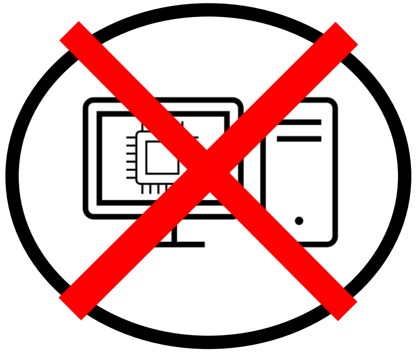
$$R_{\mathbf{yy}}(t_1) \neq R_{\mathbf{yy}}(t_2)$$

$$\mathbf{x}^*(t_1) \neq \mathbf{x}^*(t_2)$$

$\boxed{\text{Not a 1-time operation}}$

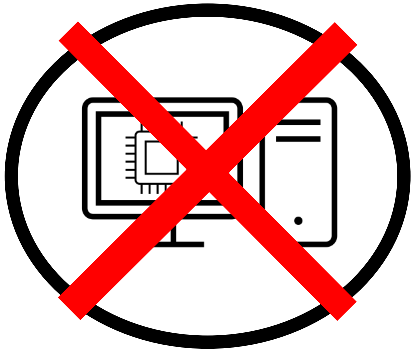


Distributed solutions for WSNs



Existing methods: Consensus, diffusion, ADMM…

Distributed solutions for WSNs

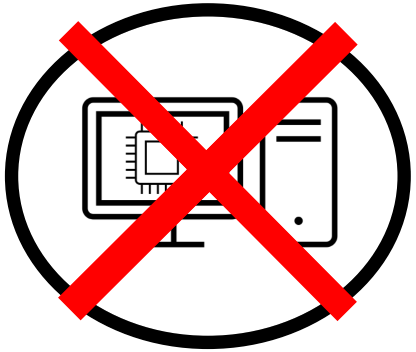


Existing methods: Consensus, diffusion, ADMM…

Node-separable objective

$$f(\mathbf{x}) = \sum_k f_k(\mathbf{x})$$

Distributed solutions for WSNs



Existing methods: Consensus, diffusion, ADMM…

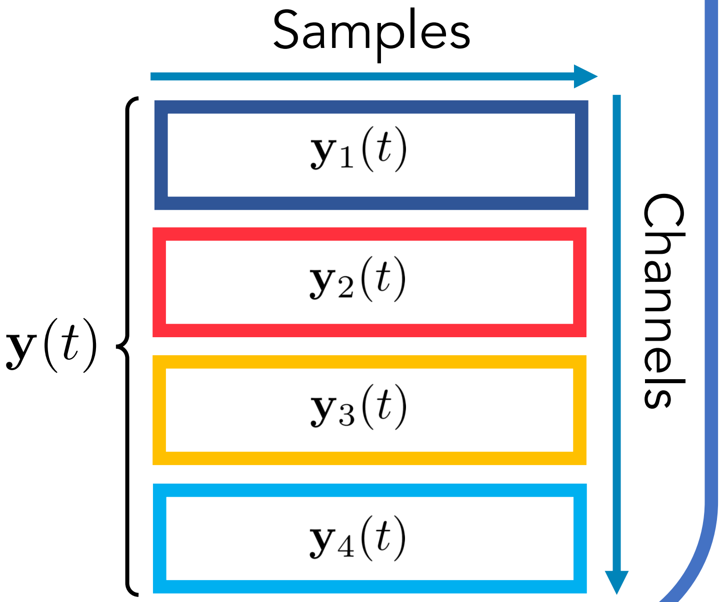
Node-separable objective

$$f(\mathbf{x}) = \sum_k f_k(\mathbf{x}) \neq$$

Spatial filtering

Objective is *not* node-separable

$$f(\mathbf{x}^T \mathbf{y}(t))$$



Distributed spatial filtering in WSNs

Task 1: MMSE

Design task-specific distributed algorithm

Task 2: LCMV

Design task-specific

distributed algorithm

Task 3: PCA

Design task-specific distributed algorithm

Distributed spatial filtering in WSNs

Task 1: MMSE

Design $\boxed{\text{task-specific}}$ distributed algorithm

Task 2: LCMV

Design $\boxed{\text{task-specific}}$ distributed algorithm

Task 3: PCA

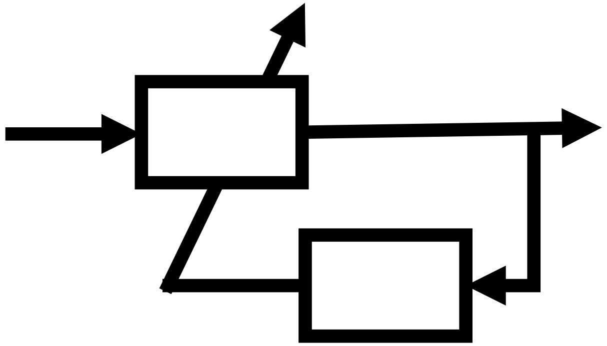
Design $\boxed{\text{task-specific}}$ distributed algorithm

Distributed spatial filtering in WSNs

Unified and Generalizable
1 method for spatial filtering tasks

Efficient communication

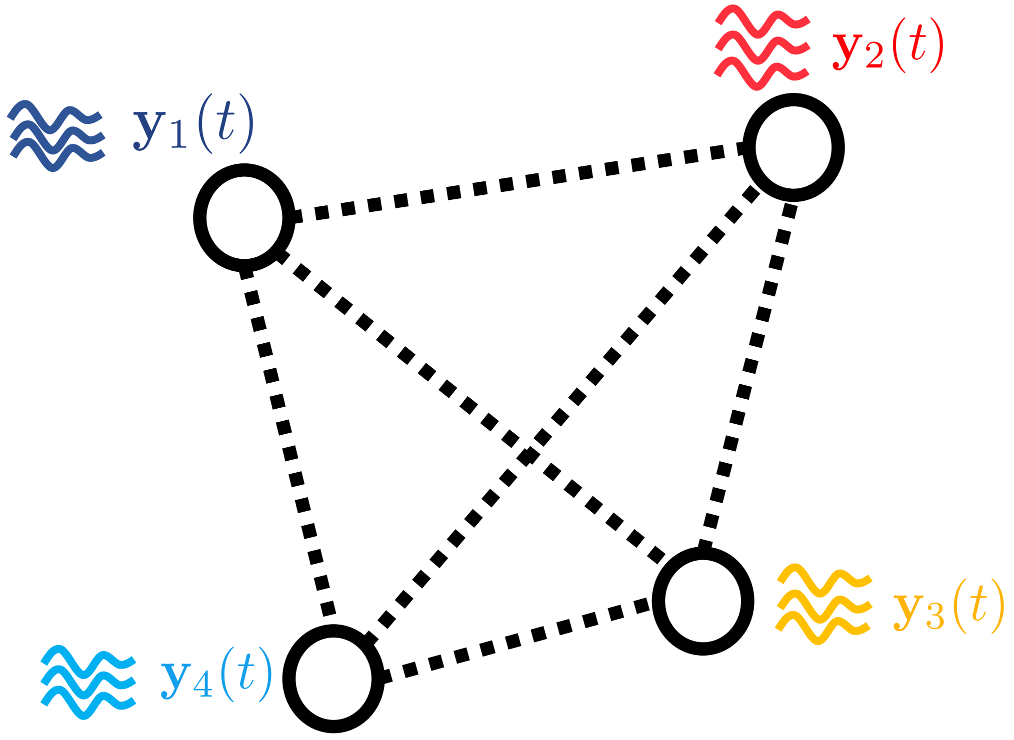
Computational efficiency



Adaptive

I. The Distributed Adaptive Signal Fusion (DASF) framework

C. A. Musluoglu and A. Bertrand, "A Unified Algorithmic Framework for Distributed Adaptive Signal and Feature Fusion Problems—Part I: Algorithm Derivation," in *IEEE Transactions on Signal Processing*, vol. 71, pp. 1863-1878, 2023, doi: 10.1109/TSP.2023.3275272.
C. A. Musluoglu, C. Hovine and A. Bertrand, "A Unified Algorithmic Framework for Distributed Adaptive Signal and Feature Fusion Problems — Part II: Convergence Properties," in *IEEE Transactions on Signal Processing*, vol. 71, pp. 1879-1894, 2023, doi: 10.1109/TSP.2023.3275273.

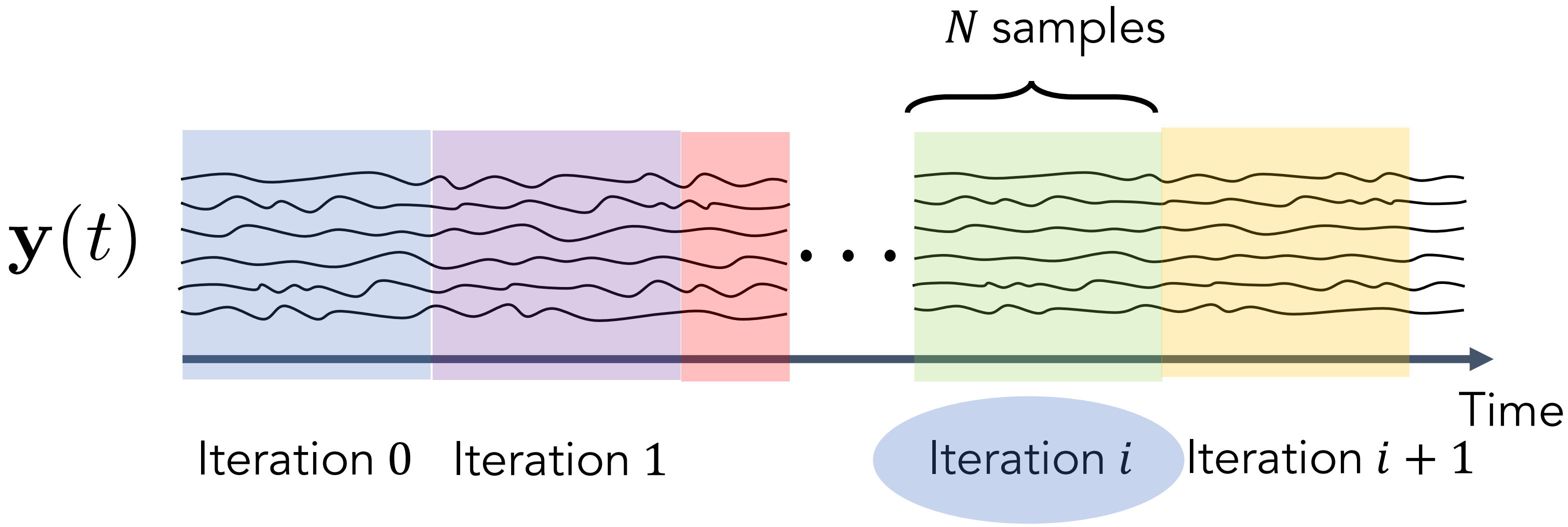


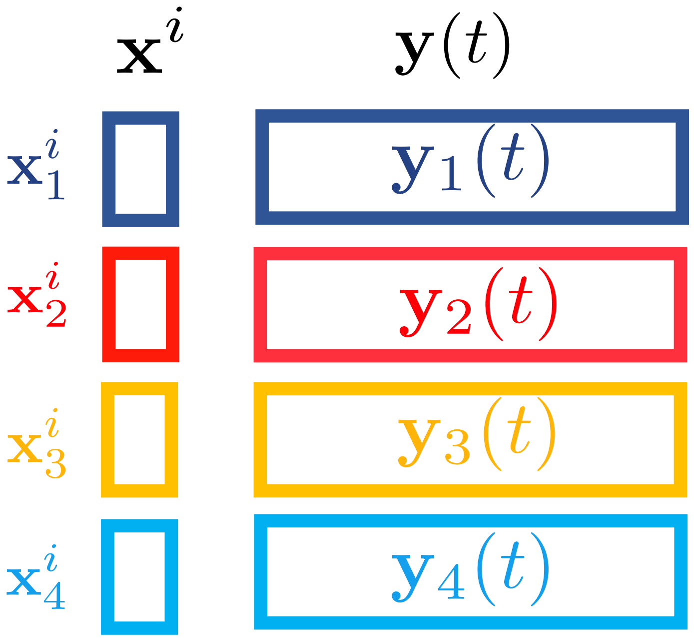
$$\begin{aligned}&\underset{\mathbf{x}}{\text{minimize}}\ f(\mathbf{x}^T\mathbf{y}(t))\\&\text{subject to } \mathbf{x}\in\mathcal{S}\end{aligned}$$

$$\Downarrow$$

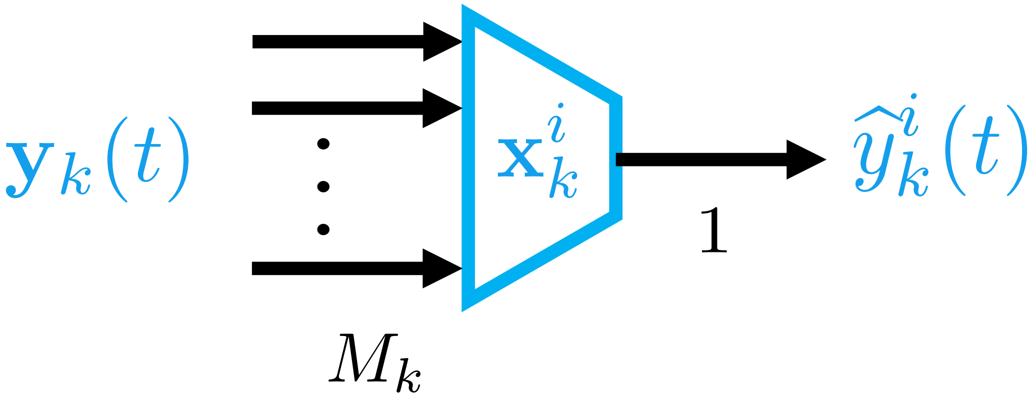
$$\mathbf{y}(t)\left\{\begin{array}{|c|}\hline \mathbf{y}_1(t)\\\hline \mathbf{y}_2(t)\\\hline \mathbf{y}_3(t)\\\hline \mathbf{y}_4(t)\\\hline\end{array}\right.$$

$$\begin{aligned}&\underset{\mathbf{x}}{\text{minimize}}\ f(\mathbf{x}^T\mathbf{y}(t))\\&\text{subject to } g(\mathbf{x}^T\mathbf{y}(t))=0\\&\qquad\qquad\quad h(\mathbf{x}^T\mathbf{y}(t))\le 0\end{aligned}$$

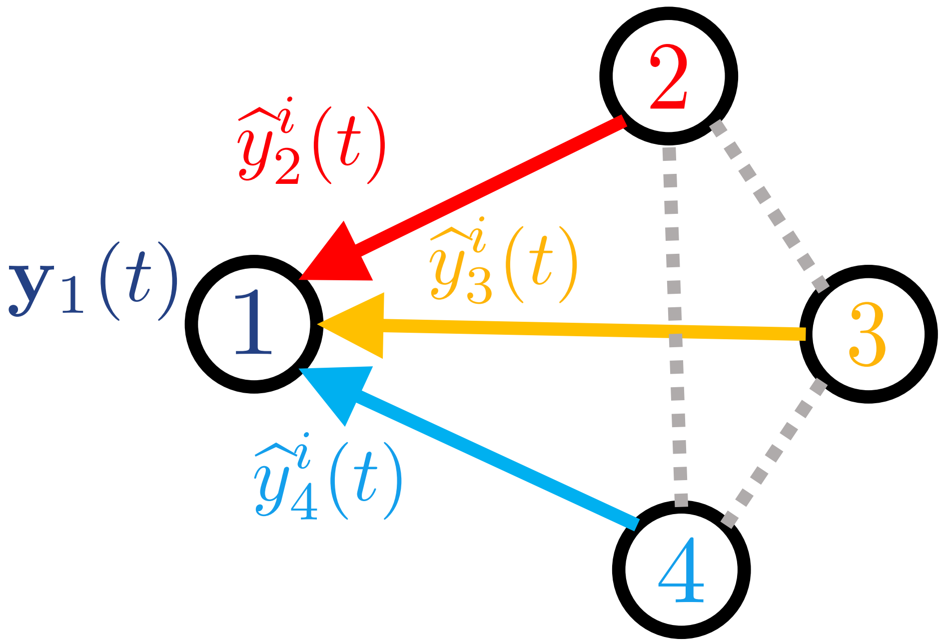


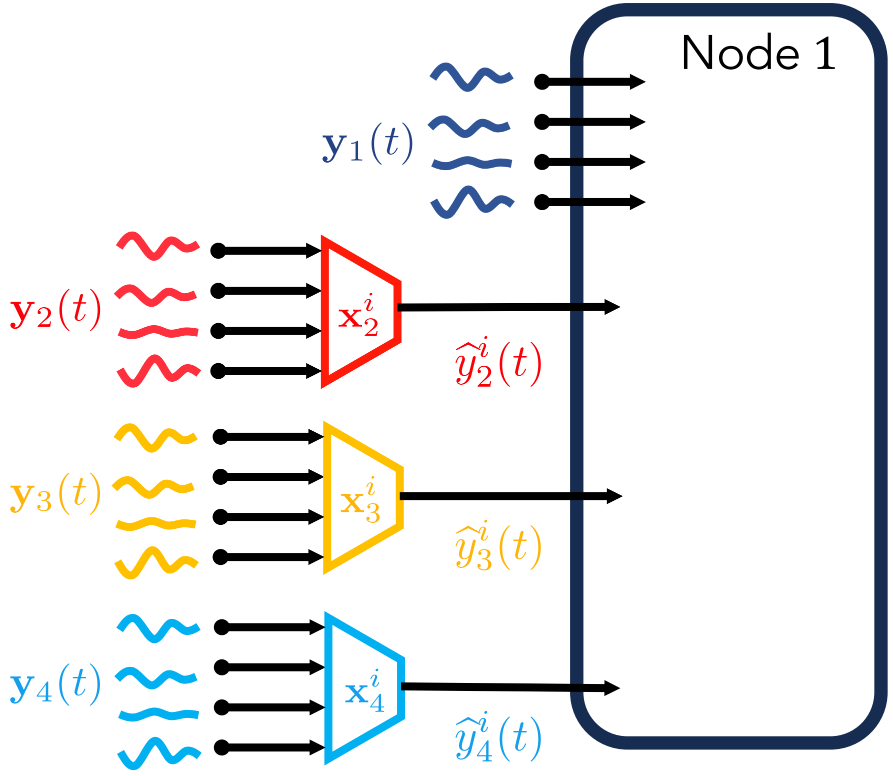


1. Collect and compress signals

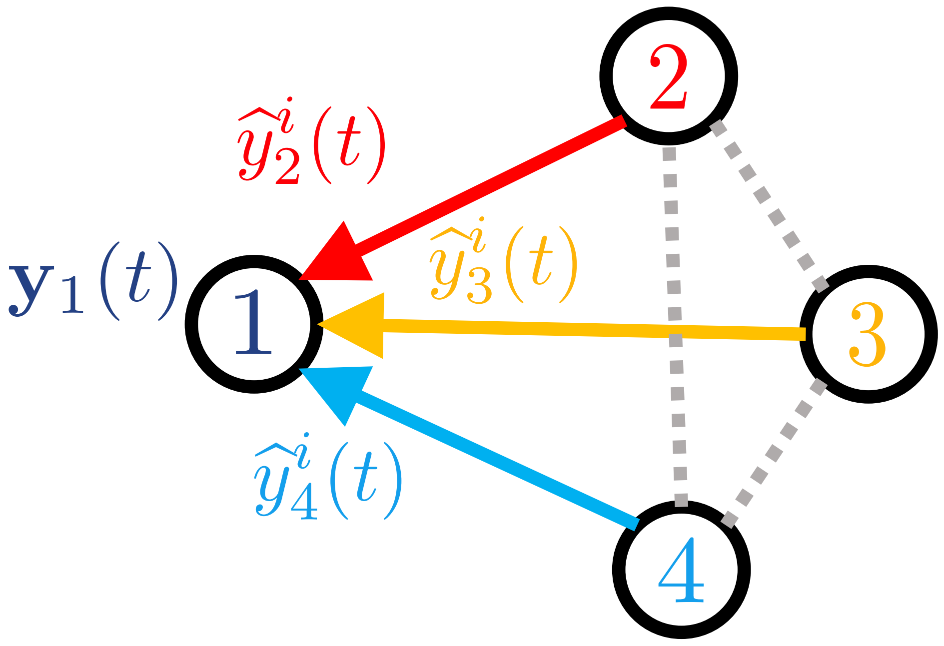


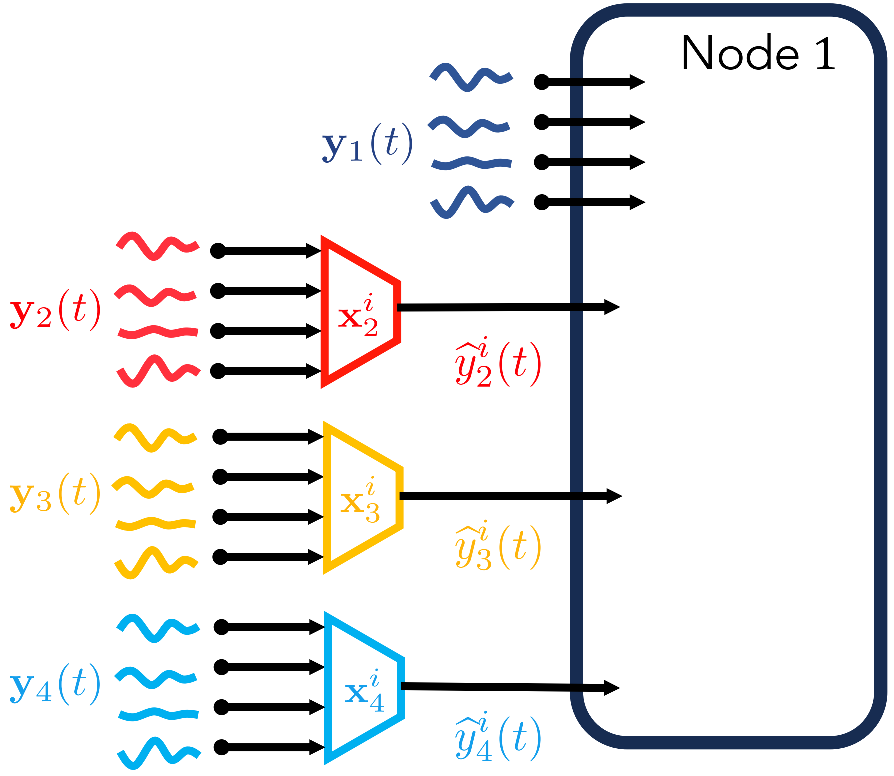
2. Select updating node and transmit compressed signals





2. Select updating node and transmit compressed signals





Efficient communication

$$\widetilde{\mathbf{y}}_1^i(t)$$

$$\boxed{\mathbf{y}_1(t)}$$

$$\boxed{\widehat{y}_2^i(t)}$$

$$\boxed{\widehat{y}_3^i(t)}$$

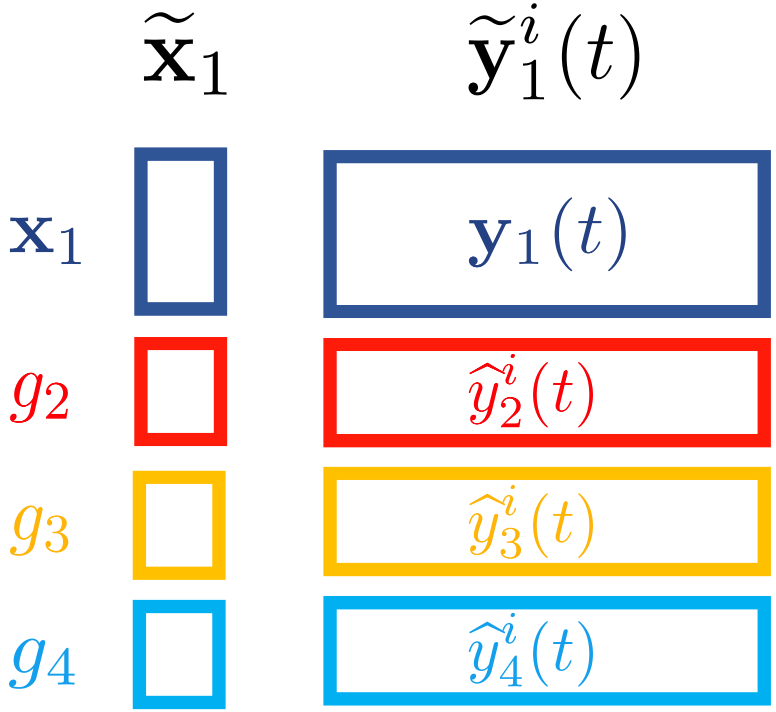
$$\boxed{\widehat{y}_4^i(t)}$$

$$
\begin{aligned}
\underset{\mathbf{x}}{\text{minimize}}\ & f(\mathbf{x}^T\mathbf{y}(t)) \\
\text{subject to}\ & g(\mathbf{x}^T\mathbf{y}(t)) = 0 \\
& h(\mathbf{x}^T\mathbf{y}(t)) \leq 0
\end{aligned}
$$

$$
\widetilde{\mathbf{y}}_1^i(t) = \begin{bmatrix} \mathbf{y}_1(t) \\ \widehat{y}_2^i(t) \\ \widehat{y}_3^i(t) \\ \widehat{y}_4^i(t) \end{bmatrix}
$$

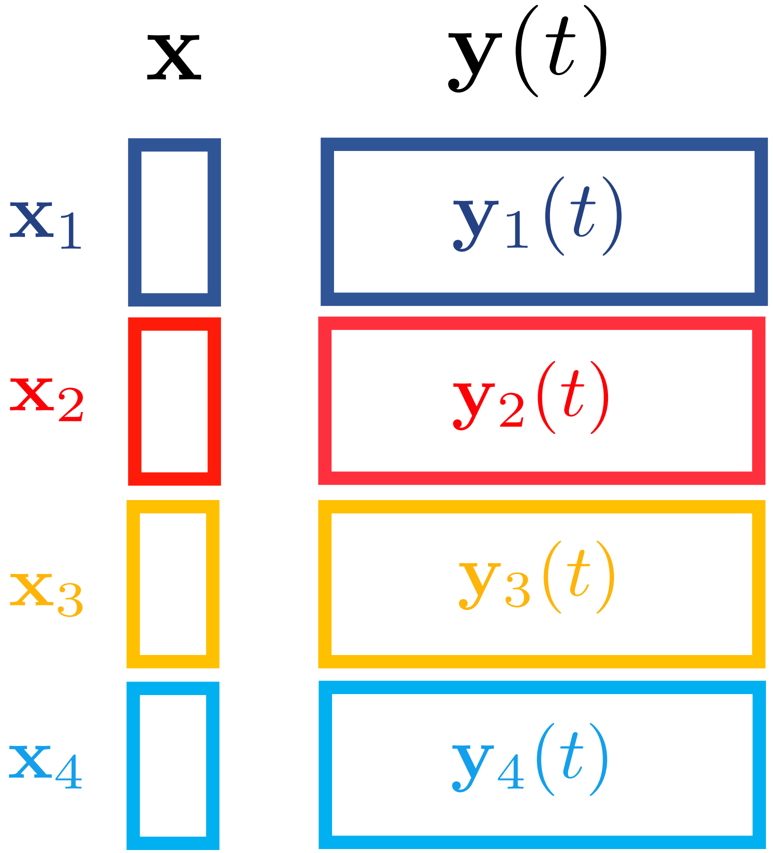
$$
\begin{array}{ccc}
 & \mathbf{x} & \mathbf{y}(t) \\
\mathbf{x}_1 & \square & \mathbf{y}_1(t) \\
\mathbf{x}_2 & \square & \mathbf{y}_2(t) \\
\mathbf{x}_3 & \square & \mathbf{y}_3(t) \\
\mathbf{x}_4 & \square & \mathbf{y}_4(t)
\end{array}
$$

$$
\begin{aligned}
\underset{\widetilde{\mathbf{x}}_1}{\text{minimize}}\ & f(\widetilde{\mathbf{x}}_1^T \widetilde{\mathbf{y}}_1^i(t)) \\
\text{subject to}\ & g(\widetilde{\mathbf{x}}_1^T \widetilde{\mathbf{y}}_1^i(t)) = 0 \\
& h(\widetilde{\mathbf{x}}_1^T \widetilde{\mathbf{y}}_1^i(t)) \leq 0
\end{aligned}
$$



vs

$$
\begin{aligned}
\underset{\mathbf{x}}{\text{minimize}}\ & f(\mathbf{x}^T \mathbf{y}(t)) \\
\text{subject to}\ & g(\mathbf{x}^T \mathbf{y}(t)) = 0 \\
& h(\mathbf{x}^T \mathbf{y}(t)) \leq 0
\end{aligned}
$$



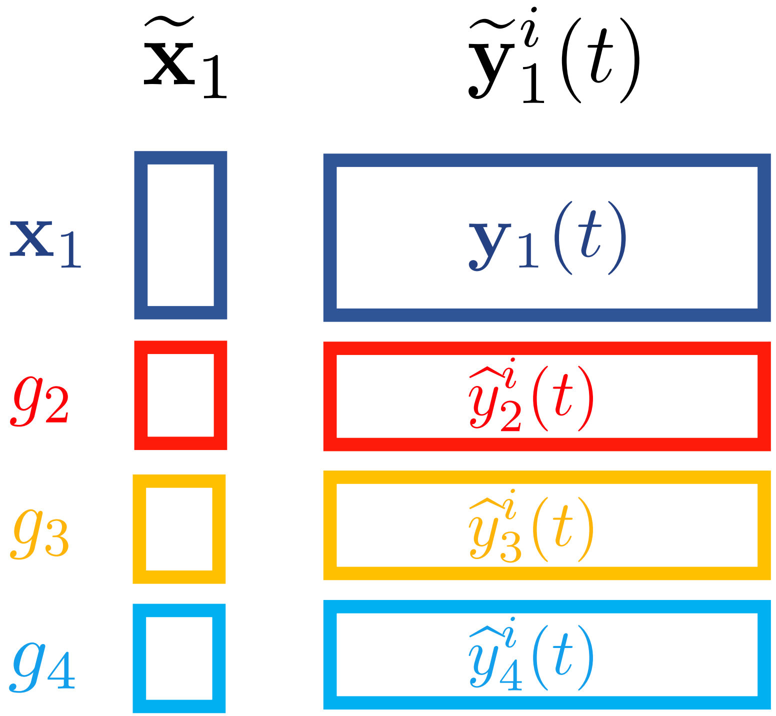
3. Build and solve local problem at updating node

Mimic the global problem locally

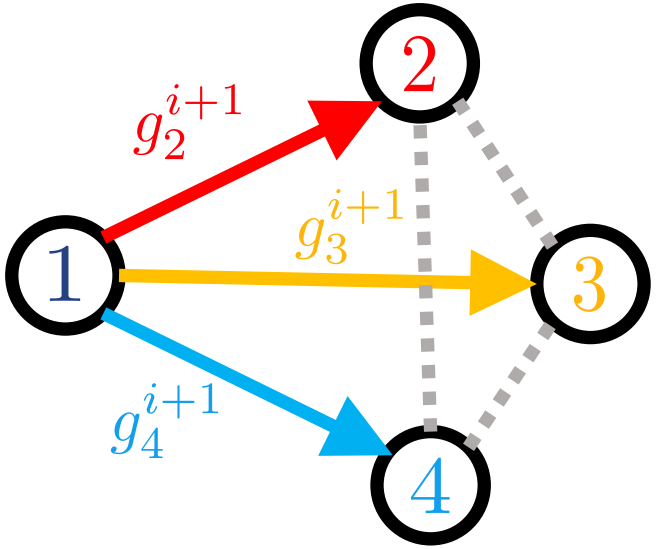
$$\widetilde{\mathbf{x}}_1^* \leftarrow \begin{aligned} \underset{\widetilde{\mathbf{x}}_1}{\text{minimize}} \ & f(\widetilde{\mathbf{x}}_1^T \widetilde{\mathbf{y}}_1^i(t)) \\ \text{subject to} \ & g(\widetilde{\mathbf{x}}_1^T \widetilde{\mathbf{y}}_1^i(t)) = 0 \\ & h(\widetilde{\mathbf{x}}_1^T \widetilde{\mathbf{y}}_1^i(t)) \leq 0 \end{aligned}$$

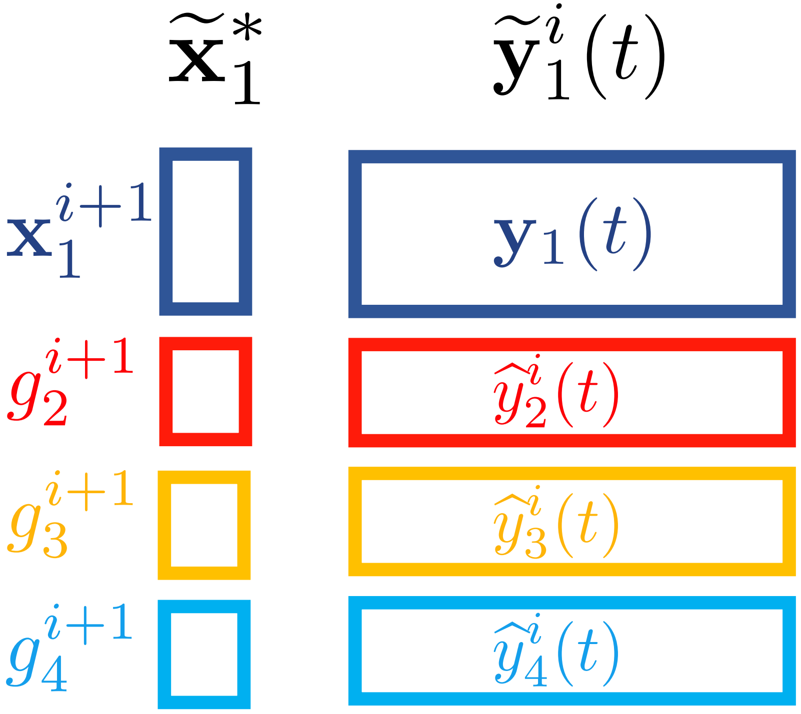
Computational efficiency

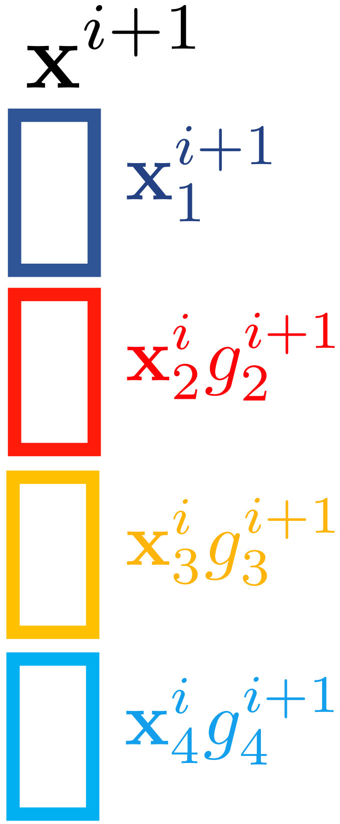
4. Make other nodes aware of this



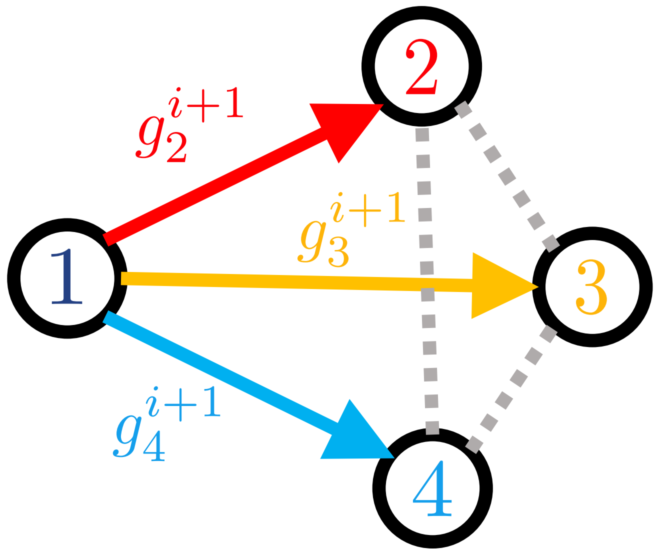
4. Make other nodes aware of this

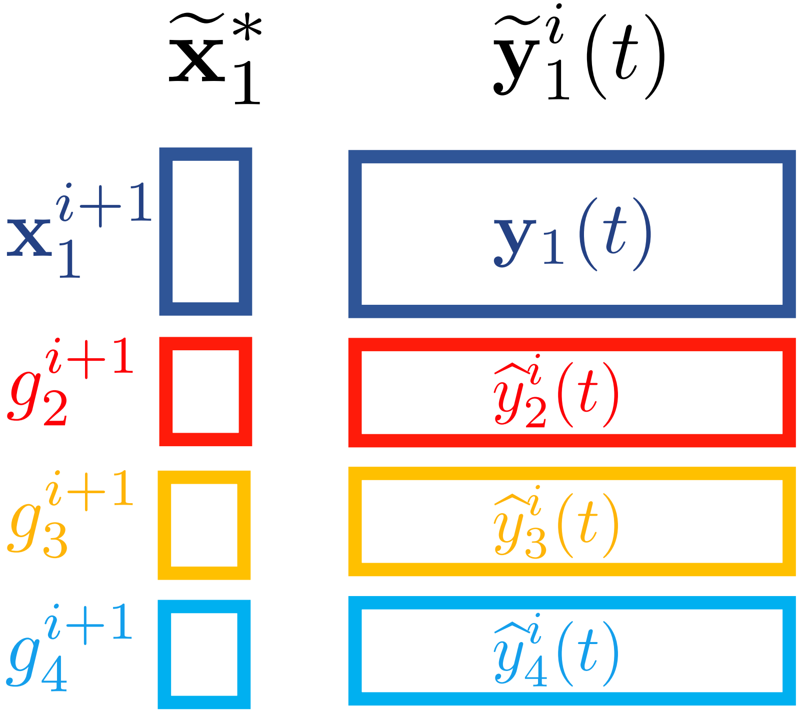


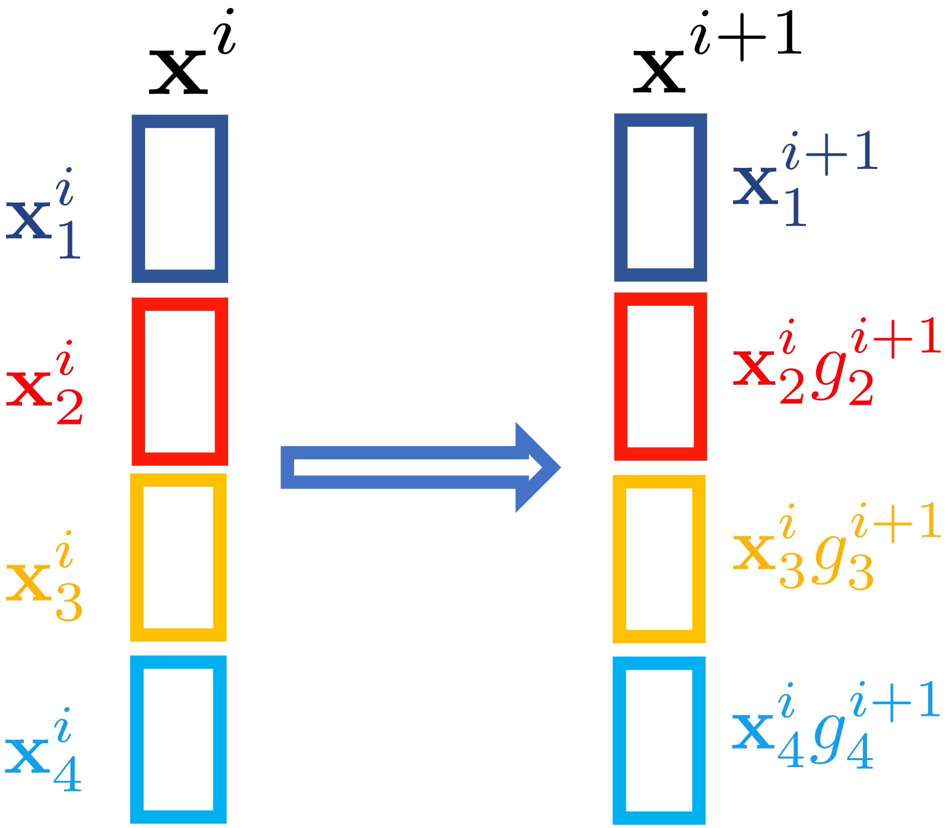


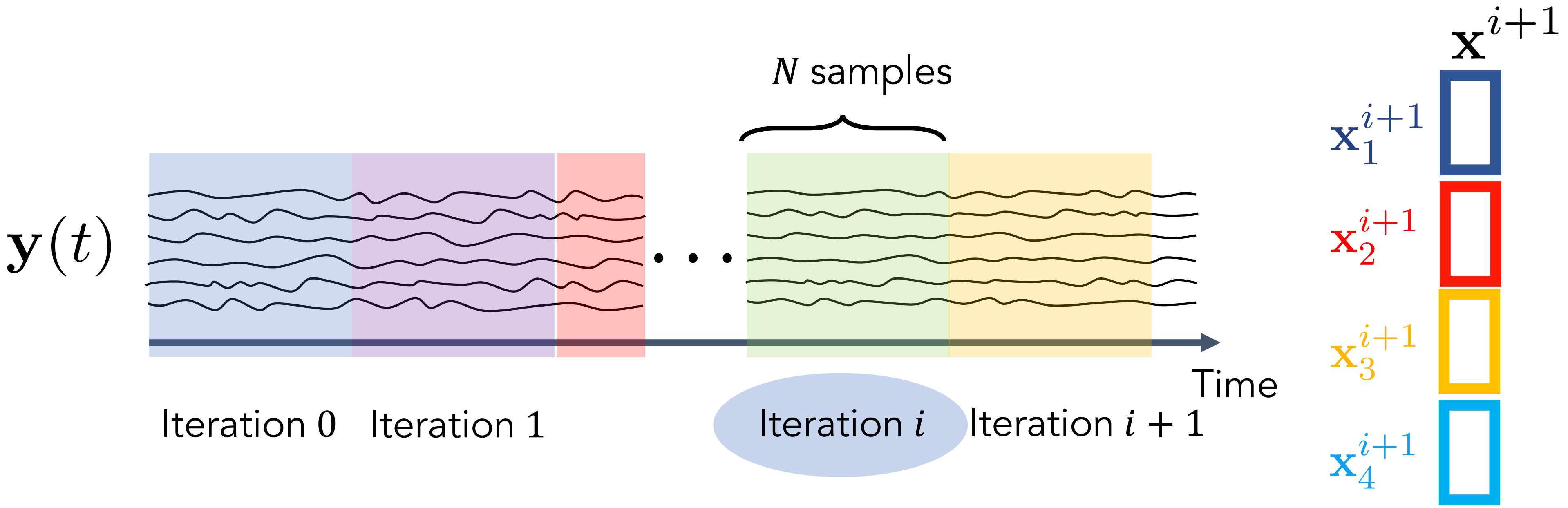


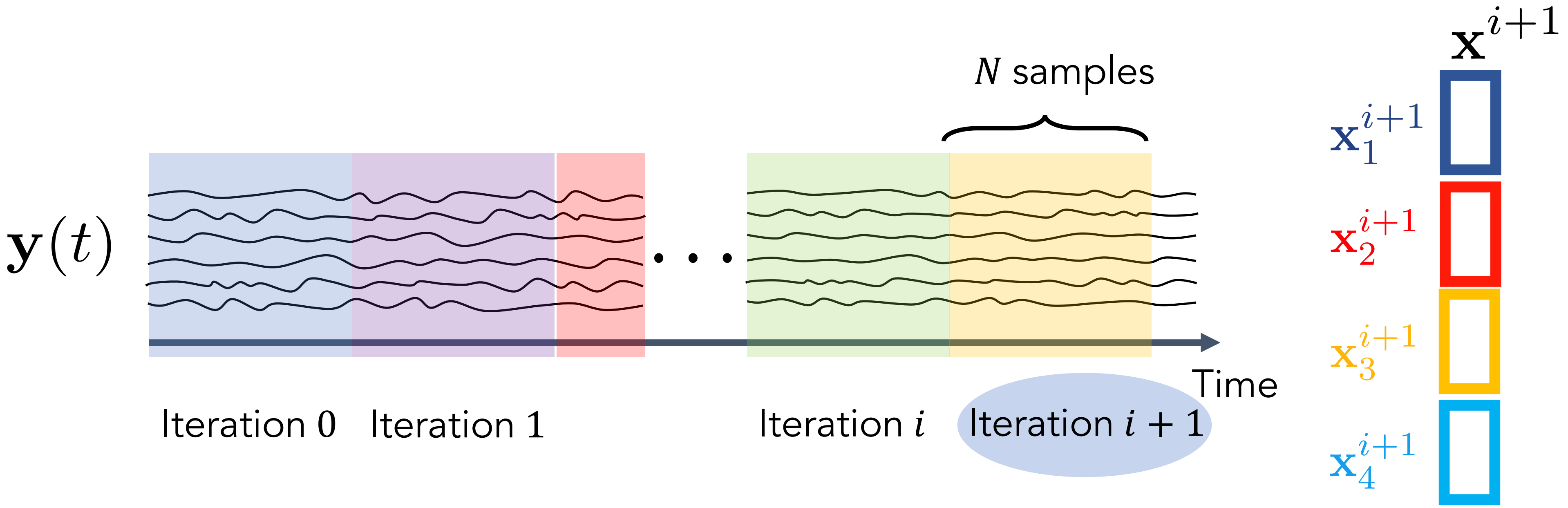
4. Make other nodes aware of this

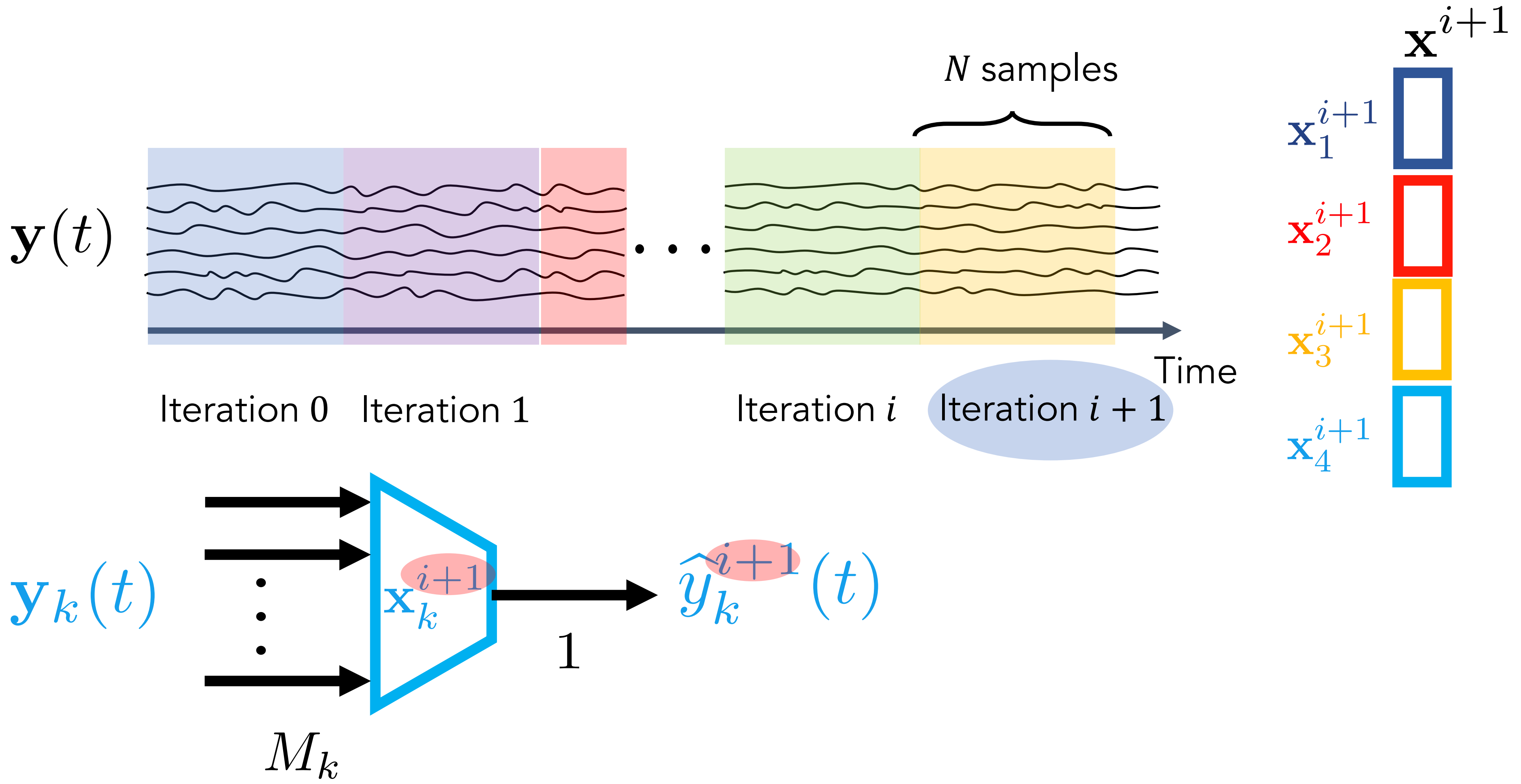




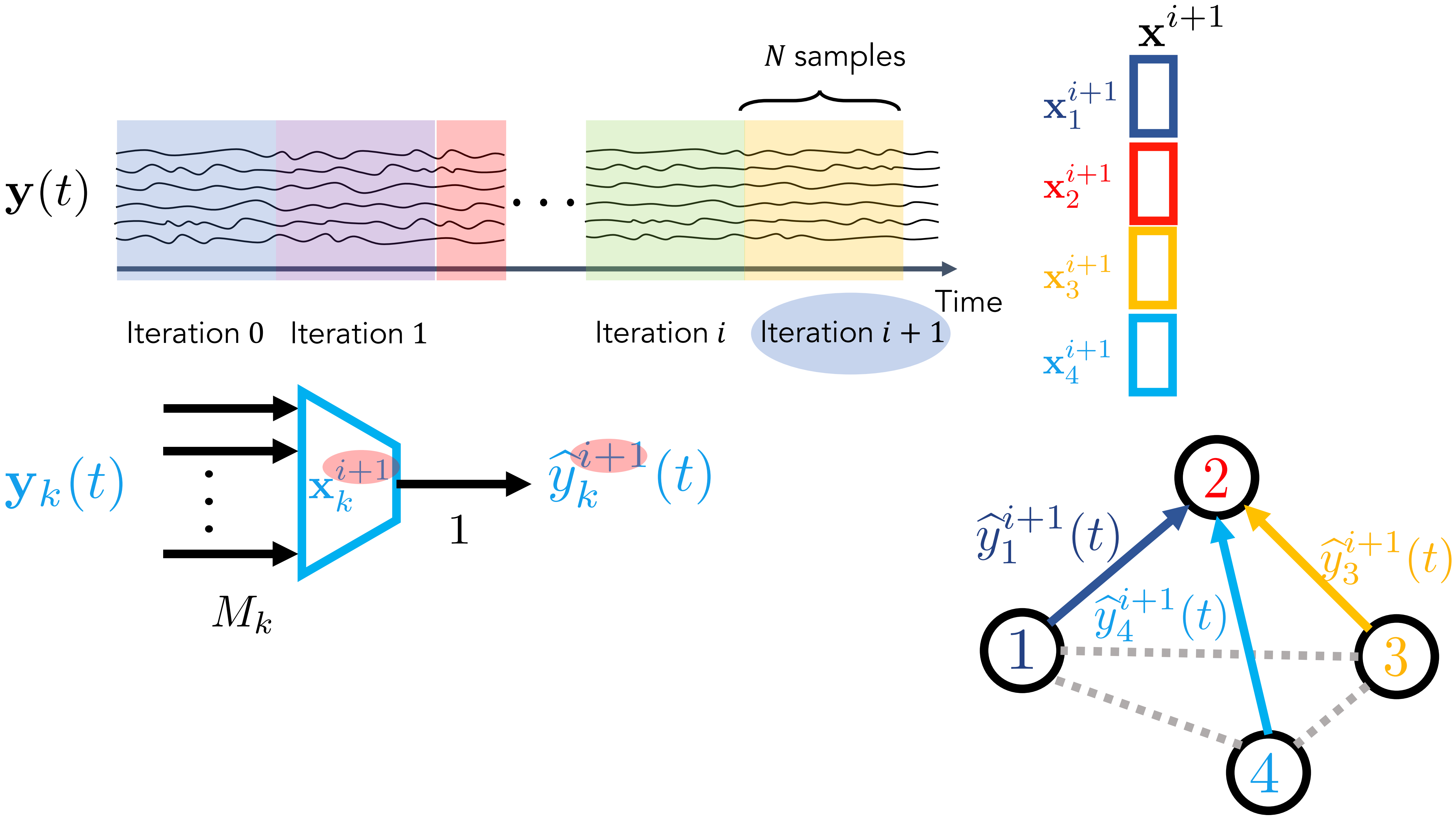



N samples
$\mathbf{y}(t)$
Time
Iteration 0
Iteration 1
Iteration i
Iteration $i+1$
$\mathbf{x}^{i+1}$
$\mathbf{x}_1^{i+1}$
$\mathbf{x}_2^{i+1}$
$\mathbf{x}_3^{i+1}$
$\mathbf{x}_4^{i+1}$

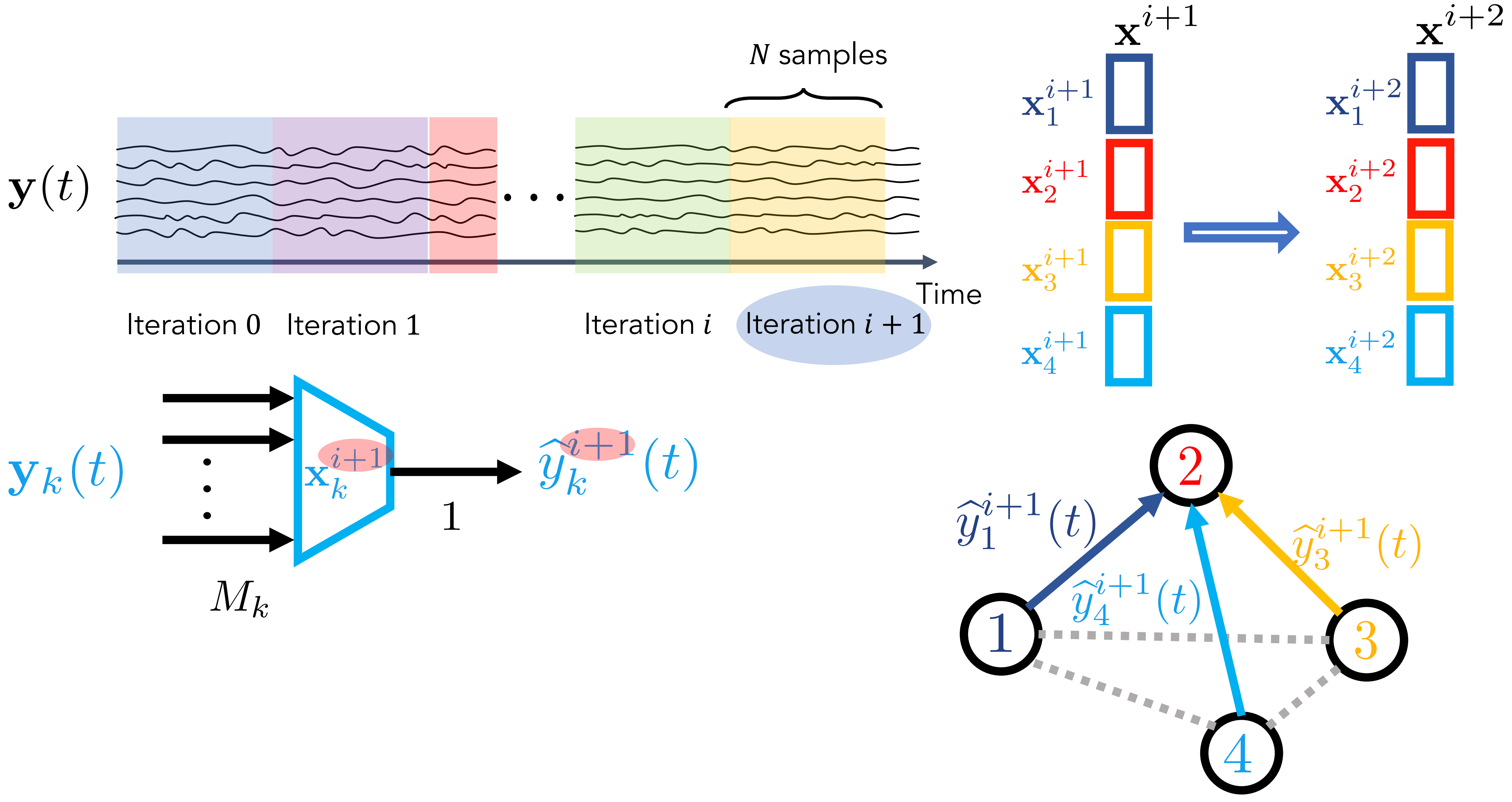

$\mathbf{y}(t)$
N samples
Time
Iteration 0
Iteration 1
Iteration i
Iteration $i+1$
$\mathbf{x}^{i+1}$
$\mathbf{x}_1^{i+1}$
$\mathbf{x}_2^{i+1}$
$\mathbf{x}_3^{i+1}$
$\mathbf{x}_4^{i+1}$

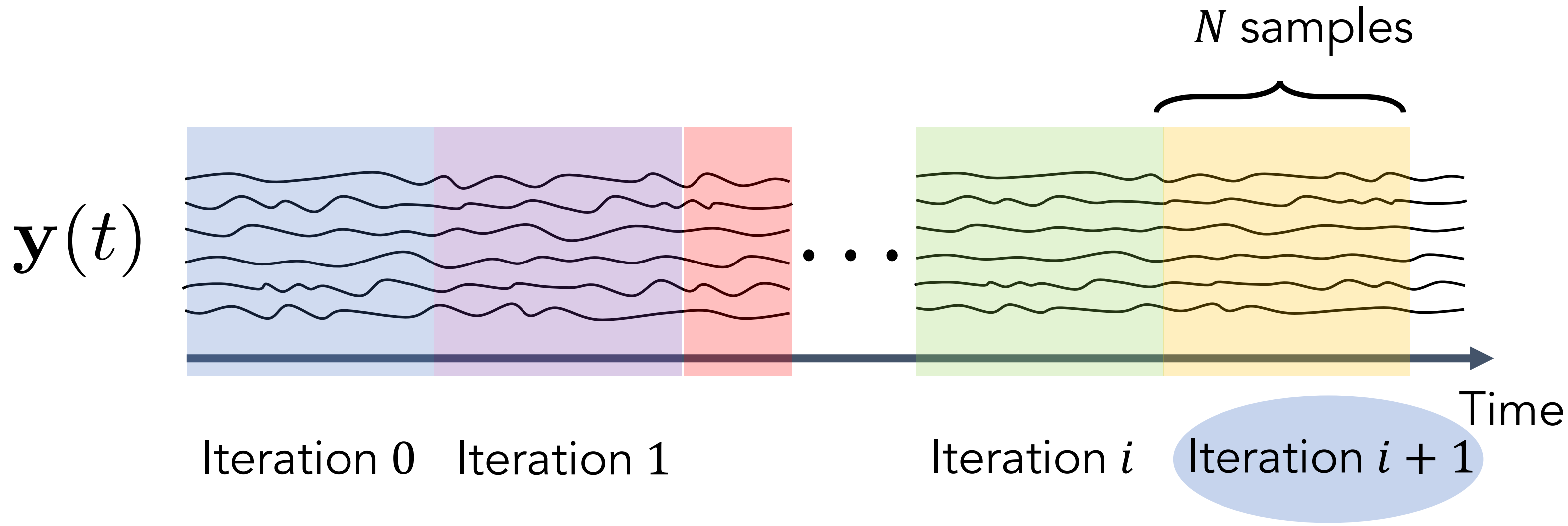


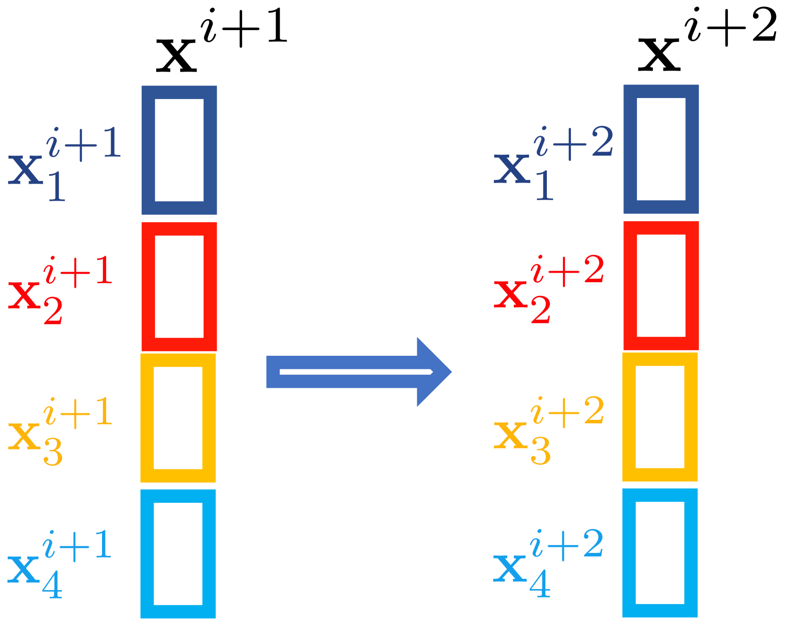
$\mathbf{x}^{i+1}$
N samples
$\mathbf{y}(t)$
Time
Iteration 0
Iteration 1
Iteration i
Iteration $i+1$
$\mathbf{x}_1^{i+1}$
$\mathbf{x}_2^{i+1}$
$\mathbf{x}_3^{i+1}$
$\mathbf{x}_4^{i+1}$
$\mathbf{y}_k(t)$
$\mathbf{x}_k^{i+1}$
$\widehat{y_k^{i+1}}(t)$
1
M_k

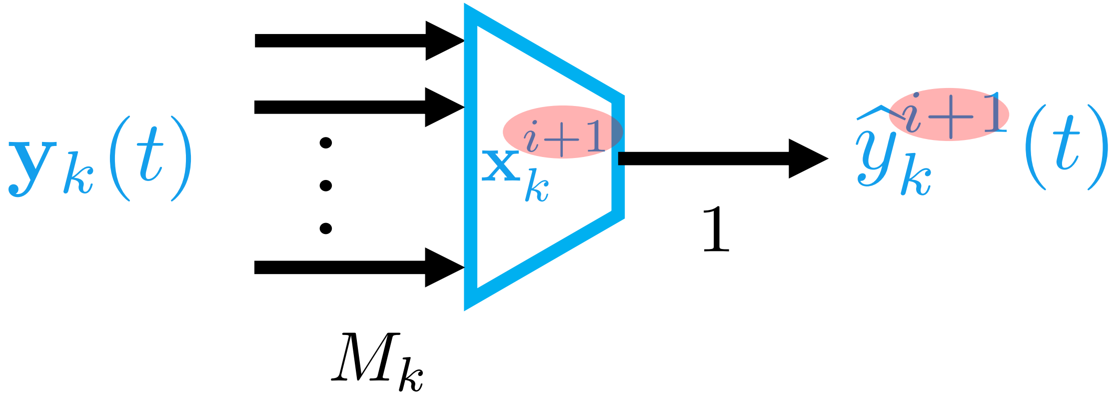


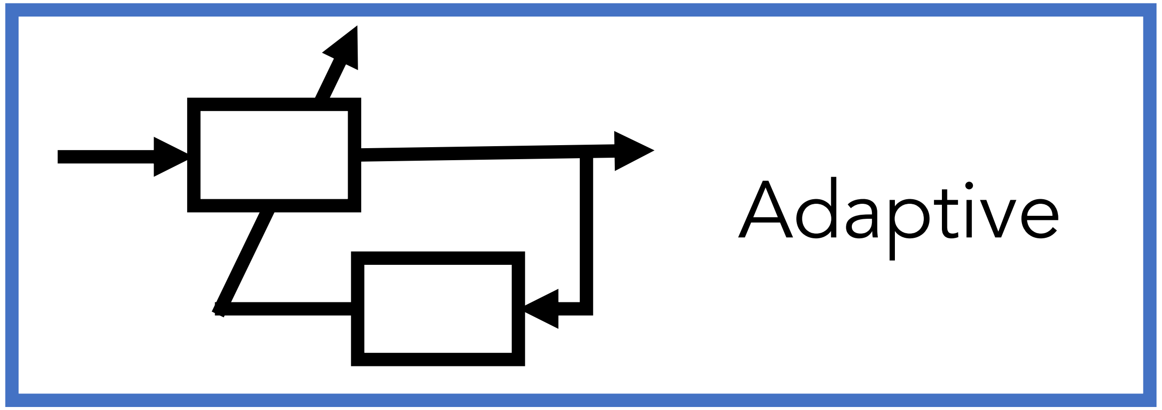
$\mathbf{x}^{i+1}$
N samples
$\mathbf{y}(t)$
$\mathbf{x}_1^{i+1}$
$\mathbf{x}_2^{i+1}$
$\mathbf{x}_3^{i+1}$
$\mathbf{x}_4^{i+1}$
Time
Iteration 0
Iteration 1
Iteration i
Iteration $i+1$
$\mathbf{y}_k(t)$
$\mathbf{x}_k^{i+1}$
$\widehat{y}_k^{i+1}(t)$
1
M_k
$\widehat{y}_1^{i+1}(t)$
$\widehat{y}_3^{i+1}(t)$
$\widehat{y}_4^{i+1}(t)$
1
2
3
4

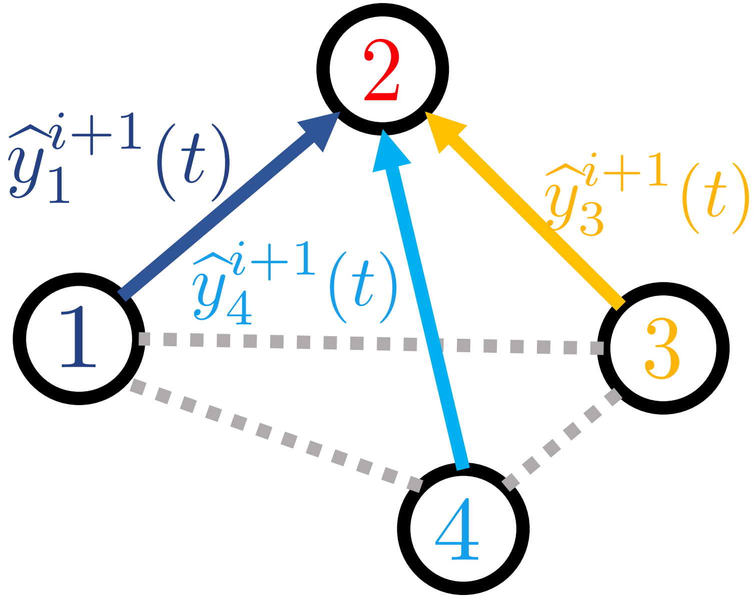

N samples
$\mathbf{y}(t)$
Time
Iteration 0
Iteration 1
Iteration i
Iteration $i+1$
$\mathbf{x}^{i+1}$
$\mathbf{x}_1^{i+1}$
$\mathbf{x}_2^{i+1}$
$\mathbf{x}_3^{i+1}$
$\mathbf{x}_4^{i+1}$
$\mathbf{x}^{i+2}$
$\mathbf{x}_1^{i+2}$
$\mathbf{x}_2^{i+2}$
$\mathbf{x}_3^{i+2}$
$\mathbf{x}_4^{i+2}$
$\mathbf{y}_k(t)$
M_k
$\mathbf{x}_k^{i+1}$
1
$\widehat{y}_k^{i+1}(t)$
$\widehat{y}_1^{i+1}(t)$
$\widehat{y}_3^{i+1}(t)$
$\widehat{y}_4^{i+1}(t)$
1
2
3
4


N samples
$\mathbf{y}(t)$
Time
Iteration 0
Iteration 1
Iteration i
Iteration $i+1$


$\mathbf{x}^{i+1}$
$\mathbf{x}^{i+2}$
$\mathbf{x}_1^{i+1}$
$\mathbf{x}_2^{i+1}$
$\mathbf{x}_3^{i+1}$
$\mathbf{x}_4^{i+1}$
$\mathbf{x}_1^{i+2}$
$\mathbf{x}_2^{i+2}$
$\mathbf{x}_3^{i+2}$
$\mathbf{x}_4^{i+2}$


$\mathbf{y}_k(t)$
$\mathbf{x}_k^{i+1}$
$\widehat{y}_k^{i+1}(t)$
1
M_k


Adaptive


$\widehat{y}_1^{i+1}(t)$
$\widehat{y}_3^{i+1}(t)$
$\widehat{y}_4^{i+1}(t)$
1
2
3
4

$$
\begin{aligned}
\min_{\mathbf{x}}.\ & f(\mathbf{x}^T\mathbf{y}(t)) \\
\text{s. t. } & g(\mathbf{x}^T\mathbf{y}(t)) = 0 \\
& h(\mathbf{x}^T\mathbf{y}(t)) \leq 0
\end{aligned}
$$

Multi-channel outputs

$$\mathbf{x} \Longrightarrow X = \begin{bmatrix} | & & | \\ \mathbf{x}(1) & \ldots & \mathbf{x}(Q) \\ | & & | \end{bmatrix}$$

Multiple signals

$$X^T \mathbf{y}(t), X^T \mathbf{v}(t), \ldots$$

GEVD

$$\begin{aligned} \min_{\mathbf{x}}. \quad & f(\mathbf{x}^T \mathbf{y}(t)) \\ \text{s. t.} \quad & g(\mathbf{x}^T \mathbf{y}(t)) = 0 \\ & h(\mathbf{x}^T \mathbf{y}(t)) \leq 0 \end{aligned}$$

Parameters

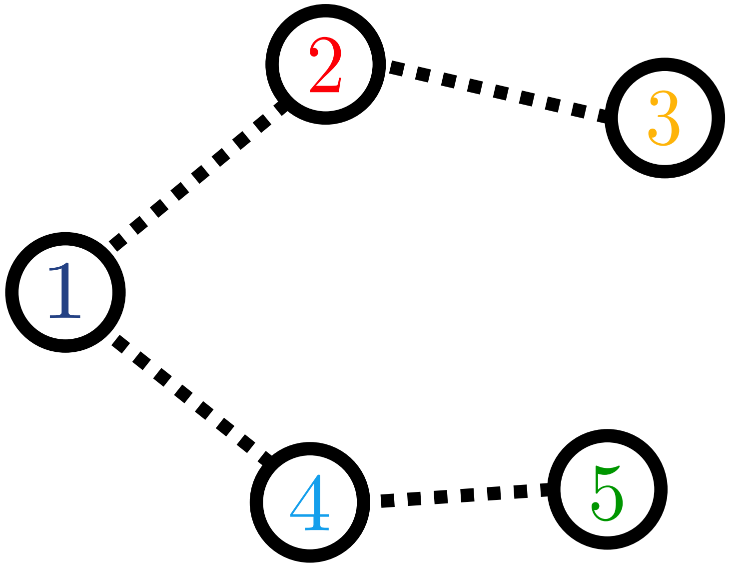
$$X^T B, X^T X, \ldots$$

LCMV, PCA, TRO

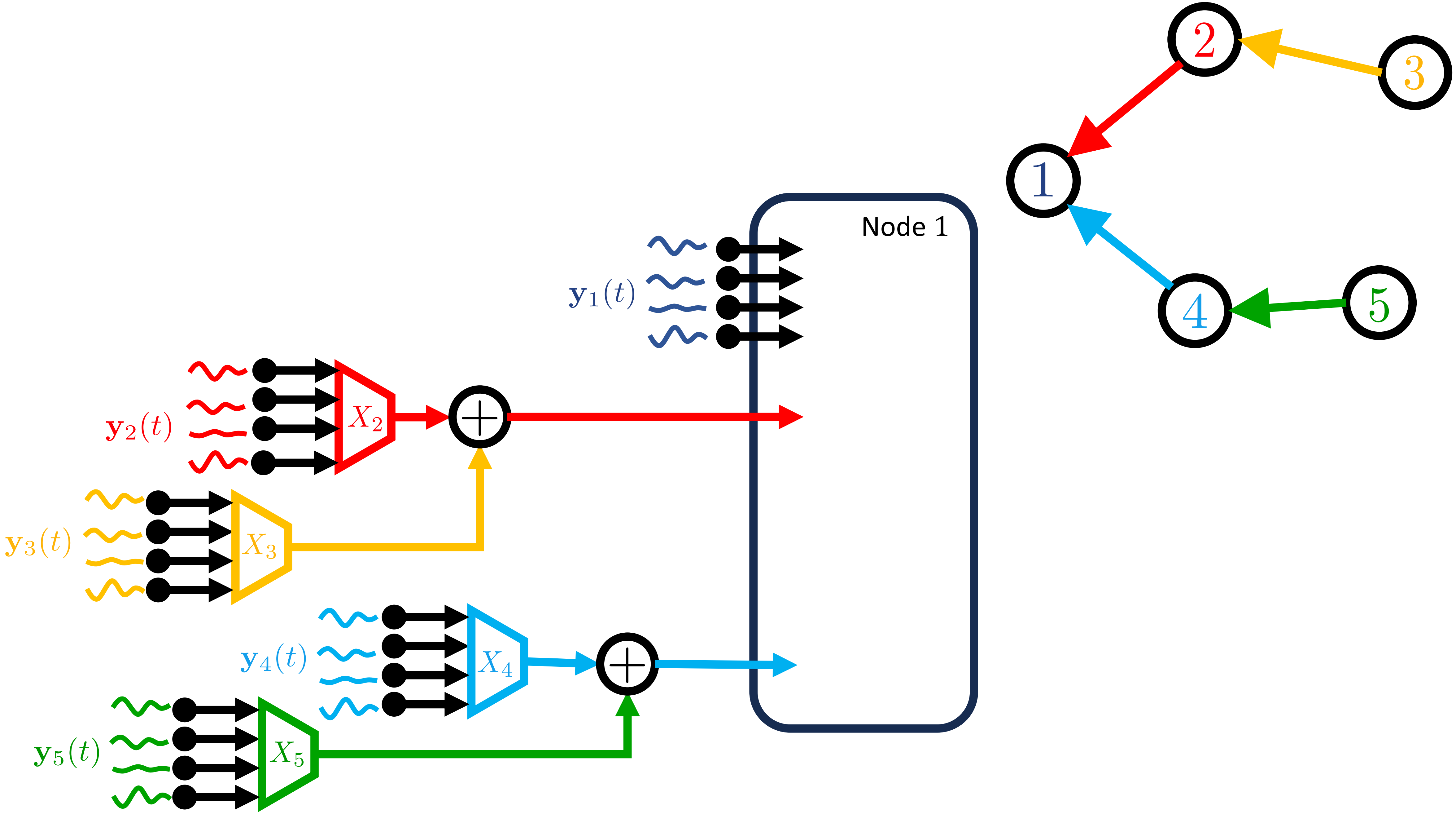
Multiple filters

$$X^T \mathbf{y}(t), W^T \mathbf{v}(t), \ldots$$

CCA



2
3
1
4
5


Node 1
$\mathbf{y}_1(t)$
$\mathbf{y}_2(t)$
X_2
$\mathbf{y}_3(t)$
X_3
$\mathbf{y}_4(t)$
X_4
$\mathbf{y}_5(t)$
X_5
1
2
3
4
5

?

$$X^i \rightarrow X^*$$

✓

$$X^i \to X^*$$

Mild technical conditions

↳ Satisfied in practice

Measuring performance of DASF

$\boxed{\text{Select task}}$

$$\min_{X} \; f(X^T \mathbf{y}(t))$$

$$\text{s. t. } \; X \in \mathcal{S}$$

$\boxed{\text{Solve}}$ $\Downarrow$

$$X^*$$

Measuring performance of DASF

Select task

$$\min_{X} \; f(X^T\mathbf{y}(t))$$

$$\text{s. t. } \; X \in \mathcal{S}$$

Run DASF on task

$$\{X^0, X^1, X^2, \ldots\}$$

Solve

$$X^*$$

Measuring performance of DASF

Select task

$$\min_{X} \; f(X^T \mathbf{y}(t))$$

$$\text{s. t. } X \in \mathcal{S}$$

Run DASF on task

$$\{X^0, X^1, X^2, \ldots\}$$

Solve

$$X^*$$

$$\frac{\|X^i - X^*\|_F^2}{\|X^*\|_F^2}$$

Measuring performance of DASF

Select task

$$\min_X \ f(X^T \mathbf{y}(t))$$

$$\text{s. t. } X \in \mathcal{S}$$

Run DASF on task

$$\Longrightarrow \{X^0, X^1, X^2, \ldots\}$$

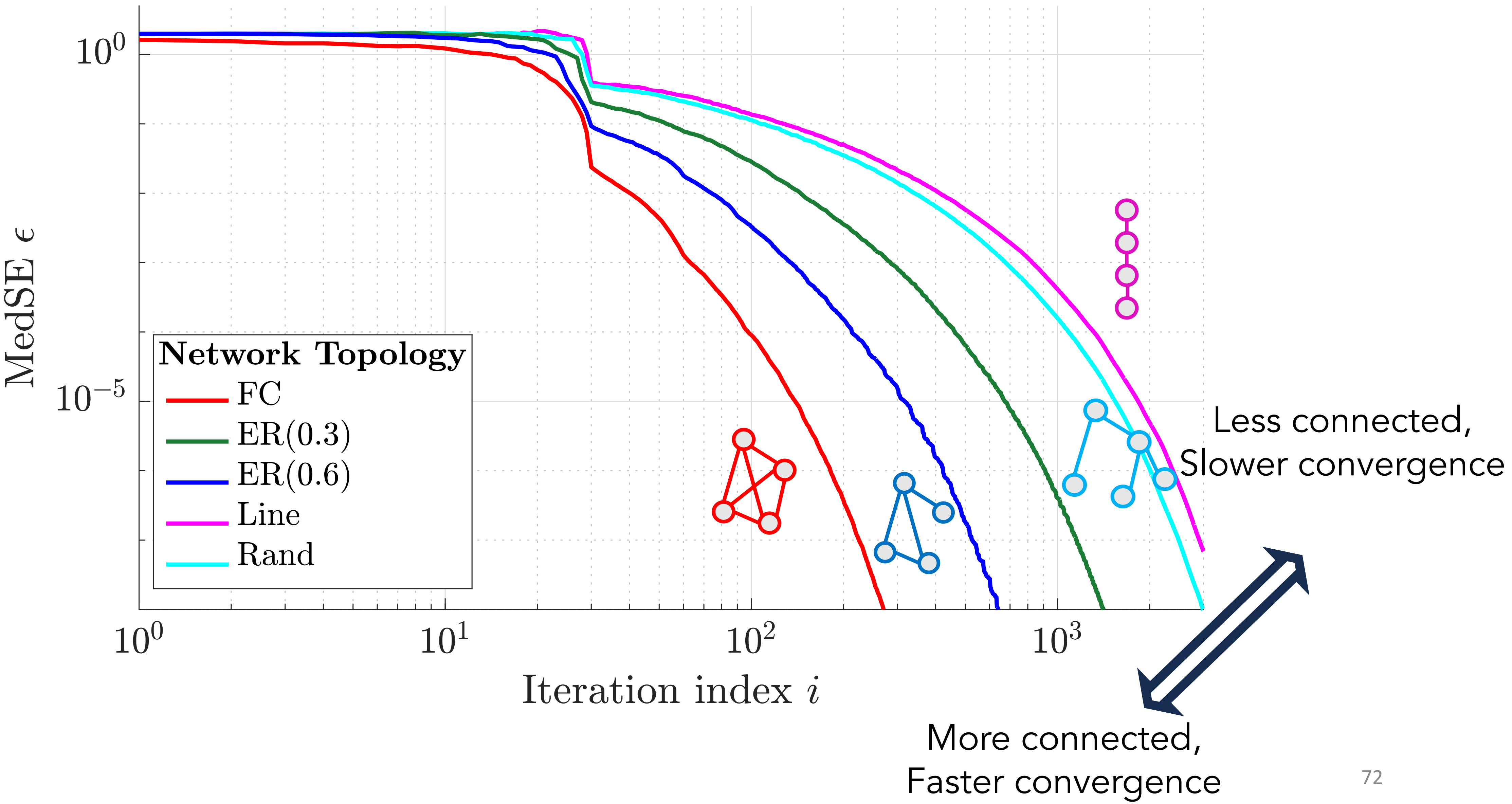
Solve

$$\Downarrow$$

$$X^*$$

$$\epsilon(i) = \text{median}\left(\frac{\|X^i - X^*\|_F^2}{\|X^*\|_F^2}\right)$$

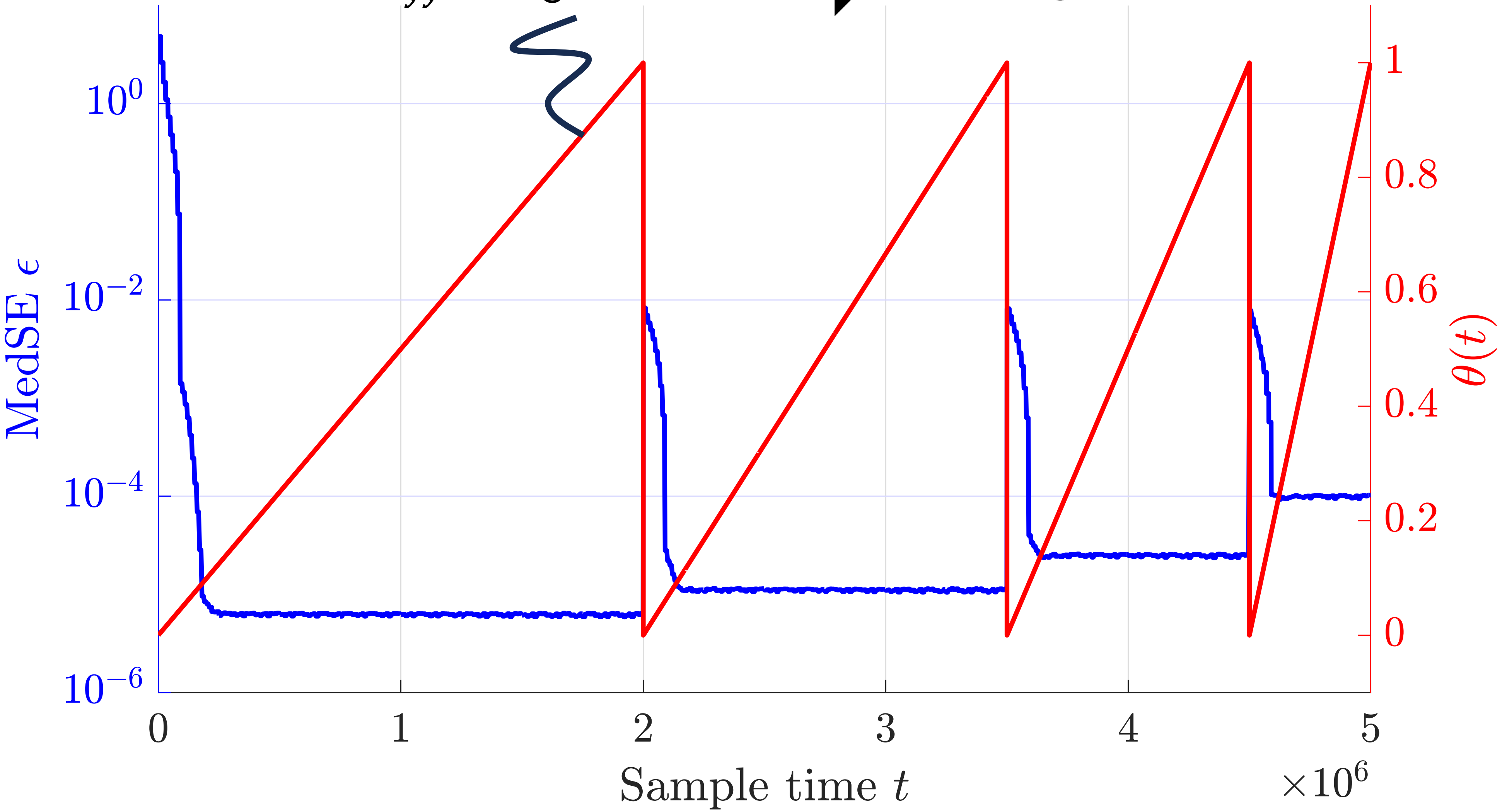
MedSE



MedSE ϵ
10^{0}
10^{-5}
Network Topology
FC
ER(0.3)
ER(0.6)
Line
Rand
10^{0}
10^{1}
10^{2}
10^{3}
Iteration index i
Less connected,
Slower convergence
More connected,
Faster convergence

Stationary vs Adaptive

R_{yy} changes in time ⇨ X^* changes in time

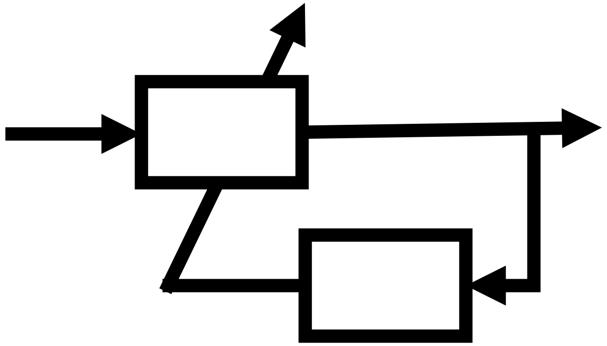


DASF framework

Unified and Generalizable
1 method for spatial filtering tasks

Efficient communication

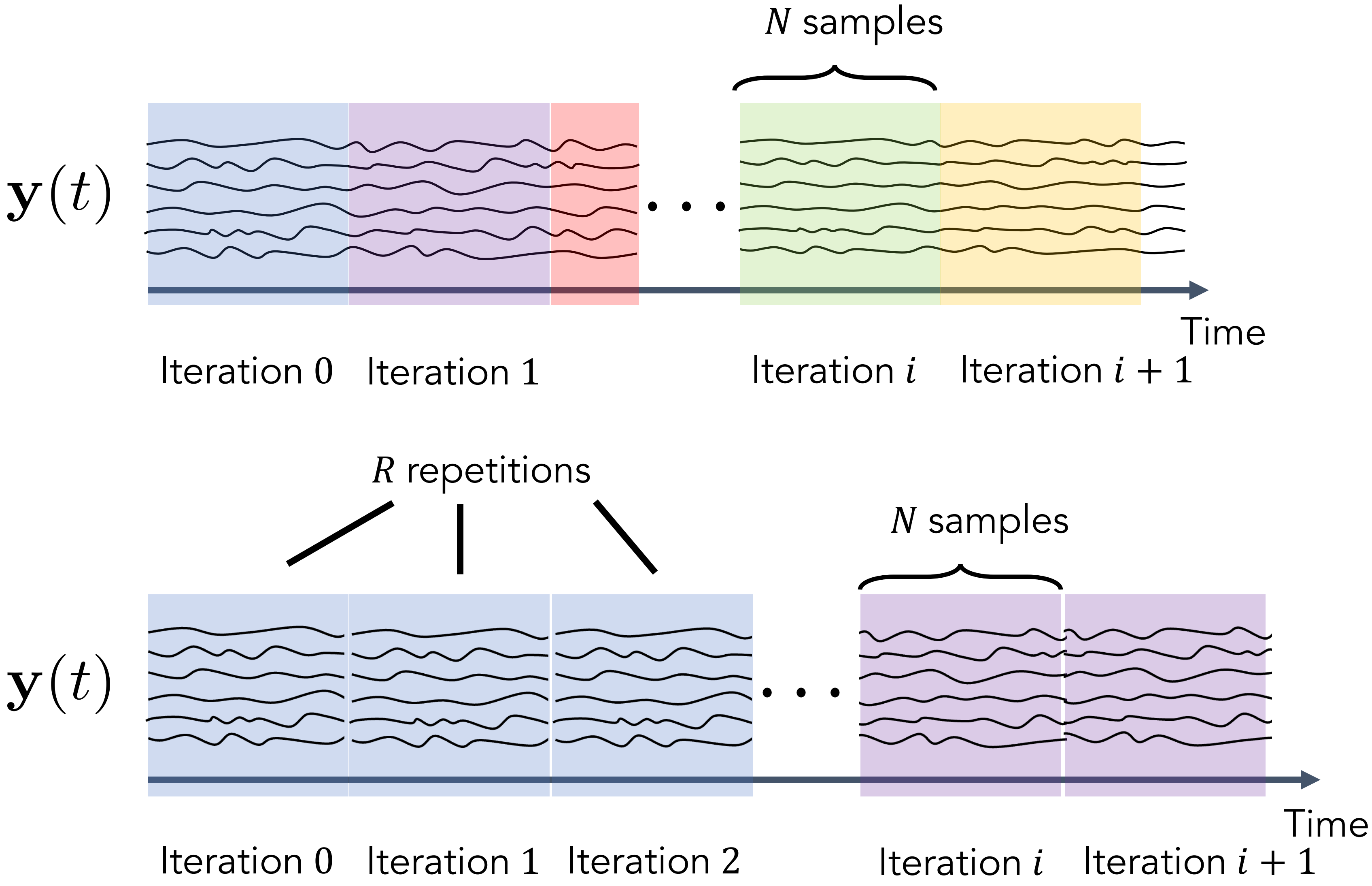
Computational efficiency



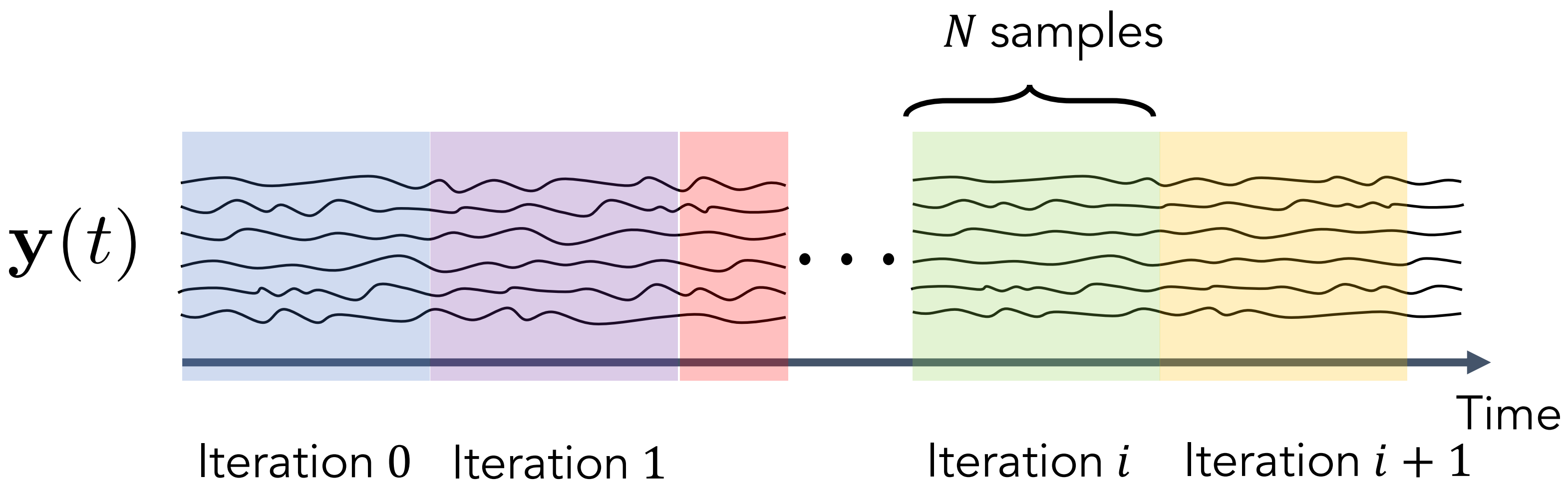
Adaptive

II. Extensions of the DASF framework

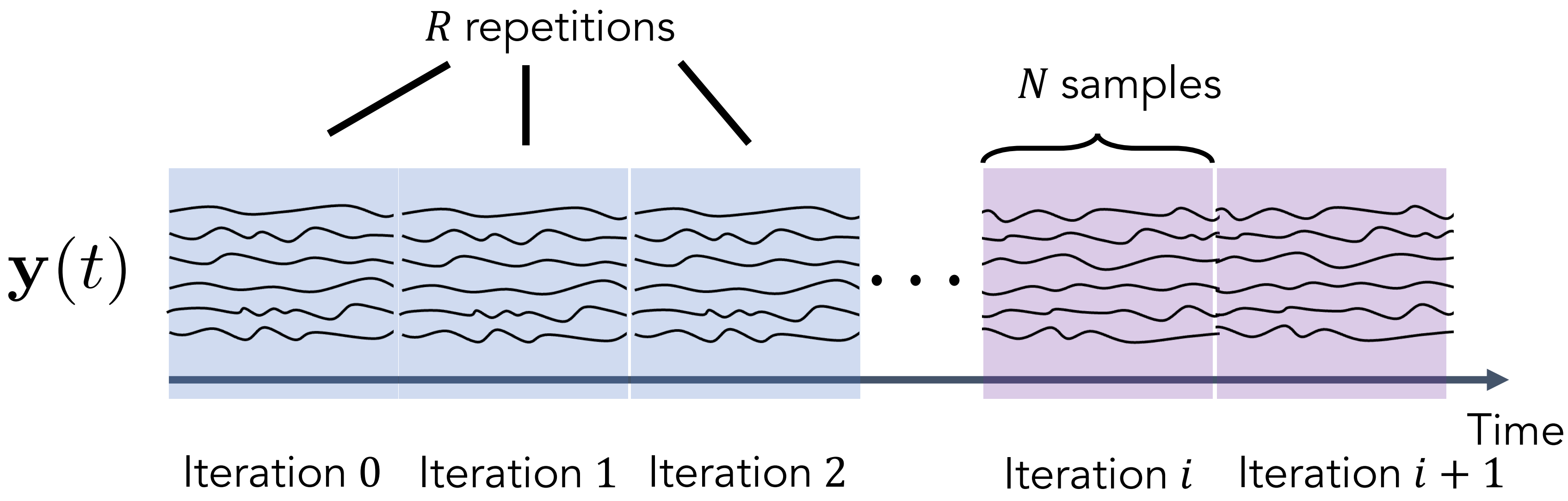
Improving adaptivity



Improving adaptivity

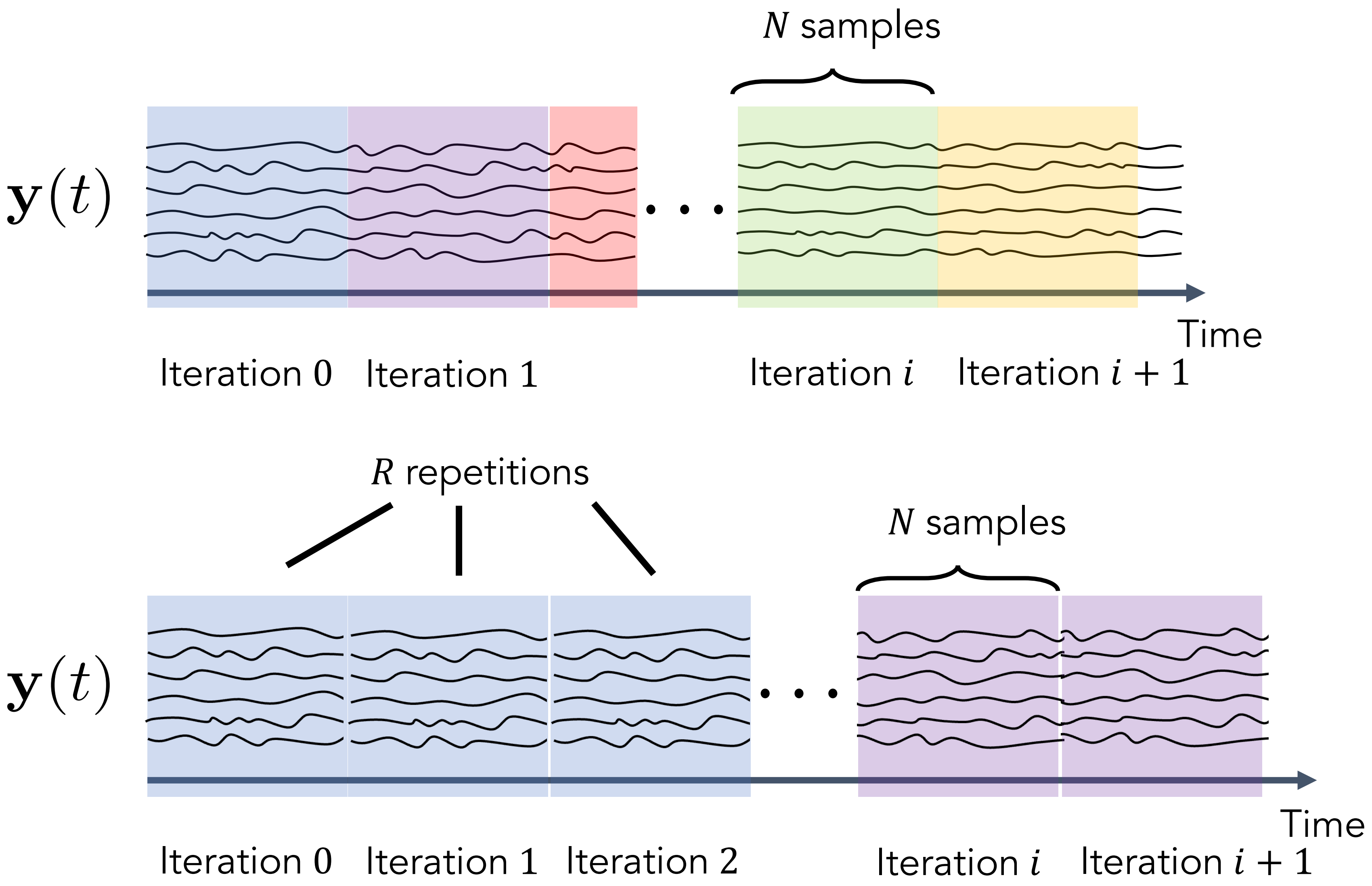


$R\times$ increase in adaptivity



$R\times$ increase in communication

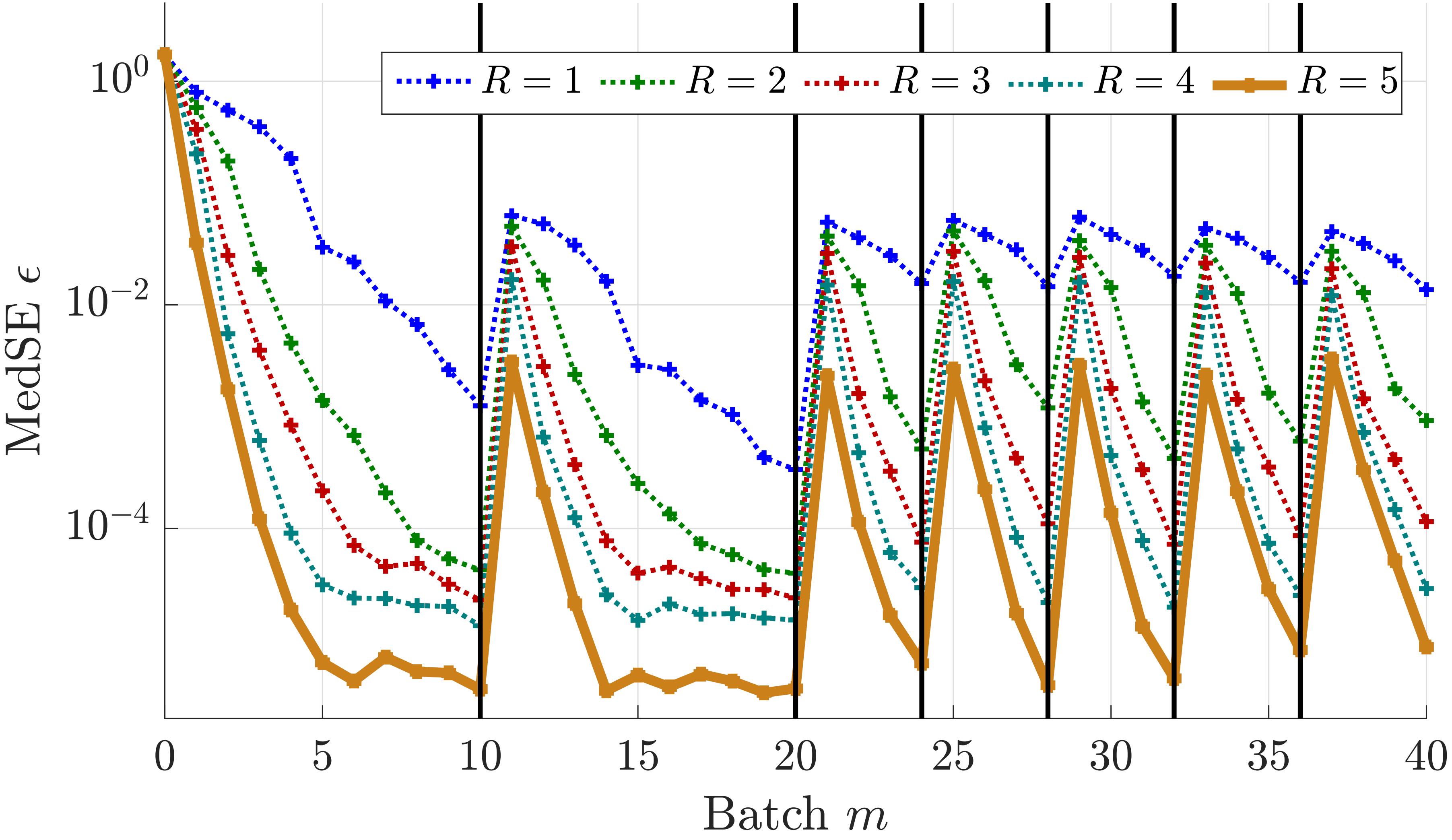
Improving adaptivity



$R\times$ increase in adaptivity

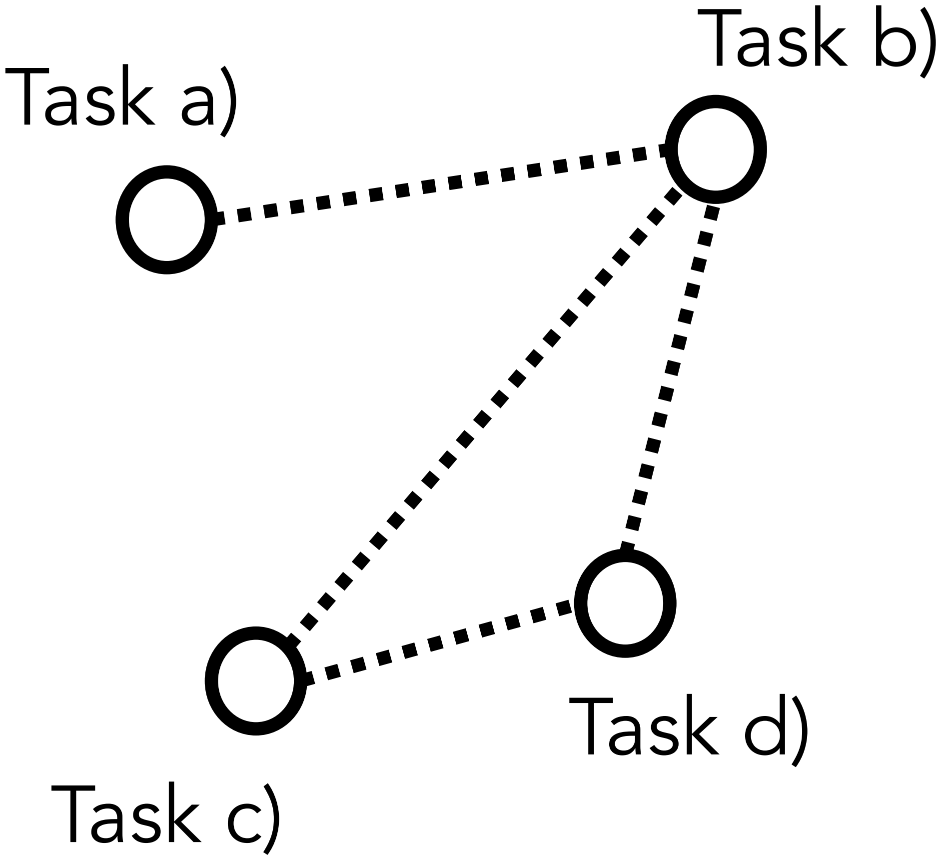
~~$R\times$ increase in communication~~

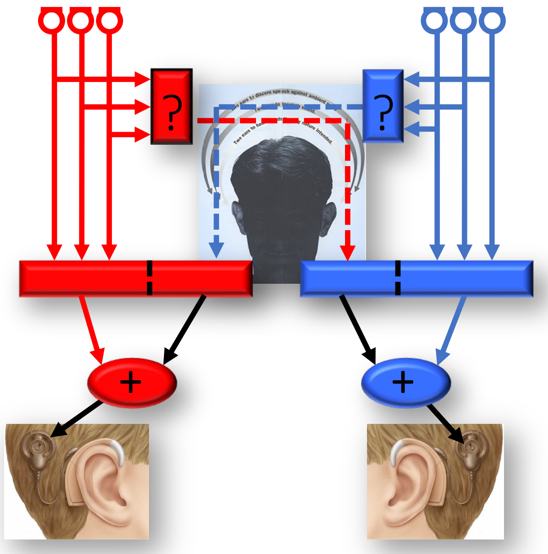
$< R\times$ increase in communication



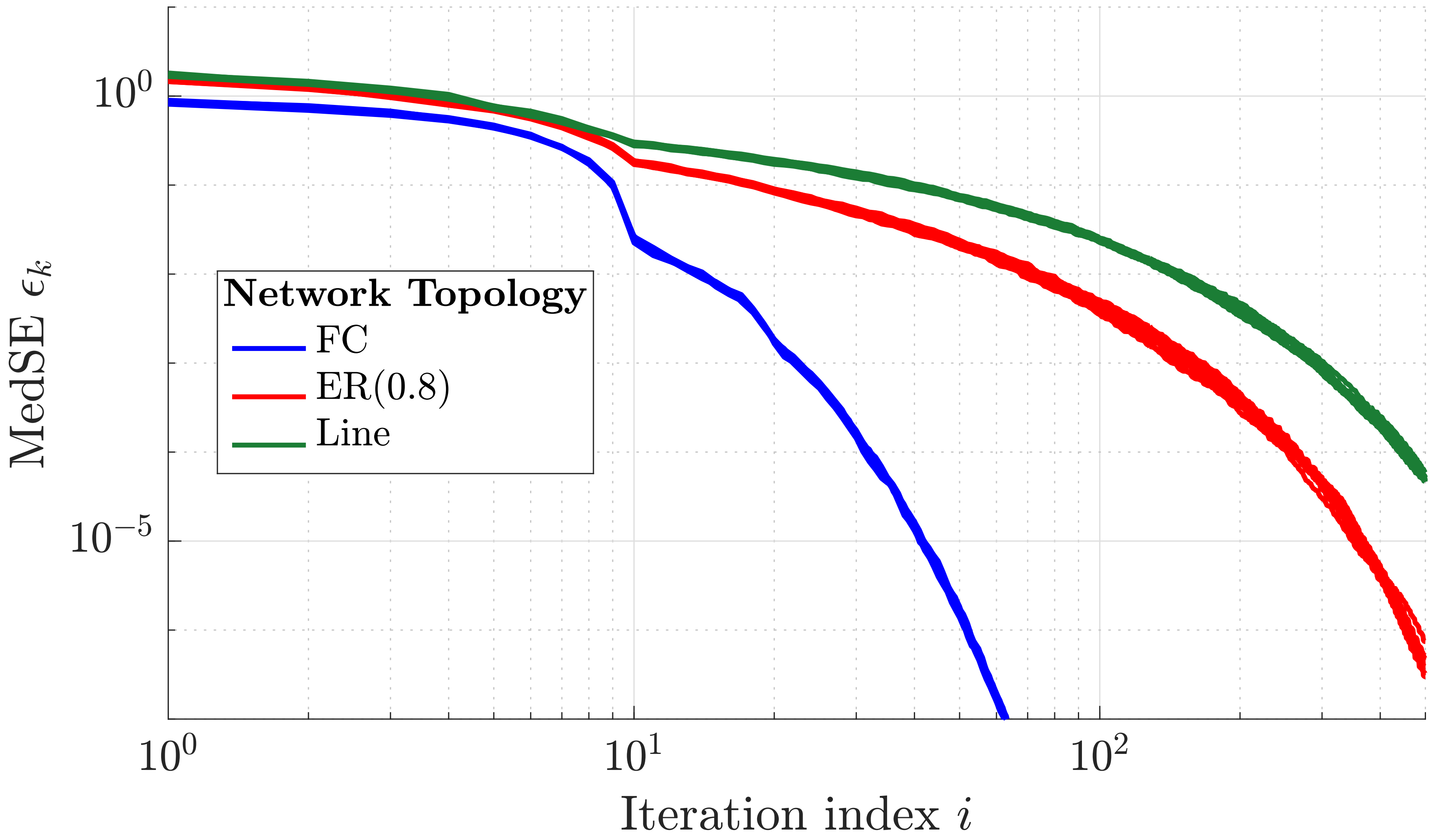
C. A. Musluoglu, M. Moonen and A. Bertrand, "Improved Tracking for Distributed Signal Fusion Optimization in a Fully-Connected Wireless Sensor Network," *2022 30th European Signal Processing Conference (EUSIPCO)*, Belgrade, Serbia, 2022, pp. 1836-1840, doi: 10.23919/EUSIPCO55093.2022.9909686.

DASF for node-specific tasks (DANSF)





Task a) ~ Task b) ~ Task c) ~ Task d)



C. A. Musluoglu and A. Bertrand, "A Distributed Adaptive Algorithm for Node-Specific Signal Fusion Problems in Wireless Sensor Networks," *2023 31st European Signal Processing Conference (EUSIPCO)*, Helsinki, Finland, 2023, pp. 1654-1658, doi: 10.23919/EUSIPCO58844.2023.10289843.

Fractional DASF (F-DASF)

$$\underset{X}{\text{minimize}}\ f(X^T\mathbf{y}(t)) = \frac{f_1(X^T\mathbf{y}(t))}{f_2(X^T\mathbf{y}(t))}$$

$$\text{subject to } X \in \mathcal{S}$$

Fractional DASF (F-DASF)

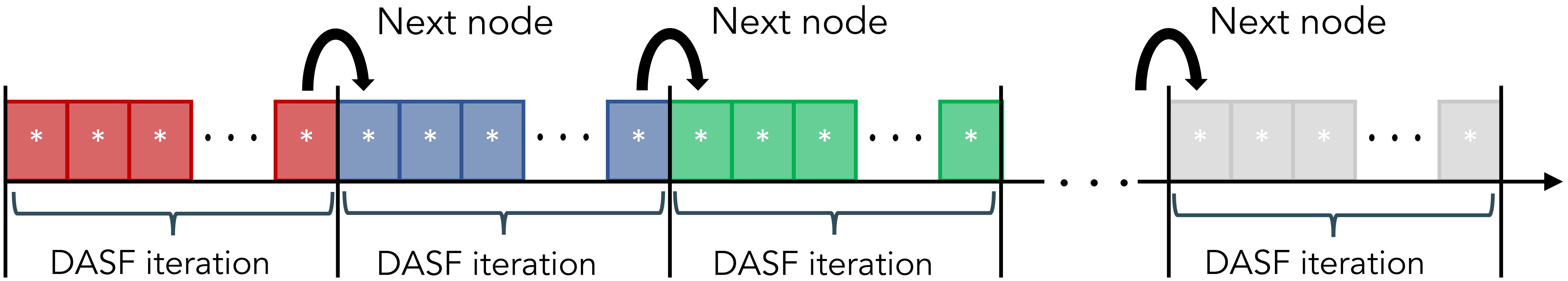
$$\underset{X}{\text{minimize}}\ f(X^T\mathbf{y}(t)) = \frac{f_1(X^T\mathbf{y}(t))}{f_2(X^T\mathbf{y}(t))} \Longrightarrow \text{Auxiliary Problem (*)}$$

$$\text{subject to } X \in \mathcal{S}$$

Fractional DASF (F-DASF)

$$\underset{X}{\text{minimize}}\ f(X^T\mathbf{y}(t)) = \frac{f_1(X^T\mathbf{y}(t))}{f_2(X^T\mathbf{y}(t))} \Longrightarrow \text{Auxiliary Problem (*)}$$

$$\text{subject to } X \in \mathcal{S}$$

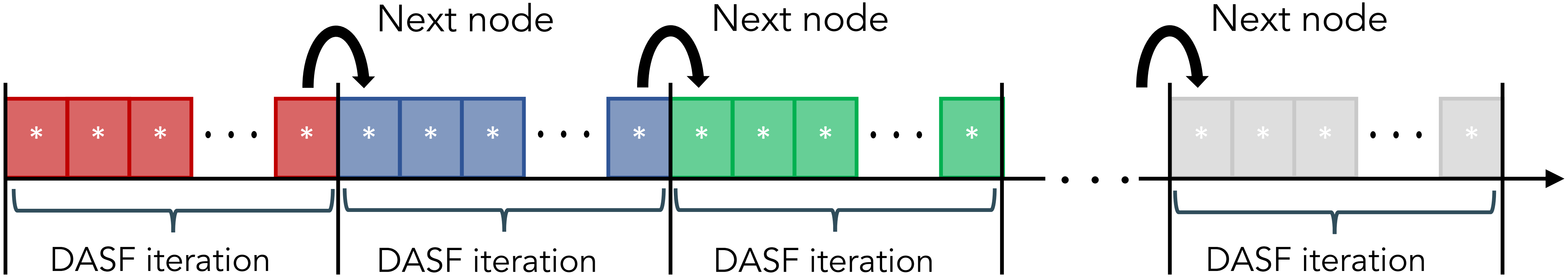


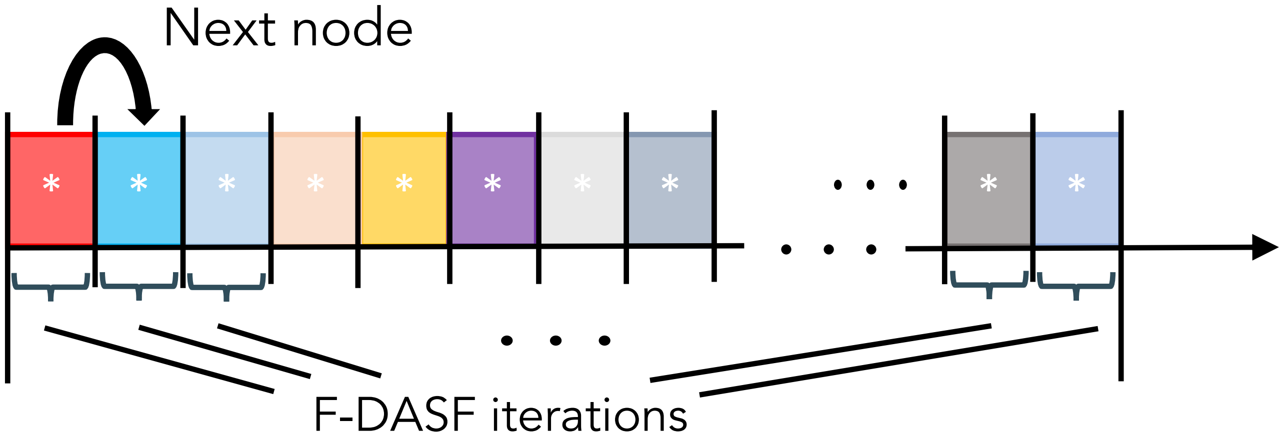
Fractional DASF (F-DASF)

$$\underset{X}{\text{minimize}}\ f(X^T\mathbf{y}(t)) = \frac{f_1(X^T\mathbf{y}(t))}{f_2(X^T\mathbf{y}(t))}$$

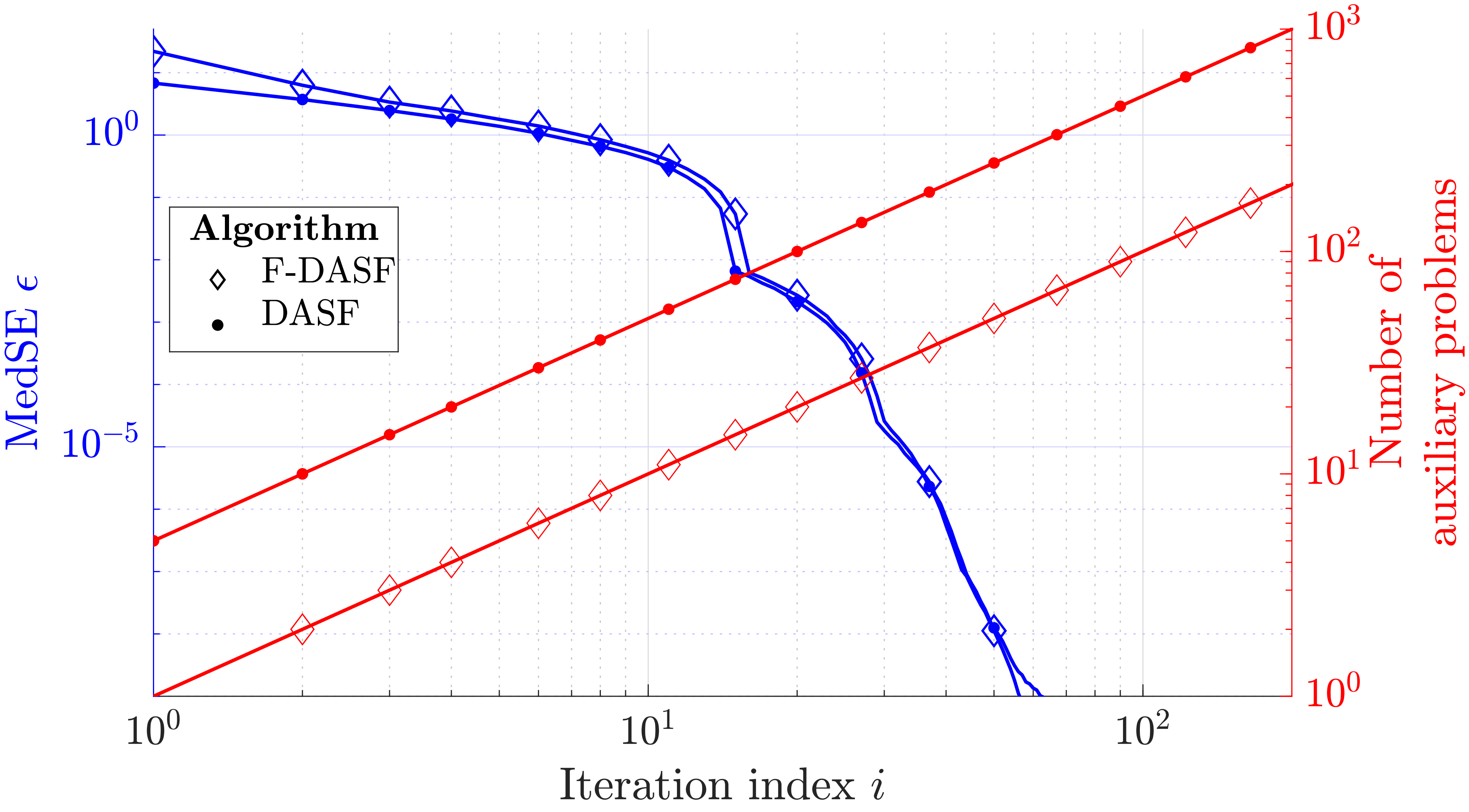
$$\text{subject to } X \in \mathcal{S}$$

$\Longrightarrow$ Auxiliary Problem (*)





1× Auxiliary Problem (*)



C. A. Musluoglu and A. Bertrand, "A Computationally Efficient Algorithm for Distributed Adaptive Signal Fusion Based on Fractional Programs," *ICASSP 2023 - 2023 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP)*, Rhodes Island, Greece, 2023, pp. 1-5, doi: 10.1109/ICASSP49357.2023.10096219.

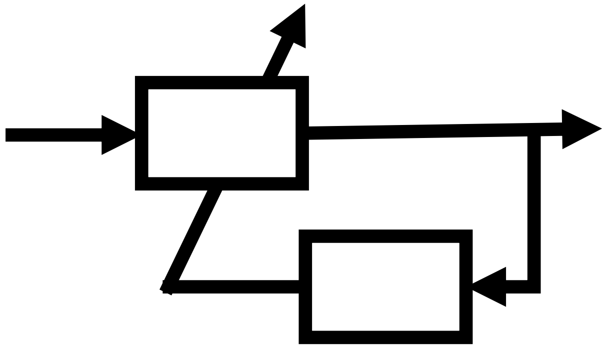
Extensions DASF framework

DASF framework

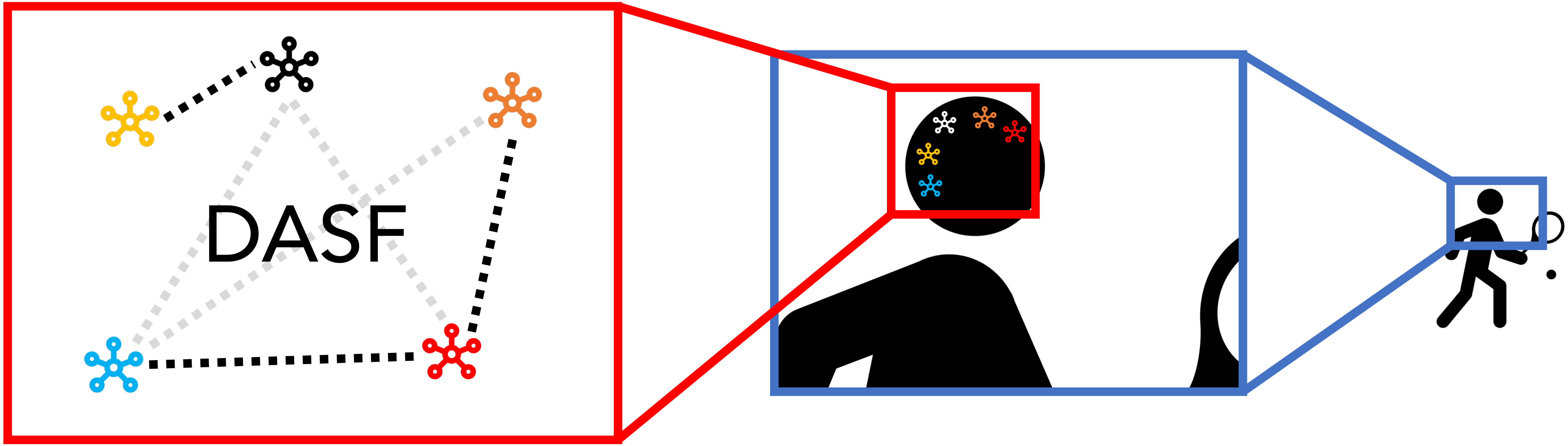
+

Efficient communication

Computational efficiency



Adaptive


DASF