



# Spiking Neural Networks for Control

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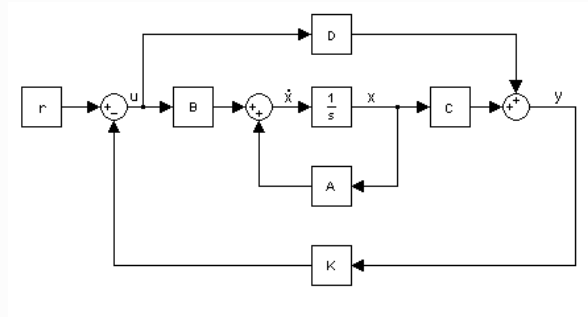
Conclusion



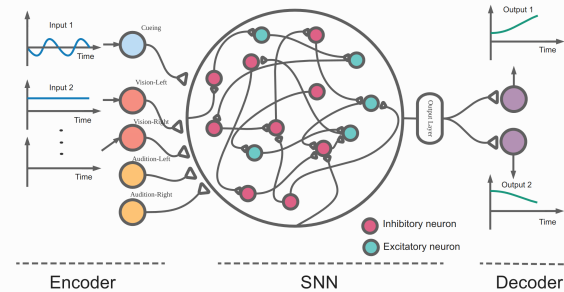
# Introduction

# What are we talking about

Control a Linear system



Use Spiking neural networks



[Xue+22]

# What are we talking about

## Control a Linear system

- Tracking of reference trajectory

$$\begin{aligned}\dot{x} &= Ax + Bu \\ y &= Cx\end{aligned}\tag{1}$$

- Only stable systems

## Use Spiking neural networks

- Third Generation of NN
- Working with discrete spikes
- Inherently fit for temporal data

## Goal / Motivation

Artificial SNN can already solve various cognitive task such as

- Memorization
- Basic Logic
- Simulation of Dynamic Systems
- Control

Although with varying levels of biologic plausibility. We set out to build a controlled dynamic system based on SNN using learning and biologic plausibility

- Allow for black-box deployment without manual parameter tuning
- "Limit ourselves to use the brains capabilities to design a controller"

# Method

## 1. Simulate

Use a spiking network to simulate a dynamic system

## 2. Control

Devise a control scheme to control the network output

## 3. Learn

Apply biologically plausible learning rules to our network

## 4. Combine

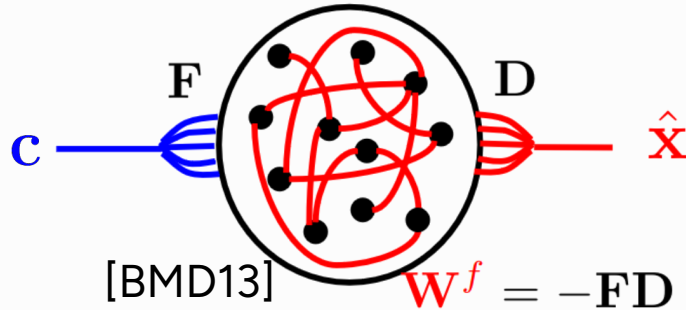
Integrate all three steps into a single controller



# Simulation



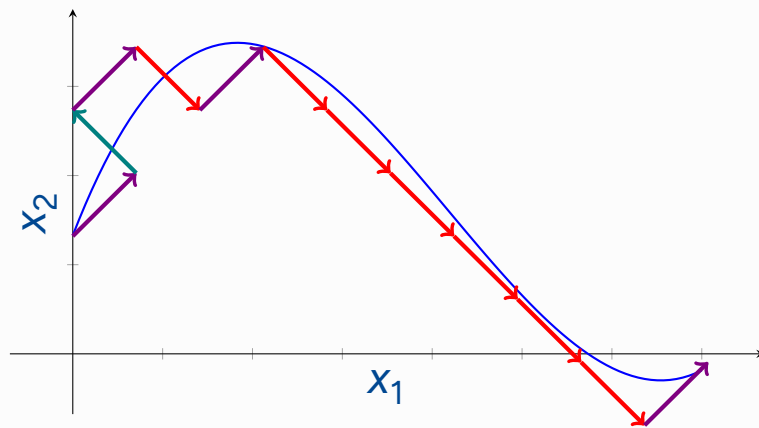
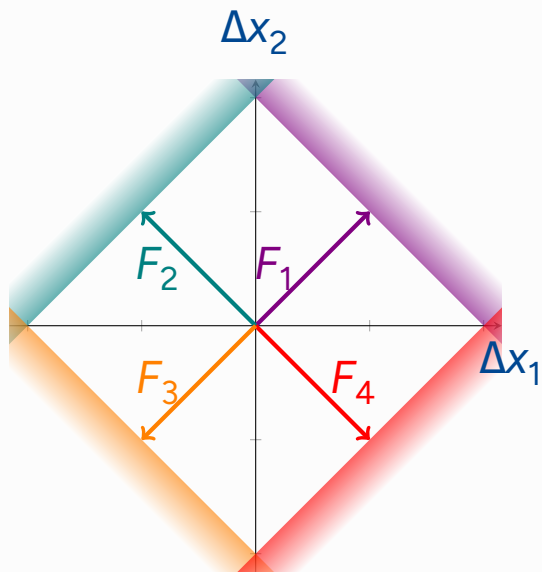
# Simulation of Linear systems



- Build NN that outputs  $\hat{x}$  from the system  $\dot{x} = Ax + c$  given  $c$
- Group of LIF neurons with with intrinsic Voltage, tracking the projected error  $V_i = F(x - \hat{x}) + \mu r_i$
- Network decoding  $\hat{x} = F^T r$

$$\dot{V} = -\lambda_V V + Fc + W^f o(t) + W^s r(t) + \sigma_V \eta(t)$$

# Geometric

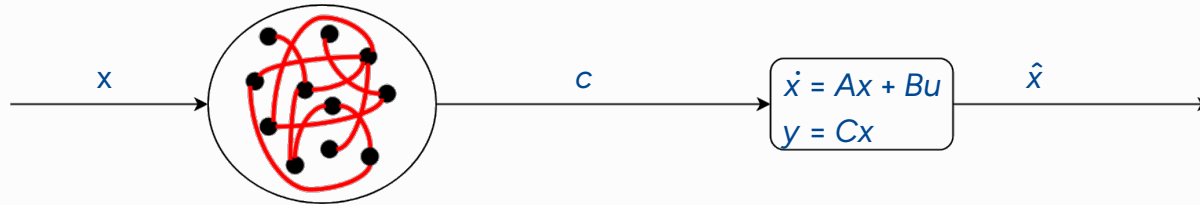






Control

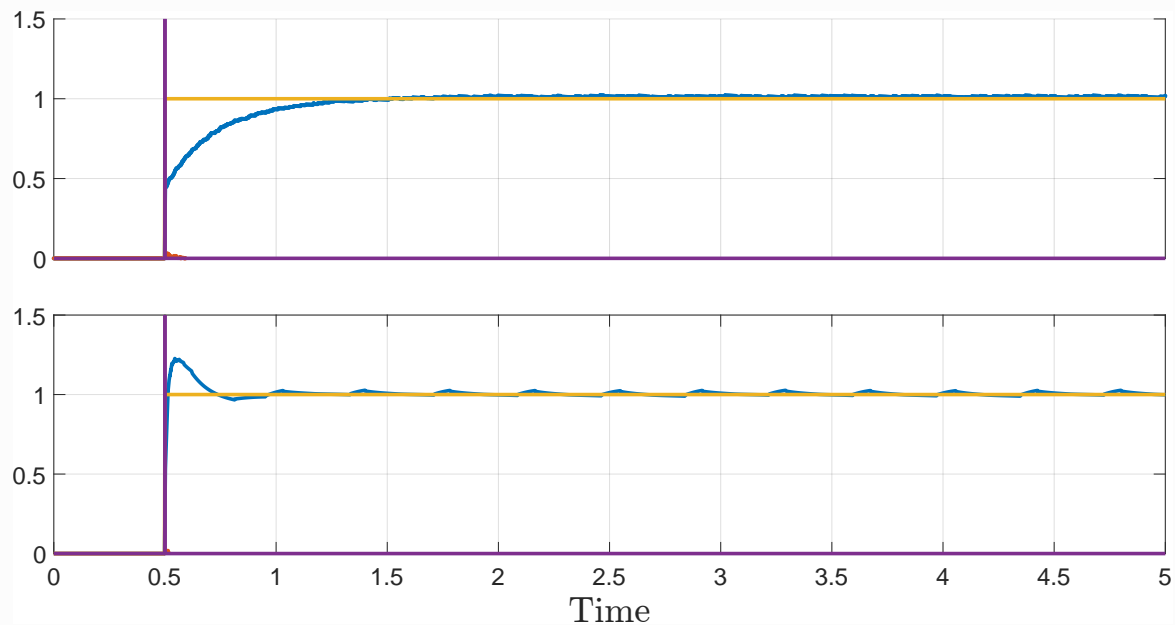
# Control Concept



[HC19]

- (Almost) identical network architecture
- Network output is external input into (previous) simulating network  $\longleftrightarrow$  Network state contains control signal
- Governed by PD-control as  $c = \dot{x} - Ax$
- In presence of output matrix  $C \neq I \leftrightarrow \text{rank}(B^T C^T) = \text{rank}(B^T)$

# Example





# Learning

## Learning rules [BD15]

**Slow Learning rule**  $W^s = F(A + \lambda_d \mathbf{I})F^T$

- Online Learning of Student teacher dynamics  $\dot{\hat{x}} = M\hat{x} + c$
- Error Feedback  $Ke$  during Training
- $\delta M \propto e\hat{x}^T \longrightarrow \delta W^s \propto F(e\hat{x}^T)F^T \approx F e r^T$
- Supervised Learning rule

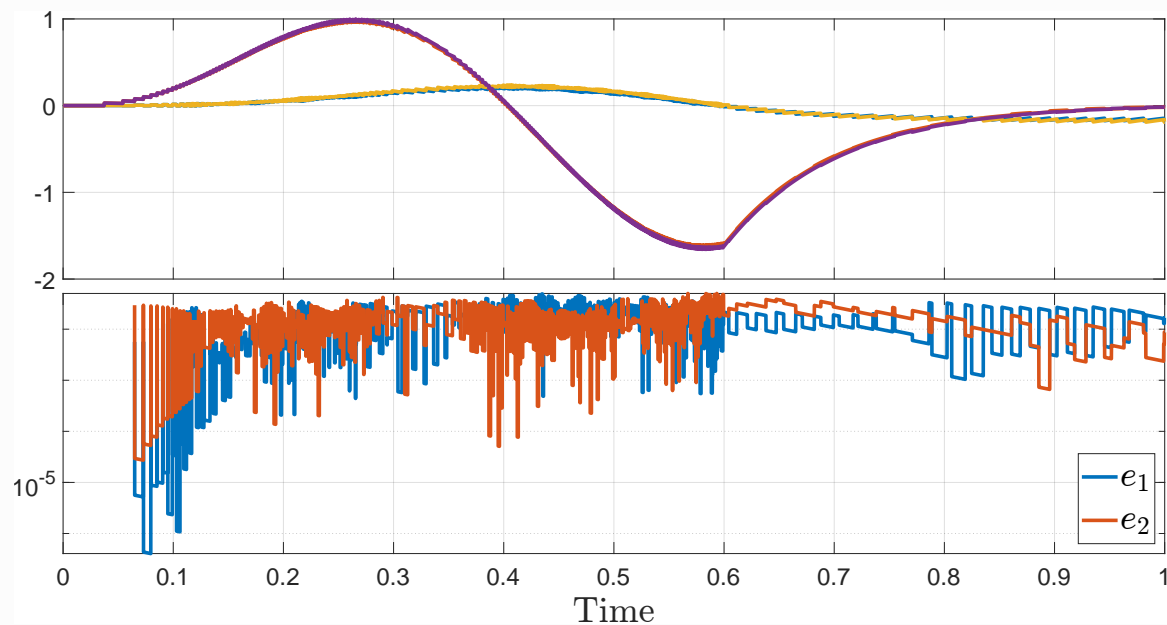
$$V_i = F_i(x - \hat{x}) - \mu r_i$$

**Fast Learning rule**  $W^f = FF^T + \mu \mathbf{I}$

- Voltage measures system error
- Minimize average Voltage outside of Neuron Threshold
- Biologically plausible  $\text{pre} \times \text{post}$  locally
- Unsupervised Learning Rule



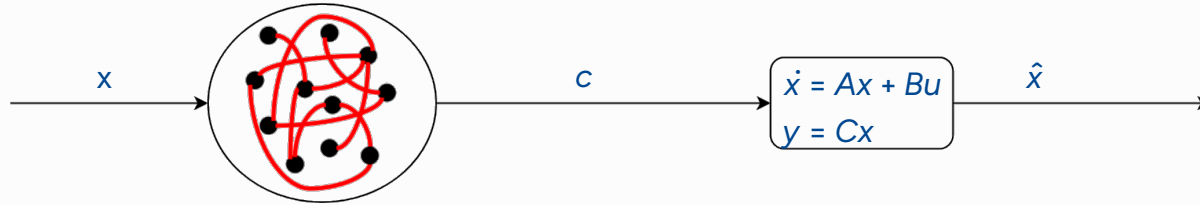
# Example





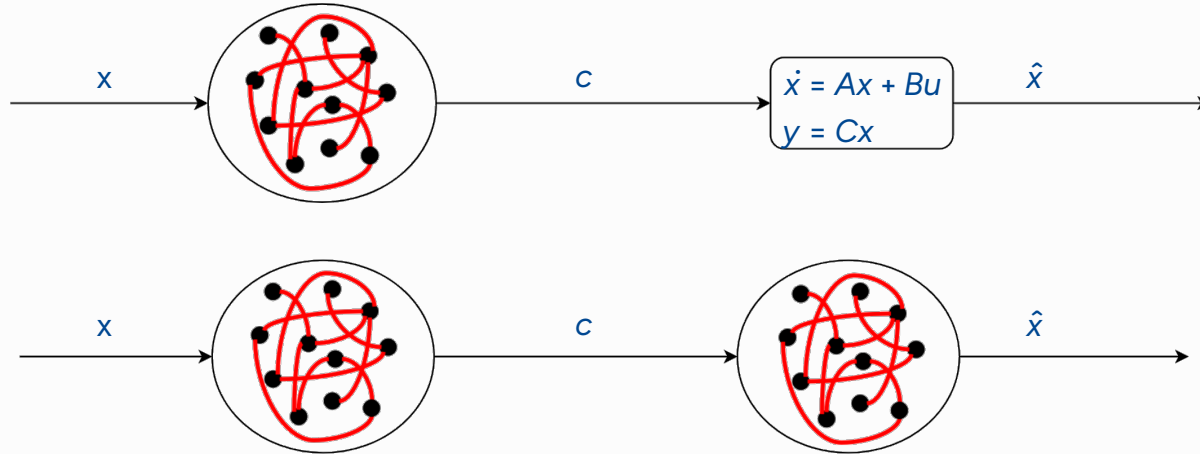
# Combined Learning

# Control Concept



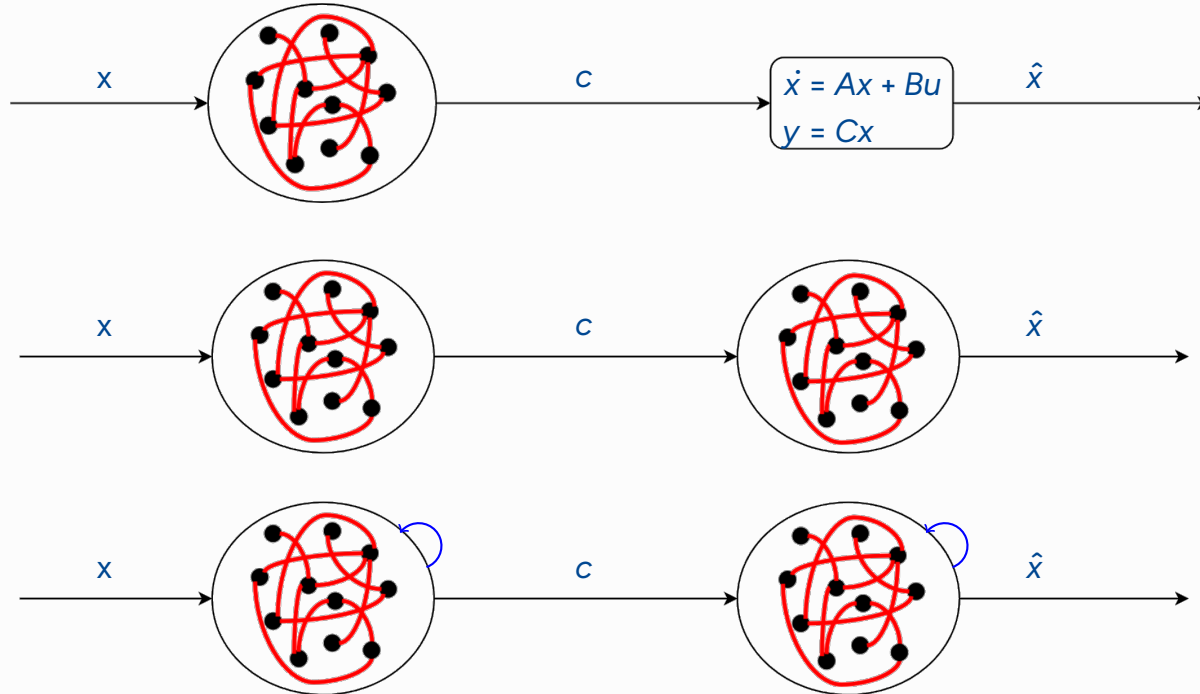
[HC19]

# Control Concept



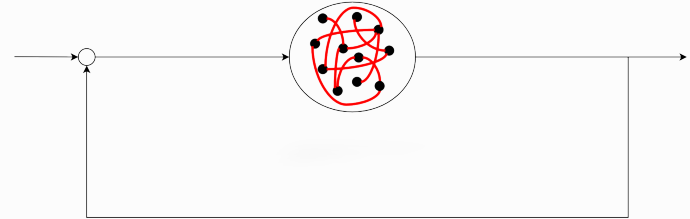
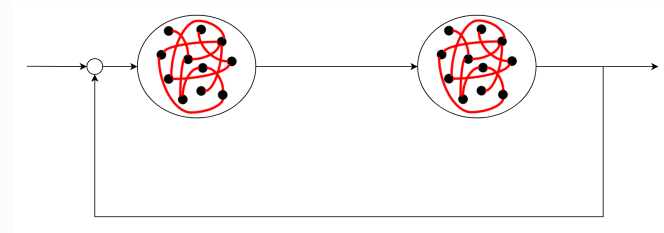
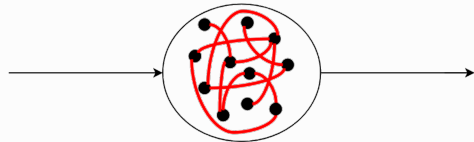
[HC19]

# Control Concept



[HC19]

# Control Concept II



# Problems

In conjunction, problems can arise:

- Divergence in Learning
- Control with Noise
- Reliance on analytic results
- Biologically implausible Learning

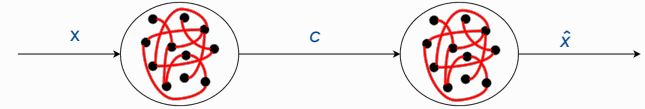
## Dual Network

No Learning rule for control network available

Open Loop Control:

- Incapable of noise detection or correction
- No Compensation of Training error

Highly dependent on governing dynamics from  $\mathbf{C}_{\text{contr}} = \dot{\mathbf{x}}_{\text{ref}} - \mathbf{A}\mathbf{x}_{\text{ref}}$





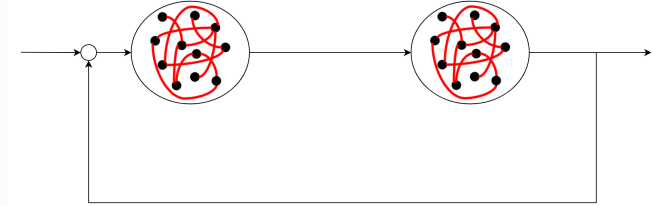
## Dual Network with Feedback

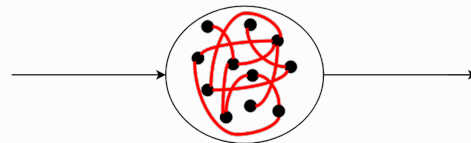
No Learning rule for control network available

Open loop Control:

- Incapable of noise detection or correction
- No Compensation of Training error

Highly dependent on governing dynamics from  $e_{\text{contr}} = \dot{x}_{\text{ref}} - Ax_{\text{ref}}$





## Single Network

~~No Learning rule for control network available~~

Open Loop Control:

- Incapable of noise detection or correction
- No Compensation of Training error

Highly dependent on governing dynamics from  $\mathbf{C}_{\text{contr}} = \dot{\mathbf{x}}_{\text{ref}} - \mathbf{A}\mathbf{x}_{\text{ref}}$

Orthonormality restriction on Input Matrix  $\mathbf{B} \in \mathbb{B} := \{\mathbf{M} \mid \mathbf{M}\mathbf{M}^T = \mathbf{I}\}$

## Single Network with Feedback

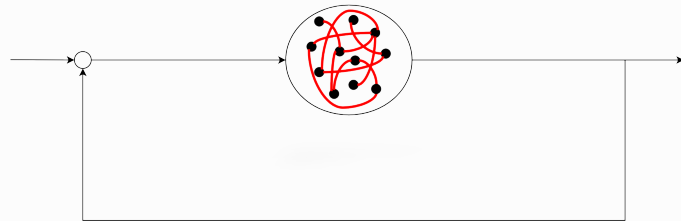
No Learning rule for control network available

Open loop Control:

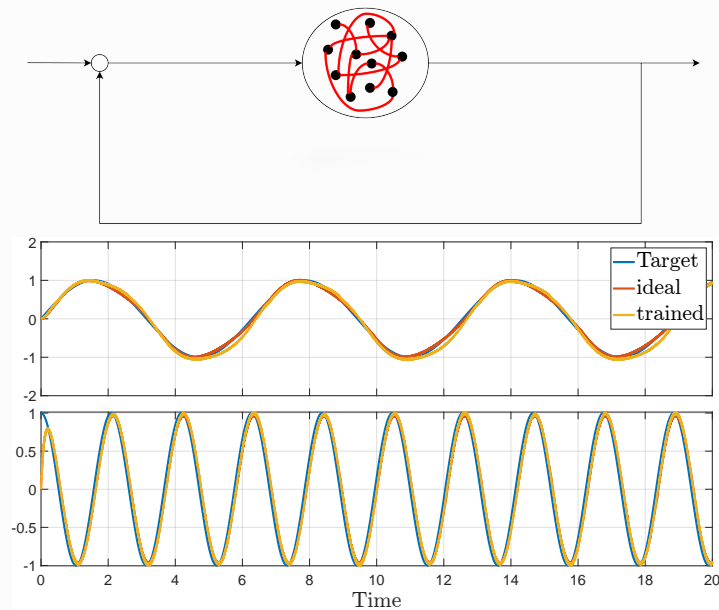
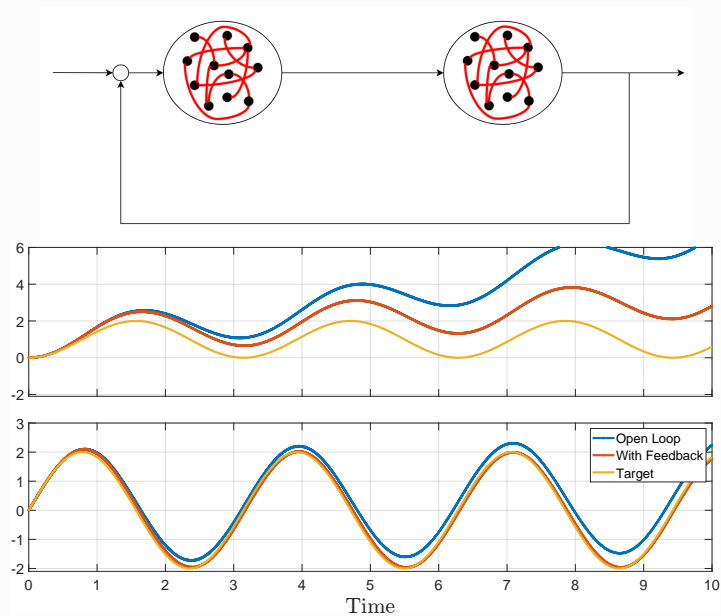
- Incapable of noise detection or correction
- No Compensation of Training error

Highly dependent on governing dynamics from  $\mathbf{c}_{\text{contr}} = \dot{\mathbf{x}}_{\text{ref}} - \mathbf{A}\mathbf{x}_{\text{ref}}$

Orthonormality restriction on Input Matrix  $\mathbf{B} \in \mathbb{B} := \{\mathbf{M} \mid \mathbf{M}\mathbf{M}^T = \mathbf{I}\}$



# Examples





# Conclusion

## Conclusion

- Open loop and inaccurate learning of slow weights  $W^s$  need to be addressed.
  - Highly dependent on initial conditions in learning
  - Impressive accuracy
- In ideal conditions useable results achievable
  - Limited Applicability → Only of theoretical Interest
  - Results are somewhat translatable to NEF and LSMs

Choice between biologic plausibility or and Input Matrix Restriction for accurate results

## Future Work

- Enable non-linear dynamics
- Obey Dale's Law for neuron excitation and inhibition
- Optimize Control
- Learning of En- and Decoder  $F$
- Allow for synaptic delays

## Bibliography I

- [BD15] Ralph Bourdoukan and Sophie Denève. “Enforcing balance allows local supervised learning in spiking recurrent networks”. In: **Advances in Neural Information Processing Systems**. Ed. by C. Cortes, N. Lawrence, D. Lee, M. Sugiyama, and R. Garnett. Vol. 28. Curran Associates, Inc., 2015. URL: [https://proceedings.neurips.cc/paper\\_files/paper/2015/file/3871bd64012152bfb53fdf04b401193f-Paper.pdf](https://proceedings.neurips.cc/paper_files/paper/2015/file/3871bd64012152bfb53fdf04b401193f-Paper.pdf).
- [BMD13] Martin Boerlin, Christian K. Machens, and Sophie Denève. “Predictive Coding of Dynamical Variables in Balanced Spiking Networks”. In: **PLOS Computational Biology** 9.11 (Nov. 14, 2013). Publisher: Public Library of Science, e1003258. ISSN: 1553-7358. DOI: [10.1371/journal.pcbi.1003258](https://doi.org/10.1371/journal.pcbi.1003258). URL: <https://journals.plos.org/ploscompbiol/article?id=10.1371/journal.pcbi.1003258> (visited on 09/20/2022).



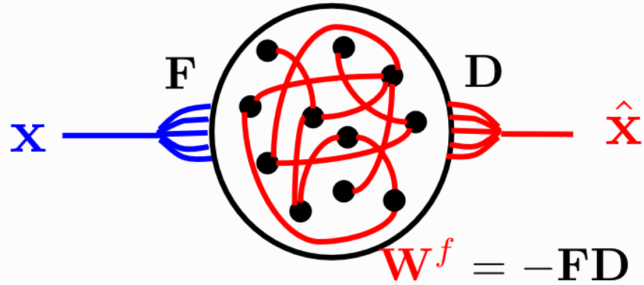
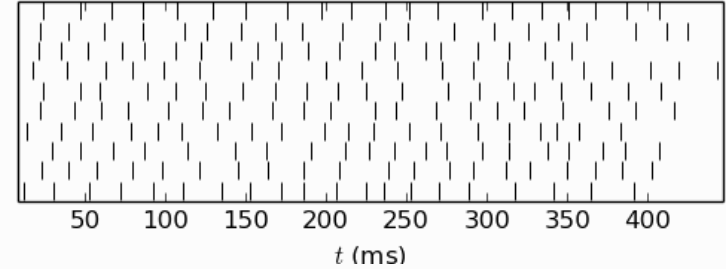
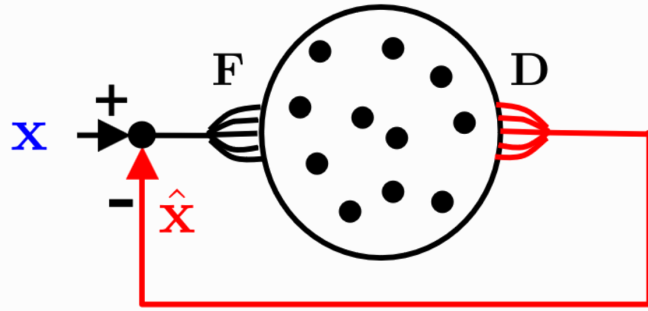
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- [HC19] Fuqiang Huang and ShiNung Ching. "Spiking networks as efficient distributed controllers". In: **Biological Cybernetics** 113.1 (Apr. 2019), pp. 179–190. ISSN: 0340-1200, 1432-0770. DOI: [10.1007/s00422-018-0769-7](https://doi.org/10.1007/s00422-018-0769-7). URL: <http://link.springer.com/10.1007/s00422-018-0769-7> (visited on 10/23/2022).
- [Xue+22] Xiaohe Xue, Ralf D. Wimmer, Michael M. Halassa, and Zhe Sage Chen. "Spiking Recurrent Neural Networks Represent Task-Relevant Neural Sequences in Rule-Dependent Computation". In: **Cognitive Computation** 15.4 (Feb. 2022), pp. 1167–1189. ISSN: 1866-9964. DOI: [10.1007/s12559-022-09994-2](https://doi.org/10.1007/s12559-022-09994-2). URL: <http://dx.doi.org/10.1007/s12559-022-09994-2>.



BackupSlides

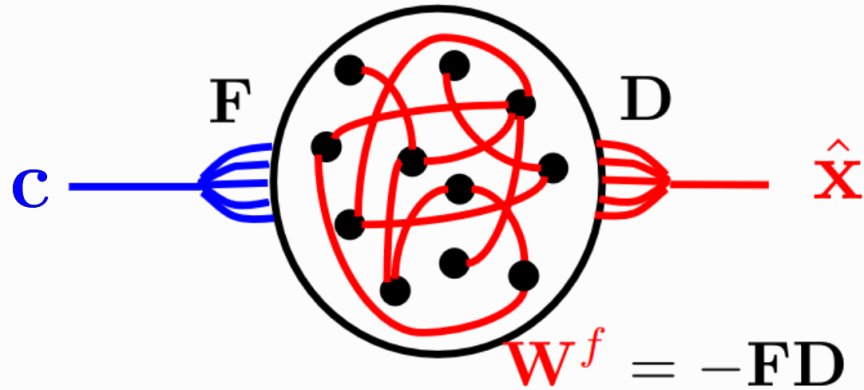
# Autoencoder



$$\begin{aligned}\hat{x} &= Do(t) \\ \dot{r} &= -\lambda r + o(t)\end{aligned}\tag{2}$$

$$\dot{r} = -\lambda r + \sigma(t)$$

## Autoencoder II

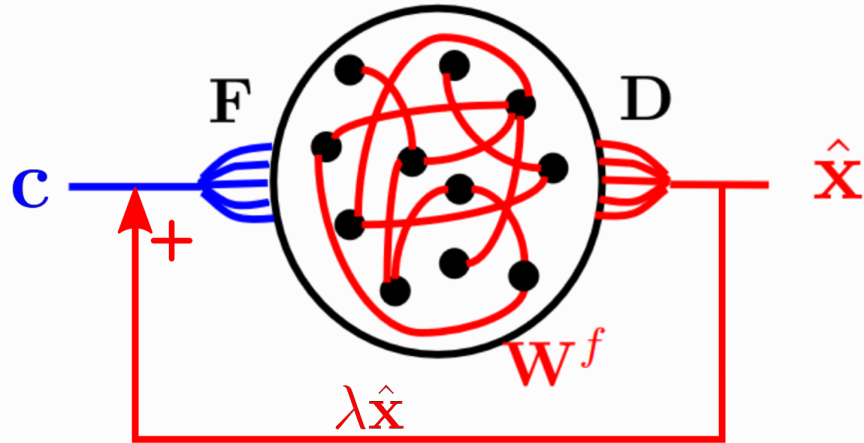


$$\begin{aligned}\dot{x} &= -\lambda x + c \\ \hat{x} &= Dr\end{aligned}\quad (3)$$

$$\dot{r} = -\lambda r + o(t)$$

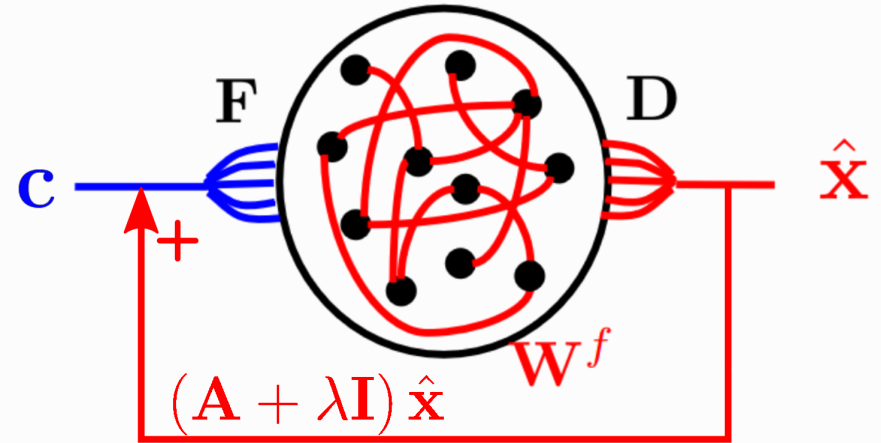
$$\hat{x} = Dr$$

## Autoencoder III



$$\dot{x} = c$$

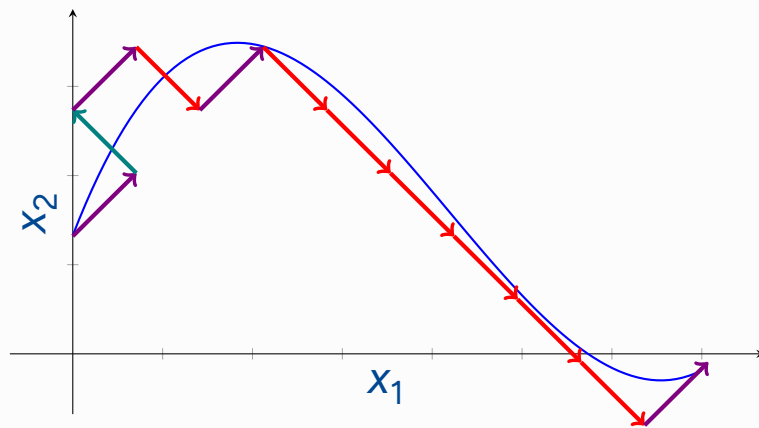
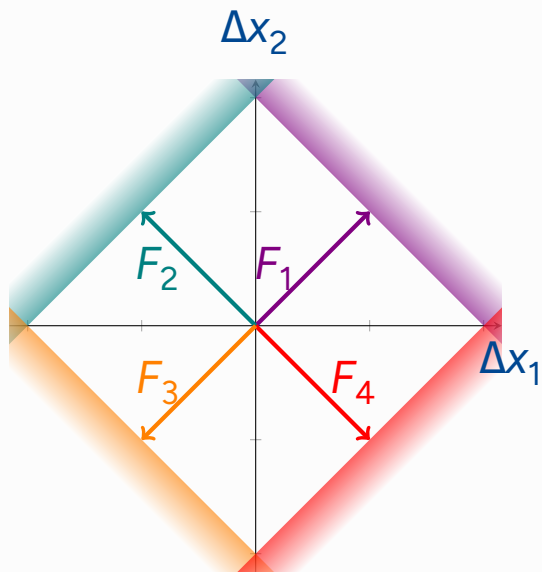
(4)



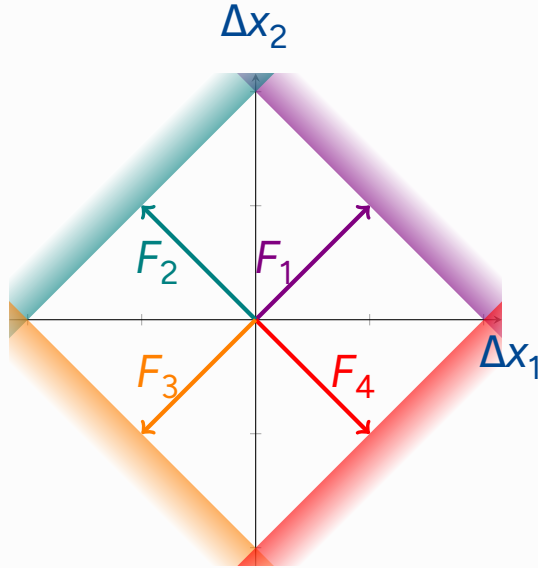
$$\dot{x} = Ax + c$$

(5)

# Geometric



# Geometric



Minimize the cost  $J$  (Greedy)

$$J = \int_0^T \|x - \hat{x}\|_2^2 + C(r) dt \quad (6)$$

$$V_i = F_i(x - \hat{x}) - \mu r_i$$

$$\dot{V}_i = -\lambda_V V_i + F_i c(t) + W^f o(t) + W^s r(t) + \sigma_V \eta(t) \quad (7)$$

$$W^f = FF^T + \mu I$$

$$W^s = F(A + \lambda_d I)F^T$$



# Example Simple

content...





# Example Big

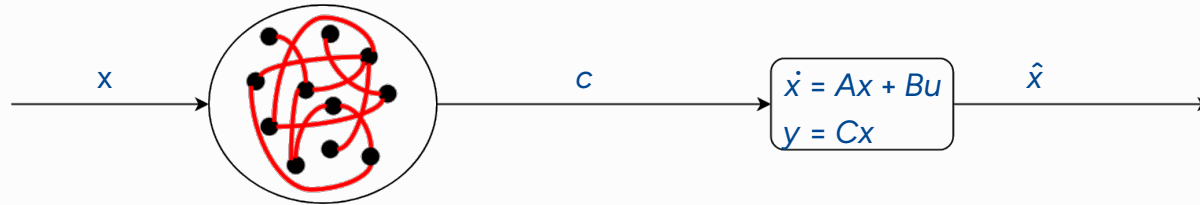
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# Conclusion

content...

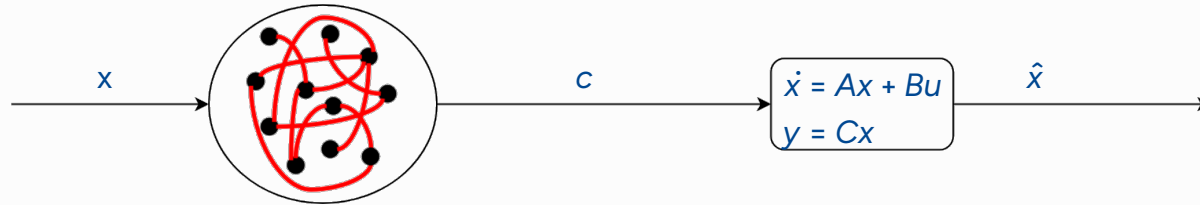
# Control Concept



[HC19]

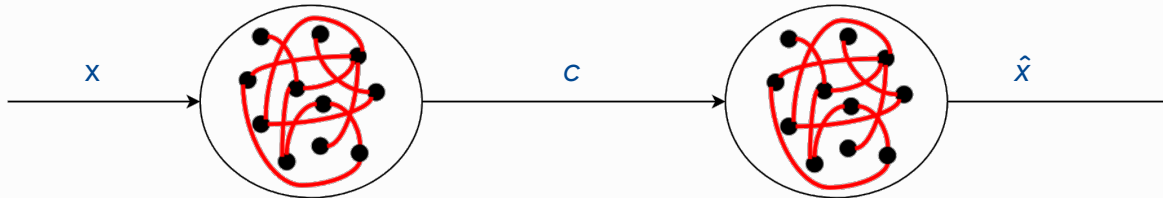
Add a separator here

# Control Concept



[HC19]

Add a separator here



# Control with SNN

$$u = F^T r + \Omega o(t) \quad (8)$$

Slow and Instantaneous decoding

$$\begin{aligned} \dot{V}(t) = & -\lambda_V V(t) + \Omega^T B^T A e(t) + \Omega^T B^T c(t) \\ & + W^s r(t) + W^f o(t) + \sigma_v \eta(t) \end{aligned} \quad (9)$$

Requires full state information on  $x$   
and  $\hat{x}$

$$c = \dot{x} - Ax \quad (10)$$

It is necessary on  $B \in \mathbb{R}^{n \times p}$

$$\text{rank}(B^T C^T) = p \quad (11)$$

## Example in Ideal Conditions

works fine+ add plot

## Example with 2 networks

works bad+ add plot



# Conclusion



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- Acceptable results in ideal conditions

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- Rank condition is limiting factor

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# Conclusion

- Acceptable results in ideal conditions
- Rank condition is limiting factor
- Network noise is invisible to the control
- Simple open loop controller in the definition of  $c$

# Fast Learning rule

## **Slow Learning rule**

Online Teacher-Student Scheme

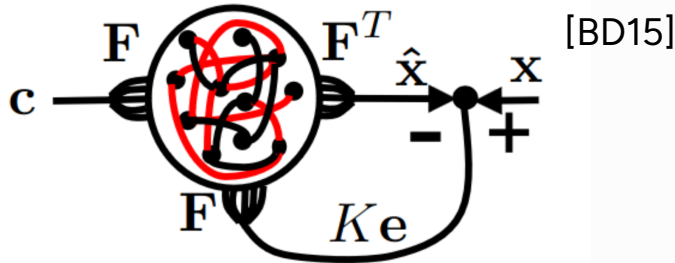
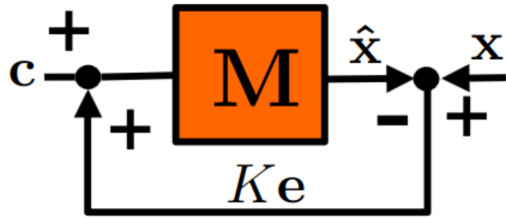
## **Fast Learning rule**

content...

$$\dot{\hat{x}} = (M - K\mathbf{I})\hat{x} + c + Kx$$

$$W^s = F(A + \lambda_d \mathbf{I})F^T$$

## Slow Learning rule



Online Teacher-Student Scheme for  $M$  under  $\dot{x} = Mx + c$

Matrix update under squared loss

$$\delta M \propto e \hat{x}^T \longrightarrow \delta W^s \propto F^T (e \hat{x}^T) F \approx F^T e r \quad (12)$$

## Conclusion

- Very limited applicability
  - Open loop + rank condition limiting factor
  - Too inaccurate learning of slow weights  $W^s$
  - Too dependent on initial conditions in learning
- In ideal conditions useable results achievable
  - Only of theoretical interest
  - Impressive accuracy
  - Results are somewhat translatable to NEF and LSMs



# Future Work



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# Frame title

## Block

Lorem ipsum!

## Bibliography

- [BD15] Ralph Bourdoukan and Sophie Denève. “Enforcing balance allows local supervised learning in spiking recurrent networks”. In: **Advances in Neural Information Processing Systems**. Ed. by C. Cortes, N. Lawrence, D. Lee, M. Sugiyama, and R. Garnett. Vol. 28. Curran Associates, Inc., 2015. URL: [https://proceedings.neurips.cc/paper\\_files/paper/2015/file/3871bd64012152bfb53fdf04b401193f-Paper.pdf](https://proceedings.neurips.cc/paper_files/paper/2015/file/3871bd64012152bfb53fdf04b401193f-Paper.pdf).
- [BMD13] Martin Boerlin, Christian K. Machens, and Sophie Denève. “Predictive Coding of Dynamical Variables in Balanced Spiking Networks”. In: **PLOS Computational Biology** 9.11 (Nov. 14, 2013). Publisher: Public Library of Science, e1003258. ISSN: 1553-7358. DOI: [10.1371/journal.pcbi.1003258](https://doi.org/10.1371/journal.pcbi.1003258). URL: <https://journals.plos.org/ploscompbiol/article?id=10.1371/journal.pcbi.1003258> (visited on 02/02/2022)

