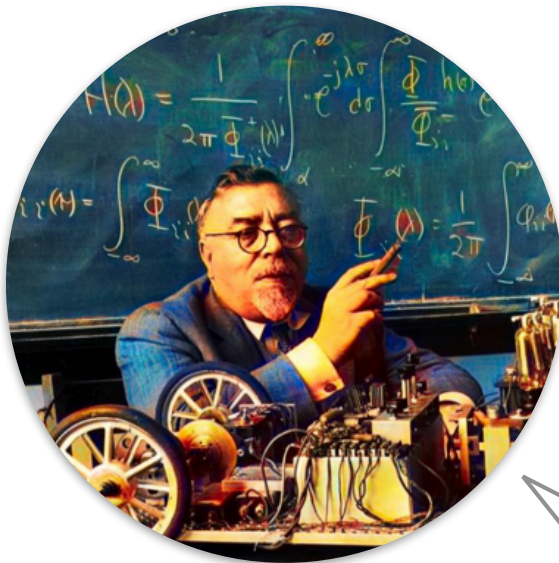
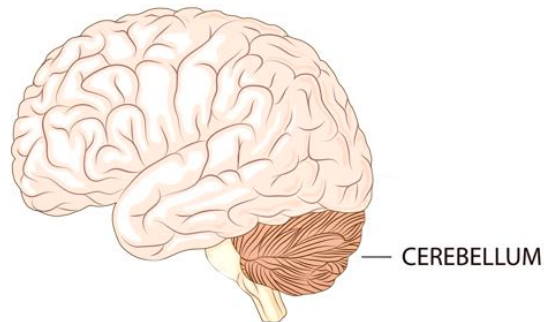

Learned
Feedback & Feedforward
Perception & Control

Joseph Marino

August 9th, 2021

Caltech



Norbert Wiener

1894 - 1964

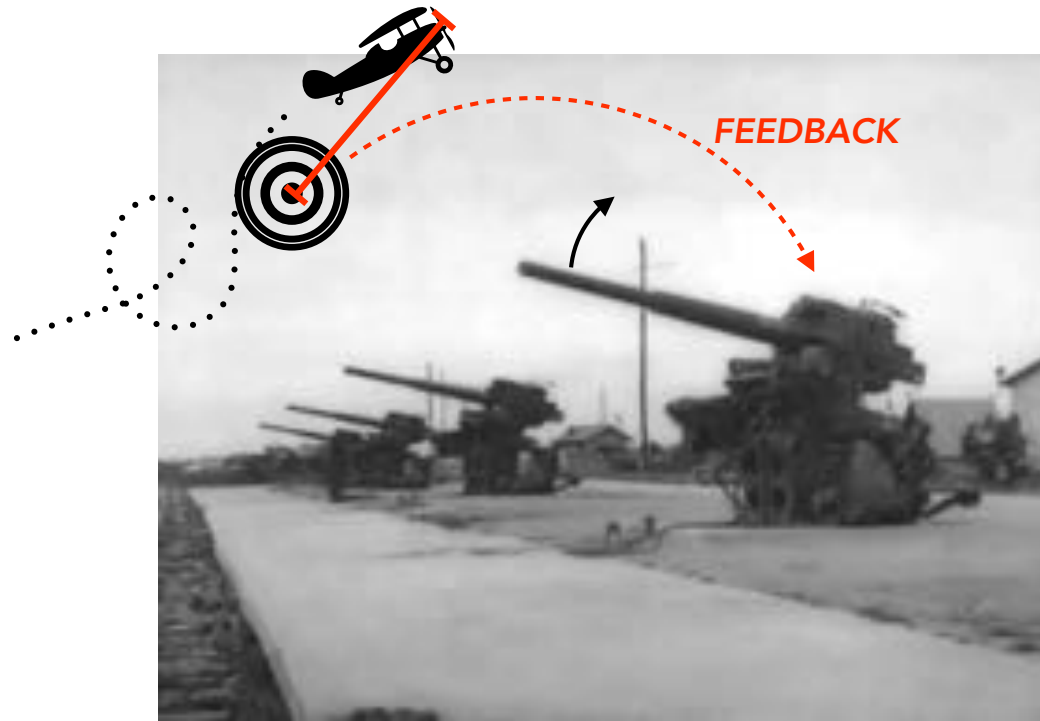
*"...undamped **feedback** is strikingly similar to...a **cerebellar** patient. If he is asked to carry a glass of water from a table to his mouth, the hand carrying the glass will execute a series of **oscillatory** motions of increasing amplitude."*

Rosenblueth, Wiener, and Bigelow, 1943



Norbert Wiener

1894 - 1964

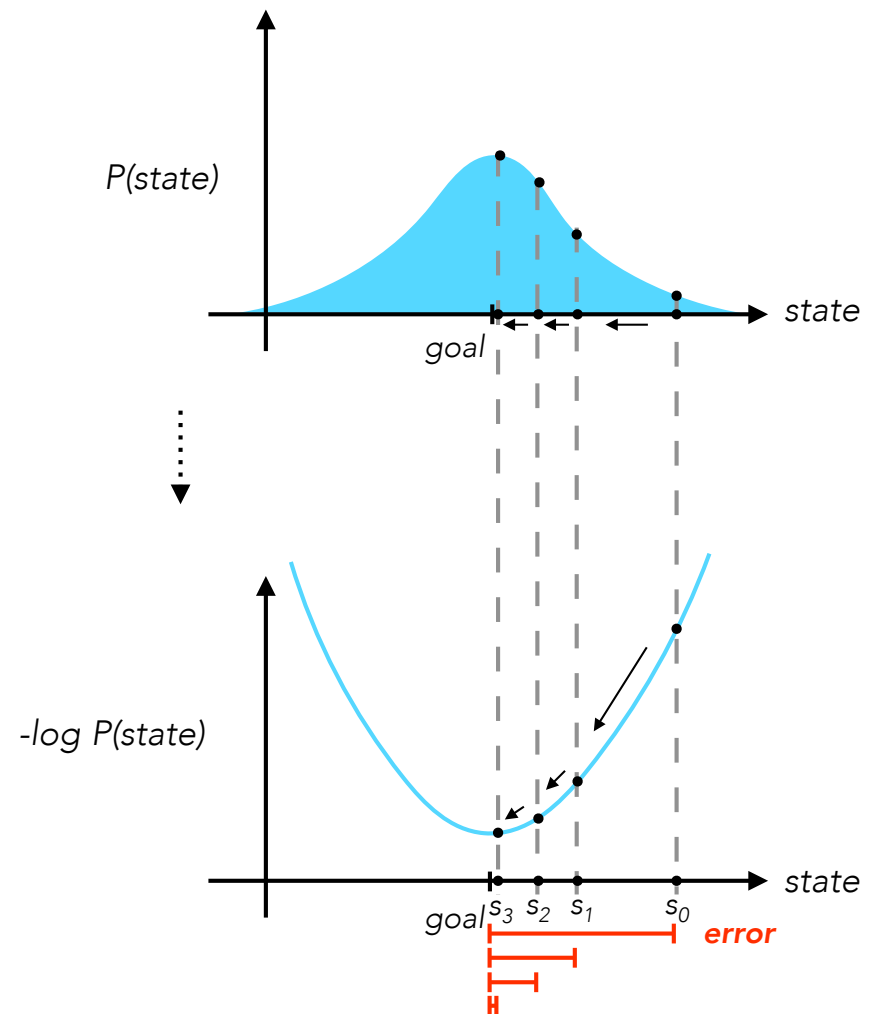


anti-aircraft guns

control as...

probability maximization

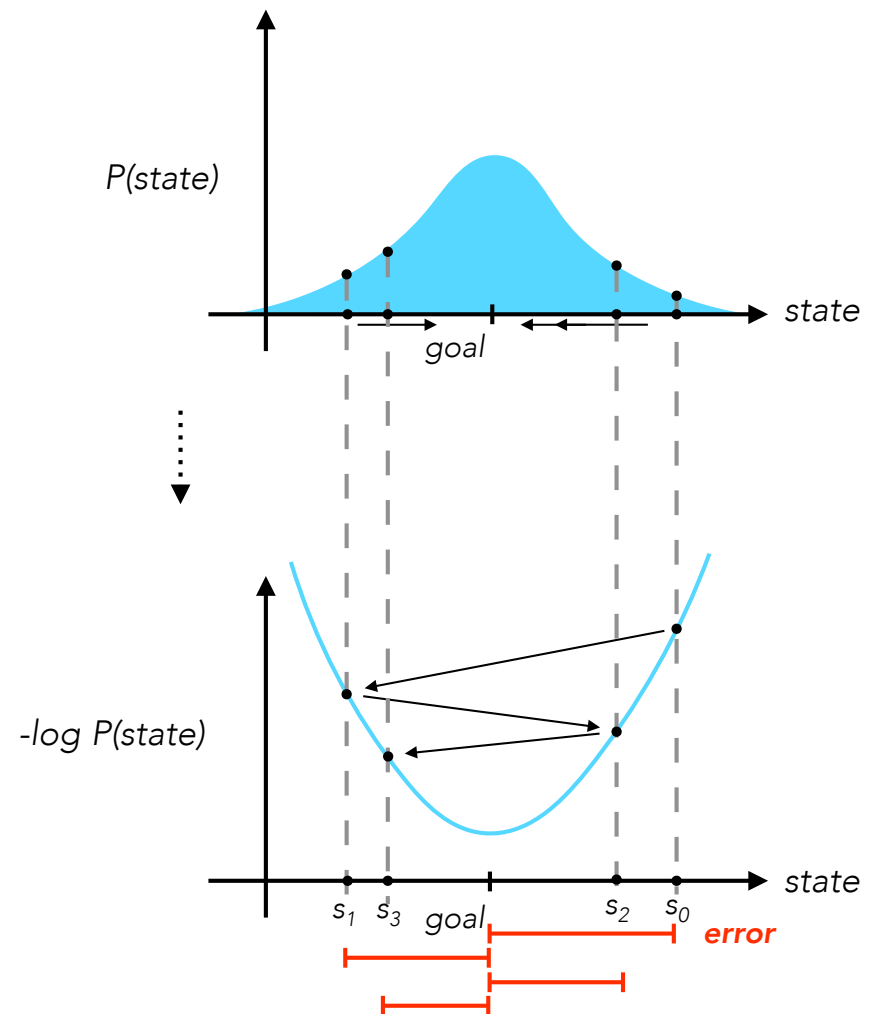
error minimization

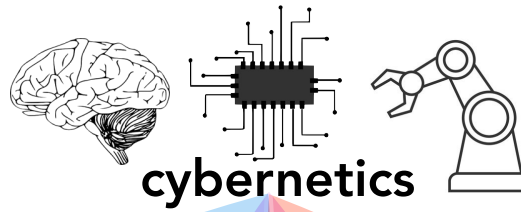


control as...

probability maximization

error minimization





information

feedback control

linear threshold unit

multi-layer
perceptrons

model-based
control

minimum
redundancy codes

backpropagation

hierarchical
control

predictive coding

reinforcement
learning

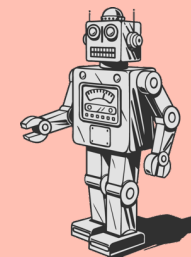
probabilistic
graphical models



**theoretical
neuroscience**



**machine
learning**

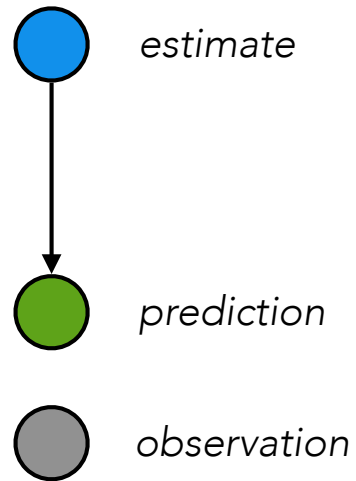


**control
theory**



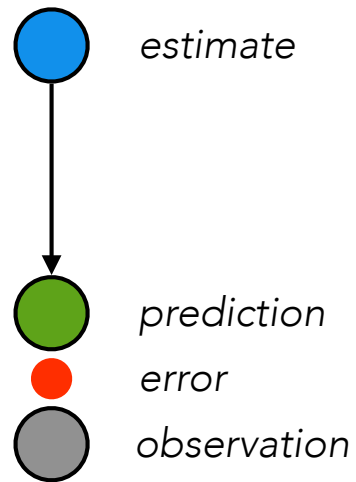
feedback

reducing an error in the moment



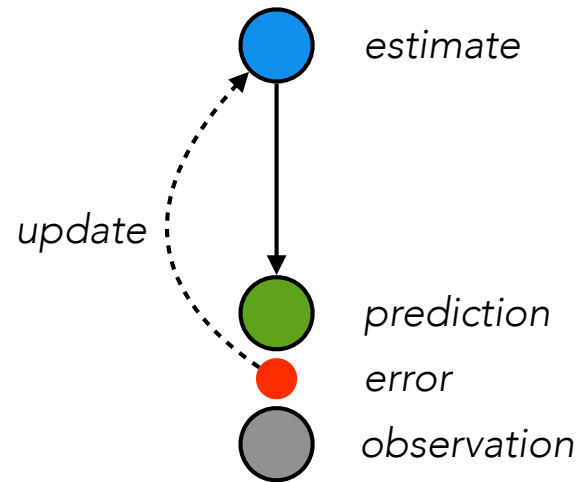
feedback

reducing an error in the moment



feedback

reducing an error in the moment



feedback

reducing an error in the moment



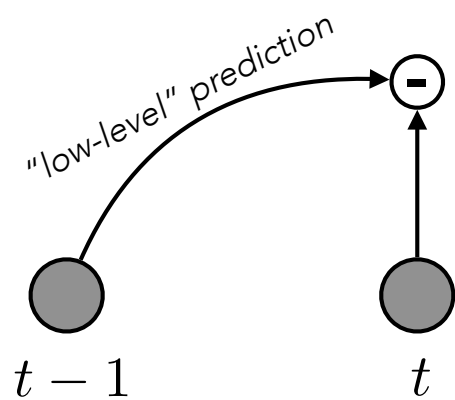
$t - 1$



t

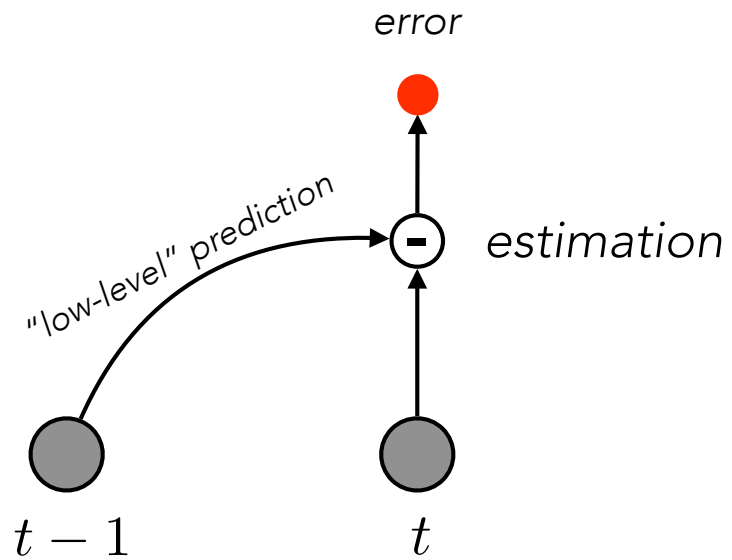
feedforward

preemptively reducing an error



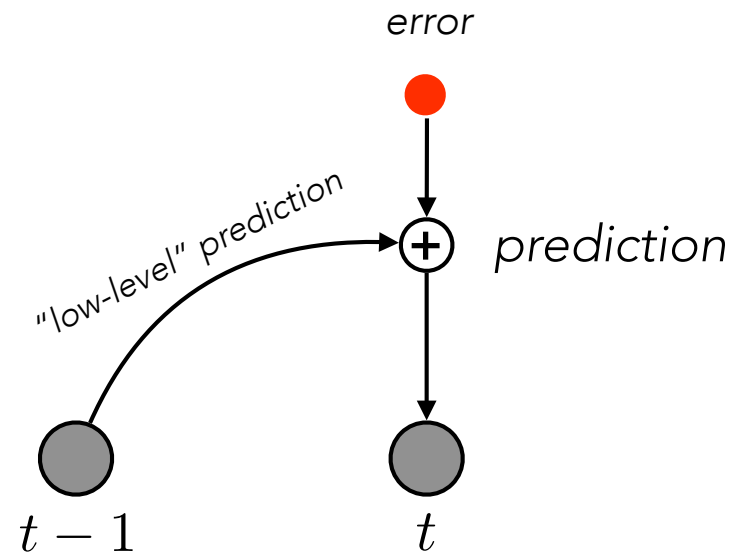
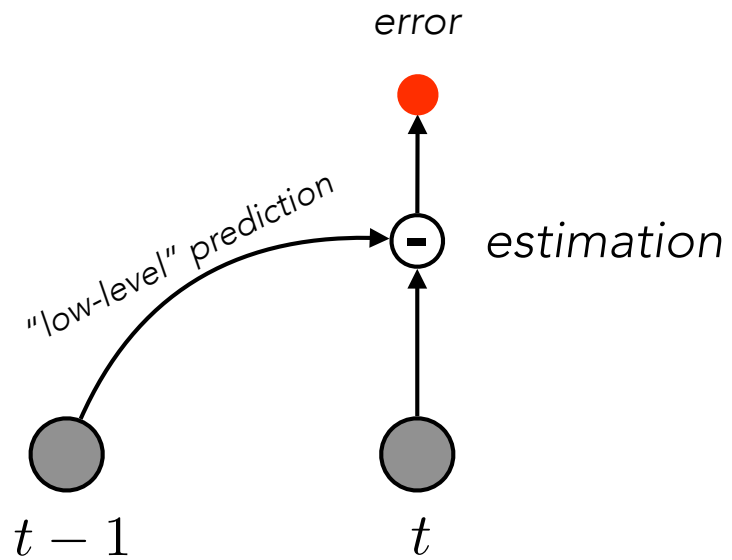
feedforward

preemptively reducing an error



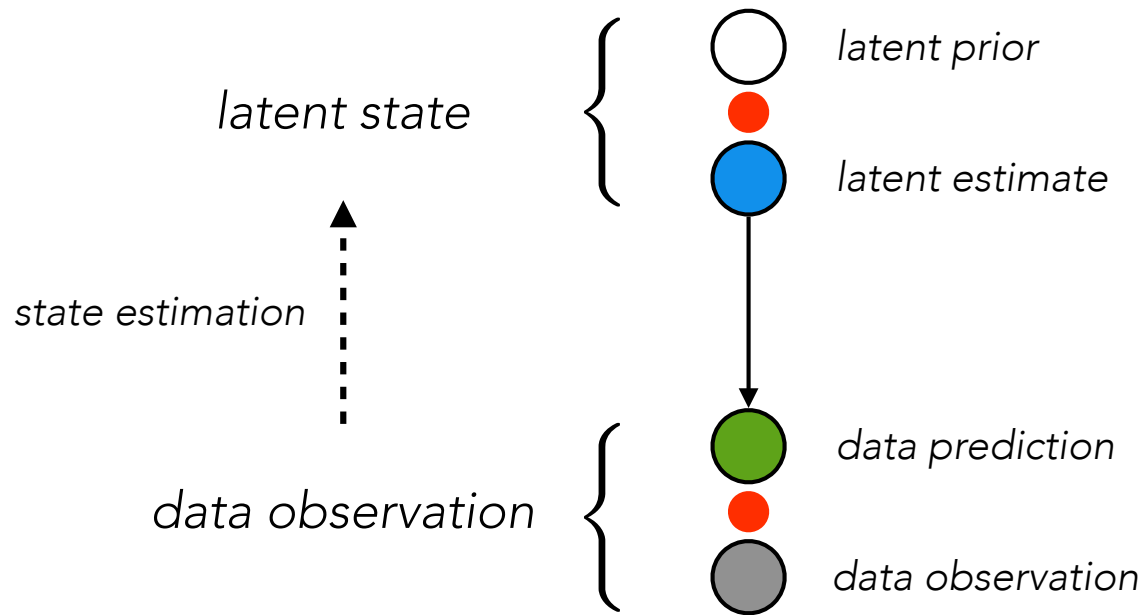
feedforward

preemptively reducing an error



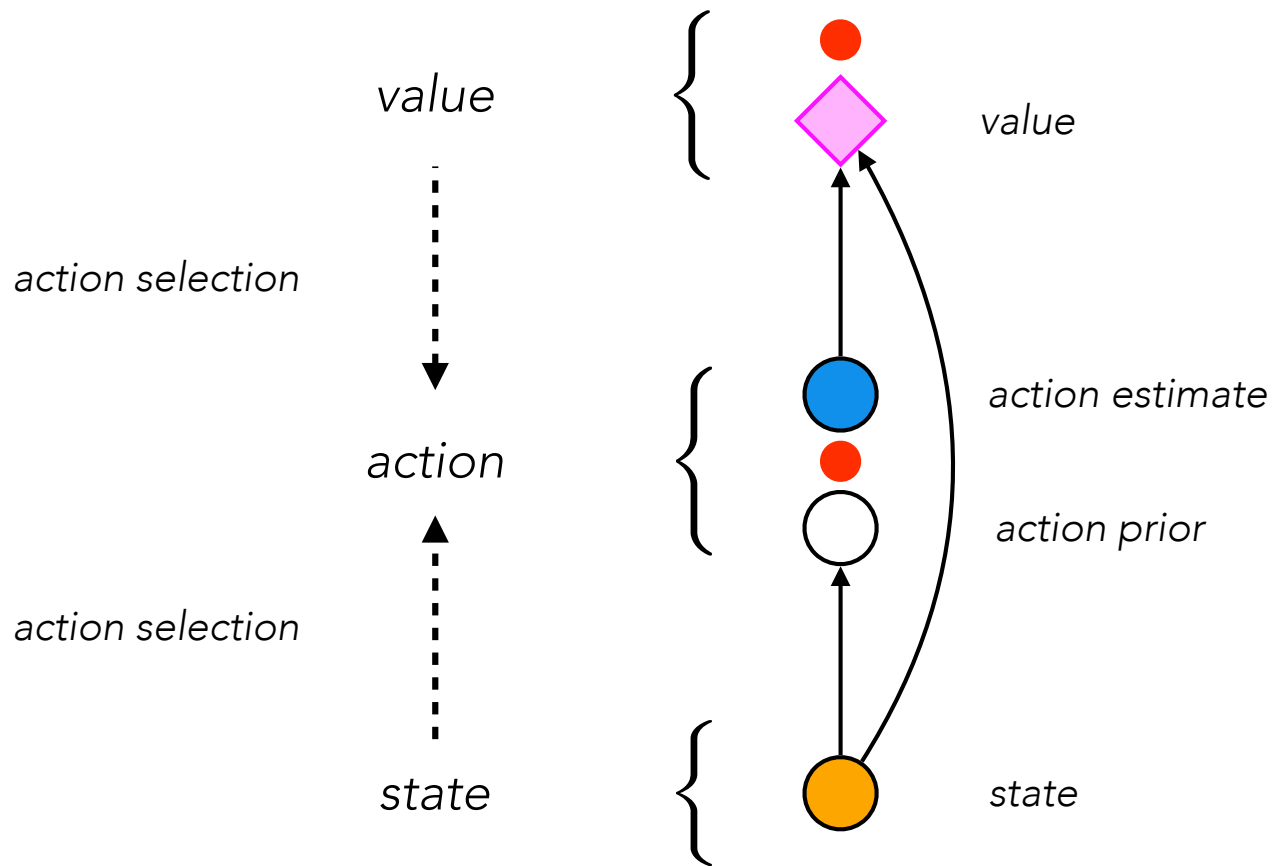
feedforward

preemptively reducing an error



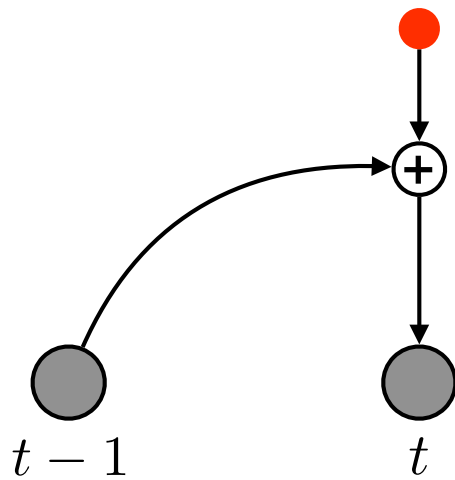
perception

state estimation

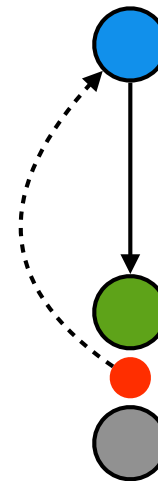


control

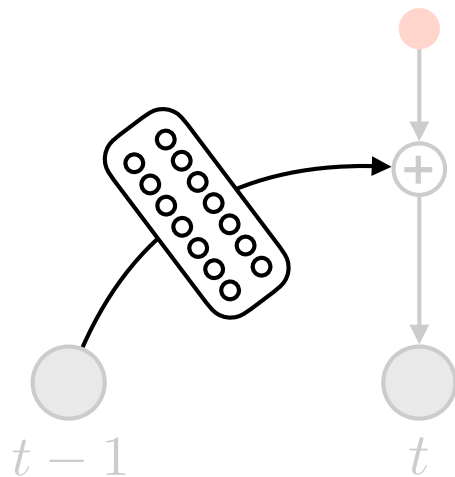
action selection



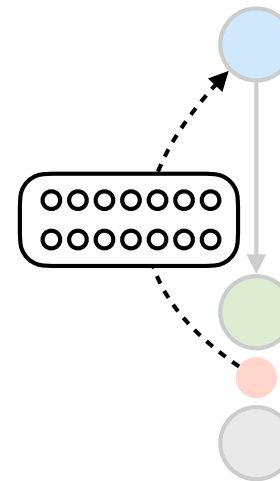
feedforward



feedback



feedforward



feedback

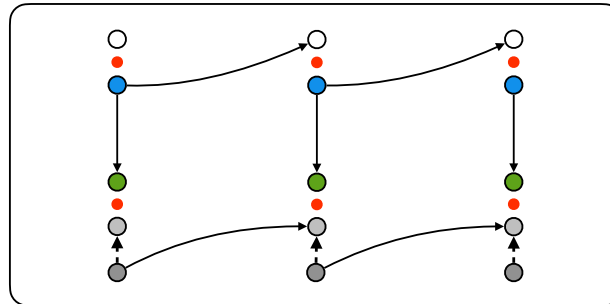
my research:

we're going to **learn** feedforward & feedback functions

THESIS OVERVIEW

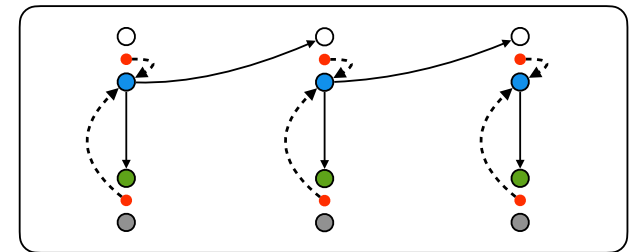
perception

feedforward



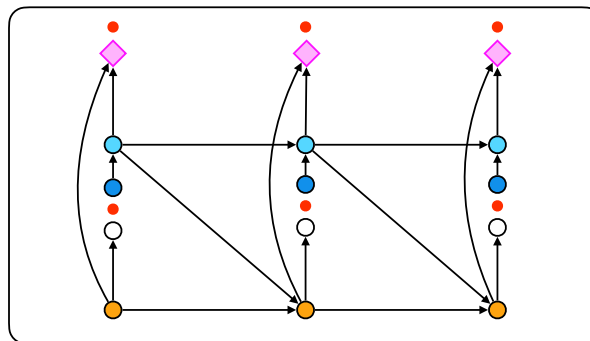
Marino, Chen, He, Mandt 2020
Yang, Yang, Marino, Mandt 2021

feedback

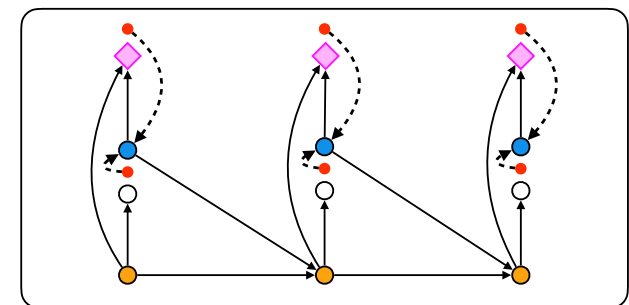


Marino, Yue, Mandt 2018
Marino, Cvitkovic, Yue, 2018

control

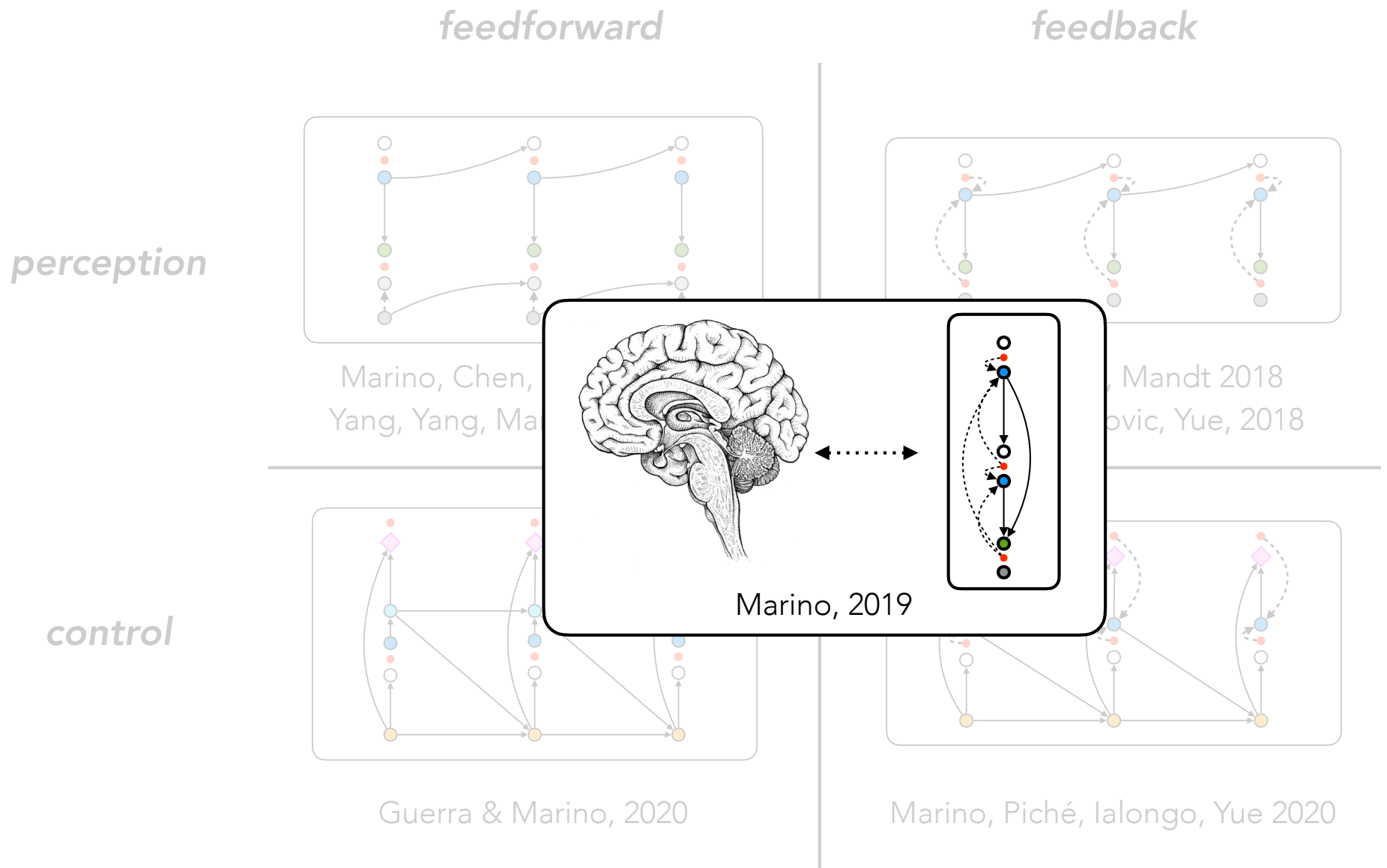


Guerra & Marino, 2020



Marino, Piché, Ialongo, Yue 2020

THESIS OVERVIEW



feedforward

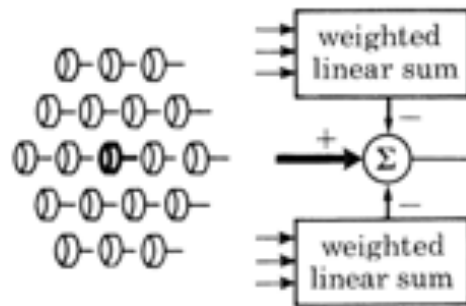
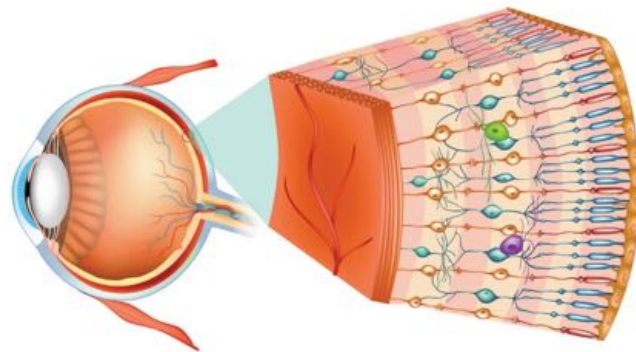
PERCEPTION

SPATIOTEMPORAL PREDICTIVE CODING

*spatiotemporal predictions **normalize** sensory inputs*

Predictive coding: a fresh view of inhibition in the retina

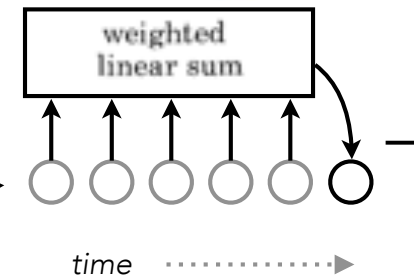
BY M. V. SRINIVASAN^{1,2†}, S. B. LAUGHLIN¹ AND A. DUBS¹ 1982



SPATIAL NORMALIZATION

Temporal Decorrelation: A Theory of Lagged and Nonlagged Responses in the Lateral Geniculate Nucleus

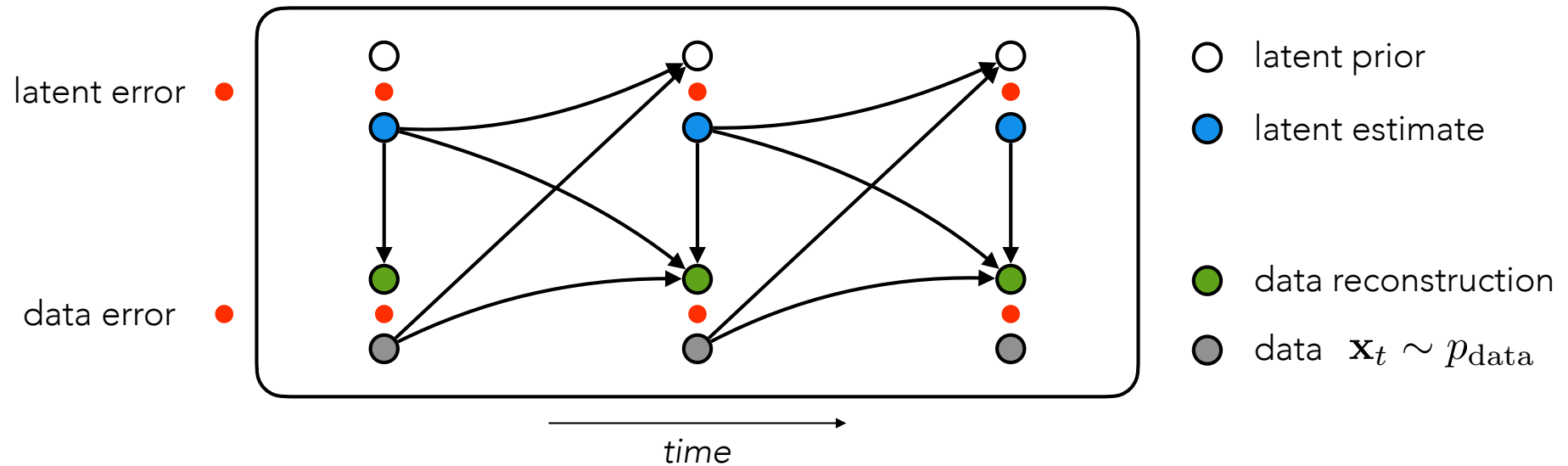
Dawei W. Dong and Joseph J. Atick 1995



TEMPORAL NORMALIZATION

FEEDFORWARD PERCEPTION

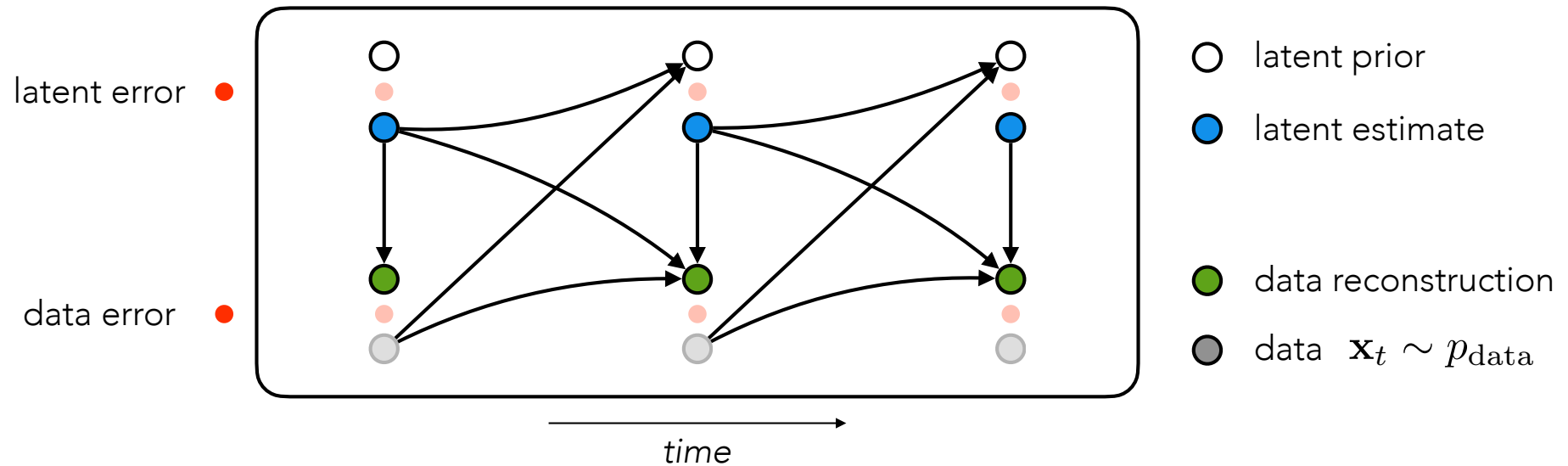
sequential latent variable model (SLVM)



to improve this setup, we can...

FEEDFORWARD PERCEPTION

sequential latent variable model (SLVM)



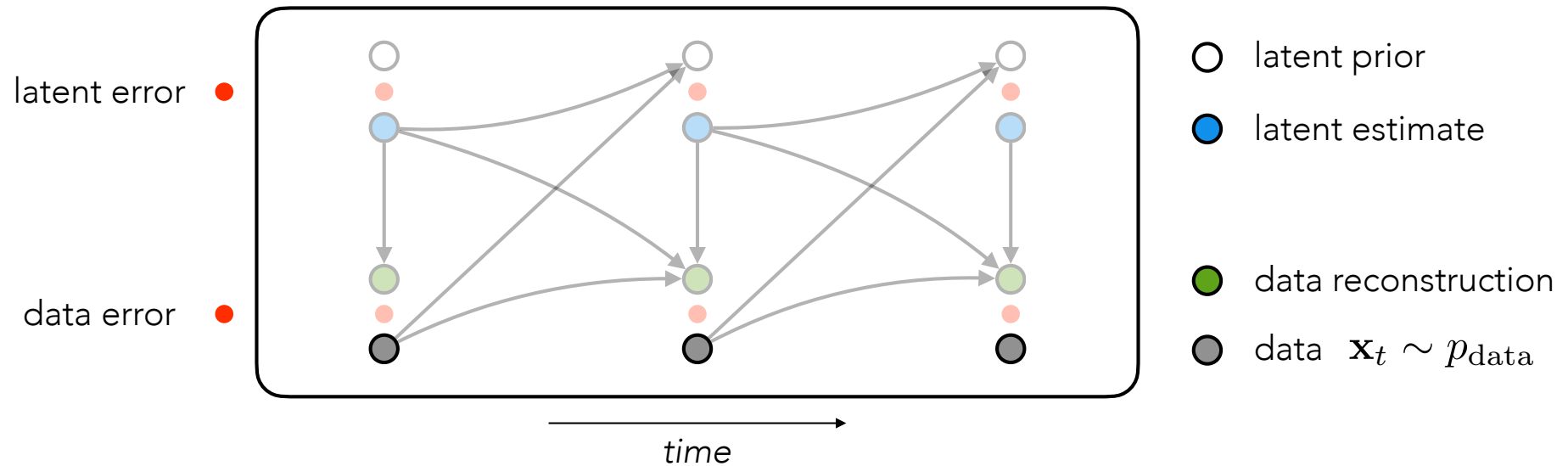
to improve this setup, we can...

improve the model

→ more dependencies, bigger functions

FEEDFORWARD PERCEPTION

sequential latent variable model (SLVM)



to improve this setup, we can...

improve the model

→ more dependencies, bigger functions

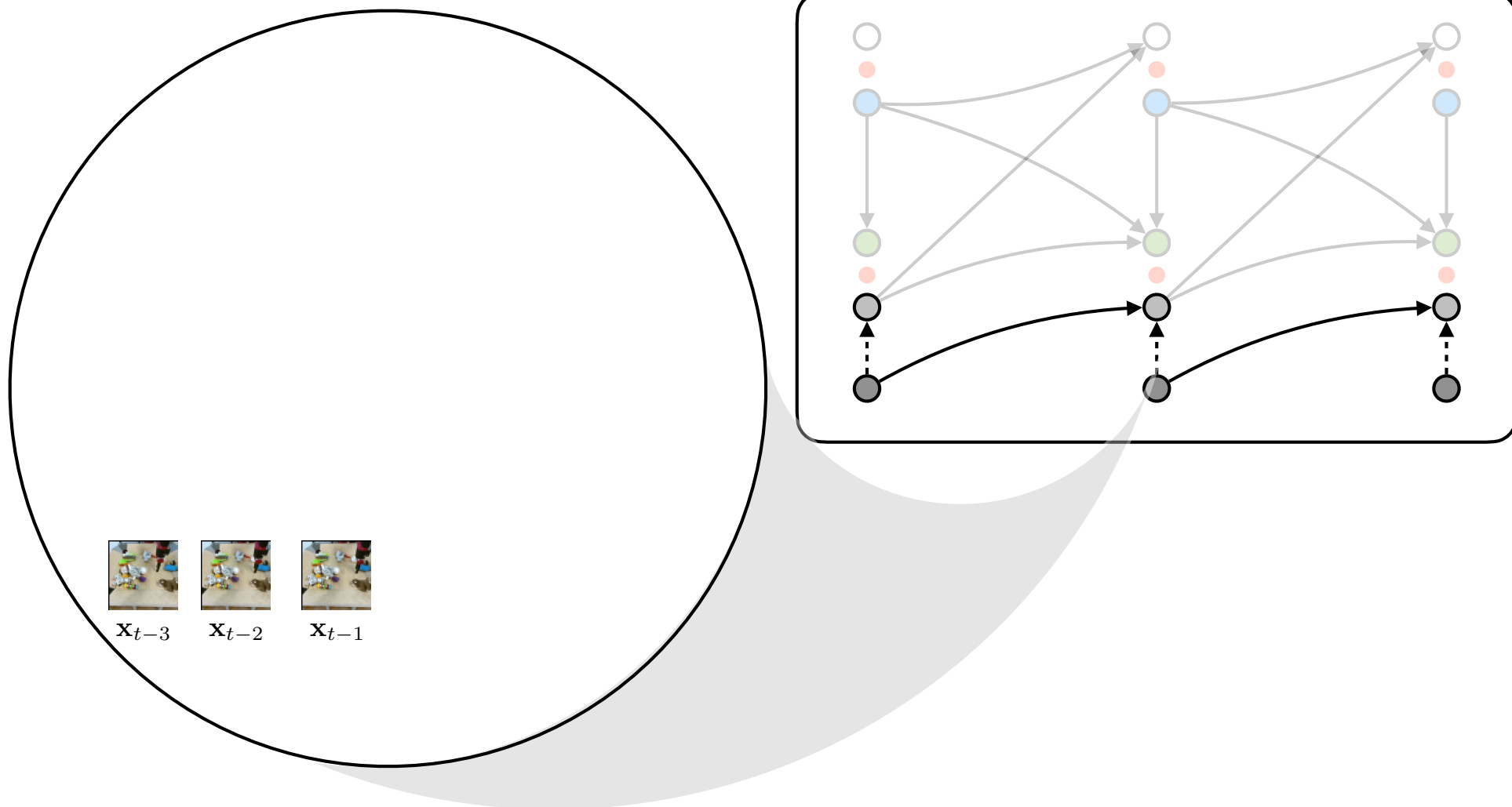
simplify the data (change the distribution)

→ e.g., model $\Delta \mathbf{x}_t = \mathbf{x}_t - \mathbf{x}_{t-1}$

FEEDFORWARD PERCEPTION

temporal normalization

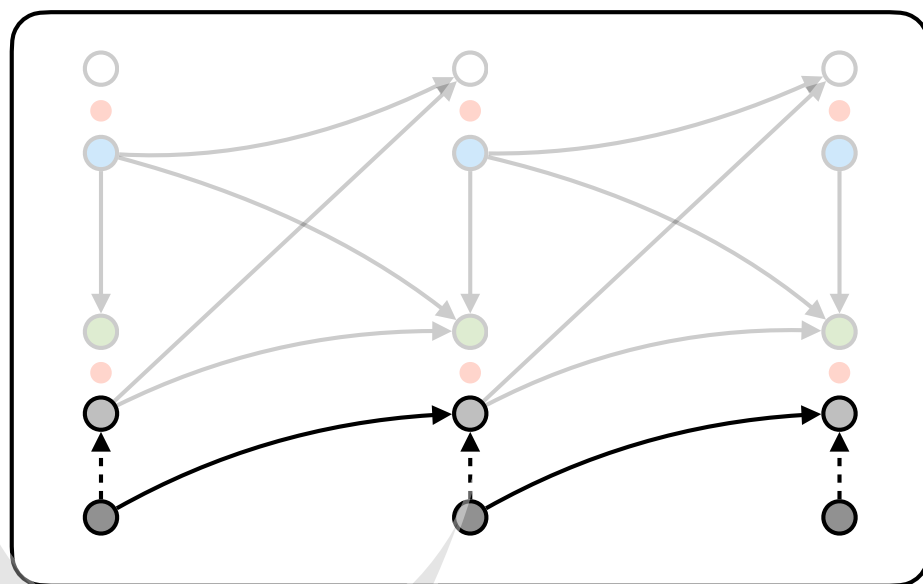
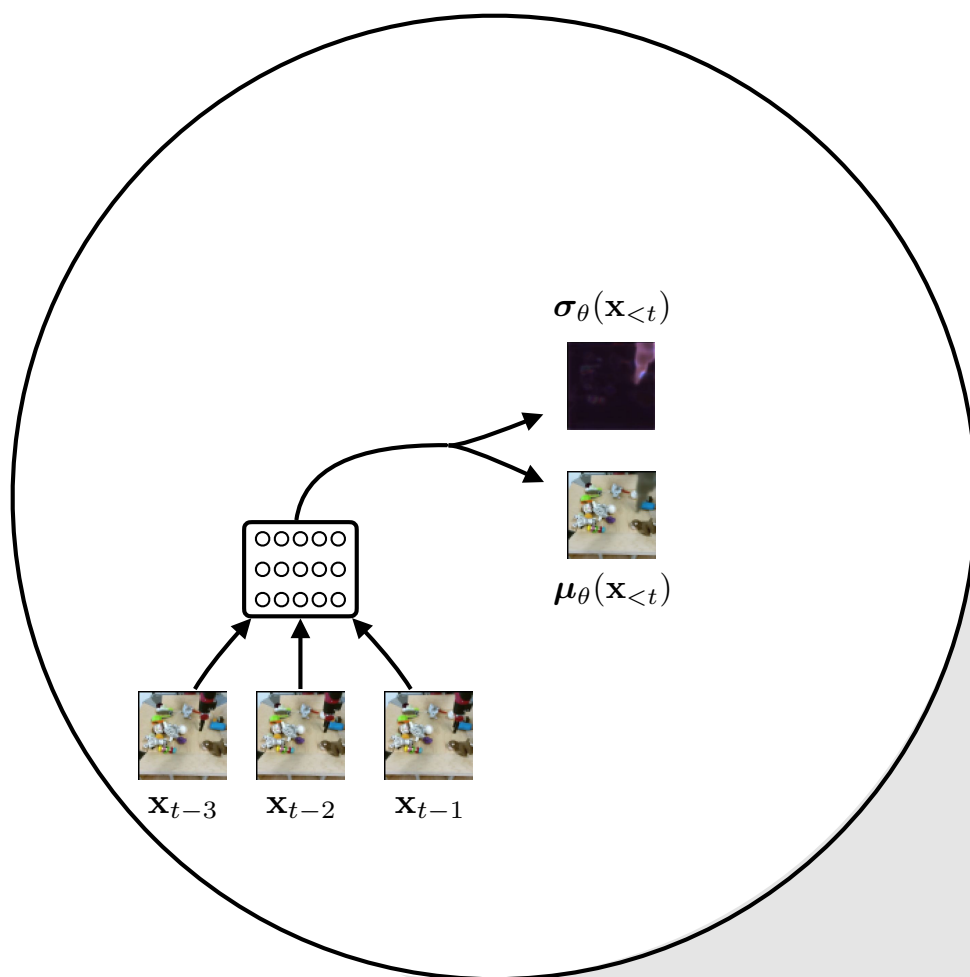
use an autoregressive model to remove a “low-level” prediction



FEEDFORWARD PERCEPTION

temporal normalization

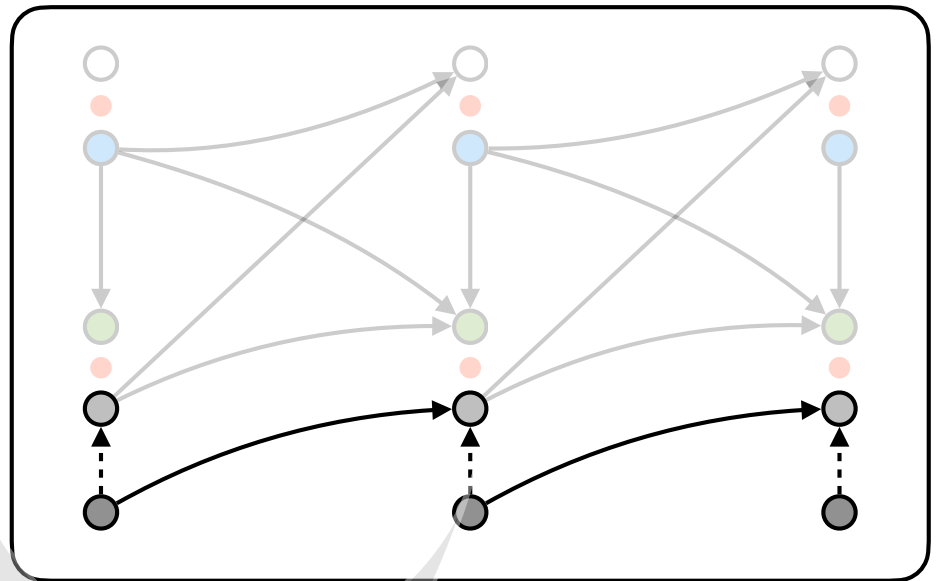
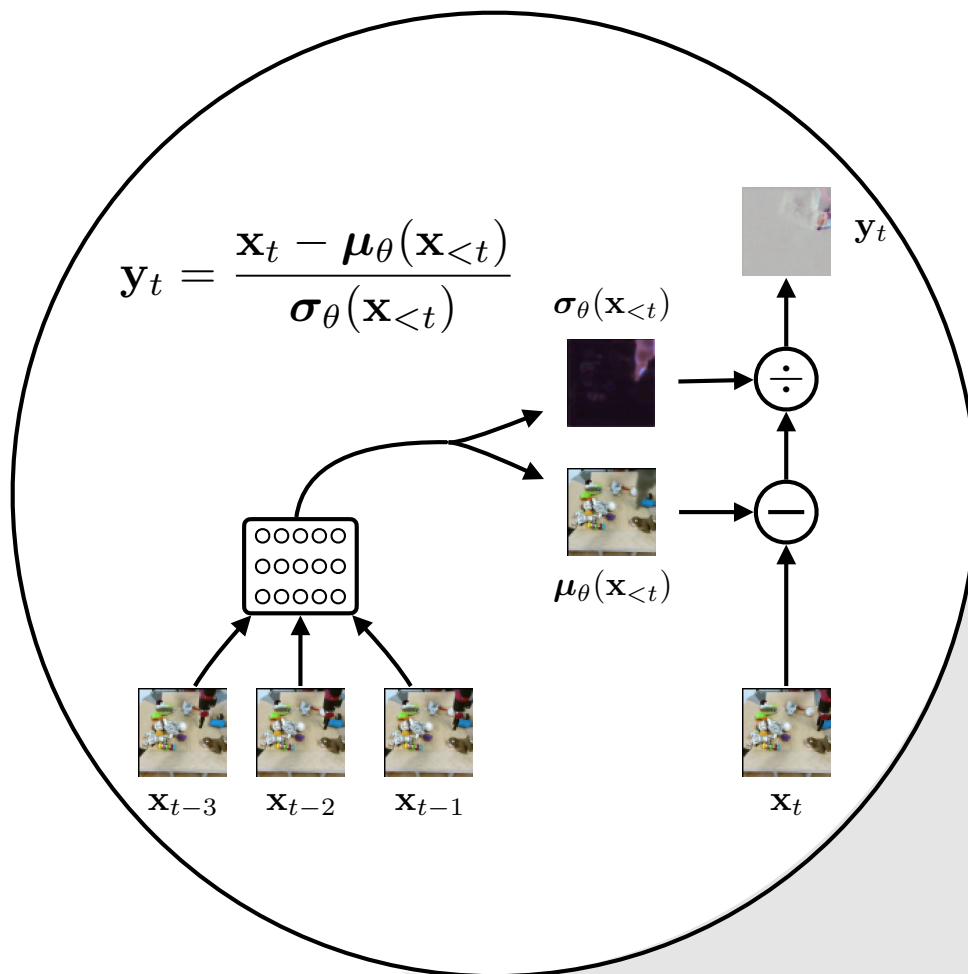
use an autoregressive model to remove a “low-level” prediction



FEEDFORWARD PERCEPTION

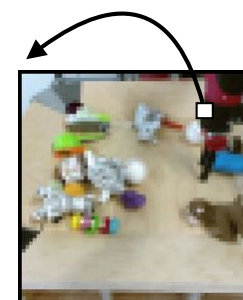
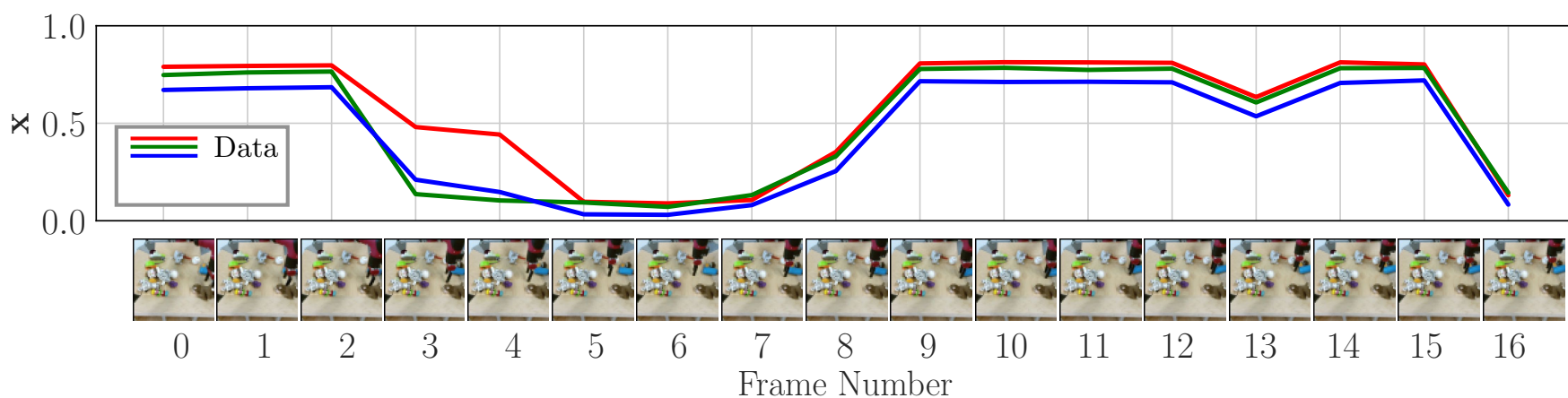
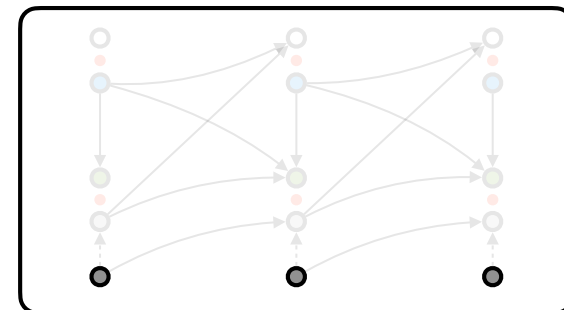
temporal normalization

use an autoregressive model to remove a “low-level” prediction

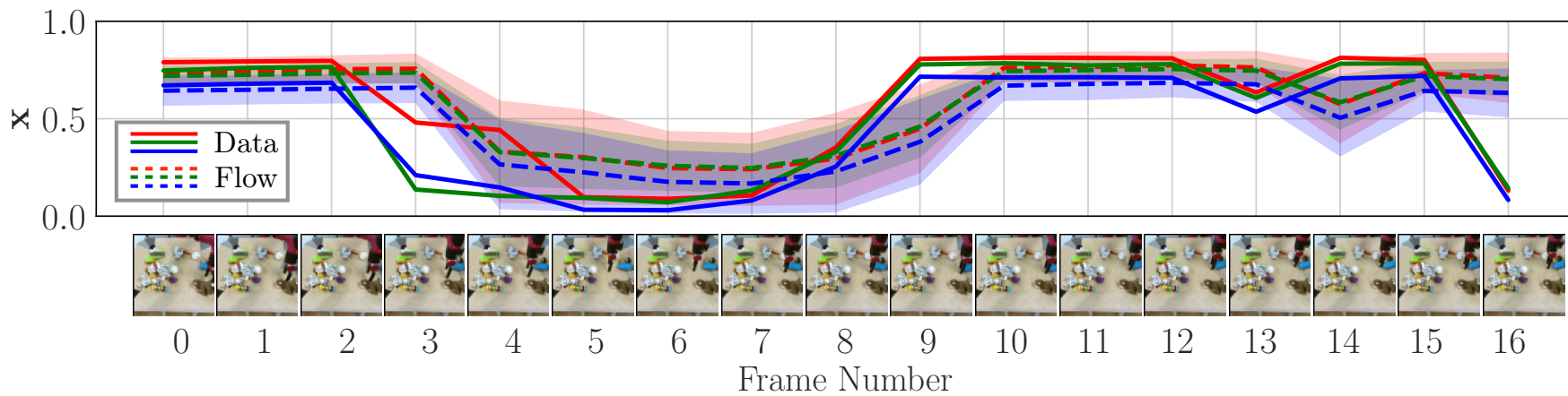
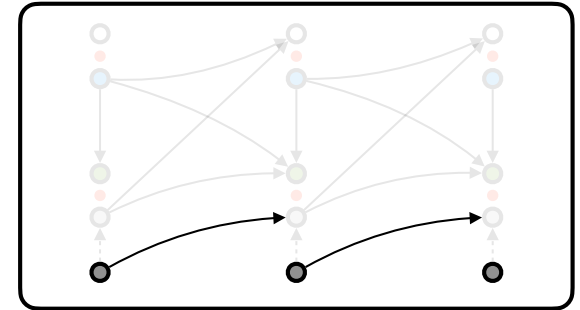


this is a
sequential autoregressive flow

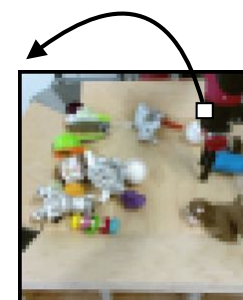
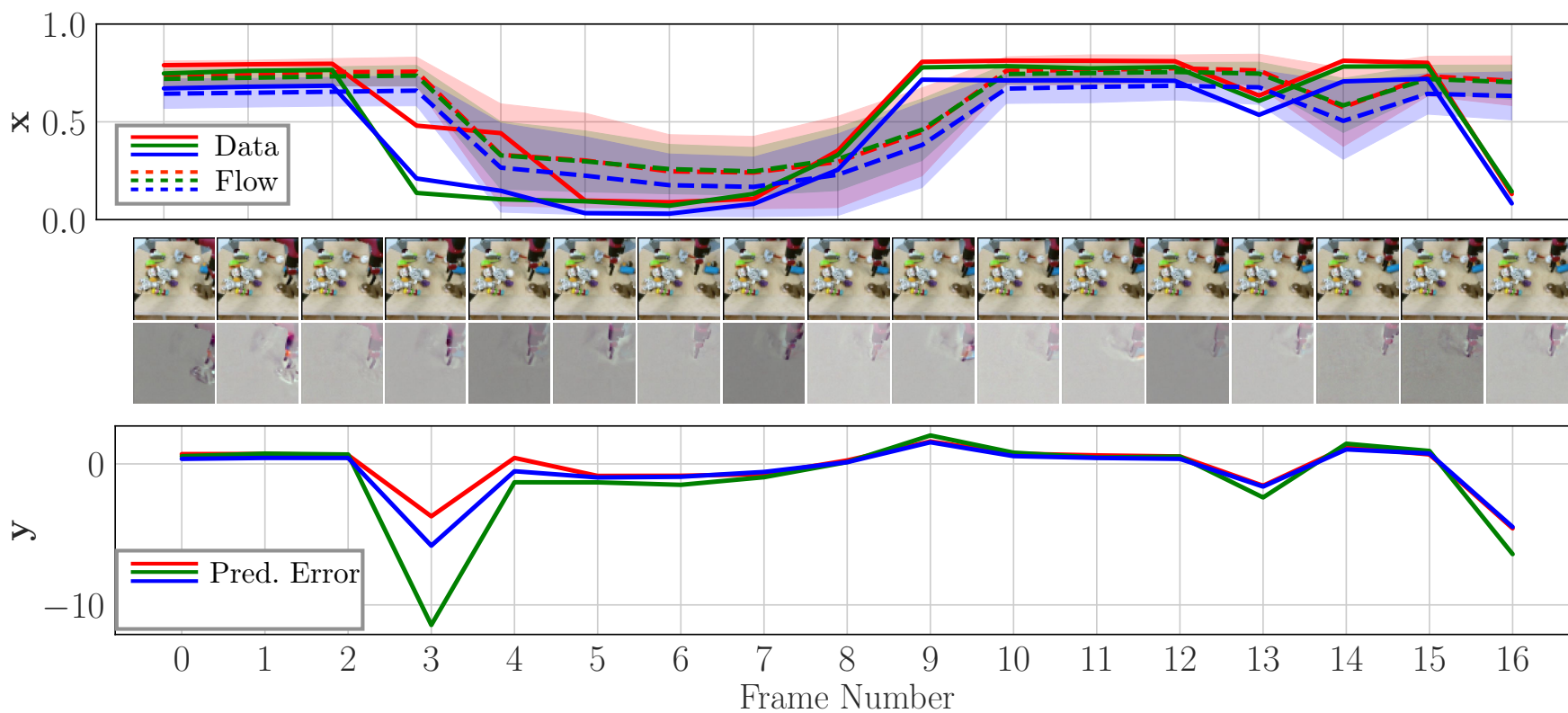
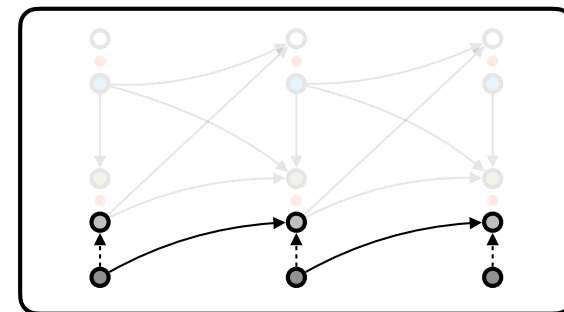
FEEDFORWARD PERCEPTION



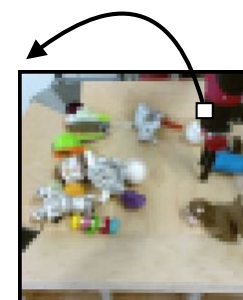
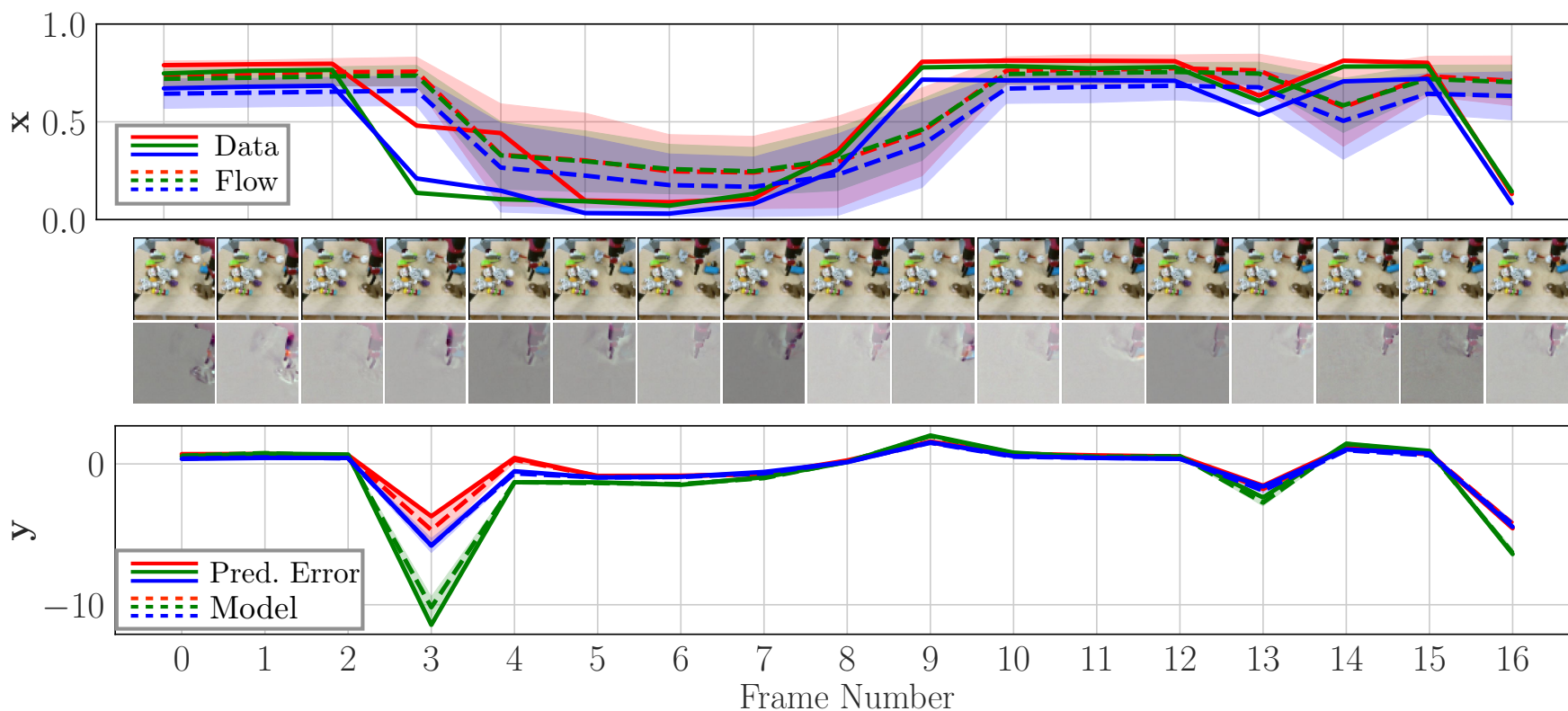
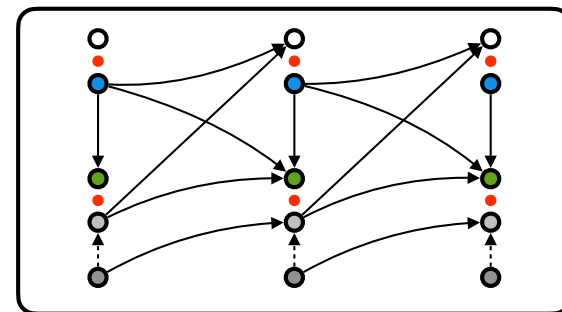
FEEDFORWARD PERCEPTION



FEEDFORWARD PERCEPTION



FEEDFORWARD PERCEPTION



FEEDFORWARD PERCEPTION

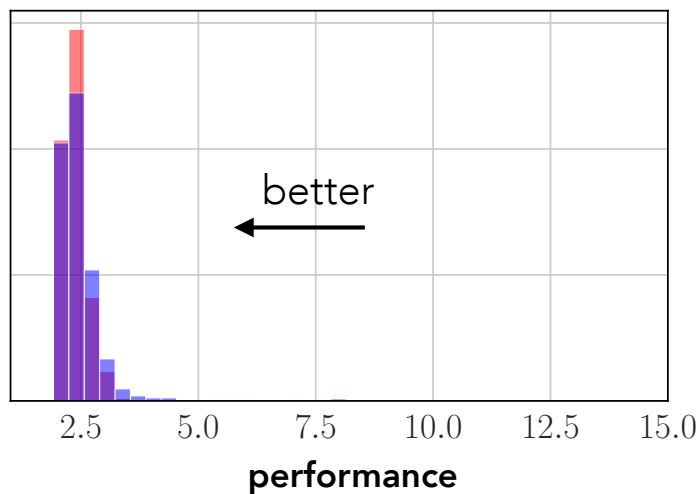
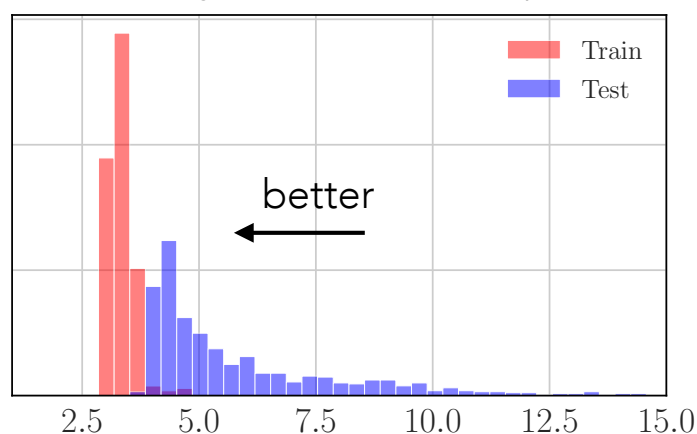
improves both **performance** & **generalization**

KTH Actions (Schuldt et al., 2005)

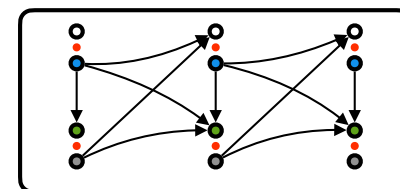


different people across train & test data

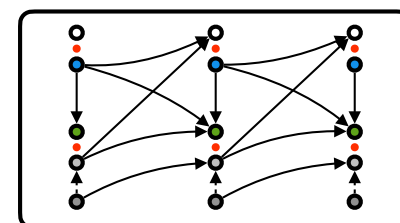
histogram over data examples



SLVM

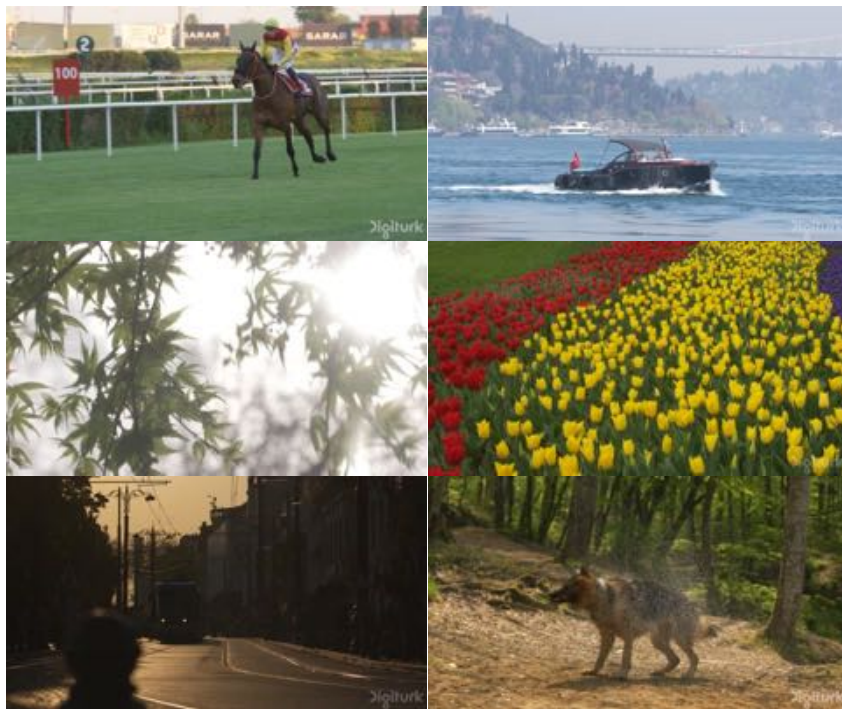


SLVM + AF

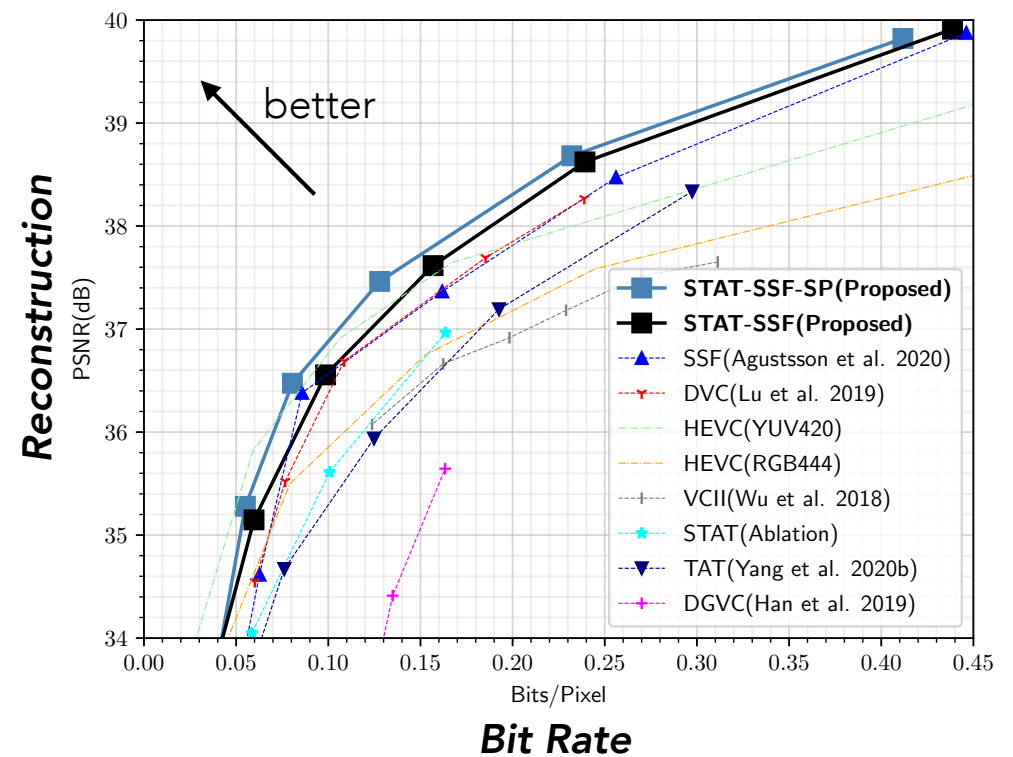


FEEDFORWARD PERCEPTION

state-of-the-art high-resolution video compression



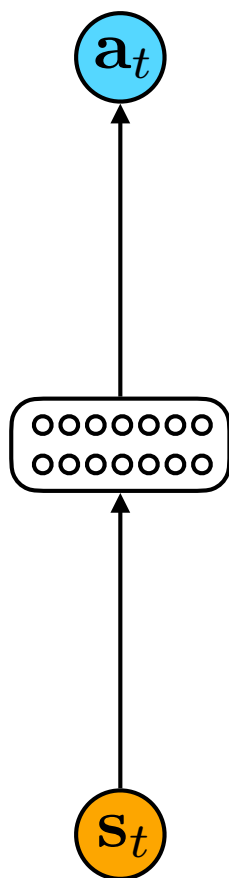
UVG dataset (Mercat et al., 2020)



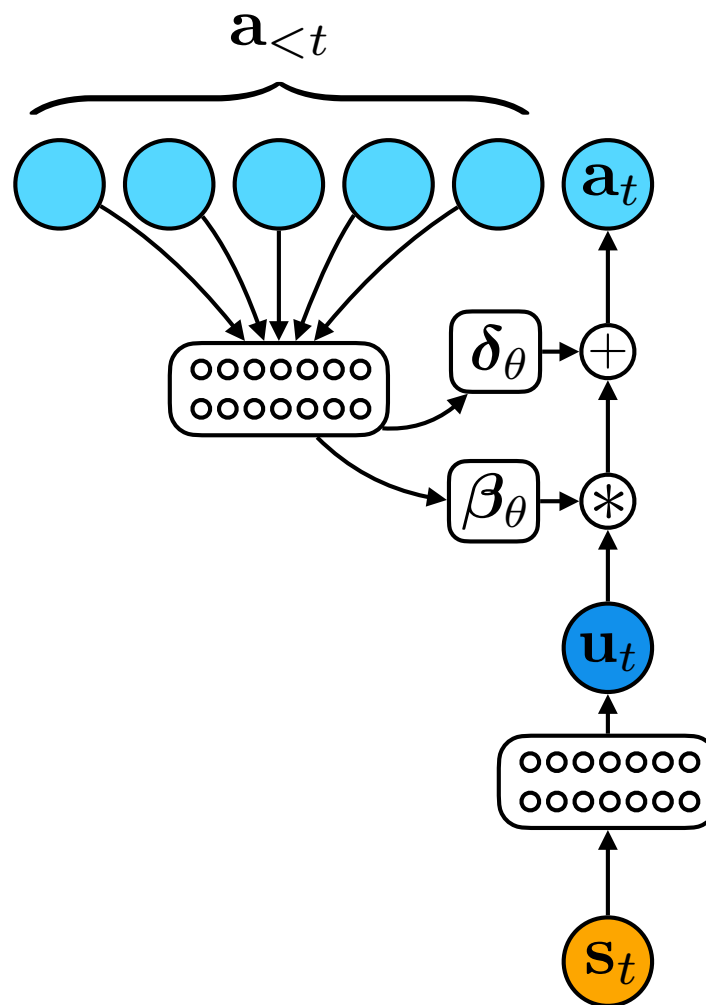
feedforward

CONTROL

FEEDFORWARD CONTROL



Direct Policy
 $\pi(\mathbf{a}_t | \mathbf{s}_t)$



Autoregressive Policy
 $\pi(\mathbf{a}_t | \mathbf{s}_t, \mathbf{a}_{<t})$

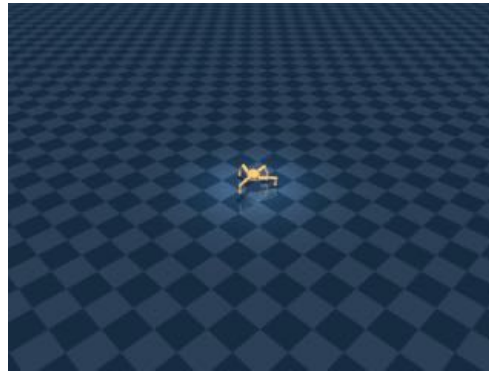
FEEDFORWARD CONTROL

simulated robotics environments from DeepMind control suite

cheetah



quadruped



hopper



walker

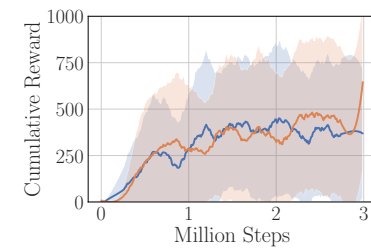
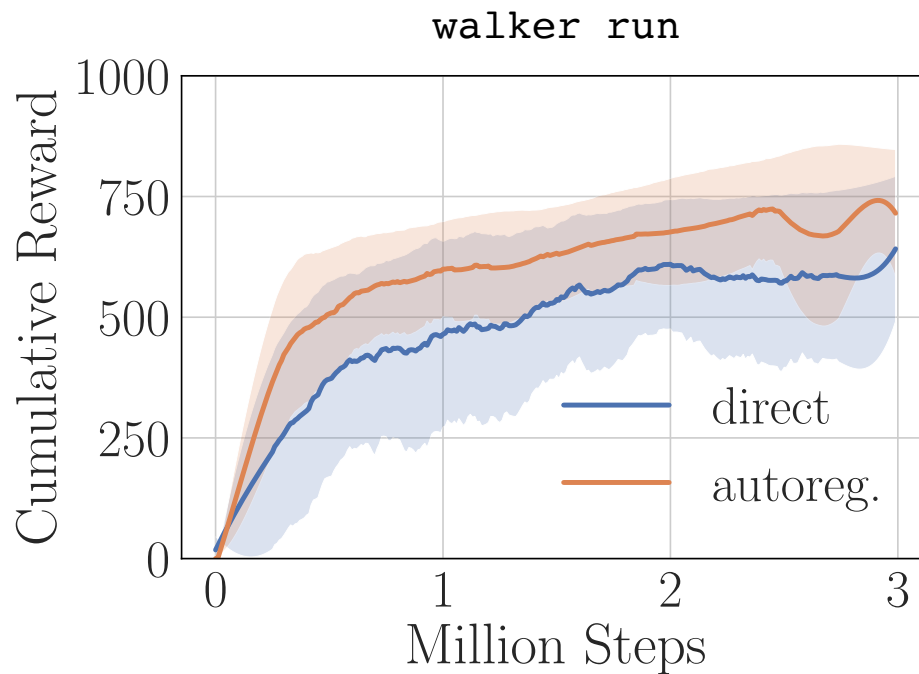


humanoid

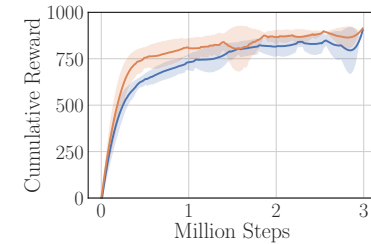


FEEDFORWARD CONTROL

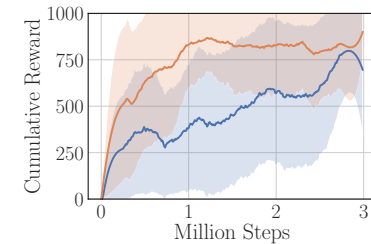
*improves **performance** across a range of environments*



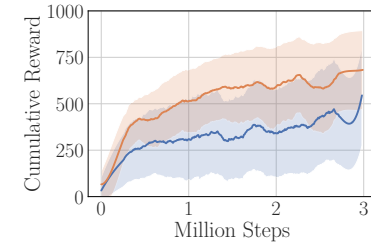
hopper
stand



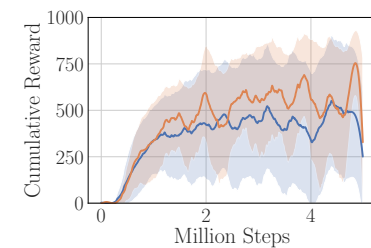
cheetah
run



quadruped
walk

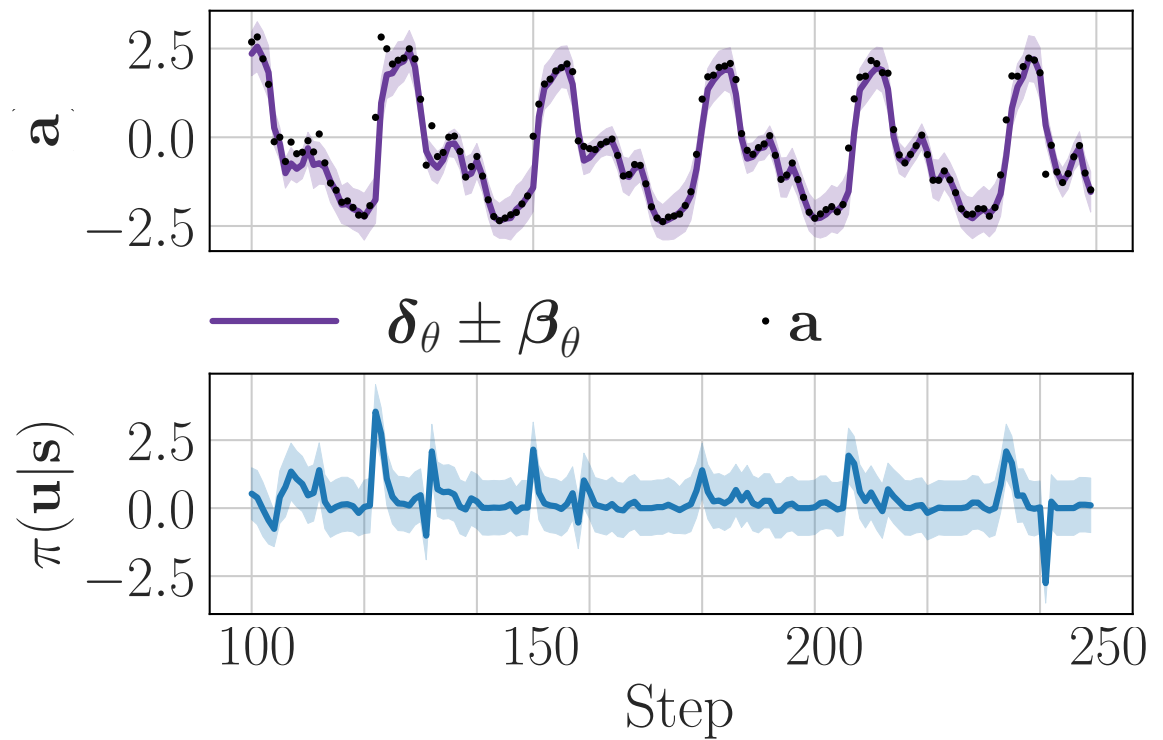
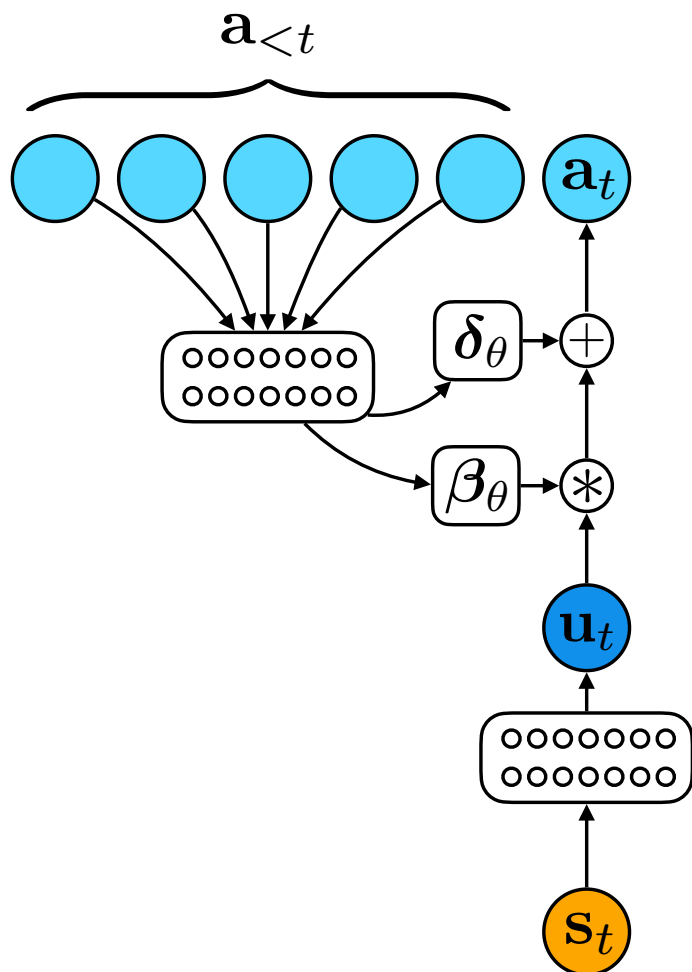


quadruped
run



humanoid
walk

FEEDFORWARD CONTROL

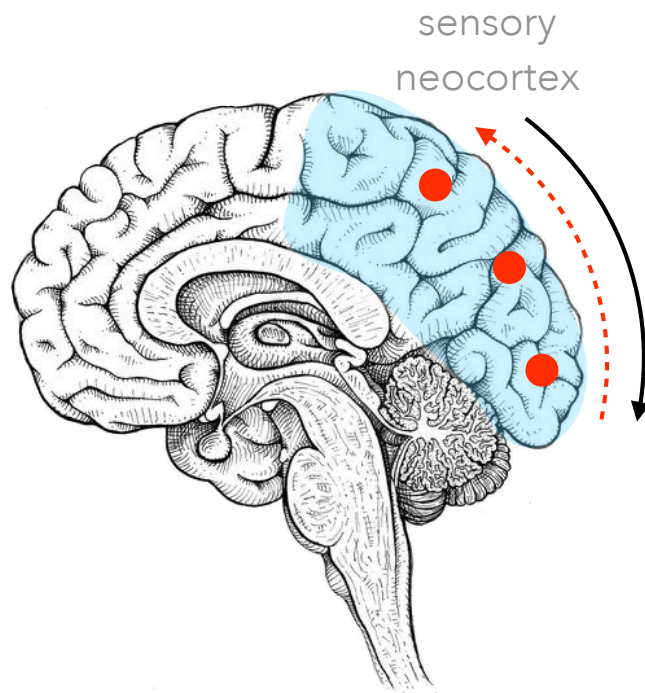


feedback

PERCEPTION

HIERARCHICAL PREDICTIVE CODING

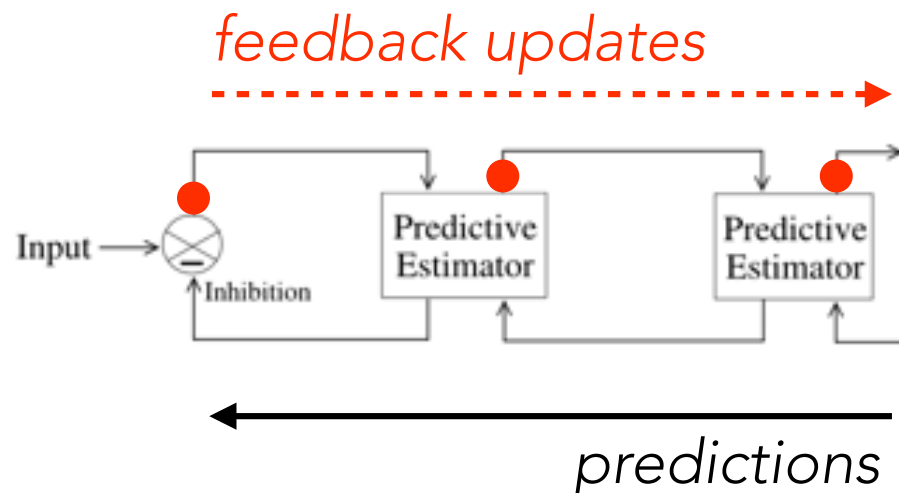
*neocortex forms hierarchical predictions of sensory inputs,
using **prediction errors** for inference and learning*



Predictive coding in the visual cortex: a functional interpretation of some extra-classical receptive-field effects

Rajesh P. N. Rao¹ and Dana H. Ballard²

1999

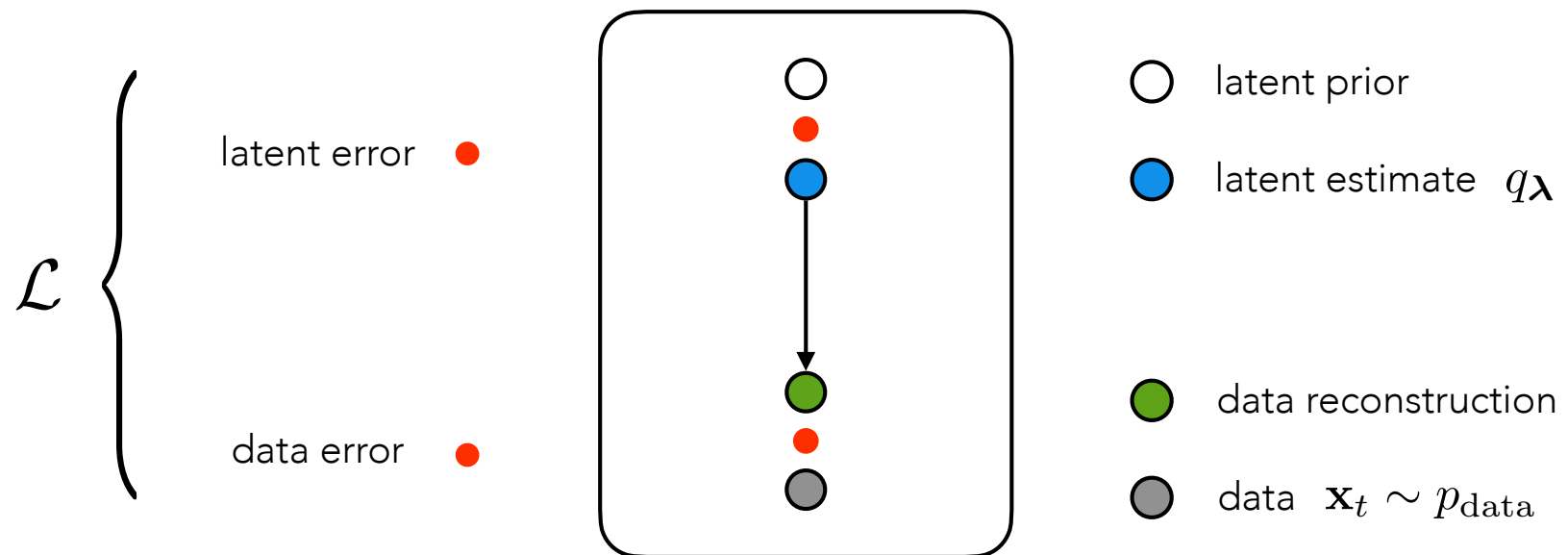


FEEDBACK PERCEPTION

state estimation as an optimization problem

$$\boldsymbol{\lambda} \leftarrow \arg \max_{\boldsymbol{\lambda}} \mathcal{L}(\mathbf{x}; q_{\boldsymbol{\lambda}})$$

restricting to parametric distributions with parameters $\boldsymbol{\lambda}$

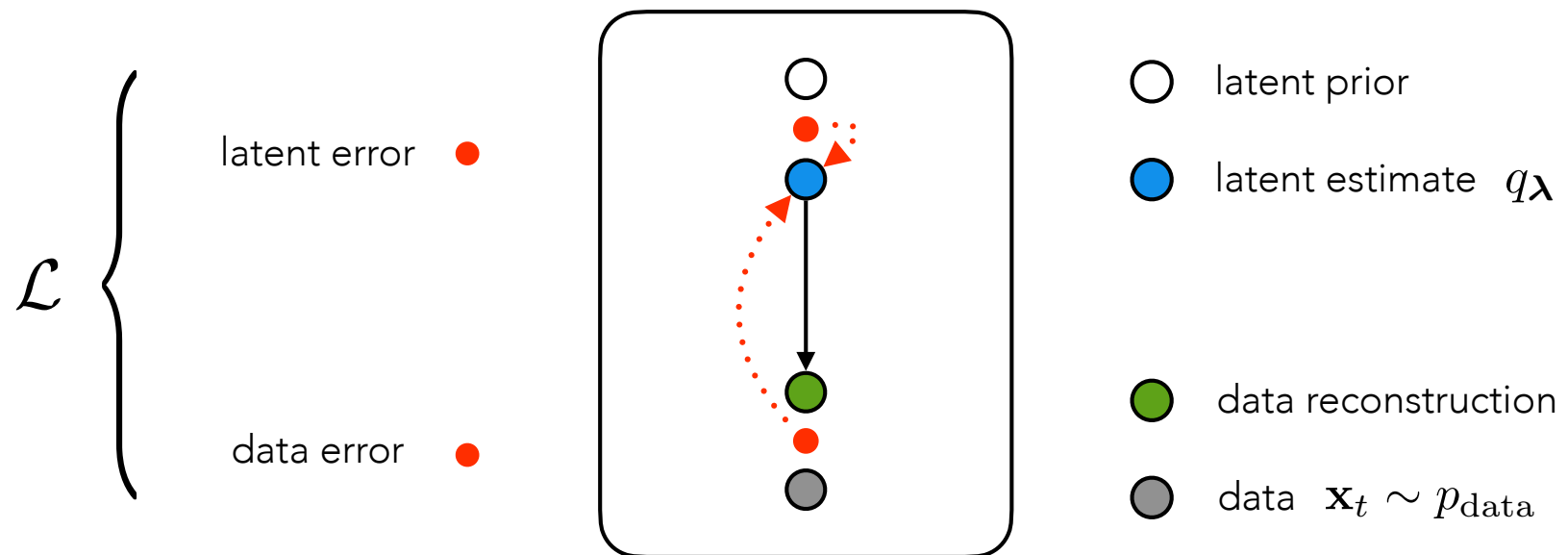


FEEDBACK PERCEPTION

state estimation as an optimization problem

$$\boldsymbol{\lambda} \leftarrow \arg \max_{\boldsymbol{\lambda}} \mathcal{L}(\mathbf{x}; q_{\boldsymbol{\lambda}})$$

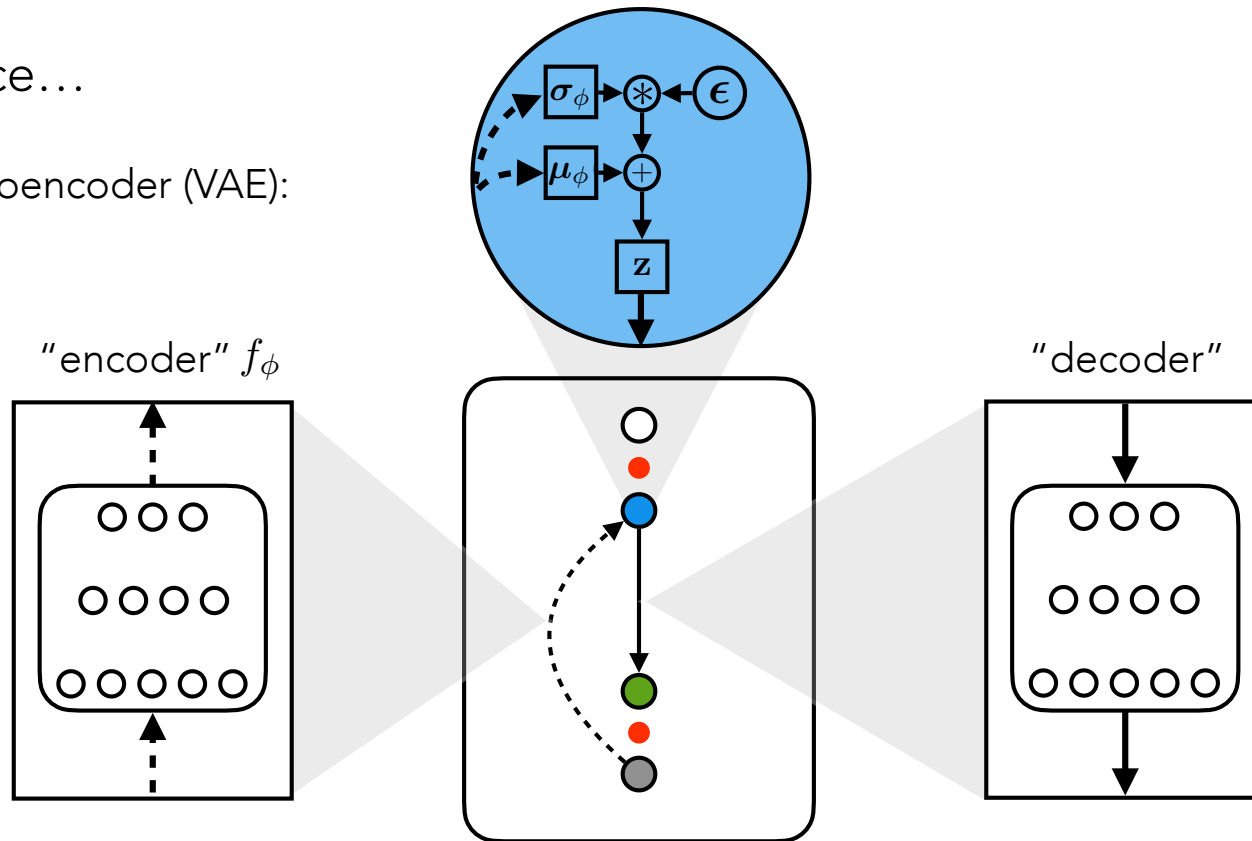
restricting to parametric distributions with parameters $\boldsymbol{\lambda}$



FEEDBACK PERCEPTION

but in practice...

variational autoencoder (VAE):



(direct) *amortization*:

$$\lambda \leftarrow f_\phi(\mathbf{x})$$

typically $\lambda = [\mu, \sigma]$

optimize the "encoder" network f_ϕ

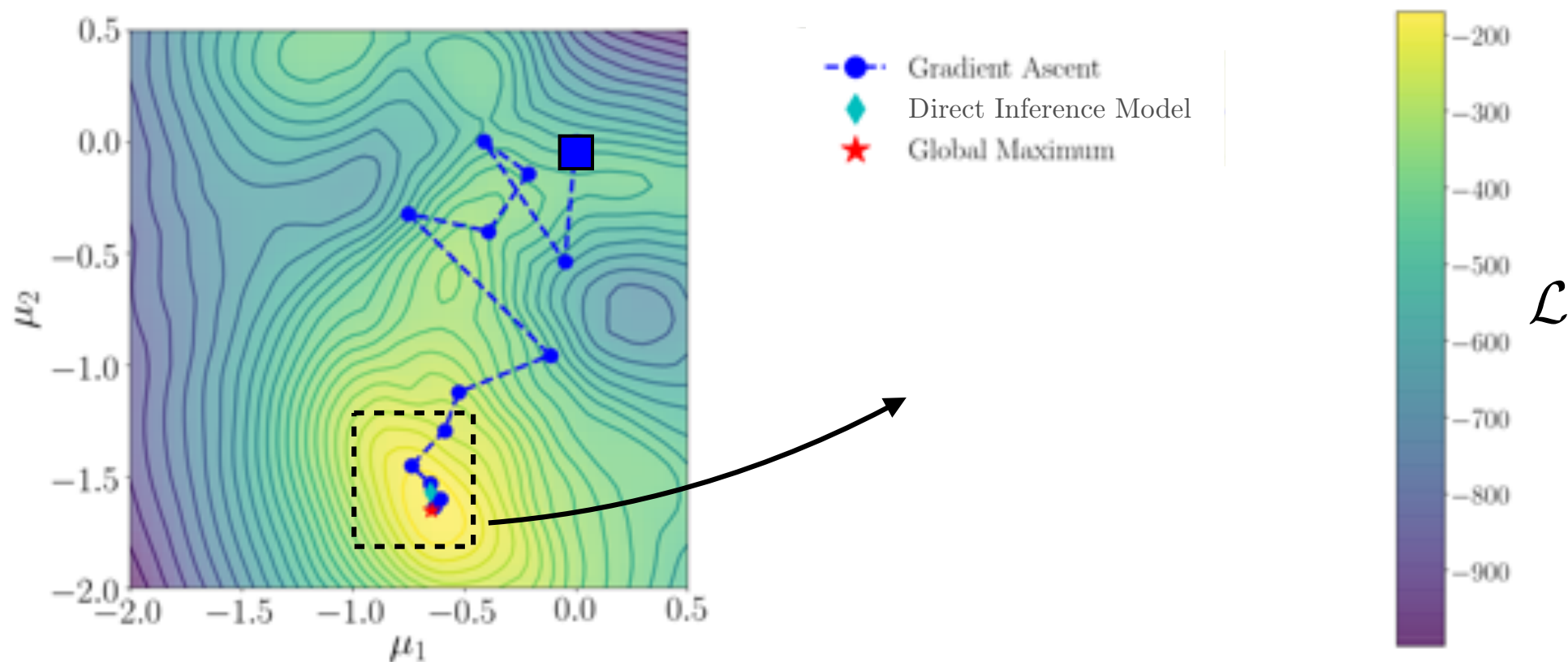
Kingma & Welling, 2014

Rezende et al., 2014

FEEDBACK PERCEPTION

direct inference models provide suboptimal estimates

"amortization gap"



see also Cremer et al., 2018

FEEDBACK PERCEPTION

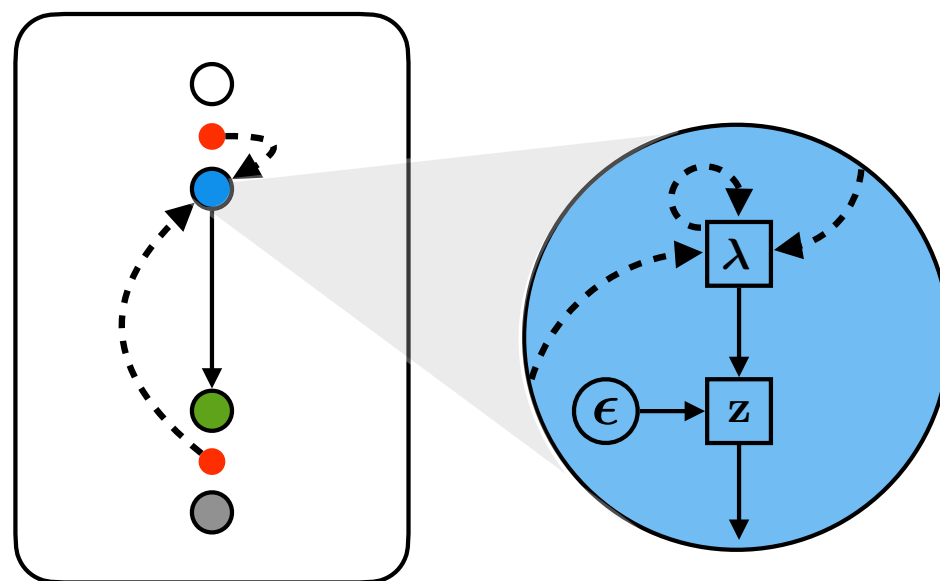
formulate inference as an **iterative** amortized process

gradient-based form

$$\lambda \leftarrow f_{\phi}(\lambda, \nabla_{\lambda} \mathcal{L})$$

error-based form (Gaussian)

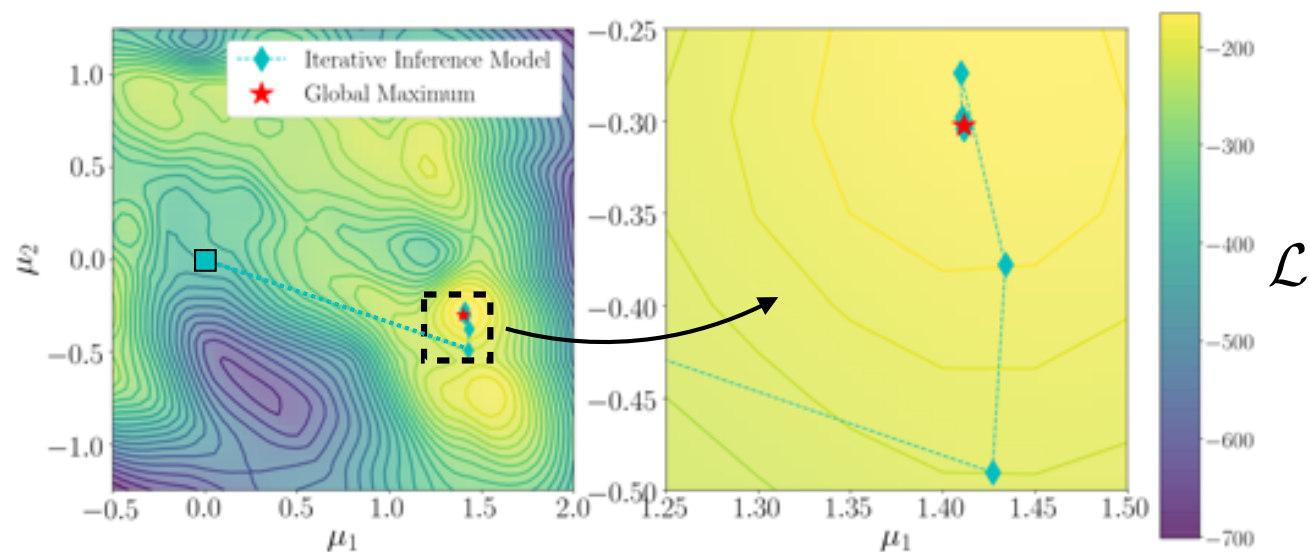
$$\lambda \leftarrow f_{\phi}(\lambda, \underbrace{\xi_{\mathbf{x}}, \xi_{\mathbf{z}}}_{\text{weighted errors}})$$



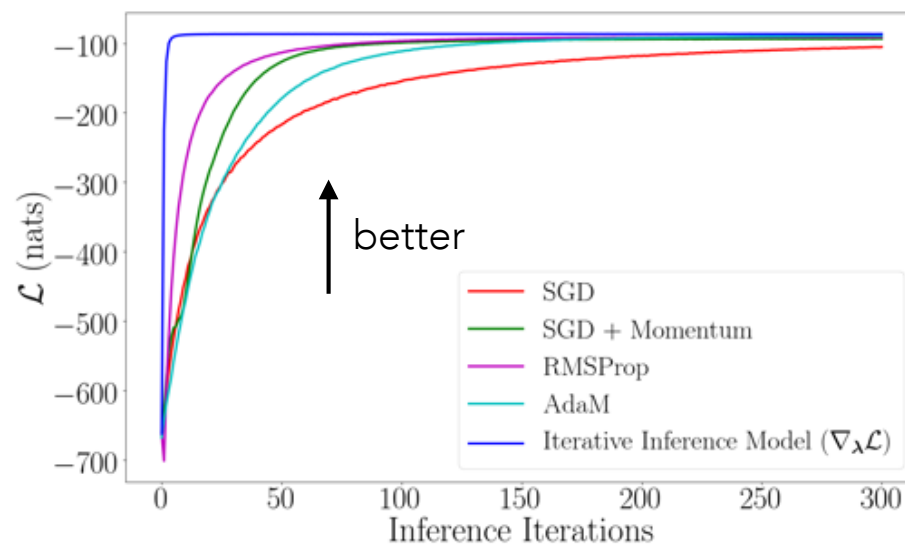
can learn to update

FEEDBACK PERCEPTION

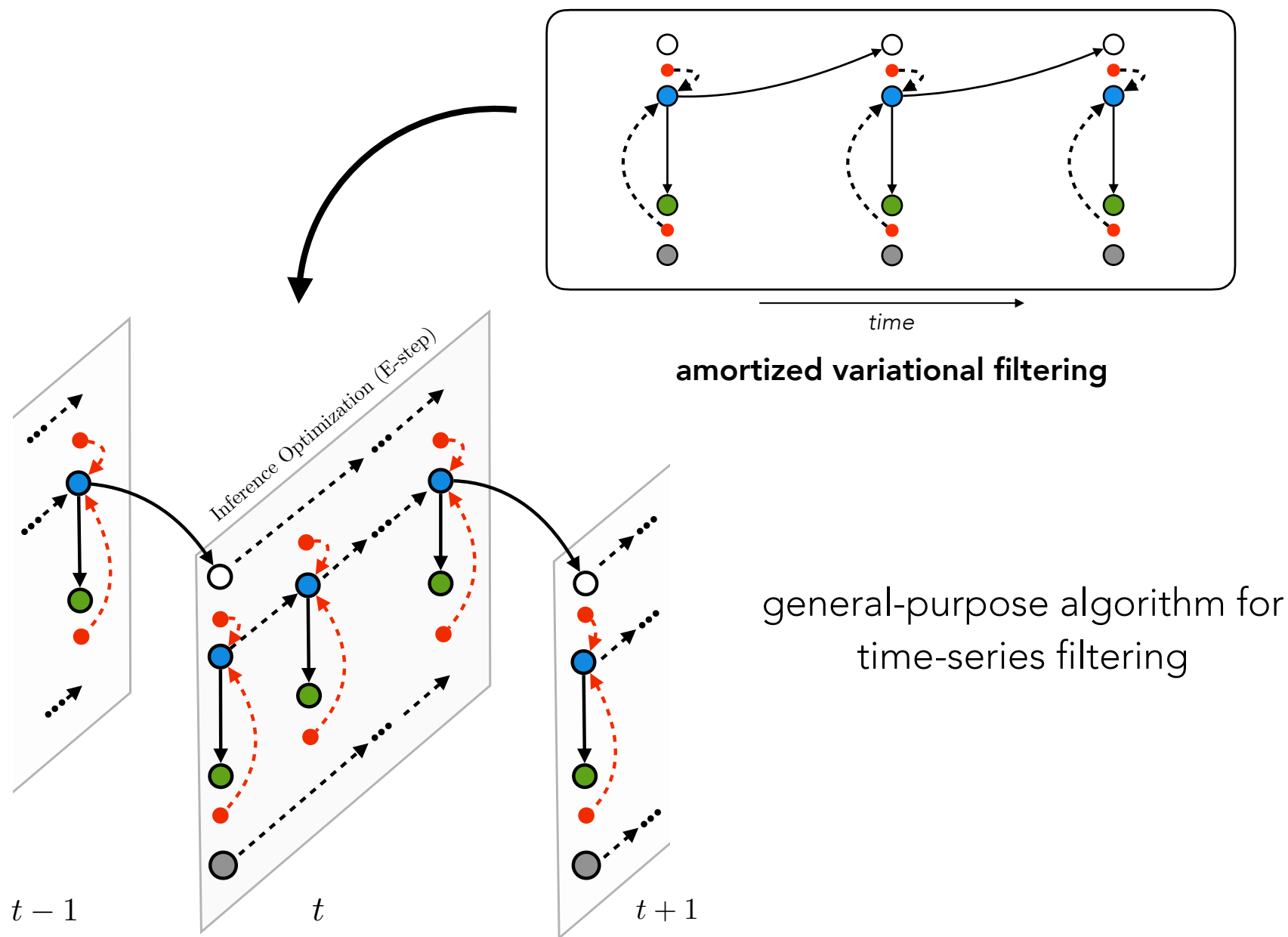
accurate
outperforms
direct amortization



efficient
faster than gradient-
based optimization

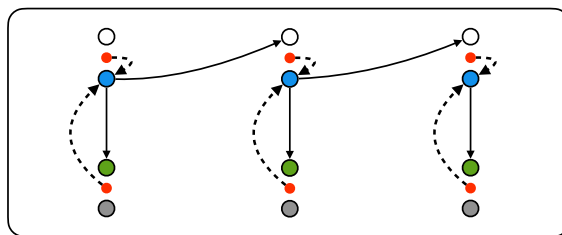


FEEDBACK PERCEPTION



FEEDBACK PERCEPTION

custom (ad-hoc) amortized inference schemes



matches or outperforms each inference model
with a **single setup/architecture**

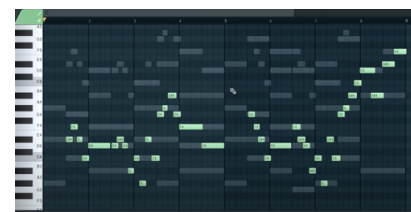
speech



video



MIDI

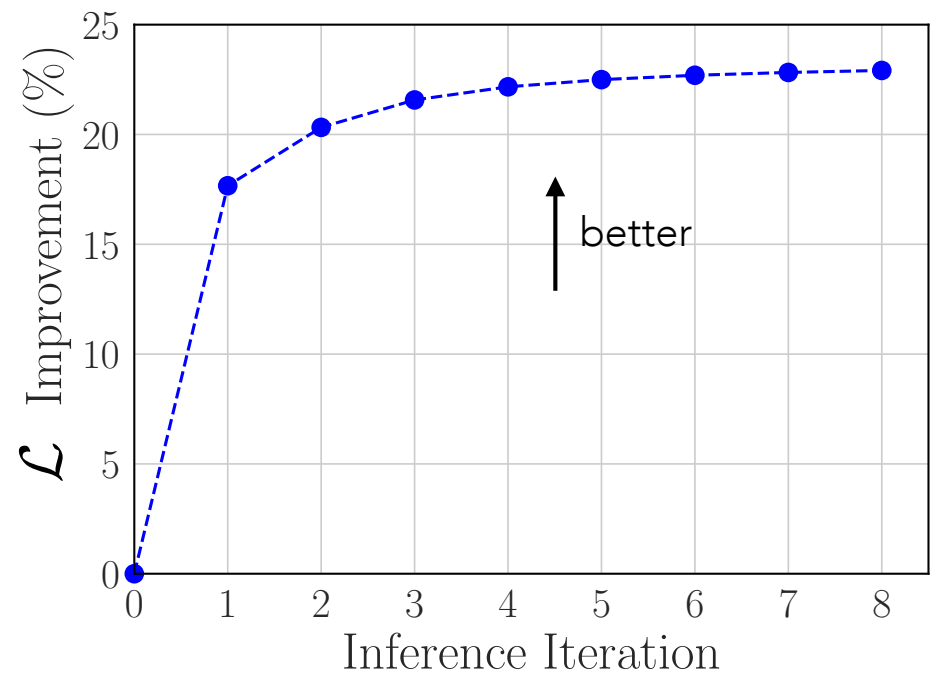
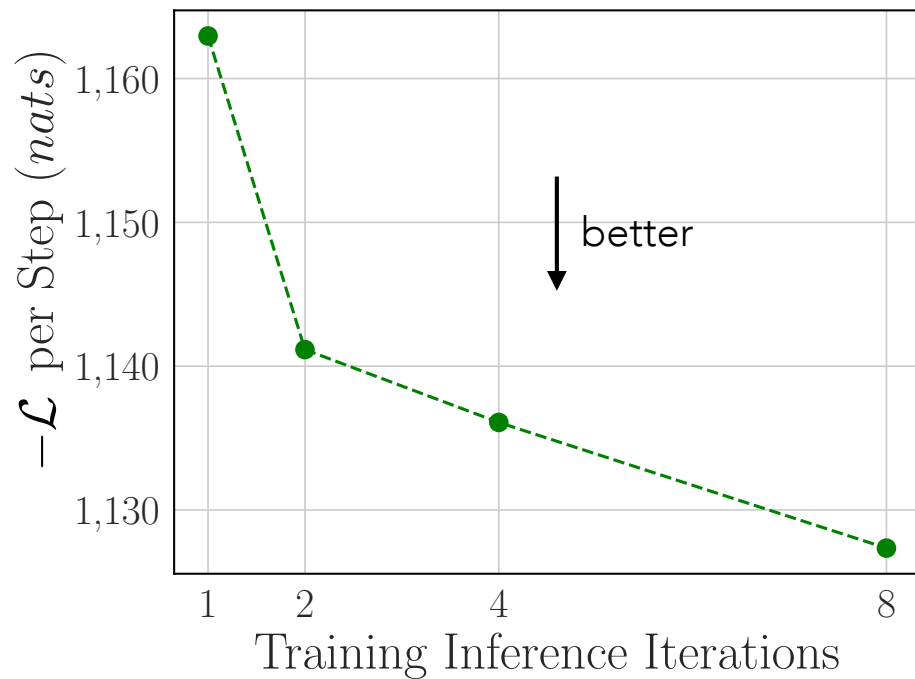


amortized variational filtering can be applied to any sequential LVM

FEEDBACK PERCEPTION

iterative improvement

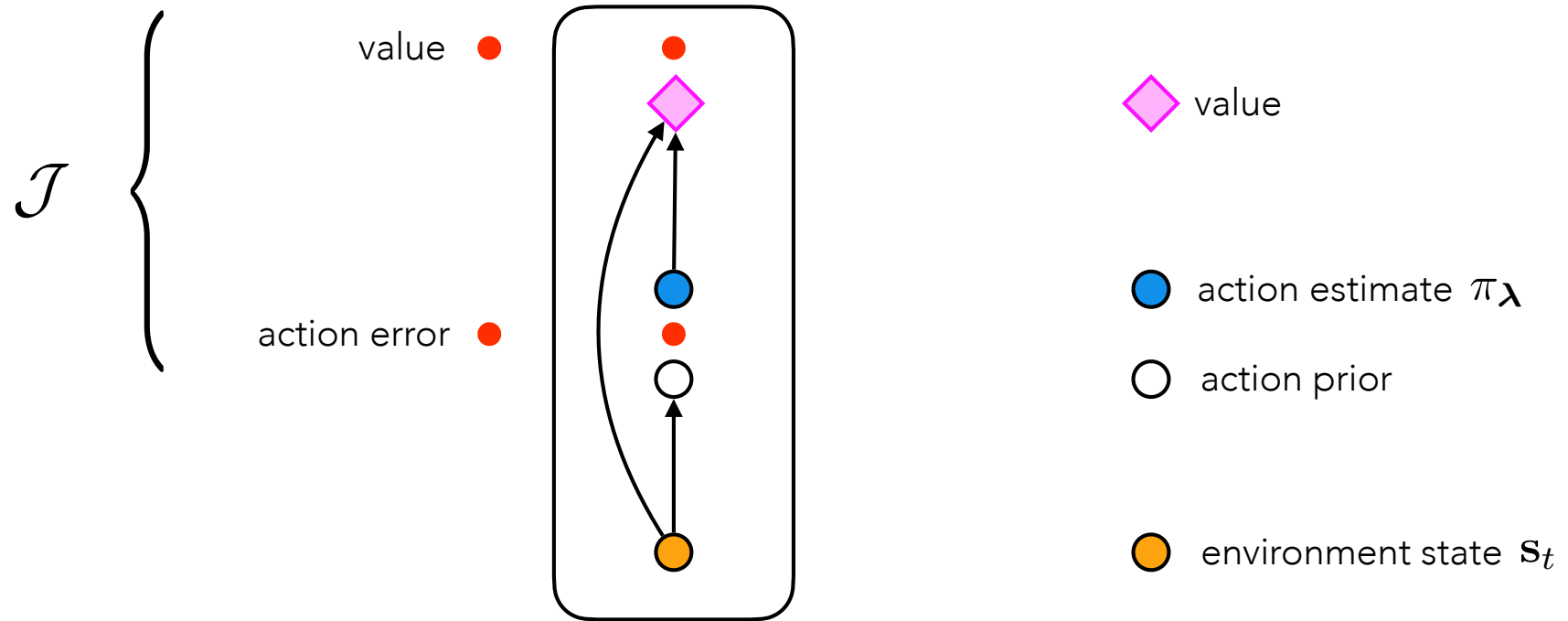
more computation $\rightarrow$ better performance



feedback

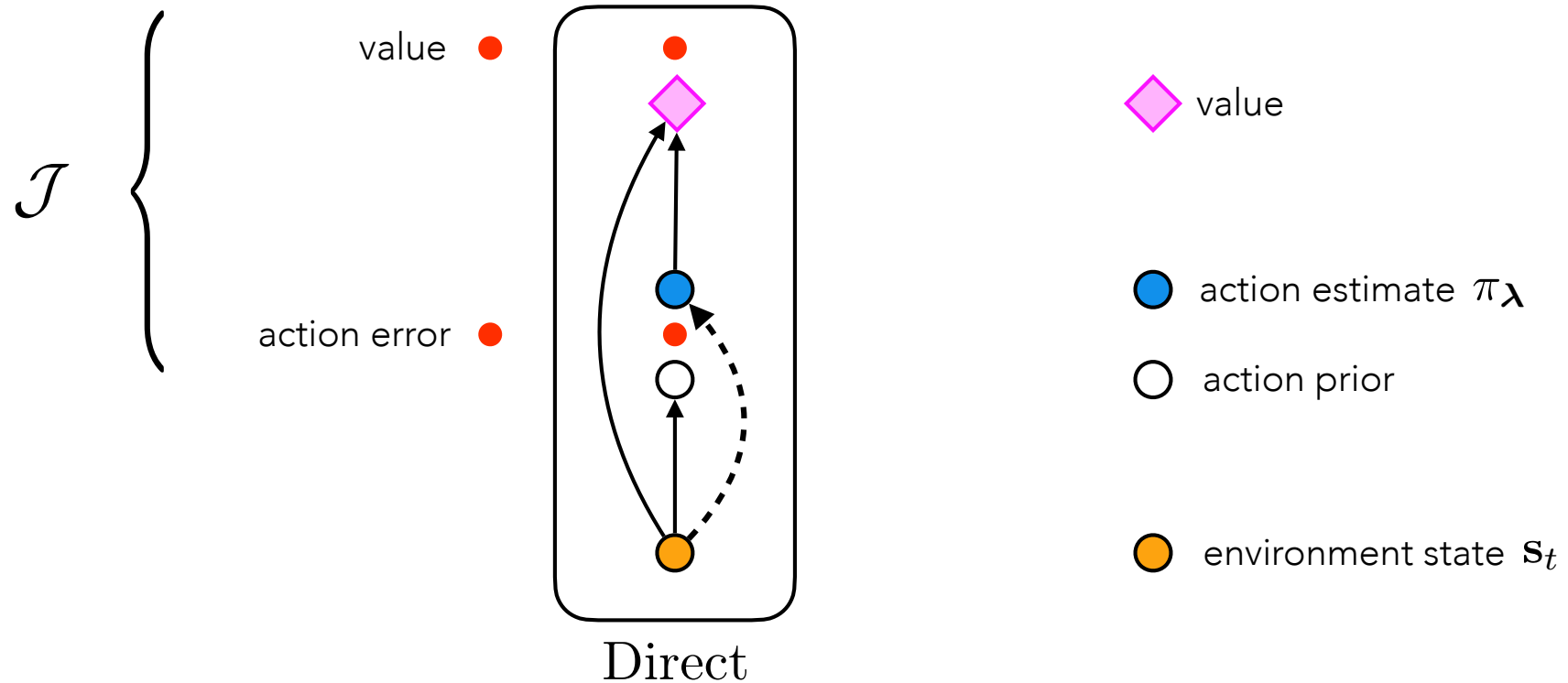
CONTROL

FEEDBACK CONTROL



$$\operatorname{argmax}_{\lambda} \mathcal{J}(\pi_{\lambda}) \quad \text{e.g., } \lambda = [\mu, \sigma]$$

FEEDBACK CONTROL

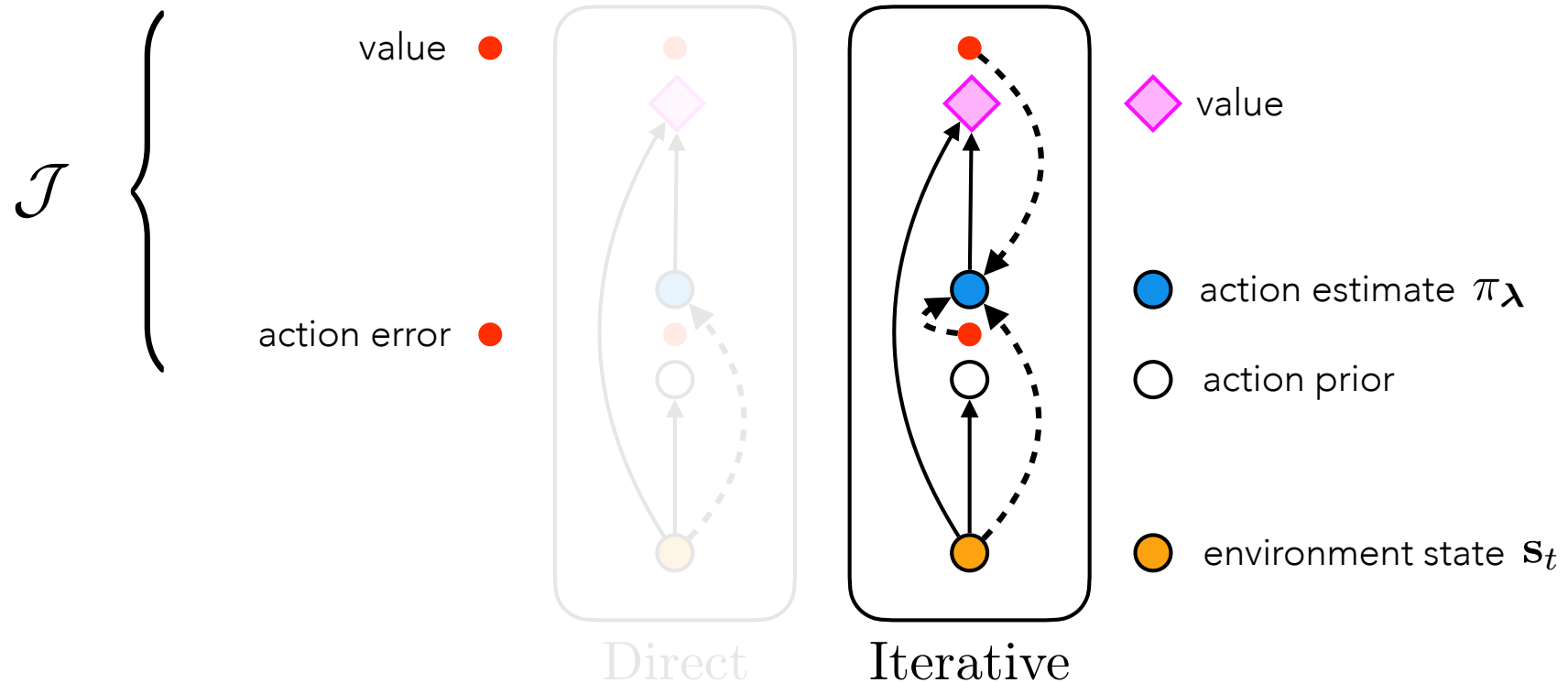


$$\operatorname{argmax}_{\lambda} \mathcal{J}(\pi_{\lambda}) \quad \text{e.g., } \lambda = [\mu, \sigma]$$

$$\lambda \leftarrow f_{\phi}(\mathbf{s}_t)$$

direct

FEEDBACK CONTROL



$$\operatorname{argmax}_{\lambda} \mathcal{J}(\pi_{\lambda}) \quad \text{e.g., } \lambda = [\mu, \sigma]$$

$$\lambda \leftarrow f_{\phi}(\mathbf{s}_t)$$

direct

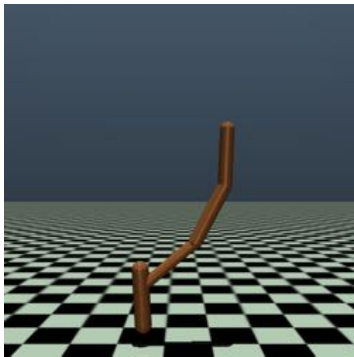
$$\lambda \leftarrow f_{\phi}(\lambda, \nabla_{\lambda} \mathcal{J}, \mathbf{s}_t)$$

iterative

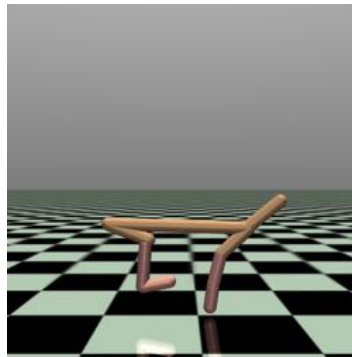
FEEDBACK CONTROL

simulated robotics environments from OpenAI gym

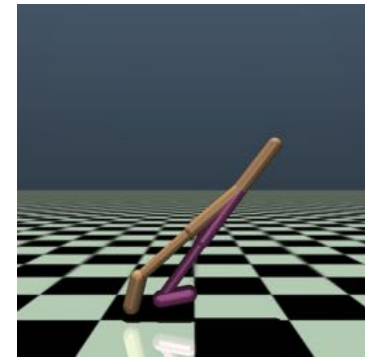
Hopper



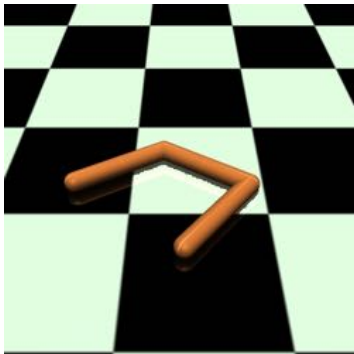
HalfCheetah



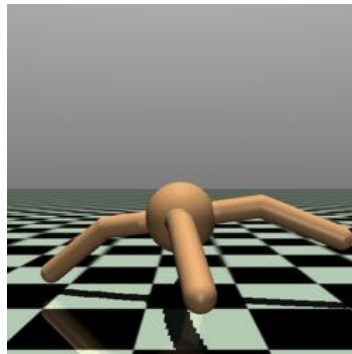
Walker2d



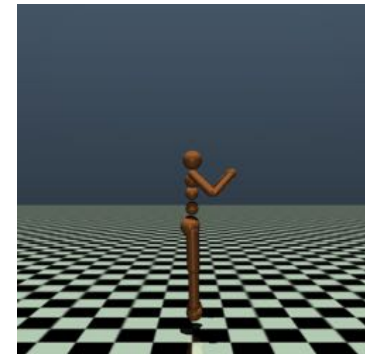
Swimmer



Ant

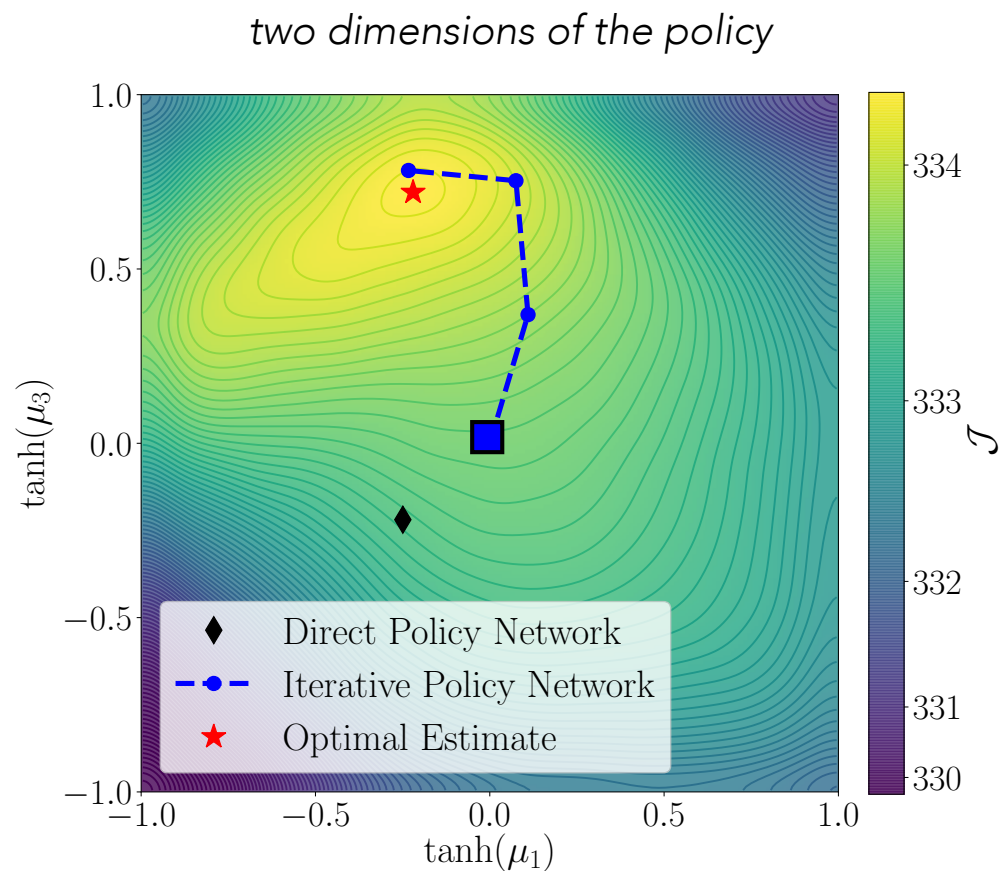


Humanoid



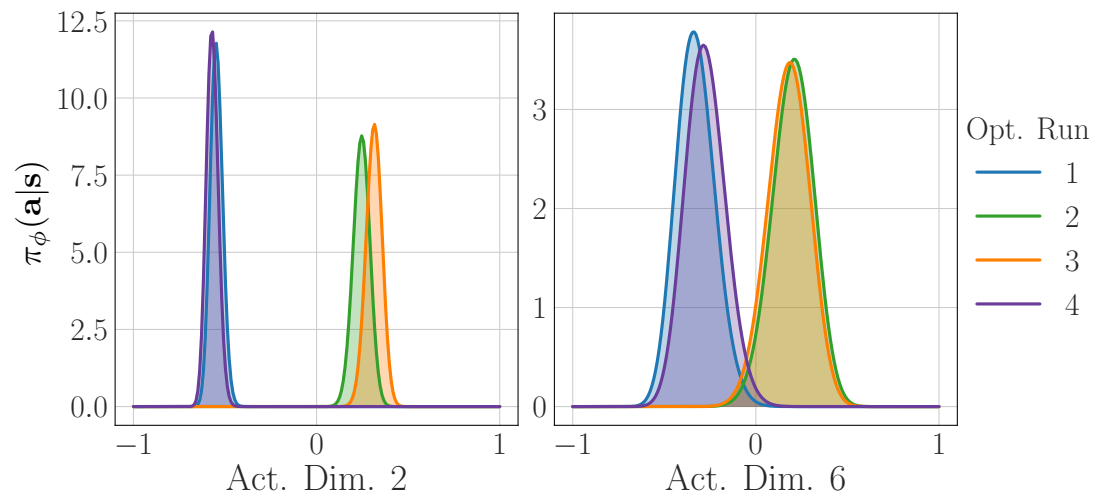
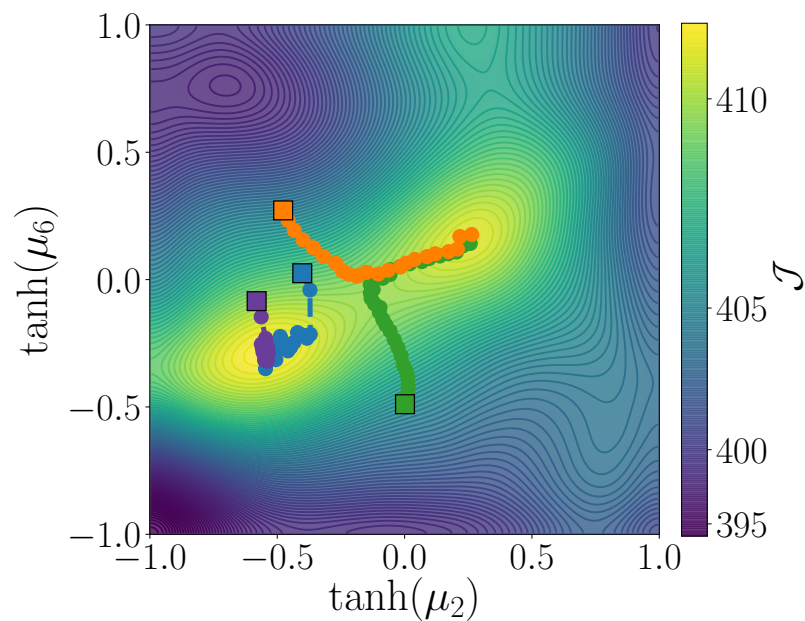
FEEDBACK CONTROL

direct policy networks yield suboptimal estimates



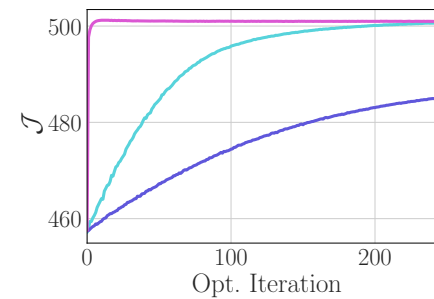
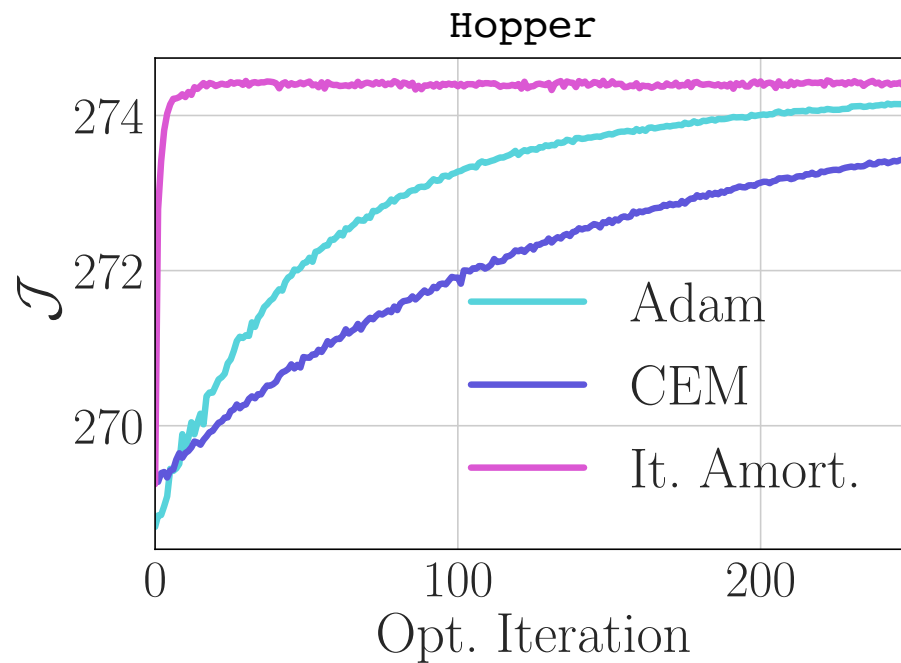
FEEDBACK CONTROL

iterative optimizers yield multiple locally optimal estimates

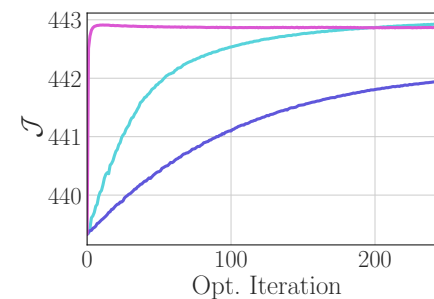


FEEDBACK CONTROL

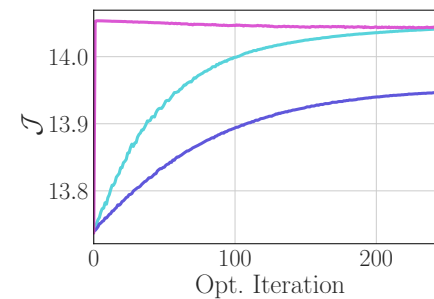
improves **efficiency** over
standard optimizers



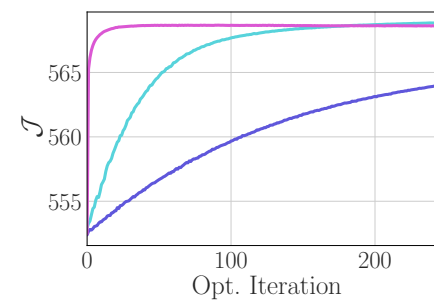
HalfCheetah



Walker2d



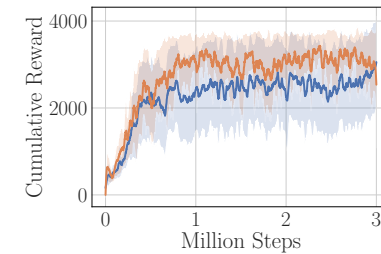
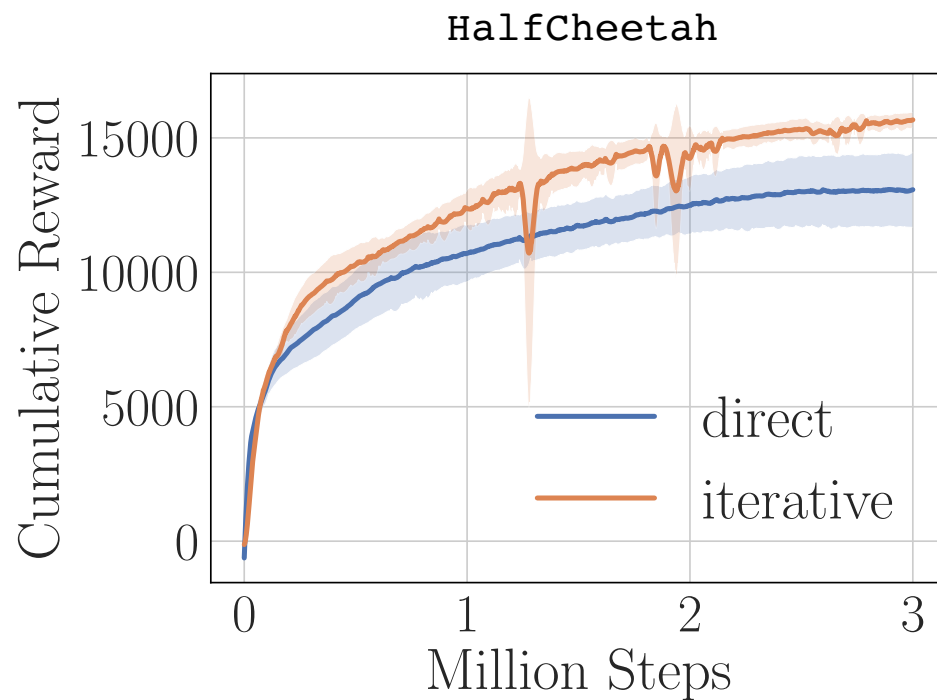
Swimmer



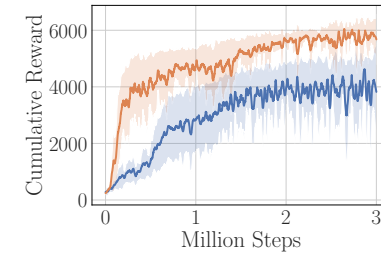
Ant

FEEDBACK CONTROL

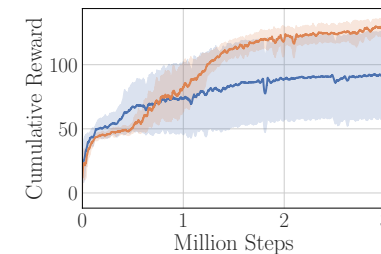
comparable or improved
performance over direct amortization



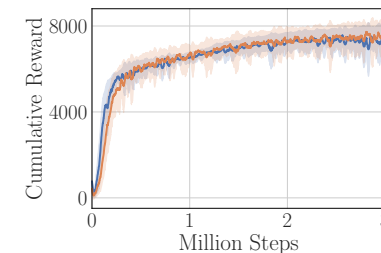
Hopper



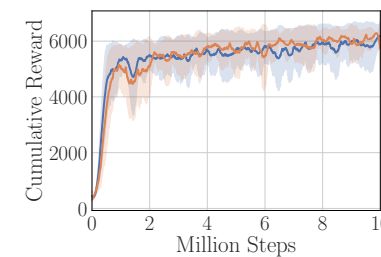
Walker2d



Swimmer



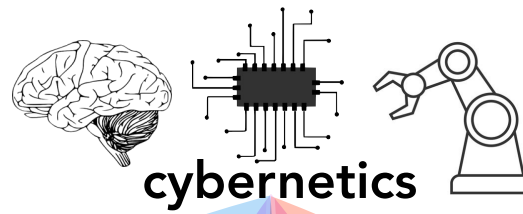
Ant



Humanoid

connections to

NEUROSCIENCE



information

feedback control

linear threshold unit

multi-layer
perceptrons

model-based
control

minimum
redundancy codes

backpropagation

hierarchical
control

predictive coding

reinforcement
learning

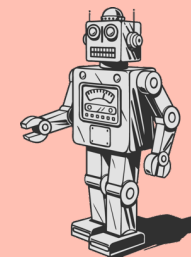
probabilistic
graphical models



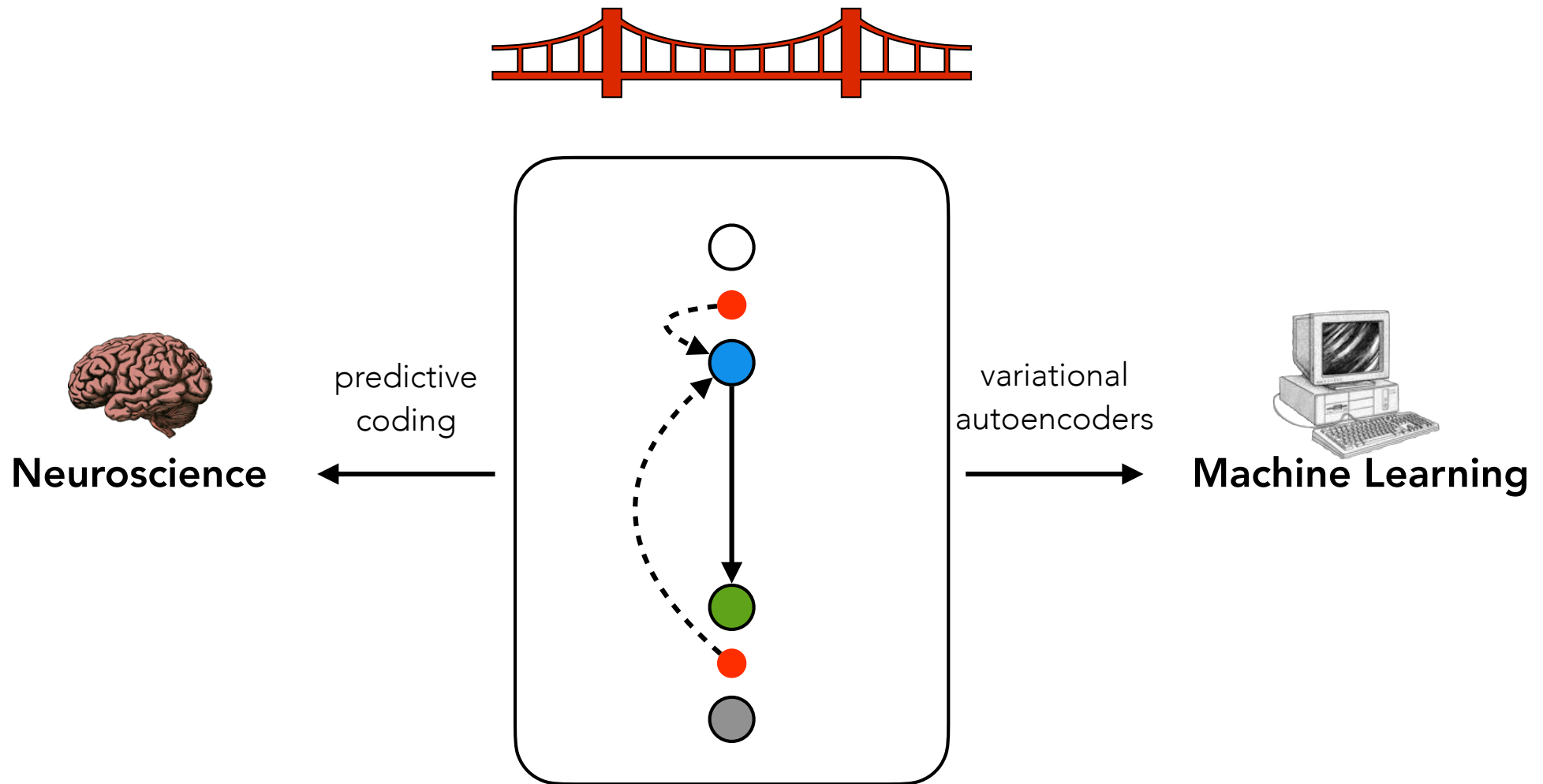
**theoretical
neuroscience**



**machine
learning**

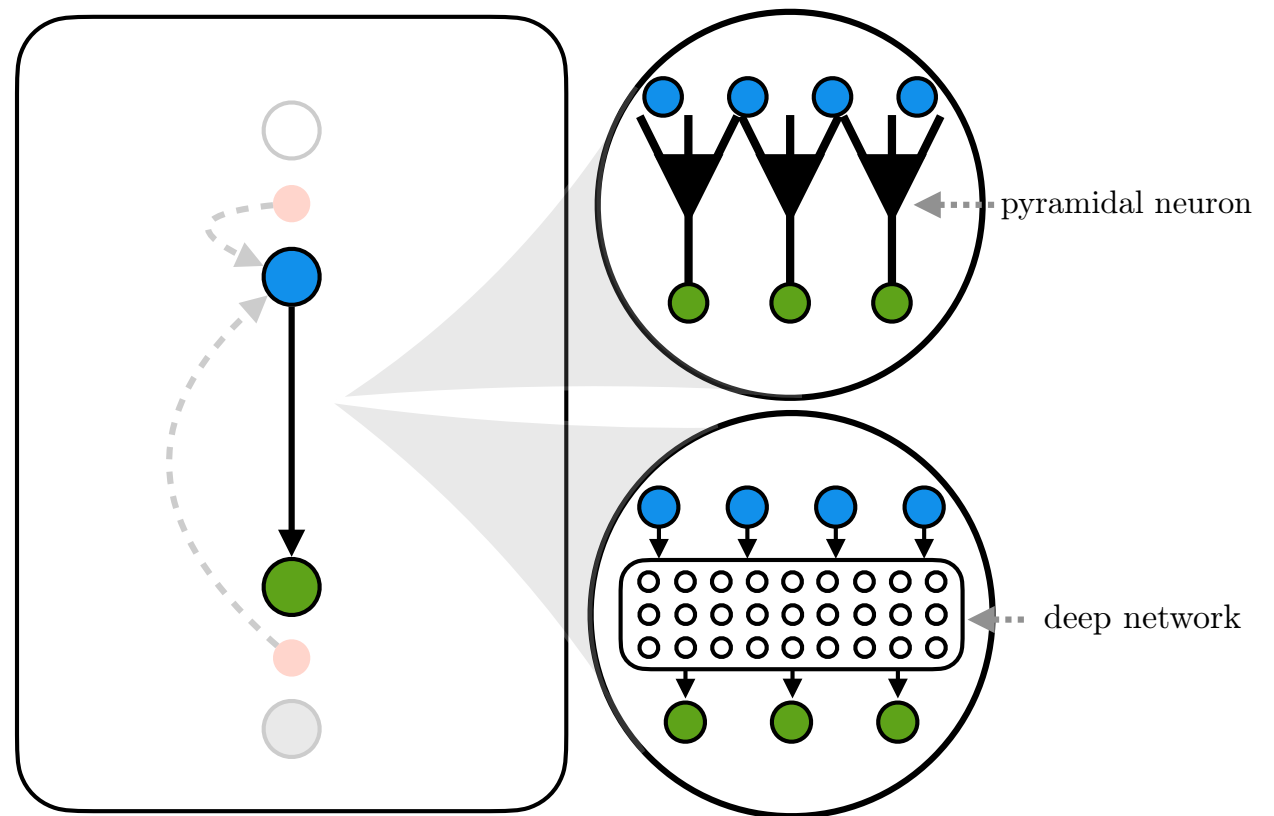


**control
theory**



providing new correspondences...

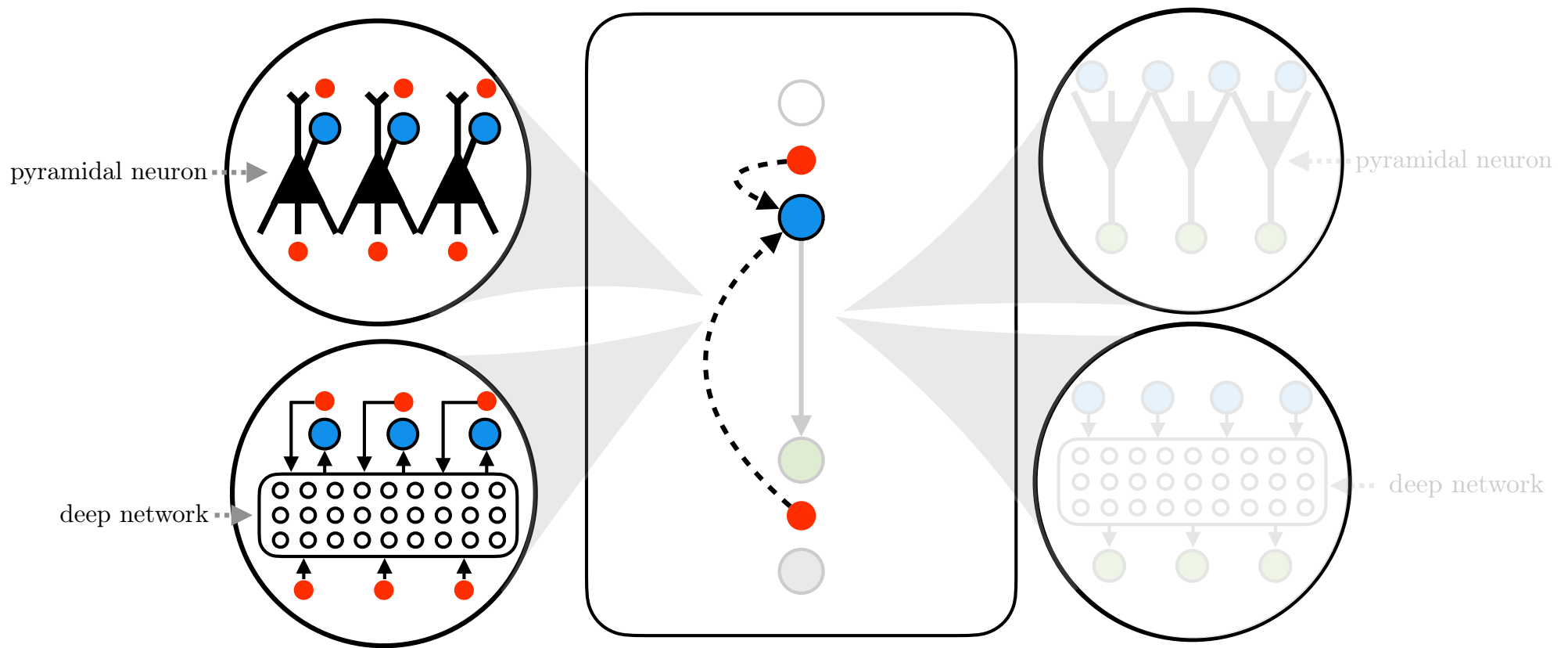
PYRAMIDAL NEURONS AS DEEP NETWORKS



pyramidal neurons as multi-layer artificial networks

(Zador et al., 1992; Mel, 1992; Poirazi et al., 2003; Polsky et al., 2004; Gidon et al., 2020...)

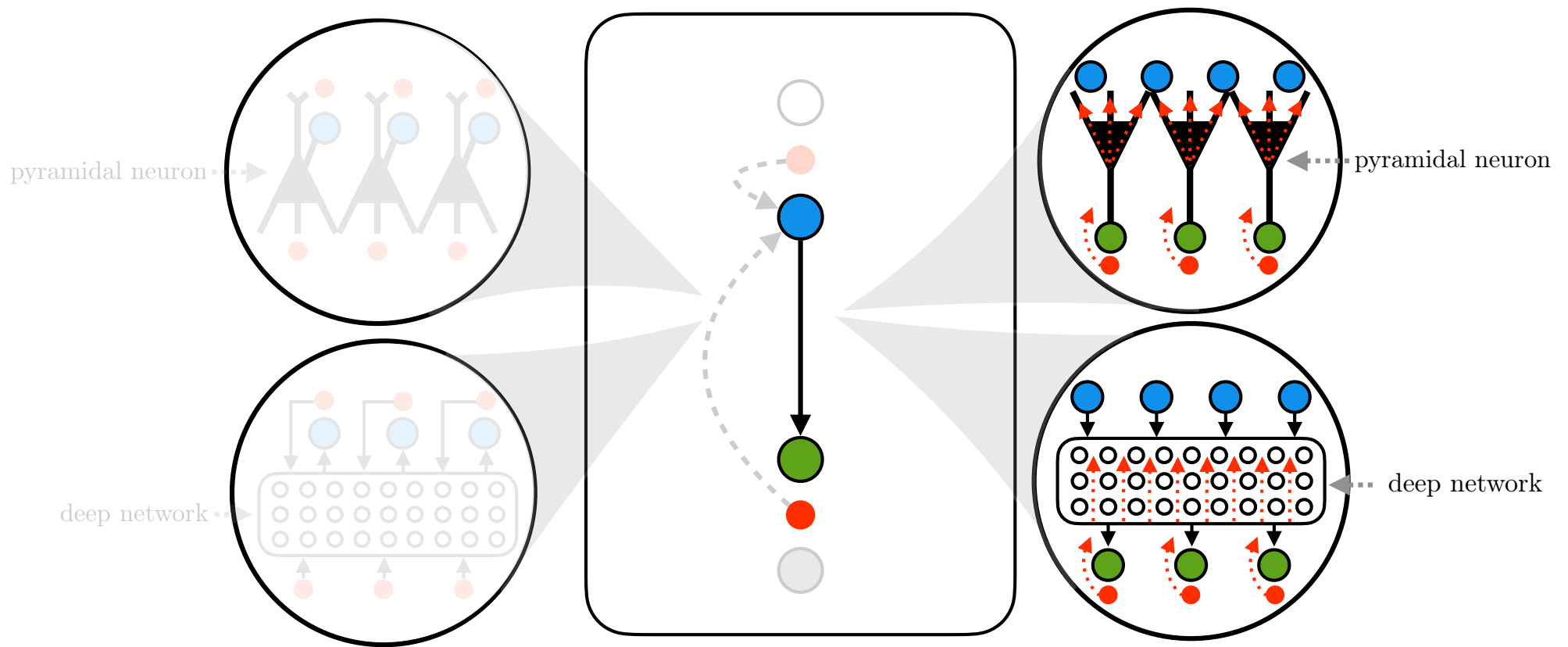
PYRAMIDAL NEURONS AS DEEP NETWORKS



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PYRAMIDAL NEURONS AS DEEP NETWORKS



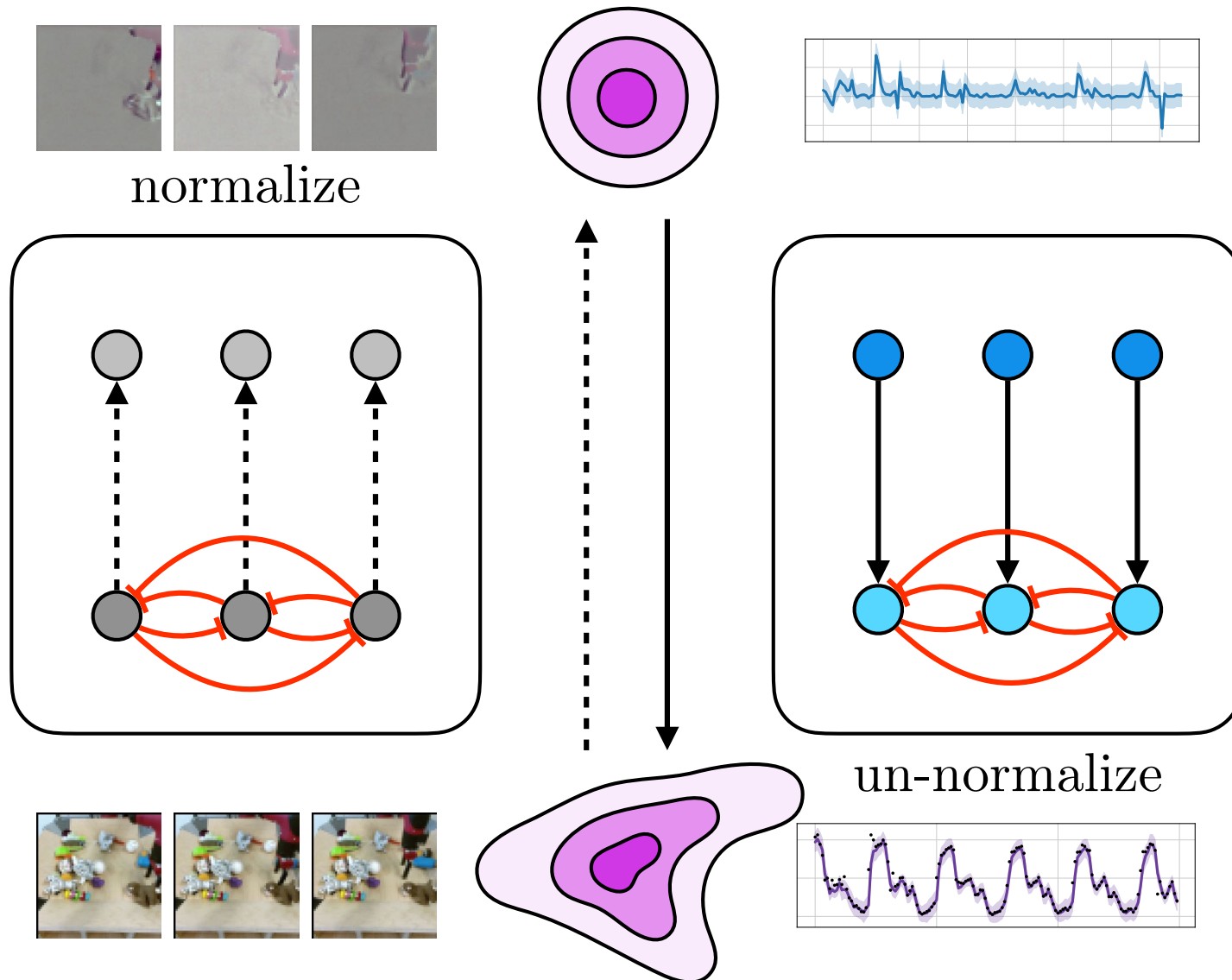
errors provide a **local** training signal

e.g., target propagation (Bengio, 2014)

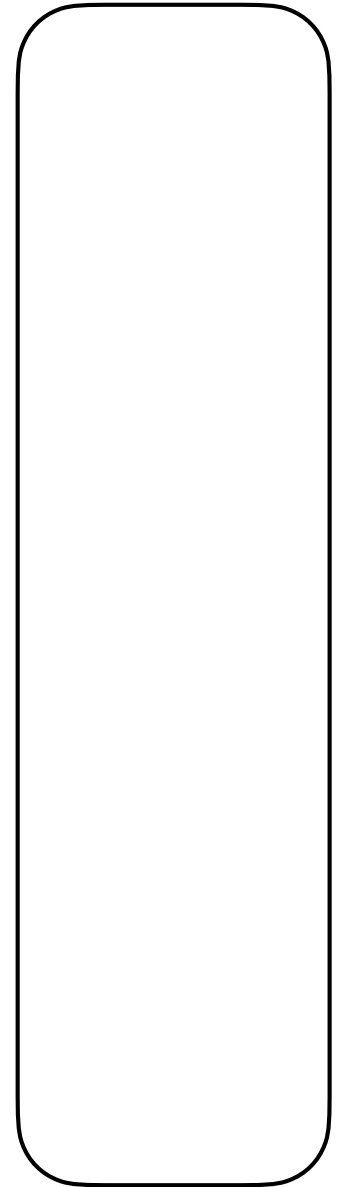
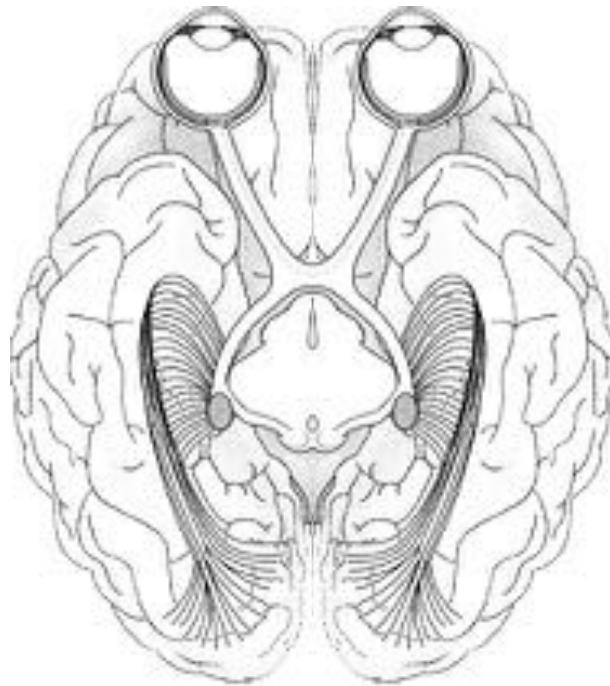
LATERAL INHIBITION & NORMALIZING FLOWS

lateral **interneurons** add or remove spatiotemporal correlations between neurons

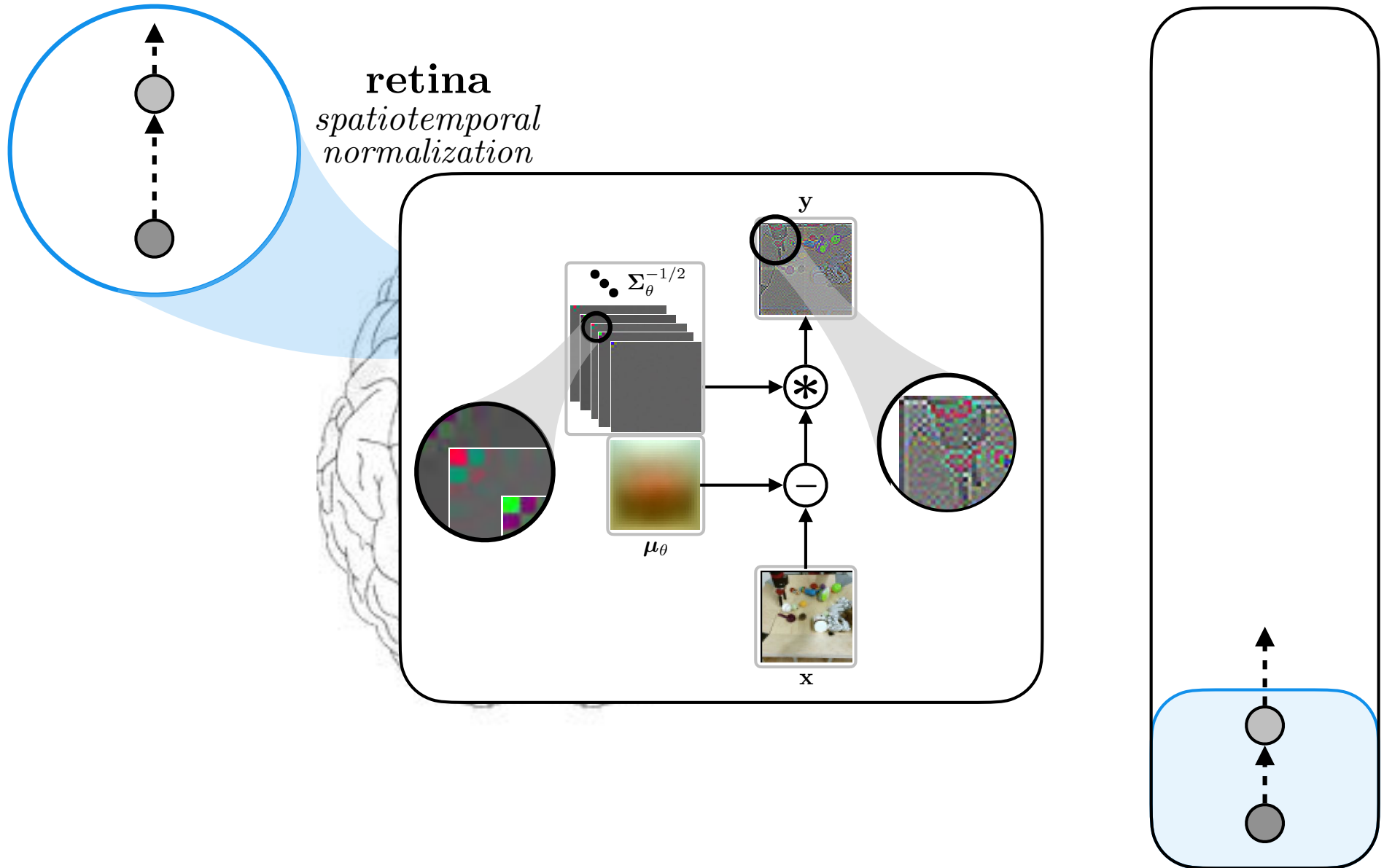
generalized by **normalizing flows** (from machine learning)



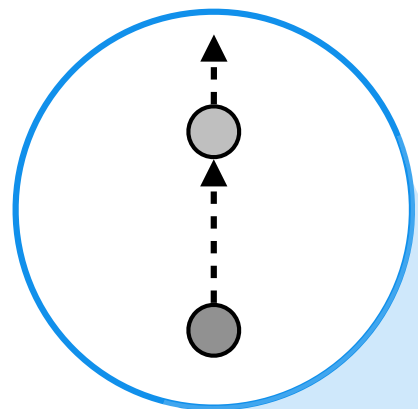
VISUAL PATHWAY



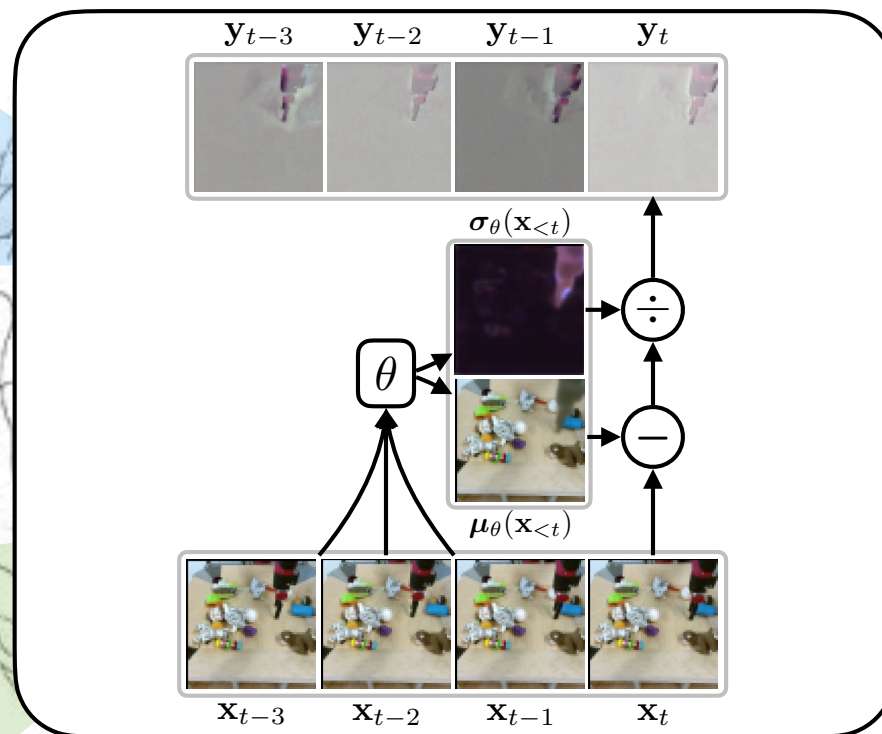
VISUAL PATHWAY



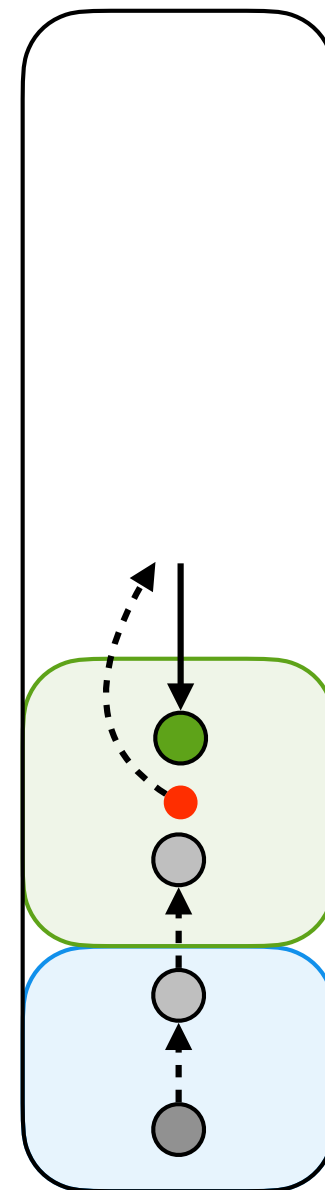
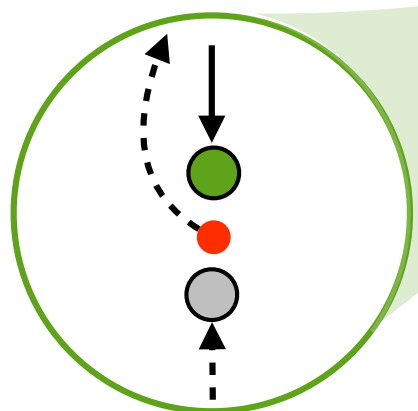
VISUAL PATHWAY



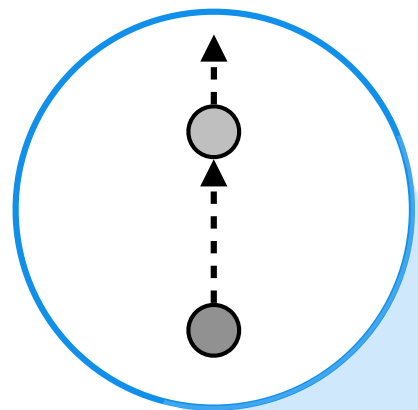
retina
*spatiotemporal
normalization*



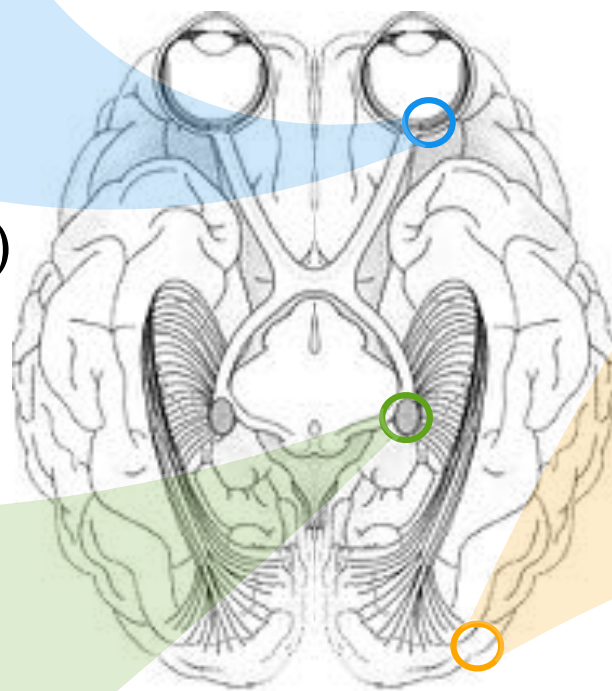
thalamus (LGN)
*temporal
normalization
 $\mathcal{E}$
error calculation*



VISUAL PATHWAY

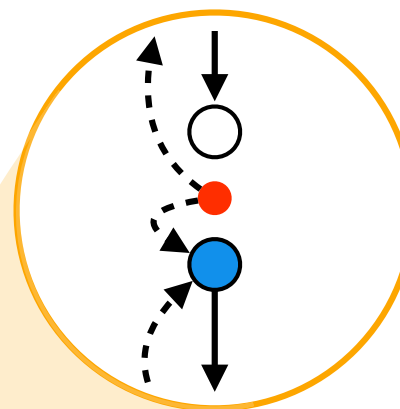
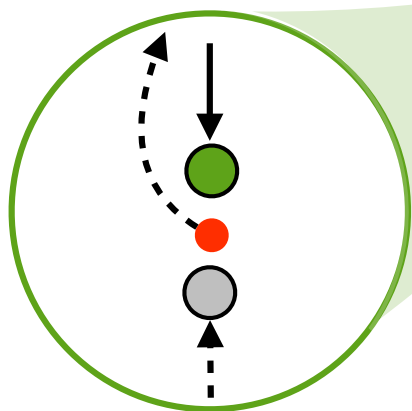


retina
*spatiotemporal
normalization*

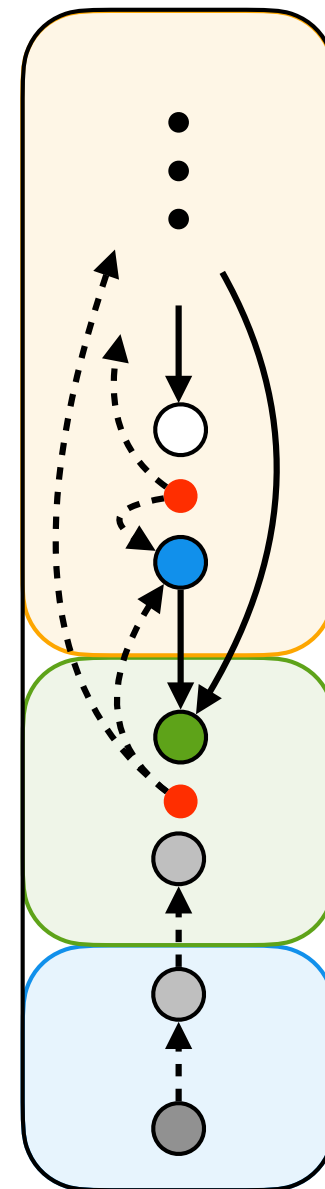


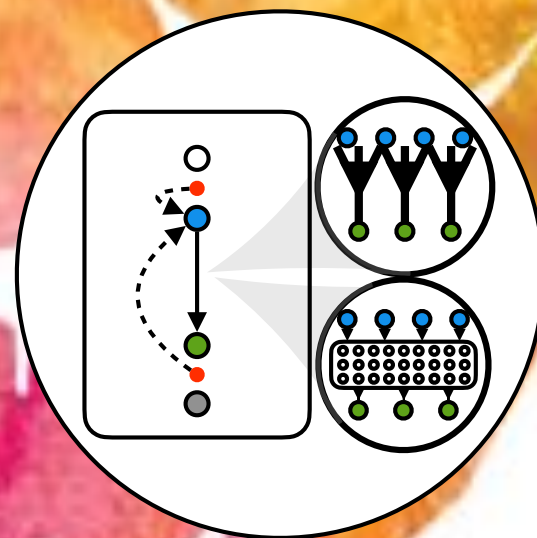
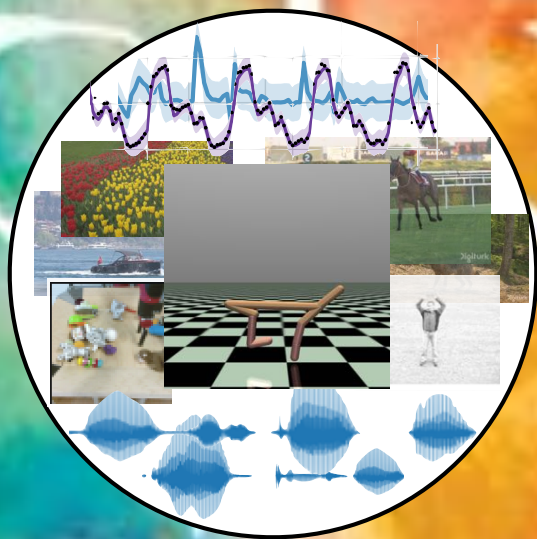
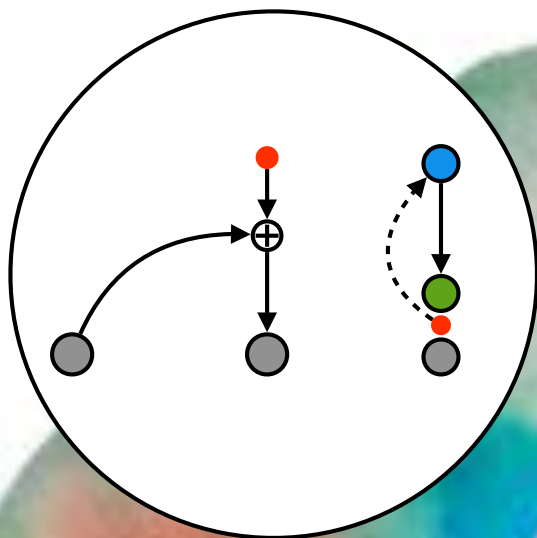
thalamus (LGN)

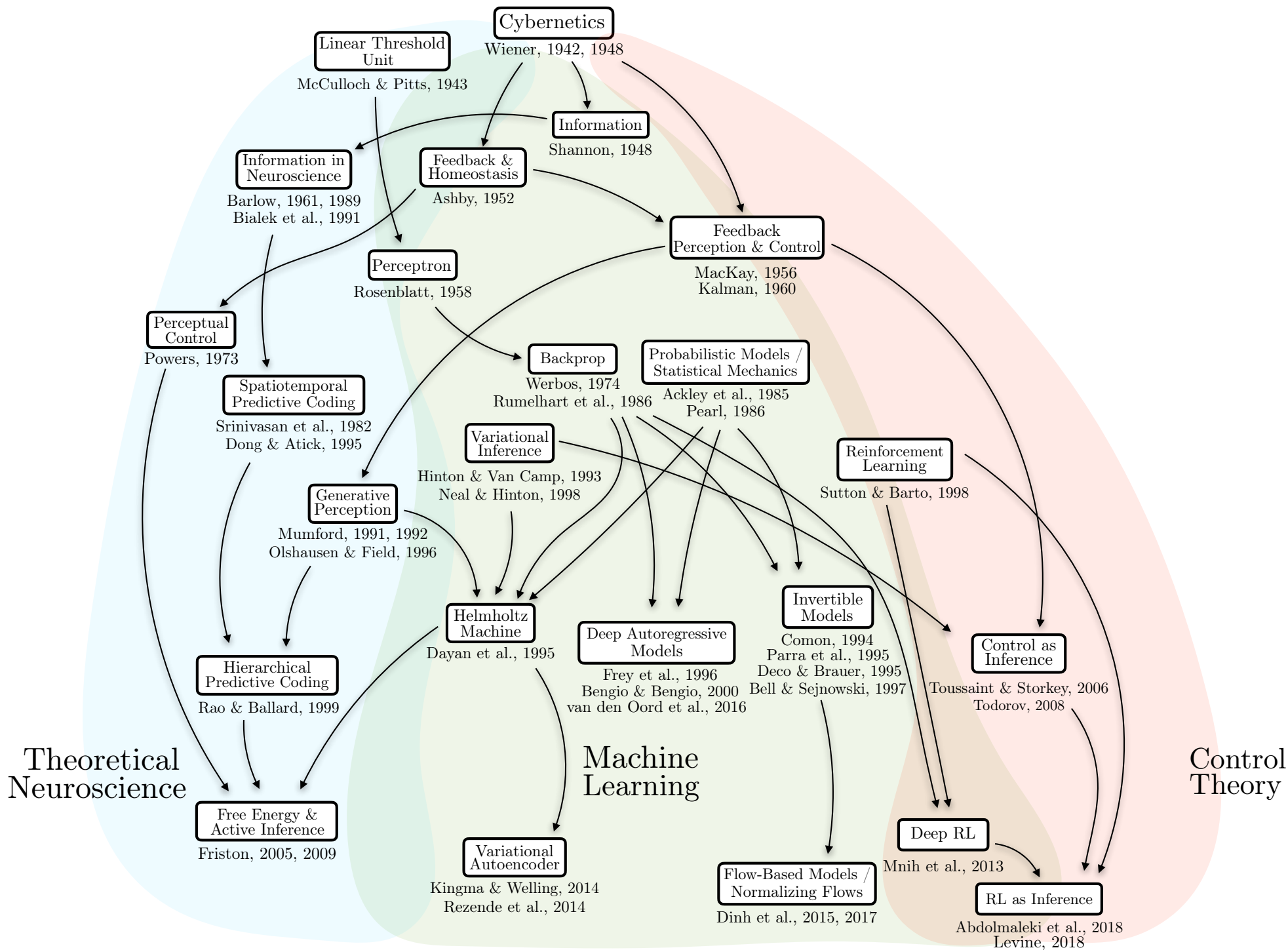
*temporal
normalization
 $\mathcal{E}$
error calculation*



cortex
*prediction,
error calculation
 $\mathcal{E}$
inference*







Collaborators



Yisong
Yue



Stephan
Mandt



Jiawei
He



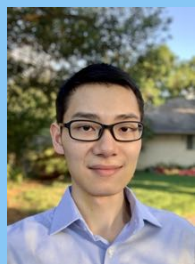
Alexandre
Piché



Alessandro
Ialongo



Alex
Guerra



Yibo
Yang



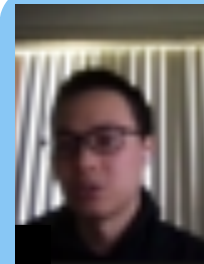
Milan
Cvitkovic



Yang
Yang



Lei
Chen



Ruihan
Yang

- Caltech
- UC Irvine
- Simon Fraser Univ.
- MILA
- Cambridge/MPII
- Qualcomm

thank you