

Distributional Control of Ensemble Systems



AFOSR D&C Program Review

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Ensemble Systems



- ▶ Population systems consisting of a large number of structurally similar dynamic units
 - ▶ Finitely or infinitely many
 - ▶ Isolated or interconnected agents

Large-Scale Dynamic Populations



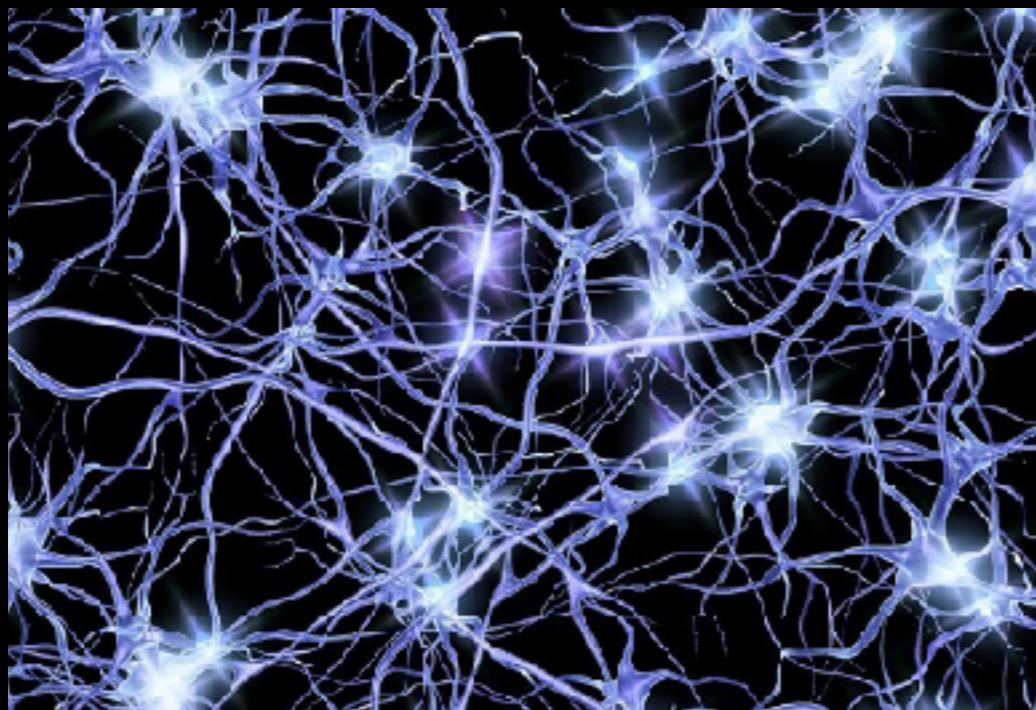
(Image credits: Jakob Schiller)



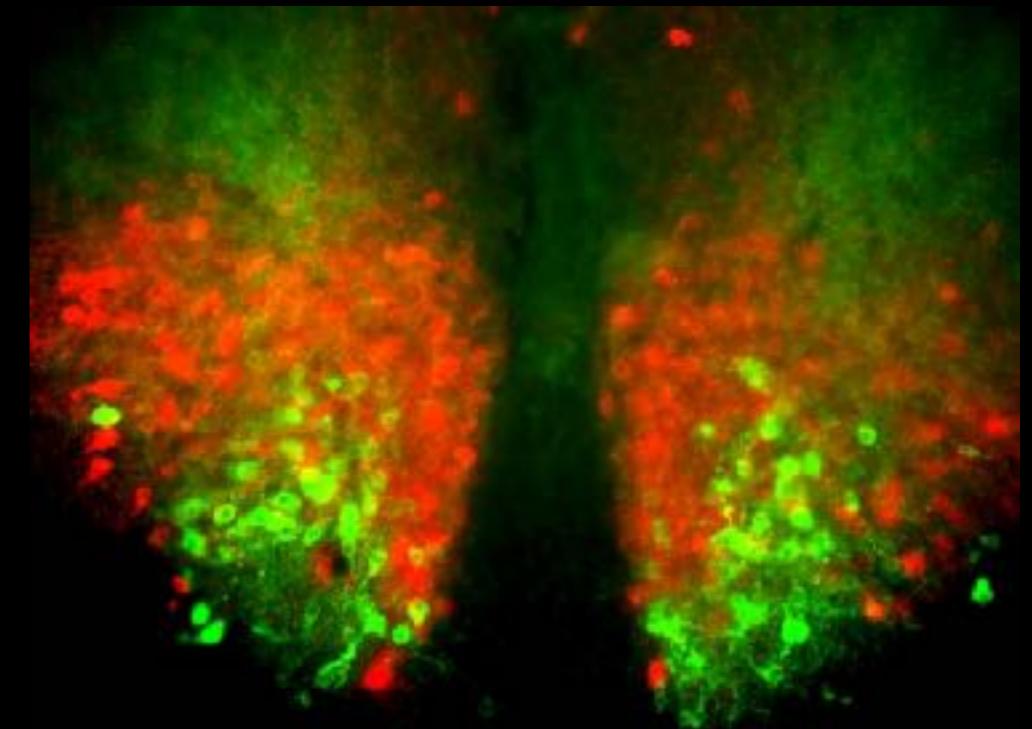
(Image credits: UPMC)



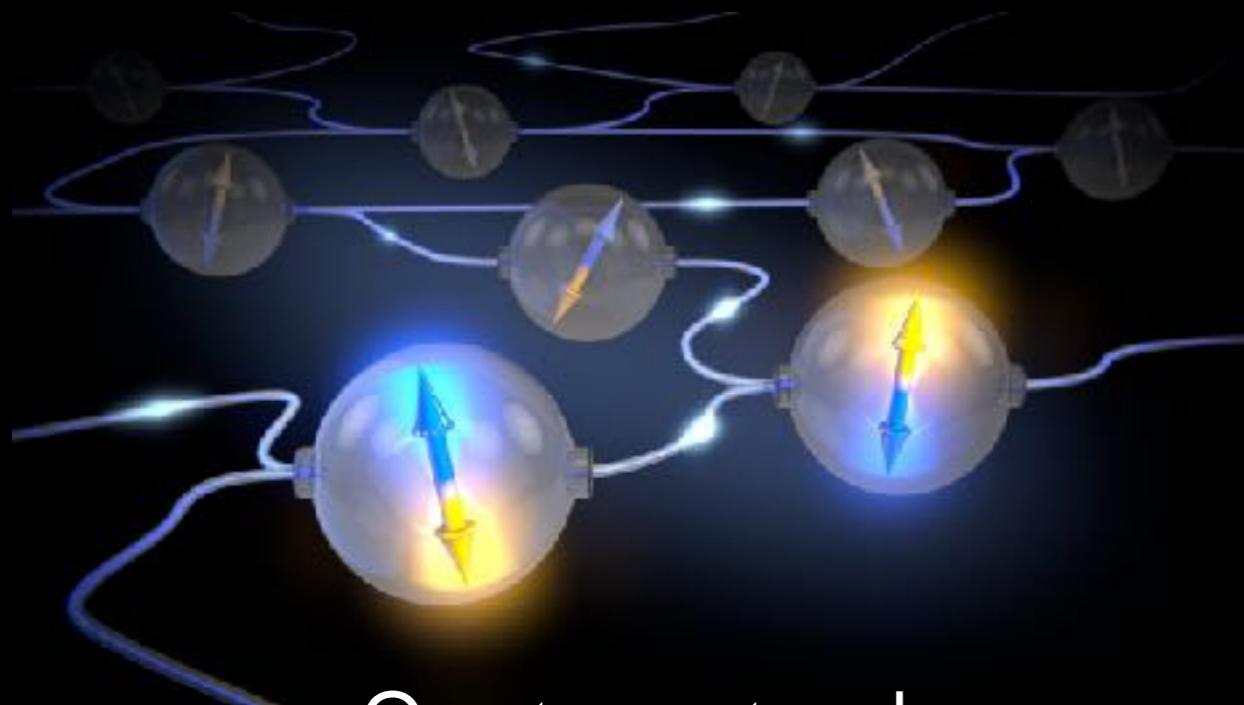
Large-Scale Dynamic Networks



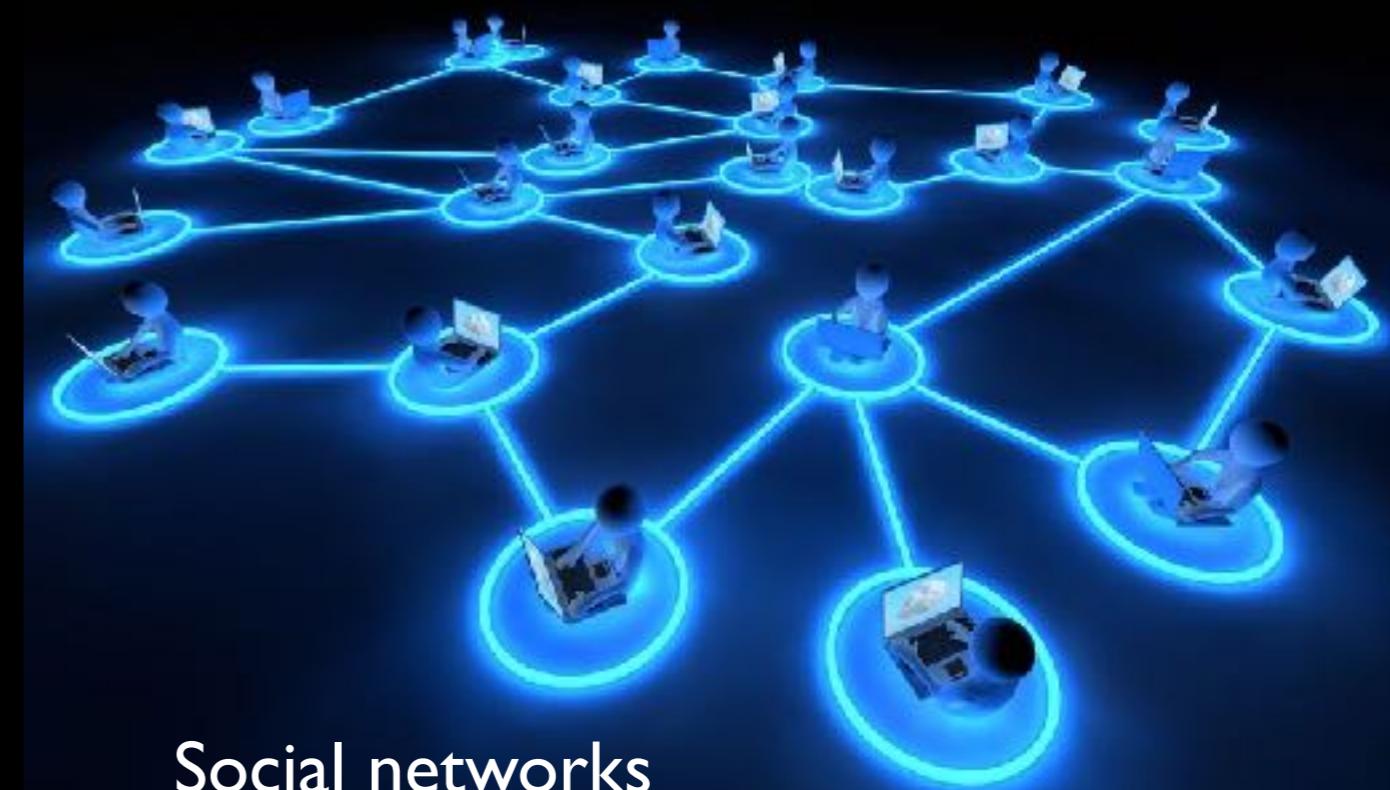
Neuronal networks



Biological networks



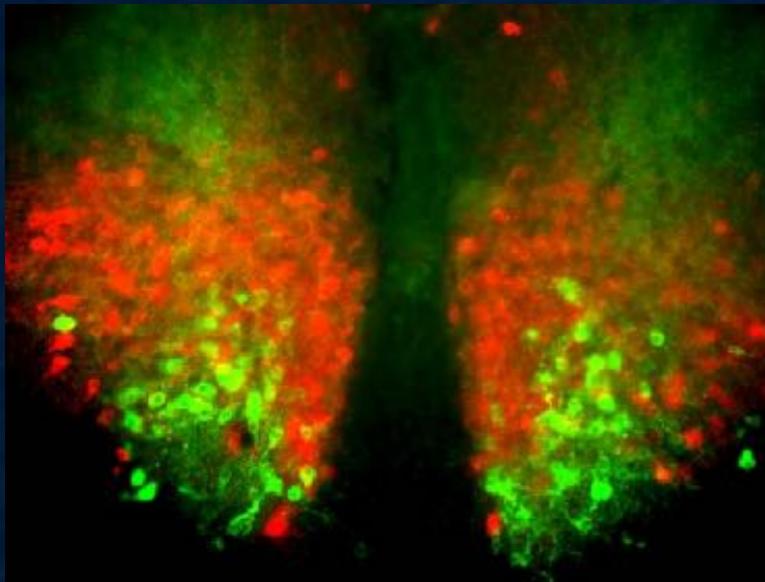
Quantum networks
(Source: QuTech)



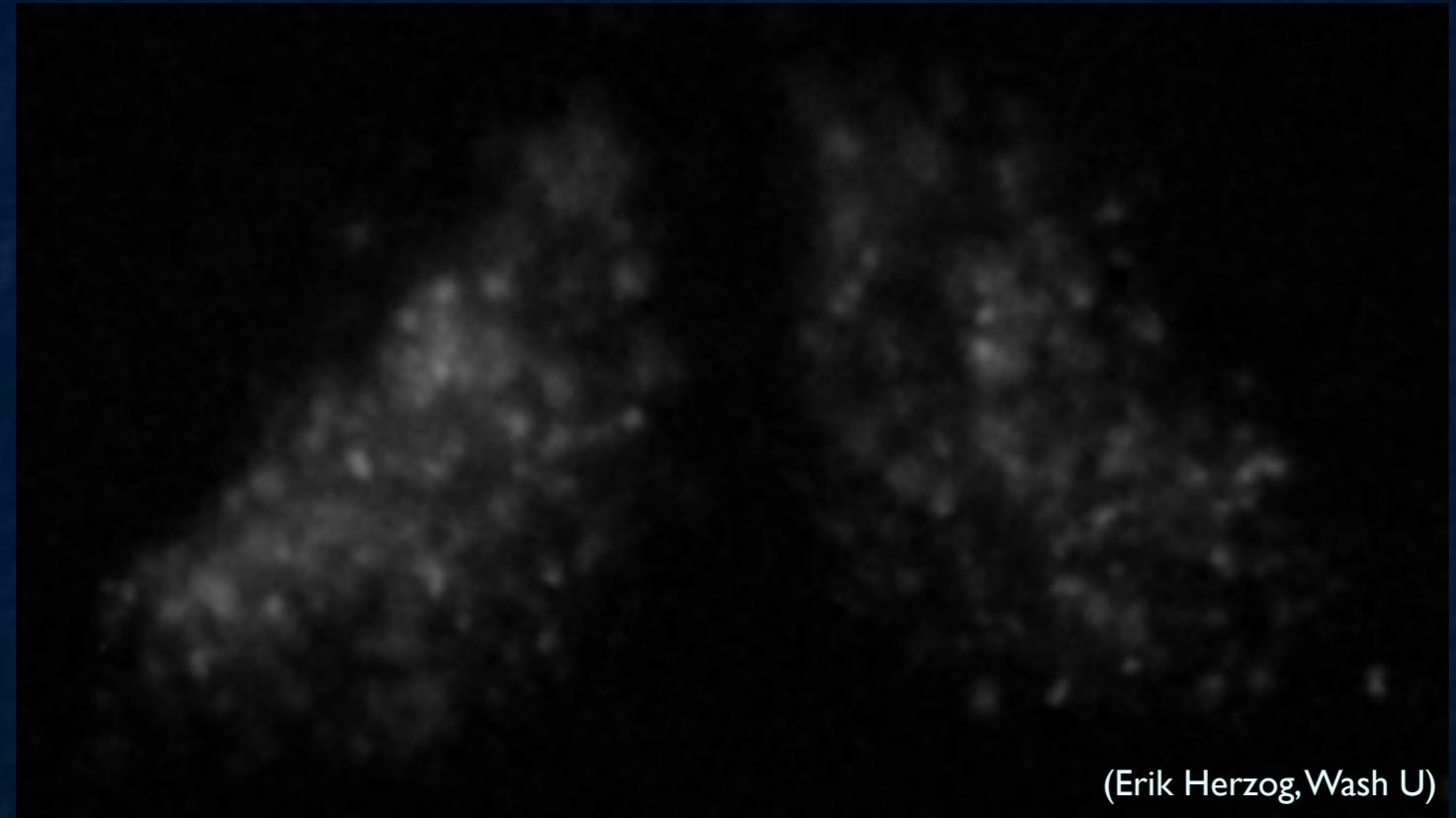
Social networks

Population Data

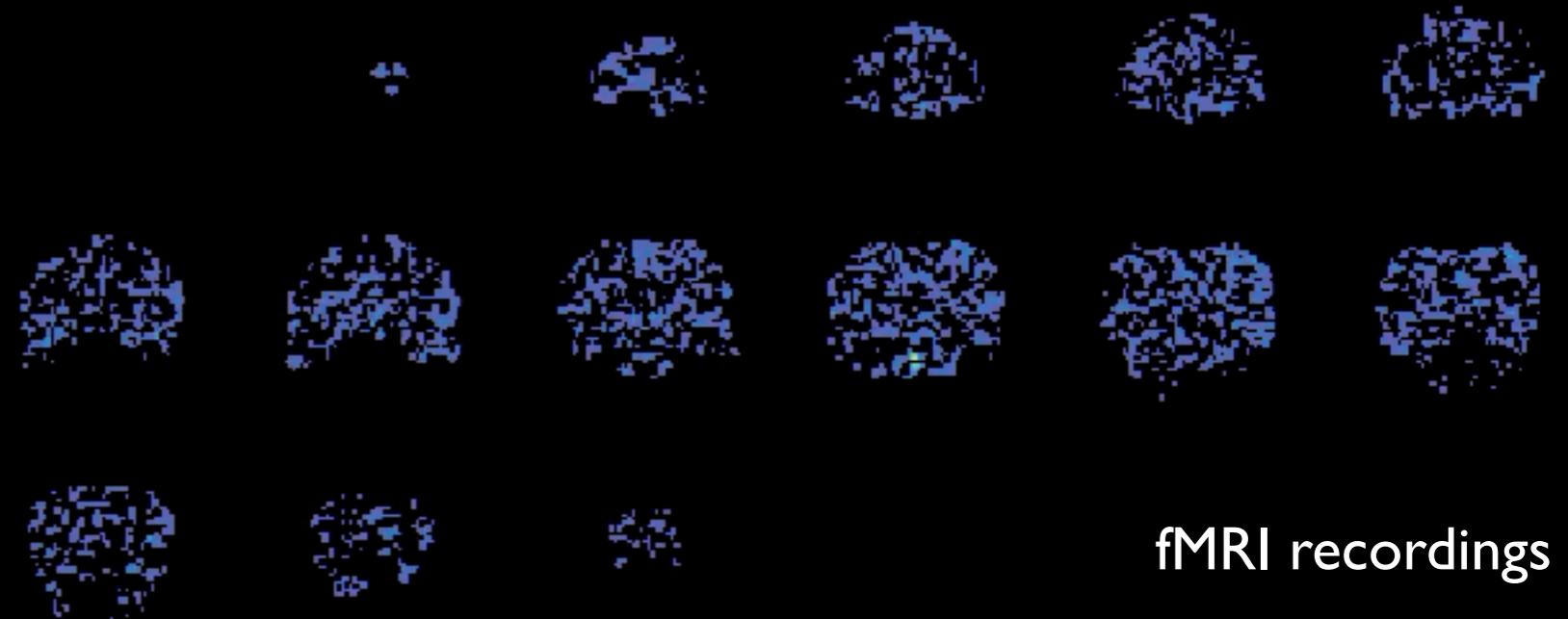
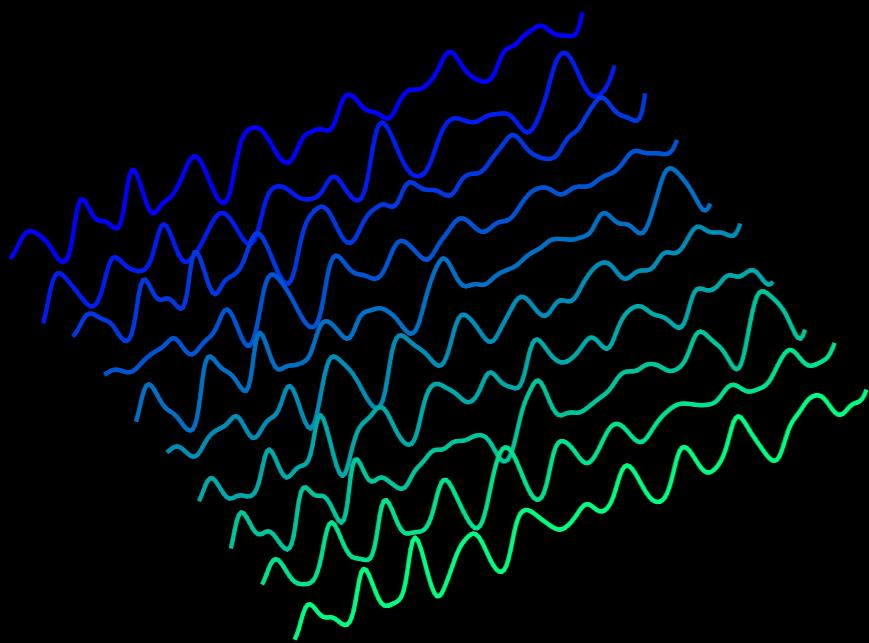
A clock in a dish: The SCN in vitro



Circadian clocks



(Erik Herzog, Wash U)



fMRI recordings

Outline

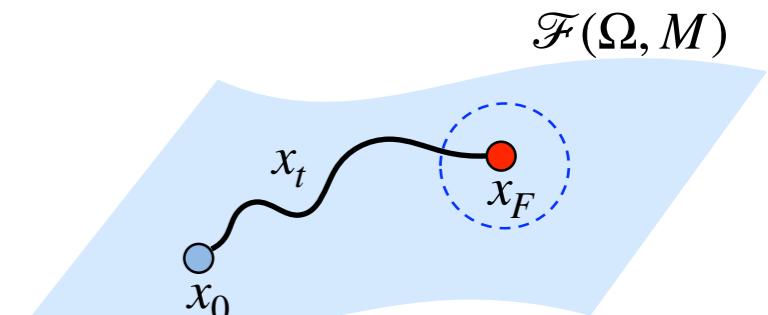
- ▶ Distributional control of ensemble systems
 - ▶ Distributional information inherent in aggregated measurements
 - ▶ Controlling output measures induced by aggregated measurements
- ▶ Dual representations generated by moment kernelization
- ▶ Link of ensemble control with optimal transport
- ▶ Distributional control on fibre space
- ▶ Ensemble control systems and representation learning

Control of Ensemble Systems

► Ensemble system

$$\frac{d}{dt}x(t, \beta) = F(t, \beta, x(t, \beta), u(t)), \quad \beta \in \Omega \subset \mathbb{R}^d$$

$$x(t, \beta) \in M \subset \mathbb{R}^n, \quad u(t) \in \mathbb{R}^m, \quad \Omega \text{ is compact}$$



$$x_t \doteq x(t, \cdot) \in \mathcal{F}(\Omega, M)$$

$$x_t : \Omega \rightarrow M$$

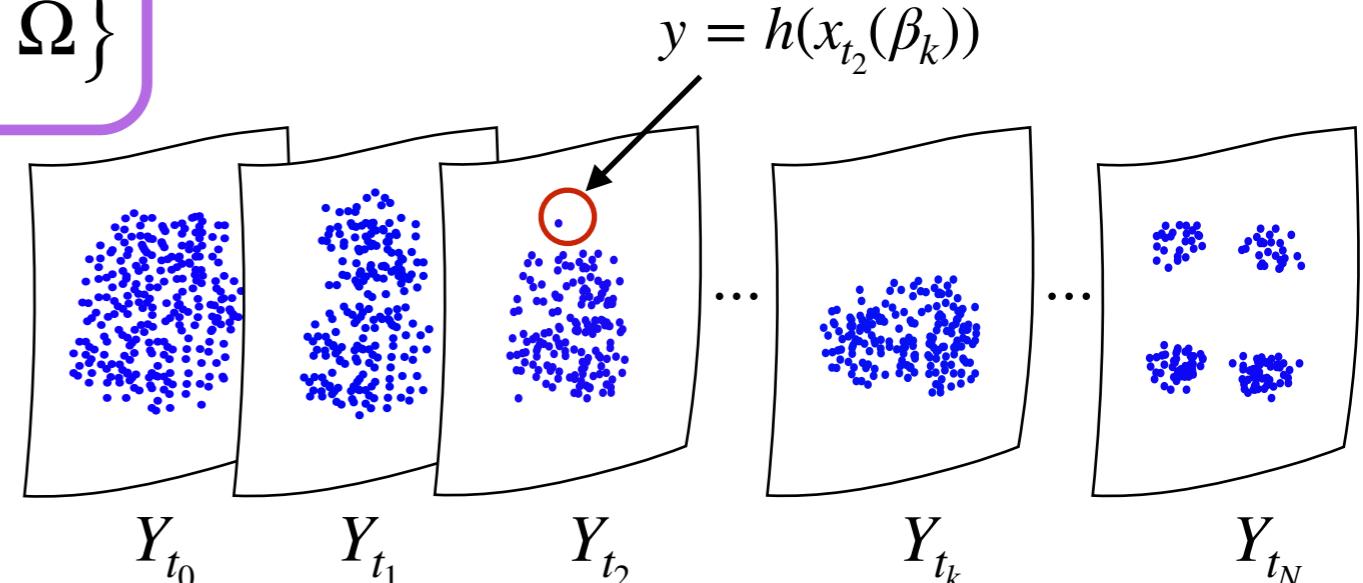
► Aggregated measurements

$$Y_t = y_t(\Omega) = h \circ x_t(\Omega)$$

$$= \{y \in \mathbb{R}^r : y = h(x(t, \beta)), \beta \in \Omega\}$$

Set-valued
measurements

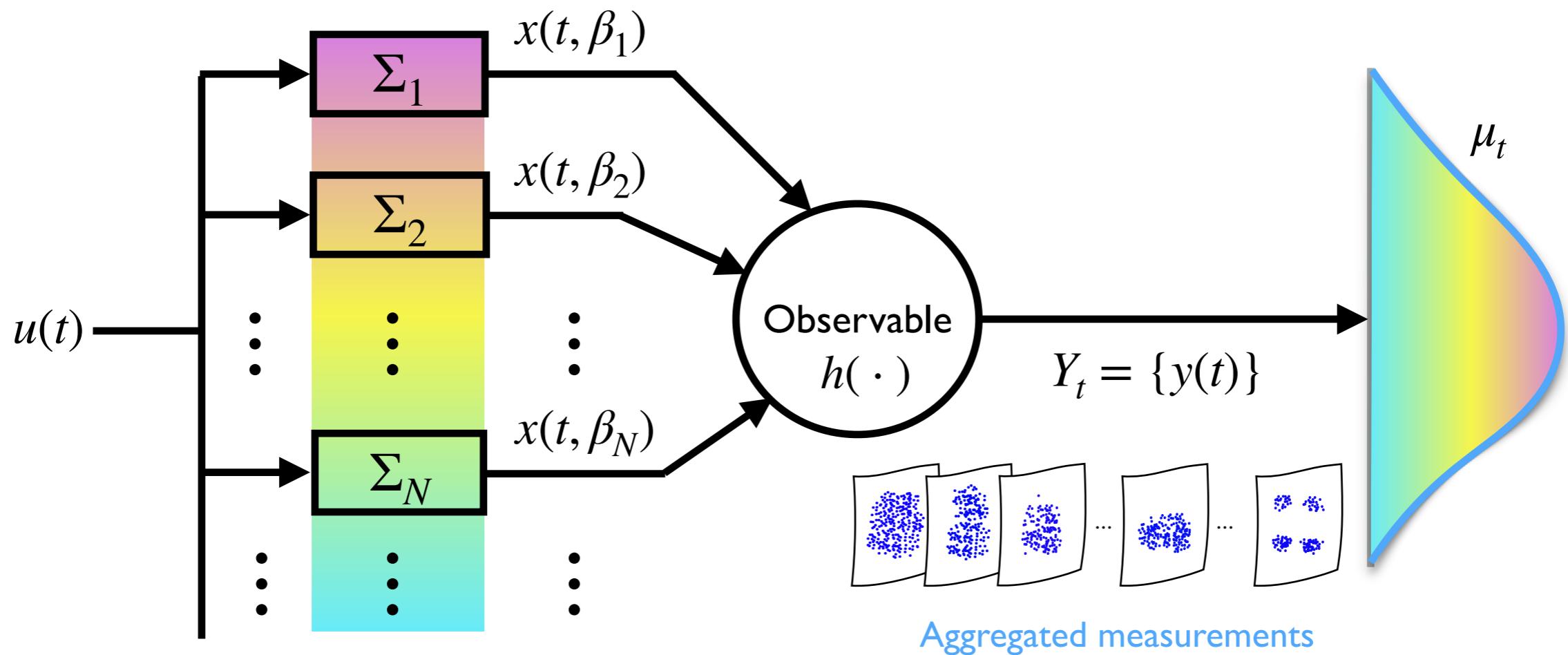
$y_t \sim \mu_t$ Probability measure



Control of Ensemble Distributions

► Shaping ensemble “distributions”

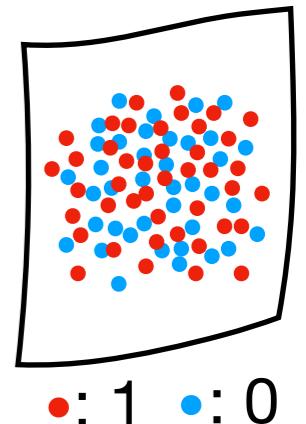
$$\frac{d}{dt}x(t, \beta) = F(t, \beta, x(t, \beta), u(t)), \quad \beta \in \Omega \subset \mathbb{R}^d$$
$$Y_t = y_t(\Omega) = h \circ x_t(\Omega)$$



Distributional Control of Ensembles

► A pedagogic example

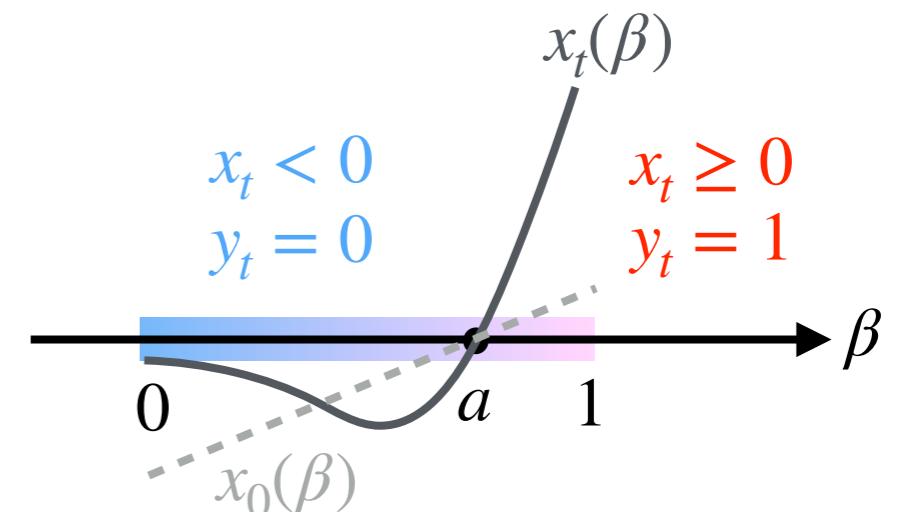
$$\begin{cases} \frac{d}{dt}x(t, \beta) = \beta x(t, \beta) + u(t), & \beta \in [0,1], \quad x(t, \beta) \in \mathbb{R} \\ y_t(\beta) = h(x_t(\beta)) = \begin{cases} 0, & \text{if } x_t(\beta) < 0 \\ 1, & \text{if } x_t(\beta) \geq 0 \end{cases} \end{cases} \rightarrow Y_t = \{0,1\}$$



► $x_0(\beta) = \beta - a, \quad u(t) = 0$

$$x_t(\beta) = e^{t\beta}x_0(\beta) \begin{cases} < 0, & \beta \in [0, a) \\ \geq 0, & \beta \in [a, 1] \end{cases}$$

$\rightarrow y_t = 1_{[a,1]}$



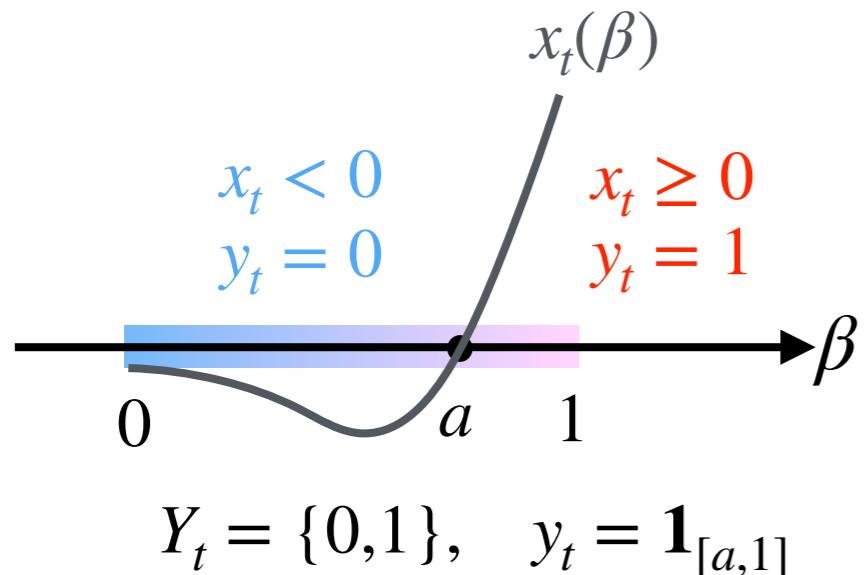
$$\mu_t(\{0\}) = a$$

$$\mu_t(\{1\}) = 1 - a$$

$$y_t \sim \mu_t : \text{Bernoulli}(a)$$

Distributional Control of Ensembles

► Mathematical formalism

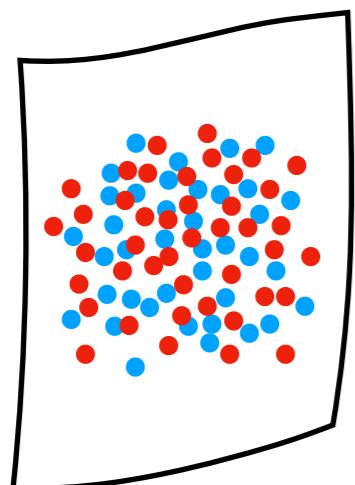


$$Y_t = \{0,1\}, \quad y_t = \mathbf{1}_{[a,1]}$$

$$\Omega = [0,1], \quad \lambda \text{ Lebesgue measure}$$

$$\mu_t(\{0\}) = \lambda([0,a)) = \lambda(y_t^{-1}(0)) = ((y_t)_\# \lambda)(\{0\})$$

$$\mu_t(\{1\}) = \lambda([a,1]) = \lambda(y_t^{-1}(1)) = ((y_t)_\# \lambda)(\{1\})$$



$$\mu_t = (y_t)_\# \lambda$$

$$d\lambda = \frac{\omega}{\text{vol}(\Omega)}$$

$$\left\{ \begin{array}{l} \mu_t(B) = \lambda(y_t^{-1}(B)) \\ \int_{\mathbb{R}^r} f d\mu_t = \int_{\Omega} f \circ y_t d\lambda \end{array} \right.$$

Distributional
control

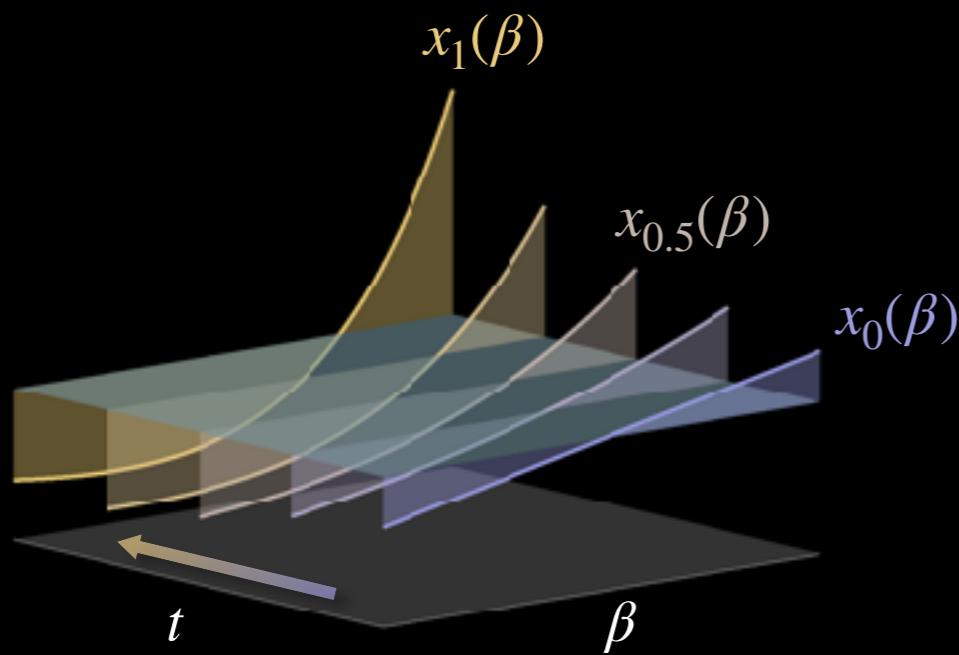


Transport of
probability measures

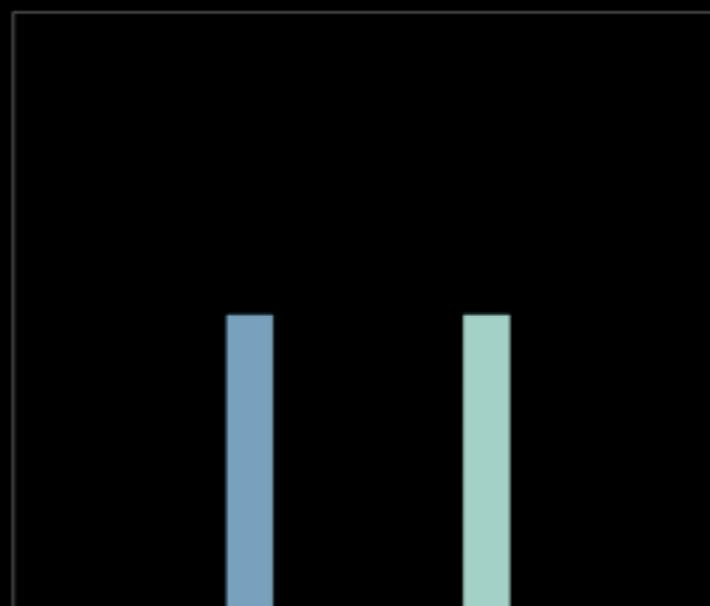
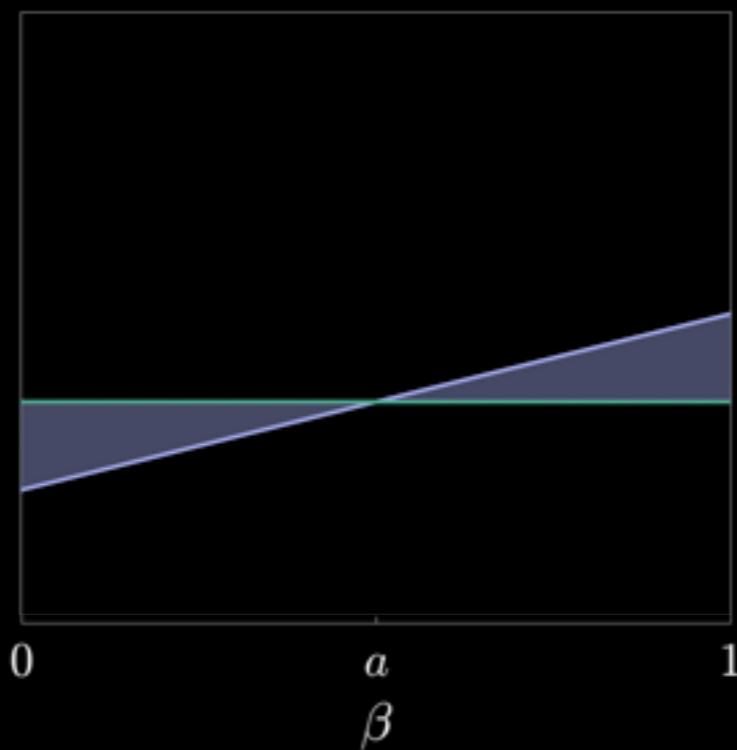
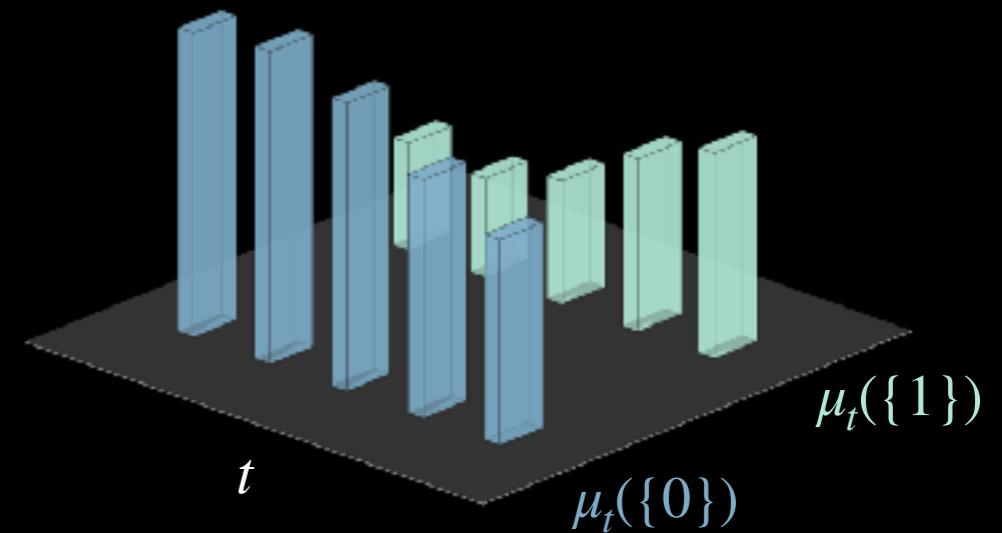
Distributional Control of Ensembles

$$\frac{d}{dt}x_t(\beta) = \beta x_t(\beta) + u(t), \quad \beta \in [0,1]$$
$$y_t(\beta) = h(x(t, \beta))$$

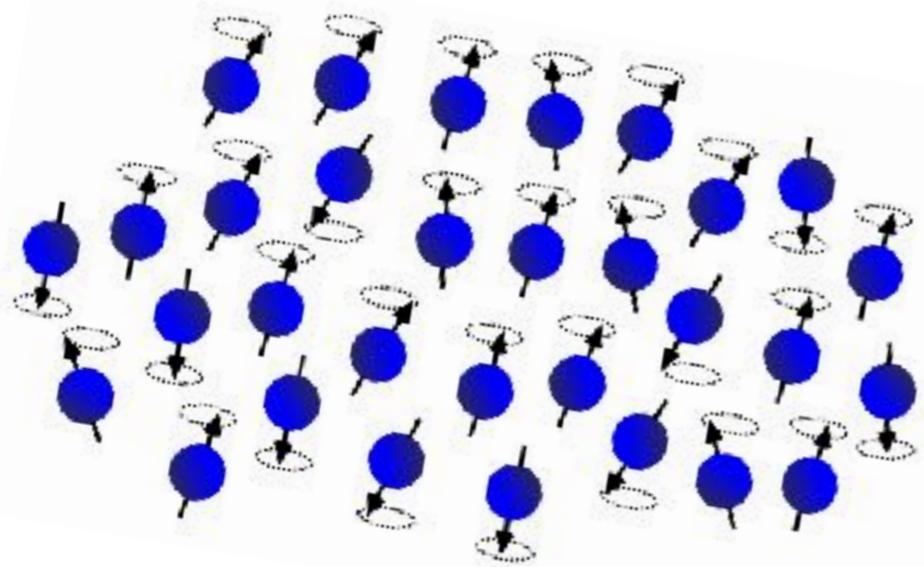
$$x_0(\beta) = \beta - 0.5$$
$$u(t) = -\sin(t)\cos(t)$$



$$(y_t)_\# \lambda$$



Distributional Control via Optimal Transport



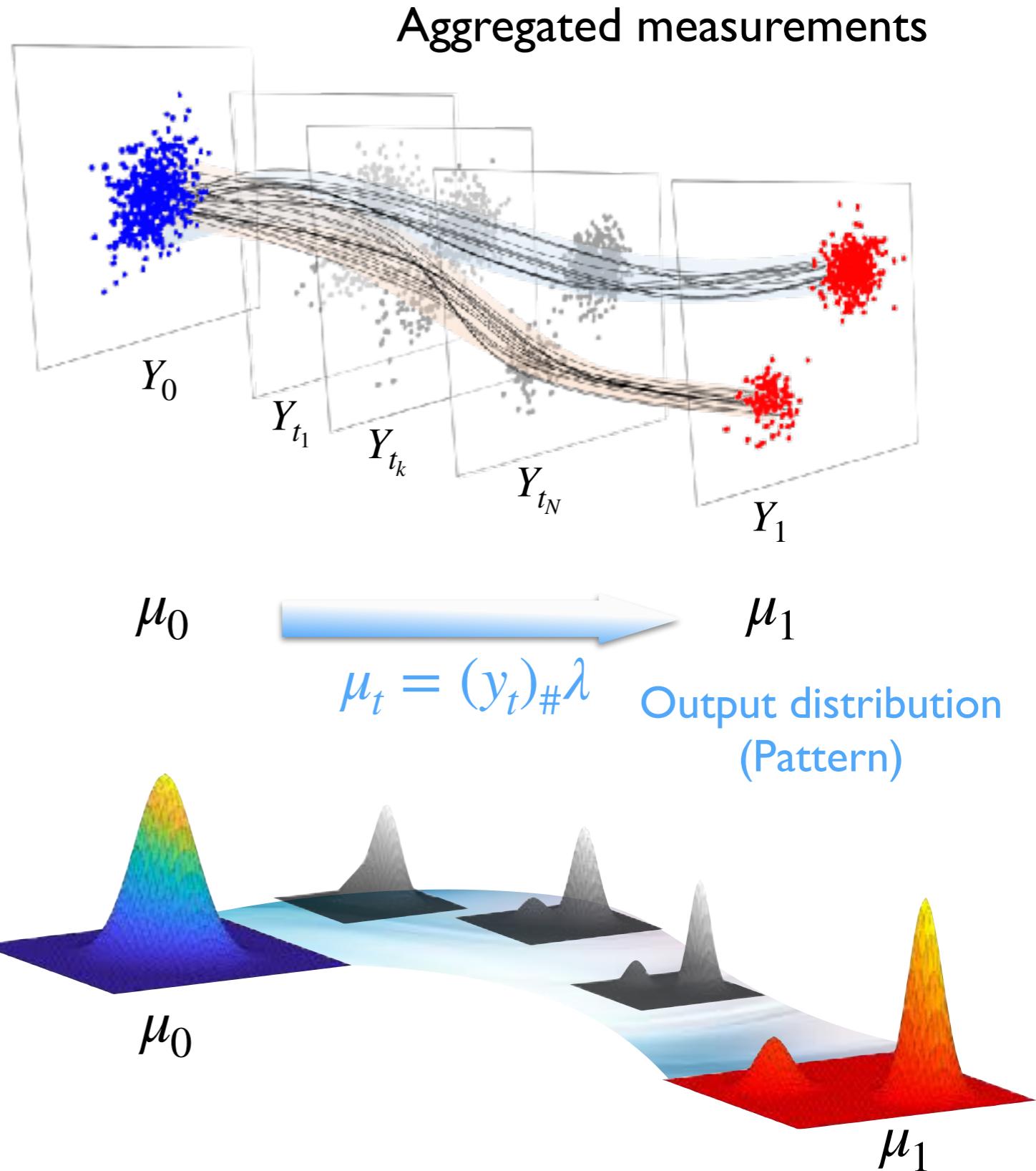
$$\frac{d}{dt}x(t, \beta) = F(t, \beta, x(t, \beta), u(t))$$

$$Y_t = y_t(\Omega) = h \circ x_t(\Omega)$$

Ensemble
control

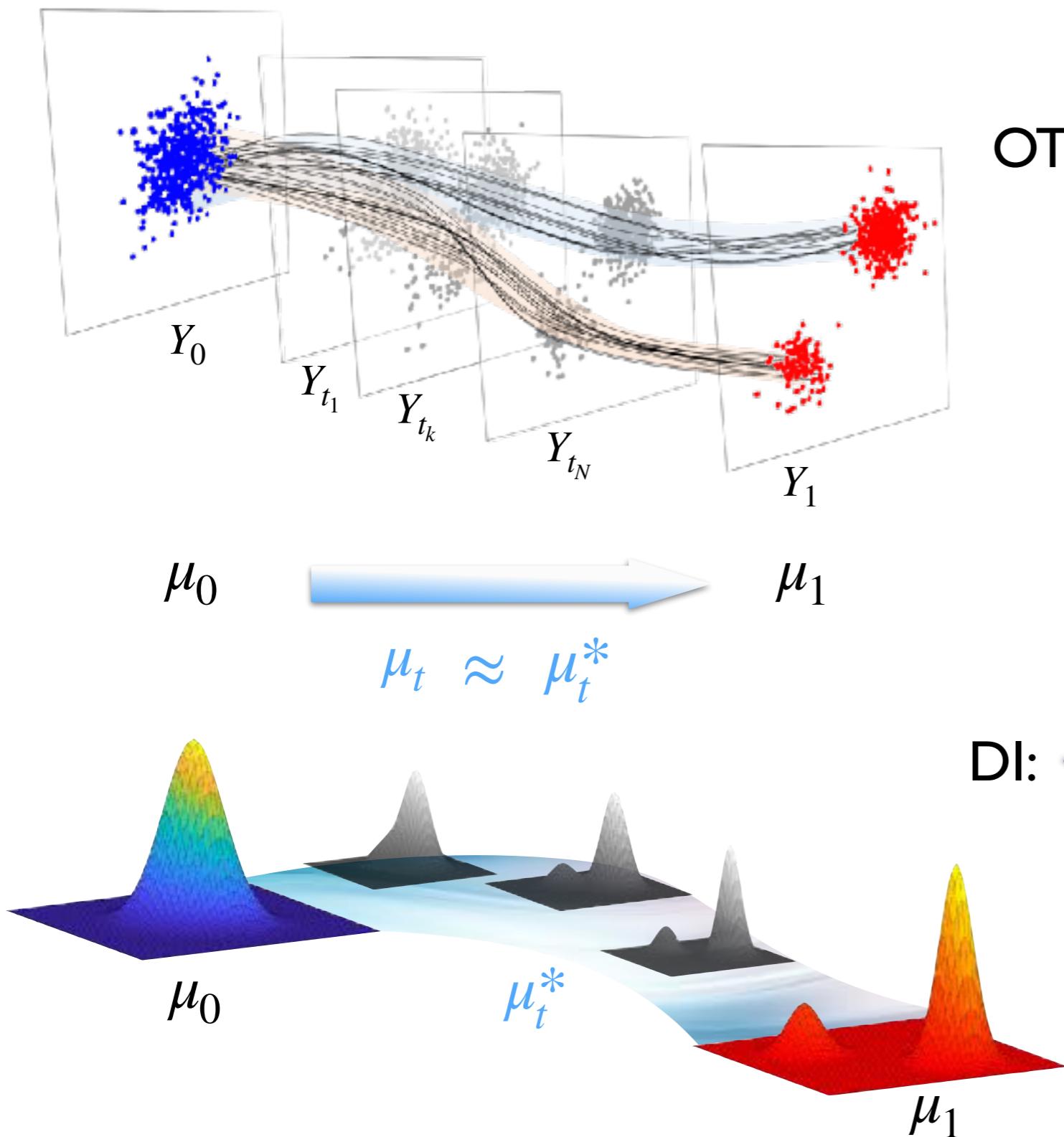


Optimal
transport



Time-Dependent Optimal Transport

► Displacement interpolation (DI)



Interpolating (μ_0, μ_1)

Optimal Transport for Ensemble Control

- ▶ Distributional control as a tracking problem

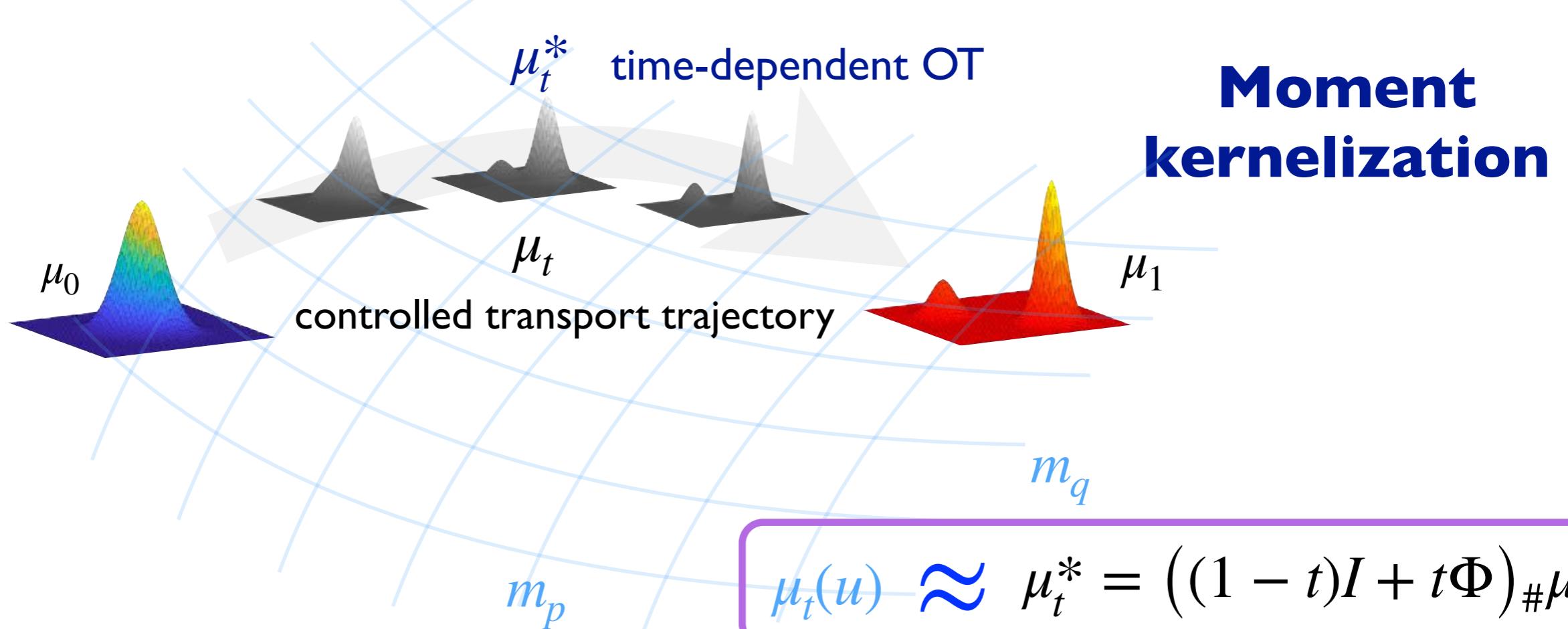
$$\frac{d}{dt}x(t, \beta) = F(t, \beta, x(t, \beta), u(t))$$

$$Y_t = y_t(\Omega) = h \circ x_t(\Omega)$$

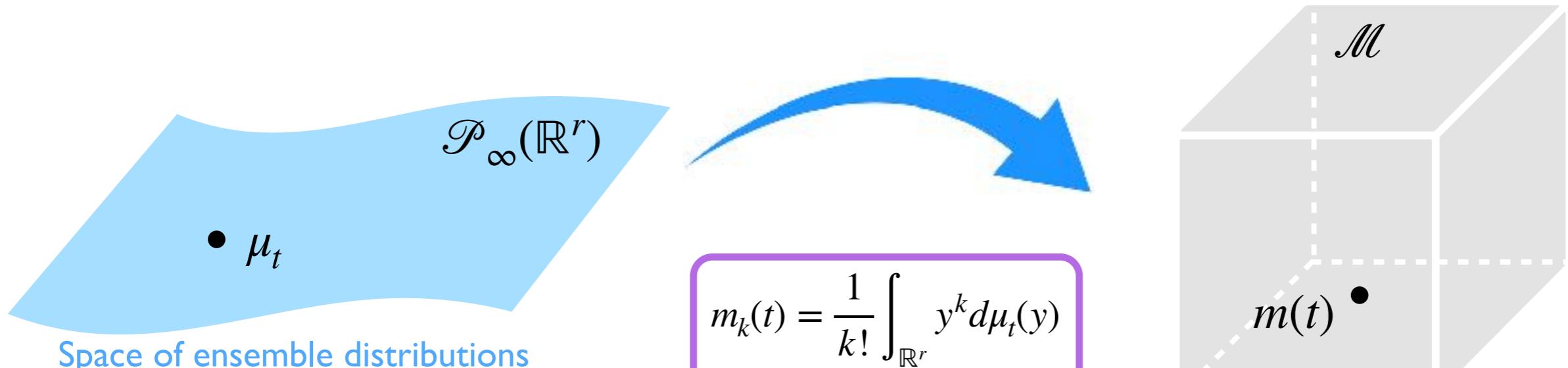
Ensemble distribution

$$\mu_t = (y_t)_\# \lambda$$

- ▶ Steering output distributions



Moment Kernel



Ensemble distributions

$$\mu_t = (y_t)_\# \lambda, \quad y_t = h \circ x_t$$

Monomial moments

Moment space

$$m(t) : \mathbb{N}^r \rightarrow \mathbb{R}$$

► k -th ensemble output moment

$$m_k(t) = \langle \varphi_k, \mu_t \rangle, \quad \{\varphi_k\}_{k \in \mathbb{N}^r} \text{ dual set of a basis of } \mathcal{P}_\infty(\mathbb{R}^r)$$

► Reproducing kernel induced by the moment transform

$$\mathcal{K} : \mathbb{N}^r \times \mathbb{N}^r \rightarrow \mathbb{R}, \quad (i, j) \mapsto k_j(i) = \langle k_i, k_j \rangle$$

Moment Kernelization

► Moment transform

$$d\mu(y) = f(y)dy$$

$$f(y) = \frac{1}{\sqrt{2\sigma^2}} e^{-\frac{y^2}{2\sigma^2}}$$

Probability measure

$$m_k = \int_{\mathbb{R}} y^k d\mu(y)$$

$$m = \begin{bmatrix} 0 \\ \sigma^2 \\ 0 \\ 3\sigma^4 \\ \vdots \end{bmatrix}$$

Moment sequence

$$\frac{d}{dt}x(t, \beta) = F(t, \beta, x(t, \beta), u(t))$$

$$Y_t = y_t(\Omega), \quad \mu_t = (y_t)_\# \lambda$$

$$m_k(t) = \int_{\mathbb{R}^r} y^k d\mu_t(y)$$

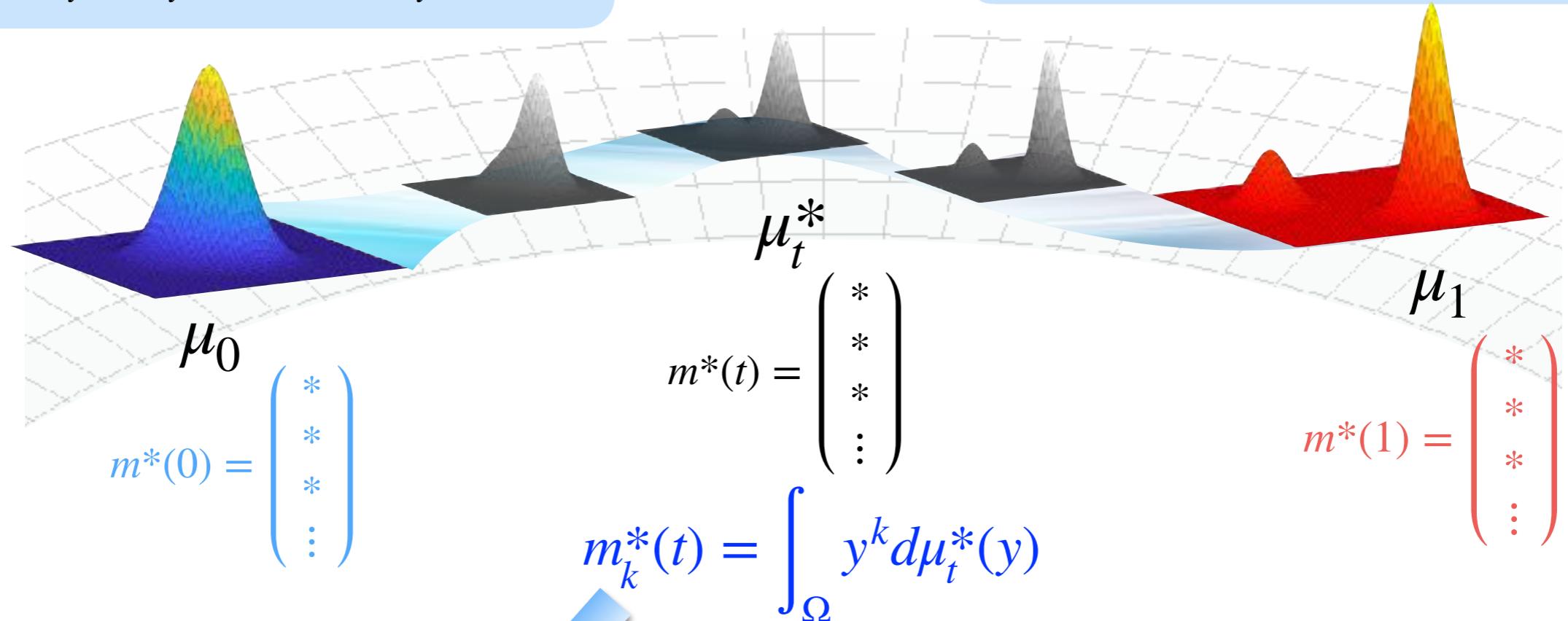
$$m(t) = (m_k(t))_{k \in \mathbb{N}^r}$$

Moment Kernelized Ensemble control

- ▶ Ensemble control as time-dependent optimal transport

$$\frac{d}{dt}x(t, \beta) = F(t, \beta, x(t, \beta), u(t))$$
$$Y_t = y_t(\Omega) = h \circ x_t(\Omega)$$

$$\frac{d}{dt}m(t) = \bar{F}(t, m(t), u(t))$$



$$\frac{d}{dt}m^*(t) = \bar{F}^*(t, m^*(t))$$

Tracking
 $m(t) \approx m^*(t)$

OT dynamics in
moment coordinates

$$\frac{d}{dt}m(t) = \bar{F}(t, m(t), u^*(t))$$

Controlled moment system

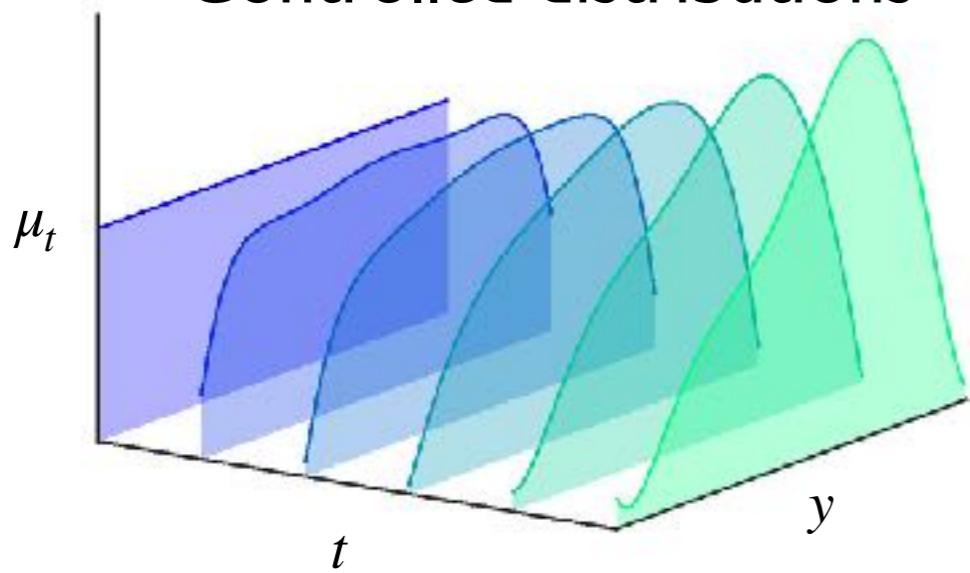
Moment Kernelized Ensemble control

► Transport from a square to a triangle wave

$$\frac{d}{dt}x(t, \beta) = \beta x(t, \beta) + \sum_{i=1}^p \beta^{i-1} u_i(t)$$

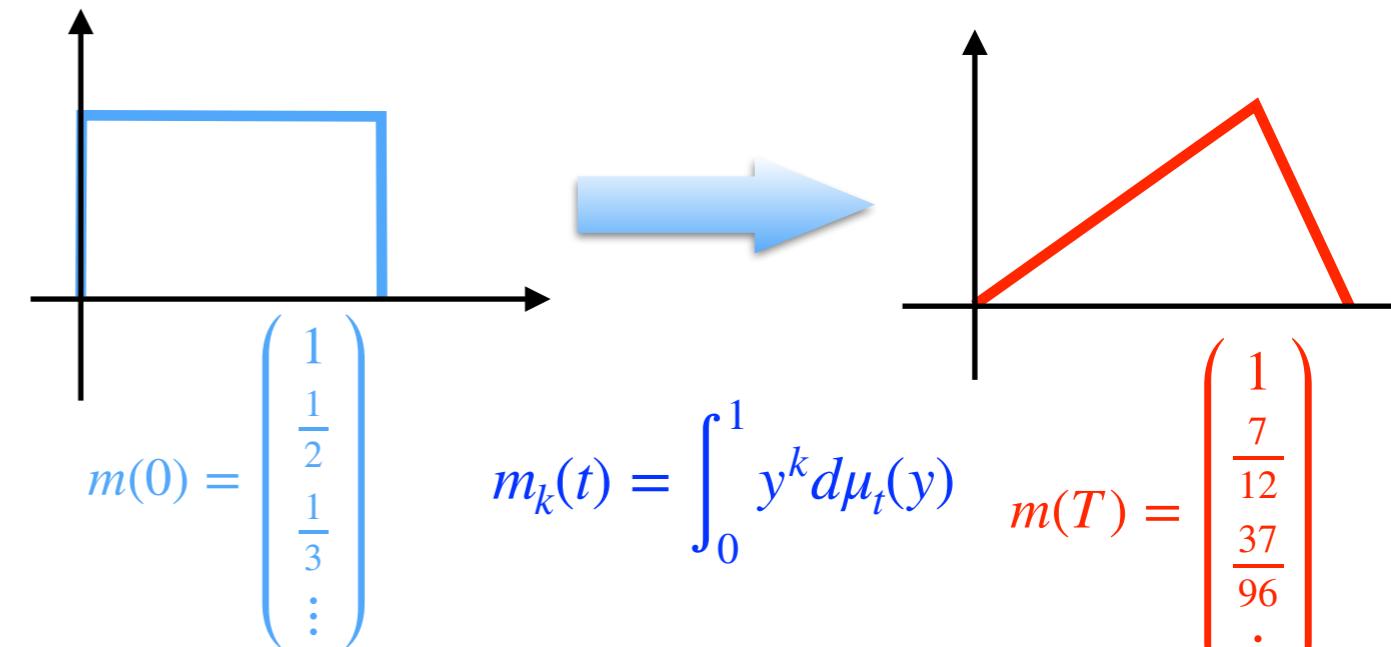
$$y_t(\beta) = h(x_t(\beta)) = x_t(\beta) \quad \beta \in [0,1]$$

Controlled distributions

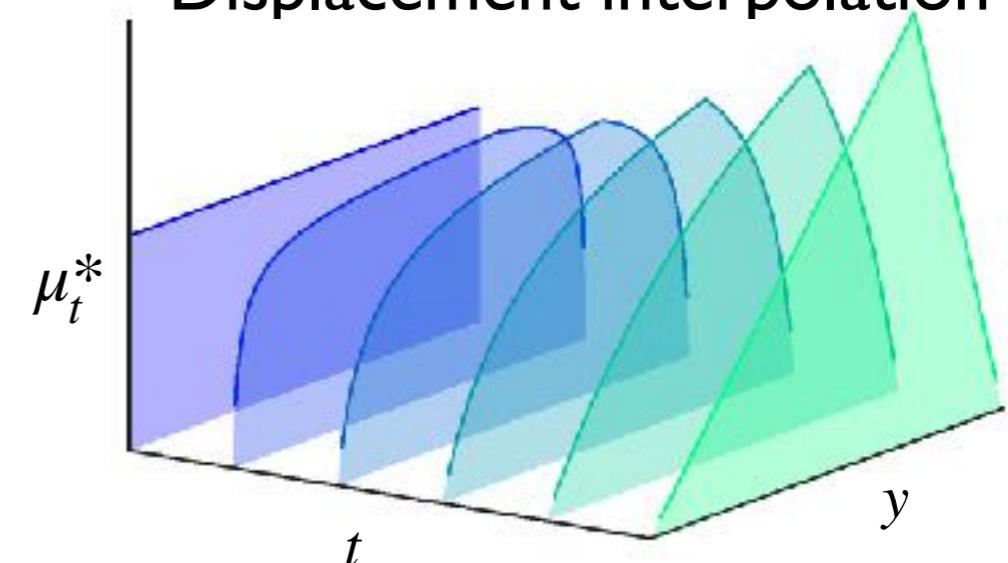


$$\frac{d}{dt}m_k(t) = m_{k+1}(t) + \sum_{i=1}^p \frac{u_i(t)}{k+i}$$

Output moment dynamics



Displacement interpolation



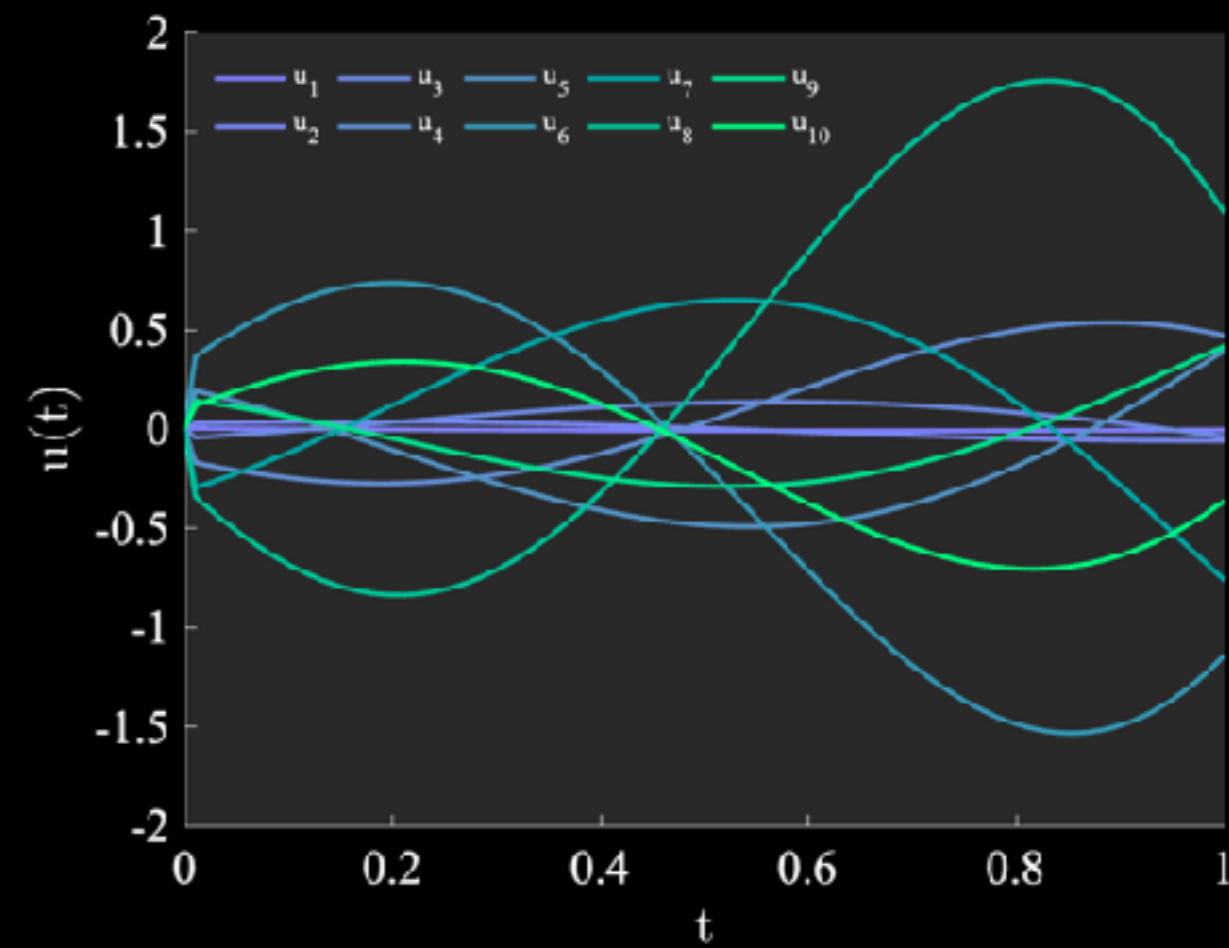
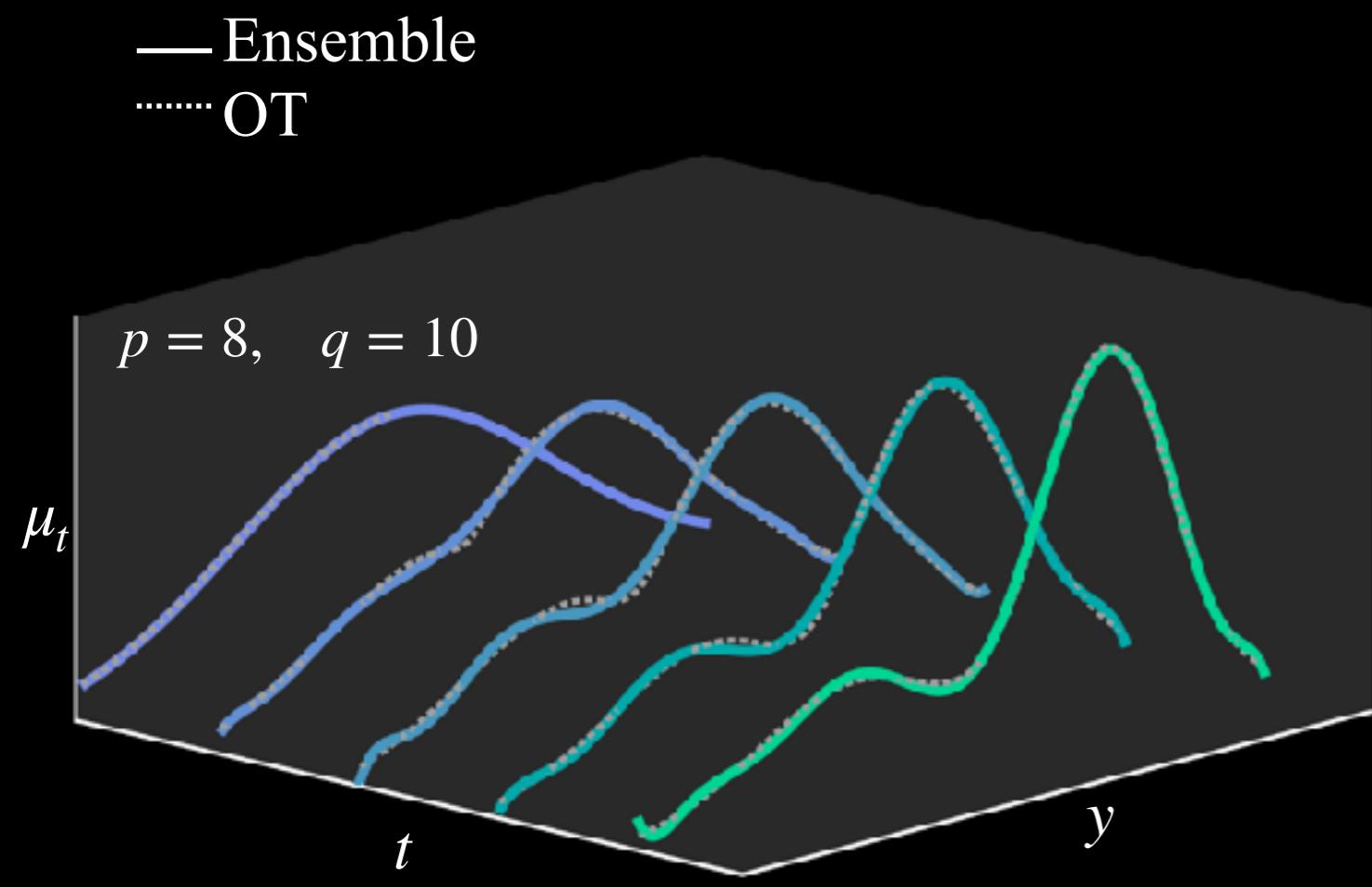
$$\frac{d}{dt}m_k^*(t) = \int_0^1 k((1-t)y + t\Phi_1(y))^{k-1}(\Phi_1(y) - y)dy$$

OT moment dynamics

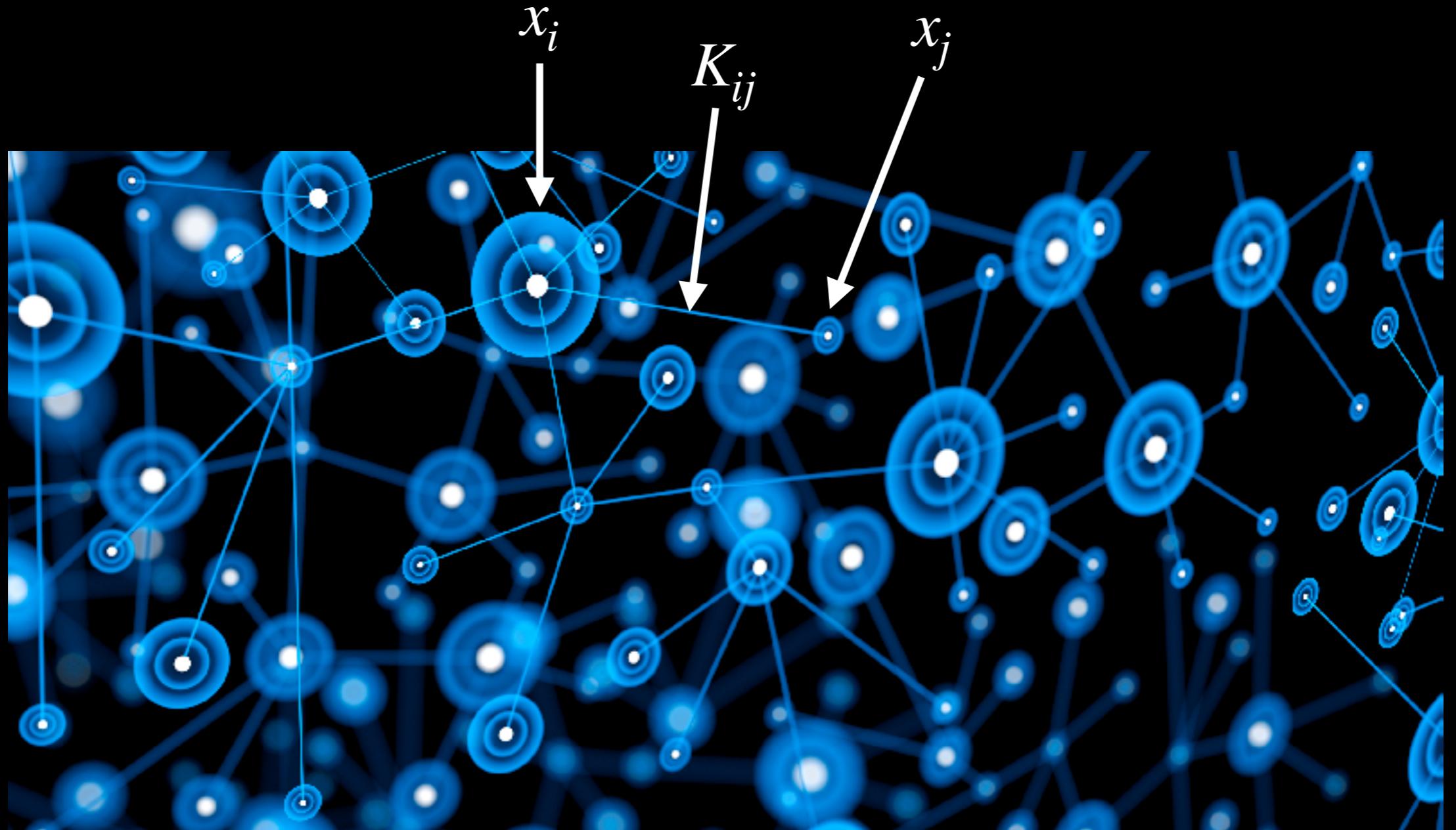
Moment Kernelized Ensemble control

$$\frac{d}{dt}x(t, \beta) = \beta x(t, \beta) + \sum_{i=1}^p \beta^{i-1} u_i(t)$$
$$y_t(\beta) = h(x_t(x)) = x_t(\beta)$$

p : number of inputs
 q : order of moments



Infinite Networks



$$\dot{x}_i(t) = f(x_i(t)) + \sum_{j=1}^N K_{ij}(x_i, x_j)$$

arbitrarily large
 $N \rightarrow \infty$
(Infinite network)

Infinite Dynamic Networks

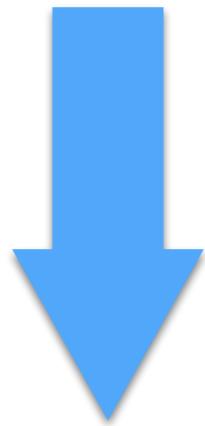
- ▶ Integral-differential system representation

$$\frac{d}{dt}x_i(t) = f_i(x_i(t)) + \frac{1}{N} \sum_{j=1}^N (x_j(t) - x_i(t))$$

Node dynamics

Diffusive coupling

$N \rightarrow \infty$



$$\frac{d}{dt}x(t, \beta) = f(\beta, x(t, \beta)) + \int_{\Omega} (x(t, \beta') - x(t, \beta)) d\beta'$$

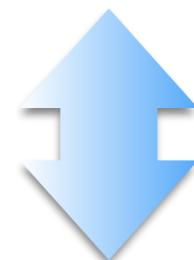
$$\beta \in \Omega \subset \mathbb{R}, \quad |\Omega| = 1$$

Infinite Dynamic Networks

► Moment kernelized infinite network

$$\frac{d}{dt}x(t, \beta) = f(\beta, x(t, \beta)) + \int_{\Omega} (x(t, \beta') - x(t, \beta)) d\beta'$$

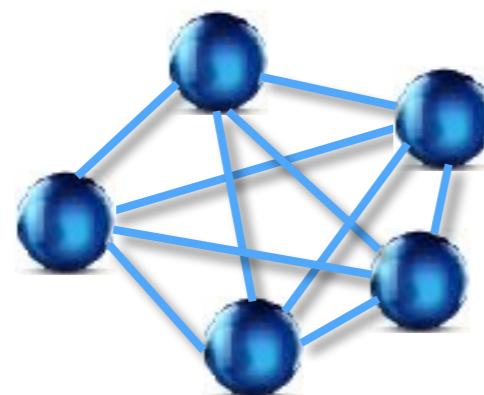
Primal
network



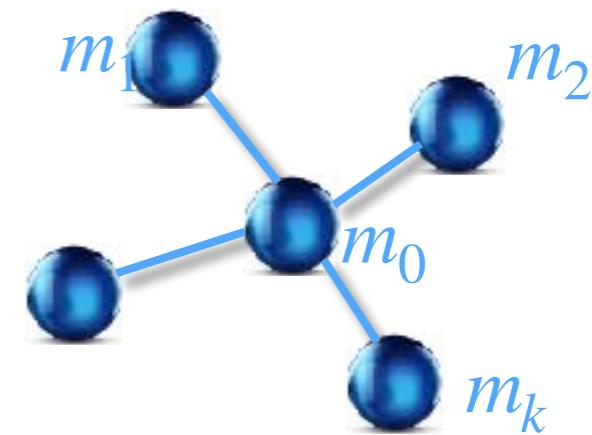
$$m(t) = (\mathcal{L}x)(t)$$

$$\frac{d}{dt}m_k(t) = \bar{f}_k(m(t)) + [c_k m_0(t) - m_k(t)]$$

Dual
network

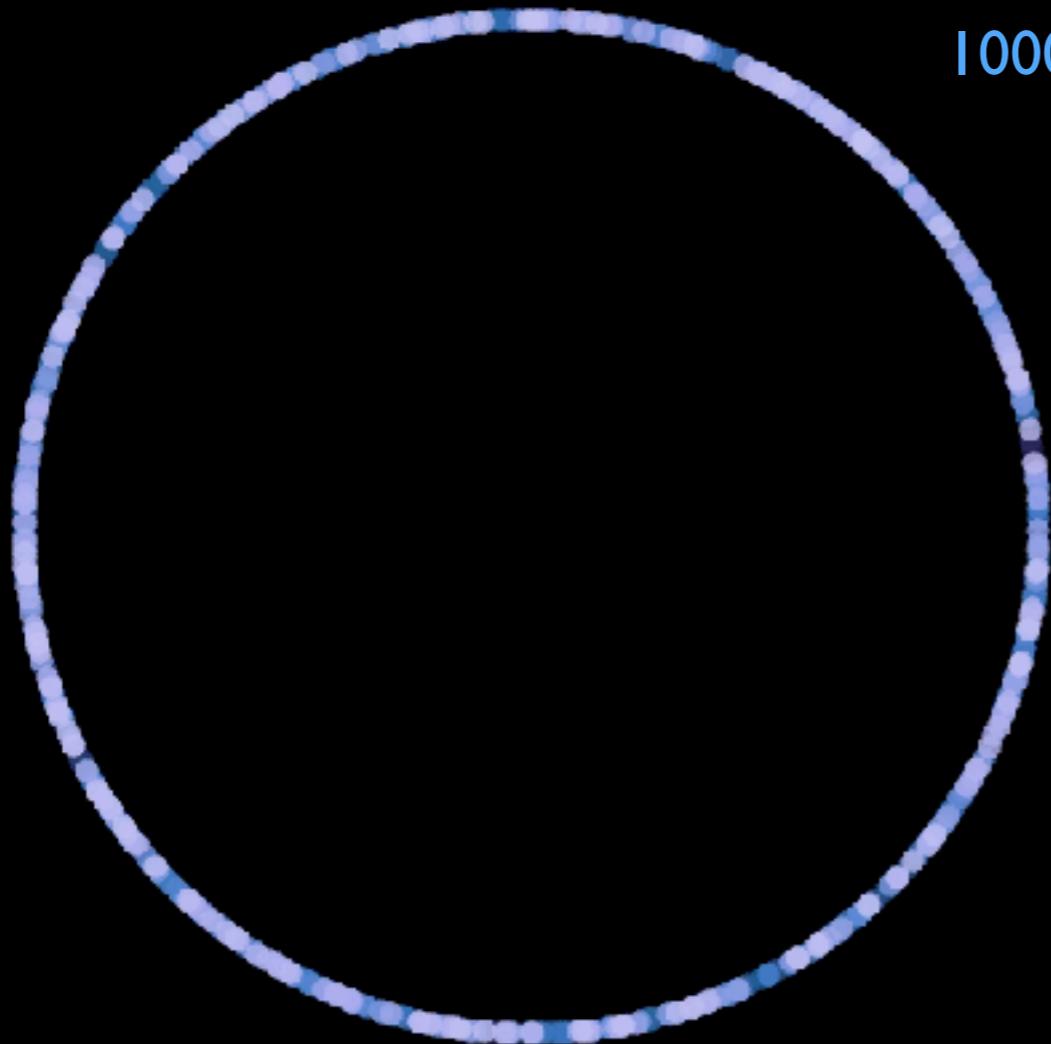


Infinite network
(all-to-all coupled)

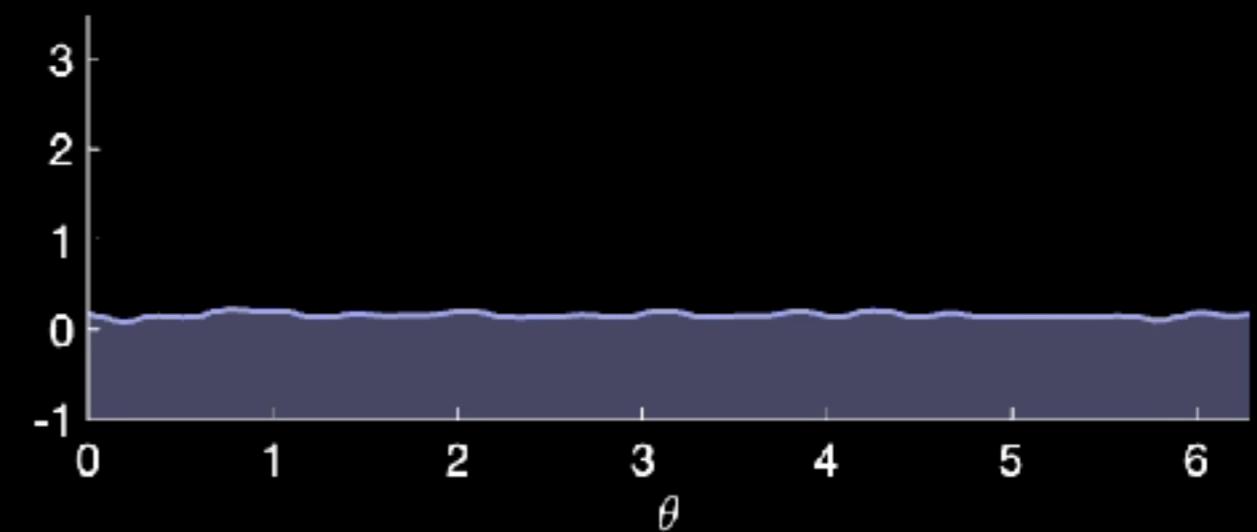
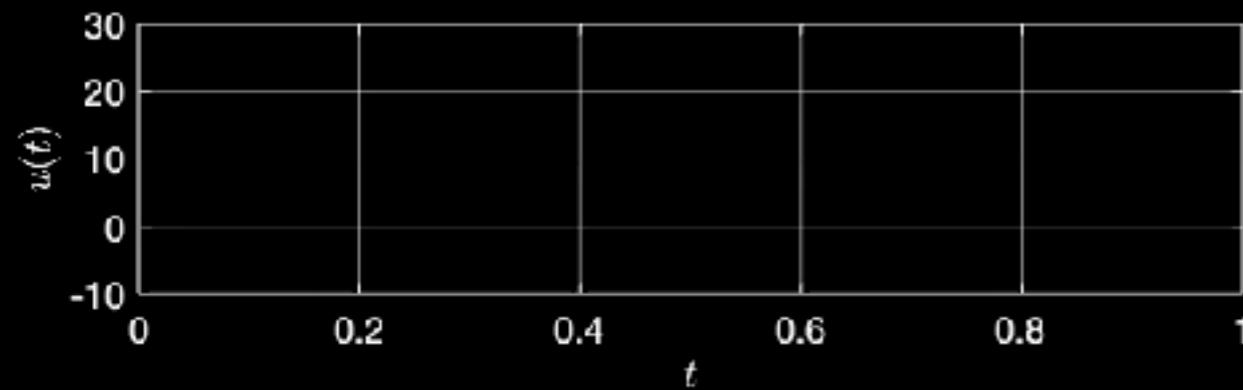
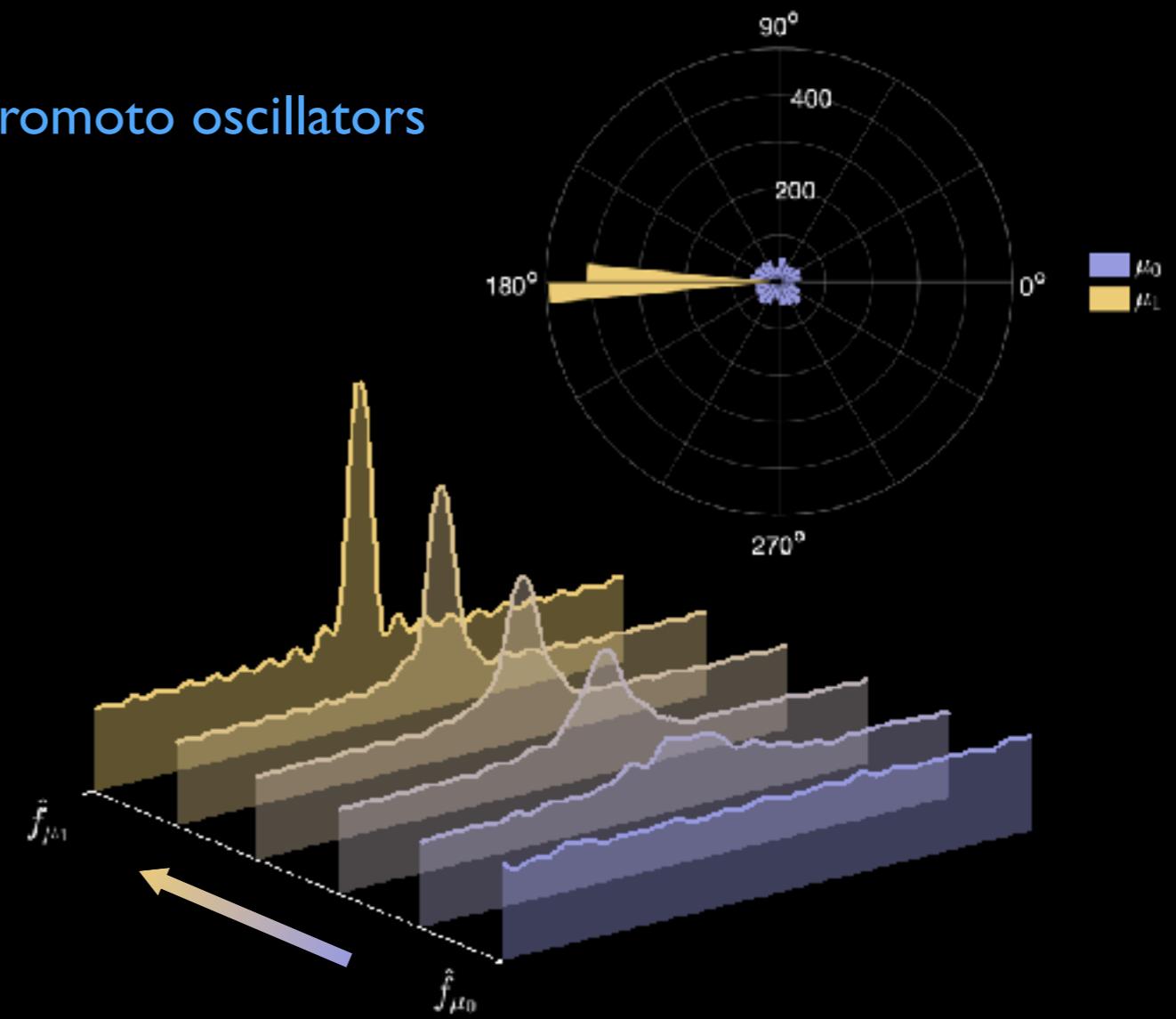


Star network
(truncatable)

Synchronization Pattern Formation



1000 Kuromoto oscillators



Geometry of Distributional Control

► Fibration over distribution space

