Contraction Theory for Optimization, Control, and Neural Networks

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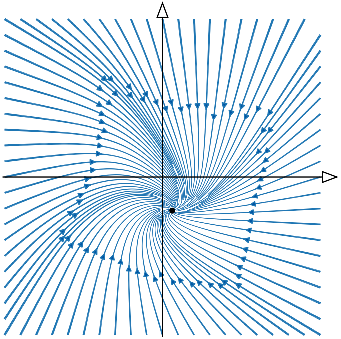
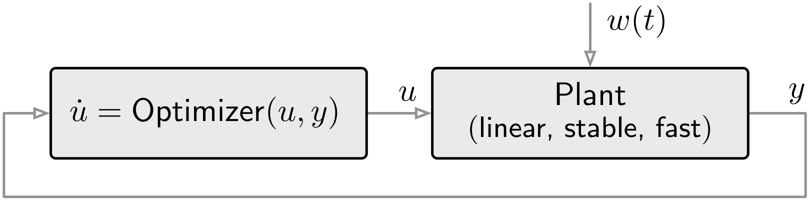
Outline



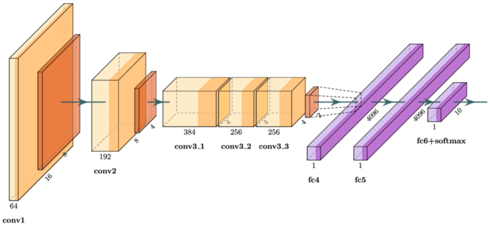
contractivity = robust computationally-friendly stability

fixed point theory + Lyapunov stability theory + geometry of metric spaces

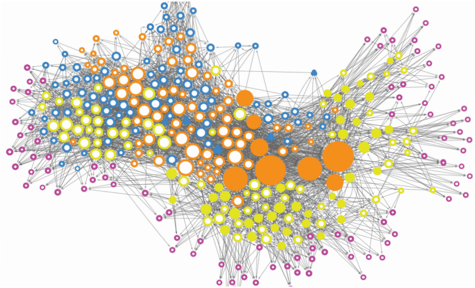


optimization via dynamical systems

online time-varying optimization, optimization-based feedback control, . . .



artificial neural network AlexNet '12



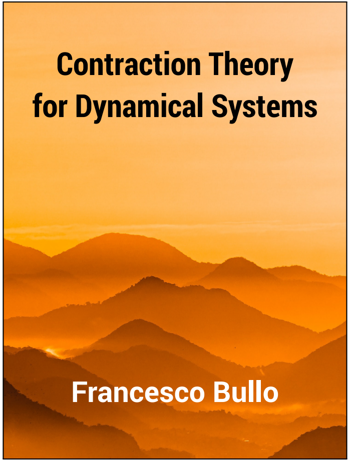
C. elegans connectome '17

recurrent neural networks

well-posedness, stability, computation and input/output robustness

A. Krizhevsky, I. Sutskever, and G. E. Hinton. Imagenet classification with deep convolutional neural networks. *Advances in Neural Information Processing Systems*, 25, 2012
G. Yan, P. E. Vértes, E. K. Towlson, Y. L. Chew, D. S. Walker, W. R. Schafer, and A.-L. Barabási. Network control principles predict neuron function in the Caenorhabditis elegans connectome. *Nature*, 550(7677):519–523, 2017.

Ongoing education and research on Contraction Theory



"Continuous improvement is better than delayed perfection"
Mark Twain

- Textbook: Contraction Theory for Dynamical Systems, Francesco Bullo, rev 1.1, Mar 2023. (Book and slides freely available) **https://fbullo.github.io/ctds**
- 2023 Comprehensive tutorial slides: **https://fbullo.github.io/ctds**
- 2023 Sep: Youtube lectures: "Minicourse on Contraction Theory" **https://youtu.be/FQV5PrRHks8** 12h in 6 lectures
- 2024 CDC Workshop "Contraction Theory for Systems, Control, Optimization, and Learning" (under review)

Outline

§1. A story in three chapters

§2. Chapter #1: Contraction theory

- Basic notions on finite-dimensional vector spaces
- Examples: gradient systems and relationship with convexity
- Selected properties

§3. Chapter #2: Optimization-based control

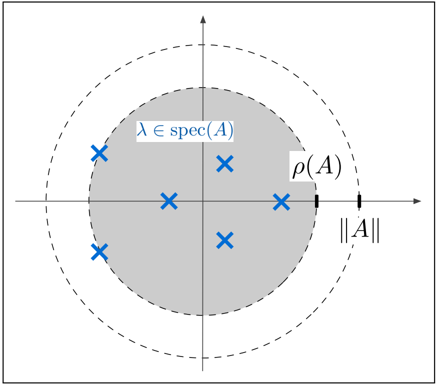
- Equilibrium tracking
- Gradient controller

§4. Chapter #3: Artificial and biological neural networks

- Implicit and reservoir computing models in ML
- Functionality and analysis of biological networks

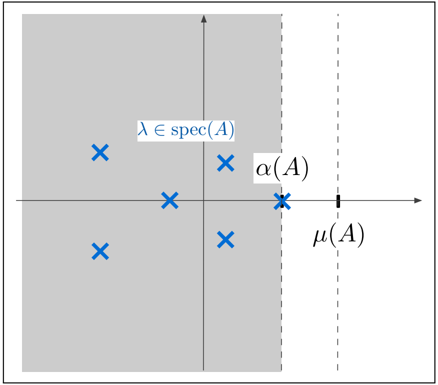
§5. Conclusions

given $n \times n$ matrix A with spectrum $\mathrm{spec}(A)$



$$\rho(A) \le \|A\|$$

discrete-time dynamics



$$\alpha(A) \le \mu(A) \le \|A\|$$

continuous-time dynamics

Continuous-time dynamics and one-sided Lipschitz constants

$$\dot{x} = \mathsf{F}(x) \qquad \text{on } \mathbb{R}^n \text{ with norm } \|\cdot\| \text{ and induced log norm } \mu(\cdot)$$

One-sided Lipschitz constant **($\approx$ maximum expansion rate)**

$$\mathsf{osLip}(\mathsf{F}) = \sup_x \mu(D\mathsf{F}(x))$$

For **scalar map** f, $\mathsf{osLip}(f) = \sup_x f'(x)$

Continuous-time dynamics and one-sided Lipschitz constants

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$$\mathsf{osLip}(\mathsf{F}) = \sup_x \mu(D\mathsf{F}(x))$$

For **scalar map** f, $\mathsf{osLip}(f) = \sup_x f'(x)$

For **affine map** $\mathsf{F}_A(x) = Ax + a$

$$\mathsf{osLip}_{2,P}(\mathsf{F}_A) = \mu_{2,P}(A) \leq \ell \qquad \iff \qquad A^\top P + AP \preceq 2\ell P$$

$$\mathsf{osLip}_{\infty,\eta}(\mathsf{F}_A) = \mu_{\infty,\eta}(A) \leq \ell \qquad \iff \qquad a_{ii} + \sum_{j \neq i} |a_{ij}|\eta_i/\eta_j \leq \ell$$

Banach contraction theorem for continuous-time dynamics:

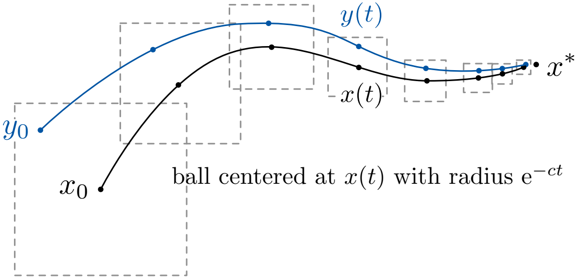
If $-c := \text{osLip}(\mathsf{F}) < 0$, then

1. F is **infinitesimally contracting:** $\|x(t) - y(t)\| \leq \mathrm{e}^{-ct}\|x_0 - y_0\|$

Banach contraction theorem for continuous-time dynamics:

If $-c := \text{osLip}(\mathsf{F}) < 0$, then

1. F is **infinitesimally contracting:** $\|x(t) - y(t)\| \;\leq\; \mathrm{e}^{-ct}\|x_0 - y_0\|$
2. F has a unique, glob exp stable equilibrium x^*
3. global Lyapunov functions $V_1(x) = \|x - x^*\|^2$ and $V_2(x) = \|\mathsf{F}(x)\|^2$



Property #1: Incremental ISS Theorem. Consider

$$\dot{x} = \mathsf{F}(x, \theta(t))$$

- **contractivity wrt x:** $\mathrm{osLip}_x(\mathsf{F}) \leq -c < 0$, uniformly in θ
- **Lipschitz wrt θ:** $\mathrm{Lip}_\theta(\mathsf{F}) \leq \ell$, uniformly in x

Property #1: Incremental ISS Theorem. Consider

$$\dot{x} = \mathsf{F}(x, \theta(t))$$

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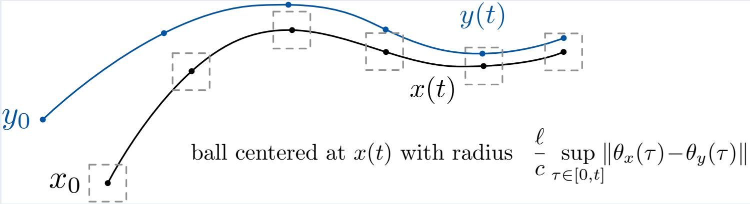
Then **incrementally ISS property**:

$$\|x(t) - y(t)\| \;\leq\; e^{-ct}\|x_0 - y_0\| \;+\; \frac{\ell}{c}(1 - e^{-ct}) \sup_\tau \|\theta_x(\tau) - \theta_y(\tau)\|$$



Example contracting systems

1. *gradient descent flows* under strong convexity assumptions
(primal-dual, distributed, saddle, pseudo, proximal, etc)

2. *neural network dynamics* under assumptions on synaptic matrix
(recurrent, implicit, reservoir computing, etc)

Example contracting systems

1. *gradient descent flows* under strong convexity assumptions
   (primal-dual, distributed, saddle, pseudo, proximal, etc)
2. *neural network dynamics* under assumptions on synaptic matrix
   (recurrent, implicit, reservoir computing, etc)

3. incremental ISS systems
4. Lur'e-type systems under LMI conditions
5. feedback linearizable systems with stabilizing controllers
6. data-driven learned models
7. nonlinear systems with a locally exponentially stable equilibrium
   are contracting with respect to appropriate Riemannian metric

Example #1: Gradient dynamics for strongly convex function

Given differentiable, strongly convex $f : \mathbb{R}^n \to \mathbb{R}$ with parameter $\nu > 0$, **gradient dynamics**

$$\dot{x} = \mathsf{F}_{\mathsf{G}}(x) := -\nabla f(x)$$

F_{G} is infinitesimally contracting wrt $\|\cdot\|_2$ with rate ν

unique globally exp stable point is global minimum

Property #2: Kachurovskii's Theorem: For differentiable $f : \mathbb{R}^n \to \mathbb{R}$, equivalent statements:

1. f is **strongly convex** with parameter ν (and minimum x^*)
2. $-\nabla f$ is ν-**strongly infinitesimally contracting** (with equilibrium x^*)

Property #2: Kachurovskii's Theorem: For differentiable $f : \mathbb{R}^n \to \mathbb{R}$, equivalent statements:

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Property #3: Euler Discretization Theorem for Contracting Dynamics

Given arbitrary norm $\|\cdot\|$ and differentiable $\mathsf{F} : \mathbb{R}^n \to \mathbb{R}^n$, equivalent statements

1. $\dot{x} = \mathsf{F}(x)$ is infinitesimally contracting
2. there exists $\alpha > 0$ such that $x_{k+1} = x_k + \alpha \mathsf{F}(x_k)$ is contracting

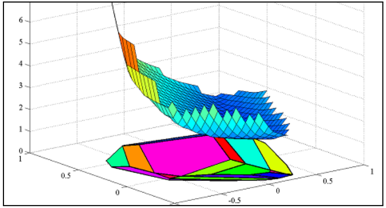
R. I. Kachurovskii. Monotone operators and convex functionals. *Uspekhi Matematicheskikh Nauk*, 15(4):213–215, 1960

S. Jafarpour, A. Davydov, A. V. Proskurnikov, and F. Bullo. Robust implicit networks via non-Euclidean contractions. In *Advances in Neural Information Processing Systems*, Dec. 2021.

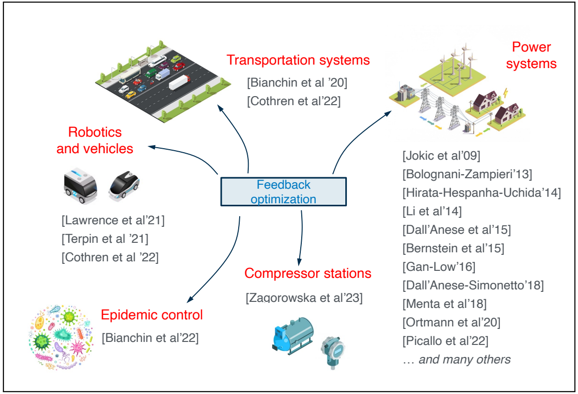
Outline

Motivation: Optimization-based control

1. parametric optimization
2. **online feedback optimization**
3. model predictive control
4. control barrier functions
5. …



parametric QP. YALMIP + Multi-Parametric Toolbox



Online feedback optimization. Courtesy of Emiliano Dall'Anese.

Parametric and time-varying convex optimization

$$\min \mathcal{E}(x) \quad \Longleftrightarrow \quad \dot{x} = \mathsf{F}(x) \qquad \rightsquigarrow \quad x^*$$

Parametric and time-varying convex optimization

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Parametric and time-varying convex optimization

1. **parametric contracting dynamics for parametric convex optimization**

$$\min \mathcal{E}(x, \theta) \quad \Longleftrightarrow \quad \dot{x} = \mathsf{F}(x, \theta) \qquad \rightsquigarrow \quad x^*(\theta)$$

2. **contracting dynamics for time-varying strongly-convex optimization**

$$\min \mathcal{E}\big(x, \theta(t)\big) \quad \Longleftrightarrow \quad \dot{x} = \mathsf{F}\big(x, \theta(t)\big) \qquad \rightsquigarrow \quad x^*\big(\theta(t)\big)$$

A. Davydov, V. Centorrino, A. Gokhale, G. Russo, and F. Bullo. Contracting dynamics for time-varying convex optimization. *IEEE Transactions on Automatic Control*, June 2023a. doi. Submitted

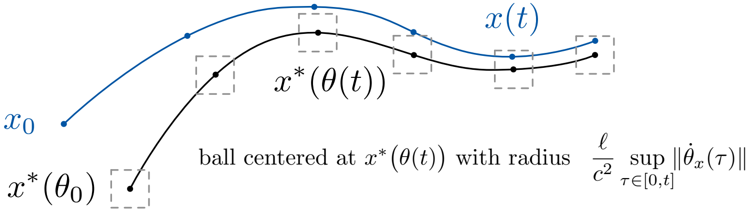
Property #4: Equilibrium Tracking Theorem. Consider

$$\dot{x} = \mathsf{F}(x, \theta(t))$$

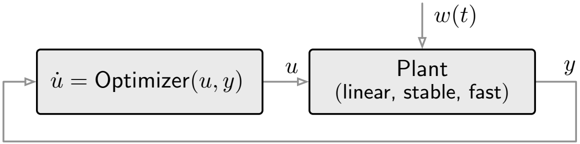
- **contractivity wrt x**: $\mathrm{osLip}_x(\mathsf{F}) \leq -c < 0$, uniformly in θ
- **Lipschitz wrt θ**: $\mathrm{Lip}_\theta(\mathsf{F}) \leq \ell$, uniformly in x

Then **equilibrium tracking property**:

$$\|x(t) - x^\star(\theta(t))\| \leq e^{-ct}\|x_0 - x^\star(\theta_0)\| + \frac{\ell}{c^2}(1 - e^{-ct}) \sup_{\tau \in [0,t]} \|\dot{\theta}(\tau)\|$$



Application: Online feedback optimization



$$\begin{cases} \min & \text{cost}_1(u) + \text{cost}_2(y) \\ \text{subj. to} & y = \text{Plant}\big(u, w(t)\big) \end{cases} \implies \begin{cases} \dot{u} = \text{Optimizer}(u, y) \\ y = \text{Plant}\big(u, w(t)\big) \end{cases}$$

Example #2: Gradient controller

Online feedback optimization

$$\begin{aligned} u^*\big(w(t)\big) \quad &:= \quad \underset{u}{\operatorname{argmin}} \quad \phi(u) + \psi(y(t)) \qquad\qquad (\nu\text{-strongly convex } \phi, \text{ convex } \psi) \\ &\quad\;\; \text{subj to} \quad y(t) = Y_u u + Y_w w(t) \end{aligned}$$

gradient controller

$$\dot{u} = \mathsf{F}_{\mathsf{GradCtrl}}(u, w) \;\; := \;\; -\nabla_u \mathcal{E}(u, w) = -\nabla\phi(u) - Y_u^\top \nabla\psi(Y_u u + Y_w w)$$

Example #2: Gradient controller

Online feedback optimization

$$u^*\big(w(t)\big) \;:=\; \underset{u}{\operatorname{argmin}} \;\; \phi(u) + \psi(y(t)) \qquad (\nu\text{-strongly convex } \phi, \text{ convex } \psi)$$

$$\text{subj to} \;\; y(t) = Y_u u + Y_w w(t)$$

gradient controller

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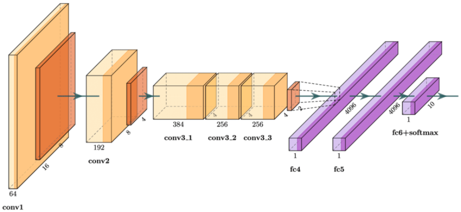
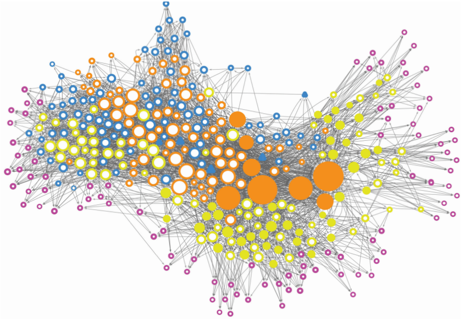
Equilibrium tracking for the gradient controller

$$\limsup_{t\to\infty} \|u(t) - u^*\big(w(t)\big)\| \;\leq\; \frac{\ell_w}{\nu^2} \limsup_{t\to\infty} \|\dot{w}(t)\|$$

Outline

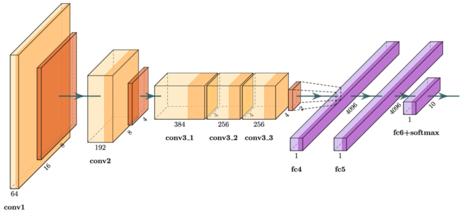


artificial neural network AlexNet ’12



C. elegans connectome ’17

Artificial and biological neural networks



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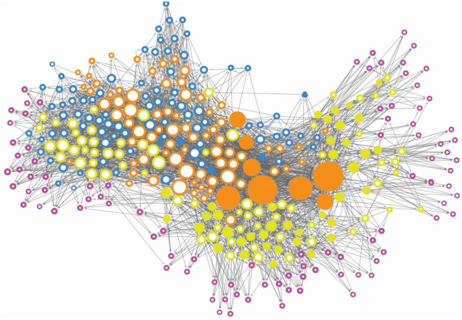


C. elegans connectome '17

Aim: dynamics of neural networks:

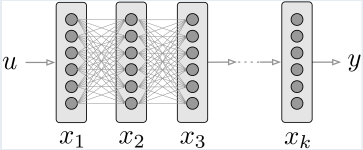
- reproducible and robust behavior in face of uncertain stimuli and dynamics
- functionality: regression, clustering, prediction, dimensionality reduction
- learning models, efficient computational tools, periodic behaviors ...

A. Krizhevsky, I. Sutskever, and G. E. Hinton. Imagenet classification with deep convolutional neural networks. *Advances in Neural Information Processing Systems*, 25, 2012

G. Yan, P. E. Vértes, E. K. Towlson, Y. L. Chew, D. S. Walker, W. R. Schafer, and A.-L. Barabási. Network control principles predict neuron function in the Caenorhabditis elegans connectome. *Nature*, 550(7677):519–523, 2017. doi

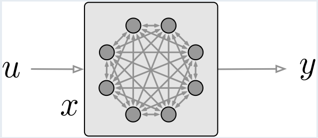
From feedforward to implicit and recurrent models

Feedforward NN



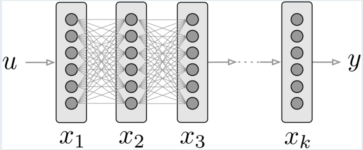
$$x_{i+1} = \Phi(A_i x_i + b_i), \quad x_0 = u,$$
$$y = C x_k + d$$

Implicit/Recurrent NN



$$x = \Phi(Ax + Bu + b),$$
$$y = Cx + d$$

Feedforward NN



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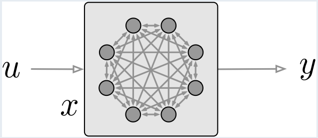
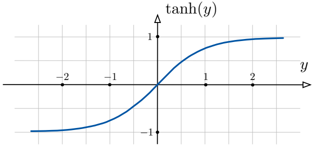
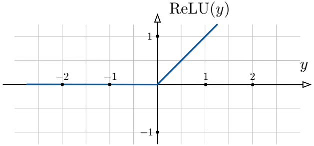


$$x = \Phi(Ax + Bu + b),$$
$$y = Cx + d$$

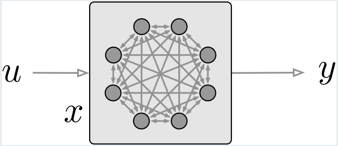
$$\dot{x} = \mathsf{F}_{\mathsf{FR}}(x) := -x + \Phi(Ax + Bu)$$

hyperbolic tangent
ReLU $= (x)_+$
$0 \le \Phi_i'(y) \le 1$





Example #3: Firing-rate networks for implicit ML



$$\dot{x} = -x + \Phi(Ax + Bu + b) \qquad \text{(*recurrent NN*)}$$

$$x = \Phi(Ax + Bu + b) \qquad \text{(*implicit NN*)}$$

$$x_{k+1} = (1-\alpha)x_k + \alpha\Phi(Ax_k + Bu + b) \qquad \text{(*Euler discrt.*)}$$

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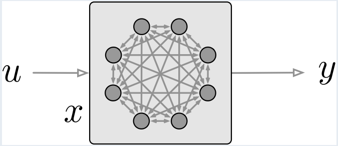

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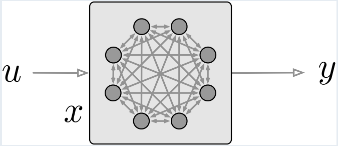
If

$$\mu_\infty(A) < 1 \qquad \Big(\text{i.e., } a_{ii} + \sum_{j\neq i} |a_{ij}| < 1 \text{ for all } i\Big)$$

- **recurrent NN is infinitesimally contracting** with rate $1 - \mu_\infty(A)_+$
- **implicit NN is well posed**
- **Euler discretization is contracting** at $\alpha^* = (1 - \min_i(a_{ii})_-)^{-1}$

Example #3: Firing-rate networks for implicit ML



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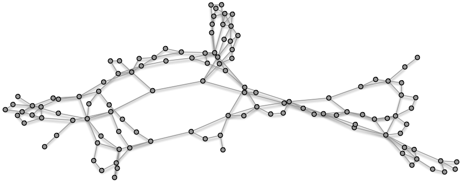
- **implicit NN is well posed**
- **Euler discretization is contracting** at $\alpha^* = (1 - \min_i(a_{ii})_-)^{-1}$

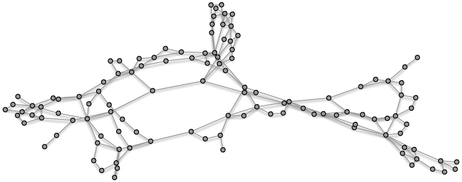
- **input-state Lipschitz constant** $\|B\|_\infty/(1-\mu_\infty(A)_+)$
- **sensitivity to unmodeled dynamics** $\frac{\|\Delta x^*\|_\infty}{\|x^*\|_\infty} \leq \frac{\|\Delta A\|_\infty}{1-\mu_\infty(A)_+}$
- **robustness to signal delays** and more



Property #5: Network Contraction Theorem. Consider interconnected subsystems

$$\dot{x}_i = \mathsf{F}_i(x_i, x_{-i}), \qquad \text{for } i \in \{1, \dots, n\}$$

- **contractivity wrt x_i**: $\mathrm{osLip}_{x_i}(\mathsf{F}_i) \leq -c_i < 0$, uniformly in x_{-i}
- **Lipschitz wrt x_j, $j \neq i$**: $\mathrm{Lip}_{x_j}(\mathsf{F}_i) \leq \ell_{ij}$, uniformly in x_{-j}



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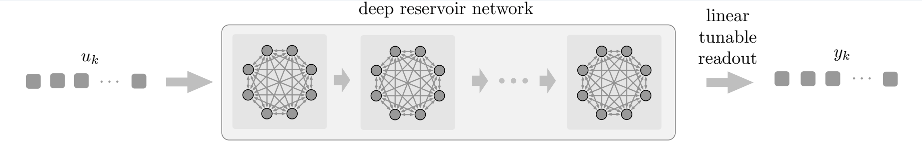
- **Lipschitz wrt x_j, $j \neq i$**: $\text{Lip}_{x_j}(\mathsf{F}_i) \leq \ell_{ij}$, uniformly in x_{-j}
- gain matrix $\begin{bmatrix} -c_1 & \dots & \ell_{1n} \\ \vdots & \ddots & \vdots \\ \ell_{n1} & \dots & -c_n \end{bmatrix}$ is **Hurwitz**

$\implies$ **interconnected system** is contracting with rate $|\alpha(\text{gain matrix})|$

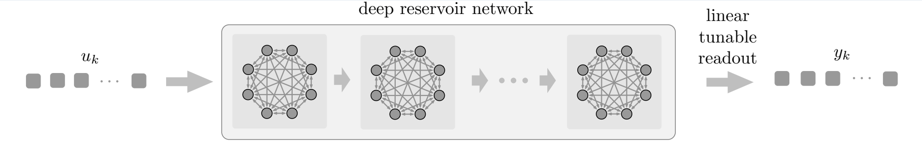
Example #4: Firing-rate networks for ML reservoir computing



$$x_{k+1}^{(1)} = (1-\alpha)x_k^{(1)} + \alpha\Phi\big(A^{(1)}x_k^{(1)} + B^{(1)}u_k + b^{(1)}\big)$$
$$x_{k+1}^{(i)} = (1-\alpha)x_k^{(i)} + \alpha\Phi\big(A^{(i)}x_k^{(i)} + B^{(i)}x_k^{(i-1)} + b^{(i)}\big)$$

(leaky integrator reservoirs)

Example #4: Firing-rate networks for ML reservoir computing



$$x^{(1)}_{k+1} = (1-\alpha)x^{(1)}_k + \alpha\Phi\big(A^{(1)}x^{(1)}_k + B^{(1)}u_k + b^{(1)}\big)$$
$$x^{(i)}_{k+1} = (1-\alpha)x^{(i)}_k + \alpha\Phi\big(A^{(i)}x^{(i)}_k + B^{(i)}x^{(i-1)}_k + b^{(i)}\big)$$

(leaky integrator reservoirs)

Deep reservoir network is contracting (and "echo state property") if

$\mu_\infty(A^{(i)}) < 1$ for each i and for $\alpha \leq \alpha^{**}$

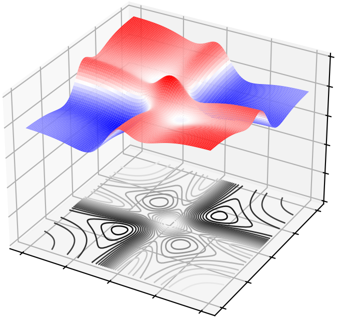
H. Jaeger. The "echo state" approach to analysing and training recurrent neural networks. Technical report, German National Research Center for Information Technology, 2001

Outline

$$\dot{x} = \mathsf{F}_{\mathsf{FR}}(x) := -x + \Phi(Ax + Bu)$$

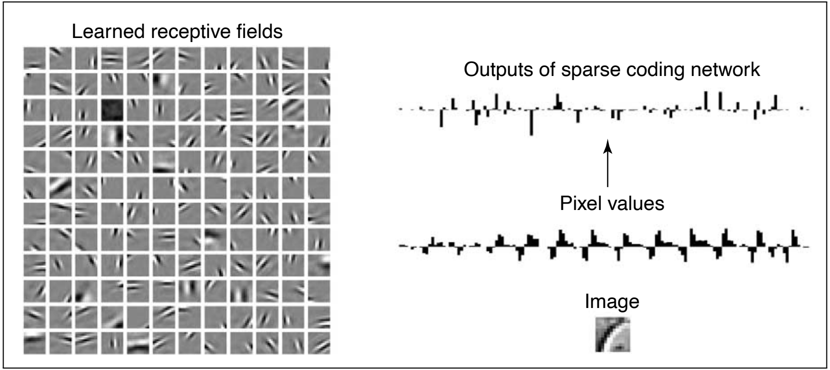
1. What is F_{FR} optimizing?
2. What is its functionality?
3. Is a normative framework for neural circuits?

4. Case study: dimensionality reduction



Energy landscape for associative memory in Hopfield models

Sparse signal reconstruction in biological neuronal circuits



- primary visual area (V1) sparsifies signals
- receptive fields (≈ dictionary) are learned empirically

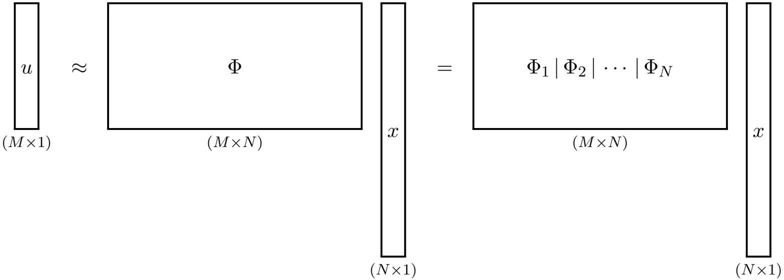
B. A. Olshausen and D. J. Field. Emergence of simple-cell receptive field properties by learning a sparse code for natural images. *Nature*, 381(6583):607–609, 1996.

B. A. Olshausen and D. J. Field. Sparse coding of sensory inputs. *Current Opinion in Neurobiology*, 14(4):481–487, 2004.

Sparse reconstruction by minimizing the lasso energy

$$\min_{x \in \mathbb{R}^N} \quad \mathcal{E}_{\text{lasso}}(x) := \frac{1}{2}\|u - \Phi x\|_2^2 + \lambda \|x\|_1$$

where Φ dictionary matrix, with $\|\Phi_i\| = 1$ and $\Phi_i \cdot \Phi_j$ = similarity between elements



Proximal gradient descent

Minimization of composite cost:

$$\min \quad \underbrace{f(x, u)}_{\text{convex in } x} \quad + \quad \underbrace{g(x)}_{\text{regularizer}}$$

Proximal gradient descent

Minimization of composite cost:

$$\min \quad \underbrace{f(x,u)}_{\text{convex in } x} \quad + \quad \underbrace{g(x)}_{\text{regularizer}}$$

proximal gradient descent:

$$\dot{x} \;=\; -x \;+\; \mathrm{prox}_{\gamma g}\big(x - \gamma \nabla_x f(x,u)\big) \quad =: \quad \mathsf{F}_{\mathsf{ProxG}}(x,u)$$

where **proximal operator** (generalized projection) of convex, closed, proper g is

$$\mathrm{prox}_{\gamma g}(z) \;:=\; \underset{x \in \mathbb{R}^n}{\mathrm{argmin}} \;\; g(x) \;+\; \frac{1}{2\gamma}\|x - z\|_2^2$$

Example #5: Proximal gradient descent

Properties of proximal gradient descent

1. **well-posed Lipschitz**

2. **equivalence:** x^* minimizes $f+g$ $\iff$ $\mathsf{F}_{\mathsf{ProxG}}(x^*) = 0$

3. **decreasing energy:**

   (when bounded) composite cost $f+g$ non-increasing along flow

4. **a recurrent neural network:**

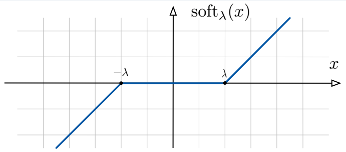
   f quadratic and $g(x) = \sum_{i=1}^{n} g_i(x_i)$ $\implies$ $\mathsf{F}_{\mathsf{ProxG}} = \mathsf{F}_{\mathsf{FR}}$

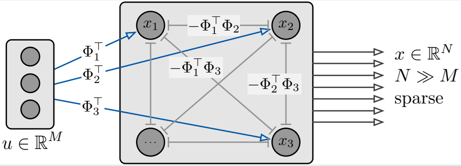
5. **contractivity:**

   $W \prec I_n$ $\implies$ F_{FR} infinitesimally contracting
   $W \preceq I_n$ $\implies$ F_{FR} infinitesimally non-expansive

Example #5: Biologically-plausible circuits for sparse reconstruction

$$\dot{x}(t) = \mathsf{F}_{\mathsf{competitive}}(x, u) := -x + \mathrm{soft}_\lambda\big((I_N - \Phi^\top \Phi)x + \Phi^\top u\big)$$





Example #5: Biologically-plausible circuits for sparse reconstruction

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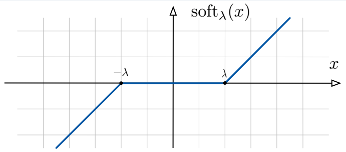

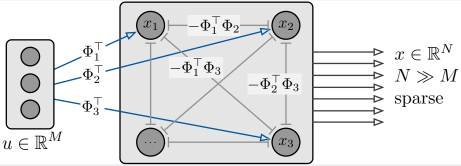

1. $x^\star$ is equilibrium $\iff$ $x^\star$ minimizes $\mathcal{E}_{\text{lasso}}(x)$
2. $\mathcal{E}_{\text{lasso}}$ is convex $\implies$ $\mathsf{F}_{\text{competitive}}$ is weakly contracting
3. Φ satisfies isometry property $\implies$ $x^\star$ is locally exp stable

$\implies$ $x^\star$ is globally linearly-exponentially stable

V. Centorrino, A. Gokhale, A. Davydov, G. Russo, and F. Bullo. Positive competitive networks for sparse reconstruction. *Neural Computation*, Jan. 2024. doi. To appear

Outline

Selected references from my group

Contraction theory:

- A. Davydov, S. Jafarpour, and F. Bullo. Non-Euclidean contraction theory for robust nonlinear stability. *IEEE Transactions on Automatic Control*, 67(12): 6667–6681, 2022a. doi
- S. Jafarpour, A. Davydov, and F. Bullo. Non-Euclidean contraction theory for monotone and positive systems. *IEEE Transactions on Automatic Control*, 68(9):5653–5660, 2023. doi
- L. Cothren, F. Bullo, and E. Dall'Anese. Singular perturbation via contraction theory. *IEEE Transactions on Automatic Control*, Oct. 2023. doi. Submitted

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- A. Davydov, A. V. Proskurnikov, and F. Bullo. Non-Euclidean contractivity of recurrent neural networks. In *American Control Conference*, pages 1527–1534, Atlanta, USA, May 2022b. doi
- V. Centorrino, A. Gokhale, A. Davydov, G. Russo, and F. Bullo. Euclidean contractivity of neural networks with symmetric weights. *IEEE Control Systems Letters*, 7:1724–1729, 2023. doi
- V. Centorrino, A. Gokhale, A. Davydov, G. Russo, and F. Bullo. Positive competitive networks for sparse reconstruction. *Neural Computation*, Jan. 2024. doi. To appear

Weak and semicontraction theory:

- S. Jafarpour, P. Cisneros-Velarde, and F. Bullo. Weak and semi-contraction for network systems and diffusively-coupled oscillators. *IEEE Transactions on Automatic Control*, 67(3):1285–1300, 2022. doi
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- A. Davydov, V. Centorrino, A. Gokhale, G. Russo, and F. Bullo. Contracting dynamics for time-varying convex optimization. *IEEE Transactions on Automatic Control*, June 2023a. doi. Submitted
- A. Gokhale, A. Davydov, and F. Bullo. Contractivity of distributed optimization and Nash seeking dynamics. *IEEE Control Systems Letters*, 7:3896–3901, 2023. doi

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W. Lohmiller and J.-J. E. Slotine. On contraction analysis for non-linear systems. *Automatica*, 34(6):683–696, 1998.

Parametric optimization:

F. Borrelli, A. Bemporad, and M. Morari. *Predictive Control for Linear and Hybrid Systems*. Cambridge University Press, 2017. ISBN 1107016886

Gradient controllers:

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Implicit neural networks:

L. El Ghaoui, F. Gu, B. Travacca, A. Askari, and A. Tsai. Implicit deep learning. *SIAM Journal on Mathematics of Data Science*, 3(3):930–958, 2021.

Deep reservoir computing:

C. Gallicchio, A. Micheli, and L. Pedrelli. Deep reservoir computing: A critical experimental analysis. *Neurocomputing*, 268:87–99, 2017.

Proximal gradient descent:

S. Hassan-Moghaddam and M. R. Jovanović. Proximal gradient flow and Douglas-Rachford splitting dynamics: Global exponential stability via integral quadratic constraints. *Automatica*, 123:109311, 2021.

Competitive neural networks for sparse reconstruction:

C. J. Rozell, D. H. Johnson, R. G. Baraniuk, and B. A. Olshausen. Sparse coding via thresholding and local competition in neural circuits. *Neural Computation*, 20(10):2526–2563, 2008.

contractivity = robust computationally-friendly stability
fixed point theory + Lyapunov stability theory + geometry of metric spaces

- theory (basic defs + 5 properties)
- examples (5 examples)
- applications to control, ML and neuroscience

Ongoing work

1. optimization-based control designs:
   model predictive control, control barrier functions, low-gain integral control
2. ML and biologically-inspired neural networks

search for contraction properties
design engineering systems to be contracting
verify correct/safe behavior via known Lipschitz constants

Supplementary Slides

Example #6: Primal-dual gradient dynamics

strongly convex function f s.t. $0 \prec \nu_{\mathsf{min}} I_n \preceq \mathrm{Hess}\, f \preceq \nu_{\mathsf{max}} I_n$

constraint matrix A s.t. $0 \prec a_{\mathsf{min}} I_m \preceq AA^\top \preceq a_{\mathsf{max}} I_m$ (independent rows)

linearly constrained optimization:

$$\begin{aligned} \min_{x \in \mathbb{R}^n} \quad & f(x) \\ \text{subj. to} \quad & Ax = b \end{aligned}$$

primal-dual gradient dynamics:

$$\begin{bmatrix} \dot{x} \\ \dot{\lambda} \end{bmatrix} = \mathsf{F}_{\mathsf{PDG}}(x, \lambda) := \begin{bmatrix} -\nabla f(x) - A^\top \lambda \\ Ax - b \end{bmatrix}$$

Example #6: Primal-dual gradient dynamics

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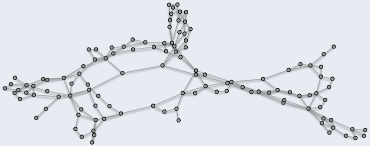
F_{PDG} is infinitesimally contracting wrt $\|\cdot\|_{2,P^{1/2}}$ with rate c

$$P = \begin{bmatrix} I_n & \alpha A^\top \\ \alpha A & I_m \end{bmatrix} \text{ with } \alpha = \frac{1}{2} \min\left\{\frac{1}{\nu_{\text{max}}}, \frac{\nu_{\text{min}}}{a_{\text{max}}}\right\} \quad \text{and} \quad c = \frac{1}{4} \min\left\{\frac{a_{\text{min}}}{\nu_{\text{max}}}, \frac{a_{\text{min}}}{a_{\text{max}}} \nu_{\text{min}}\right\}$$

A. Gokhale, A. Davydov, and F. Bullo. Contractivity of distributed optimization and Nash seeking dynamics. *IEEE Control Systems Letters*, 7:3896–3901, 2023.

Example #7: Distributed gradient dynamics



decomposable cost: $\min_{x\in\mathbb{R}} \sum_{i=1}^{n} f_i(x)$ where each f_i is ν_i-strongly convex

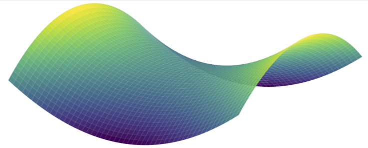
$$\begin{cases} \min_{x_{[i]}\in\mathbb{R}} & \sum_{i=1}^{n} f_i(x_{[i]}) \\ \text{subj. to} & \sum_{j=1}^{n} a_{ij}(x_i - x_j) = 0 \end{cases}$$

Laplacian-based distributed gradient (primal-dual gradient, $2n$ vars):

$$\begin{cases} \dot{x}_{[i]} = -\nabla f_i(x_{[i]}) - \sum_{j=1}^{n} a_{ij}(\lambda_i - \lambda_j) & \text{for each node } i \\ \dot{\lambda}_i = \sum_{j=1}^{n} a_{ij}(x_i - x_j) & \text{for each node } i \end{cases}$$

$\mathsf{F}_{\textbf{Laplacian-DistributedG}}$ **is infinitesimally contracting**† **with** $c = \dfrac{1}{4}\left(\dfrac{\lambda_2}{\lambda_n}\right)^2 \min_i \nu_i$

Example #8: Saddle dynamics



Assume $f : \mathbb{R}^n \times \mathbb{R}^m \to \mathbb{R}$

- $x \mapsto f(x, y)$ is ν_x-strongly convex, uniformly in y
- $y \mapsto f(x, y)$ is ν_y-strongly concave, uniformly in x

saddle dynamics (primal-descent / dual-ascent):

$$\begin{bmatrix} \dot{x} \\ \dot{y} \end{bmatrix} = \mathsf{F}_{\mathsf{S}}(x, y) := \begin{bmatrix} -\nabla_x f(x, y) \\ \nabla_y f(x, y) \end{bmatrix}$$

F_{S} is infinitesimally contracting wrt $\|\cdot\|_2$ with rate $\min\{\nu_x, \nu_y\}$

unique globally exp stable point is saddle point (min in x, max in y)

Example #9: Pseudogradient and best response play

Each player i aims to minimize its own cost function $J_i(x_i, x_{-i})$ (not a potential game)

pseudogradient dynamics (aka gradient play in game theory) $\mathsf{F}_{\mathbf{PseudoG}}$**:**

$$\dot{x}_i = -\nabla_i J_i(x_i, x_{-i})$$

- **strong convexity wrt x_i:** J_i is μ_i strongly convex wrt x_i, uniformly in x_{-i}
- **Lipschitz wrt x_{-i}:** $\mathrm{Lip}_{x_j}(\nabla_i J_i) \leq \ell_{ij}$, uniformly in x_{-j}
- $\mathsf{F}_{\mathsf{PseudoG}}$ gain matrix is Hurwitz

$\implies$ $\mathsf{F}_{\mathbf{PseudoG}}$ **is infinitesimally contracting wrt appropriate diag-weighted** $\|\cdot\|_2$

Example #10: Best response play

Each player i aims to minimize its own cost function $J_i(x_i, x_{-i})$
$\mathsf{BR}_i : x_{-i} \to \operatorname{argmin}_{x_i} J_i(x_i, x_{-i})$ best response of player i wrt other decisions x_{-i}
best response dynamics:

$$\dot{x} = \mathsf{F}_{\mathsf{BR}}(x) := \mathsf{BR}(x) - x$$
$$\iff \quad \dot{x}_i = \mathsf{BR}_i(x_{-i}) - x_i$$

- **strong convexity wrt x_i:** J_i is μ_i strongly convex wrt x_i, uniformly in x_{-i}
- **Lipschitz wrt x_{-i}:** $\mathsf{Lip}_{x_j}(\nabla_i J_i) \le \ell_{ij}$, uniformly in x_{-j}
  $\implies$ BR_i **is Lipschitz wrt x_j with constant ℓ_{ij}/μ_i**
- F_{BR} gain matrix is Hurwitz $\iff$ BR is a discrete-time contraction

  $\implies$ $\mathsf{BR} - \mathsf{Id}$ **is infinitesimally contracting wrt appropriate diag-weighted $\|\cdot\|_2$**

Equivalent statements:

1. F_{PseudoG} gain matrix: $\begin{bmatrix} -\mu_1 & \dots & \ell_{1n} \\ \vdots & & \vdots \\ \ell_{n1} & \dots & -\mu_n \end{bmatrix}$ is Hurwitz
2. F_{BR} gain matrix: $\begin{bmatrix} -1 & \dots & \ell_{1n}/\mu_1 \\ \vdots & & \vdots \\ \ell_{n1}/\mu_n & \dots & -1 \end{bmatrix}$ is Hurwitz
3. discrete-time F_{BR} gain matrix: $\begin{bmatrix} 0 & \dots & \ell_{1n}/\mu_1 \\ \vdots & & \vdots \\ \ell_{n1}/\mu_n & \dots & 0 \end{bmatrix}$ is Schur

Aggregative games: $J_i(x_i, x_{-i}) = f_i\big(x_i, \frac{1}{n}\sum_{j=1}^n x_j\big)$
assume f_i is μ_i-strongly convex wrt x_i and $\ell_i = \text{Lip}_y(\nabla_{x_i} f_i(x_i, y))$

$\mu_i > \ell_i$ for each agent i $\implies$ gain matrix is Hurwitz

A. Gokhale, A. Davydov, and F. Bullo. Contractivity of distributed optimization and Nash seeking dynamics. *IEEE Control Systems Letters*, 7:3896–3901, 2023. doi

Example #11: Projected gradient controller

Constrained feedback optimization:

$$\min_u \quad \mathcal{E}(u,w) = \phi(u) + \psi(Y_u u + Y_w w) \qquad (\nu \text{ strongly convex, } \ell_u \text{ strongly smooth, } \ell_w)$$

$$\text{subj. to} \quad u \in \mathcal{U} \qquad (\text{nonempty, closed, convex. } P_{\mathcal{U}} = \text{orthogonal projection})$$

Projected gradient controller

$$\dot{u} = \mathsf{F}_{\mathsf{PGC}}(u,w) \;:= -u + \; P_{\mathcal{U}}\big(u - \gamma \nabla_u \mathcal{E}(u,w)\big)$$

Equilibrium tracking for projected gradient controller At $\gamma = \frac{2}{\nu+\ell_u}$,

$$\limsup_{t\to\infty} \|u(t) - u^*(t)\| \quad \leq \quad \frac{\ell_{\mathsf{PGC}}}{c^2_{\mathsf{PGC}}} \limsup_{t\to\infty} \|\dot{w}(t)\| \qquad \text{(eq tracking)}$$

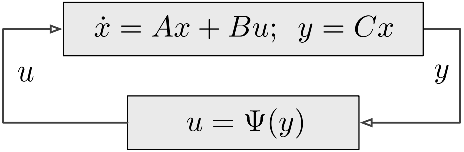
1. $\mathrm{osLip}_u(\mathsf{F}_{\mathsf{PGC}}) \leq -c_{\mathsf{PGC}} := -\dfrac{2\nu}{\nu + \ell_u}$ (contractivity prox gradient)
2. $\mathrm{Lip}_w(\mathsf{F}_{\mathsf{PGC}}) = \ell_{\mathsf{PGC}} := \dfrac{2}{\nu + \ell_u}\ell_w$

Advantages of non-Euclidean approaches

1. *well suited for certain class of systems*
   ℓ_1 for monotone flow systems
2. *computational advantages*
   ℓ_1/ℓ_∞ constraints lead to LPs, whereas ℓ_2 constraints leads to LMIs
3. *robustness to structural perturbations*
   ℓ_1/ℓ_∞ contractions are connectively robust (i.e., edge removal)
4. *adversarial input-output analysis*
   ℓ_∞ better suited for the analysis of adversarial examples than ℓ_2
5. *asynchronous distributed computation*
   ℓ_∞ contractions converge under fully asynchronous distributed execution

NonEuclidean contractions: biological transcriptional systems (Russo, Di Bernardo, and Sontag, 2010), Hopfield neural networks (Fang and Kincaid, 1996; Qiao, Peng, and Xu, 2001), chemical reaction networks (Al-Radhawi, Angeli, and Sontag, 2020), traffic networks (Coogan and Arcak, 2015; Como, Lovisari, and Savla, 2015; Coogan, 2019), multi-vehicle systems (Monteil, Russo, and Shorten, 2019), and coupled oscillators (Russo, Di Bernardo, and Sontag, 2013; Aminzare and Sontag, 2014)

Example #12: Systems in Lur'e form



For $A \in \mathbb{R}^{n\times n}$, $B \in \mathbb{R}^{m\times n}$ and $C \in \mathbb{R}^{n\times m}$, **nonlinear system in Lur'e form**

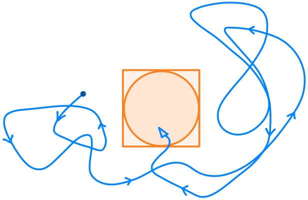
$$\dot{x} = Ax + B\Psi(Cx) \quad =: \mathsf{F}_{\text{Lur'e}}(x)$$

where $\Psi : \mathbb{R}^m \to \mathbb{R}^m$ is ρ-*cocoercive*, i.e., for all $y_1, y_2 \in \mathbb{R}^m$,

$$(\varphi(y_1) - \varphi(y_2))^\top (y_1 - y_2) \geq \rho \|\varphi(y_1) - \varphi(y_2)\|_2^2.$$

For $P = P^\top \succ 0$, following statements are equivalent:

1. $\mathsf{F}_{\text{Lur'e}}$ infinitesimally contracting wrt $\|\cdot\|_{2,P^{1/2}}$ with rate $\eta > 0$ for each ρ-cocoercive Ψ
2. there exists $\lambda \geq 0$ such that $\begin{bmatrix} A^\top P + PA + 2\eta P & PB + \lambda C^\top \\ B^\top P + \lambda C & -2\lambda\rho^{-1} I_m \end{bmatrix} \preceq 0$



Aim: **compute settling time inside a desired set**

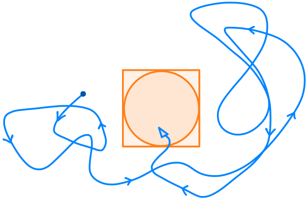
- since norms on $\mathbb{R}^n$ are equivalent, no formal difference in the choice of norm
- assume: can tolerate ± 1 error in each coordinate

  $\implies$ desired set is hypercube $= \ell_\infty$-ball
- assume: Lyapunov function is $V(x) = \|x\|_2^2$

  $\implies$ need to wait until solution enters unit ℓ_2-ball $\subset$ unit ℓ_∞-ball

Practical stability problem and the counter-intuitive nature of $\mathbb{R}^n$

Boris Polyak (1935-2023) used to say "$\mathbb{R}^n$ countradicts our intuition"



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- but n-sphere inscribed in n-hypercube is very small fraction!
  as $n \to \infty$, the ratio of volumes decreases faster than any exponential function

for large n, quadratic Lyap fnctns may provide exponentially conservative estimates

Courtesy of Anton Proskurnikov, Politecnico di Torino

$f(\mathbf{x})$	$\mathrm{dom}(f)$	$\mathrm{prox}_f(\mathbf{x})$	Assumptions	Reference
$\frac{1}{2}\mathbf{x}^T\mathbf{A}\mathbf{x} + \mathbf{b}^T\mathbf{x} + c$	$\mathbb{R}^n$	$(\mathbf{A}+\mathbf{I})^{-1}(\mathbf{x}-\mathbf{b})$	$\mathbf{A} \in \mathbb{S}^n_+$, $\mathbf{b} \in \mathbb{R}^n$, $c \in \mathbb{R}$	Section 6.2.3
λx^3	$\mathbb{R}_+$	$\frac{-1+\sqrt{1+12\lambda[x]_+}}{6\lambda}$	$\lambda > 0$	Lemma 6.5
μx	$[0,\alpha] \cap \mathbb{R}$	$\min\{\max\{x-\mu, 0\}, \alpha\}$	$\mu \in \mathbb{R}$, $\alpha \in [0,\infty]$	Example 6.14
$\lambda\Vert\mathbf{x}\Vert$	$\mathbb{E}$	$\left(1 - \frac{\lambda}{\max\{\Vert\mathbf{x}\Vert,\lambda\}}\right)\mathbf{x}$	$\Vert\cdot\Vert$—Euclidean norm, $\lambda > 0$	Example 6.19
$-\lambda\Vert\mathbf{x}\Vert$	$\mathbb{E}$	$\left(1+\frac{\lambda}{\Vert\mathbf{x}\Vert}\right)\mathbf{x}$, $\mathbf{x} \neq \mathbf{0}$, $\{\mathbf{u} : \Vert\mathbf{u}\Vert = \lambda\}$, $\mathbf{x} = \mathbf{0}$.	$\Vert\cdot\Vert$—Euclidean norm, $\lambda > 0$	Example 6.21
$\lambda\Vert\mathbf{x}\Vert_1$	$\mathbb{R}^n$	$\mathcal{T}_\lambda(\mathbf{x}) = [\lvert\mathbf{x}\rvert - \lambda\mathbf{e}]_+ \odot \mathrm{sgn}(\mathbf{x})$	$\lambda > 0$	Example 6.8
$\Vert\boldsymbol{\omega} \odot \mathbf{x}\Vert_1$	$\mathrm{Box}[-\boldsymbol{\alpha}, \boldsymbol{\alpha}]$	$\mathcal{S}_{\boldsymbol{\omega},\boldsymbol{\alpha}}(\mathbf{x})$	$\boldsymbol{\alpha} \in [0,\infty]^n$, $\boldsymbol{\omega} \in \mathbb{R}^n_+$	Example 6.23
$\lambda\Vert\mathbf{x}\Vert_\infty$	$\mathbb{R}^n$	$\mathbf{x} - \lambda P_{B_{\Vert\cdot\Vert_1}[\mathbf{0},1]}(\mathbf{x}/\lambda)$	$\lambda > 0$	Example 6.48
$\lambda\Vert\mathbf{x}\Vert_a$	$\mathbb{E}$	$\mathbf{x} - \lambda P_{B_{\Vert\cdot\Vert_{a,*}}[\mathbf{0},1]}(\mathbf{x}/\lambda)$	$\Vert\mathbf{x}\Vert_a$—arbitrary norm, $\lambda > 0$	Example 6.47
$\lambda\Vert\mathbf{x}\Vert_0$	$\mathbb{R}^n$	$\mathcal{H}_{\sqrt{2\lambda}}(x_1) \times \cdots \times \mathcal{H}_{\sqrt{2\lambda}}(x_n)$	$\lambda > 0$	Example 6.10
$\lambda\Vert\mathbf{x}\Vert^3$	$\mathbb{E}$	$\frac{2}{1+\sqrt{1+12\lambda\Vert\mathbf{x}\Vert}}\mathbf{x}$	$\Vert\cdot\Vert$—Euclidean norm, $\lambda > 0$,	Example 6.20
$-\lambda\sum_{j=1}^n \log x_j$	$\mathbb{R}^n_{++}$	$\left(\frac{x_j+\sqrt{x_j^2+4\lambda}}{2}\right)_{j=1}^n$	$\lambda > 0$	Example 6.9
$\delta_C(\mathbf{x})$	$\mathbb{E}$	$P_C(\mathbf{x})$	$\emptyset \neq C \subseteq \mathbb{E}$	Theorem 6.24
$\lambda\sigma_C(\mathbf{x})$	$\mathbb{E}$	$\mathbf{x} - \lambda P_C(\mathbf{x}/\lambda)$	$\lambda > 0$, $C \neq \emptyset$ closed convex	Theorem 6.46
$\lambda\max\{x_i\}$	$\mathbb{R}^n$	$\mathbf{x} - \lambda P_{\Delta_n}(\mathbf{x}/\lambda)$	$\lambda > 0$	Example 6.49
$\lambda\sum_{i=1}^k x_{[i]}$	$\mathbb{R}^n$	$\mathbf{x} - \lambda P_C(\mathbf{x}/\lambda)$, $C = H_{\mathbf{e},k} \cap \mathrm{Box}[\mathbf{0},\mathbf{e}]$	$\lambda > 0$	Example 6.50
$\lambda\sum_{i=1}^k \lvert x_{\langle i\rangle}\rvert$	$\mathbb{R}^n$	$\mathbf{x} - \lambda P_C(\mathbf{x}/\lambda)$, $C = B_{\Vert\cdot\Vert_1}[\mathbf{0},k] \cap \mathrm{Box}[-\mathbf{e},\mathbf{e}]$	$\lambda > 0$	Example 6.51
$\lambda M_f^\mu(\mathbf{x})$	$\mathbb{E}$	$\mathbf{x} + \frac{\lambda}{\mu+\lambda}\left(\mathrm{prox}_{(\mu+\lambda)f}(\mathbf{x}) - \mathbf{x}\right)$	$\lambda, \mu > 0$, f proper closed convex	Corollary 6.64
$\lambda d_C(\mathbf{x})$	$\mathbb{E}$	$\mathbf{x} + \min\left\{\frac{\lambda}{d_C(\mathbf{x})}, 1\right\}(P_C(\mathbf{x}) - \mathbf{x})$	$\emptyset \neq C$ closed convex, $\lambda > 0$	Lemma 6.43
$\frac{\lambda}{2}d_C^2(\mathbf{x})$	$\mathbb{E}$	$\frac{\lambda}{\lambda+1}P_C(\mathbf{x}) + \frac{1}{\lambda+1}\mathbf{x}$	$\emptyset \neq C$ closed convex, $\lambda > 0$	Example 6.65
$\lambda H_\mu(\mathbf{x})$	$\mathbb{E}$	$\left(1 - \frac{\lambda}{\max\{\Vert\mathbf{x}\Vert,\mu+\lambda\}}\right)\mathbf{x}$	$\lambda, \mu > 0$	Example 6.66
$\rho\Vert\mathbf{x}\Vert_1^2$	$\mathbb{R}^n$	$\left(\frac{v_i x_i}{v_i+2\rho}\right)_{i=1}^n$, $\mathbf{v} = \left[\sqrt{\frac{\rho}{\mu}}\lvert\mathbf{x}\rvert - 2\rho\right]_+$, $\mathbf{e}^T\mathbf{v} = 1$ ($\mathbf{0}$ when $\mathbf{x} = \mathbf{0}$)	$\rho > 0$	Lemma 6.70
$\lambda\Vert\mathbf{A}\mathbf{x}\Vert_2$	$\mathbb{R}^n$	$\mathbf{x} - \mathbf{A}^T(\mathbf{A}\mathbf{A}^T + \alpha^*\mathbf{I})^{-1}\mathbf{A}\mathbf{x}$, $\alpha^* = 0$ if $\Vert\mathbf{v}_0\Vert_2 \leq \lambda$; otherwise, $\Vert\mathbf{v}_{\alpha^*}\Vert_2 = \lambda$; $\mathbf{v}_\alpha \equiv (\mathbf{A}\mathbf{A}^T + \alpha\mathbf{I})^{-1}\mathbf{A}\mathbf{x}$	$\mathbf{A} \in \mathbb{R}^{m\times n}$ with full row rank, $\lambda > 0$	Lemma 6.68

proximal operator

well-defined for all ccp functions,
generalized form of projection,
non-expansive

helps generalize gradient algorithms/dynamics to proximal algorithms/dynamics, useful for nonsmooth, constrained, large-scale, and distributed optimization

evaluation of proximal operator requires small convex optimization,
see Summary of prox computations, Beck 2017

A. Beck. *First-Order Methods in Optimization*. SIAM, 2017. ISBN 978-1-61197-498-0

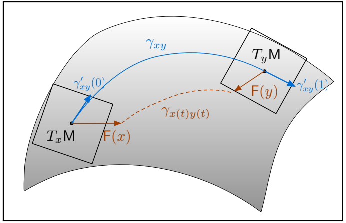
N. Parikh and S. Boyd. Proximal algorithms. *Foundations and Trends in Optimization*, 1(3):127–239, 2014.

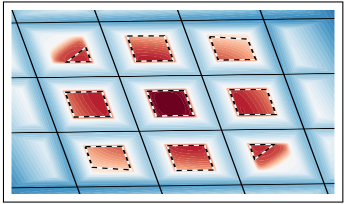
Theoretical frontiers

- higher order contraction and pseudocontration (dominance)
- relationship with monotone operator theory
- metric spaces
- computational methods

Limitations: not all stable systems are contractive:

- Lyapunov-diagonally-stable networks
- multistable and locally contracting systems
- control contraction design





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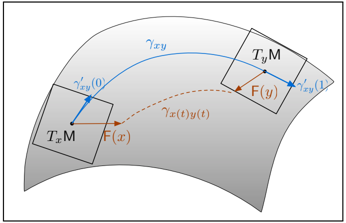

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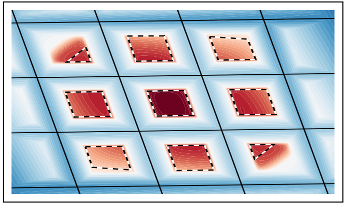
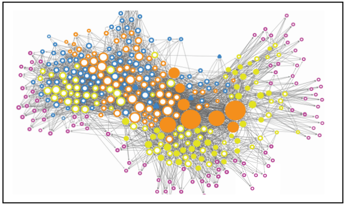


Application to networks, control and learning

1. reaction networks
2. control: optimization-based control design
3. ML: implicit models and energy-based learning
4. neuroscience: robust dynamical modeling, normative frameworks, biologically plausible learning



contractivity = robust computationally-friendly stability

fixed point theory + Lyapunov stability theory + geometry of metric spaces

	Lyapunov Theory	**Contraction Theory for Dynamical Systems**
	F admits global Lyapunov function	F is strongly contracting
existence of equilibrium	assumed	implied + computational methods
Lyapunov function	arbitrary	$\|x - x^*\|$ and $\|\mathsf{F}(x)\|$
inputs	ISS via $\mathcal{KL}$ and $\mathcal{L}$ functions	exponential iISS with explicit constants

	Krasovskiĭ-LaSalle Inv Principle	**Weakly Contracting Systems**
	generic V s.t. $\mathcal{L}_{\mathsf{F}}V \leq 0$	F is weakly contracting, that is, $\mathrm{osLip}(\mathsf{F}) \leq 0$
(no other assumptions)		Dichotomy Theorem
assuming bounded traj.	convergence to Krasovski-LaSalle set	each equilibrium is stable
assuming Krasovski-LaSalle set = $\{x^*\}$ is LAS	$\{x^*\}$ is GAS	$\{x^*\}$ is GAS, linear-exponential convergence, local ISS + explicit constants

Gradient dynamics for convex functions

Given differentiable convex $f : \mathbb{R}^n \to \mathbb{R}$, **gradient dynamics**

$$\dot{x} = \mathsf{F}_{\mathsf{G}}(x) := -\nabla f(x)$$

Dichotomy and Convergence

1. $-\nabla f$ has no equilibrium, f has no minimum, and every trajectory is unbounded, or
2. $-\nabla f$ has at least one equilibrium $x^* \in \mathbb{R}^n$ and the following properties hold:
   1. f is constant on convex set of equilibria, each local is a global minimum,
   2. every trajectory is bounded and converges to a minimum, each equilibrium is stable
   3. if x^* is locally asymptotically stable, then x^* is globally asymptotically stable
   4. if $\mu_2(-\mathrm{Hess}(f)(x^*)) < 0$, then linear exponential decay and $x \mapsto \|x - x^*\|_2$ is a global Lyap

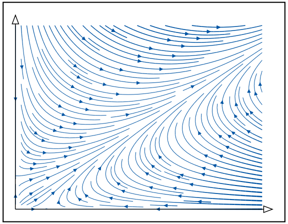
From strongly to weakly contracting systems

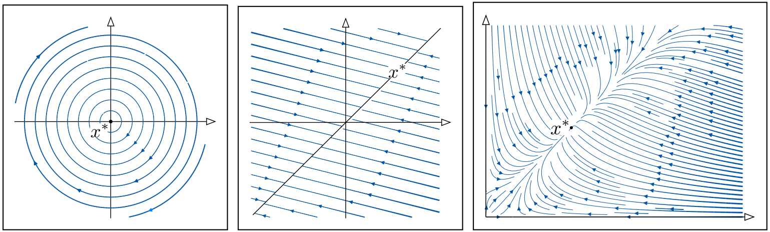
Given a norm $\|\cdot\|$, consider

$$\dot{x} = \mathsf{F}(x) \qquad \text{satisfying} \qquad \mathsf{osLip}(\mathsf{F}) = 0$$

Dichotomy for weakly-contracting systems

1. no equilibrium and every trajectory is unbounded, or
2. at least one equilibrium, every trajectory is bounded, and local asy stability $\implies$ global





Weakly contracting dynamics + locally-exp-stable equilibrium

$$\dot{x} = \mathsf{F}(t, x) \qquad \text{on } \mathbb{R}^n \text{ with norm } \|\cdot\|_{\mathsf{glo}}$$

Weakly contracting dynamics + locally-exp-stable equilibrium

$$\dot{x} = \mathsf{F}(t, x) \qquad \text{on } \mathbb{R}^n \text{ with norm } \|\cdot\|_{\mathsf{glo}}$$

1. F is weakly contracting wrt $\|\cdot\|_{\mathsf{glo}}$
2. $x^\star$ is locally-exponentially-stable equilibrium
   $\implies$ F is locally c-strongly contracting wrt $\|\cdot\|_{\mathsf{loc}}$ over forward-invariant $\mathcal{S}$

Weakly contracting dynamics + locally-exp-stable equilibrium

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