

Exponentially Fast Distributed Coordination for Nonsmooth Convex Optimization

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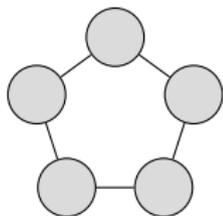
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55th IEEE Conference on Decision and Control, Las Vegas, USA



Problem. Given a network of n agents whose objective is to cooperatively solve a convex optimization problem



$$\min_{x \in X} f(x)$$

Figure: A network of agents that seek to solve a convex program



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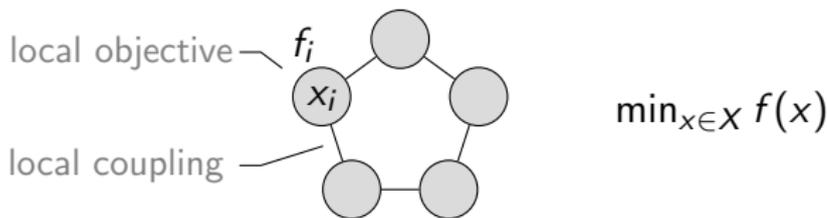


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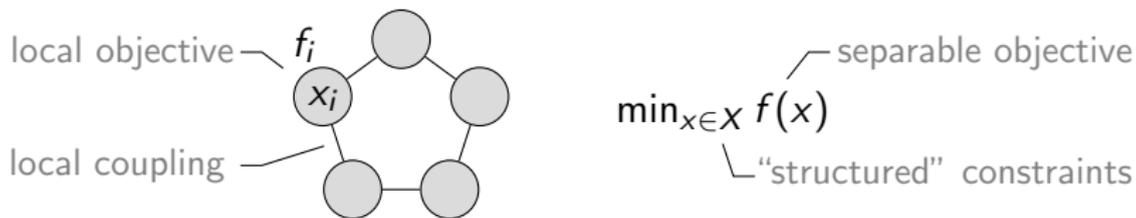


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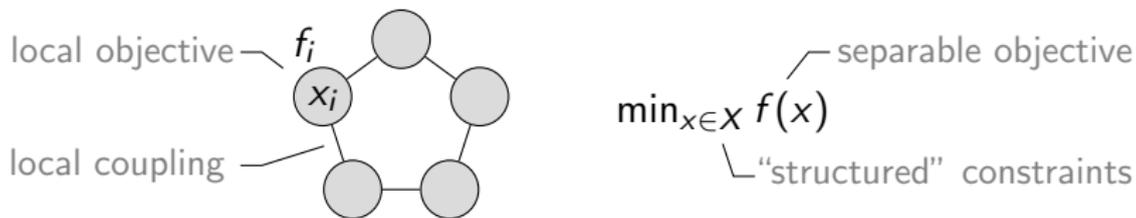


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Objective. Develop continuous-time algorithms that

- are **asymptotically correct**
- are providing **performance guarantees***
- are **amenable to distributed implementation**



- ① Distributed Convex Optimization
- ② Continuous-Time Distributed Convex Optimization
 - Problem Statement
 - Saddle-Point Dynamics
 - Saddle-Point-Like Dynamics
- ③ Performance Characterization
 - Distributed Optimization under Inequality Constraints
 - Distributed Optimization under Equality Constraints
- ④ Conclusions



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Assumptions.

- (additively) **separable** objective function f
- **local coupling** constraints h and g
- f and g are **locally Lipschitzian**



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- (P) satisfies the **strong Slater assumption**



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Idea. Saddle-point dynamics to solve (P)



Augmented Lagrangian. Let $\kappa > 0$ and $L_\kappa : \mathbb{R}^n \times \mathbb{R}^p \rightarrow \mathbb{R}$ be

$$L_\kappa(x, \lambda) = f(x) + \frac{1}{2} \|h(x)\|^2 + \langle \lambda, h(x) \rangle + \kappa \langle \mathbb{1}_m, [g(x)]^+ \rangle$$



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Saddle Points. ((P) convex \wedge strong Slater assumption) \Rightarrow

$$\forall x^* \exists (\lambda^*, \mu^*) : L_\kappa(x^*, \lambda) \leq L_\kappa(x^*, \lambda^*) \leq L_\kappa(x, \lambda^*), \quad \forall (x, \lambda)$$

given that $\kappa \geq \|\mu^*\|_\infty$



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Lemma (Saddle-point theorem). Let $L_\kappa : \mathbb{R}^n \times \mathbb{R}^p \rightarrow \mathbb{R}$ and let $(x^*, \lambda^*) \in \text{sp}(L_\kappa)$ with $\kappa > \|\mu^*\|_\infty$ for some dual solution μ^* of (P). Then, x^* is a solution of (P).

**Saddle-point dynamics.**

$$\begin{cases} \dot{x}(t) + \partial_x L_\kappa(x(t), \lambda(t)) \stackrel{a.e.}{=} 0_n, & x(t_0) \in \mathbb{R}^n \\ \dot{\lambda}(t) - \partial_\lambda L_\kappa(x(t), \lambda(t)) \stackrel{a.e.}{=} 0_p, & \lambda(t_0) \in \mathbb{R}^p \end{cases} \quad (\text{SPD})$$

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Interpretation.

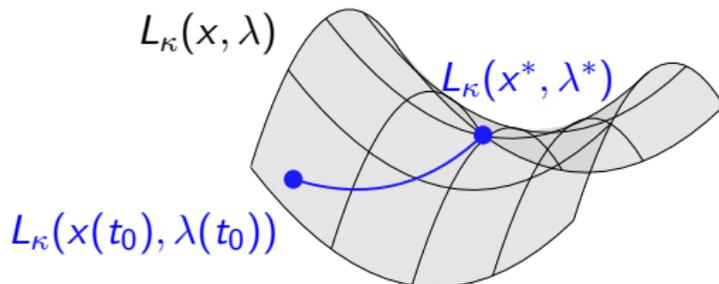
- gradient-descent dynamics in the primal variable
- gradient-ascent dynamics in the dual variable

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Theorem (Asymptotic convergence). Let $\kappa > \|\mu^*\|_\infty$ for some dual solution μ^* of (P). Let ∂f be (strictly) monotone. Then,

$$\lim_{t \rightarrow +\infty} \text{dist}((x(t), \lambda(t)), \text{sp}(L_\kappa)) = 0.$$



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Idea. Two strategies:

- 1 Let ∂f be **monotone**. Let $(x^*, \lambda^*) \in \text{sp}(L_\kappa)$ and define

$$V_1(x, \lambda) = \frac{1}{2} \|x - x^*\|^2 + \frac{1}{2} \|\lambda - \lambda^*\|^2$$

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- ② Let ∂f be **strictly monotone**. Let $(\tilde{x}, \tilde{\lambda}) \in \text{sp}(L_\kappa)$ and define

$$V_2(x, \lambda) = L_\kappa(x, \lambda) - L_\kappa(\tilde{x}, \tilde{\lambda}) + \min_{(x^*, \lambda^*) \in \text{sp}(L_\kappa)} \left(\frac{1}{2} \|x - x^*\|^2 + \frac{1}{2} \|\lambda - \lambda^*\|^2 \right)$$

\rightsquigarrow V_2 is a Liapunov function



Let $G = \{x \in \mathbb{R}^n \mid g(x) \leq 0_m\}$ and define $F : G \times \mathbb{R}^p \rightrightarrows \mathbb{R}^n$ by

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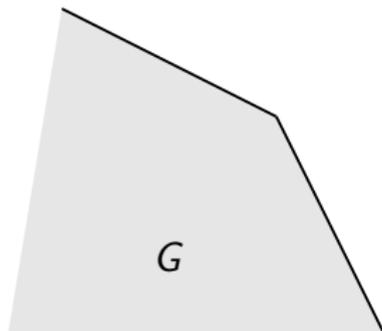
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Illustration.





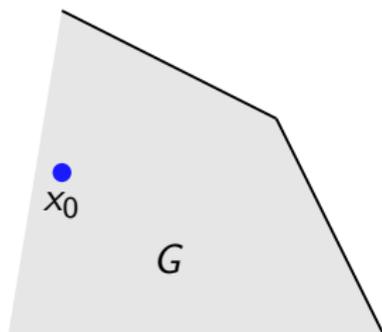
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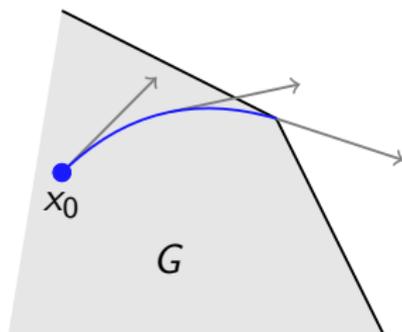
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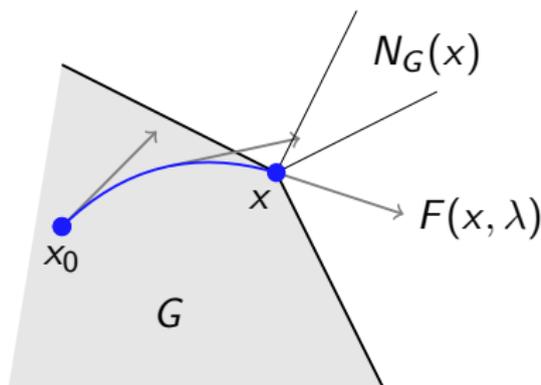
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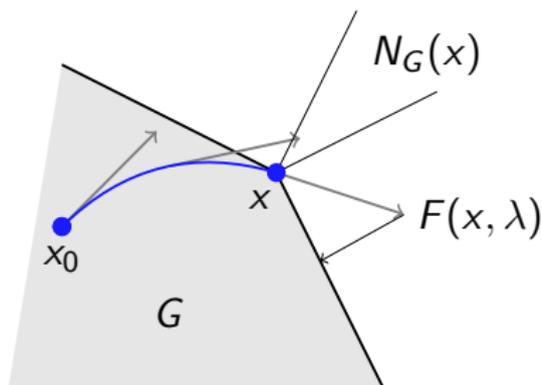
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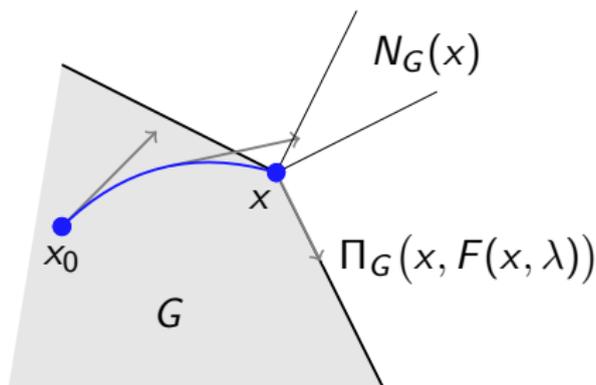
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Theorem (Relationship of solutions). Let $(x, \lambda) : [t_0, +\infty) \rightarrow G \times \mathbb{R}^p$ be any solution of (SPLD) starting from $(x_0, \lambda_0) \in G \times \mathbb{R}^p$. Then, there exists $\kappa > 0$ such that it is also a solution of (SPD).



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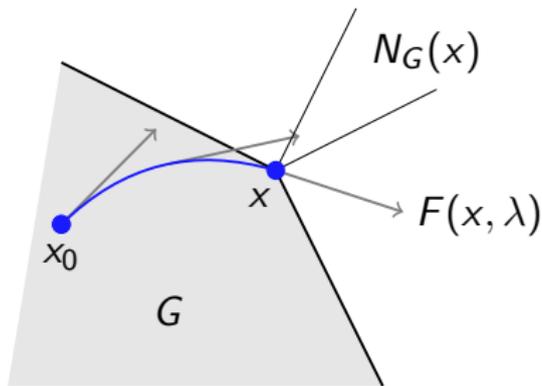
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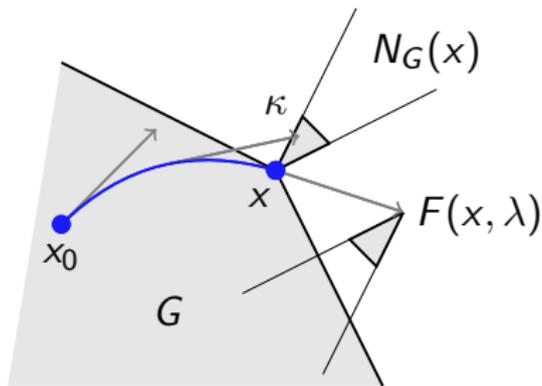




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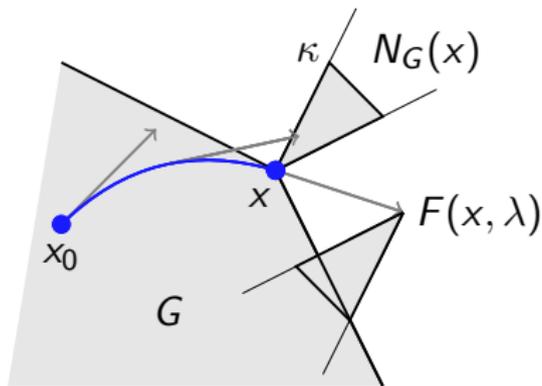




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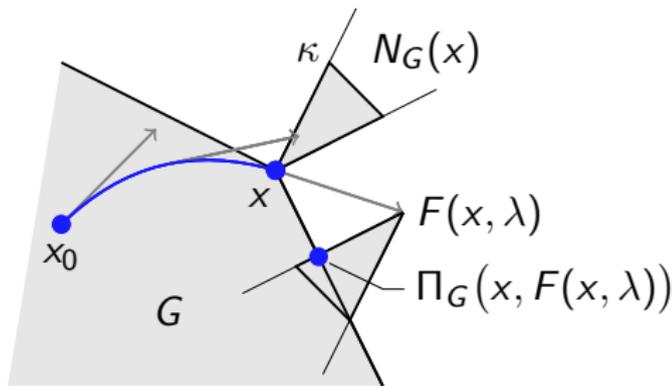




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- (iii) If ∂f is **strongly monotone**, then $\text{eq}(\partial F_\kappa)$ is strongly exponentially stable under (GD).



Example. Consider a network of $n = 10$ agents that seek to cooperatively solve the minimization problem

$$\begin{aligned} & \underset{x \in \mathbb{R}^n}{\text{minimize}} && \sum_{i \in \{1, \dots, n\}} x_i^2 / 2 + |x_i| \\ & \text{subject to} && \|(x_1 - 2, \dots, x_5 - 2)\|_\infty \leq 1 \\ & && \|(x_6 + 2, \dots, x_n + 2)\|_\infty \leq 1 \end{aligned}$$

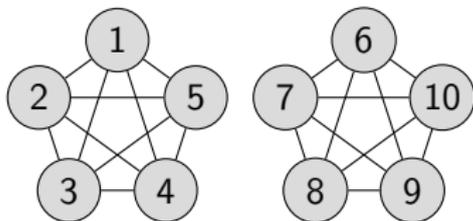


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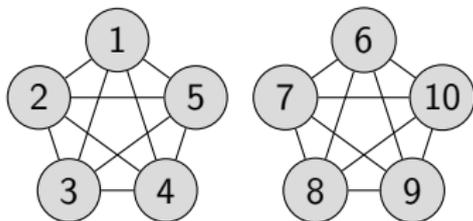


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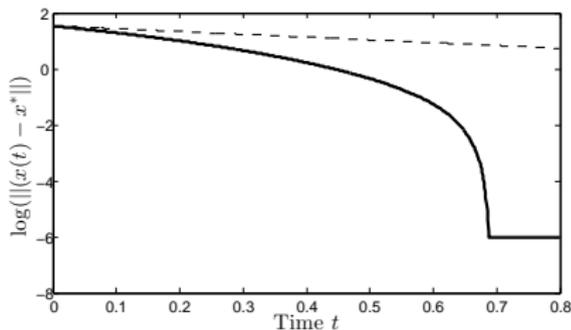
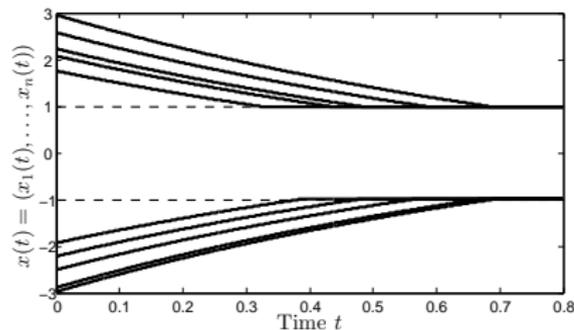


Figure: Execution of the dynamics $\dot{x}(t) - \Pi_G(x(t), -\partial f(x(t))) \stackrel{a.e.}{\geq} 0_n$

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- (iii) If $\partial(\nabla f) \succ 0$, then $\text{sp}(L)$ is exponentially stable under (SP).



Example. Consider a network of $n = 10$ agents whose objective is to cooperatively solve the minimization problem

$$\begin{aligned} & \underset{x \in \mathbb{R}^n}{\text{minimize}} && \sum_{i \in \{1, \dots, n\}} x_i^2 / 2 \\ & \text{subject to} && \text{Circ}_n(0, 1, 1/2)x = \mathbb{1}_n \end{aligned}$$

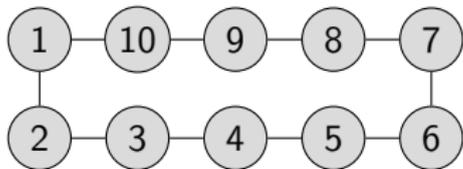


Figure: Network topology



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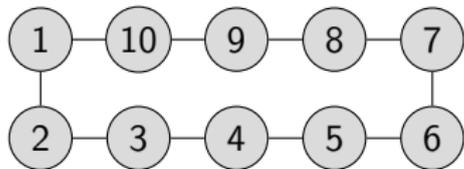


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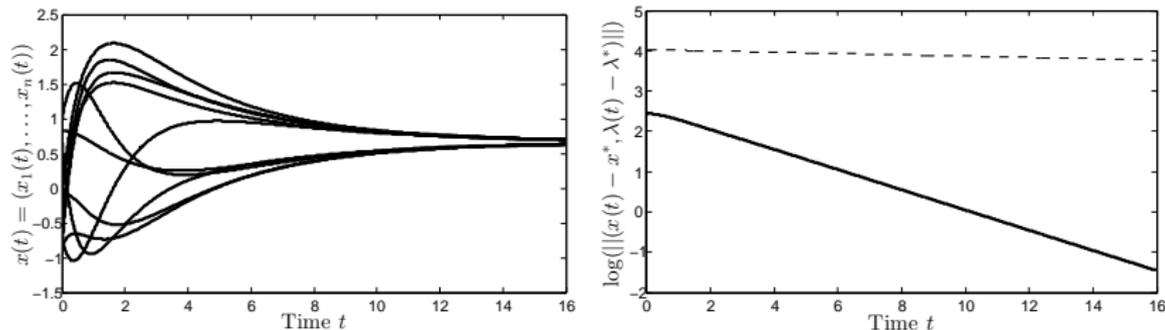


Figure: Execution of the saddle-point dynamics (SP)



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- continuous-time algorithms for distributed convex optimization
- convergence analysis of saddle-point(-like) dynamics
- identification of a nonsmooth Lyapunov function
- algorithm performance characterization for optimization subject to either inequality or equality constraints



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Thank you for your attention!