

Distributed Trajectory Estimation with Privacy and Communication Constraints: a Two-Stage Distributed Gauss-Seidel Approach

Siddharth Choudhary¹, Luca Carlone², Carlos Nieto¹, John Rogers³,
Henrik I. Christensen¹, Frank Dellaert¹

¹ Institute for Robotics and Intelligent Machines, Georgia Tech

² Laboratory for Information and Decision Systems, MIT

³ Army Research Lab

Motivation

- **Goal:** distributed estimation of trajectories of robots in a team
- **Applications:**
 - mapping
 - exploration
 - ...
- **why distributed:** avoid exchange of large amount of data
 - small flying robots
 - underwater vehicles



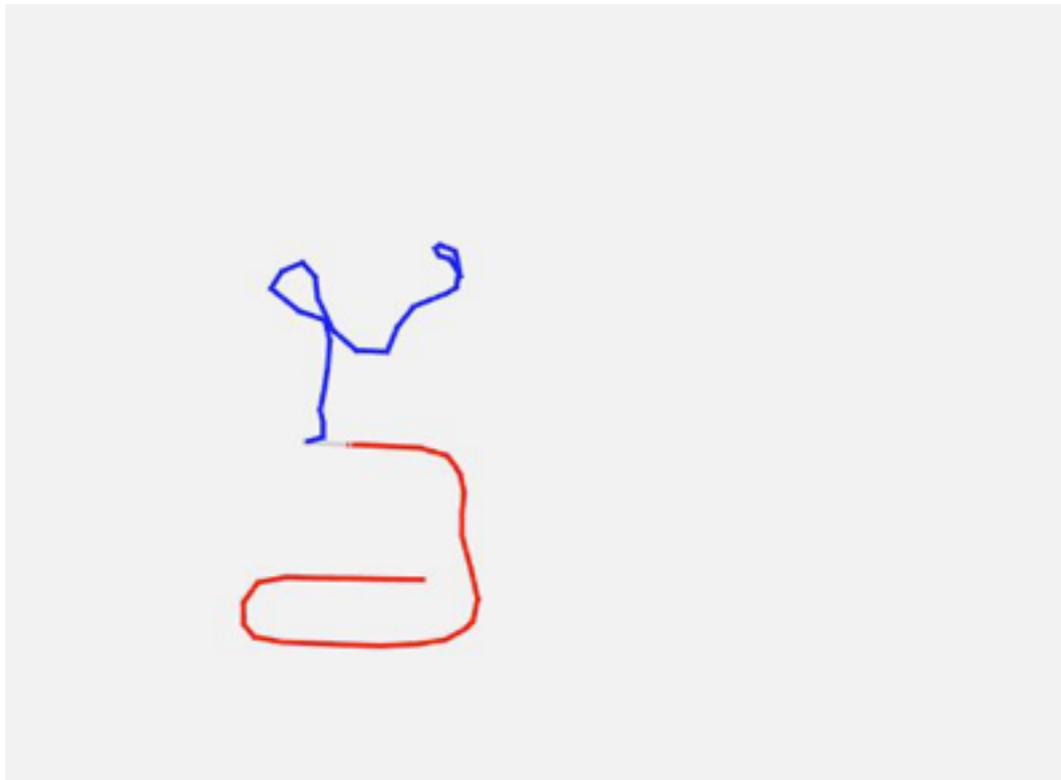
Related work:

- distributed SLAM
[Dong et al., Paull et al., Bailey et al.]
- multi robot localization
[Roumeliotis et al., Tron and Vidal]
- distributed optimization
[Cunningham et al., Nerurkar et al., Franceschelli and Gasparri, Aragues etl al.]
- ***State of the art:*** DDF-SAM requires communication cost quadratic in the number of rendezvous.

Problem Statement

Cooperative estimation of 3D robot trajectories from **relative pose measurements**, with the following constraints:

1. Communication only occurs during **rendezvous**.
2. Data exchange must be minimal (due to **limited bandwidth** and **privacy**).



Communication only occurs when two robots are close enough.



Example application of Privacy Constraint:
Optimization of Multiple trajectories
collected through Google Project Tango
(courtesy: Simon Lynen)

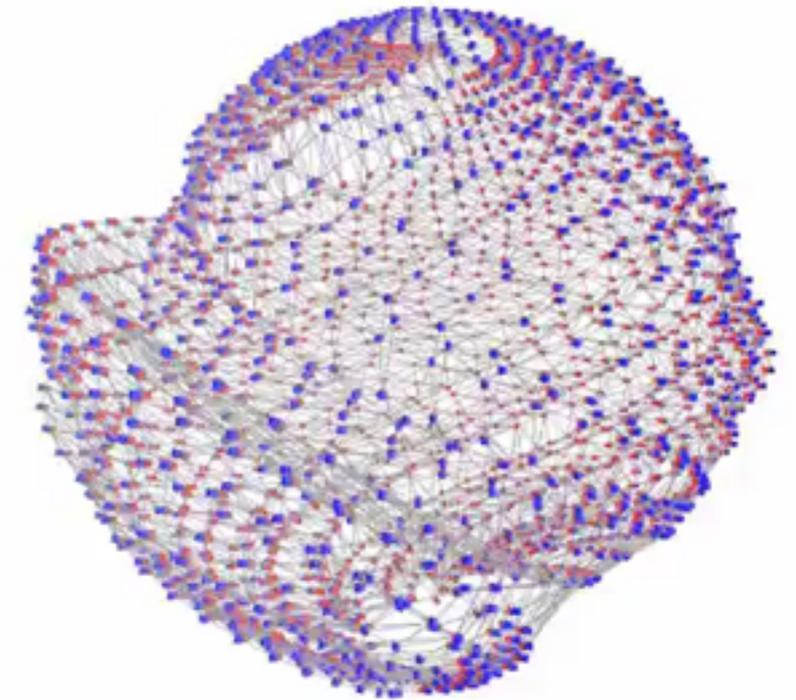
Contribution

Trajectory estimation as Pose Graph Optimization:

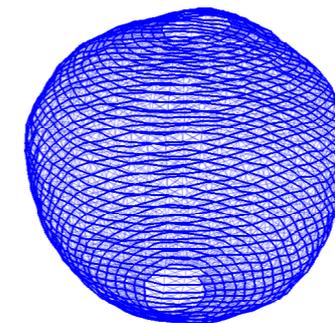
Related work: iterative optimization

Our approach: 2 stage [Carlone et al. (ICRA 2015)]

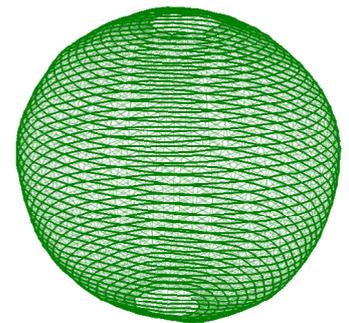
- Each phase requires solving a linear system
- We use the Gauss-Seidel algorithm as distributed linear solver



SLAM - TORO - Sphere Optimization
courtesy: Cyril Stachniss



Estimate



Optimum

Distributed Gauss-Seidel Approach

$$\min_{R_i \in \text{SO}(3)} \sum_{(i,j) \in \mathcal{E}} \omega_R^2 \|R_j - R_i \bar{R}_i^j\|_F^2$$

↓ quadratic relaxation

$$\min_{R_i} \sum_{(i,j) \in \mathcal{E}} \omega_R^2 \|R_j - R_i \bar{R}_i^j\|_F^2$$

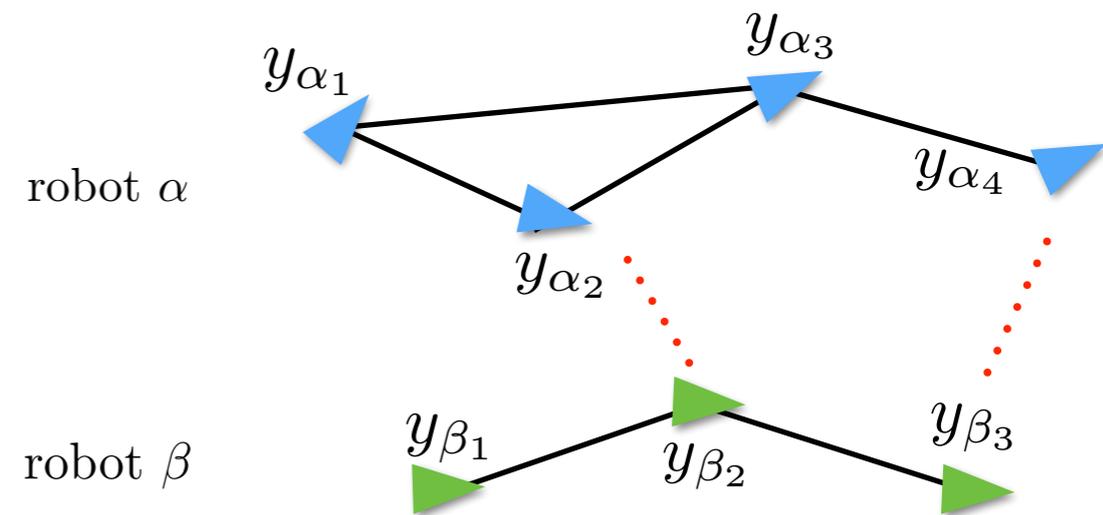
↓ rewrite

$$\min_y \|Ay - b\|^2$$

↓ normal equation

$$\underbrace{(A^T A)}_{\text{Hessian (H)}} y = \underbrace{A^T b}_g$$

$$Hy = g \quad \text{solve in a distributed manner}$$

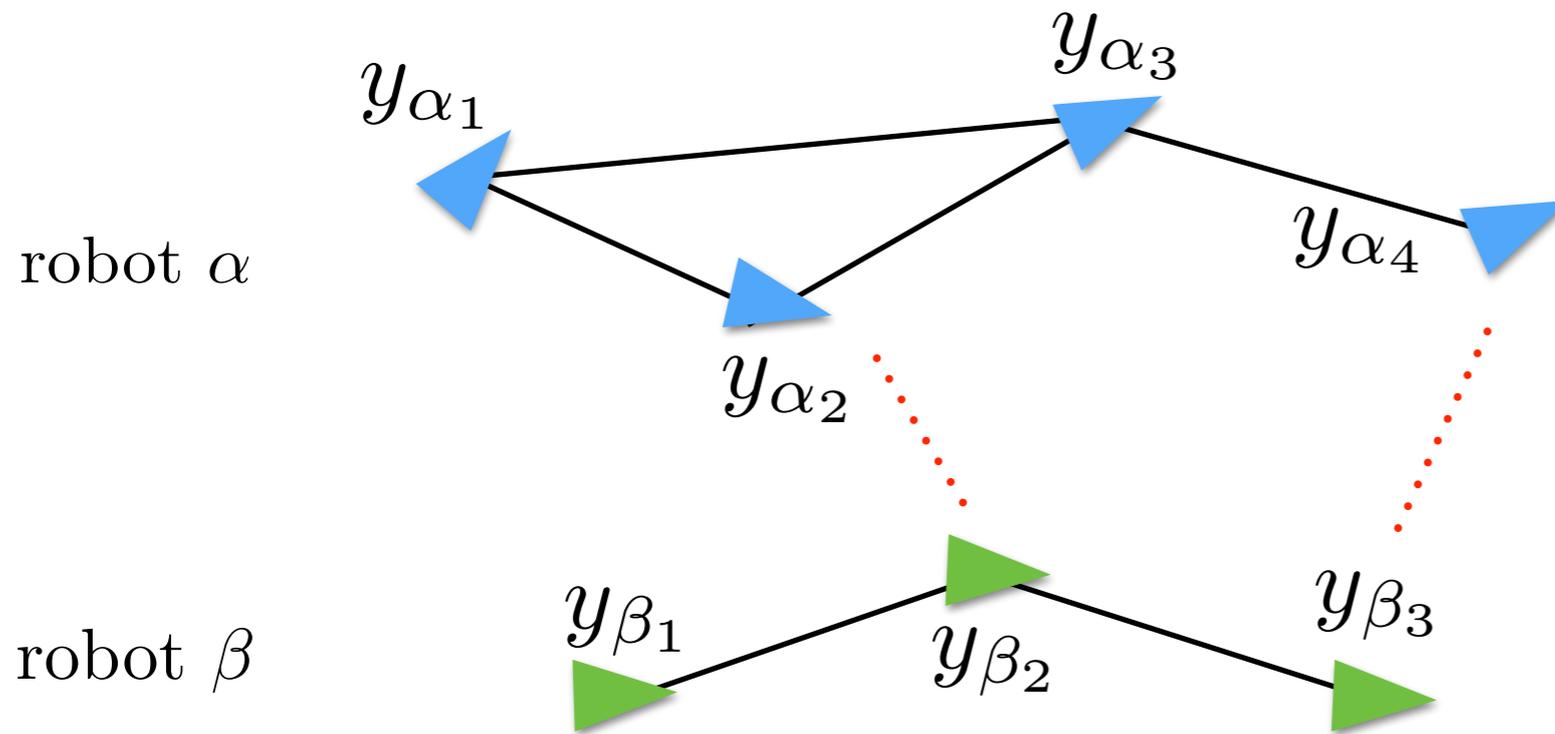


Hessian Matrix

	α_1	α_2	α_3	α_4	β_1	β_2	β_3
α_1							
α_2		$H_{\alpha\alpha}$				$H_{\alpha\beta}$	
α_3							
α_4							
β_1							
β_2		$H_{\beta\alpha}$			$H_{\beta\beta}$		
β_3							

Distributed Gauss-Seidel Approach

Trajectory Estimation Problem



Hessian Matrix

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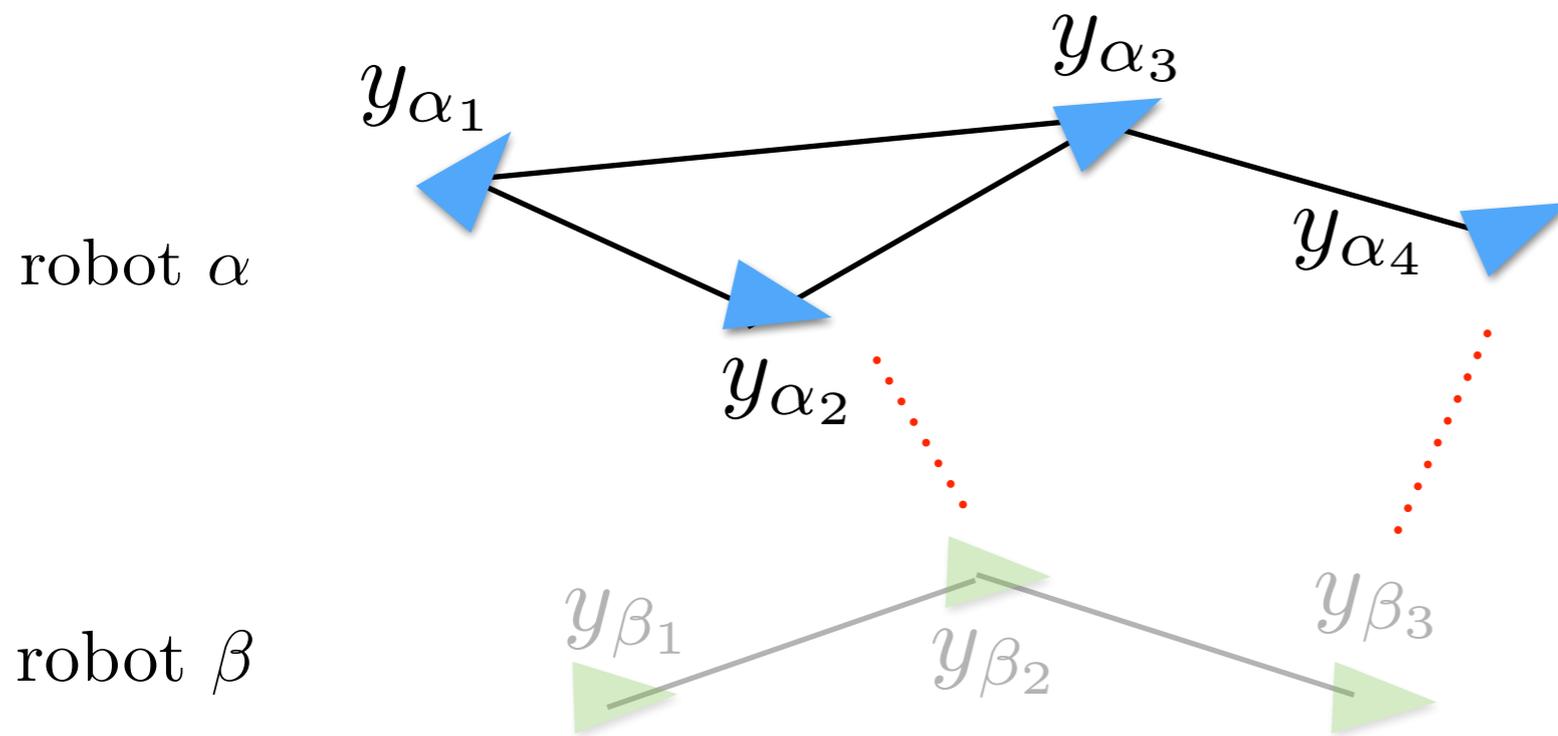
Iterate

$$\mathbf{y}_\alpha^{k+1} = \mathbf{H}_{\alpha\alpha}^{-1} \left(-\mathbf{H}_{\alpha\beta} \mathbf{y}_\beta^k + \mathbf{g}_\alpha \right)$$

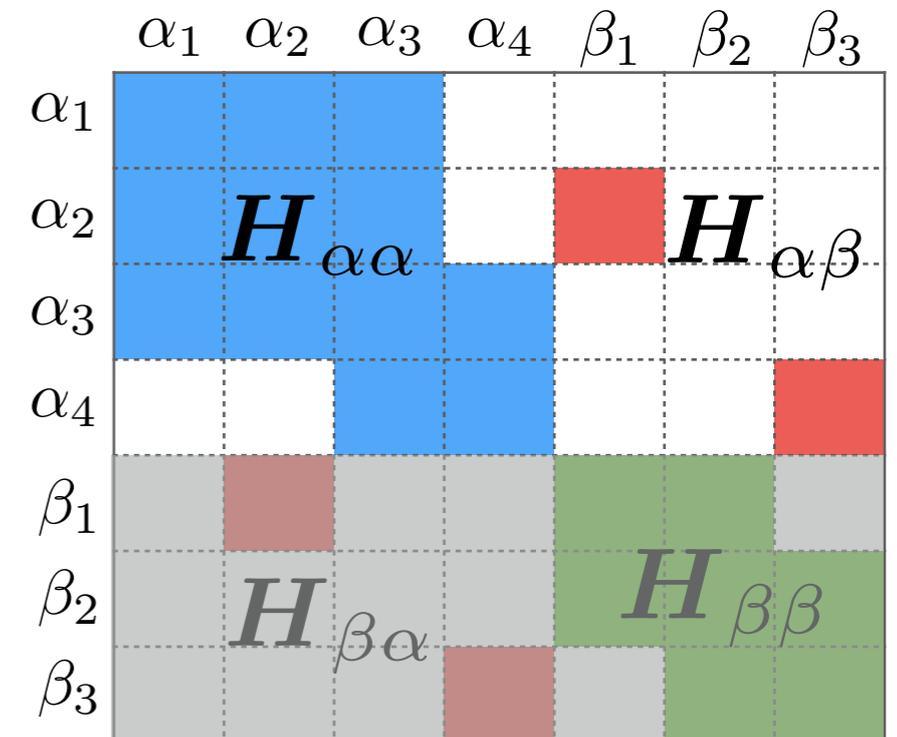
$$\mathbf{y}_\beta^{k+1} = \mathbf{H}_{\beta\beta}^{-1} \left(-\mathbf{H}_{\beta\alpha} \mathbf{y}_\alpha^k + \mathbf{g}_\beta \right)$$

Distributed Gauss-Seidel Approach

Trajectory Estimation Problem

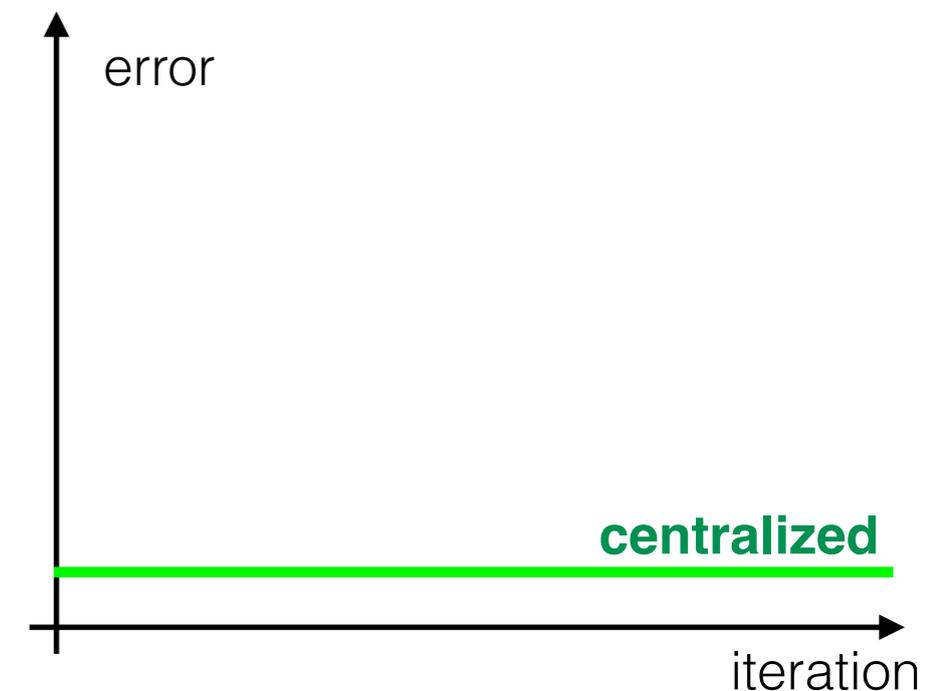


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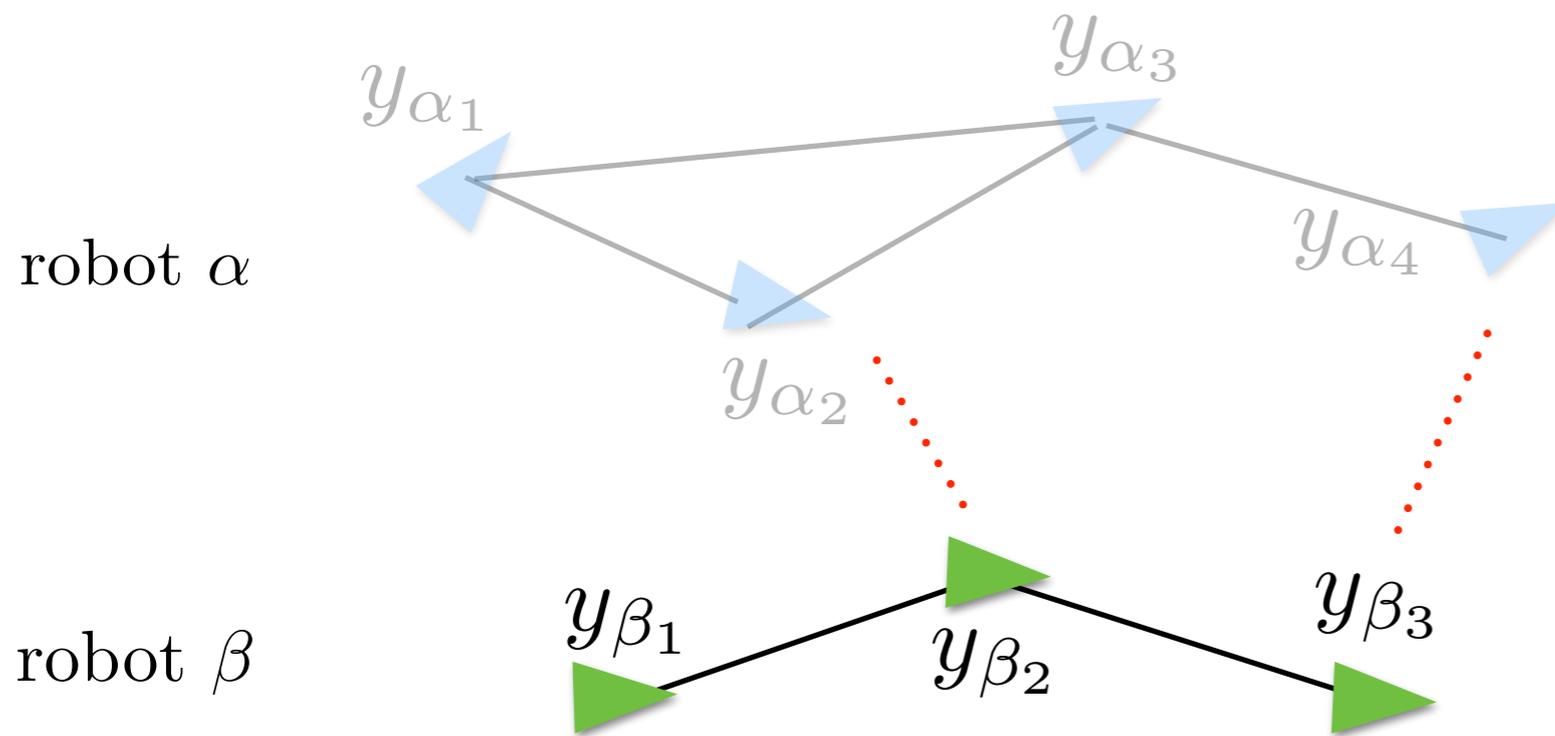
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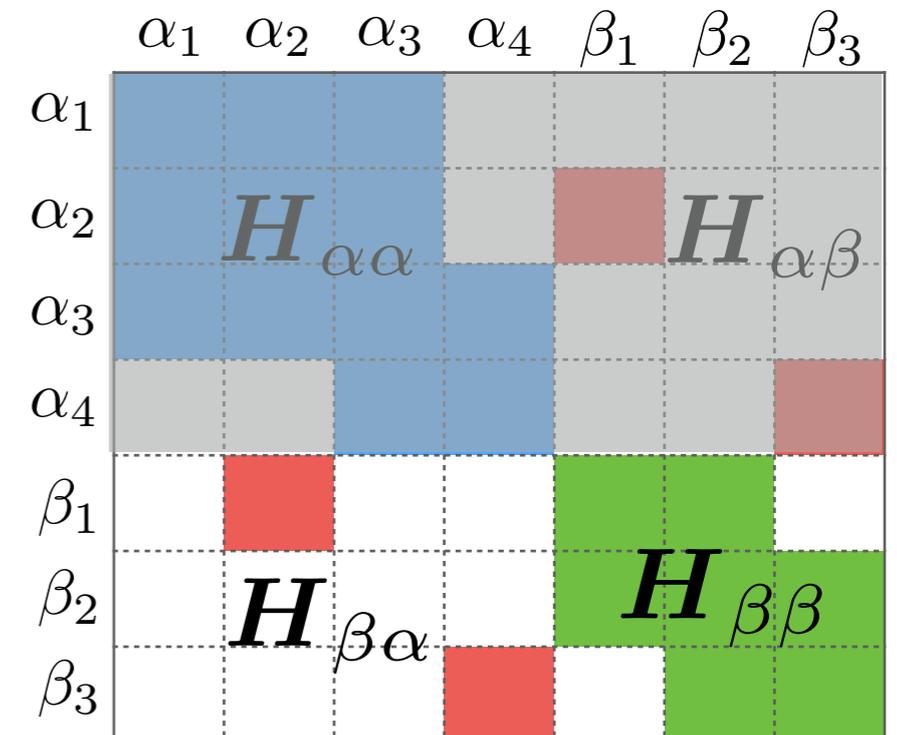


Distributed Gauss-Seidel Approach

Trajectory Estimation Problem

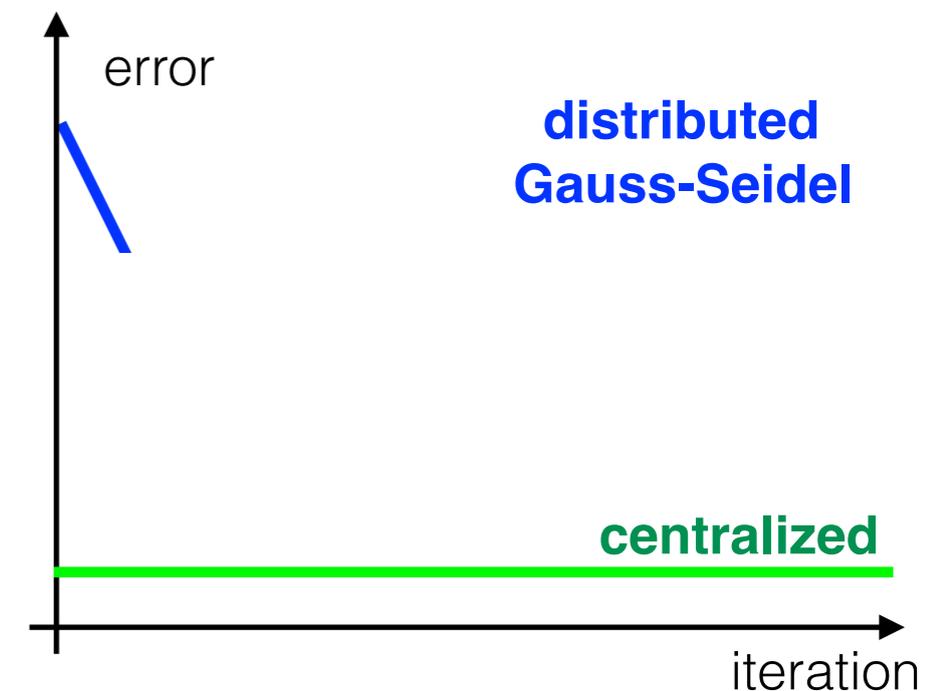


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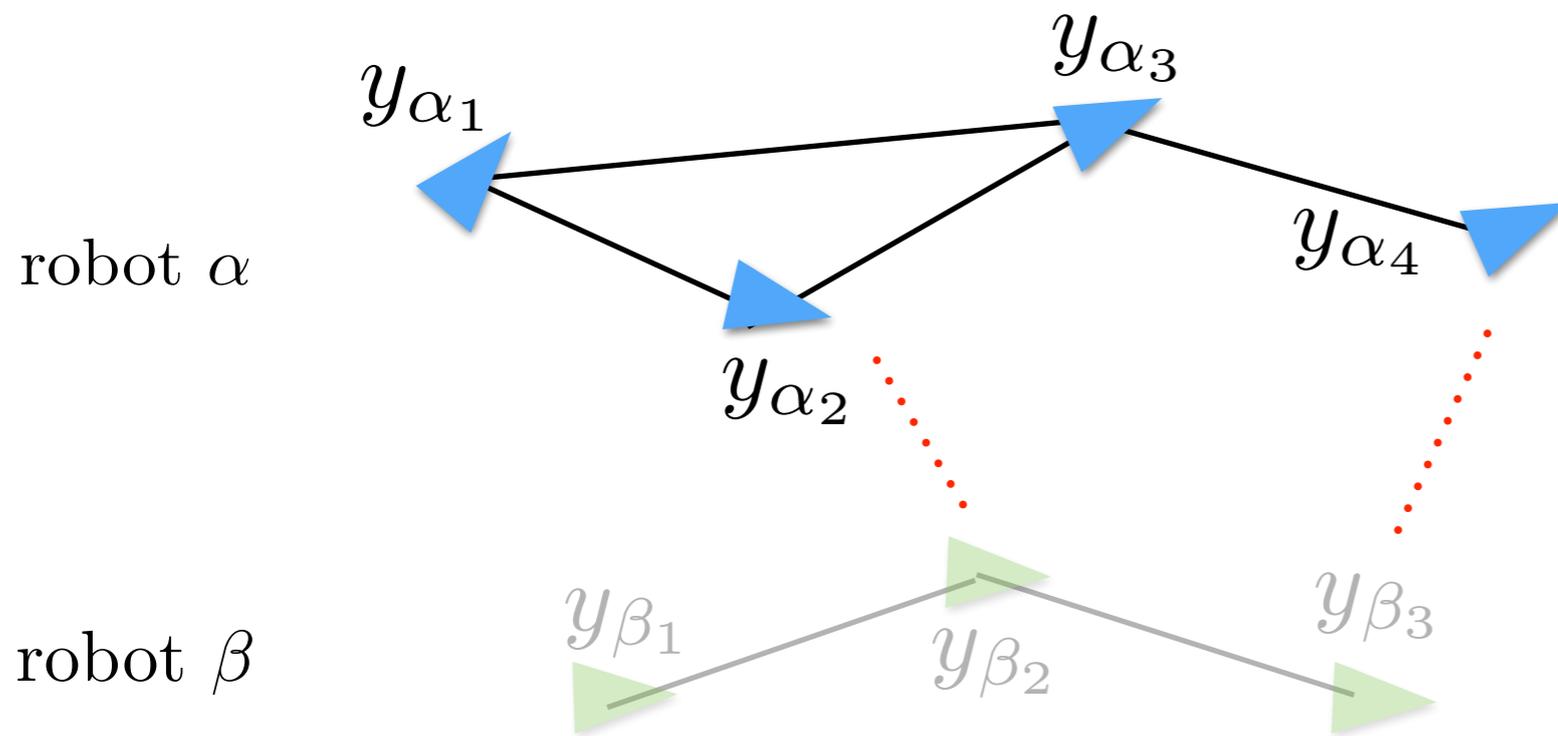
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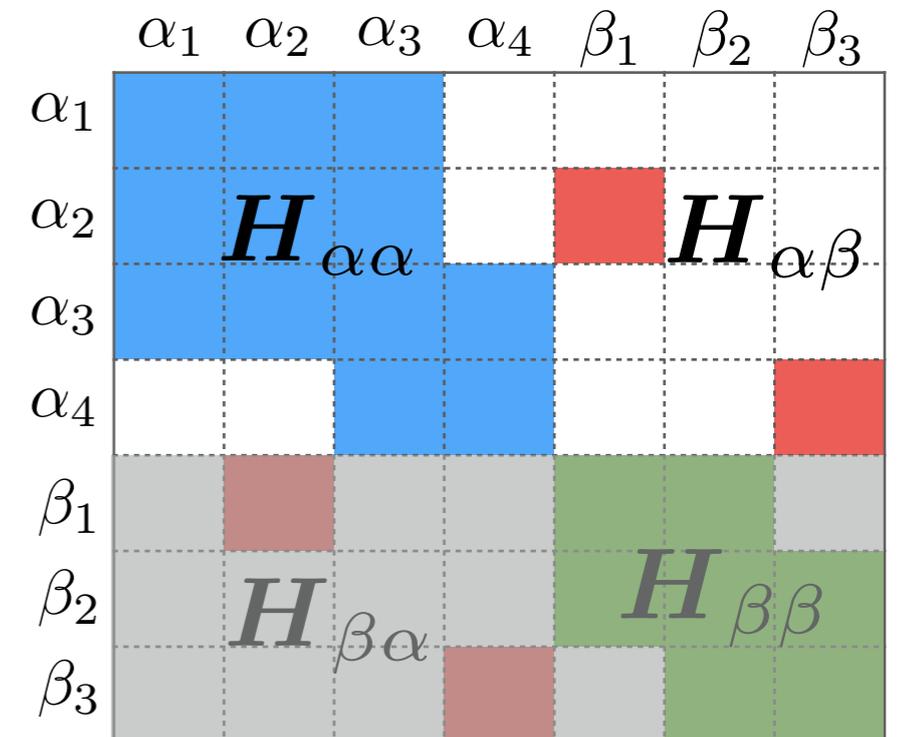


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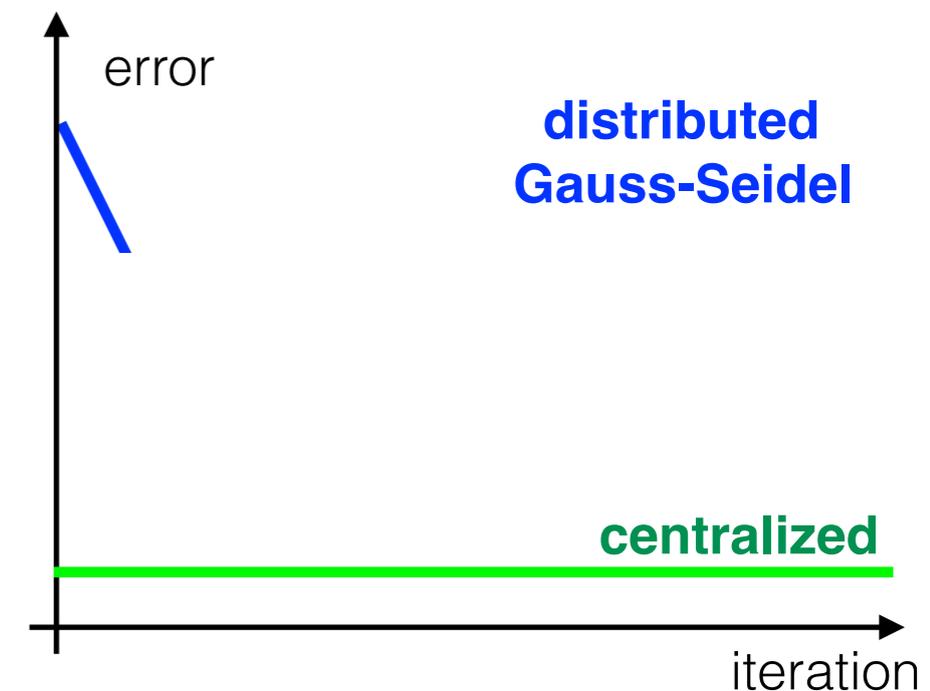


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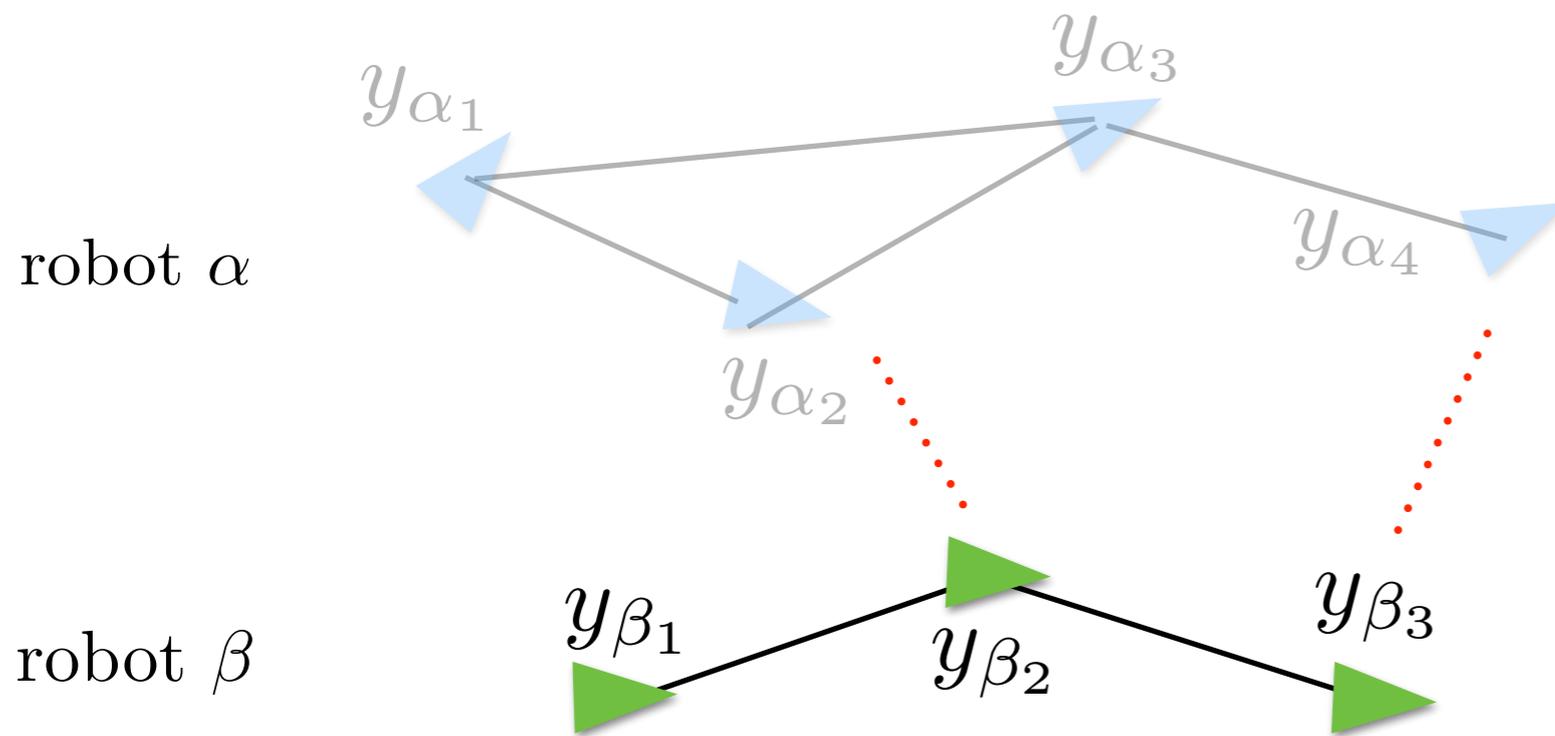
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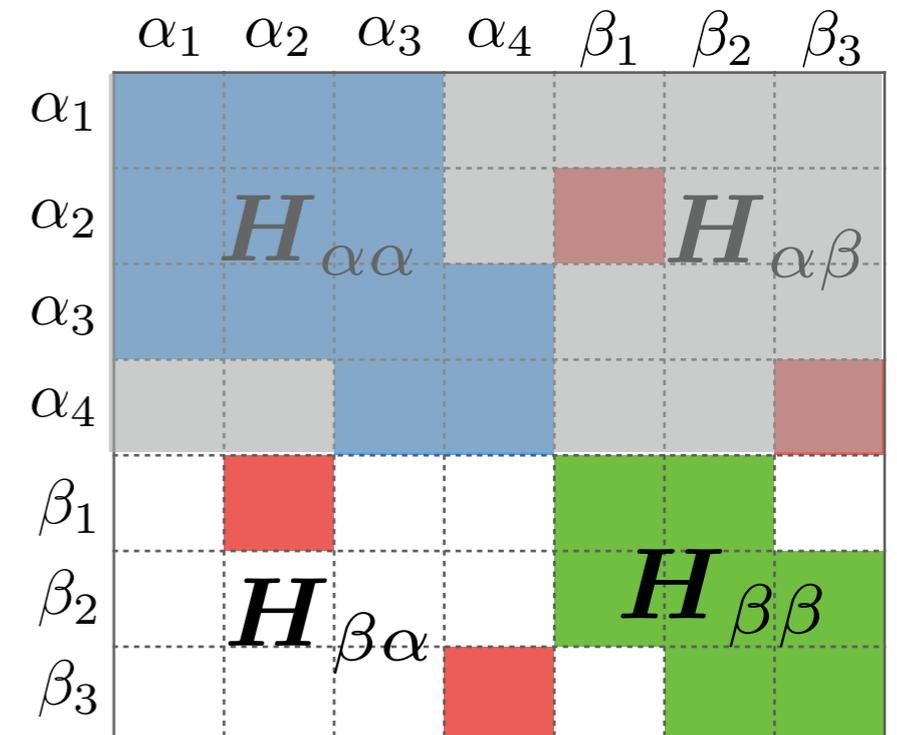


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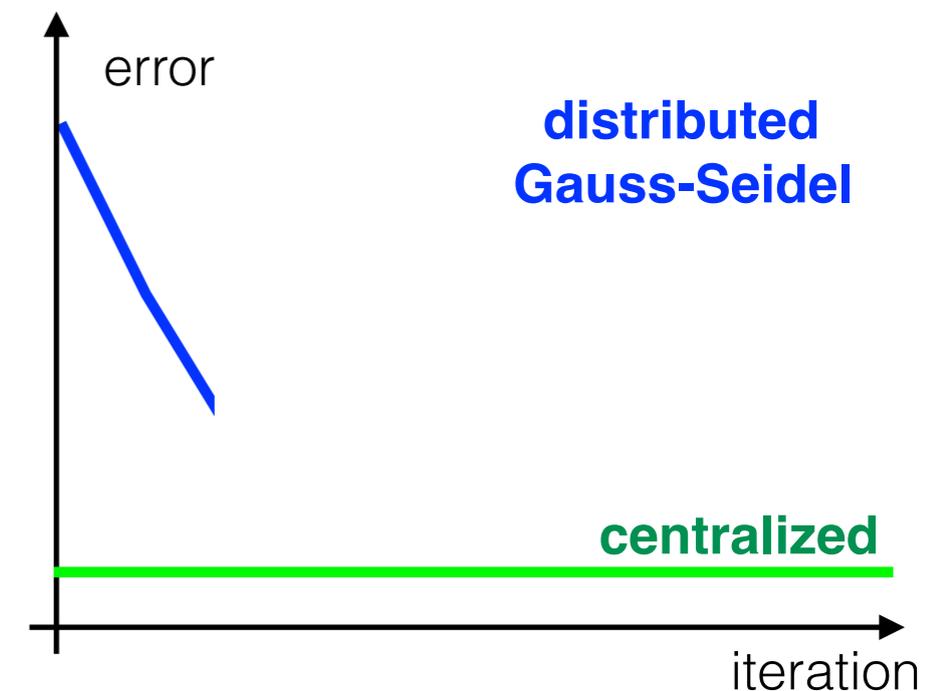


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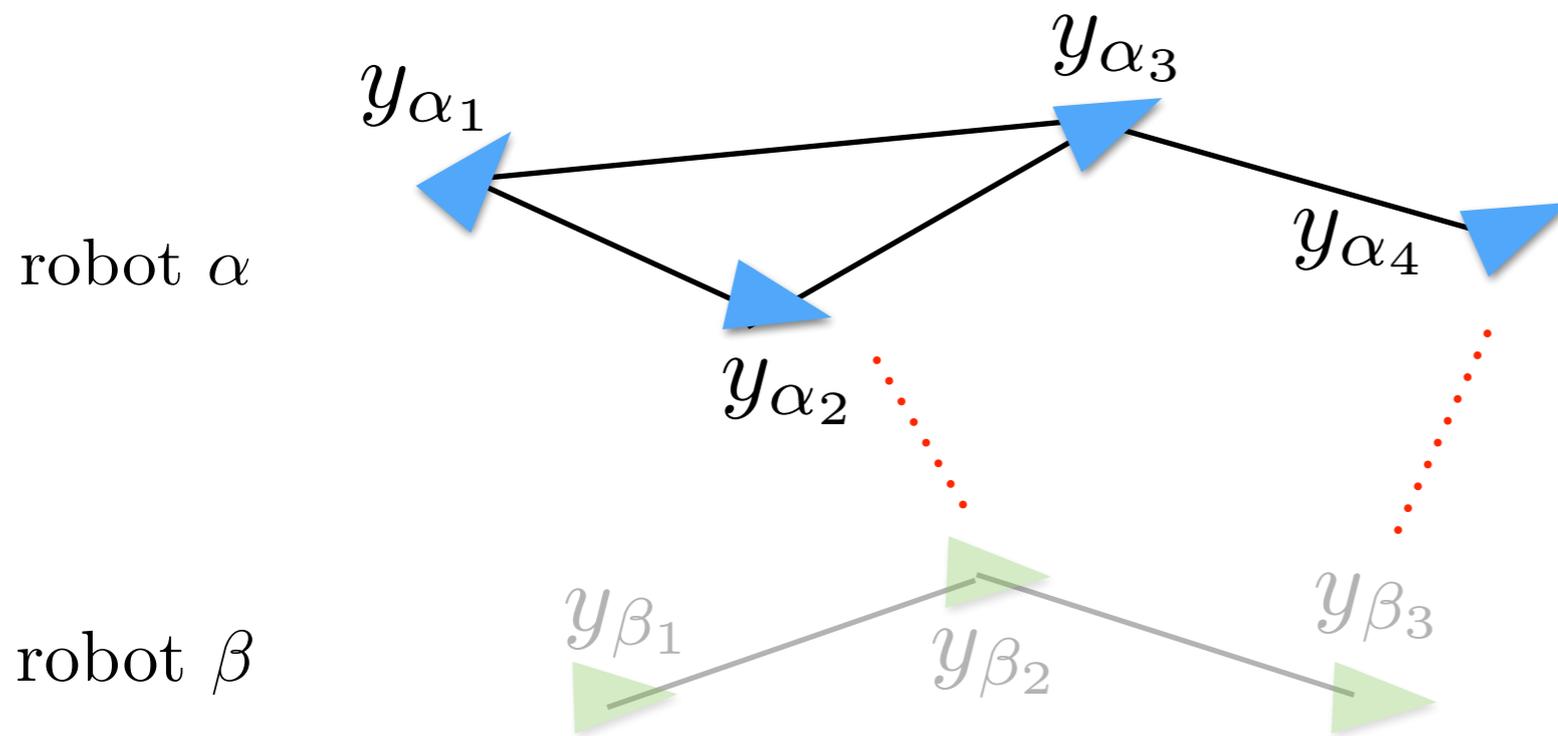
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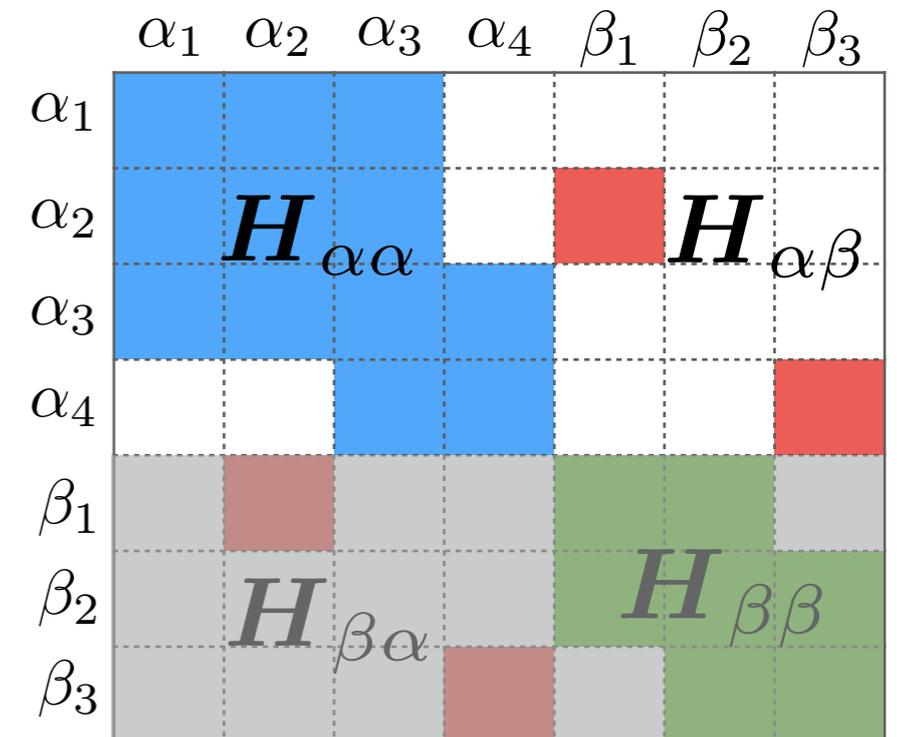


Distributed Gauss-Seidel Approach

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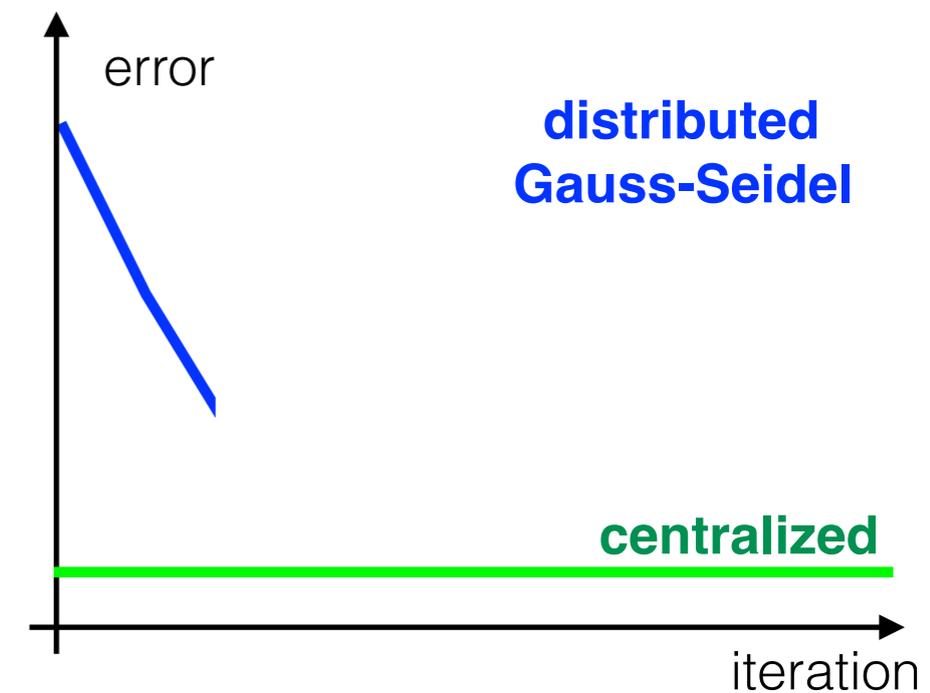


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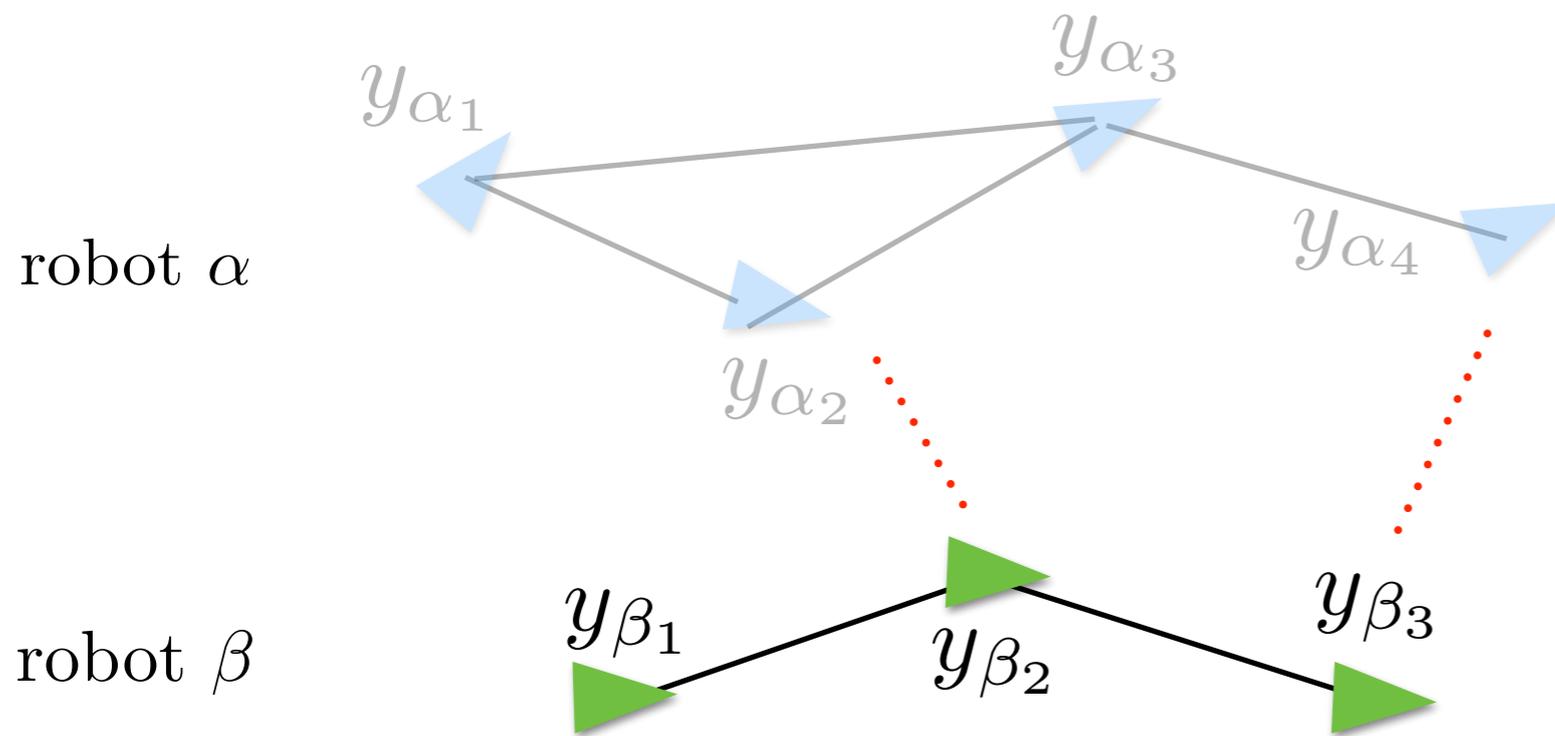
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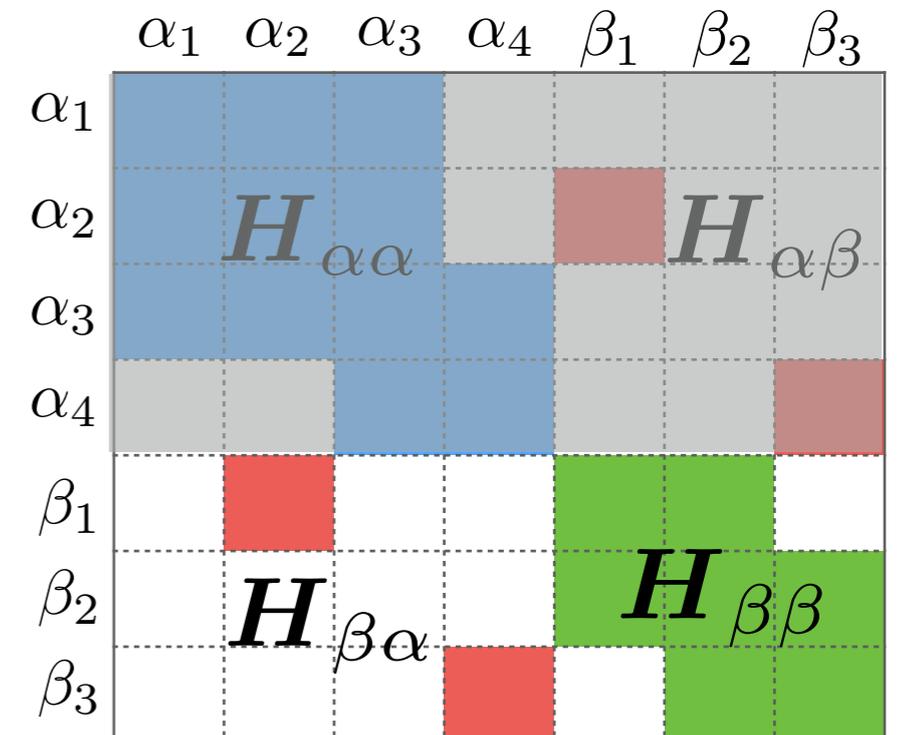


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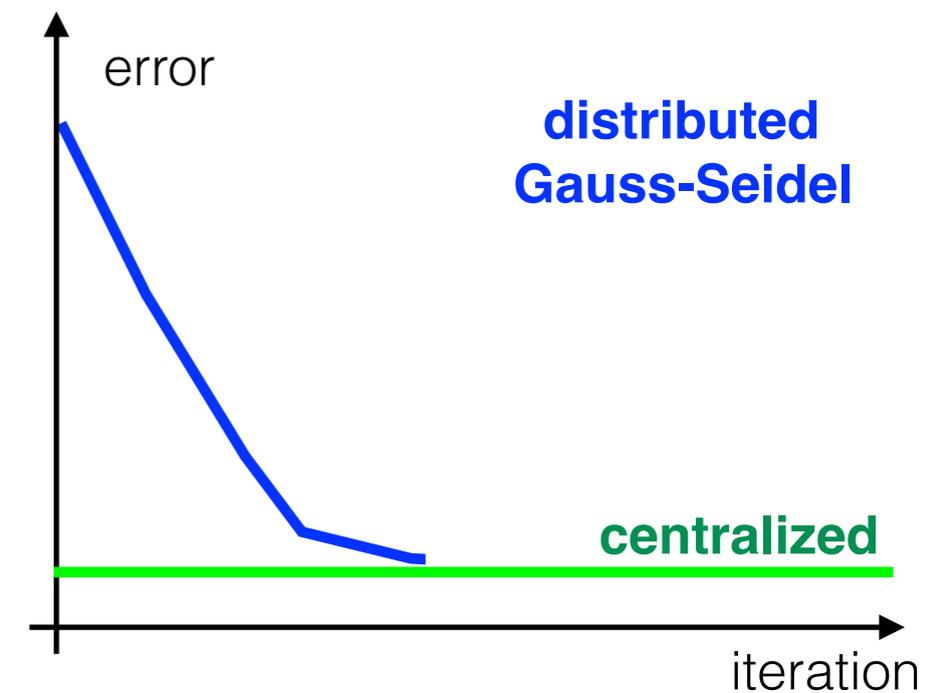


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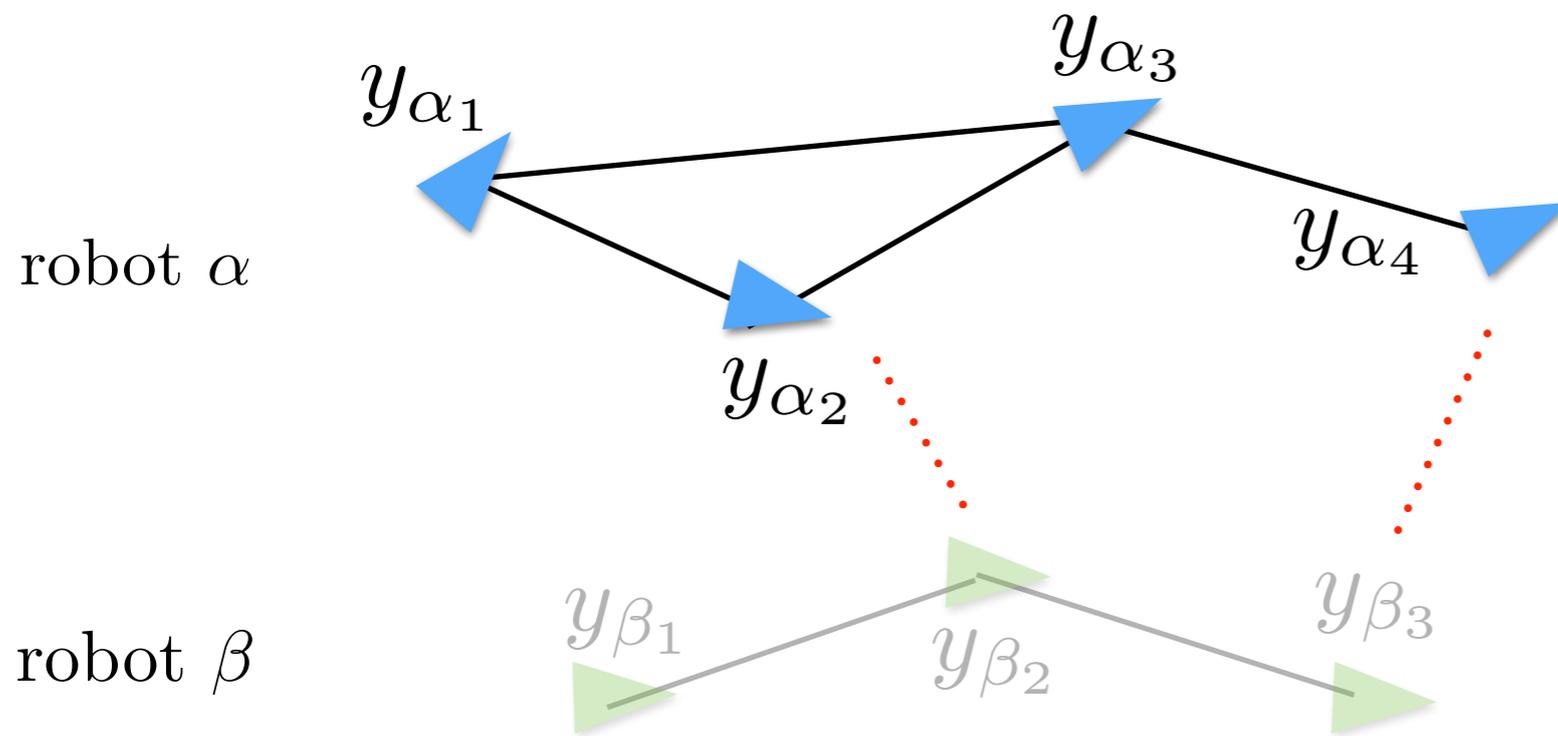
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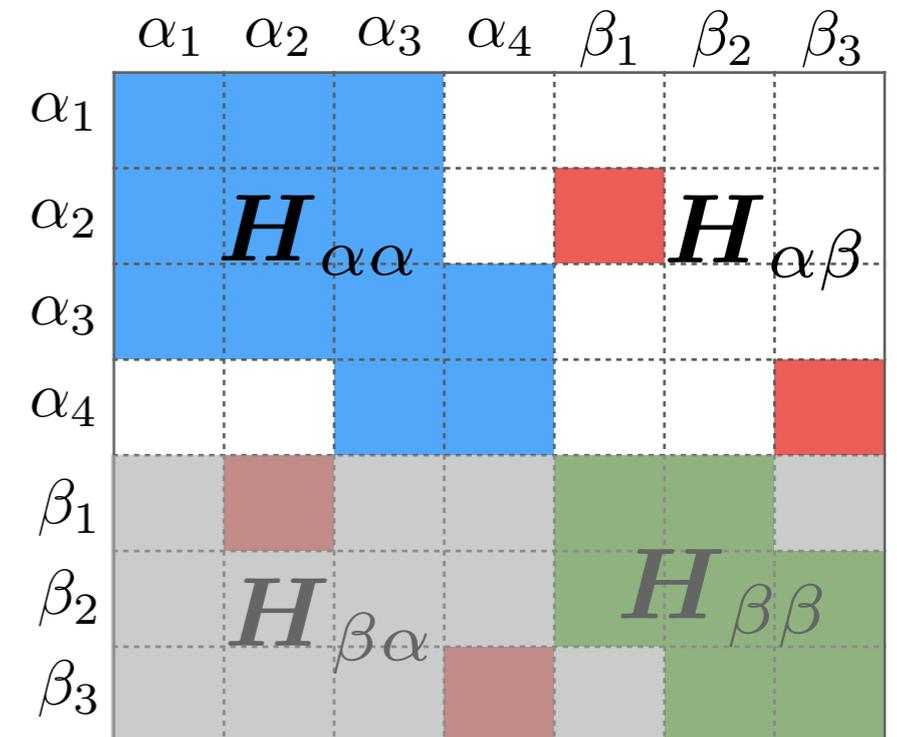


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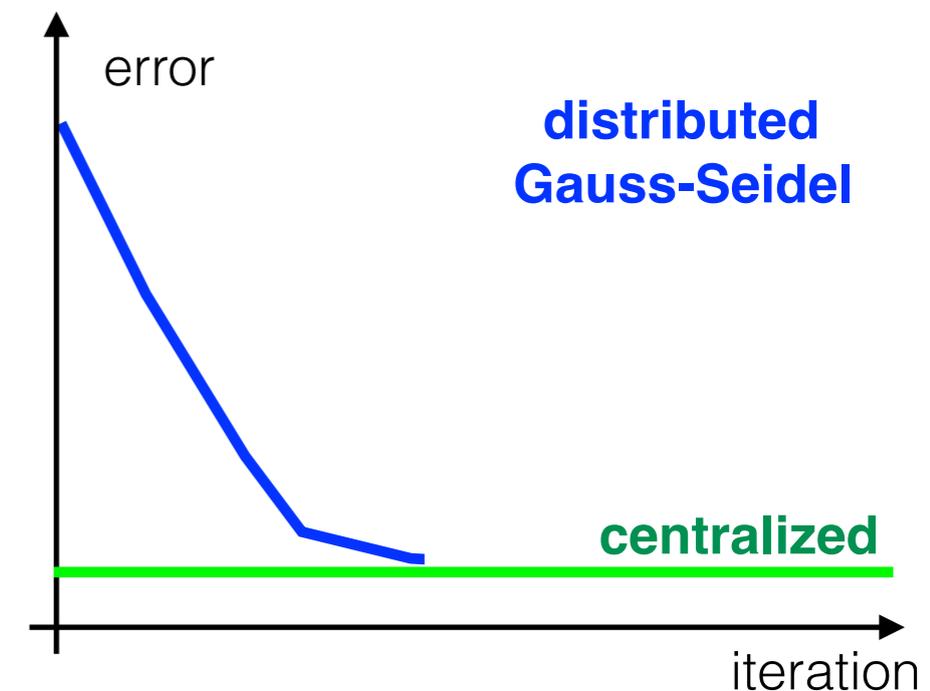


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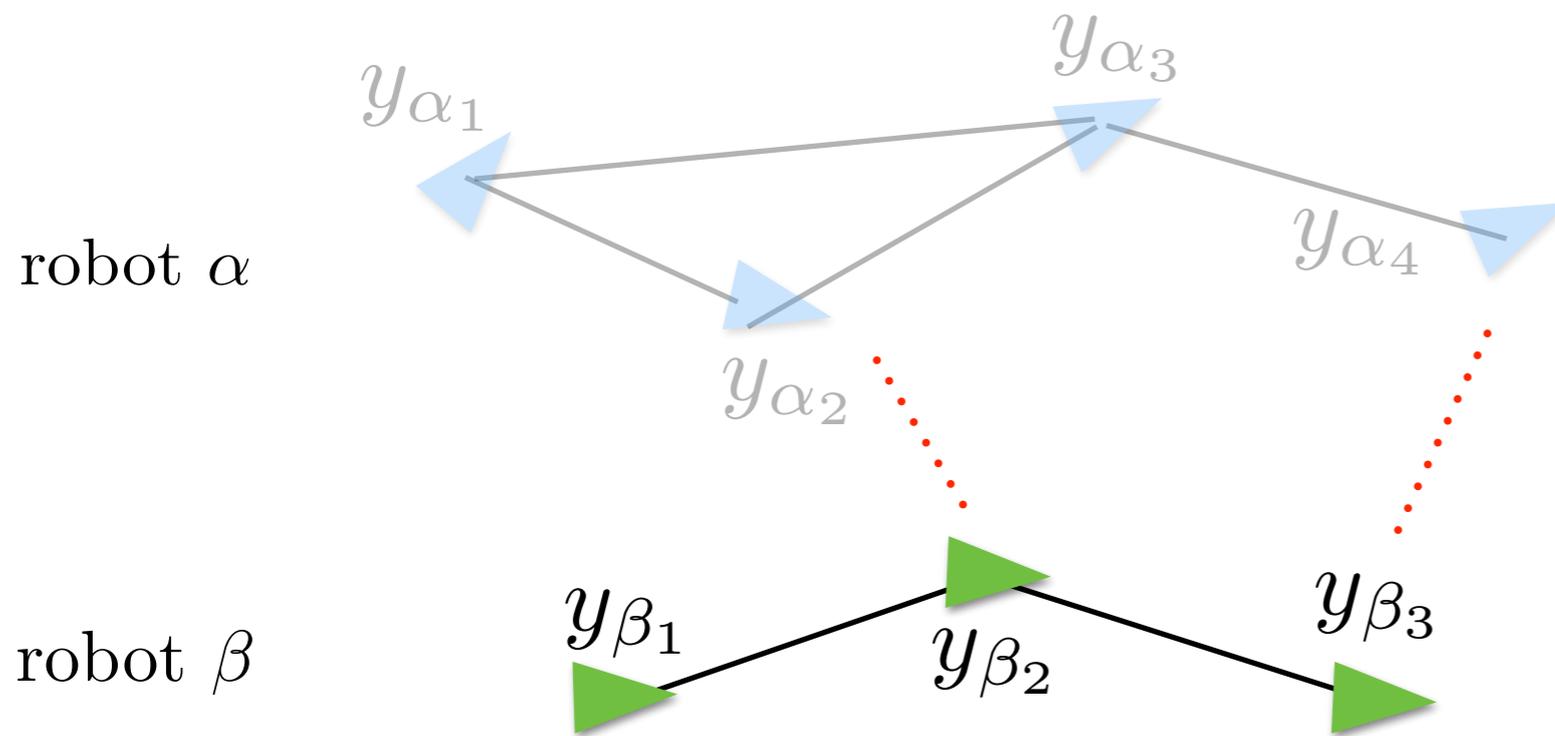
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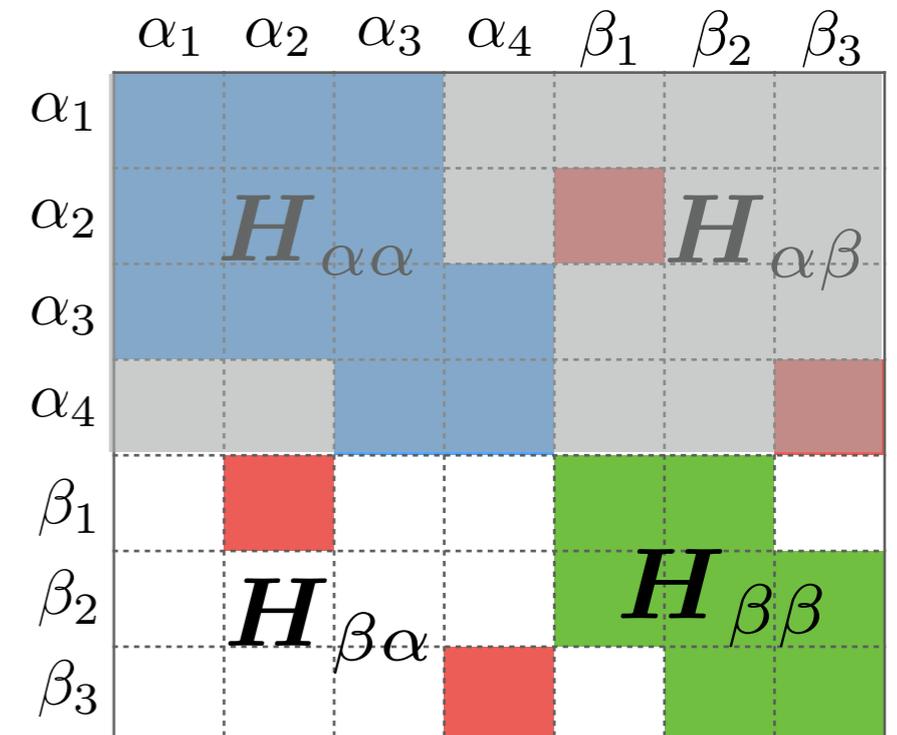


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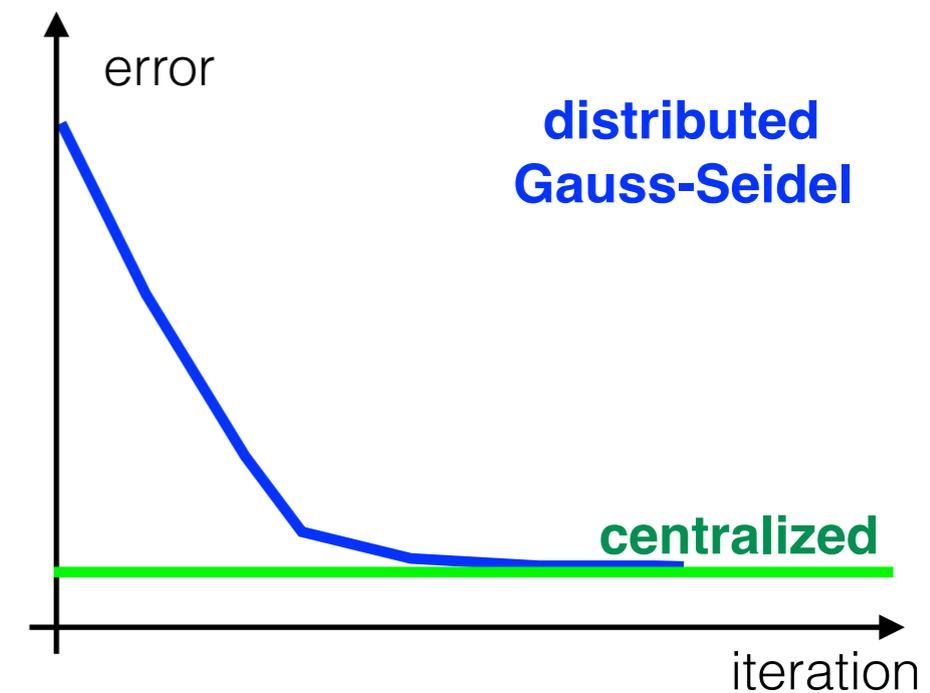


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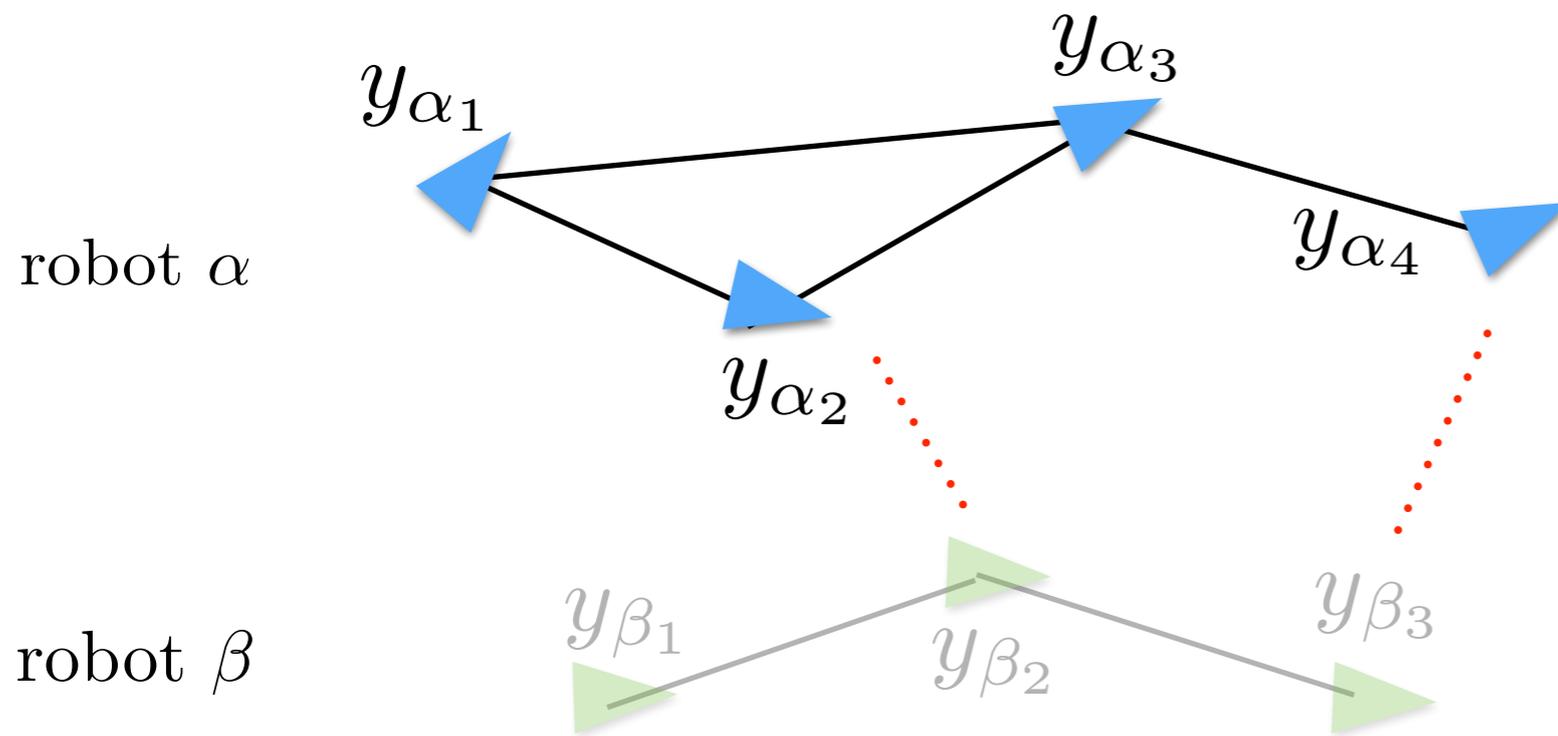
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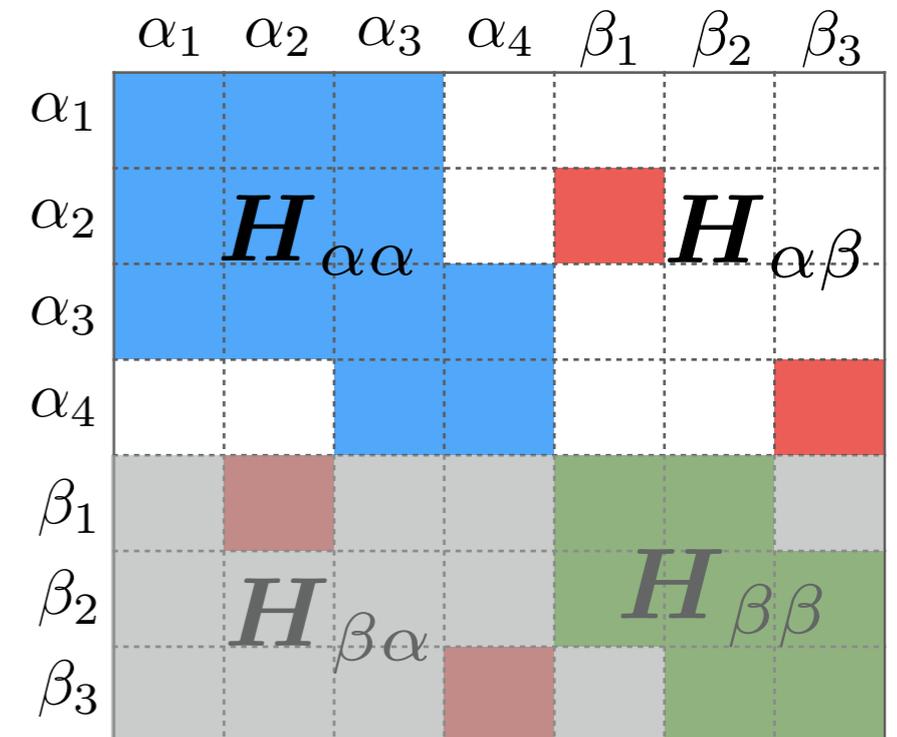


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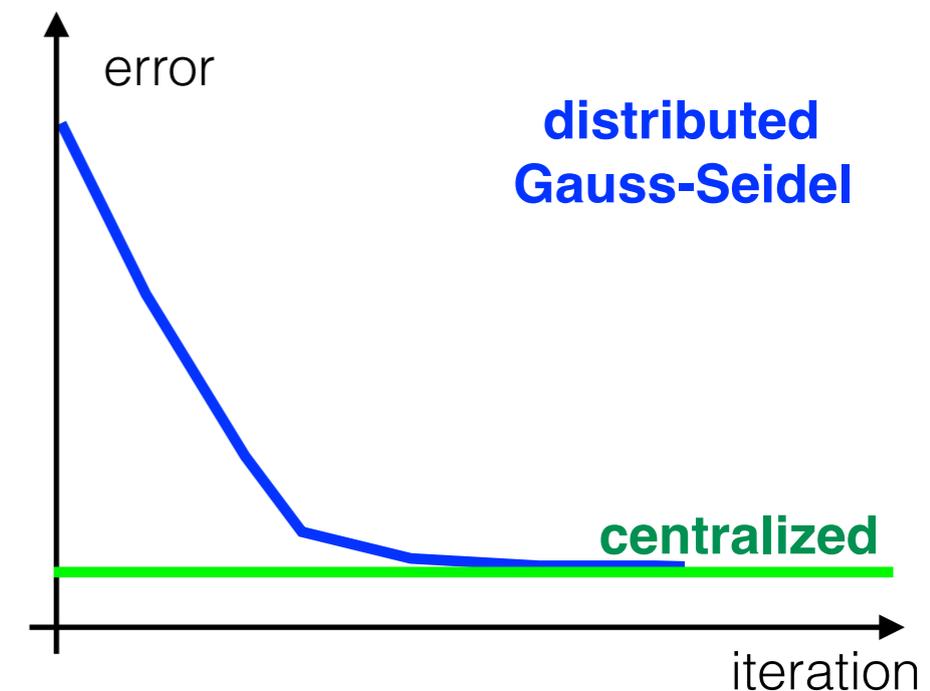


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Simulation Results

The approach has the following merits:

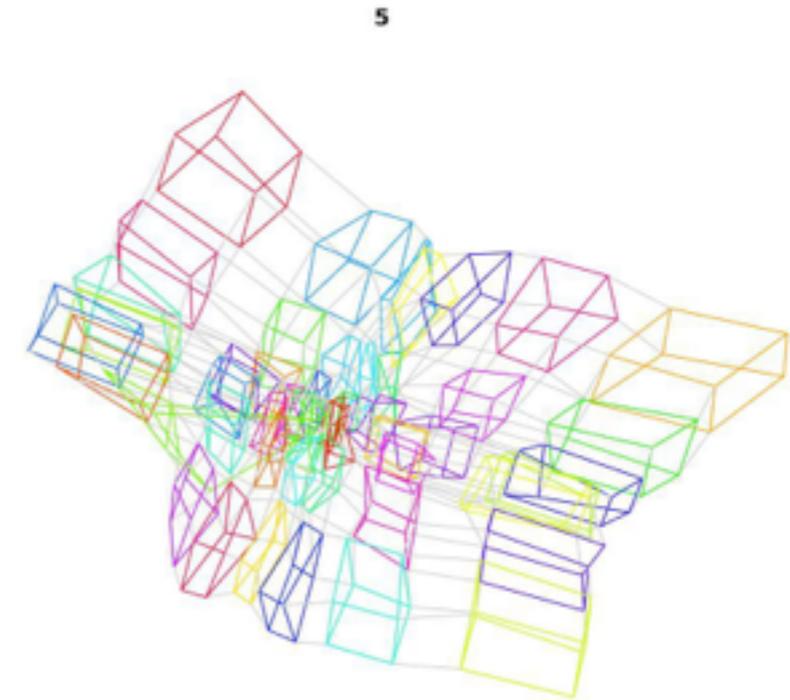
1. Proven convergence to centralized. Fast convergence with smart initialization

2. Communication is linear in number of rendezvous

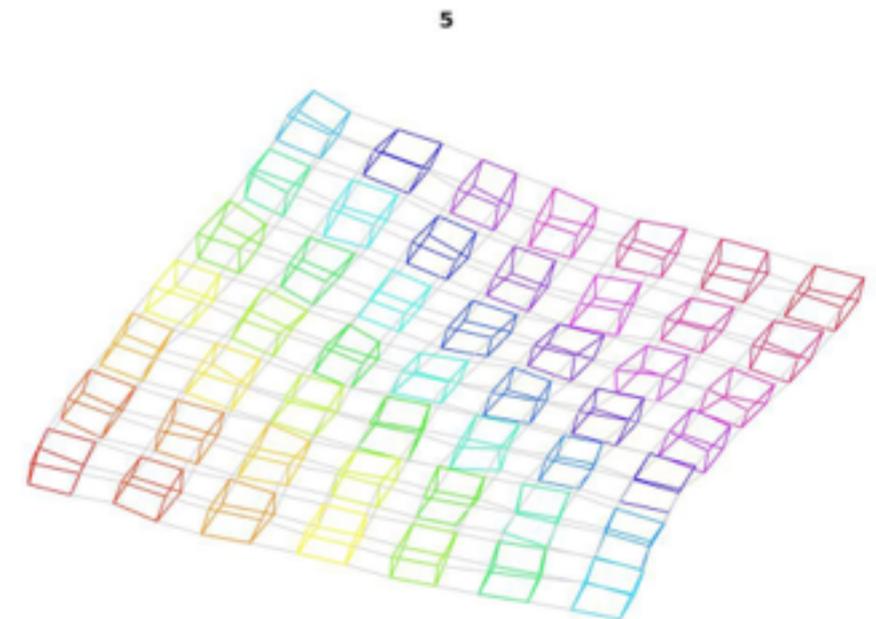
3. Scalability in the number of robots

4. Resilience to noise

Without
Flagged
Initialization



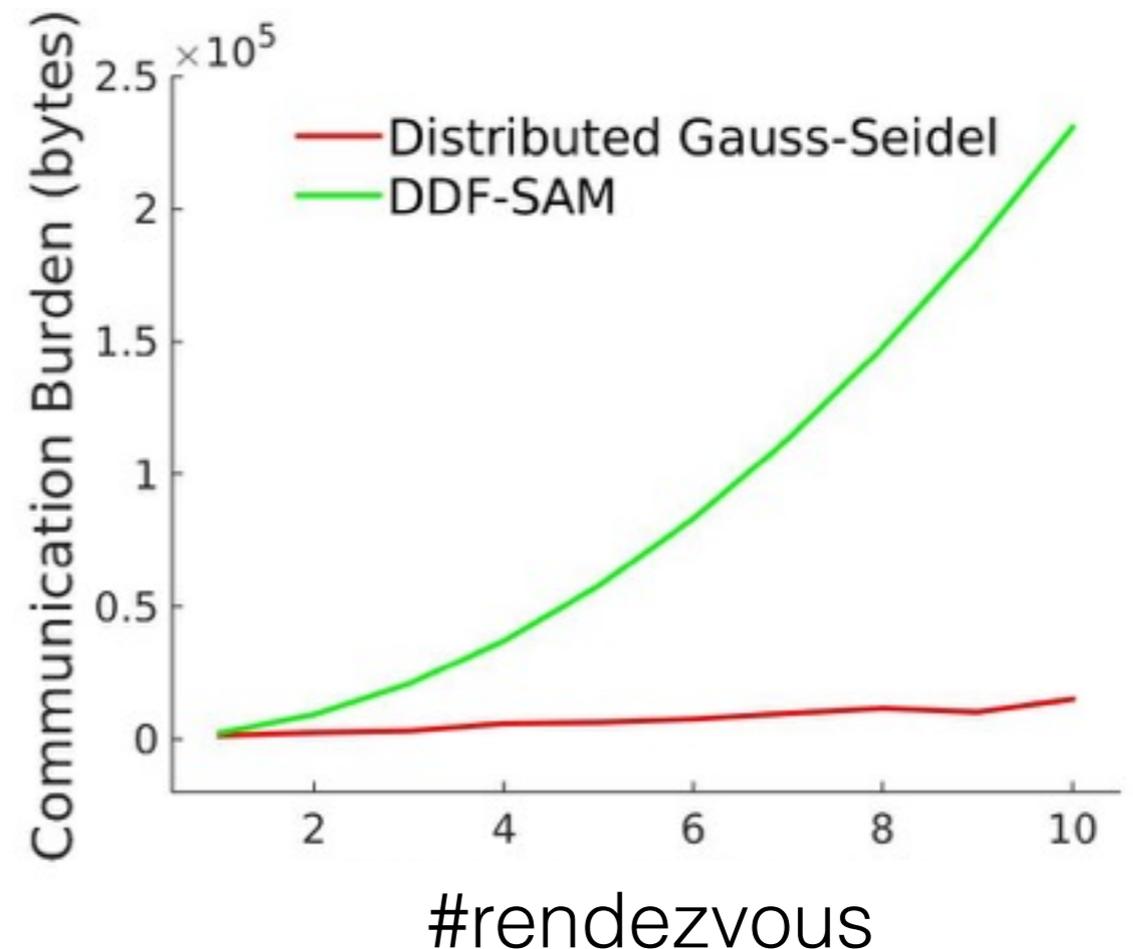
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Simulation Results

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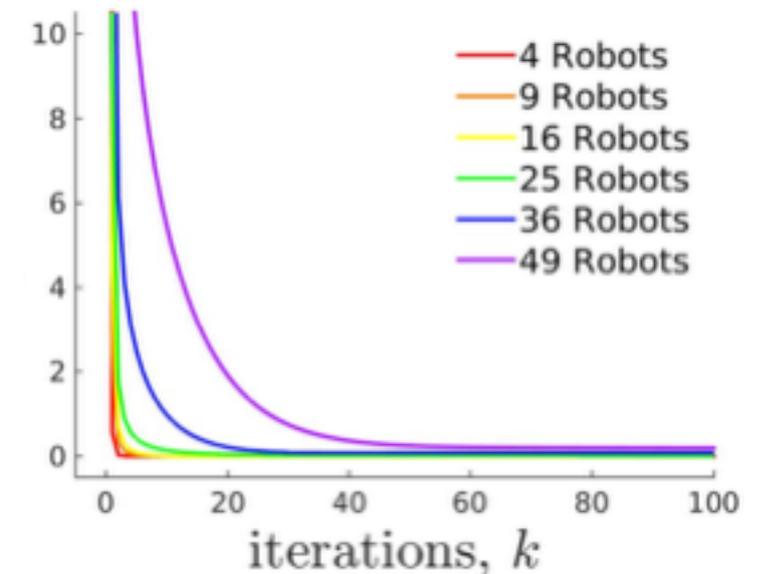


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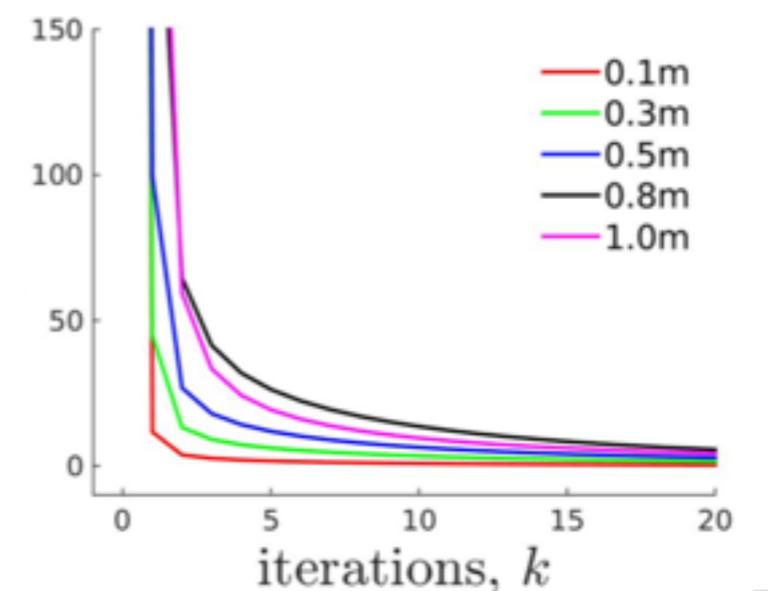
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1. Proven convergence to centralized. Fast convergence with smart initialization
2. Communication is linear in number of rendezvous
- 3. Scalability in the number of robots**
- 4. Resilience to noise**

Increasing number of robots



Increasing measurement noise



Field Experiments



We tested the proposed approach on field data collected by two to four Jackal robots, moving in a military test facility. We use the estimated trajectories to reconstruct a 3D map of the facility.



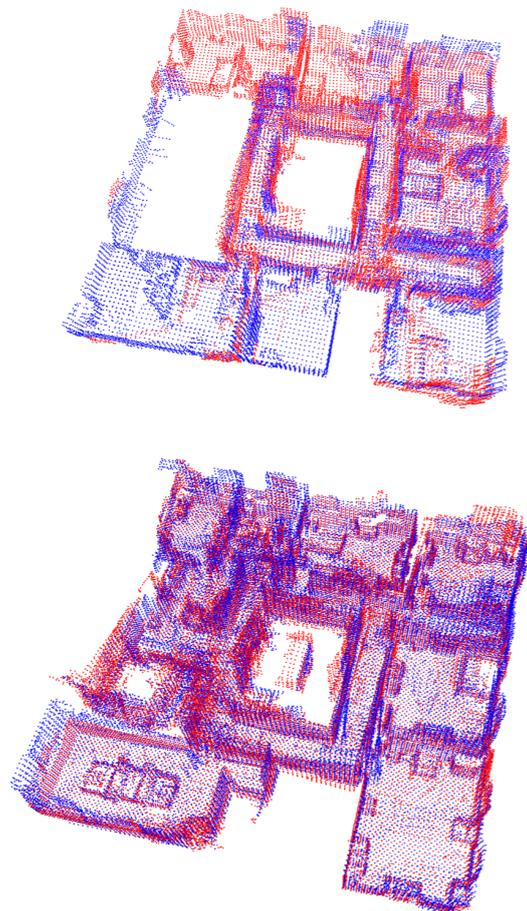
Field Experiments (4 Robots)



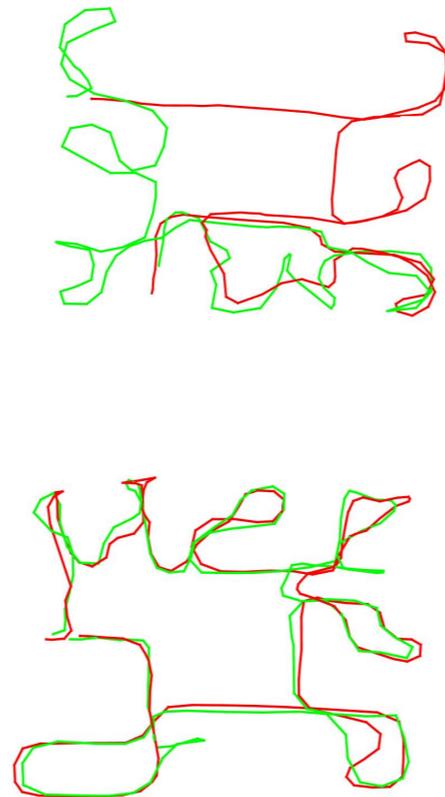
Thank you!

For further information, please come to the interactive session: **1.4 (Balcony)**

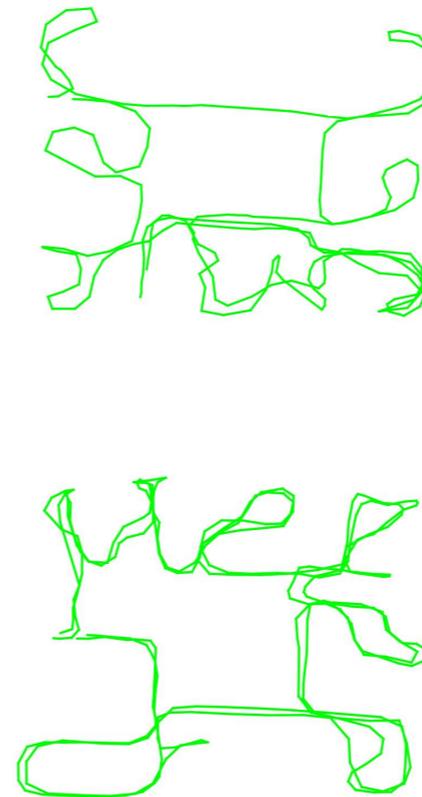
Point Cloud



Distributed



Centralized



Occupancy Grid

