Dynamic Covariance Scaling for Robust Robot Mapping

Workshop on Robust and Multimodal Inference in Factor Graphs

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Cyrill Stachniss and Wolfram Burgard

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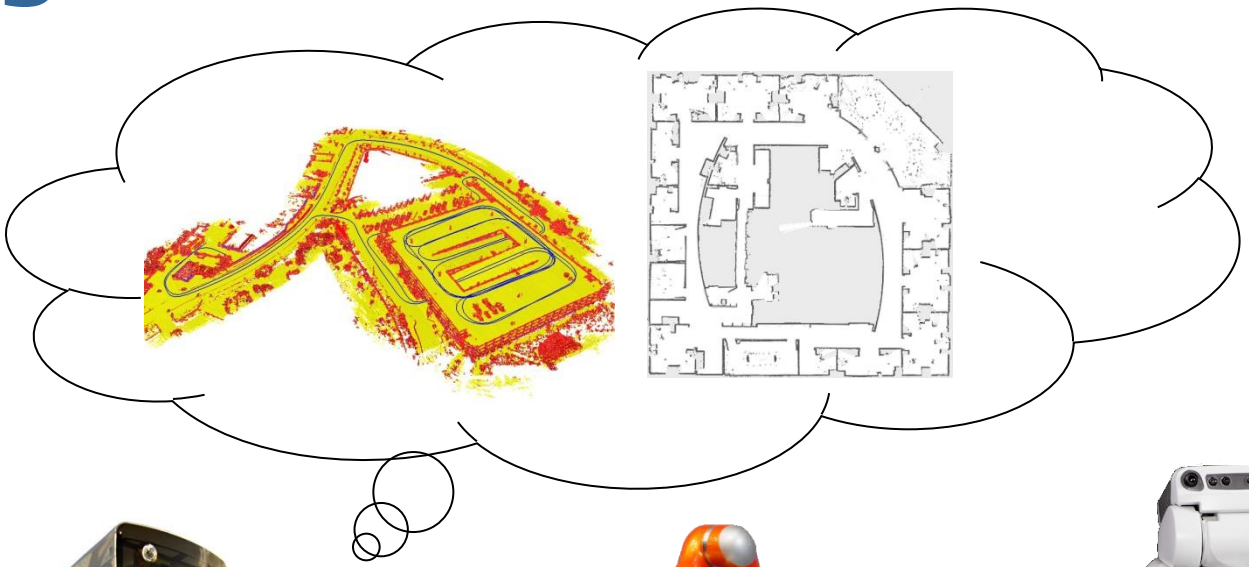
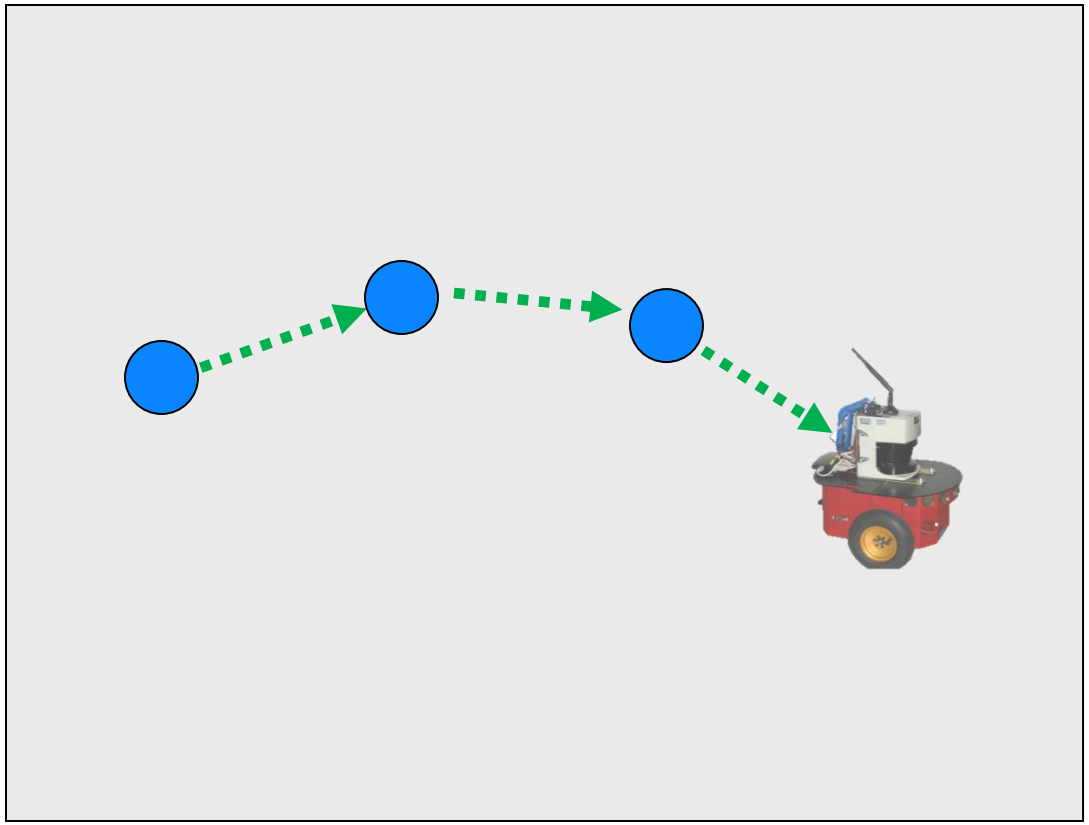
Maps are Essential for Effective Navigation



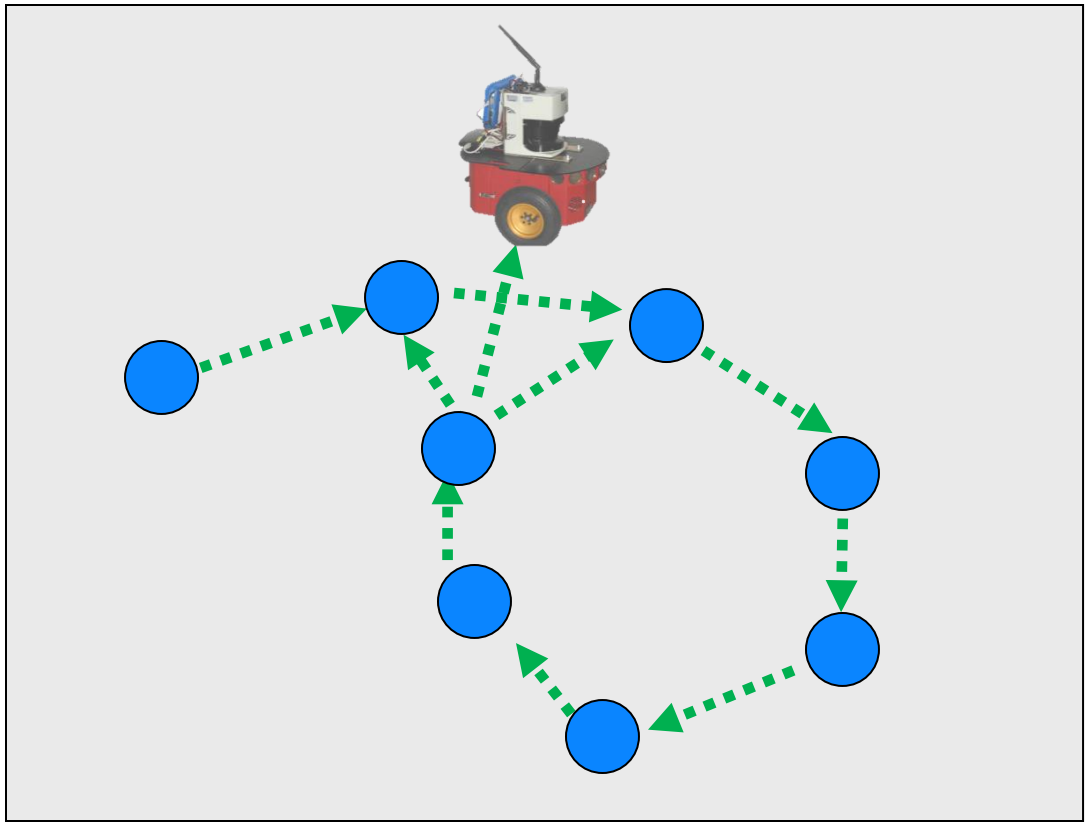
Graph-based SLAM



Robot pose

Constraint

Graph-based SLAM



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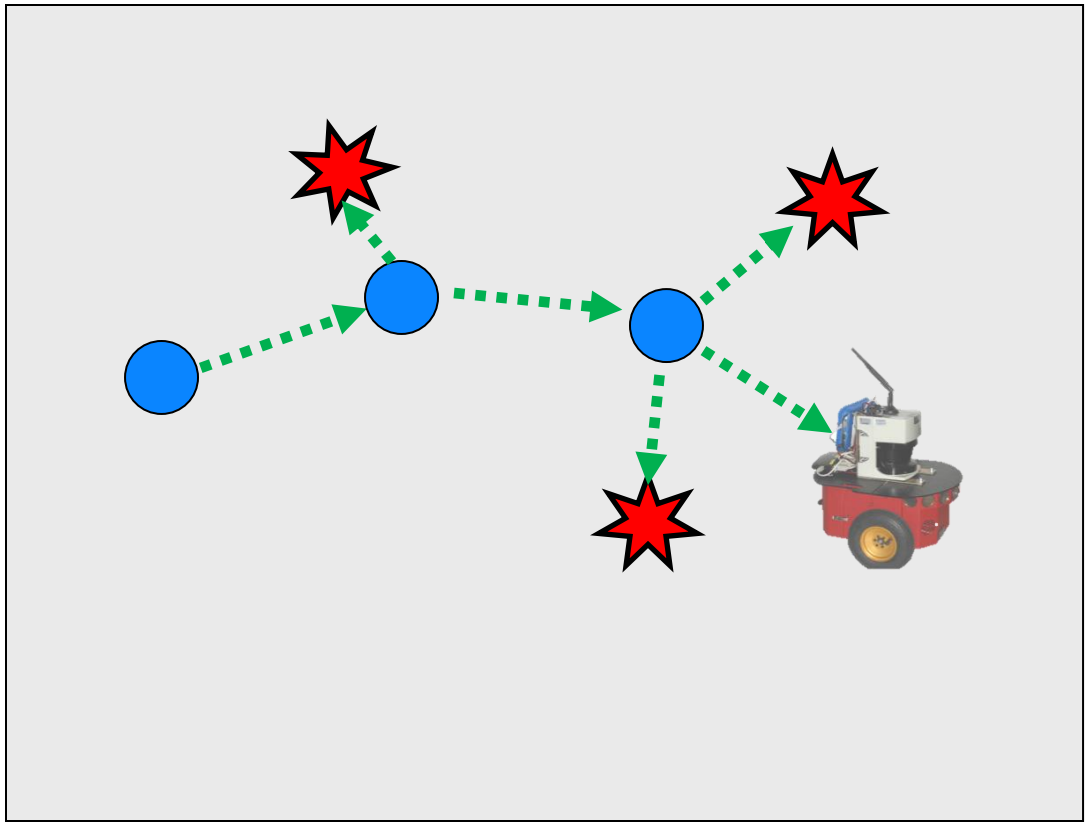
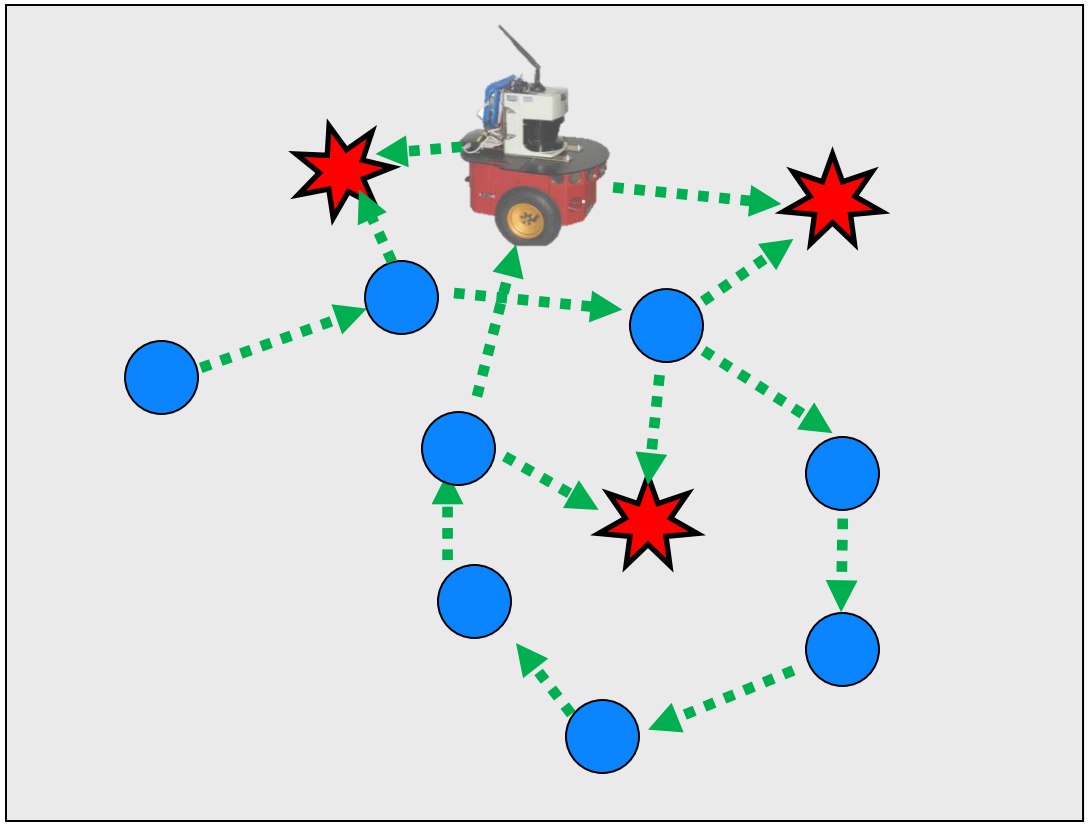


Robot pose

Constraint

Landmark

Graph-based SLAM



Robot pose

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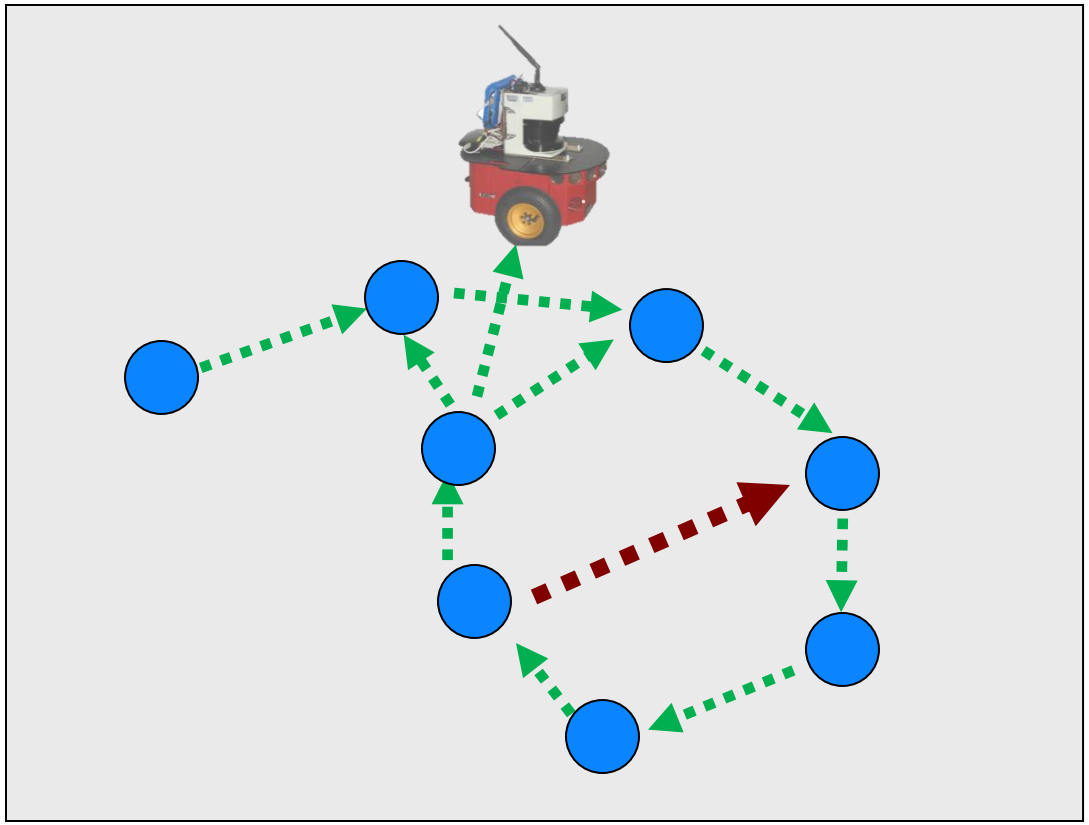
Landmark

Graph-based SLAM

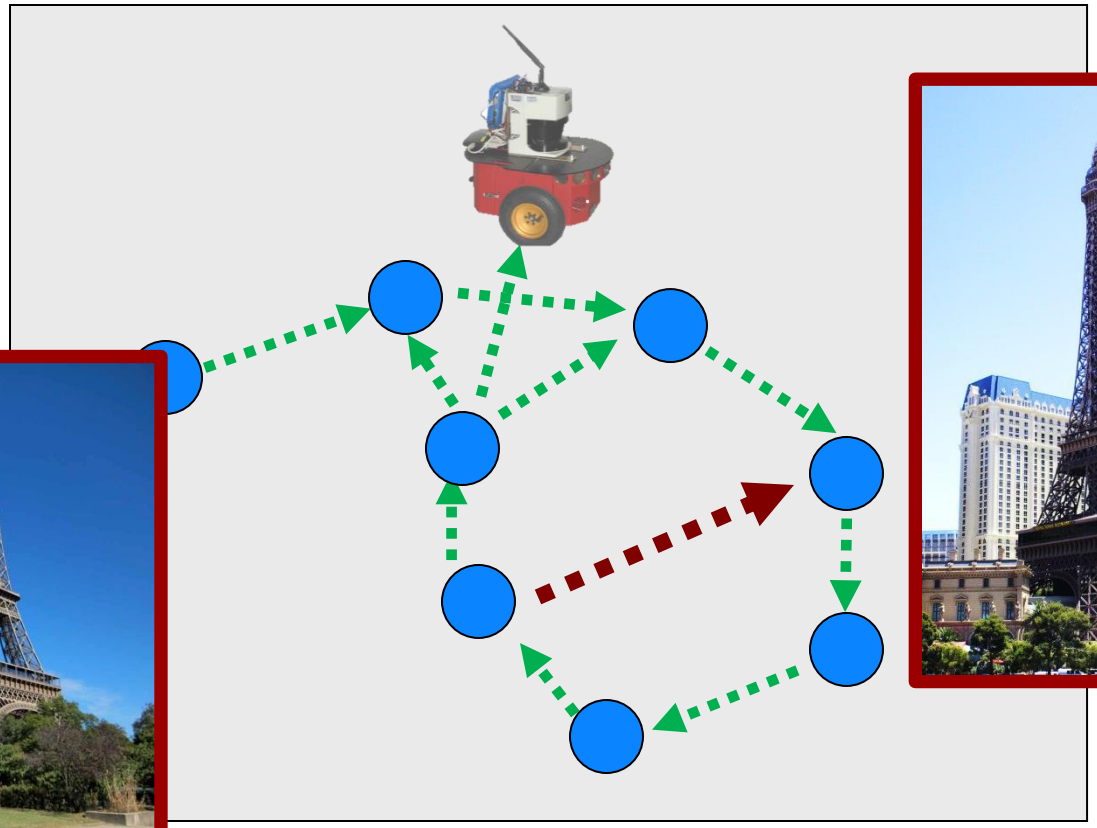


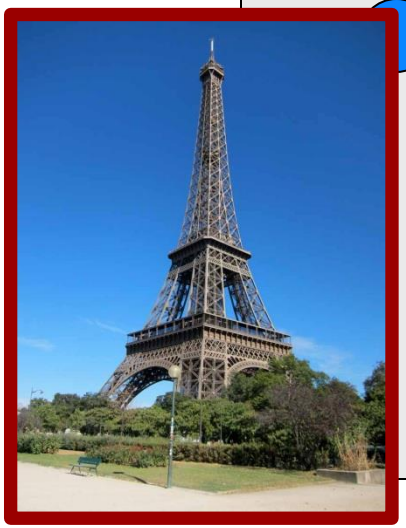
Robot pose

Constraint

a single outlier …

Graph-based SLAM



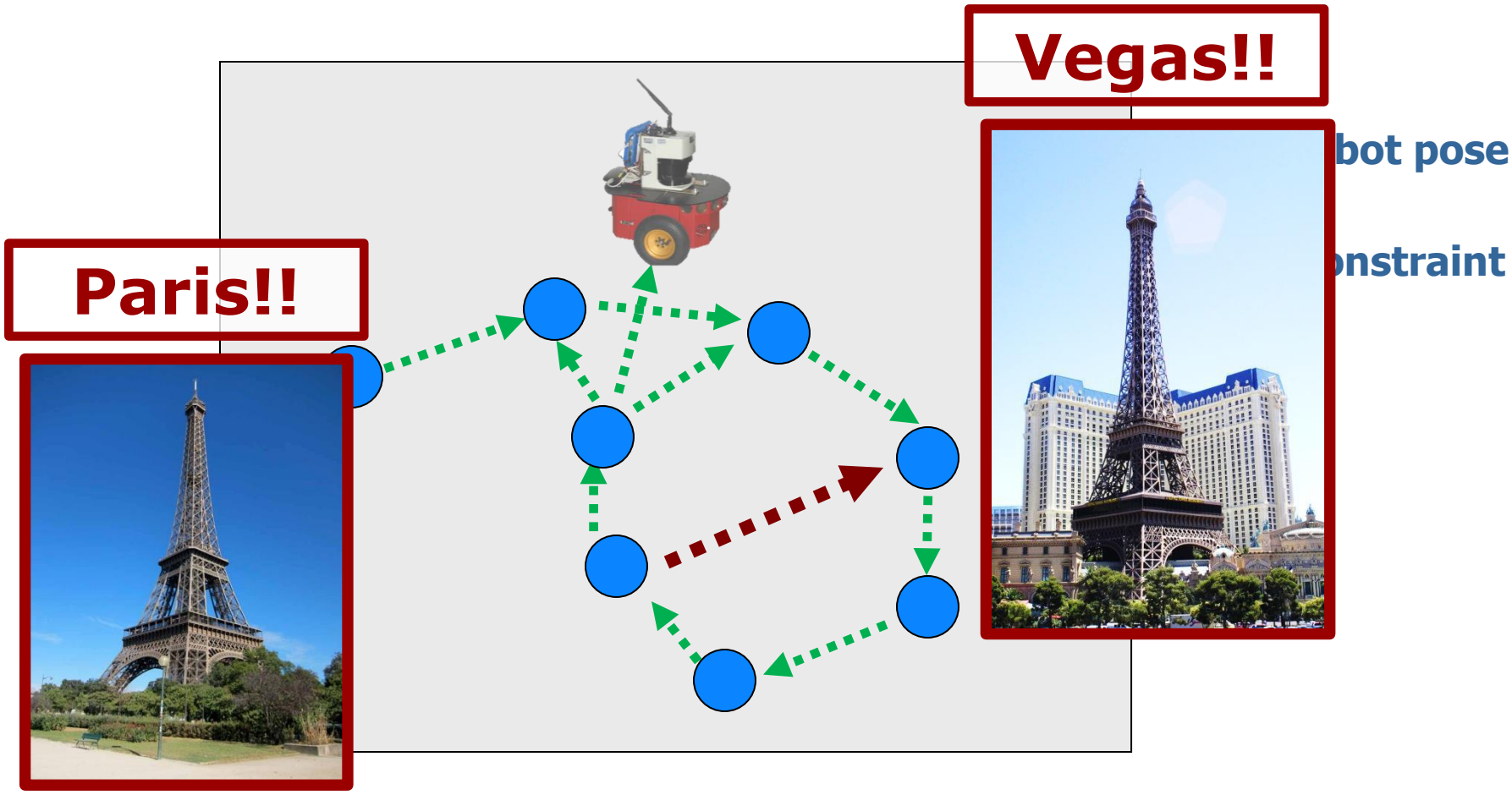


bot pose

onstraint

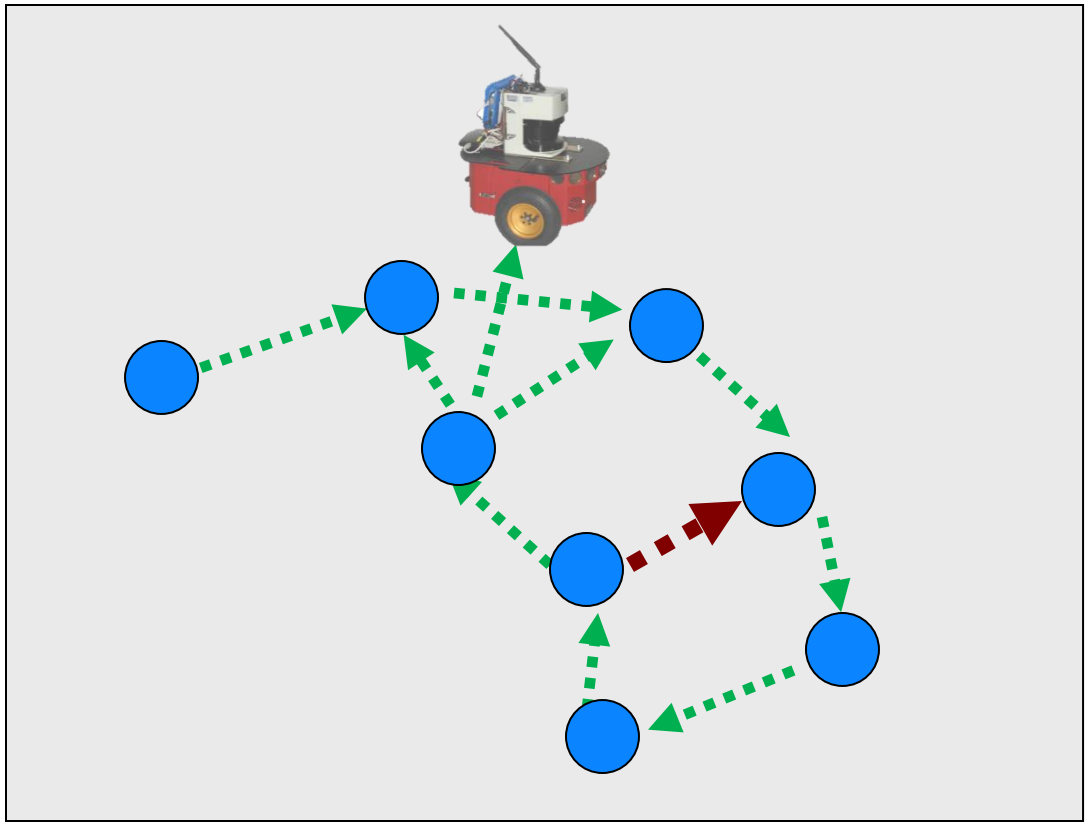
a single outlier …

Graph-based SLAM



a single outlier …

Graph-based SLAM



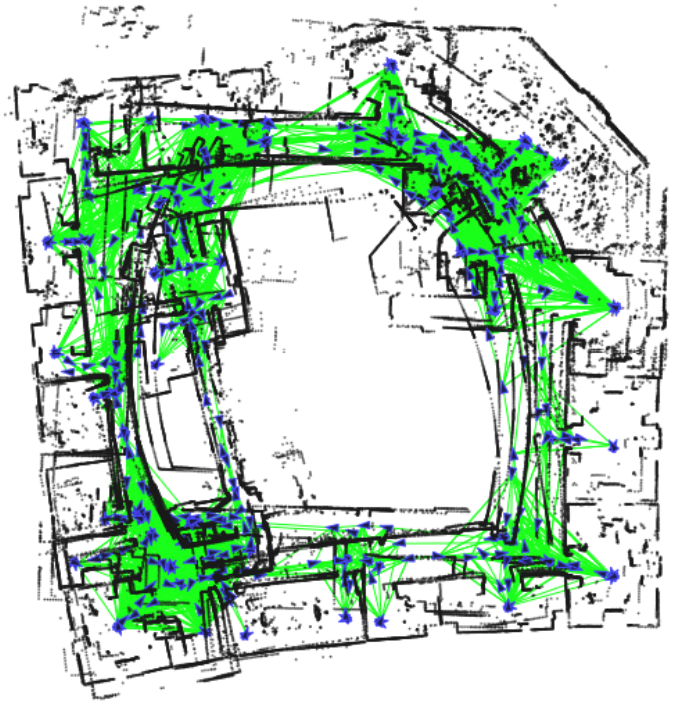
Robot pose

Constraint

a single outlier … ruins the map

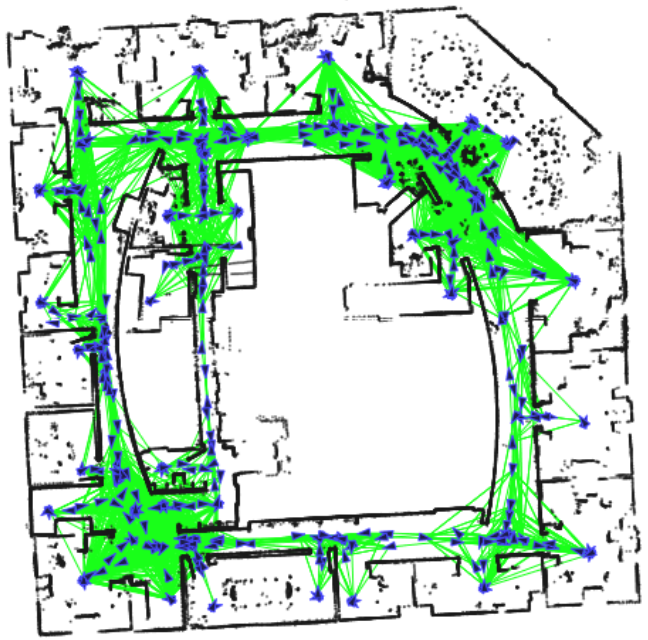
Graph-SLAM Pipeline

Front end → Validation → Back end



Assumption:

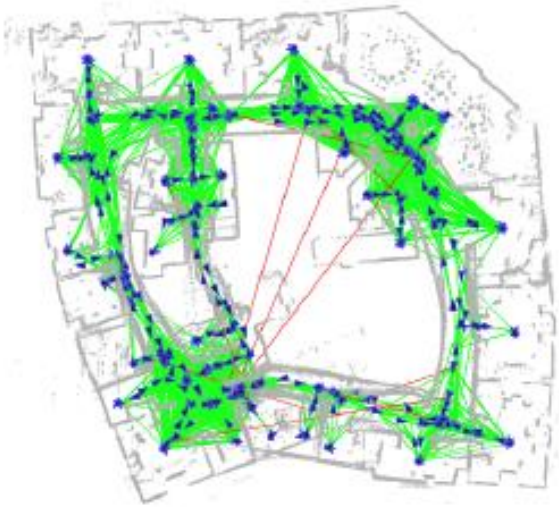
No Outliers



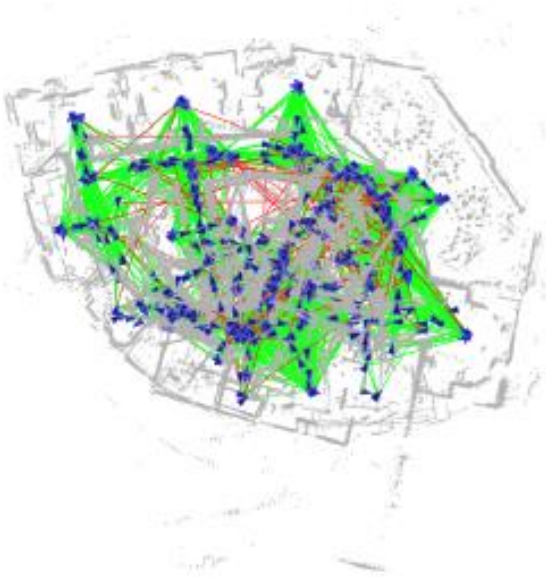
Impossible to have perfect validation

SLAM Back End Fails in the Presence of Outliers

1 Outlier

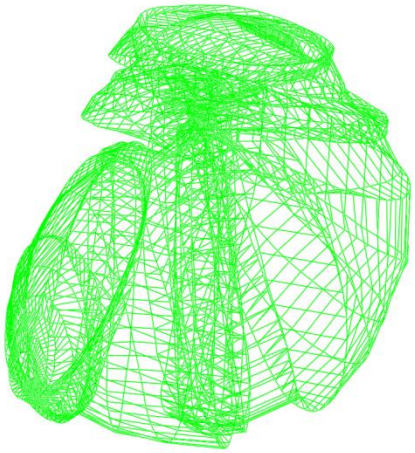


10 Outliers

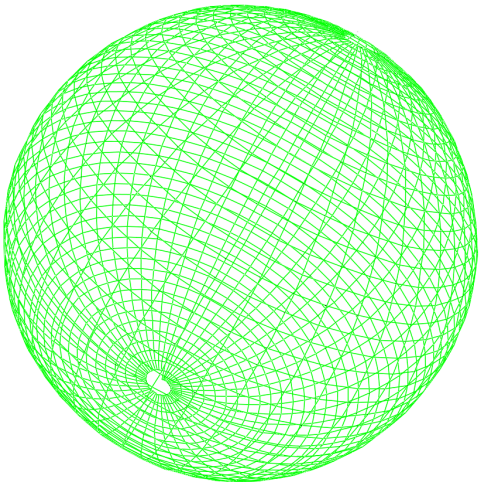


100 Outliers

SLAM Back End Depends on the Initial Guess



Good Initial Guess



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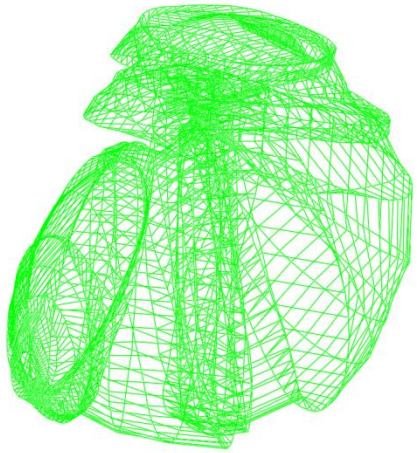
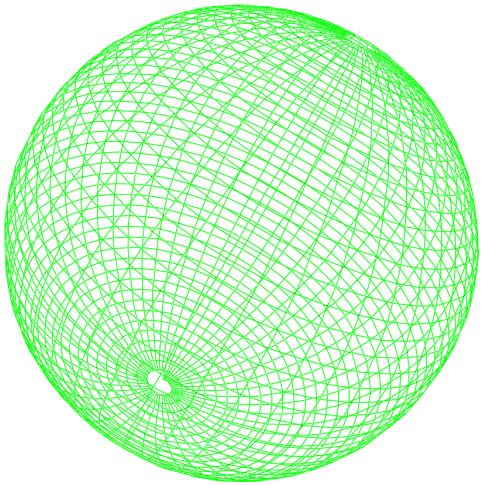
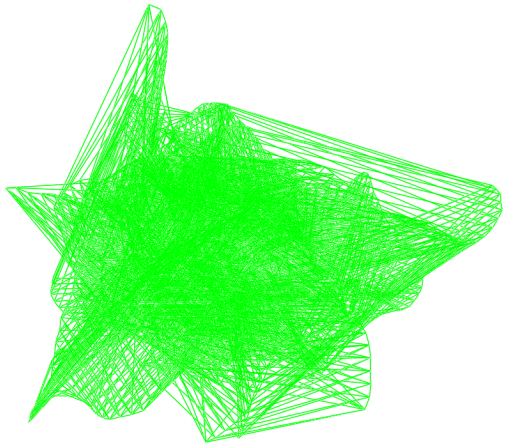


Good

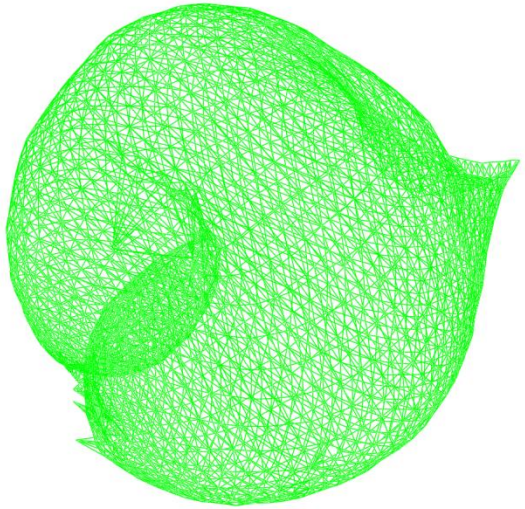
Initial Guess





Bad

Initial Guess



Typical Assumptions

- **Gaussian assumption is violated**
  - Perceptual aliasing
  - Measurement error
  - Multipath GPS measurements

Typical Assumptions

- **Gaussian assumption is violated**
  - Perceptual aliasing
  - Measurement error
  - Multipath GPS measurements
- **Linear approximation is invalid**
  - Linearization is only valid if close to optimum

Typical Assumptions in Graph-SLAM

- **No outliers**
- **Good initial guess**
- Current methods both **independently**
- Our method approaches **both problems**

Typical Assumptions in Graph-SLAM

- **No outliers**
- **Good initial guess**
- Current methods solve both **independently**
- Our method approaches **both problems**

Our Approach

- **Dynamic Covariance Scaling**

Our Approach:
Dynamic Covariance Scaling

- Successfully **rejects** outliers
- More robust to **bad initial guess**
- Does not increase state space
- Is a robust M-estimator

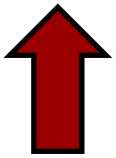
Standard Gaussian Least Squares

$$X^* = \underset{X}{\operatorname{argmin}} \sum_{ij} \underbrace{\mathbf{e}_{ij}(X)^T \Omega_{ij} \mathbf{e}_{ij}(X)}_{\chi^2_{ij}}$$

Dynamic Covariance Scaling

$$X^* = \underset{X}{\operatorname{argmin}} \sum_{ij} \underbrace{\mathbf{e}_{ij}(X)^T \Omega_{ij} \mathbf{e}_{ij}(X)}_{\chi^2_{ij}}$$

$$X^* = \underset{X}{\operatorname{argmin}} \sum_{ij} \mathbf{e}_{ij}(X)^T \left(s^2_{ij} \Omega_{ij}\right) \mathbf{e}_{ij}(X)$$



How to Determine s?

$$X^* = \underset{X}{\operatorname{argmin}} \sum_{ij} \mathbf{e}_{ij}(X)^T \left(s_{ij}^2 \Omega_{ij}\right) \mathbf{e}_{ij}(X)$$

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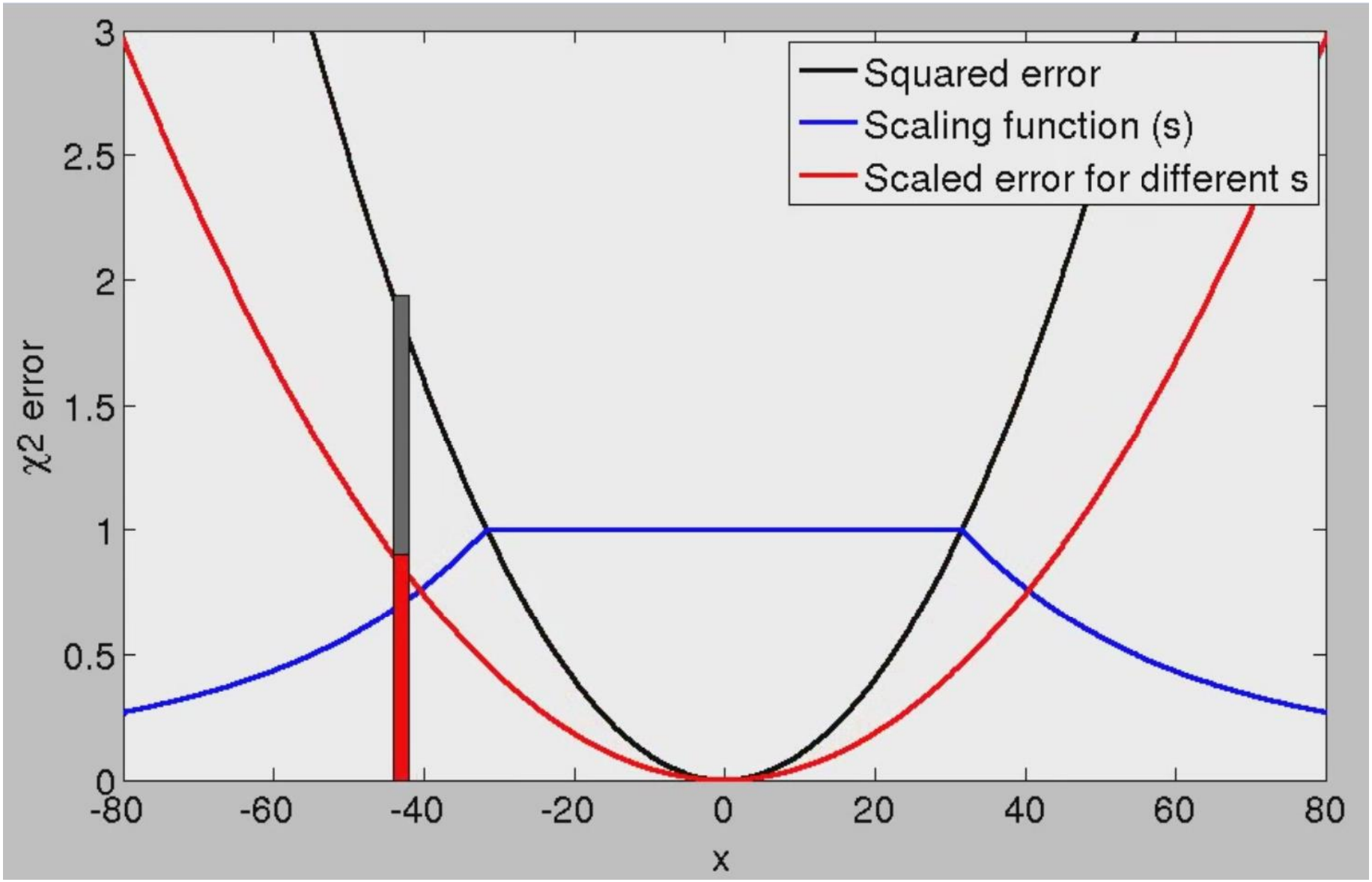
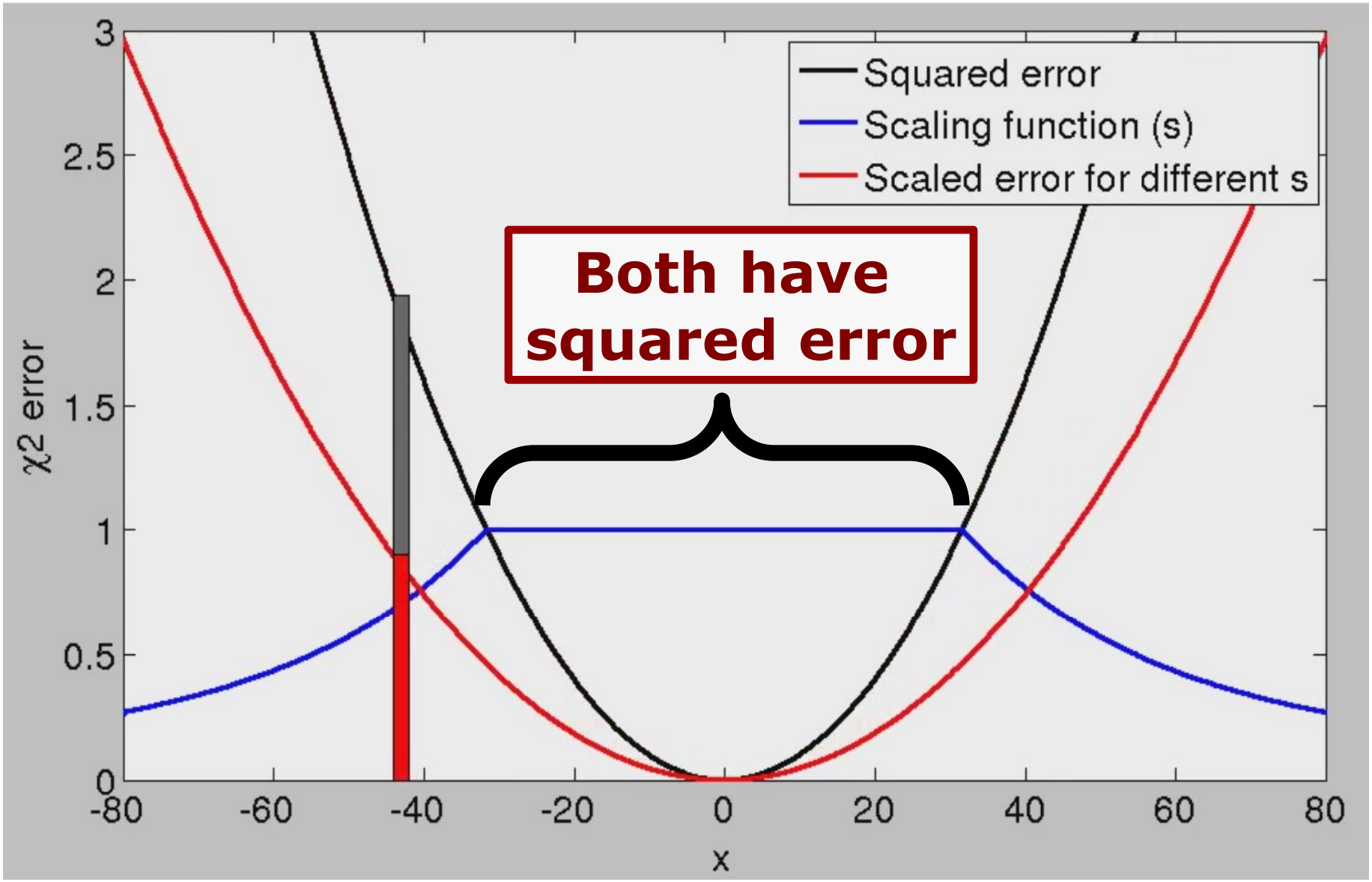
$$\Rightarrow s_{ij} = \min\left(1, \frac{2\Phi}{\Phi + \chi_{ij}^2}\right)$$

Closed form approximation of Switchable Constraints with a M-estimator

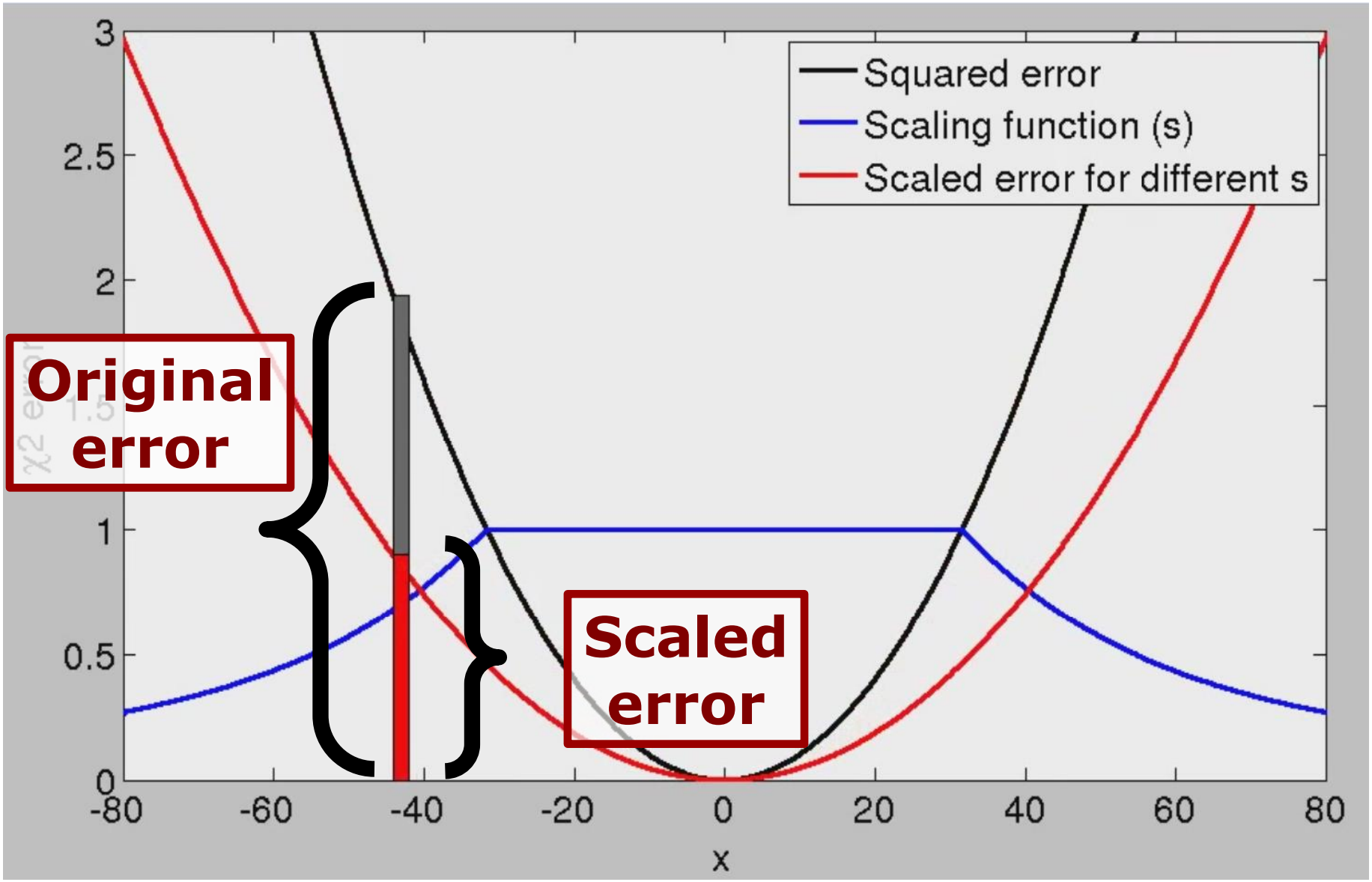
Dynamic Covariance Scaling



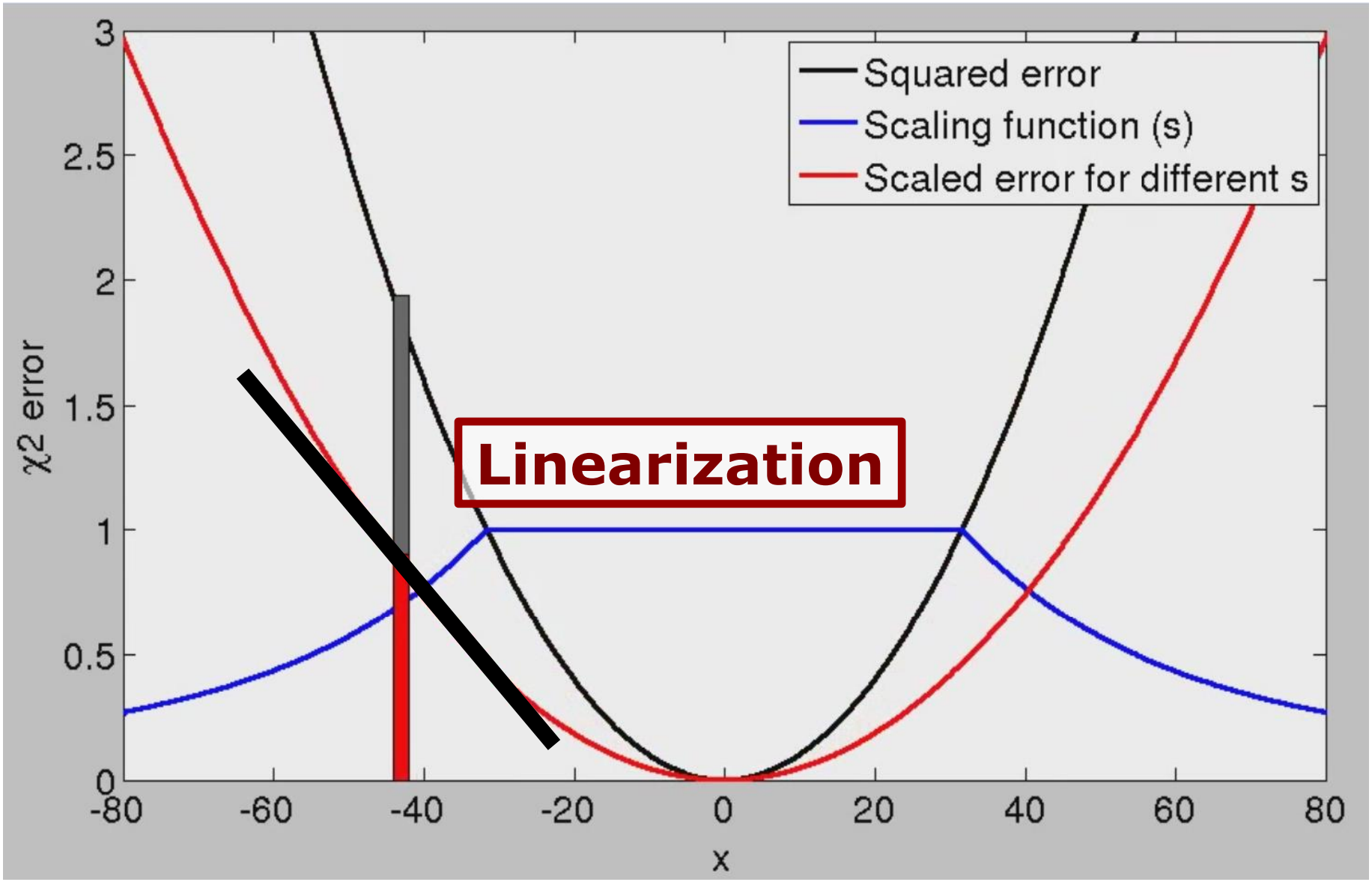
Dynamic Covariance Scaling



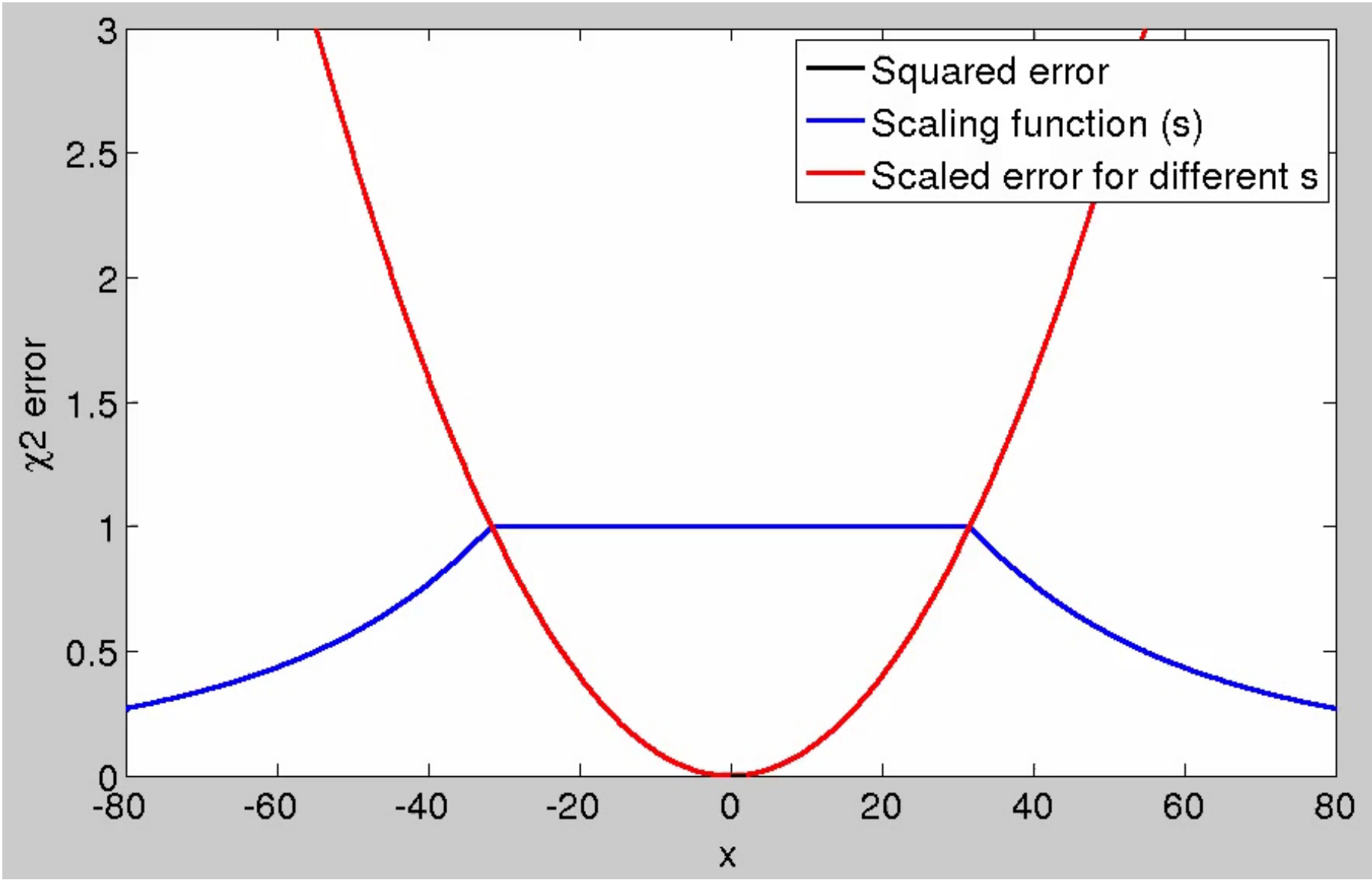
Dynamic Covariance Scaling



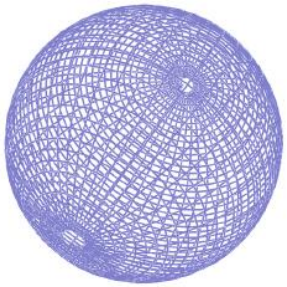
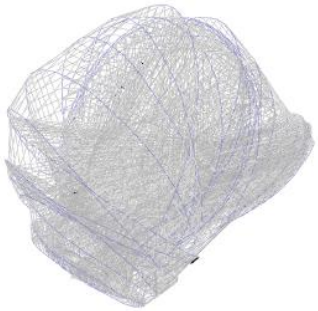
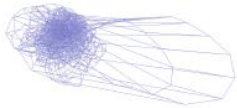
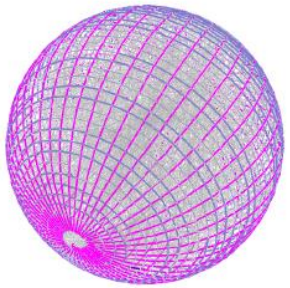
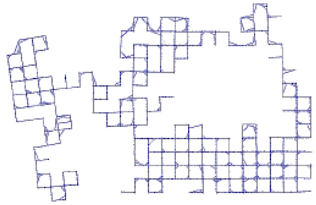
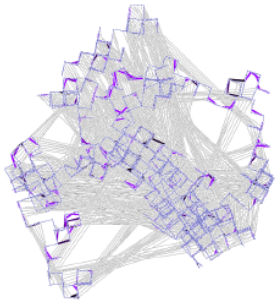
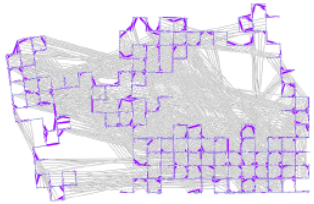
Dynamic Covariance Scaling



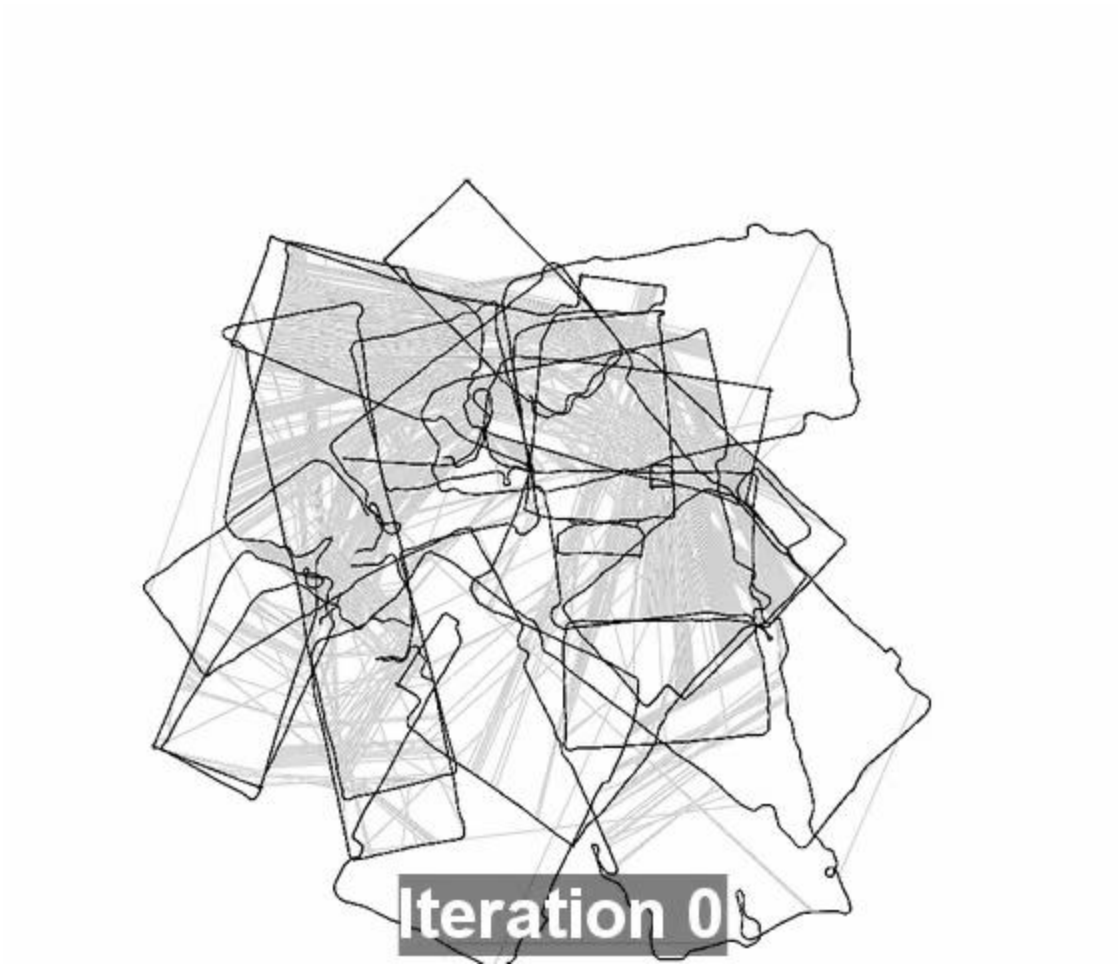
Dynamic Covariance Scaling

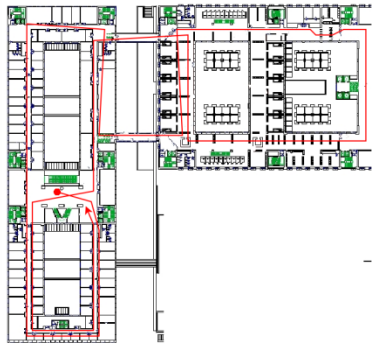


Robust SLAM with Our Method

	Ground Truth	Initialization	Gauss Newton	**Our Method**
Sphere2500 (1000 Outiers)				
Manhattan3500 (1000 Outiers)				

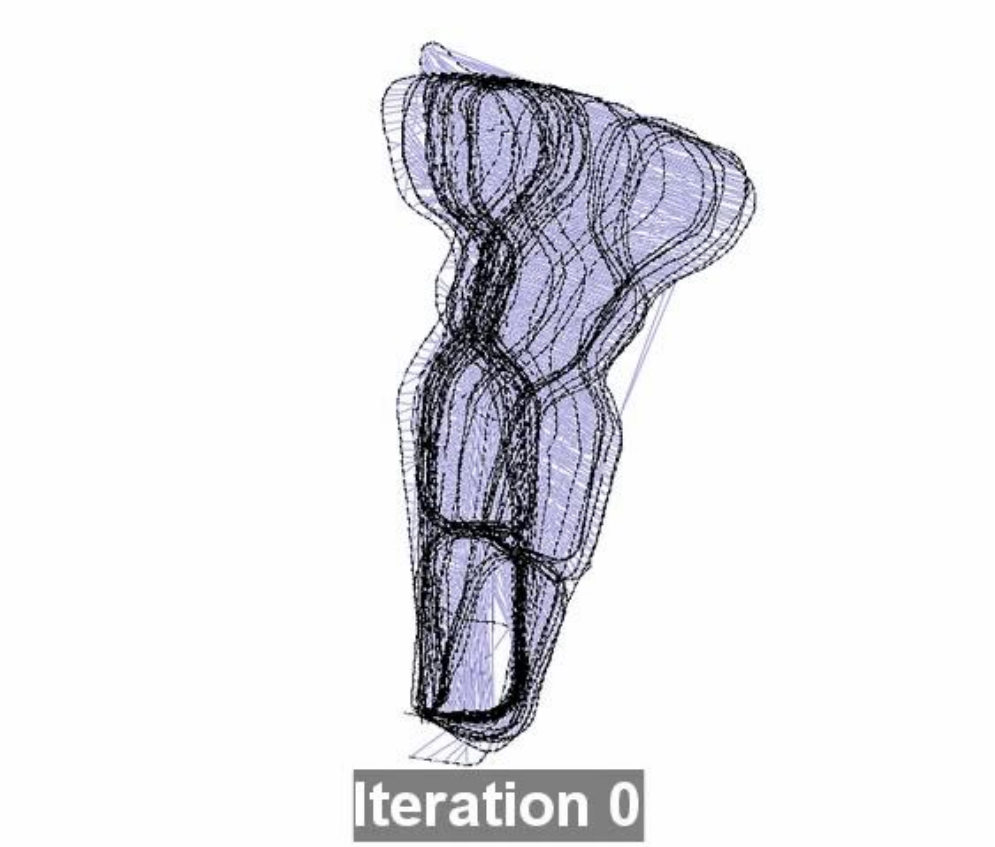
Dynamic Covariance Scaling with Front-end Outliers





Bicocca multisession dataset

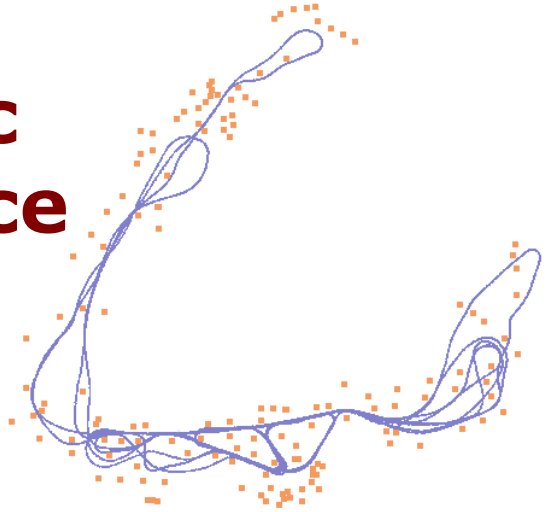
Dynamic Covariance Scaling with Front-end Outliers

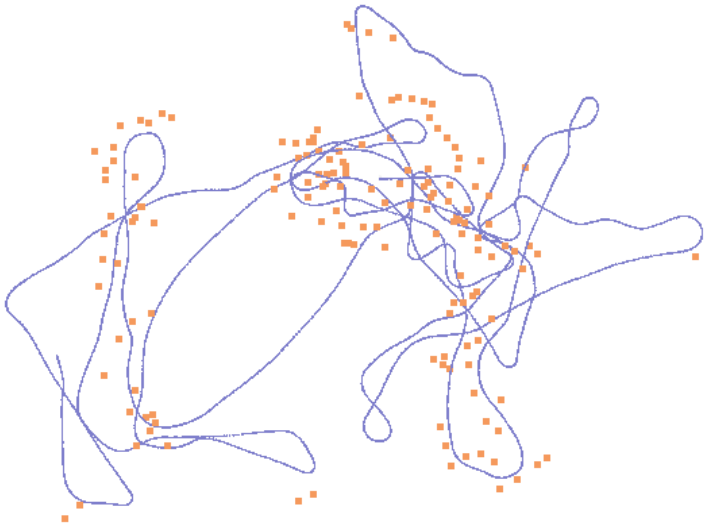


Lincoln-labs multisession dataset

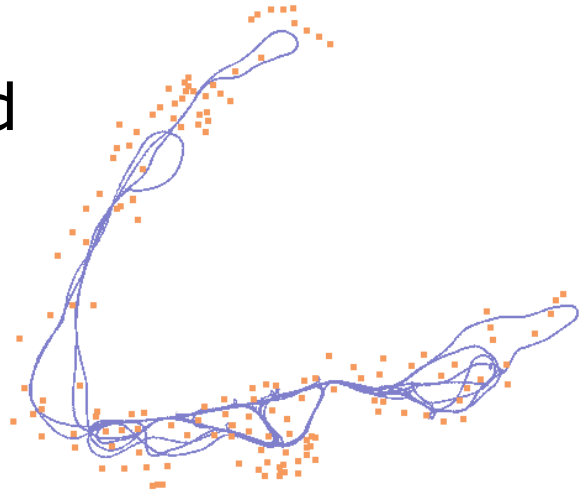
Robust SLAM with Our Method

Dynamic Covariance Scaling





Standard Gauss-Newton

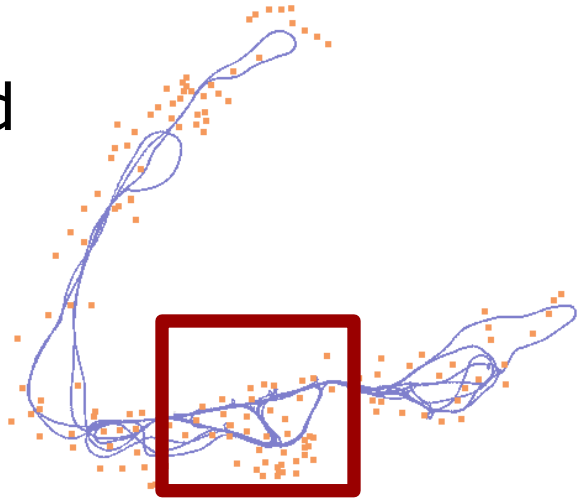


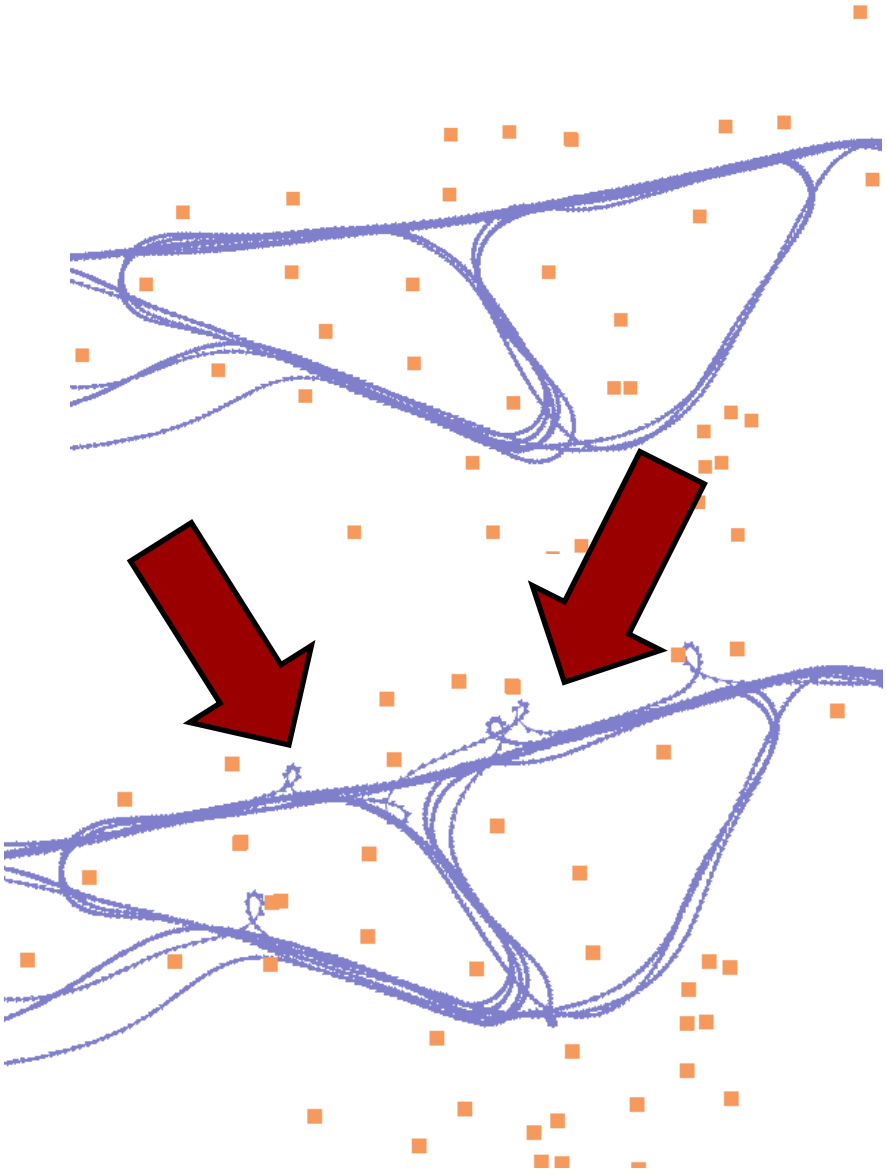
Victoria Park Initialization (Odometry)

Robust SLAM with Our Method

Dynamic Covariance Scaling

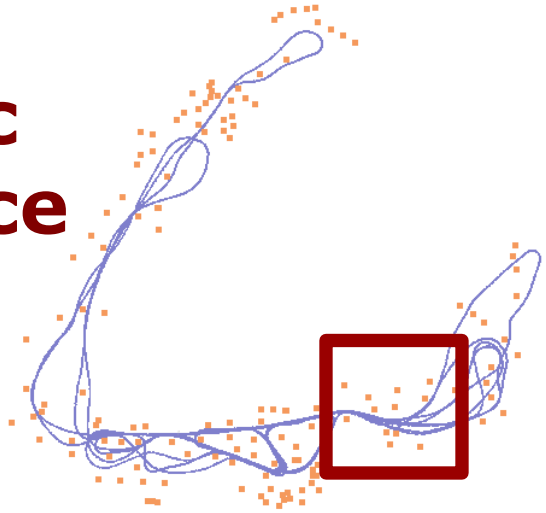
Standard Gauss-Newton

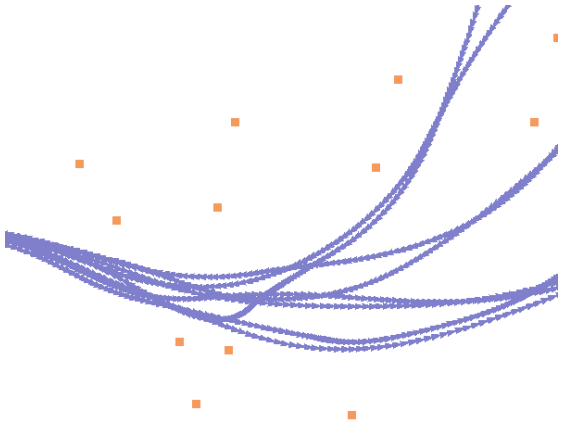




Robust SLAM with Our Method

Dynamic Covariance Scaling





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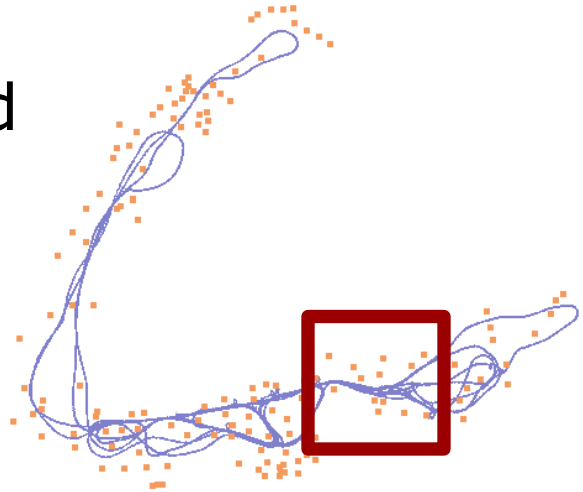
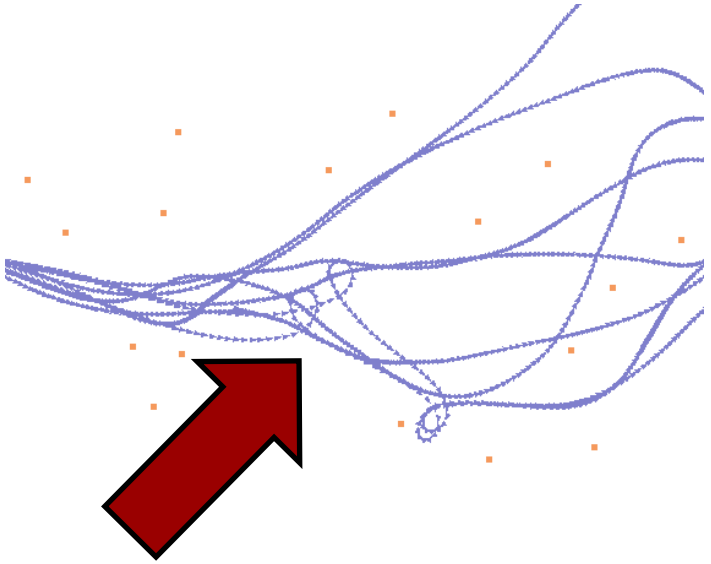
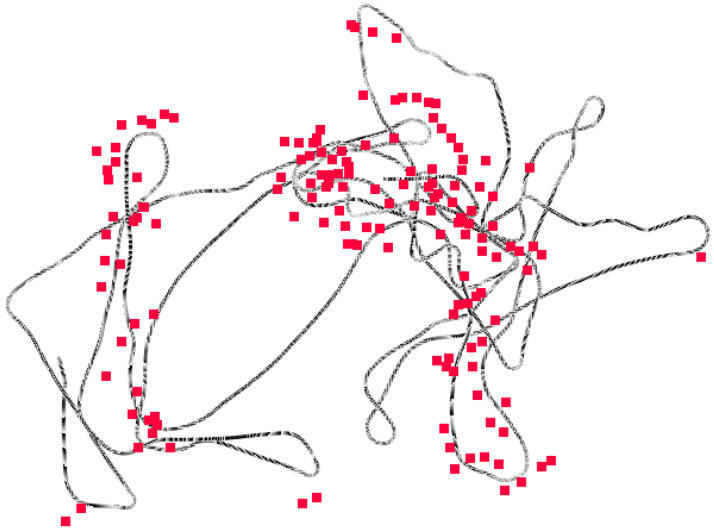
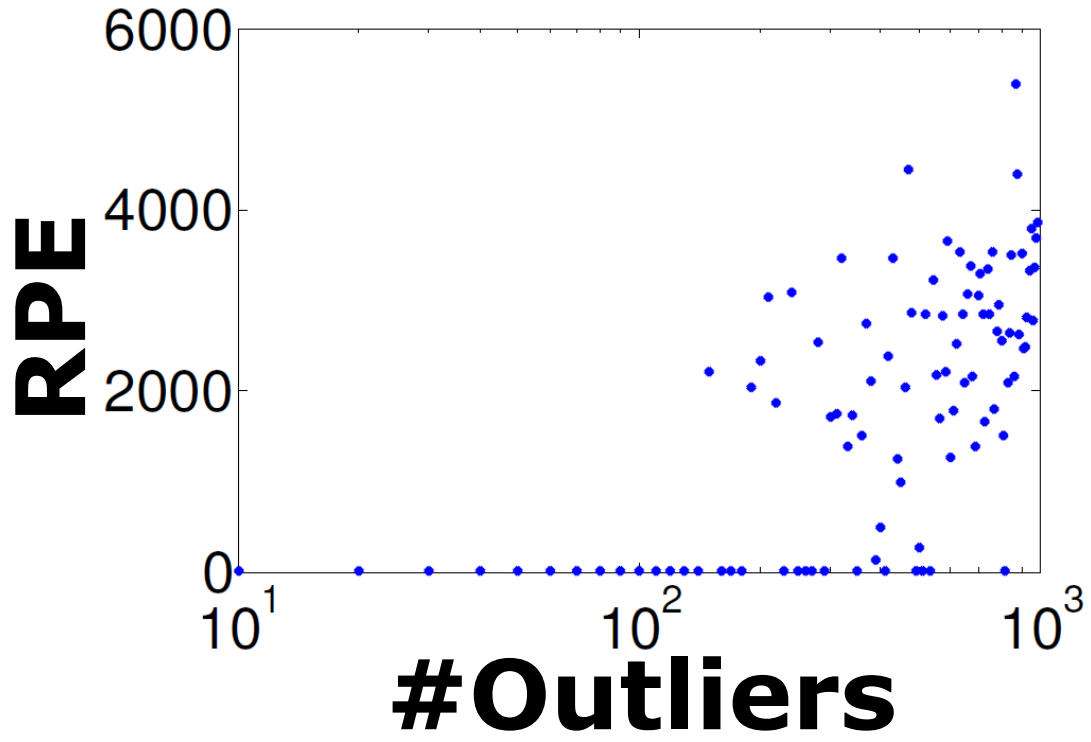




Dynamic Covariance Scaling with Outliers in Victoria Park

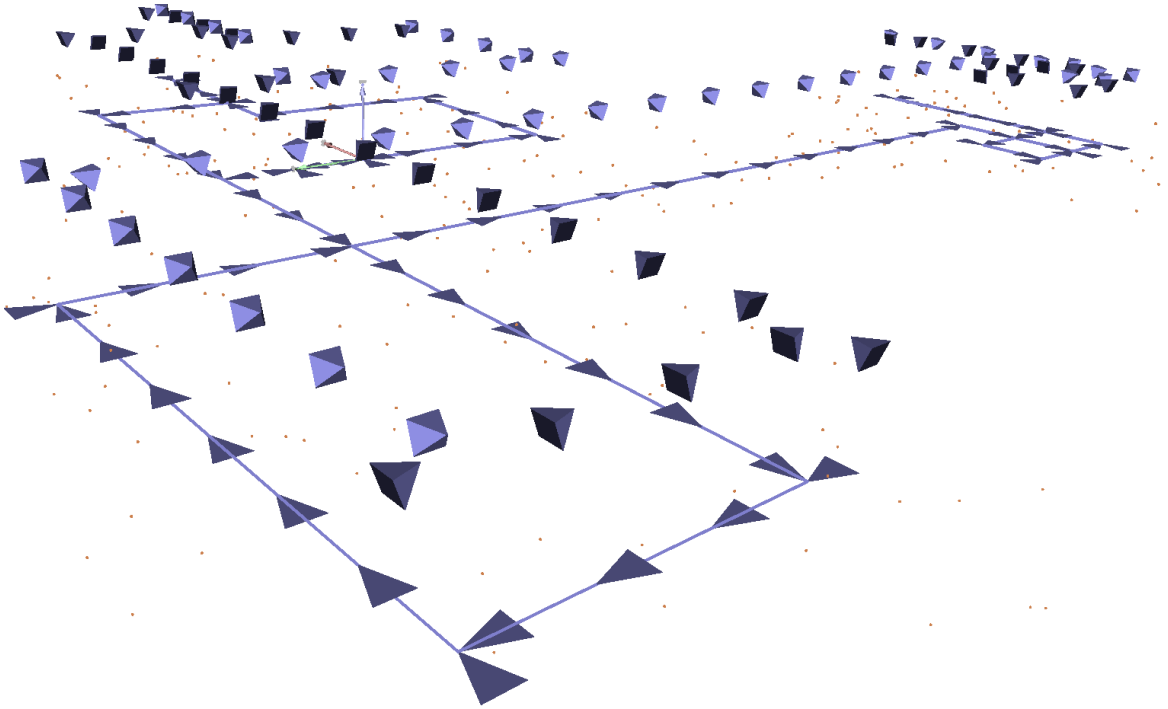




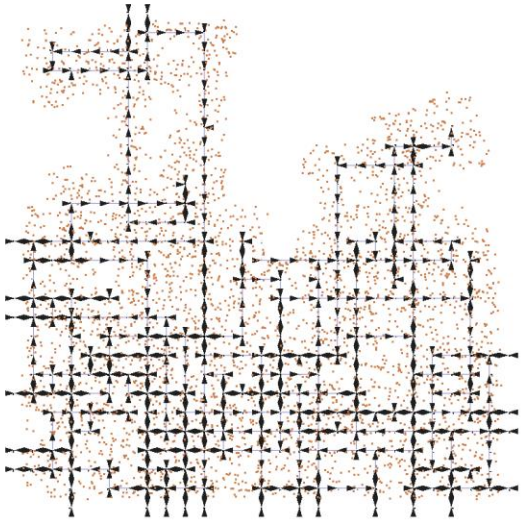
- DCS recovers correct solution
- GN fails to converge to the correct solution even for **outlier-free case**

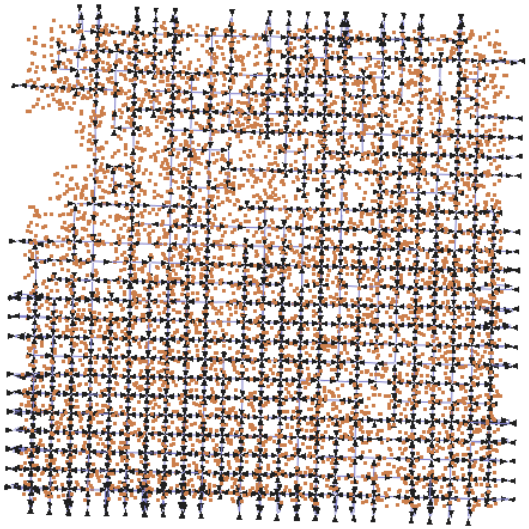
Robust Visual SLAM with Our Method

- 3D grid worlds of different sizes
- Robot perceives point landmarks



Robust Visual SLAM with Our Method





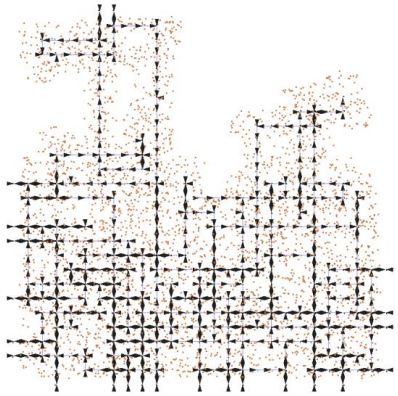
- ~1000 camera poses
- ~4000 features
- ~20K constraints

- ~5000 camera poses
- ~5000 features
- ~100K constraints

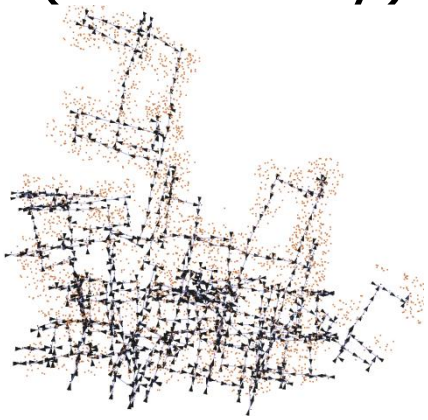
Robust Visual SLAM with DCS

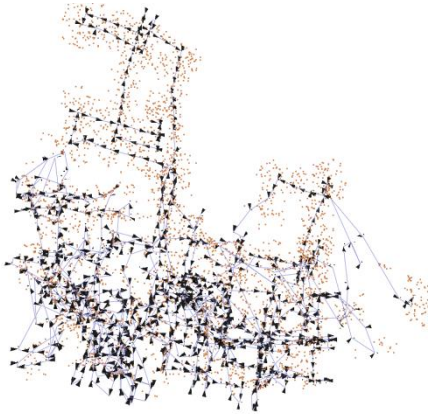
Simulated Stereo
(Bad initial guess)

Ground
Truth



Initialization
(Odometry)





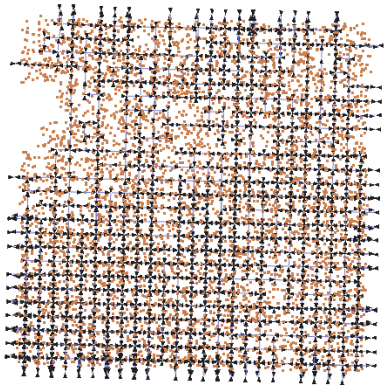
Levenberg-Marquardt
(100 iterations)

Our Method
(15 iterations)

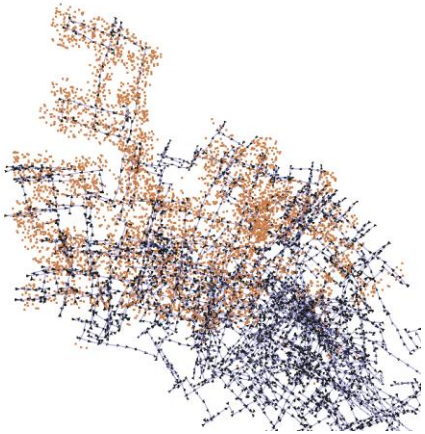
Robust Visual SLAM with DCS

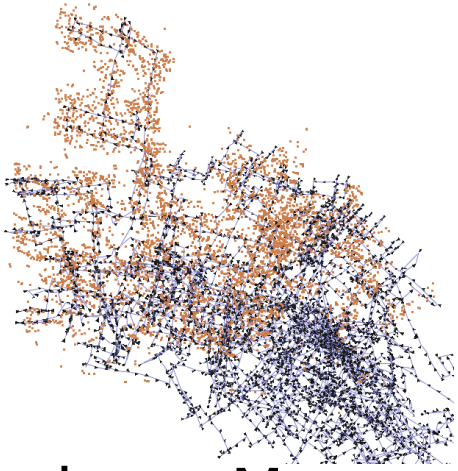
Simulated Stereo
(Bad initial guess)

Ground
Truth

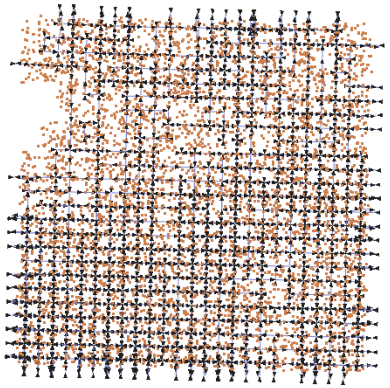


Initialization
(Odometry)



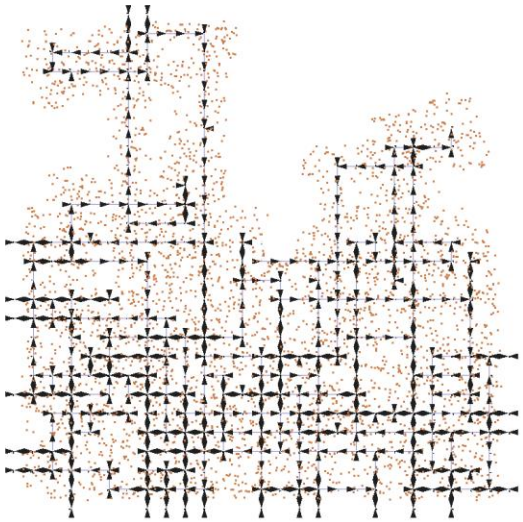


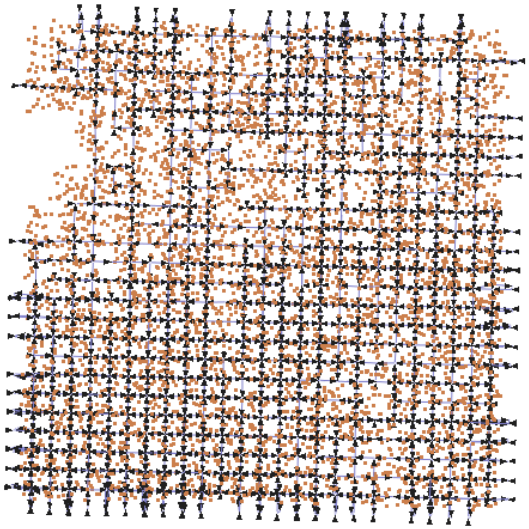
Levenberg-Marquardt
(150 iterations)



Our Method
(15 iterations)

Robust Visual SLAM with DCS





- DCS recovers correct solution in the presence of up to **25% outliers**
- LM fails to converge to the correct solution even for **outlier-free cases**

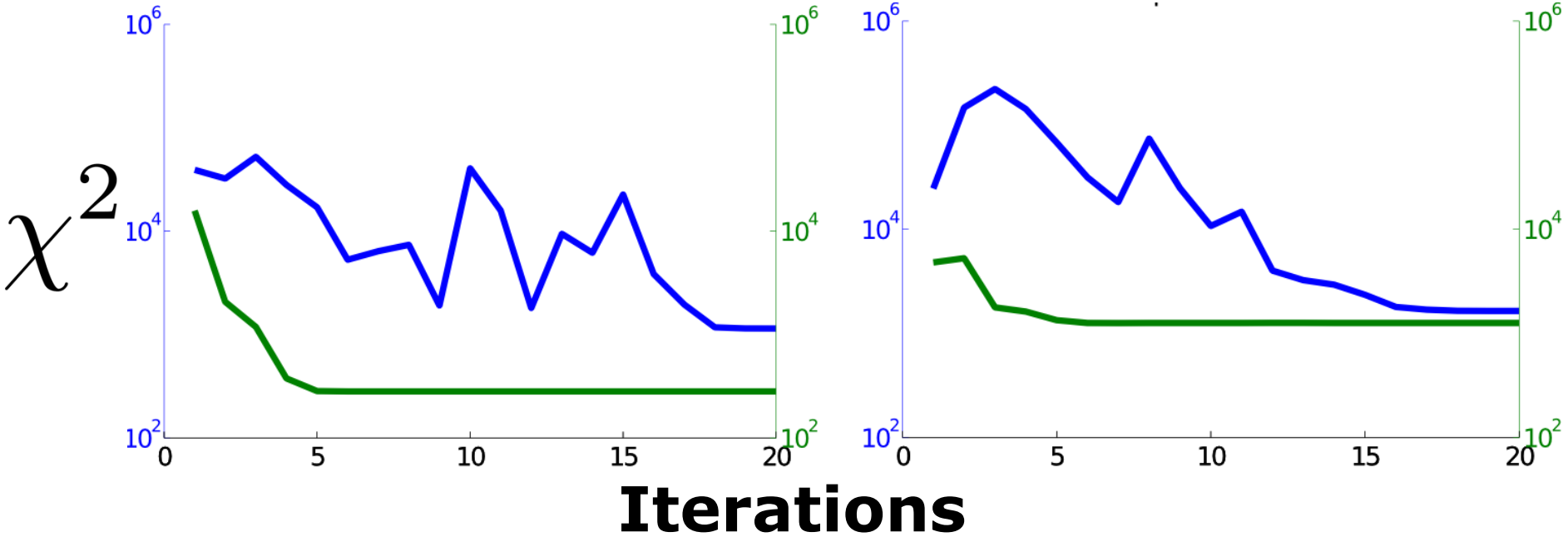
Convergence – 1000 Outliers

Switchable Constraints

Dynamic Covariance Scaling

Manhattan3500

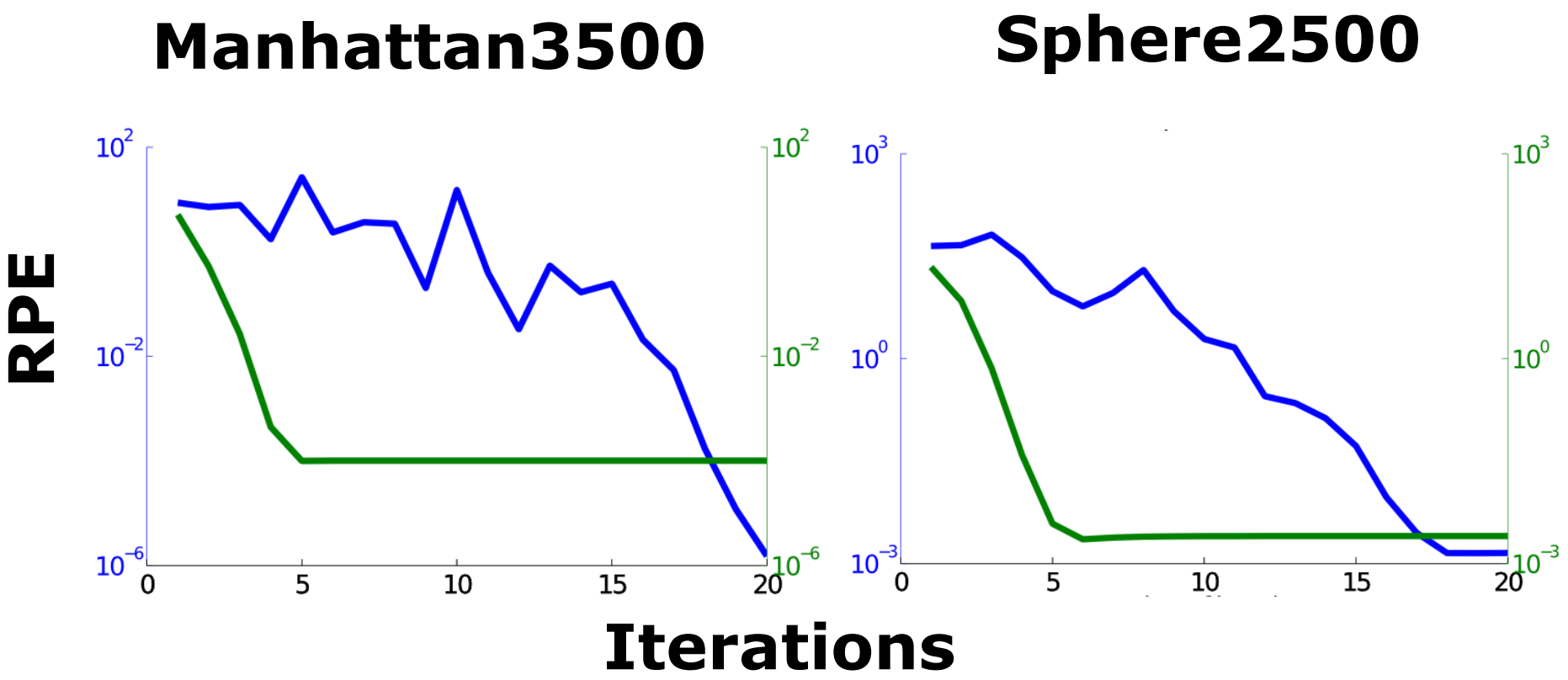
Sphere2500



Convergence – 1000 Outliers

Switchable Constraints

Dynamic Covariance Scaling

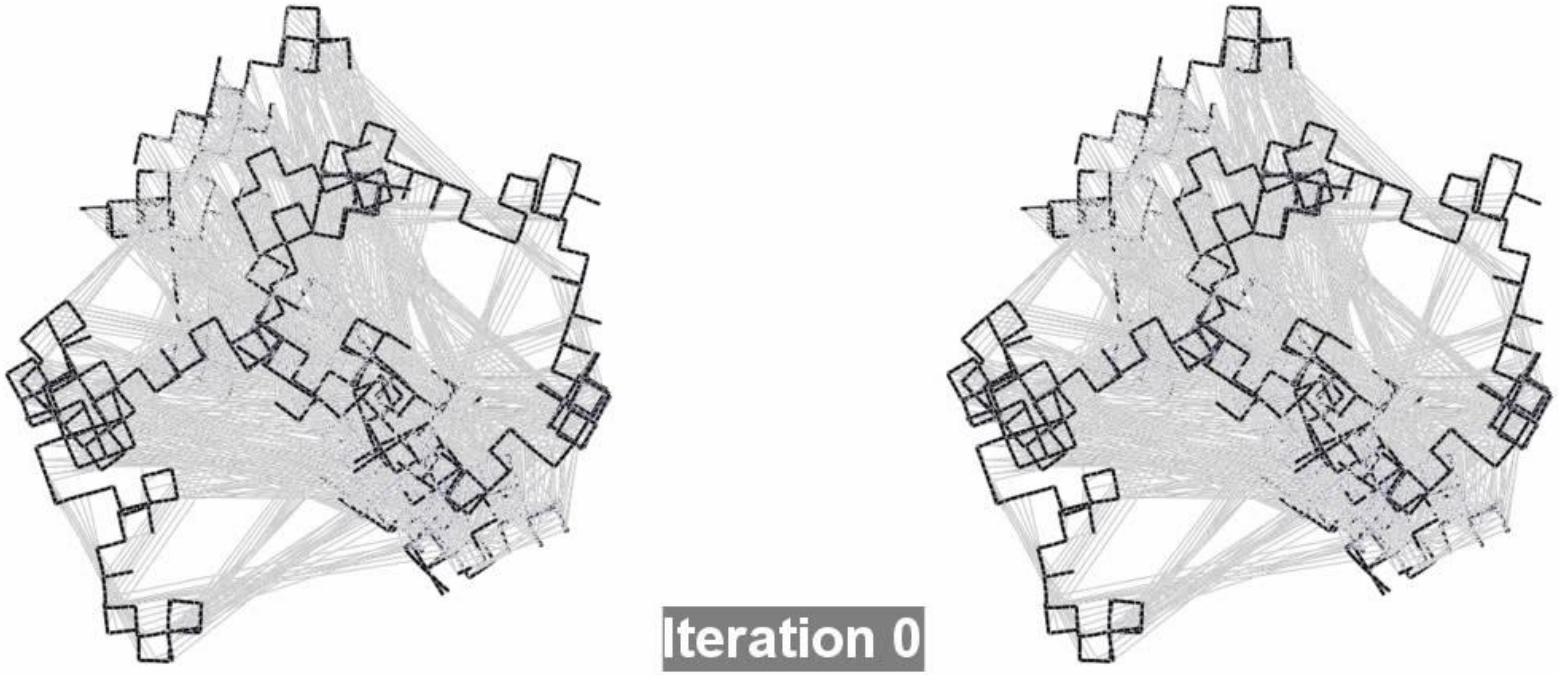


Convergence with Outliers

Switchable Constraints

Dynamic Covariance Scaling

Switchable Constraints (SC) ManhattanOlson Dynamic Covariance Scaling (DCS)



Conclusion

- **Rejects outliers** for 2D & 3D SLAM
- **No increase in computational complexity**
- More robust to **bad initial guess**
- Now **integrated in g2o**

Thank you for your attention!