Robot Map Optimization using Dynamic Covariance Scaling

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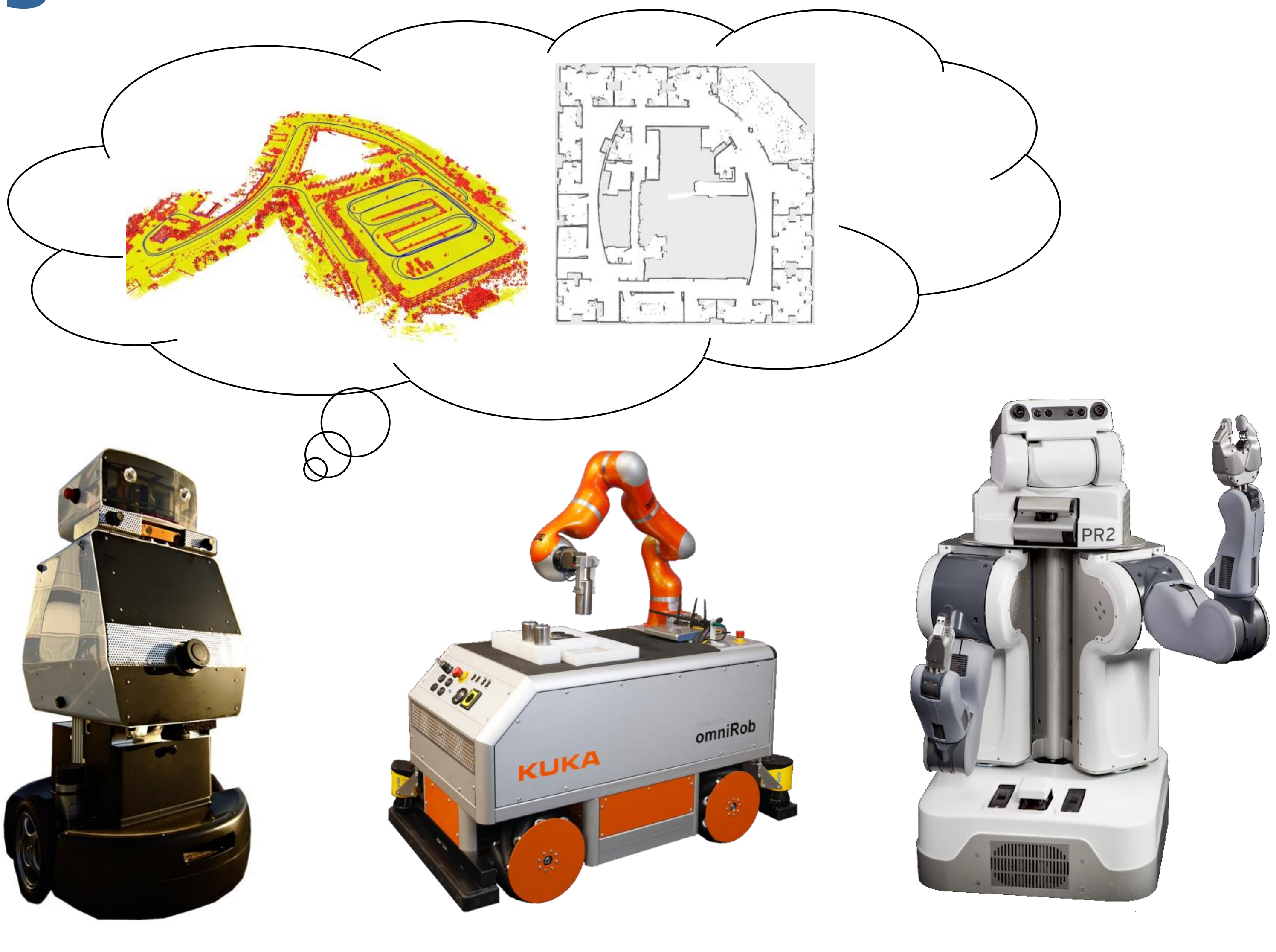
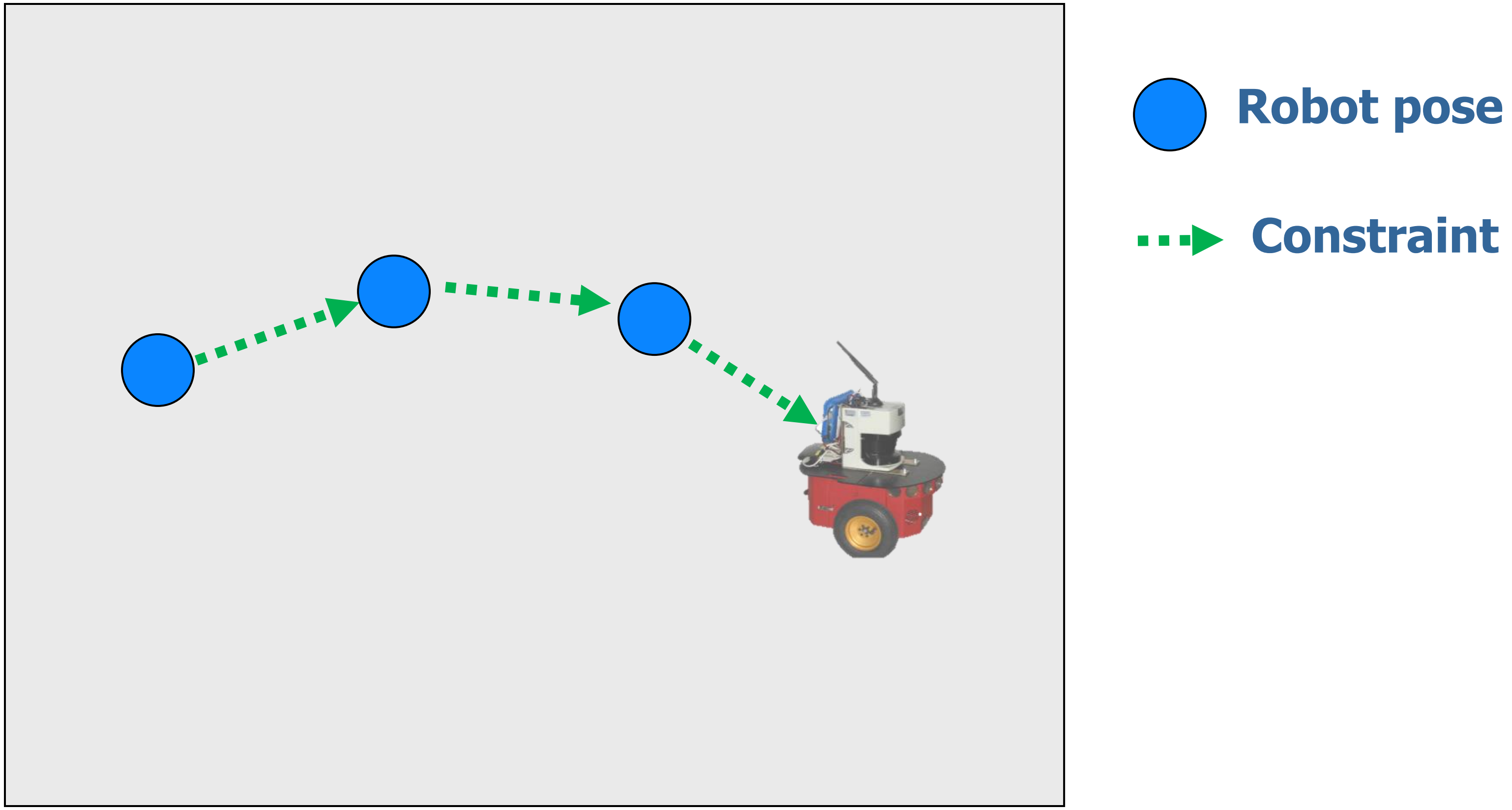
Maps are Essential for Effective Navigation



Graph-based SLAM



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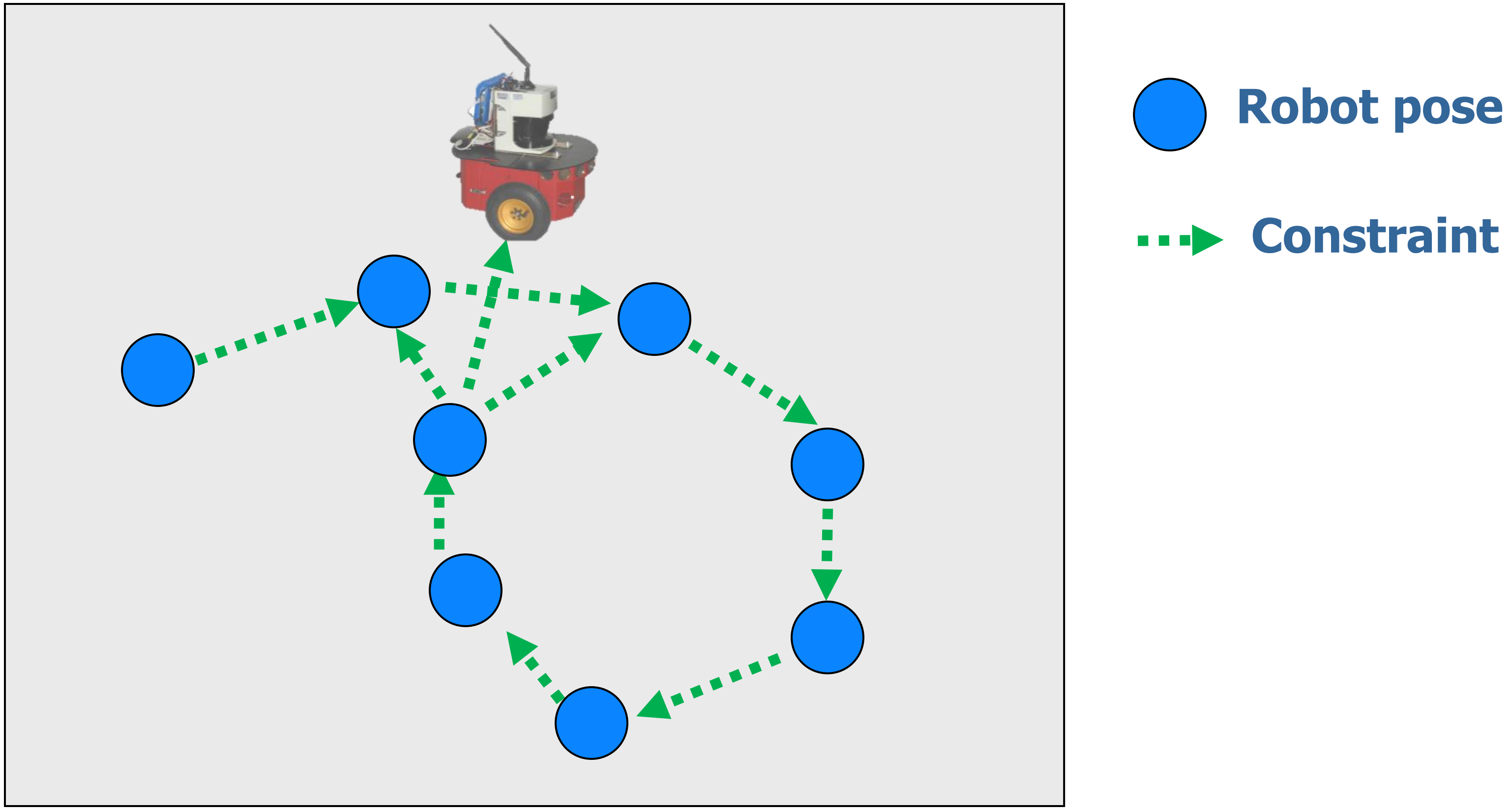

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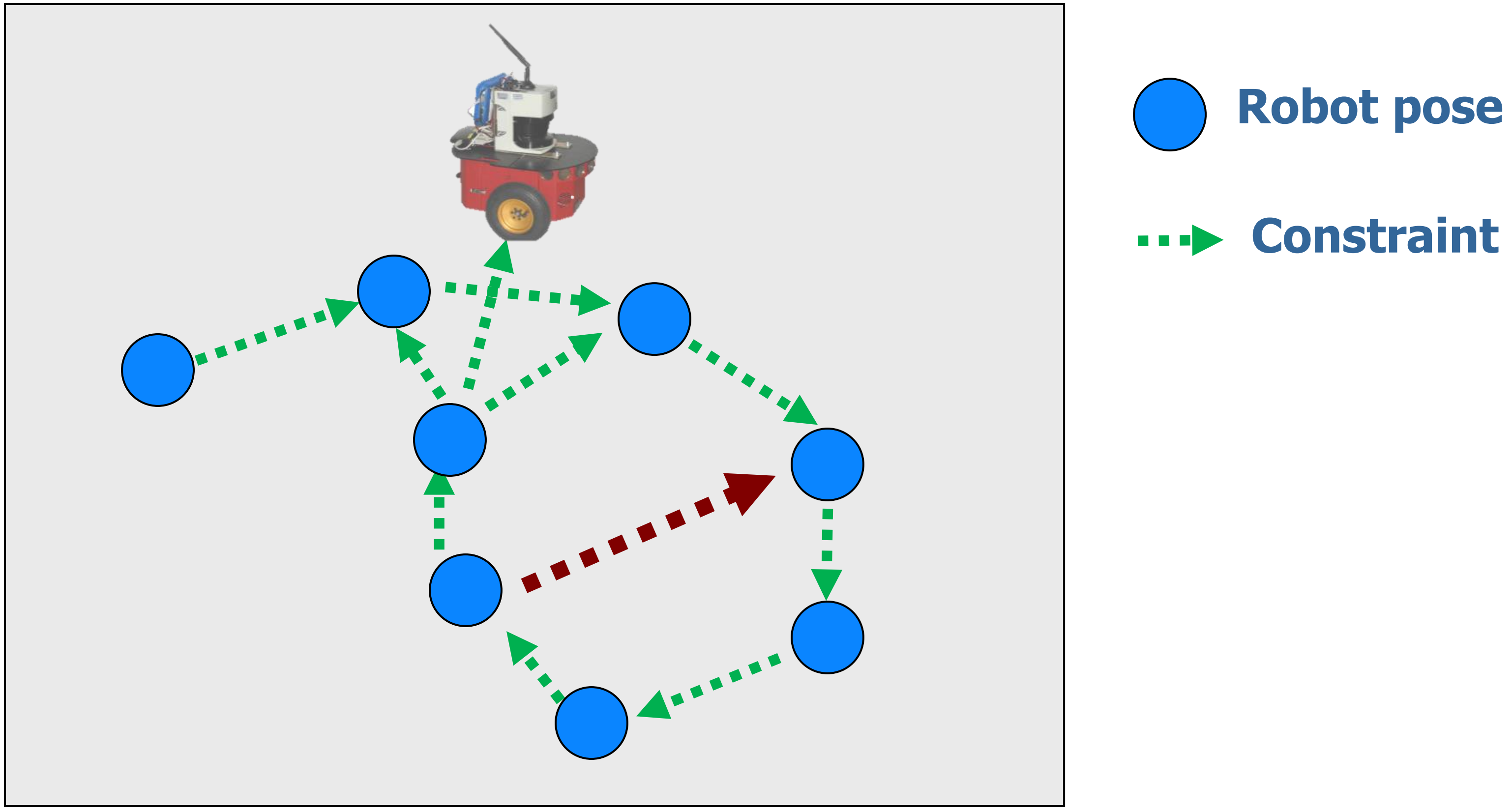
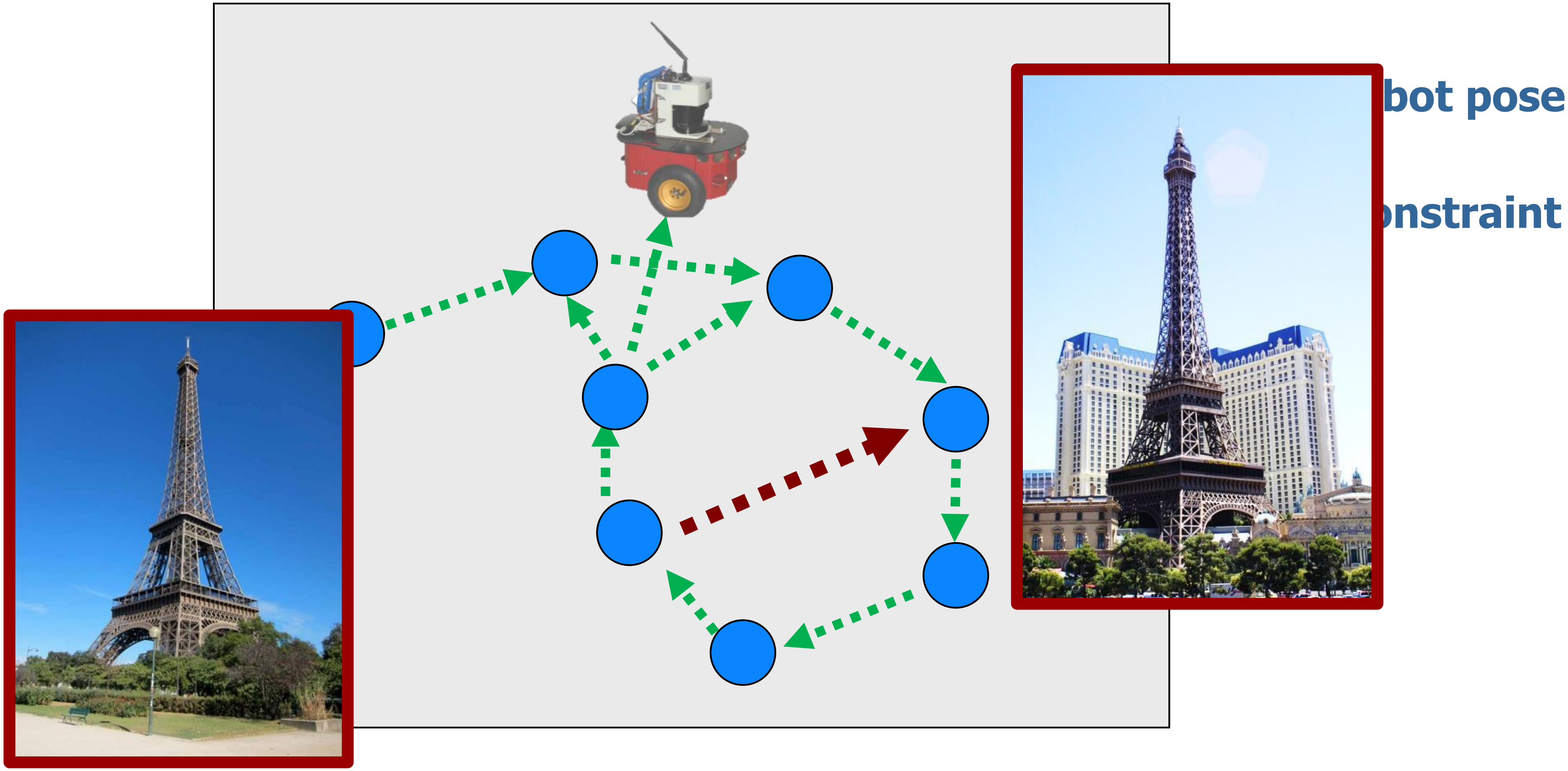


a single outlier …

Graph-based SLAM



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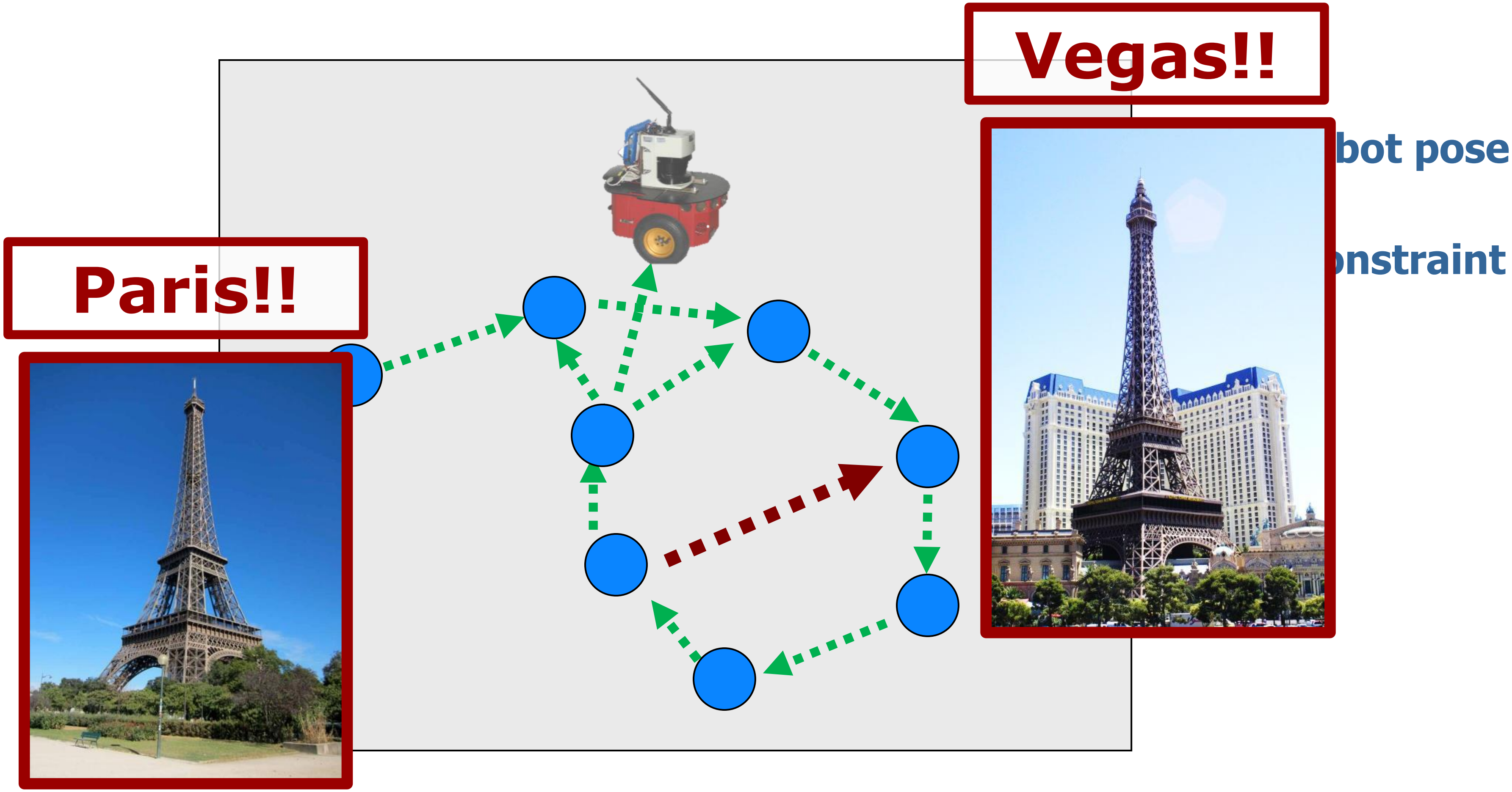
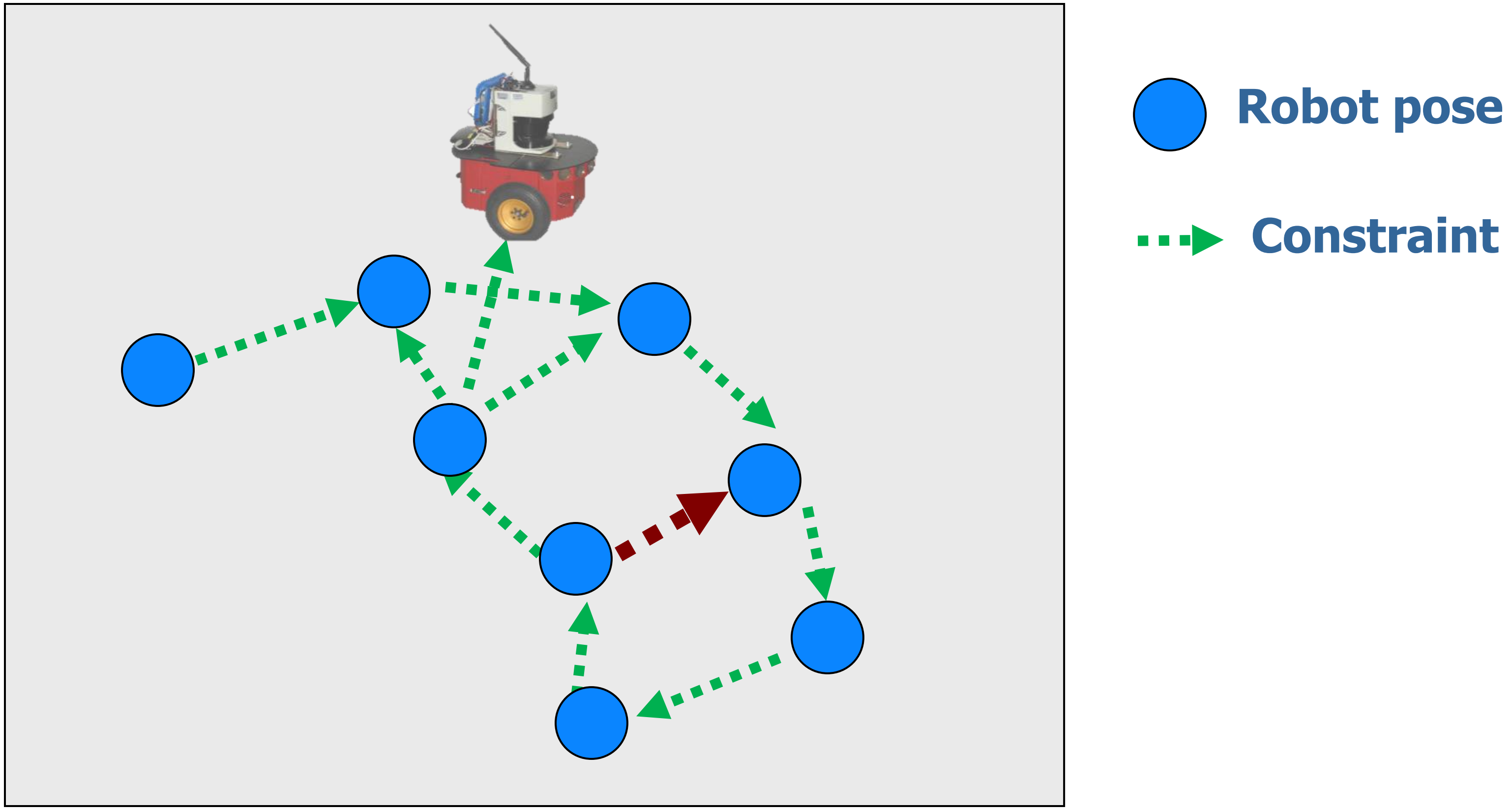
Graph-based SLAM



a single outlier …

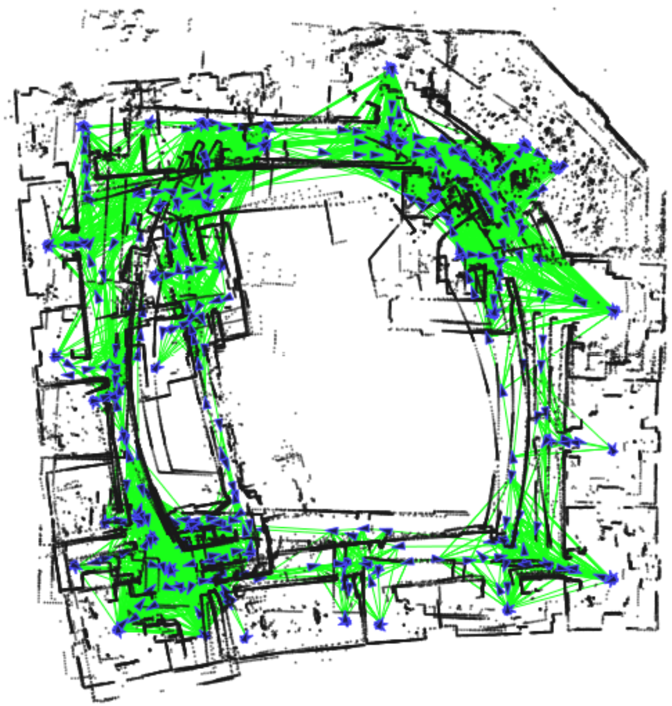
Graph-based SLAM



a single outlier … ruins the map

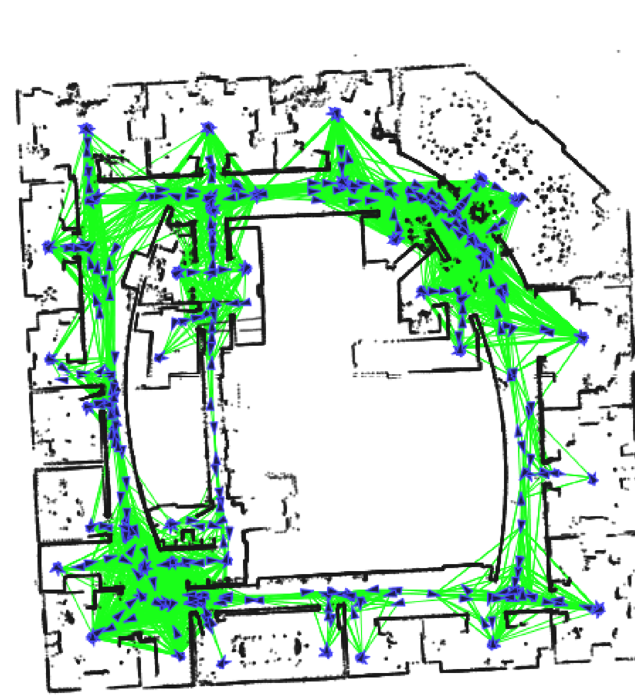
Graph-SLAM Pipeline

Front end → Validation → Back end



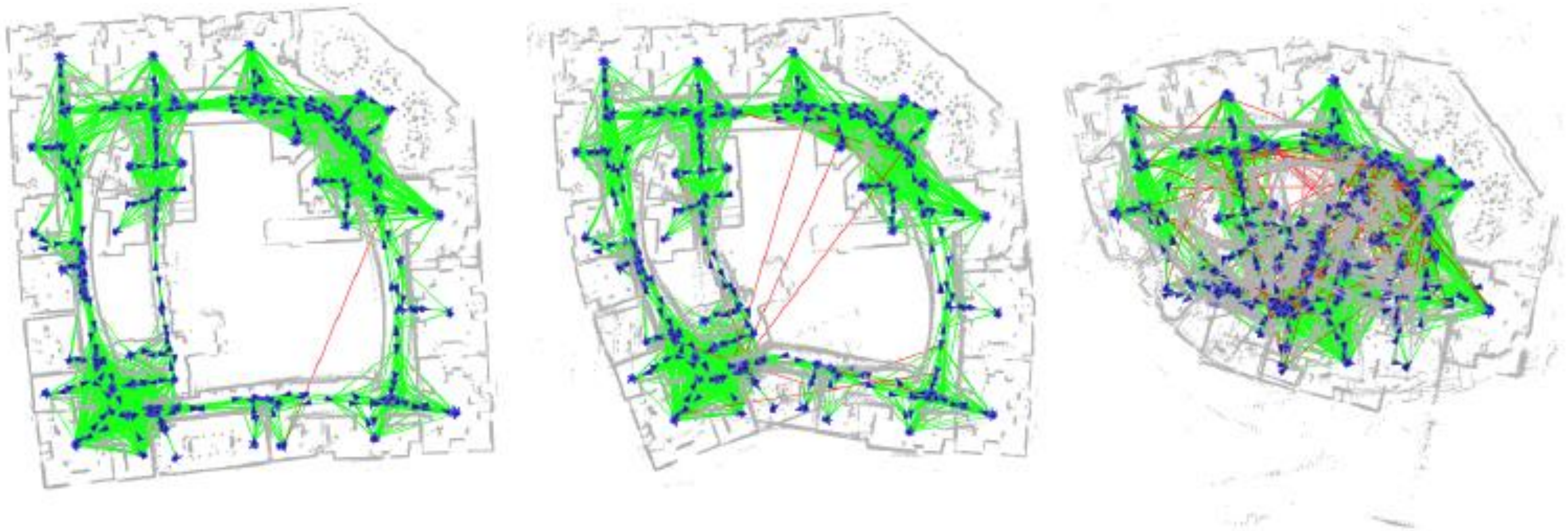
Assumption:

No Outliers



Impossible to have perfect validation

SLAM Back End Fail in the Presence of Outliers



1 Outlier | **10 Outliers** | **100 Outliers**

Why does the Mapping Fail?

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

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Alternative

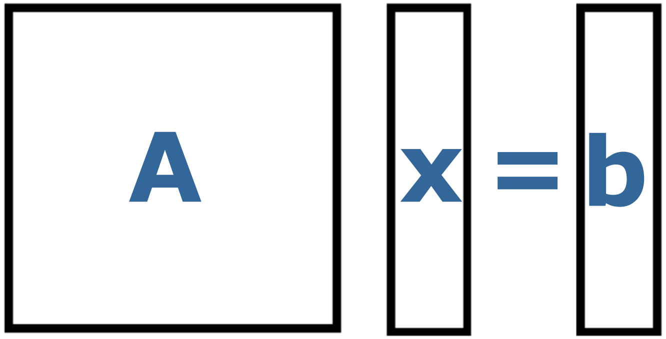
- **Let the back end do the validation job!**

Switchable Constraints

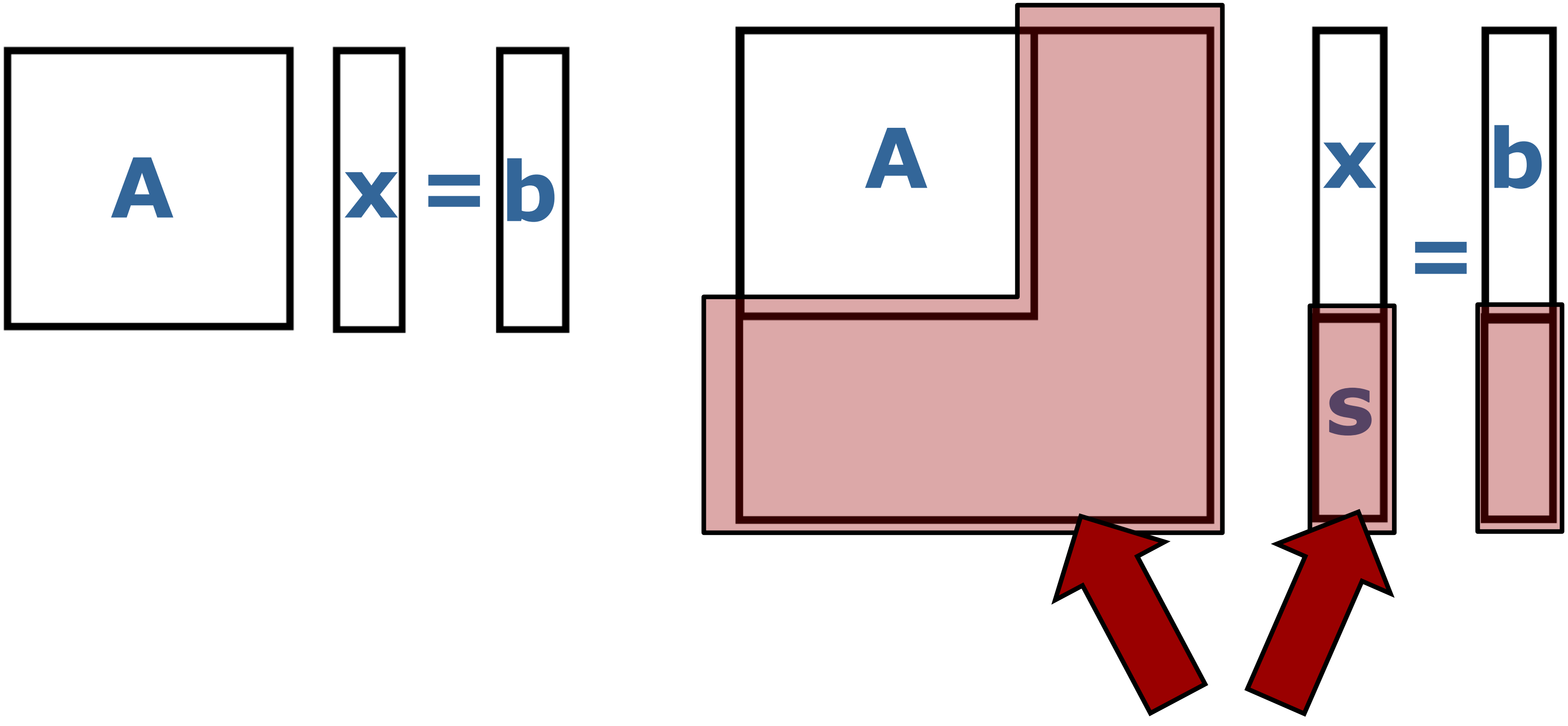
- Recent approach by Sünderhauf and Protzel
- Allows to switch off “bad” constraints
- Requires a **switch-variable** per constraint
- Additional **switch-constraint** per switch
- Robust optimization in case of outliers but increased computational complexity

[Sünderhauf and Protzel, IROS 2012]

Standard Optimization



Switchable Constraints



- Additional **switch-variable** per constraint
- Additional **switch-constraint** per switch

Our Approach: Dynamic Covariance Scaling

- Switch variables **computed in closed form**
- Does not increase state space
- Approximates Switchable Constraints
- Is a robust M-estimator
- Successfully **rejects** outliers

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

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

How to Determine s?

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

$$X^*, S^* = \underset{X,S}{\operatorname{argmin}} \underbrace{g(X_{ij \neq kl}, S_{ij \neq kl}) + \underbrace{s_{kl}^2 \chi_{l_{kl}}^2 + (1 - s_{kl})^2 \Phi}_{h(s,\chi^2)}}_{b}$$

$$\nabla b = \begin{bmatrix} \vdots \\ \frac{\partial b}{\partial s} \\ \vdots \end{bmatrix} = \begin{bmatrix} \vdots \\ 2s\chi_l^2 - 2(1 - s)\Phi \\ \vdots \end{bmatrix} = \begin{bmatrix} \vdots \\ 0 \\ \vdots \end{bmatrix}$$

$$\hat{h} = \frac{\Phi^2 \chi_l^2}{(\chi_l^2 + \Phi)^2} + \Phi - \frac{2\Phi^2}{\chi_l^2 + \Phi} + \frac{\Phi^3}{(\chi_l^2 + \Phi)^2}$$

How to Determine s?

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

Check out the paper!

$$X^*, S^* = \underset{X,S}{\operatorname{argmin}}\, g(X_{ij \neq kl}, S_{ij \neq kl}) + \underbrace{s_{kl}^2 \chi_l^2 + \underbrace{(1 - s_{kl})^2 \Phi}_{h(s,\chi^2)}}_{b}$$

$$\nabla b = \begin{bmatrix} \vdots \\ \frac{\partial b}{\partial s_l} \\ \vdots \end{bmatrix} = \begin{bmatrix} \vdots \\ 2s\chi_l^2 - 2(1-s)\Phi \\ \vdots \end{bmatrix} = \begin{bmatrix} \vdots \\ 0 \\ \vdots \end{bmatrix}$$

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

Closed form

How to Determine s?

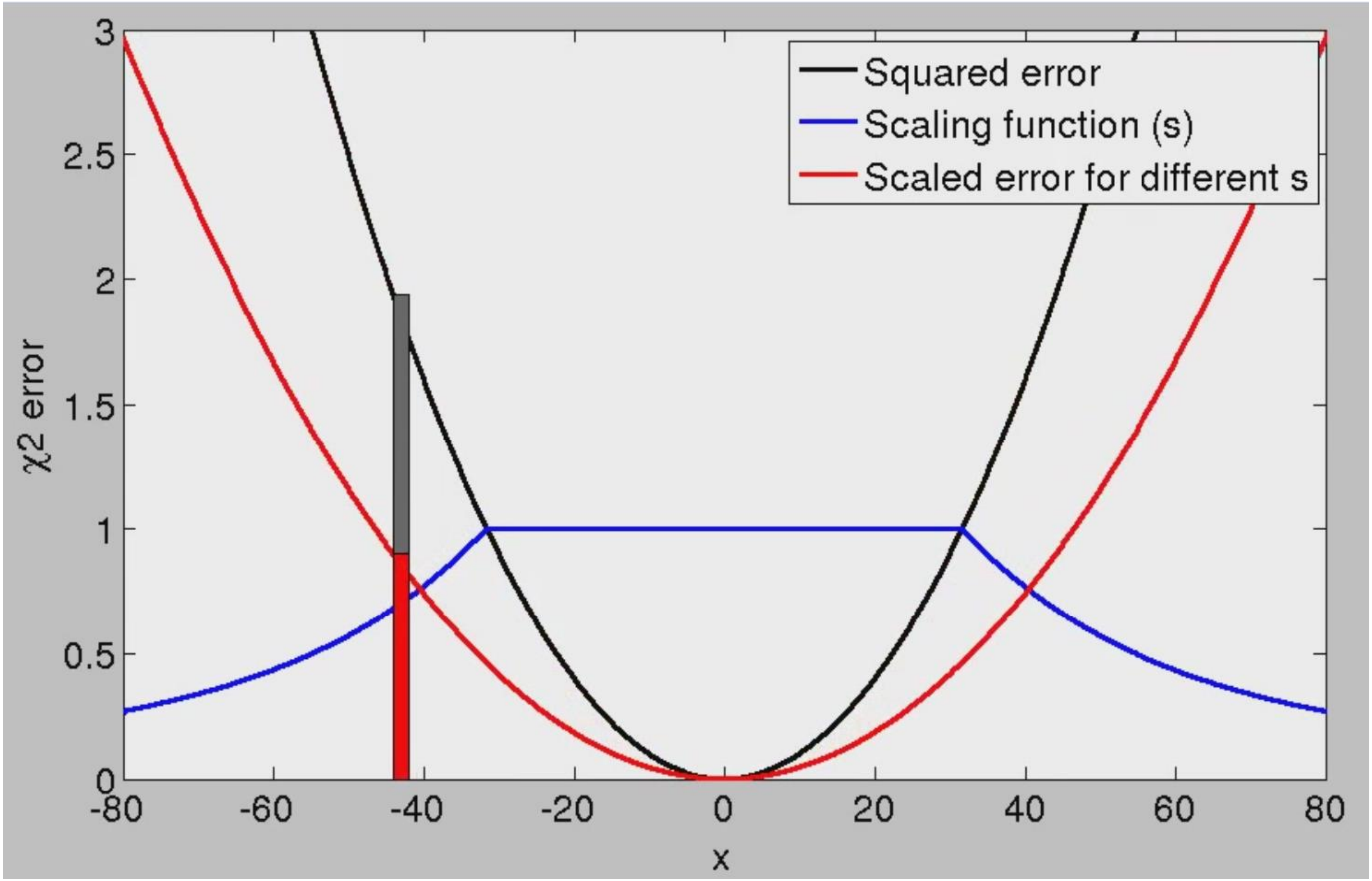
$$X^* = \underset{X}{\operatorname{argmin}} \sum_{ij} \mathbf{e}_{ij}(X)^T \left(s_{ij}^2 \Omega_{ij}\right) \mathbf{e}_{ij}(X)$$

⋮

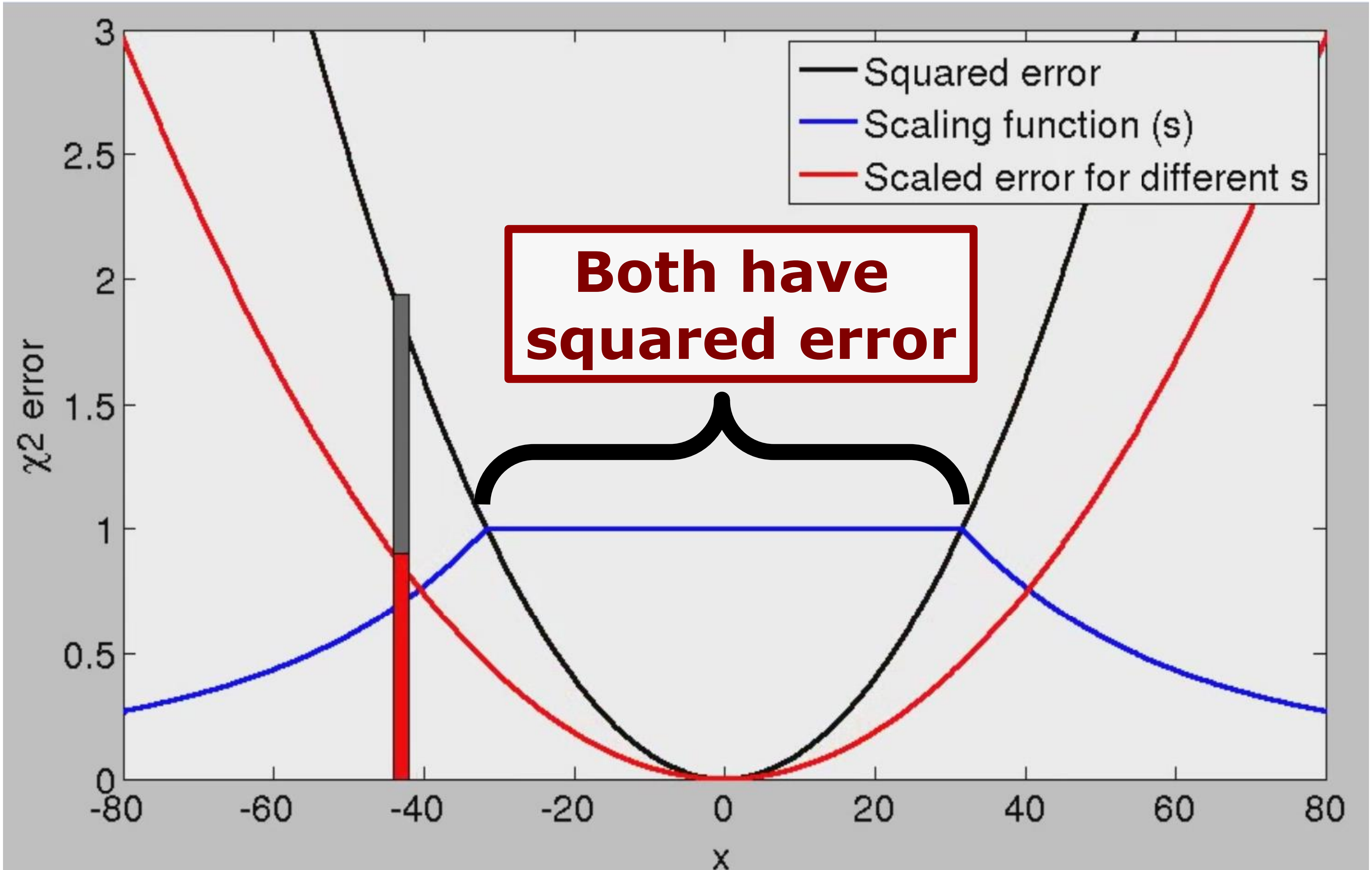
$$\Rightarrow \quad s_{ij} = \min\left(1, \frac{2\Phi}{\Phi + \chi_{ij}^2}\right)$$

Closed form

Dynamic Covariance Scaling



Dynamic Covariance Scaling



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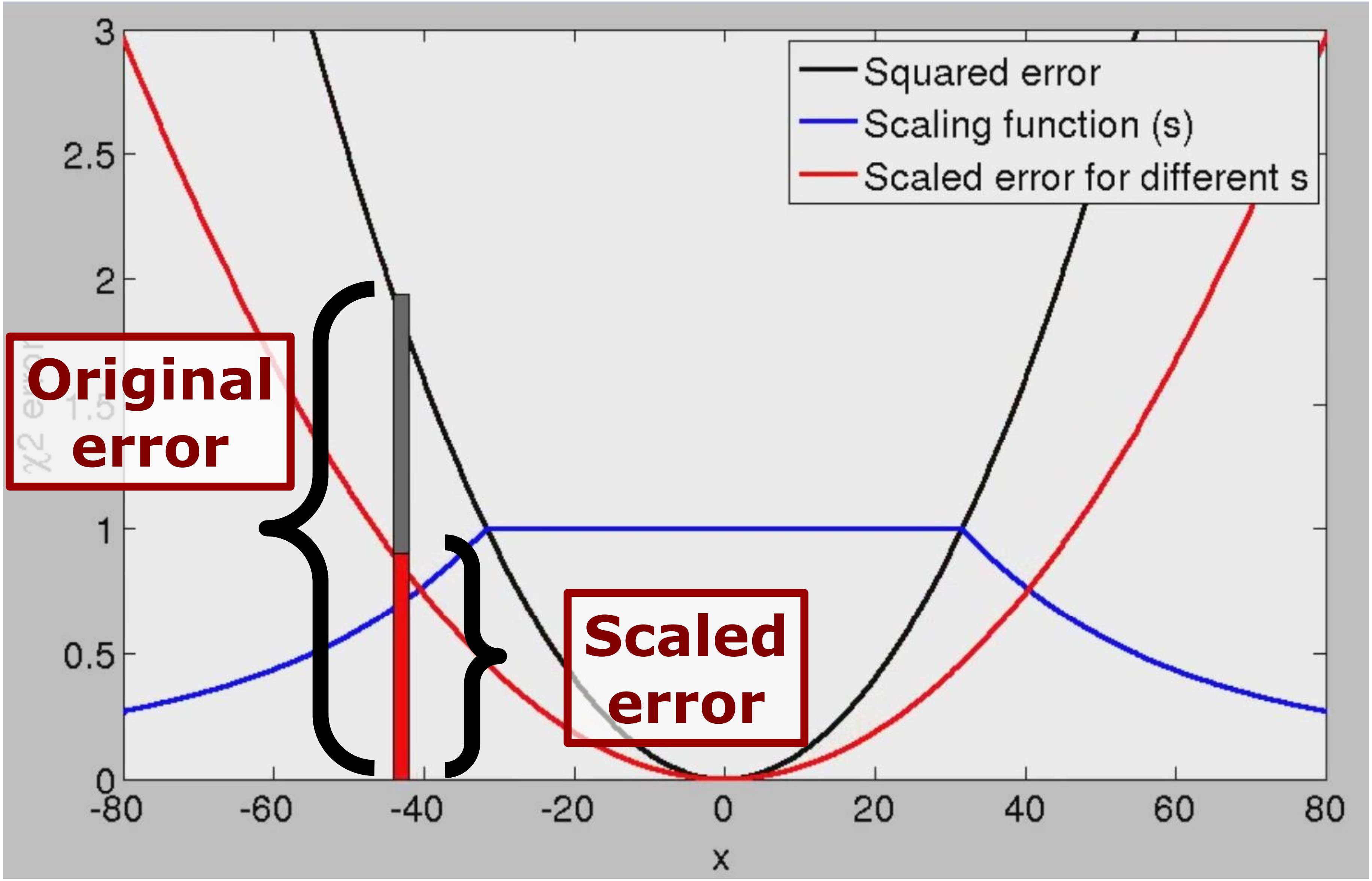

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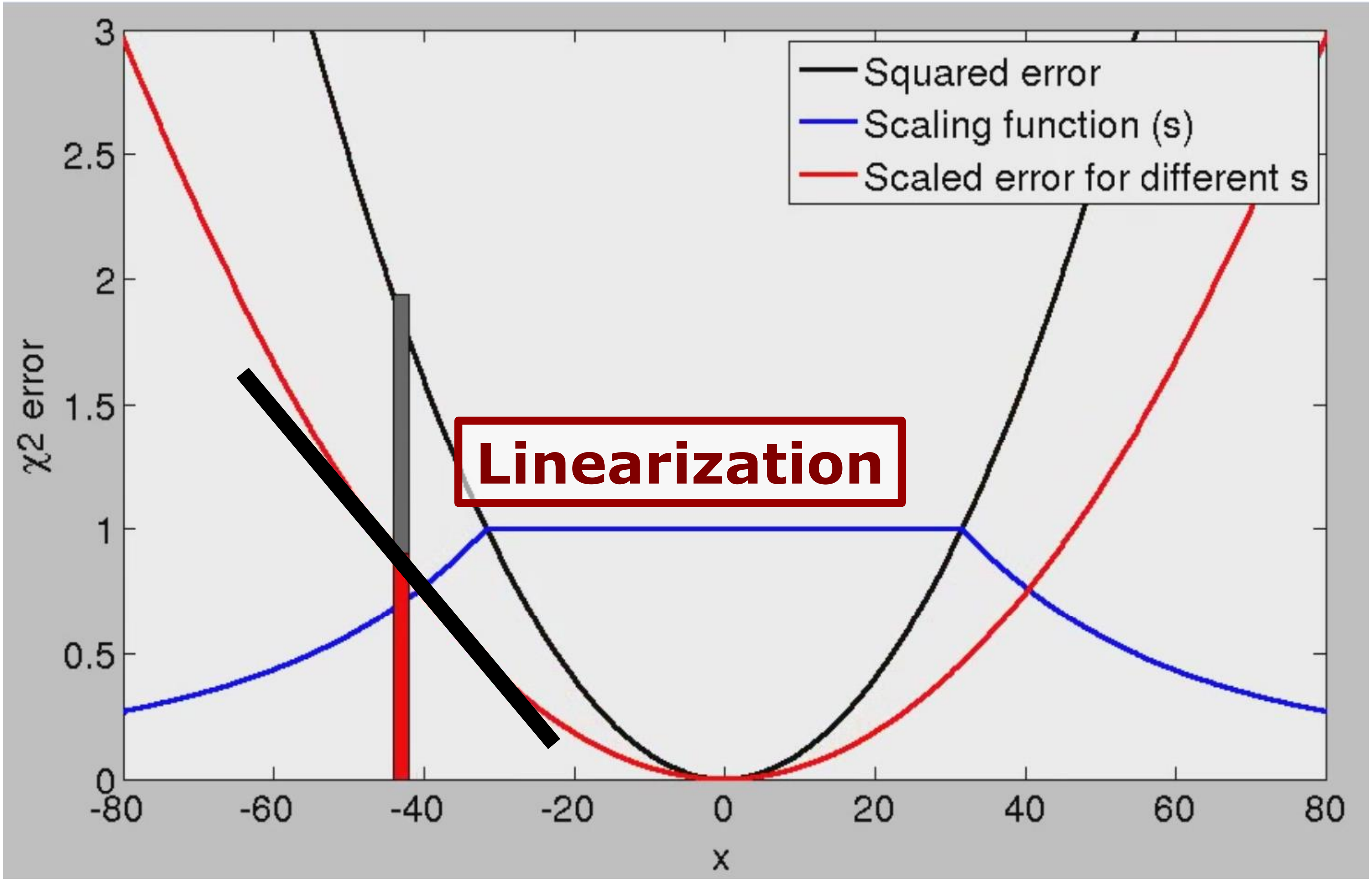

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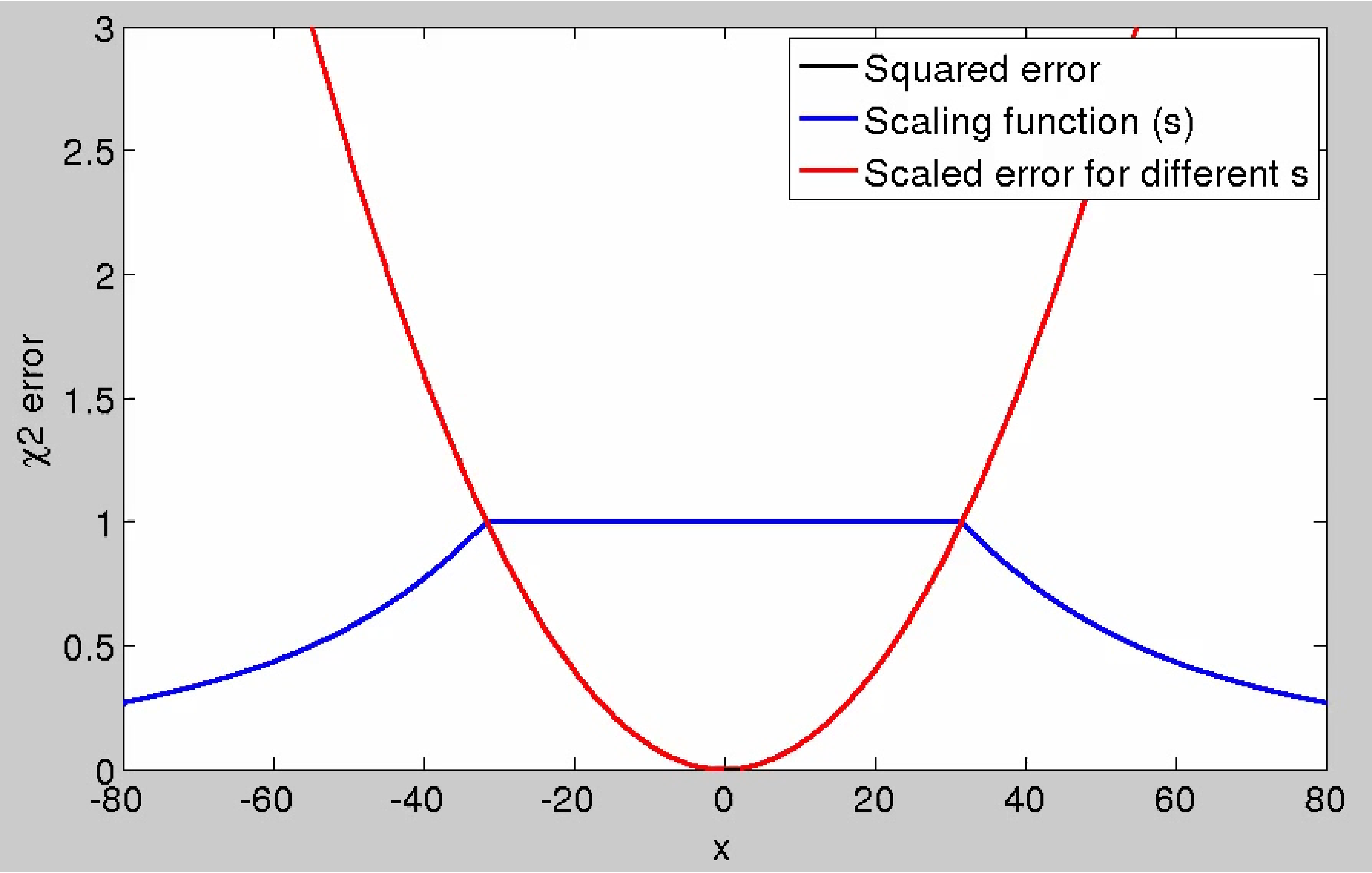
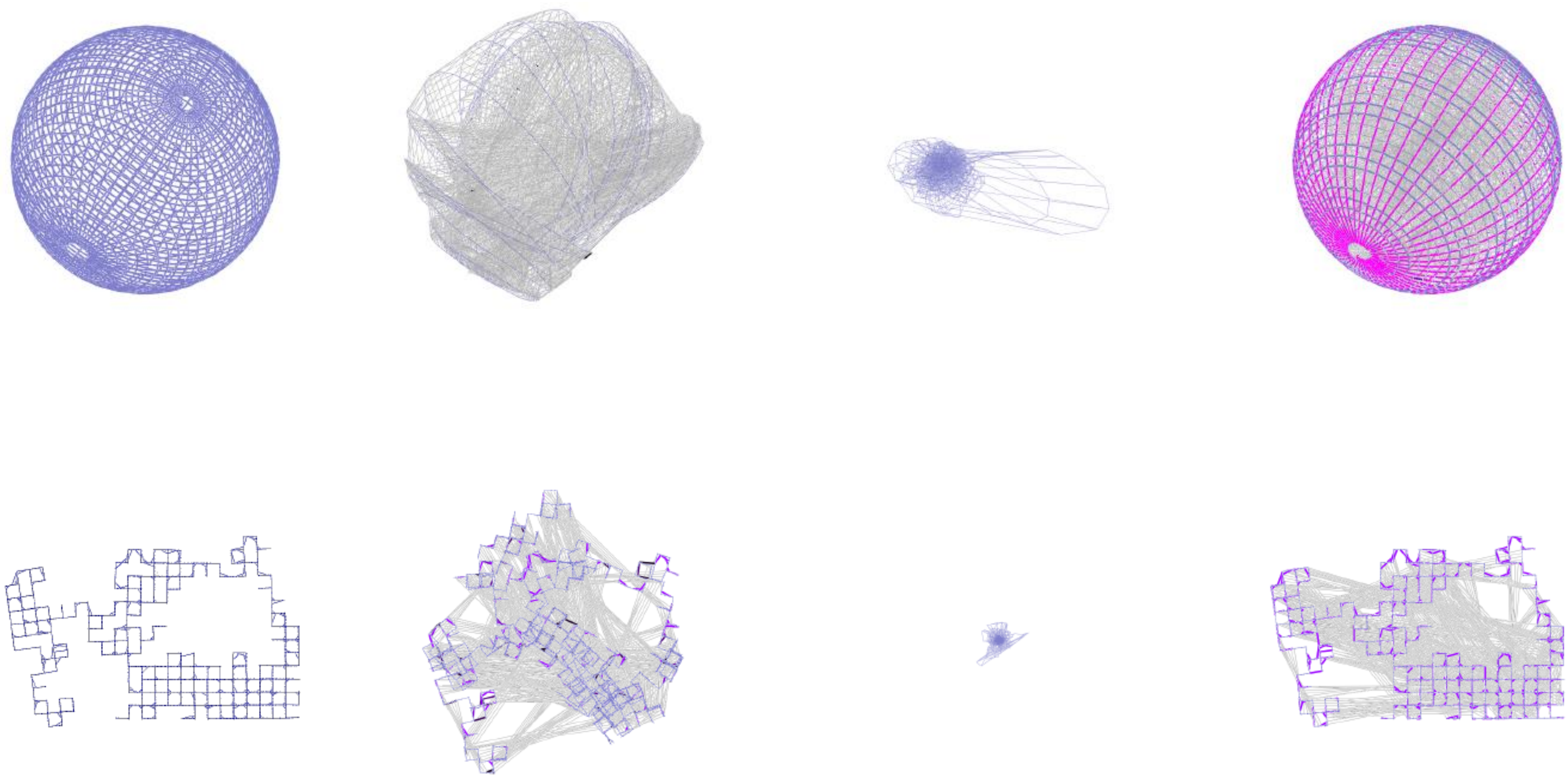
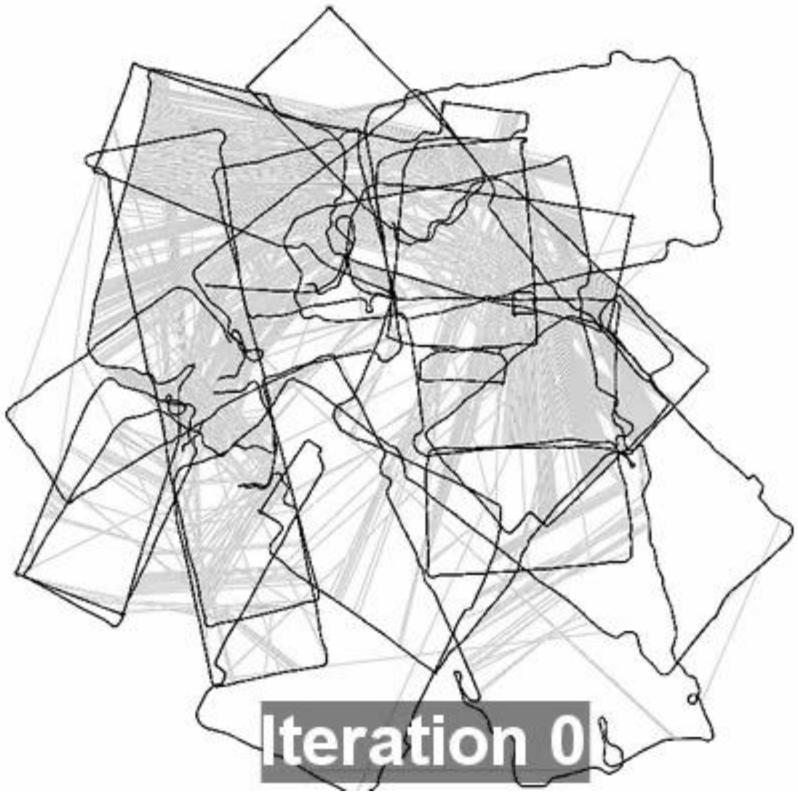
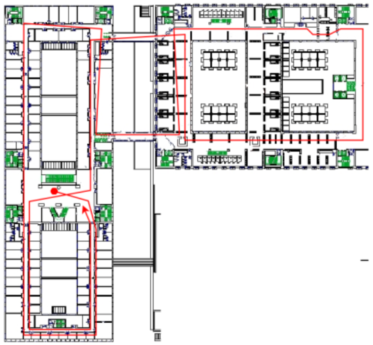


Robust SLAM with Our Method



Dynamic Covariance Scaling with Front-end Outliers

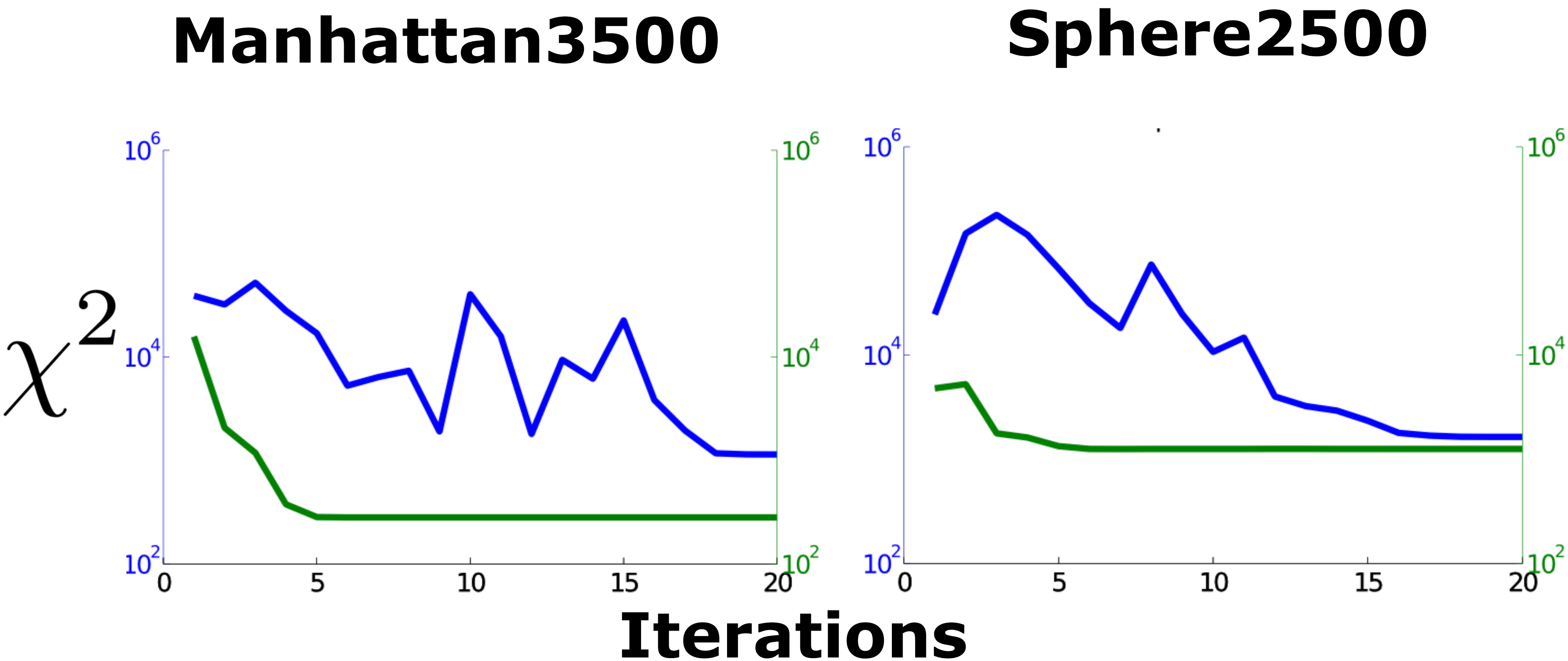




Bicocca-multisession dataset

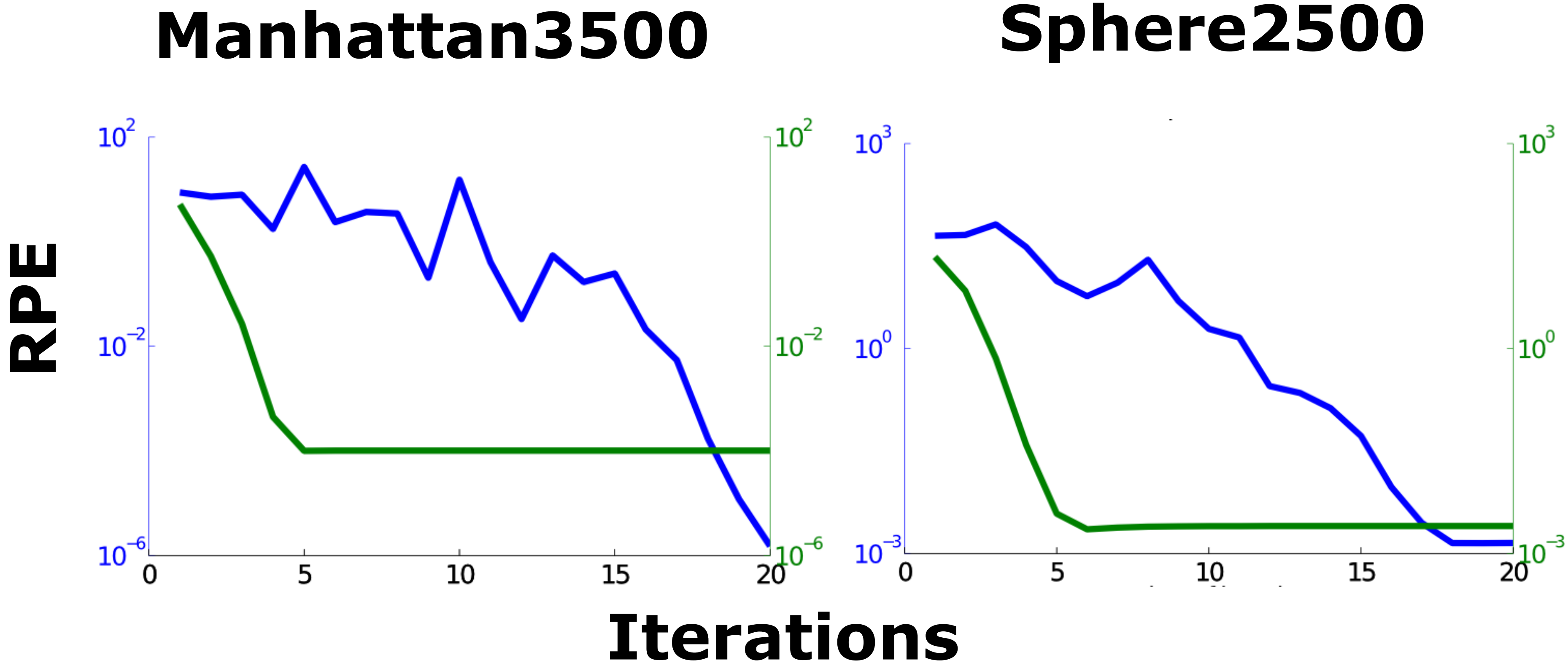
Convergence – 1000 Outliers

- **Switchable Constraints**
- **Dynamic Covariance Scaling**



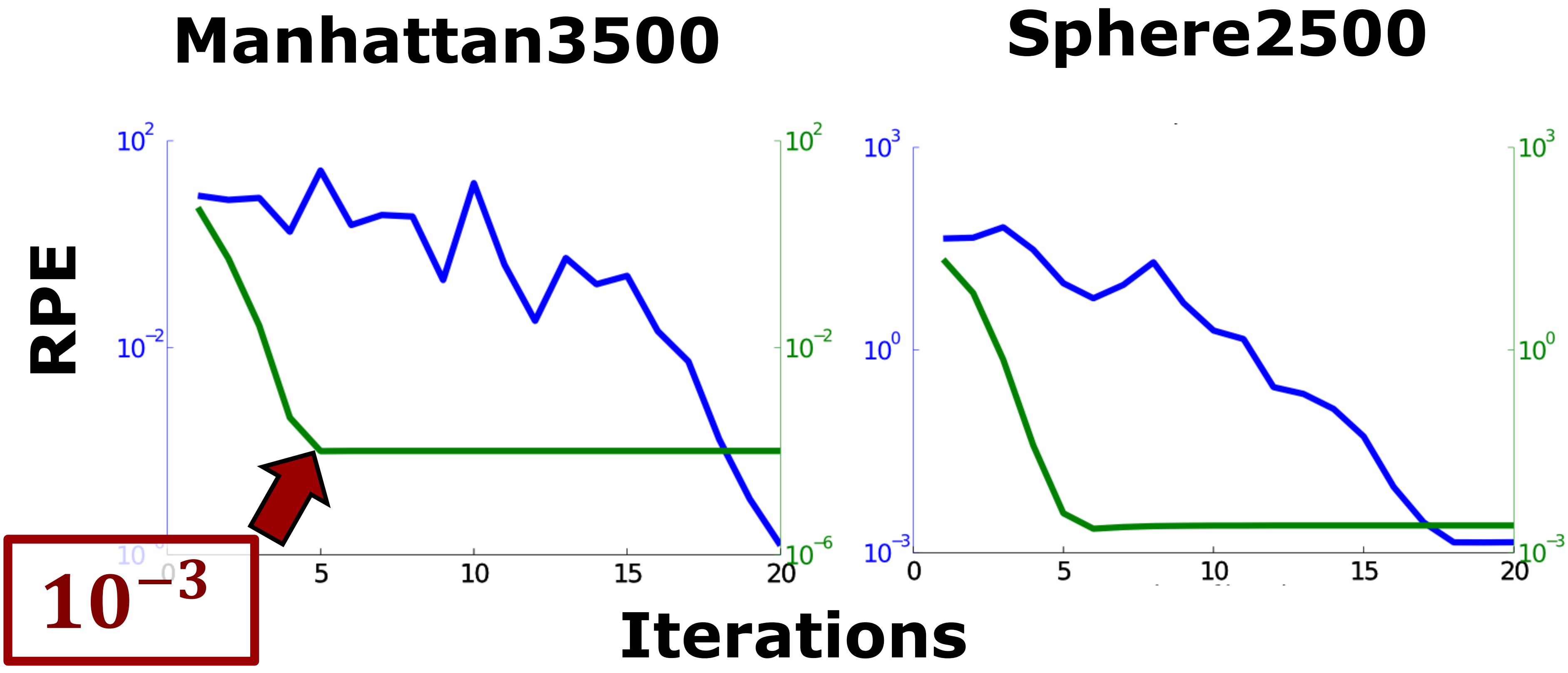
Convergence – 1000 Outliers

- Switchable Constraints
- Dynamic Covariance Scaling



Convergence – 1000 Outliers

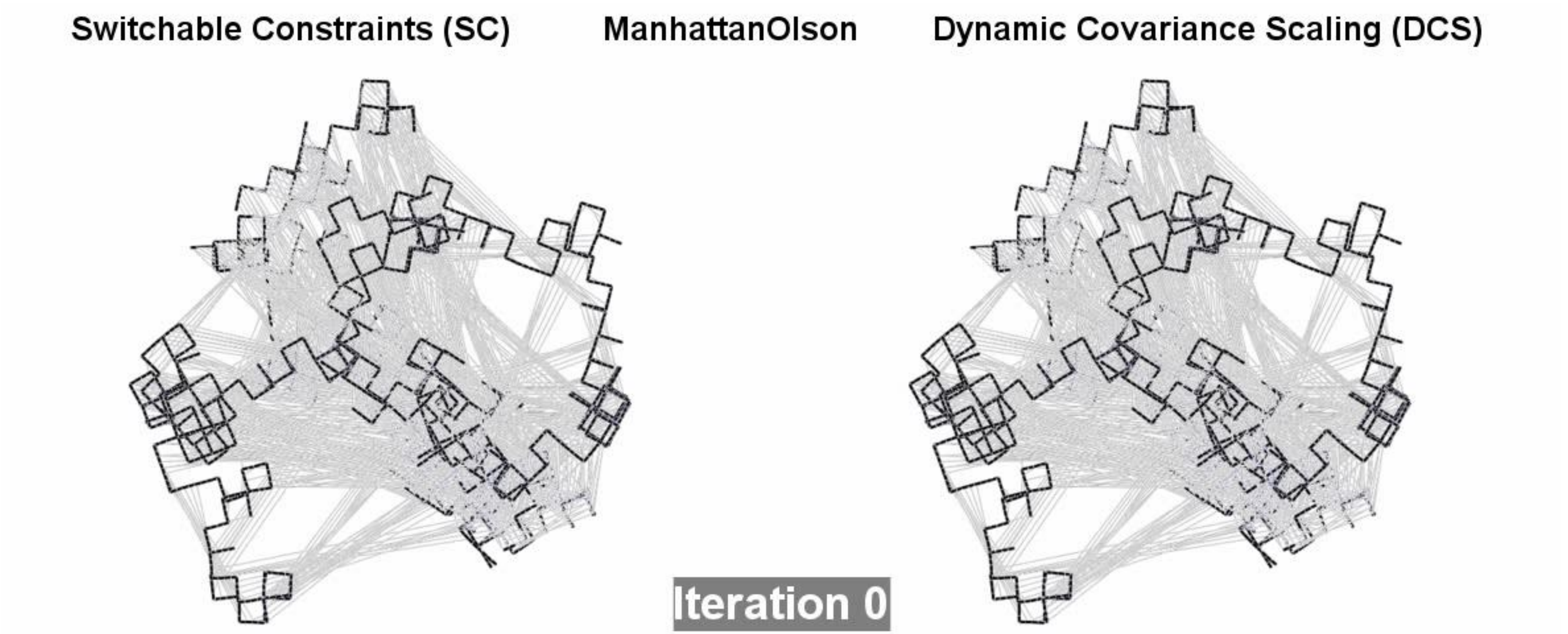
Switchable Constraints (blue)
Dynamic Covariance Scaling (green)



Convergence with Outliers

Switchable Constraints

Dynamic Covariance Scaling

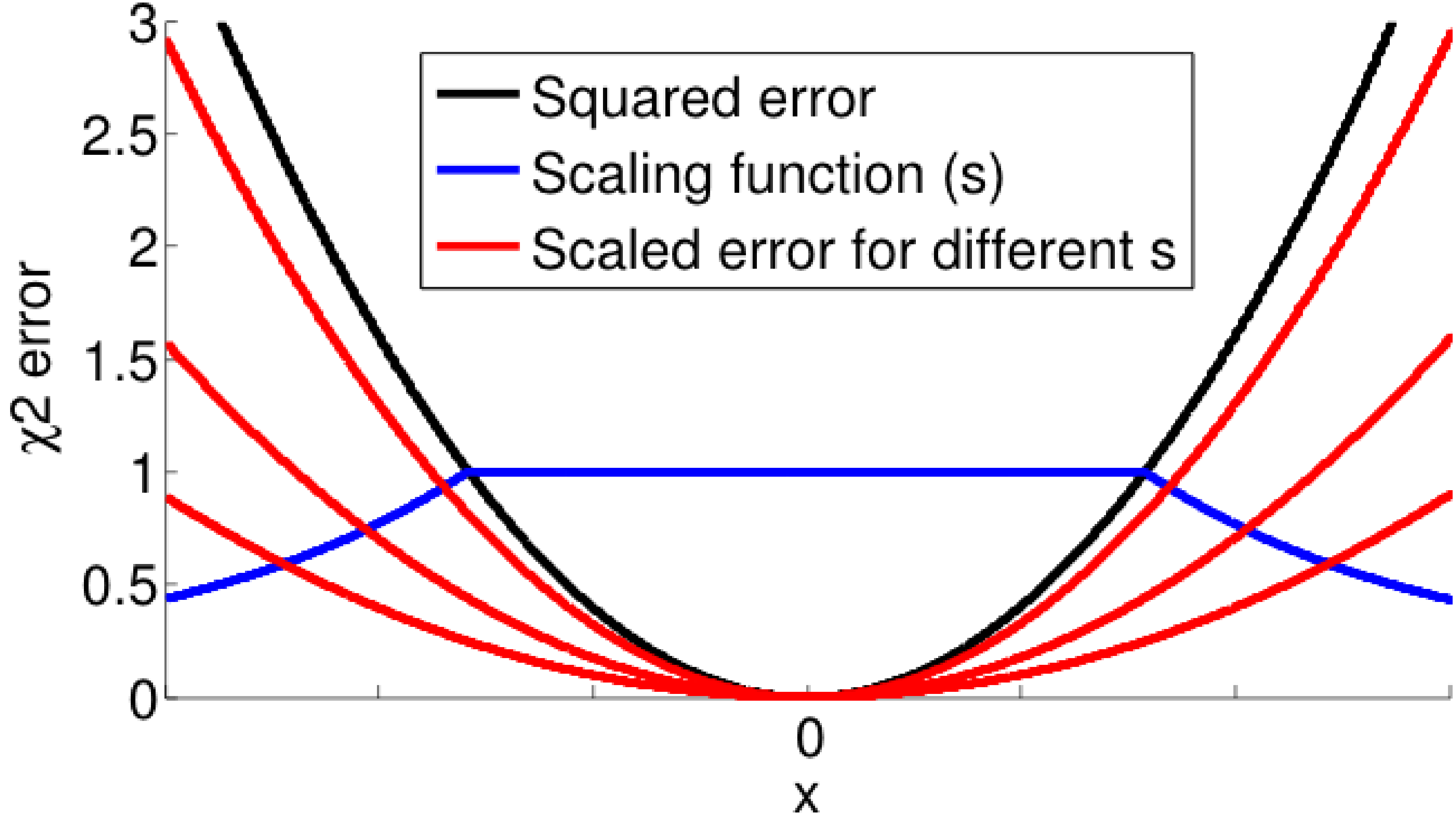


Conclusion

- **Rejects outliers** for 2D & 3D SLAM
- **No increase in computational complexity**
- Approximates switchable constraints with a robust M-estimator
- Now **integrated in g2o**

Thank you for your attention!

Questions?



Squared error
Scaling function (s)
Scaled error for different s
χ2 error
x
0
0.5
1
1.5
2
2.5
3
0