

# **CVPR 2014 Tutorial on Visual SLAM**

## **Large Scale – Reducing Computational Cost**

**Michael Kaess**

kaess@cmu.edu

The Robotics Institute  
Carnegie Mellon University

---

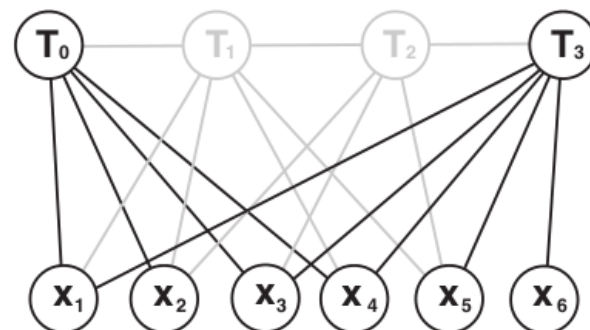
# Large-Scale Visual SLAM

Computational cost grows with time

Two approaches to reduce cost:

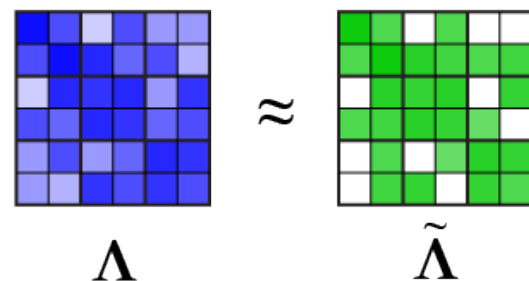
- Formulation

- Keyframes
- Submaps
- Reduced pose graph



- Simplification

- Cut old data
- Sparsification



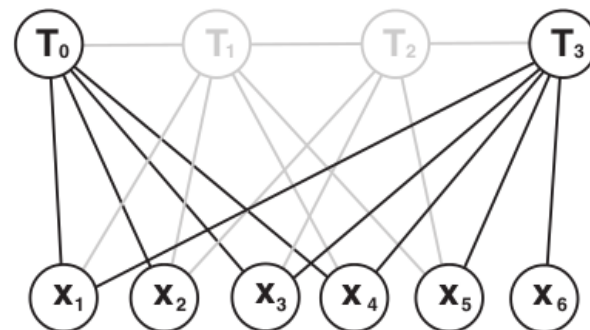
# Large-Scale Visual SLAM

Computational cost grows with time

Two approaches to reduce cost:

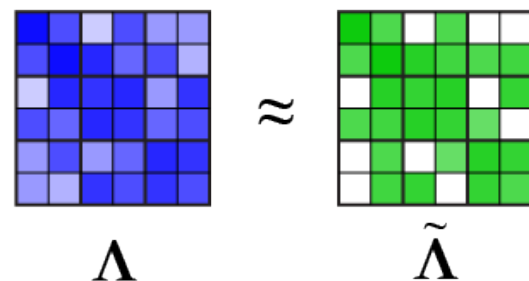
- Formulation

- Keyframes
- Submaps
- **Reduced pose graph**



- Simplification

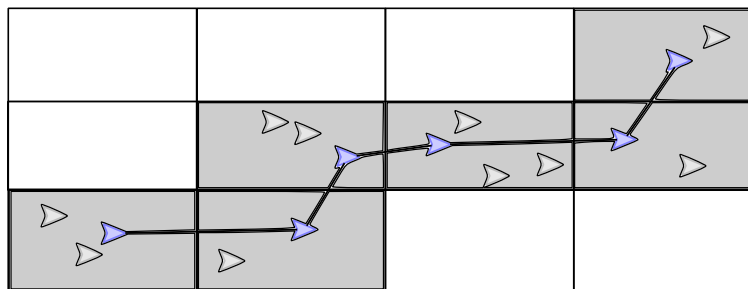
- Cut old data
- Sparsification



# Reduced pose graph

---

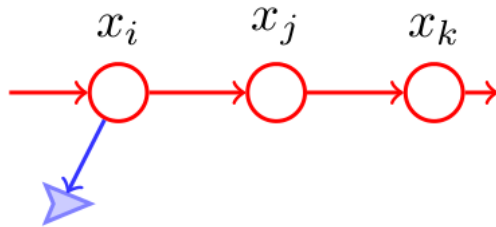
- Key-frame approach
- Reuses existing poses
- Grows with explored space, not time
- Partitions the environment
  - Maintains a set of poses that cover all the partitions



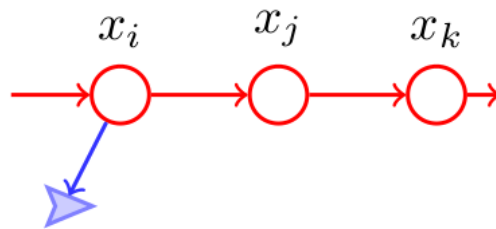
# Reduced Pose Graph (step n) - Construction

---

In general, not revisiting exactly same poses

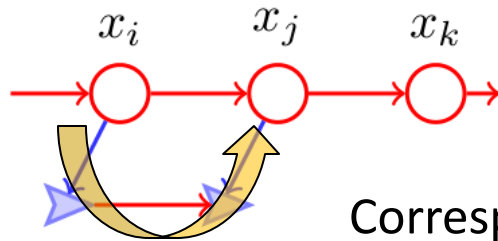


Standard pose graph:



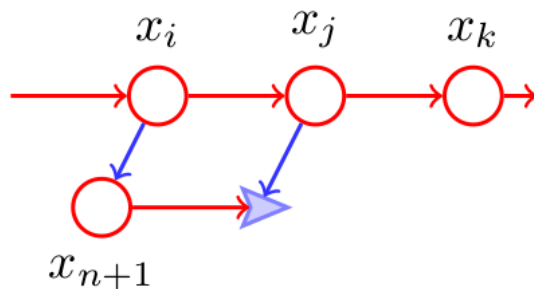
# Reduced Pose Graph (step $n+1$ )

In general, not revisiting exactly same poses



Corresponds to a constraint between  $x_i$  and  $x_j$

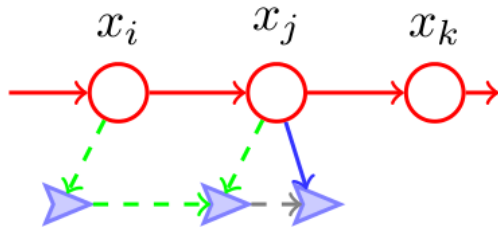
Standard pose graph:



New pose is added

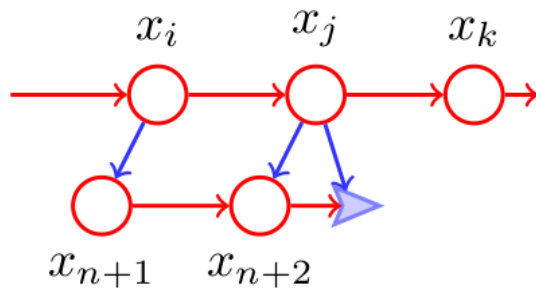
# Reduced Pose Graph (step $n+2$ )

## Avoiding inconsistency



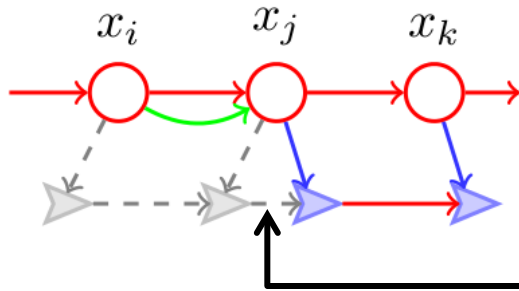
Second loop closure to  $x_j$  to avoid double use of constraint

## Standard pose graph:



# Reduced Pose Graph (step $n+3$ )

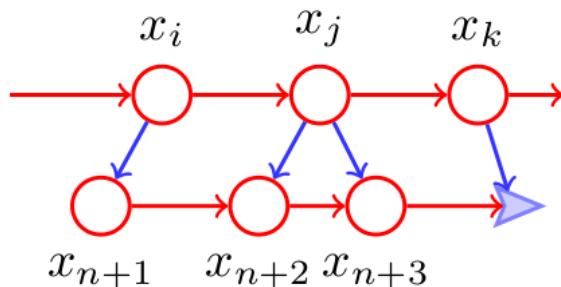
## Avoiding inconsistency



Constraint between  $x_i$  and  $x_j$  added

Omitting short odometry links

## Standard pose graph:





# Long-term Visual Mapping

---



## MIT Stata Center Dataset (publicly available)

- Duration: 6 months
- Operation time: 9 hours
- Distance travelled: 11 km (about 7 miles)
- VO keyframes: 630K

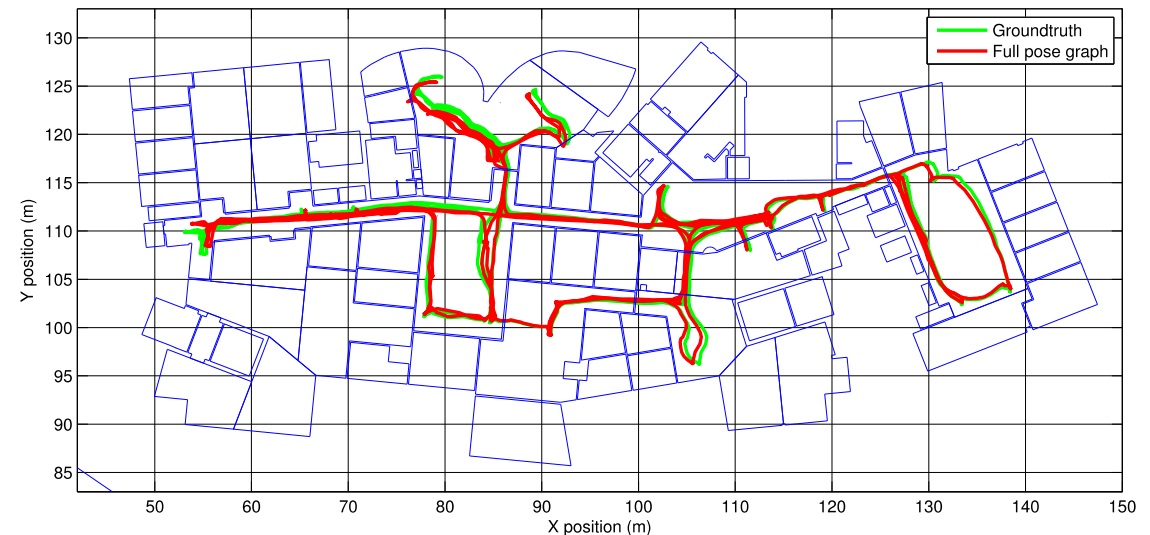
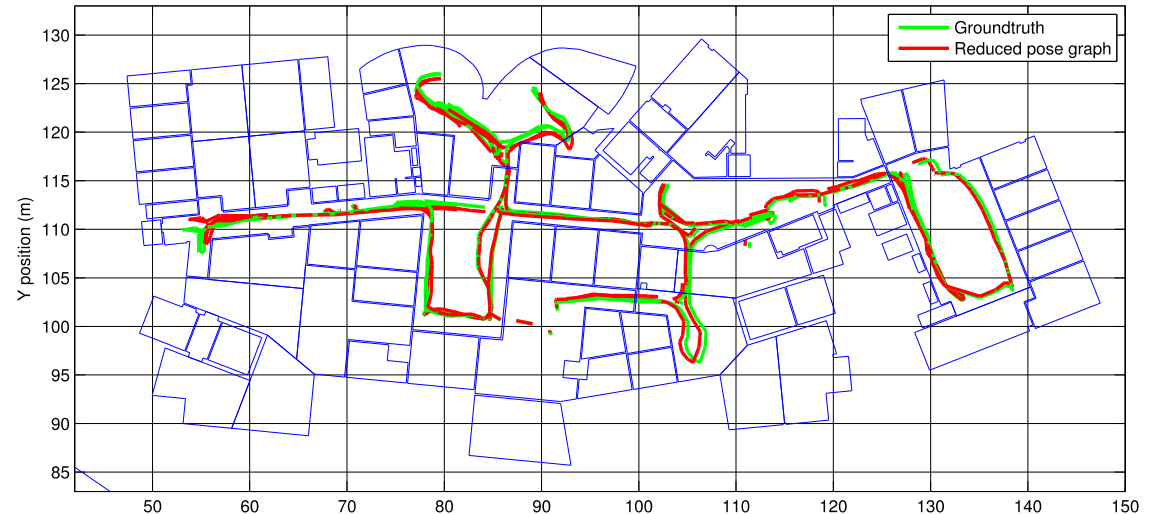
# Reduced Pose Graph – Second Floor



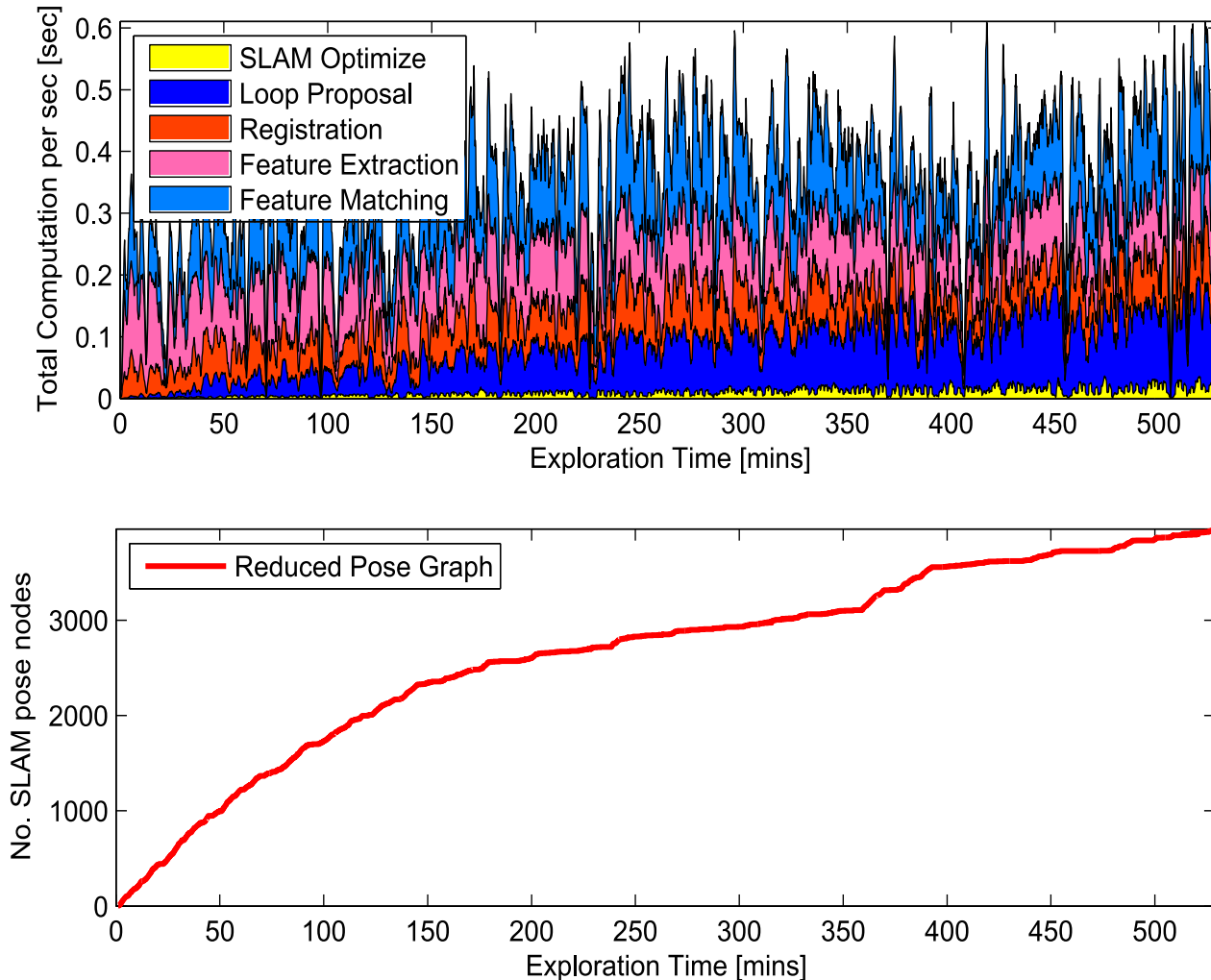
iSAM optimizes reduced pose graph

# Comparison of full vs reduced pose graph

- 4 Hours of data
- **Reduced pose graph**  
# Poses 1363  
Mean error 0.44m
- **Full pose graph**  
# Poses 28520  
Mean error 0.37m



# Timing (approx. 9 hours of mission)



# Reduced Pose Graph – 10 Floors

---

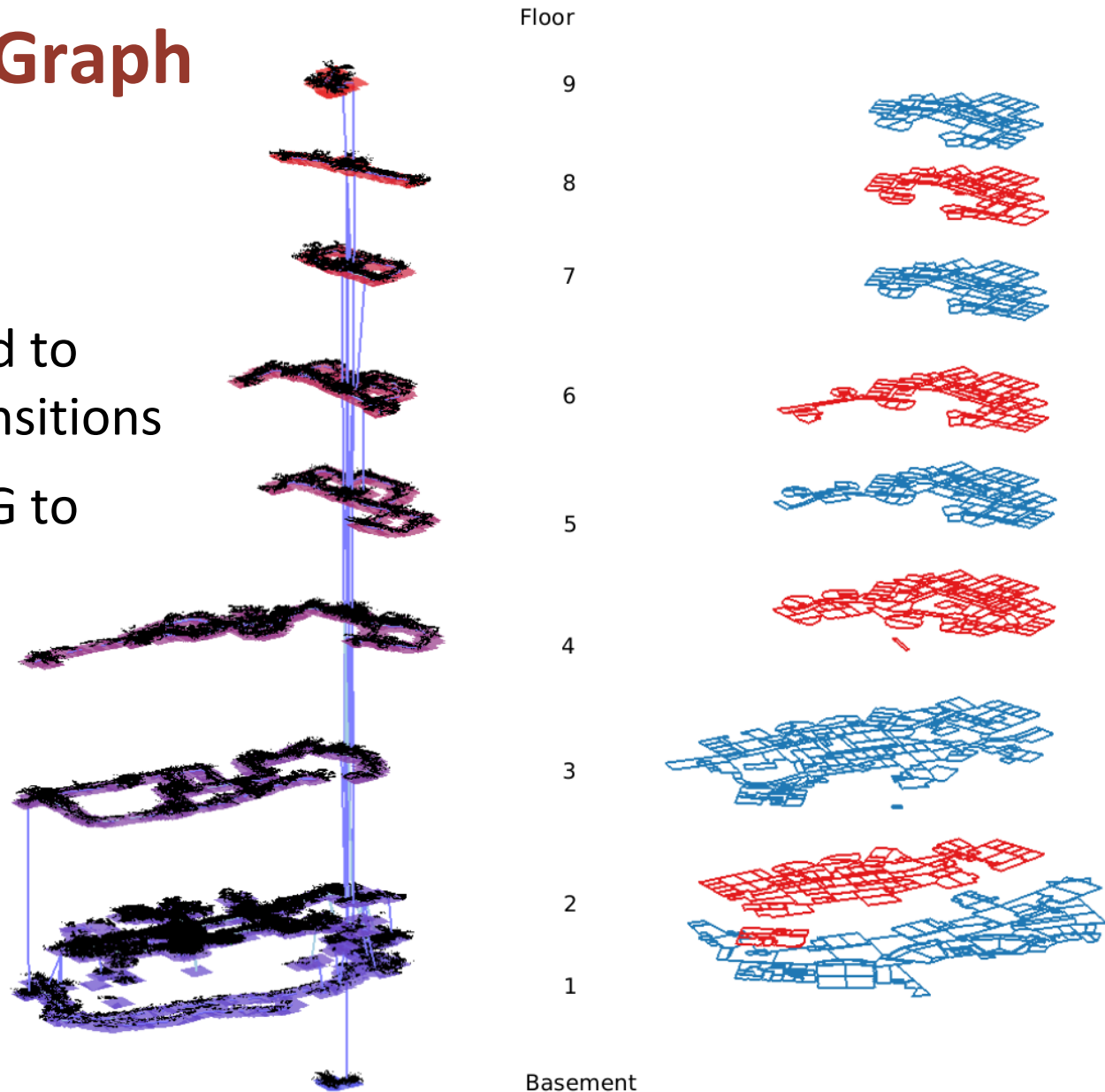


iSAM optimizes reduced pose graph

# Reduced Pose Graph

Map of 10 floors

- Accelerometer used to detect elevator transitions
- iSAM optimizes RPG to achieve real-time



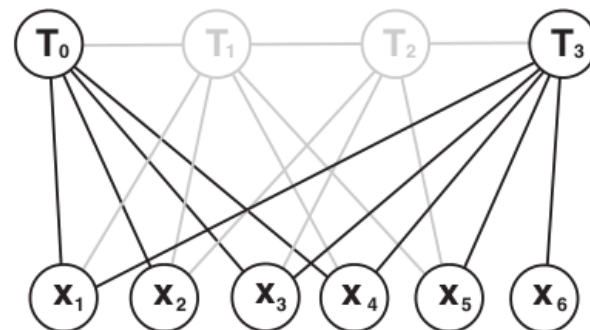
# Large-Scale Visual SLAM

Computational cost grows with time

Two approaches to reduce cost:

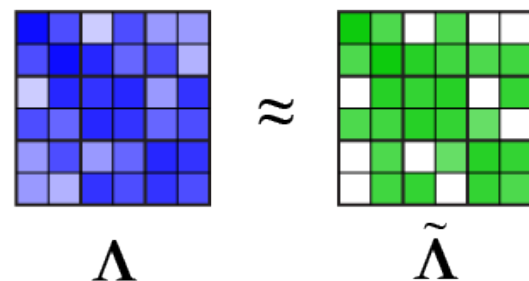
- Formulation

- Keyframes
- Submaps
- Reduced pose graph



- Simplification

- Cut old data
- **Sparsification**



# Sparsification: Factor Graph Node Removal

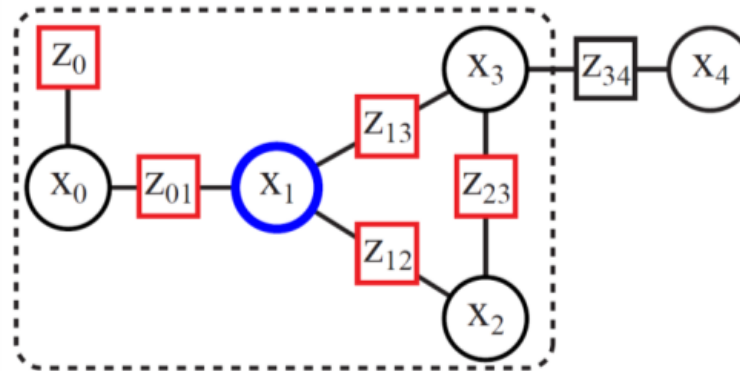
---

- Control complexity of performing inference in graph
  - Long-term multi-session SLAM
  - Reduces the size of graph
  - Storage and transmission
- Graph maintenance
  - Forgetting old views

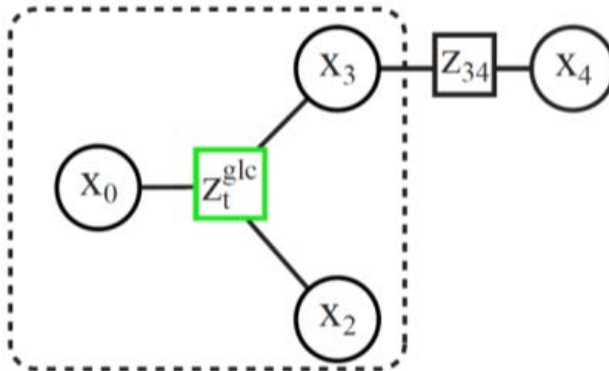


# Sparsification: Factor Graph Node Removal

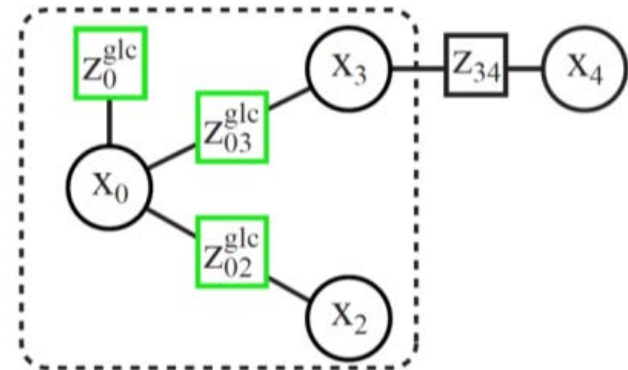
Remove node from graph  $\rightarrow$  marginalize variable from distribution



Original Graph

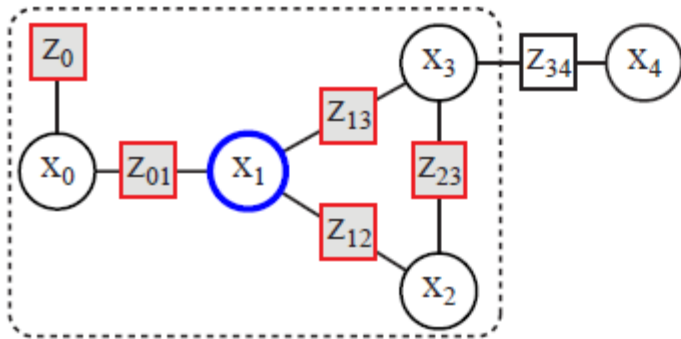


Dense Node Removal (Marginalization)

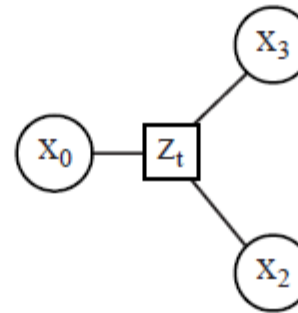


Sparse-Approximate Node Removal

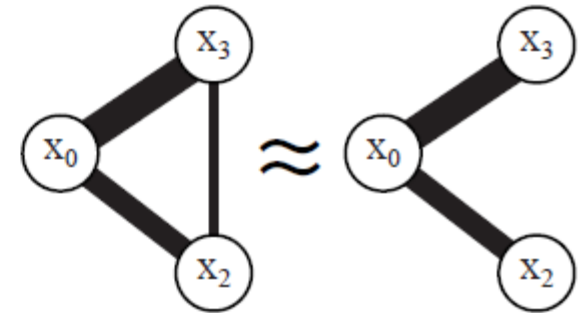
# Generic Linear Constraint Node Removal



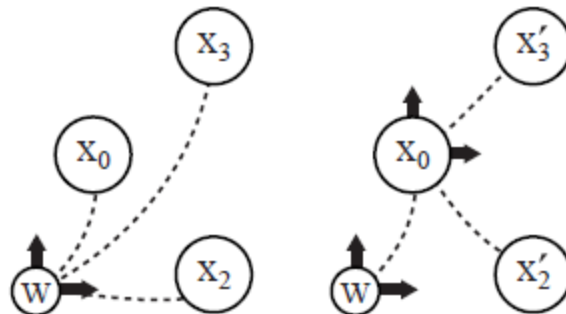
(a) Original Graph



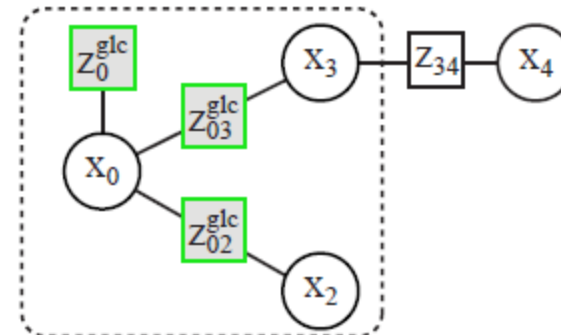
(b) Target Info.



(c) Chow-Liu Tree

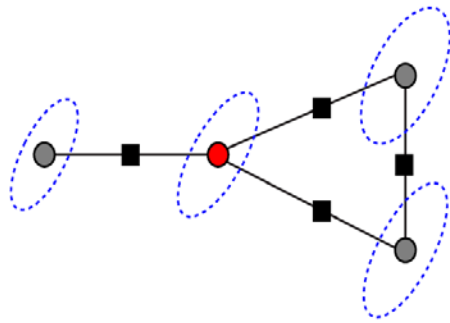


(d) Root Shift

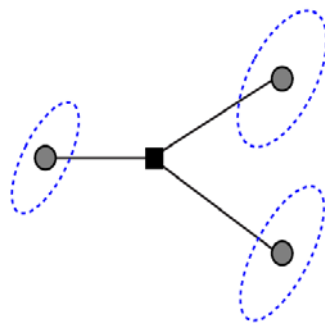


(e) Final Graph

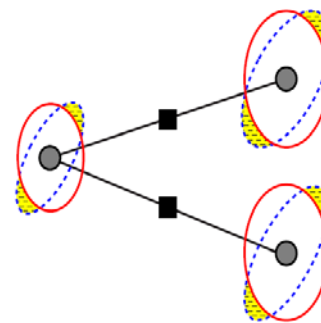
## Ensuring Conservative Approximations



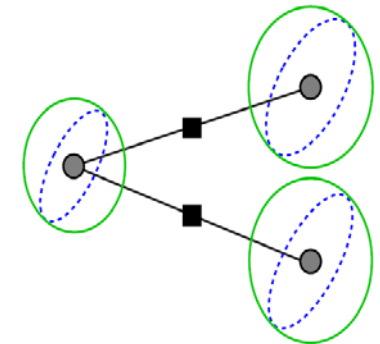
(a) Original Graph



(b) Node Marginalization



(c) Chow-Liu Tree Approx.

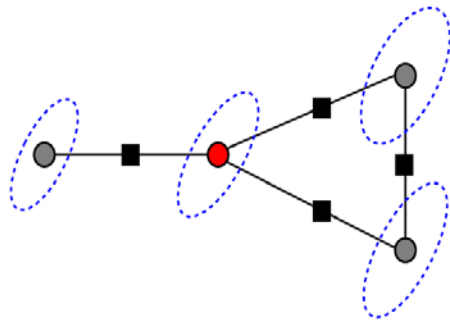


(d) Conservative Approx.

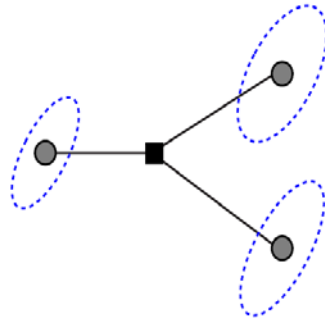
- Chow-Liu Tree minimizes KLD

$$\mathcal{D}_{KL} \left( \mathcal{N}^{-1}(\boldsymbol{\eta}_t, \Lambda_t) \parallel \mathcal{N}^{-1}(\tilde{\boldsymbol{\eta}}_t, \tilde{\Lambda}_t) \right) = \frac{1}{2} \left( \text{tr}(\tilde{\Lambda}_t \Lambda_t^{-1}) + \frac{\ln |\Lambda_t|}{\ln |\tilde{\Lambda}_t|} - \dim(\boldsymbol{\eta}_t) \right)$$

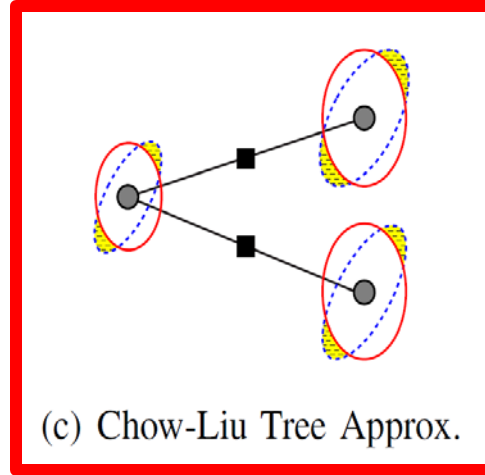
## Ensuring Conservative Approximations



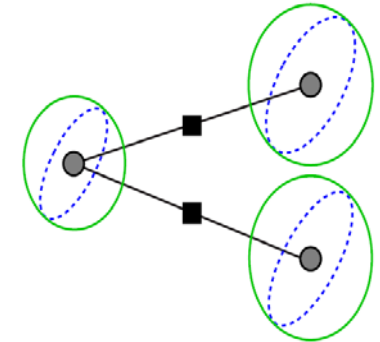
(a) Original Graph



(b) Node Marginalization



(c) Chow-Liu Tree Approx.



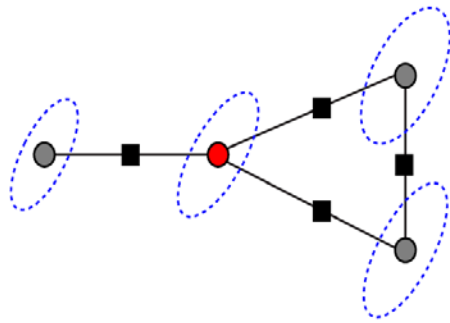
(d) Conservative Approx.

- Chow-Liu Tree minimizes KLD

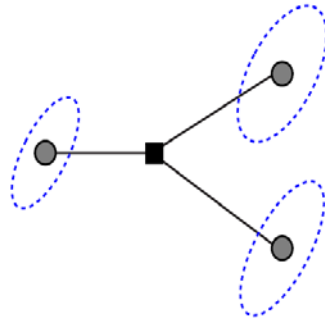
$$\mathcal{D}_{KL} \left( \mathcal{N}^{-1}(\boldsymbol{\eta}_t, \Lambda_t) \parallel \mathcal{N}^{-1}(\tilde{\boldsymbol{\eta}}_t, \tilde{\Lambda}_t) \right) = \frac{1}{2} \left( \text{tr}(\tilde{\Lambda}_t \Lambda_t^{-1}) + \frac{\ln |\Lambda_t|}{\ln |\tilde{\Lambda}_t|} - \dim(\boldsymbol{\eta}_t) \right)$$

- Often results in a slightly overconfident estimate

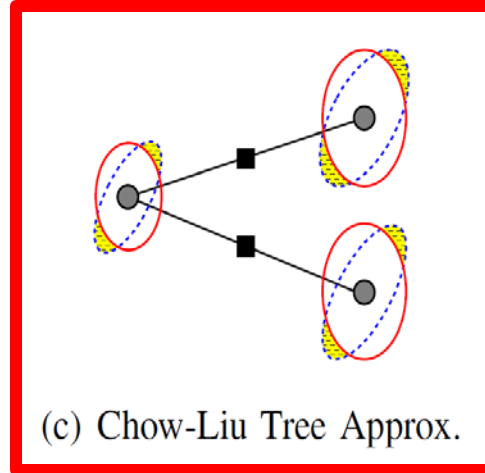
## Ensuring Conservative Approximations



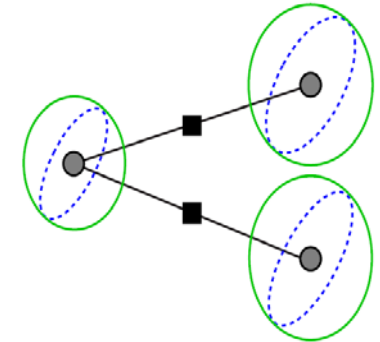
(a) Original Graph



(b) Node Marginalization



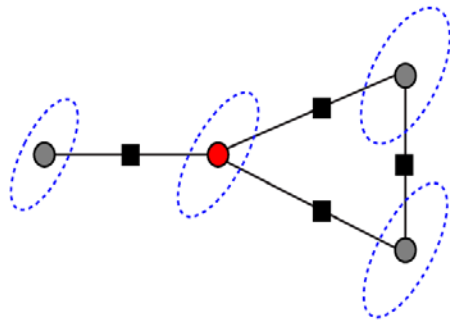
(c) Chow-Liu Tree Approx.



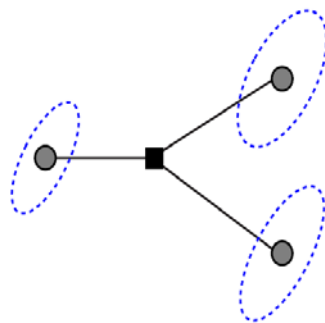
(d) Conservative Approx.

- Why care about overconfident estimates?
  - Overconfidence in pose or obstacle location → unsafe paths
  - Overconfidence in pose or landmark location → failed data association

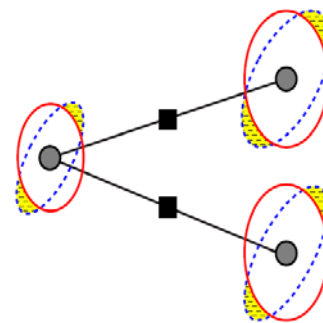
## Ensuring Conservative Approximations



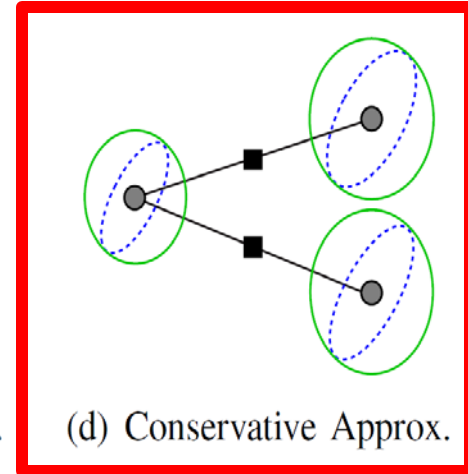
(a) Original Graph



(b) Node Marginalization



(c) Chow-Liu Tree Approx.



(d) Conservative Approx.

- Propose method to ensure conservative approximation
- Start with CLT which minimizes the KLD and then numerically adjust it to produce a conservative estimate

## Ensuring Conservative Approximations

- Constrained convex optimization problem
- Minimize the KLD

$$\mathcal{D}_{KL} \left( \mathcal{N}^{-1}(\boldsymbol{\eta}_t, \Lambda_t) \parallel \mathcal{N}^{-1}(\tilde{\boldsymbol{\eta}}_t, \tilde{\Lambda}_t) \right) = \frac{1}{2} \left( \text{tr}(\tilde{\Lambda}_t \Lambda_t^{-1}) + \frac{\ln |\Lambda_t|}{\ln |\tilde{\Lambda}_t|} - \dim(\boldsymbol{\eta}_t) \right)$$

$$f_{KL}(\tilde{\Lambda}_t) = \text{tr}(\tilde{\Lambda}_t \Lambda_t^{-1}) - \ln |\tilde{\Lambda}_t|$$

- Subject to conservative constraint (difference is PSD)

$$\tilde{\Sigma} \geq \Sigma \quad \Leftrightarrow \quad \Lambda \geq \tilde{\Lambda}$$

## Ensuring Conservative Approximations

- Constrained convex optimization problem
- Minimize the KLD

$$\mathcal{D}_{KL} \left( \mathcal{N}^{-1}(\boldsymbol{\eta}_t, \Lambda_t) \parallel \mathcal{N}^{-1}(\tilde{\boldsymbol{\eta}}_t, \tilde{\Lambda}_t) \right) = \frac{1}{2} \left( \text{tr}(\tilde{\Lambda}_t \Lambda_t^{-1}) + \frac{\ln |\Lambda_t|}{\ln |\tilde{\Lambda}_t|} - \dim(\boldsymbol{\eta}_t) \right)$$

$$f_{KL}(\tilde{\Lambda}_t) = \text{tr}(\tilde{\Lambda}_t \Lambda_t^{-1}) - \ln |\tilde{\Lambda}_t|$$

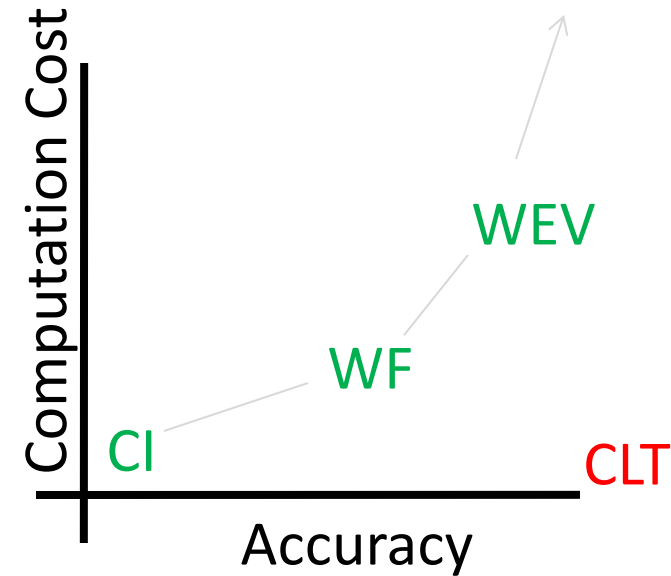
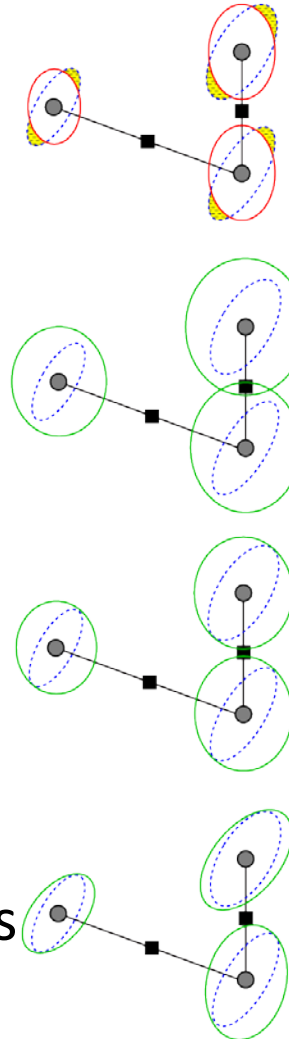
- Subject to conservative constraint (difference is PSD)

$$\tilde{\Sigma} \geq \Sigma \quad \Leftrightarrow \quad \Lambda \geq \tilde{\Lambda}$$



## Ensuring Conservative Approximations

- Start with the Chow-Liu Tree
- Consider three methods
  - Covariance Intersection
  - Weighted Factors
  - Weighted Eigenvalues
- Convex semidefinite programs



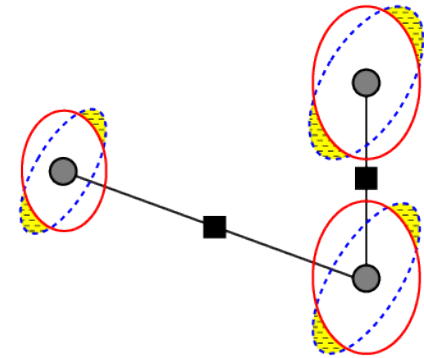
# Chow-Liu Tree Approximation

- All proposed methods start with the CLT

$$\Lambda \approx \tilde{\Lambda}_{\text{CLT}} = \Psi_1 + \Psi_2$$

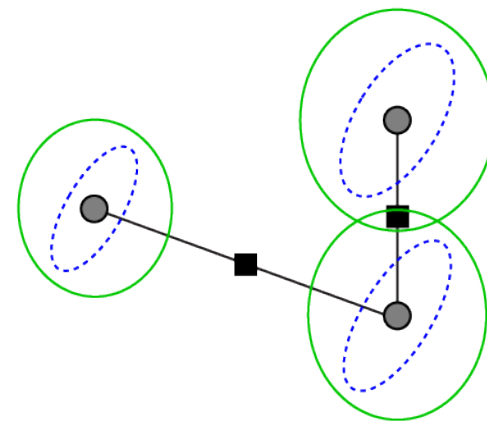
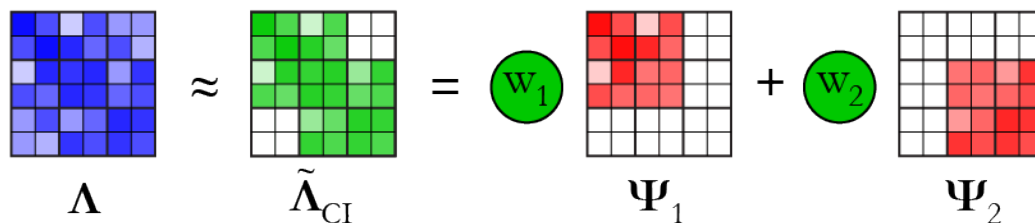
$$\mathcal{N}^{-1}(\eta_t, \Lambda_t) \approx \mathcal{N}^{-1}(\tilde{\eta}_t, \tilde{\Lambda}_{\text{CLT}}) = \prod_i p(\mathbf{x}_i | \mathbf{x}_{\text{p}(i)})$$

$$\tilde{\Lambda}_{\text{CLT}} = \sum_i \Psi_i$$



[Julier and Uhlmann, 1997]

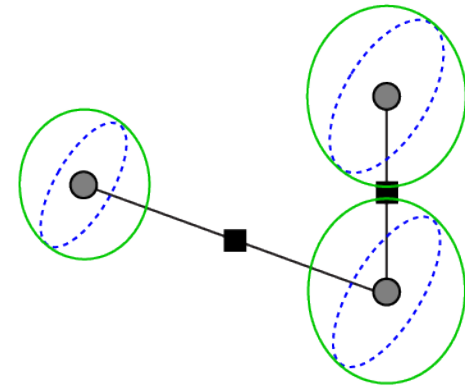
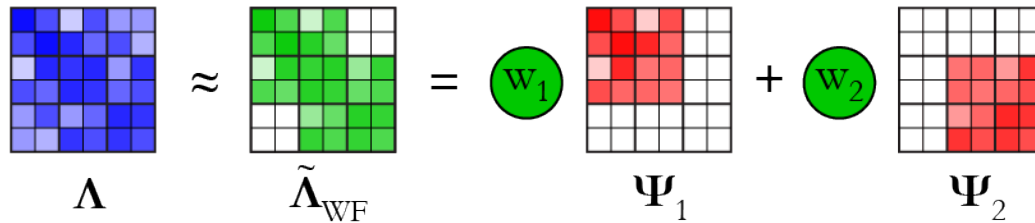
- Convex combination of correlated factors



$$\tilde{\Lambda}_{CI}(\mathbf{w}) = \sum_i w_i \Psi_i \quad \begin{array}{ll} \text{minimize}_{\mathbf{w}} & f_{KL}(\tilde{\Lambda}_{CI}(\mathbf{w})) \\ \text{subject to} & \sum_i w_i = 1 \end{array}$$

# Weighted Factors

- Replace constraint that weights sum to one

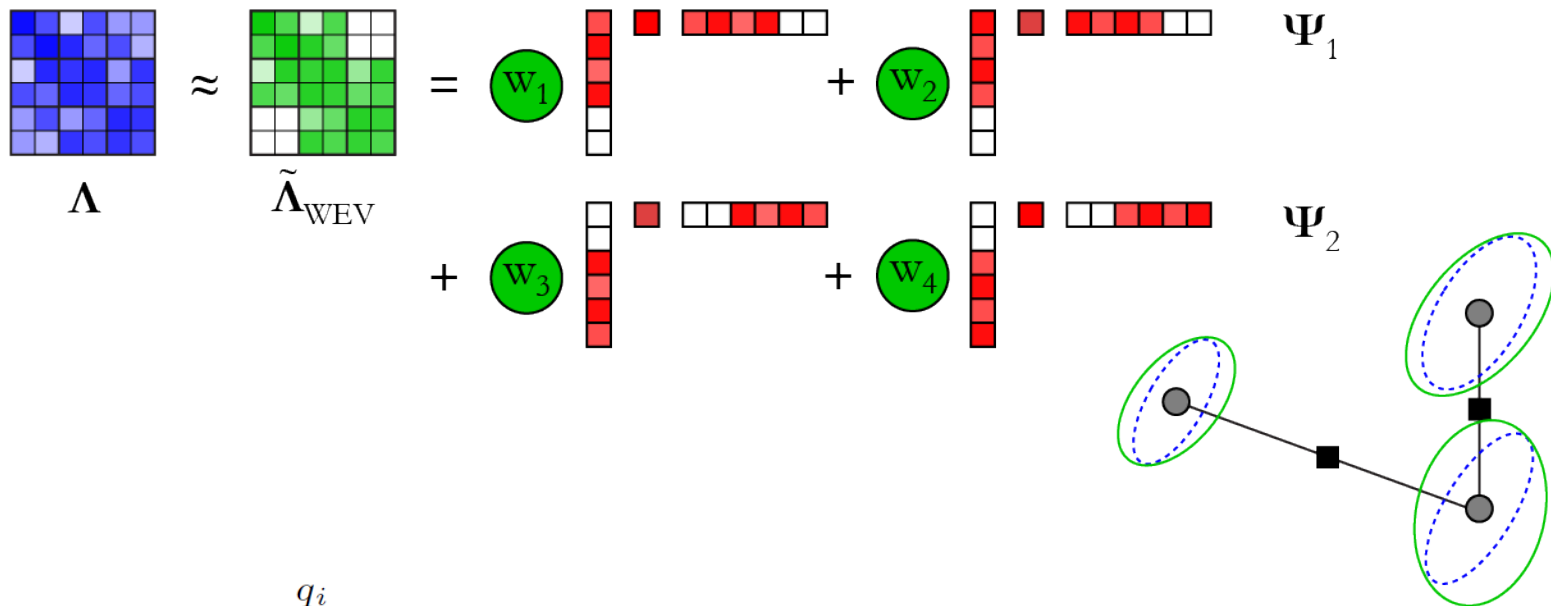


$$\tilde{\Lambda}_{WF}(\mathbf{w}) = \sum_i w_i \Psi_i$$

$$\begin{aligned} & \underset{\mathbf{w}}{\text{minimize}} && f_{KL}(\tilde{\Lambda}_{WF}(\mathbf{w})) \\ & \text{subject to} && 0 \leq w_i \leq 1, \forall i \\ & && \Lambda_t \geq \tilde{\Lambda}_{WF}(\mathbf{w}) \end{aligned}$$

# Weighted Eigenvalues

- Modify each eigenvalue of each factor

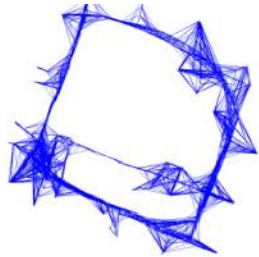


$$\begin{aligned}\tilde{\Lambda}_{WEV}(\mathbf{w}) &= \sum_i \sum_{j=1}^{q_i} w_j^i \lambda_j^i \mathbf{u}_j^i \mathbf{u}_j^{i\top} \\ &= \sum_k w_k \lambda_k \mathbf{u}_k \mathbf{u}_k^\top\end{aligned}$$

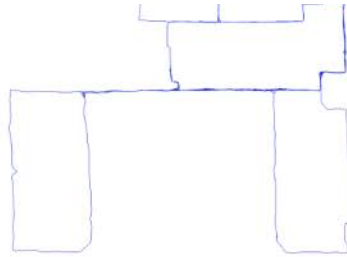
$$\begin{aligned}\underset{\mathbf{w}}{\text{minimize}} \quad & f_{KL}(\tilde{\Lambda}_{WEV}(\mathbf{w})) \\ \text{subject to} \quad & 0 \leq w_k \leq 1, \forall k \\ & \Lambda_t \geq \tilde{\Lambda}_{WEV}(\mathbf{w}).\end{aligned}$$

# Conservative GLC: Experimental Results

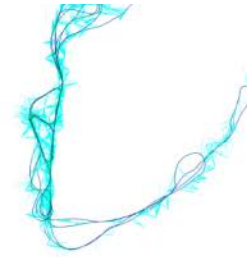
Dataset	Node Types	Factor Types	# Nodes	# Factors
<i>Intel Lab</i>	3-DOF pose	3-DOF odom., 3-DOF laser scan-matching	910	4,454
<i>Killian Court</i>	3-DOF pose	3-DOF odom., 3-DOF laser scan-matching	1,941	2,191
<i>Victoria Park</i>	3-DOF pose, 2-DOF lm.	3-DOF odom., 2-DOF landmark observation	7,120	10,609
<i>Duderstadt Center</i>	6-DOF pose	6-DOF odom., 6-DOF laser scan-matching	552	1,774
<i>EECS Building</i>	6-DOF pose	6-DOF odom., 6-DOF laser scan-matching	611	2,134
<i>USS Saratoga</i>	6-DOF pose	6-DOF odom., 5-DOF mono-vis., 1-DOF depth	1,513	5,433



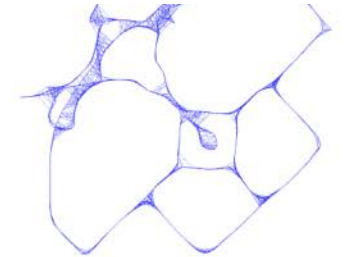
(a) Intel Lab



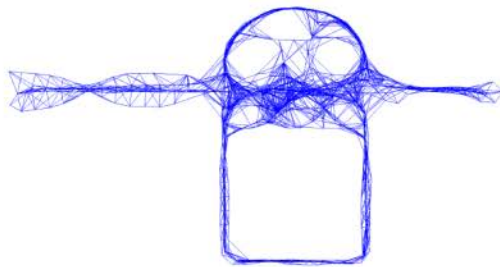
(b) Killian Court



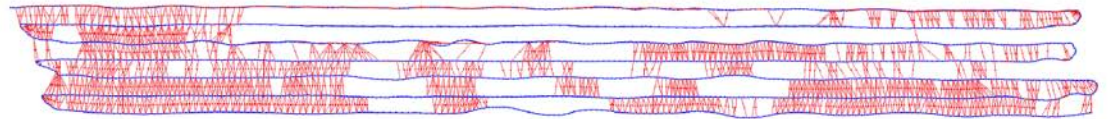
(c) Victoria Park



(d) Duderstadt Center

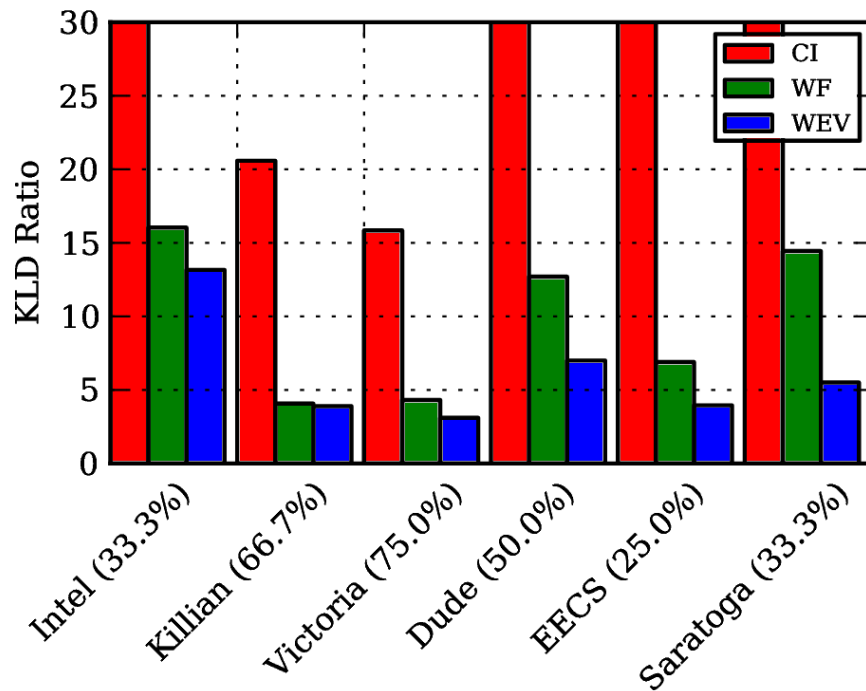


(e) EECS Building



(f) USS Saratoga

# Conservative GLC: Experimental Results



- Remove percentage of evenly spaced nodes from each graph
- CI very conservative
- WF and WEV approach performance of CLT
  - for most graphs
- Room improvement for Intel
  - Higher density of connectivity
  - All factor same strength