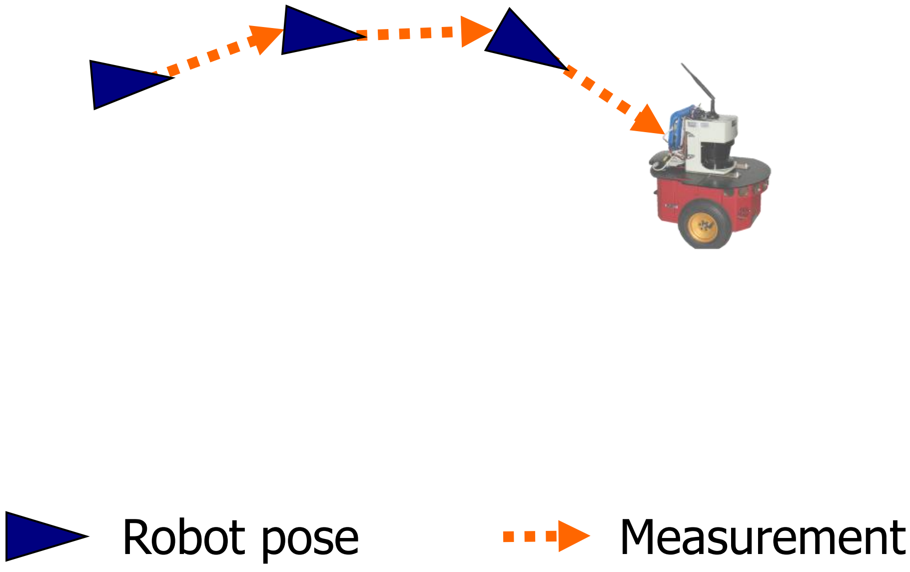
# Robot Mapping

# Hierarchical Pose-Graphs for Online Mapping

**Gian Diego Tipaldi, Wolfram Burgard**

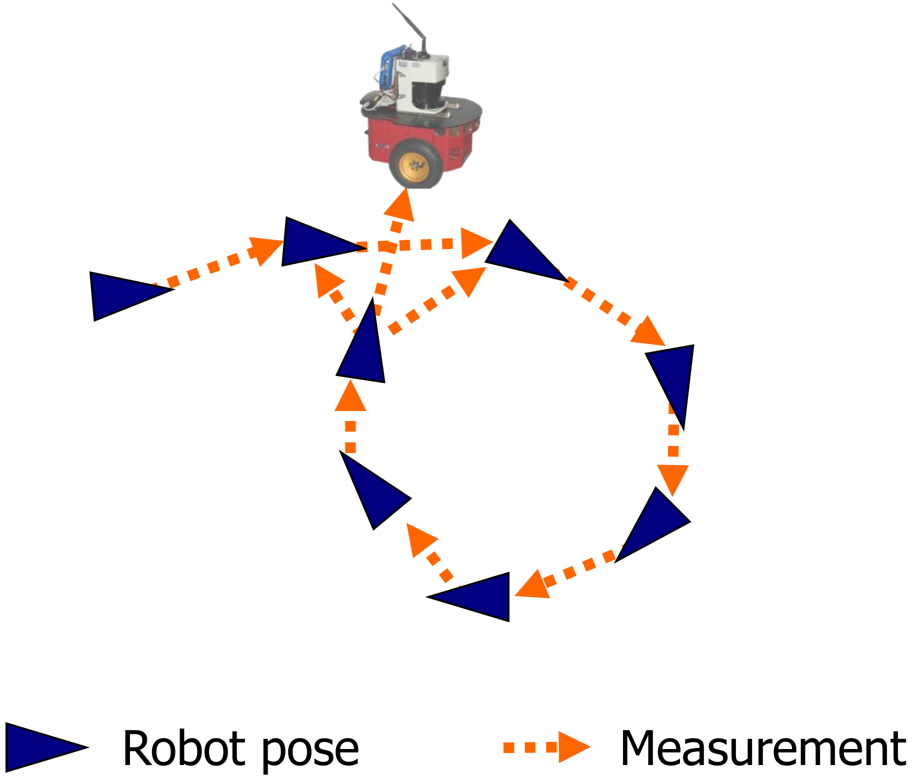
# Graph-Based SLAM

- Measurements connect the poses of the robot while it is moving
- Measurements are inherently uncertain



# Graph-Based SLAM

- Observing previously seen areas generates measurements between non-successive poses

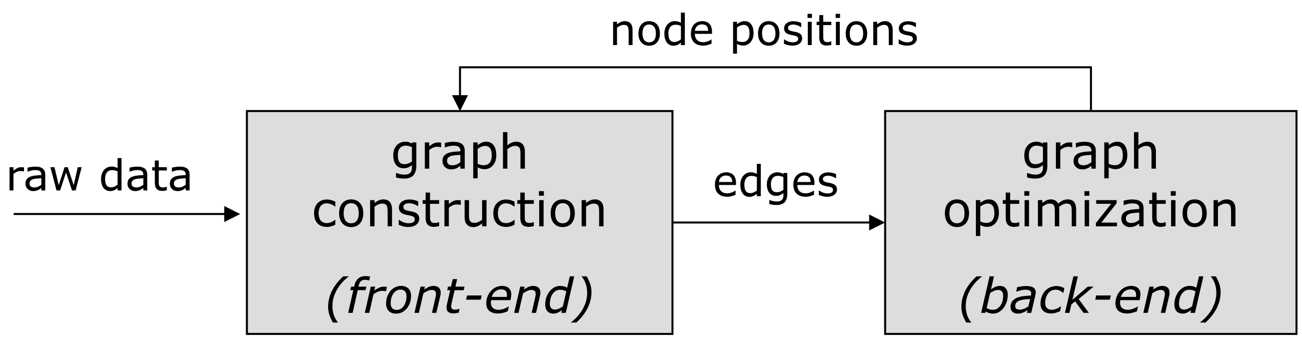


# Graph-Based SLAM

- Use a **graph** to represent the problem
- Every **node** in the graph corresponds to a pose of the robot during mapping
- Every **edge** between two nodes corresponds to a spatial measurement between them
- **Graph-Based SLAM:** Build the graph and find a node configuration that minimize the measurement error

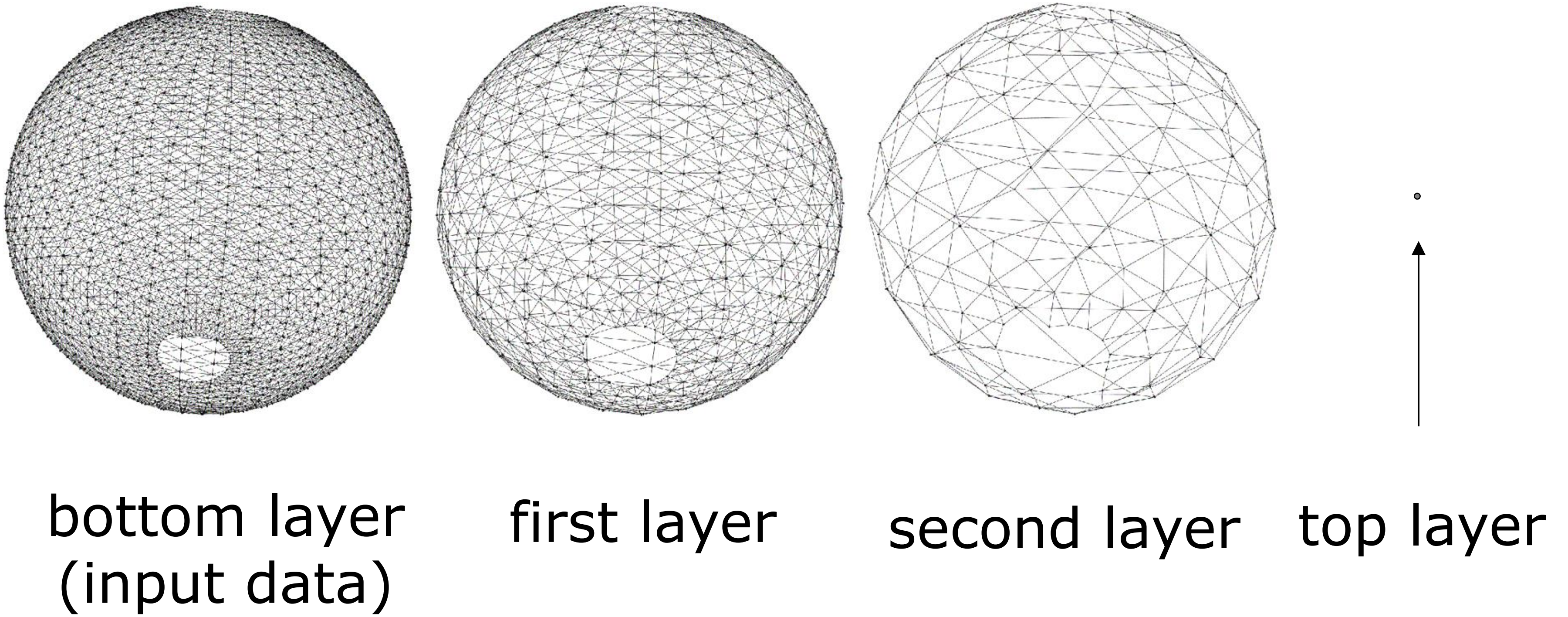
# Front-End and Back-End

- Front-end extracts constraints from the sensor data (data association!)
- Back-end optimizes the pose-graph to reduce the measurement error




Intermediate solutions are needed to make good data associations

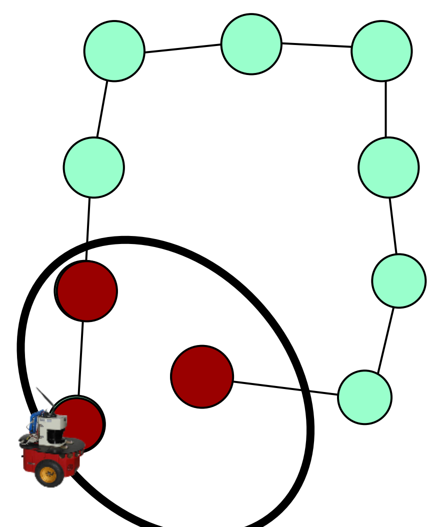
# Hierarchical Pose-Graph




“There is no need to optimize the whole graph when a new observation is obtained”

# Motivation

- SLAM front-end seeks for loop-closures
- Requires to compare observations to all previously obtained ones
- In practice, limit search to areas in which the robot is likely to be
- This requires to know **in which parts of the graph to search for data associations**

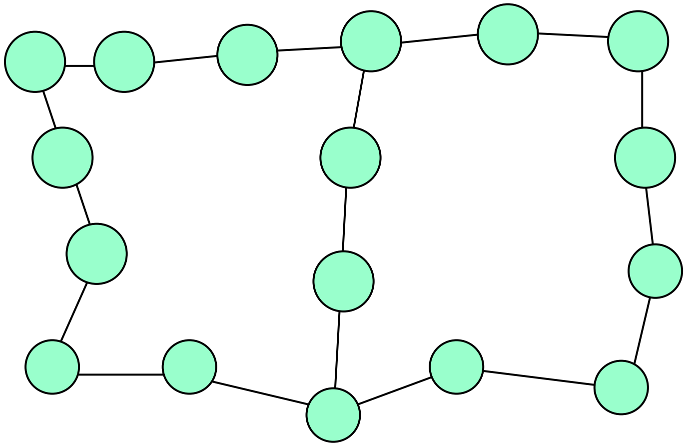


# Hierarchical Approach

- **Insight:** to find loop closing points, one doesn’t need a perfect global map
- **Idea:** correct only the core structure of the scene, not the overall graph
- The hierarchical pose-graph is a sparse approximation of the original
- It exploits the facts that in SLAM
  - Robot moved through the scene and it not “teleported” to locations
  - Sensors have a limited range

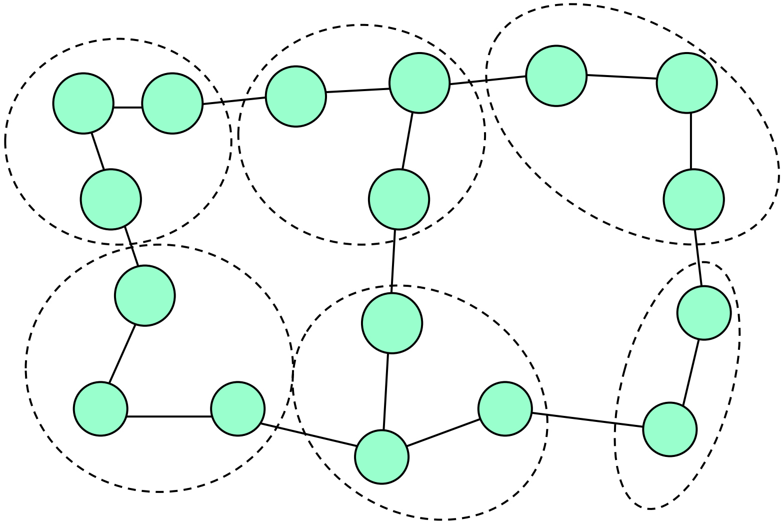
# Key Idea of the Hierarchy

- Input is the dense graph



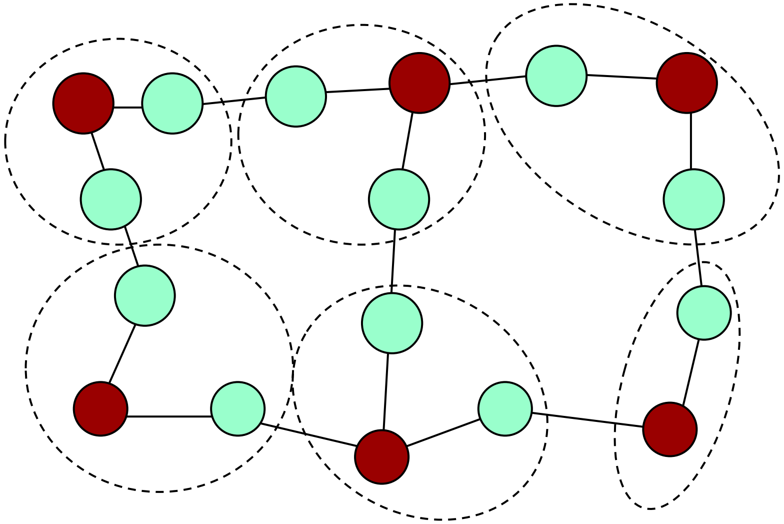
# Key Idea of the Hierarchy

- Input is the dense graph
- Group the nodes of the graph based on their local connectivity



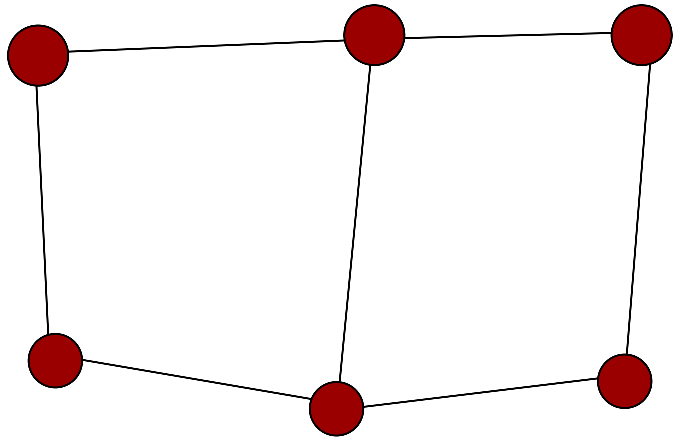
# Key Idea of the Hierarchy

- Input is the dense graph
- Group the nodes of the graph based on their local connectivity
- For each group, select one node as a "representative"



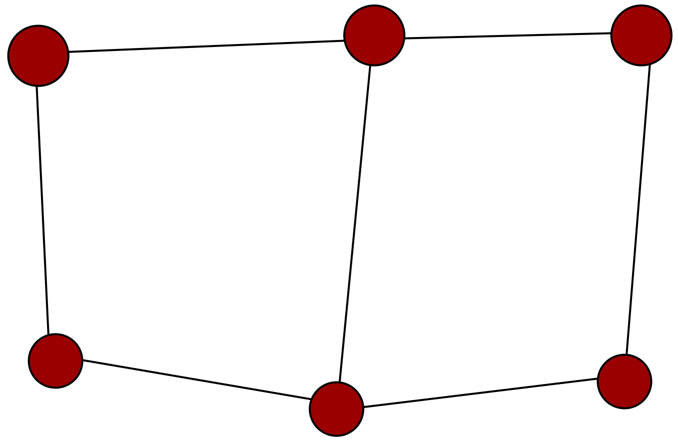
# Key Idea of the Hierarchy

- The representatives are the nodes in a new sparsified graph (upper level)



# Key Idea of the Hierarchy

- The representatives are the nodes in a new sparsified graph (upper level)
- Edges of the sparse graph are determined by the connectivity of the groups of nodes
- The parameters of the sparse edges are estimated via local optimization



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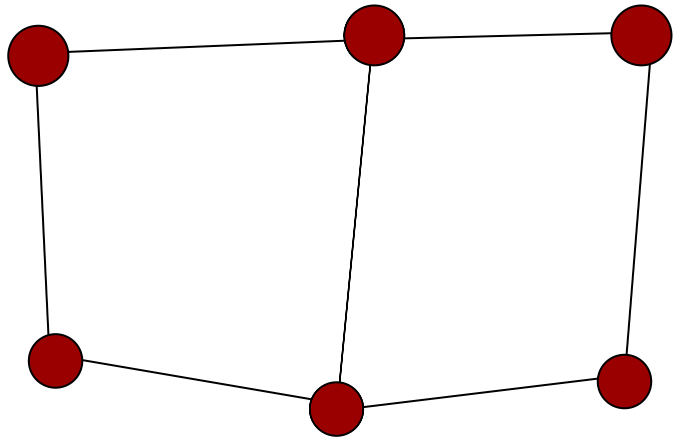
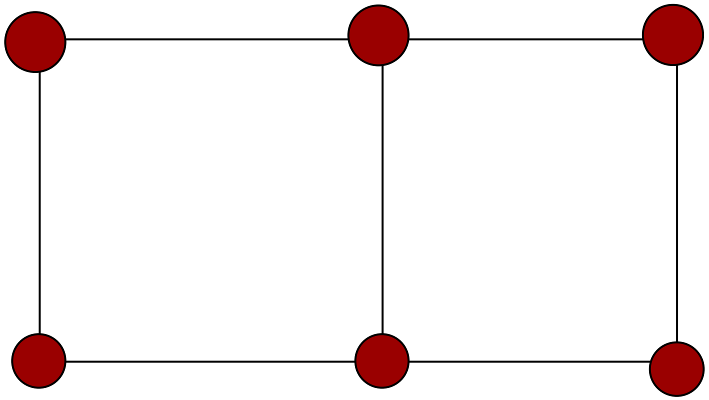


Process is repeated recursively

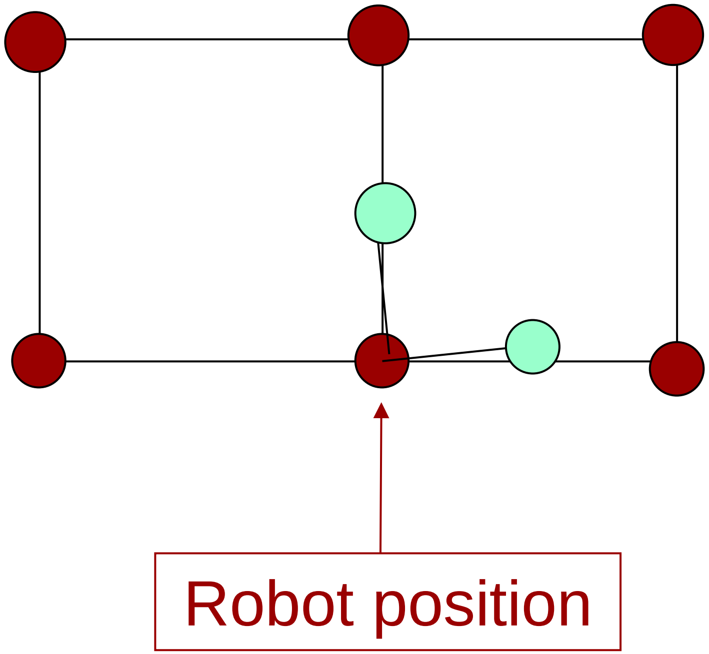
# Key Idea of the Hierarchy

- Only the upper level of the hierarchy is optimized completely



# Key Idea of the Hierarchy

- Only the upper level of the hierarchy is optimized completely
- The changes are propagated to the bottom levels only close to the current robot position
- Only this part of the graph is relevant for data association

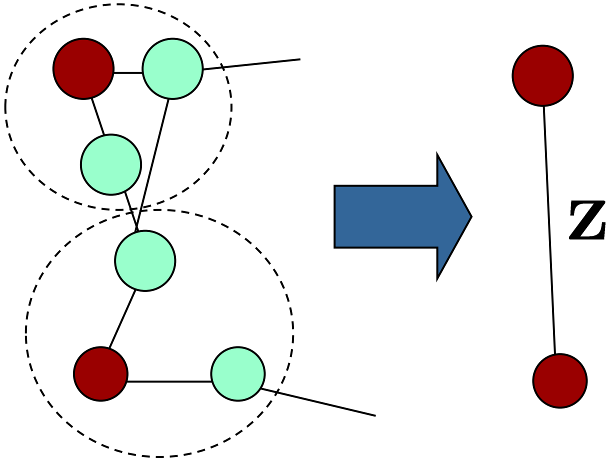


# Construction of the Hierarchy

- When and how to generate a new group?
  - A (simple) distance-based decision
  - The first node of a new group is the representative
- When to propagate information downwards?
  - Only when there are inconsistencies
- How to construct an edge in the sparsified graph?
  - Next slides
- How to propagate information downwards?
  - Next slides

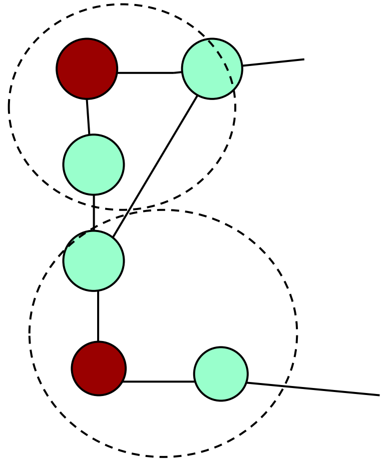
# Determining Edge Parameters

- Given two connected groups
- How to compute a virtual observation $\mathbf{z}$ and the information matrix $\Omega$ for the new edge?



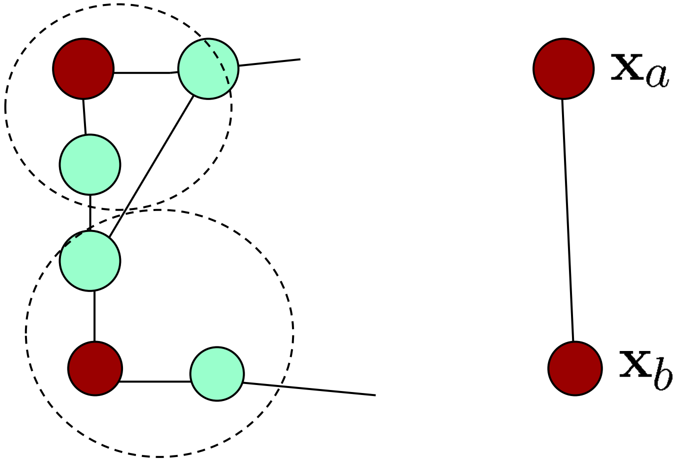
# Determining Edge Parameters

- Optimize the two sub-groups independently from the rest



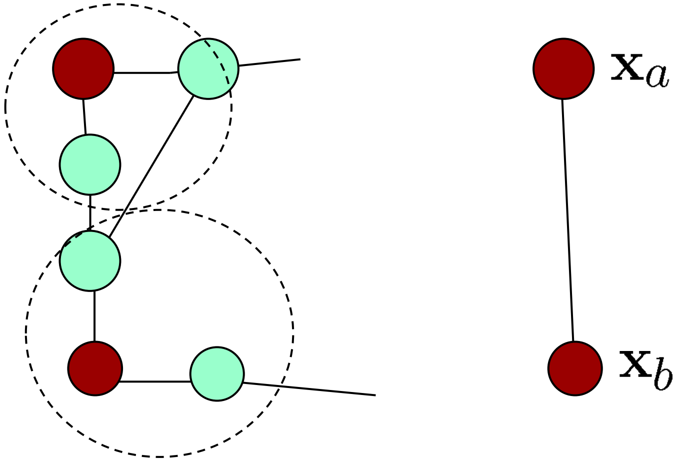
# Determining Edge Parameters

- Optimize the two sub-groups independently from the rest
- The observation is the relative transformation between the two representatives



# Determining Edge Parameters

- Optimize the two sub-groups independently from the rest
- The observation is the relative transformation between the two representatives
- The information matrix is computed from the diagonal block of the matrix ***H***

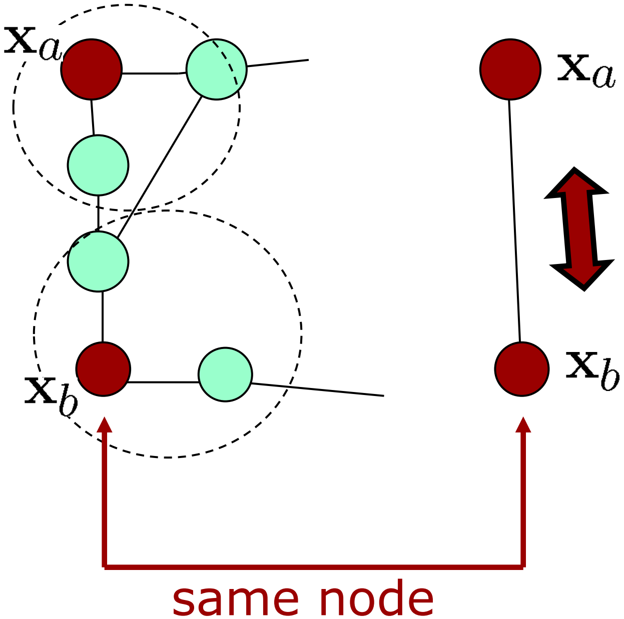



Inverse of the *[b,b]* block of ***H****$^{-1}$*

$$\Omega_{ab} = (\mathbf{H}^{-1}_{[b,b]})^{-1}$$

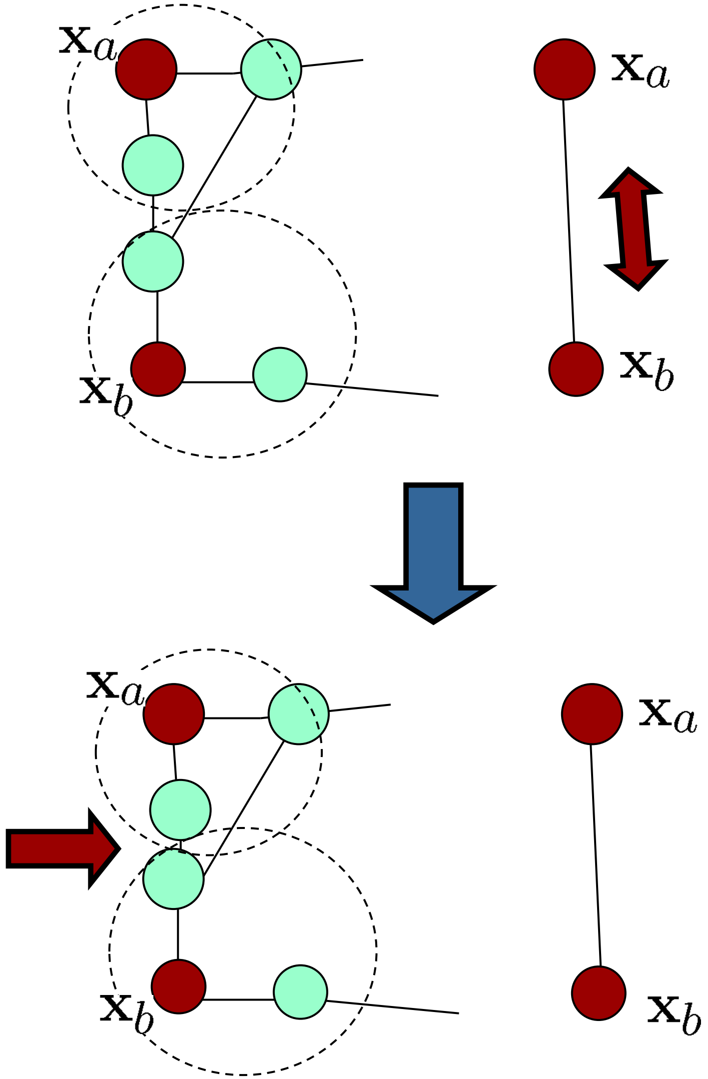
# Propagating Information Downwards

- All representatives are nodes from the lower (bottom) level



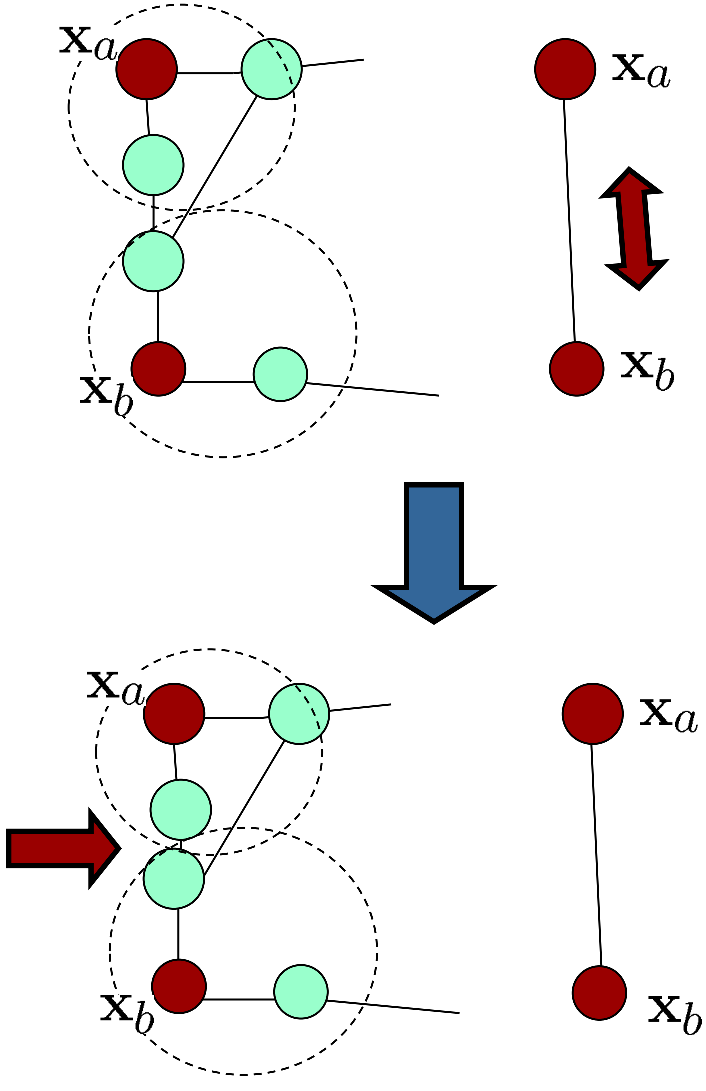
# Propagating Information Downwards

- All representatives are nodes from the lower (bottom) level
- Information is propagated downwards by transforming the group at the lower level using a rigid body transformation



# Propagating Information Downwards

- All representatives are nodes from the lower (bottom) level
- Information is propagated downwards by transforming the group at the lower level using a rigid body transformation
- Only if the lower level becomes inconsistent, optimize at the lower level



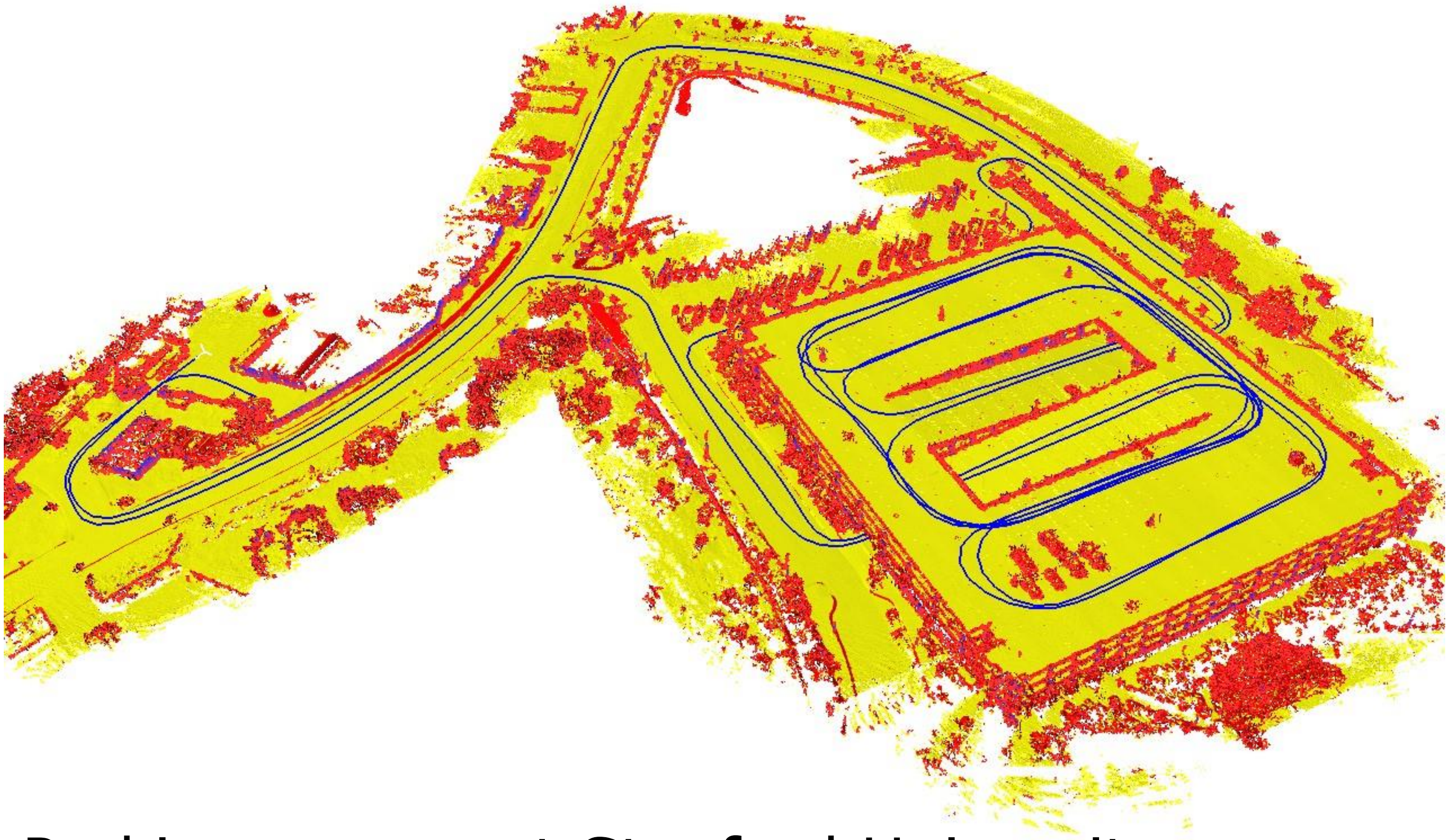
# For the Best Possible Map…

- Run the optimization on the lowest level (at the end)
- For offline processing with all measurements, the hierarchy helps convergence in case of large errors
- In this case, one pass up the tree (to construct the edges) followed by one pass down the tree is sufficient

# Stanford Garage

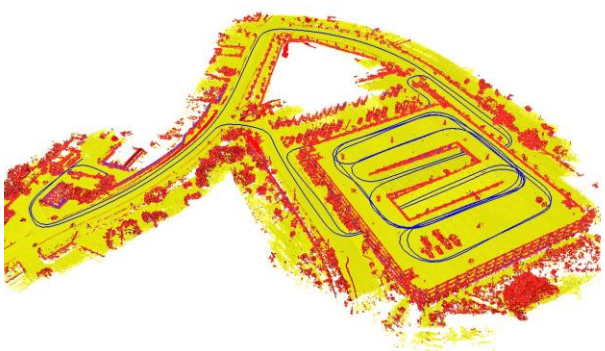
- Parking garage at Stanford University
- Nested loops, trajectory of ~7,000m

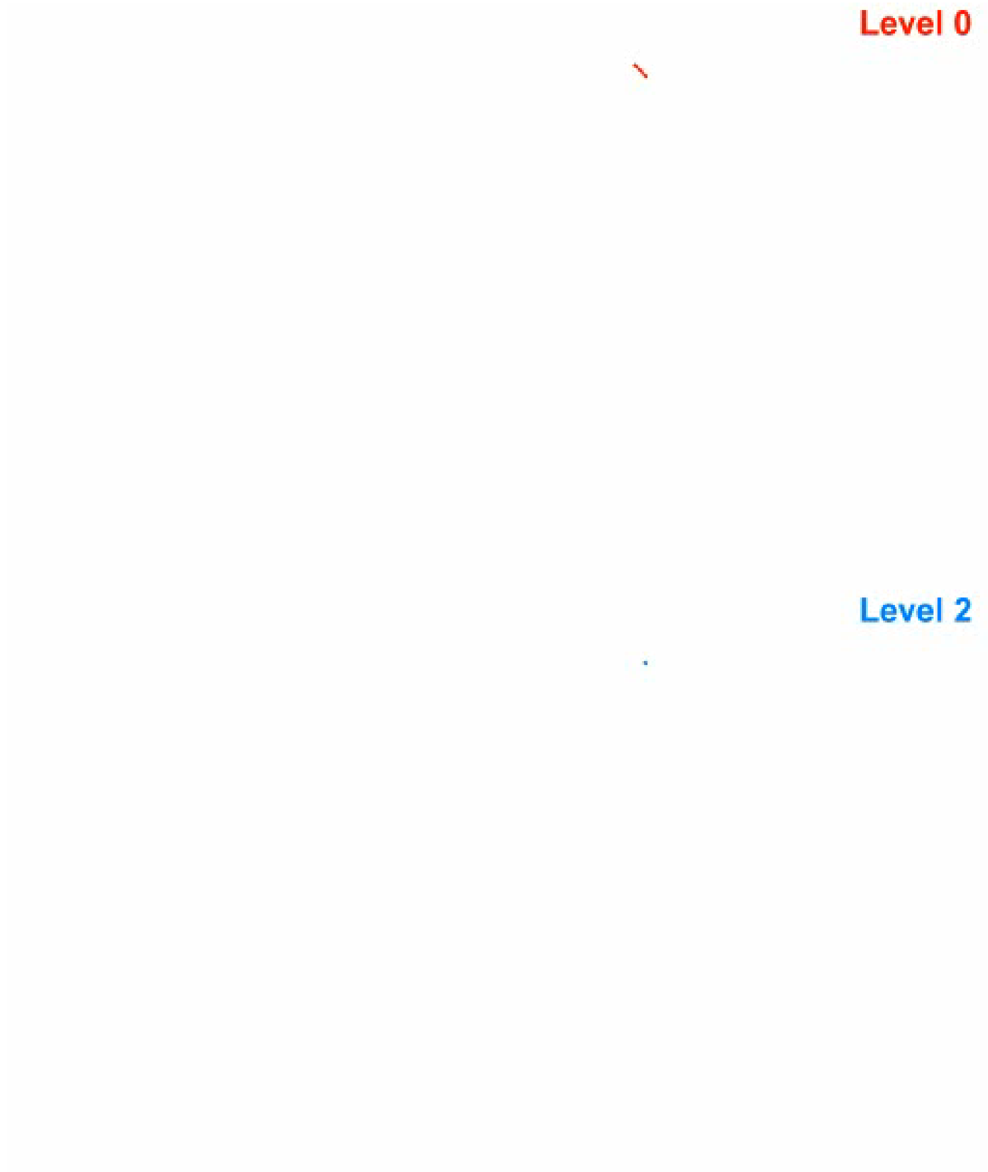
# Stanford Garage Result



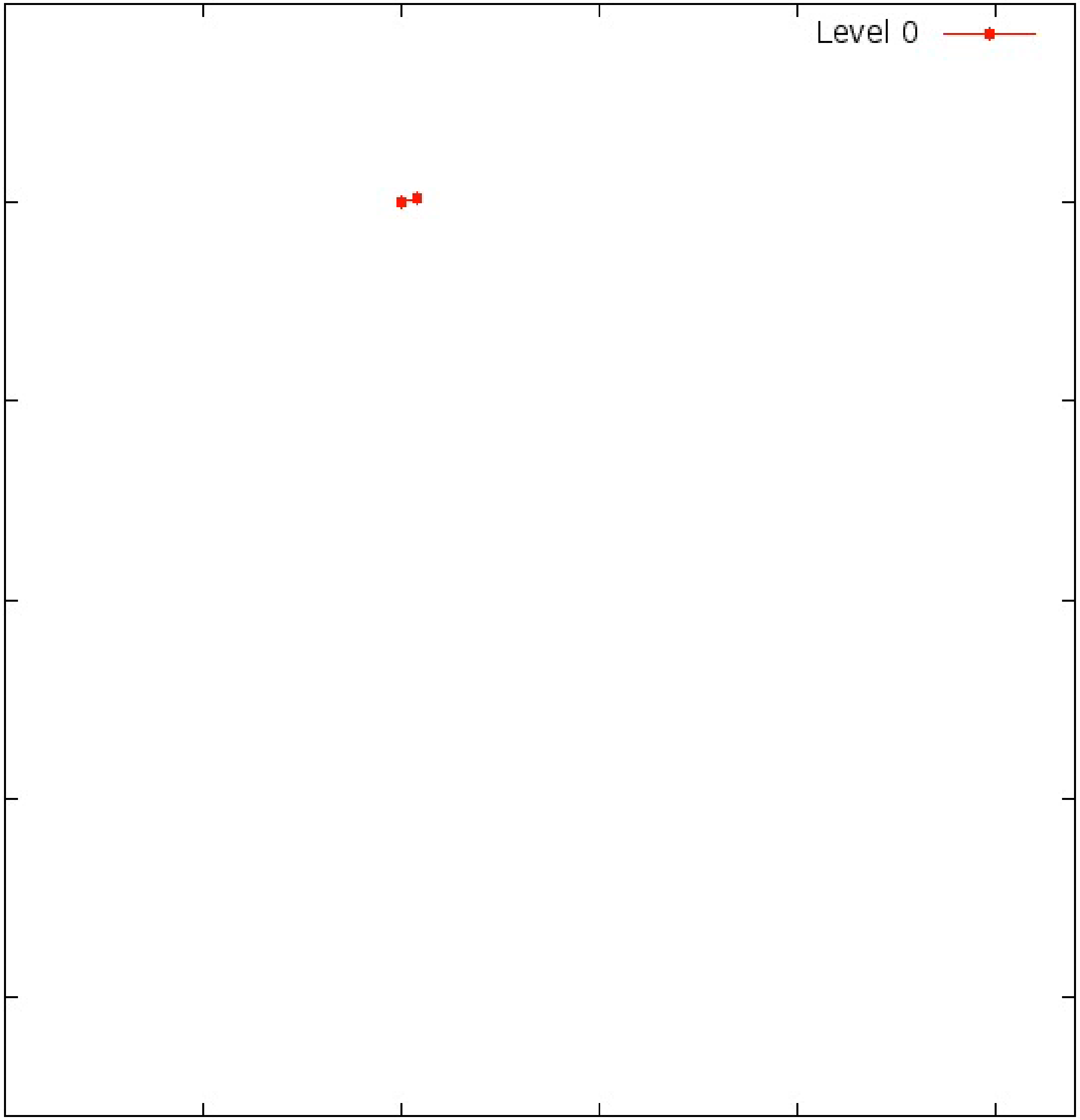
- Parking garage at Stanford University
- Nested loops, trajectory of ~7,000m

# Stanford Garage Video





# Intel Research Lab Video




# Consistency

- How well does the top level in the hierarchy represent the original input?

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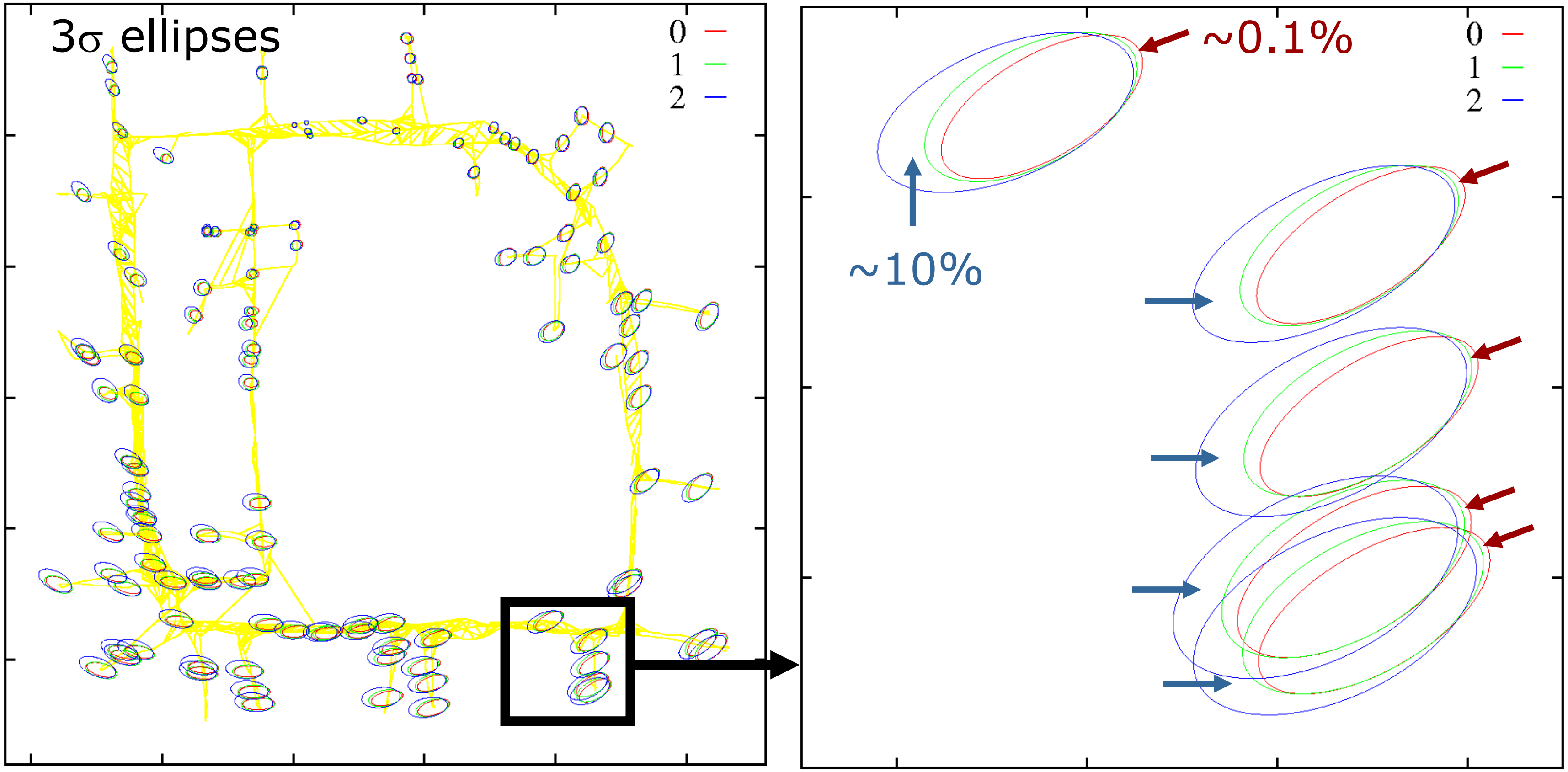
- How well does the top level in the hierarchy represent the original input?
- Probability mass of the marginal distribution in the highest level vs. the one of the true estimate (original problem, lowest level)

| | Prob. mass not covered | Prob. mass outside |
|---|---|---|
| Intel | 0.10% | 10.18% |
| W-10000 | 2.53% | 24.05% |
| Stanford | 0.01% | 7.88% |
| Sphere | 2.75% | 10.21% |

low risk of becoming overly confident

one does not ignore too much information

# Consistency




- Red: overly confident (~0.1% prob. mass)
- Blue: under confident (~10% prob. mass)

# Conclusions

- Hierarchical pose-graph to estimate the structure to support efficient data association
- Designed for online mapping (interplay between optimization and data association)
- Higher level represent simplified problem

# Literature

## Hierarchical Pose-Graph Optimization

- Grisetti, Kümmerle, Stachniss, Frese, and Hertzberg: "Hierarchical Optimization on Manifolds for Online 2D and 3D Mapping"
- Open-source implementation hosted at http://openslam.org/hog-man.html

# Slide Information

- These slides have been created by Cyrill Stachniss as part of the robot mapping course taught in 2012/13 and 2013/14. I created this set of slides partially extending existing material of Giorgio Grisetti and myself.
- I tried to acknowledge all people that contributed image or video material. In case I missed something, please let me know. If you adapt this course material, please make sure you keep the acknowledgements.
- Feel free to use and change the slides. If you use them, I would appreciate an acknowledgement as well. To satisfy my own curiosity, I appreciate a short email notice in case you use the material in your course.
- My video recordings are available through YouTube:
http://www.youtube.com/playlist?list=PLgnQpQtFTOGQrZ4O5QzbIHgl3b1JHimN_&feature=g-list

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