

VAN course

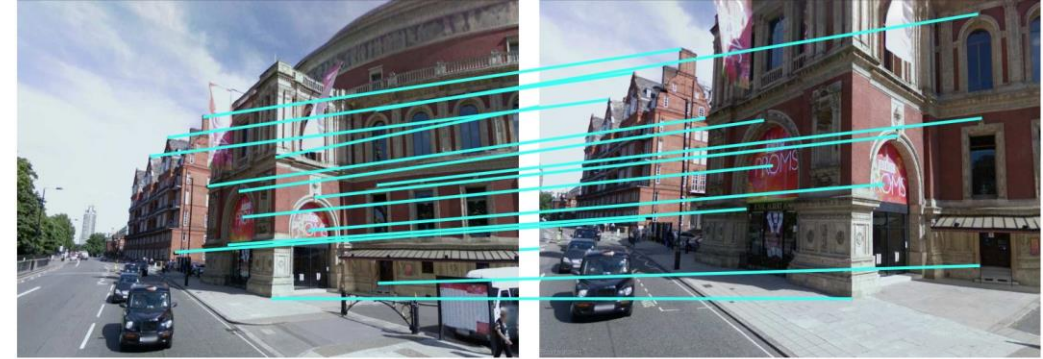
Lesson 12

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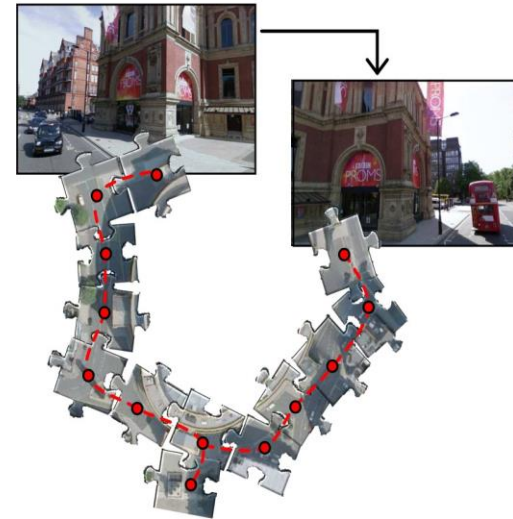
Loop Closure

Loop Closure

- Problem: Navigation drifts
 - We can reduce it, but not eliminate the problem
- If we revisit a location it can help
 - Shorter path to origin in the pose graph
 - Constraints propagate to other vertices
 - Vertices get a ‘second opinion’
- This is called a “**Loop Closure**”



(a) Robust local motion estimation

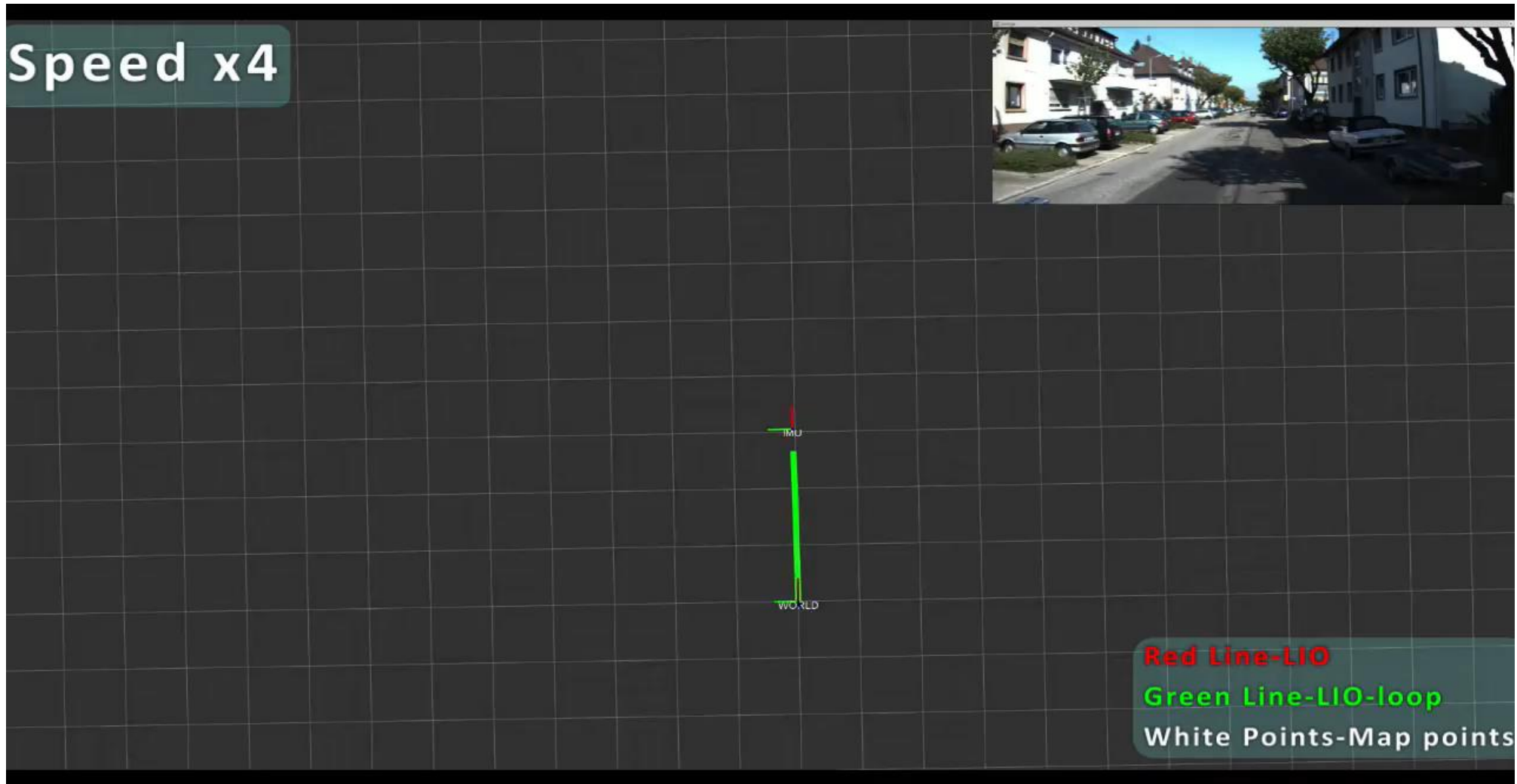


(b) Mapping and loop-closure detection



(c) Global optimisation

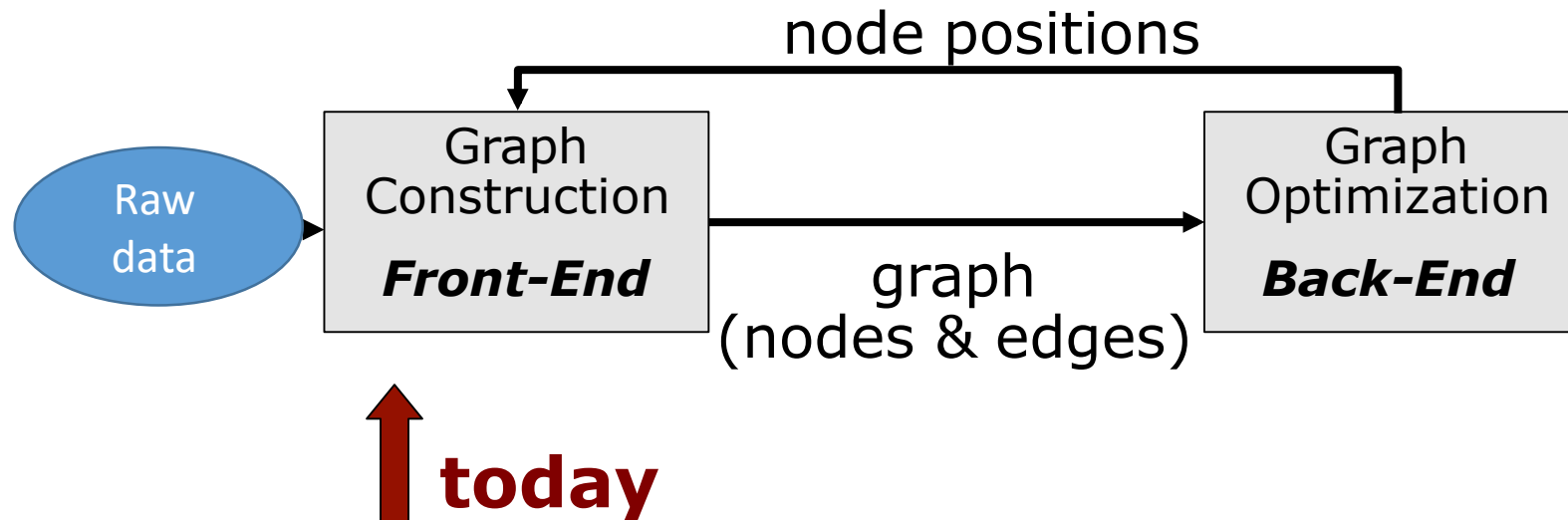
Loop Closure



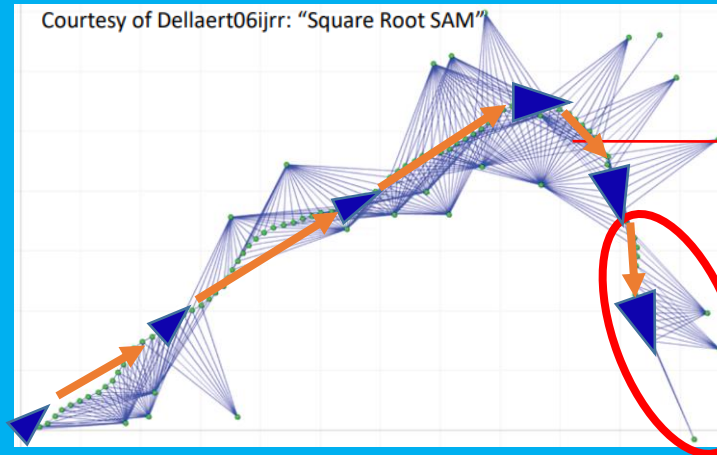
<https://www.youtube.com/watch?v=LVbzuyOCCaM>

Loop Closure

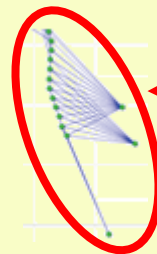
- When implementing an online system:
 - Front end
 - Find new graph edges
 - To previous vertex: Stereo tracking, PnP, factor graph (Ex 1-3)
 - To old known vertices: Loop closure (Ex. 5)
 - Backend
 - Global optimization – Pose graph (Ex. 4)



Loop Closure

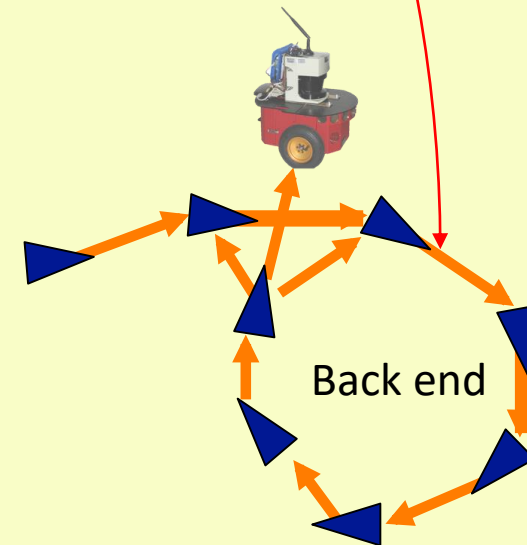


We wish to solve the whole bundle



Front end

We settle for those
sub problems

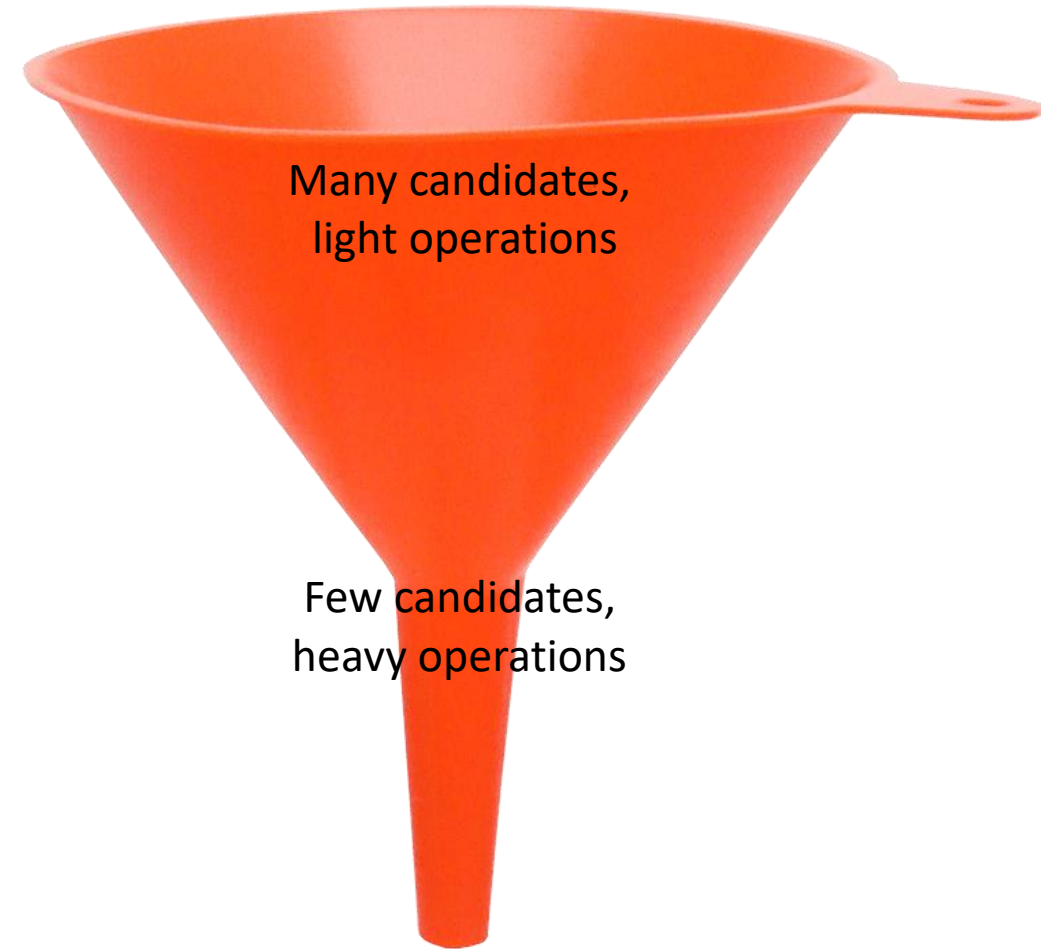


Back end

And it works!

Loop Closure

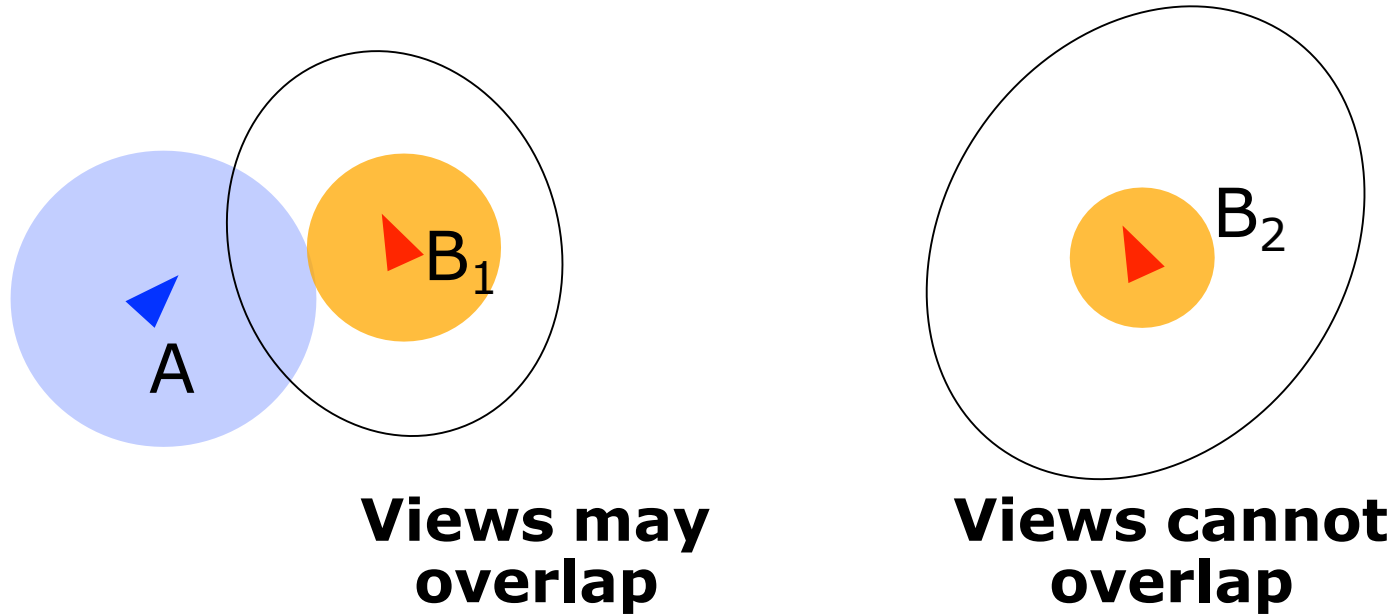
- How can we spot a loop closure?
 - Find candidates (light):
 - Using our navigation system
 - Global image descriptor
 - Validate candidates (heavy):
 - 3D points clouds matching using ICP
 - Descriptor-based matching
 - Calculate edges and factors:
 - Find transformation using matches/ICP
 - Outlier removal:
 - Olson's method



Loop Closure - Geometric intersection

Geometric intersection: Where to Search for Matches?

- Consider uncertainty of the nodes with respect to the current one



- “Intersection” means that B pose **is** pose A with high probability
- Note: even if location overlaps, pose may not.

Loop Closure - Geometric intersection

- We wish to find: $\Delta x^T \Omega_{n|i} \Delta x < d$

Where: $\Delta x = t2v(X_i^{-1} X_n)$

and $\Omega_{n|i}$ is the conditional information matrix of $x_n | x_i$

- This requires marginalization to remove all other x_j
- Inverting the full Ω is too expensive for front-end.
- Fast approximation:
 - Find shortest path using Dijkstra
 - Compose the incremental covariance along the path.

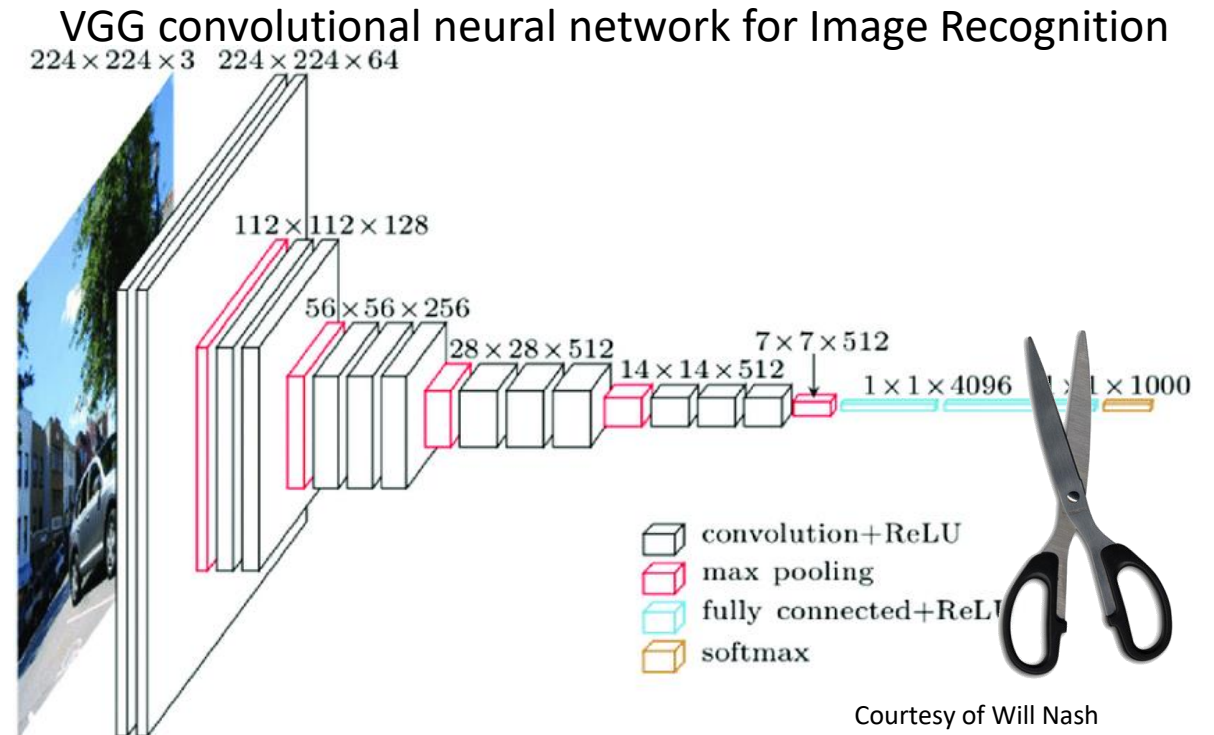
Assume $\mathbf{x} \sim \mathcal{N}(\mathbf{m}_x, \Sigma_x)$ and $\mathbf{y} \sim \mathcal{N}(\mathbf{m}_y, \Sigma_y)$ then

$$\mathbf{Ax} + \mathbf{By} + \mathbf{c} \sim \mathcal{N}(\mathbf{Am}_x + \mathbf{Bm}_y + \mathbf{c}, \mathbf{A}\Sigma_x\mathbf{A}^T + \mathbf{B}\Sigma_y\mathbf{B}^T)$$

$$x + y \sim N(m_x + m_y, \Sigma_x + \Sigma_y)$$

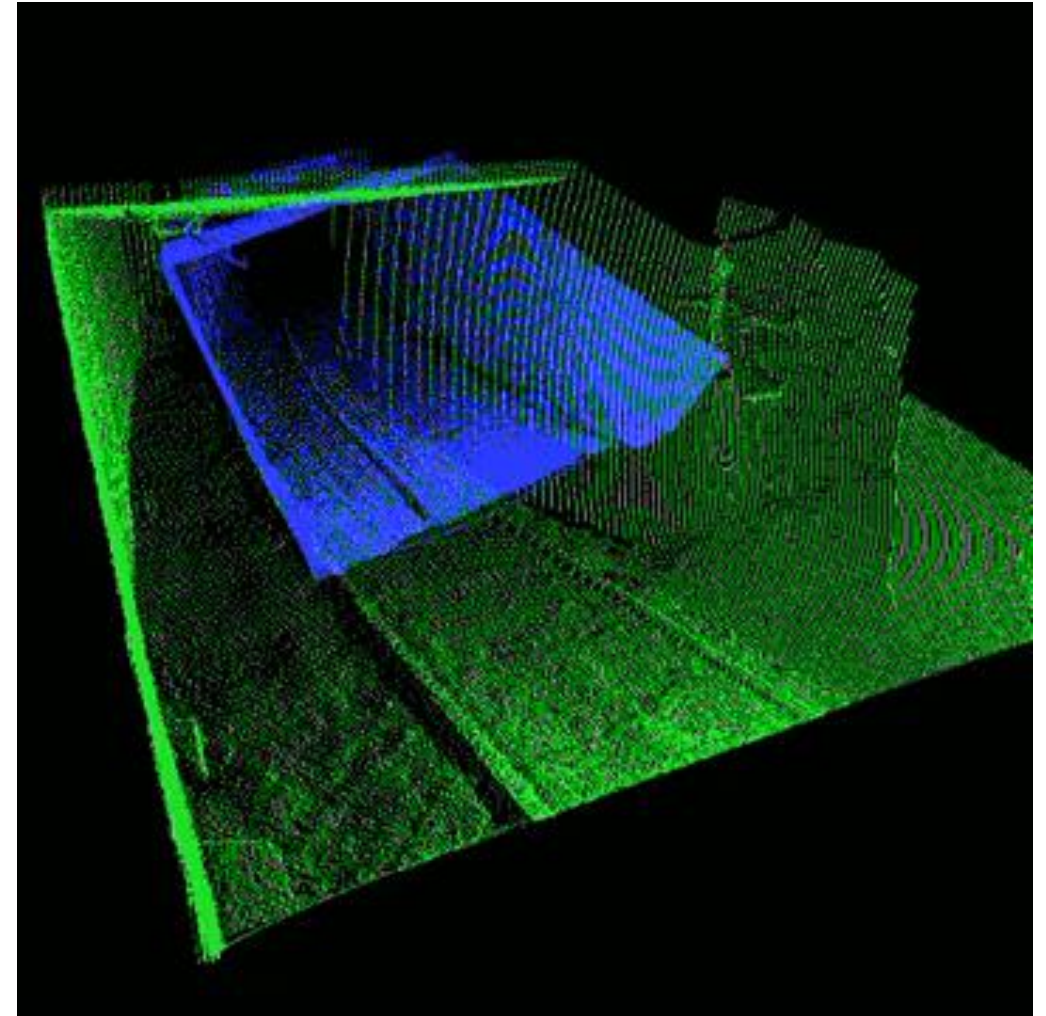
Loop Closure - Global image descriptor

- For every image:
 - Calc a global image descriptor
 - i.e. the hidden layers of a CNN
 - Save in database
- For new image:
 - Compare descriptor to database
 - Find candidates using a threshold



Loop Closure - Validate candidates with ICP

- For any candidate-pair for edge:
 - Find the corresponding 3D point cloud
 - Optional: extract unique structures
 - Like trees of cars
 - Walls are large but with low information
 - Find transformation
 - Using ICP, RANSAC and least squares minimization
 - Evaluate edge
 - Matches percent
 - Mean distance
 - If it's good, set an edge
 - The factor is the calculated relative transformation



Loop Closure - Validate candidates with ICP

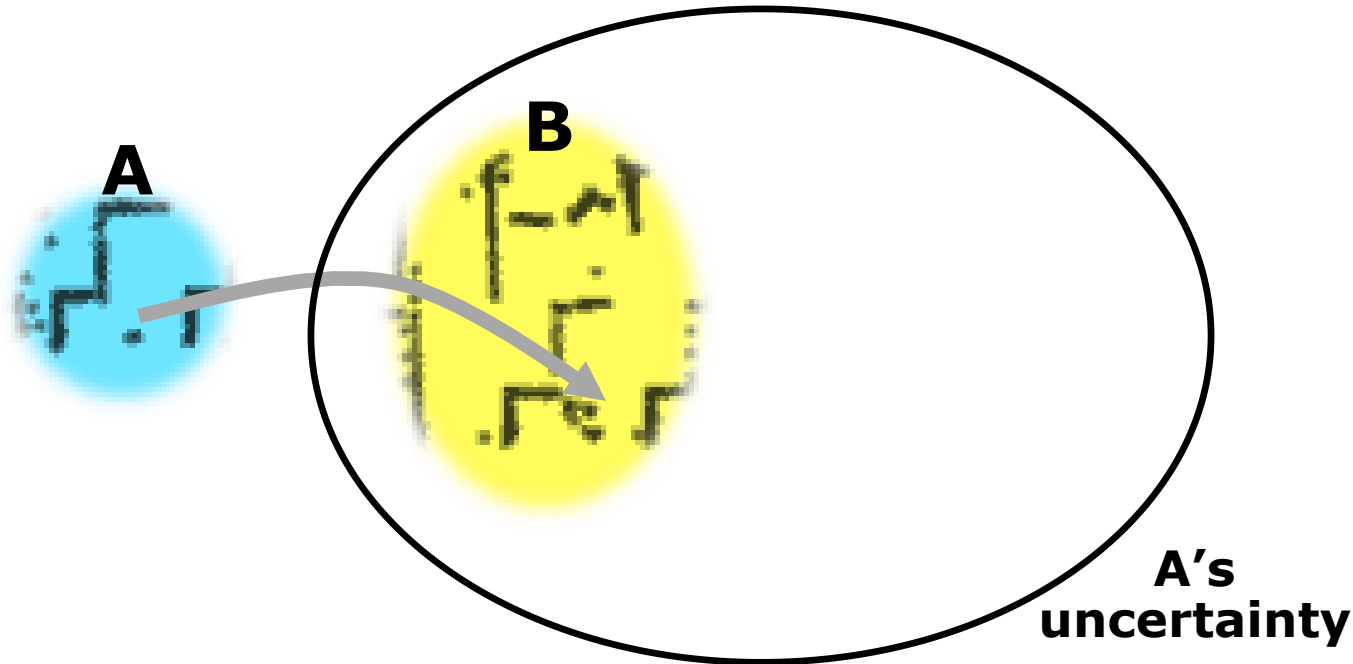
Problems

- ICP is sensitive to initial guess
- Make many initial guesses? Inefficient sampling
- Ambiguity in the environment

Loop Closure - Validate candidates with ICP

Ambiguities - Global Ambiguity

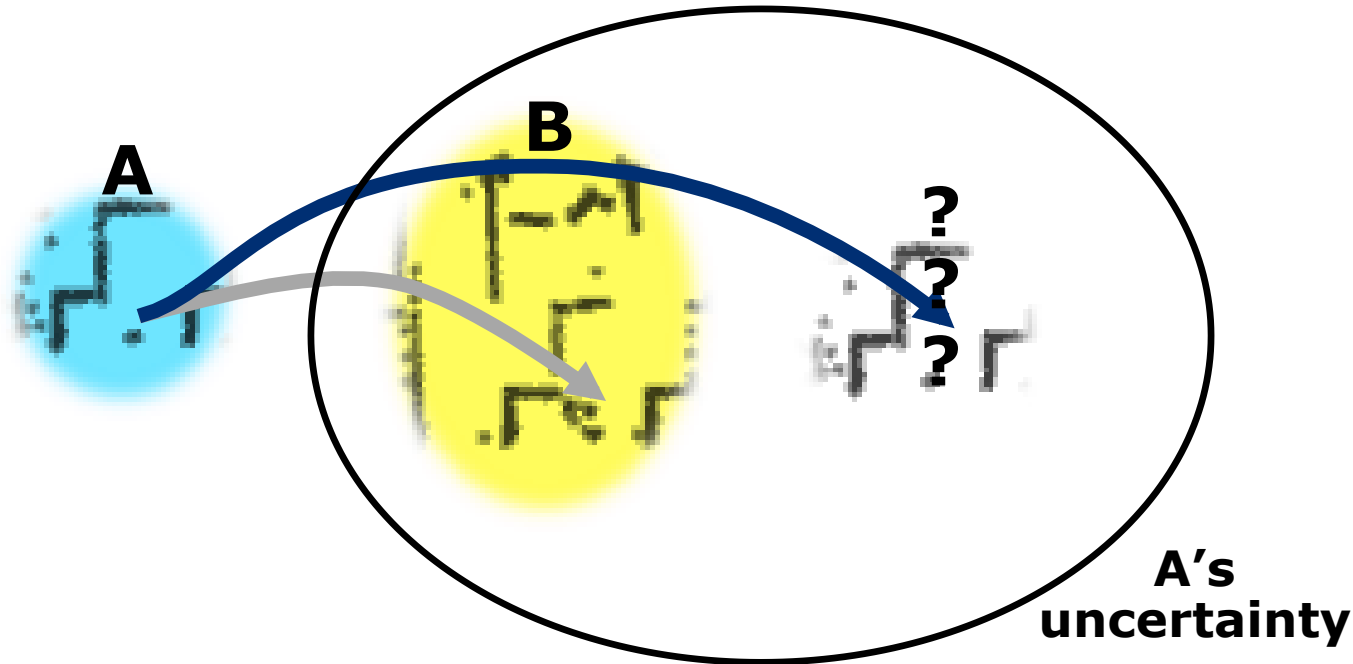
- B is inside the uncertainty ellipse of A
- Are A and B the same place?



Loop Closure - Validate candidates with ICP

Ambiguities - Global Ambiguity

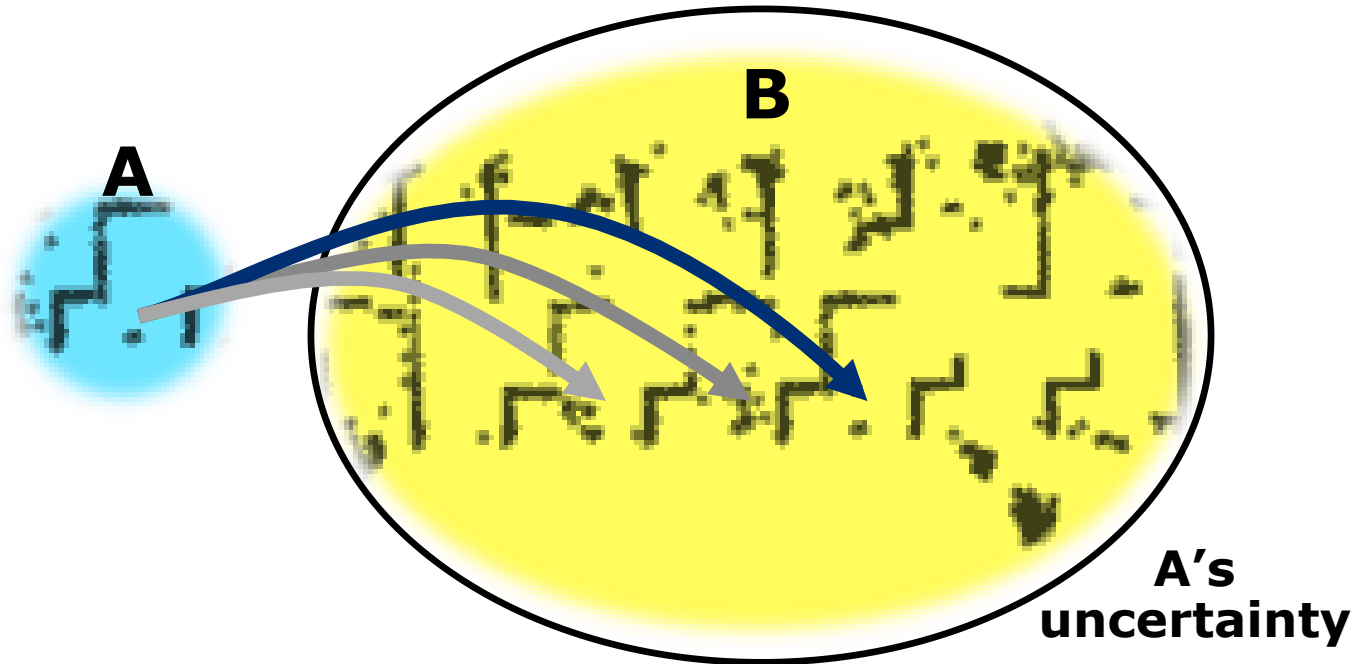
- B is inside the uncertainty ellipse of A
- A and B might not be the same place



Loop Closure - Validate candidates with ICP

Ambiguities - Global Ambiguity

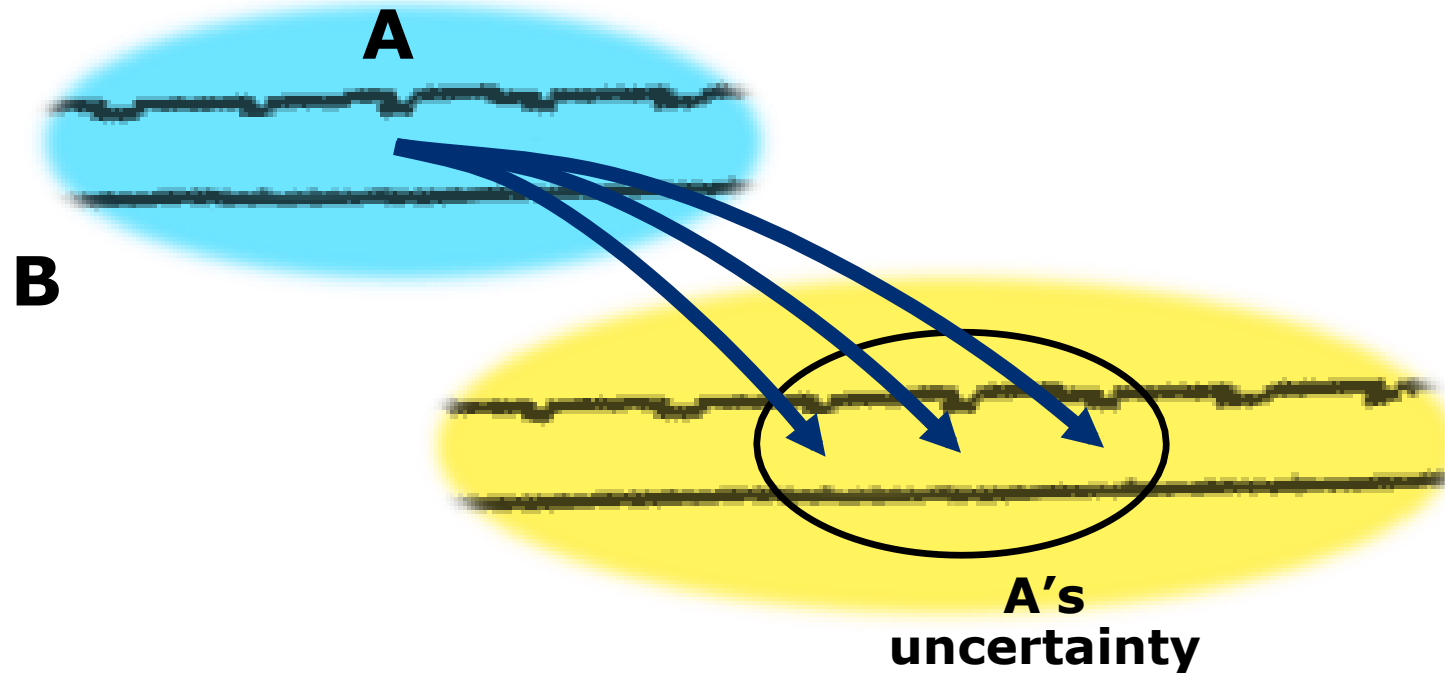
- B is inside the uncertainty ellipse of A
- A and B are not the same place



Loop Closure - Validate candidates with ICP

Ambiguities - Local Ambiguity

- “Picket Fence Problem”: largely overlapping local matches



Loop Closure - Validate with descriptors

- For any candidate-pair for edge:
 - Extract features descriptors from both images
 - Find correspondences
 - Using ANN
 - Remove outliers, evaluate edge
 - With RANSAC and Consensus matching
 - If it's good, set an edge
 - Calculated relative transformation
 - First with PnP
 - Then with small factor graph for the Cov matrix
- Much more robust than point-cloud methods
 - Low ambiguity rate
 - Relative transformation may still be wrong