

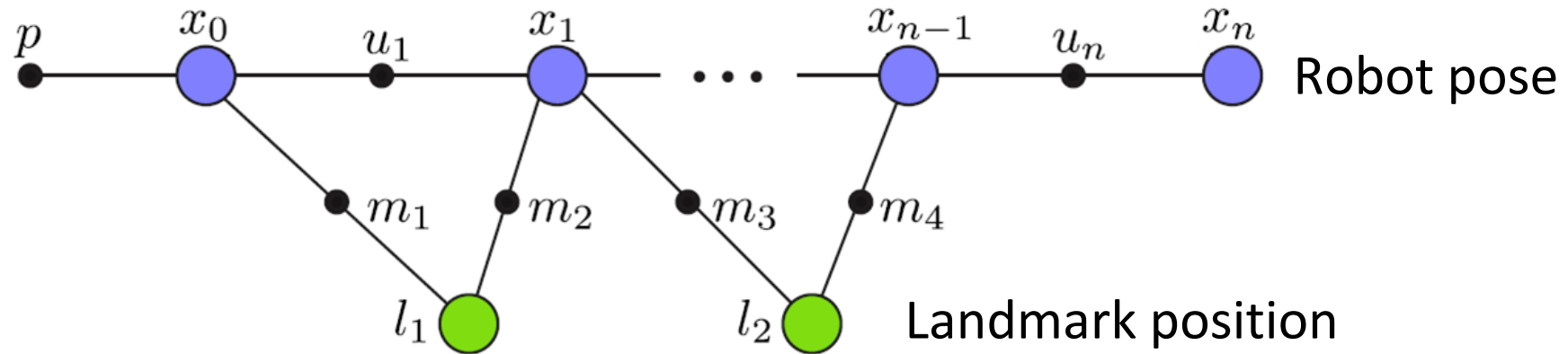
SLAM: Exploiting Sparsity

Robot Localization and Mapping 16-833

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October 4+7, 2024

Factor Graph Representation of SLAM



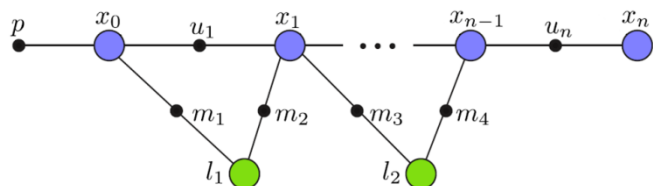
Variables: $\Theta = \{x_0, x_1 \cdots x_n, l_1, l_2\}$

Measurements: $Z = \{p, u_1 \cdots u_n, m_1 \cdots m_4\}$



Factorization: $p(Z|\Theta) = \operatorname{argmax}_{\Theta} \prod_{z \in Z} p(z|\Theta)$

SLAM as a Least-Squares Problem



$$\updownarrow \operatorname{argmax}_{\Theta} \prod_{z \in Z} p(z|\Theta)$$

\downarrow Gaussian noise

$$\operatorname{argmin}_{\Theta} \sum_i \|h_i(\Theta) - z_i\|_{\Sigma}^2$$

\downarrow $h()$ linear

$$\operatorname{argmin}_x \|Ax - b\|^2$$

Normal equations:

$$A^T A x = A^T b$$

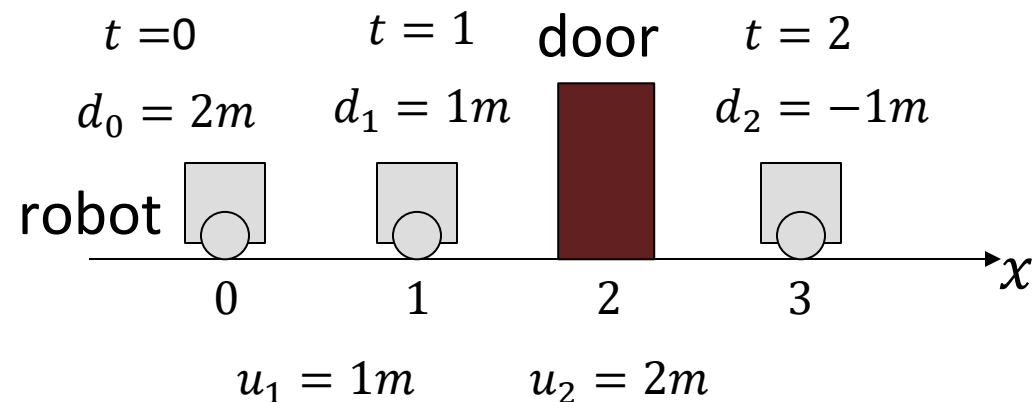
Solving for θ by matrix inversion is too expensive!

SLAM as a Least-Squares Problem: Example

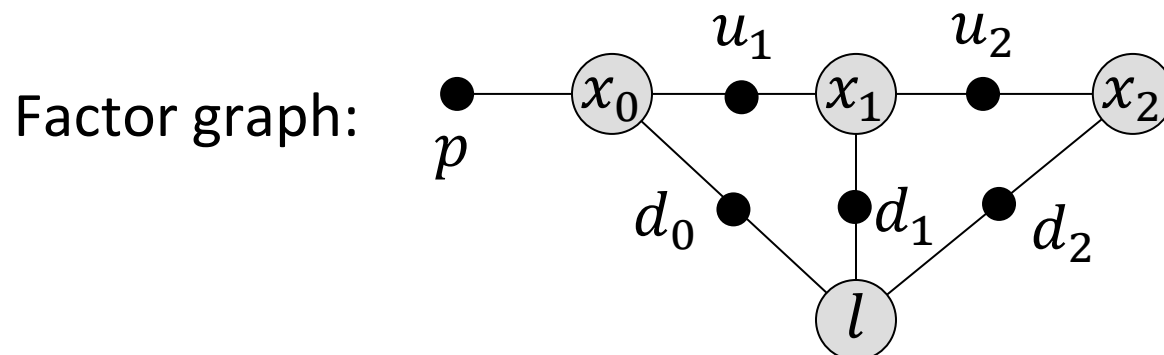
- On the board:
 - Linear 1D example

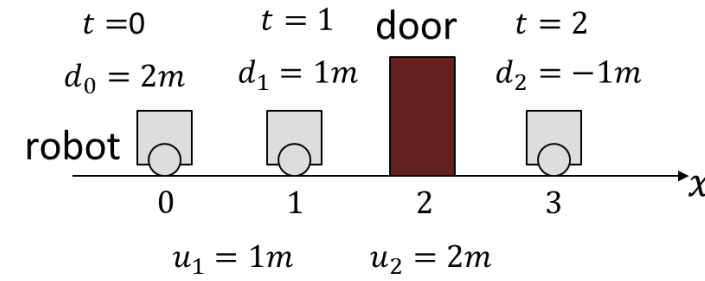
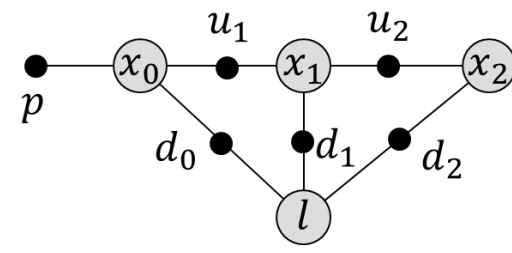
SLAM Least-Squares Example

Localize robot and door based on 1D range measurements



Measurements: distance to the door, signed





SLAM Least-Squares Example

Localize robot and door based on 1D range measurements

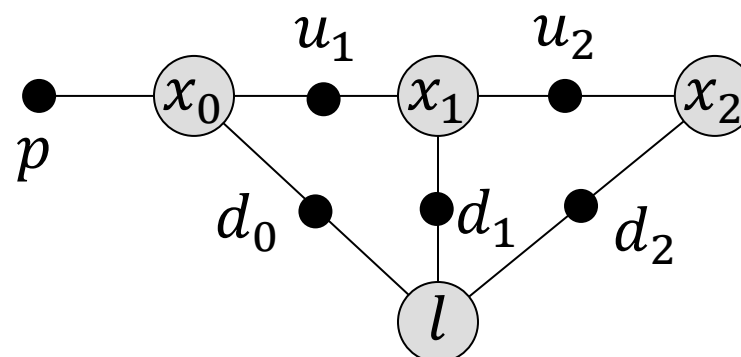
Matrix A:

Each row corresponds to a factor

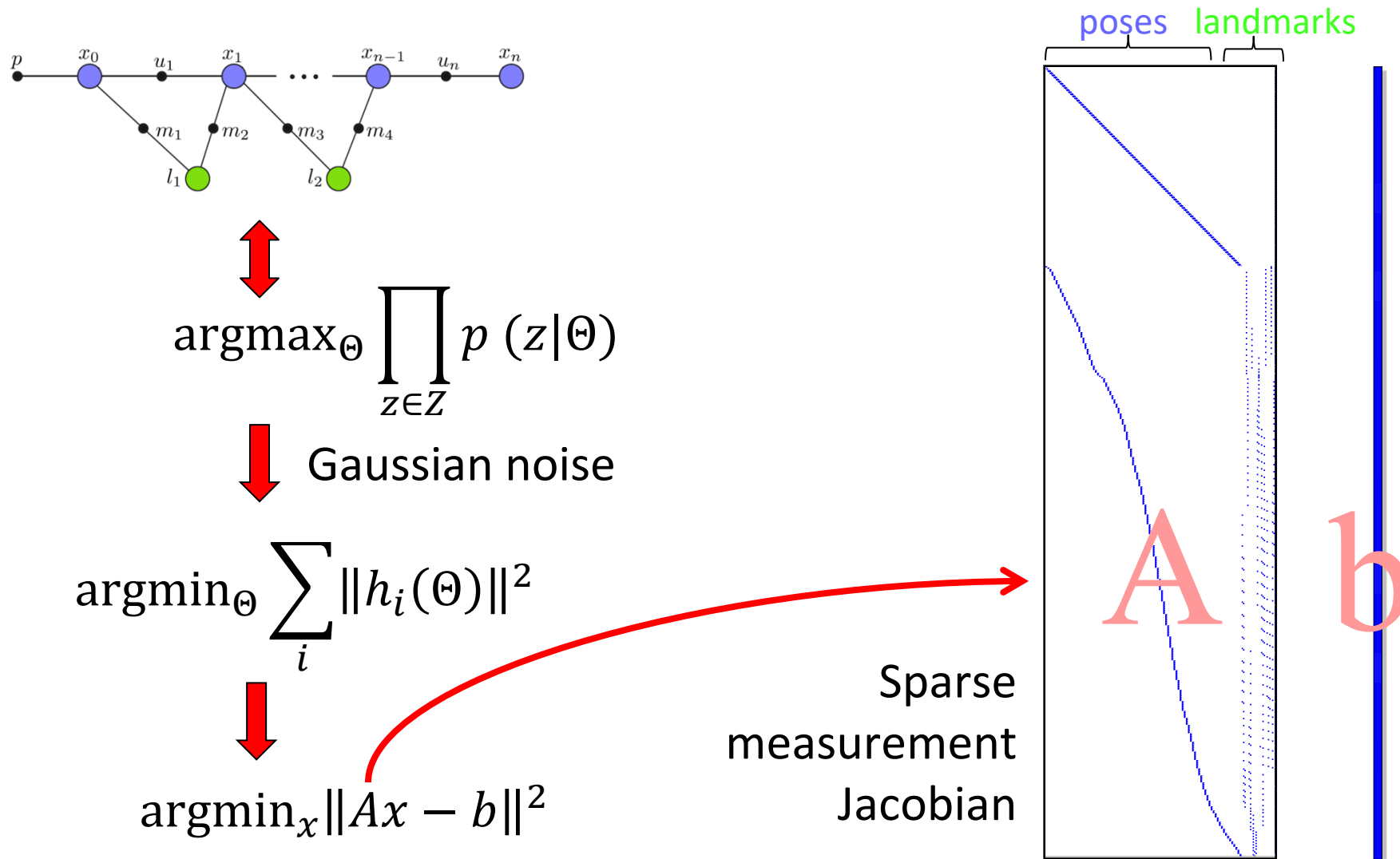
Each column to a variable

A is sparse!

	x_0	x_1	x_2	1
p				
u_1				
u_2				
d_0				
d_1				
d_2				



SLAM as a Sparse Least-Squares Problem



Efficient Solution

- On the board:
 - Sparse matrix factorization
 - Solving by backsubstitution

Efficient Solution: Cholesky Factorization

Cholesky factor R is an upper triangular matrix so that

$$R'R = A'A$$

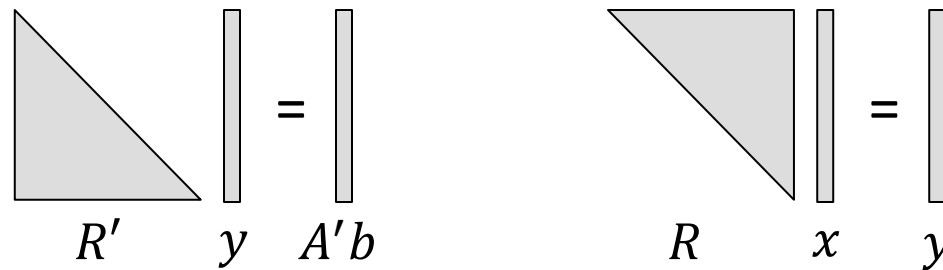
Yielding

$$R'Rx = A'b$$

Solve by forward-/backsubstitution

$$R'y = A'b$$

$$Rx = y$$



Similar: LDL' factorization, faster than Cholesky, avoids square roots

Efficient Solution: QR Factorization

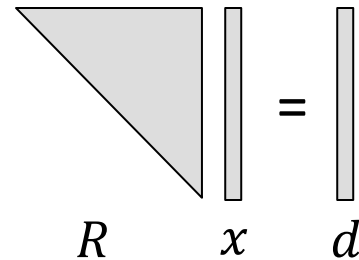
$$A = Q \begin{bmatrix} R \\ 0 \end{bmatrix}$$

Yielding

$$\|Ax - b\|^2 = \left\| Q \begin{bmatrix} R \\ 0 \end{bmatrix} x - b \right\|^2 = \left\| Q'Q \begin{bmatrix} R \\ 0 \end{bmatrix} x - \begin{bmatrix} d \\ e \end{bmatrix} \right\|^2 = \|Rx - d\|^2 + \|e\|^2$$

Solve by backsubstitution

$$Rx = d$$

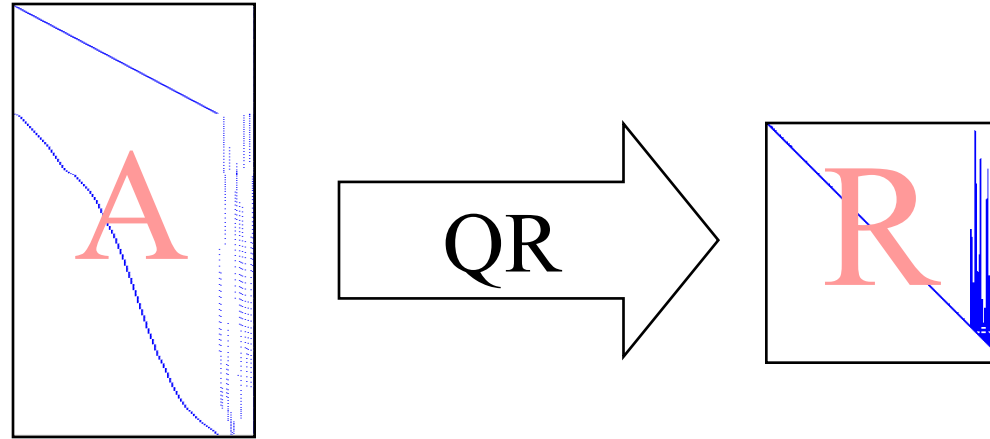


The diagram shows a shaded right-angled triangle labeled R (representing an upper triangular matrix) multiplied by a vertical vector labeled x , which equals another vertical vector labeled d . This visualizes the equation $Rx = d$.

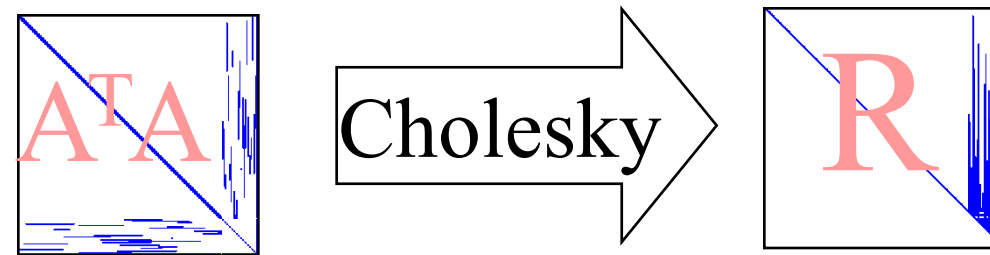
Note that in practice Q is never explicitly formed.

Matrix Factorization

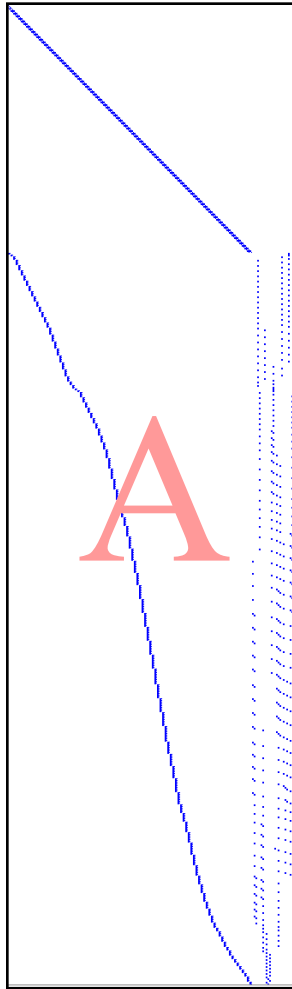
- QR on A : Numerically more stable



- Cholesky on $A^T A$: Faster



Solving the Sparse Linear Least-Squares System

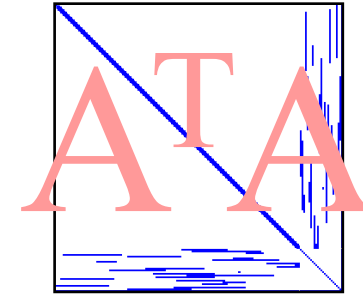


Measurement Jacobian

Solve: $\operatorname{argmin}_{\theta} \|A\theta - b\|^2$

Normal equations

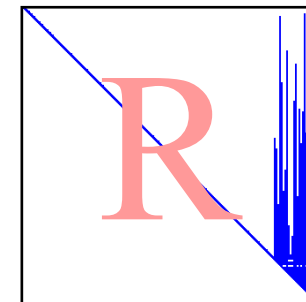
$$A^T A \theta = A^T b$$



Information matrix

Matrix factorization

$$A^T A = R^T R$$



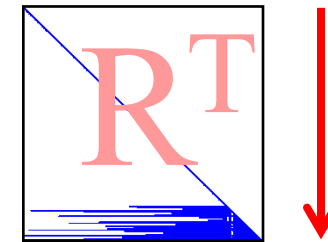
Square root information matrix

Solving by Backsubstitution

After factorization: $R^T R x = A^T b$

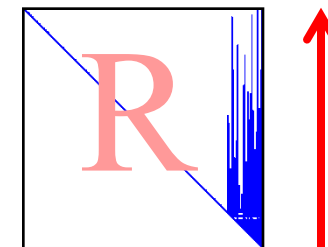
- Forward substitution

$R^T y = A^T b$, solve for y



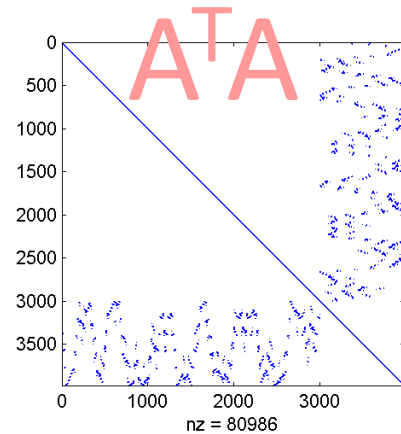
- Backsubstitution

$R x = y$, solve for x

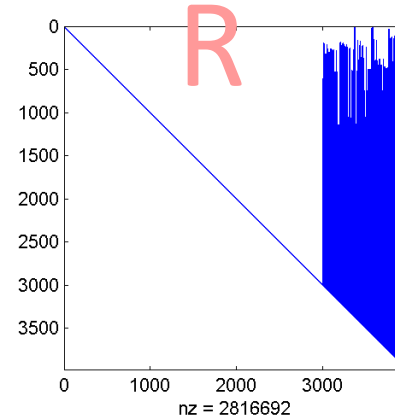


Retaining Sparsity: Variable Ordering

Fill-in depends on elimination order:

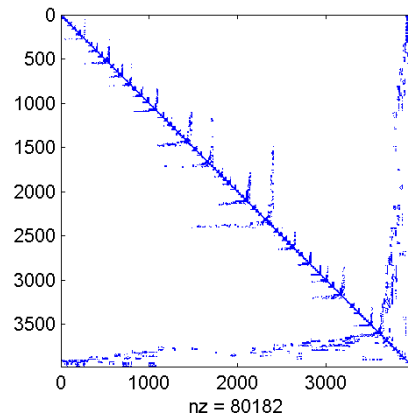


factor

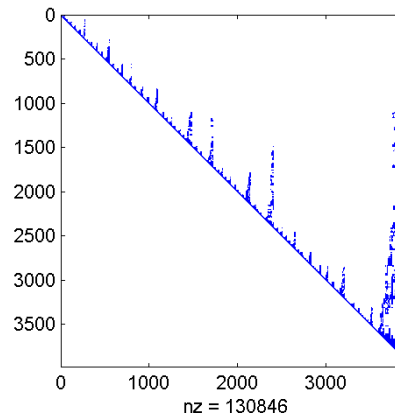


Default ordering
(poses, landmarks)

↓ permute



factor



Ordering based on
COLAMD heuristic [Davis04]
(best order: NP hard)

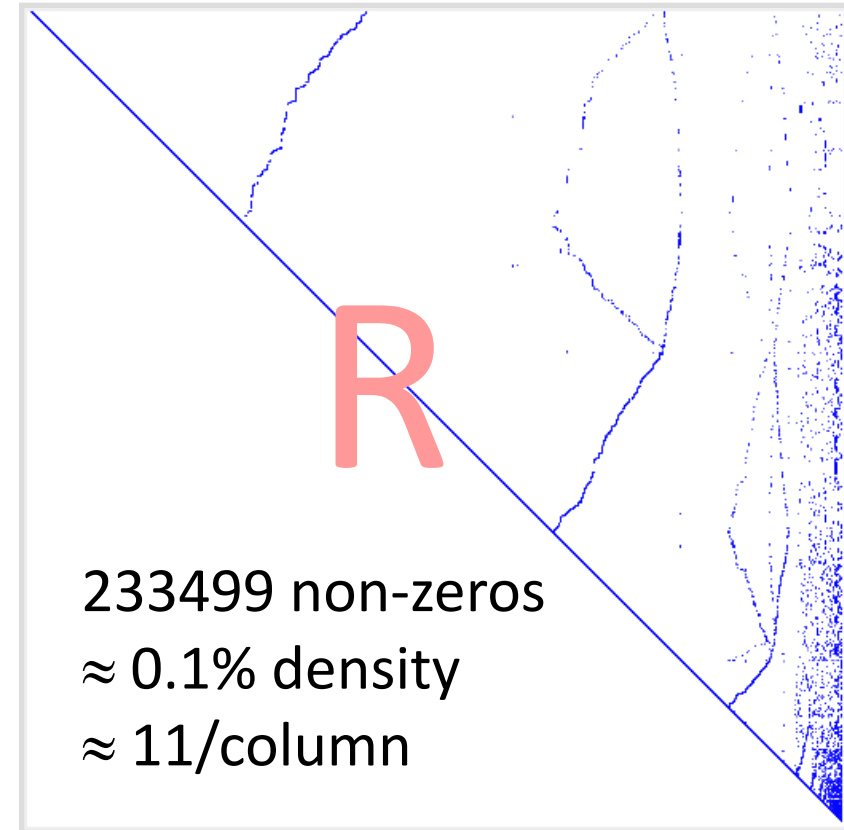
Sparse Factorization Example

Example from real sequence:

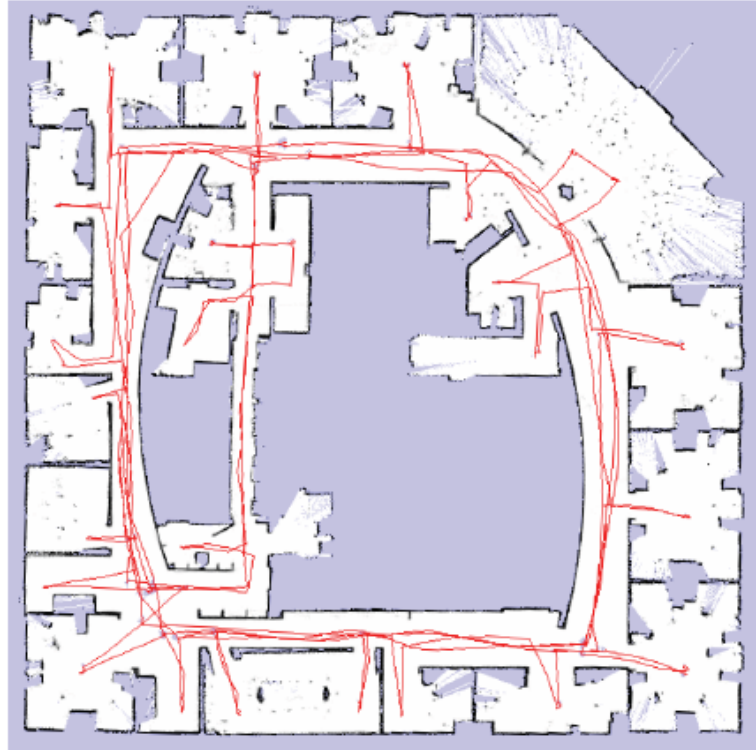
Square root inf. matrix →

Side length: 21000 variables

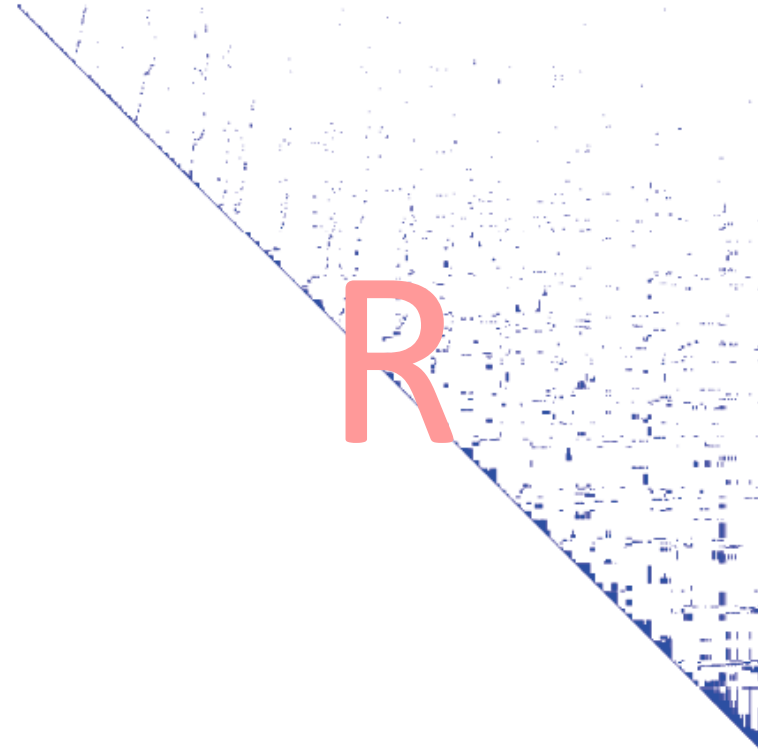
Dense: 1.7GB, sparse: 1MB



Example 2 - Standard Intel Dataset



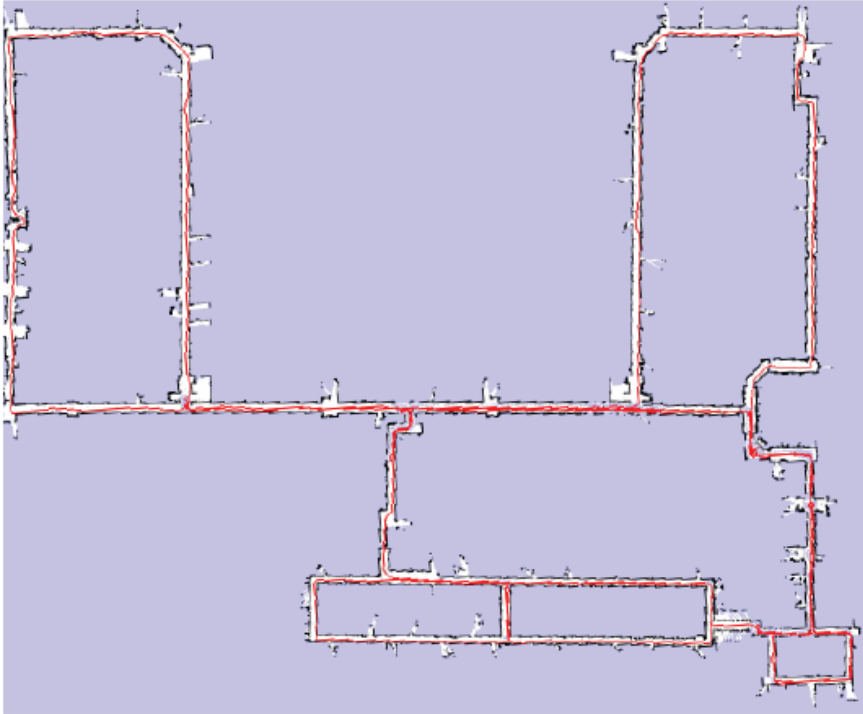
(b) Final trajectory and evidence grid map.



(c) Final R factor with side length 2730.

910 poses, 4453 constraints

Example 3 - MIT Killian Court Dataset



(b) Final trajectory and evidence grid map.

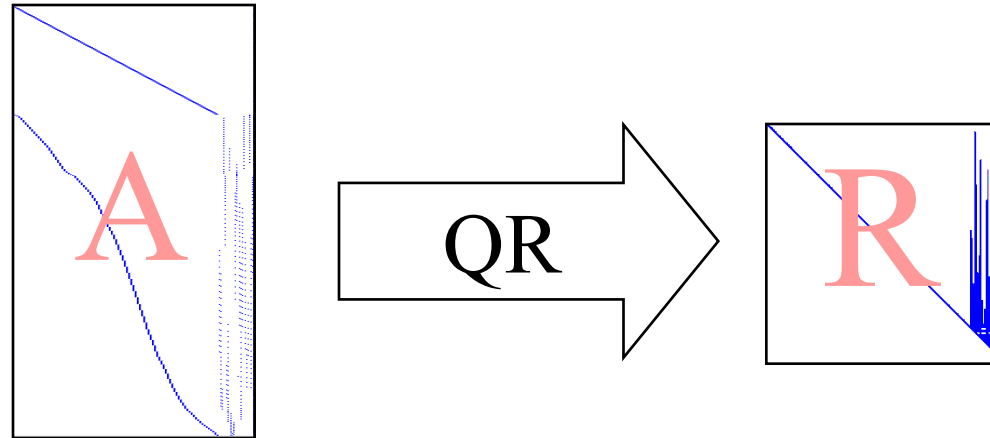


(c) Final R factor with side length 5823.

1941 poses, 2190 constraints

Questions

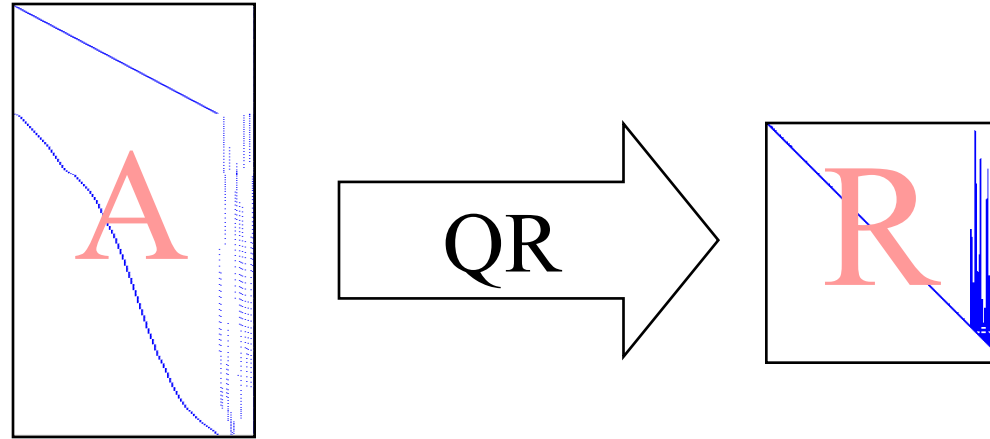
QR on A:



- Does the order of the rows of A impact fill-in?

Questions

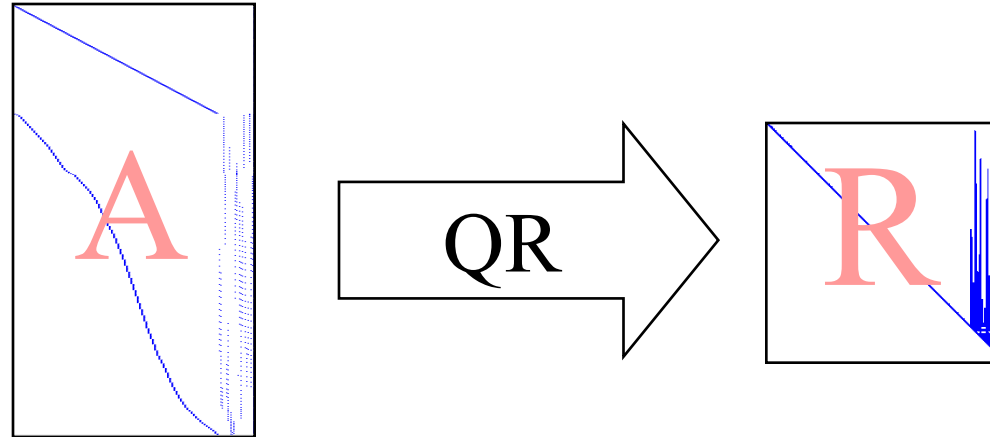
QR on A:



- Does the order of the rows of A impact fill-in?
No!
- Does the order of the columns of A impact fill-in?

Questions

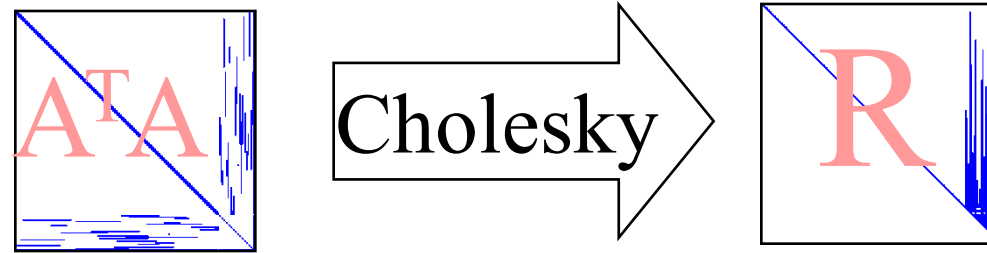
QR on A:



- Does the order of the rows of A impact fill-in?
No!
- Does the order of the columns of A impact fill-in?
Yes, the order will influence fill-in in R and therefore efficiency!

Questions

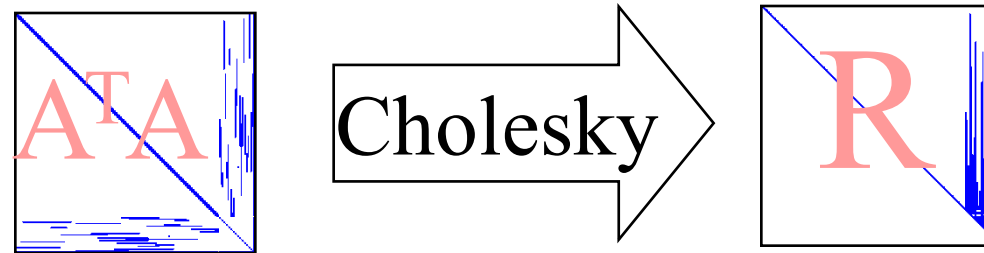
Cholesky on $A^T A$



- Does the order of the rows of $A^T A$ impact fill-in?

Questions

Cholesky on $A^T A$



- Does the order of the rows of $A^T A$ impact fill-in?

The information matrix is symmetric, have to permute both rows and columns at the same time!

The order of rows and columns does impact fill-in in R .

Summary

- Exploiting sparsity is key to efficiency
- Sparse matrix factorization avoids explicitly calculating the (dense) inverse matrix
- Next: Nonlinear Least-Squares
Factor Graphs for Robot Perception: 2.5