



MINIMIZING ANGULAR ERROR IN LABELED GRAPHS



GRAPHS

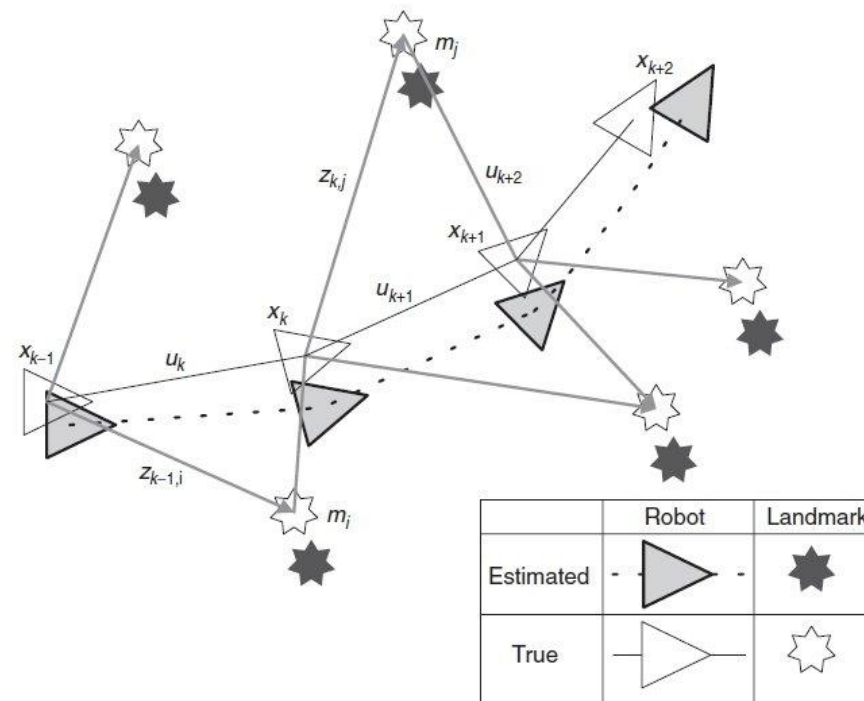
- Labeled Graph
- Directed Graph (Digraph), no edges to oneself
- Graph with angle orientation for each vertex

=> directed angular graph (DAG)

SLAM

"SLAM is a process by which a mobile robot can build a map of an environment and at the same time use this map to deduce its location."

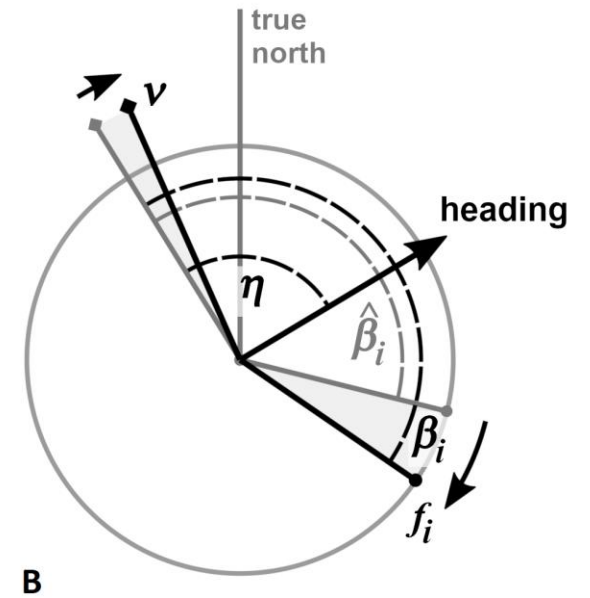
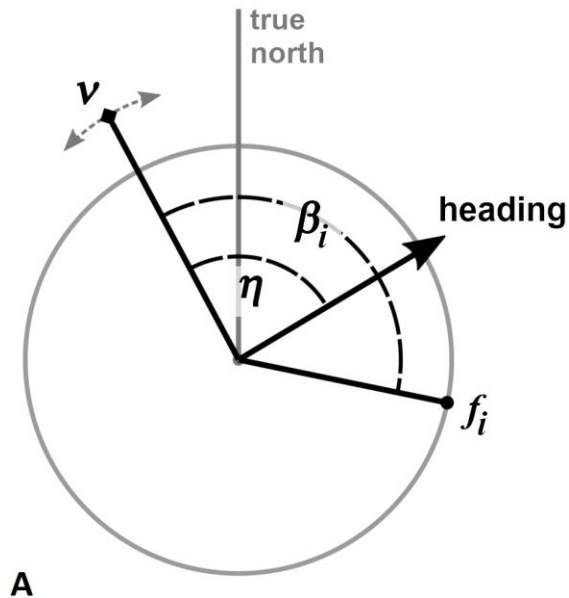
- Simultaneous localization and mapping
- Cumulative error



DUAL POPULATION CODING

Navigation model by Tristan Baumann

- Graph based spatial representation
- Estimating the global reference direction at each point



DIRECTION DRIFT



PROBLEM

Given:

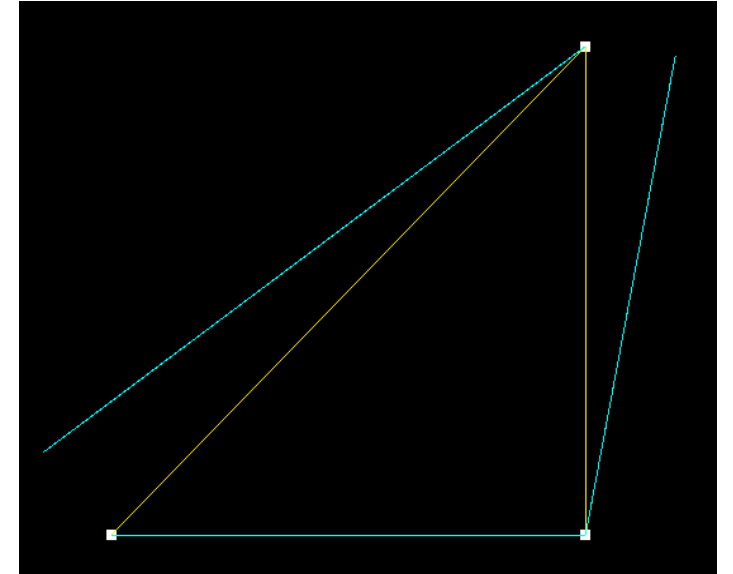
- Adjacency matrix $A = (a_{ij})$
 - directed Graph, as $a_{ij} \neq a_{ji}$ for some i, j
- Internal reference directions v_i
- Angles ϕ_{ij} (in respect to reference direction)

Goal:

- Embedding of points $(x_1, \dots, x_n), x_i \in \mathbb{R}^2$, such that $x_j - x_i \approx \lambda \begin{pmatrix} \cos \phi_{ij} \\ \sin \phi_{ij} \end{pmatrix} =: \lambda p_{ij}$
- Minimizing the Objective function: $f(x_1, \dots, x_n) = \sum_{ij} a_{ij} \left(\frac{\|x_j - x_i\|}{\lambda} - p_{ij} \right)^2$

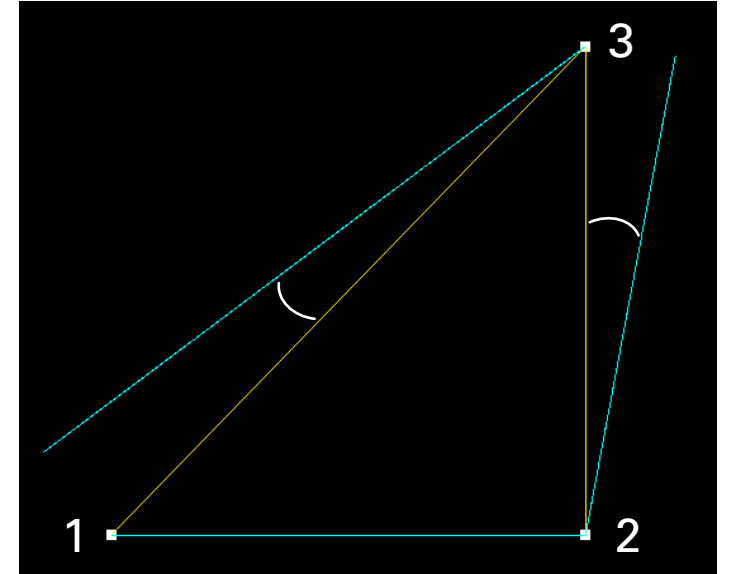
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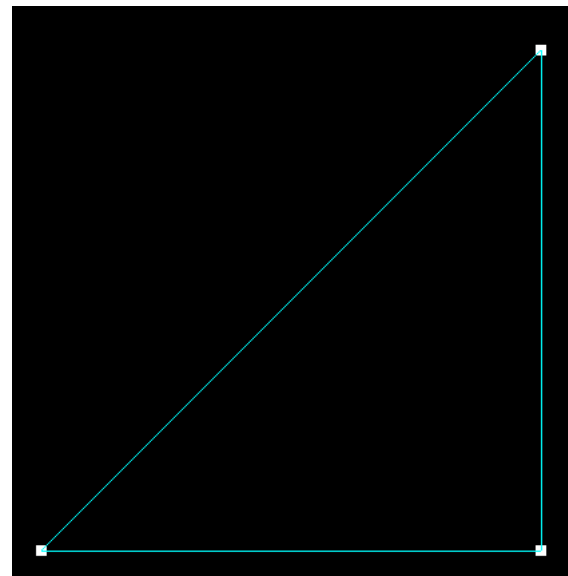
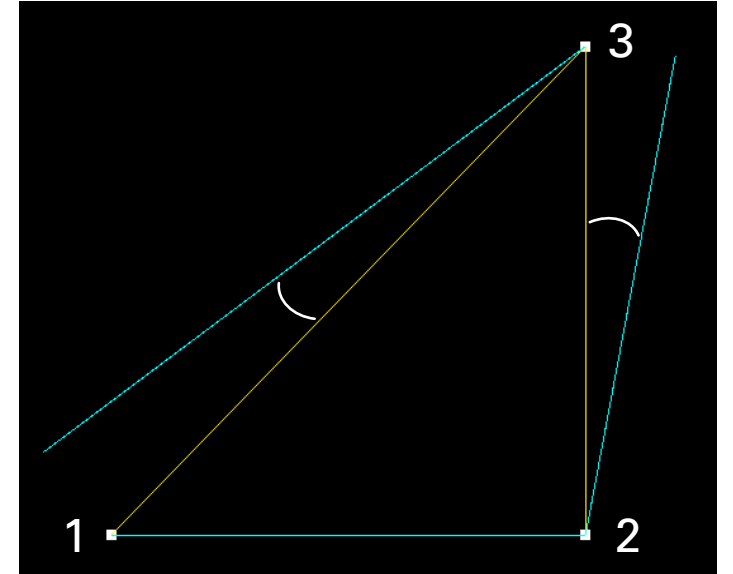
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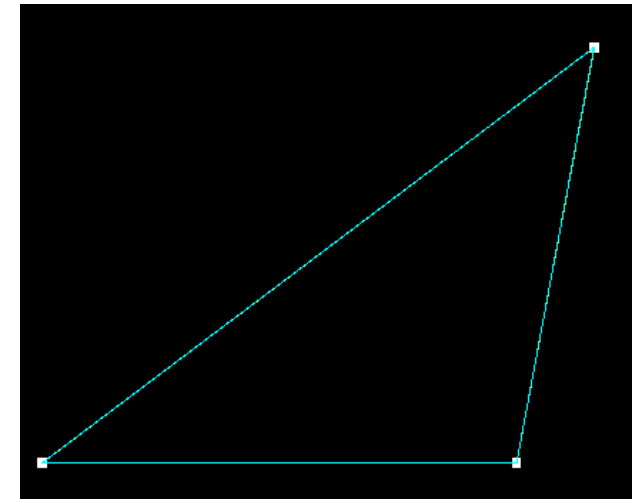
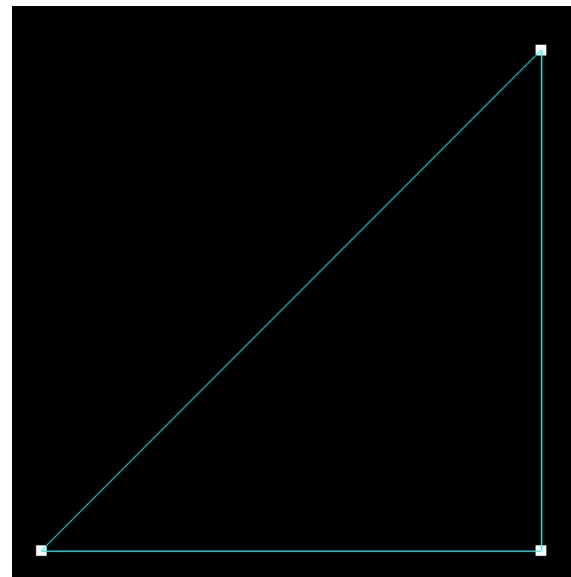
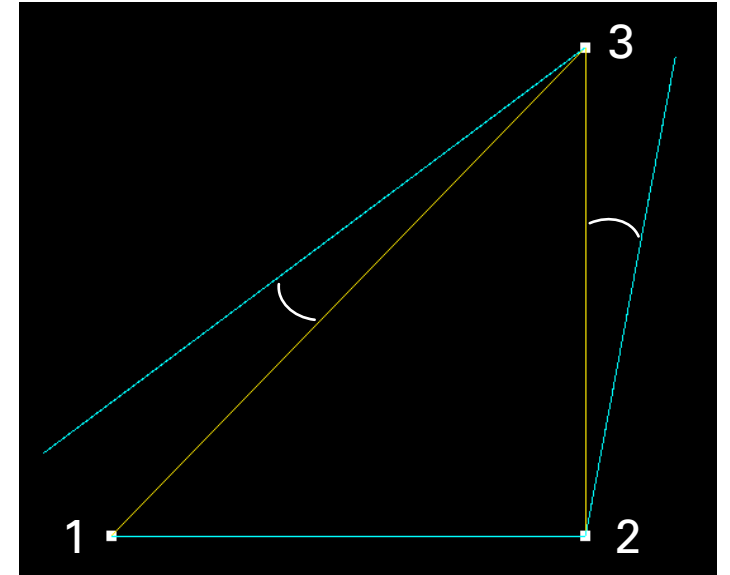
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MDS – MULTIDIMENSIONAL SCALING

Classical MDS:

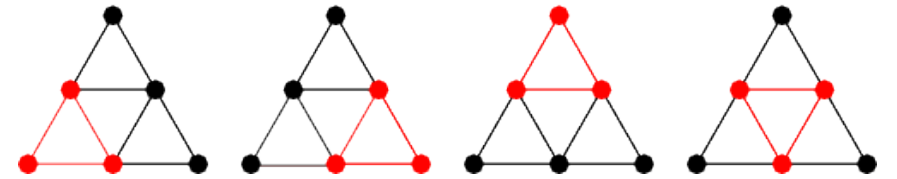
"Given a distance matrix with the distances between each pair of objects in a set [...] an MDS algorithm places each object into [...] [this] space such that the between-object distances are preserved as well as possible."

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- Broad literature of different approaches
- MDS algorithm running time $O(n^2)$ not good for big graphs
 - Many approaches for (random) sampling of pivot points
- Looking for smallest cliques throughout the graph?





MDS – MULTIDIMENSIONAL SCALING

"A valid dissimilarity matrix must satisfy both of the following constraints:

(i) self-similarity $d_{ii} = 0$ and (ii) symmetry $d_{ij} = d_{ji}$ "

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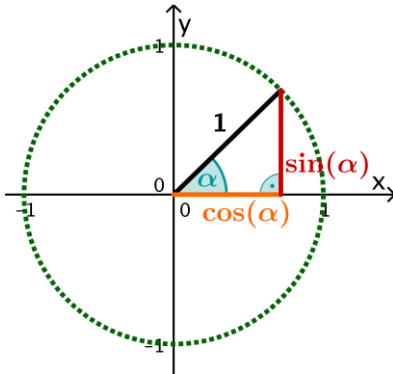
Normalized

$$f(x_1, \dots, x_n) = \sum_{ij} a_{ij} \left(\frac{x_j - x_i}{\|x_j - x_i\|} - p_{ij} \right)^2$$

Non-normalized

$$f(x_1, \dots, x_n) = \sum_{ij} a_{ij} (x_j - x_i - p_{ij})^2$$

MEASUREMENT

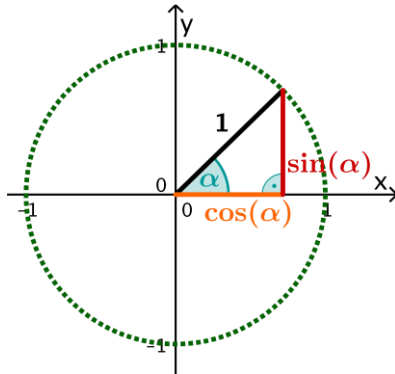


$$f(x_1, \dots, x_n) = \sum_{ij} a_{ij} \left(\frac{x_j - x_i}{\|x_j - x_i\|} - p_{ij} \right)^2$$

$$\begin{aligned} & \left(\frac{x_j - x_i}{\|x_j - x_i\|} - p_{ij} \right)^2 \\ &= (x_{ij} - p_{ij})^2 \\ &= x_{ij}^2 + p_{ij}^2 - 2(x_{ij} \circ p_{ij}) \\ &= 1 + 1 - 2(x_{ij} \circ p_{ij}) \\ &= 2 - 2 * \rho, \text{ mit } \rho \in [-1, 1] \end{aligned}$$

with $\rho = 0$ we get the worst embedding (90°)

MEASUREMENT



$$f(x_1, \dots, x_n) = \sum_{ij} a_{ij} \left(\frac{x_j - x_i}{\|x_j - x_i\|} - p_{ij} \right)^2$$

$$g(f) = \frac{f(x_1, \dots, x_n)}{\sum_{ij} a_{ij}} \in [0, 4]$$

$$g(f, \xi) = |\xi * (\frac{f(x_1, \dots, x_n)}{2 * \sum_{ij} a_{ij}} - 1)| \in [0, \xi]$$

with $g(f, \xi) = \xi$
being perfect
measured value

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