

A complex factor graph visualization with many nodes and connections. The nodes are represented by small circles, some colored purple and others cyan. The connections are shown as thin gray lines forming a dense web of triangles across the slide.

From Square Root SAM to GTSAM: Factor Graphs in Robotics

Frank Dellaert, Georgia Institute of Technology
Michael Kaess, Carnegie Mellon University

5 years ago I did a sabbatical at a startup to help them build the most advanced flying AI on the planet: the Skydio drone



12 Navigation Cameras



Earlier this year the Skydio 2 was released, which innovates in both 360 perception and superior autonomy



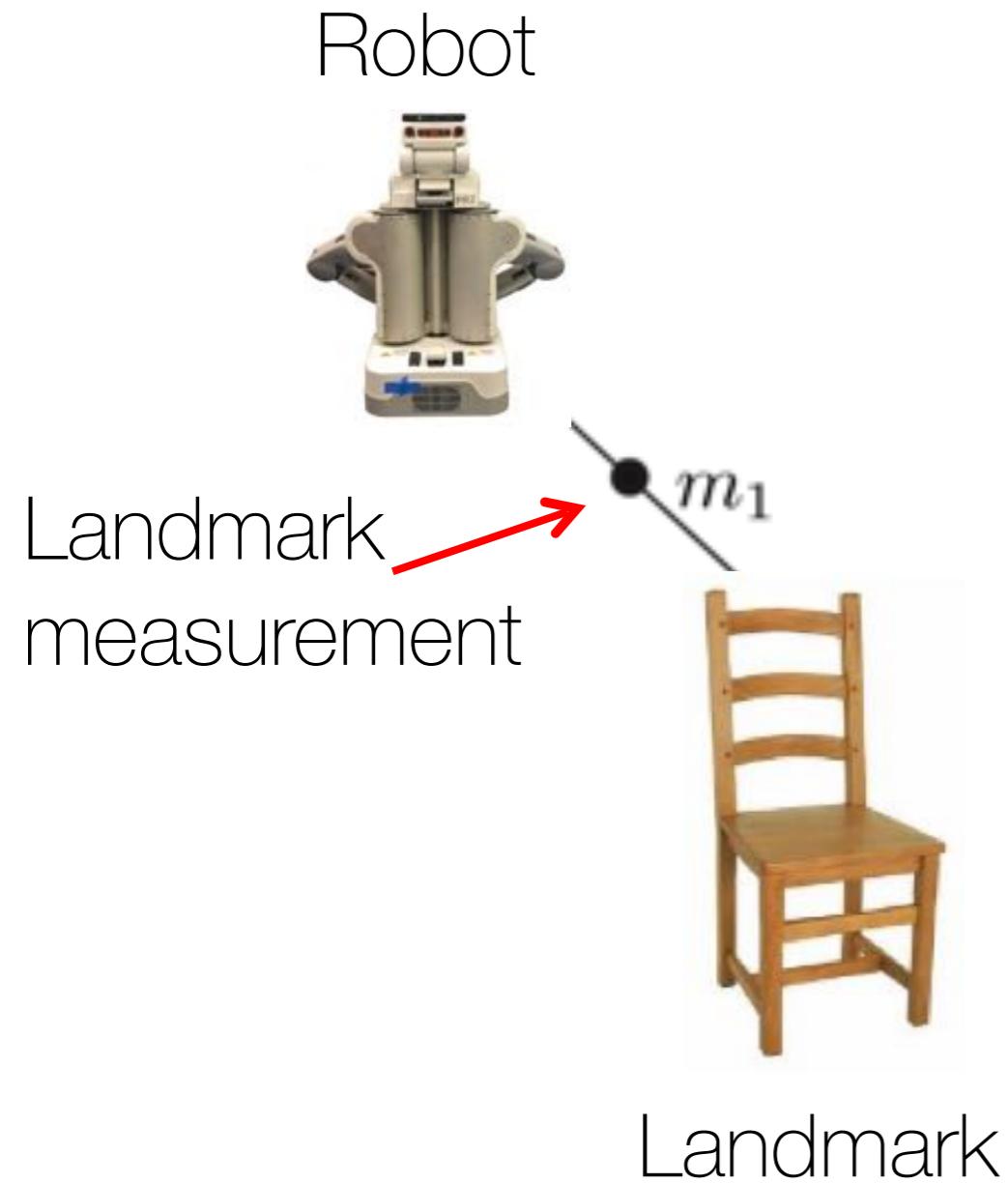
Skydio 2



To deliver value, the autonomy stack has to support superior navigation, tracking, and motion planning at very low power



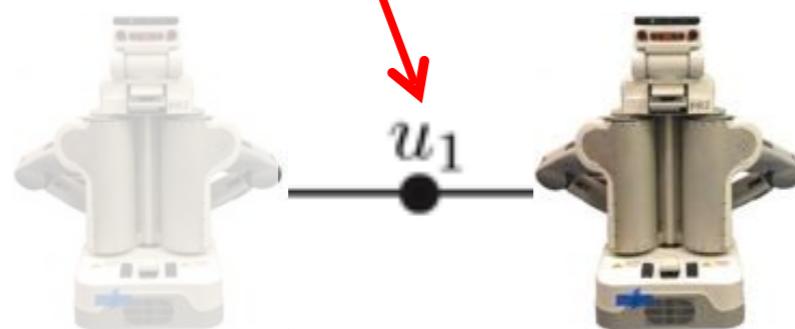
Many of these at their core are optimization problems with locality, which is captured well by *factor graphs*



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Odometry measurement

Robot



Landmark
measurement



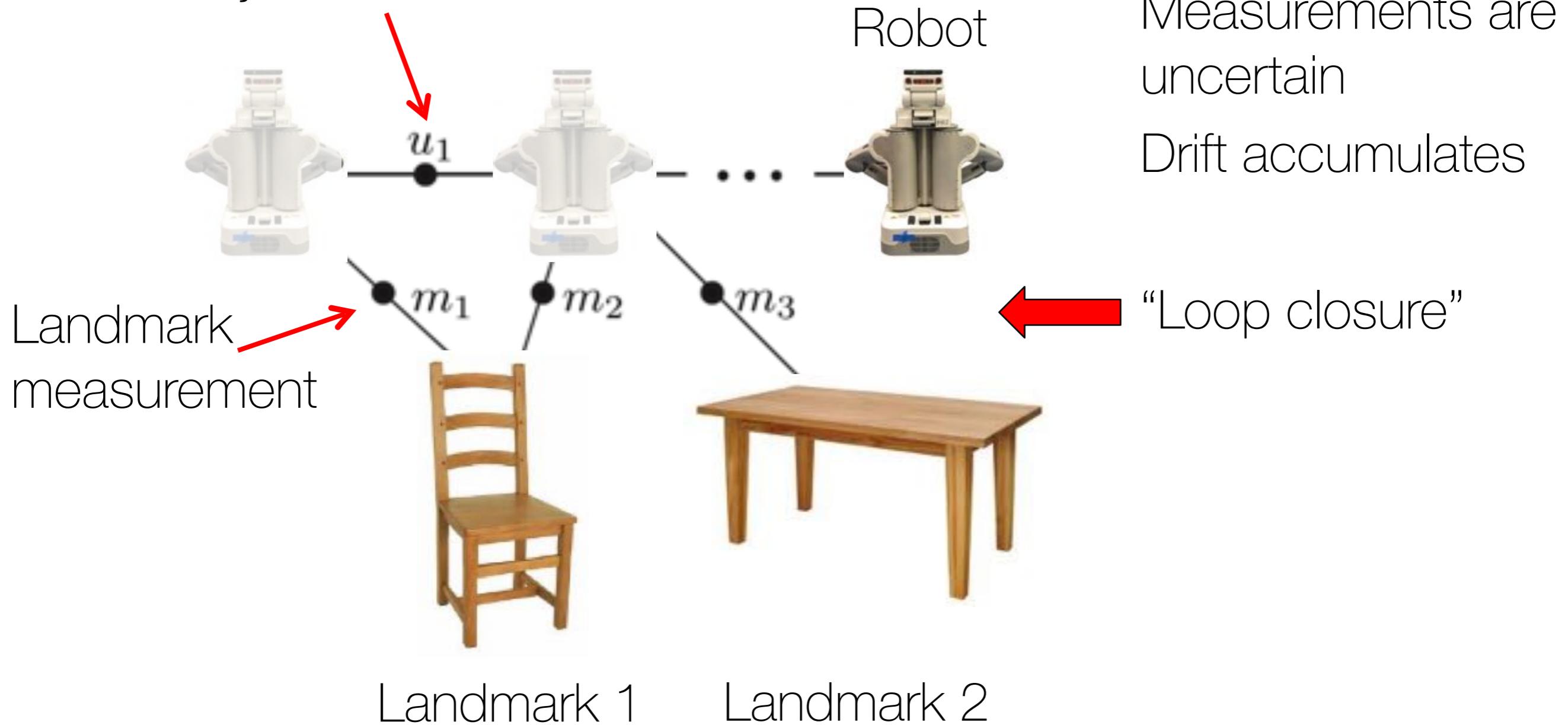
Landmark 1



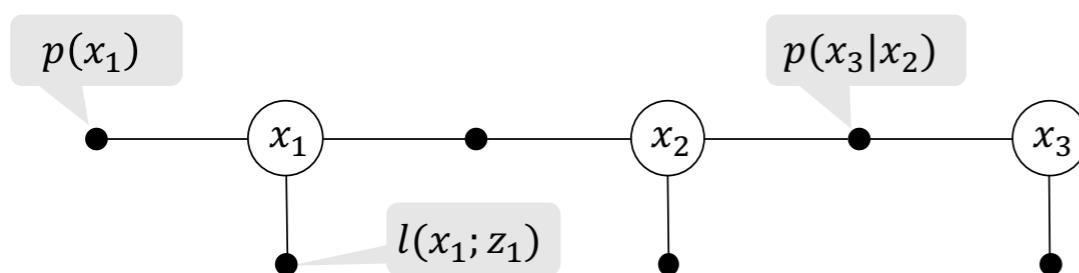
Landmark 2

Many of these at their core are optimization problems with locality, which is captured well by *factor graphs*

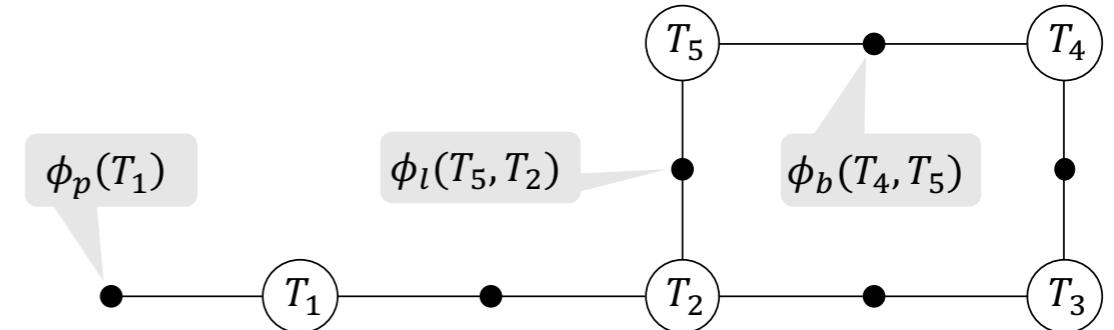
Odometry measurement



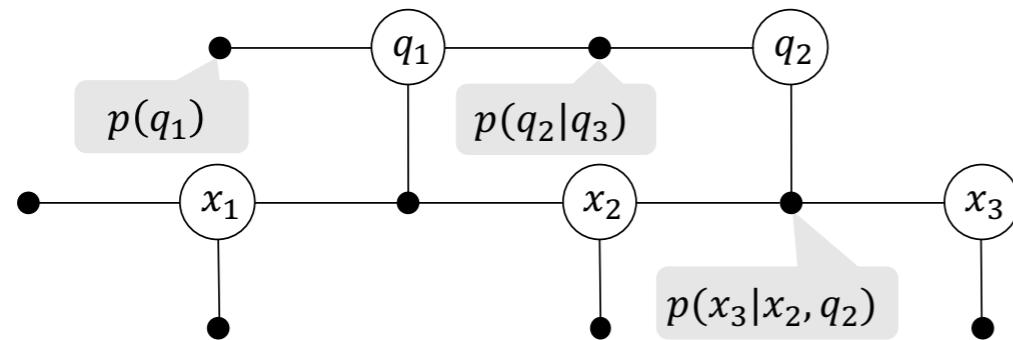
Factor graphs can represent many robotics problems, from tracking to optimal control to sophisticated 3D mapping



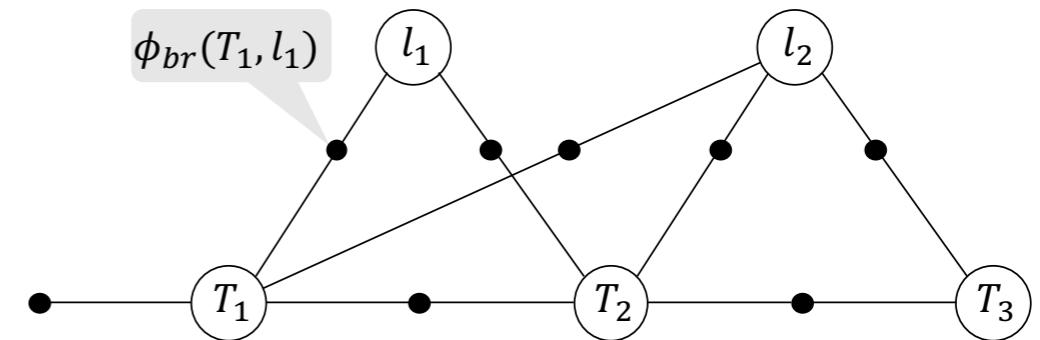
Tracking



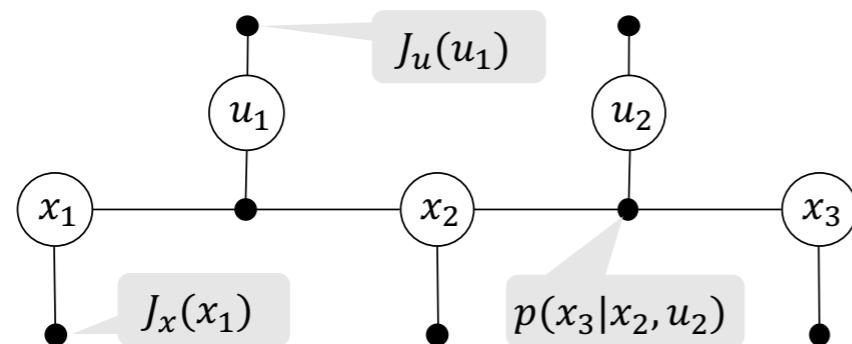
Pose graph



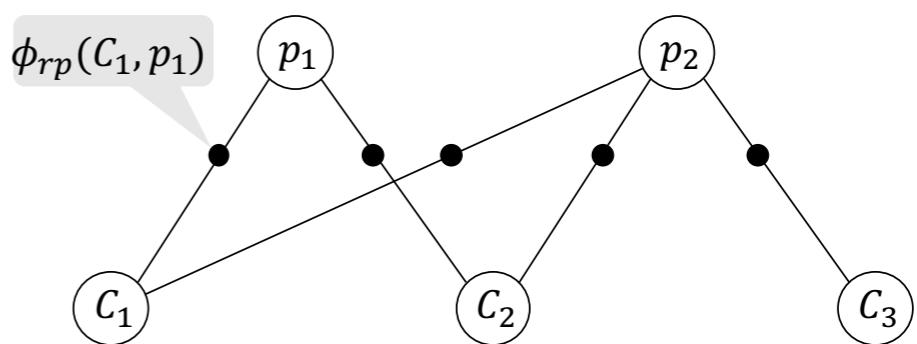
Switching System



SLAM



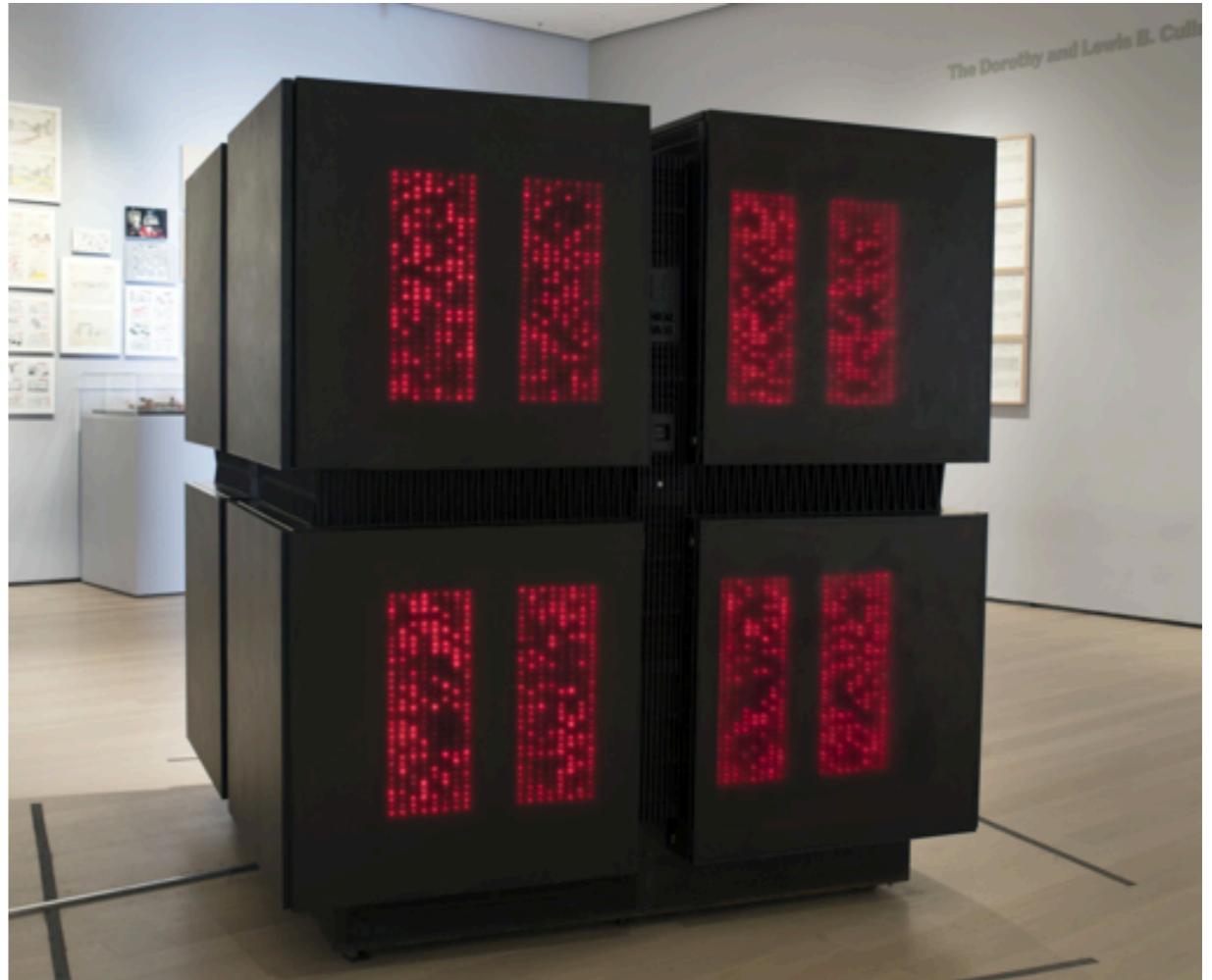
Optimal Control



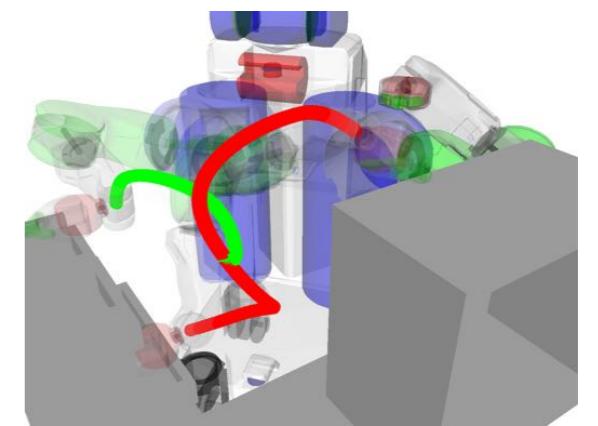
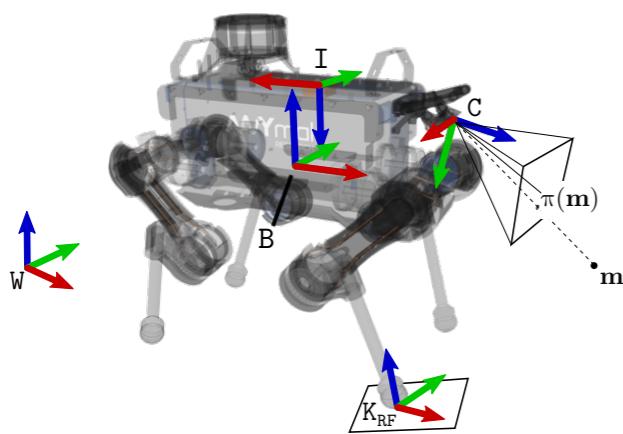
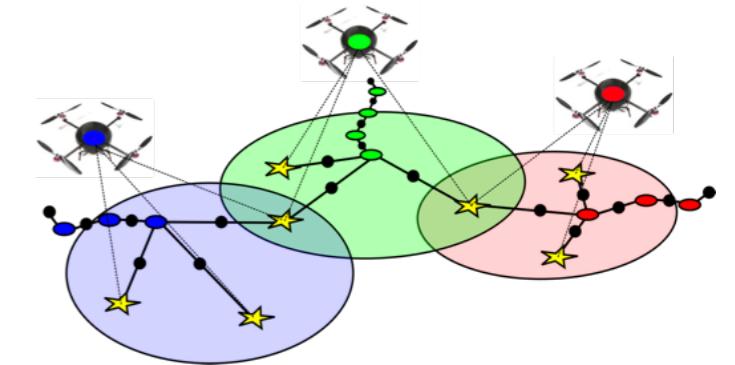
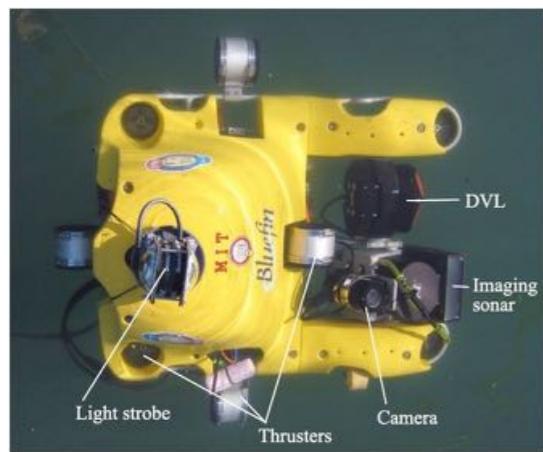
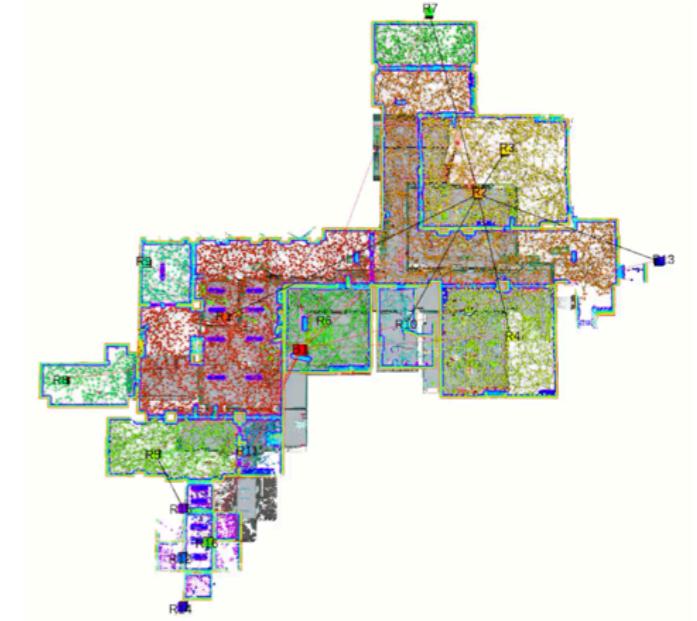
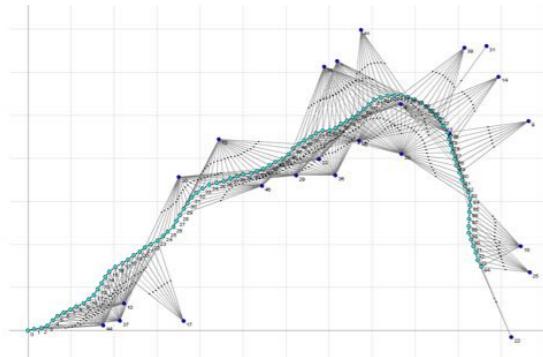
Structure from Motion

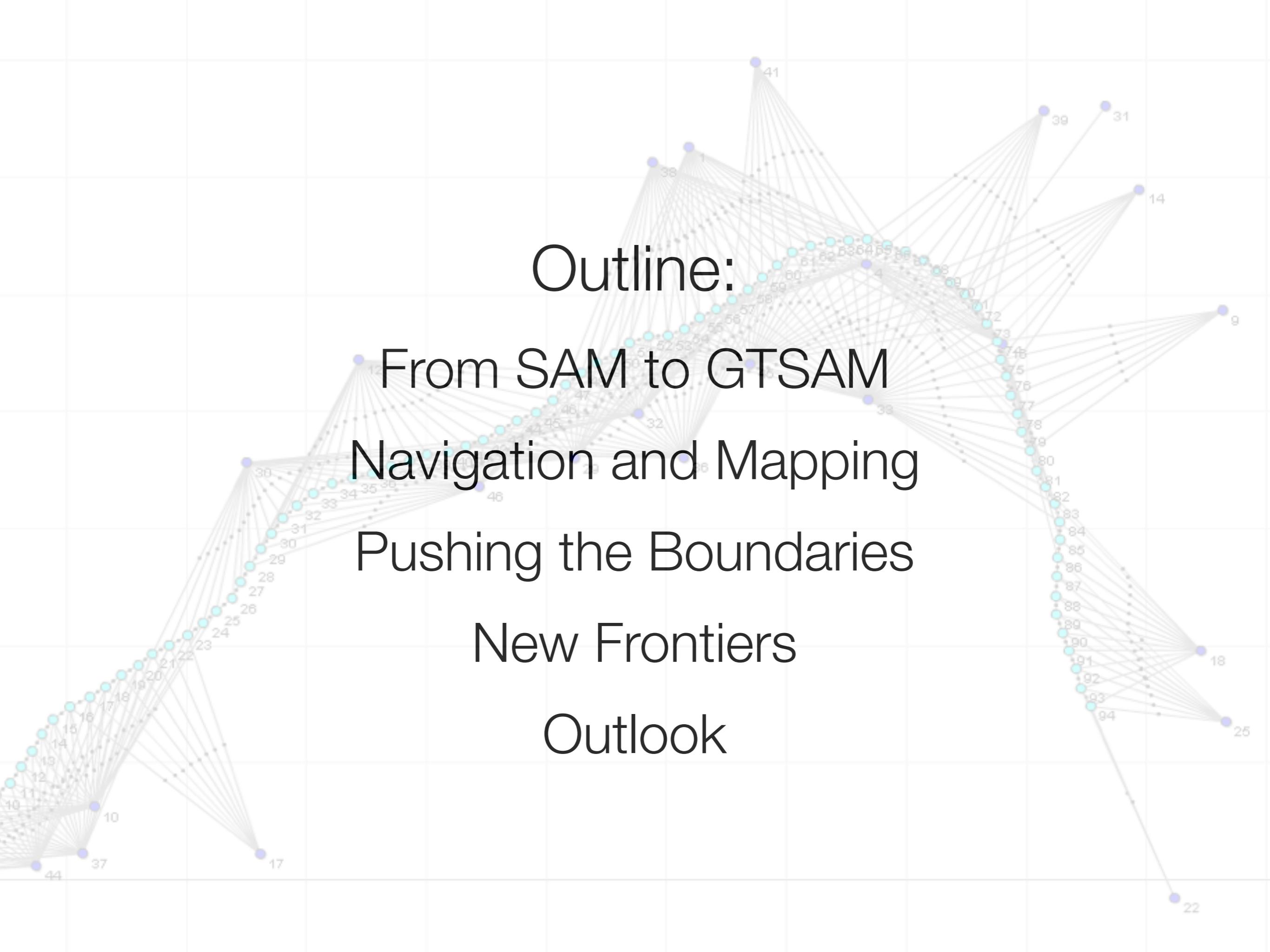
Factor graphs expose opportunities for raw speed because of the deep connection with sparse linear algebra

- Ordering heuristics
- Nested Dissection
- Sparsification
- Pre-integration
- Iterative Solvers
- Incremental Inference and the Bayes tree



Factor graphs are beneficial in designing and thinking about your problem, even aside from performance





Outline:

- From SAM to GTSAM
- Navigation and Mapping
- Pushing the Boundaries
- New Frontiers
- Outlook

Outline:

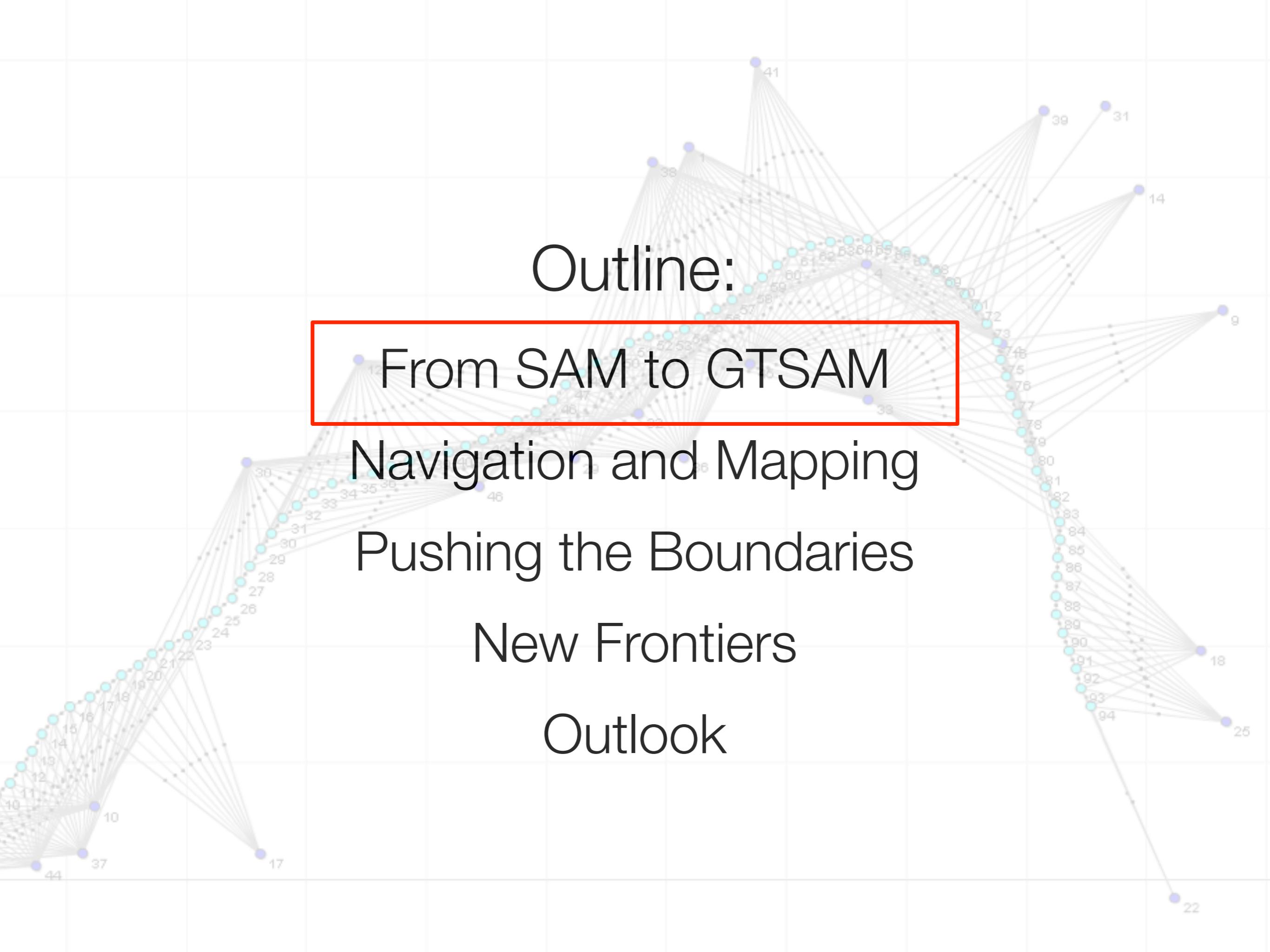
From SAM to GTSAM

Navigation and Mapping

Pushing the Boundaries

New Frontiers

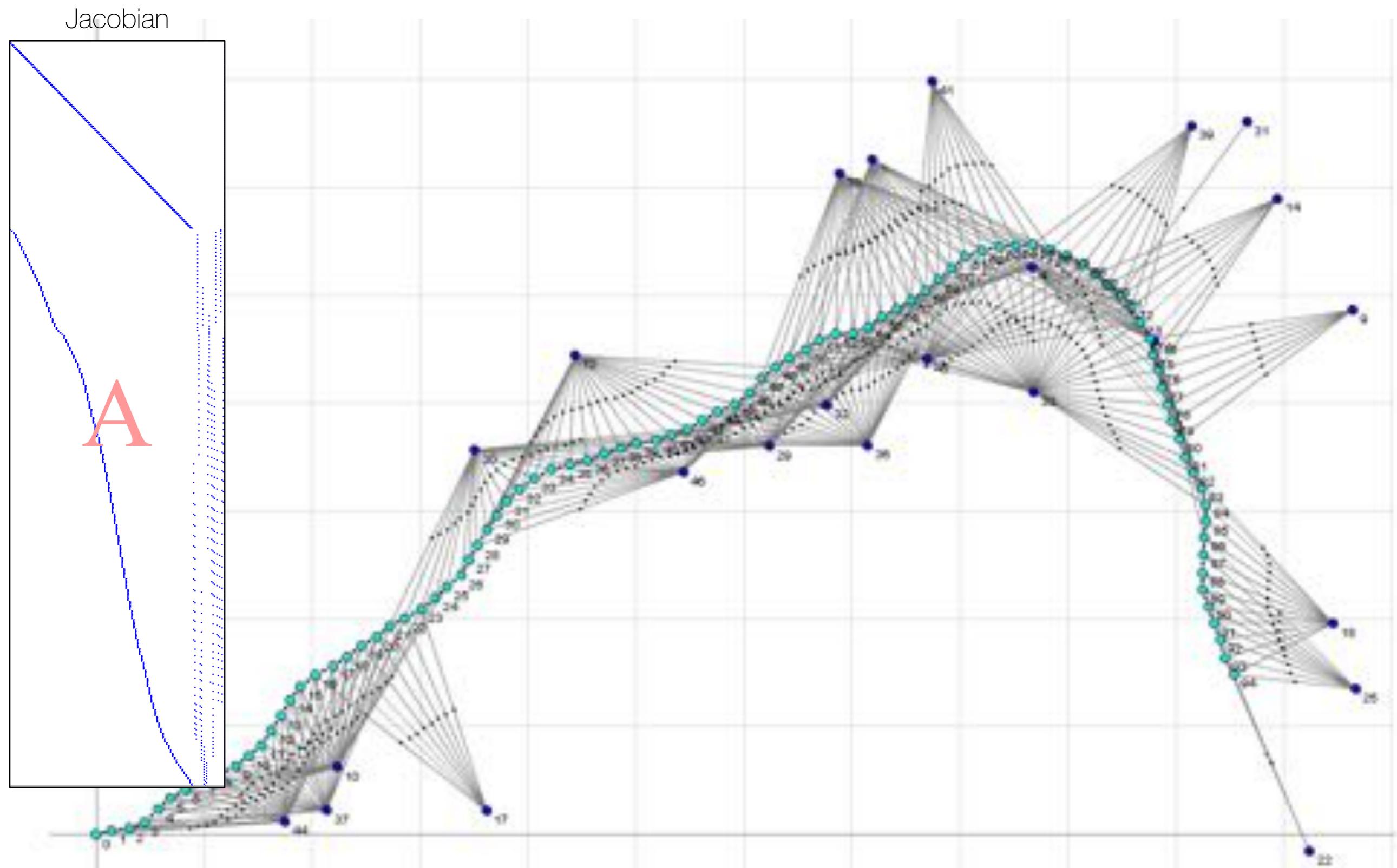
Outlook



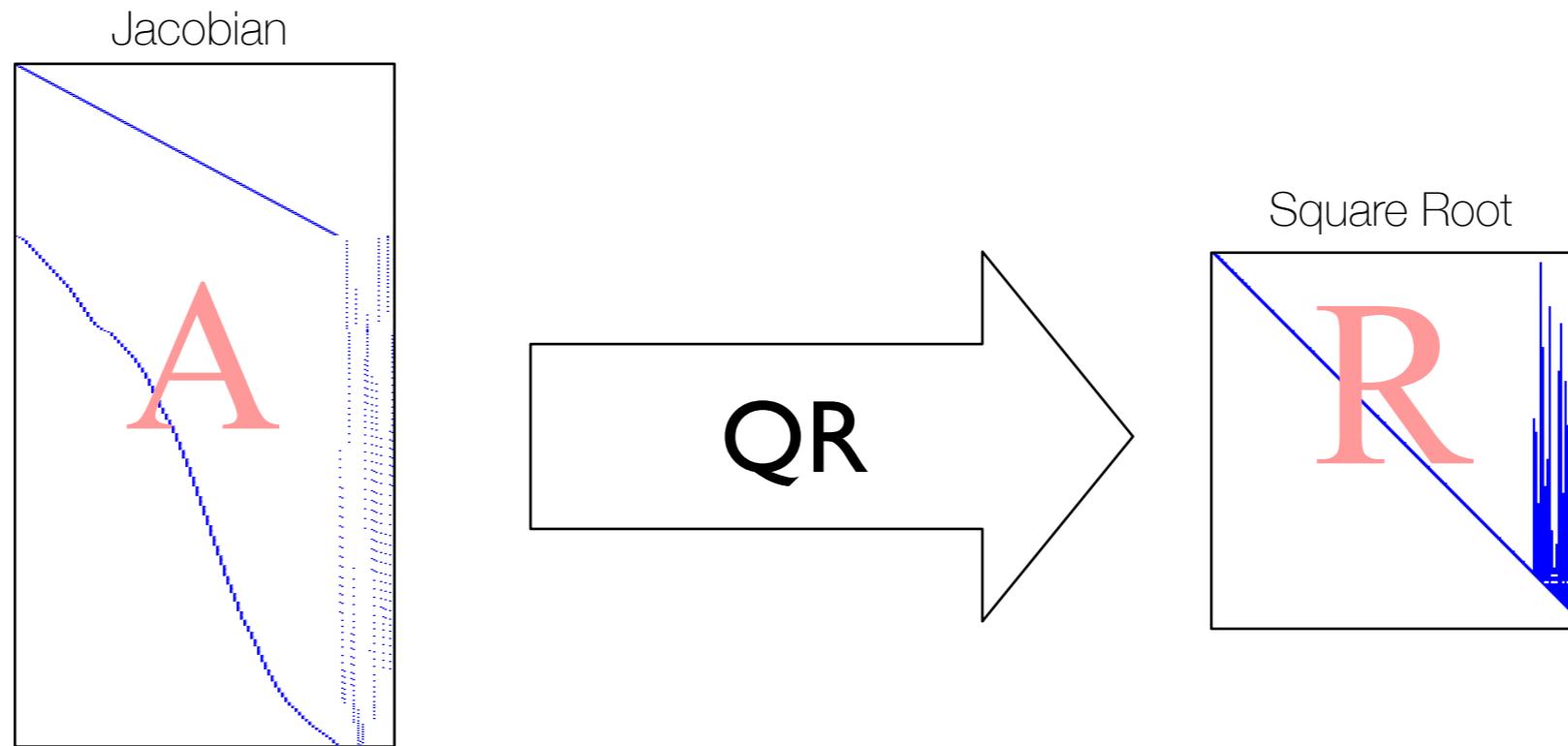
In SAM we are interested in inferring the trajectory of the robot and a map of the unknown environment



The factor graph associated with a small SAM problem
instantaneously shows the structure of the problem



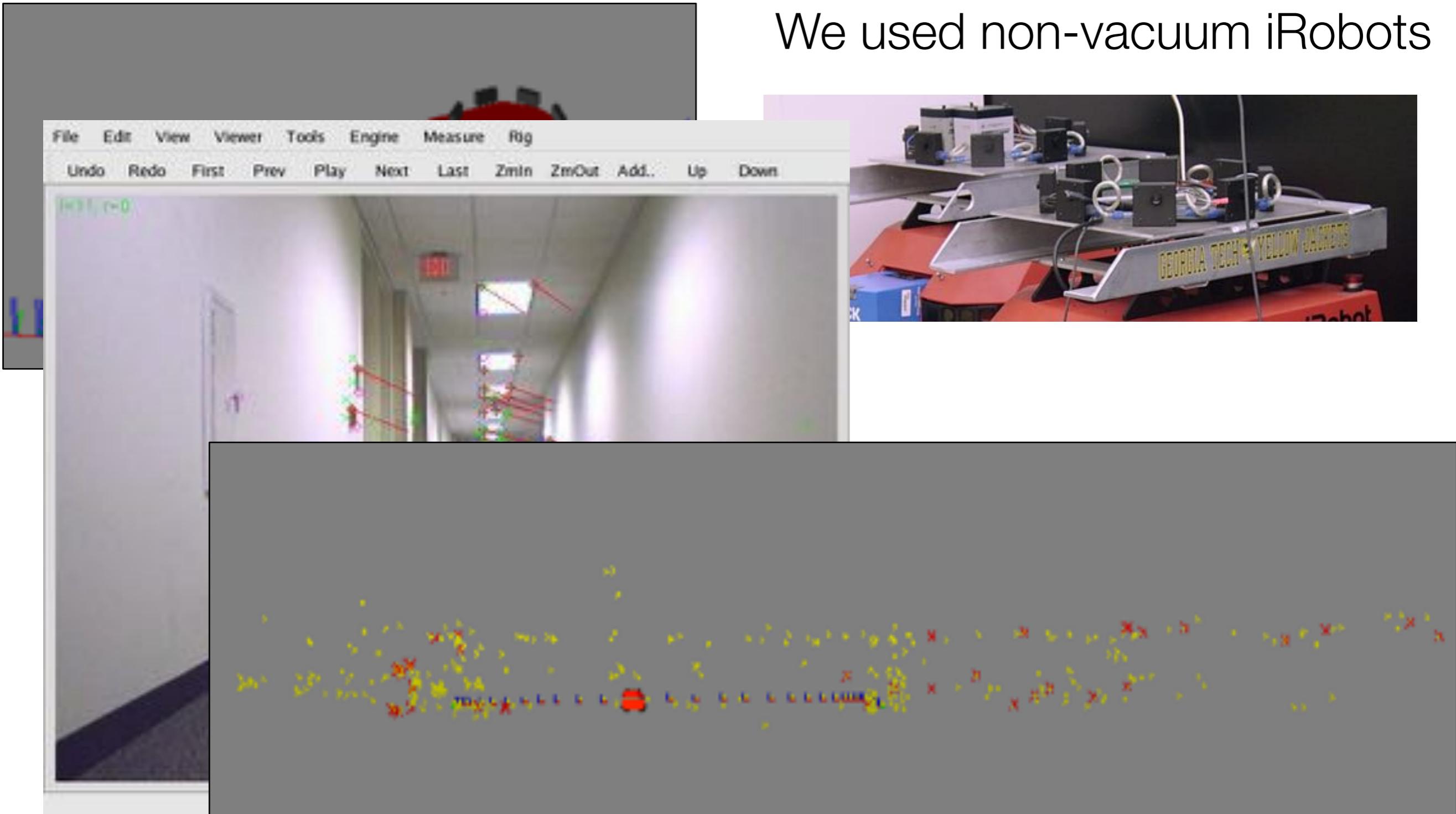
In practice, Square Root SAM is implemented using sparse matrix factorization, which is a computation on a graph



QR Factorization on Factor Graph

Visual SLAM in 2005 might have looked a bit cheesy, but we already did 8-camera visual SLAM back then

We used non-vacuum iRobots



The key points from the Square Root SAM papers have stood the test of time, but we know so much more now

- Key points:
 - Matrices \Leftrightarrow Graphs
 - Factorization \Leftrightarrow Variable Elimination
 - Improving Performance \Leftrightarrow Variable Ordering
- What we know now:
 - Factor graphs can represent many robotics problems
 - Factor graphs expose opportunities to improve computational performance
 - Factor graphs are beneficial in designing and thinking about your problem, even aside from performance

5 A GRAPHICAL MODEL PERSPECTIVE

Square Root SAM Simultaneous Localization and Mapping via Square Root Information Smoothing

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To appear in the Int'l. Journal of Robotics Research

Abstract
Solving the SLAM problem is one way to enable a robot to explore, map, and navigate in a previously unknown environment. We investigate smoothing approaches as a viable alternative to traditional EKF-based SLAM. In particular, we show that it is possible to implement SLAM that factorizes either the associated information matrix or the measurement Jacobian into square root form. Such techniques have several significant advantages over the EKF: they are faster yet more accurate, they require less memory, and they are more robust to outliers. They also allow for non-linear processes and measurement models, and yield the entire robot trajectory, at lower cost for a large class of SLAM problems. As such, they are an interesting alternative way of solving the SLAM problem. In this paper we present the theory underlying these methods, along with an implementation of them in the Square Root Information Smoother (SRIS), a novel SLAM system. We present both simulation results and actual SLAM experiments in large-scale environments that underscore the potential of these methods as an alternative to EKF-based approaches.

1 Introduction

The problem of simultaneous localization and mapping (SLAM) [69, 51, 76] has received considerable attention in mobile robotics as it is one way to enable a robot to explore and navigate in previously unknown environments. In addition, in many applications the map of the environment itself needs to be updated over time, e.g., for navigation, for teleoperation, for sensor placement, battlefield reconnaissance etc. As such, it is one of the core competencies of autonomous robots [77].

We will primarily be concerned with landmark-based SLAM, for which the earliest and most popular approach was the Extended Kalman Filter (EKF) [10, 11]. The EKF uses a linearized model of the SLAM problem. It iteratively estimates a Gaussian density over the current pose of the robot and the position of all landmarks (the map). However, it is well known that the computational complexity of the EKF becomes intractable fairly quickly, and hence a large number of efforts have focused on

As noted before in [78] and by others, the information matrix $I = A^T A$ is the matrix of the Markov random field associated with the SLAM problem. Again, the *block-level* sparsity pattern of I reflects the sparsity of the associated MRF. The *node-level* sparsity pattern in Equation 5 corresponds to a pairwise Markov random field (MRF) [81, 82] through the Hammersley-Clifford theorem [81], and the nodes in the MRF correspond to the robot states and the landmarks.

In [65, 78] the MRF graph view is taken to expose the correlation structure inherent in the filtering version of SLAM. It is shown there that inevitably, when marginalizing the past trajectory, the MRF graph becomes increasingly sparse. However, these approaches are still slow; these approaches try to selectively remove links to reduce the computational cost of the filter, with great success. In contrast, in this paper we consider the MRF associated with the smoothing information matrix I , which does not become dense, as past states are never marginalized out.

5.2 Factorization \Leftrightarrow Variable Elimination

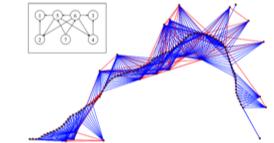


Figure 5: The triangulated graph for a good ordering (column, as in Figure 4). This is a directed graph, where each edge corresponds to a non-zero in the Cholesky triangle R . Note that we have dropped the arrows in the simulation example for simplicity.

The single question left is what graph the square root information matrix R corresponds to? Remember that R is the result of factorizing either I or A as in Section 4. Cholesky or QR factorization of I is well-known, but the factorization of A has been studied much less. In fact, it is much more recently developed methods for inference in graphical models [11]. It will be seen below that R is essentially in correspondence with a junction tree known from inference in graphical models and also known as a SLAM junction tree.

Both factorization methods, QR and Cholesky (or LDL), are based on the variable elimination algorithm [4, 11]. The difference between these methods is that QR eliminates variable nodes from the factor graph and obtains $A = QR$, while Cholesky or LDL start from the MRF and hence obtain

5 A GRAPHICAL MODEL PERSPECTIVE

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from the leaves to the root to factorize a square matrix, and then from the root to the leaves to perform a backward substitution step. A complete treatment of the relationship between square root information matrices and clique trees is beyond the scope of the current paper, but in other work we have used the clique-tree structure in novel algorithms for distributed inference [19].

5.3 Improving Performance \Leftrightarrow Reducing Fill-in

The single most important factor to good performance is the order in which variables are eliminated. Different variable orderings can yield dramatically more or less fill-in, defined as the number of edges added into the graph during the factorization. A good ordering corresponds to a non-zero pattern that is sparse and triangular, both the cost of computing R and back-substitution are heavily dependent on how much fill-in occurs. Unfortunately, finding an optimal ordering is NP-complete.

Developing algorithms that approach the optimization is an active area of research in numerical linear algebra. A popular method for the related problem of column pivoting is the column pivoting algorithm [11], which works on the columns of A .

Another popular method, based on graph theory and often used to speed up finite element methods, is generalized nested dissection [1].

Comparing QR with Cholesky factorization, we see that both algorithms require $O(mn^2)$ operations when $m > n$, but that QR-factorization is a factor of 2 slower. While these numbers are valid for dense matrices only, we have seen that in practice LDL and Cholesky factorization for square-root information on sparse problems as well, and just by a constant factor.

From the lesson above it can now be readily appreciated that the measurement Jacobian A is the matrix of the factor graph associated with SLAM. We can understand this statement at two levels. First, every block of A corresponds to one of the least-squares criterion (8), either a landmark constraint, a robot motion constraint, and every block-diagonal structure in A corresponds to the factor graph. Within each block-row, the sparsity pattern indicates which unknown poses and landmarks are connected to the factor. Hence, the block-structure of A corresponds exactly to the block-structure of the factor graph.

Second, at the scalar level, every row A_i in (see Figure 4) corresponds to a scalar term

$$\|A\delta - h_i\|_2^2 \text{ in the sparse matrix least-squares criterion (9), as}$$

Hence, this defines a finely structured factor graph, via

$$P(\delta) \propto \exp -\frac{1}{2} \|A\delta - h\|_2^2 = \prod_i \exp -\frac{1}{2} \|A_i\delta - h_i\|_2^2$$

It is important to realize, that in this view, the block-structure of the SLAM problem is discarded, and that it is this graph that is examined by general-purpose linear algebra methods. By working with the block-structure instead, we will be able to do better.

Given a factor graph ordering, the cost in general, heuristics or domain-specific knowledge can do much better than general-purpose algorithms. A simple idea is to use a standard method such as column, but have a walk on the sparsity pattern of the blocks instead of passing it the original measurement Jacobian. In other words, we can use a graph search to find a better ordering of x and y positions and orientation o as a single variable and create a smaller graph which encapsulates the constraints between these blocks rather than the individual variables. Not only is it cheaper to call column ordering on a smaller graph, it is also easier to implement.

As mentioned above, the block-structure is real knowledge about the SLAM problem and is not accessible to column or any other appropriate ordering algorithm. As such, it is a waste of time to call column ordering on a large graph. We have found that it is work on the SLAM MRF instead of on the sparse matrix A directly can yield improvements of 2 to sometimes 100-fold, with 15 being a good average.

Note that there are cases in which any ordering will result in the same large fill-in. The worst-case scenario is a fully connected bipartite MRF: every landmark is seen from every location. In that case, eliminating any variable will completely connect variables on the other side, and after that the remaining variables will be fully connected. As such, any ordering will result in the same fill-in for the entire map, and all passes will be computed once the map is known. Vice versa, if a landmark is chosen, the trajectory will be the clique tree clique, and computation will proceed as in an expand-one trajectory optimizer, following a very similar set of steps.

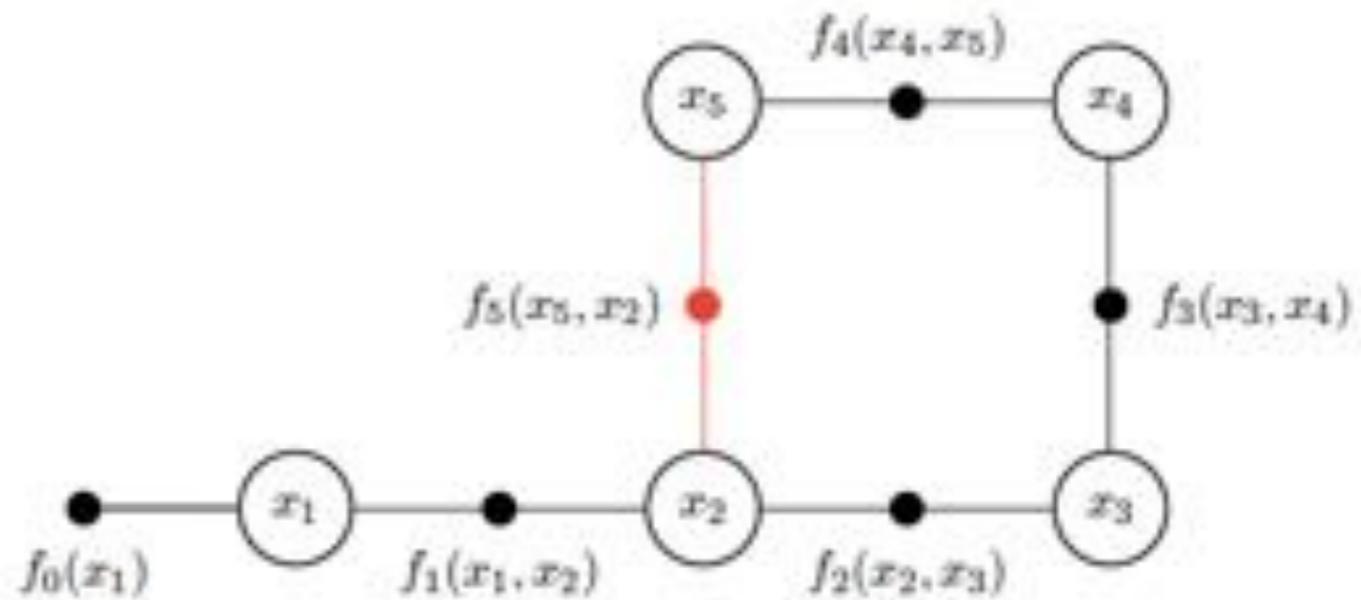
Interestingly, these two cases form the basis of the standard partitioned inverse, or “Schor complement”, which is well-known in structural finite element applications [79, 41] and also used in GraphSLAM [77].

However, the worst-case scenario outlined above is an exceptional case in robotics: sensors have small range and resolution, landmarks, objects, buildings, etc. This is especially true in large-scale robotics applications, and it follows that the MRF will in general be sparsely connected, even though it is a large connected component.

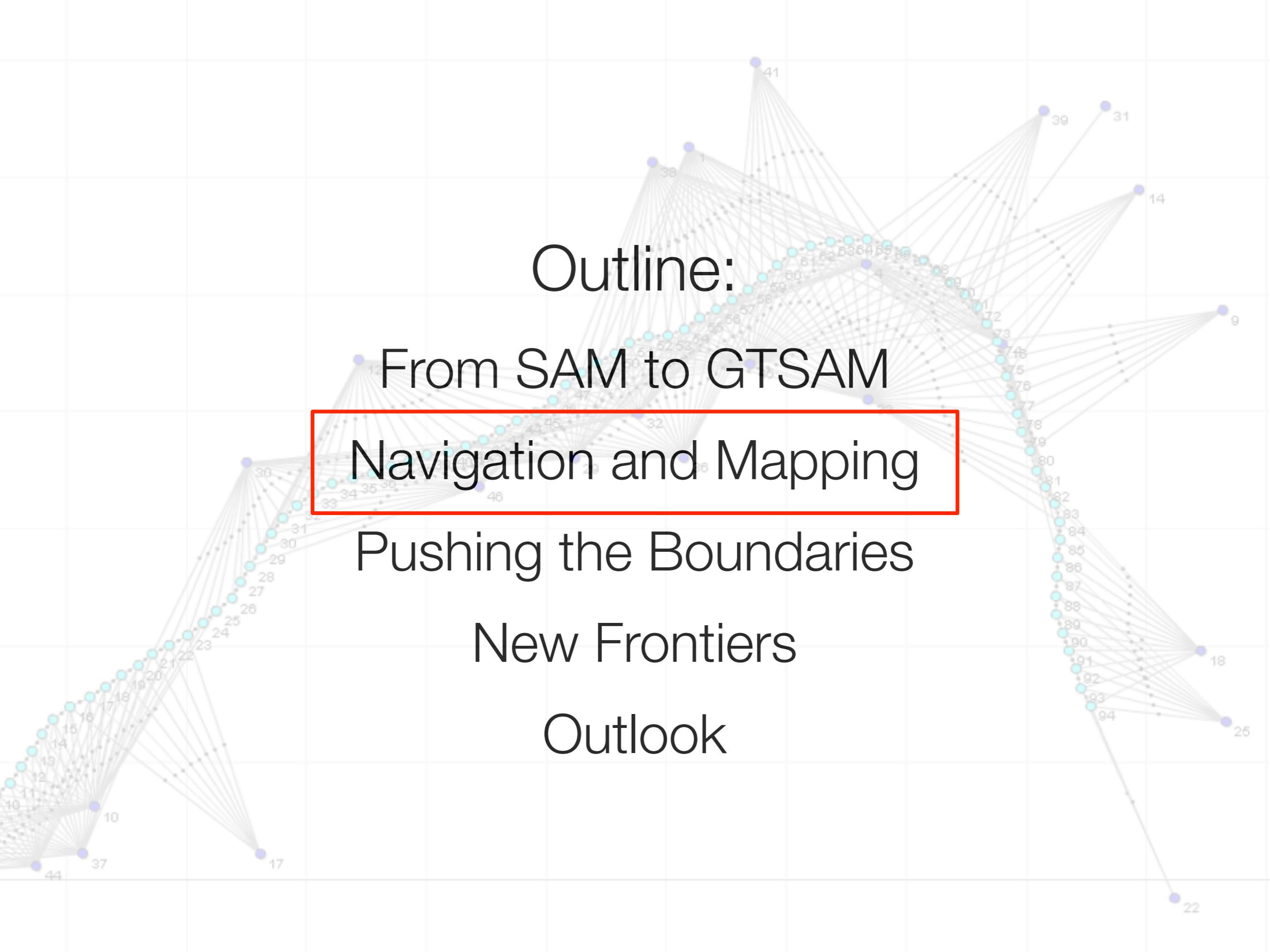
^abipartite is here used to indicate the partition of variables into poses and landmarks, not in the factor graph sense.

GTSAM embodies many of the ideas we and others have developed around factor graphs since then

- C++ library: gtsam.org
- python & Matlab wrappers
- Open-source, BSD-licensed
- Optimization on Manifolds and Lie groups
- Reverse AD Expression Language



```
1 NonlinearFactorGraph graph;
2 noiseModel::Diagonal::shared_ptr priorNoise =
3     noiseModel::Diagonal::Sigmas(Vector_(3, 0.3, 0.3, 0.1));
4 graph.add(PriorFactor<Pose2>(1, Pose2(0,0,0), priorNoise));
5
6 // Add odometry factors
7 noiseModel::Diagonal::shared_ptr model =
8     noiseModel::Diagonal::Sigmas(Vector_(3, 0.2, 0.2, 0.1));
9 graph.add(BetweenFactor<Pose2>(1, 2, Pose2(2, 0, 0), model));
10 graph.add(BetweenFactor<Pose2>(2, 3, Pose2(2, 0, M_PI_2), model));
11 graph.add(BetweenFactor<Pose2>(3, 4, Pose2(2, 0, M_PI_2), model));
12 graph.add(BetweenFactor<Pose2>(4, 5, Pose2(2, 0, M_PI_2), model));
13
14 // Add pose constraint
15 graph.add(BetweenFactor<Pose2>(5, 2, Pose2(2, 0, M_PI_2), model));
```



Outline:

- From SAM to GTSAM

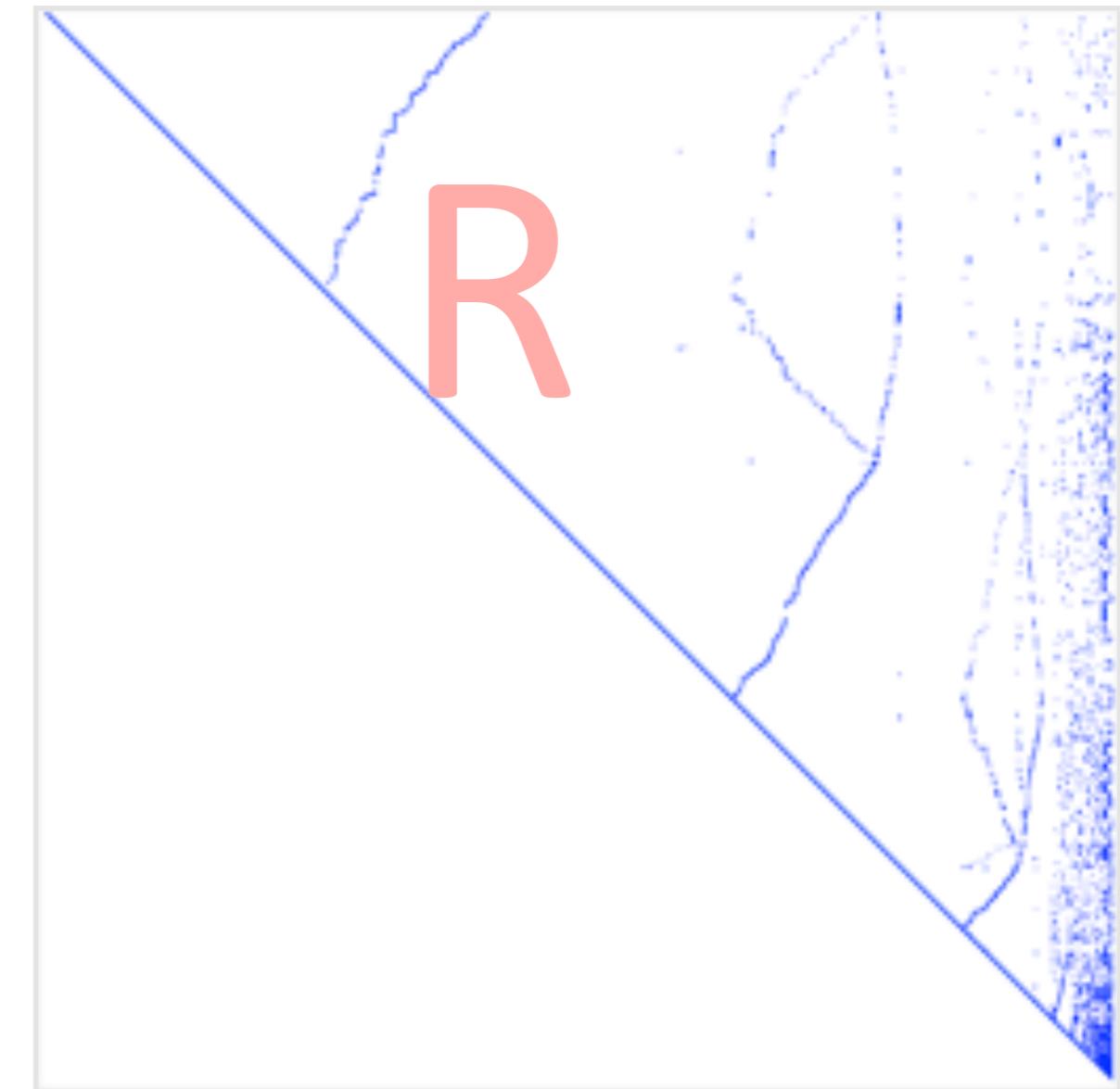
Navigation and Mapping

Pushing the Boundaries

New Frontiers

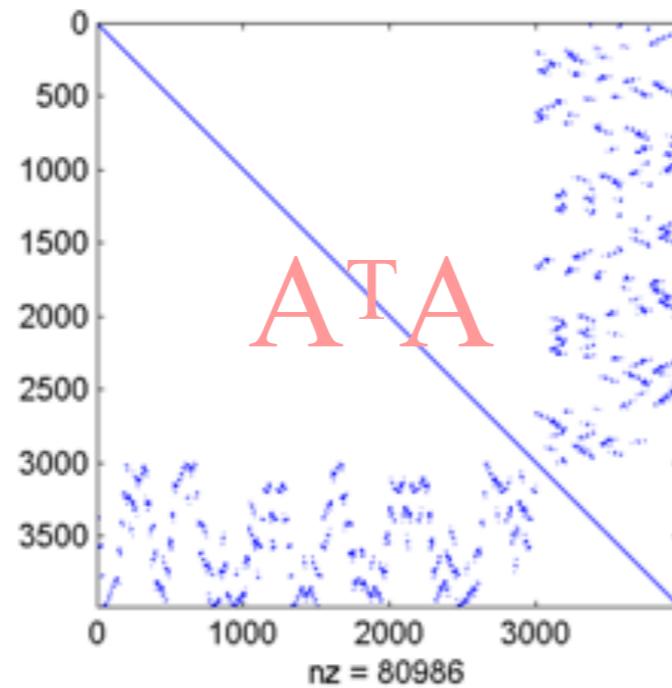
Outlook

Square Root SAM on real sequence, the Sydney Victoria Park dataset, shows how sparsity is key to performance

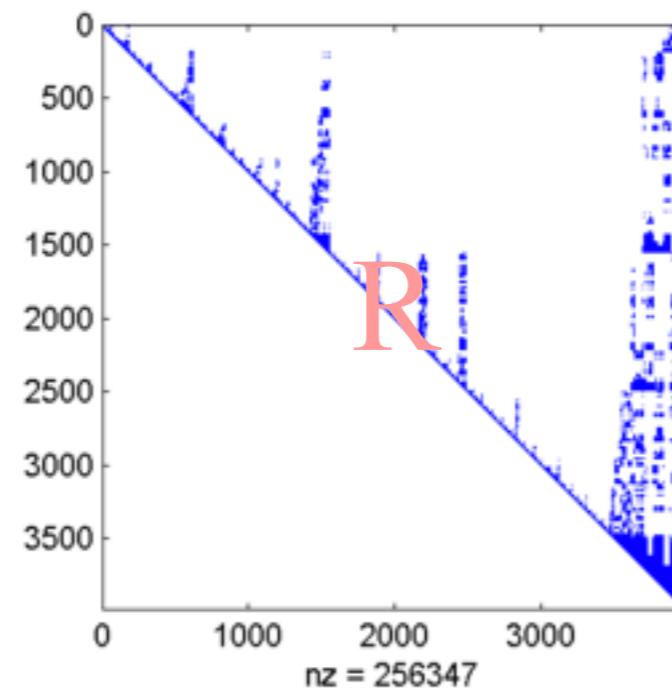


While finding an optimal ordering is NP complete, heuristics coupled with domain knowledge can do wonders

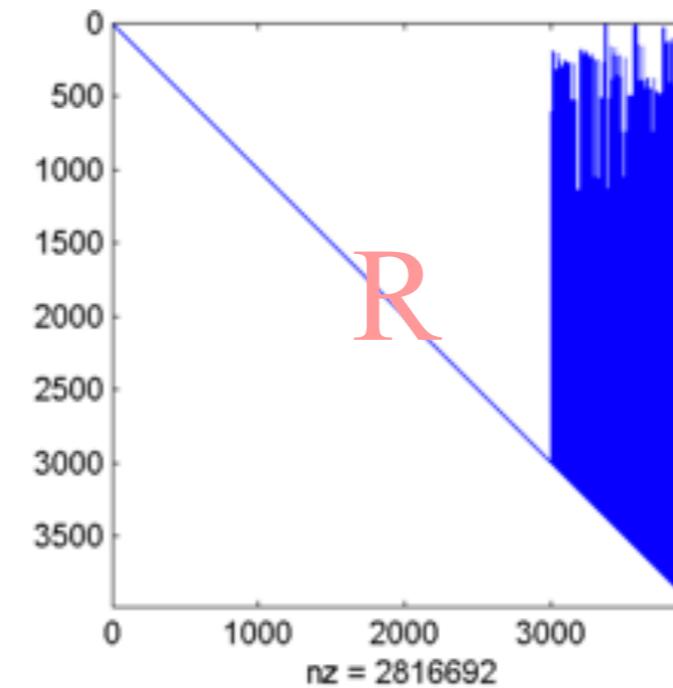
Information matrix



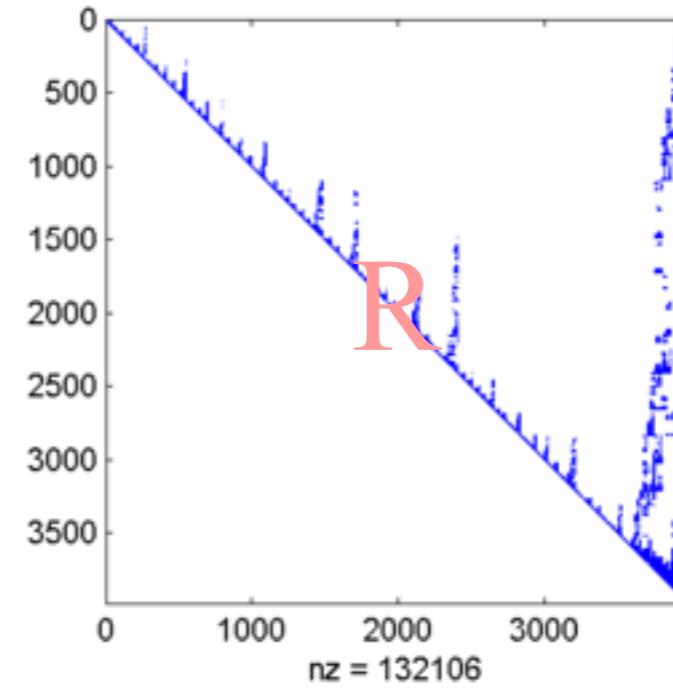
Square Root:
AMD



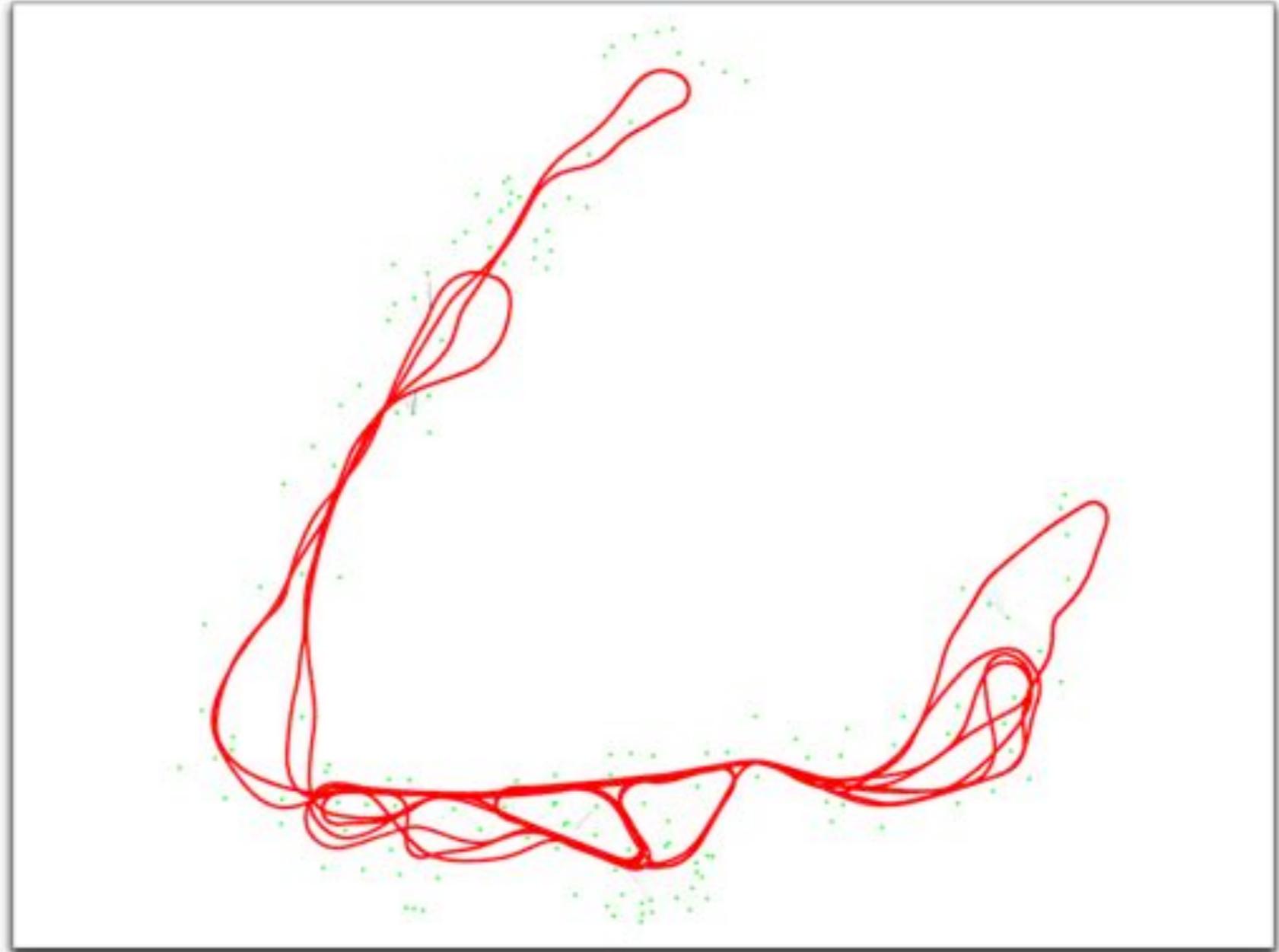
Square Root:
Naive



Square Root:
AMD on blocks



Domain knowledge often shows how to break up graphs, a generalization of “nested dissection” [Kai Ni et al. IROS ’10]



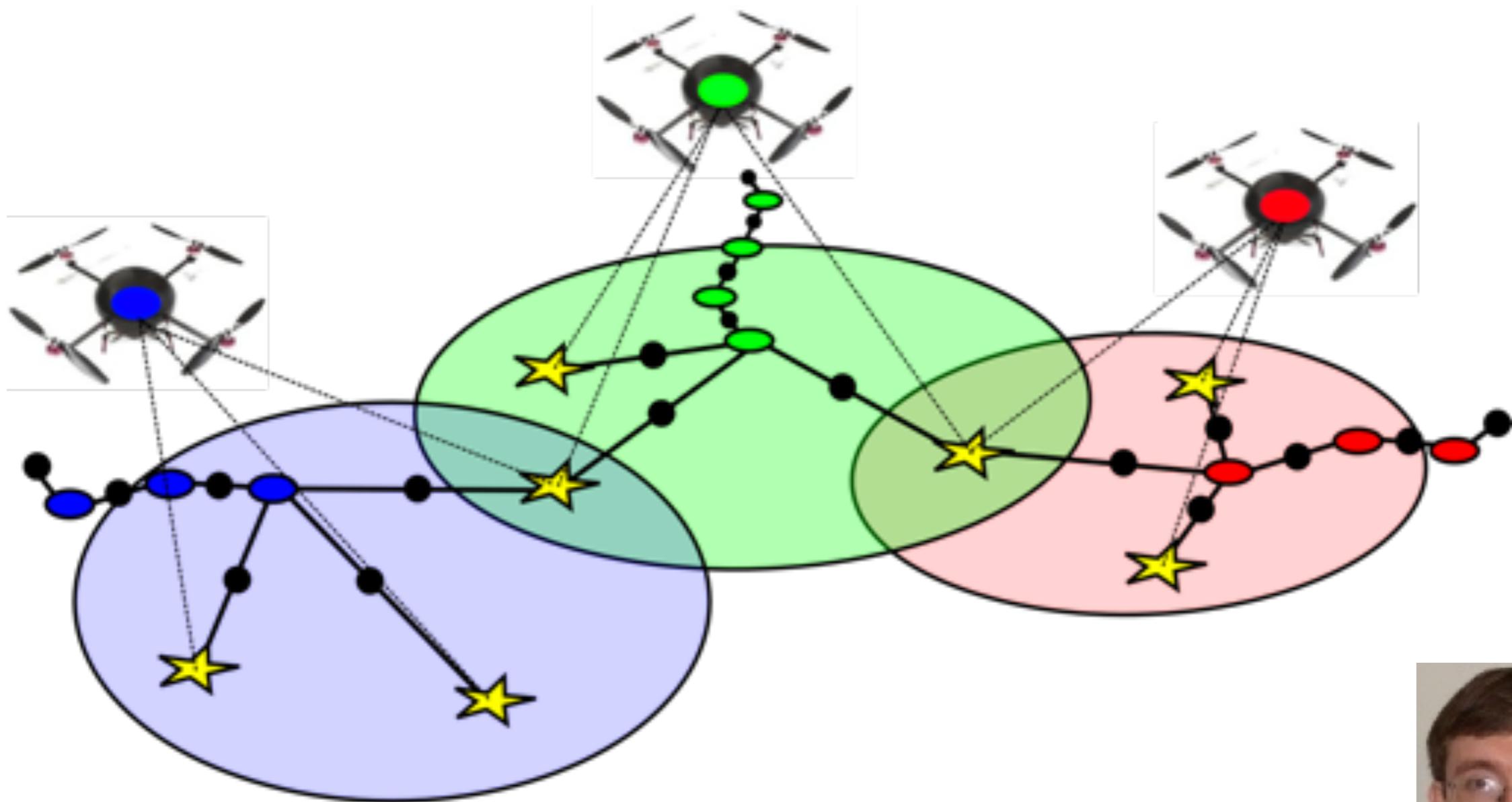
Now CEO of Beijing autonomous driving startup

 HOLOMATIC 禾多科技

Hyper-SFM applies hierarchical nested dissection to the structure from motion problem [Ni et al. 3DIMPVT'12]

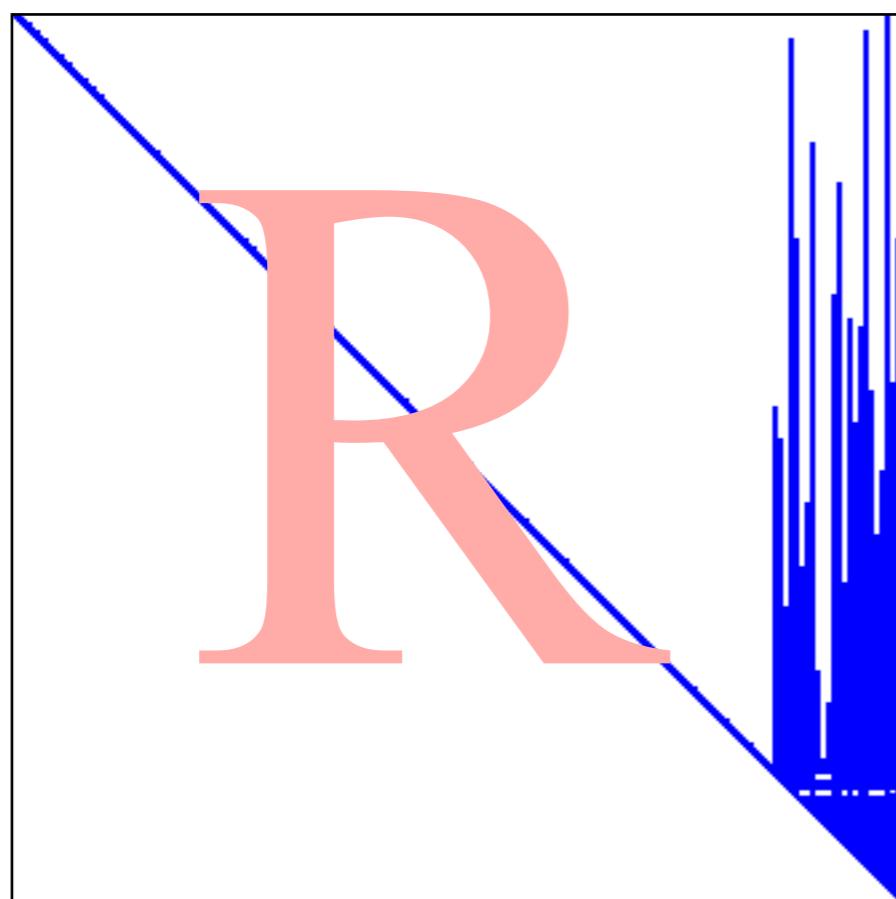


Breaking up graphs can lead to powerful new paradigms for distributed mapping [Alex Cunningham et al, ICRA '13]

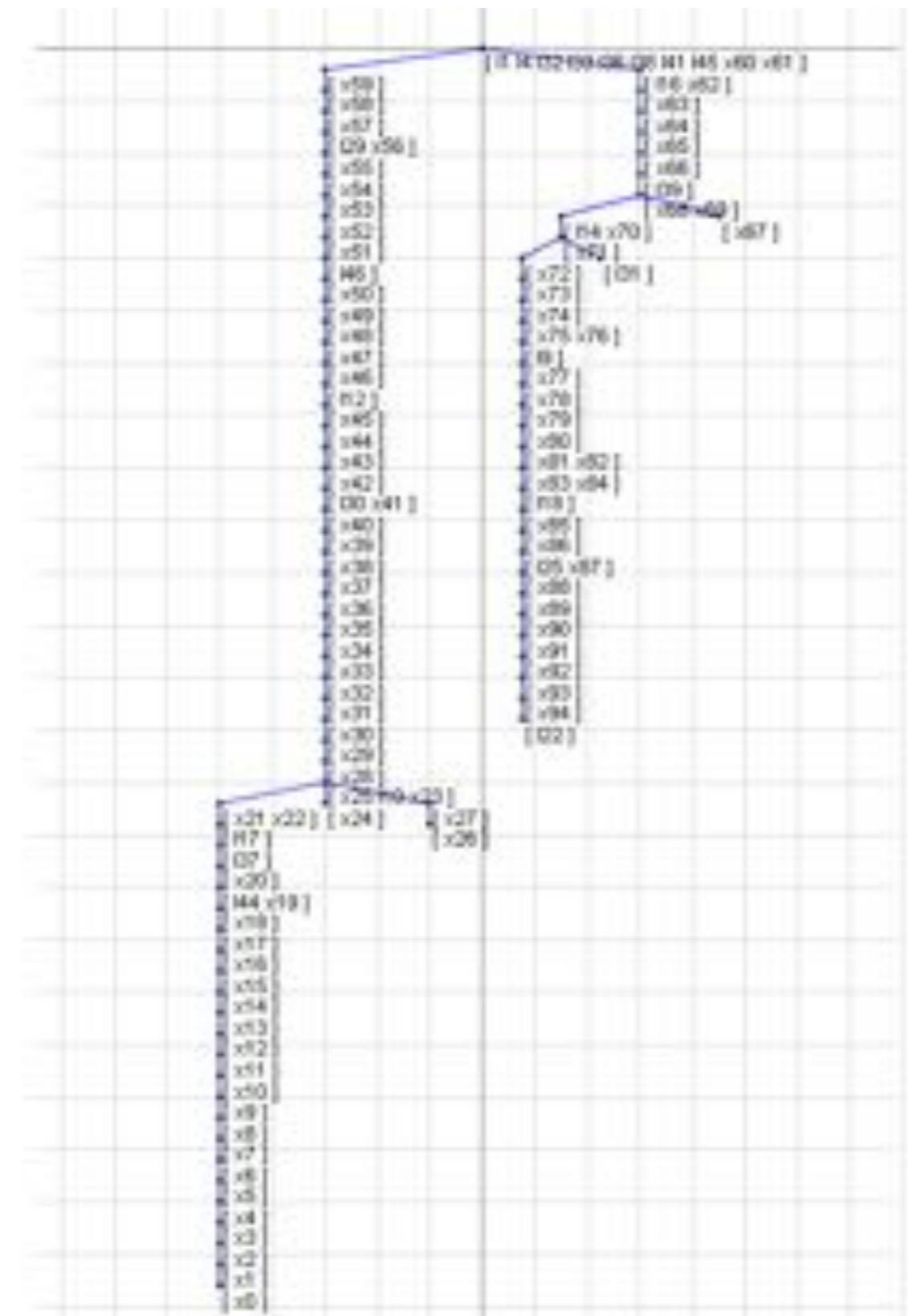


The Bayes tree is a powerful graphical model that enables incremental Smoothing and Mapping (iSAM) [IJRR ‘12]

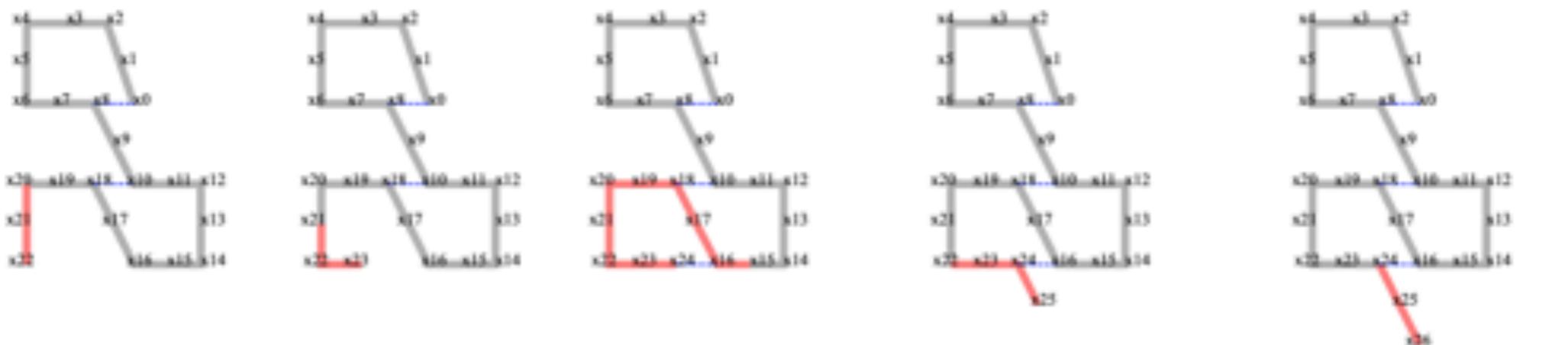
Exploit the fact that the square root information matrix can be understood as a directed junction tree: **the Bayes tree**



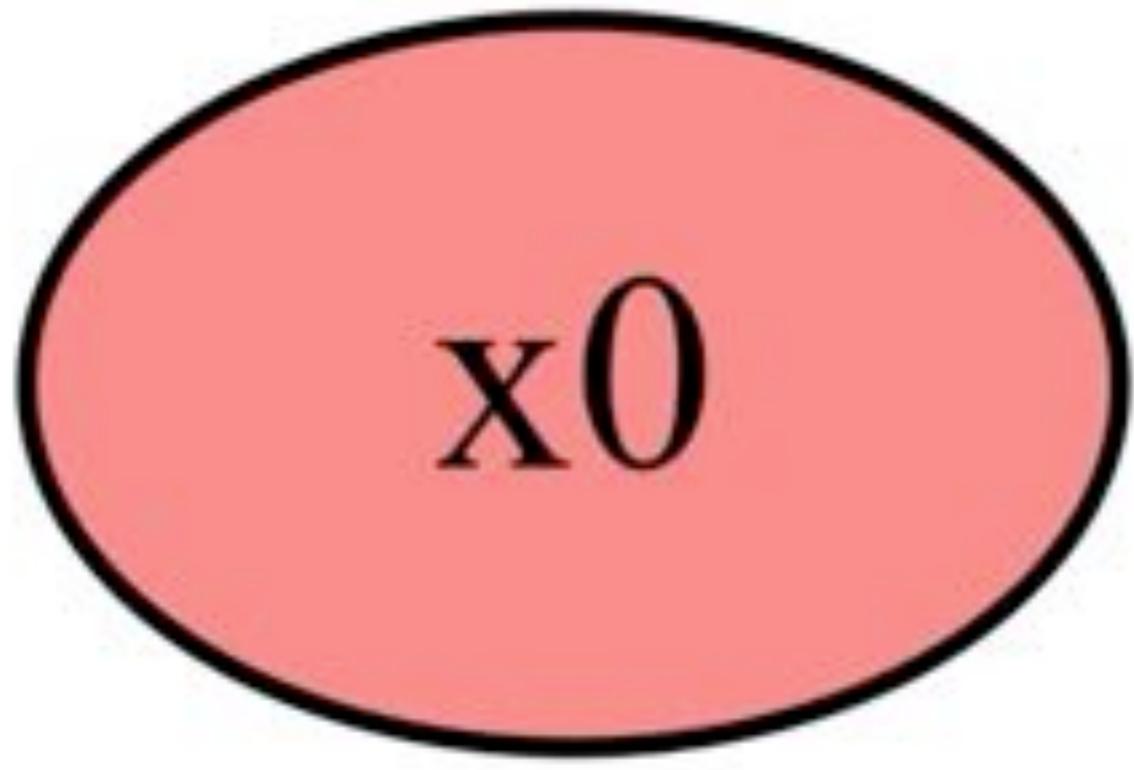
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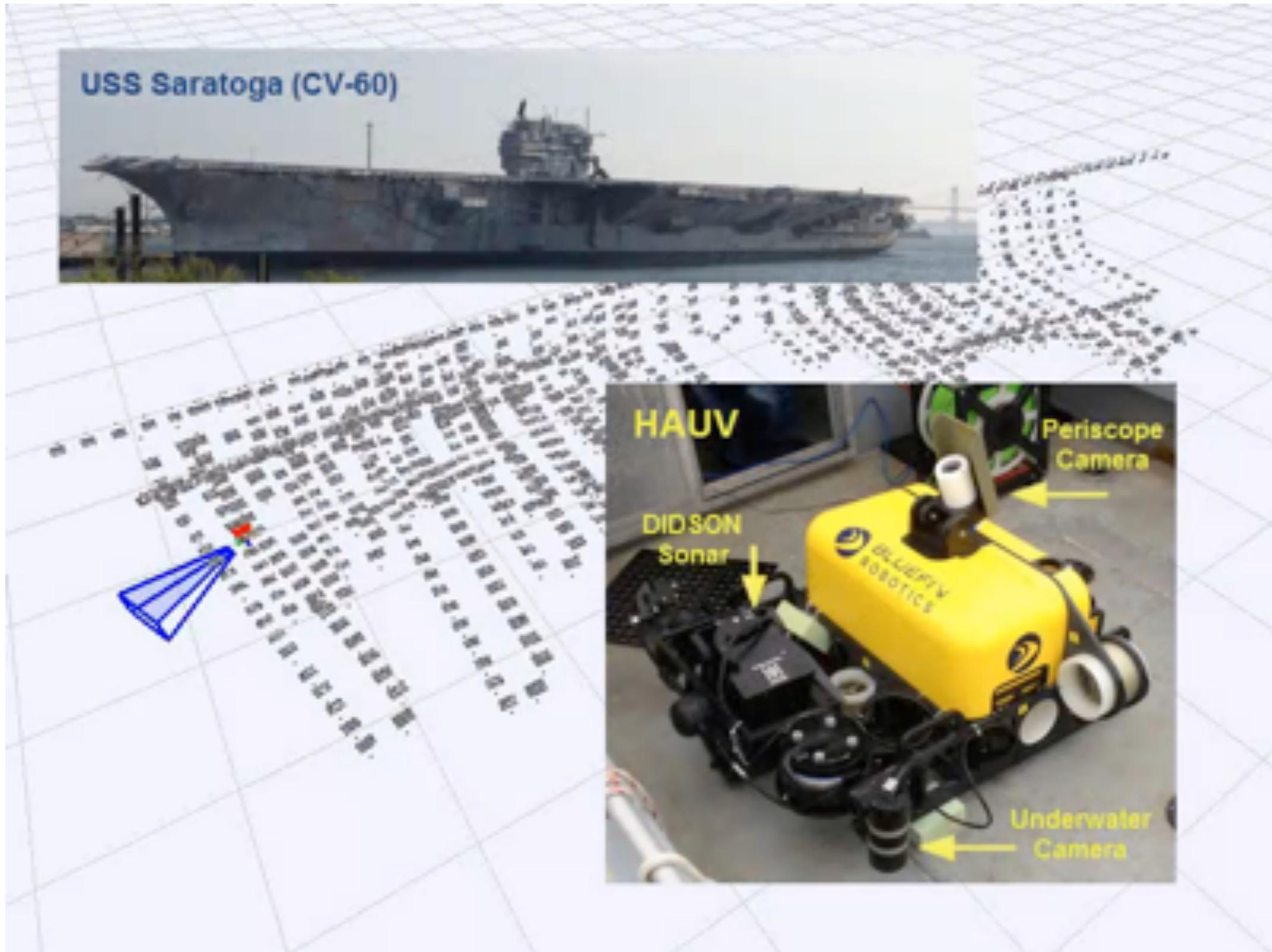
iSAM edits a Bayes tree as new measurements arrive



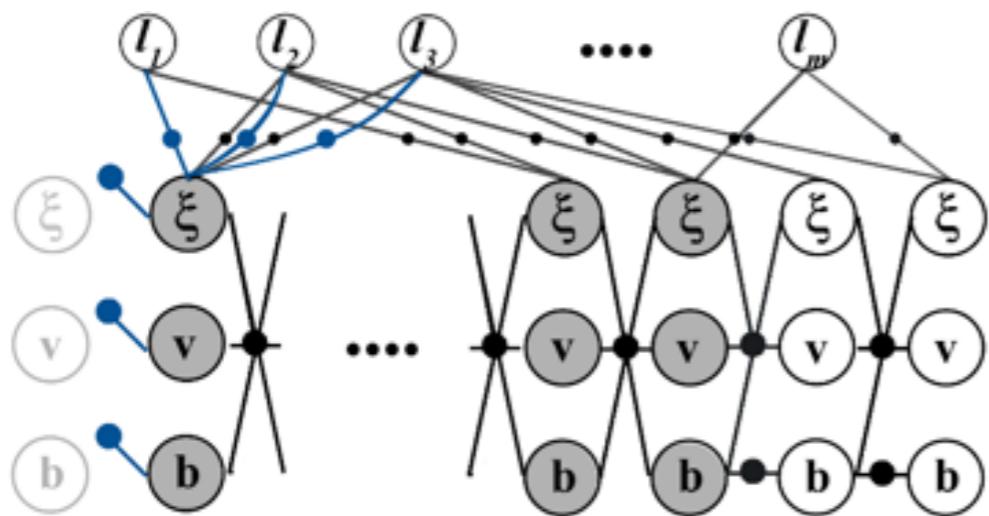
iSAM2 at work on a synthetic sequence really shows off the reduction in amortized costs afforded by the Bayes tree



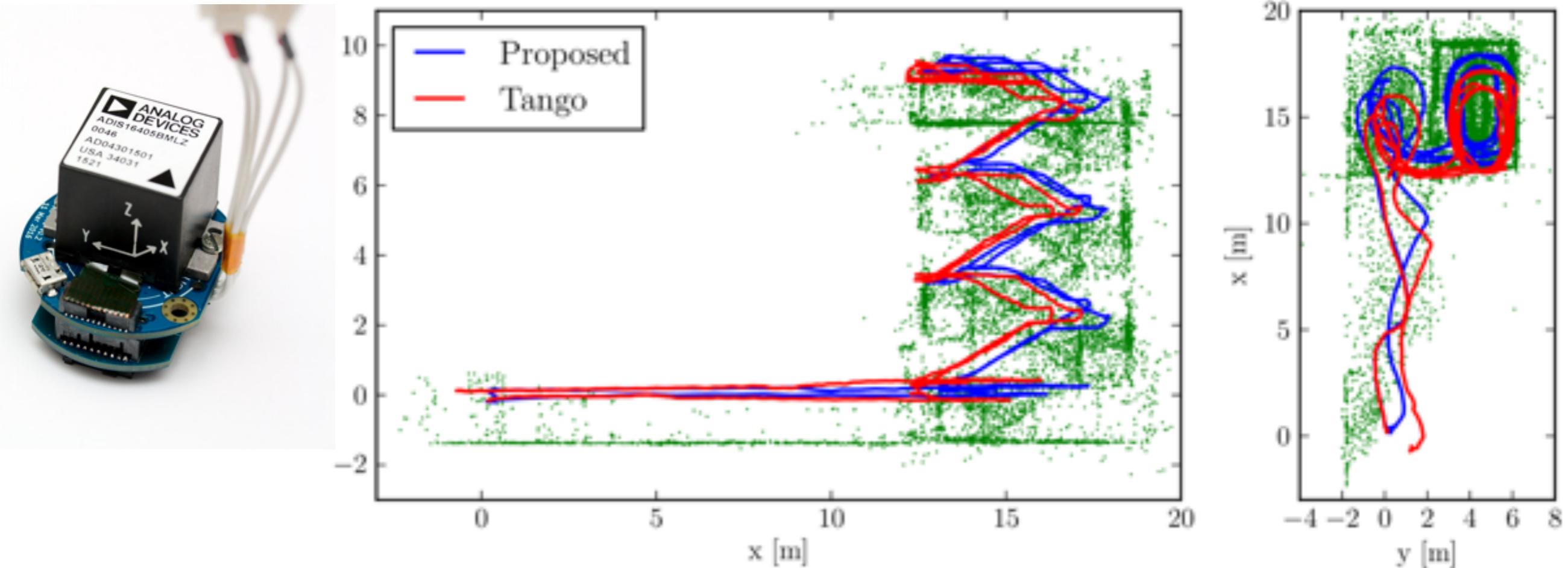
iSAM has been applied in many applications, from mapping aircraft carriers [Kim et al 2013] to experiments on the ISS



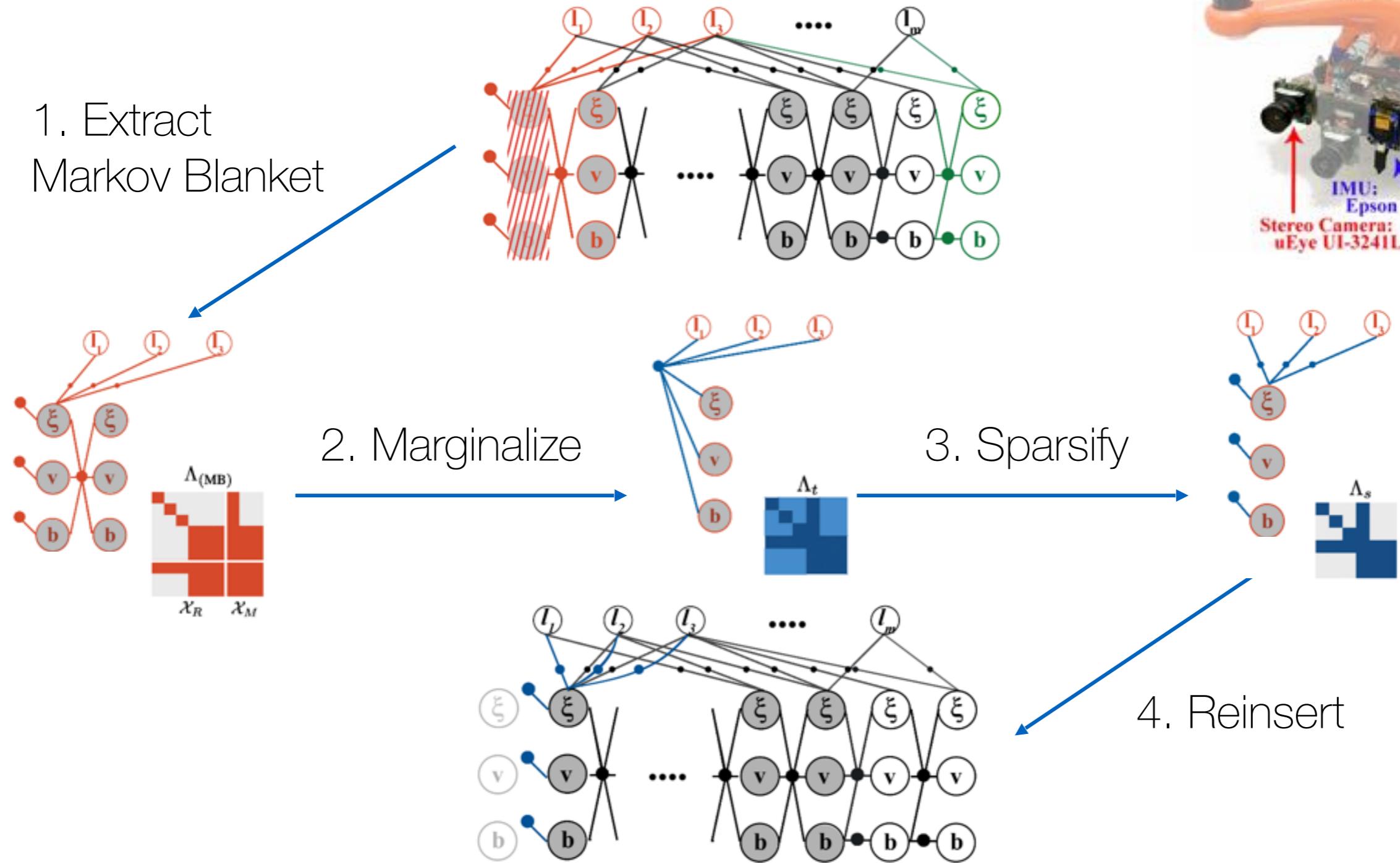
Pre-integrating IMU measurements yields state of the art visual-inertial navigation [Forster et al. TRO'17]

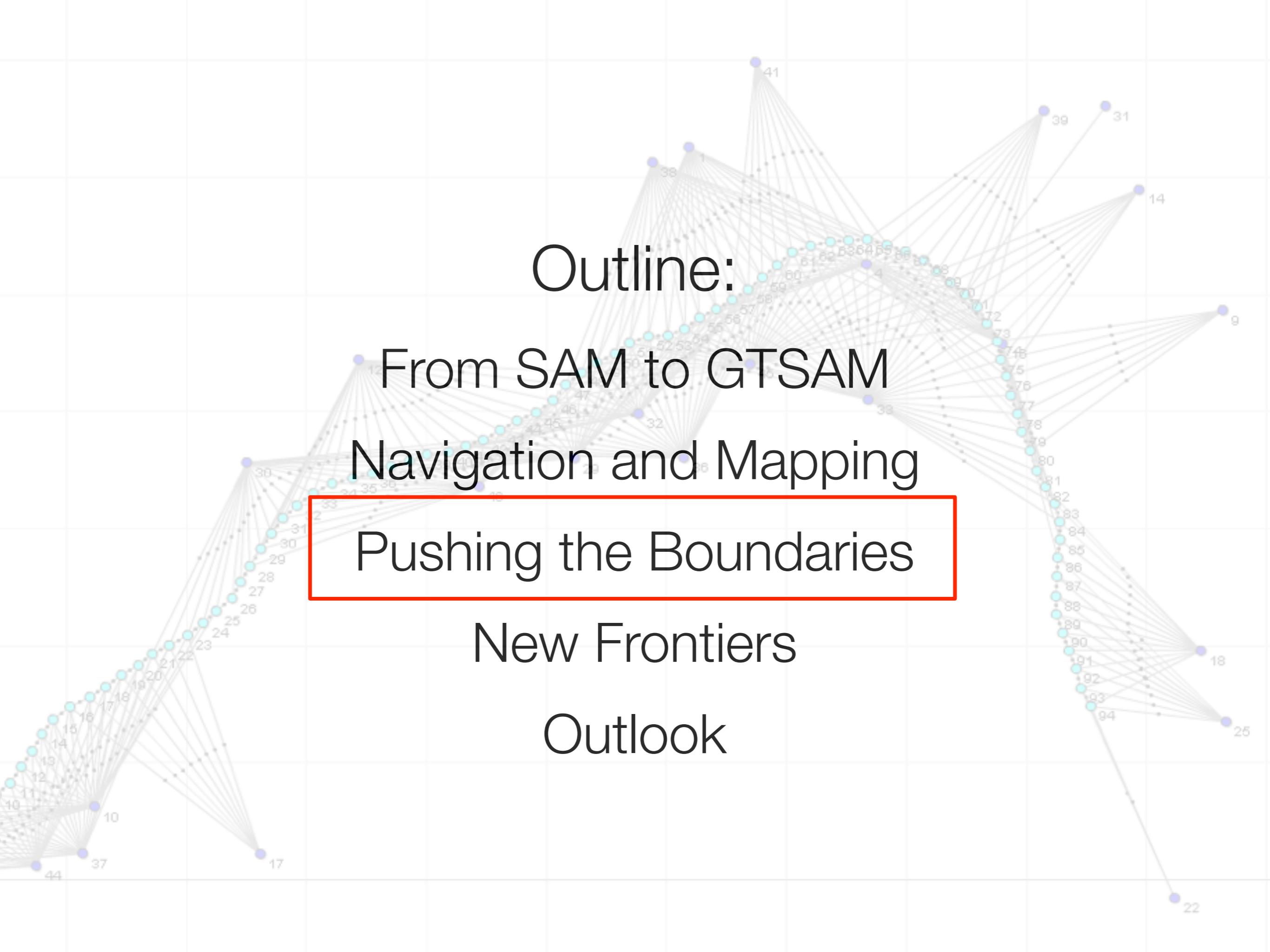


- VIO pre-integrated IMU
- Integrates IMU measurements between poses, subtracting gravity
- Efficient and accurate!



Sparsification in visual-inertial navigation strikes a perfect balance between efficiency and accuracy





Outline:

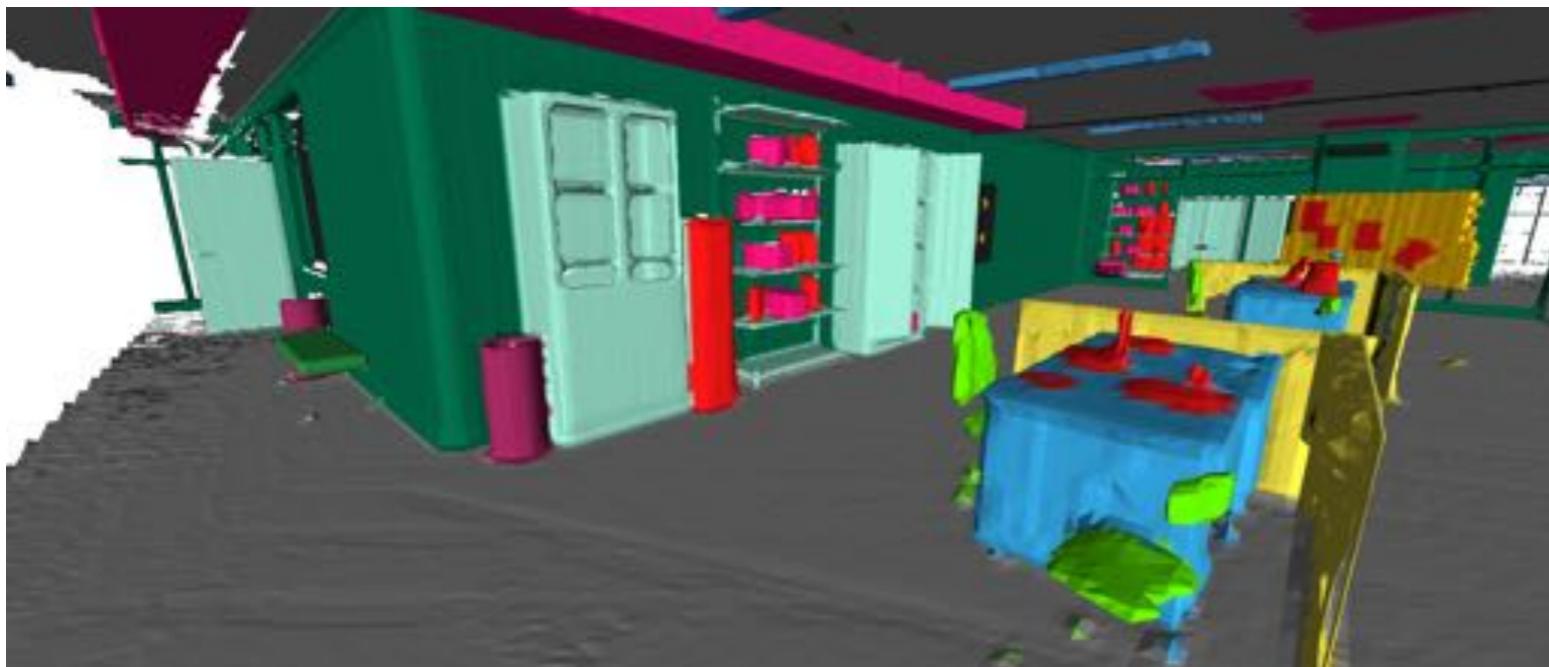
- From SAM to GTSAM
- Navigation and Mapping

Pushing the Boundaries

New Frontiers

Outlook

MIT's Kimera is a state of the art metric-semantic SLAM built upon factor graphs and GTSAM [Rosinol et al. ICRA '20]

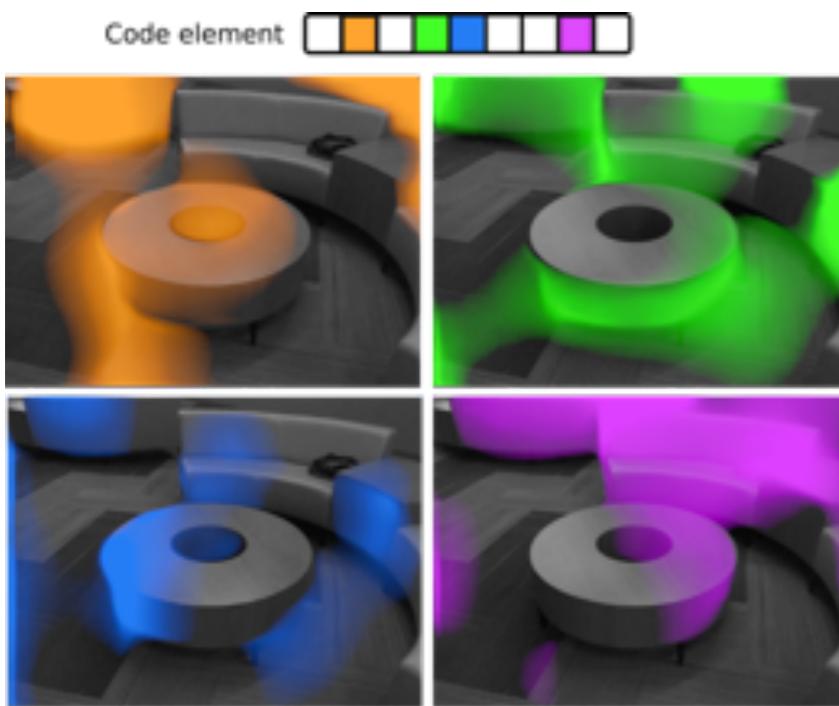
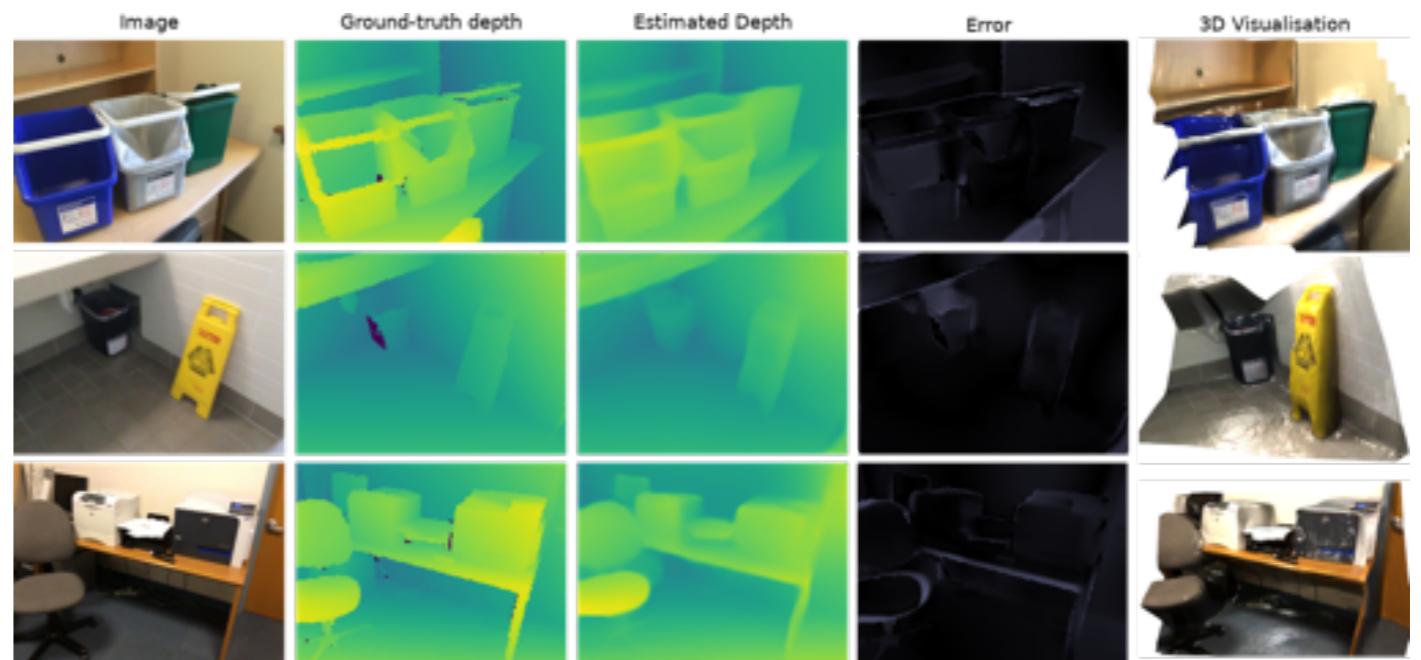
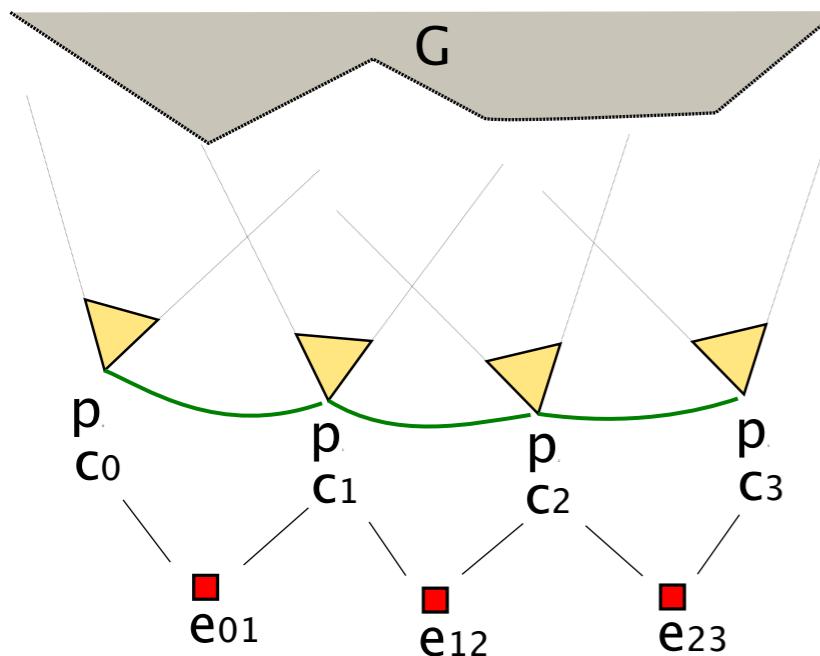


- Four modules:
 - VIO pre-integrated IMU
 - Robust factor-graph-based pose graph
 - Real-time meshing module
 - Semantics module fuses semantic 2D information into the 3D mesh representation.

Rosinol et al. will present the impressive Dynamic Scene Graphs here at RSS, which builds upon Kimera

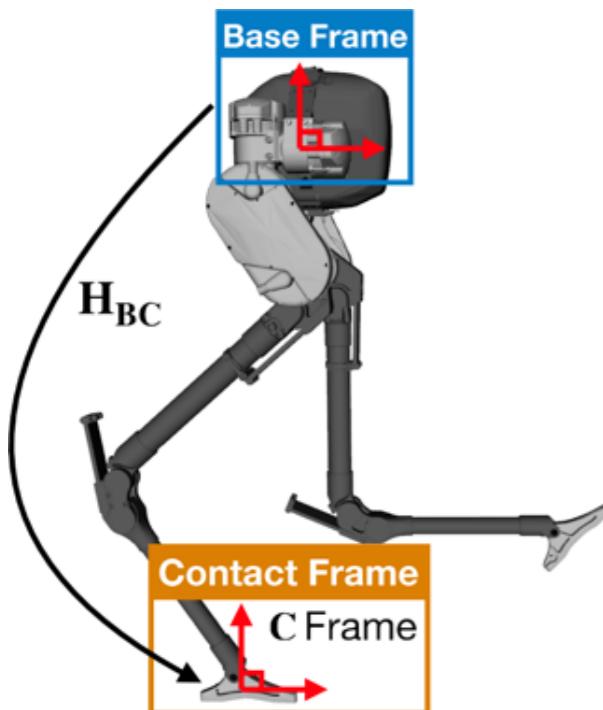
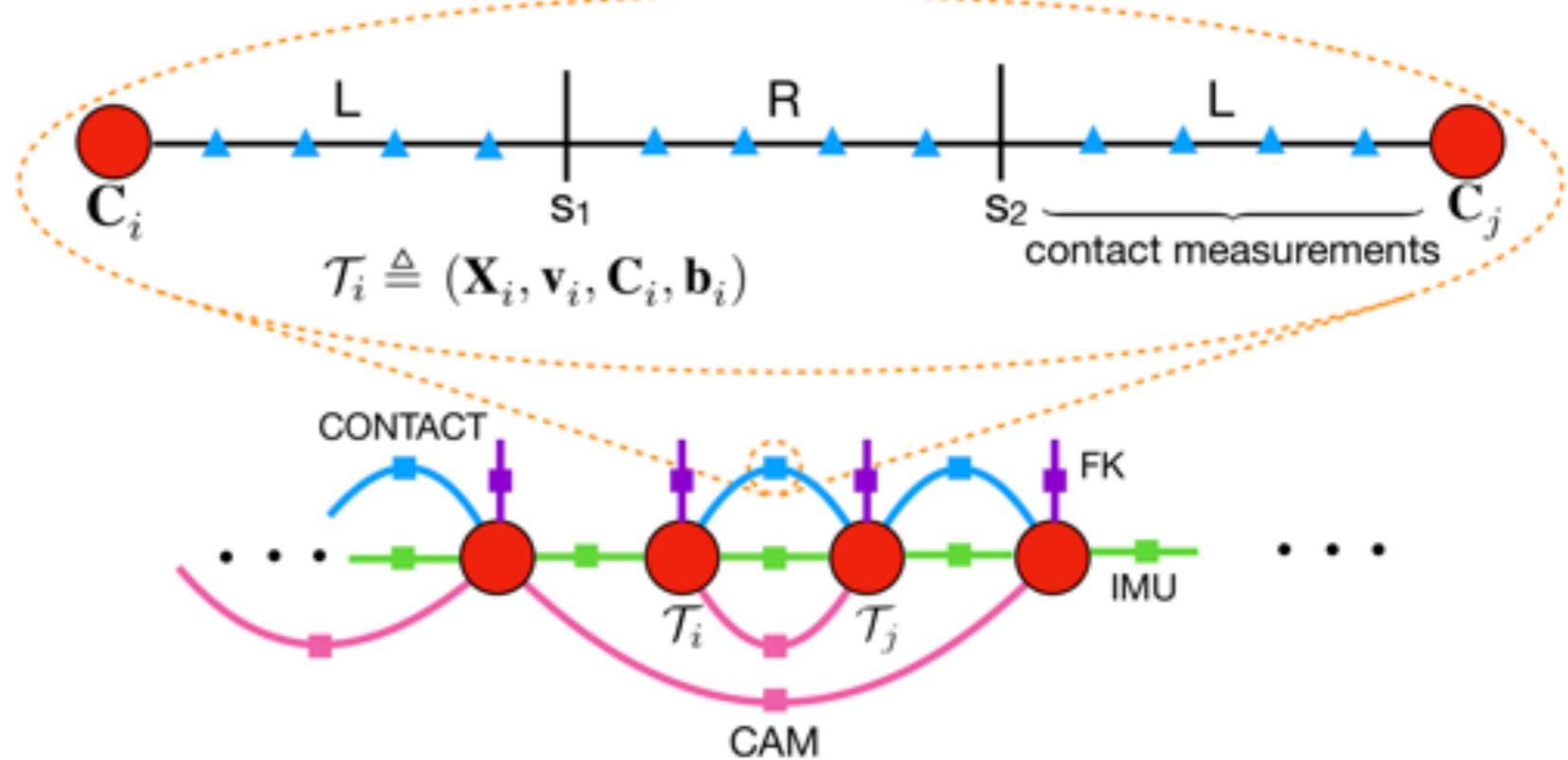


Czarnowski et al. [RAL '19] integrated deep VAEs into factor graphs to build a real-time, dense SLAM system



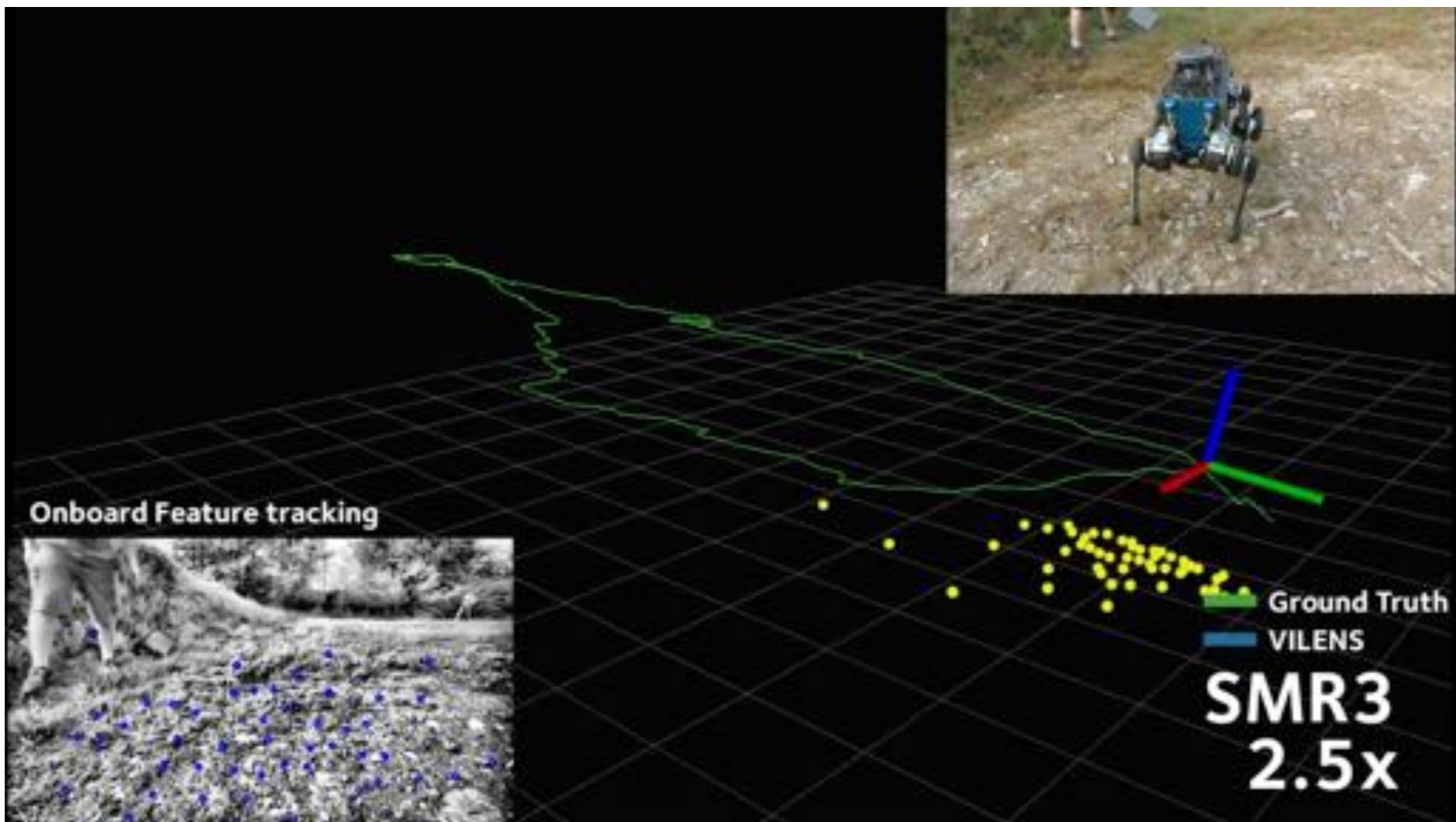
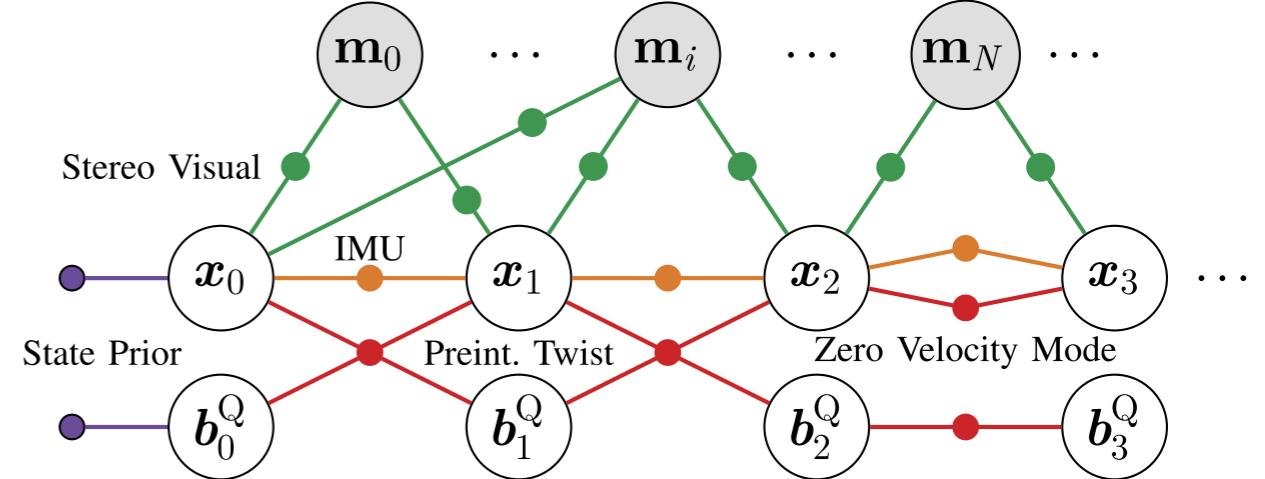
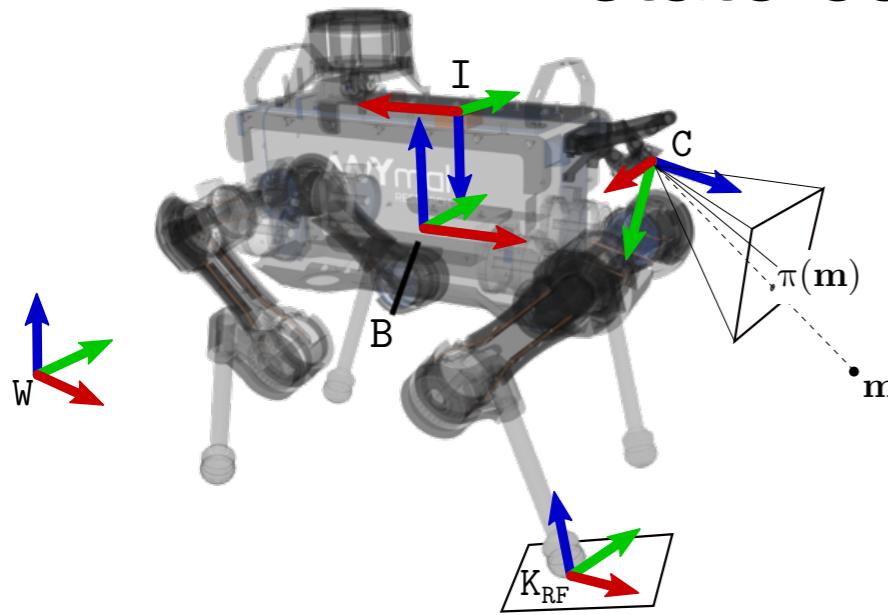
- Real-time dense SLAM system
 - Variational auto-encoder (VAE)
 - Compact “latent” codes
 - Codes are unknowns in a iSAM-based SLAM system

Factor graphs have been used in humanoid state estimation at University of Michigan... [Hartley et al. IROS '18] (1/2)

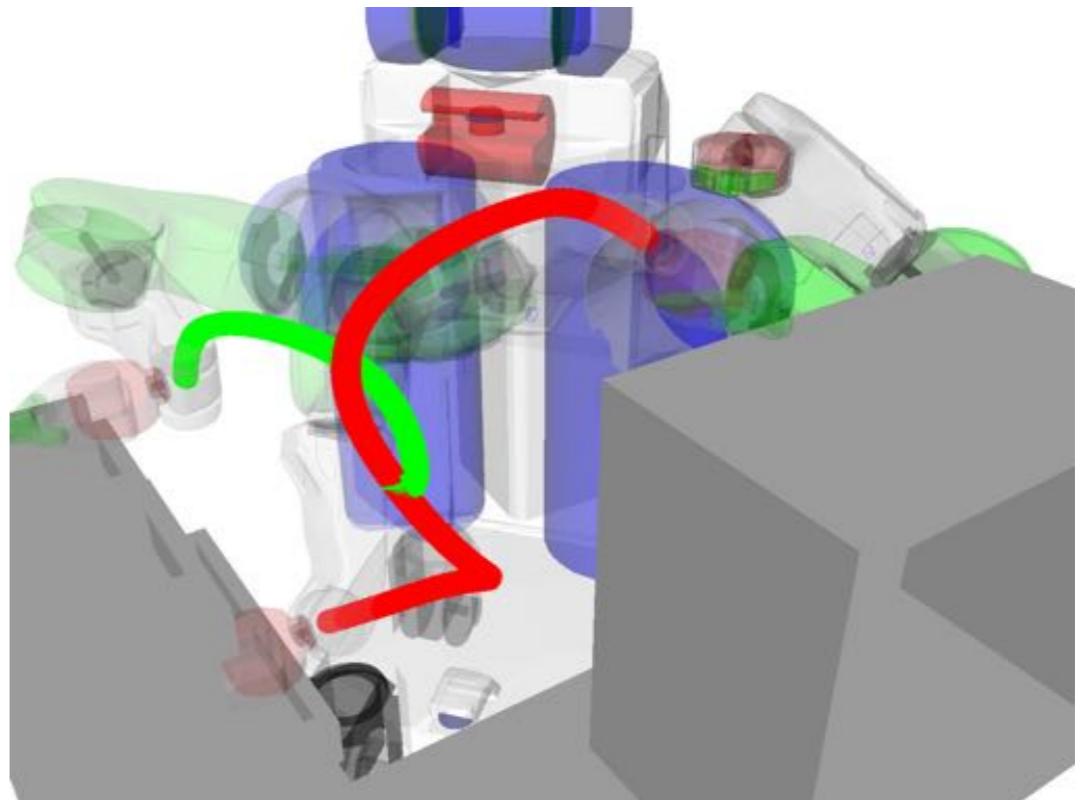
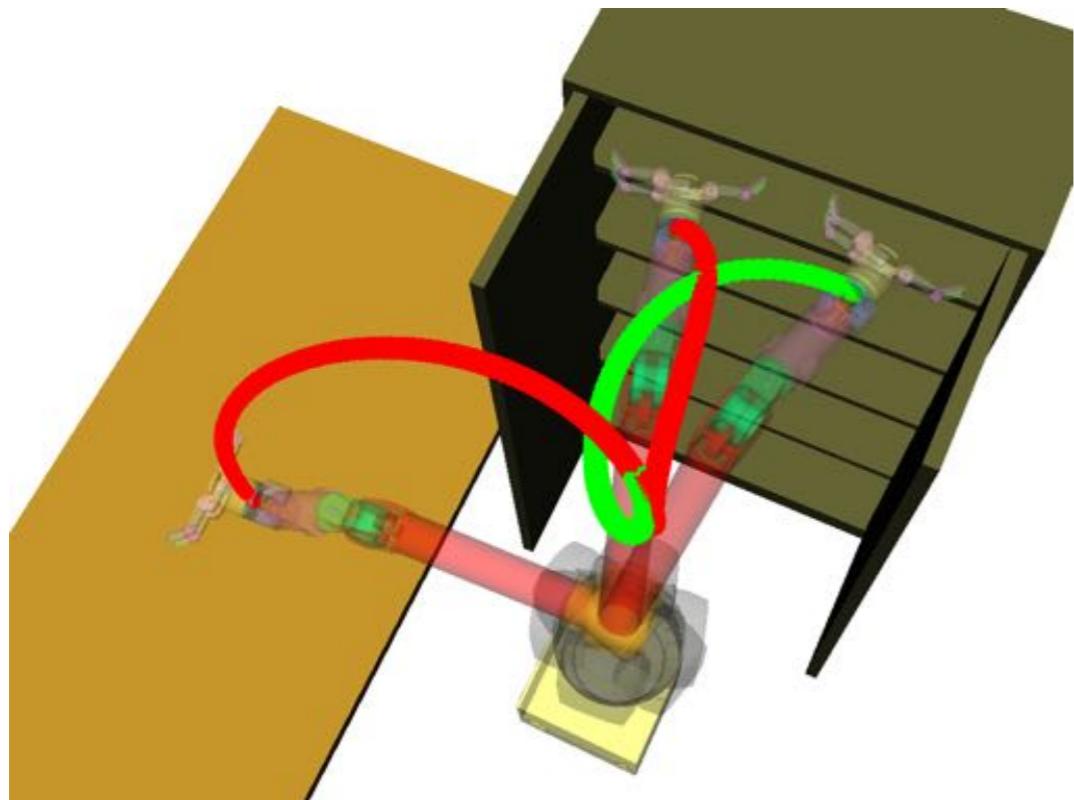


- Fuse inertial with visual and domain specific knowledge about legged robots.
- Forward kinematics (FK).
- Pre-integrated contact factors, which integrate foot contacts.

...and at Oxford for fusing visual odometry and quadruped state estimation [Wisth et al. '19-20]



Factor graphs turn out to be an excellent framework in which to innovate in motion planning [Mukadam et al. IJRR '18]



- Factors for:
 - Overall task-related objective
 - Gaussian Process motion prior factors
 - Obstacle avoidance, joint limits, etc...
- Fast incremental replanning using the Bayes Tree

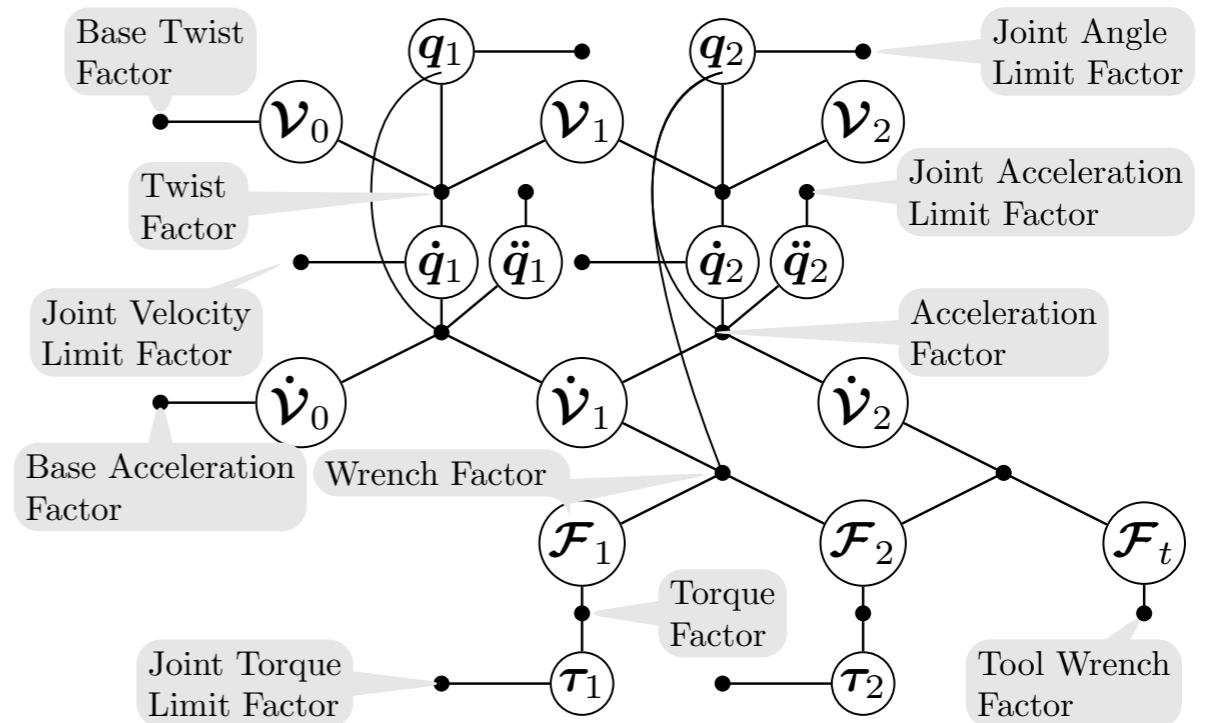
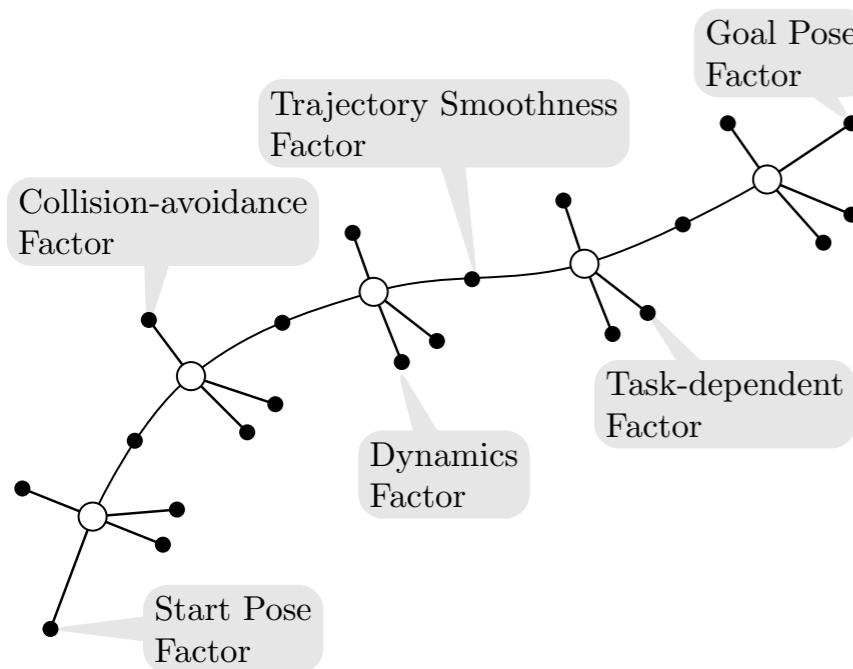
We used factor-graph-based motion planning to plan artistic action such as robot calligraphy [Wang et al. IROS '20]

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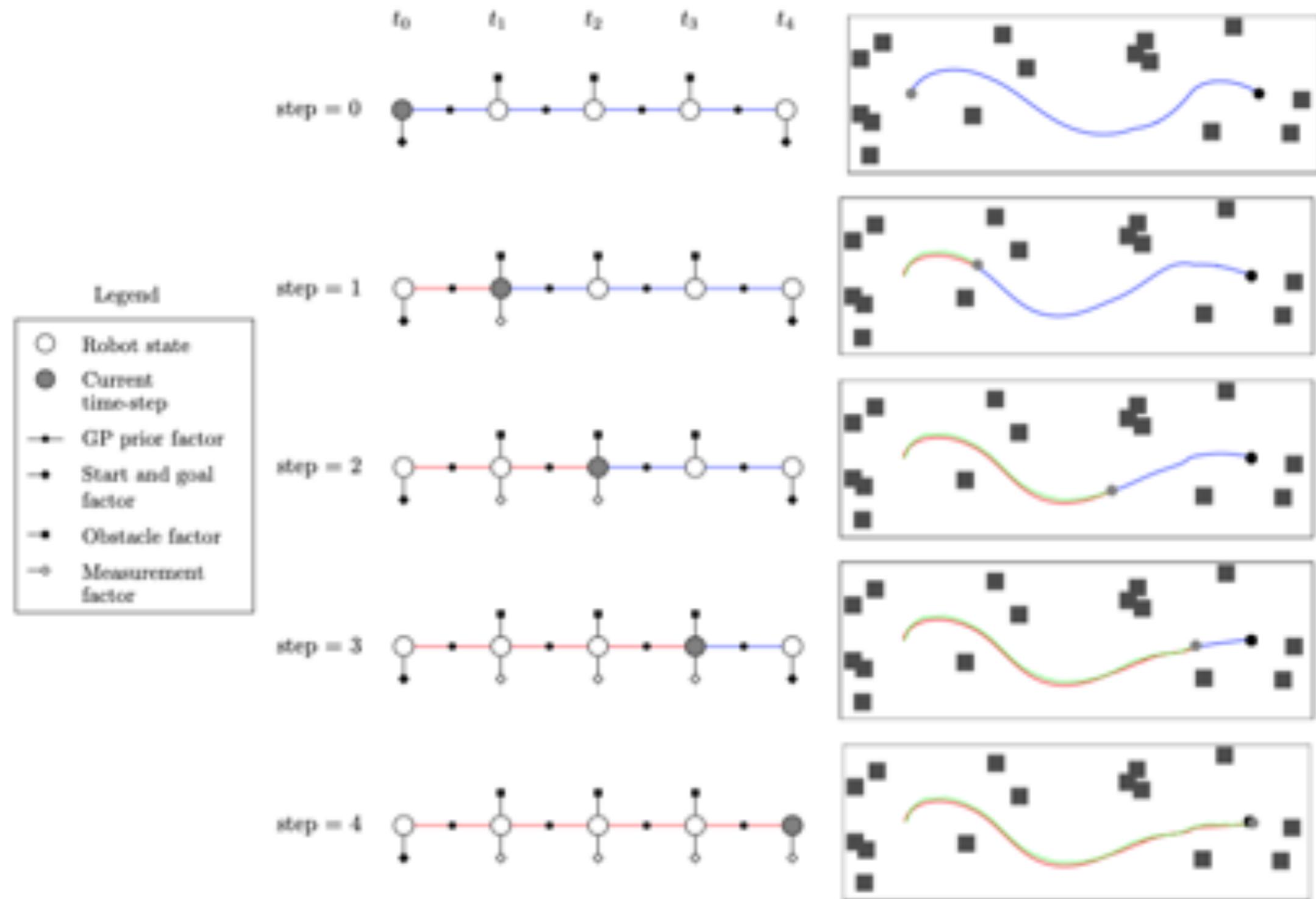
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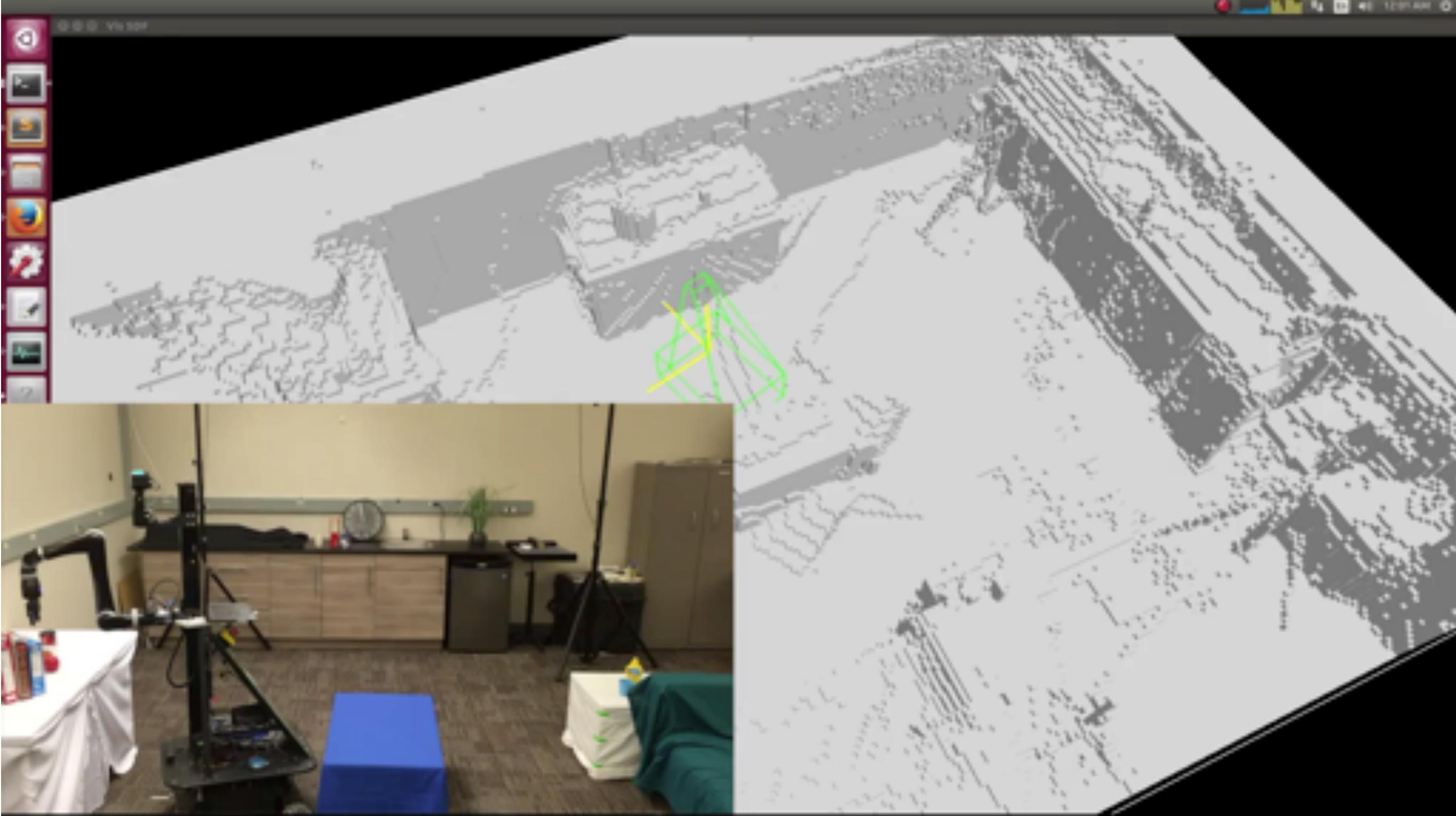
We used factor graphs to encode robot dynamics and applied to kino-dynamic motion planning [Xie et al. '20]



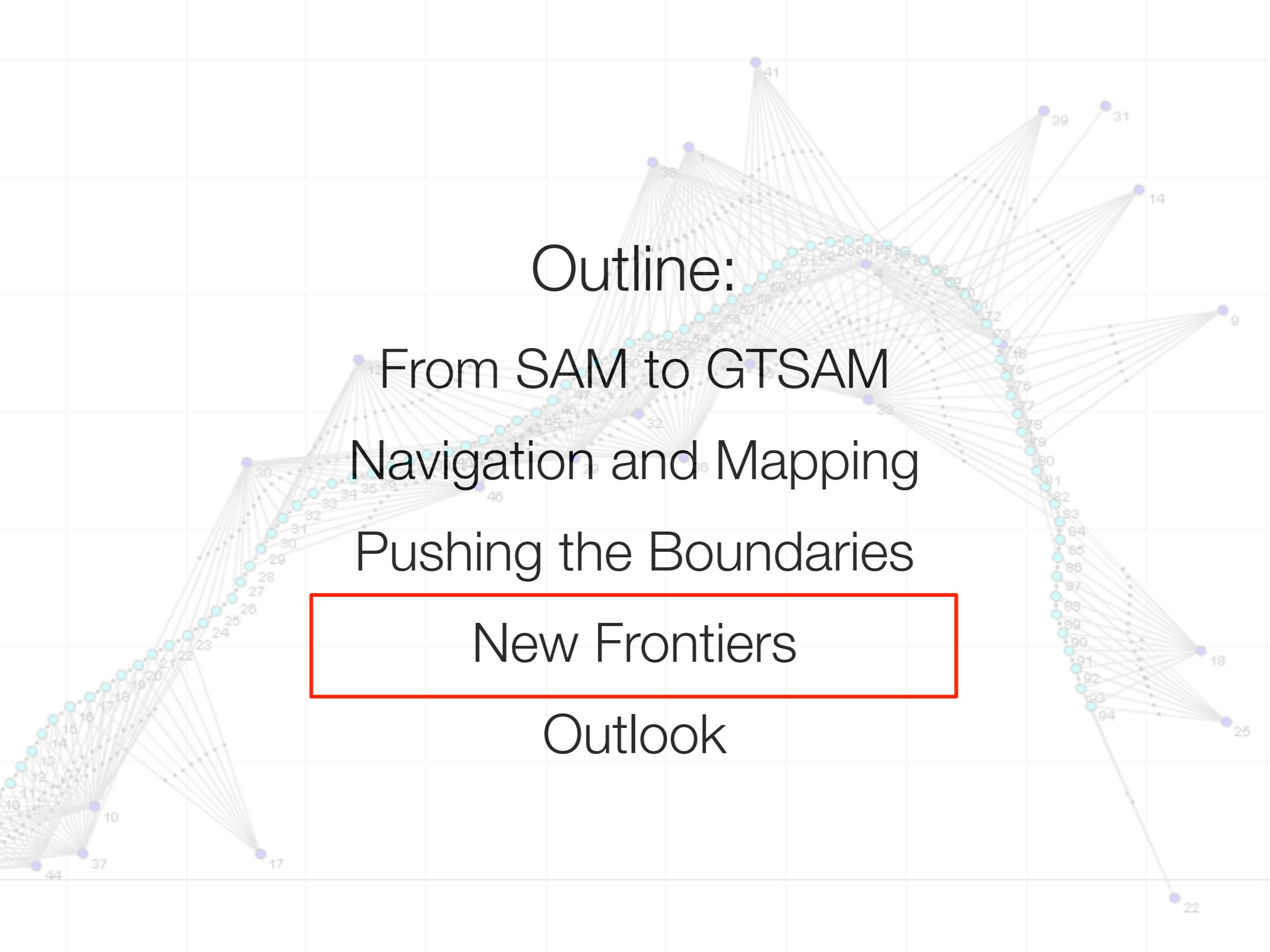
- Recipe:
 - Take Lynch & Park modern dynamics formulation
 - Turn into factor graph
 - Optimize with sparse (incremental) solvers

STEAP does both: simultaneous trajectory estimation & (motion) planning [Mukadam Euro'18]





Mustafa Mukadam, Jing Dong, Frank Dellaert & Byron Boots
Robotics: Science and Systems, 2017, Autonomous Robotics, 2018



Outline:

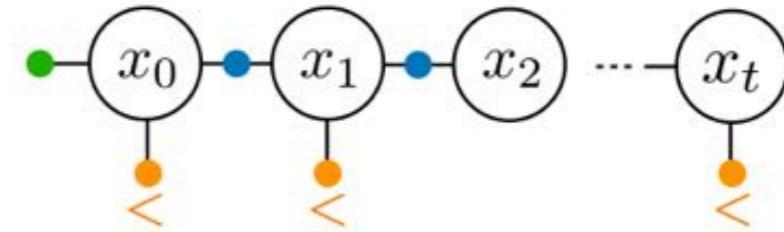
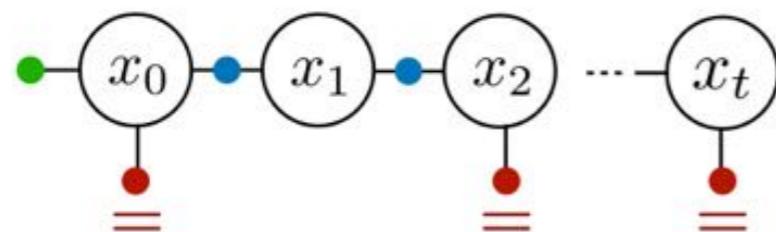
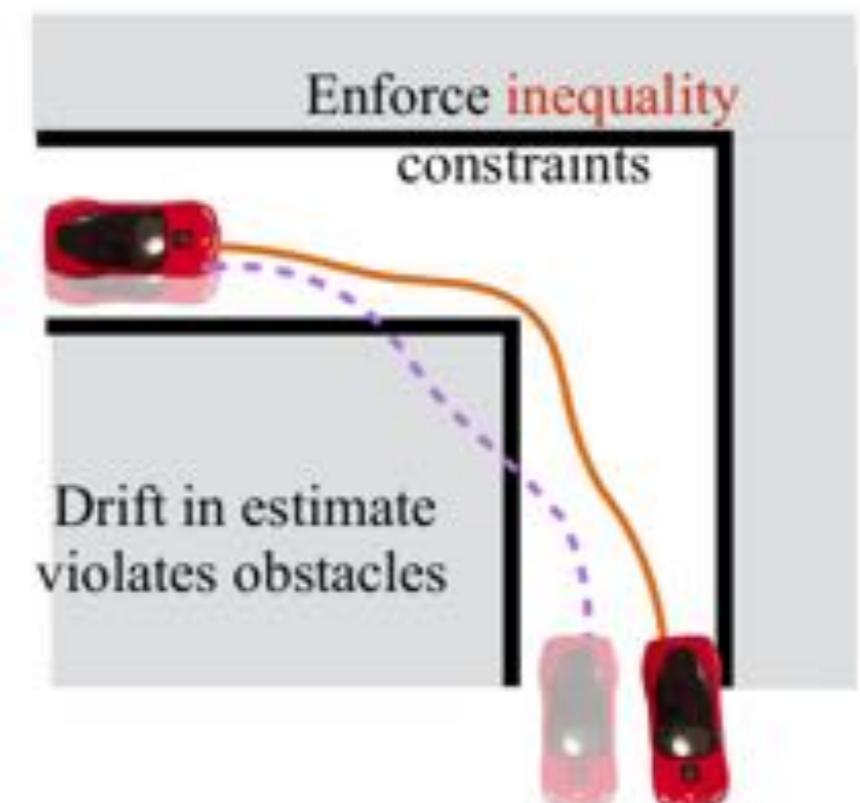
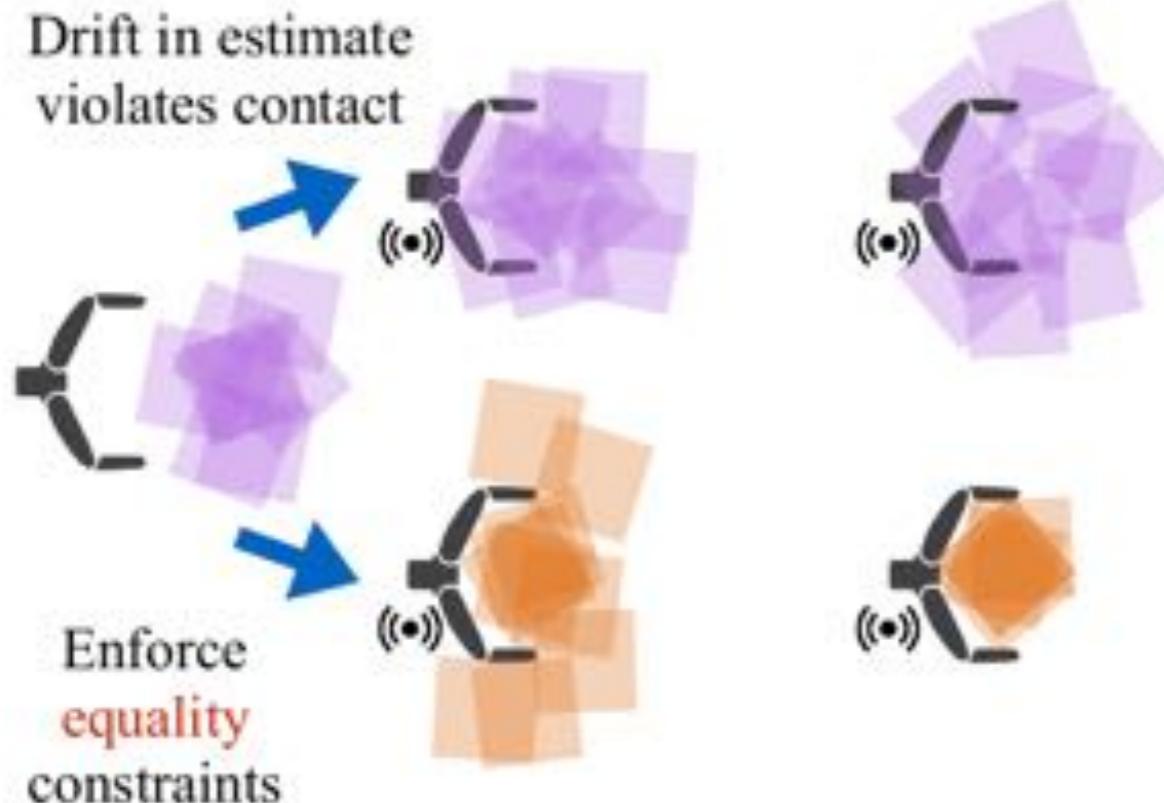
- From SAM to GTSAM
- Navigation and Mapping

Pushing the Boundaries

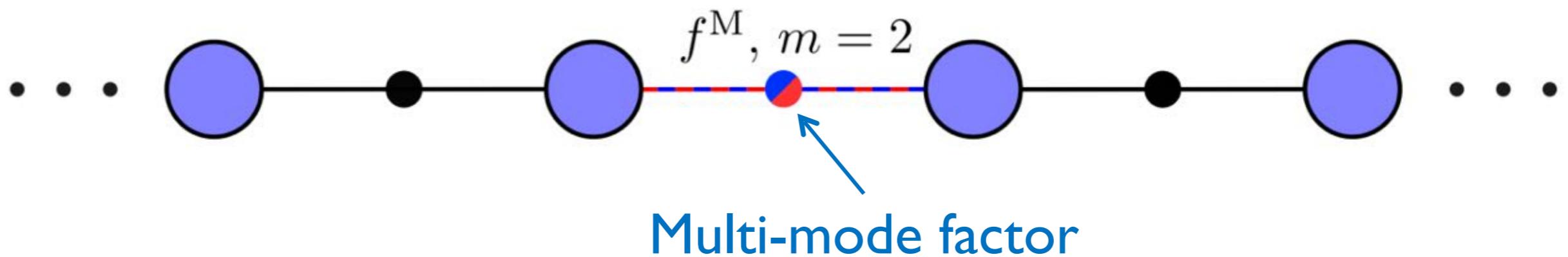
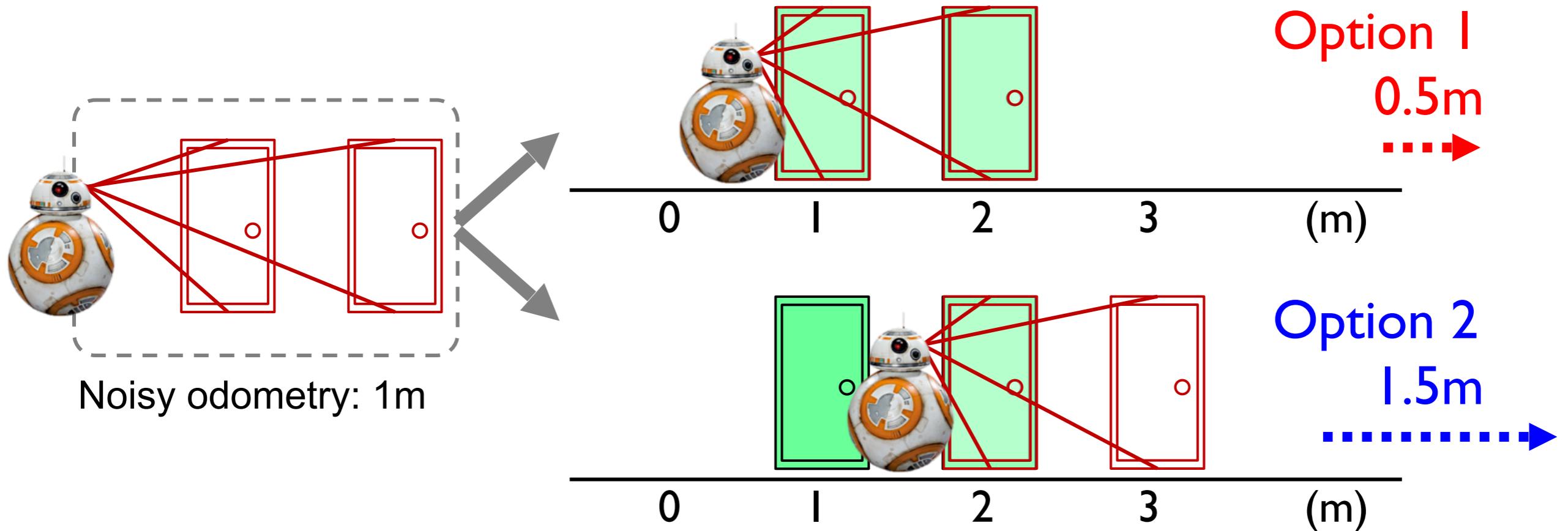
New Frontiers

Outlook

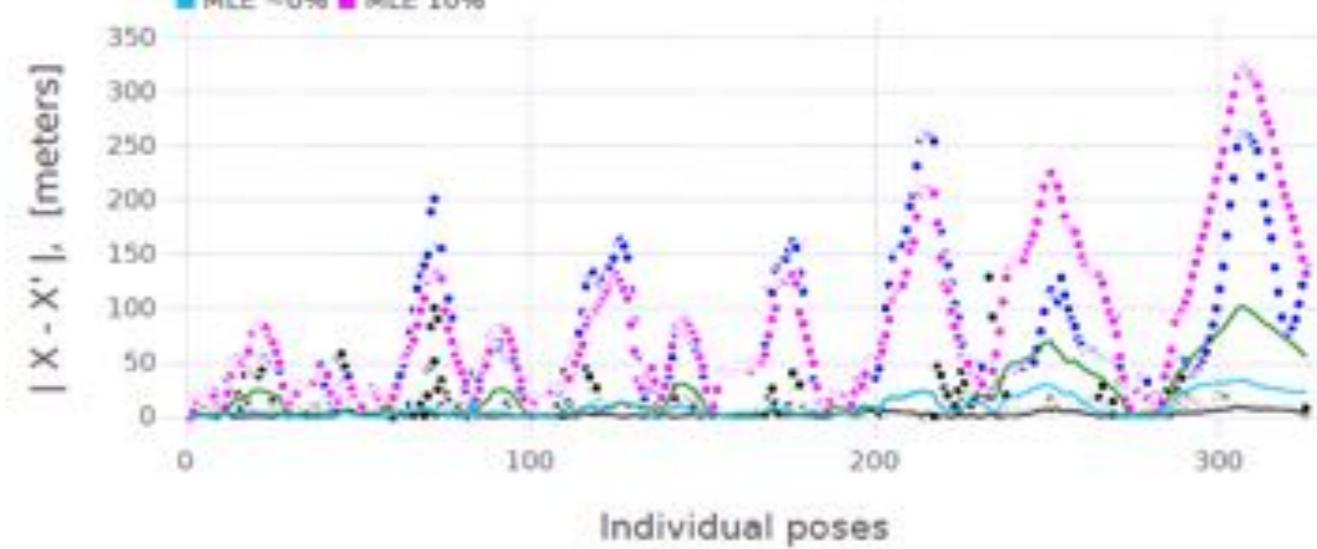
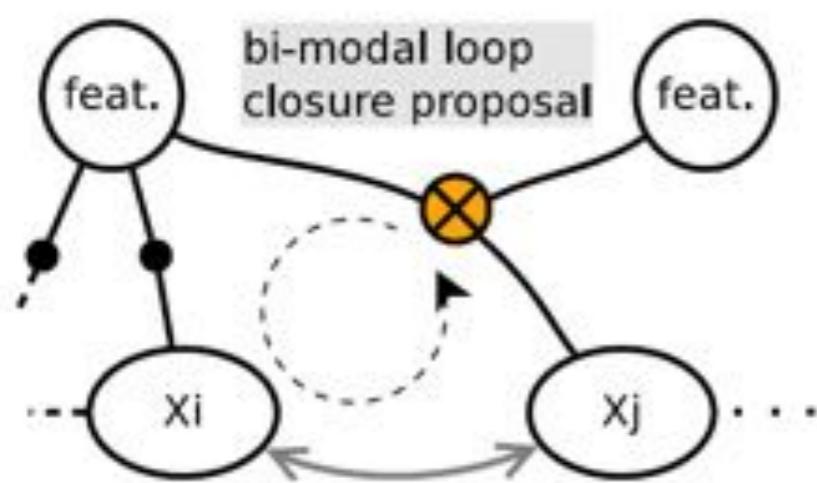
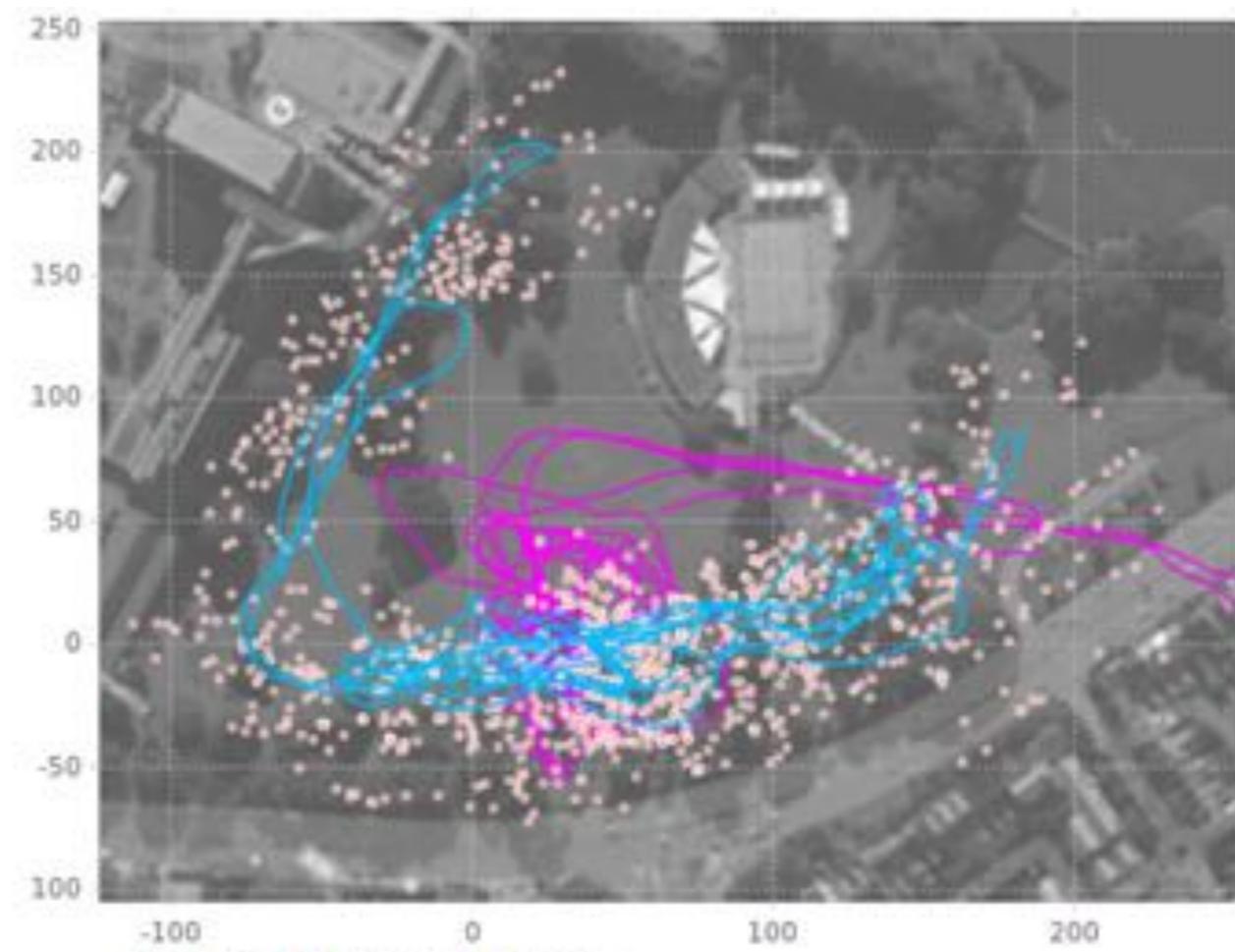
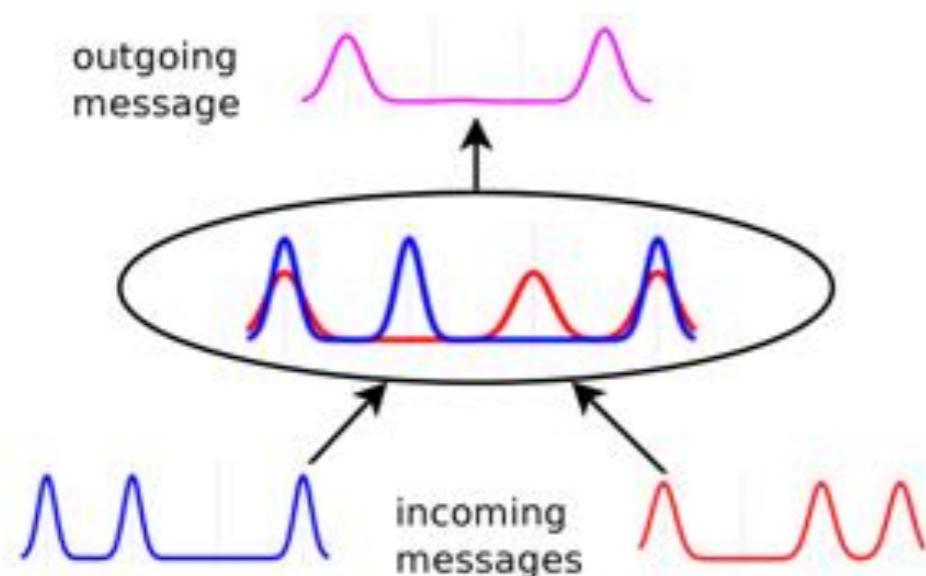
Hard constraints for Bayes tree significantly expand iSAM2 capabilities [Sodhi et al 2020]



Factor graphs support modeling ambiguous situations,
but what about inference?

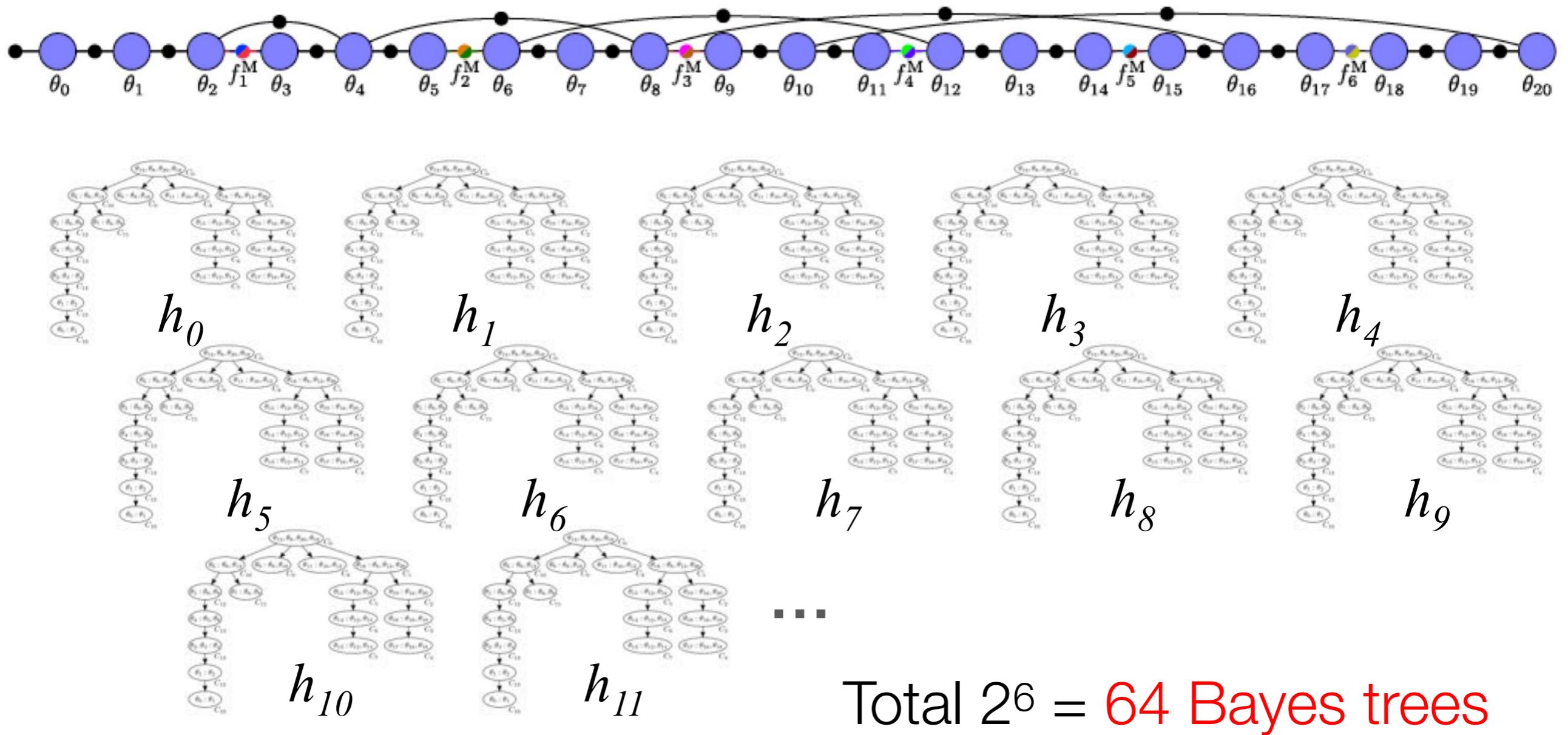


Non-Gaussian inference using nonparametric belief propagation on the Bayes tree [Fourie et al 2016]

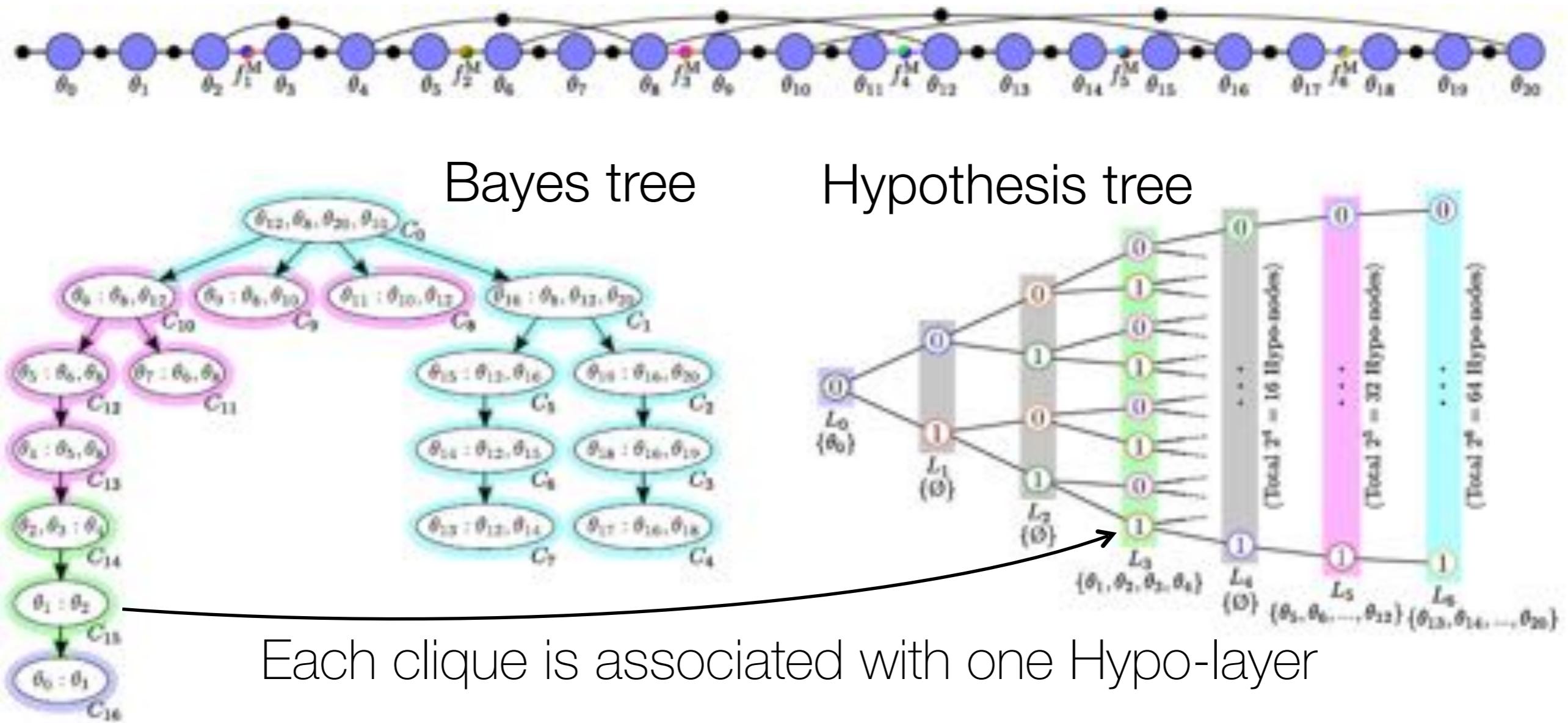


For Gaussian problems with ambiguity, multi-hypothesis tracking run multiple parallel instances of inference

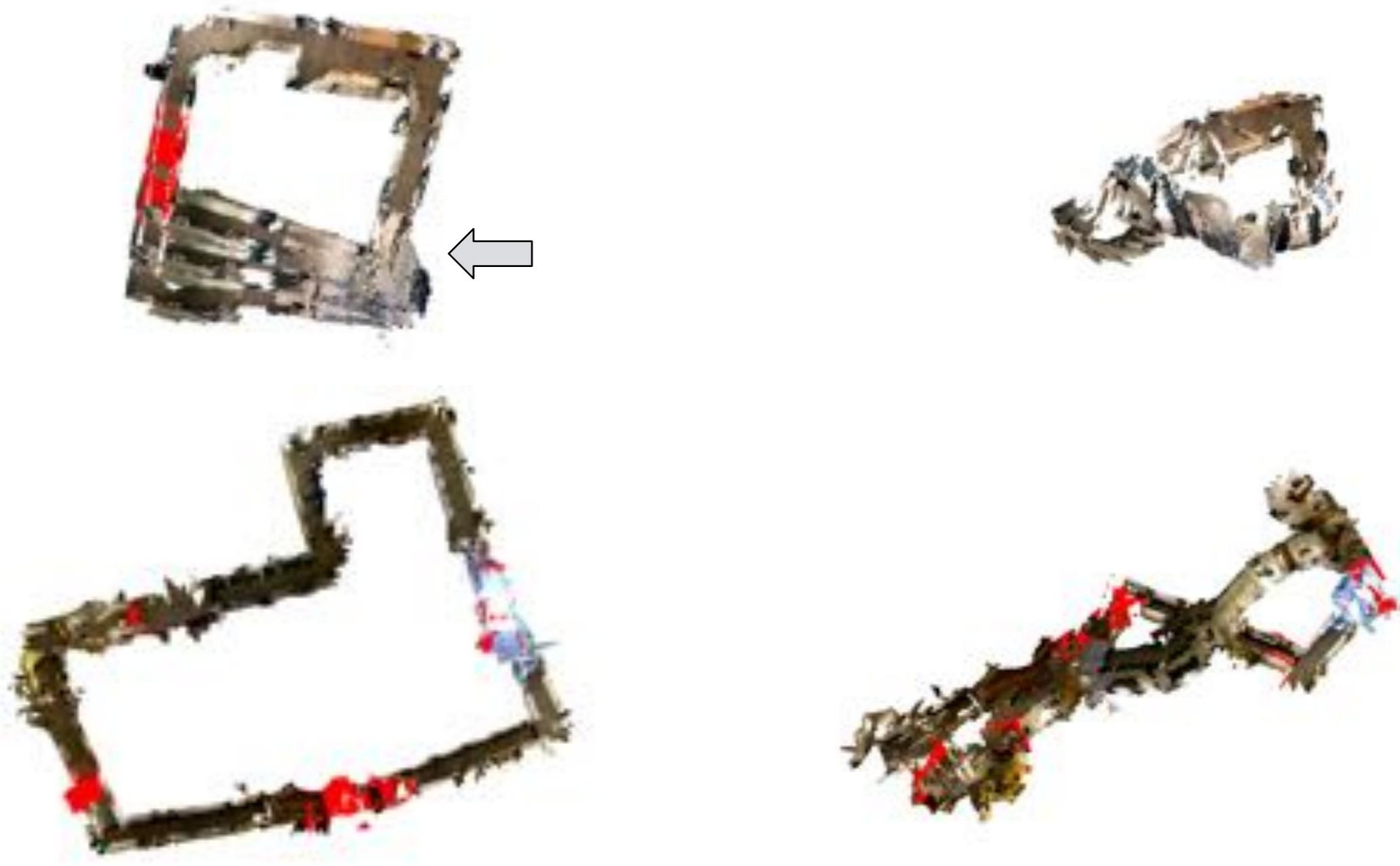
- One Bayes tree per hypothesis
- Exponential growth: Pruning



Multi-hypothesis Bayes tree saves computation by avoiding redundant computation [Hsiao et al 2019]



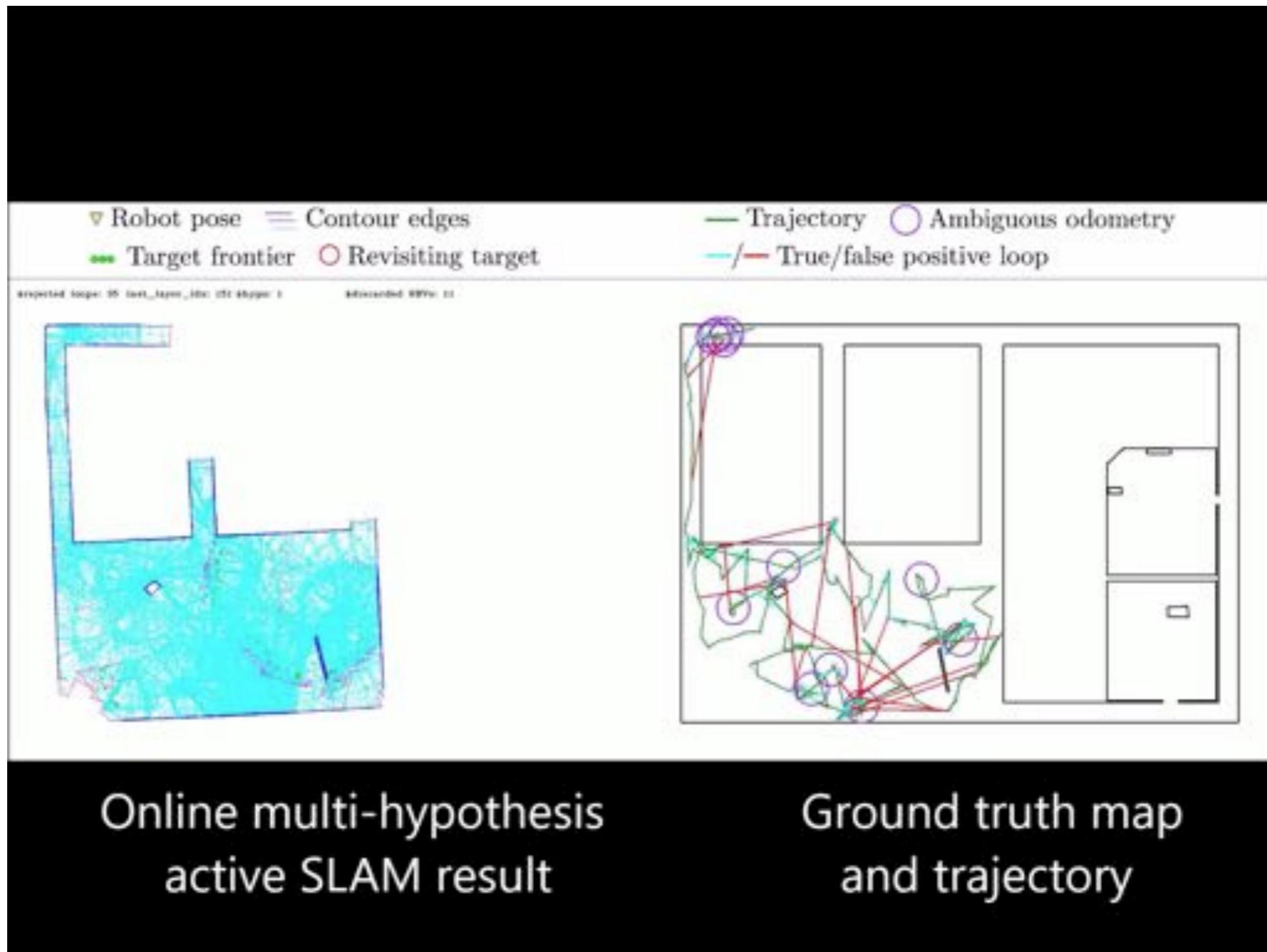
Multi-hypothesis RGB-D mapping avoids wrong decisions
and can provide multiple plausible solutions



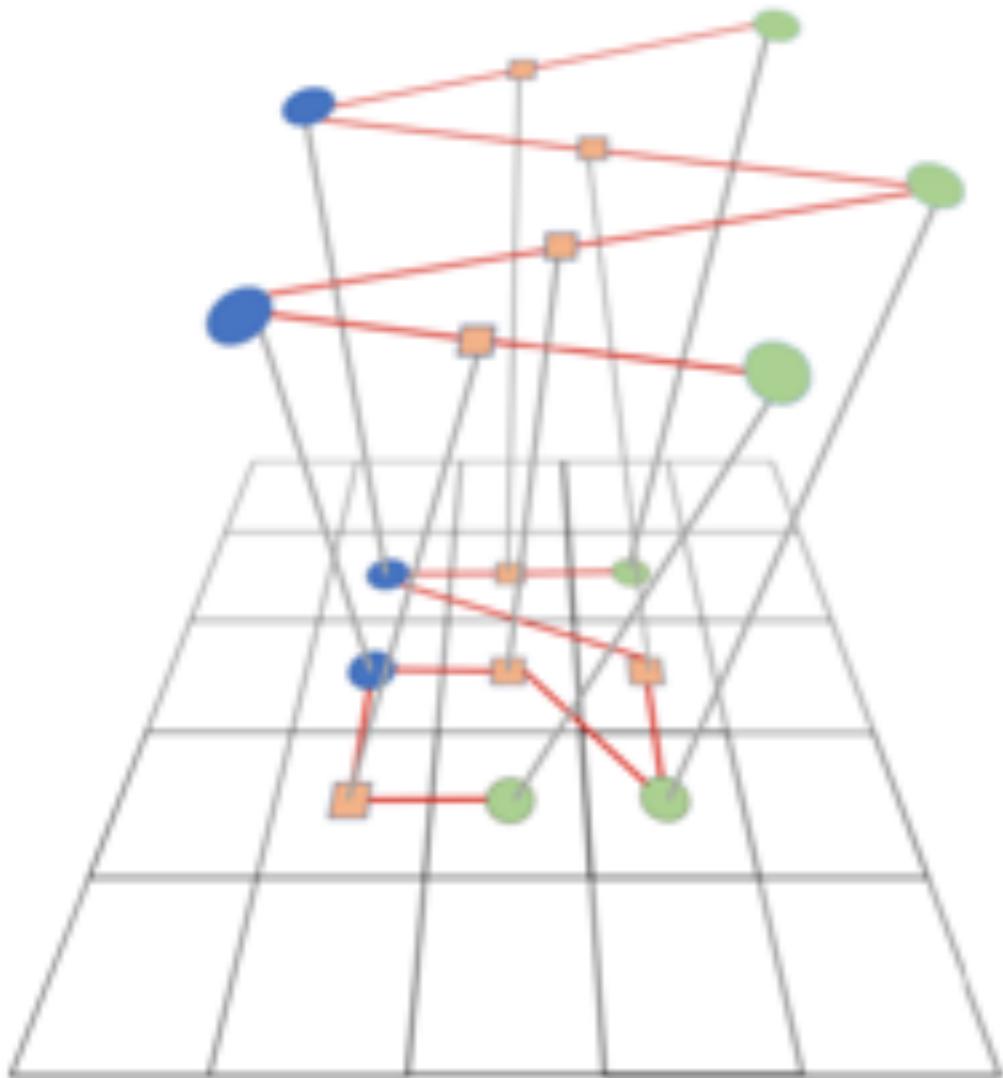
Multi-hypothesis

Single hypothesis

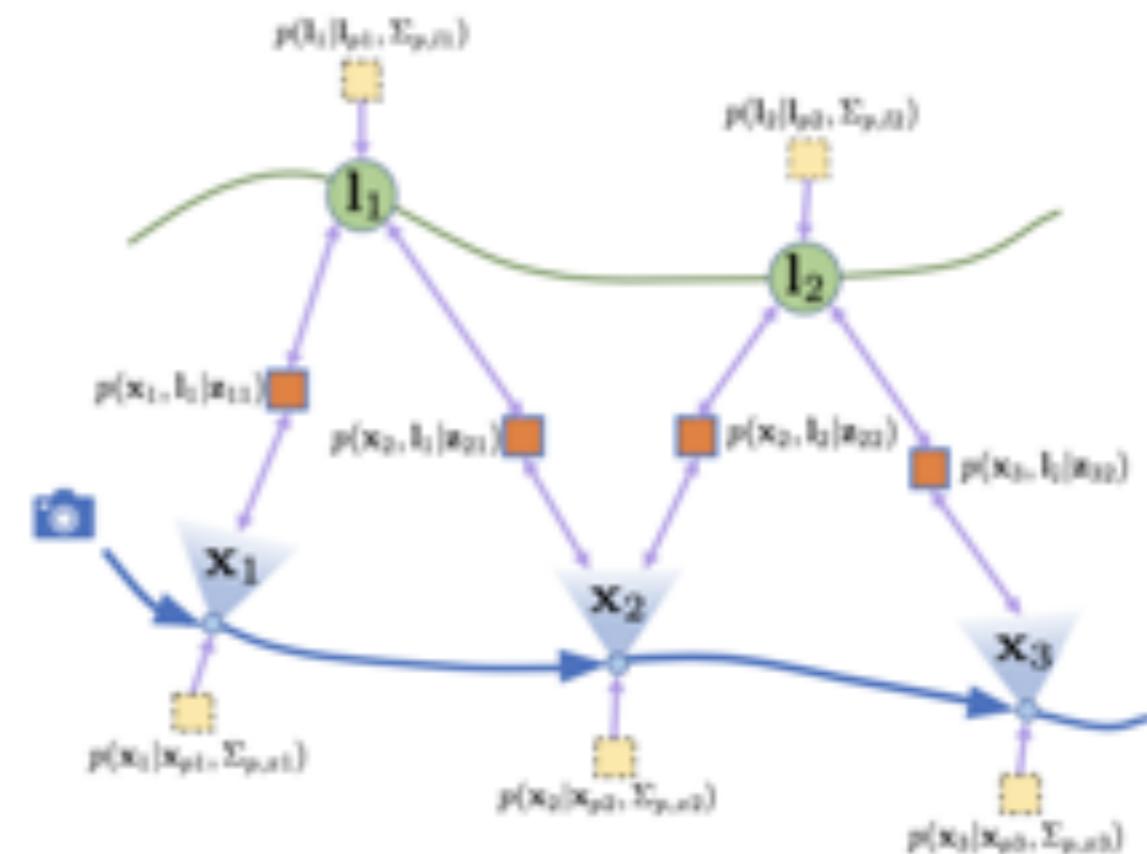
Knowledge about ambiguity is useful for planning including active SLAM [Hsiao et al 2020]



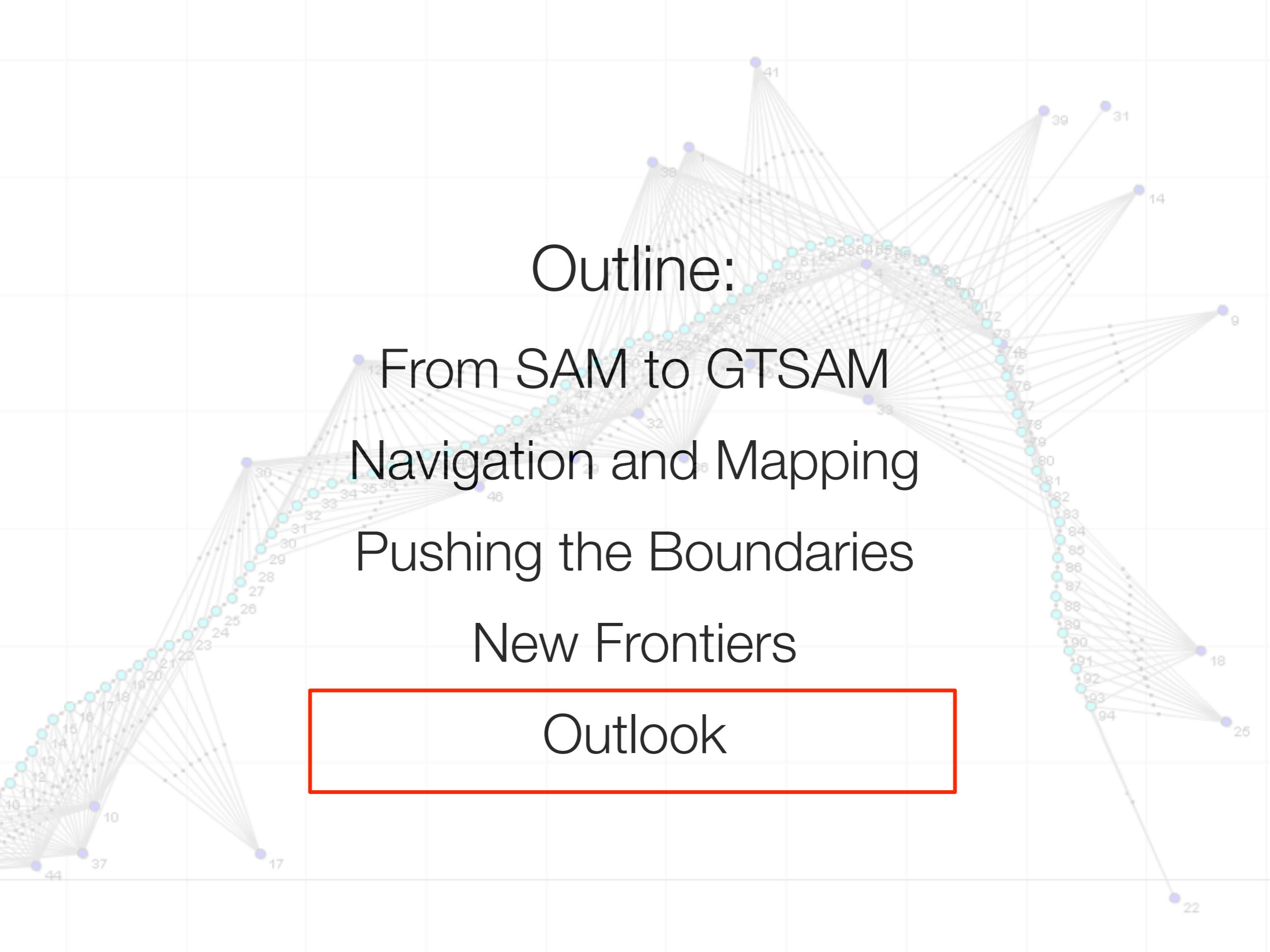
Is loopy belief propagation on factor graphs a better match to the hardware of the future [Davison et al 2020]?



GRAPHCORE



- Factor graphs on a graph processor
- Loopy belief propagation
- Well suited for parallel hardware
- CVPR: 30x faster SfM !

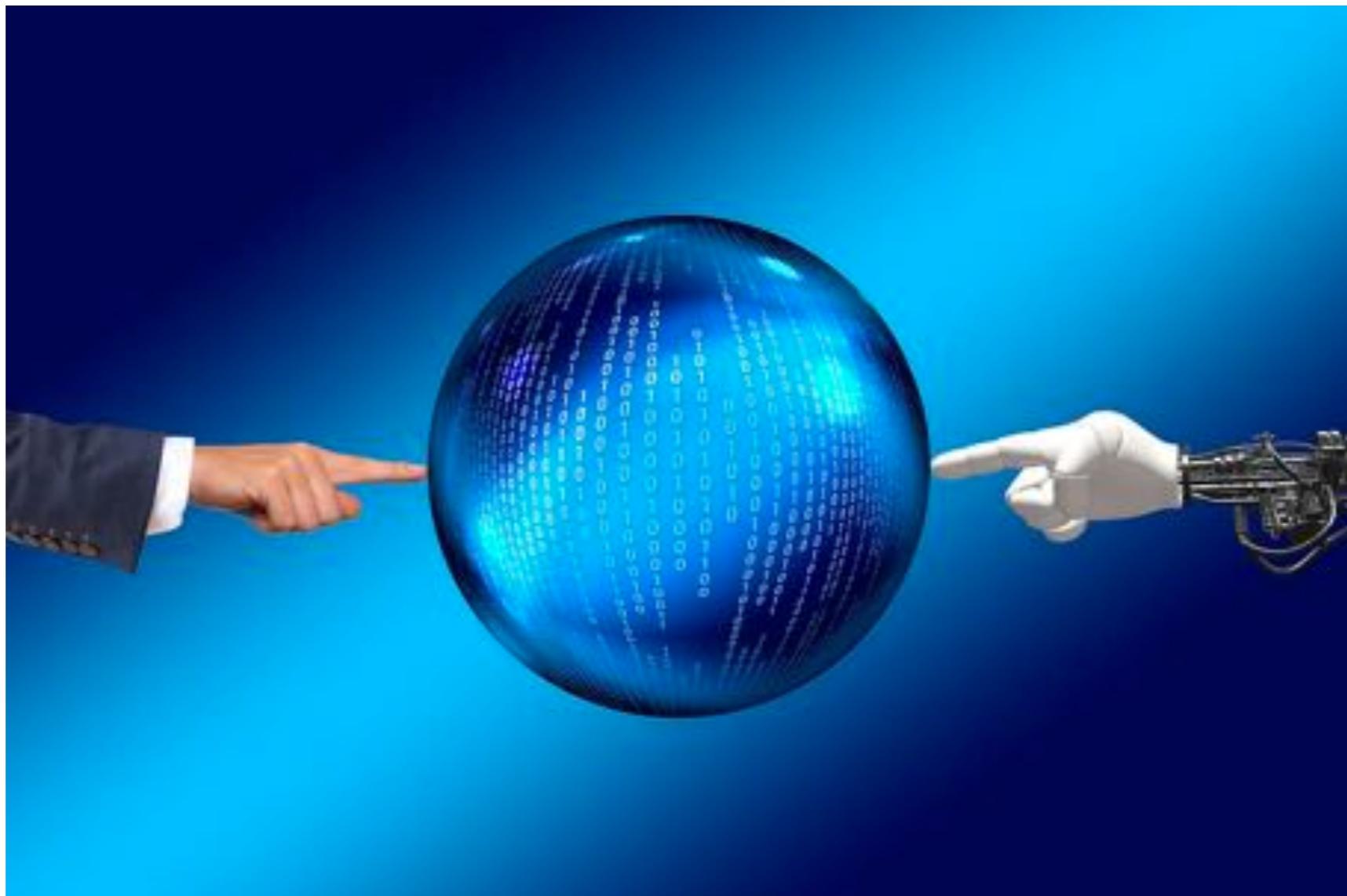


Outline:

- From SAM to GTSAM
- Navigation and Mapping
- Pushing the Boundaries
- New Frontiers

Outlook

Working on Square Root SAM 15 years ago we had no crystal ball, but we certainly imagined more robots around



The outlook for airborne autonomy is relatively positive, as the airspace environment is the easiest to conquer



- Planning state space is just 6D
- The airspace is relatively uncluttered
- Skydio has shown convincing results
- Efforts by NASA/DARPA to assure safe airspace
- Crashes of light-weight drones are probably non-lethal

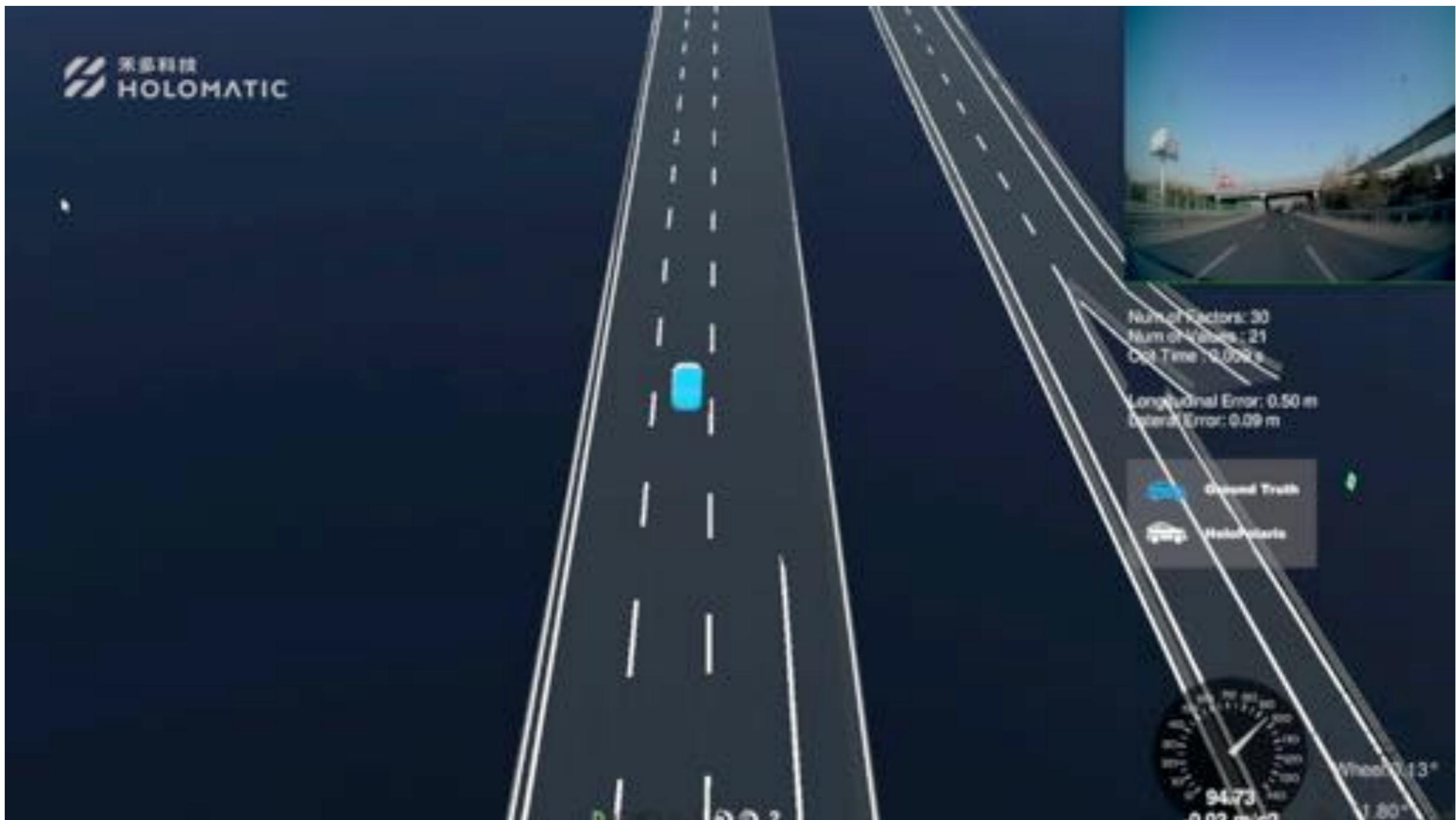
The timeline for self-driving cars is less clear, because of the “long tail”, bugs, and their possibly lethal consequences



Image by Andrej Karpathy, Tesla



Factor graphs and GTSAM have been used in several autonomous driving companies, e.g., Zoox, Holomatic



We started a non-profit initiative, [OpenSAM.org](#), to advance certifiable factor graphs for embedded applications

OpenSAM

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OpenSAM

Factor graphs for Sensor Fusion in Robotics.

Get Started >

The OpenSAM Foundation (OSF) is a non-profit organization that seeks to advance the use of factor graphs for sensor fusion in robotics and computer vision applications.

- GTSAM for back-office and Research
- OpenSAM: reference implementation for embedded systems
 - Collaboration with Holomatic and other companies...
 - Goal: fast, **certifiable** code for a subset of GTSAM functionality
 - Looking for industry memberships/collaborations!

GTSAM is used by



The most difficult environment to deploy robots in is the home, because of perception/manipulation/HRI



- Perception is very challenging due to clutter, occlusion...
- Manipulation in those environments is yet unsolved
- Expectations of people are mismatched

Our new effort, SwiftFusion, is focused on combining estimation and optimal control with the data-driven revolution

- Google collaboration: **SwiftFusion**
 - Seamless integration with TensorFlow
 - Fast, automatically differentiated factors
 - Sparse factor graphs and dense tensor processing in one language
- Which will enable:
 - Combine probabilistic estimation and optimal control with data-driven factors
- Collaborators wanted, DM me @fdellaert



<https://github.com/borglab/SwiftFusion>

All of this was only possible by amazing collaborations over the years, in academia, on github.com, and industry



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Questions?

