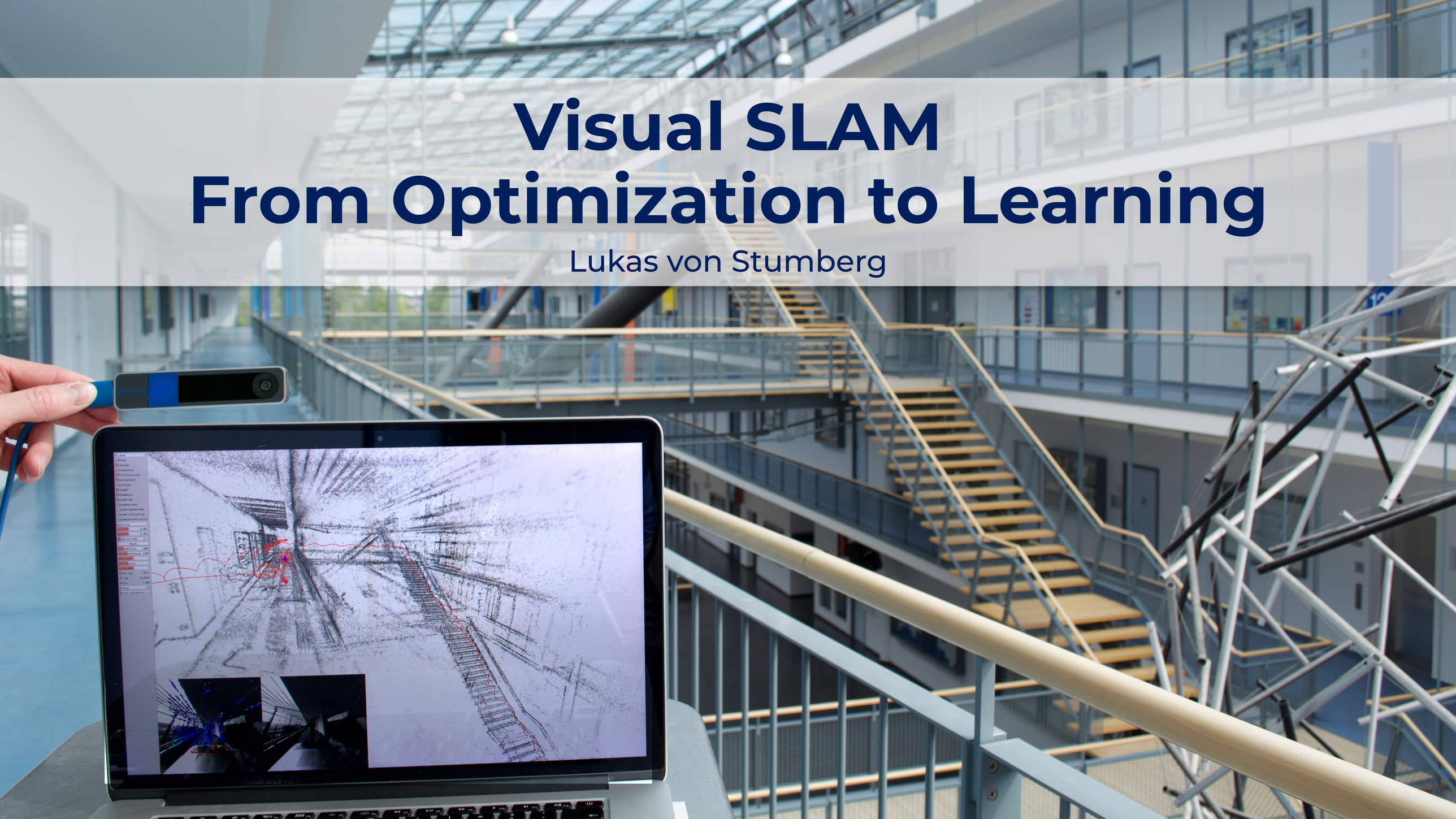
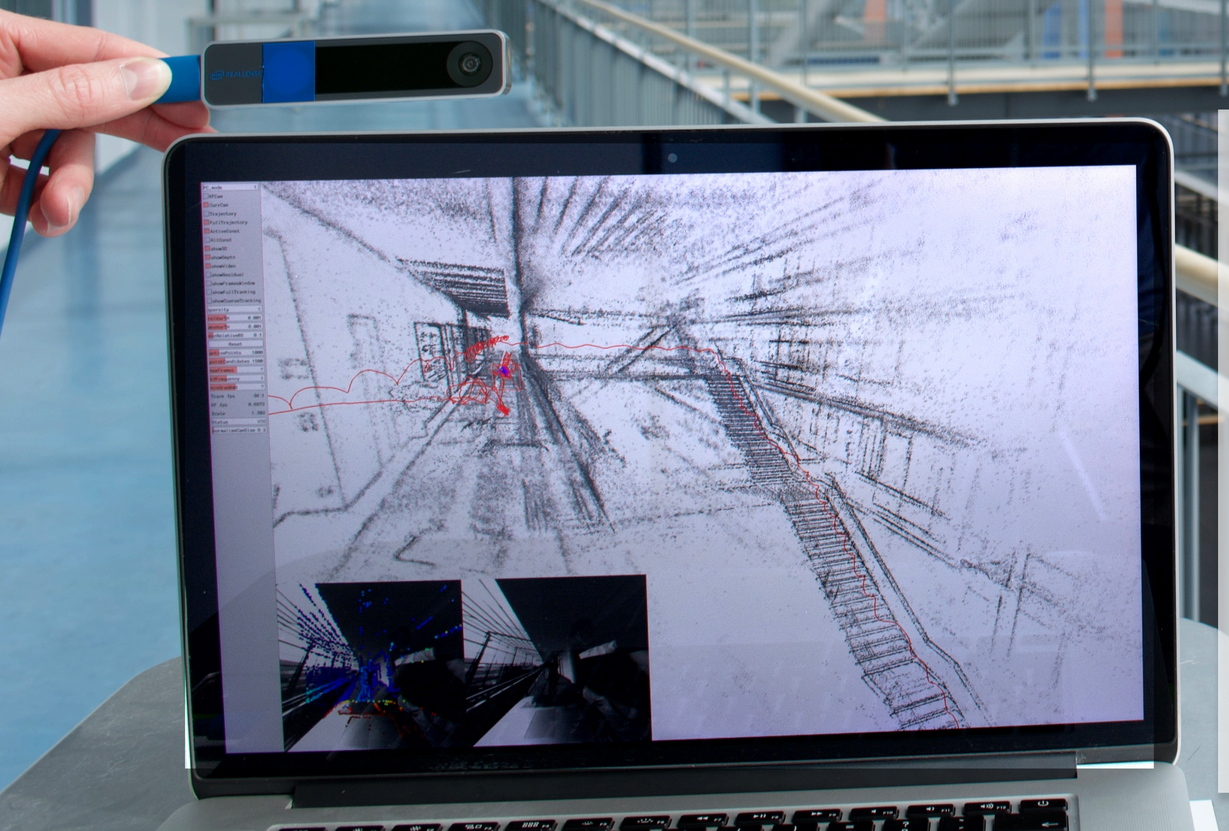
Visual SLAM
From Optimization to Learning

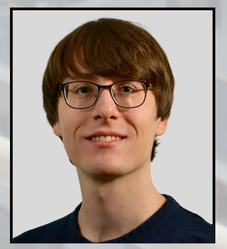
Lukas von Stumberg



Visual SLAM
From Optimization to Learning

Lukas von Stumberg





Lukas von Stumberg

Nan Yang

Patrick Wenzel

Felix Wimbauer

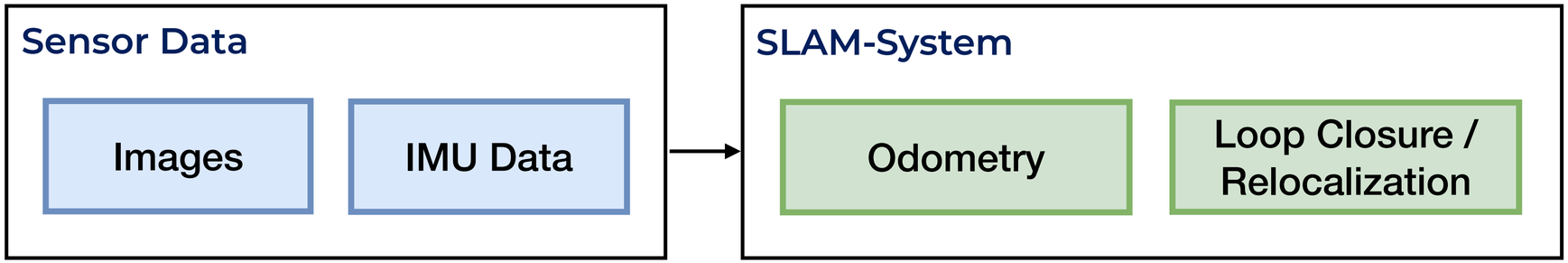
Qadeer Khan

Rui Wang

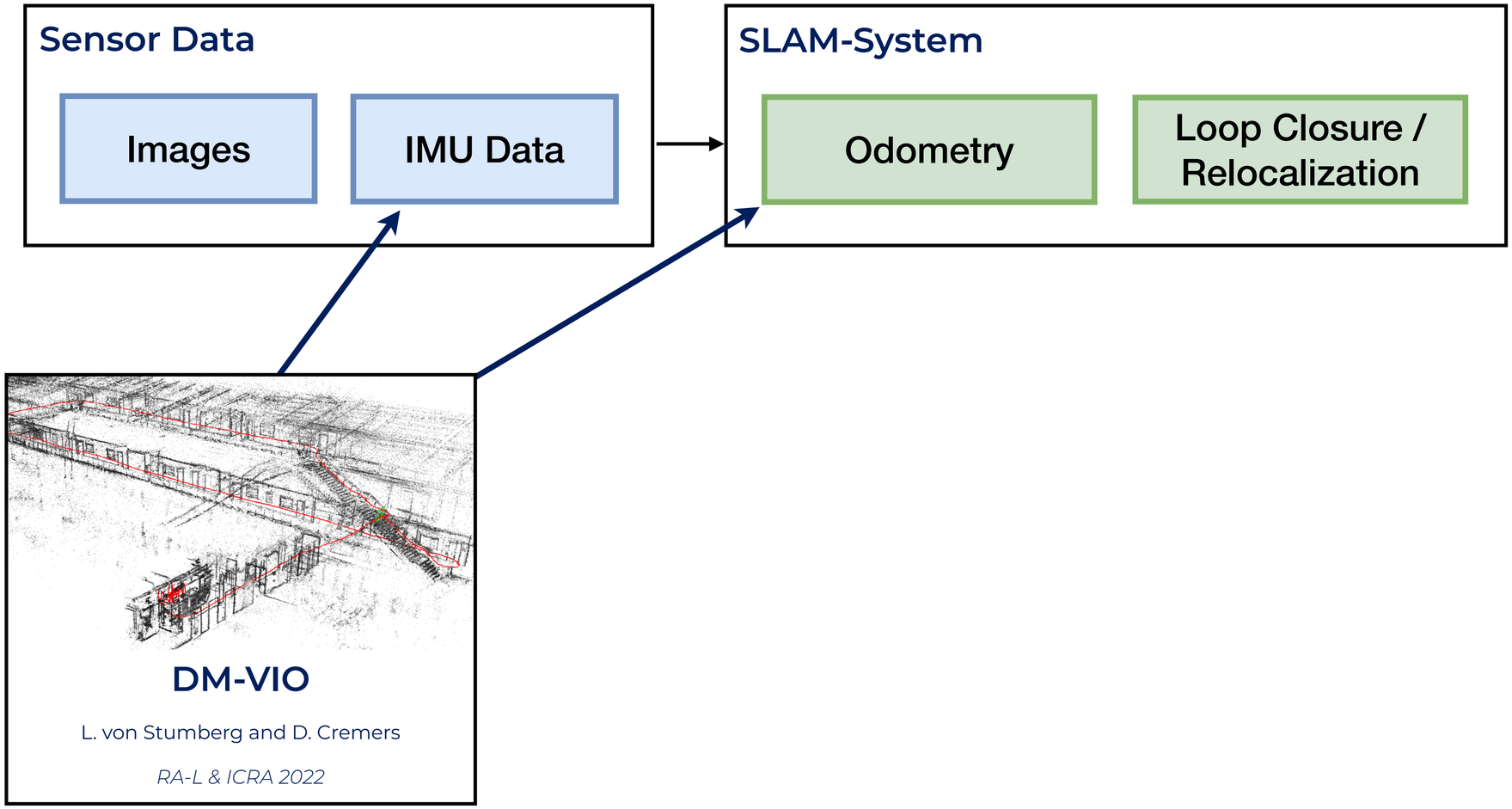
Niclas Zeller

Daniel Cremers

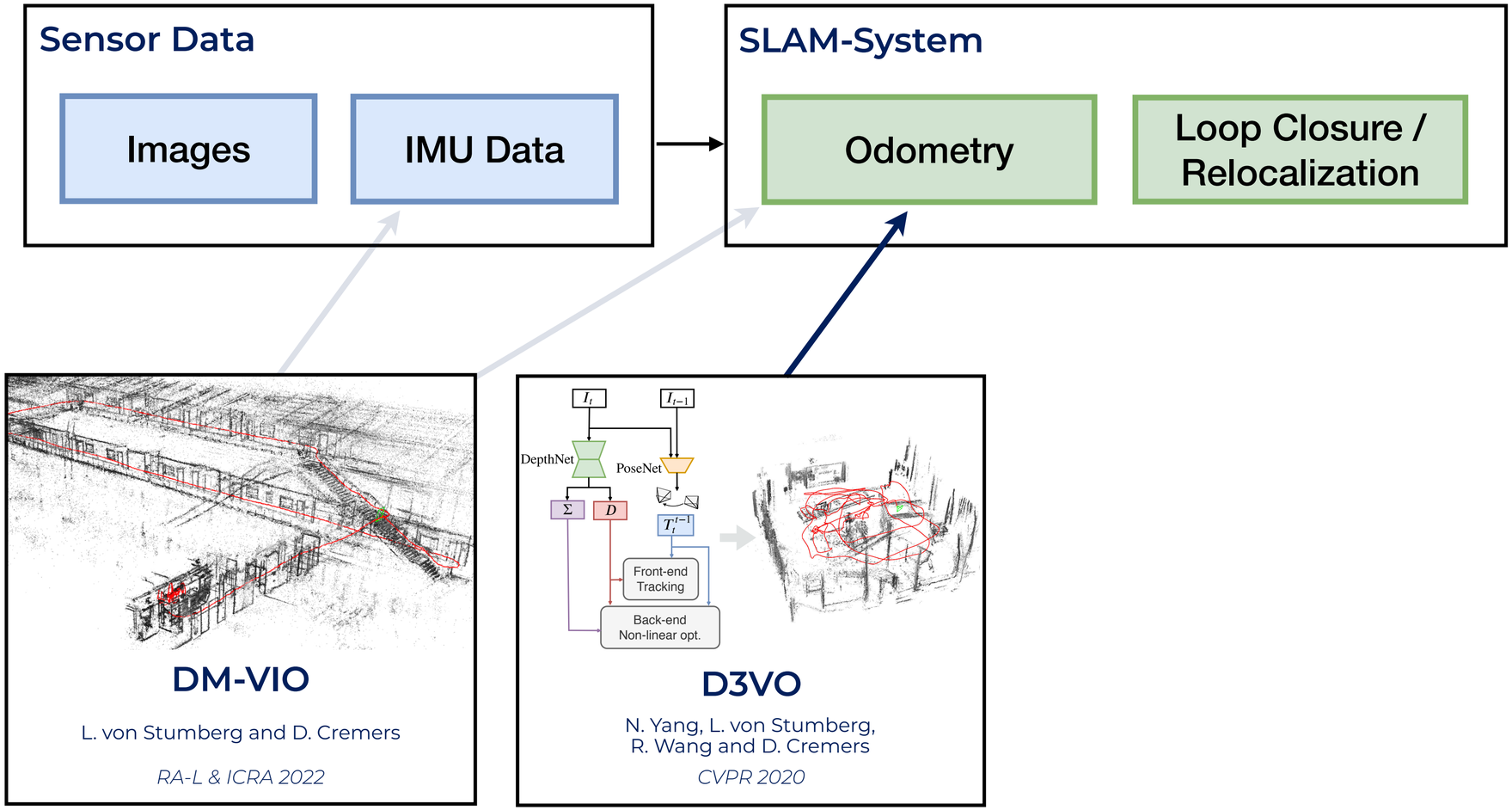
Visual SLAM
From Optimization to Learning



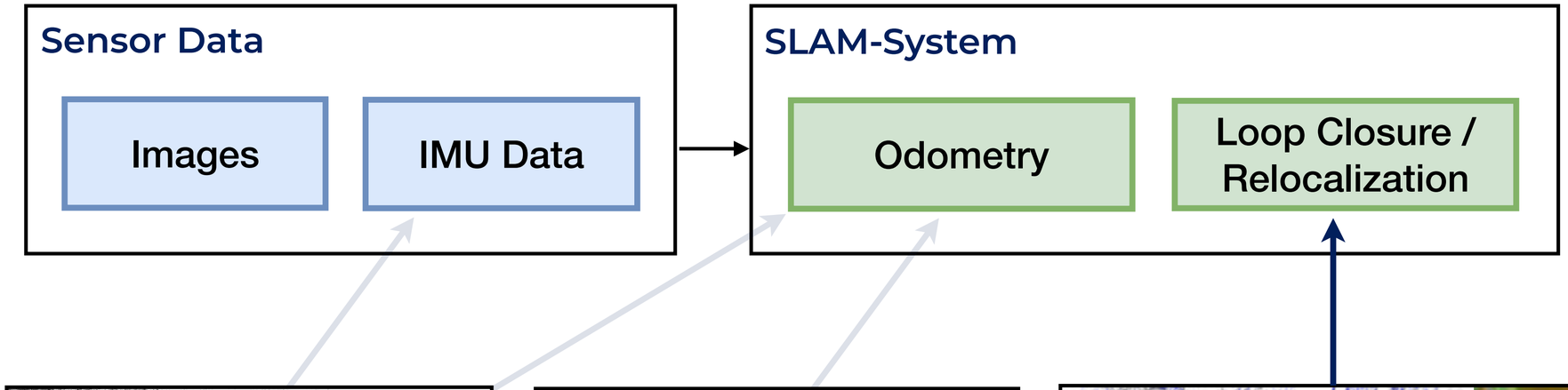
Visual SLAM
From Optimization to Learning

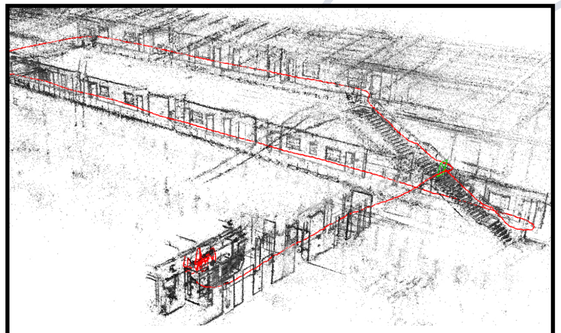


Visual SLAM
From Optimization to Learning



Visual SLAM
From Optimization to Learning

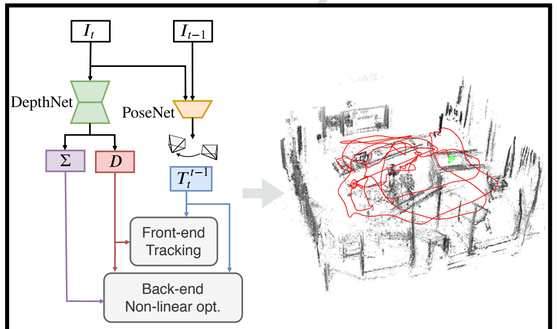




DM-VIO

L. von Stumberg and D. Cremers

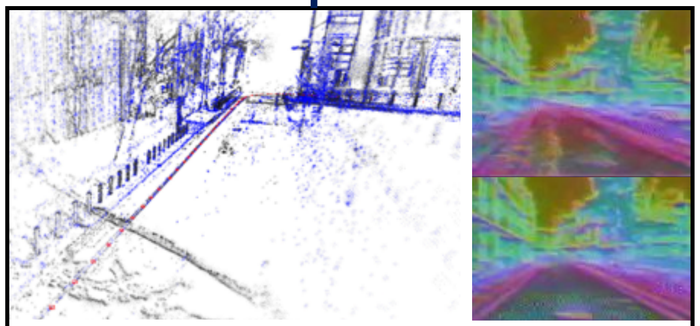
RA-L & ICRA 2022



D3VO

N. Yang, L. von Stumberg, R. Wang and D. Cremers

CVPR 2020



GN-Net

L. von Stumberg, P. Wenzel, Q. Khan, D. Cremers

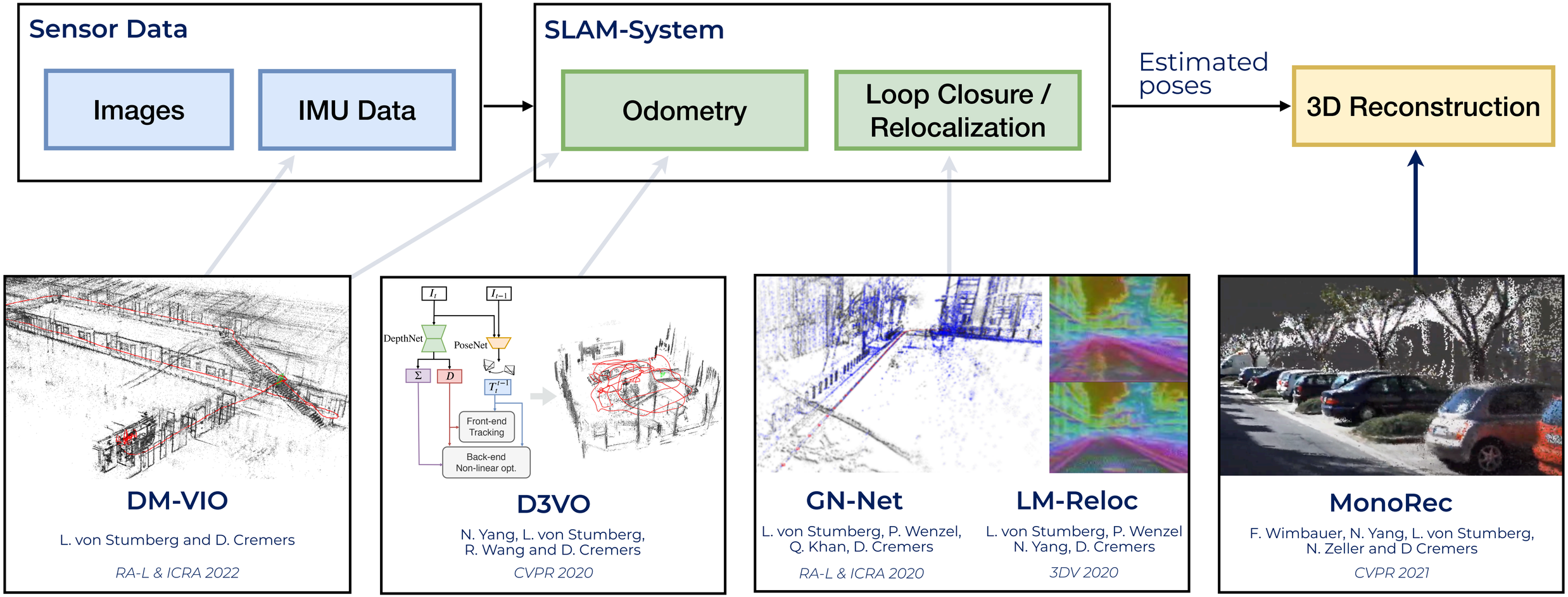
RA-L & ICRA 2020

LM-Reloc

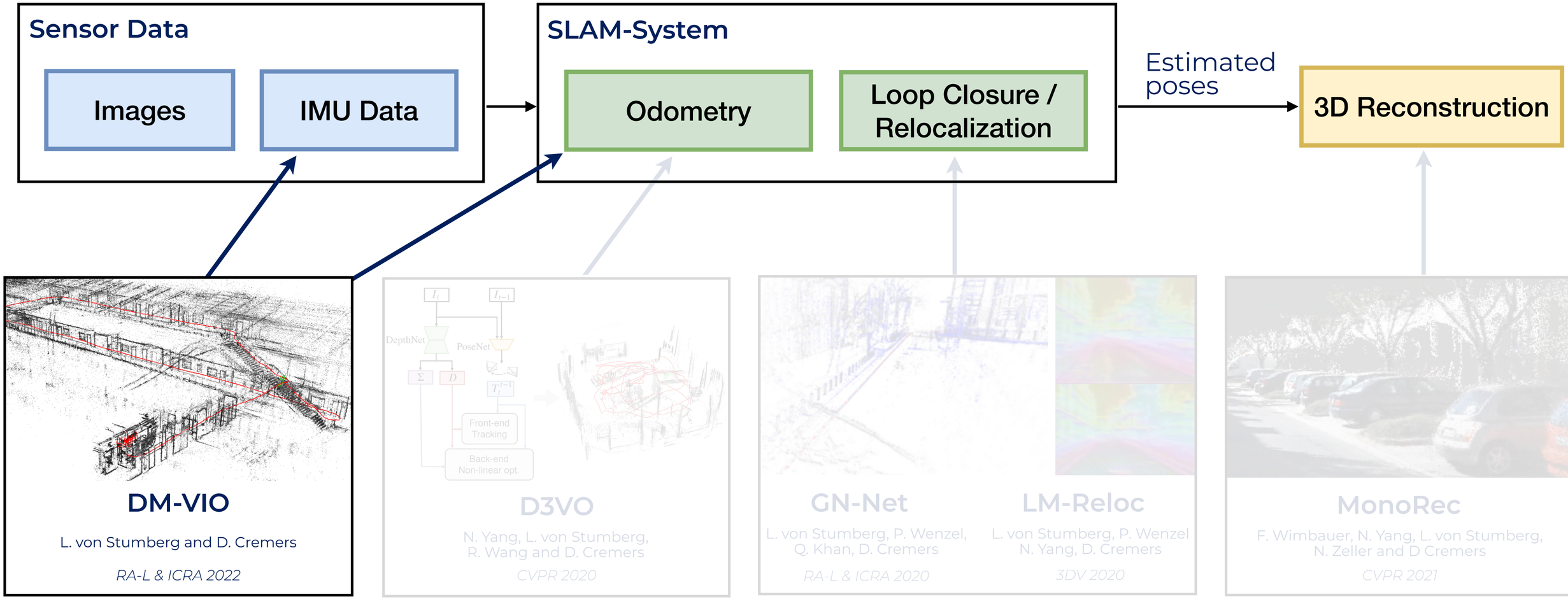
L. von Stumberg, P. Wenzel N. Yang, D. Cremers

3DV 2020

Visual SLAM
From Optimization to Learning



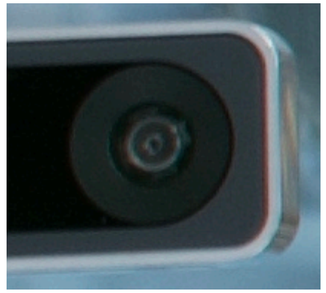
Visual SLAM
From Optimization to Learning



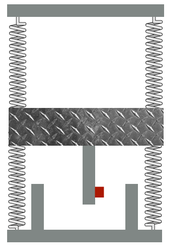
Visual-Inertial Odometry

Track motion of the system using

Camera



IMU (Inertial Measurement Unit)

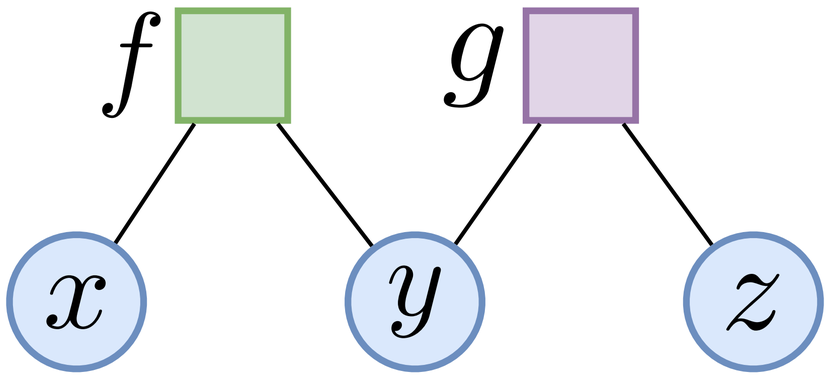


accelerometer + gyroscope

$$E = E_{\text{visual}} + E_{\text{inertial}}$$

Related work:
A. Mourikis and S. Roumeliotis. A multi-state constraint Kalman filter for vision-aided inertial navigation. ICRA 2007

Factor graphs



- **Energy function:**

$$E = f(x, y) + g(y, z)$$

Bundle Adjustment

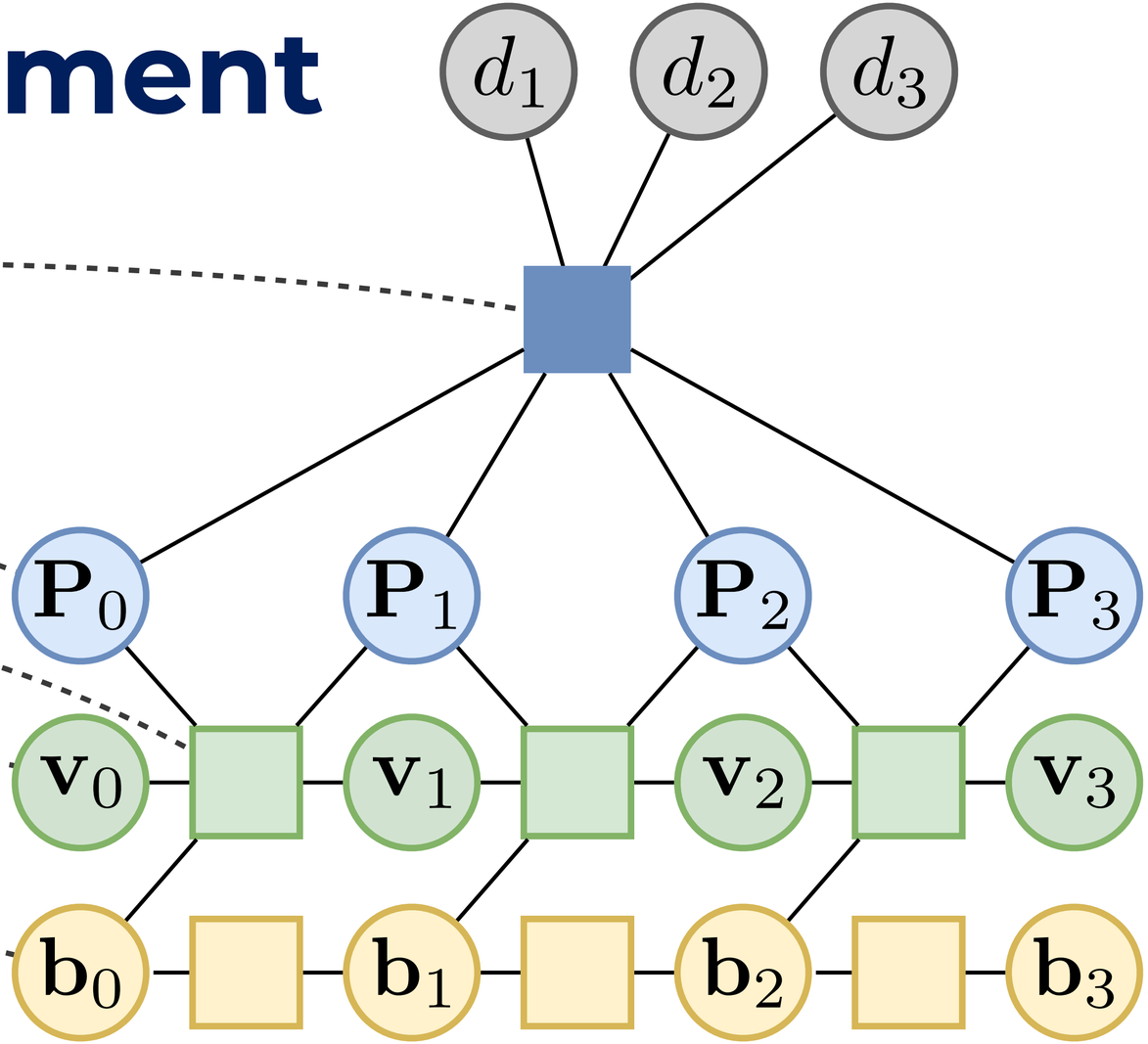
photometric error

poses

inertial error

velocities

biases



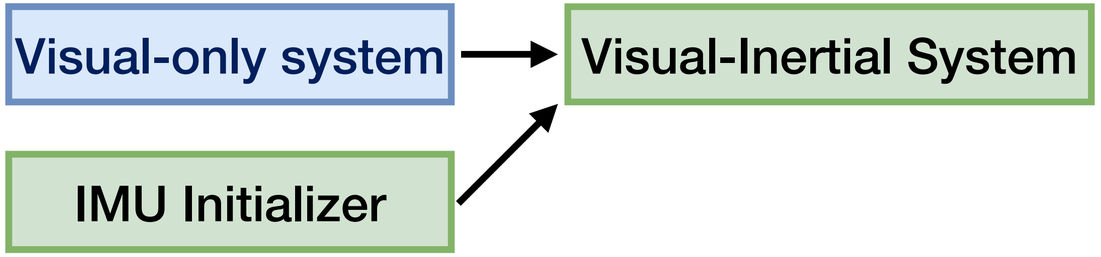
$$E(\mathbf{s}) = E_{\text{photo}}$$

Related work:
C. Forster, L. Carlone, F. Dellaert, and D. Scaramuzza. IMU preintegration on manifold for efficient visual-inertial maximum-a-posteriori estimation, RSS 2015

Related work:
J. Engel, V. Koltun and D. Cremers, Direct Sparse Odometry, TPAMI 2017

IMU Initialization

Most systems (e.g. ORB-SLAM 3)



- Trade-off when to initialize. If too early the scale might be inaccurate

VI-DSO (previous work)

Visual-Inertial System with scale optimization + special marginalization

- Pro: Use IMU data immediately
- Might fail if initial scale is very off
- Scale convergence takes longer

IMU Initialization

Most systems (e.g. ORB-SLAM 3)

Visual-only system → Visual-Inertial System

IMU Initializer → Visual-Inertial System

- Trade-off when to initialize. If too early the scale might be inaccurate

VI-DSO (previous work)

Visual-Inertial System with scale optimization + special marginalization

- Pro: Use IMU data immediately
- Might fail if initial scale is very off
- Scale convergence takes longer

DM-VIO

Visual-only system → Visual-Inertial System with scale optimization + special marginalization

IMU Initializer → Visual-Inertial System with scale optimization + special marginalization

- We can initialize early
- Works in general environments
- Converges quickly as soon as scale is observable

Bundle Adjustment

photometric error

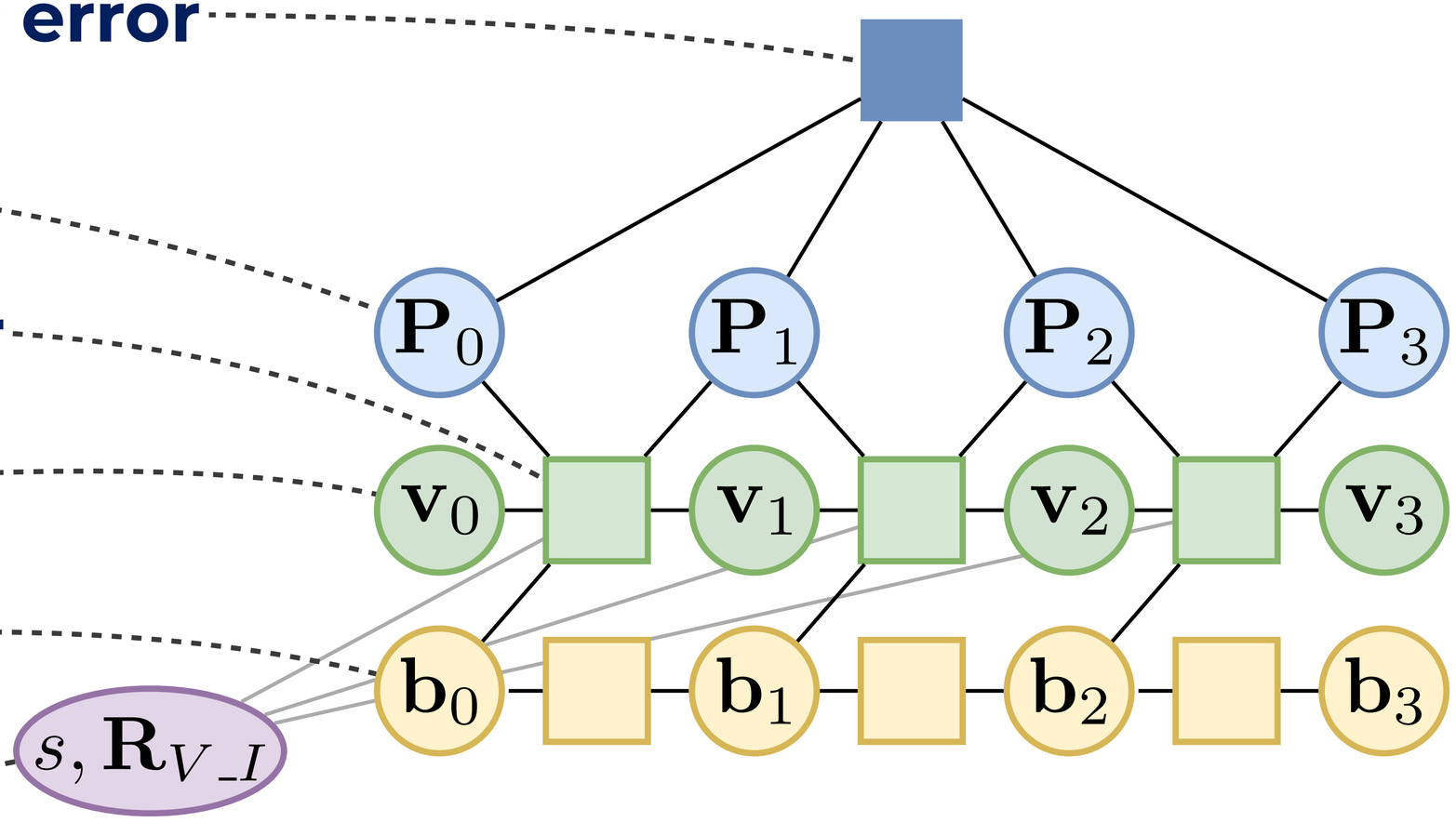
poses

inertial error

velocities

biases

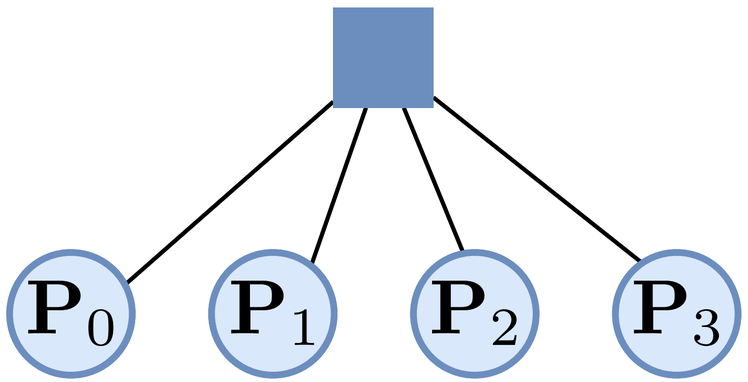
scale,
gravity direction



$$E(\mathbf{s}) = E_{\text{photo}} + E_{\text{imu}}$$

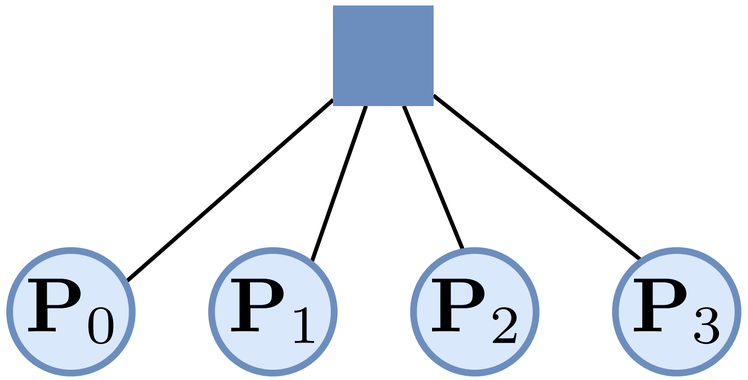
Marginalization order: $\mathbf{P}_1 \rightarrow \mathbf{P}_2 \rightarrow \mathbf{P}_3 \rightarrow \mathbf{P}_4 \rightarrow \mathbf{P}_0$

Marginalization order: $\mathbf{P}_1 \rightarrow \mathbf{P}_2 \rightarrow \mathbf{P}_3 \rightarrow \mathbf{P}_4 \rightarrow \mathbf{P}_0$

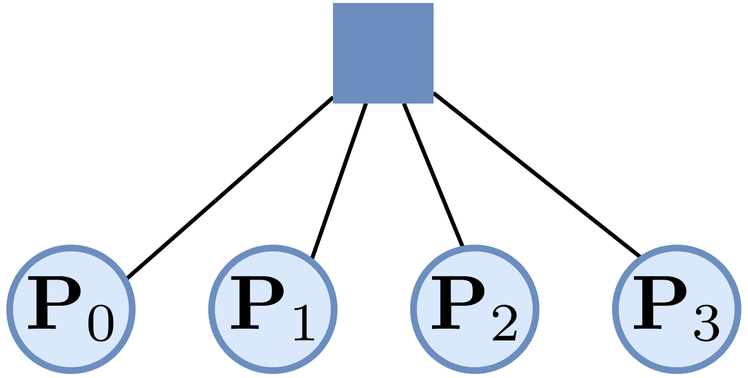


Normal graph

Marginalization order: $\mathbf{P}_1 \rightarrow \mathbf{P}_2 \rightarrow \mathbf{P}_3 \rightarrow \mathbf{P}_4 \rightarrow \mathbf{P}_0$

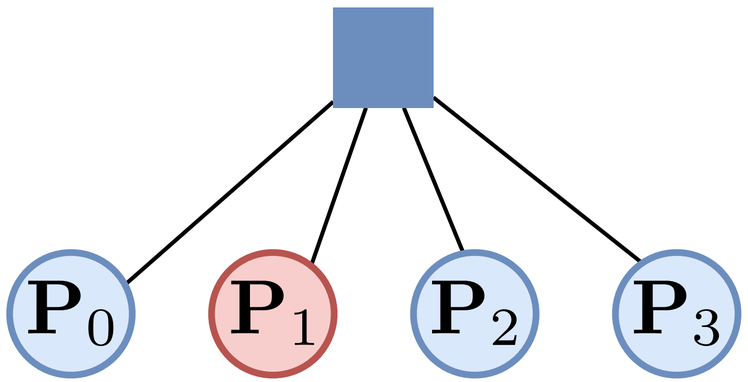


Normal graph

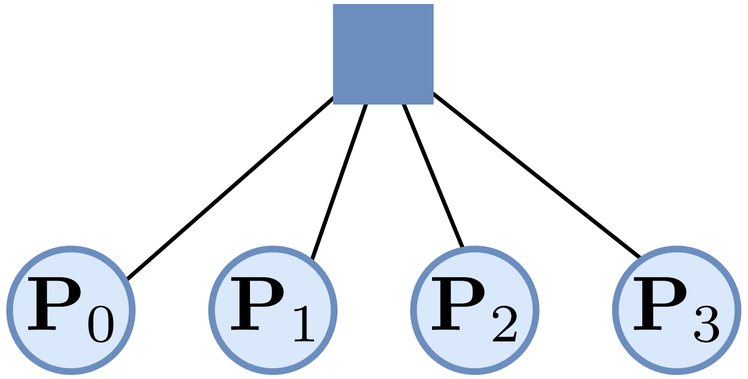


Delayed graph

Marginalization order: $\mathbf{P}_1 \rightarrow \mathbf{P}_2 \rightarrow \mathbf{P}_3 \rightarrow \mathbf{P}_4 \rightarrow \mathbf{P}_0$

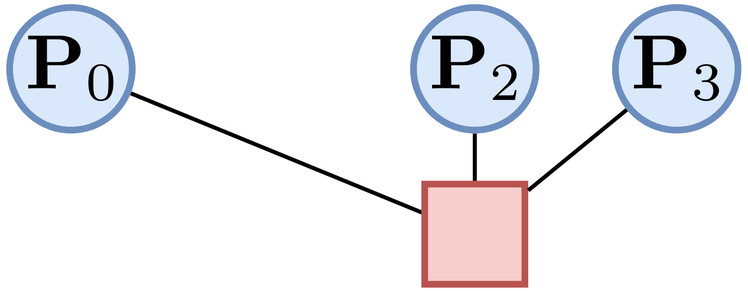


Normal graph

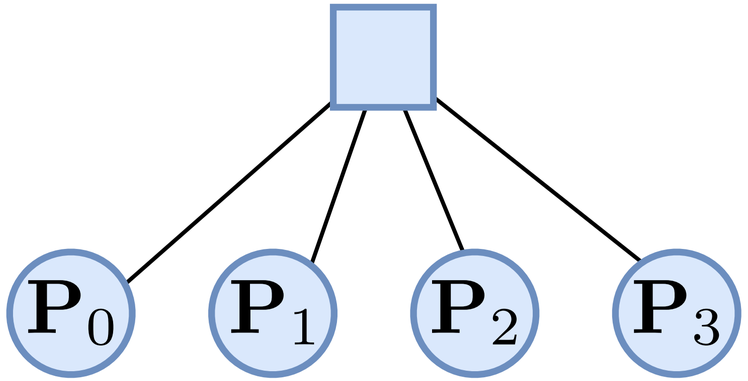


Delayed graph

Marginalization order: $\mathbf{P}_1 \rightarrow \mathbf{P}_2 \rightarrow \mathbf{P}_3 \rightarrow \mathbf{P}_4 \rightarrow \mathbf{P}_0$

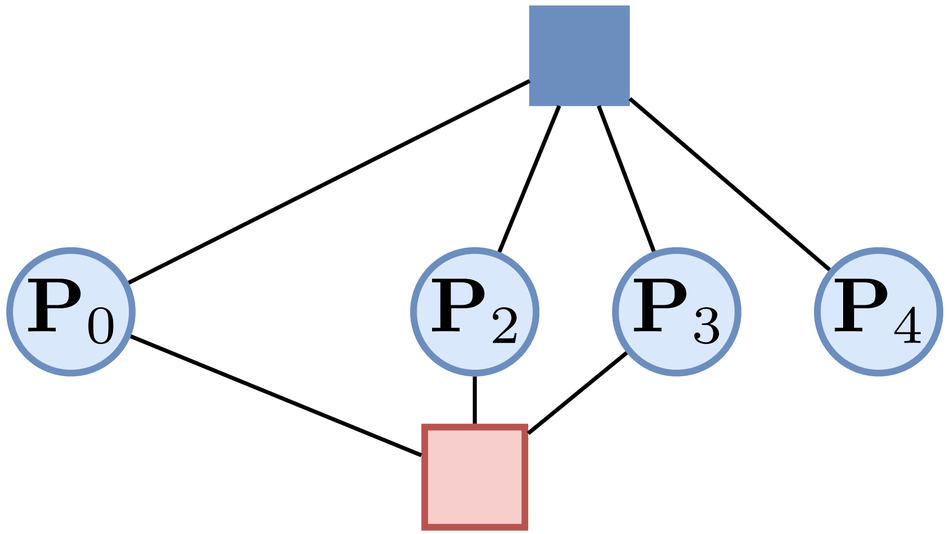


Normal graph

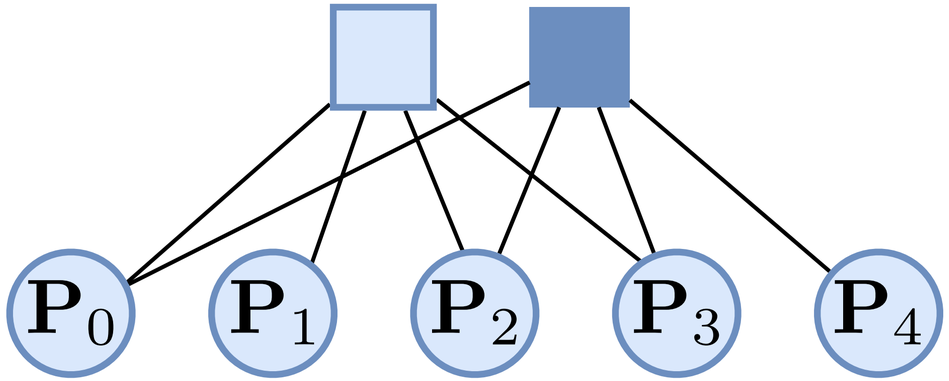


Delayed graph

Marginalization order: $\mathbf{P}_1 \rightarrow \mathbf{P}_2 \rightarrow \mathbf{P}_3 \rightarrow \mathbf{P}_4 \rightarrow \mathbf{P}_0$

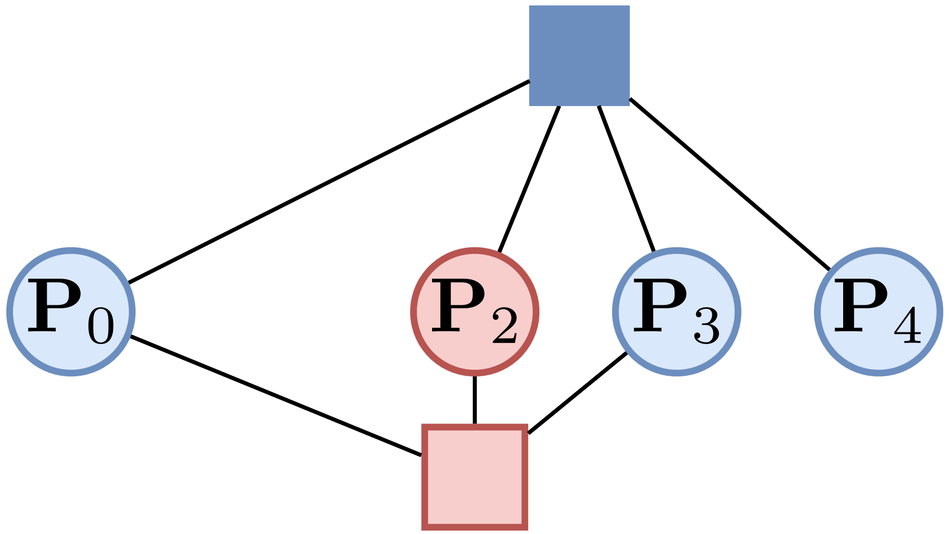


Normal graph

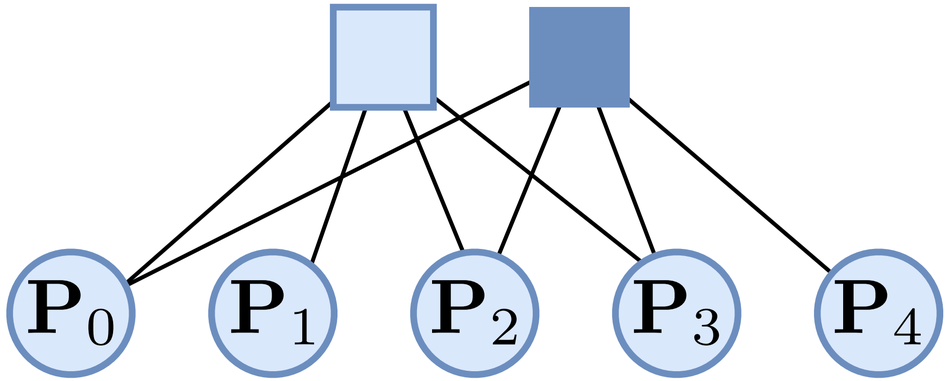


Delayed graph

Marginalization order: $\mathbf{P}_1 \rightarrow \mathbf{P}_2 \rightarrow \mathbf{P}_3 \rightarrow \mathbf{P}_4 \rightarrow \mathbf{P}_0$

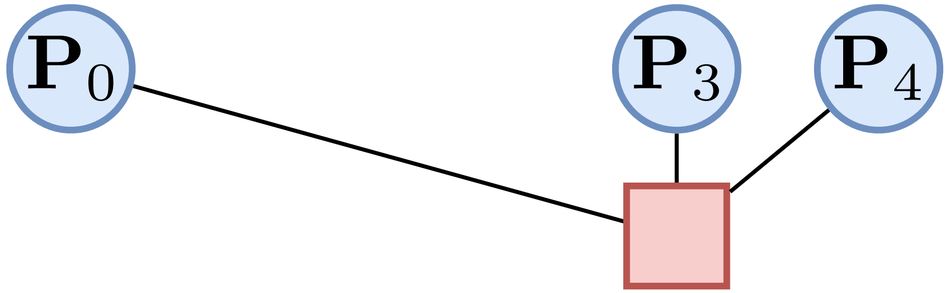


Normal graph



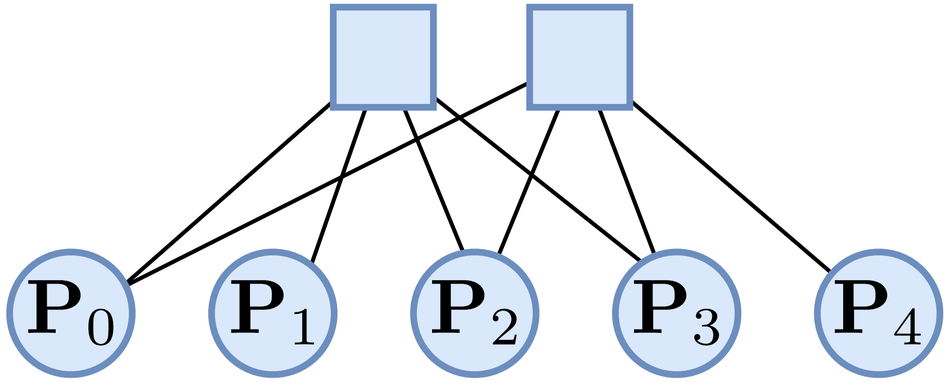
Delayed graph

Marginalization order: $P_1 \rightarrow P_2 \rightarrow P_3 \rightarrow P_4 \rightarrow P_0$



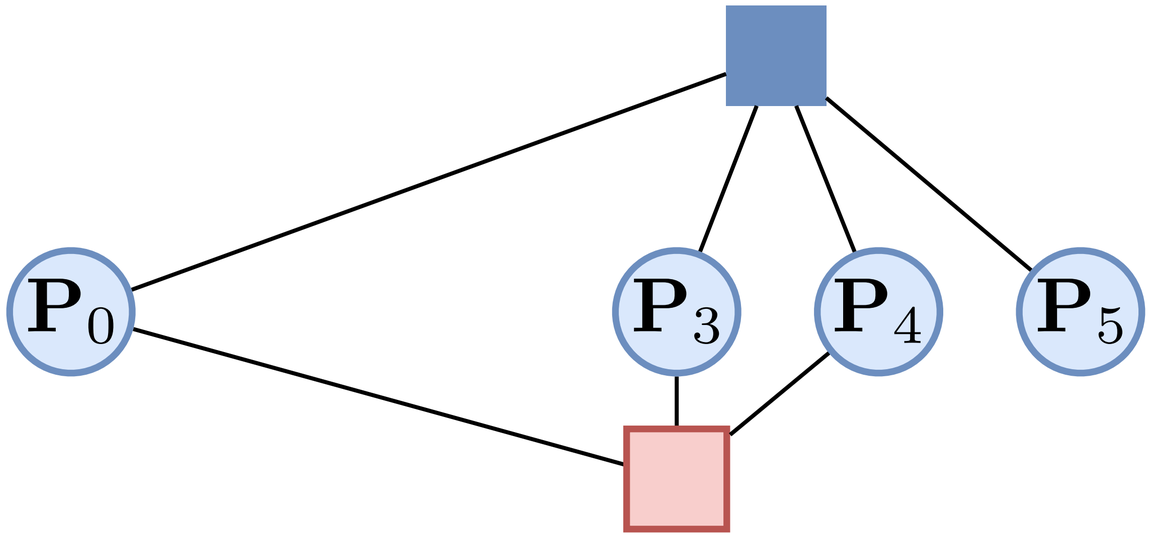
Normal graph

delay=4



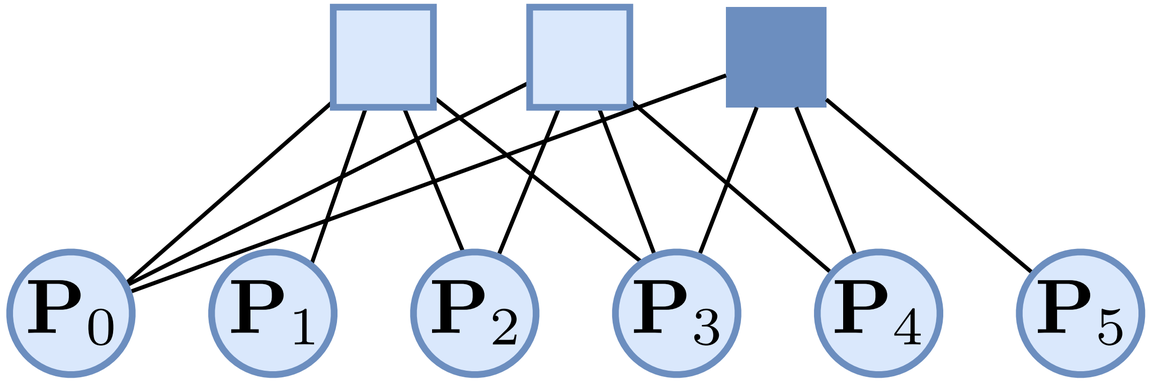
Delayed graph

Marginalization order: $P_1 \rightarrow P_2 \rightarrow P_3 \rightarrow P_4 \rightarrow P_0$



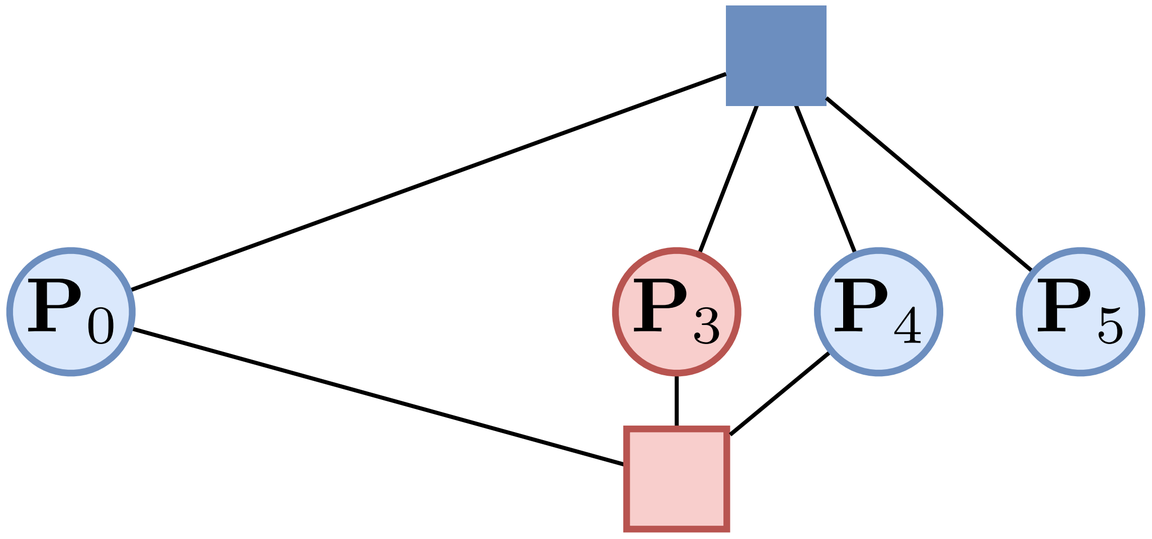
Normal graph

delay=4



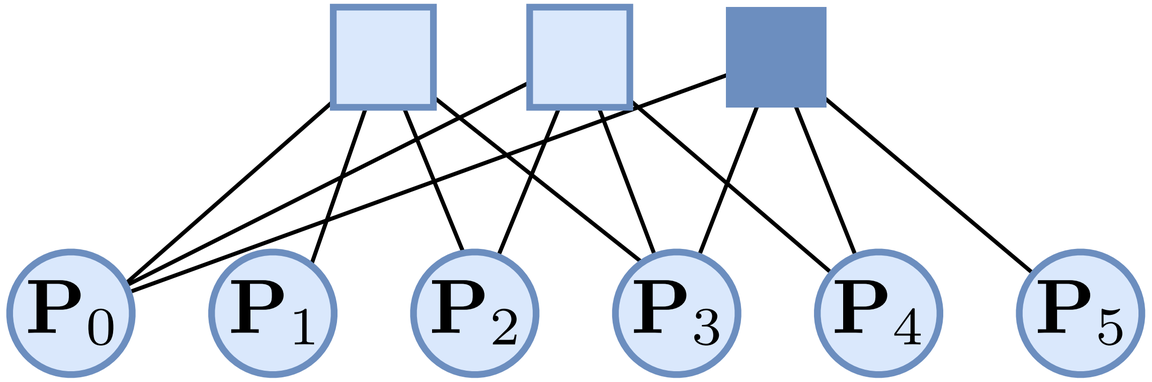
Delayed graph

Marginalization order: $P_1 \rightarrow P_2 \rightarrow P_3 \rightarrow P_4 \rightarrow P_0$



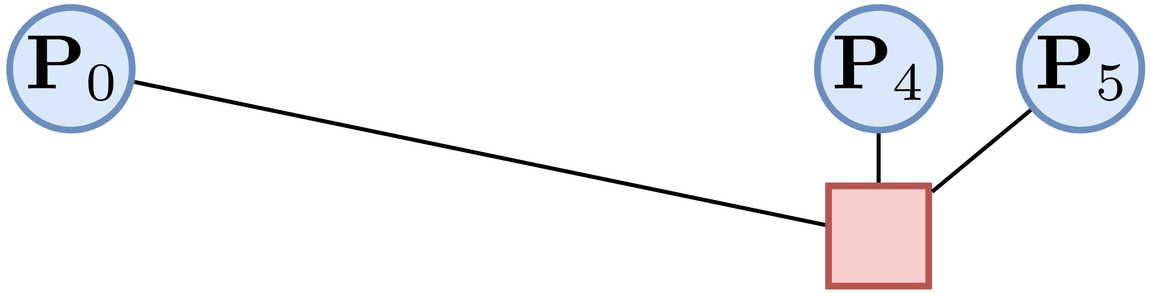
Normal graph

delay=4



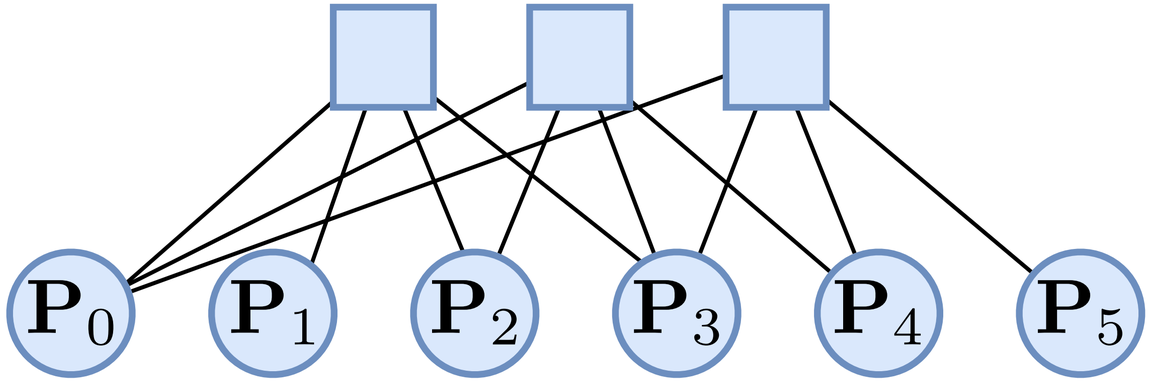
Delayed graph

Marginalization order: $P_1 \rightarrow P_2 \rightarrow P_3 \rightarrow P_4 \rightarrow P_0$



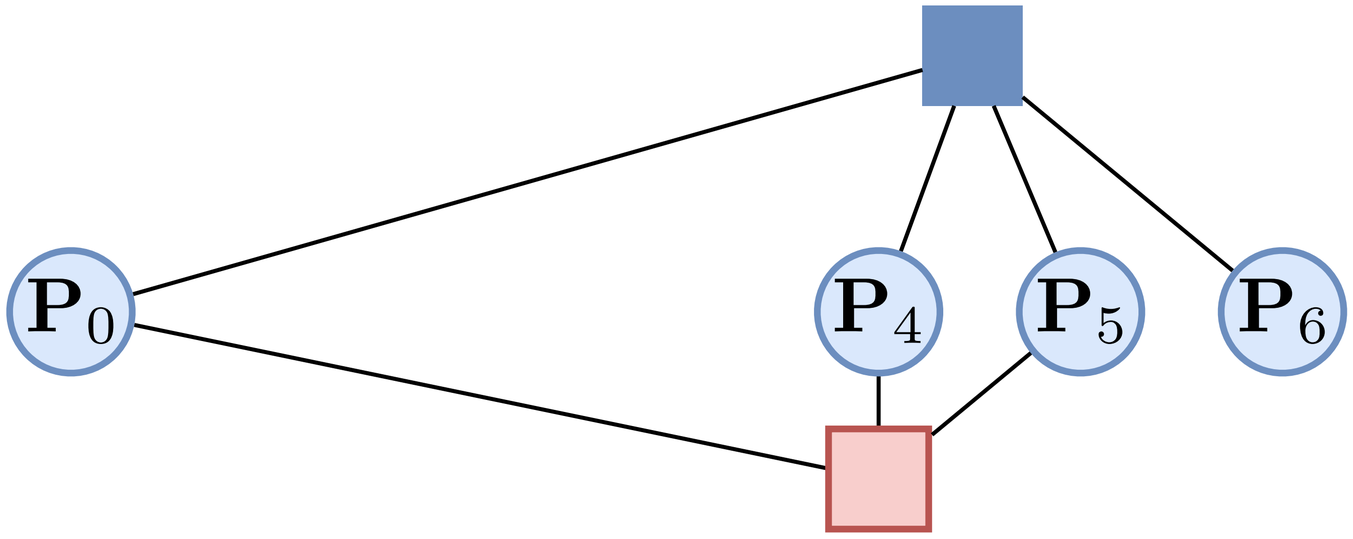
Normal graph

delay=4



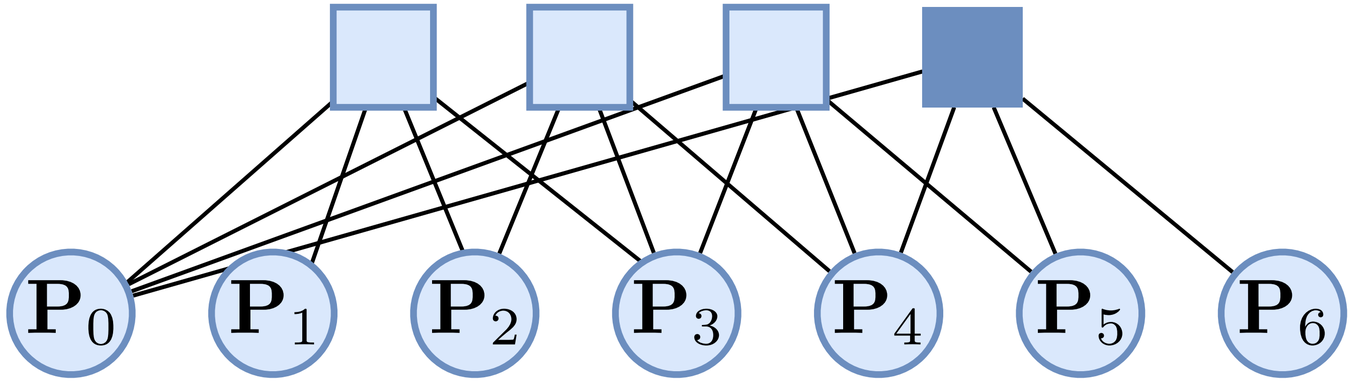
Delayed graph

Marginalization order: $P_1 \rightarrow P_2 \rightarrow P_3 \rightarrow P_4 \rightarrow P_0$



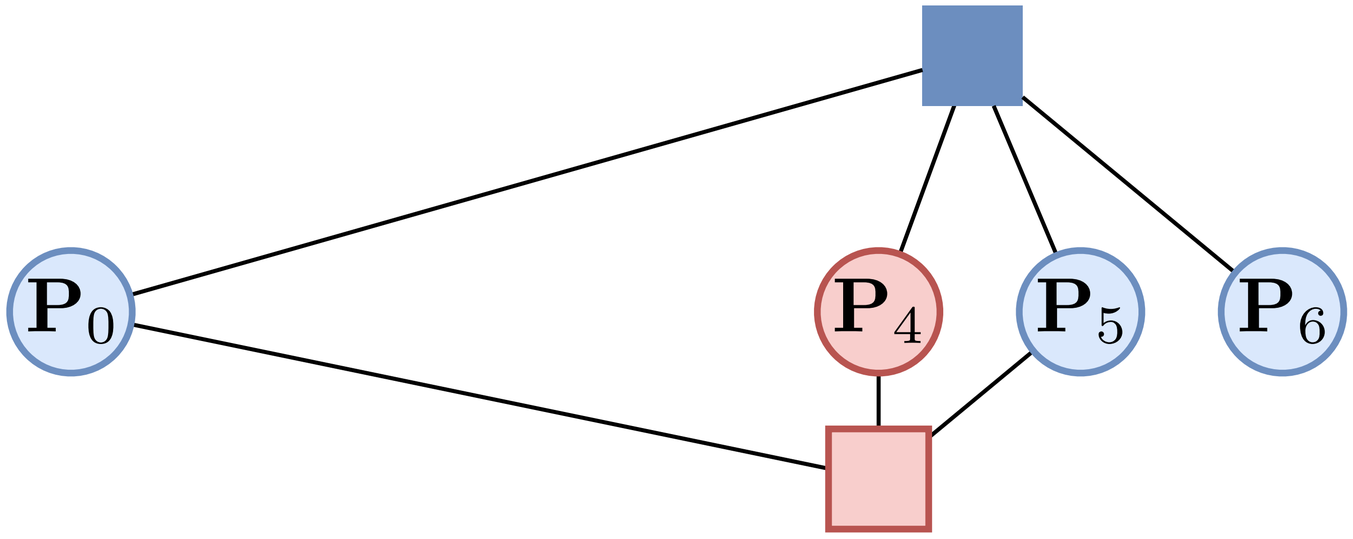
Normal graph

delay=4



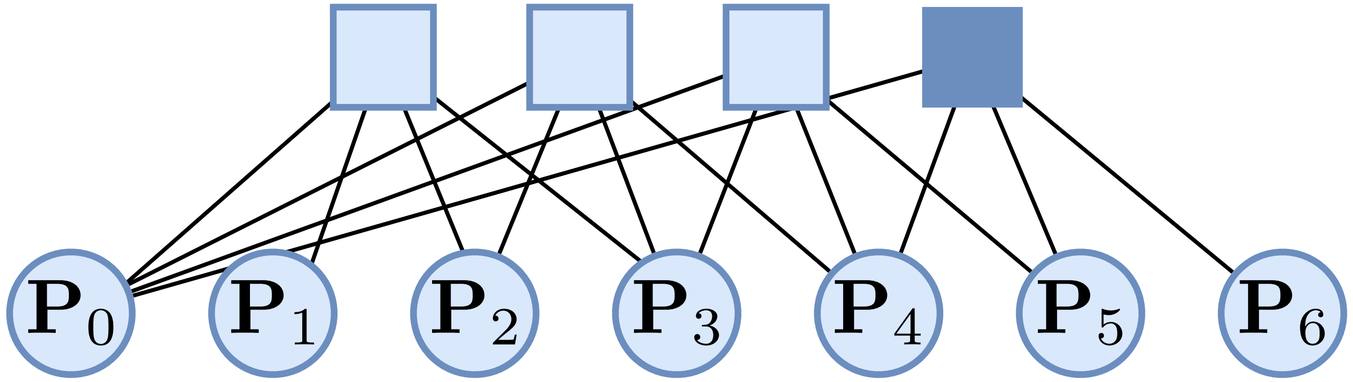
Delayed graph

Marginalization order: $P_1 \rightarrow P_2 \rightarrow P_3 \rightarrow P_4 \rightarrow P_0$



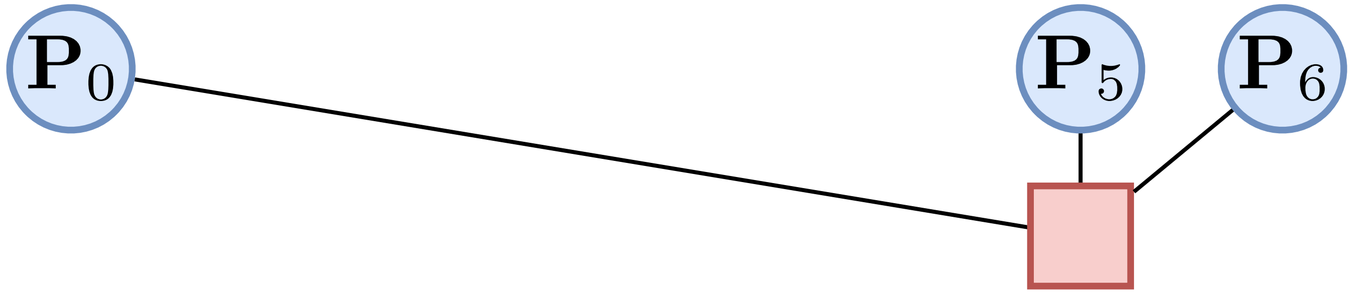
Normal graph

delay=4



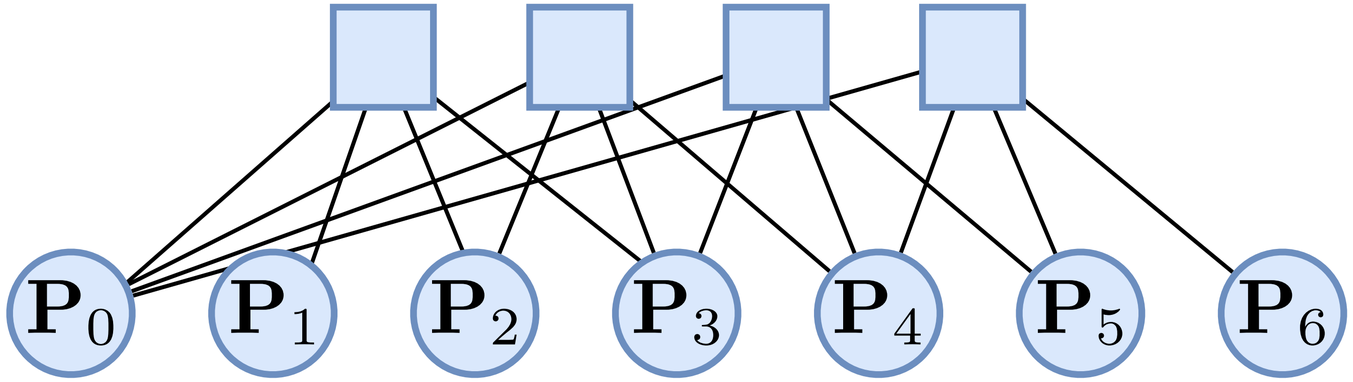
Delayed graph

Marginalization order: $P_1 \rightarrow P_2 \rightarrow P_3 \rightarrow P_4 \rightarrow P_0$



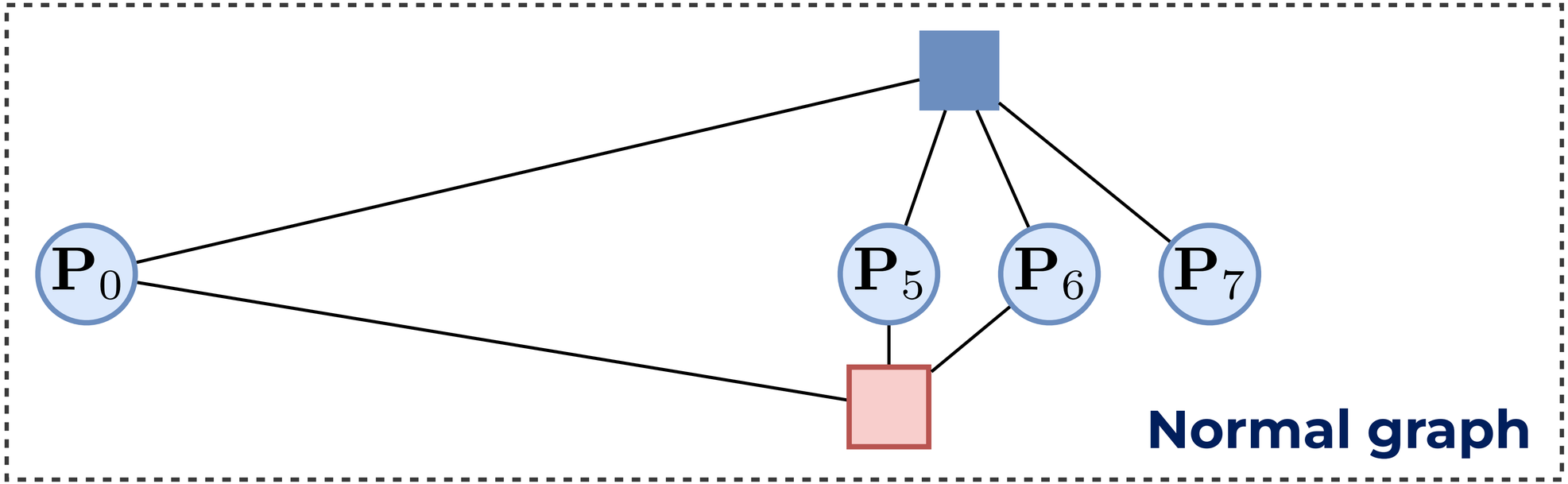
Normal graph

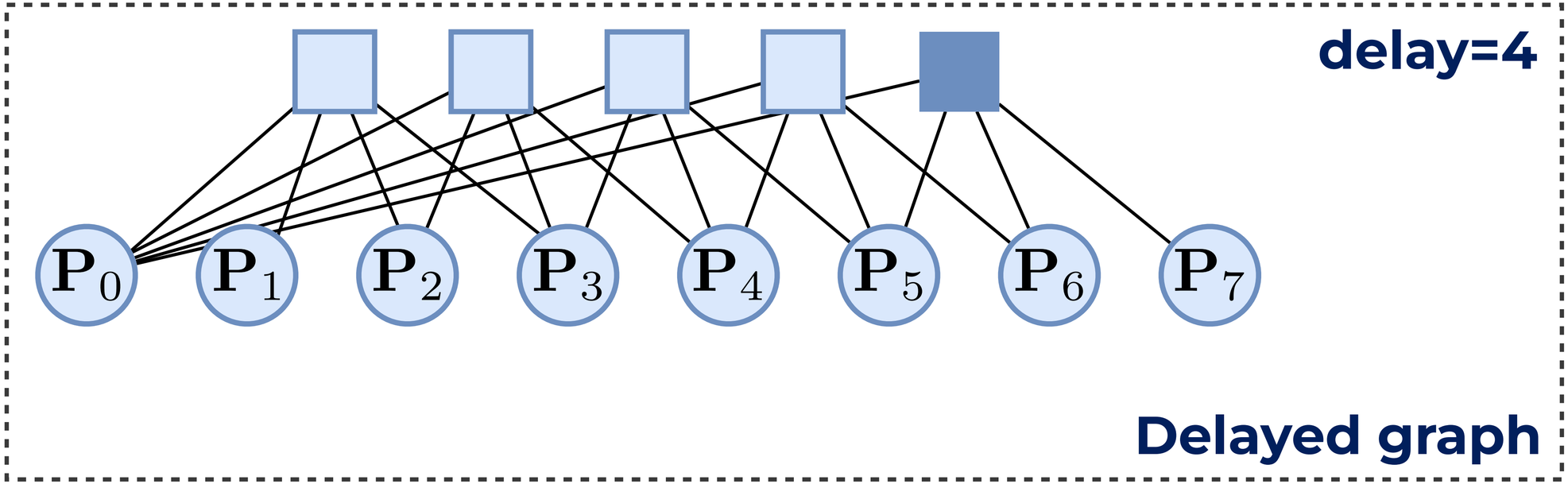
delay=4



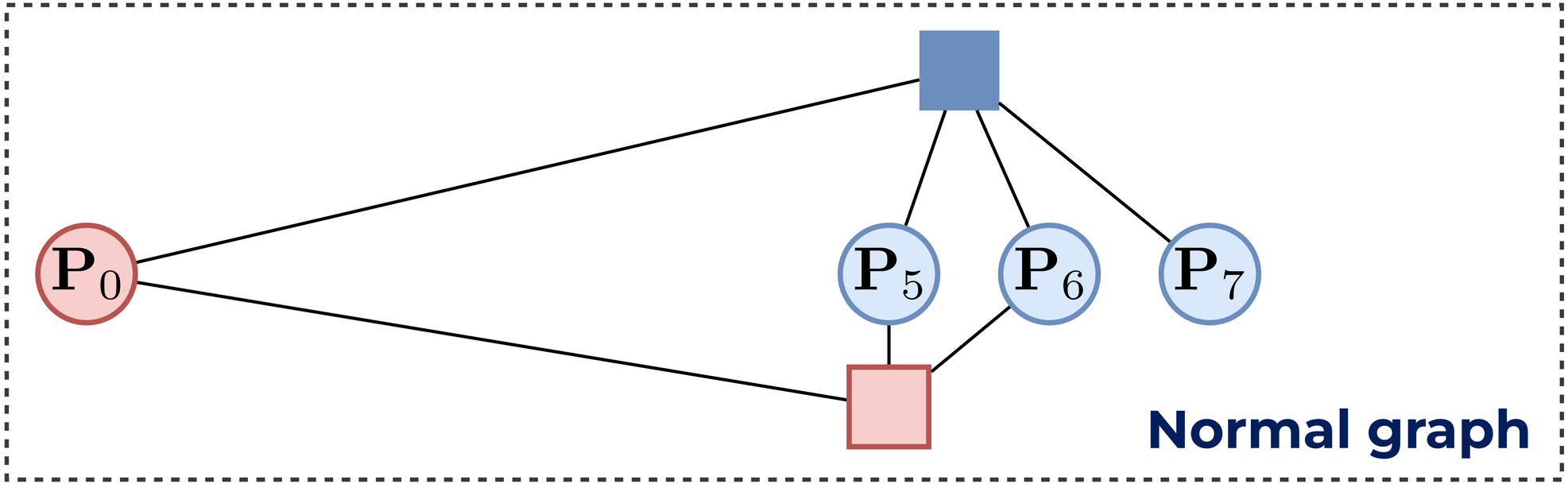
Delayed graph

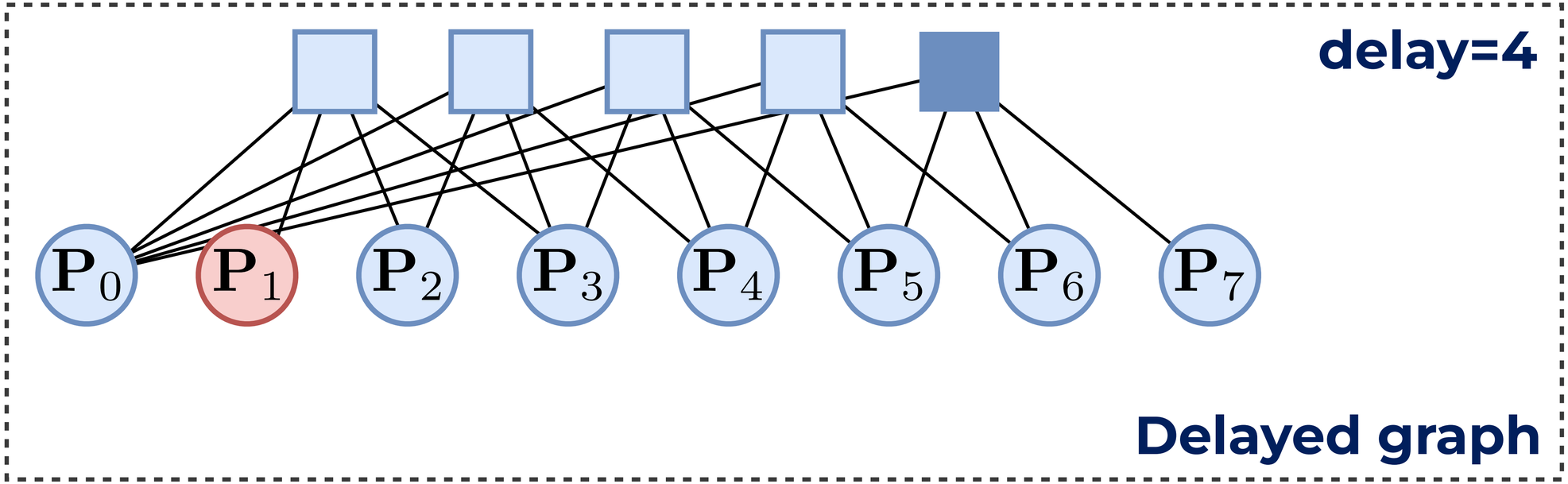
Marginalization order: $P_1 \rightarrow P_2 \rightarrow P_3 \rightarrow P_4 \rightarrow P_0$



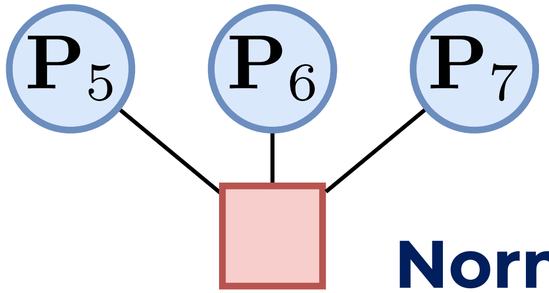


Marginalization order: $\boxed{P_1} \rightarrow P_2 \rightarrow P_3 \rightarrow P_4 \rightarrow P_0$



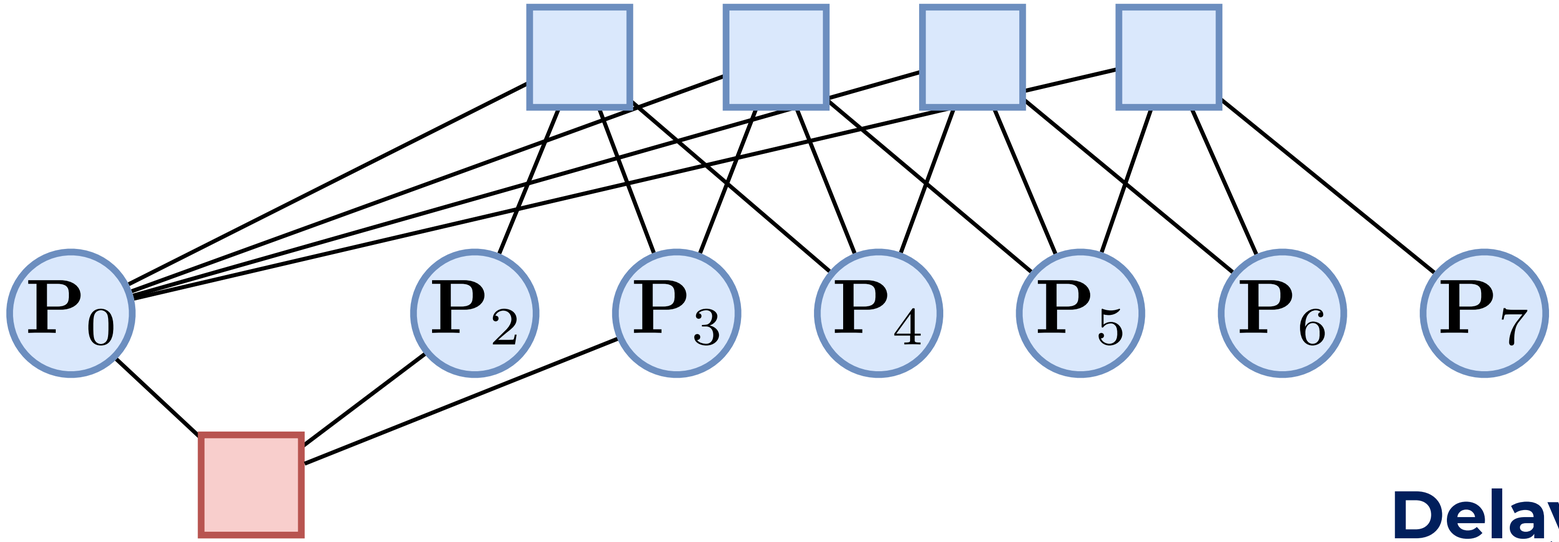


Marginalization order: $\boxed{P_1} \rightarrow P_2 \rightarrow P_3 \rightarrow P_4 \rightarrow P_0$



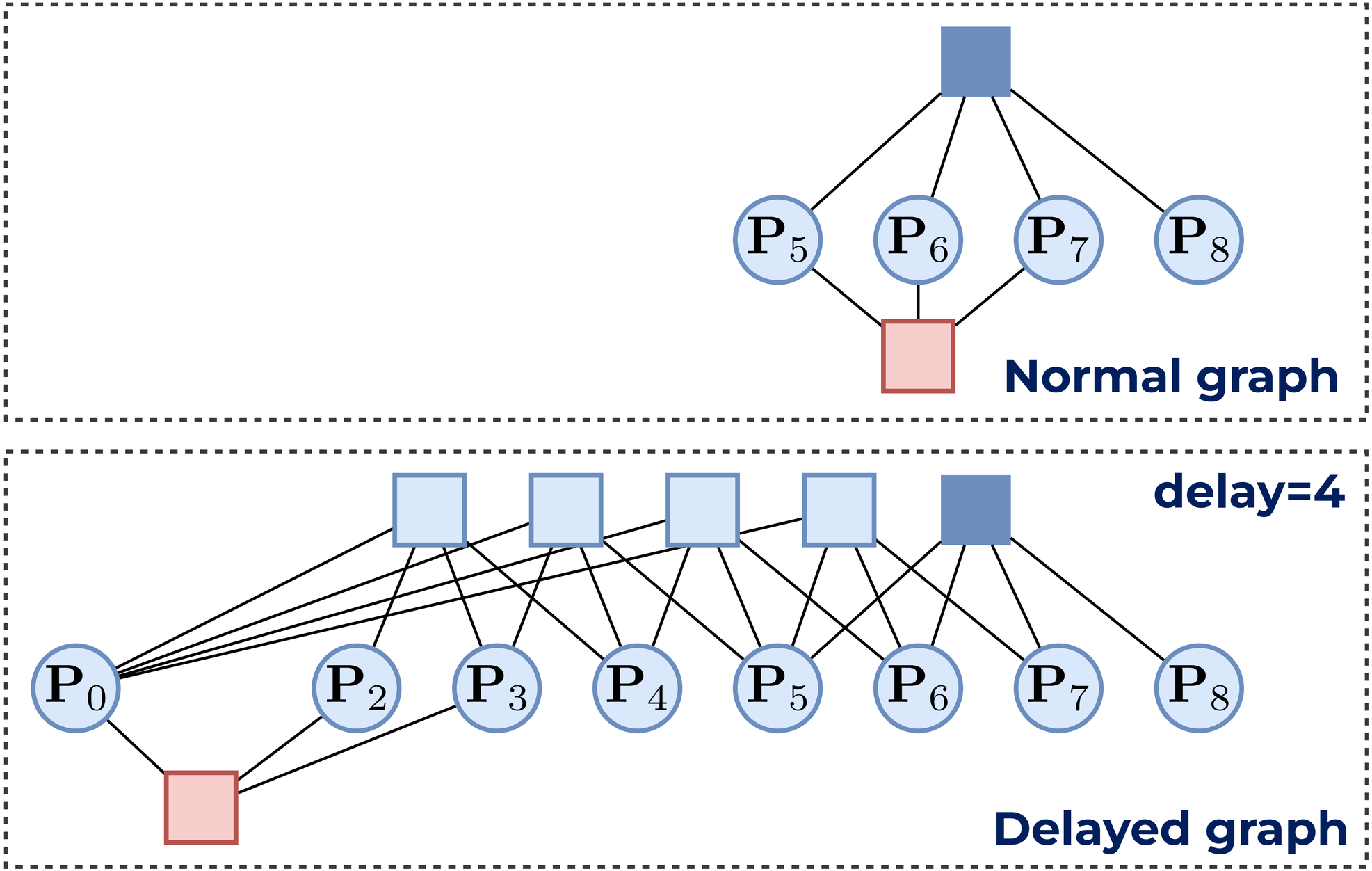
Normal graph

delay=4

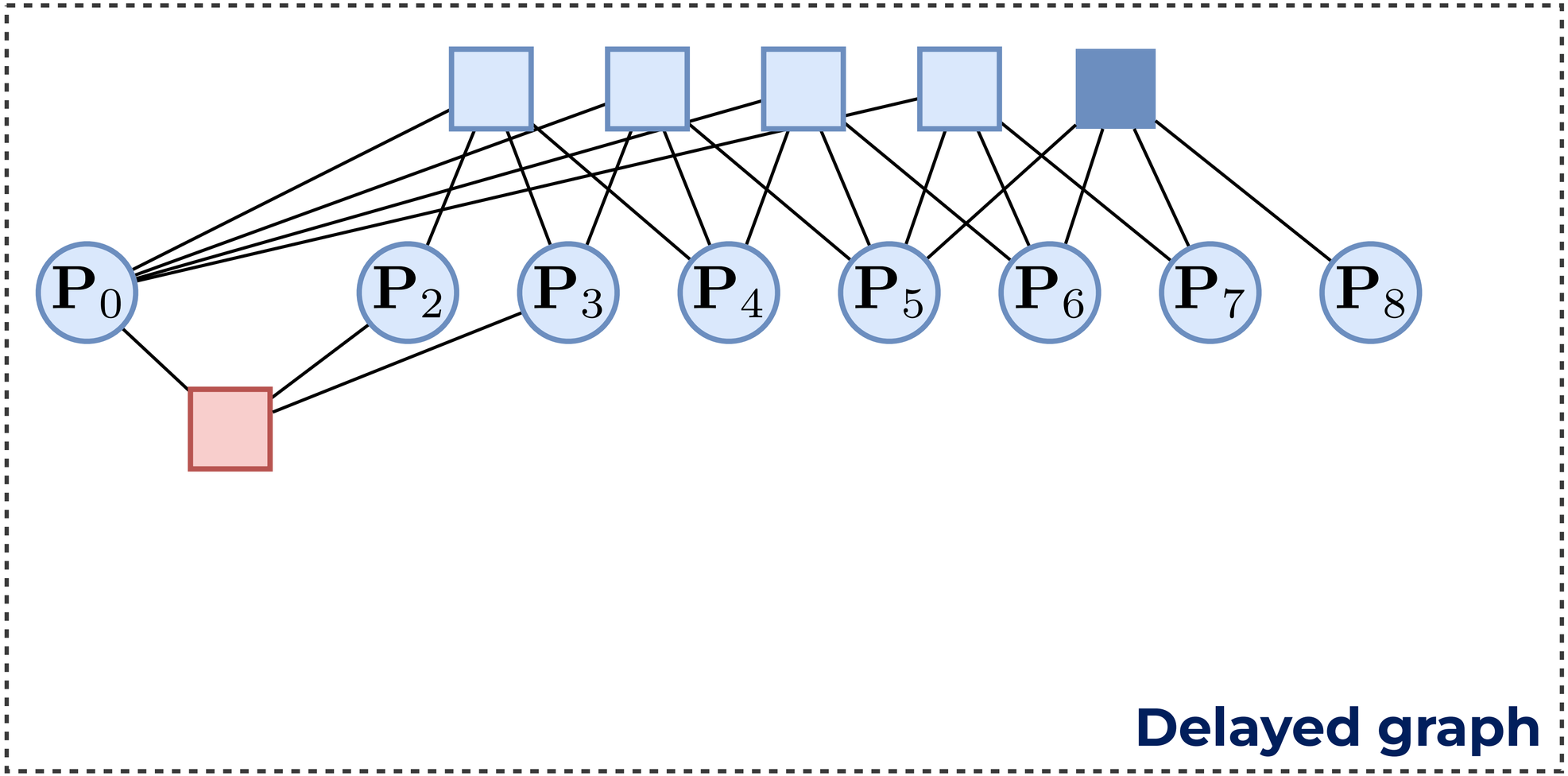


Delayed graph

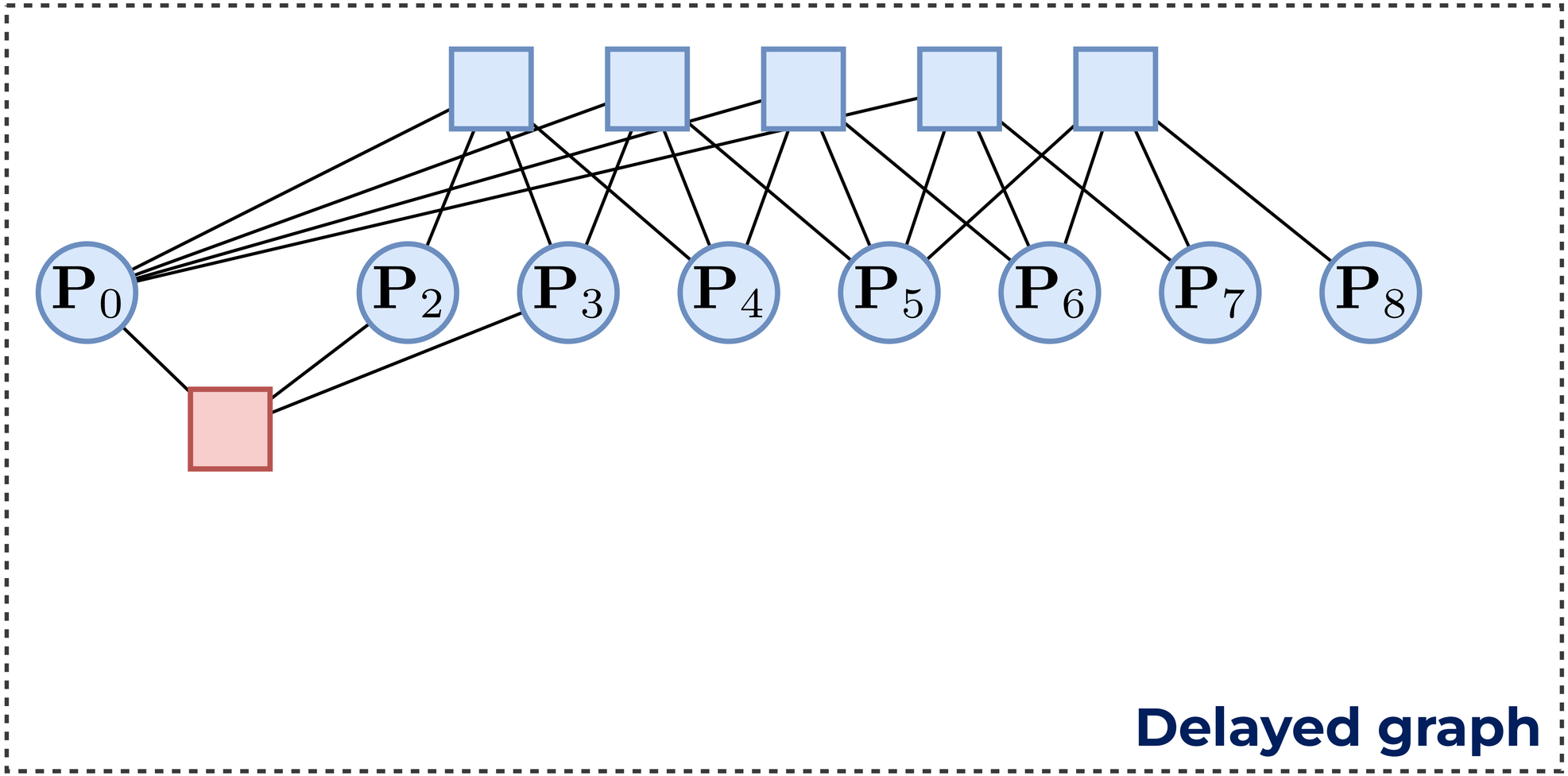
Marginalization order: $P_1 \rightarrow P_2 \rightarrow P_3 \rightarrow P_4 \rightarrow P_0$



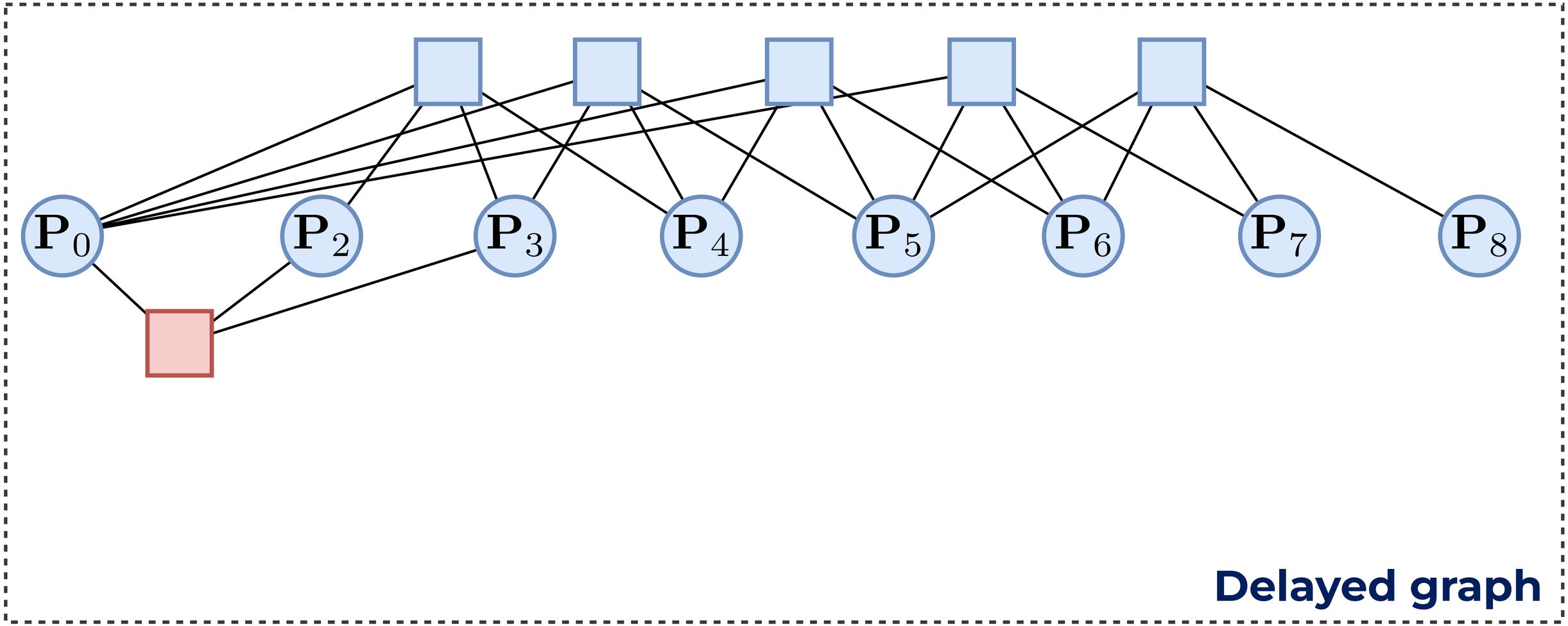
Pose Graph Bundle Adjustment (PGBA)



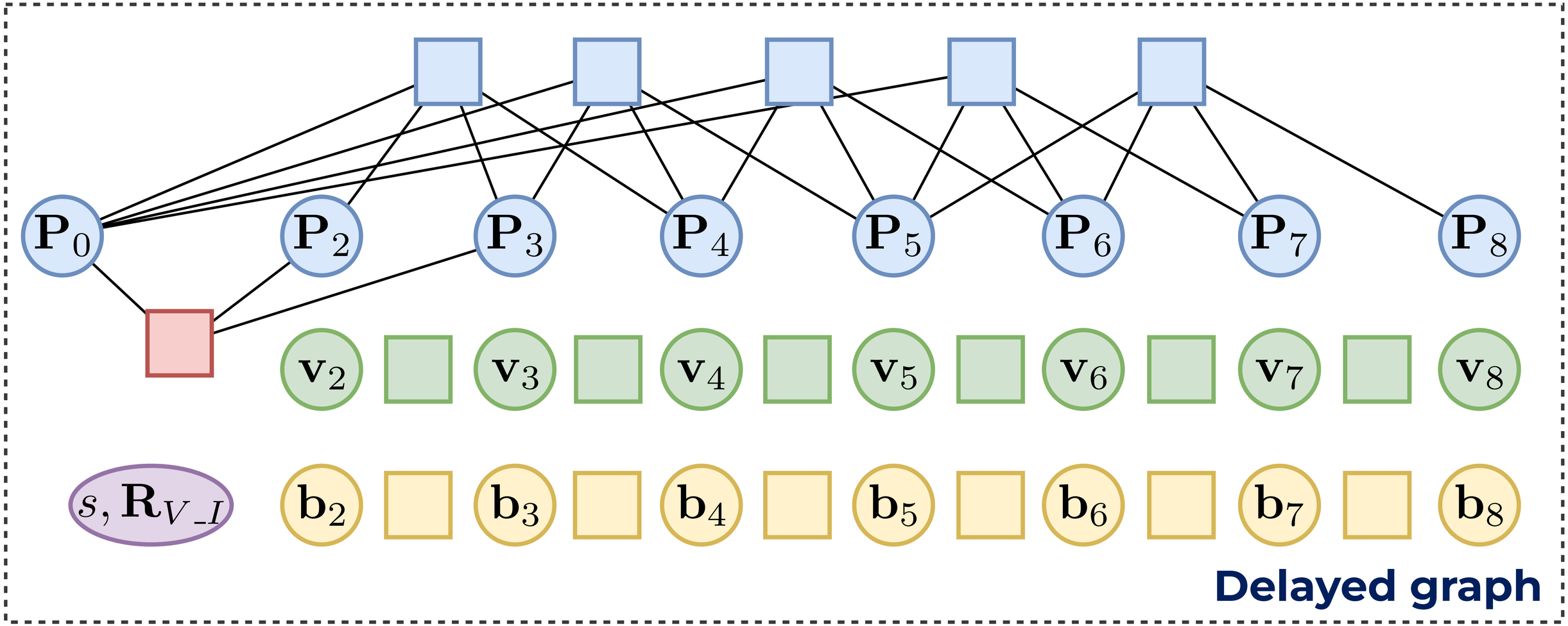
Pose Graph Bundle Adjustment (PGBA)



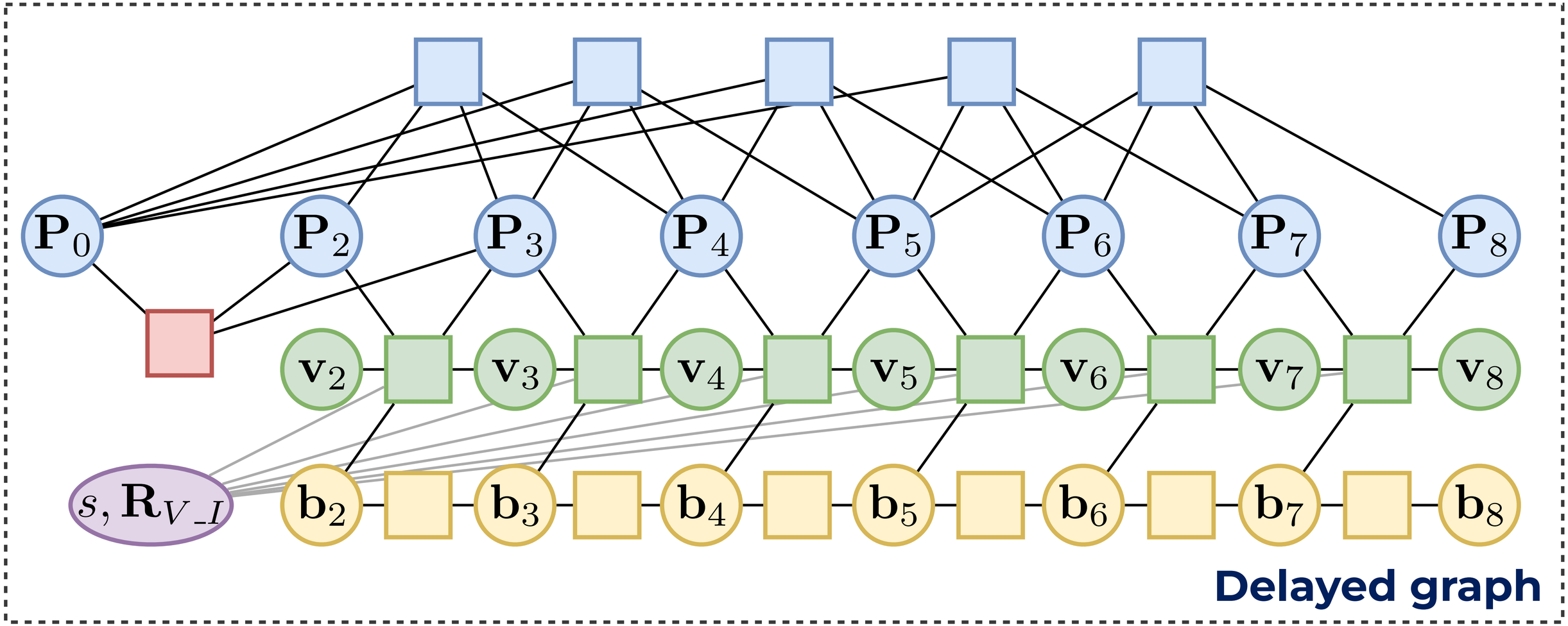
Pose Graph Bundle Adjustment (PGBA)



Pose Graph Bundle Adjustment (PGBA)

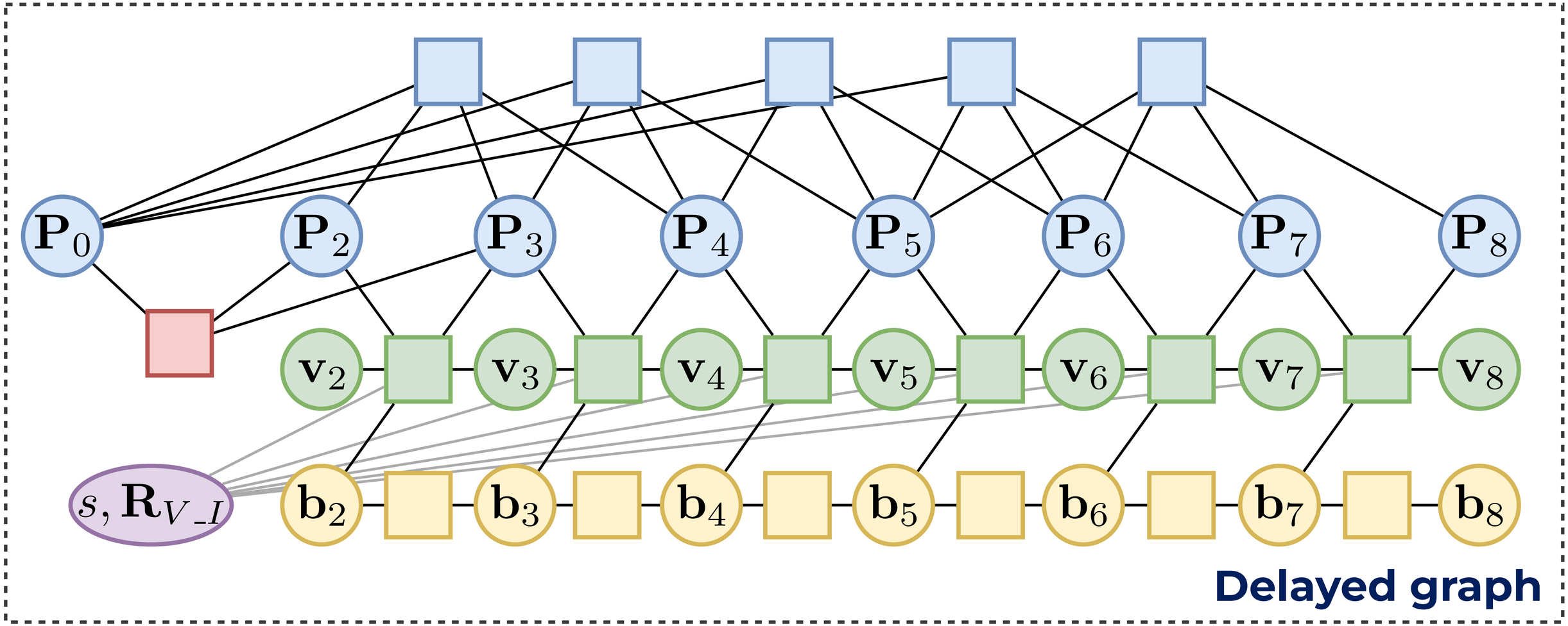


Pose Graph Bundle Adjustment (PGBA)



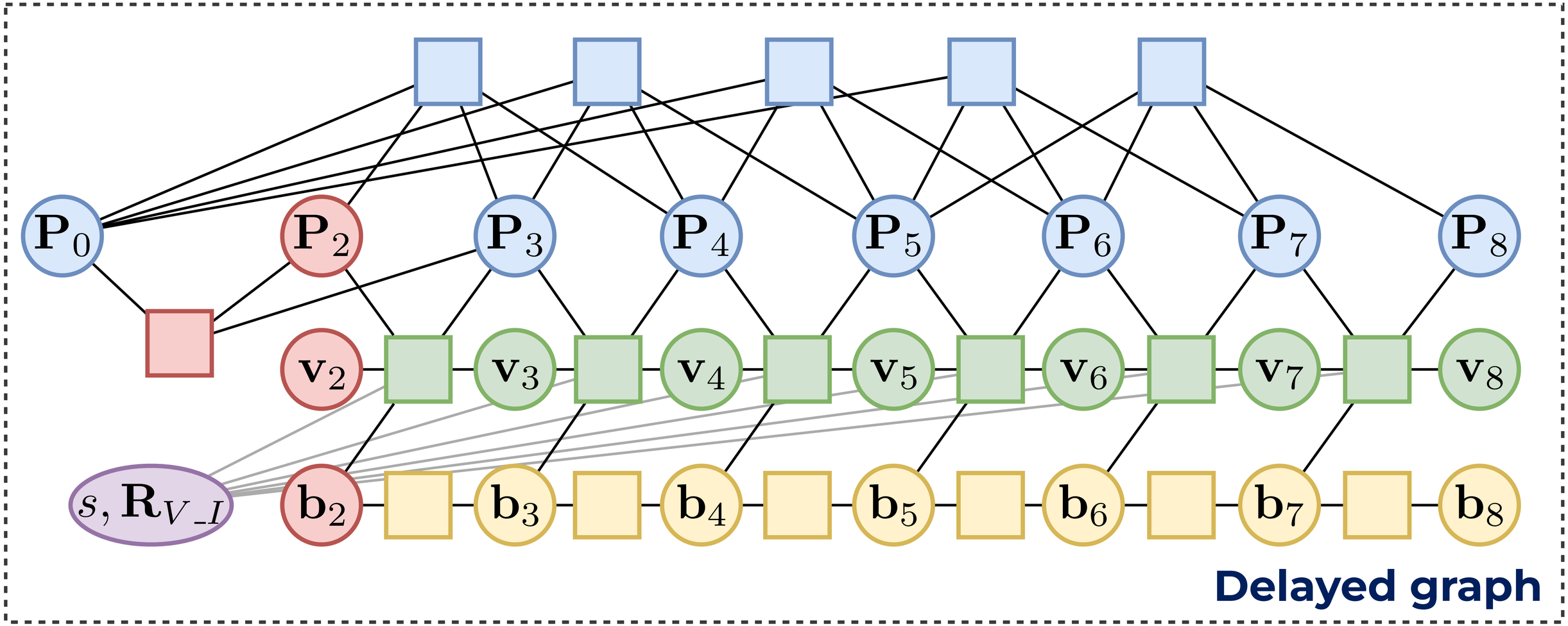
Marginalization order: $\mathbf{P}_1 \rightarrow \mathbf{P}_2 \rightarrow \mathbf{P}_3 \rightarrow \mathbf{P}_4 \rightarrow \mathbf{P}_0$

Readvancing



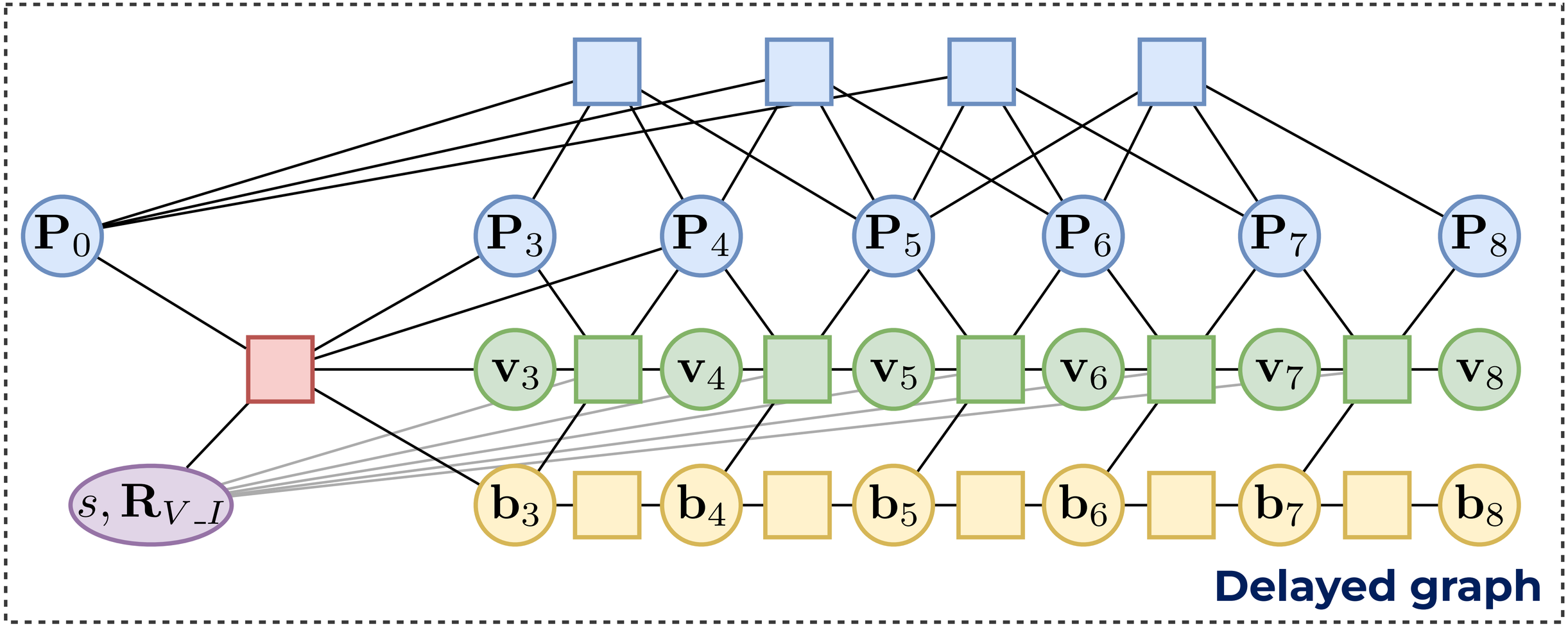
Marginalization order: $\mathbf{P}_1 \rightarrow \boxed{\mathbf{P}_2} \rightarrow \mathbf{P}_3 \rightarrow \mathbf{P}_4 \rightarrow \mathbf{P}_0$

Readvancing



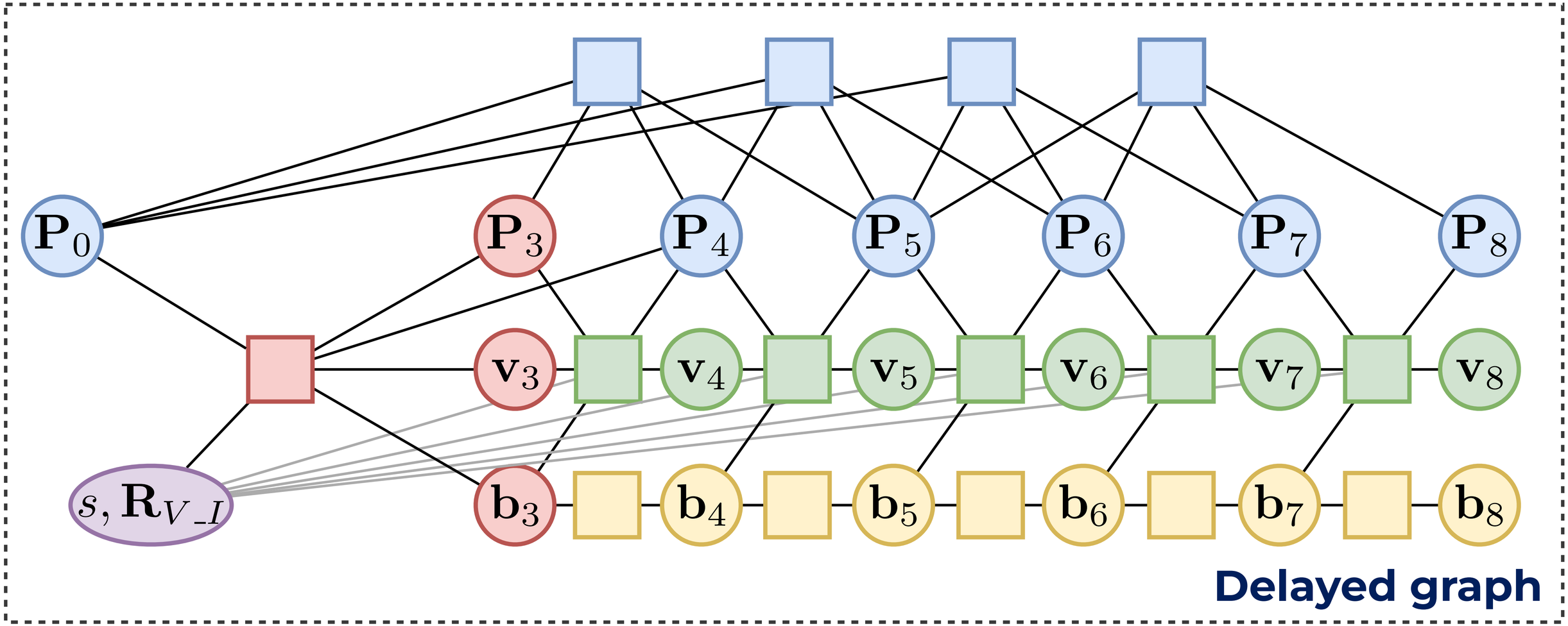
Marginalization order: $\mathbf{P}_1 \rightarrow \boxed{\mathbf{P}_2} \rightarrow \mathbf{P}_3 \rightarrow \mathbf{P}_4 \rightarrow \mathbf{P}_0$

Readvancing



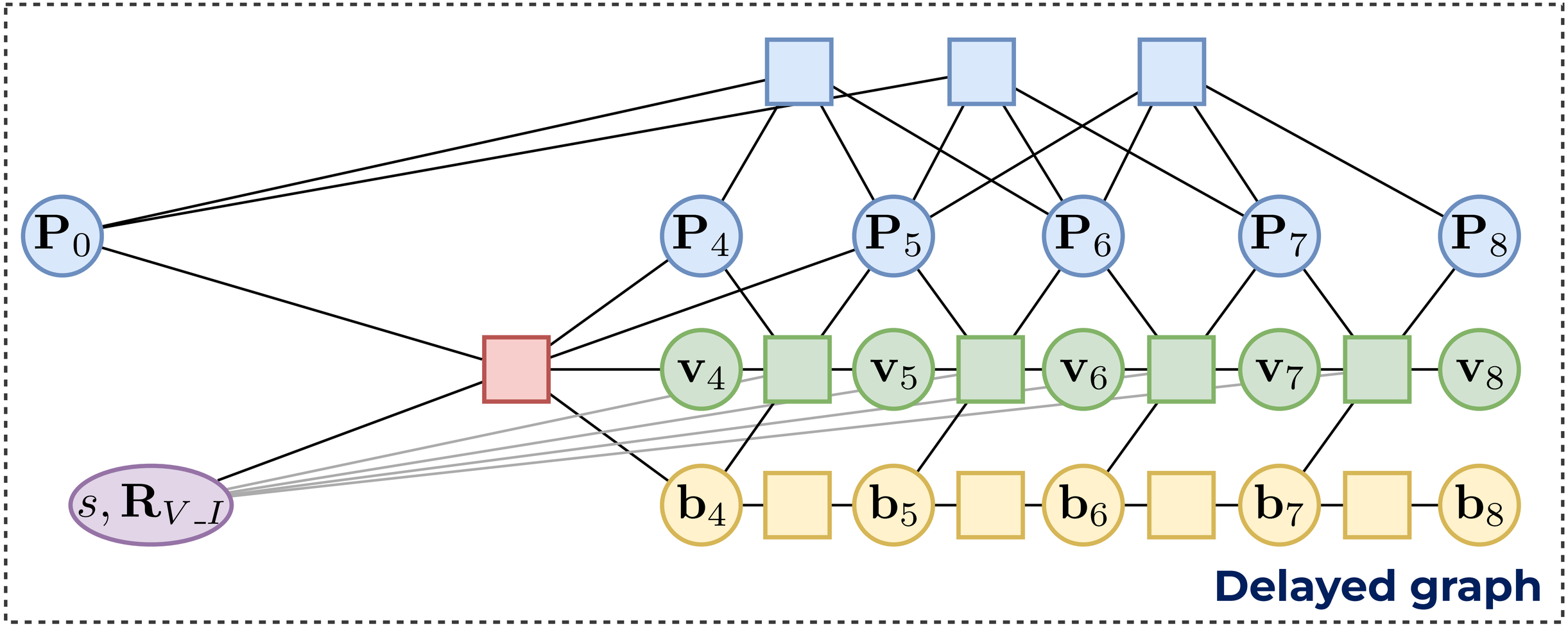
Marginalization order: $\mathbf{P}_1 \rightarrow \mathbf{P}_2 \rightarrow \boxed{\mathbf{P}_3} \rightarrow \mathbf{P}_4 \rightarrow \mathbf{P}_0$

Readvancing



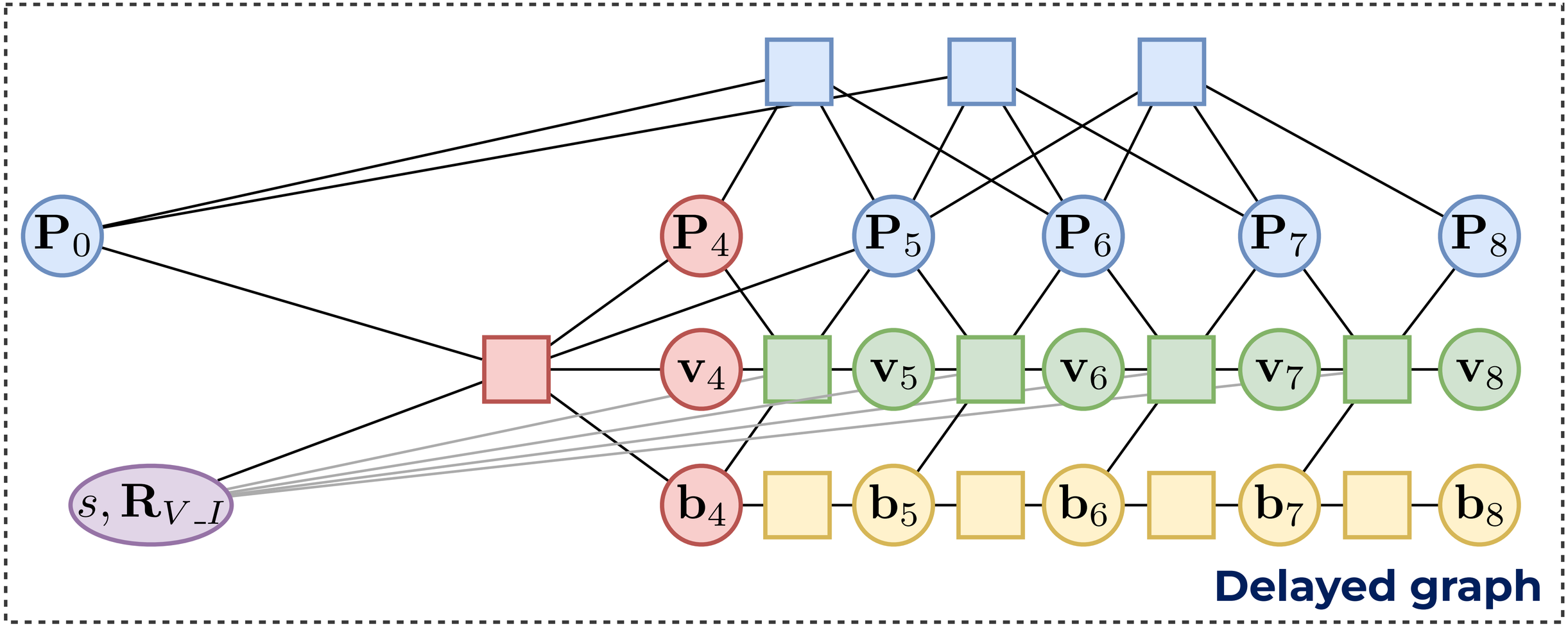
Marginalization order: $\mathbf{P}_1 \rightarrow \mathbf{P}_2 \rightarrow \boxed{\mathbf{P}_3} \rightarrow \mathbf{P}_4 \rightarrow \mathbf{P}_0$

Readvancing



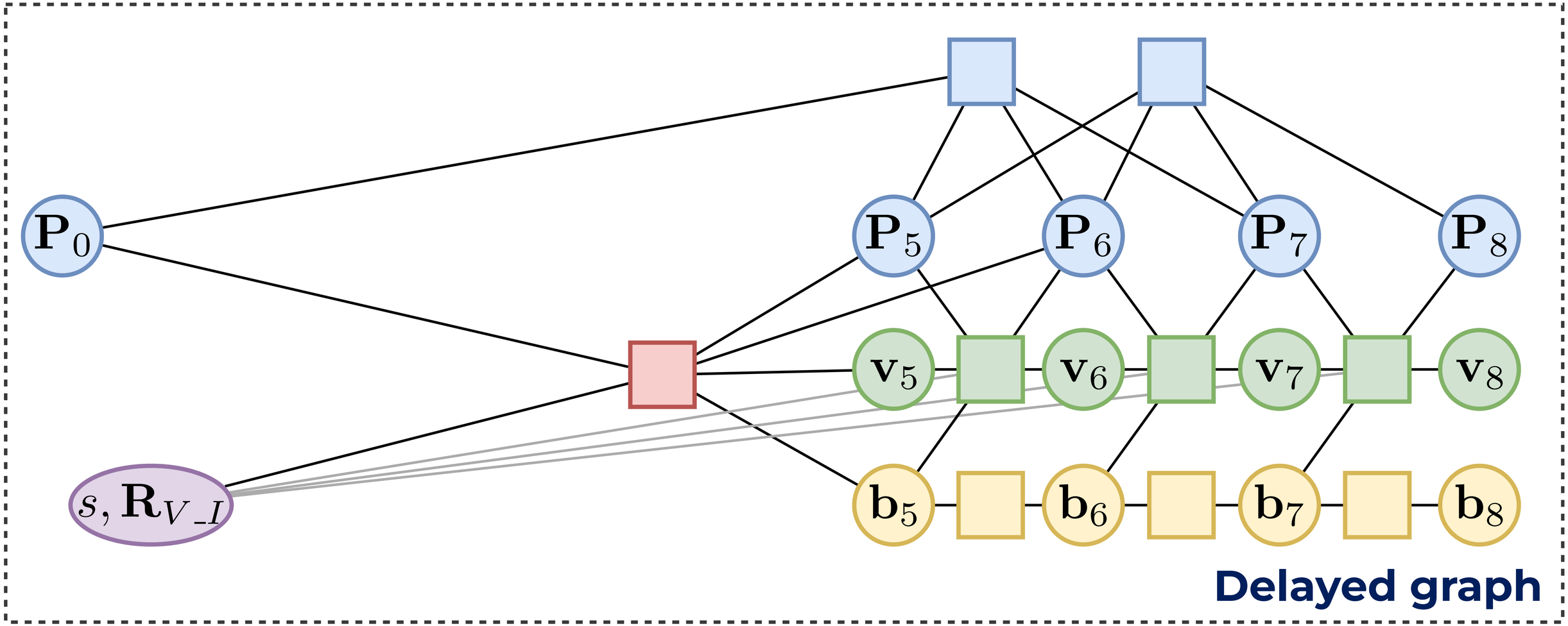
Marginalization order: $\mathbf{P}_1 \rightarrow \mathbf{P}_2 \rightarrow \mathbf{P}_3 \rightarrow \boxed{\mathbf{P}_4} \rightarrow \mathbf{P}_0$

Readvancing



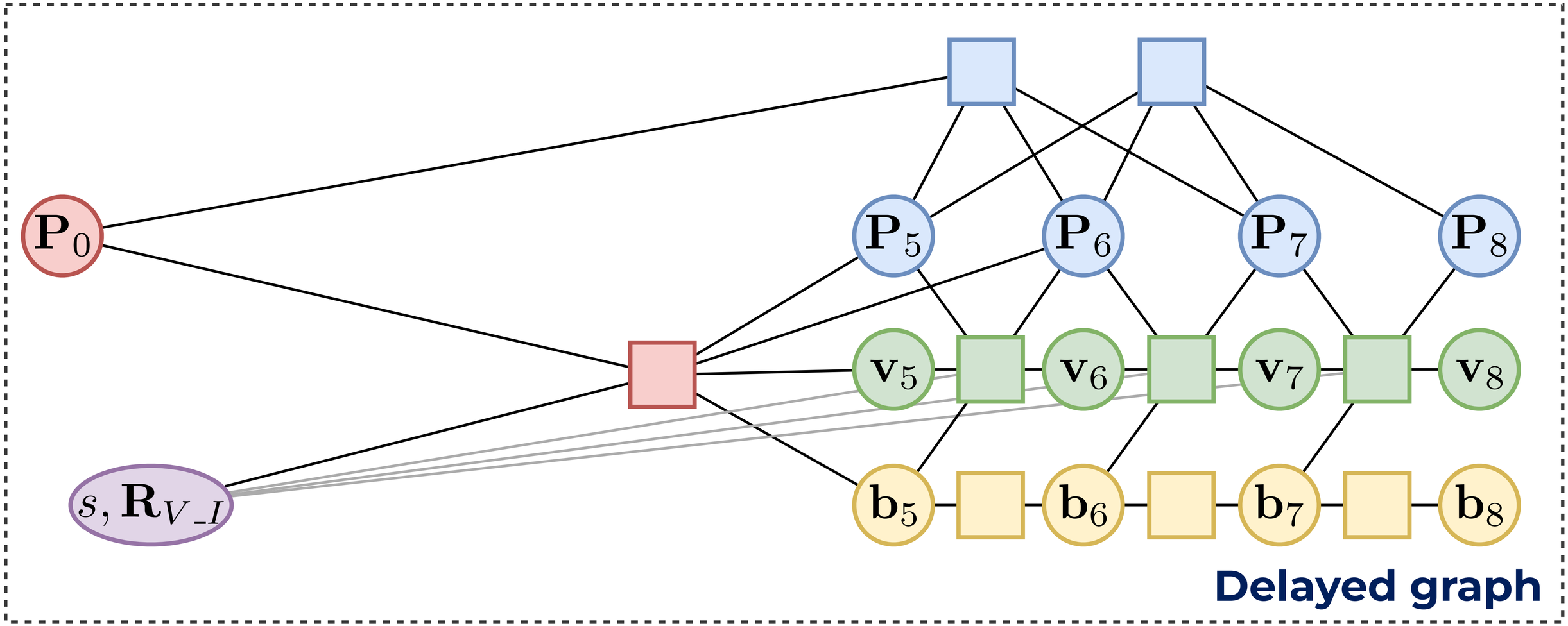
Marginalization order: $\mathbf{P}_1 \rightarrow \mathbf{P}_2 \rightarrow \mathbf{P}_3 \rightarrow \boxed{\mathbf{P}_4} \rightarrow \mathbf{P}_0$

Readvancing

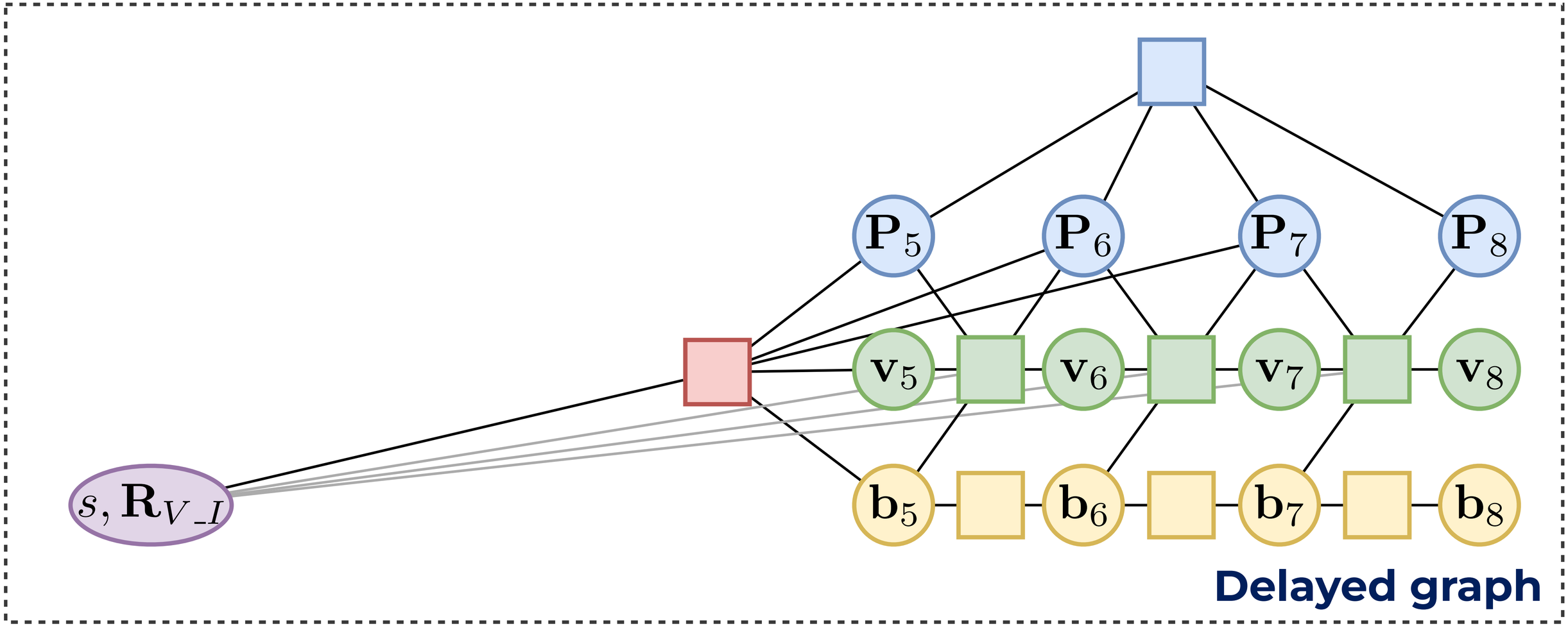


Marginalization order: $\mathbf{P}_1 \rightarrow \mathbf{P}_2 \rightarrow \mathbf{P}_3 \rightarrow \mathbf{P}_4 \rightarrow \boxed{\mathbf{P}_0}$

Readvancing

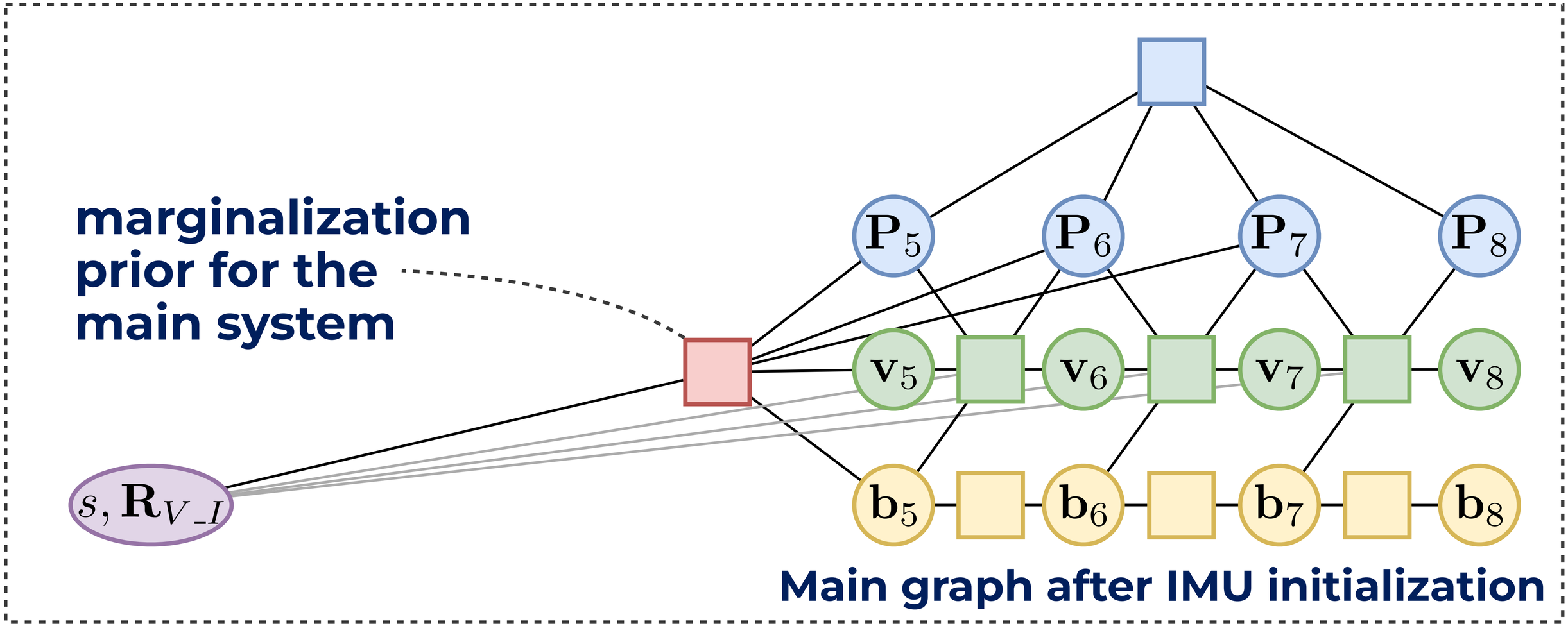


Readvancing

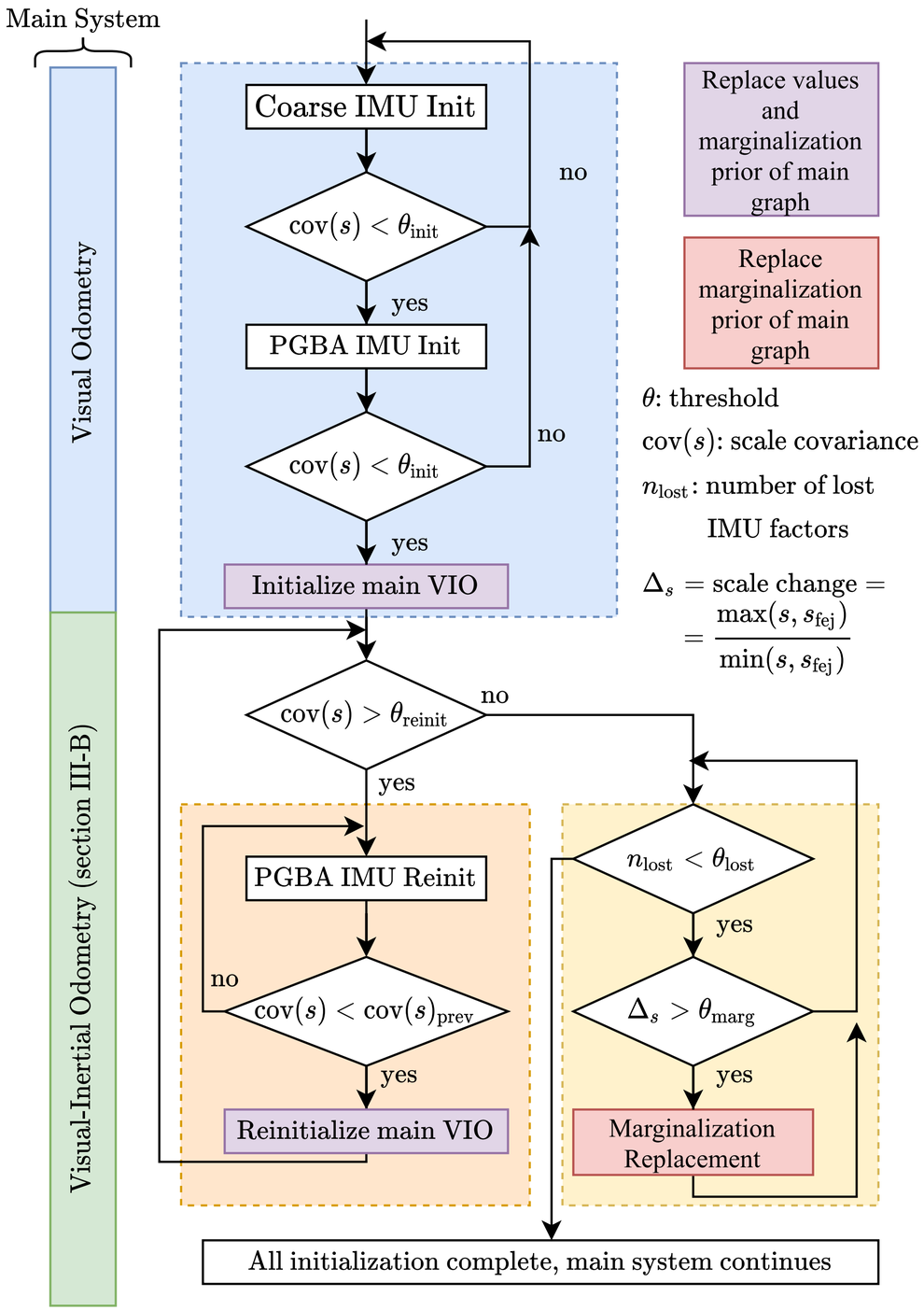


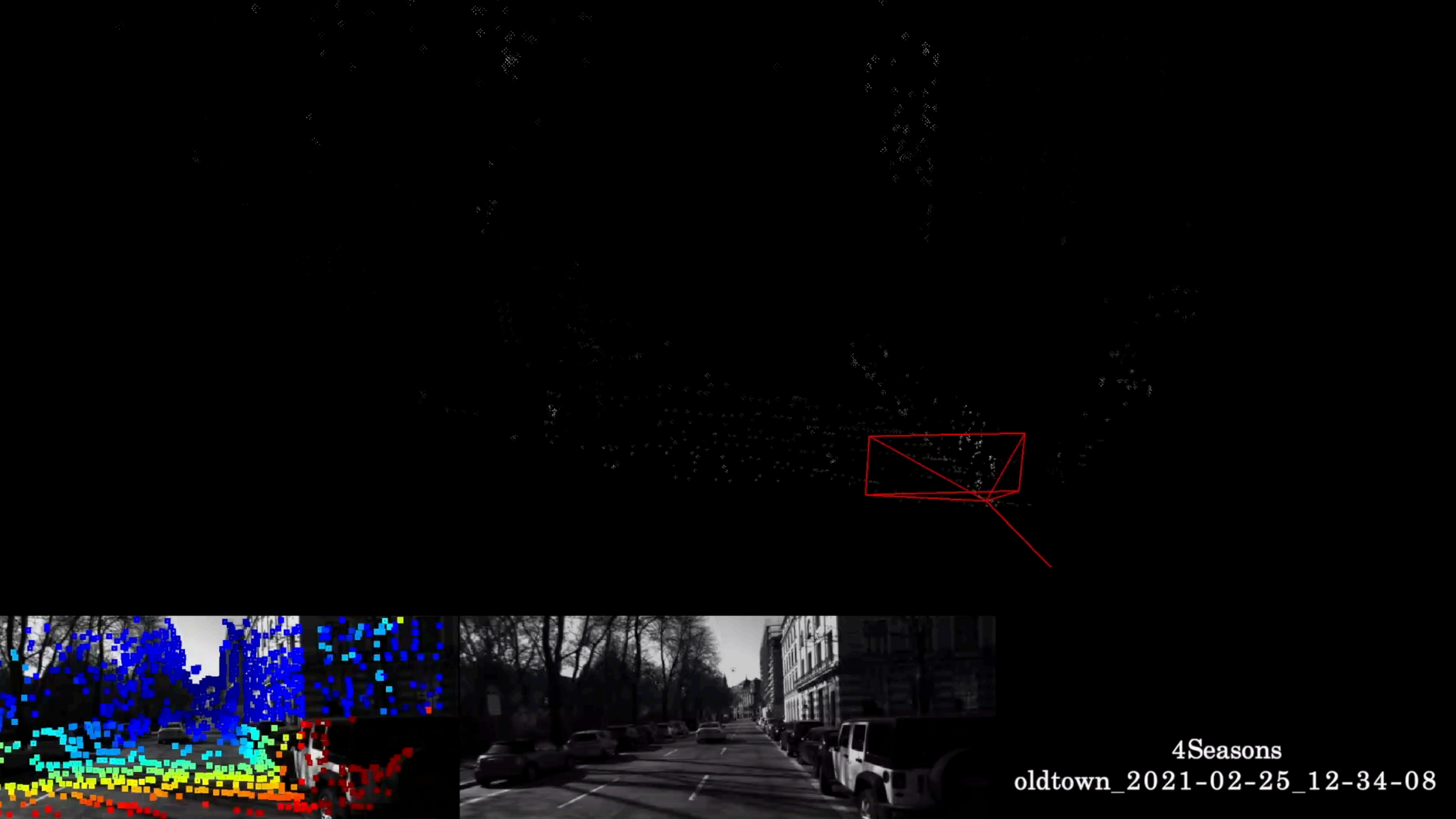
Marginalization order: $\mathbf{P}_1 \rightarrow \mathbf{P}_2 \rightarrow \mathbf{P}_3 \rightarrow \mathbf{P}_4 \rightarrow \mathbf{P}_0$

Readvancing



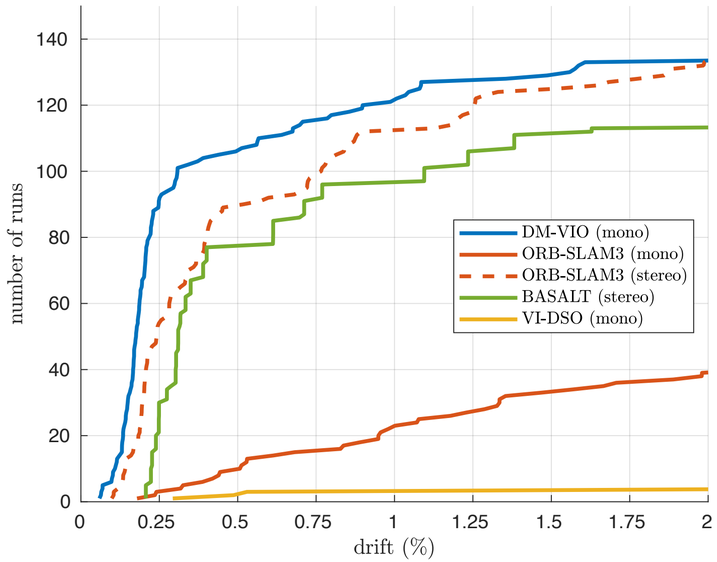
Multi-stage IMU initializer




4Seasons
oldtown_2021-02-25_12-34-08

Results

4Seasons



EuRoC

Sequence		MH1	MH2	MH3	MH4	MH5	V11	V12	V13	V21	V22	V23	Avg
MCSKF[2] [1] (M)	RMSE	0.42	0.45	0.23	0.37	0.48	0.34	0.20	0.67	0.10	0.16	1.13	0.414
OKVIS[1] [19] (M)	RMSE	0.33	0.37	0.25	0.27	0.39	0.094	0.14	0.21	0.090	0.17	0.23	0.231
ROVIO[2] [18] (M)	RMSE	0.21	0.25	0.25	0.49	0.52	0.10	0.10	0.14	0.12	0.14	0.14	0.224
VINS-Mono [3] (M)	RMSE	0.15	0.15	0.22	0.32	0.30	0.079	0.11	0.18	0.080	0.16	0.27	0.184
Kimera [21] (S)	RMSE	0.11	0.10	0.16	0.24	0.35	0.05	0.08	0.07	0.08	0.10	0.21	0.141
Online VIO [23] (M)	RMSE	0.14	0.13	0.20	0.22	0.20	0.05	0.07	0.16	0.04	0.11	0.17	0.135
VI-DSO [6] (M)	RMSE	**0.062**	**0.044**	0.117	0.132	0.121	0.059	0.067	0.096	0.040	0.062	0.174	0.089
	Scale Error (%)	1.1	0.5	0.4	0.2	0.8	1.1	1.1	0.8	1.2	0.3	0.4	0.7
BASALT [20] (S)	RMSE	0.07	0.06	**0.07**	0.13	0.11	**0.04**	0.05	0.10	0.04	**0.05**	-	0.072
DM-VIO (M)	RMSE	0.065	**0.044**	0.097	**0.102**	**0.096**	0.048	**0.045**	**0.069**	**0.029**	**0.050**	**0.114**	**0.069**
	Scale Error (%)	1.3	0.9	0.4	0.2	0.4	0.4	1.0	0.3	0.02	0.6	0.8	0.6

TUM-VI

Sequence	ROVIO stereo	VINS mono	OKVIS stereo	BASALT stereo	DM-VIO mono	length [m]
corridor1	0.47	0.63	0.33	0.34	**0.19**	305
corridor2	0.75	0.95	0.47	**0.42**	0.47	322
corridor3	0.85	1.56	0.57	0.35	**0.24**	300
corridor4	**0.13**	0.25	0.26	0.21	**0.13**	114
corridor5	2.09	0.77	0.39	0.37	**0.16**	270
magistrale1	4.52	2.19	3.49	**1.20**	2.35	918
magistrale2	13.43	3.11	2.73	**1.11**	2.24	561
magistrale3	14.80	**0.40**	1.22	0.74	1.69	566
magistrale4	39.73	5.12	**0.77**	1.58	1.02	688
magistrale5	3.47	0.85	1.62	**0.60**	0.73	458
magistrale6	X	2.29	3.91	3.23	**1.19**	771
outdoors1	101.95	**74.96**	X	255.04	123.24	2656
outdoors2	21.67	133.46	73.86	64.61	**12.76**	1601
outdoors3	26.10	36.99	32.38	38.26	**8.92**	1531
outdoors4	X	16.46	19.51	17.53	**15.25**	928
outdoors5	54.32	130.63	13.12	7.89	**7.16**	1168
outdoors6	149.14	133.60	96.51	65.50	**34.86**	2045
outdoors7	49.01	21.90	13.61	**4.07**	5.00	1748
outdoors8	36.03	83.36	16.31	13.53	**2.11**	986
room1	0.16	0.07	0.06	0.09	**0.03**	146
room2	0.33	**0.07**	0.11	**0.07**	0.13	142
room3	0.15	0.11	**0.07**	0.13	0.09	135
room4	0.09	0.04	**0.03**	0.05	0.04	68
room5	0.12	0.20	0.07	0.13	**0.06**	131
room6	0.05	0.08	0.04	**0.02**	**0.02**	67
slides1	13.73	0.68	0.86	0.32	**0.31**	289
slides2	0.81	0.84	2.15	**0.32**	0.87	299
slides3	4.68	0.69	2.58	0.89	**0.60**	383
avg drift%	16.83*	1.700	0.815*	0.939	**0.472**	normalized

Product Solutions Open Source Pricing Search or jump to... / Sign in Sign up

lukasvst / dm-vio Public

Notifications Fork 142 Star 758

Code Issues 14 Pull requests 2 Actions Projects Security Insights

master 2 branches 0 tags Go to file Code

Lukas von Stumberg Parallelized the most time-intensive part of CoarseInitializer::c... 3b5319a on Jun 6 9 commits

cmake	Initial commit with the first version of the code.	last year
configs	Added live-version of DM-VIO for the Realsense T265 camera. It will ...	last year
doc	Added live-version of DM-VIO for the Realsense T265 camera. It will ...	last year
src	Parallelized the most time-intensive part of CoarseInitializer::calcR...	last month
test	Added live-version of DM-VIO for the Realsense T265 camera. It will ...	last year
thirdparty	Initial commit with the first version of the code.	last year
.gitmodules	Initial commit with the first version of the code.	last year
CMakeLists.txt	Added follow-cam mode to the GUI to smoothly follow the camera tr...	2 months ago
LICENSE	Initial commit with the first version of the code.	last year
README.md	Added follow-cam mode to the GUI to smoothly follow the camera tr...	2 months ago

README.md

DM-VIO: Delayed Marginalization Visual-Inertial Odometry

Paper | Video | Project Page

When using this project in academic work, please consider citing:

About

Source code for the paper DM-VIO: Delayed Marginalization Visual-Inertial Odometry

Readme
GPL-3.0 license
Activity
758 stars
53 watching
142 forks
Report repository

Releases

No releases published

Packages

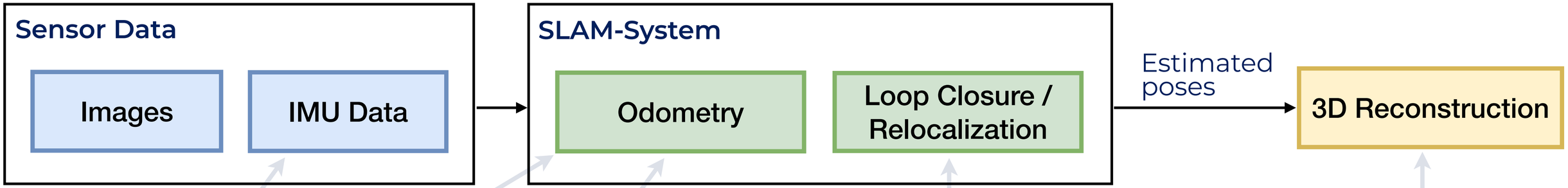
No packages published

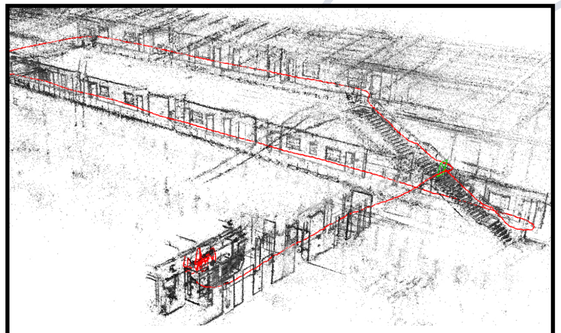
Languages

C++ 98.7% CMake 1.3%

Code online: https://github.com/lukasvst/dm-vio

Visual SLAM
From Optimization to Learning

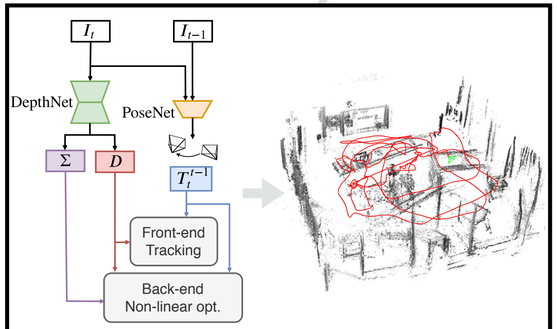




DM-VIO

L. von Stumberg and D. Cremers

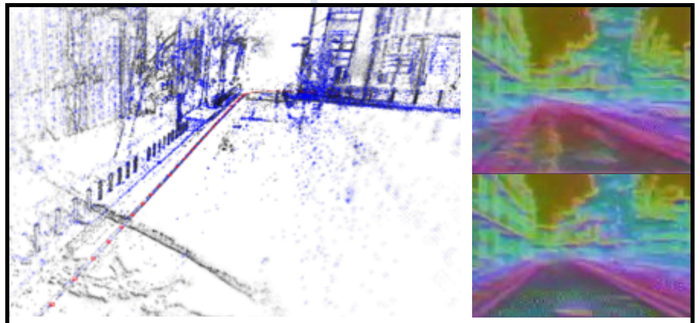
RA-L & ICRA 2022



D3VO

N. Yang, L. von Stumberg, R. Wang and D. Cremers

CVPR 2020



GN-Net

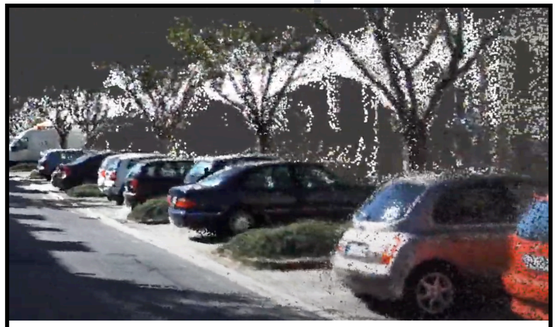
L. von Stumberg, P. Wenzel, Q. Khan, D. Cremers

RA-L & ICRA 2020

LM-Reloc

L. von Stumberg, P. Wenzel N. Yang, D. Cremers

3DV 2020

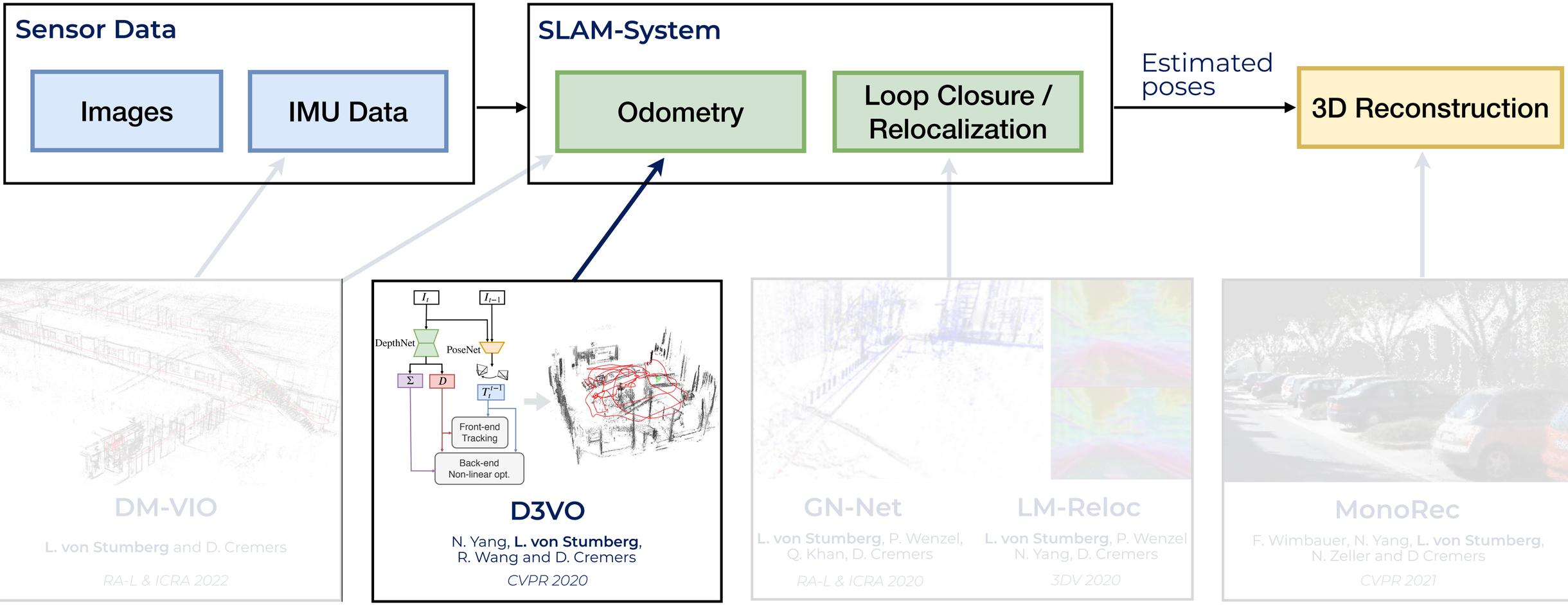


MonoRec

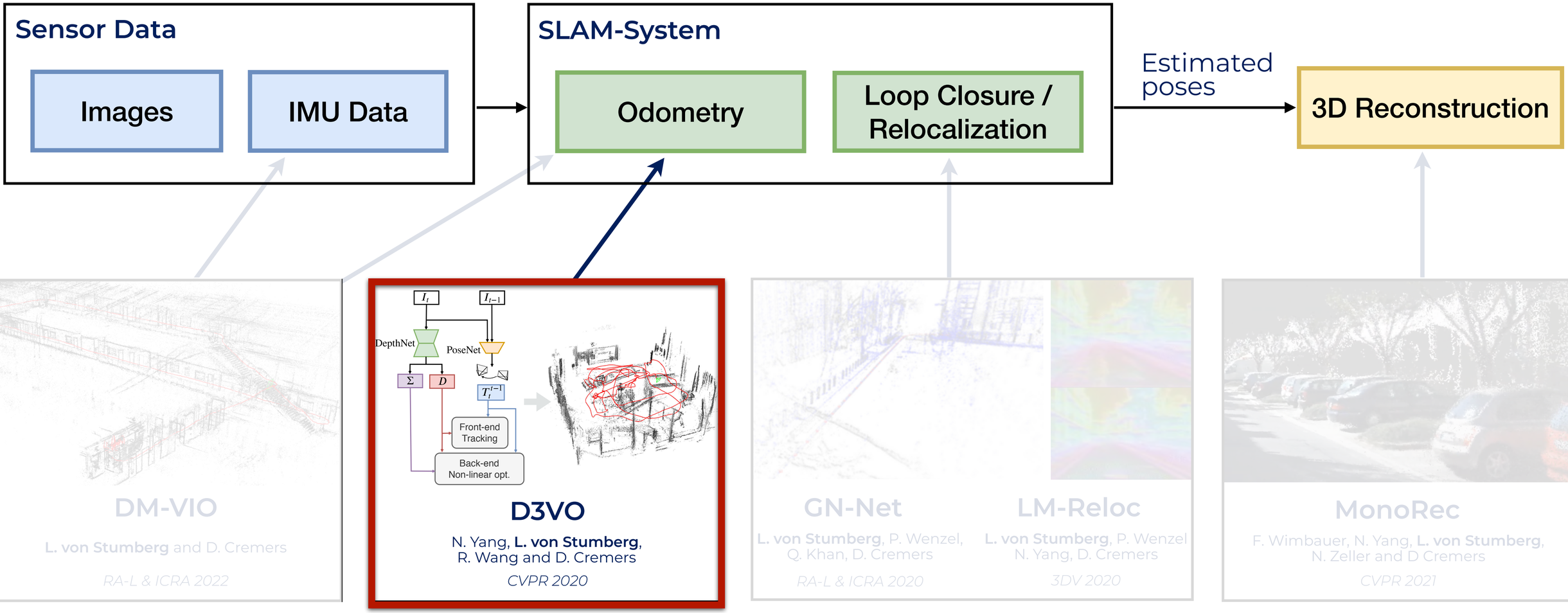
F. Wimbauer, N. Yang, L. von Stumberg, N. Zeller and D Cremers

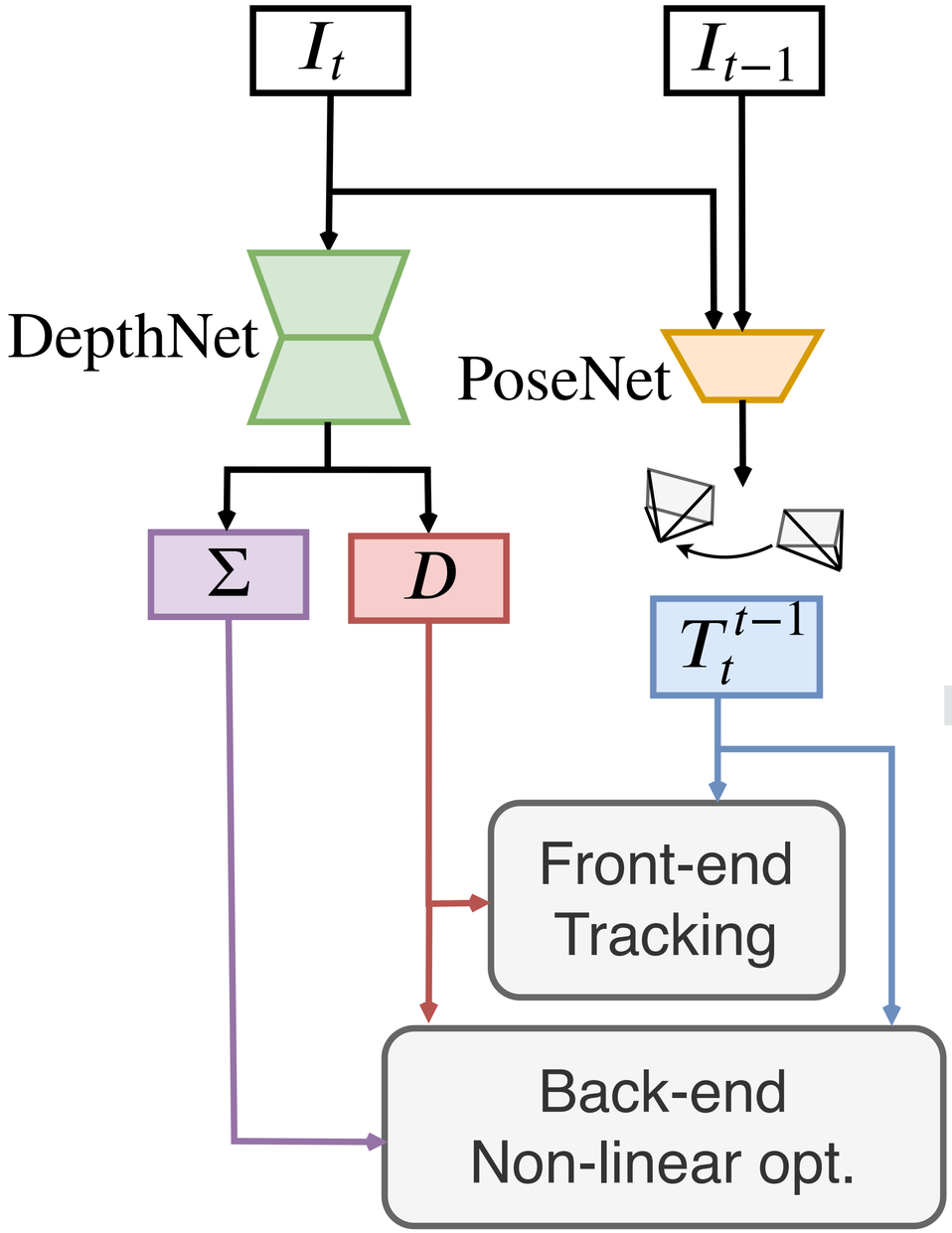
CVPR 2021

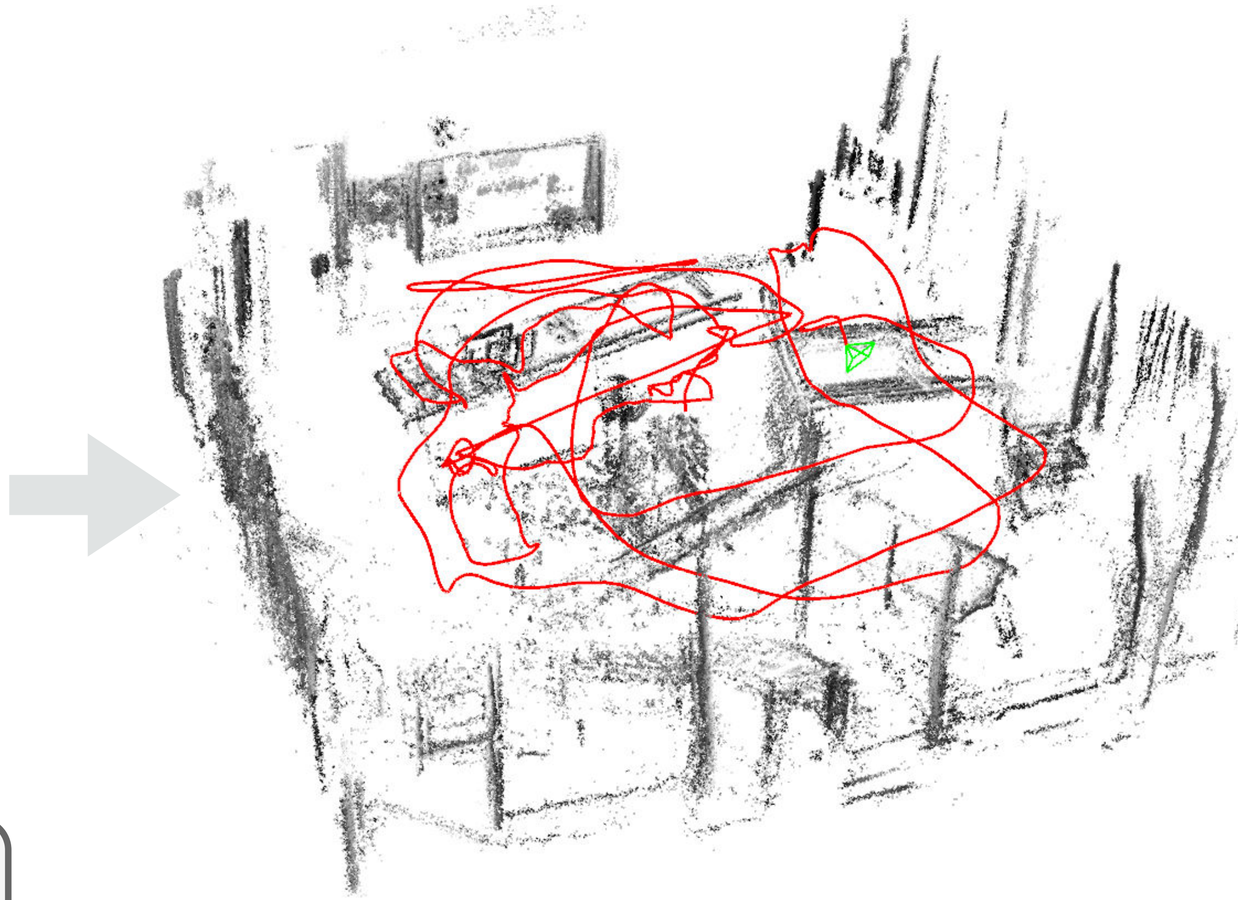
Visual SLAM
From Optimization to Learning



Visual SLAM
From Optimization to Learning

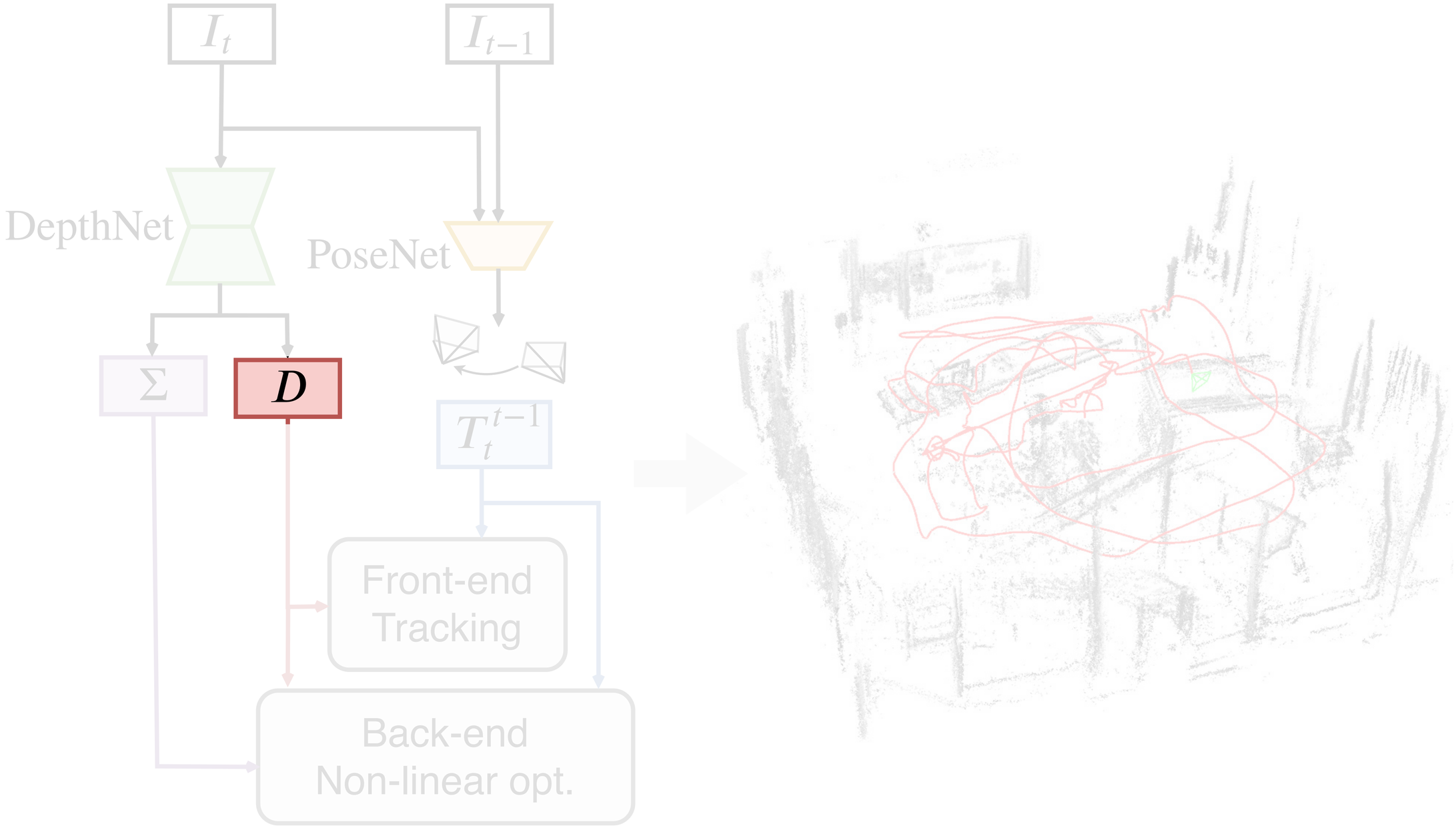






D3VO Deep Depth, Deep Pose and Deep Uncertainty for Monocular Visual Odometry

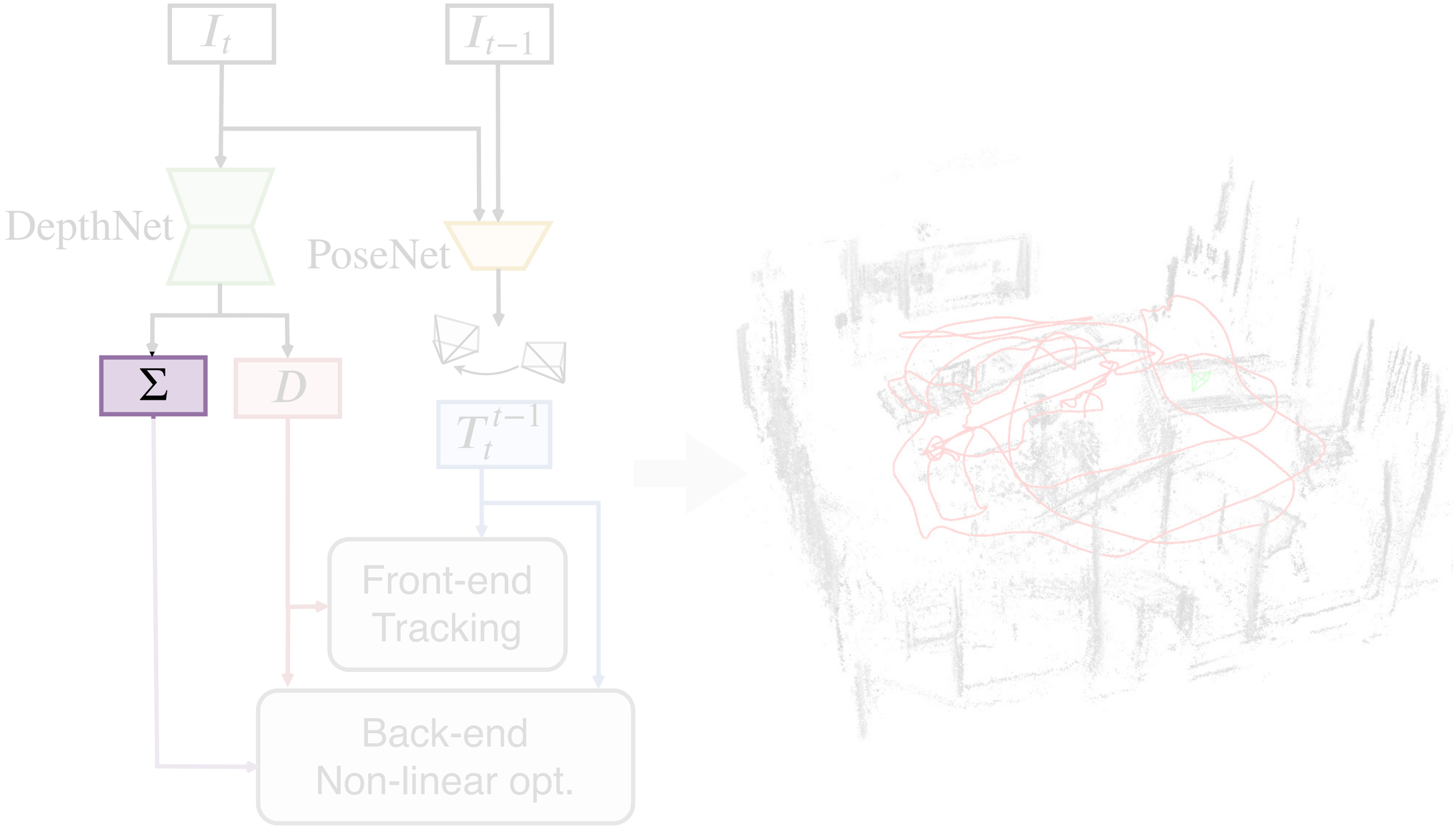
CVPR 2020 N. Yang, L. von Stumberg, R. Wang and D. Cremers



D3VO Deep Depth, Deep Pose and Deep Uncertainty for Monocular Visual Odometry

CVPR 2020

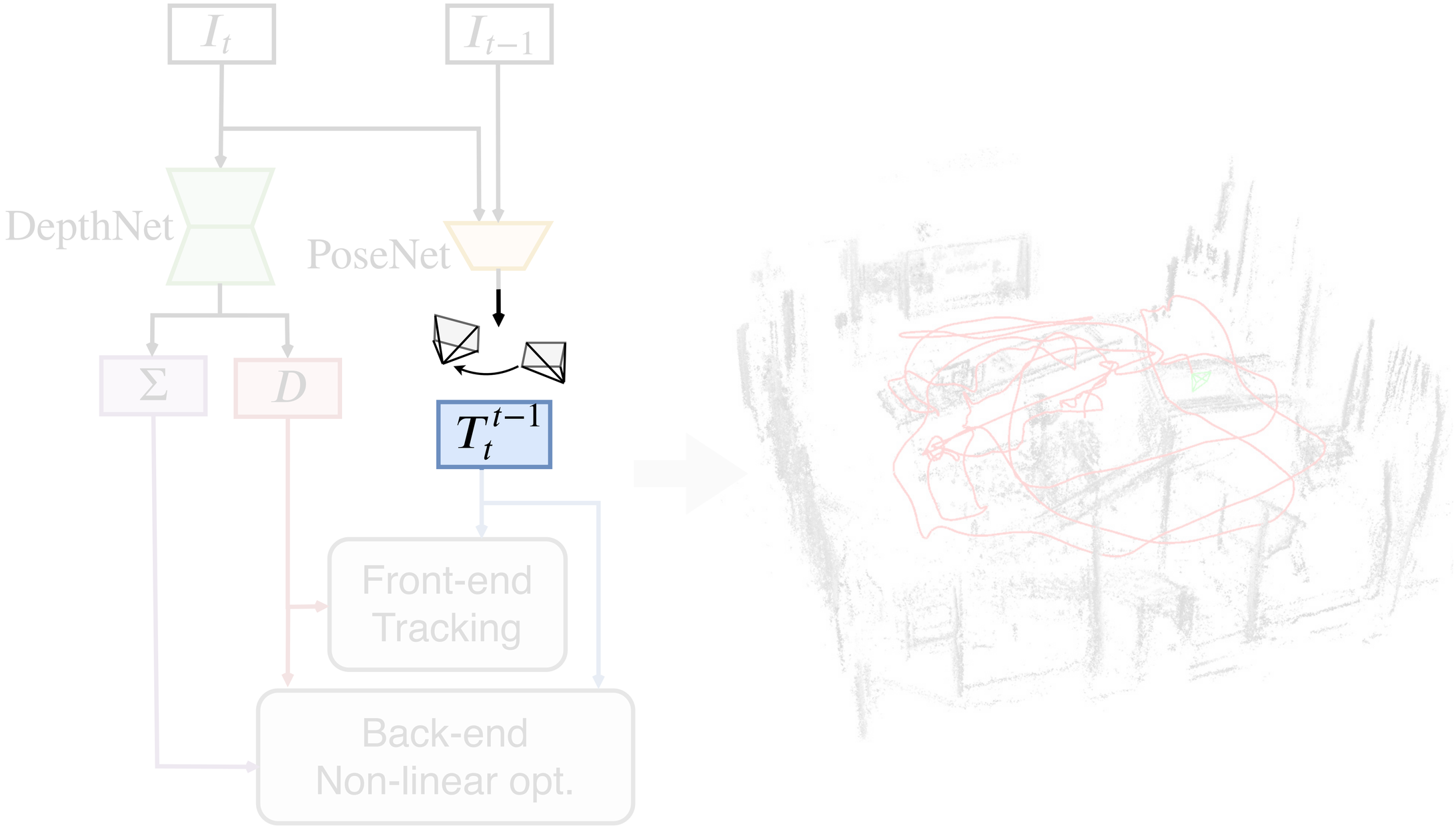
N. Yang, L. von Stumberg, R. Wang and D. Cremers



D3VO Deep Depth, Deep Pose and Deep Uncertainty for Monocular Visual Odometry

CVPR 2020

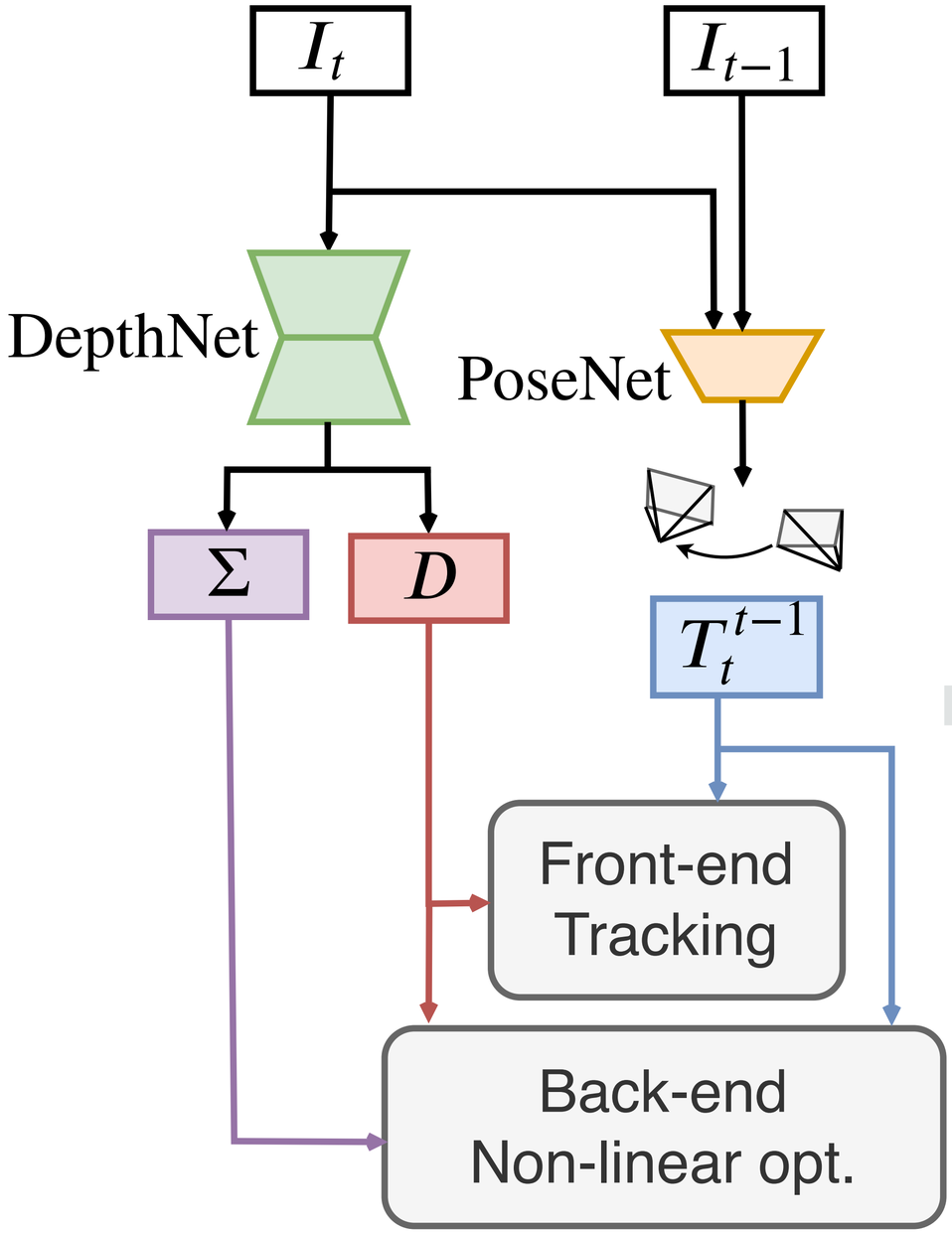
N. Yang, L. von Stumberg, R. Wang and D. Cremers

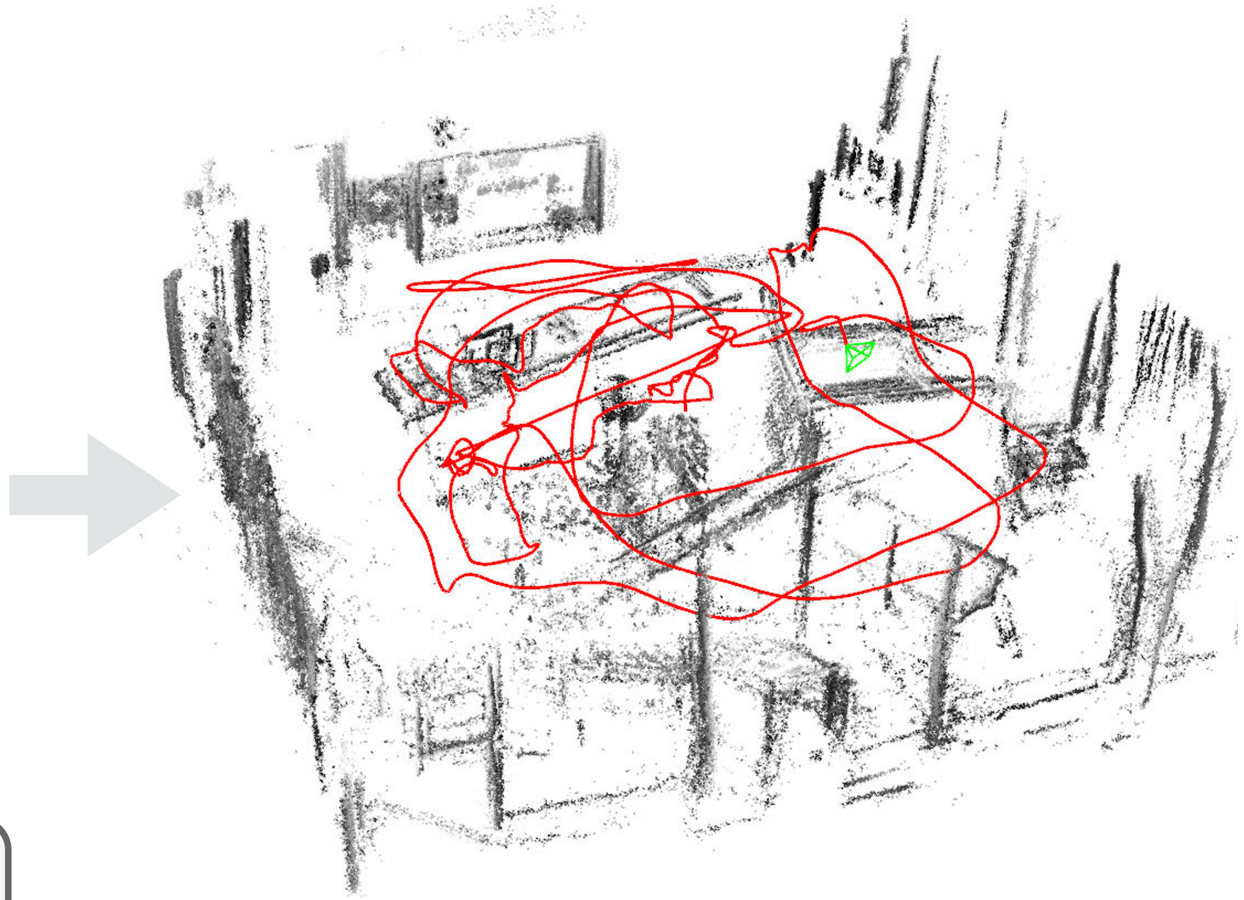


D3VO Deep Depth, Deep Pose and Deep Uncertainty for Monocular Visual Odometry

CVPR 2020

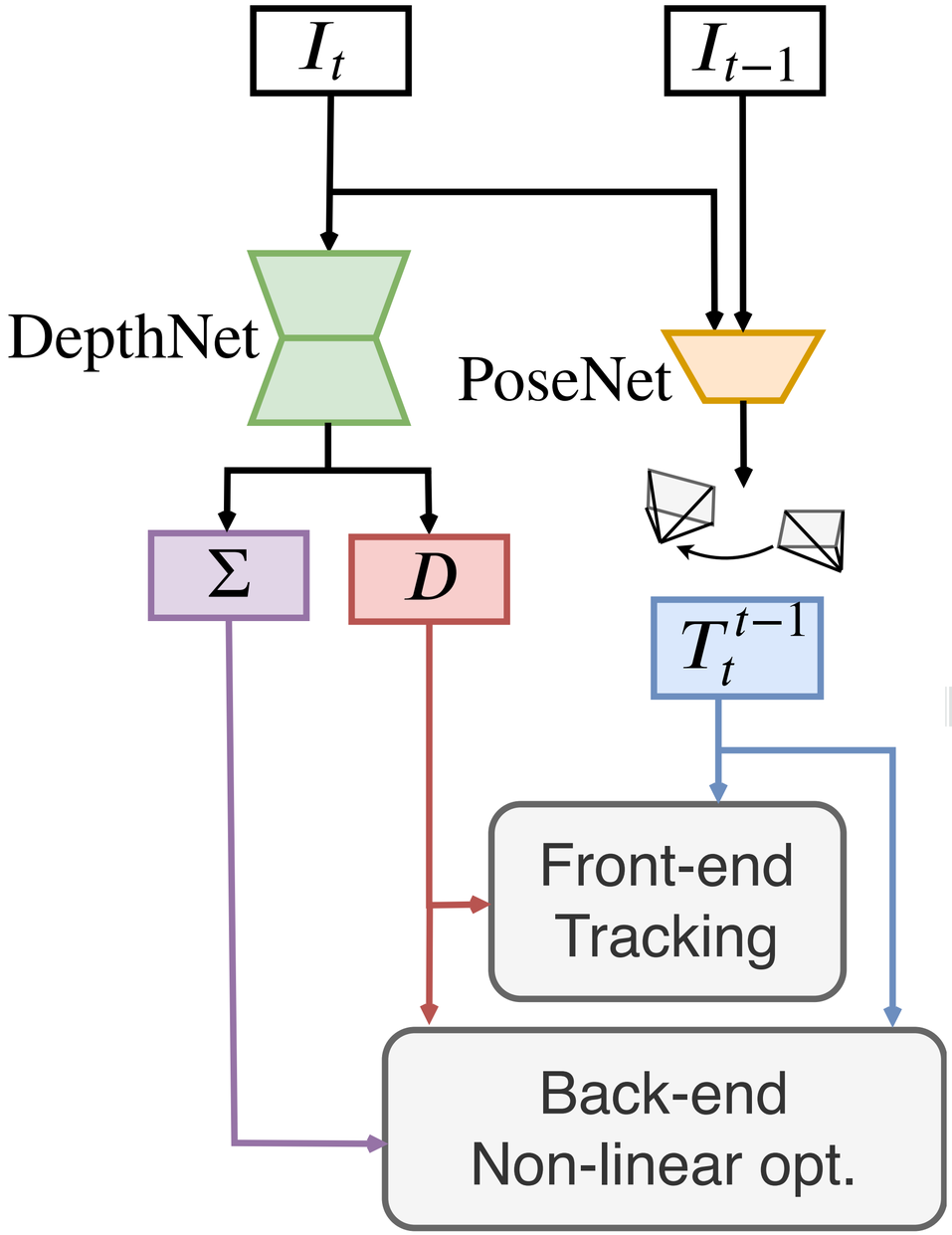
N. Yang, L. von Stumberg, R. Wang and D. Cremers

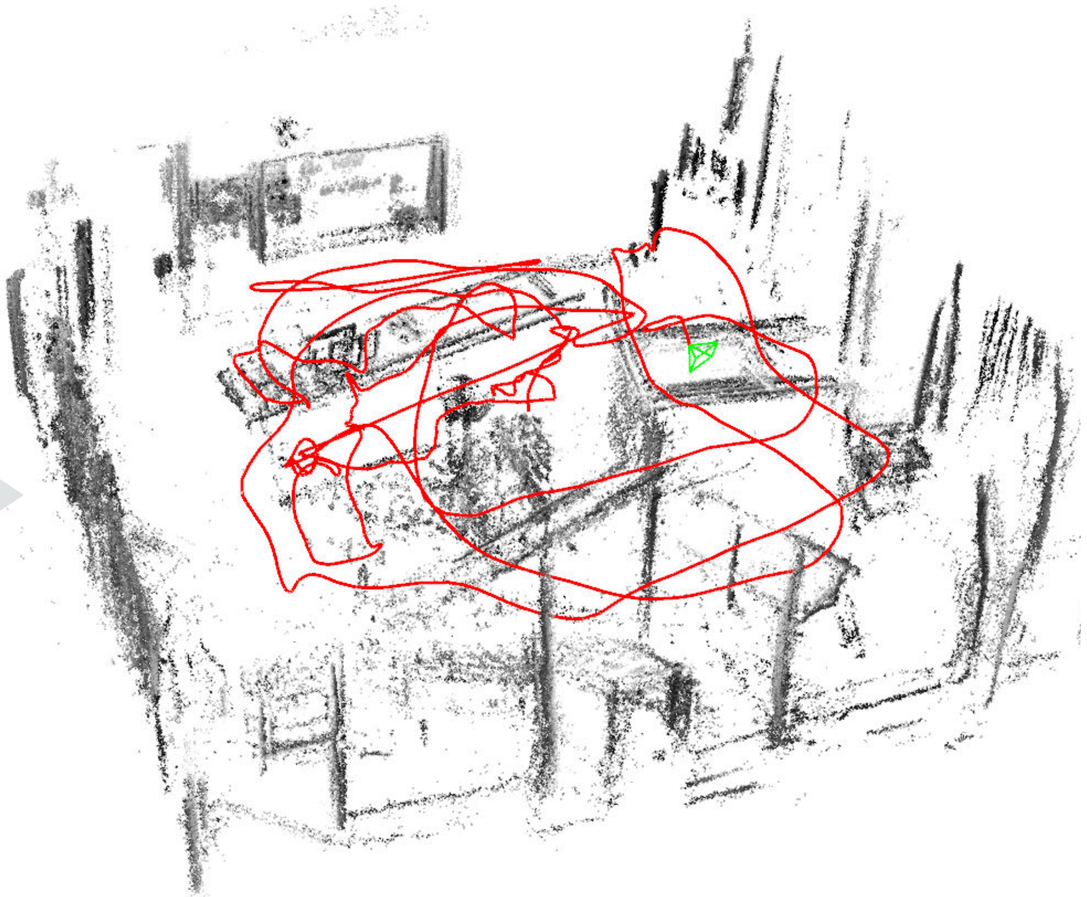




D3VO Deep Depth, Deep Pose and Deep Uncertainty for Monocular Visual Odometry

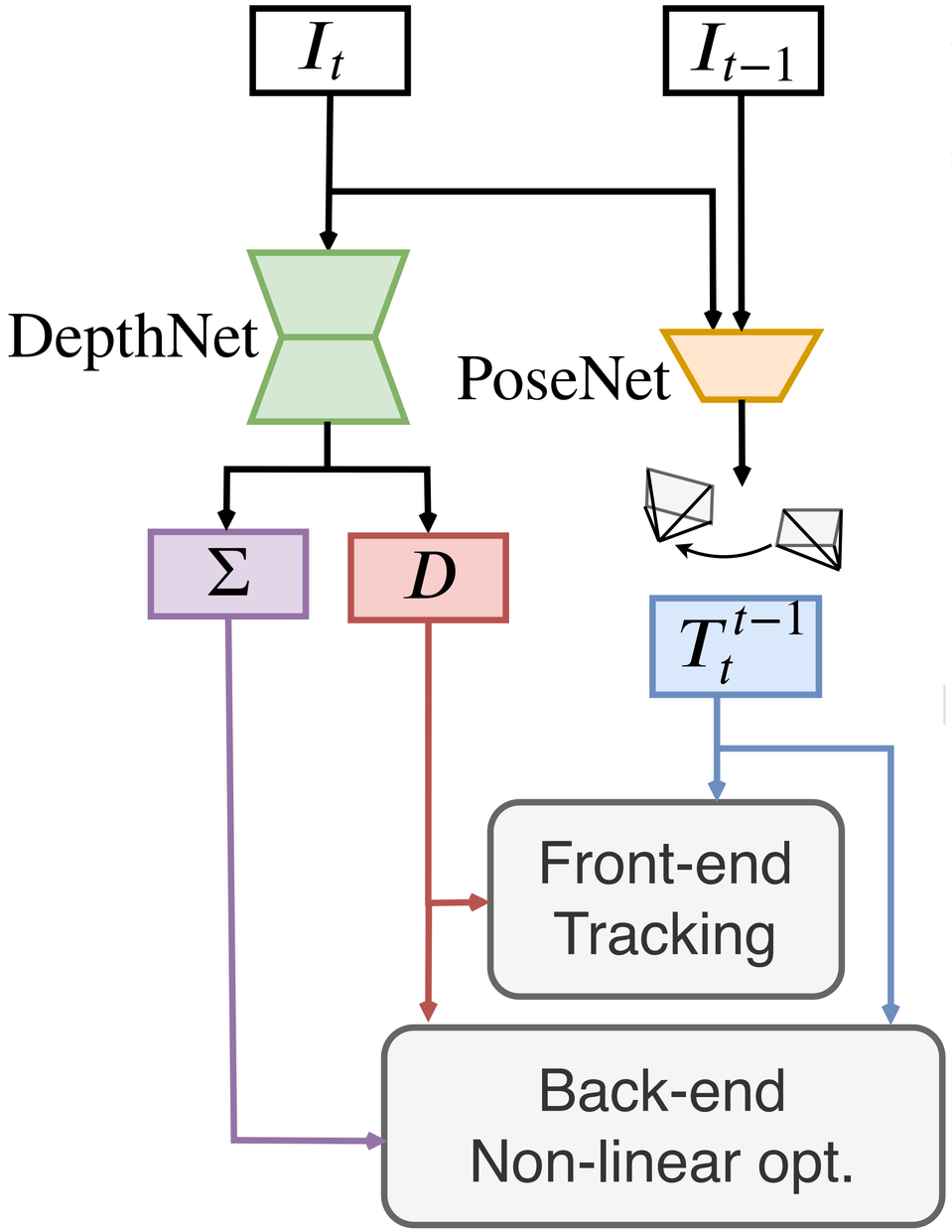
CVPR 2020 N. Yang, L. von Stumberg, R. Wang and D. Cremers



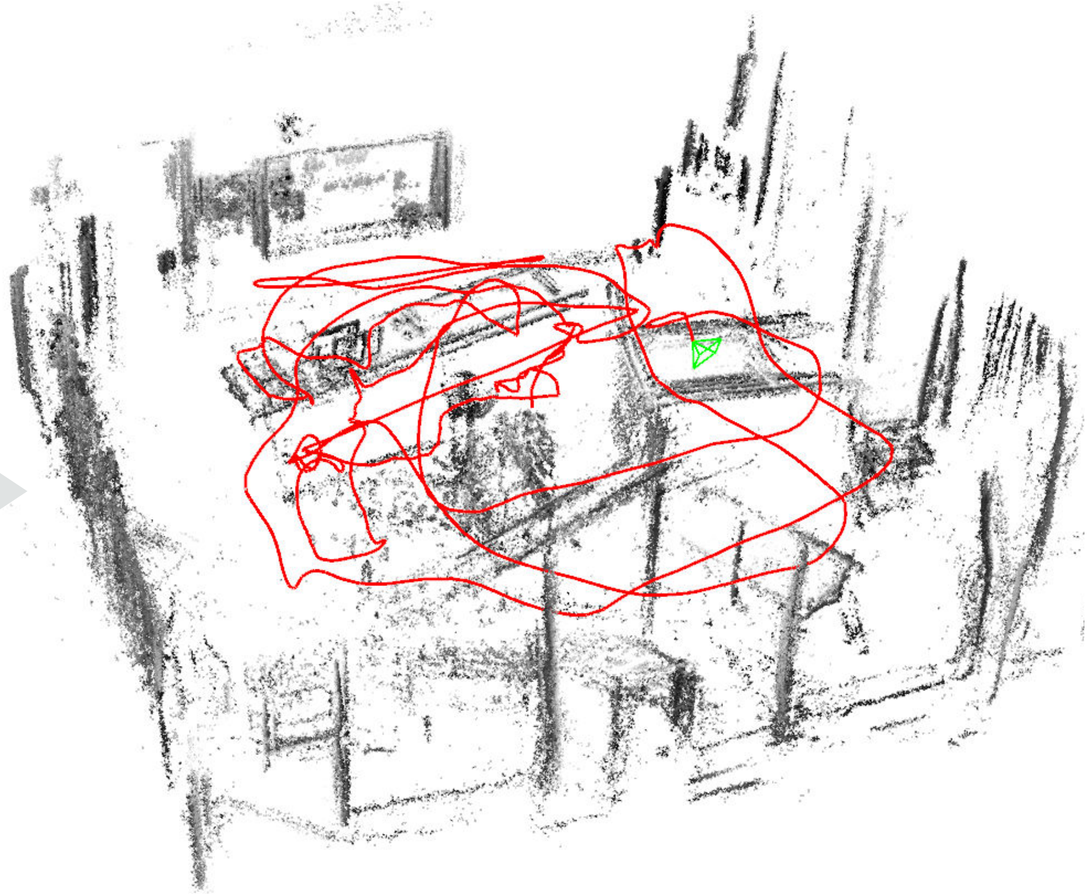


D3VO Deep Depth, Deep Pose and Deep Uncertainty for Monocular Visual Odometry

CVPR 2020 N. Yang, L. von Stumberg, R. Wang and D. Cremers



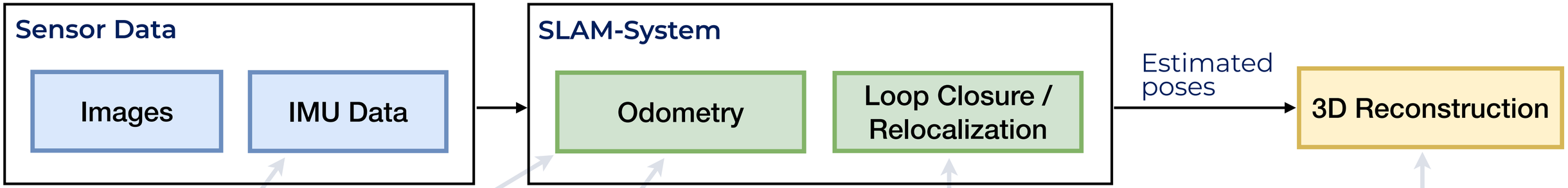
		M03	M05	V103	V202	V203	mean
M	DSO [15]	0.18	0.11	1.42	0.12	0.56	0.48
	ORB [24]	**0.08**	0.16	1.48	1.72	0.17	0.72
S+I	VINS [175]	0.23	0.19	*0.11*	*0.10*	-	*0.17*
	OKVIS [40]	0.23	0.36	0.13	0.17	-	0.22
	Basalt [34]	**0.06**	*0.12*	**0.10**	**0.05**	-	**0.08**
	D3VO	*0.08*	**0.09**	*0.11*	**0.05**	-	**0.08**

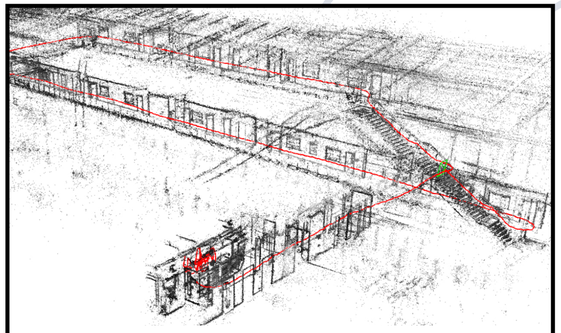


D3VO Deep Depth, Deep Pose and Deep Uncertainty for Monocular Visual Odometry

CVPR 2020 N. Yang, L. von Stumberg, R. Wang and D. Cremers

Visual SLAM
From Optimization to Learning

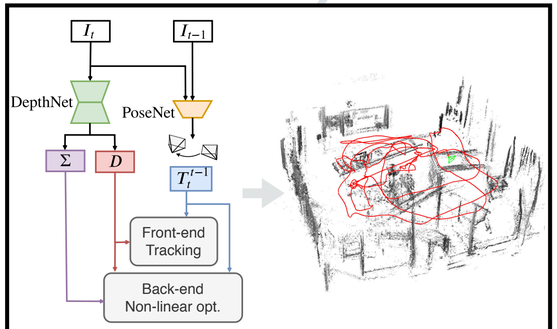




DM-VIO

L. von Stumberg and D. Cremers

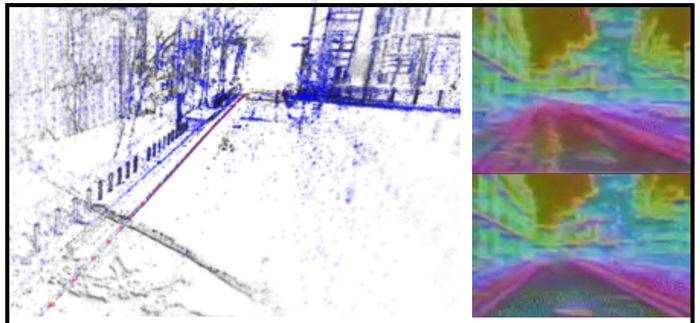
RA-L & ICRA 2022



D3VO

N. Yang, **L. von Stumberg**, R. Wang and D. Cremers

CVPR 2020



GN-Net

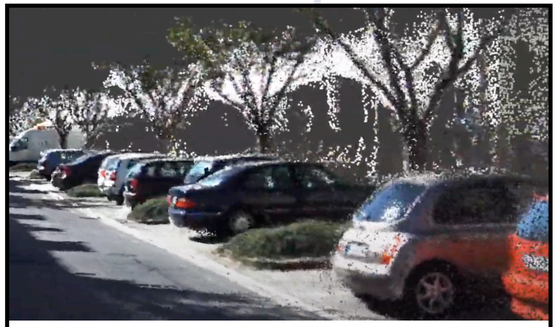
L. von Stumberg, P. Wenzel, Q. Khan, D. Cremers

RA-L & ICRA 2020

LM-Reloc

L. von Stumberg, P. Wenzel N. Yang, D. Cremers

3DV 2020

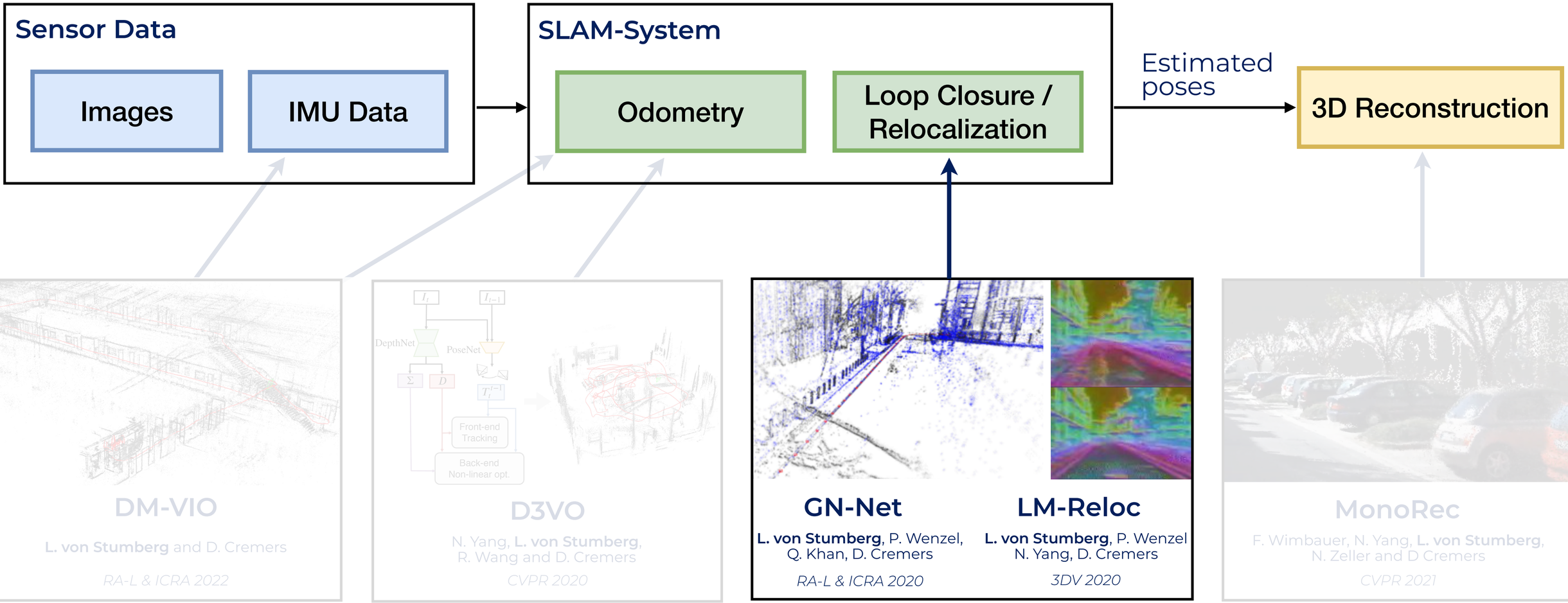


MonoRec

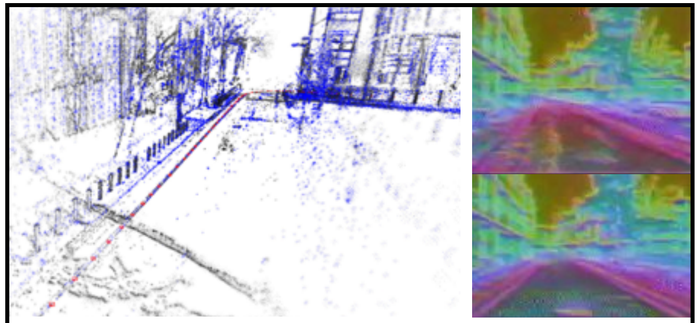
F. Wimbauer, N. Yang, **L. von Stumberg**, N. Zeller and D Cremers

CVPR 2021

Visual SLAM
From Optimization to Learning



Visual SLAM
From Optimization to Learning



GN-Net

L. von Stumberg, P. Wenzel, Q. Khan, D. Cremers

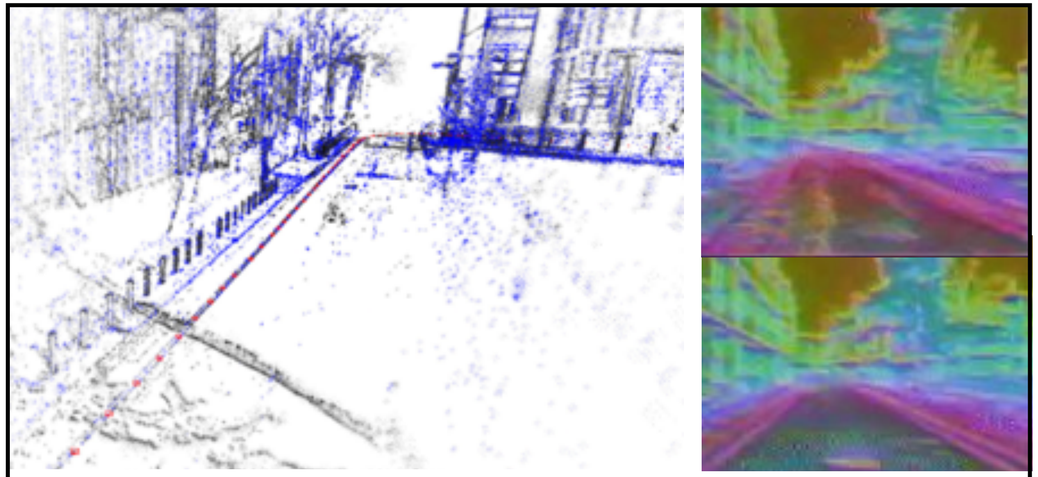
RA-L & ICRA 2020

LM-Reloc

L. von Stumberg, P. Wenzel N. Yang, D. Cremers

3DV 2020

Visual SLAM
From Optimization to Learning



GN-Net

L. von Stumberg*, P. Wenzel*,
Q. Khan, D. Cremers

RA-L & ICRA 2020

LM-Reloc

L. von Stumberg*, P. Wenzel*
N. Yang, D. Cremers

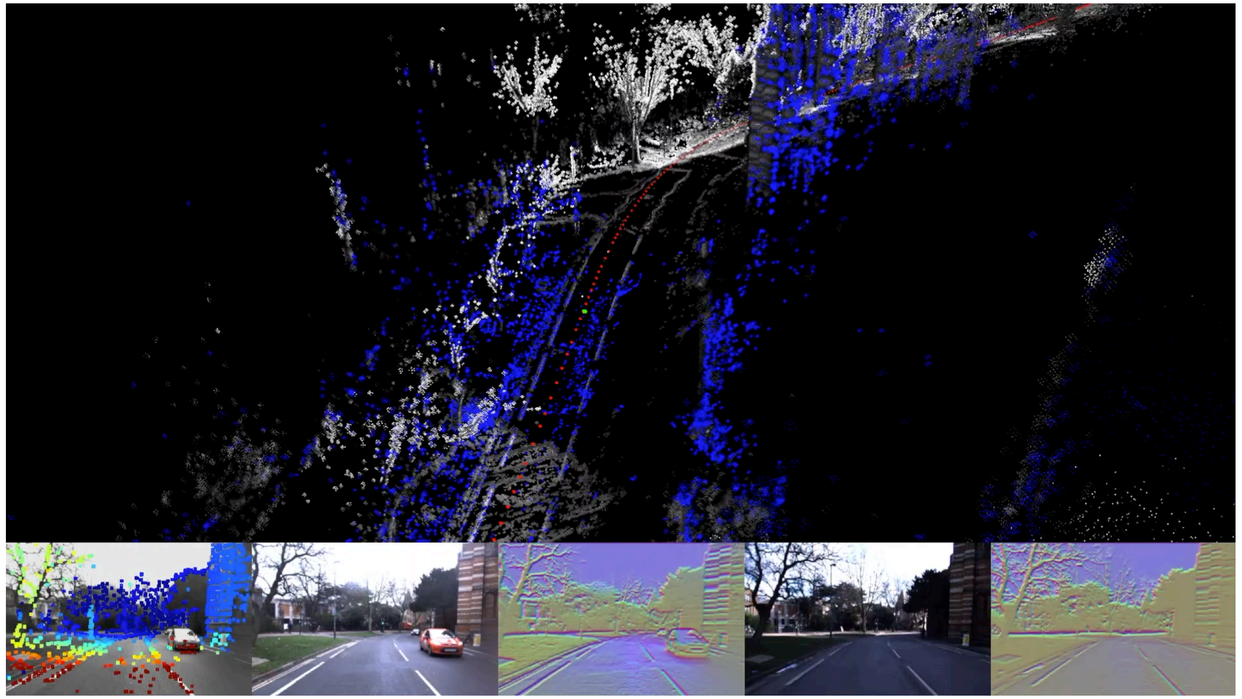
3DV 2020

*equal contribution

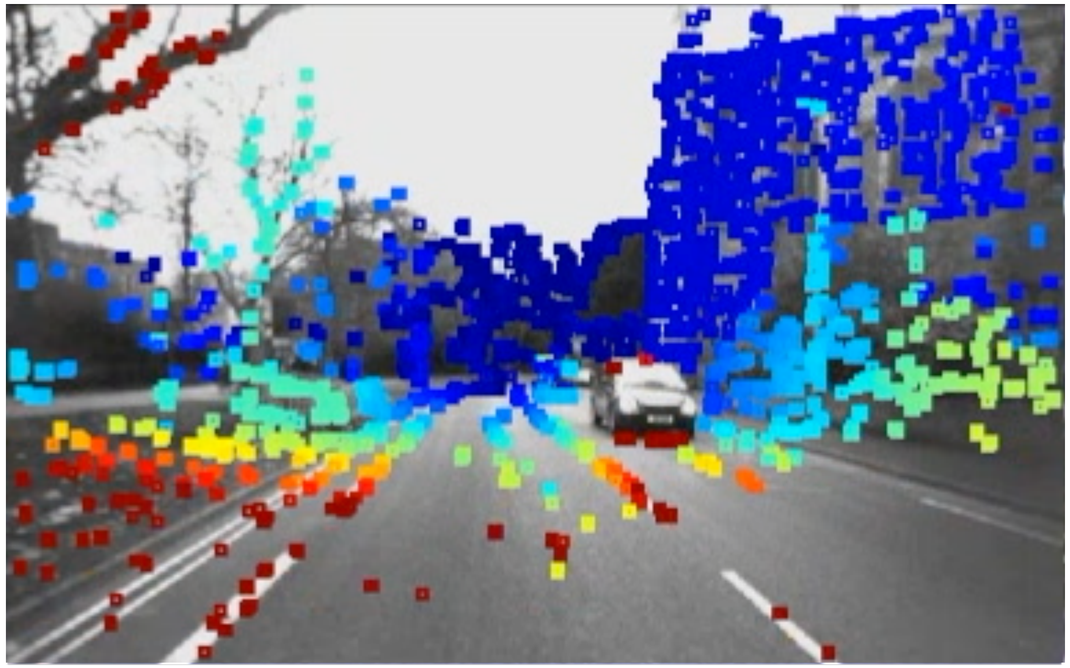
Direct Methods

- Drawbacks:
  - Need a good initialization
  - Cannot handle strong lighting / weather changes

➡ Relocalization predominantly done with indirect methods for a long time



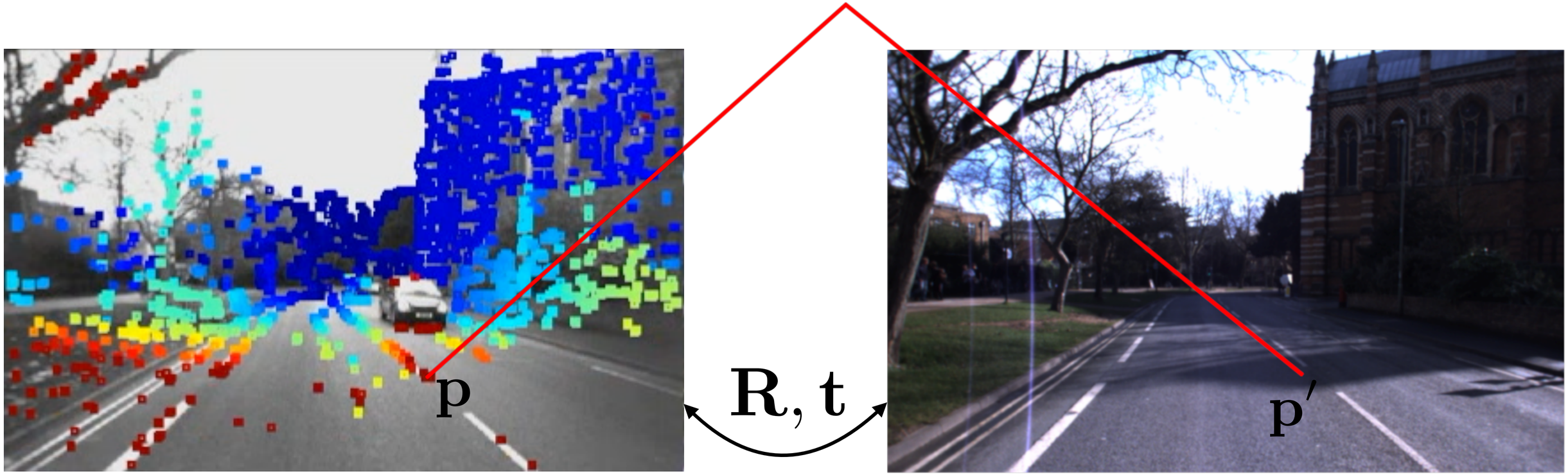
Direct Image Alignment



I

I'

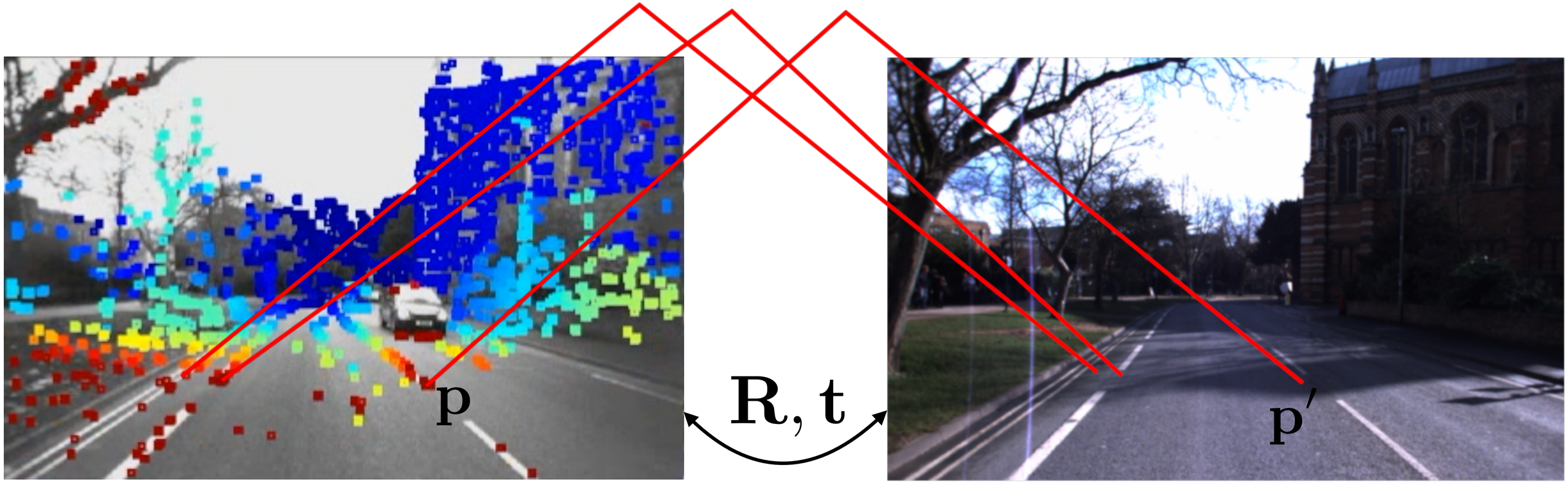
Direct Image Alignment



I $\qquad$ I'

$$E(\mathbf{R}, \mathbf{t}) = \left\| I'(\mathbf{p}') - I(\mathbf{p}) \right\|$$

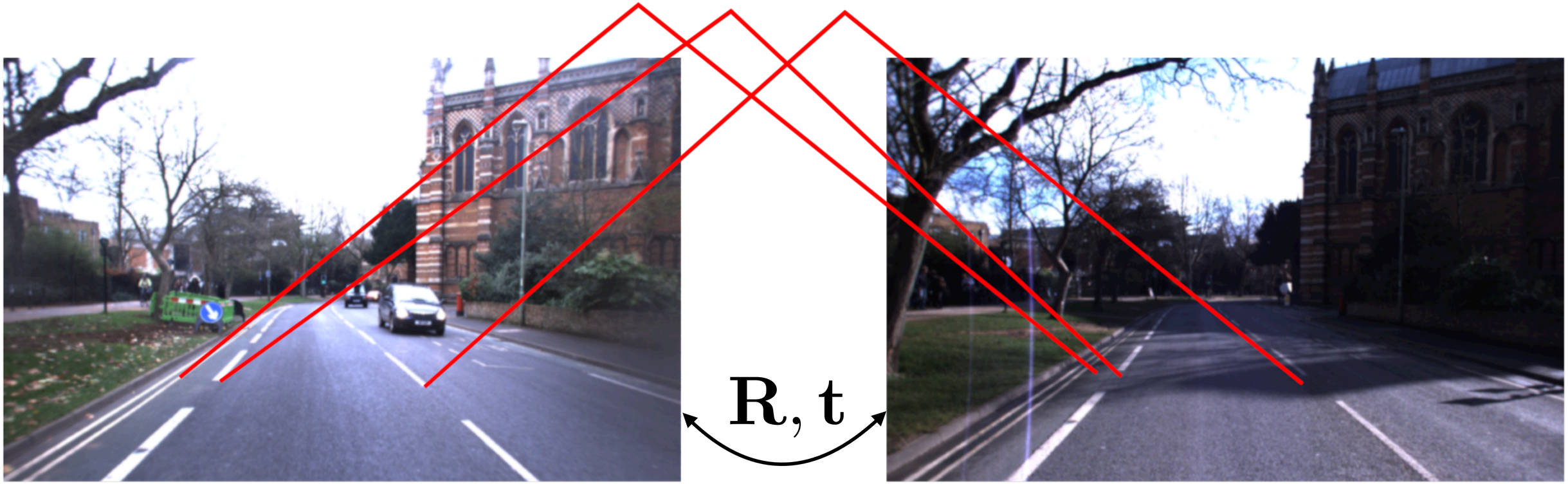
Direct Image Alignment



I $\qquad$ I'

$$E(\mathbf{R}, \mathbf{t}) = \left\| I'(\mathbf{p}') - I(\mathbf{p}) \right\|$$

Direct Image Alignment

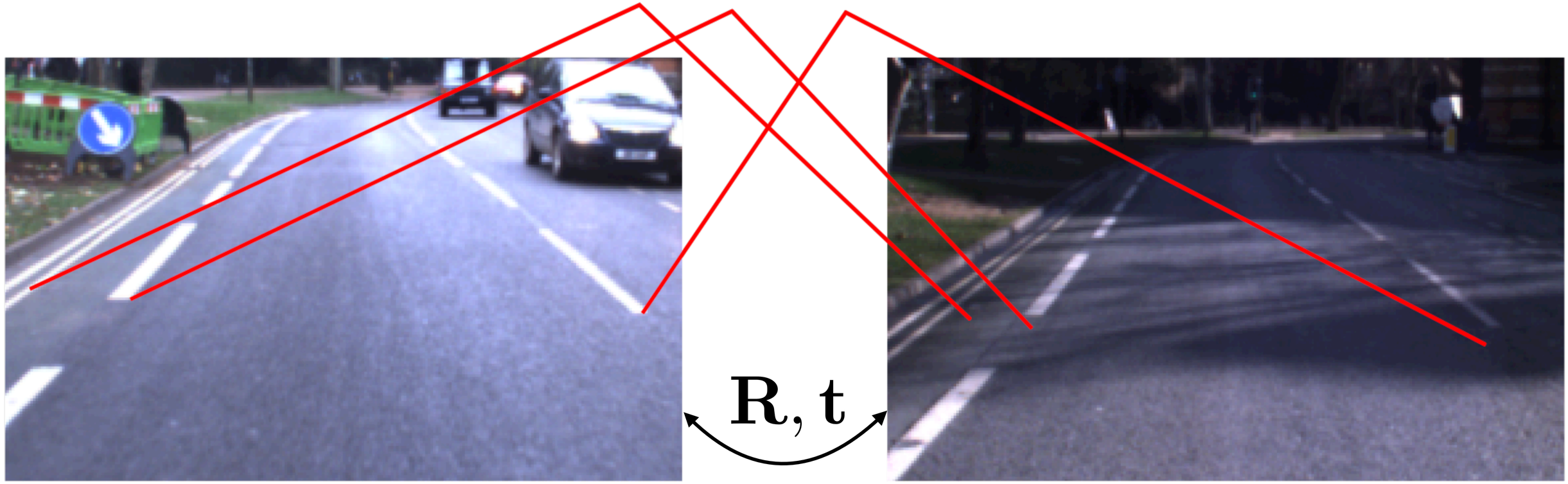


I I'

LM / Gauss-Newton Optimization

$$E(\mathbf{R}, \mathbf{t}) = \sum_{\mathbf{p}} \left\| I'(\mathbf{p}') - I(\mathbf{p}) \right\|$$

Direct Image Alignment

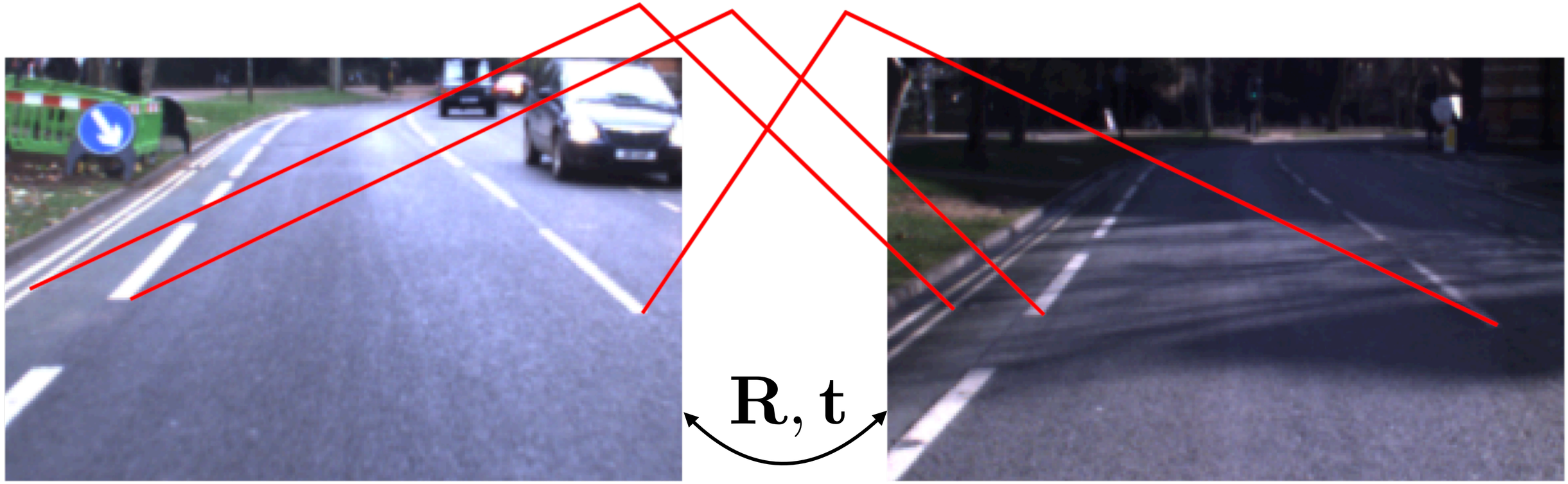


I I'

LM / Gauss-Newton Optimization

$$E(\mathbf{R}, \mathbf{t}) = \sum_{\mathbf{p}} \left\| I'(\mathbf{p}') - I(\mathbf{p}) \right\|$$

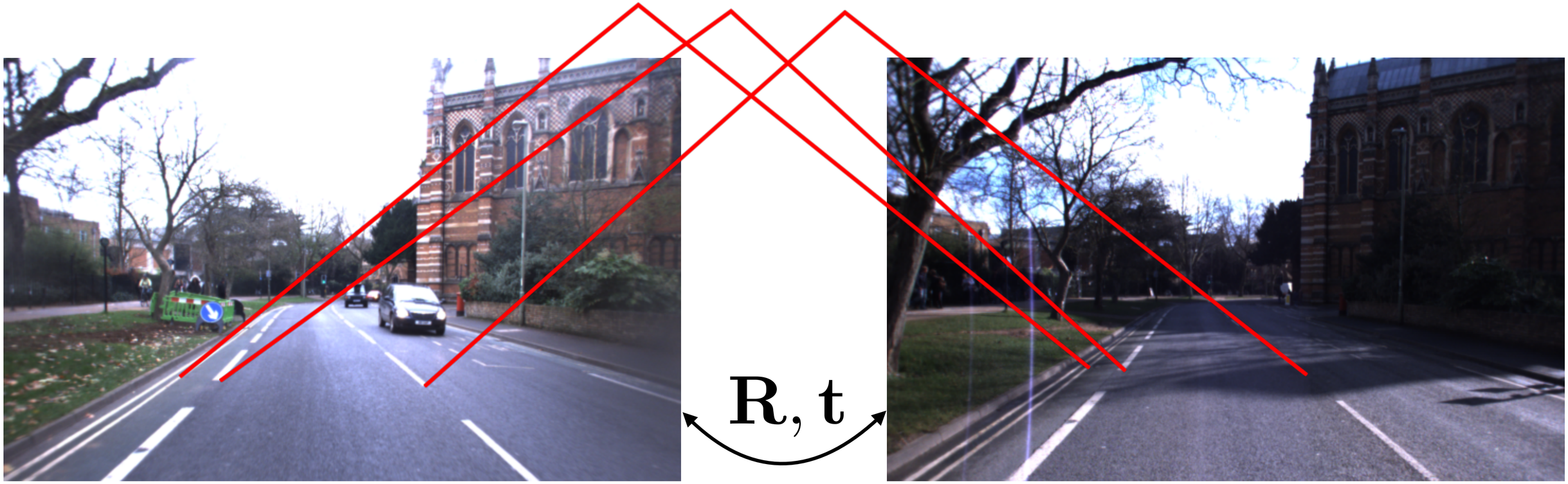
Direct Image Alignment



I I'

LM / Gauss-Newton Optimization

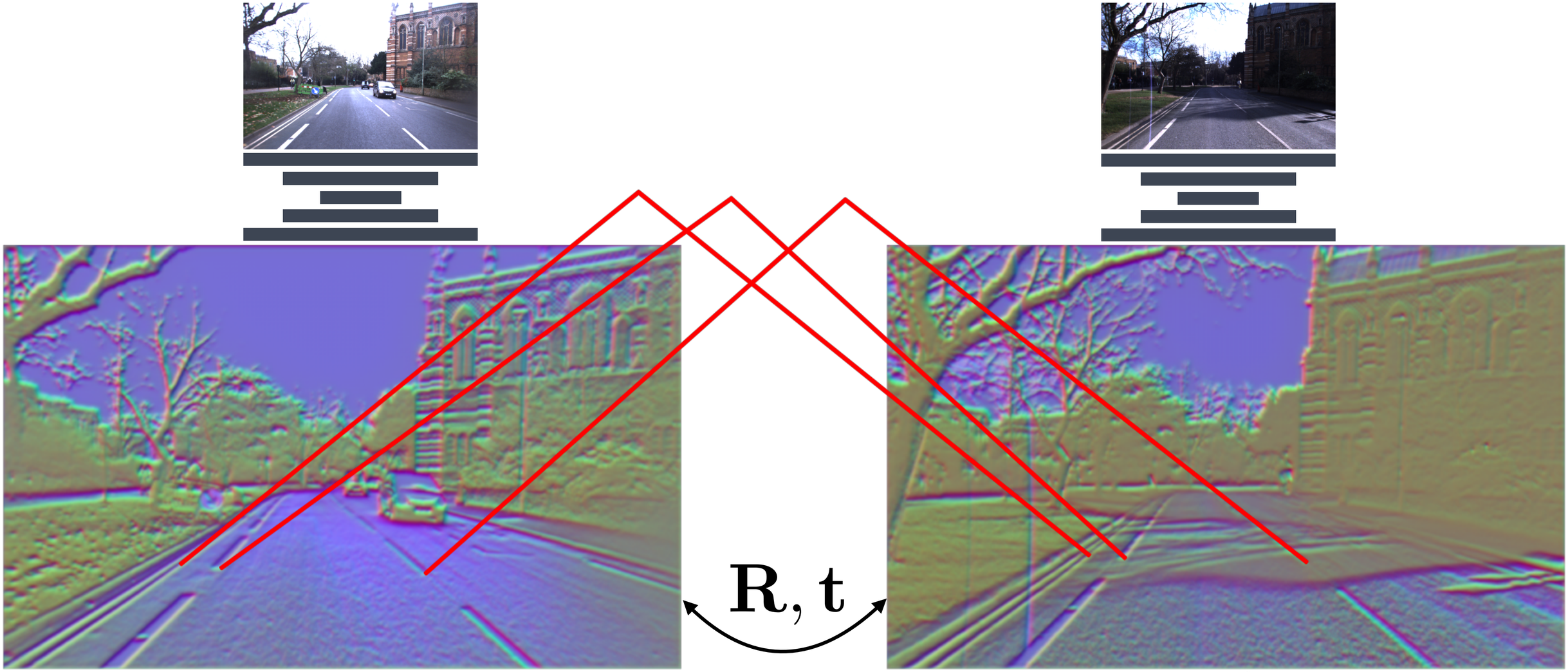
$$E(\mathbf{R}, \mathbf{t}) = \sum_{\mathbf{p}} \left\| I'(\mathbf{p}') - I(\mathbf{p}) \right\|$$



I I'

LM / Gauss-Newton Optimization

$$E(\mathbf{R}, \mathbf{t}) = \sum_{\mathbf{p}} \left\| I'(\mathbf{p}') - I(\mathbf{p}) \right\|$$

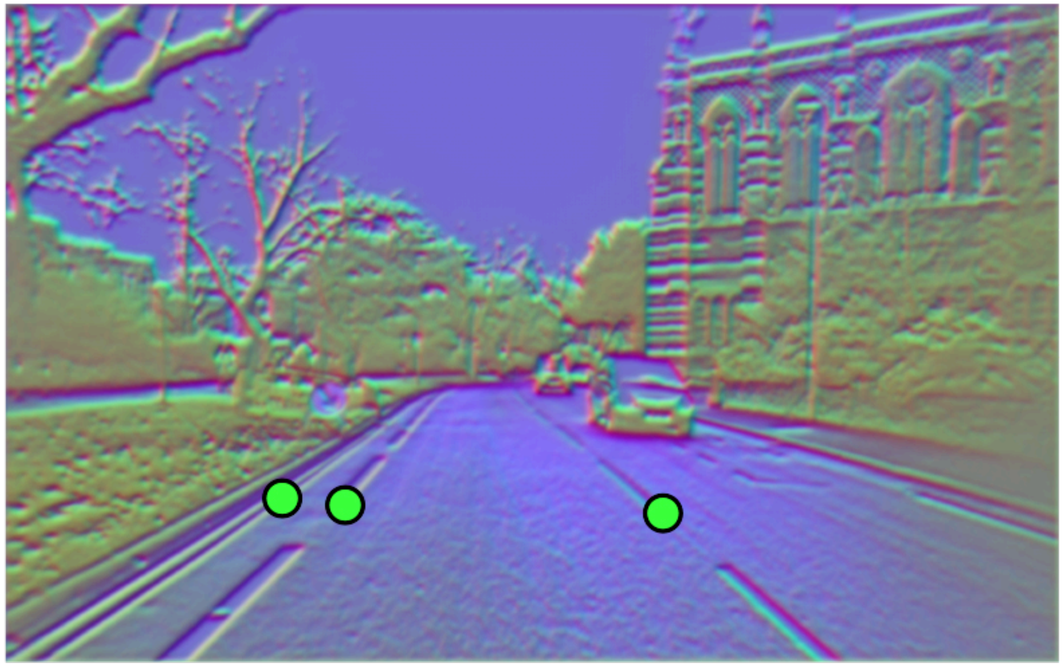


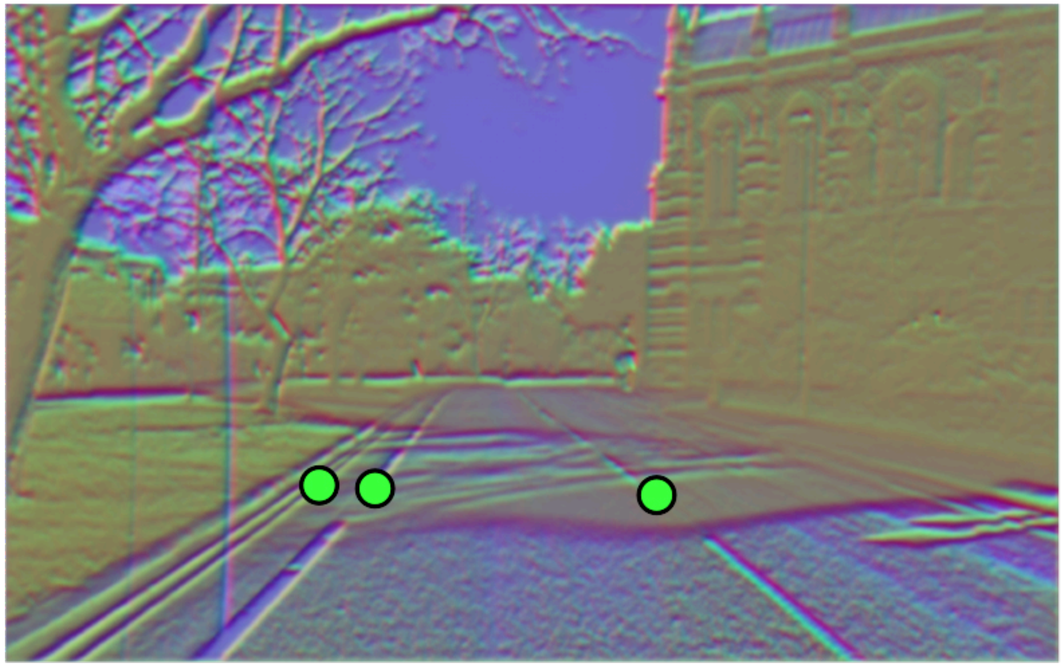
F F'

LM / Gauss-Newton Optimization

$$E(\mathbf{R}, \mathbf{t}) = \sum_{\mathbf{p}} \left\| I'(\mathbf{p}') - I(\mathbf{p}) \right\|$$

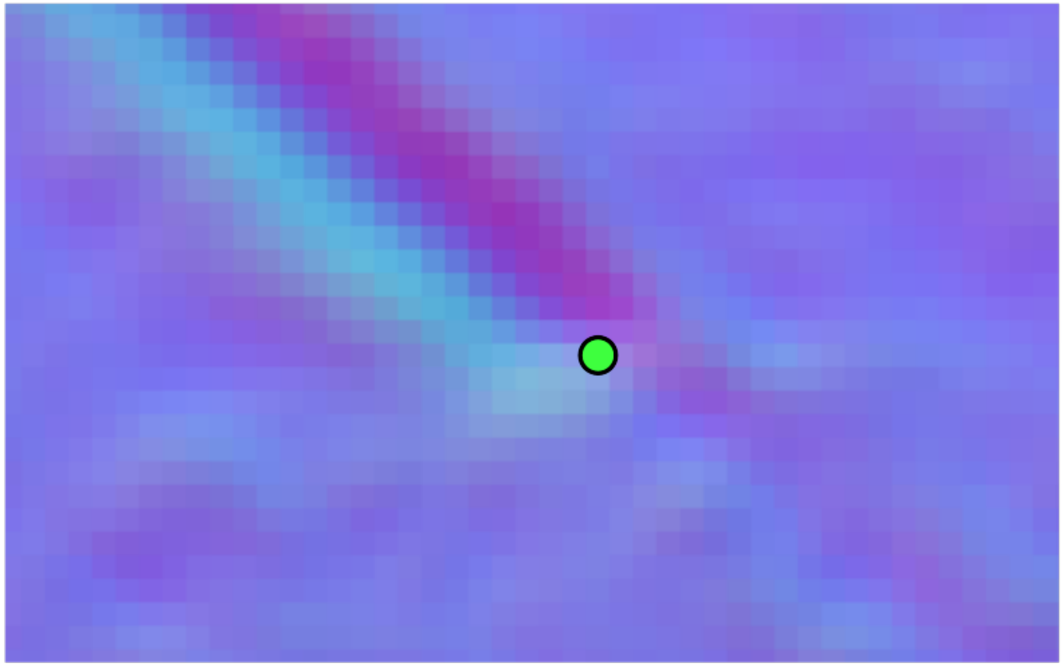
Gauss-Newton Loss

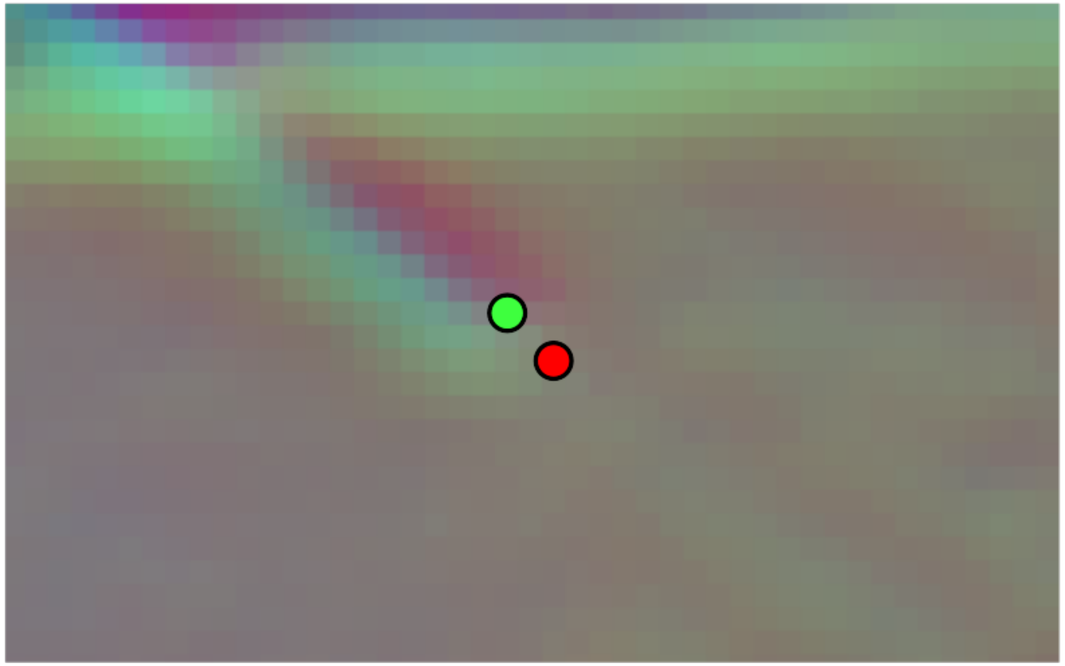




Green: Ground truth correspondence

Gauss-Newton Loss

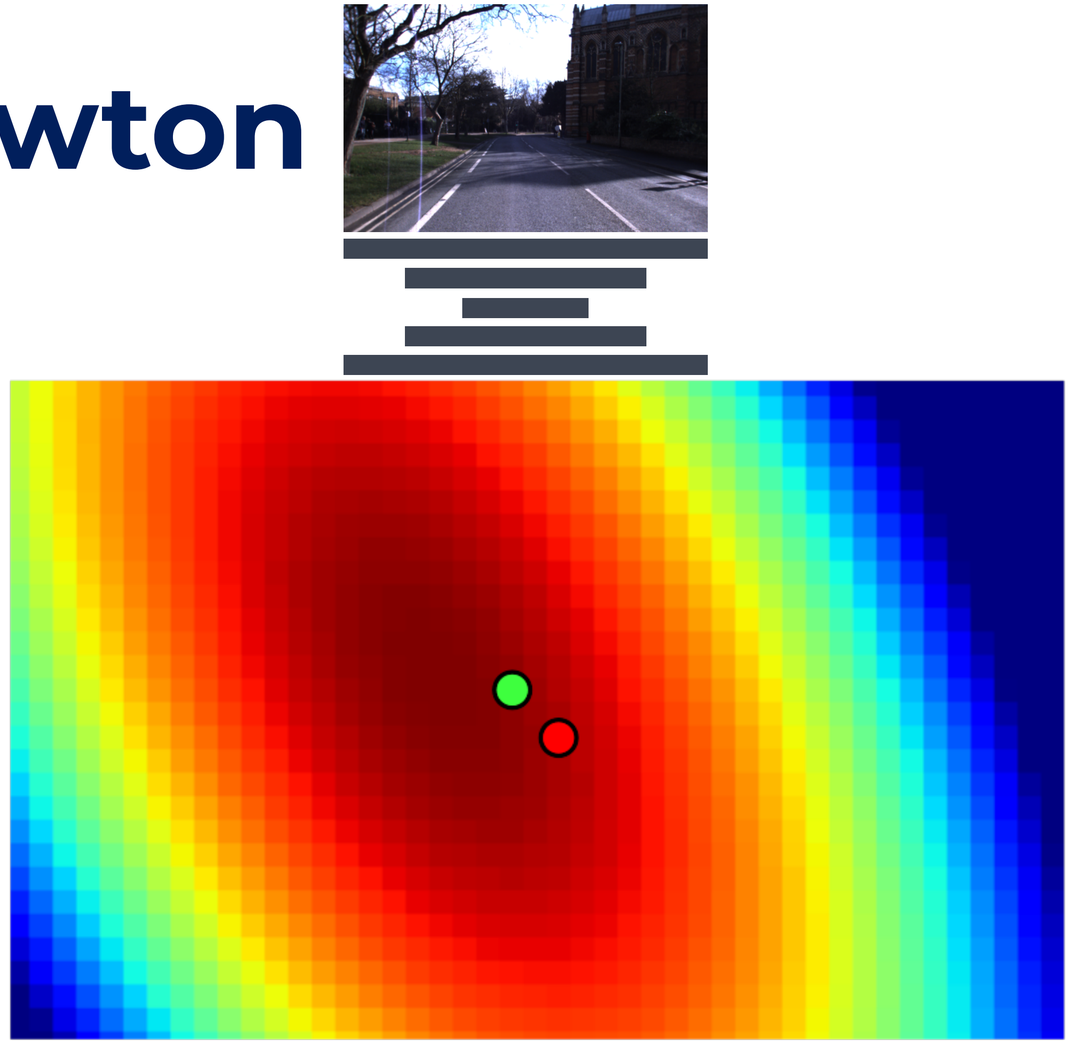




Green: Ground truth correspondence, Red: Initial solution

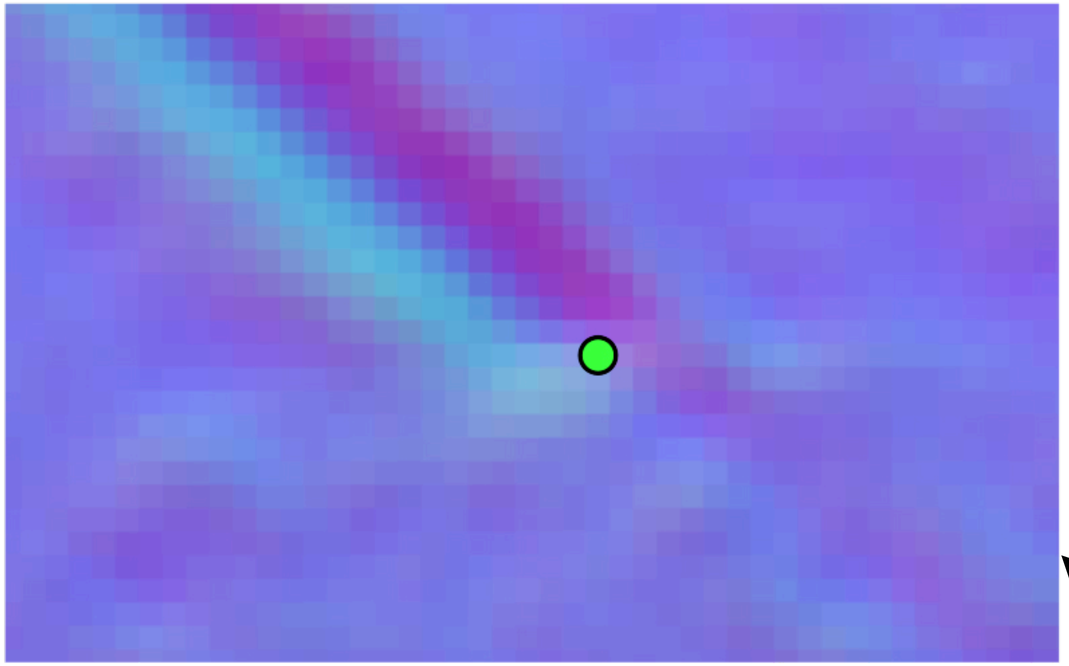
Gauss-Newton Loss

Green: Ground truth correspondence, Red: Initial solution

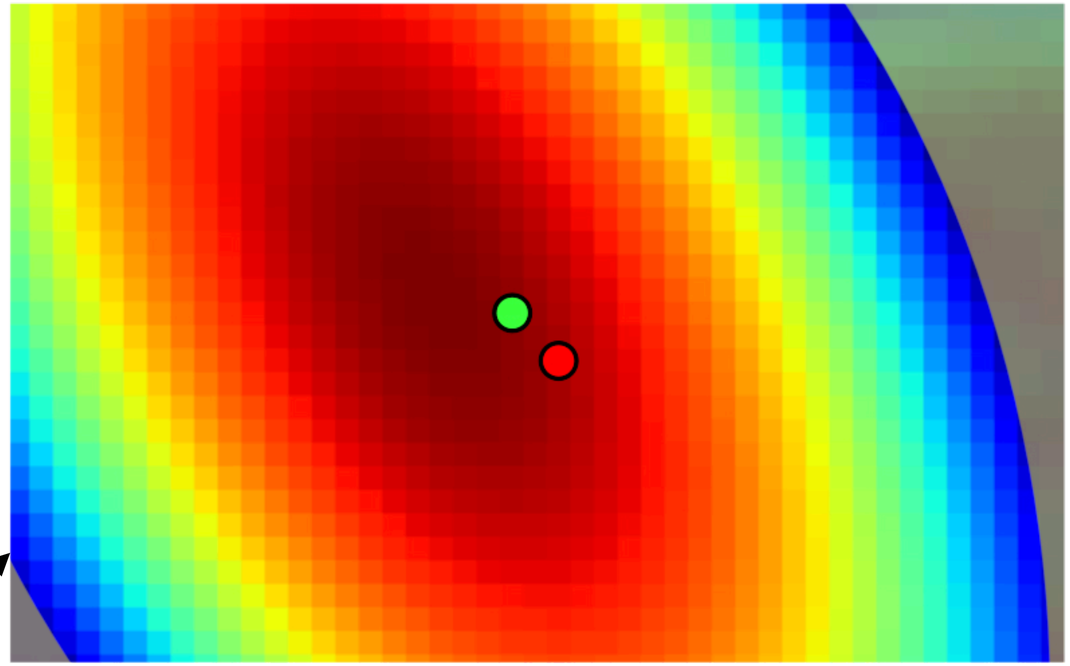


Ellipse: Gaussian distribution

Gauss-Newton Loss



$\mathbf{R}, \mathbf{t}$

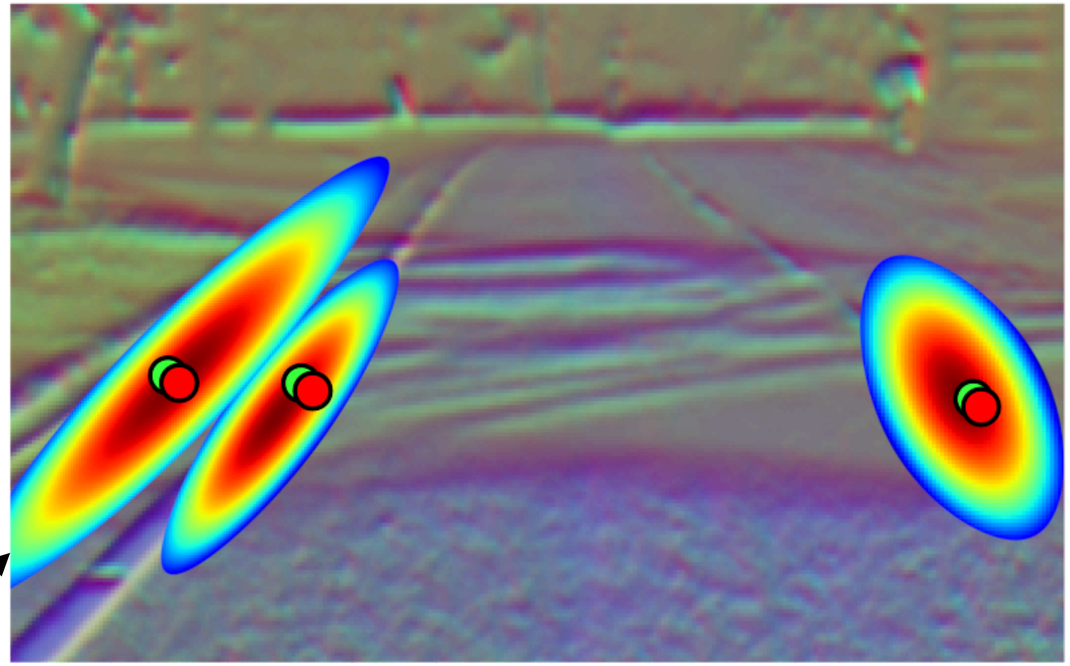


Green: Ground truth correspondence, Red: Initial solution

Ellipse: Gaussian distribution

Gauss-Newton Loss

$\mathbf{R}, \mathbf{t}$

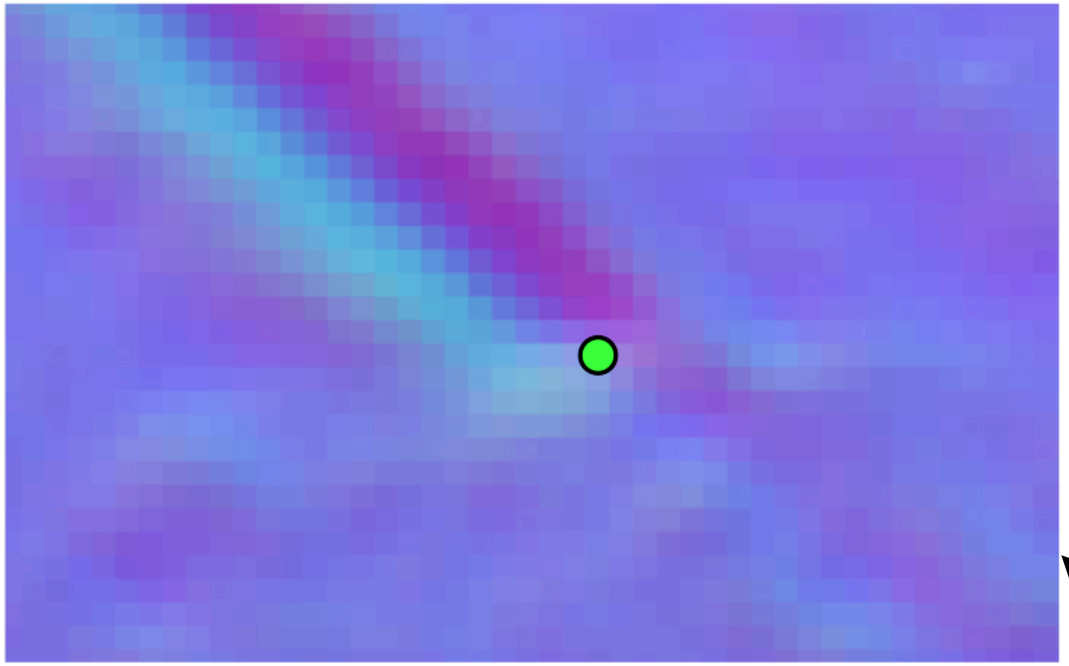


Green: Ground truth correspondence, Red: Initial solution

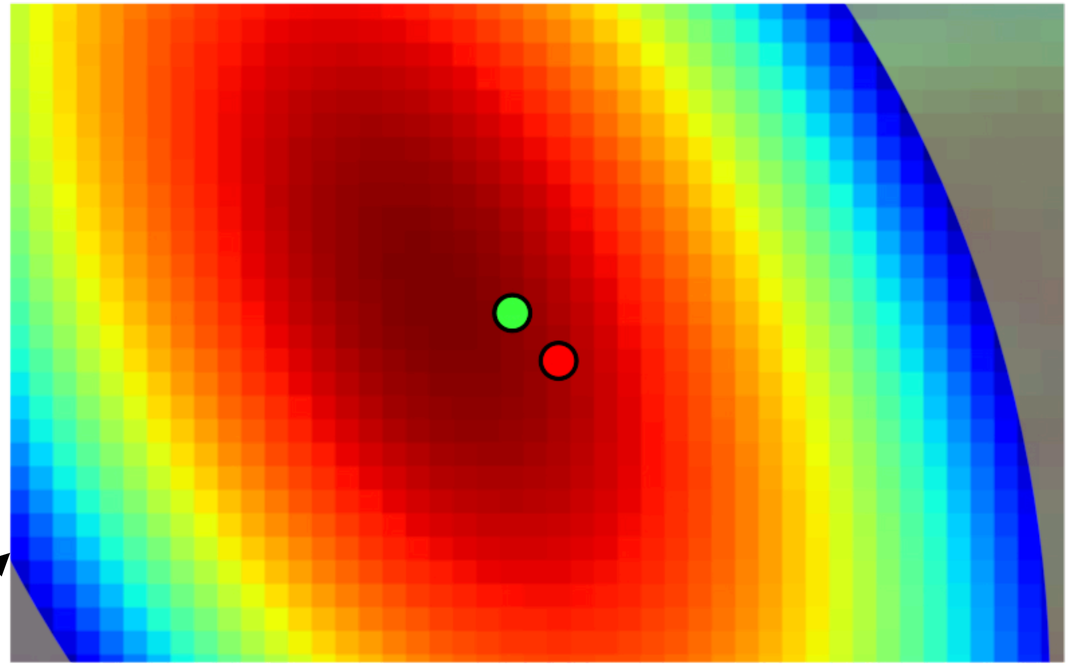
Ellipse: Gaussian distribution

Gauss-Newton Loss:
Maximize estimated probability
of ground truth correspondence

Gauss-Newton Loss



$\mathbf{R}, \mathbf{t}$

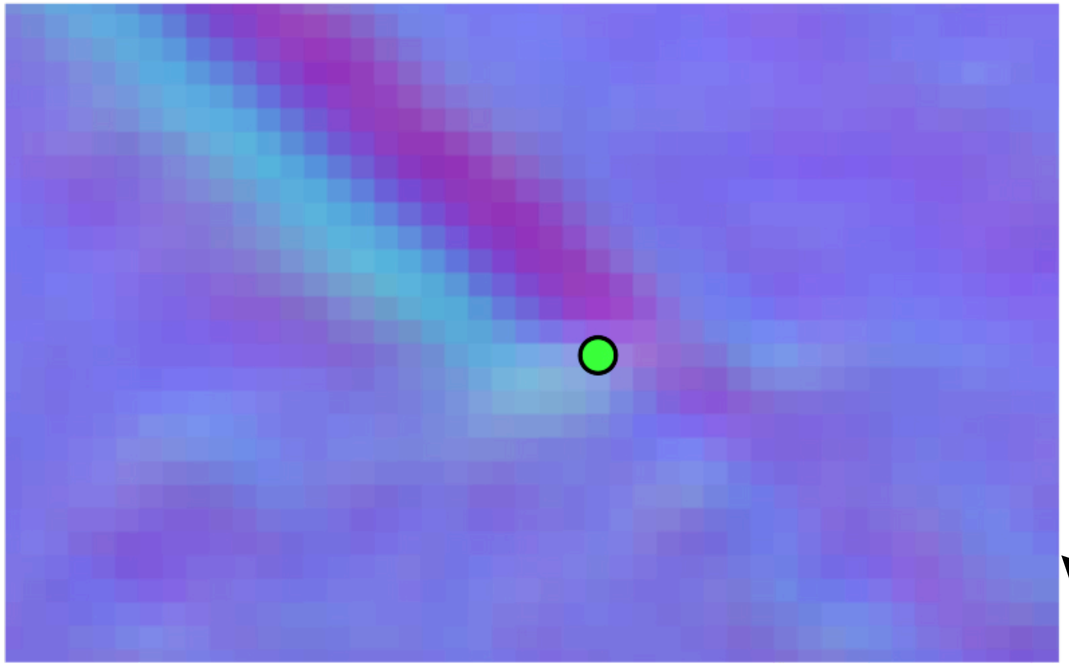


Green: Ground truth correspondence, Red: Initial solution

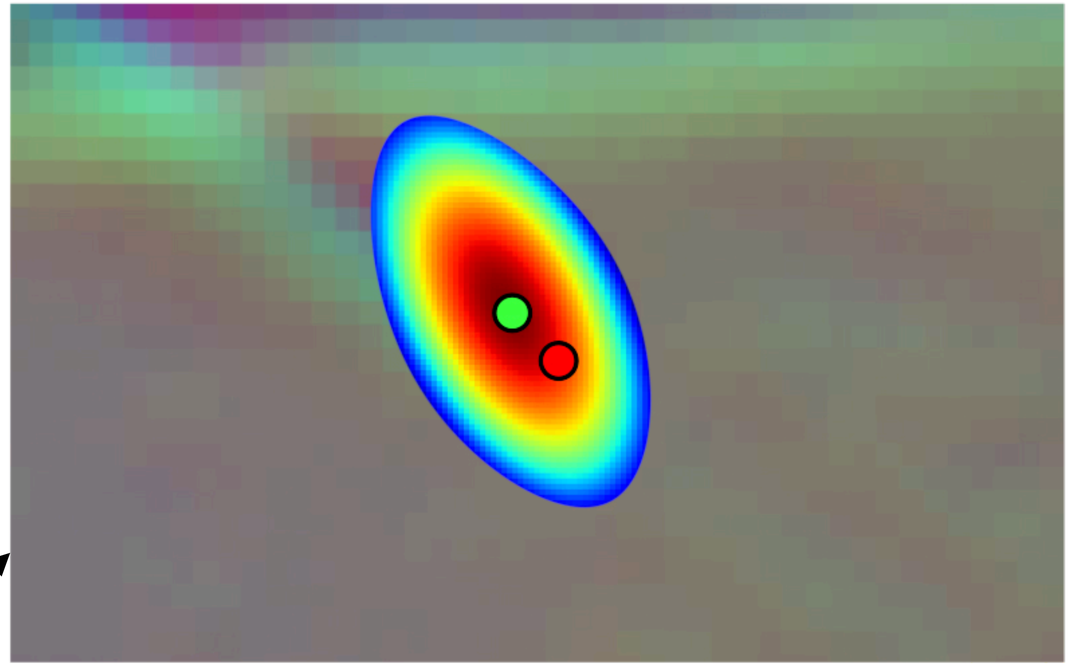
Ellipse: Gaussian distribution

Gauss-Newton Loss:
Maximize estimated probability of ground truth correspondence

Gauss-Newton Loss



$\mathbf{R}, \mathbf{t}$

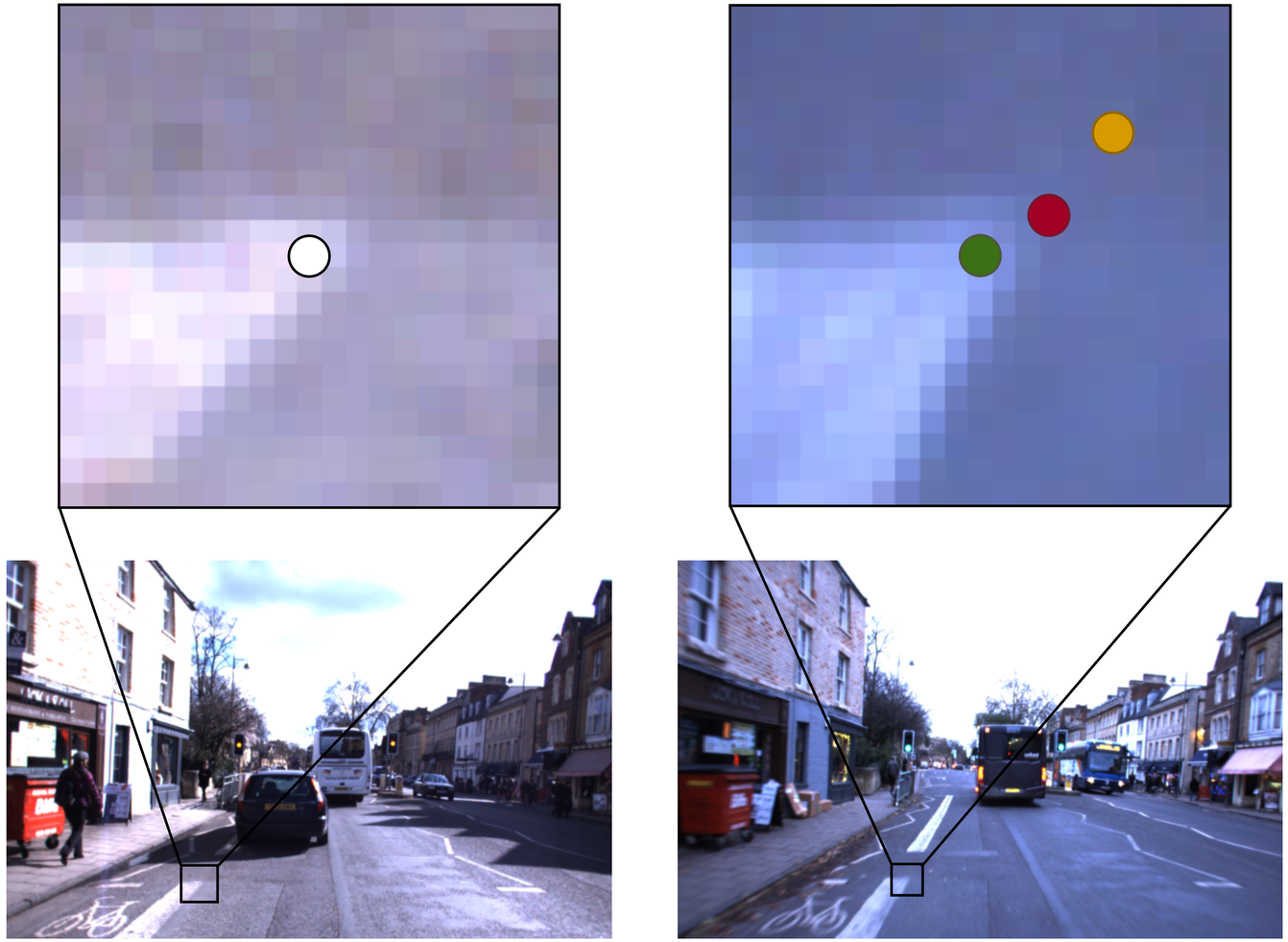


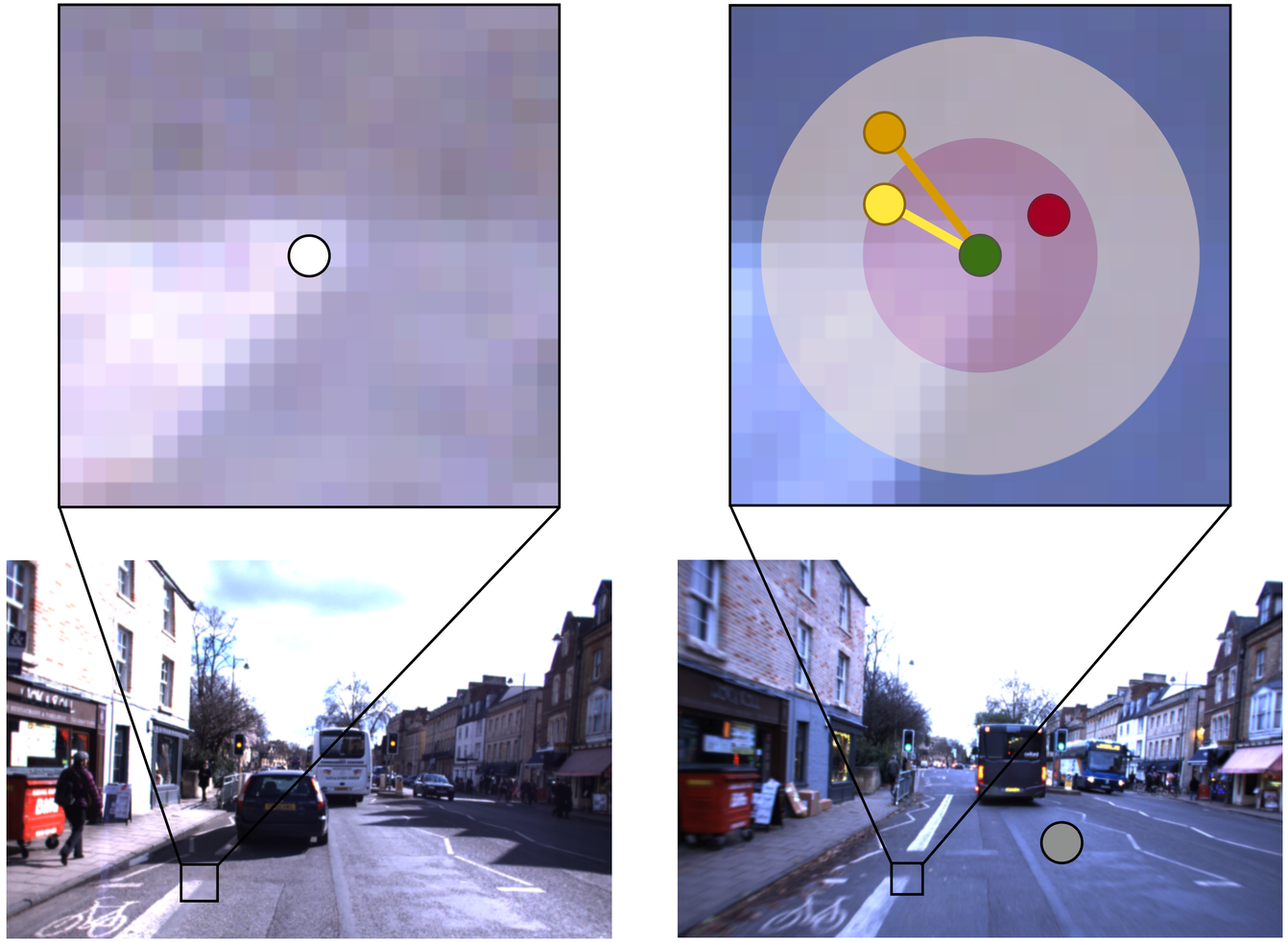
Green: Ground truth correspondence, Red: Initial solution

Ellipse: Gaussian distribution

Gauss-Newton Loss:
Maximize estimated probability
of ground truth correspondence

Loss Formulation:





Loss Formulation:

1. The point is at the correct location

➡ The residual should be small!

$$E_{\text{pos}} = \|F(\bigcirc) - F'(\bullet)\|^2$$

2. The point is an outlier

➡ The residual should be large!

$$E_{\text{neg}} = \|F(\bigcirc) - F'(\bullet)\|^2 > M$$

3. The point is relatively far

➡ Gradient shall point in right direction

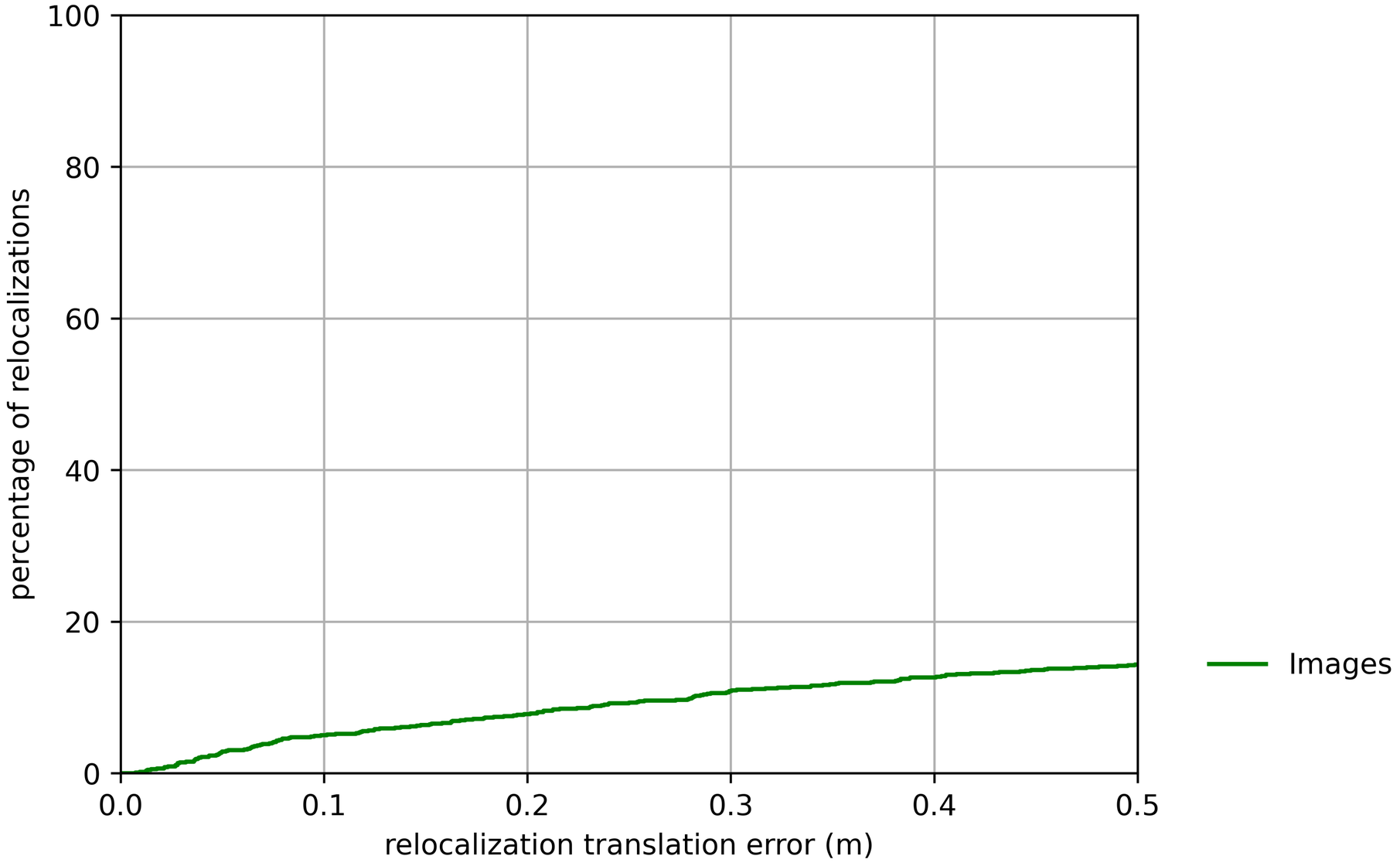
$$E_{\text{GD}} = \underline{\text{dist}_{\text{after}}} < \underline{\text{dist}_{\text{before}}} - \delta$$

4. The point is very close

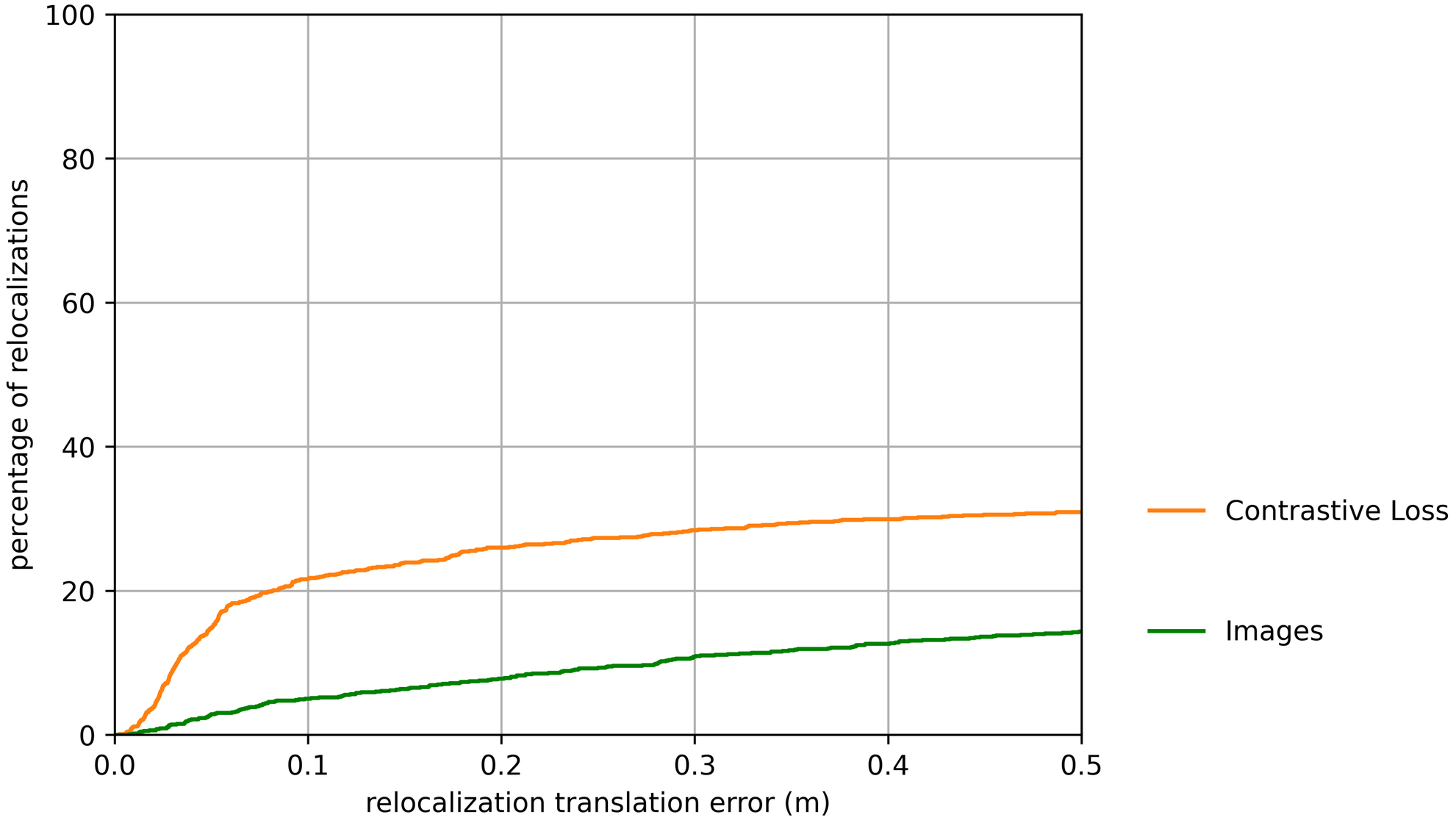
➡ Now we should converge quickly.

$E_{\text{GN}} =$ **Gauss-Newton Loss**

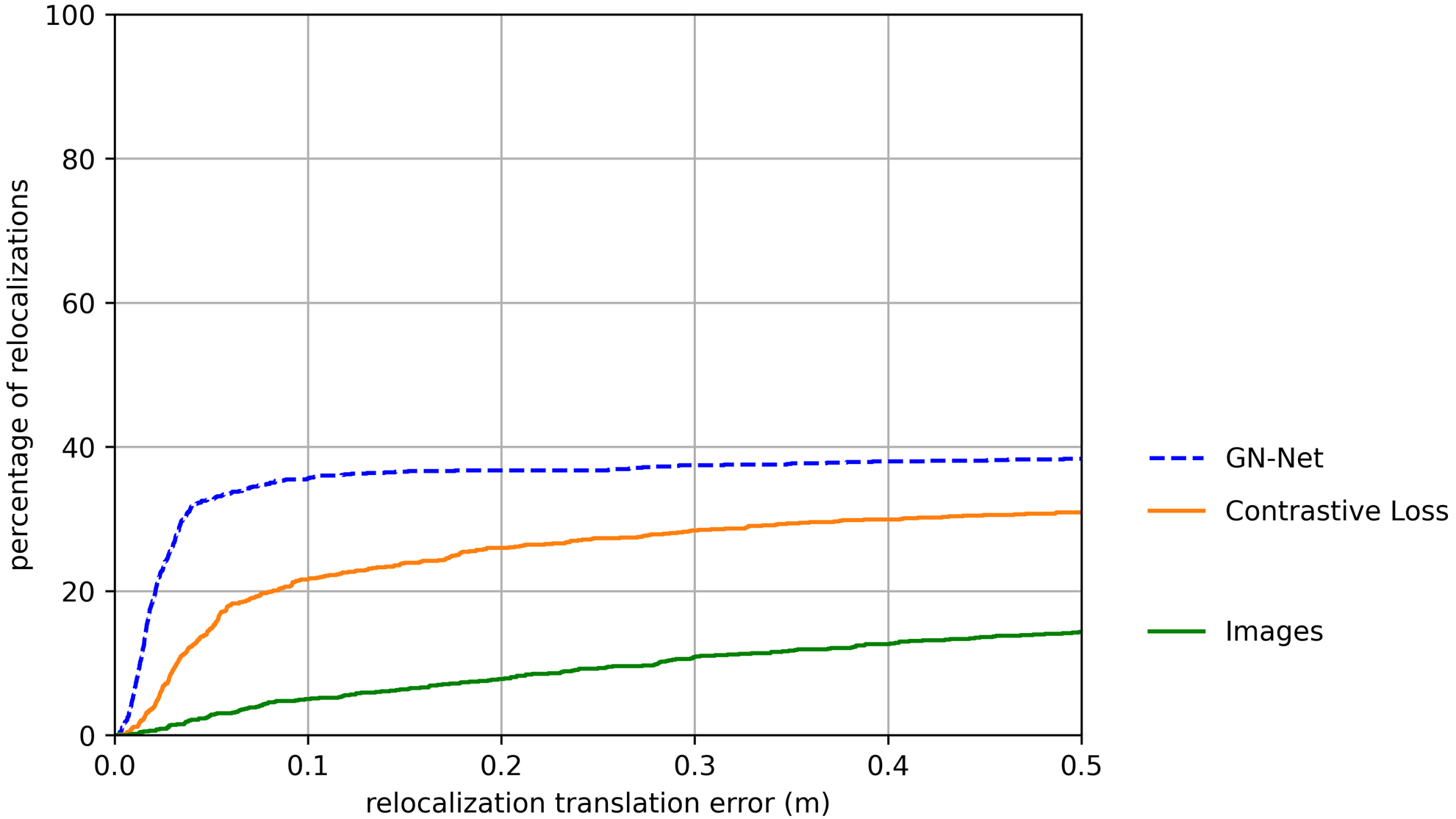
Relocalization Tracking Benchmark



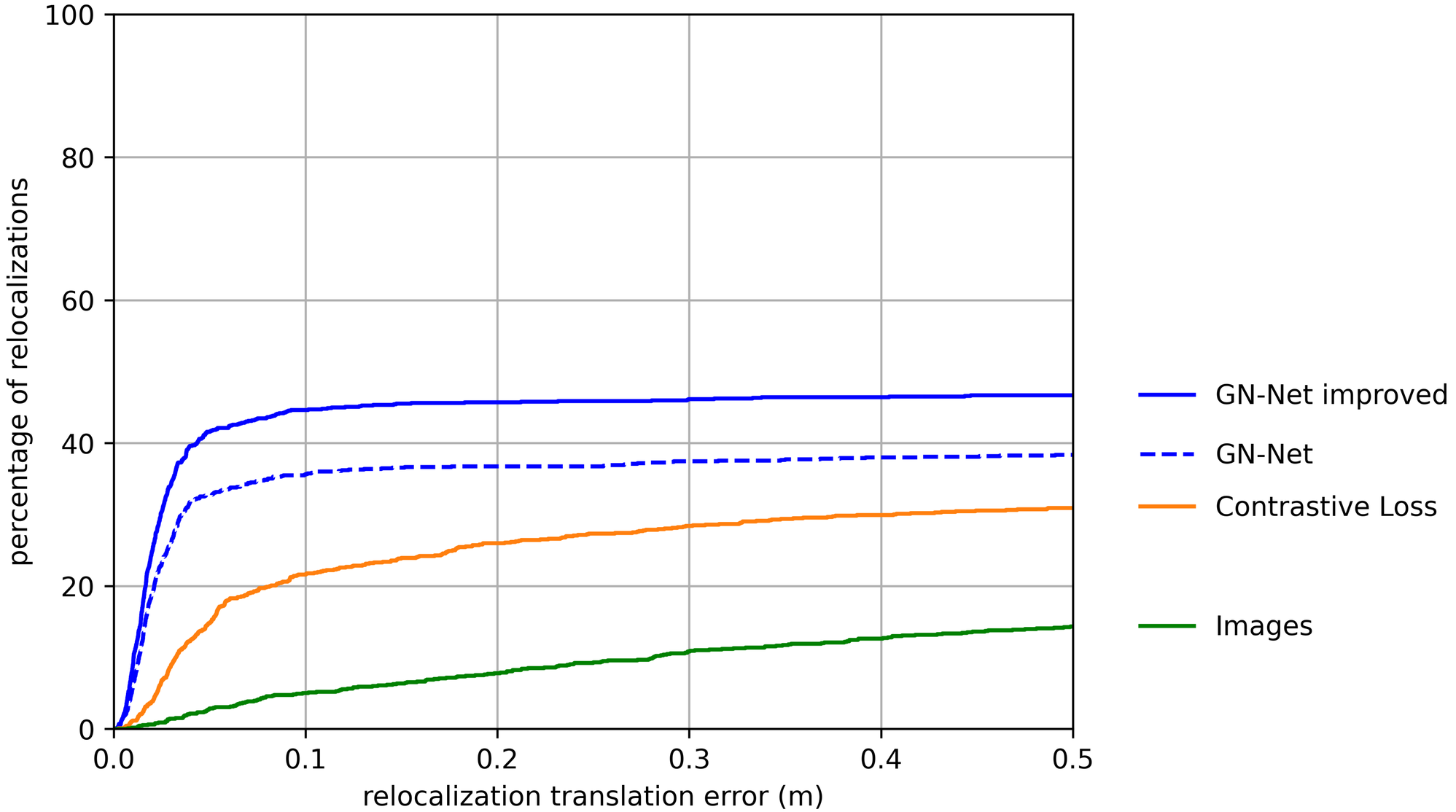
Relocalization Tracking Benchmark



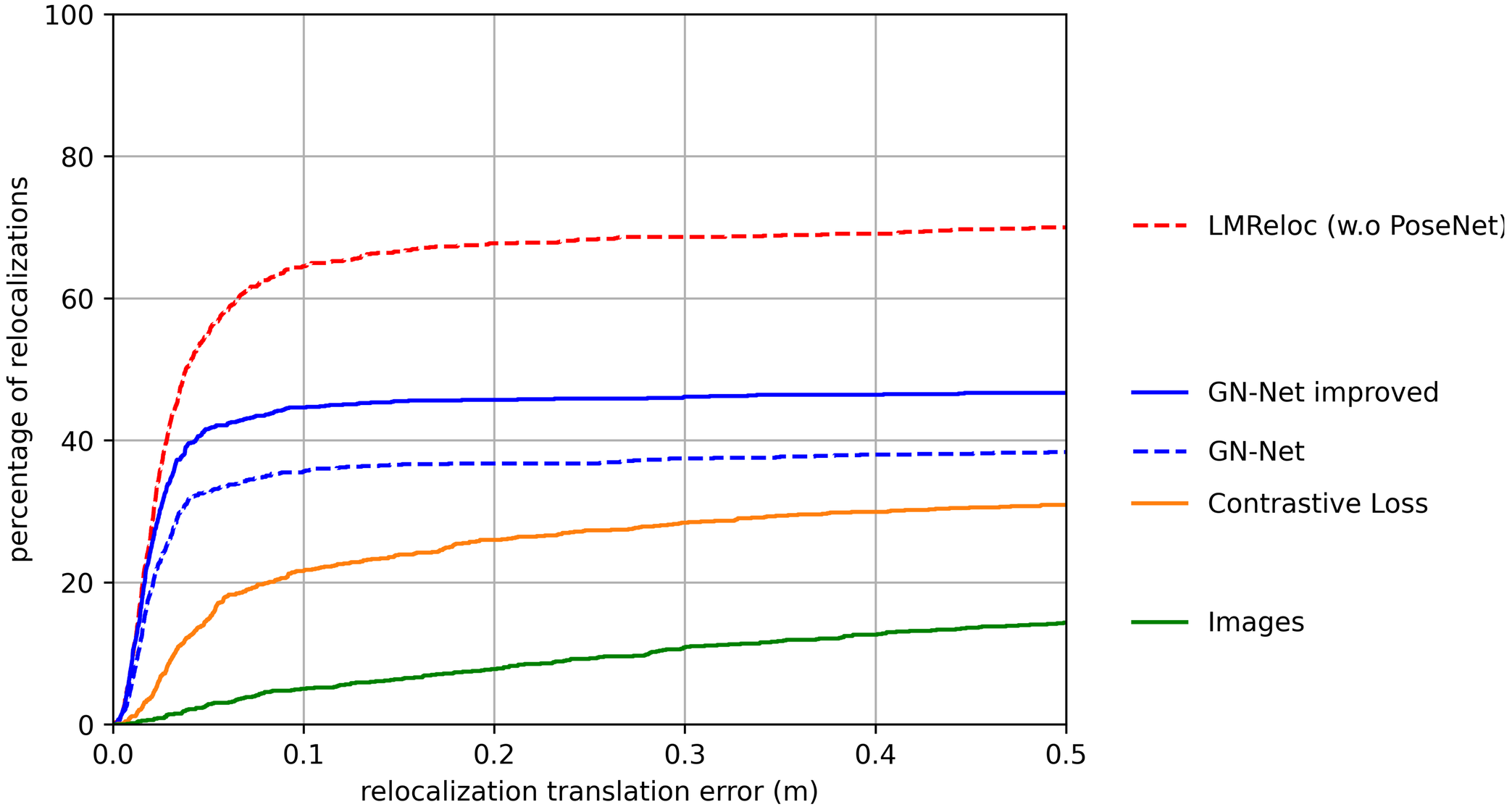
Relocalization Tracking Benchmark



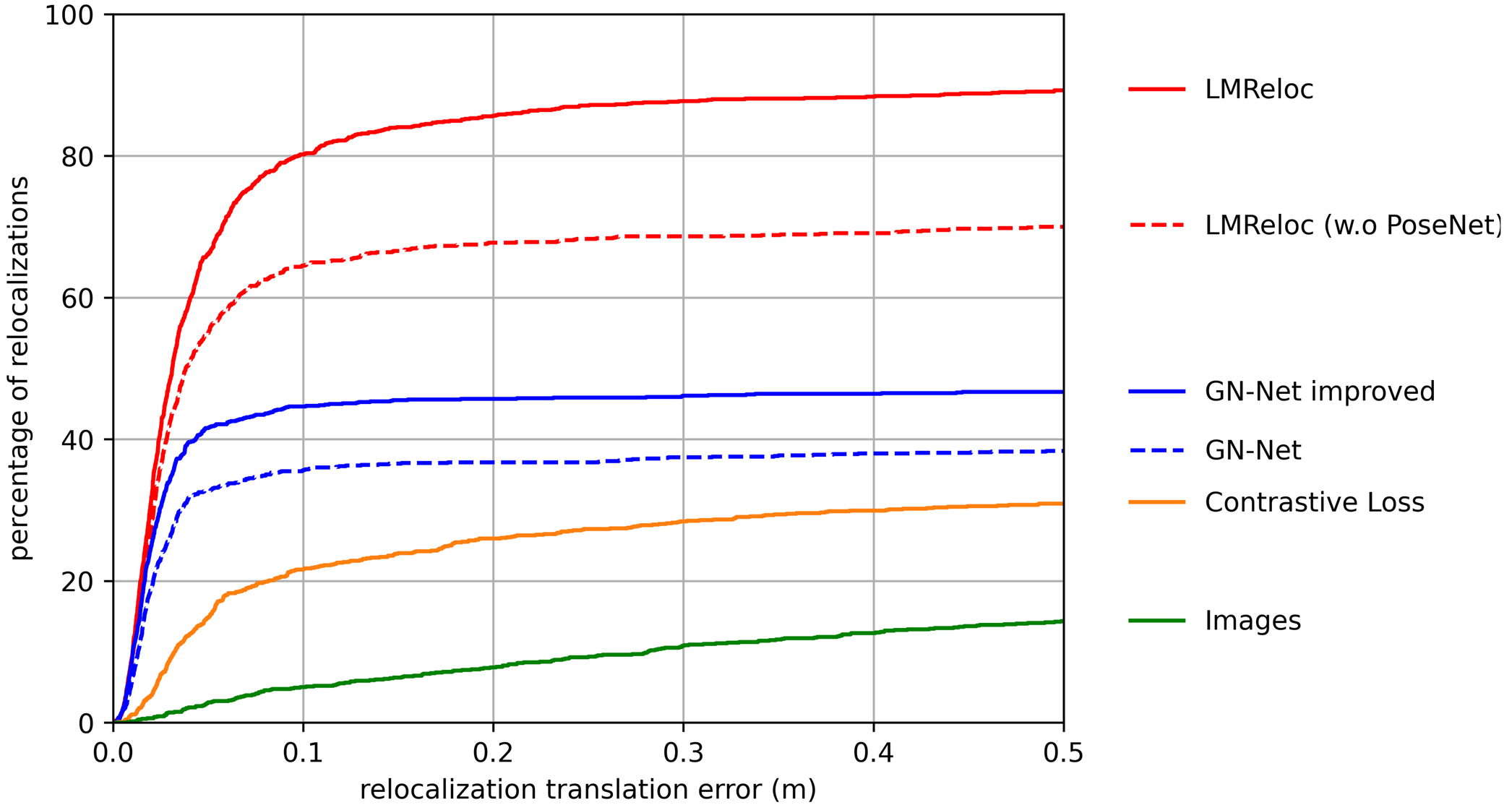
Relocalization Tracking Benchmark

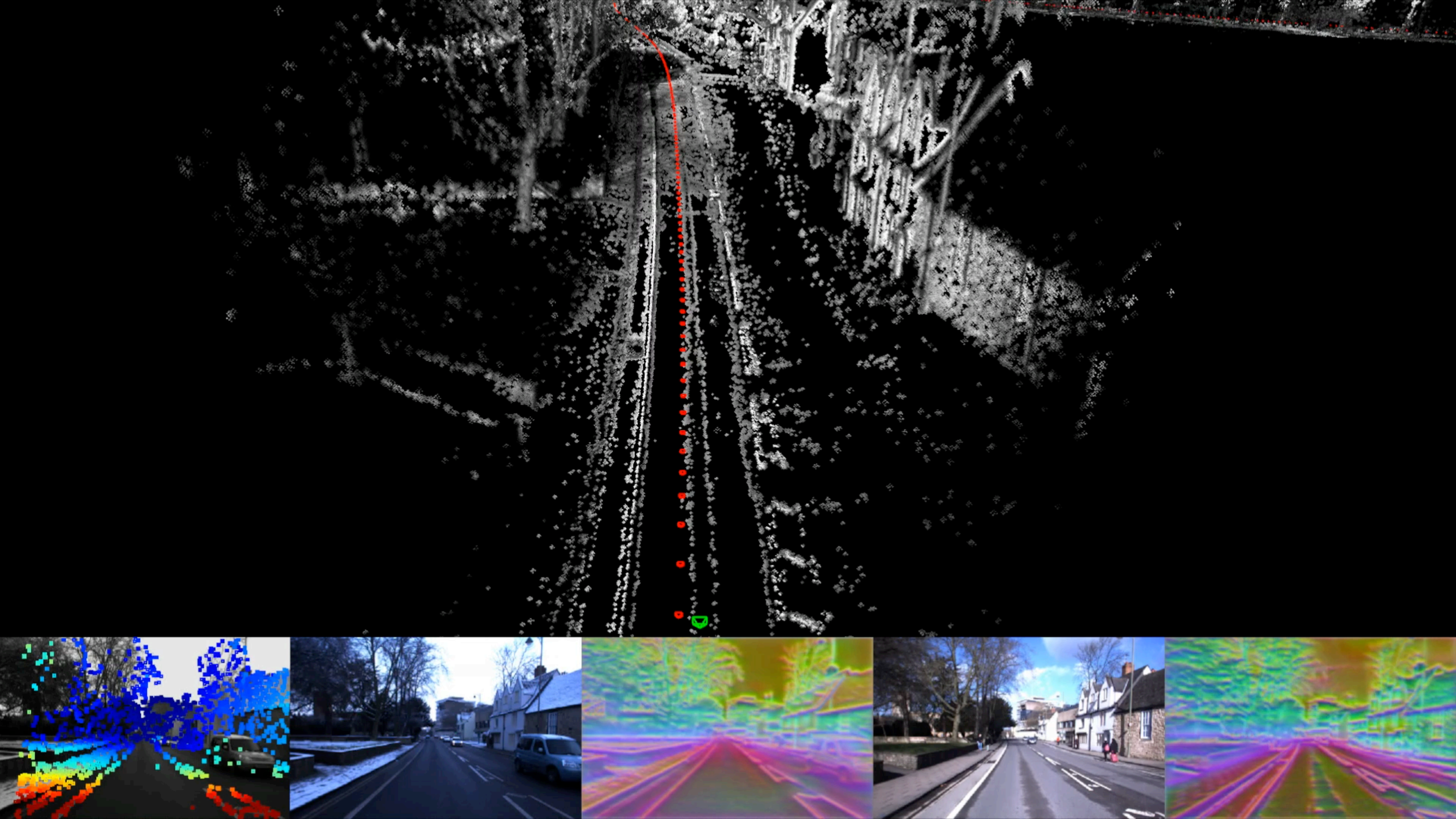


Relocalization Tracking Benchmark

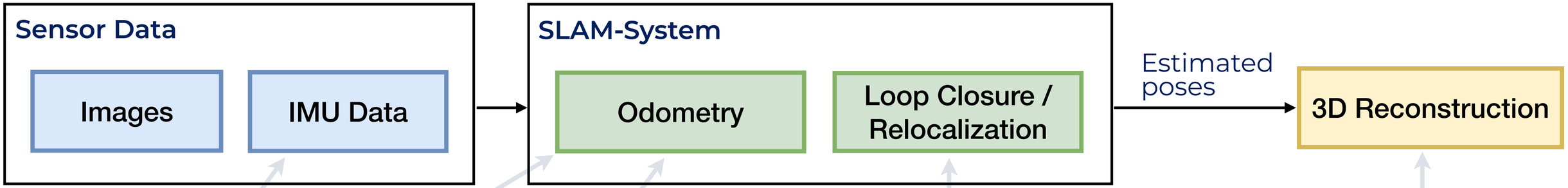


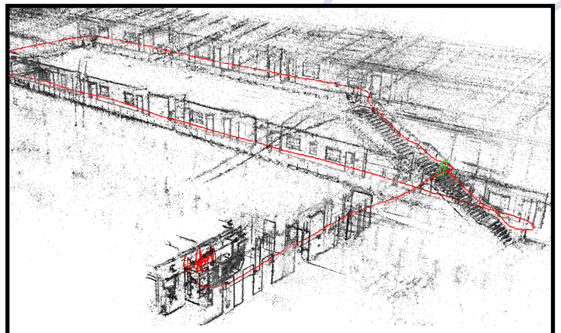
Relocalization Tracking Benchmark





Visual SLAM
From Optimization to Learning

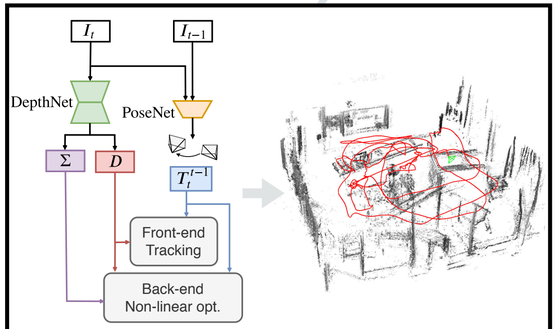




DM-VIO

L. von Stumberg and D. Cremers

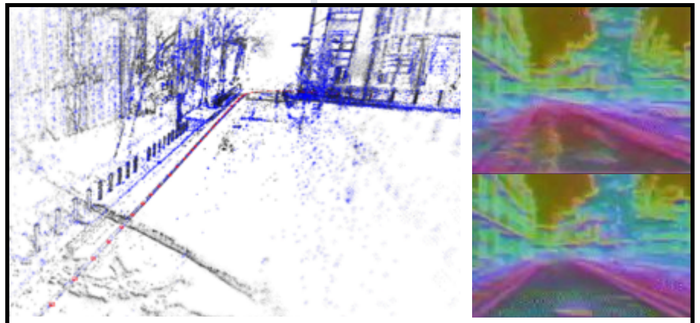
RA-L & ICRA 2022



D3VO

N. Yang, **L. von Stumberg**, R. Wang and D. Cremers

CVPR 2020



GN-Net

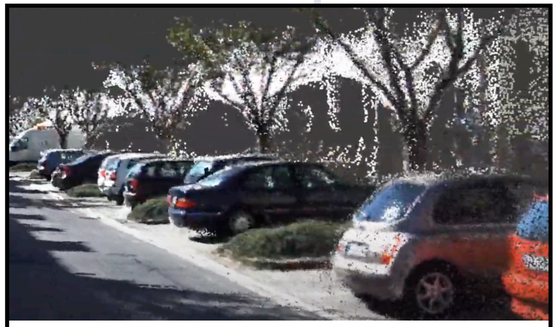
L. von Stumberg, P. Wenzel, Q. Khan, D. Cremers

RA-L & ICRA 2020

LM-Reloc

L. von Stumberg, P. Wenzel N. Yang, D. Cremers

3DV 2020

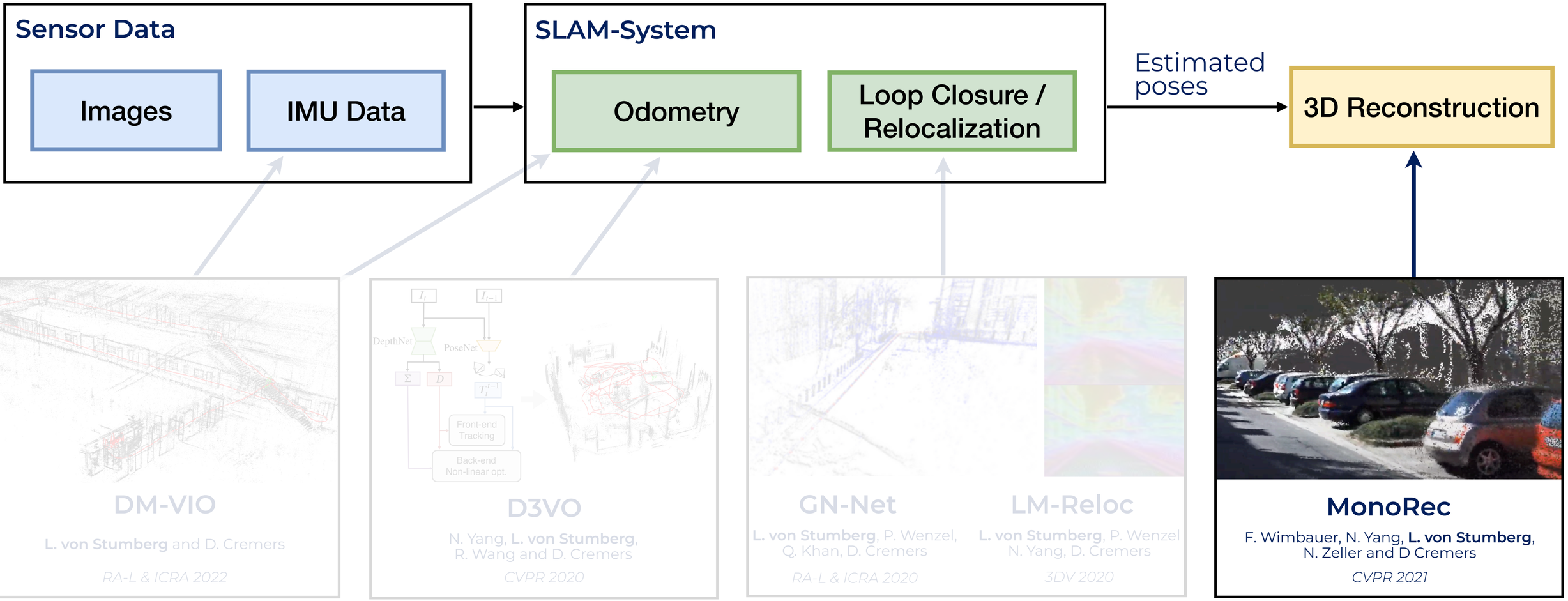


MonoRec

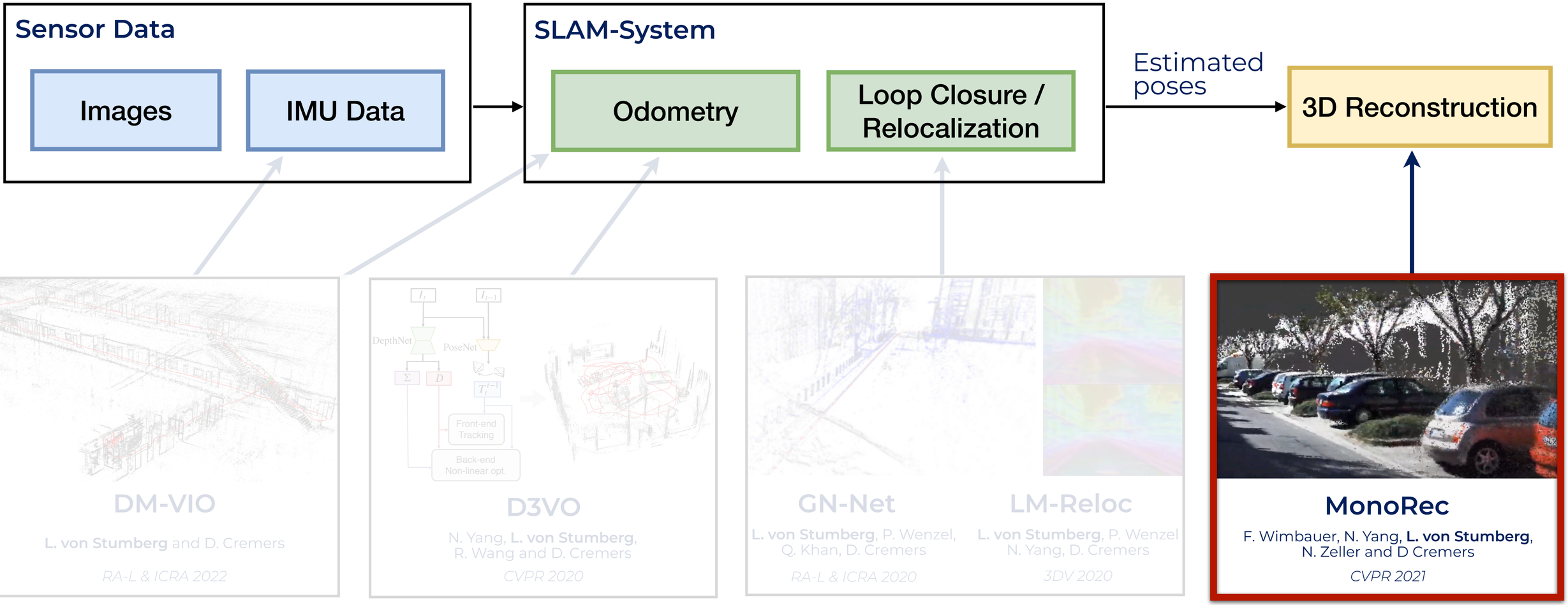
F. Wimbauer, N. Yang, **L. von Stumberg**, N. Zeller and D Cremers

CVPR 2021

Visual SLAM
From Optimization to Learning



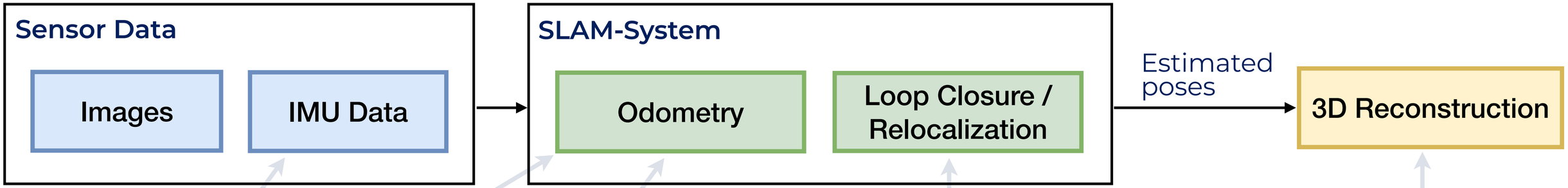
Visual SLAM
From Optimization to Learning

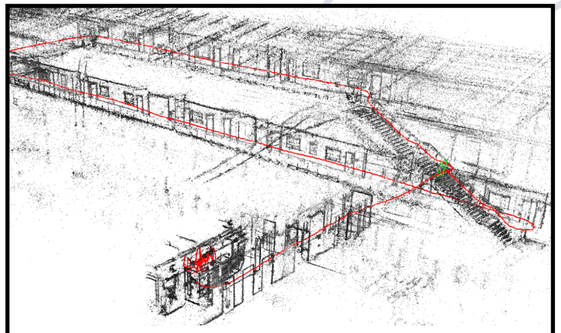


MonoRec: Semi-Supervised Dense Reconstruction... *CVPR 2021* F. Wimbauer, N. Yang, L. von Stumberg, N. Zeller and D Cremers

MonoRec: Semi-Supervised Dense Reconstruction... *CVPR 2021* F. Wimbauer, N. Yang, L. von Stumberg, N. Zeller and D Cremers

Visual SLAM
From Optimization to Learning

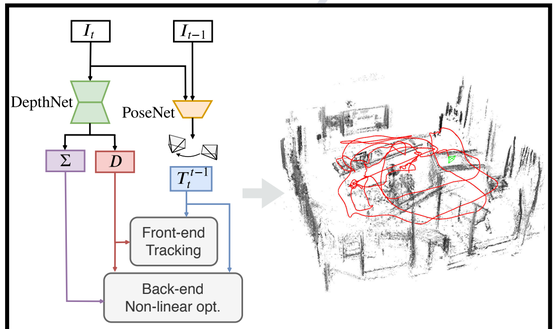




DM-VIO

L. von Stumberg and D. Cremers

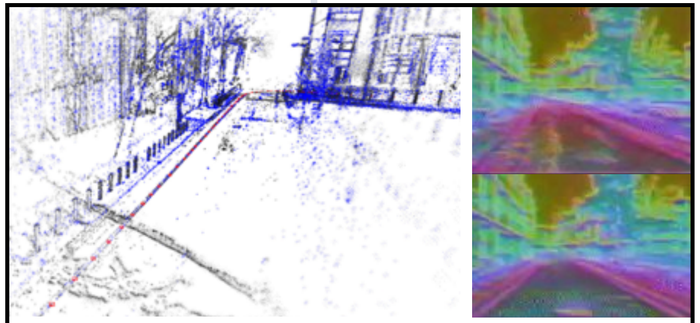
RA-L & ICRA 2022



D3VO

N. Yang, L. von Stumberg, R. Wang and D. Cremers

CVPR 2020



GN-Net

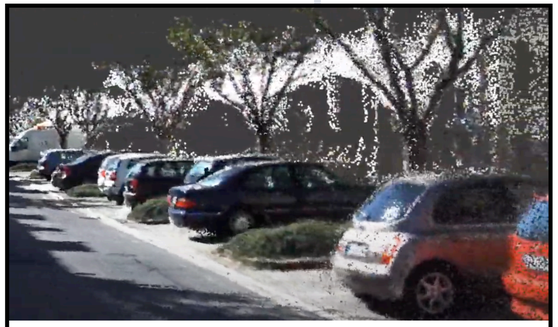
L. von Stumberg, P. Wenzel, Q. Khan, D. Cremers

RA-L & ICRA 2020

LM-Reloc

L. von Stumberg, P. Wenzel N. Yang, D. Cremers

3DV 2020



MonoRec

F. Wimbauer, N. Yang, L. von Stumberg, N. Zeller and D Cremers

CVPR 2021