Submap-based Bundle Adjustment for 3D Reconstruction from RGB-D Data

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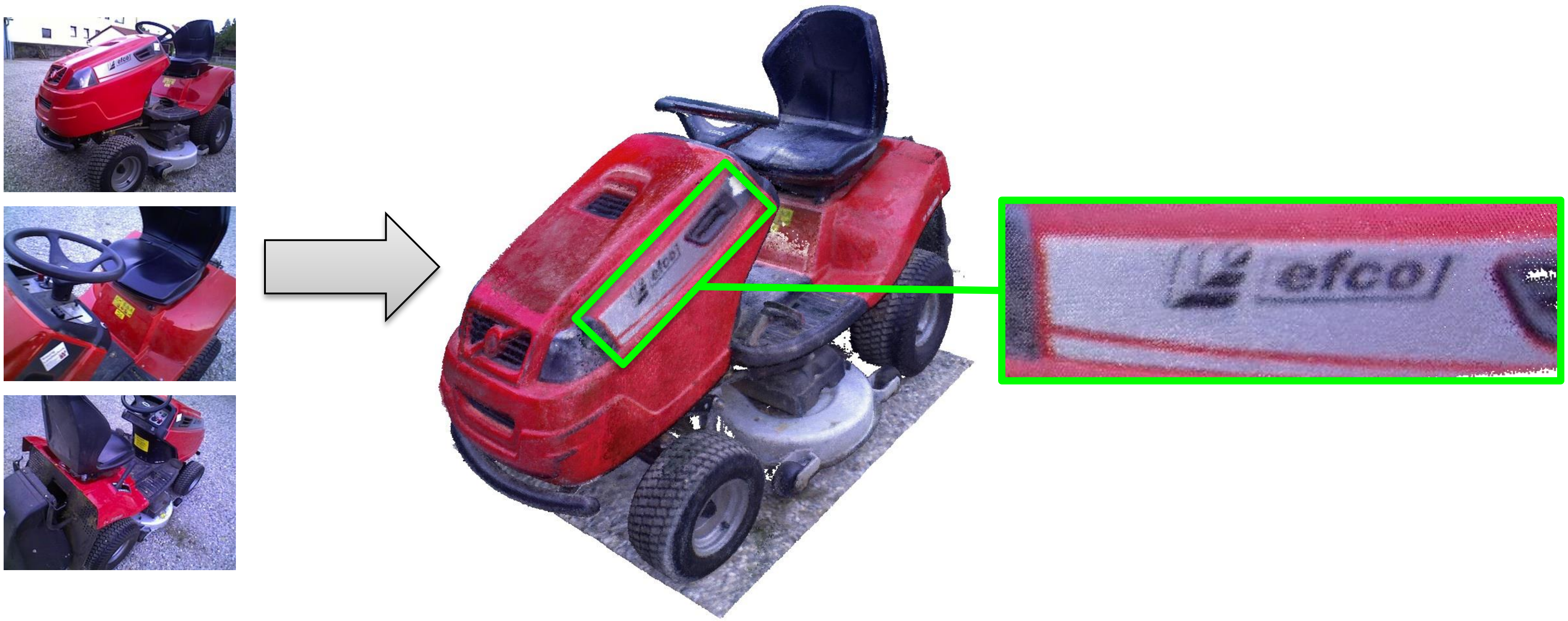
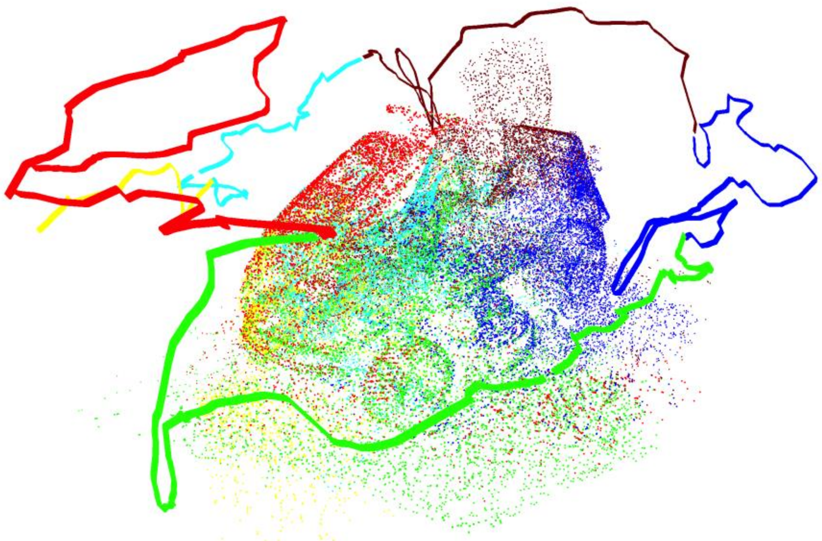
Motivation

- Given: Low-cost RGB-D sensors
- Wanted: 3D reconstruction of highly accurate 3D models (e.g. for reverse-engineering)



Submap-based Bundle Adjustment

- Problem:
  - Incremental tracking and mapping methods prone to drift
  - Full bundle adjustment (BA) too slow
- Our solution: Novel submap-based BA method for RGB-D based 3D reconstruction



Related Work

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- RGB-D SLAM systems
  - An evaluation of the RGB-D SLAM system [Endres et al., ICRA 2012]
  - RGB-D mapping: Using Kinect-Style Depth Cameras for Dense 3D Modeling of Indoor Environments [Henry et al., IJRR 2012]
  - Using depth in visual simultaneous localisation and mapping [Scherer et al., ICRA 2012]

Pose Graph Optimization

Sparse Bundle Adjustment

3D Bundle Adjustment

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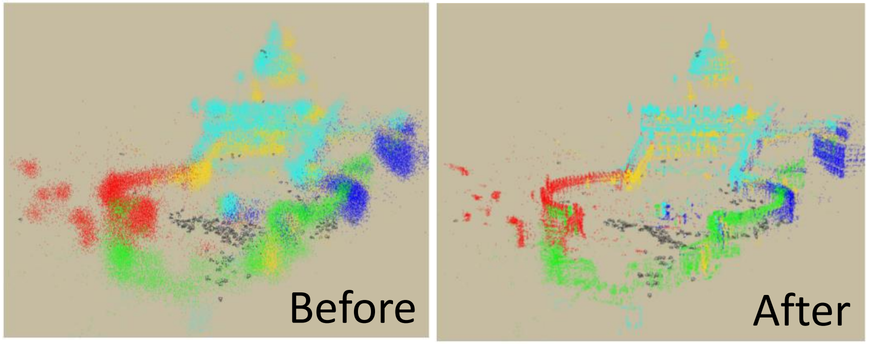
Sparse Bundle Adjustment

3D Bundle Adjustment

- Out-of-core bundle adjustment for large-scale 3D reconstruction [Ni et al., ICCV 2007]

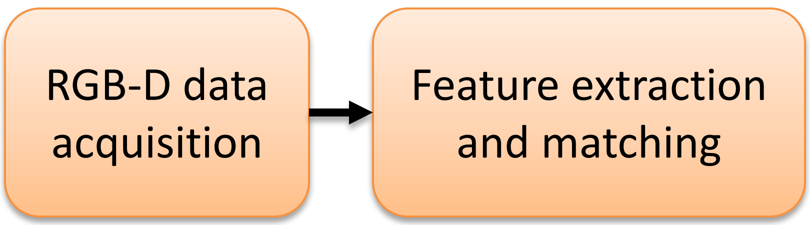
Submap-based Bundle Adjustment



Feature-based 3D Reconstruction System

RGB-D data acquisition

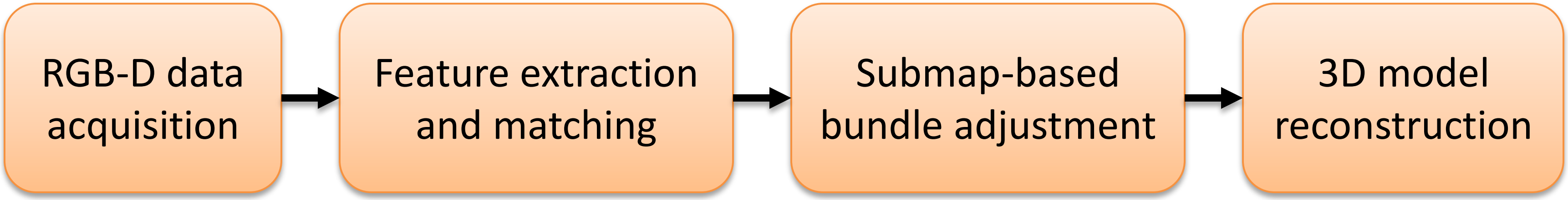
Feature-based 3D Reconstruction System



Feature-based 3D Reconstruction System

RGB-D data acquisition → Feature extraction and matching → Submap-based bundle adjustment

Feature-based 3D Reconstruction System



Graph-based map representation

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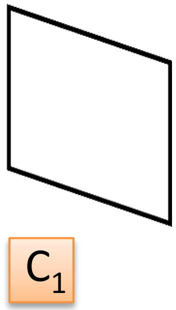
- Camera poses $C_i \in SE(3)$ (with $i \in 1 \ldots M$)



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- Camera poses $C_i \in SE(3)$ (with $i \in 1 \ldots M$)
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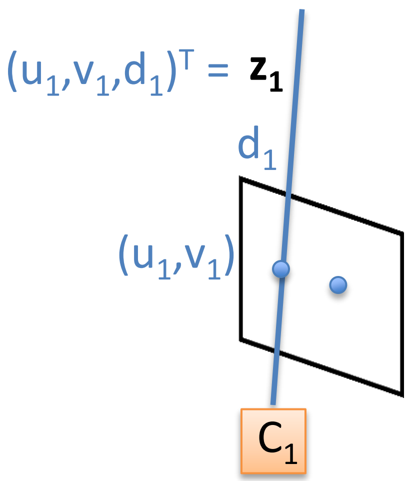

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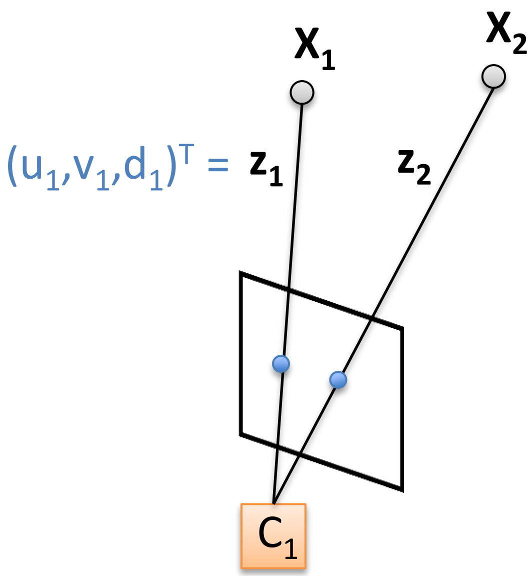

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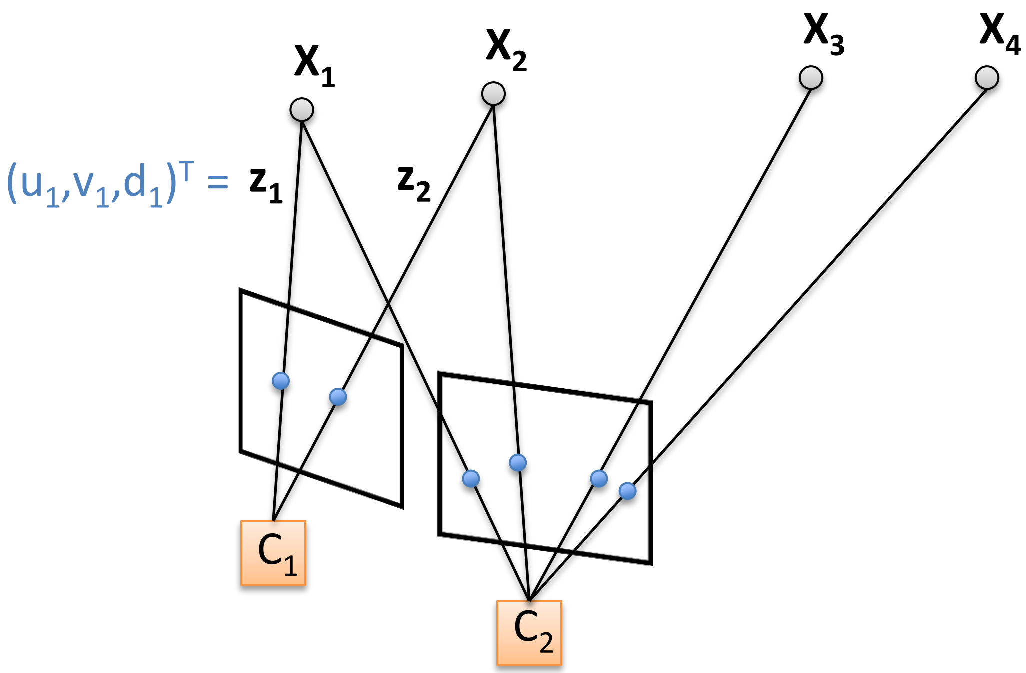

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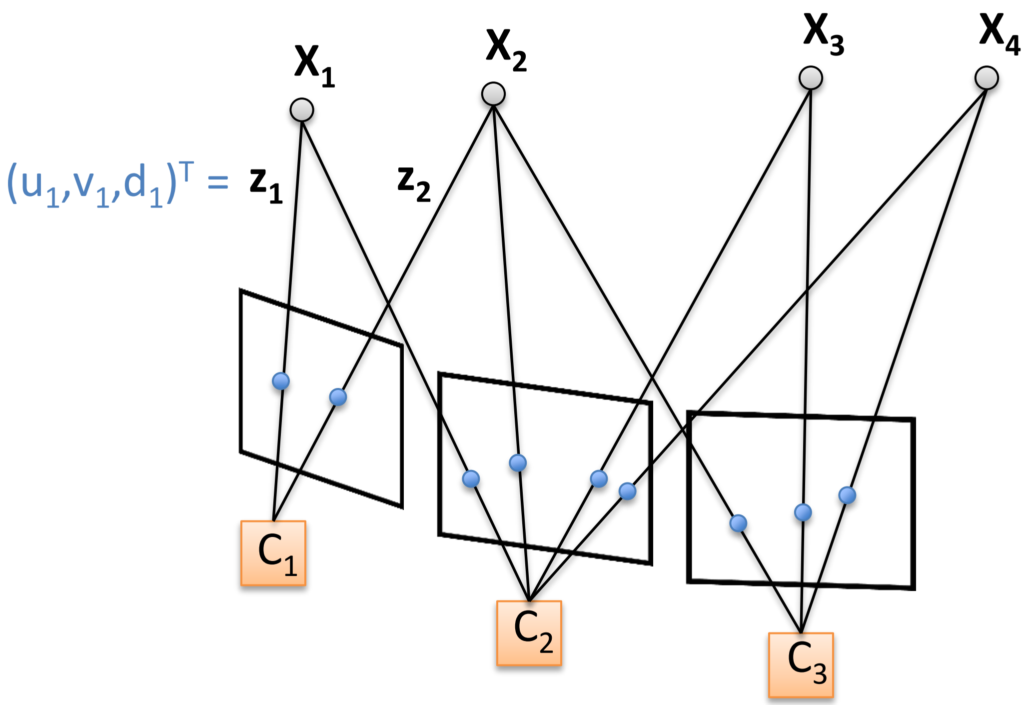

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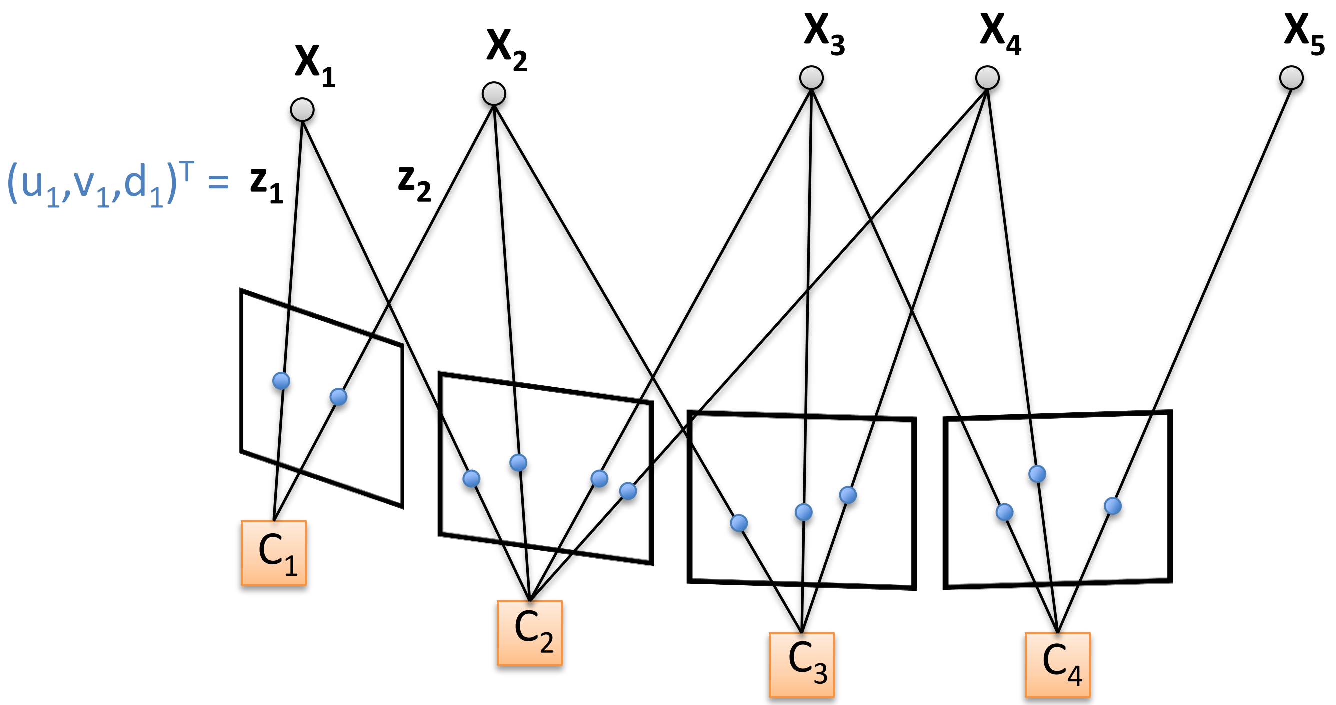

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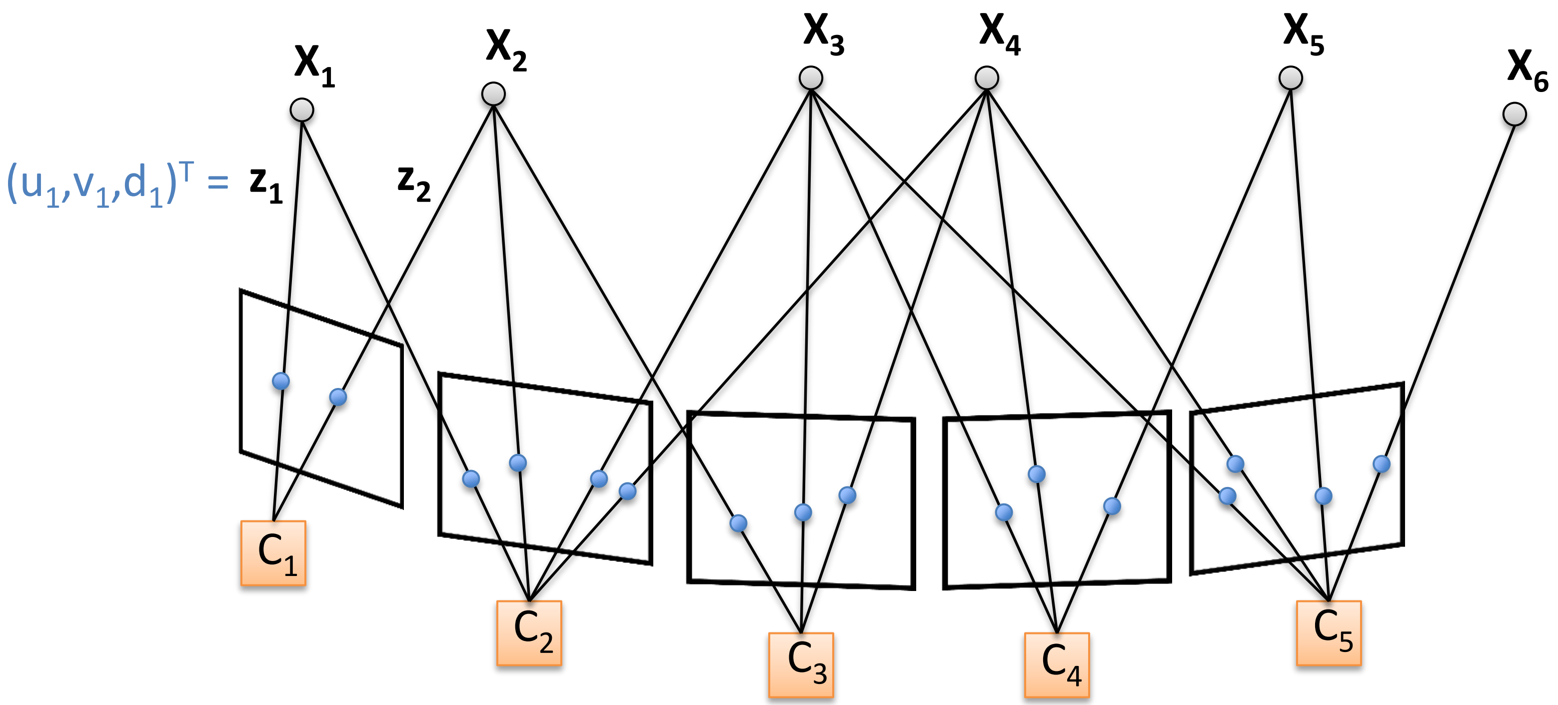

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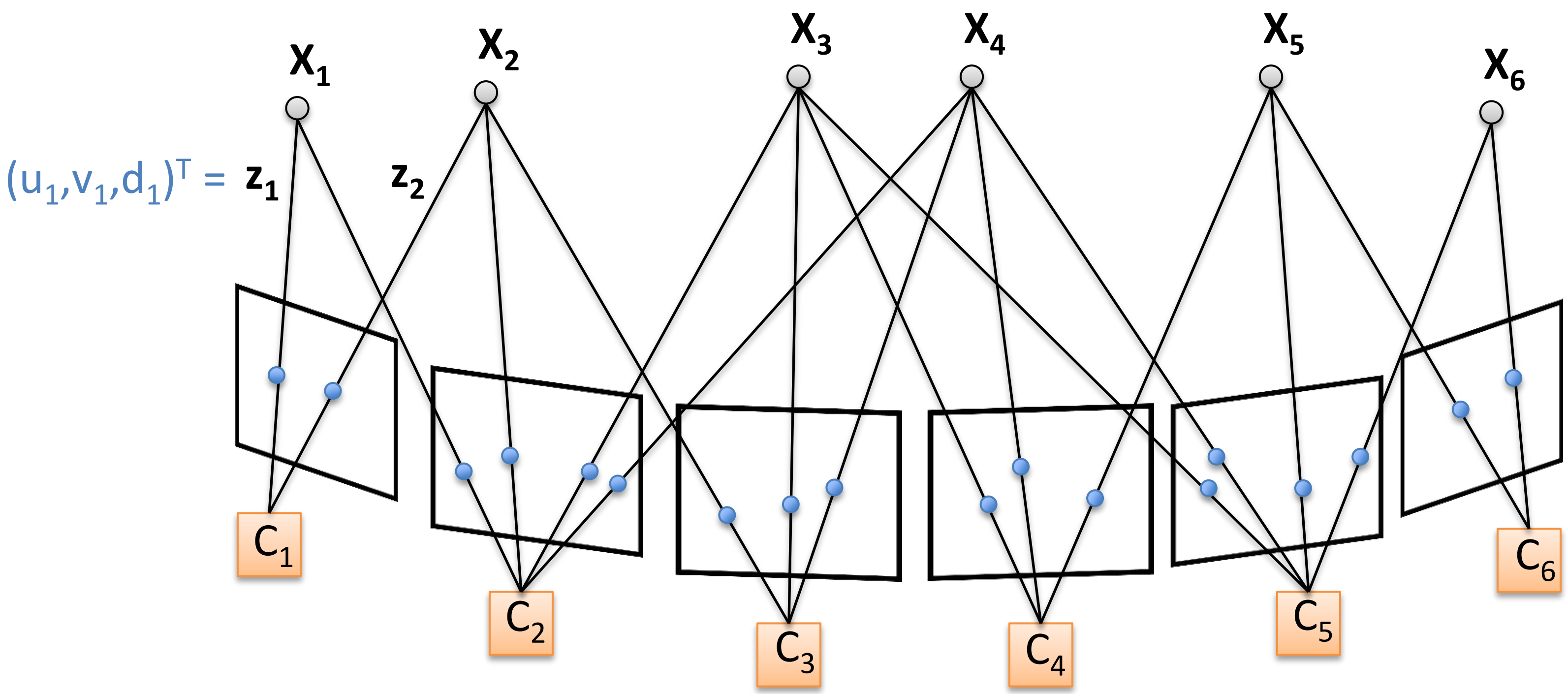
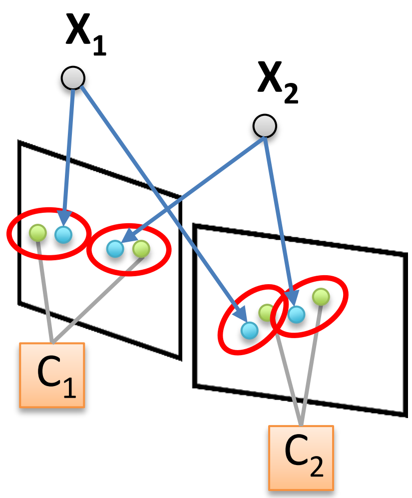


Full Bundle Adjustment for RGB-D Sensors

2D reprojection error

$$\min_{C_{i_k}, \mathbf{X}_{j_k}} \sum_{k=1}^{K} ||\pi(\mathcal{T}^{-1}(C_{i_k}, \mathbf{X}_{j_k})) - (u_k, v_k)^\top||^2$$



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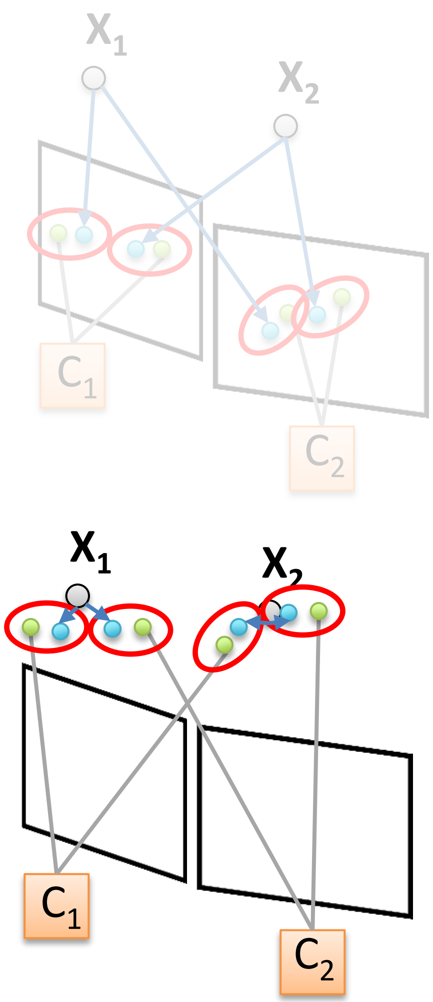

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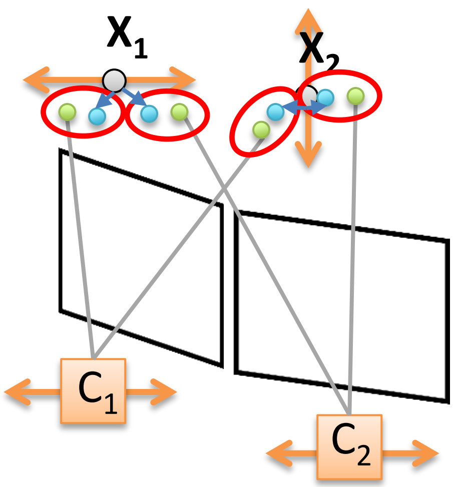
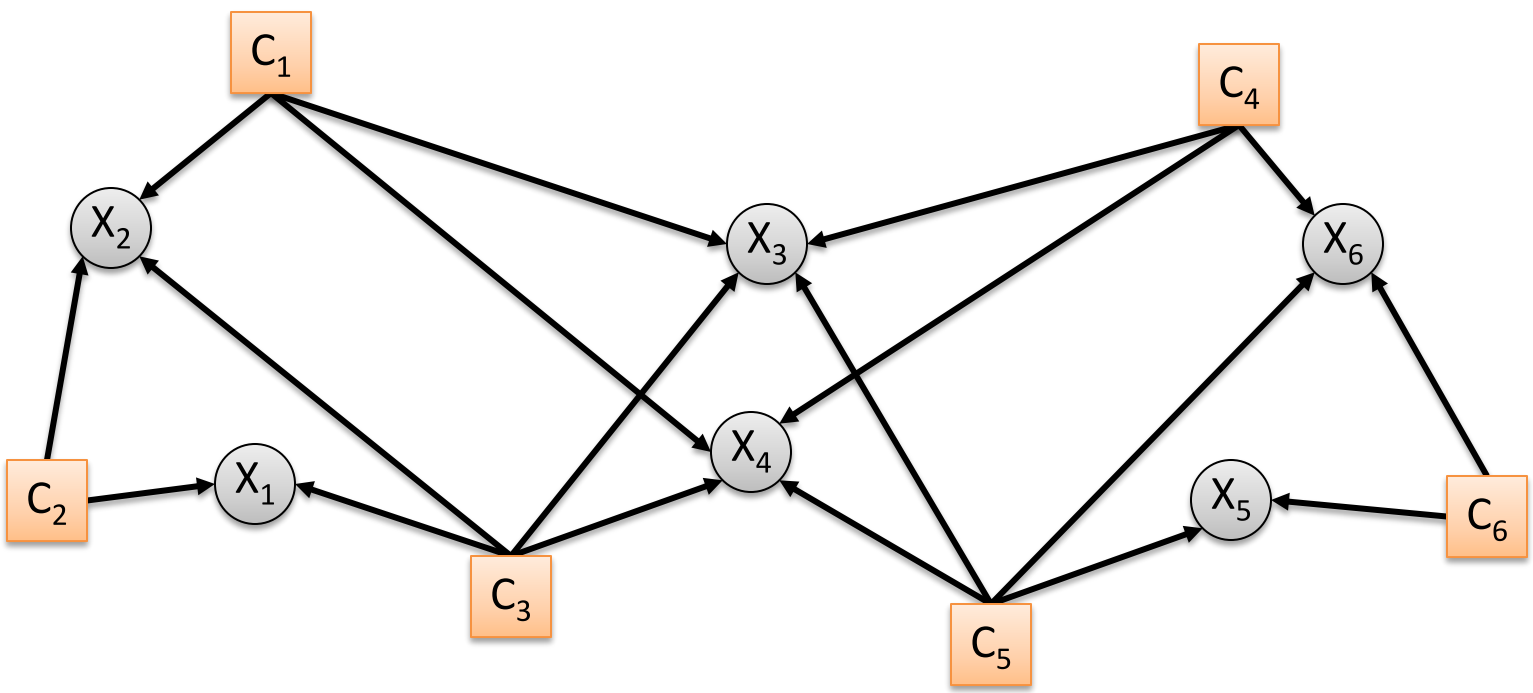


Efficient Bundle Adjustment for RGB-D Sensors using Submapping

1. Graph partitioning into submaps
2. Submap optimization
3. Global submaps alignment
4. Submap optimization with fixed separator

Stage 1: Graph partitioning into submaps



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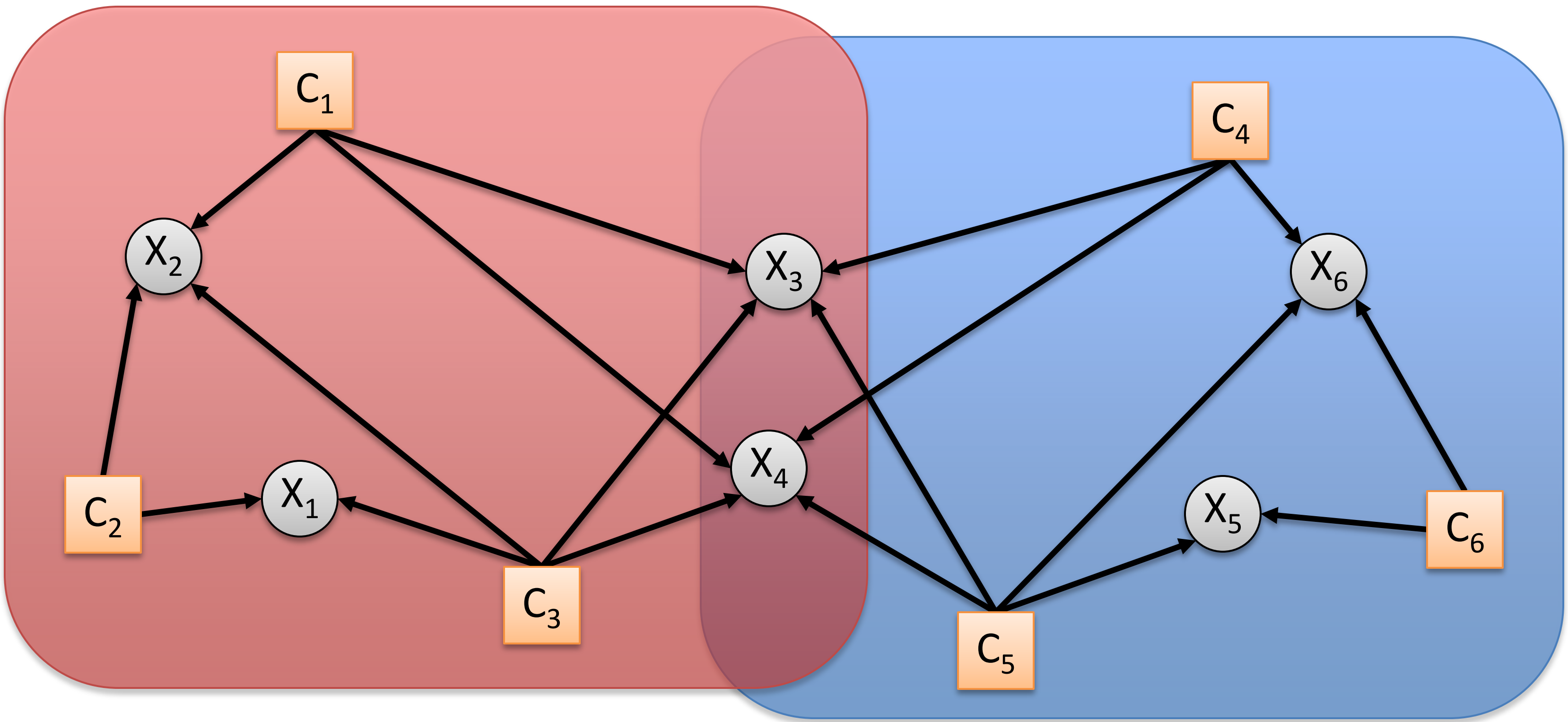

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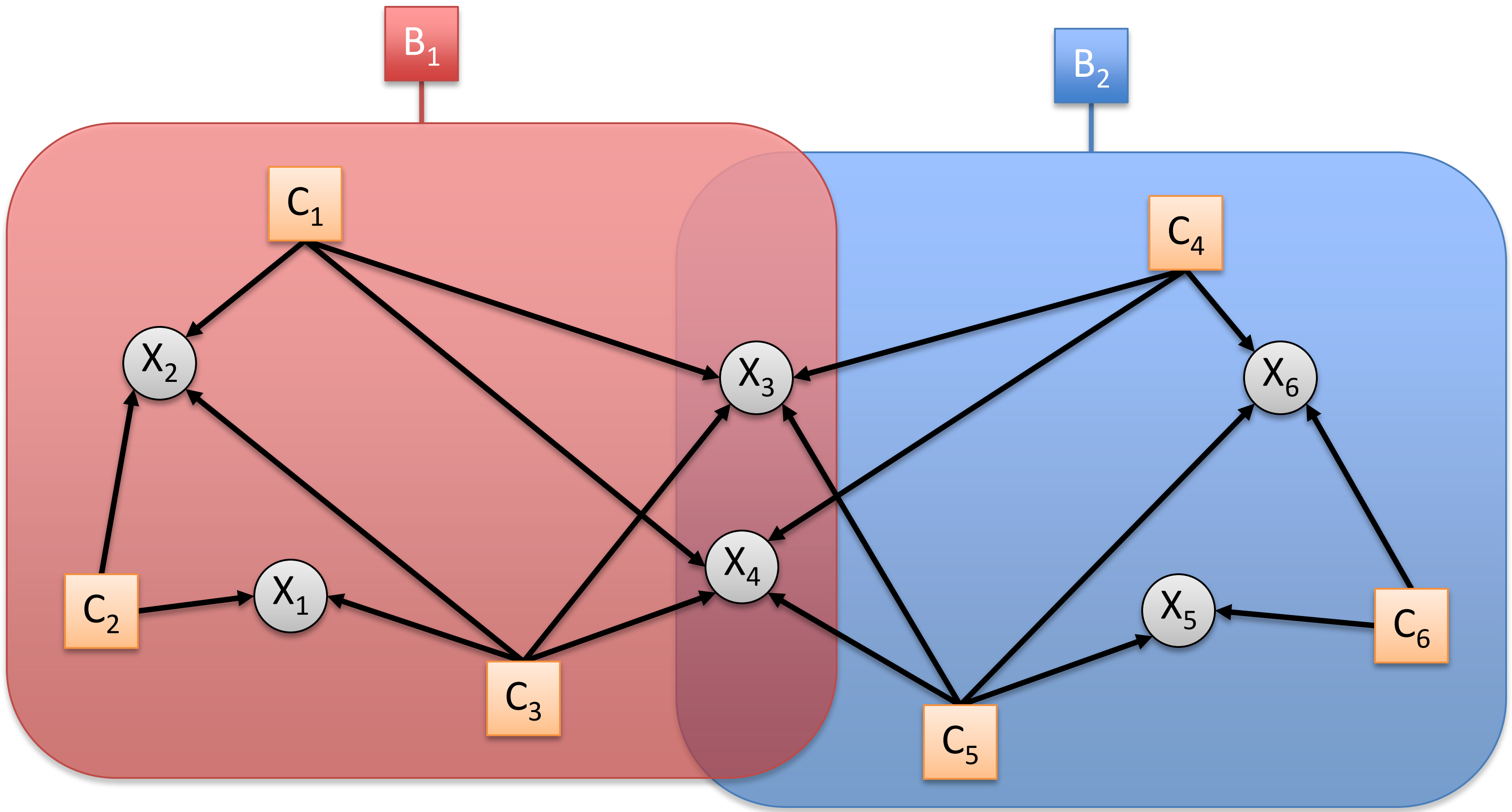

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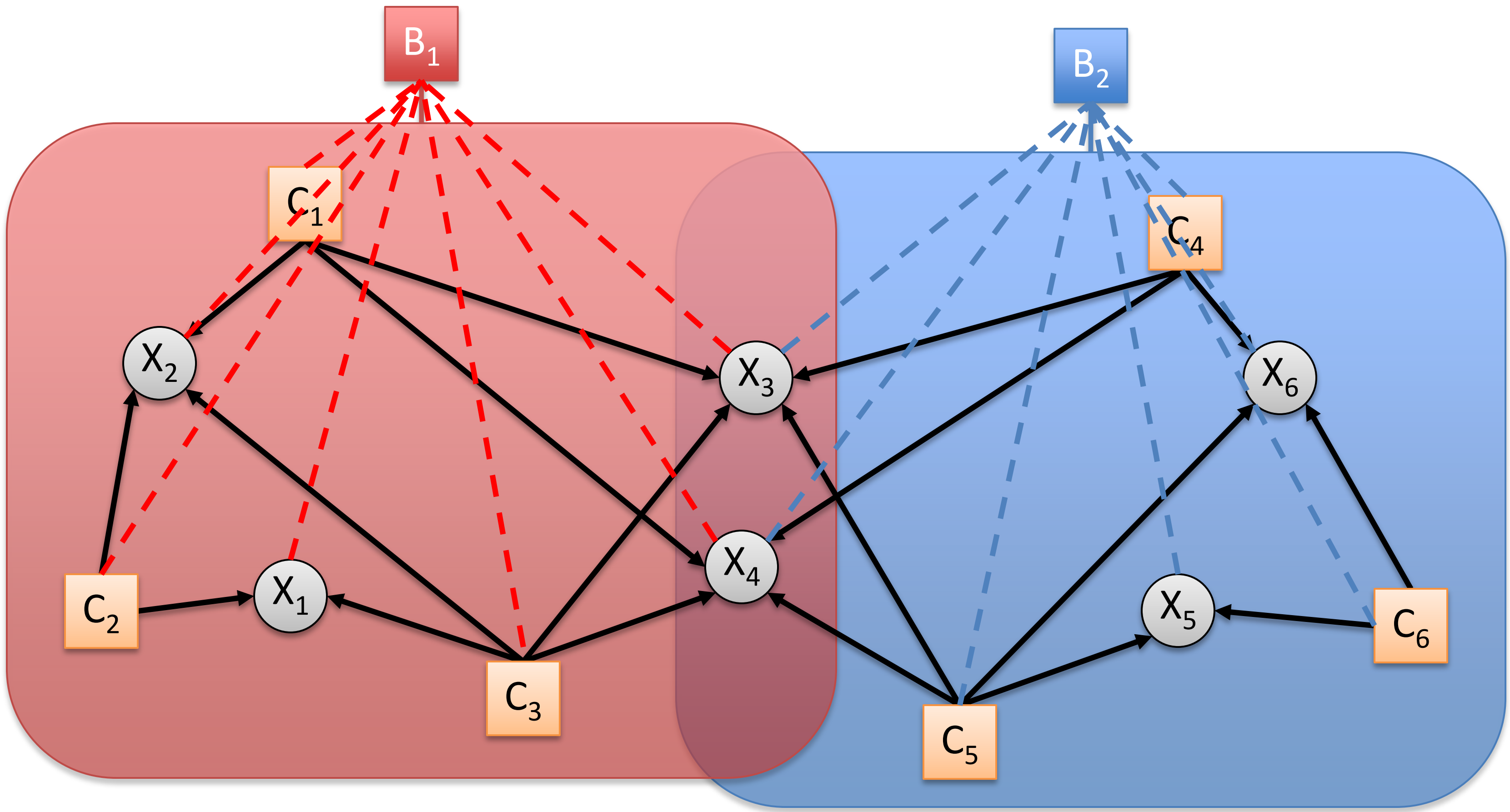

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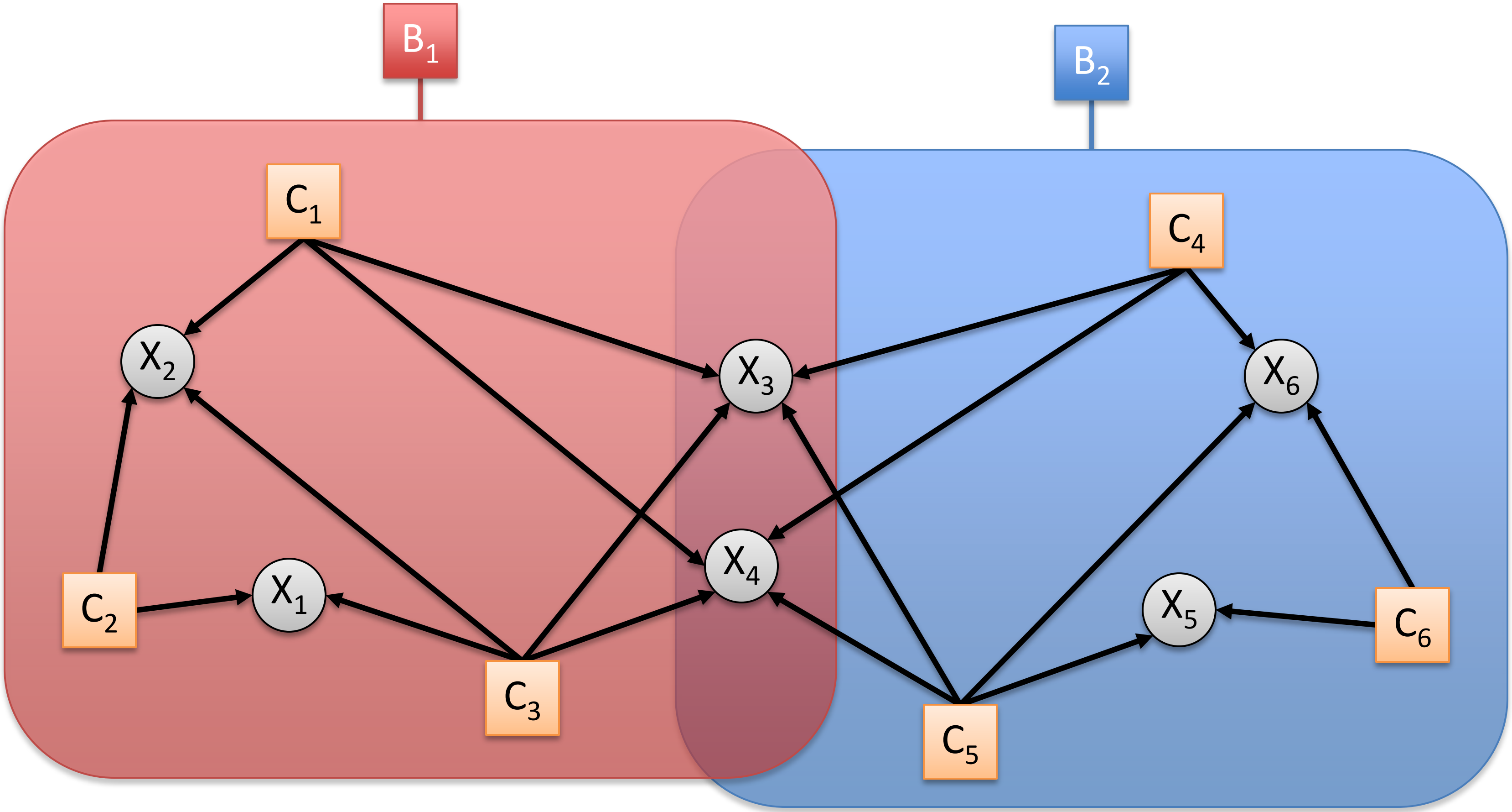

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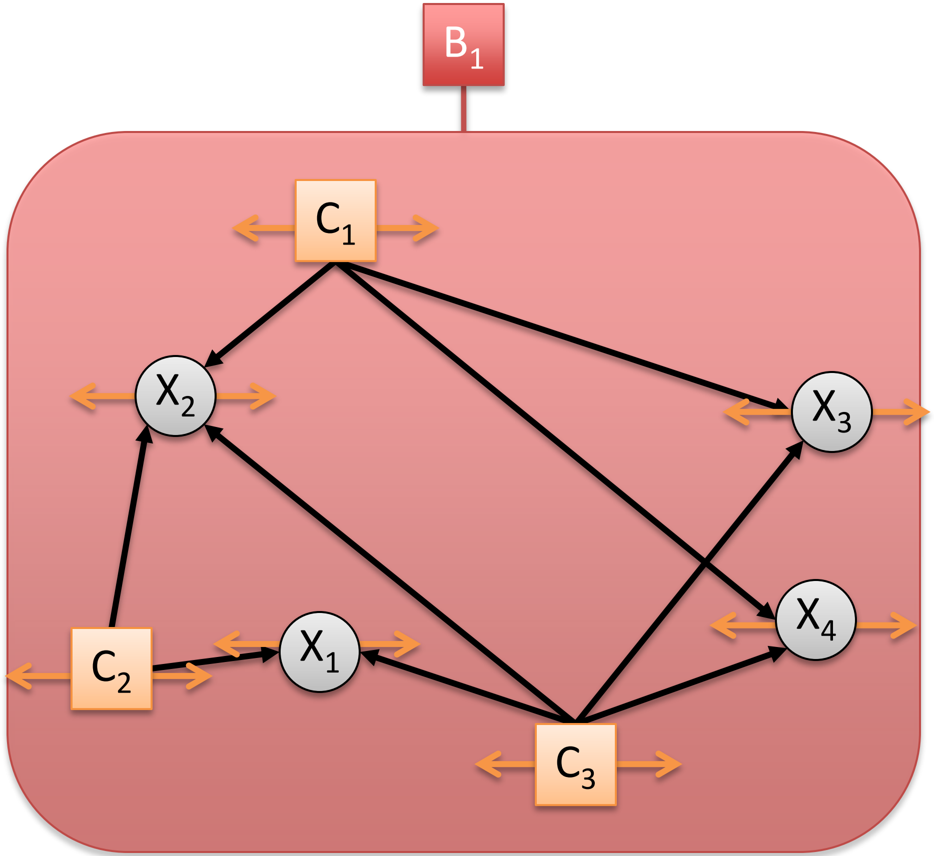

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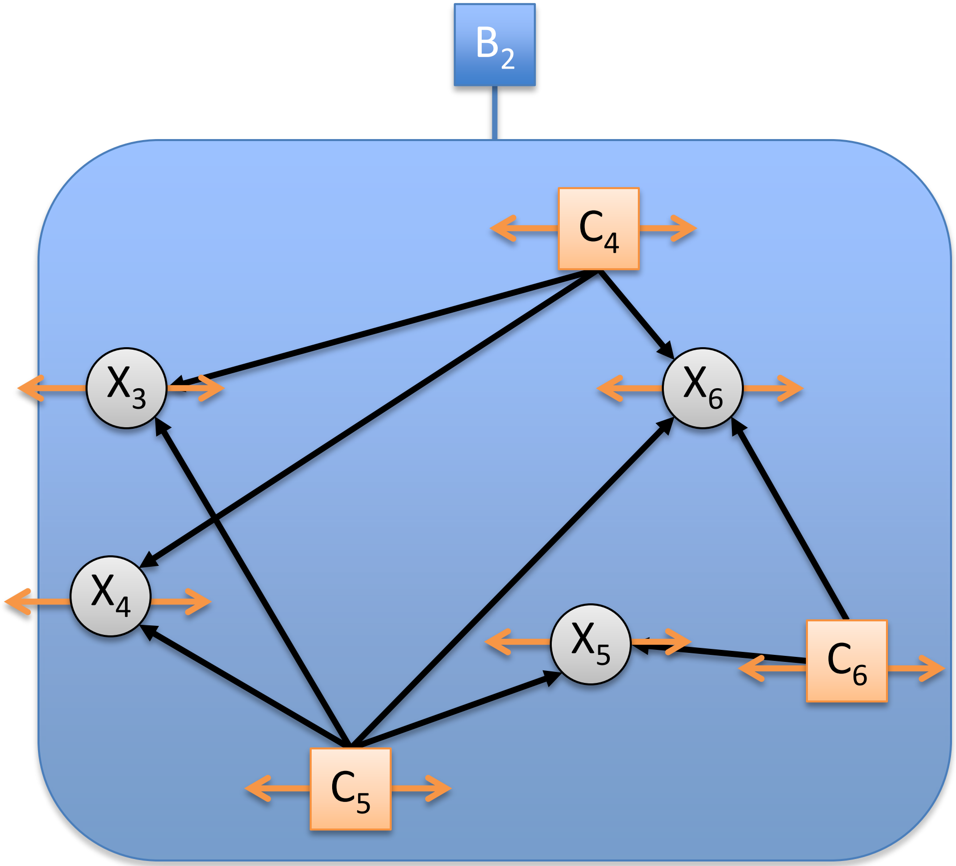
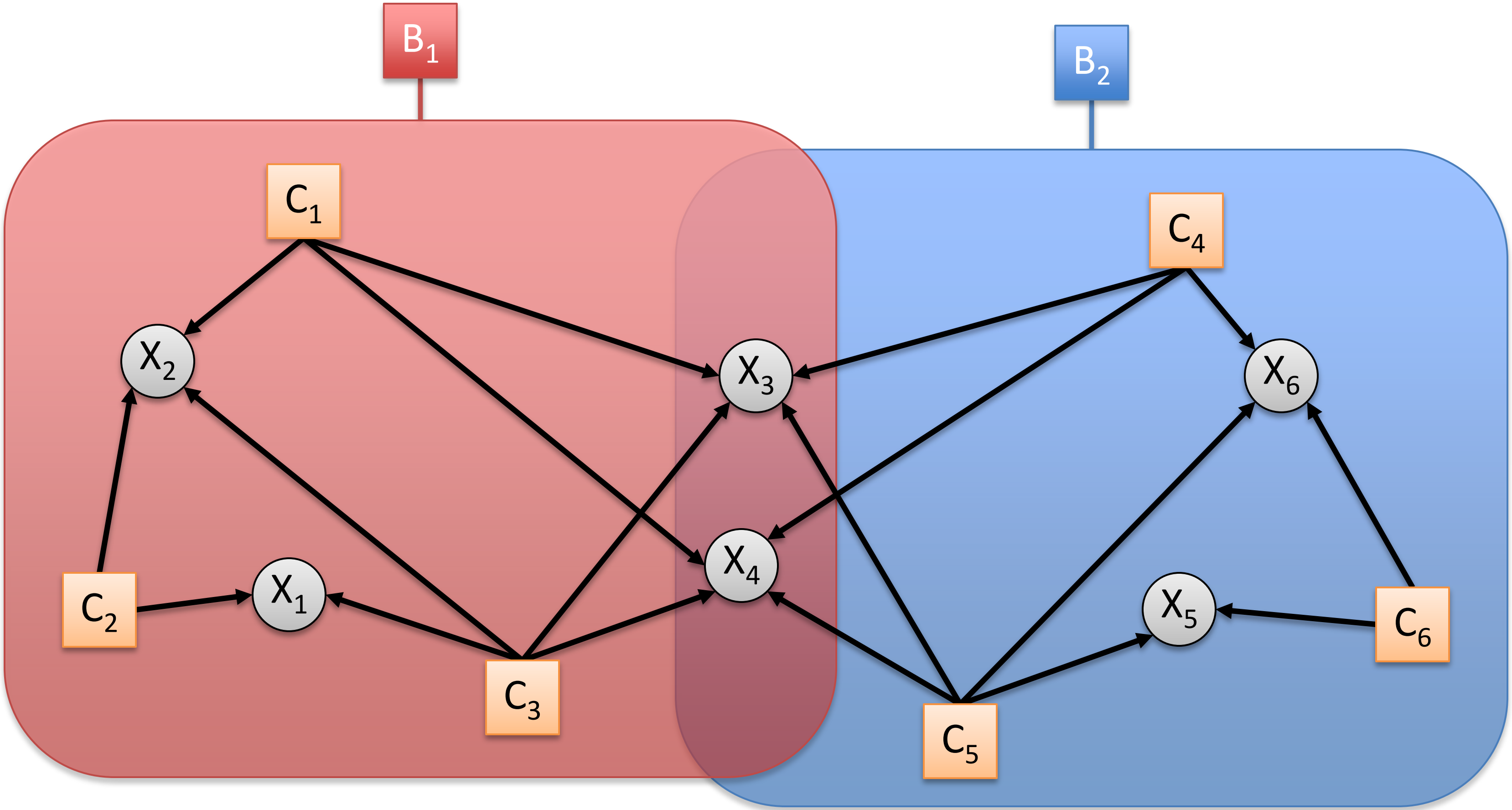


Stage 3: Global submaps alignment



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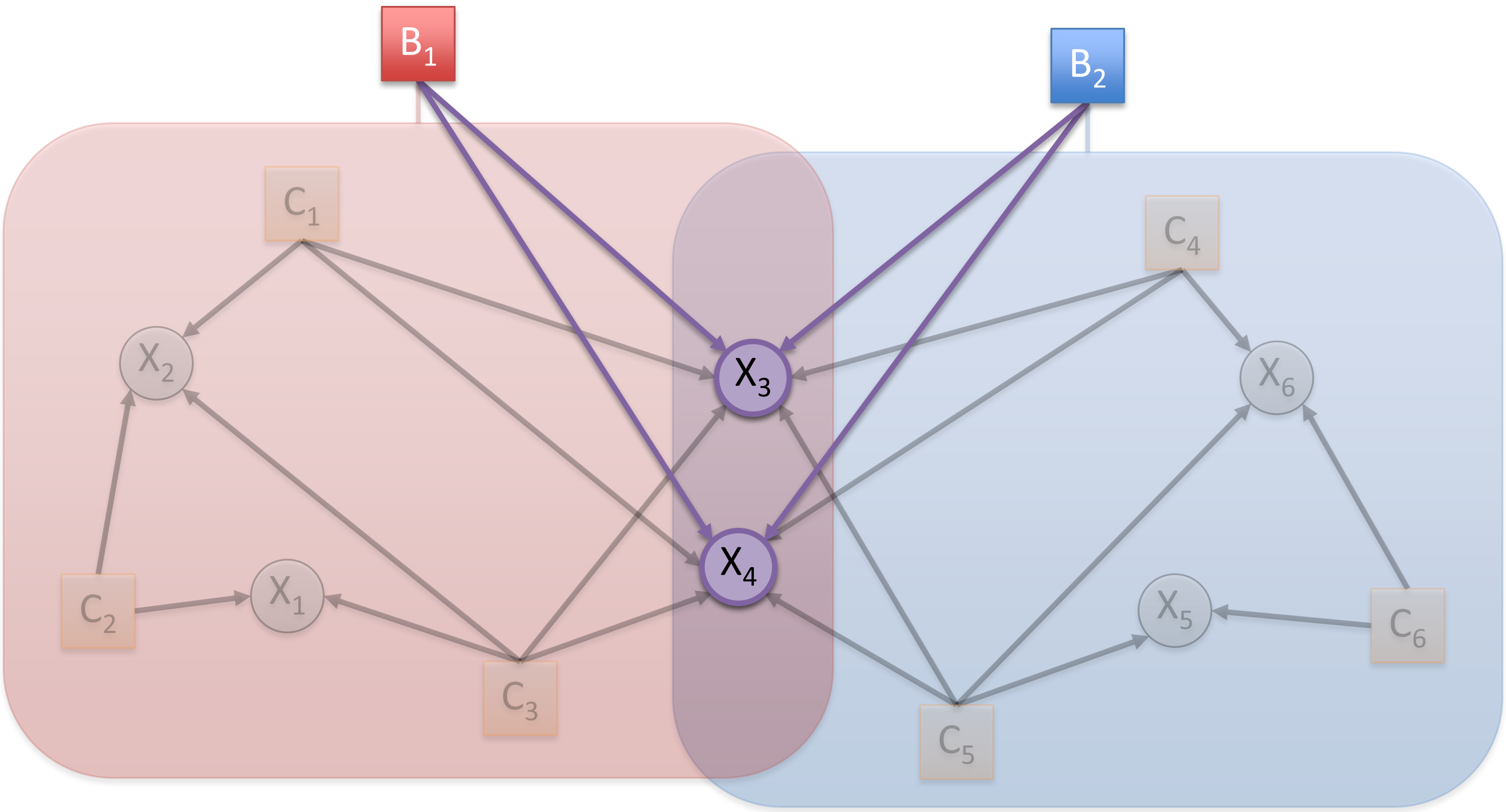

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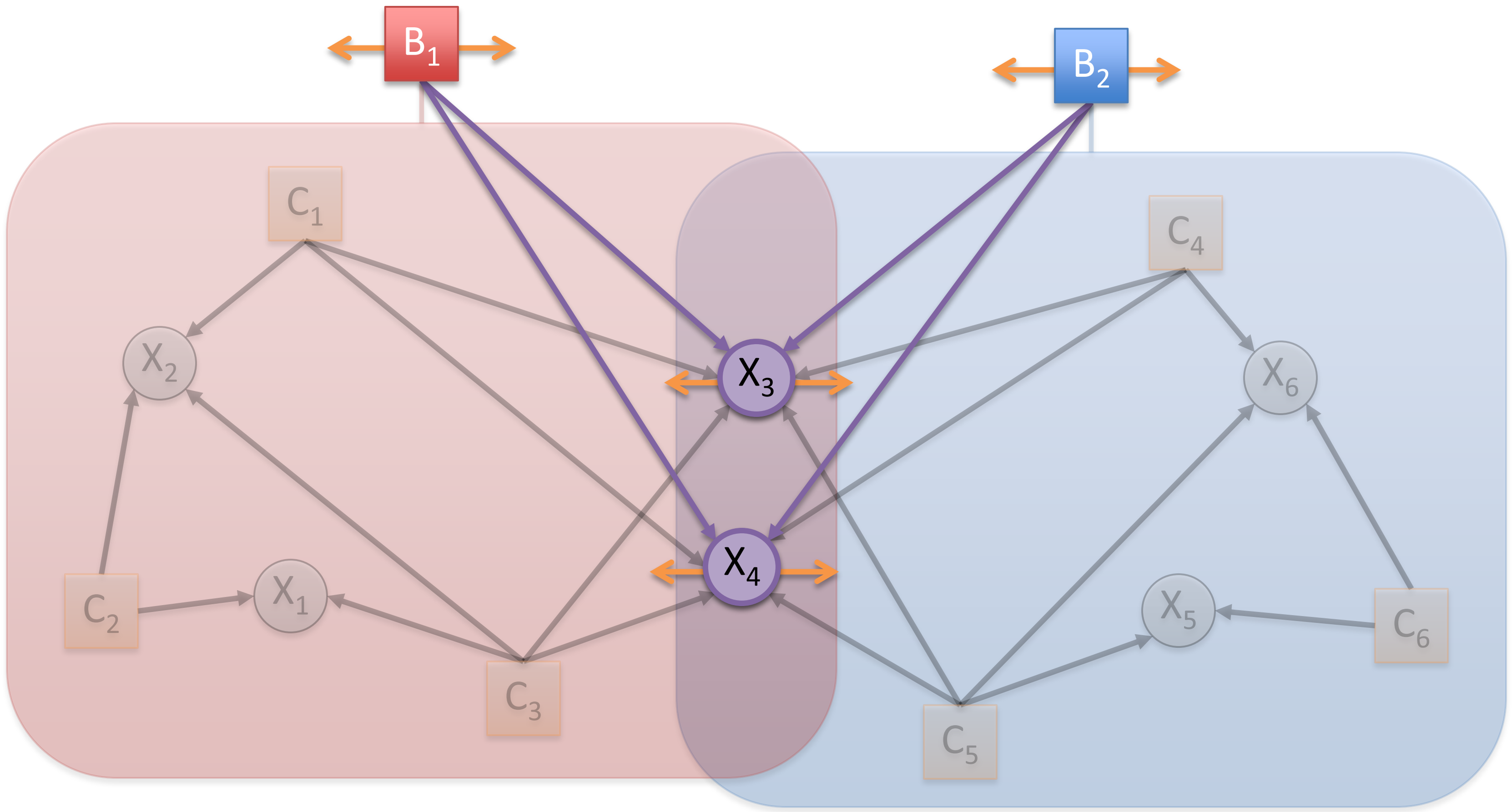
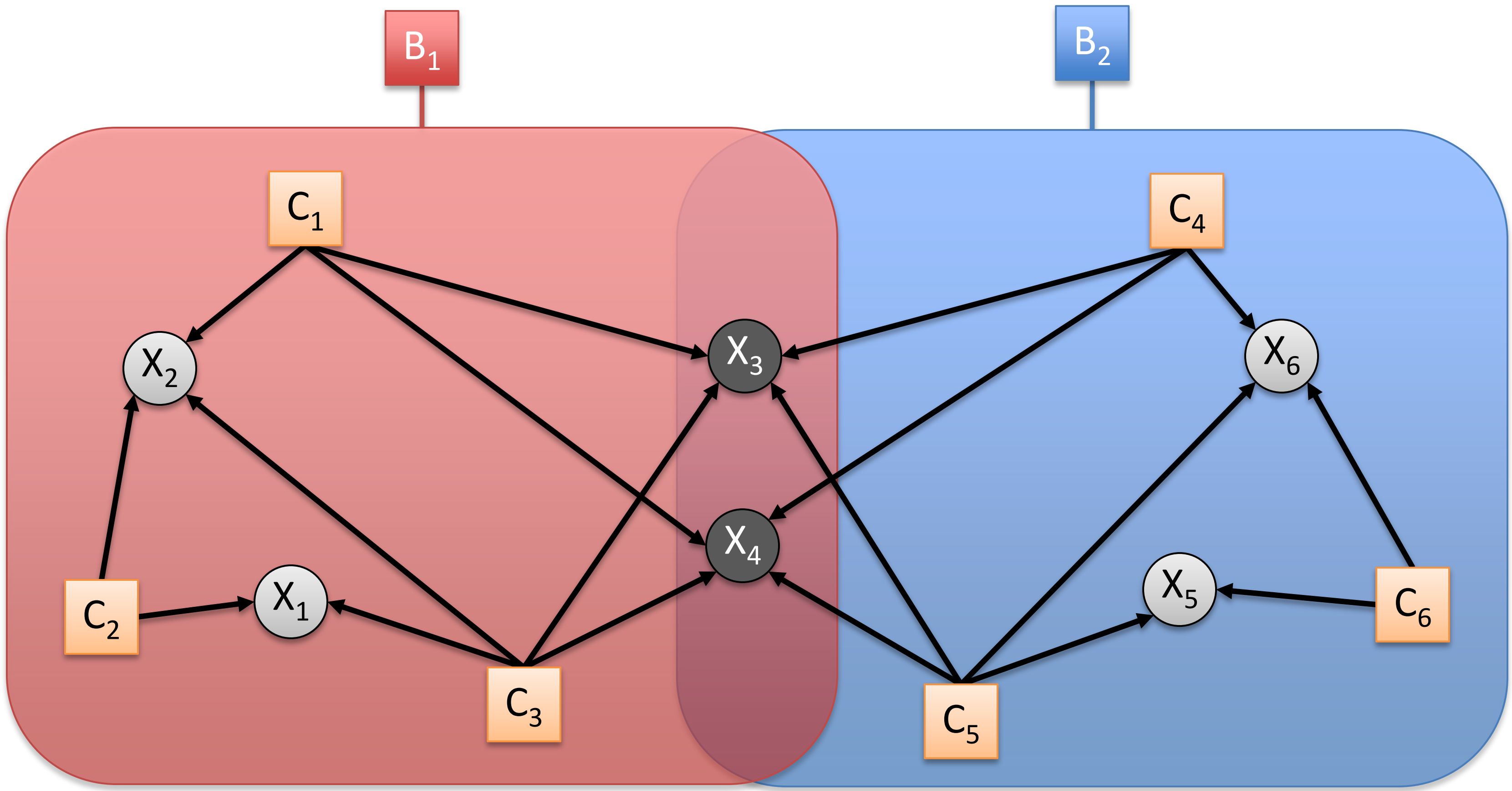


Stage 4: Internal submap update



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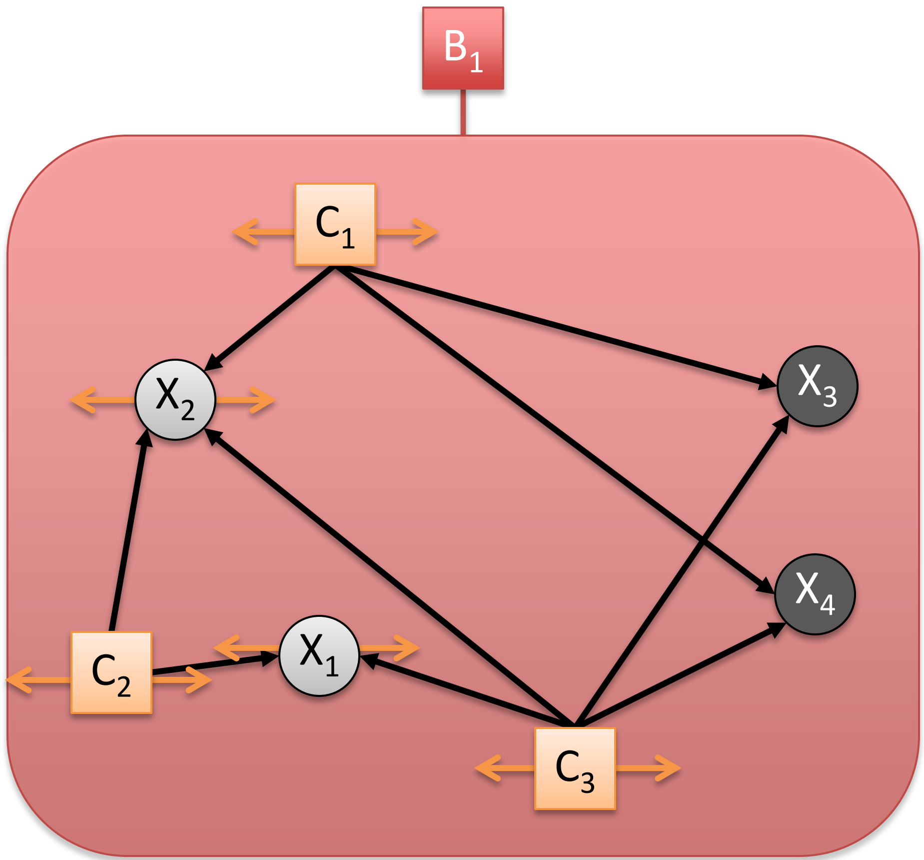

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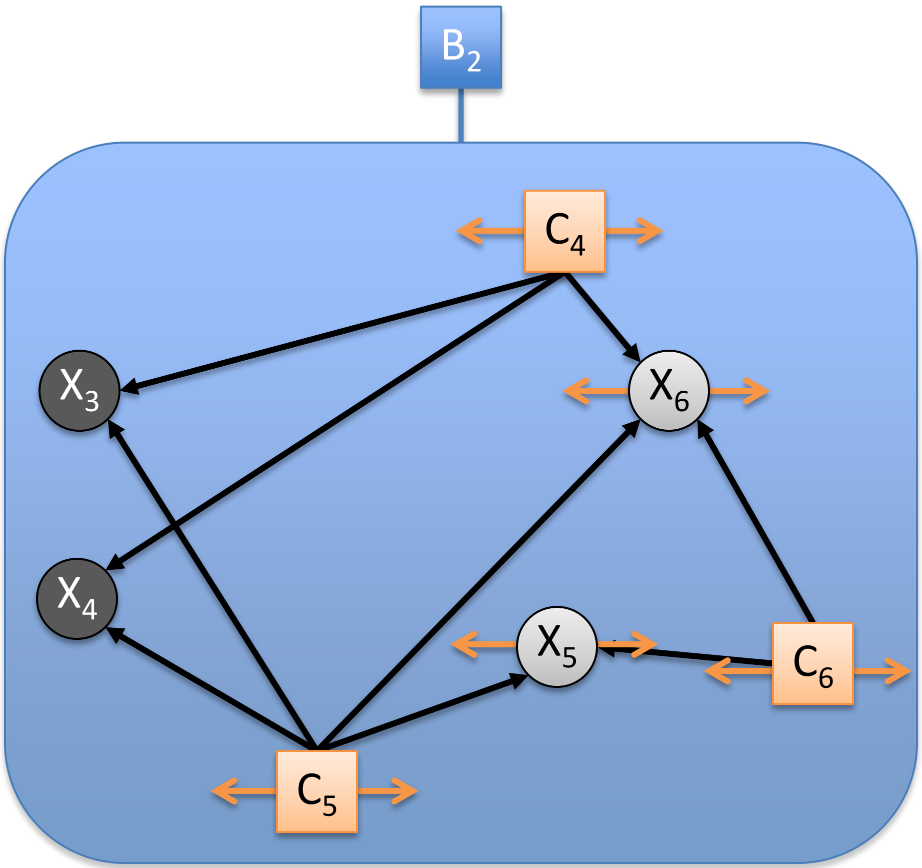

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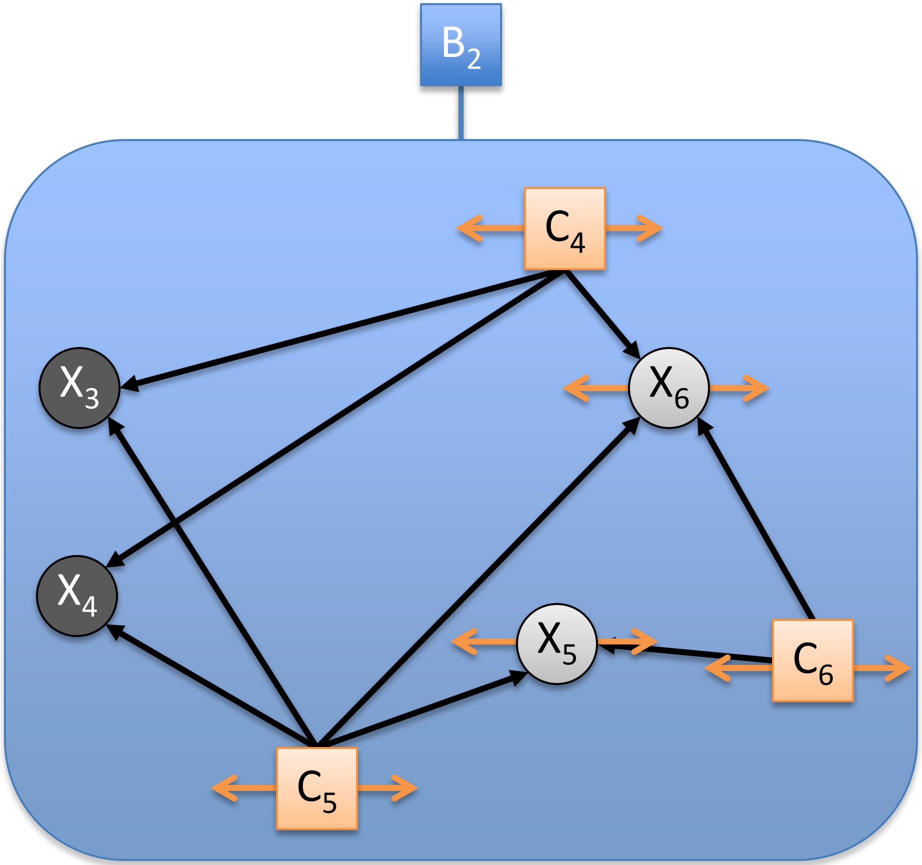
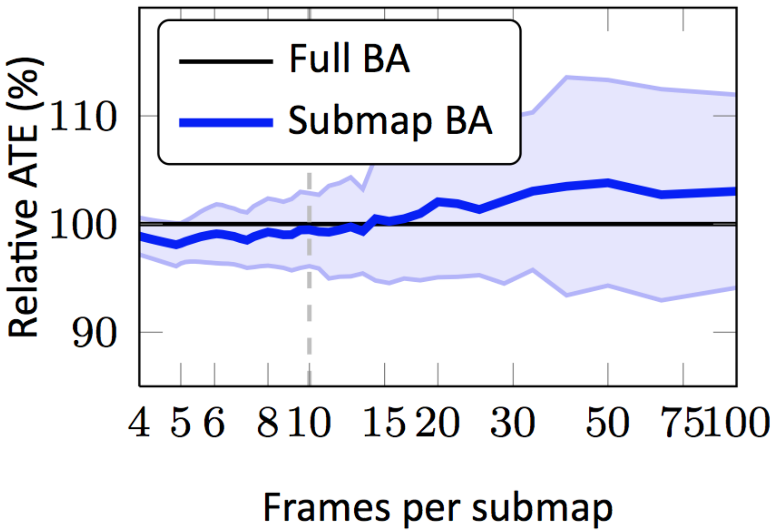
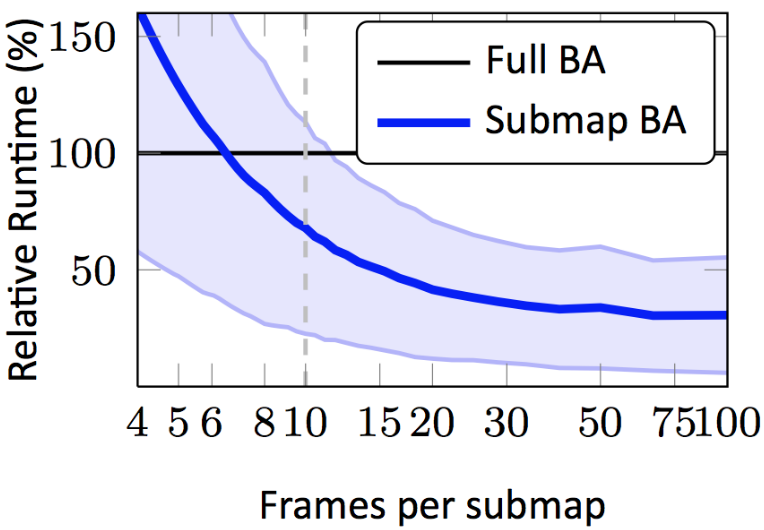


➔ Use final camera poses to fuse RGB-D frames into 3D octree model

Evaluation: Size of Submaps

- Evaluation of Absolute Trajectory Error (ATE) over 10 sequences of TUM RGB-D benchmark [Sturm et al., IROS 2012]





- Small submaps: smaller ATE than full BA
- Large submaps: increase efficiency but decrease accuracy
- Good speed/accuracy trade-off: 10 frames per submap

Evaluation: Performance

- Benchmark sequences (4 of 10 sequences):

Sequence	No BA	Full 2D	Full 3D		Submap-based 3D BA				
	ATE	ATE	ATE	time	submaps	ATE	$\pm(\%)$	time	$\pm(\%)$
FR1/desk2	0.098	0.044	0.030	27.23	62	0.031	+3.4	21.36	-21.5
FR1/room	0.275	0.228	0.085	125.46	135	0.086	+1.7	77.30	-38.4
FR2/desk	0.201	0.080	0.079	2355.26	289	0.076	-3.3	372.20	-84.2
FR3/office	0.176	0.039	0.036	1290.24	248	0.035	-3.0	242.88	-81.2
...	...	...	...	...	...	...	...	...	...
average	0.129	0.066	0.047			0.047	-0.5		-32.0

  - Similar accuracy as Full 3D BA at reduced cost (-32%)
  - Runtime improvement of up to 84% for long sequences

  - Comparison with state-of-the-art approaches:
    - RGB-D SLAM [Endres et al., ICRA 2012]: 13% (0.047m vs. 0.054m)
    - Direct SDF tracking [Bylow et al., RSS 2013]: 17% (0.047m vs. 0.058m)

Examples of Submap-based 3D Reconstructions

- Soil auger

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Thank you!