An Invitation to 3D Vision:
Multi-View Geometry

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Multi-view Geometry

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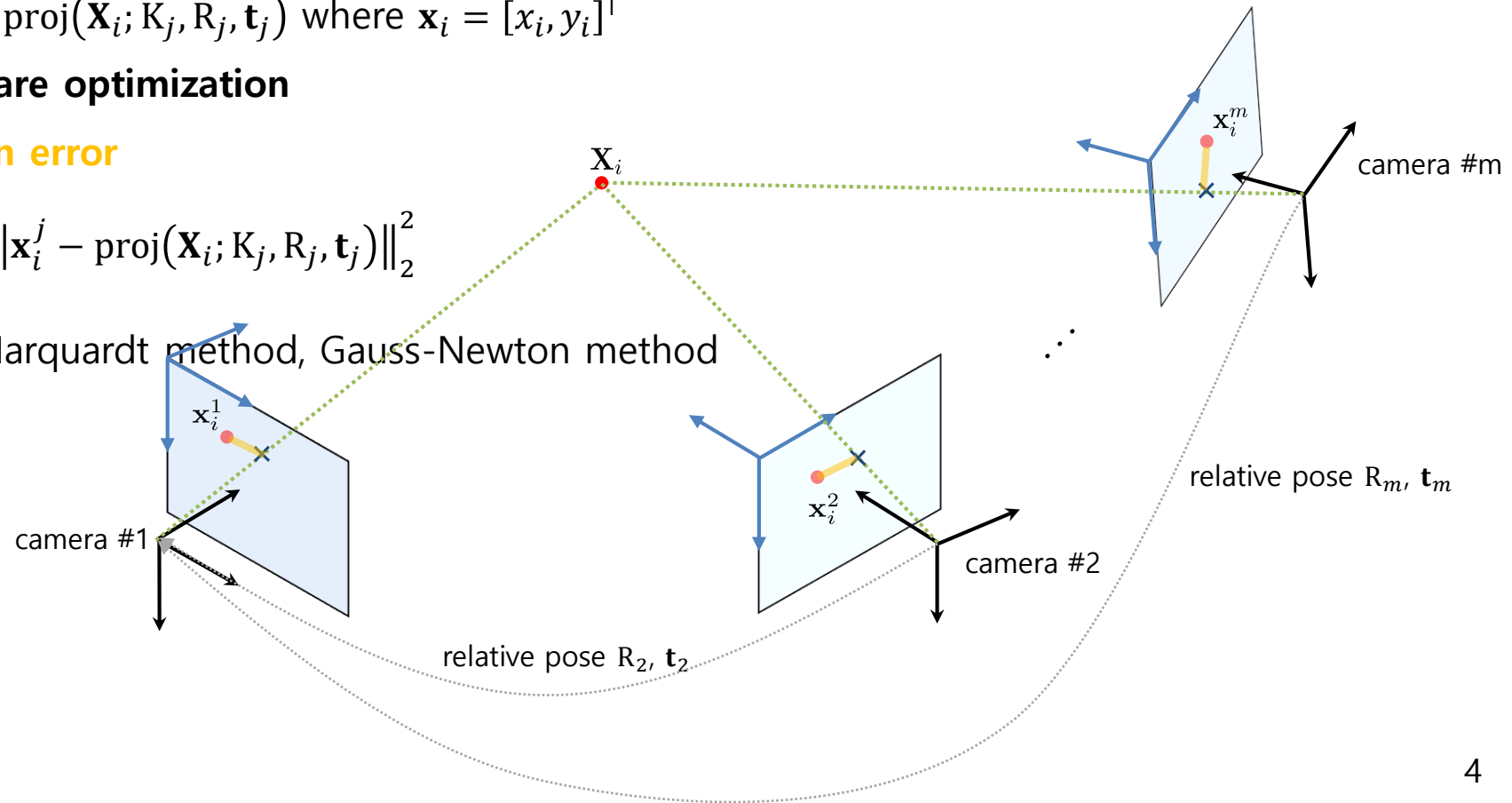Image: [The Stanford Multi-Camera Array (2002)](#)

Bundle Adjustment

- **Bundle adjustment** (shortly BA)

  - Unknown: 3D points ($\mathbf{X}_1, \mathbf{X}_2, ..., \mathbf{X}_i, ..., \mathbf{X}_n$) and each camera's relative pose ($R_j, \mathbf{t}_j$) ($3n + 6m$ DOF)

  - Given: Point correspondence $\mathbf{x}_i^j$, camera matrices K_j, 3D points $\mathbf{X}_i$, and each camera's relative pose ($R_j, \mathbf{t}_j$)

  - ~~Constraints: $m \times n \times$ projection $\mathbf{x}_i^j = K_j \left[R_j | \mathbf{t}_j \right] \mathbf{X}_i$~~

  - More general constraints: $\mathbf{x}_i^j = \mathrm{proj}(\mathbf{X}_i; K_j, R_j, \mathbf{t}_j)$ where $\mathbf{x}_i = [x_i, y_i]^\top$

  - Solution: **Non-linear least-square optimization**

    - Cost Function: **Reprojection error**

$$\widehat{\mathbf{X}}_{...}, \widehat{R}_{...}, \widehat{\mathbf{t}}_{...} = \underset{\mathbf{X}_{...}, R_{...}, \mathbf{t}_{...}}{\mathrm{argmin}} \sum_{j=1}^{m} \sum_{i=1}^{n} \left\| \mathbf{x}_i^j - \mathrm{proj}(\mathbf{X}_i; K_j, R_j, \mathbf{t}_j) \right\|_2^2$$

    - Optimization: Levenberg–Marquardt method, Gauss-Newton method

$\mathbf{X}_i$

$\mathbf{x}_i^m$

camera #m

$\mathbf{x}_i^1$

$\mathbf{x}_i^2$

camera #1

camera #2

relative pose $R_m, \mathbf{t}_m$

relative pose $R_2, \mathbf{t}_2$

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Bundle Adjustment

- **Bundle adjustment** (shortly BA)

    - Unknown: 3D points ($\mathbf{X}_1$, $\mathbf{X}_2$, ..., $\mathbf{X}_i$, ..., $\mathbf{X}_n$) and each camera's relative pose (R_j, $\mathbf{t}_j$) ($3n + 6m$ DOF)

    - Given: Point correspondence $\mathbf{x}_i^j$, camera matrices K_j, 3D points $\mathbf{X}_i$, and each camera's relative pose (R_j, $\mathbf{t}_j$) cf. initial values

    - More general constraints: $\mathbf{x}_i^j = \mathrm{proj}(\mathbf{X}_i; \mathrm{K}_j, \mathrm{R}_j, \mathbf{t}_j)$ where $\mathbf{x}_i = [x_i, y_i]^\mathsf{T}$

    - Solution: **Non-linear least-square optimization** $\sum_i^n \sum_j^m v_i^j \left\| \mathbf{x}_i^j - \mathrm{P}_j \mathbf{X}_i \right\|_\Sigma^2$ where $v_i^j = \begin{cases} 1 & \text{if } \mathbf{x}_i^j \text{ is visible} \\ 0 & \text{otherwise} \end{cases}$

        - Cost Function: **Reprojection error**

$$\hat{\mathbf{X}}_{...}, \hat{\mathrm{R}}_{...}, \hat{\mathbf{t}}_{...} = \underset{\mathbf{X}_{...}, \mathrm{R}_{...}, \mathbf{t}_{...}}{\mathrm{argmin}} \sum_{j=1}^m \sum_{i=1}^n \left\| \mathbf{x}_i^j - \mathrm{proj}(\mathbf{X}_i; \mathrm{K}_j, \mathrm{R}_j, \mathbf{t}_j) \right\|_2^2$$

   - Optimization: Levenberg–Marquardt method, Gauss-Newton method

- **Bundle adjustment tools**

    - Bundle adjustment: sba (Sparse BA), SSBA (Simple Sparse BA), pba (Multicore BA), DABA (Decentralized and Accelerated Large-scale BA)

    - (Graph) optimization: g2o (General Graph Optimization), iSAM (Incremental Smoothing and Mapping), GTSAM, Ceres Solver in C++ / SciPy, PyTorch, ... in Python
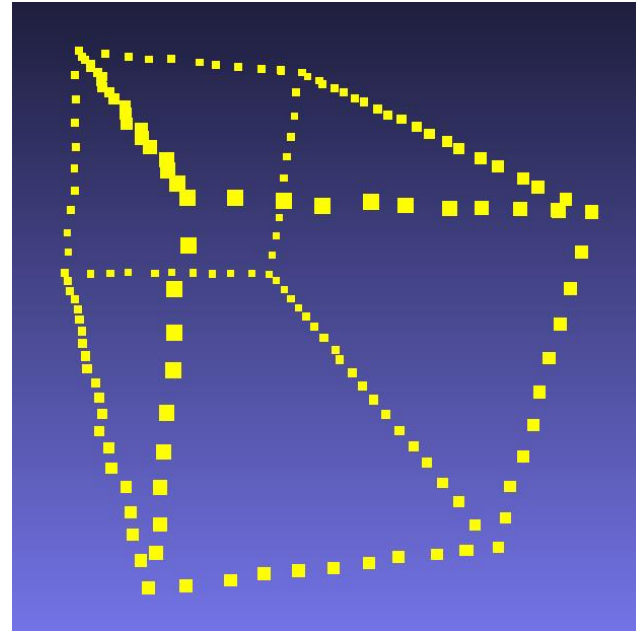
Bundle Adjustment

- Example) **Bundle adjustment** [bundle_adjustment_global.cpp, bundle_adjustment.hpp]
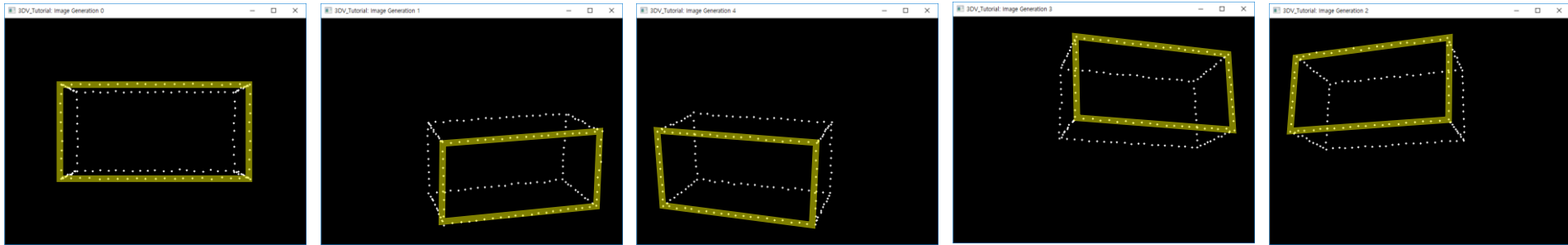
Result: "triangulation.xyz"
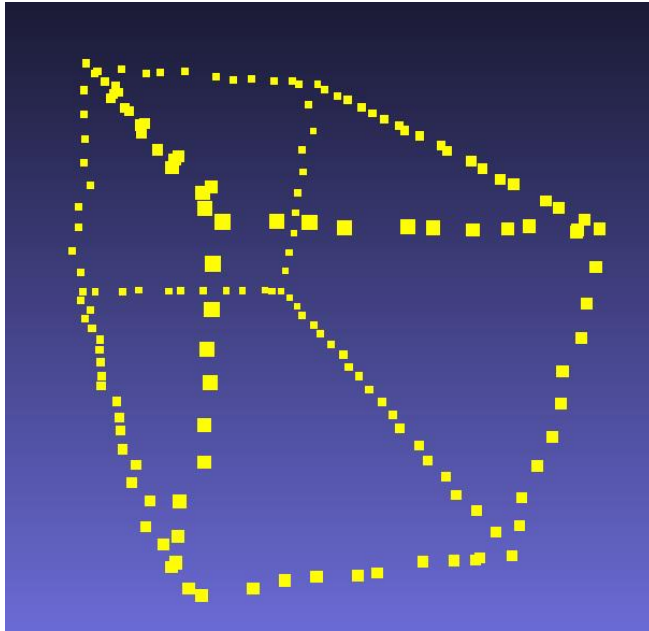
Result: "bundle_adjustment_global.xyz"

[Given]

- **Intrinsic parameters**: camera matrices K_j (all cameras has same and fixed camera matrix.)

- **2D point correspondence** $\mathbf{x}_i^j$ (all points are visible on all camera views.)

[Unknown]

- **Extrinsic parameters**: camera poses

$$R_0 = I_{3x3} \qquad R_1 = I_{3x3} \qquad R_2 = I_{3x3} \qquad R_3 = I_{3x3} \qquad R_4 = I_{3x3}$$

$$\mathbf{t}_0 = [0,0,0]^\top \qquad \mathbf{t}_1 = [0,0,0]^\top \qquad \mathbf{t}_2 = [0,0,0]^\top \qquad \mathbf{t}_3 = [0,0,0]^\top \qquad \mathbf{t}_4 = [0,0,0]^\top$$

- **3D points** $\mathbf{X}_i = [0,0,5.5]^\top$ initial values

Ceres Solver (non-linear least-square optimization)

$$\sum_i^n \sum_j^m v_i^j \left\| \mathbf{x}_i^j - P_j \mathbf{X}_i \right\|_\Sigma^2 \quad \text{where} \quad v_i^j = 1 \ (\because \text{all points are visible})$$

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```cpp
1.  #include "bundle_adjustment.hpp"

2.  int main()
3.  {
4.      // cf. You need to run 'image_formation.cpp' to generate point observation.
5.      const char* input = "image_formation%d.xyz";
6.      int input_num = 5;
7.      double f = 1000, cx = 320, cy= 240;

8.      // Load 2D points observed from multiple views
9.      std::vector<std::vector<cv::Point2d>> xs;
10.     ...

11.     // Initialize cameras and 3D points
12.     std::vector<cv::Vec6d> cameras(xs.size());
13.     std::vector<cv::Point3d> Xs(xs.front().size(), cv::Point3d(0, 0, 5.5));

14.     // Run bundle adjustment
15.     ceres::Problem ba;
16.     for (size_t j = 0; j < xs.size(); j++)
17.     {
18.         for (size_t i = 0; i < xs[j].size(); i++)
19.         {
20.             ceres::CostFunction* cost_func = ReprojectionError::create(xs[j][i], f, cv::Point2d(cx, cy));
21.             double* view = (double*)(&(cameras[j]));
22.             double* X = (double*)(&(Xs[i]));
23.             ba.AddResidualBlock(cost_func, NULL, view, X);
24.         }
25.     }
26.     ceres::Solver::Options options;
27.     options.linear_solver_type = ceres::ITERATIVE_SCHUR;
28.     options.num_threads = 8;
29.     options.minimizer_progress_to_stdout = true;
30.     ceres::Solver::Summary summary;
31.     ceres::Solve(options, &ba, &summary);

32.     // Store the 3D points and camera pose to an XYZ file
33.     ...
34.         cv::Vec3d rvec(cameras[j][0], cameras[j][1], cameras[j][2]), t(cameras[j][3], cameras[j][4], cameras[j][5]);
35.         cv::Matx33d R;
36.         cv::Rodrigues(rvec, R);
37.     ...
38.     return 0;
39. }
```
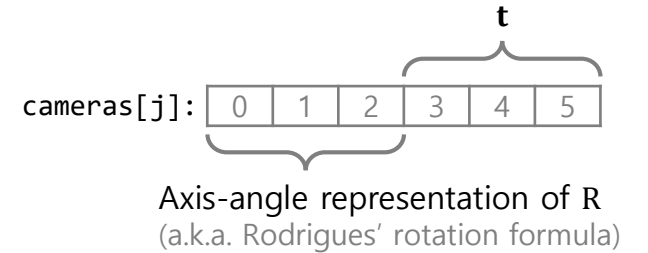
cameras[j]:

| 0 | 1 | 2 | 3 | 4 | 5 |

t

Axis-angle representation of R
(a.k.a. Rodrigues' rotation formula)

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```
1.  #include "opencv2/opencv.hpp"
2.  #include "ceres/ceres.h"
3.  #include "ceres/rotation.h"

4.  // Reprojection error for bundle adjustment
5.  struct ReprojectionError
6.  {
7.      ReprojectionError(const cv::Point2d& _x, double _f, cv::Point2d& _c) : x(_x), f(_f), c(_c) { }

8.      template <typename T>
9.      bool operator()(const T* const camera, const T* const point, T* residuals) const
10.     {
11.         // X' = R*X + t
12.         T X[3];
13.         ceres::AngleAxisRotatePoint(camera, point, X);
14.         X[0] += camera[3];
15.         X[1] += camera[4];
16.         X[2] += camera[5];

17.         // x' = K*X'
18.         T x_p = f * X[0] / X[2] + cx;
19.         T y_p = f * X[1] / X[2] + cy;

20.         // residual = x – x'
21.         residuals[0] = T(x.x) - x_p;
22.         residuals[1] = T(x.y) - y_p;
23.         return true;
24.     }

25.     static ceres::CostFunction* create(const cv::Point2d& _x, double _f, cv::Point2d& _c)
26.     {
27.         return (new ceres::AutoDiffCostFunction<ReprojectionError, 2, 6, 3>(new ReprojectionError(_x, _f, _c)));
28.     }

29. private:
30.     const cv::Point2d x;
31.     const double f;
32.     const cv::Point2d c;
33. };
```

$$x - PX$$

Structure-from-Motion

- **Structure-from-Motion** (shortly SfM)
    - Goal: 3D structures + each camera's *relative pose*
    - Given: 2D images from different viewpoints (a.k.a. *relative pose* or *motion*)
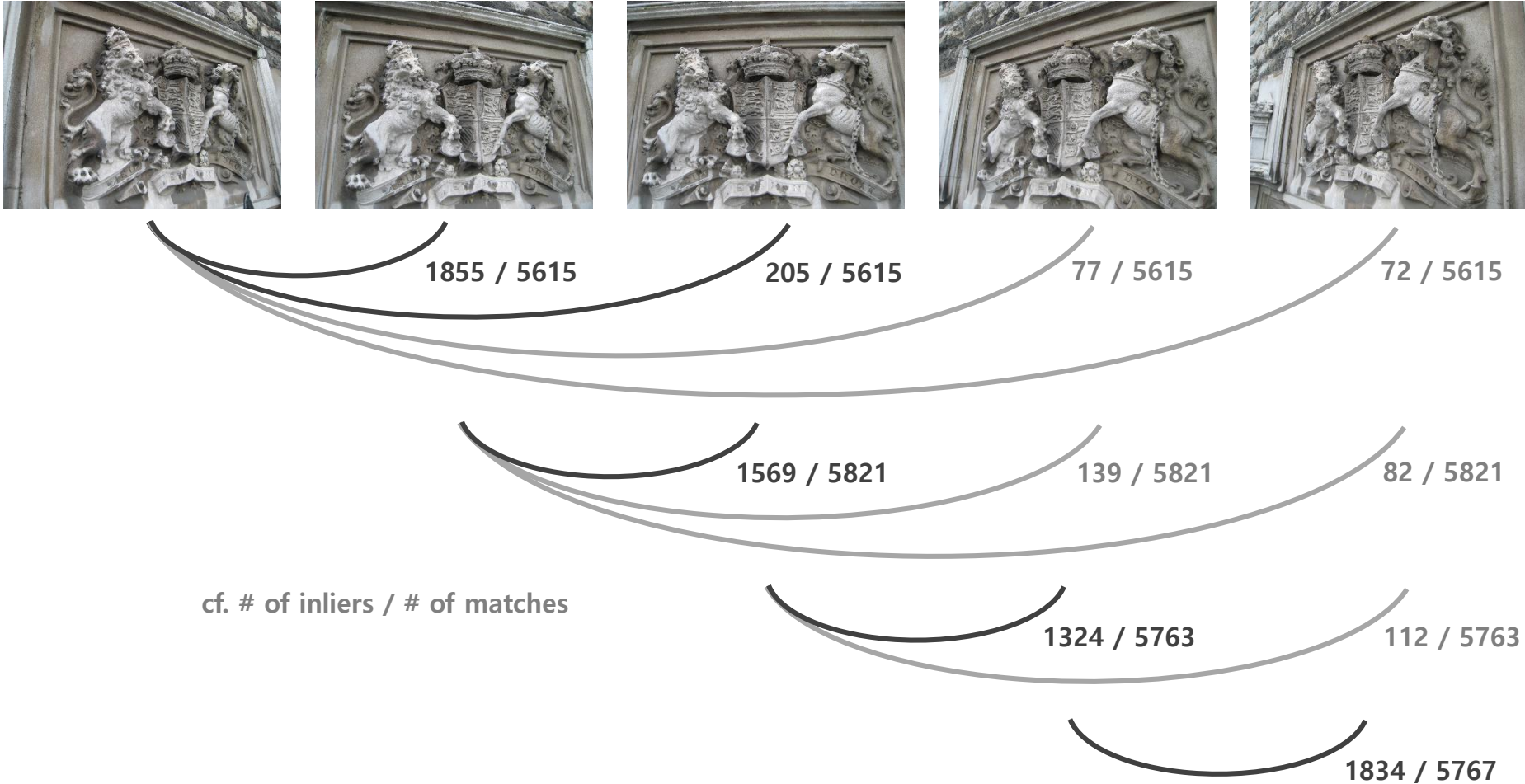

- **Structure-from-Motion tools**
    - Bundler, COLMAP, MVE, Theia, openMVG, OpenSfM, Toy SfM / VisualSFM (GUI, binary only)

Image: Bundler

Structure-from-Motion

- Example) **Structure-from-Motion (batch version)** [sfm_global.cpp]

   0) Load images and extract features

   0) Match features and find good matches (which has enough inliers)

1855 / 5615

205 / 5615

77 / 5615

72 / 5615

1569 / 5821

139 / 5821

82 / 5821

cf. # of inliers / # of matches

1324 / 5763

112 / 5763

1834 / 5767

Structure-from-Motion

- Example) **Structure-from-Motion (batch version)** [sfm_global.cpp]

    0) Load images and extract features

    0) Match features and find good matches (which has enough inliers)

    1855 / 5615   1569 / 5615   1324 / 5615   1834 / 5615

    205 / 5615

    1) Initialize cameras (R, t, f, …)

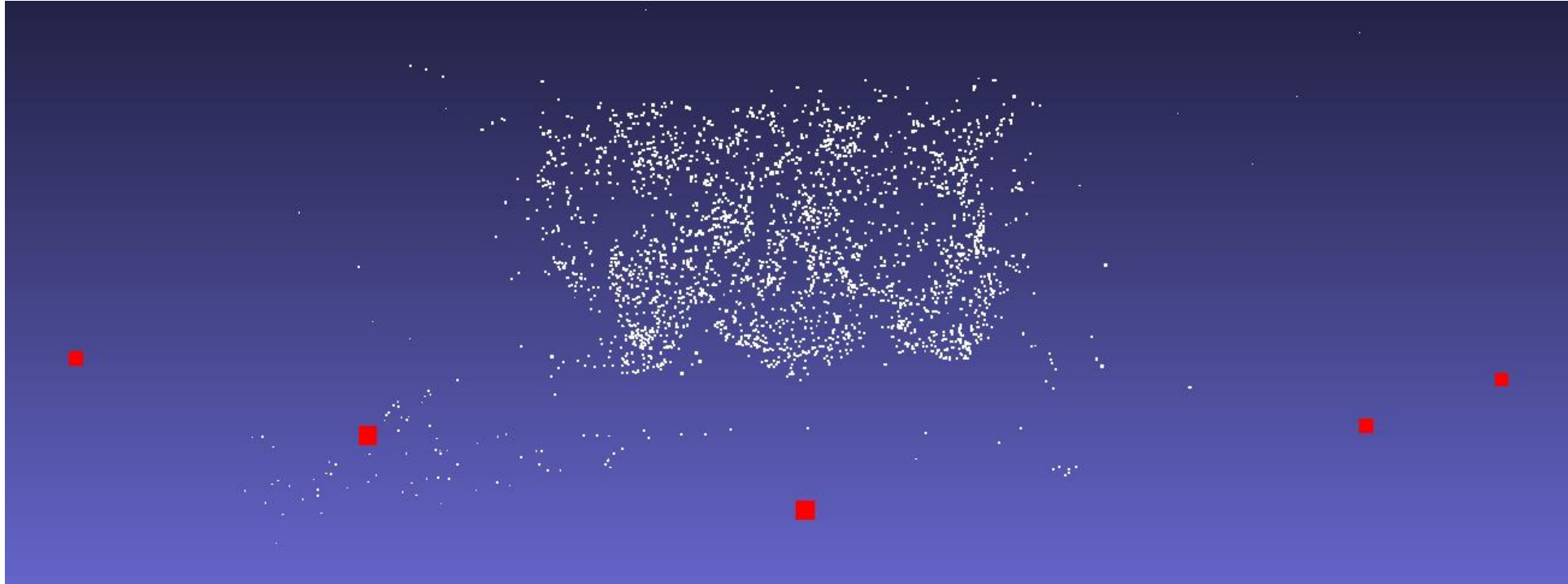   **2) Initialize 3D points and build a visibility graph**

    3) Optimize camera pose and 3D points together (BA)

$$\mathrm{K}_i = \begin{bmatrix} f & 0 & w/2 \\ 0 & f & h/2 \\ 0 & 0 & 1 \end{bmatrix}, \quad \mathrm{R}_i = \mathrm{I}_{3x3}, \quad \text{and} \quad \mathbf{t}_i = [0,0,0]^\top$$

$$\mathbf{X}_i = [0,0,2]^\top$$

Ceres Solver (non-linear least-square optimization)

Structure-from-Motion

- Example) **Structure-from-Motion (batch version)** `[sfm_global.cpp]`

Structure-from-Motion

- Example) **Structure-from-Motion (incremental version)** [sfm_inc.cpp]

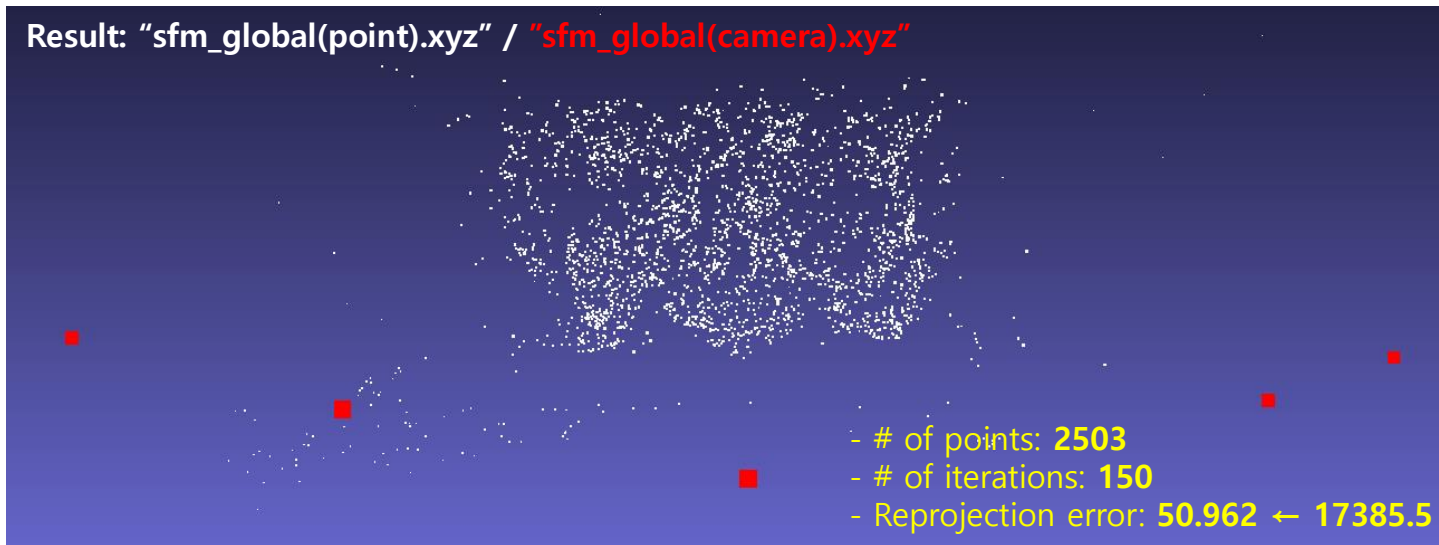**0) Build a viewing graph (well-matched pairs) while finding inliers**

1855 / 5615   1569 / 5615   1324 / 5615   1834 / 5615

1) Select the best pair

2) Estimate relative pose from the best two views (epipolar geometry)

3) Reconstruct 3D points of the best two views (triangulation)

4) Select the next image to add
Separate points into known and unknown for PnP (known) and triangulation (unknown)

5) Estimate relative pose of the next view (PnP)

6) Reconstruct newly observed 3D points (triangulation)

7) Optimize camera pose and 3D points together (BA)

Incrementally add more views

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Structure-from-Motion

Result: "sfm_global(point).xyz" / "sfm_global(camera).xyz"

- # of points: **2503**
- # of iterations: **150**
- Reprojection error: **50.962** ← **17385.5**

Result: "sfm_inc(point).xyz" / "sfm_inc(camera).xyz"

- # of points: **2133**
- # of iterations: **26 + 23 + 25**
- Reprojection error: **0.380** ← **1.261**
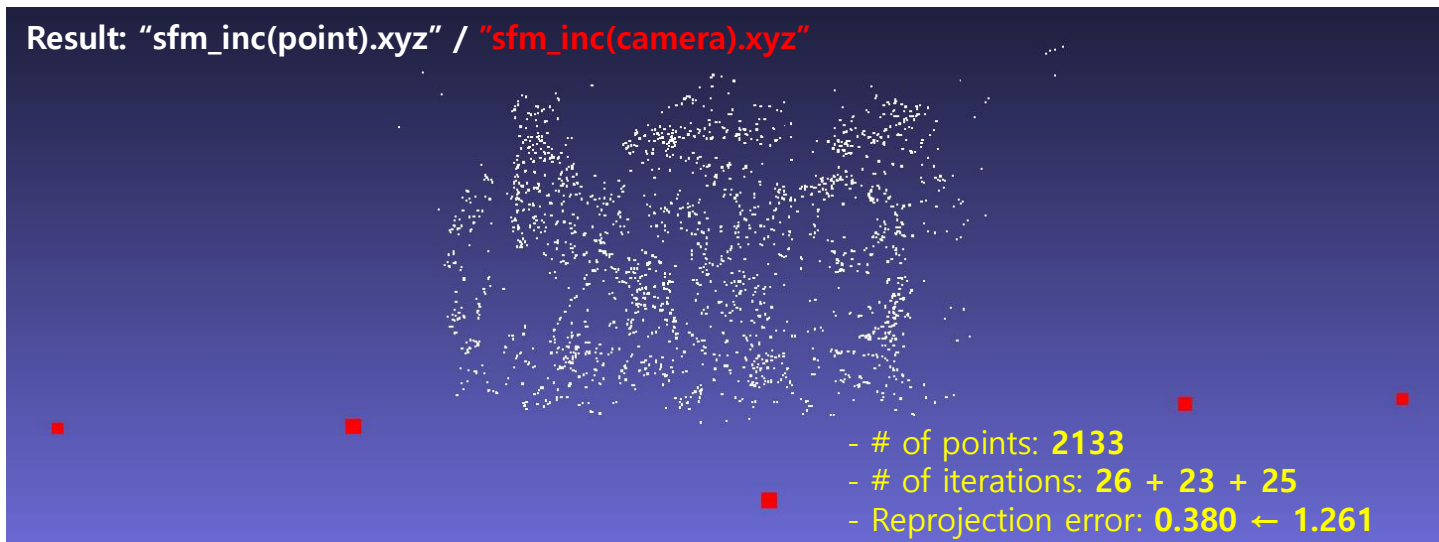
Summary

- **Bundle Adjustment**
  - Problem)
  - Optimization of reprojection error

- **Structure-from-Motion**
  - Problem)
  - Two approaches: Global vs. Incremental
  - COLMAP (2016): The state-of-the-art incremental SfM and more

COLMAP (2016)

- **The state-of-the-art incremental SfM and more**
    - The author won the PAMI Mark Everingham Prize (2020) for COLMAP SfM and MVS.

- **References**
    - Code repositories
        - COLMAP (BSD license): Homepage, Documentation, Github
        - Note) COLMAP binary files are also available for rapid deployment.
    - Papers
        - Schonberger et al., *Structure-from-Motion Revisited*, CVPR, 2016 PDF DOI
        - Schonberger et al., *Pixelwise View Selection for Unstructured Multi-view Stereo*, ECCV, 2016 PDF DOI
        - Schonberger et al., *A Vote-and-Verify Strategy for Fast Spatial Verification in Image Retrieval*, ACCV, 2016 PDF DOI

COLMAP (2016)

- **The <u>state-of-the-art</u> incremental SfM and more**
  - The best performance in the view of **accuracy** and **time/space complexity** [Bianco et al., 2018]

Table 3. SfM camera pose evaluation results. N_c is the percentage of used cameras. $\bar{x}$ is the mean distance from ground truth of reconstructed camera positions and s_x its standard deviation. $\bar{r}$ is the mean rotation difference from ground truth of reconstructed camera orientations and s_r its standard deviation. n.a. means measure not available.

Model	COLMAP					OpenMVG					Theia					VisualSFM				
	N_c	$\bar{x}$ [m]	s_x [m]	$\bar{r}$ [°]	s_r [m]	N_c	$\bar{x}$ [m]	s_x [m]	$\bar{r}$ [°]	s_r [m]	N_c	$\bar{x}$ [m]	s_x [m]	$\bar{r}$ [°]	s_r [m]	N_c	$\bar{x}$ [m]	s_x [m]	$\bar{r}$ [°]	s_r [m]
Statue	100	0.08	0.01	0.04	0.05	100	0.27	0.03	0.47	0.22	100	1.86	0.09	0.45	0.22	100	1.45	0.91	3.55	2.88
E. Vase	100	0.01	0.01	0.51	0.05	83	0.78	1.62	32.19	64.89	100	0.13	0.07	0.91	0.35	94	0.15	0.14	4.91	5.07
Bicycle	88	0.04	0.02	0.25	0.19	94	0.60	1.09	7.00	12.53	37	0.60	0.03	1.10	0.31	47	0.27	0.14	1.32	1.03
Hydrant	82	2.63	2.09	72.28	64.98	3	–	–	–	–	6	3.49	0.29	174.27	0.51	80	2.43	1.76	66.29	58.90
Jeep	63	0.04	0.02	0.26	0.11	92	0.24	1.32	4.80	26.33	95	0.43	0.42	1.33	5.67	83	1.02	2.79	9.68	22.84
Ignatius	100	n.a.	n.a.	n.a.	n.a.	100	n.a.	n.a.	n.a.	n.a.	100	n.a.	n.a.	n.a.	n.a.	100	n.a.	n.a.	n.a.	n.a.

Table 5. Pipelines execution times in seconds and memory usage in MB.

Model	COLMAP				OpenMVG				Theia				VisualSFM			
	SfM		MVS		SfM		MVS		SfM		MVS		SfM		MVS	
	t [s]	RAM	t [s]	RAM	t [s]	RAM	t [s]	RAM	t [s]	RAM	t [s]	RAM	t [s]	RAM	t [s]	RAM
Statue	59	897	86	1062	43	1359	115	1300	196	1984	98	1249	86	1406	144	1452
Empire Vase	53	897	154	2101	28	628	130	1734	129	1988	134	1926	62	1226	159	2095
Bicycle	98	896	117	1356	57	1467	146	1720	63	1722	58	548	64	1226	68	641
Hydrant	19	894	55	793	16	1547	–	–	17	2048	3	1249	36	997	56	1452
Jeep	38	897	121	1812	69	1550	275	3209	213	2083	280	3293	109	1406	254	3078
Ignatius	1225	1825	430	5082	401	1555	494	5926	992	2588	484	5626	1639	2381	345	4742

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COLMAP (2016)

- **The state-of-the-art incremental SfM and <u>more</u>**
  - COLMAP includes not only **sparse reconstruction**, but also **dense reconstruction** and **mesh reconstruction**.
  - COLMAP highly utilizes multi-core CPU and GPU (CUDA for dense reconstruction).
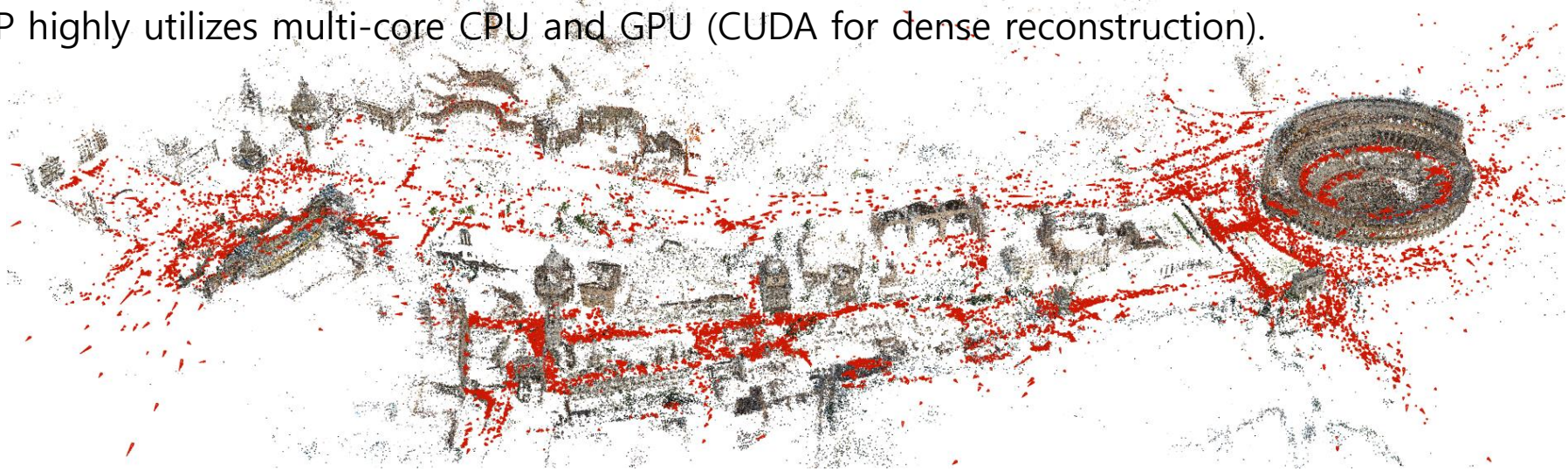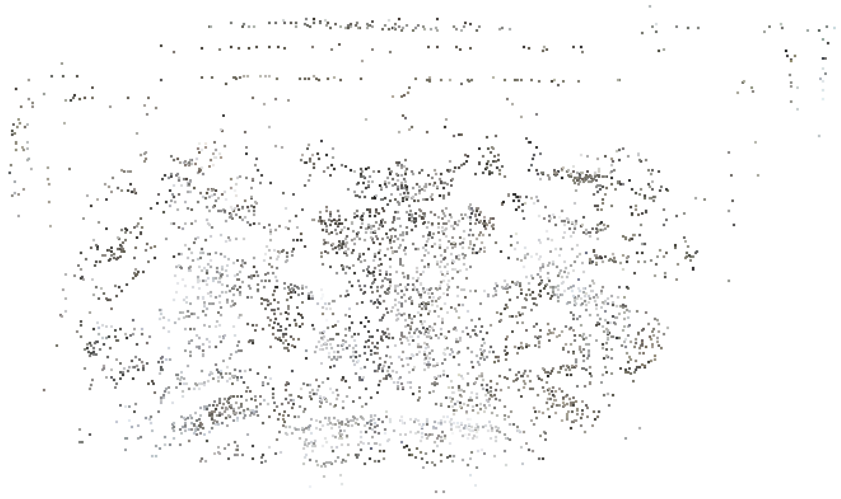

A sparse model of *central Rome* using 21K photos produced by COLMAP's SfM pipeline

Dense models of several landmarks produced by COLMAP's MVS pipeline

Note) Sparse vs. Dense vs. Mesh Reconstruction (by VisualSFM)
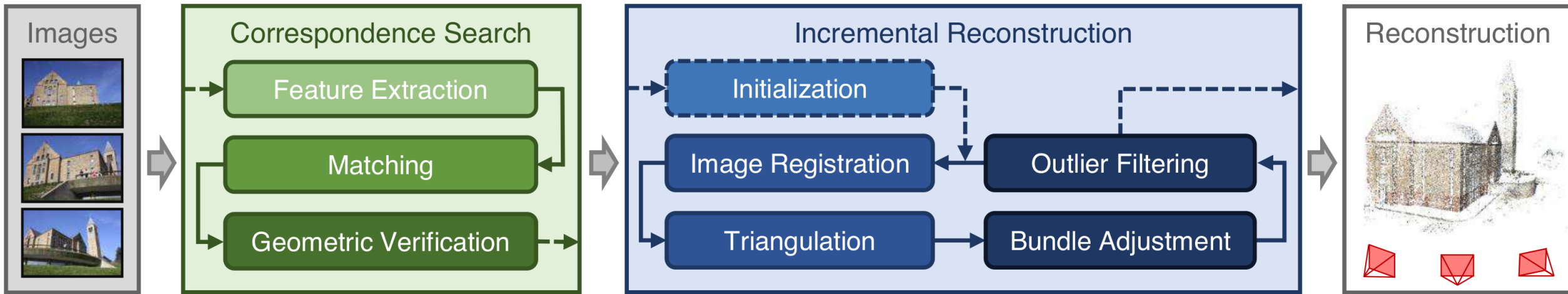
Sparse Reconsturction (SiftGPU and pba)

Mesh Reconstruction (Poisson Surface Reconstruction)

Dense 3D Reconsturction (CMVS and PMVS2)

Review) Incremental Structure-from-Motion

- **Correspondence Search**

  - **Feature extraction**

    - The features should be invariant under radiometric and geometric changes.
    - **SIFT** and its derivatives, learned features vs. binary features (better efficiency with reduced robustness)

  - **Matching** → Feature correspondence

    - Exhaustive search (time complexity: $O(N_I^2 N_F^2)$) vs. more efficient search (for scalability)

  - **Geometric verification** → Scene graph (node: images, edge: feature/geometric relationship)

    - Geometric relations: H (for pure rotation and a planar scene) vs. F and E (for moving camera in a general scene)
   - Issues) Outliers: **RANSAC** / Model selection: **GRIC**, QDEGSAC

Review) Incremental Structure-from-Motion
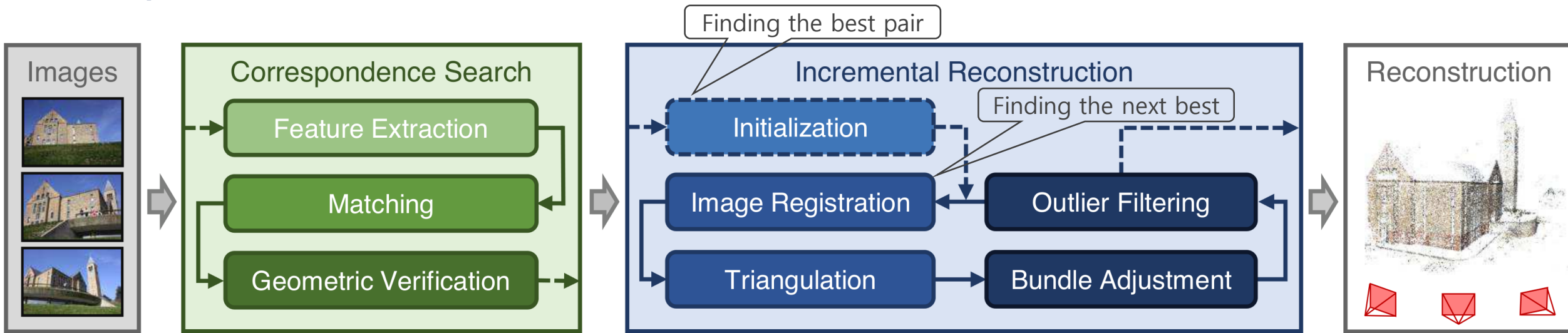
- **Incremental Reconstruction**

  - **Initialization**: Two-view reconstruction from the best pair of images [critical]

  - **Image Registration**: PnP (+ intrinsic parameters) with 2D-3D correspondences and RANSAC

  - **Triangulation**: Adding more 2D-3D correspondences

  - **Bundle Adjustment (BA)**

    - Motivation) SfM usually drifts quickly without additional refinement to image registration and triangulation.

    - The joint non-linear ~~minimization~~ refinement of camera parameters $\mathbf{P}_c$ and 3D points $\mathbf{X}_k$

$$E = \sum_j \rho_j \left(\left\| \pi(\mathbf{X}_k; \mathbf{P}_c) - \mathbf{x}_j \right\|_2^2 \right)$$ with a loss function ρ_j (against outliers)

    - Choices) Solvers: LM, ..., exact vs. inexact methods / Error functions: Direct vs. sparse direct vs. **indirect**

Review) Incremental Structure-from-Motion
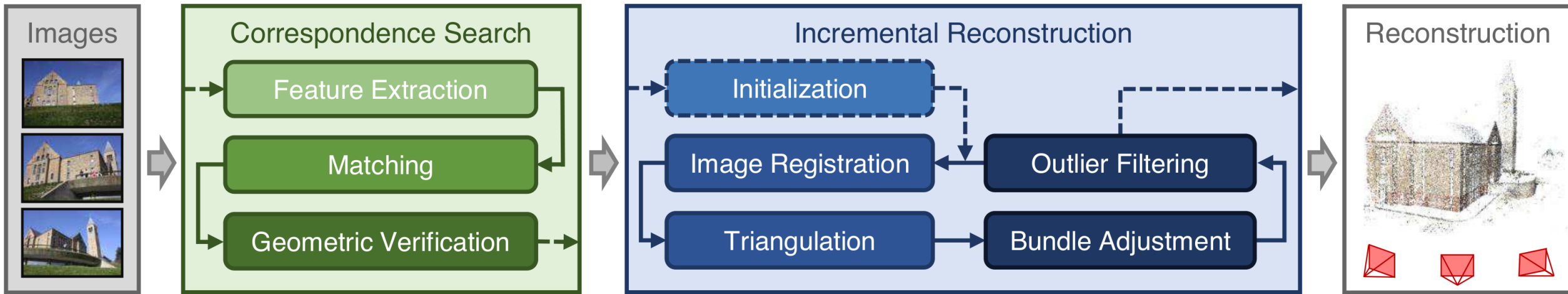
- **Problems**
  - SfM systems fail to register a large fraction of images.
  - SfM systems produce broken models due to mis-registrations or drift.
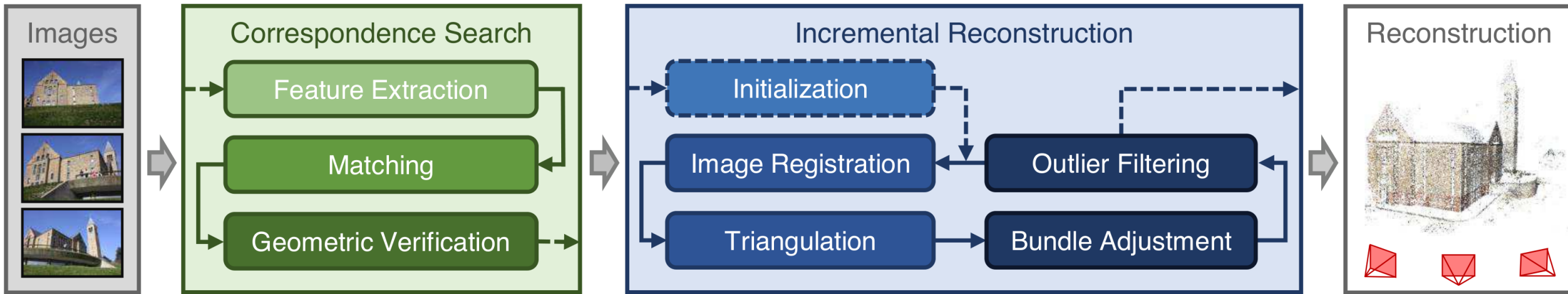
- **Why?**
  - Incomplete scene graph @ Correspondence Search
  - Missing or inaccurate scene structure @ Image Registration and Triangulation

- **Challenges**
  - Improving completeness, robustness, and accuracy while boosting efficiency

COLMAP (2016): Contributions

- **Multi-model** scene graph generation
- **Next best view selection** with **multi-resolution scoring**
- **Multi-view** triangulation using **recursive RANSAC**
- **Iterative** BA, **re-triangulation**, and outlier filtering
- **Redundant view grouping**

COLMAP (2016): Contributions

- **Multi-model scene graph generation**
 - Motivation) Each model has its degenerate (undefined) situations.
    - Models: F, E, and H
  - **Multi-model geometric verification**
    - Note) N_M: the number of inliers for model M, α: triangulation angle
    - $N_H/N_F < \epsilon_{HF} \rightarrow$ Moving camera in a general scene
    - $N_E/N_F > \epsilon_{EF} \rightarrow$ Correct calibration
    - median$(\alpha_0, \alpha_1, \dots) \rightarrow$ Pure rotation (panoramic) or planar scenes (planar)
    - Model types (for edges): General, panoramic, planar | uncalibrated, calibrated
      - The first best pair is selected among *non-panoramic* and (preferably) *calibrated* image pairs.
      - Triangulation is not applied to *panoramic* image pairs.
 - **Watermarks, timestamps, and frames (WTFs) detection**
    - Note) S: A similarity transformation at the image border
    - $N_S/N_F > \epsilon_{SF}$ and $N_S/N_E > \epsilon_{SE} \rightarrow$ WTFs $\rightarrow$ The pair is not used

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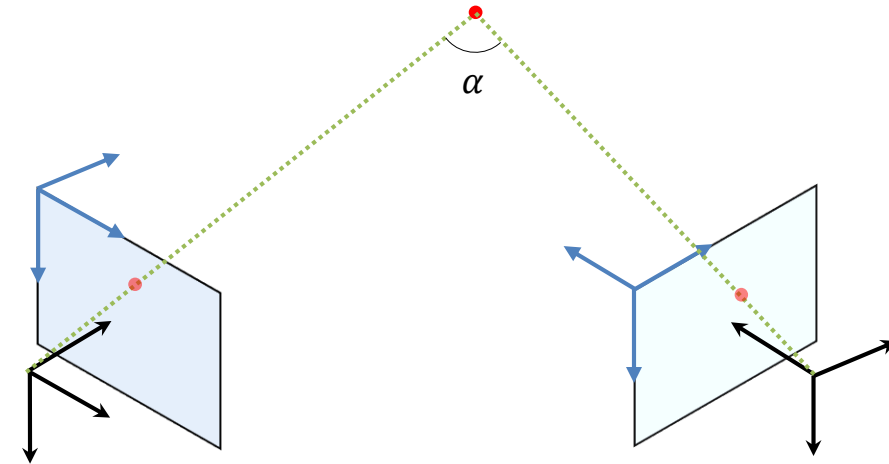
COLMAP (2016): Contributions

- **Next best view selection with multi-resolution scoring**
  - Motivation) More visible and more uniformly distributed points get higher score.
    - Q) Why are uniformed distributed points preferred? (a.k.a. bucketing)
  - **Multi-resolution scoring**
    - Cell size: K_l bins for both dimension (Note: $K_l = 2^l$)
    - Cell states: *Empty* and *full*
    - Score: $S = \sum_{l=1}^{L} K_l N_l$
      - Note) N_l: The number of full cells at K_l resolution

Score = 66

Score = 146

Score = 80

Score = 200
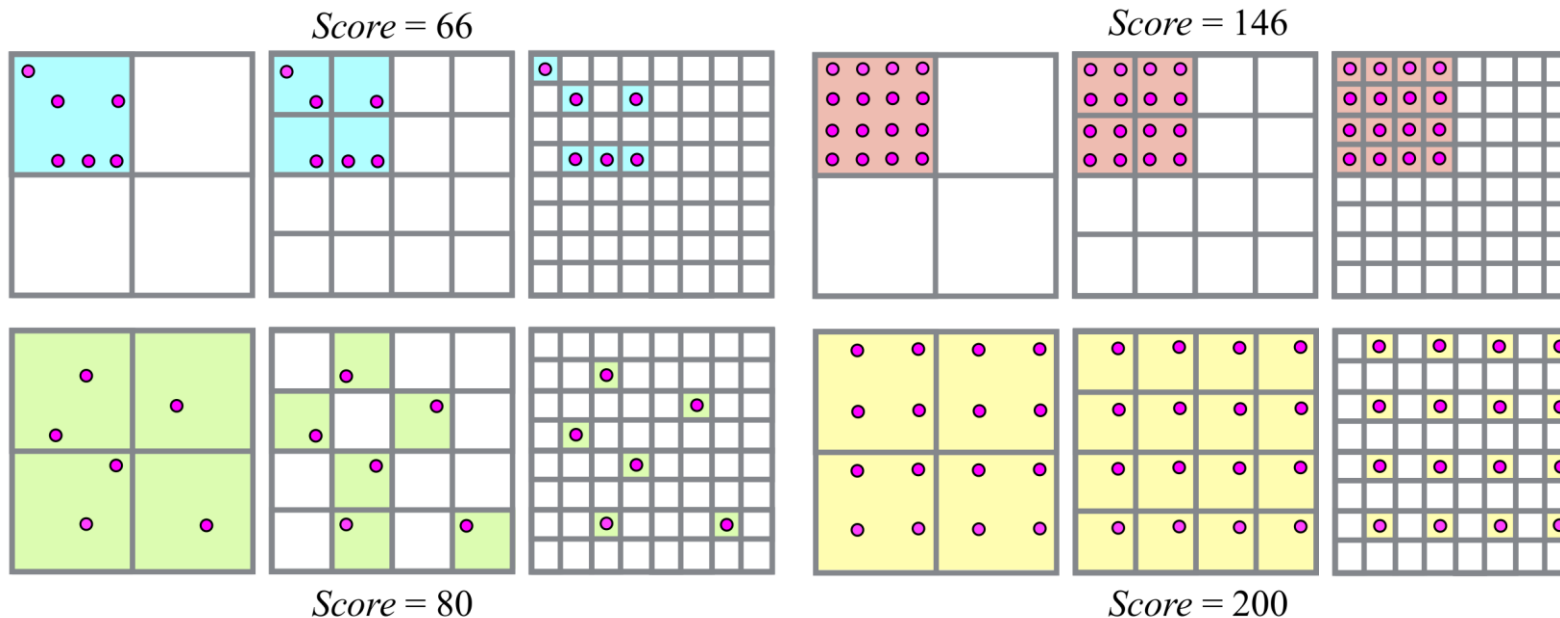
COLMAP (2016): Contributions

- **Multi-view triangulation using recursive RANSAC**

    - Motivation

        - Two-view (small baseline) → Multi-view (larger baseline)
        - Outliers (from other feature tracks) → (recursive) RANSAC

    - **Multi-view triangulation using <u>RANSAC</u>**

        - Given data: Normalized 2D points for a single feature track

            - Note) $\bar{\mathbf{x}}_i$ on the i-th normalized image (or camera or view)

        - Model: Their 3D point $\mathbf{X}$

        - Model estimation: Two-view triangulation using DLT

        - Error measure: Reprojection error between $\bar{\mathbf{x}}_i$ and $\mathbf{X}$

        - RANSAC objective: Maximizing the number of supporting 2D points (~ camera or view)

            - Constraints #1) A sufficient triangulation angle α
            - Constraints #2) The positive depth constraint (a.k.a. the cheirality constraint)

        - Note) RANSAC is performed recursively after separating the consensus set from the remaining data.

        - Note) RANSAC is terminated adaptively using $\frac{\log(1-\eta)}{\log(1-\epsilon^2)}$ where η is success rate and ε is the inlier ratio.

Feature track #1:
Feature track #2:

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COLMAP (2016): Contributions

- **Iterative BA, re-triangulation, and outlier filtering**
  - **Bundle adjustment (BA)**
    - A simple camera model: 1 x focal length and 1 x radial distortion parameter
      - The fixed principal point at the image center (← Its estimation is ill-posed problem.)
    - Optimization: PCG (preconditioned conjugate gradient) in Ceres Solver
      - Loss function: Cauchy function
    - Note) Local BA after every image registration
    - Note) Global BA after growing the model by a certain percentage (for an amortized linear runtime of SfM)
  - **Re-triangulation (RT)**
    - Pre-BA RT step (for reducing drift effect similar to *VisualSFM*)
    - Post-BA RT step (for recovering failed triangulation due to inaccurate pose)
  - **Filtering**
    - Filtering observations with large reprojection error
    - Filtering cameras with an abnormal field-of-view or a large distortion coefficient (← panoramas, artificial images)

COLMAP (2016): Contributions

- Motivation
  - BA is a major ~~performance~~ computing time bottleneck in SfM.
  - Internet photo collections usually have a highly non-uniform visibility pattern due to POI (points of interest).

- **Redundant view grouping**
  - View grouping using visibility overlap
    - Visibility overlap $V_{ab} = \|\mathbf{v}_a \wedge \mathbf{v}_b\| / \|\mathbf{v}_a \vee \mathbf{v}_b\|$
    - Many small and highly overlapping groups (~ submaps)
    - Note) More efficient than graph-cut (non-overlapping submaps)
  - BA for grouped images (with group-local coordinate frame)

    - $E_g = \sum_j \rho_j \left(\left\| \pi_g(\mathbf{X}_k; \mathbf{G}_r, \mathbf{P}_c) - \mathbf{x}_j \right\|_2^2 \right)$ with fixed $\mathbf{P}_c$
      - $\mathbf{G}_r$: The extrinsic group parameters ($\in \mathbf{SE}(3)$)
      - $\mathbf{P}_{cr} = \mathbf{P}_c \, \mathbf{G}_r$: The projection matrix in the group r
    - Note) For standard BA, $E = \sum_j \rho_j \left(\left\| \pi(\mathbf{X}_k; \mathbf{P}_c) - \mathbf{x}_j \right\|_2^2 \right)$

$\mathbf{v}_a = 1 \qquad \mathbf{v}_b = 1$

vs.
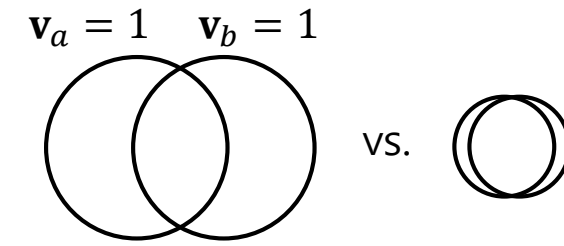
COLMAP (2016): Experiments

- **Next best view selection with multi-resolution scoring**
 - Data: Synthetic data
    - Pyramid level $L = 6$
    - Gaussian-distributed image points with spread σ and location μ
  - Results
    - A larger σ and a more central μ → A more uniform distribution → A higher score
    - The score was regardless of the number of points.
      - However, the score was affected when the number of points is small.
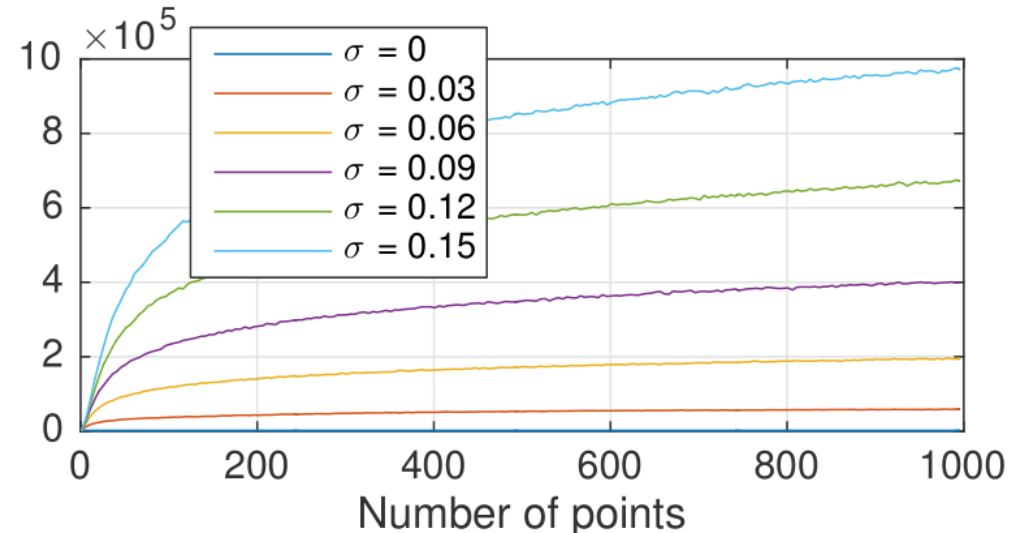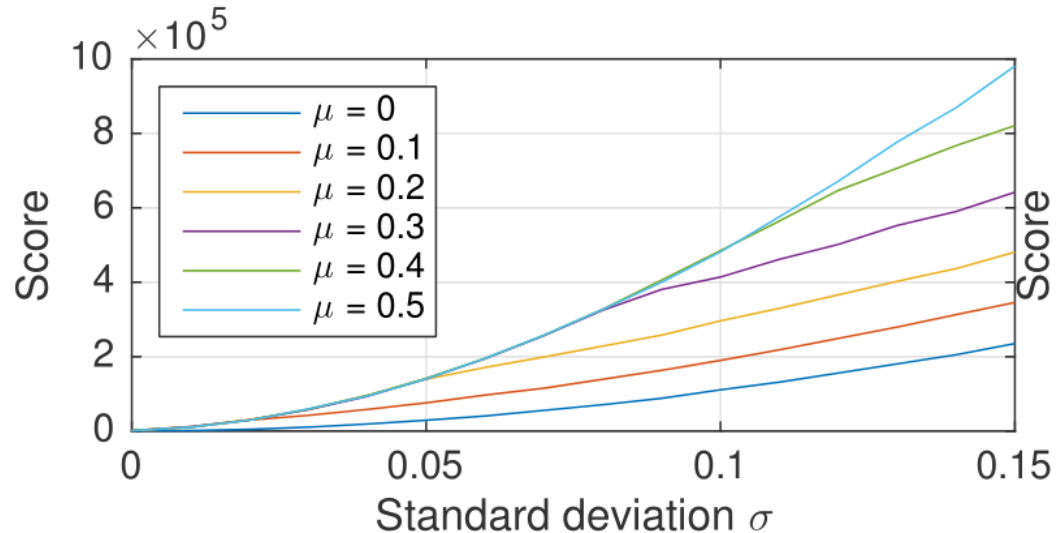
COLMAP (2016): Experiments

- **Next best view selection with multi-resolution scoring**

  - Data: *Quad* dataset with ground-truth camera positions

  - Comparison

    - Pyramid: The proposed method

    - Ratio: Maximizes the ratio of visible over potentially visible points

    - Number: Maximizes the number of triangulated points (used in *Bundler*)

  - Results

    - Pyramid produced the most accurate reconstruction by choosing a better registration order for the images.

    - All strategies converged to the same set of registered images.
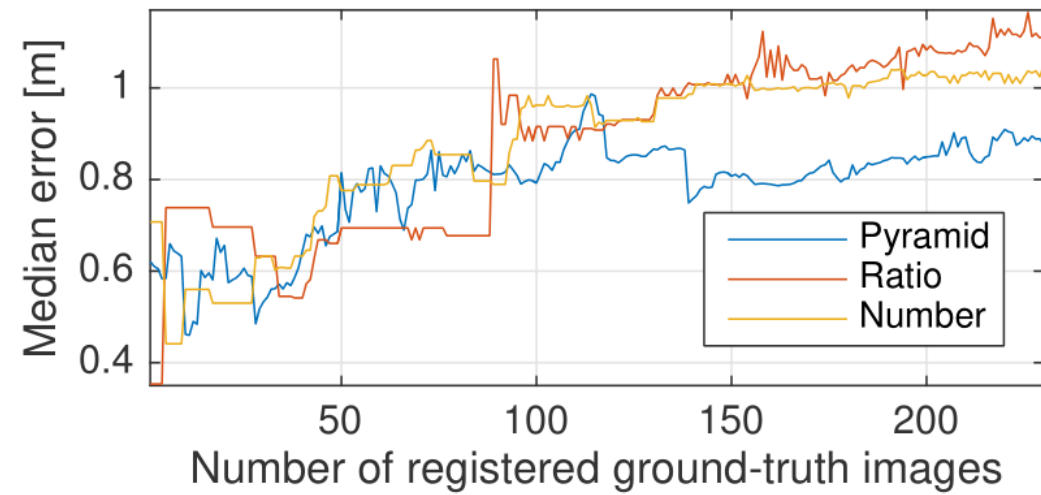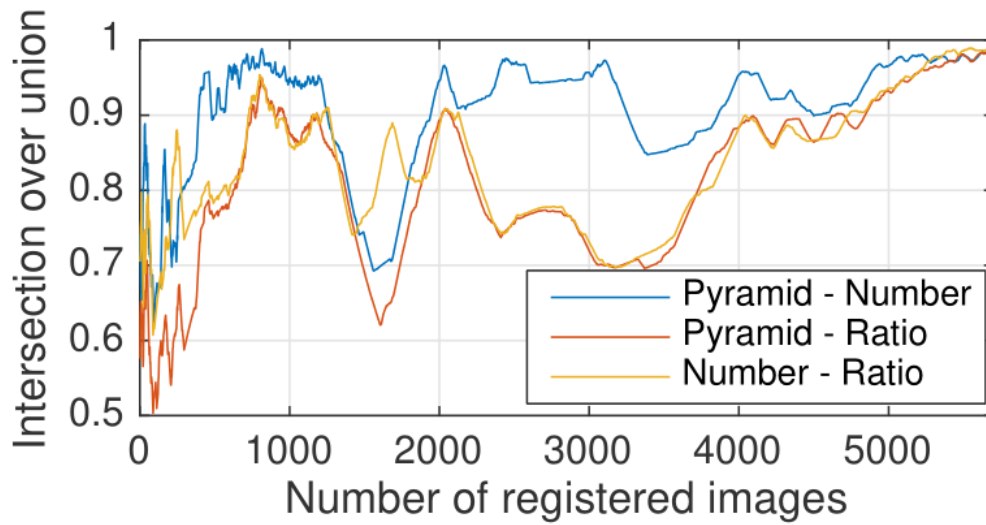
COLMAP (2016): Experiments

- **Multi-view triangulation using recursive RANSAC**
  - Data: *Dubrovnik* dataset
    - 2.9M feature tracks from 47M matches
  - Comparison: *Bundler*, exhaustive strategy (limit: 10K iterations ~ η: ~~0.999~~ 0.99, ϵ: 0.02), recursive RANSAC
  - Results
    - The recursive approaches recovered more feature tracks and longer feature tracks.
    - The RANSAC-based approaches ($\eta_1 = 0.99$, $\eta_2 = 0.5$) were faster 10-40x than the exhaustive strategy.

	#Points	#Elements	Avg. Track Length	#Samples
Bundler	713,824	5.58 M	7.824	136.34 M
Non-recursive				
Exhaustive	861,591	7.64 M	8.877	120.44 M
RANSAC, η_1	861,591	7.54 M	8.760	3.89 M
RANSAC, η_2	860,422	7.46 M	8.682	3.03 M
Recursive				
Exhaustive	894,294	8.05 M	9.003	145.22 M
RANSAC, η_1	902,844	8.03 M	8.888	12.69 M
RANSAC, η_2	906,501	7.98 M	8.795	7.82 M

COLMAP (2016): Experiments

- **Redundant view grouping**

  - Data: An unordered collection of densely distributed images

  - Comparison: Standard BA, grouped BA (V: Scene overlap)

  - Results

	S. BA	G. BA ($V = 0.6$)	G. BA ($V = 0.3$)	G. BA ($V = 0.1$)
The effective speed-up	-	5%	14%	32%
The average reprojection error	0.26px	0.27px	0.28px	0.29px

    - The reconstruction quality is comparable for all choices of $V > 0.3$ and increasingly degrades for a smaller V.

    - The total runtime for *Colosseum* with $V = 0.4$ reduces by 36% with an equivalent reconstruction.
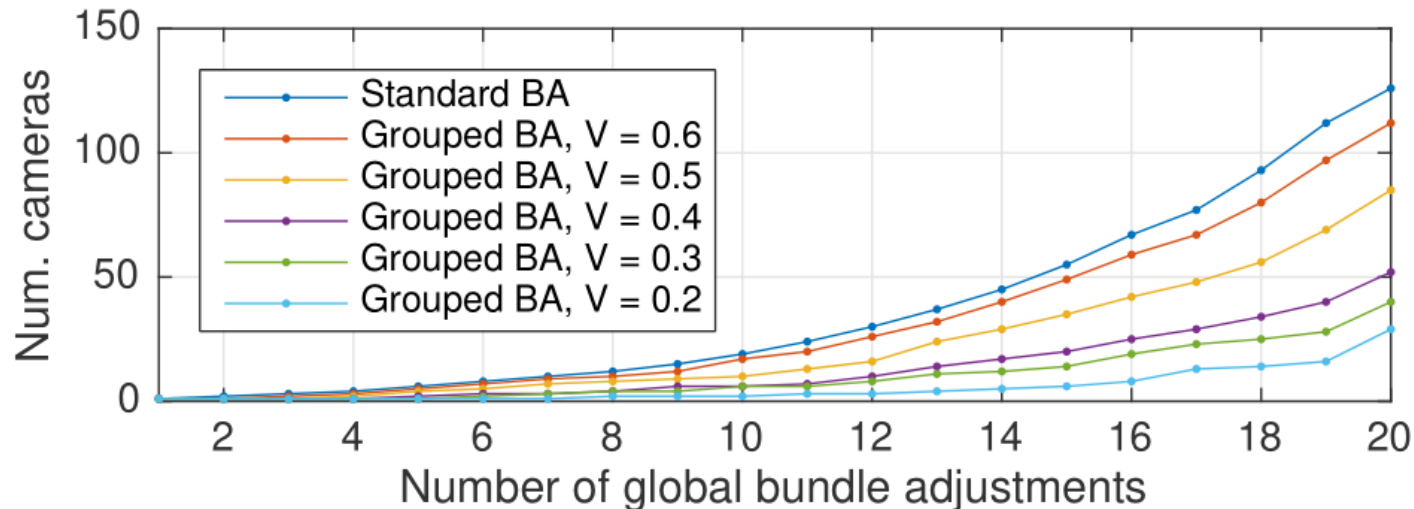
COLMAP (2016): Experiments

- **Overall**
  - Comparison: Global SfM - *Theia* (a.k.a. DISCO) / Incremental SfM - Bundler, VisualSFM, COLMAP
  - Results
    - Computing time: Theia > VisualSFM > COLMAP >> Bundler
    - Completeness (# of registered images, # of points, and avg. track length): COLMAP > ...
    - Accuracy (@ *Quad* dataset): COLMAP 0.85m > VisualSFM 0.89m > Bundler 1.01m > Theia 1.16m

	# Images	# Registered				# Points (Avg. Track Length)				Time [s]				Avg. Reproj. Error [px]			
		Theia	*Bundler*	*VSFM*	*Ours*	*Theia*	*Bundler*	*VSFM*	*Ours*	*Theia*	*Bundler*	*VSFM*	*Ours*	*Theia*	*Bundler*	*VSFM*	*Ours*
Rome [14]	74,394	–	13,455	14,797	20,918	–	5.4M	12.9M	5.3M	–	295,200	6,012	10,912	–	–	–	–
Quad [14]	6,514	–	5,028	5,624	5,860	–	10.5M	0.8M	1.2M	–	223,200	2,124	3,791	–	–	–	–
Dubrovnik [36]	6,044	–	–	–	5,913	–	–	–	1.35M	–	–	–	3,821	–	–	–	–
Alamo [61]	2,915	582	647	609	666	146K (6.0)	127K (4.5)	124K (8.9)	94K (11.6)	874	22,025	495	882	1.47	2.29	0.70	0.68
Ellis Island [61]	2,587	231	286	297	315	29K (4.9)	39K (4.1)	61K (5.5)	64K (6.8)	94	12,798	240	332	2.41	2.24	0.71	0.70
Gendarmenmarkt [61]	1,463	703	302	807	861	87K (3.8)	93K (3.7)	138K (4.9)	123K (6.1)	202	465,213	412	627	2.19	1.59	0.71	0.68
Madrid Metropolis [61]	1,344	351	330	309	368	47K (5.0)	27K (3.2)	48K (5.2)	43K (6.6)	95	21,633	203	251	1.48	1.62	0.59	0.60
Montreal Notre Dame [61]	2,298	464	501	491	506	154K (5.4)	135K (4.6)	110K (7.1)	98K (8.7)	207	112,171	418	723	2.01	1.92	0.88	0.81
NYC Library [61]	2,550	339	400	411	453	66K (4.1)	71K (3.7)	95K (5.5)	77K (7.1)	194	36,462	327	420	1.89	1.84	0.67	0.69
Piazza del Popolo [61]	2,251	335	376	403	437	36K (5.2)	34K (3.7)	50K (7.2)	47K (8.8)	89	33,805	275	380	2.11	1.76	0.76	0.72
Piccadilly [61]	7,351	2,270	1,087	2,161	2,336	197K (4.9)	197K (3.9)	245K (6.9)	260K (7.9)	1,427	478,956	1,236	1,961	2.33	1.79	0.79	0.75
Roman Forum [61]	2,364	1,074	885	1,320	1,409	261K (4.9)	281K (4.4)	278K (5.7)	222K (7.8)	1,302	587,451	748	1,041	2.07	1.66	0.69	0.70
Tower of London [61]	1,576	468	569	547	578	140K (5.2)	151K (4.8)	143K (5.7)	109K (7.4)	201	184,905	497	678	1.86	1.54	0.59	0.61
Trafalgar [61]	15,685	5,067	1,257	5,087	5,211	381K (4.8)	196K (3.7)	497K (8.7)	450K (10.1)	1,494	612,452	3,921	5,122	2.09	2.07	0.79	0.74
Union Square [61]	5,961	720	649	658	763	35K (5.3)	48K (3.7)	43K (7.1)	53K (8.2)	131	56,317	556	693	2.36	3.22	0.68	0.67
Vienna Cathedral [61]	6,288	858	853	890	933	259K (4.9)	276K (4.6)	231K (7.6)	190K (9.8)	764	567,213	899	1,244	2.45	1.69	0.80	0.74
Yorkminster [61]	3,368	429	379	427	456	143K (4.5)	71K (3.9)	130K (5.2)	105K (6.8)	164	34,641	661	997	2.38	2.61	0.72	0.70

COLMAP (2016): Conclusion

- **The state-of-the-art ~~incremental~~ SfM**
  - In terms of completeness, robustness, accuracy, and efficiency (~ computing time)
  - Comprehensive experiments and validation with large-scale datasets (individual components and overall system)
  - An open-source with BSD license

- **My opinions**
  - COLMAP works really well.
  - SLAM and SfM is not a (small) module, but a kind of (large) systems.
  - This is a kind of implementation papers (including many small tips).