

FACULTY **OF ELECTRICAL** ENGINEERING CTU IN PRAGUE

## Image Matching Challenge 2019 - 2024

#### How to move the goalposts: coming up with yet unsolved challenges for SfM

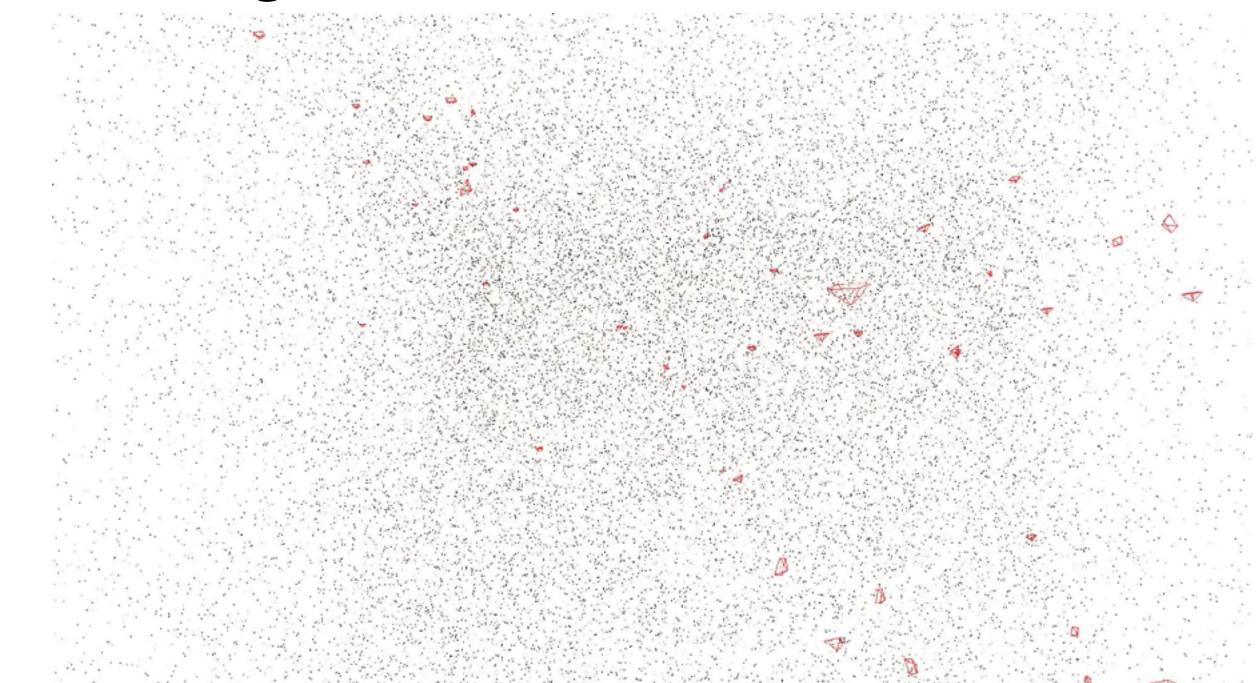
**Dmytro Mishkin, Faculty of Electrical Engineering, CTU in Prague / HOVER Inc.** 

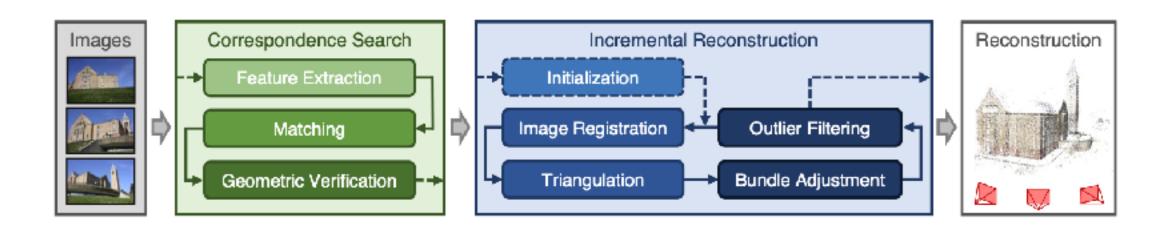
Presented research is supported by OP VVV funded project CZ.02.1.01/0.0/0.0/16.019/0000765 "Research Center for Informatics"



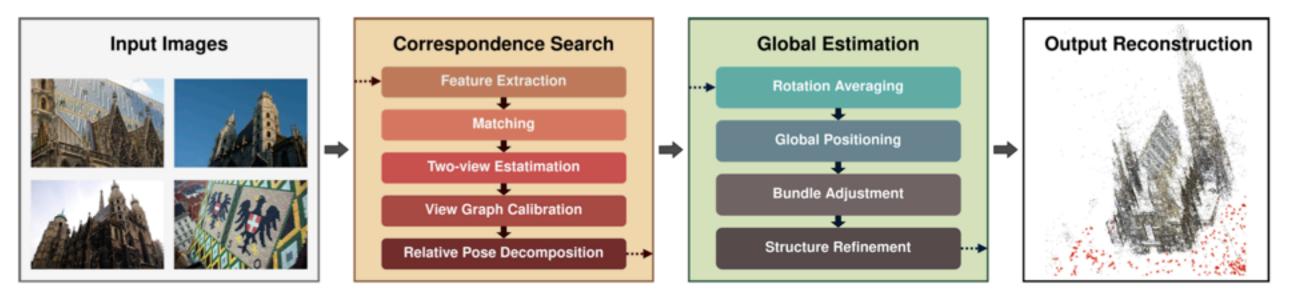


#### A slide about how cool SfM is We all know it, right?

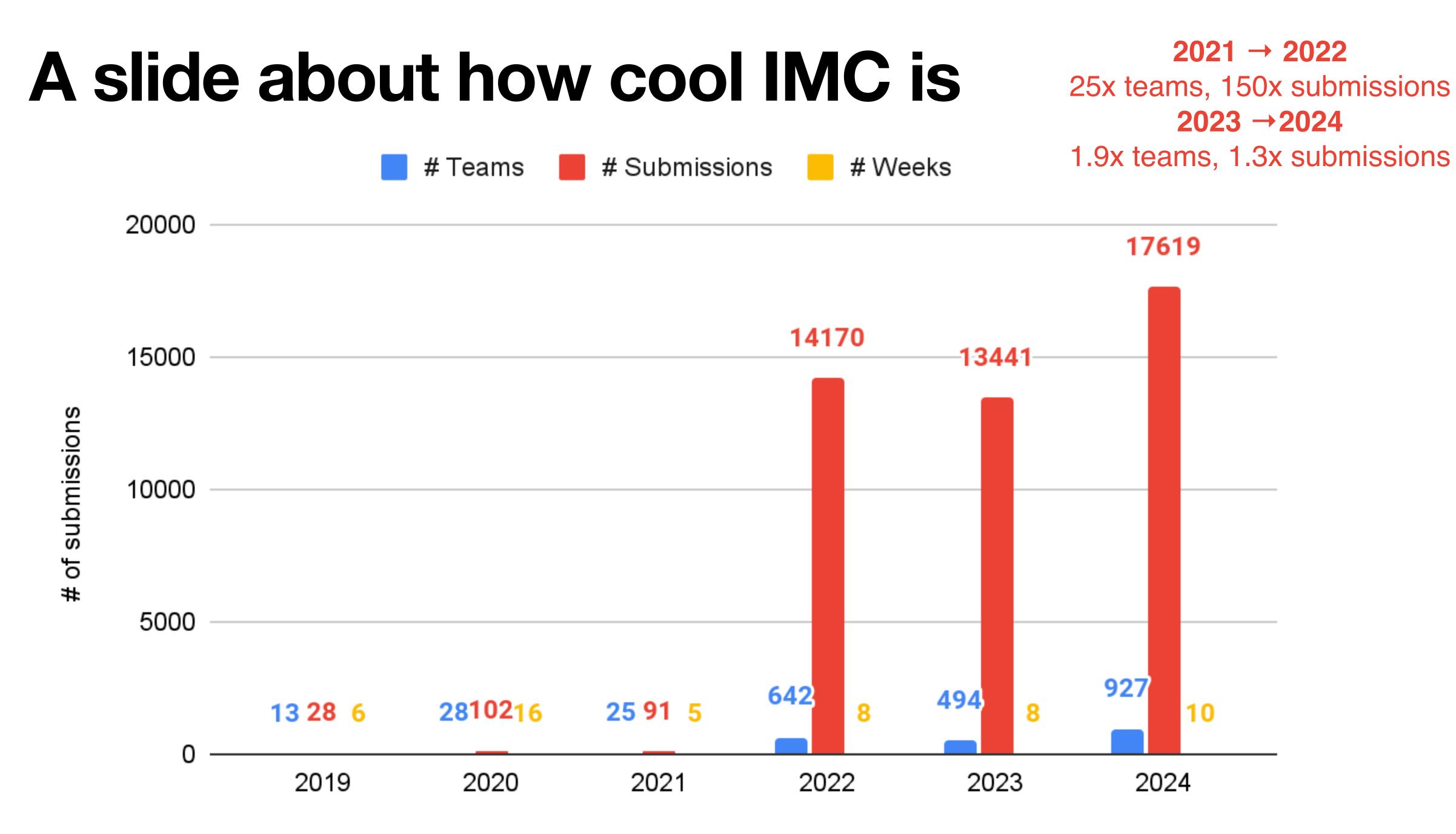




https://demuc.de/papers/schoenberger2016sfm.pdf



https://lpanaf.github.io/eccv24\_glomap/



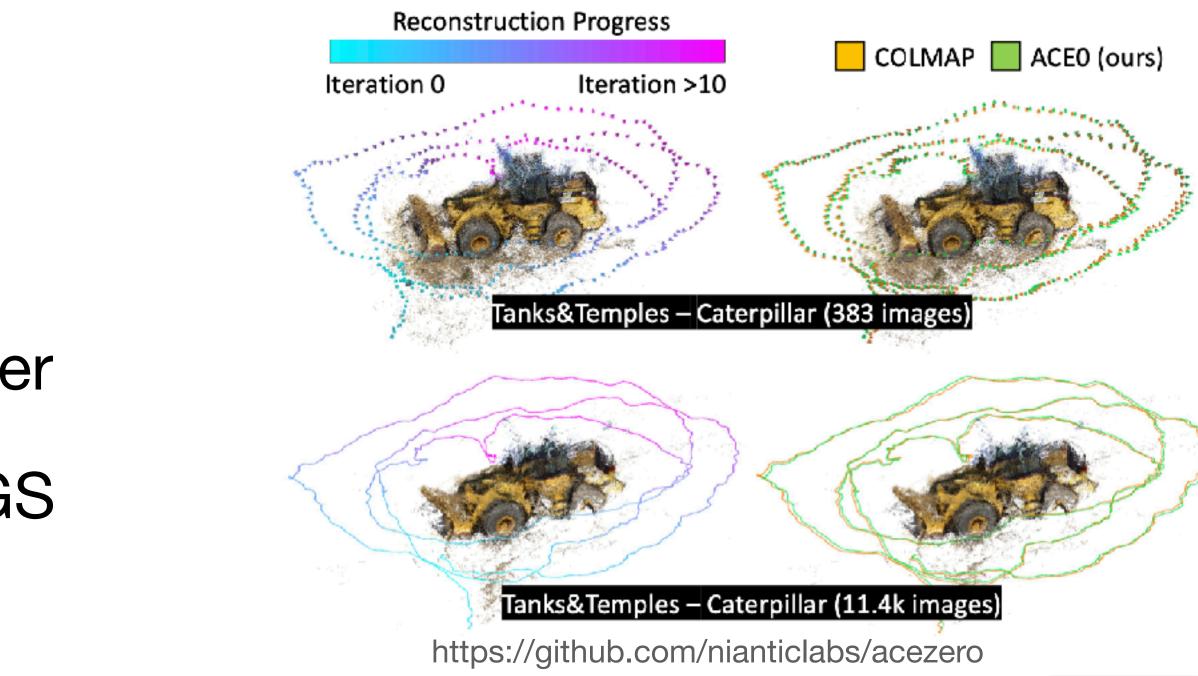


#### How do we benchmark image matching in 2024? as a part of SfM typically

- Downstream metric:
  - Pose accuracy one way or another
    - Photo-consistency via NERF/GS
- Suitable for any method



https://research.nianticlabs.com/mapfree-reloc-benchmark



CZECH TECHNICAL UNIVERSITY IN PRAGUE · RESEARCH CODE COMPETITION · 3 MONTHS AGO

Late Submission

#### Image Matching Challenge 2024 - Hexathlon

t 3D scenes from 2D images over six different domains



https://www.kaggle.com/competitions/image-matching-challenge-2024/leaderboard

https://www.visuallocalization.net/benchmark/







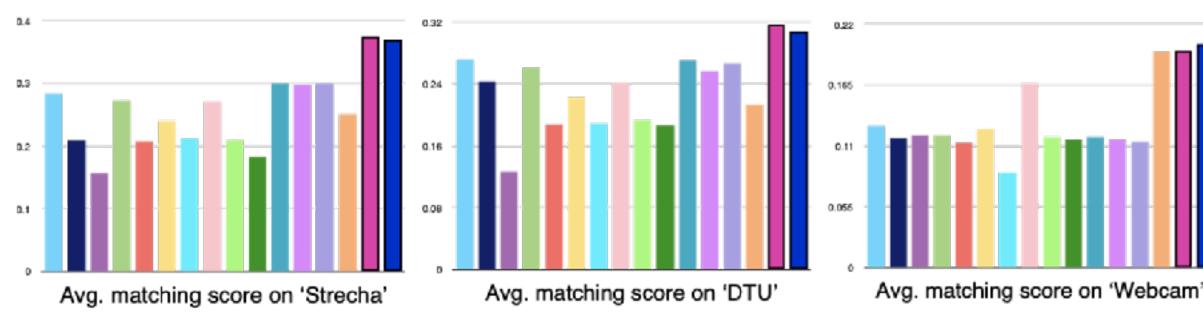




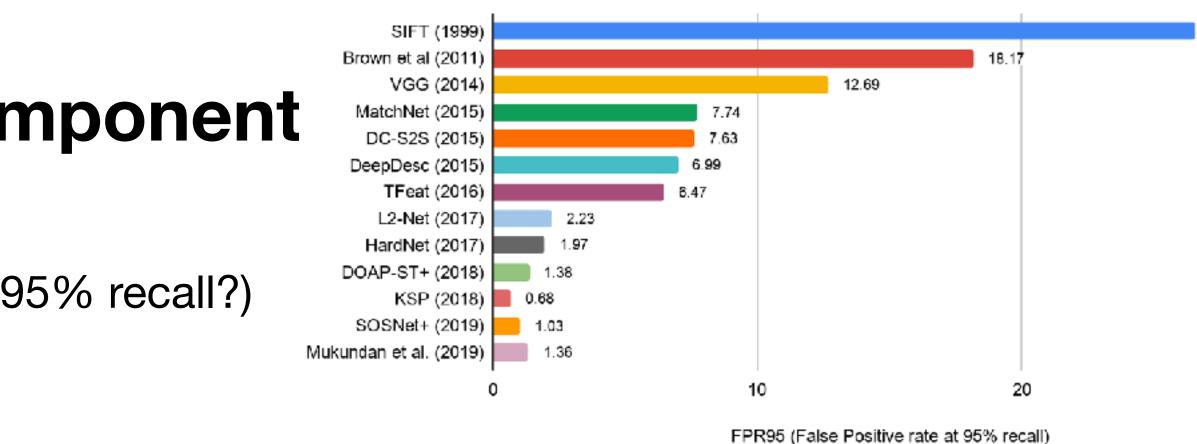
It was not always like this

#### **Before 2019: Bunch of metrics per some component**

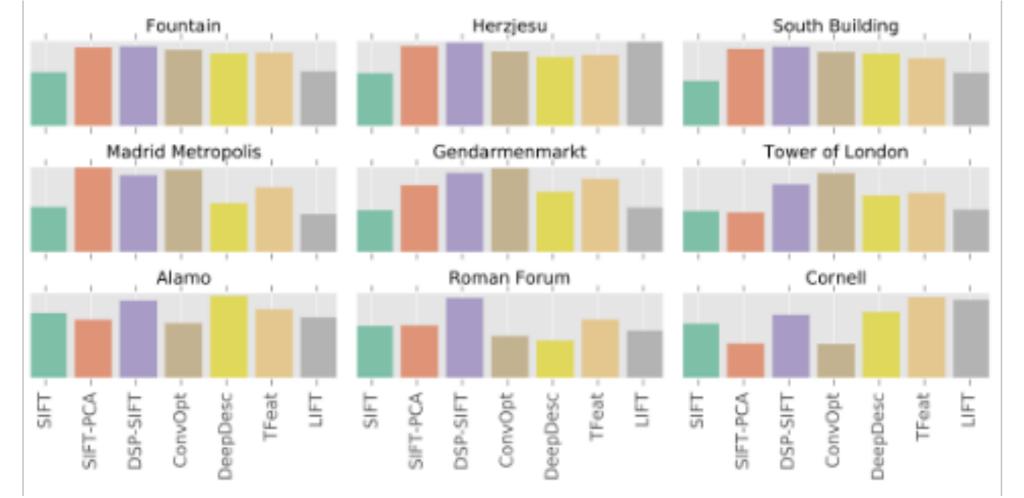
- Brown dataset FPR@95@ recall (who said we need 95% recall?)
- "Average matching score" on DTU/Stretcha
- HPatches mean average precision for patch classification/retrieval/matching
- (used in HardNet) mean average precision @ *image retrieval on Oxford 5k* with Bag-of-Words
- Schönberger et al., CVPR'17 number of registered image and 3D points.
- RANSAC? What is RANSAC?











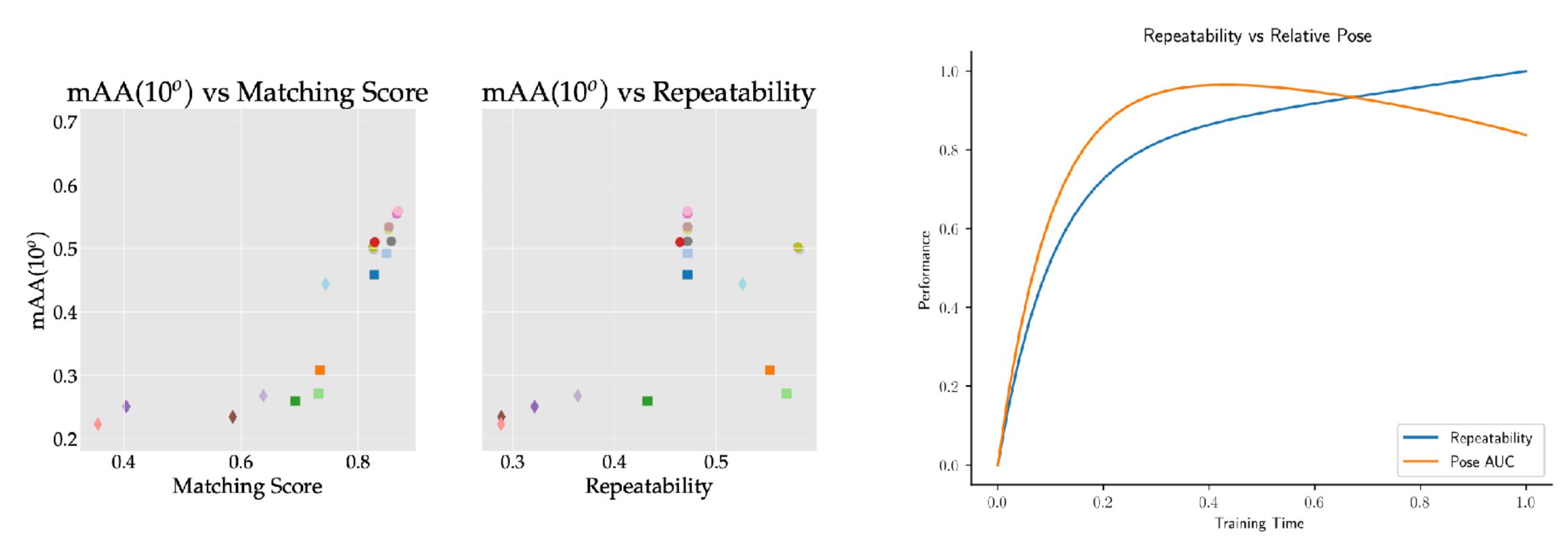


26.55



#### Why downstream metrics? Because per-component metrics do not predict the final outcome

Even for the single method — as shown in DeDoDe v2 paper



Matching Across Wide Baselines: From Paper to Practice

DeDoDe v2: Analyzing and Improving the DeDoDe Keypoint Detector

# Image Matching Challenge 2019



Vassileios Balntas Scape Technologies Vincent Lepetit Johannes Schönberger U. Bordeaux Microsoft

Still available at https://image-matching-workshop.github.io/leaderboard/

Eduard Trulls Google

Kwang Moo Yi U. Victoria

### Image Matching Challenge 2019: first attempt

- ✓ Large-scale: ~30k images
- V Downstream metric: camera pose accuracy
- $\sqrt{2}$  tasks: SfM and stereo
- all images.
- ~1000s

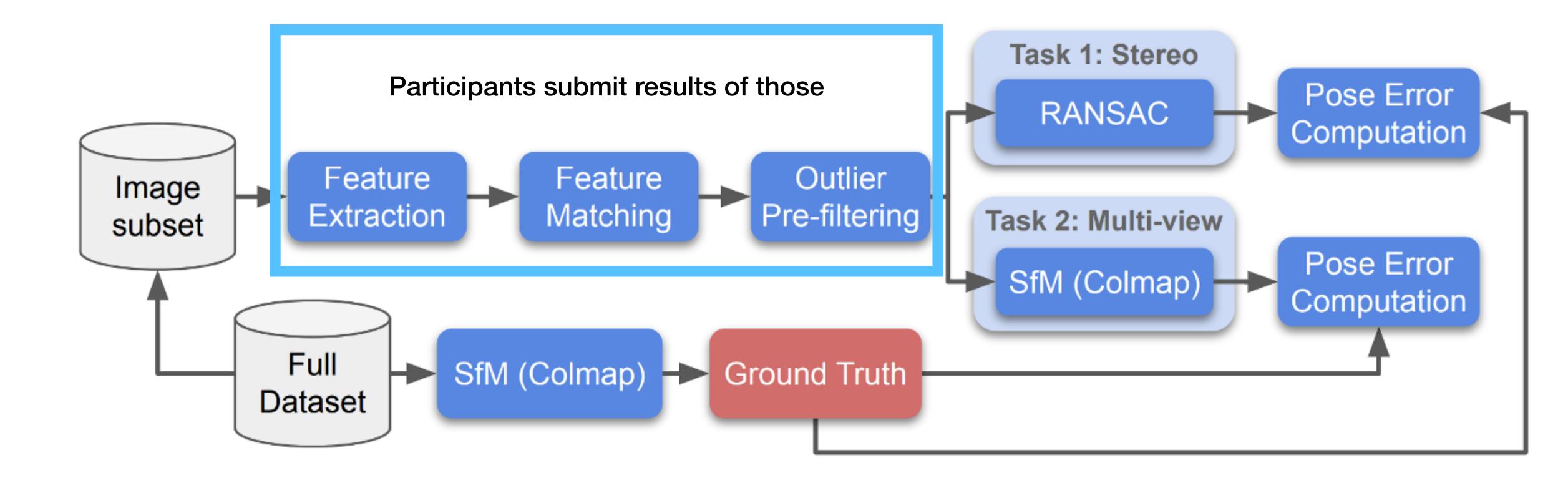
Verify Phototourism data: viewpoint, sensors, illumination, motion blur, occlusions, etc.



"Quasi" ground truth data is generated by performing SfM with COLMAP with

Assumption: Images registered in COLMAP are accurate given enough images

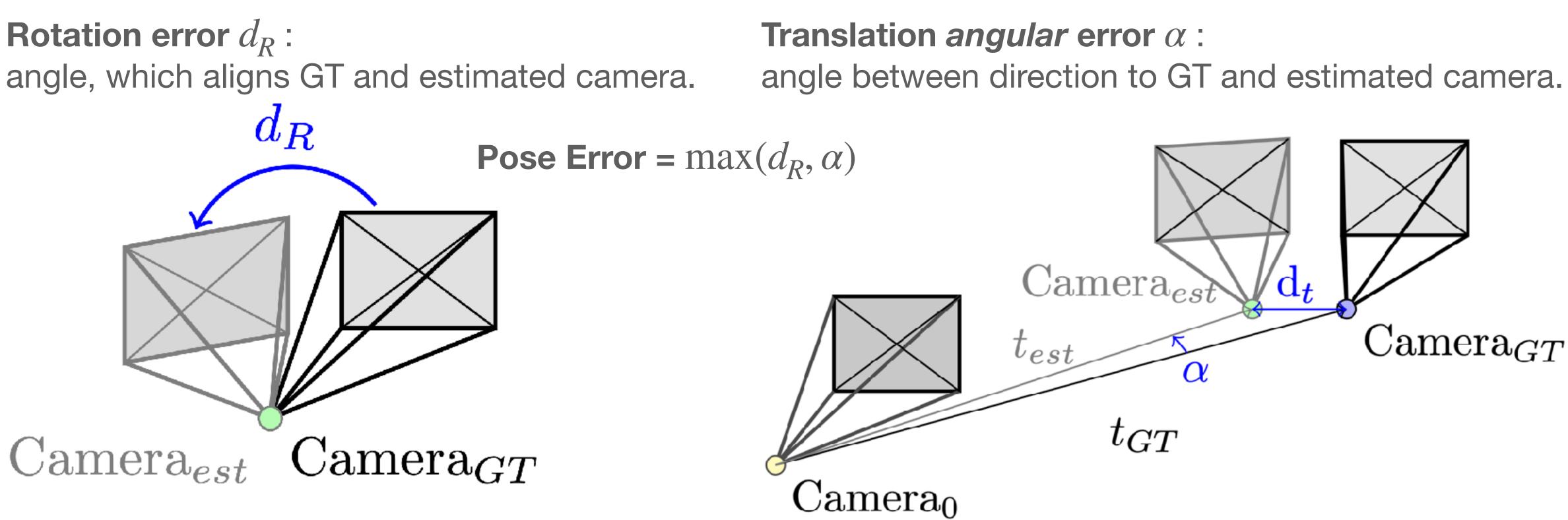
#### **IMC benchmark idea** 2019 was more "Local feature quality evaluation"



### **Metric: what is mAA@10°?**

The mean Average Accuracy is a robust aggregate of the pose error of all image pairs and scenes. If an error is below a threshold, the camera pair is considered correct,

The pose error has two components: **rotation** and **translation**. Because the scale of the estimate and ground truth are both unknown, we rely exclusively on angles



# There were some problems as well

#### Image Matching Challenge 2019: first attempt Submission: tentative correspondences only

- Stereo best mAP15: 8%
- SfM best mAP15: 73%

Why? Seems that something is wrong?

Yes! Under evaluation framework, stereo pose estimation was done badly:

- RANSAC is not tuned
- No Lowe's ratio test for SIFT

#### [P1] Phototourism dataset - Stereo task

Performance in stereo matching, averaged over all the test sequences.

Click here for a breakdown by sequence

| Show 10 • entries   |   |          |            | Search:   |              |                     |                      |                      |                      |  |
|---|---|----------|------------|-----------|--------------|---------------------|----------------------|----------------------|----------------------|--|
|   |   | \$       | Stereo — a | veraged o | ver all sequ | ences               |                      |                      |                      |  |
| Method  | 0 | Date 🌒   | Туре 🌖     | #kp ♦     | MS 🔶         | mAP <sup>5°</sup> ≬ | mAP <sup>10°</sup> ♦ | mAP <sup>15°</sup> ▼ | mAP <sup>20°</sup> ♦ |  |
| SIFT + ContextDesc + Inlier<br>Classification V2<br>kp:8000, match:custom |   | 19-05-28 | F/M        | 7515.2    | 0.3633       | 0.0016              | 0.0217               | 0.0823               | 0.1818               |  |

#### [P2] Phototourism dataset — Multi-view task

Performance in SfM reconstruction, averaged over all the test sequences.

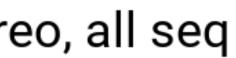
- · Click here for a breakdown by sequence
- · Click here for a breakdown by subset size

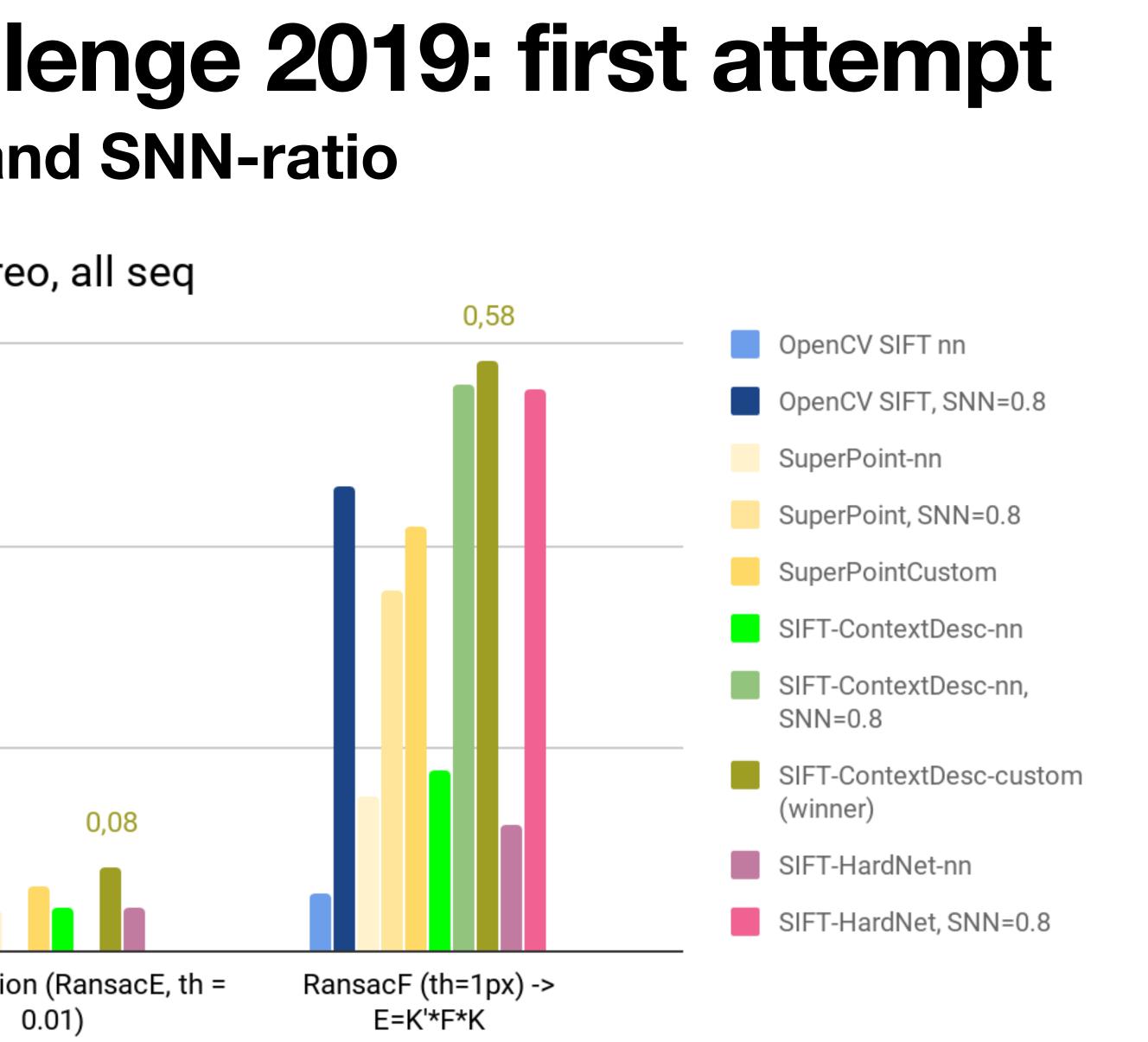
| Show 10 r entries |  |               |          |        |           |        | Search:  |              |          |                      |                      |                      |                      |     |
|-------------------|--|---------------|----------|--------|-----------|--------|----------|--------------|----------|----------------------|----------------------|----------------------|----------------------|-----|
|                   |  |               |          |        |           | MVS -  | averaged | d over all s | equences |                      |                      |                      |                      |     |
| M                 | lethod   | $\frac{1}{2}$ | Date 🍦   | Туре 🌐 | lms (%) 🍦 | #Pts ≑ | SR ≑     | <u>TL</u> ≑  | mAP⁵° ≑  | mAP <sup>10°</sup> ≑ | mAP <sup>15°</sup> 🔻 | mAP <sup>20*</sup> ≑ | mAP <sup>25°</sup> ≑ | ATE |
| ۲                 | SIFT +<br>ContextDesc +<br>Inlier<br>Classification V2<br>kp:8000,<br>matchcoustom | ł             | 19 05 28 | E/M    | 98.5      | 6125.0 | 97.5     | 3.44         | 0.5755   | 0.6830               | 0.7309               | 0.7750               | 0.8006               |     |



#### Image Matching Challenge 2019: first attempt **Results after tuning RANSAC and SNN-ratio**

|                          | mAP 15°, stere |
|--------------------------|----------------|
| Results change           | 0,60           |
| drastically after tuning | -              |
| SIFT is strong           |                |
| SIFT detector (DoG) +    | 0.40           |
| learned patch descriptor | 0,10           |
| +outlier rejection is a  |                |
| winner                   | 0.20           |
| Winner didn't change     | 0,20           |
| after RANSAC tuning,     |                |
| but its margin did       |                |
|                          | Competitio     |





# Image Matching Challenge 2020



Still available at https://www.cs.ubc.ca/research/image-matching-challenge/2020/leaderboard/



Johannes Schönberger Microsoft



Eduard Trulls Google



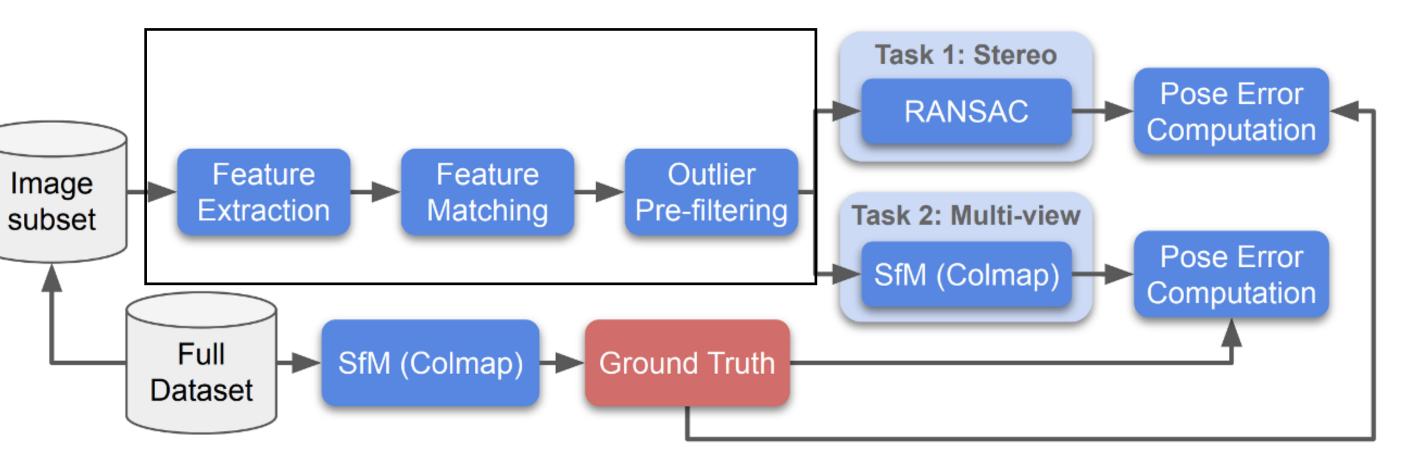
Kwang Moo Yi University of Victoria



Yuhe Jin University of **British Columbia** 

### IMC 2020: evaluation convergence

- Empirical evidence that you can create "ground truth" with 1000s of SfM data, which is not biased towards used local features
- Provide the codebase <u>https://github.com/ubc-vision/image-matching-benchmark/</u>
  - Also baselines repo <u>https://github.com/ubc-vision/image-matching-benchmark-baselines</u>
- Establish RANSAC-tuning protocol
- You give features & matches
  → we do reconstruction & results
- Publish a paper



### IMC 2020 paper: messages to community

- RANSAC implementation matters
  - Use PoseLib, USAC\_MAGSAC or pydegensac
- You have to tune RANSAC threshold
- Correspondence filtering matters (Lowe's SNN ratio!)
- SIFT is still great
- All components should be tuned together

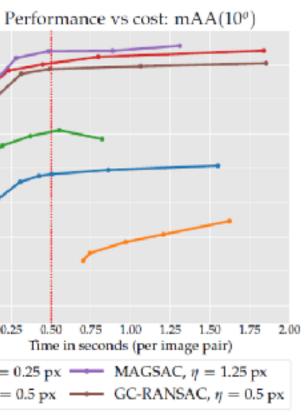
https://arxiv.org/abs/2003.01587

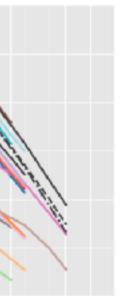
0.36Time in seconds (per image pair) Time in seconds (per image pair --- CV-RANSAC,  $\eta = 0.5 \text{ px}$  --- PyRANSAC,  $\eta = 0.25 \text{ px}$  ---- MAGSAC,  $\eta = 1.25 \text{ px}$ sklearn-RANSAC,  $\eta = 0.75 \text{ px} \longrightarrow \text{DEGENSAC}$ ,  $\eta = 0.5 \text{ px} \longrightarrow \text{GC-RANSAC}$ ,  $\eta = 0.5 \text{ px}$ 

Performance vs cost: mAA(5<sup>o</sup>)

0.52

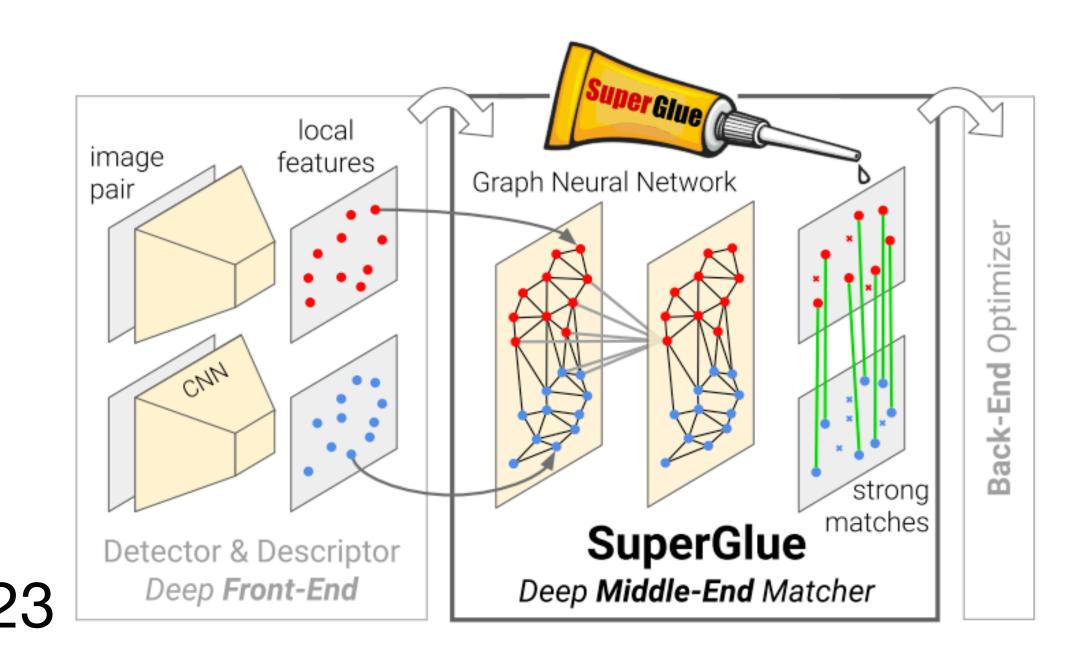
STEREO: mAA(10<sup>o</sup>) vs Inlier Threshold (a) PyRANSAC (b) DEGENSAC





### Findings from IMC 2020

- SuperGlue dominated the field
  - Not only in 2020, but until LightGlue in 2023
- Tons of features (8k) with decent outlier rejection are good enough for PhotoTourism (DoG + HardNet + AdaLAM / OANet)
- **DISK** appeared!



SuperGlue: Learning Feature Matching with Graph Neural Networks



# There were some problems as well

### IMC 2020 issues

- Evaluation is very compute-intensive up to a day of compute for tuning and getting results for 8k submission
  - 100 CPU-years per 2020 competition on Compute Canada
- Hard (impossible?) to evaluate detectorless (optical flow) methods.
- Even worse pose regression methods
- PhotoTourism is a limited domain, and looks like saturated
- People don't like to not having access to GT (sorry, not changing that)



# Image Matching Challenge 2021



Vassileios Balntas Scape Technologies



Vincent Lepetit University of Bordeaux





Jiri Dmytro Johannes Matas Mishkin Schönberger Czech Technical Czech Technical Microsoft University University

Still available at https://www.cs.ubc.ca/research/image-matching-challenge/2021/leaderboard/





Eduard Trulls Google



Kwang Moo Yi University of Victoria



Yuhe Jin University of British Columbia

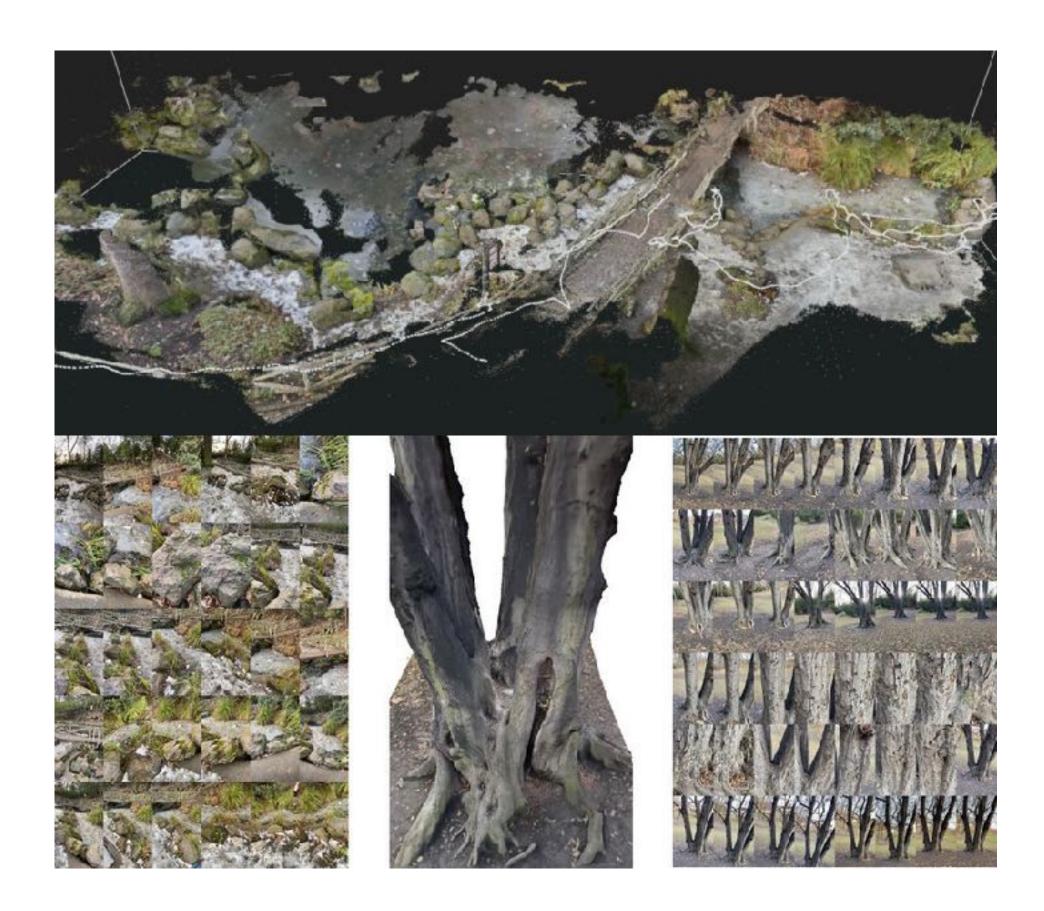
#### **IMC 2021 Dataset expansion + tutorials**

- Google Urban dataset lower quality mobile photos, close-ups, etc
- PragueParks more "nature" scenes
- Tutorials [features], [matchers]



Mountain View













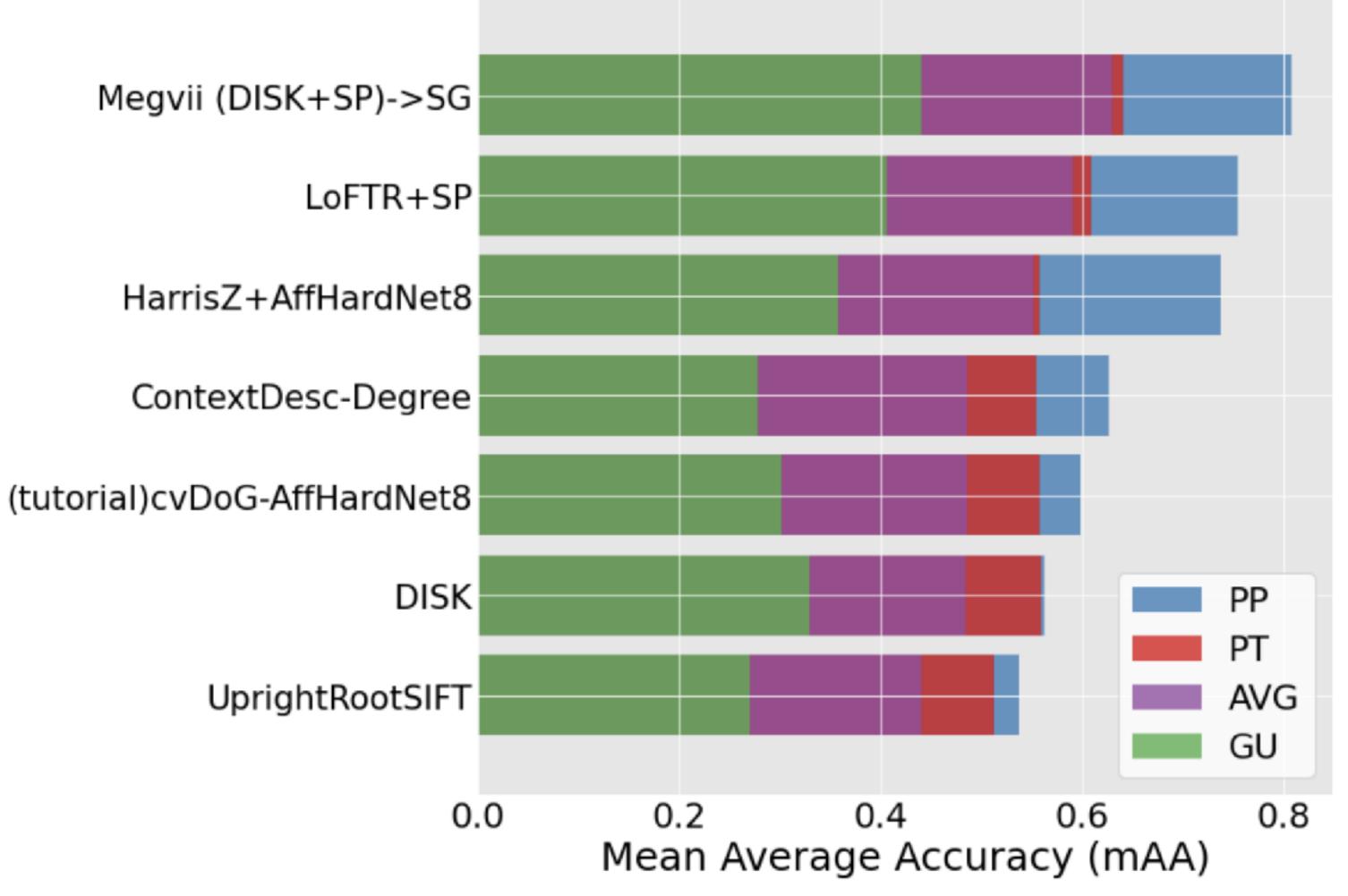




Bangkok

#### New data better shows difference between methods

STEREO 8k:  $mAA(10^{\circ})$ 



Methods, that perform the same on the PhotoTourism (red), perform very different on other datasets GoogleUrban and PragueParks

People managed to add LoFTR, by "snapping" to closest SuperPoints.





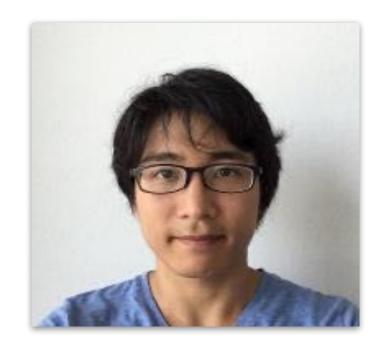
# Image Matching Challenge 2022



Yuhe Jin Univ. British Columbia



**Eduard Trulls** Google



Kwang Moo Yi Univ. British Columbia



**Jiri Matas CTU** Prague



**Dmytro Mishkin** CTU Prague/HOVER Inc.

Still available at https://www.kaggle.com/competitions/image-matching-challenge-2022

### **IMC2022: Before the competition**

We were looking for:

- allowing dense (detector-less) methods
- we had to delete it since then)
- safe way to run docker images w/o tons of infra work

Kaggle was satisfying all the conditions, and Eduard Trulls worked with Kaggle to make it happen.

Huge Kaggle community as bonus

fully hidden test set — Google Urban dataset was super hard to release (and

### **IMC2022: Before the competition**

Drawbacks:

- installing colmap was infeasible — stereo only.
- Metrics has to be implemented by us in C# (not anymore since 2024)
- Training set was phototourism, but test set was Google Urban-like.

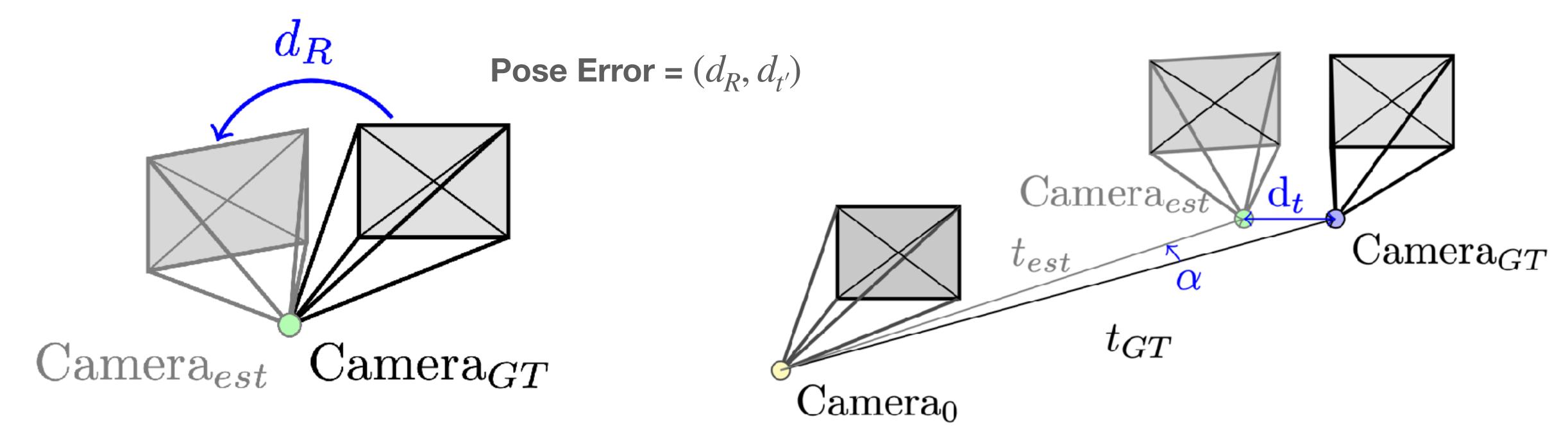




### **2022 Metric change: semi-metric translation**

Now we annotated the scale for all our datasets, so we know ground truth translation  $t_{GT}$  in meters. However, we still cannot estimate true translation error  $d_t$ , because we don't have scale for submission. So we "grant GT scale" to the submission and calculate  $d_{t'} = |t_{GT} - t_{est} \frac{|t_{GT}|}{|t_{est}|}|$ 

**Rotation error**  $d_R$  : angle, which aligns GT and estimated camera.



**Translation** *semi-metric* error  $d_{t'}$ : distance estimate between GT and estimated camera

#### **IMC2022: Results** New component in the image matching pipeline?

- zoom-in and refine are keys for stereo matching
- people tuned the baselines to extreme, which is good
- 25x more teams, 150x more submission
- LoFTR + SuperGlue
- Does it transfer to the SfM?

Papers with after-IMC22 ideas:

[MKPC], [ASpanFormer]

original image pair

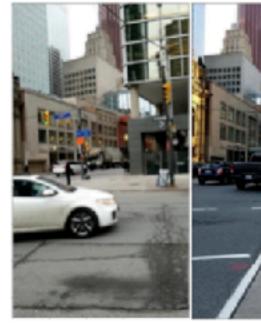
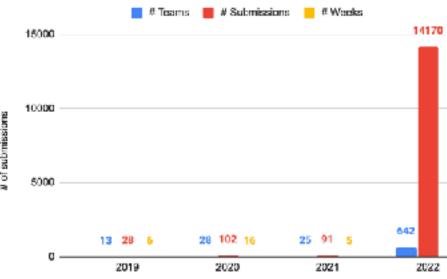
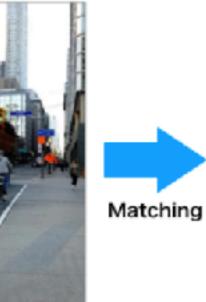
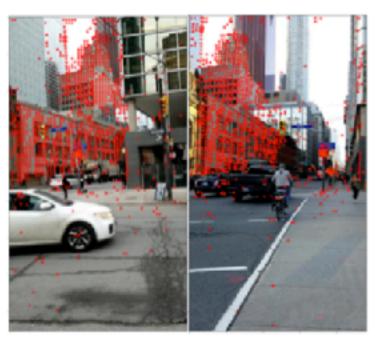


Image Matching Challenge: 2019-2022

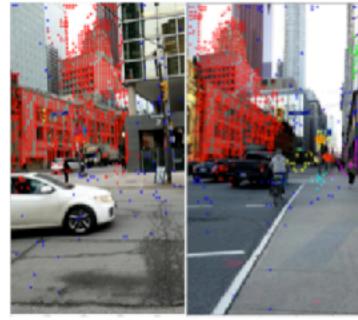






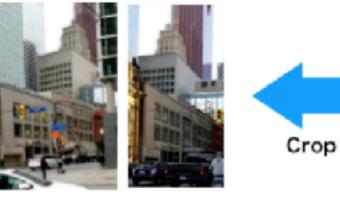






Extract clusters containing the top 80~90% matching points











**Fabio Bellavia** Univ. Palermo

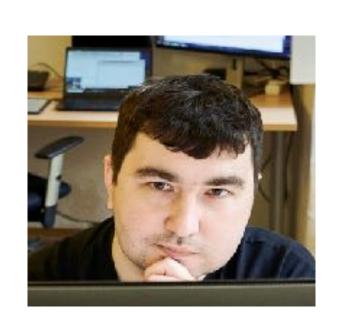


Weiwei Sun **U.** British Columbia

## Image Matching Challenge 2023



**Jiri Matas** CTU Prague



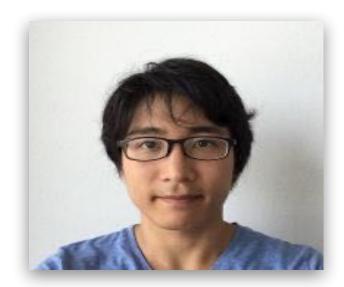
**Dmytro Mishkin** CTU Prague/HOVER Inc.

Still available at https://www.kaggle.com/competitions/image-matching-challenge-2023



**Eduard Trulls** 

Google



Kwang Moo Yi **U. British Columbia** 





Luca Morelli Univ. Trento/BFK



**Fabio Remondino Bruno Kessler Foundation** 

#### **INC2023** 2021 and 2022, but better

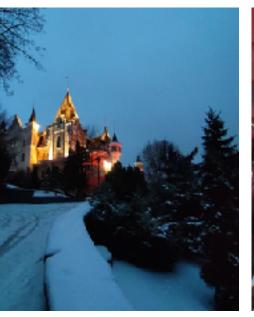
- SfM track: installed pycolmap and kornia to kaggle
- More datasets!
  - Urban day/night
  - Haiper NERF-like capture
  - Heritage: also with UAV
- \$50k minimal prize requirement from Kaggle
  - Thanks to Haiper and Google for sponsorship



















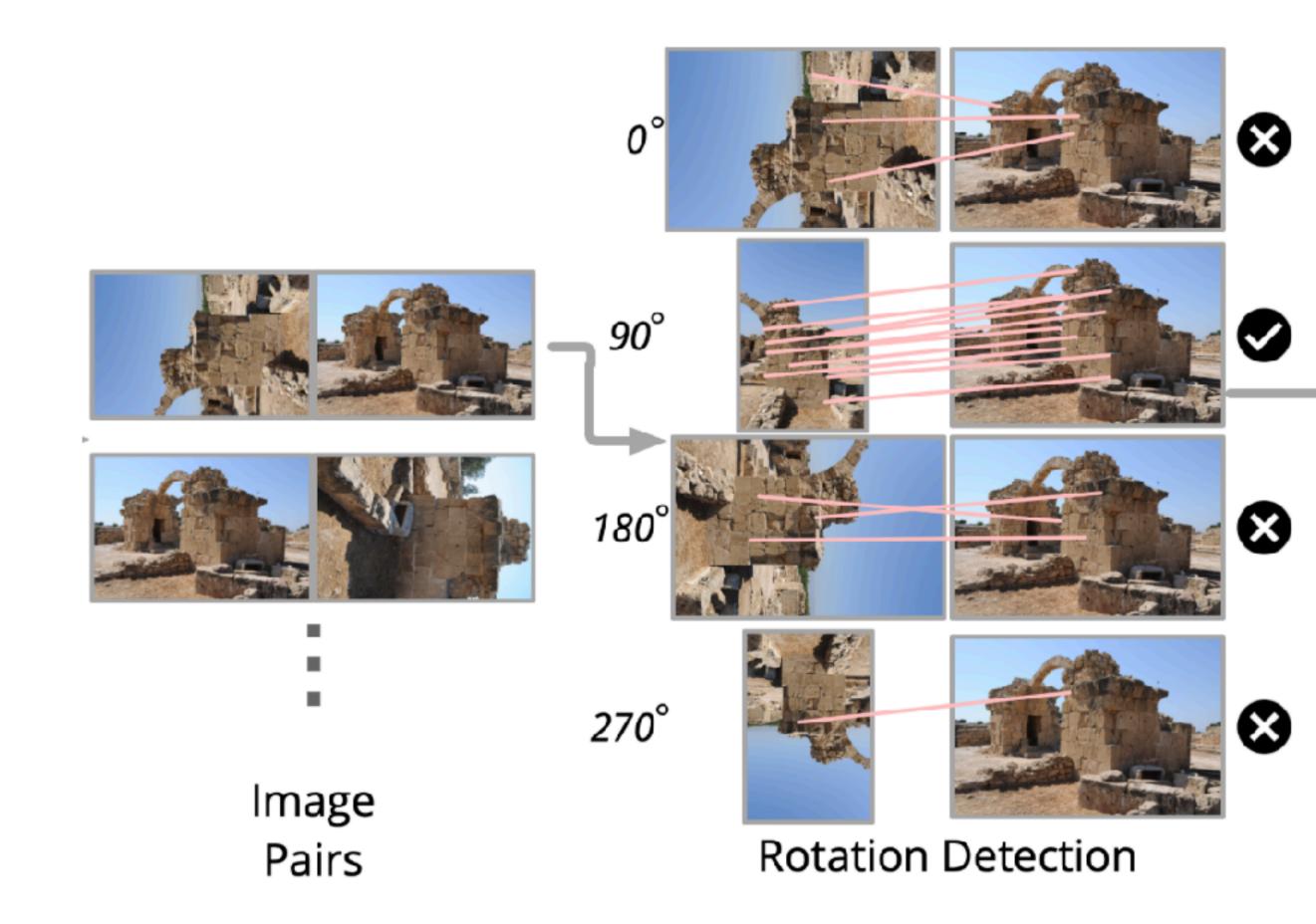
#### INC2023 Results

- Even harder to debug SfM on Kaggle
- Not many academics took part

Technical results:

- Brute-force rotation estimation for SuperGlue/LoFTR
- Detector-free SfM appeared
- LightGlue appeared!
- Handcrafted off-the-shelf kornia local feature got 5th place!

https://ducha-aiki.github.io/wide-baseline-stereo-blog/2023/07/05/IMC2023-Recap.html



### Why do we do benchmarking?

- Understand the state-of-the-art. Many people stop here.
- Measure the progress of the field
- Find open questions
- Direct the research in a certain way
  - Can be area, practices, etc.

We spent 2019 - 2023 trying to understand the SoTA and measure the progress.

We also all the time advocated for downstream methods and proper RANSACs, and that seems to be successful.

Now we are trying to direct Image Matching/SfM into more diverse areas.



Weiwei Sun U. British Columbia



**Amy Tabb USDA-ARS-AFRS** 



**Fabio Bellavia** Univ. Palermo



**Jiri Matas CTU** Prague



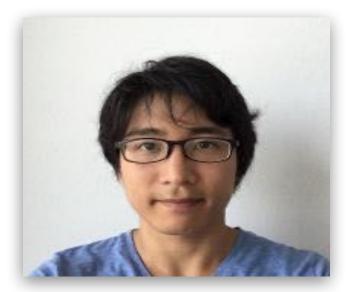
**Dmytro Mishkin** CTU Prague/HOVER Inc.

Still available at https://www.cs.ubc.ca/research/image-matching-challenge/2021/leaderboard/



**Eduard Trulls** 

Google



Kwang Moo Yi U. British Columbia

Image Matching Challenge 2024





Luca Morelli



Fabio Remondino Univ. Trento/BFK Bruno Kessler Foundation

### **IMC2024:** before the start

- Standard two-view matching is mostly solved
- So we need to try new things
  - either SfM-based
  - or super hard images





RoMa: Robust Dense Feature Matching

#### IMC 2022

| Method $\downarrow$ | $mAA \rightarrow$ | @10 ↑ |
|---------------------|-------------------|-------|
| SiLK [21]           |                   | 68.6  |
| SP [14]+Super       | 72.4              |       |
| LoFTR [44] cvi      | 78.3              |       |
| MatchFormer [       | 78.3              |       |
| QuadTree [46]       | 81.7              |       |
| ASpanFormer         | 83.8              |       |
| DKM [17] CVPR       | 83.1              |       |
| RoMa                | 88.0              |       |



Dust3r







#### DUSt3R: Geometric 3D Vision Made Easy



#### IMC2024: Hexathlon



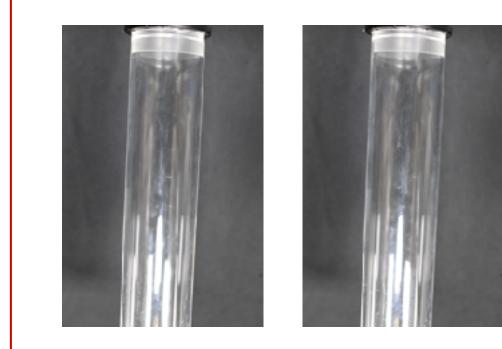
#### temporal changes



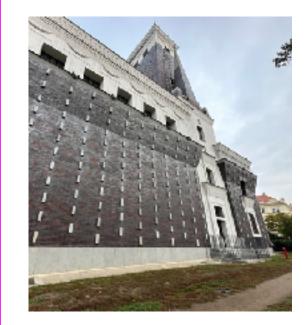
#### aerial and aerial/ground



#### historical preservation



#### transparent objects





symmetries and repeated structures

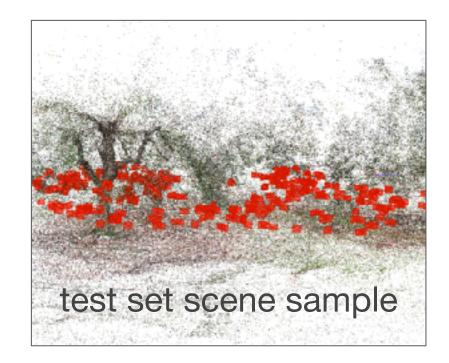


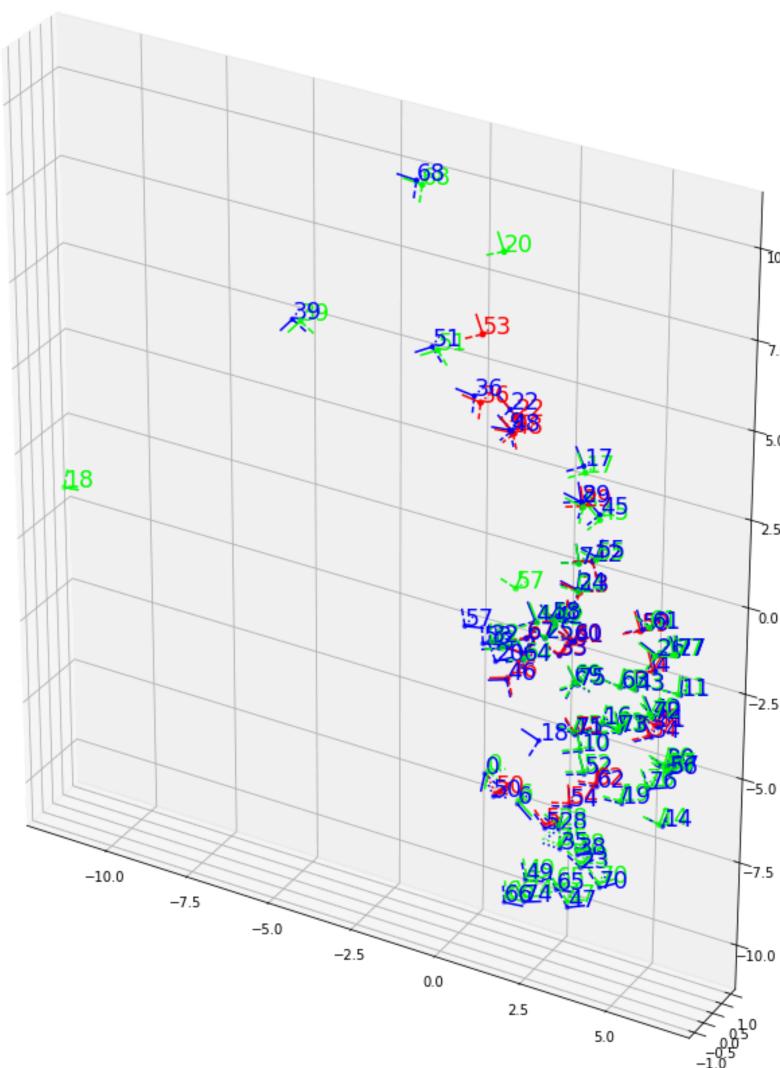
# **IMC2024: registration-based metric**

- Cameras are aligned with exhaustive RANSAC-like registration with list of triplets for Horn-based solver.
- Metric is mAA on purely translation error between GT and solution







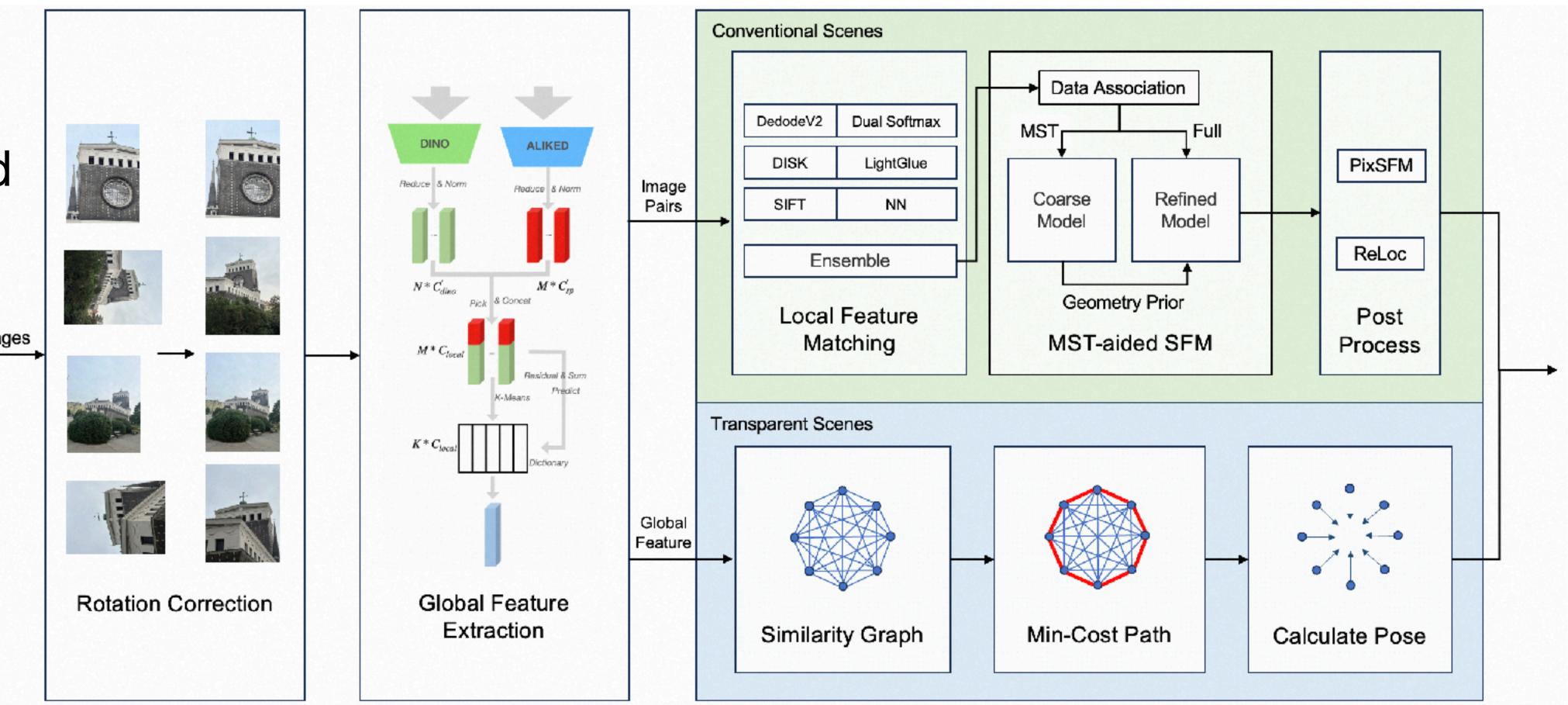


best submission (public/private split) aligned with ground-truth

### **IMC2024: results**

Good thing:

Winners actually tried to solve covisibility graph first Images



https://www.kaggle.com/competitions/image-matching-challenge-2024/discussion/510499

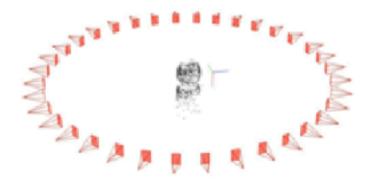
#### **IMC2024: our failures** Any shortcuts will be exploited on Kaggle

Issue #1: transparent objects were sh some objects.

We thought that scrambling image order made the task hard enough.

It turns out, that local order is recoverable, and that is enough together with hardcoding positions





#### Issue #1: transparent objects were shoot on turntable. Moreover, we leaked

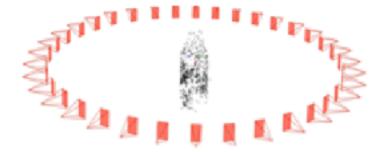
Object (b)





Object (d)









#### **IMC2024: our failures** Any shortcuts will be exploited on Kaggle

Issue #2: It is extremely hard to debug on Kaggle Issue #3: People also like to see the images from the test set.

- This is bad from a benchmark fairness point of view
- But it is good for the community to know what to work on
- Having bigger training/validation set would help, but that is hard to get

### Challenges on Kaggle

Good:

- Fair benchmark with a hidden test set
- challenge the over-complicated methods vs crowd-source tuned baselines
- solving non fancy and "unpublishable" things
- "free" compute for participants
- Kaggle may provide \$50k prizes via their academic program

Bad:

- cannot do long term leaderboard
- debugging
- high entry threshold for non-python stuff
- single metric only
- \$50k minimum prize fund

### Why participate?

- You got a fair result of your method on a challenging problem
  - But it is hard to be sota, so maybe bad for convincing R2.
- But if you beat Kaggle, then you are really good!
  - Some things are not obvious before you try
  - E.g., running on GPU-poor machines in real scenario
    - VGGSfM (2024) has to be significantly optimized to be even able to run on IMC2024
- Prizes are big :)

### **IMC Summary (research and practical)**

- Downstream metrics are the way to go for image matching
- Tune all the components of the system (best by crowd-sourcing on Kaggle)
- Two-view matching is solved for many cases, while the SfM is not
- SfM Scalability is under-explored (and we don't do BoW retrieval anymore)
- Diversity in the datasets is essential
- Proper metrics are hard
- Do multi-year benchmarks

### Image Matching Challenge 2025

- Probably will be on Kaggle (we are in discussing it)
- No transparent objects
- Improve metric a little bit more
- Add another practical difficulty (secret for now)

### I hank you for your attention!





