COCO
Common Objects in Context

1st Keypoints Challenge

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ImageNet and COCO Visual Recognition Challenges Workshop

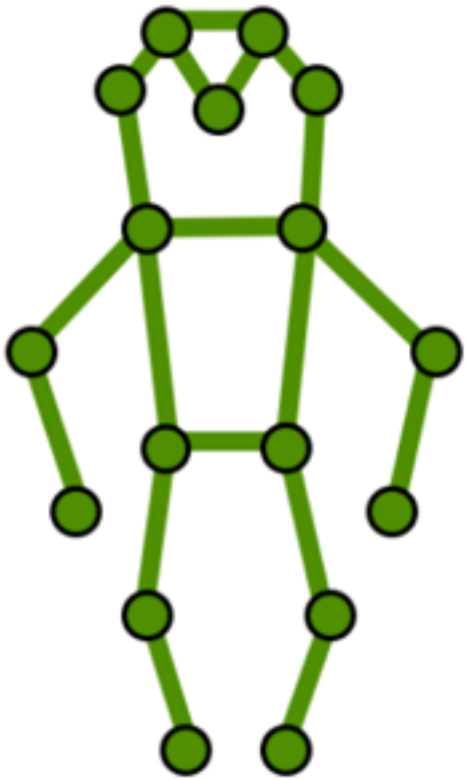
Sunday, October 9th, ECCV 2016

COCO
Common Objects in Context

NEW Keypoints Dataset

Dataset Statistics (I)

Keypoints Dataset



Dataset Statistics (I)

COCO
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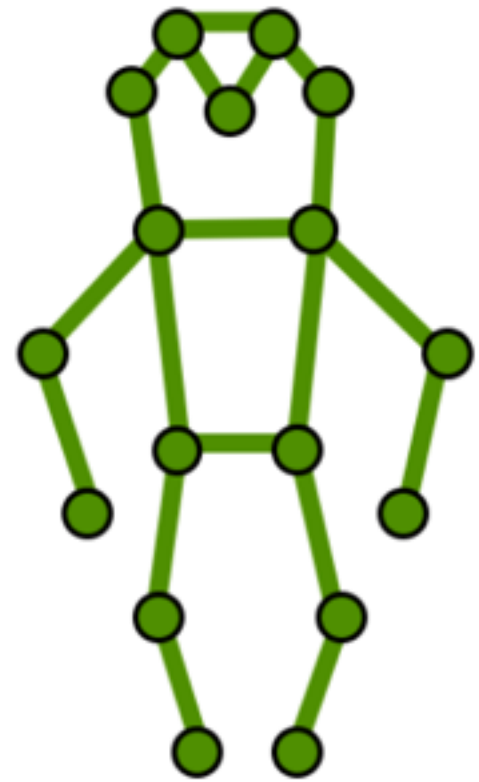
Keypoints Dataset

- 17 types of keypoints.



Dataset Statistics (I)

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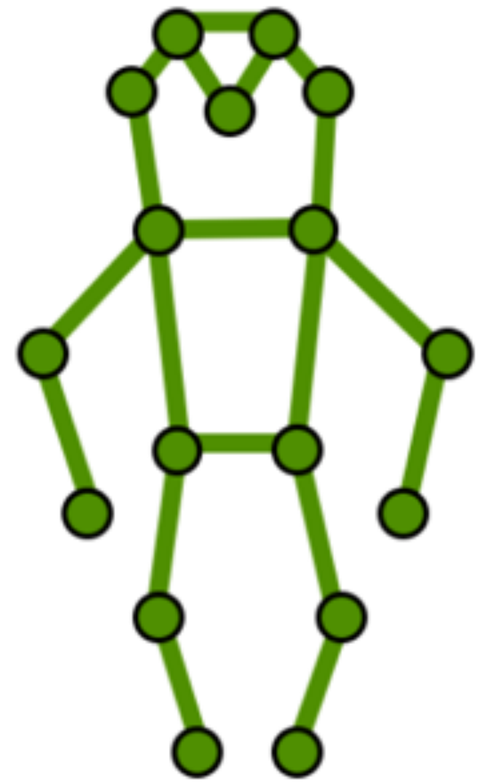
Keypoints Dataset

- 17 types of keypoints.
- Visibility flag annotations.



Dataset Statistics (I)

COCO
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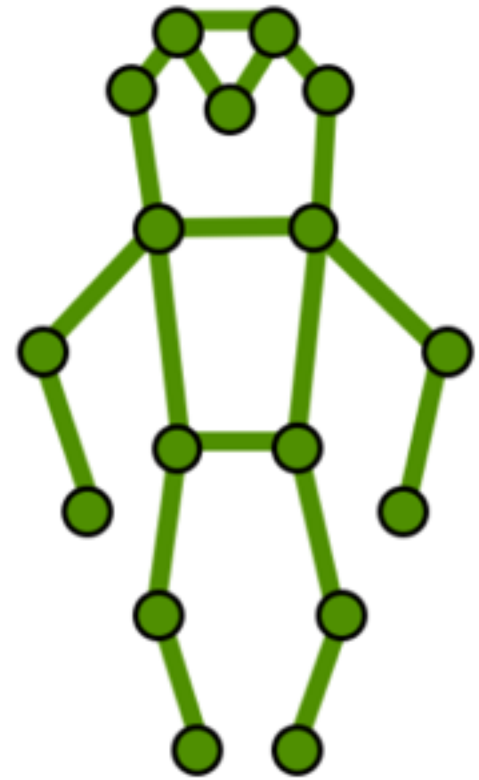
Keypoints Dataset

- 17 types of keypoints.
- Visibility flag annotations.
- 105,698 annotated people.

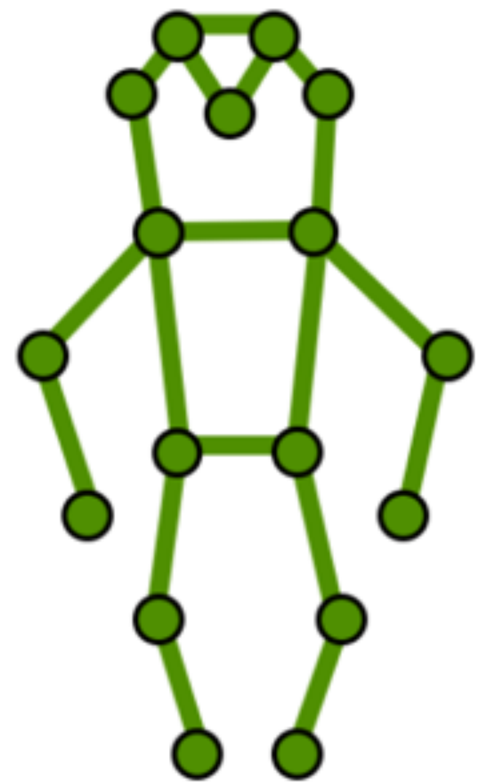


Dataset Statistics (I)

COCO
Common Objects in Context

Keypoints Dataset

- 17 types of keypoints.
- Visibility flag annotations.
- 105,698 annotated people.
- 1,161,667 annotated keypoints.



Dataset Statistics (I)

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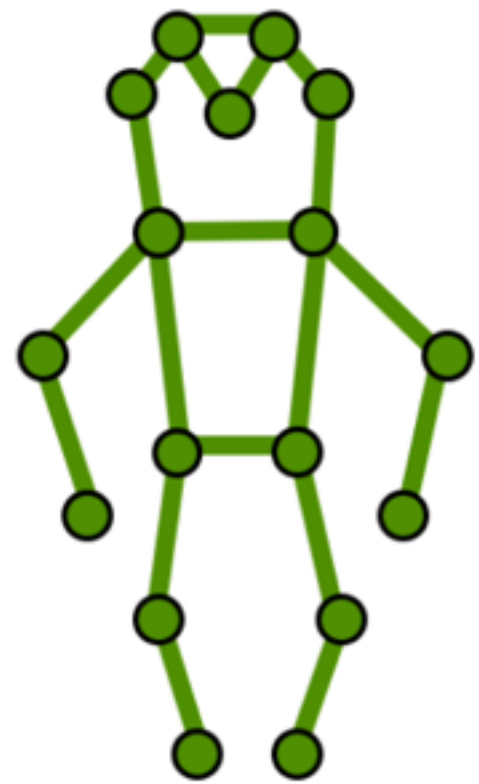
Keypoints Dataset

- 17 types of keypoints.
- Visibility flag annotations.
- 105,698 annotated people.
- 1,161,667 annotated keypoints.
- 45,174 unique images (train/val)

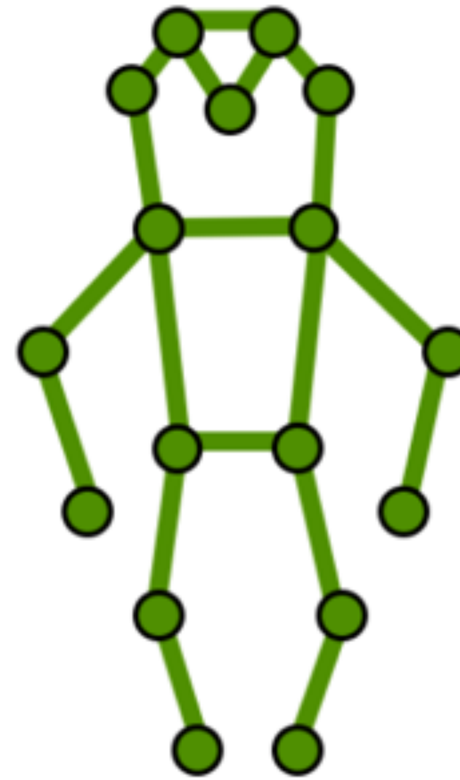


Dataset Statistics (I)

COCO
Common Objects in Context

Keypoints Dataset

- 17 types of keypoints.
- Visibility flag annotations.
- 105,698 annotated people.
- 1,161,667 annotated keypoints.
- 45,174 unique images (train/val)
- Only medium and large size people annotated



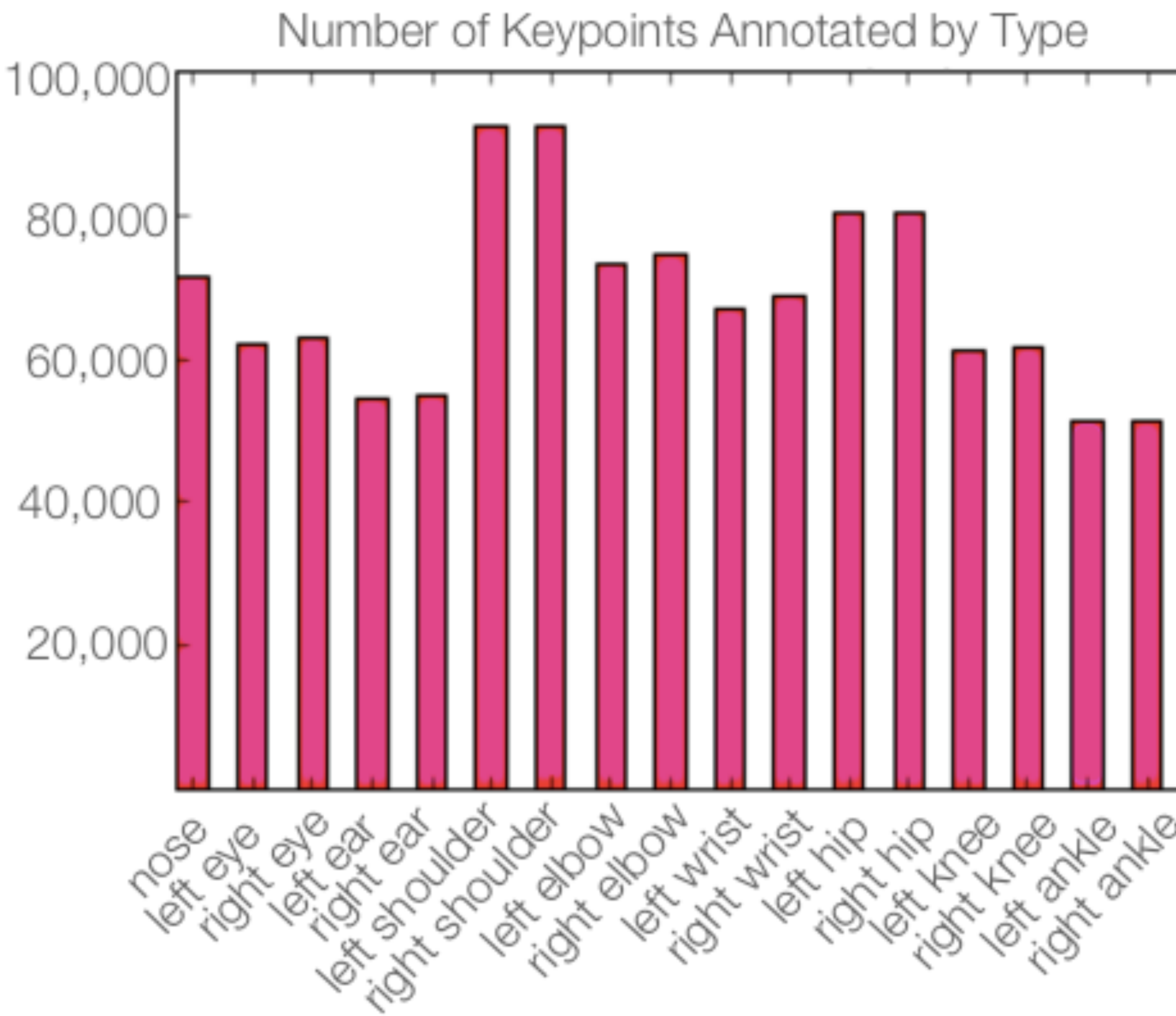
Dataset Statistics (II)

- Max people per image: **13**
- Mean people per image: **2.65**

Visibility Flag v_i

- Mean annotations per person: **11**
- 6,000 people with > 17 annotations
- 2,300 people with only 1 keypoint
- shoulders, hips, elbows, noses most popular

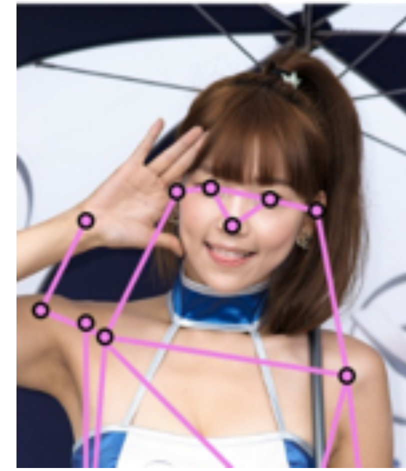
Dataset Statistics (III)

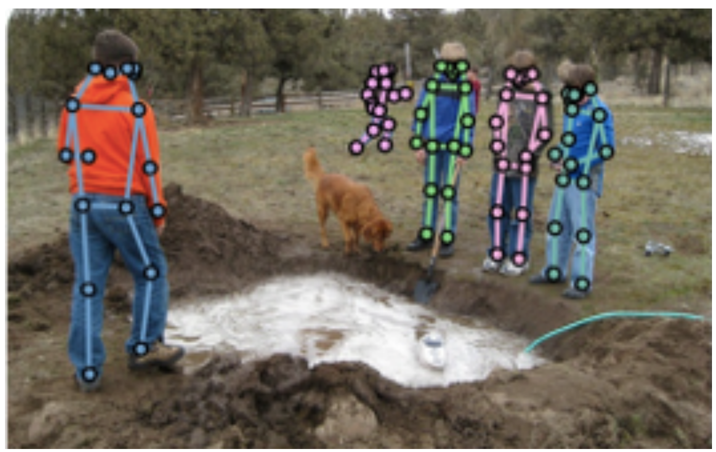


2016 COCO Keypoints Challenge

- New Task - Keypoint Detection and Localization

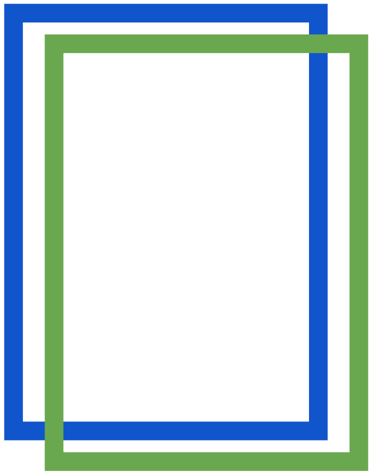
- New Metric - Object Keypoint Similarity (OKS)



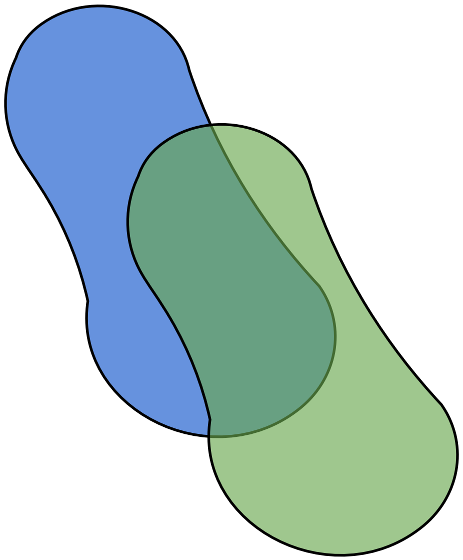


Evaluating BBoxes, Segmentations and Keypoints

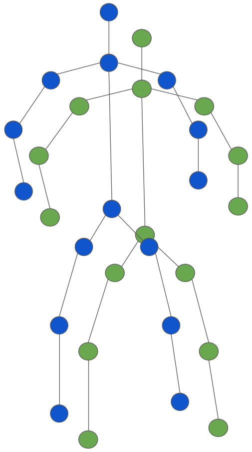
To calculate AP we need:



Bounding Box IoU

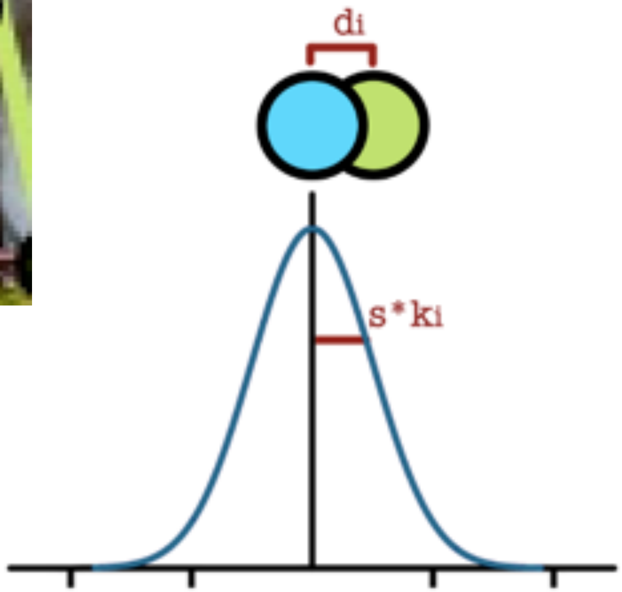


Mask IoU



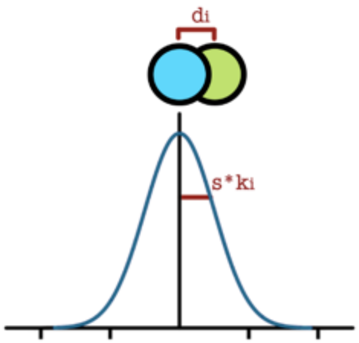
Object Keypoint Similarity

Object Keypoint Similarity -OKS



Object Keypoint Similarity

$$OKS = \frac{\sum_i e^{-\frac{d_i^2}{2s^2k_i^2}} \delta(v_i > 0)}{\sum_i \delta(v_i > 0)}$$



- d_i are the Euclidean distances between each ground truth and detected keypoint
- v_i are the visibility flags of the ground truth
- $s * k_i$(scale * keypoint constant) is the standard deviation of this gaussian
- Scale and Keypoint constant needed to equalize the importance of each keypoint
  - Eye location more precise than Hip location
- Perfect predictions will have OKS=1
- Predictions with keypoints wrong by more than a few standard deviations will have OKS~0

Scale and Standard Deviation

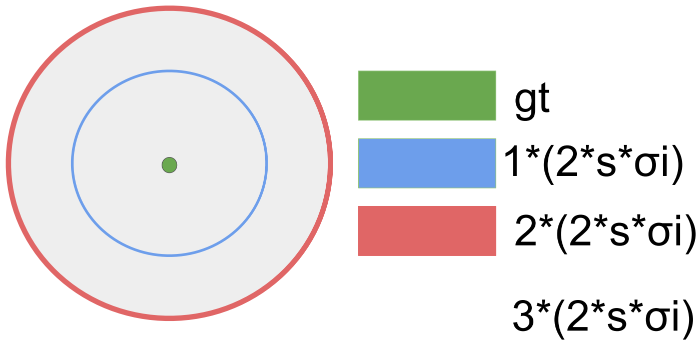
s scale

k_i keypoint

Standard Deviation per Keypoint type

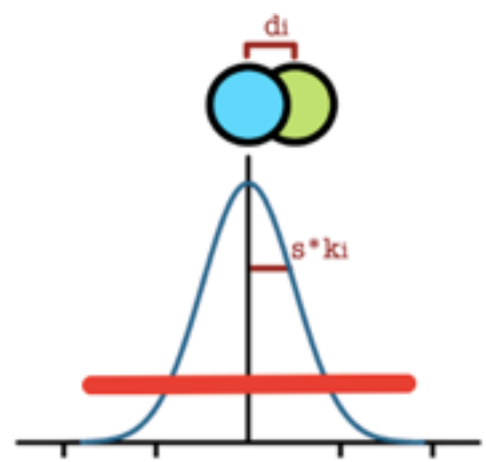
Keypoint	k_i
hips	0.107
ankles	0.089
knees	0.087
shoulders	0.079
elbows	0.072
wrists	0.062
ears	0.035
nose	0.026
eyes	0.025

OKS Cut-off



OKS = 1
OKS = .88
OKS = .61
OKS = .32

- Minimum OKS value is 0.5
- We analyze only keypoints that lie within ~2.77 of their standard deviation



From OKS to COCO AP

From OKS to COCO AP

COCO AP is the area under the PR curve

From OKS to COCO AP

COCO AP is the area under the PR curve

precision

1
0.8
0.6
0.4
0.2

precision

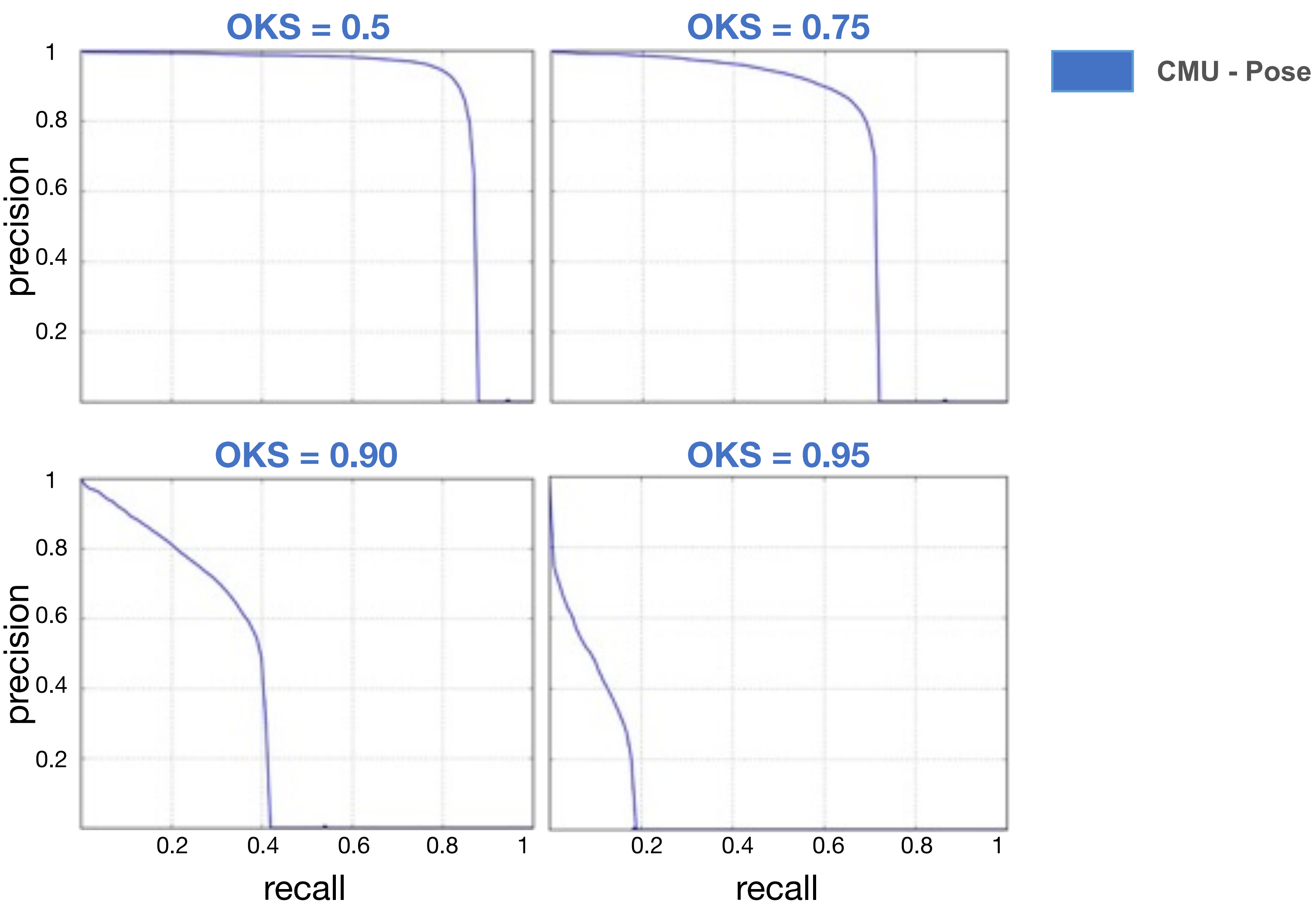
1
0.8
0.6
0.4
0.2

0.2 0.4 0.6 0.8 1
recall

0.2 0.4 0.6 0.8 1
recall

From OKS to COCO AP

COCO AP is the area under the PR curve



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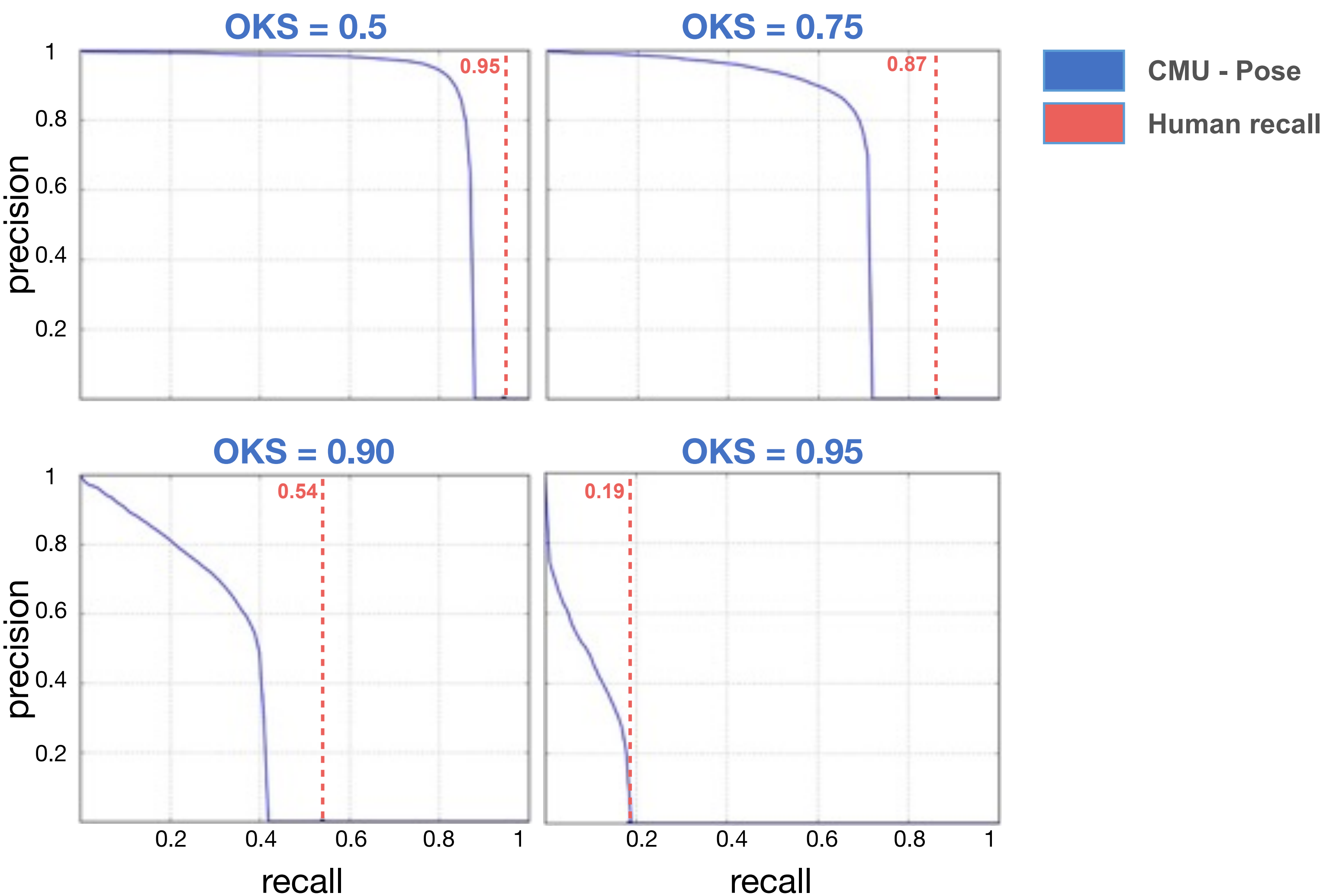

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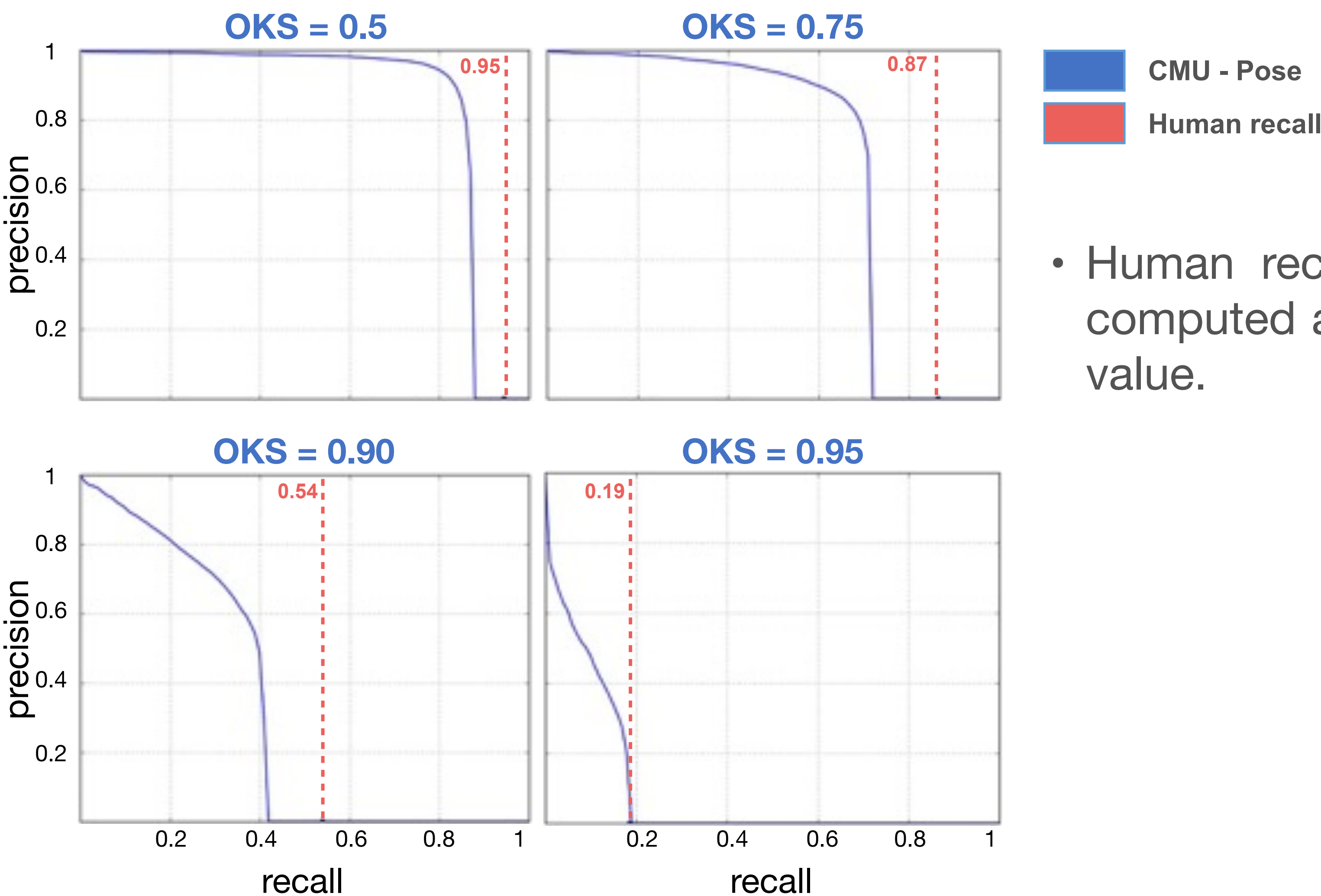
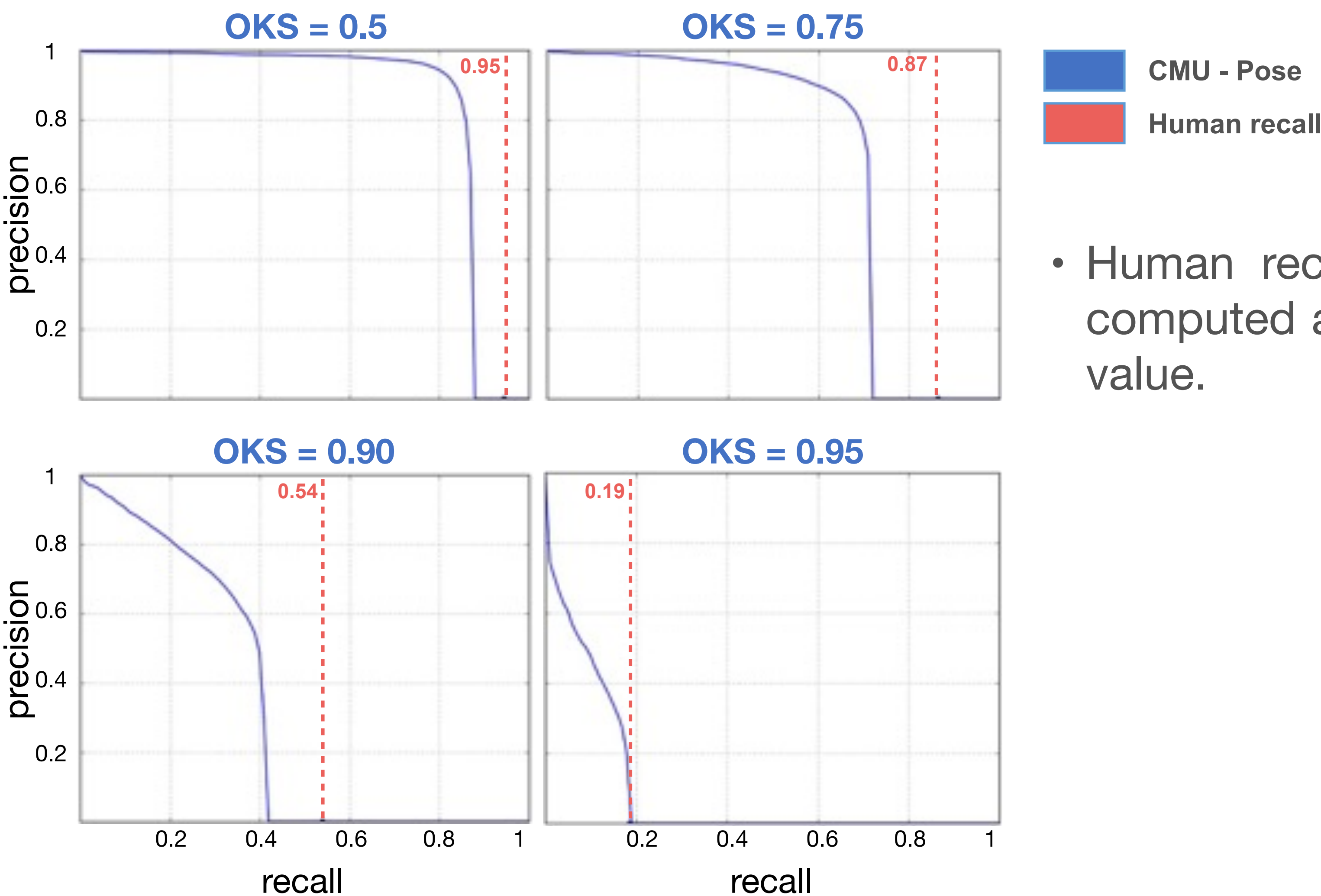


- Human recall can be computed at any OKS value.

From OKS to COCO AP

COCO AP is the area under the PR curve



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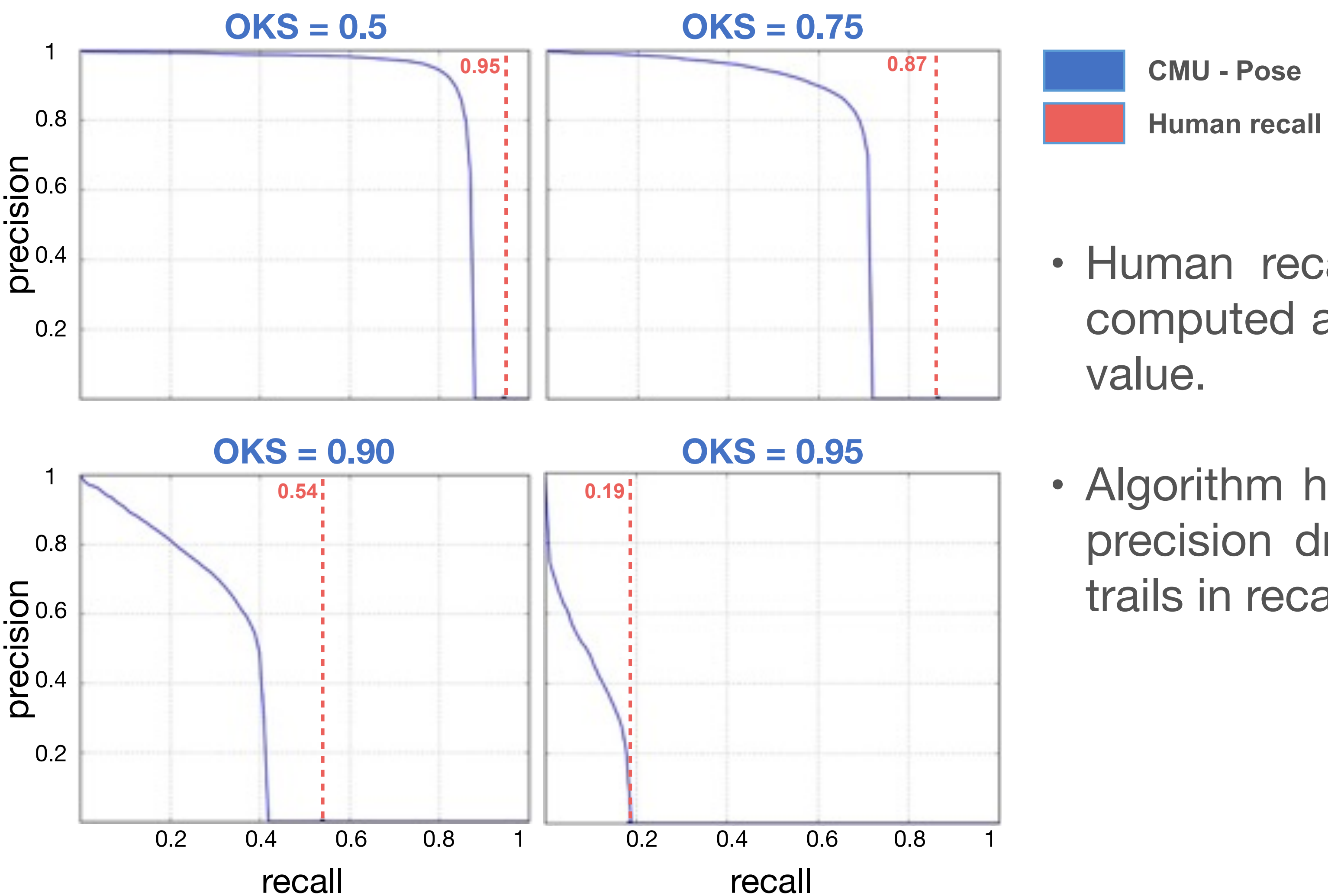
From OKS to COCO AP

COCO AP is the area under the PR curve



- Human recall can be computed at any OKS value.
- Algorithm has smooth precision drop-off but trails in recall.

COCO Challenge Results

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Keypoints

Keypoints Leaderboard (I)

COCO AP (over all OKS)

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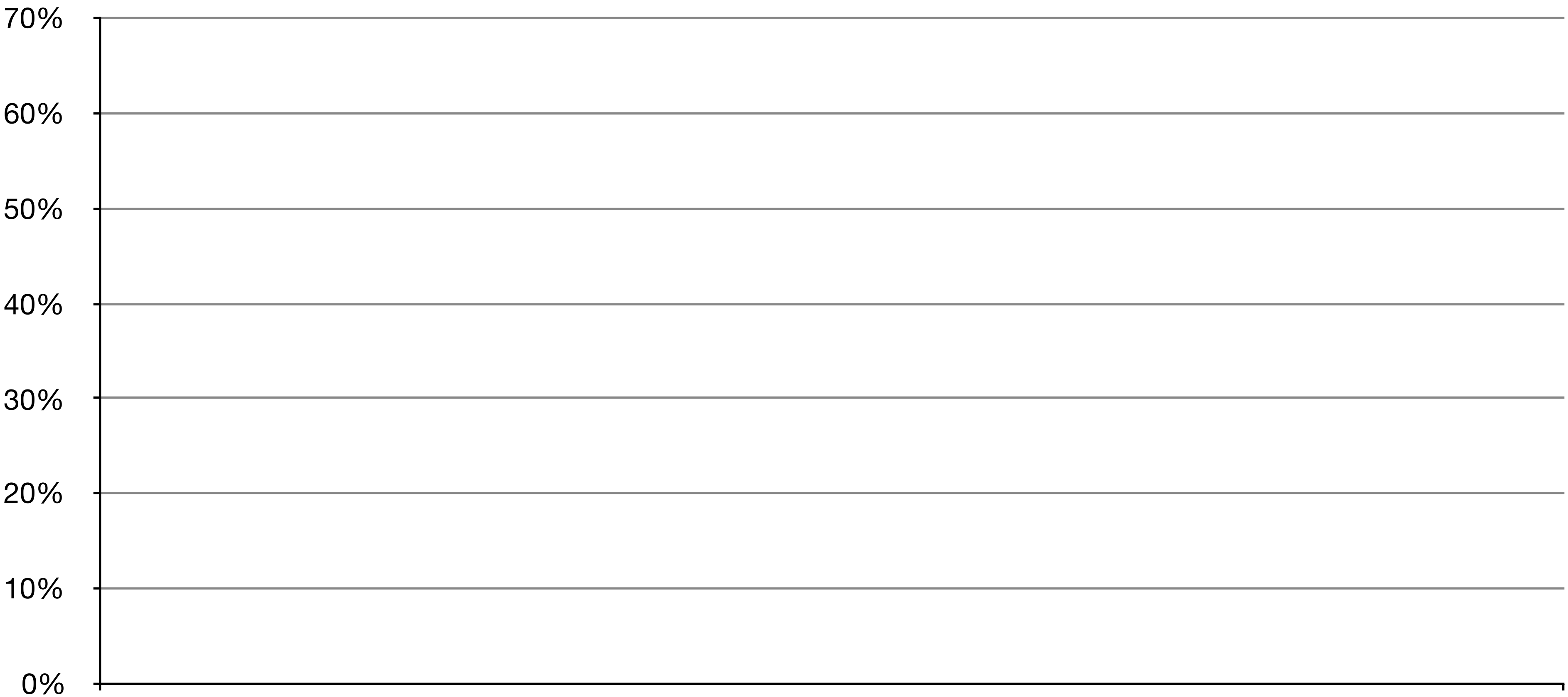
COCO AP (over all OKS)



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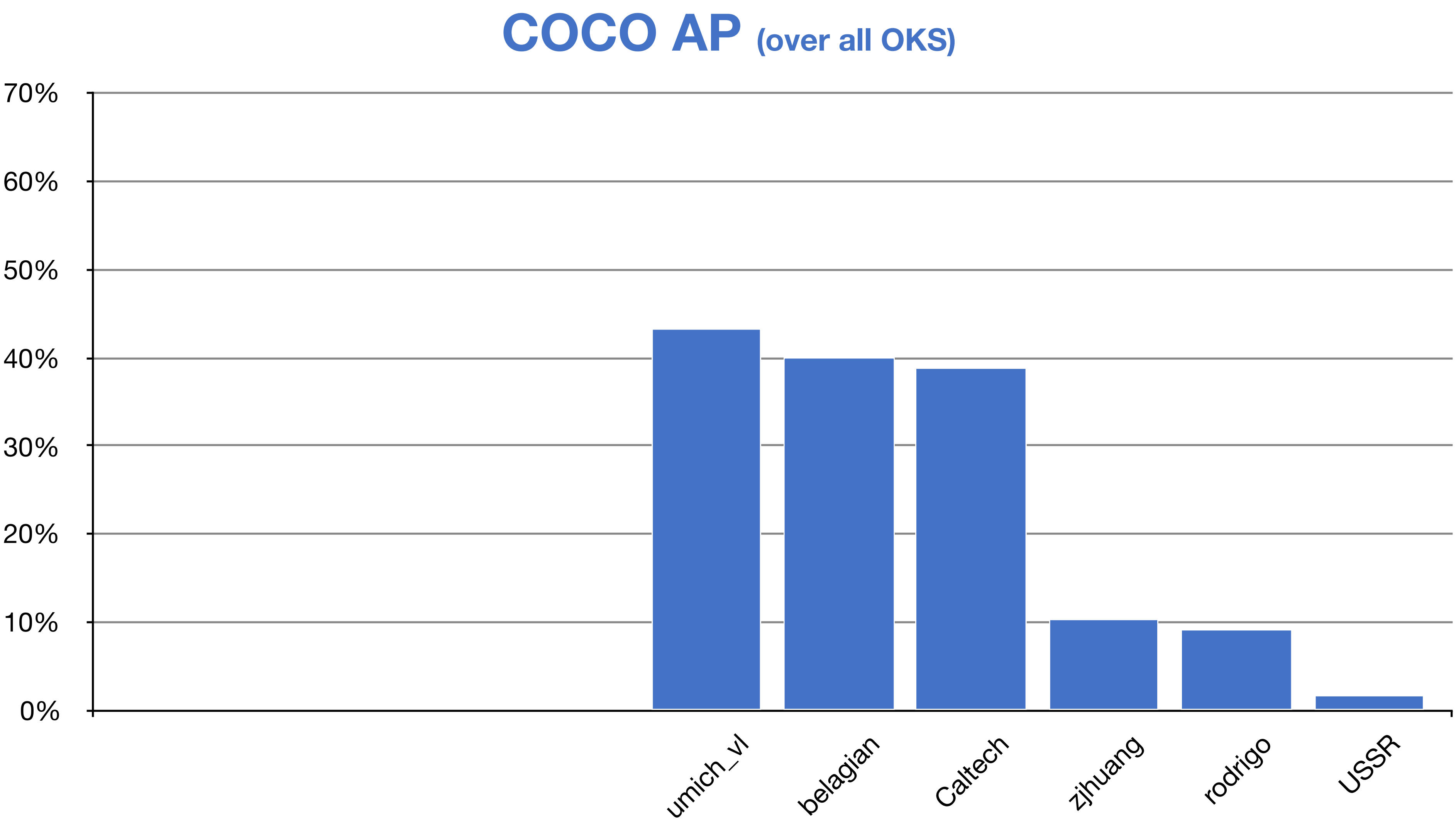

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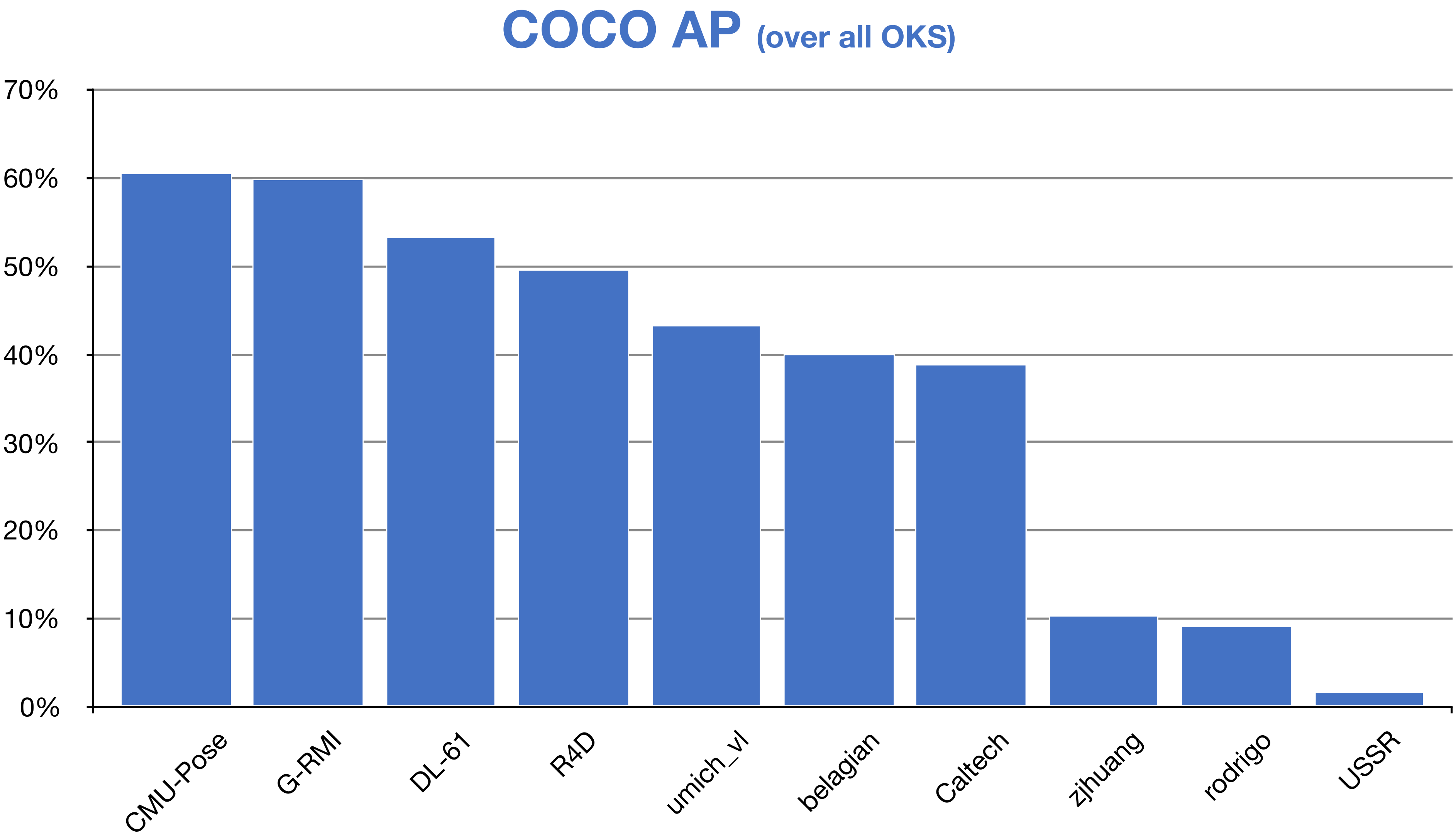

Keypoints Leaderboard (II)

Instance localization affects also keypoints

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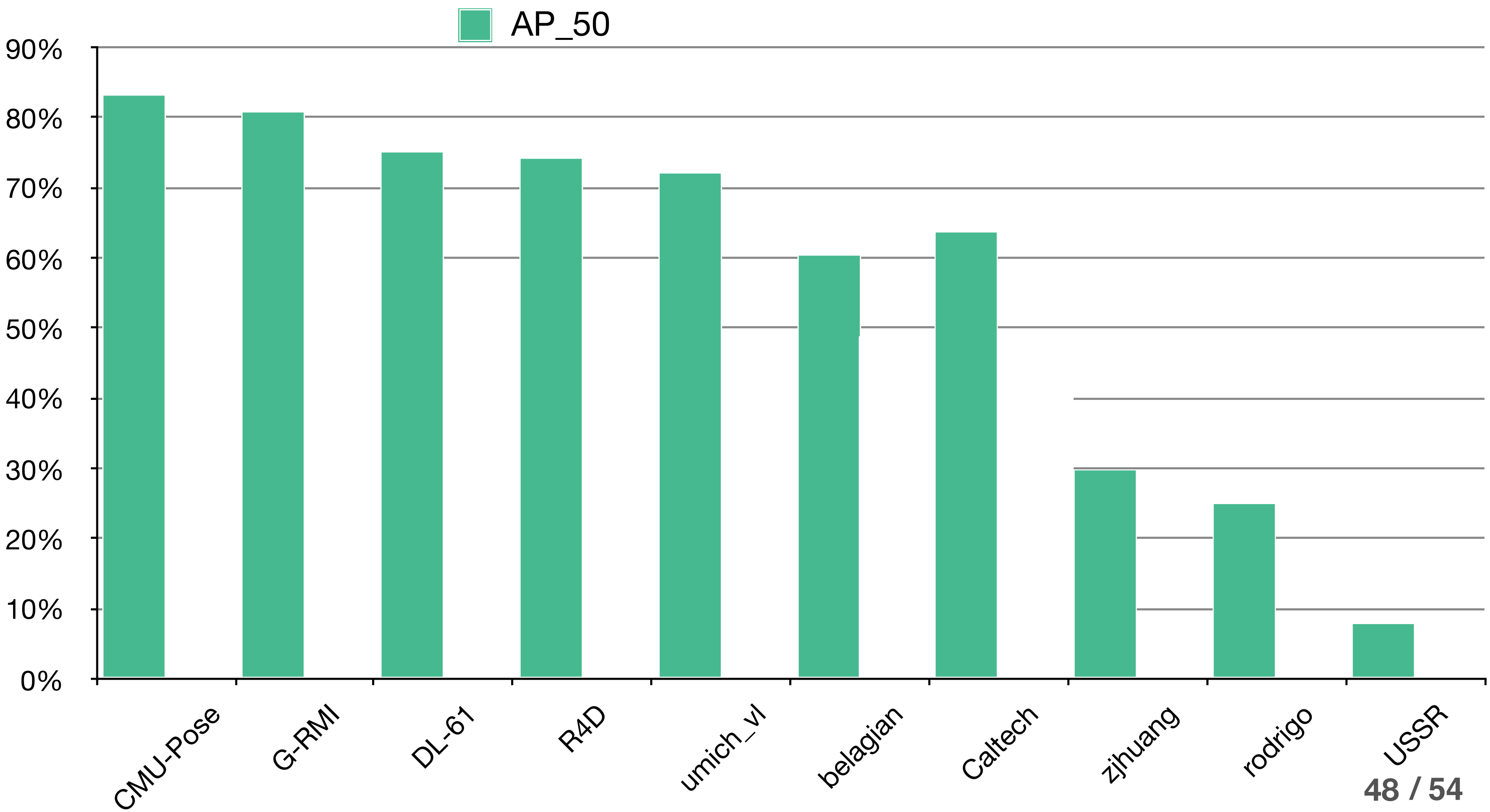

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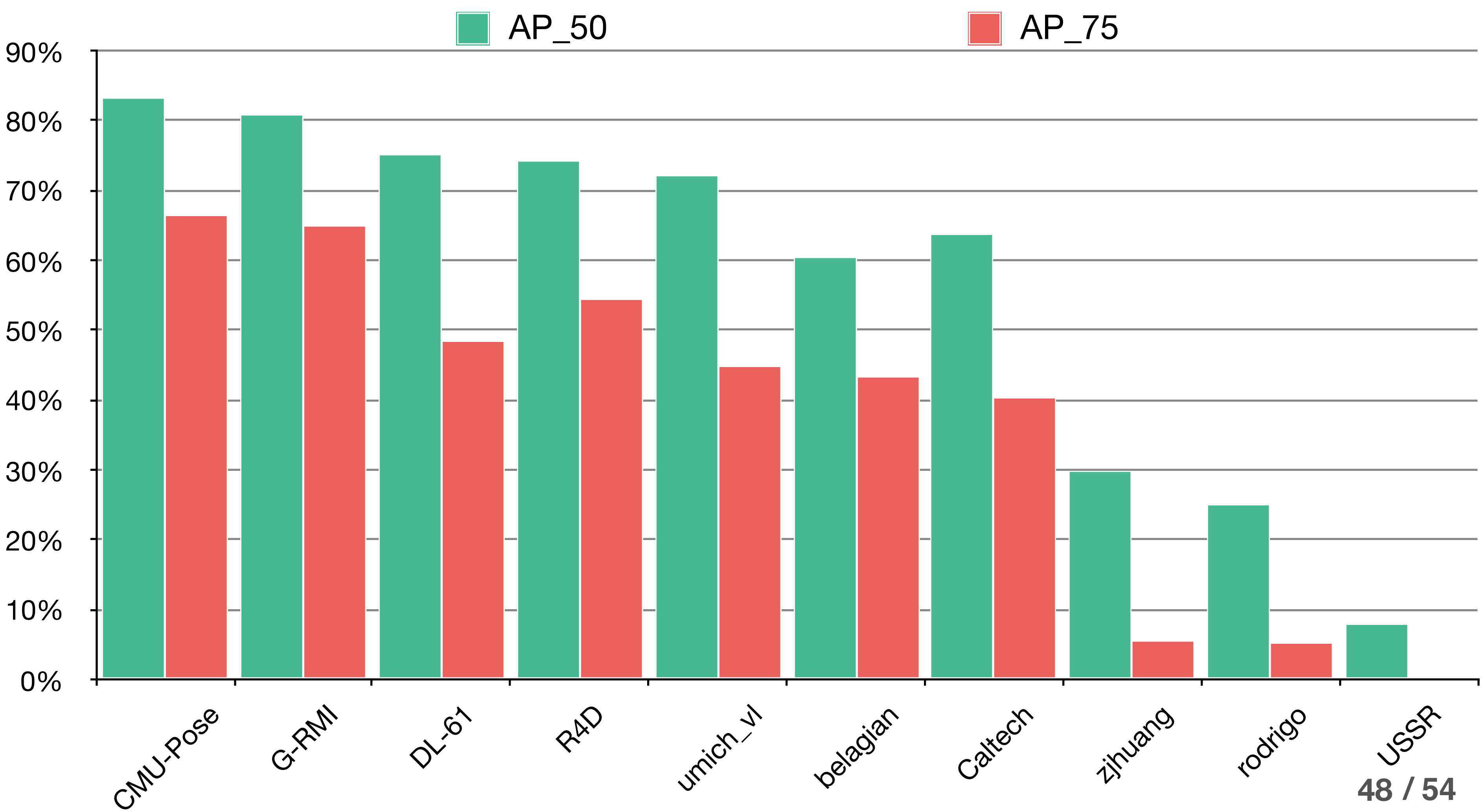

Keypoints Leaderboard (III)

Instance scale is an important factor

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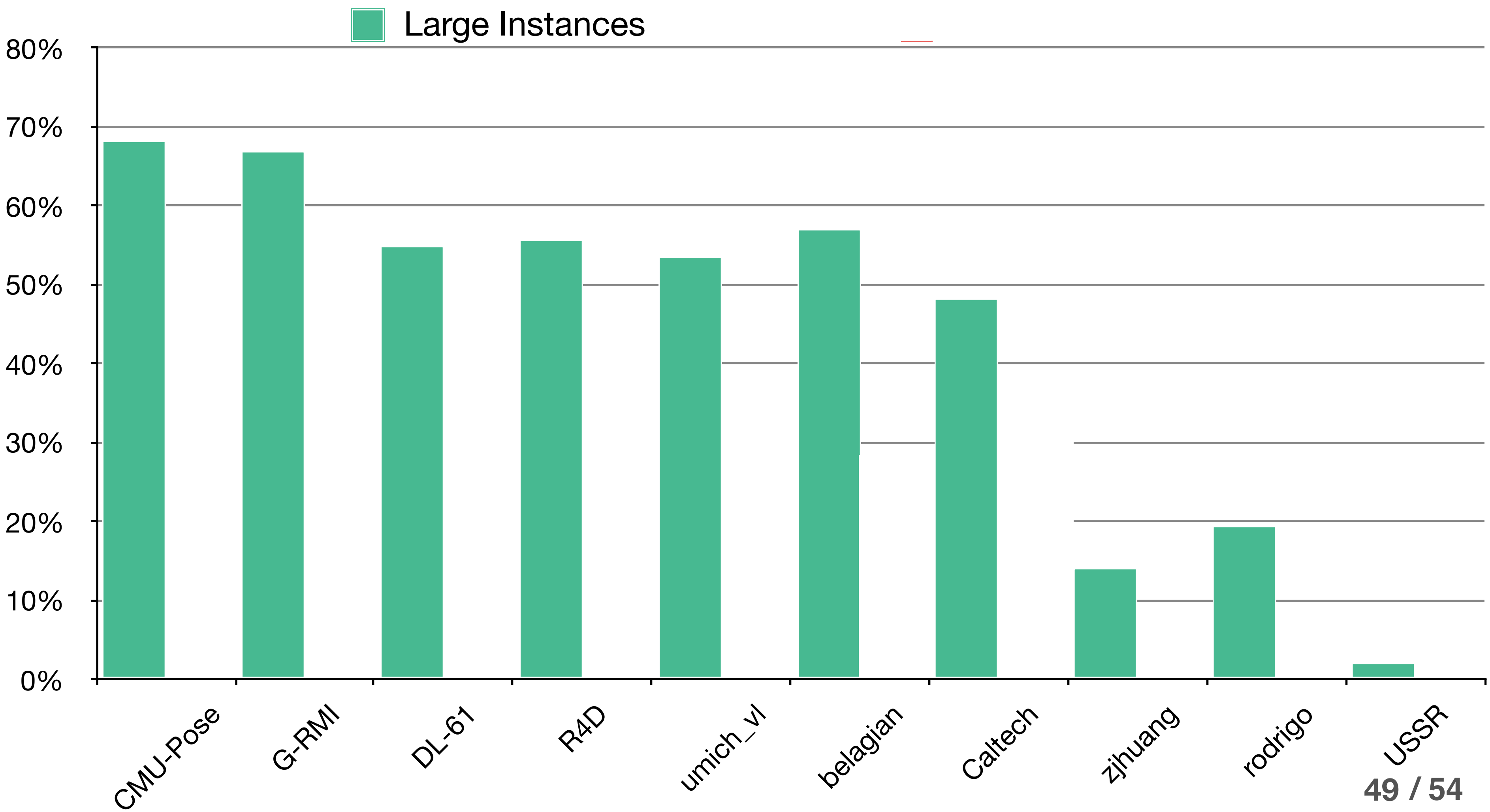

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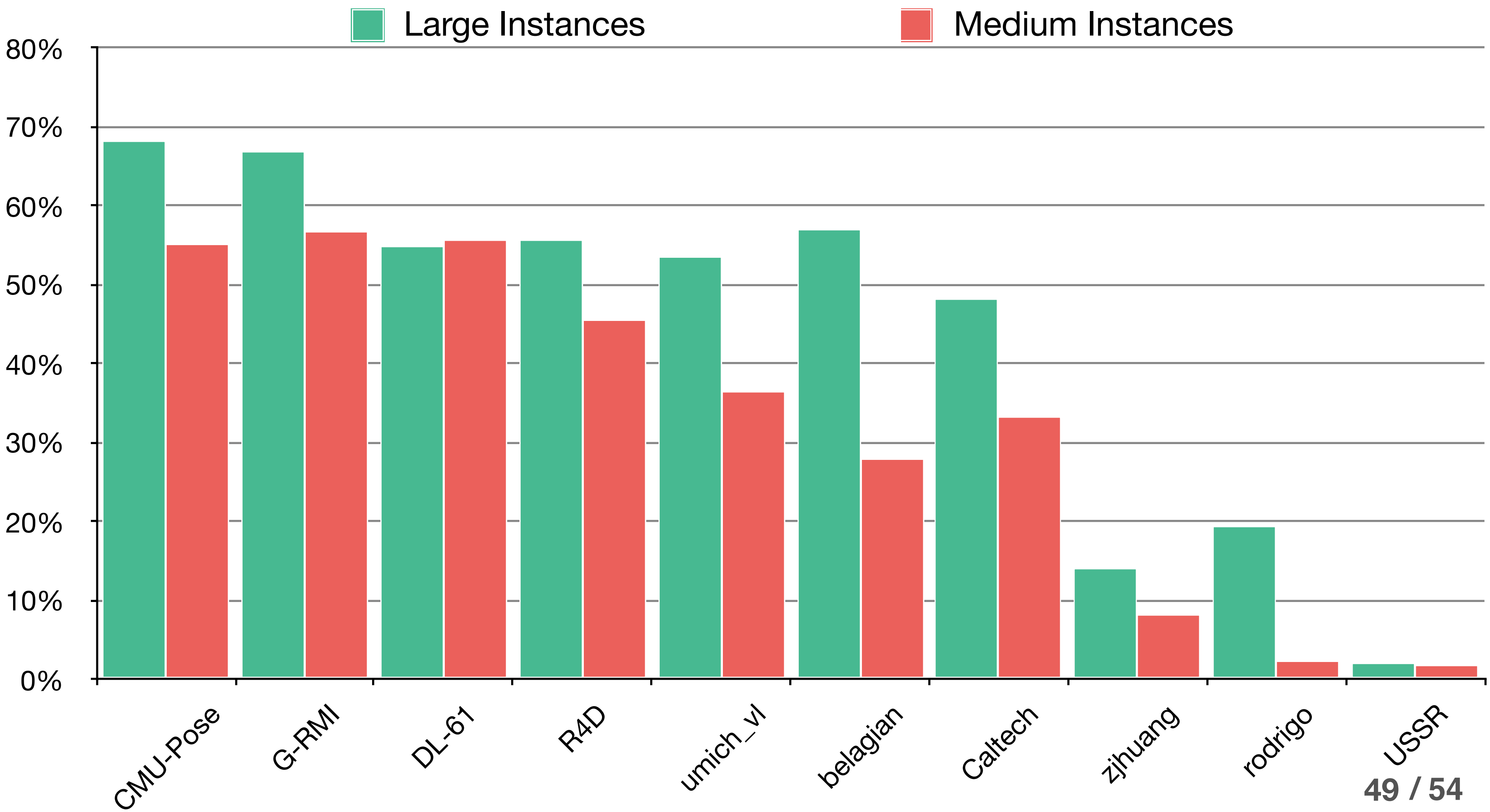

Performance Breakdown (I)

COCO AP varies across keypoints

CMU-Pose G-RMI DL-61 R4D
umich_vl belagian Caltech

100%

75%

50%

25%

0%

Performance Breakdown (I)

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- CMU-Pose
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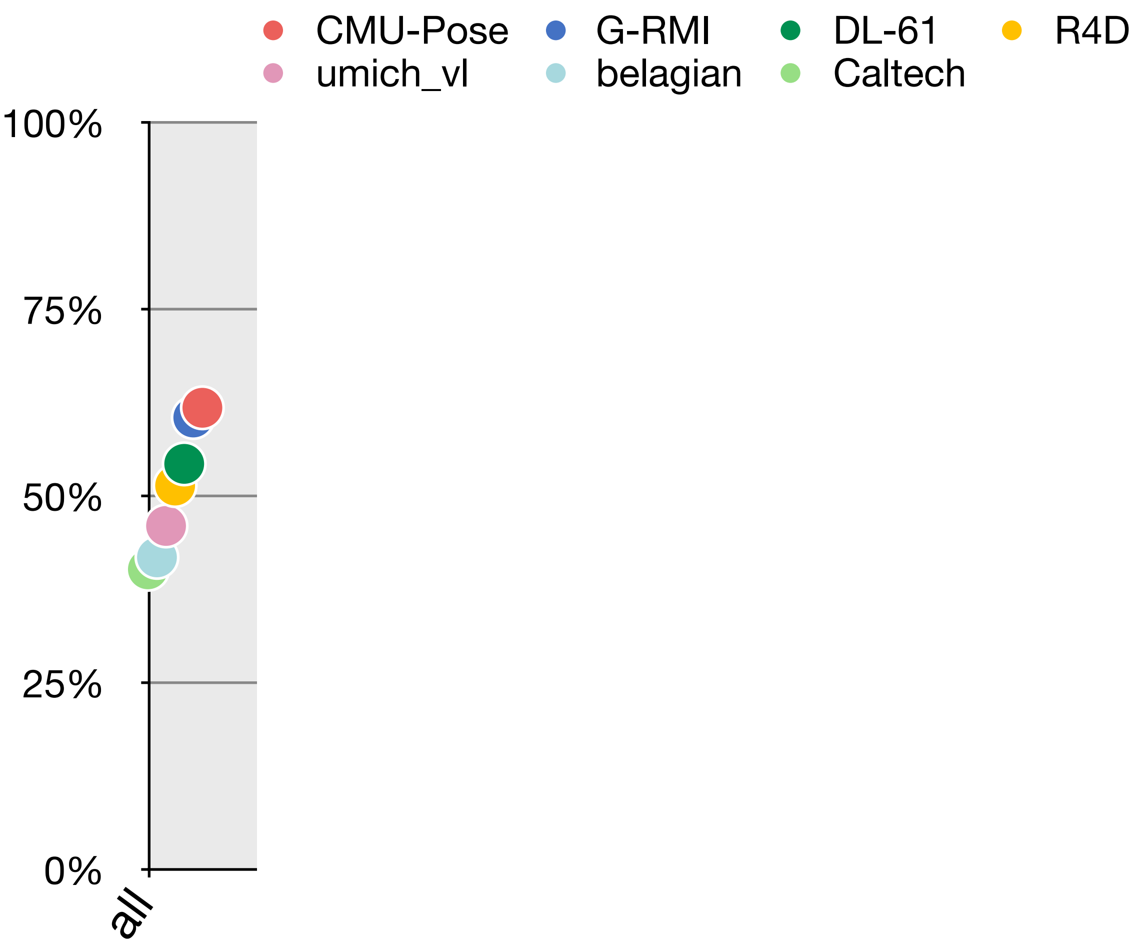

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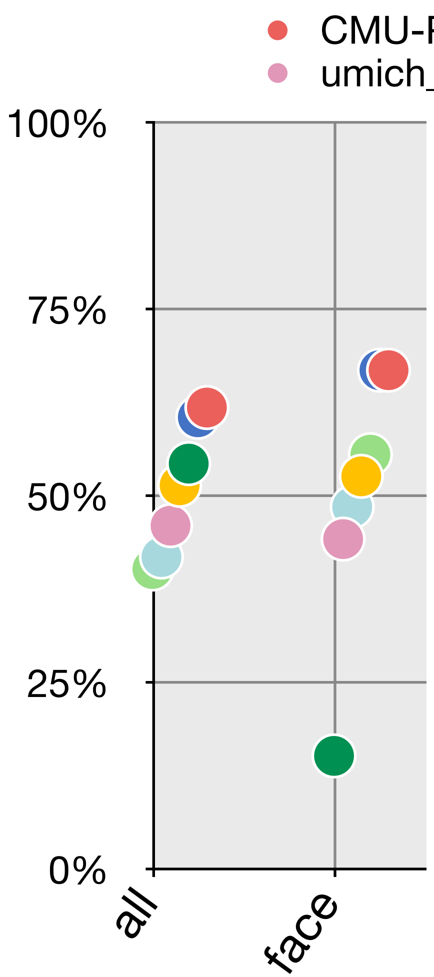

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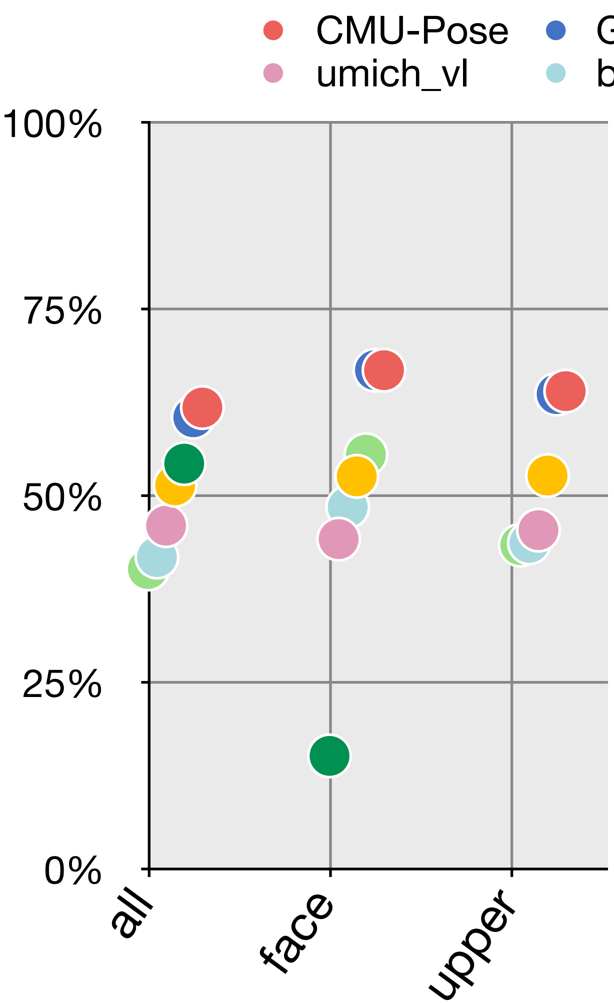

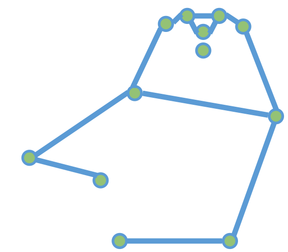

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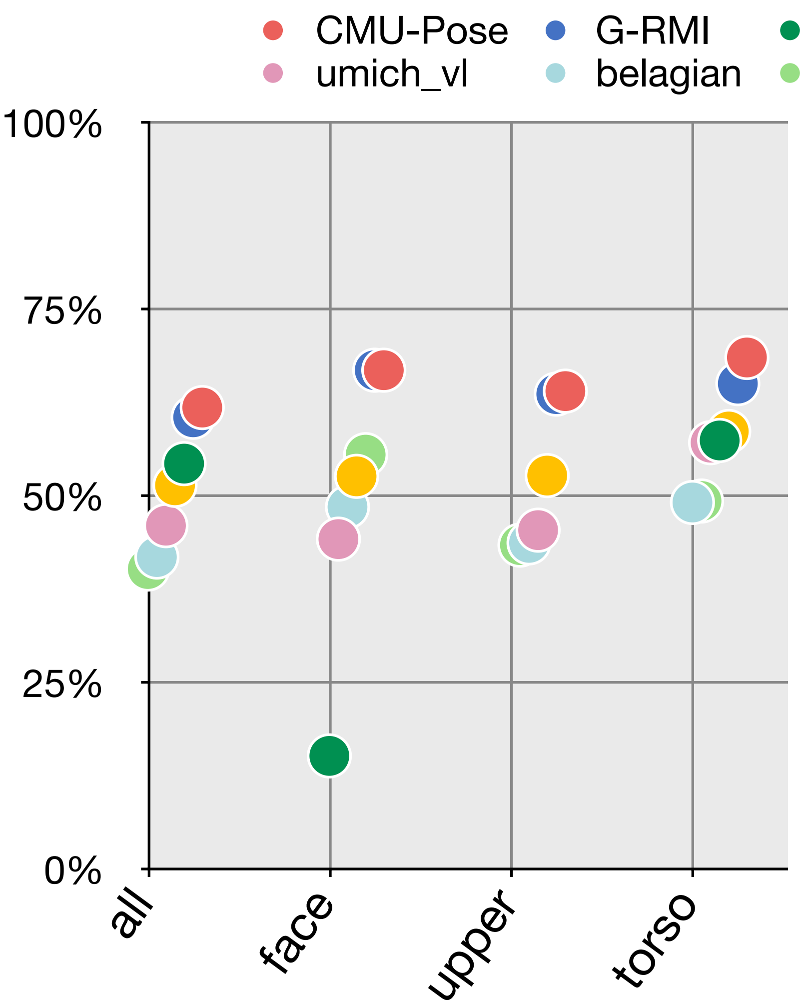

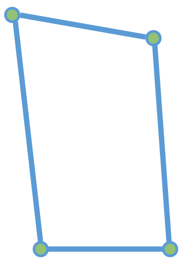

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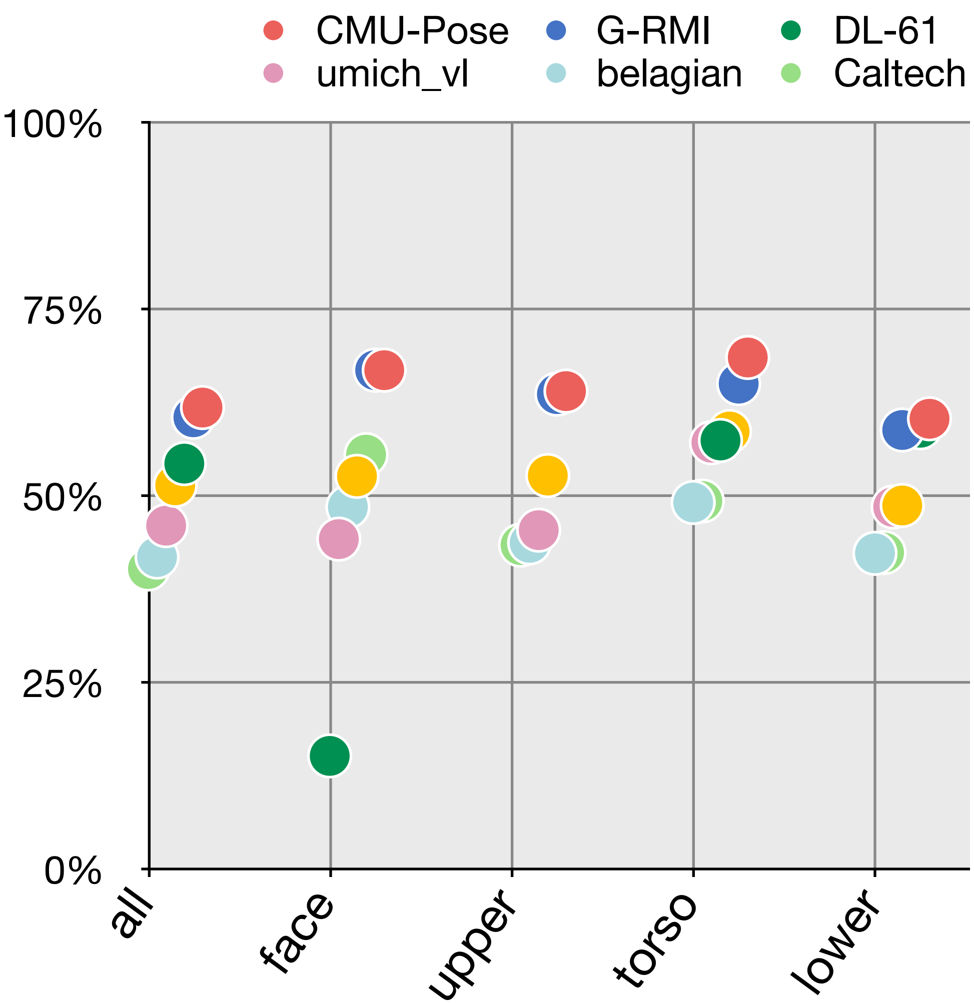

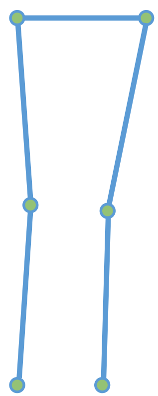

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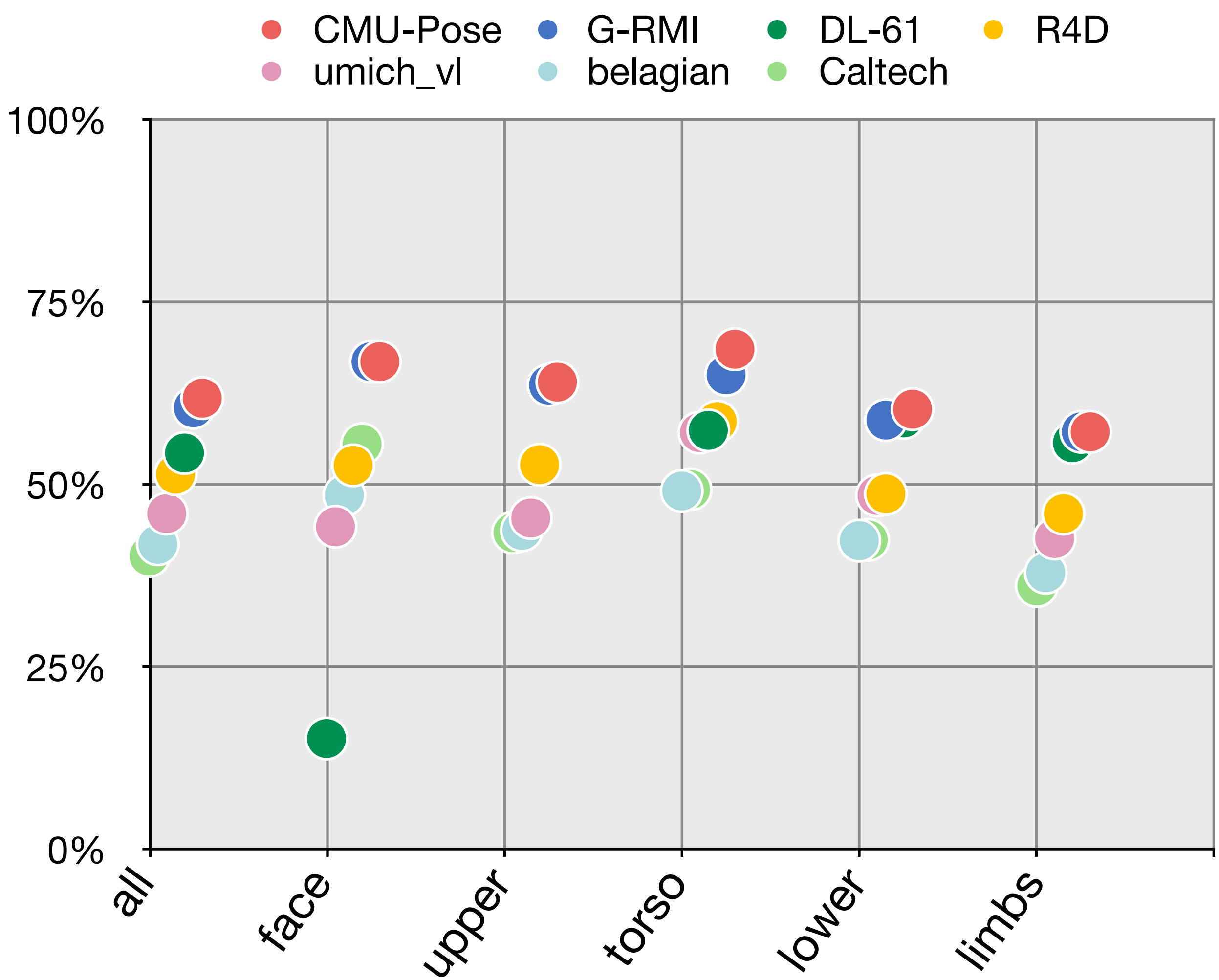

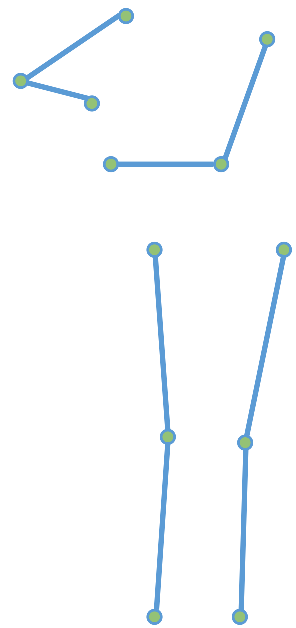

Correlation between methods

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How similarly do algorithms perform?

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CMU-Pose

G-RMI

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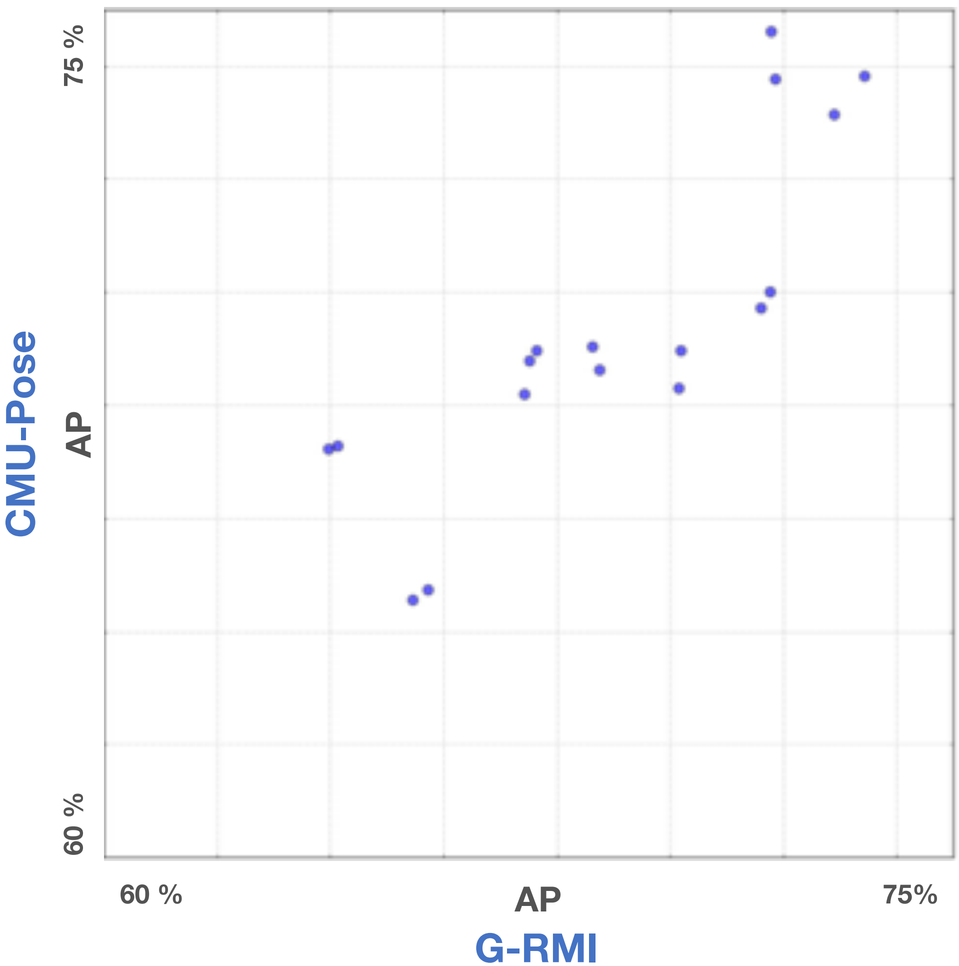

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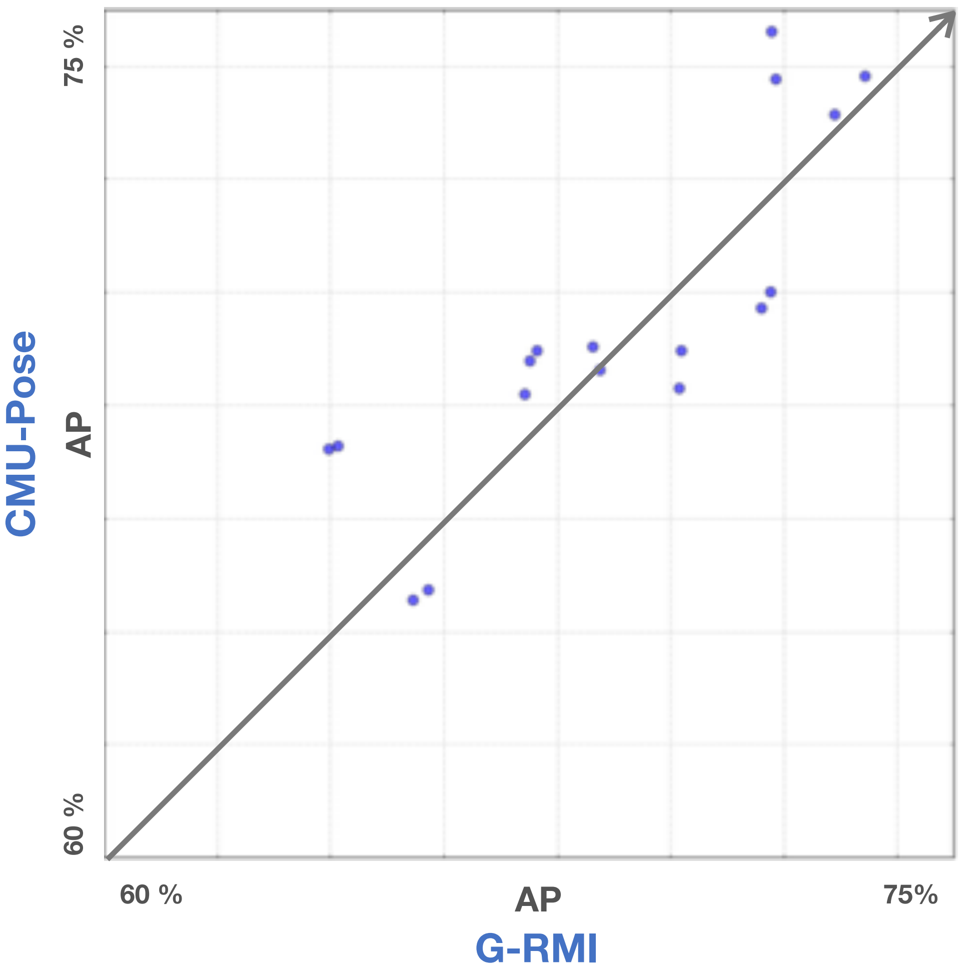

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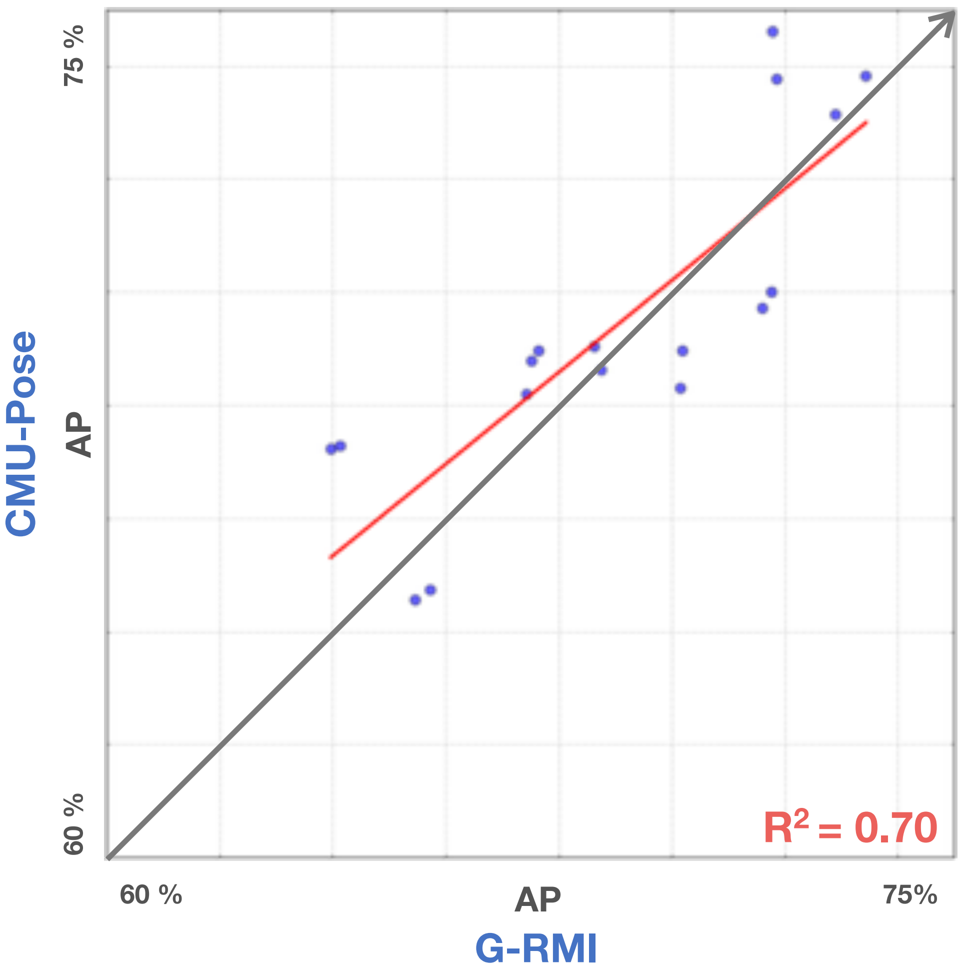

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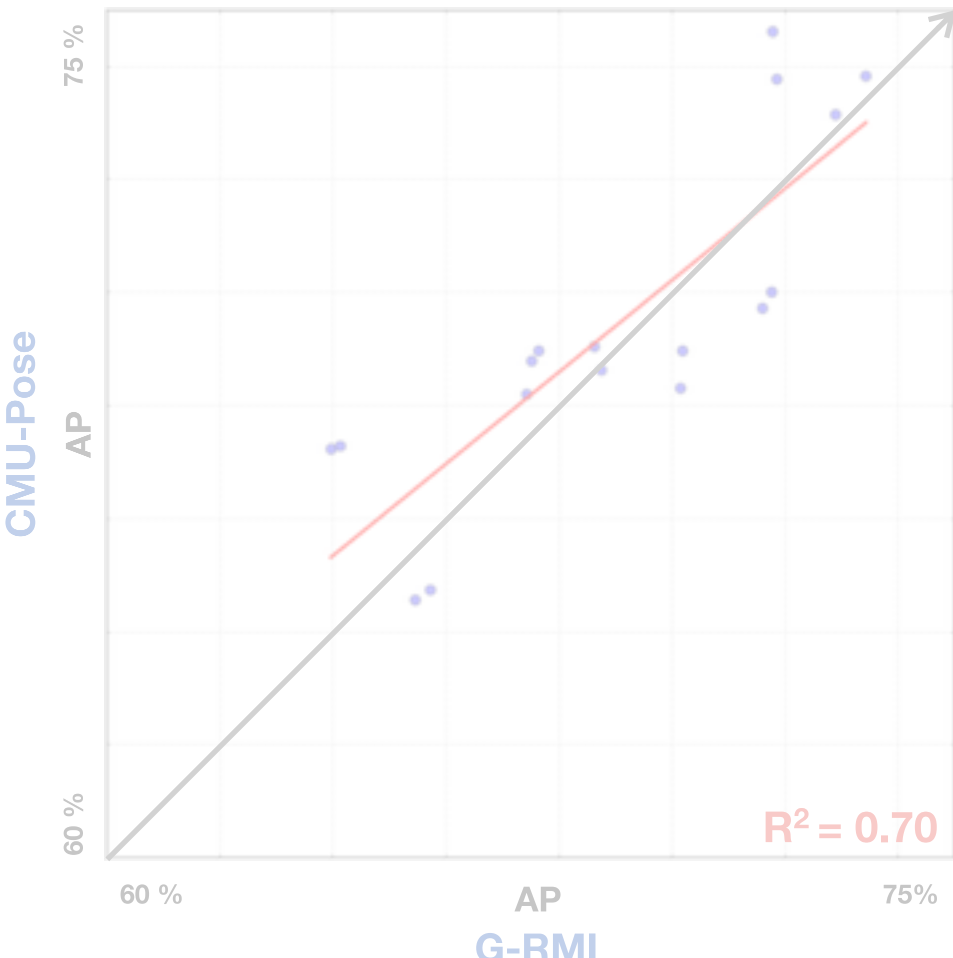

G-RMI

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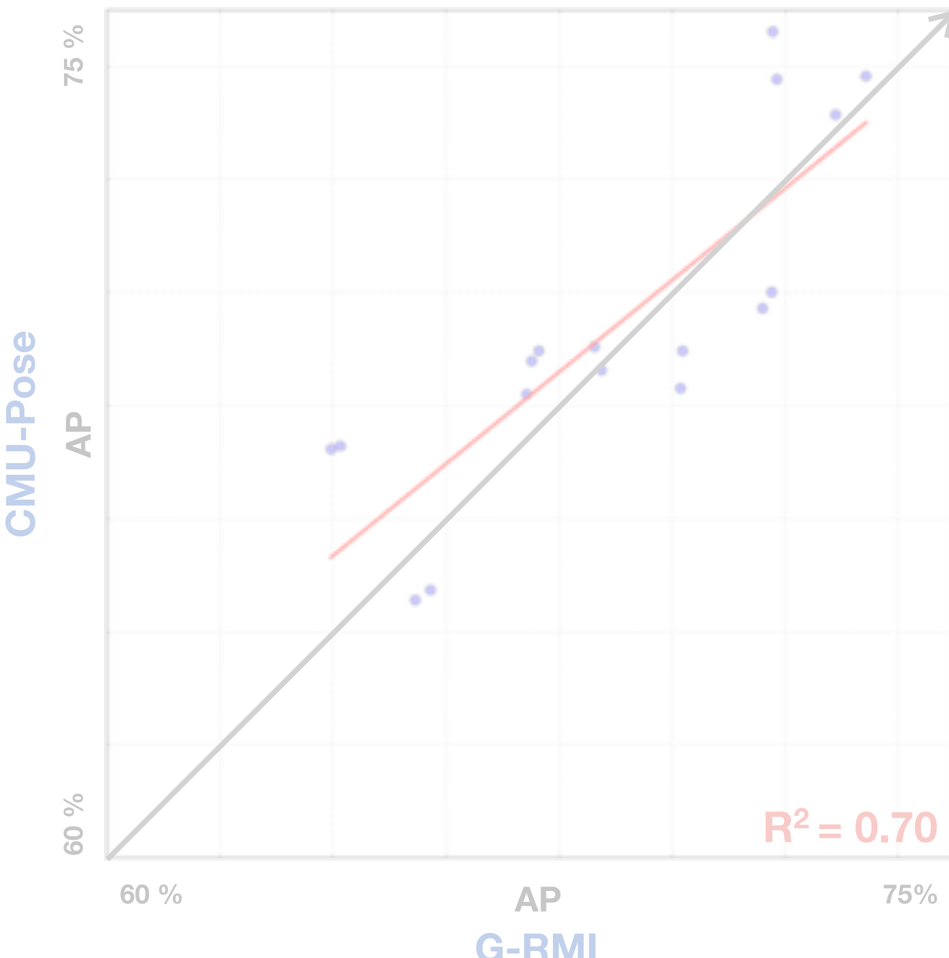

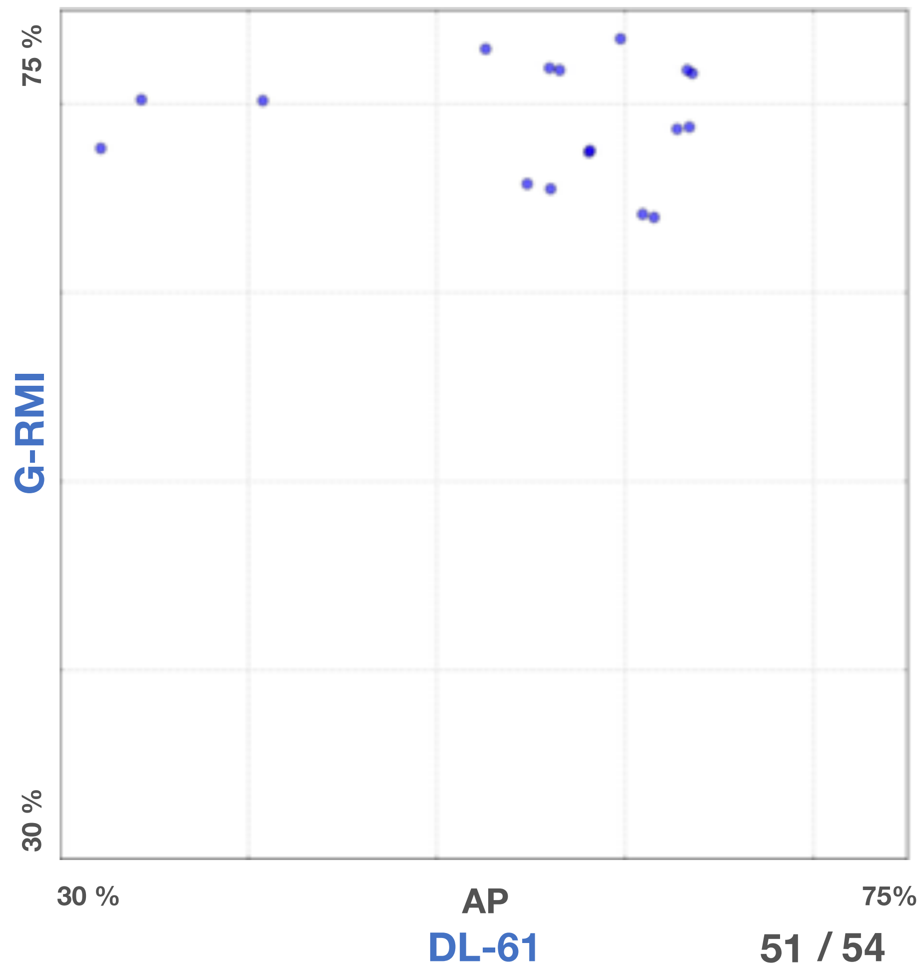

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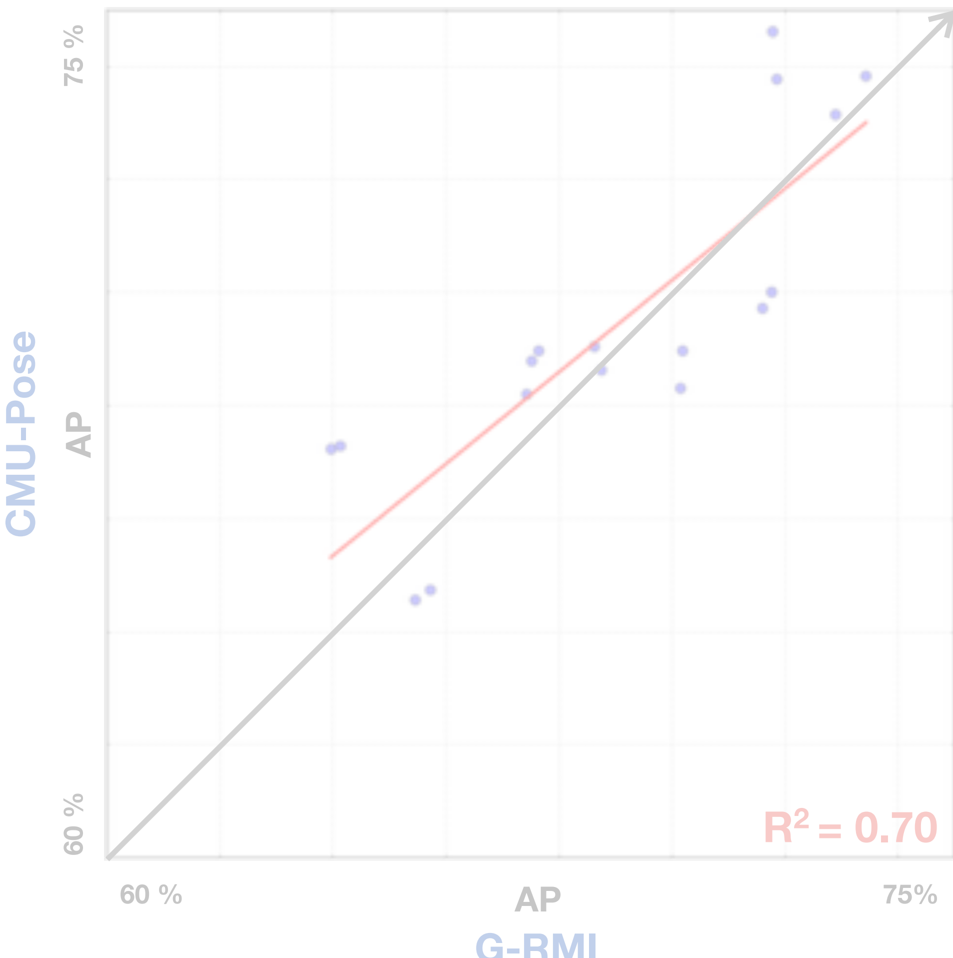

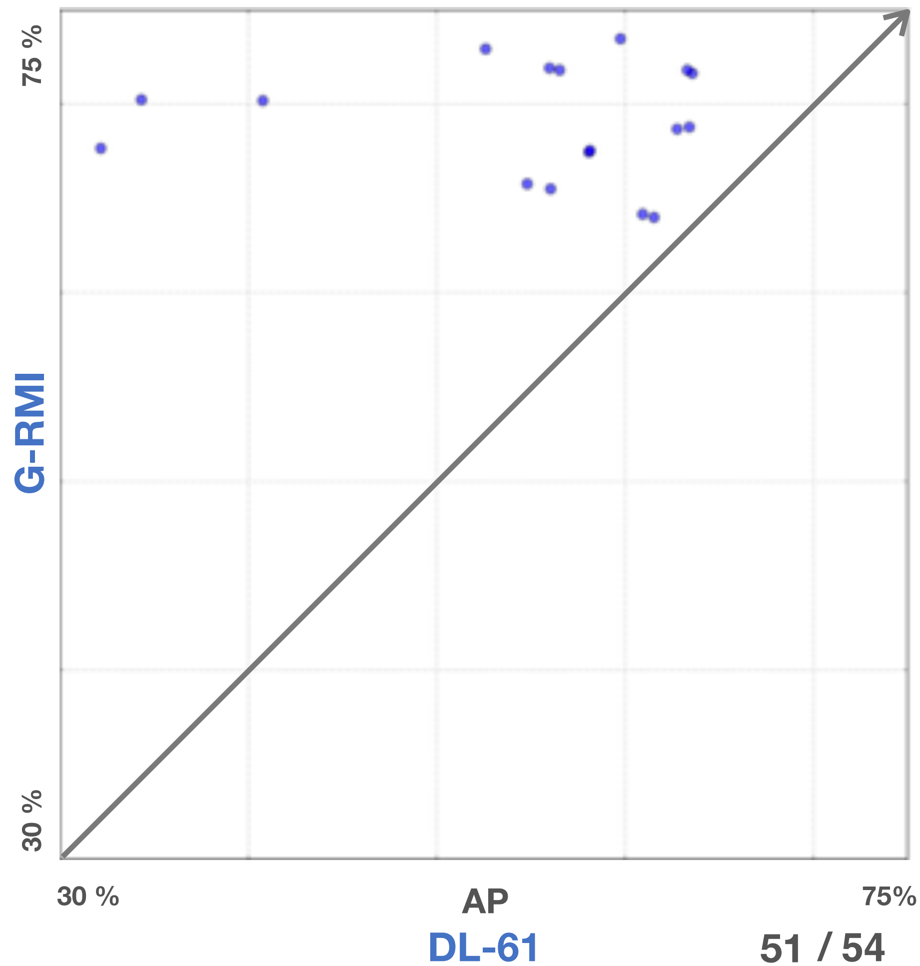

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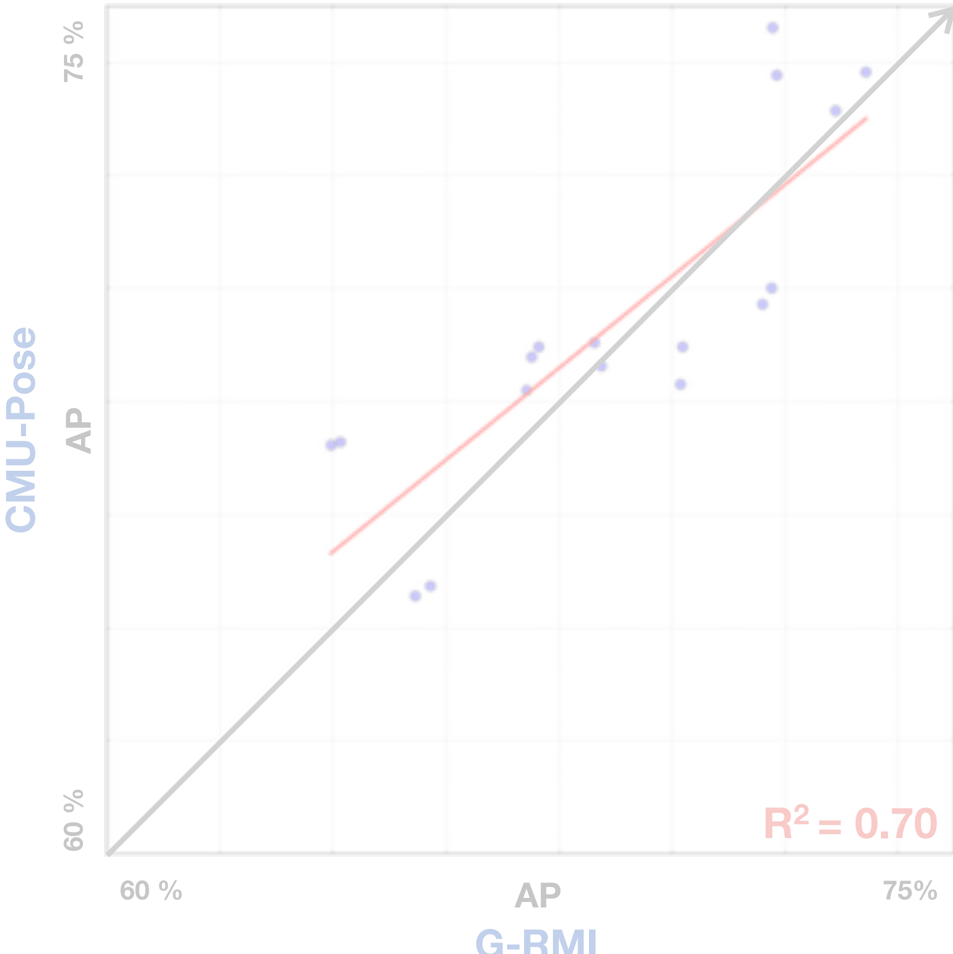

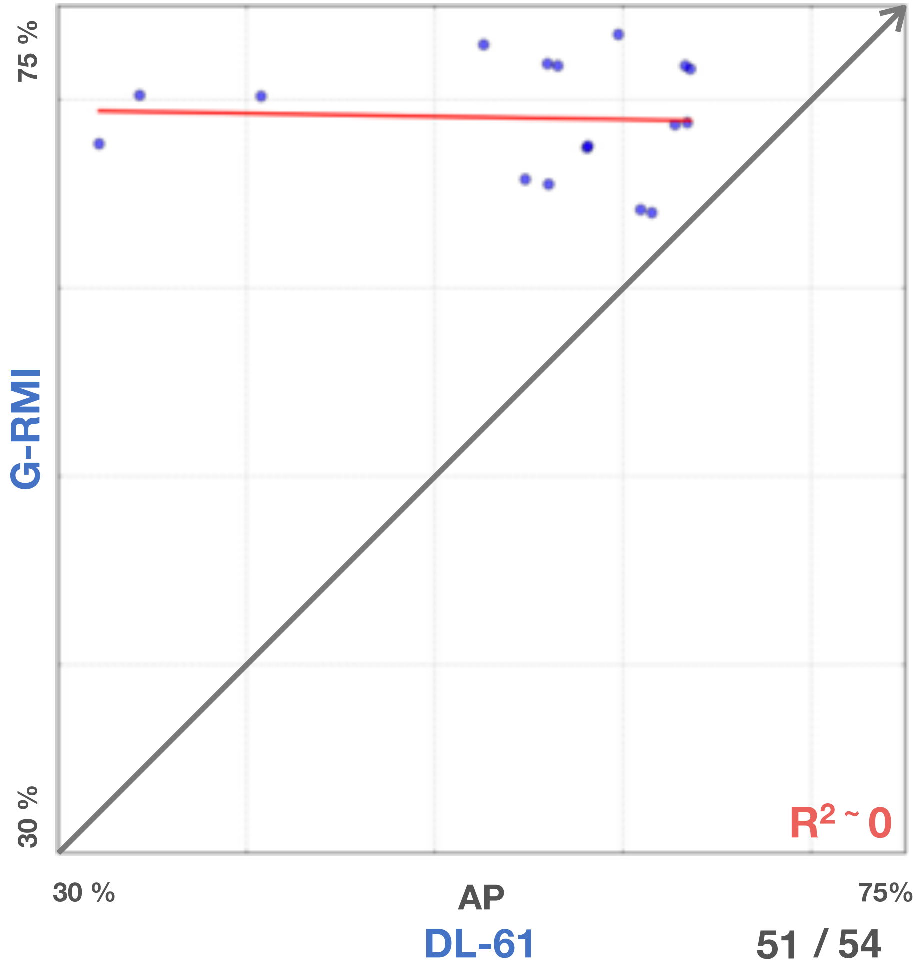

Types of Keypoint Errors

Types of Keypoint Errors

Excusable false positives.

Types of Keypoint Errors

Errors with high OKS impact.

Types of Keypoint Errors

Errors with low OKS impact.

Summary of Findings

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2016 Keypoint Challenge Take-aways

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- OKS is a new distance metric designed to equalize contribution of all keypoints.

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- Localization errors are predominant.
- Size of instances is impactful on performance.
- Performance can vary greatly across different keypoint sets.

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2016 Keypoint Challenge Take-aways

- OKS is a new distance metric designed to equalize contribution of all keypoints.
- Localization errors are predominant.
- Size of instances is impactful on performance.
- Performance can vary greatly across different keypoint sets.
- Human baselines are coming soon!

Challenge Ranking

Challenge Ranking

Team	Keypoints
CMU-Pose	1st
G-RMI	2nd
DL-61	3rd

Challenge Ranking

Team	Keypoints
CMU-Pose	1st
G-RMI	2nd
DL-61	3rd

Invited Speakers:

- CMU-Pose / (4:00pm - 4:15pm)
- G-RMI / (4:15pm - 4:30pm)