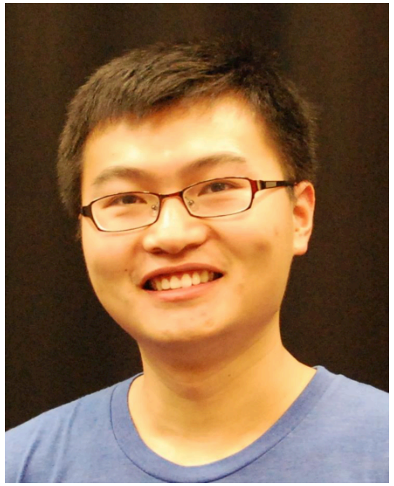
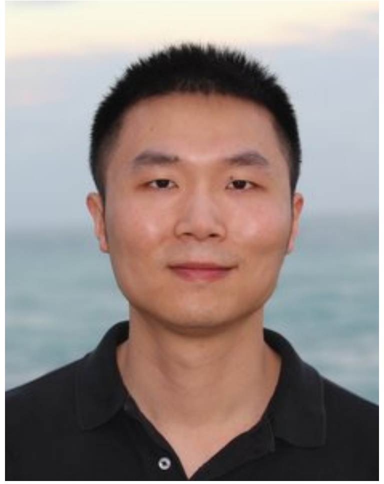
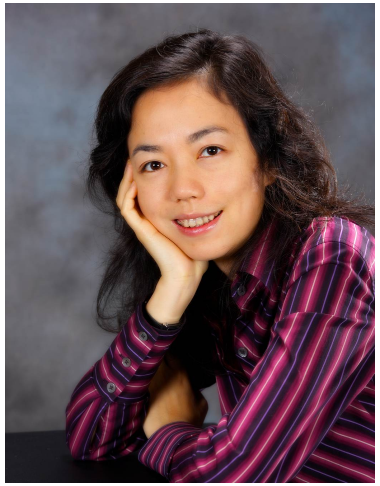
IMAGENET Large Scale Visual Recognition Challenge (ILSVRC) 2016

Object Detection (DET)


Wei Liu
UNC Chapel Hill

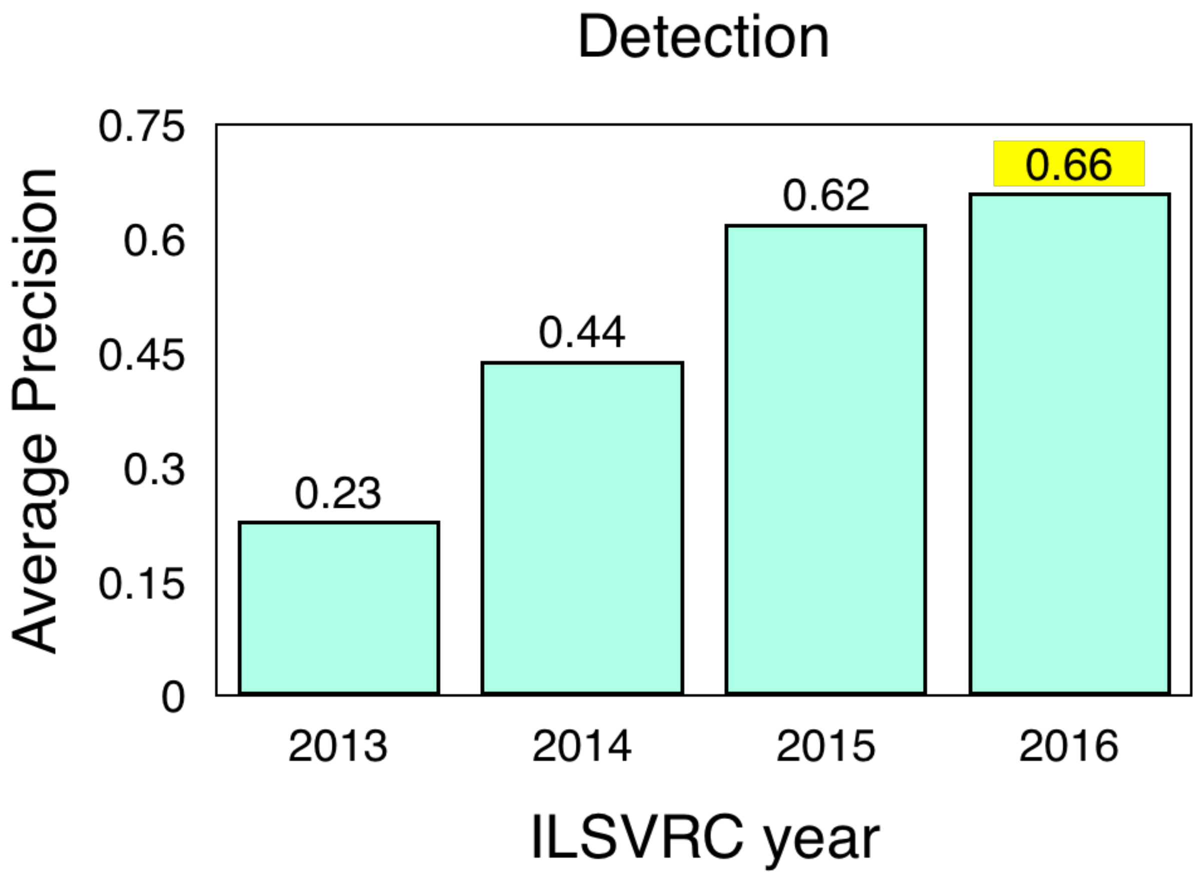

Olga Russakovsky
CMU


Jia Deng
Univ. of Michigan

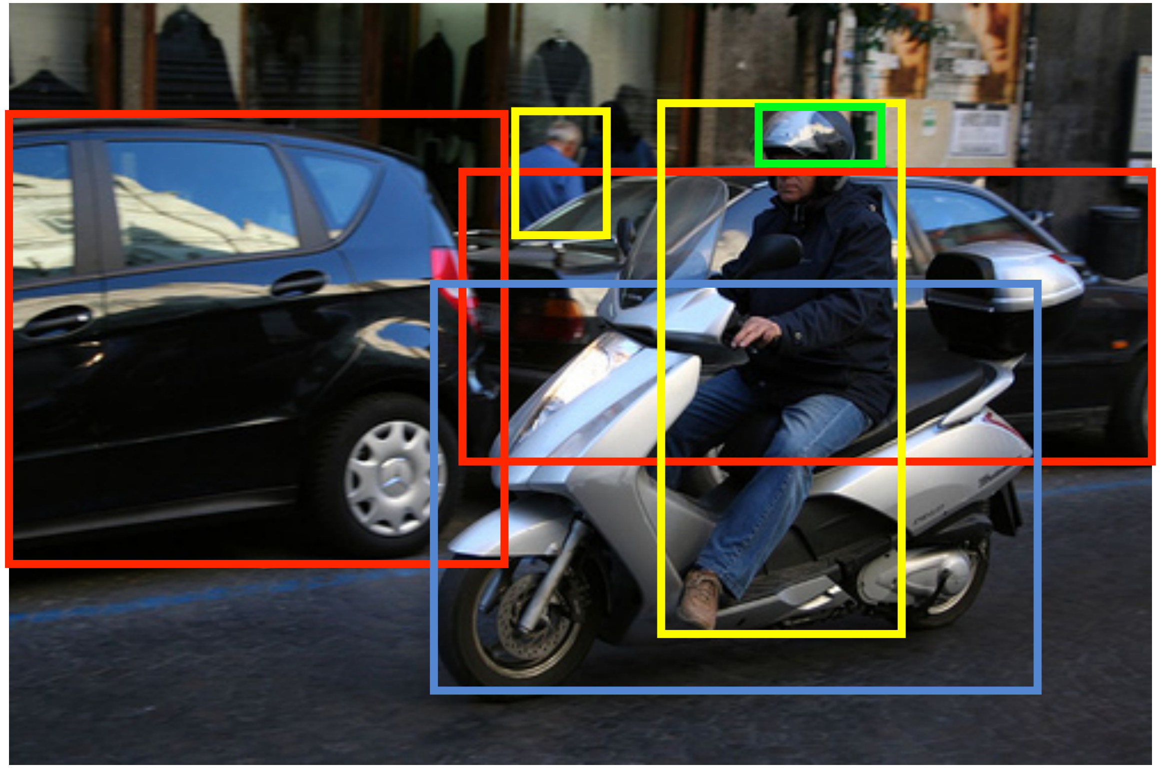

Fei-Fei Li
Stanford


Alex Berg
UNC Chapel Hill

Result in ILSVRC over the years



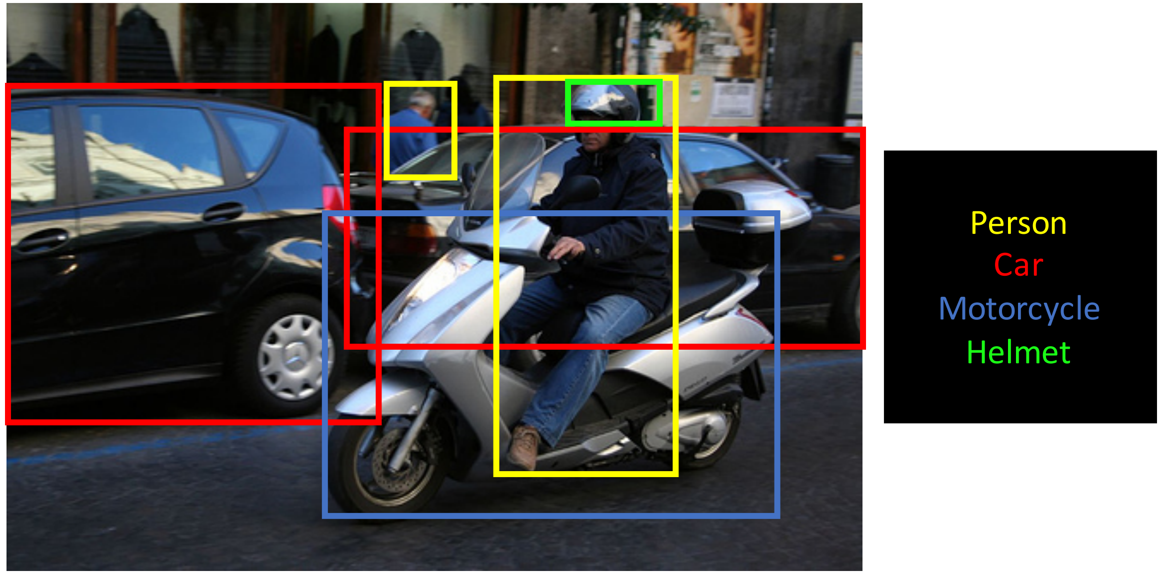
ILSVRC object detection (DET) task



Person
Car
Motorcycle
Helmet

200 object classes **527,982 images** **DET**

ILSVRC object detection (DET) task



This year: 11142 new test images with bounding boxes fully annotated

Evaluation modeled after PASCAL VOC:

- Algorithm outputs a list of bounding box detections with confidences
- A detection is considered correct if intersection over union (IoU) overlap with ground truth > threshold (0.5)
- Evaluated by average precision per object class
- Winners of challenge is the team that wins the most object categories

Everingham, Van Gool, Williams, Winn and Zisserman.
The PASCAL Visual Object Classes (VOC) Challenge. IJCV 2010.

ILSVRC 2016 DET new test data collection

- Step 1: Retrieve images with 129 manually curated queries from Flickr

afternoon tea
ant bridge building
armadillo race
…
zoo feeding
zoo in austrialia

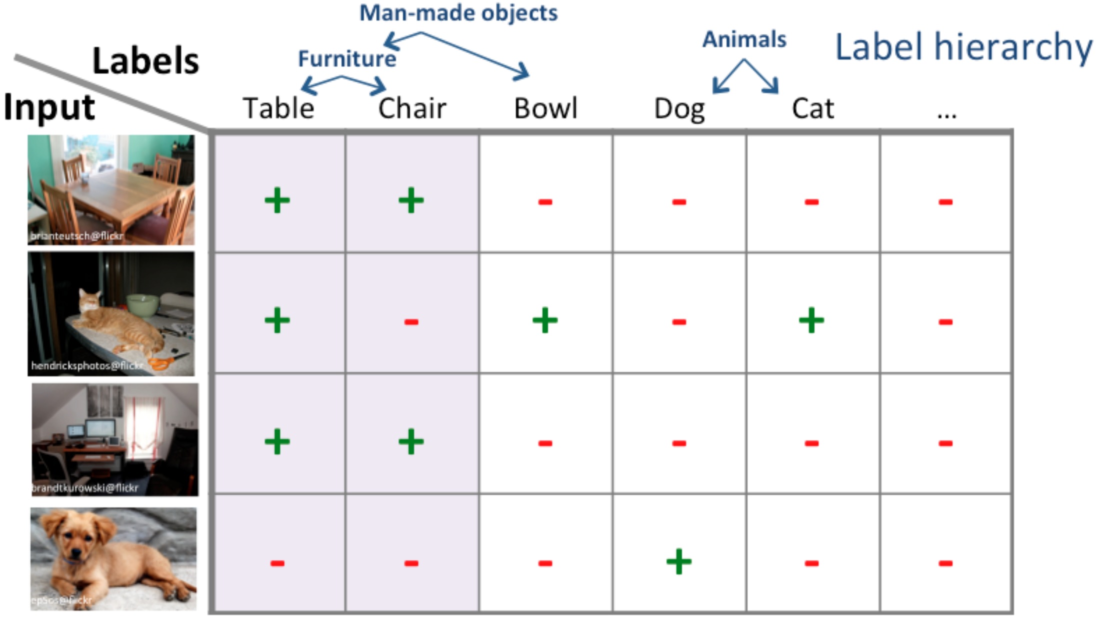
flickr

…

Olga Russakovsky, Jia Deng, et.al.
ImageNet Large Scale Visual Recognition Challenge. IJCV 2015.

ILSVRC 2016 DET new test data collection

- Step 1: Retrieve images with 129 manually curated queries from Flickr
- Step 2: Annotate images completely with all categories



Scalable Multi-Label Annotation
Jia Deng, Olga Russakovsky, et.al. CHI 2014.

ILSVRC 2016 DET new test data collection

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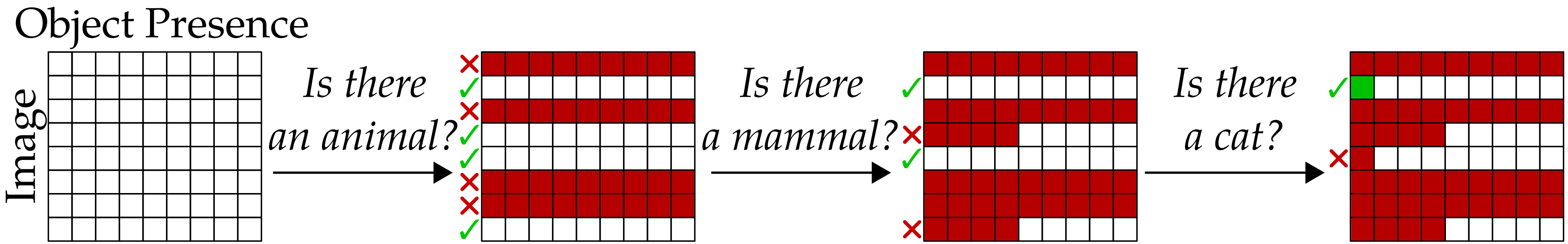


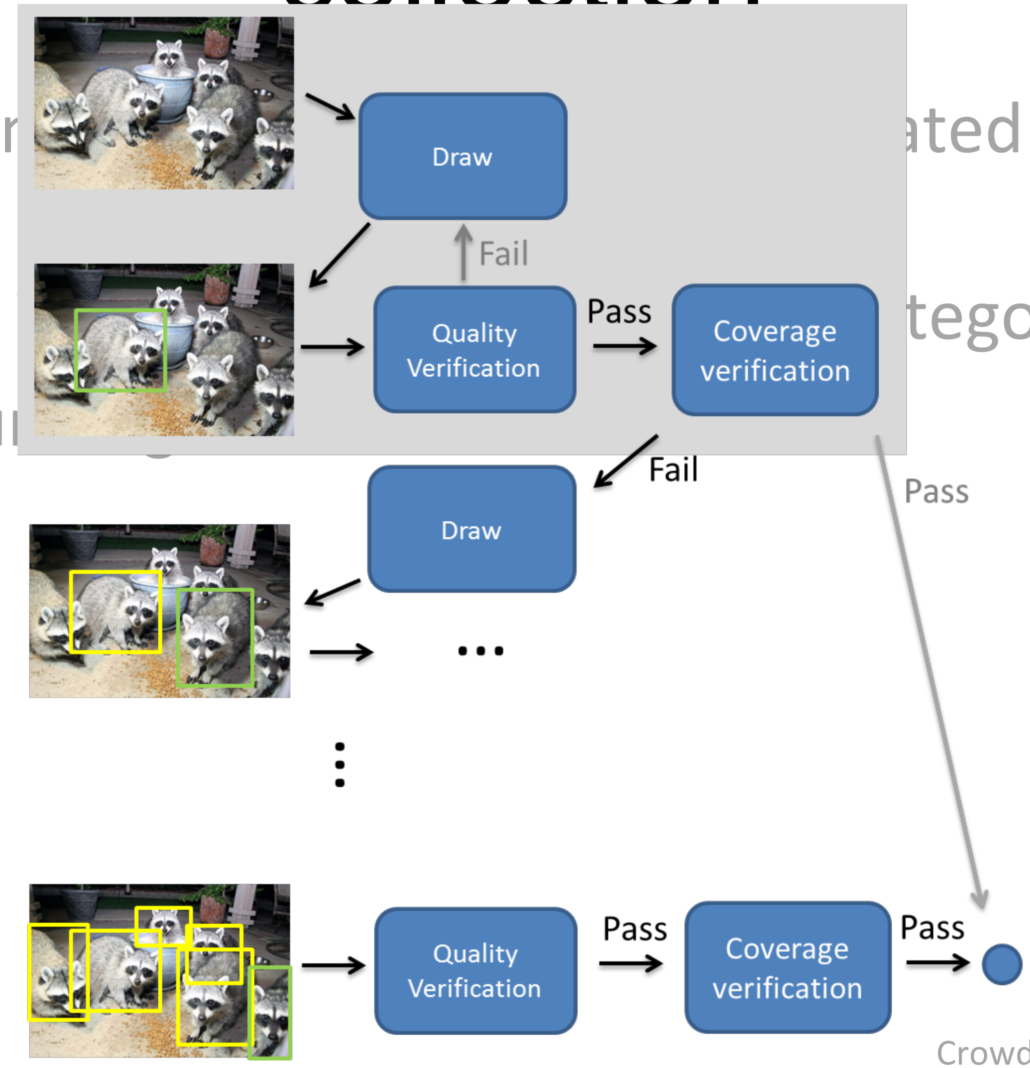
Scalable Multi-Label Annotation
Jia Deng, Olga Russakovsky, et.al. CHI 2014.

ILSVRC 2016 DET new test data collection

- Step 1: Retrieve images with 129 manually curated queries from Flickr
- Step 2: Annotate images completely with all categories
- Step 3: Draw bounding boxes

ILSVRC 2016 DET new test data collection

- Step 1: Retrieve i… …ated queries from Flickr
- Step 2: Annotate … …tegories
- Step 3: Draw bou…



Crowdsourcing Annotations for Visual Object Detection
Hao Su, Jia Deng, Li Fei-Fei. AAAI 2012 workshop.

ILSVRC2016 DET results – with “provided” data

Team Name	Number of categories won	Mean Average Precision(%)
CUImage	109	66.3
Hikvision	30	65.3
NUIST	15	60.9
Trimps-Soushen	8	61.8
360+MCG-ICT-CAS_DET	4	61.6

CUImage:
Wanli Ouyang, Junjie Yan, Xingyu Zeng, Hongsheng Li, Tong Xiao, Kun Wang, Xin Zhu, Yucong Zhou, Yu Liu, Buyu Li, Zhiwei Fang, Changbao Wang, Zhe Wang, Hui Zhou, Liping Zhang, Xingcheng Zhang, Zhizhong Li, Hongyang Li, Ruohui Wang, Shengen Yan, Dahua Lin, Xiaogang Wang

The Chinese University of Hong Kong, SenseTime Group Limited

Hikvision:
Qiaoyong Zhong*, Chao Li, Yingying Zhang(#), Haiming Sun*, Shicai Yang*, Di Xie, Shiliang Pu

(* indicates equal contribution)
Hikvision Research Institute
(#)ShanghaiTech University, is done at HRI

ILSVRC2016 DET results – with "external" data

Team Name	Number of categories won	Mean Average Precision(%)
CUImage	176	66.0
Trimps-Soushen	22	61.7
NUIST	1	54.3
DPAI Vision	0	53.5

CUImage:
Wanli Ouyang, Junjie Yan, Xingyu Zeng, Hongsheng Li, Tong Xiao, Kun Wang, Xin Zhu, Yucong Zhou, Yu Liu, Buyu Li, Zhiwei Fang, Changbao Wang, Zhe Wang, Hui Zhou, Liping Zhang, Xingcheng Zhang, Zhizhong Li, Hongyang Li, Ruohui Wang, Shengen Yan, Dahua Lin, Xiaogang Wang

The Chinese University of Hong Kong, SenseTime Group Limited

Trimps-Soushen:
Jie Shao, Xiaoteng Zhang, Zhengyan Ding, Yixin Zhao, Yanjun Chen, Jianying Zhou, Wenfei Wang, Lin Mei, Chuanping Hu

The Third Research Institute of the Ministry of Public Security, P.R. China.

Object detection (DET)

Winner with "provided" and "external" data

CUImage:
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The Chinese University of Hong Kong,
SenseTime Group Limited

COCO
Common Objects in Context

2nd Detection / Segmentation Challenge

Yin Cui, Tsung-Yi Lin, Matteo Ruggero Ronchi, Genevieve Patterson

ECCV'16
EUROPEAN CONFERENCE ON COMPUTER VISION
October 8 – 16, 2016 | Amsterdam | the Netherlands

ImageNet and COCO Visual Recognition Challenges Workshop

Sunday, October 9th, ECCV 2016

Workshop Organizers

Tsung-Yi Lin
Cornell Tech

Yin Cui
Cornell Tech

Matteo Ruggero Ronchi
Caltech

Genevieve Patterson
Brown University

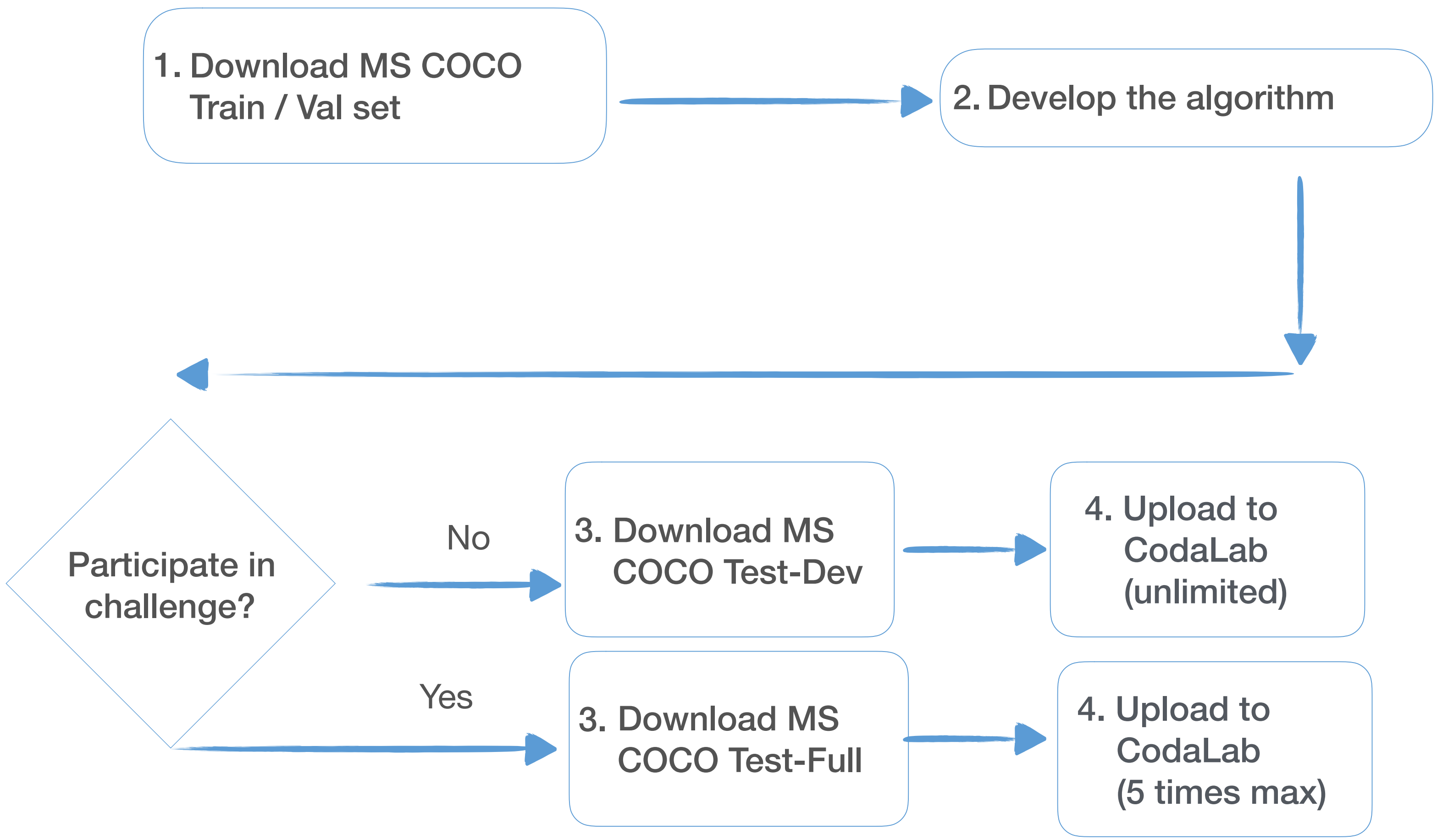
Workshop Advisors:

Michael Maire
Serge Belongie
Lubomir Bourdev
Ross Girshick
James Hays
Pietro Perona
Larry Zitnick
Piotr Dollár

Award Committee:

Deva Ramanan
Pietro Perona
Michael Maire
Lubomir Bourdev
Serge Belongie
Matteo Ruggero Ronchi
Genevieve Patterson
Yin Cui

Outline


1. Download MS COCO Train / Val set
2. Develop the algorithm
Participate in challenge?
No
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4. Upload to CodaLab (unlimited)
3. Download MS COCO Test-Full
4. Upload to CodaLab (5 times max)

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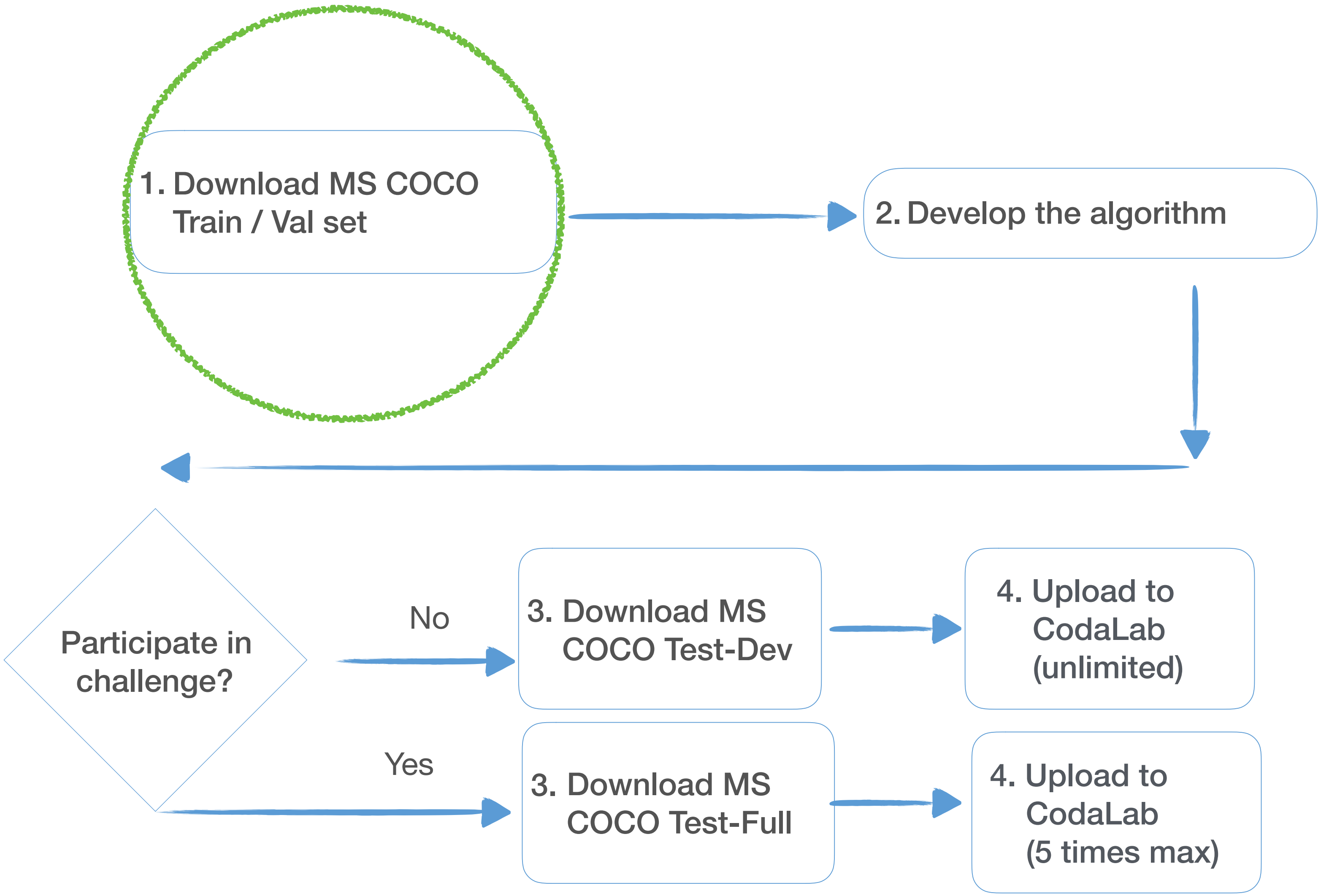
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COCO Dataset

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Common Objects in Context

- 80 object categories
- 200k images
- 1.2M instances (350k people)
- Every instance segmented

Available for download at
mscoco.org

COCO Dataset

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Common Objects in Context

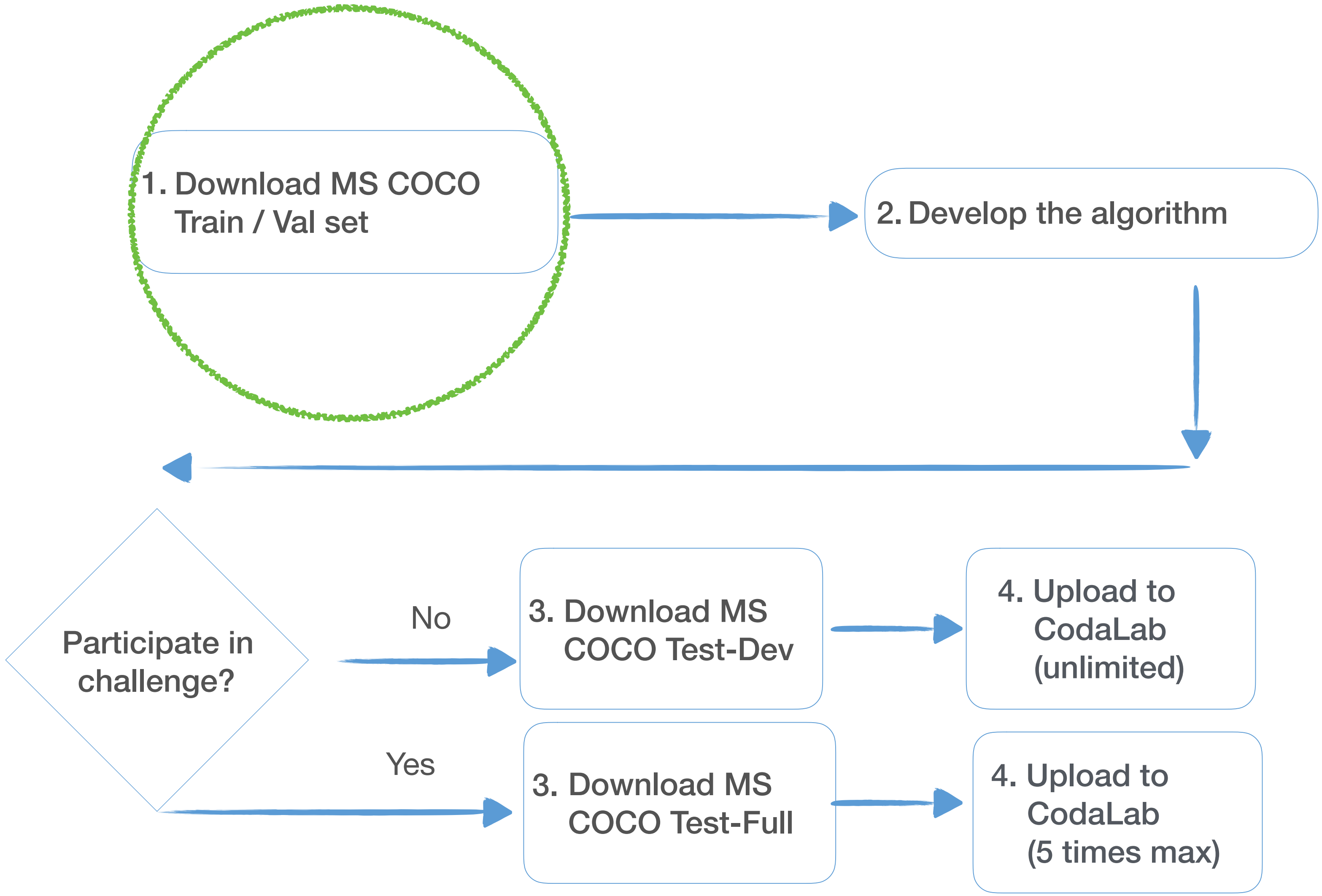
- 80 object categories
- 200k images
- 1.2M instances (350k people)
- Every instance segmented
- **106k people with keypoints** NEW

Available for download at
mscoco.org

COCO 3rd Party Datasets

Available for download at
mscoco.org/external

Outline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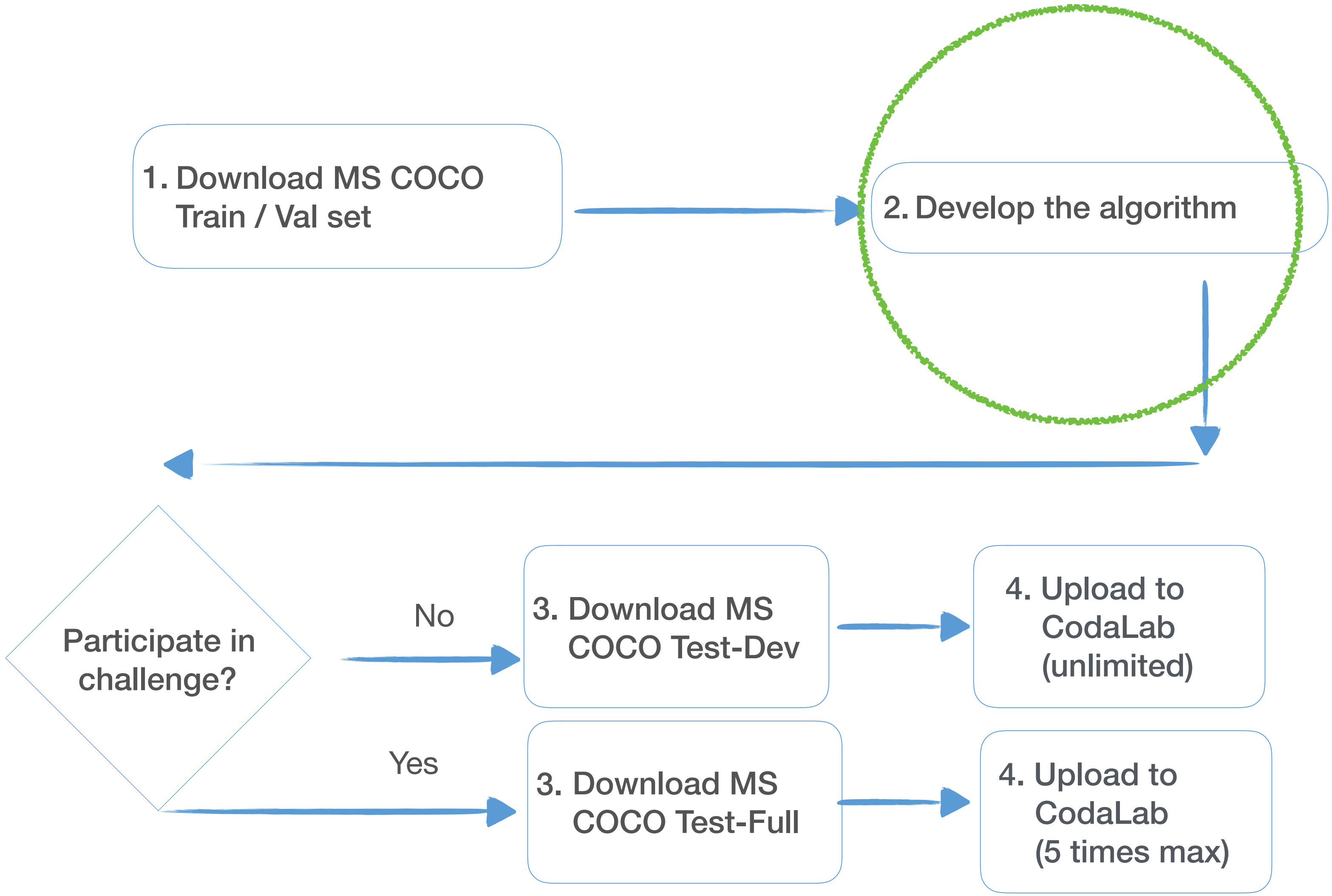
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Shout-out to previous algorithms!

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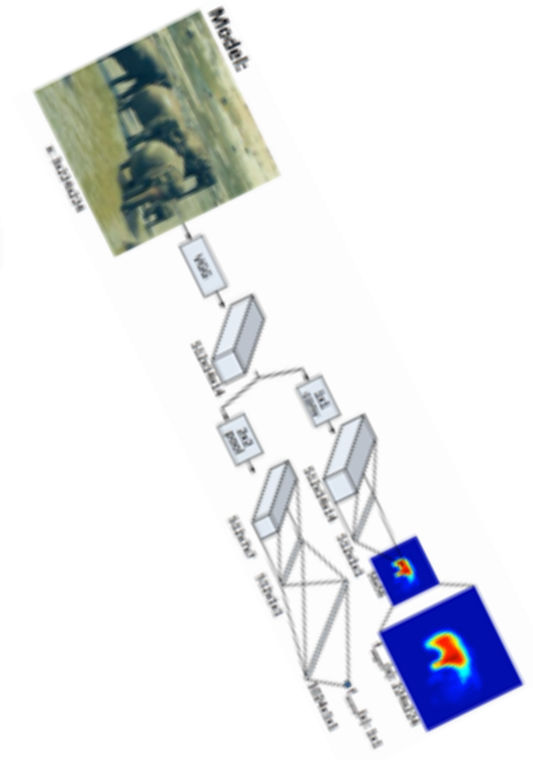
ResNet, 152 layers
(ILSVRC 2015)



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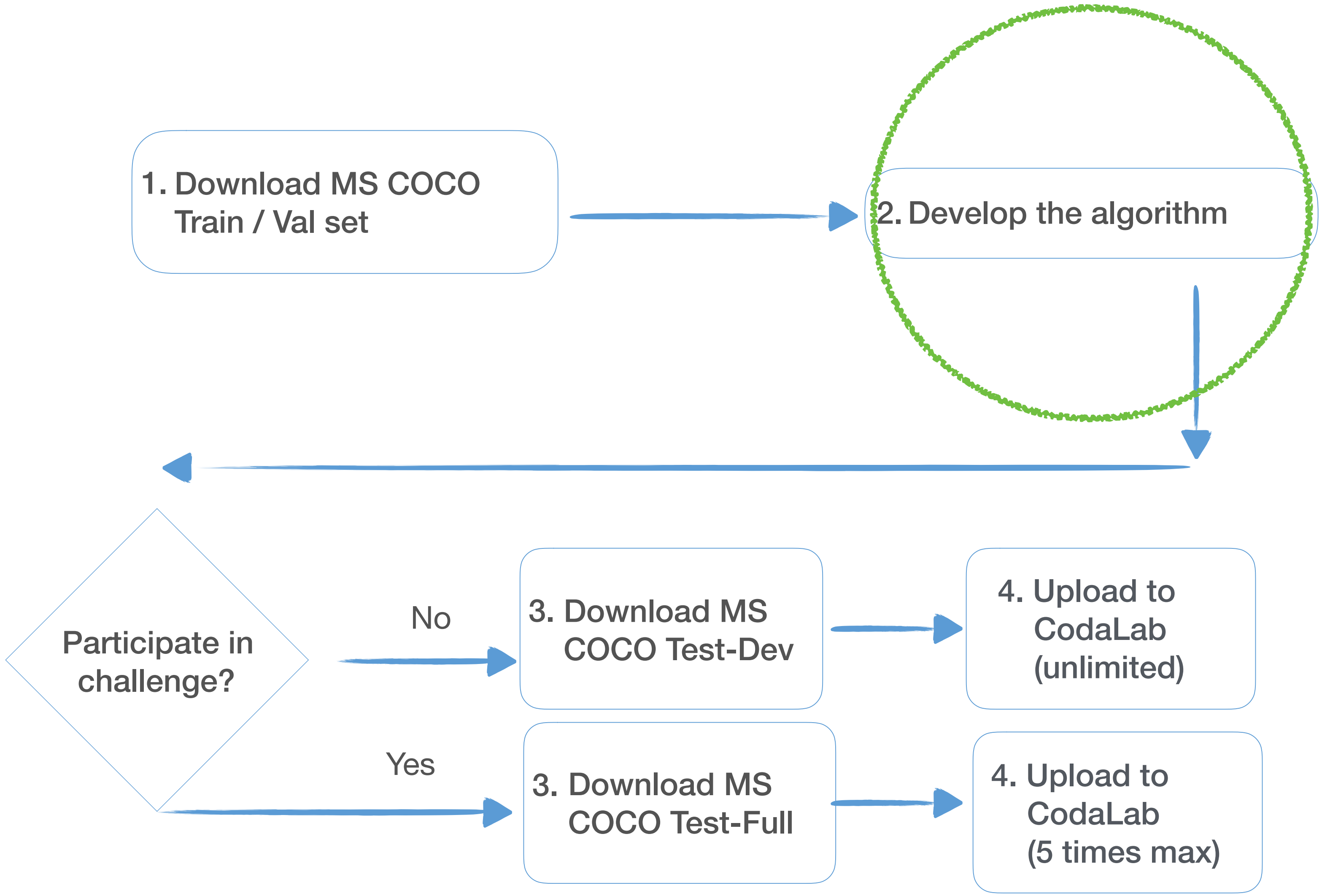
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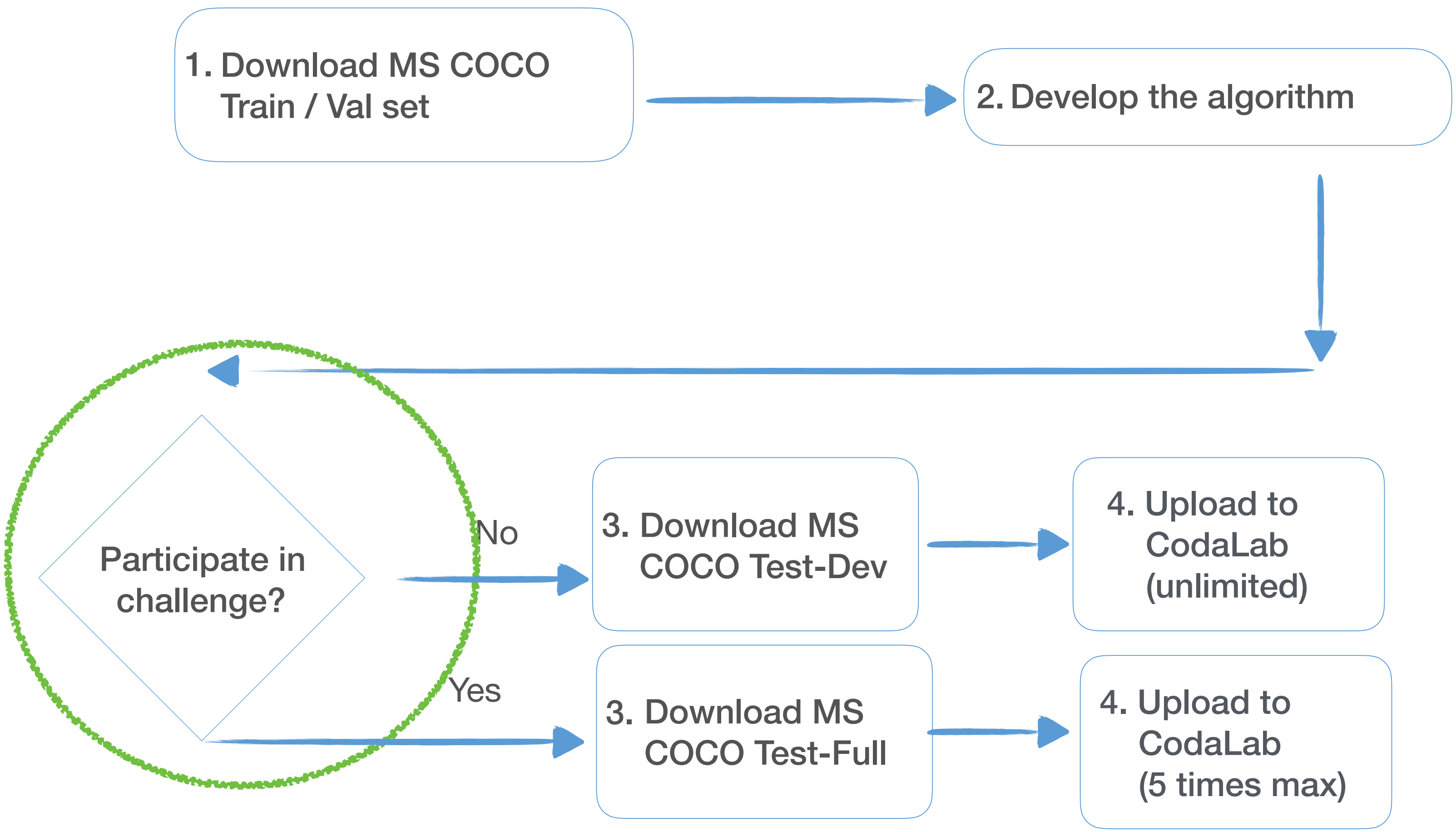
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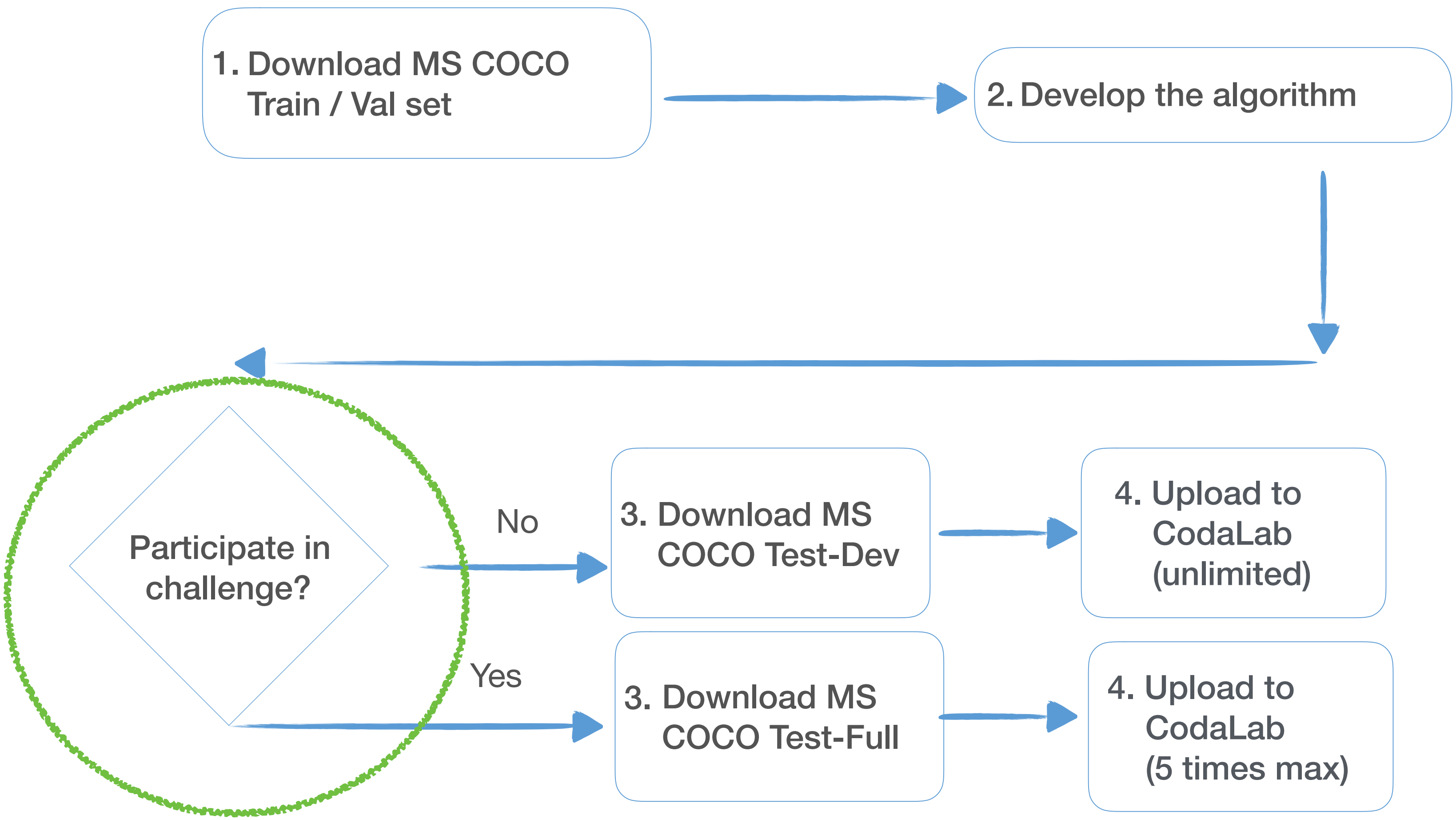
Challenges at ECCV 2016

COCO
Common Objects in Context

Detection | Segmentation | Keypoints

Outline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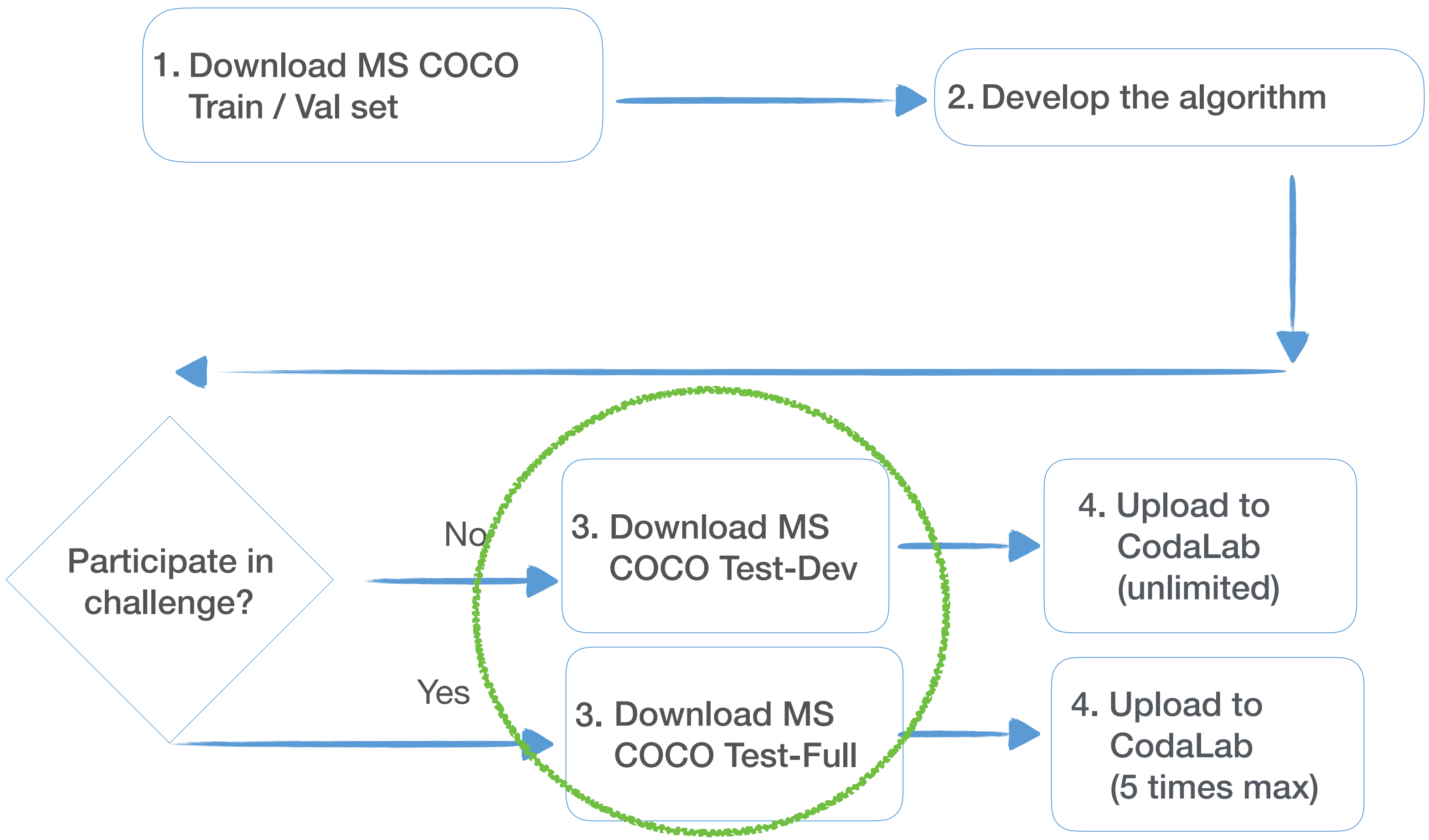
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Used to score entries for the Public Leaderboard.

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Used to score workshop competition.

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Test-dev (development)

Debugging, Validation and Ablation Studies.
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Test-standard (publications)

Used to score entries for the Public Leaderboard.

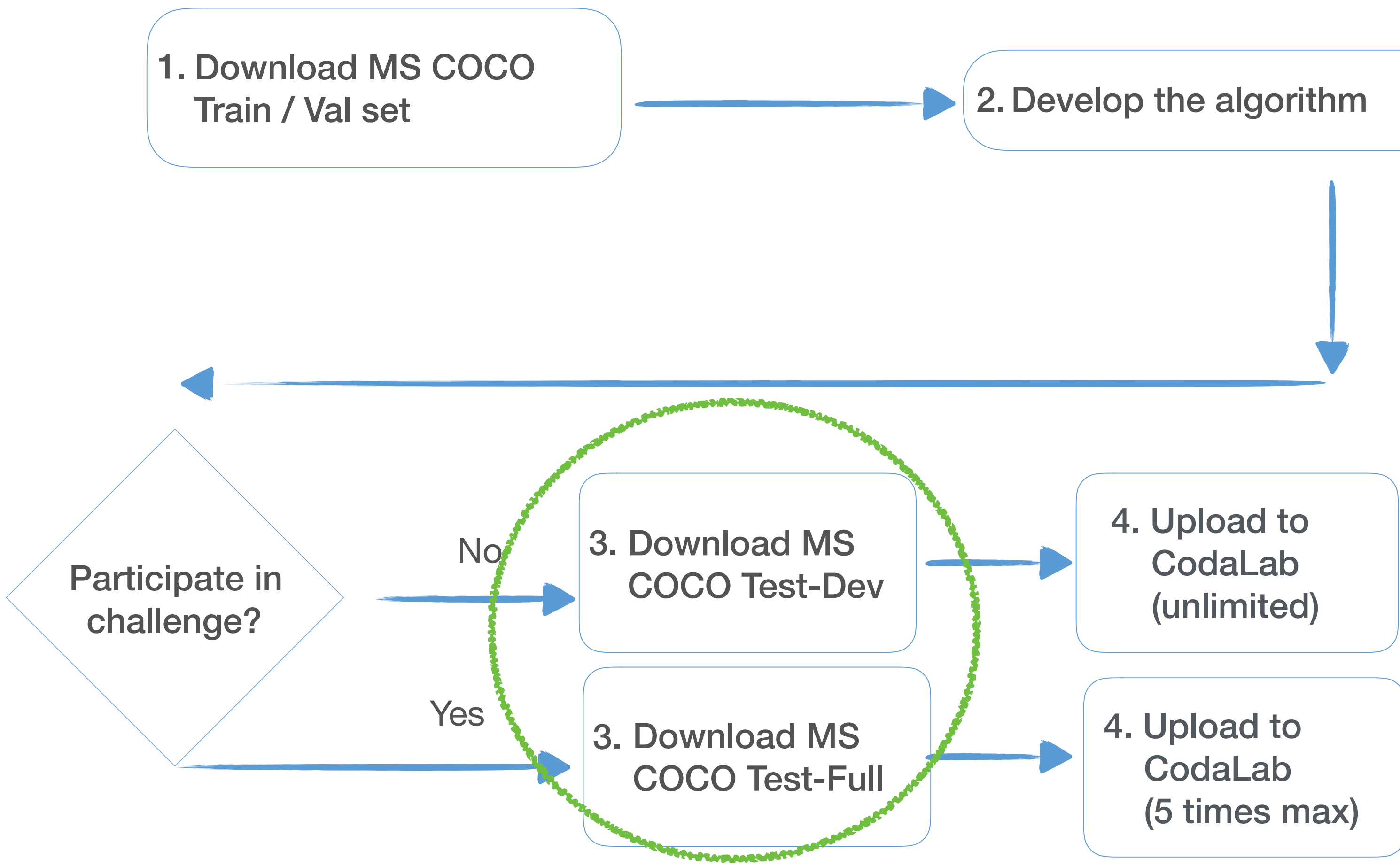
Test-challenge (competitions)

Used to score workshop competition.

Test-reserve (security)

Used to estimate overfitting. Scores on this set are never released.

Outline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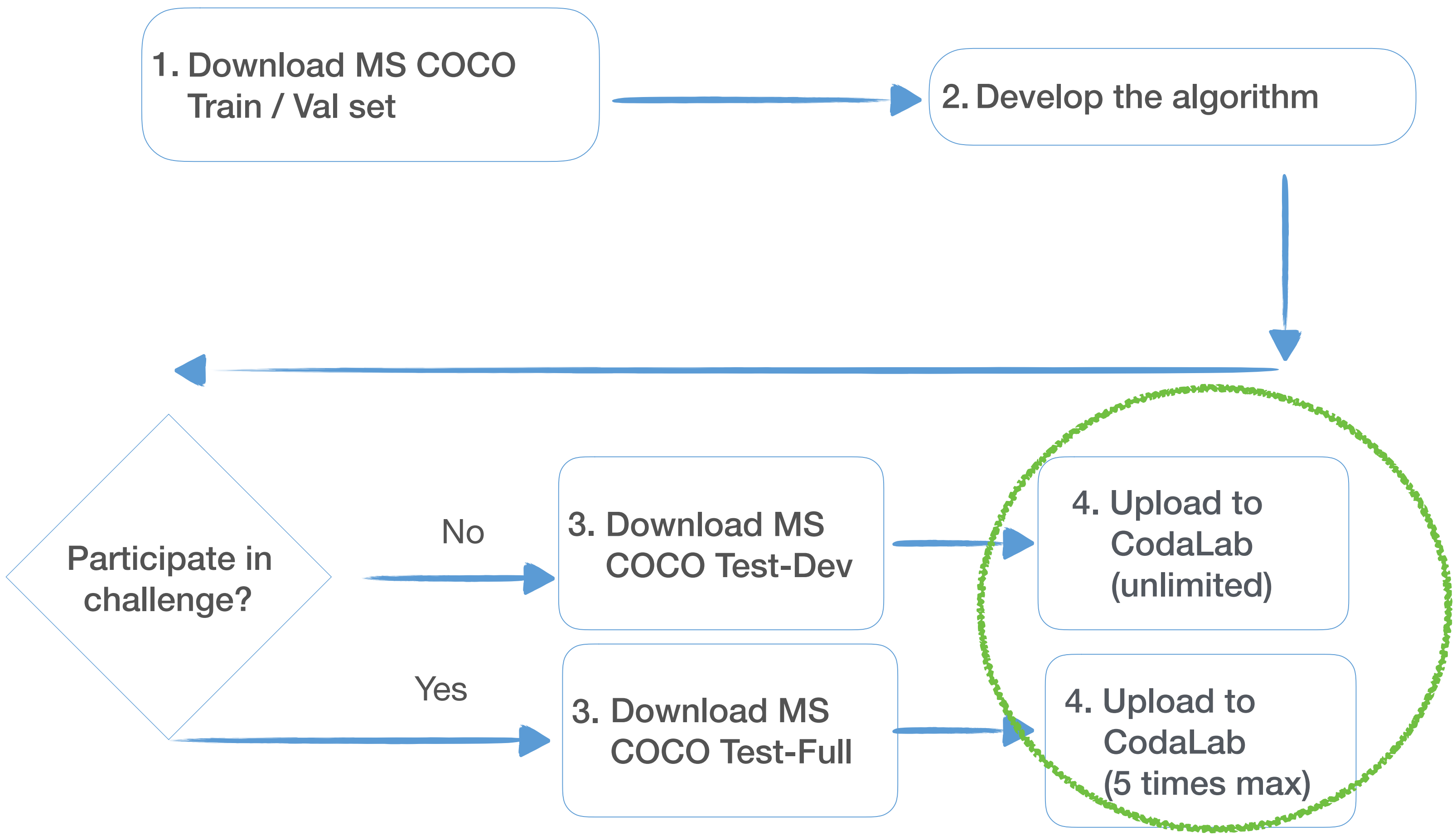
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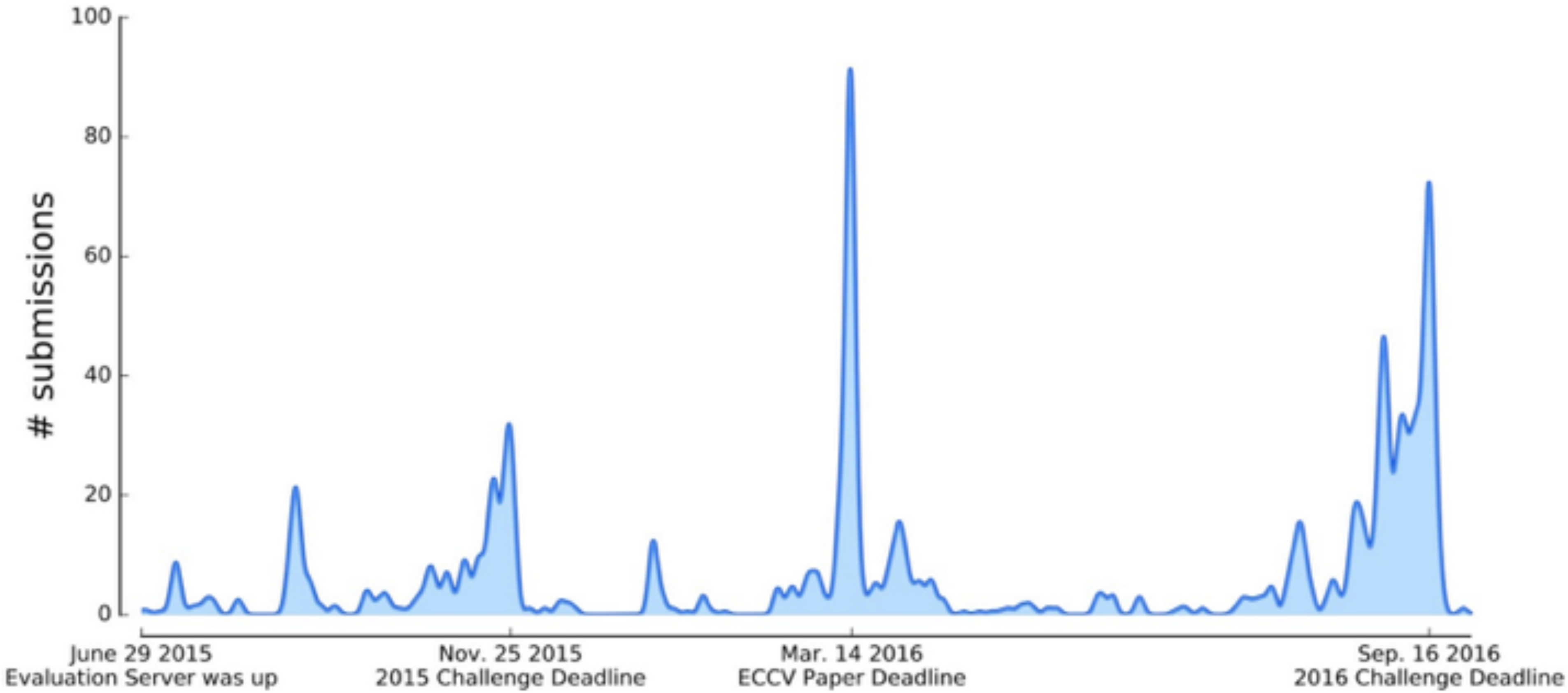
Evaluation Server Usage

Submissions to all test sets



Evaluation Metrics

Average Precision (AP):

AP	% AP at IoU=.50:.05:.95 **(determines challenge winner)**
$AP^{IoU=.50}$	% AP at IoU=.50 (PASCAL VOC metric)
$AP^{IoU=.75}$	% AP at IoU=.75 (strict metric)

AP Across Scales:

AP^{small}	% AP for small objects: area < 32^2
AP^{medium}	% AP for medium objects: 32^2 < area < 96^2
AP^{large}	% AP for large objects: area > 96^2

Average Recall (AR):

$AR^{max=1}$	% AR given 1 detection per image
$AR^{max=10}$	% AR given 10 detections per image
$AR^{max=100}$	% AR given 100 detections per image

AR Across Scales:

AR^{small}	% AR for small objects: area < 32^2
AR^{medium}	% AR for medium objects: 32^2 < area < 96^2
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Evaluation Metrics

Average Precision (AP):

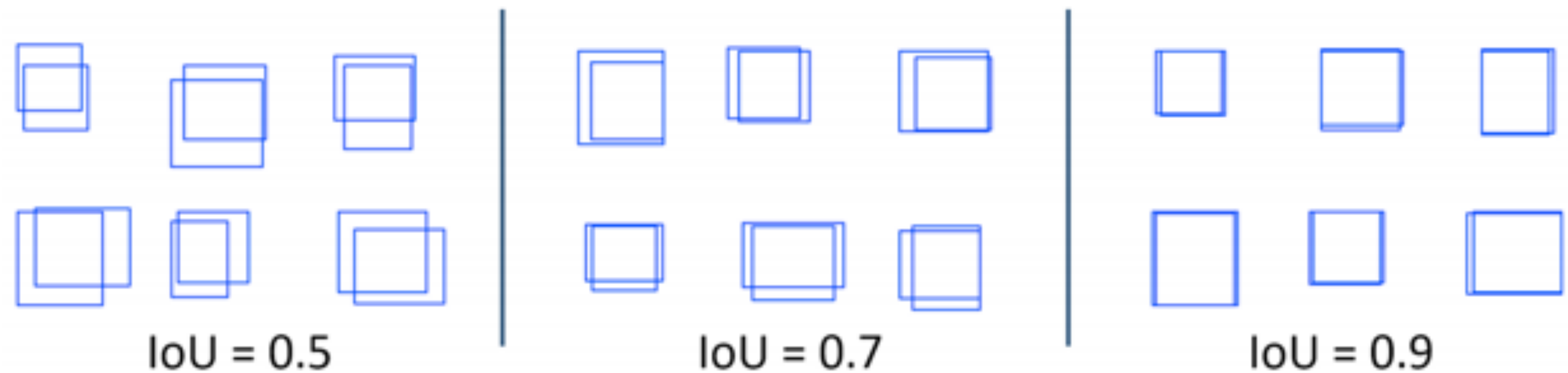
AP % AP at IoU=.50:.05:.95 **(determines challenge winner)**

$AP^{IoU=.50}$ % AP at IoU=.50 (PASCAL VOC metric)

$AP^{IoU=.75}$ % AP at IoU=.75 (strict metric)

Challenges Score: AP

- AP is averaged over multiple IoU values between 0.5 and 0.95.
- More comprehensive metric than the traditional AP at a fixed IoU value (0.5 for PASCAL).



Evaluation Metrics

AP Across Scales:

AP^{small}	% AP for small objects: area < 32^2
AP^{medium}	% AP for medium objects: 32^2 < area < 96^2
AP^{large}	% AP for large objects: area > 96^2

Other Scores: Size AP

- AP is averaged over instance size:
  - small (A < 32 x 32)
  - medium (32x 32 < A < 96 x 96)
  - large (A > 96 x 96)

A < 32x32

32x32 < A < 96x96

A > 96x96

Evaluation Metrics

```
Average Recall (AR):
   AR^{max=1}          % AR given 1 detection per image
   AR^{max=10}         % AR given 10 detections per image
   AR^{max=100}        % AR given 100 detections per image
AR Across Scales:
   AR^{small}          % AR for small objects: area < 32^2
   AR^{medium}         % AR for medium objects: 32^2 < area < 96^2
   AR^{large}          % AR for large objects: area > 96^2
```

Other Scores: AR

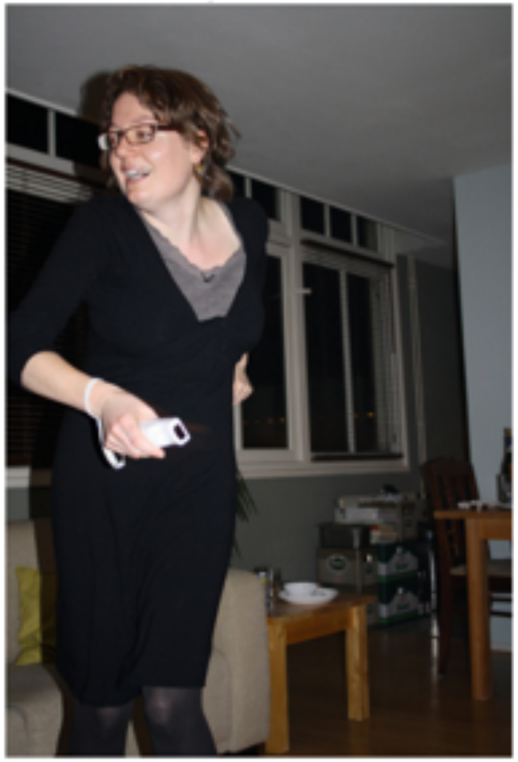
- Measures the maximum recall over a fixed number of detections allowed in the image of 1, 10, 100.
- AR is averaged over small (A < 32 x 32), medium (32x 32 < A < 96 x 96) and large (A > 96 x 96) instances of objects.

Evaluation Ambiguity

Which one is better?

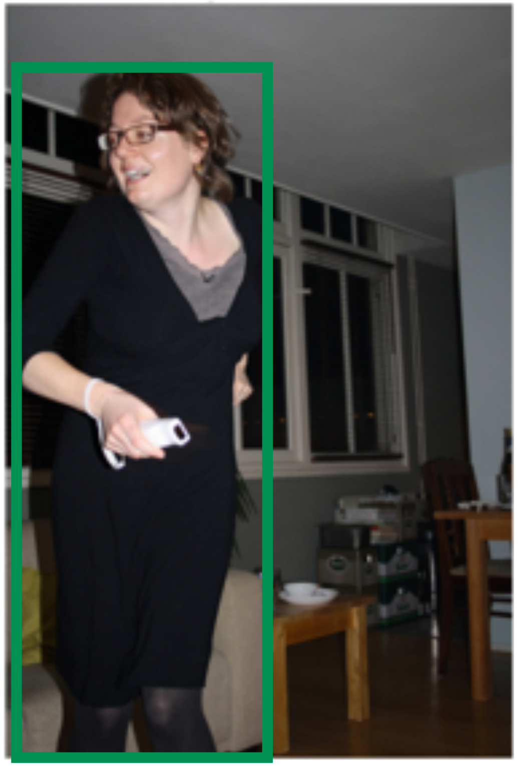
Evaluation Ambiguity

Which one is better?



Evaluation Ambiguity

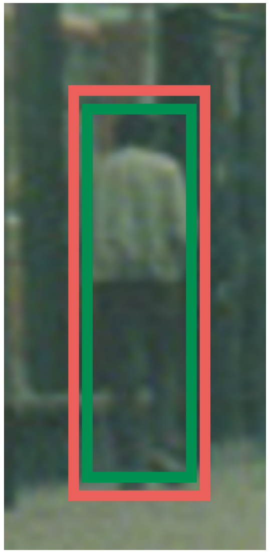
Which one is better?

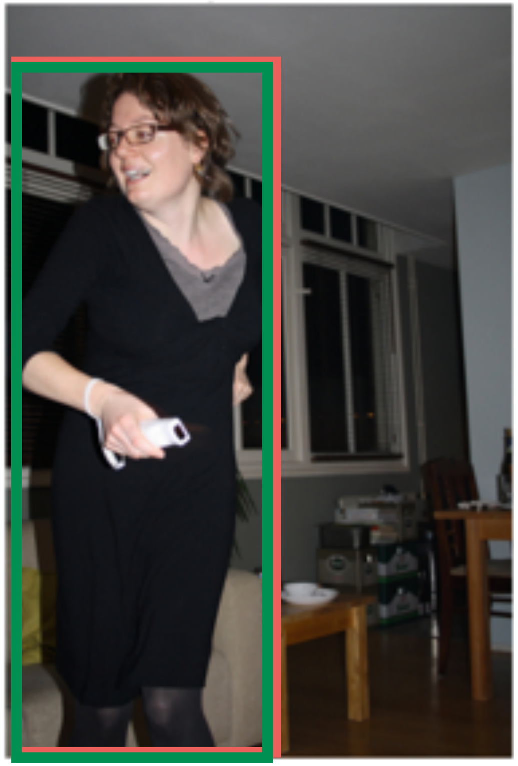


Ground-Truth BBox

Evaluation Ambiguity

Which one is better?





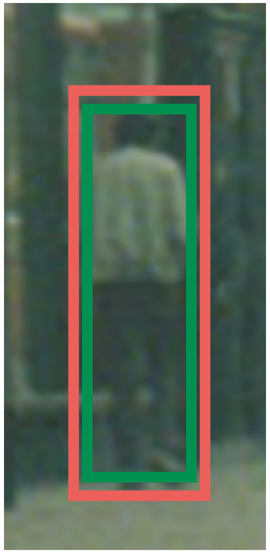
Ground-Truth BBox Detection BBox

Evaluation Ambiguity

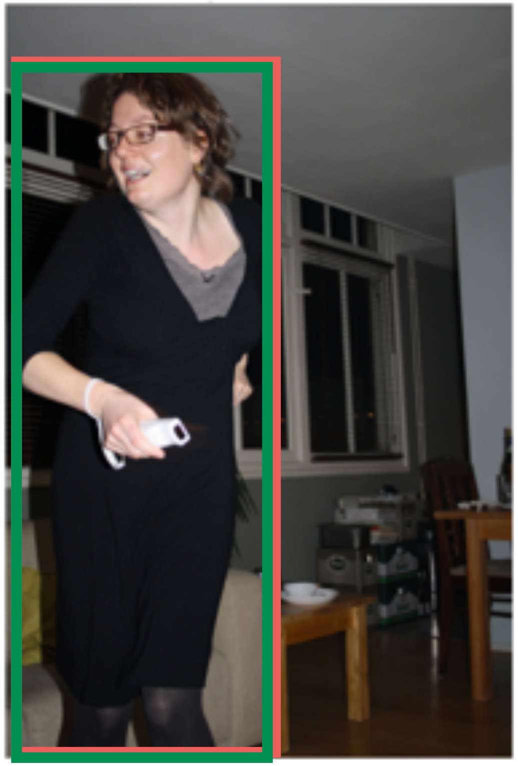
Which one is better?

IoU = 0.5

IoU = 0.7



IoU = 0.95



Ground-Truth BBox Detection BBox

COCO Challenges Results

COCO
Common Objects in Context

Detection | Segmentation

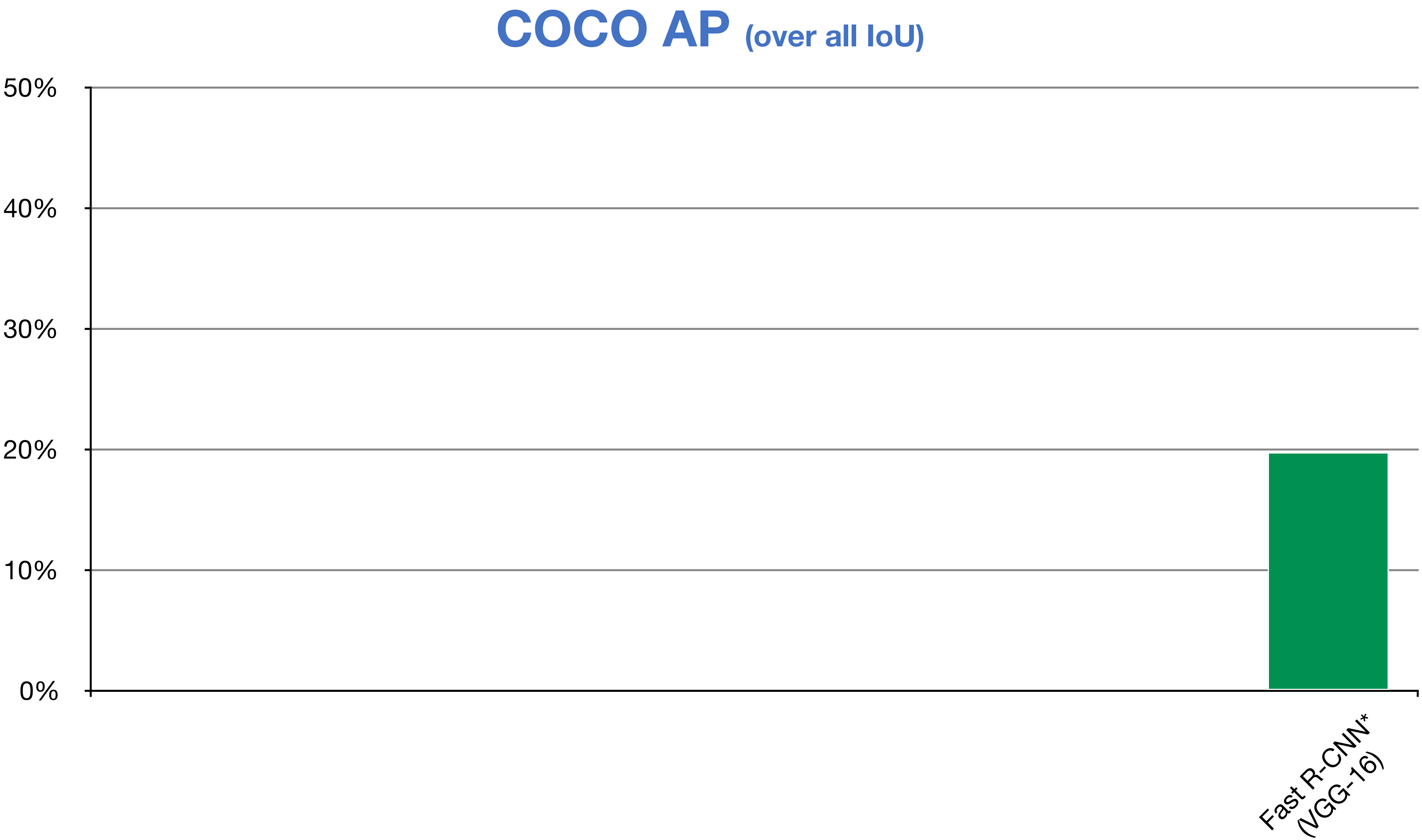
Bounding Boxes Leaderboard (I)

COCO AP (over all IoU)

Bounding Boxes Leaderboard (I)

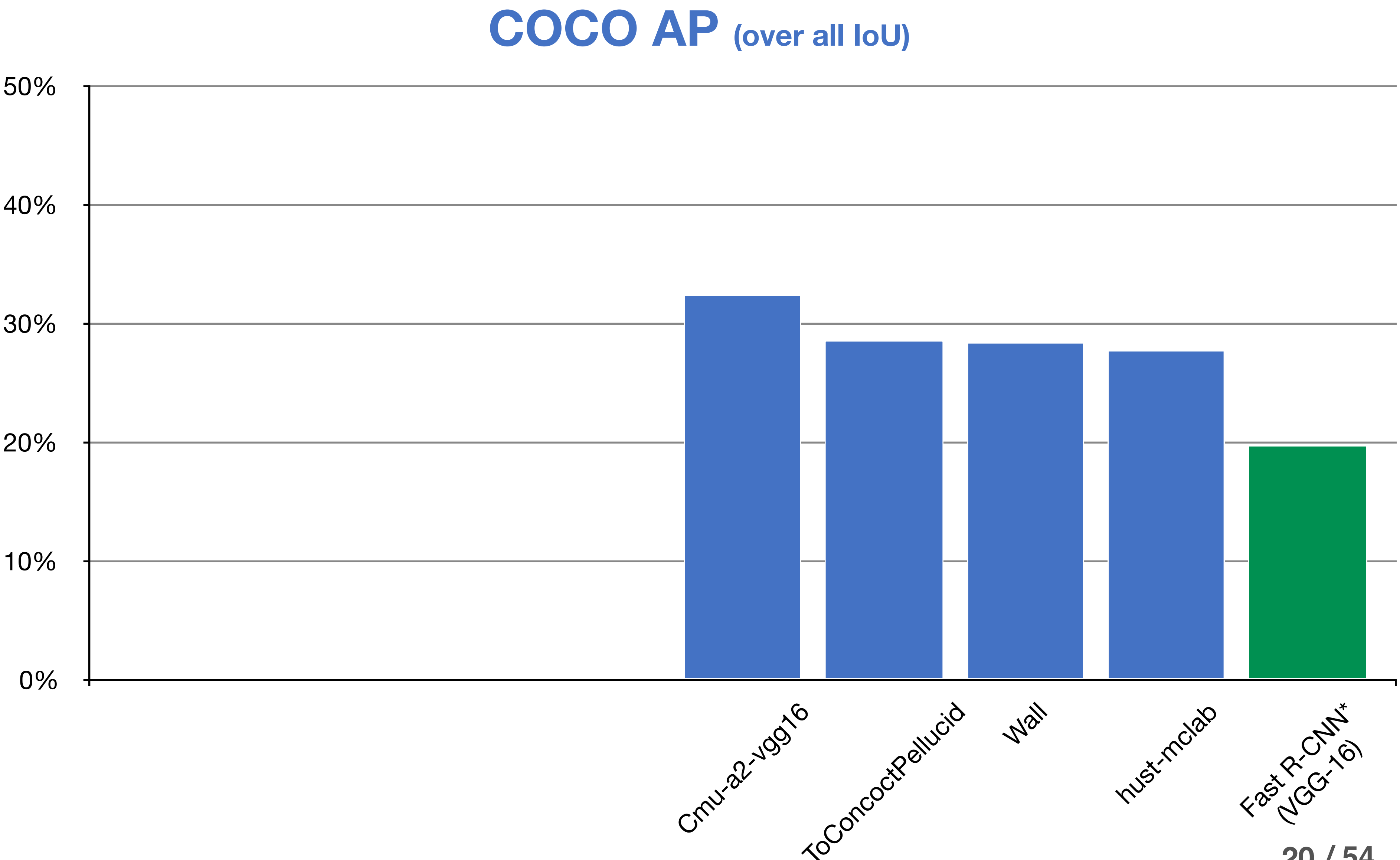
COCO AP (over all IoU)

Bounding Boxes Leaderboard (I)



(*) Performance on Test-Dev

Bounding Boxes Leaderboard (I)



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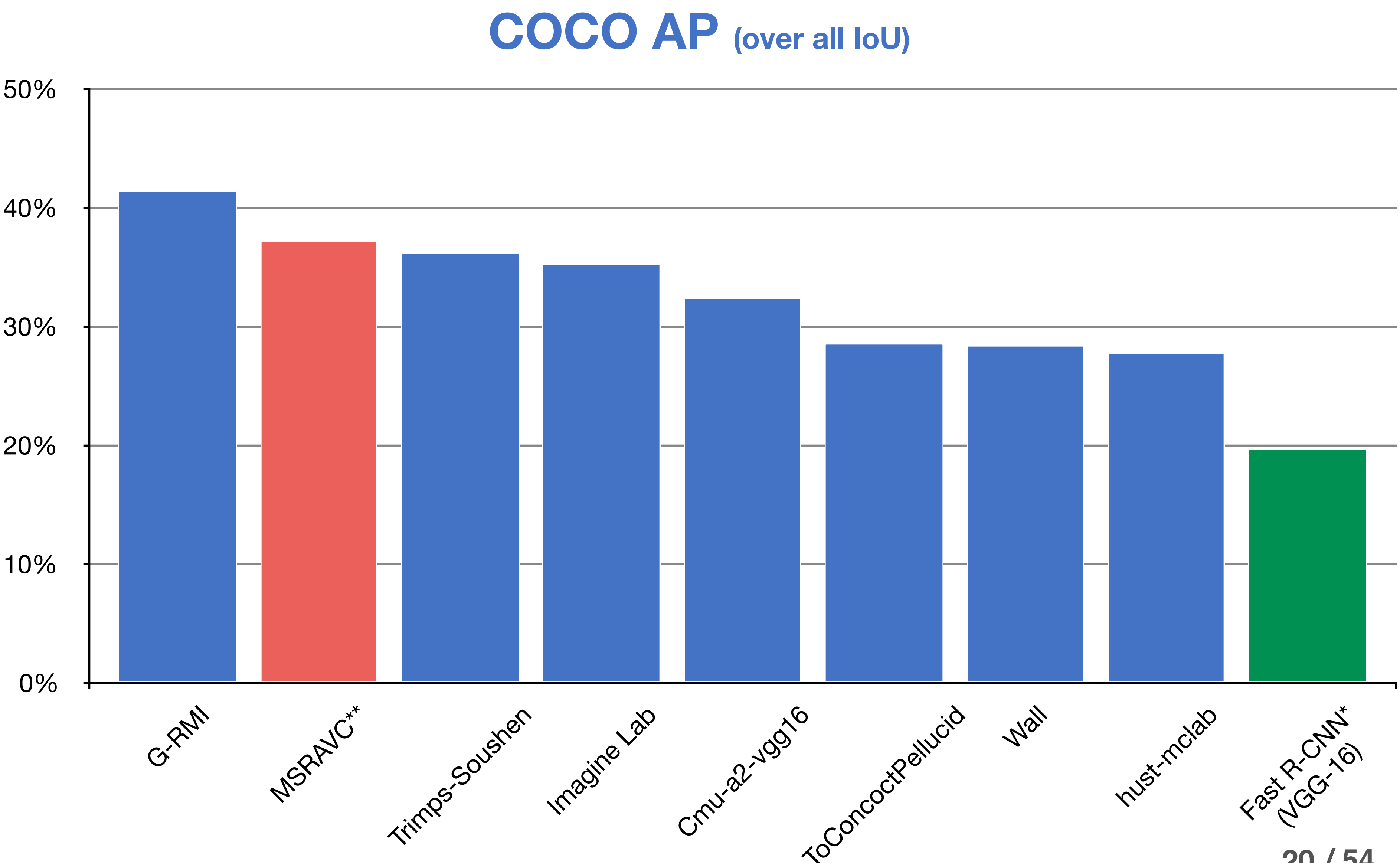

(*) Performance on Test-Dev (**) 2015 Winner

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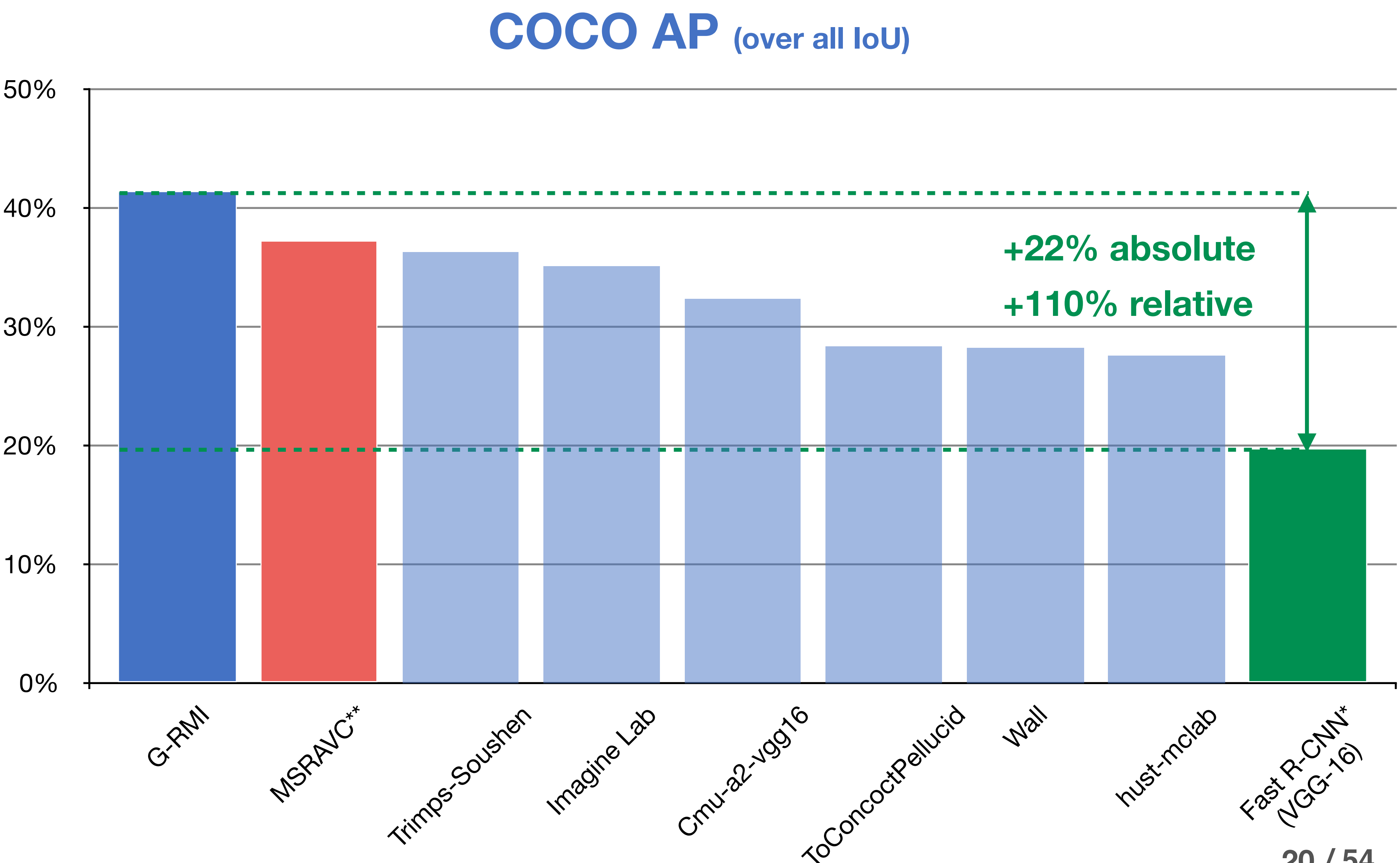

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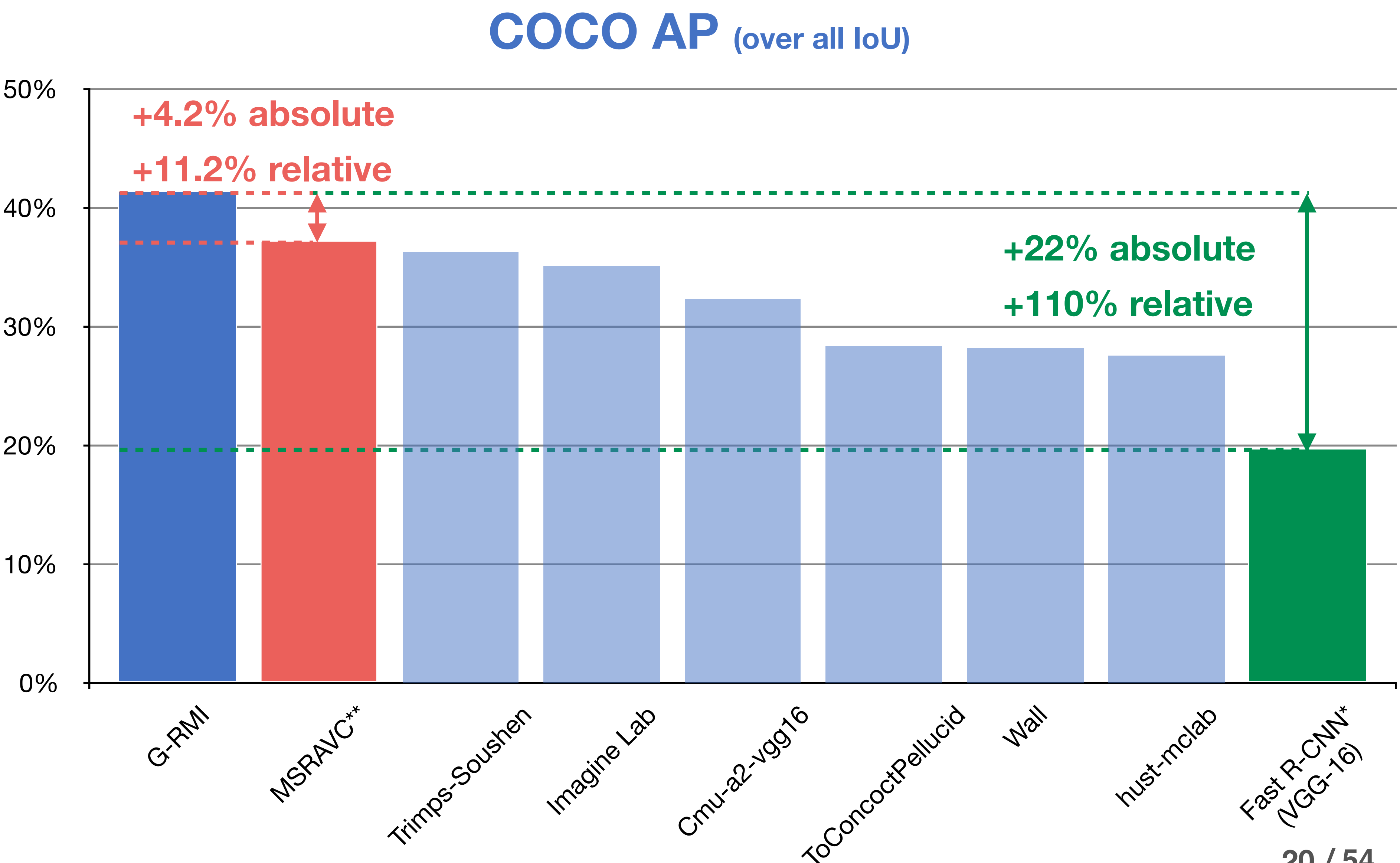

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Segmentation Leaderboard (I)

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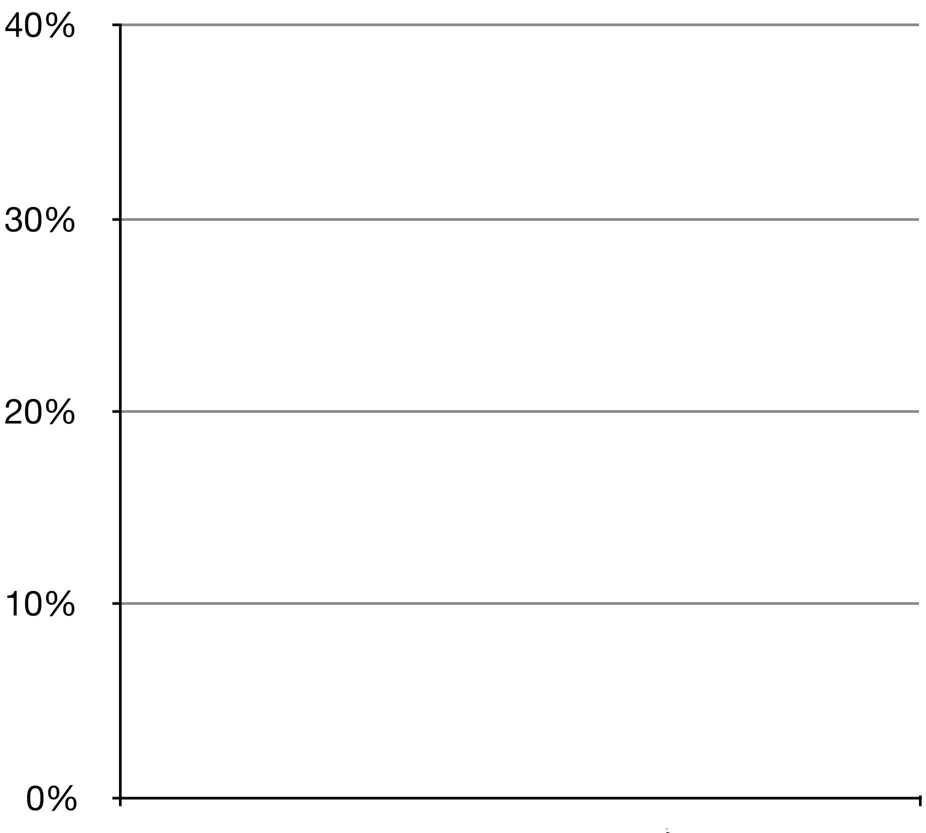

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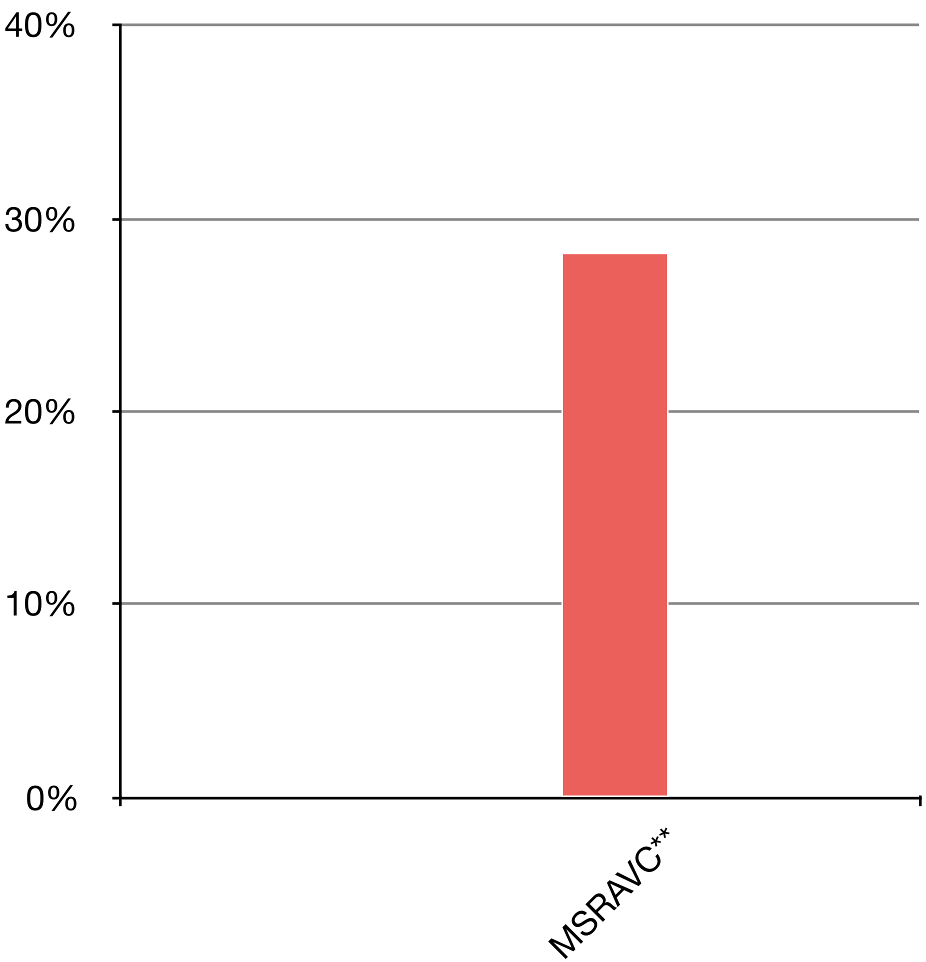

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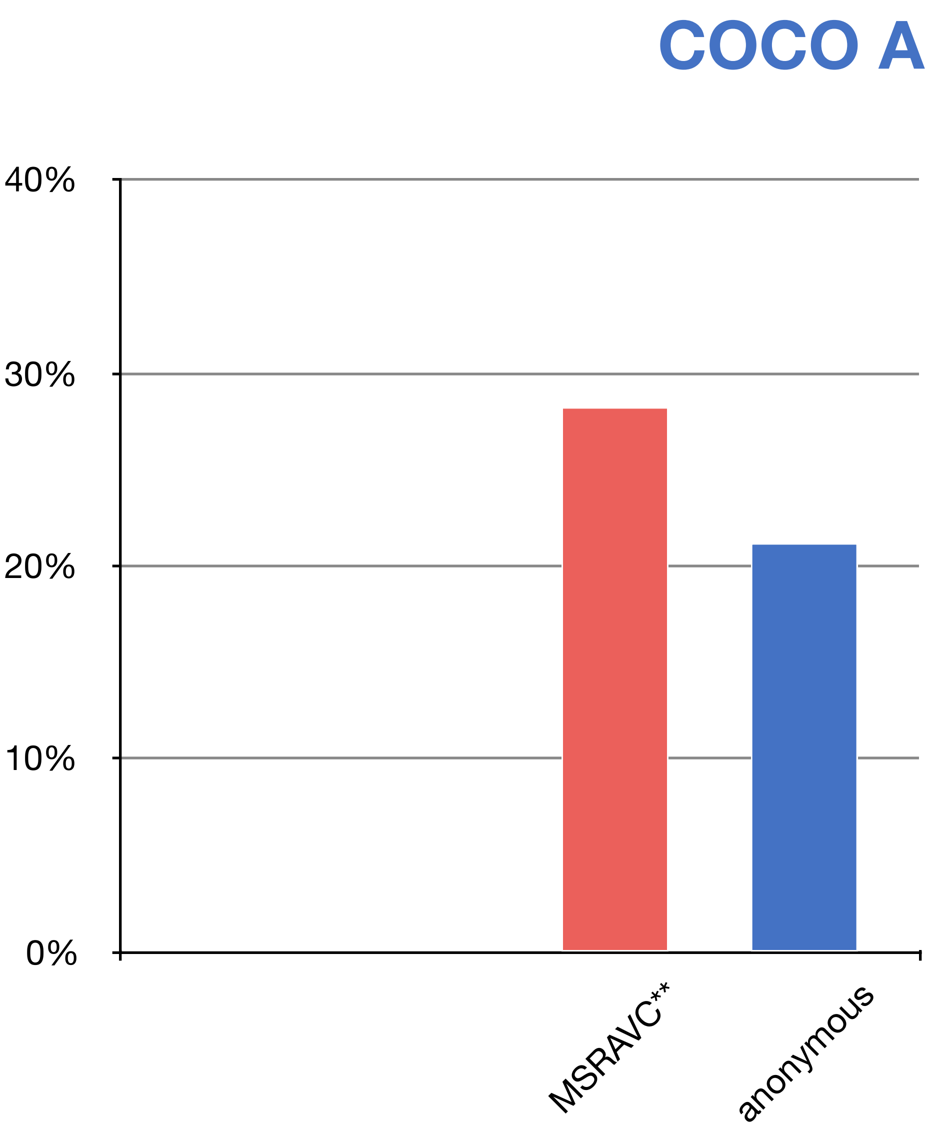

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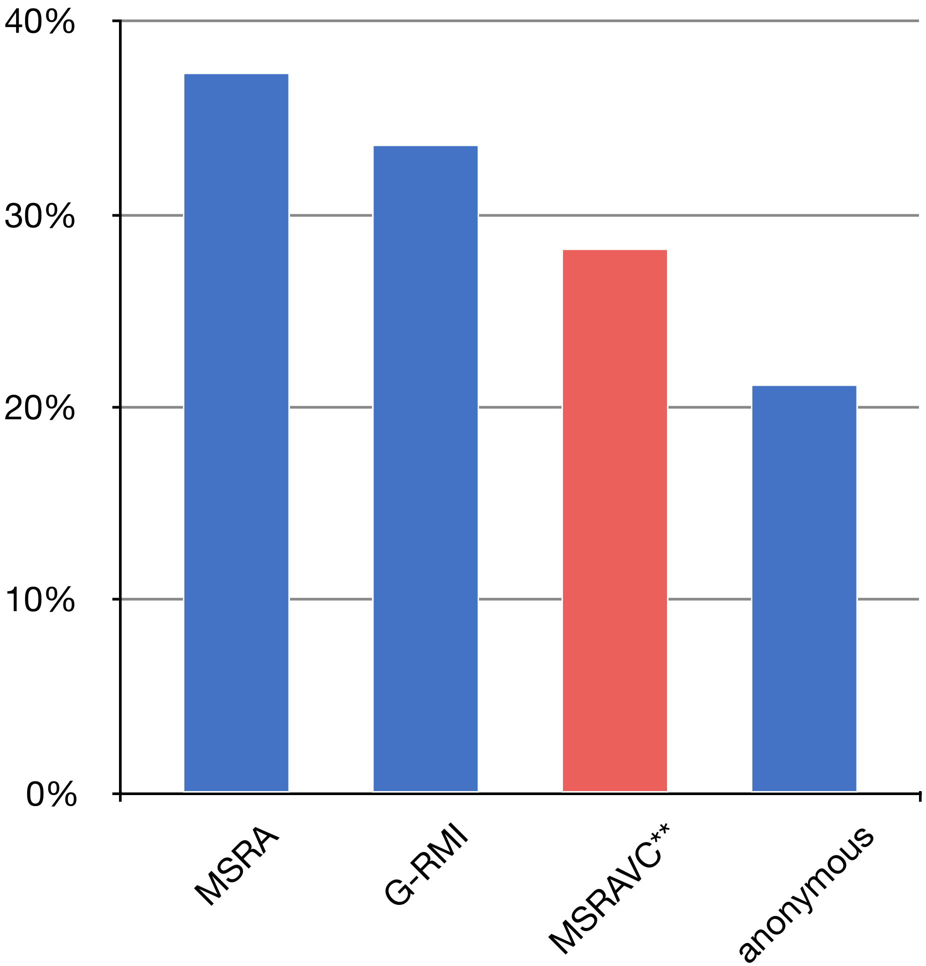
Segmentation Leaderboard (I)

COCO AP (over all IoU)



(**) 2015 Winner

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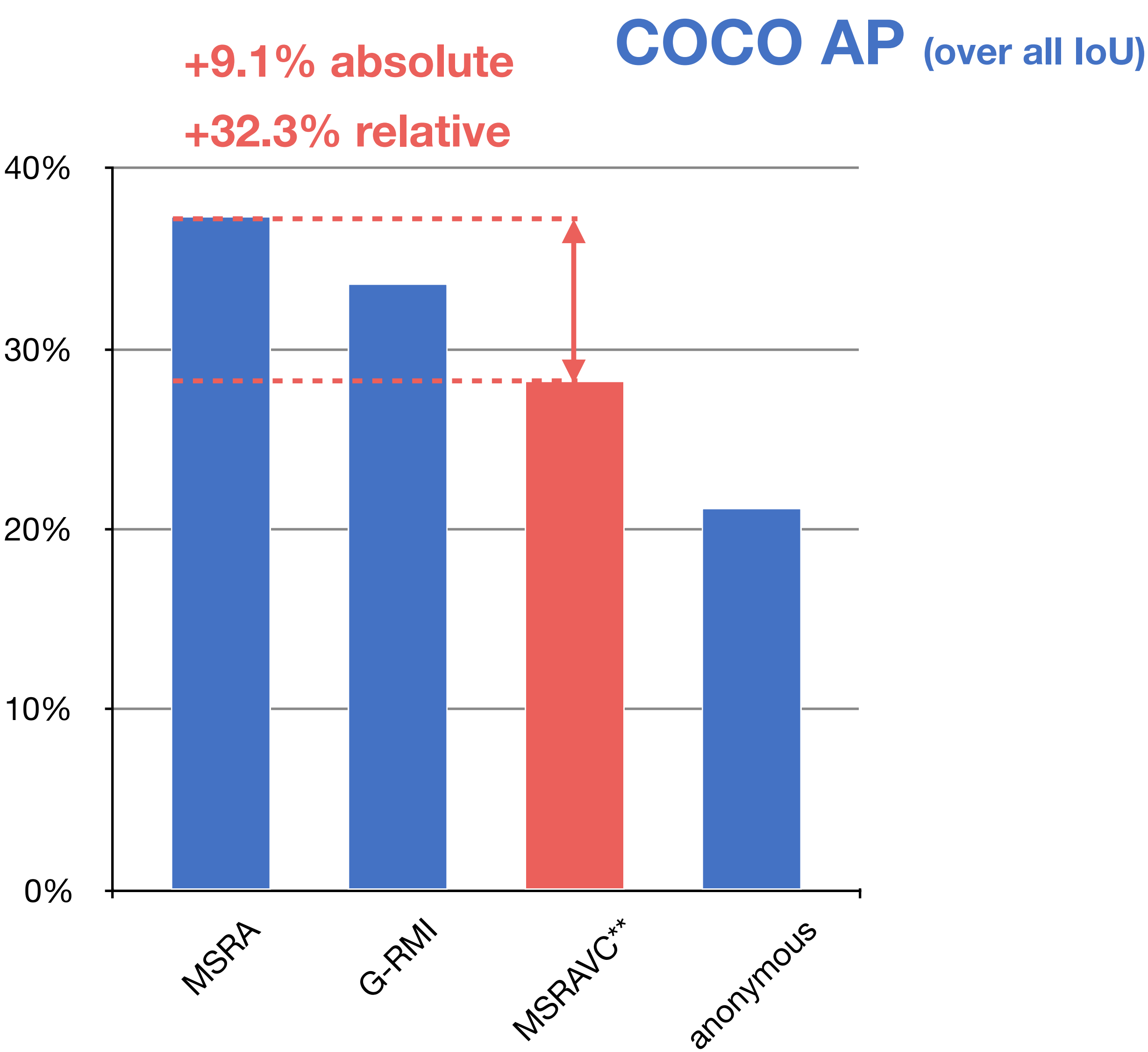
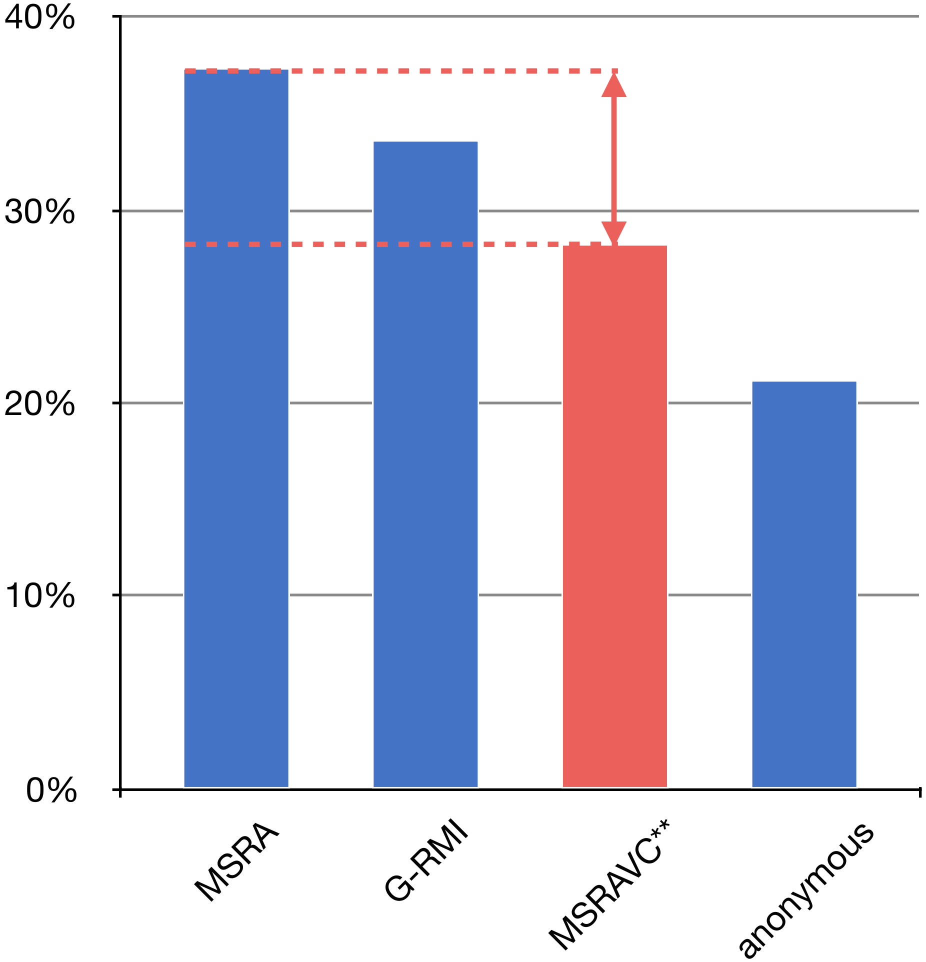


(**) 2015 Winner

Segmentation Leaderboard (I)

+9.1% absolute
+32.3% relative

COCO AP (over all IoU)



COCO AP for segmentation winner trails the one for bbox detection by ~4%:

- Last year the gap was ~10%
- Localization is harder for segmentation

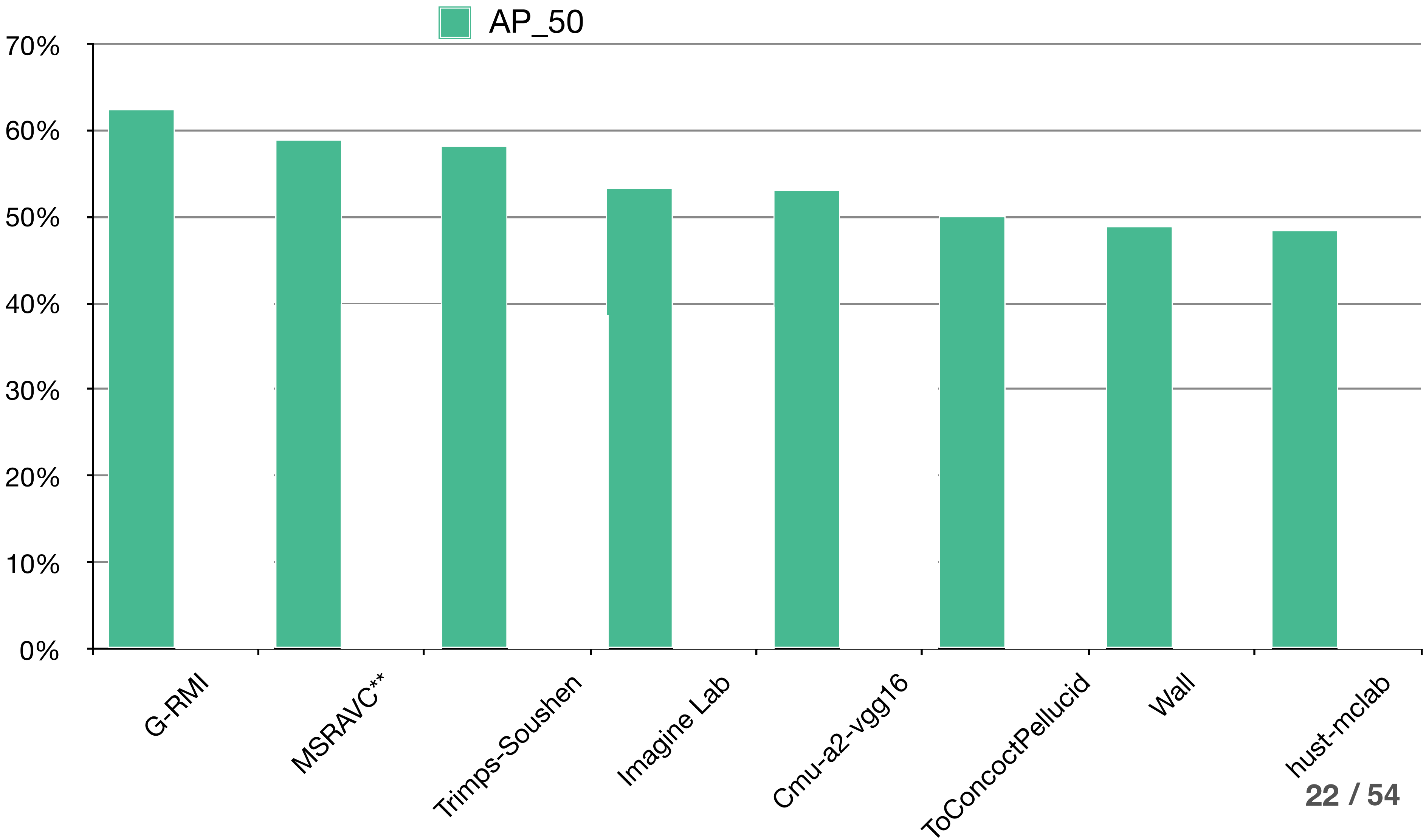
(**) 2015 Winner

Bounding Boxes Leaderboard (II)

Object Localization is improving

Bounding Boxes Leaderboard (II)

Object Localization is improving



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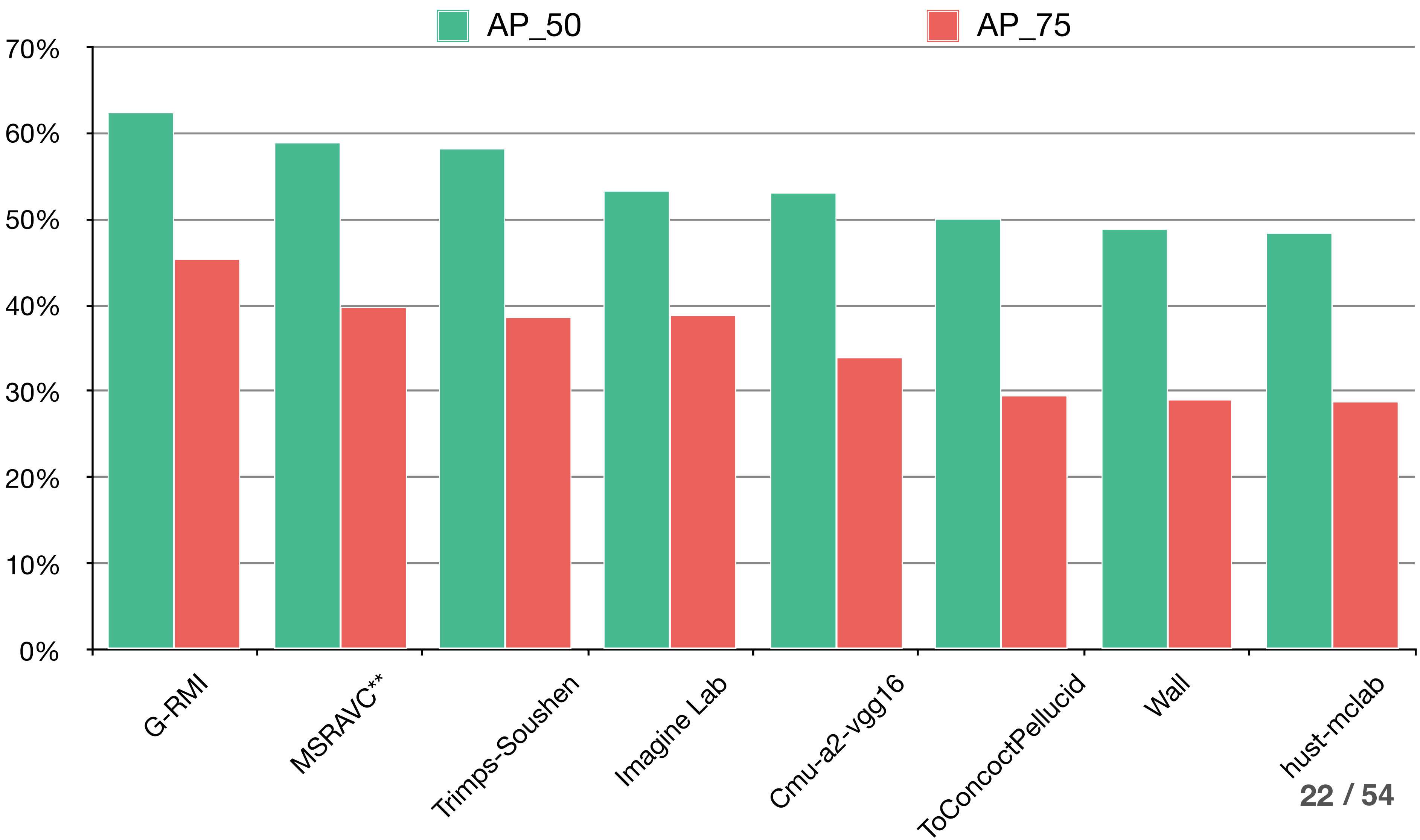

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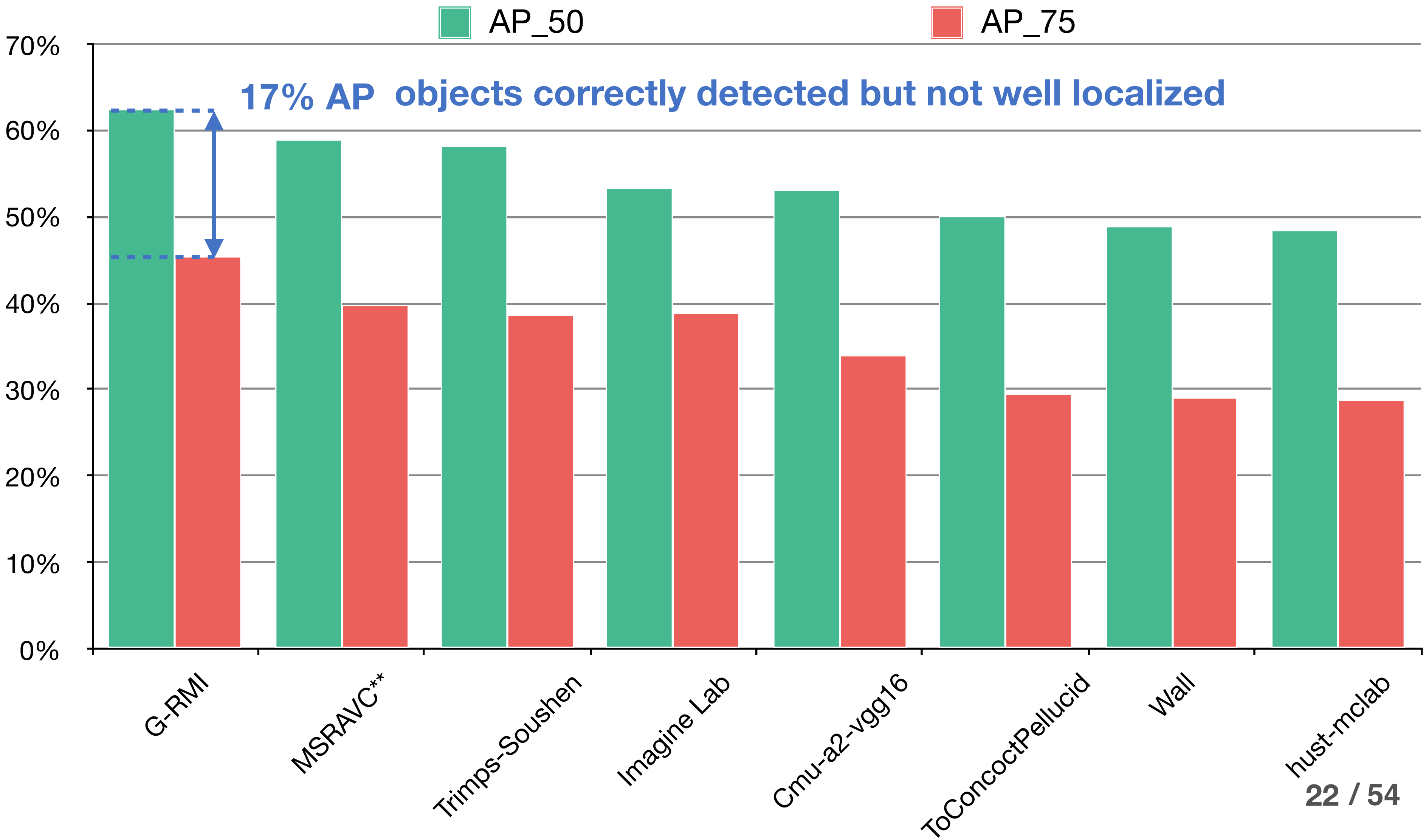

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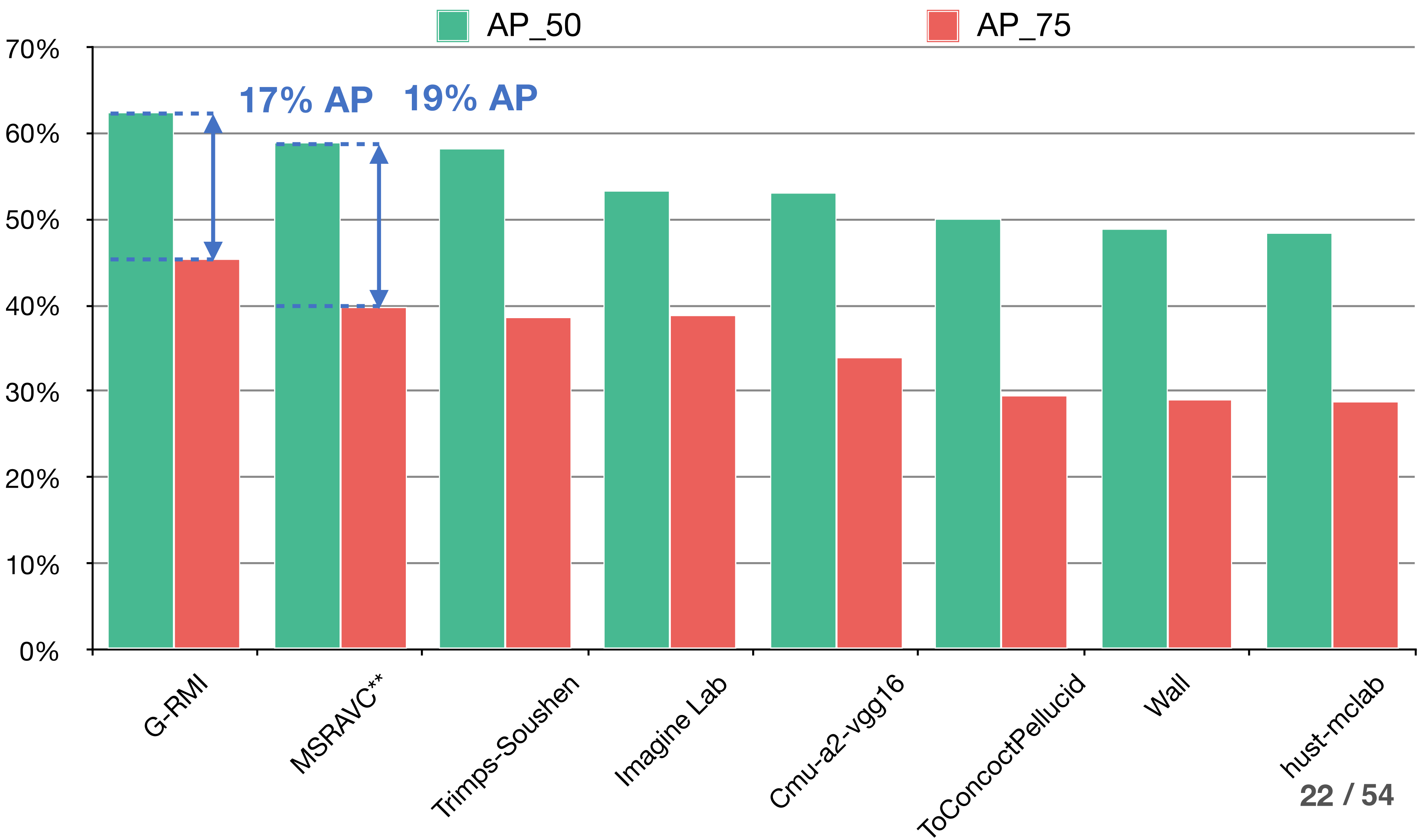

Mask localization can improve

Segmentation Leaderboard (II)

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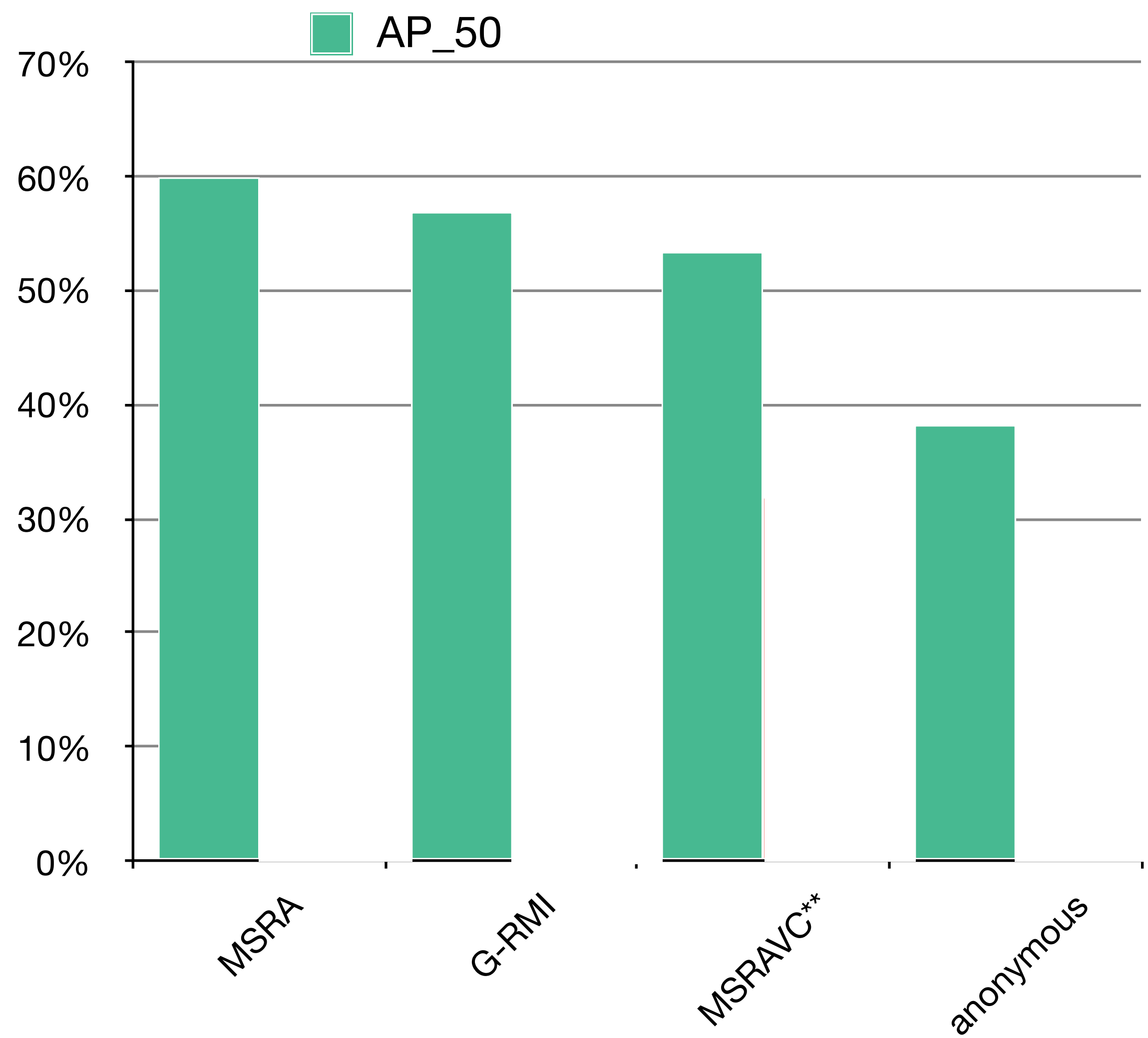

Segmentation Leaderboard (II)

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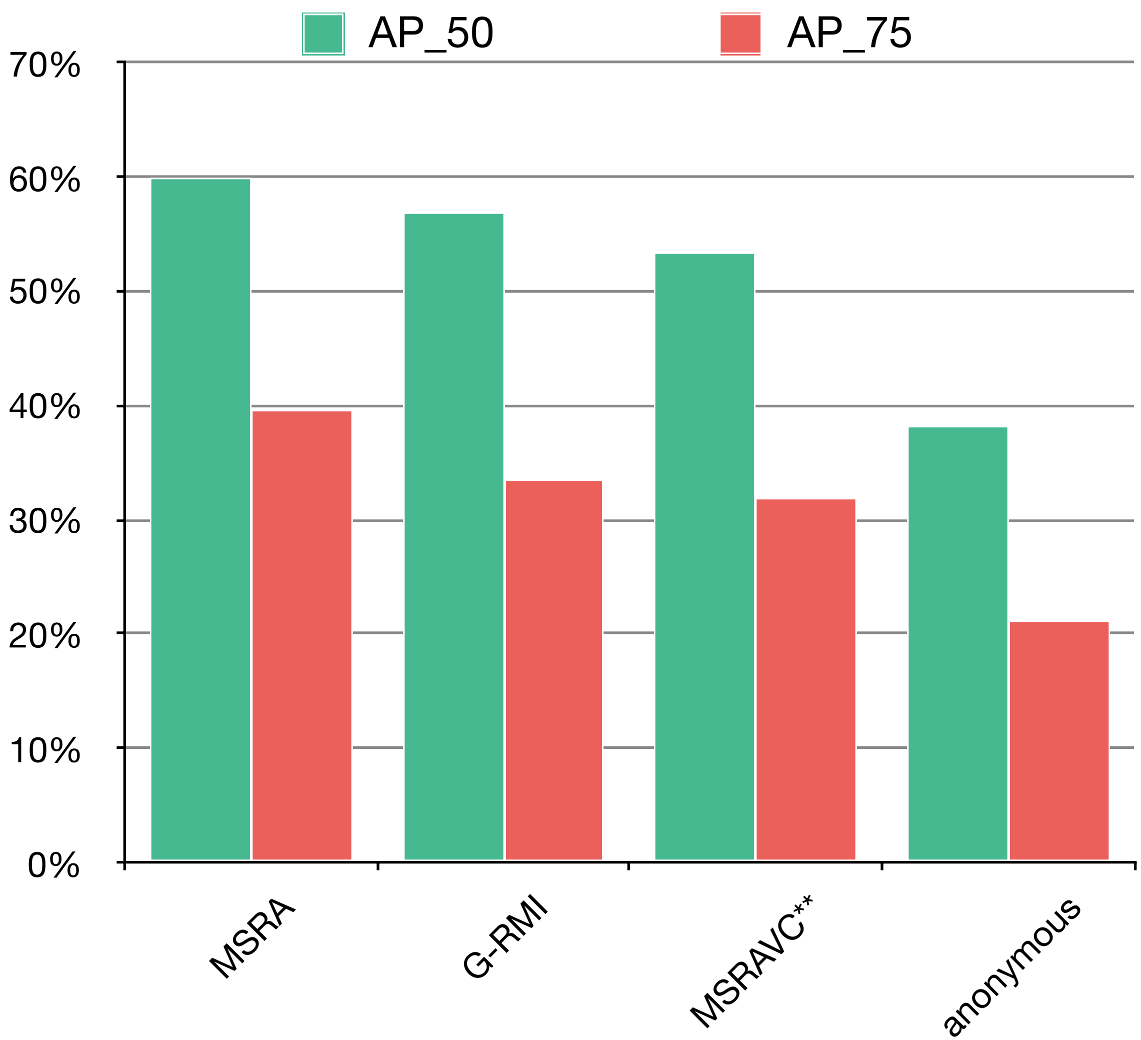

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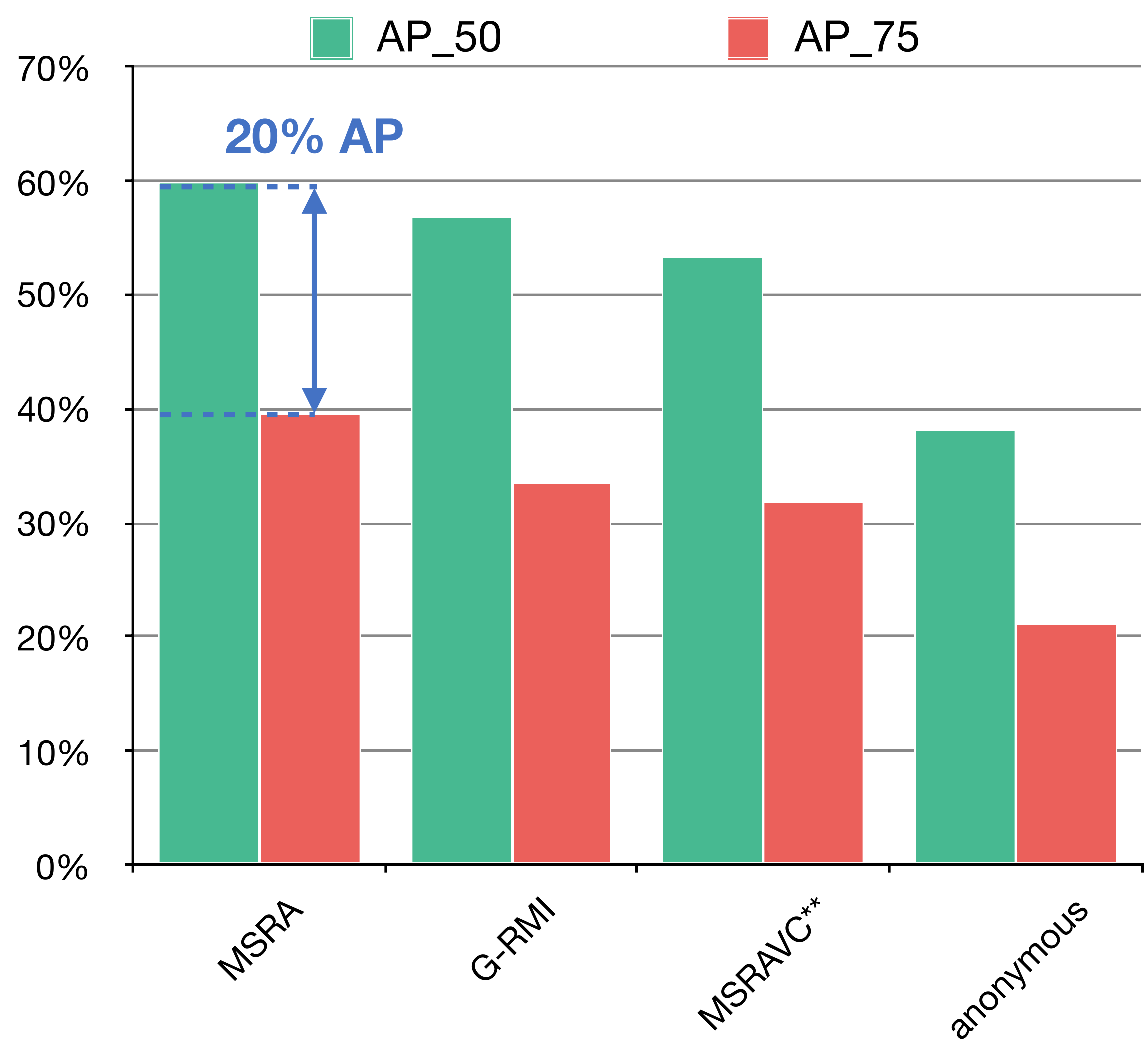

Bounding Boxes vs Segmentation

Segmentation provides great bounding boxes!

Bounding Boxes vs Segmentation

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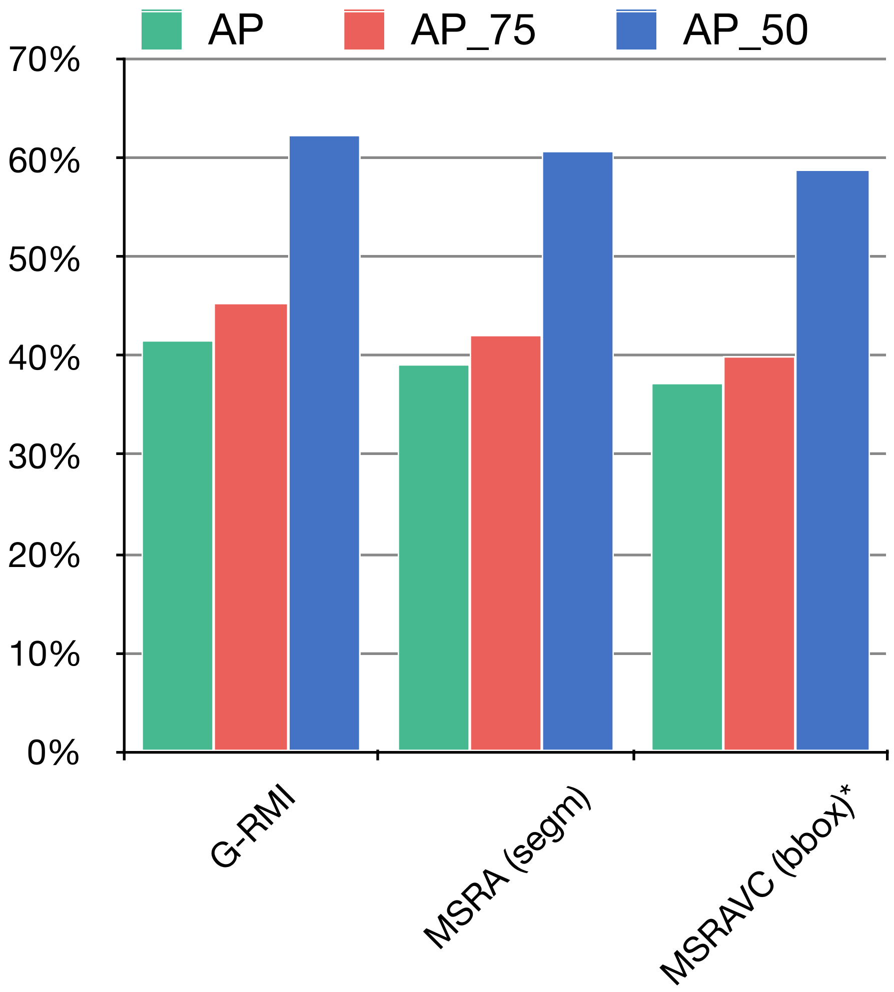

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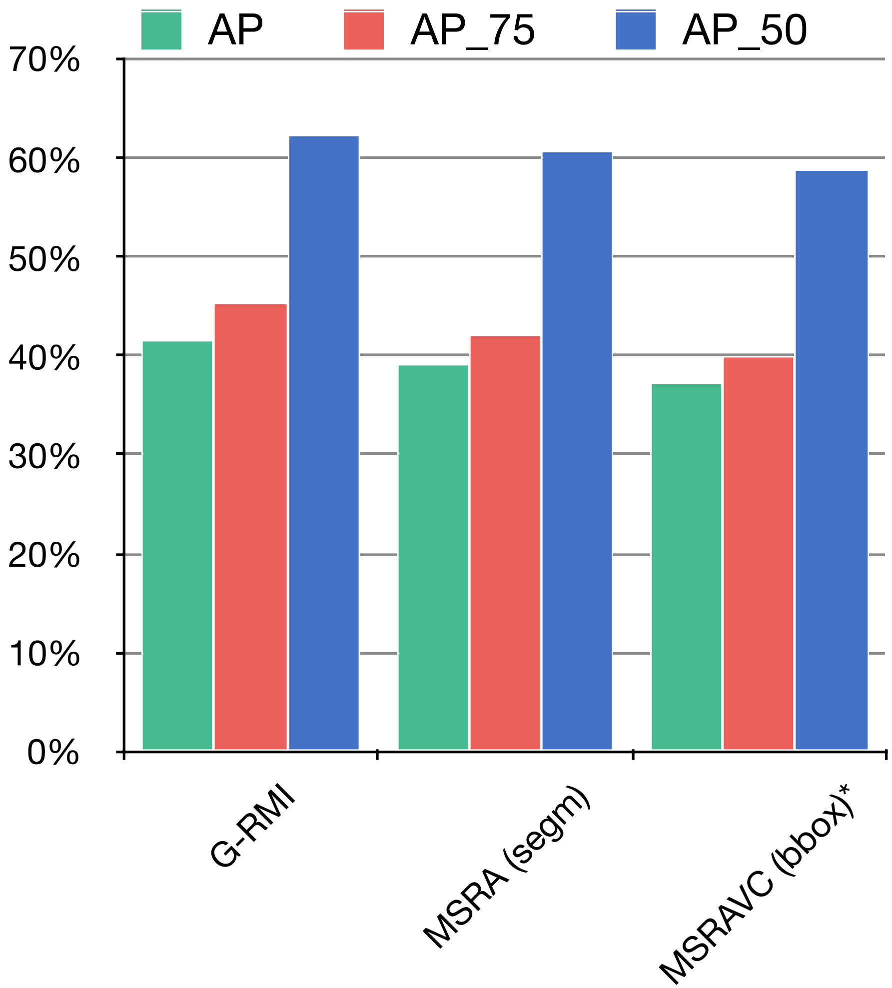

COCO AP for segmentation winner trails the one for bbox detection by ~2%:

(*) 2015 Winner

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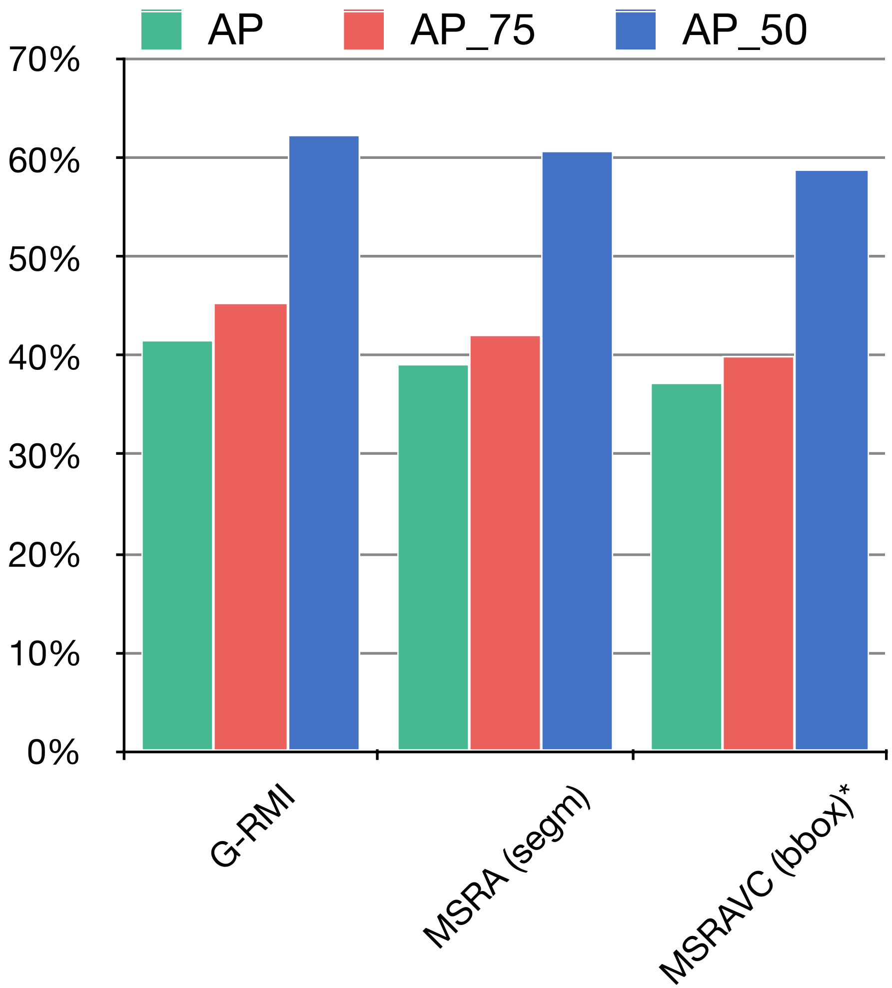

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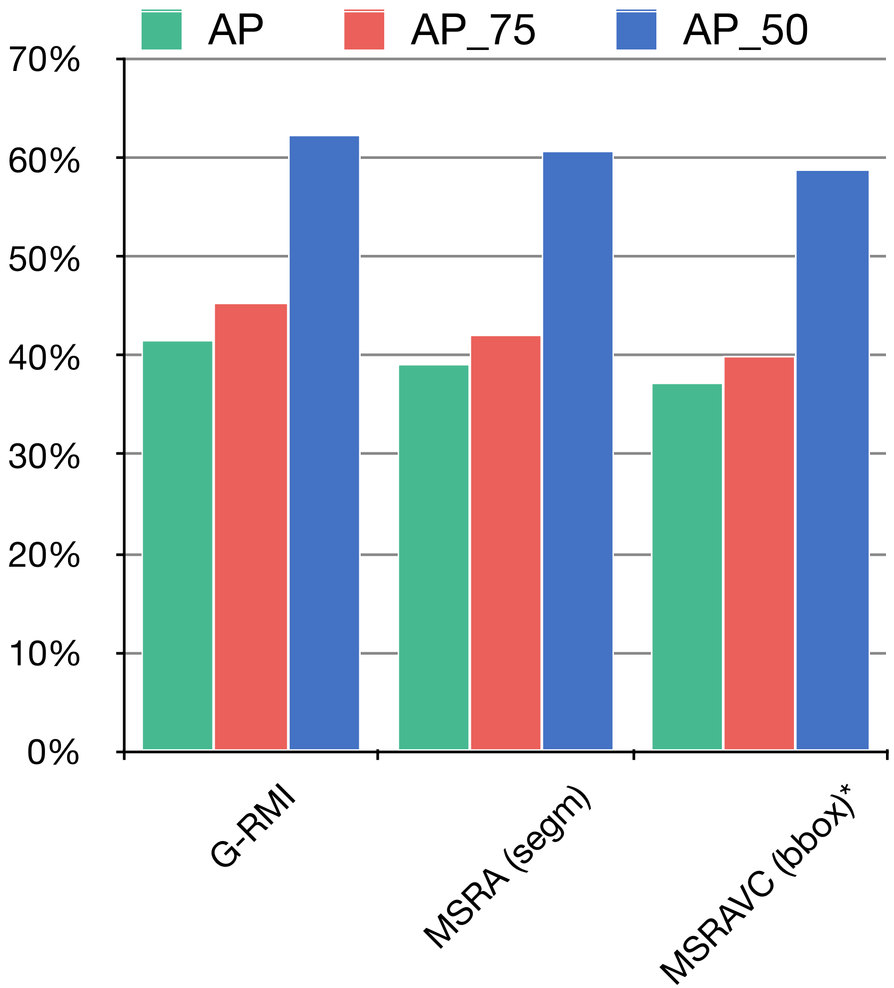

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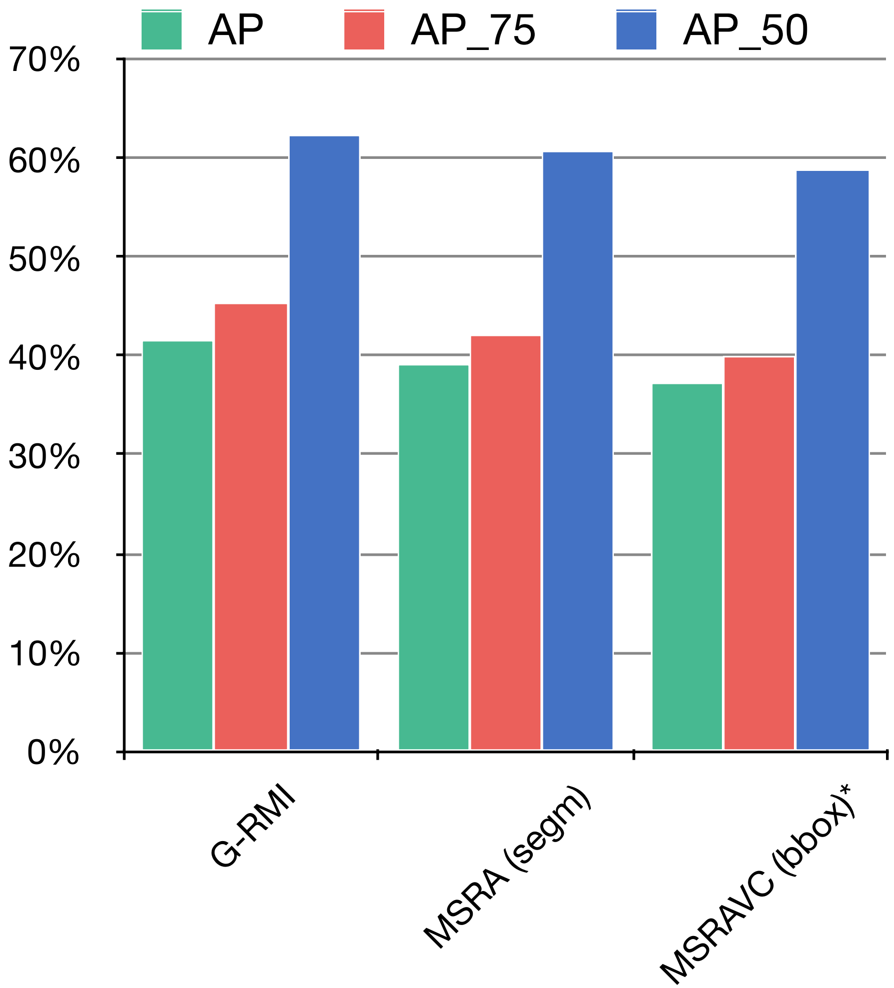

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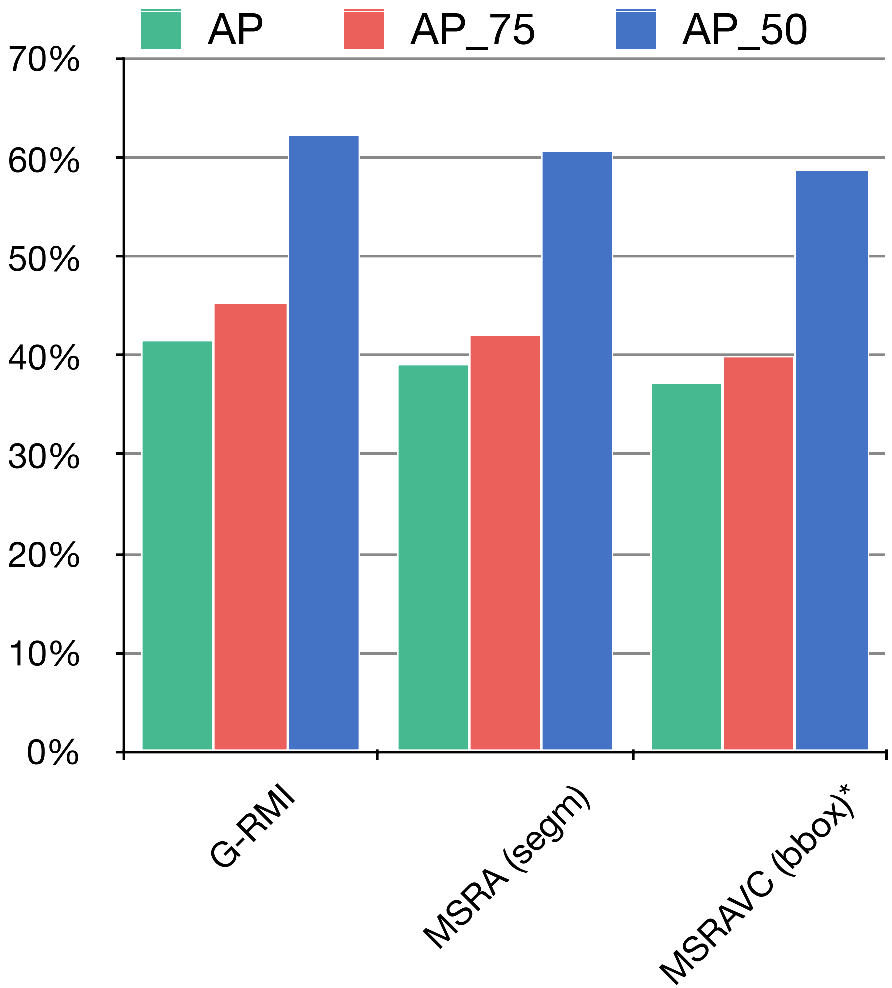

COCO AP for segmentation winner trails the one for bbox detection by ~2%:

- Results in 2nd place in the bbox challenge!
- Gap is about constant at multiple IoU values.
- **Participate in Segmentation Challenge!**

(*) 2015 Winner

Performance Breakdown (I)

COCO AP varies across supercategories and size

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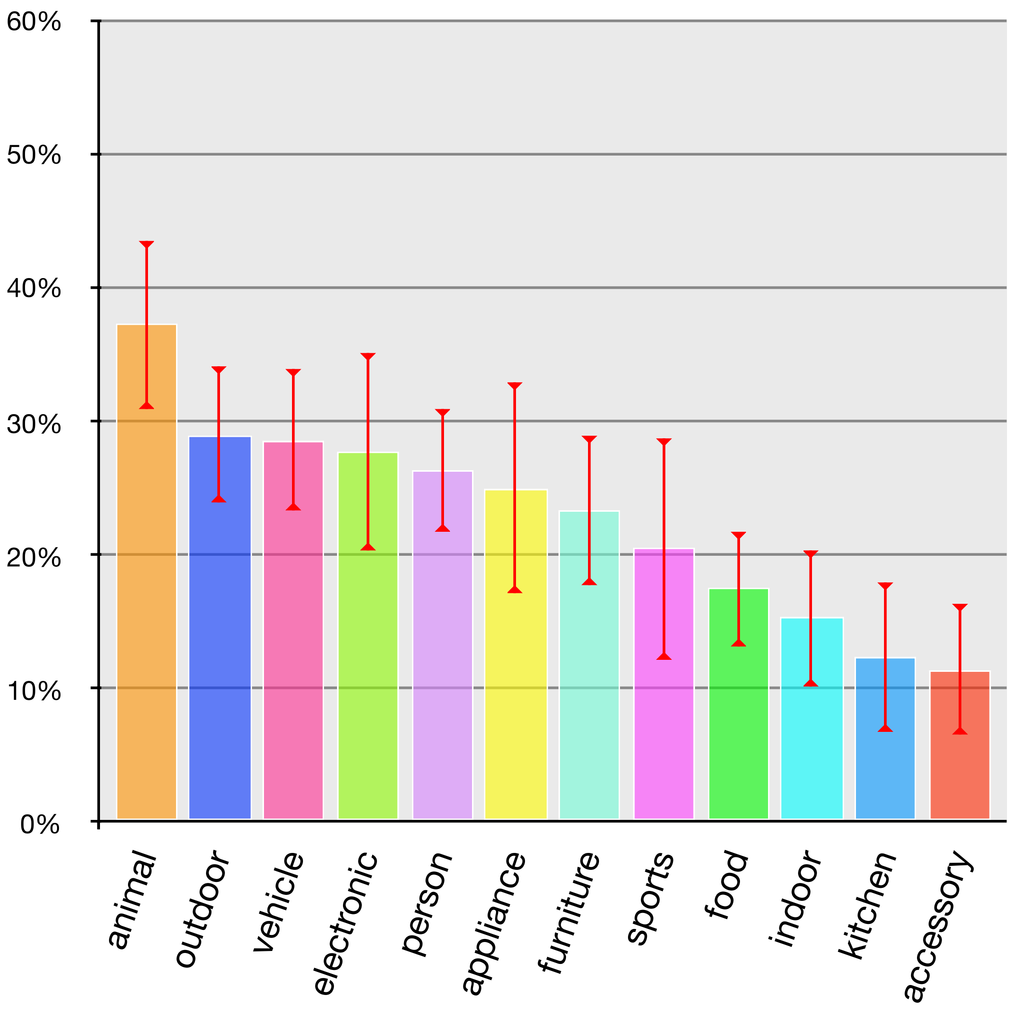

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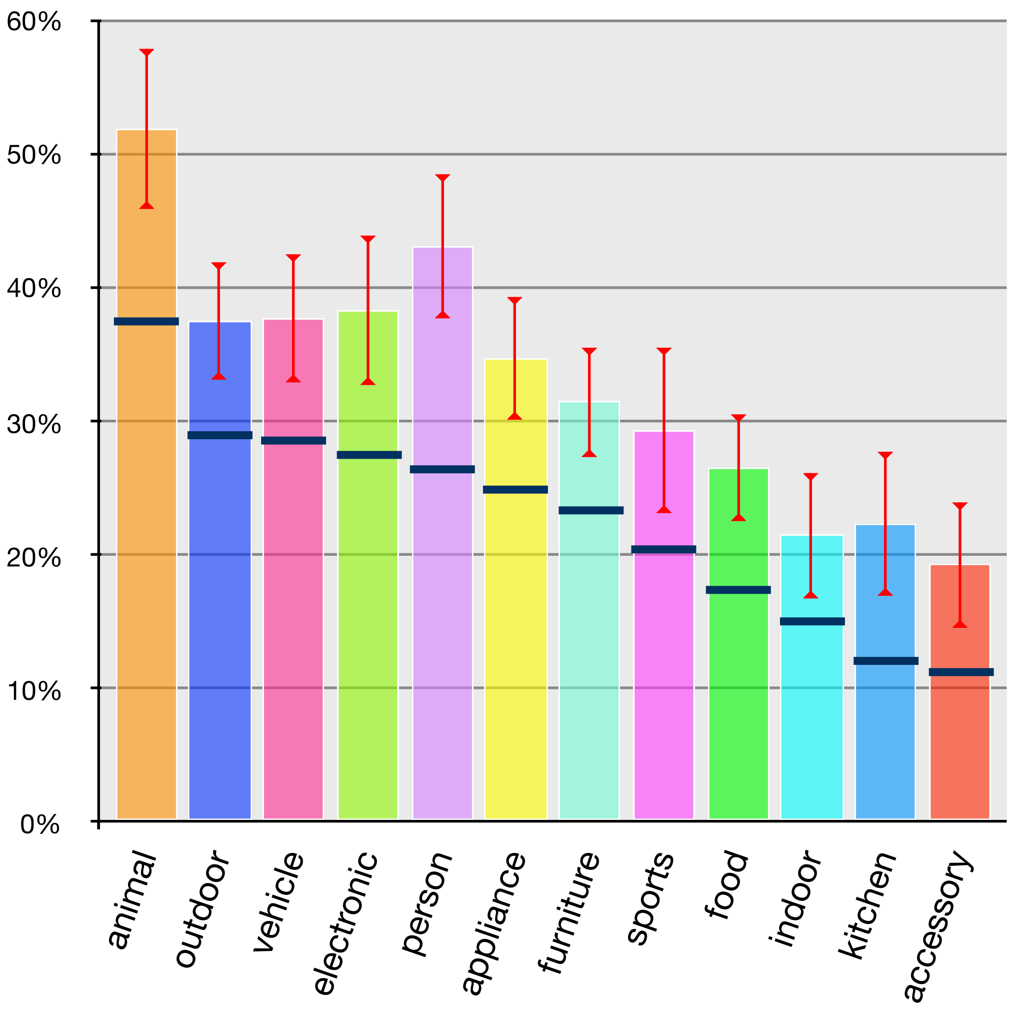
COCO AP varies across supercategories and size



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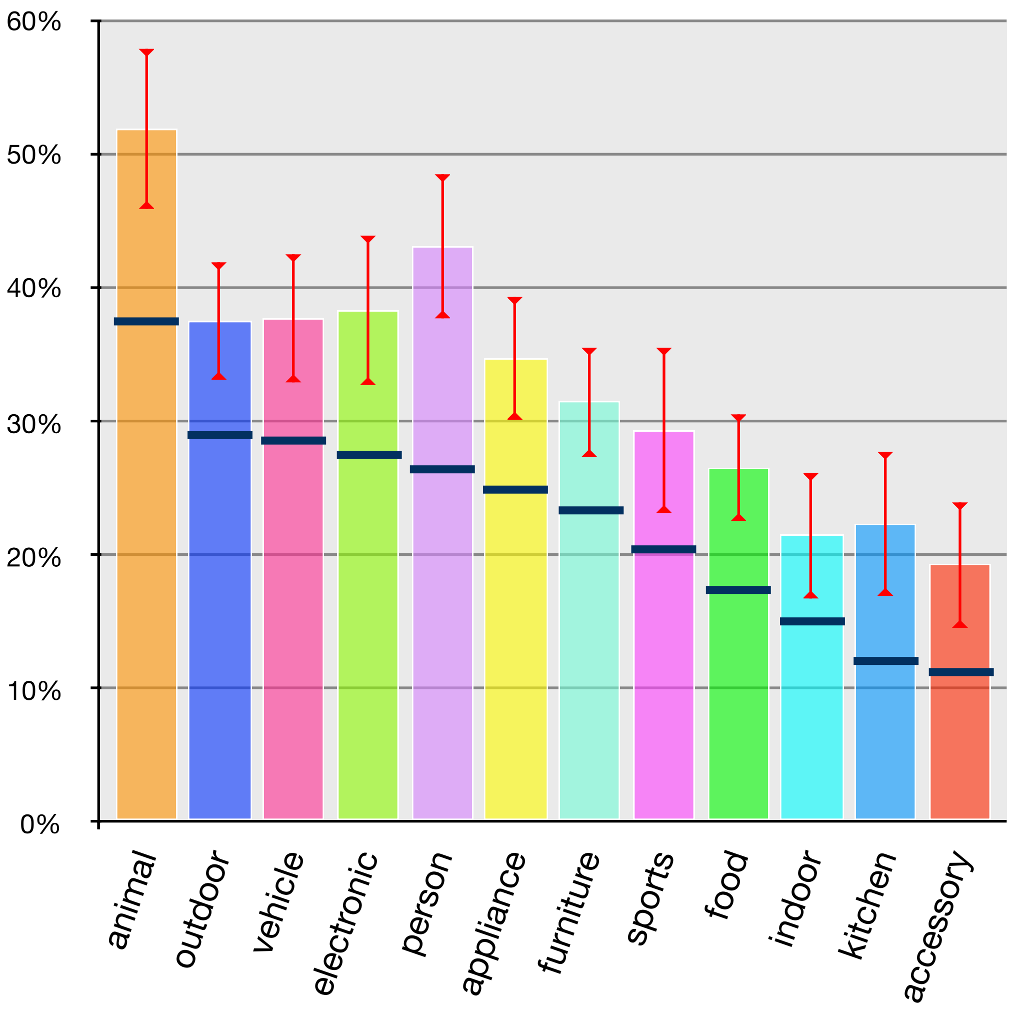
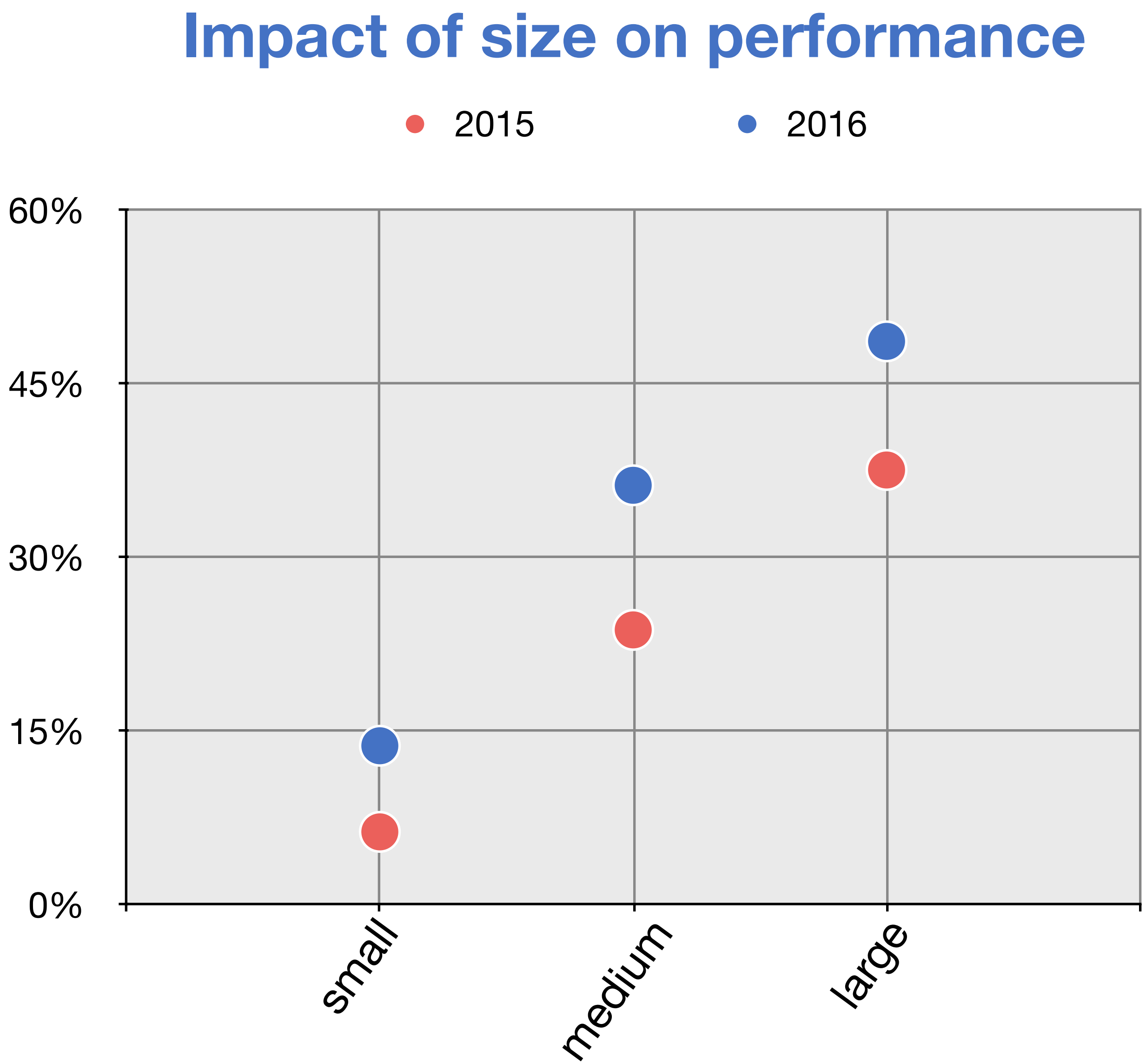
COCO AP varies across supercategories and size



Performance across teams improved on all supercategories

- Average AP increase of ~10%.
- Average Standard Deviation decrease of ~1%.

Performance Breakdown (II)



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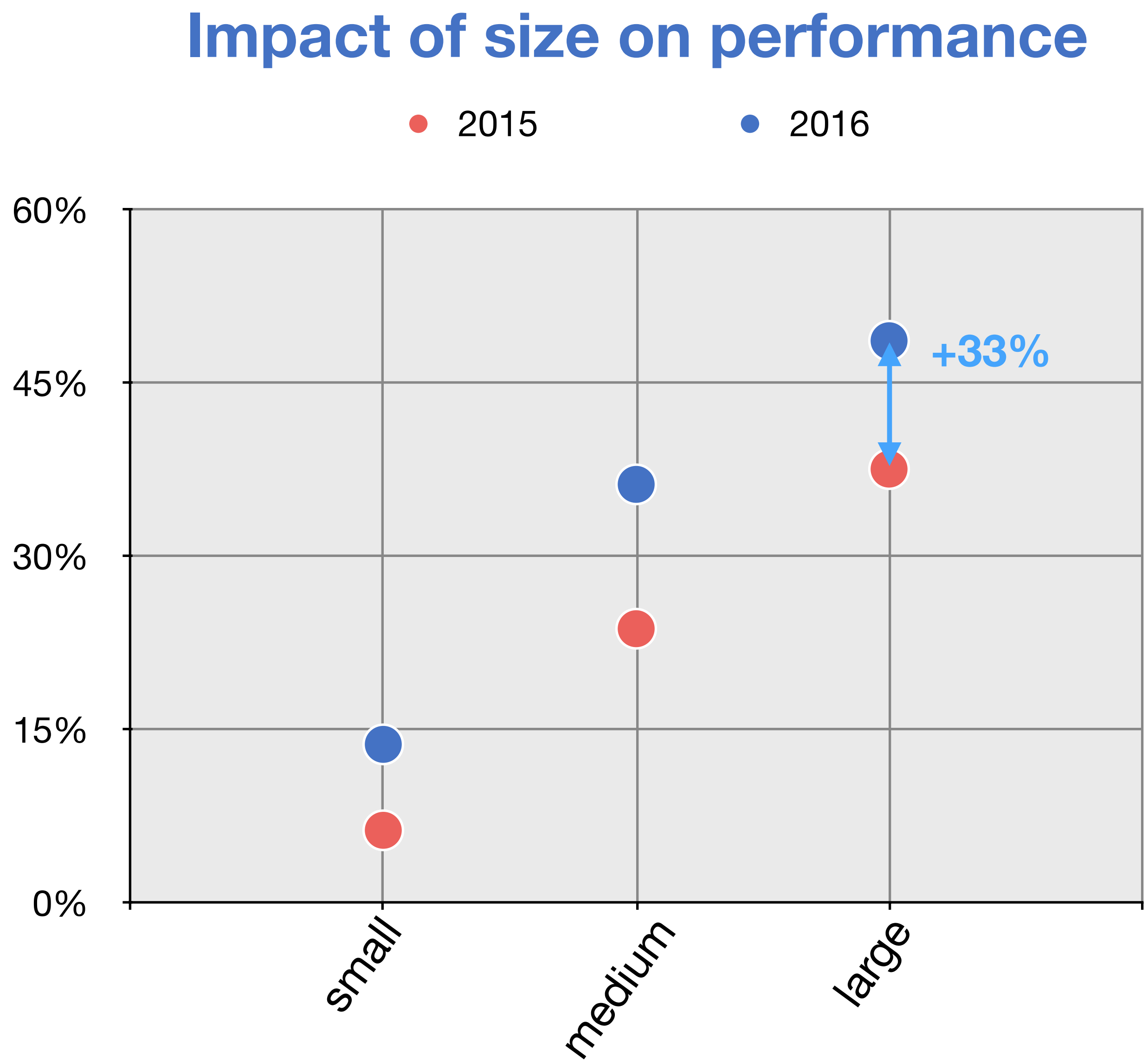

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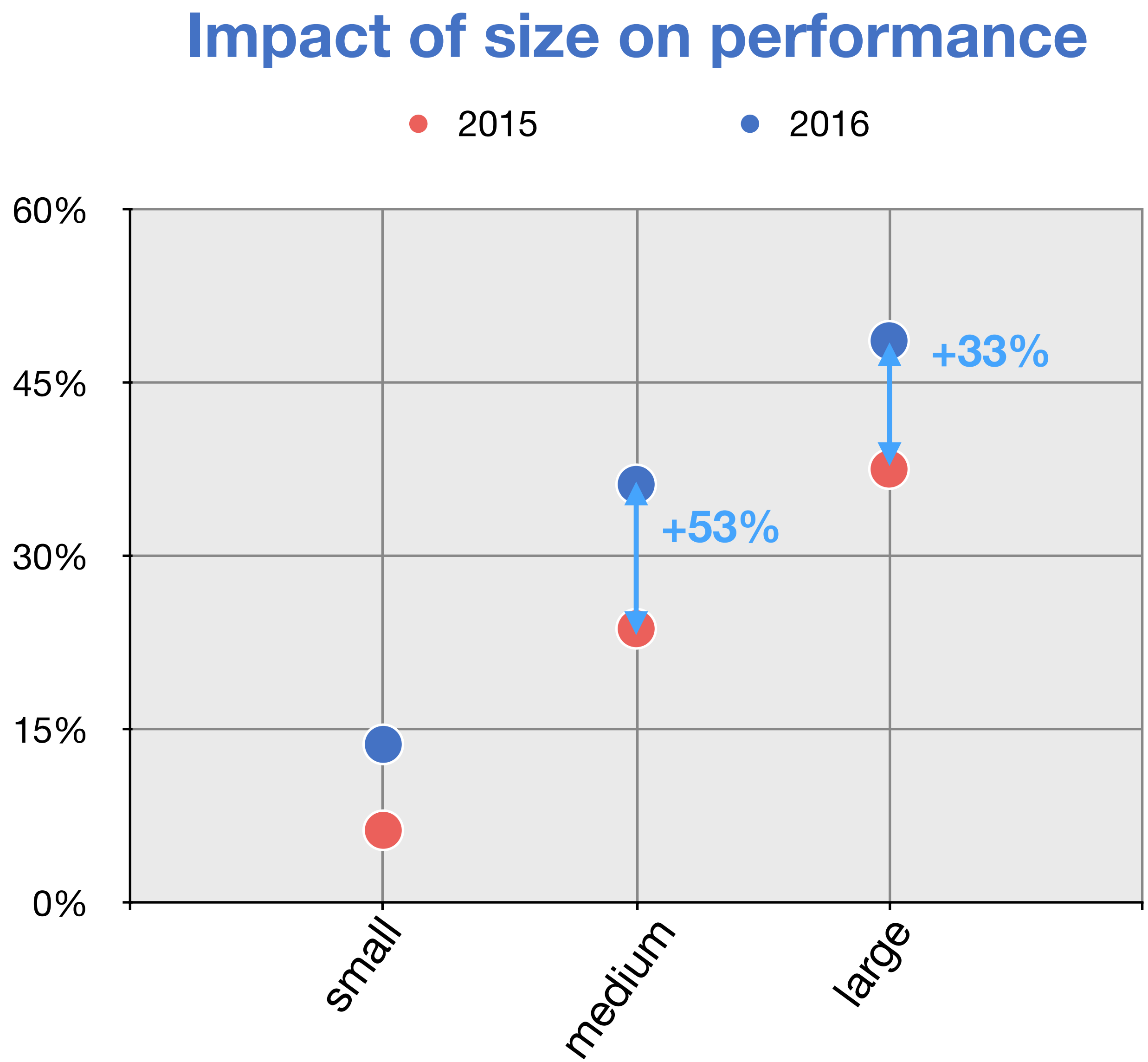

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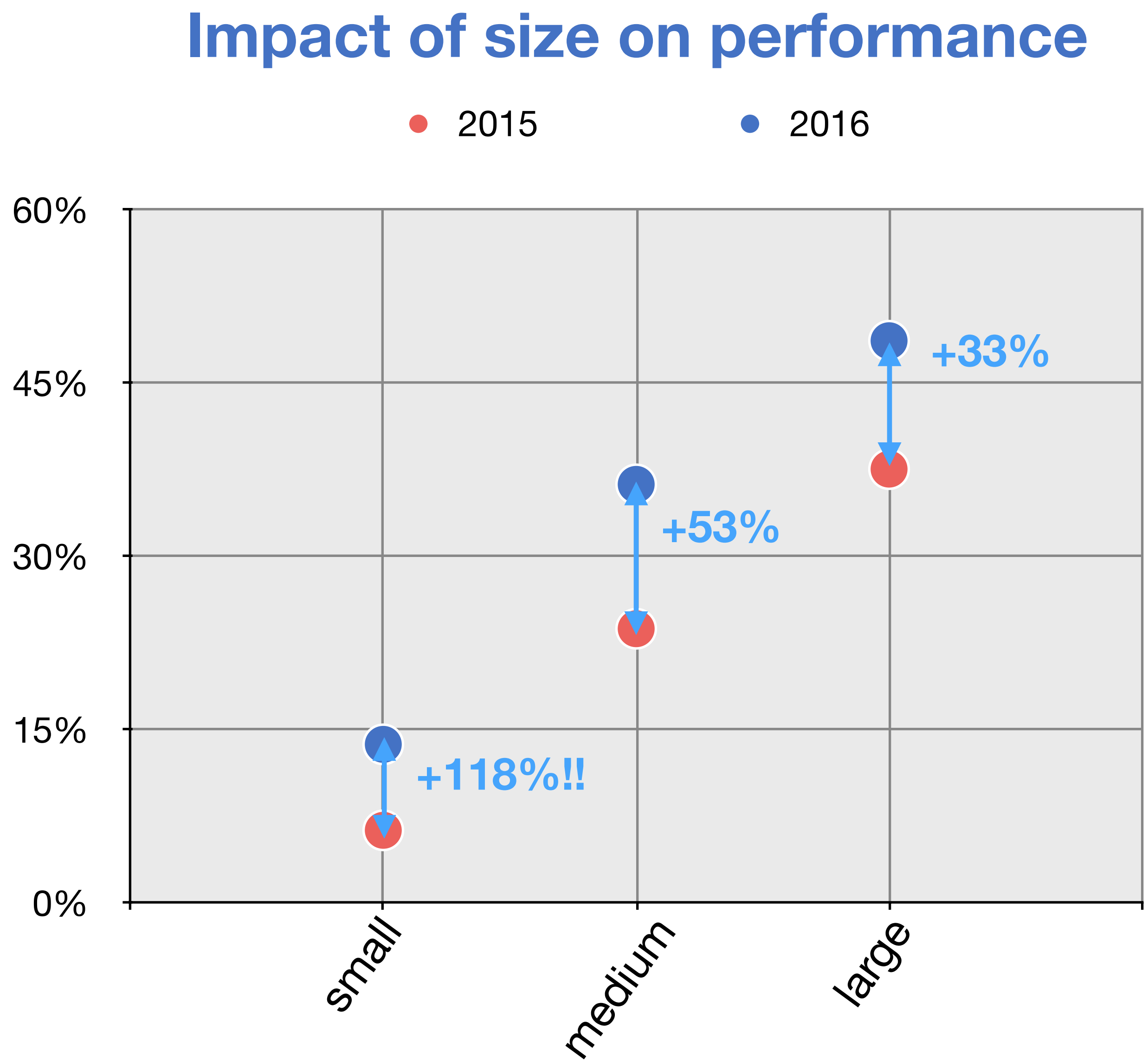

Correlation between methods

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How similarly do algorithms perform?

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Bounding Boxes

G-RMI

MSRAVC*

(*) 2015 Winner

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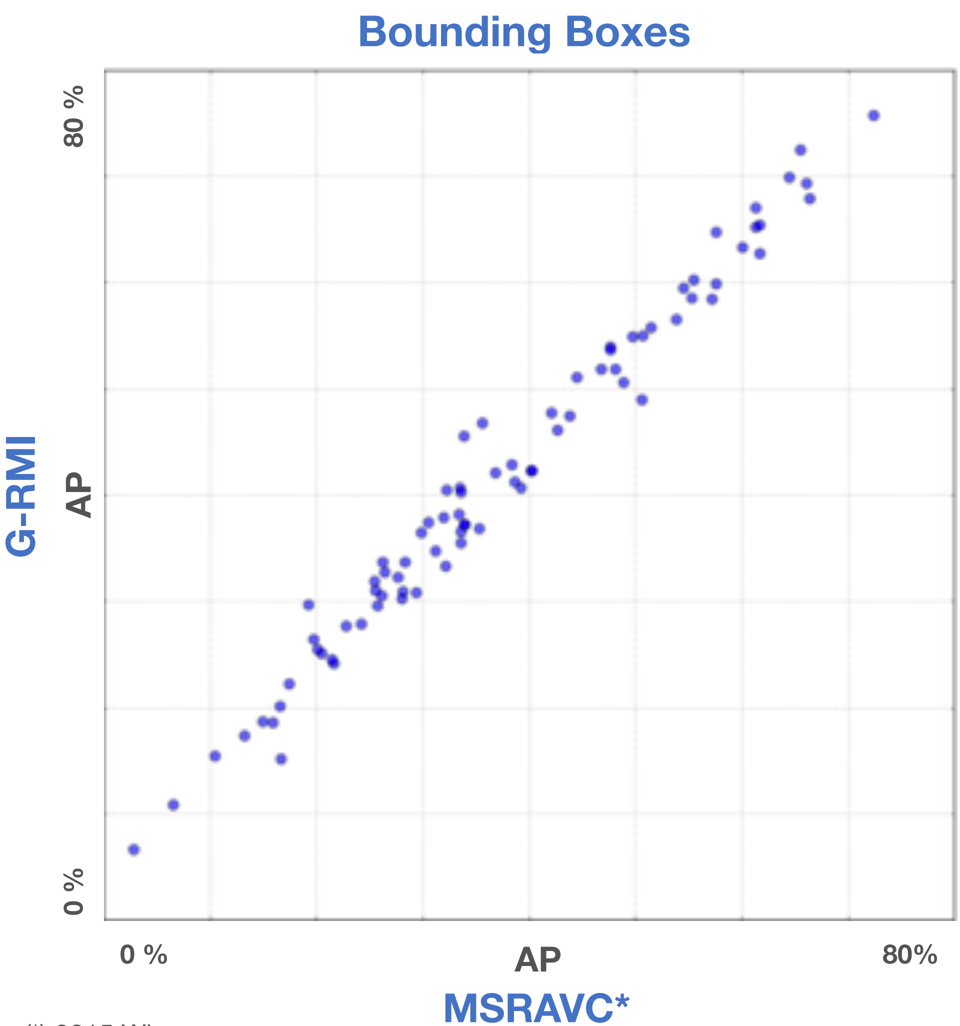

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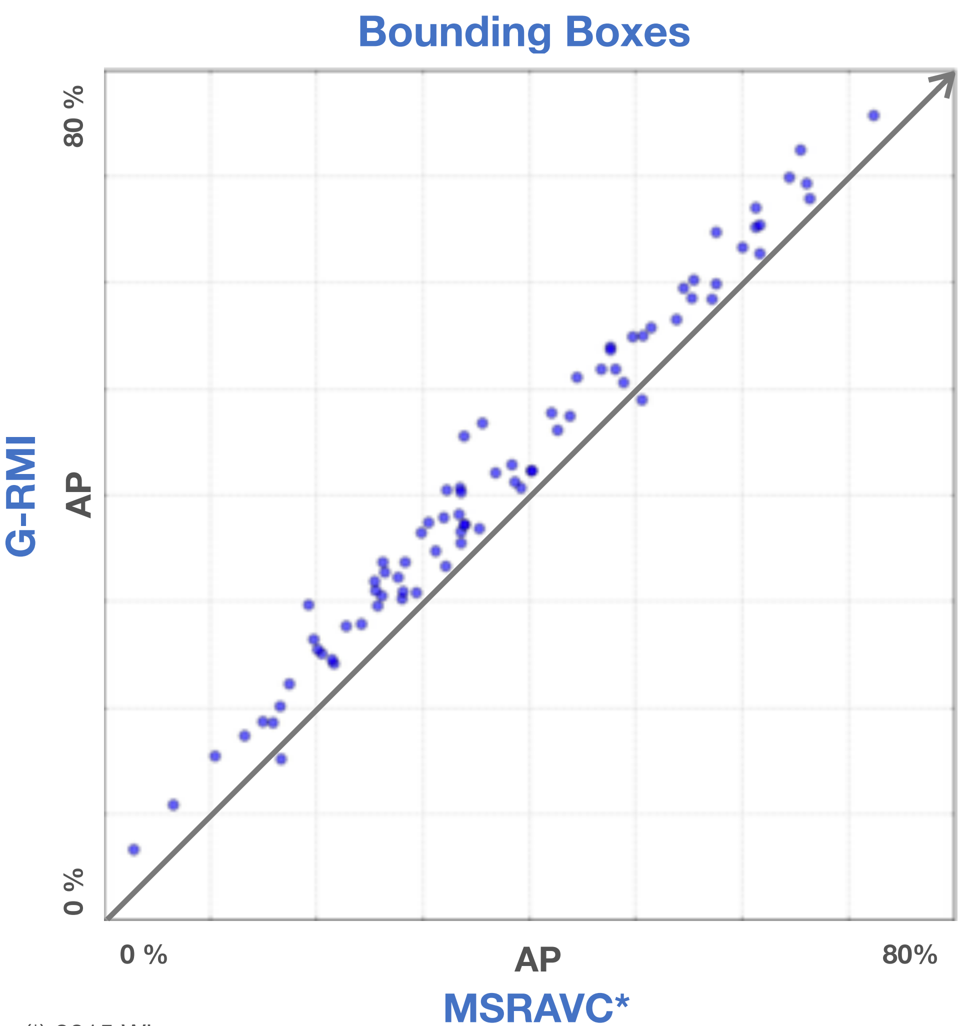

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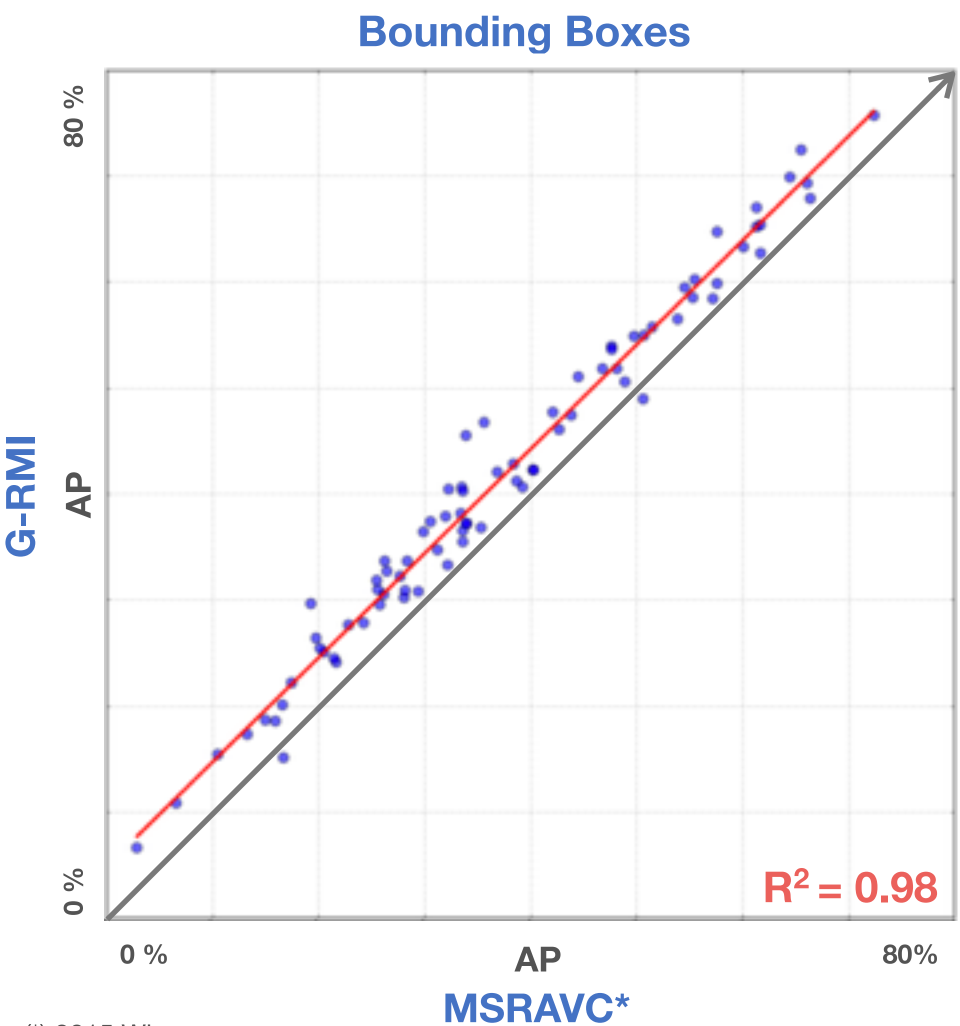

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Correlation between methods

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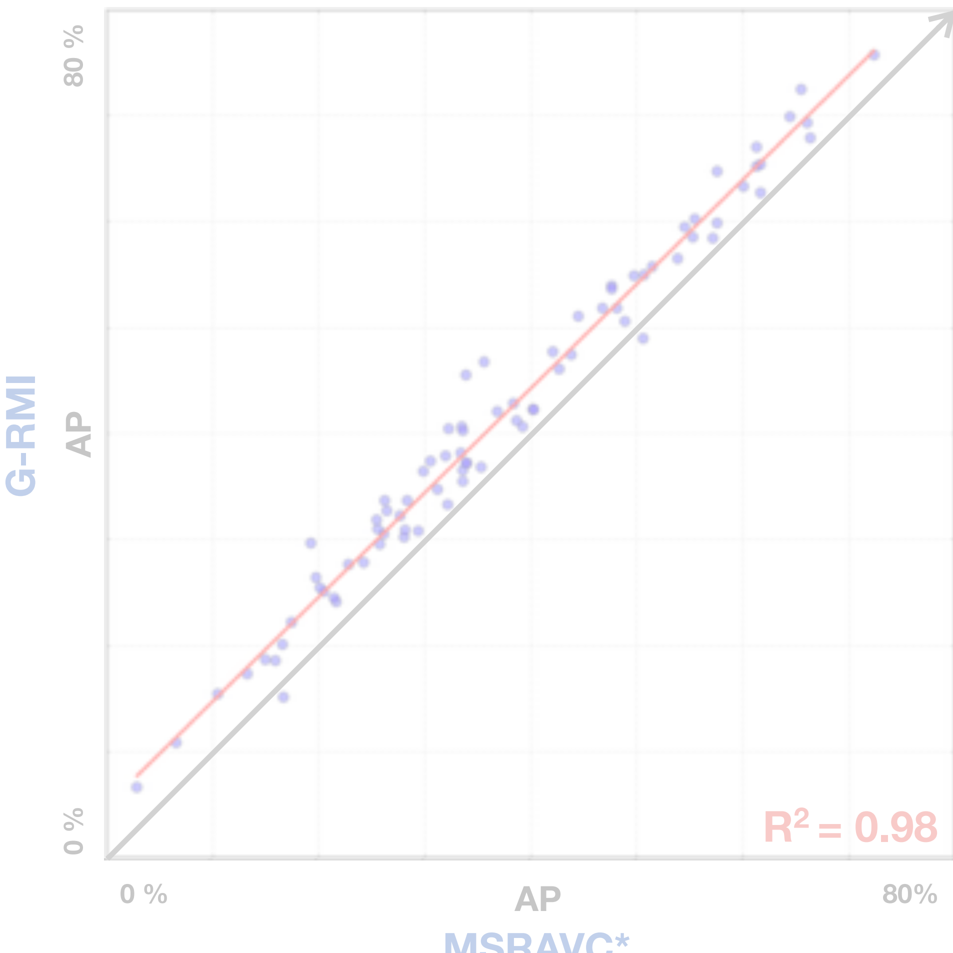
Bounding Boxes

Segmentation



MSRA

G-RMI

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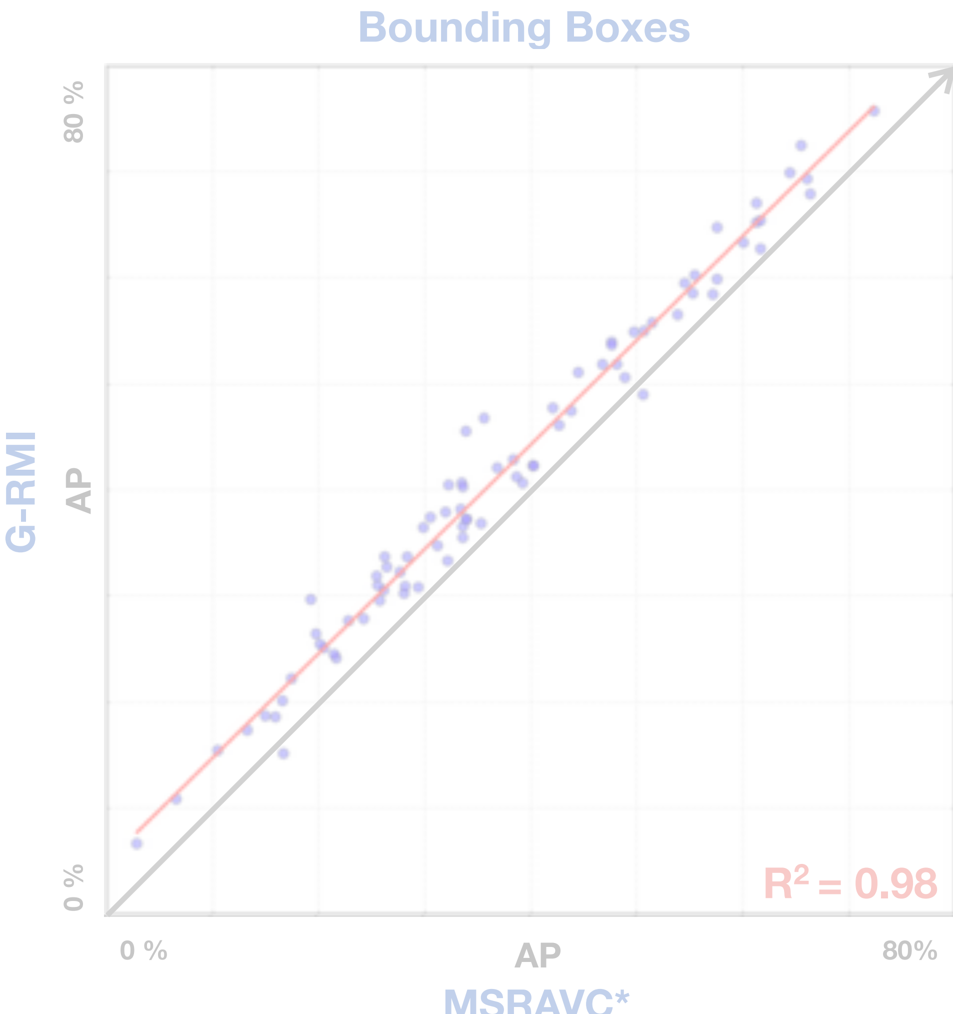

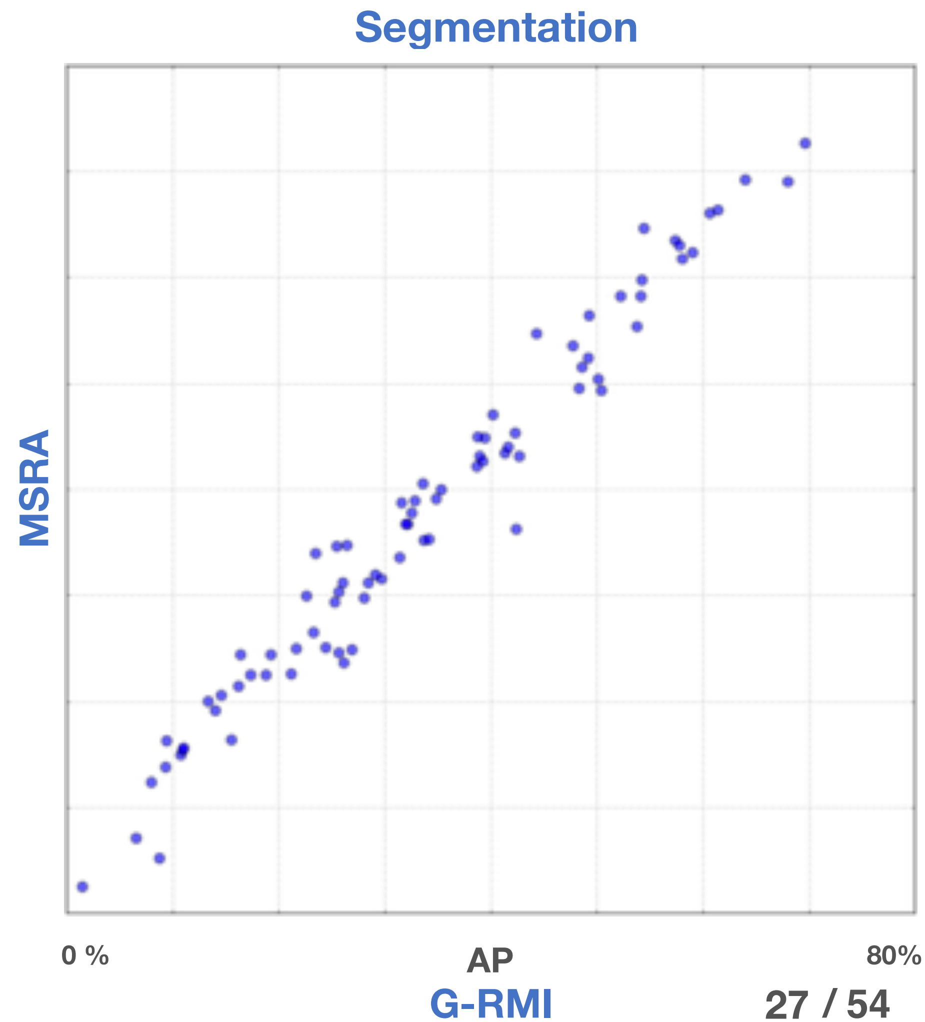

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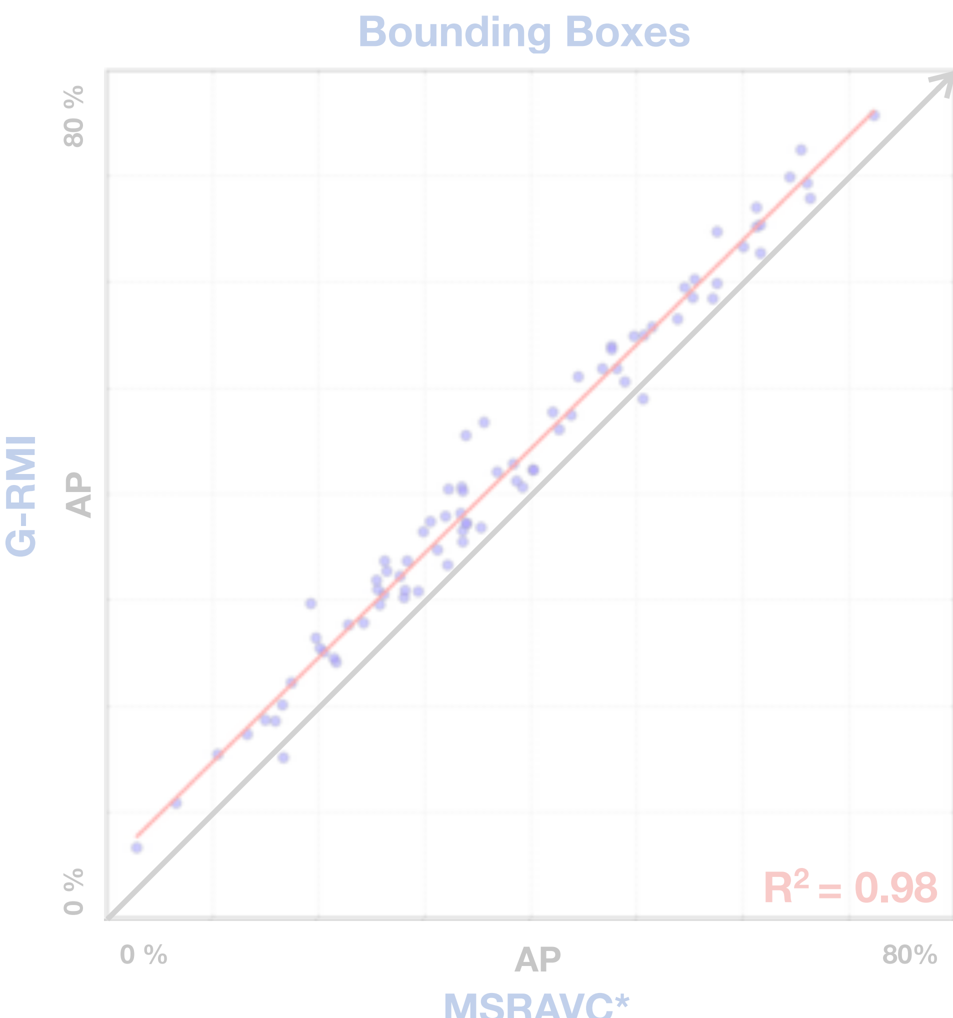

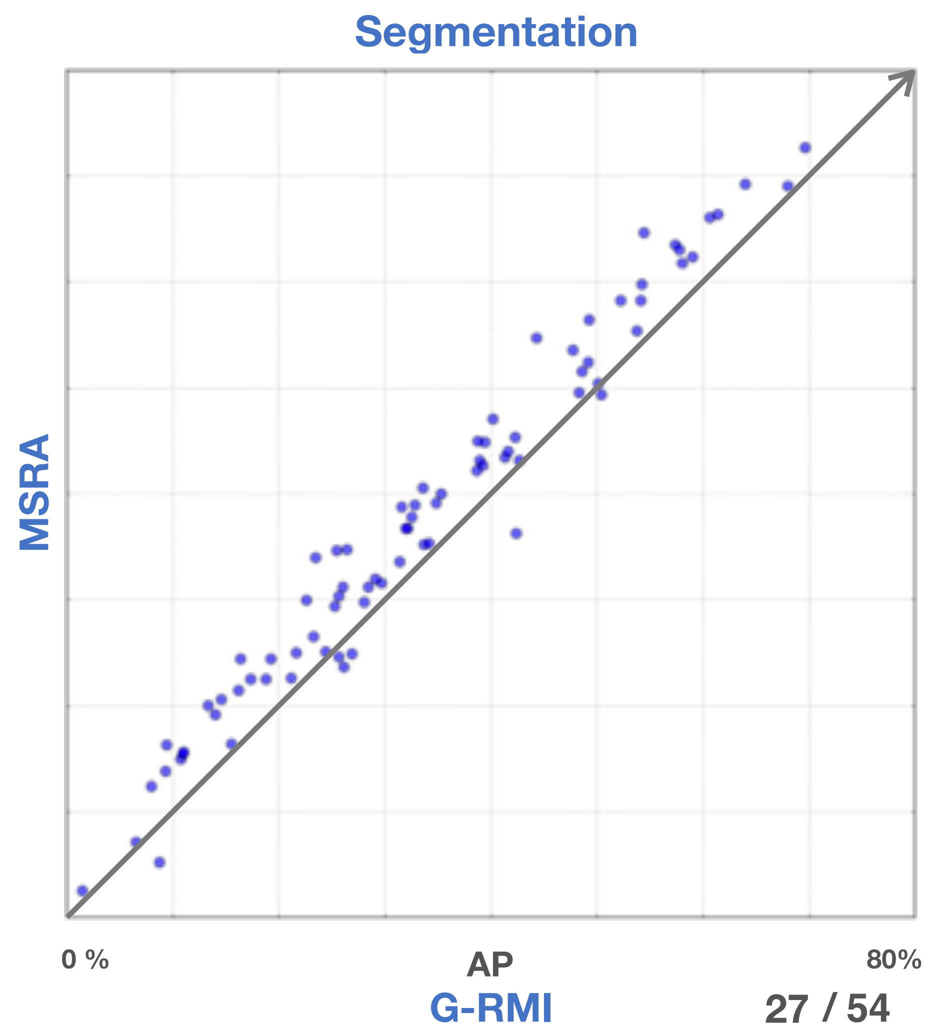

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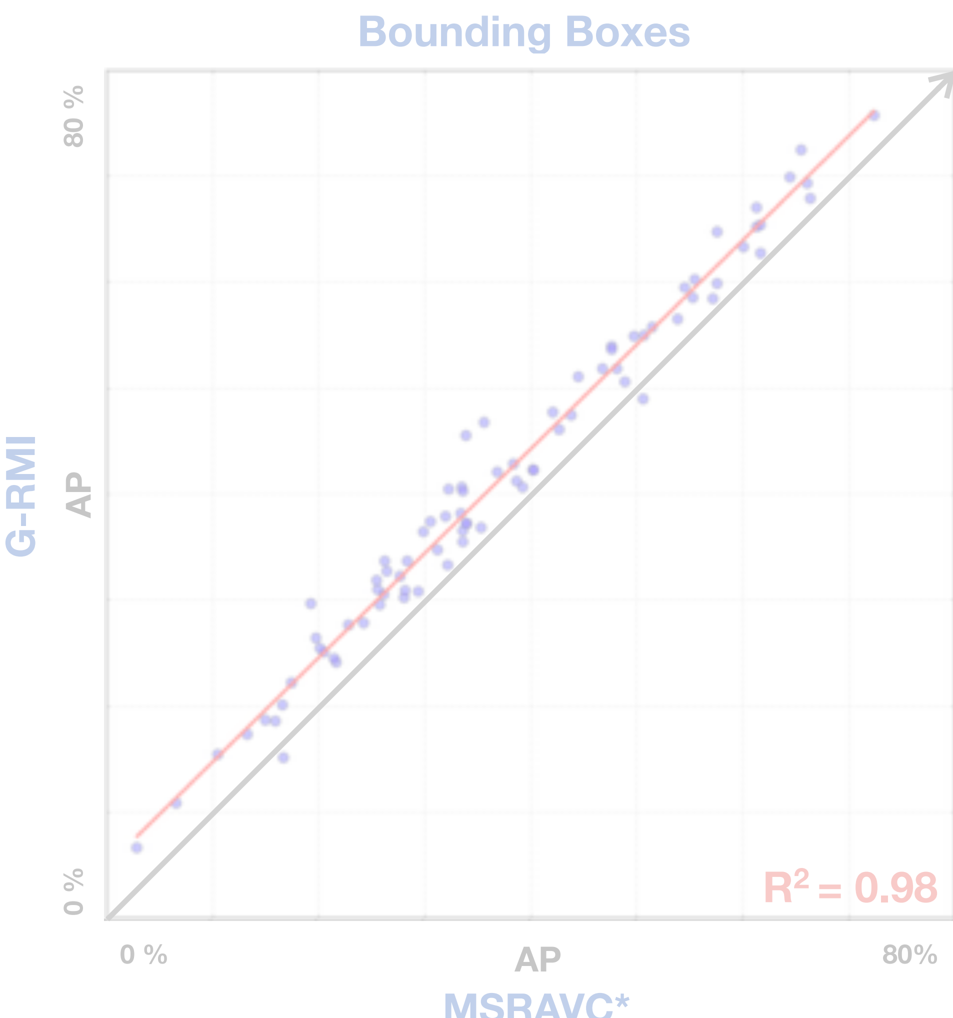

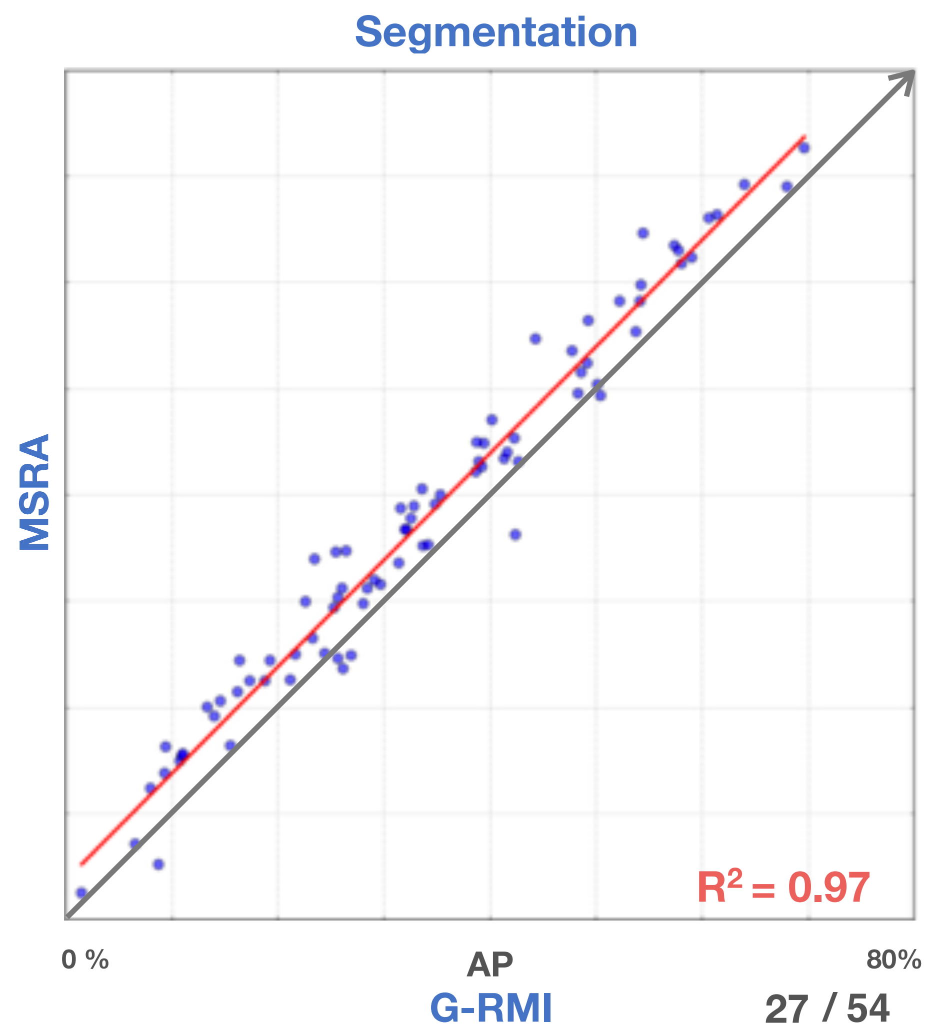

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Bounding Box Detection Errors

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How similarly do top algorithms perform?

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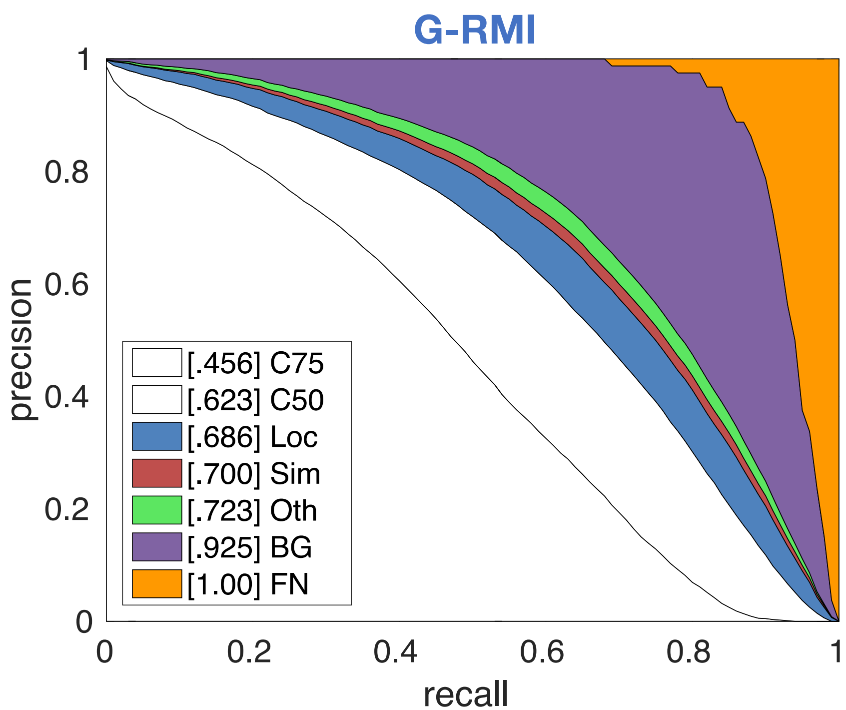
AP @ IoU = [0.5; 0.75]
AP @ IoU = 0.1
Super-category FP removed
Category FP removed
Background FP removed
All errors are removed



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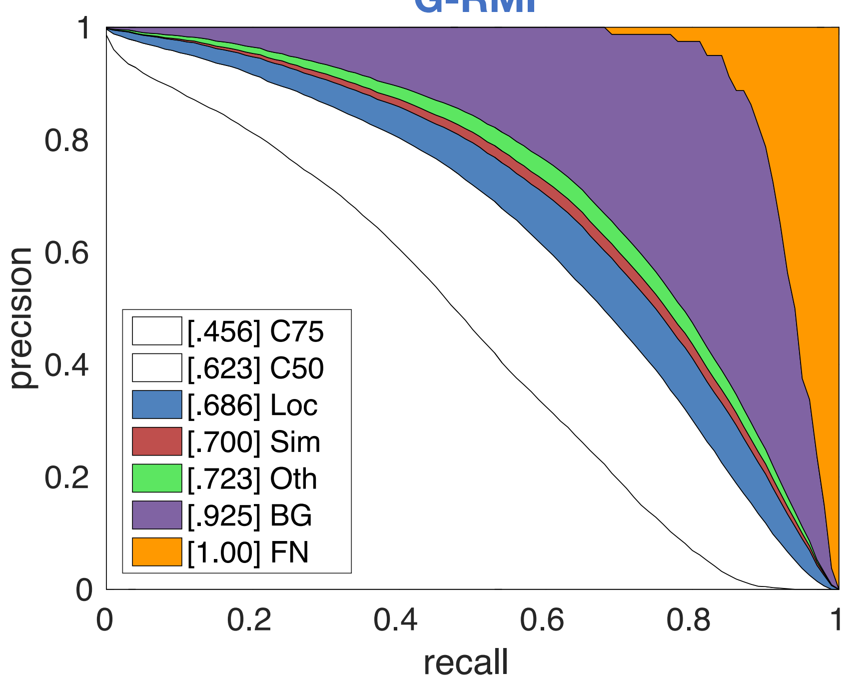
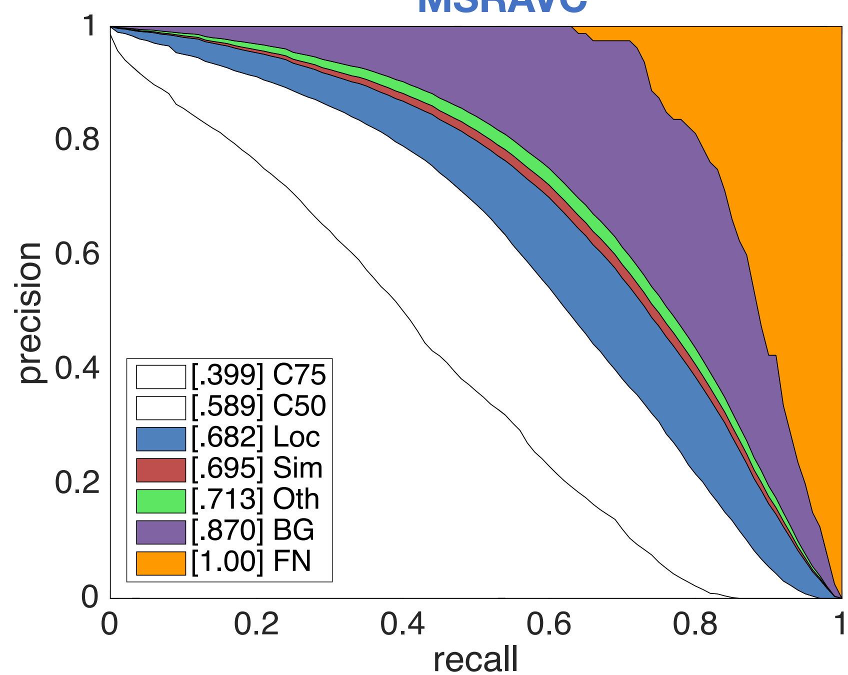
G-RMI



MSRAVC*



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Bounding Box Detection Errors (I)

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What type of errors are algorithms doing?

Bounding Box Detection Errors (I)

(white swatch)	AP @ IoU = [0.5; 0.75]
(blue swatch)	AP @ IoU = 0.1
(red swatch)	Super-category FP removed
(green swatch)	Category FP removed
(purple swatch)	Background FP removed
(orange swatch)	All errors are removed

Bounding Box Detection Errors (I)

AP @ IoU = [0.5; 0.75]

AP @ IoU = 0.1

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Category FP removed

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All errors are removed

G-RMI

MSRAVC*

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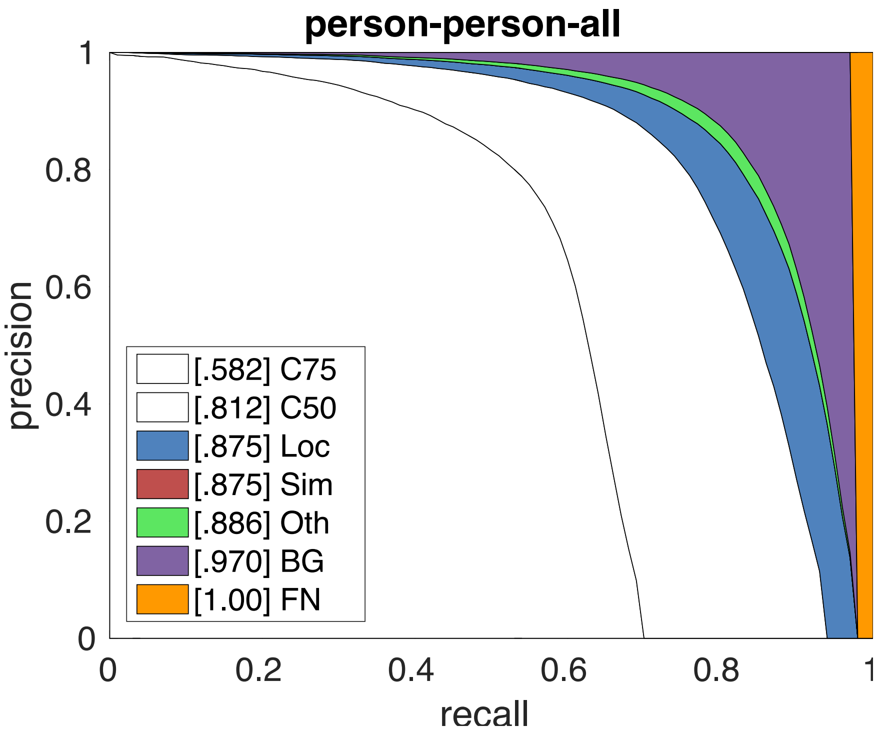
Bounding Box Detection Errors (I)

(white)	AP @ IoU = [0.5; 0.75]	(red)	Super-category FP removed	(purple)	Background FP removed
(blue)	AP @ IoU = 0.1	(green)	Category FP removed	(orange)	All errors are removed

G-RMI



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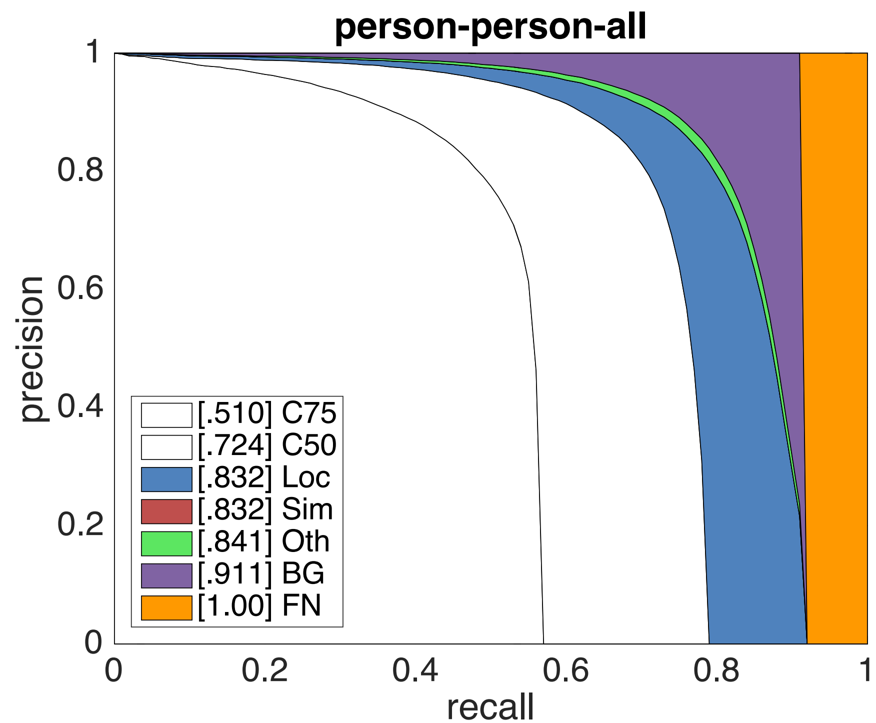

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What type of errors are algorithms doing?

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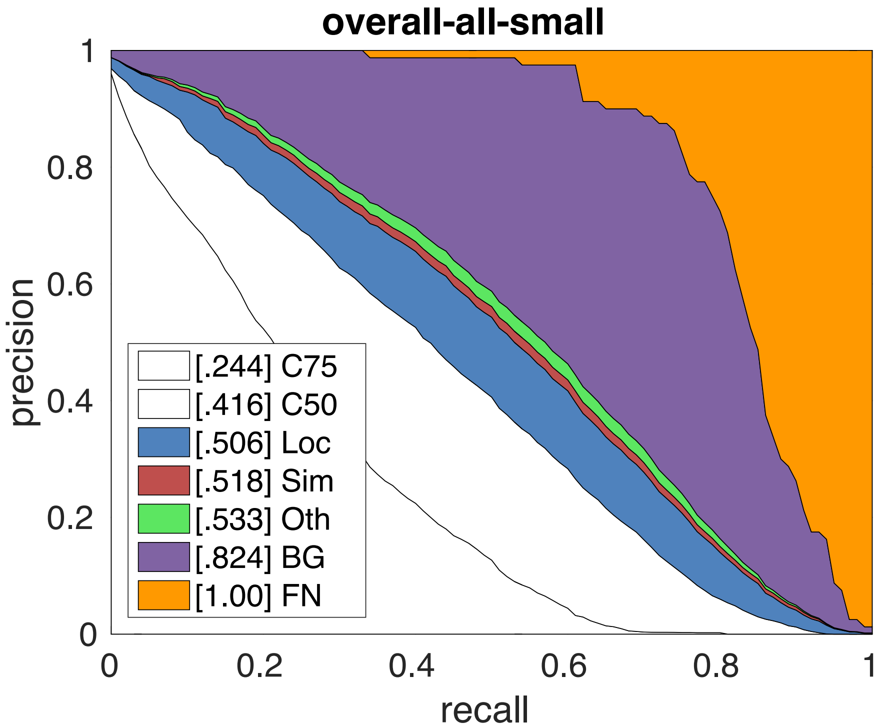

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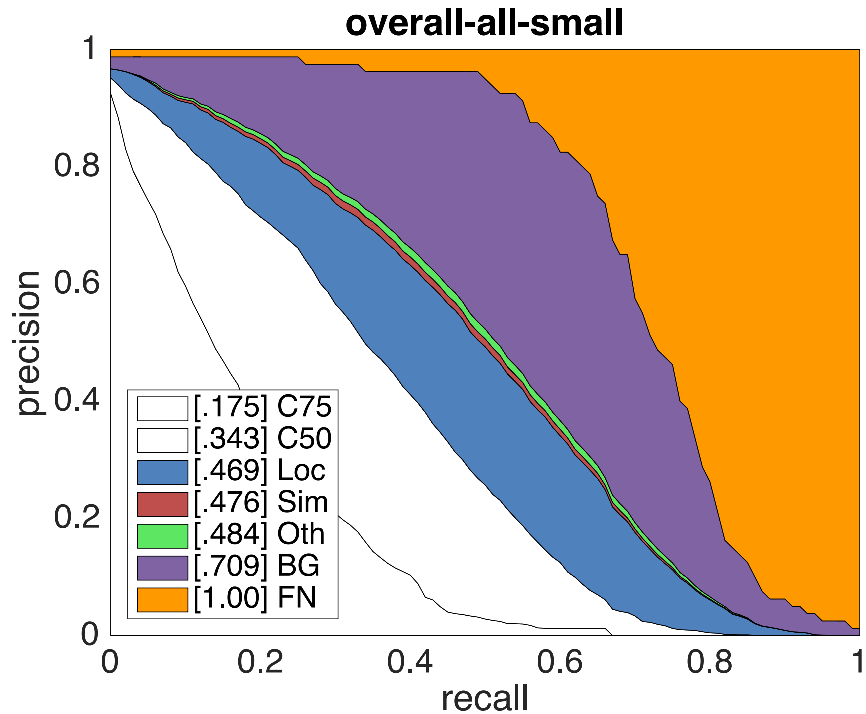

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Summary of Findings

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- Localization improved greatly in both challenges.
- High relative improvement on small object instances.
- False negatives are reduced, thus better recall of teams.

Challenges Ranking

Challenges Ranking

Team	BBox	Segmentation
G-RMI	1^{st}	2^{nd}
MSRA	-	1^{st}
Trimps-Soushen	2^{nd}	-
Imagine Lab	3^{rd}	-

Challenges Ranking

Team	BBox	Segmentation
G-RMI	1st	2nd
MSRA	-	1st
Trimps-Soushen	2nd	-
Imagine Lab	3rd	-

Invited Speakers:

- G-RMI / Object Detection / (2:30pm - 2:45pm)
- MSRA / Segmentation / (2:45pm - 3:00pm)