Recent Advances on Object Detection in MSRA

Jifeng Dai, Han Hu, Lu Yuan and Yichen Wei

Visual Computing Group, Microsoft Research Asia

Outline

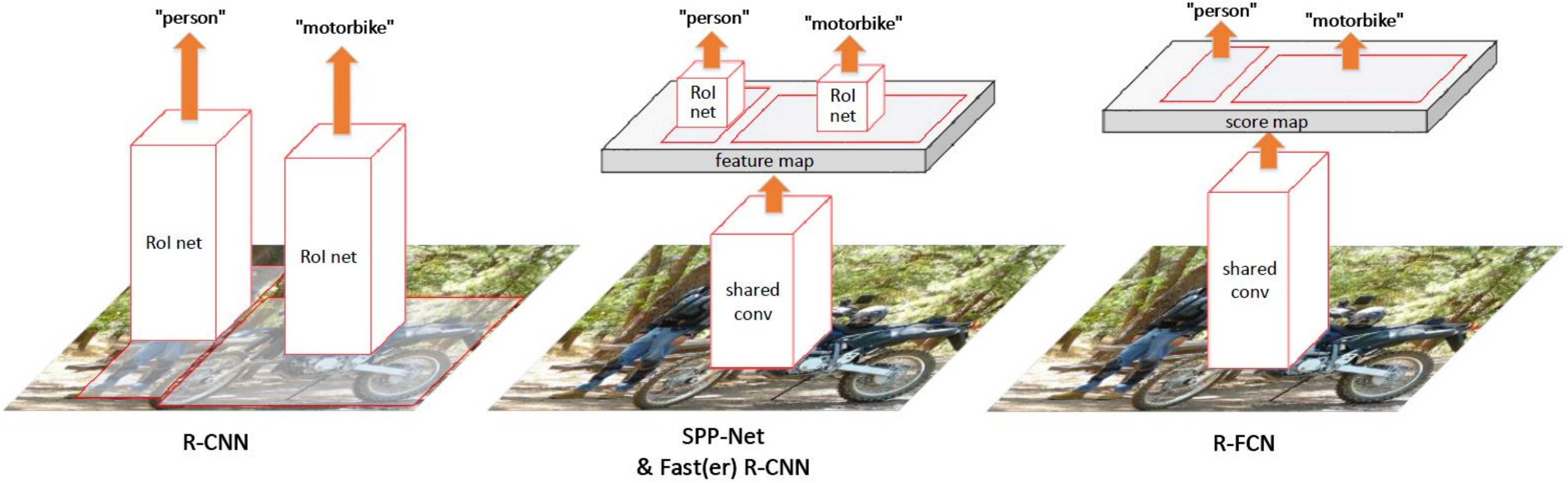
- R-FCN and its extensions
- Deformable ConvNets and its extensions
- Video object detection
- Summary

Highlights

- Region-based, fully-convolutional networks for object detection
- Fast and accurate
- Motivate many extensions

Code is available at https://github.com/daijifeng001/R-FCN

Region-based Object Detectors



- Methodologies of region-based detectors using ResNet-101

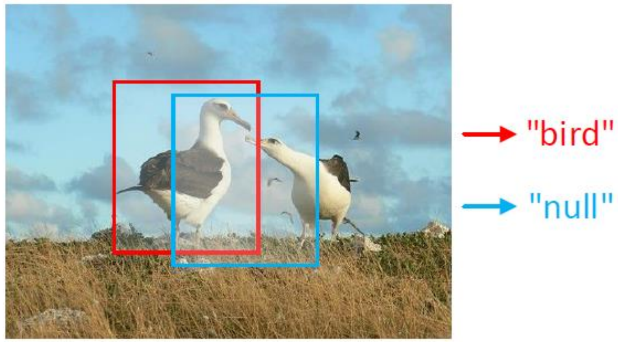
	R-CNN	Faster R-CNN	R-FCN [ours]
depth of shared conv subnetwork	0	91	101
depth of RoI-wise subnetwork	101	10	**0**

Respecting Translation Variance for Detection

- Increasing translation invariance for image classification
  - Shift of an object inside an image should be indiscriminative
  - Leading deep (fully) convolutional architectures are translation-invariant

- Respecting translation variance for object detection
  - Responses should reflect how candidate boxes overlap with objects
  - A considerable deep per-ROI subnet in Faster-RCNN using ResNet-101

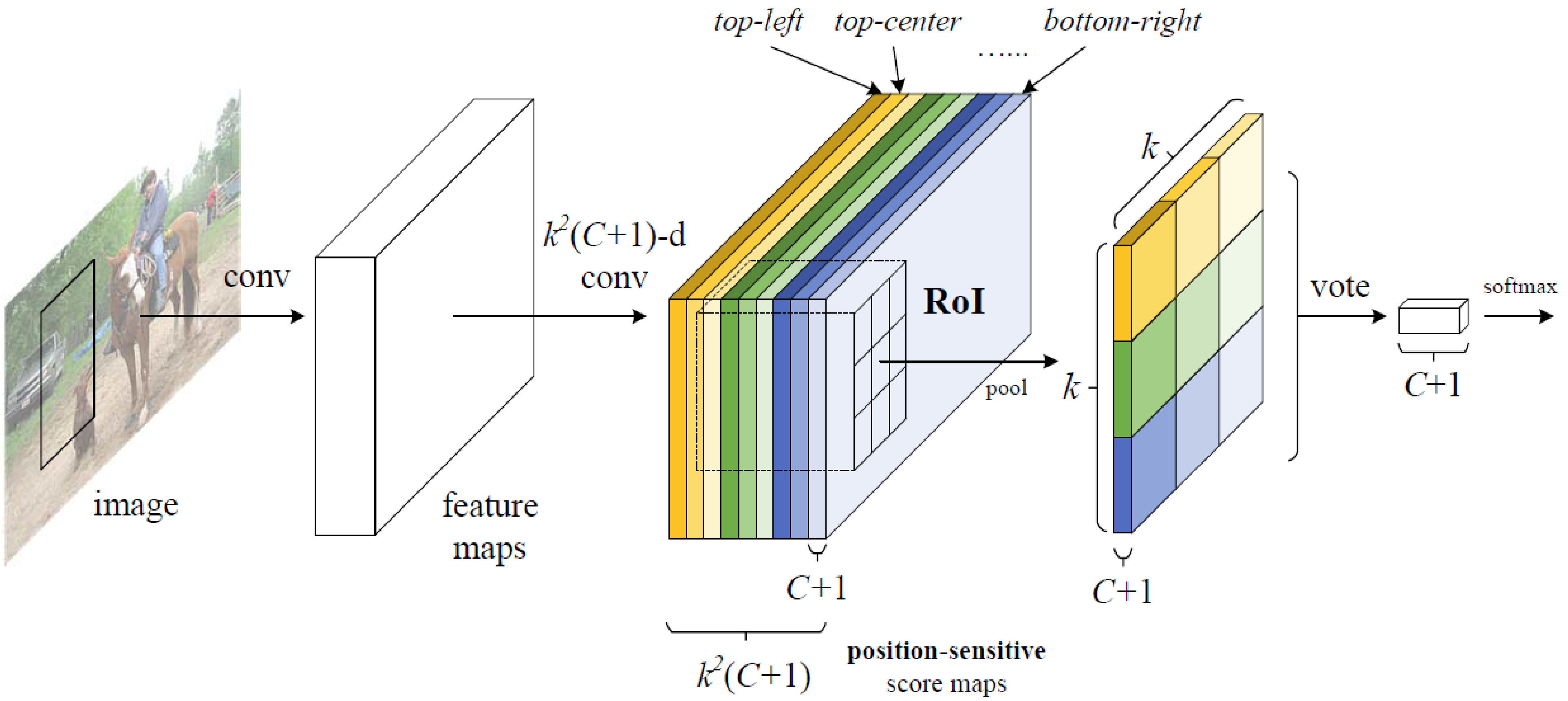
image classification



object detection

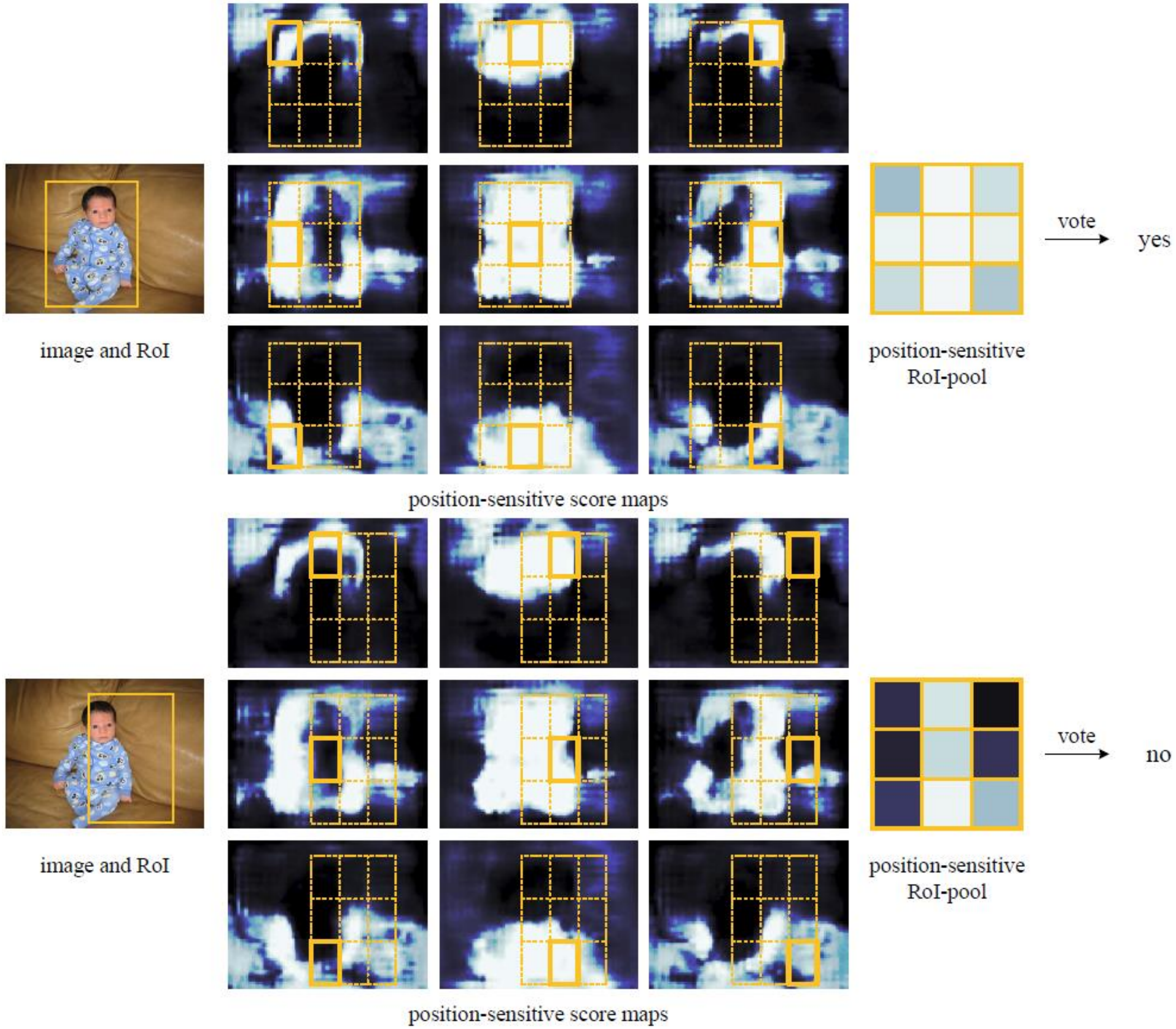
R-FCN

- Key idea of R-FCN for object detection
  - Position-sensitive score maps (kxk, e.g., k = 3)
  - Position-sensitive RoI pooling



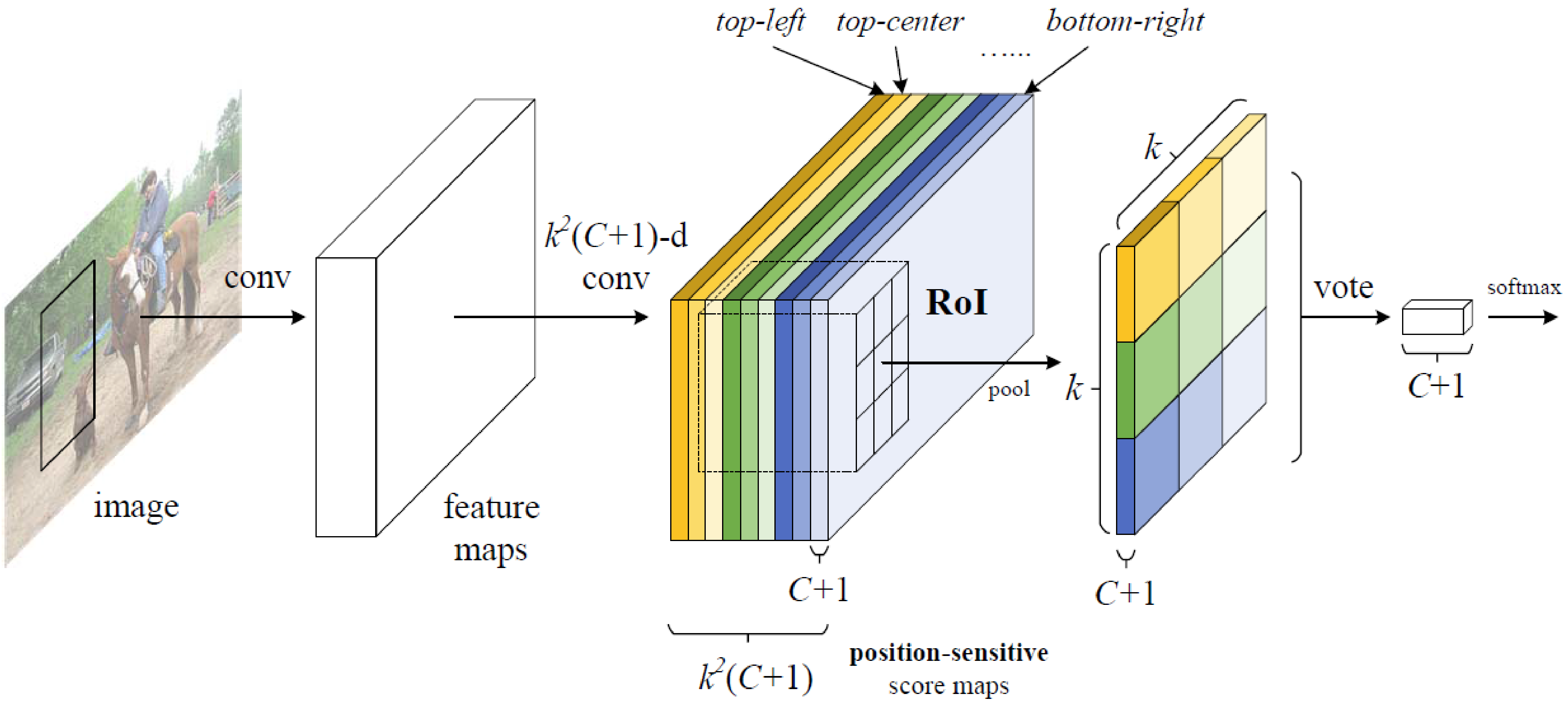
R-FCN

- Spatial information is encoded by position-sensitive score maps



R-FCN

- Key properties of **R-FCN**
  - Negligible per-RoI computational cost (in both training/inference)
  - The whole architecture is end-to-end trainable



Experiments

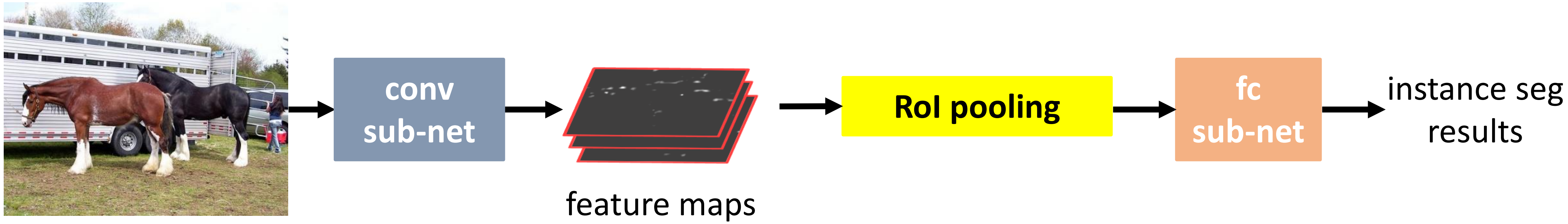
- Comparisons between Faster R-CNN and R-FCN using ResNet-101

	depth of per-RoI subnetwork	training w/ OHEM?	train time (sec/img)	test time (sec/img)	mAP (%) on VOC07
Faster R-CNN	10		1.2	0.42	76.4
R-FCN	0		0.45	0.17	76.6
Faster R-CNN	10	✓ (300 RoIs)	1.5	0.42	79.3
R-FCN	0	✓ (300 RoIs)	0.45	0.17	**79.5**
Faster R-CNN	10	✓ (2000 RoIs)	2.9	0.42	*N/A*
R-FCN	0	✓ (2000 RoIs)	0.46	0.17	79.3

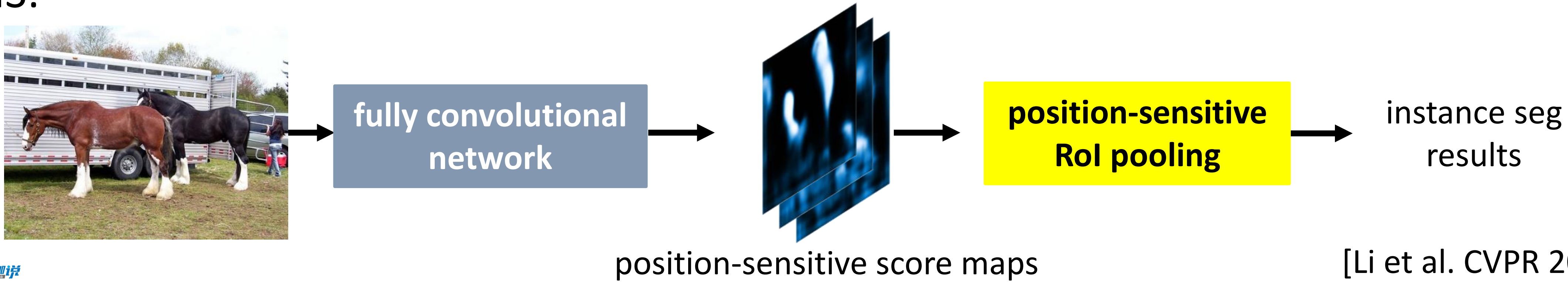
R-FCN extensions: fully convolutional instance segmentation

- First pure fully convolutional solution for instance segmentation
  - Accurate: no feature warping/resizing or fc layers
  - Fast: negligible per-region computation

Previous best & fastest:



FCIS:



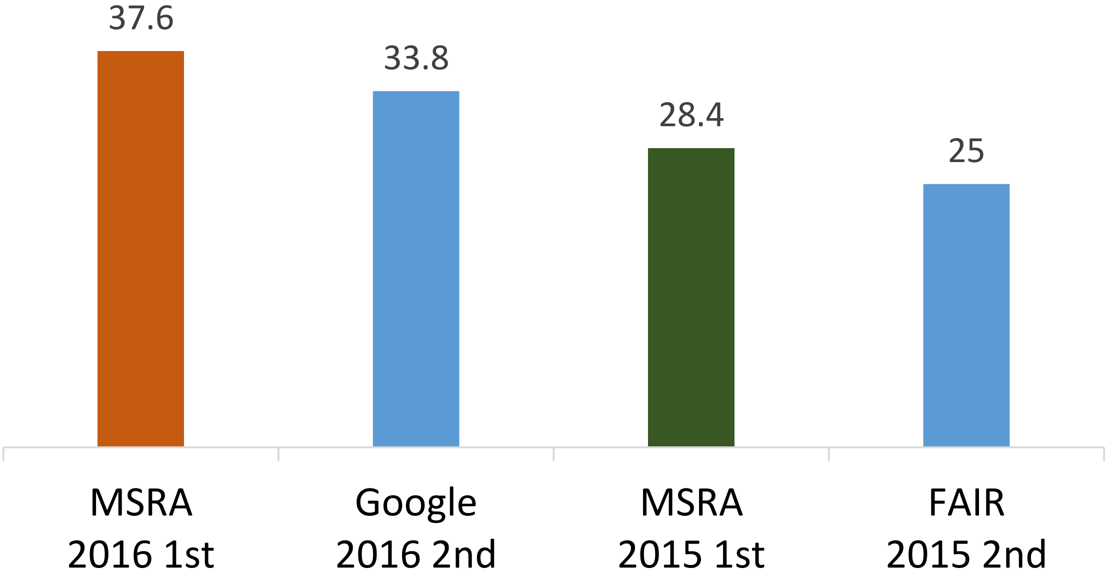
[Li et al. CVPR 2017.]

COCO Segmentation Challenge 2016

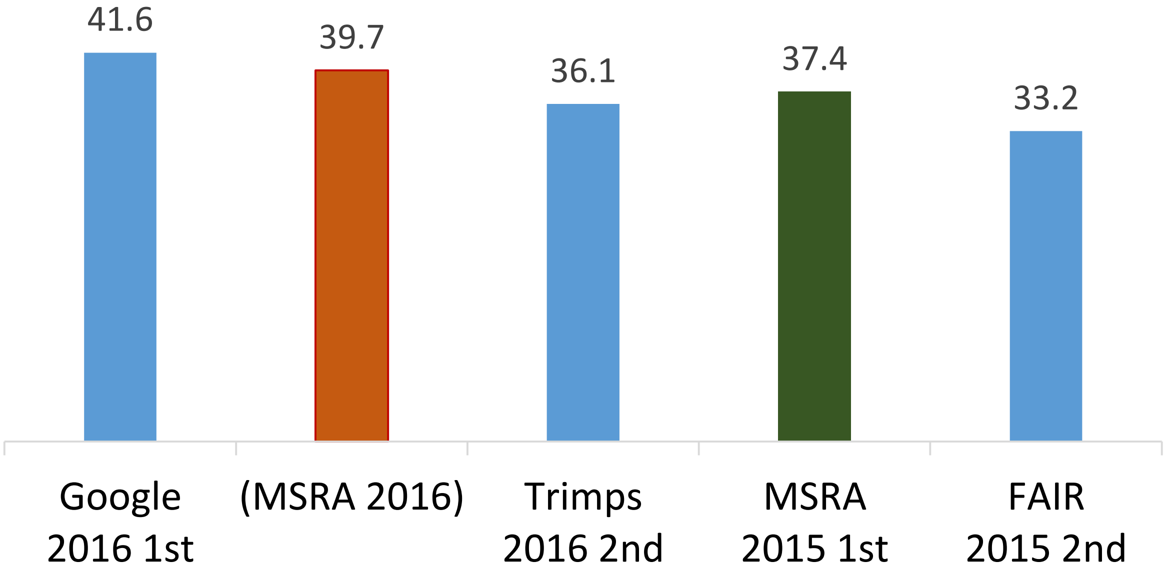
- MSRA won 1st place back-to-back
  - 11% relatively better than 2016 2nd (Google)
  - 33% relatively better than 2015 1st (MSRA)
  - Excellent on box: 2nd place in detection if public

COCO
Common Objects in Context

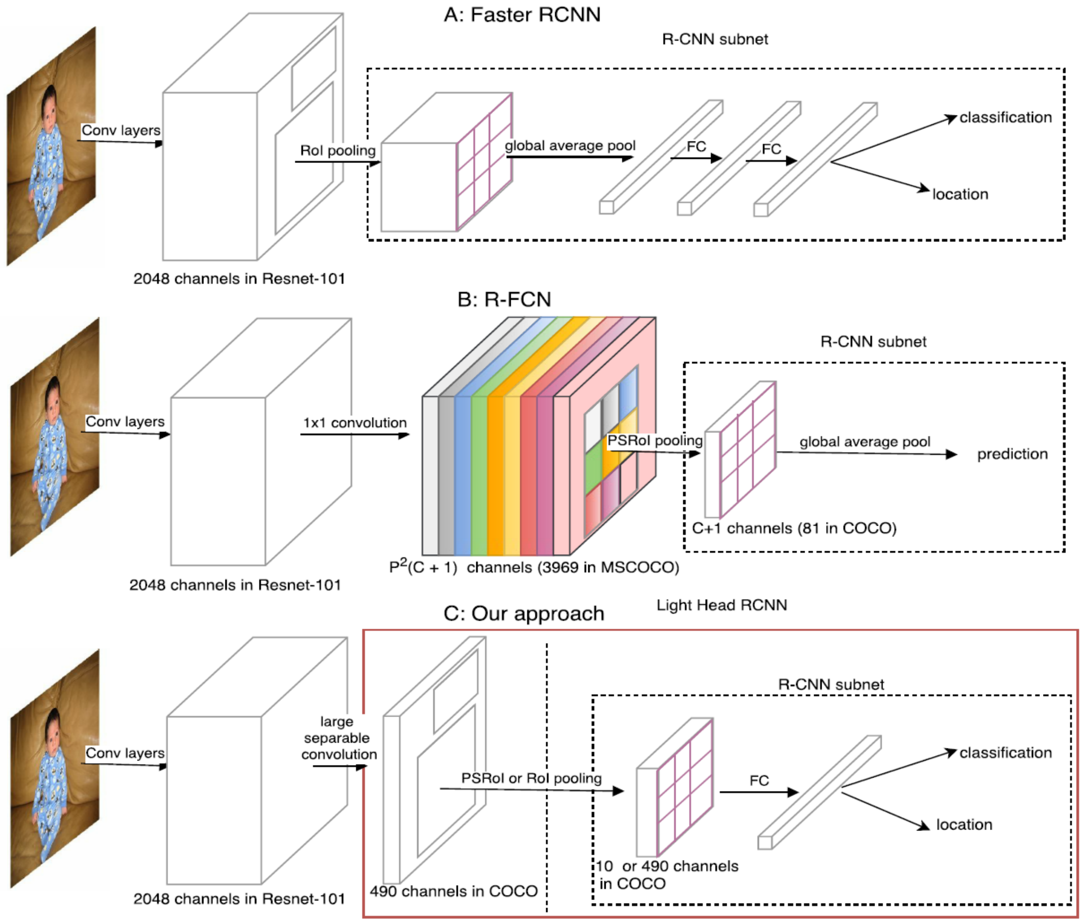
COCO Segmentation Accuracy (%)



COCO Detection Accuracy (%)



R-FCN extensions: Light-head R-CNN

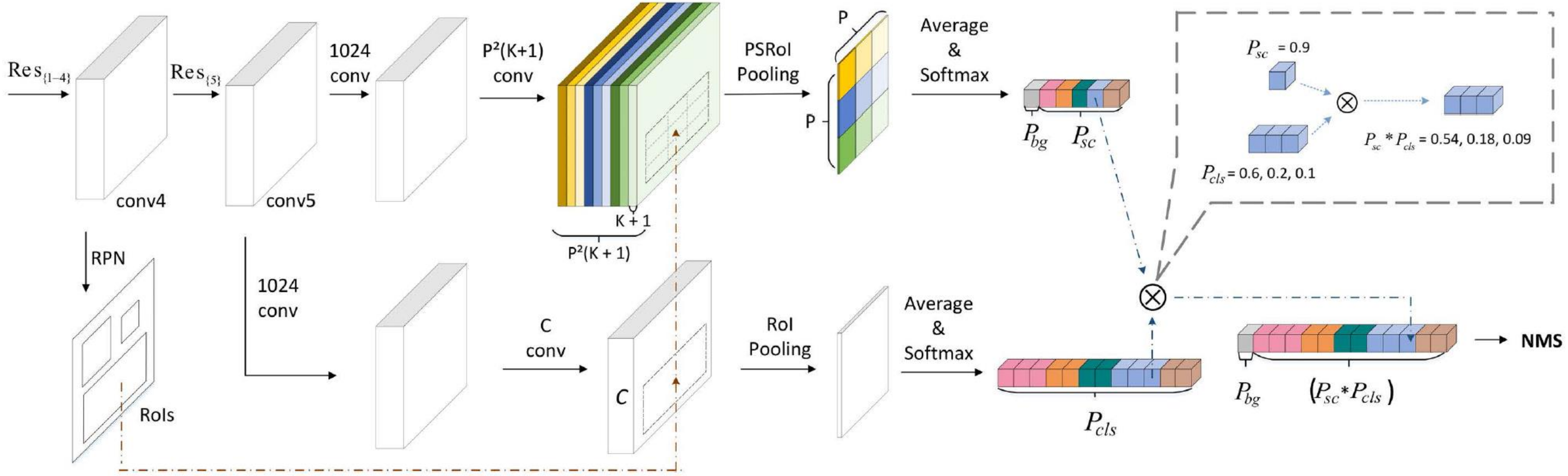


- PS scores-> PS features, followed by ultra-light detection head
  - Fast and accurate
  - Adopted in products

[Li et al. CVPR 2018.]

R-FCN extensions: R-FCN-3000 at 30fps

- Decoupled classification and localization for scaling up



[Singh et al. CVPR 2018.]

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Highlights

- **Enabling effective modeling of spatial transformation** in ConvNets
- **No additional supervision** for learning spatial transformation
- **Significant accuracy improvements** on sophisticated vision tasks

Code is available at https://github.com/msracver/Deformable-ConvNets

Modeling Spatial Transformations

- A long standing problem in computer vision

Deformation:

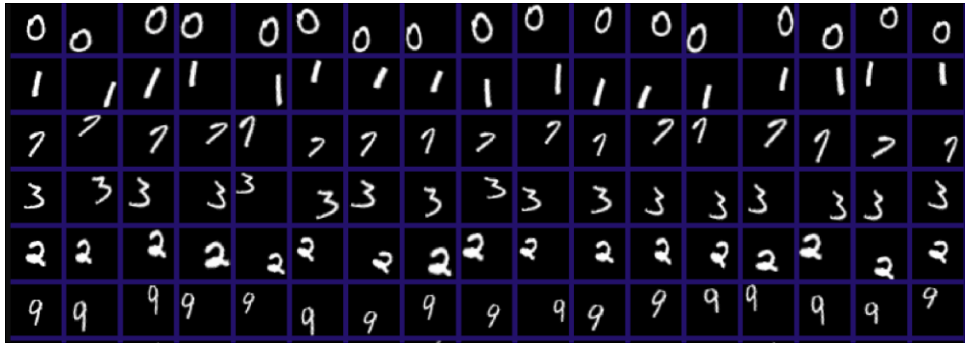
Scale:

Viewpoint variation:

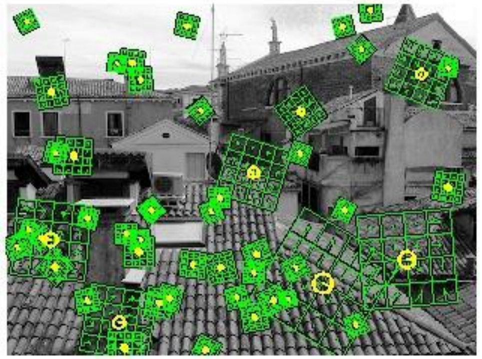
Intra-class variation:

Traditional Approaches

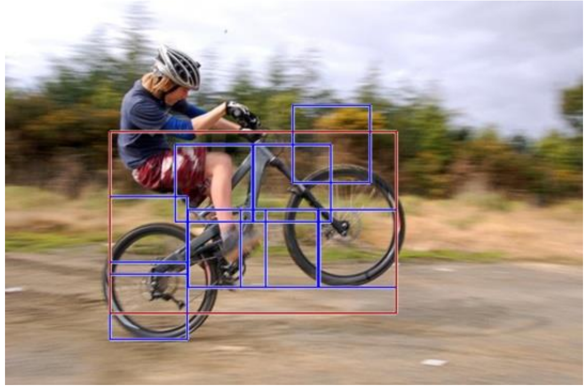
- 1) To build training datasets with sufficient desired variations



- 2) To use transformation-invariant features and algorithms



Scale Invariant Feature Transform (SIFT)

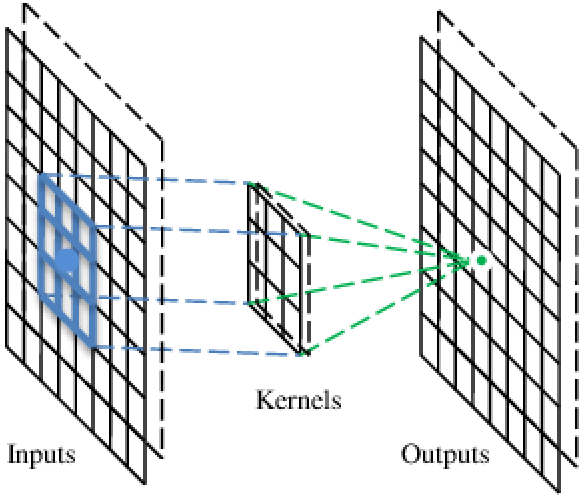


Deformable Part-based Model (DPM)

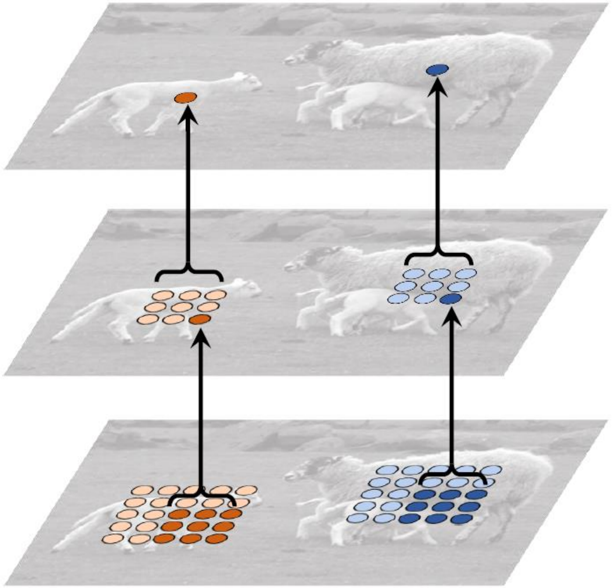
- Drawbacks: geometric transformations are assumed fixed and known, hand-crafted design of invariant features and algorithms

Spatial Transformations in CNNs

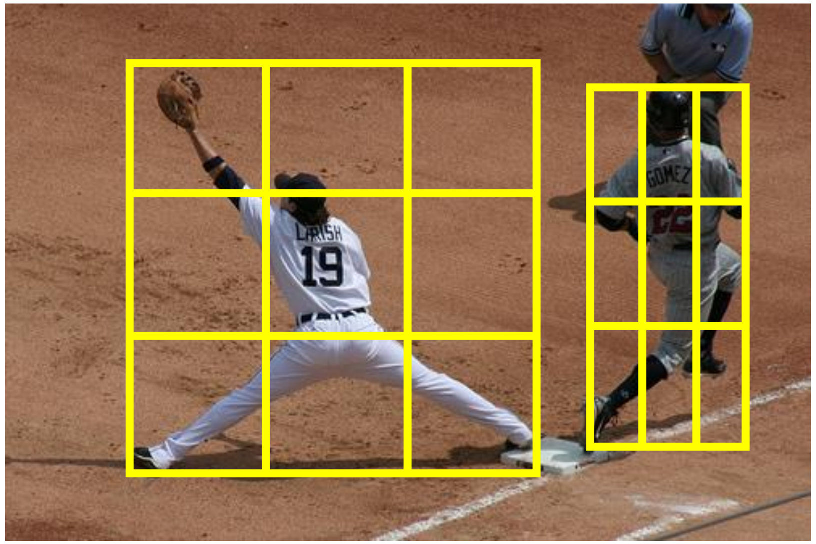
- Regular CNNs are inherently limited to model large unknown transformations
  - The limitation originates from the fixed geometric structures of CNN modules



regular convolution



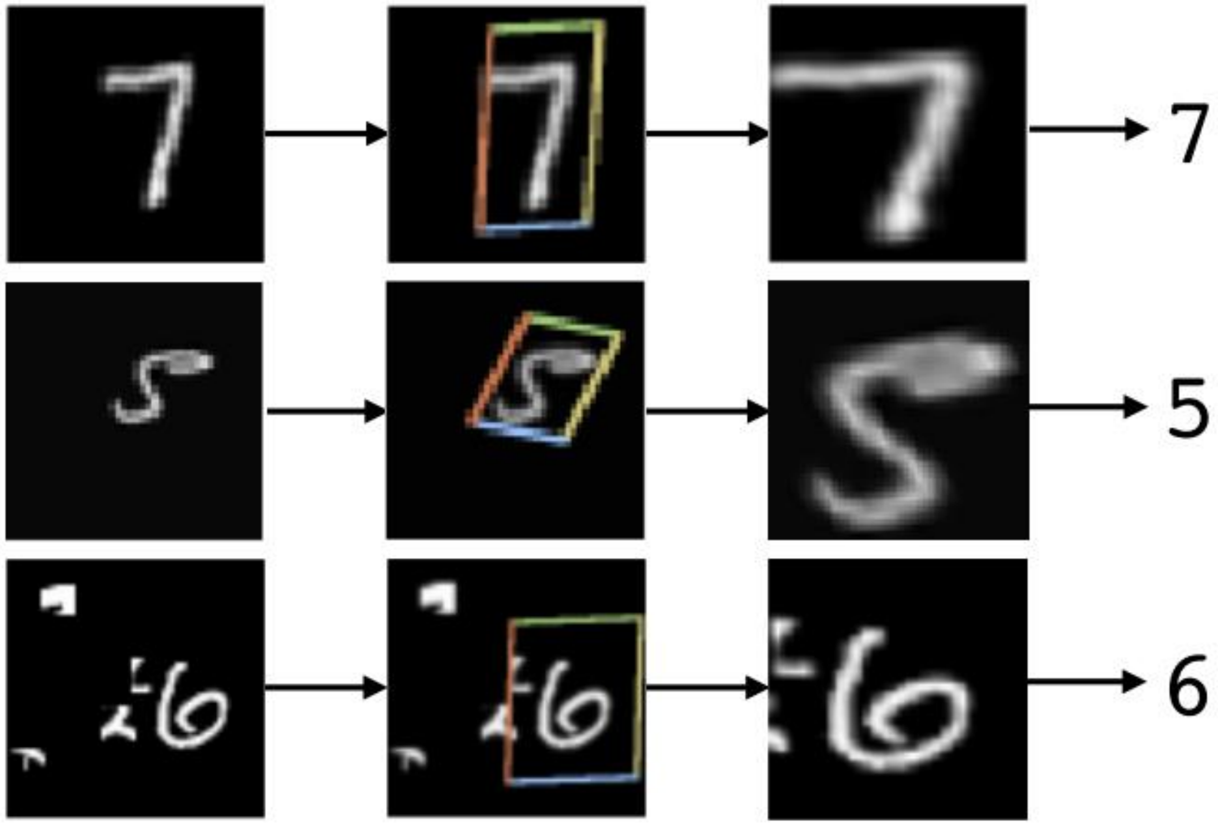
2 layers of regular convolution



regular RoI Pooling

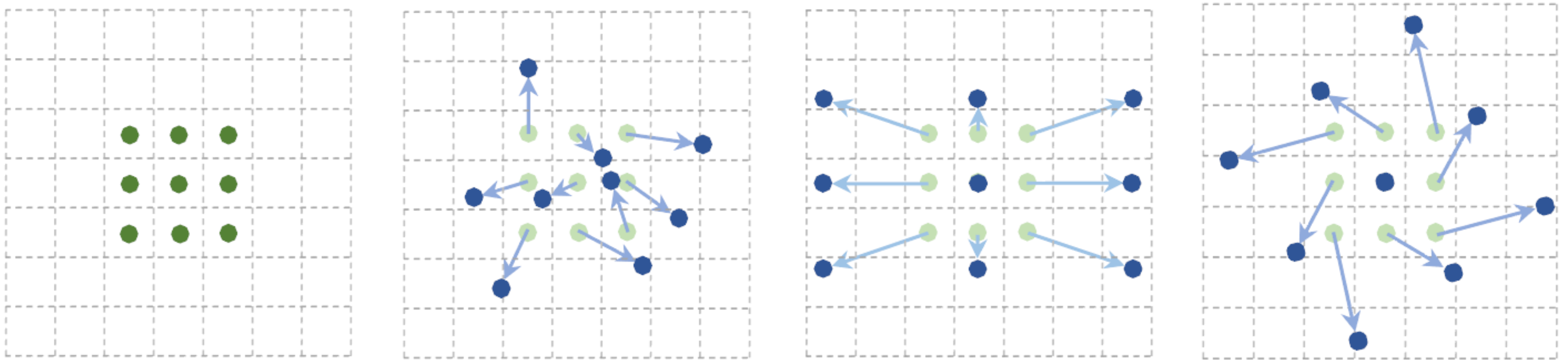
Spatial Transformer Networks

- Learning a global, parametric transformation on feature maps
  - Prefixed transformation family, infeasible for complex vision tasks



Deformable Convolution

- Local, dense, non-parametric transformation
  - Learning to deform the sampling locations in the convolution/RoI Pooling modules



regular deformed scale & aspect ratio rotation

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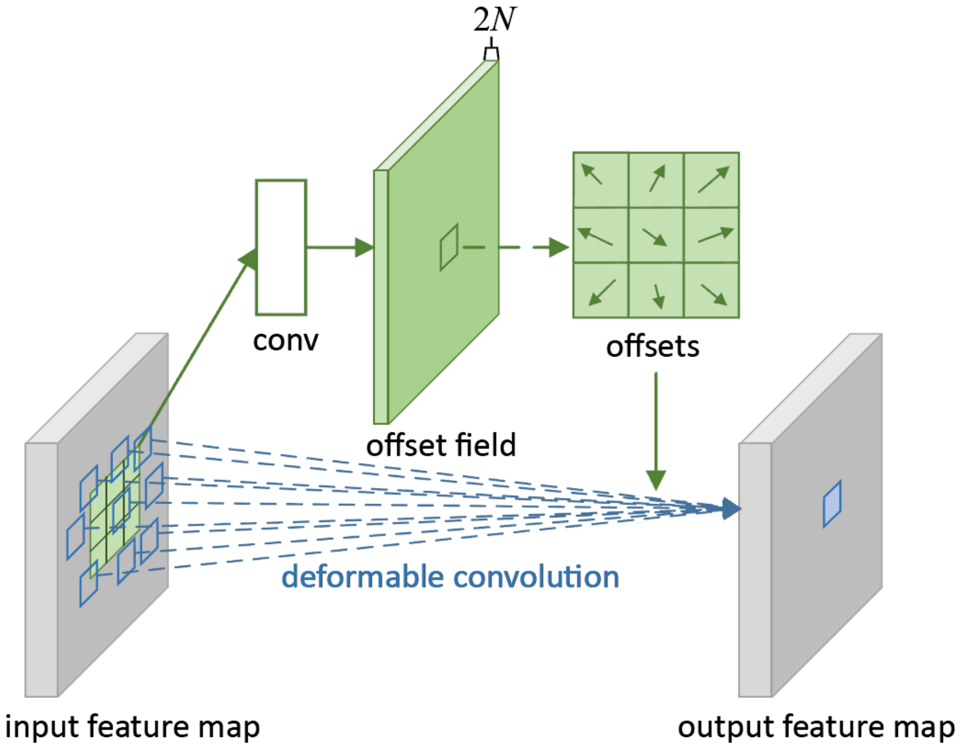
Deformable Convolution



Regular convolution

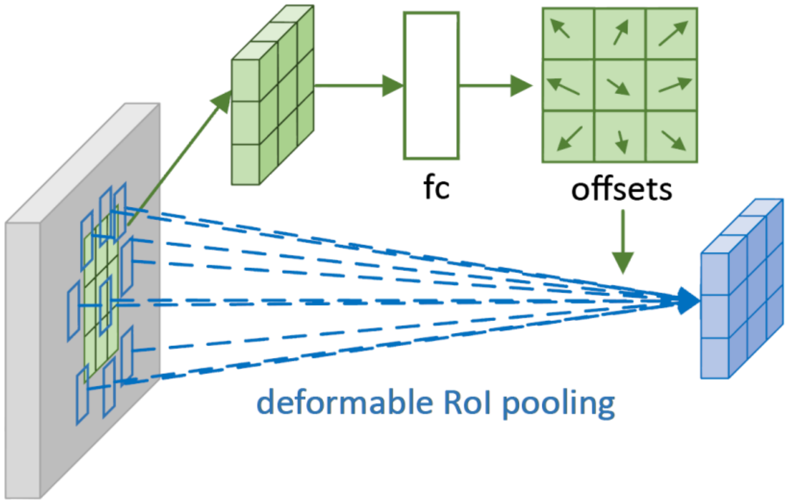
$$\mathbf{y}(\mathbf{p}_0) = \sum_{\mathbf{p}_n \in \mathcal{R}} \mathbf{w}(\mathbf{p}_n) \cdot \mathbf{x}(\mathbf{p}_0 + \mathbf{p}_n)$$

Deformable convolution

$$\mathbf{y}(\mathbf{p}_0) = \sum_{\mathbf{p}_n \in \mathcal{R}} \mathbf{w}(\mathbf{p}_n) \cdot \mathbf{x}(\mathbf{p}_0 + \mathbf{p}_n + \Delta \mathbf{p}_n)$$

where $\Delta \mathbf{p}_n$ is generated by a sibling branch of regular convolution

Deformable RoI Pooling



deformable RoI Pooling

Regular RoI pooling

$$\mathbf{y}(i,j) = \sum_{\mathbf{p} \in bin(i,j)} \mathbf{x}(\mathbf{p}_0 + \mathbf{p})/n_{ij}$$

Deformable RoI pooling

$$\mathbf{y}(i,j) = \sum_{\mathbf{p} \in bin(i,j)} \mathbf{x}(\mathbf{p}_0 + \mathbf{p} + \Delta\mathbf{p}_{ij})/n_{ij}$$

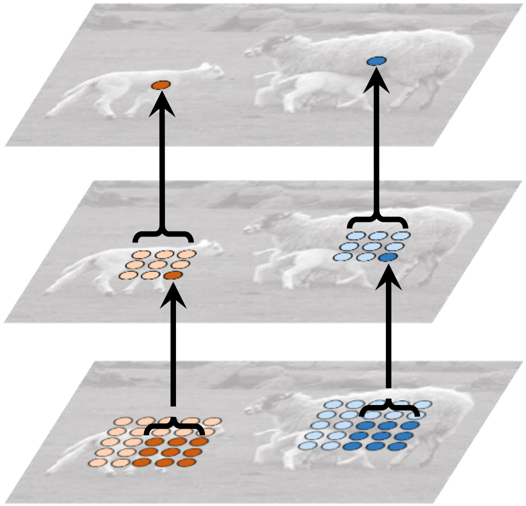
where $\Delta\mathbf{p}_{ij}$ is generated by a sibling fc branch

Deformable ConvNets

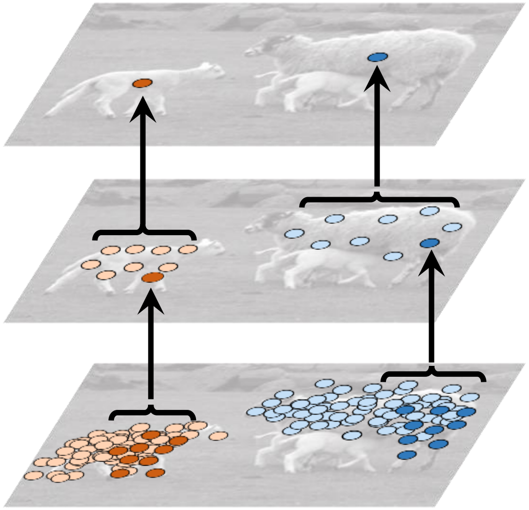
- Same input & output as the plain versions
  - Regular convolution -> deformable convolution
  - Regular RoI pooling -> deformable RoI pooling

- End-to-end trainable without additional supervision

Sampling Locations of Deformable Convolution

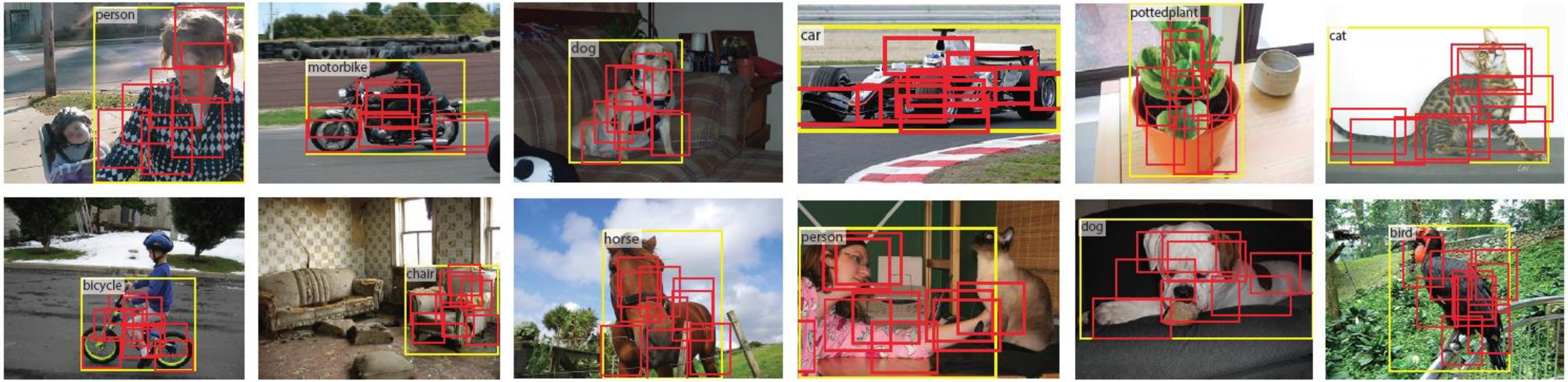


(a) standard convolution



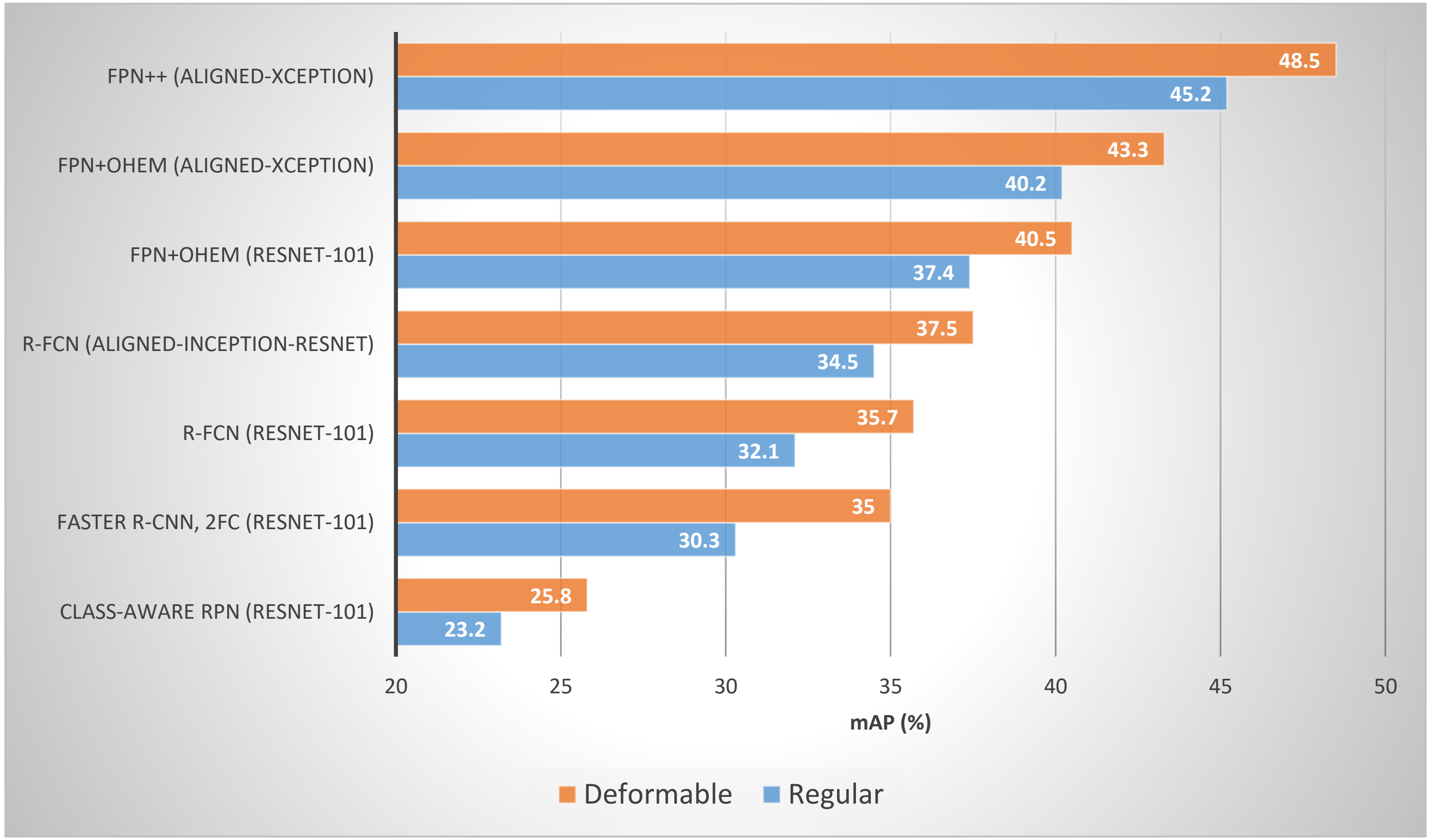
(b) deformable convolution

Part Offsets in Deformable RoI Pooling



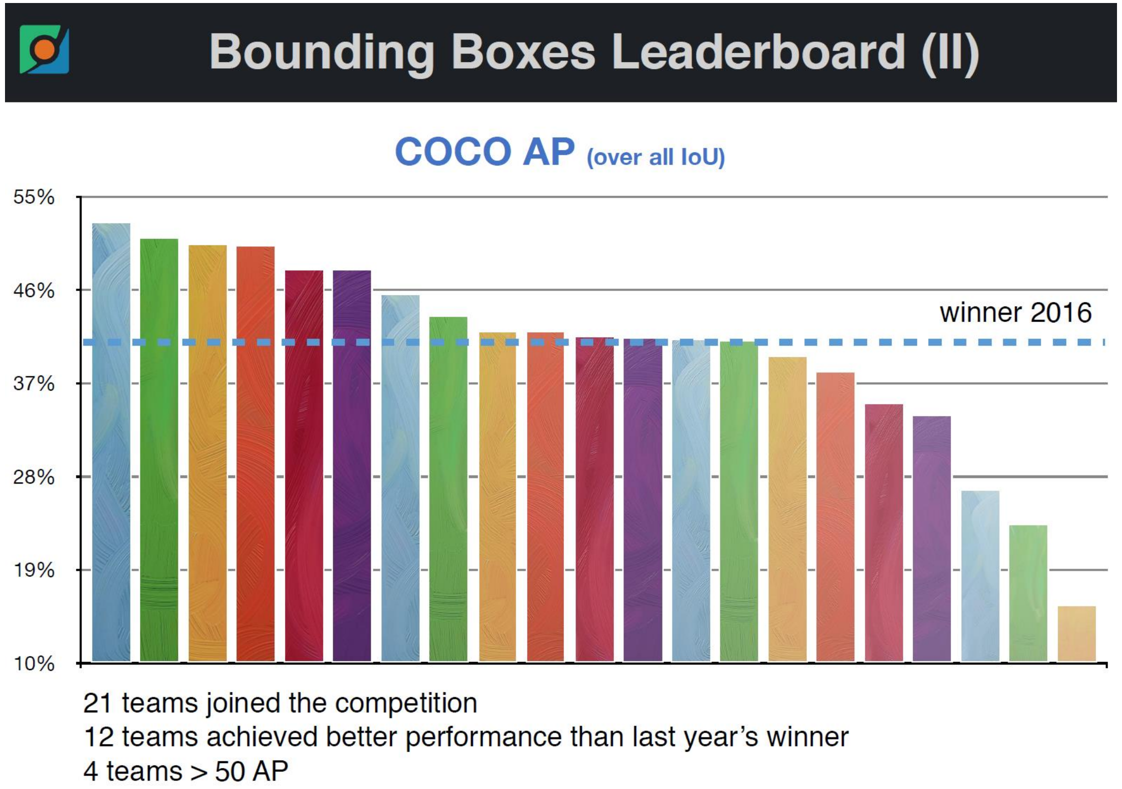
Object Detection on COCO (Test-dev)

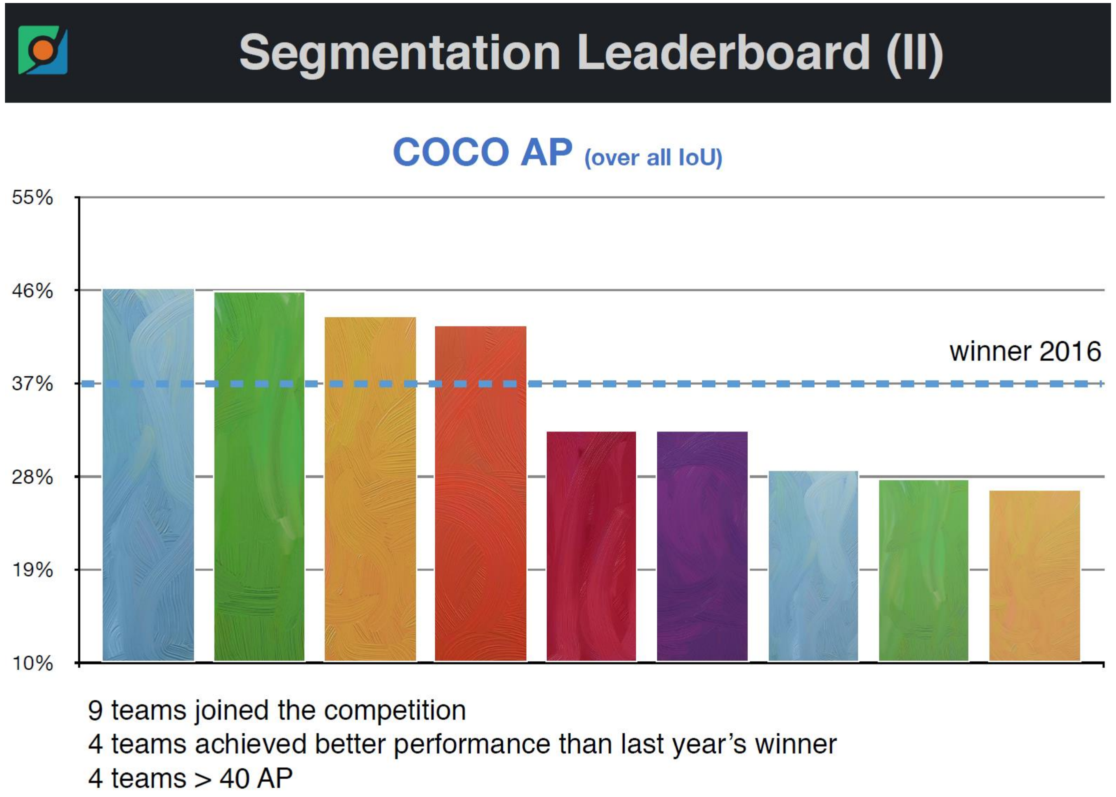
- Deformable ConvNets v.s. regular ConvNets
  - Noticeable improvements for varies baselines
  - Marginal parameter & computation overhead



COCO Detection & Segmentation Challenge 2017

- Focus shifted from ImageNet to COCO in 2017
- Top-4 teams are quite close, surpassing others clearly





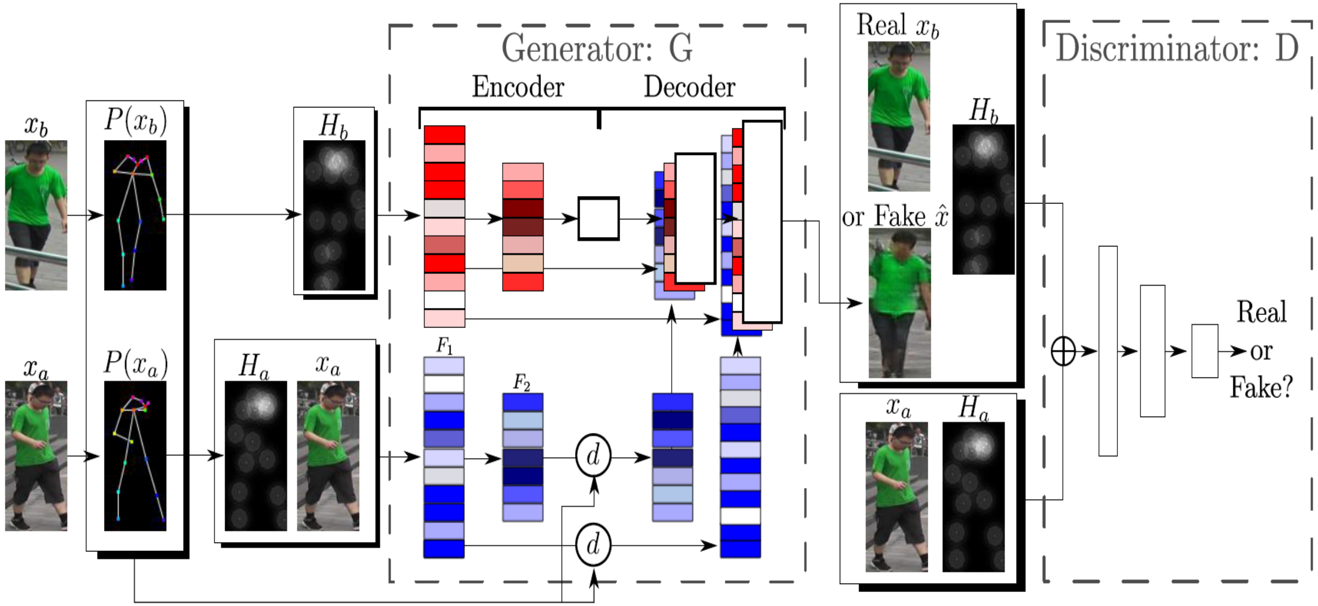
COCO Detection & Segmentation Challenge 2017

- Few tricks and hacks are adopted by MSRA and FAIR team
- Our accuracy is on par with FAIR team, at much smaller model size
- Deformable ConvNets are also adopted by other teams

Team	BBox	Segmentation	Tricks & Hacks	Model Ensembled	Utilize of Deformable CNNs
Megvii (Face++)	1st	2nd	Many	Unknown	Unknown
Ucenter (SenseTime)	2nd	1st	Many	Unknown	***Yes***
MSRA	3rd	4th	***Few***	**6**	***Yes***
FAIR	4th	3rd	***Few***	**30**	No

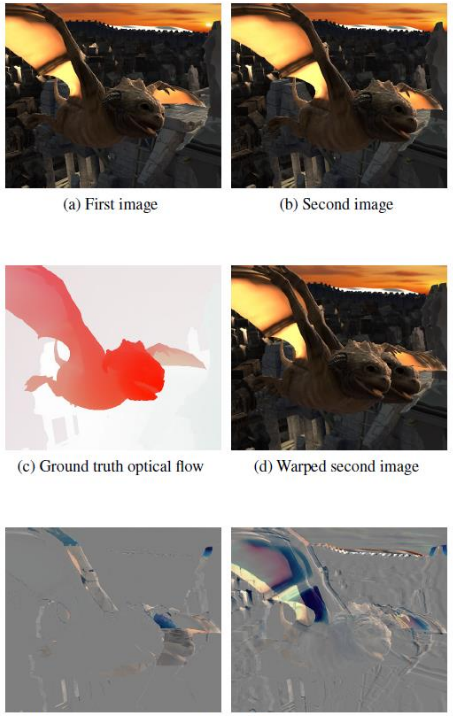
Deformable ConvNets Extensions I

- Deformable GANs



[Siarohin et al. Arxiv Tech Report, 2017.]

- Deformable volume network for flow estimation

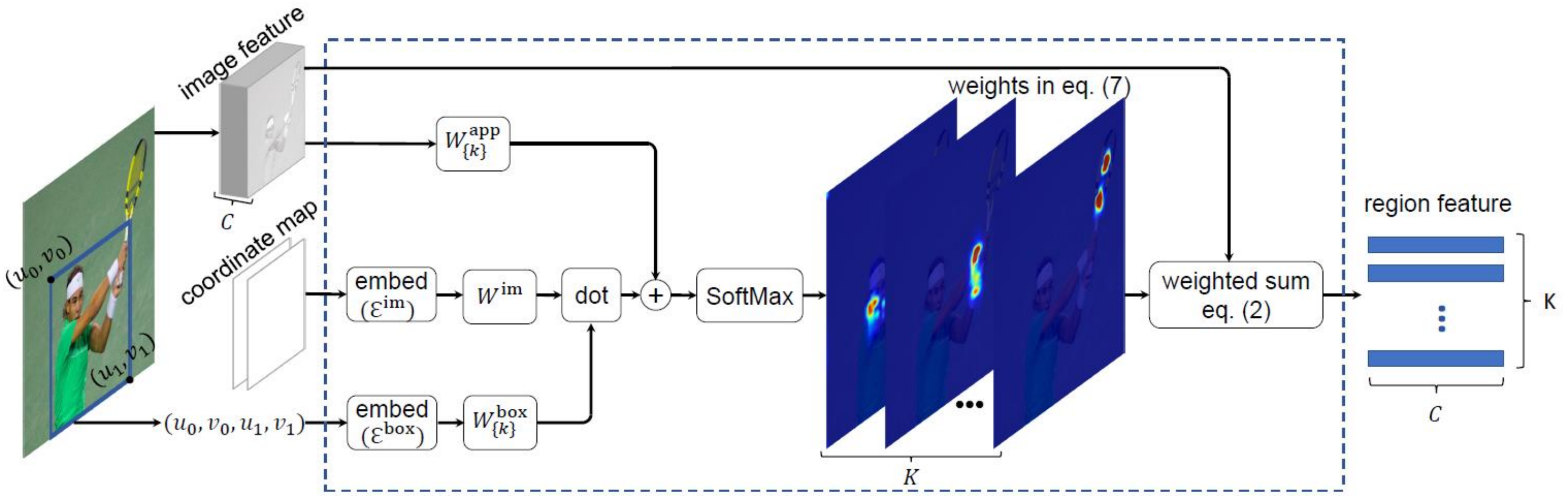


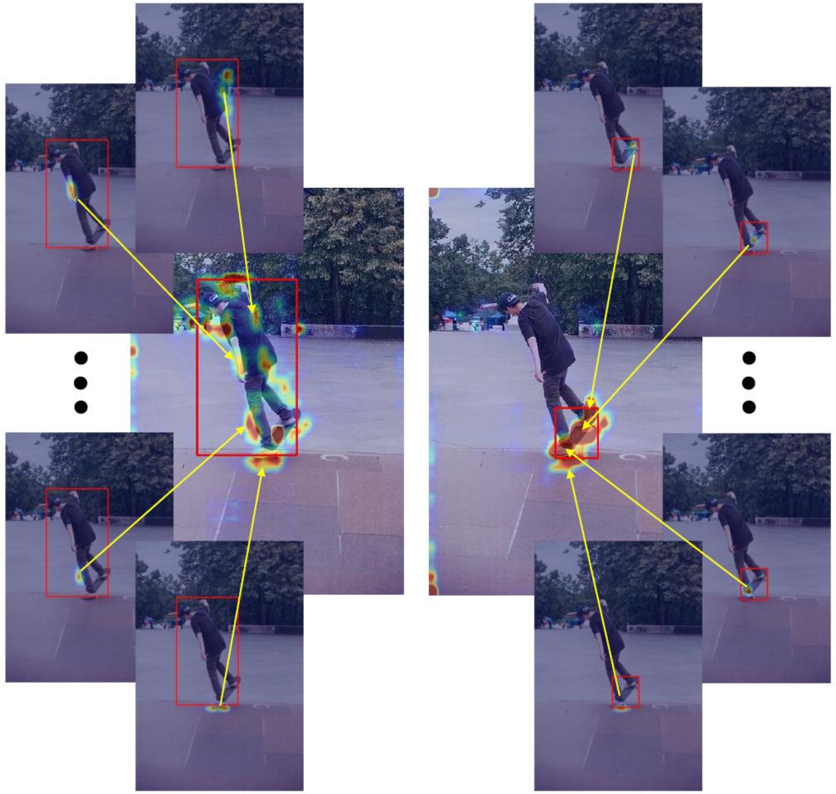
(a) First image
(b) Second image
(c) Ground truth optical flow
(d) Warped second image
(e) Warped second image subtracted by the first image
(f) Warped second image subtracted by the second image

[Lu et al. Arxiv Tech Report, 2018.]

Deformable ConvNets Extensions II

- Fully learnable region feature extraction
  - Deformed regular grid, offset learning -> Free-form shape, attention weight learning





[Gu et al. Arxiv Tech Report, 2018.]

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Per-frame recognition in video is problematic

High Computational Cost

Infeasible for practical needs

Task	Image Size	ResNet-50	ResNet-101
Detection	1000x600	6.27 fps	4.05 fps
Segmentation	2048x1024	2.24 fps	1.52 fps

FPS: frames per second
(NVIDIA K40 and Intel Core i7-4790)

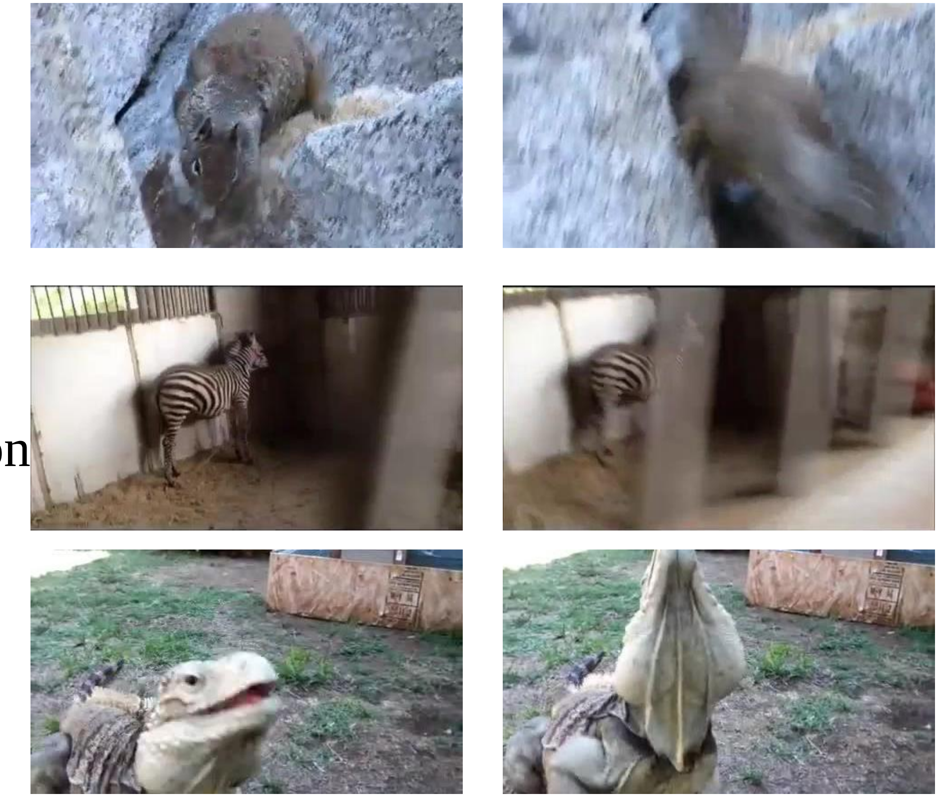
Deteriorated Frame Appearance

Poor feature and recognition accuracy

motion blur

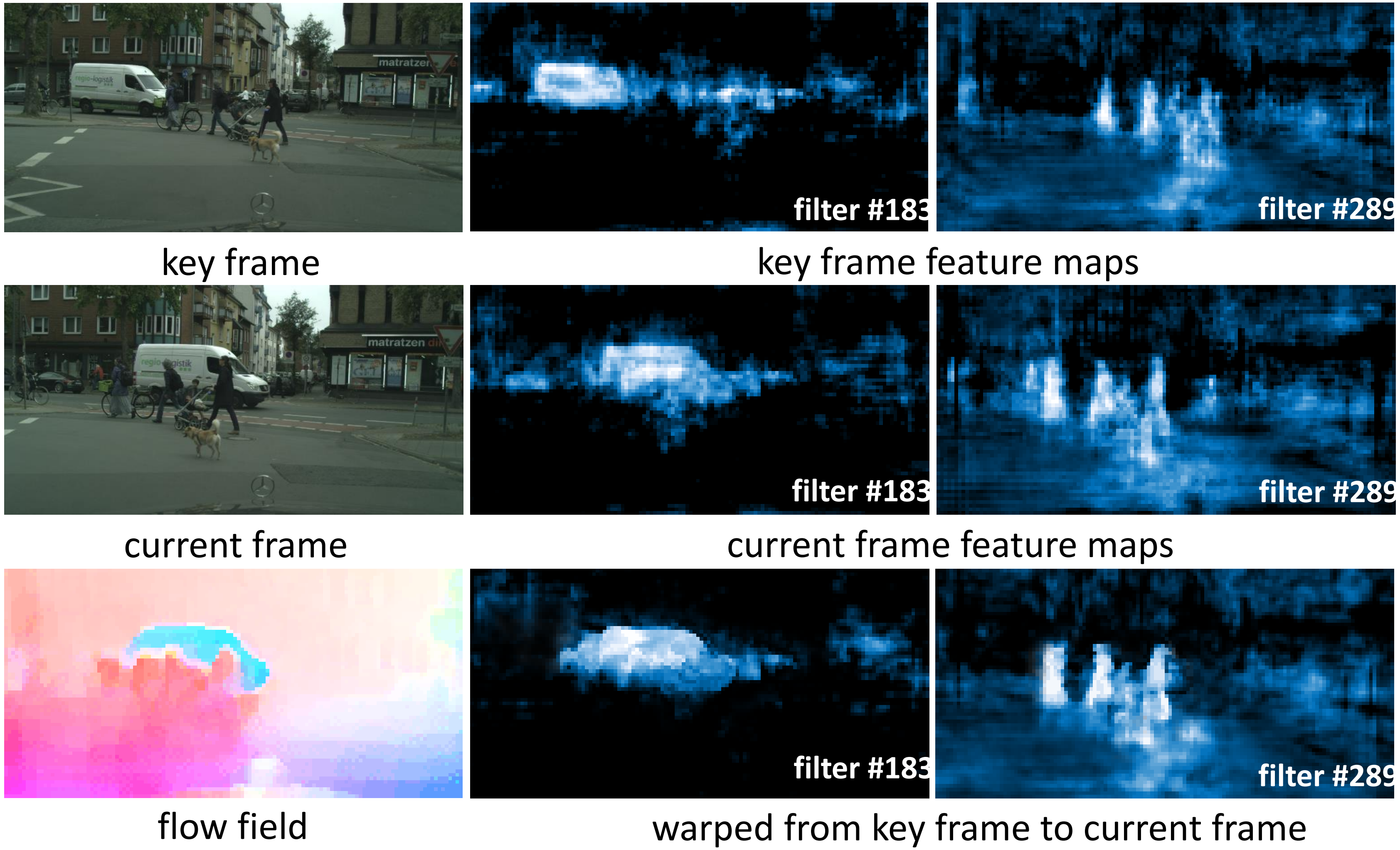
part occlusion

rare poses



Key idea

- Flow-guided feature propagation & aggregation



Powering the winner of ImageNet VID 2017

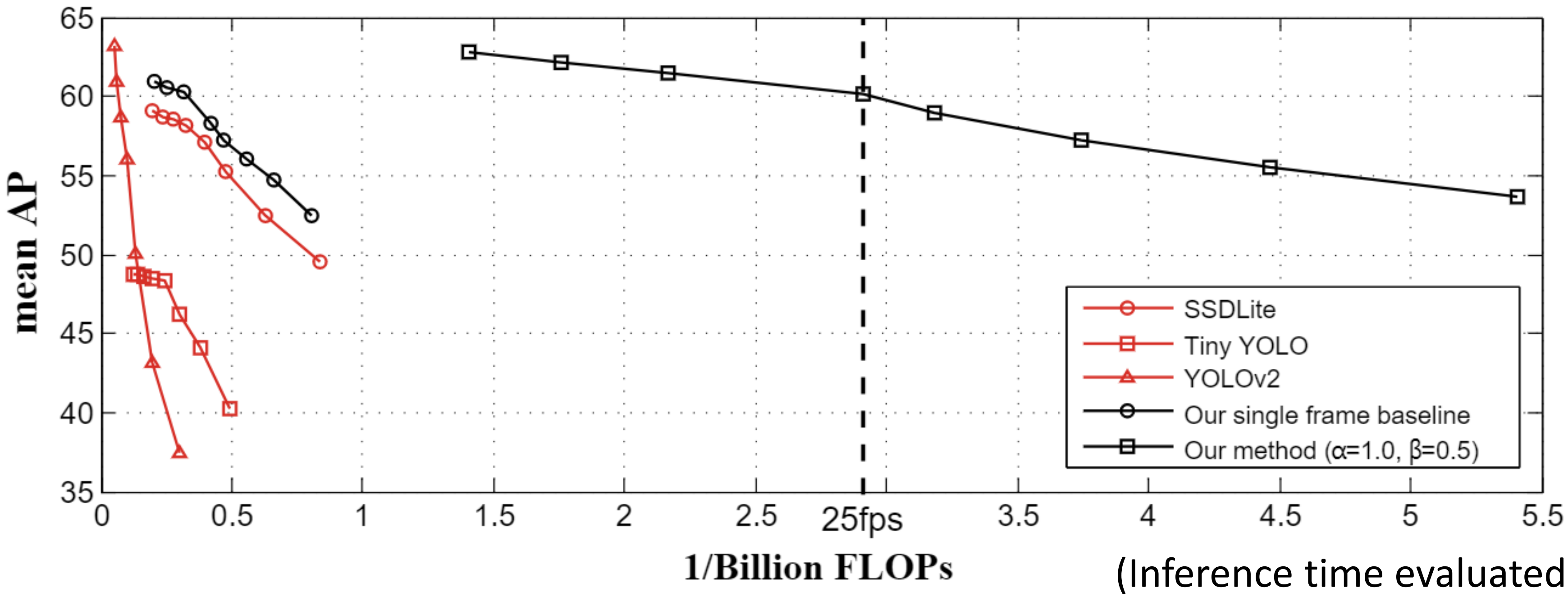
Team name	Entry description	**Number of object categories won**	mean AP
IC&USYD	provide_submission3	15	0.817265
IC&USYD	provide_submission1	6	0.808847
IC&USYD	provide_submission2	4	0.818309
NUS-Qihoo-UIUC_DPNs (VID)	no_extra + seq + mca + mcs	3	0.757772
NUS-Qihoo-UIUC_DPNs (VID)	no_extra + seq + vcm + mcs	1	0.757853
NUS-Qihoo-UIUC_DPNs (VID)	Faster RCNN + Video Context	1	0.748493
THU-CAS	merge-new	0	0.730498
THU-CAS	old-new	0	0.728707
THU-CAS	new-new	0	0.691423
GoerVision	Deformable R-FCN single model+ResNet101	0	0.669631
GoerVision	Ensemble 2 model, use ResNet101 as foundamental classification network and deformable R-FCN to detect video frames, multi-scale testing	0	0.665693
GoerVision	o train the video objectWe use the ResNet101 and Deformable R-FCN for the detection.	0	0.655686
GoerVision	Using R-FCN to detect video object, multi scale testing applied.	0	0.646965
FACEALL_BUPT	SSD based on Resnet101 networks	0	0.195754

[top]

IC&USYD	Jiankang Deng(1), Yuxiang Zhou(1), Baosheng Yu(2), Zhe Chen(2), Stefanos Zafeiriou(1), Dacheng Tao(2), (1)Imperial College London, (2)University of Sydney	Flow acceleration[1,2] is used. Final scores are adaptively chosen between the detector and tracker. [1] Deep Feature Flow for Video Recognition Xizhou Zhu, Yuwen Xiong, Jifeng Dai, Lu Yuan, and Yichen Wei, IEEE Conference on Computer Vision and Pattern Recognition (CVPR), 2017. [2] Flow-Guided Feature Aggregation for Video Object Detection, Xizhou Zhu, Yujie Wang, Jifeng Dai, Lu Yuan, and Yichen Wei. Arxiv tech report, 2017.

Towards High Performance Video Object Detection for Mobiles

- Accurate, real-time video object detection on mobiles for the first time
- An order faster than previous fastest object detectors with on par accuracy



(Inference time evaluated on Huawei Mate 8)

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Summary

- General object detection is still an open, unsolved, fundamental vision problem
  - Recognition of objects with large appearance variations
  - Low recognition latency on mobile devices
  - Panoramic scene understanding

- Careful investigation and prototyping is necessary in application in products