An Introduction to Modern Object Detection

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Visual Recognition

A fundamental task in computer vision

- Classification
- Object Detection
- Semantic Segmentation
- Instance Segmentation
- Key point Detection
- VQA
...

Face++ 旷视
Category-level Recognition

Instance-level Recognition
Representation

- Bounding-box
  - Face Detection, Human Detection, Vehicle Detection, Text Detection, general Object Detection
- Point
  - Semantic segmentation (Instance Segmentation)
- Keypoint
  - Face landmark
  - Human Keypoint
Outline

• Detection
• Conclusion
Outline

- Detection
- Conclusion
Detection - Evaluation Criteria

Average Precision (AP) and mAP

Precision and recall are single-value metrics based on the whole list of documents returned by the system. For systems that return a ranked sequence of documents, it is desirable to also consider the order in which the returned documents are presented. By computing a precision and recall at every position in the ranked sequence of documents, one can plot a precision-recall curve, plotting precision $p(r)$ as a function of recall $r$. Average precision computes the average value of $p(r)$ over the interval from $r = 0$ to $r = 1$:

$$\text{AveP} = \int_0^1 p(r) \, dr$$

Figures are from wikipedia
Detection - Evaluation Criteria

**mmAP**

---

**Average Precision (AP):**
- AP
- AP\_IoU=0.50
- AP\_IoU=0.75
- AP Across Scales:
  - AP\_small
  - AP\_medium
  - AP\_large
- Average Recall (AR):
  - AR\_top1
  - AR\_top10
  - AR\_top100

**Average Precision:**

<table>
<thead>
<tr>
<th>Metric</th>
<th>Formula</th>
</tr>
</thead>
<tbody>
<tr>
<td>AP</td>
<td>% AP at IoU=0.50:0.95 (primary challenge metric)</td>
</tr>
<tr>
<td>AP_IoU=0.50</td>
<td>% AP at IoU=0.50 (PASCAL VOC metric)</td>
</tr>
<tr>
<td>AP_IoU=0.75</td>
<td>% AP at IoU=0.75 (strict metric)</td>
</tr>
</tbody>
</table>

**Average Recall:**

<table>
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<tbody>
<tr>
<td>AR_top1</td>
<td>% AR given 1 detection per image</td>
</tr>
<tr>
<td>AR_top10</td>
<td>% AR given 10 detections per image</td>
</tr>
<tr>
<td>AR_top100</td>
<td>% AR given 100 detections per image</td>
</tr>
</tbody>
</table>

**Average Precision Across Scales:**

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<tr>
<td>AP_small</td>
<td>% AP for small objects: area &lt; 32(^2)</td>
</tr>
<tr>
<td>AP_medium</td>
<td>% AP for medium objects: 32(^2) &lt; area &lt; 96(^2)</td>
</tr>
<tr>
<td>AP_large</td>
<td>% AP for large objects: area &gt; 96(^2)</td>
</tr>
</tbody>
</table>

**Average Recall Across Scales:**

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<td>% AR for medium objects: 32(^2) &lt; area &lt; 96(^2)</td>
</tr>
<tr>
<td>AR_large</td>
<td>% AR for large objects: area &gt; 96(^2)</td>
</tr>
</tbody>
</table>

---

1. Unless otherwise specified, AP and AR are averaged over multiple Intersection over Union (IoU) values. Specifically, we use 10 IoU thresholds of 0.50:0.05:0.95. This is a break from tradition, where AP is computed at a single IoU of 0.50 (which corresponds to our metric AP\_IoU=0.50). Averaging over IoUs rewards detectors with better localization.
2. AP is averaged over all categories. Traditionally, this is called “mean average precision” (mAP). We make no distinction between AP and mAP (and likewise AR and mAR) and assume the difference is clear from context.
3. AP (averaged across all 10 IoU thresholds and all 80 categories) will determine the challenge winner. This should be considered the single most important metric when considering performance on COCO.
4. In COCO, there are more small objects than large objects. Specifically, approximately 41% of objects are small (area < 32\(^2\)), 34% are medium (32\(^2\) < area < 96\(^2\)), and 24% are large (area > 96\(^2\)). Area is measured as the number of pixels in the segmentation mask.
5. AR is the maximum recall given a fixed number of detections per image, averaged over categories and IoUs. AR is related to the metric of the same name used in proposal evaluation but is computed on a per-category basis.
6. All metrics are computed allowing for at most 100 top-scoring detections per image (across all categories).
7. The evaluation metrics for detection with bounding boxes and segmentation masks are identical in all respects except for the IoU computation (which is performed over boxes or masks, respectively).

Figures are from http://cocodataset.org
How to perform a detection?

- Sliding window: enumerate all the windows (up to millions of windows)
  - VJ detector: cascade chain
- Fully Convolutional network
  - shared computation

Robust Real-time Object Detection; Viola, Jones; IJCV 2001
General Detection Before Deep Learning

• Feature + classifier
• Feature
  • Haar Feature
  • HOG (Histogram of Gradient)
  • LBP (Local Binary Pattern)
  • ACF (Aggregated Channel Feature)
  • ...
• Classifier
  • SVM
  • Bootsing
  • Random Forest
Traditional Hand-crafted Feature: HoG

Traditional Hand-crafted Feature: HoG

In each triplet: (1) the input image, (2) the corresponding R-HOG feature vector (only the dominant orientation of each cell is shown), and (3) the dominant orientations selected by the SVM (obtained by multiplying the feature vector by the corresponding weights from the linear SVM).
General Detection Before Deep Learning

Traditional Methods

- **Pros**
  - Efficient to compute (e.g., HAAR, ACF) on CPU
  - Easy to debug, analyze the bad cases
  - Reasonable performance on limited training data

- **Cons**
  - Limited performance on large dataset
  - Hard to be accelerated by GPU
Deep Learning for Object Detection

Based on the whether following the “proposal and refine”

• One Stage
  • Example: Densebox, YOLO (YOLO v2), SSD, Retina Net
  • Keyword: Anchor, Divide and conquer, loss sampling

• Two Stage
  • Example: RCNN (Fast RCNN, Faster RCNN), RFCN, FPN, MaskRCNN
  • Keyword: speed, performance
A bit of History

One stage detector

Two stages detector

Image → Feature Extractor → classification

localization (bbox)

Proposal

Image → Feature Extractor → classification

localization (bbox)

classification

localization (bbox)

Refine

OverFeat (2013)
MultiBox (2014)

DSSD (2017)

RetinaNet (2017)

Anchor Free

Anchor imported

YOLov2 (2016)

SSD (2015)

RON (2017)

RetinaNet (2017)

DSSD (2017)

RetinaNet (2017)

Anchor Free

Anchor imported
One Stage Detector: Densebox

Figure 1: The DenseBox Detection Pipeline. 1) Image pyramid is fed to the network. 2) After several layers of convolution and pooling, upsampling feature map back and apply convolution layers to get final output. 3) Convert output feature map to bounding boxes, and apply non-maximum suppression to all bounding boxes over the threshold.

https://arxiv.org/abs/1509.04874
One Stage Detector: Densebox

- No Anchor: GT Assignment
  - A sub-circle in the GT is labeled as positive
    - fail when two GT highly overlaps
    - the size of the sub-circle matters
    - more attention (loss) will be placed to large faces

- Loss sampling
  - All pos/negative positions will be used to compute the cls loss
One Stage Detector: Densebox

Problems

- L2 loss is not robust to scale variation (UnitBox)
  - learnt features are not robust
- GT assignment issue (SSD)
  - Fail to handle the crowd case
- relatively large localization error (Two stages detector)
- more false positive (FP) (Two stages detector)
  - does not obviously kill the fp
One Stage Detector: Densebox -> UnitBox

Figure 1: Illustration of IoU loss and $\ell_2$ loss for pixel-wise bounding box prediction.

$\ell_2$ loss = $\| \Box - \Box \|^2$

IoU loss = $-\ln \frac{\text{Intersection}(\Box, \Box)}{\text{Union}(\Box, \Box)}$

Figure 5: Compared to $\ell_2$ loss, the IoU loss is much more robust to scale variations for bounding box prediction.
One Stage Detector: Densebox -> UnitBox->EAST

Figure 2. Comparison of pipelines of several recent works on scene text detection: (a) Horizontal word detection and recognition pipeline proposed by Jaderberg et al. [12]; (b) Multi-orient text detection pipeline proposed by Zhang et al. [48]; (c) Multi-orient text detection pipeline proposed by Yao et al. [41]; (d) Horizontal text detection using CTPN, proposed by Tian et al. [34]; (e) Our pipeline, which eliminates most intermediate steps, consists of only two stages and is much simpler than previous solutions.

EAST: An Efficient and Accurate Scene Text Detector, Zhou etc, CVPR 2017

https://arxiv.org/abs/1704.03155
One Stage Detector: YOLO

You Only Look Once: Unified, Real-Time Object Detection, Redmon etc, CVPR 2016

https://arxiv.org/abs/1506.02640
One Stage Detector: YOLO

Figure 3: The Architecture. Our detection network has 24 convolutional layers followed by 2 fully connected layers. Alternating $1 \times 1$ convolutional layers reduce the features space from preceding layers. We pretrain the convolutional layers on the ImageNet classification task at half the resolution (224 $\times$ 224 input image) and then double the resolution for detection.

You Only Look Once: Unified, Real-Time Object Detection, Redmon etc, CVPR 2016

https://arxiv.org/abs/1506.02640
One Stage Detector: YOLO

• No Anchor
  • GT assignment is based on the cells (7x7)
• Loss sampling
  • all pos/neg predictions are evaluated (but more sparse than densebox)

You Only Look Once: Unified, Real-Time Object Detection, Redmon etc, CVPR 2016
https://arxiv.org/abs/1506.02640
One Stage Detector: YOLO

Discussion

- fc reshape (4096-> 7x7x30)
  - more context
  - but not fully convolutional
- One cell can output up to two boxes in one category
  - fail to work on the crowd case
- Fast speed
  - small imagenet base model
  - small input size (448x448)

You Only Look Once: Unified, Real-Time Object Detection, Redmon etc, CVPR 2016
https://arxiv.org/abs/1506.02640
One Stage Detector: YOLO

Experiments on general detection

<table>
<thead>
<tr>
<th>Method</th>
<th>VOC 2007 test</th>
<th>VOC 2012 test</th>
<th>COCO</th>
<th>time</th>
<th>fps:</th>
</tr>
</thead>
<tbody>
<tr>
<td>YOLO</td>
<td>57.9/NA</td>
<td>52.7/63.4</td>
<td>NA</td>
<td></td>
<td>45/155</td>
</tr>
</tbody>
</table>
One Stage Detector: YOLO -> YOLOv2

<table>
<thead>
<tr>
<th></th>
<th>YOLO</th>
<th>YOLOv2</th>
</tr>
</thead>
<tbody>
<tr>
<td>batch norm?</td>
<td>✓</td>
<td>✓</td>
</tr>
<tr>
<td>hi-res classifier?</td>
<td>✓</td>
<td>✓</td>
</tr>
<tr>
<td>convolutional?</td>
<td>✓</td>
<td>✓</td>
</tr>
<tr>
<td>anchor boxes?</td>
<td>✓</td>
<td>✓</td>
</tr>
<tr>
<td>new network?</td>
<td>✓</td>
<td>✓</td>
</tr>
<tr>
<td>dimension priors?</td>
<td>✓</td>
<td>✓</td>
</tr>
<tr>
<td>location prediction?</td>
<td>✓</td>
<td>✓</td>
</tr>
<tr>
<td>passthrough?</td>
<td>✓</td>
<td>✓</td>
</tr>
<tr>
<td>multi-scale?</td>
<td>✓</td>
<td>✓</td>
</tr>
<tr>
<td>hi-res detector?</td>
<td>✓</td>
<td>✓</td>
</tr>
<tr>
<td>VOC2007 mAP</td>
<td>63.4</td>
<td>65.8</td>
</tr>
<tr>
<td></td>
<td>69.5</td>
<td>69.2</td>
</tr>
<tr>
<td></td>
<td>69.6</td>
<td>74.4</td>
</tr>
<tr>
<td></td>
<td>75.4</td>
<td>76.8</td>
</tr>
<tr>
<td></td>
<td><strong>78.6</strong></td>
<td></td>
</tr>
</tbody>
</table>

Table 2: The path from YOLO to YOLOv2. Most of the listed design decisions lead to significant increases in mAP. Two exceptions are switching to a fully convolutional network with anchor boxes and using the new network. Switching to the anchor box style approach increased recall without changing mAP while using the new network cut computation by 33%.
One Stage Detector: YOLO -> YOLOv2

Experiments:

<table>
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<tr>
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<tbody>
<tr>
<td>YOLO</td>
<td>52.7/63.4</td>
<td>57.9/NA</td>
<td>NA</td>
<td>fps: 45/155</td>
</tr>
<tr>
<td>YOLOv2</td>
<td>78.6</td>
<td>73.4</td>
<td>21.6</td>
<td>fps: 40</td>
</tr>
</tbody>
</table>

YOLO9000: Better, Faster, Stronger Redmon etc, CVPR 2016
https://arxiv.org/abs/1612.08242
One Stage Detector: YOLO -> YOLOv2

Video demo: https://pjreddie.com/darknet/yolo/

YOLO9000: Better, Faster, Stronger Redmon etc, CVPR 2016
https://arxiv.org/abs/1612.08242
One Stage Detector: SSD

(a) Image with GT boxes  (b) 8 × 8 feature map  (c) 4 × 4 feature map

Face++ 旷视

SSD: Single Shot MultiBox Detector, Liu etc
One Stage Detector: SSD

SSD: Single Shot MultiBox Detector, Liu etc, ECCV 2016
One Stage Detector: SSD

- Anchor
  - GT-anchor assignment
    - GT is predicted by one best matched (IOU) anchor or matched with an anchor with IOU > 0.5
      - better recall
    - dense or sparse anchor?

- Divide and Conquer
  - Different layers handle the objects with different scales
    - Assume small objects can be predicted in earlier layers (not very strong semantics)

- Loss sampling
  - OHEM: negative positions are sampled (not balanced pos/neg ratio)
  - negative:pos is at most 3:1
One Stage Detector: SSD

Discussion:

• Assume small objects can be predicted in earlier layers (not very strong semantics) (DSSD, RON, RetinaNet)
• strong data augmentation
• VGG model (Replace by resnet in DSSD)
  • cannot be easily adapted to other models
  • a lot of hacks
• A long tail (Large computation)
One Stage Detector: SSD

Experiments

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<th>Method</th>
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<td>78.6</td>
<td>73.4</td>
<td>21.6</td>
<td>40</td>
</tr>
<tr>
<td>SSD</td>
<td>77.2/79.8</td>
<td>75.8/78.5</td>
<td>25.1/28.8</td>
<td>46/19</td>
</tr>
</tbody>
</table>

SSD: Single Shot MultiBox Detector, Liu etc, ECCV 2016
One Stage Detector: SSD -> DSSD

DSSD : Deconvolutional Single Shot Detector, Fu etc 2017,
https://arxiv.org/abs/1701.06659
**One Stage Detector: DSSD**

**Experiments**

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</tr>
<tr>
<td>DSSD</td>
<td>81.5</td>
<td>80.0</td>
<td>33.2</td>
<td>5.5</td>
</tr>
</tbody>
</table>

One Stage Detector: SSD -> RON

Figure 2. RON object detection overview. Given an input image, the network firstly computes features of the backbone network. Then at each detection scale: (a) adds reverse connection; (b) generates objectness prior; (c) detects object on its corresponding CNN scales and locations. Finally, all detection results are fused and selected with non-maximum suppression.
One Stage Detector: RON

- Anchor
- Divide and conquer
  - Reverse Connect (similar to FPN)
- Loss Sampling
  - Objectness prior
    - pos/neg unbalanced issue
    - split to 1) binary cls 2) multi-class cls

RON: Reverse Connection with Objectness Prior Networks for Object Detection, Kong etc, CVPR 2017
One Stage Detector: RON

Experiments

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<td>81.5</td>
<td>80.0</td>
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<td>5.5</td>
</tr>
<tr>
<td>RON</td>
<td>81.3</td>
<td>80.7</td>
<td>27.4</td>
<td>15</td>
</tr>
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RON: Reverse Connection with Objectness Prior Networks for Object Detection, Kong etc, CVPR 2017
One Stage Detector: SSD -> RetinaNet

**Focal Loss for Dense Object Detection, Lin etc, ICCV 2017**


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Figure 1. We propose a novel loss we term the Focal Loss that adds a factor \((1 - p_i)^\gamma\) to the standard cross entropy criterion. Setting \(\gamma > 0\) reduces the relative loss for well-classified examples \((p_i > .5)\), putting more focus on hard, misclassified examples. As our experiments will demonstrate, the proposed focal loss enables training highly accurate dense object detectors in the presence of vast numbers of easy background examples.

Figure 2. Speed (ms) versus accuracy (AP) on COCO test-dev. Enabled by the focal loss, our simple one-stage RetinaNet detector outperforms all previous one-stage and two-stage detectors, including the best reported Faster R-CNN [27] system from [19]. We show variants of RetinaNet with ResNet-50-FPN (blue circles) and ResNet-101-FPN (orange diamonds) at five scales (400-800 pixels). Ignoring the low-accuracy regime (AP<25), RetinaNet forms an upper envelope of all current detectors, and a variant trained for longer (not shown) achieves 39.1 AP. Details are given in §5.
One Stage Detector: SSD -> RetinaNet

Focal Loss for Dense Object Detection, Lin etc, ICCV 2017
One Stage Detector: RetinaNet

- Anchor
- Divide and Conquer
  - FPN
- Loss Sampling
  - Focal loss
    - pos/neg unbalanced issue
    - new setting (e.g., more anchor)

Focal Loss for Dense Object Detection, Lin etc, ICCV 2017
One Stage Detector: RetinaNet

Experiments

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<td>80.7</td>
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<td>15</td>
</tr>
<tr>
<td>RetinaNet</td>
<td>NA</td>
<td>N</td>
<td>39.1</td>
<td>5</td>
</tr>
</tbody>
</table>

Focal Loss for Dense Object Detection, Lin etc, ICCV 2017
One Stage Detector: SFace

- Integrate Anchor-free and Anchor-based idea to address the scale issue in face detection

SFace: An Efficient Network for Face Detection in Large Scale Variations
Jianfeng Wang, Ye Yuan, Boxun Li, Gang Yu, Sun Jian
One Stage Detector: SFace

- Standard face sizes:
  - Anchor based solution
  - Good performance
- Too small/Large faces:
  - Anchor-free based solution
  - Flexible, Fast speed for inference

SFace: An Efficient Network for Face Detection in Large Scale Variations
Jianfeng Wang, Ye Yuan, Boxun Li, Gang Yu, Sun Jian
## One Stage Detector: SFace

### Table 3. The ablation study of SFace on the WIDER FACE validation dataset.

<table>
<thead>
<tr>
<th>Min size</th>
<th>1080</th>
<th>1200</th>
<th>1500</th>
<th>2160</th>
</tr>
</thead>
<tbody>
<tr>
<td>Time</td>
<td>12.46ms</td>
<td>14.30ms</td>
<td>21.53ms</td>
<td>41.13ms</td>
</tr>
<tr>
<td>AP (WIDER FACE hard)</td>
<td>76.7</td>
<td>78.4</td>
<td>80.7</td>
<td>78.8</td>
</tr>
</tbody>
</table>
One Stage Detector: Summary

- **Anchor**
  - No anchor: YOLO, densebox/unitbox/east
  - Anchor: YOLOv2, SSD, DSSD, RON, RetinaNet

- **Divide and conquer**
  - SSD, DSSD, RON, RetinaNet

- **loss sample**
  - all sample: densebox
  - OHEM: SSD
  - focal loss: RetinaNet
One Stage Detector: Discussion

Anchor (YOLO v2, SSD, RetinaNet) or Without Anchor (Densebox, YOLO)

- Model Complexity
  - Difference on the extremely small model (< 30M flops on 224x224 input)
- Sampling
- Application
  - No Anchor: Face
  - With Anchor: Human, General Detection
- Problem for one stage detector
  - Unbalanced pos/neg data
  - Pool localization precision
Two Stages Detector: RCNN

R-CNN: Regions with CNN features

1. Input image  
2. Extract region proposals (~2k)  
3. Compute CNN features  
4. Classify regions

Rich feature hierarchies for accurate object detection and semantic segmentation, Girshirk etc, CVPR 2014  
Two Stages Detector: RCNN

Discussion

- Extremely slow speed
  - selective search proposal (CPU)/warp
- not end-to-end optimized
- Good for small objects

Rich feature hierarchies for accurate object detection and semantic segmentation, Girshirk etc, CVPR 2014
## Two Stages Detector: RCNN

### Experiments

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<td>RCNN</td>
<td>66</td>
<td>NA</td>
<td>NA</td>
<td>47s</td>
</tr>
</tbody>
</table>

Rich feature hierarchies for accurate object detection and semantic segmentation, Girshirk etc, CVPR 2014
Two Stages Detector: RCNN -> Fast RCNN

Figure 1. Fast R-CNN architecture. An input image and multiple regions of interest (RoIs) are input into a fully convolutional network. Each RoI is pooled into a fixed-size feature map and then mapped to a feature vector by fully connected layers (FCs). The network has two output vectors per RoI: softmax probabilities and per-class bounding-box regression offsets. The architecture is trained end-to-end with a multi-task loss.
Two Stages Detector: Fast RCNN

Discussion

• slow speed
  • selective search proposal (CPU)
• not end-to-end optimized
• ROI pooling
  • alignment issue
  • sampling
  • aspect ratio changes

Fast R-CNN, Girshick etc, ICCV 2015
## Two Stages Detector: Fast RCNN

### Experiments

<table>
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<tr>
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Fast R-CNN, Girshick etc, ICCV 2015
Two Stages Detector: RCNN -> Fast RCNN -> FasterRCNN

Figure 2: Faster R-CNN is a single, unified network for object detection. The RPN module serves as the ‘attention’ of this unified network.

Faster R-CNN: Towards Real-Time Object Detection with Region Proposal Networks, Ren etc, CVPR 2016
Two Stages Detector: Faster RCNN

Discussion

• speed
  • selective search proposal (CPU) -> RPN
• alternative optimization/end-to-end optimization
• Recall issue due to two stages detector

Faster R-CNN: Towards Real-Time Object Detection with Region Proposal Networks, Ren etc, CVPR 2016
## Two Stages Detector: Faster RCNN

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Faster R-CNN: Towards Real-Time Object Detection with Region Proposal Networks, Ren etc, CVPR 2016

Two Stages Detector:
RCNN -> Fast RCNN -> FasterRCNN -> RFCN

Figure 1: Key idea of R-FCN for object detection. In this illustration, there are $k \times k = 3 \times 3$ position-sensitive score maps generated by a fully convolutional network. For each of the $k \times k$ bins in an RoI, pooling is only performed on one of the $k^2$ maps (marked by different colors).

Two Stages Detector: RFCN

Discussion

• Share convolution
  • fasterRCNN: shared Res1-4 (RPN), not shared Res5 (RCNN)
  • RFCN: shared Res1-5 (both RPN and RCNN)
• PSPooling
  • a large number of channels: (7x7x\(C\))xWxH
  • Problems in ROIPooling also exist
• Fully connected vs Convolution
  • fc: global context
  • conv: can be shared but the context is relative small
  • trade-off: large kernel

## Two Stages Detector: RFCN

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<td>170ms</td>
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Two Stages Detector:
RFCN -> Deformable Convolutional Networks

Deformable Convolutional Networks, Dai etc, ICCV 2017
https://arxiv.org/abs/1703.06211
Two Stages Detector: RFCN -> Deformable Convolutional Networks

Figure 6: Each image triplet shows the sampling locations ($9^3 = 729$ red points in each image) in three levels of $3 \times 3$ deformable filters (see Figure 5 as a reference) for three activation units (green points) on the background (left), a small object (middle), and a large object (right), respectively.

Figure 7: Illustration of offset parts in deformable (positive sensitive) RoI pooling in R-FCN [7] and $3 \times 3$ bins (red) for an input RoI (yellow). Note how the parts are offset to cover the non-rigid objects.
Two Stages Detector: 
RFCN -> Deformable Convolutional Networks

Discussion

• Deformable pool is similar to ROIAlign (in Mask RCNN)
• Deformable conv
  • flexible to learn the non-rigid objects
Two Stages Detector:  
RCNN -> Fast RCNN -> FasterRCNN -> FPN
Two Stages Detector: FPN

Discussion

• FasterRCNN reproduced (setting)
• Deeply supervised (better feature)
# Two Stages Detector: FPN

## Experiments

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</table>

Feature Pyramid Networks for Object Detection, Lin etc, CVPR 2017
Two Stages Detector:
RCNN -> Fast RCNN -> FasterRCNN -> FPN -> MaskRCNN

Figure 1. The Mask R-CNN framework for instance segmentation.
Two Stages Detector:
RCNN -> Fast RCNN -> FasterRCNN -> FPN -> MaskRCNN

<table>
<thead>
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<th>align?</th>
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<td>31.8</td>
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<tr>
<td></td>
<td>✓</td>
<td>ave</td>
<td>30.3</td>
<td>51.2</td>
<td>31.5</td>
</tr>
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</table>

(c) **RoIAlign** (ResNet-50-C4): Mask results with various RoI layers. Our RoIAlign layer improves AP by ≈3 points and AP75 by ≈5 points. Using proper alignment is the only factor that contributes to the large gap between RoI layers.
Two Stages Detector: Mask RCNN

Discussion

• Alignment issue in ROI Pooling -> ROIAlign
• Multi-task learning: detection & mask

Mask R-CNN, He etc, ICCV 2017
### Two Stages Detector: Mask RCNN

#### Experiments

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Mask R-CNN, He etc, ICCV 2017
Two Stages Detector: Light Head R-CNN

- Improve Inference speed in detection algorithms

---

Light-Head R-CNN: In Defense of Two-Stage Object Detector, Li etc, 
Two Stages Detector: Light Head R-CNN

- Improve Inference speed in detection algorithms

Two Stages Detector: MegDet

- Batchsize issue in general object detection
- Problems in small batch size
  - Long training time
  - Inaccurate BN statistics
  - Inbalanced positive and negative ratios

MegDet: A Large Mini-Batch Object Detector, Peng etc, CVPR2018
Two Stages Detector: MegDet

Figure 1: Validation accuracy of the same FPN object detector trained on COCO dataset, with mini-batch size 16 (on 8 GPUs) and mini-batch size 256 (on 128 GPUs). The large mini-batch detector is more accurate and its training is nearly an order-of-magnitude faster.

Table 1: Performance comparison of different object detectors.

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<td><strong>MegDet (Ensemble)</strong></td>
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<td><strong>69.0</strong></td>
</tr>
</tbody>
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4: Result of (enhanced) MegDet on test-dev of COCO.

Two Stages Detector: DetNet

- Pretrain the backbone network for Detection
- Problems with the ImageNet pretrain model
  - Target for the classification problem, not localization friendly
  - Gap between the backbone and detection network
    - Not initialization for P6 (and P7)
- Train the Backbone by maintaining the spatial resolution (localization) and receptive field (classification)
Two Stages Detector: DetNet

DetNet: A Backbone network for Object Detection, Li etc
https://arxiv.org/abs/1804.06215
Two Stages Detector: DetNet

DetNet: A Backbone network for Object Detection, Li etc
https://arxiv.org/abs/1804.06215
Two Stages Detector: DetNet

Table 7. Comparison of object detection results between our approach and state-of-the-art on MSCOCO test-dev datasets. Based on our simple and effective backbone DetNet-59, our model outperforms all previous state-of-the-art. It is worth noting that DetNet-59 yields better results with much lower FLOPs.
Two Stages Detector: Summary

- **Speed**
  - RCNN -> Fast RCNN -> Faster RCNN -> RFCN -> Light Head R-CNN
- **Performance**
  - Divide and conquer
    - FPN
  - Deformable Pool/ROIAlign
  - Deformable Conv
  - Multi-task learning
  - Multi-GPU BN
Two Stages Detector: Discussion

FasterRCNN vs RFCN
One stage vs two Stage
Open Problem in Detection

- FP
- NMS (detection in crowd)
  - CrowdHuman Dataset: https://sshao0516.github.io/CrowdHuman/
- GT assignment issue
- Detection in video
  - detect & track in a network
Outline

- Detection
- Conclusion
Conclusion

• Detection
  • One stage: Densebox, YOLO, SSD, RetinaNet
  • Two Stage: RCNN, Fast RCNN, FasterRCNN, RFCN, FPN, Mask RCNN
Introduction to Face++ Detection Team
• Category-level Recognition
  • Detection
    • Face Detection:
    • Human Detection:
      • Repulsion loss: https://arxiv.org/abs/1711.07752
    • General Object Detection:
      • Light Head: https://arxiv.org/pdf/1711.07264.pdf
        https://github.com/zengarden/light_head_rcnn
  • Segmentation
  • Skeleton:
    • https://github.com/chenyilun95/tf-cpn
Thanks