Chapter 2 - Section 6

Object Detection

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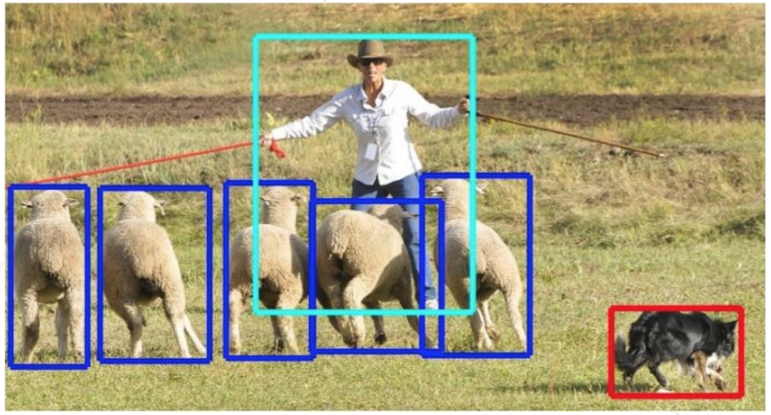
Acknowledge : Hongyang Li, Wang Cheng

Outline

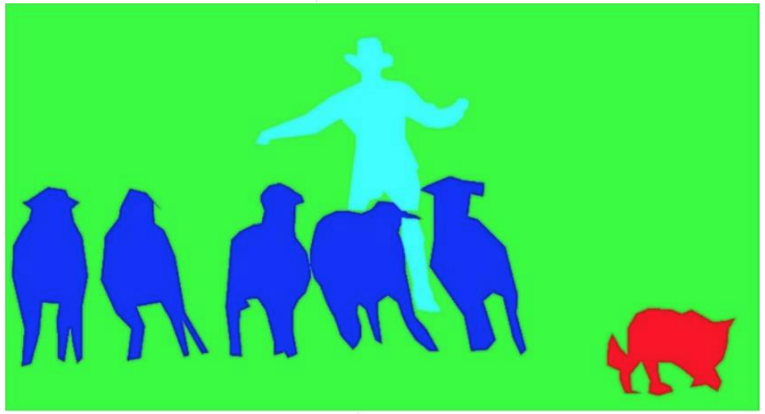
Introduction to Object Detection

- Type of computer vision tasks

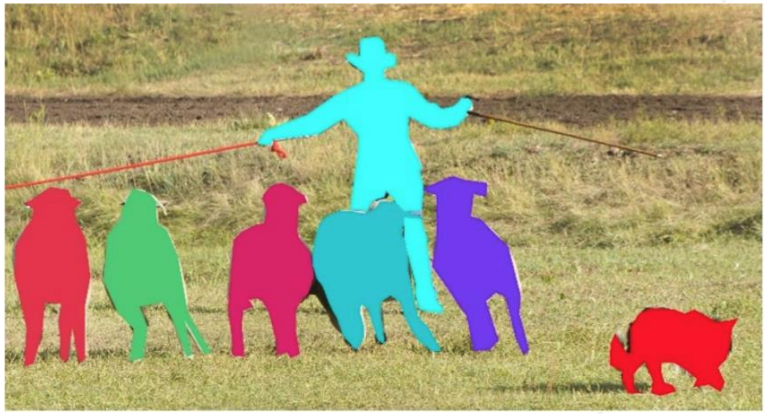
Image classification



Object detection



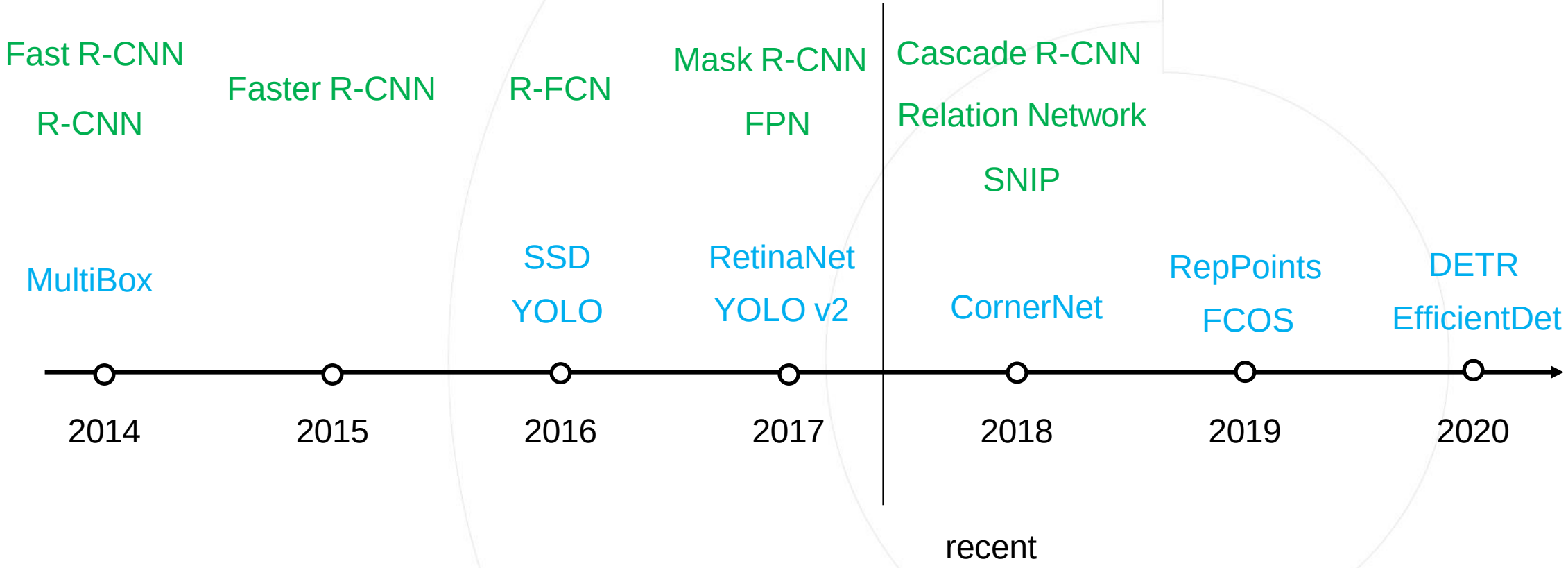
Semantic segmentation



Instance segmentation

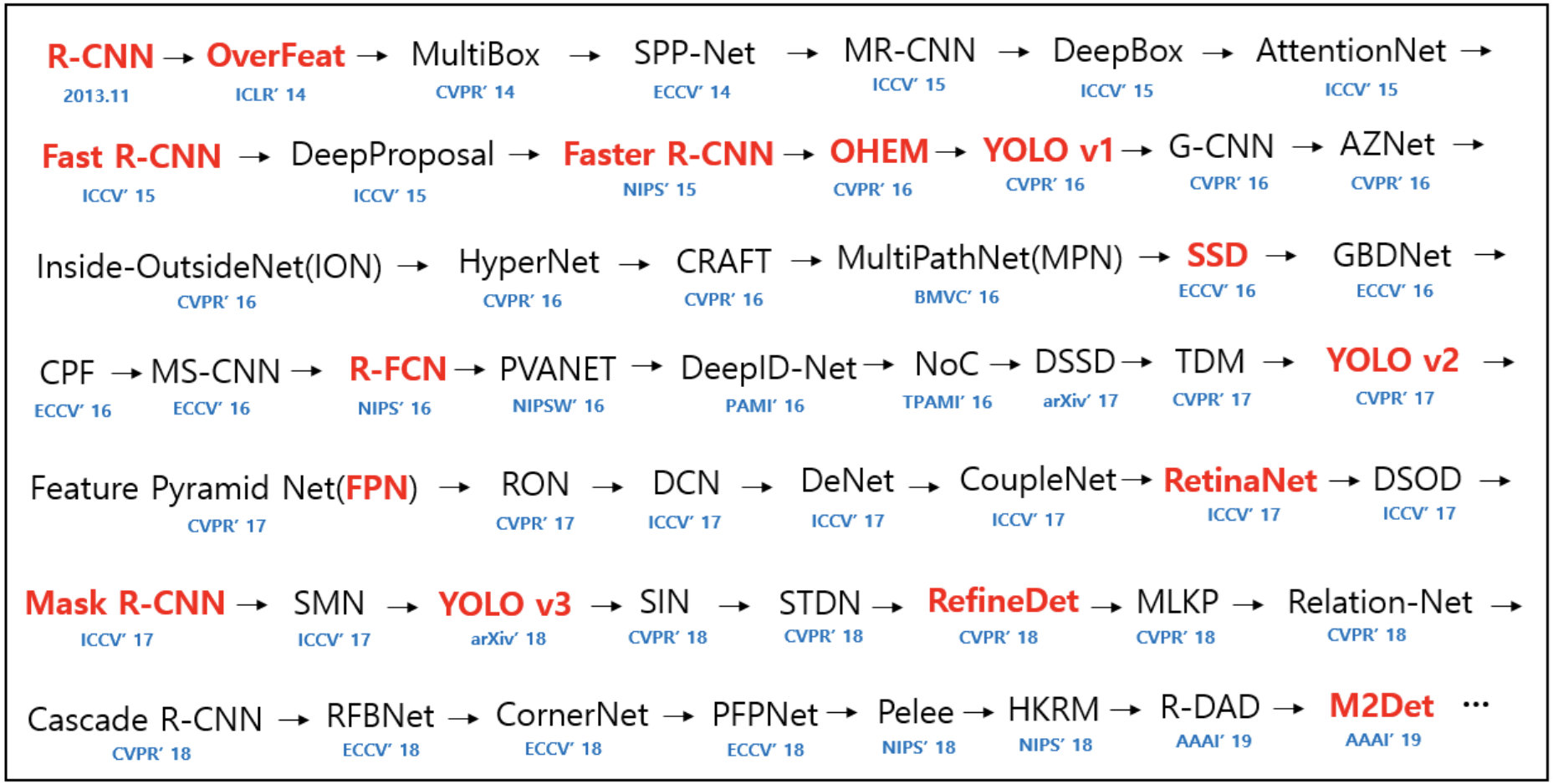
Introduction to Object Detection

- Progress

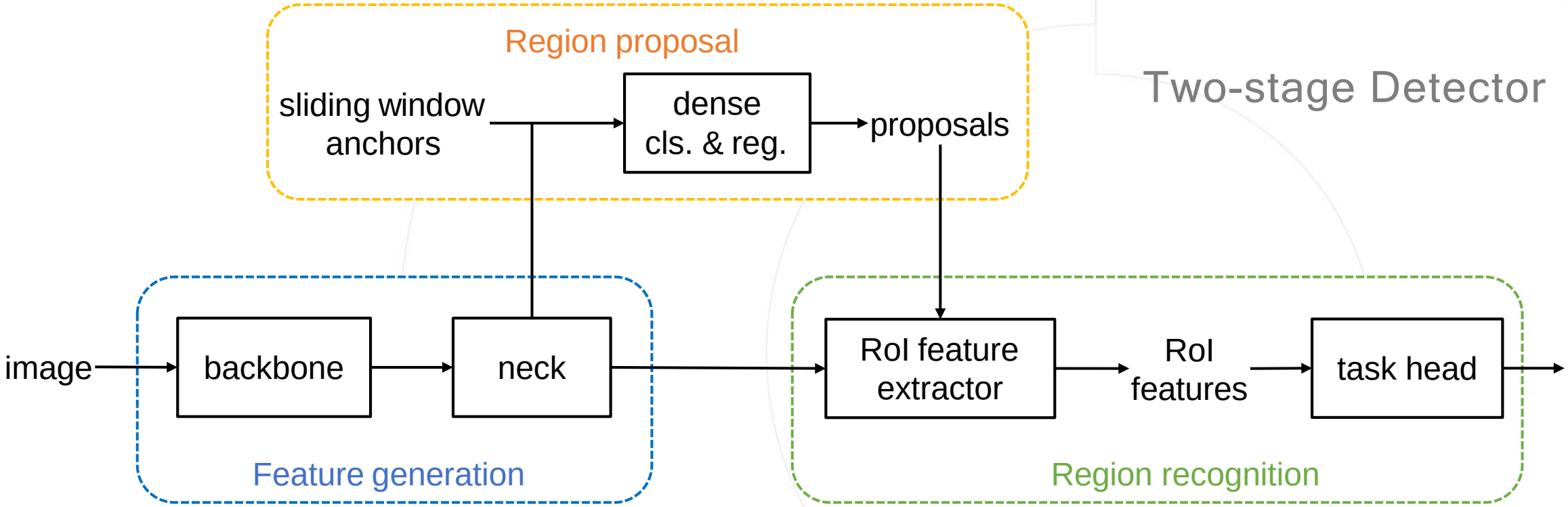


Introduction to Object Detection

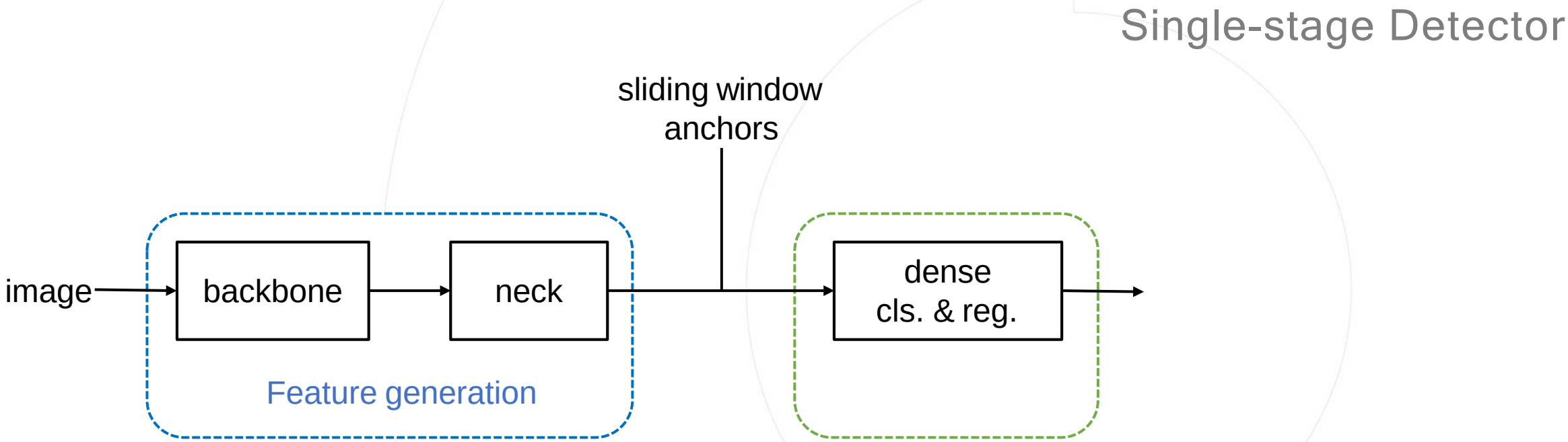
- History: a complete version



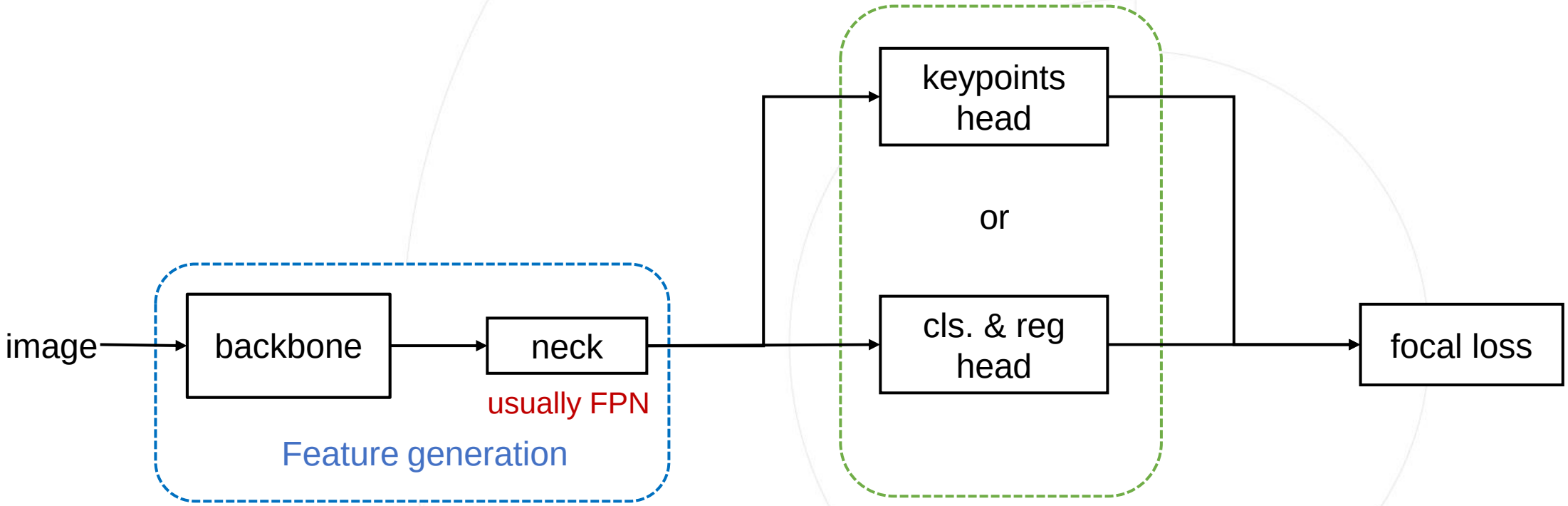
- General pipeline – two-stage pipeline



- General pipeline – one-stage pipeline



- General pipeline – anchor-free pipeline



Introduction to Object Detection

- Datasets and evaluation metrics
  - PASCAL VOC
  - MSCOCO
  - KITTI
  - Objects365
  - WIDER FACE,
  - mAP, FPPI
  - AP_{50}, AP_{75}, AP@[.5:.95]

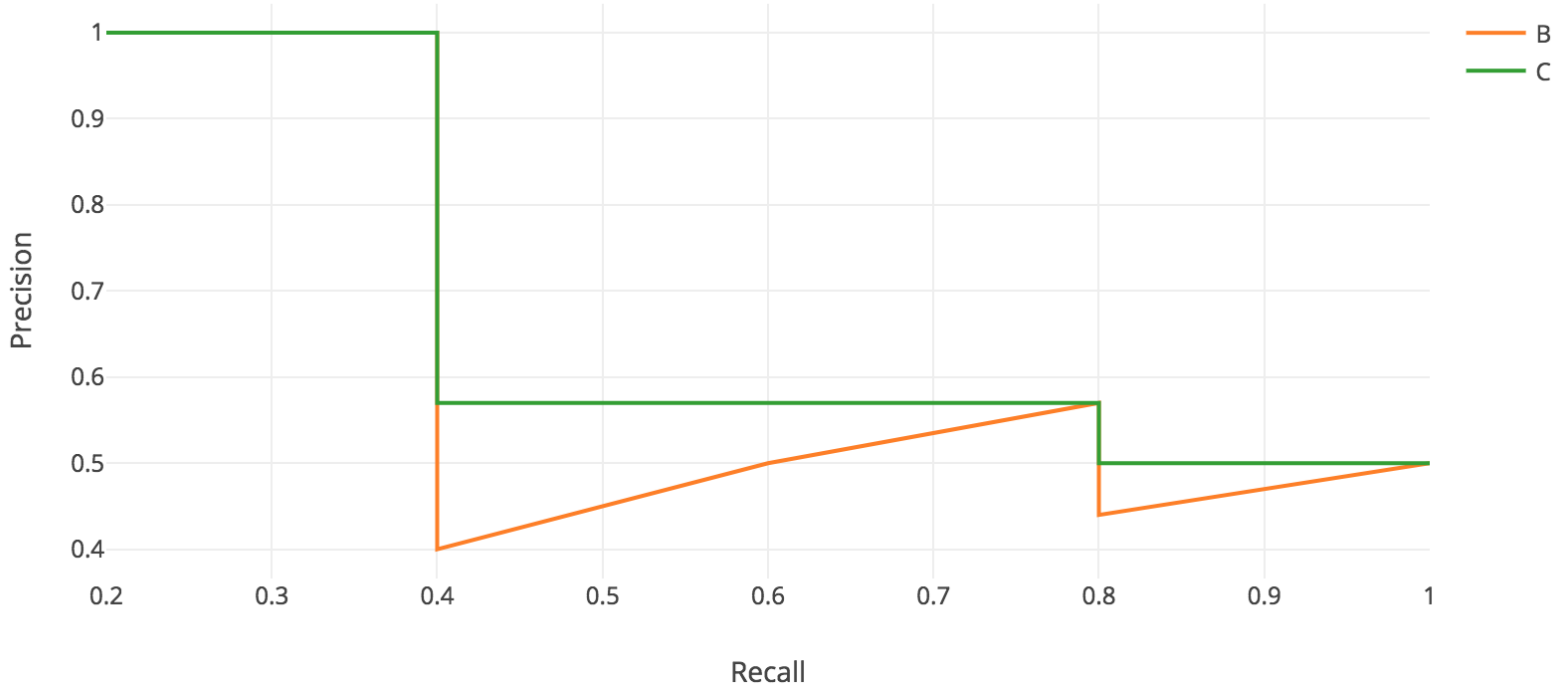
- PASCAL VOC Detection Competition
  - Homepage: http://host.robots.ox.ac.uk/pascal/VOC/
  - 每一张图对应一个 xml 文件：
    - bndbox 即 bounding box，目标在照片中可见部分的包围框
    - truncated 表明这个目标因为某种原因被截断
    - occluded 表明这个目标的重要部分被遮挡
    - difficult 表明这个目标识别难度较大

Year	Statistics
2007	20 classes: Person(1), Animal(6), Vehicle(7), Indoor(6) Train/validation/test: 9,963 images containing 24,640 annotated objects.
2012	20 classes. The train/val data has 11,530 images containing 27,450 ROI annotated objects and 6,929 segmentations.

Everingham M, Eslami S M A, Van Gool L, et al. The pascal visual object classes challenge: A retrospective. International journal of computer vision, 2015

- PASCAL VOC Detection Competition
  - interpolated average precision (before 2010)

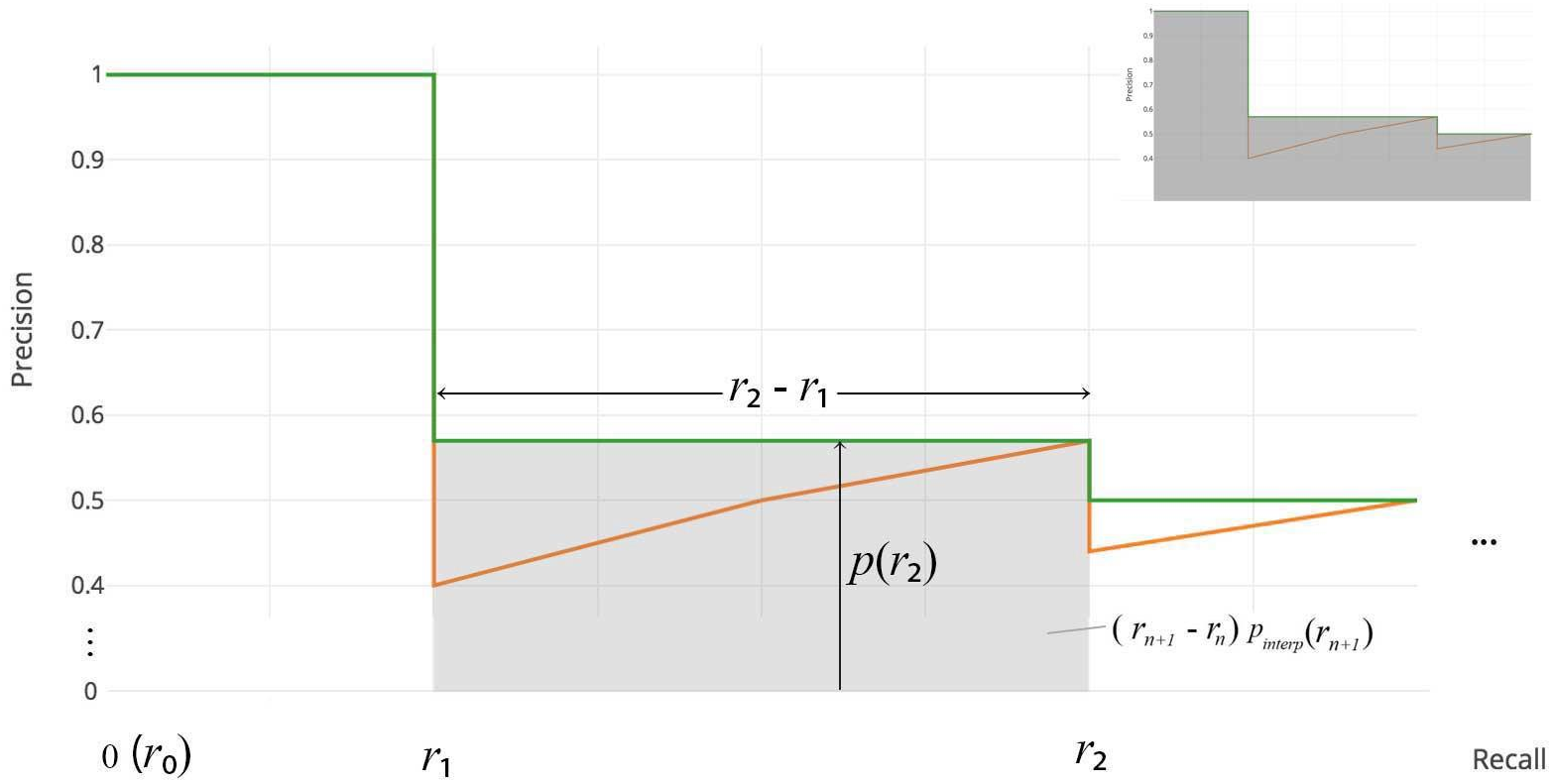
$$AP = \frac{1}{11} \sum_{0,0.1...1.0} P_{smooth}(i)$$



- PASCAL VOC Detection Competition
  - 新 ap 指标 Area under curve AUC (after 2010)

$$\mathrm{AP} = \sum \left(r_{n+1} - r_n \right) p_{interp}(r_{n+1})$$

$$p_{interp}(r_{n+1}) = \max_{\tilde{r} \geq r_{n+1}} p(\tilde{r})$$

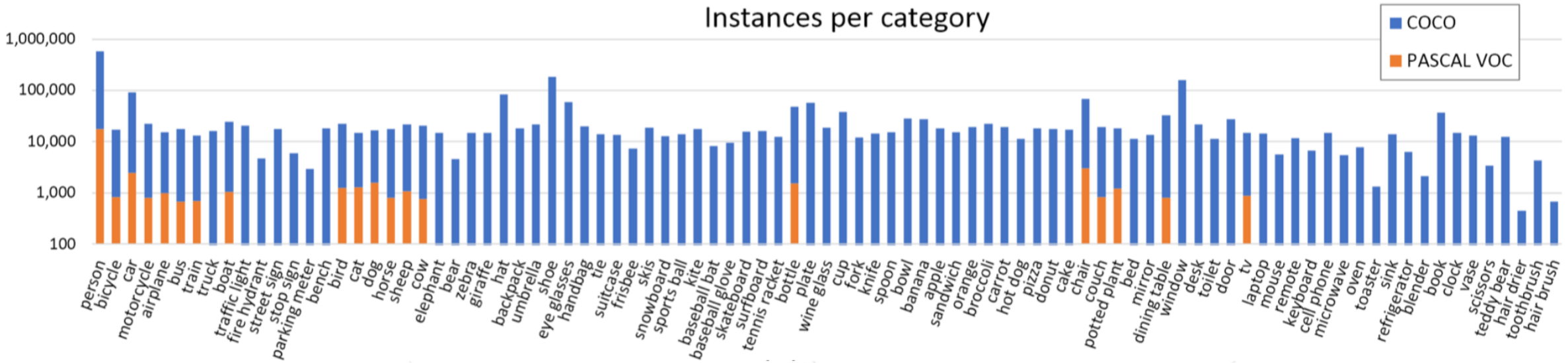


- Common Objects in Context (COCO)
  - Homepage: cocodataset.org
  - 使用 JSON 文件保存标注
    - images：图片基本信息。“file_name” 为图片名称，“id” 为图片序号，“height” 和 “width” 为图像的高宽
    - annotations：标注信息。“image_id” 为图片序号，“bbox” 为矩形框坐标 [x, y, w, h]。“category_id” 为类别
    - categories：对应类别信息。“id” 为类别序号，“name” 为类别名称。

Lin T Y, Maire M, Belongie S, et al. Microsoft coco: Common objects in context. ECCV2014

Introduction to Object Detection

- Common Objects in COntext
  - The 2014 release contains 82,783 training, 40,504 validation, and 40,775 testing images
  - 80 categories



- Common Objects in Context

注意与 PASCAL VOC 中 AP 的区别

Matrix	Details
AP	AP at IoU=.50:.05:.95 (primary challenge metric)
AP_{50}	AP at IoU=.50 (PASCAL VOC metric)
AP_{75}	AP at IoU=.75
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

- Objects365
  - 11 个 大类： human and related accessories, living room, clothes, kitchen, instrument, transportation, bathroom, electronics, food (vegetables), office supplies, and animal
  - 365 个小类，覆盖 PASCAL VOC 和 COCO

Dataset	Images	Boxes	Categories	Boxes/img	Fully Annotated
Pascal VOC	11.5k	27k	20	2.4	Yes
ImageNet All	477k	534k	200	1.1	Yes
ImageNet Dense	80k	186k	200	2.3	Yes
COCO	123k	896k	80	7.3	Yes
OpenImages	1,515k	14,815k	600	9.8	Partial
Objects365	**638k**	**10,101k**	**365**	**15.8**	Yes

Shao S, Li Z, Zhang T, et al. Objects365: A large-scale, high-quality dataset for object detection. ICCV2019

Introduction to Object Detection

- KITTI
  - 自动驾驶领域的数据集
  - Object Detection Evaluation 方向包括 2D、3D和鸟瞰视角的 benchmark
  - 包括汽车，行人，自行车分类
  - calib.txt 保存标定参数
  - label.txt 保存标注结果

```
Truck 0.00 0 -1.57 599.41 156.40 629.75 189.25 2.85 2.63 12.34 0.47 1.49 69.44 -1.56
Car 0.00 0 1.85 387.63 181.54 423.81 203.12 1.67 1.87 3.69 -16.53 2.39 58.49 1.57
Cyclist 0.00 3 -1.65 676.60 163.95 688.98 193.93 1.86 0.60 2.02 4.59 1.32 45.84 -1.55
DontCare -1 -1 -10 503.89 169.71 590.61 190.13 -1 -1 -1 -1000 -1000 -1000 -10
```

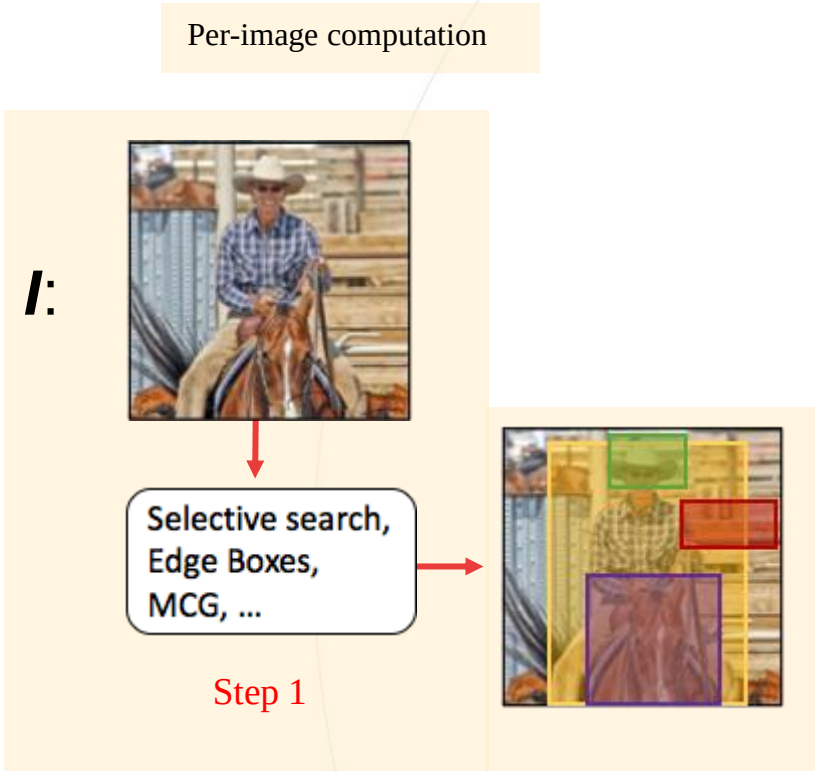
Geiger A, Lenz P, Urtasun R. Are we ready for autonomous driving? the kitti vision benchmark suite. CVPR2012

商汤 sensetime

清華大學 Tsinghua University

Outline

- RCNN method

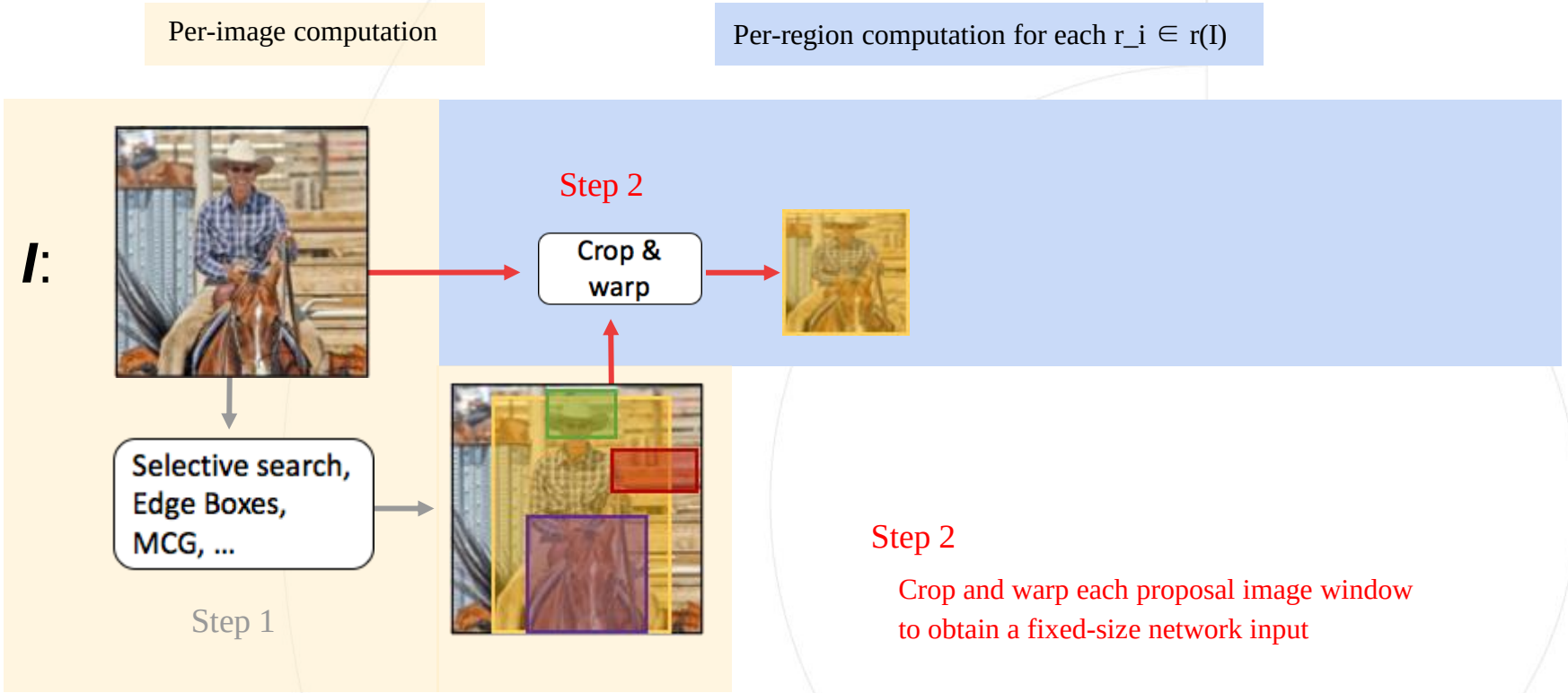


Step 1

Use an off-the-shelf region/object/detection proposal algorithm (~2k proposals per image)

Girshick R, Donahue J, Darrell T, et al. Rich feature hierarchies for accurate object detection and semantic segmentation. CVPR2014

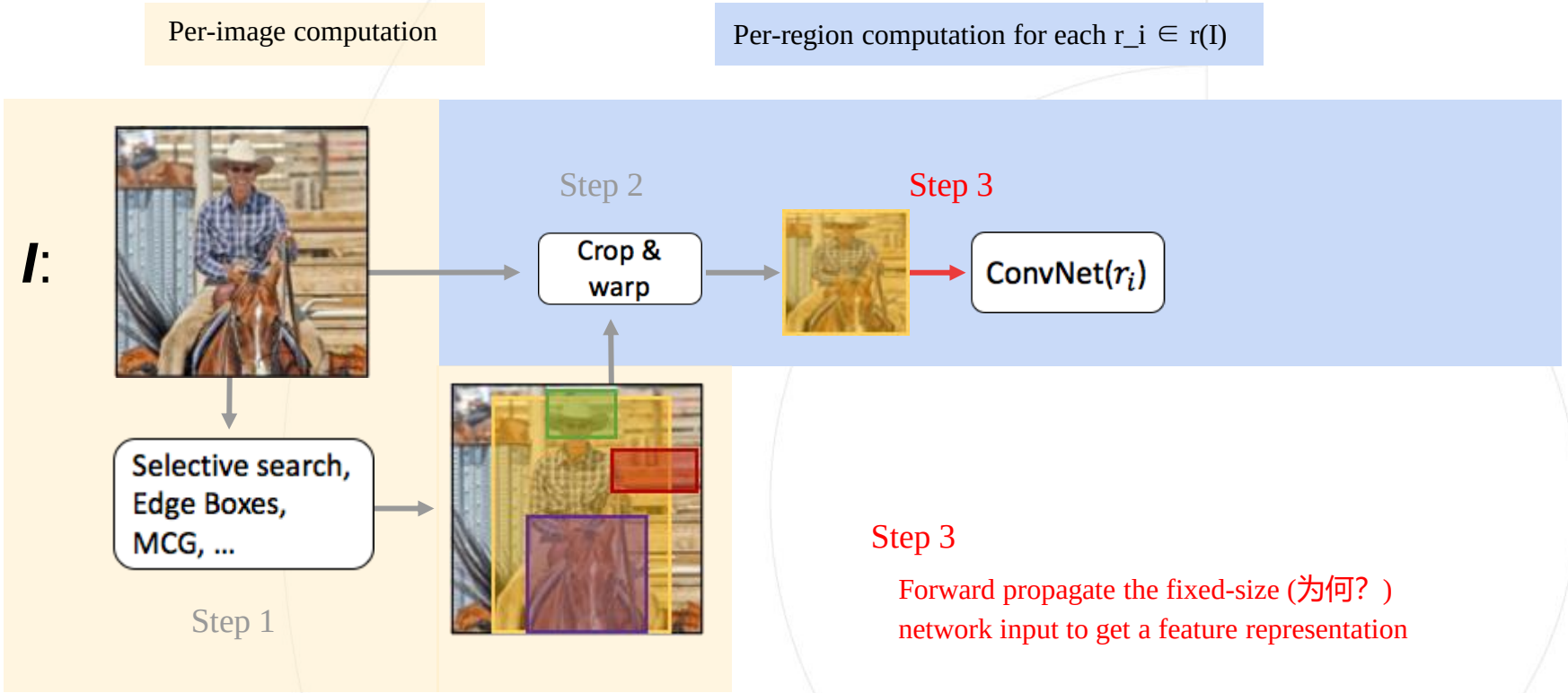
- RCNN method



Step 2

Crop and warp each proposal image window to obtain a fixed-size network input

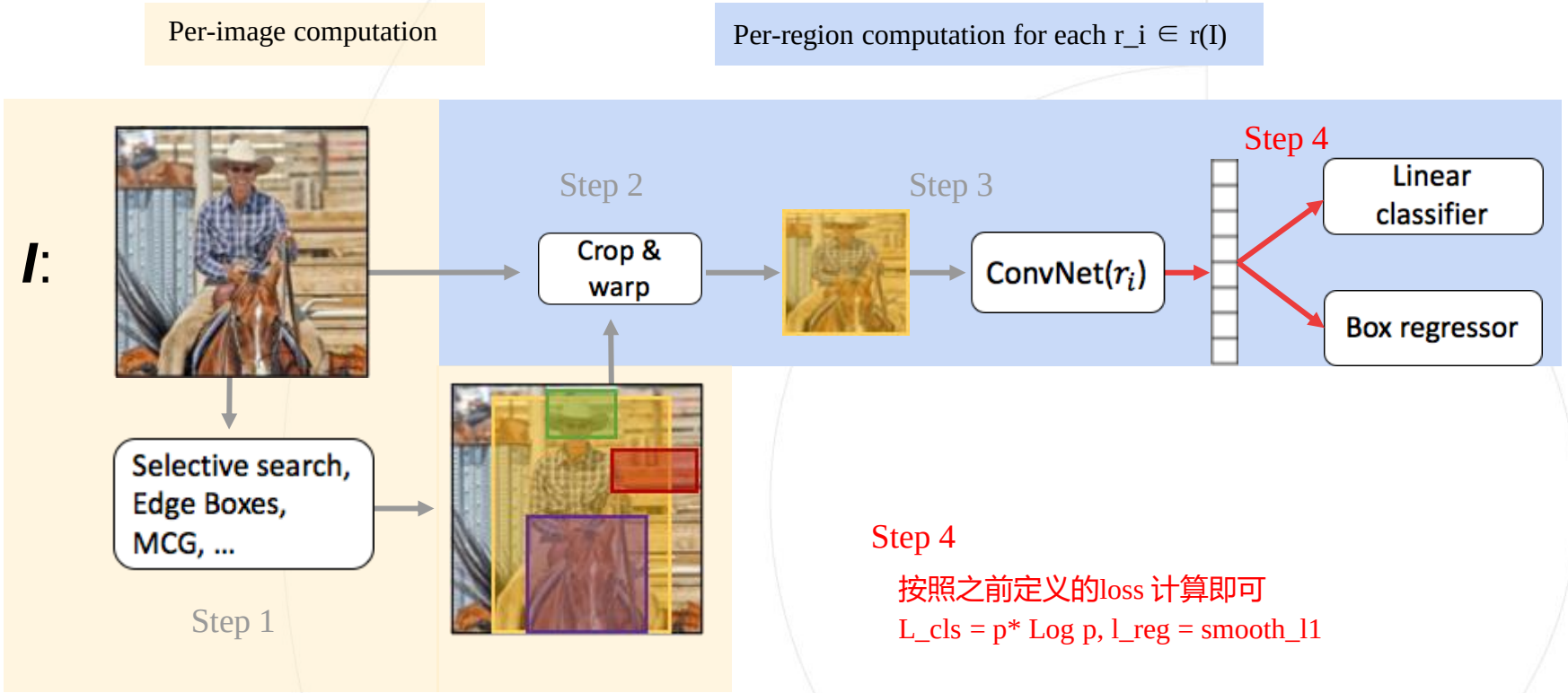
- RCNN method



Step 3

Forward propagate the fixed-size (为何？) network input to get a feature representation

- RCNN method



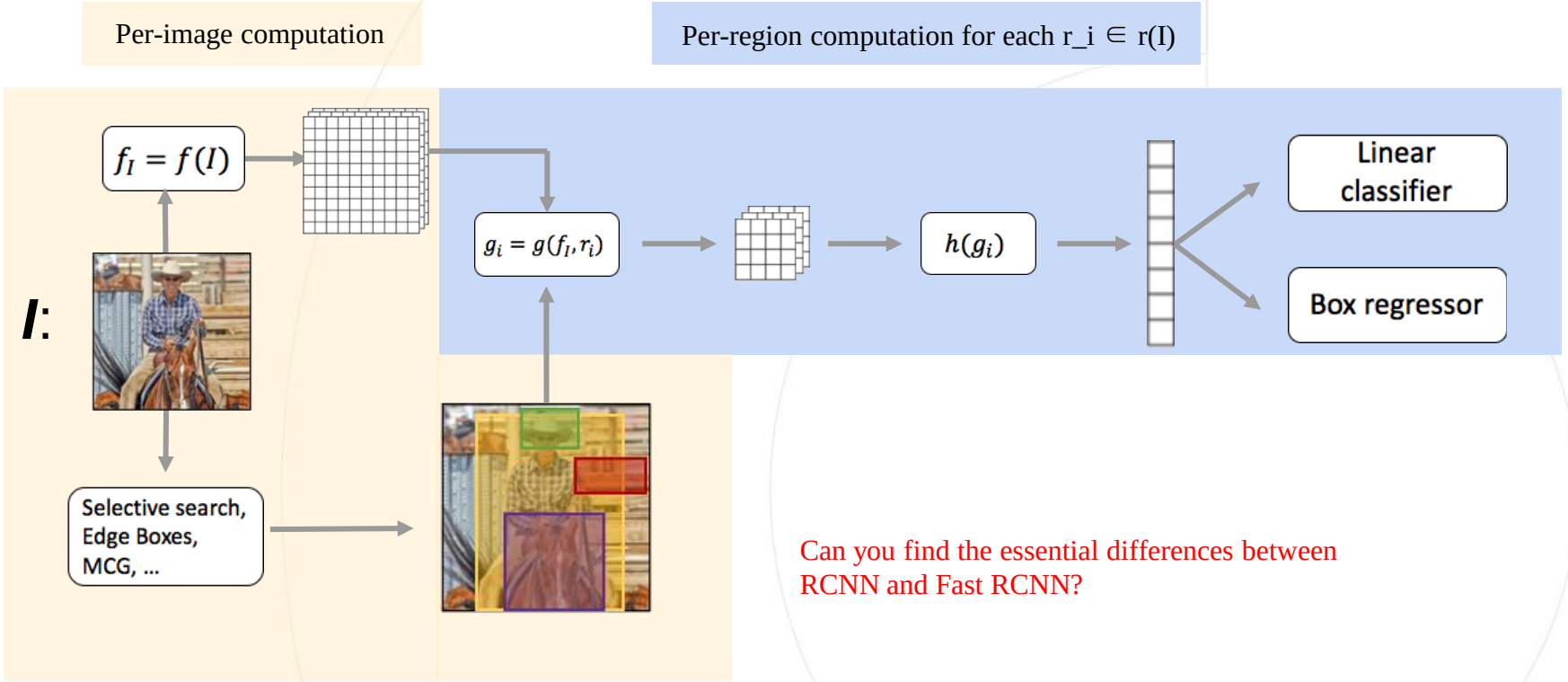
Step 4

按照之前定义的loss 计算即可

L_cls = p* Log p, l_reg = smooth_l1

- The bottleneck of RCNN

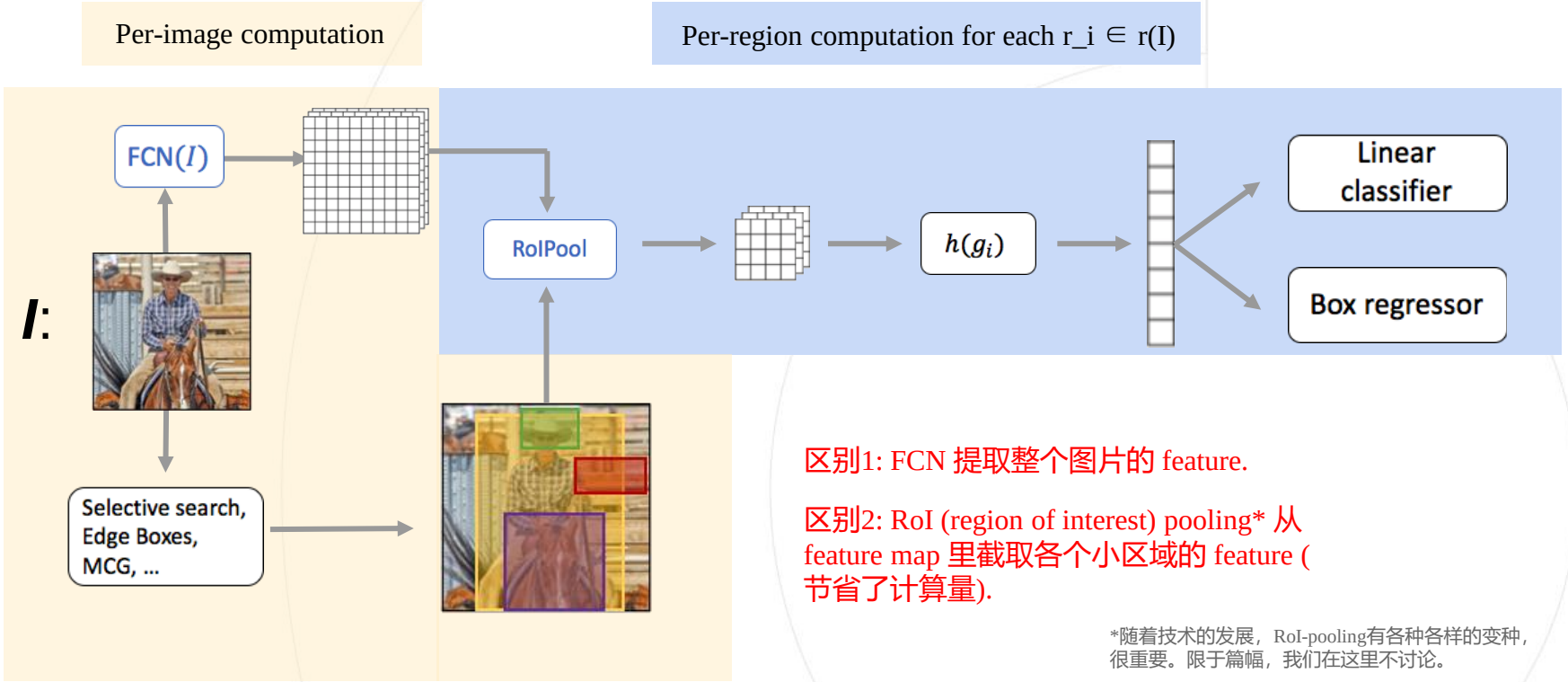
- Fast RCNN



Can you find the essential differences between RCNN and Fast RCNN?

Girshick R. Fast r-cnn. CVPR2015

- Fast RCNN

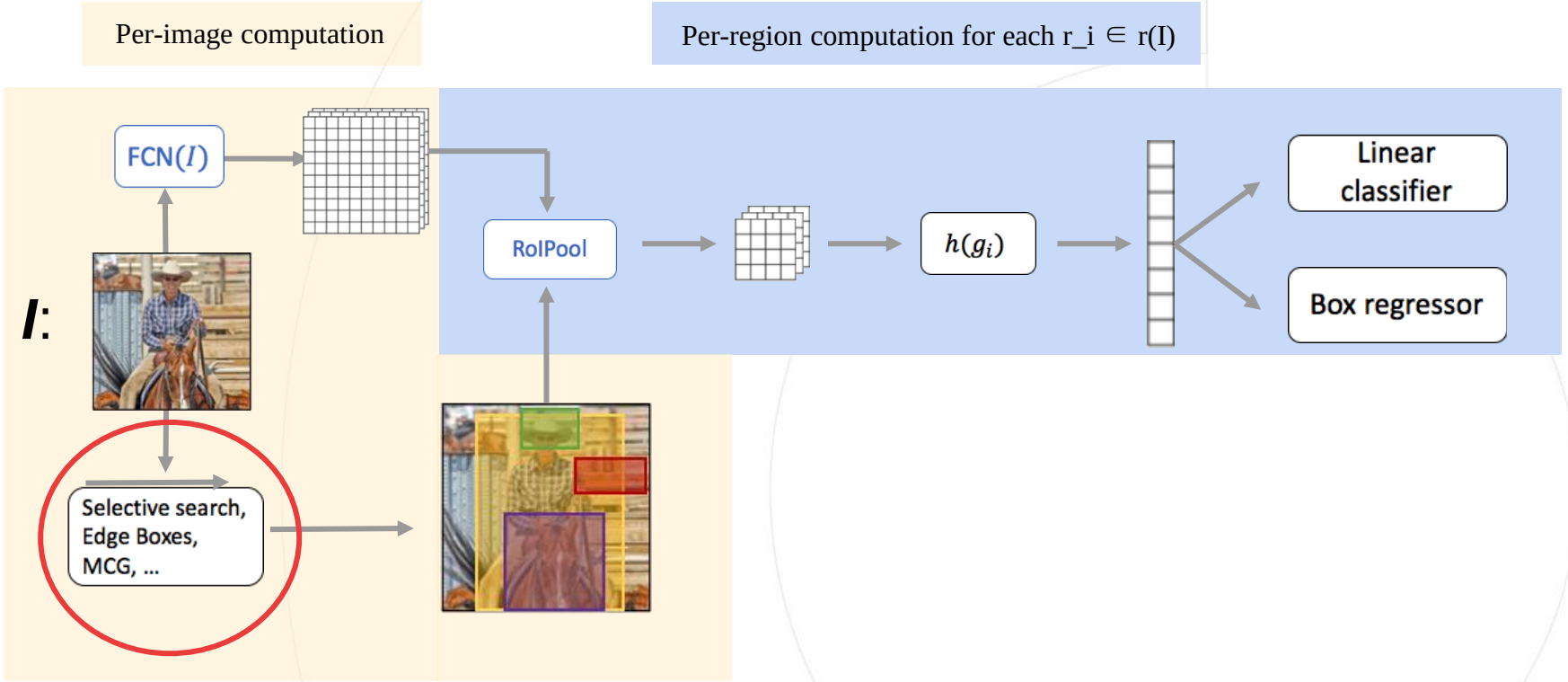


区别1: FCN 提取整个图片的 feature.

区别2: RoI (region of interest) pooling* 从 feature map 里截取各个小区域的 feature (节省了计算量).

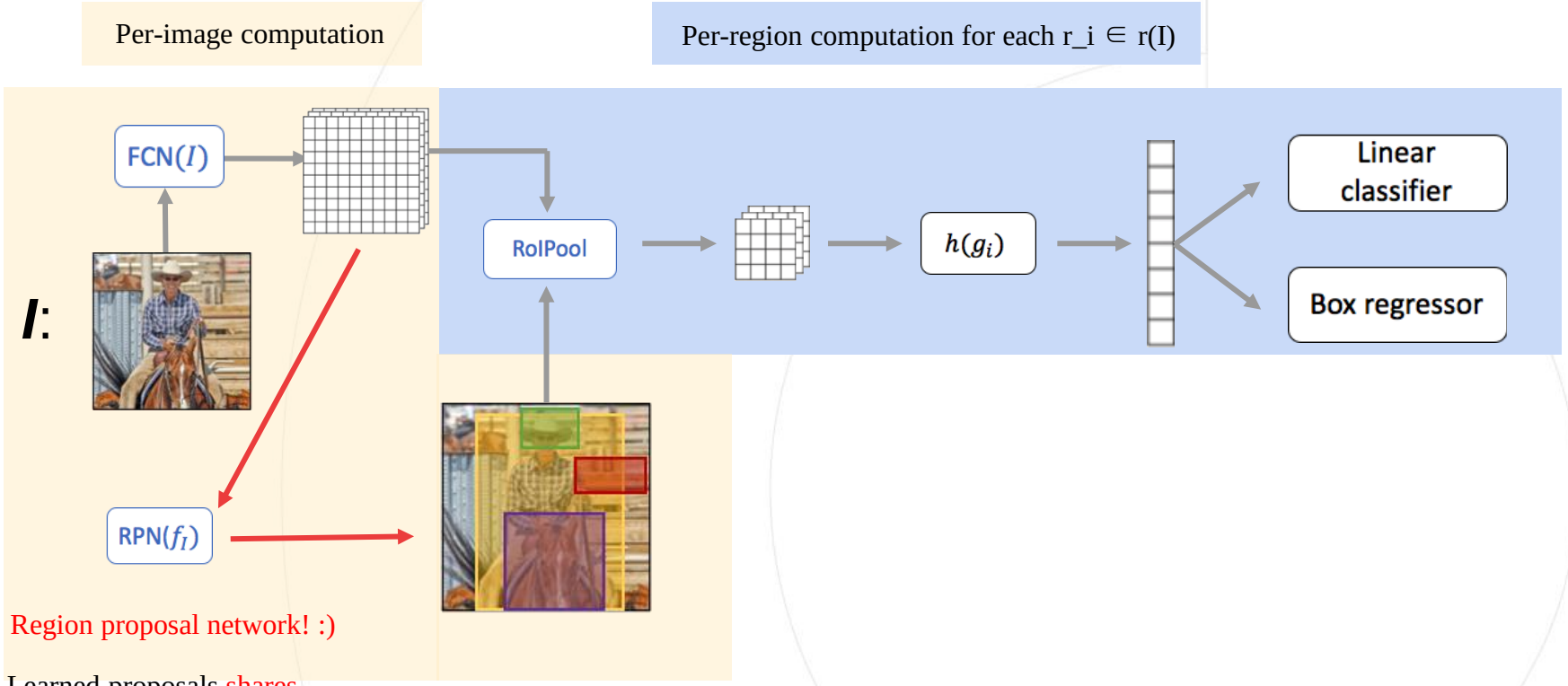
*随着技术的发展，RoI-pooling有各种各样的变种，很重要。限于篇幅，我们在这里不讨论。

- The **bottleneck** of Fast RCNN



Region proposals have very poor recall (ok for PASCAL VOC, major bottleneck for COCO) Also, they can be slow

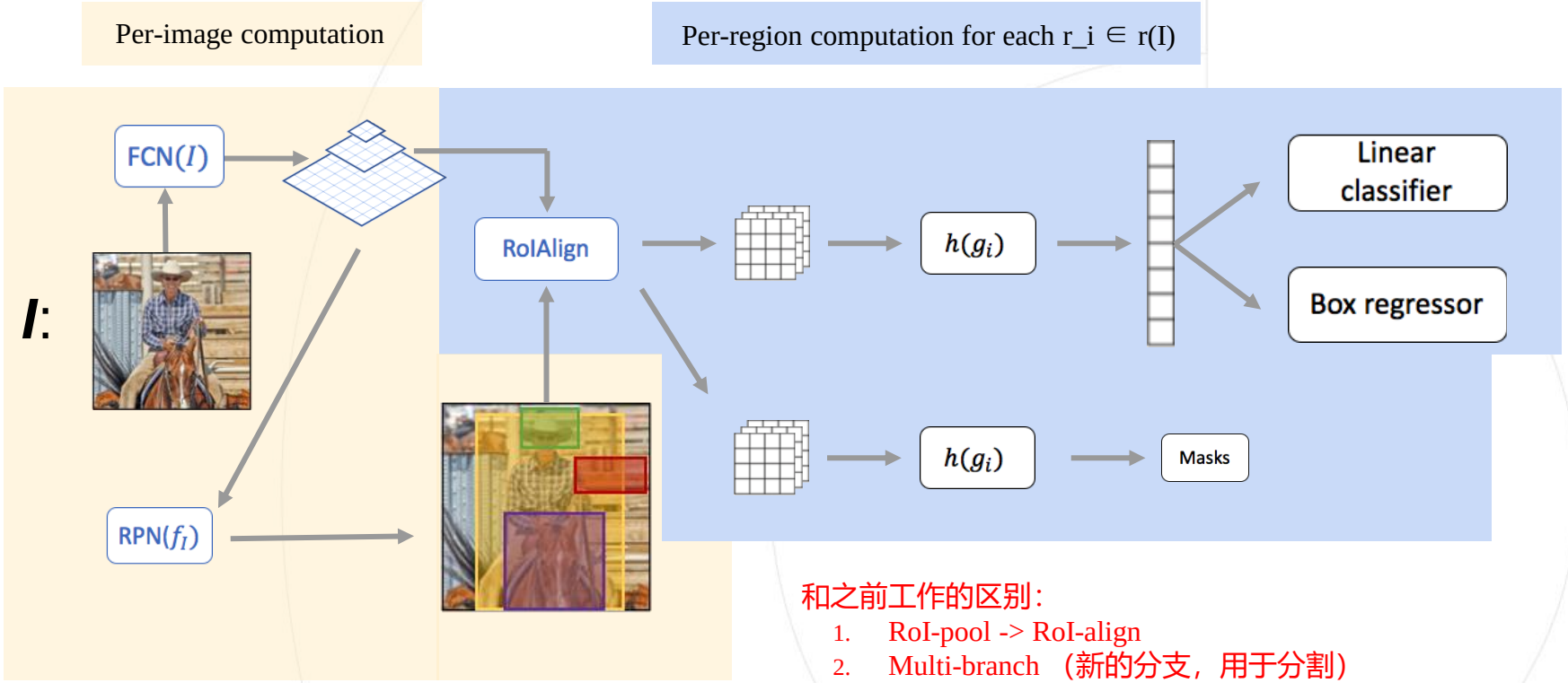
- The solution: Faster RCNN



Learned proposals shares computation with whole-image network

Ren S, He K, Girshick R, et al. Faster r-cnn: Towards real-time object detection with region proposal networks. PAMI, 2016, 39(6): 1137-1149.

- Mask RCNN

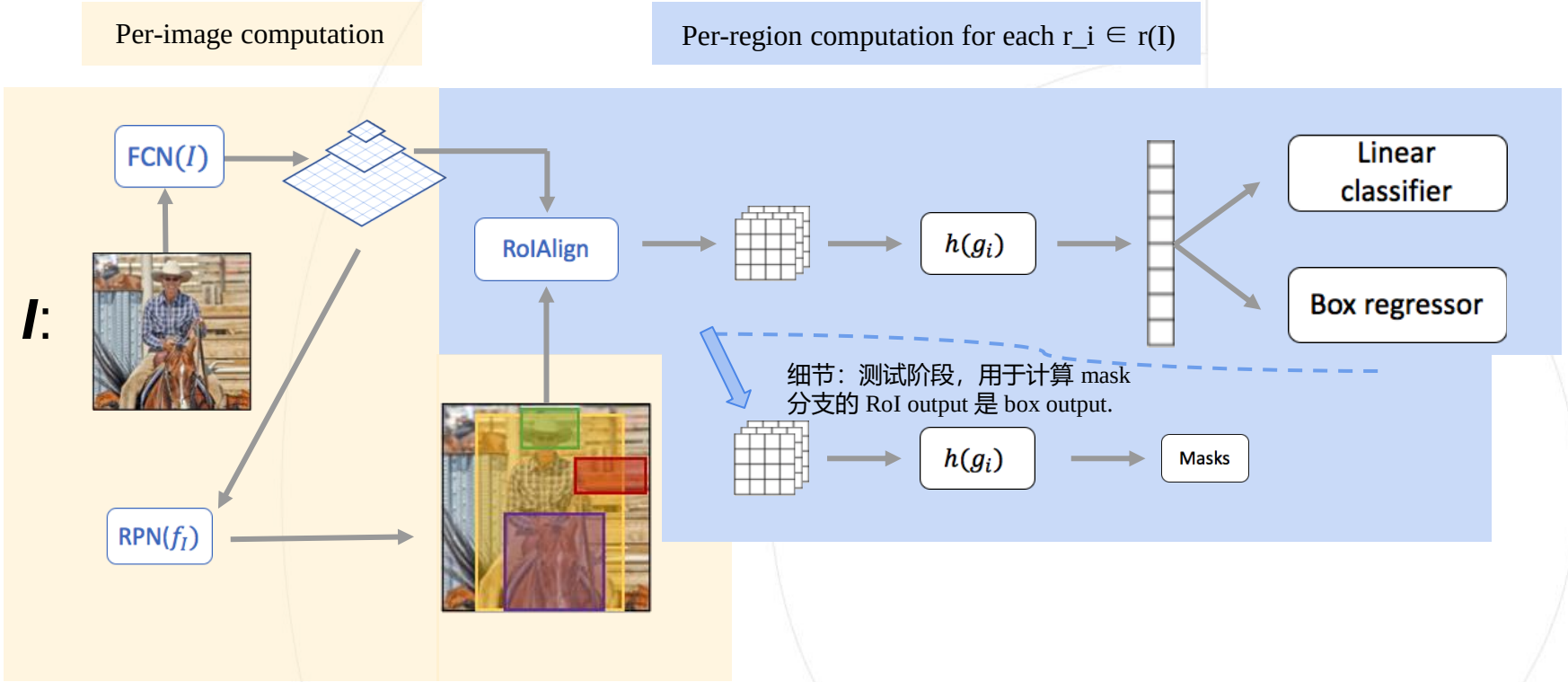


和之前工作的区别：

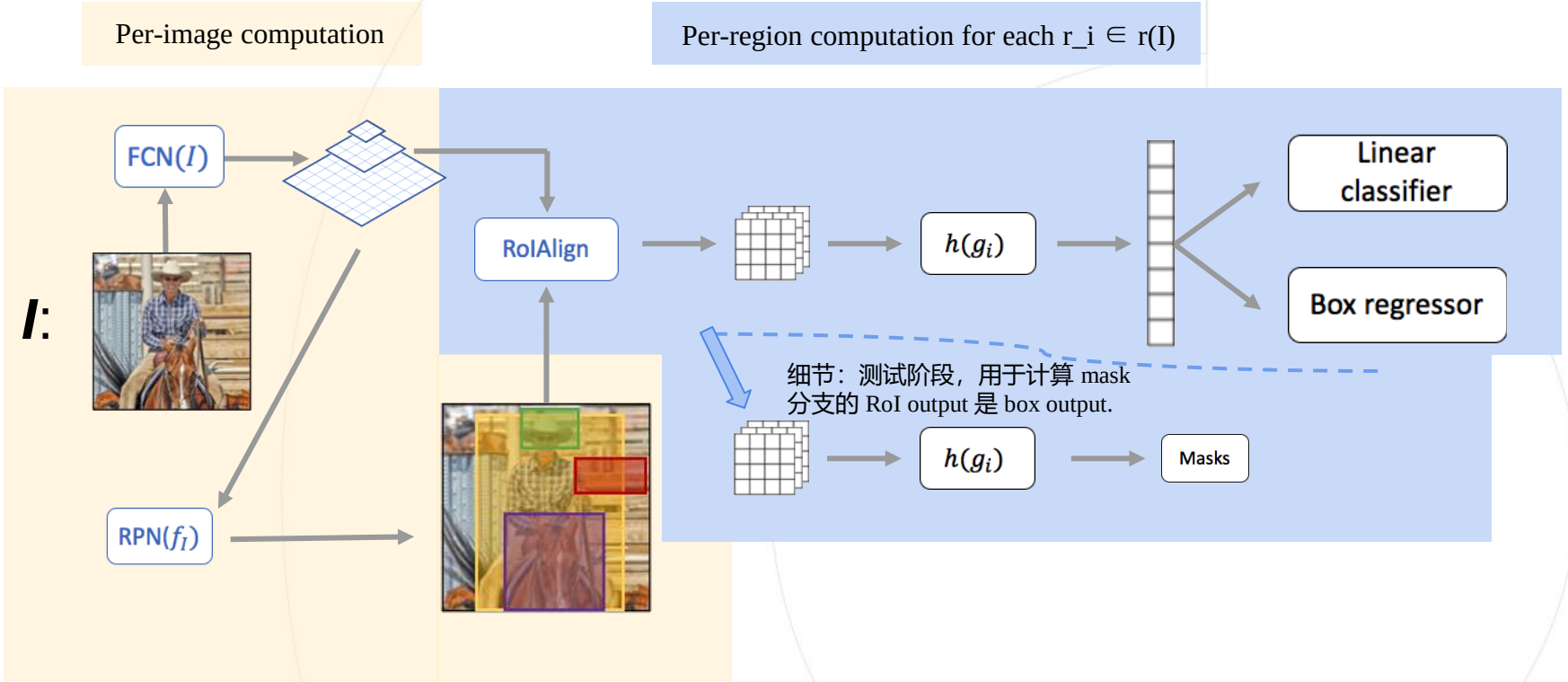
1. RoI-pool -> RoI-align
2. Multi-branch （新的分支，用于分割）

He K, Gkioxari G, Dollár P, et al. Mask r-cnn. ICCV2017

- Mask RCNN


Per-image computation
Per-region computation for each r_i ∈ r(I)
FCN(I)
I:
RPN(f_I)
RoIAlign
$h(g_i)$
Linear classifier
Box regressor
细节：测试阶段，用于计算 mask 分支的 RoI output 是 box output.
$h(g_i)$
Masks

- Mask RCNN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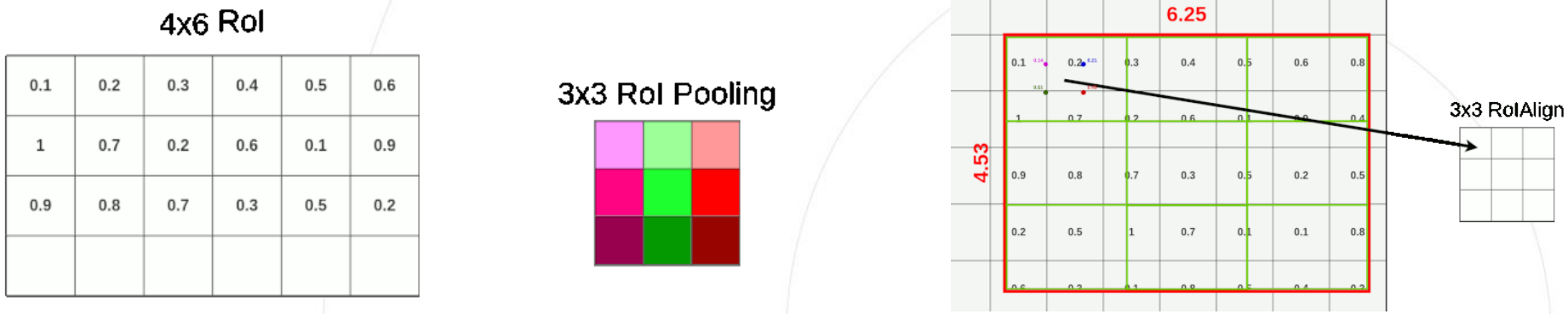
$h(g_i)$
Masks

Extension: Variants of RoI Pooling

- Can you identify deficiencies of RoI Pooling?



(a) RoI Pooling

(b) RoI Align

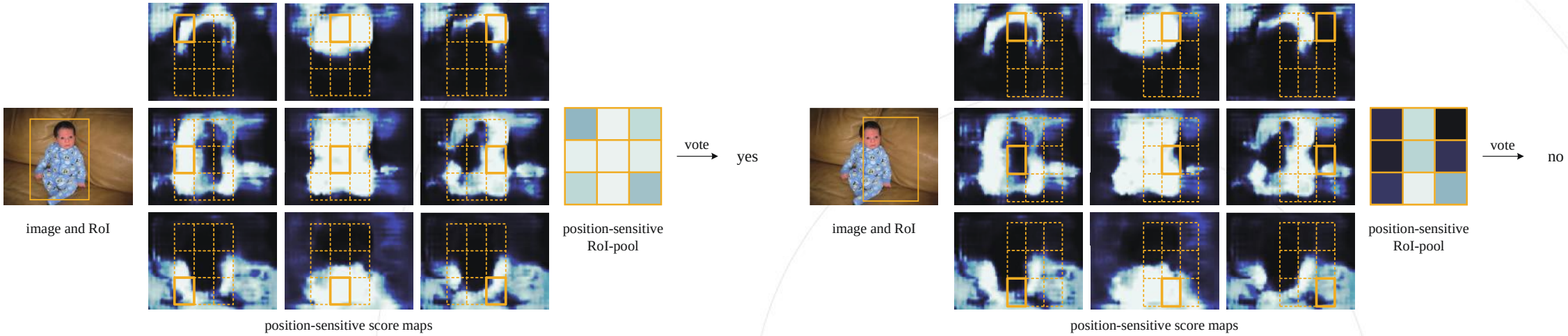
RoI Pooling 需要在 feature map 上对坐标进行量化。Feature map 上 (x1: 9.25, y1: 6, x2: 15.5, y: 10.5) 的 RoI 将被量化成 4*6

执行 Pooling 时需要第二次量化。例如上图中由于 4/3=1.33，最后一行 feature 将被丢弃

两次量化后，实际使用的 feature 是 (x1: 9, y1: 6, x2: 15, y: 10) 中的

Extension: Variants of RoI Pooling

- Position-sensitive ROI Pooling



(a) Position-sensitive ROI Pooling

Problem：faster R-CNN 经过 RoI pooling 后， ConvNet 是不共享的， 导致冗余的计算。如果一副图片有 500 个 region proposals，那么需要分别进行 500 次卷积操作

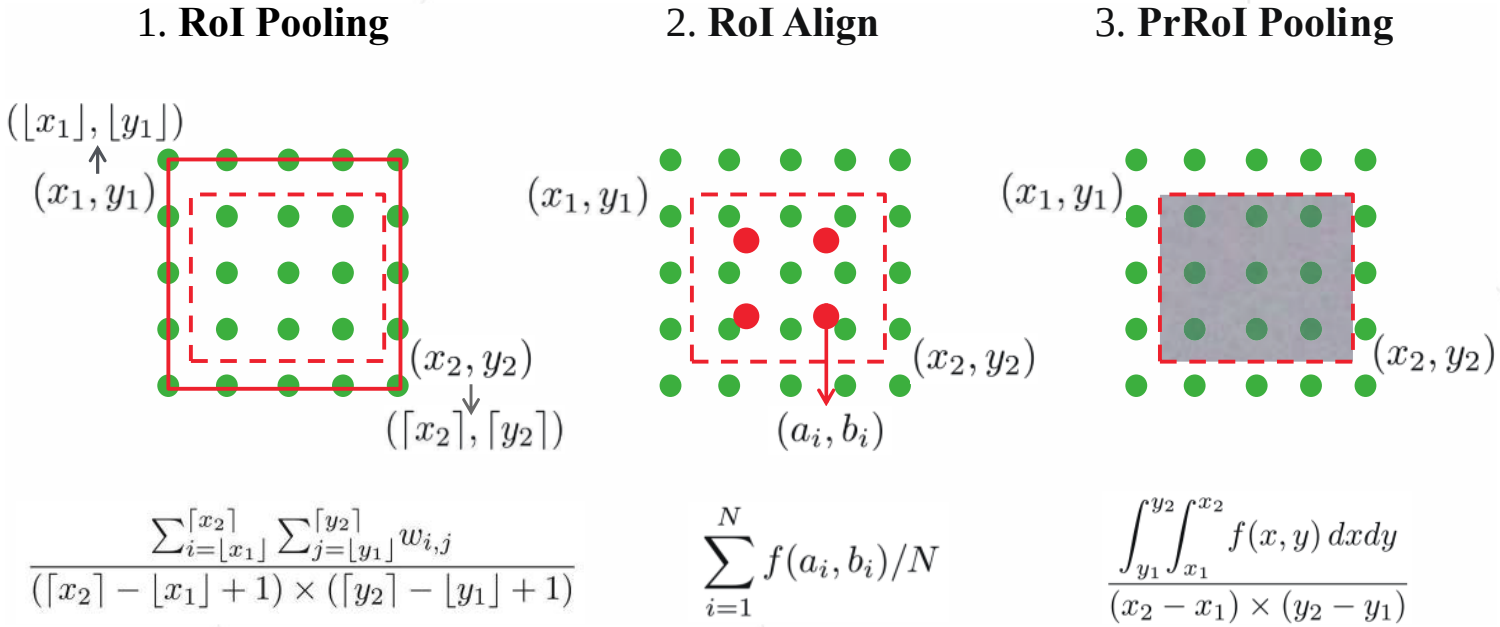
Motivation：将 RoI pooling 后的 FC layer 换成 Conv layer 并且共享，从而加速计算

基于 feature maps 提取 (C+1)-dim position-sensitive score maps，这个 score maps 对于所有 proposals 是共享的

Dai J, Li Y, He K, et al. R-fcn: Object detection via region-based fully convolutional networks[J]. arXiv preprint arXiv:1605.06409, 2016.

Extension: Variants of RoI Pooling

- Precise RoI Pooling



(b) PrRoI Pooling

Problem：RoI Pooling 的量化问题

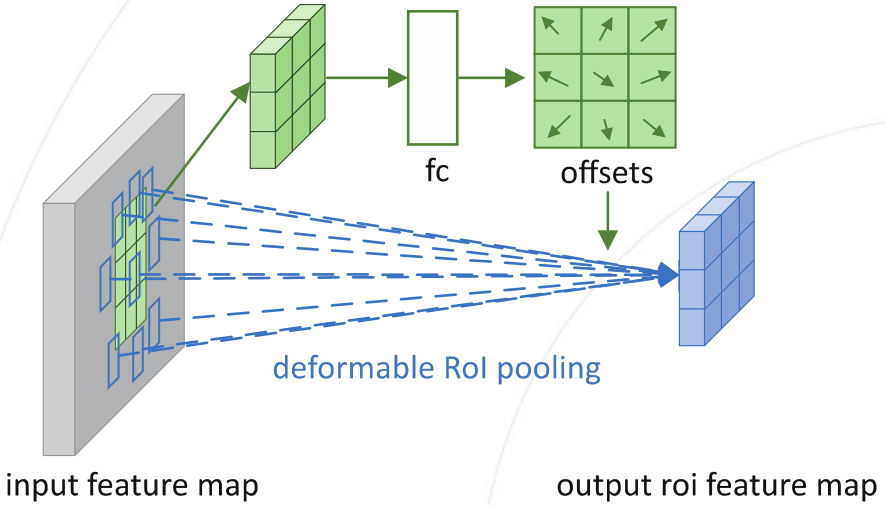
Motivation： IoU-Net directly estimates IoU(box_{det}, box_{gt}). PrRoI Pooling avoids any quantization of coordinates and has a continuous gradient on bounding box coordin

PrRoI Pooling 将 feature maps 连续化，通过积分求和除以面积得到 Pooling 结果

Jiang B, Luo R, Mao J, et al. Acquisition of localization confidence for accurate object detection. ECCV2018

Extension: Variants of RoI Pooling

- Deformable RoI Pooling



(c) Deformable RoI Pooling
Problem: RoI Pooling 无法考虑不规则目标
Motivation：给 RoI Pooling 中每一个 bin 加入一个 offset 来产生偏移

首先使用 RoI Pooing 生成 pooled feature maps；一个 FC layer 生成 normalized offsets 给每一个 bin；使用 offsets 即可在 input feature map 上做 deformable RoI Pooling

Dai J, Qi H, Xiong Y, et al. Deformable convolutional networks. ICCV2017

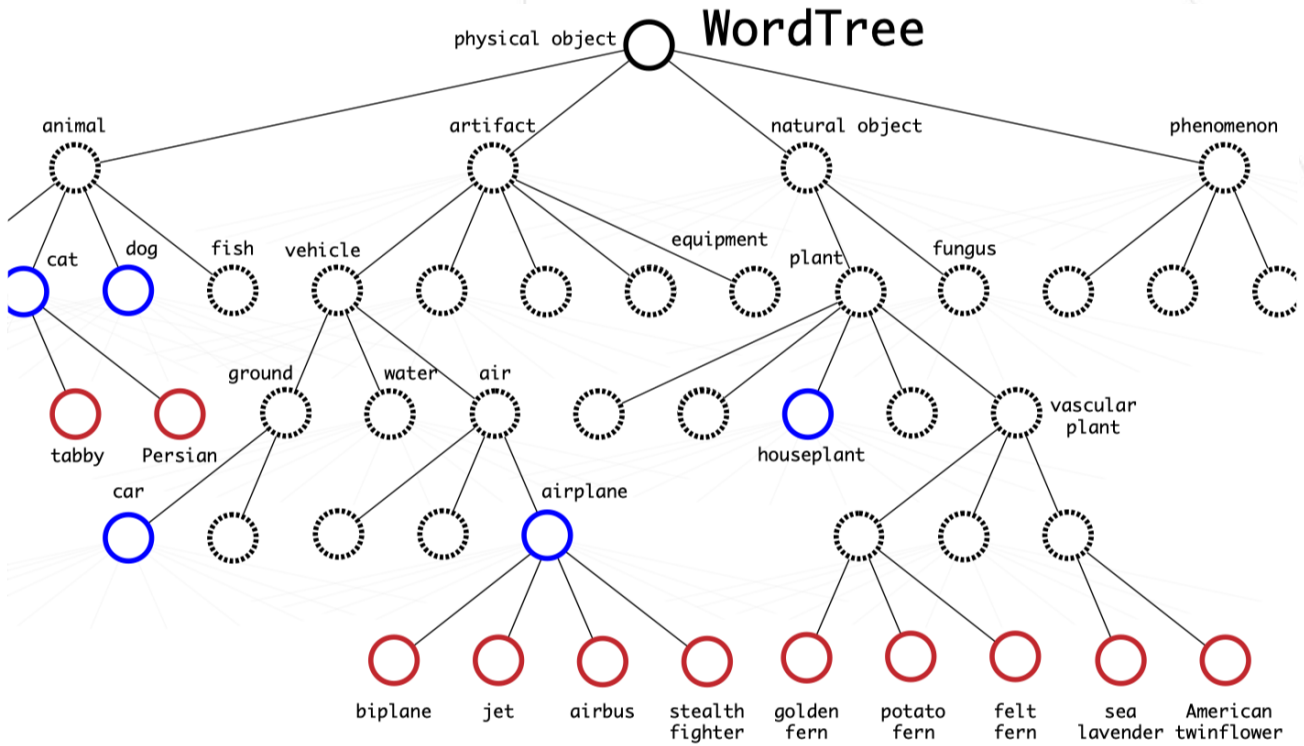
Extension: One-stage Framework

- 样本不均衡问题研究历史（在 two stage 方法中通过 two-stage cascade 和 sampling heuristics 避免
  - Yolo2 提出了 Hierarchical classification 方法，通过 Data Augmentation 达到局部平衡，并做局部 softmax。（不同类别样本均衡=性能一致?
  - OHEM 提出对 classification loss 较大的样本做 back propagation。（loss 依然是类别 balanced
  - 引出类别 imbalanced 的 Focal loss

Lin T Y, Goyal P, Girshick R, et al. Focal loss for dense object detection. ICCV2019

Extension: One-stage Framework

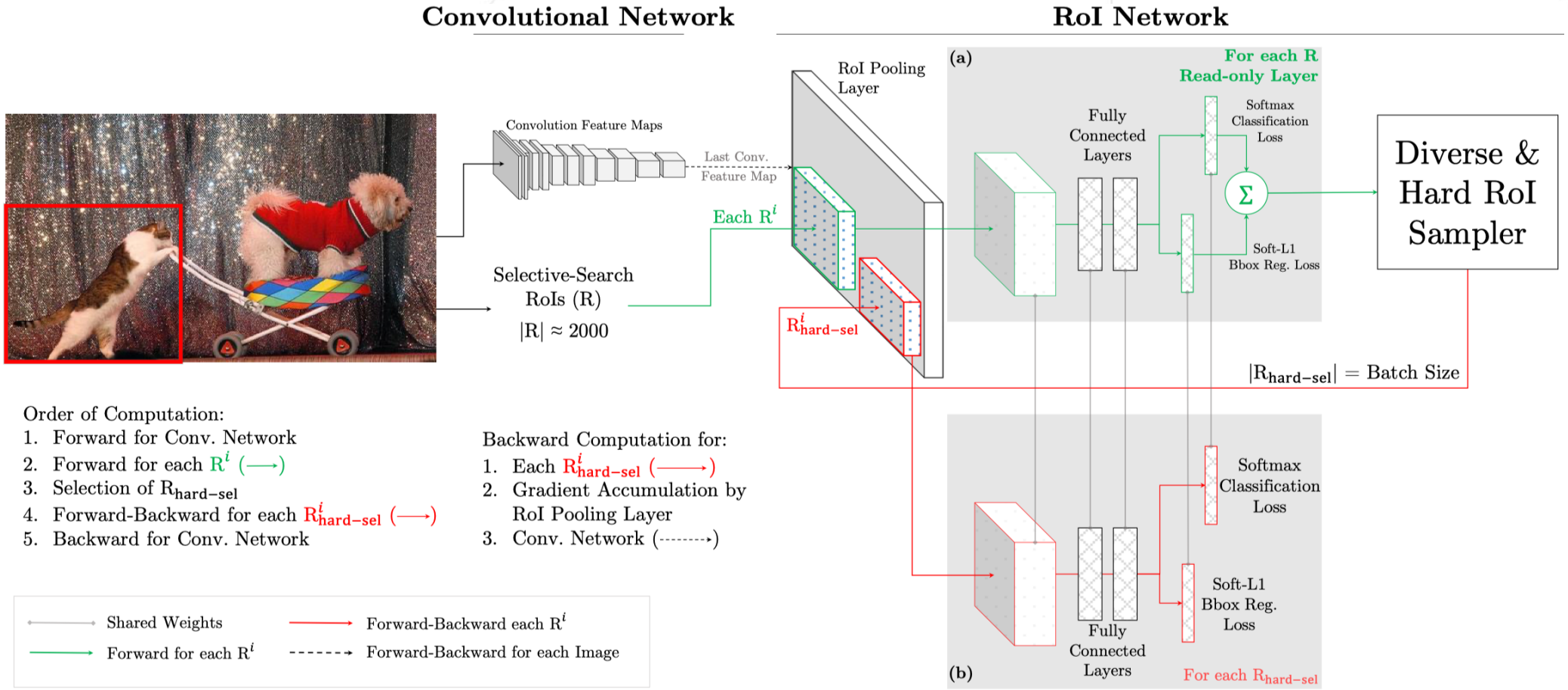
- Hierarchical classification
  - WordTree 中每个节点的子节点属于同一子类，对同一子类进行 softmax 处理
  - 在给出某个类别的预测概率时，需要找到其所在的位置，遍历这个 path，然后计算 path 上各个节点的概率之积



Redmon J, Farhadi A. YOLO9000: better, faster, stronger. CVPR2017

Extension: One-stage Framework

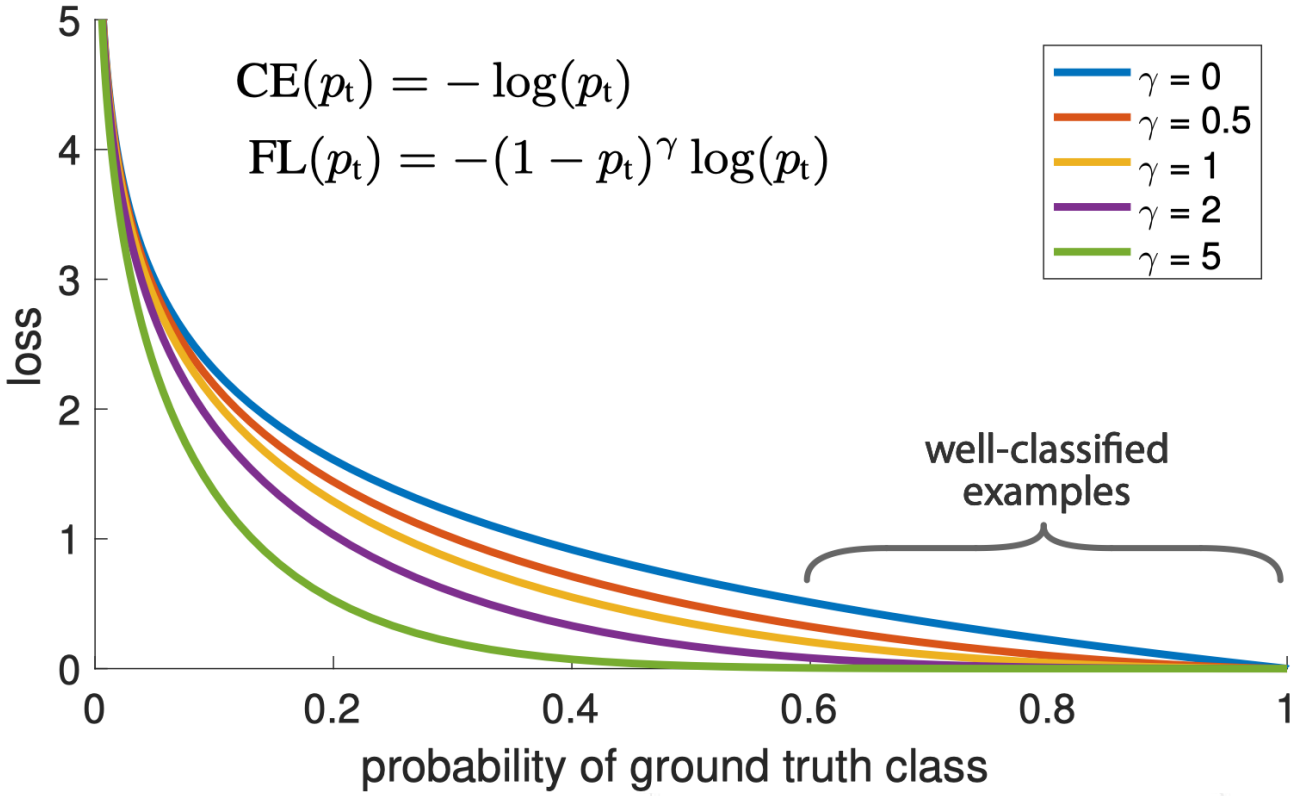
- OHEM



Shrivastava A, Gupta A, Girshick R. Training region-based object detectors with online hard example mining. CVPR2016

Extension: One-stage Framework

- Focal loss

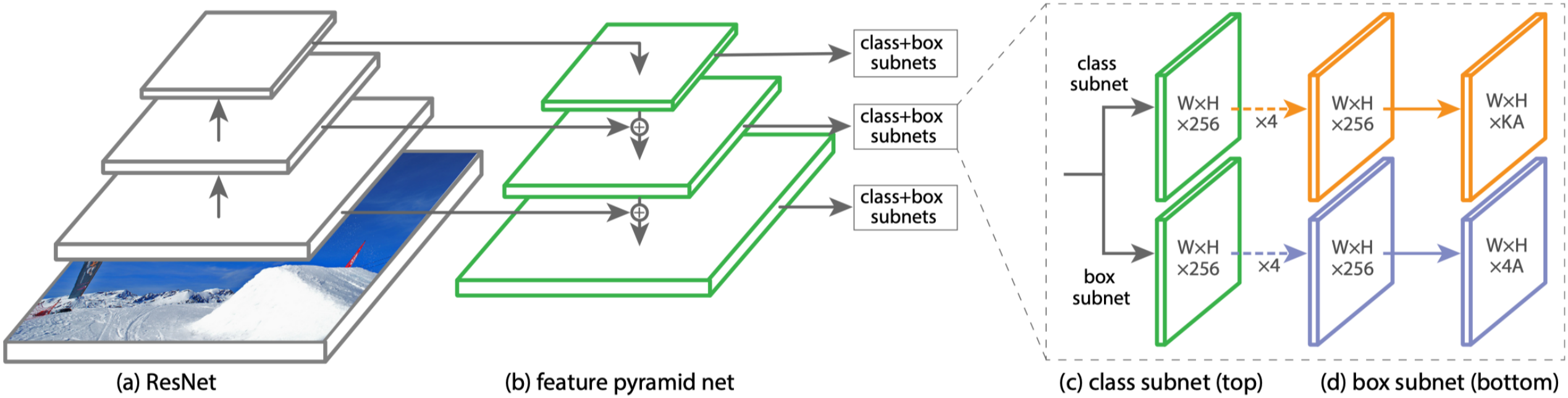


- 将分类难易体现在 loss 上
- 当 negative examples 远比 positive examples 多时，负类的 $(1-p_t)^{\gamma}$ 较小，模型倾向于正类样本

Lin T Y, Goyal P, Girshick R, et al. Focal loss for dense object detection. ICCV2019

Extension: One-stage Framework

- RetinaNet
  - 基于 FPN 和 Focal loss，提出了 RetinaNet，该网络对 anchor-free 方法有很大影响

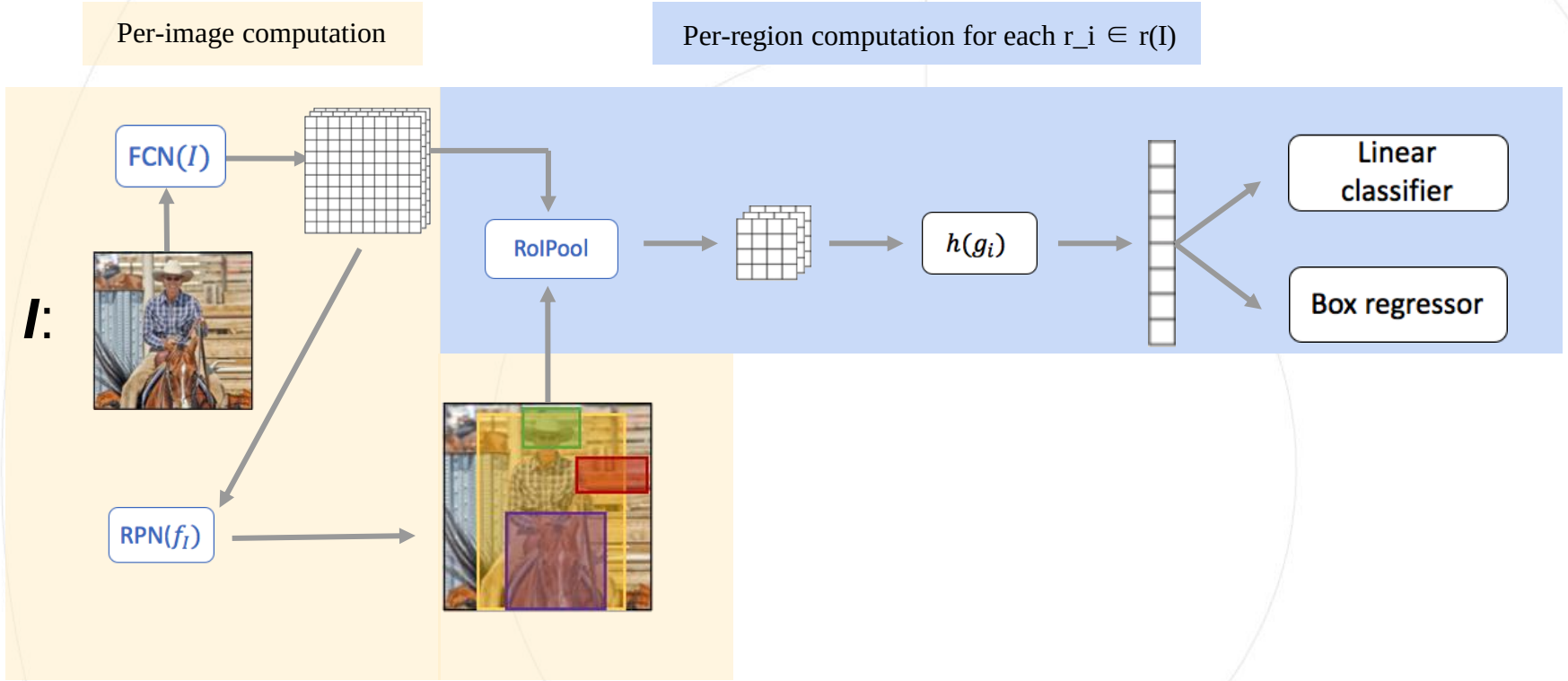


Discussion: Anchor-based or Anchor-free?

- The problem in anchor-based methods

1) Huge imbalance between positive and negative anchor boxes and slows down training. Anchor-based methods need a very large set of anchor boxes, while only a tiny fraction of anchor boxes will overlap with ground truth

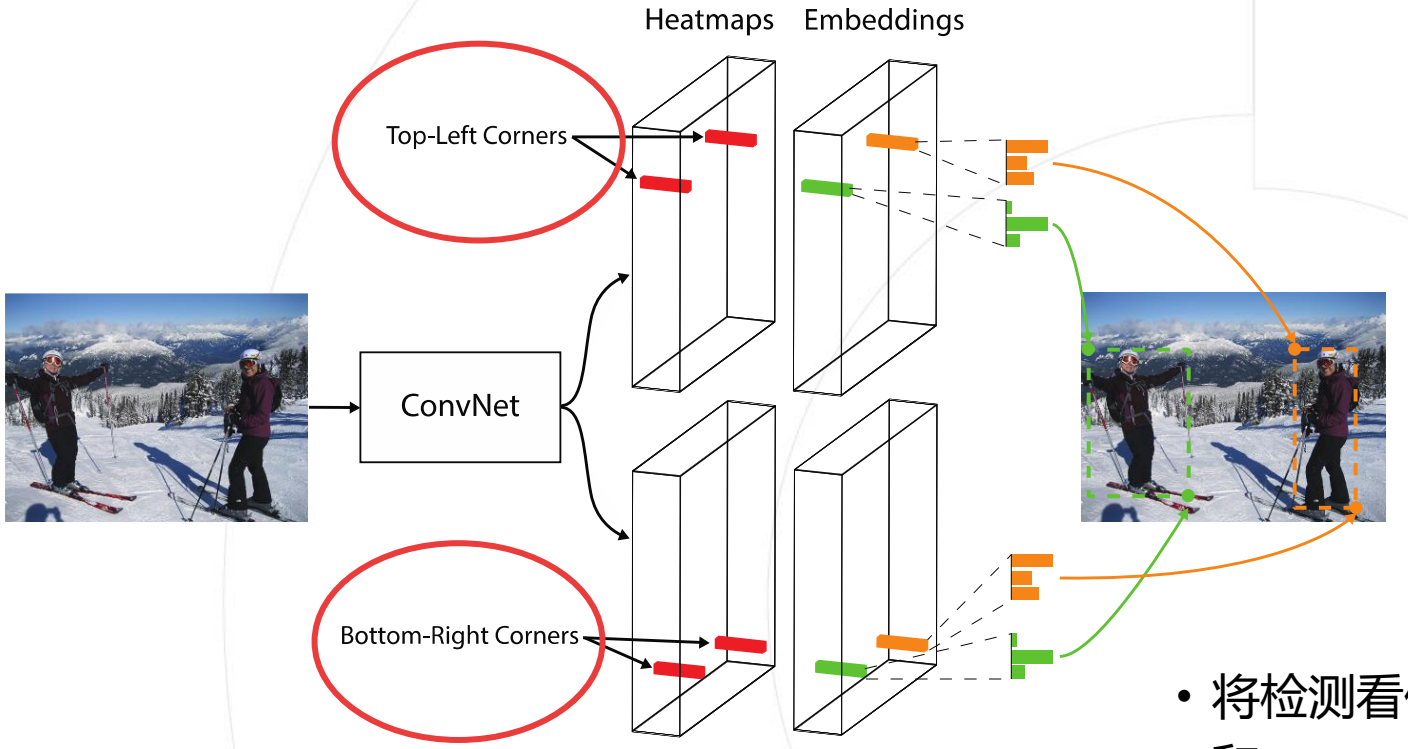
2) The use of anchor boxes introduces many hyperparameters and design choices, such as how many boxes, what sizes, and what aspect ratios.



Outline

Anchor-free Solution

- CornerNet: Detecting Objects as Paired Keypoints



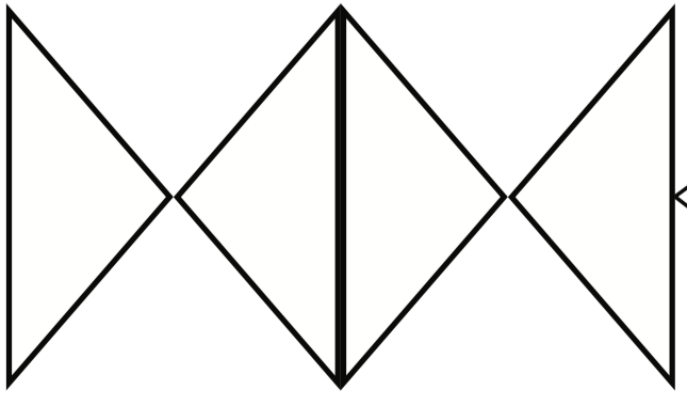
Discussion
How does this idea differentiate with anchor-based methods?

- 将检测看作预测物体的 Top-left Corner 和 Bottom-Right Corner；
- 为了寻找 Top-left Corner，提出 corner pooling 来定位点与物体间的关系

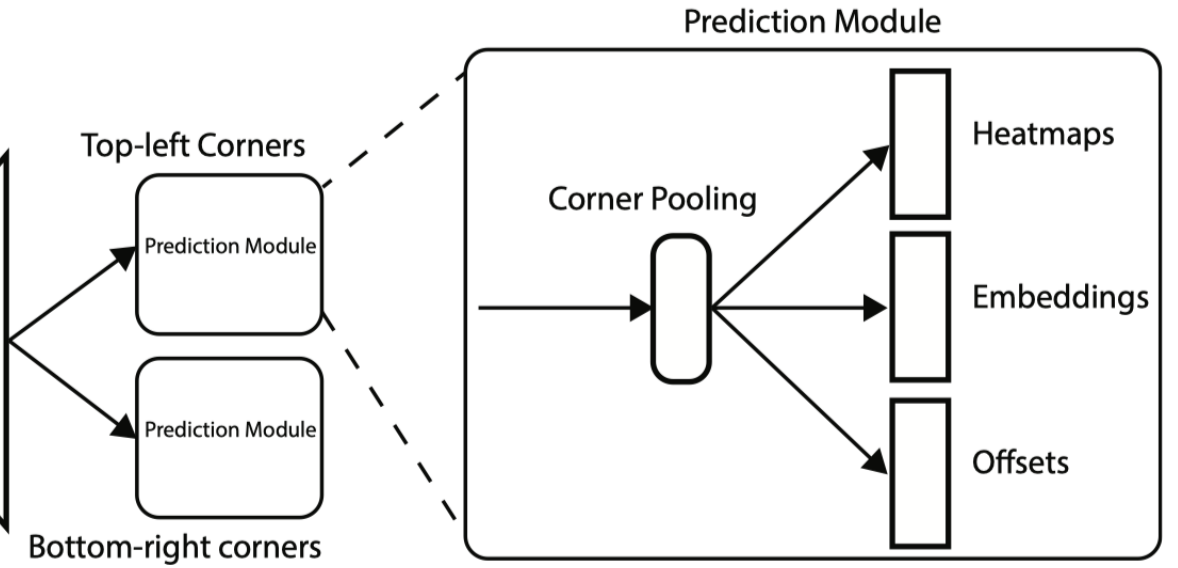
Law H, Deng J. Cornernet: Detecting objects as paired keypoints. ECCV2018

Anchor-free Solution

- CornerNet Network structure
  - Hourglass Network, Corner Pooling, A variant of focal loss
  - 为 top-left corners 和 bottom-right corners 预测两个 heatmaps，channel 数等于类别数 C，每一维为一个 binary mask



Hourglass Network



Anchor-free Solution

- A variant of focal loss
  - Let p_{cij} be the score at location (i, j) for class c in the predicted heatmaps
  - Let y_{cij} be the GT heatmap augmented with the unnormalized Gaussians.

$$L_{det} = \frac{-1}{N} \sum_{c=1}^{C} \sum_{i=1}^{H} \sum_{j=1}^{W} \begin{cases} (1 - p_{cij})^{\alpha} \log(p_{cij}) & \text{if } y_{cij} = 1 \\ (1 - y_{cij})^{\beta} (p_{cij})^{\alpha} \log(1 - p_{cij}) & \text{otherwise} \end{cases}$$

  - N is the number of objects in an image
  - α and β are the hyper-parameters which control the contribution of each point

Anchor-free Solution

- Offset loss
  - 由于下采样后热点图比原图分辨率低，因此引入 offset loss 对 corners 进行微调

$$L_{off} = \frac{1}{N}\sum_{k=1}^{N}\text{SmoothL1Loss}\left(\boldsymbol{o}_k, \hat{\boldsymbol{o}}_k\right)$$

Anchor-free Solution

- Grouping Corners
  - 同一张图中可能会有多个目标，模型生成多组 top-left corners 和 bottom-right corners
  - 使用 pull loss 拉近同一目标的 corners

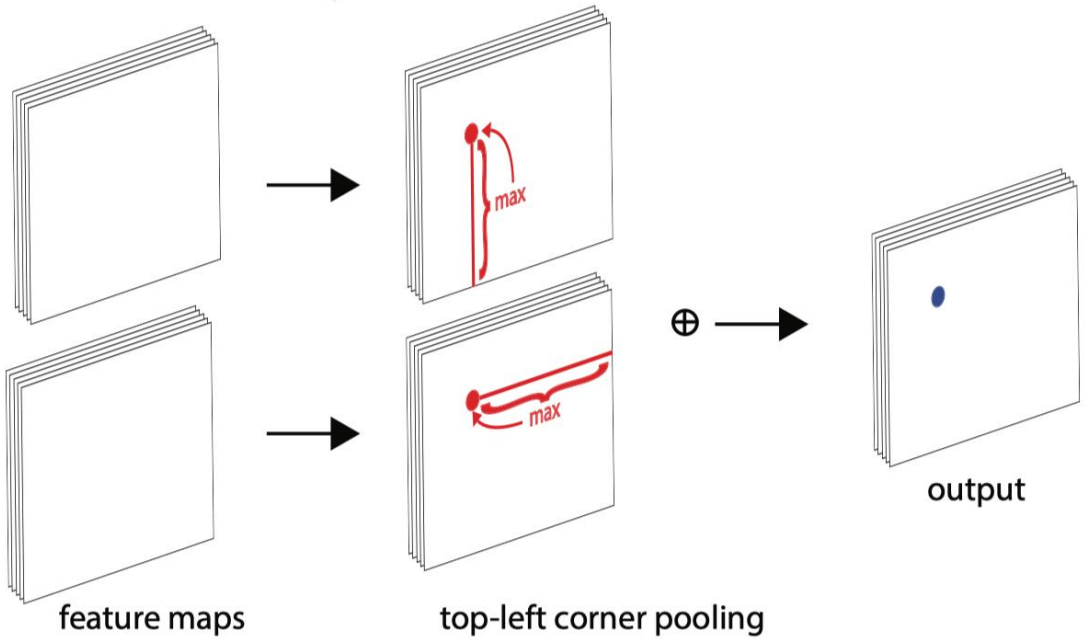
$$L_{pull} = \frac{1}{N}\sum_{k=1}^{N}\left[(e_{t_k} - e_k)^2 + (e_{b_k} - e_k)^2\right],$$

  - 使用 push loss 推远不同目标的 corners

$$L_{push} = \frac{1}{N(N-1)}\sum_{k=1}^{N}\sum_{\substack{j=1 \\ j\neq k}}^{N}\max\left(0, \Delta - |e_k - e_j|\right),$$

Anchor-free Solution

- Corner Pooling



$$t_{ij} = \begin{cases} \max\left(f_{t_{ij}}, t_{(i+1)j}\right) & \text{if } i < H \\ f_{t_{Hj}} & \text{otherwise} \end{cases}$$

$$l_{ij} = \begin{cases} \max\left(f_{l_{ij}}, l_{i(j+1)}\right) & \text{if } j < W \\ f_{l_{iW}} & \text{otherwise} \end{cases}$$

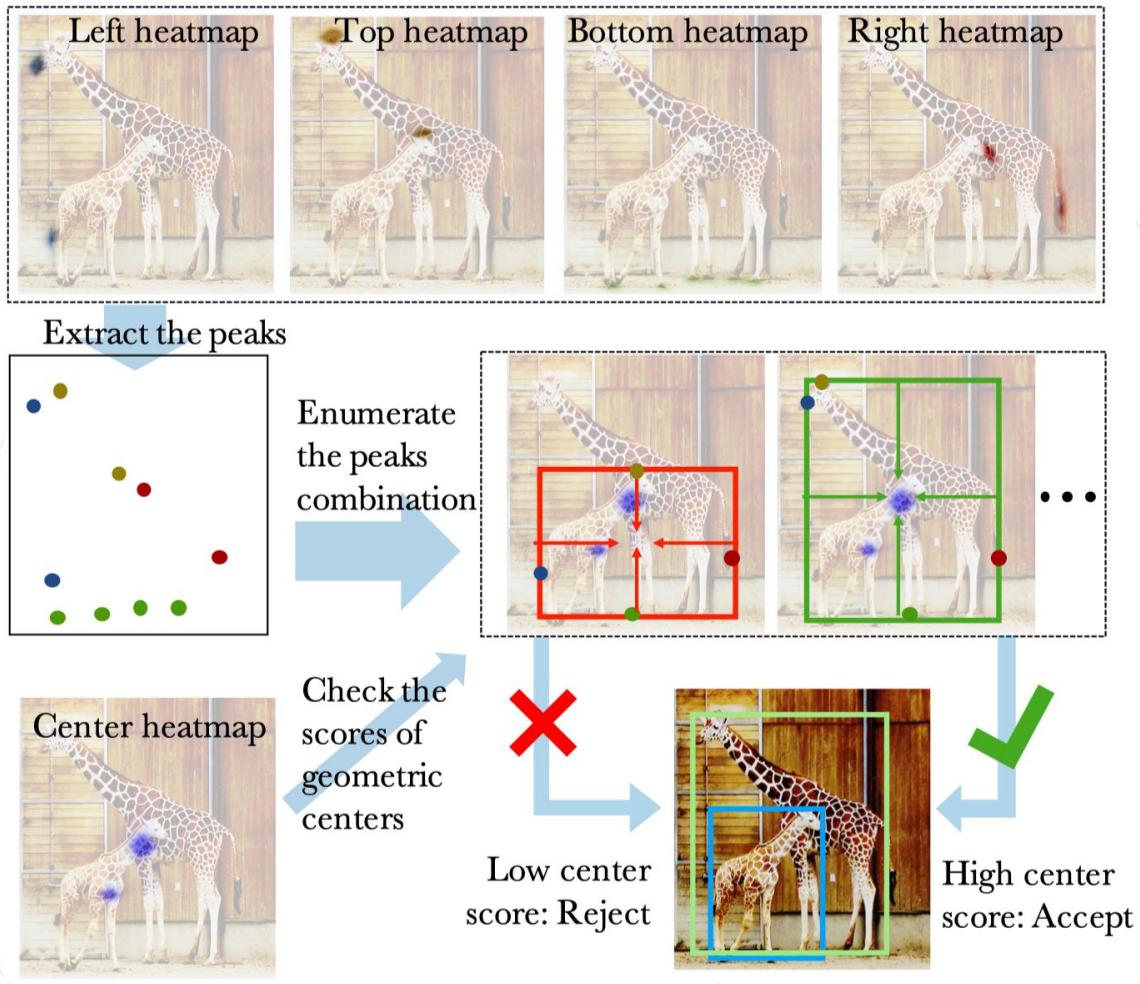
Fig. 3 Corner pooling: for each channel, we take the maximum values *(red dots)* in two directions *(red lines)*, each from a separate feature map, and add the two maximums together *(blue dot)*.

Anchor-free Solution

- Anchor-free 中的 Bottom-up 思路

  area regression -> keypoints location。
  即优化的目标 GT 不再是矩形框

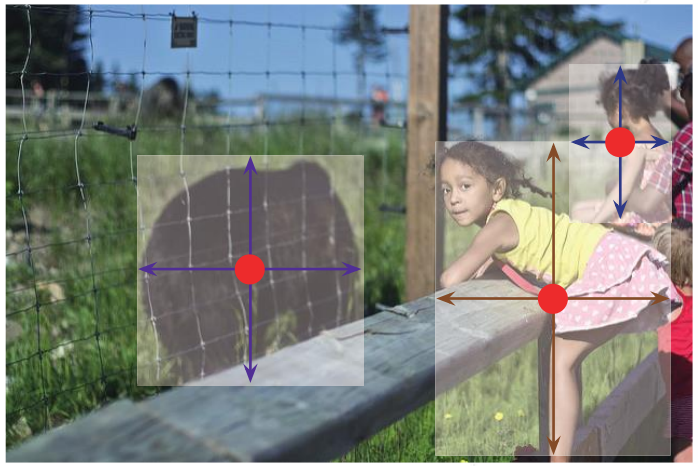
  相似的工作还有 ExtremeNet（右图）。
  ExtremeNet 的关键点为四边的极值点和框中心点

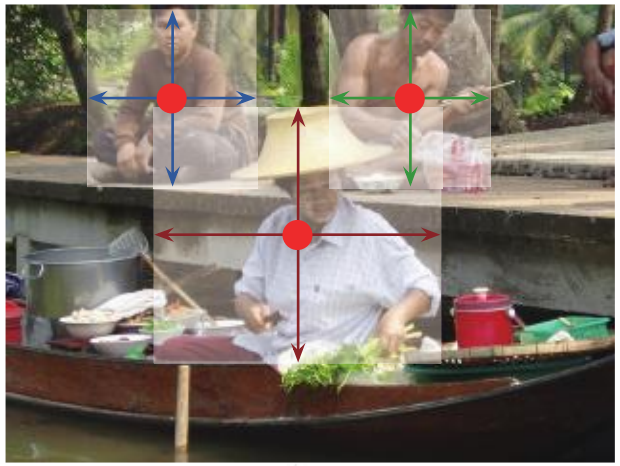


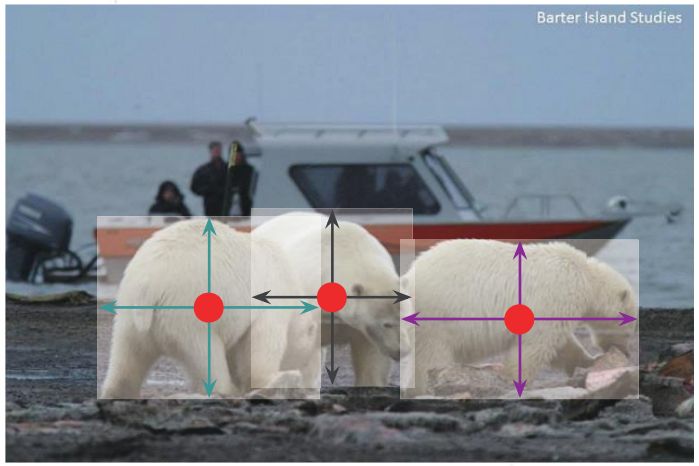
Zhou X, Zhuo J, Krahenbuhl P. Bottom-up object detection by grouping extreme and center points. CVPR2019.

Anchor-free Solution

- CenterNet: Objects as Points







- Objects as Points. 物体的中心点即代表这个物体，物体的 size 需要回归
- 基于 Hourglass backbone
- 三个分支，分别输出：HeatMap，中心点位置；Offset， refine Heatmap；Height&Width，检测框的宽高

Zhou X, Wang D, Krähenbühl P. Objects as points. arXiv preprint arXiv:1904.07850, 2019.

Anchor-free Solution

- CenterNet: Objects as Points

  Produce GT keypoint heatmap

  - Keypoint types 标注为物体种类
  - 使用 Gaussian kernel 从 point 生成 heatmap

$$Y_{xyc} = \exp\left(-\frac{(x-\tilde{p}_x)^2+(y-\tilde{p}_y)^2}{2\sigma_p^2}\right)$$

  中心点预测 loss function （focal loss）

$$L_k = \frac{-1}{N}\sum_{xyc}\begin{cases}(1-\hat{Y}_{xyc})^{\alpha}\log(\hat{Y}_{xyc}) & \text{if } Y_{xyc}=1\\ (1-Y_{xyc})^{\beta}(\hat{Y}_{xyc})^{\alpha} & \text{otherwise}\\ \log(1-\hat{Y}_{xyc}) & \end{cases}$$

  Offset loss funtion

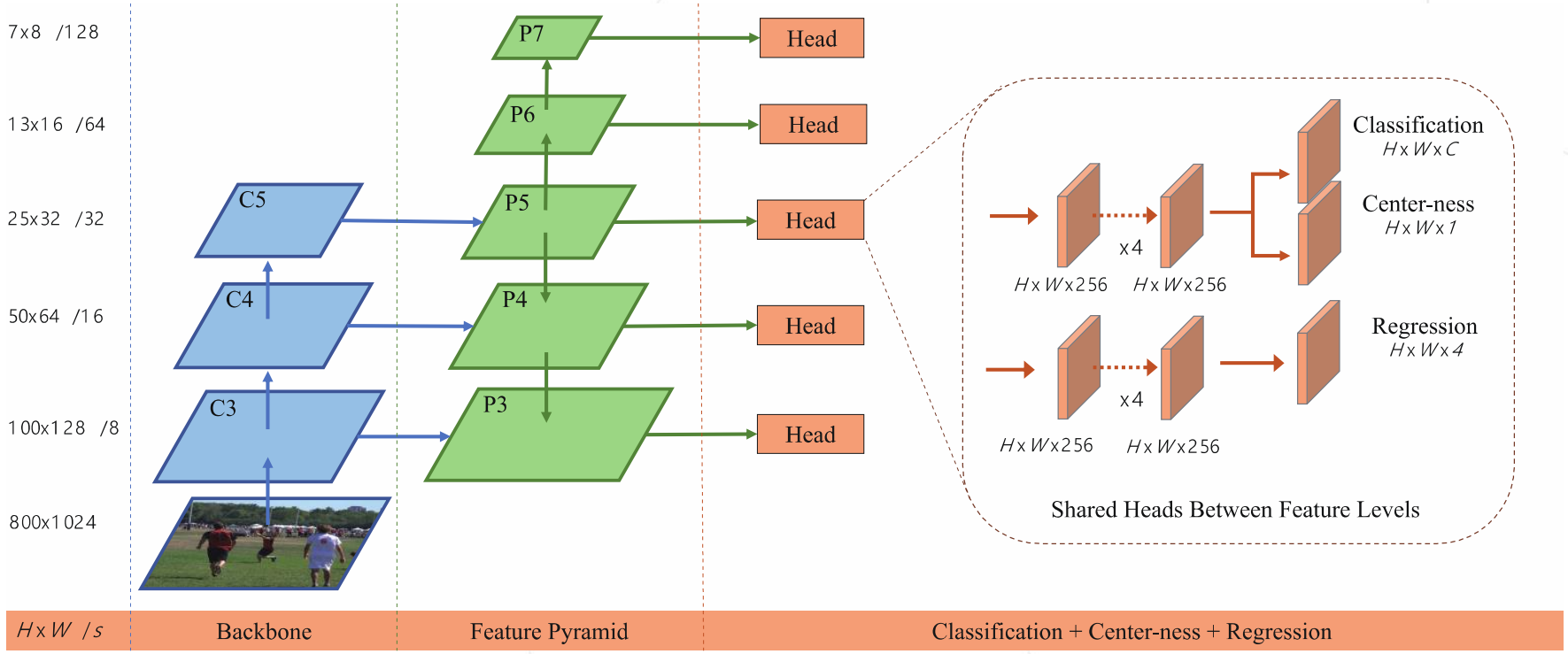
$$L_{off} = \frac{1}{N}\sum_{p}\left|\hat{O}_{\tilde{p}} - \left(\frac{p}{R}-\tilde{p}\right)\right|$$

Anchor-free Solution

- CenterNet: Objects as Points
  - One problem: center point collision
  - CenterNet 中网络下采样 stride 为 4，在 COCO 中存在 614 对物体出现 center point collision
  - CenterNet is unable to predict < 0.1% of objects. This is much fewer than anchor-based methods miss due to insufficient anchor placement (20.0% for Faster-RCNN with 15 anchors at 0.5 IOU threshold).

Zhou X, Wang D, Krähenbühl P. Objects as points. arXiv preprint arXiv:1904.07850, 2019.

- FCOS: Fully Convolutional One-Stage Object Detection



- FCOS 将 feature maps 每个位置都作为训练样本；
- 使用 Feature Pyramid，多级框预测解决 GT box 重叠问题
- 训练一个分支预测 Center-ness，测试时用于抑制远离中心的框

Tian Z, Shen C, Chen H, et al. Fcos: Fully convolutional one-stage object detection. ICCV2019

Anchor-free Solution

- GT box 重叠问题
  - 两个物体中心相同，例如运动员手持球拍，那么如何解决这个问题呢（理论分析、常识、统计数据
  - 大多数情况下，这种重叠区域的 box 尺寸差异明显，因此可以使用基于 FPN 的结构将其分到不同层

Tian Z, Shen C, Chen H, et al. Fcos: Fully convolutional one-stage object detection. ICCV2019

- FCOS: Fully Convolutional One-Stage Object Detection

回归目标：(l, t, r, b)

$$l^* = x - x_0^{(i)}, \quad t^* = y - y_0^{(i)},$$
$$r^* = x_1^{(i)} - x, \quad b^* = y_1^{(i)} - y.$$

对 feature map 中，（映射回原图后）属于 GT box 的点做回归

$$L(\{\boldsymbol{p}_{x,y}\}, \{\boldsymbol{t}_{x,y}\}) = \frac{1}{N_{\text{pos}}} \sum_{x,y} L_{\text{cls}}(\boldsymbol{p}_{x,y}, c^*_{x,y}) + \frac{\lambda}{N_{\text{pos}}} \sum_{x,y} \mathbb{1}_{\{c^*_{x,y}>0\}} L_{\text{reg}}(\boldsymbol{t}_{x,y}, \boldsymbol{t}^*_{x,y}),$$

L_{reg}为 IoU Loss

Anchor-free Solution

- Anchor-free 中的 Point 先验思路
  1. anchor 先验 -> point 先验。不再提取 anchor，而是将 feature map 上的点作为中心点优化。PS：依然使用矩形区域
  2. 该类型的工作一般使用 FPN neck + Focal loss
  3. 以上介绍的以及 FoveaBox、FSAF 等工作都可以在 MMDetection 看到复现代码

master · mmdetection / configs / foveabox / fovea_r50_fpn_4x4_1x_coco.py / Jump to

yhcao6 clean op (#3232) ...

4 contributors

52 lines (52 sloc) | 1.51 KB

```
_base_ = [
    '../_base_/datasets/coco_detection.py',
    '../_base_/schedules/schedule_1x.py', '../_base_/default_runtime.py'
]
# model settings
model = dict(
    type='FOVEA',
    pretrained='torchvision://resnet50',
    backbone=dict(
        type='ResNet',
        depth=50,
        num_stages=4,
        out_indices=(0, 1, 2, 3),
        frozen_stages=1,
        norm_cfg=dict(type='BN', requires_grad=True),
        norm_eval=True,
        style='pytorch'),
    neck=dict(
        type='FPN',
        in_channels=[256, 512, 1024, 2048],
        out_channels=256,
        start_level=1,
        num_outs=5,
        add_extra_convs='on_input'),
    bbox_head=dict(
        type='FoveaHead',
        num_classes=80,
        in_channels=256,
        stacked_convs=4,
        feat_channels=256,
        strides=[8, 16, 32, 64, 128],
        base_edge_list=[16, 32, 64, 128, 256],
        scale_ranges=((1, 64), (32, 128), (64, 256), (128, 512), (256, 2048)),
        sigma=0.4,
        with_deform=False,
        loss_cls=dict(
            type='FocalLoss',
            use_sigmoid=True,
            gamma=1.50,
            alpha=0.4,
            loss_weight=1.0),
        loss_bbox=dict(type='SmoothL1Loss', beta=0.11, loss_weight=1.0)))
# training and testing settings
```

Chen K, Wang J, Pang J, et al. Mmdetection: Open mmlab detection toolbox and benchmark. arXiv preprint arXiv:1906.07155, 2019.

- Experimental results and discussion

Table 6: Comparison of RepPoints v2 to state-of-the-art detectors on COCO `test-dev`. * denote that the number is obtained by multi-scale testing.

method	backbone	epoch	AP	AP_{50}	AP_{75}	AP_S	AP_M	AP_L
RetinaNet [16]	ResNet-101	18	39.1	59.1	42.3	21.8	42.7	50.2
FCOS [27]	ResNeXt-101	24	43.2	62.8	46.6	26.5	46.2	53.3
DCN V2* [36]	ResNet-101+DCN	18	46.0	67.9	50.8	27.8	49.1	59.5
RepPoints* [30]	ResNet-101+DCN	24	46.5	67.4	50.9	30.3	49.7	57.1
MAL* [11]	ResNeXt-101	24	47.0	66.1	51.2	30.2	50.1	58.9
FreeAnchor* [33]	ResNeXt-101	24	47.3	66.3	51.5	30.6	50.4	59.0
ATSS* [32]	ResNeXt-101+DCN	24	50.7	68.9	56.3	33.2	52.9	62.4
TSD* [25]	SENet154+DCN	24	51.2	71.9	56.0	33.8	54.8	64.2
CornerNet [13]	HG-104	100	40.5	56.5	43.1	19.4	42.7	53.9
ExtremeNet [35]	HG-104	100	40.2	55.5	43.2	20.4	43.2	53.1
CenterNet [4]	HG-104	100	44.9	62.4	48.1	25.6	47.4	57.4
RepPoints v2	ResNet-50	24	44.4	63.5	47.7	26.6	47	54.6
RepPoints v2	ResNet-101	24	46.0	65.3	49.5	27.4	48.9	57.3
RepPoints v2	ResNeXt-101	24	47.8	67.3	51.7	29.3	50.7	59.5
RepPoints v2	ResNet-101+DCN	24	48.1	67.5	51.8	28.7	50.9	60.8
RepPoints v2	ResNeXt-101+DCN	24	49.4	68.9	53.4	30.3	52.1	62.3
RepPoints v2*	ResNeXt-101+DCN	24	**52.1**	70.1	57.5	34.5	54.6	63.6

Discussion
Anchor-based or anchor-free, what's your opinion?

Anchor-free Solution

- Anchor-free Paper list

  https://github.com/XinZhangNLPR/awesome-anchor-free-object-detection

awesome-anchor-free-object-detection awesome

for anyone who wants to do research about anchor free object detection.

If you find the awesome paper/code/dataset or have some suggestions, please contact xin.zhang2018@nlpr.ia.ac.cn, nuo.xu@nlpr.ia.ac.cn and xswang@wayne.edu. Thanks for your valuable contribution to the research community 😃

- Recent papers (from 2015)

Statistics: 🔥code is available & stars >= 100

2020

- [arXiv] OneNet: End-to-End One-Stage Object Detection by Classification Cost.[pytorch]🔥
- [arXiv] End-to-End Object Detection with Fully Convolutional Network
- [arXiv] Sparse R-CNN: End-to-End Object Detection with Learnable Proposals.[pytorch]🔥
- [arXiv] End-to-End Object Detection with Transformers.[pytorch]🔥
- [arXiv] AutoAssign: Differentiable Label Assignment for Dense Object Detection.

商汤 sensetime

清華大學 Tsinghua University

Outline

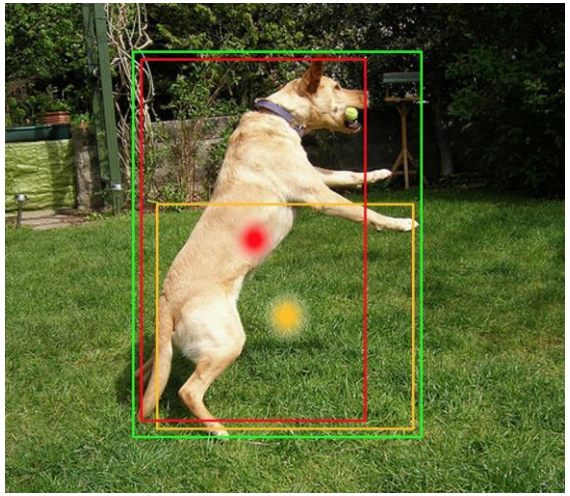
课后阅读内容

Click to jump to Part 5

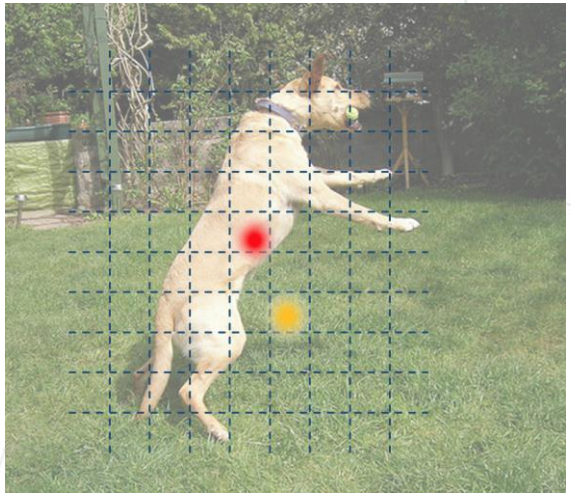
Extension: Misaligned Classification and Localization

- Discover the problem

课后阅读内容



(a) Original image



(b) Feature grid

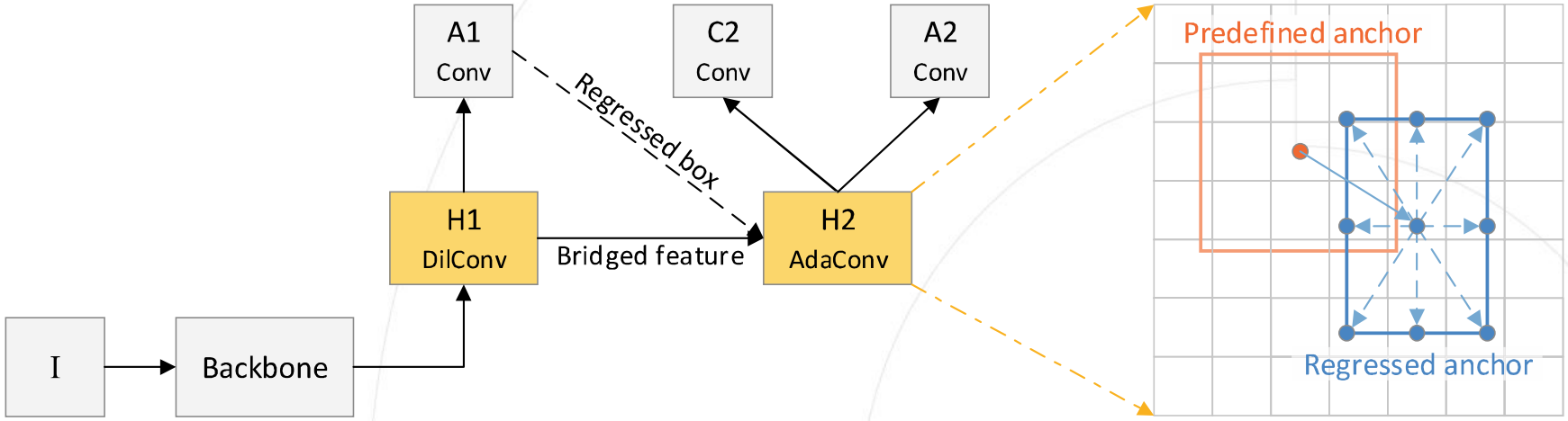
(a) green: ground truth, orange: original anchor, red: refined anchor
(b) Location of center points for original and refined anchors in the feature grid

Do you think simply extracting features from the previous location is reasonable?
This problem appears in heuristic sampling (RPN) and any one-stage detector

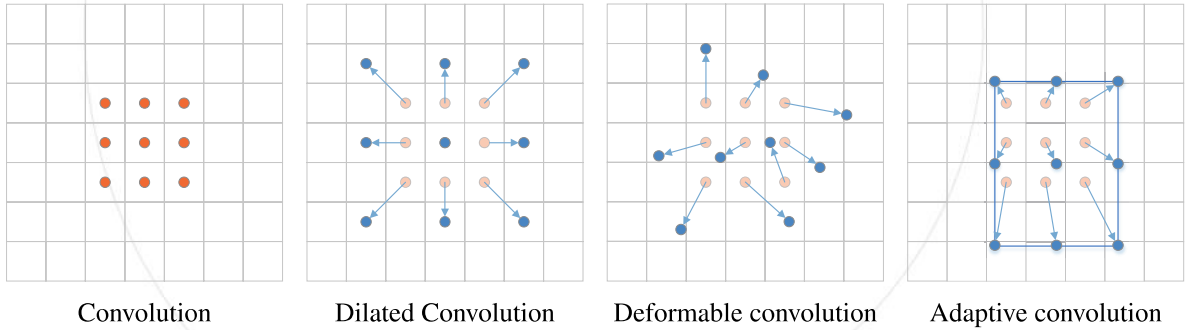
Extension: Misaligned Classification and Localization

- A solution: Cascade RPN

课后阅读内容



Cascade RPN uses adaptive convolution to perform sampling within the anchors to ensure alignment between the anchors and features



Vu T, Jang H, Pham T X, et al. Cascade rpn: Delving into high-quality region proposal network with adaptive convolution. NIPS2019

Extension: Misaligned Classification and Localization

- Recommended reading

课后阅读内容

Cascade RPN: Delving into High-Quality Region Proposal Network with Adaptive Convolution

- 引入 adaptive convolution 来对齐 anchor 和 feature

Revisiting Feature Alignment for One-stage Object Detection

- 提出 RoI Convolution，根据偏移在 feature 上做 RoI Convolution 得到对齐的特征，然后再做 regression

Cascade RetinaNet: Maintaining Consistency for Single-Stage Object Detection

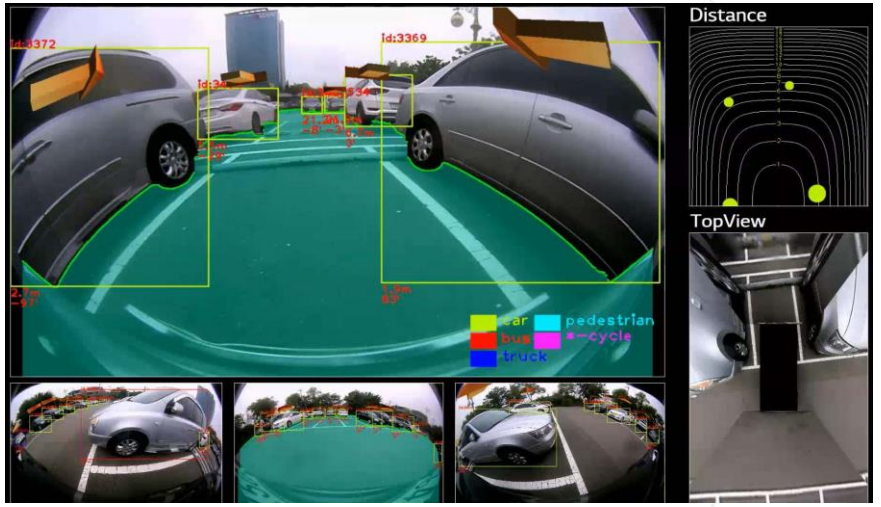
- 提出 FCM 来将当前阶段的特征修正到新的位置（而不是上一 stage 的位置）

Extension: Detection on Omnidirectional Cameras

- Problem Formulation
  - What do the omnidirectional images look like?
  - Why we need to make research on this problem?
  - Introduction to some existing methods.

课后阅读内容

(a) Example of omnidirectional image in VR application



(b) Example of omnidirectional image in autonomous driving application

Extension: Detection on Omnidirectional Cameras

- Why we need to make research on this problem?

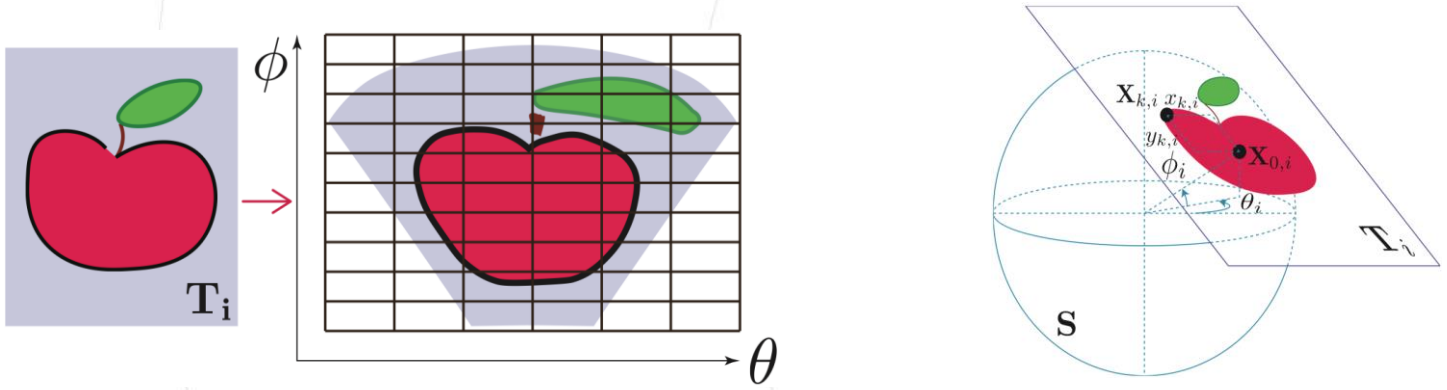
课后阅读内容

针对普通平面图像的方法不适用于 Omnidirectional Cameras

下图为 tangent plane 中的一张苹果的图片，和对应在 sphere 上的点。

a) 普通的卷积能否融合 lens geometry knowledge；

b) 当图片与球面的切点不同时，我们还能得到相同的卷积结果吗？



Example of the equirectangular representation of the image (left), and the gnomonic projection (right)

Extension: Detection on Omnidirectional Cameras

- Scene Understanding Networks for Autonomous Driving based on Around View Monitoring System

课后阅读内容

Task：Around View Monitoring (AVM) system, free drivable area

Method：网络接受 columns 形式的输入，每一 column 经过 conv layers 输出该列障碍物对应 bottom pixel 的位置。例如原图高为 720，则是一个 720 类分类任务。结合每一列障碍物 bottom pixel，即可得到 free drivable area

该网络每个 column 之间有大量 overlap，作者进而设计了一个端到端的网络结构，此处不再细说

A columnwise prediction for a corresponding pixel augmented with the adjacent 24 pixels area

Yeol Baek J, Veronica Chelu I, Iordache L, et al. Scene understanding networks for autonomous driving based on around view monitoring system. CVPRW2018

Extension: Detection on Omnidirectional Cameras

- Eliminating the Blind Spot: Adapting 3D Object Detection and Monocular Depth Estimation to 360◦ Panoramic Imagery

课后阅读内容

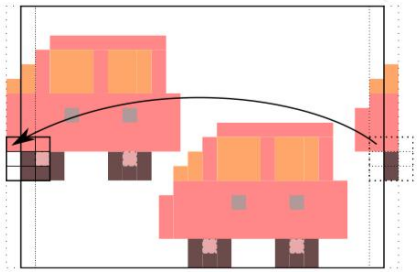
Method： 全景图像使用 equirectangular projection 表示。

调整 rectilinear imagery 上的网络来适应 equirectangular panoramic imagery。通过 GAN 网络生成全景图像

基于 faster R-CNN 算法，输出类和象限（quadrant）分类，边框的位置、目标中心、距离和朝向

当一个物体在展开图边界时，作者提出在边缘进行填充计算 conv

(a) A 360° equirectangular image can be folded over itself until the ends meet.



(b) A 3 × 3 convolution kernel, a column of padding copied from the other side is added at each extremity

Payen de La Garanderie G, et al. Eliminating the blind spot: Adapting 3d object detection and monocular depth estimation to 360 panoramic imagery. ECCV2018

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Outline

清華大學 Tsinghua University

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Detection in Action

2D物体检测实战

实战 1: where to start?

对于初学者：
mmdetection/code link
detectron2/code link

如果你已经很了解物体检测：
通过 paperswithcode 掌握 Object Detection 的新进展与性能榜单
在 Kaggle 尝试参与竞赛

Object Detection

Edit Task

Computer Vision ● 3D Object Detection

1056 papers with code **27** benchmarks

About

Edit

Object detection is the task of detecting instances of objects of a certain class within an image. The state-of-the-art methods can be categorized into two main types: one-stage methods and two stage-methods. One-stage methods prioritize inference speed, and example models include YOLO, SSD and RetinaNet. Two-stage methods prioritize detection accuracy, and example models include Faster R-CNN, Mask R-CNN and Cascade R-CNN.

The most popular benchmark is the MSCOCO dataset. Models are typically evaluated according to a Mean Average Precision metric.

(Image credit: Detectron)

Benchmarks

Add a Result

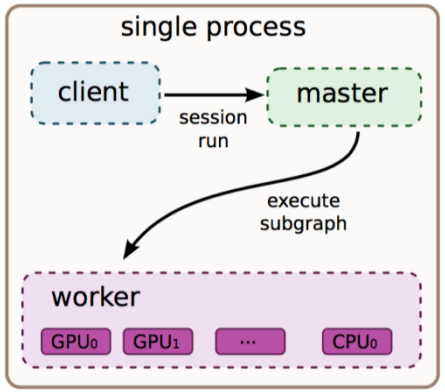
TREND	DATASET	BEST METHOD	PAPER TITLE	PAPER	CODE	COMPARE
	COCO test-dev	Cascade Eff-B7 NAS-FPN (1280, self-training Copy Paste, single-scale)	Simple Copy-Paste is a Strong Data Augmentation Method for Instance Segmentation			See all
	COCO minival	Cascade Eff-B7 NAS-FPN (1280, self-training Copy Paste, single-scale)	Simple Copy-Paste is a Strong Data Augmentation Method for Instance Segmentation			See all
	PASCAL VOC 2007	Cascade Eff-B7 NAS-FPN (Copy Paste pre-training, single-scale)	Simple Copy-Paste is a Strong Data Augmentation Method for Instance Segmentation			See all
	KITTI Cars Easy	Patches	Patch Refinement -- Localized 3D Object Detection			See all
	CrowdHuman (full body)	IterDet (Faster RCNN, ResNet50, 2 iterations)	IterDet: Iterative Scheme for ObjectDetection in Crowded Environments			See all
	KITTI Cars Moderate	Patches	Patch Refinement -- Localized 3D Object Detection			See all

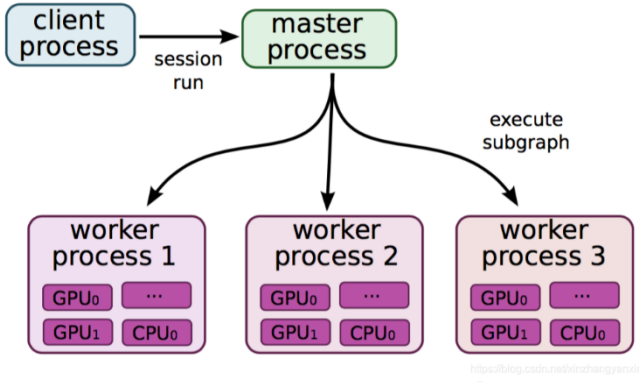
实战 2: 多卡训练

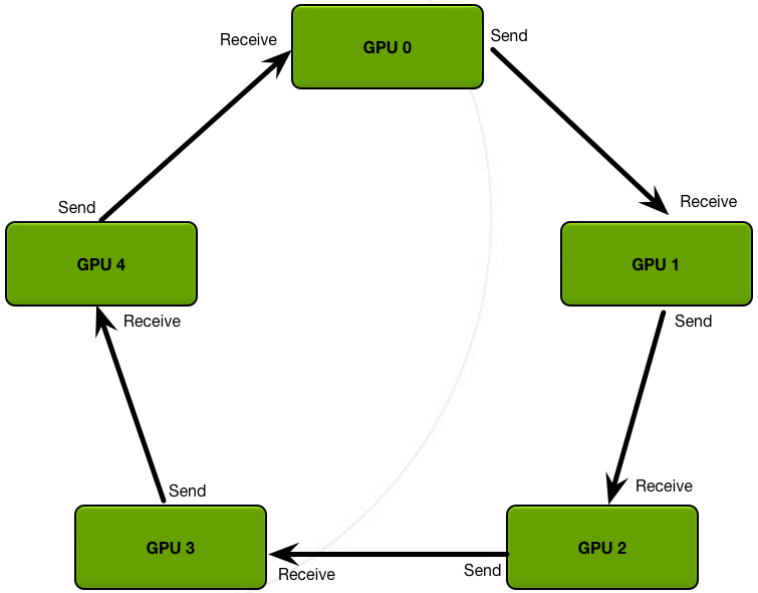
- Pytorch 中的 nn.DataParallel 与 torch.distributed
  - torch.distributed 基于 MPI 和 NCCL， 解决 DataParallel 速度慢，GPU 负载不均衡的问题
- Apex 混合精度训练时的多卡
  - apex.parallel.DistributedDataParallel
  - amp.scale_loss
- BN 层统计量问题
  - nn.DataParallel 不支持 BN 同步， torch.distributed 支持
- Learning rate 的调整

实战 2: 多卡训练

- Parameter Server 与 Ring AllReduce 算法
  - Parameter Server：GPU 0 将数据分成 N 份分到各个卡上，每张卡负责自己的那一份 mini-batch 的训练，得到 gradient 后，返回给 GPU 0 上做累积，得到更新的权重参数后，再分发给各个卡。
  - Ring AllReduce：N 张 GPU 以环形相连，每张卡都有左手卡和右手卡，一个负责接收，一个负责发送，循环4次完成梯度累积，再循环 N-1 次做参数同步。分为 Scatter Reduce 和 All Gather 两个环节。







实战 2: 多卡训练

- Pytorch 中的 nn.DataParallel 与 torch.distributed
  - DataParallel（DP）
    - Parameter Server 模式
    - 模型较大时，GPU 0 负载较严重
    - 不支持同步 BN。每次计算 BN 时，DP 会把 GPU 0 上的数据计算的 mean 和 variance 广播给其他卡
    - 使用方法

```
model = nn.DataParallel(model)
```

实战 2: 多卡训练

- Pytorch 中的 nn.DataParallel 与 torch.distributed
  - 推荐：DistributedDataParallel（DDP）
    - All-Reduce 模式，既可以分布式训练，也可用于单机多卡
    - 支持同步 BN。 前传在各 GPU 上计算各自的小 batch mean 和小 batch variance。 各 GPU 对小 batch mean和小 batch variance 进行 all_gather 操作，每个进程都得到全局量。接下来，延续正常的BN计算

```
# DDP init
dist.init_process_group(backend='nccl’)
#使用普通 BN 方式定义模型
model = MyModel()
# 引入SyncBN
model = torch.nn.SyncBatchNorm.convert_sync_batchnorm(model).to(device)
# 构造DDP模型
model = DDP(model, device_ids=[local_rank], output_device=local_rank)
```

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END