深蓝学院
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# 通用物体检测

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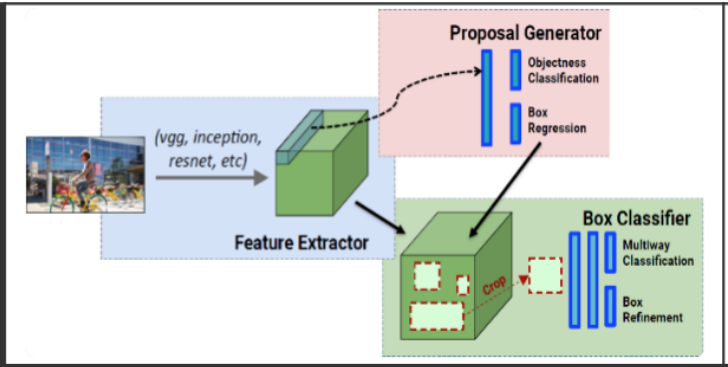
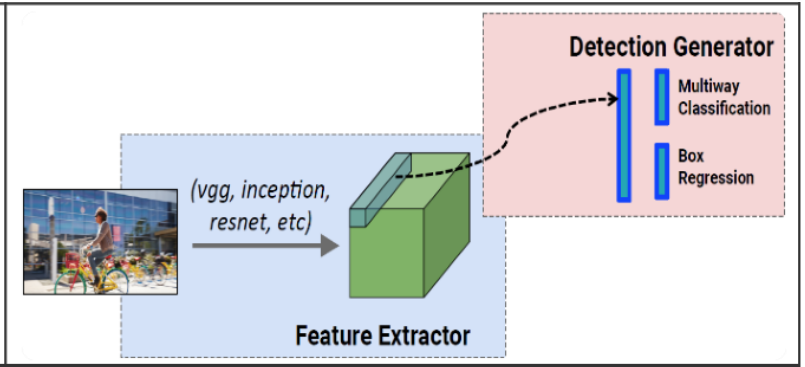
模式识别国家重点实验室

# 内容回顾：物体检测算法的总结

基于锚框

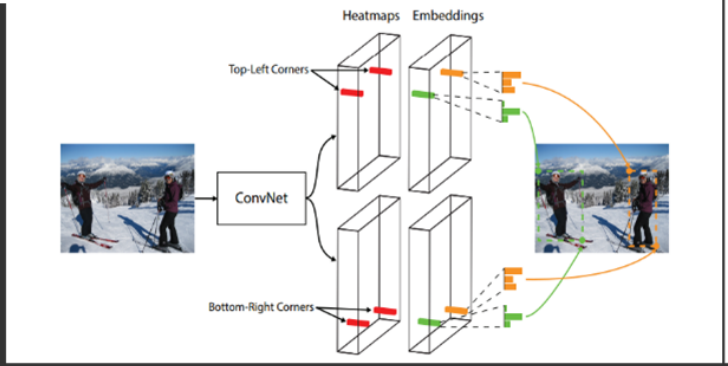



多阶段法

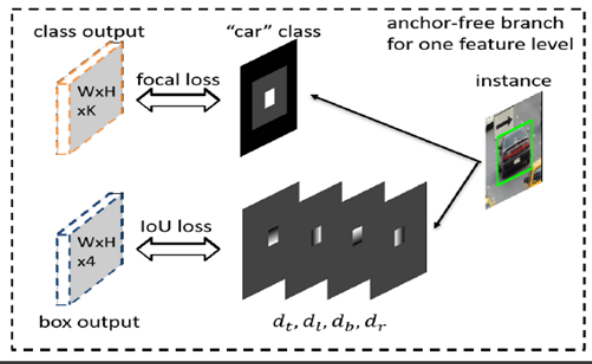



单阶段法

无需锚框



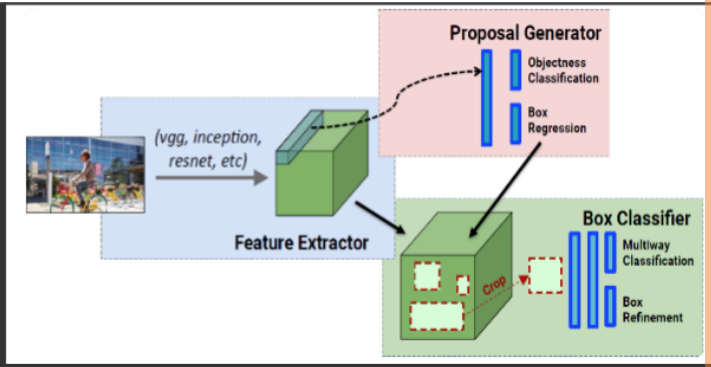

关键点法



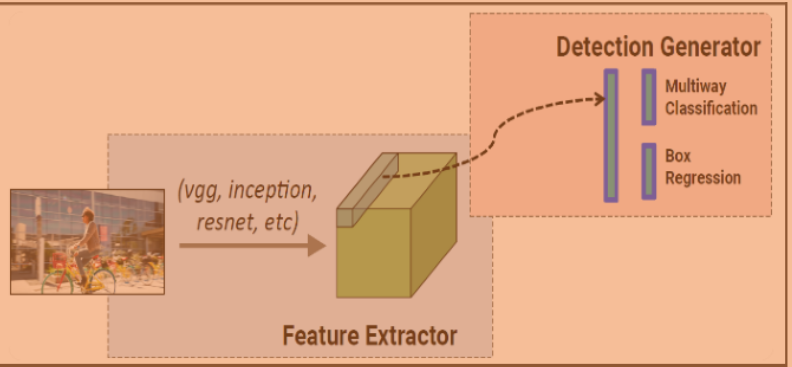

中心域法

# 内容回顾：物体检测算法的总结

基于锚框

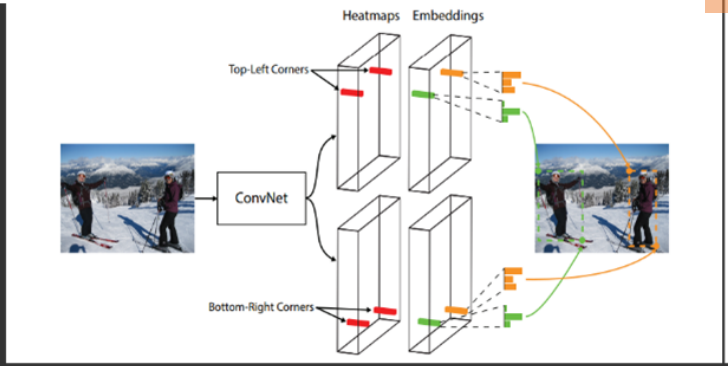



多阶段法

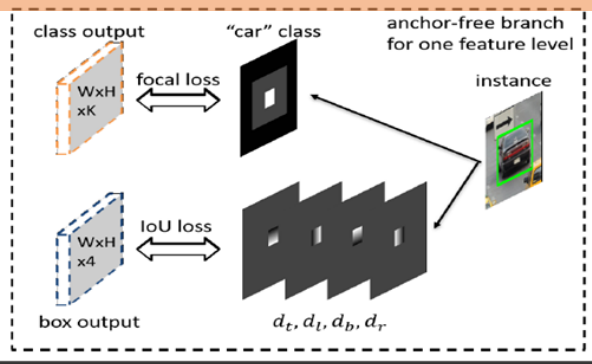



单阶段法

无需锚框




关键点法

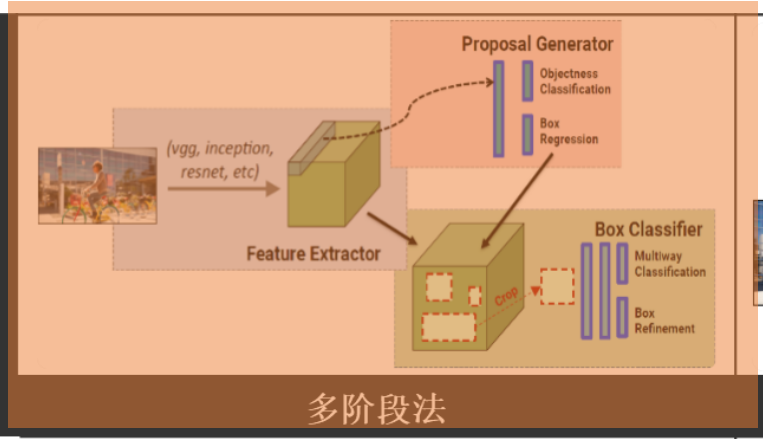



中心域法

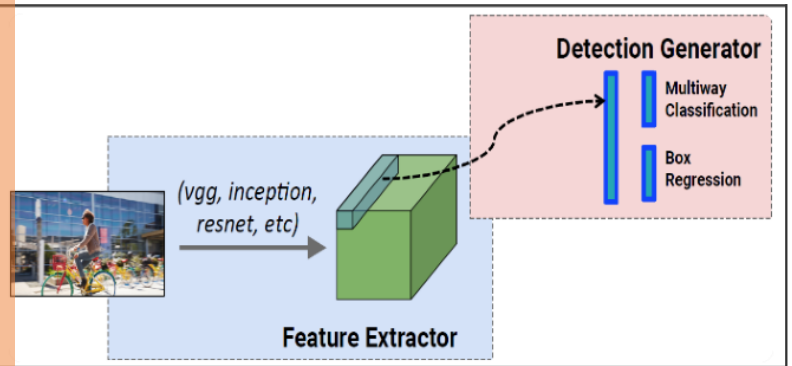
# 基于锚框的单阶段法（SSD/RetinaNet）

# 内容回顾：物体检测算法的总结

基于锚框

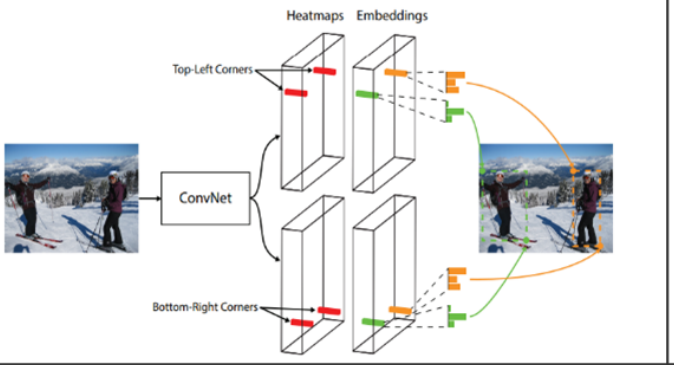



多阶段法

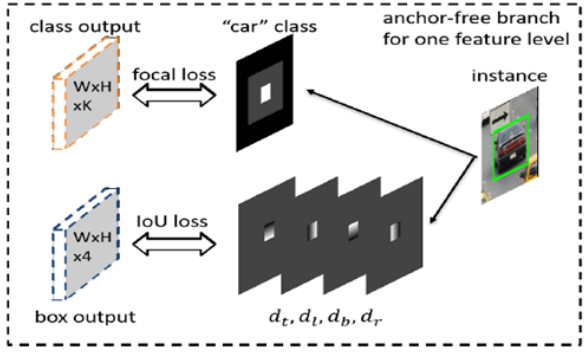



单阶段法

无需锚框

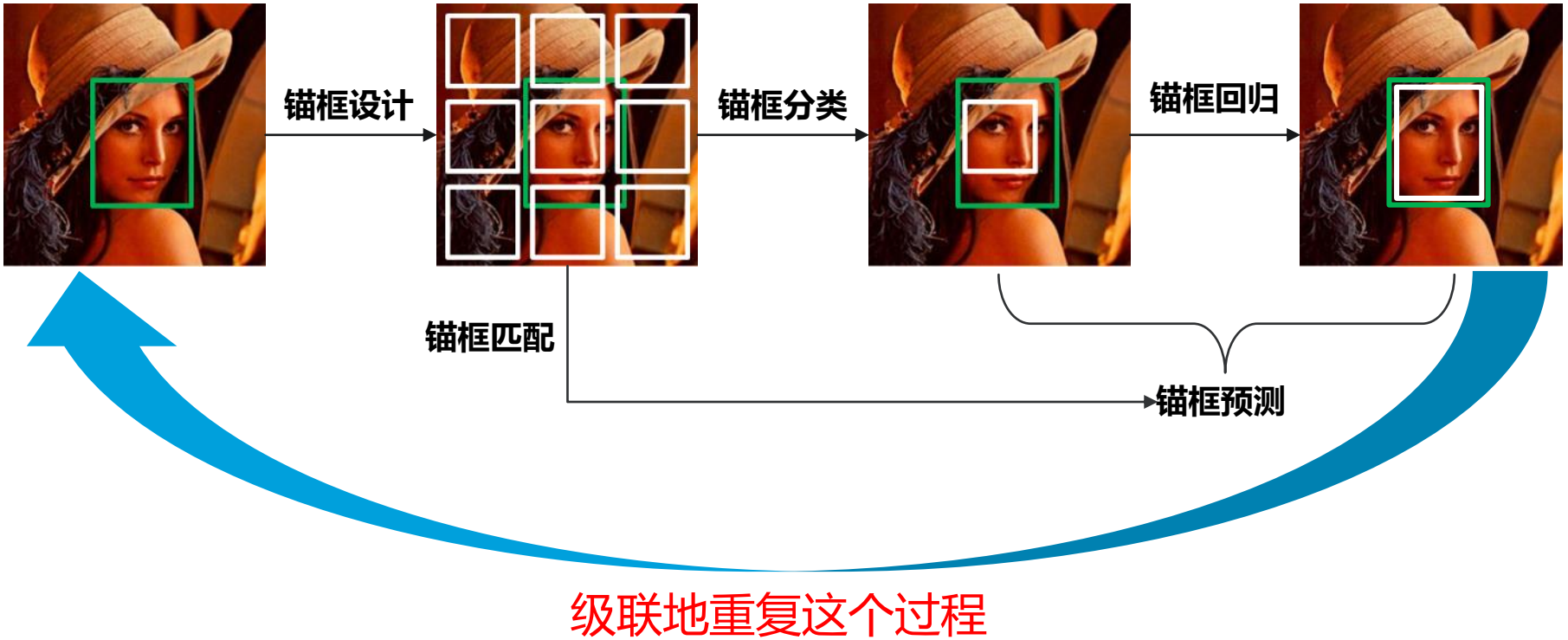



关键点法




中心域法

# 基于锚框的多阶段法（Faster R-CNN）

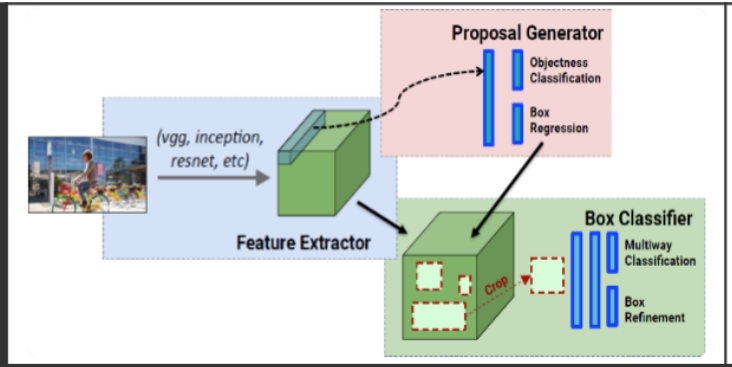


# 内容回顾：物体检测算法的总结（基于锚框）

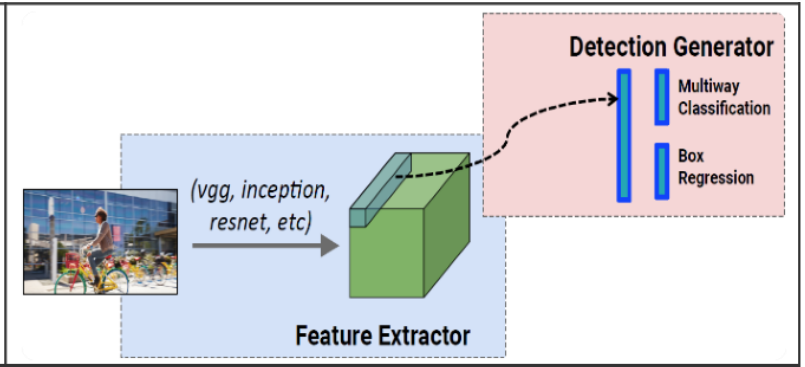
| 基于锚框的检测算法 | | 多阶段法 | 单阶段法 |
|---|---|---|---|
| 相同点 | 检测思想 | 铺设的锚框为检测起点，对锚框的类别和位置进行矫正 | |
| | 检测起点 | 铺设的锚框 | |
| | 检测结果 | 矫正的锚框 | |
| 不同点 | 难点问题之一 | 小尺度物体<br>人脸检测讲 | 正负样本的平衡 |
| | 锚框矫正次数 | ≥2次 | 1次 |
| | 检测精度 | 较高 | 较低 |
| | 检测速度 | 较慢 | 较快 |

# 内容回顾：物体检测算法的总结

基于锚框

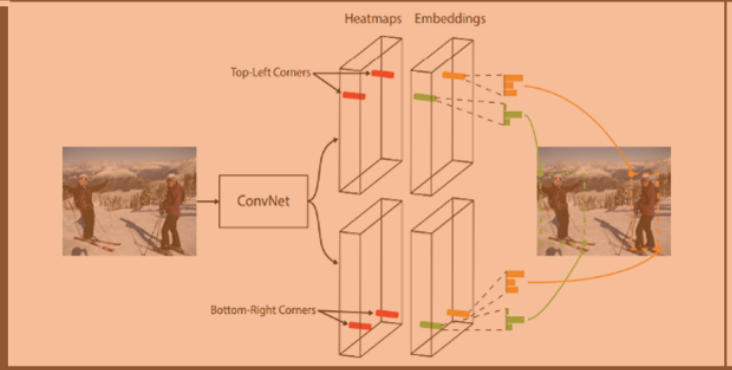



多阶段法

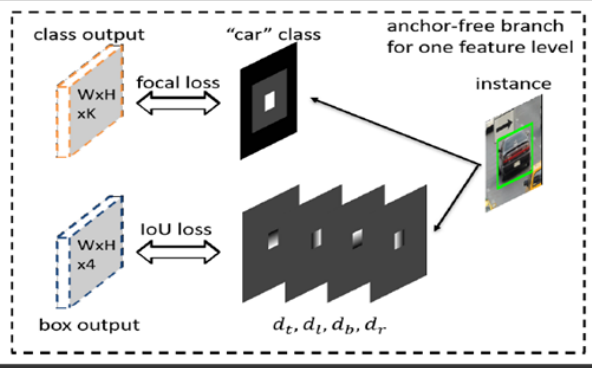



单阶段法

无需锚框

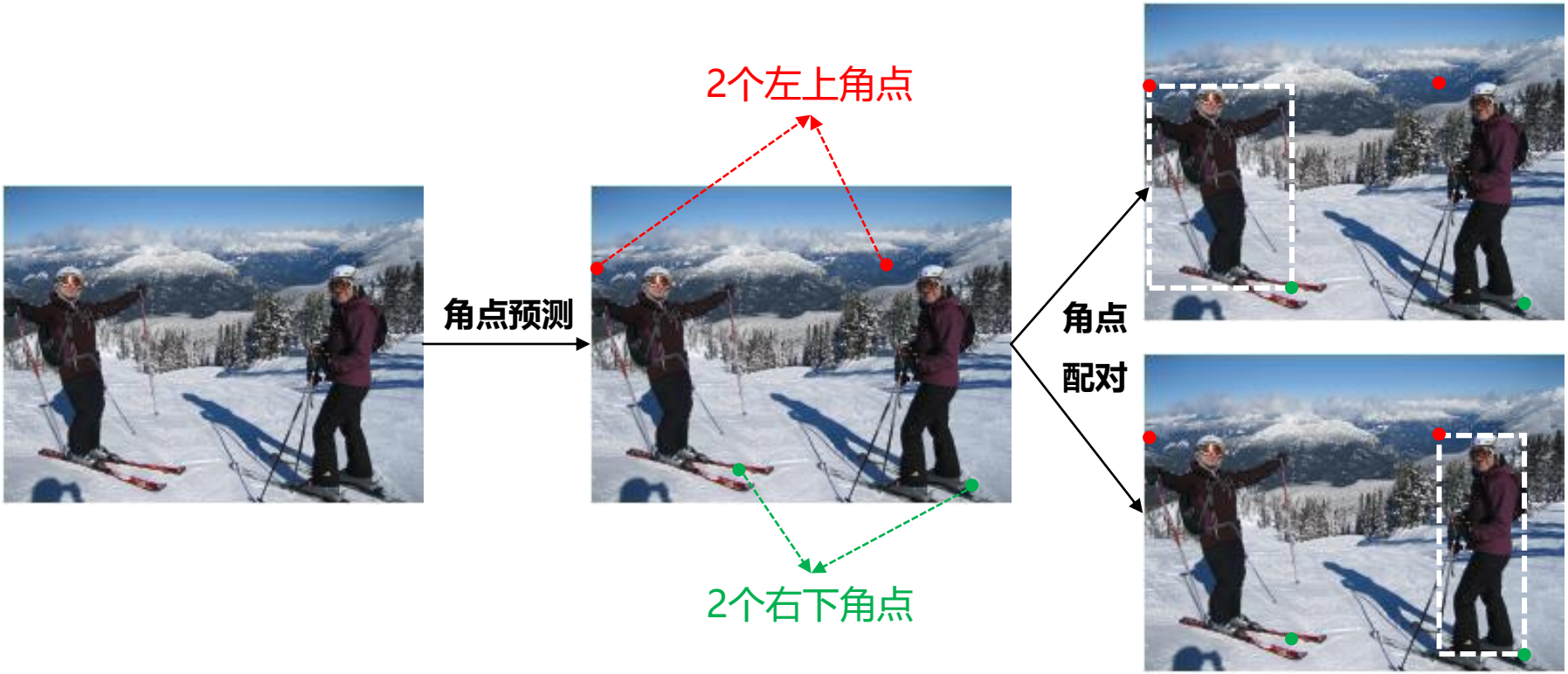



关键点法



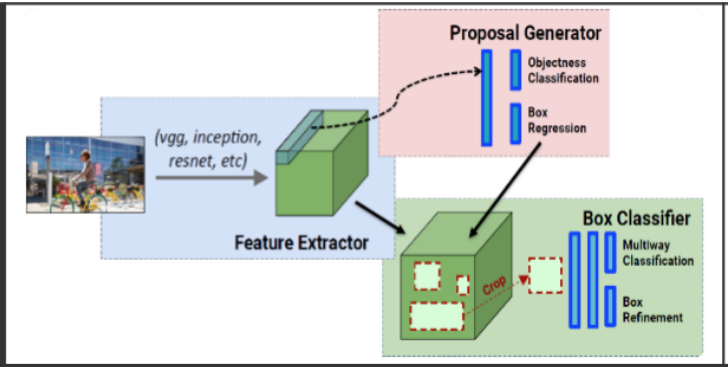

中心域法

# 无需锚框的关键点法（CornerNet）

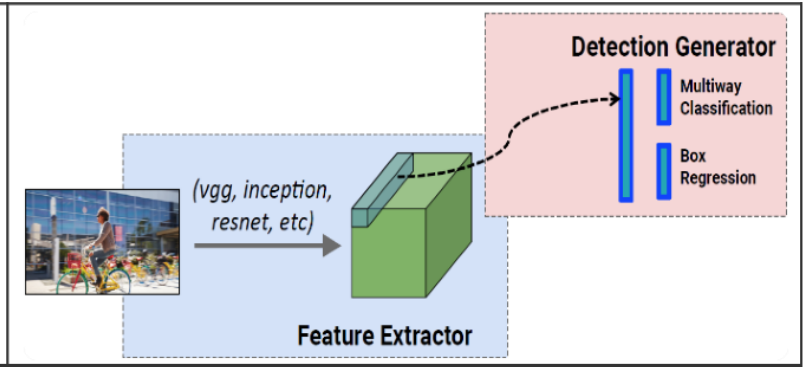


# 内容回顾：物体检测算法的总结

基于锚框

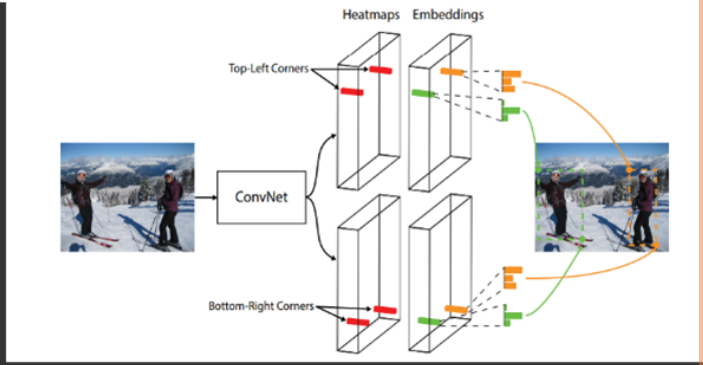



多阶段法

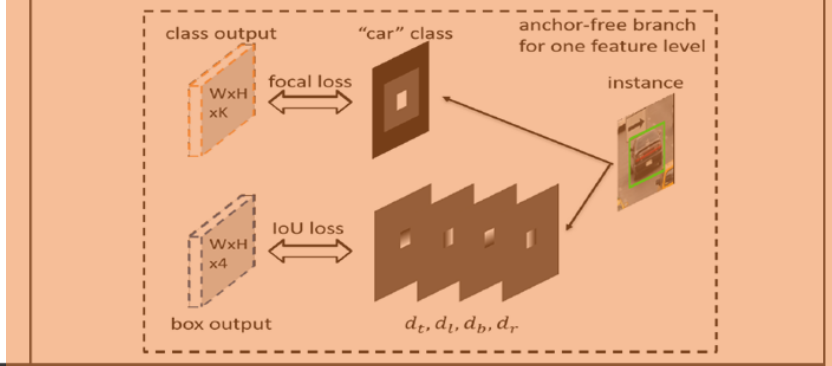



单阶段法

无需锚框

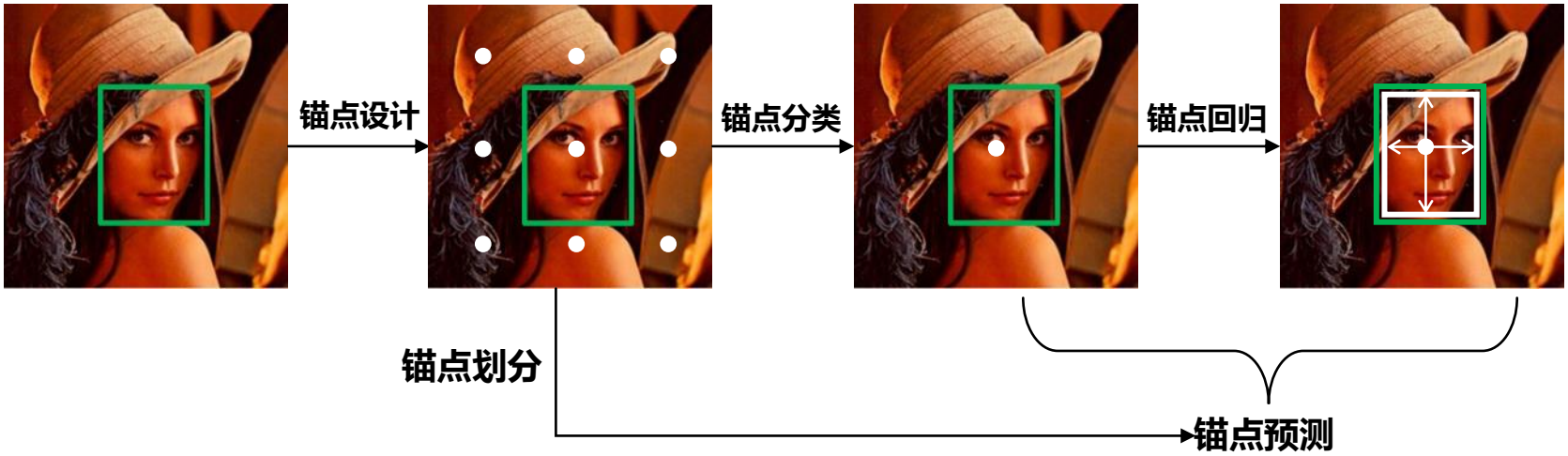



关键点法




中心域法

# 无需锚框的中心域法（FCOS）



# 内容回顾：物体检测算法的总结（无需锚框）

| 无需锚框算法 | 关键点法 | 中心域法 |
| --- | --- | --- |
| 算法动机 | 移除掉锚框，减少超参数，增加灵活性 | |
| 算法思想 | 先检测关键点，再进行配对来框定物体 | 铺设锚点替代锚框来检测物体 |
| 算法优点 | 全新的检测流程，为检测带来了新的思路 | 减少超参数，简化计算 |
| 算法难点 | 不同关键点之间的配对问题 | 正负样本的划分问题 |
| 计算速度 | 流程比较复杂，速度相对较慢 | 流程比较简单，速度相对较快 |
| 检测精度 | 精度能达到甚至超过基于锚框的单阶段法 | |

# 目录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基于锚框的检测算法

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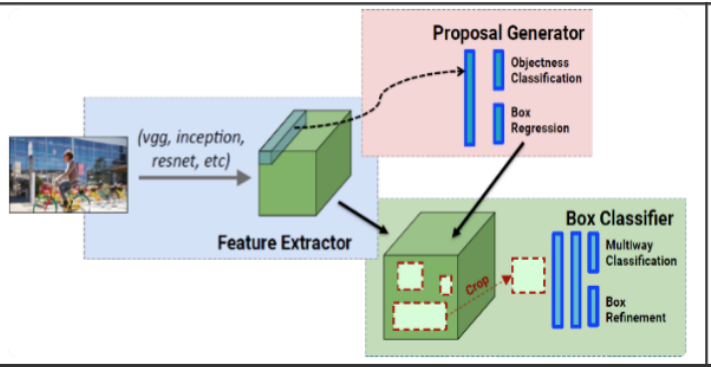
物体检测算法的对比总结

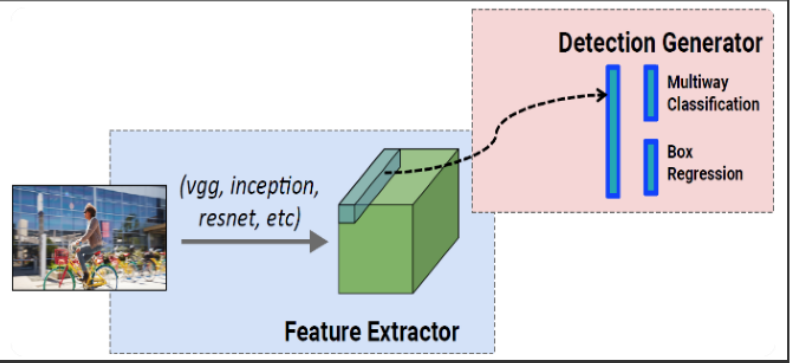
**实用检测算法的研究思路**

# 实用检测算法的研究思路：对比探索

基于锚框

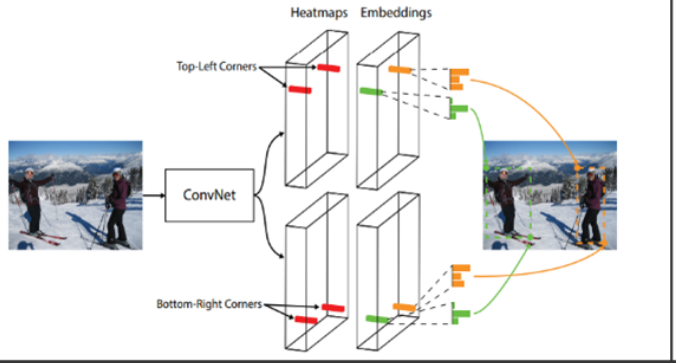



多阶段法

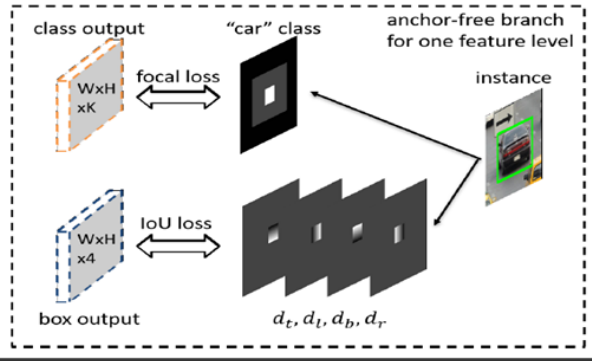



单阶段法

无需锚框

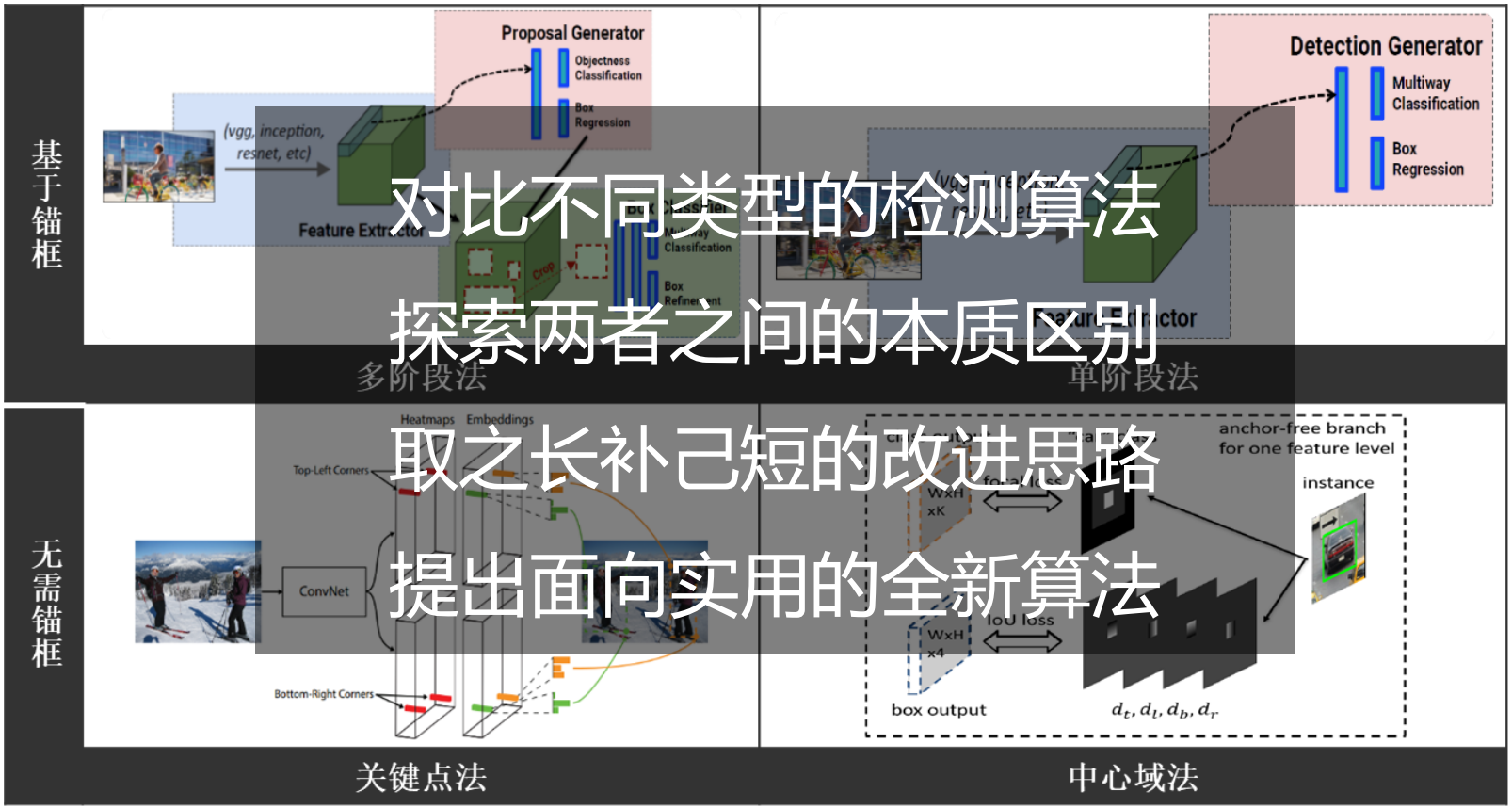



关键点法




中心域法

# 实用检测算法的研究思路：对比探索




对比不同类型的检测算法

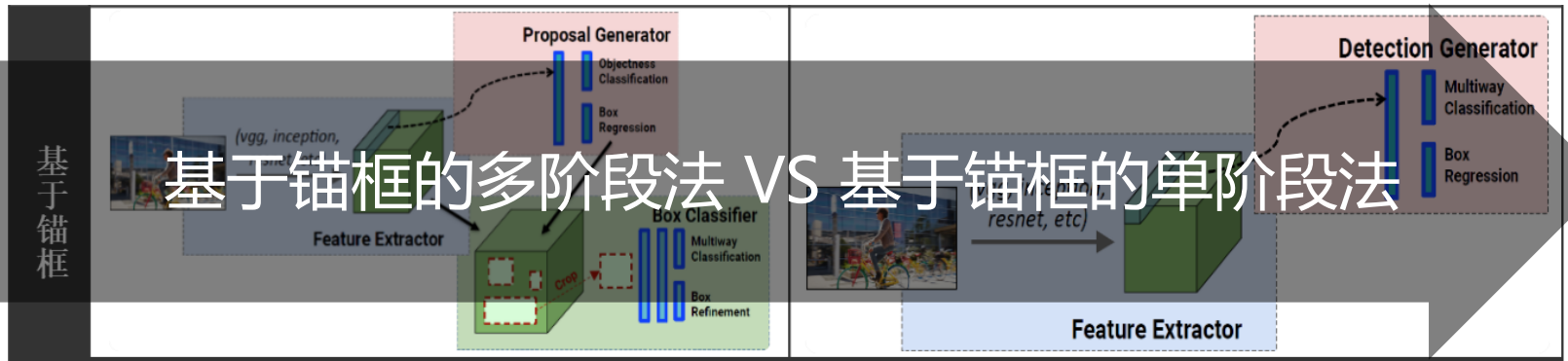
探索两者之间的本质区别

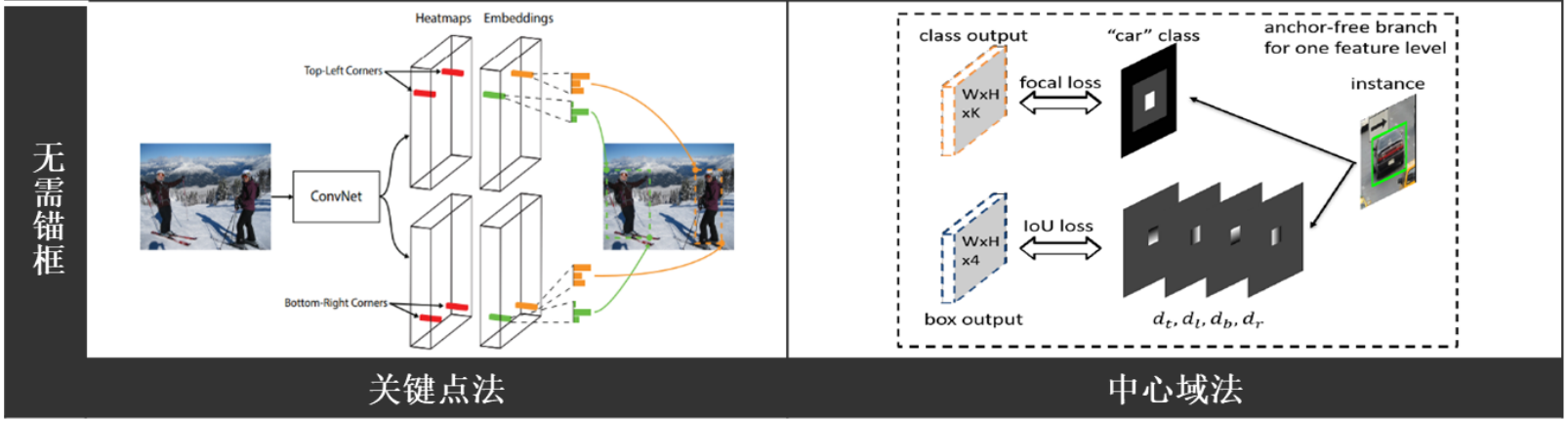
取之长补己短的改进思路

提出面向实用的全新算法

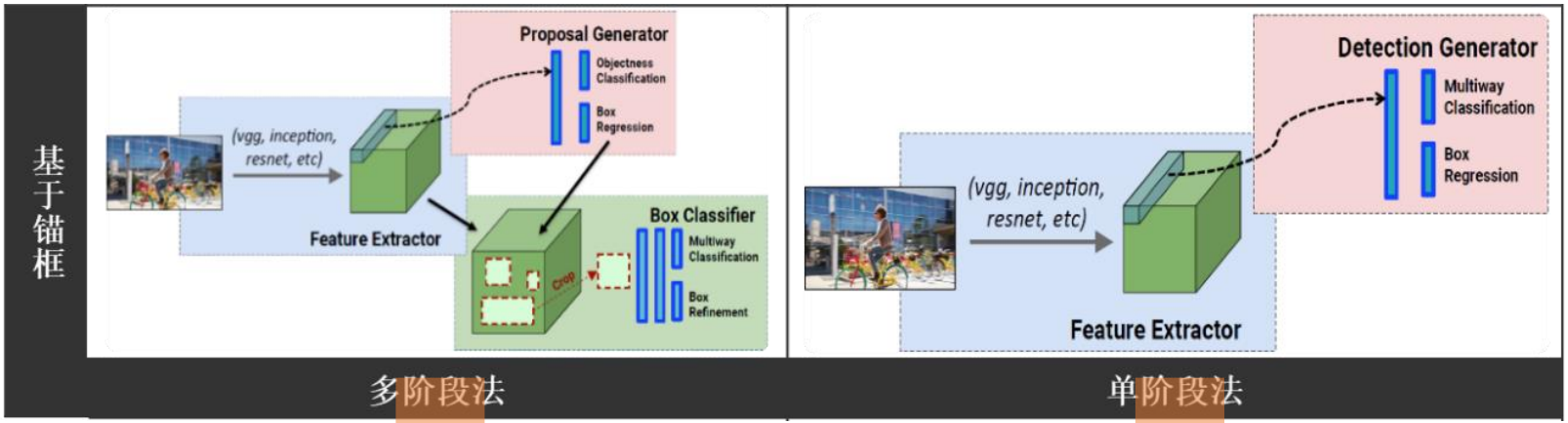
# 基于锚框的多阶段法 VS 单阶段法

基于锚框的多阶段法 VS 基于锚框的单阶段法



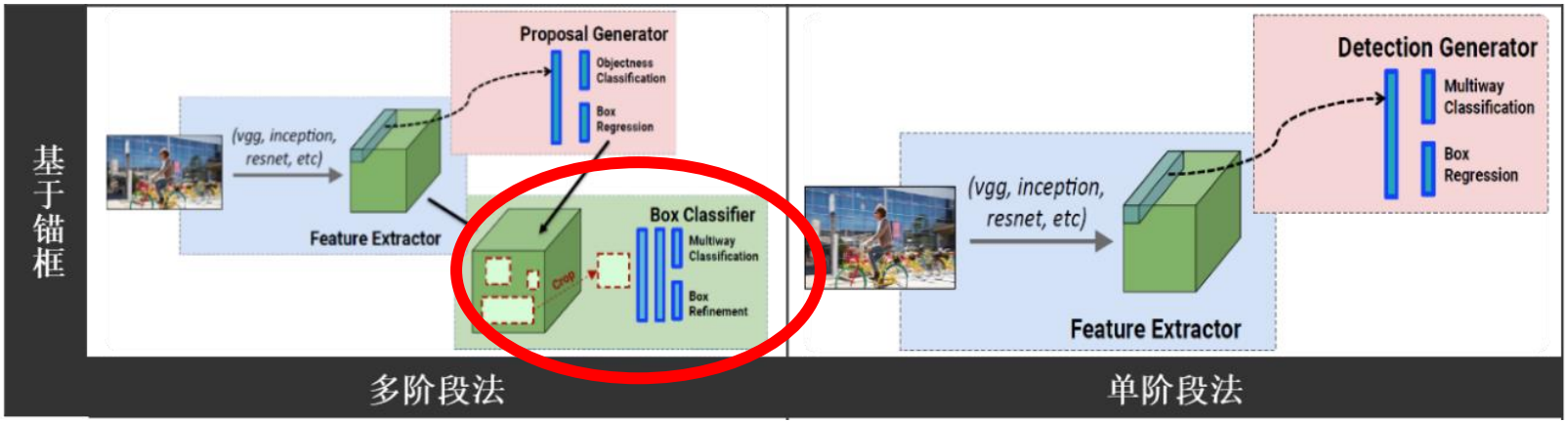
# 基于锚框的多阶段法 VS 单阶段法：本质区别




**精度较高，但速度较慢** VS **速度较快，但精度较低**

哪些区别带来的差异?

# 基于锚框的多阶段法 VS 单阶段法：本质区别

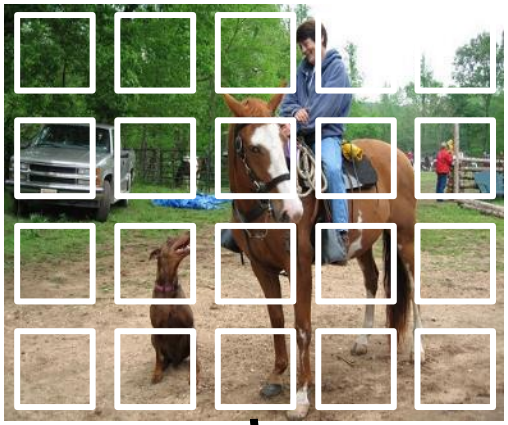


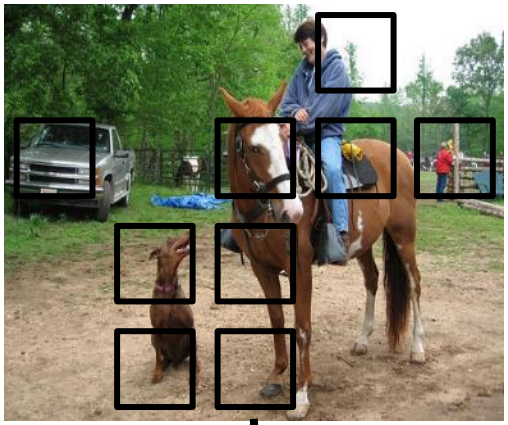

- 多阶段法与单阶段法的主要区别：多了一个额外的检测步骤
- 该步骤让多阶段法具备以下特点：① 二阶段的分类；② 二阶段的回归

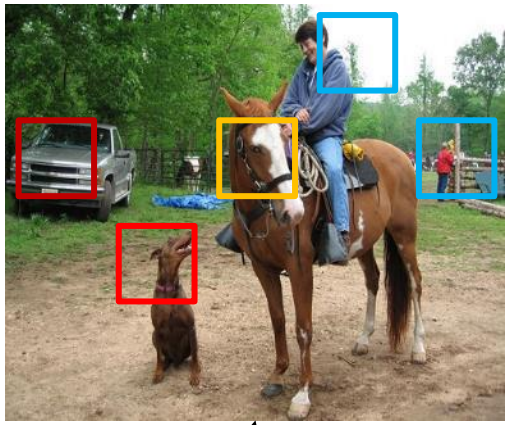
③ 二阶段的特征；④ 特征的校准

# 基于锚框的多阶段法 VS 单阶段法：二阶段分类

## 多阶段法的二阶段分类过程







第一阶段的二分类

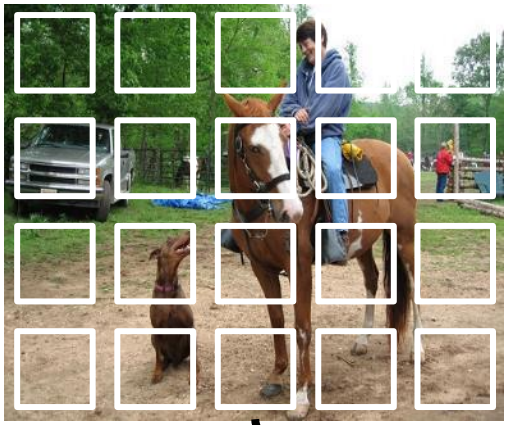
(背景 or 前景)

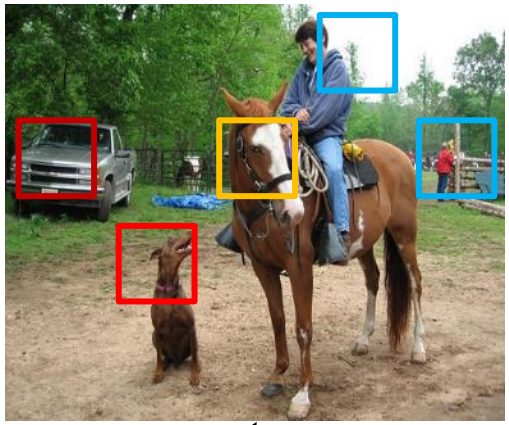
第二阶段的多分类

(具体类别)

# 基于锚框的多阶段法 VS 单阶段法：二阶段分类

## 单阶段法的一阶段分类过程



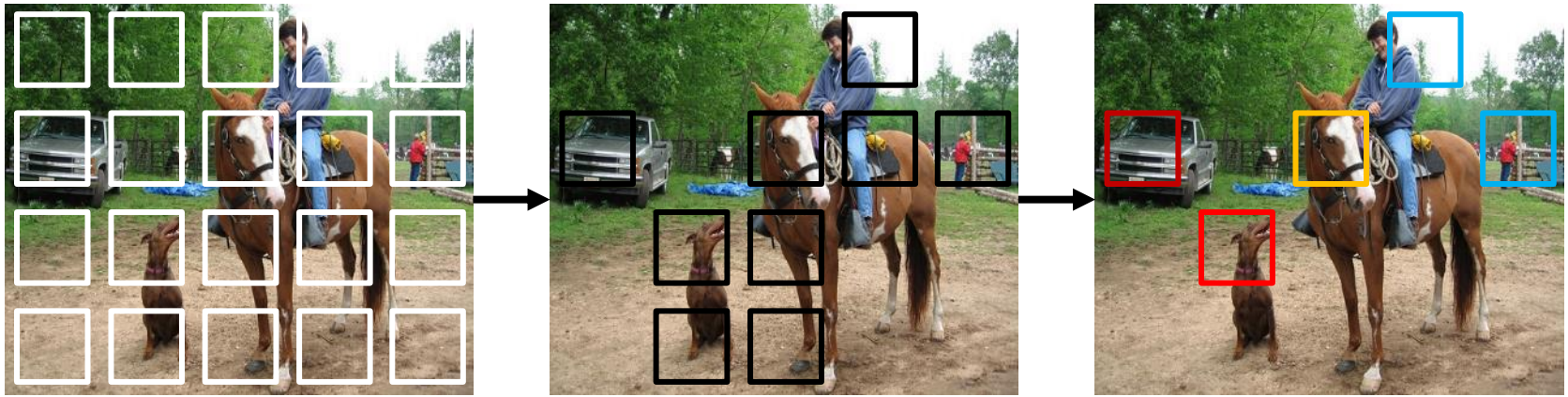


多分类

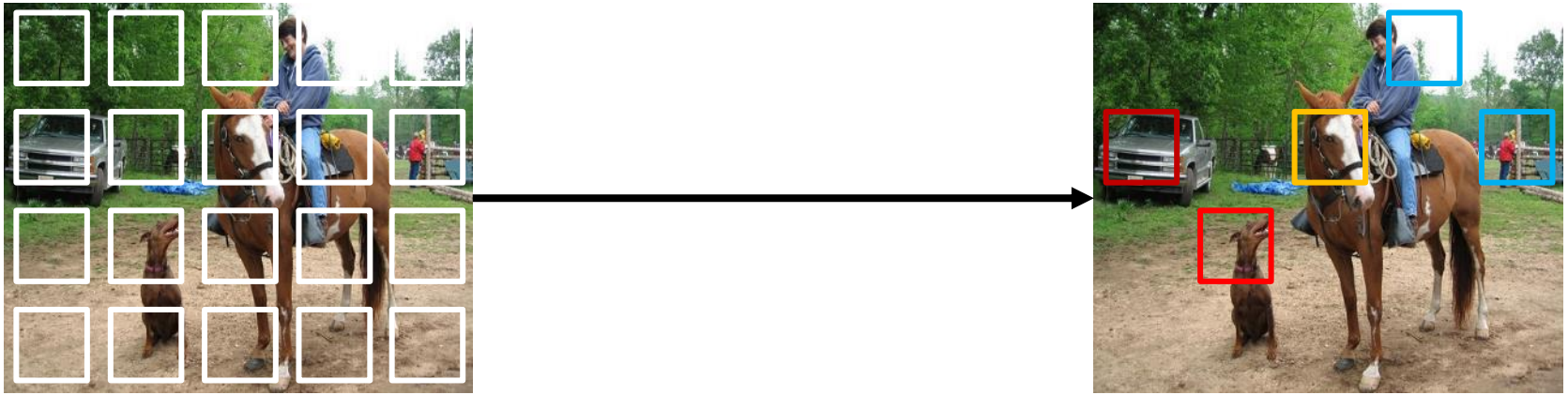
(具体类别)

# 基于锚框的多阶段法 VS 单阶段法：二阶段分类

二阶段分类

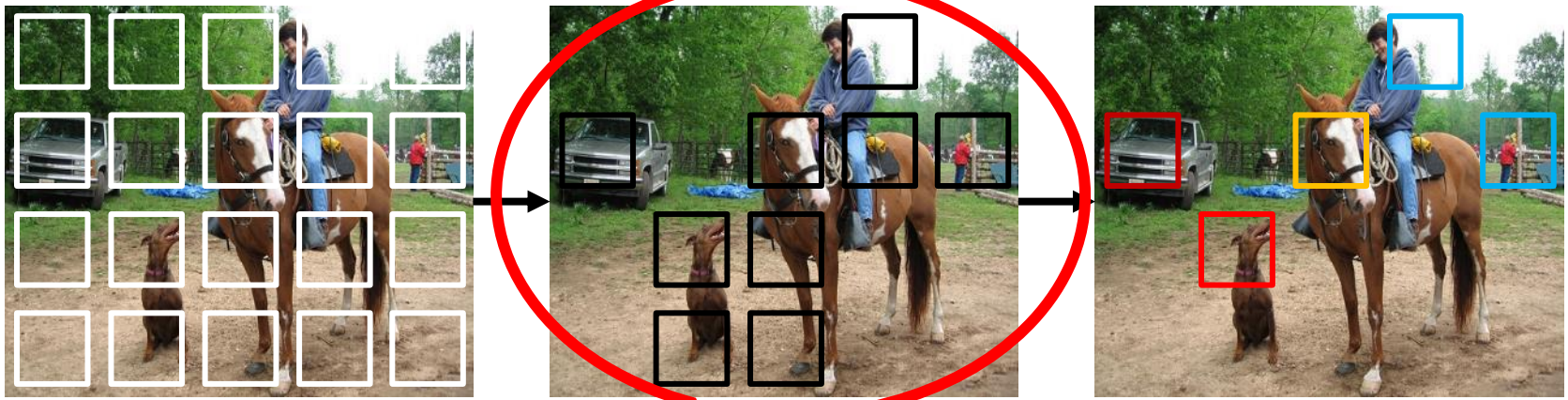


一阶段分类

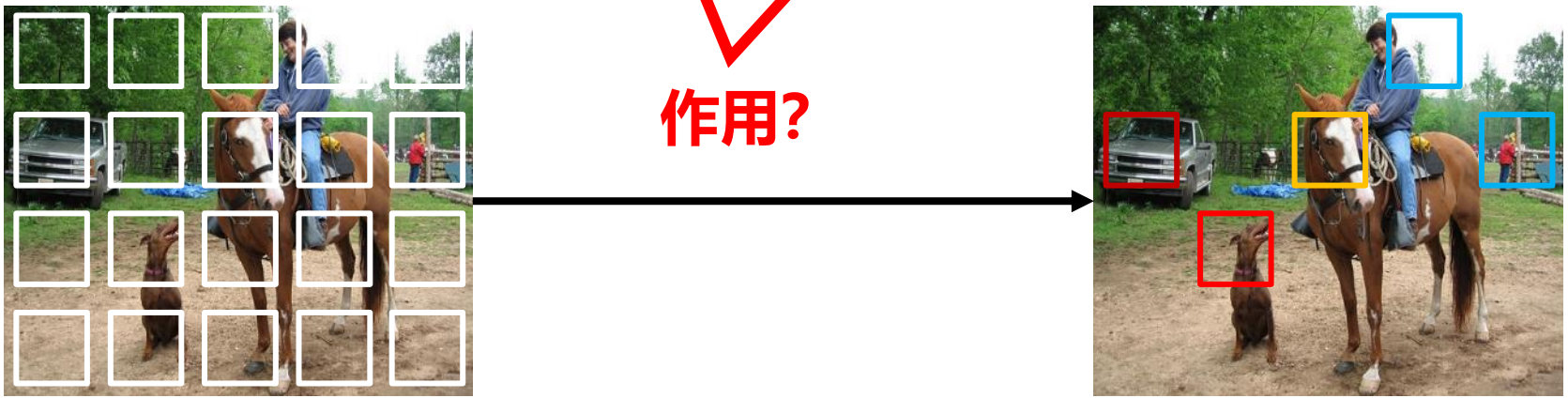


# 基于锚框的多阶段法 VS 单阶段法：二阶段分类

二阶段分类

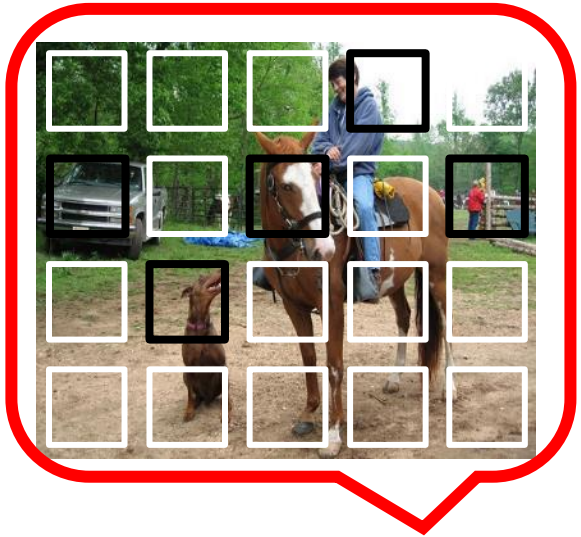


一阶段分类



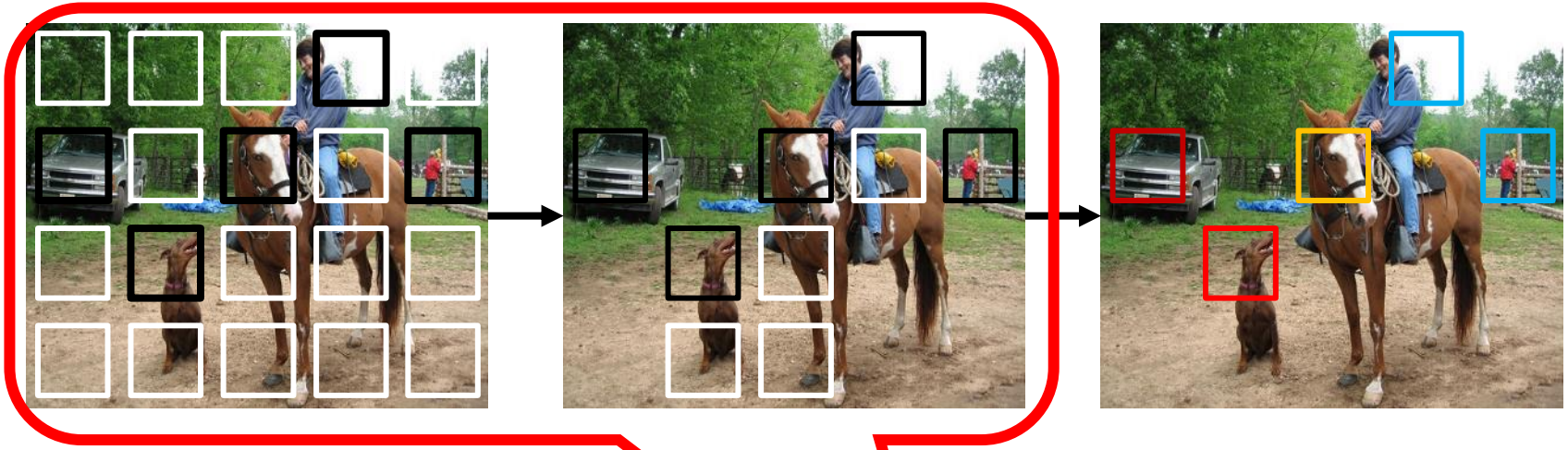
作用?

# 基于锚框的多阶段法 VS 单阶段法：二阶段分类



- 问题：正负样本极度失衡（图中黑色为正，白色为负，比例为5:15）
- 影响：负样本极多，难以训练，导致分类效果不佳
- 方案：二阶段分类可以缓解该问题

# 基于锚框的多阶段法 VS 单阶段法：二阶段分类

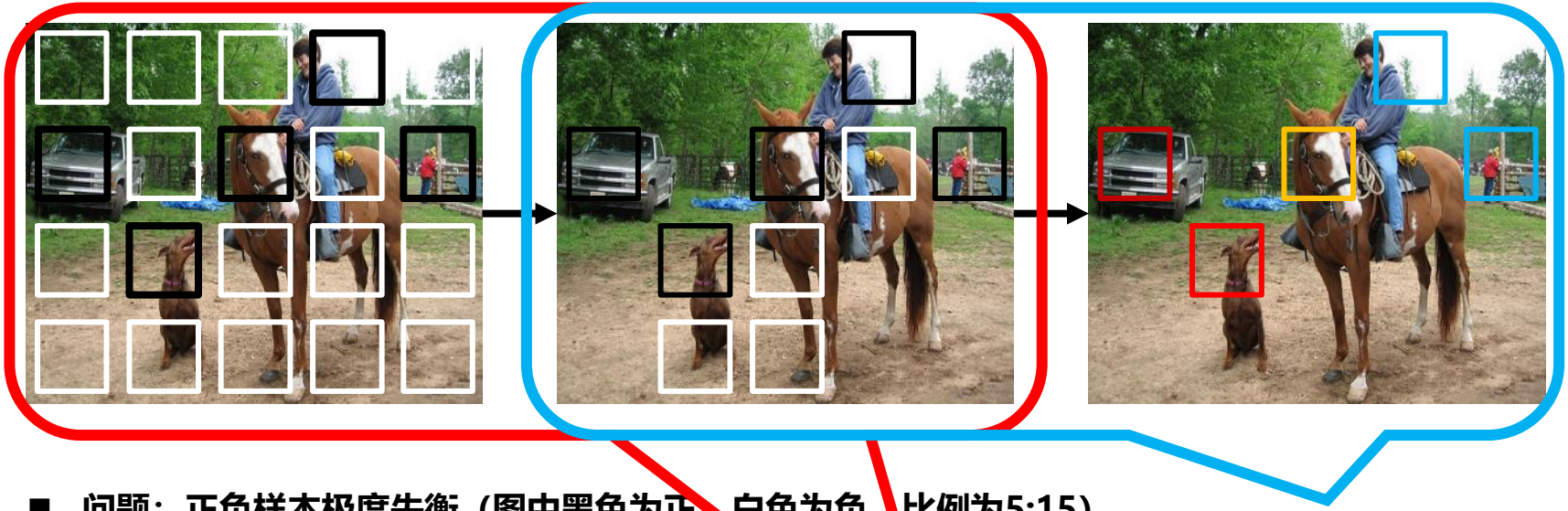


- 问题：正负样本极度失衡（图中黑色为正，白色为负，比例为5:15）
- 影响：负样本极多，难以训练，导致分类效果不佳
- 方案：二阶段分类可以缓解该问题

虽然正负样本比例为5:15

但只做简单的二分类任务

# 基于锚框的多阶段法 VS 单阶段法：二阶段分类



- 问题：正负样本极度失衡（图中黑色为正，白色为负，比例为5:15）
- 影响：负样本极多，难以训练，导致分类效果不佳
- 方案：二阶段分类可以缓解该问题

经过第一阶段二分类的过滤之后

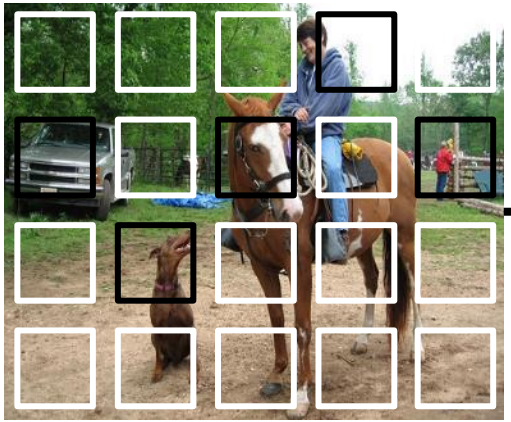
第二阶段多分类正负样本比例约1:1

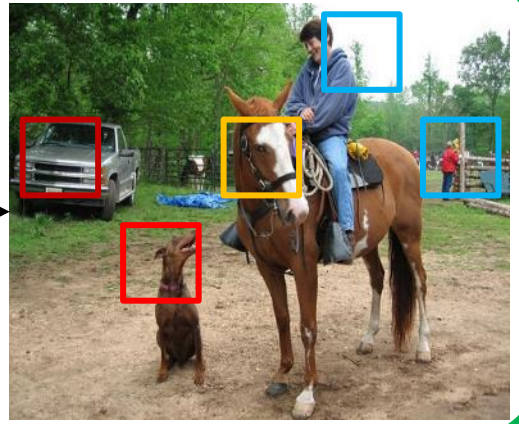
虽然正负样本比例为5:15

但只做简单的二分类任务

# 基于锚框的多阶段法 VS 单阶段法：二阶段分类

一阶段分类





不仅正负样本比例为5:15

而且是复杂的多分类任务

# 基于锚框的多阶段法 VS 单阶段法：二阶段回归

## 多阶段法的二阶段回归过程

第一阶段

的初步回归矫正

第二阶段

的精准回归矫正

# 基于锚框的多阶段法 VS 单阶段法：二阶段回归

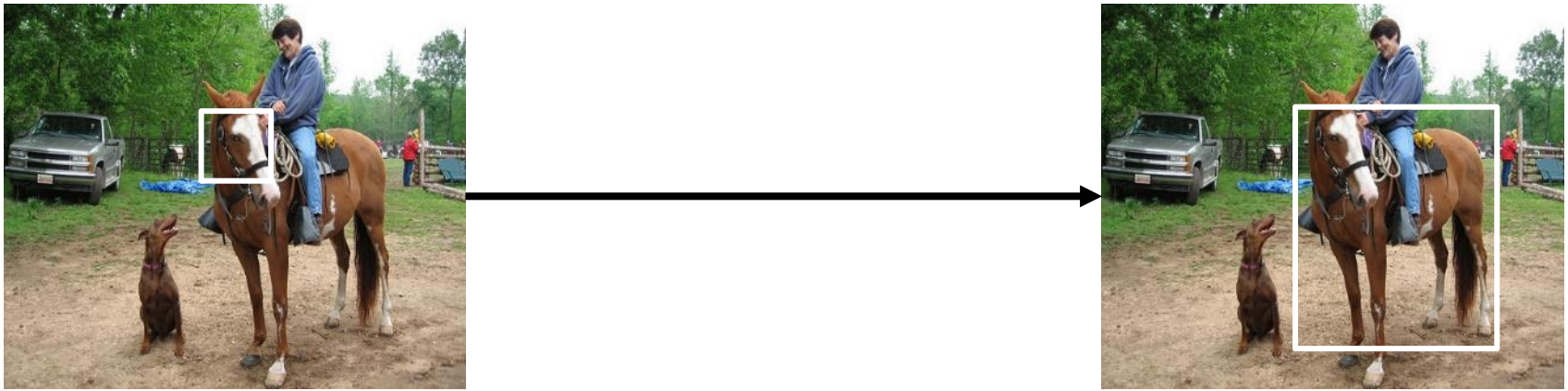
## 单阶段法的一阶段回归过程

单阶段的回归矫正

# 基于锚框的多阶段法 VS 单阶段法：二阶段回归

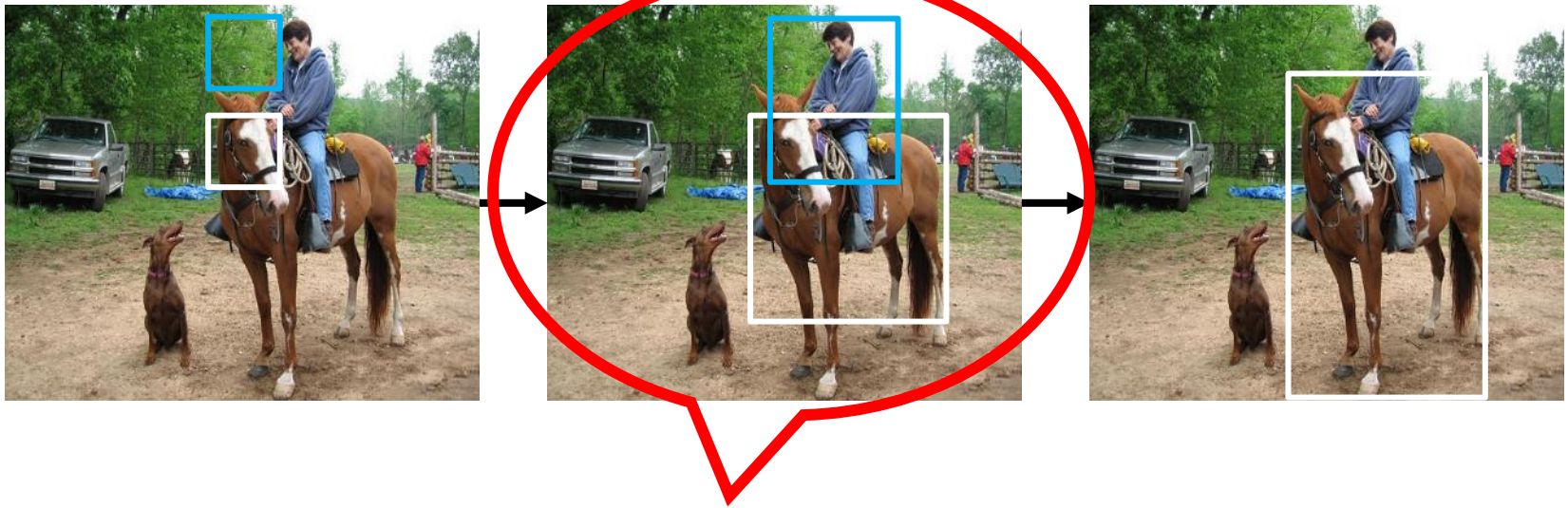
二阶段回归

一阶段分类



# 基于锚框的多阶段法 VS 单阶段法：二阶段回归

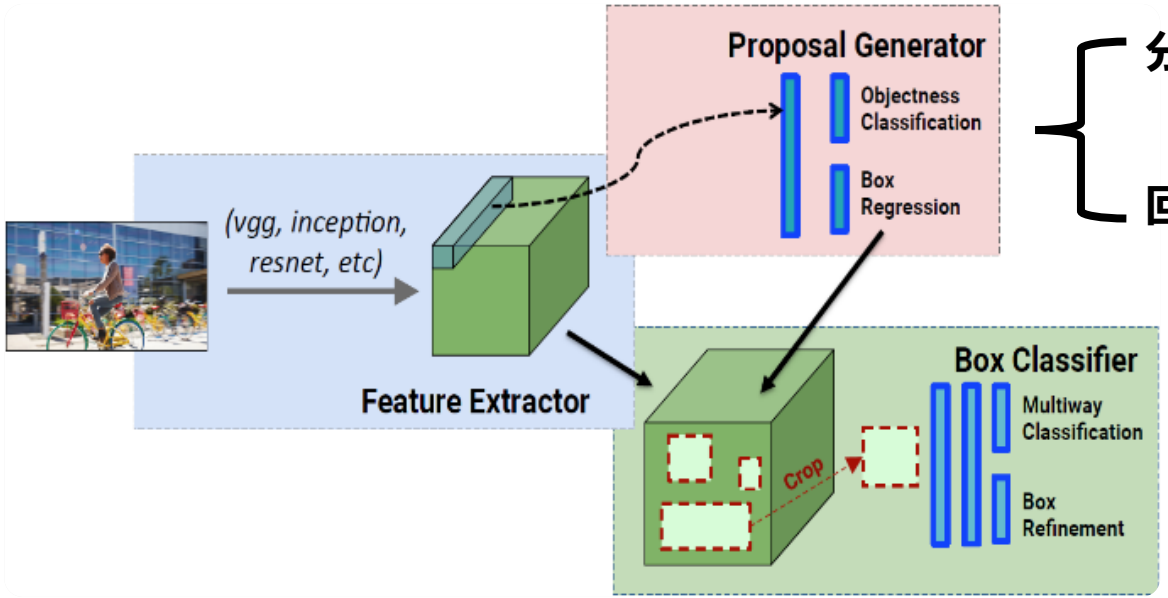
二阶段回归



①经过两个阶段的回归矫正，使得检测结果的位置更加精准

②经过第一阶段的回归矫正，可以为第二阶段提供更多的正样本

# 基于锚框的多阶段法 VS 单阶段法：二阶段特征




分类：简单的二分类

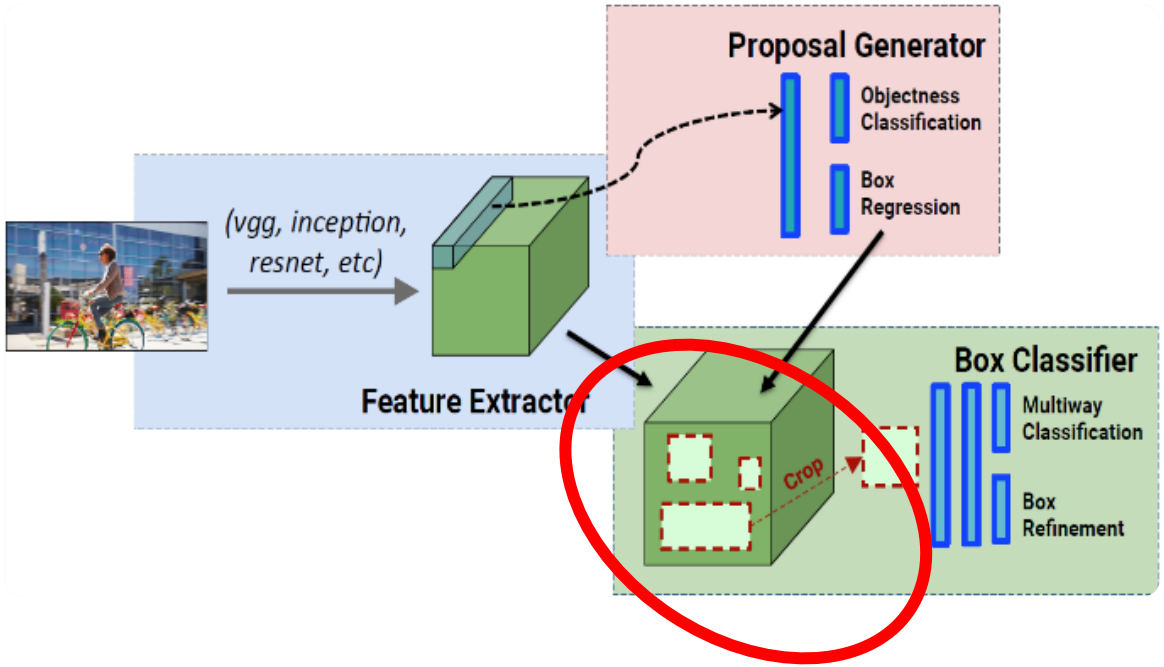
回归：初步的位置矫正

分类：困难的多分类

回归：精准的位置矫正

- 基础网络的特征是共享的
- 但两个阶段有着自己独有的特征来负责难度不同的任务

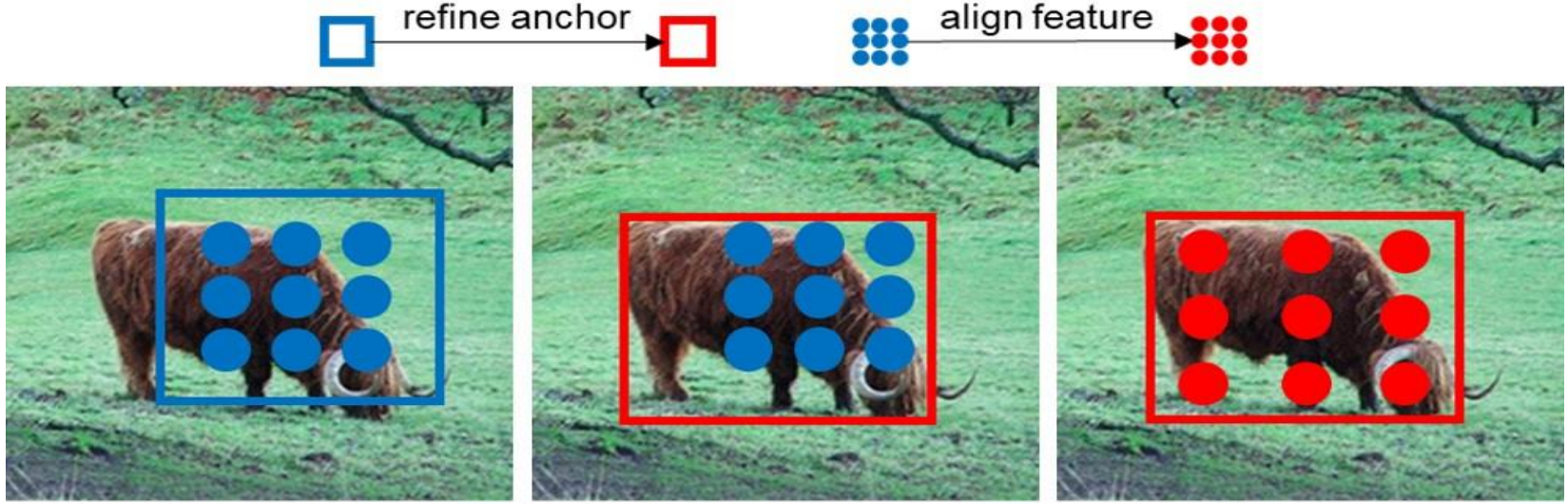
# 基于锚框的多阶段法 VS 单阶段法：特征的校准




为什么要做特征校准?

- 多阶段法会使用一个RoI池化的操作，根据矩形框把特征扣出来进行校准

# 基于锚框的多阶段法 VS 单阶段法：特征的校准

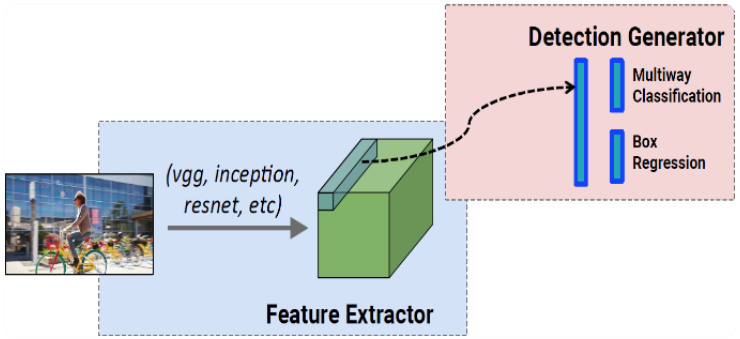



(a)：第一阶段中，初始的锚框，初始的特征；图(b)：经过第一阶段校正后的锚框，初始的特征；(c)：经过第一阶段校正后的锚框，经过RoI池化校准后的特征

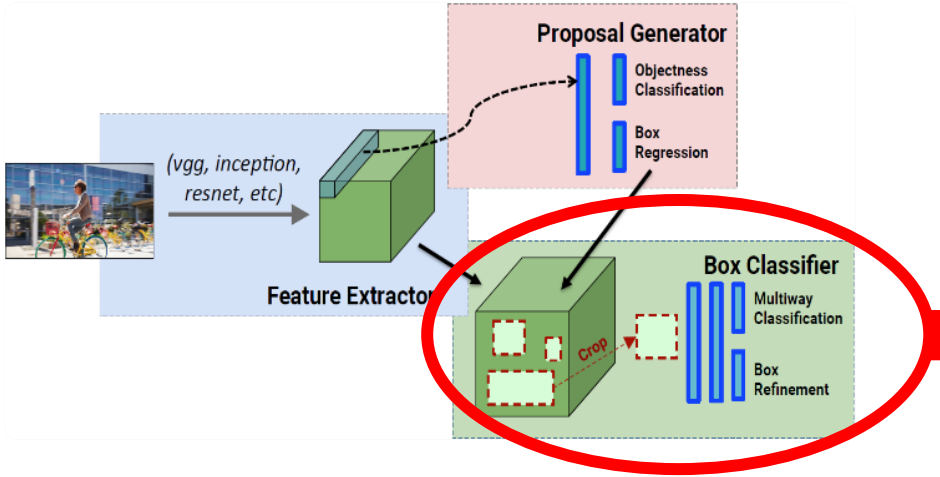
- **锚框回归后位置发生改变，因此特征应根据锚框进行校准，提高准确度**
- **调整特征大小，使其一致易于批处理**

# 基于锚框的多阶段法 VS 单阶段法：总结

单阶段法




多阶段法

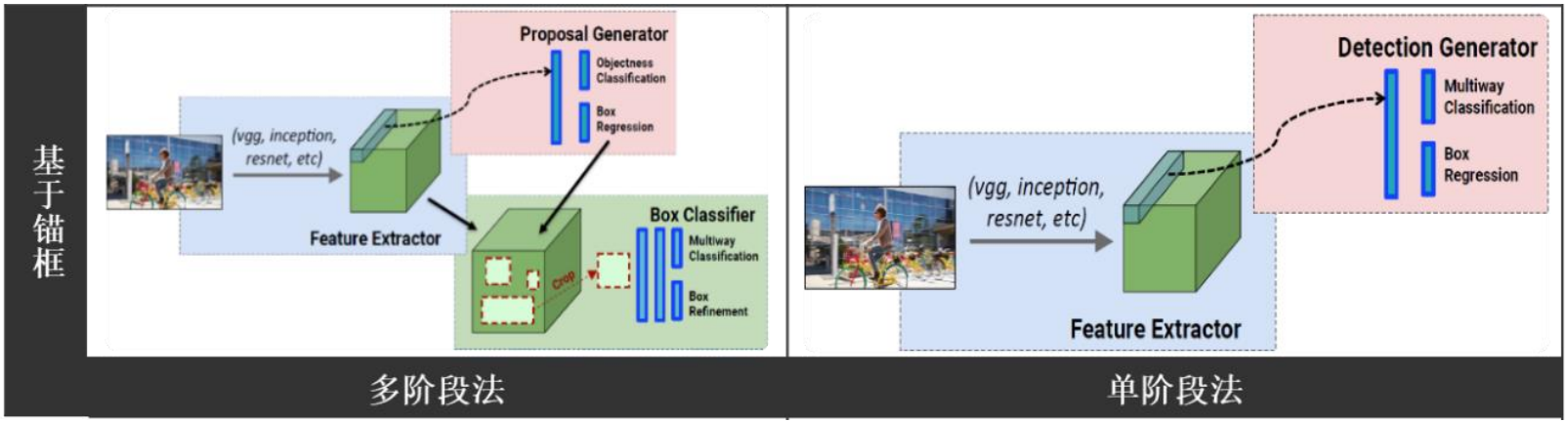



精度提高，但速度也变慢

① 二阶段的分类；② 二阶段的回归

③ 二阶段的特征；④ 特征的校准

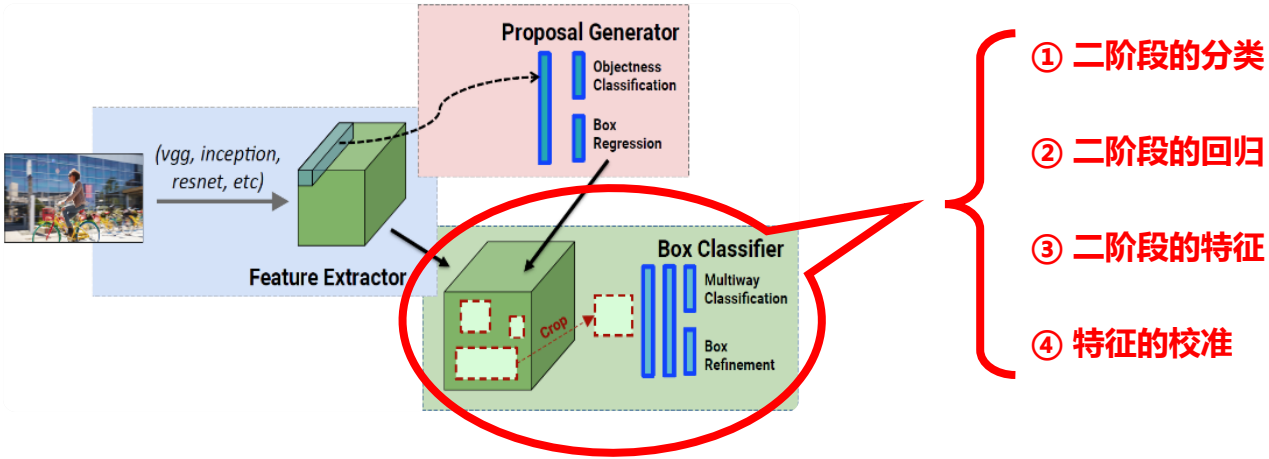
# 实用物体检测算法RefineDet




- 多阶段法：精度较高，速度较慢
- 单阶段法：精度较低，速度较快
- 找到两者的本质区别，取之长补己短的改进思路
- 提出RefineDet算法：单阶段法的速度+多阶段法的精度

Single-Shot Refinement Neural Network for Object Detection, CVPR 2018

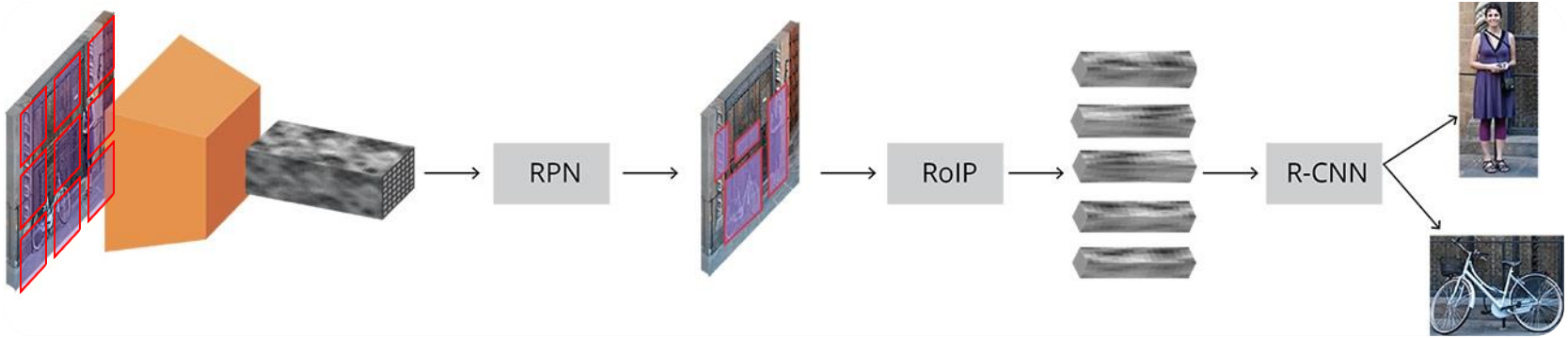
# 实用物体检测算法RefineDet：改进思路




- 多阶段法精度较高的原因：第二阶段带来的4个方面改进，让精度得以提升
- 多阶段法速度较慢的原因：4个改进中有些改进比较耗时，导致速度变慢
- 前3个改进可以在单阶段法中高效实现：二阶段分类、回归、特征（高性价比）
- 最后1个改进，需要逐区域进行，导致速度变慢，且提升有限（低性价比）

Single-Shot Refinement Neural Network for Object Detection, CVPR 2018

# 实用物体检测算法RefineDet：特征校准RoI池化




Faster R-CNN中RPN步骤：

① 整张图传入VGG16或ResNet提取特征

② 选择下采样倍数为16的特征层作为检测层

③ 根据检测层预设一系列大小和比例的锚框（9个）

④ 对锚框进行二分类和回归得到若干候选区域

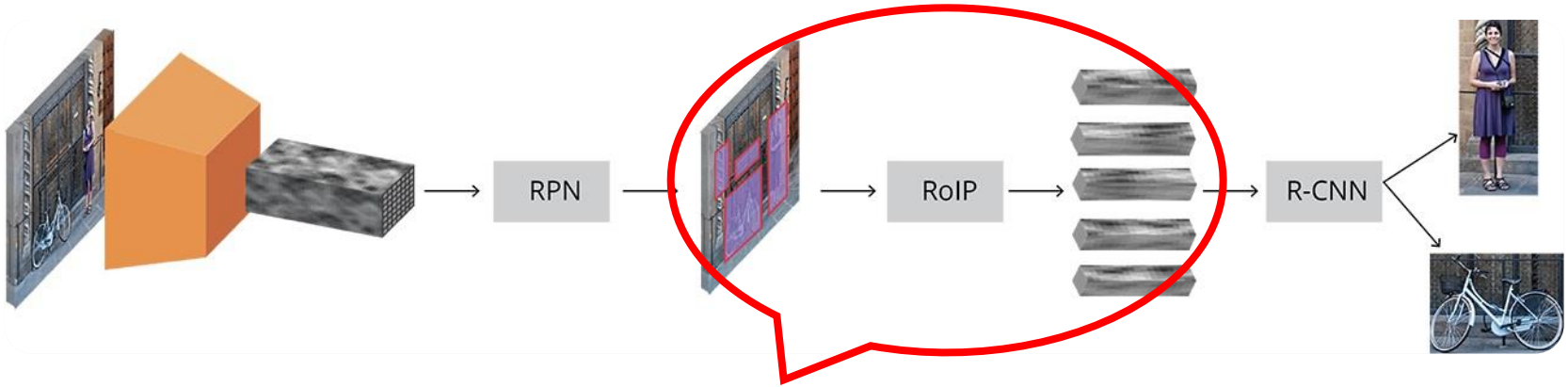
Faster R-CNN中Fast R-CNN步骤：

① **利用RoIPooling在检测层的特征上提取每个候选区域对应的特征**

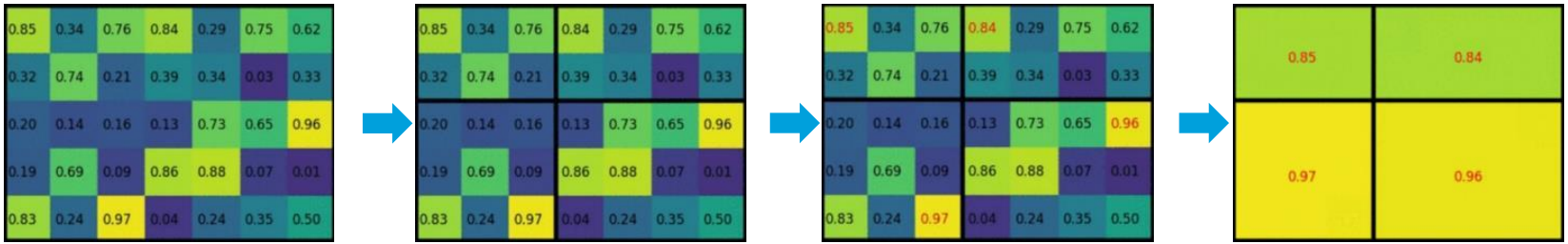
② 输入CNN/FC子网络来增强候选区域的特征

③ 对候选区域进行多分类和回归得到检测结果

# 实用物体检测算法RefineDet：特征校准RoI池化

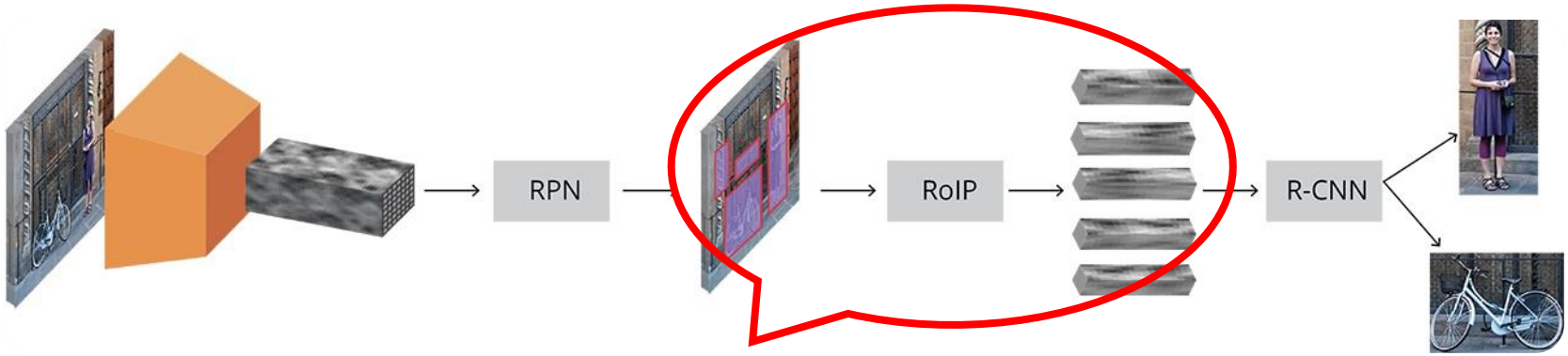



利用RoIPooling在检测层的特征上提取每个候选区域对应的特征，并转换为大小一致的特征

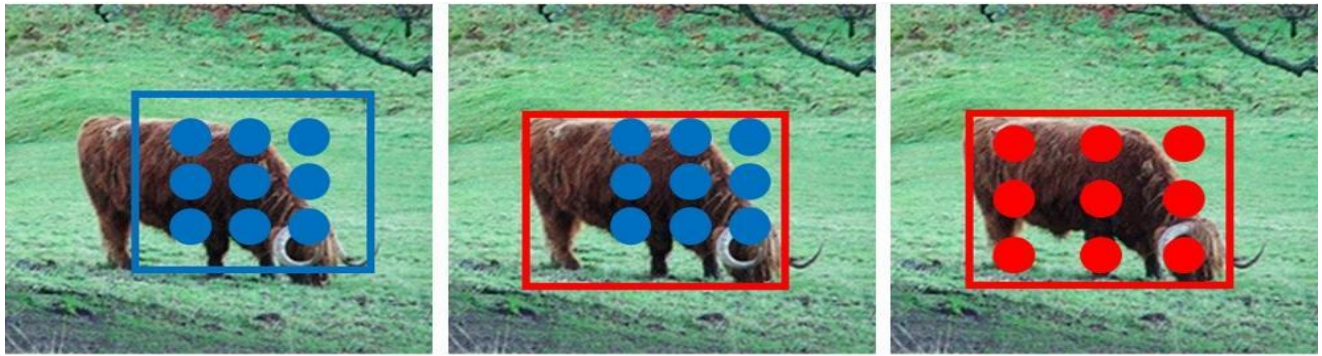



映射并取整　　分块并取整　　选取最大值　　转换为2x2特征

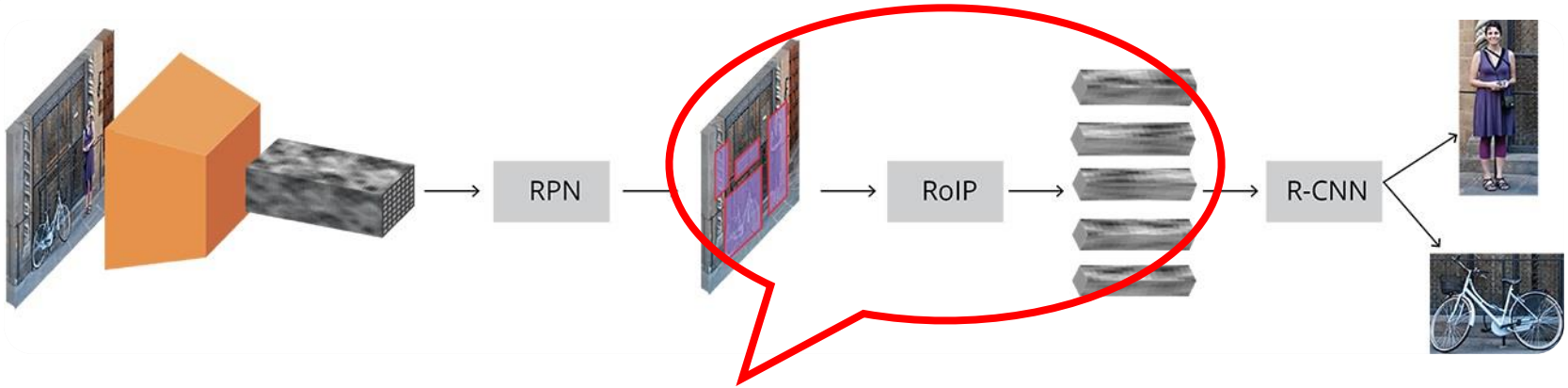
# 实用物体检测算法RefineDet：特征校准RoI池化




- 目的①：特征大小一致后，不同候选区域可以组成一个批次，从而进行批处理
- 目的②：进过第一阶段的校准，锚框的位置发生了变化，因此需要进行特征校准



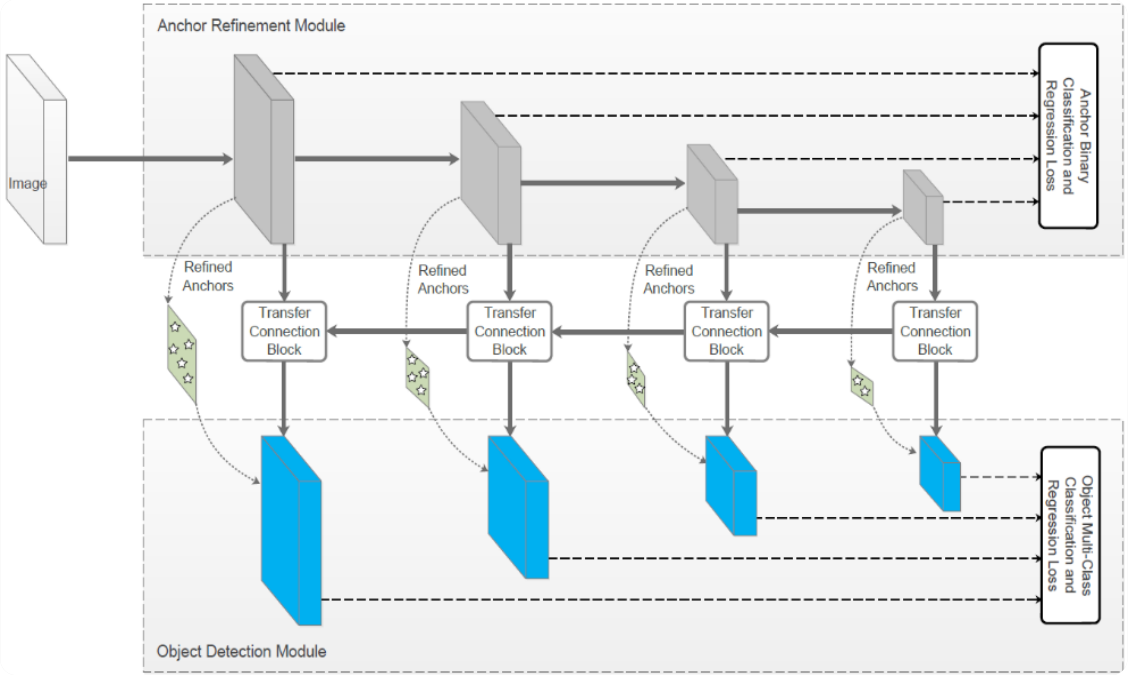
# 实用物体检测算法RefineDet：特征校准RoI池化




- 每个候选区域的大小不一样，位置不一样
- 每个候选区域需要单独处理，不能并行加速
- RoI池化以及其改进版，涉及到取整或插值等操作
- 因此，特征校准的RoI池化比较慢，尤其是候选区域较多时

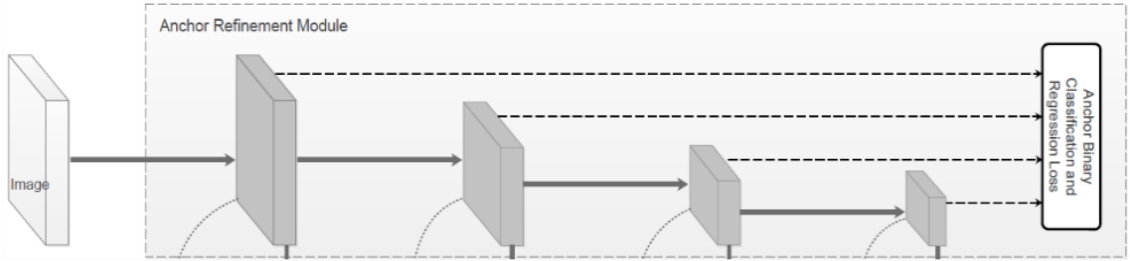
# 实用物体检测算法RefineDet：整体框架

- **在单阶段法中，集成多阶段法中高性价比的改进，抛弃低性价比的改进**
- **从而在保持单阶段法的速度的同时，获得多阶段法的精度**

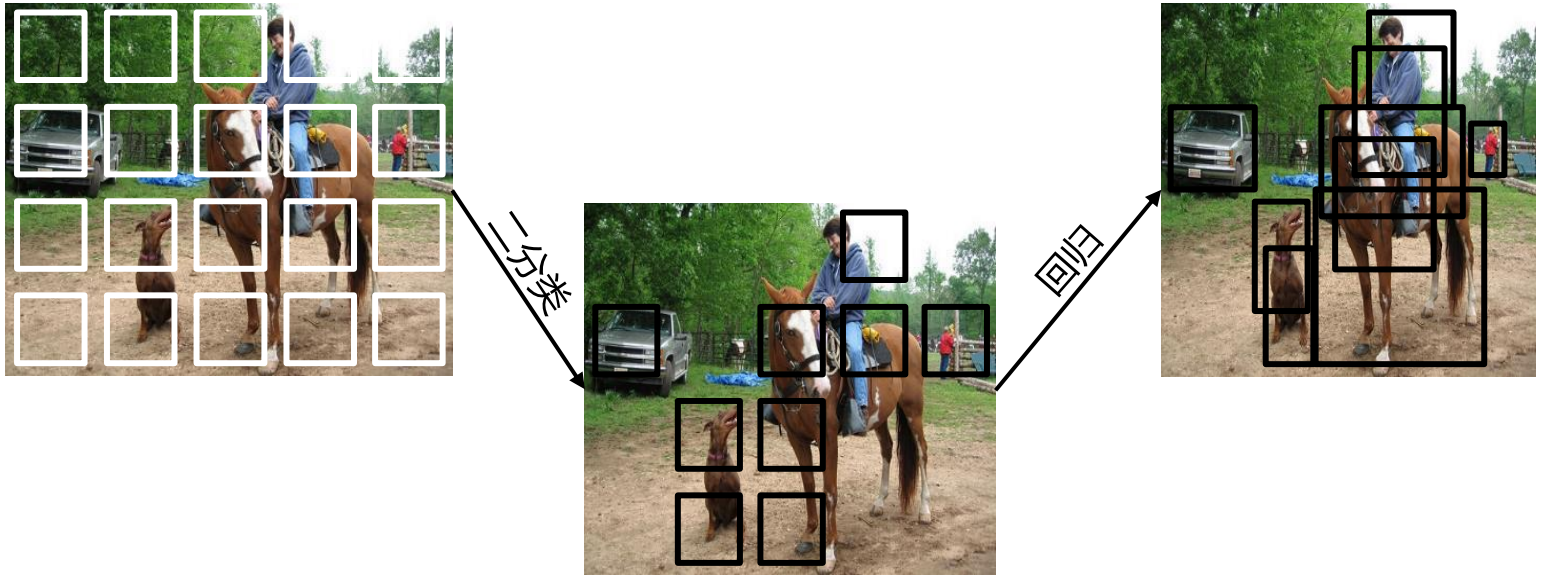



- 锚框校准模块（ARM）
  - 过滤负样本
  - 初步的边框校正
- 传输连接模块（TCB）
  - 转换ARM特征
  - 融合高层特征
- 物体检测模块（ODM）
  - 更好的特征
  - 精细的分类和回归

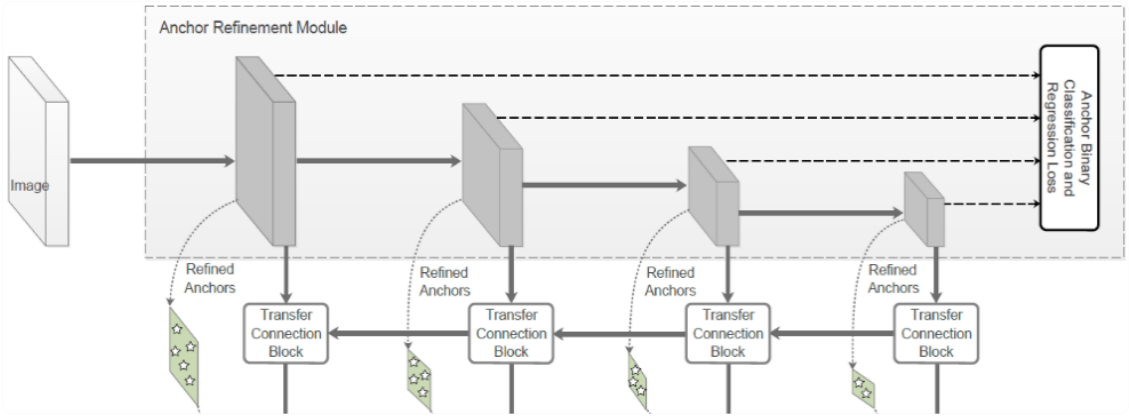
# 实用物体检测算法RefineDet：锚框校准模块



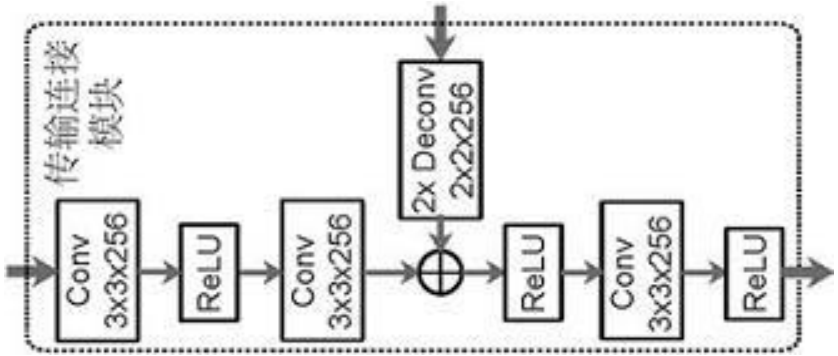

- 锚框校准模块（ARM）
  - 过滤负样本
  - 初步的边框校正



# 实用物体检测算法RefineDet：传输连接模块

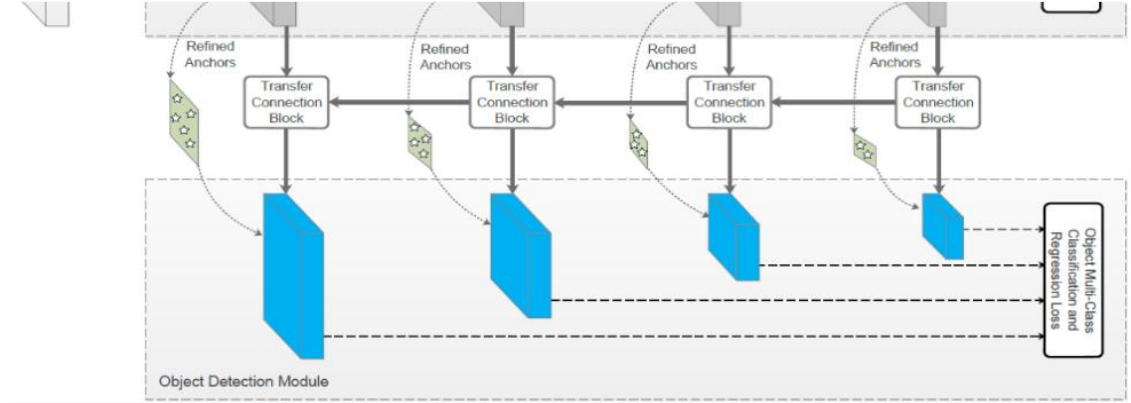



- 锚框校准模块（ARM）
  - 过滤负样本
  - 初步的边框校正
- 传输连接模块（TCB）
  - 转换ARM特征
  - 融合高层特征

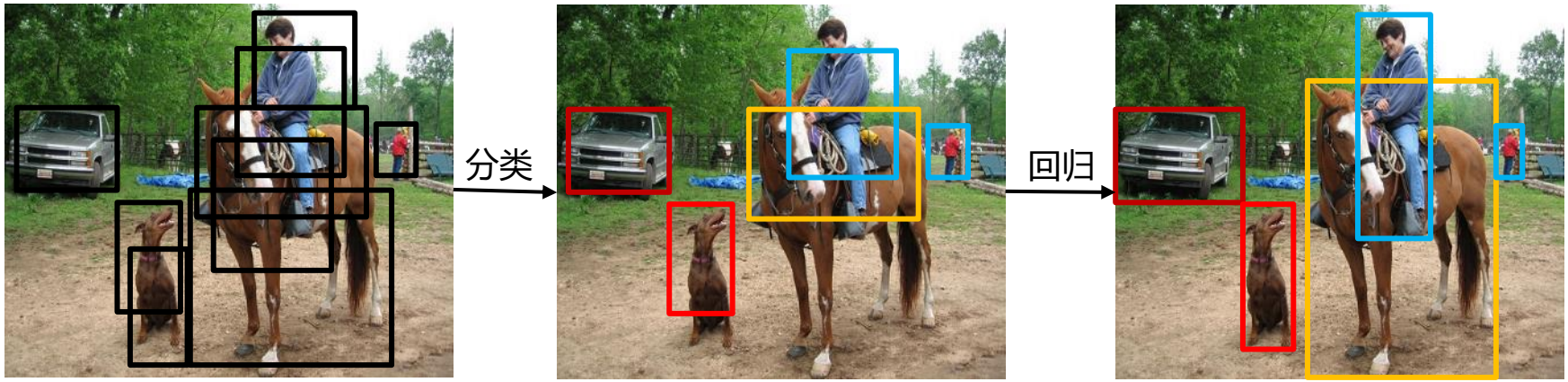



- 传输连接模块≈FPN
- 当时FPN没有公布代码
- 实现的TCB有些细节不一样
- 使用ReLU, DeConv等

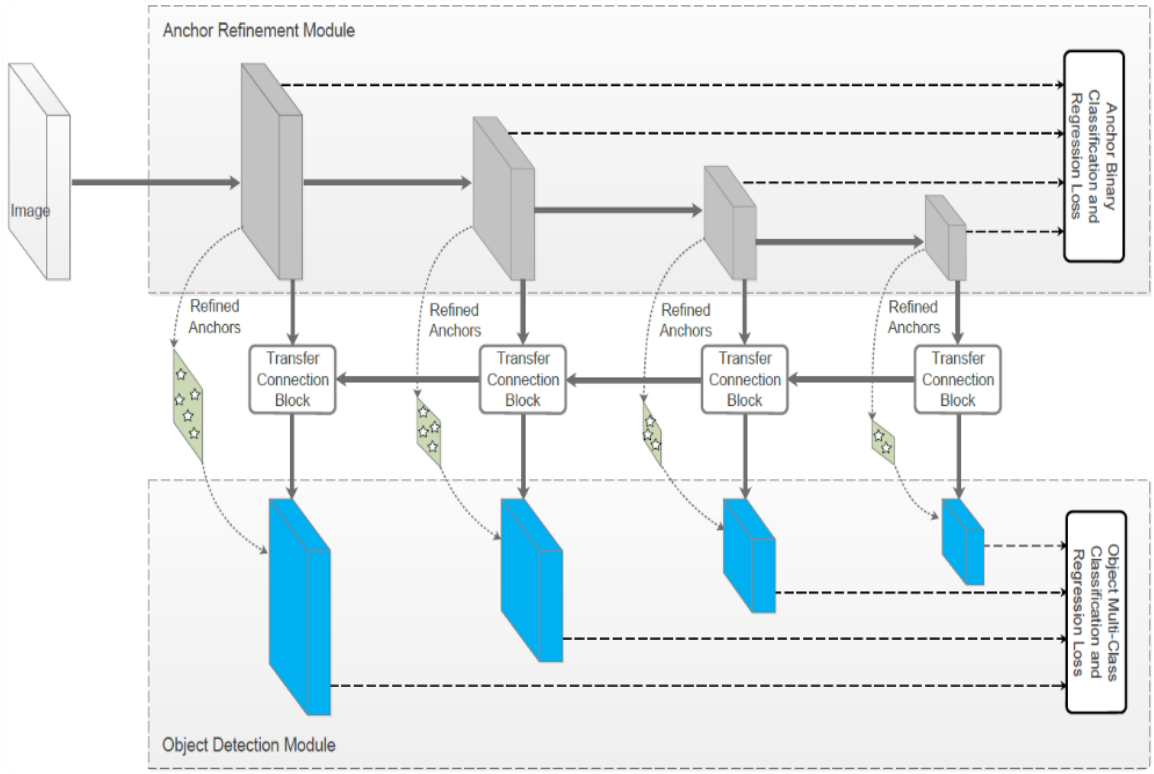
# 实用物体检测算法RefineDet：物体检测模块




- 传输连接模块（TCB）
  - 转换ARM特征
  - 融合高层特征
- 物体检测模块（ODM）
  - 更好的特征
  - 精细的分类和回归



# 实用物体检测算法RefineDet：二阶段分类



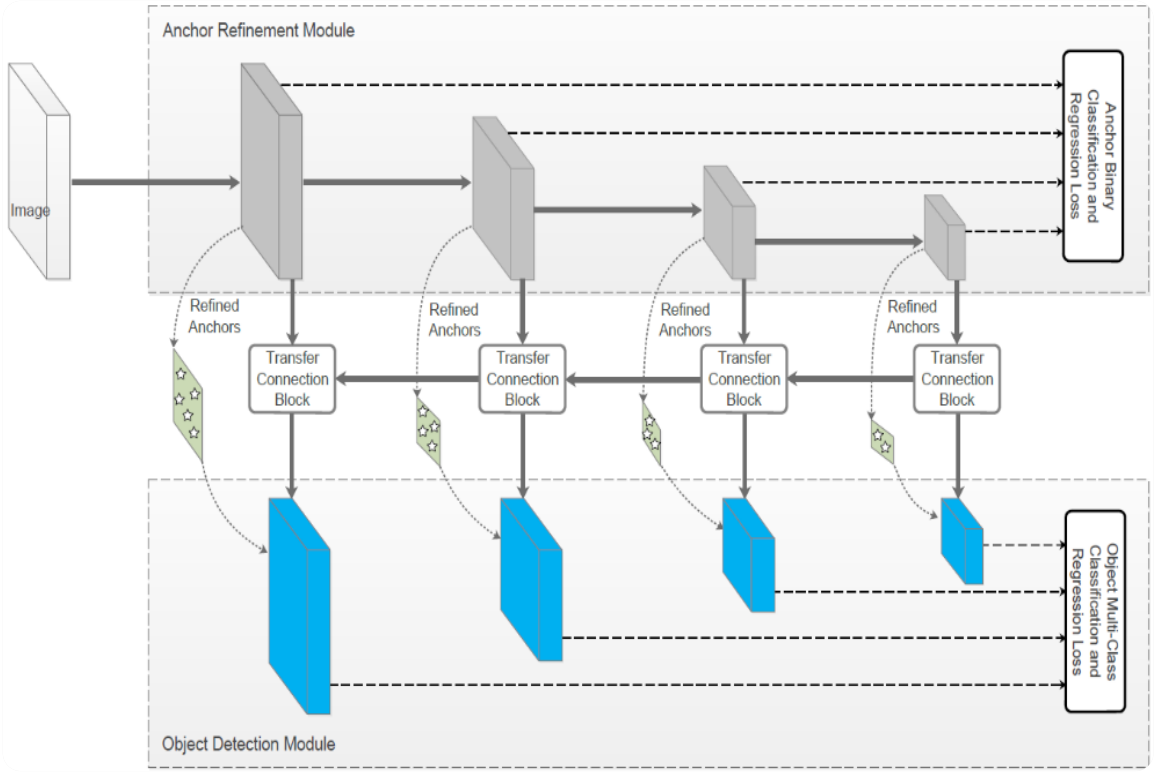

第一阶段分类

（二分类）

第二阶段分类

（多分类）

# 实用物体检测算法RefineDet：二阶段回归



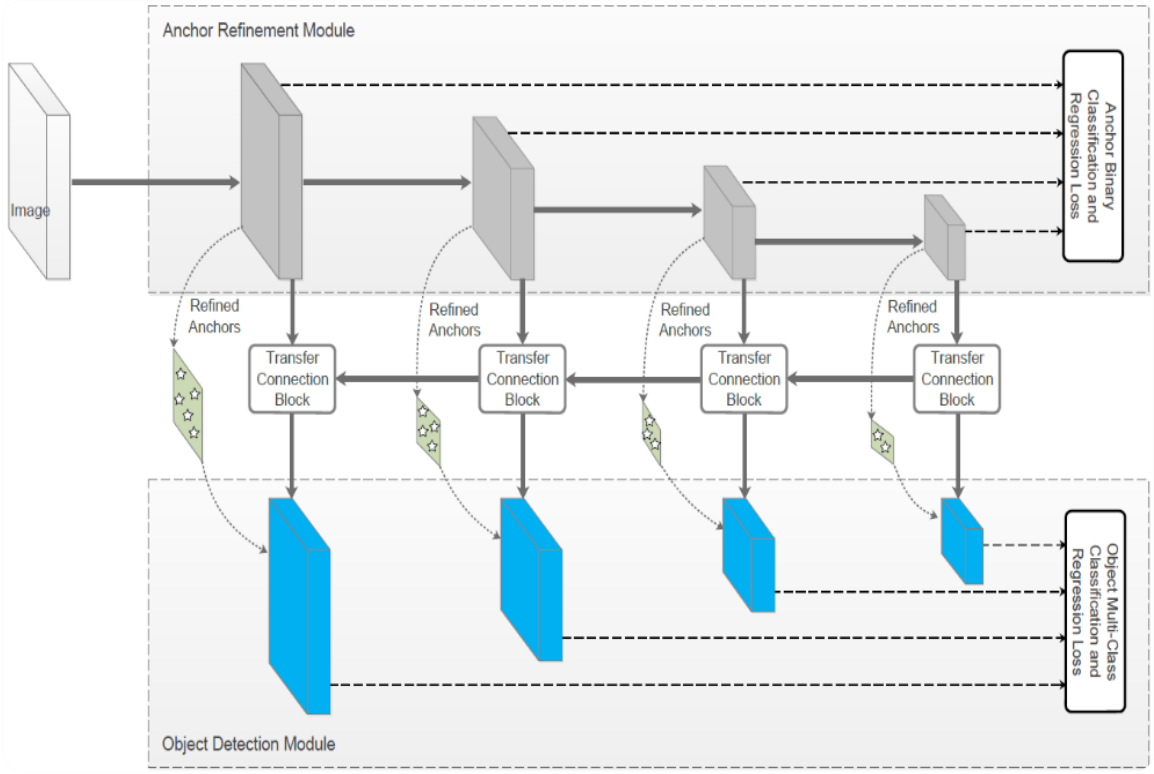

**第一阶段回归**

**（初始矫正）**

**第二阶段回归**

**（精准矫正）**

# 实用物体检测算法RefineDet：二阶段特征



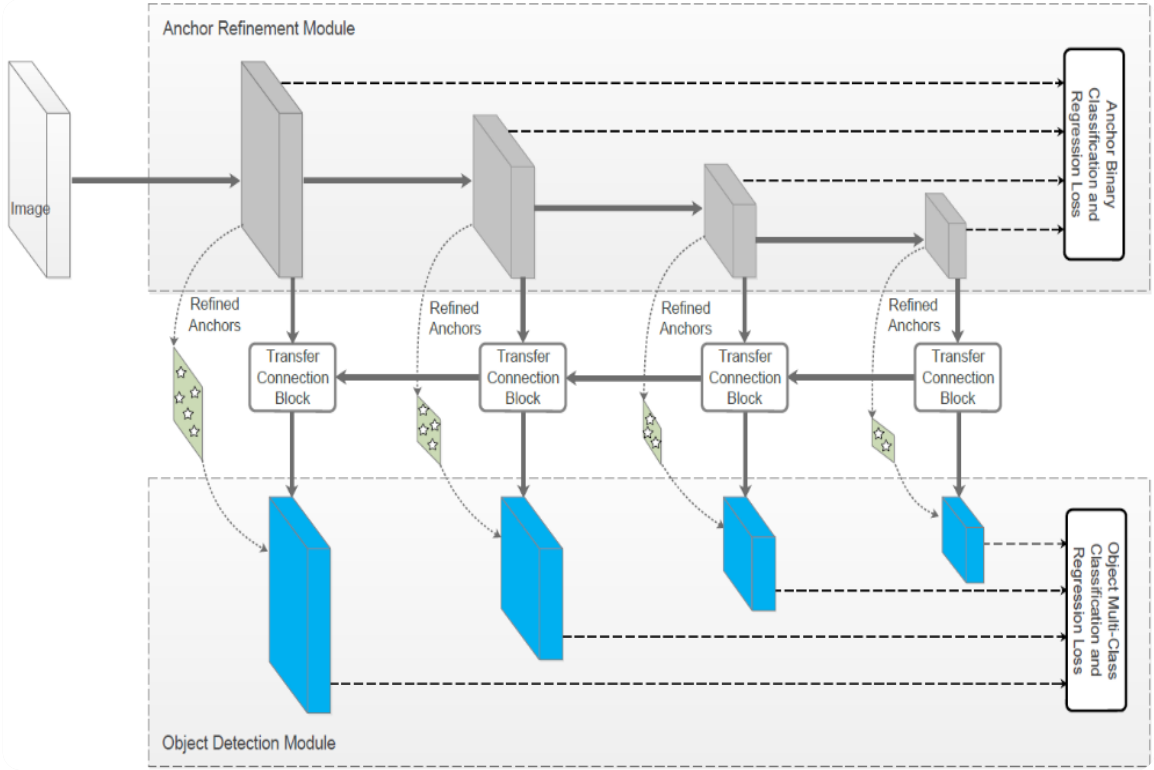

第一阶段特征

（基础网络）

第二阶段特征

（FPN强化）

# 实用物体检测算法RefineDet：二阶段特征




**全卷积网络实现**

**少量额外计算**

# 实用物体检测算法RefineDet：速度精度

| System | VOC2007 test *mAP* | FPS (Titan X) | Number of Boxes | Input resolution |
|---|---|---|---|---|
| Faster R-CNN (VGG16) | 73.2 | 7 | ~6000 | ~1000 x 600 |
| YOLO (GoogleNe) | 63.4 | 45 | 98 | 448 x 448 |
| YOLOv2 (Darknet-19) | 78.6 | 40 | 845 | 544 x 544 |
| SSD300* (VGG16) | 77.2 | 46 | 8732 | 300 x 300 |
| SSD512* (VGG16) | 79.8 | 19 | 24564 | 512 x 512 |
| RefineDet320 (VGG16) | 80.0 | 40 | 6375 | 320 x 320 |
| RefineDet512 (VGG16) | **81.8** | 24 | 16320 | 512 x 512 |

- 单阶段法的速度
- 多阶段法的精度

# 实用物体检测算法RefineDet：速度精度

| System | VOC2007 test *mAP* | FPS (Titan X) | Number of Boxes | Input resolution |
|---|---|---|---|---|
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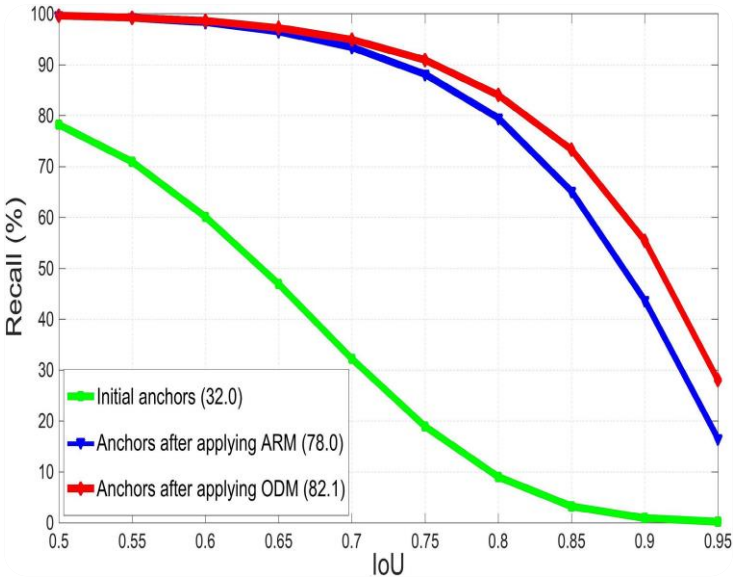
| SSD300* (VGG16) | 77.2 | 46 | 8732 | 300 x 300 |
| SSD512* (VGG16) | 79.8 | 19 | 24564 | 512 x 512 |
| RefineDet320 (VGG16) | 80.0 | 40 | 6375 | 320 x 320 |
| RefineDet512 (VGG16) | **81.8** | 24 | 16320 | 512 x 512 |

- 相对于baseline的SSD，不仅精度提高2个点，速度变快5 FPS
- 精度提高得益于二阶段分类、二阶段回归、二阶段特征
- 速度变快是因为①用了更少的检测层 (6->4)；②用了更少锚框(25K->16K)

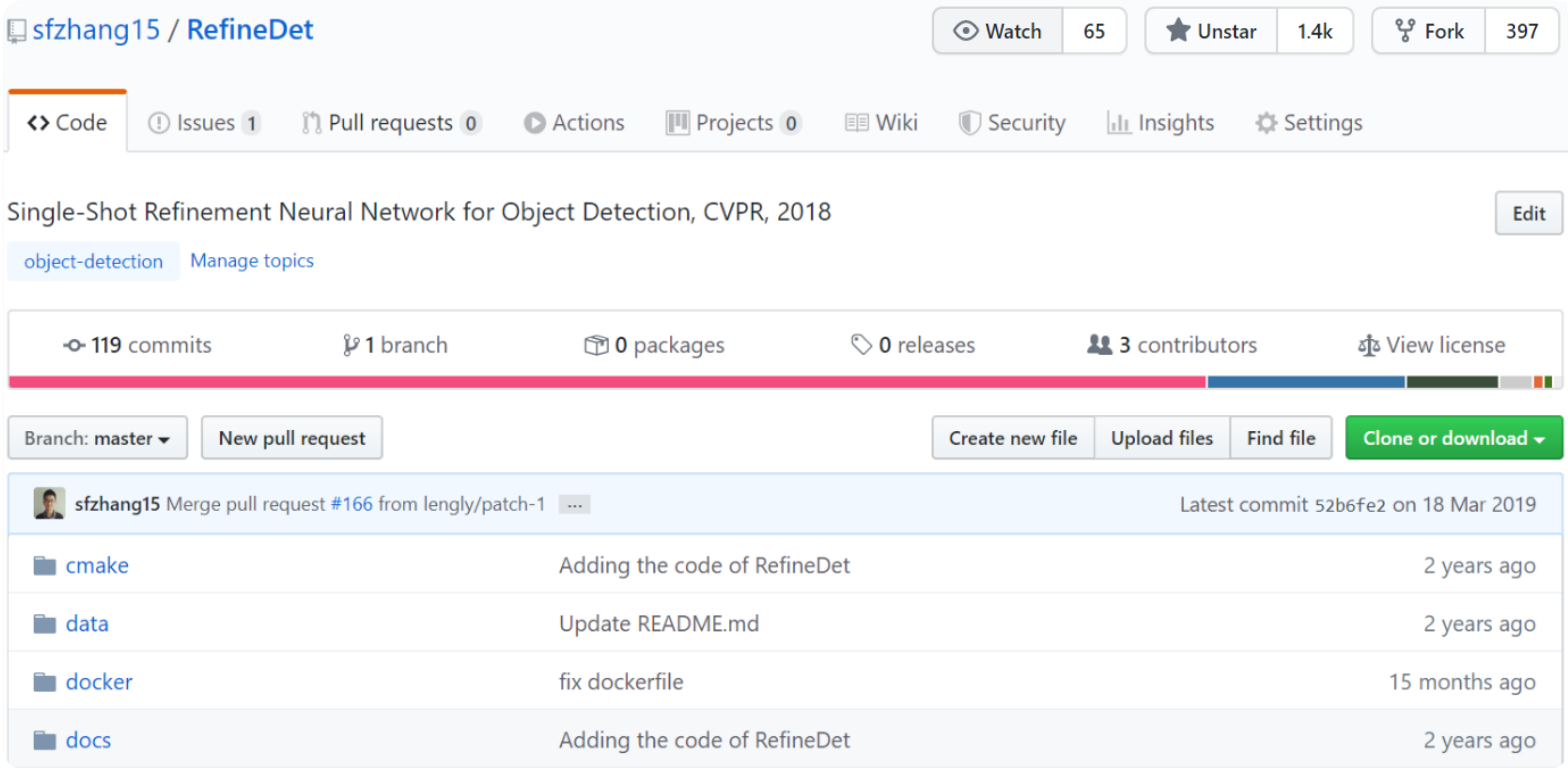
# 实用物体检测算法RefineDet：有效性验证

| Component | RefineDet320 | | | |
|---|---|---|---|---|
| negative anchor filtering? | ✓ | | | |
| two-step cascaded regression? | ✓ | ✓ | | |
| transfer connection block? | ✓ | ✓ | ✓ | |
| mAP (%) | 80.0 | 79.5 | 77.3 | 76.2 |



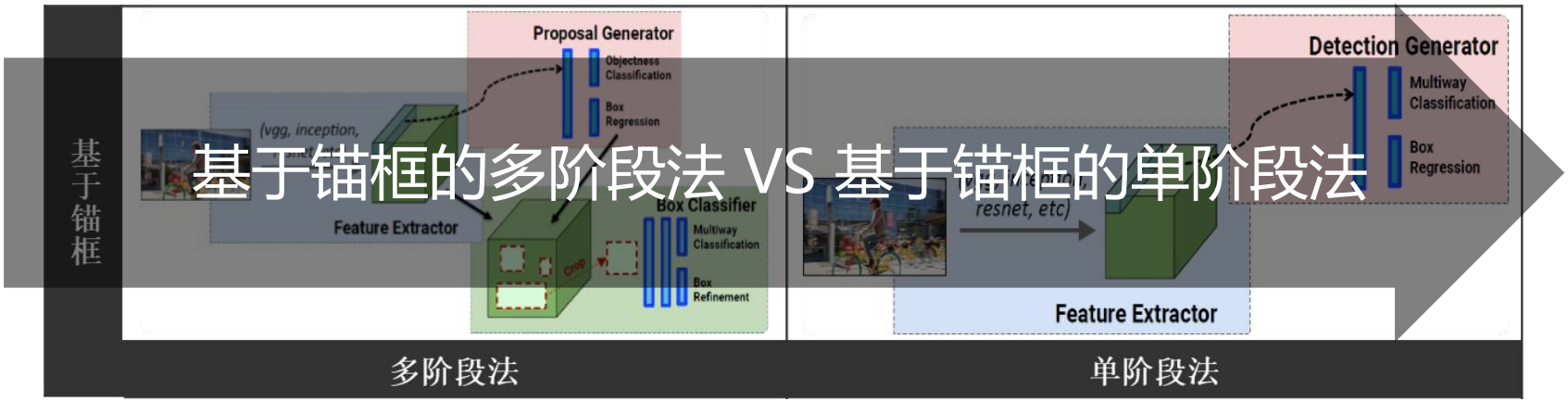

- 二阶段分类 **+0.5**
- 二阶段回归 **+2.2**
- 二阶段特征 **+1.1**

# 实用物体检测算法RefineDet：代码开源



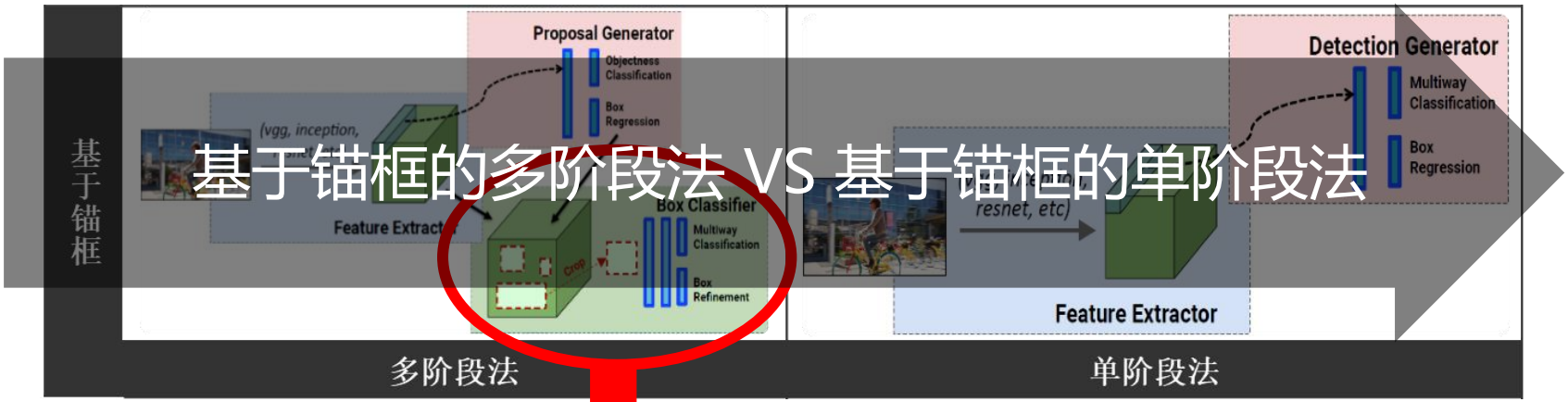

https://github.com/sfzhang15/RefineDet

# 实用物体检测算法RefineDet




基于锚框的多阶段法 VS 基于锚框的单阶段法

# 实用物体检测算法RefineDet




基于锚框的多阶段法 VS 基于锚框的单阶段法

① 二阶段的分类

② 二阶段的回归

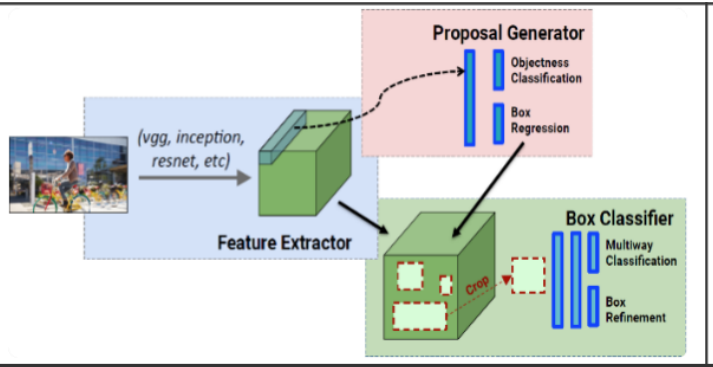
③ 二阶段的特征

~~④ 特征的校准~~

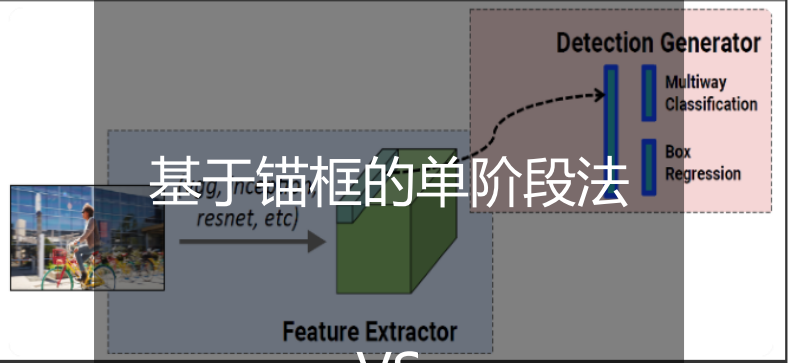
实用物体检测算法 RefineDet

# 实用检测算法的研究思路：对比探索

基于锚框




多阶段法

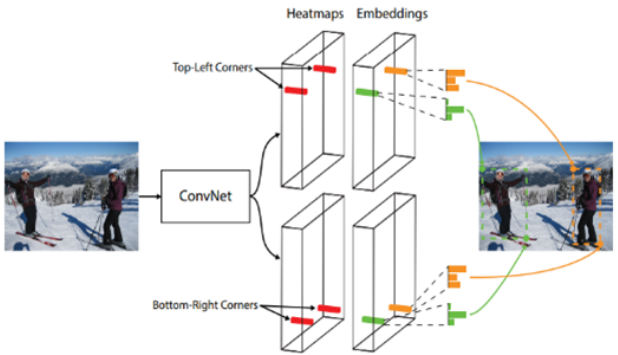



单阶段法

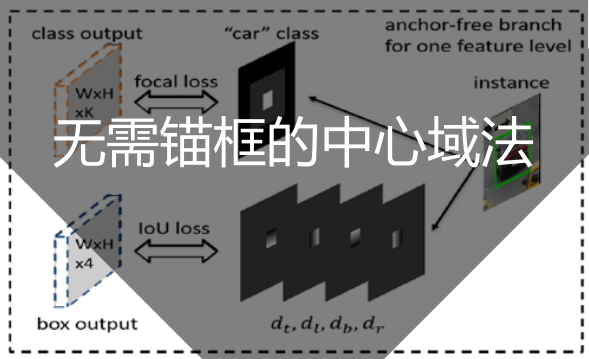
基于锚框的单阶段法

VS

无需锚框




关键点法




中心域法

无需锚框的中心域法

# 基于锚框的单阶段法 VS 无需锚框的中心域法

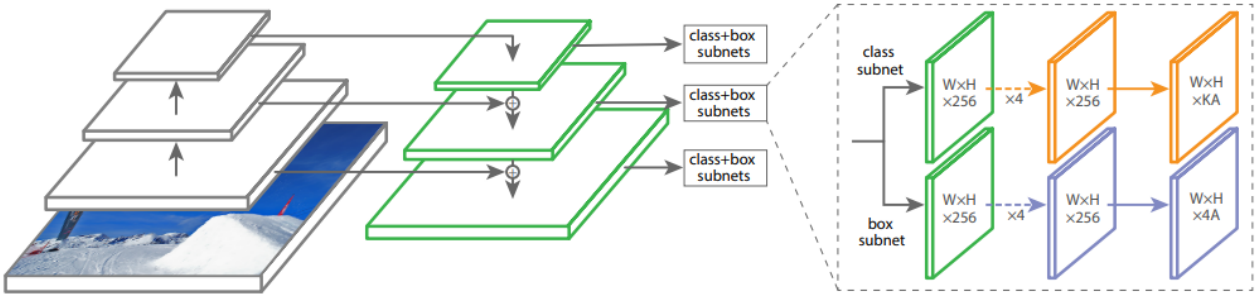
检测流程非常相似

基于锚框的单阶段法

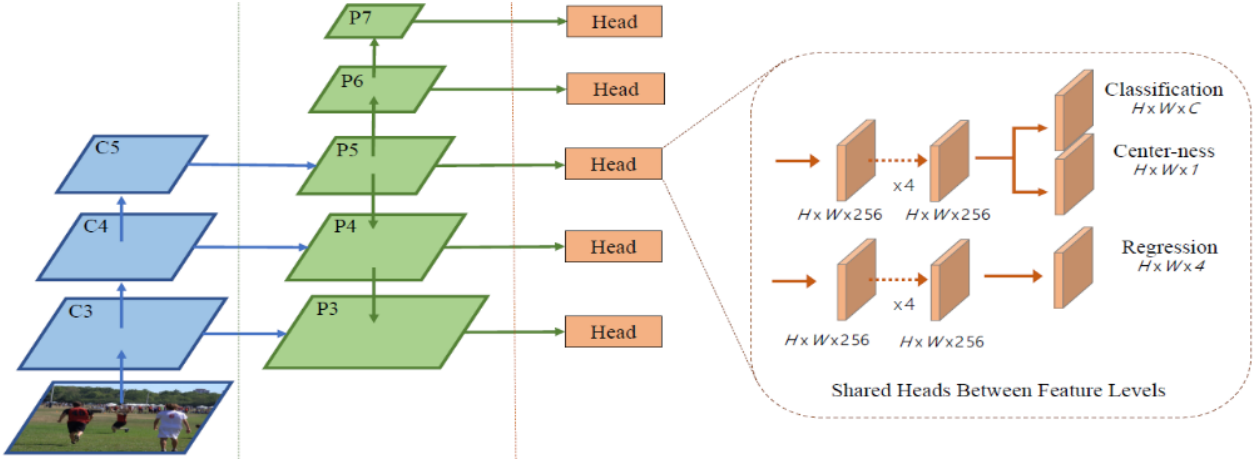

无需锚框的中心域法

# RetinaNet 与FCOS 的相同点

基于锚框的单阶段法
RetinaNet




无需锚框的中心域法
FCOS

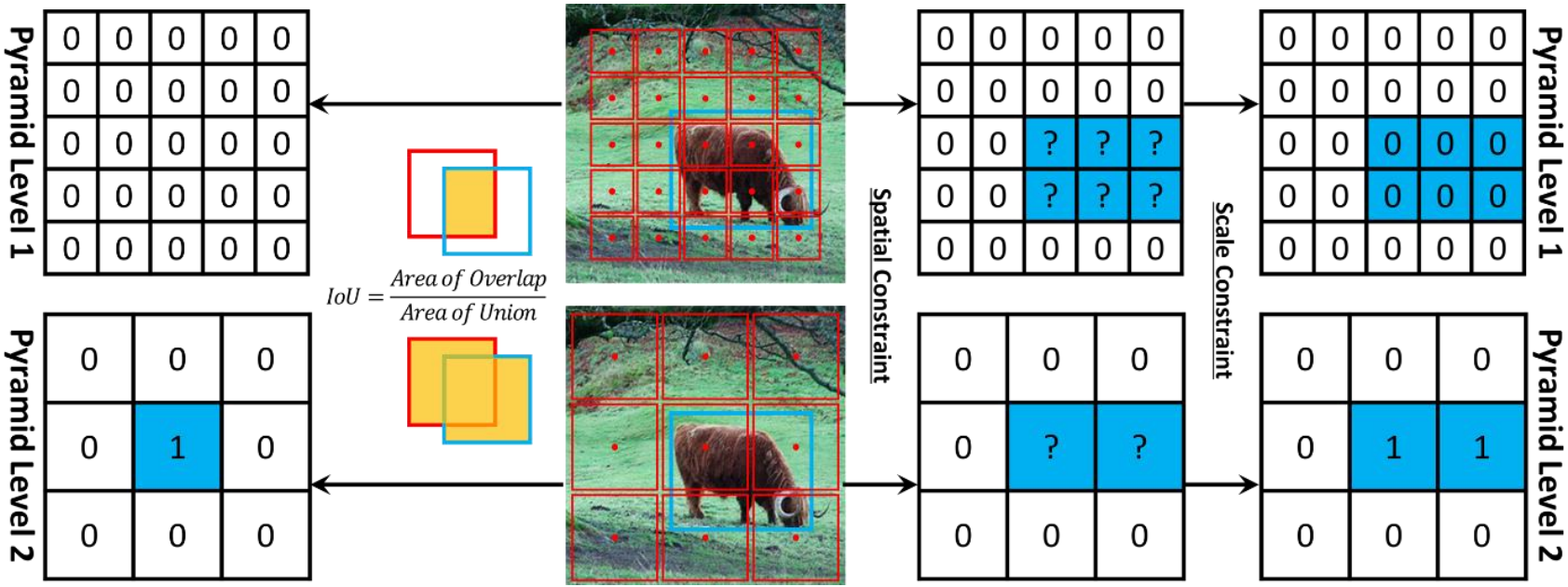



- 相同的基础网络
- 特征金字塔
- 分类子网络
- 回归子网络

# RetinaNet和FCOS的不同点

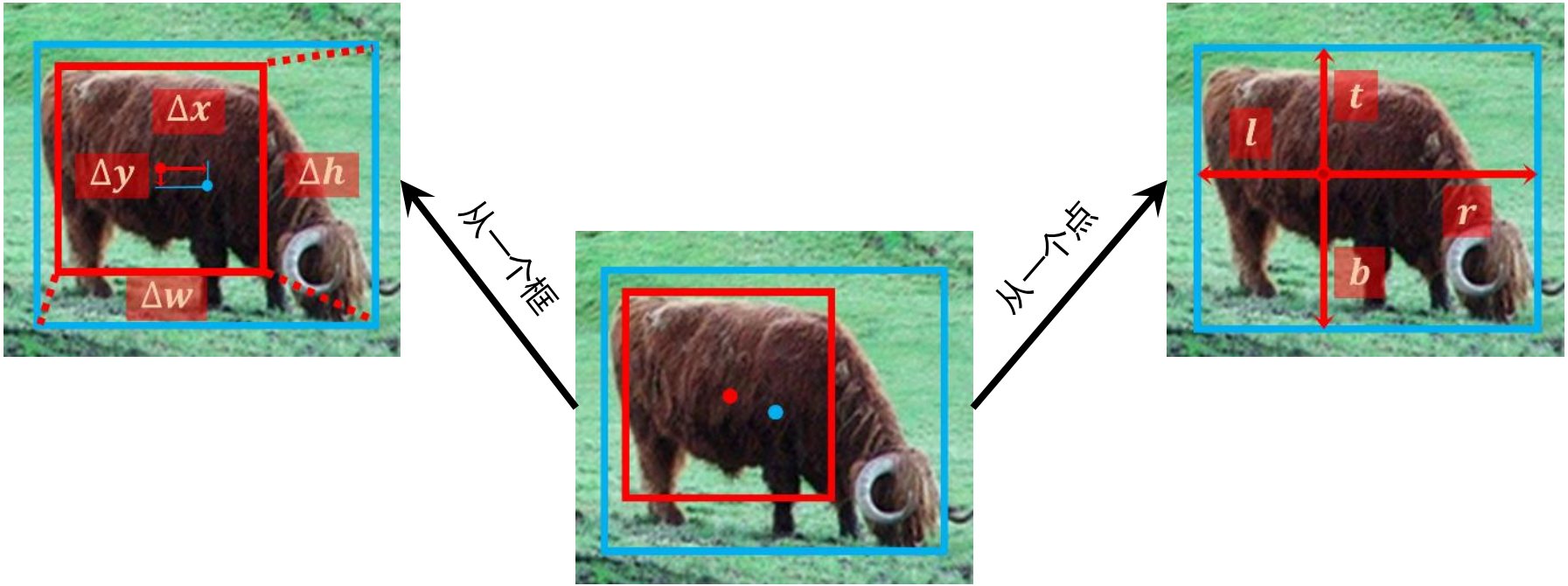
# RetinaNet和FCOS的不同点：①正负样本定义

- RetinaNet：利用IoU选取正负训练样本
- FCOS：利用空间和尺度上的限制来选取正负训练样本



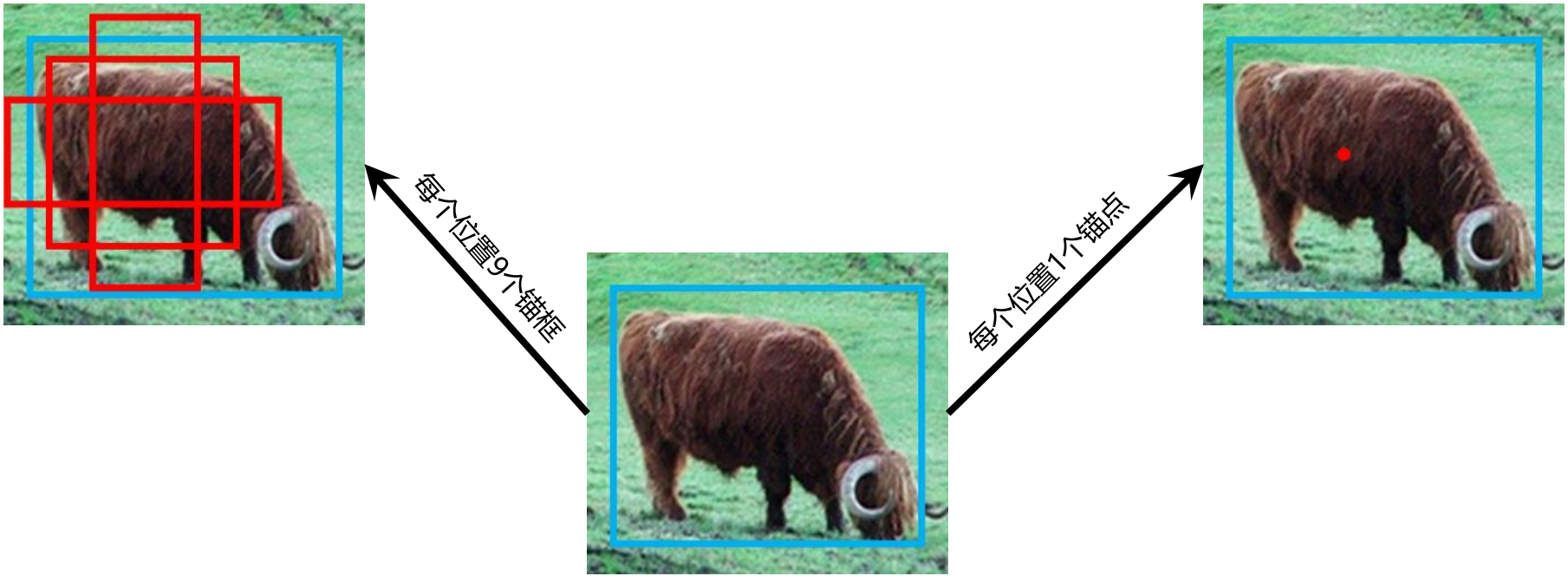
# RetinaNet和FCOS的不同点：②回归起点

- RetinaNet：从一个矩形框（锚框）开始回归物体
- FCOS：从一个点（锚点）开始回归物体



# RetinaNet和FCOS的不同点：③每个位置铺设的样本个数

- RetinaNet：在每个位置铺设了9个锚框（3个比例和3个尺度）
- FCOS：在每个位置只铺设了一个锚点



# RetinaNet和FCOS的不同点

① 正负训练样本定义的不同

② 回归的起点不同

③ 每个位置铺设的样本个数不同

**哪一个是本质区别?**

**让FCOS在速度稍微变快的同时，精度得到提高**

**找到这个高效的本质区别，并加以改进提出ATSS**

Bridging the Gap Between Anchor-based and Anchor-free Detection via Adaptive Training Sample Selection, CVPR 2000

# 实用物体检测算法ATSS：排除实现不一致

① 正负训练样本定义的不同

② 回归的起点不同

| Inconsistency | FCOS | RetinaNet (#A=1) | | | | | |
|---|---|---|---|---|---|---|---|
| GroupNorm | ✓ | | ✓ | ✓ | ✓ | ✓ | ✓ |
| GIoU Loss | ✓ | | | ✓ | ✓ | ✓ | ✓ |
| In GT Box | ✓ | | | | ✓ | ✓ | ✓ |
| Centerness | ✓ | | | | | ✓ | ✓ |
| Scalar | ✓ | | | | | | ✓ |
| AP (%) | 37.8 | 32.5 | 33.4 | 34.9 | 35.3 | 36.8 | 37.0 |

# 实用物体检测算法ATSS：排除实现不一致

① 正负训练样本定义的不同

② 回归的起点不同

| Inconsistency | FCOS | RetinaNet (#A=1) | | | | |
|---|---|---|---|---|---|---|
| GroupNorm | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| GIoU Loss | ✓ | | ✓ | ✓ | ✓ | ✓ |
| In GT Box | ✓ | | | ✓ | ✓ | ✓ |
| Centerness | ✓ | | | | ✓ | ✓ |
| Scalar | ✓ | | | | | ✓ |
| AP (%) | 37.8 | 32.5 | 33.4 | 34.9 | 35.3 | 36.8 | 37.0 |

# 实用物体检测算法ATSS：排除实现不一致

① 正负训练样本定义的不同

② 回归的起点不同

| Inconsistency | FCOS | RetinaNet (#A=1) | | | | |
|---|---|---|---|---|---|---|
| GroupNorm | ✓ | | ✓ | ✓ | ✓ | ✓ | ✓ |
| GIoU Loss | ✓ | | | ✓ | ✓ | ✓ | ✓ |
| In GT Box | ✓ | | | | ✓ | ✓ | ✓ |
| Centerness | ✓ | | | | | ✓ | ✓ |
| Scalar | ✓ | | | | | | ✓ |
| AP (%) | 37.8 | 32.5 | 33.4 | 34.9 | 35.3 | 36.8 | 37.0 |

# 实用物体检测算法ATSS：排除实现不一致

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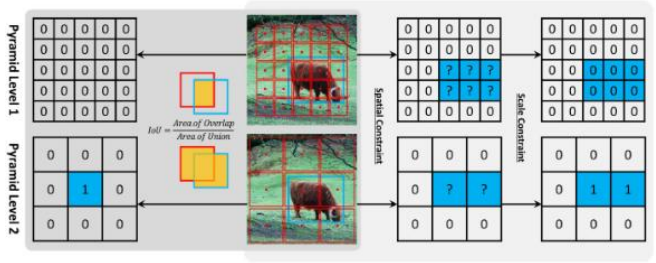
② 回归的起点不同

| Inconsistency | FCOS | RetinaNet (#A=1) | | | | | |
|---|---|---|---|---|---|---|---|
| GroupNorm | ✓ | | ✓ | ✓ | ✓ | ✓ | ✓ |
| GIoU Loss | ✓ | | | ✓ | ✓ | ✓ | ✓ |
| In GT Box | ✓ | | | | ✓ | ✓ | ✓ |
| Centerness | ✓ | | | | | ✓ | ✓ |
| Scalar | ✓ | | | | | | ✓ |
| AP (%) | 37.8 | 32.5 | 33.4 | 34.9 | 35.3 | 36.8 | 37.0 |

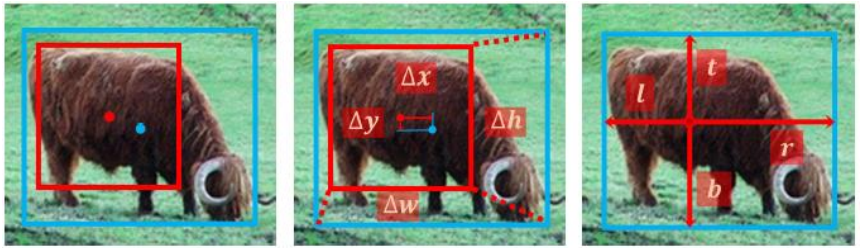
# 实用物体检测算法ATSS：探索本质区别

① 正负训练样本定义的不同

② 回归的起点不同




(a) RetinaNet (b) FCOS



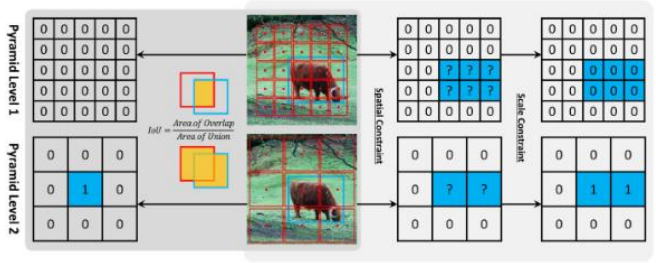

(a) Positive sample (b) RetinaNet (c) FCOS

| Classification \ Regression | Box | Point |
|---|---|---|
| Intersection over Union | 37.0 | 36.9 |
| Spatial and Scale Constraint | 37.8 | 37.8 |

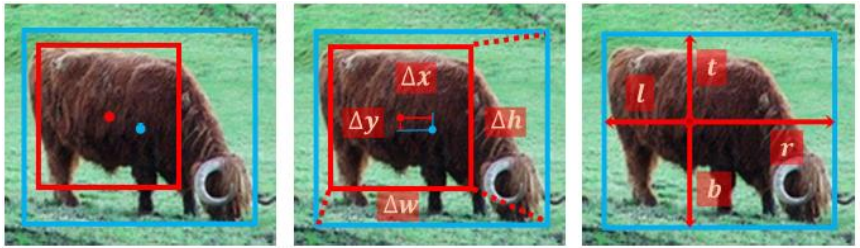
# 实用物体检测算法ATSS：探索本质区别

① 正负训练样本定义的不同

② 回归的起点不同




(a) RetinaNet (b) FCOS



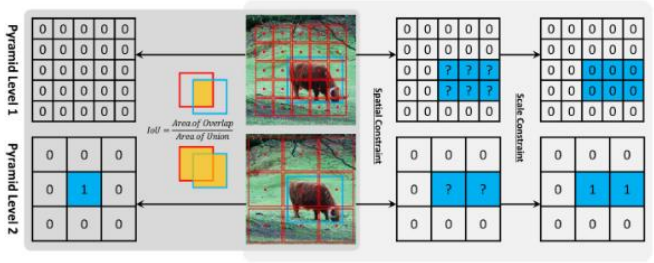

(a) Positive sample (b) RetinaNet (c) FCOS

| Classification \ Regression | Box | Point |
|---|---|---|
| Intersection over Union | 37.0 | 36.9 |
| Spatial and Scale Constraint | 37.8 | 37.8 |

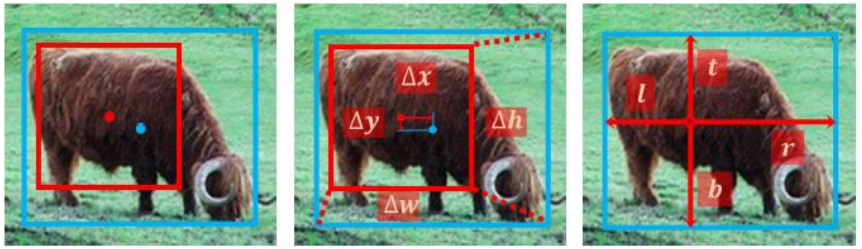
# 实用物体检测算法ATSS：探索本质区别

① 正负训练样本定义的不同

② ~~回归的起点不同~~




(a) RetinaNet (b) FCOS




(a) Positive sample (b) RetinaNet (c) FCOS

| Classification \ Regression | Box | Point |
|---|---|---|
| Intersection over Union | 37.0 | 36.9 |
| Spatial and Scale Constraint | 37.8 | 37.8 |

# 实用物体检测算法ATSS：自适应训练样本选取

① 正负训练样本定义的不同

~~② 回归的起点不同~~

# 实用物体检测算法ATSS：自适应训练样本选取

① 正负训练样本定义的不同

② ~~回归的起点不同~~

**for** each level $i \in [1, \mathcal{L}]$ **do**
  $\mathcal{S}_i \leftarrow$ select $k$ anchors from $A_i$ whose center are closest to the center of ground-truth $g$ based on L2 distance;
  $\mathcal{C}_g = \mathcal{C}_g \cup \mathcal{S}_i$;
**end for**
compute IoU between $\mathcal{C}_g$ and $g$: $\mathcal{D}_g = IoU(\mathcal{C}_g, g)$;
compute mean of $\mathcal{D}_g$: $m_g = Mean(\mathcal{D}_g)$;
compute standard deviation of $\mathcal{D}_g$: $v_g = Std(\mathcal{D}_g)$;
compute IoU threshold for ground-truth $g$: $t_g = m_g + v_g$;

- $L$是检测层的个数
- $A_i$是第$i$个检测层所关联的锚框
- $g$是真实标注
- $k$是超参数，默认值为9
- $S_i$是$g$在第$i$个检测层上选取的$k$个候选正样本
- $C_g$是$g$所有的候选正样本

# 实用物体检测算法ATSS：自适应训练样本选取

① 正负训练样本定义的不同

~~② 回归的起点不同~~

**for** each level $i \in [1, \mathcal{L}]$ **do**
$\mathcal{S}_i \leftarrow$ select $k$ anchors from $A_i$ whose center are closest to the center of ground-truth $g$ based on L2 distance;
$\mathcal{C}_g = \mathcal{C}_g \cup \mathcal{S}_i$;
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compute IoU between $\mathcal{C}_g$ and $g$: $\mathcal{D}_g = IoU(\mathcal{C}_g, g)$;
compute mean of $\mathcal{D}_g$: $m_g = Mean(\mathcal{D}_g)$;
compute standard deviation of $\mathcal{D}_g$: $v_g = Std(\mathcal{D}_g)$;
compute IoU threshold for ground-truth $g$: $t_g = m_g + v_g$;

■ $D_g$是所有候选正样本$C_g$跟$g$的IoU

# 实用物体检测算法ATSS：自适应训练样本选取

① 正负训练样本定义的不同

~~② 回归的起点不同~~

**for** each level $i \in [1, \mathcal{L}]$ **do**
  $\mathcal{S}_i \leftarrow$ select $k$ anchors from $A_i$ whose center are closest to the center of ground-truth $g$ based on L2 distance;
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**end for**
compute IoU between $\mathcal{C}_g$ and $g$: $\mathcal{D}_g = IoU(\mathcal{C}_g, g)$;
compute mean of $\mathcal{D}_g$: $m_g = Mean(\mathcal{D}_g)$;
compute standard deviation of $\mathcal{D}_g$: $v_g = Std(\mathcal{D}_g)$;
compute IoU threshold for ground-truth $g$: $t_g = m_g + v_g$;

- $m_g$是$g$跟所有候选正样本$\mathcal{C}_g$的IoU的均值
- $v_g$是$g$跟所有候选正样本$\mathcal{C}_g$的IoU的标准差

# 实用物体检测算法ATSS：自适应训练样本选取

每个物体都有一个自适应阈值

① 正负训练样本定义的不同

② ~~回归的起点不同~~

**for** each level $i \in [1, \mathcal{L}]$ **do**
  $\mathcal{S}_i \leftarrow$ select $k$ anchors from $A_i$ whose center are closest
  to the center of ground-truth $g$ based on L2 distance;
  $\mathcal{C}_g = \mathcal{C}_g \cup \mathcal{S}_i$;
**end for**
compute IoU between $\mathcal{C}_g$ and $g$: $\mathcal{D}_g = IoU(\mathcal{C}_g, g)$;
compute mean of $\mathcal{D}_g$: $m_g = Mean(\mathcal{D}_g)$;
compute standard deviation of $\mathcal{D}_g$: $v_g = Std(\mathcal{D}_g)$;
compute IoU threshold for ground-truth $g$: $t_g = m_g + v_g$;

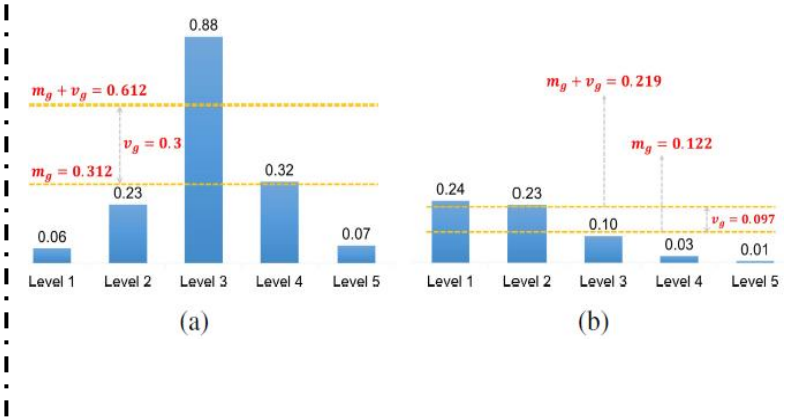
■ $t_g$是$g$从所有候选正样本$\mathcal{C}_g$中选取最终正样本的阈值

# 实用物体检测算法ATSS：自适应训练样本选取

① 正负训练样本定义的不同

② ~~回归的起点不同~~

**for** each level $i \in [1, \mathcal{L}]$ **do**
  $\mathcal{S}_i \leftarrow$ select $k$ anchors from $A_i$ whose center are closest to the center of ground-truth $g$ based on L2 distance;
  $\mathcal{C}_g = \mathcal{C}_g \cup \mathcal{S}_i$;
**end for**
compute IoU between $\mathcal{C}_g$ and $g$: $\mathcal{D}_g = IoU(\mathcal{C}_g, g)$;
compute mean of $\mathcal{D}_g$: $m_g = Mean(\mathcal{D}_g)$;
compute standard deviation of $\mathcal{D}_g$: $v_g = Std(\mathcal{D}_g)$;
compute IoU threshold for ground-truth $g$: $t_g = m_g + v_g$;



# 实用物体检测算法ATSS：自适应训练样本选取

① 正负训练样本定义的不同

② ~~回归的起点不同~~

**for** each level $i \in [1, \mathcal{L}]$ **do**
  $\mathcal{S}_i \leftarrow$ select $k$ anchors from $A_i$ whose center are closest to the center of ground-truth $g$ based on L2 distance;
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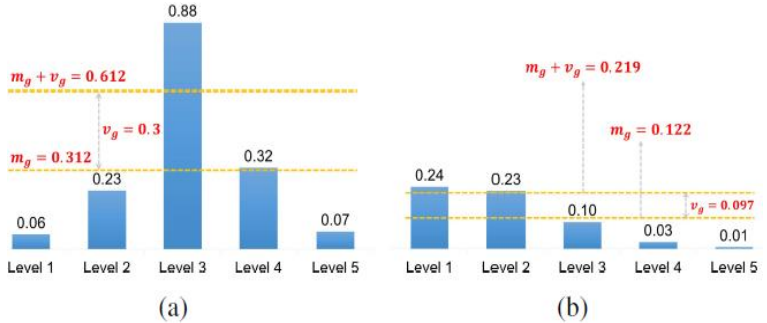
**end for**
compute IoU between $\mathcal{C}_g$ and $g$: $\mathcal{D}_g = IoU(\mathcal{C}_g, g)$;
compute mean of $\mathcal{D}_g$: $m_g = Mean(\mathcal{D}_g)$;
compute standard deviation of $\mathcal{D}_g$: $v_g = Std(\mathcal{D}_g)$;
compute IoU threshold for ground-truth $g$: $t_g = m_g + v_g$;




| Method | AP | $AP_{50}$ | $AP_{75}$ | $AP_S$ | $AP_M$ | $AP_L$ |
|---|---|---|---|---|---|---|
| RetinaNet (#A=1) | 37.0 | 55.1 | 39.9 | 21.4 | 41.2 | 48.6 |
| RetinaNet (#A=1) + ATSS | 39.3 | 57.5 | 42.8 | 24.3 | 43.3 | 51.3 |
| FCOS | 37.8 | 55.6 | 40.7 | 22.1 | 41.8 | 48.8 |
| FCOS + Center sampling | 38.6 | 57.4 | 41.4 | 22.3 | 42.5 | 49.8 |
| FCOS + ATSS | 39.2 | 57.3 | 42.4 | 22.7 | 43.1 | 51.5 |

| | | | | | | |
|---|---|---|---|---|---|---|
| ResNet-101 | 43.6 | 62.1 | 47.4 | 26.1 | 47.0 | 53.6 |
| ResNeXt-32x8d-101 | 45.1 | 63.9 | 49.1 | 27.9 | 48.2 | 54.6 |
| ResNeXt-64x4d-101 | 45.6 | 64.6 | 49.7 | 28.5 | 48.9 | 55.6 |
| ResNet-101-DCN | 46.3 | 64.7 | 50.4 | 27.7 | 49.8 | 58.4 |
| ResNeXt-32x8d-101-DCN | 47.7 | 66.6 | 52.1 | 29.3 | 50.8 | 59.7 |
| ResNeXt-64x4d-101-DCN | 47.7 | 66.5 | 51.9 | 29.7 | 50.8 | 59.4 |
| ResNeXt-32x8d-101-DCN | 50.6 | 68.6 | 56.1 | **33.6** | **52.9** | 62.2 |
| ResNeXt-64x4d-101-DCN | **50.7** | **68.9** | **56.3** | 33.2 | **52.9** | **62.4** |

# 实用物体检测算法ATSS：超参数分析

| $k$ | 3 | 5 | 7 | 9 | 11 | 13 | 15 | 17 | 19 |
|---|---|---|---|---|---|---|---|---|---|
| AP (%) | 38.0 | 38.8 | 39.1 | 39.3 | 39.1 | 39.0 | 39.1 | 39.2 | 38.9 |

- 超参k很鲁棒

# 实用物体检测算法ATSS：超参数分析

| $k$ | 3 | 5 | 7 | 9 | 11 | 13 | 15 | 17 | 19 |
|---|---|---|---|---|---|---|---|---|---|
| AP (%) | 38.0 | 38.8 | 39.1 | 39.3 | 39.1 | 39.0 | 39.1 | 39.2 | 38.9 |

| Scale | AP | $AP_{50}$ | $AP_{75}$ | $AP_S$ | $AP_M$ | $AP_L$ |
|---|---|---|---|---|---|---|
| 5 | 39.0 | 57.9 | 41.9 | 23.2 | 42.8 | 50.5 |
| 6 | 39.2 | 57.6 | 42.5 | 23.5 | 42.8 | 51.1 |
| 7 | 39.3 | 57.6 | 42.4 | 22.9 | 43.2 | 51.3 |
| 8 | 39.3 | 57.5 | 42.8 | 24.3 | 43.3 | 51.3 |
| 9 | 38.9 | 56.5 | 42.0 | 22.9 | 42.4 | 50.3 |

| Aspect Ratio | AP | $AP_{50}$ | $AP_{75}$ | $AP_S$ | $AP_M$ | $AP_L$ |
|---|---|---|---|---|---|---|
| 4:1 | 39.1 | 57.2 | 42.3 | 23.1 | 43.1 | 51.4 |
| 2:1 | 39.0 | 56.9 | 42.5 | 23.3 | 43.5 | 50.6 |
| 1:1 | 39.3 | 57.5 | 42.8 | 24.3 | 43.3 | 51.3 |
| 2:1 | 39.3 | 57.4 | 42.3 | 22.8 | 43.4 | 51.0 |
| 4:1 | 39.1 | 56.9 | 42.6 | 22.9 | 42.9 | 50.7 |

- 超参k很鲁棒
- ATSS只在每个位置铺设一个锚框
- ATSS使用不同尺度和比例的锚框，精度变化不大
- ATSS对不同尺度和比例的锚框非常鲁棒

# 实用物体检测算法ATSS：最后一个不同点

① 正负训练样本定义的不同

~~② 回归的起点不同~~

③ 每个位置铺设的样本个数不同？

| Inconsistency | FCOS | RetinaNet (#A=1) | | | | | |
|---|---|---|---|---|---|---|---|
| GroupNorm | ✓ | | ✓ | ✓ | ✓ | ✓ | ✓ |
| GIoU Loss | ✓ | | | ✓ | ✓ | ✓ | ✓ |
| In GT Box | ✓ | | | | ✓ | ✓ | ✓ |
| Centerness | ✓ | | | | | ✓ | ✓ |
| Scalar | ✓ | | | | | | ✓ |
| AP (%) | 37.8 | 32.5 | 33.4 | 34.9 | 35.3 | 36.8 | 37.0 |

| Method | #sc | #ar | AP | $AP_{50}$ | $AP_{75}$ |
|---|---|---|---|---|---|
| RetinaNet (#A=9) | 3 | 3 | 36.3 | 55.2 | 38.8 |
| +Imprs. | 3 | 3 | 38.4 | 56.2 | 41.6 |
| +Imprs.+ATSS | 3 | 3 | 39.2 | 57.6 | 42.7 |
| +Imprs.+ATSS | 3 | 1 | 39.3 | 57.7 | 42.6 |
| +Imprs.+ATSS | 1 | 3 | 39.2 | 57.1 | 42.5 |
| +Imprs.+ATSS | 1 | 1 | 39.3 | 57.5 | 42.8 |

- 在基于IoU选取正负样本的情况下，每个位置铺设更多的锚框可以提升精度

# 实用物体检测算法ATSS：最后一个不同点

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| +Imprs.+ATSS | 3 | 3 | 39.2 | 57.6 | 42.7 |
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| +Imprs.+ATSS | 1 | 3 | 39.2 | 57.1 | 42.5 |
| +Imprs.+ATSS | 1 | 1 | 39.3 | 57.5 | 42.8 |

- 在基于IoU选取正负样本的情况下，每个位置铺设更多的锚框可以提升精度
- 在所提出的ATSS算法下，每个位置铺设更多的锚框没有带来性能的提升

# 实用物体检测算法ATSS：最后一个不同点

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| GIoU Loss | ✓ | | | ✓ | ✓ | ✓ | ✓ |
| In GT Box | ✓ | | | | ✓ | ✓ | ✓ |
| Centerness | ✓ | | | | | ✓ | ✓ |
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| AP (%) | 37.8 | 32.5 | 33.4 | 34.9 | 35.3 | 36.8 | 37.0 |

| Method | #sc | #ar | AP | $AP_{50}$ | $AP_{75}$ |
|---|---|---|---|---|---|
| RetinaNet (#A=9) | 3 | 3 | 36.3 | 55.2 | 38.8 |
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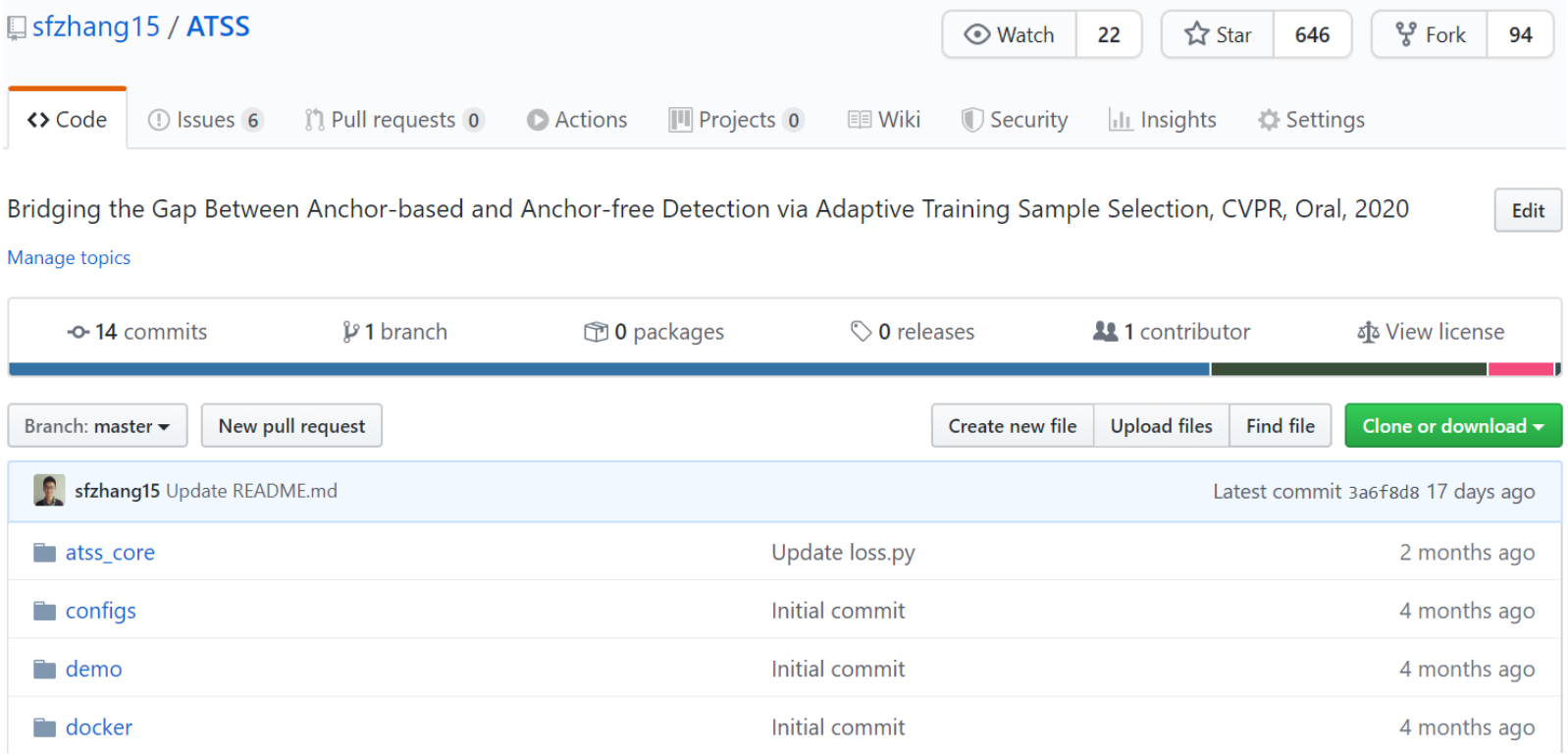
| +Imprs.+ATSS | 1 | 1 | 39.3 | 57.5 | 42.8 |

- 在选取正负样本的情况下，每个位置铺设更多的锚框可以提升精度
- 在所提出的ATSS算法下，每个位置铺设更多的锚框没有带来性能的提升
- 因此，只要合理地选取训练正负样本，每个位置铺设多少个锚框，最终结果都相似
- 结论：如果发挥多层锚框的作用，还需要进一步探索

# 实用物体检测算法ATSS：代码开源




https://github.com/sfzhang15/ATSS

# 实用物体检测算法ATSS：CVPR2020最佳论文奖提名

## Paper award nominees

Weakly-supervised Domain Adaptation via GAN and Mesh Model for Estimating 3D Hand Poses Interacting Objects
Seungryul Baek; Kwang In Kim; Tae-Kyun Kim

Unsupervised Learning of Probably Symmetric Deformable 3D Objects from Images in the Wild
Shangzhe Wu; Christian Rupprecht; Andrea Vedaldi

Bridging the Gap Between Anchor-based and Anchor-free Detection via Adaptive Training Sample Selection
Shifeng Zhang; Cheng Chi; Yongqiang Yao; Zhen Lei; Stan Li

Momentum Contrast for Unsupervised Visual Representation Learning
Kaiming He; Haoqi Fan; Yuxin Wu; Saining Xie; Ross Girshick

BSP-Net: Generating Compact Meshes via Binary Space Partitioning
Zhiqin Chen; Andrea Tagliasacchi; Hao Zhang

Disentangled image generation through structured noise injection
Yazeed Alharbi; Peter Wonka

UC-Net: Uncertainty Inspired RGB-D Saliency Detection via Conditional Variational Autoencoders
Jing Zhang; Deng-Ping Fan; Yuchao Dai; Saeed Anwar; Fatemeh Sadat Saleh; Tong Zhang; Nick Barnes

TextureFusion: High-Quality Texture Acquisition for Real-Time RGB-D Scanning
Joo Ho Lee; Hyunho Ha; Yue Dong; Xin Tong; Min H. Kim

Controllable Orthogonalization in Training DNNs
Lei Huang; Li Liu; Fan Zhu; Diwen Wan; Zehuan Yuan; Bo Li; Ling Shao

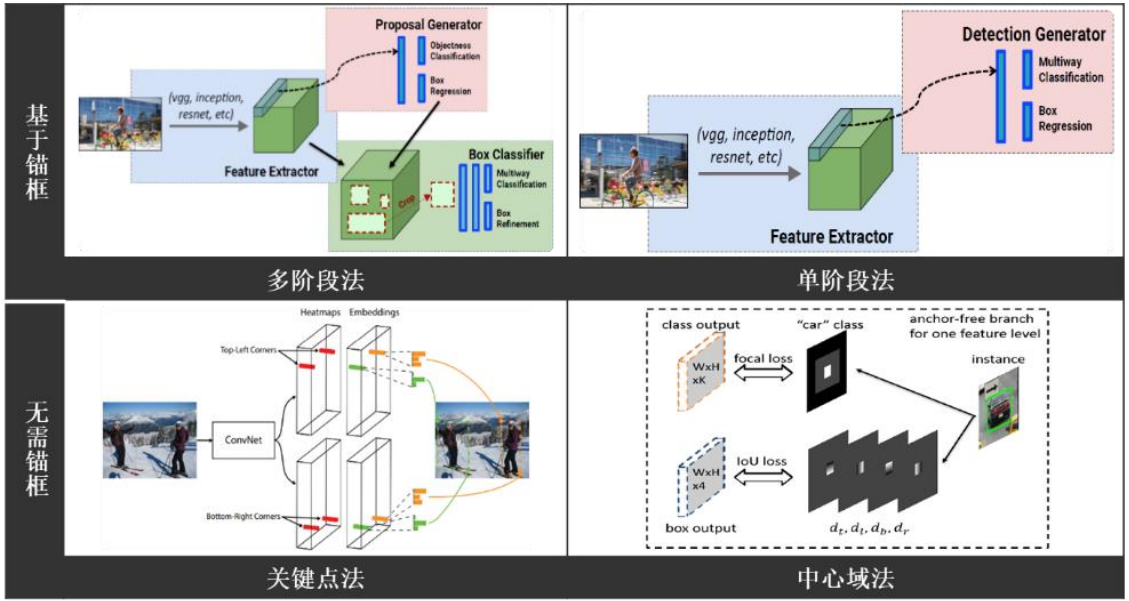
DeepCap: Monocular Human Performance Capture Using Weak Supervision
Marc Habermann; Weipeng Xu; Michael Zollhöfer; Gerard Pons-Moll; Christian Theobalt

Total3DUnderstanding: Joint Layout, Object Pose and Mesh Reconstruction for Indoor Scenes from a Single Image
Yinyu Nie; Xiaoguang Han; Shihui Guo; Yujian Zheng; Jian Chang; Jian.J Zhang

Transferring Cross-domain Knowledge for Video Sign Language Recognition
Dongxu Li; Xin Yu; Chenchen Xu; Lars Petersson; Hongdong Li

# 实用检测算法的研究思路：对比探索

- 对比不同类型的检测算法，探索两者之间的本质区别
- 取之长补己短的改进思路，提出面向实用的全新算法



# 实用检测算法的研究思路：对比探索

- 对比不同类型的检测算法，探索两者之间的本质区别
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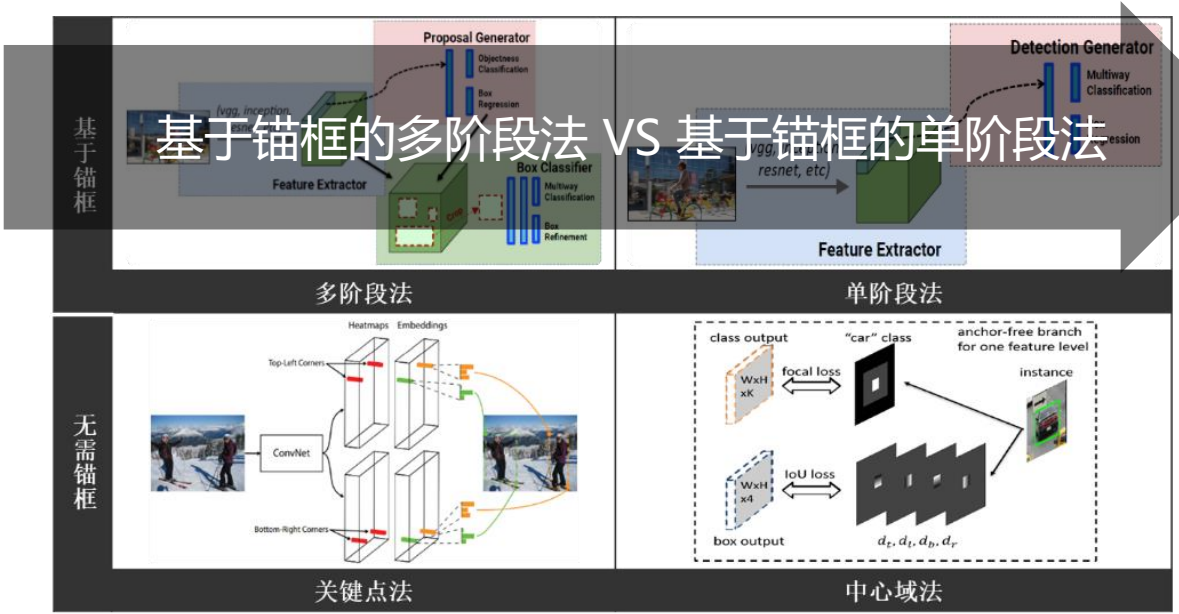


基于锚框的多阶段法 VS 基于锚框的单阶段法

① 二阶段的分类

② 二阶段的回归

③ 二阶段的特征

④特征校准

**RefineDet算法**

# 实用检测算法的研究思路：对比探索

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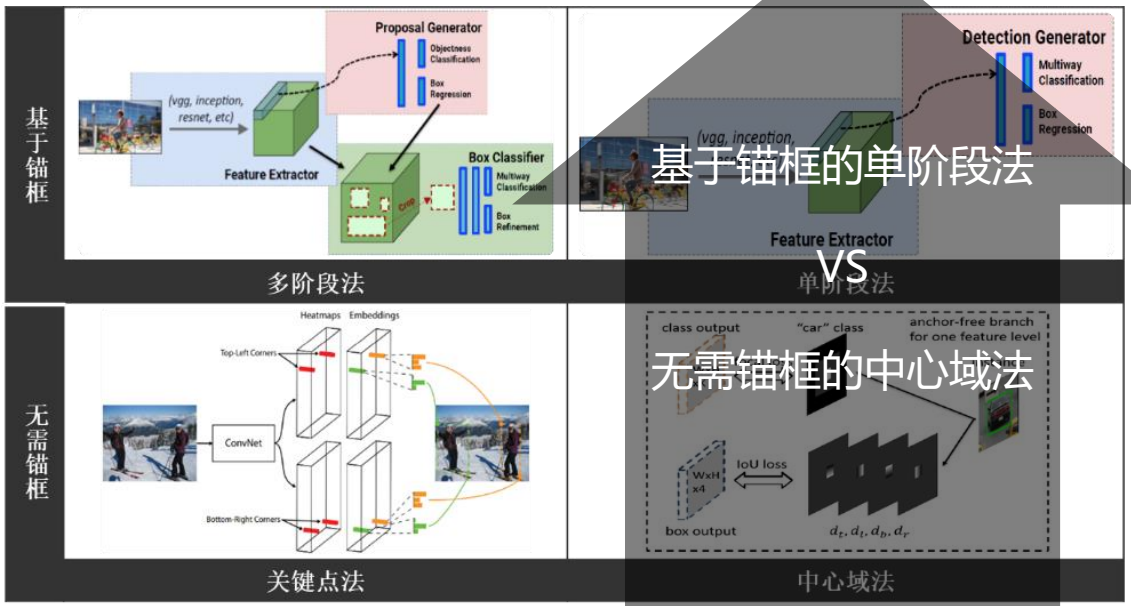


基于锚框的单阶段法

VS

无需锚框的中心域法

① 正负样本定义

~~② 回归起始状态~~

~~③ 每个位置样本数量~~

**ATSS算法**

# 课程作业

- 单步调试ATSS代码，总结RetinaNet和FCOS的区别

1. 代码链接（https://github.com/sfzhang15/ATSS）

2. 按照安装教程，利用Anaconda配置ATSS的环境

3. 利用PyCharm单步调试ATSS的代码

4. 总结RetinaNet和FCOS的区别，熟悉ATSS的改进

# 感谢聆听！

Thanks for Listening