运动分析

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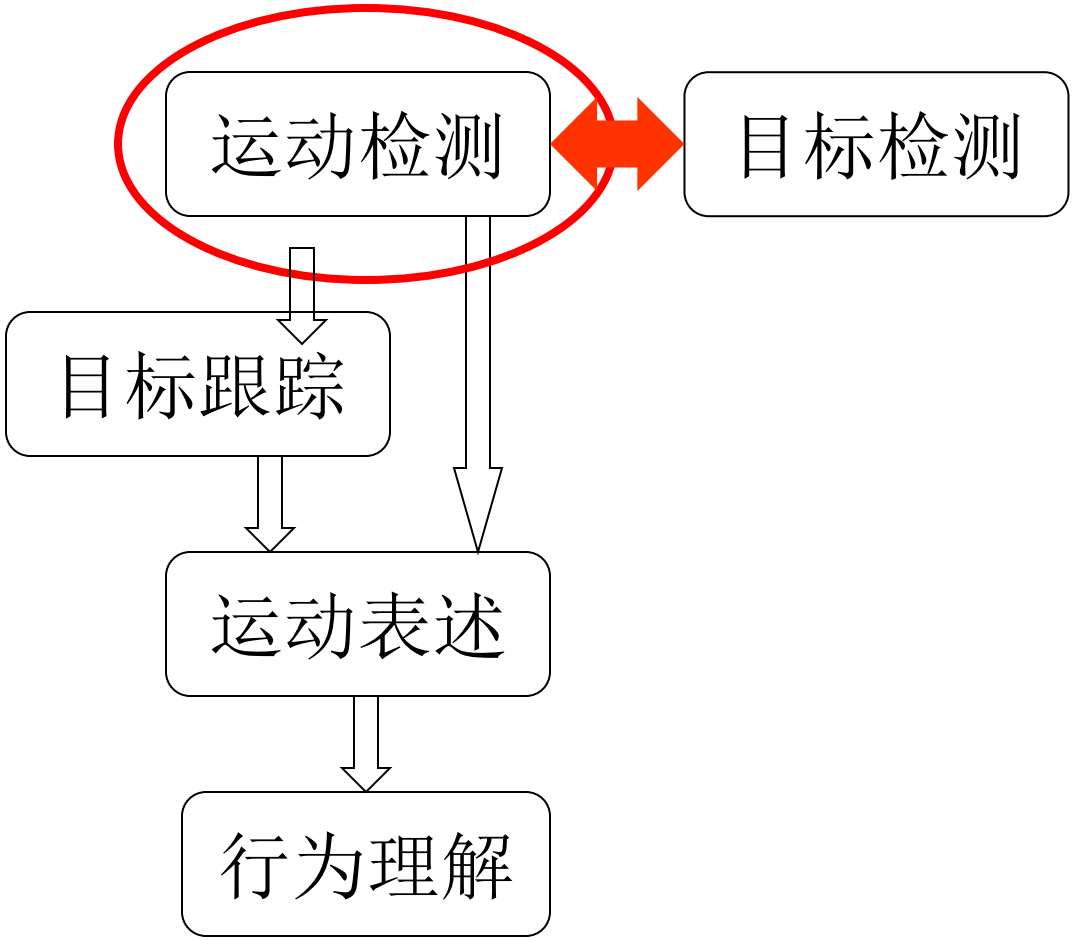
运动分析

- 什么是运动分析？

　　就是在不需要人为干预的情况下，综合利用计算机视觉、模式识别、图像处理、人工智能等诸多方面的知识对摄像机拍录的图像序列进行自动分析，实现对动态场景中人的定位、跟踪和识别，并在此基础上分析和判断人的行为。

运动分析

- 运动分析框图



运动检测

运动检测

- 什么是运动检测(Motion detection)？
  - 将运动前景从图像序列中提取出来，也就是说将背景与运动前景分离开。

运动检测

- 运动检测的重要性：
  - 是目标跟踪、运动表述和行为理解等后续处理的基础。
- 运动检测的难点：
  - 受天气、光照、阴影等诸多外界因素以及背景物体内在因素的影响，图像中的背景也常常是动态变化的。

运动检测

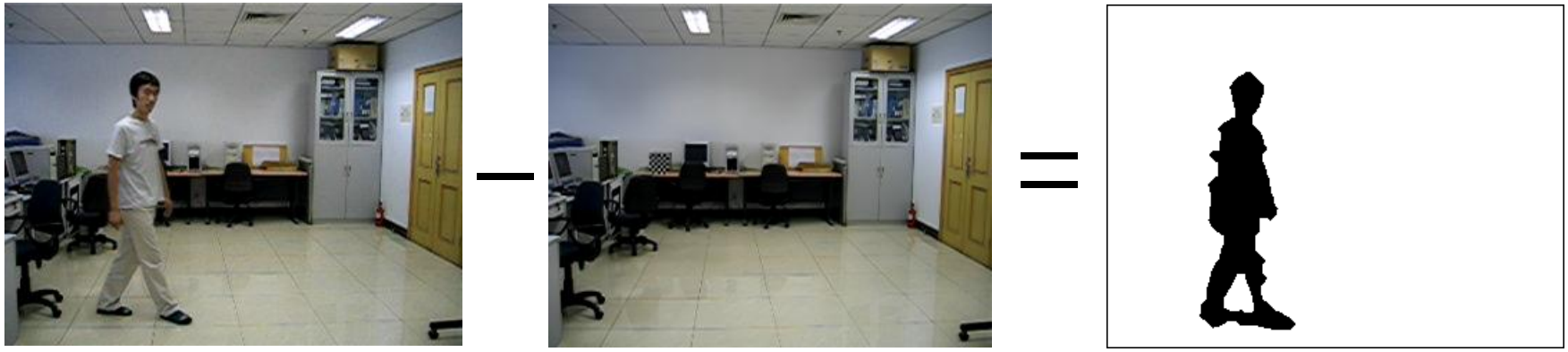
- 两种总体思路：

1. 直接利用前景所特有的信息检测前景；

基于前景信息

运动检测

2. 先得到背景图象，然后将输入图象减去背景图像从而得到前景图象。



运动检测

- 到底哪种思路好呢？也就是说，前景和背景哪一个相对好检测一些呢？

  没有绝对的好与不好，要视具体环境而定：

  ■一些场景的背景相对固定，而前景变化较大；

  ■一些场景的背景有较大变化，而前景的一些特征变化不大。

运动检测

- 常规的运动检测方法：
  - 背景差法(background subtraction)
  - 光流(optical flow)
  - 帧间差分(frame differencing)

背景差法

- 原理：计算当前图像与背景图像的逐象素的灰度差，再通过设置阈值来确定运动前景区域。

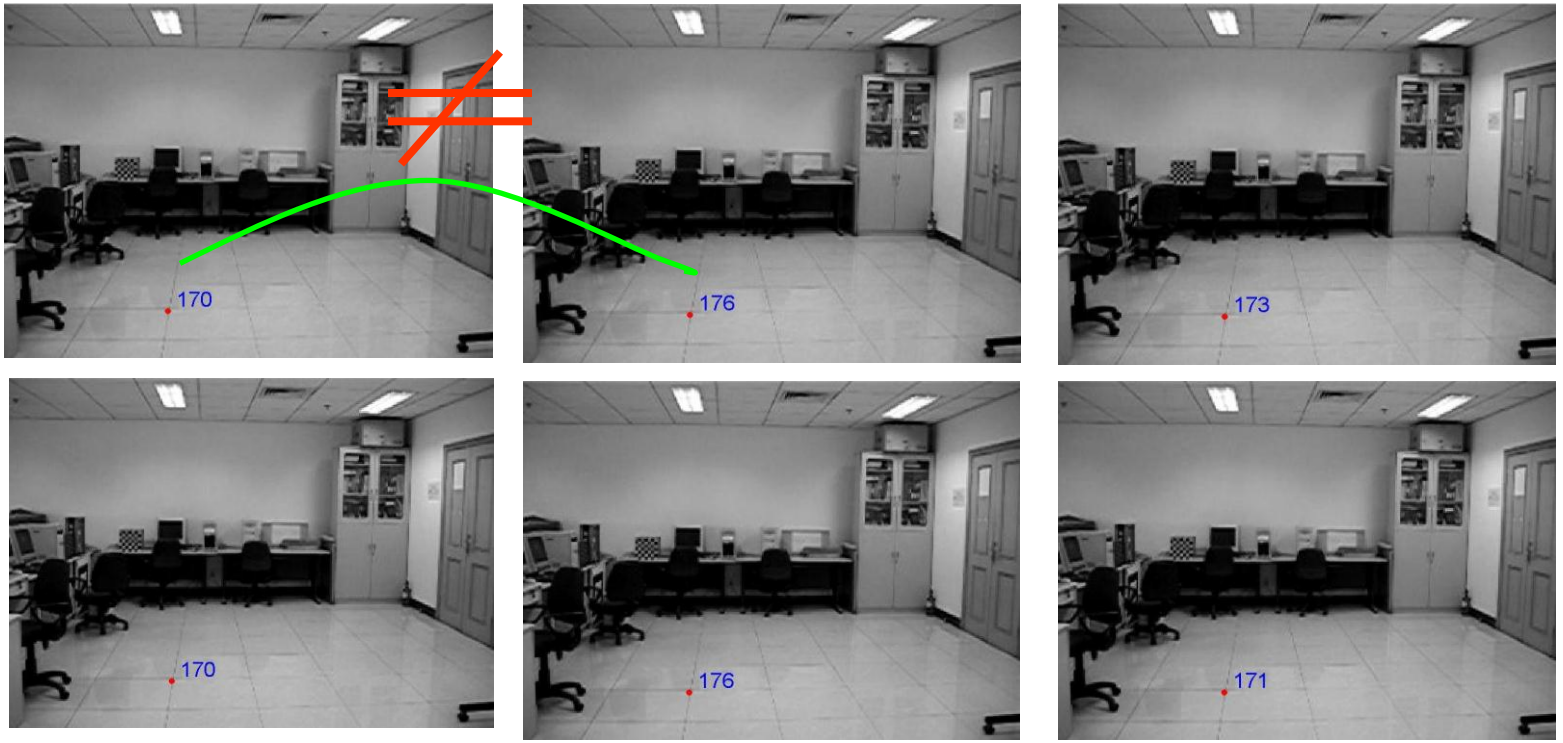
输入图象　　背景图象

已知背景的情况——均值图像

- 均值图像：将若干背景图像求逐点的灰度均值。
- 什么是逐点的灰度均值？

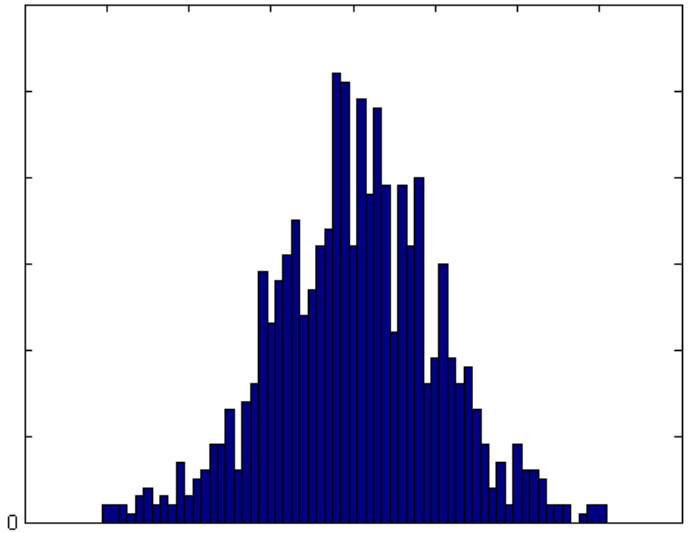
均值图像

- 为什么要将若干背景图像的均值图像作为背景，而不是直接从中选一张作为背景呢？



单高斯模型

- 什么是单高斯模型？
  - 对于每一个像素，用一个高斯分布来描述其在不同时刻的灰度分布情况的背景模型。
- 使用高斯分布来描述背景的假设是什么呢？
  - 背景在图像序列中总是最经常被观测到



单高斯模型



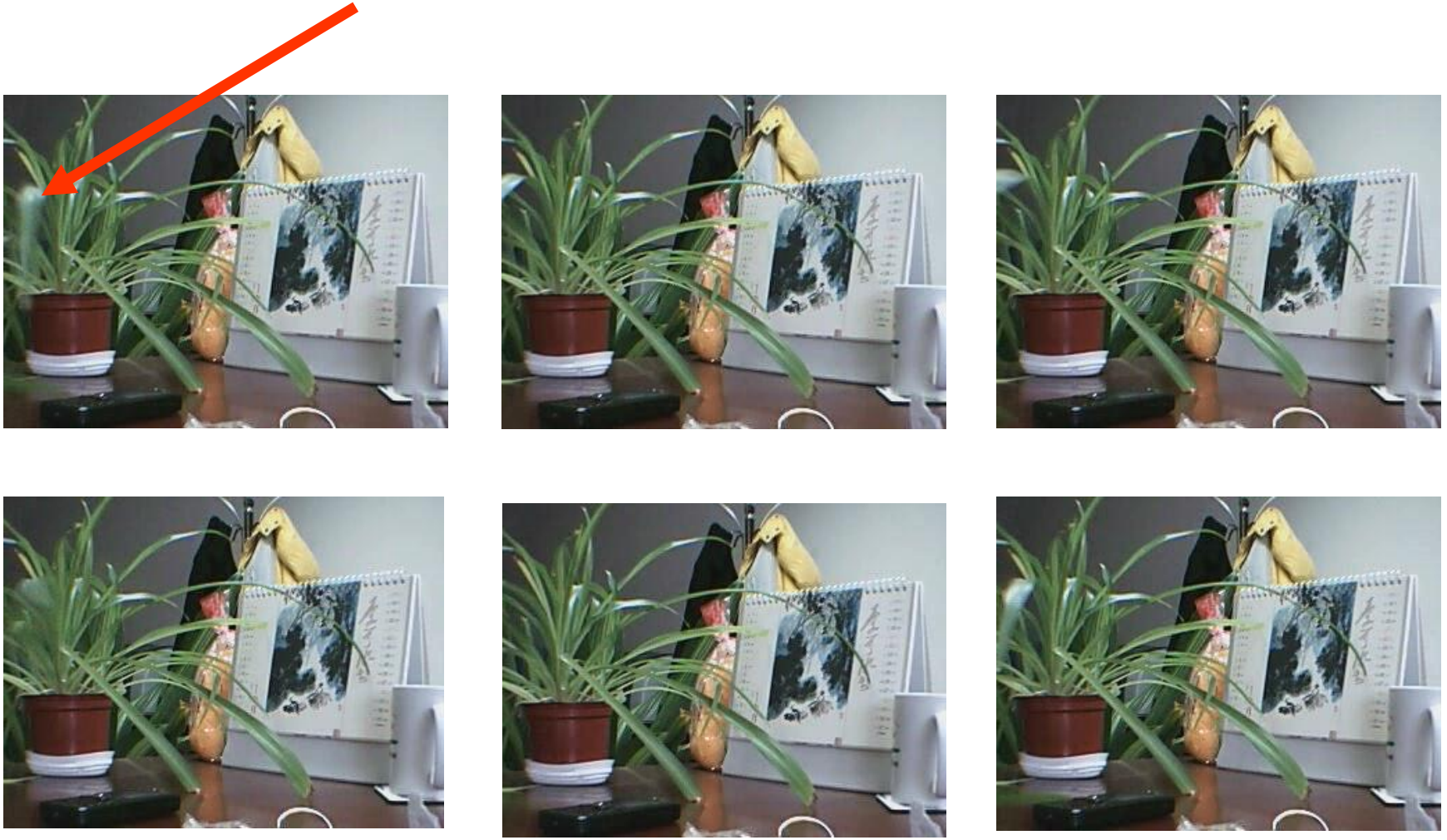





单高斯模型

单高斯模型

- 单高斯模型有没有不足呢？
- 背景往往不是绝对静止的，而是时常变化的！尤其对于室外场景。
- 例子：
  - 树枝摇曳；
  - 窗帘晃动；
  - 等等。



混合高斯模型

- 与单高斯模型类似，混合高斯模型采用混合高斯分布来描述每个象素在不同时刻的灰度分布情况。
- 其假设依然是背景在图像序列中总是最经常被观测到。

混合高斯模型

- 设用来描述每个像素的高斯分布共K个（K通常取$3-7$个），像素z_{uv}的概率函数：

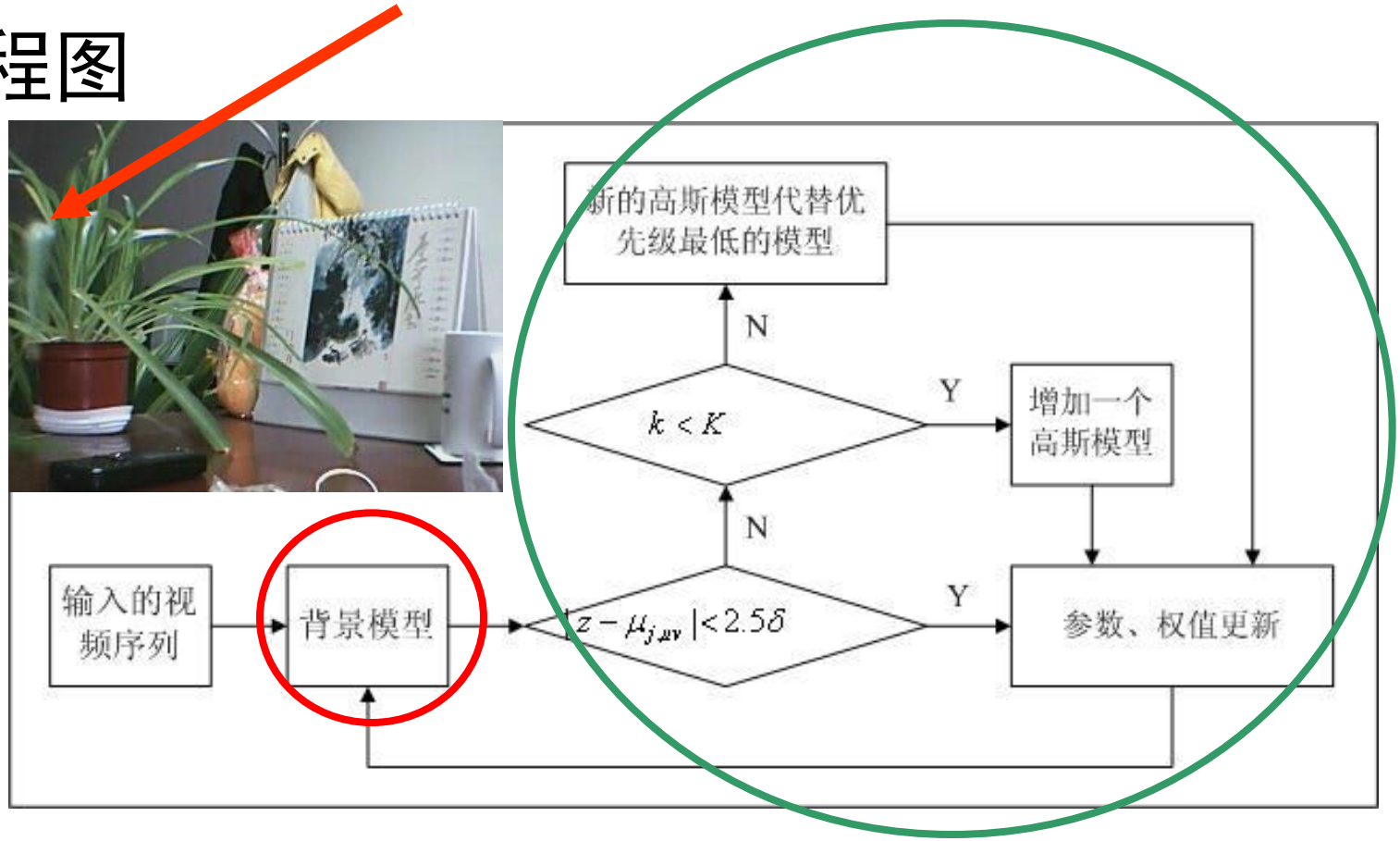
$$P(z_{uv}) = \sum_{j=1}^{K} \omega_{j,uv}\, N(z_{uv}|\mu_{j,uv}, \Sigma_{j,uv})$$

其中$\omega_{j,uv}$是第j个高斯分布权重

$$N(z|\mu, \Sigma) = \frac{1}{(2\pi)^{n/2}\Sigma^{1/2}}\, e^{-\frac{1}{2}(z-\mu)^T\Sigma^{-1}(z-\mu)}$$

混合高斯模型

- 流程图


新的高斯模型代替优先级最低的模型
N
Y
$k < K$
增加一个高斯模型
N
Y
输入的视频序列
背景模型
$|z - \mu_{j,w}| < 2.5\delta$
参数、权值更新

混合高斯模型

背景建模过程（仅针对单个像素）：

1. 初始化：用第一幅图像该点的像素值作为均值，给定一个较大的方差和较小的权值。
2. 模型学习

$\omega_{j,w,t} = (1-\alpha)\omega_{j,w,t-1} + \alpha\left(M_{j,w,t-1}\right)$, $M_{j,w,t-1}$是个0/1函数

$$\mu_{j,w,t} = (1-\rho)\mu_{j,w,t-1} + \rho z_{j,w,t}$$

$${\sigma_{j,w,t}}^2 = (1-\rho){\sigma_{j,w,t-1}}^2 + \rho(z_{j,w,t} - \mu_{j,w,t})^T(z_{j,w,t} - \mu_{j,w,t})$$

$$\rho = \alpha N(z_{j,w,t}|\mu_{j,w,t}, \Sigma_{j,w,t})$$

混合高斯模型

- 这K个高斯模型是否应该都用上呢？
  - 由于噪声的影响或前景物体的存在，某些像素值并不能代表背景，因此由这些像素值构造的高斯分布应该去掉。
- 定义各个高斯分布的优先级：

$$p_{j,uv} = \omega_{j,uv}/\sigma_{j,uv}$$

混合高斯模型

- 如何去掉多余的高斯分布？
  - 前面提到的假设：前景和噪声不会在同一位置太长时间，这样，前景和噪声对应的高斯模型的权值和优先级都比较小，因此可以将K个高斯分布按优先级由高到低排列，用如下策略选取前 B 个分布作为背景模型：
- B的定义：

$$B = \min_b \left(\sum_{j=1}^{b} \omega_{j,uv} > M \right)$$

其中M为预设的阈值。（如果M较小，则为单高斯模型）

混合高斯模型

- 前景检测：将待测图像的每一个像素点与该像素点对应的混合高斯模型的各个模型分别进行比较，若有 $\left|z-\mu_{j,uv}\right|<a\sigma$（$a$为一常数），则该点属于背景，否则属于前景。

运动检测

- 常规的运动检测方法：
  - 背景差法(background subtraction)
  - 光流(optical flow)
  - 帧间差分(frame differencing)

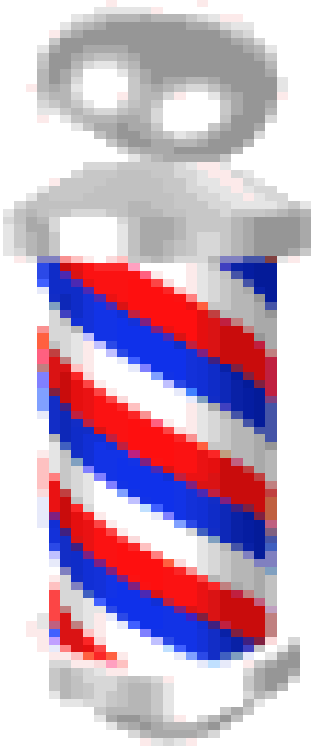
光流法

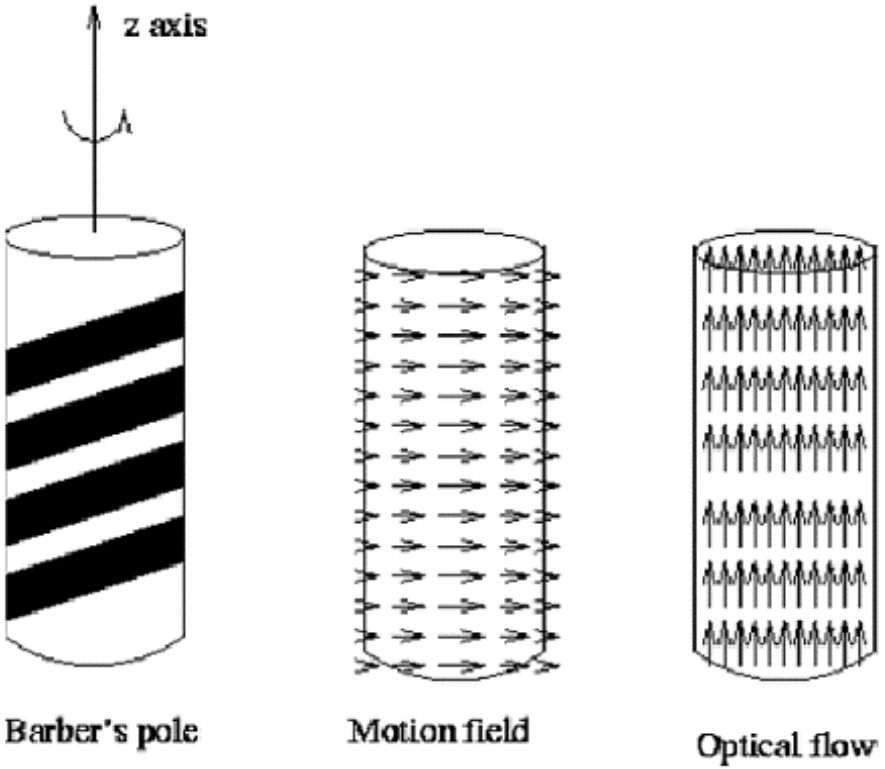
什么是光流？

- 当人的眼睛观察运动物体时，物体的景象在人眼的视网膜上形成一系列连续变化的图像，这一系列连续变化的信息不断“流过”视网膜（即图像平面），好像一种光的 “流”，故称之为光流（optical flow）。
- 光流是空间运动物体在观测成像面上的像素运动的瞬时速度。光流的研究是利用图像序列中的像素强度数据的时域变化和相关性来确定各自像素位置的“运动”。

光流法

- Barber pole illusion

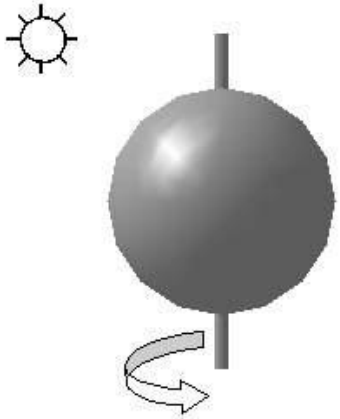




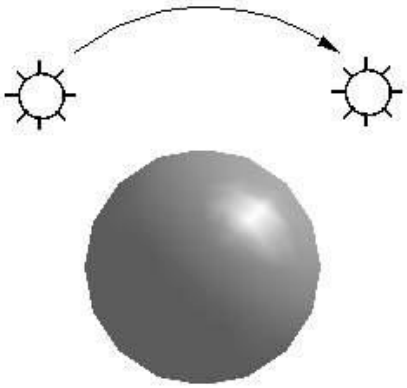
光流法

- 点的光流和点的实际运动有什么区别和联系呢？
  - 运动场(motion field)：一个运动物体在空间产生一个三维的速度场，运动前后空间对应点在图象上的投影形成一个二维运动场。
  - 光流场(optical flow field)：是指图像亮度模式的表观（或视在）运动，是二维矢量场。它包含的信息即是各像点的瞬时运动速度矢量信息。

光流法



光流等于零，但运动场却不等于零。



光流不等于零，但运动场为零。

光流法

- 为什么要研究光流呢？
  - 事实上，仅仅通过图像序列很难计算出物体的空间位置进而得到真实的运动场。而光流表达了图像的变化，包含了目标一定的运动信息，通过计算光流场可以从图像中近似计算不能直接得到的运动场。

光流法

- 如何计算光流呢？
  - 1981 年，Horn和Schunck创造性地将二维速度场与灰度相联系，引入光流约束方程，得到光流计算的基本算法。

光流约束方程

光流一致性假设（Brightness constancy assumption）

$$I(x + u\Delta t, y + v\Delta t, t + \Delta t) = I(x, y, t)$$

方程左侧按Taylor级数展开，化简:

$$\frac{\partial I}{\partial x}\frac{\partial x}{\partial t} + \frac{\partial I}{\partial y}\frac{\partial y}{\partial t} + \frac{\partial I}{\partial t} = 0$$

光流约束方程

令 $u=\frac{\partial x}{\partial t}, v=\frac{\partial y}{\partial t}, I_x=\frac{\partial I}{\partial x}, I_y=\frac{\partial I}{\partial y}, I_t=\frac{\partial I}{\partial t}$

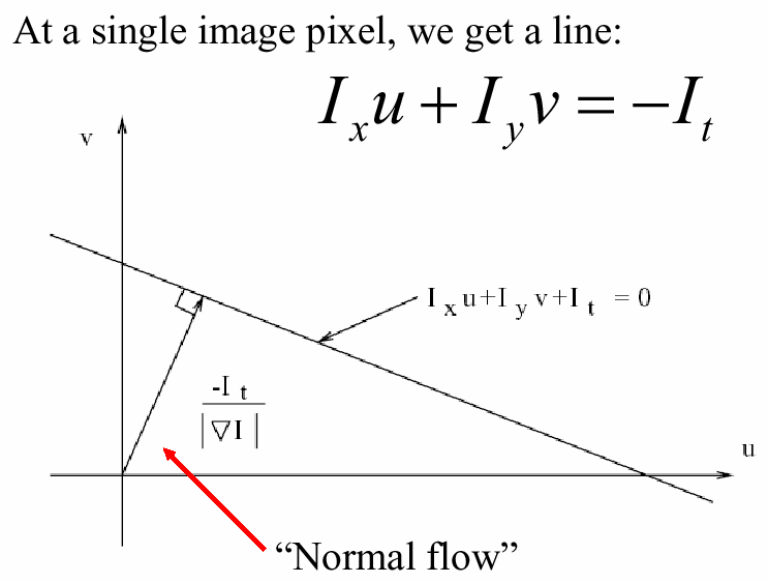
则方程 $\frac{\partial I}{\partial x}\frac{\partial x}{\partial t}+\frac{\partial I}{\partial y}\frac{\partial y}{\partial t}+\frac{\partial I}{\partial t}=0$

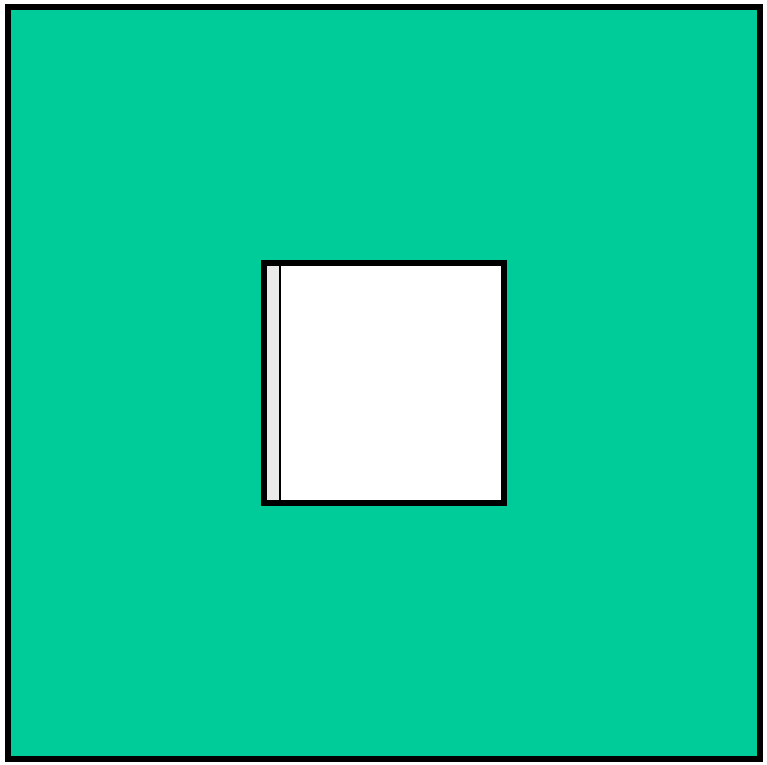
化为如下光流约束方程：

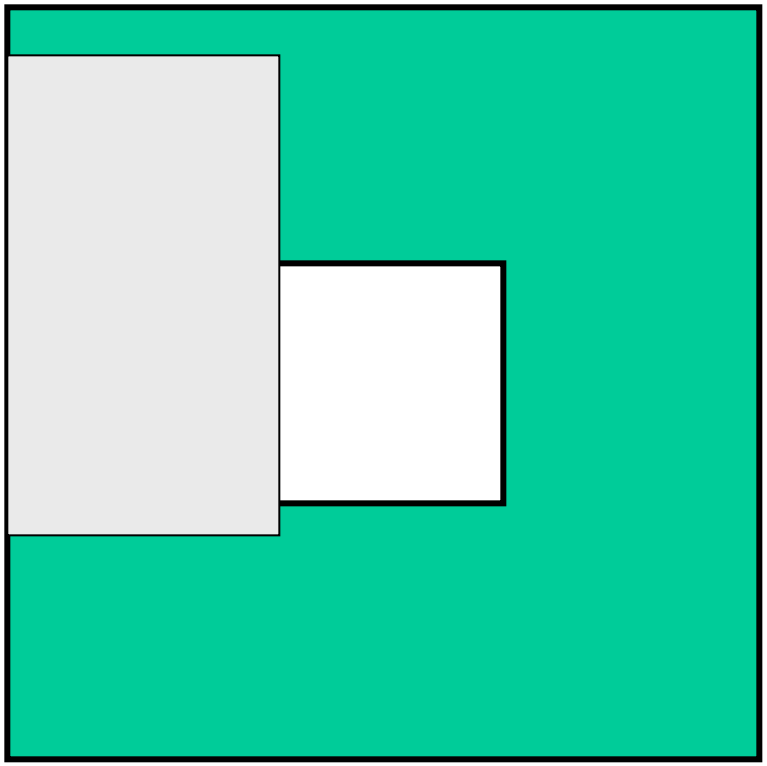
$$I_x u + I_y v + I_t = 0$$

孔径问题

- 由光流约束方程可见：该方程两个未知数u和v。因此，只使用一个点上的信息是不能确定光流的。人们将这种不确定问题称为孔径问题(aperture problem)。







怎样为每个像素建立更多的方程呢？

光流计算

- 基本的解决思路：添加其它的约束。
- 光流的五种计算方法：
  - 基于梯度的方法
  - 基于匹配的方法
  - 基于能量的方法
  - 基于相位的方法
  - 神经动力学方法

基于梯度的方法——Lucas-Kanade方法

通常附加的约束是：假设光流场是局部平滑的。

Lucas-Kanade方法[3]的约束则更强一些：假设每个像素领域内的像素具有相对的速度。

$$E(u,v) = \sum_{(x,y)\in\Omega} (I_x(x,y)u + I_y(x,y)v + I_t)^2$$

对其两边求偏导：

Lucas-Kanade方法

$$\frac{\partial E(u,v)}{\partial u} = \sum_{(x,y)\in\Omega} 2I_x(I_x(x,y)u + I_y(x,y)v + I_t) \quad = 0$$

$$\frac{\partial E(u,v)}{\partial v} = \sum_{(x,y)\in\Omega} 2I_y(I_x(x,y)u + I_y(x,y)v + I_t) \quad = 0$$

$$\Rightarrow \quad \begin{bmatrix} \Sigma {I_x}^2 & \Sigma I_x I_y \\ \Sigma I_x I_y & \Sigma {I_y}^2 \end{bmatrix} \begin{bmatrix} u \\ v \end{bmatrix} = -\begin{bmatrix} \Sigma I_x I_t \\ \Sigma I_y I_t \end{bmatrix}$$

$$\Rightarrow \quad (\Sigma \nabla I \nabla I^T)\vec{U} = -\Sigma \nabla I I_t$$

Lucas-Kanade方法

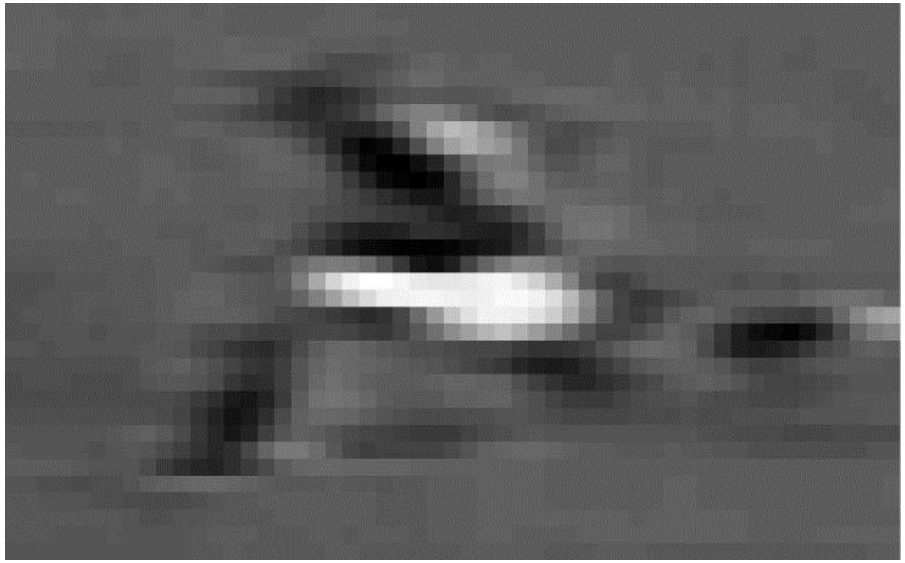
令 $A = \Sigma \nabla I \nabla I^T, \vec{U} = [u, v]^T, b = -\Sigma \nabla I I_t$

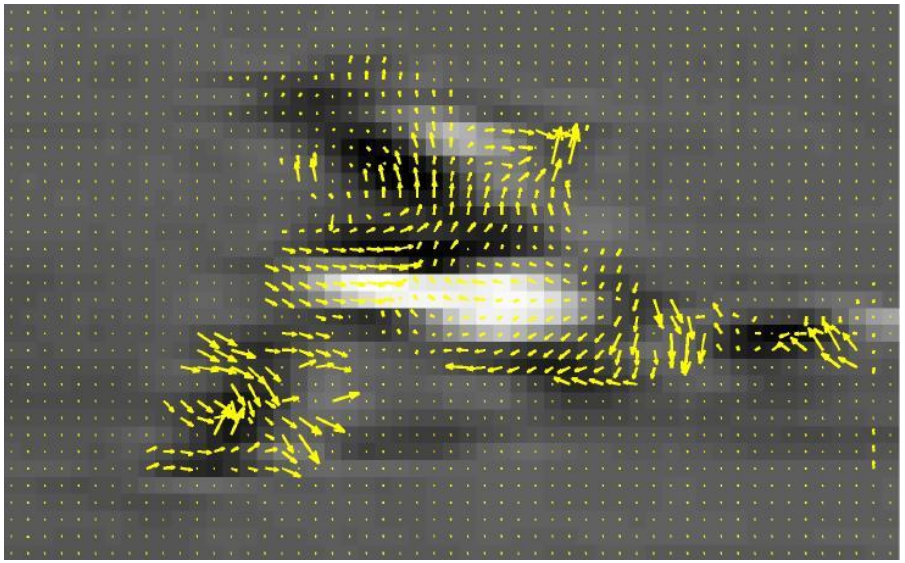
则有：

$$A\vec{U} = b$$

此时，原问题转化为一个最小二乘问题。

注意，考虑可解性！





光流法

- 光流法的优点
  - 直观的表述运动模式；
  - 不易受运动物体外表的干扰。
- 光流法的不足
  - 计算量比较大；
  - 易产生较大噪声。

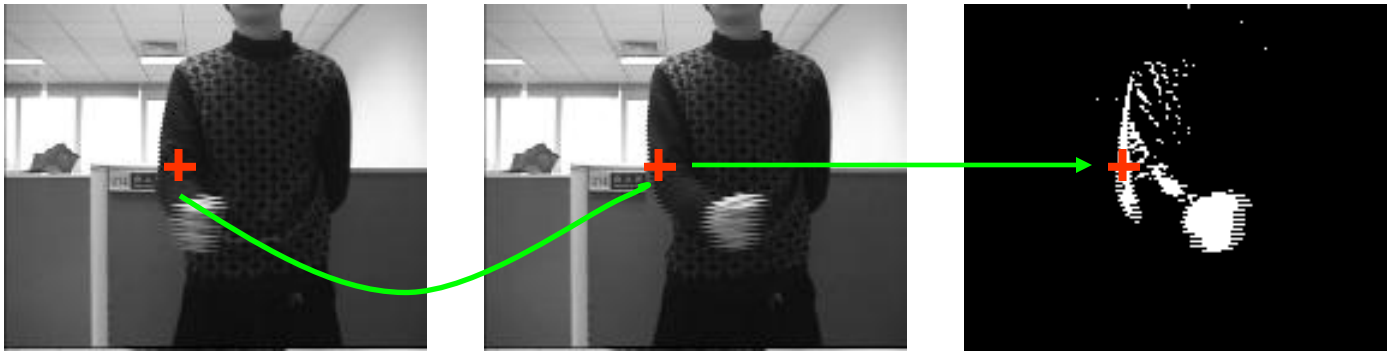
运动检测

- 常规的运动检测方法：
  - 背景差法(background subtraction)
  - 光流法 (optical flow)
  - 帧间差分(frame differencing)

帧间差分

- 原理：

  在相邻两帧（也可以为多帧）间计算逐象素的灰度差，并通过设置阈值来确定对应运动前景的象素，进而得到运动前景区域。



双帧差分

- 数学表述：

  如果I_n, I_{n-1}表示图像序列中任意相邻的两帧图像，则逐象素的差分图D_n可以定义为：

$$D_n(i,j) = |I_n(i,j) - I_{n-1}(i,j)|$$

对上述差分图阈值化（假设预先设定的阈值为T），即可确定运动前景区域M_n：

$$M_n(i,j) = \begin{cases} 0 & D_n(i,j) < T \\ I_n(i,j) & D_n(i,j) \geq T \end{cases}$$

三帧差分

- 扩展——三帧差分：其原理与双帧差分的原理是一样的，只是在具体构造差分图上有些许不同。

I_{n-1}

I_n

I_{n+1}

三帧差分方法

- 三帧差分方法的数学表述：

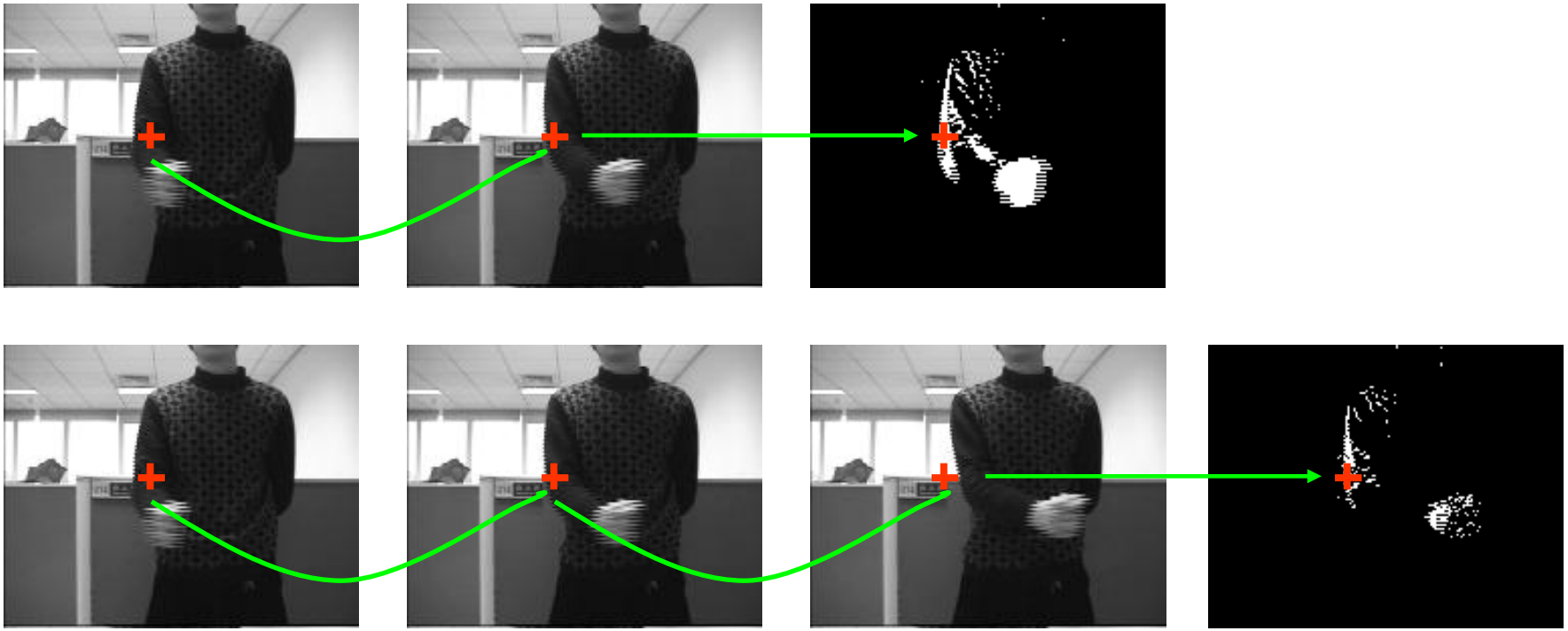
  如果I_{n-1}, I_n, I_{n+1}表示图像序列中任意连续的三帧图像，则逐象素的差分图定义为：

$$D_n(i,j) = |I_{n-1}(i,j) - I_n(i,j)| \times |I_n(i,j) - I_{n+1}(i,j)|$$

  对上述差分图阈值化（假设预先设定的阈值为T），即可确定运动前景区域M_n：

$$M_n(i,j) = \begin{cases} 0 & D_n(i,j) < T \\ I_n(i,j) & D_n(i,j) \geq T \end{cases}$$

对比效果图



帧间差分

- 优点：
  - 适用于动态变化的背景环境。
- 不足：
  - 较难准确检测运动速度过快的物体；
  - 较难准确检测运动速度过慢的物体；
  - 较难准确检测场景中同时存在的多个运动物体。

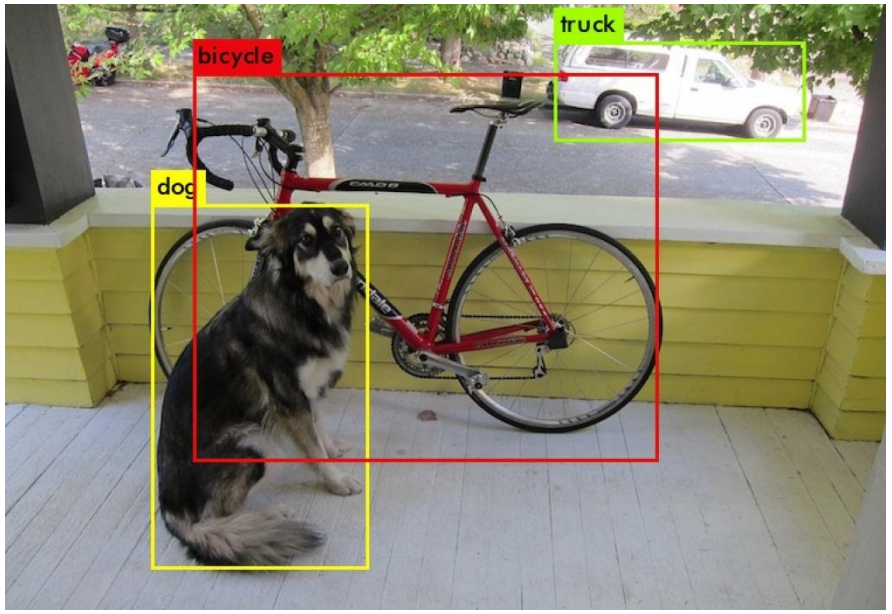
目标检测

目标检测

- 常规的目标检测方法
  - AdaBoost
- 基于DNN的目标检测方法
  - RCNN系列
  - YOLO系列

目标检测

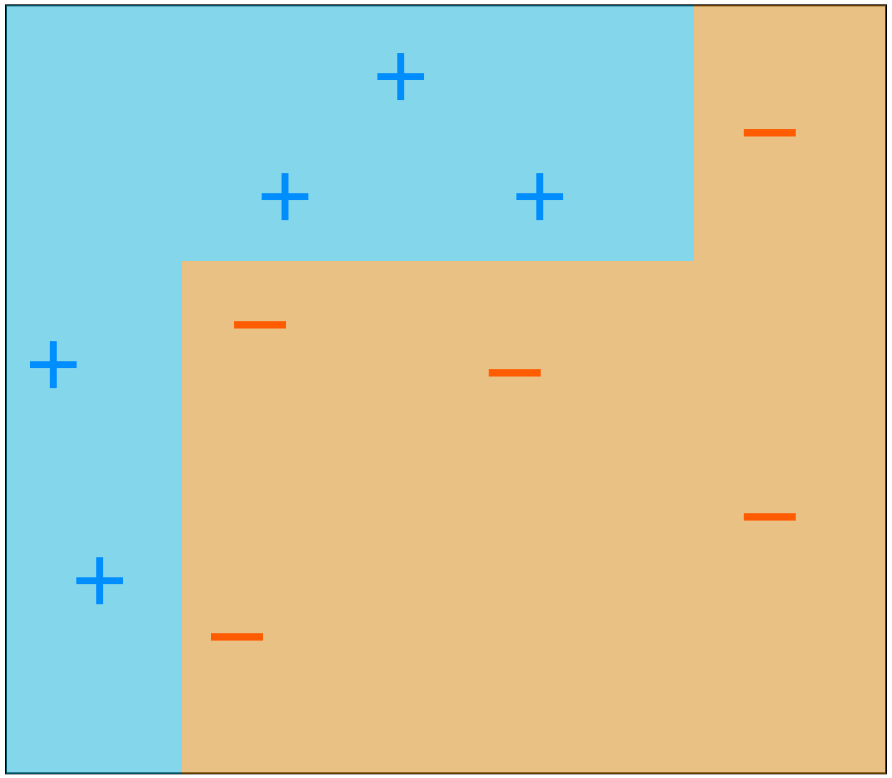
- 研究目标：自动确定目标在图像中的位置和类别。



AdaBoost

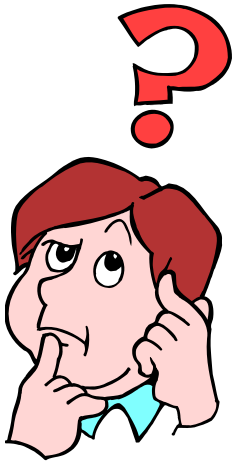
Toy problem

- 怎样把两类点区分开呢？



AdaBoost

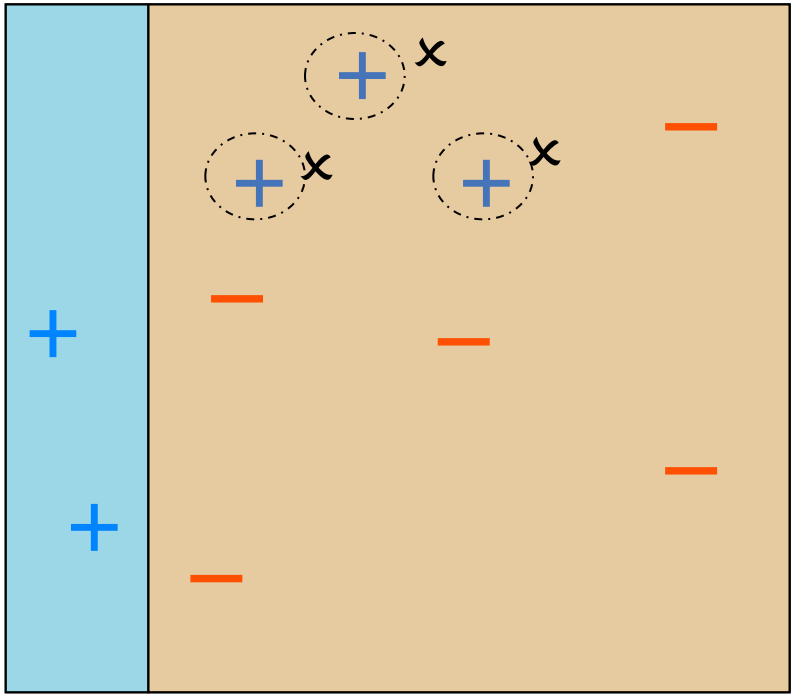
“要善于‘退’，足够地‘退’，退到最原始而不失去重要性的地方，退到我们最容易看清楚的地方……”



哪里是“最原始而不失去重要性的地方”呢？

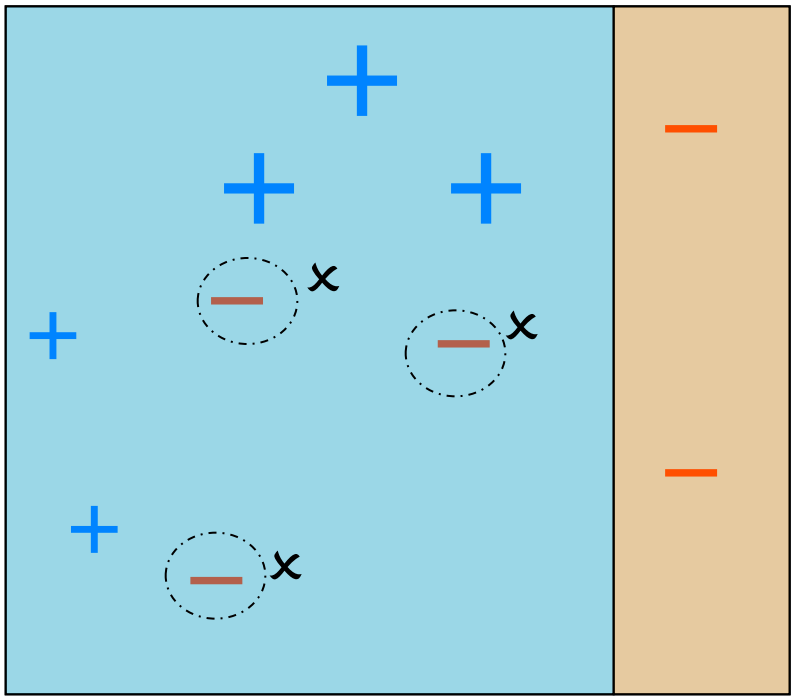
Toy problem

- 第一种划分：



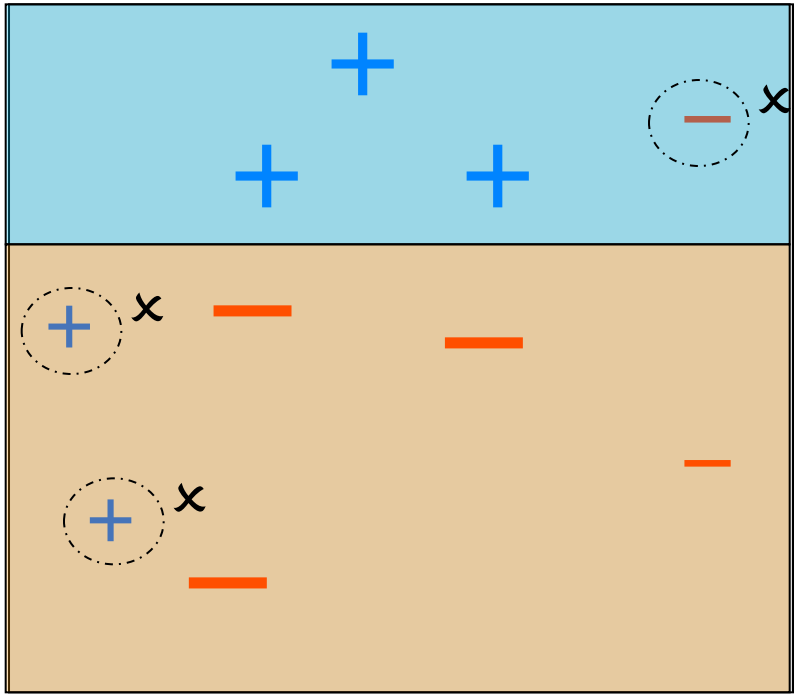
Toy problem

- 第二种划分：

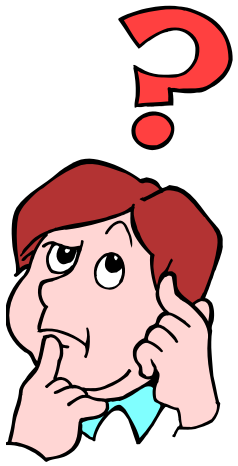


Toy problem

- 第三种划分：



AdaBoost



“最原始而不失去重要性的地方”找到了，然后怎么办呢？

换言之：

- 弱分类器：准确率不高（仅比随机猜测略好）；
- 强分类器：准确率很高的分类器；
- 怎么样将弱分类器提升为强分类器呢？

AdaBoost

- AdaBoost（adaptive boosting）Boosting算法中的一种变形。

- 目的：就是根据已有的样本，融合多个弱分类器形成一个整体的强分类器，并提高分类准确率。

AdaBoost

- 发展历史：
  - Proved the fact: learners, each performing only slightly better than random, can be combined to form an arbitrarily good ensemble hypothesis. (Kearns and Valiant 1989)
  - Boost-by-majority algorithm (Freund 1990)
  - AdaBoost (Freund and Schapire 1994-1996)
  - Generalized version of AdaBoost (Schapire and Singer 1997)
  - AdaBoost in face detection (Viola and Jones 2001)

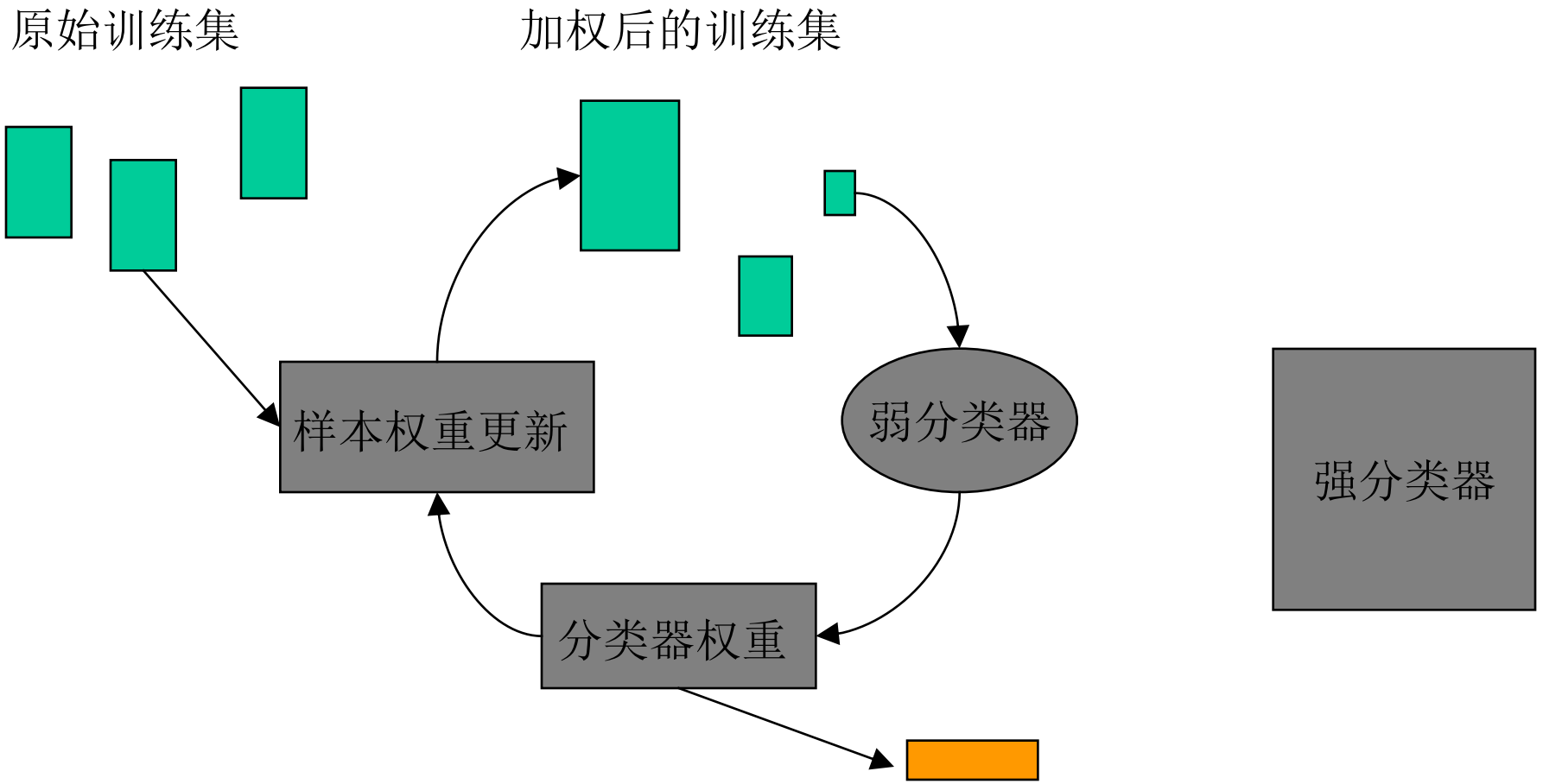
两个问题

- AdaBoost具体解决两个问题：
  - 怎样处理训练样本？
  - 怎样合并弱分类器成为一个强分类器？

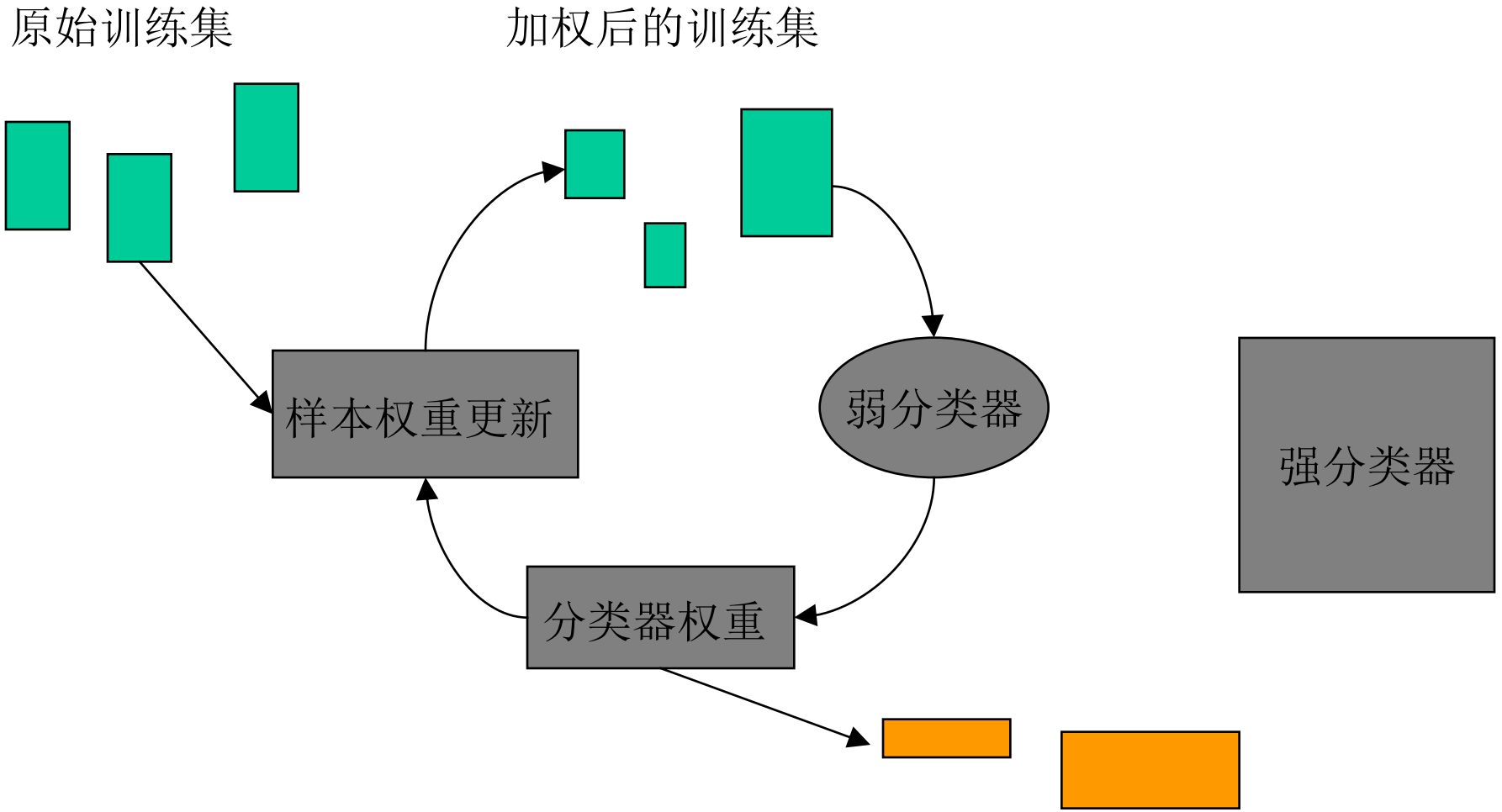
问题答案

- 怎样处理样本？
  - 在AdaBoost中，每个样本都被赋予一个权重。如果某个样本没有被正确分类，它的权重就会被提高，反之则降低。这样， AdaBoost方法将注意力更多地放在“难分”的样本上。
- 怎样合并弱分类器？
  - 强分类器表示为若干弱分类器的线性加权和形式，准确率越高的弱学习机权重越高。

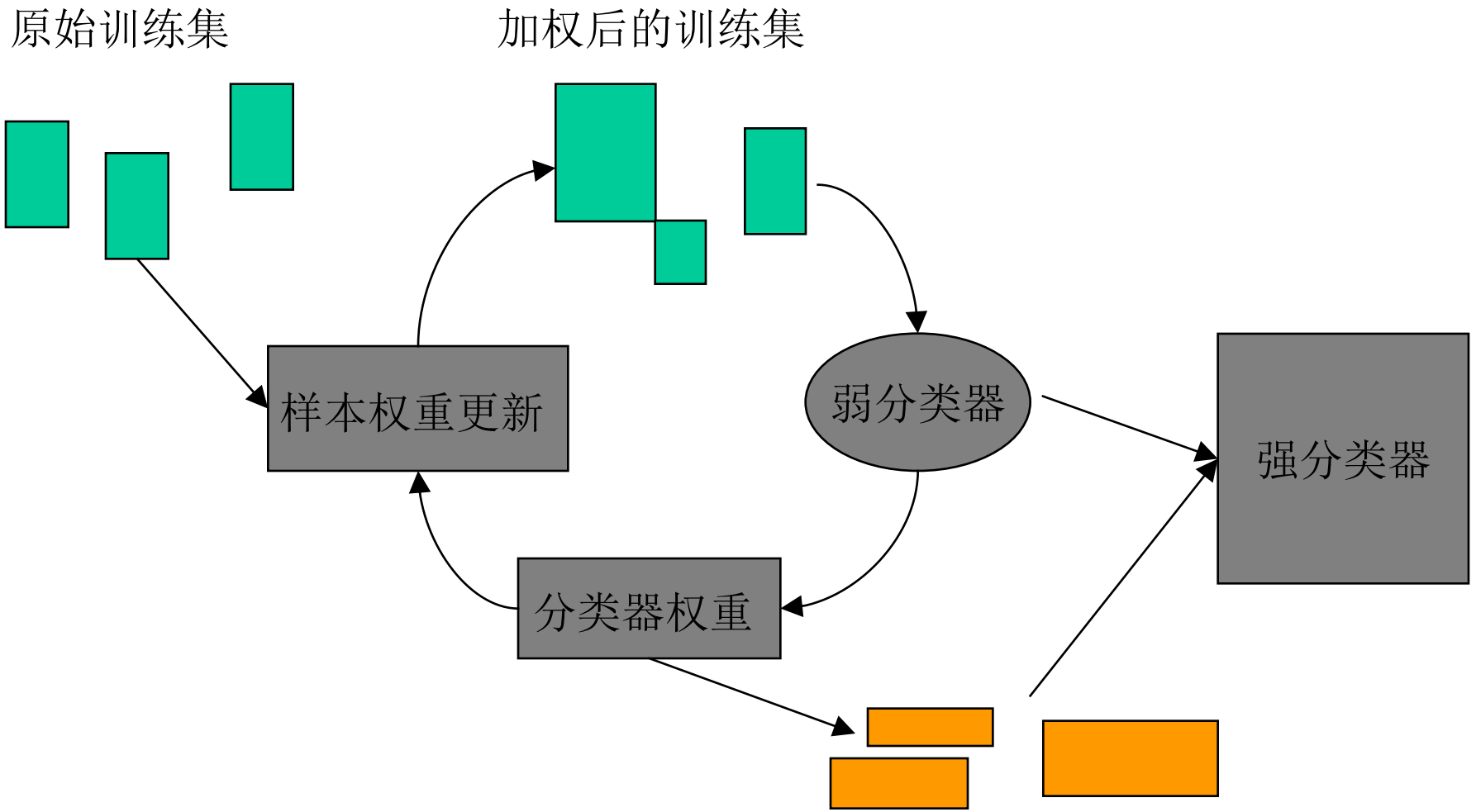
AdaBoost流程(loop1)



AdaBoost流程(loop2)



AdaBoost流程(loop3)



AdaBoost法则

输入：m个样本$(x_1, y_1), \ldots, (x_m, y_m)$, 其中$x_i \in X, y_i \in Y = \{-1,1\}$

初始化样本权重 $D_{t+1}(i) = 1/m$

For $t = 1$ to T

1. 找到弱分类器h_t ，并得到其分类误差ε_t
2. 计算分类器权重$\alpha_t = \frac{1}{2}\ln(\frac{1-\varepsilon_t}{\varepsilon_t})$
3. 更新样本权重

ε_t 越大， α_t 越小

$$D_{t+1}(i) = \frac{D_t(i)}{Z_t} \times \begin{cases} e^{-\alpha_t} & if\ h_t(x_i) = y_i \\ e^{\alpha_t} & if\ h_t(x_i) \neq y_i \end{cases}$$

Z_t 是归一化因子

输出：

$$H(x) = \text{sign}(\sum_{t=1}^{T} \alpha_t h_t(x))$$

AdaBoost法则

怎样获得每次循环的弱分类器？

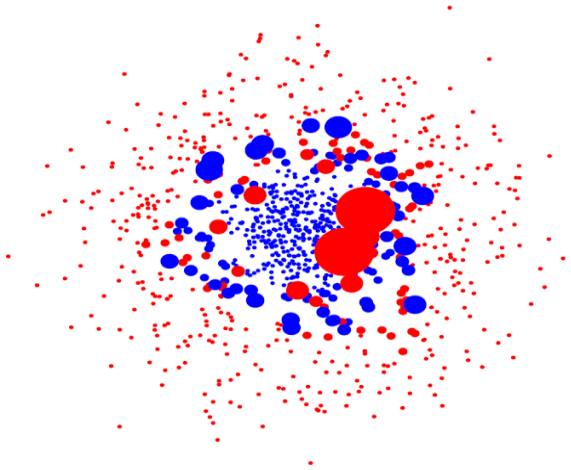
1. $h_t = \text{argmin}_{h_j}\{\varepsilon_j = \sum_{i=1}^{m} D_t(i)\,[y_i \neq h_j(x_i)]\}$
2. 先决条件：$\varepsilon_t < 1/2$ ，否则终止循环

弱分类器的例子：如决策树等等。

AdaBoost法则

样本权重更新过程：

$$D_{t+1}(i) = \frac{D_t(i)}{Z_t} \times \begin{cases} e^{-\alpha_t} & if\ h_t(x_i) = y_i \\ e^{\alpha_t} & if\ h_t(x_i) \neq y_i \end{cases}$$



增加被错分样本的权重，同时减小被正确划分的样本的权重

AdaBoost法则再回顾

初始化；

For $t = 1$ to T

1. 找到弱分类器：
$h_t = \text{argmin}_{h_j}\{\varepsilon_j = \sum_{i=1}^{m} D_t(i)\,[y_i \neq h_j(x_i)]\}$

2. $\varepsilon_t < 1/2$，否则终止循环；

3. 计算分类器权重：$\alpha_t = \frac{1}{2}\ln(\frac{1-\varepsilon_t}{\varepsilon_t})$

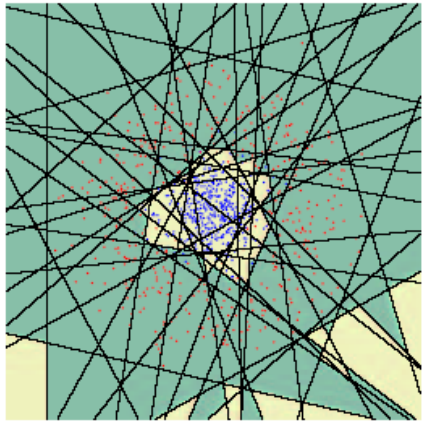
4. 更新样本权重：

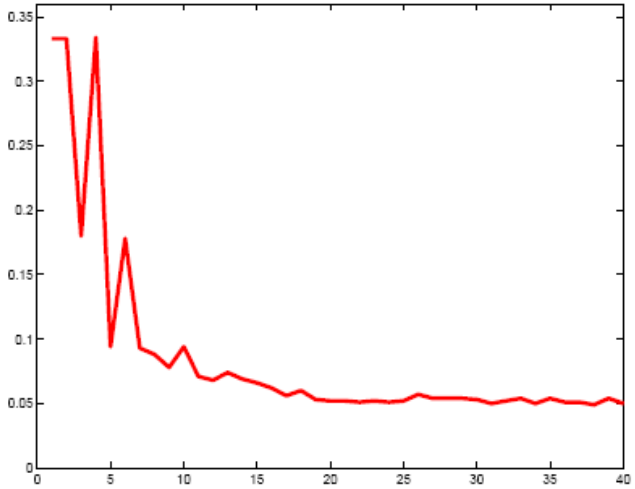
$$D_{t+1}(i) = \frac{D_t(i)}{Z_t} \times \begin{cases} e^{-\alpha_t} & if\ h_t(x_i) = y_i \\ e^{\alpha_t} & if\ h_t(x_i) \neq y_i \end{cases}$$

输出强分类器：

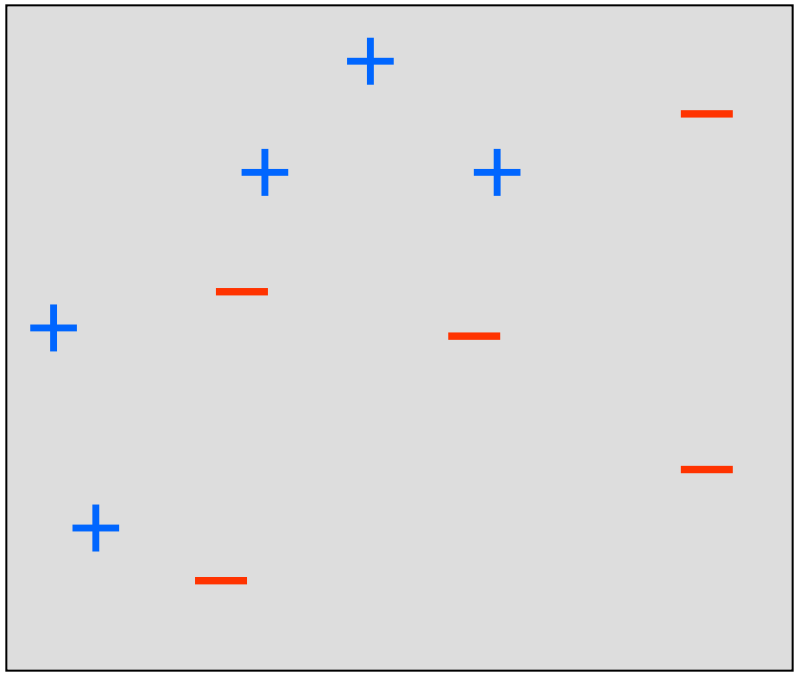
$$H(x) = \text{sign}(\sum_{t=1}^{T} \alpha_t h_t(x))$$

$t = 40$





Toy problem再回顧



Train data

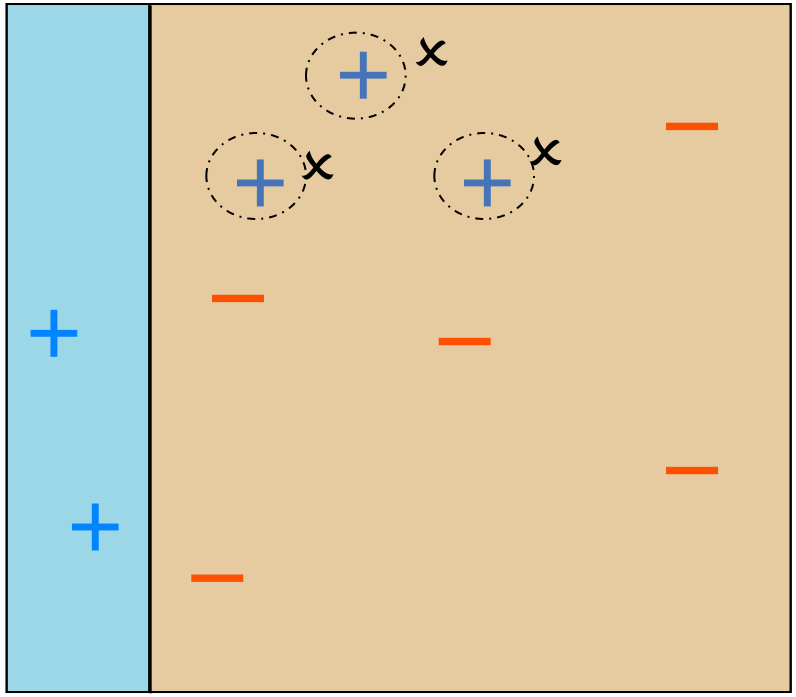
x1	x2	y
1	5	+
2	3	+
3	2	–
4	6	–
4	7	+
5	9	+
6	5	–
6	7	+
8	5	–
8	8	–

Initialization

D1
0.10
0.10
0.10
0.10
0.10
0.10
0.10
0.10
0.10
0.10
0.10
1.00

Toy problem再回顧

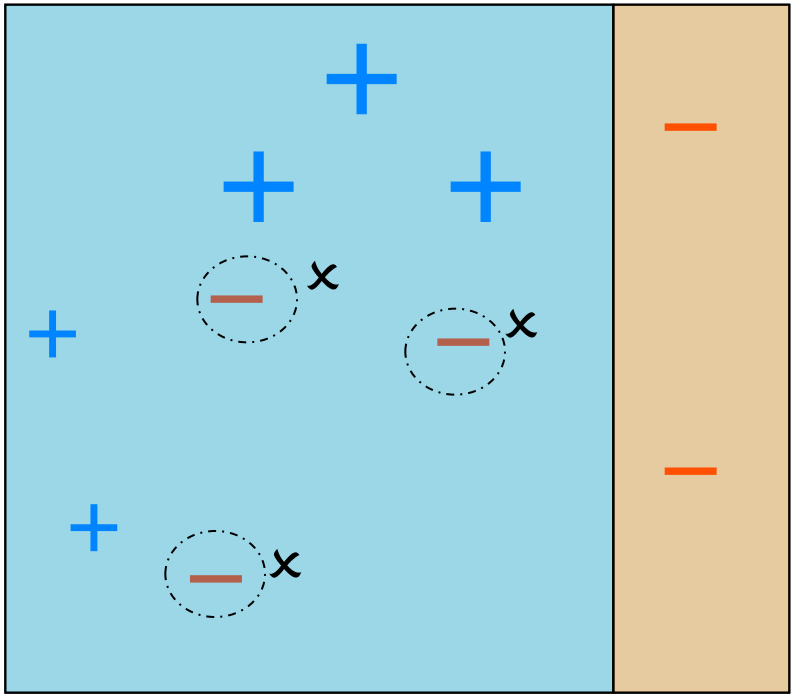
第一次循环：



h1e	ε	D2
0	0.00	0.07
0	0.00	0.07
0	0.00	0.07
0	0.00	0.07
1	0.10	0.17
1	0.10	0.17
0	0.00	0.07
1	0.10	0.17
0	0.00	0.07
0	0.00	0.07
ε1	0.30	1.00
α1	0.42	↕
	Zt	0.92

Toy problem再回顧

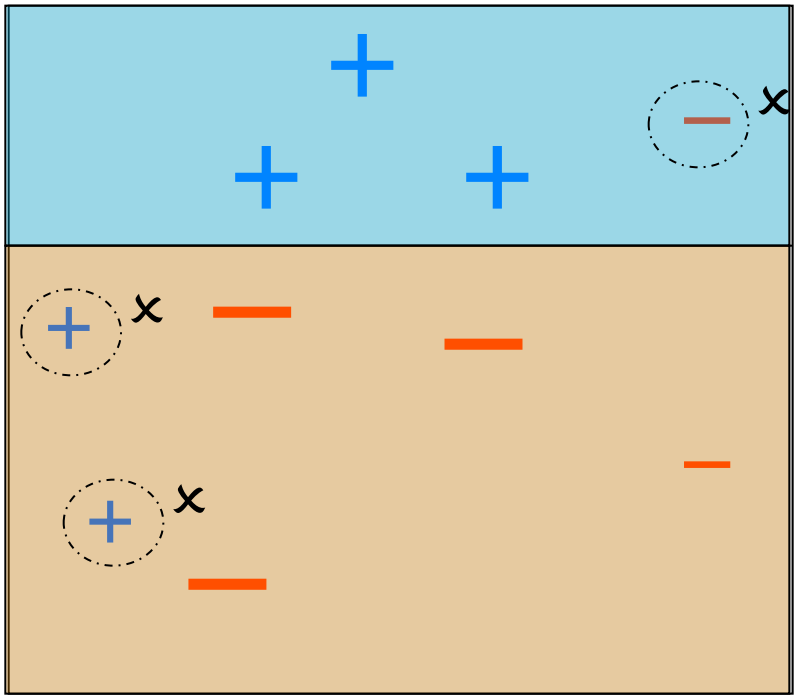
第二次循环：



h2e	ε	D3
0	0.00	0.05
0	0.00	0.05
1	0.07	0.17
1	0.07	0.17
0	0.00	0.11
0	0.00	0.11
1	0.07	0.17
0	0.00	0.11
0	0.00	0.05
0	0.00	0.05
ε2	0.21	1.00
α2	0.65	↕
	Zt	0.82

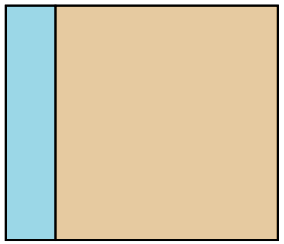
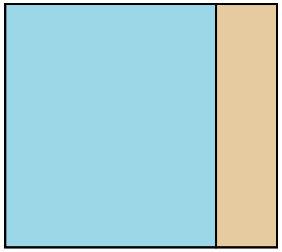
Toy problem再回顾

第三次循环：

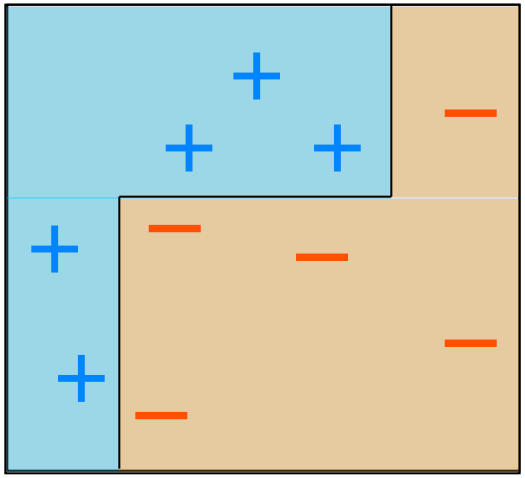


h3e	ε
1	0.05
1	0.05
0	0.00
0	0.00
0	0.00
0	0.00
0	0.00
0	0.00
0	0.00
1	0.05
ε3	0.14
α3	0.92

Toy problem再回顧

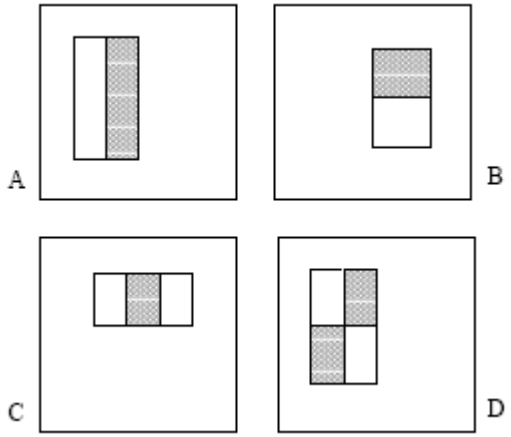
$H(x) = \text{sign}$ 0.42  + 0.65  + 0.92 

= sign[0.42(h1? 1|-1) + 0.65(h2? 1|-1) + 0.92(h3? 1|-1)]

= 

实例——人脸检测

- 特征选取：



实例——人脸检测

- 面临的挑战：
  - 特征数目太多！！！
- 是否其中少量特征的组合可以构成一个有效的分类器？
- 如何找到这些有区分能力的特征？

一个AdaBoost的变体

- Given example images (x_1,y_1) , … , (x_n,y_n) where $y_i = 0, 1$ for negative and positive examples respectively.
- Initialize weights $w_{1,i} = 1/(2m), 1/(2l)$ for training example i, where m and l are the number of negatives and positives respectively.

For $t = 1 \ldots T$

1) Normalize weights so that w_t is a distribution
2) For each feature j train a classifier h_j and evaluate its error ε_j with respect to w_t
3) Chose the classifier h_j with lowest error.
4) Update weights according to:

$$w_{t+1,i} = w_{t,i}\beta_t^{1-\varepsilon_i}$$

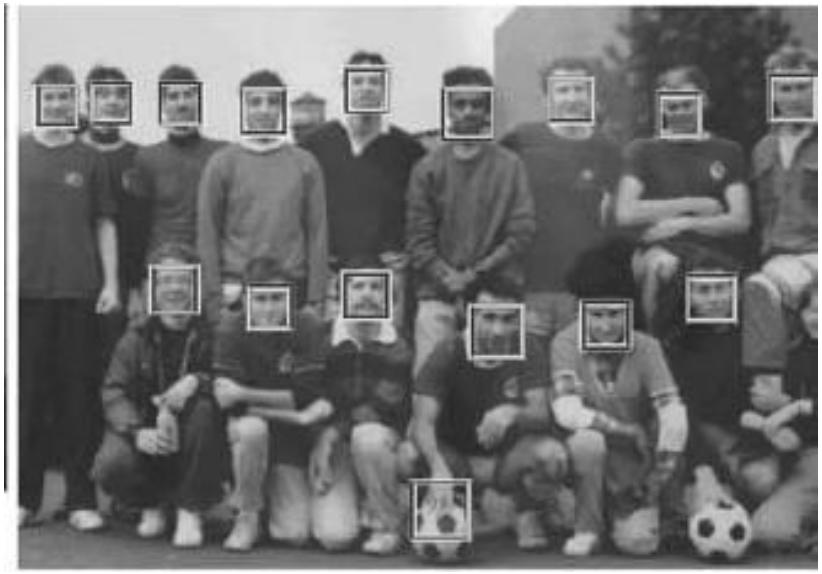
where $e_i = 0$ is x_i is classified correctly, 1 otherwise, and

$$\beta_t = \frac{\varepsilon_t}{1-\varepsilon_t}$$

- The final strong classifier is:

$$h(x) = \begin{cases} 1 & \sum_{t=1}^{T}\alpha_t h_t(x) \geq \frac{1}{2}\sum_{t=1}^{T}\alpha_t, \\ 0 & otherwise \end{cases} \qquad \text{where} \qquad \alpha_t = \log(\frac{1}{\beta_t})$$

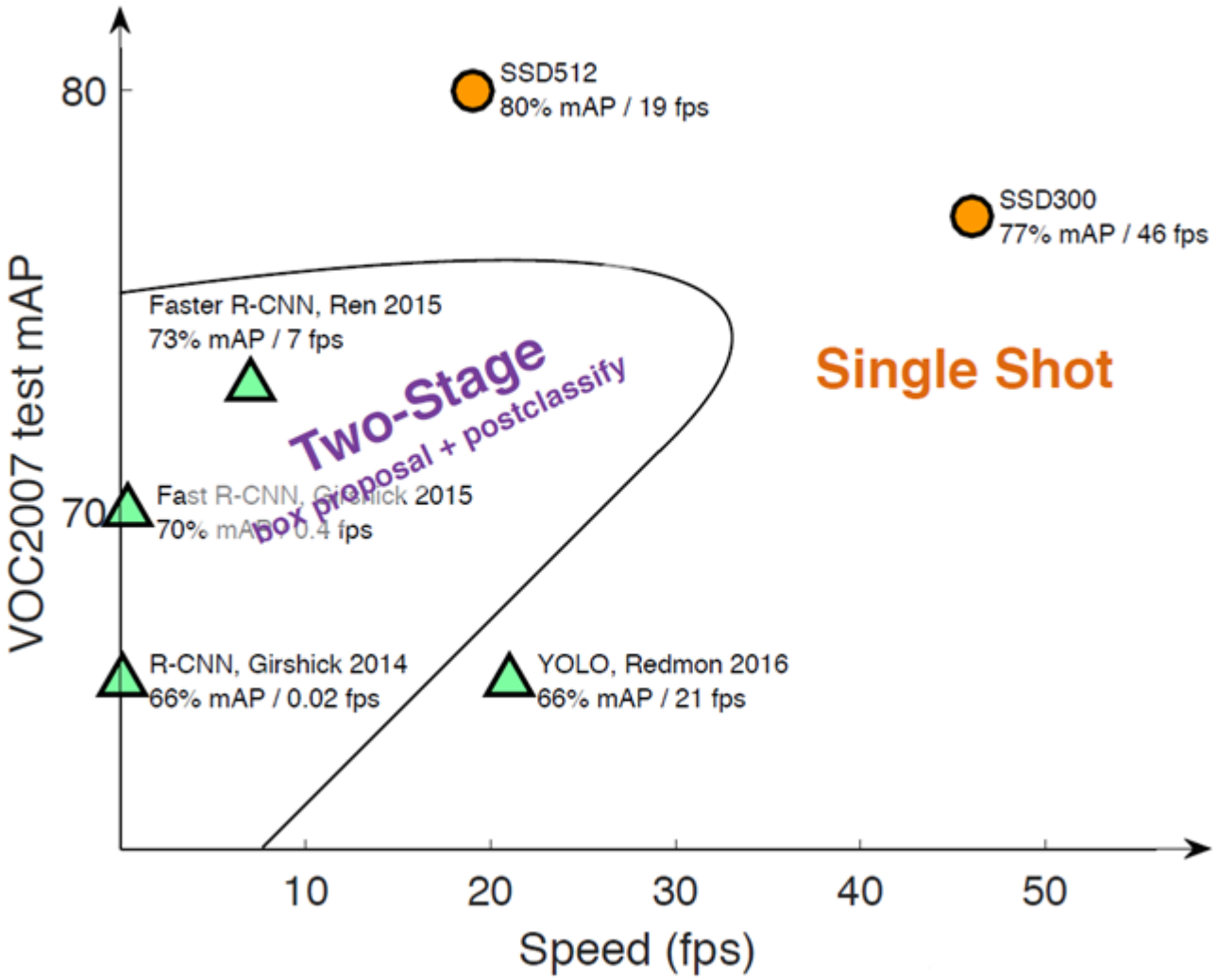
实例——人脸检测



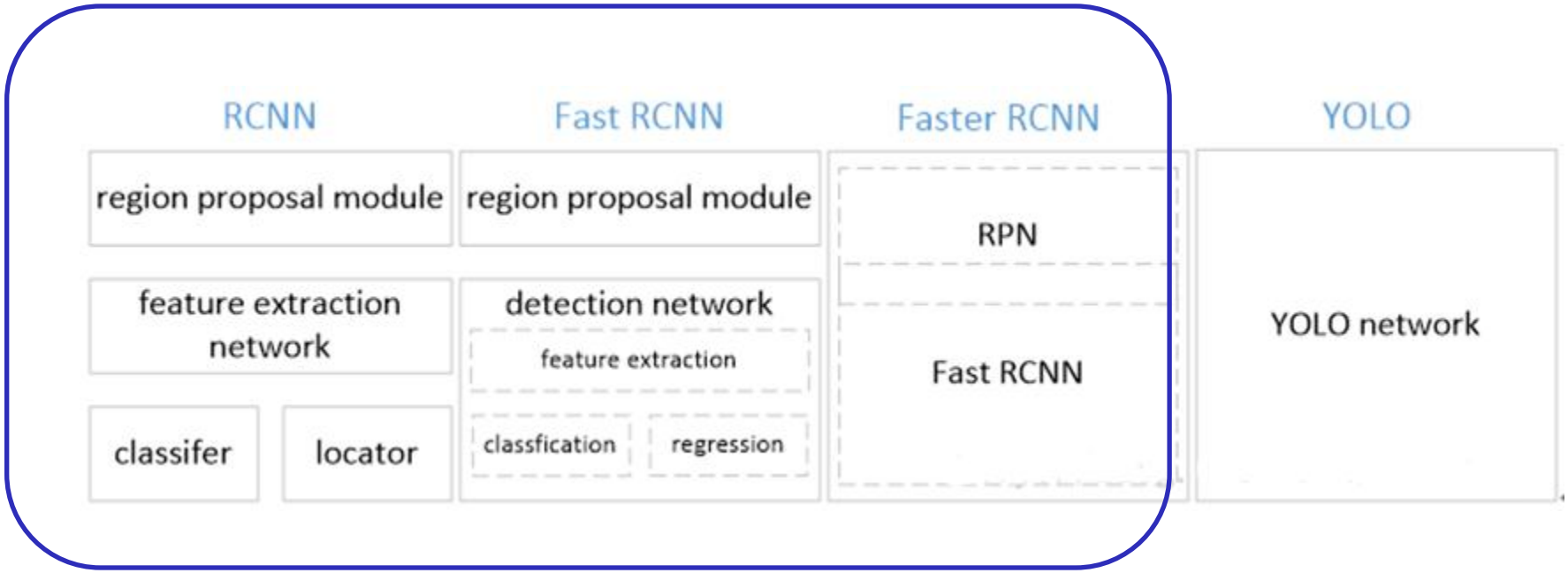

?
YOKA
space.yoka.com
CONSUMETION JUNCTION.COM
Fkueyygy1984.51.com

基于DNN的物体检测

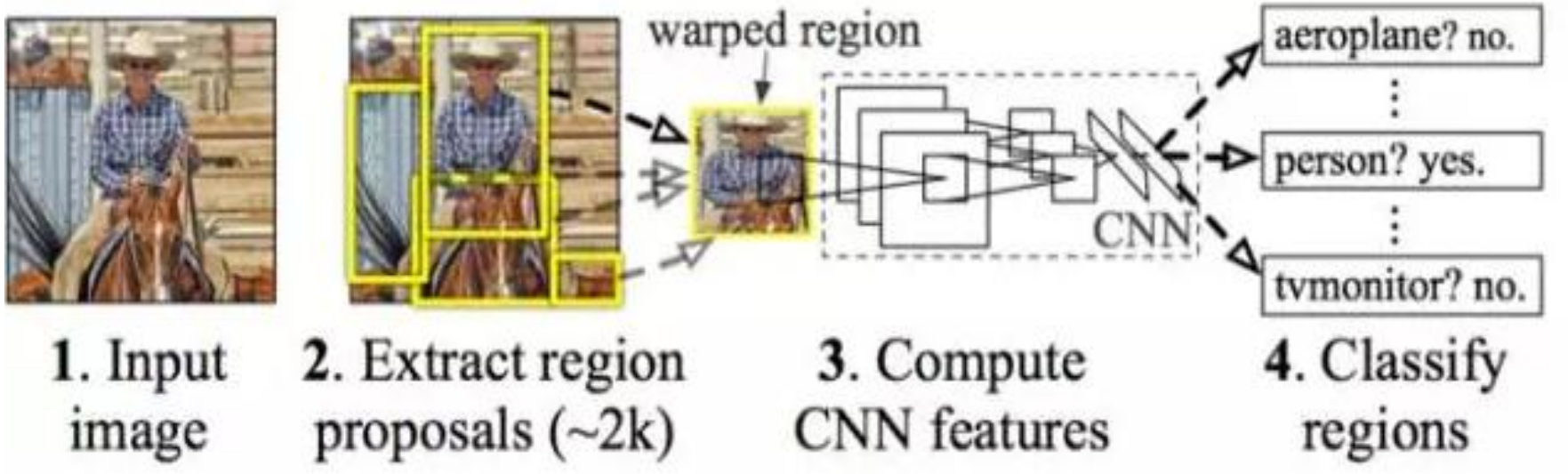
基于DNN的物体检测


80
70
VOC2007 test mAP
SSD512
80% mAP / 19 fps
SSD300
77% mAP / 46 fps
Faster R-CNN, Ren 2015
73% mAP / 7 fps
Two-Stage
box proposal + postclassify
Single Shot
Fast R-CNN, Girshick 2015
70% mAP / 0.4 fps
R-CNN, Girshick 2014
66% mAP / 0.02 fps
YOLO, Redmon 2016
66% mAP / 21 fps
10
20
30
40
50
Speed (fps)

基于DNN的物体检测


RCNN
region proposal module
feature extraction network
classifer
locator
Fast RCNN
region proposal module
detection network
feature extraction
classfication
regression
Faster RCNN
RPN
Fast RCNN
YOLO
YOLO network

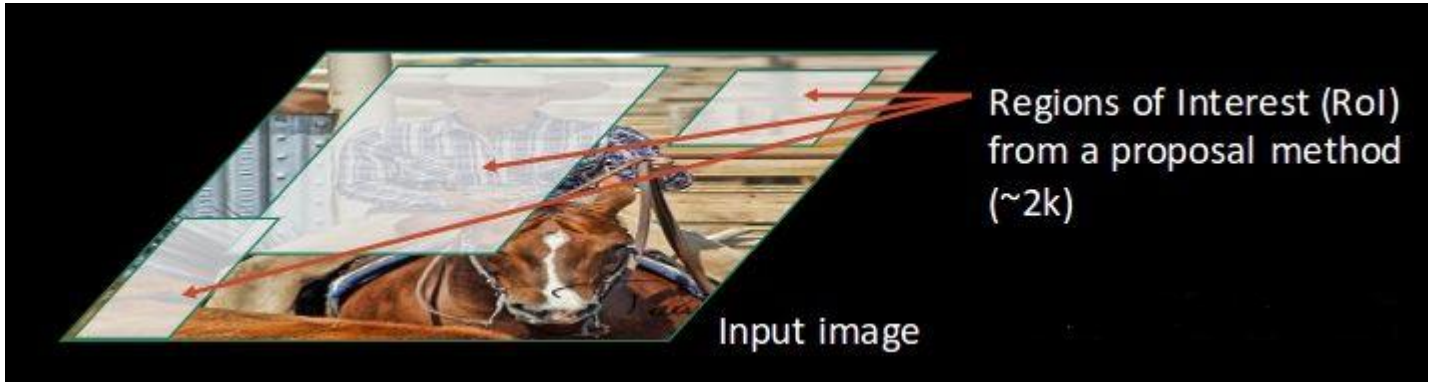
RCNN系列


warped region
CNN
aeroplane? no.
person? yes.
tvmonitor? no.
1. Input image
2. Extract region proposals (~2k)
3. Compute CNN features
4. Classify regions

RCNN

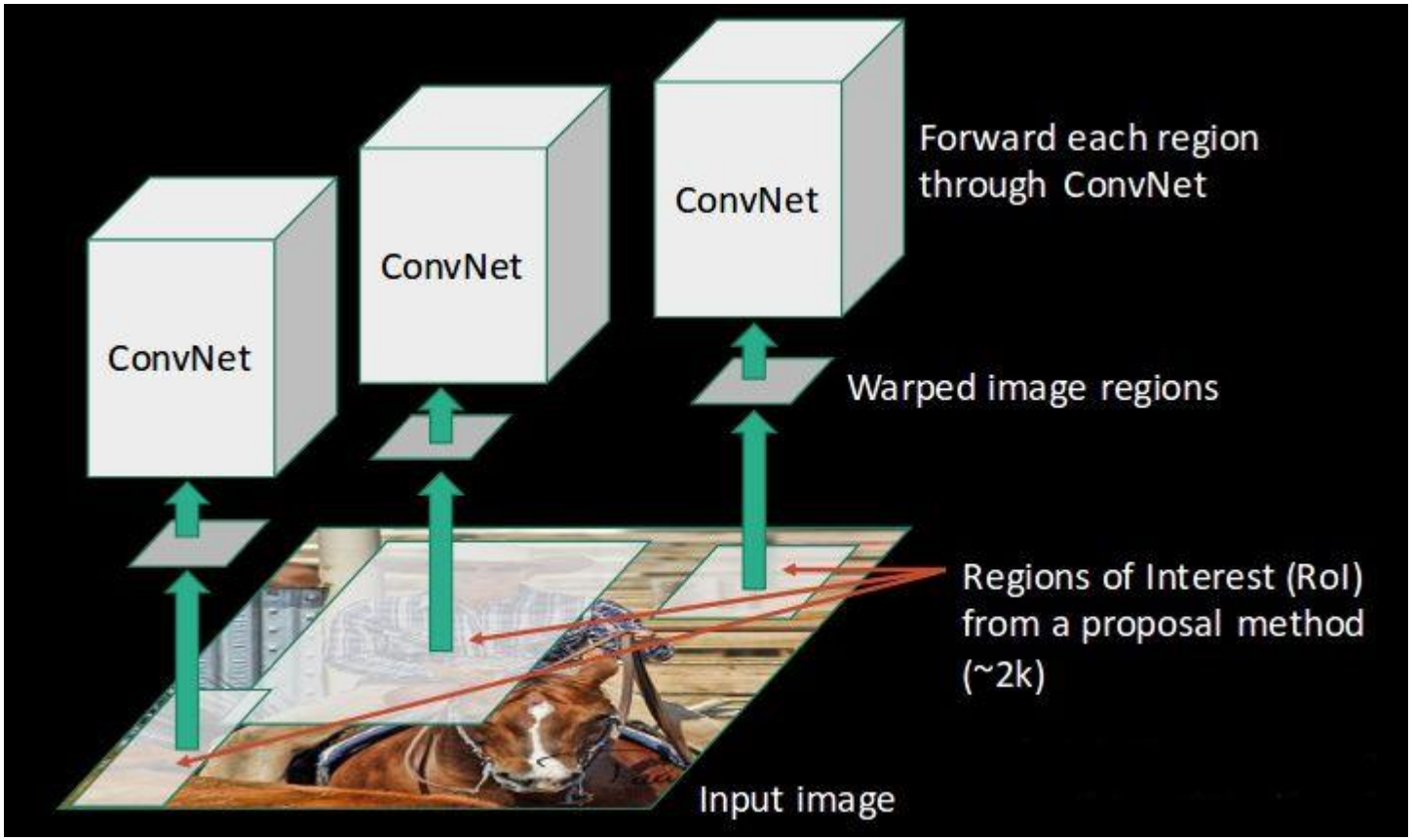
输入图片

区域建议



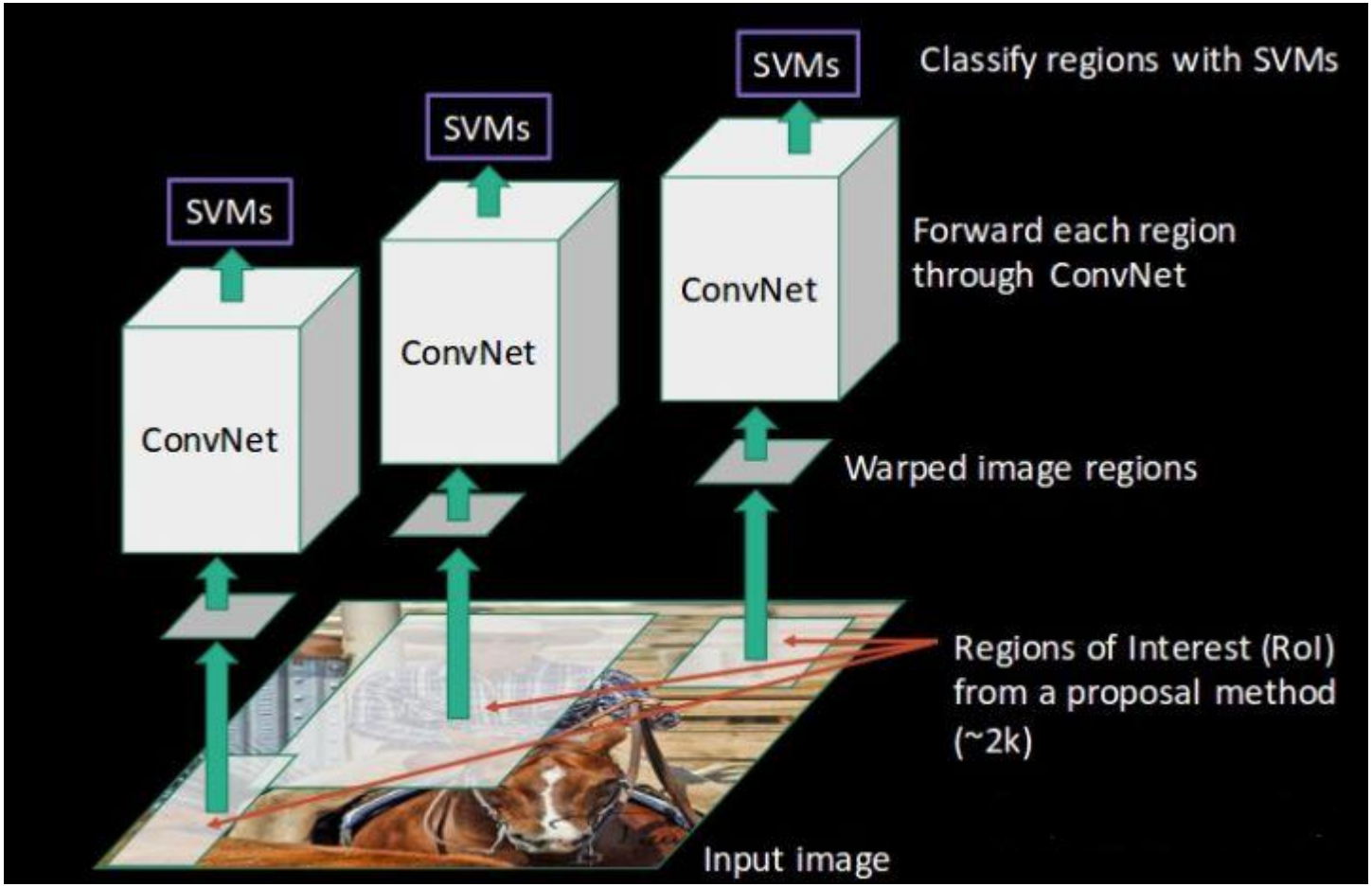
RCNN

Reshape与CNN



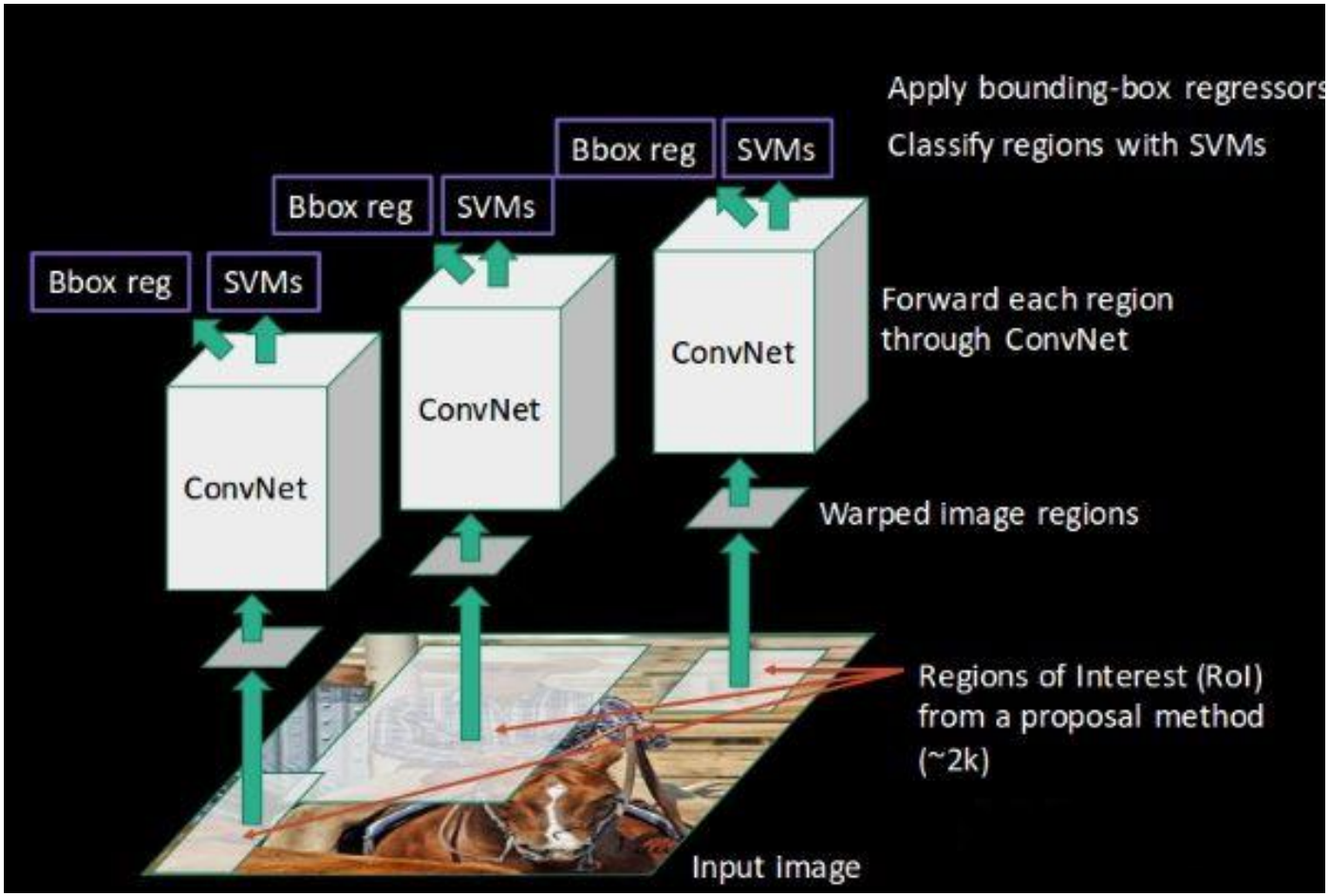
RCNN

SVM分类


SVMs
SVMs
SVMs
Classify regions with SVMs
ConvNet
ConvNet
ConvNet
Forward each region through ConvNet
Warped image regions
Regions of Interest (RoI) from a proposal method (~2k)
Input image

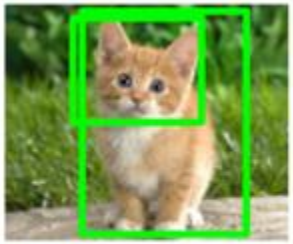
RCNN

边界框回归


Apply bounding-box regressors
Classify regions with SVMs
Bbox reg
SVMs
Bbox reg
SVMs
Bbox reg
SVMs
ConvNet
ConvNet
ConvNet
Forward each region through ConvNet
Warped image regions
Regions of Interest (RoI) from a proposal method (~2k)
Input image

RCNN-Region Proposal

Image



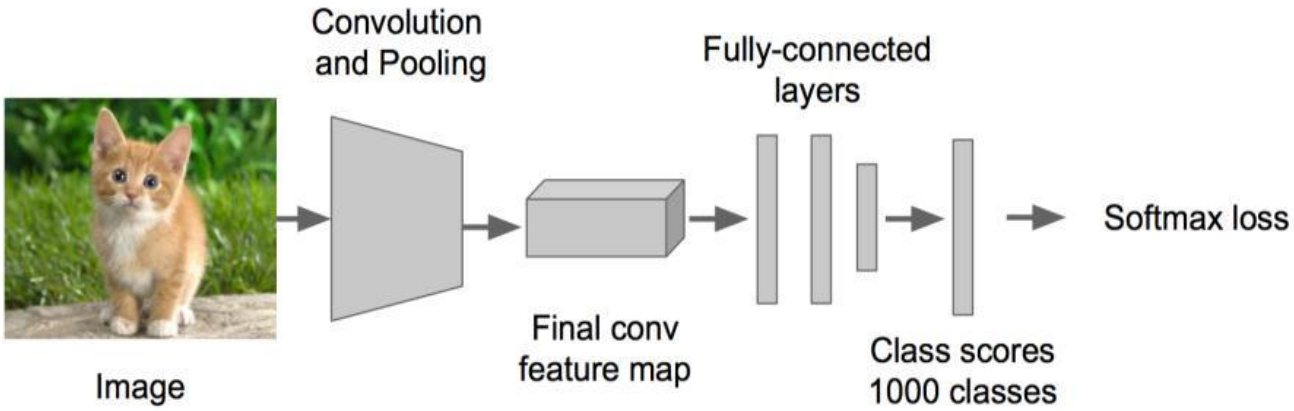
Region Proposals

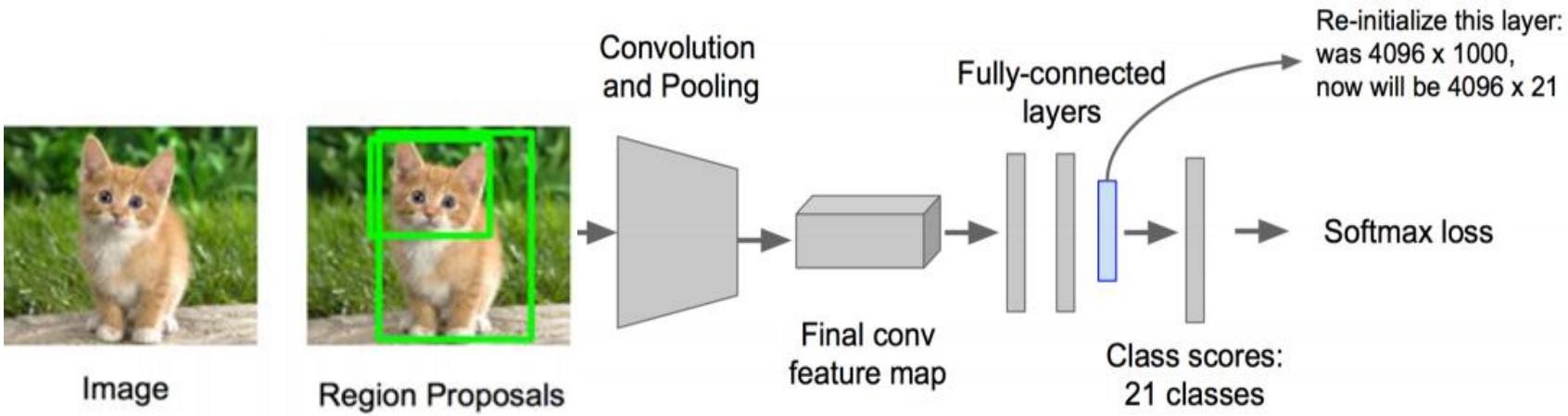
Region Proposal：利用图像中的纹理、边缘、颜色等信息，找出可能含有物体的区域。

- Selective Search、EdgeBoxes等等。
- What makes for effective detection proposals？——PAMI2015

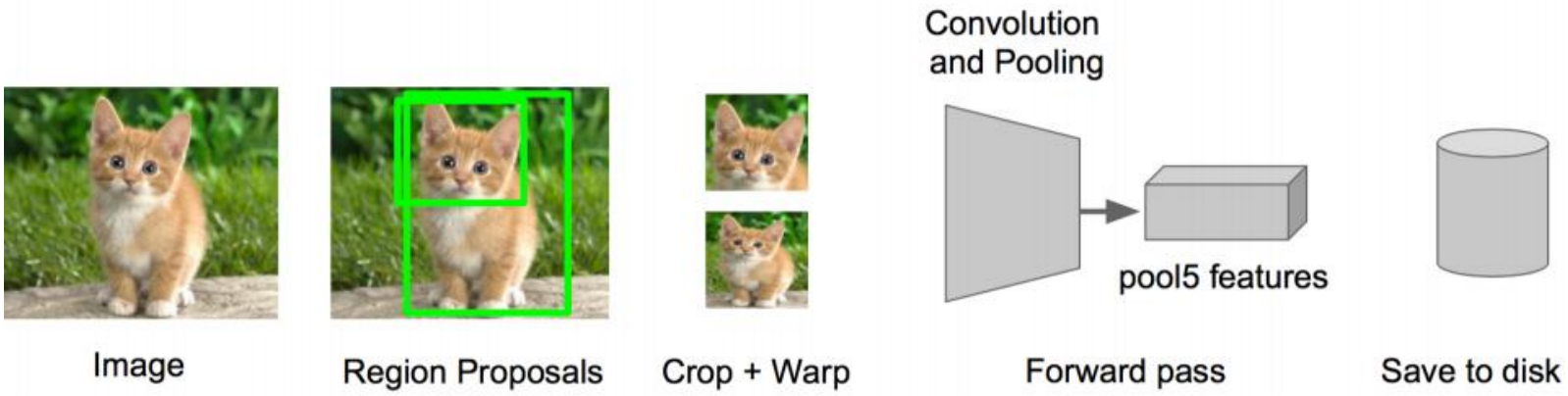
Method	Approach	Outputs Segments	Outputs Score	Control #proposals	Time (sec.)	Repea-tability	Recall Results	Detection Results
Bing [18]	Window scoring		✓	✓	0.2	★★★	★	·
CPMC [19]	Grouping	✓	✓	✓	250	-	★★	★
EdgeBoxes [20]	Window scoring		✓	✓	0.3	★★	★★★	★★★
Endres [21]	Grouping	✓	✓	✓	100	-	★★★	★★
Geodesic [22]	Grouping	✓		✓	1	★	★★★	★★
MCG [23]	Grouping	✓	✓	✓	30	★	★★★	★★★
Objectness [24]	Window scoring		✓	✓	3	·	★	·
Rahtu [25]	Window scoring		✓	✓	3	·	·	★
RandomizedPrim's [26]	Grouping	✓		✓	1	★	★	★★
Rantalankila [27]	Grouping	✓		✓	10	★★	·	★★
Rigor [28]	Grouping	✓		✓	10	★	★★	★★
SelectiveSearch [29]	Grouping	✓	✓	✓	10	★★	★★★	★★★
Gaussian				✓	0	·	·	★
SlidingWindow				✓	0	★★★	·	·
Superpixels		✓			1	★	·	·
Uniform				✓	0	·	·	·

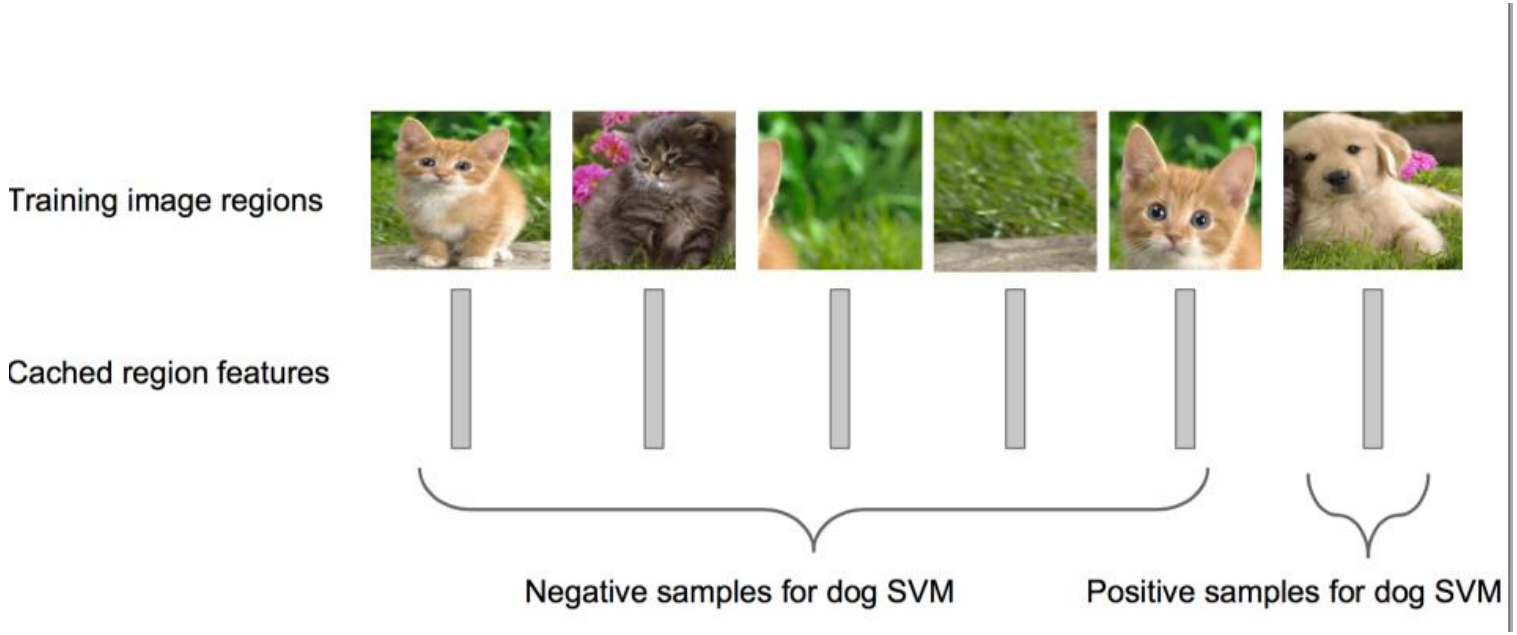
RCNN-卷积网络


Convolution
and Pooling
Fully-connected
layers
Softmax loss
Image
Final conv
feature map
Class scores
1000 classes

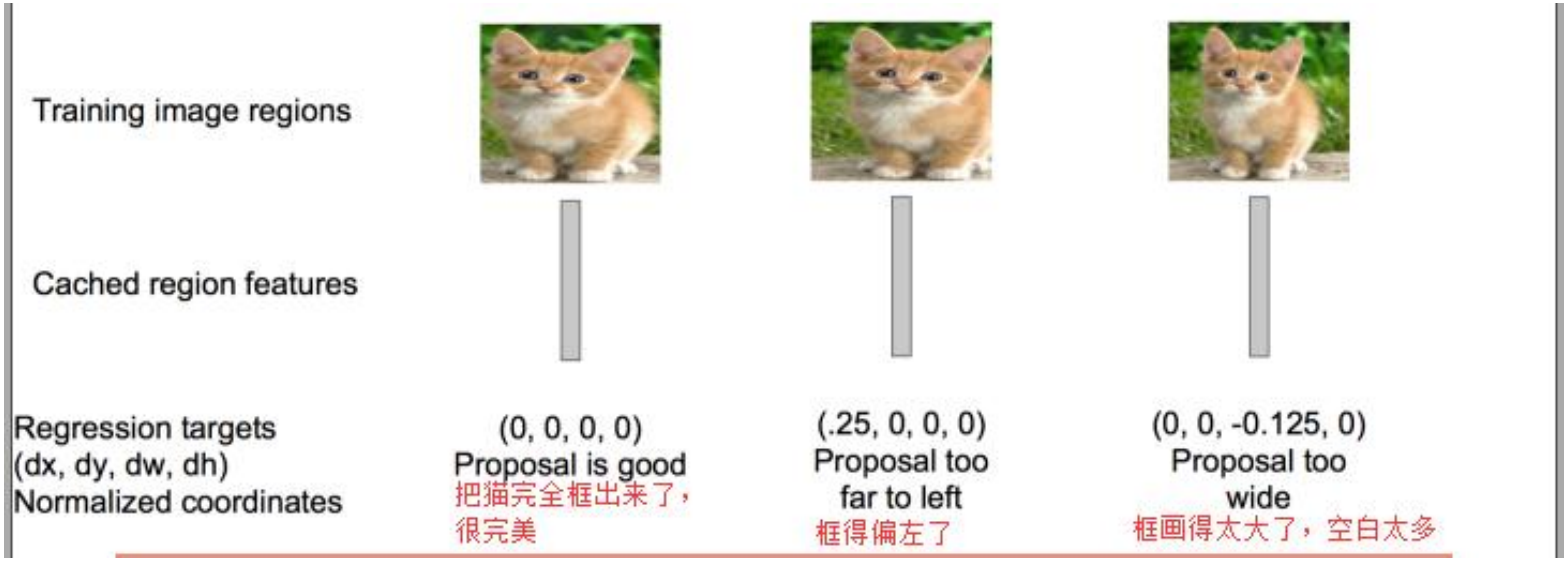

Re-initialize this layer:
was 4096 x 1000,
now will be 4096 x 21
Convolution
and Pooling
Fully-connected
layers
Softmax loss
Image
Region Proposals
Final conv
feature map
Class scores:
21 classes

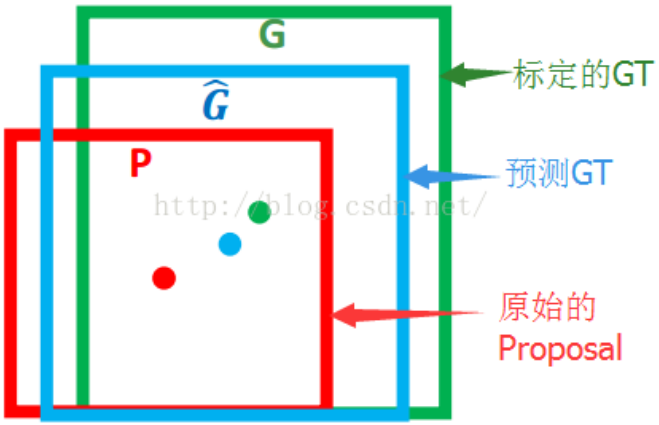
RCNN-SVM


Convolution
and Pooling
pool5 features
Image
Region Proposals
Crop + Warp
Forward pass
Save to disk


Training image regions
Cached region features
Negative samples for dog SVM
Positive samples for dog SVM

RCNN-边界框回归





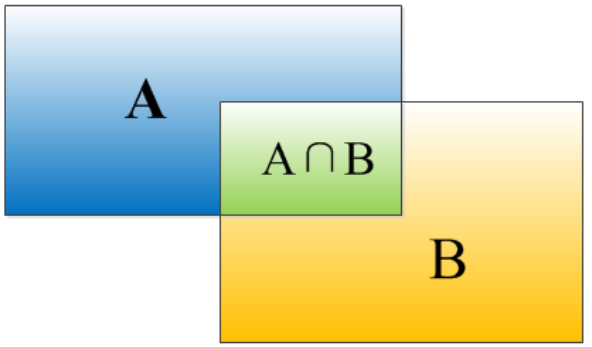
给定(P_x, P_y, P_w, P_h)，寻找一种映射f，使得：

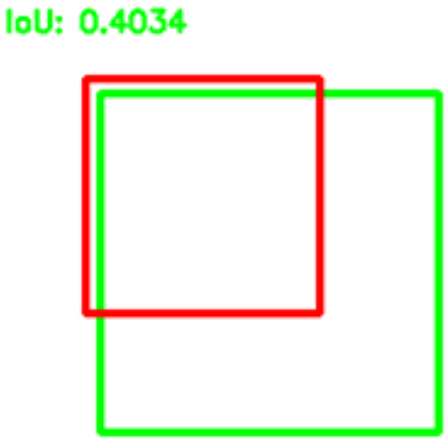
$$f(P_x, P_y, P_w, P_h) = (\widehat{G_x}, \widehat{G_y}, \widehat{G_w}, \widehat{G_h}) \approx (G_x, G_y, G_w, G_h)$$

RCNN-IoU

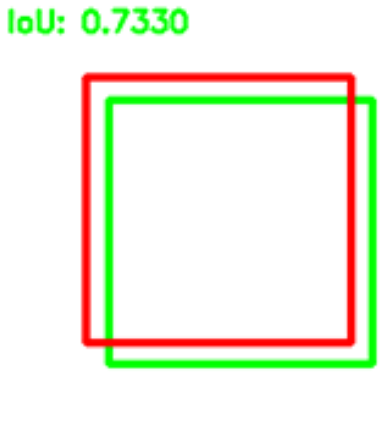
IoU(Intersection over Union)

- IOU=(A∩B)/(A∪B)

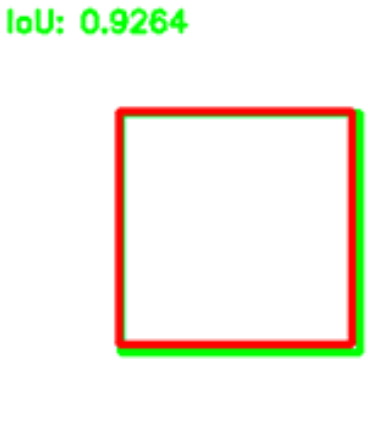




Poor

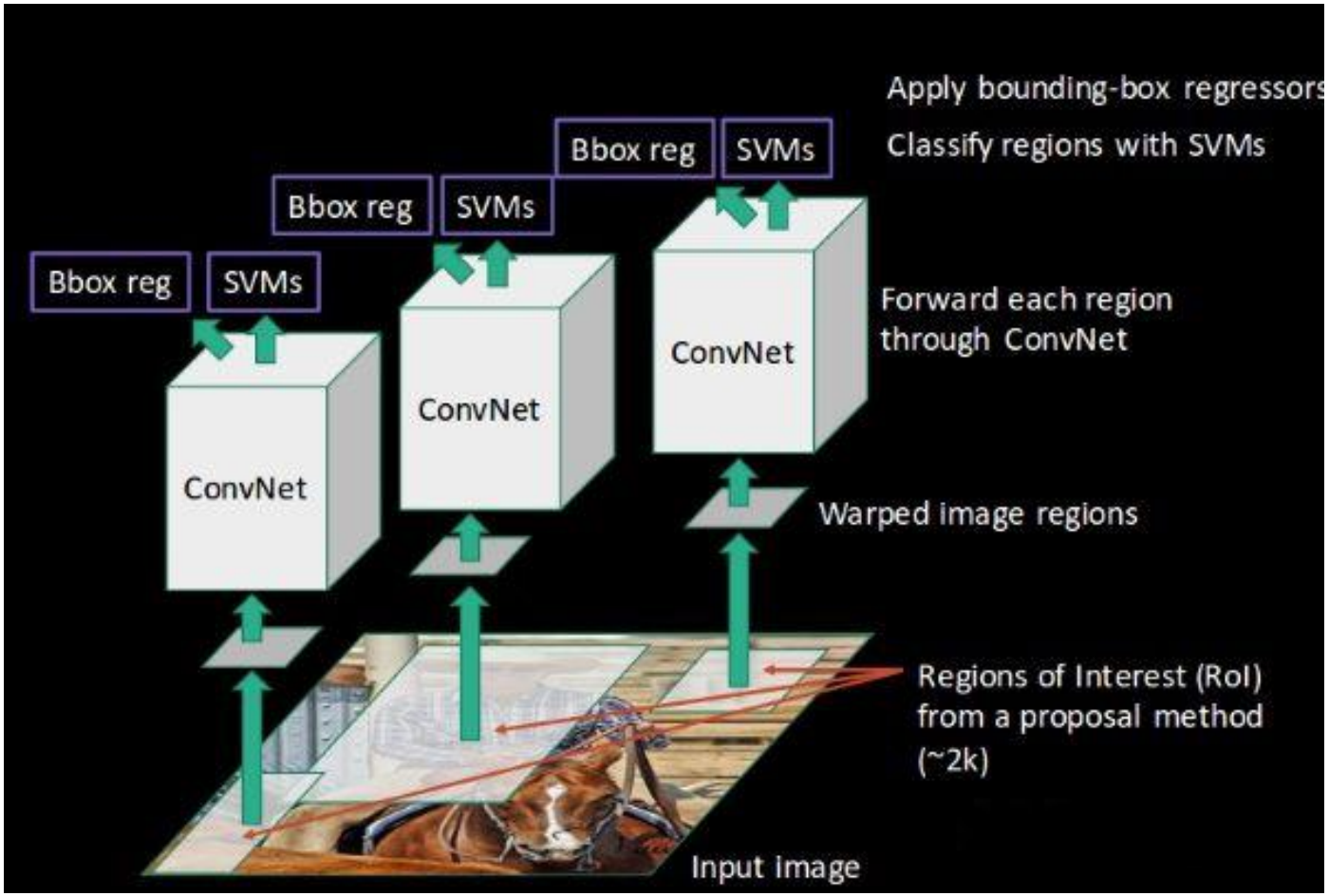


Good



Excellent

RCNN Revisiting



YOLO

- YOLO： You Only Look Once: Unified, Real-Time Object Detection
  - Joseph Redmon, Santosh Divvala, Ross Girshick, Ali Farhadi， CVPR2016
- History：
  - YOLO
  - YOLOv2
  - YOLO9000 = YOLOv2 + joint training
  - YOLOv3、Tiny YOLOv3

YOLO

- YOLO：将 object detection 的框架设计为regression problem，直接从图像像素到 bounding box 以及 probabilities。

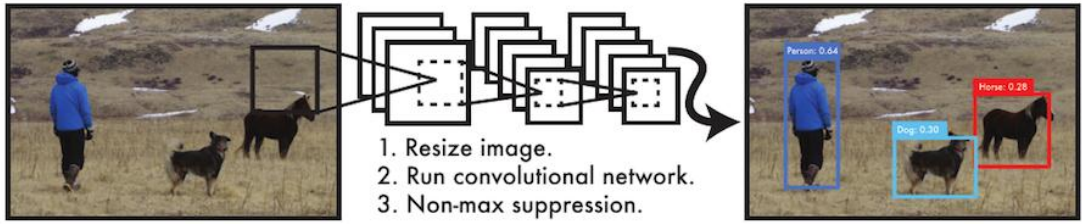


Figure 1: The YOLO Detection System. Processing images with YOLO is simple and straightforward. Our system (1) resizes the input image to 448 × 448, (2) runs a single convolutional network on the image, and (3) thresholds the resulting detections by the model's confidence.

YOLO

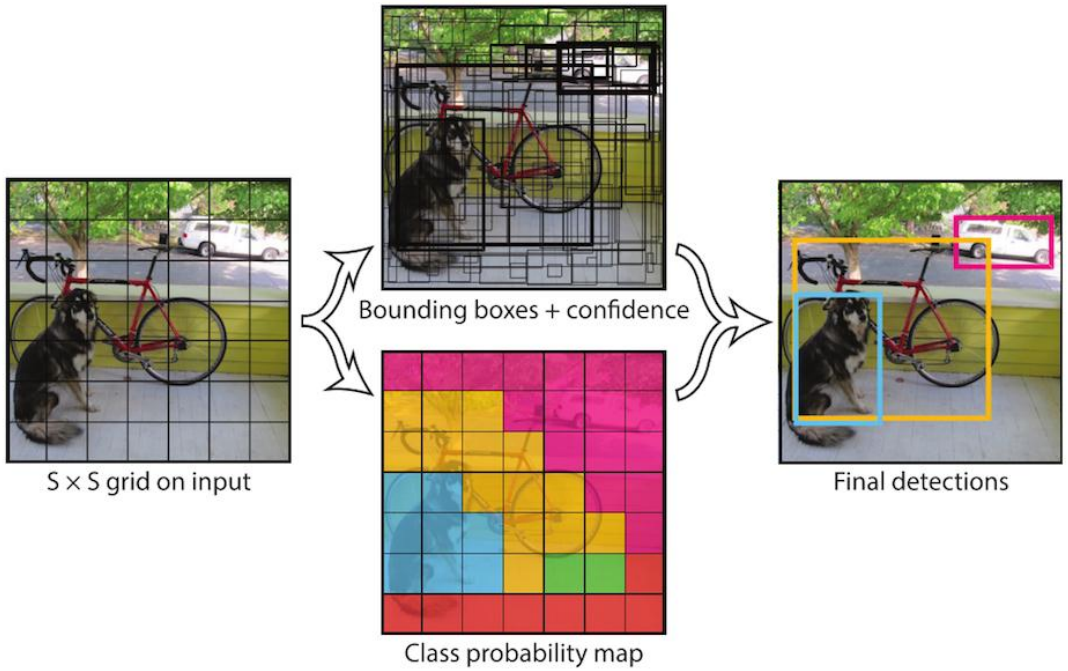
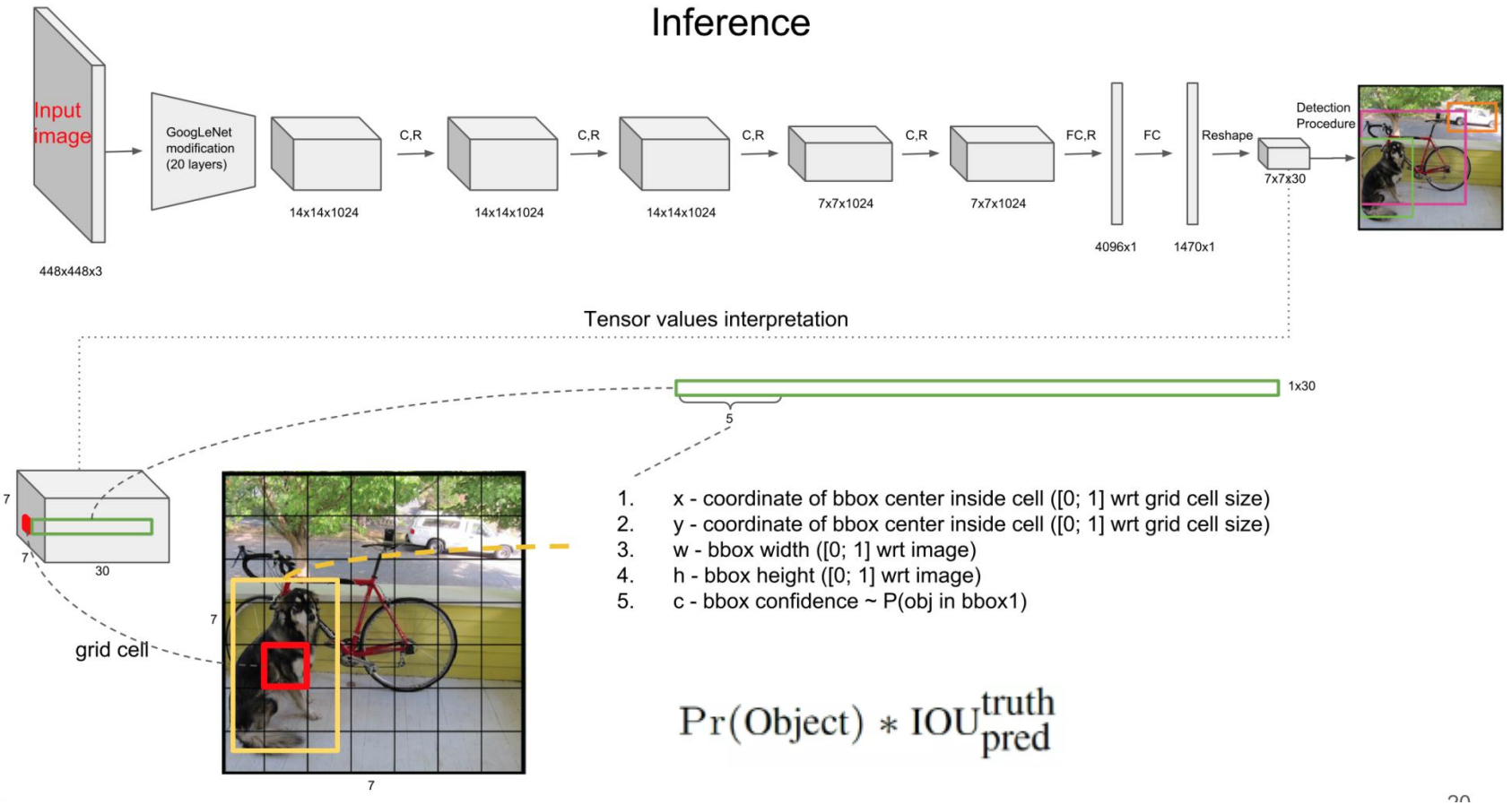


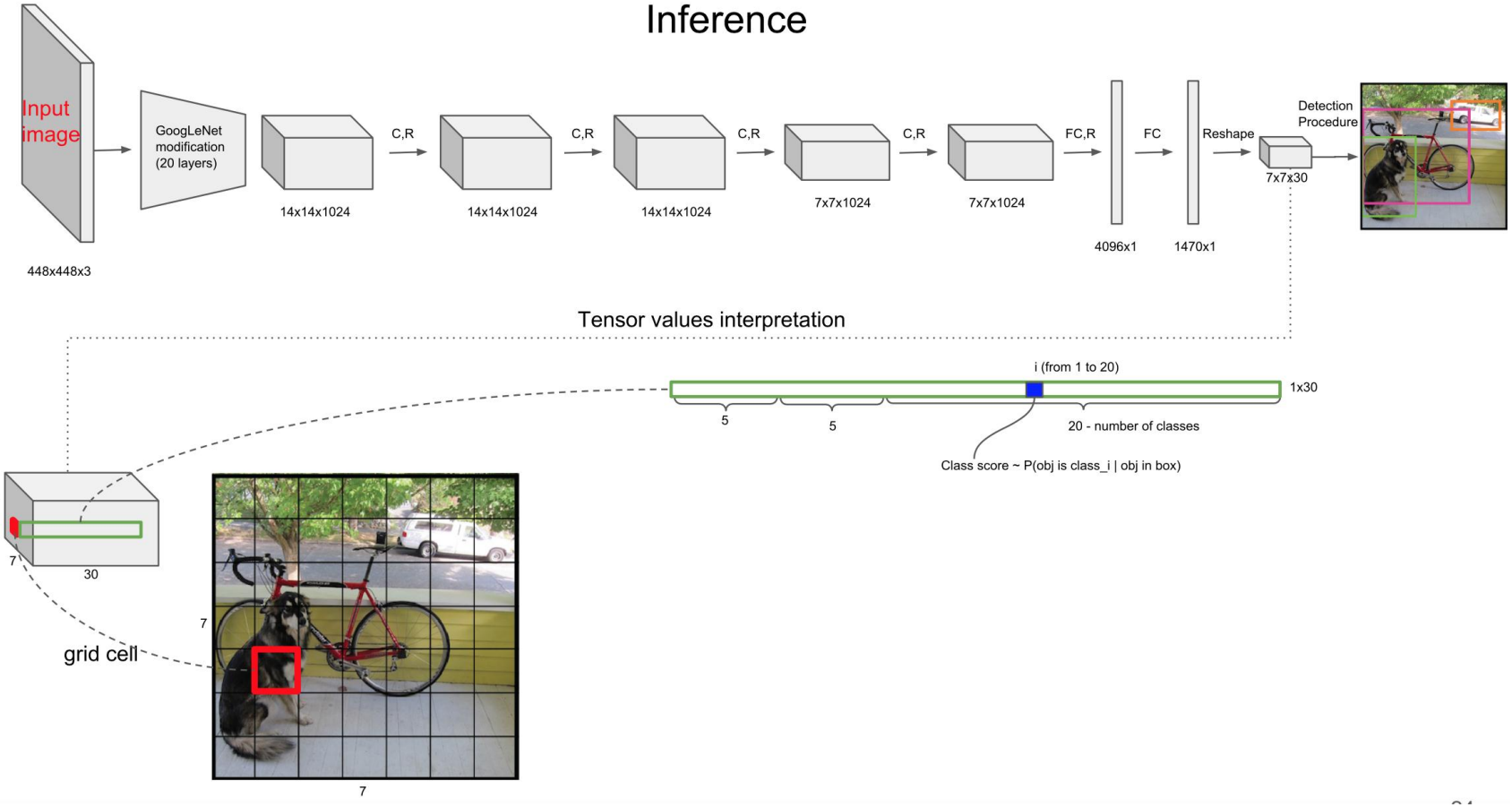
Figure 2: The Model. Our system models detection as a regression problem. It divides the image into an $S \times S$ grid and for each grid cell predicts B bounding boxes, confidence for those boxes, and C class probabilities. These predictions are encoded as an $S \times S \times (B * 5 + C)$ tensor.

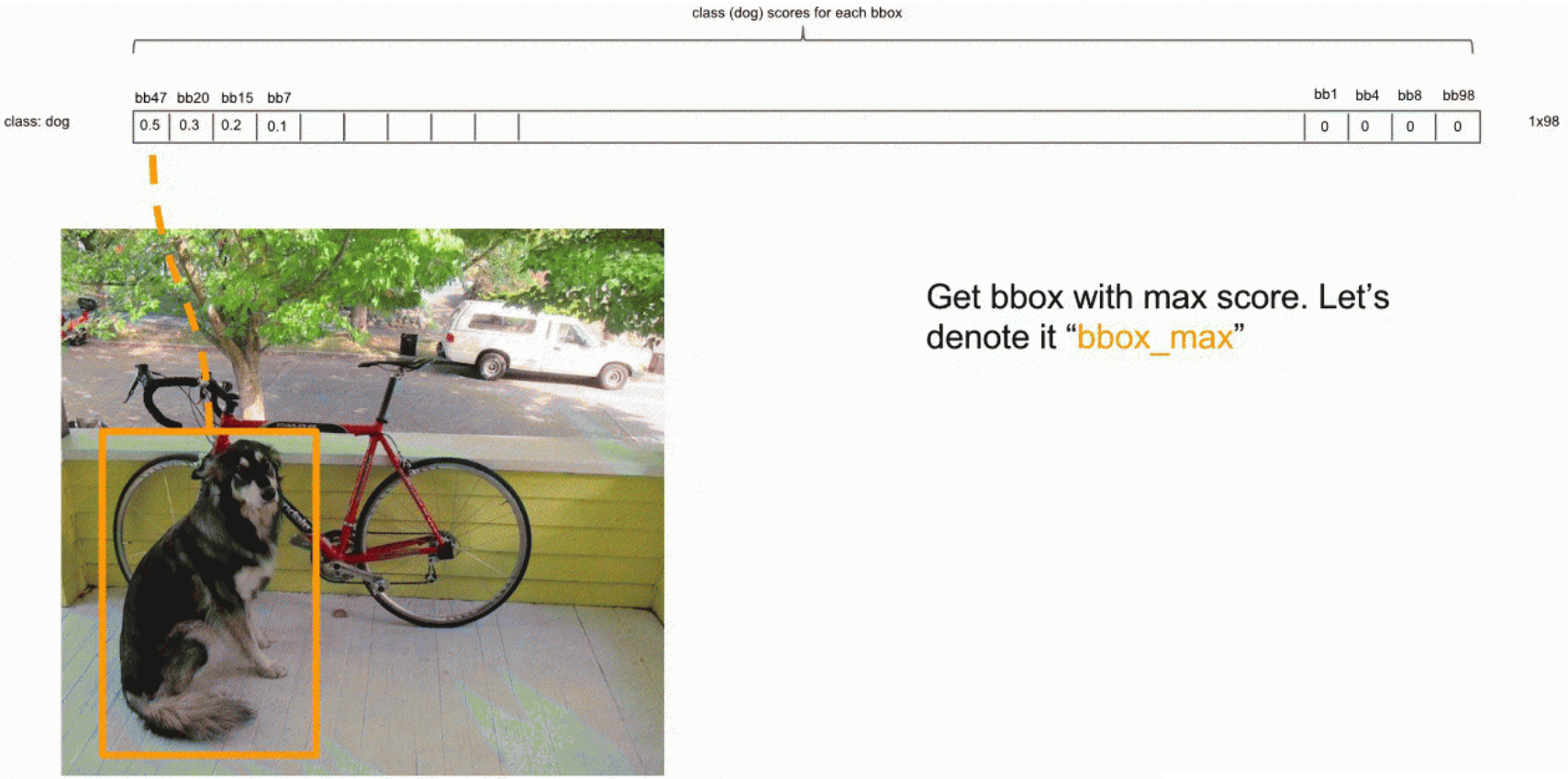
YOLO

图像输入为448x448，取S=7，B=2，一共有20个类别(C=20)。则输出就是7x7x30的一个tensor：



Inference


Input image
448x448x3
GoogLeNet modification (20 layers)
14x14x1024
C,R
14x14x1024
C,R
14x14x1024
C,R
7x7x1024
C,R
7x7x1024
FC,R
4096x1
FC
1470x1
Reshape
7x7x30
Detection Procedure
Tensor values interpretation
i (from 1 to 20)
1x30
5
5
20 - number of classes
Class score ~ P(obj is class_i | obj in box)
7
7
30
grid cell
7
7



Get bbox with max score. Let's denote it "bbox_max"

$$\Pr(\text{Class}_i|\text{Object}) * \Pr(\text{Object}) * \text{IOU}_{\text{pred}}^{\text{truth}} = \Pr(\text{Class}_i) * \text{IOU}_{\text{pred}}^{\text{truth}}$$

YOLOv2

	YOLO							YOLOv2
batch norm?		✓	✓	✓	✓	✓	✓	✓	✓
hi-res classifier?			✓	✓	✓	✓	✓	✓	✓
convolutional?				✓	✓	✓	✓	✓	✓
anchor boxes?				✓	✓				
new network?					✓	✓	✓	✓	✓
dimension priors?						✓	✓	✓	✓
location prediction?						✓	✓	✓	✓
passthrough?							✓	✓	✓
multi-scale?								✓	✓
hi-res detector?									✓
VOC2007 mAP	63.4	65.8	69.5	69.2	69.6	74.4	75.4	76.8	**78.6**

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%.

Results

Detection Frameworks	Train	mAP	FPS
Fast R-CNN [5]	2007+2012	70.0	0.5
Faster R-CNN VGG-16[15]	2007+2012	73.2	7
Faster R-CNN ResNet[6]	2007+2012	76.4	5
YOLO [14]	2007+2012	63.4	45
SSD300 [11]	2007+2012	74.3	46
SSD500 [11]	2007+2012	76.8	19
YOLOv2 288 × 288	2007+2012	69.0	91
YOLOv2 352 × 352	2007+2012	73.7	81
YOLOv2 416 × 416	2007+2012	76.8	67
YOLOv2 480 × 480	2007+2012	77.8	59
YOLOv2 544 × 544	2007+2012	**78.6**	40

Table 3: Detection frameworks on PASCAL VOC 2007. YOLOv2 is faster and more accurate than prior detection methods. It can also run at different resolutions for an easy tradeoff between speed and accuracy. Each YOLOv2 entry is actually the same trained model with the same weights, just evaluated at a different size. All timing information is on a Geforce GTX Titan X (original, not Pascal model).

YOLO9000

- Stronger: joint training，即把detection dataset 和classification dataset 结合起来训练检测器。
  - 处理思路：训练时如果遇到来自检测集的图片则计算完整的Loss，如果遇到来自分类集的图片则只计算分类的Loss。
  - 处理细节：通常使用的softmax假定类间独立，而Imagenet(分类集)包含了100多种狗，COCO(检测集)就只有狗这一类。为了解决这个无法融合的问题，作者使用了multi-label模型，即假定一张图片可以有多个label，并且不要求label间独立。

YOLO9000

- Hierarchical Classification
- Dataset Combination With WordTree
- Joint Classification and Detection
- 最终制作了一个9418分类的WordTree
  和COCO的数据比例为4:1。

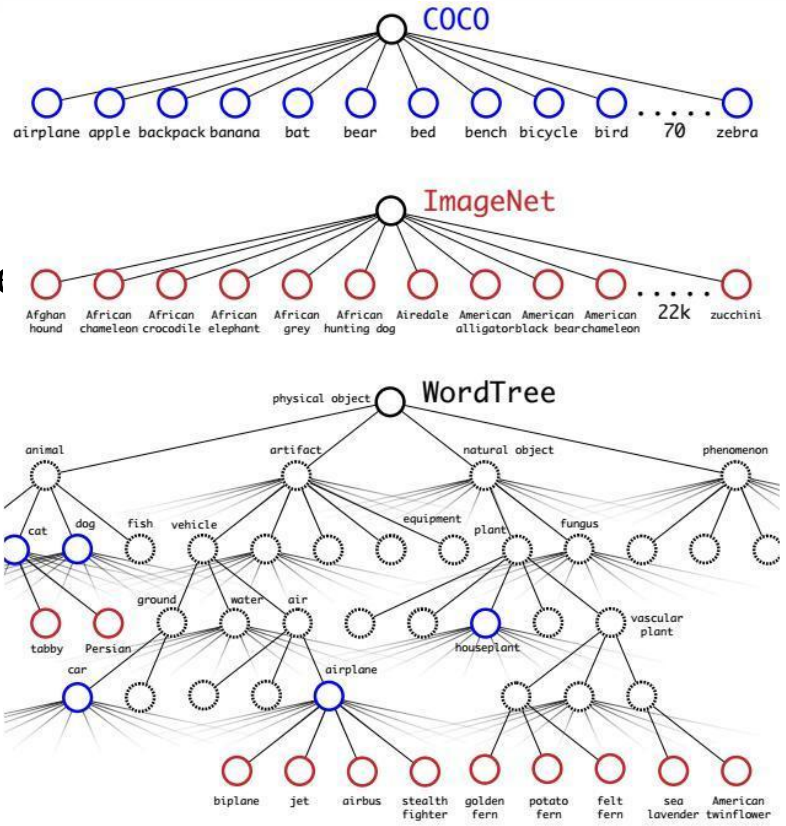


Figure 6: Combining datasets using WordTree hierarchy. Using the WordNet concept graph we build a hierarchical tree of visual concepts. Then we can merge datasets together by mapping the classes in the dataset to synsets in the tree. This is a simplified view of WordTree for illustration purposes.

Results

- ImageNet detection task (200 categories): The detection task for ImageNet shares on 44 object categories with COCO which means that YOLO9000 has only seen classification data for the majority of the test images, not detection data. YOLO9000 gets 19.7 mAP overall with 16.0 mAP on the disjoint 156 object classes that it has never seen any labelled detection data for.

diaper	0.0
horizontal bar	0.0
rubber eraser	0.0
sunglasses	0.0
swimming trunks	0.0
...	
red panda	50.7
fox	52.1
koala bear	54.3
tiger	61.0
armadillo	61.7

Table 7: YOLO9000 Best and Worst Classes on ImageNet. The classes with the highest and lowest AP from the 156 weakly supervised classes. YOLO9000 learns good models for a variety of animals but struggles with new classes like clothing or equipment.

小节

- 混合高斯模型
- 光流
- 帧间差分
- AdaBoost
- 基于DNN的物体检测

谢谢！