Formula

2024年12月23日　15:34

Convolutional layer

Input　$C_{in} \times H \times W$

hyp: Kernel size　$K_H \times K_W$　通常 $K_H = K_W$

#filters　C_{out}　32, 64, 128, 256　2^n

Padding　P　图像边界额外加P圈0 → preserving more spatial info → imp performance

$P = \frac{K-1}{2}$

$$\begin{cases} P=0, \text{ No (Zero) Padding} \\ P=1, \text{ One pixel (Zero) } \sim, \text{ zero-padding} \\ P=\lfloor \frac{K-1}{2} \rfloor, \text{ Same } \sim \text{ (zero)} \\ P=K-1, \text{ FULL Zero } \sim \end{cases}$$

Stride　S

$$\begin{cases} S=1, \text{ Unit stride, highest resolution} \\ >\ \text{ Strided conv, } \downarrow \\ <\ \text{ Fractional stride, used in transposed conv. } Size_{out} > Size_{in} \end{cases}$$

Weight matrix　$C_{out} \times C_{in} \times K_H \times K_W$

#filters

Bias vector　C_{out}

Output size (# output ele)　$C_{out} \times H' \times W'$

$$H' = \frac{(H-K+2P)}{S} + 1$$

$$W' = \frac{(W-K+2P)}{S} + 1$$

无法整除则 Floor

Memory usage

For 32-bit floating point, bytes per ele : 4　(unit)

Weights m $= C_{in} \times C_{out} \times K_H \times K_W \times 4$　①

biased m $= C_{out} \times 4$　②

feature maps m:

input m $= H_{in} \times W_{in} \times C_{in} \times 4$　③

out m $= H' \times W' \times C_{out} \times 4$　④

Total mem $= \sum_{①}^{④}$

Full Form	Units	Bytes
1 Bit	Binary Digit (0/1)	
1 Nibble	4 bits	
1 Byte	8 bits	
1 kilobyte(KB)	1024 byte	2^{10} bytes
1 Megabyte(MB)	1024 KB	2^{20} bytes
1 Gigabyte (GB)	1024 MB	2^{30} bytes
1 Terabyte(TB)	1024 GB	2^{40} bytes
1 Petabyte(PB)	1024 TB	2^{50} bytes
1 Exabyte(EB)	1024 PB	2^{60} bytes
1 Zettabyte(ZB)	1024 EB	2^{70} bytes
1 Yottabyte(YB)	1024 ZB	2^{80} bytes
1 Brontobyte	1024 YB	2^{90} bytes
1 Geopbyte	1024 Brontobyte	2^{100} bytes

#Para (#weight) = weight shape + bias shape
$= C_{in} \times C_{out} \times K_W \times K_H + C_{out}$

#FLOP = # Output size × Oper per out ele

Floating pt. oper. $= C_{out} \times H' \times W' \times C_{in} \times K_H \times K_W$

Pooling,

无可学习参数, $C_{in} = C_{out}$, 有 S, P. $H'W'$ 计算同 conv.

FLOP $= C_{out} \times H' \times W' \times \begin{cases} (K \times K - 1) \\ K \times K \end{cases}$　max-pooling / avg - ~

Flatten

无可学习参数

Output size　$C_{in} \times H \times W$

FLOP　0

无可学习参数

Output size $\quad C_{in} \times H \times W$

FLOP $\quad 0$

Memory $= C_{in} \times H \times W \times 4$

For each class:
e.g. person

confidence score — the probability that the prediction is correct.

Non-Maximum Suppression

removes **redundant** bounding boxes from a set of detected objects

① Bounding box generation

② Sorting by cs (conf score)

③ Suppression:

1) Select the box with the highest cs
2) Cal IoU with all other boxes
3) Suppress overlapping boxes (exceeds a predefined IoU threshold)
4) Repeat — This continues until all boxes have been either selected as a detection or suppressed.

IOU intersection-to-parallel ratio (Jaccard)

1° 给定坐标 → 画图 → 面积交集除以并集

2° 给定矩阵 → pred 标记 → $\frac{TP}{TP+FP+FN}$

TP、FP、FN 点 — 重叠 边角料

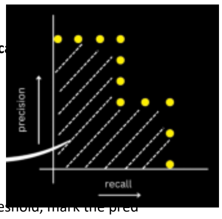
DICE $= \frac{2TP}{2TP+FP+FN}$

precision $= \frac{TP}{TP+FP}$ → 预测的 1 — 预测精度

recall $= \frac{TP}{TP+FN}$ → 真实 1 中哪些预测到。召回

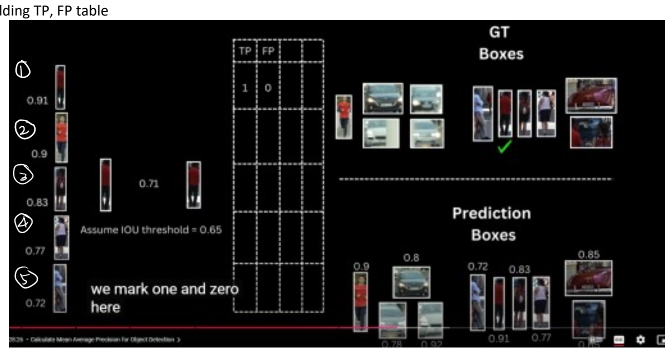
average precision (AP) src:[Mean Average Precision (mAP) | Explanation and Implementation for Object Detection]

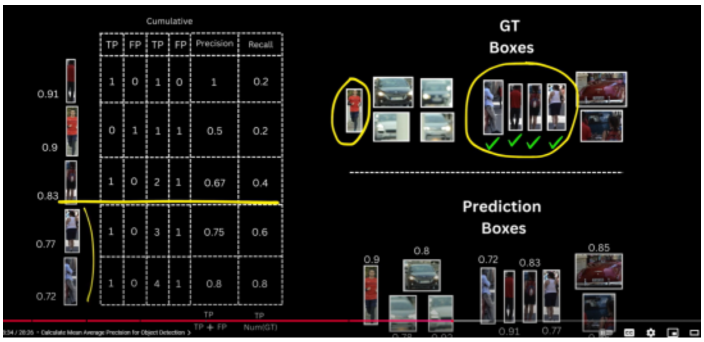
The average of precision **at different recall levels**. It is calculated as the **area under the precision-rec**[all curve] interpolation of precision at different recall points.
Improving one often comes at the cost of reducing the other.



AP for person class:

a. take all the predicted boxes that have person as the pred class
b. sort them in the decreasing order of confidence scores
c. For each, find the best matching ground truth box for matching (based on overlap(Area of this GT box has not been matched before, and its IoU us greater than some predefined threshold, mark the pred as a TP, GT as matched.
d. building TP, FP table

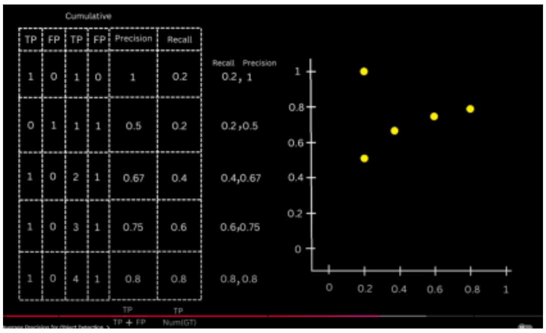
i. 

ii. 

We got the precision and recall values using different confidence threshold. e.g. 0.83. 2 detection below it will be ignored.? ?

For all classes/queries. $\quad mAP = \frac{1}{N}\sum_{i=1}^{N} AP_i$

mean



link them -> precision recall curce -> Find the area under the curve (AUC-PR).
For object detection tasks, AP (Average Precision) is equivalent to the area under the Precision-Recall curve.

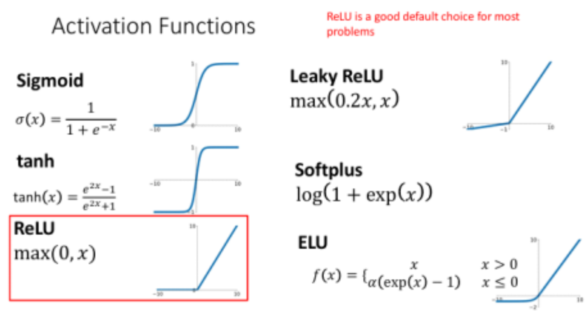
For all classes
mean average precision

In VOC 2007, AP is calculated using the 11-point interpolation method, but modern object detection frameworks often use a finer, continuous approximation to compute AP.

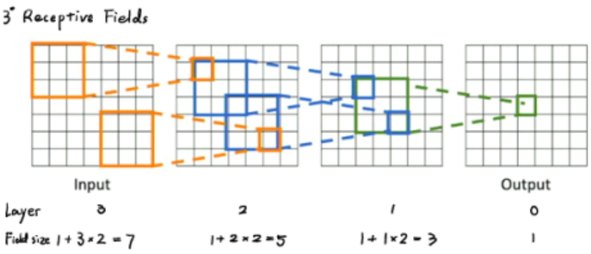
In VOC2012, mAP = meanPrecision * meanRecall

Doing this among all classes and doing the mean of the APs, will get mAP.

Activation function



Receptive fields



L Layer receptive field size = 1 + L × (K−1)
fil size

e.g. input 1000×1000, K=3, L=?
1000 = 1 + L×(3−1)
L = 999 ÷ 2 = 499.5

Large imgs need many layers for each outps to "see" the whole img, sol:
(gloabal context)