Deep Learning for Computer Vision

CNNs for Object Detection - II

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Exercise: Smooth L1 Loss

Why is Smooth L1 loss less sensitive to outliers than L2 loss?

If the deviation of predicted output from ground truth is very high, squaring the difference explodes the gradient. This can happen in L2 loss for outliers, and is mitigated in the Smooth L1 loss.

Recall: Contemporary Object Detection Methods

Region Proposal-based:

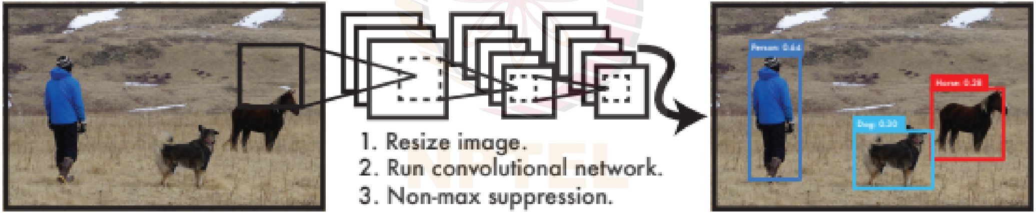
- Two-stage detection framework
- In the first stage, potential object regions are proposed (through methods such as Selective Search or Region Proposal Network, which we will see soon)
- In the second stage, a classifier processes the candidate regions
- More robust in performance but slower

Dense Sampling-based:

- One-stage detection framework
- Integrates region proposals and detection by acting on a dense sampling of possible locations
- Simple and fast but performance not as good as Region Proposal-based methods

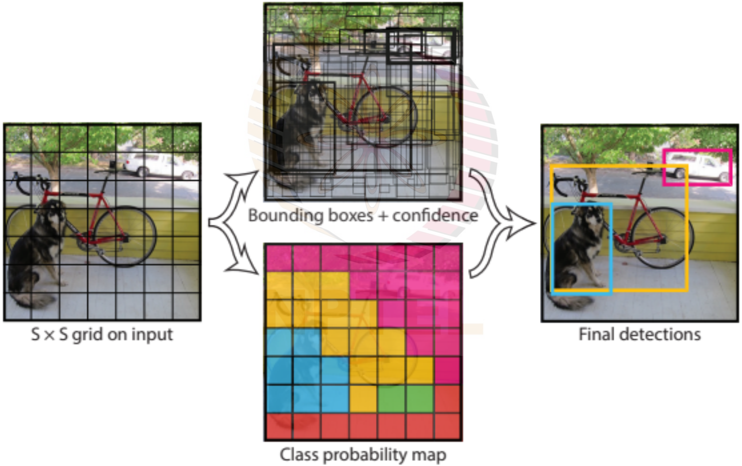
You Only Look Once (YOLO): v1[1]

- Single-stage detector based on Overfeat
- Speed with good performance the main aim

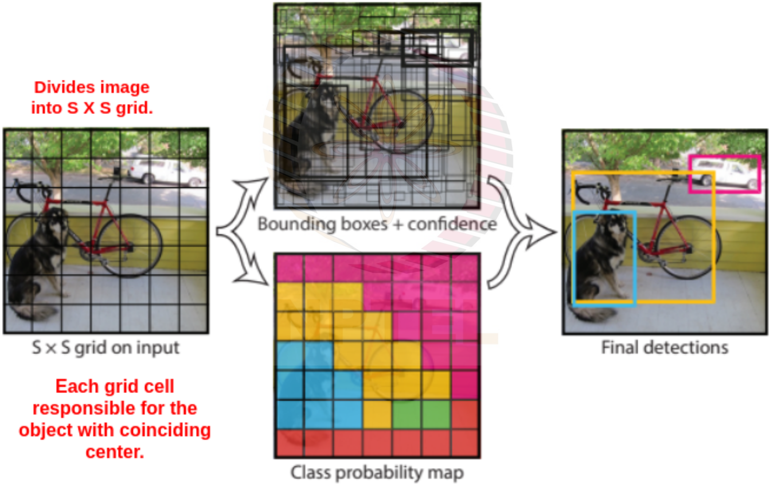


[1] Redmon et al, You Only Look Once: Unified, Real-Time Object Detection, CVPR 2016

YOLO v1: Unified Detection

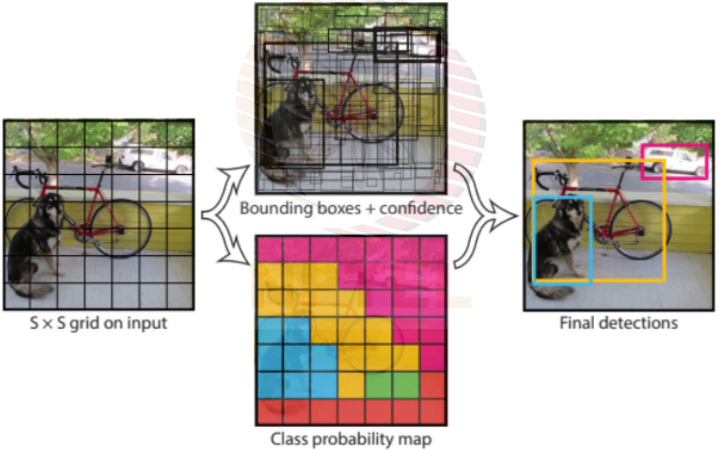


YOLO v1: Unified Detection

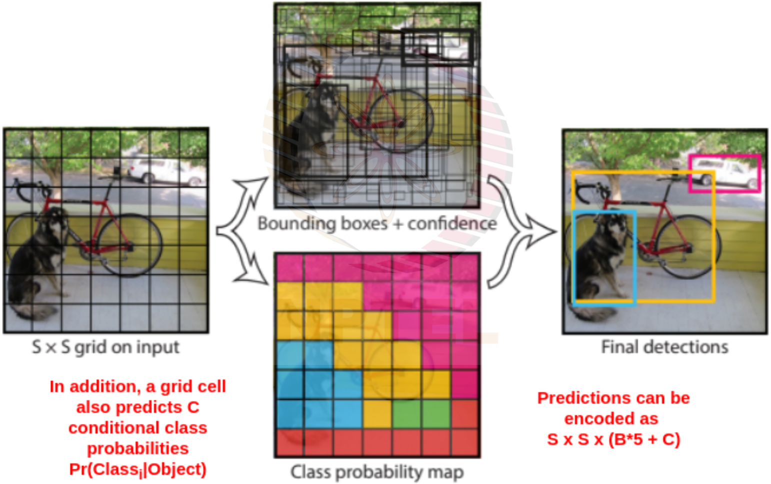


YOLO v1: Unified Detection

Each grid cell predicte B bounding boxes and confidence scores of the boxes.



YOLO v1: Unified Detection



In addition, a grid cell also predicts C conditional class probabilities $Pr(Class_i|Object)$

Predictions can be encoded as $S \times S \times (B*5 + C)$

YOLO v1: Bounding Boxes and Confidence Scores

Bounding Boxes:

- Each bounding box gives 4 coordinates x, y, w, h
- $(x, y) =$ Coordinates representing center of the object **relative to the grid cell**
- $(w, h) =$ Width and height of the object **relative to the whole image**

YOLO v1: Bounding Boxes and Confidence Scores

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Confidence Score:

- Reflects how confident the model is that the box contains an object and also how accurate it thinks the box is
- Formally,

$$\text{Confidence} = Pr(\text{Object}) * IOU_{pred}^{truth}$$

YOLO v1: Conditional Class Probabilities

- Regardless of number of boxes B, we only predict one set of class probabilities per grid cell
- At test time, class-specific confidence scores for each box are given by:

$$Pr(Class_i|Object) * Pr(Object) * IOU_{pred}^{truth} = Pr(Class_i) * IOU_{pred}^{truth}$$

YOLO v1: Loss Function

Loss function used to train YOLO v1 given by:

$$\lambda_{\text{coord}} \sum_{i=0}^{S^2} \sum_{j=0}^{B} \mathbb{1}_{ij}^{\text{obj}} \left[(x_i - \hat{x}_i)^2 + (y_i - \hat{y}_i)^2 \right]$$

$$+\lambda_{\text{coord}} \sum_{i=0}^{S^2} \sum_{j=0}^{B} \mathbb{1}_{ij}^{\text{obj}} \left[(\sqrt{w_i} - \sqrt{\hat{w}_i})^2 + (\sqrt{h_i} - \sqrt{\hat{h}_i})^2 \right] + \sum_{i=0}^{S^2} \sum_{j=0}^{B} \mathbb{1}_{ij}^{\text{obj}} \left(C_i - \hat{C}_i \right)^2$$

$$+\lambda_{\text{noobj}} \sum_{i=0}^{S^2} \sum_{j=0}^{B} \mathbb{1}_{ij}^{\text{noobj}} \left(C_i - \hat{C}_i \right)^2 + \sum_{i=0}^{S^2} \mathbb{1}_{i}^{\text{obj}} \sum_{c \in \text{classes}} (p_i(c) - \hat{p}_i(c))^2$$

where:

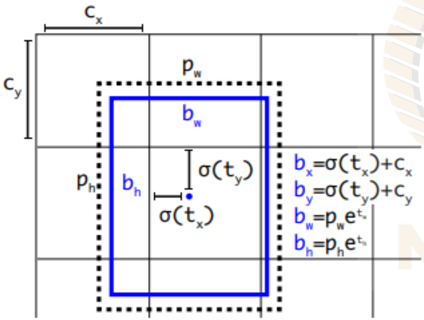
- $\mathbb{1}_{i}^{\text{obj}}$ denotes if object appears in cell i
- $\mathbb{1}_{ij}^{\text{obj}}$ denotes that j^{th} bounding box predictor in cell i is ‘responsible’ for that prediction

YOLO v1: Limitations

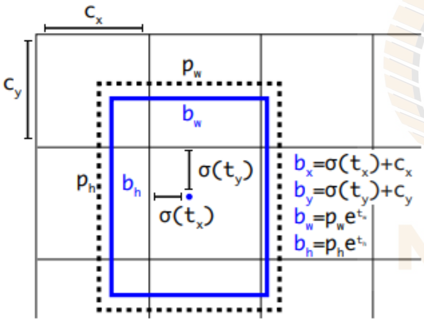
YOLO v1: Limitations

- Detects only a small number of objects
- Cannot detect objects that are small or close due to strong spatial constraints
- High localization error
- Relatively low recall

YOLO v2: Anchor Boxes

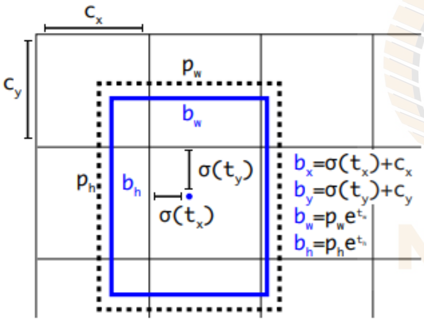


YOLO v2: Anchor Boxes



- Predicts 5 coordinates per anchor box: t_x, t_y, t_h, t_w, t_o

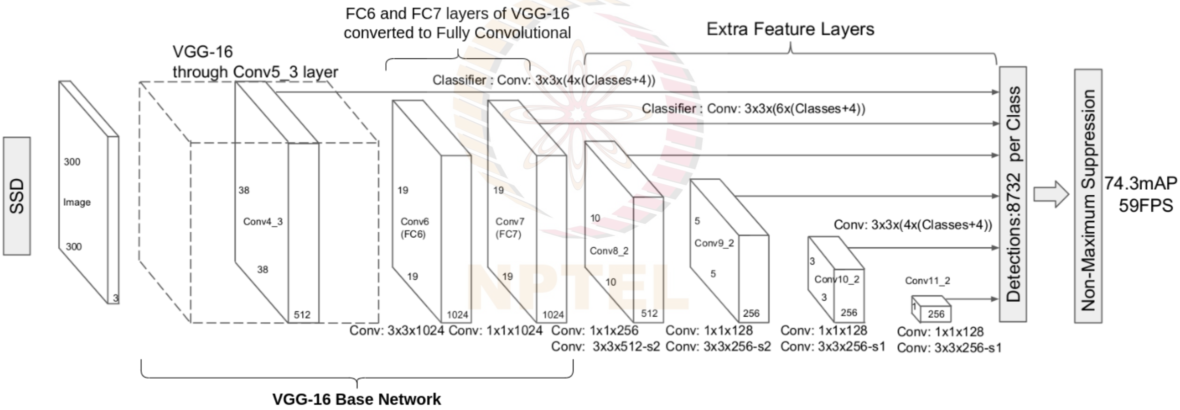
YOLO v2: Anchor Boxes



- Predicts 5 coordinates per anchor box: t_x, t_y, t_h, t_w, t_o
- If cell is offset from top left corner of image by (c_x, c_y) and bounding box has width and height p_w, p_h, then predictions correspond to:

$$b_x = \sigma(t_x) + c_x$$
$$b_y = \sigma(t_y) + c_y$$
$$b_w = p_w e^{t_w}$$
$$b_h = p_h e^{t_h}$$
$$Pr(\text{object}) * IOU(b, \text{object}) = \sigma(t_o)$$

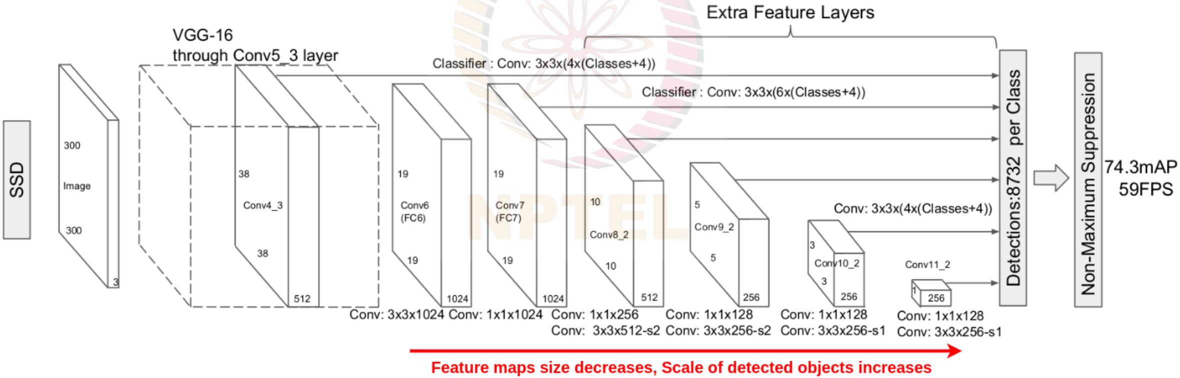
Single Shot MultiBox Detector (SSD)[2]



[2]Liu et al, SSD: Single Shot MultiBox Detector, ECCV 2016

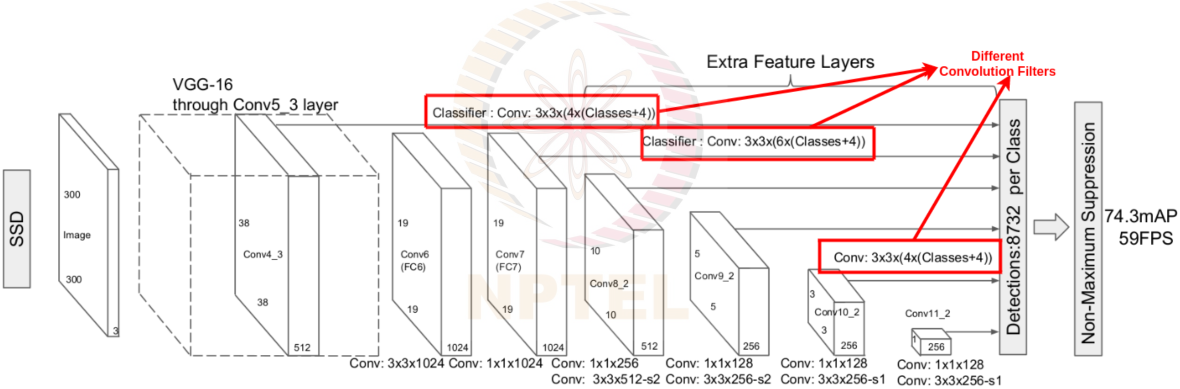
SSD: Model

Multi-scale Feature maps for Detection



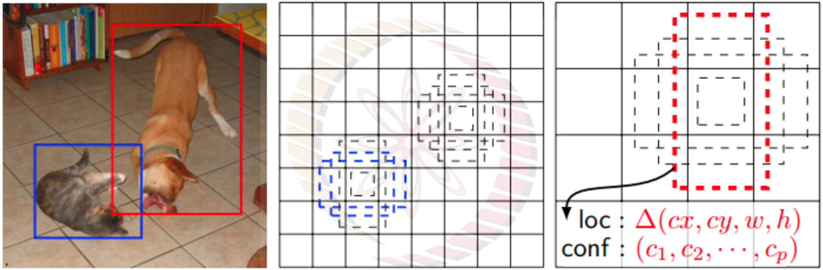
SSD: Model

Exclusive convolutional predictors for each feature map



A feature layer of size $m \times n$ with c channels gives $m \times n$ locations (grid cells); bounding box offsets output values relative to grid cell location (like in Faster R-CNN)

SSD: Anchor Boxes and Aspect Ratios



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

- For each of k default boxes with different aspect ratios, SSD predicts c class-specific scores and 4 anchor box offsets
- For an $m \times n$ feature map, there are $(c + 4)kmn$ outputs

SSD: Loss Function

Weighted sum of localization loss (`loc`) and confidence loss (`conf`):

$$L(x, c, l, g) = \frac{1}{N}(L_{conf}(x, c) + \alpha L_{loc}(x, l, g))$$

where:

- x_{ij}^p is $\{1,0\}$ if i^{th} default box matches j^{th} ground truth box of category p
- $c =$ class probabilities
- $l, g =$ predicted and ground truth box parameters

SSD: Loss Function

- **Localization loss** L_{loc} given by:

$$L_{loc}(x,l,g) = \sum_{i \in Pos}^{N} \sum_{m \in \{cx,cy,w,h\}} x_{ij}^{k} \mathrm{smooth}_{\mathrm{L1}}(l_i^m - \hat{g}_j^m)$$

$$\hat{g}_j^{cx} = (g_j^{cx} - d_i^{cx})/d_i^w \qquad \hat{g}_j^{cy} = (g_j^{cy} - d_i^{cy})/d_i^h$$

$$\hat{g}_j^{w} = \log\left(\frac{g_j^w}{d_i^w}\right) \qquad \hat{g}_j^{h} = \log\left(\frac{g_j^h}{d_i^h}\right)$$

Regress offsets for center (cx, cy) of anchor box (d) and its width (w) and height (h)

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  Regress offsets for center (cx, cy) of anchor box (d) and its width (w) and height (h)

- **Confidence loss** L_{conf} is softmax loss of class confidences (probabilities):

$$L_{conf}(x,c) = -\sum_{i \in Pos}^{N} x_{ij}^{p} log(\hat{c}_i^p) - \sum_{i \in Neg} log(\hat{c}_i^0) \quad \text{where} \quad \hat{c}_i^p = \frac{\exp(c_i^p)}{\sum_p \exp(c_i^p)}$$

SSD: Practical Implementation

Hard Negative Mining:

- Similar to Faster R-CNN, most anchor boxes are negative
- To counter it, select negative examples that have highest confidence loss such that ratio between negatives and positives is $\sim 3:1$

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Data Augmentation: Training samples are obtained as below:

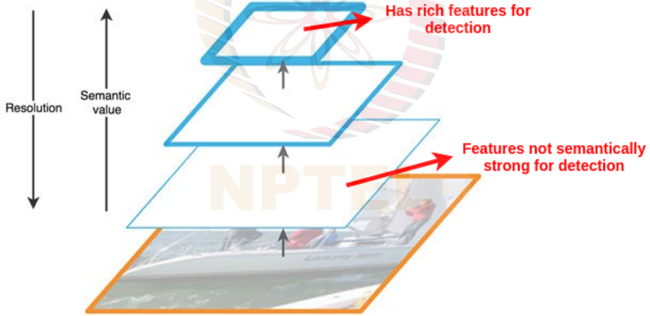
- Use original image
- Randomly sample a patch, such that minimum IoU with objects is in $\{0.1, 0.3, 0.5, 0.7, 0.9\}$

SSD: Performance

Method	mAP	FPS	batch size	# Boxes	Input resolution
Faster R-CNN (VGG16)	73.2	7	1	~ 6000	$\sim 1000 \times 600$
Fast YOLO	52.7	155	1	98	448×448
YOLO (VGG16)	66.4	21	1	98	448×448
SSD300	74.3	46	1	8732	300×300
SSD512	76.8	19	1	24564	512×512
SSD300	74.3	59	8	8732	300×300
SSD512	76.8	22	8	24564	512×512

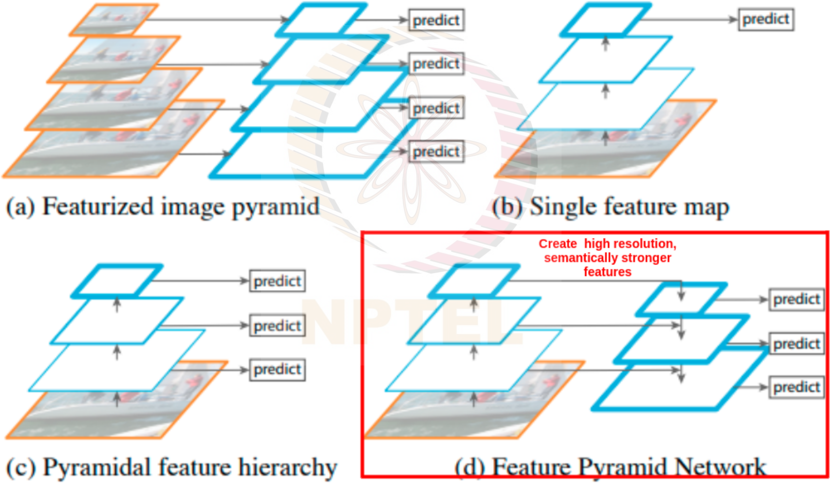
Feature Pyramid Network (FPN)[3]

- Feature maps from initial layers (which are high resolution) cannot be used for detection
- FPN provides a top-down pathway to construct higher resolution layers from a semantically rich layer

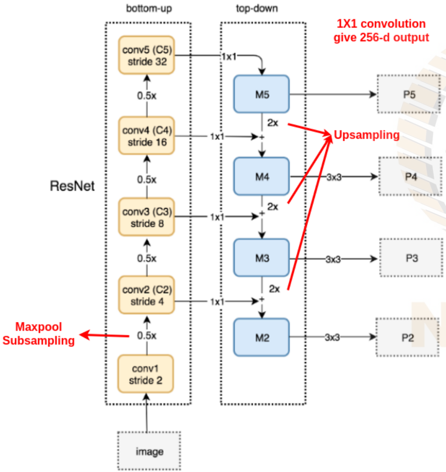


[3]Lin et al, Feature Pyramid Networks for Object Detection, CVPR 2017

Feature Pyramid Network



Feature Pyramid Network: Methodology



- All convolutional feature maps are treated with a 1×1 convolution with 256 channels

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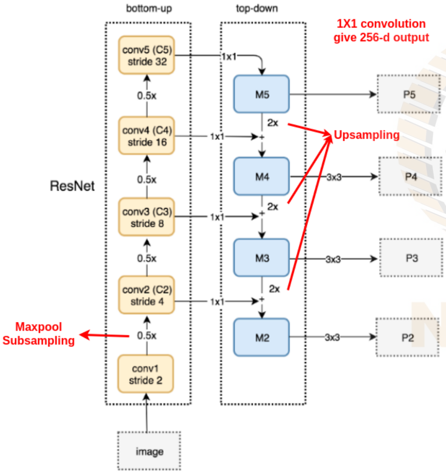

- All convolutional feature maps are treated with a 1×1 convolution with 256 channels
- M5 is upsampled by a factor of 2 (Maxpool at $1/2 \times 1/2$)

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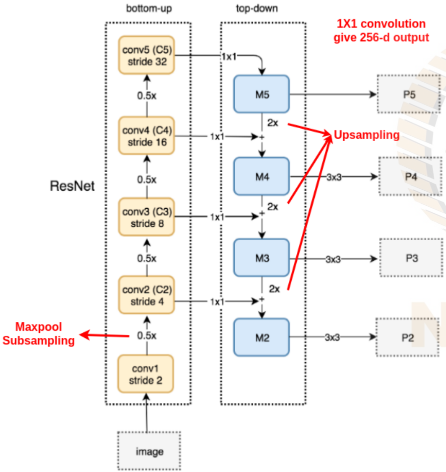

- All convolutional feature maps are treated with a 1×1 convolution with 256 channels
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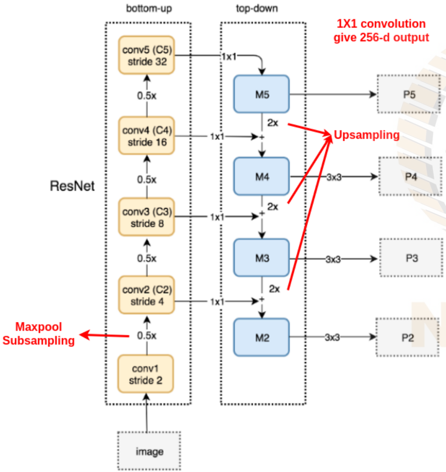

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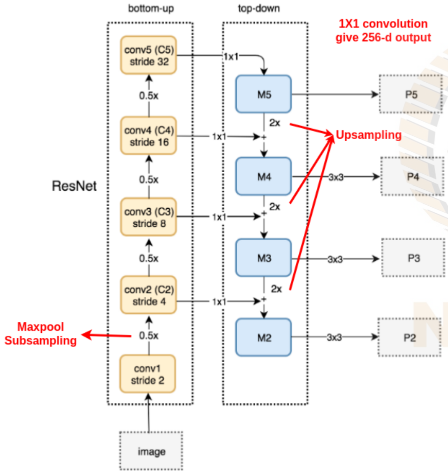
Feature Pyramid Network: Methodology



Credit: *Jonathan Hui, Medium.com*

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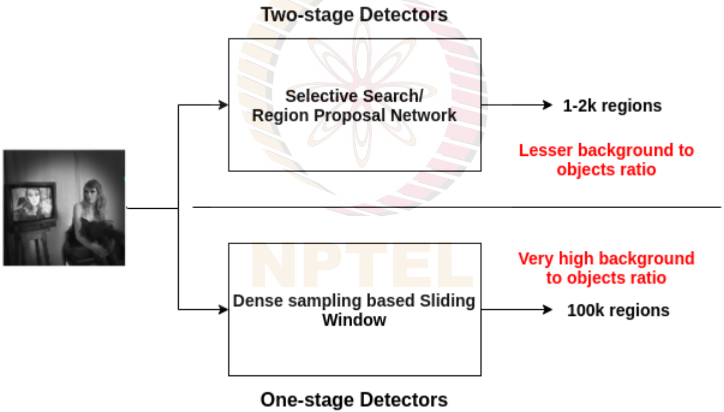
- M5 and C4 signals are element-wise added to give M4; similarly followed in the downward direction
- 3×3 convolution is used to reduce aliasing effect of Ms
- Finally, Ps are individually fed into exclusive object detectors

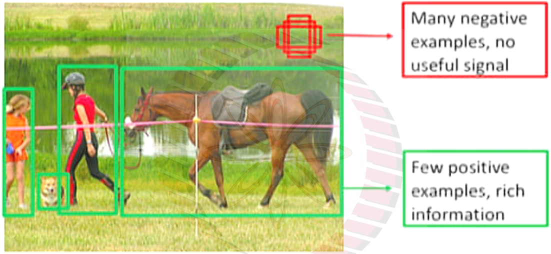
RetinaNet[4]

Intuition: Two-stage detectors are more accurate than one-stage detectors due to lesser class imbalance between background (negative) and object-containing (positive) proposals



[4]Lin et al, Focal Loss for Dense Object Detection, ICCV 2017

Class Imbalance in Object Detection: The Problems



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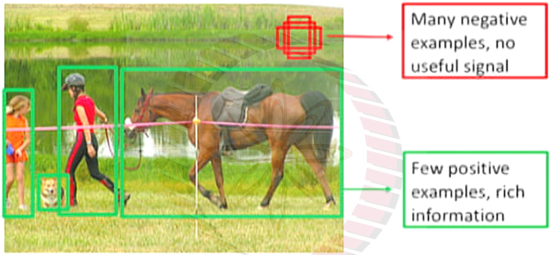

- Training is inefficient as easy negatives contribute no useful signal

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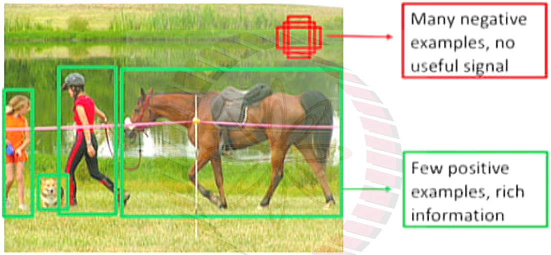
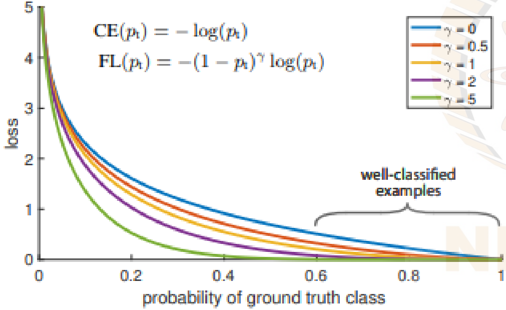


- Training is inefficient as easy negatives contribute no useful signal
- Loss due to easy negatives overwhelms loss due to positives and thereby, training process can lead to degenerate models; hard negative training alleviates it to some extent

Credit: Sik-Ho Tsang, TowardsDataScience.com

CE Loss is Bad[5]



- CE Loss for binary classification is typically implemented as:

$$\mathrm{CE}(p, y) = \begin{cases} -\log(p) & \text{if } y = 1 \\ -\log(1-p) & \text{otherwise.} \end{cases}$$

- Can be rewritten as $CE(p, y) = CE(p) = -\log(p_t)$

[5] Lin et al, Focal Loss for Dense Object Detection, ICCV 2017

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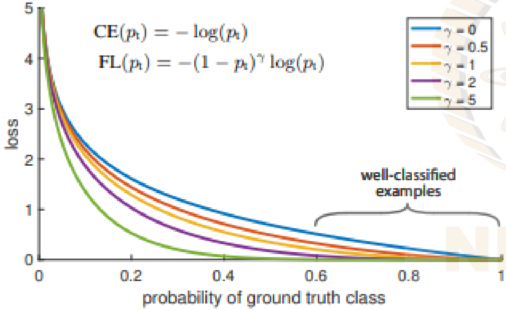

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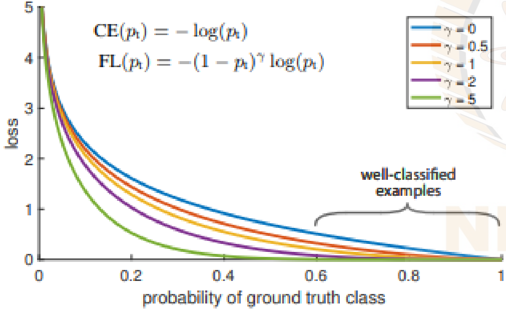
- Can be rewritten as $CE(p, y) = CE(p) = -\log(p_t)$
- Can be observed in graph ($\gamma = 0$ curve) that easily classifiable examples ($p >> .5$) incur loss of non-trivial magnitude

[5] Lin et al, Focal Loss for Dense Object Detection, ICCV 2017

RetinaNet: Balanced Cross Entropy and Focal Loss

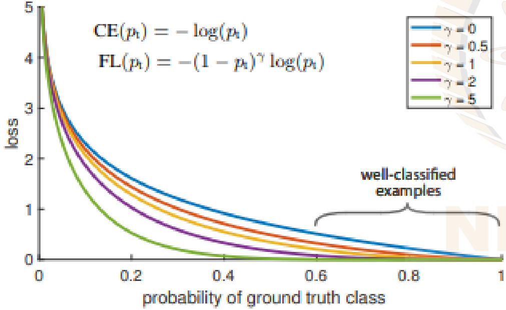


Balanced Cross Entropy:

- Introduces a weighting factor $\alpha \in [0, 1]$ which can be inverse class frequency or a hyperparameter
- α-balanced CE loss is given by:

$$CE(p_t) = -\alpha \log(p_t)$$

RetinaNet: Balanced Cross Entropy and Focal Loss



Balanced Cross Entropy:

- Introduces a weighting factor $\alpha \in [0, 1]$ which can be inverse class frequency or a hyperparameter
- α-balanced CE loss is given by:

$$CE(p_t) = -\alpha \log(p_t)$$

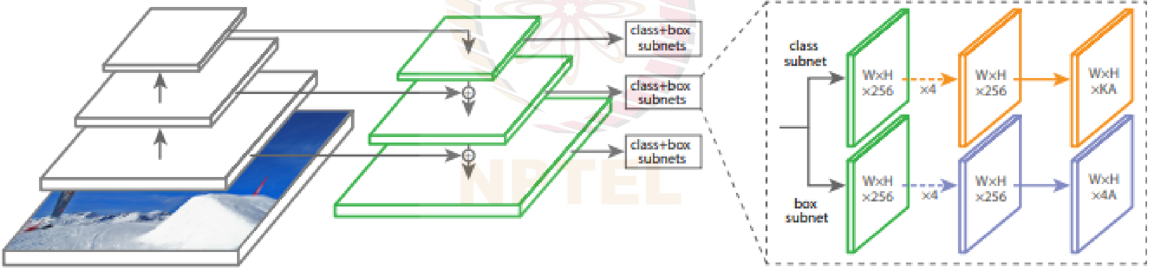
Focal Loss:

- Adds a modulating factor $(1 - p_t)^\gamma$ to CE loss, with tunable focusing parameter $\gamma \geq 0$.
- Focal loss is given by:

$$FL(p_t) = -(1 - p_t)^\gamma \log(p_t)$$

RetinaNet: Architecture

FPN + Focal Loss



(a) ResNet (b) feature pyramid net (c) class subnet (top) (d) box subnet (bottom)

Detectron

- Framework developed by Facebook AI Research (FAIR) to implement state-of-the-art object detection algorithms
- Highly flexible providing support across various algorithms and backbone networks
- See Detectron and Detectron2 for details

Homework

Readings

- Object Detection for Dummies, Part 4
- YOLO Family: All you want to know
- Understanding SSD
- Understanding FPN
- Understanding RetinaNet

Homework

Exercises

- YOLO9000 and YOLOv3 were follow-ups of YOLOv2. What was different in these extensions? Find out! (*Hint:* see the YOLO Family: All you want to know link)
- Given two bounding boxes in an image: an upper-left box which is 2×2, and a lower-right box which is 2×3 and an overlapping region of 1×1, what is the IoU between the two boxes?
- Consider using YOLO object detector on a 19×19 grid, on a detection problem with 20 classes, and with 5 anchor boxes. During training, for each image, you will need to construct an output volume y as the target value for the neural network; this corresponds to the last layer of the neural network. (y may include background). What is the dimension of this output volume?

References

- Wei Liu et al. "Ssd: Single shot multibox detector". In: *European conference on computer vision*. Springer. 2016, pp. 21–37.
- Joseph Redmon et al. "You only look once: Unified, real-time object detection". In: *Proceedings of the IEEE conference on computer vision and pattern recognition*. 2016, pp. 779–788.
- Tsung-Yi Lin et al. "Feature pyramid networks for object detection". In: *Proceedings of the IEEE conference on computer vision and pattern recognition*. 2017, pp. 2117–2125.
- Tsung-Yi Lin et al. "Focal loss for dense object detection". In: *Proceedings of the IEEE international conference on computer vision*. 2017, pp. 2980–2988.
- Joseph Redmon and Ali Farhadi. "YOLO9000: better, faster, stronger". In: *Proceedings of the IEEE conference on computer vision and pattern recognition*. 2017, pp. 7263–7271.