Towards Accurate and Fast Object Detection

Mateusz Pach

ACCEPTED CONFERENCE ON COMPUTER VISION AND PATTERN RECOGNITION 2001

Rapid Object Detection using a Boosted Cascade of Simple Features

Paul Viola
viola@merl.com
Mitsubishi Electric Research Labs
201 Broadway, 8th FL
Cambridge, MA 02139

Michael Jones
mjones@crl.dec.com
Compaq CRL
One Cambridge Center
Cambridge, MA 02142

Abstract

This paper describes a machine learning approach for visual object detection which is capable of processing images extremely rapidly and achieving high detection rates. This

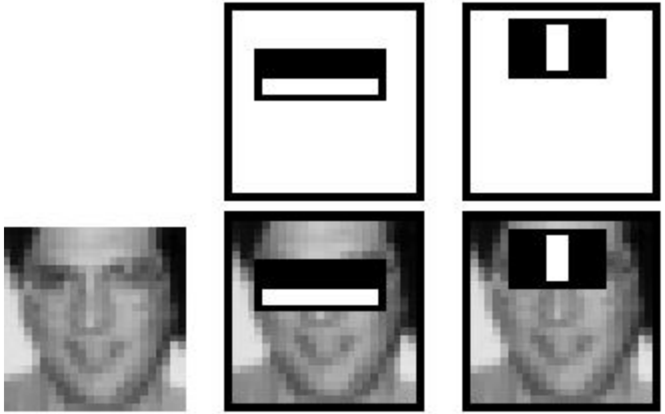
tected at 15 frames per second on a conventional 700 MHz Intel Pentium III. In other face detection systems, auxiliary information, such as image differences in video sequences, or pixel color in color images, have been used to achieve high frame rates. Our system achieves high frame rates

Motivation

- Need for rapid and robust detection of faces, e.g in low power devices.
- Current methods rely on color and multiple frames to get high accuracy.

Compaq iPaq H3641 pocket PC

Method: Rectangle features



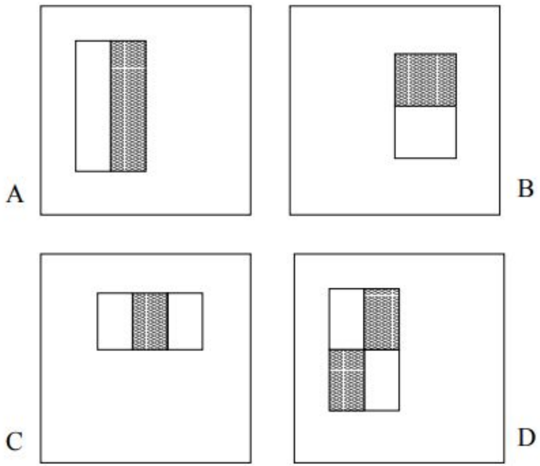


Figure 1: Example rectangle features shown relative to the enclosing detection window. The sum of the pixels which lie within the white rectangles are subtracted from the sum of pixels in the grey rectangles. Two-rectangle features are shown in (A) and (B). Figure (C) shows a three-rectangle feature, and (D) a four-rectangle feature.

Method: Integral image

aka 2D prefix-sum

$$ii(x, y) = \sum_{x' \le x, y' \le y} i(x', y')$$

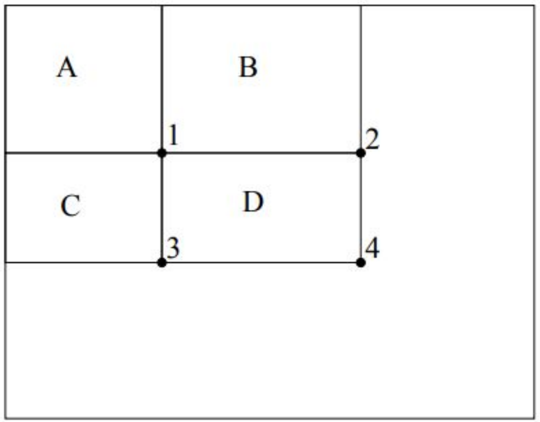
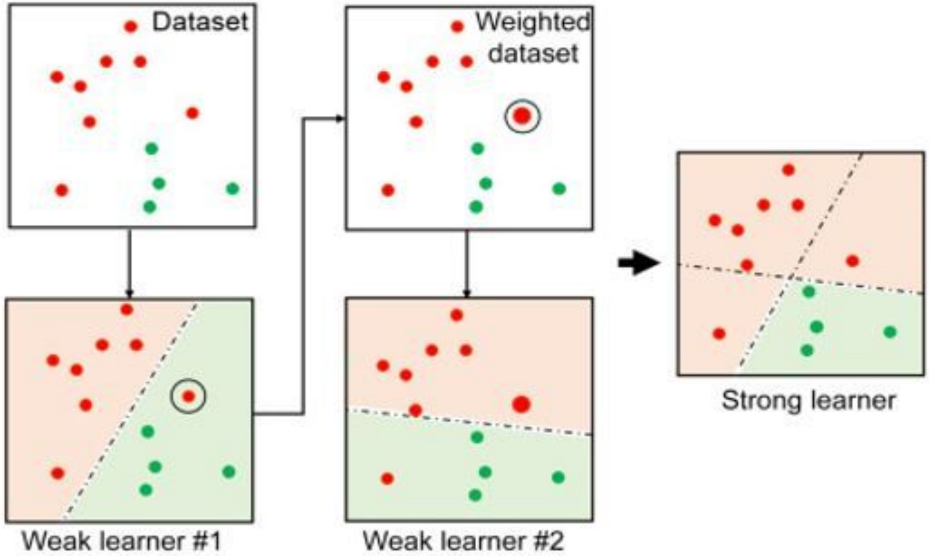


Figure 2: The sum of the pixels within rectangle D can be computed with four array references. The value of the integral image at location 1 is the sum of the pixels in rectangle A. The value at location 2 is $A + B$, at location 3 is $A + C$, and at location 4 is $A + B + C + D$. The sum within D can be computed as $4 + 1 - (2 + 3)$.

Method: AdaBoost



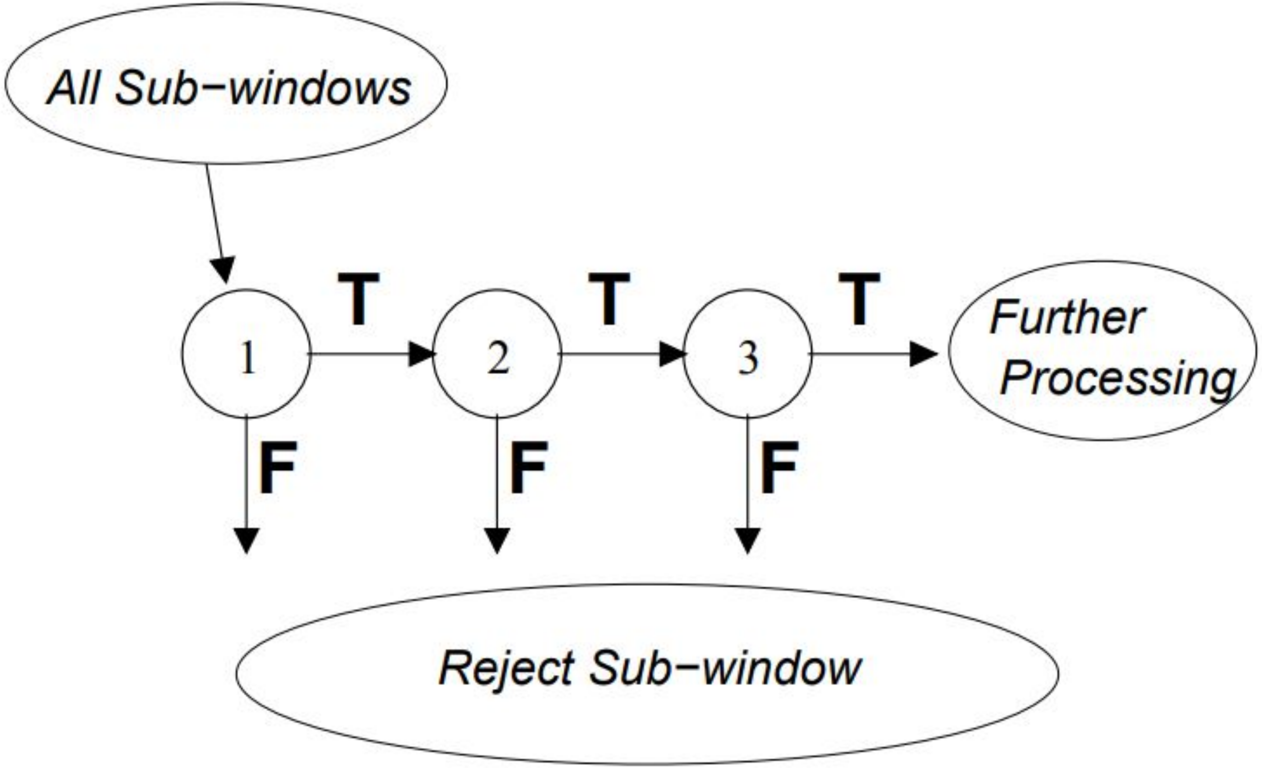
- Given example images $(x_1, y_1), \ldots, (x_n, y_n)$ where $y_i = 0, 1$ for negative and positive examples respectively.
- Initialize weights $w_{1,i} = \frac{1}{2m}, \frac{1}{2l}$ for $y_i = 0, 1$ respectively, where m and l are the number of negatives and positives respectively.
- For $t = 1, \ldots, T$:
  1. Normalize the weights,
  $$w_{t,i} \leftarrow \frac{w_{t,i}}{\sum_{j=1}^{n} w_{t,j}}$$
  so that w_t is a probability distribution.
  2. For each feature, j, train a classifier h_j which is restricted to using a single feature. The error is evaluated with respect to w_t, $\epsilon_j = \sum_i w_i \left| h_j(x_i) - y_i \right|$.
  3. Choose the classifier, h_t, with the lowest error ϵ_t.
  4. Update the weights:
  $$w_{t+1,i} = w_{t,i} \beta_t^{1-e_i}$$
  where $e_i = 0$ if example x_i is classified correctly, $e_i = 1$ otherwise, and $\beta_t = \frac{\epsilon_t}{1-\epsilon_t}$.
- The final strong classifier is:

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

where $\alpha_t = \log \frac{1}{\beta_t}$

A Short Introduction to Boosting (Freund et al. 1999)
Exploring budgeted learning for data-driven semantic inference via urban functions (Iddianozie et al. 2017)

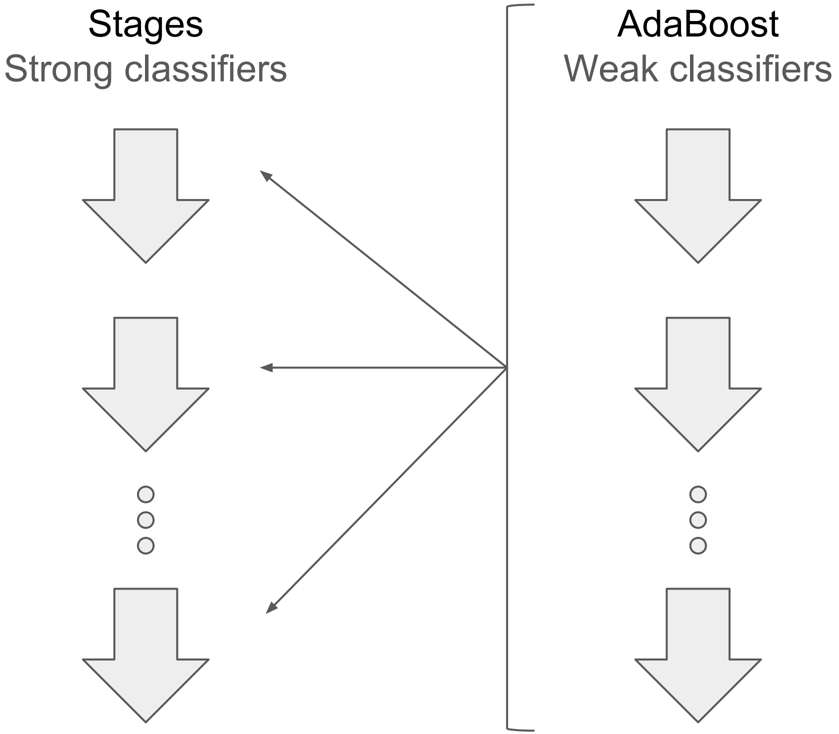
Method: Attentional cascade



Method

Sequentially eliminate sub-windows with strong classifiers.

Each strong classifier has bounded number of false positives and decrease in detection.



Find sufficiently many weak classifiers by boosting.

Each weak classifier uses a single feature and has simple form

$$h_j(x) = \begin{cases} 1 & \text{if } p_j f_j(x) < p_j \theta_j \\ 0 & \text{otherwise} \end{cases}$$

38 stages with over 6000 features, average of 10 feature evaluations per subwindow

Databases

- Training
  - web crawl
  - 9832 faces from
    4916 hand labeled faces
  - 10000 non-faces from
    9544 non-face images
  - 24 by 24 pixels
- Evaluation
  - MIT-CMU

Figure 5: Example of frontal upright face images used for training.

Results

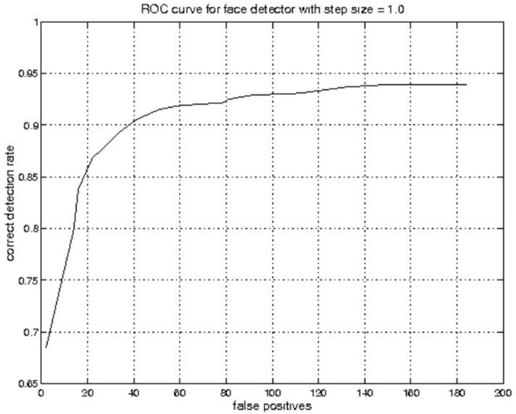
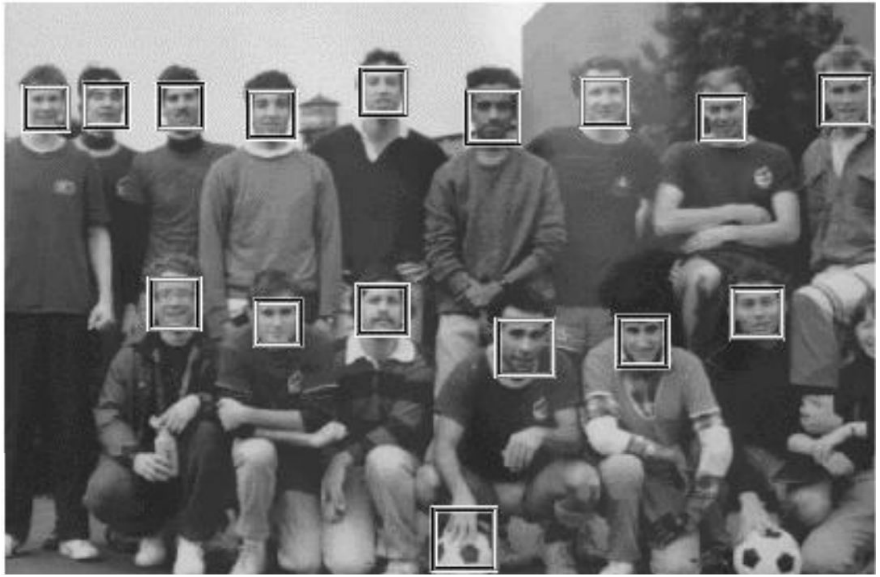


Figure 6: ROC curve for our face detector on the MIT+CMU test set. The detector was run using a step size of 1.0 and starting scale of 1.0 (75,081,800 sub-windows scanned).



Time

15x

600x

Detector \ False detections	10	31	50	65	78	95	167
Viola-Jones	76.1%	88.4%	91.4%	92.0%	92.1%	92.9%	93.9%
Viola-Jones (voting)	81.1%	89.7%	92.1%	93.1%	93.1%	93.2 %	93.7%
Rowley-Baluja-Kanade	83.2%	86.0%	-	-	-	89.2%	90.1%
Schneiderman-Kanade	-	-	-	94.4%	-	-	-
Roth-Yang-Ahuja	-	-	-	-	(94.8%)	-	-

Table 2: Detection rates for various numbers of false positives on the MIT+CMU test set containing 130 images and 507 faces.

Conclusions

- The approach achieves high detection accuracy with minimal computation time, making it faster than previous approaches.
- The algorithms, representations, and insights presented have broader applications in computer vision and image processing.
- The experiments conducted on a difficult face detection dataset demonstrate the conclusions drawn are unlikely to be experimental artifacts.

- The method may be prone to racial biases.

Focal Loss for Dense Object Detection

Tsung-Yi Lin Priya Goyal Ross Girshick Kaiming He Piotr Dollár
Facebook AI Research (FAIR)

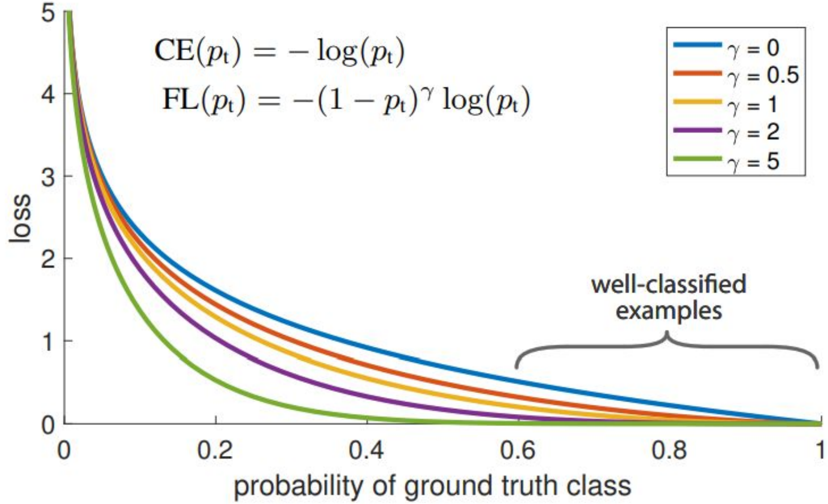
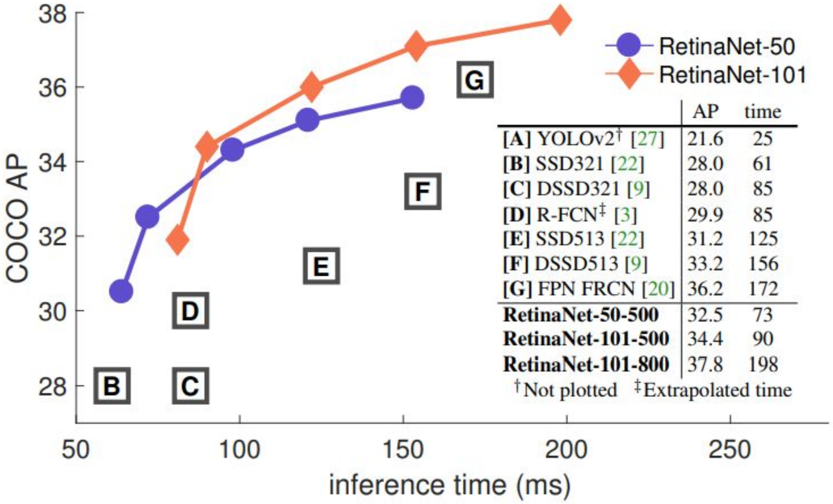


Figure 1. We propose a novel loss we term the *Focal Loss* that adds a factor $(1-p_t)^\gamma$ to the standard cross entropy criterion.



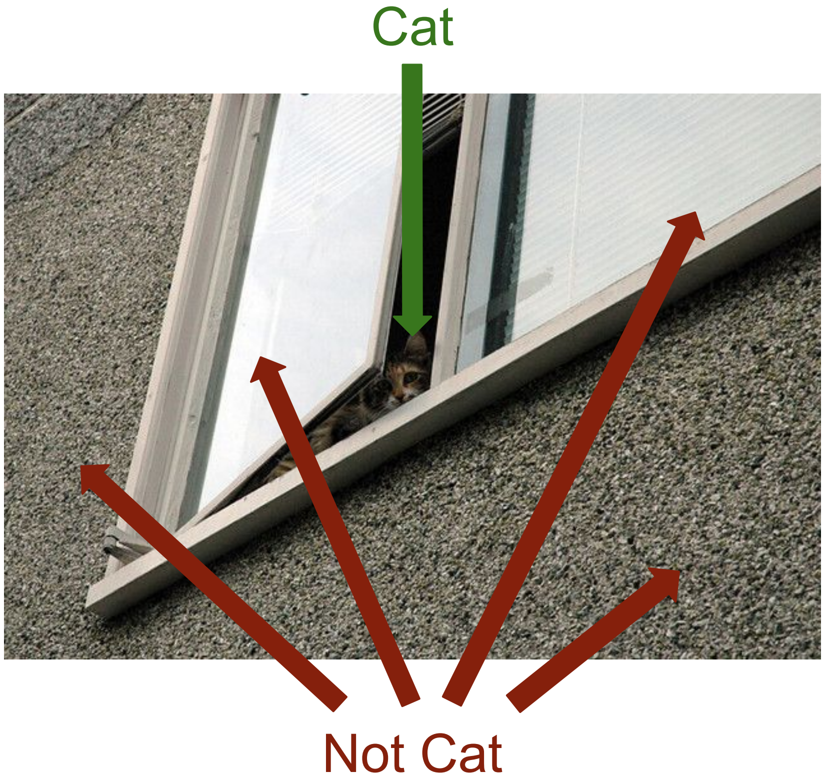
	AP	time
[A] YOLOv2† [27]	21.6	25
[B] SSD321 [22]	28.0	61
[C] DSSD321 [9]	28.0	85
[D] R-FCN‡ [3]	29.9	85
[E] SSD513 [22]	31.2	125
[F] DSSD513 [9]	33.2	156
[G] FPN FRCN [20]	36.2	172
RetinaNet-50-500	32.5	73
RetinaNet-101-500	34.4	90
RetinaNet-101-800	37.8	198

†Not plotted ‡Extrapolated time

Figure 2. Speed (ms) versus accuracy (AP) on COCO `test-dev`. Enabled by the focal loss, our simple one-stage *RetinaNet* detec-

Motivation

- Current SOTA detectors require two stages (propose and classify).
- Single stage detectors perform worse.
- The reason may be the foreground-background class imbalance.
- Let's build a new single stage detector outperforming SOTA by introducing new family of loss functions.

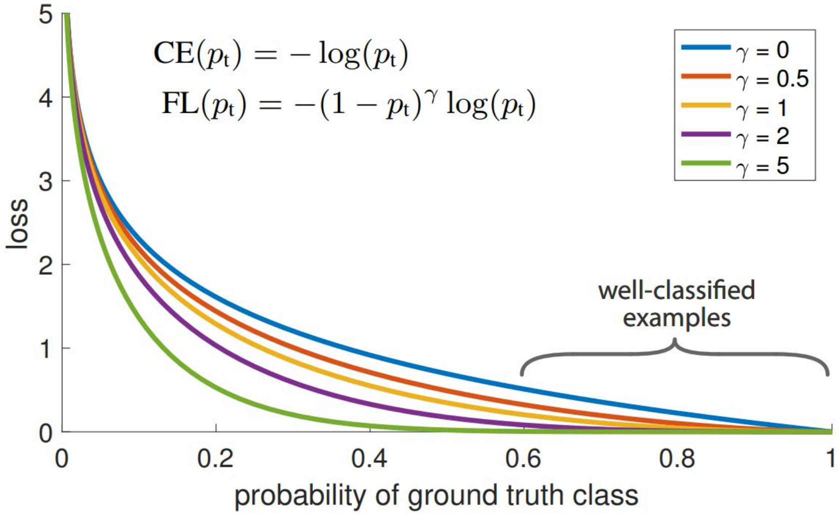


Method: Focal Loss

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

$$p_{\mathrm{t}} = \begin{cases} p & \text{if } y = 1 \\ 1-p & \text{otherwise,} \end{cases}$$

$$\mathrm{CE}(p, y) = \mathrm{CE}(p_{\mathrm{t}}) = -\log(p_{\mathrm{t}}).$$



$$\mathrm{FL}(p_{\mathrm{t}}) = -(1-p_{\mathrm{t}})^{\gamma}\log(p_{\mathrm{t}})$$

Method: RetinaNet

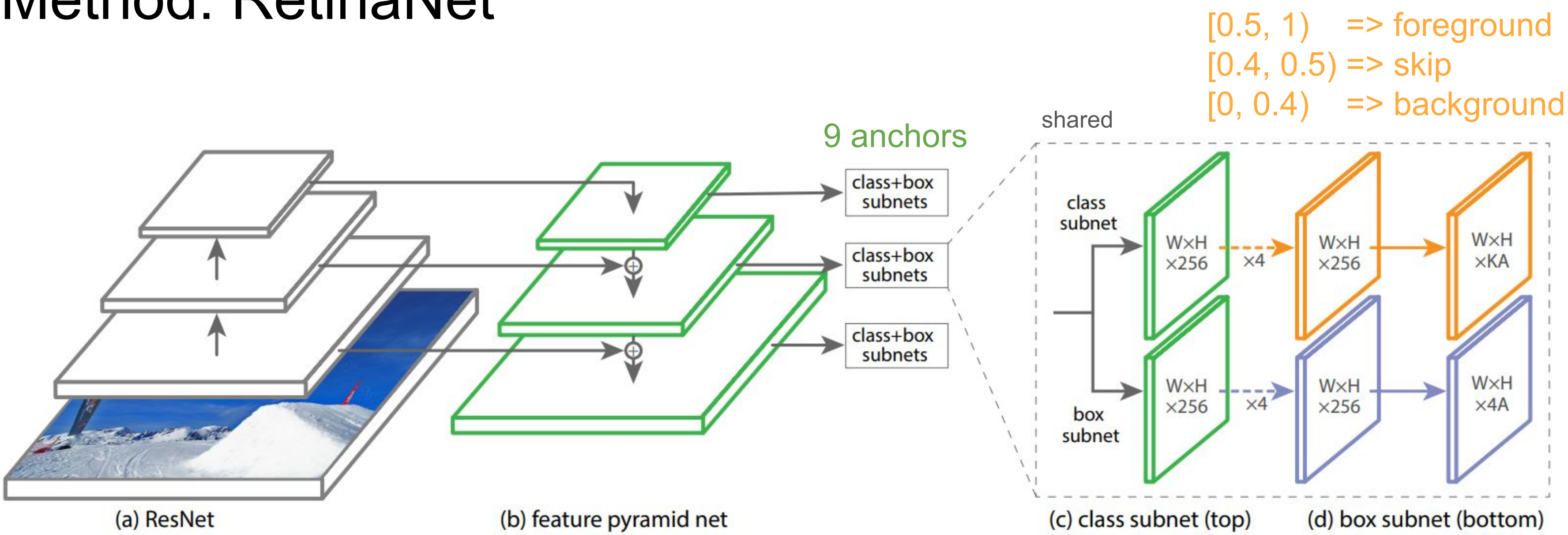


Figure 3. The one-stage **RetinaNet** network architecture uses a Feature Pyramid Network (FPN) [20] backbone on top of a feedforward ResNet architecture [16] (a) to generate a rich, multi-scale convolutional feature pyramid (b). To this backbone RetinaNet attaches two subnetworks, one for classifying anchor boxes (c) and one for regressing from anchor boxes to ground-truth object boxes (d). The network design is intentionally simple, which enables this work to focus on a novel focal loss function that eliminates the accuracy gap between our one-stage detector and state-of-the-art two-stage detectors like Faster R-CNN with FPN [20] while running at faster speeds.

Databases

COCO

- Training
  - trainval35k
- Evaluation
  - minival
  - test-dev (hidden from public)

Results

	backbone	AP	AP_{50}	AP_{75}	AP_S	AP_M	AP_L
Two-stage methods							
Faster R-CNN+++ [16]	ResNet-101-C4	34.9	55.7	37.4	15.6	38.7	50.9
Faster R-CNN w FPN [20]	ResNet-101-FPN	36.2	59.1	39.0	18.2	39.0	48.2
Faster R-CNN by G-RMI [17]	Inception-ResNet-v2 [34]	34.7	55.5	36.7	13.5	38.1	52.0
Faster R-CNN w TDM [32]	Inception-ResNet-v2-TDM	36.8	57.7	39.2	16.2	39.8	**52.1**
One-stage methods							
YOLOv2 [27]	DarkNet-19 [27]	21.6	44.0	19.2	5.0	22.4	35.5
SSD513 [22, 9]	ResNet-101-SSD	31.2	50.4	33.3	10.2	34.5	49.8
DSSD513 [9]	ResNet-101-DSSD	33.2	53.3	35.2	13.0	35.4	51.1
RetinaNet (ours)	ResNet-101-FPN	39.1	59.1	42.3	21.8	42.7	50.2
RetinaNet (ours)	ResNeXt-101-FPN	**40.8**	**61.1**	**44.1**	**24.1**	**44.2**	51.2

Table 2. **Object detection** *single-model* results (bounding box AP), *vs.* state-of-the-art on COCO `test-dev`. We show results for our RetinaNet-101-800 model, trained with scale jitter and for 1.5× longer than the same model from Table 1e. Our model achieves top results, outperforming both one-stage and two-stage models. For a detailed breakdown of speed versus accuracy see Table 1e and Figure 2.

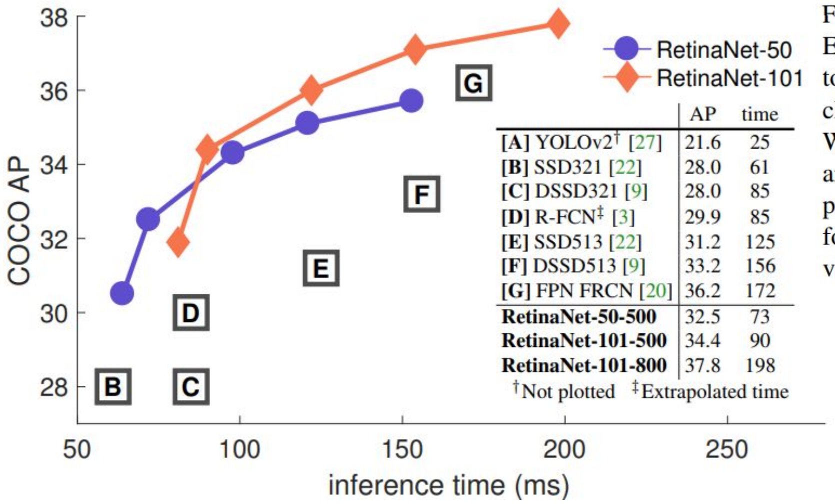


Figure 2. Speed (ms) versus accuracy (AP) on COCO `test-dev`. Enabled by the focal loss, our simple one-stage *RetinaNet* detector outperforms all previous one-stage and two-stage detectors, including the best reported Faster R-CNN [28] system from [20]. We show variants of RetinaNet with ResNet-50-FPN (blue circles) and ResNet-101-FPN (orange diamonds) at five scales (400-800 pixels). Ignoring the low-accuracy regime (AP<25), RetinaNet forms an upper envelope of all current detectors, and an improved variant (not shown) achieves 40.8 AP. Details are given in §5.

```
Average Precision (AP):
   AP               % AP at IoU=.50:.05:.95 (primary challenge metric)
   AP^IoU=.50       % AP at IoU=.50 (PASCAL VOC metric)
   AP^IoU=.75       % AP at IoU=.75 (strict metric)
AP Across Scales:
   AP^small         % AP for small objects: area < 32^2
   AP^medium        % AP for medium objects: 32^2 < area < 96^2
   AP^large         % AP for large objects: area > 96^2
```

Conclusions

- Class imbalance is the primary obstacle for one-stage object detectors to outperform two-stage methods.
- The focal loss addresses class imbalance by focusing learning on hard negative examples.
- The proposed approach achieves state-of-the-art accuracy and speed, making it a promising solution for overcoming class imbalance in one-stage object detectors.