

Adaptive Feeding: Achieving Fast and Accurate Detections by **Adaptively Combining Object Detectors**

Learning And Mining from DatA http://lamda.nju.edu.cn

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Motivation: Fast AND Accurate

✓ In most images, the fast detector is as precise as the accurate one (and in few cases it is even better).

• Easy: Fast ≥ Accurate • **Hard:** Fast < Accurate

- ✓ Let Fast model deal with **Easy** images while the Accurate model should focus on Hard ones. So we can speed up the detection process while keep accuracy.
- ✓ In Pascal VOC datasets, the percentage of Easy examples is large (around 80%).

A Brief Introduction Why not combine them? 85 Accurate but Slow Precision (mAP) • R-FCN Fast but Inaccurate **SSD500** Faster R-CNN **SSD300** Fast R-CNN **R-CNN** Wean 65 YOLO 60 50 40 Frames Per Second (FPS)

An Effective Framework

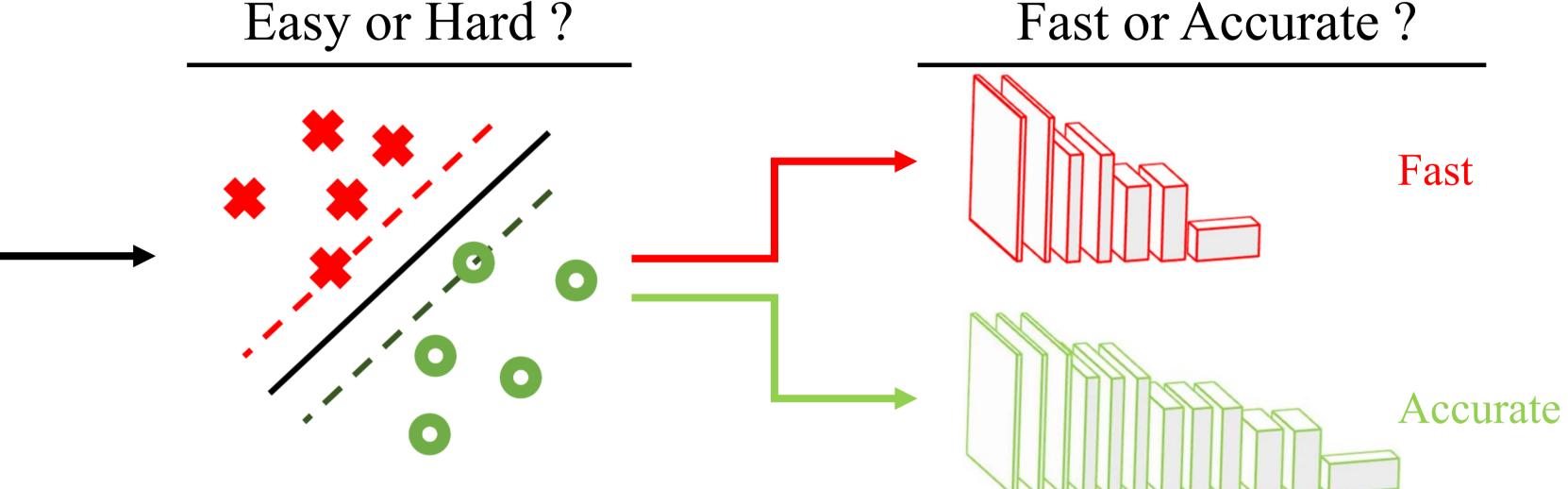
Instance Proposals score 1 xmin 1 ymin 1 w 1 h 1 score_2 xmin_2 ymin_2 w_2 h_2

score k xmin k ymin k w k h k



- We take instance proposals as features.
- > Feature generation process should be extremely fast to maintain speed.
- Features are supposed to be strong enough in order to discriminate Hard images to keep accuracy.
- ✓ Best feature form: class hist + (conf + coords) \times top-k. A naïve combination is already stronger than SSD500.

Fast or Accurate? Easy or Hard?



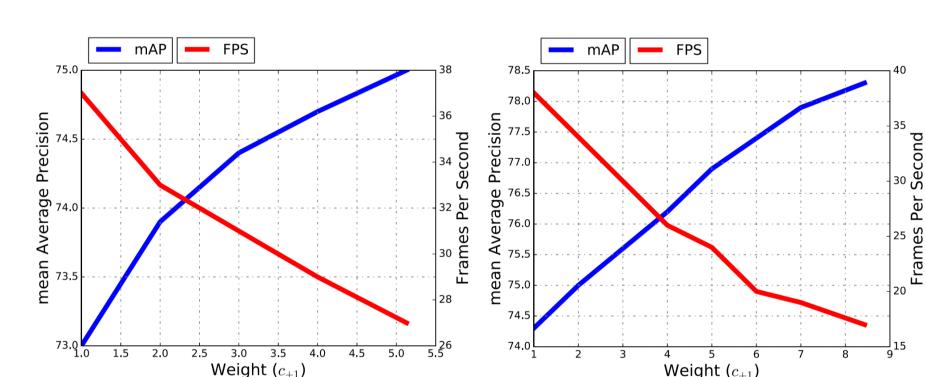
Learning the Easy vs. Hard Classifier

Imbalanced SVM Classification

> Since the number of Easy images is much larger than that of Hard ones, the problem is imbalanced.

$$\min_{\overrightarrow{w},b} \frac{1}{2} \overrightarrow{w}^T \overrightarrow{w} + C \sum_{i=1}^n c_{y_i} \varepsilon_i$$
s.t. $y_i (\overrightarrow{w}^T \overrightarrow{x}_i + b) \ge 1 - \varepsilon_i, \varepsilon_i \ge 0, 1 \le i \le n.$

 $y_i \in \{-1, +1\}$ is image's label (Easy or Hard). A larger c_{y_i} value puts more emphasis on the correct classification of hard images, and hence will in general lead to higher recall.



• Impact of sampling weights on mAP and FPS. The experiments are performed on VOC07 test.

Experimental Results

Pascal VOC 2007

SUR: Speed-Up Ratio. DmAP: Decreased mAP based on accurate model. A: the accurate mode. F: the fast mode. W: the compline weight

W: the sampling weight.								
Method	\mathbf{W}	mAP	\mathbf{FPS}	\mathbf{SUR}	\mathbf{DmAP}			
SSD300	_	72.1	46	-	_			
SSD400	-	74.0	32	-	-			
SSD500	-	74.9	19	_	_			
Simple Ensemble	-	73.0	19	_	_			
R-FCN	-	79.0	8	-	-			
300-500-A	5.13	75.0	27	42%	-0.1			
300-500-F	3	74.4	33	74%	0.5			
300-R-FCN-A	8.43	78.3	17	113%	0.7			
300-R-FCN-F	5	76.9	24	200%	2.1			

MSCOCO 2015 test-dev

$oxed{\mathrm{Method}}$	\mathbf{W}	$ ext{test}$	$\overline{\mathbf{FPS}}$	AP	AP^{50}	AP^{75}	AP^S	AP^M	$\overline{{ m AP}^L}$
SSD300 SSD500	_ _	test-dev test-dev	46 19	$20.8 \\ 24.4$	38.0 43.7	$20.5 \\ 24.7$	3.9 7.2	$18.5 \\ 25.3$	38.7 40.1
R-FCN	-	test-dev	8	28.6	48.8	30.1	8.8	31.4	44.1
300-500-A 300-500-F	$\begin{array}{c} 1.16 \\ 2 \end{array}$	test-dev test-dev	25 31	$23.7 \\ 23.0$	42.7 41.6	$23.9 \\ 23.1$	6.6 6.0	$23.7 \\ 22.2$	39.8 39.5
300-R-FCN-A 300-R-FCN-F	$\begin{array}{c} 1.07 \\ 2 \end{array}$	test-dev test-dev	$\frac{15}{21}$	27.0 26.2	$47.4 \\ 46.7$	$29.2 \\ 27.9$	7.5 6.3	$29.9 \\ 28.8$	43.1 41.9

Statistics on COCO minival

- ➤ When IoU increases, the number of Hard images is up.
- > But our approach still works with different sampling weights.

Fa	Fast	Accurate	Dataset	IoU = 0.5			
	2 300 0			$\geqslant 0 \text{ (Easy)}$	< 0 (Hard)		
•	SSD300	SSD500	minival2014	53.6%	46.4%		
	SSD300	R-FCN	minival 2014	51.7%	48.3%		

SVM Visualization

Weights of Each Group in SVM

Method	dataset	class	conf	xmin	ymin	width	height
300-500 300-R-FCN						-0.55 -0.89	
300-500 300-R-FCN	coco						

- ✓ An image with many objects might be hard for a detector.
- ✓ Large proposal hints Easy images.
- ✓ Easy images prefer shorter proposals (w>h) while Hard images like taller instances.
- ✓ Positions of proposals have small impacts.



