Object Classification, Localization and Detection Part 3: SSD and M2DeT

CS8004: Deep Learning and Applications

Today

- Last time YOLO, a single shot detector that trains a single CNN once only for all the objects in the scene.

- Today we shall discuss another single shot detector
  - Single Shot MultiBox Detector by Liu et al. (2015).

SSD: Single Shot MultiBox Detector

- Developed by Liu et al (December 2015) and as reported in their paper –
- Faster than Yolo, as accurate as two stage methods like Faster R-CNN.
- Predicts categories and box offsets.
- Uses small convolutional filters applied to feature maps.
- Makes predictions using feature maps of different scales

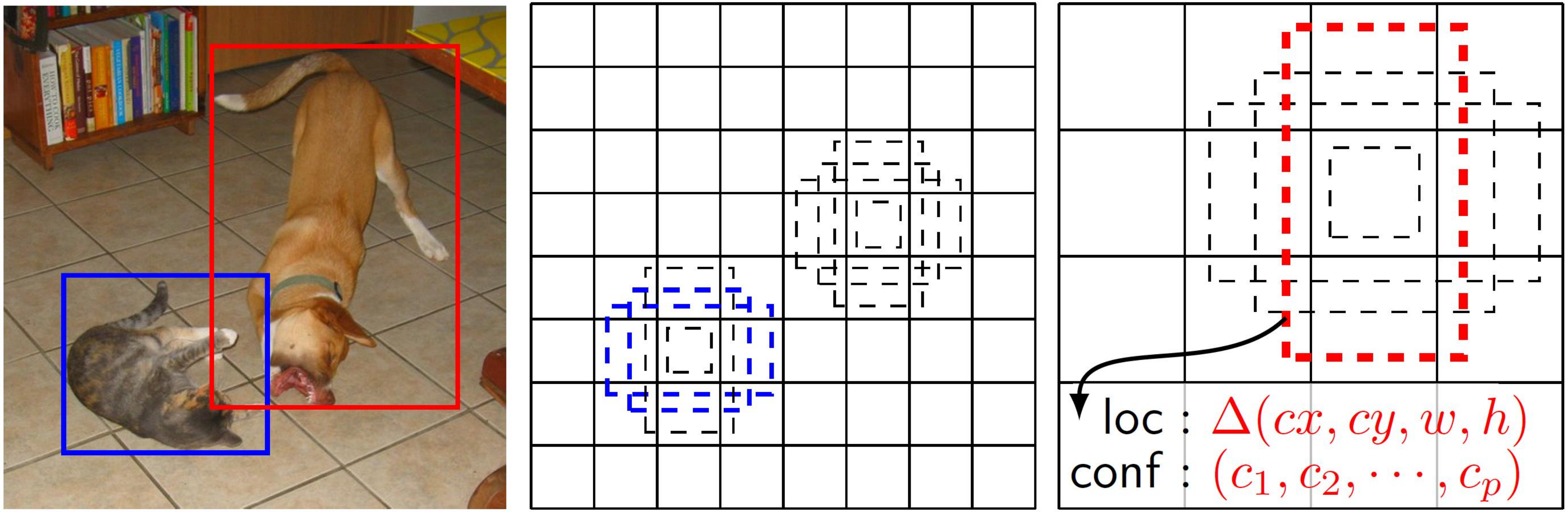
SSD Framework

- SSD only needs an input image and ground truth boxes for each object during training.
- Through CNN a small set (e.g. 4) of default boxes of different aspect ratios is evaluated at each location
- This is done in several feature maps with different scales (e.g. 8 X 8 and 4 X 4).

SSD Framework

- For each default box, both the shape offsets and the confidences for all object categories are predicted.
- At training time, these default boxes are matched with the ground truth boxes.
- The model loss is a weighted sum between localization loss and confidence loss.

SSD Framework



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

Two default boxes with the cat and one with the dog are matched, which are treated as positives and the rest as negatives.

SSD Model

- The SSD approach is based on a feed-forward convolutional network that produces a fixed-size collection of bounding boxes and scores for the presence of object class instances in those boxes.

- This is followed by a non-maximum suppression step to produce the final detections.

- The early network layers are based on a standard architecture used for high quality image classification (truncated before any classification layers). This is called base network.

SSD Model …

- Then the auxiliary structure is added to the network to produce detections with the following key features:
  - Multi-scale feature maps for detection,
  - Convolutional predictors for detection,
  - Default boxes and aspect ratios.

SSD Model vs YOLO Model

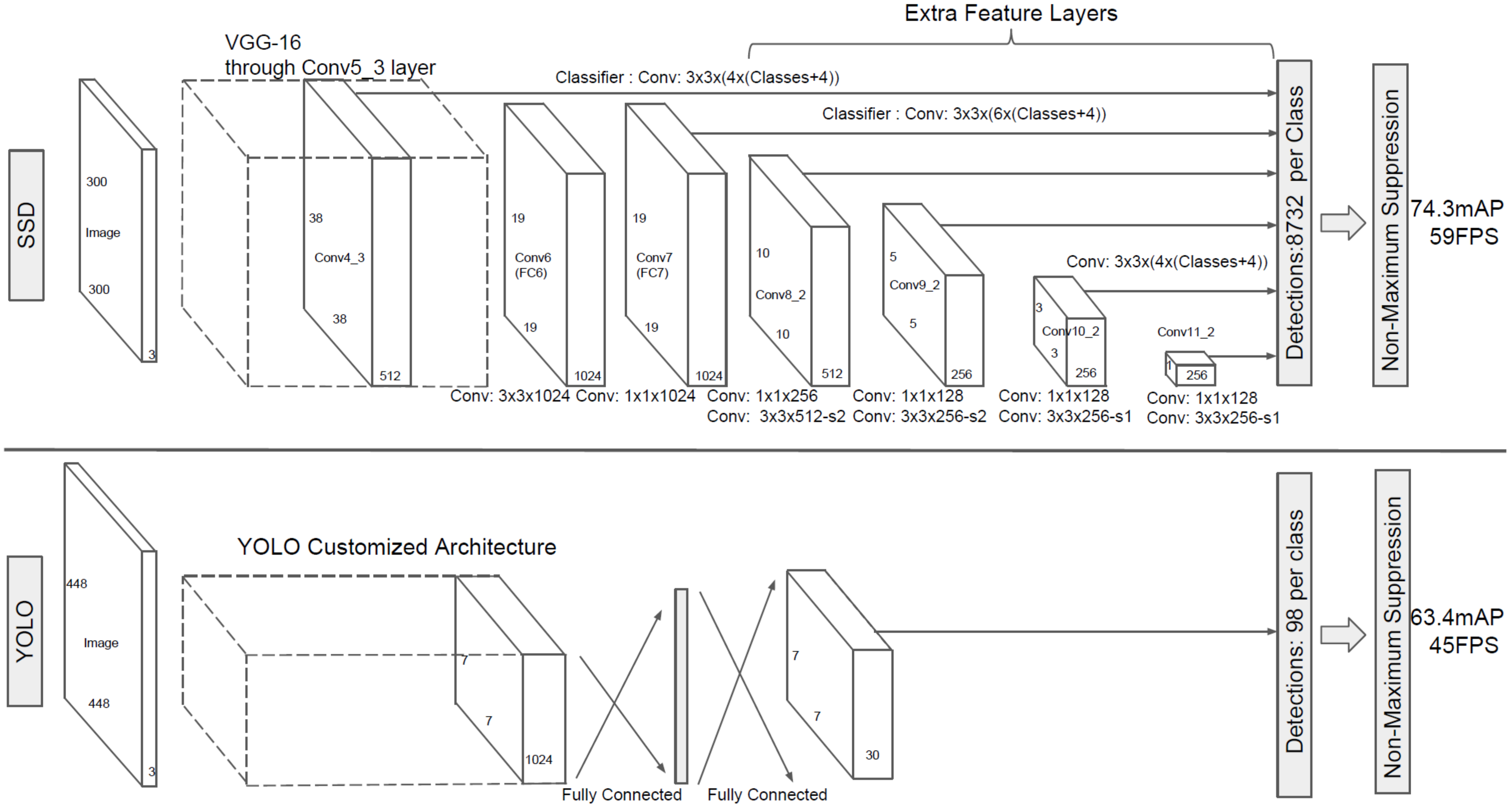


Image source :Liu et al., Single Shot MultiBox Detector, December 2015.

Default Box and Class Predictions

- 3X3 convolution applied to each cell shown here. Each cell predicts (say) 4 default box dimensions and a class score (A 21-size for 20 classes, one for no object)

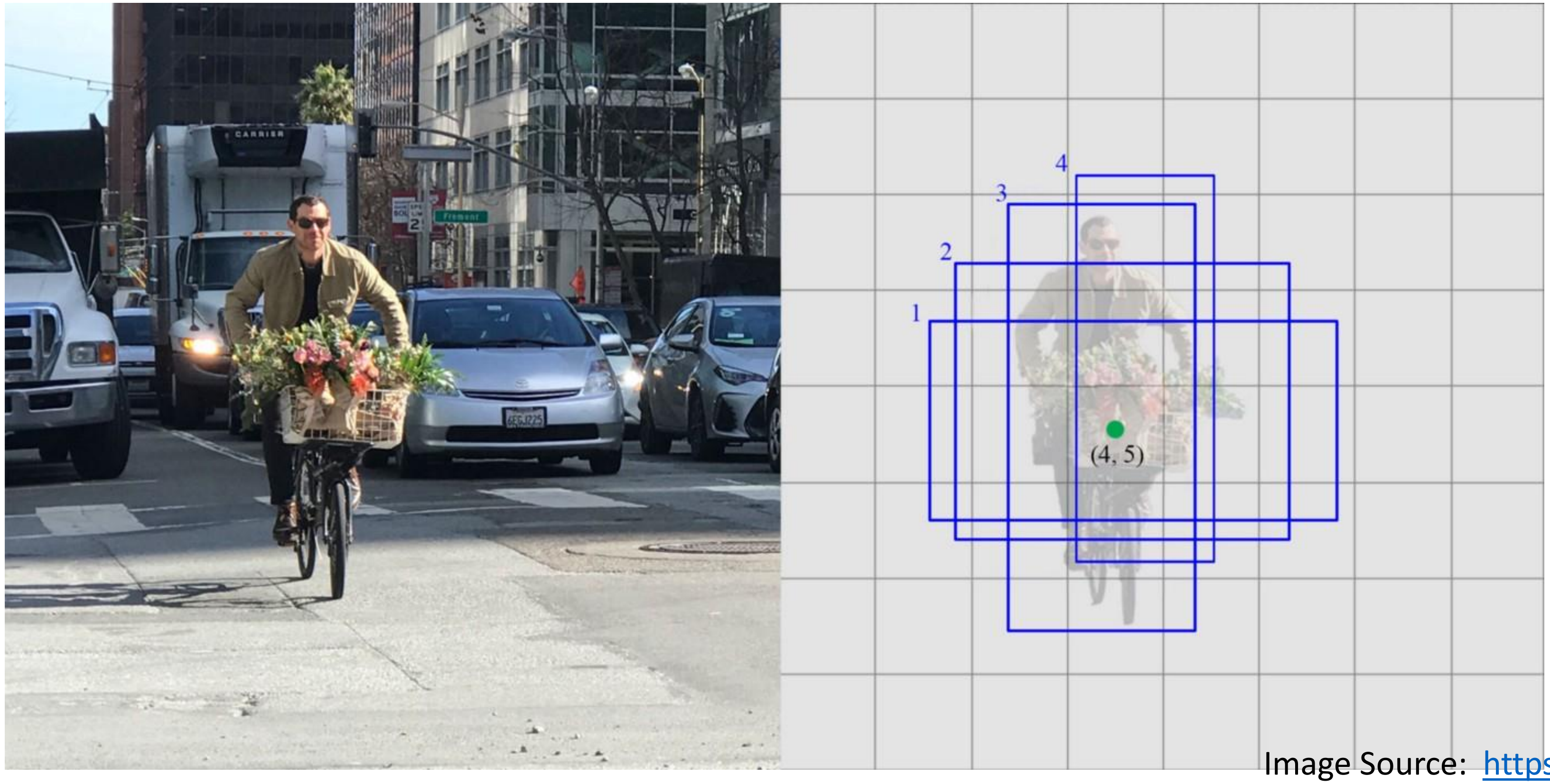


Image Source: https://medium.com/@jonathan_hui

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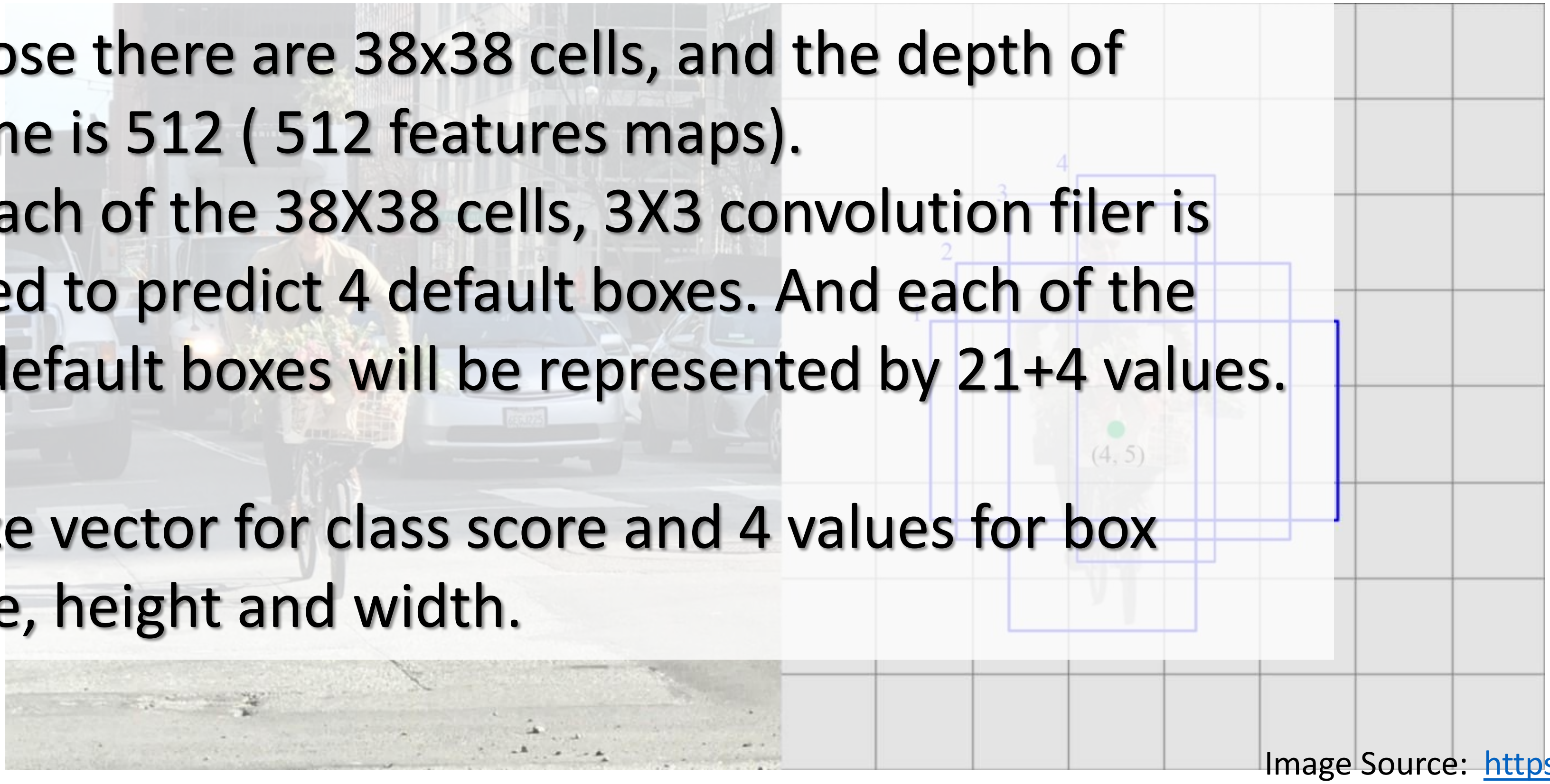


Suppose there are 38x38 cells, and the depth of Volume is 512 (512 features maps).
On each of the 38X38 cells, 3X3 convolution filer is applied to predict 4 default boxes. And each of the four default boxes will be represented by 21+4 values.

21-size vector for class score and 4 values for box centre, height and width.

Image Source: https://medium.com/@jonathan_hui

Convolutional Predictors for Detection

- Each added feature layer (or optionally an existing feature layer from the base network) can produce a fixed set of detection predictions using a set of convolutional filters.

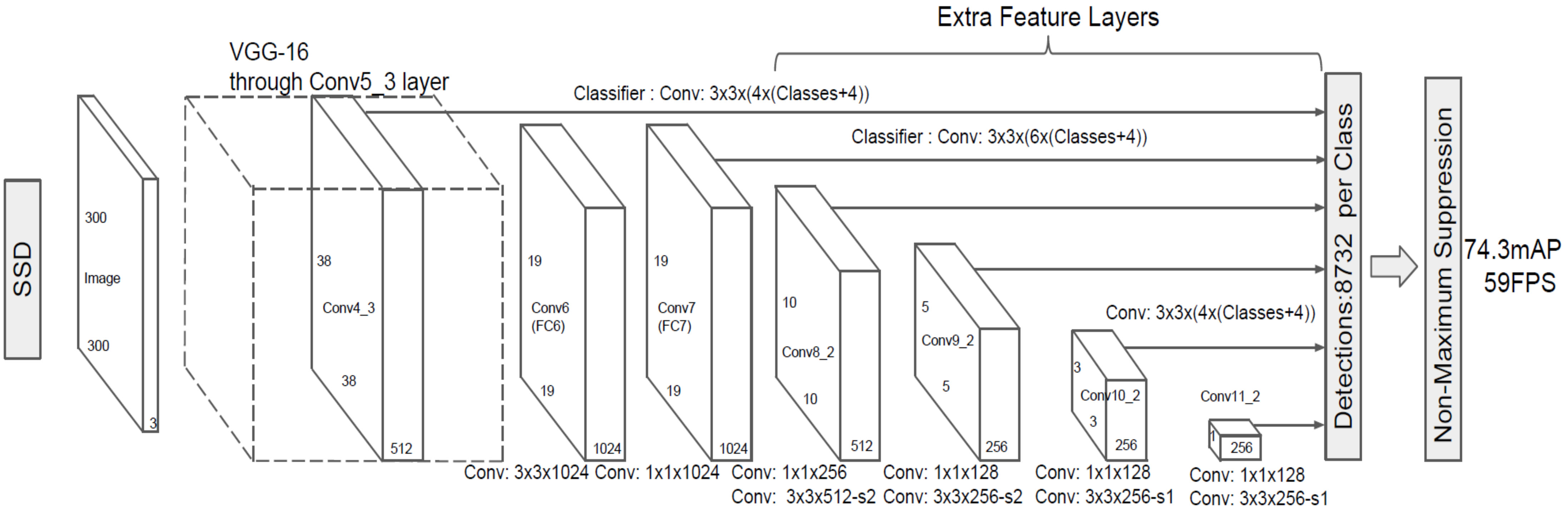


Image source :Liu et al., Single Shot MultiBox Detector, December 2015.

Convolutional Predictors for Detection

- For a feature layer of size m X n with p channels, the basic element for predicting parameters of a potential detection is a 3 X 3 X p small kernel.
- This element produces either a score for a category, or a shape offset relative to the default box coordinates.
- At each of the m X n locations where the kernel is applied, it produces an output value.
- Remember that YOLO uses an intermediate fully connected layer instead of a convolutional filter for this step.

Default Boxes and Aspect Ratios

- A set of default bounding boxes with each feature map cell, for multiple feature maps at the top of the network.

- At each feature map cell, we predict the offsets relative to the default box shapes in the cell, as well as the per-class scores that indicate the presence of a class instance in each of those boxes.

Default Boxes and Aspect Ratios

- For each box at a given location, a c class scores and the 4 offsets relative to the original default box shape are computed (Total k boxes).

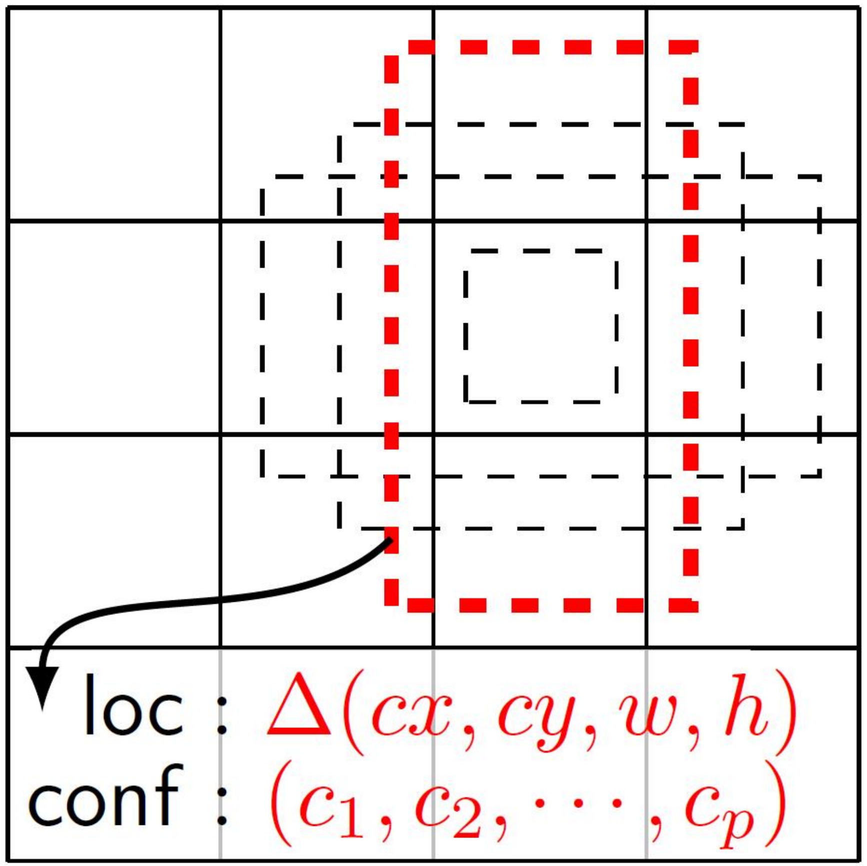
- Default box is like the Anchor box of YOLO.

- This results in a total of $(c + 4)k$ filters that are applied around each location in the feature map

- This yields $(c + 4)kmn$ outputs for a m X n feature map.

Default Boxes and Aspect Ratios

- Allowing different default box shapes in several feature maps let us efficiently discretize the space of possible output box shapes.



(c) 4×4 feature map

Image source :Liu et al., Single Shot MultiBox Detector, December 2015.

Feature Maps of Different Scales

- Lower resolution feature maps detect larger scale objects and higher resolution feature maps detect lower scale objects.

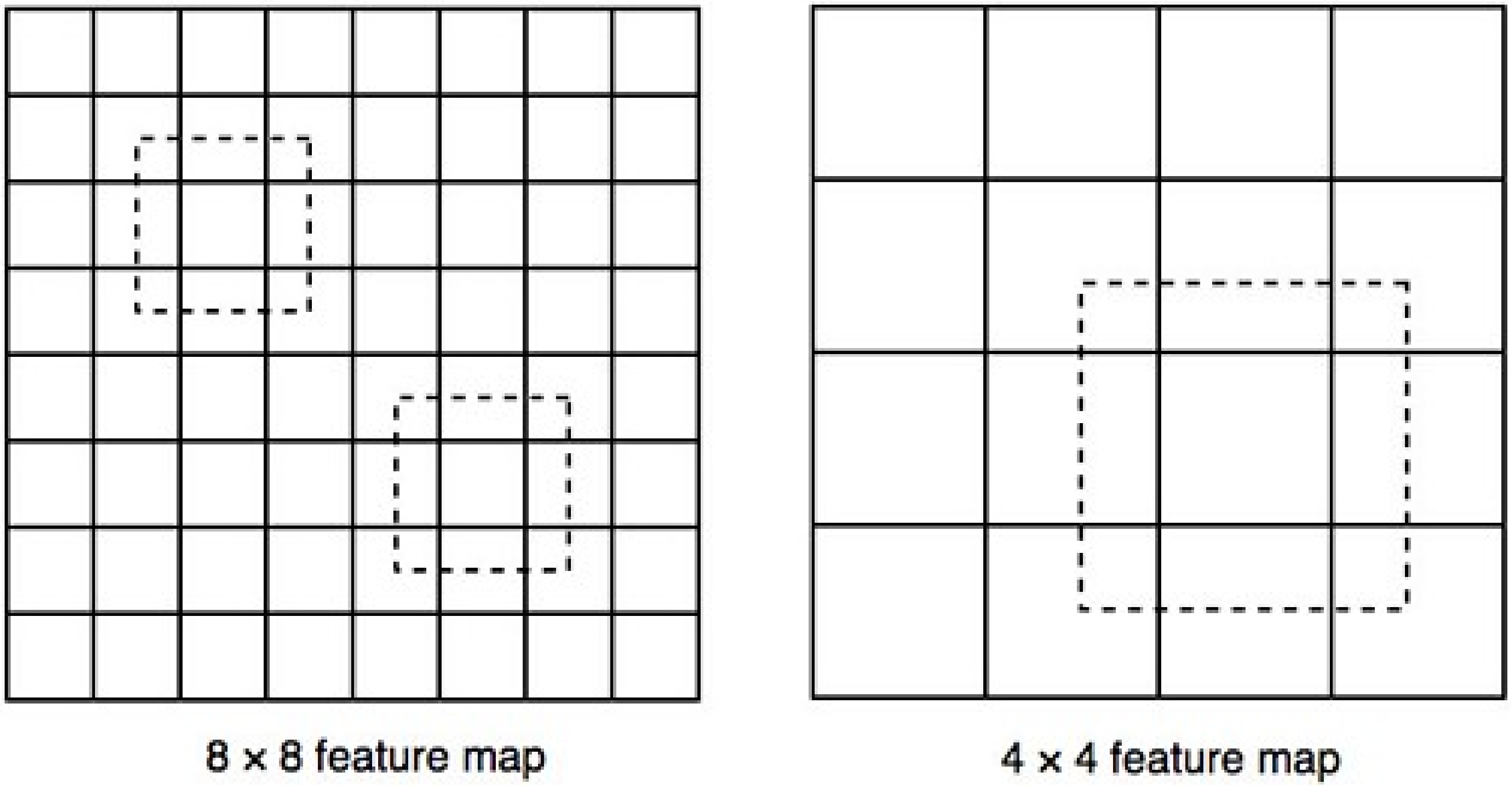


Image Source: https://medium.com/@jonathan_hui

Training

- During training one needs to determine which default boxes correspond to a ground truth detection and train the network accordingly.

- For each ground truth box, selections are made from default boxes that vary over location, aspect ratio, and scale.

- Matches each ground truth box to the default box with the best Jaccard similarity measure (>= 0.5 selected). It is the same as IoU discussed before.

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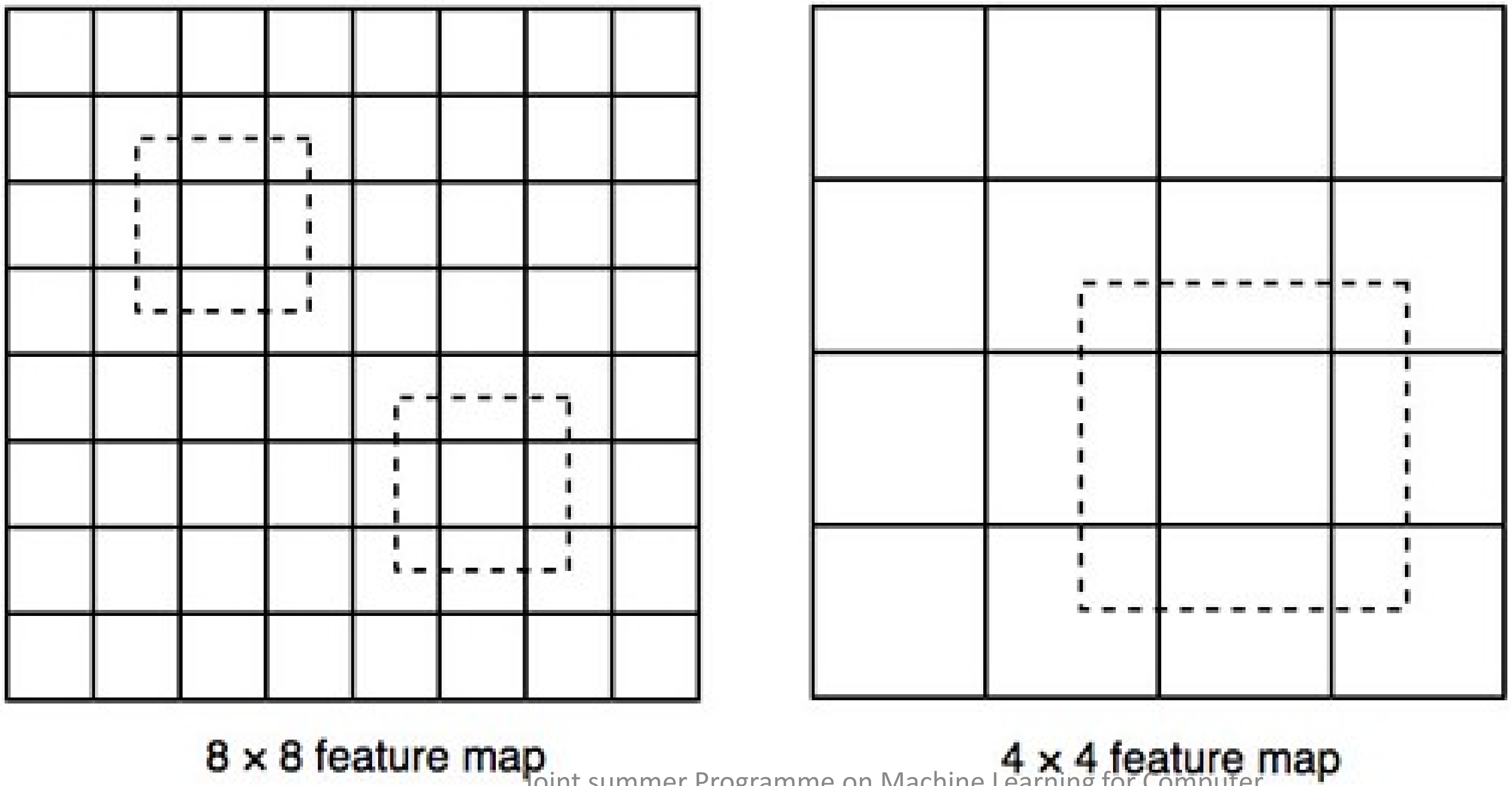
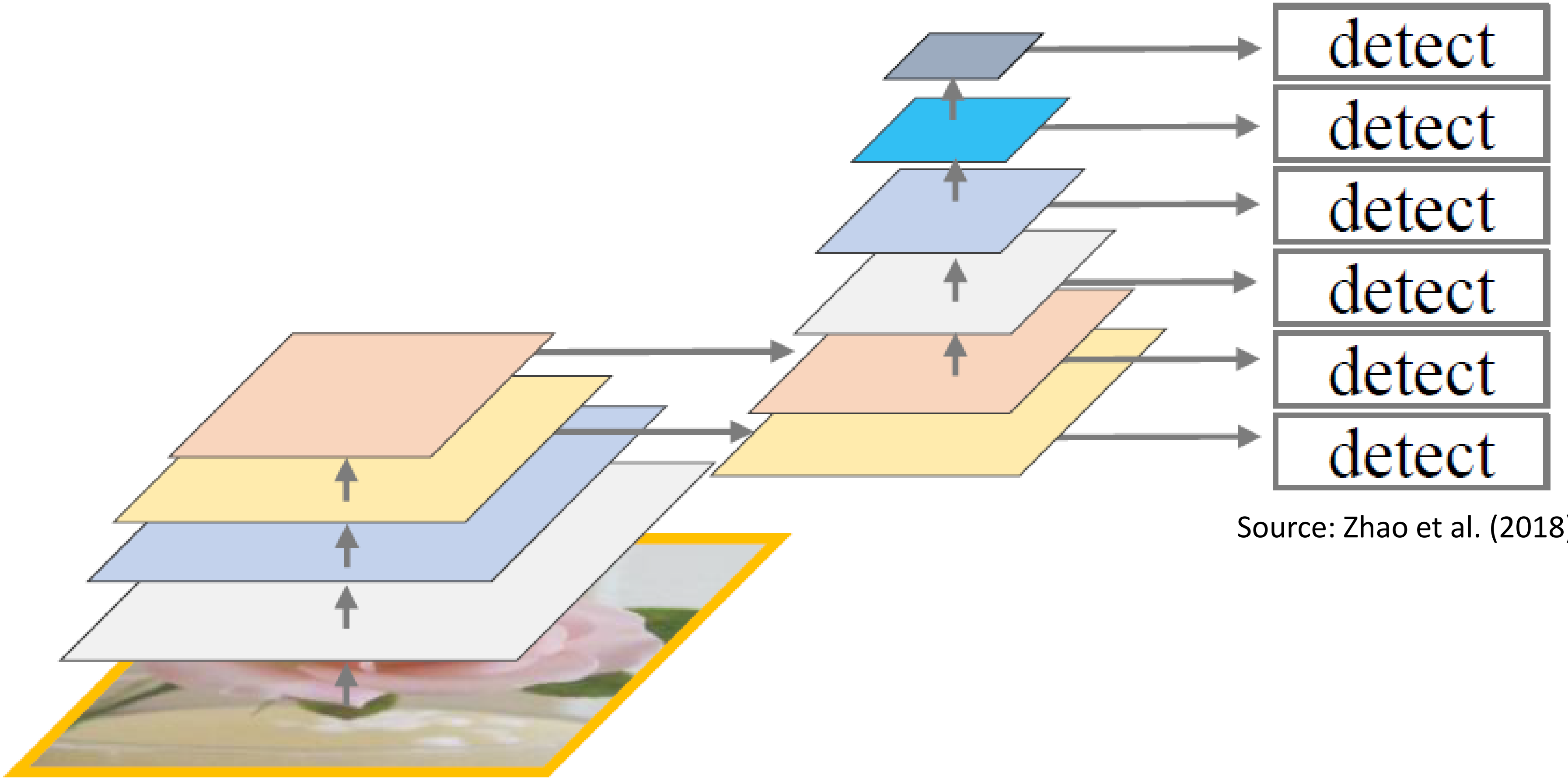


Image Source: https://medium.com/@jonathan_hui

Multi-Scale Feature Maps for Detection

- Convolutional feature layers are added to the end of the truncated base network.
- These layers decrease in size progressively and allow predictions of detections at multiple scales.
- The convolutional model for predicting detections is different for each feature layer.

Feature Pyramid of Different Scales



Source: Zhao et al. (2018)

Results

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

Source: https://towardsdatascience.com

Real Time Performance Evaluation

- Let us check out their real time performance

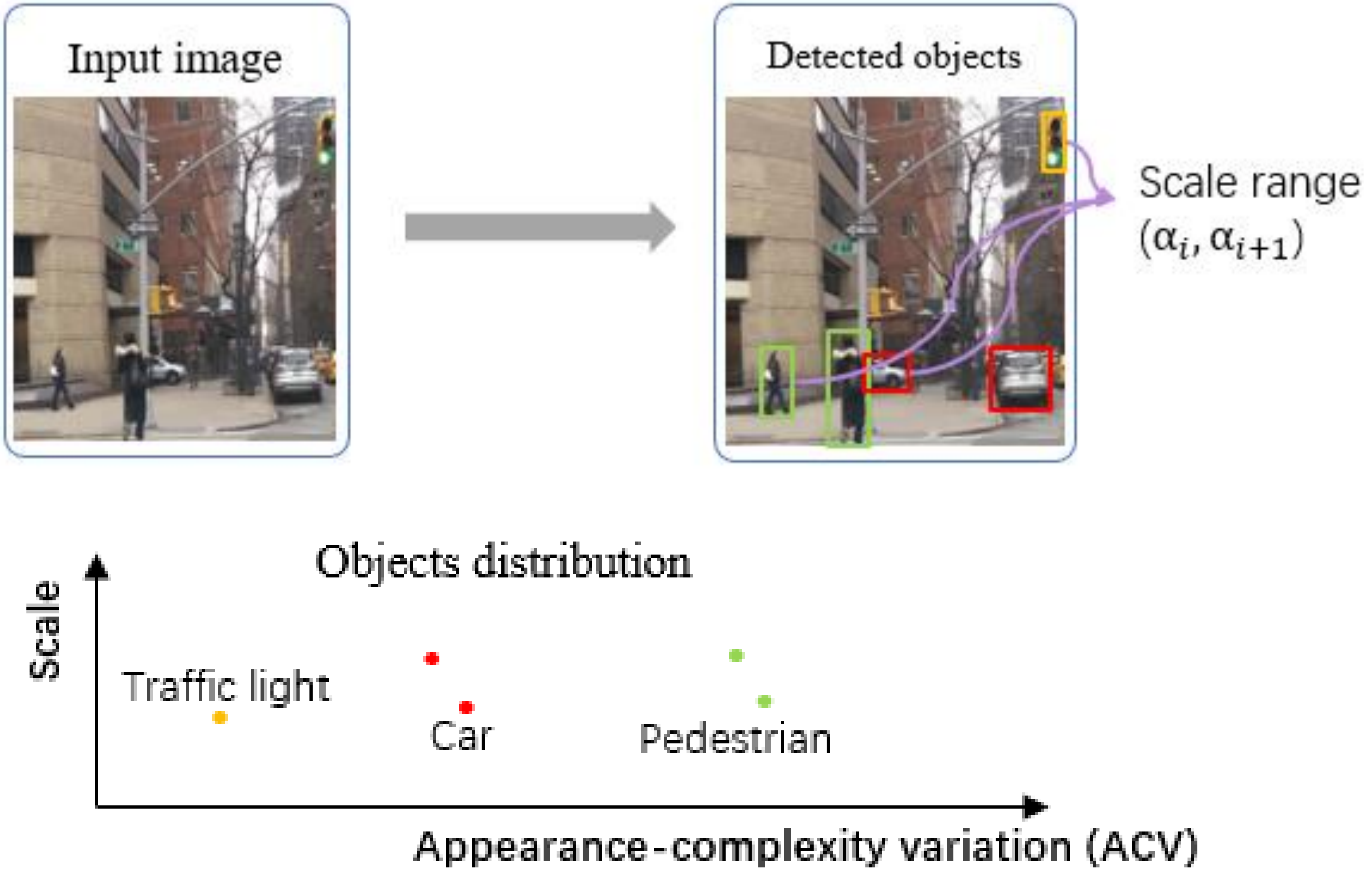
Recent Single Shot Detectors

- Li et al., FSSD: Feature Fusion Single Shot Multibox Detector
- Fu et al., DSSD, 2017: Deconvolutional Single Shot Detector
- Lin, Goyal, et al., 2017, RetinaNet
- **Zhao et al, 2018, M2Det**
- **Tan et al., EfficientDet, 2020**

M2DeT

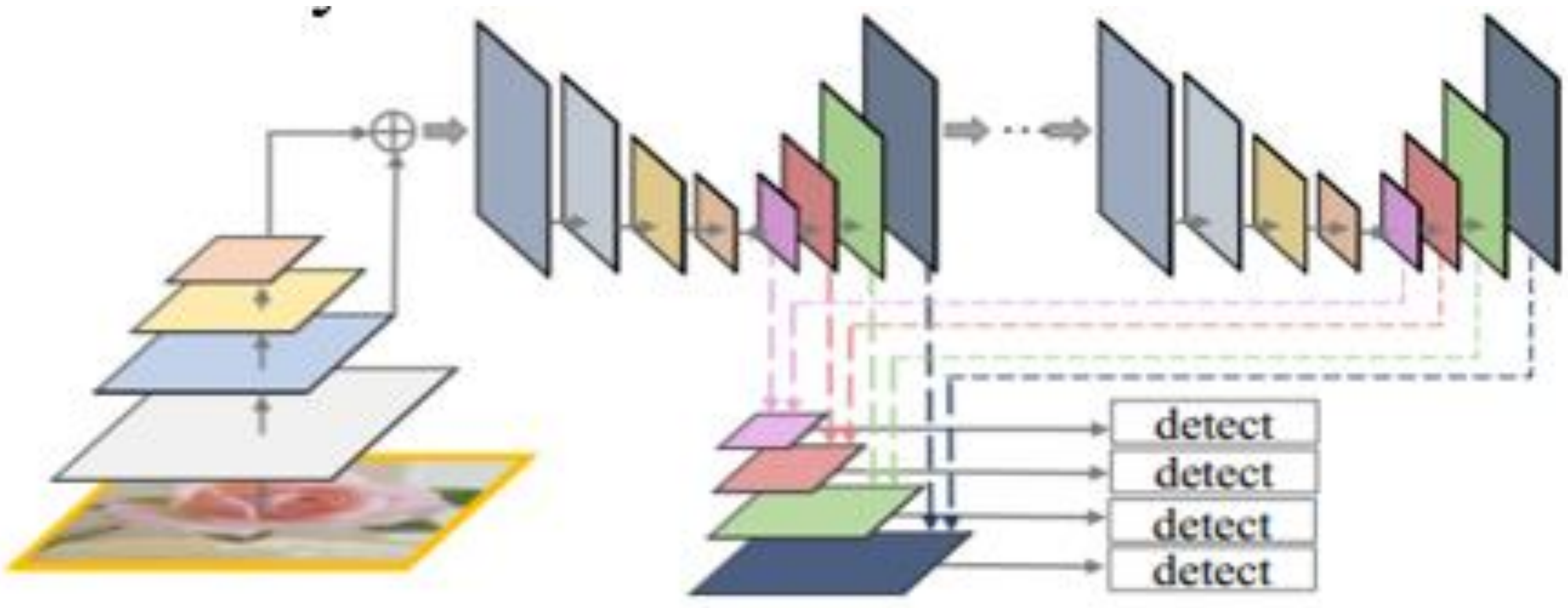
- Zhao et al. (2018) introduced a new single shot object detector based on multi-level feature pyramid network.
- Apart from scale variation, appearance-complexity variation should also be considered for the object detection task.
- Object instances with similar size can be quite different.
- M2Det adds a new dimension to multi-scale detection - **multi-level learning**.
- Deeper level learns features for objects with more appearance-complexity variation (e.g., pedestrian in a road), while shallower level learns features for more simplistic objects(e.g., traffic light).

M2DeT



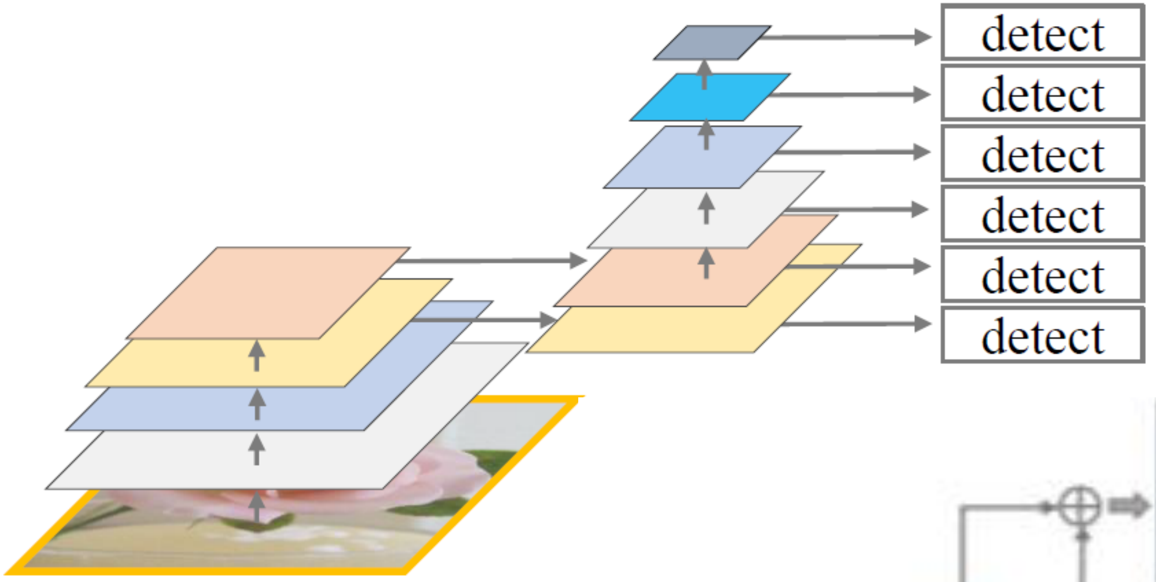
Source: Zhao et al. (2018)

m2DeT: Multi Level Features

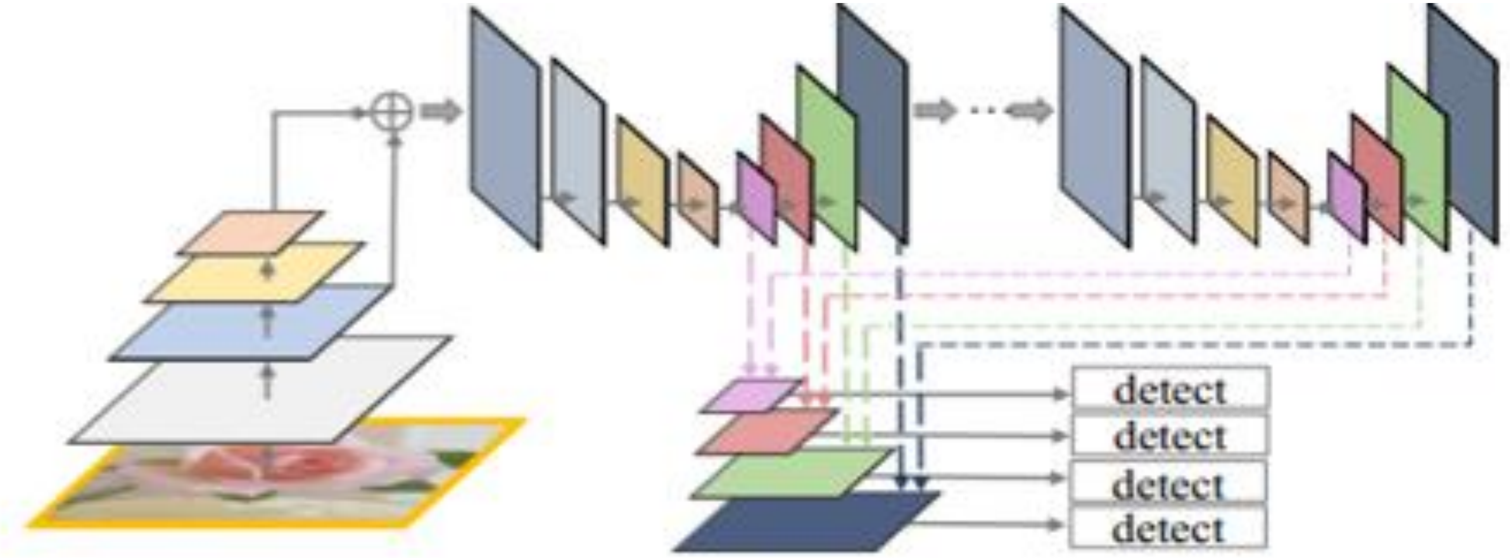


Source: Zhao et al. (2018)

m2DeT vs SSD : Feature Maps



SSD

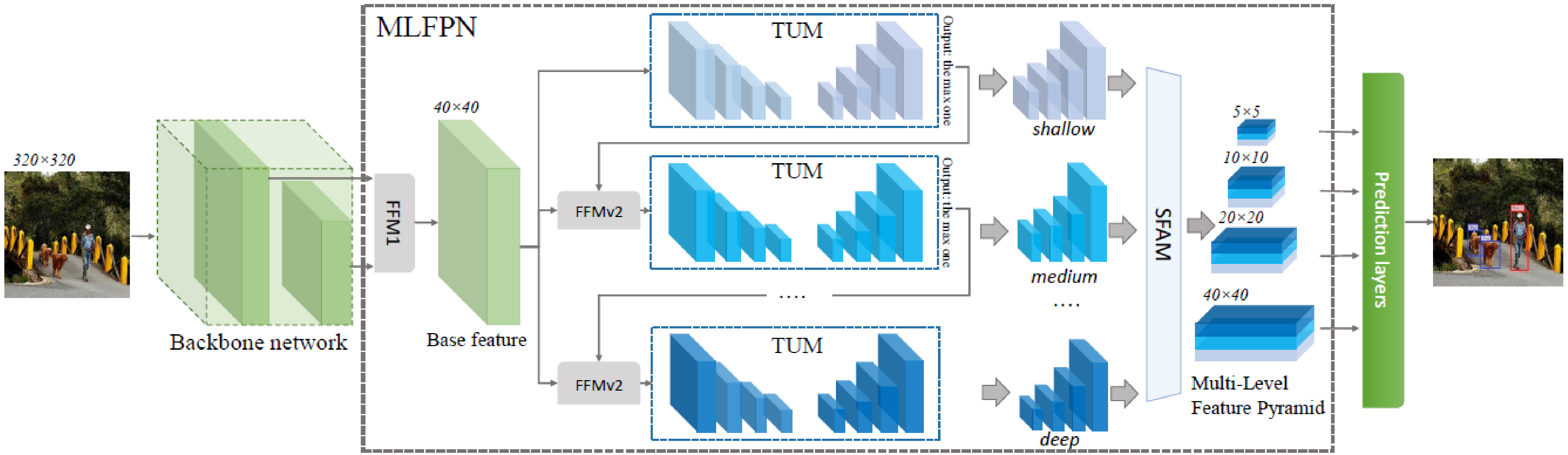


Source: Zhao et al. (2018)

M2DeT

M2DeT

- Three modules : Feature Fusion Module (FFM), Thinned U-shape Module (TUM) and Scale-wise Feature Aggregation Module (SFAM).



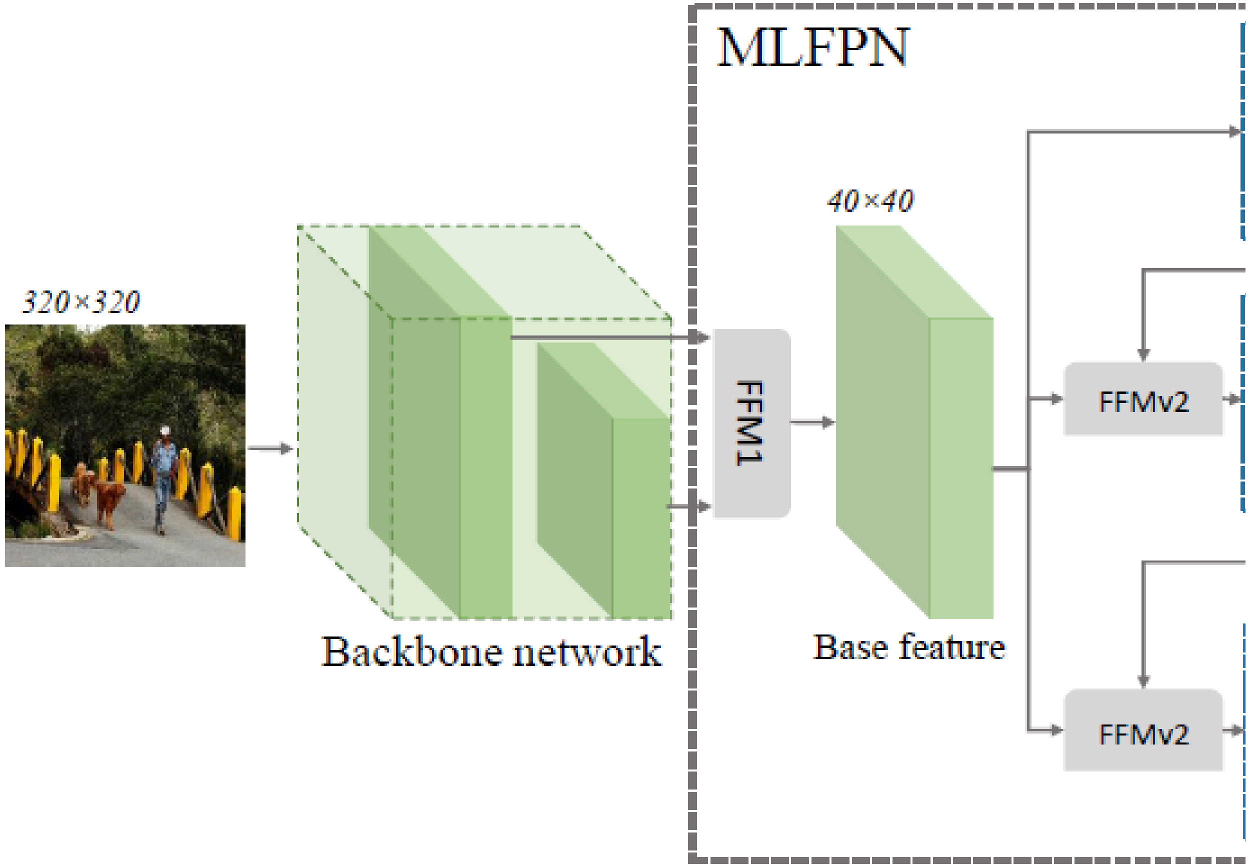
Source: Zhao et al. (2018)

[Real Time Performance](#)

M2DeT: Feature Fusion Module

- **FFMv1** enriches semantic information into base features by fusing feature maps of the backbone.

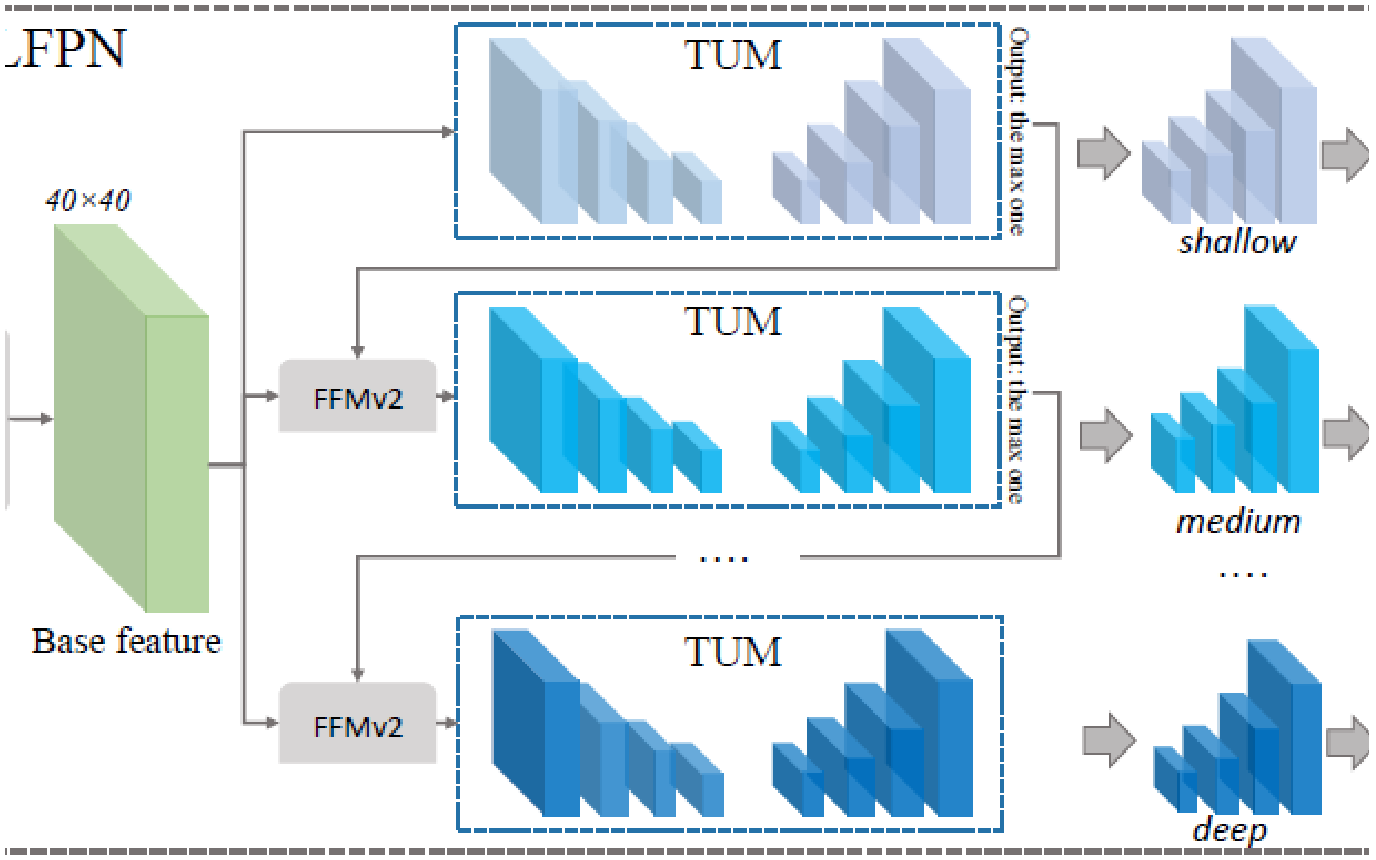
- **FFMv2** modules extract multi-level multiscale features together with TUMs.



Source: Zhao et al. (2018)

M2DeT: Thinned U-shape Module

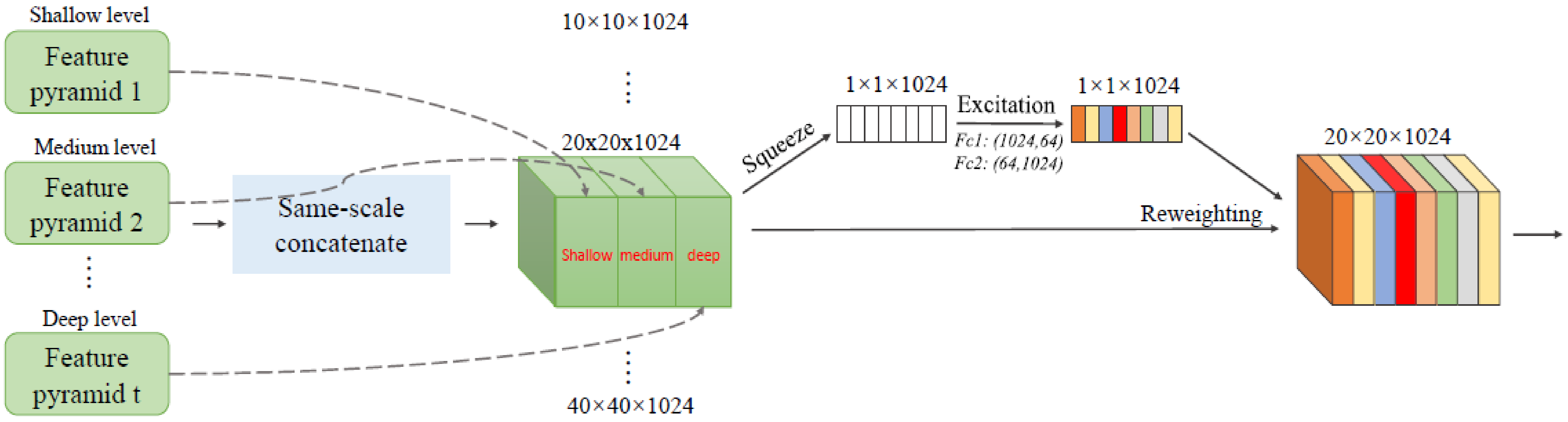
- Each **TUM** generates a group of multi-scale features.
- **TUM**s and **FFMv2**s together extract multi-level multiscale features.



Source: Zhao et al. (2018)

M2DeT: Scale-wise Feature Aggregation Module

- SFAM aggregates the multi-level multiscale features generated by TUMs into a multi-level feature pyramid



Source: Zhao et al. (2018)

M2DeT Performance

Method	Backbone	Input size	MultiScale	FPS	Avg. Precision, IoU: 0.5:0.95	0.5	0.75	Avg. Precision, Area: S	M	L
YOLOv3 (Redmon and Farhadi 2018)	DarkNet-53	608×608	False	19.8	33.0	57.9	34.4	18.3	35.4	41.9
SSD512* (Liu et al. 2016)	VGG-16	512×512	False	22	28.8	48.5	30.3	10.9	31.8	43.5
DSSD513 (Fu et al. 2017)	ResNet-101	513×513	False	5.5	33.2	53.3	35.2	13.0	35.4	51.1
RetinaNet500 (Lin et al. 2017b)	ResNet-101	~832×500	False	11.1	34.4	53.1	36.8	14.7	38.5	49.1
RefineDet512 (Zhang et al. 2018)	VGG-16	512×512	False	22.3	33.0	54.5	35.5	16.3	36.3	44.3
RefineDet512 (Zhang et al. 2018)	ResNet-101	512×512	True	-	41.8	62.9	45.7	25.6	45.1	54.1
CornerNet (Law and Deng 2018)	Hourglass	512×512	False	4.4	40.5	57.8	45.3	20.8	44.8	56.7
CornerNet (Law and Deng 2018)	Hourglass	512×512	True	-	42.1	57.8	45.3	20.8	44.8	56.7
M2Det (Ours)	VGG-16	512×512	False	18.0	37.6	56.6	40.5	18.4	43.4	51.2
M2Det (Ours)	VGG-16	512×512	True	-	42.9	62.5	47.2	28.0	47.4	52.8
M2Det (Ours)	ResNet-101	512×512	False	15.8	38.8	59.4	41.7	20.5	43.9	53.4
M2Det (Ours)	ResNet-101	512×512	True	-	**43.9**	**64.4**	**48.0**	**29.6**	**49.6**	**54.3**
RetinaNet800 (Lin et al. 2017b)	Res101-FPN	~1280×800	False	5.0	39.1	59.1	42.3	21.8	42.7	50.2
M2Det (Ours)	VGG-16	800×800	False	11.8	41.0	59.7	45.0	22.1	46.5	53.8
M2Det (Ours)	VGG-16	800×800	True	-	**44.2**	**64.6**	**49.3**	**29.2**	**47.9**	**55.1**

Source: Zhao et al. (2018)

Summary

- Object Detection is a growing area of research.
- YOLO and SSD are quite promising. RetinaNet, M2Det improve the performance for object detection in different scales.
- Still there are challenges –
  - Small objects
  - Irregularly shape objects
  - Applications to motion estimation, activity detection, pose detection, salient object detection etc.

References

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References

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- Andrew Ng Course on Convolutional Neural Networks, Coursera (deeplearning. ai)