

YOLOv7: Trainable bag-of-freebies sets new state-of-the-art for real-time object detectors

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Abstract

Real-time object detection is one of the most important research topics in computer vision. As new approaches regarding architecture optimization and training optimization are continually being developed, we have found two research topics that have spawned when dealing with these latest state-of-the-art methods. To address the topics, we propose a trainable bag-of-freebies oriented solution. We combine the flexible and efficient training tools with the proposed architecture and the compound scaling method. YOLOv7 surpasses all known object detectors in both speed and accuracy in the range from 5 FPS to 120 FPS and has the highest accuracy 56.8% AP among all known real-time object detectors with 30 FPS or higher on GPU V100. Source code is released in <https://github.com/WongKinyu/yolov7>.

1. Introduction

Real-time object detection is a very important topic in computer vision, as it is often a necessary component in computer vision systems. For example, multi-object tracking [90, 91], autonomous driving [17, 39], robotics [34, 55], medical image analysis [33, 44], etc. The computing devices that execute real-time object detection is usually some mobile CPUs or GPUs, as well as various neural processing units (NPUs). For example, the Apple neural engine (Apple), the neural compute stick (Intel), Jetson AI edge devices (Nvidia), the edge TPU (Google), the neural processing engine (Qualcomm), the AI processing unit (MediaTek), and the AI SoCs (Kneron), are all NPUs. Some of edge devices focus on speeding up different operations such as vanilla convolution, depth-wise convolution, or MLP operations. In this paper, the real-time object detector we proposed mainly hopes that it can support both mobile GPU and GPU devices from the edge to the cloud.

In recent years, the real-time object detector is still developed for different edge devices. For example, the develop-

Figure 1. Comparison with other real-time object detectors, our proposed methods achieve state-of-the-arts performance.

ment of MCUNet [46, 47] and NanoDet [51] focused on producing low-power single-chip and improving the inference speed on edge CPU. As for methods such as YOLOX [20] and YOLOR [79], they focus on improving the inference speed of various GPUs. More recently, the development of real-time object detector has focused on the design of efficient architecture. As for real-time object detectors that can be used on CPU [51, 81, 82, 86], their design is mostly based on MobileNet [26, 27, 63], ShuffleNet [52, 89], or GhostNet [24]. Another real-time object detectors are developed for GPU [20, 79, 94], they mostly use ResNet [25], DarkNet [60], or DLA [85], and then use the CSPNet [77] strategy to optimize the architecture. The development direction of the proposed methods in this paper are different from that of the current real-time object detectors. In addition to architecture optimization, our proposed methods will focus on the optimization of the training process. Our focus will be on some optimized modules and optimization methods which may strengthen the training cost for improving the accuracy of object detection, but without increasing the inference cost. We call these modules and optimization methods trainable bag-of-freebies.

Recently, model re-parameterization [11, 12, 28] and dynamic label assignment [16, 19, 40] have become important topics in network training and object detection. Mainly after the above new concepts are proposed, the training of object detector evolves many new issues. In this paper, we will present some of the new issues we have discovered and devise effective methods to address them. For model re-parameterization, we analyze the model re-parameterization strategies applicable to layers in different networks with the concept of gradient propagation path, and propose planned re-parameterization model. In addition, when we discover that with dynamic label assignment technology, the training of model with multiple output layers will generate new issues. That is: “How to assign dynamic targets for the outputs of different branches?” For this problem, we propose a new label assignment method called coarse-to-fine lead guided label assignment.

The contributions of this paper are summarized as follows: (1) we design several trainable bag-of-freebies methods, so that real-time object detection can greatly improve the detection accuracy without increasing the inference cost; (2) for the evolution of object detection methods, we found two new issues, namely how re-parameterization module replaces original module, and how dynamic label assignment strategy deals with assignment to different output layers. In addition, we also propose methods to address the difficulties arising from these issues; (3) we propose “extend” and “compound scaling” methods for the real-time object detector that can effectively utilize parameters and computation; and (4) the method we proposed can effectively reduce large amount of parameters and computation of state-of-the-art real-time object detector, and has faster inference speed and higher detection accuracy.

2. Related work

2.1. Real-time object detectors

Currently state-of-the-art real-time object detectors are mainly based on YOLO [58–60] and FCOS [73, 74], which are [2, 20, 22, 51, 76, 79, 83]. Being able to become a state-of-the-art real-time object detector usually requires the following characteristics: (1) a faster and stronger network architecture; (2) a more effective feature integration method [8, 21, 29, 36, 43, 56, 71, 94]; (3) a more accurate detection method [66, 73, 74]; (4) a more robust loss function [5, 53, 54, 61, 92, 93]; (5) a more efficient label assignment method [16, 19, 40, 80, 96]; and (6) a more efficient training method. In this paper, we do not intend to explore self-supervised learning or knowledge distillation methods that require additional data or large model. Instead, we will design new trainable bag-of-freebies method for the issues derived from the state-of-the-art methods associated with (4), (5), and (6) mentioned above.

2.2. Model re-parameterization

Model re-parameterization techniques [3, 9–13, 18, 23, 28, 30, 32, 68, 72, 75] merge multiple computational modules into one at inference stage. The model re-parameterization technique can be regarded as an ensemble technique, and we can divide it into two categories, i.e., module-level ensemble and model-level ensemble. There are two common practices for model-level re-parameterization to obtain the final inference model. One is to train multiple identical models with different training data, and then average the weights of multiple trained models. The other is to perform a weighted average of the weights of models at different iteration number. Module-level re-parameterization is a more popular research issue recently. This type of method splits a module into multiple identical or different module branches during training and integrates multiple branched modules into a completely equivalent module during inference. However, not all proposed re-parameterization module can be perfectly applied to different architectures. With this in mind, we have developed new re-parameterization module and designed related application strategies for various architectures.

2.3. Model scaling

Model scaling [1, 14, 15, 49, 57, 69–71] is a way to scale up or down an already designed model and make it fit in different computing devices. The model scaling method usually uses different scaling factors, such as resolution (size of input image), depth (number of layer), width (number of channel), and stage (number of feature pyramid), so as to achieve a good trade-off for the amount of network parameters, computation, inference speed, and accuracy. Network architecture search (NAS) is one of the commonly used model scaling methods. NAS can automatically search for suitable scaling factors from search space without defining too complicated rules. The disadvantage of NAS is that it requires very expensive computation to complete the search for model scaling factors. In [14], the researcher analyzes the relationship between scaling factors and the amount of parameters and operations, trying to directly estimate some rules, and thereby obtain the scaling factors required by model scaling. Checking the literature, we found that almost all model scaling methods analyze individual scaling factor independently, and even the methods in the compound scaling category also optimized scaling factor independently. The reason for this is because most popular NAS architectures deal with scaling factors that are not very correlated. We observed that all concatenation-based models, such as DenseNet [31] or VoVNet [38], will change the input width of some layers when the depth of such models is scaled. Since the proposed architecture is concatenation-based, we have to design a new compound scaling method for this model.

Figure 2. Extended efficient layer aggregation networks. The proposed extended ELAN (E-ELAN) does not change the gradient transmission path of the original architecture at all, but use group convolution to increase the cardinality of the added features, and combine the features of different groups in a shuffle and merge cardinality manner. This way of operation can enhance the features learned by different feature maps and improve the use of parameters and calculations.

3. Architecture

3.1. Extended efficient layer aggregation networks

In most of the literature on designing the efficient architectures, the main considerations are no more than the number of parameters, the amount of computation, and the computational density. Starting from the characteristics of memory access cost, Ma *et al.* [52] analyzed the influence of the input/output channel ratio, the number of branches of the architecture, and the element-wise operation on the network inference speed. Dollár *et al.* [14] additionally considered activation when performing model scaling, that is, to put more consideration on the number of elements in the output tensors of convolutional layers. The design of CSPVoVNet [76] in Figure 2 (b) is a variation of VoVNet [38]. In addition to considering the aforementioned basic designing concerns, the architecture of CSPVoVNet [76] also analyzes the gradient path, in order to enable the weights of different layers to learn more diverse features. The gradient analysis approach described above makes inferences faster and more accurate. ELAN [78] in Figure 2 (c) considers the following design strategy – “How to design an efficient network?”. They came out with a conclusion: By controlling the longest shortest gradient path, a deeper network can learn and converge effectively. In this paper, we propose Extended-ELAN (E-ELAN) based on ELAN and its main architecture is shown in Figure 2 (d).

Regardless of the gradient path length and the stacking number of computational blocks in large-scale ELAN, it has reached a stable state. If more computational blocks are stacked unlimitedly, this stable state may be destroyed, and the parameter utilization rate will decrease. The proposed E-ELAN uses expand, shuffle, merge cardinality to achieve

the ability to continuously enhance the learning ability of the network without destroying the original gradient path. In terms of architecture, E-ELAN only changes the architecture in computational block, while the architecture of transition layer is completely unchanged. Our strategy is to use group convolution to expand the channel and cardinality of computational blocks. We will apply the same group parameter and channel multiplier to all the computational blocks of a computational layer. Then, the feature map calculated by each computational block will be shuffled into g groups according to the set group parameter g , and then concatenate them together. At this time, the number of channels in each group of feature map will be the same as the number of channels in the original architecture. Finally, we add g groups of feature maps to perform merge cardinality. In addition to maintaining the original ELAN design architecture, E-ELAN can also guide different groups of computational blocks to learn more diverse features.

3.2. Model scaling for concatenation-based models

The main purpose of model scaling is to adjust some attributes of the model and generate models of different scales to meet the needs of different inference speeds. For example the scaling model of EfficientNet [69] considers the width, depth, and resolution. As for the scaled-YOLOv4 [76], its scaling model is to adjust the number of stages. In [14], Dollár *et al.* analyzed the influence of vanilla convolution and group convolution on the amount of parameter and computation when performing width and depth scaling, and used this to design the corresponding model scaling method. The above methods are mainly used in architectures such as PlainNet or ResNet. When these architectures are in execut-

Figure 3. Model scaling for concatenation-based models. From (a) to (b), we observe that when depth scaling is performed on concatenation-based models, the output width of a computational block also increases. This phenomenon will cause the input width of the subsequent transmission layer to increase. Therefore, we propose (c), that is, when performing model scaling on concatenation-based models, only the depth in a computational block needs to be scaled, and the remaining of transmission layer is performed with corresponding width scaling.

ing scaling up or scaling down, the in-degree and out-degree of each layer will not change, so we can independently analyze the impact of each scaling factor on the amount of parameters and computation. However, if these methods are applied to the concatenation-based architecture, we will find that when scaling up or scaling down is performed on depth, the in-degree of a transition layer which is immediately after a concatenation-based computational block will decrease or increase, as shown in Figure 3 (a) and (b).

It can be inferred from the above phenomenon that we cannot analyze different scaling factors separately for a concatenation-based model but must be considered together. Take scaling-up depth as an example, such an action will cause a ratio change between the input channel and output channel of a transition layer, which may lead to a decrease in the hardware usage of the model. Therefore, we must propose the corresponding compound model scaling method for a concatenation-based model. When we scale the depth factor of a computational block, we must also calculate the change of the output channel of that block. Then, we will perform width factor scaling with the same amount of change on the transition layers, and the result is shown in Figure 3 (c). Our proposed compound scaling method can maintain the properties that the model had at the initial design and maintains the optimal structure.

4. Trainable bag-of-freebies

4.1. Planned re-parameterization model

Although RepConv [12] has achieved excellent performance on the VGG [65], when we directly apply it to ResNet [25] and DenseNet [31] and other non-plain architectures, its accuracy will be significantly reduced. We use gradient flow propagation paths to analyze how re-parameterization convolution should be combined with different network. We also designed planned re-parameterization model accordingly.

RepConv actually combines 3×3 convolution, 1×1 convolution, and identity connection in one convolutional layer. After analyzing the combination and corresponding perfor-

Figure 4. Planned re-parameterization model. In the proposed planned re-parameterization model, we found that a layer with residual or concatenation connections, its RepConv should not have identity connection. Under these circumstances, it can be replaced by RepConvN that contains no identity connections.

mance of RepConv and different architectures, we find that the identity connection in RepConv destroys the residual in ResNet and the concatenation in DenseNet, which provides more diversity of gradients for different feature maps. For the above reasons, we use RepConv without identity connection (RepConvN) to design the architecture of planned re-parameterization model. In our thinking, when a convolutional layer with residual or concatenation is replaced by re-parameterization convolution, there should be no identity connection. Figure 4 shows examples of how our designed “planned re-parameterization model” is applied in PlainNet and ResNet. As for the complete planned re-parameterization model experiment in residual-based model and concatenation-based model, it will be presented in the ablation study session.

4.2. Coarse for auxiliary and fine for lead loss

Deep supervision [37] is a technique used for training deep networks. Its main concept is to add extra auxiliary

Figure 5. Coarse for auxiliary and fine for lead head label assigner. Compare with normal model (a), the schema in (b) has auxiliary head. Different from the usual independent label assigner (c), we propose (d) lead head guided label assigner and (e) coarse-to-fine lead head guided label assigner. The proposed label assigner is optimized by lead head prediction and the ground truth to get the labels of training lead head and auxiliary head at the same time. The detailed implementation and constraint details will be elaborated in Appendix.

head in the middle layers of the network, and the shallow network weights with assistant loss as the guide. Even for architectures such as ResNet [25] and DenseNet [31] which usually converge well, deep supervision [45, 48, 62, 64, 67, 80, 84, 95] can still significantly improve the performance of the model on many tasks. Figure 5 (a) and (b) show, respectively, the object detector architecture “without” and “with” deep supervision. In this paper, we call the head responsible for the final output as the lead head, and the head used to assist training is called auxiliary head.

Next we want to discuss the issue of label assignment. In the past, in the training of deep network, label assignment usually refers directly to the ground truth and generate hard label according to the given rules. However, in recent years, if we take object detection as an example, researchers often use the quality and distribution of prediction output by the network, and then consider together with the ground truth to use some calculation and optimization methods to generate a reliable soft label [7, 16, 19, 35, 40–42, 58, 87, 88, 96]. For example, YOLO [58] use IoU of prediction of bounding box regression and ground truth as the soft label of objectness. In this paper, we call the mechanism that considers the network prediction results together with the ground truth and then assigns soft labels as “label assigner.”

Deep supervision needs to be trained on the target objectives regardless of the circumstances of auxiliary head or lead head. During the development of soft label assigner related techniques, we accidentally discovered a new derivative issue, i.e., “How to assign soft label to auxiliary head and lead head?” To the best of our knowledge, the relevant literature has not explored this issue so far. The results of the most popular method at present is shown in Figure 5 (c), which is to separate auxiliary head and lead head, and then use their own prediction results and the ground truth to execute label assignment. The method proposed in this paper is a new label assignment method that guides both auxiliary head and lead head by the lead head prediction. In other words, we use lead head prediction as guidance to generate coarse-to-fine hierarchical labels, which are used for auxiliary head and lead head learning, respectively. The

two proposed deep supervision label assignment strategies are shown in Figure 5 (d) and (e), respectively.

Lead head guided label assigner is mainly calculated based on the prediction result of the lead head and the ground truth, and generate soft label through the optimization process. This set of soft labels will be used as the target training model for both auxiliary head and lead head. The reason to do this is because lead head has a relatively strong learning capability, so the soft label generated from it should be more representative of the distribution and correlation between the source data and the target. Furthermore, we can view such learning as a kind of generalized residual learning. By letting the shallower auxiliary head directly learn the information that lead head has learned, lead head will be more able to focus on learning residual information that has not yet been learned.

Coarse-to-fine lead head guided label assigner also used the predicted result of the lead head and the ground truth to generate soft label. However, in the process we generate two different sets of soft label, i.e., coarse label and fine label, where fine label is the same as the soft label generated by lead head guided label assigner, and coarse label is generated by allowing more grids to be treated as positive target by relaxing the constraints of the positive sample assignment process. The reason for this is that the learning ability of an auxiliary head is not as strong as that of a lead head, and in order to avoid losing the information that needs to be learned, we will focus on optimizing the recall of auxiliary head in the object detection task. As for the output of lead head, we can filter the high precision results from the high recall results as the final output. However, we must note that if the additional weight of coarse label is close to that of fine label, it may produce bad prior at final prediction. Therefore, in order to make those extra coarse positive grids have less impact, we put restrictions in the decoder, so that the extra coarse positive grids cannot produce soft label perfectly. This mechanism allows the importance of fine label and coarse label to be dynamically adjusted during the learning process, and makes the optimizable upper bound of fine label always higher than coarse label.

Table 1. Comparison of baseline object detectors.

| Model | #Param. | FLOPs | Size | AP ^{val} | AP ^{val} ₅₀ | AP ^{val} ₇₅ | AP ^{val} _S | AP ^{val} _M | AP ^{val} _L |
|----------------------|---------|--------|------|-------------------|---------------------------------|---------------------------------|--------------------------------|--------------------------------|--------------------------------|
| YOLOv4 [2] | 64.4M | 142.8G | 640 | 49.7% | 68.2% | 54.3% | 32.9% | 54.8% | 63.7% |
| YOLOR-u5 (r6.1) [79] | 46.5M | 109.1G | 640 | 50.2% | 68.7% | 54.6% | 33.2% | 55.5% | 63.7% |
| YOLOv4-CSP [76] | 52.9M | 120.4G | 640 | 50.3% | 68.6% | 54.9% | 34.2% | 55.6% | 65.1% |
| YOLOR-CSP [79] | 52.9M | 120.4G | 640 | 50.8% | 69.5% | 55.3% | 33.7% | 56.0% | 65.4% |
| YOLOv7 | 36.9M | 104.7G | 640 | 51.2% | 69.7% | 55.5% | 35.2% | 56.0% | 66.7% |
| improvement | -43% | -15% | - | +0.4 | +0.2 | +0.2 | +1.5 | = | +1.3 |
| YOLOR-CSP-X [79] | 96.9M | 226.8G | 640 | 52.7% | 71.3% | 57.4% | 36.3% | 57.5% | 68.3% |
| YOLOv7-X | 71.3M | 189.9G | 640 | 52.9% | 71.1% | 57.5% | 36.9% | 57.7% | 68.6% |
| improvement | -36% | -19% | - | +0.2 | -0.2 | +0.1 | +0.6 | +0.2 | +0.3 |
| YOLOv4-tiny [76] | 6.1 | 6.9 | 416 | 24.9% | 42.1% | 25.7% | 8.7% | 28.4% | 39.2% |
| YOLOv7-tiny | 6.2 | 5.8 | 416 | 35.2% | 52.8% | 37.3% | 15.7% | 38.0% | 53.4% |
| improvement | +2% | -19% | - | +10.3 | +10.7 | +11.6 | +7.0 | +9.6 | +14.2 |
| YOLOv4-tiny-3l [76] | 8.7 | 5.2 | 320 | 30.8% | 47.3% | 32.2% | 10.9% | 31.9% | 51.5% |
| YOLOv7-tiny | 6.2 | 3.5 | 320 | 30.8% | 47.3% | 32.2% | 10.0% | 31.9% | 52.2% |
| improvement | -39% | -49% | - | = | = | = | -0.9 | = | +0.7 |
| YOLOR-E6 [79] | 115.8M | 683.2G | 1280 | 55.7% | 73.2% | 60.7% | 40.1% | 60.4% | 69.2% |
| YOLOv7-E6 | 97.2M | 515.2G | 1280 | 55.9% | 73.5% | 61.1% | 40.6% | 60.3% | 70.0% |
| improvement | -19% | -33% | - | +0.2 | +0.3 | +0.4 | +0.5 | -0.1 | +0.8 |
| YOLOR-D6 [79] | 151.7M | 935.6G | 1280 | 56.1% | 73.9% | 61.2% | 42.4% | 60.5% | 69.9% |
| YOLOv7-D6 | 154.7M | 806.8G | 1280 | 56.3% | 73.8% | 61.4% | 41.3% | 60.6% | 70.1% |
| YOLOv7-E6E | 151.7M | 843.2G | 1280 | 56.8% | 74.4% | 62.1% | 40.8% | 62.1% | 70.6% |
| improvement | = | -11% | - | +0.7 | +0.5 | +0.9 | -1.6 | +1.6 | +0.7 |

4.3. Other trainable bag-of-freebies

In this section we will list some trainable bag-of-freebies. These freebies are some of the tricks we used in training, but the original concepts were not proposed by us. The training details of these freebies will be elaborated in the Appendix, including (1) Batch normalization in conv-bn-activation topology: This part mainly connects batch normalization layer directly to convolutional layer. The purpose of this is to integrate the mean and variance of batch normalization into the bias and weight of convolutional layer at the inference stage. (2) Implicit knowledge in YOLOR [79] combined with convolution feature map in addition and multiplication manner: Implicit knowledge in YOLOR can be simplified to a vector by pre-computing at the inference stage. This vector can be combined with the bias and weight of the previous or subsequent convolutional layer. (3) EMA model: EMA is a technique used in mean teacher [72], and in our system we use EMA model purely as the final inference model.

5. Experiments

5.1. Experimental setup

MS COCO dataset is used to conduct experiments. All our models were trained from scratch. We used train 2017 set for training, and then used val 2017 set for verification and choosing hyperparameters. Finally, test 2017 set is used to compare with the state-of-the-art object detectors. Detailed training settings are described in Appendix.

We designed basic model for edge GPU, normal GPU, and cloud GPU, and they are respectively called YOLOv7-tiny, YOLOv7, and YOLOv7-W6. We also use basic model for model scaling for different service requirements. For YOLOv7, we do stack scaling on neck, and use the proposed compound scaling method to perform scaling-up of the depth and width of the entire model to obtain YOLOv7-X. As for YOLOv7-W6, we use the newly proposed compound scaling method to obtain YOLOv7-E6 and YOLOv7-D6. In addition, we use the proposed E-ELAN for YOLOv7-E6, and thereby complete YOLOv7-E6E. Since YOLOv7-tiny is an edge GPU-oriented architecture, it will use leaky ReLU as activation function. As for other models we use SiLU as activation function. We will describe the scaling factor of each model in detail in Appendix.

5.2. Baselines

We choose previous version of YOLO [2, 76] and state-of-the-art object detector YOLOR [79] as our baselines. Table 1 shows the comparison of our proposed YOLOv7 models and those baseline that are trained with the same settings.

From the results we see that YOLOv7-based models outperform the baseline models in terms of number of parameters, amount of computation, and accuracy. For models designed for normal GPU, YOLOv7 and YOLOv7x reduce about 40% parameters and 20% computations, and still achieve higher AP. For model designed for edge GPU, YOLOv7-tiny reduce 39% parameters and 49% computation and achieve same AP as YOLOv4-tiny-3l.

Table 2. Comparison of state-of-the-art object detectors. (no-TRT, without extra object detection training data)

| Model | #Param. | FLOPs | Size | FPS ^{V100} | AP ^{test} / AP ^{val} | AP ^{test} ₅₀ | AP ^{test} ₇₅ |
|------------------------|---------|--------|------|---------------------|----------------------------------------|----------------------------------|----------------------------------|
| YOLOv7-tiny-SiLU | 6.2M | 13.8G | 640 | 273 | 38.7% / 38.7% | 56.7% | 41.7% |
| PPYOLOE-S [83] | 7.9M | 17.4G | 640 | 208 | 43.1% / 42.7% | 60.5% | 46.6% |
| YOLOv5-N (r6.1) [22] | 1.9M | 4.5G | 640 | 159 | - / 28.0% | - | - |
| YOLOv5-S (r6.1) [22] | 7.2M | 16.5G | 640 | 156 | - / 37.4% | - | - |
| PPYOLOE-M [83] | 23.4M | 49.9G | 640 | 123 | 48.9% / 48.6% | 66.5% | 53.0% |
| YOLOv5-N6 (r6.1) [22] | 3.2M | 18.4G | 1280 | 123 | - / 36.0% | - | - |
| YOLOv5-S6 (r6.1) [22] | 12.6M | 67.2G | 1280 | 122 | - / 44.8% | - | - |
| YOLOv5-M (r6.1) [22] | 21.2M | 49.0G | 640 | 122 | - / 45.4% | - | - |
| YOLOv7 | 36.9M | 104.7G | 640 | 118 | 51.4% / 51.2% | 69.7% | 55.9% |
| YOLOR-CSP [79] | 52.9M | 120.4G | 640 | 106 | 51.1% / 50.8% | 69.6% | 55.7% |
| YOLOX-S [20] | 9.0M | 26.8G | 640 | 102 | 40.5% / 40.5% | - | - |
| YOLOv5-L (r6.1) [22] | 46.5M | 109.1G | 640 | 99 | - / 49.0% | - | - |
| YOLOv7-X | 71.3M | 189.9G | 640 | 98 | 53.1% / 52.9% | 71.2% | 57.8% |
| YOLOv5-M6 (r6.1) [22] | 35.7M | 200.0G | 1280 | 90 | - / 51.3% | - | - |
| YOLOR-CSP-X [79] | 96.9M | 226.8G | 640 | 87 | 53.0% / 52.7% | 71.4% | 57.9% |
| YOLOv5-X (r6.1) [22] | 86.7M | 205.7G | 640 | 83 | - / 50.7% | - | - |
| YOLOX-M [20] | 25.3M | 73.8G | 640 | 81 | 47.2% / 46.9% | - | - |
| YOLOv7-W6 | 70.4M | 360.0G | 1280 | 80 | 54.9% / 54.6% | 72.6% | 60.1% |
| PPYOLOE-L [83] | 52.2M | 110.1G | 640 | 78 | 51.4% / 50.9% | 68.9% | 55.6% |
| YOLOR-P6 [79] | 37.2M | 325.6G | 1280 | 76 | 53.9% / 53.5% | 71.4% | 58.9% |
| YOLOX-L [20] | 54.2M | 155.6G | 640 | 69 | 50.1% / 49.7% | - | - |
| YOLOR-W6 [79] | 79.8G | 453.2G | 1280 | 66 | 55.2% / 54.8% | 72.7% | 60.5% |
| YOLOv5-L6 (r6.1) [22] | 76.8M | 445.6G | 1280 | 63 | - / 53.7% | - | - |
| YOLOX-X [20] | 99.1M | 281.9G | 640 | 58 | 51.5% / 51.1% | - | - |
| YOLOv7-E6 | 97.2M | 515.2G | 1280 | 54 | 56.0% / 55.9% | 73.5% | 61.2% |
| YOLOR-E6 [79] | 115.8M | 683.2G | 1280 | 45 | 55.8% / 55.7% | 73.4% | 61.1% |
| PPYOLOE-X [83] | 98.4M | 206.6G | 640 | 45 | 52.2% / 51.9% | 69.9% | 56.5% |
| YOLOv7-D6 | 154.7M | 806.8G | 1280 | 43 | 56.6% / 56.3% | 74.0% | 61.8% |
| YOLOv5-X6 (r6.1) [22] | 140.7M | 839.2G | 1280 | 38 | - / 55.0% | - | - |
| YOLOv7-E6E | 151.7M | 843.2G | 1280 | 35 | 56.8% / 56.8% | 74.4% | 62.1% |
| YOLOR-D6 [79] | 151.7M | 935.6G | 1280 | 34 | 56.5% / 56.1% | 74.1% | 61.9% |
| Deformable DETR [97] | 40.0M | 173.0G | - | 19 | - / 46.2% | - | - |
| Swin-B (C-M-RCNN) [50] | 145.0M | 982.0G | 1333 | 11.6 | - / 51.9% | - | - |
| EfficientDet-D7x [71] | 77.0M | 410.0G | 1536 | 6.5 | 55.1% / 54.4% | 72.4% | 58.4% |
| ViT-Adapter-B [6] | 122.0M | 997.0G | - | 4.4 | - / 50.8% | - | - |
| Dual-Swin-B (HTC) [45] | 235.0M | - | 1600 | 2.5 | 58.7% / 58.4% | - | - |

5.3. Comparison with state-of-the-art

We compare the proposed method with state-of-the-art object detectors, and the results are shown in Table 2. From Table 2 we know that the proposed method has the best speed-accuracy trade-off comprehensively.

5.4. Ablation study

5.4.1 Proposed compound scaling method

Table 3 shows the results obtained when using different model scaling strategies for scaling up. Among them, our proposed compound scaling method is to scale up the depth of computational block by 1.5 times and the width of transition block by 1.25 times. It can be seen from the results of Table 3 that our proposed compound scaling strategy can utilize parameters and computation more efficiently.

5.4.2 Proposed planned re-parameterization model

In order to verify the generality of our proposed planned re-parameterization model, we use it on concatenation-based

Table 3. Ablation study on proposed model scaling.

| Model | #Param. | FLOPs | Size | AP ^{val} | AP ^{val} ₅₀ | AP ^{val} ₇₅ |
|---------------------|---------|--------|------|-------------------|---------------------------------|---------------------------------|
| base (v7-X light) | 47.0M | 125.5G | 640 | 51.7% | 70.1% | 56.0% |
| width only (1.25 w) | 73.4M | 195.5G | 640 | 52.4% | 70.9% | 57.1% |
| depth only (2.0 d) | 69.3M | 187.6G | 640 | 52.7% | 70.8% | 57.3% |
| compound (v7-X) | 71.3M | 189.9G | 640 | 52.9% | 71.1% | 57.5% |
| improvement | - | - | - | +1.2 | +1.0 | +1.5 |

model and residual-based model respectively for verification. The concatenation-based model and residual-based model we chose for verification are 3-stacked ELAN and CSPDarknet, respectively.

In the experiment of concatenation-based model, we replace the 3 × 3 convolutional layers in different positions in 3-stacked ELAN with RepConv, and the detailed configuration is shown in Figure 6. From the results shown in Table 4 we see that all higher AP values are present on our proposed planned re-parameterization model.

In the experiment of residual-based model, we design a reversed dark block to fit our design strategy for the exper-

Figure 6. Planned RepConv 3-stacked ELAN. Blue circles are the position we replace Conv by RepConv.

Table 4. Ablation study on planned RepConcatenation model.

| Model | AP ^{val} | AP ^{val} ₅₀ | AP ^{val} ₇₅ | AP ^{val} _S | AP ^{val} _M | AP ^{val} _L |
|-----------------|-------------------|---------------------------------|---------------------------------|--------------------------------|--------------------------------|--------------------------------|
| base (3-S ELAN) | 52.26% | 70.41% | 56.77% | 35.81% | 57.00% | 67.59% |
| Figure 6 (a) | 52.18% | 70.34% | 56.90% | 35.71% | 56.83% | 67.51% |
| Figure 6 (b) | 52.30% | 70.30% | 56.92% | 35.76% | 56.95% | 67.74% |
| Figure 6 (c) | 52.33% | 70.56% | 56.91% | 35.90% | 57.06% | 67.50% |
| Figure 6 (d) | 52.17% | 70.32% | 56.82% | 35.33% | 57.06% | 68.09% |
| Figure 6 (e) | 52.23% | 70.20% | 56.81% | 35.34% | 56.97% | 66.88% |

iment, whose architecture is shown in Figure 7. The experiment results illustrated in Table 5 fully confirm that the proposed planned re-parameterization model is equally effective on residual-based model. We find that the design of RepCSPResNet [83] also fits our design pattern.

Figure 7. Reversed CSPDarknet. We reverse the position of 1 1 and 3 3 convolutional layer in dark block to fit our planned re-parameterization model design strategy.

Table 5. Ablation study on planned RepResidual model.

| Model | AP ^{val} | AP ^{val} ₅₀ | AP ^{val} ₇₅ | AP ^{val} _S | AP ^{val} _M | AP ^{val} _L |
|------------------|-------------------|---------------------------------|---------------------------------|--------------------------------|--------------------------------|--------------------------------|
| base (YOLOR-W6) | 54.82% | 72.39% | 59.95% | 39.68% | 59.38% | 68.30% |
| RepCSP | 54.67% | 72.50% | 59.58% | 40.22% | 59.61% | 67.87% |
| RCSP | 54.36% | 71.95% | 59.54% | 40.15% | 59.02% | 67.44% |
| RepRCSP | 54.85% | 72.51% | 60.08% | 40.53% | 59.52% | 68.06% |
| base (YOLOR-CSP) | 50.81% | 69.47% | 55.28% | 33.74% | 56.01% | 65.38% |
| RepRCSP | 50.91% | 69.54% | 55.55% | 34.44% | 55.74% | 65.46% |

5.4.3 Proposed assistant loss for auxiliary head

In the assistant loss for auxiliary head experiments, we compare the general independent label assignment for lead head and auxiliary head methods, and we also compare the two proposed lead guided label assignment methods. We show all comparison results in Table 6. From the results listed in Table 6, it is clear that any model that increases assistant loss can significantly improve the overall performance.

Table 6. Ablation study on proposed auxiliary head.

| Model | Size | AP ^{val} | AP ^{val} ₅₀ | AP ^{val} ₇₅ |
|----------------------------|------|-------------------|---------------------------------|---------------------------------|
| base (v7-E6) | 1280 | 55.6% | 73.2% | 60.7% |
| independent | 1280 | 55.8% | 73.4% | 60.9% |
| lead guided | 1280 | 55.9% | 73.5% | 61.0% |
| coarse-to-fine lead guided | 1280 | 55.9% | 73.5% | 61.1% |

In Table 7 we further compared the results of with/without the introduction of upper bound constraint. Judging from the numbers in the Table, the method of constraining the upper bound of objectness by the distance from the center of the object can achieve better performance.

Table 7. Ablation study on constrained auxiliary head.

| Model | Size | AP ^{val} | AP ^{val} ₅₀ | AP ^{val} ₇₅ |
|------------------------|------|-------------------|---------------------------------|---------------------------------|
| base (v7-E6) | 1280 | 55.6% | 73.2% | 60.7% |
| aux without constraint | 1280 | 55.9% | 73.5% | 61.0% |
| aux with constraint | 1280 | 55.9% | 73.5% | 61.1% |

Directly connect auxiliary head to the pyramid in the middle layer for training can make up for information that may be lost in the next level pyramid prediction. To solve this issue, our approach is to connect auxiliary head after one of the sets of feature map before merging cardinality of E-ELAN. Table 8 shows the results obtained using coarse-to-fine lead guided and partial coarse-to-fine lead guided methods. Obviously, the partial coarse-to-fine lead guided method has a better auxiliary effect.

Table 8. Ablation study on partial auxiliary head.

| Model | Size | AP ^{val} | AP ^{val} ₅₀ | AP ^{val} ₇₅ |
|---------------|------|-------------------|---------------------------------|---------------------------------|
| base (v7-E6E) | 1280 | 56.3% | 74.0% | 61.5% |
| aux | 1280 | 56.5% | 74.0% | 61.6% |
| partial aux | 1280 | 56.8% | 74.4% | 62.1% |

6. Conclusions

In this paper we propose a new architecture of real-time object detector and the corresponding model scaling method. Furthermore, we find that the evolving process of object detection methods generates new research topics. During the research process, we found the replacement problem of re-parameterization module and the allocation problem of dynamic label assignment. To solve the problem, we propose the trainable bag-of-freebies method to enhance the accuracy of object detection. Based on the above, we have developed the YOLOv7 series of object detection systems, which receives the state-of-the-art results.

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