## Weighted Boxes Fusion: ensembling boxes for object detection models

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### **Abstract**

In this work, we introduce a novel Weighted Box Fusion (WBF) ensembling algorithm that boosts the performance by ensembling predictions from different object detection models. Method was tested on predictions of different models trained on large Open Images Dataset. The source code for our approach is publicly available at https://github.com/ZFTurbo/Weighted-Boxes-Fusion

#### 1. Introduction

One of the popular problems solved using neural networks is the Object Detection task [6]. In this task, you need to find objects of a given class in the image and mark them with a rectangle. The prediction of the model for the image is a set of separate predictions, consisting of 6 numbers: 4 coordinates of the rectangle, class ID of the object (for example, a person - 1, a car - 2, an animal - 3, etc.) and a probability from 0 to 1 - how confident the model is that this object is really in this place. Suppose we have several different models and predictions for each of them. Such case is often used in practice, when the predictions are additionally obtained from a vertically reflected image. The question arises whether it is possible to combine predictions in such a way that the quality of predictions for a given metric improves. The answer to this question is yes. For this, NMS (Non-maximum Suppression) method and its Soft-NMS extension [2] are often used, which give good results. In this paper we propose a new Weighted Boxes Fusion (WBF) method that allows you to combine the predictions of various Object Detection models. Unlike the above methods, which simply remove part of the predictions, the proposed method uses all the predicted rectangles, which can significantly improve the quality of the combined rectangles. Similar method called NMW was presented in [9] but it has some differences from WBF:

- 1) NMW doesnt change confidence value
- 2) NMW uses IoU value to weight boxes, while WBF doesnt
- 3) NMW uses box with max confidence to compare with, while WBF uses average box at each step to check intersection of each next box.
- 4) NMW doesn't use information about how many models predict given box in cluster.

### 2. Description of Weighted Boxes Fusion

Lets suppose we have bounding box predictions from  ${\bf N}$  different models for the same image. In such a way, predictions on the mirrored images are considered as independent model predictions.

WBF algorithm can be described in following steps:

- Each predicted box from each model is added in single list B. And this list is sorted in a decreasing order of confidence scores C.
- 2. We create empty list L and empty list F (Fusion).
- 3. We iterate boxes in cycle, from start of the list **B**. So that, we try to find matched box in the list **F**. Match is the box with maximum Intersection over Union (IOU) for the same class larger than some threshold **THR** (in our experiments **THR**=0.55 was mostly close to an optimal threshold).
- 4. If match is not found we add this box to the end of list L and to the end of list F.

5. If match is found, we add this box in the list L at the position pos found as match in the list F. So, each position in the list L can contain multiple different boxes - which form some kind of cluster. After that we recalculate box at pos position in F using all boxes T at L[pos] with the following fusion formulas:

$$\mathbf{C} = \frac{\mathbf{C}_1 + \mathbf{C}_2 + \dots + \mathbf{C}_T}{T},\tag{1}$$

$$\mathbf{X1} = \frac{\mathbf{C}_1 * \mathbf{B} \cdot \mathbf{X1}_1 + \mathbf{C}_2 * \mathbf{B} \cdot \mathbf{X1}_2 + \dots + \mathbf{C}_T * \mathbf{B} \cdot \mathbf{X1}_T}{\mathbf{C}_1 + \mathbf{C}_2 + \dots + \mathbf{C}_T}$$
(2)

$$\mathbf{X2} = \frac{\mathbf{C}_1 * \mathbf{B} \cdot \mathbf{X2}_1 + \mathbf{C}_2 * \mathbf{B} \cdot \mathbf{X2}_2 + \dots + \mathbf{C}_T * \mathbf{B} \cdot \mathbf{X2}_T}{\mathbf{C}_1 + \mathbf{C}_2 + \dots + \mathbf{C}_T}$$
(3)

$$\mathbf{Y1} = \frac{\mathbf{C}_{1} * \mathbf{B}_{-}\mathbf{Y1}_{1} + \mathbf{C}_{2} * \mathbf{B}_{-}\mathbf{Y1}_{2} + ... + \mathbf{C}_{T} * \mathbf{B}_{-}\mathbf{Y1}_{T}}{\mathbf{C}_{1} + \mathbf{C}_{2} + ... + \mathbf{C}_{T}},$$
(4)

$$\mathbf{Y2} = \frac{\mathbf{C}_{1} * \mathbf{B}_{-}\mathbf{Y2}_{1} + \mathbf{C}_{2} * \mathbf{B}_{-}\mathbf{Y2}_{2} + ... + \mathbf{C}_{T} * \mathbf{B}_{-}\mathbf{Y2}_{T}}{\mathbf{C}_{1} + \mathbf{C}_{2} + ... + \mathbf{C}_{T}},$$
(5)

In short, it can be formulated like we set confidence for a fused box as average confidence of all boxes that form it. Coordinates of the fused box is a weighted sum of coordinates of each box where weights are confidence for boxes. The logic behind is that boxes that have large confidence must give more influence to fused box coordinates rather than boxes with low confidence. (Note: we can use some nonlinear weights like  ${\bf C}^2$  to check if it is better or not etc).

6. After all boxes in B are processed we need to rescale confidences in F list. For that, we need to multiply it by number of boxes in a cluster and divide by number of models N. Why we need this? Its because if number of boxes in the cluster is low it could mean that only small number of models actually predict it and we need to decrease confidence for such case. It can be done in two ways: in some cases number of boxes in one cluster can be more than number of models. So we can either use

$$\mathbf{C} = \mathbf{C} * \frac{\min(T, N)}{N},\tag{6}$$

or

$$\mathbf{C} = \mathbf{C} * \frac{T}{N},\tag{7}$$

Results of both variants differ not too much. First was a little bit better in experiments.

# 3. Why WBF can be better than NMS or Soft-NMS

Both NMS and Soft-NMS exclude some boxes, but WBF uses information from all boxes. It can fix some cases where all boxes are predicted inaccurate by all models. NMS will leave only one inaccurate box, while WBF will fix it using information from all 3 boxes (see the example in Fig. 1, red predictions, blue ground truth).

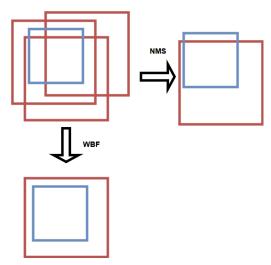


Figure 1. NMS vs WBF boxes.

### 4. Experimental results

First experiment was performed using four RetinaNet [9] models with different ResNet [3] backbones trained on Open Images Dataset [4]. It is currently the largest open dataset for object detection with more than 500 different classes with hierarchical structure and several millions of images. We compared results for 3 methods NMS, Soft-NMS and proposed WBF method.

OD Model + backbone	Independent mAP
1) RetinaNet + ResNet152	0.5180
2) RetinaNet + ResNet101	0.4997
3) RetinaNet + ResNet50	0.4613
RetinaNet + ResNet152	0.5123
(other train algo)	0.0120

Table 1. Initial object detection models for ensemble.

We used grid search to find optimal parameters for each of 3 methods to find the best possible mAP. The results are the following:

- NMS (Best THR IoU = 0.3): Best mAP: **0.5442**
- Soft-NMS Gaussian (Best Sigma = 0.05): Best mAP:
   0.5428

• WBF (Best IoU: 0.55): Best mAP: **0.5665** 

Second experiment was performed on Open Images Dataset using 5 totally different models. One model is based on RetinaNet [9], 2 different Faster-RCNNs models with different backbones from Tensorpack [8], one MMdetection HTC model [5] and Faster-RCNN Inception ResNet v2 (Atrous) from Tensorflow Model ZOO [7]. These models had comparable performance in terms of mAP. While first experiment was about how WBF works on similar models, second experiment is about ensembling highly different models.

OD Model + backbone	Independent mAP
1) RetinaNet Mix	0.5164
2) Mask-RCNN + ResNext101	0.5019
3) Cascade-RCNN + ResNext101 + FPN + GN	0.5144
4) MMDet HTC + X-101-64x4d-FPN	0.5152
Faster RCNN  5) Inception ResNet v2 (Atrous)	0.4910

Table 2. Initial object detection models for second experiment.

We compared 4 methods including NMW. The results are presented in the list below:

- NMS (Best THR IoU = 0.5): Best mAP: **0.5642**
- Soft-NMS Gaussian (Best Sigma = 0.1, Best THR: 1e-03): Best mAP: 0.5616
- NMW (Best IoU: 0.5): Best mAP: 0.5667
- WBF (Best IoU: 0.6): Best mAP: **0.5982**

### 5. Notes and potential improvements

- We tested this ensemble method on predictions from models which were already processed by NMS with THR=0.5. In other cases it could work poor or could require other N (not 0.55). Also we need to test if the method works for models which were processed with different THR for NMS. It probably must be tested on some raw output to check how it works. But we do not think it is the problem by two reasons: 1) we can add NMS (THR=0.5) preprocess as the first stage of algorithm. 2) Actual use cases for modern Object Detection models already output boxes processed with NMS. So WBF ensemble algorithm can be used on top of that.
- 2. We think there can be problem with ensembling models where range of probabilities is different. For example some model mostly gives probs  $\sim 0.8$  0.9 while other 0.00008 0.00009. Both models can have similar

- mAP, because probs are only used for sorting of boxes during mAP calculation. This issue can be somehow fixed with confidence normalization at the first stages of the algorithm.
- 3. WBF is currently slower than NMS or Soft-NMS. While speed depends on set of boxes, number of classes and software implementation. WBF on average was around 3 times slower than standard NMS.

### 6. Conclusion

The proposed method shows very good performance comparing to widely used NMS methods for object detection models. There are still many ways to improve this method and check it using other non-mAP metrics. Code for WBF method with usage examples is available at GitHub [1].

### References

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