



Bridging the Gap Between Anchor-based and Anchor-free Detection via Adaptive Training Sample Selection

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Motivation



Motivation



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① Definition of positive and negative training samples



- ① Definition of positive and negative training samples
- ② Regression starting status



- ① Definition of positive and negative training samples
- ② Regression starting status
- ③ Number of anchors tiled per location



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Which one is the essential difference?

- ① Definition of positive and negative training samples
- Regression starting status



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Essential Difference

- ① Definition of positive and negative training samples
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Essential Difference

1 Definition of positive and negative training samples

Regression starting status



- **①** Definition of positive and negative training samples
- Regression starting status

1 Definition of positive and negative training samples

Regression starting status

for each level $i \in [1, \mathcal{L}]$ do $S_i \leftarrow$ select k anchors from A_i whose center are closest to the center of ground-truth g based on L2 distance; $C_g = C_g \cup S_i$; end for

compute IoU between C_g and g: $\mathcal{D}_g = IoU(C_g, g)$; compute mean of \mathcal{D}_g : $m_g = Mean(\mathcal{D}_g)$; compute standard deviation of \mathcal{D}_g : $v_g = Std(\mathcal{D}_g)$; compute IoU threshold for ground-truth g: $t_g = m_g + v_g$;

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Regression starting status

for each level $i \in [1, \mathcal{L}]$ do

 $S_i \leftarrow$ select k anchors from A_i whose center are closest to the center of ground-truth g based on L2 distance;

 $\mathcal{C}_g = \mathcal{C}_g \cup \mathcal{S}_i;$

end for

compute IoU between C_g and g: $\mathcal{D}_g = IoU(C_g, g)$;

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1 Definition of positive and negative training samples

Regression starting status

for each level $i \in [1, \mathcal{L}]$ do

 $S_i \leftarrow$ select k anchors from A_i whose center are closest to the center of ground-truth q based on L2 distance;

$$\mathcal{C}_g = \mathcal{C}_g \cup \mathcal{S}_i;$$

end for

compute IoU between C_q and q: $\mathcal{D}_q = IoU(C_q, q)$; compute mean of \mathcal{D}_g : $m_g = Mean(\mathcal{D}_g)$; compute standard deviation of \mathcal{D}_g : $v_g = Std(\mathcal{D}_g)$; compute IoU threshold for ground-truth g: $t_g = m_g + v_g$;

① Definition of positive and negative training samples

2 Regression starting status

for each level $i \in [1, \mathcal{L}]$ do

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$$\mathcal{C}_g = \mathcal{C}_g \cup \mathcal{S}_i;$$

end for

compute IoU between C_g and g: $\mathcal{D}_g = IoU(C_g, g)$; compute mean of \mathcal{D}_g : $m_g = Mean(\mathcal{D}_g)$; compute standard deviation of \mathcal{D}_g : $v_g = Std(\mathcal{D}_g)$;

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Method	AP	AP_{50}	AP_{75}	AP_S	AP_M	AP_L
RetinaNet (#A=1)	37.0	55.1	39.9	21.4	41.2	48.6
RetinaNet (#A=1) + ATSS	39.3	57.5	42.8	24.3	43.3	51.3
FCOS	37.8	55.6	40.7	22.1	41.8	48.8
FCOS + Center sampling	38.6	57.4	41.4	22.3	42.5	49.8
FCOS + ATSS	39.2	57.3	42.4	22.7	43.1	51.5



ResNet-101	43.6	62.1	47.4	26.1	47.0	53.6
ResNeXt-32x8d-101	45.1	63.9	49.1	27.9	48.2	54.6
ResNeXt-64x4d-101	45.6	64.6	49.7	28.5	48.9	55.6
ResNet-101-DCN	46.3	64.7	50.4	27.7	49.8	58.4
ResNeXt-32x8d-101-DCN	47.7	66.6	52.1	29.3	50.8	59.7
ResNeXt-64x4d-101-DCN	47.7	66.5	51.9	29.7	50.8	59.4
ResNeXt-32x8d-101-DCN	50.6	68.6	56.1	33.6	52.9	62.2
ResNeXt-64x4d-101-DCN	50.7	68.9	56.3	33.2	52.9	62.4

Analysis

k	3	5	7	9	11	13	15	17	19
AP (%)	38.0	38.8	39.1	39.3	39.1	39.0	39.1	39.2	38.9

Hyperparameter k is quite robust

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Analysis

k	3	5	7	9	11	13	15	17	19
AP (%)	38.0	38.8	39.1	39.3	39.1	39.0	39.1	39.2	38.9

Scale	AP	AP_{50}	AP_{75}	AP_S	AP_M	AP_L
5	39.0	57.9	41.9	23.2	42.8	50.5
6	39.2	57.6	42.5	23.5	42.8	51.1
7	39.3	57.6	42.4	22.9	43.2	51.3
8	39.3	57.5	42.8	24.3	43.3	51.3
9	38.9	56.5	42.0	22.9	42.4	50.3

Aspect Ratio	AP	AP_{50}	AP_{75}	AP_S	AP_M	AP_L
4:1	39.1	57.2	42.3	23.1	43.1	51.4
2:1	39.0	56.9	42.5	23.3	43.5	50.6
1:1	39.3	57.5	42.8	24.3	43.3	51.3
2:1	39.3	57.4	42.3	22.8	43.4	51.0
4:1	39.1	56.9	42.6	22.9	42.9	50.7

- Hyperparameter k is quite robust
- ATSS only tiles one anchor boxes per location

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- ATSS is robust to different anchor scales
- ATSS is robust to different anchor aspect ratios

Discussion

- 1 Definition of positive and negative training samples
- 2 Regression starting status
- **③** Number of anchors tiled per location?

Inconsistency	FCOS	RetinaNet (#A=1)						Method	#sc	#ar	AP	AP_{50}	AP_{75}
GroupNorm	\checkmark		\checkmark	\checkmark	\checkmark	\checkmark	\checkmark	RetinaNet (#A=9)	3	3	36.3	55.2	38.8
GIoU Loss	\checkmark			\checkmark	\checkmark	\checkmark	\checkmark	+Imprs.	3	3	38.4	56.2	41.6
In GT Box	\checkmark				\checkmark	\checkmark	\checkmark	+Imprs.+ATSS	3	3	39.2	57.6	42.7
Centerness	\checkmark					\checkmark	\checkmark	+Imprs.+ATSS	3	1	39.3	57.7	42.6
Scalar	\checkmark							+Imprs.+ATSS	1	3	39.2	57.1	42.5
AP (%)	37.8	32.5	33.4	34.9	35.3	36.8	37.0	+Imprs.+ATSS	1	1	39.3	57.5	42.8

• Under the IoU-based sample selection strategy, tiling more anchor boxes per location is effective

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GroupNorm	\checkmark		\checkmark	\checkmark	\checkmark	\checkmark	\checkmark	RetinaNet (#A=9)	3	3	36.3	55.2	38.8
GIoU Loss	\checkmark			\checkmark	\checkmark	\checkmark	\checkmark	+Imprs.	3	3	38.4	56.2	41.6
In GT Box	\checkmark				\checkmark	\checkmark	\checkmark	+Imprs.+ATSS	3	3	39.2	57.6	42.7
Centerness	\checkmark					\checkmark	\checkmark	+Imprs.+ATSS	3	1	39.3	57.7	42.6
Scalar	\checkmark						\checkmark	+Imprs.+ATSS	1	3	39.2	57.1	42.5
AP (%)	37.8	32.5	33.4	34.9	35.3	36.8	37.0	+Imprs.+ATSS	1	1	39.3	57.5	42.8

- Under the IoU-based sample selection strategy, tiling more anchor boxes per location is effective
- Under the proposed ATSS, tiling multiple anchors per location is a useless operation

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Centerness	\checkmark					\checkmark	\checkmark	+Imprs.+ATSS	3	1	39.3	57.7	42.6
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AP (%)	37.8	32.5	33.4	34.9	35.3	36.8	37.0	+Imprs.+ATSS	1	1	39.3	57.5	42.8

- Under the IoU-based sample selection strategy, tiling more anchor boxes per location is effective
- Under the proposed ATSS, tiling multiple anchors per location is a useless operation
- Select positive samples appropriately, different number of anchors per location has the same result
- Further study is needed to discover the right role of tiling multiple anchors per location

Thanks

