Adaptive Word Embedding Module for Semantic Reasoning in Large-scale Detection

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Abstract

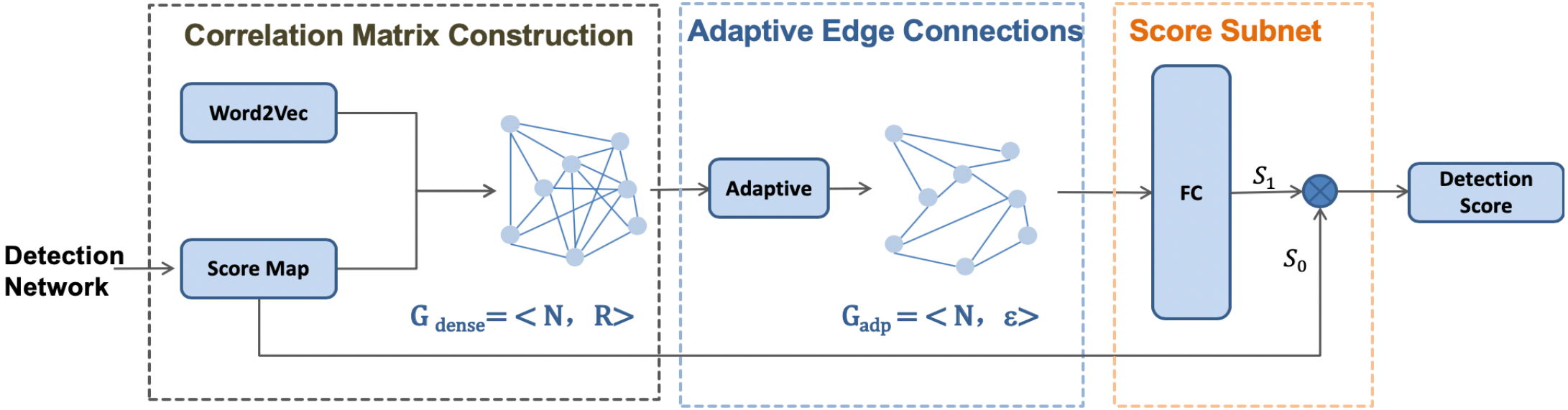
Problem In recent years, convolutional neural networks have achieved rapid development in the field of object detection. However, the overall performance of the previous detection network has dropped sharply when dataset extended to the large-scale with hundreds and thousands of categories.

Reasons The imbalance of data, high costs in labor and uneven level of data labeling in large-scale detection.

Approach The embedding of external semantic knowledge can bring new additional information to reduce the cost of annotation and improve the performance of large-scale detection.

Results Compared with Faster RCNN, the algorithm on the MSCOCO dataset was significantly improved by 4.1%, and the mAP value has reached 32.8%. On the VG_{1000} dataset, it increased by 0.9% to 6.7%.

Overall Framework



The schema of Adaptive Word Embedding Module.

- Correlation Matrix Construction can obtain the dense region-to-region graph $G_{dense} = < N, R >$ according to the classification score of detection network and word2vec pre-trained model.
- Adaptive Edge Connections emphasize semantic features and suppress less useful ones to obtain an adaptive region-to-region graph $G_{adp} = < N, \varepsilon >$.
- Score Subnet performs score recalibration.

Experimental Results on COCO2017

Method	AP	AP_{50}	AP_{75}	AP_S	AP_M	AP_L	AR	AR_{10}	AR_{100}	AR_S	AR_M	AR_L
Faster RCNN	28.7	49.5	29.8	10.7	32.7	44.1	27.2	39.4	40.3	18.2	45.9	60.0
Without adaption	23.0	36.2	25.1	8.5	26.0	32.2	25.1	38.1	38.9	16.5	44.7	58.6
Ours	**32.8**	**53.2**	**34.8**	**13.3**	**37.3**	**49.7**	**29.7**	**43.6**	**44.6**	**22.4**	**50.5**	**64.1**

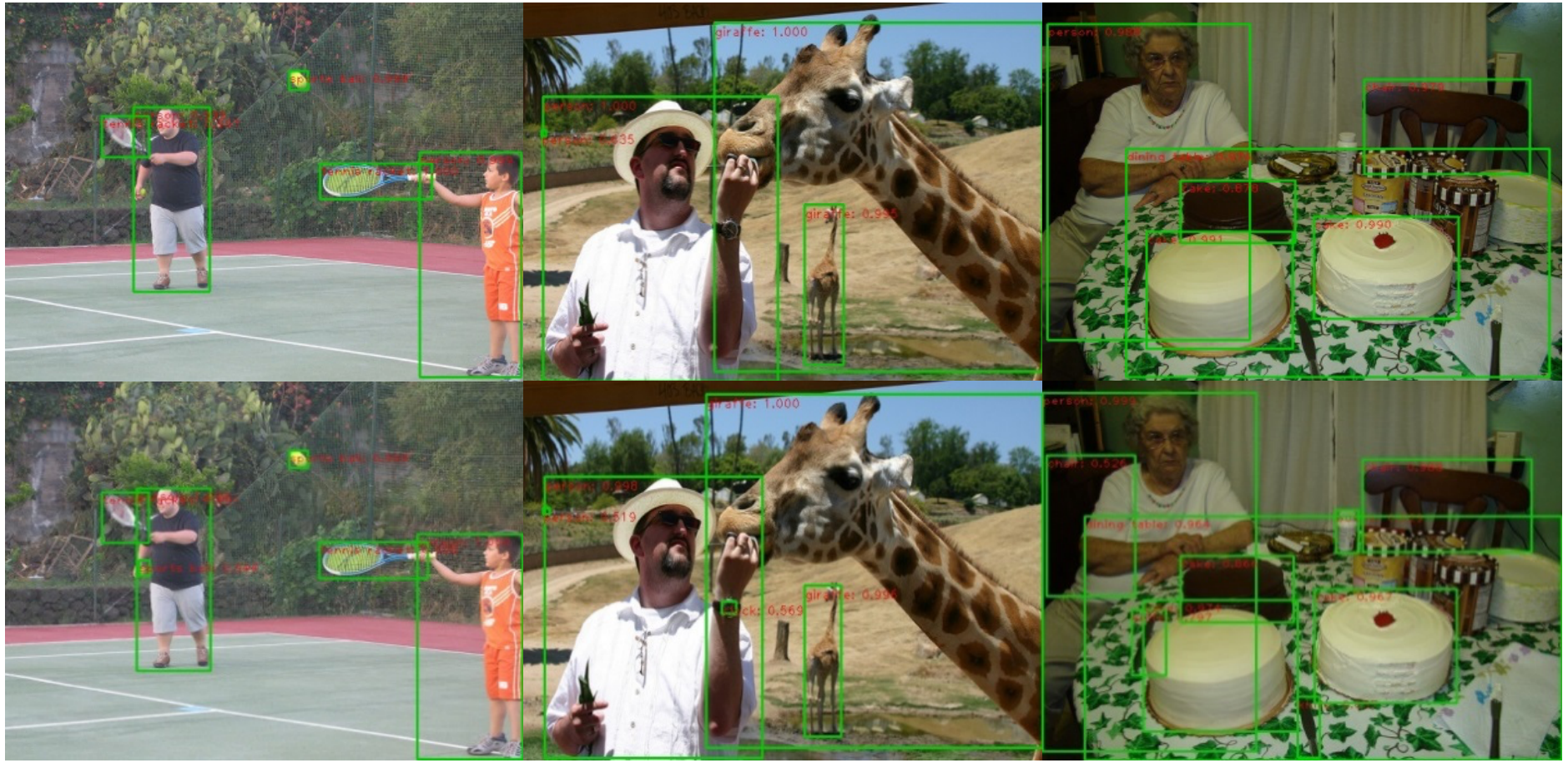
In Table , as it can be seen, if $G_{dense} = < N, R >$ directly embedded in the external semantic knowledge map, without adaptive edge connection, the experimental results turn out to be even worse than the Faster RCNN. After adaptive edge connection is adopted, our approach outperforms the baseline Faster RCNN. MSCOCO 2017 significantly increase mAP over the baseline by 4.1 points.

Experimental Results of Large-scale Detection

Dataset	Method	AP	AP_{50}	AP_{75}	AP_S	AP_M	AP_L	AR	AR_{10}	AR_{100}	AR_S	AR_M	AR_L
VG_{1000}	Faster RCNN	5.8	10.7	5.7	1.9	5.8	10.0	13.7	17.2	17.2	4.9	15.7	25.3
	HKRM	7.8	13.4	8.1	4.1	8.1	12.7	18.1	22.7	22.7	9.6	20.8	31.4
	Ours	**6.7**	**12.2**	**6.6**	**2.8**	**7.0**	**11.3**	**15.8**	**20.0**	**20.1**	**7.5**	**18.9**	**27.7**
ADE	Faster RCNN	7.9	14.7	7.5	2.1	5.8	13.2	10.6	14.2	14.4	4.5	11.9	22.4
	HKRM	10.3	18.0	10.4	7.9	16.8	16.8	13.6	18.3	18.5	7.1	15.5	28.4
	Ours	**10.0**	**18.0**	**9.9**	**3.9**	**8.0**	**16.7**	**13.7**	**18.0**	**18.2**	**7.0**	**15.5**	**28.1**

Table is comparative experiments of large-scale detection on VG_{1000} and ADE. The mAP on VG_{1000} after embedding the Adaptive Word Embedding Module increased by 0.9% to 6.7%. The mAP on ADE increased by 2.1% to 10.0%.

Visualization of Experimental Results



All of these comparisons further show that the detection confidence for small objects is improved, and the occluded objects are also found after learning adaptive edge connections, such as the tennis ball in the hand of the adult, the watch, the knives and the bottle.

Conclusion

We presented a novel Adaptive Word Embedding Module for global semantic reasoning. The experiments indicated the superior performance of our approach over the baseline detection network on COCO, VG and ADE. We demonstrate that Adaptive Word Embedding Module can alleviate the problems of large-scale object detection. As future work, we intend to explore fusing semantic and spatial knowledge graph.

THANKS FOR WATCHING