Object Detection with Deep Reinforcement Learning

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github: https://github.com/kongfusmallside/NYCU-CV-Team20

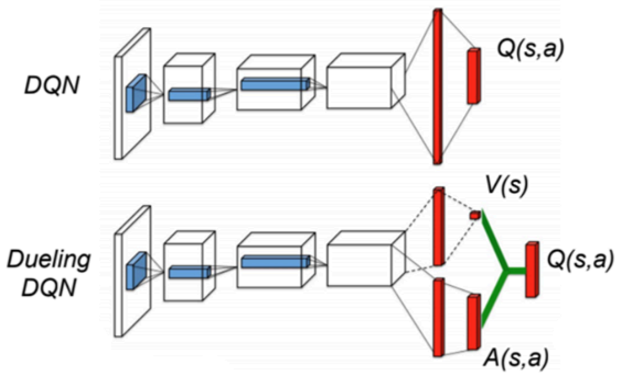
Goal:

The objective of this final project is to reproduce and compare the advantages of object detection as presented in two papers, addressing their respective limitations, and proposing adjustments to enhance their methodologies. The reward function design in Hierarchical Object Detection is deemed too simplistic, potentially limiting its effectiveness in guiding the learning process. By adopting more sophisticated reward functions or improving the DQN model, we aim to improve the effectiveness and efficiency of object detection algorithms.

Improve method:

Moving forward, in our efforts to enhance the models, we pursued two strategies applicable to both papers.

1. Dueling DQN
   Involved transforming the DQN into a Dueling DQN. This technique involves breaking down the Q-value function into the state-value function V(s) and the advantage function A(s,a). By doing so, the network can more accurately assess the overall value of a given state and the relative advantages of different actions. This allows the network to better assess state value and action advantages, improving differentiation between actions. Moreover, it also enhances stability and target identification in complex, noisy environments.



2. Reward function
   Only IoU was used as a metric to calculate the reward. In order to explore more aspects, We added Ground Truth Coverage and Center Deviation to evaluate the reward function. Ground Truth Coverage is the percentage of the ground truth that is covered by the current bounding box. Center Deviation describes the distance between the center of the bounding box and the center of the ground truth in relation to the length of the diagonal of the original image.
   New reward in movement action, and we set α1, α2, α3 all to be 1.

$$r(b,g,d) = \alpha_1 iou(b,g) + \alpha_2 gtc(b,g) + \alpha_3 (1 - cd(b,g,d))$$

Difficulty

1. We noted that the paper ”Hierarchical Object Detection with Deep Reinforcement Learning” used two CNN models for feature extraction. However, since the original authors didn't provide pretrained weights and our focus is on training with reinforcement learning, we used the same pretrained CNN model as the previous paper for fairness.
2. The original paper's code had some issues with the bounding box calculations, which resulted in the computed IOU (Intersection over Union) being greater than 1. This posed a challenge, and we had to spend a significant amount of time modifying the code to address this problem.
3. Objects that are partially occluded by other objects or scene elements are harder to detect. The model needs to be able to reason about the complete shape and location of the object despite partial visibility.

Experiment

Dataset:

In our experiments, the training data consists of the trainval sets from Pascal VOC 2007 and 2012, while the testing data uses the test sets from Pascal VOC 2007. We use the pretrained CNN VGG16 weights from ImageNet and set the training to run for 50 episodes. Additionally, during testing, the terminal condition for each image is an IOU greater than 0.5.

Evaluation:

1. Average IOU
2. Percentage of IOU exceeding 0.5
3. Number of regions analyze per object

Experiment Result:

1. Average IOU
   In the experimental results, we compared two papers and found that Active Object Localization performed better in both the original and improved versions. However, the improved method we proposed did not meet our expectations in terms of Average IOU performance.

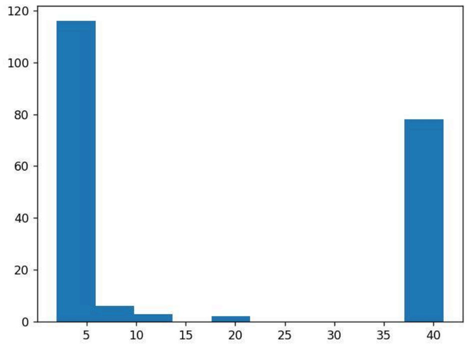
	Active Object Localization	Hierarchical Object Detection
origin	0.44325	0.40189
improved	0.38509	0.31737

2. Percentage of IOU exceeding 0.5
   In terms of Percentage of IOU exceeding 0.5, Active Object Localization still outperformed, and the improved method is still weeker than the original version. As for the poorer performance of the improved version, we attribute it to two possible reasons. Firstly, due to time constraints, we couldn't fine-tune the hyperparameters of Dueling DQN, which may have prevented us from fully leveraging its advantages.

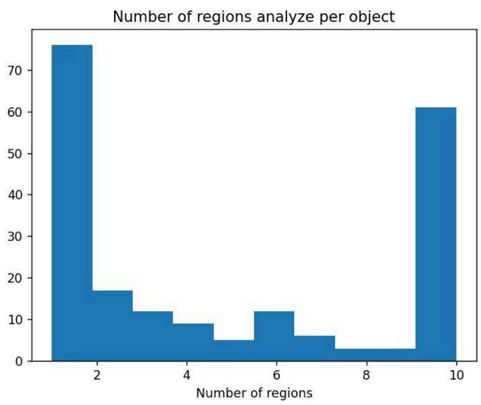
Secondly, although we incorporated GTC and CD into the training to calculate the reward, we only considered whether the IOU exceeds 0.5 as the terminal action, without taking into account GTC and CD during test.

	Active Object Localization	Hierarchical Object Detection
origin	0.59024	0.55882
improved	0.42439	0.33824

3. Number of regions analyze per object
   The paper sets a termination condition at 40 steps. But we found that most objects are detected within 15 steps. If the process exceeds 15 steps, the same actions tend to be repeated. Additionally, we initially believed that Hierarchical Object Detection would perform better in terms of the Number of regions per object. However, Hierarchical Object Detection did not show a significant improvement. A possible reason for this is that in images with larger objects, Hierarchical Object Detection divides the image into four parts, which can result in the object being split across these parts, leading to incorrect action predictions.
   - Active Object Localization



   - Hierarchical Object Detection



Ablation study:

In the Ablation study, we tuned the trigger threshold from 0.5 to 0.6 and observed its impact on Average IOU and Percentage of IOU exceeding 0.5.

1. Average IOU

	Active Object Localization	Hierarchical Object Detection
0.5	0.38509	0.31737
0.6	0.38013	0.26807

2. Percentage of IOU exceeding 0.5

	Active Object Localization	Hierarchical Object Detection
0.5	0.42439	0.33823
0.6	0.4	0.33333

We found that both metrics slightly decreased with a threshold of 0.6. This could be due to: A larger value for the threshold has a negative effect on performance because the agent learns that only clearly visible objects are worth triggering, and tends to avoid truncated or naturally occluded objects.

Contribution

- 109550046 楊竣傑 (50%)
  - reproduce
  - improve methods
  - Oral Presentation
- 109550056 黃韋傑 (50%)
  - reproduce
  - Oral Presentation
  - report

Reference

Picture:

- https://encord.com/blog/object-detection/
- https://medium.com/@sthanikamsanthosh1994/reinforcement-learning-part-3-dueling-dqn-using-tensorflow-45b024c5b7d9

Paper and code:

- Hierarchical Object Detection with Deep Reinforcement Learning
  - https://github.com/XL2013/Pytorch_Deep_RL_1
- Active Object Localization with Deep Reinforcement Learning
  - https://github.com/rayanramoul/Active-Object-Localization-Deep-Reinforcement-Learning/tree/master
- MULTI-STAGE REINFORCEMENT LEARNING FOR OBJECT DETECTION
- Deep Reinforcement Learning in Computer Vision: A Comprehensive Survey