Learning Without Forgetting Approaches for Lifelong Robotic Vision

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Overview

Recent advances in deep learning have achieved exciting results in object detection, object recognition, object localization etc. However, robotic vision poses new challenges for applying visual algorithms due to varying distribution of images from real world and it requires that the model is able to learn knowledge continuously. This competition is about developing lifelong learning algorithms which can be deployed to the robotic vision system. This work describes approaches that we submit to this open challenge.

Methodology

Our approach is based on the learning without forgetting (LwF) [1] which is shown in Fig. 1. This framework only caches the parameters trained by using the previous one task e.g., when training the model on task 3, the optimized weights on task 2 are used as a regularized term for the loss function. There is no replay used in this framework. Therefore, this model computational efficient especially when the number of tasks is huge. Details of training strategy can be seen in Fig. 2.

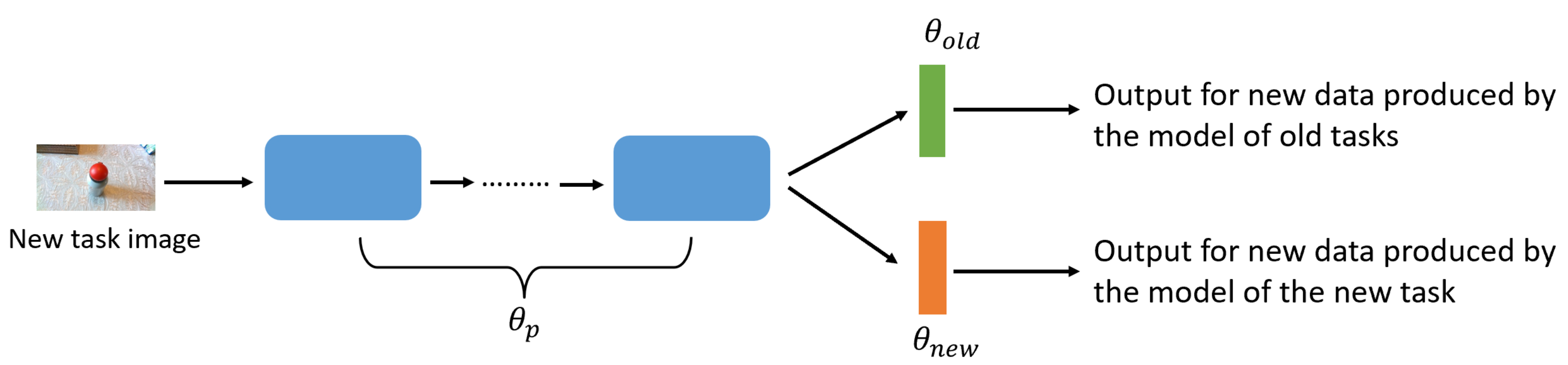

Fig. 1. Model architecture used in this work. We used a pretrained MobileNet V2 where the bottleneck weights are trained from scratch and other weights are fine tuned.

Algorithm 1 Training details

Inputs:

Training images $\mathbf{X}$, labels $\mathbf{Y}$ of the new task and the pretrained parameters θ_p

Initialize:

1: $\mathbf{Y}_{old} \leftarrow \mathcal{M}_{\hat{\theta}_p,\theta_{old}}(\mathbf{X})$ // *Output labels using model trained by previous tasks. Both $\hat{\theta}_p$ and θ_{old} are updated by using previous tasks*

2: $\theta_{new} \leftarrow$ Xavier-init(θ_{new}) // *Use Xavier initialization for the bottleneck weights*

3: Load the pretrained weights θ_p to the new model

Train:

4: $\theta_p^*, \theta_{new}^* \leftarrow \underset{\hat{\theta}_p,\hat{\theta}_{new}}{\operatorname{argmin}}(\lambda\mathcal{L}_{old}(\mathbf{Y}, \mathbf{Y}_{old}) + \mathcal{L}_{new}(\mathbf{Y}, \mathbf{Y}_{new}))$

5: $\theta_{old} \leftarrow \theta_{new}$ // *Cache the updated weights which are going to be used as old weights for the next task.*

Fig. 2. Training details of our approach.

Results

We compared three models in the experiment. $\mathrm{M_{LwF}}$ is our final submitted approach which initializes θ_p by using pretrained weights for each task. $\mathrm{M_1}$ does not deploy any lifelong learning strategy. $\mathrm{M_2}$ fine tunes θ_p continuously for all tasks.

Model	Accuracy
$\mathrm{M_{LwF}}$	76.7 %
$\mathrm{M_1}$	60.9%
$\mathrm{M_2}$	74.3%

Table 1. Performance of three models.

Conclusion

In this work, we described the approach we used for solving the lifelong robotic vision challenge. The core backend of our approach is LwF which was proposed to overcome the catastrophically forgetting issue arisen from the lifelong learning. We modified the original approach in order to be more suitable to deal with this challenge.

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References

[1] Z. Li and D. Hoiem, "Learning without forgetting," *IEEE transactions on pattern analysis and machine intelligence*, vol. 40, no. 12, pp. 2935–2947, 2017.