

Learn Git and GitHub without any code!

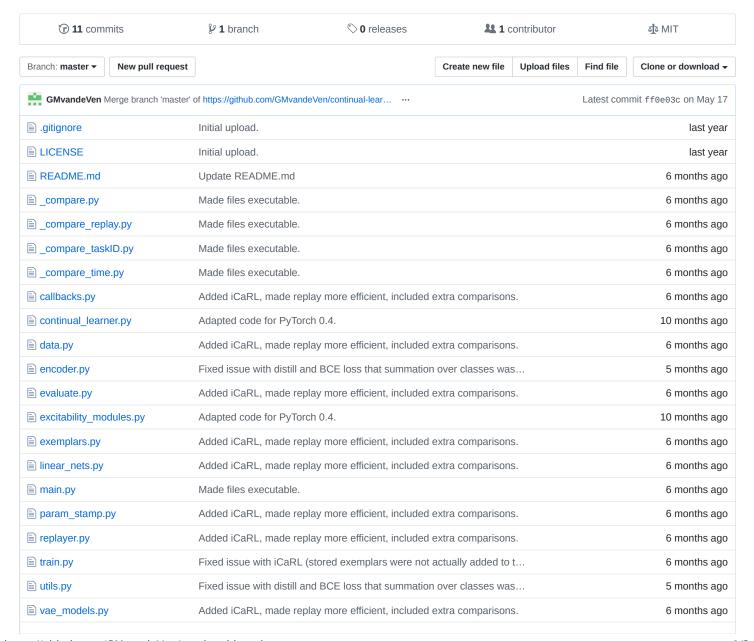
Using the Hello World guide, you'll start a branch, write comments, and open a pull request.

Read the guide

GMvandeVen / continual-learning

PyTorch implementation of various methods for continual learning (XdG, EWC, online EWC, SI, LWF, DGR, DGR+distill, RtF, iCaRL).

#deep-learning #artificial-neural-networks #continual-learning #lifelong-learning #incremental-learning #replay #distillation #generative-models #variational-autoencoder #elastic-weight-consolidation #replay-through-feedback #icarl



visual_plt.py	Added iCaRL, made replay more efficient, included extra comparisons.	6 months ago
visual_visdom.py	Added iCaRL, made replay more efficient, included extra comparisons.	6 months ago

README.md

Continual Learning

This is a PyTorch implementation of the continual learning experiments described in the following papers:

- Three scenarios for continual learning (link)
- Generative replay with feedback connections as a general strategy for continual learning (link)

Requirements

The current version of the code has been tested with:

- pytorch 0.4.1
- torchvision 0.2.1

Running the experiments

Individual experiments can be run with main.py. Main options are:

- --experiment : which task protocol? (splitMNIST | permMNIST)
- --scenario: according to which scenario? (task | domain | class)
- --tasks: how many tasks?

To run specific methods, use the following:

- Context-dependent-Gating (XdG): ./main.py --xdg=0.8
- Elastic weight consolidation (EWC): ./main.py --ewc --lambda=5000
- Online EWC: ./main.py --ewc --online --lambda=5000 --gamma=1
- Synaptic intelligenc (SI): ./main.py --si --c=0.1
- Learning without Forgetting (LwF): ./main.py --replay=current --distill
- Deep Generative Replay (DGR): ./main.py --replay=generative
- DGR with distillation: ./main.py --replay=generative --distill
- Replay-trough-Feedback (RtF): ./main.py --replay=generative --distill --feedback
- iCaRL: ./main.py --icarl --budget=2000

For information on further options: ./main.py -h.

Running comparisons from the papers

"Three CL scenarios"-paper

This paper describes three scenarios for continual learning (Task-IL, Domain-IL & Class-IL) and provides an extensive comparion of recently proposed continual learning methods. It uses the permuted and split MNIST task protocols, with both performed according to all three scenarios.

A comparison of all methods included in this paper can be run with <code>_compare.py</code> . The comparison in Appendix B can be run with <code>_compare_taskid.py</code> , and Figure C.1 can be recreated with <code>_compare_replay.py</code> .

"Replay-through-Feedback"-paper

The three continual learning scenarios were actually first identified in this paper, after which this paper introduces the Replay-through-Feedback framework as a more efficent implementation of generative replay.

A comparison of all methods included in this paper can be run with _compare_time.py . This includes a comparison of the time these methods take to train (Figures 4 and 5).

We should note that the results reported in this paper were obtained with this earlier version of the code.

On-the-fly plots during training

With this code it is possible to track progress during training with on-the-fly plots. This feature requires visdom, which can be installed as follows:

```
pip install visdom
```

Before running the experiments, the visdom server should be started from the command line:

```
python -m visdom.server
```

The visdom server is now alive and can be accessed at http://localhost:8097 in your browser (the plots will appear there). The flag --visdom should then be added when calling ./main.py to run the experiments with on-the-fly plots.

For more information on visdom see https://github.com/facebookresearch/visdom.

Citation

Please consider citing our papers if you use this code in your research:

```
@article{vandeven2019three,
   title={Three scenarios for continual learning},
   author={van de Ven, Gido M and Tolias, Andreas S},
   journal={arXiv preprint arXiv:1904.07734},
   year={2019}
}

@article{vandeven2018generative,
   title={Generative replay with feedback connections as a general strategy for continual learning},
   author={van de Ven, Gido M and Tolias, Andreas S},
   journal={arXiv preprint arXiv:1809.10635},
   year={2018}
}
```

Acknowledgments

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