SelfSupervised

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September 11, 2023

1 What are the references about?

The references in this document are all papers that introduce methods for self supervised continual learning methods.

- [12]: Focuses on class incremental learning. Talk about Prior Information Loss (PIL) which is the information the network has lost by not learning features from previous data that may later be useful. Propose to minimize PIL and CF by using SSL backbone with two heads: projection head (trained with SSL loss) and Classifier head (trained with Orthogonal Weights Modification (OWM) [9])
- [3]: Introduces CaSSLe a "simple and effective framework for continual self supervised learning". Uses knowledge distillation.
- [4]: Uses SSL for pretraining and the uses existing supervised CL methods for continual learning.
- [8]: Implement a buffer technique that tries to overcome three challenges (data efficient training, correlated data sources, non-stationary data streams).
- [7]: Has one network trained with SSL loss and one in supervised manner with cross entropy loss. The SSL network is the "slow learner" and the supervised net the "fast learner". Feature information from the SSL network is shared with the supervised network.
- [1]: Uses a buffer and a distillation loss.
- [10]: Use correlation between tasks to inform the freezing of layers in the network. Also uses a buffer and LUMP [6].
- [5]: Uses knowledge distillation with temporal projection network.
- [11]: Uses a buffer, distillation loss and a pseudo-supervised contrastive loss.
- [2]: Modifies SSL loss to include knowledge distillation and makes losses symmetric.
- [6]: Uses mix-up and a buffer.

2 References

References

[1] Hyuntak Cha, Jaeho Lee, and Jinwoo Shin. Co2l: Contrastive continual learning. In *Proceedings of the IEEE/CVF International conference on computer vision*, pages 9516–9525, 2021.

[2] Sungmin Cha and Taesup Moon. Sy-con: Symmetric contrastive loss for continual self-supervised representation learning. *arXiv preprint arXiv:2306.05101*, 2023.

[3] Enrico Fini, Victor G Turrisi Da Costa, Xavier Alameda-Pineda, Elisa Ricci, Karteek Alahari, and Julien Mairal. Self-supervised models are continual learners. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, pages 9621–9630, 2022.

[4] Jhair Gallardo, Tyler L Hayes, and Christopher Kanan. Self-supervised training enhances online continual learning. *arXiv preprint arXiv:2103.14010*, 2021.

[5] Alex Gomez-Villa, Bartlomiej Twardowski, Lu Yu, Andrew D Bagdanov, and Joost van de Weijer. Continually learning self-supervised representations with projected functional regularization. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, pages 3867–3877, 2022.

[6] Divyam Madaan, Jaehong Yoon, Yuanchun Li, Yunxin Liu, and Sung Ju Hwang. Representational continuity for unsupervised continual learning. *arXiv preprint arXiv:2110.06976*, 2021.

[7] Quang Pham, Chenghao Liu, and Steven Hoi. Dualnet: Continual learning, fast and slow. *Advances in Neural Information Processing Systems*, 34:16131–16144, 2021.

[8] Senthil Purushwalkam, Pedro Morgado, and Abhinav Gupta. The challenges of continuous self-supervised learning. In *European Conference on Computer Vision*, pages 702–721. Springer, 2022.

[9] Gehui Shen, Song Zhang, Xiang Chen, and Zhi-Hong Deng. Generative feature replay with orthogonal weight modification for continual learning. In *2021 International Joint Conference on Neural Networks (IJCNN)*, pages 1–8. IEEE, 2021.

[10] Li Yang, Sen Lin, Fan Zhang, Junshan Zhang, and Deliang Fan. Efficient self-supervised continual learning with progressive task-correlated layer freezing. *arXiv preprint arXiv:2303.07477*, 2023.

[11] Xiaofan Yu, Yunhui Guo, Sicun Gao, and Tajana Rosing. Scale: Online self-supervised lifelong learning without prior knowledge. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, pages 2483–2494, 2023.

[12] Song Zhang, Gehui Shen, Jinsong Huang, and Zhi-Hong Deng. Self-supervised learning aided class-incremental lifelong learning. *arXiv preprint arXiv:2006.05882*, 2020.