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Open-world continual learning via knowledge transfer

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Bibliography

- [1] Parisi, G.I., Kemker, R., Part, J.L., Kanan, C., Wermter, S.: Continual lifelong learning with neural networks: A review. *Neural Networks* **113** (2019) 54–71
- [2] Ke, Z., Liu, B., Huang, X.: Continual learning of a mixed sequence of similar and dissimilar tasks. *Advances in Neural Information Processing Systems* **33** (2020) 18493–18504
- [3] Han, R., Ren, X., Peng, N.: Econet: Effective continual pretraining of language models for event temporal reasoning. In: *Proceedings of the 2021 Conference on Empirical Methods in Natural Language Processing*. (2021) 5367–5380
- [4] Kudithipudi, D., Aguilar-Simon, M., Babb, J., Bazhenov, M., Blackiston, D., Bongard, J., Brna, A.P., Chakravarthi Raja, S., Cheney, N., Clune, J., et al.: Biological underpinnings for lifelong learning machines. *Nature Machine Intelligence* **4** (2022) 196–210
- [5] Wang, L., Zhang, X., Su, H., Zhu, J.: A comprehensive survey of continual learning: theory, method and application. *IEEE Transactions on Pattern Analysis and Machine Intelligence* (2024)
- [6] Van de Ven, G.M., Tolias, A.S.: Three scenarios for continual learning. *arXiv:1904.07734* (2019)
- [7] Van de Ven, G.M., Siegelmann, H.T., Tolias, A.S.: Brain-inspired replay for continual learning with artificial neural networks (2020)
- [8] Liu, B., Mazumder, S., Robertson, E., Grigsby, S.: AI autonomy: Self-initiated open-world continual learning and adaptation. *AI Magazine* **44** (2023) 185–199
- [9] Chen, Z., Liu, B.: *Lifelong machine learning*. Morgan & Claypool Publishers (2018)
- [10] Yang, G., Fini, E., Xu, D., Rota, P., Ding, M., Nabi, M., Alameda-Pineda, X., Ricci, E.: Uncertainty-aware contrastive distillation for incremental semantic segmentation. *IEEE Transactions on Pattern Analysis and Machine Intelligence* **45** (2022) 2567–2581
- [11] McClelland, J.L., McNaughton, B.L., O’Reilly, R.C.: Why there are complementary learning systems in the hippocampus and neocortex: insights from the successes and failures of connectionist models of learning and memory. *Psychological Review* **102** (1995) 419
- [12] McCloskey, M., Cohen, N.J.: Catastrophic interference in connectionist networks: The sequential learning problem. In: *Psychology of learning and motivation*. Volume 24. Elsevier (1989) 109–165
- [13] Wang, H., Liu, B., Wang, S., Ma, N., Yang, Y.: Forward and backward knowledge transfer for sentiment classification. In: *Proceedings of the Asian Conference on Machine Learning*, PMLR (2019) 457–472
- [14] Zhou, D.W., Wang, Q.W., Qi, Z.H., Ye, H.J., Zhan, D.C., Liu, Z.: Class-incremental learning: A survey. *IEEE Transactions on Pattern Analysis and Machine Intelligence* (2024)
- [15] Bendale, A., Boulton, T.: Towards open world recognition. In: *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition*. (2015) 1893–1902
- [16] Fei, G., Wang, S., Liu, B.: Learning cumulatively to become more knowledgeable. In: *Proceedings of the 22nd ACM SIGKDD Conference on Knowledge Discovery and Data Mining*. (2016) 1565–1574

- [17] Tulving, E., Kroll, N.: Novelty assessment in the brain and long-term memory encoding. *Psychonomic bulletin & review* **2** (1995) 387–390
- [18] Murty, V.P., Ballard, I.C., Macduffie, K.E., Krebs, R.M., Adcock, R.A.: Hippocampal networks habituate as novelty accumulates. *Learning & Memory* **20** (2013) 229–235
- [19] Kim, G., Xiao, C., Konishi, T., Ke, Z., Liu, B.: A theoretical study on solving continual learning. *Advances in Neural Information Processing Systems* **35** (2022) 5065–5079
- [20] Scheirer, W.J., de Rezende Rocha, A., Sapkota, A., Boulton, T.E.: Toward open set recognition. *IEEE Transactions on Pattern Analysis and Machine Intelligence* **35** (2012) 1757–1772
- [21] Kirkpatrick, J., Pascanu, R., Rabinowitz, N., Veness, J., Desjardins, G., Rusu, A.A., Milan, K., Quan, J., Ramalho, T., Grabska-Barwinska, A., et al.: Overcoming catastrophic forgetting in neural networks. *Proceedings of the national academy of sciences* **114** (2017) 3521–3526
- [22] Zenke, F., Poole, B., Ganguli, S.: Continual learning through synaptic intelligence. In Precup, D., Teh, Y.W., eds.: *Proceedings of the 34th International Conference on Machine Learning*. Volume 70 of PMLR., PMLR (2017) 3987–3995
- [23] Kishida, I., Chen, H., Baba, M., Jin, J., Amma, A., Nakayama, H.: Object recognition with continual open set domain adaptation for home robot. In: *Proceedings of the IEEE/CVF Winter Conference on Applications of Computer Vision*. (2021) 1517–1526
- [24] Truong, T.D., Nguyen, H.Q., Raj, B., Luu, K.: Fairness continual learning approach to semantic scene understanding in open-world environments. *Advances in Neural Information Processing Systems* **36** (2023) 65456–65467
- [25] Kim, G., Xiao, C., Konishi, T., Ke, Z., Liu, B.: Open-world continual learning: Unifying novelty detection and continual learning. *Artificial Intelligence* **338** (2025) 104237
- [26] Dhar, P., Singh, R.V., Peng, K.C., Wu, Z., Chellappa, R.: Learning without memorizing. In: *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, IEEE (2019) 5138–5146
- [27] Vijayan, P., Bhat, P., Zonooz, B., Arani, E.: Trire: A multi-mechanism learning paradigm for continual knowledge retention and promotion. In: *Advances in Neural Information Processing Systems*. (2023)
- [28] Masana, M., Liu, X., Twardowski, B., Menta, M., Bagdanov, A.D., Van De Weijer, J.: Class-incremental learning: survey and performance evaluation on image classification. *IEEE Transactions on Pattern Analysis and Machine Intelligence* **45** (2022) 5513–5533
- [29] Lo, S.Y., Oza, P., Patel, V.M.: Adversarially robust one-class novelty detection. *IEEE Transactions on Pattern Analysis and Machine Intelligence* **45** (2022) 4167–4179
- [30] Li, Y., Yang, X., Wang, H., Wang, X., Li, T.: Learning to prompt knowledge transfer for open-world continual learning. In: *Proceedings of the AAAI Conference on Artificial Intelligence*. Volume 38(12). (2024) 13700–13708
- [31] Mundt, M., Pliushch, I., Majumder, S., Hong, Y., Ramesh, V.: Unified probabilistic deep continual learning through generative replay and open set recognition. *Journal of Imaging* **8** (2022) 93
- [32] Wang, Z., Zhang, Z., Lee, C.Y., Zhang, H., Sun, R., Ren, X., Su, G., Perot, V., Dy, J., Pfister, T.: Learning to prompt for continual learning. In: *Proceedings of the IEEE/CVF conference on computer vision and pattern recognition*. (2022) 139–149
- [33] Hounsby, N., Giurigu, A., Jastrzebski, S., Morrone, B., De Laroussilhe, Q., Gesmundo, A., Attariyan, M., Gelly, S.: Parameter-efficient transfer learning for nlp. In: *International conference on machine learning*, PMLR (2019) 2790–2799
- [34] Liu, P., Yuan, W., Fu, J., Jiang, Z., Hayashi, H., Neubig, G.: Pre-train, prompt, and predict: A systematic survey of prompting methods in natural language processing. *ACM Computing Surveys* **55** (2023) 1–35
- [35] Li, Y., Wang, X., Yang, X., Bonsangue, M., Zhang, J., Li, T.: Improving open-world continual learning under the constraints of scarce labeled data. In: *Proceedings of the 31st*

- ACM SIGKDD International Conference on Knowledge Discovery and Data Mining. (2025)
- [36] Fei, N., Gao, Y., Lu, Z., Xiang, T.: Z-score normalization, hubness, and few-shot learning. In: Proceedings of the IEEE/CVF International Conference on Computer Vision. (2021) 142–151
 - [37] Trosten, D.J., Chakraborty, R., Løkse, S., Wickstrøm, K.K., Jenssen, R., Kampffmeyer, M.C.: Hubs and hyperspheres: Reducing hubness and improving transductive few-shot learning with hyperspherical embeddings. In: Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition. (2023) 7527–7536
 - [38] Li, Y., Lai, G., Yang, X., Li, Y., Bonsangue, M., Li, T.: Exploring open-world continual learning with knowns-unknowns knowledge transfer. arXiv:2502.20124 (2025)
 - [39] Li, Y., Yang, Y., Gao, Q., Yang, X.: Cross-regional fraud detection via continual learning (special program). In: Proceedings of the AAAI Conference on Artificial Intelligence. Volume 37. (2023) 16260–16261
 - [40] Li, Y., Yang, X., Gao, Q., Wang, H., Zhang, J., Li, T.: Cross-regional fraud detection via continual learning with knowledge transfer. IEEE Transactions on Knowledge and Data Engineering (2024)
 - [41] Shin, H., Lee, J.K., Kim, J., Kim, J.: Continual learning with deep generative replay. Advances in Neural Information Processing Systems **30** (2017)
 - [42] Rebuffi, S.A., Kolesnikov, A., Sperl, G., Lampert, C.H.: icarl: Incremental classifier and representation learning. In: Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition. (2017) 2001–2010
 - [43] Serra, J., Suris, D., Miron, M., Karatzoglou, A.: Overcoming catastrophic forgetting with hard attention to the task. In: International conference on machine learning, PMLR (2018) 4548–4557
 - [44] Lopez-Paz, D., Ranzato, M.: Gradient episodic memory for continual learning. Advances in Neural Information Processing Systems **30** (2017)
 - [45] Mirzadeh, S.I., Farajtabar, M., Pascanu, R., Ghasemzadeh, H.: Understanding the role of training regimes in continual learning. Advances in Neural Information Processing Systems **33** (2020) 7308–7320
 - [46] Ahn, H., Cha, S., Lee, D., Moon, T.: Uncertainty-based continual learning with adaptive regularization. Advances in Neural Information Processing Systems **32** (2019)
 - [47] Chaudhry, A., Ranzato, M., Rohrbach, M., Elhoseiny, M.: Efficient lifelong learning with a-gem. In: International Conference on Learning Representations. (2018)
 - [48] Yang, R., Wang, S., Zhang, H., Xu, S., Guo, Y., Ye, X., Hou, B., Jiao, L.: Knowledge decomposition and replay: A novel cross-modal image-text retrieval continual learning method. In: Proceedings of the 31st ACM International Conference on Multimedia, New York, NY, USA, Association for Computing Machinery (2023) 6510–6519
 - [49] Li, Z., Hoiem, D.: Learning without forgetting. IEEE Transactions on Pattern Analysis and Machine Intelligence **40** (2017) 2935–2947
 - [50] Wu, Y., Chen, Y., Wang, L., Ye, Y., Liu, Z., Guo, Y., Fu, Y.: Large scale incremental learning. In: Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition. (2019) 374–382
 - [51] Lai, G., Li, Y., Wang, X., Zhang, J., Li, T., Yang, X.: Order-robust class incremental learning: Graph-driven dynamic similarity grouping. In: Proceedings of the IEEE/CVF conference on computer vision and pattern recognition. (2025)
 - [52] Xu, J., Zhu, Z.: Reinforced continual learning. Advances in Neural Information Processing Systems **31** (2018)
 - [53] Aljundi, R., Chakravarty, P., Tuytelaars, T.: Expert gate: Lifelong learning with a network of experts. In: Proceedings of the IEEE conference on computer vision and pattern recognition. (2017) 3366–3375
 - [54] Mallya, A., Lazebnik, S.: Packnet: Adding multiple tasks to a single network by iterative

- pruning. In: Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition. (2018) 7765–7773
- [55] Joseph, K.J., Khan, S., Khan, F.S., Balasubramanian, V.N.: Towards open world object detection. In: Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition. (2021) 5830–5840
- [56] Dhamija, A.R., Günther, M., Boulton, T.: Reducing network agnostophobia. *Advances in Neural Information Processing Systems* **31** (2018)
- [57] Bendale, A., Boulton, T.E.: Towards open set deep networks. In: Proceedings of the IEEE conference on computer vision and pattern recognition. (2016) 1563–1572
- [58] Shu, L., Xu, H., Liu, B.: Doc: Deep open classification of text documents. In: Proceedings of the 2017 Conference on Empirical Methods in Natural Language Processing. (2017) 2911–2916
- [59] Dang, S., Cao, Z., Cui, Z., Pi, Y., Liu, N.: Open set incremental learning for automatic target recognition. *IEEE Transactions on Geoscience and Remote Sensing* **57** (2019) 4445–4456
- [60] Zhu, X., Zhang, R., He, B., Guo, Z., Zeng, Z., Qin, Z., Zhang, S., Gao, P.: Pointclip v2: Prompting clip and gpt for powerful 3d open-world learning. In: Proceedings of the IEEE/CVF International Conference on Computer Vision. (2023) 2639–2650
- [61] Zhao, X., Ma, Y., Wang, D., Shen, Y., Qiao, Y., Liu, X.: Revisiting open world object detection. *IEEE Transactions on Circuits and Systems for Video Technology* (2023)
- [62] Liang, S., Li, Y., Srikant, R.: Enhancing the reliability of out-of-distribution image detection in neural networks. In: International Conference on Learning Representations. (2018)
- [63] Liu, W., Wang, X., Owens, J., Li, Y.: Energy-based out-of-distribution detection. *Advances in Neural Information Processing Systems* **33** (2020) 21464–21475
- [64] Lin, Z., Roy, S.D., Li, Y.: Mood: Multi-level out-of-distribution detection. In: Proceedings of the IEEE/CVF conference on Computer Vision and Pattern Recognition. (2021) 15313–15323
- [65] Djuricic, A., Bozanic, N., Ashok, A., Liu, R.: Extremely simple activation shaping for out-of-distribution detection. In: The Eleventh International Conference on Learning Representations. (2023)
- [66] Morteza, P., Li, Y.: Provable guarantees for understanding out-of-distribution detection. In: Proceedings of the AAAI Conference on Artificial Intelligence. Volume 36. (2022) 7831–7840
- [67] Hsu, Y.C., Shen, Y., Jin, H., Kira, Z.: Generalized odin: Detecting out-of-distribution image without learning from out-of-distribution data. In: Proceedings of the IEEE/CVF conference on computer vision and pattern recognition. (2020) 10951–10960
- [68] Lee, K., Lee, K., Min, K., Zhang, Y., Shin, J., Lee, H.: Hierarchical novelty detection for visual object recognition. In: Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition. (2018) 1034–1042
- [69] Huang, R., Li, Y.: Mos: Towards scaling out-of-distribution detection for large semantic space. In: Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition. (2021) 8710–8719
- [70] Linderman, R., Zhang, J., Inkawich, N., Li, H., Chen, Y.: Fine-grain inference on out-of-distribution data with hierarchical classification. In: Conference on Lifelong Learning Agents, PMLR (2023) 162–183
- [71] Liu, X., Zhai, J.T., Bagdanov, A.D., Li, K., Cheng, M.M.: Task-adaptive saliency guidance for exemplar-free class incremental learning. In: Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition. (2024) 23954–23963
- [72] Wang, Y., Ding, Y., He, X., Fan, X., Lin, C., Li, F., Wang, T., Luo, Z., Luo, J.: Novelty detection and online learning for chunk data streams. *IEEE Transactions on Pattern Analysis and Machine Intelligence* **43** (2020) 2400–2412
- [73] Yu, L., Liu, X., Van de Weijer, J.: Self-training for class-incremental semantic segmentation. *IEEE Transactions on Neural Networks and Learning Systems* **34** (2022) 9116–9127

- [74] Chan, R., Rottmann, M., Gottschalk, H.: Entropy maximization and meta classification for out-of-distribution detection in semantic segmentation. In: *Proceedings of the IEEE/CVF international conference on computer vision*. (2021) 5128–5137
- [75] Mazumder, S., Liu, B.: *Lifelong and Continual Learning Dialogue Systems*. Springer Nature (2024)
- [76] Schlachter, P., Liao, Y., Yang, B.: Deep open set recognition using dynamic intra-class splitting. *SN Computer Science* **1** (2020) 1–12
- [77] Aljundi, R., Reino, D.O., Chumerin, N., Turner, R.E.: Continual novelty detection. In: *Conference on Lifelong Learning Agents*, PMLR (2022) 1004–1025
- [78] Oza, P., Patel, V.M.: C2ae: Class conditioned auto-encoder for open-set recognition. In: *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*. (2019) 2307–2316
- [79] Lee, K., Lee, K., Lee, H., Shin, J.: A simple unified framework for detecting out-of-distribution samples and adversarial attacks. In: *Advances in Neural Information Processing Systems*. Volume 31. (2018) 7167–7177
- [80] Hendrycks, D., Gimpel, K.: A baseline for detecting misclassified and out-of-distribution examples in neural networks. *arXiv:1610.02136* (2016)
- [81] Dosovitskiy, A., Beyer, L., Kolesnikov, A., Weissenborn, D., Zhai, X., Unterthiner, T., Dehghani, M., Minderer, M., Heigold, G., Gelly, S., et al.: An image is worth 16x16 words: Transformers for image recognition at scale. *arXiv:2010.11929* (2020)
- [82] Vaswani, A., Shazeer, N., Parmar, N., Uszkoreit, J., Jones, L., Gomez, A.N., Kaiser, Ł., Polosukhin, I.: Attention is all you need. In: *Advances in Neural Information Processing Systems*. (2017) 5998–6008
- [83] Wang, Z., Zhang, Z., Ebrahimi, S., Sun, R., Zhang, H., Lee, C.Y., Ren, X., Su, G., Perot, V., Dy, J., et al.: Dualprompt: Complementary prompting for rehearsal-free continual learning. In: *European conference on computer vision*, Springer (2022) 631–648
- [84] Wang, L., Xie, J., Zhang, X., Huang, M., Su, H., Zhu, J.: Hierarchical decomposition of prompt-based continual learning: Rethinking obscured sub-optimality. *Advances in Neural Information Processing Systems* **36** (2023) 69054–69076
- [85] Lester, B., Al-Rfou, R., Constant, N.: The power of scale for parameter-efficient prompt tuning. *arXiv:2104.08691* (2021)
- [86] Li, X.L., Liang, P.: Prefix-tuning: Optimizing continuous prompts for generation. In: *Proceedings of the 59th Annual Meeting of the Association for Computational Linguistics and the 11th International Joint Conference on Natural Language Processing (Volume 1: Long Papers)*. (2021) 4582–4597
- [87] Zhou, D.W., Sun, H.L., Ning, J., Ye, H.J., Zhan, D.C.: Continual learning with pre-trained models: a survey. In: *Proceedings of the Thirty-Third International Joint Conference on Artificial Intelligence*. (2024) 8363–8371
- [88] Smith, J.S., Karlinsky, L., Gutta, V., Cascante-Bonilla, P., Kim, D., Arbelle, A., Panda, R., Feris, R., Kira, Z.: Coda-prompt: Continual decomposed attention-based prompting for rehearsal-free continual learning. In: *Proceedings of the IEEE/CVF conference on computer vision and pattern recognition*. (2023) 11909–11919
- [89] Jung, D., Han, D., Bang, J., Song, H.: Generating instance-level prompts for rehearsal-free continual learning. In: *Proceedings of the IEEE/CVF International Conference on Computer Vision*. (2023) 11847–11857
- [90] Wang, Y., Huang, Z., Hong, X.: S-prompts learning with pre-trained transformers: An occam’s razor for domain incremental learning. *Advances in Neural Information Processing Systems* **35** (2022) 5682–5695
- [91] Zhou, D.W., Cai, Z.W., Ye, H.J., Zhan, D.C., Liu, Z.: Revisiting class-incremental learning with pre-trained models: Generalizability and adaptivity are all you need. *International Journal of Computer Vision* **133** (2025) 1012–1032

- [92] Zhou, D.W., Zhang, Y., Wang, Y., Ning, J., Ye, H.J., Zhan, D.C., Liu, Z.: Learning without forgetting for vision-language models. *IEEE Transactions on Pattern Analysis and Machine Intelligence* (2025)
- [93] Zhou, D.W., Sun, H.L., Ye, H.J., Zhan, D.C.: Expandable subspace ensemble for pre-trained model-based class-incremental learning. In: *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*. (2024) 23554–23564
- [94] Chen, S., Ge, C., Tong, Z., Wang, J., Song, Y., Wang, J., Luo, P.: Adaptformer: Adapting vision transformers for scalable visual recognition. *Advances in Neural Information Processing Systems* **35** (2022) 16664–16678
- [95] Radford, A., Kim, J.W., Hallacy, C., Ramesh, A., Goh, G., Agarwal, S., Sastry, G., Askell, A., Mishkin, P., Clark, J., Krueger, G., Sutskever, I.: Learning transferable visual models from natural language supervision. In: *Proceedings of the 38th International Conference on Machine Learning*. Volume 139 of *Proceedings of Machine Learning Research*. (2021) 8748–8763
- [96] Aljundi, R., Babiloni, F., Elhoseiny, M., Rohrbach, M., Tuytelaars, T.: Memory aware synapses: Learning what (not) to forget. In: *Proceedings of the European conference on computer vision (ECCV)*. (2018) 139–154
- [97] Quanz, B., Huan, J., Mishra, M.: Knowledge transfer with low-quality data: A feature extraction issue. *IEEE Transactions on Knowledge and Data Engineering* **24** (2012) 1789–1802
- [98] Krizhevsky, A., Hinton, G., et al.: Learning multiple layers of features from tiny images. Master’s thesis, University of Toronto (2009)
- [99] Ebrahimi, S., Meier, F., Calandra, R., Darrell, T., Rohrbach, M.: Adversarial continual learning. In: *Computer Vision–ECCV 2020: 16th European Conference, Glasgow, UK, August 23–28, 2020, Proceedings, Part XI 16*, Springer (2020) 386–402
- [100] Yu, Q., Aizawa, K.: Unsupervised out-of-distribution detection by maximum classifier discrepancy. In: *Proceedings of the IEEE/CVF International Conference on Computer Vision*. (2019) 9518–9526
- [101] Basart, S., Mantas, M., Mohammadreza, M., Jacob, S., Dawn, S.: Scaling out-of-distribution detection for real-world settings. In: *International Conference on Machine Learning*. (2022)
- [102] Buzzega, P., Boschini, M., Porrello, A., Abati, D., Calderara, S.: Dark experience for general continual learning: a strong, simple baseline. *Advances in Neural Information Processing Systems* **33** (2020) 15920–15930
- [103] Van der Maaten, L., Hinton, G.: Visualizing data using t-sne. *Journal of Machine Learning Research* **9** (2008)
- [104] McInnes, L., Healy, J., Saul, N., Großberger, L.: Umap: Uniform manifold approximation and projection. *Journal of Open Source Software* **3** (2018)
- [105] Ahmad, T., Dhamija, A.R., Cruz, S., Rabinowitz, R., Li, C., Jafarzadeh, M., Boulton, T.E.: Few-shot class incremental learning leveraging self-supervised features. In: *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*. (2022) 3900–3910
- [106] Yoon, J., Madjid, S., Hwang, S.J., Yoo, C.D., et al.: On the soft-subnetwork for few-shot class incremental learning. In: *International Conference on Learning Representations, International Conference on Learning Representations* (2023)
- [107] Qin, C., Joty, S.: Lfpt5: A unified framework for lifelong few-shot language learning based on prompt tuning of t5. In: *International Conference on Learning Representations*. (2021)
- [108] Tao, X., Hong, X., Chang, X., Dong, S., Wei, X., Gong, Y.: Few-shot class-incremental learning. In: *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*. (2020) 12183–12192
- [109] Wah, C., Branson, S., Welinder, P., Perona, P., Belongie, S.: The caltech-ucsd birds-200-2011 dataset (2011)
- [110] Vinyals, O., Blundell, C., Lillicrap, T., Wierstra, D., et al.: Matching networks for one shot

- learning. *Advances in Neural Information Processing Systems* **29** (2016)
- [111] Hendrycks, D., Basart, S., Mazeika, M., Zou, A., Kwon, J., Mostajabi, M., Steinhardt, J., Song, D.: Scaling out-of-distribution detection for real-world settings. In: *International Conference on Machine Learning*, PMLR (2022) 8759–8773
 - [112] Sehwag, V., Chiang, M., Mittal, P.: Ssd: A unified framework for self-supervised. In: *International Conference on Machine Learning*. (2021)
 - [113] Wang, H., Li, Z., Feng, L., Zhang, W.: Vim: Out-of-distribution with virtual-logit matching. In: *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*. (2022) 4921–4930
 - [114] Sun, Y., Ming, Y., Zhu, X., Li, Y.: Out-of-distribution detection with deep nearest neighbors. In: *International Conference on Machine Learning*, PMLR (2022) 20827–20840
 - [115] Park, J., Jung, Y.G., Teoh, A.B.J.: Nearest neighbor guidance for out-of-distribution detection. In: *Proceedings of the IEEE/CVF International Conference on Computer Vision*. (2023) 1686–1695
 - [116] Zhang, C., Song, N., Lin, G., Zheng, Y., Pan, P., Xu, Y.: Few-shot incremental learning with continually evolved classifiers. In: *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*. (2021) 12455–12464
 - [117] Chi, Z., Gu, L., Liu, H., Wang, Y., Yu, Y., Tang, J.: Metafscl: A meta-learning approach for few-shot class incremental learning. In: *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*. (2022) 14166–14175
 - [118] Peng, C., Zhao, K., Wang, T., Li, M., Lovell, B.C.: Few-shot class-incremental learning from an open-set perspective. In: *European Conference on Computer Vision*, Springer (2022) 382–397
 - [119] Zhou, D.W., Ye, H.J., Ma, L., Xie, D., Pu, S., Zhan, D.C.: Few-shot class-incremental learning by sampling multi-phase tasks. *IEEE Transactions on Pattern Analysis and Machine Intelligence* (2022)
 - [120] Yang, Y., Yuan, H., Li, X., Lin, Z., Torr, P., Tao, D.: Neural collapse inspired feature-classifier alignment for few-shot class-incremental learning. In: *The Eleventh International Conference on Learning Representations*. (2022)
 - [121] Ji, Z., Hou, Z., Liu, X., Pang, Y., Li, X.: Memorizing complementation network for few-shot class-incremental learning. *IEEE Transactions on Image Processing* **32** (2023) 937–948
 - [122] Wang, X., Liu, Y., Fan, J., Wen, W., Xue, H., Zhu, W.: Continual few-shot learning with transformer adaptation and knowledge regularization. In: *Proceedings of the ACM Web Conference*. Volume 2023. (2023)
 - [123] Li, J., Bai, Y., Lou, Y., Linghu, X., He, J., Xu, S., Bai, T.: Memory-based label-text tuning for few-shot class-incremental learning. *arXiv:2207.01036* (2022)
 - [124] Agarwal, A., Banerjee, B., Cuzzolin, F., Chaudhuri, S.: Semantics-driven generative replay for few-shot class incremental learning. In: *Proceedings of the 30th ACM International Conference on Multimedia*. (2022) 5246–5254
 - [125] D’Alessandro, M., Alonso, A., Calabrés, E., Galar, M.: Multimodal parameter-efficient few-shot class incremental learning. In: *Proceedings of the IEEE/CVF International Conference on Computer Vision*. (2023) 3393–3403
 - [126] Zhu, P., Zhang, W., Wang, Y., Hu, Q.: Multi-granularity inter-class correlation based contrastive learning for open set recognition. *Int. J. Softw. Informatics* **12** (2022) 157–175
 - [127] Huang, H., Wang, Y., Hu, Q., Cheng, M.M.: Class-specific semantic reconstruction for open set recognition. *IEEE Transactions on Pattern Analysis and Machine Intelligence* **45** (2022) 4214–4228
 - [128] Zhou, Y., Liu, P., Qiu, X.: Knn-contrastive learning for out-of-domain intent classification. In: *Proceedings of the 60th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)*. (2022) 5129–5141
 - [129] van de Ven, G.M., Tolias, A.S.: Three continual learning scenarios. In: *Advances in Neural*

- Information Processing Systems. Volume 1(9). (2018)
- [130] McDonnell, M.D., Gong, D., Parvaneh, A., Abbasnejad, E., van den Hengel, A.: Ranpac: Random projections and pre-trained models for continual learning. *Advances in Neural Information Processing Systems* **36** (2024)
 - [131] Zhou, D.W., Ye, H.J., Zhan, D.C., Liu, Z.: Revisiting class-incremental learning with pre-trained models: Generalizability and adaptivity are all you need. *arXiv:2303.07338* (2023)
 - [132] Fang, Z., Lu, J., Liu, A., Liu, F., Zhang, G.: Learning bounds for open-set learning. In: *International conference on machine learning*, PMLR (2021) 3122–3132
 - [133] Shi, H., Wang, H.: A unified approach to domain incremental learning with memory: Theory and algorithm. *Advances in Neural Information Processing Systems* **36** (2024)
 - [134] Anthony, M., Bartlett, P.L., Bartlett, P.L., et al.: *Neural network learning: Theoretical foundations*. Volume 9. cambridge university press Cambridge (1999)
 - [135] Lian, D., Zhou, D., Feng, J., Wang, X.: Scaling & shifting your features: A new baseline for efficient model tuning. *Advances in Neural Information Processing Systems* **35** (2022) 109–123
 - [136] Jia, M., Tang, L., Chen, B.C., Cardie, C., Belongie, S., Hariharan, B., Lim, S.N.: Visual prompt tuning. In: *European Conference on Computer Vision*, Springer (2022) 709–727
 - [137] Chen, C.P.: A rapid supervised learning neural network for function interpolation and approximation. *IEEE Transactions on Neural Networks* **7** (1996) 1220–1230
 - [138] Huang, G.B., Zhu, Q.Y., Siew, C.K.: Extreme learning machine: theory and applications. *Neurocomputing* **70** (2006) 489–501
 - [139] Lomonaco, V., Maltoni, D.: Core50: a new dataset and benchmark for continuous object recognition. In: *Conference on robot learning*, PMLR (2017) 17–26
 - [140] Breunig, M.M., Kriegel, H.P., Ng, R.T., Sander, J.: Lof: identifying density-based local outliers. In: *Proceedings of the 2000 ACM SIGMOD international conference on Management of data*. (2000) 93–104
 - [141] Shi, H., Tayebi, M.A., Pei, J., Cao, J.: Cost-sensitive learning for medical insurance fraud detection with temporal information. *IEEE Transactions on Knowledge and Data Engineering* (2023) 1–14
 - [142] Kerpici, M., Ozkan, H., Kozat, S.S.: Online anomaly detection with bandwidth optimized hierarchical kernel density estimators. *IEEE Transactions on Neural Networks and Learning Systems* **32** (2021) 4253–4266
 - [143] Ma, X., Wu, J., Xue, S., Yang, J., Zhou, C., Sheng, Q., Xiong, H., Akoglu, L.: A comprehensive survey on graph anomaly detection with deep learning. *IEEE Transactions on Knowledge and Data Engineering* (2021)
 - [144] Li, Z., Liu, G., Jiang, C.: Deep representation learning with full center loss for credit card fraud detection. *IEEE Transactions on Computational Social Systems* **7** (2020) 569–579
 - [145] Fanai, H., Abbasimehr, H.: A novel combined approach based on deep autoencoder and deep classifiers for credit card fraud detection. *Expert Systems with Applications* (2023) 119562
 - [146] Chung, J., Gulcehre, C., Cho, K., Bengio, Y.: Empirical evaluation of gated recurrent neural networks on sequence modeling. In: *NIPS 2014 Workshop on Deep Learning*, December 2014. (2014)
 - [147] Benchaji, I., Douzi, S., El Ouahidi, B., Jaafari, J.: Enhanced credit card fraud detection based on attention mechanism and lstm deep model. *Journal of Big Data* **8** (2021) 1–21
 - [148] Xie, Y., Liu, G., Yan, C., Jiang, C., Zhou, M.: Time-aware attention-based gated network for credit card fraud detection by extracting transactional behaviors. *IEEE Transactions on Computational Social Systems* (2022)
 - [149] Ergen, T., Kozat, S.S.: Unsupervised anomaly detection with lstm neural networks. *IEEE Transactions on Neural Networks and Learning Systems* **31** (2019) 3127–3141
 - [150] Wu, W., He, L., Lin, W., Su, Y., Cui, Y., Maple, C., Jarvis, S.: Developing an unsupervised

- real-time anomaly detection scheme for time series with multi-seasonality. *IEEE Transactions on Knowledge and Data Engineering* **34** (2020) 4147–4160
- [151] Wang, D., Lin, J., Cui, P., Jia, Q., Wang, Z., Fang, Y., Yu, Q., Zhou, J., Yang, S., Qi, Y.: A semi-supervised graph attentive network for financial fraud detection. In: *ICDM, IEEE* (2019) 598–607
 - [152] Kipf, T., Welling, M.: Semi-supervised classification with graph convolutional networks. In: *International Conference on Learning Representations*. (2016)
 - [153] Hamilton, W.L., Ying, R., Leskovec, J.: Inductive representation learning on large graphs. In: *NIPS*. (2017) 1025–1035
 - [154] Veličković, P., Cucurull, G., Casanova, A., Romero, A., Liò, P., Bengio, Y.: Graph attention networks. In: *International Conference on Learning Representations*. (2018)
 - [155] Peng, L., Mo, Y., Xu, J., Shen, J., Shi, X., Li, X., Shen, H.T., Zhu, X.: Grlc: Graph representation learning with constraints. *IEEE Transactions on Neural Networks and Learning Systems* (2023)
 - [156] Wang, X., Ji, H., Shi, C., Wang, B., Ye, Y., Cui, P., Yu, P.S.: Heterogeneous graph attention network. In: *The world wide web conference*. (2019) 2022–2032
 - [157] Cheng, D., Wang, X., Zhang, Y., Zhang, L.: Graph neural network for fraud detection via spatial-temporal attention. *IEEE Transactions on Knowledge and Data Engineering* (2020)
 - [158] Hei, Y., Yang, R., Peng, H., Wang, L., Xu, X., Liu, J., Liu, H., Xu, J., Sun, L.: Hawk: Rapid android malware detection through heterogeneous graph attention networks. *IEEE Transactions on Neural Networks and Learning Systems* (2021)
 - [159] Wang, C., Dou, Y., Chen, M., Chen, J., Liu, Z., Philip, S.Y.: Deep fraud detection on non-attributed graph. In: *Big Data, IEEE* (2021) 5470–5473
 - [160] Chen, Z., Sun, A.: Anomaly detection on dynamic bipartite graph with burstiness. In: *2020 IEEE International Conference on Data Mining (ICDM), IEEE* (2020) 966–971
 - [161] Gan, J., Hu, R., Mo, Y., Kang, Z., Peng, L., Zhu, Y., Zhu, X.: Multigraph fusion for dynamic graph convolutional network. *IEEE Transactions on Neural Networks and Learning Systems* **35** (2022) 196–207
 - [162] Zhang, X., Song, D., Tao, D.: Hierarchical prototype networks for continual graph representation learning. *IEEE Transactions on Pattern Analysis and Machine Intelligence* **45** (2023) 4622–4636
 - [163] Dou, Y., Liu, Z., Sun, L., Deng, Y., Peng, H., Yu, P.S.: Enhancing graph neural network-based fraud detectors against camouflaged fraudsters. In: *CIKM*. (2020) 315–324
 - [164] Lin, H., Liu, G., Wu, J., Zuo, Y., Wan, X., Li, H.: Fraud detection in dynamic interaction network. *IEEE Transactions on Knowledge and Data Engineering* **32** (2020) 1936–1950
 - [165] Wang, J., Song, G., Wu, Y., Wang, L.: Streaming graph neural networks via continual learning. In: *Proceedings of the 29th ACM international conference on information & knowledge management*. (2020) 1515–1524
 - [166] Zhou, F., Cao, C.: Overcoming catastrophic forgetting in graph neural networks with experience replay. In: *Proceedings of the AAAI Conference on Artificial Intelligence*. Number 5 (2021) 4714–4722
 - [167] Zhang, P., Yan, Y., Li, C., Wang, S., Xie, X., Song, G., Kim, S.: Continual learning on dynamic graphs via parameter isolation. In: *Proceedings of the 46th International ACM SIGIR Conference on Research and Development in Information Retrieval*. (2023) 601–611
 - [168] Zhu, Y., Ma, J., Yuan, C., Zhu, X.: Interpretable learning based dynamic graph convolutional networks for alzheimer’s disease analysis. *Information Fusion* **77** (2022) 53–61
 - [169] Liu, Z., Chen, C., Yang, X., Zhou, J., Li, X., Song, L.: Heterogeneous graph neural networks for malicious account detection. In: *Proceedings of the 27th ACM international conference on information and knowledge management*. (2018) 2077–2085
 - [170] Mo, Y., Chen, Y., Lei, Y., Peng, L., Shi, X., Yuan, C., Zhu, X.: Multiplex graph represen-

- tation learning via dual correlation reduction. *IEEE Transactions on Knowledge and Data Engineering* **35** (2023) 12814–12827
- [171] Perozzi, B., Al-Rfou, R., Skiena, S.: Deepwalk: online learning of social representations. In: *Proceedings of the 20th ACM SIGKDD International Conference on Knowledge Discovery and Data Mining*, ACM (2014) 701–710
- [172] Zhang, J., Zhang, J., Ghosh, S., Li, D., Zhu, J., Zhang, H., Wang, Y.: Regularize, expand and compress: Nonexpansive continual learning. In: *Proceedings of the IEEE/CVF winter conference on applications of computer vision*. (2020) 854–862
- [173] Tang, B., Matteson, D.S.: Graph-based continual learning. In: *International Conference on Learning Representations*. (2020)

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