**Paper list 2020/9/21**

Legend: Classic/old paper Recent paper of interests

**Domain Adaptation (Traditional methods)**

1. Long, Mingsheng, et al. "Transfer feature learning with joint distribution adaptation." Proceedings of the IEEE international conference on computer vision. 2013.
2. Pan, Sinno Jialin, et al. "Domain adaptation via transfer component analysis." IEEE Transactions on Neural Networks 22.2 (2010): 199-210.
3. Wei, Ying, Yu Zhang, and Qiang Yang. "Learning to transfer." arXiv preprint arXiv:1708.05629 (2017).
4. Wang, Jindong, et al. "Visual domain adaptation with manifold embedded distribution alignment." Proceedings of the 26th ACM international conference on Multimedia. 2018.
5. Lee, Chen-Yu, et al. "Sliced wasserstein discrepancy for unsupervised domain adaptation." Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition. 2019.

**Domain Adaptation (Deep/Adversarial methods)**

1. Zhang, Yizhou, et al. "Dane: Domain adaptive network embedding." arXiv preprint arXiv:1906.00684 (2019).
2. Naseer, Muhammad Muzammal, et al. "Cross-domain transferability of adversarial perturbations." Advances in Neural Information Processing Systems. 2019.
3. Zhang, Yinghua, Yu Zhang, and Qiang Yang. "Parameter transfer unit for deep neural networks." arXiv preprint arXiv:1804.08613 (2018).
4. Cui, Yin, et al. "Large scale fine-grained categorization and domain-specific transfer learning." Proceedings of the IEEE conference on computer vision and pattern recognition. 2018.
5. Long, Mingsheng, et al. "Learning transferable features with deep adaptation networks." International conference on machine learning. PMLR, 2015.
6. Sun, Baochen, and Kate Saenko. "Deep coral: Correlation alignment for deep domain adaptation." European conference on computer vision. Springer, Cham, 2016.
7. Saito, Kuniaki, et al. "Maximum classifier discrepancy for unsupervised domain adaptation." Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition. 2018.
8. Ganin, Yaroslav, et al. "Domain-adversarial training of neural networks." The Journal of Machine Learning Research 17.1 (2016): 2096-2030.
9. Shu, Yang, et al. "Transferable curriculum for weakly-supervised domain adaptation." Proceedings of the AAAI Conference on Artificial Intelligence. Vol. 33. 2019.
10. Shen, Jian, et al. "Wasserstein distance guided representation learning for domain adaptation." arXiv preprint arXiv:1707.01217 (2017).

**Openset/Partial/Universal Domain Adaptation**

1. Ren, Chuan-Xian, et al. "Learning Target-Domain-Specific Classifier for Partial Domain Adaptation." IEEE Transactions on Neural Networks and Learning Systems (2020).
2. Zhang, Jing, et al. "Importance weighted adversarial nets for partial domain adaptation." Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition. 2018.
3. Panareda Busto, Pau, and Juergen Gall. "Open set domain adaptation." Proceedings of the IEEE International Conference on Computer Vision. 2017.
4. Saito, Kuniaki, et al. "Open set domain adaptation by backpropagation." Proceedings of the European Conference on Computer Vision (ECCV). 2018.
5. Cao, Zhangjie, et al. "Partial adversarial domain adaptation." Proceedings of the European Conference on Computer Vision (ECCV). 2018.
6. Saito, Kuniaki, et al. "Universal domain adaptation through self supervision." arXiv preprint arXiv:2002.07953 (2020).
7. You, Kaichao, et al. "Universal domain adaptation." Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition. 2019.

**Meta Learning**

1. Finn, Chelsea, Pieter Abbeel, and Sergey Levine. "Model-agnostic meta-learning for fast adaptation of deep networks." arXiv preprint arXiv:1703.03400 (2017).
2. Sun, Qianru, et al. "Meta-transfer learning for few-shot learning." Proceedings of the IEEE conference on computer vision and pattern recognition. 2019.
3. Achille, Alessandro, et al. "Task2vec: Task embedding for meta-learning." Proceedings of the IEEE International Conference on Computer Vision. 2019.

**Transferability**

1. Nguyen, Cuong V., et al. "LEEP: A New Measure to Evaluate Transferability of Learned Representations." arXiv preprint arXiv:2002.12462 (2020).
2. Bao, Yajie, et al. "An Information-Theoretic Approach to Transferability in Task Transfer Learning." 2019 IEEE International Conference on Image Processing (ICIP). IEEE, 2019.
3. Tran, Anh T., Cuong V. Nguyen, and Tal Hassner. "Transferability and hardness of supervised classification tasks." Proceedings of the IEEE International Conference on Computer Vision. 2019.

**Multi-source Transfer Learning**

1. Redko, Ievgen, et al. "Optimal transport for multi-source domain adaptation under target shift." The 22nd International Conference on Artificial Intelligence and Statistics. 2019.
2. Zhu, Yongchun, Fuzhen Zhuang, and Deqing Wang. "Aligning domain-specific distribution and classifier for cross-domain classification from multiple sources." Proceedings of the AAAI Conference on Artificial Intelligence. Vol. 33. 2019.
3. Mansour, Yishay, Mehryar Mohri, and Afshin Rostamizadeh. "Domain adaptation with multiple sources." Advances in neural information processing systems. 2009.
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**Few-shot Learning**

1. Tokmakov, Pavel, Yu-Xiong Wang, and Martial Hebert. "Learning compositional representations for few-shot recognition." Proceedings of the IEEE International Conference on Computer Vision. 2019.
2. Xing, Chen, et al. "Adaptive cross-modal few-shot learning." Advances in Neural Information Processing Systems. 2019.
3. Zhang, Jian, et al. "Variational few-shot learning." Proceedings of the IEEE International Conference on Computer Vision. 2019.

**Multi-task Learning**

1. Ren, Yazhou, et al. "Self-paced multi-task clustering." Neurocomputing 350 (2019): 212-220.
2. Sener, Ozan, and Vladlen Koltun. "Multi-task learning as multi-objective optimization." Advances in Neural Information Processing Systems. 2018.
3. Liu, Shikun, Edward Johns, and Andrew J. Davison. "End-to-end multi-task learning with attention." Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition. 2019.
4. Strezoski, Gjorgji, Nanne van Noord, and Marcel Worring. "Learning task relatedness in multi-task learning for images in context." Proceedings of the 2019 on International Conference on Multimedia Retrieval. 2019.
5. Luo, Yong, Yonggang Wen, and Dacheng Tao. "Heterogeneous multitask metric learning across multiple domains." IEEE transactions on neural networks and learning systems 29.9 (2017): 4051-4064.
6. J. Glover and C. Hokamp, “Task Selection Policies for Multitask Learning,” 2019.

**Optimal transport based methods**

1. Flamary, R. "Optimal transport for domain adaptation." IEEE Transactions on Pattern Analysis and Machine Intelligence (2016).
2. Courty, Nicolas, et al. "Joint distribution optimal transportation for domain adaptation." Advances in Neural Information Processing Systems. 2017.
3. Bhushan Damodaran, Bharath, et al. "Deepjdot: Deep joint distribution optimal transport for unsupervised domain adaptation." Proceedings of the European Conference on Computer Vision (ECCV). 2018.
4. Redko, Ievgen, et al. "Optimal transport for multi-source domain adaptation under target shift." The 22nd International Conference on Artificial Intelligence and Statistics. 2019.
5. Xu, Renjun, et al. "Reliable Weighted Optimal Transport for Unsupervised Domain Adaptation." Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition. 2020.
6. Ackaouy, Antoine, et al. "Unsupervised domain adaptation with optimal transport in multi-site segmentation of multiple sclerosis lesions from MRI data." Frontiers in computational neuroscience 14 (2020): 19.

**Others**

1. Goodfellow, Ian, et al. "Generative adversarial nets." Advances in neural information processing systems. 2014.
2. Wang, Bokun, et al. "Adversarial cross-modal retrieval." Proceedings of the 25th ACM international conference on Multimedia. 2017.
3. Arjovsky, Martin, Soumith Chintala, and Léon Bottou. "Wasserstein gan." arXiv preprint arXiv:1701.07875 (2017).
4. Liu, Anqi, and Brian Ziebart. "Robust classification under sample selection bias." Advances in neural information processing systems. 2014.

**Representation Learning on Graphs/Networks**

1. W. L. Hamilton, R. Ying, and J. Leskovec, “Representation Learning on Graphs: Methods and Applications,” pp. 1–23, 2017. (long survey)
2. M. Gao, X. He, L. Chen, T. Liu, J. Zhang, and A. Zhou, “Learning Vertex Representations for Bipartite Networks,” IEEE Trans. Knowl. Data Eng., pp. 1–1, 2020.
3. Bryan Perozzi, Rami Al-Rfou, and Steven Skiena. Deep- walk: online learning of social representations. In The 20th ACM SIGKDD International Conference on Knowl- edge Discovery and Data Mining, KDD ’14, New York, NY, USA - August 24 - 27, 2014, pages 701–710, 2014.
4. R. Trivedi, M. Farajtabar, P. Biswal, and H. Zha, “Dyrep: Learning representations over dynamic graphs,” 7th Int. Conf. Learn. Represent. ICLR 2019, pp. 1–25, 2019.

**Social Network Community Detection**

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2. M. Azaouzi, D. Rhouma, and L. Ben Romdhane, Community detection in large-scale social networks: state-of-the-art and future directions, vol. 9, no. 1. Springer Vienna, 2019. (survey)

Data mining on social network