FID3018 - Opposition Report

Opposition to presentation of Abubakrelsedik Karali

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I. Summary

The seminar presents topics on self-supervised learning methods for learning through large unlabeled datasets. The three papers selected touch on topics of self-supervised learning on computer vision tasks. The seminar is very interesting and has very good slides.

II. Choice of Papers

1) Gidaris, Spyros, Praveer Singh, and Nikos Komodakis. ”Unsupervised Representation Learning by Predicting Image Rotations.” *International Conference on Learning Representations*. 2018. [1]
2) Mundhenk, T. Nathan, Daniel Ho, and Barry Y. Chen. ”Improvements to context based self-supervised learning.” *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition*. 2018. [2]
3) Kolesnikov, Alexander, Xiaohua Zhai, and Lucas Beyer. ”Revisiting self-supervised visual representation learning.” *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*. 2019. [3]

The three papers selected all study the topic of self-supervised visual representation learning which is concerned with learning visual representations on large unlabeled datasets by some predefined tasks that do not need manual labeling. The first paper aims to learn visual representations by predicting the rotations of images. The second paper aims to improve the qualities of learning by preventing the model to learn from common artifacts in images such as chromatic aberration. The third paper studies the choice of convolutional neural networks (CNNs) in self-supervised learning and uncovers that standard designs CNN models that have a good performance on supervised tasks do not necessarily translate to good performance in self-supervised learning settings.

Overall, the choice of papers focuses on the recent progress in self-supervised visual representation learning and can be viewed as one way of mining through massive datasets without explicit supervision.

III. Presentation

The presentation is clear and coherent with a nice choice of papers. The presentation of each paper follows the same strategy with motivation, contributions, methods, strong points, and weak points. The transition between the three papers is smooth. The presenter also gives the necessary background needed for understanding each paper which is always appreciable. The inclusion of personal summaries on each paper is also welcomed.

The slides are also nicely made with clear and concise visualizations that capture the key points that the presenter tries to convey. It would be interesting if more self-supervised learning tasks can be introduced and compared with the ones in the selected papers. Although it is outside the scope of visual representation learning of the seminar, it would be also interesting to see how well self-supervised learning methods proposed for visual representation learning can transfer to learning tasks of other domains, e.g., natural language processing.

Despite some network issues during the seminar, the presentation went smoothly. The presenter has a decent understanding of the topic and the discussion session is also inspiring and insightful.

References

[1] S. Gidaris, P. Singh, and N. Komodakis, “Unsupervised representation learning by predicting image rotations,” in *International Conference on Learning Representations*, 2018.
[2] T. N. Mundhenk, D. Ho, and B. Y. Chen, “Improvements to context based self-supervised learning,” in *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition*, 2018, pp. 9339–9348.
[3] A. Kolesnikov, X. Zhai, and L. Beyer, “Revisiting self-supervised visual representation learning,” in *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, 2019, pp. 1920–1929.

Opposition report for FID3018 (HT20-VT21) : Advanced Course in Data Mining and Analytics.

FID3018 - Opposition Report

Opposition to presentation of Sina Sheikholeslami

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I. Summary

The seminar presents the topic of the effect of dataset configuration in Deep Neural Networks (DNNs) training. The three papers selected to address topics including active learning and parallel training. The seminar is very interesting and engaging with a good discussion on the key contribution of each paper.

II. Choice of Papers

1) Shallue, Christopher J., et al. "Measuring the Effects of Data Parallelism on Neural Network Training." *Journal of Machine Learning Research* 20.112 (2019): 1-49. [1]
2) Chang, Haw-Shiuan, et al. "Active bias: training more accurate neural networks by emphasizing high variance samples." *Proceedings of the 31st International Conference on Neural Information Processing Systems*. 2017. [2]
3) Chitta, Kashyap, et al. "Training Data Distribution Search with Ensemble Active Learning." *arXiv preprint arXiv:1905.12737* (2019). [3]

While the first paper study the effect of batch size on parallel neural network training time, the second and the third paper focus on how training data distribution and data sampling methods will affect the training process in the field of active learning.

Although parallel neural network training and active learning might not seem to be connected at first glance, they are both addressing the topic for training neural networks more efficiently, e.g., train the neural network faster that can also make better predictions. In turn, the topics presented address the challenges of extracting knowledge from massive datasets more efficiently. The combination of parallel training and active learning can be a very interesting research topic that attracts many deep learning researchers.

III. Presentation

The presentation is nicely structured, with proper background information and a clear summary of the motivations and contributions of each work. The brief introduction of active learning gives the audience a proper starting point for understanding the active learning papers. The presentation demonstrates how different strategies of selecting samples for training from a given dataset can affect the speed of training progress (e.g., faster to converge) and the quality of the trained model (e.g., more robust to outliers). The final summary of the presentation also gives a nice aggregated conclusion over the selected papers and what are the interesting aspects to study in the future.

The presentation is easy to follow at a good pace. The bullet points in the slides are very detailed and easy to read through. However, some of the figures presented have small font sizes that might be too condensed to read.

Overall, the speaker offers a nice presentation with an interesting topic that is easy to follow. The presentation also opens up possible ways of combining parallel training and active learning which many researchers will find interesting.

References

[1] C. J. Shallue, J. Lee, J. Antognini, J. Sohl-Dickstein, R. Frostig, and G. E. Dahl, "Measuring the effects of data parallelism on neural network training," *Journal of Machine Learning Research*, vol. 20, pp. 1–49, 2019.
[2] H.-S. Chang, E. Learned-Miller, and A. McCallum, "Active bias: training more accurate neural networks by emphasizing high variance samples," in *Proceedings of the 31st International Conference on Neural Information Processing Systems*, 2017, pp. 1003–1013.
[3] K. Chitta, J. M. Alvarez, E. Haussmann, and C. Farabet, "Training data distribution search with ensemble active learning," *arXiv preprint arXiv:1905.12737*, 2019.

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