Opposition Deba

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I opposed Deba, who presented papers mainly about *calibration* of neural networks, in other words the problem of having networks reflecting a true uncertainty in their predictions.

1 Content

Deba chose three papers. The first paper, *On Calibration of Modern Neural Networks* [1] discusses 3 main reasons (increased model capacity, batch normalization and less explicit regularization, specifically l_2-regularization) why modern neural networks. Furthermore, they introduce a technique, temperature scaling, which learns a single parameter T on a validation set to recalibrate a neural networks to make it more calibrated.

The second paper, *Verified Uncertainty Calibration* [2] shows that techniques such as temperature scaling are less calibrated than they show, and it is not possible to say how calibrated they actually are. Theoretical justifications show that methods such as temperature scaling are optimistic estimators of the uncertainty, which is of course not desirable, and they therefore develop a new method that mitigates these issues. This method can not only perform better, but it can also give information on how calibrated they actually are. They do this by combining two previously existing approaches; histogram binning and platt scaling, and adopting the best characteristics from both; histogram binning [5] and platt scaling [3].

The last paper, Learning for single-shot confidence calibration in deep neural networks through stochastic inferences [4]. It proposes a new way of calibrating neural network through a single pass by using stochastic methods, and shows its superority in comparison to previous methods such as temperature scaling [1]. This does not require a separate validation set onto which one optimizes the calibration, and is therefore highly beneficial in this sense.

2 Suitability of the chosen papers

The suitability for this course can be put into question, as none of the papers focus on what has been described as the focus of the course (algorithms and system on large scale graph processing, stream processing, social network analytics and decentralized machine learning). However, I think it is still appropriate as this is Deba's personal focus in his research, and I think it brings a certain amount of diversity into what we have discussed in this course. It was therefore however also hard for me to oppose since the area was completely new to me, but Deba did a good job in presenting the papers.

3 Links between the papers

The link between the papers was very clear as they all treat the same problem; calibrating neural networks towards reflecting true uncertainties in their predictions. They all propose different solutions and state different problems in both actual architectures and other methods for calibrating neural networks.

4 Quality of presentation

Deba's way of talking was very intuitive and pedagogical. It was easy to follow what he was saying and he explained things in simple terms, allowing most people to understand the topic despite not having the proper background. However, I think the presentation was too long (although to be fair, he was interrupted several times for questions during his presentation). I think he could have planned the time better; he also could have used more visual slides and less equations. Given that the area was new to us all, I think it would have served us well with more visual slides and less equations. However, as I mentioned, I think he orally explained things very well and in simple terms, so by listening, it was easy to understand and follow.

References

[1] Chuan Guo, Geoff Pleiss, Yu Sun, and Kilian Q Weinberger. On calibration of modern neural networks. In *International Conference on Machine Learning*, pages 1321–1330. PMLR, 2017.

[2] Ananya Kumar, Percy Liang, and Tengyu Ma. Verified uncertainty calibration. *arXiv preprint arXiv:1909.10155*, 2019.

[3] John Platt et al. Probabilistic outputs for support vector machines and comparisons to regularized likelihood methods. *Advances in large margin classifiers*, 10(3):61–74, 1999.

[4] Seonguk Seo, Paul Hongsuck Seo, and Bohyung Han. Learning for single-shot confidence calibration in deep neural networks through stochastic inferences. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, pages 9030–9038, 2019.

[5] Bianca Zadrozny and Charles Elkan. Obtaining calibrated probability estimates from decision trees and naive bayesian classifiers. In *Icml*, volume 1, pages 609–616. Citeseer, 2001.

Suzanna's presentation - a review

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This is a report on the presentation made by Suzanna Pozzoli on the 26th November 2020 for the course *Advanced Course in Data Mining and Analytics*. Overall, I found it to be a good presentation, and below follows my opinion on the matters in question.

1 Content

The content of the papers were interesting, as it concerned questions on how to extract higher-order structures on graphs; both on a large and a small scale.

Starting with the first paper, *Higher-order organization of complex networks* [1] it presented a highly scalable algorithm that can, given a motif (see 5) or a range of them, derive insights into which nodes play particular roles and are important when partitioning the network and by identifying different motif structures. I am a bit concerned that the method is a bit too dependent on which motif one chooses, and the way to find a suitable motif is very computationally intensive. However, I still find the paper very interesting with possibilities to extend.

Regarding the second paper, *Annotated hypergraphs: models and applications* [2], I am slightly more concerned about the content. It presents new methods and frameworks that treats the question on how to extract information from graphs that have polyadic interactions; in other words, where more than 2 nodes can be involved in a single edge, and a node can have different roles in different edges. While the theory is soundly elaborated and the techniques are well presented, I was not extremely impressed by the use cases shown. It has, in my opinion, more potential than what was shown. As in the first paper, I am a bit concerned regarding some choices that the common practitioner has to make him- or herself. An example is the role-interaction kernel $\mathbf{R}$ that is far from clear how to construct, and which values that should be imposed between different roles in this matrix is not straightforward. Here, more work is needed to motivate this, and possibly even a learning framework that can automatically learn and optimize the construction of this matrix, rather than leaving it as a hyper parameter.

Finally, coming to the last paper, *A structural graph representational learning framework* [3], this might be the most interesting one. It presents a technique on how to derive rich node embeddings that contains and represents information related to the higher-order structure of the nodes. It also presents two use cases; link prediction and visitor stitching, and shows how it outperforms state-of-the-art such as `node2vec` and other techniques. It also presents and proposes many different extensions and shows how the framework is highly modifiable, which is also a strength.

2 Suitability of the chosen papers

In terms of suitability and whether it fits into the course, I have no doubt it does fit into the scope of the course. They all touch upon questions on graph analytics and deriving insights or useful embeddings by extracting some type of information from different graphs.

3 Links between the papers

The presentation were connected in the sense that they all touched upon the theme of higher-order organization of networks. The first [1] touched upon analyzing and deriving insights based on motif structures, the second [2] concerned deriving metrics and analysis from networks where nodes can have different roles in different edges and the third [3] created a high-quality embedding based on motif structures found in a network. In that sense, they all leverage different ways of extracting higher-order organizations and "meta-information" about graphs for different application purposes, so they had a clear link. However, the use-cases were a bit different, but I do not think that it is necessarily a bad thing; it rather shows the usefulness of the perspective in question.

4 Quality of presenting

The presentation was clear and well-articulated. It was easy to follow, and I think she highlighted most of the important points.

If there was anything I missed in the presentation, it would have been some more figures and graphs to both show examples (such as the last figure in [3]) and more visual examples of how some of the things worked, instead of mathematical formulations. One example of what I would have liked to see more is examples like her demonstration of the null model from [2]. That was a really good presentation of how the sampling worked, and more examples like that would have helped improve the quality of the presentation.

5 Explanations

- Motif - Network motifs - building blocks for complex networks, basically smaller network subgraphs. See [1] for a more thorough explanation.

References

[1] Austin R Benson, David F Gleich, and Jure Leskovec. Higher-order organization of complex networks. *Science*, 353(6295):163–166, 2016.

[2] Philip Chodrow and Andrew Mellor. Annotated hypergraphs: Models and applications. *Applied Network Science*, 5(1):9, 2020.

[3] Ryan A Rossi, Nesreen K Ahmed, Eunyee Koh, Sungchul Kim, Anup Rao, and Yasin Abbasi-Yadkori. A structural graph representation learning framework. In *Proceedings of the 13th International Conference on Web Search and Data Mining*, pages 483–491, 2020.