Statement Of Purpose

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I think an amazing research topic should have sufficient complexity to keep the excitement going, should have the potential to cause sufficient impact on human life to keep the motivation going and should look doable to keep the persistence going. I think all of the three are true for the use of deep learning techniques in the biomedical field. As I see it, a sincere work on something like cancer research is much more important than the entire work to create better phones or other smart devices for comfort, luxury or for mundane utility. With my experience in computer vision as a research assistant (RA) for more than six months, experience in machine learning as a data scientist for three years and my considerable familiarity and interest in computational biology owing to multiple college courses and projects including my master's thesis, I feel myself being in the right place in pursuing deep learning focused research on biomedical data.

Why PhD: While I really enjoyed working in the company, I was unsatisfied with the meaningfulness of impact my work would create. I also desired for greater technical challenge in terms of problem complexity in my work. After leaving the company, I spent the next year updating my knowledge in different actively researched deep learning sub-fields by doing Coursera courses and quite successfully applying some of them in Kaggle competitions. After this self motivated adventure of mine, I became quite optimistic about doing research and therefore I joined the research assistant (RA) position. My experience as a RA has only made me more optimistic about doing a PhD.

My Eligibility for PhD: From my RA experience, I found that I'm become pretty good in the cyclical process of implementation, result analysis and brainstorming. I already had significant mastery over the implementation phase owing to my experience in industry. There, I wrote code spanning multiple repositories which was used for automated trading. This did not had any room for a single bug as that would mean huge losses in trading. This strict and intense coding experience in the startup environment has given me the skill and confidence to write error free code quickly. As a RA, I introduced the problem of Gaze estimation in my lab. Naturally, besides the professor, I could not find much help from the lab. Additionally, if one reads my Gaze estimation paper, it would become evident that both the main contributions of handling backward gazes and tackling magnification levels came out of result analysis. There was no preconceived notion about an idea for which we could have created a working implementation. I think it was due to my ability to do quick implementations of ideas and insightful analysis that I was able to make my work publication ready in 6 months. Finally, I've the experience to both work alone (RA job) and with people (Industry) which makes me eligible to fit in any kind of research role.

Challenges in the field: As I see it, explainability and reliability are the two main challenges when working with deep learning models in the biomedical field. Black box nature of deep learning models and performance degradation with domain shifts makes people skeptic in using deep learning in biomedical field. Data augmentation [5, 1], fine tuning network weights to new domain [4], using multiple components in the model setup with deep learning model being one component and rest being semantically explainable simpler formulations [2], Continual learning [3] etc are some of the recent relevant mainstream approaches to this, none of which have got the desired level of performance.

My initial thoughts towards a solution: Like in artificial neural networks, we don't know how human inference works. However, in any decision, there are sufficient number of intermediate inferences due to which we feel confident. For example, for inferring that someone has some disease, a doctor makes multiple observations many of which can be binarized and on the basis of which a final inference is made. I think one approach would be to develop an architecture which will naturally enable the model to take this route of having to learn multiple intermediate binary decisions. The architecture would have multiple bottleneck layers at different depths. These bottleneck layers would be allowed to predict values between zero and one. One can expect it to handle overfitting and therefore achieve better generalization. Additionally, in case we have additional information, this architecture can provide a natural way to incorporate them as intermediate target values. Finally, even in absence of any other data, we might be able to infer a meaning to the output of these binarizable bottleneck layers.

I also have given some thought to brain inspired Continual learning. For learning a new task, new neurons are created in the brain. Additionally, the brain also shows cortical organization meaning different regions are responsible for different tasks. Finally, old information containing neurons have a lower 'learning rate' as opposed to new neurons. Inspired from this, I think one can explore network pruning as a way to ensure cortical organization and availability of extra neurons for a new task. After a task is learnt, we can do a joint network pruning over all learnt tasks. This should give us a lot of unused weights which could then be used along with all other weights for learning the new task. We can also experiment with having a per-weight learning rate. Average of magnitude of gradient of loss with respect to a weight can be used to assign learning rate. Higher average magnitude of gradient would mean that the weight is pretty significant for learnt tasks. Such weights should be assigned a lower learning rate.

References

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