NIPS
Neural Information Processing Systems
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Reviews For Paper

Paper ID	1703
Title	Quantifying the transferability of features in deep neural networks

Masked Reviewer ID: Assigned_Reviewer_13
Review:

Question	
Comments to author(s). First provide a summary of the paper, and then address the following criteria: Quality, clarity, originality and significance. (For detailed reviewing guidelines, see http://nips.cc /PaperInformation /ReviewerInstructions)	This paper aims to quantify the transferrability of features in deep neural networks, both in terms of the difference between source and target tasks and in terms of the depth of the features being transferred. To this end, the authors take an existing network (Krizhevsky et al. 2012), and performs generalization by fixing different layer depth and by transferring between different splits of the ImageNet dataset. I find the paper sufficiently interesting in the sense that, despite the many papers describing the success of feature transfer (e.g. Decaf, deconvnet, overfeat), we still lack a principled way to analyze why, and to what level, such feature transfer may be successful. The paper provides a reasonable effort in doing so. Another interesting finding is that transfer + fine-tuning almost always helps, even if the target task has sufficient data to train classifiers from scratch (see Figure 2). On the other side, this paper seems a bit empirical, in the sense that experiments are carried out on some manual decisions (such as split of source and target tasks). It would be good to see a quantitative criterion analyzing the correlation between the two factors raised in the paper and the final performance. Of course, the authors have fairly acknowledged so, and have not overclaimed anything beyond what is presented. The reviewer does not have a strong opinion on the paper, but believe that the analysis presented in the paper may benefit vision practitioners, especially those who would like to apply deep neural networks in a transfer learning fashion.
Please summarize your review in 1-2 sentences	This paper provides an experimental analysis on the transferrability of features in deep neural networks, using the de-facto standard benchmark of ImageNet and Krizhevsky's 2012 model.
Quality Score - Does the paper deserves to be published?	8: Top 50% of accepted NIPS papers

Impact Score - Independently of the Quality Score above, this is your opportunity to identify papers that are very different, original, or otherwise potentially impactful for the NIPS community.	2: This work is different enough from typical submissions to potentially have a major impact on a subset of the NIPS community.
Confidence	4: Reviewer is confident but not absolutely certain

Masked Reviewer ID: Assigned_Reviewer_35

Review:

Question	
Comments to author(s). First provide a summary of the paper, and then address the following criteria: Quality, clarity, originality and significance. (For detailed reviewing guidelines, see http://nips.cc/PaperInformation/ReviewerInstructions)	This paper systematically studies the transferrability of deep convnet features across a few experimental settings. The experiments are focused on the "AlexNet" architecture and the ILSVRC-2012 dataset, with the main set of results on transfer learning problems induced by dividing the 1000 ILSVRC-2012 object classes into random 500/500 splits. The N-layer network is trained on split A, then layers 1 through k are copied to a new network and layers k+1 through N are randomly initialized and retrained on split B. Results are reported across both choices of allowing layers 1 through k to be fine-tuned vs. frozen, and across all choices of k. Another set of results shows these in the setting of a manually chosen split of natural vs. man-made classes, and yet another set of results explores using random, un-trained weights in some layers. Many interesting observations are made which were not previously reported, particularly results #3 and #5 in section 4.1. Despite the large number of papers that either extract features from or fine-tune the ImageNet-pretrained "AlexNet" CNN, this is the first work I know of to do a clean, thorough exploration of the space of choices one has to make when using this class of methods. While the paper offers little in the way of technical or mathematical novelty, it does not strive to -- it provides an extensive, clean set of numerical answers to many commonly asked questions, and I believe its results give valuable practical insight to researchers and practitioners of modern deep learning methods. The authors also promise to release the code they use to run these experiments, allowing other researchers to explore how these experiments generalize to other architectures, etc.

Please summarize your review in 1-2 sentences	This paper systematically explores the transferrability of deep CNN features depending on the fine-tuning protocol and the layer of the network used. It does not propose any new method, but offers an extensive set of reference results and plenty of valuable insight about the "how" and "why" of transfer learning using deep networks
Quality Score - Does the paper deserves to be published?	8: Top 50% of accepted NIPS papers
Impact Score - Independently of the Quality Score above, this is your opportunity to identify papers that are very different, original, or otherwise potentially impactful for the NIPS community.	2: This work is different enough from typical submissions to potentially have a major impact on a subset of the NIPS community.
Confidence	4: Reviewer is confident but not absolutely certain

Masked Reviewer ID: Assigned_Reviewer_40

Review:

Question	
Comments to author(s). First provide a summary of the paper, and then address the following criteria: Quality, clarity, originality and significance. (For detailed reviewing guidelines, see http://nips.cc /PaperInformation /ReviewerInstructions)	This paper addresses the transferability of features in deep networks when trained on some data and tested on other, in a systematic way. In a first stage, two deep networks are trained on two separate halves of ImageNet. Then the networks are split at all possible intermediate networks, and various cross-training schemes are compared (e.g., freezing the bottom part, or training the whole network, on the same or a different part of ImageNet). A set of interesting conclusions are presented; e.g., joint training of a network leads to co-adaptation if too many layers are kept frozen, so that performance decreases even if the same part of the training set is used to re-train. Cross-training between two different training sets and keeping too much of the original network leads to even more loss of performance when too many layers are kept. And an exciting result is that pre-training on another training set, then training the whole network on the final training set, gives the best performance of all. The paper is well written and very clear. The thoroughness of the approach is appealing. While this paper does not improve the state of the art, it gives valuable insight into what happens when a network is switched from one training set to another. It is also great to know that the code for this paper will be released.

Please summarize your review in 1-2 sentences	This well-written paper thoroughly explores how pre-training on a given training set and transferring to another training set is affected by the depth of the pre-trained network, the training procedure, and the similarity of training sets. The contribution is focused but valuable, and I believe this systematic set of experiments would be of interest to many researchers.
Quality Score - Does the paper deserves to be published?	9: Top 15% of accepted NIPS papers
Impact Score - Independently of the Quality Score above, this is your opportunity to identify papers that are very different, original, or otherwise potentially impactful for the NIPS community.	2: This work is different enough from typical submissions to potentially have a major impact on a subset of the NIPS community.
Confidence	5: Reviewer is absolutely certain