Representation Transferability in Neural Networks Across Datasets and Tasks

Abstract

Deep neural networks, which are built from multiple layers with hierarchical distributed representations, tend to learn low-level features in their initial layers and shift to high-level features in subsequent layers. Transfer learning, multi-task learning, and continual learning paradigms leverage this hierarchical distributed representation to share knowledge across different datasets and tasks. This paper studies the layer-wise transferability of representations in deep networks across several datasets and tasks, noting interesting empirical observations.

1 Introduction

Deep networks, constructed with multiple layers and hierarchical distributed representations, learn low-level features in initial layers and shift to high-level features as the network becomes deeper. Generic hierarchical distributed representations allow for the sharing of knowledge across datasets and tasks in paradigms such as transfer learning, multi-task learning, and continual learning. In transfer learning, for example, the transfer of low-level features from one dataset to another can boost performance on the target task when data is limited, provided that the datasets are related. Transferring high-level features, with the learning of low-level features, can also be useful when the tasks are similar but the data distributions differ slightly.

This paper studies the layer-wise transferability of representations in deep networks across several datasets and tasks, and reports some interesting observations. First, we demonstrate that the layer-wise transferability between datasets or tasks can be non-symmetric, with features learned from a source dataset being more relevant to a target dataset, despite similar sizes. Secondly, the characteristics of the datasets or tasks and their relationship have a greater effect on the layer-wise transferability of representations than factors such as the network architecture. Third, we propose that the layer-wise transferability of representations can be a proxy for measuring task relatedness. These observations emphasize the importance of curriculum methods and structured approaches to designing systems for multiple tasks that maximize knowledge transfer and minimize interference between datasets or tasks.

2 Citation Networks

2.1 Methods

We have produced a citation graph using citation data from NeurIPS papers from SemanticScholar, and institutional information about authors from AMiner. From the NeurIPS website, we first gathered all paper titles from 2012 to 2021. We then mapped the paper titles to their Semantic Scholar paper IDs using the Semantic Scholar Academic Graph (S2AG) API. Unmatched papers were manually searched for, with all but one being found in the Semantic Scholar database. For each paper, we used the S2AG API to identify authors, and the authors of their references.

We used AMiner to identify institutional information for each author. The 9460 NeurIPS papers contain 135,941 authors, with institutions found for 83,515 (61%) of them. Papers lacking author

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information were removed from our dataset. We then marked institutes automatically by country name and common cities and regions in China. We supplemented automatic annotations with existing regional matchings and added 364 additional rules for regional matching. We also removed major multinational corporate labs. Of the remaining 5422 papers, we removed papers that were not from China, the US, or Europe, or included collaborators from multiple regions, leaving us with 1792 papers. Finally, we calculated the average number and proportion of citations between papers from each region.

2.2 Results

Our results show how American and Chinese papers fail to cite each other. While 60% of the data set comes from American papers, they only compose 34% of Chinese citations. American citations of Chinese papers are even more dramatic, with the 34% of the dataset coming from Chinese papers only accounting for 9% of American citations. These numbers are even more significant when compared to American citations of European papers; we found that American institutions cite European papers more often than Chinese papers despite our dataset containing six times more Chinese papers than European.

Each region tends to cite its own papers more often: China 21%, the USA 41%, and Europe 14%. The separation between American and Chinese research is more pronounced than would be expected based solely on regional preference. American and European research communities demonstrate similar citation patterns with few citations to Chinese papers. Chinese institutions, on the other hand, cite both American and European papers less than either of those regions.

	USA	China	Europe
USA	41	9	12
China	34	21	6
Europe	15	9	14

Table 1: Proportion of papers from given regions citing other regions or endogenously. Values are in percentage.

3 Limitations

The results presented here have some limitations. Firstly, while we have labeled the work of any university located in the United States as American, it is possible that such labs still have close ties to China, leading to an underestimate of the divide between US and Chinese AI research. Secondly, we have excluded papers where author information was not available on AMiner, a Chinese company, and therefore, there could be more Chinese papers in our dataset than we have determined. The 43% of discarded papers due to missing author information also likely represent a biased sample.

4 Consequences

While American and Chinese researchers publish in the same venues, they represent two parallel communities with limited impact on each other's research. This can, partly, be attributed to differing research interests arising from distinct cultural norms that influence research priorities. For instance, multi-object tracking is an active area of research in China with large scale benchmarks, whereas, concerns surrounding misuse of biometric data in North America have led researchers there to avoid such research. Likewise, US researchers are heavily represented at conferences regarding fairness in AI, while the Chinese are not.

This separation impacts not only the research topics, but also how they evolve. In addition, abstract topics or architectures that are popular in one region may not be popular in the other. For example, PCANet which is a popular image classification architecture has most of its 1200 citations from East Asian institutions, while Deep Forests has most of its 600 citations from Chinese institutions.

Another limitation is related to differences in the approach to ethics. The North American and European AI communities have begun to publish research on the ethics of AI and have included systems for reviewers to flag ethical concerns and ask authors to provide ethics statements. Engagement with Chinese researchers in this topic remains limited, even though ethics statements from Chinese AI institutions show many similarities to western ones. A clear example of this disconnect is the Provisional Draft of the NeurIPS Code of Ethics where, at the time of initial publication, all the authors were based in the US or Australia, but none were based in Asia. Although similar statements exist across regions, disagreements in research practice still arise. One such example is where Duke University stopped using the Duke-MTMC dataset because researchers had not obtained consent from the students they collected images from, yet similar datasets like Market-1501 from China continue to be used.

The divide between these two communities impacts individual researchers, the machine learning community as a whole, and potentially the societies impacted by AI research, highlighting the need for a discussion to overcome this barrier.