

From Categories to Subcategories: Large-scale Image Classification with Partial Class Label Refinement

Xuewen Yang

July 14 2018

Abstract

The number of digital images is growing extremely rapidly, and so is the need for their classification. But, as more images of pre-defined categories become available, they also become more diverse and cover finer semantic differences. Ultimately, the categories themselves need to be divided into subcategories to account for that semantic refinement. Image classification in general has improved significantly over the last few years, but it still requires a massive amount of manually annotated data.

In this work, the author investigate how coarse category labels can be used to improve the classification of subcategories. To this end, the author adopt the framework of Random Forests and propose a regularized objective function that takes into account relations between categories and subcategories. Compared to approaches that disregard the extra coarse labeled data, they achieve a relative improvement in subcategory classification accuracy of up to 22% in our large-scale image classification experiments.

1. Introduction

The research community has since then moved to more challenging, larger datasets, such as ImageNet, which contain thousands of categories and millions of images. In such datasets, categories are often organized in a hierarchy. The deeper one goes in the hierarchy, the finer the categories are and annotated training data becomes rare. In order to obtain training data for fine subcategories, a natural approach is to search for images of coarser categories and refine the labels. This can be very expensive, especially if the subcategories require expert knowledge [2] (e.g., breeds of dogs, bird or flower species, etc.). In this work, the author are interested in such a scenario where only a subset of the training data is annotated with fine subcategory labels while the rest has only coarse category labels (cf. Figure 1).

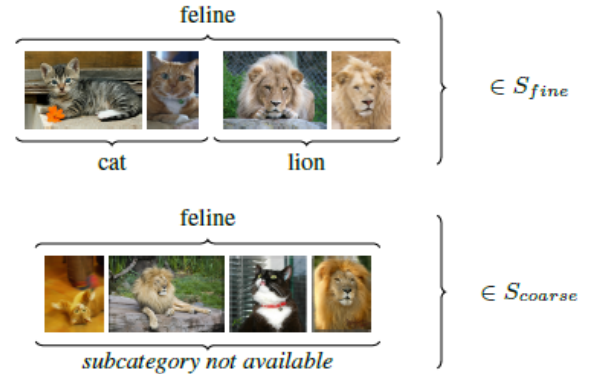


Figure 1. Given training data annotated with a set of categories like feline, our goal is to refine the classification into subcategories like cat and lion. We assume that the refined labels are available only for a subset of the training data S_{fine} , while for the rest, S_{coarse} , subcategory labels are not available.

2. Related Work

Image classification on large-scale data sets has gained much attention in recent years. While deep convolutional networks (CNN) achieve high classification accuracy [3], they are computationally intensive and take weeks to train. Simpler classifiers, such as nearest class mean classifiers (NCM) combined with a learned metric [4], proved to be a viable alternative with much shorter running times and near-zero costs for integrating new classes. In [1], NCMs were integrated in a random forest framework which increased the performance and enabled fast incremental learning on a large scale. In this work, the author address the problem of learning a classifier for the finest category level when only a part of the training data is annotated at that level, while the other training samples have only the labels of a coarser level. This is related to approaches for semi-supervised or transfer learning.

3. Regularized NCM Forests

NCM forests have been shown to provide a good trade-off between training time and accuracy for large-scale image classification [1]. The author first briefly discuss NCM forests. They propose a novel objective function for training NCM forests, which takes into account the information gain and the computational cost of a splitting function to automatically set important parameters of NCM forests. In this experiments, they show that this modification improves performance. They then proceed to show how their classification accuracy can be increased when only a fraction of the training labels are refined.

4. Conclusion

In this paper, the author have addressed the problem of learning subcategory classifiers when only a fraction of the training data is labeled with fine labels while the rest only has labels of coarser categories. To this end, they proposed to use random forests based on nearest class mean classifiers and extended the method by introducing a regularized objective function for training. They also experimentally showed that the additional training data with the category-only labels improves the classification of sub-categories up to 22% in a large-scale setting. Finally, they have presented experimental evidence that the approaches taking into account the hierarchical relations between categories and sub-categories perform better than approaches ignoring these relations.

References

- [1] M. Gilliam. Incremental learning of NCM forests for large-scale image classification. In *CVPR*, 2014. 1, 2
- [2] D. Jia, J. Krause, and F. F. Li. Fine-grained crowdsourcing for fine-grained recognition. In *CVPR*, 2013. 1
- [3] A. Krizhevsky, I. Sutskever, and G. E. Hinton. ImageNet classification with deep convolutional neural networks. In *NIPS*, 2012. 1
- [4] T. Mensink, J. Verbeek, F. Perronnin, and G. Csorka. Distance-based image classification: Generalizing to new classes at near zero cost. *IEEE TPAMI*, 2013. 1