Approaches of large-scale images recognition with more than 50,000 categories
Wanhong Huang, Dalian University of Technology
Rui Geng, Dalian University of Technology

Abstract

Though current CV models have been able to achieve high levels of accuracy on small-scale images classification dataset with hundreds or thousands of categories, many models become infeasible in computational or space consumption when it comes to large-scale dataset with more than 50,000 categories. In this paper, we provide a viable solution for classifying large-scale species datasets using traditional CV techniques such as features extraction and processing, BOVW (Bag of Visual Words) and some statistical learning techniques like Mini-Batch K-Means, SVM which are used in our works. And then mixed with a neural network model. When applying these techniques, we have done some optimization in time and memory consumption, so that it can be feasible for large-scale dataset. And we also use some techniques to reduce the impact of mislabeling data. We use a dataset with more than 50,000 categories, and all operations are done on common computer with 16GB RAM and a CPU of 3.0GHz. Our contributions are: 1) analysis what problems may meet in the training processes, and presents several feasible ways to solve these problems. 2) Make traditional CV models combined with neural network models provide some feasible scenarios for training large-scale classified datasets within the constraints of time and spatial resources.

1. Introduction

On small-scale images categories dataset, It has been possible to achieve very high accuracy using current deep learning models. However, almost most current models are trained on datasets of small-scale species datasets with hundreds or thousands categories' images. We cannot expect these models to yield particularly good performances on large-scale species datasets. Because the scale of the image species is too large relative to the feature output dimension of current neural network models. And the distribution of image features is very dense on features space. For large-scale species datasets, we know from paper [1] that in the classification of large-scale species datasets, the semantic information of images becomes important and the semantics are naturally hierarchical. The BOVW model have achieved relatively good results with the SVM classification. But for larger scale dataset, the time and space consumption of the visual word bag model and SVM is also significant. For these reasons, we hope to find some ways to train large data sets in a limited space as well as time. The research of classification works on large-scale species data sets is one of the important ways to break the bottleneck in CV field. However, it is an area that is rarely studied due to the complexity of space and time. Today's models based on deep learning have reached or even surpassed human levels of classification on small scale data categories, but the accuracy of neural networks in large-scale category classification datasets will be greatly affected because the complexity of most current neural network models cannot afford to extract features for large-scale categories. The spatially dense distribution of the features of the large-scale categories datasets is very dense. More complex neural network models are needed for neural networks to perform better on large-scale species. But it also comes with a huge cost in time and space. Distributed high-speed computing is one solution. But we wanted to find some solutions that have less complexity on time and space. Some very valuable relevant research works listed below.

1.1. Large-Scale images data's characteristic

When it comes to large-scale datasets, we are faced with a completely different situation. Many models cannot be implemented with limited time and space resources, or do not get a good performance. According to the [1], we know as the classification scale of image datasets becomes larger, many algorithms become powerless, and the space and time consumption for each algorithm becomes important. In large-scale classification, features are dense and the semantic information of the image plays a very important role.

1.2. BOVW

The bagging of words (BOW) is a concept in natural language processing, but nowadays it has been introduced to the field of machine vision and plays an important role in
mining the semantic information of images, image search algorithms. Many current image search algorithms or large-scale image recognition algorithms are based on bagging of words techniques. It works well with the SVM algorithm. In the paper [1], the accuracy reached about 5% when classifying images of 10,000 categories using SVM+BOW. This is already a high level of accuracy for large-scale categories.

1.3. Improved SVM

As the data set becomes larger, the SVM becomes unfeasible. As a result, many SVM algorithms with improved spatial or temporal complexity have emerged in order to handle large-scale data. In paper [2], an approximation of an SVM for handling large-scale data is presented. In the paper [3], CNN was fused with SVM to improve accuracy and speed. CNN was able to learn the unchanging features well, while SVM was able to learn the subinterface better. The SVM + Conv approach has a minimum test error rate of 5.9% in the original authors' tests, and the time consumption is similar to convolutional networks and much faster than pure SVM.

2. Our Approaches

2.1. Dataset

The dataset we use is a nearly 100GB product dataset provided by the Retail Vision Workshop, containing 50030 product categories and labels are not fully reliable.

2.2. Images pre-processing

Since many of the images in the dataset have problems with under or overexposure, before the train we first make these images histogram equalized and converted them to the same size of 512*512 for convenience.

2.3. Image Feature Extraction

There are many feature extraction algorithms for images, such as ORB, SURF, SIFT, etc. where the calculation speed is ORB>>SURF>>SIFT, but we choose SURF as image feature extraction algorithm. After apply it, each image would get features with shape of (N, 64).

2.4. Division K-means

Since the entire dataset has over 50,000 categories and over 3 million images in total. According to the usual word bagging technique, a specified number of visual words is obtained by clustering all images after extracting features, but we cannot implement this directly under such a large dataset. It would takes more than 5TB of RAM to store 3 million images' features, it is not possible to load all image features before clustering them. We needs to division and use clustering algorithm separately. In our work, we first read the features of all the images under each category. Since there may be too many image features under one category, RAM cannot store these features. So for categories where extracted more than 10,000 features, we randomly selected 10,000 features. And retain only 10,000 randomly selected features. Then, for each category we apply K-means Algorithm to the extracted features, and get 50 representative visual words, and save them into filesystem temporarily. It's a effective way to use 110 system when processing large-scale datasets.
2.5. Mini-Batch K-means

We want to get our work done within limited time and space resources. In the processing of large datasets, any algorithm we have to consider the consumption of time and space. So we use Mini-Batch K-means algorithm there. So that it can process the dataset faster. We took 4 days to finish all these works.

2.6. Second time K-means

We generated a total of 50*50,030 = 250,150's SURF features' representation, which also known as visual words. But 250,150's words is too large for us to do the next works. You need more than 500GB's RAM, if you want you use 250,150's visual words to do the distance calculation in the follows' works. So we applied K-means again to make visual words reduced to 10,000. Finally we retain a dictionary with shape of (10,000, 64). The second time K-means is fast with compare to previous operations. It took no more than half an hour.

2.7. Categories' Bagging of Words Generation

After getting the visual words' dictionary. Now we can move to generate the BOW of categories. Because there are too much images in the dataset. And it would take extremely large consumption of time if we create BOW for each image in the dataset. So what we are saying is "generate the BOW of categories". In previous work, we have extracted features for each category. And a dictionary of visual words has been produced using these features through the k-mean algorithm. Now we want to calculate the distance from these features to the visual word dictionary, so that we can generate a Bow of a category. Finally, the generated Bows are also saved in the file system. What need attention is that because the number of features in each category are varies, we need to normalize the Bow by dividing the word bag vector by its number of features. And we can visualize one of the category's Bow.

![Figure 4. The visualization of one of categories' Bow](image)

From figure 4. We can find that a bag of visual words for a category is like a "spectrum" of categories. Now our classification problem can be translated into this: For a new image, its "spectrum" is most similar to which category's "spectrum". This problem can be solved by many algorithms. It's the last problem. This operation took the most long time. I took us about 6 days. But computer not running all the day.

2.8. Test Images' Bagging of Words Generation

For each image in the test set, the same algorithm was used to extract its features and then generate the corresponding visual word bag. Still the bow of images are written to the file system. Then we can get many bow file with matrix shape of (N,10000). Each file represents a single image.

3. Solve the final Problem

Now, we have the Bow of categories and the Bow of images in test set. To solve the final problem "A test image's BOW is most similar to which categories' ?". There are some approaches can solve this problem.

3.1. Distance Calculation

It's the most simple approach.

\[
\text{index} = \arg\min \sum_{axis=1} ||C_{BowDic} - ImgBow||^2
\]

We choice a L2 distance there. Because it more convenient to apply matrix operation when using L2 with compare to L1.

![Figure 3. The visualization of one of categories' Bow](image)

What we found is that -when a picture corresponds to a category, the value of its BOW feature after subtraction is very small.

3.2. Neural Network Approach

The easiest way to do this is to use a fully connected network. And the input is the image we want to test. Output is a softmax layer. We can get probability of each category directly. But in this way, we only used the BOW features information of the test image and discarded the category BOW feature information. In order to be able to apply both, we can use two neural networks. On the first neural network, the input is the word bag feature of the test picture. The output is a feature of the same size as the input. We want the characteristics of the output to be as identical as possible to the characteristics of the corresponding category. The loss function is therefore as follows:
\[ \text{cost} = \frac{1}{2} \| \text{CBow} - \text{predict} \|^2 \]

The design for the intermediate layer depends on the support of the machine's own arithmetic power. The easiest way is to reach the output layer directly by linear transformation without using the hidden layer. Because in this way you only need to manage a matrix with shape of \((10000, 10000)\) and a bias with shape of \((10000)\). The we use the second neural network to predict the probability of each category.

Figure 5. Two Neural Network used to predict an image.

4. Improve ways

There are also some tricks we can use to improve accuracy. For example, make traditional CV techniques be combined with deep learning models. The traditional CV model is better able to collect semantic information, while the CNN model is able to collect some features that are essential for image classification. Therefore, we can extract image features using both traditional CV techniques and deep learning models like CNN, and eventually merge them, use a decomposition algorithm to eliminate features with large linear correlations, and then apply the usual methods to predict model classes. We can also use some traditional CV tricks to improve quality of features like Image Pyramid.

5. Conclusion

Traditional CV techniques are more spatially and temporally feasible than neural network models when large-scale classification labels are present in the dataset. In the Large Scale Classification Label Dataset. For every detail of every algorithm used we need to consider its space and time consumption. Techniques such as using the file system and I/O read/write to solve space problems and manually releasing temporarily allocated memory are very useful. To improve model performance, we can consider combining traditional CV techniques with deep learning techniques. In this way, the features of the image can contain more semantic information while reducing the time consumption of simply using the neural network model in the process of training the features.

References

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