Dynamic Multi-view Combination for Image Classification

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Abstract. Multi-view learning is widely used in image classification tasks to better explore the discriminative information of different views. However, existing multi-view methods commonly rely on some pre-defined assumptions or fail to fully take advantage of the combination commonality between individual images. This paper presents an efficient dynamic multi-view combination approach to dynamically combine the discriminative power of different views. Specially, we firstly utilize a group of pre-trained CNNs to extract different views of an image. Secondly, we apply a dynamic gating module to the image, which will generate a weight vector of these views to model the image-level information for the multi-view learning. Finally, the weight vector and the views are combined for the classification. Experimental results and analysis on CIFAR-10 and ImageNet show the effectiveness of the proposed dynamic multi-view combination method (DMVC) for visual classification.

1. Introduction

Visual information of the images in computer vision tasks is very important. Hence, developing discriminative visual representations is an urgent demand to be satisfied. There are various visually based models. For examples, the bag-of-visual-words feature [1], spatial pyramid matching feature [2], fisher vector based model [3] are models based on traditional hand-crafted features. Especially, convolutional neural networks (CNN) based models such as AlexNet [4], VGG [5], ResNet [6], GoogleNet [7], DenseNet [8] and their variants [9, 10] have achieved impressive high performance on image classification. In general, an individual view is not enough to describe an object, because there are huge variations. Thus, there is an urgent need of multiple views for joint representations. Ordinarily, two resenting forms of the views can be adopted. One is the visual representations generated by different models [11, 12]. The other is the representations using the hand-of-the-craft features, such as color histogram and SIFT. The combination of multiple views features will result in better classification performance.

Numbers of multi-view learning algorithms have been designed and successfully applied to kinds of computer vision and intelligent system problems, such as music emotion recognition [13], multi-label image classification and etc. However, these methods are either relied on the pre-defined assumption or ensure view consistency. Moreover, these methods only train class-level classifiers, without considering the distinctive character of a particular image. The class-level information and image-level information should be combined for better classification.

To solve these problems, in this paper, we propose a dynamic multi-view combination method (DMVC) for efficient visual classification. To bridge the gaps of class-level information and the
image-level information, we add an additional dynamic gating module, which is designed to be independent to all the views. The dynamic gating module works by accepting a single image and then generating image-level combination weights for features of each view. The class-level informations are encoded by each single classifier and the image-level information is encoded by the weights generated by the dynamic gating module. The multiple views and the dynamic gating module combined into a whole system. During training, we optimize over the dynamic gating module by fixing the feature extractors of all the views. Experimental results on CIFAR-10, SVHN, and ImageNet well demonstrate the effectiveness of the proposed DMVC method for image classification.

The main contributions of this paper can be summarized as three aspects:

First, we propose to use both the class-level information and the image-level information for multi-view visual representations and classifications.

Second, we add a dynamic gating module to link the class-level information and the image-level information.

We build an end-to-end system for multi-view image classification, which supports to optimize the dynamic gating module or any single classifiers or all of them together.

2. Related Work

There were various methods in the literature to improve the performance of image classification. The bag of words model [1], spatial pyramid matching [2], fisher vectors [3] and locality constrained linear coding [14] are traditional features.

Krizhevsky et al. [3] firstly designing deep convolutional neural networks for image classification using ImageNet. Simonyan and Zisserman [5] designed VGG, which aims to increase the depth of CNNs and achieve better performance. He et al. introduced ResNet [6] to reduce the gradient vanishing and explosion via skip connections, which highly increase the depth of the network at the same time.

Commonly, the structure of different CNNs was different and thus CNNs can extract distinct features even for the same image. These features can be regarded as different views of the image [11, 12]. To improve the multi-view classification performances, many works made use of strategies [15, 16] and greatly boosted the accuracies.

Traditional combination methods include Averaging, Voting, Stacking, and some other methods like Dynamic Classifier Section (DCS) and Mixture of Experts (ME). DCS dynamically selected one learner for each test instance [17] and was proved to be promising in mining data streams with concept drifting or with significant noise. ME was an effective approach to exploit multiple learners and works in a divide-and-conquer strategy, where a task is broken up into some simpler subtasks, and individual expert is trained for each different subtasks. Gating is usually employed to combine the experts to achieve the learning ability of CNNs while keeping the model complexity. In this paper, we extends the ensemble method Mixture of Experts to multi-view learning.

3. Approach

We propose an efficient dynamic multi-view combination (DMVC) method for image classification, which has three key components: the multiple views, the dynamic gating module, and the combination module.

3.1. The Multiple Views

The intention of DMVC is to better integrate the class-level information and image-level information for multi-view image classifications.

In this paper, a classifier is regarded as a single view. Then, the class-level information is encoded by the multiple views, due to they are all trained using the class label information. That is to say, the features of a single view tend to discriminate images of different class, but ignores some similarities between individual images at the same time. For multi-view learning problems, this similarity lies in the way of the combination of different views.
In this paper, we use CNNs as different views. Take figure 1 for example, we adopt ResNet [6], AlexNet [4], VGG [5], and DenseNet [8] as four different views. For each image in ImageNet dataset, the four CNNs extract different features, which are regarded as different views of this image. The difference is shown as different shapes in figure 1. In real scenarios, different features have different sizes or different emphases of the characteristics of the original image.

3.2. The Dynamic Gating Module
In this paper, we propose to use a well-known ensemble learning method Mixture of Experts (ME) to link the class-level informations and the image-level informations for a multi-view learning problem.

The linkage is generated by a well designed dynamic gating module, which aims to provide image-level informations for the combinations of the multiple views. As shown in figure 1 the image is inputed to both four CNNs and a dynamic gating module, where CNNs generate four different features as four different views and the dynamic gating module outputs a weight vector. Then, the view features and the weight vector are combined in the followed combination module. The dynamic gating module can be any model forms, as long as it can accept an image and output a weight vector of the desired shape.

Moreover, the weight vector performs as a gating of the given different views in the followed combination module. Thus, further constraints can be added to the gating module to provide specific features. For example, we can constrain that the gating module outputs a weight vector with at most two non-zero elements, if the computation resources is limited in the real application scenarios.

In figure 1, there are four CNNs has large variances both in the network structure and the performance on ImageNet dataset, which ensures the diversity of the views. The “Dynamic” module generates a weight vector to represent the image-level information for the multi-view learning process. The four views are combined in the followed combination module, which will output a vector for the final classification.

![Figure 1. The structure of the proposed method.](image)

3.3. The Combination Module
Given a set of views $v_1, v_2, \cdots, v_N$, and the gating weight vector generated by the dynamic gating module $w = [w_1, w_2, \cdots, w_N]$, the combination is defined as

$$o = \sum_{i=1}^{N} w_i v_i$$

where $o$ is the combination vector for the final classification decision process.

3.4. Dynamic Multi-View Combination
In order to jointly optimize the dynamic gating module and all the individual views, we build an whole system supporting end-to-end training. As shown in figure 1, the system includes three key parts, the multi-views (four CNNs), the dynamic gating module, and the combination module.
In practice, we usually take pre-trained CNNs, fix their parameters, and optimize the dynamic gating module firstly. After the gating module is optimized, we can free the CNNs and optimize the whole system together.

There are two testing modes. One is inputting test images to the whole system and output the class prediction, which is the same to the forward pass in the training phase. The other is inputting test images to the dynamic gating module and generating the combination weight vector, then inputting each test image into different groups of CNNs according to the weight vector. If some elements of the weight vector for one test image are zeros, corresponding CNNs will not be used for this test image.

4. Experiments

We verify our approach on the most widely used image classification datasets, CIFAR-10 [18] consists of colored natural scene images, with 32×32 pixels each and totally 10 classes. There are 50,000 and 10,000 images in the train and test set respectively. The data augmentation scheme we use is same to [6, 19]. However, we split the training dataset into two subsets, one with 40,000 images, named CIFAR-10-40k, and one with 10,000 images, named CIFAR-10-10k, which are all randomly and evenly chosen from all the 10 classes. We apply a single-crop or 10-crop with size 224x224 at test time.

4.1. Results on CIFAR-10

In this experiment, the individual learners is fixed and we just try to find the best combination policies of each image. The dynamic module choose ResNet18, whose last layer is replace by a fully-connected layer with 7 nodes. The chosen CNNs are trained on CIFAR-10-40k dataset individually and the dynamic gating module is trained on the whole training dataset of CIFAR-10. The experiments are implemented with pytorch framework.

Table 1 gives the comparisons of DMVC (7 views) with other methods on the CIFAR-10 dataset. We can see from table 1 that the proposed method can improve the classification performances over all the CNNs and the baseline methods. Moreover, Plurality Voting achieves comparable results with Overall Averaging. The reason might be there are 7 views for 10 classes of CIFAR-10. The performance of individual CNNs have a large range from 88.50% to 94.85%, which results that the performance of Overall Averaging is comparable to the best single model. Finally, by combining the accuracy of the proposed DMVC and the Overall Averaging, DMVC outperforms about 0.5% only. To some extent, DMVC is a dynamic averaging method, the experiment proves the effectiveness of the dynamic gating module. The reason of the small improvement might lie in the classes of CIFAR-10 can be easily separated and the image-level information of multi-views is not obvious.

| ID  | Model Name         | Top-1 Accuracy |
|-----|-------------------|----------------|
| 0   | VGG19             | 92.48          |
| 1   | ResNet18          | 94.50          |
| 2   | PreActResNet      | 94.11          |
| 5   | ResNeXt29_2x64d   | 94.85          |
| 6   | MobileNet         | 88.50          |
| 8   | ShuffleNet        | 89.66          |
| 9   | SENet             | 94.35          |
|     | Plurality Voting  | 94.99          |
| 0125689 | Overall Averaging | 94.98          |
|     | **DMVC**         | **95.55**      |
4.2. Results on ImageNet
This experiment on ImageNet [20] uses four widely used deep neural networks: ResNet18 [6], AlexNet [3], VGG16 [5], and DenseNet121 [8]. The performances of the pre-trained individual CNNs are shown in table 2 and the dynamic gating module is trained using the ImageNet training dataset. The SqueezeNet is taken as the gating module, which outputs 4 weights dynamically for each image.

ImageNet dataset has large number of classes (1000), which will cause much more difficulties for training a classification model, for examples, the confusion of the large number of classes, especially the fine-grained classes.

| ID | Model Name | Top-1 | Top-5 |
|----|------------|-------|-------|
| 1  | ResNet18   | 69.64 | 88.98 |
| a  | AlexNet    | 56.63 | 79.06 |
| 0  | VGG16      | 71.63 | 90.37 |
| 4  | DenseNet121| 74.47 | 91.97 |
| 1a04 | Overall Averaging | 75.32 | 92.41 |
| DMVC |           | **76.47** | **93.05** |

Table 2 gives the average precision comparisons of DMVC (4 views) with other baseline methods on the ImageNet dataset. The first column is the model name and the last two columns are the performances on ImageNet. From table 2, we can find that the proposed DMVC (4 views) method improves the performances over the baseline method by 1.15% on the top1 accuracy, which is much larger than the case of CIFAR-10 dataset. On analysis of the ImageNet dataset, we conclude that DMVC could achieve higher improvement for the datasets with more classes or higher similarities between classes.

5. Conclusion
This paper presents an efficient dynamic multi-view combination approach for visual representation and classification. We propose to use both the class-level information and the image-level information by adding a dynamic gating module. The multiple views and the dynamic gating module can be combined to an end-to-end system, which supports to optimize the dynamic gating module or any single classifiers or all of them together. Experiments and analysis prove the effectiveness of the proposed method.

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