Weather Classification with Deep Learning

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Abstract

Scene classification is an important field in computer vision. For similar weather condition, there are some obstacles for extracting features from outdoor images. We present a novel approach to classify cloudy and sunny weather. Inspired by recent study of deep convolutional neural network(CNN) and spatial pyramid polling, we generate a model based on ImageNet dataset. Starting with parameters trained from more than 1 million images, we fine-tune the parameters. Experiment demonstrates that our classifier can achieve the state of the art accuracy.

Introduction

As usually defined, image understand by a machine can be seen as an attempt to find a relation between input images and previously established models of the observed world [2].One of scenario is understanding weather conditions. People usually judge weather by views, and bureau of meteorology uses special complex instruments, which include satellite. These approaches are labour consuming and expensive. In this paper, we state a computational approach to classify two similar weather conditions-sunny and cloudy.

Some obstacles are in front of weather classification. First of all, sunny and cloudy are similar weather conditions. There are no decisive features, say brightness and lightness, to classify them. Second, it is not easy to extract middle level features and follow a set of decision rules to put a image into a category. For example, shade can be found in sunny and cloudy weather. Last but not least, outdoor images are various.

Datasets and Methods

The datasets for training CNN is from ImageNet, there are more than 1 million images in 1000 categories. The datasets for fine-tuning are from [1]. There are 10,000 images. The half are cloudy and other half are sunny. We take out 1000 images randomly for testing and 9000 images for training. We will achieve the objective with following method.

1. Implement spatial pyramid match layer.
2. Train CNN model with ImageNet dataset.
3. Fine tune model with weather images.

Mathematical and Diagrams

For a multilayer neural networks, the mathematical representation can be represented as

$$y_m = \hat{f}\Big(\sum_{j=0}^{m} w_{j4}^{(2)} f\big(\sum_{i=0}^{n} w_{4i}^{(1)} x_i\big)\Big) \tag{1}$$

In the 1, outer activation function could be different with the inner one.

We use the architecture which achieved excellent performance in 2012 ImageNet classification competition.

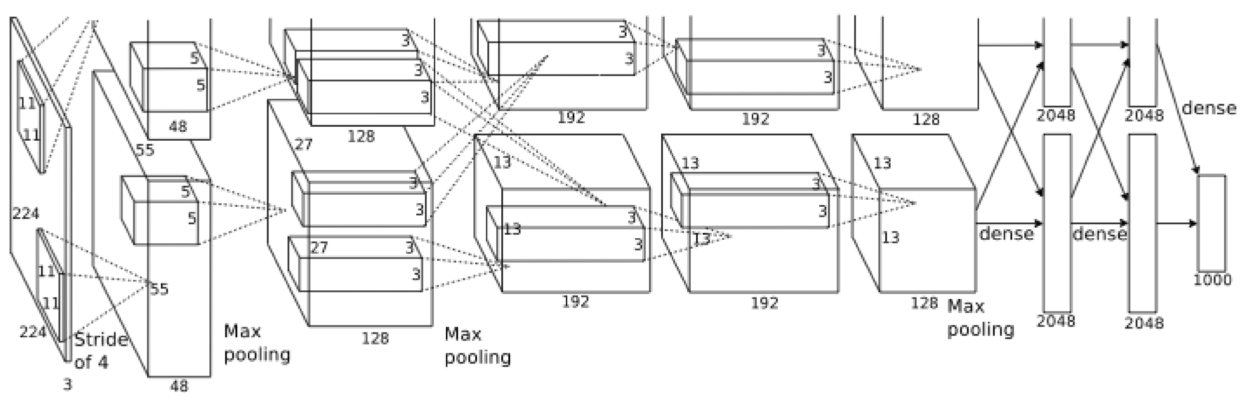

Figure 1: Architecture of CNN

Backpropagation is a method of training CNN used with an optimization method. It can be represent as

$$\Delta w(jk) = -\eta \frac{\partial E}{\partial w_{jk}} = -\eta \delta_k y_j \tag{2}$$

where

$$\delta_k = \frac{\partial E}{\partial a_k} = (y_k - t_k) y_k (1 - y_k)$$

Spatial pyramid match[?] is used to classify high-level semantic attributes, based on low-level features. The method subdivides a image in several different levels of resolution and counts features falling in each spatial bin. It extends bags of features and derives spatial information from images.

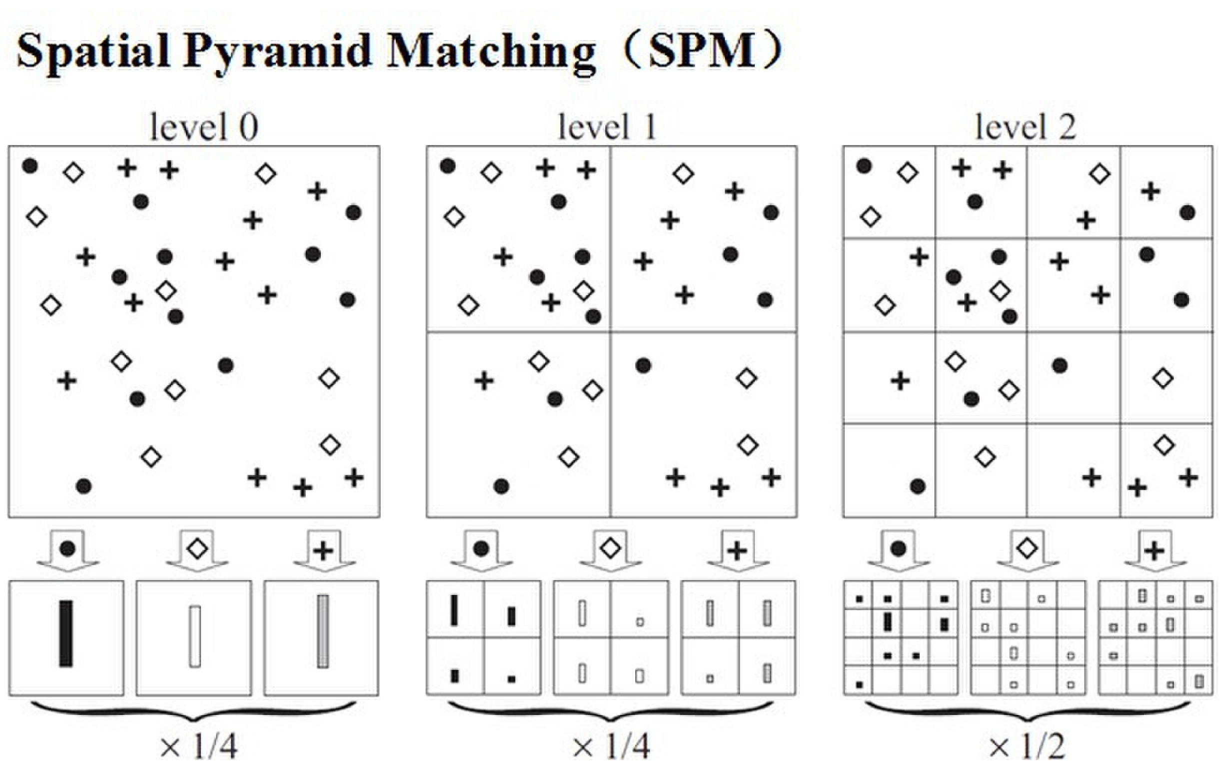

Figure 2: Diagram of Spatial Pyramid Match.

SPM can be represented as

$$\begin{aligned}\kappa^L(X,Y) &= \mathcal{I}^L + \sum_{l=0}^{L-1} \frac{1}{2^{L-l}}(\mathcal{I}^l - \mathcal{I}^{l+1}) \\ &= \frac{1}{2^L}\mathcal{I}^0 + \sum_{l=1}^{L} \frac{1}{2^{L-l+1}}\mathcal{I}^l\end{aligned}$$

Results

We can see from Table that the model has an excellent performance on two class weather classification. The methods CNN+SVM and SPP+SVM mean that we extract features from pretrained models and train linear SVM classifiers. The next two methods fine tune pretrained models with weather images.

CNN+SVM	SPP+SVM	Finetune on CNN	Finetune on SPP
84.8%	82.1%	93.1%	93.98%

Table 1: Classification Accuracy

Analysis

Some intuition on how CNN works.

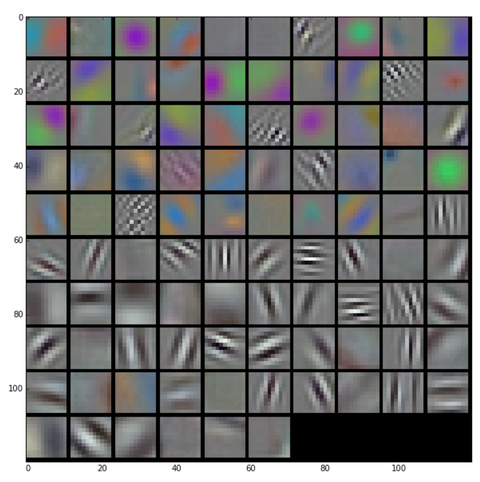

Figure 3: 36 filters in the first convolutional layer

Then we can use the filters to transform original images and compare the outputs.

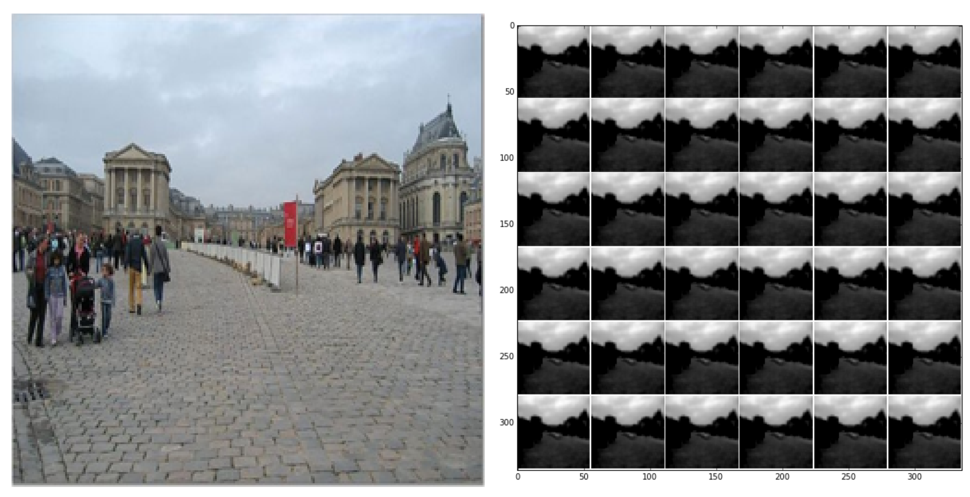

Figure 4: A cloudy image and outputs of the first layer

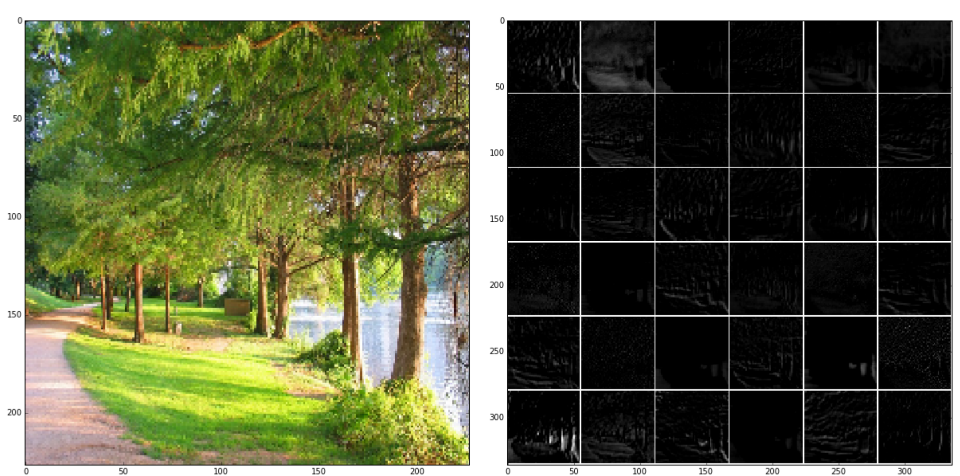

Figure 5: A sunny image and outputs of the first layer

Conclusions

- CNN has power capability of recognizing images.
- Fine tune can save computation in terms of time and power, reducing from one week to one day.
- Fine tune can reduce overfitting risk.

Forthcoming Research

Although CNN achieve success in image classification, we still have little knowledge of why and how it works. In future research, we will focus on analysing working mechanism of deep layers and the interaction between data and model.

References

[1] Cewu Lu, Di Lin, Jiaya Jia, and Chi-Keung Tang. Two-class weather classification. *IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*, 2014.

[2] Milan Sonka, Vaclav Hlavac, and Roger Boyle. Image processing, analysis, and machine vision. 1999. *Champion & Hall*, pages 2–6, 1998.