

MSBD 6000B Project II Report

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I. Introduction

In this project, I tried two different methods to classify flower photos. Firstly, I trained and evaluated a CNN model with training and validation sets, the validation accuracy is about 78%, which is not good enough. Training an entire CNN model from scratch could not achieve a satisfactory performance since we only had limited data (2500+ for training and 500+ for validation). So I considered to use a pretrained model with a large scale of data, and treated the last layer output as initialization for my prediction model. With the help of this transfer learning workflow, my validation accuracy increased to 90%.

II. Stage 1: Training a CNN model with random initialization

a. Pre-processing

Resize image: The row input image is too large and not unique. I need to resize those images with a fixed size, and the size of image should not be too large so that my laptop can handle.

Normalization: Before training, normalize all image arrays into range 0-1

One hot encoding: For labels, use one hot encoding to transform them into vectors.

b. Train CNN model

The model structure is shown below:

1st Part: Convolutional layer (32 features and 3*3 filter size, SAME padding) with batch normalization and ReLU activation. No pooling layer, no drop-out layer.

2nd Part: Convolutional layer (32 features and 3*3 filter size, SAME padding) with batch normalization and ReLU activation. Has one max pooling layer with pool_size = 2, and drop-out rate is 0.25.

3rd Part: Convolutional layer (64 features and 3*3 filter size, SAME padding) with batch normalization and ReLU activation. No pooling layer, and drop-out rate is 0.25.

4th Part: Convolutional layer (64 features and 3*3 filter size, SAME padding) with batch normalization and ReLU activation. Has one max pooling layer with pool_size = 2, and drop-out rate is 0.25.

5th Part: Flatten fully connected layer with 512 units, batch normalization layer and ReLU activation. Drop-out rate is 0.5

6th: Soft-max layer.

c. Some tricks I use

Batch normalization: Adding batch normalization layer improved my validation accuracy.

Alternate pooling layer: I only used max pooling in layers with first two even part.

Drop-out : I set a lower drop-out rate to avoid overfitting at the first 4 parts, but in the dense fully connected layer, the drop-out rate should be a little higher since the features in this stage is more meaningful and worthy.

d. Validation accuracy

the final validation accuracy is 78%

III. Stage 2: Transfer learning

Since the performance for CNN model is not good enough, then I considered to use transfer learning method (see reference) to make some improvement. I use the code provided by tensorflow's Github, loading a pre-trained Inception v3 model.

a. Pre-processing

No special preprocessing stage in my transfer learning model, just follow Inception v3 model workflow.

b. Train the model

1. Load pre-trained Inception v3 model and flower dataset
2. Calculates the bottleneck values for each image
3. Train a new model on the top of bottleneck values
4. Model evaluation and prediction

d. Validation accuracy

the final validation accuracy is 90%

IV. Model selection and evaluation

You can use my transfer learning model prediction output for grading since it achieved higher validation accuracy. Meanwhile, I list the evaluation result on validation set for those two methods:

Keras CNN:

	precision	recall	f1-score	support
class 0	0.87	0.82	0.84	110
class 1	0.76	0.80	0.78	122
class 2	0.65	0.73	0.69	93
class 3	0.80	0.91	0.85	103
class 4	0.82	0.64	0.72	122
avg / total	0.78	0.78	0.78	550

Transfer learning with Tensorflow:

	precision	recall	f1-score	support
class 0	0.86	0.91	0.88	122
class 1	0.85	0.83	0.84	93
class 2	0.91	0.93	0.92	122
class 3	0.95	0.86	0.90	103
class 4	0.94	0.95	0.95	110
avg / total	0.90	0.90	0.90	550

V. Reference

1. Keras: https://github.com/fchollet/keras/blob/master/examples/cifar10_cnn.py
2. Transfer learning: https://www.tensorflow.org/tutorials/image_retraining