

MLND: Capstone Project

Ming-Cheng Yen June 20, 2018

I. Definition

Project Overview

As shoppers move online, it'd be a dream come true to have products in photos classified automatically. But, automatic product recognition is challenging because for the same product, a picture can be taken in different lighting, angles, backgrounds, and levels of occlusion. Meanwhile different fine-grained categories may look very similar, for example, ball chair vs egg chair for furniture, or dutch oven vs french oven for cookware. Many of today's general-purpose recognition machines simply can't perceive such subtle differences between photos, yet these differences could be important for shopping decisions.[1]

Problem Statement

This is a competition of automatic image classification from Kaggle, for this competition we have a dataset of furniture images, each image has one ground truth label, and our goal is classify the furniture correctly, even they are in similarly. For this problem, we will need to build a CNN model to do image classification.

Metrics

For this competition each image has one ground truth label. An algorithm to be evaluated will produce 1 label per image. If the predicted label is the same as the groundtruth label, then the error for that image is 0, otherwise it is 1. The final score is the error averaged across all images.

II. Analysis

Data Exploration

Datasets and Inputs

Overview

train.json: training data with image urls and labels

validation.json: validation data with the same format as train.json

test.json: images of which the participants need to generate predictions. Only image URLs are provided.

sample_submission_randomlabel.csv: example submission file with random predictions to illustrate the submission file format

Training Data

The training dataset includes images from 128 furniture and home goods classes with one ground truth label for each image. It includes a total of 194,828 images for training and 6,400 images for validation and 12,800 images for testing. Train and validation sets have the same format as shown below:

```
{
  "images" : [image], "annotations" : [annotation], }
image{
  "image_id" : int,
  "url": [string]
}
annotation{
  "image_id" : int,
  "label_id" : int
}
```

Testing data and submissions

The testing data only has images as shown below: {

```
"images" : [image],
}
```

```
image { "image_id" : int,
```

```
"url" : [string], }
```

JSON to Data Frame

Train Data Shape:(194828, 3)

First 5 records of training data

	image_id	label_id	url
0	1	5	https://img13.360buyimg.com/imgzone/jfs/t2857/...
1	2	5	http://www.tengdakeli.cn/350/timg01/uploaded/i..
2	3	5	https://img13.360buyimg.com/imgzone/jfs/t8899/...
3	4	5	http://img4.tbcdn.cn/tfscom/i1/2855447419/TB2S...
4	5	5	http://a.vpimg4.com/upload/merchandise/287883/...

Validation Data Shape:(6400, 3)

First 5 records of validation data

	image_id	label_id	url
0	1	38	http://www.ghs.net/public/images/fb/3d/51/3beb...
1	2	63	https://img.alicdn.com/imgextra/TB2chFei9YH8KJ...
2	3	33	http://static-news.17house.com/web/news/201602..
3	4	126	http://img000.hc360.cn/g6/M07/CB/88/wKhQsFN NVJ...
4	5	18	https://img.alicdn.com/imgextra/T1sLtpFH8aXXX X...

Test Data Shape:(12800, 2)

First 5 records of test data

	image_id	url
0	1	https://img13.360buyimg.com/imgzone/jfs/t13174...
1	2	http://img35.ddimg.cn/79/22/1258168705-1_u.jpg
2	3	https://img.alicdn.com/imgextra/TB19HtjKXXXXXC..
3	4	https://img13.360buyimg.com/imgzone/jfs/t16498...
4	5	http://img4.99114.com/group1/M00/7D/C5/wKgGTff...

Checking Data

Missing Data in Taining Data set

	Total	Percent
url	0	0
label_id	0	0
iamge_id	0	0

Missing Data in Validation Data set

	Total	Percent
url	0	0
label_id	0	0
iamge_id	0	0

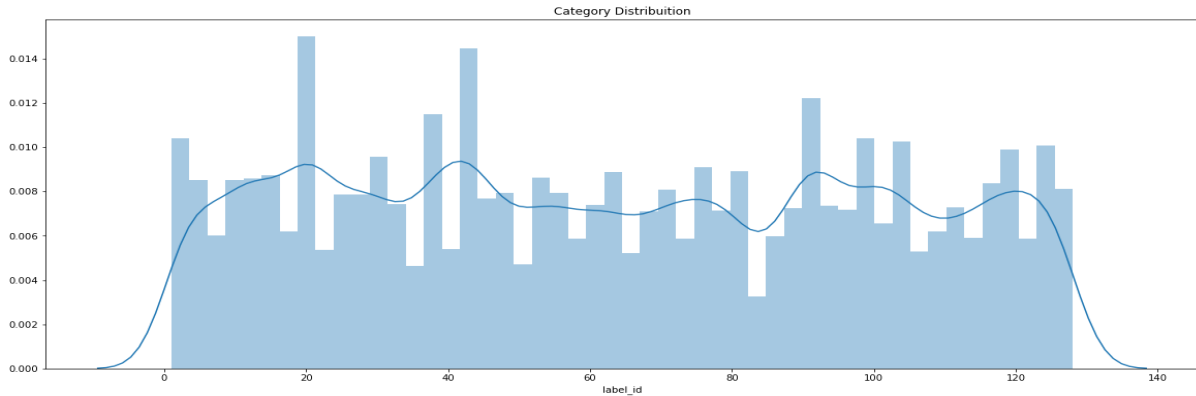
Missing Data in Test Data set

	Total	Percent
--	-------	---------

url	0	0
label_id	0	0

Distribution

Distribution of Training Data



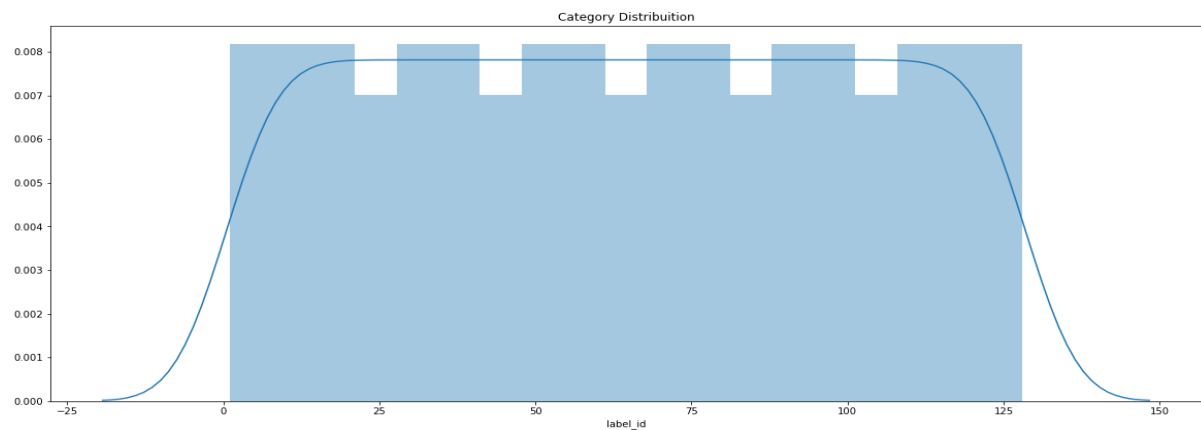
Most frequent of class in training data

	0	1	2	3	4	5	6	7	8	9
label_id	20	42	92	12	125	21	122	3	89	93
count	3996	3973	2666	2609	2598	2577	2462	2368	2353	2350

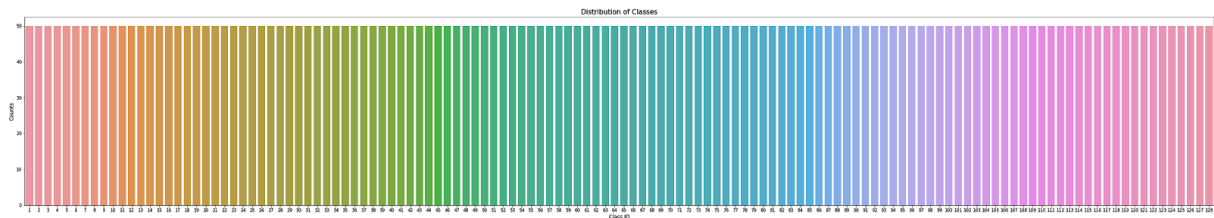
Least frequent of class in training data

	0	1	2	3	4	5	6	7	8	9
label_id	89	66	124	121	9	25	77	85	41	74
count	332	342	415	442	477	527	543	621	625	629

Distribution of validation data

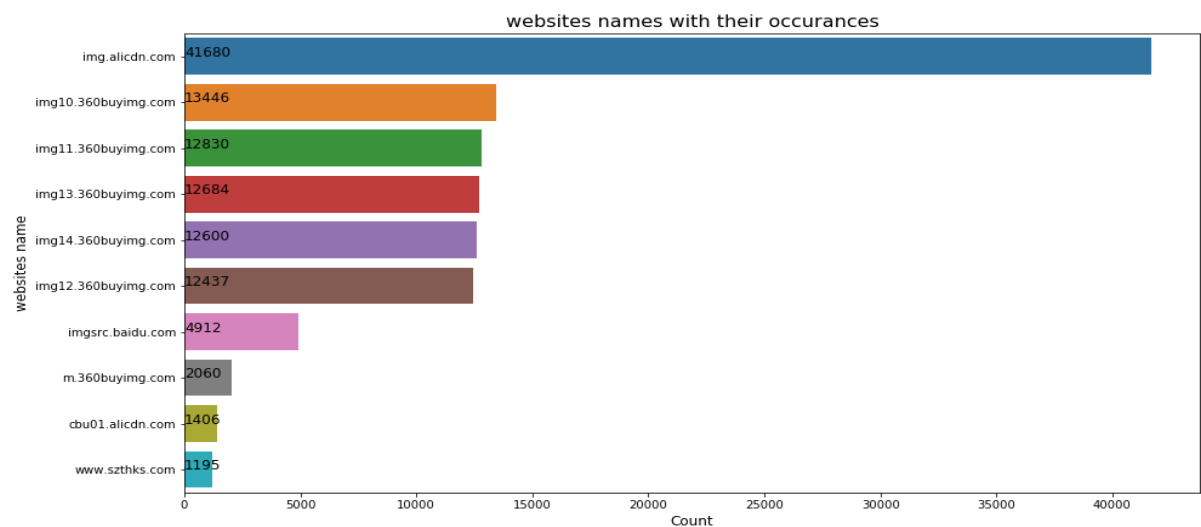


Detail counts of validation data

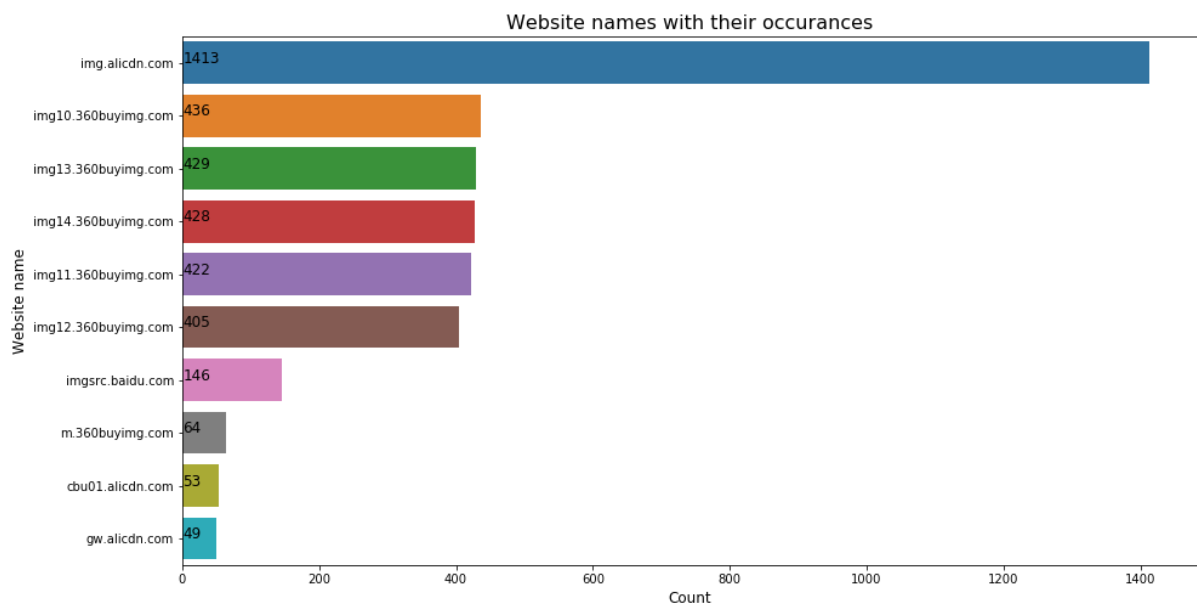


Extract website name

Top occurrences of websites in training data



Top occurrences of websites in training data



Algorithms and Techniques

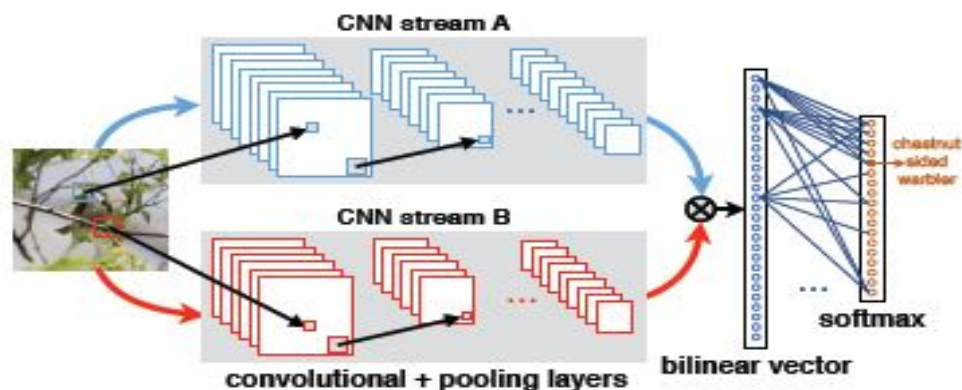
Bilinear CNN namely BCNN for short

Since our Images have no object bounding, we need to build an end to end model, and the key of a good solution is fine-grained image classification, hence I plan to build a bilinear CNN model, which it is determined to be a good solution of the fine-grained visual classification.

What is BCNN?

BCNN is a recognition architecture that consists of two feature extractors whose outputs are multiplied using outer product at each location of the image and pooled to obtain an image descriptor(as cited in http://vis-www.cs.umass.edu/bcnn/docs/bcnn_iccv15.pdf).

So basically we need to use two feature extractors, namely A and B, and use the outer product of A and B as the input of FC-layer, the whole architecture as below.



Benchmark

According Lin and others work[2], their bilinear CNN models include classification of birds and aircrafts and cars, they got over 80% of accuracy roughly, compare with the condition of above, this competition we have 128 classes and 194,828 images for training, for the model that I plan to build, 80% of accuracy it could be reasonable.

III. Methodology

Data Preprocessing

Since I have kinds difference size of images, I have to resize all of the images to the same size as input for one model, hence I want to know which size should I use?

	width size	height size
unique	2054	2091
top	800	800
freq	98467	96811
mean size	761.169280	723.012783

It seems to me use the size of the image around 761x723 would be a good idea, but consider the computing costs, first I would try to resize to 96x96, and then use another size 128x128 to determine if the result of bigger size is better.

Step 1.convert training images and validation images to .h5 file with RGB channel, use `util.create_train_val_h5_file`.

Step 2.convert test images to .h5 file with RGB channel, use `util.create_train_val_h5_file`.

I would have the files as below:

1.size of 96x96:

- training.h5
- validation.h5
- test.h5

2.size of 128x128:

- training.h5
- validation.h5

- test.h5

Implementation

In this project, I used pretrained model of VGG16. For BCNN it requires two feature extractors, here I let two feature extractors be the same. It can save the costs of training because the weights of two feature extractors are the same during the training, hence I can just take the outer product of one feature extractor as the input of FC layer, instead of training two feature extractors.

Here are two model architectures and utils as below:

- Model A: load weights from VGG16 and only last FC layer trainable.
- Model B: load weights from Model A and the entire model trainable.
- Random flip: For each batch images randomly flip them right to left.

Furthermore to more saving costs of training, I used two-step training as below:

- Step 1: Training Model A with Momentum optimizer (learning rate=0.9, momentum=0.9).
- Step 2: Training Model B with Momentum optimizer (learning rate=0.001, momentum=0.9).

Refinement

In this project here are two main processes:

1. First step training use `main.first_step_training`:

- import model A and load VGG16 weights.
- after training model A with 100 epochs.
- extract weights of model A and save to weights file.
- output prediction.

2. Second step training use `main.second_step_training`:

- import model B and load weights from model A.
- training model B, and check if model overfitting during the training period.
- extract weights of model B and save to weights file.
- output prediction.

IV. Results

Model Evaluation and Validation

At first, I resize images to 96x96 and after 62 epochs training, model got overfitting, and I got accuracy around 76%.

And then I resize images to 128x128 and after 30 epochs training, model got overfitting, and I got accuracy around 78%.

All the accuracy as above are evaluated by upload predict result to Kaggle, for the detail see as below:

Overview	Data	Kernels	Discussion	Leaderboard	Rules	Team	My Submissions	Late Submission
12 submissions for boby							Sort by	Private Score
All Successful Selected								
Submission and Description				Private Score	Public Score	Use for Final Score		
pred.csv 19 days ago by boby full layer 128X128--30 epochs				0.20919	0.22306	<input type="checkbox"/>		
pred.csv 23 days ago by boby full layer 96X96--62 epochs				0.22815	0.23993	<input type="checkbox"/>		

Justification

The final results I got the accuracy is around 78% with image size 128x128.

Compare to the accuracy of benchmark is over 80%, it seems not good enough, but consider the result from image size of 96x96 accuracy is 76%, hence I expected if increase the image size, the accuracy would be improve to over 80%.

benchmark model	model with 96x96 image size	model with 128x128 image size
accuracy over 80%	accuracy 76%	accuracy 78%

V. Conclusion

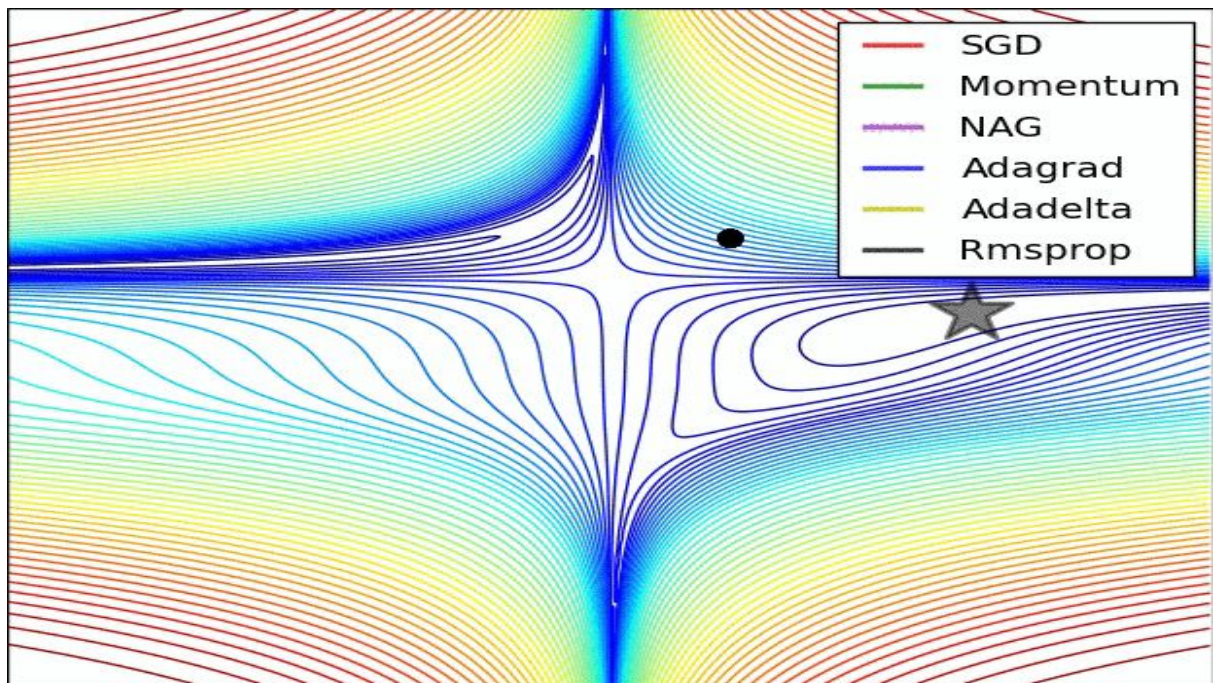
Free-Form Visualization

optimizer:

In this project consider the amounts of training data and compare to our target categories, I think the input data is not sparse, we should not use adaptive learning-rate methods, such as RMSprop or Adam[3].

Hence I use momentum optimizer to accelerate training, but if we want to more approach the optimal, maybe we could try SGD optimizer.

See SGD optimization on loss surface contours as belowe[3]:



Reflection

This project is a competition from Kaggle, and all the data we need to download from URLs that Kaggle provided, hence the first we need to write program to download all these images automatically.

After finish download all these images, we have kinds of different size of image, hence the first we need to resize all the image, then convert these images to .h5 file, and implement the BCNN architecture specifically is the architecture of BCNN[D,D] [2], the interesting thing is I can just take the outer product of one feature extractor as the input of FC layer, because the weights of two feature extractors are same during the training.

The most difficult thing I think is saving the costs of computing, for this competition I already spends over 200 dollars on the GCP.

I think at begining I should use very small portion of images to figure out whitch size of image is good and affordable to computing.

Improvement

Here are some idea I think that would improve the result:

- Increase Image size: I got the image mean size arround 800x800, and I tried two different image size from 96x96 to 128x128 the accuracy is increase, hence I expect increase image size is helpful.
- Shuffling the training data after every epoch: I have tried to do this but unfortunately memory is not affordable.
- Use SGD optimizer: Generally if training data is big I think use SGD optimizer is most likely to approach optimal.

VI. References

[1] <https://www.kaggle.com/c/imaterialist-challenge-furniture-2018>

[2] T.-Y. Lin, A. RoyChowdhury, and S. Maji. Bilinear CNN models for fine-grained visual recognition. In Proceedings of IEEE International Conference on Computer Vision, pages 1449–1457, Sandiago, Chile, Dec. 2015.

[3] <http://runder.io/optimizing-gradient-descent/>