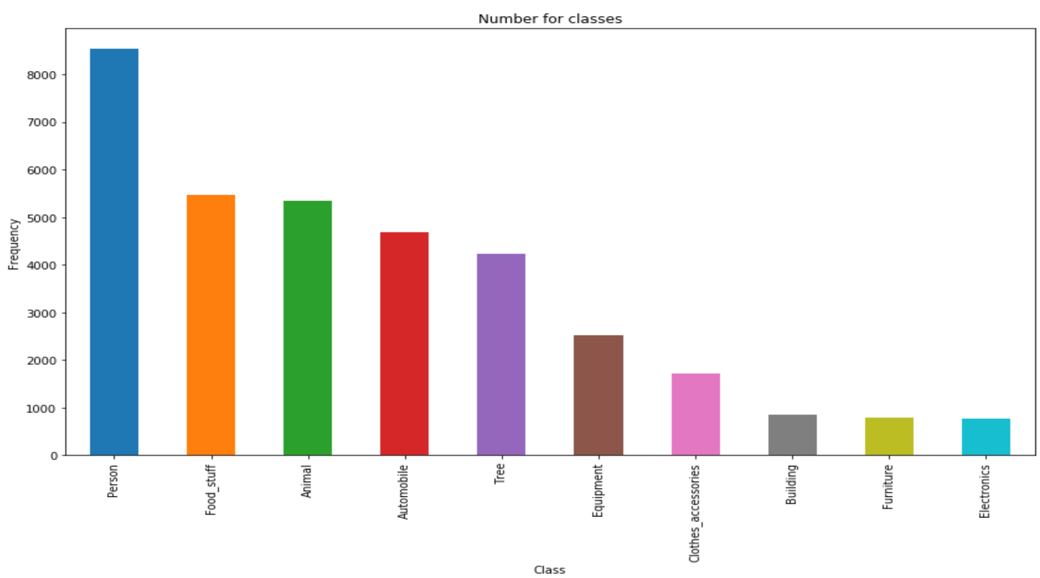
Google AI Open Image Classification
Individual Report

1.1 Introduction

In this project, we have chosen Google AI Open Images dataset. This dataset is available on Google Open Image Dataset V4 website. It is built for the purpose of object detection and segmentation. It consists of natural images that reflect everyday scene and provides contextual information. There are total 516 classes with total 9 million images. The original size of image is 1024x760. The type of objects in these datasets vary in shape, size and color across the same class. Since the raw dataset is very large, we only used a portion of it for our analysis. The aim of this project is to classify the different images in our dataset. The below figure shows the total 10 classes which we are using in this project.



The first step of the learning process is to create an usable set of images for training and testing from the raw image files. The first thing that we did on the dataset was to resize all the images in one size that is (60x60) and give 3 channels for training and testing purposes. The original size of image has a very high resolution of 1024x760 and also had some gray images in our dataset, we only considered coloured images. After this preprocessing, we ended up with 34,471 images and since the data is huge, training the data in our own computer is not feasible, therefore we are working on GCP and AWS.

Framework

For our project, we have used tensorflow as the framework. It is an open source API developed by Google mainly for machine learning and deep learning. The advantages of using tensorflow is that it has many built-in functions. Our main motivation for this project is to learn how to set up, train and build CNN's in tensorflow and other frameworks. We also used keras as our framework to compare our results. We have used RELU and softmax activation functions with different frameworks.

Convolution Network:

We used the convolutional neural network for our project because the main idea of the project is to be able to classify the images. We think that it makes sense to use Deep convolutional neural networks. CNN has been used to great effect in applications such as image classification, object detection and other applications. A common choice for the structure of our CNN consists of layers of convolutional and max pooling layers which are then combined in a deep layer. It has size of the filter, the kernel size, strides, padding and activation function. For max pooling layer, the parameters are kernel size and strides. The functions applied in this project are RELU and softmax. In this case, we are using a max pooling layer which is a common choice for convolutional neural networks. We have also used other commonly used layers that are flatten and dropout layers. Dropout layers are used to prevent overfitting.

CNN has two major advantages:

1. Feature engineering / preprocessing – turn our images into something that the algorithm can interpret more efficiently
2. Classification – train the algorithm to map our images to the given classes, and understand the underlying relationship

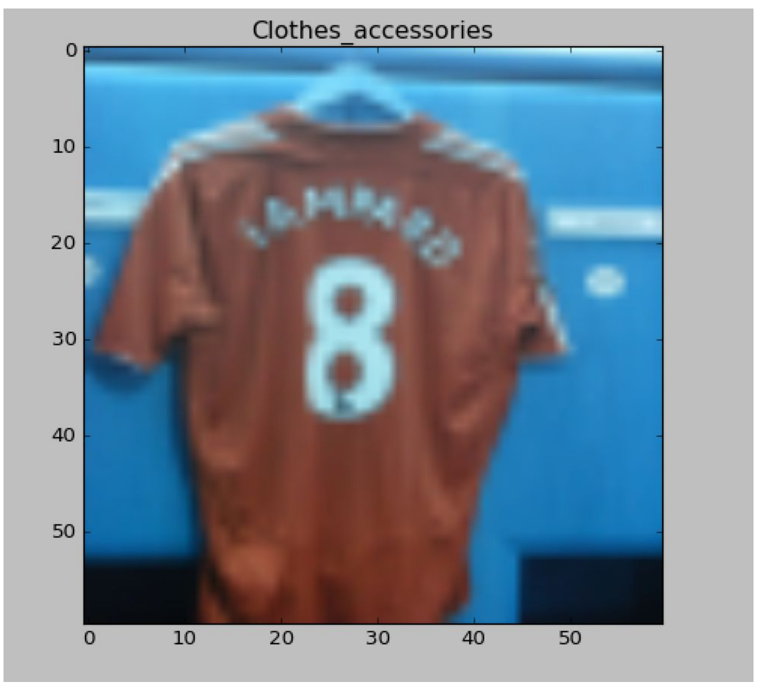
The next step is to choose the loss function. For classification problems, one of the most popular choices for loss function is softmax cross entropy function and we have used the softmax cross entropy function in our project. The parameters available for the loss function includes weights, biases. By minimizing the loss function during the training process, the error of the network is minimized.

Data Problem:

We have following issues with the data when we started the project:

i. We have many images that has no labels.
ii. The format of the image IDs does not match with labels image ID
iii. The dataset has both gray images and color images
iv. Images are not in the same shape

To do my analysis, tried on small dataset to build network when the network is ready, we started implemented on the main dataset which is 37000 images. Since the dataset considered gray scale images, considered only coloured images and resized all the images to square as they are in different shapes.



After resizing images, started building network, started with convolutional layers and came up with this layer.

```
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
conv2d_1 (Conv2D)            (None, 56, 56, 32)        2432
_________________________________________________________________
batch_normalization_1 (Batch (None, 56, 56, 32)        128
_________________________________________________________________
max_pooling2d_1 (MaxPooling2 (None, 28, 28, 32)        0
_________________________________________________________________
conv2d_2 (Conv2D)            (None, 24, 24, 64)        51264
_________________________________________________________________
batch_normalization_2 (Batch (None, 24, 24, 64)        256
_________________________________________________________________
max_pooling2d_2 (MaxPooling2 (None, 12, 12, 64)        0
_________________________________________________________________
conv2d_3 (Conv2D)            (None, 9, 9, 64)          65600
_________________________________________________________________
batch_normalization_3 (Batch (None, 9, 9, 64)          256
_________________________________________________________________
max_pooling2d_3 (MaxPooling2 (None, 4, 4, 64)          0
_________________________________________________________________
flatten_1 (Flatten)          (None, 1024)              0
_________________________________________________________________
dense_1 (Dense)              (None, 256)               262400
_________________________________________________________________
batch_normalization_4 (Batch (None, 256)               1024
_________________________________________________________________
dropout_1 (Dropout)          (None, 256)               0
_________________________________________________________________
dense_2 (Dense)              (None, 10)                2570
=================================================================
Total params: 385,930
Trainable params: 385,098
Non-trainable params: 832
```

6.1 Model Accuracy and Results:

The training data was split into train/test set with the help of python functions. 0.80 and 0.30 was the train and test split simultaneously. When trained on this data without batch normalization the resulting of model reached as high as 37% accuracy in tensorflow taking 500 epochs with Adam optimizer and 4 layers. We have also trained the CNN models with batch normalization. We have trained with 20 epochs. The result from one of the CNN model with batch normalization on test set is 50% with 4 layers. We tried with different parameters and best kernel size was 5x5 with 2 fully connected layers.

We found that implementing batch normalization improves our model from 35% accuracy to 50% accuracy.

We only have results from small dataset because, unfortunately we were not able to get results on the whole data set due to various problems. In large dataset, we tried to use with 120,000 images, but we were experiencing memory errors. Even though we use GPU because it runs slow, but generating the data itself was also too slow.

7.1 Conclusion

The accuracy from our small dataset is low and we think it could be because of the lack of data. It could also be because of an unfit model for this data. Probably, the biggest challenge we faced in this project is the size of the data. It severely limited what we could actually produce and massively slowed down the training and testing. This approach would have been interesting if we have more data for our 10 numbers of classes. Instead, we have each model with less training data, it would also be very interesting to see the comparison of one model trained on the full dataset and another model on the smaller data. Distribution of classes was very unequal in the dataset, some classes had 10 products in one category and some of them had thousands, which is not very good, so for better training on late stages we might have to use some data augmentation.