Capstone Project

Machine Learning Engineer Nanodegree

Oluwatomiwa Ijaware Wisdom

September 15th, 2016

I. Definition

Project Overview

In this project, we will be training a deep learning model to automatically recognize digits within an image. The science here can be applied to a large scale problem, such as recognising house numbers from google street view images. We noticed that a housing number is a sequence of digits. To help understand this, we can build a classifier that understands how to classify digits and use a convolution neural networks to scan through an image, returning only the parts that it believes contains a digit. Our primary dataset for this study is public street view dataset available here.

Problem Statement

In this project, we are going to train a machine learning model to decode a sequence of digits within a natural image. To do so, we'll first create a synthetic dataset from the MINST dataset and use that to train our model. We'll then validate the model synthetic test data. Once we are satisfied with the results, we'll validate that the model performs well using the SVHN dataset. If it performs well, we would have done a great job. If it doesn't, we'll review our model and learn what was not working.

STEP 0: Exploring using the 32x32 pixels images

The first step followed was to explore the dataset with simple fully connected neural networks. We would create a validation set from train and test by randomly selecting a few entries. We then use these values to train the network.

STEP 1: Synthetic Data Creation

We would create a synthetic dataset by concatenating digits in the MNIST dataset. These values would then be split into train, validation and test dataset.

STEP 2: Data Extraction.

The goal here is to extract data and make it meaningful for deep learning. We could use gaussian normalization to ensure that our dataset gives us the best results. If the images are not the same size, we would have to resize the images to all have the same size.

Step 3: Modelling

Here, we'd create a convolution neural networks using a similar build up as Alex net. We would then train our network using the training and validation synthetic dataset.

Step 4: Evaluation

We'd then evaluate the model using the test dataset to see how well it performs.

Step 5: Testing with Live data

We'd test the network we have trained on live data from the SVHN dataset. If it does not perform well, we'd retrain the network using the SVHN dataset and reevaluate the network's performance

Step 6: Deployment

We'd deploy the model to either an android app or a web service.

Metrics

Since this problem is quite delicate - we don't want to mislead people with wrong house numbers, we would only give credit when all digits in the sequence are predicted. We would use the percentage of correctly predicted sequences to measure the performance of our model

II. Analysis

Data Exploration

The dataset has been separated into three. One for train, test and extra data. Also an additional dataset is provided which contains cropped 32x32 pixel images. With this additional dataset, we can run experiments such as train a logistic regression model and see how it performs. The original exists as a gunzipped file which once extracted contains the raw images as well as a digitStruct.mat file.

The .mat file here is a dictionary specifying the sample as well as important attributes of the sample. The important attributes are

1. The digit contained in the email
2. The bounding box of each digit
3. The filename of the actual image.

Loading this file requires the hd5f python library which is free to use. Since the dataset has already been separated into train, test and extra, we also know that the sample has been randomly selected, we have little need to shuffle the data.

SVHN is a real-world image dataset for developing machine learning and object recognition algorithms with minimal requirement on data preprocessing and formatting. It can be seen as similar in flavor to MNIST (e.g., the images are of small cropped digits), but incorporates an order of magnitude more labeled data (over 600,000 digit images) and comes from a significantly harder, unsolved, real world problem (recognizing digits and numbers in natural scene images). SVHN is obtained from house numbers in Google Street View images.

Exploratory Visualization

According to the SVHN website, We are the original, variable-resolution, color house-number images with character level bounding boxes.

Character Height

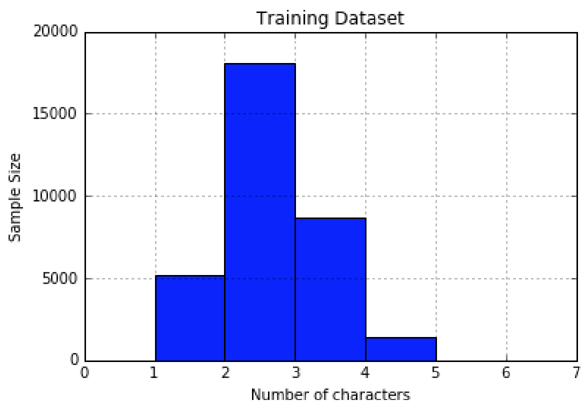
The character height is distance between the top and the bottom of the bounding box.

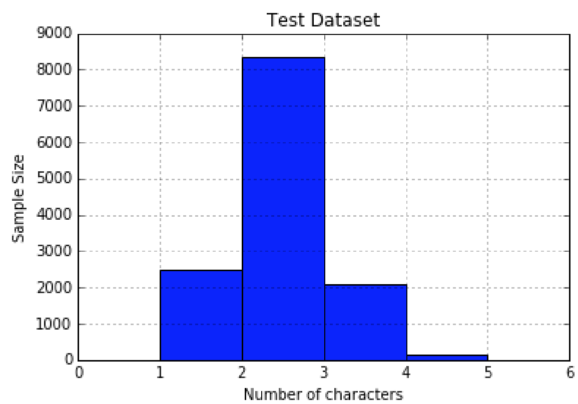
Dataset	Mean	Median	Standard Deviation
Train	34.366	30.0	19.378
Test	27.898	24.0	13.459

This shows that the train dataset is potentially a more difficult dataset because the data is more spread out and it contains larger character heights.

Number of Characters

Each image contains a number of characters and here is a visualization to show the number of digits. From our table, it is optimal to train on images with 1 - 5 characters.

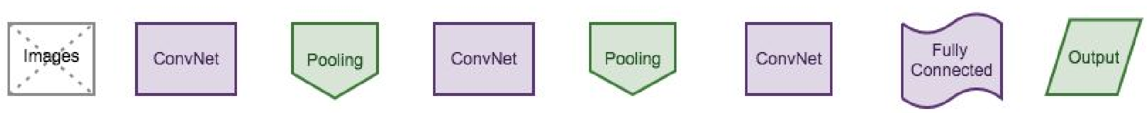




Algorithms and Techniques

I'll be using a Convolution Neural Network(convnet) to predict recognize a sequence of digits. This is largely due to to the network being able to identify images at different scales. Another advantage here is that a convnet is able to directly work on raw pixels.

We'll be using an architecture similar to the one made popular by the tensor flow website to solve the CIFAR-10 dataset.



Images / Input Layer

This layer holds the the input which is equivalent to a store of the the pixels of all images.

Convnet / Convolution Layer

Convnets are neural networks that share their parameters across space. It works by sliding over the vector with depth, height and width and producing another matrix(called a convolution) that has a different weight, depth height. Essentially, rather than having multiple matrix multipliers, we have a set of convolutions. For example, if we have an image of size 1024x1024px in 3 channels, we could progressively create convolutions till our final convolution has a size of 32x32px and a much larger depth.

Pooling (Max Pooling)

Pooling is a technique that can be used to reduce the spatial extent of a convnet. Pooling finds a way to combine all information from a previous convolution into new convolution. For our example, we'll be using max-pooling, takes the maximum of all the responses in a given neighborhood. We choose it because it does not add to our feature space and yet gives accurate responses.

Fully Connected Layer

This layer connects every neuron from the previous convolutions to every neuron that it has. It converts a spatial-like network to a 1d network, so we can then use this network to produce our outputs

The Output layer

The output from this layer are logits which represents matrix showing the probabilities that of having a character in a particular position

Benchmark

The primary benchmark here would be the accuracy of prediction. During our data exploration experiments, our classifier was able to predict single digits with 59% accuracy. Accuracy score is the percentage of correctly predicted data. According to Google's streetview data, humans are able to recognize street numbers with 97% accuracy. To create a model that can help, it needs to be able to perform either close to or better than humans.

III. Methodology

Data Preprocessing

We performed the following steps to preprocess data:

1. Extract information from the digit Struct and save it in a python friendly format.
2. Generate new images using the bounding boxes in the previous image.
3. Resize our new images to 32x32 pixels.

4. Now we generate final training, testing and validation dataset. The validation set is selected by sampling the extra dataset.

Implementation

Model Setup

Our model is setup in this way:

- C1: convolutional layer, batch_size x 28 x 28 x 16, convolution size: 5 x 5 x 1 x 16
- S2: sub-sampling layer, batch_size x 14 x 14 x 16
- C3: convolutional layer, batch_size x 10 x 10 x 32, convolution size: 5 x 5 x 16 x 32
- S4: sub-sampling layer, batch_size x 5 x 5 x 32
- C5: convolutional layer, batch_size x 1 x 1 x 64, convolution size: 5 x 5 x 32 x 64
- Dropout F6: fully-connected layer, weight size: 64 x 16
- Output layer, weight size: 16 x 10

That brings it up to 7 layers.

To train, we read the already preprocessed data into the model and train it in batches. During the training, we try to minimize loss and log the accuracy we are achieving so we can keep track of how well our model is improving. Once the model is trained, we evaluate it using our test step. One step further would be to save the model and load the model so it can be used in other applications such as an android app.

Refinement

The initial solution was to synthetically create a new dataset by combining digits together from either MNIST or SVHN 32x32px dataset. My earlier experiments worked when predicting one character and 5 characters in a sequence but performed poorly on a real dataset. So I used the bounding boxes instead.

Another thing here was to resize images into 32x32px images. My earlier model used 800x600px images to simulate what a phone screen might look like. I was unable to train it because of the sheer amount of memory needed to process that dataset. I rented a 60GB virtual machine in the cloud and I have over 30GB of memory used up on the first 2000 images using this architecture.

I also converted images to grayscale by averaging the pixels. This was to further reduce the memory footprint. Some other scholars believe there is a certain ratio of Green, Red and Blue that makes an image appear closer to human perspective, however, I did not explore that option.

IV. Results

Model Evaluation and Validation

At the end of my training, I was able to achieve the following:

Minibatch loss: 1.077957

Minibatch accuracy: 93.8%

Validation accuracy: 75.3%

Test accuracy: 85.9%

Training was done in batches, hence the word minibatch. What this means is that after training our model with 30,000 images, we were able to correctly predict the characters in an image correctly 75.3% of the time using our validation set and also 85.9% using our final test dataset.

Justification

In this section, your model's final solution and its results should be compared to the benchmark you established earlier in the project using some type of statistical analysis. You should also justify whether these results and the solution are significant enough to have solved the problem posed in the project. Questions to ask yourself when writing this section:

- *Are the final results found stronger than the benchmark result reported earlier?*
- *Have you thoroughly analyzed and discussed the final solution?*
- *Is the final solution significant enough to have solved the problem?*

V. Conclusion

Free-Form Visualization

To test how well our model is working, we created random images and used it for our prediction. Here is the actual images and their labels:

These images were then passed through our model and here is what our model predicted the values to be

We can see that our model did a pretty good job at predicting data and it did so with a training set of just over 30000. If we continue to train with the larger set of 200,000 images, we will achieve even better results, however, my computer might take a really long time to do that, since i am training on a CPU.

Reflection

Deep learning is an interesting field of machine learning that can be applied to many exciting problems. The problem we have applied it to is housing number digit recognition.

While it is capable of solving many problems, the part that I find most challenging is the specialized compute resource needed to get good results. GPUs are becoming cheaper and I believe that every device would soon be able to train deep learning models, or at least retrain their models based on new information.

The Udacity forum has been really helpful as many of the ideas from this project comes from the course and the forum.

Improvement

There are several ways this implementation can be improved.

One of which is to run this model on a GPU. Scholars have written on how this can provide up to 10x improvement in the training time for deep neural networks.

Another improvement here would be to explore Recurrent neural networks. Using that implementation, we would be able to predict beyond 5 digits at once. My implementation makes use of 5 classifiers which might be seen as wasteful.

References

- http://ufldl.stanford.edu/housenumbers
- http://static.googleusercontent.com/media/research.google.com/en//pubs/archive/42241.pdf
- https://en.wikipedia.org/wiki/Convolutional_neural_network
- https://www.tensorflow.org/versions/r0.10/tutorials/deep_cnn/index.html
- http://www.wildml.com/2015/12/implementing-a-cnn-for-text-classification-in-tensorflow
- The Udacity Forum