Udacity Machine Learning Engineer Nanodegree Project 5 - Deep Learning for Satellite Image Recognition

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1 Introduction

In the past few years, development of affordable satellites has increased the availability of satellite images. Several startups and companies are leveraging image recognition powered by machine learning algorithms and the availability of satellite images to produce actionable insights about a variety of subjects.

For example, Skybox Imaging was able to use satellite images to count all the cars in every Walmart parking lot in America on Black Friday [1]. Others are using satellite images to predict seasonal yields and monitor crop health, estimate the world's supply of oil, and map human rights infractions in developing countries.

One type of machine learning algorithm that has gained popularity for image classification in recent years are convolutional neural networks (CNNs). CNNs are a type of machine learning algorithm that were inspired by the organization of the neurons in an animal visual cortex. For image classification, the algorithm takes several images, makes a prediction about what class they belong to, and adjusts the way it makes its prediction based on how close its prediction was compared to the classes the images actually belong to. This process is repeated several times until the CNN arrives at a decent model which can make accurate predictions on images it hasn't seen yet.

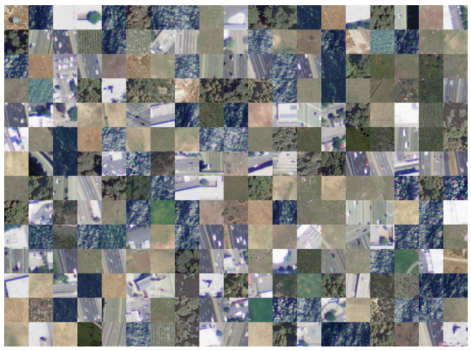
In this study, we use a CNN to classify satellite images into 6 different land cover types ('buildings', 'barren_ land', 'trees', 'grassland', 'roads', 'water_ bodies'). In Section 2 we explore the dataset and preprocess the images. In Section 3 we describe the architecture of the CNN, and in Section 4 we share the results of training and testing our CNN.

[1] http://spectrum.ieee.org/aerospace/satellites/9-earthimaging-startups-to-watch

2 Dataset

The dataset was created in part of a study first authored by Saikat Basu of Louisiana State University [2]. The images were taken from the National Agriculture Imagery Program (NAIP) dataset, and consists of 405,000 images. Each image is a picture of land cover taken at a 1-m ground sample distance and is 28 x 28 pixels, with 4 bands (red, green, blue, and near-infrared). Each image is labeled with its corresponding land cover type. Figure 1 shows a sample of the images.

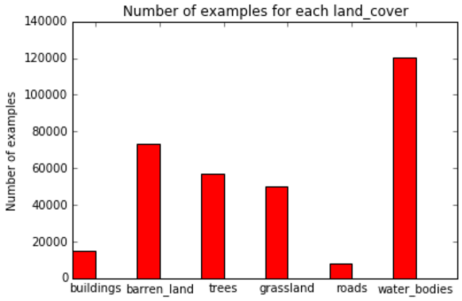
Figure 1: A sample of images in the SAT6 dataset



2.1 Data Exploration

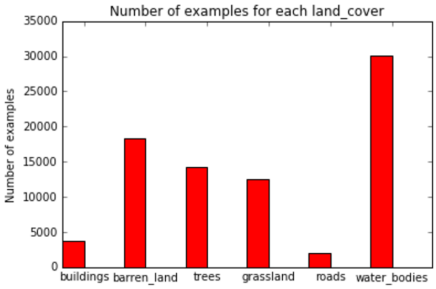
Next, we check to see if the data is balanced across classes.

Figure 2: Distribution of examples for the Training Set



[2] http://csc.lsu.edu/ saikat/deepsat/

Figure 3: Distribution of examples for the Test Set



By visual inspection, the data looks balanced across sets. While the data is balanced across sets (training, validation, and testing) the data is not balanced across classes within each set. This is not necessarily bad, since the distribution of the classes reflects the distribution of land cover types that a classifier trained on this data will see.

Using all 405,000 images to train and test our CNN is beyond the scope of this project. Instead, we will cut our dataset to 20,000 training images and 5,000 test images.

2.2 Preprocessing

Before we started feeding our images through our CNN, we need to preprocess the images. When executing numerical computations, we have to be concerned about calculating values that are too large or too small, which can introduce error into our calculations. In order to avoid error, we want our mean to be equal to zero and our variances to be equal across variables. Our dataset includes the pixel values of four layers (Red, Green, Blue, and Near-Infared) with values between 0 and 255. We can normalize the values, which will convert each pixel value to a value between -1 and 1.

3 CNN Architecture

Our CNN consists of two convolution layers followed by a fully connected layer. Let's investigate what happens at each level of our CNN.

The 28x28 pixel image with 4 feature maps is fed through the first convolutional layer. We take a small patch of the image (in the case of the first convolutional layer, the patch size is 5x5) and run it through a tiny neural network and receive 32 outputs. If you can imagine, the first patch that we run through the tiny neural network is in the bottom left corner. We then shift to the right by 1 (since our stride size is 1) and run it through the tiny neural network again. We slide across and then vertically until the entire image has been processed. Since we are using same padding, the new image that is formed from the compilation of the outputs of our tiny neural networks is now 28x28 with a depth of 32.

When we run it through the neural network, the patch is multiplied by a matrix of weights and then a bias is added to it. Next, the resulting matrix is run through a rectified linear unit (RELU) function, which produces 0 if x is less than 0 and x if x is greater than x. Next, we implement max pooling, where we look at every point on the feature map, look at a small neighborhood around that point, and compute the maximum of all the responses around it. Using max pooling often makes our model more accurate [3].

The data flows next into the second convolutional layer. The second layer is similar to the first, except our output now has a depth of 64 as opposed to 32.
After going through the second convolutional layer, the data goes into a fully connected layer. We reshape the output to fit the fully connected layer input first and then multiply by a set of weights and add a set of biases, which gives us an output of 1024 units. We then pass the output through a RELU function and apply dropout.
Dropout is another technique to prevent overfitting. It works in the following way: randomly select half (or for our purposes, one out of four) of the activations that go from one layer to the next and drop them, or randomly set them to 0. When we initiate dropout, the network can never rely on any given activation to be present because it might be squashed. So it is forced to learn a redundant representation for everything to make sure that at least some of the information remains. During training we zero out the activations that we drop and scale the remaining activations by a factor of two. This way, when it comes time to average them, we just remove the dropout and scaling and we get something that is properly scaled. It is only

[3] http://andrew.gibiansky.com/blog/machine-learning/convolutional-neural-networks/

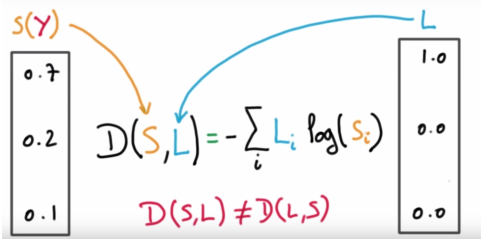
used during training and not evaluation [4].

The data is now a 6x1 matrix, with each element representing a land cover class. Our model then takes the element with the maximum value and makes a prediction about what land cover class our example belongs to.

3.1 Training the CNN

In the training phase of the CNN we use stochastic gradient descent to minimize our cost function. Our cost function is used to assess how accurate the predictions of the model are. For our purposes, we measure the cross entropy between the predictions the model makes and the actual label [5]. Cross entropy is essentially the distance between the vector of the prediction and the vector of the label.

Figure 4: A visual representation of the Cross Entropy Function



In the figure shown above, D represents the cross entropy function, S represents a vector of all the prediction vectors, L a vector of all the label vectors, and

$$L_i$$

and

$$S_i$$

represent the prediction and label vector for the ith example.

We want to try and minimize the entropy function as best as we can. In order to find the minimum value of the entropy function, we can take the derivative of it, set it equal to 0, and solve for the set of weights and biases

[4] https://www.udacity.com/course/deep-learning–ud730
[5] https://www.udacity.com/course/deep-learning–ud730

values.

The method we use to minimize the entropy function is gradient descent. We can use gradient descent algorithms to find the optimal weights and biases by taking the derivative of our cost function and iterate several times to minimize our cost (or loss).

It would be difficult to iterate through our dataset, since we have several thousand pictures. We can use stochastic gradient descent to speed up this process. Stochastic gradient descent takes a random sample of a fraction of the total training set (for our purposes we are using a batch of 128 examples) and iterates through the model and finds the optimal weights and biases to minimize the cost. Stochastic gradient descent will be unlikely to converge at the global minimum and will instead wander around it randomly, but usually yields a result that is close enough.

There are two ways that we can help stochastic gradient descent reach an optimal minimum value for our cost function. The first way is using momentum. Momentum uses a running average of the weights and biases of the gradients as opposed to using the weights and biases generated from the latest batch to update the weights and biases for our model. The second way is using learning rate decay. As we get closer to our (hopefully) global minimum, we want to take smaller and smaller steps. Learning rate decay enables this, and allows the weights and biases generated by the batch to affect the weights and biases less and less as we iterate through more and more batches. We will implement both by using the AdamOptimizer, available through tensorflow.

3.2 Metrics

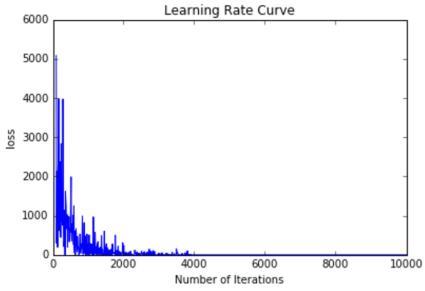
In order to test the accuracy of our model, we will use a simple accuracy metric, which is the ratio between the number of correctly identified examples and the total number of examples.

As a benchmark for our model, we will use the overall accuracy of 79.06% attained from the CNN model used by Basu et al. in 2015.

4 Results and Conclusion

Using the CNN architecture described above, we have achieved an accuracy rate of 99.74% on the test set, which is an increase of 26.12% from our benchmark accuracy. The training time for 500,000 iterations of stochastic gradient descent was 2,415.82 seconds and prediction time on the test dataset was 8.66 seconds. Figure 5 shows the value of our loss for each iteration from 10 to 100,000 [6].

Figure 5: Learning rate curve for CNN from Iteration 10 to 100,000



The project could be expanded in a few different ways. First, we could test several hyperparameters and parameters using a validation set. We could try different architectures, mixing and matching layers to see which one gave us the best result. We could also change some of the parameters. For example, instead of using a stride size of 1, we could use a stride size of 2 or increase the depth of the output from one of our convolutional layers. We could try using less iterations to prevent overfitting, since it seemed our CNN model converged to an optimal cost around iteration 270,000. Finally, we could use the entire dataset. CNNs work well when we use lots of data, so using the entire dataset could increase the accuracy of our model.

[6] I decided to remove iterations 100,001 to 500,000, since many had values of 0