




# Final Project:

By AJ, Tyler, and Justus



```
time = time.time()

self.load(self.checkpoint_dir):
    print(" [*] Load SUCCESS")
else:
    print(" [!] Load failed...")

for epoch in xrange(config.epoch):
    if config.dataset == 'mnist':
        batch_idxs = min(len(data_X), config.train_size)
    else:
        data = glob(os.path.join("./data", config.data_dir))
        batch_idxs = min(len(data), config.train_size)

    for idx in xrange(0, batch_idxs):
        if config.dataset == 'mnist':
            batch_images = data_X[idx*config.batch_size:(idx+1)*config.batch_size]
            batch_labels = data_y[idx*config.batch_size:(idx+1)*config.batch_size]
        else:
            batch_files = data[idx*config.batch_size:(idx+1)*config.batch_size]
            [get_image(batch_file, self.image_size, self.image_size, self.image_channels)]
```



# Our Question:

Can we get an AI to recognize numbers in the MNIST data set?



# Our Algorithms

We used a CNN, and used a total of 6 different architecture. Each of our models had 3 convo2d layers, and 2 dense layers.

## 4x4 Filter

Each of the 3 convo2d Layers have a filter size of 4x4

## 2x2 Filter

Each of the 3 convo2d Layers have a filter size of 2x2

## 3x3 Filter

Each of the 3 convo2d Layers have a filter size of 3x3

## MaxPooling

The original code written by Tyler uses "MaxPooling" and "Dropout" Layers. I had one version of each model with and without the pooling and dropout layers



# MaxPooling and Dropout Layers

## MaxPooling

MaxPooling simplifies the data, making it easier for future layers to work with it, and make the model less prone to overfitting.

```
layers.Conv2D(32, (4, 4), activation='relu', input_shape=(28, 28, 1)),  
layers.MaxPooling2D((2, 2)),  
layers.Conv2D(64, (4, 4), activation='relu'),  
layers.MaxPooling2D((2, 2)),  
layers.Conv2D(64, (4, 4), activation='relu'),
```

## Dropout

Sets random neuron values to 0 during training to prevent overfitting.

```
layers.Dense(64, activation='relu'),  
layers.Dropout(0.5),|  
layers.Dense(10, activation='softmax')
```





# Measurements

## Accuracy

How many of the testing data set it correctly identifies, measures how successfully we trained the algorithm.

## Time to Learn

The time it takes to learn from the data set, as it taking too long can be a problem.





# Performance

## 2x2 pooling

Test accuracy: 0.9921

Time elapsed: 45.48 seconds

## 3x3 pooling

Test accuracy: 0.9919

Time elapsed: 79.79 seconds

## 4x4 pooling

Test accuracy: 0.9932

Time elapsed: 46.82 seconds

## 2x2 no pooling

Test accuracy: 0.9871

Time elapsed: 219.68 seconds

## 3x3 no pooling

Test accuracy: 0.9892

Time elapsed: 236.42 seconds

## 4x4 no pooling

Test accuracy: 0.9853

Time elapsed: 264.92 seconds



# Best algorithm

```
model = models.Sequential([
    layers.Conv2D(32, (4, 4), activation='relu', input_shape=(28, 28, 3)),
    layers.MaxPooling2D((2, 2)),
    layers.Conv2D(64, (4, 4), activation='relu'),
    layers.MaxPooling2D((2, 2)),
    layers.Conv2D(64, (4, 4), activation='relu'),
    layers.Flatten(),
    layers.Dense(64, activation='relu'),
    layers.Dropout(0.5),
    layers.Dense(10, activation='softmax')
])
```

We found that the best algorithm was a model with 4x4 filters, as it had the highest percentage correct at 99.32%, and barely had a worse time than 2x2 filters.

All the Pooling models also did better than the no pooling models, as all the pooling models got about 99% accuracy, but none of the no pooling models did, and the no pooling models took much longer.