

## NOISE REDUCTION.

### IMAGE ~~IDENTIFICATION~~ WITH AUTOENCODERS

#### USING TENSOR-FLOW

~~Task~~ Objective → Train a neural network to identify images numbers displayed in handwritten images (mnist) Dataset. Same we used in Basic Image Classification with tensorflow.

→ Add noise and denoise the data so that we can teach our network what important things to focus on while denoising the data which will be given in real time.

#### TASK-1 Import ~~Libraries~~ Libraries

#### TASK-2 Data Preprocessing.

numpy arrays.

$(X_{train}, Y_{train}), (X_{test}, Y_{test}) = \text{mnist.read_data1}()$

Values are in range of 0-255 so we will normalize them next.

$X_{train} = X_{train}.astype('float') / 255$

$X_{test} = X_{test}.astype('float') / 255$

→ Normalizing the data i.e. getting them in range 0-1. This is not a good



approach and only valid when the data starts from 0 and we know an upper limit.

$x\_train = np.reshape(x\_train, (6000, 784))$   
 $x\_test = np.reshape(x\_test, (10000, 784))$   
Reshaping from  $(6000, (28, 28))$  to  $(6000, 784)$   
original shape  $28 \times 28 = 784$ . This

### TASK-3 ADDING NOISE

Random values b/w 0,1  
 $x\_train\_noisy = x\_train + np.random.randn(60000, 784) * 0.9$   
is done so that we can have 784 features in first input layer.  
shape of random values → scaling them down

Each value of  $x\_train$  will have something added to them randomly. This will be the noise.

We multiplied with 0.9 to ensure values do not get too large

$x\_test\_noisy = x\_test + np.random.randn(10000, 784) * 0.9$

$x\_train\_noisy = np.clip(x\_train\_noisy, 0, 1)$   
Input array      min value      max value

$np.clip$  will return the input array but where values are less than minimum it will be replaced by min value and those greater than max will be replaced by max value.

`>>> a = np.arange(10)` [0, 1, 2, 3, 4, 5, 6, 7, 8, 9]

`>>> np.clip(a, 1, 8)` → [1, 1, 2, 3, 4, 5, 6, 7, 8, 8]

But it won't change actual  $a$  if not assigned to  $a$ .

Eg →  $a = np.clip(a, 1, 8)$  → will change  
 $np.clip(a, 1, 8)$  → won't change

In short it RETURNS the clipped array

`>>> np.clip(a, 3, 6, out=a)` [3, 3, 3, 3, 4, 5, 6, 6, 6, 6]

This changes the original array without assignment

`>>> a = [0, 1, 2, 3, 4, 5, 6, 7, 8, 9]`  
`>>> np.clip(a, [3, 4, 1, 1, 1, 4, 4, 4, 4, 4], 8)`

min value for each

max value

Output → [3, 4, 2, 3, 4, 5, 6, 7, 8, 8]

`def plot(x, y, labels=False):`  
→ array to plot → default false. labels will be used later.  
→ prediction for each will be used later

`plt.figure(figsize=(20, 2))` → The total dimension of display panel not individual images.



show() displays the figure. You shouldn't call it until you have plotted things and want them to be displayed.

→ display only first 10.

plt.imshow()  
draws an image  
on current figure.

for i in range(10):  
plt.subplot(1, 10, i+1)

1 row 10 columns  
We will start index from 1 as

plt.imshow just finishes  
drawing a picture instead of printing  
it. plt.show will print  
it.

if from 0 is not allowed. ~~between 0 and 10~~

getting back to original  
shape (28, 28), shape  
can be binary  
cmap

plt.imshow(x[i].reshape(28, 28), shape  
cmap = binary)

x ticks & y ticks  
are kind of labels  
on x-axis & y-axis

values on x-axis like 0, 10, 20 etc

plt.xticks([])  
plt.yticks([]) } Removing x ticks & y ticks

If predictions  
are there then  
display on x-axis

[ If labels:

plt.xlabel(np.argmax(p[i]))

plt.show() → Finally display plot.

plot(x\_train, None)

## TAS/2-4 Building & Training a Classifier

We will train a classifier on non-noisy  
data and we will see how it does  
on noisy data.

Model of keras in which we only need  
to input the rows of layers as rows

classifier = Sequential ([

First layer → Dense (258, activation = 'relu', input\_shape = (784,)),  
Dense no. of activation rectified  
layer nodes function linear unit. ~~nodes~~ <sup>Input</sup> <sub>needs</sub>

Second layer → Dense (256, activation = 'relu'),

Output layer → Dense (10, activation = 'softmax')  
10 because 10 classes in end i.e 1 to 10  
to get probability score

classifier.compile(  
optimizer = 'adam'

loss function  
adaptive moment estimate

loss = 'sparse\_categorical\_crossentropy',

metrics = ['accuracy']

)

classifier.fit (X\_train, Y\_train, batch\_size = 512,  
epochs = 3)  
no. of training examples utilized in one iteration



loss, accuracy = classifier.evaluate (x-test, y-test)

## TASK-5 Building Autoencoders

Our noisy data gave accuracy of 20% (approx) which is not good.

So, we will ~~us~~ built auto encoders to denoise this data.

input-image = Input (shape = (784,))

encoded = Dense(64, activation='relu')(input-image)

↓  
Squeeze to  
less nodes to make it  
learn only the important ones

decoded = Dense(784, activation='sigmoid')(encoded)

↓  
Bringing the dimensionality back.  
i.e. de noised data.

Creating  
the model

autoencoders = Model (input-image, decoded)

autoencoders.compile (loss = 'binary\_crossentropy',  
optimizer = 'adam')

## TASK-6 Training the <sup>Auto</sup> Encoder.

```
autoencoders.fit(X_train_noisy, X_train, epochs=100,  
batch_size=512, validation_split=0.2,  
verbose=False,
```

```
callbacks=[  
    EarlyStopping(monitor='val_loss', patience=5),  
    LambdaCallback -----  
])
```

## TASK-7 Denoised Images.

→ predictions = autoencoder.predict(X\_test\_noisy)

Denoised Images

plot(X\_test\_noisy, None) → Noisy data

plot(predictions, None) → Denoised images.

loss, accuracy = classifier.evaluate(predictions, y\_test)

print(accuracy) → from 20% to 90% approx.

## TASK-8 Composite Model.

Combine classifier and encoder to first denoise then classify images. This will be a composite model which completes the prediction pipeline.

So we send whether noisy or non noisy data the Model works.



input-image = Input(shape=(784,))

$\rightarrow x = \text{autoencoder}(\text{input-image})$

Denoised  
Image.

$y = \text{classifier}(x)$

denoise-and-classify = Model(input-image, y)  
model name.

Here it is 1 to 10

predictions = denoise-and-classify.predict(x-test-noisy)

plot(x-test-noisy, predictions, True)

These help in comparison  
between expected and  
true output.

plot(x-test, one-hot-encoded(y-test), True)  
original test set.      one hot encoded values

## Quiz

Point 1  $\rightarrow x = \text{np.reshape}(x, (10000, 74))$  and  
 $x = x.reshape((10000, 74))$  are same things.

Point 2  $\rightarrow v = [0, 1, 1, 0, 5, 2, 1, 0, 2]$   
 $\text{np.argmax}(v) \rightarrow$  It returns the index of max  
value in  $v$

Point 3  $\rightarrow$  When classification problem eg  $\rightarrow 10$  classes,  
we can use these loss functions  
P10  $\rightarrow$



Loss function 1  $\rightarrow$  Sparse Categorical cross entropy  
when labels are not encoded

or

Loss function 2  $\rightarrow$  Categorical cross entropy  
after one-hot encoding  
labels.

Point 3  $\rightarrow$  Auto encoding can be used for  
lossy data compression where the  
compression is dependent on data itself.

$\rightarrow$  Auto encoding is algo to help reduce  
dimensionality of data.

$\rightarrow$  This algo to reduce dimensionality of  
data, as learned from data itself,  
can also be used for reducing  
noise in data.