Assignment 4: Tensorflow and Data Privacy

By

Rachael Joan Dias

0651897

Addressed to,

Professor Brian Srivastava

Trent University

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1. Machine Learning Problems

The Keras library contains several pretrained models, each model is broken into 2 parts, model architecture and pretrained weights, since the weights are very large the are not bundled with Keras. I used the VGG16 model and loaded ImageNet weights. ImageNet is a large database that contains 14 million images that belong to 20,000 classes [1].

We start by importing all the necessary libraries, from Keras we use the VGG model which we initialize by specifying imagenet weights.

```
import keras
import numpy as np
from keras.applications import vgg16, inception_v3, resnet50, mobilenet
#Load the VGG model
vgg_model = vgg16.VGG16(weights='imagenet')
```

Next, we must load images and preprocess them so that we can apply them to the VGG model. We import all the preprocessing libraries from Keras, and other libraries such as numpy, os and matplotlib that are needed for converting the data to the right format and visualization

The os library helps us to read all the images that are saved in a folder. "BASE_DIR" is the current working directory and within that directory we specify the directory "images" which contains all the images which we will use for our prediction. Using a for loop we iterate through all the .jpg, .png and .jpeg files that are present.

We use load_img() to load the image, then we convert it into a size of 224x2244 and save it as the original image. In the next step we convert the image into a numpy array using the img_to_array() function. Since the network requries a 4-dimensional Tensor as input we convert the numpy array to batch format by adding an extra dimension to the image.

```
# load an image in PIL format
original = load_img(path, target_size=(224, 224))
print('PIL image size', original.size)
plt.imshow(original)
plt.show()
# convert the PIL image to a numpy array
# IN PIL - image is in (width, height, channel)
# In Numpy - image is in (height, width, channel)
numpy_image = img_to_array(original)
plt.imshow(np.uint8(numpy_image))
plt.show()
print('numpy array size',numpy_image.shape)
# Convert the image / images into batch format
# expand dims will add an extra dimension to the data at a particular axis
# We want the input matrix to the network to be of the form (batchsize, height, width, channels)
# Thus we add the extra dimension to the axis 0.
image batch = np.expand dims(numpy image, axis=0)
print('image batch size', image_batch.shape)
plt.imshow(np.uint8(image_batch[0]))
```

Once this is complete we pass the image to the vgg16 model by passing it to the preprocess_input() function. Predictions can be made on the image, as the predictions returned are an array the decode_predictions() function will give us the labels for each of the predictions

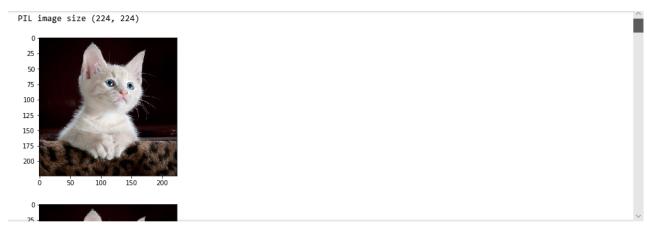
```
# prepare the image for the VGG model
processed_image = vgg16.preprocess_input(image_batch.copy())

# get the predicted probabilities for each class
predictions = vgg_model.predict(processed_image)

# print predictions

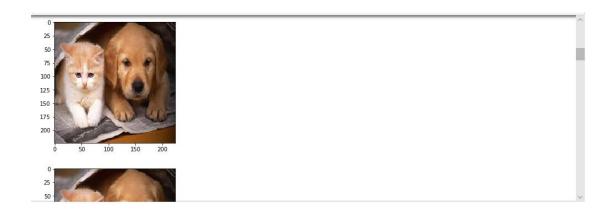
# convert the probabilities to class labels
# We will get top 5 predictions which is the default
label = decode_predictions(predictions)
print (label)
```

Below we can see the output image. The first image is in PIL format, the second image is the numpy array and finally we have the predictions for the image. The VGG16 model predicts that the cat looks like an Egyptian cat, tabby, lynx, tiger cart or Persian cat. Similarly, for all the other images the model makes a couple of predictions.



```
0
25
50
75
100
125
150
175
200
0 50 100 150 200

numpy array size (224, 224, 3)
image batch size (1, 224, 224, 3)
[[('n02124075', 'Egyptian_cat', 0.4049535), ('n02123045', 'tabby', 0.3942576), ('n02127052', 'lynx', 0.10080725), ('n0212315
9', 'tiger_cat', 0.05541087), ('n02123394', 'Persian_cat', 0.012944666)]]
PTI image size (224, 224)
```



The model can detect the golden retriever from the image

```
25

50-

75-

100-

125-

150-

175-

200-

0 50 100 150 200

numpy array size (224, 224, 3)

image batch size (1, 224, 224, 3)

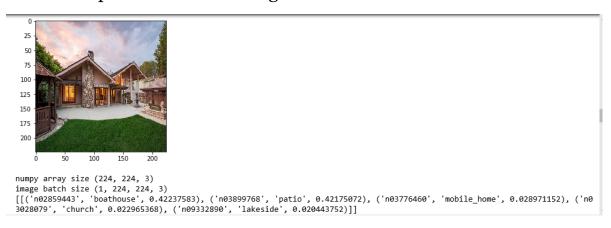
[[('n02099601', 'golden_retriever', 0.62682486), ('n02099712', 'Labrador_retriever', 0.26682746), ('n02808304', 'bath_towe

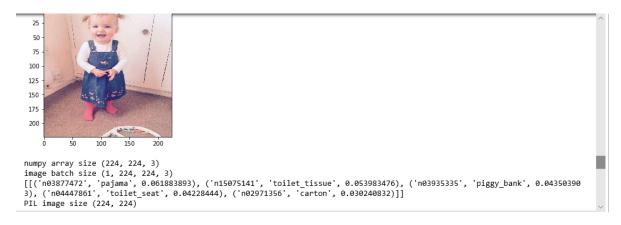
1', 0.011000982), ('n02088466', 'bloodhound', 0.006998717), ('n02090379', 'redbone', 0.0055709733)]]

PIL image size (224, 224)
```

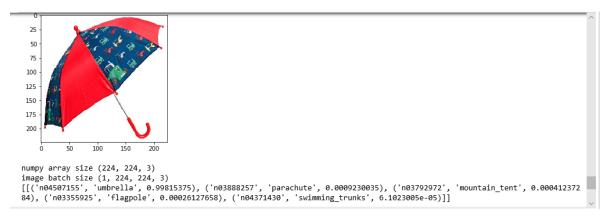
The model predicts that the fish looks like a puffer fish, anemone fish, stingray, electric ray and rock beauty fish

The model predicts that the image below looks like a boathouse





The first prediction for the image below is umbrella



Script Name: assgn#4 1.ipynb

2. TensorFlow Sample Problem

a. Applying the Tensorflow model that was trained on the IMDB dataset I was able to classify positive and negative reviews of my dataset. I used the airline tweets dataset which consists of reviews of American airlines. The predictions gave values between 0 and 1, 0 represents negative sentiments and 1 indicates positive sentiments

The screenshots below show how the model was trained on the IMDB dataset

[1, 14, 22, 16, 43, 530, 973, 1622, 1385, 65, 458, 4468, 66, 3941, 4, 173, 36, 256, 5, 25, 100, 43, 838, 112, 50, 670, 2, 9, 3 5, 480, 284, 5, 150, 4, 172, 112, 167, 2, 336, 385, 39, 4, 172, 4536, 1111, 17, 546, 38, 13, 447, 4, 192, 50, 16, 6, 147, 2025, 19, 14, 22, 4, 1920, 4613, 469, 4, 22, 71, 87, 12, 16, 43, 530, 38, 76, 15, 13, 1247, 4, 22, 17, 515, 17, 12, 16, 626, 18, 2, 5, 62, 386, 12, 8, 316, 8, 106, 5, 4, 2223, 5244, 16, 480, 66, 3785, 33, 4, 130, 12, 16, 38, 619, 5, 25, 124, 51, 36, 135, 48, 25, 1415, 33, 6, 22, 12, 215, 28, 77, 52, 5, 14, 407, 16, 82, 2, 8, 4, 107, 117, 5952, 15, 256, 4, 2, 7, 3766, 5, 723, 36, 71, 43, 530, 476, 26, 400, 317, 46, 7, 4, 2, 1029, 13, 104, 88, 4, 381, 15, 297, 98, 32, 2071, 56, 26, 141, 6, 194, 7486, 18, 4, 22 6, 22, 21, 134, 476, 26, 480, 5, 144, 30, 5535, 18, 51, 36, 28, 224, 92, 25, 104, 4, 226, 65, 16, 38, 1334, 88, 12, 16, 283, 5, 16, 4472, 113, 103, 32, 15, 16, 5345, 19, 178, 32]

len(train_data[0]), len(train_data[1])

(218, 189)

```
# A dictionary mapping words to an integer index
word_index = imdb.get_word_index()

# The first indices are reserved
word_index = {k:(v+3) for k,v in word_index.items()}
word_index["<PAD>"] = 0
word_index["<START>"] = 1
word_index["<UNK>"] = 2 # unknown
word_index["<UNUSED>"] = 3

reverse_word_index = dict([(value, key) for (key, value) in word_index.items()])

def decode_review(text):
    return ' '.join([reverse_word_index.get(i, '?') for i in text])
```

decode_review(train_data[0])

"<START> this film was just brilliant casting location scenery story direction everyone's really suited the part they played an d you could just imagine being there robert <UNK> is an amazing actor and now the same being director <UNK> father came from the same scottish island as myself so i loved the fact there was a real connection with this film the witty remarks throughout the film were great it was just brilliant so much that i bought the film as soon as it was released for <UNK> and would recommend it to everyone to watch and the fly fishing was amazing really cried at the end it was so sad and you know what they say if you cry at a film it must have been good and this definitely was also <UNK> to the two little boy's that played the <UNK> of norman and paul they were just brilliant children are often left out of the <UNK> list i think because the stars that play them all grown up are such a big profile for the whole film but these children are amazing and should be praised for what they have done don't you think the whole story was so lovely because it was true and was someone's life after all that was shared with us all"

```
len(train_data[0]), len(train_data[1])
```

(256, 256)

```
print(train_data[0])
    1
         14
               22
                     16
                           43
                                530
                                      973 1622 1385
                                                         65
                                                             458 4468
                                                                           66 3941
    4
        173
               36
                    256
                            5
                                 25
                                      100
                                             43
                                                  838
                                                        112
                                                               50
                                                                    670
                                                                            2
                                                                                  9
   35
        480
              284
                      5
                          150
                                  4
                                      172
                                            112
                                                  167
                                                          2
                                                              336
                                                                    385
                                                                           39
                                                                                  4
  172 4536 1111
                     17
                          546
                                 38
                                       13
                                            447
                                                    4
                                                        192
                                                               50
                                                                     16
                                                                            6
                                                                               147
                            4 1920 4613
 2025
         19
               14
                     22
                                            469
                                                    4
                                                         22
                                                               71
                                                                     87
                                                                           12
                                                                                 16
                                 13 1247
   43
        530
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                                                   22
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                                                             515
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               38
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  626
         18
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                      5
                           62
                                386
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                                                             106
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 5244
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   52
               14
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                                                             117
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                7 3766
                            5
    4
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                                                        530
                                                             476
                                                                     26
                                                                          400
                                                                               317
   46
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                      2 1029
                                 13
                                      104
                                             88
                                                        381
                                                               15
                                                                    297
                                                                           98
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 2071
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               26
                    141
                            6
                                194 7486
                                             18
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                                                   36
                                                         28
                                                              224
                                                                     92
                                                                           25
                                                                               104
                                       18
    4
        226
               65
                     16
                           38 1334
                                       88
                                             12
                                                   16
                                                        283
                                                                5
                                                                     16 4472
                                                                               113
  103
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               15
                     16 5345
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                      0]
```

```
# input shape is the vocabulary count used for the movie reviews (10,000 words)
vocab_size = 10000

model = keras.Sequential()
model.add(keras.layers.Embedding(vocab_size, 16))
model.add(keras.layers.GlobalAveragePooling1D())
model.add(keras.layers.Dense(16, activation=tf.nn.relu))
model.add(keras.layers.Dense(1, activation=tf.nn.sigmoid))
model.summary()
```

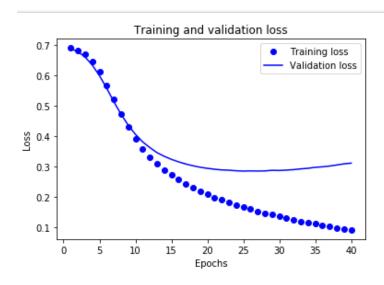
WARNING:tensorflow:From C:\Users\17059\Anaconda3\lib\site-packages\tensorflow\python\ops\resource_variable_ops.py:435: colocate _with (from tensorflow.python.framework.ops) is deprecated and will be removed in a future version. Instructions for updating:

Colocations handled automatically by placer.

Layer (type)	Output	Shape	Param #		
embedding (Embedding)	(None,	None, 16)	160000		
global_average_pooling1d (Gl	(None,	16)	0		
dense (Dense)	(None,	16)	272		
dense_1 (Dense)	(None,	1)	17		
Total params: 160,289					

Total params: 160,289 Trainable params: 160,289 Non-trainable params: 0

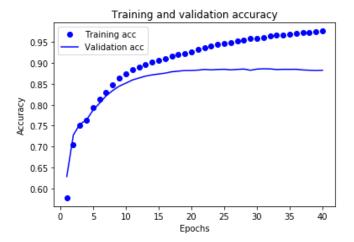
```
model.compile(optimizer='adam',
                loss='binary_crossentropy',
                metrics=['acc'])
 x_val = train_data[:10000]
 partial_x_train = train_data[10000:]
 y_val = train_labels[:10000]
 partial_y_train = train_labels[10000:]
 history = model.fit(partial_x_train,
                      partial y train,
                      epochs=40,
                      batch_size=512,
                      validation_data=(x_val, y_val),
                      verbose=1)
 Epoch 36/40
 15000/15000 [
             Epoch 37/40
 15000/15000 [
                  ========] - 1s 93us/sample - loss: 0.1031 - acc: 0.9719 - val_loss: 0.3023 - val_acc: 0.8833
 Epoch 38/40
 Epoch 39/40
 15000/15000 [
              Epoch 40/40
 15000/15000 [=
             results = model.evaluate(test_data, test_labels)
 print(results)
 [0.33292325684547425, 0.8716]
: history_dict = history.history
 history_dict.keys()
: dict_keys(['loss', 'acc', 'val_loss', 'val_acc'])
 import matplotlib.pyplot as plt
 acc = history_dict['acc']
 val_acc = history_dict['val_acc']
 loss = history_dict['loss']
 val_loss = history_dict['val_loss']
 epochs = range(1, len(acc) + 1)
 # "bo" is for "blue dot"
 plt.plot(epochs, loss, 'bo', label='Training loss')
 # b is for "solid blue line"
 plt.plot(epochs, val_loss, 'b', label='Validation loss')
 plt.title('Training and validation loss')
 plt.xlabel('Epochs')
 plt.ylabel('Loss')
 plt.legend()
 plt.show()
```



```
plt.clf() # clear figure

plt.plot(epochs, acc, 'bo', label='Training acc')
plt.plot(epochs, val_acc, 'b', label='Validation acc')
plt.title('Training and validation accuracy')
plt.xlabel('Epochs')
plt.ylabel('Accuracy')
plt.legend()

plt.show()
```



Below is a screenshot of the data the first column is airline sentiment which indicates if the reviews are positive or negative the text column contains passenger reviews.

m jnardino m jnardino m jnardino m jnardino	@VirginAr @VirginAr @VirginA	merica it's merica and	really aggr	essive to b	olast obno	xious "ente		•	uests' fac	es & th	ney have lit	tle recou
n jnardino n jnardino	@VirginAr	merica and					ertainmen	t" in your g	uests' fac	es & th	ney have lit	tle recou
m jnardino	@VirginA		it's a reall	y big bad t	hing abou	t it						
-						t it						
n simoginni												
n cjinicginni:	@VirginAr	merica yes	, nearly ev	ery time I	fly VX this	"ear w	orm†wor	n't go av	vay :)			
n dhepburn	@virginan	nerica Wel	l, I didn'tâŧ	E¦but NOV	V I DO! :-D							
n YupitsTate	@VirginAr	merica it w	as amazin	g, and arriv	ved an hou	r early. Yo	u're too go	od to me.				
n HyperCan	@VirginAr	merica I &l	t;3 pretty g	graphics, so	o much be	tter than m	ninimal ico	nography.	:D			
n HyperCan	@VirginAr	merica This	s is such a g	great deal!	! Already tl	hinking abo	out my 2nd	trip to @A	ustralia 8	kamp; I have	en't even g	one on i
n mollande	@VirginAr	merica @v	irginmedia	I'm flying	your #fab	ulous #Sed	uctive skie	s again! U	take all th	e #stress av	way from tr	avel htt
n sjespers	@VirginAr	merica Tha	nks!									
n smartwate	@VirginAr	merica SFC)-PDX sche	dule is stil	I MIA.							
	m dhepburn m YupitsTate m HyperCam m HyperCam m mollande m sjespers m smartwate	m dhepburn @virginan m YupitsTate @VirginA m HyperCam @VirginA m HyperCam @VirginA m mollande @VirginA m sjespers @VirginA n smartwate @VirginA	m dhepburn @virginamerica Wel m YupitsTate @VirginAmerica it w m HyperCarr @VirginAmerica I &l m HyperCarr @VirginAmerica Thi m mollande @VirginAmerica @v m sjespers @VirginAmerica Tha	n dhepburn @virginamerica Well, I didn'tâd n YupitsTate @VirginAmerica it was amazin n HyperCam @VirginAmerica I <3 pretty g n HyperCam @VirginAmerica This is such a g n mollandei @VirginAmerica @virginmedia n sjespers @VirginAmerica SFO-PDX sche n smartwate @VirginAmerica SFO-PDX sche	n dhepburn @virginamerica Well, I didn't…but NOV m YupitsTat∢@VirginAmerica it was amazing, and arriv m HyperCam @VirginAmerica I <3 pretty graphics. s m HyperCam @VirginAmerica This is such a great deal m mollandei @VirginAmerica @virginmedia I'm flying m sjespers @VirginAmerica Thanks! m smartwat∢@VirginAmerica SFO-PDX schedule is stil	n dhepburn @virginamerica Well, I didn't…but NOW I DO!:-D m YupitsTat∢@VirginAmerica it was amazing, and arrived an hou m HyperCam @VirginAmerica I <3 pretty graphics. so much be m HyperCam @VirginAmerica This is such a great deal! Already ti m mollandei @VirginAmerica @virginmedia I'm flying your #fabi m sjespers @VirginAmerica Thanks! m smartwat∢@VirginAmerica SFO-PDX schedule is still MIA.	m dhepburn @virginamerica Well, I didn't…but NOW I DO!:-D m YupitsTate @VirginAmerica it was amazing, and arrived an hour early. You m HyperCam @VirginAmerica I <3 pretty graphics. so much better than m m HyperCam @VirginAmerica This is such a great deal! Already thinking abo m mollandei @VirginAmerica @virginmedia I'm flying your #fabulous #Sed m sjespers @VirginAmerica Thanks! m smartwate @VirginAmerica SFO-PDX schedule is still MIA.	m dhepburn @virginamerica Well, I didn't… but NOW I DO! :-D m YupitsTate @VirginAmerica it was amazing, and arrived an hour early. You're too go m HyperCam @VirginAmerica I <3 pretty graphics. so much better than minimal ico m HyperCam @VirginAmerica This is such a great deal! Already thinking about my 2nd m mollandei @VirginAmerica @virginmedia I'm flying your #fabulous #Seductive skie m sjespers @VirginAmerica Thanks! m smartwate @VirginAmerica SFO-PDX schedule is still MIA.	m dhepburn @virginamerica Well, I didn't… but NOW I DO! :-D m YupitsTate @VirginAmerica it was amazing, and arrived an hour early. You're too good to me. m HyperCam @VirginAmerica I <3 pretty graphics. so much better than minimal iconography. m HyperCam @VirginAmerica This is such a great deal! Already thinking about my 2nd trip to @A m mollandei @VirginAmerica @virginmedia I'm flying your #fabulous #Seductive skies again! U m sjespers @VirginAmerica Thanks! m smartwate @VirginAmerica SFO-PDX schedule is still MIA.	m dhepburn @virginamerica Well, I didn't…but NOW I DO! :-D m YupitsTate @VirginAmerica it was amazing, and arrived an hour early. You're too good to me. m HyperCam @VirginAmerica I <3 pretty graphics. so much better than minimal iconography. :D m HyperCam @VirginAmerica This is such a great deal! Already thinking about my 2nd trip to @Australia & m mollande @VirginAmerica @virginmedia I'm flying your #fabulous #Seductive skies again! U take all th m sjespers @VirginAmerica Thanks! m smartwate @VirginAmerica SFO-PDX schedule is still MIA.	m dhepburn @virginamerica Well, I didn't…but NOW I DO! :-D m YupitsTate @VirginAmerica it was amazing, and arrived an hour early. You're too good to me. m HyperCam @VirginAmerica I <3 pretty graphics. so much better than minimal iconography. :D m HyperCam @VirginAmerica This is such a great deal! Already thinking about my 2nd trip to @Australia & I have m mollande @VirginAmerica @virginmedia I'm flying your #fabulous #Seductive skies again! U take all the #stress an m sjespers @VirginAmerica Thanks! m smartwate @VirginAmerica SFO-PDX schedule is still MIA.	m dhepburn @virginamerica Well, I didn't… but NOW I DO! :-D m YupitsTate @VirginAmerica it was amazing, and arrived an hour early. You're too good to me. m HyperCam @VirginAmerica I <3 pretty graphics. so much better than minimal iconography. :D m HyperCam @VirginAmerica This is such a great deal! Already thinking about my 2nd trip to @Australia & I haven't even go m mollandei @VirginAmerica @virginmedia I'm flying your #fabulous #Seductive skies again! U take all the #stress away from tr m sjespers @VirginAmerica Thanks! m smartwate @VirginAmerica SFO-PDX schedule is still MIA.

First, we import the pandas module to read the .csv file and specify the encoding as utf-8 the file is saved as a data frame "df" from which we select only the text column and save as another dataframe test_samples.

From Tensorflow we import the preprocessing modules required Tokenizer and pad_sequences. The text column data has to be converted into tokens using the tokenzier, and then into a series of sequences using the pad_sequence function. This can be fed to the sentiment analysis model to make predictions. As, you can see we get an array of values between 0 and 1, those which are closer to 0 are classified as negative sentiments while those which are closer to 1 are positive sentiments [2].

```
import pandas as pd
df=pd.read csv('Tweets.csv',encoding='utf-8')
test samples=df['text']
from tensorflow.python.keras.preprocessing.text import Tokenizer
from tensorflow.python.keras.preprocessing.sequence import pad sequences
vocabulary_size = 10000
tokenizer = Tokenizer(num_words= vocabulary size, filters='')
tokenizer.fit_on_texts(test_samples)
sequences = tokenizer.texts to sequences(test samples)
data = pad sequences(sequences, maxlen= 256)
pred=model.predict(x=data)
print(pred)
[[0.52036375]
 [0.43659645]
 [0.38662496]
 [0.6484683]
 [0.49651265]
 [0.5504872 ]]
```

The first sentinment is positive while the second and third sentiments are negative. The model predicts .52, .436 and .386 for first, second and third respectively so we can assume that the first review is a positive review and the second and third reviews are negative.

Script Name: Assgn#4_2a

b. MNSIT model

```
from __future__ import print_function
import math
import os
import glob
from IPython import display
from matplotlib import cm
from matplotlib import gridspec
from matplotlib import pyplot as plt
import numpy as np
import pandas as pd
import seaborn as sns
from sklearn import metrics
import tensorflow as tf
from tensorflow.python.data import Dataset
tf.logging.set verbosity(tf.logging.ERROR)
pd.options.display.max_rows = 10
pd.options.display.float_format = '{:.1f}'.format
mnist_dataframe = pd.read_csv(
  "https://download.mlcc.google.com/mledu-datasets/mnist_train_small.csv",
  sep=",",
  header=None)
# Use just the first 10,000 records for training/validation.
mnist_dataframe = mnist_dataframe.head(10000)
mnist_dataframe = mnist_dataframe.reindex(np.random.permutation(mnist_dataframe.index))
```

```
mnist datarrame.nead()
1:
            0 1 2 3 4 5 6 7 8 9 ... 775 776 777
                                                                778
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                                                                                       782
                                                                                            783
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  def parse_labels_and_features(dataset):
      "Extracts labels and features.
    This is a good place to scale or transform the features if needed.
   Args:
      dataset: A Pandas `Dataframe`, containing the label on the first column and monochrome pixel values on the remaining columns, in row major order.
    Returns:
      A `tuple` `(labels, features)`:
        labels: A Pandas `Series`
        features: A Pandas `DataFrame`.
   labels = dataset[0]
    # DataFrame.loc index ranges are inclusive at both ends.
   features = dataset.loc[:,1:784]
    # Scale the data to [0, 1] by dividing out the max value, 255.
   features = features / 255
   return labels, features
  training_targets, training_examples = parse_labels_and_features(mnist_dataframe[:7500])
  training_examples.describe()
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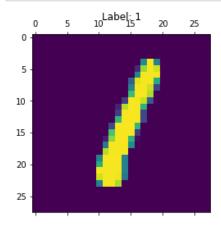
0.0

validation_targets, validation_examples = parse_labels_and_features(mnist_dataframe[7500:10000])
validation_examples.describe()

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count	2500.0	2500.0	2500.0	2500.0	2500.0	2500.0	2500.0	2500.0	2500.0	2500.0	 2500.0	2500.0	2500.0	2500.0	2500.0	2500.0	2500.0	2500.0	2500.0
mean	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	 0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
std	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	 0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
min	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	 0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
25%	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	 0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
50%	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	 0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
75%	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	 0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
max	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	 0.5	0.1	0.0	0.2	1.0	0.2	0.0	0.0	0.0

8 rows × 784 columns

```
rand_example = np.random.choice(training_examples.index)
_, ax = plt.subplots()
ax.matshow(training_examples.loc[rand_example].values.reshape(28, 28))
ax.set_title("Label: %i" % training_targets.loc[rand_example])
ax.grid(False)
```



```
def construct_feature_columns():
    """Construct the TensorFlow Feature Columns.

Returns:
    A set of feature columns
    """

# There are 784 pixels in each image.
    return set([tf.feature_column.numeric_column('pixels', shape=784)])
```

```
def train_nn_classification_model(
    learning_rate,
    steps,
    batch_size,
    hidden_units,
    training_examples,
    training_targets,
    validation_examples,
    validation_targets):
""Trains a neural network classification model for the MNIST digits dataset.

In addition to training, this function also prints training progress information,
    a plot of the training and validation loss over time, as well as a confusion
matrix.

Args:
    learning_rate: A `float`, the learning rate to use.
    steps: A non-zero `int`, the total number of training steps. A training step
        consists of a forward and backward pass using a single batch.
    batch_size: A non-zero `int`, the batch size.
    hidden_units: A `list` of int values, specifying the number of neurons in each layer.
    training_examples: A `DataFrame` containing the training features.
    training_targets: A `DataFrame` containing the validation features.
    validation_examples: A `DataFrame` containing the validation features.
    validation_targets: A `DataFrame` containing the validation labels.

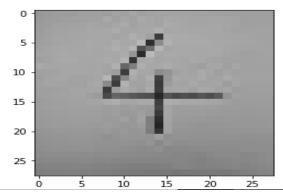
Returns:
    The trained `DNNClassifier` object.
"""

periods = 10
```

In order to apply the classifier to my handwritten image we need to convert the image to grayscale and resize it to 28x28. The code below converts the image to grayscale.

```
import numpy as np
import keras
from matplotlib import pyplot as plt
from PIL import Image
from keras.preprocessing.image import img_to_array
%matplotlib inline
import pandas as pd

#converting image to Gryscale
filename="myimage.jpg"
x=Image.open(filename)
x=x.convert("L")
plt.imshow(x)
x.save('x.jpg')
```



Next, the image has to be in the correct size and format after converting it to an array of 28x28 we then convert it to a dataframe and pass the image to the parse_labels_and_features() function. Now, we can use the classifier to make predictions on the image, the classifier does not give very good results on the image

```
#converting image to 28X28
x = np.resize(x, (28,28,1))
imZarr = np.array(x)
imZarr = im2arr.reshape(1,28,28,1)
mnsit = pd.DataFrame(im2arr.reshape(len(im2arr),-1))
df1 = pd.DataFrame(ip2arr.reshape(len(im2arr),-1))
mytest = pd.concat([df1, mnsit], ignore_index=True,axis=1)

#parsing LabeLs and features
test_targets, test_examples = parse_labels_and_features(mytest)
test_examples.describe()
predict_test_input_fn = create_predict_input_fn(
    test_examples, test_targets, batch_size=10)

#making predictions
test_predictions = classifier.predict(input_fn=predict_test_input_fn)
test_predictions = np.array([item['class_ids'][0] for item in test_predictions])
print(test_predictions)
accuracy = metrics.accuracy_score(test_targets, test_predictions)
print("Accuracy on test data: %0.2f" % accuracy)

[0]
Accuracy on test data: 0.00
```

Script Name: assgn#4_2b.ipynb

3. Data Privacy

In November of 2018, Marriott International hotels reported that cyber thieves had stolen data from 500 million customers. The breach began on systems supporting Starwood hotel brands in the year 2014. The cyber thieves continued to remain in the system after the Marriott group acquired Starwood in 2016 and remained undiscovered until September 2018 [3].

It is believed that for some of the victims only their name and contact information was compromised. However, the attackers also extracted passport information, Starwood Preferred Guest numbers, travel information and other personal information. There are claims that credit card information and expiration dates of as many as 100 million customers were stolen, although Marriott is not certain if the hackers were able to decrypt the credit card numbers [3].

The breach was attributed to a Chinese intelligence group which was trying to gather information on US citizens. A few individuals who were brief after an investigation also reported that the intelligence group hacked health insurers and security clearance files of millions of more Americans [3].

It is suspected that the hackers were working on behalf of the Ministry of State Security, the country's Communist-controlled civilian spy agency. This discovery was made while the Trump was planning actions to target China's trade, cyber and economics policies. The actions included criminal accusations against Chinese hackers working for intelligence services and the military, the Trump administration also plans on revealing intelligence reports that reveal Chinese efforts to set up a database containing the names of executives and American governments officials with security clearance [3].

Some of the other options included making it harder for Chinese companies to obtain critical components from telecommunications equipment, as stated by a senior American official [3].

Despite the 90-day truce negotiated by president Trump and President Xi Jinping in Buenos Aires, the administration believes this might do very little to change China's behavior. Since China has coerced American companies to hand over valuable technology if they wish to enter the Chinese market, this also includes theft of industrial secrets on behalf of state-owned companies [3].

The Yahoo data breach was one of the largest data breaches in history, it impacted over 3 billion user accounts. While Yahoo was making negotiations to sell itself to Verizon it revealed that it had been a victim of the biggest data breach, that had been likely committed by a state-sponsored hacker in 2014, the announcement was made in September 2016, 2 years after the breach happened. The data breach compromised the real names, email addresses, date of birth and phone number of 500 million users. Yahoo

reported that most of the passwords involved had been hashed by the bcrypt algorithm [3].

A few months later in the month of December 2018 it covered up the earlier record with the disclosure that a breach in 2013, by another group of cyber thieves had compromised 1 billion accounts. Aside from the names, dates of birth, email addresses and passwords that were protected not as well as the ones involved in the 2014 breach, it is estimated the even security questions and answers were compromised. By October of 2017, Yahoo reviewed that estimate, stating that all 3 billion user accounts had been compromised [3].

The data breaches severely affected Yahoo's sales prices knocking of an estimated \$350 million of the company's sales price. Yahoo, founded in 1994, had been valued at \$100 billion, ultimately Verizon paid \$4.48 billion for Yahoo's core internet business. The agreement meant that the two companies had to share regulatory and legal liabilities from the breaches. Yahoo failed to thoroughly investigate the data breaches and carried on carelessly which ultimately led to the downfall of the company [3].

In late 2016 personal information of 57 million Uber accounts and 600,00 drivers was exposed, Uber did not handle the breach well. By late 2016 the company learned that 2 hackers had extracted names, email addresses, and mobile numbers of 57 million users on the Uber app. They also hacked the drivers license numbers of 600,00 Uber drivers. Apart from this not other information such as credit card and Social Security numbers were stolen. The hackers accessed the information through Uber's GitHub account, where thy were able to find username and password credentials to Uber's AWS account. The username and password credentials should have never been on the GitHub account in the first place [3].

It wasn't until about a year after the incident happened that Uber made the breach public. The worst part was that they paid the hackers \$100,000 to destroy the data with no way of verifying that it was destroyed. Eventually Uber fired it's CSO because of the breach, putting all the blame on him [3].

The breach cost Uber a lot of money and ruined it reputation. At the time when the breach was announced the company was negotiating to sell a stake of the company to Softbank. Uber's was initially valued at \$68 billion by the time the deal was sealed in December; its value dropped to \$48 billion [3].

Data is growing at an exponential rate; it is estimated that nearly 1.7 megabytes of data are created every second. This makes it extremely hard for organizations to keep up and protect their customer's personal information. Poor security practices such as the Uber data breach put organization at risk of a data breach [4].

A data breach can cost an organization millions of dollars and ruin its reputation. In the year 2017, the average cost of a breach was \$3.62 million. If a data breach occurs the

organization faces intense regulatory penalties from an array of institutions. Companies dealing with customer information in the European Union that face a huge breach because of lack of security control can face a penalty of up to 4% Adjusted Gross Revenue or 20 million euros. In order to avoid this companies must make investments in key security technologies such as data archiving, backup and redundant infrastructure to protect their data [4].

Human error is the biggest challenge that is faced in data privacy and security. Employees that are unaware may use weak passwords, mistakenly delete data, browse websites that are not acceptable. Data loss prevention tools can help prevent leaking sensitive data [4].

References

- [1] https://www.learnopencv.com/keras-tutorial-using-pre-trained-imagenet-models/
- [2] <u>https://stackoverflow.com/questions/51699001/tokenizer-texts-to-sequences-keras-tokenizer-gives-almost-all-zeros</u>
- $[3] \qquad \underline{\text{https://www.csoonline.com/article/2130877/the-biggest-data-breaches-of-the-21st-century.html} \\$
- [4] http://blog.cipher.com/the-5-biggest-challenges-in-global-data-privacy-and-data-protection