

Deep_Learning_HW2

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1 Anly 590 HW 2

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1.1.1 (1) Autoencoder

This first problem will deal with images in the mnist fashion data set.

```
In [98]: from keras.layers import Input, Dense, Embedding, LSTM, Bidirectional, SimpleRNN
        from keras.models import Model, Sequential
        from keras.datasets import mnist
        from keras import applications
        import numpy as np
        import matplotlib.pyplot as plt
        %matplotlib inline
        import pandas as pd
        from sklearn.model_selection import train_test_split
        from keras import optimizers
        from keras.layers.convolutional import Conv2D, MaxPooling2D,
        ZeroPadding2D, AveragePooling2D, Conv1D, MaxPooling1D
        from keras.callbacks import EarlyStopping
        from keras.preprocessing.image import ImageDataGenerator
        from keras.layers.normalization import BatchNormalization
        from keras.layers.core import Dense, Dropout, Activation, Flatten, Reshape
        from keras.optimizers import SGD, RMSprop
        from keras.utils import np_utils, to_categorical
        from keras.regularizers import l2
        from keras.preprocessing import sequence
        from sklearn.model_selection import train_test_split
        import string
        from sklearn.metrics import roc_auc_score
        import tensorflow as tf
        from keras.preprocessing.sequence import pad_sequences

In [99]: (x_train, y_train), (x_test, y_test) = tf.keras.datasets.fashion_mnist.load_data()

In [100]: # =====
          # Reshaping data
```

```
# =====
x_train = x_train.reshape(x_train.shape[0], 28, 28,1).astype('float32') / 255
x_test = x_test.reshape(x_test.shape[0], 28, 28,1).astype('float32') / 255
y_train = np_utils.to_categorical(y_train, 10)
y_test = np_utils.to_categorical(y_test, 10)
```

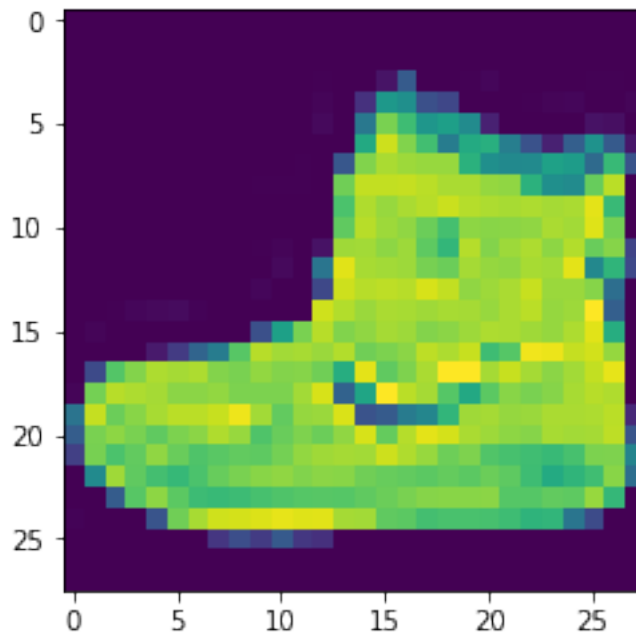
```
In [101]: print(x_train.shape)
          print(x_train[0].flatten().shape)
          x_val = x_train.reshape(60000,28,28)
          x_val = x_val.reshape(60000,784)
```

```
(60000, 28, 28, 1)
(784,)
```

Here is a sample image:

```
In [102]: # example image
          plt.imshow(x_train[0,:,:,:0])
```

```
Out[102]: <matplotlib.image.AxesImage at 0x1e4fe37b70>
```



```
In [103]: # auto encoder model
          auto = Sequential()
          auto.add(Conv2D(filters = 32,kernel_size=(3, 3),
                          activation='relu', strides=(1, 1),
```

```

        padding='valid',
        input_shape=(28,28,1)))
auto.add(Conv2D(filters = 32,kernel_size=(3, 3),
        activation='relu', strides=(1, 1),
        padding='valid'))
auto.add(MaxPooling2D(pool_size=(2,2)))
auto.add(Dropout(0.25))
auto.add(Flatten())
auto.add(Dense(64, activation='relu'))
auto.add(Dropout(0.5))
auto.add(Dense(784, activation='sigmoid'))

```

```
In [104]: auto.compile(optimizer='adadelata', loss='mean_squared_error')
```

```
In [105]: # fit model
auto.fit(x_train, x_val,
        epochs=5,
        batch_size=256,
        shuffle=True,
        verbose=1,
        validation_data=(x_train, x_val))
```

Train on 60000 samples, validate on 60000 samples

Epoch 1/5

60000/60000 [=====] - 129s 2ms/step - loss: 0.1303 - val_loss: 0.0856

Epoch 2/5

60000/60000 [=====] - 131s 2ms/step - loss: 0.0894 - val_loss: 0.0709

Epoch 3/5

60000/60000 [=====] - 131s 2ms/step - loss: 0.0703 - val_loss: 0.0507

Epoch 4/5

60000/60000 [=====] - 131s 2ms/step - loss: 0.0583 - val_loss: 0.0442

Epoch 5/5

60000/60000 [=====] - 130s 2ms/step - loss: 0.0532 - val_loss: 0.0410

```
Out[105]: <keras.callbacks.History at 0x1c3ae65898>
```

```
In [106]: auto.summary()
```

Layer (type)	Output Shape	Param #
conv2d_1 (Conv2D)	(None, 26, 26, 32)	320
conv2d_2 (Conv2D)	(None, 24, 24, 32)	9248
max_pooling2d_1 (MaxPooling2D)	(None, 12, 12, 32)	0
dropout_11 (Dropout)	(None, 12, 12, 32)	0

```

-----
flatten_2 (Flatten)          (None, 4608)          0
-----
dense_11 (Dense)             (None, 64)            294976
-----
dropout_12 (Dropout)         (None, 64)            0
-----
dense_12 (Dense)             (None, 784)           50960
=====
Total params: 355,504
Trainable params: 355,504
Non-trainable params: 0
-----

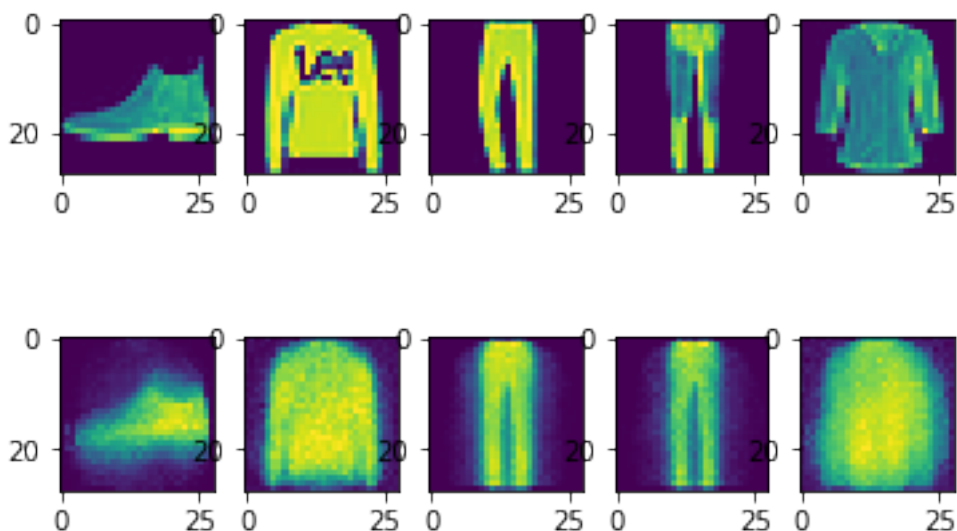
```

```
In [107]: # view some of the reconstructed images
```

```

n=5
for k in range(n):
    ax = plt.subplot(2, n, k+1)
    plt.imshow(x_test[k:k+1,:].reshape((28,28)))
    ax = plt.subplot(2, n, k+1 + n)
    reconstruction = auto.predict(x_test[k:k+1,:])
    #print(reconstruction.shape)
    reconstruction.resize((28,28))
    plt.imshow(reconstruction)

```



Above are some of the original images compared to their reconstructions via the auto encoder.

1.1.2 (2) Image Classification

1.1.3 (2.1) Deep CNN

```
In [108]: # build model
dmodel = Sequential()

dmodel.add(Conv2D(filters = 32, kernel_size=(3, 3),
                  activation='relu', strides=(1, 1),
                  padding='valid', input_shape=(28,28,1)))
dmodel.add(Dropout(0.5))

dmodel.add(Conv2D(filters = 32, kernel_size=(3, 3),
                  activation='relu', strides=(1, 1),
                  padding='valid', input_shape=(28,28,1)))
dmodel.add(Dropout(0.5))

dmodel.add(Conv2D(filters = 32, kernel_size=(3, 3),
                  activation='relu', strides=(1, 1),
                  padding='valid', input_shape=(28,28,1)))
dmodel.add(MaxPooling2D(pool_size=(2, 2)))
dmodel.add(Dropout(0.5))

dmodel.add(Flatten())
dmodel.add(Dense(64))
dmodel.add(Dense(10))
dmodel.add(Activation('softmax'))
```

```
In [112]: # train model
l_rate = 1
sgd = SGD(lr=l_rate, momentum=0.0, decay=0.0, nesterov=False)
dmodel.compile(loss='categorical_crossentropy', optimizer='adam',
               metrics=['accuracy'])
dmodel.fit(x_train, y_train, epochs=1,
           verbose=1, validation_data=(x_test, y_test))
```

Train on 60000 samples, validate on 10000 samples

Epoch 1/1

60000/60000 [=====] - 211s 4ms/step - loss: 0.3041 - acc: 0.8882 - va

Out[112]: <keras.callbacks.History at 0xb20fdd278>

Training accuracy: 88.8%, test accuracy: 90.2%

```
In [123]: # use predefined weights
conv_base = applications.VGG16(weights="imagenet", include_top=False,
                                input_shape=(32,32,3))

model2 = Sequential()
model2.add(conv_base)
```

```

model2.add(Flatten())
model2.add(Dense(128, activation="relu"))
model2.add(Dense(10, activation="sigmoid"))
model2.summary()

```

```

-----
Layer (type)                 Output Shape              Param #
=====
vgg16 (Model)                (None, 1, 1, 512)        14714688
-----
flatten_6 (Flatten)          (None, 512)               0
-----
dense_19 (Dense)              (None, 128)               65664
-----
dense_20 (Dense)              (None, 10)                1290
=====
Total params: 14,781,642
Trainable params: 14,781,642
Non-trainable params: 0
-----

```

```

In [124]: conv_base.trainable = False
          model2.trainable_weights

```

```

Out[124]: [<tf.Variable 'dense_19/kernel:0' shape=(512, 128) dtype=float32_ref>,
            <tf.Variable 'dense_19/bias:0' shape=(128,) dtype=float32_ref>,
            <tf.Variable 'dense_20/kernel:0' shape=(128, 10) dtype=float32_ref>,
            <tf.Variable 'dense_20/bias:0' shape=(10,) dtype=float32_ref>]

```

```

In [125]: model2.compile(loss="categorical_crossentropy", optimizer=RMSprop(1e-4),
                        metrics=["acc"])

```

```

In [119]: x_train2 = np.zeros(60000*32*32*3).reshape(60000,32,32,3)
          x_test2 = np.zeros(10000*32*32*3).reshape(10000,32,32,3)

```

```

for i in range(0,x_train.shape[0]):
    x_train2[i,:,:,:0] = np.pad(x_train[i,:,:,:0],2,mode="constant")
    x_train2[i,:,:,:1] = np.pad(x_train[i,:,:,:0],2,mode="constant")
    x_train2[i,:,:,:2] = np.pad(x_train[i,:,:,:0],2,mode="constant")

```

```

In [126]: x_train2.shape

```

```

Out[126]: (60000, 32, 32, 3)

```

```

In [129]: # fit the model
          datagen = ImageDataGenerator(
              featurewise_center=True,
              featurewise_std_normalization=True,

```

```

        rotation_range=20,
        width_shift_range=0.2,
        height_shift_range=0.2,
        horizontal_flip=True)

    datagen.fit(x_train2)

    model2.fit_generator(datagen.flow(x_train2, y_train, batch_size=32),
                        steps_per_epoch=len(x_train) / 32, epochs=1)

```

```

Epoch 1/1
1875/1875 [=====] - 926s 494ms/step - loss: 0.5530 - acc: 0.7996

```

```
Out[129]: <keras.callbacks.History at 0x1e684c96d8>
```

This model achieved lower accuracy than the Deep CNN, though perhaps with more training the accuracy would increase.

1.1.4 (3) Text Classification

This problem will utilize different NNs to classify web urls as benign or malignant.

```

In [2]: # benign urls from text file
        benign = pd.read_csv("benign-urls.txt", header=None)
        benign.head()

```

```

Out[2]:
0
0          # GOOGLE
1      .0.blogger.gmodules.com
2  .0.client-channel.google.com
3          .0.docs.google.com
4          .0.drive.google.com

```

```

In [3]: benign = benign.iloc[1:]
        benign.head()

```

```

Out[3]:
1      .0.blogger.gmodules.com
2  .0.client-channel.google.com
3          .0.docs.google.com
4          .0.drive.google.com
5          .0.gvt0.cn

```

```

In [4]: # malignant urls from text file
        mal = pd.read_csv("malicious-urls.txt", header=None)
        mal.head()

```

```
Out[4]:
```

	0
0	.1337x.pl
1	.1link.io
2	.1n.pm
3	.22apple.com
4	.22find.com

```
In [5]: benign["type"] = 0
mal["type"] = 1
```

```
In [6]: # concat two dfs
text_class = pd.concat([benign, mal])
text_class.columns = ["url", "type"]
text_class.rename_axis(None)
text_class.head()
```

```
Out[6]:
```

	url	type
1	.0.blogger.gmodules.com	0
2	.0.client-channel.google.com	0
3	.0.docs.google.com	0
4	.0.drive.google.com	0
5	.0.gvt0.cn	0

```
In [7]: text_class[::-1][:10]
```

```
Out[7]:
```

	url	type
1295	.zzbuckettownrock.com	1
1294	.zorpia.com	1
1293	.zophar.net	1
1292	.zoneiasiteoh.com	1
1291	.zkmobi.com	1
1290	.zippyshare.com	1
1289	.zipleisurefansstyles.com	1
1288	.zenmate.com	1
1287	.zend2.com	1
1286	.zebrametalmadnesscast.com	1

```
In [64]: # train test split
x_train, x_test, y_train, y_test = train_test_split(text_class["url"],
                                                    text_class["type"], test_size=0.3
                                                    random_state=42)

x_train[0]
```

```
Out[64]: '.1337x.pl'
```

```
In [65]: print(x_train.shape)
print(x_train[0])
```

```
(47146,)
.1337x.pl
```



```
In [66]: from keras.preprocessing.text import Tokenizer
tokenizer = Tokenizer(char_level=True)
tokenizer.fit_on_texts(x_train)
```

```
In [67]: # convert url strings to character strings
x_train = tokenizer.texts_to_sequences(x_train)
print(x_train[0])
```

```
tokenizer = Tokenizer(char_level=True)
tokenizer.fit_on_texts(x_test)
```

```
x_test = tokenizer.texts_to_sequences(x_test)
print(x_test[0])
```

```
[1, 19, 12, 6, 3, 1, 14, 2, 18, 1, 16, 28]
```

```
[1, 5, 10, 2, 6, 3, 1, 8, 30, 1, 28, 7, 5, 17, 3, 6, 5, 28, 30, 1, 4, 2, 8]
```

```
In [68]: print(type(x_train))
len(x_train)
```

```
<class 'list'>
```

```
Out[68]: 47146
```

```
In [69]: # strings are of different lengths, so pad them
x_train = pad_sequences(x_train, maxlen=86)
x_test = pad_sequences(x_test, maxlen=86)
```

```
In [79]: x_train = np.array(x_train).reshape(47146,86)
x_test = np.array(x_test).reshape(20206,86)
```

The first model will use a Simple RNN

```
In [80]: # build model
model = Sequential()
model.add(Embedding(input_length=86, input_dim=47146, output_dim=4))
model.add(SimpleRNN(16))
model.add(Dropout(0.1))
model.add(Dense(1, activation='sigmoid'))
model.compile('adam', 'binary_crossentropy', metrics=['accuracy'])
```

```
In [83]: model.summary()
```

```
-----
Layer (type)                Output Shape                Param #
=====
embedding_11 (Embedding)    (None, 86, 4)              188584
-----
```

simple_rnn_8 (SimpleRNN)	(None, 16)	336

dropout_10 (Dropout)	(None, 16)	0

dense_10 (Dense)	(None, 1)	17
=====		
Total params: 188,937		
Trainable params: 188,937		
Non-trainable params: 0		

```
In [86]: # fit model
         model.fit(x_train, y_train, epochs=2, verbose=1)
```

```
Epoch 1/2
47146/47146 [=====] - 39s 829us/step - loss: 0.0594 - acc: 0.9810
Epoch 2/2
47146/47146 [=====] - 38s 799us/step - loss: 0.0545 - acc: 0.9812
```

```
Out[86]: <keras.callbacks.History at 0x1a267781d0>
```

This model uses a 1D CNN

```
In [18]: model2 = Sequential()
         model2.add(Conv1D(filters = 32, kernel_size=(3),
                           activation='relu', strides=(1),
                           padding='valid',
                           input_shape=(86,1)))
         model2.add(Conv1D(filters = 32, kernel_size=(3),
                           activation='relu', strides=(1),
                           padding='valid'))
         model2.add(MaxPooling1D(pool_size=(1)))
         model2.add(Dropout(0.25))
         model2.add(Flatten())
         model2.add(Dense(64, activation='relu'))
         model2.add(Dropout(0.5))
         model2.add(Dense(1, activation='sigmoid'))
```

```
In [19]: model2.summary()
```

Layer (type)	Output Shape	Param #
=====		
conv1d_1 (Conv1D)	(None, 84, 32)	128

conv1d_2 (Conv1D)	(None, 82, 32)	3104

```

max_pooling1d_1 (MaxPooling1 (None, 82, 32)          0
-----
dropout_2 (Dropout)          (None, 82, 32)          0
-----
flatten_1 (Flatten)          (None, 2624)          0
-----
dense_2 (Dense)              (None, 64)          168000
-----
dropout_3 (Dropout)          (None, 64)          0
-----
dense_3 (Dense)              (None, 1)           65
=====
Total params: 171,297
Trainable params: 171,297
Non-trainable params: 0
-----

```

```
In [20]: model2.compile(optimizer="rmsprop", loss="binary_crossentropy",
                        metrics=["acc"])
```

```
In [25]: model2.fit(x_train, y_train,
                    epochs=2,
                    batch_size=32,
                    verbose = 1)
```

Epoch 1/2

47146/47146 [=====] - 15s 309us/step - loss: 0.0788 - acc: 0.9800

Epoch 2/2

47146/47146 [=====] - 15s 312us/step - loss: 0.0732 - acc: 0.9805

Out[25]: <keras.callbacks.History at 0x1a2294e2e8>

```
In [87]: y_pred = model.predict_proba(x_test)
        y_guess = (y_pred > .0025)*1
```

```
In [93]: # test accuracy
        round(sum((np.array(list(y_test)) == y_guess)[0]) / y_guess.shape[0],4)
```

Out[93]: 0.9813

```
In [94]: # AUC
        round(roc_auc_score(y_test, y_guess), 2)
```

Out[94]: 0.86

```
In [95]: # set a threshold
        x_test = x_test.reshape(20206,86,1)
        y_pred2 = model2.predict(x_test)
        y_guess2 = (y_pred2 > .0025)*1
```

```
In [96]: # test accuracy
         round(sum((np.array(list(y_test)) == y_guess2)[0]) / y_guess2.shape[0], 4)
```

```
Out[96]: 0.9813
```

```
In [97]: # AUC
         round(roc_auc_score(y_test, y_guess2), 2)
```

```
Out[97]: 0.86
```

The two models have the same test accuracy and the same AUC. They likely get the same results for each url in the test set.