## 1 Autoencoder

Build and fit a convolutional autoencoder for the Fashion MNIST dataset.

- The components of this network will be many of the same pieces we've used with convolutional classification networks: Conv2D, MaxPooling, and so on.
- The encoder part of the network should run the input image through a few convolutional layers of your choice.
- The decoder part of the network will utilize UpSampling2D to get the representation back to the original image size.
- · After training your network, visualize some examples of input images and their decoded reconstruction.

```
In [4]: import tensorflow as tf
        import matplotlib.pyplot as plt
        from keras.datasets import fashion mnist
        from keras.utils import np utils
        %matplotlib inline
        (x_train, y_train), (x_test, y_test) = fashion_mnist.load_data()
        # Reshaping the array to 4-dims so that it can work with the Keras API
        x train = x train.reshape(x train.shape[0], 28, 28, 1)
        x \text{ test} = x \text{ test.reshape}(x \text{ test.shape}[0], 28, 28, 1)
        input shape = (28, 28, 1)
        # Making sure that the values are float so that we can get decimal points after division
        x train = x train.astype('float32')
        x test = x test.astype('float32')
        # Normalizing the RGB codes by dividing it to the max RGB value.
        x train /= 255
        x test /= 255
        #y train = np utils.to categorical(y train, 10)
        #y test = np utils.to categorical(y test, 10)
        print('x train shape:', x train.shape)
        print('Number of images in x train', x train.shape[0])
        print('Number of images in x test', x test.shape[0])
        Downloading data from http://fashion-mnist.s3-website.eu-central-1.amazonaws.com/train-labels-idx1-ubyte.gz
```

```
In [3]: from keras.layers import Input, Dense, Conv2D, MaxPooling2D, UpSampling2D
        from keras.models import Model
        from keras import backend as K
        input img = Input(shape=(28, 28, 1)) # adapt this if using `channels first` image data format
        x = Conv2D(32, (3, 3), activation='relu', padding='same')(input_img)
        x = MaxPooling2D((2, 2), padding='same')(x)
        x = Conv2D(16, (3, 3), activation='relu', padding='same')(x)
        x = MaxPooling2D((2, 2), padding='same')(x)
        x = Conv2D(8, (3, 3), activation='relu', padding='same')(x)
        encoded = MaxPooling2D((2, 2), padding='same')(x)
        # at this point the representation is (4, 4, 8) i.e. 128-dimensional
        x = Conv2D(8, (3, 3), activation='relu', padding='same')(encoded)
        x = UpSampling2D((2, 2))(x)
        x = Conv2D(16, (3, 3), activation='relu', padding='same')(x)
        x = UpSampling2D((2, 2))(x)
        x = Conv2D(32, (3, 3), activation='relu')(x)
        x = UpSampling2D((2, 2))(x)
        decoded = Conv2D(1, (3, 3), activation='sigmoid', padding='same')(x)
        autoencoder = Model(input img, decoded)
        autoencoder.summary()
        autoencoder.compile(optimizer='adadelta', loss='binary crossentropy')
```

(None 20 20 1)	
(None, 28, 28, 1)	0
(None, 28, 28, 32)	320
(None, 14, 14, 32)	0
(None, 14, 14, 16)	4624
(None, 7, 7, 16)	0
(None, 7, 7, 8)	1160
(None, 4, 4, 8)	0
(None, 4, 4, 8)	584
(None, 8, 8, 8)	0
(None, 8, 8, 16)	1168
(None, 16, 16, 16)	0
(None, 14, 14, 32)	4640
(None, 28, 28, 32)	0
(None, 28, 28, 1)	289
	(None, 14, 14, 32) (None, 14, 14, 16) (None, 7, 7, 16) (None, 7, 7, 8) (None, 4, 4, 8) (None, 4, 4, 8) (None, 8, 8, 8) (None, 8, 8, 16) (None, 16, 16, 16) (None, 14, 14, 32) (None, 28, 28, 32)

Non-trainable params: 0

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Train on 60000 samples, validate on 10000 samples Epoch 1/100 Epoch 2/100 Epoch 3/100 Epoch 4/100 60000/60000 [============= ] - 7s 122us/step - loss: 0.3051 - val loss: 0.3076 Epoch 5/100 Epoch 6/100 Epoch 7/100 Epoch 8/100 Epoch 9/100 60000/60000 [============= ] - 7s 122us/step - loss: 0.2935 - val loss: 0.2961 Epoch 10/100 Epoch 11/100 Epoch 12/100 Epoch 13/100 Epoch 14/100 Epoch 15/100 Epoch 16/100 Epoch 17/100 Epoch 18/100 Epoch 19/100 60000/60000 [============= ] - 7s 122us/step - loss: 0.2855 - val loss: 0.2860 Epoch 20/100 Epoch 21/100 Epoch 22/100 Epoch 23/100 Epoch 24/100 60000/60000 [=============] - 7s 122us/step - loss: 0.2838 - val loss: 0.2857 Epoch 25/100 Epoch 26/100 Epoch 27/100

					H W 2_	12			
60000/60000 [======	] –	7s	121us/step	-	loss:	0.2832	- v	al_loss:	0.2834
Epoch 28/100									
6000/6000 [==============	] –	7s	121us/step	-	loss:	0.2825	- v	al_loss:	0.2853
Epoch 29/100		7	101/			0 0004		. 1 . 1	0 0071
60000/60000 [======= Epoch 30/100	] –	/S	121us/step	-	loss:	0.2824	- V	al_loss:	0.28/1
60000/60000 [=================================	1	7.0	121ug/g+op		1000.	0 2021		al logg.	0 2015
Epoch 31/100	] -	75	121us/step	-	TOSS:	0.2821	- v	al_loss:	0.2845
60000/60000 [========================	1 _	7s	121115/sten	_	loss:	0.2818	- 17	al loss:	0.2847
Epoch 32/100	J	, 5	121ub/bccp		1000.	0.2010	•	u1_1000.	0.2017
60000/60000 [========================	1 –	7s	121us/step	_	loss:	0.2817	- v	al loss:	0.2841
Epoch 33/100	•		-					_	
60000/60000 [=============	] –	7s	122us/step	_	loss:	0.2813	- v	al_loss:	0.2824
Epoch 34/100									
60000/60000 [=========	] -	7s	122us/step	-	loss:	0.2811	- v	al_loss:	0.2835
Epoch 35/100									
60000/60000 [=============	] –	7s	121us/step	-	loss:	0.2810	- v	al_loss:	0.2832
Epoch 36/100		7	101/		1	0 0000		. 1 . 1	0 0010
60000/60000 [======================== Epoch 37/100	J –	/S	121us/step	-	loss:	0.2808	- V	al_loss:	0.2819
60000/60000 [=================================	1 _	7 c	12111g/gten	_	1000.	0 2807	_ 37	al logg.	0 2843
Epoch 38/100	]	75	12105/5002		1055.	0.2007	_ v	u1_1055.	0.2013
60000/60000 [=================================	1 –	7s	121us/step	_	loss:	0.2806	- v	al loss:	0.2811
Epoch 39/100	•							_	
=======================================	] –	7s	121us/step	-	loss:	0.2804	- v	al_loss:	0.2817
Epoch 40/100									
60000/60000 [=======	] –	7s	121us/step	-	loss:	0.2803	- v	al_loss:	0.2830
Epoch 41/100		_							
60000/60000 [=================================	] -	7s	122us/step	-	loss:	0.2796	- V	al_loss:	0.2795
Epoch 42/100 60000/60000 [=================================	1	7.0	121ug/g+op		1000.	0 2706		al logg.	0 2022
Epoch 43/100	J –	75	121us/scep	_	1055.	0.2790	- v	a1_1055.	0.2033
60000/60000 [========================	1 –	7s	121us/step	_	loss:	0.2797	- v	al loss:	0.2847
Epoch 44/100	,								
60000/60000 [=================================	] –	7s	120us/step	_	loss:	0.2795	- v	al_loss:	0.2851
Epoch 45/100									
60000/60000 [=======	] -	7s	121us/step	-	loss:	0.2794	- v	al_loss:	0.2811
Epoch 46/100									
60000/60000 [=================================	] –	7s	121us/step	-	loss:	0.2791	- v	al_loss:	0.2828
Epoch 47/100 60000/60000 [=================================	,	7.0	121,12 / 2+05		1000.	0 2701		ol logg.	0 2007
Epoch 48/100	J –	75	121us/scep	_	1055;	0.2/91	- v	ai_ioss:	0.2007
60000/60000 [=========================	1 –	7s	121us/step	_	loss:	0.2783	- v	al loss:	0.2793
Epoch 49/100	J	, 5	12145, 500p		10221	0.2.00	•	u	002,50
60000/60000 [=================================	] –	7s	122us/step	_	loss:	0.2782	- v	al_loss:	0.2793
Epoch 50/100									
6000/60000 [=========	] –	7s	121us/step	-	loss:	0.2783	- v	al_loss:	0.2800
Epoch 51/100		_			_				
60000/60000 [=================================	] –	7s	121us/step	-	loss:	0.2781	- v	al_loss:	0.2797
Epoch 52/100 60000/60000 [=================================	1	7~	121112/2+25		logge	0 2702		al logg:	0 2012
Epoch 53/100	J –	15	121us/scep	-	1055:	0.2/02	- v	u1_1055;	0.2012
60000/60000 [=================================	1 –	7s	122us/step	_	loss:	0.2780	- v	al loss:	0.2828
Epoch 54/100		. ~	, 200p				•		, <b>C _ C</b>
-									

Epoch 00072: early stopping

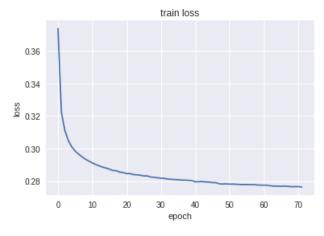
```
Epoch 55/100
Epoch 56/100
60000/60000 [=============] - 7s 122us/step - loss: 0.2779 - val_loss: 0.2798
Epoch 57/100
Epoch 58/100
60000/60000 [=============] - 7s 121us/step - loss: 0.2778 - val loss: 0.2845
Epoch 59/100
Epoch 60/100
Epoch 61/100
Epoch 62/100
60000/60000 [==============] - 7s 121us/step - loss: 0.2774 - val loss: 0.2777
Epoch 63/100
60000/60000 [=============] - 7s 121us/step - loss: 0.2771 - val loss: 0.2779
Epoch 64/100
Epoch 65/100
Epoch 66/100
Epoch 67/100
60000/60000 [============] - 7s 122us/step - loss: 0.2769 - val_loss: 0.2786
Epoch 68/100
60000/60000 [=============] - 7s 121us/step - loss: 0.2768 - val loss: 0.2783
Epoch 69/100
Epoch 70/100
Epoch 71/100
Epoch 72/100
60000/60000 [============== ] - 7s 121us/step - loss: 0.2764 - val loss: 0.2819
```

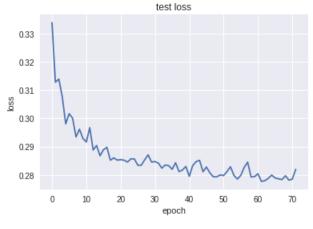
file:///Users/Wupeng/Downloads/HW2\_v2.html

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```
In [5]: # Evaluate

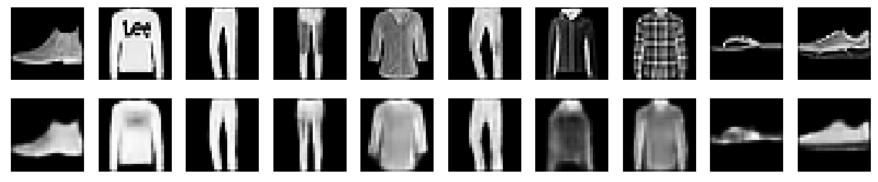
plt.plot(model.history['loss'])
plt.ylabel('loss')
plt.xlabel('epoch')
plt.title('train loss')
plt.show()
plt.plot(model.history['val_loss'])
plt.ylabel('loss')
plt.xlabel('epoch')
plt.title('test loss')
plt.show()
```





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```
In [6]: decoded_imgs = autoencoder.predict(x_test)
        n = 10
        plt.figure(figsize=(20, 4))
        for i in range(n):
            # display original
            ax = plt.subplot(2, n, i+1)
            plt.imshow(x_test[i].reshape(28, 28))
            plt.gray()
            ax.get_xaxis().set_visible(False)
            ax.get_yaxis().set_visible(False)
            # display reconstruction
            ax = plt.subplot(2, n, i + n+1)
            plt.imshow(decoded imgs[i].reshape(28, 28))
            plt.gray()
            ax.get_xaxis().set_visible(False)
            ax.get_yaxis().set_visible(False)
        plt.show()
```



# **Image Classification**

# 2.1Deep CNN

Build a deep CNN to classify the images.

- Provide a brief description of the architectural choices you've made: kernel sizes, strides, padding, network depth.
- Train your network end-to-end. Report on your model's performance on training set and test set.

# In [11]: import tensorflow as tf (x\_train, y\_train), (x\_test, y\_test) = fashion\_mnist.load\_data() # Reshaping the array to 4-dims so that it can work with the Keras API x\_train = x\_train.reshape(x\_train.shape[0], 28, 28, 1) x\_test = x\_test.reshape(x\_test.shape[0], 28, 28, 1) input\_shape = (28, 28, 1) # Making sure that the values are float so that we can get decimal points after division x\_train = x\_train.astype('float32') x\_test = x\_test.astype('float32') # Normalizing the RGB codes by dividing it to the max RGB value. x\_train /= 255 x\_test /= 255 print('x\_train shape:', x\_train.shape) print('Number of images in x\_train', x\_train.shape[0]) print('Number of images in x\_test', x\_test.shape[0])

x\_train shape: (60000, 28, 28, 1)
Number of images in x\_train 60000
Number of images in x test 10000

In [12]: # Importing the required Keras modules containing model and layers from keras.models import Sequential from keras.layers import Dense, Conv2D, Dropout, Flatten, MaxPooling2D from keras.callbacks import EarlyStopping # Creating a Sequential Model and adding the layers model = Sequential() model.add(Conv2D(28, kernel\_size=(3,3), input\_shape=input\_shape)) model.add(MaxPooling2D(pool size=(2, 2))) model.add(Flatten()) # Flattening the 2D arrays for fully connected layers model.add(Dense(128, activation=tf.nn.relu)) model.add(Dropout(0.2)) model.add(Dense(10,activation=tf.nn.softmax)) model.summary() model.compile(optimizer='adam', loss='sparse\_categorical\_crossentropy', metrics=['accuracy']) eary\_stopping = EarlyStopping( monitor='val loss', min\_delta=0, patience=10, verbose=1, mode='auto') callbacks = [eary stopping] deep\_cnn\_model=model.fit(x=x\_train, y=y train, batch\_size=64, epochs=100, validation\_data=(x\_test, y\_test), callbacks=callbacks)

Epoch 00016: early stopping

Layer (type)	Output	Shape	Param #
conv2d_6 (Conv2D)	(None,	26, 26, 28)	280
max_pooling2d_6 (MaxPooling2	(None,	13, 13, 28)	0
flatten_6 (Flatten)	(None,	4732)	0
dense_11 (Dense)	(None,	128)	605824
dropout_6 (Dropout)	(None,	128)	0
dense_12 (Dense)	(None,	10)	1290
Total params: 607,394 Trainable params: 607,394 Non-trainable params: 0			

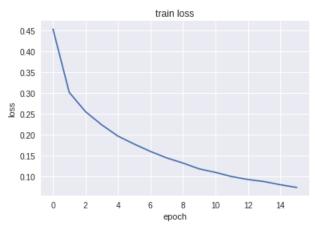
Train on 60000 samples, validate on 10000 samples Epoch 1/100 60000/60000 [===============] - 8s 137us/step - loss: 0.4531 - acc: 0.8393 - val\_loss: 0.3405 - val\_acc: 0.8742 Epoch 2/100 60000/60000 [==============] - 8s 128us/step - loss: 0.3014 - acc: 0.8908 - val loss: 0.3050 - val acc: 0.8886 Epoch 3/100 Epoch 4/100 Epoch 5/100 Epoch 6/100 Epoch 7/100 60000/60000 [=============] - 8s 128us/step - loss: 0.1598 - acc: 0.9409 - val loss: 0.2687 - val acc: 0.9127 Epoch 8/100 60000/60000 [=============] - 8s 127us/step - loss: 0.1443 - acc: 0.9463 - val loss: 0.2618 - val acc: 0.9137 Epoch 9/100 Epoch 10/100 60000/60000 [============== ] - 8s 129us/step - loss: 0.1180 - acc: 0.9556 - val loss: 0.2618 - val acc: 0.9135 Epoch 11/100 60000/60000 [=================] - 8s 129us/step - loss: 0.1096 - acc: 0.9596 - val loss: 0.2821 - val\_acc: 0.9161 Epoch 12/100 60000/60000 [=============] - 8s 129us/step - loss: 0.0995 - acc: 0.9628 - val loss: 0.2898 - val acc: 0.9153 Epoch 13/100 Epoch 14/100 Epoch 15/100 60000/60000 [============== ] - 8s 128us/step - loss: 0.0799 - acc: 0.9701 - val loss: 0.3181 - val acc: 0.9164 Epoch 16/100

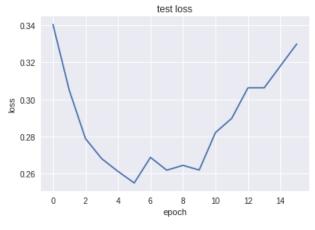
file:///Users/Wupeng/Downloads/HW2\_v2.html

```
In [13]: #Evaluate

plt.plot(deep_cnn_model.history['loss'])
plt.ylabel('loss')
plt.xlabel('epoch')
plt.title('train loss')
plt.show()

plt.plot(deep_cnn_model.history['val_loss'])
plt.ylabel('loss')
plt.xlabel('epoch')
plt.xlabel('epoch')
plt.title('test loss')
plt.show()
```





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# 2.2 Transfer Learning

Repeat the same task, but this time

- utilize a pre-trained network for the major- ity of your model.
- You should only train the final Dense layer, all other weights should be fixed.
- You can use whichever pre-trained backbone you like (ResNet, VGG, etc).
- Report on your model's performance on training set and test set.

```
In [7]: from keras.preprocessing.image import img to array, array to img
        from keras.applications.vgg16 import VGG16, preprocess_input, decode_predictions
        import numpy as np
         # Transfer Learning
        (x train, y train), (x test, y test) = fashion mnist.load_data()
        x_train = x_train.reshape(x_train.shape[0], 784).astype('float32')
        x_test = x_test.reshape(x_test.shape[0], 784).astype('float32')
        # Convert the images into 3 channels
        x_train=np.dstack([x_train] * 3)
        x test=np.dstack([x test]*3)
        x train = x train.reshape(x train.shape[0],28,28,3).astype('float32')
        x_test = x_test.reshape(x_test.shape[0],28,28,3).astype('float32')
        x train = np.asarray([img to array(array to img(im, scale=False).resize((48,48))) for im in x train])
        x test = np.asarray([img to array(array to img(im, scale=False).resize((48,48))) for im in x test])
        x_{train} = x_{train} / 255
        x \text{ test} = x \text{ test} / 255
        #label for each image
        y train = np utils.to categorical(y train, 10)
        y_test = np_utils.to_categorical(y_test, 10)
        IMG WIDTH = 48
        IMG_HEIGHT = 48
        IMG_DEPTH = 3
        BATCH SIZE = 16
        x train = preprocess input(x train)
        x_test = preprocess_input (x_test)
        vgg = VGG16(weights='imagenet',
                          include_top=False,
                          input shape=(IMG HEIGHT, IMG WIDTH, IMG DEPTH)
        vgg.summary()
```

 $Downloading \ data \ from \ https://github.com/fchollet/deep-learning-models/releases/download/v0.1/vgg16\_weights\_tf\_dim\_ordering\_tf\_kernels\_notop.h5$ 

Layer (type)	Output Shape	Param #
input_1 (InputLayer)	(None, 48, 48, 3)	0
block1_conv1 (Conv2D)	(None, 48, 48, 64)	1792
block1_conv2 (Conv2D)	(None, 48, 48, 64)	36928
block1_pool (MaxPooling2D)	(None, 24, 24, 64)	0
block2_conv1 (Conv2D)	(None, 24, 24, 128	73856
block2_conv2 (Conv2D)	(None, 24, 24, 128	147584
block2_pool (MaxPooling2D)	(None, 12, 12, 128	) 0
block3_conv1 (Conv2D)	(None, 12, 12, 256)	) 295168
block3_conv2 (Conv2D)	(None, 12, 12, 256)	590080
block3_conv3 (Conv2D)	(None, 12, 12, 256)	590080
block3_pool (MaxPooling2D)	(None, 6, 6, 256)	0
block4_conv1 (Conv2D)	(None, 6, 6, 512)	1180160
block4_conv2 (Conv2D)	(None, 6, 6, 512)	2359808
block4_conv3 (Conv2D)	(None, 6, 6, 512)	2359808
block4_pool (MaxPooling2D)	(None, 3, 3, 512)	0
block5_conv1 (Conv2D)	(None, 3, 3, 512)	2359808
block5_conv2 (Conv2D)	(None, 3, 3, 512)	2359808
block5_conv3 (Conv2D)	(None, 3, 3, 512)	2359808
block5_pool (MaxPooling2D)	(None, 1, 1, 512)	0

Total params: 14,714,688
Trainable params: 14,714,688
Non-trainable params: 0

```
In [8]: # Extracting features
         train features = vgg.predict(np.array(x train), batch size=BATCH SIZE, verbose=1)
         test_features = vgg.predict(np.array(x_test), batch_size=BATCH_SIZE, verbose=1)
         # # Flatten extracted features
         train features flat = np.reshape(train features, (60000, 1*1*512))
         test_features_flat = np.reshape(test_features, (10000, 1*1*512))
         60000/60000 [============ ] - 68s lms/step
         10000/10000 [============ ] - 11s 1ms/step
In [11]: from keras.layers.advanced activations import LeakyReLU
         from keras.optimizers import SGD, Adam, RMSprop
         from keras.models import Sequential, Model
         from keras.layers import Embedding, LSTM, Dense, Dropout, Activation, Flatten, Input, Conv2D, MaxPooling2D, UpSampling2D
         NB_TRAIN_SAMPLES = train_features_flat.shape[0]
         trans model = Sequential()
         trans_model.add(Dense(512, activation='relu', input_dim=(1*1*512)))
         trans model.add(LeakyReLU(alpha=0.1))
         trans model.add(Dense(10, activation='softmax'))
         trans model.compile(
             loss='categorical_crossentropy',
             optimizer=Adam(),
             metrics=['acc'])
         trans_model.summary()
```

Layer (type)	Output	Shape	Param #
dense_1 (Dense)	(None,	512)	262656
leaky_re_lu_1 (LeakyReLU)	(None,	512)	0
dense_2 (Dense)	(None,	10)	5130
Total params: 267,786 Trainable params: 267,786 Non-trainable params: 0			

Epoch 1/100	-				11-	176/		1 2010 -		0 4070
60000/60000	[======	=======	=======	= ] -	IIS	1/6us/ste	p - loss:	1.3918 – a	cc:	0.4879
Epoch 2/100	-				10-	160/		1 0242 -		0 (101
60000/60000	[======	=======	=======	= ] -	105	169us/ste	p - loss:	1.0343 – a	cc:	0.6181
Epoch 3/100	r			_ 1	10-	160/		0.0520 -		0 (402
60000/60000	[======	=======	=======	= ] -	105	169us/ste	p - loss:	0.9538 - a	cc:	0.6492
Epoch 4/100					10-	170/		0.0066		0.6660
60000/60000	[======	=======	=======	= ] -	105	1/Uus/ste	p - loss:	0.9066 - a	cc:	0.6660
Epoch 5/100	-				10-	170/		0.0000 -		0 6720
60000/60000	[======	=======	=======	= ] -	105	1/Uus/ste	p - loss:	0.8822 - a	cc:	0.6/39
Epoch 6/100	r			_ 1	10-	170/		0.0600		0 (020
60000/60000	[=====			= ] -	105	1/ous/ste	p - loss:	0.8600 - a	cc:	0.6838
Epoch 7/100	r			_ 1	10-	170/		0.0426		0 (000
60000/60000	[=====			= ] -	105	1/ous/ste	p - loss:	0.8426 - a	cc:	0.6908
Epoch 8/100 60000/60000	·			_ 1	100	16700/040	<b>n</b> logg.	0 0220 -	~~.	0 6026
Epoch 9/100	[			-] -	105	10/us/ste	p - 10ss:	0.8320 - a	.cc:	0.0920
60000/60000	r			_ 1	100	160119/9+0	n logg.	0 0210 2	~~.	0 6000
Epoch 10/100				- J -	105	10ous/ste	p - 1055:	0.0210 - a	cc:	0.0909
60000/60000				<b>–</b> 1	100	169119/940	n logg.	0 9166 a	~~•	0 7000
Epoch 11/100				_] _	105	10005/500	p - 1055.	0.0100 - a	cc.	0.7000
60000/60000				=1 _	100	168119/9+0	n - loss.	0 8017 - a	cc •	0 7043
Epoch 12/100				1	105	10005/500	P - 1055.	0.0017 - 4		0.7013
60000/60000				=1 _	100	169119/9+0	n - loss.	0 8004 - a	cc •	0 7057
Epoch 13/100				1	105	10)45/500	P - 1055.	0.0004 - 0		0.7037
60000/60000		=======	========	=1 -	10s	169us/ste	n - loss:	0.7877 - a	cc:	0.7097
Epoch 14/100				,	105	10342,200	P 10001	01,0,,		00,00,
60000/60000		=======		=1 -	10s	169us/ste	p - loss:	0.7841 - a	cc:	0.7102
Epoch 15/100				•			-			
60000/60000		=======	========	=1 -	10s	169us/ste	p - loss:	0.7807 - a	cc:	0.7135
Epoch 16/100				•			-			
60000/60000	[======			=] -	10s	169us/ste	p - loss:	0.7749 - a	cc:	0.7145
Epoch 17/100										
60000/60000	[======			=] -	10s	169us/ste	p - loss:	0.7703 - a	cc:	0.7143
Epoch 18/100	)									
60000/60000	[======	=======	=======	= ] -	10s	171us/ste	p - loss:	0.7653 - a	cc:	0.7182
Epoch 19/100										
60000/60000	[======	=======	========	=] -	10s	168us/ste	p - loss:	0.7627 - a	cc:	0.7200
Epoch 20/100										
60000/60000	[======	=======	========	=] -	10s	168us/ste	p - loss:	0.7601 - a	cc:	0.7195
Epoch 21/100										
60000/60000	-	=======	========	=] -	10s	168us/ste	p - loss:	0.7545 - a	cc:	0.7217
Epoch 22/100										
60000/60000	[======	=======	========	=] -	10s	168us/ste	p - loss:	0.7514 - a	cc:	0.7241
Epoch 23/100										
60000/60000	-	=======	=======	=] -	10s	168us/ste	p - loss:	0.7481 – a	cc:	0.7262
Epoch 24/100				_						
60000/60000				=] -	10s	170us/ste	p - loss:	0.7458 – a	cc:	0.7240
Epoch 25/100				_						
60000/60000		=======	=======	=] -	10s	170us/ste	p - loss:	0.7430 - a	cc:	0.7253
Epoch 26/100				_		167 ( )	,	0 7467		
60000/60000				=] -	10s	16/us/ste	p - loss:	0.7407 - a	cc:	0.7284
Epoch 27/100				,	1.0	167 / :	1	0 7255		0.7000
60000/60000	[=====	=======	=======	= ] -	10s	16/us/ste	p - loss:	u./355 – a	cc:	0./298

Epoch 28/100								
-		 .=====1	_ 10c	168110/0	sten - loss	. 0 7344	- 200.	0 7300
Epoch 29/100		 j	- 108	100us/s	scep - 10ss	. 0./544	- acc.	0.7300
-		 .======1	_ 10s	168119/9	ten - loss	• 0 7318 .	- acc:	0 7302
Epoch 30/100		J	- 101	10005/2	3ccp - 1055	. 0.7510	acc.	0.7502
-		 ======1	- 109	167us/s	step - loss	. 0.7293	- acc:	0.7312
Epoch 31/100		,		. 10,45,2	700P 100D	00,230	4001	017012
		 ======1	- 105	167us/s	step - loss	. 0.7271	- acc:	0.7325
Epoch 32/100		,						
-		 -=====]	- 10s	167us/s	step - loss	. 0.7227	- acc:	0.7359
Epoch 33/100		-			-			
60000/60000	[=======	 =====]	- 10s	166us/s	step - loss	: 0.7200	- acc:	0.7348
Epoch 34/100	)							
60000/60000	[=======	 =====]	- 10s	167us/s	step - loss	<b>0.</b> 7209 -	- acc:	0.7347
Epoch 35/100								
60000/60000	[======	 ======]	- 10s	167us/s	step - loss	<b>:</b> 0.7186 ·	- acc:	0.7353
Epoch 36/100								
		 =====]	- 10s	168us/s	step - loss	: 0.7146	- acc:	0.7385
Epoch 37/100								
		 ======]	- 10s	168us/s	step - loss	: 0.7126	- acc:	0.7381
Epoch 38/100		_	1.0	266 /		0 5100		0 5006
		 -==== j	- 108	166us/s	step - loss	: 0./128	- acc:	0./396
Epoch 39/100		 1	100	16000/		. 0 7117		0 7276
Epoch 40/100		 J	- 108	100us/s	step - Ioss	. 0./11/	- acc:	0./3/6
		 .======1	_ 10s	168119/9	sten - loss	• 0 7093 .	_ acc•	0 7392
Epoch 41/100		J	- 101	10005/2	3ccp - 1055	. 0.7033	- ucc.	0.7352
		 ======1	- 10s	169us/s	step - loss	. 0.7078	- acc:	0.7404
Epoch 42/100		,						
		 -=====]	- 10s	169us/s	step - loss	. 0.7024	- acc:	0.7417
Epoch 43/100		-			-			
60000/60000	[========	 ======]	- 10s	168us/s	step - loss	: 0.7051	- acc:	0.7413
Epoch 44/100	)							
60000/60000	[=======	 =====]	- 108	168us/s	step - loss	: 0.7011 -	- acc:	0.7436
Epoch 45/100								
		 -====]	- 10s	168us/s	step - loss	: 0.7043	- acc:	0.7423
Epoch 46/100								
		 ======]	- 10s	168us/s	step - loss	<b>:</b> 0.6987 ·	- acc:	0.7450
Epoch 47/100		_	1.0	1.60 /		0 5011		0 = 400
	-	 =====]	- 10s	169us/s	step - loss	: 0.7011	- acc:	0.7422
Epoch 48/100		 1	10-	. 170/-		- 0 6000		0 7420
60000/60000 Epoch 49/100		 -==== j	- 108	1/0us/s	step - loss	. 0.6990	- acc:	0.7438
-		 1	100	169110/0	ton loss	. 0 6050	200.	0 7/35
Epoch 50/100		 j	- 108	100us/s	scep - 10ss	. 0.0936	- acc.	0.7433
_		 :=====1	- 109	16605/5	step - loss	. 0.6904	- acc:	0.7460
Epoch 51/100	•	J	101		-5P 1000	. 0.0501		3.,100
		 :======1	- 109	168us/s	step - loss	• 0.6954 ·	- acc:	0.7459
Epoch 52/100		,	-		_			
		 ======]	- 10s	167us/s	step - loss	0.6905	- acc:	0.7449
Epoch 53/100	1							
		 =====]	- 108	167us/s	step - loss	<b>0.</b> 6918 -	- acc:	0.7483
Epoch 54/100								
60000/60000	[=======	 ======]	- 10s	167us/s	step - loss	: 0.6901	- acc:	0.7480

Epoch 55/100	
60000/60000 [=================================	6
Epoch 56/100	,
60000/60000 [=================================	٥
Epoch 57/100	,
60000/60000 [=================================	Λ
Epoch 58/100	J
60000/60000 [=================================	_
Epoch 59/100	J
60000/60000 [=================================	۵
	9
Epoch 60/100	0
60000/60000 [============== ] - 10s 166us/step - loss: 0.6826 - acc: 0.7498	3
Epoch 61/100	_
60000/60000 [=================================	J
Epoch 62/100	_
60000/60000 [=============] - 10s 167us/step - loss: 0.6823 - acc: 0.749	3
Epoch 63/100	
60000/60000 [=============] - 10s 166us/step - loss: 0.6785 - acc: 0.751	9
Epoch 64/100	
60000/60000 [============] - 10s 168us/step - loss: 0.6811 - acc: 0.750	4
Epoch 65/100	
60000/60000 [=================================	0
Epoch 66/100	
60000/60000 [=================================	7
Epoch 67/100	
60000/60000 [=================================	6
Epoch 68/100	
60000/60000 [=================================	1
Epoch 69/100	
60000/60000 [=================================	6
Epoch 70/100	
60000/60000 [=================================	1
Epoch 71/100	
60000/60000 [=================================	5
Epoch 72/100	
60000/60000 [=================================	3
Epoch 73/100	
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Epoch 74/100	-
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Epoch 75/100	,
60000/60000 [=================================	1
Epoch 76/100	1
60000/60000 [=================================	Ω
	5
Epoch 77/100 60000/60000 [=================================	Ω
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Epoch 78/100	7
60000/60000 [============== ] - 10s 168us/step - loss: 0.6693 - acc: 0.753	1
Epoch 79/100	4
60000/60000 [=================================	4
Epoch 80/100	_
60000/60000 [=============] - 10s 166us/step - loss: 0.6651 - acc: 0.756	2
Epoch 81/100	_
60000/60000 [============== ] - 10s 167us/step - loss: 0.6710 - acc: 0.755	2

```
Epoch 82/100
  60000/60000 [============= ] - 10s 167us/step - loss: 0.6645 - acc: 0.7581
  Epoch 83/100
  Epoch 84/100
  Epoch 85/100
  Epoch 86/100
  Epoch 87/100
  60000/60000 [============= ] - 10s 169us/step - loss: 0.6604 - acc: 0.7588
  Epoch 88/100
  Epoch 89/100
  Epoch 90/100
  Epoch 91/100
  Epoch 92/100
  60000/60000 [============ ] - 10s 168us/step - loss: 0.6565 - acc: 0.7614
  Epoch 93/100
  Epoch 94/100
  Epoch 95/100
  Epoch 96/100
  Epoch 97/100
  60000/60000 [=============] - 10s 169us/step - loss: 0.6566 - acc: 0.7606
  Epoch 98/100
  Epoch 99/100
  Epoch 100/100
  In [13]: # Evaluate the model
```

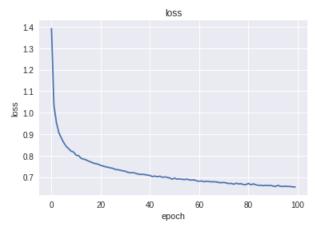
print('Test Loss and Accuracy:', score)

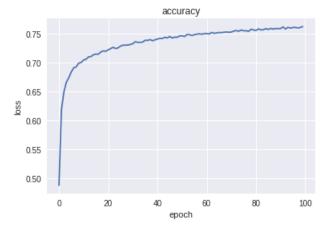
Test Loss and Accuracy: [0.6929168213844299, 0.7504]

score = trans model.evaluate(test\_features\_flat, y\_test, verbose=0)

```
In [16]: #Evaluate

plt.plot(transfer_model.history['loss'])
    plt.ylabel('loss')
    plt.xlabel('epoch')
    plt.title('loss')
    plt.show()
    plt.plot(transfer_model.history['acc'])
    plt.ylabel('loss')
    plt.xlabel('epoch')
    plt.xlabel('epoch')
    plt.title('accuracy')
    plt.show()
```





# 3 Text classification

### **3.1 RNN**

Build and train a Recurrent Neural Network to solve this text classification task. You can use any type of RNN you wish (SimpleRNN, GRU, LSTM).

```
In [2]: %matplotlib inline
        import numpy as np
        import tensorflow as tf
        import pandas as pd
        import matplotlib.pyplot as plt
        import skimage
        import itertools
        from string import printable
        from keras import backend as K
        from skimage.transform import resize
        from keras.datasets import fashion mnist
        from keras import regularizers
        from keras import callbacks
        from keras.models import Sequential, Model
        from keras.layers import Embedding, LSTM, Dense, Dropout, Activation, Flatten, Input, Conv2D, MaxPooling2D, UpSampling2D
        from keras.layers import BatchNormalization, Lambda, Convolution1D, Convolution2D, ELU, concatenate
        from keras.utils import np utils
        from keras.applications.vgg16 import VGG16, preprocess input, decode predictions
        from keras.preprocessing import image
        from keras.preprocessing.image import img to array, array to img
        from keras.preprocessing.text import Tokenizer
        from keras.preprocessing.sequence import pad sequences
        from sklearn.model_selection import train_test_split
        from sklearn.feature extraction.text import CountVectorizer
        from sklearn.metrics import roc curve, auc
        from keras.optimizers import SGD, Adam, RMSprop
        from keras.layers.advanced activations import LeakyReLU
        from keras.callbacks import EarlyStopping
```

Using TensorFlow backend.

```
In [7]: import urllib3 # the lib that handles the url stuff
        http = urllib3.PoolManager()
        r benign = http.request('GET', 'https://s3.amazonaws.com/anly-590/url-classification/benign-urls.txt')
        beni=r benign.data.decode('utf-8').splitlines()
        beni=[w for w in beni if "#" not in w]
        r mali = http.request('GET', 'https://s3.amazonaws.com/anly-590/url-classification/malicious-urls.txt')
        mali=r mali.data.decode('utf-8').splitlines()
        mali=[w for w in mali if "#" not in w]
        /usr/local/lib/python3.6/dist-packages/urllib3/connectionpool.py:858: InsecureRequestWarning: Unverified HTTPS request is being m
        ade. Adding certificate verification is strongly advised. See: https://urllib3.readthedocs.io/en/latest/advanced-usage.html#ssl-w
        arnings
          InsecureRequestWarning)
        /usr/local/lib/python3.6/dist-packages/urllib3/connectionpool.py:858: InsecureRequestWarning: Unverified HTTPS request is being m
        ade. Adding certificate verification is strongly advised. See: https://urllib3.readthedocs.io/en/latest/advanced-usage.html#ssl-w
        arnings
          InsecureRequestWarning)
In [0]: import numpy as np
        import pandas as pd
        from string import printable
        from keras.preprocessing.sequence import pad sequences
        from sklearn.model selection import train test split
        x train = beni + mali
        y train = np.concatenate( [ np.ones(len(beni)), np.zeros(len(mali)) ])
        df = pd.DataFrame({'urls':x_train, 'label':y_train})
        # considering Python's 100 printable characters only and convert them to int
        url int tokens = [[printable.index(x) + 1 for x in url if x in printable] for url in df.urls]
        # All URLs have to be of the same length. This results in cropping or padding with zeros. I choose a max length of 75 characters.
        max len=75
        X = pad sequences(url int tokens, maxlen=max len)
        # convert labels form df to numpy array
        target = np.array(df.label)
```

file:///Users/Wupeng/Downloads/HW2 v2.html

X train, X test, target train, target test = train test split(X, target, test size=0.25, random state=33)

In [10]: from keras import regularizers from keras.layers import Embedding, LSTM, Dense, Dropout, Activation, Flatten, Input, Conv2D from keras.models import Sequential, Model from keras.optimizers import SGD, Adam, RMSprop # LSTM Model main input = Input(shape=(75,), dtype='int32', name='main input') # Embedding layer emb = Embedding(input\_dim=100, output\_dim=32, input\_length=75, dropout=0.2, W regularizer=regularizers.12(1e-4))(main input) # LSTM layer lstm = LSTM(32)(emb)lstm = Dropout(0.5)(lstm)# Output layer (last fully connected layer) output = Dense(1, activation='sigmoid', name='output')(lstm) # Compile model and define optimizer model = Model(input=[main input], output=[output]) adam = Adam(1r=1e-4, beta 1=0.9, beta 2=0.999, epsilon=1e-08, decay=0.0)model.compile(optimizer=adam, loss='binary crossentropy', metrics=['accuracy']) model.summary()

/usr/local/lib/python3.6/dist-packages/ipykernel\_launcher.py:10: UserWarning: The `dropout` argument is no longer support in `Emb edding`. You can apply a `keras.layers.SpatialDropout1D` layer right after the `Embedding` layer to get the same behavior.

# Remove the CWD from sys.path while we load stuff.

/usr/local/lib/python3.6/dist-packages/ipykernel\_launcher.py:10: UserWarning: Update your `Embedding` call to the Keras 2 API: `Embedding(input\_dim=100, output\_dim=32, input\_length=75, embeddings\_regularizer=<keras.reg...)`

# Remove the CWD from sys.path while we load stuff.

Layer (type)	Output Shape	Param #
main_input (InputLayer)	(None, 75)	0
embedding_2 (Embedding)	(None, 75, 32)	3200
lstm_1 (LSTM)	(None, 32)	8320
dropout_8 (Dropout)	(None, 32)	0
output (Dense)	(None, 1)	33
Total params: 11,553 Trainable params: 11,553 Non-trainable params: 0		

/usr/local/lib/python3.6/dist-packages/ipykernel\_launcher.py:20: UserWarning: Update your `Model` call to the Keras 2 API: `Model (inputs=[<tf.Tenso..., outputs=[<tf.Tenso...)`

```
In [26]: from keras.callbacks import EarlyStopping
   eary stopping = EarlyStopping(
     monitor='loss',
     min delta=0,
     patience=10,
     verbose=1,
     mode='auto')
   model.fit(X train, target train, epochs=10, batch size=32, callbacks=[eary stopping])
   Epoch 1/10
   Epoch 2/10
   Epoch 3/10
   Epoch 4/10
   Epoch 5/10
   50483/50483 [============] - 84s 2ms/step - loss: 0.0194 - acc: 0.9912
   Epoch 6/10
   Epoch 7/10
   Epoch 8/10
   Epoch 9/10
   Epoch 10/10
   Out[26]: <keras.callbacks.History at 0x7f517ece7ef0>
In [27]: loss, accuracy = model.evaluate(X test, target test, verbose=1)
   print('Accuracy: ', accuracy, '\n')
   Accuracy: 0.98924411690544
```

### **3.2 CNN**

Build and train a 1D CNN for this text classification task. You might gain some insight and inspiration from these text classification approaches: • <a href="http://www.aclweb.org/anthology/D14-1181">http://www.aclweb.org/anthology/D14-1181</a>) • <a href="http://www.aclweb.org/anthology/D14-1181">https://arxiv.org/abs/1702.08568</a> (https://arxiv.org/abs/1702.08568)

```
In [28]: # CNN Model
         max len=75
         emb dim=32
         max vocab len=100
         W reg=regularizers.12(1e-4)
         main_input = Input(shape=(max_len,), dtype='int32', name='main_input')
         # Embedding layer
         emb = Embedding(input dim=max vocab len, output dim=emb dim, input length=max len,
                     W regularizer=W reg)(main input)
         emb = Dropout(0.25)(emb)
         /usr/local/lib/python3.6/dist-packages/ipykernel launcher.py:11: UserWarning: Update your `Embedding` call to the Keras 2 API: `E
         mbedding(input dim=100, output dim=32, input length=75, embeddings regularizer=<keras.reg...)
           # This is added back by InteractiveShellApp.init path()
In [29]: def sum 1d(X):
             return K.sum(X, axis=1)
         def get conv layer(emb, kernel size=5, filters=256):
             # Conv layer
             conv = Convolution1D(kernel size=kernel size, filters=filters, \
                          border_mode='same')(emb)
             conv = ELU()(conv)
             conv = Lambda(sum 1d, output shape=(filters,))(conv)
             #conv = BatchNormalization(mode=0)(conv)
             conv = Dropout(0.5)(conv)
             return conv
         # Multiple Conv Layers
         # calling custom conv function from above
         conv1 = get conv layer(emb, kernel size=2, filters=256)
         conv2 = get conv layer(emb, kernel size=3, filters=256)
         conv3 = get conv layer(emb, kernel size=4, filters=256)
         conv4 = get conv layer(emb, kernel size=5, filters=256)
         /usr/local/lib/python3.6/dist-packages/ipykernel launcher.py:6: UserWarning: Update your `Conv1D` call to the Keras 2 API: `Conv1
         D(kernel size=2, filters=256, padding="same")
         /usr/local/lib/python3.6/dist-packages/ipykernel launcher.py:6: UserWarning: Update your `Conv1D` call to the Keras 2 API: `Conv1
         D(kernel size=3, filters=256, padding="same")
         /usr/local/lib/python3.6/dist-packages/ipykernel launcher.py:6: UserWarning: Update your `Conv1D` call to the Keras 2 API: `Conv1
         D(kernel size=4, filters=256, padding="same")
         /usr/local/lib/python3.6/dist-packages/ipykernel launcher.py:6: UserWarning: Update your `Conv1D` call to the Keras 2 API: `Conv1
         D(kernel size=5, filters=256, padding="same")
```

```
In [30]: # Fully Connected Layers
         merged = concatenate([conv1,conv2,conv3,conv4], axis=1)
         hidden1 = Dense(1024)(merged)
         hidden1 = ELU()(hidden1)
         hidden1 = BatchNormalization(mode=0)(hidden1)
         hidden1 = Dropout(0.5)(hidden1)
         hidden2 = Dense(1024)(hidden1)
         hidden2 = ELU()(hidden2)
         hidden2 = BatchNormalization(mode=0)(hidden2)
         hidden2 = Dropout(0.5)(hidden2)
         # Output layer (last fully connected layer)
         output = Dense(1, activation='sigmoid', name='output')(hidden2)
         # Compile model and define optimizer
         cnn model = Model(input=[main input], output=[output])
         adam = Adam(lr=1e-4, beta_1=0.9, beta_2=0.999, epsilon=1e-08, decay=0.0)
         cnn model.compile(optimizer=adam, loss='binary crossentropy', metrics=['accuracy'])
         cnn model.summary()
```

/usr/local/lib/python3.6/dist-packages/ipykernel\_launcher.py:5: UserWarning: Update your `BatchNormalization` call to the Keras 2 API: `BatchNormalization()`

/usr/local/lib/python3.6/dist-packages/ipykernel\_launcher.py:10: UserWarning: Update your `BatchNormalization` call to the Keras 2 API: `BatchNormalization()`

# Remove the CWD from sys.path while we load stuff.

Layer (type) 	Output	Shape	Param #	Connected to
main_input (InputLayer)	(None,	75)	0	
embedding_6 (Embedding)	(None,	75, 32)	3200	main_input[0][0]
dropout_12 (Dropout)	(None,	75, 32)	0	embedding_6[0][0]
conv1d_5 (Conv1D)	(None,	75, 256)	16640	dropout_12[0][0]
convld_6 (ConvlD)	(None,	75, 256)	24832	dropout_12[0][0]
conv1d_7 (Conv1D)	(None,	75, 256)	33024	dropout_12[0][0]
convld_8 (ConvlD)	(None,	75, 256)	41216	dropout_12[0][0]
elu_7 (ELU)	(None,	75, 256)	0	convld_5[0][0]
elu_8 (ELU)	(None,	75, 256)	0	convld_6[0][0]
elu_9 (ELU)	(None,	75, 256)	0	conv1d_7[0][0]
elu_10 (ELU)	(None,	75, 256)	0	conv1d_8[0][0]
lambda_5 (Lambda)	(None,	256)	0	elu_7[0][0]
lambda_6 (Lambda)	(None,	256)	0	elu_8[0][0]
lambda_7 (Lambda)	(None,	256)	0	elu_9[0][0]
lambda_8 (Lambda)	(None,	256)	0	elu_10[0][0]
dropout_13 (Dropout)	(None,	256)	0	lambda_5[0][0]
dropout_14 (Dropout)	(None,	256)	0	lambda_6[0][0]
dropout_15 (Dropout)	(None,	256)	0	lambda_7[0][0]
dropout_16 (Dropout)	(None,	256)	0	lambda_8[0][0]
concatenate_2 (Concatenate)	(None,	1024)	0	dropout_13[0][0] dropout_14[0][0] dropout_15[0][0] dropout_16[0][0]
dense_3 (Dense)	(None,	1024)	1049600	concatenate_2[0][0]
elu_11 (ELU)	(None,	1024)	0	dense_3[0][0]
batch_normalization_3 (BatchNor	(None,	1024)	4096	elu_11[0][0]
dropout_17 (Dropout)	(None,	1024)	0	batch_normalization_3[0][0]

```
dropout_17[0][0]
     dense 4 (Dense)
                       (None, 1024)
                                  1049600
     elu 12 (ELU)
                       (None, 1024)
                                  0
                                         dense_4[0][0]
     batch_normalization_4 (BatchNor (None, 1024)
                                  4096
                                         elu_12[0][0]
     dropout 18 (Dropout)
                                  0
                                         batch normalization 4[0][0]
                       (None, 1024)
     output (Dense)
                       (None, 1)
                                  1025
                                         dropout 18[0][0]
     Total params: 2,227,329
     Trainable params: 2,223,233
     Non-trainable params: 4,096
     /usr/local/lib/python3.6/dist-packages/ipykernel launcher.py:17: UserWarning: Update your `Model` call to the Keras 2 API: `Model
     (inputs=[<tf.Tenso..., outputs=[<tf.Tenso...)
In [31]: epochs = 10
     batch size = 25
     eary stopping = EarlyStopping(
       monitor='loss',
       min delta=0,
       patience=10,
       verbose=1,
       mode='auto')
     cnn model.fit(X train, target train, epochs=epochs, batch size=batch size, callbacks=[eary stopping])
     Epoch 1/10
     Epoch 2/10
     Epoch 3/10
     Epoch 4/10
     Epoch 5/10
     Epoch 6/10
     Epoch 7/10
     Epoch 8/10
     Epoch 9/10
     Epoch 10/10
     50483/50483 [============= ] - 195s 4ms/step - loss: 0.0447 - acc: 0.9828
Out[31]: <keras.callbacks.History at 0x7f517df3df60>
```

### 3.3

Be sure to directly compare your two methods with an ROC curve or similar validation method. Don't forget to create a train-test split.

```
In [33]: # LSTM and CNN ROC Curve
         y pred keras = model.predict(X test).ravel()
         fpr_keras, tpr_keras, thresholds_keras = roc_curve(target_test, y_pred_keras)
         auc_keras = auc(fpr_keras, tpr_keras)
         cnn y pred keras = cnn model.predict(X test).ravel()
         cnn fpr keras, cnn tpr keras, cnn thresholds keras = roc curve(target test, cnn y pred keras)
         cnn auc keras = auc(cnn fpr keras, cnn tpr keras)
         plt.figure(1)
         plt.plot([0, 1], [0, 1], 'k--')
         plt.plot(fpr keras, tpr keras, label='LSTM (area = {:.3f})'.format(auc keras))
         plt.plot(cnn fpr keras, cnn tpr keras, label='CNN (area = {:.3f})'.format(cnn auc keras))
         plt.xlabel('False positive rate')
         plt.ylabel('True positive rate')
         plt.title('ROC curve')
         plt.legend(loc='best')
         plt.show()
```

