RNN - IMDB Review

This project is to use RNN to explore the sentiment analysis using IMDB dataset.

Keras comes with few built-in datasets and IMDB review is one of them. It's easy to use this dataset as there is no text prepressing needed.

Load and take a peak on IMDB dataset

More details of the dataset can be found here (https://keras.io/datasets/)

In [30]:
```
import keras
import tensorflow as tf
import numpy as np
from keras import datasets, layers, utils

# To reproduce the same result
np.random.seed(0)
tf.set_random_seed(0)

print(tf.__version__)
print(keras.__version__)
```

```
1.3.0
2.0.8
```

In [31]:
```
dir(datasets)
```

Out[31]:
```
['__builtins__',
 '__cached__',
 '__doc__',
 '__file__',
 '__loader__',
 '__name__',
 '__package__',
 '__path__',
 '__spec__',
 'absolute_import',
 'boston_housing',
 'cifar',
 'cifar10',
 'cifar100',
 'imdb',
 'mnist',
 'reuters']
```

In [32]:
```
imdb = datasets.imdb
print(dir(imdb))
print(imdb.load_data.__doc__)
```

```
['__builtins__', '__cached__', '__doc__', '__file__', '__loader__', '__name__', '__package__', '__spec__', '_remove_long_seq', 'absolu
te_import', 'get_file', 'get_word_index', 'json', 'load_data', 'np', 'warnings', 'zip']
Loads the IMDB dataset.

    # Arguments
        path: where to cache the data (relative to `~/.keras/dataset`).
        num_words: max number of words to include. Words are ranked
            by how often they occur (in the training set) and only
            the most frequent words are kept
        skip_top: skip the top N most frequently occurring words
            (which may not be informative).
        maxlen: truncate sequences after this length.
        seed: random seed for sample shuffling.
        start_char: The start of a sequence will be marked with this character.
            Set to 1 because 0 is usually the padding character.
        oov_char: words that were cut out because of the `num_words`
            or `skip_top` limit will be replaced with this character.
        index_from: index actual words with this index and higher.

    # Returns
        Tuple of Numpy arrays: `(x_train, y_train), (x_test, y_test)`.

    # Raises
        ValueError: in case `maxlen` is so low
            that no input sequence could be kept.

    Note that the 'out of vocabulary' character is only used for
    words that were present in the training set but are not included
    because they're not making the `num_words` cut here.
    Words that were not seen in the training set but are in the test set
    have simply been skipped.
```

In [33]:
```
# Get the top 5000 words
(x_train, y_train), (x_test, y_test) = imdb.load_data(num_words=5000, seed=0)
print("Shape of x_train: ", x_train.shape)
print("Shape of y_train: ", y_train.shape)
print("Shape of x_test: ", x_test.shape)
print("Shape of y_test: ", y_test.shape)
X = np.concatenate((x_train, x_test), axis=0)
y = np.concatenate((y_train, y_test), axis=0)
```

```
Shape of x_train:  (25000,)
Shape of y_train:  (25000,)
Shape of x_test:  (25000,)
Shape of y_test:  (25000,)
```

In [34]:
```
# Get the word to index of IMDB, then convert it to index to word
word_index = imdb.get_word_index()
index_word = {v:k for k, v in word_index.items()}

# Convert the index to word, not so readable, but this is how NLP works
restore_word = [index_word[i] for i in X[0]]
print("Index:\n", X[0])
print("Word:\n", ' '.join(restore_word))
```

```
Index:
 [1, 4078, 2, 9, 448, 725, 4, 2, 241, 2, 241, 38, 111, 2, 500, 40, 91, 374, 500, 679, 102, 13, 62, 135, 4, 2159, 92, 2, 83, 6, 275, 34
49, 66, 73, 5, 15, 271, 18, 14, 31, 99, 2149, 10, 10, 225, 6, 184, 196, 2, 63, 2568, 5, 732, 4, 863, 18, 4, 65, 5, 4, 1397, 1111, 23,
63, 6, 564, 4892, 2, 5, 27, 476, 577, 2, 2, 2, 5, 492, 2, 2, 2, 216, 8, 847, 83, 4, 2, 92, 168, 32, 99, 2575, 5, 515, 195, 481, 2017,
9, 348, 44, 4, 2, 23, 4, 1111, 8, 789, 2, 280, 4, 2, 517, 2, 10, 10, 1958, 5, 1364, 183, 380, 8, 140, 2, 5, 263, 2, 140, 23, 6, 1973,
3318, 187, 4, 3450, 8, 1974, 618, 51, 9, 1448, 23, 14, 2, 1111, 19, 94, 680, 2, 21, 11, 882, 25, 80, 24, 1414, 19, 803, 170, 23, 17,
2, 5, 2447, 2953, 79, 1376, 11, 8, 2, 4, 114, 60, 53, 51, 16, 66, 3742, 12, 83, 4, 2, 7, 78, 212, 26, 94, 2, 1815, 2611, 46, 7, 4, 2,
388, 63, 43, 2266, 2, 2, 33, 94, 2099, 3002, 366, 45, 1852, 76, 303, 45, 31, 155, 269, 8, 216, 56, 5, 984, 142, 1393, 21, 160, 155, 39
9, 12, 4521, 5, 19, 2, 2380, 10, 10, 466, 12, 2, 11, 467, 1552, 234, 13, 104, 45, 6, 189, 20, 2, 8, 28, 15, 17, 6, 2, 2, 12, 408, 15,
220, 107, 534, 235, 19, 94, 550, 2, 8, 376, 51, 12, 494, 8, 183, 895, 8, 1261, 56, 1841, 4, 236, 891, 234, 21, 45, 6, 356, 420, 7, 99,
117, 99, 522, 10, 10, 51, 3220, 4, 20, 9, 89, 12, 1443, 2, 5, 94, 3411, 33, 4, 130, 174, 14, 9, 6, 1141, 2701, 343, 8, 353, 5, 2, 6, 1
573, 606, 189, 20, 83, 142, 6, 117, 227, 1727, 11, 4, 440, 7, 2, 35, 311, 12, 679, 46, 247, 2, 21, 889, 6, 78, 2, 17, 490, 235, 4563,
643, 50, 26, 107, 771, 6, 1009, 80, 97, 25, 235, 12, 345, 2, 4, 20, 8, 6, 906, 651, 42, 1568, 25, 19, 15, 2, 547, 472, 4078, 2, 2, 53,
8, 4, 1569, 10, 10, 4, 1907, 1698, 80, 30, 94, 627, 19, 94, 361, 7, 641, 3788, 5, 2, 21, 13, 80, 30, 15, 3759, 45, 131, 24, 290, 4, 5
8, 38, 128, 8, 798, 14]
Word:
 the brains and it fans moving of and am and am her plot and b just its remember b modern characters was story why of pair then and fi
rst is money bride had much to for book but as by movies utter i i music is around both and really vietnam to oscar of surprise but of
their to of hey visual are really is violence ham and to be history chance and and and to works and and and saw in learn first of and
then few an movies crying to sometimes that's totally foot it dead has of and are of visual in feature and true of and gave and i i op
posite to contains seems sex in through and to comes and through are is blonde bears however of occurs in here's musical when it likab
le are as and visual film make call and not this nor have into his feelings film sorry part are movie and to texas interpretation also
historical this in and of little which up when with had warrior that first of and br do must he make and gold san some br of and under
stand really out rules and and they make thomas stylish friends if creating get seem if by 10 looks in saw she to create back numbers
not funny 10 early that miike to film and europe i i throughout that and this 4 impressed since was two if is fact on and in one for m
ovie is and and that lines for family seen stories might film make anyway and in stupid when that tries in seems credits in glad she s
oap of performance unless since not if is need liked br movies over movies etc i i when larger of on it don't that six and to make llo
yd they of here cast as it is appreciate interview short in classic to and is winning hell fact on first back is over far character's
this of mr br and so night that modern some girl and not meets is do and movie guys might virginia cool more he seen haven't is missin
g into could have might that given and of on in is meet happy it's stuck have film for and slow □ brains and and up in of extreme i i
of villains williams into at make ends film make low br usual hysterical to and not was into at for poster if these his main of my her
still in typical as
```

Preprocessing

In [35]:
```
# The max and min length of a review in terms of the count of words
print("Max length of a review: ", max(len(str) for str in X))
print("Min length of a review: ", min(len(str) for str in X))

# Let's use 300 as the cut-off value
max_words = 300
gt300 = sum(len(str) > max_words for str in X)
print("There are {:.0%}".format(gt300/len(X)), "of reviews are more than", max_words, "words")
```

```
Max length of a review:  2494
Min length of a review:  7
There are 23% of reviews are more than 300 words
```

In [36]:
```
# Padding or truncating the reviews to limit it to 300 words
from keras.preprocessing.sequence import pad_sequences
X = pad_sequences(X, maxlen=max_words)

# A sample of padding at the end
print(X[2])
print(y[2])
```

```
[   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    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    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    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    0    0    0    0    0    0    0    0    0    0    1   14    9
   31    7  148  102  198  269    8   30 4378    5 3094    5  305  630   56
    2   32  120  410  260  110   12   33    6    2   22 1413   13   16 3704
   34    4  185 1170    2  825  355  901   56  190  120   32 1054   56  179
  685   10   10   45  254    8    2    6  283   65  237  225   24   76   15
   70   30  224   44    4  114   21   13  258   14 4229 3650    5    2 2279
   45  465    5  220 2950 3370    6    2  948 3174    7    4 4039   19    2
  228    5    2  491 1969   12   43  152  157   49  139  121   38  954   15
  305    7    2 4299   61  311   16    2    2    5 2660  523   10   10    4
   65   47   35  221  863   21   14   43    2    2   83    6  465 4309    2]
0
```

Build and train the model

In [41]:
```
from keras.models import Sequential, Model
from keras.layers import Dense, LSTM, Dropout, Input
from keras.layers.embeddings import Embedding
from keras.optimizers import RMSprop, Adam
from keras.callbacks import ModelCheckpoint, ReduceLROnPlateau, LambdaCallback, EarlyStopping
from sklearn.model_selection import train_test_split
import keras.backend as K

#X = X.reshape(X.shape[0], X.shape[1], 1)
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3, random_state=0)

print(X_train.shape)
print(X_test.shape)
```

```
(35000, 300)
(15000, 300)
```

In [42]:
```
# Size of the vacabulary
num_top_words = 5000
# Output Embedding dimension
embedding_vector_len = 64

inp = Input(shape=(X_train.shape[1],))
x = Embedding(num_top_words, embedding_vector_len, input_length=max_words)(inp)
x = LSTM(100, return_sequences=True)(x)
x = LSTM(100)(x)
x = Dropout(0.2)(x)
output = Dense(1, activation='sigmoid')(x)

model = Model(inputs=inp, outputs=output)
model.summary()
```

```
_________________________________________________________________
Layer (type)                 Output Shape              Param #   
=================================================================
input_6 (InputLayer)         (None, 300)               0         
_________________________________________________________________
embedding_6 (Embedding)      (None, 300, 64)           320000    
_________________________________________________________________
lstm_9 (LSTM)                (None, 300, 100)          66000     
_________________________________________________________________
lstm_10 (LSTM)               (None, 100)               80400     
_________________________________________________________________
dropout_3 (Dropout)          (None, 100)               0         
_________________________________________________________________
dense_6 (Dense)              (None, 1)                 101       
=================================================================
Total params: 466,501
Trainable params: 466,501
Non-trainable params: 0
_________________________________________________________________
```

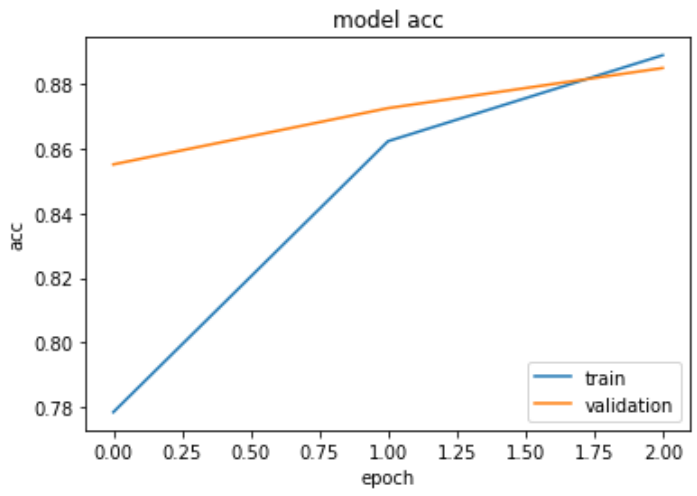
In [43]:
```
# Even though below callback may not be necessary, still included in this project
reduce_lr = ReduceLROnPlateau(monitor='val_loss', factor=0.9, patience=3, min_lr=0.0001)
lr_print = LambdaCallback(on_epoch_begin=lambda epoch,logs: print("lr:", K.eval(model.optimizer.lr)))
early_stopping = EarlyStopping(monitor='val_loss',min_delta=0,patience=3,verbose=1,mode='auto')
checkpoint = ModelCheckpoint(filepath, monitor='loss', verbose=1, save_best_only=True)

filepath = 'IMDB.h5'
model.compile(loss='binary_crossentropy', optimizer='RMSprop', metrics=['accuracy'])
```

In [44]:
```
history = model.fit(X_train, y_train, epochs=3, batch_size = 100,
                    callbacks=[checkpoint, reduce_lr, lr_print, early_stopping],
                    validation_split=0.2)
```

```
Train on 28000 samples, validate on 7000 samples
lr: 0.001
Epoch 1/3
27900/28000 [============================>.] - ETA: 0s - loss: 0.4730 - acc: 0.7782Epoch 00000: loss improved from inf to 0.47273, sav
ing model to IMDB.h5
28000/28000 [==============================] - 274s - loss: 0.4727 - acc: 0.7784 - val_loss: 0.3367 - val_acc: 0.8551
lr: 0.001
Epoch 2/3
27900/28000 [============================>.] - ETA: 0s - loss: 0.3406 - acc: 0.8621Epoch 00001: loss improved from 0.47273 to 0.34025,
saving model to IMDB.h5
28000/28000 [==============================] - 290s - loss: 0.3403 - acc: 0.8623 - val_loss: 0.3057 - val_acc: 0.8726
lr: 0.001
Epoch 3/3
27900/28000 [============================>.] - ETA: 1s - loss: 0.2801 - acc: 0.8890Epoch 00002: loss improved from 0.34025 to 0.28011,
saving model to IMDB.h5
28000/28000 [==============================] - 333s - loss: 0.2801 - acc: 0.8890 - val_loss: 0.2836 - val_acc: 0.8850
```

Plot the training, validation and test accuracy

In [49]:
```
%matplotlib inline
import matplotlib.pyplot as plt
def plot_train(hist):
    h = hist.history
    if 'acc' in h:
        meas='acc'
        loc='lower right'
    else:
        meas='loss'
        loc='upper right'
    plt.plot(hist.history[meas])
    plt.plot(hist.history['val_'+meas])
    plt.title('model '+meas)
    plt.ylabel(meas)
    plt.xlabel('epoch')
    plt.legend(['train', 'validation'], loc=loc)

plot_train(history)
```



In [51]:
```
# Test against X_test and y_test dataset.
from keras.models import load_model
model = load_model('IMDB.h5')
score = model.evaluate(X_test, y_test, verbose=0)
print('Test loss:', score[0])
print('Test accuracy:', score[1])
```

```
Test loss: 0.295858772373
Test accuracy: 0.880800000032
```

What about model without embedding?

In [58]:
```
X_train2 = X_train.reshape(X_train.shape[0], X_train.shape[1], 1)
X_test2 = X_test.reshape(X_test.shape[0], X_test.shape[1], 1)
inp = Input(shape=(X_train2.shape[1], X_train2.shape[2]))
#x = Embedding(num_top_words, embedding_vector_len, input_length=max_words)(inp)
x = LSTM(100, return_sequences=True)(inp)
x = LSTM(100)(x)
x = Dropout(0.2)(x)
output = Dense(1, activation='sigmoid')(x)

model = Model(inputs=inp, outputs=output)
model.summary()
```

```
(35000, 300, 1)
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
input_10 (InputLayer)        (None, 300, 1)            0
_________________________________________________________________
lstm_14 (LSTM)               (None, 300, 100)          40800
_________________________________________________________________
lstm_15 (LSTM)               (None, 100)               80400
_________________________________________________________________
dropout_4 (Dropout)          (None, 100)               0
_________________________________________________________________
dense_7 (Dense)              (None, 1)                 101
=================================================================
Total params: 121,301
Trainable params: 121,301
Non-trainable params: 0
_________________________________________________________________
```

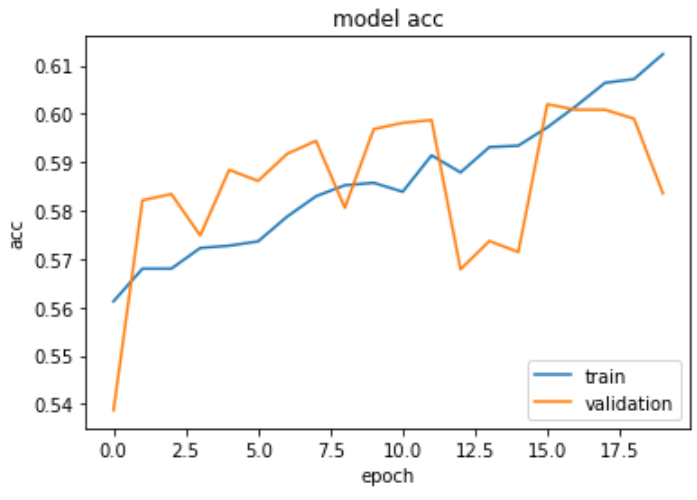
In [60]:
```
# Even though below callback may not be necessary, still included in this project
reduce_lr = ReduceLROnPlateau(monitor='val_loss', factor=0.9, patience=3, min_lr=0.0001)
lr_print = LambdaCallback(on_epoch_begin=lambda epoch,logs: print("lr:", K.eval(model.optimizer.lr)))
early_stopping = EarlyStopping(monitor='val_loss',min_delta=0,patience=3,verbose=1,mode='auto')
checkpoint = ModelCheckpoint(filepath, monitor='loss', verbose=1, save_best_only=True)

filepath = 'IMDB_wo_embedding.h5'
model.compile(loss='binary_crossentropy', optimizer='RMSprop', metrics=['accuracy'])
```

In [65]:
```
history = model.fit(X_train2, y_train, epochs=80, batch_size = 100,
                    callbacks=[checkpoint, reduce_lr, lr_print, early_stopping],
                    validation_split=0.2)
```

```
Train on 28000 samples, validate on 7000 samples
lr: 0.001
Epoch 1/80
27900/28000 [============================>.] - ETA: 0s - loss: 0.6807 - acc: 0.5612Epoch 00000: loss improved from 0.68325 to 0.
68071, saving model to IMDB_wo_embedding.h5
28000/28000 [==============================] - 289s - loss: 0.6807 - acc: 0.5612 - val_loss: 0.6969 - val_acc: 0.5387
lr: 0.001
Epoch 2/80
27900/28000 [============================>.] - ETA: 0s - loss: 0.6795 - acc: 0.5678Epoch 00001: loss improved from 0.68071 to 0.
67940, saving model to IMDB_wo_embedding.h5
28000/28000 [==============================] - 282s - loss: 0.6794 - acc: 0.5680 - val_loss: 0.6740 - val_acc: 0.5821
lr: 0.001
Epoch 3/80
27900/28000 [============================>.] - ETA: 1s - loss: 0.6785 - acc: 0.5681Epoch 00002: loss improved from 0.67940 to 0.
67856, saving model to IMDB_wo_embedding.h5
28000/28000 [==============================] - 300s - loss: 0.6786 - acc: 0.5680 - val_loss: 0.6748 - val_acc: 0.5834
lr: 0.001
Epoch 4/80
27900/28000 [============================>.] - ETA: 1s - loss: 0.6775 - acc: 0.5724Epoch 00003: loss improved from 0.67856 to 0.
```

In [66]:
```
from keras.models import load_model
plot_train(history)
model = load_model('IMDB_wo_embedding.h5')
score = model.evaluate(X_test2, y_test, verbose=0)
print('Test loss:', score[0])
print('Test accuracy:', score[1])
```

```
Test loss: 0.680497623062
Test accuracy: 0.582866666698
```



Without embedding, the model performed very poorly.

In [ ]: