Assignment 8: Recurrent Neural Networks

Claire Boetticher, MSDS 422, SEC 56

Colab: https://colab.research.google.com/drive/1Vkt5HBDAbYzQFdxDBu3rgDrEAF32He6K

Objective and data preparation

This benchmark study employs recurrent neural networks (RNN) to demonstrate sequence learning's performance with the binary classification task of assigning a positive or negative polarity score to IMDB movie reviews using text as features. The 1000 movie reviews, comprised of individual text files, are split equally across positive and negative classes. Data is prepared by removing common stop-words, removing punctuation, and tokenization with a minimum occurrence threshold of two. Next, a vocabulary of all tokens in the training dataset is developed to provide a consistent mapping from words in the vocabulary to unique integers. Finally, to ensure all documents are the same length (required for efficient Keras computation), sequences are truncated or padded with zero values to the maximum length, found by calculating the longest review. These steps all intend to utilize features that best represent the meaning, and by extension, sentiment of each review and discard those that are less meaningful. Models are fitted and evaluated in Colab with all of the training data using an 80/20 train/test split.

Study design

This benchmark study evaluates neural network models with either recurrent (using LSTM) or convolutional layers, trained with either learned embeddings or pre-trained gloVe embeddings (100-dimensional and 300-dimensional vectors). The embedding vectors serve as a compressed representation of the information in the sequences of words in the text, and form part of the deep networks. Architecture for each model is as follows:

Type of Neural Net	Layers	Network Architecture	Embedding
RNN 1	4	1 Bidirectional LSTM layer (64 memory units) 0.5 Dropout layer Sigmoid activation	Learned
RNN 2	4	1 Bidirectional LSTM layer (64 memory units) 0.5 Dropout layer Sigmoid activation	Pre-trained (100d)
RNN 3	4	1 Bidirectional LSTM layer (64 memory units) 0.5 Dropout layer Sigmoid activation	Pre-trained (300d)
RNN 4	4	1 Bidirectional LSTM layer (64 memory units) 0.5 Dropout layer ReLU activation	Learned
RNN 5	4	1 Bidirectional LSTM layer (64 memory units) 0.5 Dropout layer ReLU activation	Pre-trained (100d)
RNN 6	4	1 Bidirectional LSTM layer (64 memory units) 0.5 Dropout layer ReLU activation	Pre-trained (300d)
CNN 1	6	1 convolutional layer (32 filters, kernel size = 8) 1 max pooling layer ReLU and Sigmoid activation	Learned
CNN 2	5	1 convolutional layer (32 filters, kernel size = 8) 1 max pooling layer Sigmoid activation	Pre-trained (100d)
CNN 3	5	1 convolutional layer (32 filters, kernel size = 8) 1 max pooling layer Sigmoid activation	Pre-trained (300d)

After various tuning efforts on the baseline model, the following hyperparameters and settings are employed across all nine study models:

- Activation: ReLU and Sigmoid
- Epochs: 10
- Batch size: 64
- Loss function and optimizer: Binary Crossentropy and Adam
- Max features: 20,000

Dropout regularization is added in network structures in attempt to reduce overfitting in both the RNN and CNN models.

Results

The table below shows model evaluation results, with binary classification accuracy and loss included:

Type of Neural Net	Processing Time (in seconds)	Acc (Train)	Acc (Test)	Loss (Test)
RNN 1	254.27	0.9975	0.8850	0.3303
RNN 2	235.51	0.8038	0.7150	0.5887
RNN 3	241.48	0.8962	0.7800	0.5014
RNN 4	260.68	0.8650	0.7400	0.6022
RNN 5	241.25	0.5563	0.5600	0.6782
RNN 6	243.03	0.7175	0.6400	0.5835
CNN 1	8.74	1.0000	0.8600	0.3091
CNN 2	3.61	1.0000	0.7250	0.6683
CNN 3	4.96	1.0000	0.7550	0.6134

RNN 1 and CNN 1, both with learned embeddings, perform best overall in terms of training accuracy, loss, and performance on unseen test data. Models with learned embeddings consistently outperform those with pre-trained gloVe embeddings, perhaps as a result of the short length and specificity of the review data. Of the models with a pre-trained embedding layer, performance is slightly higher and loss slightly lower with 300-dimensional vectors. Models with a learned layer consistently take longer to train. All models exhibit loss that would likely need addressing through additional data and further tuning and training, ranging from 33 percent at best to 67 percent at worst.

Findings and recommendation

Applying language models to customer reviews and call/complaint logs would likely provide a useful means of efficiently identifying customers needing attention. Given the likelihood of strong wording in a review or call log, and thus polarity under the assumption that a customer taking the time likely either has had a strong positive or negative reaction, sentiment classification using the methods this study employs could help automate the evaluation and identification of customer “satisfaction” classes. The results of this study suggest that either a RNN or CNN with embeddings could serve as useful baselines with more sophisticated data pre-processing; given the criticality of identifying dissatisfied customers quickly enough to respond on time and effectively, subject matter expert involvement in task-specific feature engineering would likely result in performance improvement and overall reliability of the classification system. Additional attention to and experimentation with tuning (train-test ratio, batch size, max features length, OOV cutoff, type and dimensionality of pre-trained embeddings if used) and different architectures (e.g., combining LSTM and convolutional layers) could benefit the system as well. Overall, a thorough understanding of the company and product to which customers are responding plus the varying types of customers and their interactions with the company and product are critical inputs to feature engineering, language model development, and successful deployment. Models will need regular maintenance and re-training as customer input evolves (for example, in the case where a major issue is identified and the company wishes to see if complaints persist after addressing). Data scientists can help substantially in developing and deploying language models in this scenario: tap into the expertise of those in customer service functions as much as possible throughout feature engineering and development, fine-tune models to the specificities of the customer service tasks and review regularly, and actively monitor how models are deployed and how well they perform on future customer service data given the expected (and unexpected) issues involved.

Import dependencies and mount Drive

In [0]:
```
from string import punctuation
import os
import re
import time
import datetime
from os import listdir
from random import shuffle

from string import punctuation
from os import listdir
from collections import Counter
import nltk
from nltk.corpus import stopwords
from nltk.util import ngrams

import string
from sklearn.model_selection import train_test_split
from sklearn import metrics

import numpy as np
from numpy import array
from numpy import asarray
from numpy import zeros
import pandas as pd

!pip install tensorflow==1.15 as tf
from keras.preprocessing.text import Tokenizer
from keras.preprocessing.sequence import pad_sequences
from keras.models import Sequential
from keras.layers import Dense, Activation, Flatten, Embedding, Dro
pout, LSTM, Bidirectional
from keras.layers.convolutional import Conv1D
from keras.layers.convolutional import MaxPooling1D

import matplotlib.pyplot as plt
import seaborn as sns

# !pip install h5py pyyaml
```

```
Requirement already satisfied: tensorflow==1.15 in /usr/local/lib/
python3.6/dist-packages (1.15.0)
Requirement already satisfied: as in /usr/local/lib/python3.6/dist
-packages (0.1)
Requirement already satisfied: tf in /usr/local/lib/python3.6/dist
-packages (1.0.0)
Requirement already satisfied: google-pasta>=0.1.6 in /usr/local/l
ib/python3.6/dist-packages (from tensorflow==1.15) (0.1.8)
Requirement already satisfied: opt-einsum>=2.3.2 in /usr/local/lib
/python3.6/dist-packages (from tensorflow==1.15) (3.1.0)
Requirement already satisfied: wheel>=0.26 in /usr/local/lib/pytho
n3.6/dist-packages (from tensorflow==1.15) (0.34.2)
Requirement already satisfied: tensorflow-estimator==1.15.1 in /us
r/local/lib/python3.6/dist-packages (from tensorflow==1.15) (1.15.
1)
Requirement already satisfied: astor>=0.6.0 in /usr/local/lib/pyth
on3.6/dist-packages (from tensorflow==1.15) (0.8.1)
Requirement already satisfied: gast==0.2.2 in /usr/local/lib/pytho
n3.6/dist-packages (from tensorflow==1.15) (0.2.2)
Requirement already satisfied: keras-preprocessing>=1.0.5 in /usr/
local/lib/python3.6/dist-packages (from tensorflow==1.15) (1.1.0)
Requirement already satisfied: numpy<2.0,>=1.16.0 in /usr/local/li
b/python3.6/dist-packages (from tensorflow==1.15) (1.17.5)
Requirement already satisfied: tensorboard<1.16.0,>=1.15.0 in /usr
/local/lib/python3.6/dist-packages (from tensorflow==1.15) (1.15.
0)
Requirement already satisfied: wrapt>=1.11.1 in /usr/local/lib/pyt
hon3.6/dist-packages (from tensorflow==1.15) (1.11.2)
Requirement already satisfied: keras-applications>=1.0.8 in /usr/l
ocal/lib/python3.6/dist-packages (from tensorflow==1.15) (1.0.8)
Requirement already satisfied: six>=1.10.0 in /usr/local/lib/pytho
n3.6/dist-packages (from tensorflow==1.15) (1.12.0)
Requirement already satisfied: protobuf>=3.6.1 in /usr/local/lib/p
ython3.6/dist-packages (from tensorflow==1.15) (3.10.0)
Requirement already satisfied: absl-py>=0.7.0 in /usr/local/lib/py
thon3.6/dist-packages (from tensorflow==1.15) (0.9.0)
Requirement already satisfied: grpcio>=1.8.6 in /usr/local/lib/pyt
hon3.6/dist-packages (from tensorflow==1.15) (1.27.1)
Requirement already satisfied: termcolor>=1.1.0 in /usr/local/lib/
python3.6/dist-packages (from tensorflow==1.15) (1.1.0)
Requirement already satisfied: markdown>=2.6.8 in /usr/local/lib/p
ython3.6/dist-packages (from tensorboard<1.16.0,>=1.15.0->tensorfl
ow==1.15) (3.2.1)
Requirement already satisfied: werkzeug>=0.11.15 in /usr/local/lib
/python3.6/dist-packages (from tensorboard<1.16.0,>=1.15.0->tensor
flow==1.15) (1.0.0)
Requirement already satisfied: setuptools>=41.0.0 in /usr/local/li
b/python3.6/dist-packages (from tensorboard<1.16.0,>=1.15.0->tenso
rflow==1.15) (45.1.0)
Requirement already satisfied: h5py in /usr/local/lib/python3.6/di
st-packages (from keras-applications>=1.0.8->tensorflow==1.15) (2.
8.0)
```

In [0]:
```
# nltk.download('stopwords')
```

```
[nltk_data] Downloading package stopwords to /root/nltk_data...
[nltk_data]   Unzipping corpora/stopwords.zip.
```

Out[0]:
```
True
```

In [0]:
```
# Mount Drive
from google.colab import drive
drive.mount('/content/gdrive')
```

```
Go to this URL in a browser: https://accounts.google.com/o/oauth2/
auth?client_id=947318989803-6bn6qk8qdgf4n4g3pfee6491hc0brc4i.apps.
googleusercontent.com&redirect_uri=urn%3aietf%3awg%3aoauth%3a2.0%3
aoob&response_type=code&scope=email%20https%3a%2f%2fwww.googleapi
s.com%2fauth%2fdocs.test%20https%3a%2f%2fwww.googleapis.com%2faut
h%2fdrive%20https%3a%2f%2fwww.googleapis.com%2fauth%2fdrive.photo
s.readonly%20https%3a%2f%2fwww.googleapis.com%2fauth%2fpeopleapi.r
eadonly

Enter your authorization code:
··········
Mounted at /content/gdrive
```

In [0]:
```
# Establish working directory
%cd /content/gdrive/My\ Drive/MSDS422/weekeight
!pwd
!ls
print('Working Directory')
print(os.getcwd())
work_dir = "/content/gdrive/My\ Drive/MSDS422/weekeight"
# # data_dir = work_dir +"data/"
# chp_id = "rnn"
```

```
/content/gdrive/My Drive/MSDS422/weekeight
/content/gdrive/My Drive/MSDS422/weekeight
input   results   vocab.txt
Working Directory
/content/gdrive/My Drive/MSDS422/weekeight
```

Define functions

In [0]:
```
# Load doc into memory
def load_doc(filename):
        # open the file as read only
        file = open(filename, 'r')
        # read all text
        text = file.read()
        # close the file
        file.close()
        return text

# Turn a doc into clean tokens
def clean_doc(doc):
        # split into tokens by white space
        tokens = doc.split()
        # remove punctuation from each token
        table = str.maketrans('', '', punctuation)
        tokens = [w.translate(table) for w in tokens]
        # remove remaining tokens that are not alphabetic
        tokens = [word for word in tokens if word.isalpha()]
        # filter out stop words
        stop_words = set(stopwords.words('english'))
        # stop_words = stop_words.extend(newStopWords)
        tokens = [w for w in tokens if not w in stop_words]
        # filter out short tokens
        tokens = [word for word in tokens if len(word) > 1]
        return tokens

# Load doc and add to vocab
def add_doc_to_vocab(filename, vocab):
        # load doc
        doc = load_doc(filename)
        # clean doc
        tokens = clean_doc(doc)
        # update counts
        vocab.update(tokens)

# Load all docs in a directory
def process_docs(directory, vocab):
        # walk through all files in the folder
        for filename in listdir(directory):
                # # skip any reviews in the test set
                # if is_train:
                #       continue
                # if not is_train:
                #       continue
                # create the full path of the file to open
                path = directory + '/' + filename
                # add doc to vocab
                add_doc_to_vocab(path, vocab)
```

Explore and define vocabulary

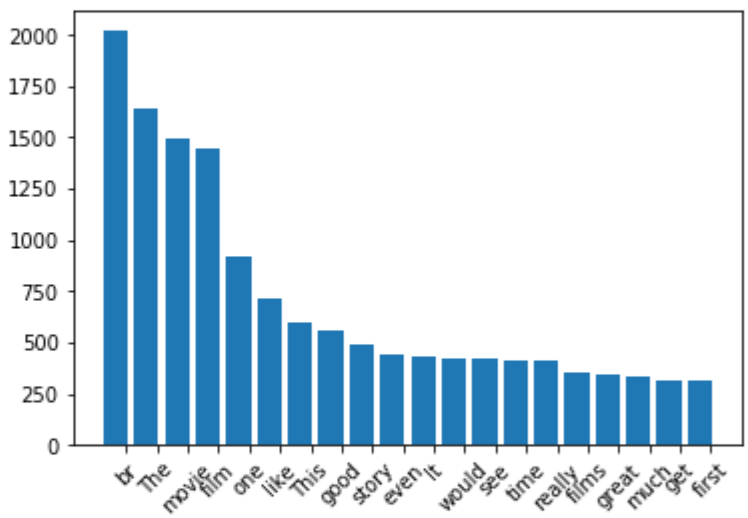
In [0]:
```
# Define vocab
vocab = Counter()
# Add all docs to vocab
process_docs('input/rnn/movie-reviews-negative', vocab)
process_docs('input/rnn/movie-reviews-positive', vocab)
```

In [0]:
```
# Print the size of the vocab
print(len(vocab))

# Print the top words in the vocab
print(vocab.most_common(50))
```

```
20433
[('br', 2020), ('The', 1645), ('movie', 1490), ('film', 1449), ('o
ne', 916), ('like', 716), ('This', 601), ('good', 560), ('story',
486), ('even', 445), ('It', 429), ('would', 421), ('see', 417), ('
time', 415), ('really', 413), ('films', 353), ('great', 343), ('mu
ch', 334), ('get', 315), ('first', 314), ('bad', 309), ('movies',
309), ('made', 307), ('also', 303), ('people', 294), ('could', 28
8), ('make', 287), ('seen', 283), ('well', 278), ('two', 276), ('d
ont', 275), ('think', 272), ('characters', 271), ('plot', 269), ('
acting', 266), ('character', 252), ('But', 250), ('many', 246), ('
Its', 246), ('way', 246), ('And', 242), ('never', 232), ('little',
228), ('life', 223), ('watch', 222), ('love', 221), ('ever', 217),
('scene', 211), ('better', 210), ('best', 205)]
```

Figure 1: Most common 20 words in reviews

In [0]:
```
# Visualize 20 most common words
plot_words = dict(Counter(vocab).most_common(20))
labels, values = zip(*plot_words.items())

# Sort values in descending order
indSort = np.argsort(values)[::-1]

# Rearrange data
labels = np.array(labels)[indSort]
values = np.array(values)[indSort]
indexes = np.arange(len(labels))

# Plot and add labels
bar_width = 0.35
plt.bar(indexes, values)
# fig = plt.figure(figsize=(6,3))
plt.xticks(indexes + bar_width, labels, rotation=45)
# xticks(rotation=45) rotate x-axis labels by 45 degrees
plt.show()
```



In [0]:
```
# Print the 50 least common words
n = 50
print(vocab.most_common()[:-n-1:-1])
```

```
[('interference', 1), ('sexiness', 1), ('lighter', 1), ('Morricone
', 1), ('outfits', 1), ('Fabulous', 1), ('quibbles', 1), ('unforgi
vable', 1), ('Convoluted', 1), ('figurine', 1), ('videoDVD', 1),
('unavailable', 1), ('sporadic', 1), ('Valentinestyle', 1), ('fati
gues', 1), ('delicately', 1), ('sugarcoated', 1), ('temptations',
1), ('rammed', 1), ('Amenabar', 1), ('Majorettes', 1), ('crossbree
d', 1), ('swaps', 1), ('entices', 1), ('heralds', 1), ('concrete',
1), ('template', 1), ('Kruegar', 1), ('clawfingered', 1), ('bogeym
an', 1), ('playgroundbr', 1), ('maniacs', 1), ('panicstricken',
1), ('jogging', 1), ('creepilymasked', 1), ('Predator', 1), ('Schw
arzenegger', 1), ('approached', 1), ('excels', 1), ('dorm', 1), ('
Madrid', 1), ('assassinbr', 1), ('malevolent', 1), ('homicidal',
1), ('Hunters', 1), ('remoteness', 1), ('storekeeper', 1), ('armou
ry', 1), ('adversarybr', 1), ('proposes', 1)]
```

In [0]:
```
# Keep tokens with a minimum occurrence
min_occurrence = 2
tokens = [k for k,c in vocab.items() if c >= min_occurrence]
print(len(tokens))
```

```
9588
```

In [0]:
```
# Save list to file
def save_list(lines, filename):
        # convert lines to a single blob of text
        data = '\n'.join(lines)
        # open file
        file = open(filename, 'w')
        # write text
        file.write(data)
        # close file
        file.close()

# Save tokens to a vocabulary file
save_list(tokens, 'vocab.txt')
```

Pre-processing functions

In [0]:
```
# Turn a doc into clean tokens
def clean_doc(doc, vocab):
        # split into tokens by white space
        tokens = doc.split()
        # remove punctuation from each token
        table = str.maketrans('', '', punctuation)
        tokens = [w.translate(table) for w in tokens]
        # filter out tokens not in vocab
        tokens = [w for w in tokens if w in vocab]
        tokens = ' '.join(tokens)
        return tokens

# Load all docs in a directory
def process_docs(directory, vocab):
        documents = list()
        # walk through all files in the folder
        for filename in listdir(directory):
                # # skip any reviews in the test set
                # if is_trian and filename.startswith('cv9'):
                #       continue
                # if not is_trian and not filename.startswith('cv9
'):
                #       continue
                # # create the full path of the file to open
                path = directory + '/' + filename
                # load the doc
                doc = load_doc(path)
                # clean doc
                tokens = clean_doc(doc, vocab)
                # add to list
                documents.append(tokens)
        return documents
```

Load train and test data

In [0]:
```
# Load the vocabulary
vocab_filename = 'vocab.txt'
vocab = load_doc(vocab_filename)
vocab = vocab.split()
vocab = set(vocab)
```

In [0]:
```
# Load all training reviews
positive_docs = process_docs('input/rnn/movie-reviews-positive', vo
cab)
negative_docs = process_docs('input/rnn/movie-reviews-negative', vo
cab)
```

In [0]:
```
# Assign training reviews
train_positive = positive_docs[100:]
train_negative = negative_docs[100:]
train_docs = train_positive + train_negative

# Create the tokenizer
tokenizer = Tokenizer()
# Fit the tokenizer on the documents
tokenizer.fit_on_texts(train_docs)

# Sequence encode
encoded_docs = tokenizer.texts_to_sequences(train_docs)

# Pad sequences
max_length = max([len(s.split()) for s in train_docs])

X_train = pad_sequences(encoded_docs, maxlen=max_length, padding='p
ost')

# Define training labels
y_train = array([0 for _ in range(400)] + [1 for _ in range(400)])
```

In [0]:
```
# Load all test reviews
test_positive = positive_docs[:100]
test_negative = negative_docs[:100]
test_docs = test_positive + test_negative

# Sequence encode
encoded_docs = tokenizer.texts_to_sequences(test_docs)

# Pad sequences
X_test = pad_sequences(encoded_docs, maxlen=max_length, padding='po
st')
# Define test labels
y_test = array([0 for _ in range(100)] + [1 for _ in range(100)])
```

In [0]:
```
print("Train and test dataset shapes:")
print("X_train: " + str(X_train.shape))
print("X_test: " + str(X_test.shape))
print("y_train: " + str(y_train.shape))
print("y_test: " + str(y_test.shape))
```

```
Train and test dataset shapes:
X_train: (800, 588)
X_test: (200, 588)
y_train: (800,)
y_test: (200,)
```

In [0]:
```
# Define vocabulary size (largest integer value)
vocab_size = len(tokenizer.word_index) + 1
```

Prepare pre-trained embeddings

In [0]:
```
# Load embedding as a dict
def load_embedding(filename):
        # load embedding into memory, skip first line
        file = open(filename,'r')
        lines = file.readlines()
        file.close()
        # create a map of words to vectors
        embedding = dict()
        for line in lines:
                parts = line.split()
                # key is string word, value is numpy array for vect
or
                embedding[parts[0]] = asarray(parts[1:], dtype='flo
at32')
        return embedding
```

In [0]:
```
# Create a weight matrix for the Embedding layer from a loaded embe
dding
def get_weight_matrix(embedding, vocab):
        # total vocabulary size plus 0 for unknown words
        vocab_size = len(vocab) + 1
        # define weight matrix dimensions with all 0
        # weight_matrix = zeros((vocab_size, 100))
        weight_matrix = zeros((vocab_size, 300))
        # step vocab, store vectors using the Tokenizer's integer m
apping
        for word, i in vocab.items():
                vector = embedding.get(word)
                if vector is not None:
                        weight_matrix[i] = vector
        return weight_matrix
```

In [0]:
```
# Load 100d embedding from file
raw_embedding_small = load_embedding('input/rnn/embeddings/gloVe.6B
/glove.6B.100d.txt')
# Get vectors in the right order
embedding_vectors_small = get_weight_matrix(raw_embedding_small, to
kenizer.word_index)
# Create the embedding layer
embedding_layer_small = Embedding(vocab_size, 100, weights=[embeddi
ng_vectors_small], input_length=max_length, trainable=False)
```

```
WARNING:tensorflow:From /usr/local/lib/python3.6/dist-packages/ker
as/backend/tensorflow_backend.py:66: The name tf.get_default_graph
is deprecated. Please use tf.compat.v1.get_default_graph instead.
```

In [0]:
```
# Load 300d embedding from file
raw_embedding_large = load_embedding('input/rnn/embeddings/gloVe.6B
/glove.6B.300d.txt')
# Get vectors in the right order
embedding_vectors_large = get_weight_matrix(raw_embedding_large, to
kenizer.word_index)
# Create the embedding layer
embedding_layer_large = Embedding(vocab_size, 300, weights=[embeddi
ng_vectors_large], input_length=max_length, trainable=False)
```

Model 1: learned embeddings with LSTM + sigmoid activation

In [0]:
```
max_features = 20000

model_1 = Sequential()
model_1.add(Embedding(max_features, 128, input_length=max_length))
model_1.add(Bidirectional(LSTM(64)))
model_1.add(Dropout(0.5))
model_1.add(Dense(1, activation='sigmoid'))
print(model_1.summary())
```

```
Model: "sequential_2"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
embedding_4 (Embedding)      (None, 588, 128)          2560000
_________________________________________________________________
bidirectional_2 (Bidirection (None, 128)               98816
_________________________________________________________________
dropout_2 (Dropout)          (None, 128)               0
_________________________________________________________________
dense_2 (Dense)              (None, 1)                 129
=================================================================
Total params: 2,658,945
Trainable params: 2,658,945
Non-trainable params: 0
_________________________________________________________________
None
```

In [0]:
```
# Compile model
model_1.compile(loss='binary_crossentropy', optimizer='adam', metri
cs=['accuracy'])
```

In [0]:

```
# Fit network
start_time = time.time()
history = model_1.fit(X_train, y_train, epochs=10, batch_size=64, v
erbose=2)
elapsed_time = time.time() - start_time
print('--------------------------')
print('Training time in seconds: ', round(elapsed_time,2))
print('--------------------------')

# Save models locally after fitting
save_dir = "results/"
model_name = 'keras_rnn_model_1.h5'
model_path = os.path.join(save_dir, model_name)
model_1.save(model_path)
print('Saved trained model at %s ' % model_path)
print('--------------------------')
```

```
Epoch 1/10
 - 26s - loss: 0.6930 - acc: 0.5012
Epoch 2/10
 - 25s - loss: 0.6777 - acc: 0.6950
Epoch 3/10
 - 25s - loss: 0.6540 - acc: 0.7925
Epoch 4/10
 - 25s - loss: 0.5212 - acc: 0.8825
Epoch 5/10
 - 25s - loss: 0.3869 - acc: 0.9700
Epoch 6/10
 - 25s - loss: 0.1809 - acc: 0.9750
Epoch 7/10
 - 25s - loss: 0.0927 - acc: 0.9888
Epoch 8/10
 - 26s - loss: 0.0514 - acc: 0.9950
Epoch 9/10
 - 25s - loss: 0.0339 - acc: 0.9988
Epoch 10/10
 - 25s - loss: 0.0242 - acc: 0.9975
--------------------------
Training time in seconds:  254.27
--------------------------
Saved trained model at results/keras_rnn_model_1.h5
--------------------------
```

In [0]:
```
# Final evaluation of the model
scores = model_1.evaluate(X_test, y_test, verbose=0)
print('Testing scores:')
# print("Baseline Error: %.4f" % (100-scores[1]*100))
print("Accuracy score: %.4f" % scores[1])
print("Loss: %.4f" % scores[0])
```

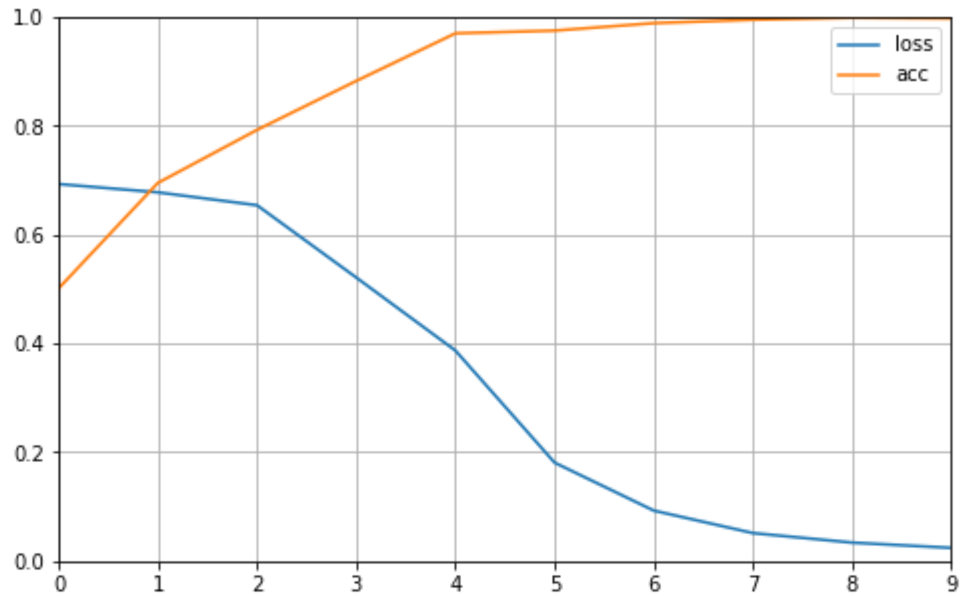
```
Testing scores:
Accuracy score: 0.8850
Loss: 0.3303
```

In [0]:
```
# # Loads the weights
# checkpoint_path = model_path = "results/keras_rnn_model_1.h5"
# # model_name = 'keras_rnn_model_1.h5'
# model_1.load_weights(checkpoint_path)

# # Re-evaluate the model
# scores_revised = model_1.evaluate(X_test, y_test, verbose=0)
# print('Testing scores:')
# print("Accuracy score: %.4f" % scores_revised[1])
# print("Loss: %.4f" % scores_revised[0])
```

```
Testing scores:
Accuracy score: 0.8850
Loss: 0.3303
```

Figure 2: Learning curves for model 1

In [0]:
```
# Plot learning curves
pd.DataFrame(history.history).plot(figsize=(8, 5))
plt.grid(True)
plt.gca().set_ylim(0, 1) # set the vertical range to [0-1]
plt.show()
```



In [0]:
```
# Make test predictions
y_pred = model_1.predict(X_test)
```

In [0]:
```
# Remember, we mapped the positive outputs to 1 and the negative ou
tputs to 0. However, the sigmoid function predicts floating
# value between 0 and 1. If the value is less than 0.5, the sentime
nt is considered negative where as if the value is
# greater than 0.5, the sentiment is considered as positive. The se
ntiment value for our single instance is 0.33 which means
# that our sentiment is predicted as negative, which actually is th
e case.
```

Positive outputs are mapped to 1 and negative outputs to 0. However, the sigmoid function predicts a floating value between 0 and 1. If the value is less than 0.5, the sentiment is considered negative where as if the value is greater than 0.5, the sentiment is considered as positive.

In [0]:
```
# Test on 2 reviews
print('Predicted prediction:')
print(y_pred[99])
print('----------')
print('Review text:')
print(test_docs[99])
print('----------')
print('Predicted prediction:')
print(y_pred[187])
print('----------')
print('Review text:')
print(test_docs[187])
```

```
Predicted prediction:
[0.06757104]
----------
Review text:
Although obviously lowbudget production performances songs movie w
orth seeing One Walkens musical roles date marvelous dancer singer
demonstrates skills well watch Also starring Jason Connery great c
hildrens story likable characters
----------
Predicted prediction:
[0.04520619]
----------
Review text:
premise rates low unfortunately also struggles raise laughs intere
st Only Hawns wellknown charm allows thin ice Goldies gotta conten
der actress whos done much career little quality material br
```

Model 2: pre-trained embeddings (100d) with LSTM + sigmoid activation

In [0]:
```
# Define model
model_2 = Sequential()
model_2.add(embedding_layer_small)
model_2.add(Bidirectional(LSTM(64)))
model_2.add(Dropout(0.5))
model_2.add(Dense(1, activation='sigmoid'))
print(model_2.summary())
```

```
Model: "sequential_3"
_________________________________________________________________
Layer (type)                 Output Shape              Param #   
=================================================================
embedding_1 (Embedding)      (None, 588, 100)          845200    
_________________________________________________________________
bidirectional_3 (Bidirection (None, 128)               84480     
_________________________________________________________________
dropout_3 (Dropout)          (None, 128)               0         
_________________________________________________________________
dense_3 (Dense)              (None, 1)                 129       
=================================================================
Total params: 929,809
Trainable params: 84,609
Non-trainable params: 845,200
_________________________________________________________________
None
```

In [0]:
```
# Compile model
model_2.compile(loss='binary_crossentropy', optimizer='adam', metri
cs=['accuracy'])
```

In [0]:
```
# Fit network
start_time = time.time()
history = model_2.fit(X_train, y_train, epochs=10, batch_size=64, v
erbose=2)
elapsed_time = time.time() - start_time
print('--------------------------')
print('Training time in seconds: ', round(elapsed_time,2))
print('--------------------------')

# Save models locally after fitting
save_dir = "results/"
model_name = 'keras_rnn_model_2.h5'
model_path = os.path.join(save_dir, model_name)
model_2.save(model_path)
print('Saved trained model at %s ' % model_path)
print('--------------------------')
```

```
Epoch 1/10
 - 25s - loss: 0.6999 - acc: 0.4863
Epoch 2/10
 - 23s - loss: 0.6744 - acc: 0.5750
Epoch 3/10
 - 23s - loss: 0.6426 - acc: 0.6288
Epoch 4/10
 - 23s - loss: 0.5880 - acc: 0.7013
Epoch 5/10
 - 24s - loss: 0.5381 - acc: 0.7338
Epoch 6/10
 - 23s - loss: 0.5037 - acc: 0.7737
Epoch 7/10
 - 23s - loss: 0.4865 - acc: 0.7762
Epoch 8/10
 - 23s - loss: 0.4714 - acc: 0.7875
Epoch 9/10
 - 23s - loss: 0.4944 - acc: 0.7812
Epoch 10/10
 - 23s - loss: 0.4508 - acc: 0.8038
--------------------------
Training time in seconds:  235.51
--------------------------
Saved trained model at results/keras_rnn_model_2.h5
--------------------------
```

In [0]:
```
# Final evaluation of the model
scores = model_2.evaluate(X_test, y_test, verbose=0)
print('Testing scores:')
# print("Baseline Error: %.4f" % (100-scores[1]*100))
print("Accuracy score: %.4f" % scores[1])
print("Loss: %.4f" % scores[0])
```

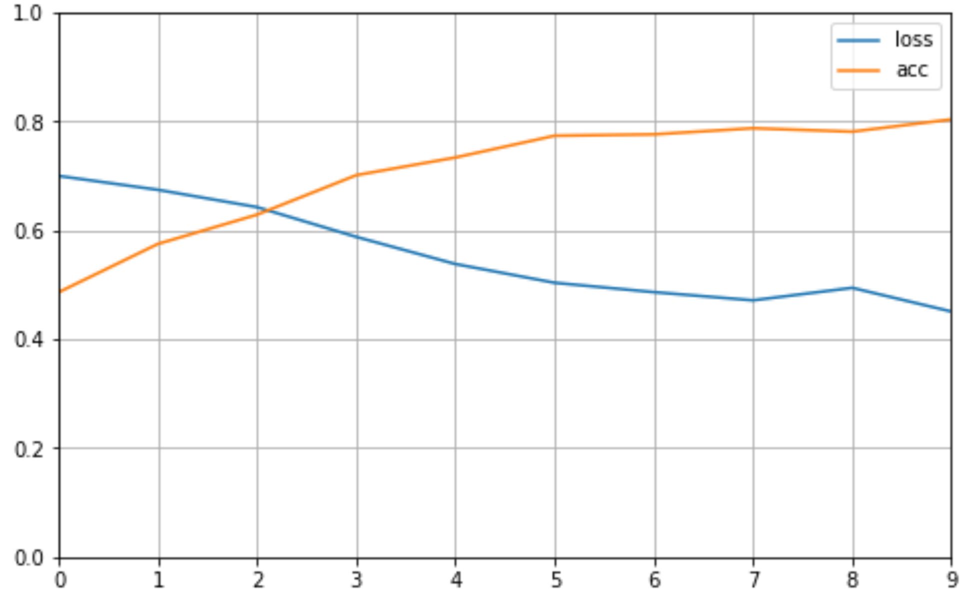
```
Testing scores:
Accuracy score: 0.7150
Loss: 0.5887
```

In [0]:
```
# # Loads the weights
# checkpoint_path = model_path = "results/keras_rnn_model_2.h5"
# # model_name = 'keras_rnn_model_2.h5'
# model_2.load_weights(checkpoint_path)

# # Re-evaluate the model
# scores_revised = model_2.evaluate(X_test, y_test, verbose=0)
# print('Testing scores:')
# print("Accuracy score: %.4f" % scores_revised[1])
# print("Loss: %.4f" % scores_revised[0])
```

```
Testing scores:
Accuracy score: 0.7150
Loss: 0.5887
```

Figure 3: Learning curves for model 2

In [0]:
```
# Plot learning curves
pd.DataFrame(history.history).plot(figsize=(8, 5))
plt.grid(True)
plt.gca().set_ylim(0, 1) # set the vertical range to [0-1]
plt.show()
```



In [0]:
```
# Make test predictions
y_pred = model_2.predict(X_test)
```

In [0]:
```
# Test on 2 reviews
print('Predicted prediction:')
print(y_pred[99])
print('----------')
print('Review text:')
print(test_docs[99])
print('----------')
print('Predicted prediction:')
print(y_pred[187])
print('----------')
print('Review text:')
print(test_docs[187])
```

```
Predicted prediction:
[0.09684515]
----------
Review text:
Although obviously lowbudget production performances songs movie w
orth seeing One Walkens musical roles date marvelous dancer singer
demonstrates skills well watch Also starring Jason Connery great c
hildrens story likable characters
----------
Predicted prediction:
[0.38425595]
----------
Review text:
premise rates low unfortunately also struggles raise laughs intere
st Only Hawns wellknown charm allows thin ice Goldies gotta conten
der actress whos done much career little quality material br
```

Model 3: # pre-trained embeddings (300d) with LSTM + sigmoid activation

In [0]:
```
# Define model
model_3 = Sequential()
model_3.add(embedding_layer_large)
model_3.add(Bidirectional(LSTM(64)))
model_3.add(Dropout(0.5))
model_3.add(Dense(1, activation='sigmoid'))
print(model_3.summary())
```

```
Model: "sequential_4"
_________________________________________________________________
Layer (type)                 Output Shape              Param #   
=================================================================
embedding_2 (Embedding)      (None, 588, 300)          2535600   
_________________________________________________________________
bidirectional_4 (Bidirection (None, 128)               186880    
_________________________________________________________________
dropout_4 (Dropout)          (None, 128)               0         
_________________________________________________________________
dense_4 (Dense)              (None, 1)                 129       
=================================================================
Total params: 2,722,609
Trainable params: 187,009
Non-trainable params: 2,535,600
_________________________________________________________________
None
```

In [0]:
```
# Compile model
model_3.compile(loss='binary_crossentropy', optimizer='adam', metri
cs=['accuracy'])
```

In [0]:
```
# Fit network
start_time = time.time()
history = model_3.fit(X_train, y_train, epochs=10, batch_size=64, v
erbose=2)
elapsed_time = time.time() - start_time
print('--------------------------')
print('Training time in seconds: ', round(elapsed_time,2))
print('--------------------------')

# Save models locally after fitting
save_dir = "results/"
model_name = 'keras_rnn_model_3.h5'
model_path = os.path.join(save_dir, model_name)
model_3.save(model_path)
print('Saved trained model at %s ' % model_path)
print('--------------------------')
```

```
Epoch 1/10
 - 25s - loss: 0.6904 - acc: 0.5262
Epoch 2/10
 - 23s - loss: 0.6461 - acc: 0.6438
Epoch 3/10
 - 24s - loss: 0.5854 - acc: 0.7087
Epoch 4/10
 - 24s - loss: 0.4993 - acc: 0.7725
Epoch 5/10
 - 24s - loss: 0.4526 - acc: 0.7975
Epoch 6/10
 - 24s - loss: 0.4017 - acc: 0.8263
Epoch 7/10
 - 24s - loss: 0.3398 - acc: 0.8588
Epoch 8/10
 - 24s - loss: 0.3335 - acc: 0.8675
Epoch 9/10
 - 24s - loss: 0.3199 - acc: 0.8725
Epoch 10/10
 - 24s - loss: 0.2601 - acc: 0.8962
--------------------------
Training time in seconds:  241.48
--------------------------
Saved trained model at results/keras_rnn_model_3.h5
--------------------------
```

In [0]:
```
# Final evaluation of the model
scores = model_3.evaluate(X_test, y_test, verbose=0)
print('Testing scores:')
# print("Baseline Error: %.4f" % (100-scores[1]*100))
print("Accuracy score: %.4f" % scores[1])
print("Loss: %.4f" % scores[0])
```

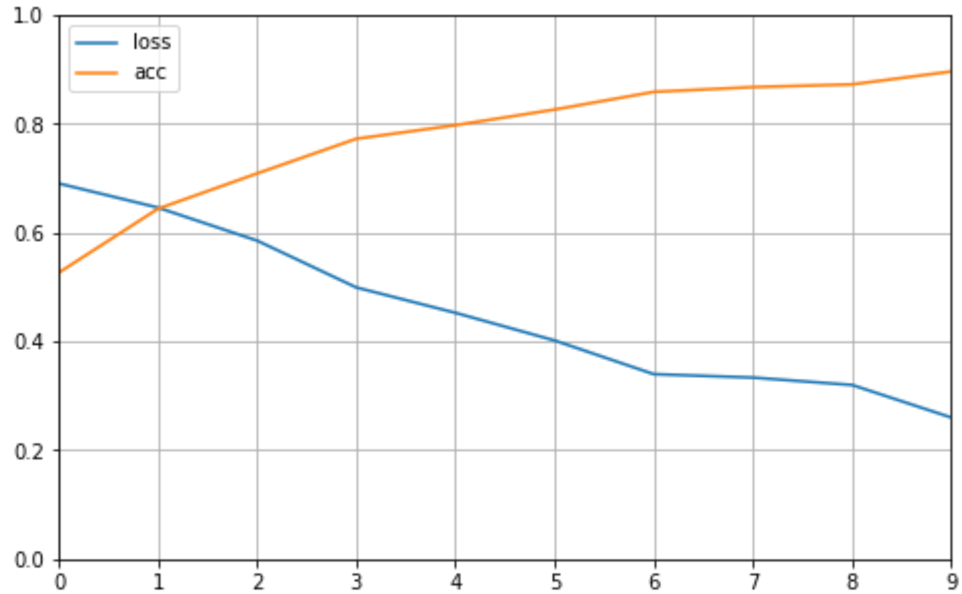
```
Testing scores:
Accuracy score: 0.7800
Loss: 0.5014
```

In [0]:
```
# # Load the weights
# checkpoint_path = model_path = "results/keras_rnn_model_3.h5"
# # model_name = 'keras_rnn_model_3.h5'
# model_3.load_weights(checkpoint_path)

# # Re-evaluate the model
# scores_revised = model_3.evaluate(X_test, y_test, verbose=0)
# print('Testing scores:')
# print("Accuracy score: %.4f" % scores_revised[1])
# print("Loss: %.4f" % scores_revised[0])
```

```
Testing scores:
Accuracy score: 0.7800
Loss: 0.5014
```

Figure 4: Learning curves for model 3

In [0]:
```
# Plot learning curves
pd.DataFrame(history.history).plot(figsize=(8, 5))
plt.grid(True)
plt.gca().set_ylim(0, 1) # set the vertical range to [0-1]
plt.show()
```



In [0]:
```
# Make test predictions
y_pred = model_3.predict(X_test)
```

In [0]:
```
# Test on 2 reviews
print('Predicted prediction:')
print(y_pred[99])
print('----------')
print('Review text:')
print(test_docs[99])
print('----------')
print('Predicted prediction:')
print(y_pred[187])
print('----------')
print('Review text:')
print(test_docs[187])
```

```
Predicted prediction:
[0.01844606]
----------
Review text:
Although obviously lowbudget production performances songs movie w
orth seeing One Walkens musical roles date marvelous dancer singer
demonstrates skills well watch Also starring Jason Connery great c
hildrens story likable characters
----------
Predicted prediction:
[0.49519494]
----------
Review text:
premise rates low unfortunately also struggles raise laughs intere
st Only Hawns wellknown charm allows thin ice Goldies gotta conten
der actress whos done much career little quality material br
```

Model 4: learned embeddings with LSTM + ReLU activation

In [0]:

```
model_4 = Sequential()
model_4.add(Embedding(max_features, 128, input_length=max_length))
model_4.add(Bidirectional(LSTM(64)))
model_4.add(Dropout(0.5))
model_4.add(Dense(1, activation='relu'))
print(model_4.summary())
```

```
Model: "sequential_5"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
embedding_5 (Embedding)      (None, 588, 128)          2560000
_________________________________________________________________
bidirectional_5 (Bidirection (None, 128)               98816
_________________________________________________________________
dropout_5 (Dropout)          (None, 128)               0
_________________________________________________________________
dense_5 (Dense)              (None, 1)                 129
=================================================================
Total params: 2,658,945
Trainable params: 2,658,945
Non-trainable params: 0
_________________________________________________________________
None
```

In [0]:

```
# Compile model
model_4.compile(loss='binary_crossentropy', optimizer='adam', metri
cs=['accuracy'])
```

In [0]:
```
# Fit network
start_time = time.time()
history = model_4.fit(X_train, y_train, epochs=10, batch_size=64, v
erbose=2)
elapsed_time = time.time() - start_time
print('--------------------------')
print('Training time in seconds: ', round(elapsed_time,2))
print('--------------------------')

# Save models locally after fitting
save_dir = "results/"
model_name = 'keras_rnn_model_4.h5'
model_path = os.path.join(save_dir, model_name)
model_4.save(model_path)
print('Saved trained model at %s ' % model_path)
print('--------------------------')
```

```
Epoch 1/10
 - 28s - loss: 1.3264 - acc: 0.5025
Epoch 2/10
 - 26s - loss: 0.6856 - acc: 0.5787
Epoch 3/10
 - 26s - loss: 0.5810 - acc: 0.7737
Epoch 4/10
 - 26s - loss: 0.6565 - acc: 0.7275
Epoch 5/10
 - 26s - loss: 0.5293 - acc: 0.6100
Epoch 6/10
 - 26s - loss: 0.4240 - acc: 0.8313
Epoch 7/10
 - 26s - loss: 0.2976 - acc: 0.9563
Epoch 8/10
 - 26s - loss: 0.1914 - acc: 0.9575
Epoch 9/10
 - 25s - loss: 0.1049 - acc: 0.9300
Epoch 10/10
 - 25s - loss: 0.0573 - acc: 0.8650
--------------------------
Training time in seconds:  260.68
--------------------------
Saved trained model at results/keras_rnn_model_4.h5
--------------------------
```

In [0]:
```
# Final evaluation of the model
scores = model_4.evaluate(X_test, y_test, verbose=0)
print('Testing scores:')
# print("Baseline Error: %.4f" % (100-scores[1]*100))
print("Accuracy score: %.4f" % scores[1])
print("Loss: %.4f" % scores[0])
```

```
Testing scores:
Accuracy score: 0.7400
Loss: 0.6022
```

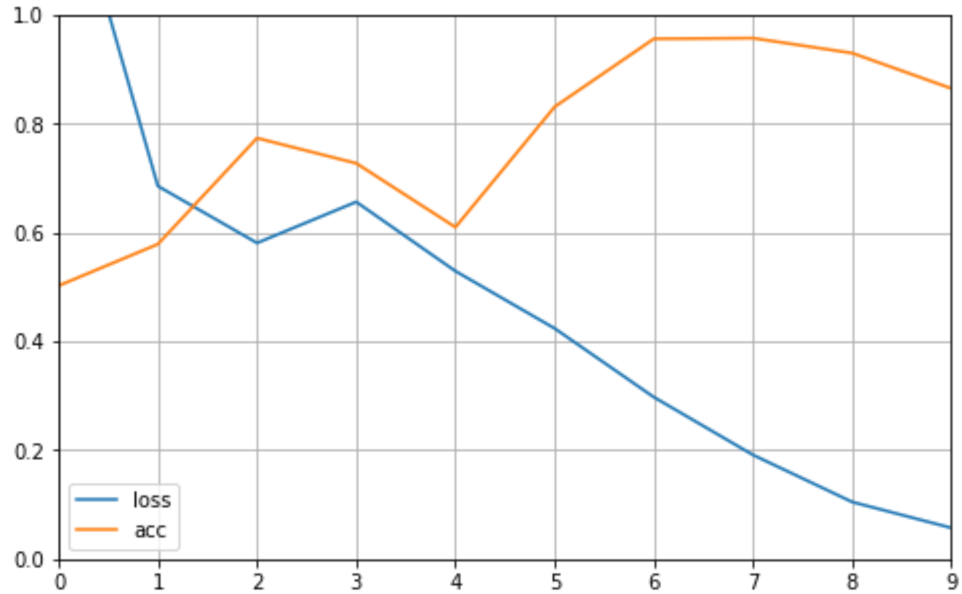
In [0]:
```
# # Load the weights
# checkpoint_path = model_path = "results/keras_rnn_model_4.h5"
# # model_name = 'keras_rnn_model_4.h5'
# model_4.load_weights(checkpoint_path)

# # Re-evaluate the model
# scores_revised = model_4.evaluate(X_test, y_test, verbose=0)
# print('Testing scores:')
# print("Accuracy score: %.4f" % scores_revised[1])
# print("Loss: %.4f" % scores_revised[0])
```

```
Testing scores:
Accuracy score: 0.7400
Loss: 0.6022
```

Figure 5: Learning curves for model 4

In [0]:

```
# Plot learning curves
pd.DataFrame(history.history).plot(figsize=(8, 5))
plt.grid(True)
plt.gca().set_ylim(0, 1) # set the vertical range to [0-1]
plt.show()
```



In [0]:

```
# Make test predictions
y_pred = model_4.predict(X_test)
```

In [0]:
```
# Test on 2 reviews
print('Predicted prediction:')
print(y_pred[99])
print('----------')
print('Review text:')
print(test_docs[99])
print('----------')
print('Predicted prediction:')
print(y_pred[187])
print('----------')
print('Review text:')
print(test_docs[187])
```

```
Predicted prediction:
[0.7112041]
----------
Review text:
Although obviously lowbudget production performances songs movie w
orth seeing One Walkens musical roles date marvelous dancer singer
demonstrates skills well watch Also starring Jason Connery great c
hildrens story likable characters
----------
Predicted prediction:
[0.52824414]
----------
Review text:
premise rates low unfortunately also struggles raise laughs intere
st Only Hawns wellknown charm allows thin ice Goldies gotta conten
der actress whos done much career little quality material br
```

Model 5: pre-trained embeddings (100d) with LSTM + ReLU activation

In [0]:

```
# Define model
model_5 = Sequential()
model_5.add(embedding_layer_small)
model_5.add(Bidirectional(LSTM(64)))
model_5.add(Dropout(0.5))
model_5.add(Dense(1, activation='relu'))
print(model_5.summary())
```

```
Model: "sequential_6"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
embedding_1 (Embedding)      (None, 588, 100)          845200
_________________________________________________________________
bidirectional_6 (Bidirection (None, 128)               84480
_________________________________________________________________
dropout_6 (Dropout)          (None, 128)               0
_________________________________________________________________
dense_6 (Dense)              (None, 1)                 129
=================================================================
Total params: 929,809
Trainable params: 84,609
Non-trainable params: 845,200
_________________________________________________________________
None
```

In [0]:

```
# Compile model
model_5.compile(loss='binary_crossentropy', optimizer='adam', metri
cs=['accuracy'])
```

In [0]:
```
# Fit network
start_time = time.time()
history = model_5.fit(X_train, y_train, epochs=10, batch_size=64, v
erbose=2)
elapsed_time = time.time() - start_time
print('--------------------------')
print('Training time in seconds: ', round(elapsed_time,2))
print('--------------------------')

# Save models locally after fitting
save_dir = "results/"
model_name = 'keras_rnn_model_5.h5'
model_path = os.path.join(save_dir, model_name)
model_5.save(model_path)
print('Saved trained model at %s ' % model_path)
print('--------------------------')
```

```
Epoch 1/10
 - 26s - loss: 1.6345 - acc: 0.5175
Epoch 2/10
 - 24s - loss: 0.9490 - acc: 0.4925
Epoch 3/10
 - 24s - loss: 0.9786 - acc: 0.4788
Epoch 4/10
 - 23s - loss: 0.8335 - acc: 0.5262
Epoch 5/10
 - 24s - loss: 0.7562 - acc: 0.5288
Epoch 6/10
 - 24s - loss: 0.7081 - acc: 0.5650
Epoch 7/10
 - 23s - loss: 0.7292 - acc: 0.5425
Epoch 8/10
 - 24s - loss: 0.7816 - acc: 0.5225
Epoch 9/10
 - 24s - loss: 0.7126 - acc: 0.5337
Epoch 10/10
 - 23s - loss: 0.6901 - acc: 0.5563
--------------------------
Training time in seconds:  241.25
--------------------------
Saved trained model at results/keras_rnn_model_5.h5
--------------------------
```

In [0]:
```python
# Final evaluation of the model
scores = model_5.evaluate(X_test, y_test, verbose=0)
print('Testing scores:')
# print("Baseline Error: %.4f" % (100-scores[1]*100))
print("Accuracy score: %.4f" % scores[1])
print("Loss: %.4f" % scores[0])
```

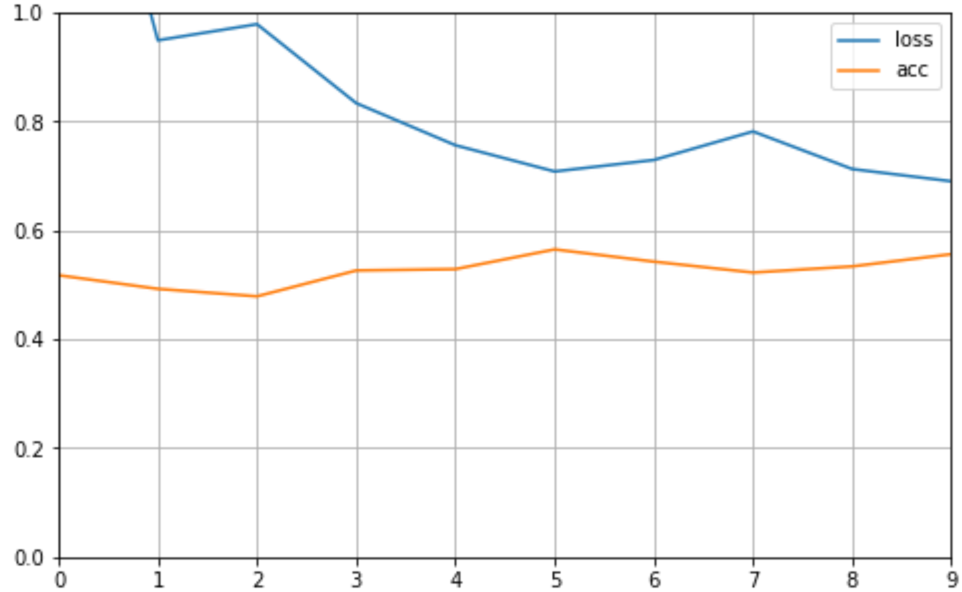
```
Testing scores:
Accuracy score: 0.5600
Loss: 0.6782
```

In [0]:
```python
# # Load the weights
# checkpoint_path = model_path = "results/keras_rnn_model_5.h5"
# # model_name = 'keras_rnn_model_4.h5'
# model_5.load_weights(checkpoint_path)

# # Re-evaluate the model
# scores_revised = model_5.evaluate(X_test, y_test, verbose=0)
# print('Testing scores:')
# print("Accuracy score: %.4f" % scores_revised[1])
# print("Loss: %.4f" % scores_revised[0])
```

```
Testing scores:
Accuracy score: 0.5600
Loss: 0.6782
```

Figure 6: Learning curves for model 5

In [0]:
```
# Plot learning curves
pd.DataFrame(history.history).plot(figsize=(8, 5))
plt.grid(True)
plt.gca().set_ylim(0, 1) # set the vertical range to [0-1]
plt.show()
```



In [0]:
```
# Make test predictions
y_pred = model_5.predict(X_test)
```

In [0]:
```
# Test on 2 reviews
print('Predicted prediction:')
print(y_pred[99])
print('----------')
print('Review text:')
print(test_docs[99])
print('----------')
print('Predicted prediction:')
print(y_pred[187])
print('----------')
print('Review text:')
print(test_docs[187])
```

```
Predicted prediction:
[0.3794259]
----------
Review text:
Although obviously lowbudget production performances songs movie w
orth seeing One Walkens musical roles date marvelous dancer singer
demonstrates skills well watch Also starring Jason Connery great c
hildrens story likable characters
----------
Predicted prediction:
[0.5480095]
----------
Review text:
premise rates low unfortunately also struggles raise laughs intere
st Only Hawns wellknown charm allows thin ice Goldies gotta conten
der actress whos done much career little quality material br
```

Model 6: pre-trained embeddings (300d) with LSTM + ReLU activation

In [0]:

```
# Define model
model_6 = Sequential()
model_6.add(embedding_layer_large)
model_6.add(Bidirectional(LSTM(64)))
model_6.add(Dropout(0.5))
model_6.add(Dense(1, activation='relu'))
print(model_6.summary())
```

```
Model: "sequential_7"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
embedding_2 (Embedding)      (None, 588, 300)          2535600
_________________________________________________________________
bidirectional_7 (Bidirection (None, 128)               186880
_________________________________________________________________
dropout_7 (Dropout)          (None, 128)               0
_________________________________________________________________
dense_7 (Dense)              (None, 1)                 129
=================================================================
Total params: 2,722,609
Trainable params: 187,009
Non-trainable params: 2,535,600
_________________________________________________________________
None
```

In [0]:

```
# Compile model
model_6.compile(loss='binary_crossentropy', optimizer='adam', metri
cs=['accuracy'])
```

In [0]:
```
# Fit network
start_time = time.time()
history = model_6.fit(X_train, y_train, epochs=10, batch_size=64, v
erbose=2)
elapsed_time = time.time() - start_time
print('--------------------------')
print('Training time in seconds: ', round(elapsed_time,2))
print('--------------------------')

# Save models locally after fitting
save_dir = "results/"
model_name = 'keras_rnn_model_6.h5'
model_path = os.path.join(save_dir, model_name)
model_6.save(model_path)
print('Saved trained model at %s ' % model_path)
print('--------------------------')
```

```
Epoch 1/10
 - 27s - loss: 1.9822 - acc: 0.4587
Epoch 2/10
 - 24s - loss: 0.8187 - acc: 0.5450
Epoch 3/10
 - 23s - loss: 0.7823 - acc: 0.5587
Epoch 4/10
 - 24s - loss: 0.6958 - acc: 0.6038
Epoch 5/10
 - 24s - loss: 0.6557 - acc: 0.6187
Epoch 6/10
 - 24s - loss: 0.6869 - acc: 0.6187
Epoch 7/10
 - 24s - loss: 0.6220 - acc: 0.6575
Epoch 8/10
 - 23s - loss: 0.6054 - acc: 0.6613
Epoch 9/10
 - 24s - loss: 0.6007 - acc: 0.6950
Epoch 10/10
 - 24s - loss: 0.5687 - acc: 0.7175
--------------------------
Training time in seconds:  243.03
--------------------------
Saved trained model at results/keras_rnn_model_6.h5
--------------------------
```

In [0]:
```
# Final evaluation of the model
scores = model_6.evaluate(X_test, y_test, verbose=0)
print('Testing scores:')
# print("Baseline Error: %.4f" % (100-scores[1]*100))
print("Accuracy score: %.4f" % scores[1])
print("Loss: %.4f" % scores[0])
```

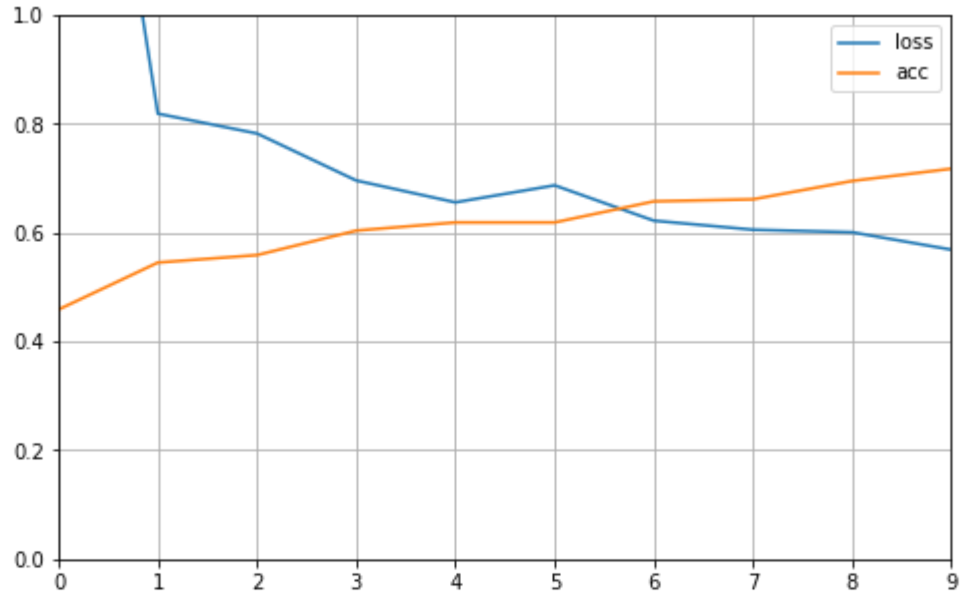
```
Testing scores:
Accuracy score: 0.6400
Loss: 0.5835
```

In [0]:
```
# # Load the weights
# checkpoint_path = model_path = "results/keras_rnn_model_6.h5"
# # model_name = 'keras_rnn_model_6.h5'
# model_6.load_weights(checkpoint_path)

# # Re-evaluate the model
# scores_revised = model_6.evaluate(X_test, y_test, verbose=0)
# print('Testing scores:')
# print("Accuracy score: %.4f" % scores_revised[1])
# print("Loss: %.4f" % scores_revised[0])
```

```
Testing scores:
Accuracy score: 0.6400
Loss: 0.5835
```

Figure 7: Learning curves for model 6

In [0]:
```
# Plot learning curves
pd.DataFrame(history.history).plot(figsize=(8, 5))
plt.grid(True)
plt.gca().set_ylim(0, 1) # set the vertical range to [0-1]
plt.show()
```



In [0]:
```
# Make test predictions
y_pred = model_6.predict(X_test)
```

In [0]:
```python
# Test on 2 reviews
print('Predicted prediction:')
print(y_pred[99])
print('----------')
print('Review text:')
print(test_docs[99])
print('----------')
print('Predicted prediction:')
print(y_pred[187])
print('----------')
print('Review text:')
print(test_docs[187])
```

```
Predicted prediction:
[0.17665206]
----------
Review text:
Although obviously lowbudget production performances songs movie w
orth seeing One Walkens musical roles date marvelous dancer singer
demonstrates skills well watch Also starring Jason Connery great c
hildrens story likable characters
----------
Predicted prediction:
[0.5807091]
----------
Review text:
premise rates low unfortunately also struggles raise laughs intere
st Only Hawns wellknown charm allows thin ice Goldies gotta conten
der actress whos done much career little quality material br
```

Model 7: learned embedding with convolutional and pooling layers

In [0]:

```
# Model 7
model_7 = Sequential()
model_7.add(Embedding(vocab_size, 100, input_length=max_length))
model_7.add(Conv1D(filters=32, kernel_size=8, activation='relu'))
model_7.add(MaxPooling1D(pool_size=2))
model_7.add(Flatten())
model_7.add(Dense(10, activation='relu'))
model_7.add(Dense(1, activation='sigmoid'))
print(model_7.summary())
```

```
WARNING:tensorflow:From /usr/local/lib/python3.6/dist-packages/ker
as/backend/tensorflow_backend.py:4267: The name tf.nn.max_pool is
deprecated. Please use tf.nn.max_pool2d instead.

Model: "sequential_8"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
embedding_6 (Embedding)      (None, 588, 100)          845200
_________________________________________________________________
conv1d_1 (Conv1D)            (None, 581, 32)           25632
_________________________________________________________________
max_pooling1d_1 (MaxPooling1 (None, 290, 32)           0
_________________________________________________________________
flatten_1 (Flatten)          (None, 9280)              0
_________________________________________________________________
dense_8 (Dense)              (None, 10)                92810
_________________________________________________________________
dense_9 (Dense)              (None, 1)                 11
=================================================================
Total params: 963,653
Trainable params: 963,653
Non-trainable params: 0
_________________________________________________________________
None
```

In [0]:

```
# Compile network
model_7.compile(loss='binary_crossentropy', optimizer='adam', metri
cs=['accuracy'])
```

In [0]:
```
# Fit network
start_time = time.time()
history = model_7.fit(X_train, y_train, epochs=10, verbose=2, batch
_size=64)
elapsed_time = time.time() - start_time
print('--------------------------')
print('Training time in seconds: ', round(elapsed_time,2))
print('--------------------------')

# Save models locally after fitting
save_dir = "results/"
model_name = 'keras_rnn_model_7.h5'
model_path = os.path.join(save_dir, model_name)
model_7.save(model_path)
print('Saved trained model at %s ' % model_path)
print('--------------------------')
```

```
Epoch 1/10
 - 8s - loss: 0.6944 - acc: 0.5050
Epoch 2/10
 - 0s - loss: 0.6754 - acc: 0.6388
Epoch 3/10
 - 0s - loss: 0.5892 - acc: 0.9450
Epoch 4/10
 - 0s - loss: 0.3959 - acc: 0.9713
Epoch 5/10
 - 0s - loss: 0.1582 - acc: 0.9850
Epoch 6/10
 - 0s - loss: 0.0400 - acc: 0.9925
Epoch 7/10
 - 0s - loss: 0.0115 - acc: 0.9988
Epoch 8/10
 - 0s - loss: 0.0049 - acc: 1.0000
Epoch 9/10
 - 0s - loss: 0.0027 - acc: 1.0000
Epoch 10/10
 - 0s - loss: 0.0019 - acc: 1.0000
--------------------------
Training time in seconds:  8.74
--------------------------
Saved trained model at results/keras_rnn_model_7.h5
--------------------------
```

In [0]:
```
# Final evaluation of the model
scores = model_7.evaluate(X_test, y_test, verbose=0)
print('Testing scores:')
# print("Baseline Error: %.2f%%" % (100-scores[1]*100))
print("Accuracy score: %.4f" % scores[1])
print("Loss: %.4f" % scores[0])
```

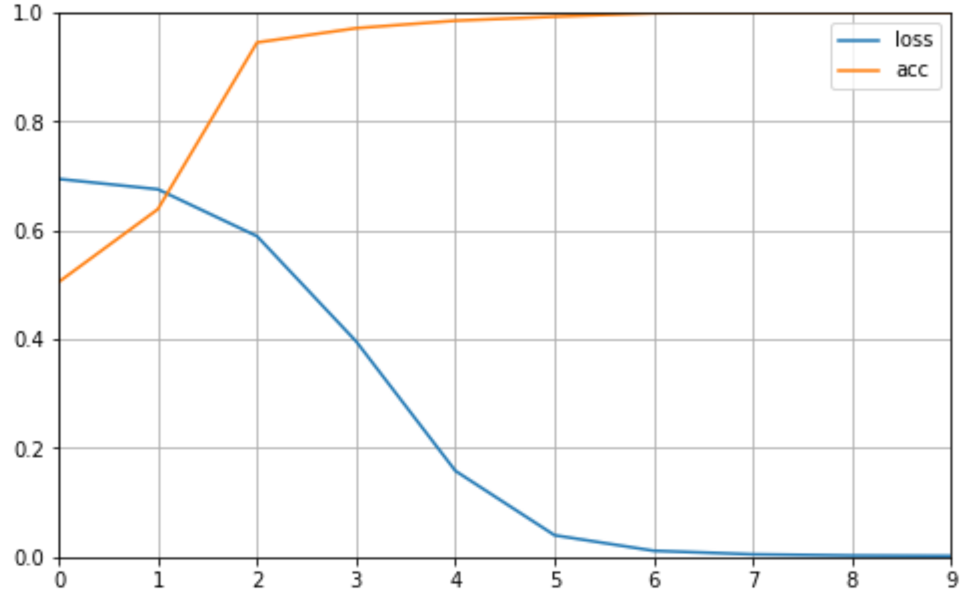
```
Testing scores:
Accuracy score: 0.8600
Loss: 0.3091
```

In [0]:
```
# # Load the weights
# checkpoint_path = model_path = "results/keras_rnn_model_7.h5"
# # model_name = 'keras_rnn_model_7.h5'
# model_7.load_weights(checkpoint_path)

# # Re-evaluate the model
# scores_revised = model_7.evaluate(X_test, y_test, verbose=0)
# print('Testing scores:')
# print("Accuracy score: %.4f" % scores_revised[1])
# print("Loss: %.4f" % scores_revised[0])
```

```
Testing scores:
Accuracy score: 0.8600
Loss: 0.3091
```

Figure 8: Learning curves for model 8

In [0]:
```
# Plot learning curves
pd.DataFrame(history.history).plot(figsize=(8, 5))
plt.grid(True)
plt.gca().set_ylim(0, 1) # set the vertical range to [0-1]
plt.show()
```



In [0]:
```
# Make test predictions
y_pred = model_7.predict(X_test)
```

In [0]:
```
# Test on 2 reviews
print('Predicted prediction:')
print(y_pred[99])
print('----------')
print('Review text:')
print(test_docs[99])
print('----------')
print('Predicted prediction:')
print(y_pred[187])
print('----------')
print('Review text:')
print(test_docs[187])
```

```
Predicted prediction:
[0.21395832]
----------
Review text:
Although obviously lowbudget production performances songs movie w
orth seeing One Walkens musical roles date marvelous dancer singer
demonstrates skills well watch Also starring Jason Connery great c
hildrens story likable characters
----------
Predicted prediction:
[0.4227588]
----------
Review text:
premise rates low unfortunately also struggles raise laughs intere
st Only Hawns wellknown charm allows thin ice Goldies gotta conten
der actress whos done much career little quality material br
```

Model 8: pre-trained embedding (100d) with convolutional and pooling layers

In [0]:
```
# Define model
model_8 = Sequential()
model_8.add(embedding_layer_small)
model_8.add(Conv1D(filters=128, kernel_size=8, activation='relu'))
model_8.add(MaxPooling1D(pool_size=2))
model_8.add(Flatten())
model_8.add(Dense(1, activation='sigmoid'))
print(model_8.summary())
```

```
Model: "sequential_9"
_________________________________________________________________
Layer (type)                 Output Shape              Param #   
=================================================================
embedding_1 (Embedding)      (None, 588, 100)          845200    
_________________________________________________________________
conv1d_2 (Conv1D)            (None, 581, 128)          102528    
_________________________________________________________________
max_pooling1d_2 (MaxPooling1 (None, 290, 128)          0         
_________________________________________________________________
flatten_2 (Flatten)          (None, 37120)             0         
_________________________________________________________________
dense_10 (Dense)             (None, 1)                 37121     
=================================================================
Total params: 984,849
Trainable params: 139,649
Non-trainable params: 845,200
_________________________________________________________________
None
```

In [0]:
```
# Compile network
model_8.compile(loss='binary_crossentropy', optimizer='adam', metri
cs=['accuracy'])
```

In [0]:
```
# Fit network
start_time = time.time()
history = model_8.fit(X_train, y_train, epochs=10, verbose=2, batch
_size=64)
elapsed_time = time.time() - start_time
print('--------------------------')
print('Training time in seconds: ', round(elapsed_time,2))
print('--------------------------')

# Save models locally after fitting
save_dir = "results/"
model_name = 'keras_rnn_model_8.h5'
model_path = os.path.join(save_dir, model_name)
model_8.save(model_path)
print('Saved trained model at %s ' % model_path)
print('--------------------------')
```

```
Epoch 1/10
 - 2s - loss: 0.7693 - acc: 0.5212
Epoch 2/10
 - 0s - loss: 0.6214 - acc: 0.6975
Epoch 3/10
 - 0s - loss: 0.5125 - acc: 0.8237
Epoch 4/10
 - 0s - loss: 0.4041 - acc: 0.8438
Epoch 5/10
 - 0s - loss: 0.3161 - acc: 0.8800
Epoch 6/10
 - 0s - loss: 0.2226 - acc: 0.9587
Epoch 7/10
 - 0s - loss: 0.1557 - acc: 0.9800
Epoch 8/10
 - 0s - loss: 0.1044 - acc: 0.9950
Epoch 9/10
 - 0s - loss: 0.0730 - acc: 0.9975
Epoch 10/10
 - 0s - loss: 0.0551 - acc: 1.0000
--------------------------
Training time in seconds:  3.61
--------------------------
Saved trained model at results/keras_rnn_model_8.h5
--------------------------
```

In [0]:
```
# Final evaluation of the model
scores = model_8.evaluate(X_test, y_test, verbose=0)
print('Testing scores:')
# print("Baseline Error: %.4f" % (100-scores[1]*100))
print("Accuracy score: %.4f" % scores[1])
print("Loss: %.4f" % scores[0])
```

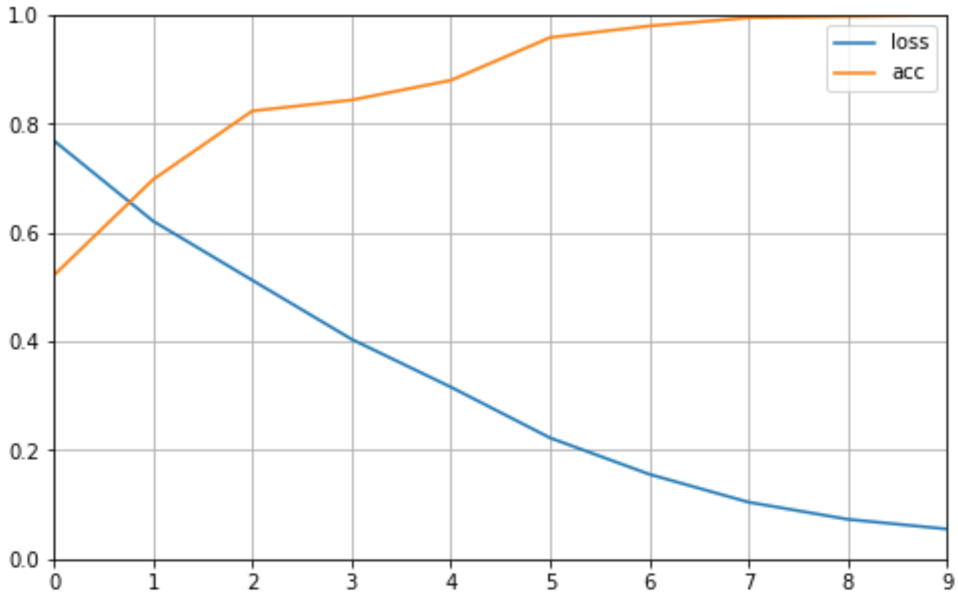
```
Testing scores:
Accuracy score: 0.7250
Loss: 0.6683
```

In [0]:
```
# # Load the weights
# checkpoint_path = model_path = "results/keras_rnn_model_8.h5"
# # model_name = 'keras_rnn_model_8.h5'
# model_8.load_weights(checkpoint_path)

# # Re-evaluate the model
# scores_revised = model_8.evaluate(X_test, y_test, verbose=0)
# print('Testing scores:')
# print("Accuracy score: %.4f" % scores_revised[1])
# print("Loss: %.4f" % scores_revised[0])
```

```
Testing scores:
Accuracy score: 0.7250
Loss: 0.6683
```

Figure 9: Learning curves for model 8

In [0]:
```
# Plot learning curves
pd.DataFrame(history.history).plot(figsize=(8, 5))
plt.grid(True)
plt.gca().set_ylim(0, 1) # set the vertical range to [0-1]
plt.show()
```



In [0]:
```
# Make test predictions
y_pred = model_8.predict(X_test)
```

In [0]:
```
# Test on 2 reviews
print('Predicted prediction:')
print(y_pred[99])
print('----------')
print('Review text:')
print(test_docs[99])
print('----------')
print('Predicted prediction:')
print(y_pred[187])
print('----------')
print('Review text:')
print(test_docs[187])
```

```
Predicted prediction:
[0.02216437]
----------
Review text:
Although obviously lowbudget production performances songs movie w
orth seeing One Walkens musical roles date marvelous dancer singer
demonstrates skills well watch Also starring Jason Connery great c
hildrens story likable characters
----------
Predicted prediction:
[0.22648856]
----------
Review text:
premise rates low unfortunately also struggles raise laughs intere
st Only Hawns wellknown charm allows thin ice Goldies gotta conten
der actress whos done much career little quality material br
```

Model 9: pre-trained embedding (300d) with convolutional and pooling layers

In [0]:
```
# Define model
model_9 = Sequential()
model_9.add(embedding_layer_large)
model_9.add(Conv1D(filters=128, kernel_size=8, activation='relu'))
model_9.add(MaxPooling1D(pool_size=2))
model_9.add(Flatten())
model_9.add(Dense(1, activation='sigmoid'))
print(model_9.summary())
```

```
Model: "sequential_10"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
embedding_2 (Embedding)      (None, 588, 300)          2535600
_________________________________________________________________
conv1d_3 (Conv1D)            (None, 581, 128)          307328
_________________________________________________________________
max_pooling1d_3 (MaxPooling1 (None, 290, 128)          0
_________________________________________________________________
flatten_3 (Flatten)          (None, 37120)             0
_________________________________________________________________
dense_11 (Dense)             (None, 1)                 37121
=================================================================
Total params: 2,880,049
Trainable params: 344,449
Non-trainable params: 2,535,600
_________________________________________________________________
None
```

In [0]:
```
# Compile network
model_9.compile(loss='binary_crossentropy', optimizer='adam', metri
cs=['accuracy'])
```

In [0]:

```
# Fit network
start_time = time.time()
history = model_9.fit(X_train, y_train, epochs=10, verbose=2, batch
_size=64)
elapsed_time = time.time() - start_time
print('--------------------------')
print('Training time in seconds: ', round(elapsed_time,2))
print('--------------------------')

# Save models locally after fitting
save_dir = "results/"
model_name = 'keras_rnn_model_9.h5'
model_path = os.path.join(save_dir, model_name)
model_9.save(model_path)
print('Saved trained model at %s ' % model_path)
print('--------------------------')
```

```
Epoch 1/10
 - 3s - loss: 0.7121 - acc: 0.5275
Epoch 2/10
 - 0s - loss: 0.4973 - acc: 0.8600
Epoch 3/10
 - 0s - loss: 0.2860 - acc: 0.9237
Epoch 4/10
 - 0s - loss: 0.1544 - acc: 0.9662
Epoch 5/10
 - 0s - loss: 0.0823 - acc: 0.9975
Epoch 6/10
 - 0s - loss: 0.0448 - acc: 1.0000
Epoch 7/10
 - 0s - loss: 0.0239 - acc: 1.0000
Epoch 8/10
 - 0s - loss: 0.0151 - acc: 1.0000
Epoch 9/10
 - 0s - loss: 0.0107 - acc: 1.0000
Epoch 10/10
 - 0s - loss: 0.0083 - acc: 1.0000
--------------------------
Training time in seconds:  4.96
--------------------------
Saved trained model at results/keras_rnn_model_9.h5
--------------------------
```

In [0]:
```
# Final evaluation of the model
scores = model_9.evaluate(X_test, y_test, verbose=0)
print('Testing scores:')
# print("Baseline Error: %.4f" % (100-scores[1]*100))
print("Accuracy score: %.4f" % scores[1])
print("Loss: %.4f" % scores[0])
```

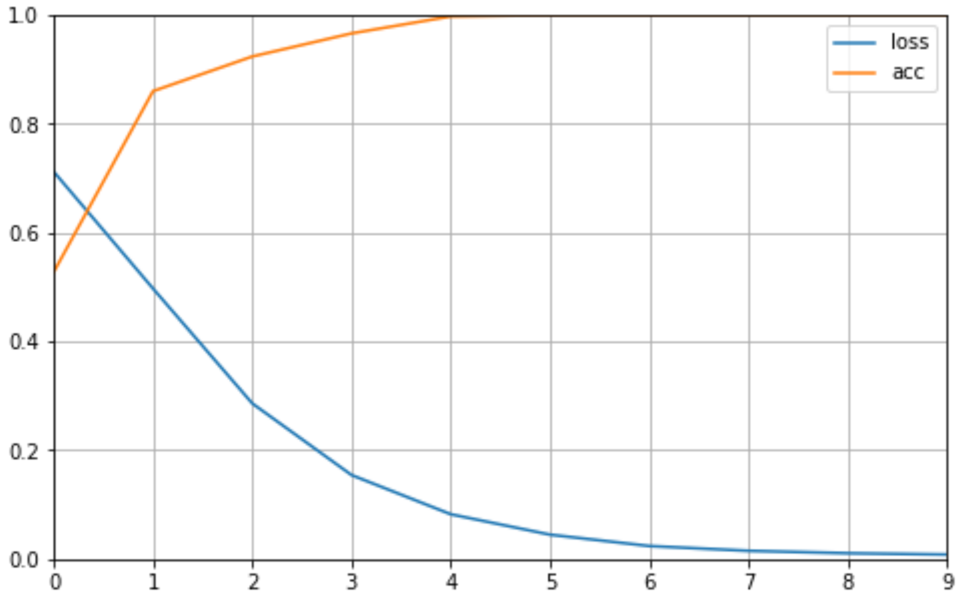
```
Testing scores:
Accuracy score: 0.7550
Loss: 0.6134
```

In [0]:
```
# # Load the weights
# checkpoint_path = model_path = "results/keras_rnn_model_9.h5"
# # model_name = 'keras_rnn_model_9.h5'
# model_9.load_weights(checkpoint_path)

# # Re-evaluate the model
# scores_revised = model_9.evaluate(X_test, y_test, verbose=0)
# print('Testing scores:')
# print("Accuracy score: %.4f" % scores_revised[1])
# print("Loss: %.4f" % scores_revised[0])
```

```
Testing scores:
Accuracy score: 0.7550
Loss: 0.6134
```

Figure 10: Learning curves for model 9

In [0]:
```
# Plot learning curves
pd.DataFrame(history.history).plot(figsize=(8, 5))
plt.grid(True)
plt.gca().set_ylim(0, 1) # set the vertical range to [0-1]
plt.show()
```



In [0]:
```
# Make test predictions
y_pred = model_9.predict(X_test)
```

In [0]:
```
# Test on 2 reviews
print('Predicted prediction:')
print(y_pred[99])
print('----------')
print('Review text:')
print(test_docs[99])
print('----------')
print('Predicted prediction:')
print(y_pred[187])
print('----------')
print('Review text:')
print(test_docs[187])
```

```
Predicted prediction:
[0.0088219]
----------
Review text:
Although obviously lowbudget production performances songs movie w
orth seeing One Walkens musical roles date marvelous dancer singer
demonstrates skills well watch Also starring Jason Connery great c
hildrens story likable characters
----------
Predicted prediction:
[0.3938866]
----------
Review text:
premise rates low unfortunately also struggles raise laughs intere
st Only Hawns wellknown charm allows thin ice Goldies gotta conten
der actress whos done much career little quality material br
```

In [0]:
```

```