

```
In [1]: # Credits: https://machinelearningmastery.com/sequence-classification-lstm-recurrent-neural-networks-python-keras/
# LSTM for sequence classification in the IMDB dataset
import numpy
from keras.datasets import imdb
from keras.preprocessing.text import Tokenizer
from keras.models import Sequential
from keras.layers import Dense
from keras.layers import LSTM
from keras.layers.embeddings import Embedding
from keras.preprocessing import sequence
# fix random seed for reproducibility
numpy.random.seed(7)
```

Using TensorFlow backend.

```
In [0]: import warnings
warnings.filterwarnings("ignore")
warnings.simplefilter(action='ignore', category=FutureWarning)
```

```
In [3]: # Using Prettytable for displaying the observations
from prettytable import PrettyTable
table = PrettyTable()
table.field_names = ["Embedding Len", "Architechture", "Accuracy", "Loss"]
print(table)
```

```
+-----+-----+-----+-----+
| Embedding Len | Architechture | Accuracy | Loss |
+-----+-----+-----+-----+
+-----+-----+-----+-----+
```

```
In [0]: # 1. Please remove the imdb code as it causes confusion.
# 2. Plot the loss and accuracies for both train and test data.
# 3. Make sure none of your models overfit.
# 4. Add a pretty table in the end comparing all the models.
```

```
In [4]: from google.colab import drive
drive.mount('/content/drive')
```

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%3Aawg%3Aoauth%3A2.0%3Aaob&scope=email%20https%3A%2F%2Fwww.googleapis.com%2Fauth%2Fdocs.test%20https%3A%2F%2Fwww.googleapis.com%2Fauth%2Fdrive%20https%3A%2F%2Fwww.googleapis.com%2Fauth%2Fdrive.photos.readonly%20https%3A%2F%2Fwww.googleapis.com%2Fauth%2Fpeopleapi.readonly&response\\_type=code](https://accounts.google.com/o/oauth2/auth?client_id=947318989803-6bn6qk8qdgf4n4g3pfee6491hc0brc4i.apps.googleusercontent.com&redirect_uri=urn%3Aietf%3Aawg%3Aoauth%3A2.0%3Aaob&scope=email%20https%3A%2F%2Fwww.googleapis.com%2Fauth%2Fdocs.test%20https%3A%2F%2Fwww.googleapis.com%2Fauth%2Fdrive%20https%3A%2F%2Fwww.googleapis.com%2Fauth%2Fdrive.photos.readonly%20https%3A%2F%2Fwww.googleapis.com%2Fauth%2Fpeopleapi.readonly&response_type=code)

Enter your authorization code:  
.....

Mounted at /content/drive

```
In [0]: import sqlite3
import os, re
from tqdm import tqdm
import numpy as np
import pandas as pd
from bs4 import BeautifulSoup
import matplotlib.pyplot as plt
```

```
In [0]: from sklearn.model_selection import train_test_split
```

```
In [0]: dir_path='/content/drive/My Drive/Colab Notebooks/AppliedAI/'
```

```
In [0]: # Subsequent code copied from previous assignments

con = sqlite3.connect(dir_path+'database.sqlite')
filtered_data = pd.read_sql_query(
    "SELECT * FROM Reviews WHERE Score < 3 LIMIT 50000", con)

filtered_data = filtered_data.append(pd.read_sql_query(
    "SELECT * FROM Reviews WHERE Score > 3 LIMIT 50000", con))
filtered_data.reset_index(drop=True, inplace=True)
```

```
In [0]: # changing reviews with score less than 3 to be positive and vice-versa
filtered_data['Score']=filtered_data['Score'].apply(lambda x : 0 if x<3 else 1)
```

```
In [0]: #Sorting data according to ProductId in ascending order
sorted_data=filtered_data.sort_values('ProductId', axis=0, ascending=True,
    inplace=False,kind='quicksort',na_position='last')
```

```
In [10]: #Deduplication of entries
final=sorted_data.drop_duplicates(subset={"UserId","ProfileName",
    "Time","Text"},keep='first', inplace=False)

final.shape
```

Out[10]: (83317, 10)

```
In [0]: final=final[final.HelpfulnessNumerator<=final.HelpfulnessDenominator]
```

```
In [12]: print(final.shape)
#How many positive and negative reviews are present in our dataset?
final['Score'].value_counts()

(83315, 10)
```

Out[12]: 1      45420  
0      37895  
Name: Score, dtype: int64

```
In [0]: def decontracted(phrase):
    # specific
    phrase = re.sub(r"won't", "will not", phrase)
    phrase = re.sub(r"can't", "can not", phrase)
    # general
    phrase = re.sub(r"n't", " not", phrase)
    phrase = re.sub(r"\ 're", " are", phrase)
    phrase = re.sub(r"\ 's", " is", phrase)
    phrase = re.sub(r"\ 'd", " would", phrase)
    phrase = re.sub(r"\ 'll", " will", phrase)
    phrase = re.sub(r"\ 't", " not", phrase)
    phrase = re.sub(r"\ 've", " have", phrase)
    phrase = re.sub(r"\ 'm", " am", phrase)
    return phrase
```

```
In [0]: stopwords= set(['br', 'the', 'i', 'me', 'my', 'myself', 'we', 'our', 'ours',\
                        'ourselves', 'you', "you're", "you've",\
                        "you'll", "you'd", 'your', 'yours', 'yourself', 'yourselves', 'he', 'him',\
                        'his', 'himself', \
                        'she', "she's", 'her', 'hers', 'herself', 'it', "it's", 'its', 'itself', \
                        'they', 'them', 'their',\
                        'theirs', 'themselves', 'what', 'which', 'who', 'whom', 'this', 'that',\
                        "that'll", 'these', 'those', \
                        'am', 'is', 'are', 'was', 'were', 'be', 'been', 'being', 'have', 'has',\
                        'had', 'having', 'do', 'does', \
                        'did', 'doing', 'a', 'an', 'the', 'and', 'but', 'if', 'or', 'because', \
                        'as', 'until', 'while', 'of', \
                        'at', 'by', 'for', 'with', 'about', 'against', 'between', 'into', 'through',\
                        'during', 'before', 'after',\
                        'above', 'below', 'to', 'from', 'up', 'down', 'in', 'out', 'on', 'off',\
                        'over', 'under', 'again', 'further',\
                        'then', 'once', 'here', 'there', 'when', 'where', 'why', 'how', 'all',\
                        'any', 'both', 'each', 'few', 'more',\
                        'most', 'other', 'some', 'such', 'only', 'own', 'same', 'so', 'than',\
                        'too', 'very', \
                        's', 't', 'can', 'will', 'just', 'don', "don't", 'should', "should've",\
                        'now', 'd', 'll', 'm', 'o', 're', \
                        've', 'y', 'ain', 'aren', "aren't", 'couldn', "couldn't", 'didn',\
                        "didn't", 'doesn', "doesn't", 'hadn',\
                        "hadn't", 'hasn', "hasn't", 'haven', "haven't", 'isn', "isn't",\
                        'ma', 'mightn', "mightn't", 'mustn',\
                        "mustn't", 'needn', "needn't", 'shan', "shan't", 'shouldn',\
                        "shouldn't", 'wasn', "wasn't", 'weren', "weren't", \
                        'won', "won't", 'wouldn', "wouldn't"])
```

```
In [15]: preprocessed_reviews = []
review_score = []
# tqdm is for printing the status bar
for sentence, score in tqdm(final[['Text', 'Score']].values):
    sentence = re.sub(r"http\S+", "", sentence)
    sentence = BeautifulSoup(sentence, 'lxml').get_text()
    sentence = decontracted(sentence)
    sentence = re.sub("\S*\d\S*", "", sentence).strip()
    sentence = re.sub('[^A-Za-z]+', ' ', sentence)
    # https://gist.github.com/sebleier/554280
    sentence = ' '.join(e.lower() for e in sentence.split() \
                        if e.lower() not in stopwords)
    preprocessed_reviews.append(sentence.strip())
    review_score.append(score)
```

100%|██████████| 83315/83315 [00:33<00:00, 2491.64it/s]

```
In [16]: ## Similarly you can do preprocessing for review summary also.
# Combining all the above students
preprocessed_summary = []
for summary in tqdm(final['Summary'].values):
    summary = re.sub(r"http\S+", "", summary)
    summary = BeautifulSoup(summary, 'lxml').get_text()
    summary = decontracted(summary)
    summary = re.sub("\S*\d\S*", "", summary).strip()
    summary = re.sub('[^A-Za-z0-9]+', ' ', summary)
    # adding 0-9 in the regex
    summary = ' '.join(e.lower() for e in summary.split() \
                        if e.lower() not in stopwords)
    preprocessed_summary.append(summary.strip())
```

100%|██████████| 83315/83315 [00:20<00:00, 4020.21it/s]

```
In [17]: preprocessed_text = [str(rev+' '+summ) for rev, summ in \
zip(preprocessed_reviews, preprocessed_summary)]
print(preprocessed_text[:5])
```

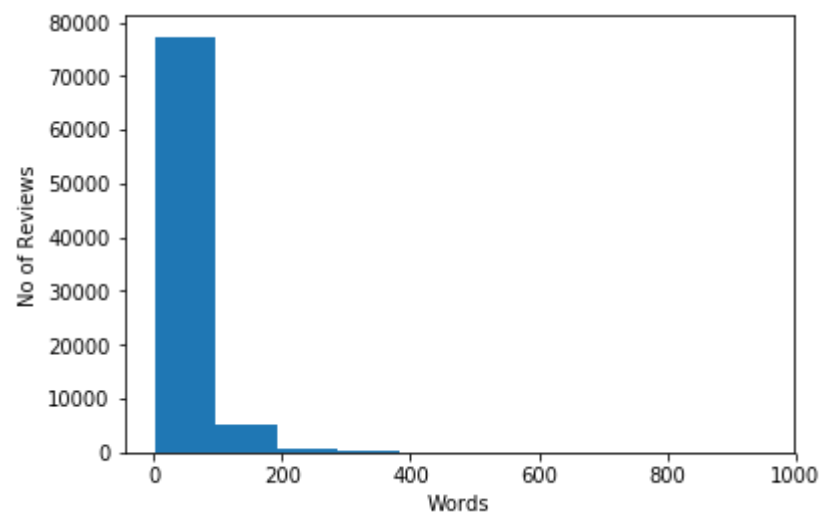
```
['one best children books ever written mini version book not portrayed one priced product sent email regarding bewilderment amazon got no response awesome book poor siz
e', 'give five stars maurice sendak story one star printed edition book children older copy book familiar previous softcover version ordered granddaughters embarrassed gi
ve gift looks puny book size postcard think overpriced learned lesson not buying softcover children books next time get used copy story great softcover book disappointin
g', 'dogs loves chicken product china wont buying anymore hard find chicken products made usa one isnt bad good product wont take chances till know going china imports ma
de china', 'dogs love saw pet store tag attached regarding made china satisfied safe dog lover delites', 'received containers previously opened seals opened top container
s decent pieces liver grisley pieces lot powder bottom never buy liver treats amazon big rip review freeze dried liver treats dogs']
```

```
In [0]: # PLOt the length of the text
text_lens = [len(text.split()) for text in preprocessed_text]
```

```
In [19]: max(text_lens)
```

Out[19]: 952

```
In [20]: plt.hist(text_lens, bins=10)
plt.ylabel('No of Reviews')
plt.xlabel('Words')
plt.show()
```



```
In [0]: # Although the maximum value of length of text is 952, but we can fix that to
# 400 as that would cover almost whole of the data (as seen from plot)
```

```
In [0]: # this is random splitting into train, test and cross validation set
X_train, X_test, y_train, y_test = train_test_split(preprocessed_text,
                                                    review_score, test_size=0.30, random_state = 0,
                                                    stratify = review_score)
```

```
In [0]: X_cv, X_test, y_cv, y_test = train_test_split(X_test, y_test,
                                                    test_size=0.50, random_state = 0,
                                                    stratify = y_test)
```

```
In [0]: ### Create Tokenizer
vocabulary_size = 5000
tokenizer = Tokenizer(num_words= vocabulary_size)
tokenizer.fit_on_texts(X_train)
```

```
In [0]: # Convert text to int sequences
X_train = tokenizer.texts_to_sequences(X_train)
X_test = tokenizer.texts_to_sequences(X_test)
X_cv = tokenizer.texts_to_sequences(X_cv)
```

```
In [0]: # truncate and/or pad input sequences
max_review_length = 400
X_train = sequence.pad_sequences(X_train, maxlen=max_review_length)
X_test = sequence.pad_sequences(X_test, maxlen=max_review_length)
X_cv = sequence.pad_sequences(X_cv, maxlen=max_review_length)
```

```
In [27]: print(X_train.shape)
print(X_test.shape)
print(X_cv.shape)
```

(58320, 400)  
(12498, 400)  
(12497, 400)

```
In [28]: # create the model
embedding_vecor_length = 32
model = Sequential()
model.add(Embedding(vocabulary_size+1, embedding_vecor_length,
                    input_length=max_review_length))
model.add(LSTM(50))
# , activation='tanh', use_bias=True,
#           kernel_initializer='glorot_uniform'
model.add(Dense(1, activation='sigmoid'))
model.compile(loss='binary_crossentropy',
              optimizer='adam', metrics=['accuracy'])
print(model.summary())
#Refer: https://datascience.stackexchange.com/questions/10615/number-of-parameters-in-an-lstm-model
```

WARNING:tensorflow:From /usr/local/lib/python3.6/dist-packages/keras/backend/tensorflow\_backend.py:66: The name tf.get\_default\_graph is deprecated. Please use tf.compat.v1.get\_default\_graph instead.

WARNING:tensorflow:From /usr/local/lib/python3.6/dist-packages/keras/backend/tensorflow\_backend.py:541: The name tf.placeholder is deprecated. Please use tf.compat.v1.placeholder instead.

WARNING:tensorflow:From /usr/local/lib/python3.6/dist-packages/keras/backend/tensorflow\_backend.py:4432: The name tf.random\_uniform is deprecated. Please use tf.random.uniform instead.

WARNING:tensorflow:From /usr/local/lib/python3.6/dist-packages/keras/optimizers.py:793: The name tf.train.Optimizer is deprecated. Please use tf.compat.v1.train.Optimizer instead.

WARNING:tensorflow:From /usr/local/lib/python3.6/dist-packages/keras/backend/tensorflow\_backend.py:3657: The name tf.log is deprecated. Please use tf.math.log instead.

WARNING:tensorflow:From /usr/local/lib/python3.6/dist-packages/tensorflow\_core/python/ops/nn\_impl.py:183: where (from tensorflow.python.ops.array\_ops) is deprecated and will be removed in a future version.

Instructions for updating:  
Use tf.where in 2.0, which has the same broadcast rule as np.where  
Model: "sequential\_1"

Layer (type)	Output Shape	Param #
=====		
embedding_1 (Embedding)	(None, 400, 32)	160032
-----		
lstm_1 (LSTM)	(None, 50)	16600
-----		
dense_1 (Dense)	(None, 1)	51
=====		
Total params: 176,683		
Trainable params: 176,683		
Non-trainable params: 0		
-----		
None		

In [29]: `# https://stackoverflow.com/questions/41908379/keras-plot-training-validation-and-test-set-accuracy`

```
history = model.fit(X_train, y_train, validation_data=(X_cv, y_cv),
                    nb_epoch=10, batch_size=128, verbose =2)
```

WARNING:tensorflow:From /usr/local/lib/python3.6/dist-packages/keras/backend/tensorflow\_backend.py:1033: The name tf.assign\_add is deprecated. Please use tf.compat.v1.assign\_add instead.

WARNING:tensorflow:From /usr/local/lib/python3.6/dist-packages/keras/backend/tensorflow\_backend.py:1020: The name tf.assign is deprecated. Please use tf.compat.v1.assign instead.

WARNING:tensorflow:From /usr/local/lib/python3.6/dist-packages/keras/backend/tensorflow\_backend.py:3005: The name tf.Session is deprecated. Please use tf.compat.v1.Session instead.

Train on 58320 samples, validate on 12497 samples

Epoch 1/10

WARNING:tensorflow:From /usr/local/lib/python3.6/dist-packages/keras/backend/tensorflow\_backend.py:190: The name tf.get\_default\_session is deprecated. Please use tf.compat.v1.get\_default\_session instead.

WARNING:tensorflow:From /usr/local/lib/python3.6/dist-packages/keras/backend/tensorflow\_backend.py:197: The name tf.ConfigProto is deprecated. Please use tf.compat.v1.ConfigProto instead.

WARNING:tensorflow:From /usr/local/lib/python3.6/dist-packages/keras/backend/tensorflow\_backend.py:207: The name tf.global\_variables is deprecated. Please use tf.compat.v1.global\_variables instead.

WARNING:tensorflow:From /usr/local/lib/python3.6/dist-packages/keras/backend/tensorflow\_backend.py:216: The name tf.is\_variable\_initialized is deprecated. Please use tf.compat.v1.is\_variable\_initialized instead.

WARNING:tensorflow:From /usr/local/lib/python3.6/dist-packages/keras/backend/tensorflow\_backend.py:223: The name tf.variables\_initializer is deprecated. Please use tf.compat.v1.variables\_initializer instead.

- 243s - loss: 0.2863 - acc: 0.8756 - val\_loss: 0.2030 - val\_acc: 0.9185

Epoch 2/10

- 240s - loss: 0.1823 - acc: 0.9307 - val\_loss: 0.1933 - val\_acc: 0.9225

Epoch 3/10

- 242s - loss: 0.1640 - acc: 0.9370 - val\_loss: 0.1975 - val\_acc: 0.9241

Epoch 4/10

- 242s - loss: 0.1456 - acc: 0.9461 - val\_loss: 0.1981 - val\_acc: 0.9229

Epoch 5/10

- 240s - loss: 0.1269 - acc: 0.9526 - val\_loss: 0.2144 - val\_acc: 0.9236

Epoch 6/10

- 242s - loss: 0.1135 - acc: 0.9586 - val\_loss: 0.2275 - val\_acc: 0.9184

Epoch 7/10

- 236s - loss: 0.0992 - acc: 0.9642 - val\_loss: 0.2229 - val\_acc: 0.9187

Epoch 8/10

- 236s - loss: 0.0891 - acc: 0.9683 - val\_loss: 0.2501 - val\_acc: 0.9193

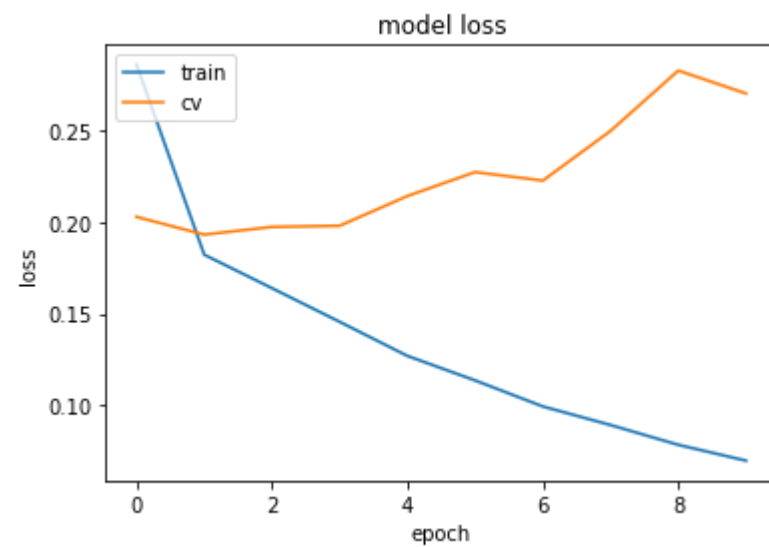
Epoch 9/10

- 236s - loss: 0.0783 - acc: 0.9735 - val\_loss: 0.2831 - val\_acc: 0.9173

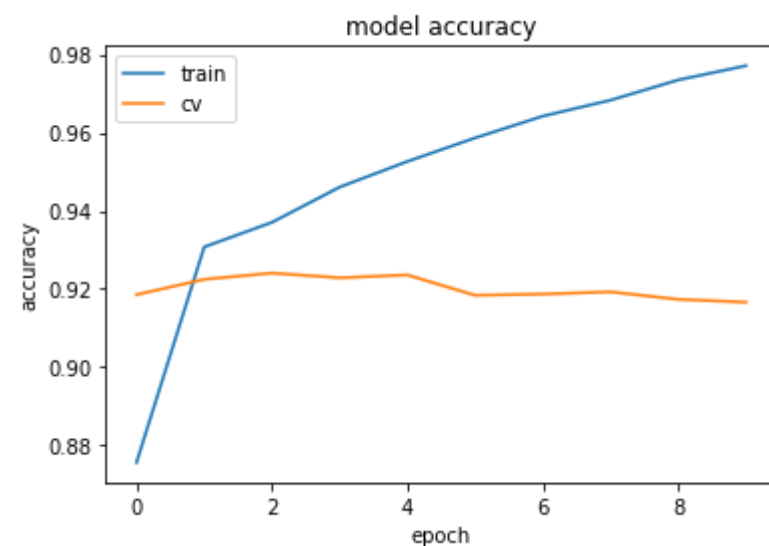
Epoch 10/10

- 236s - loss: 0.0696 - acc: 0.9771 - val\_loss: 0.2706 - val\_acc: 0.9166

```
In [30]: # This is for plotting the model loss
plt.plot(history.history['loss'])
plt.plot(history.history['val_loss'])
plt.title('model loss')
plt.ylabel('loss')
plt.xlabel('epoch')
plt.legend(['train', 'cv'], loc='upper left')
plt.show()
```



```
In [31]: # This is for plotting the model accuracy
plt.plot(history.history['acc'])
plt.plot(history.history['val_acc'])
plt.title('model accuracy')
plt.ylabel('accuracy')
plt.xlabel('epoch')
plt.legend(['train', 'cv'], loc='upper left')
plt.show()
```



```
In [32]: # Final evaluation of the model
scores = model.evaluate(X_test, y_test, verbose=0)
print("Accuracy: %.2f%%" % (scores[1]*100))
print("Loss : %.2f%%" % (scores[0]))
```

Accuracy: 91.41%  
Loss : 0.27%

```
In [0]: table.add_row([32, 'LSTM(50)-Dense', 'Train: 97% Test:91%',
                        'Train: 0.06 Test: 0.27'])
```

In [0]: `# Model 2`

```
In [35]: # create the model
embedding_vecor_length = 64
model = Sequential()
model.add(Embedding(vocabulary_size+1, embedding_vecor_length,
                    input_length=max_review_length))
model.add(LSTM(32, return_sequences=True, dropout=0.3))
model.add(LSTM(16, dropout=0.3))
model.add(Dense(1, activation='sigmoid'))
model.compile(loss='binary_crossentropy',
              optimizer='adam', metrics=['accuracy'])
print(model.summary())
#Refer: https://datascience.stackexchange.com/questions/10615/number-of-parameters-in-an-lstm-model
```

WARNING:tensorflow:From /usr/local/lib/python3.6/dist-packages/keras/backend/tensorflow\_backend.py:148: The name tf.placeholder\_with\_default is deprecated. Please use tf.compat.v1.placeholder\_with\_default instead.

WARNING:tensorflow:From /usr/local/lib/python3.6/dist-packages/keras/backend/tensorflow\_backend.py:3733: calling dropout (from tensorflow.python.ops.nn\_ops) with keep\_prob is deprecated and will be removed in a future version.  
Instructions for updating:  
Please use `rate` instead of `keep\_prob`. Rate should be set to `rate = 1 - keep\_prob`.  
Model: "sequential\_2"

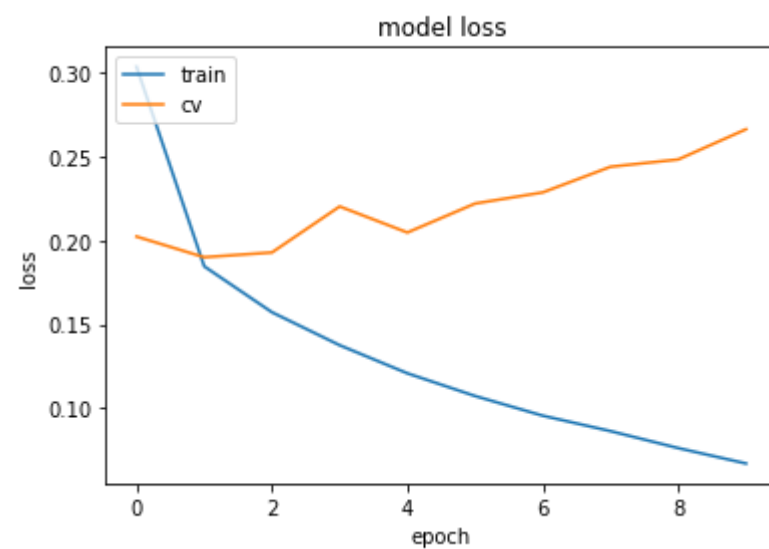
Layer (type)	Output Shape	Param #
embedding_2 (Embedding)	(None, 400, 64)	320064
lstm_2 (LSTM)	(None, 400, 32)	12416
lstm_3 (LSTM)	(None, 16)	3136
dense_2 (Dense)	(None, 1)	17
Total params: 335,633		
Trainable params: 335,633		
Non-trainable params: 0		
None		



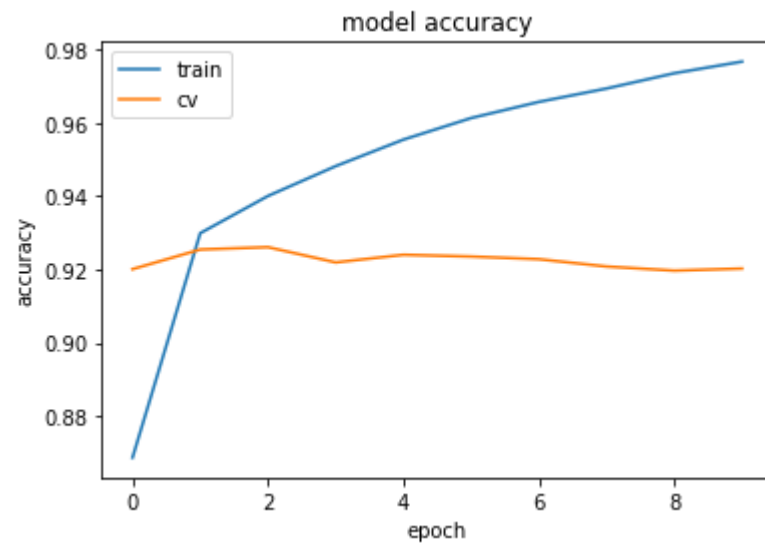
```
In [36]: history = model.fit(X_train, y_train, nb_epoch=10, batch_size=128,
                             validation_data=(X_cv, y_cv), verbose=2)

Train on 58320 samples, validate on 12497 samples
Epoch 1/10
- 425s - loss: 0.3034 - acc: 0.8686 - val_loss: 0.2022 - val_acc: 0.9201
Epoch 2/10
- 422s - loss: 0.1845 - acc: 0.9299 - val_loss: 0.1899 - val_acc: 0.9254
Epoch 3/10
- 421s - loss: 0.1571 - acc: 0.9400 - val_loss: 0.1927 - val_acc: 0.9261
Epoch 4/10
- 416s - loss: 0.1375 - acc: 0.9482 - val_loss: 0.2201 - val_acc: 0.9219
Epoch 5/10
- 416s - loss: 0.1208 - acc: 0.9554 - val_loss: 0.2046 - val_acc: 0.9240
Epoch 6/10
- 418s - loss: 0.1072 - acc: 0.9613 - val_loss: 0.2219 - val_acc: 0.9235
Epoch 7/10
- 404s - loss: 0.0955 - acc: 0.9657 - val_loss: 0.2285 - val_acc: 0.9228
Epoch 8/10
- 402s - loss: 0.0863 - acc: 0.9693 - val_loss: 0.2438 - val_acc: 0.9208
Epoch 9/10
- 402s - loss: 0.0762 - acc: 0.9735 - val_loss: 0.2481 - val_acc: 0.9197
Epoch 10/10
- 409s - loss: 0.0670 - acc: 0.9767 - val_loss: 0.2661 - val_acc: 0.9202
```

```
In [37]: # This is for plotting the model loss
plt.plot(history.history['loss'])
plt.plot(history.history['val_loss'])
plt.title('model loss')
plt.ylabel('loss')
plt.xlabel('epoch')
plt.legend(['train', 'cv'], loc='upper left')
plt.show()
```



```
In [38]: # This is for plotting the model accuracy
plt.plot(history.history['acc'])
plt.plot(history.history['val_acc'])
plt.title('model accuracy')
plt.ylabel('accuracy')
plt.xlabel('epoch')
plt.legend(['train', 'cv'], loc='upper left')
plt.show()
```



```
In [39]: # Final evaluation of the model
scores = model.evaluate(X_test, y_test, verbose=0)
print("Accuracy: %.2f%%" % (scores[1]*100))
print("Loss : %.2f%%" % (scores[0]))
```

Accuracy: 91.82%  
Loss : 0.28%

```
In [0]: table.add_row([64, 'LSTM(32)-LSTM(16)-Dense', 'Train: 97.6% Test:91.8%',  
                      'Train: 0.06 Test: 0.28'])
```

```
In [0]:
```

```
In [0]: # Model 3
```

```
In [42]: # create the model
embedding_vecor_length = 32
model = Sequential()
model.add(Embedding(vocabulary_size+1, embedding_vecor_length,
                    input_length=max_review_length))
model.add(LSTM(50, activation='tanh', use_bias=True,
               kernel_initializer='glorot_uniform'))
model.add(Dense(1, activation='sigmoid'))
model.compile(loss='binary_crossentropy',
              optimizer='adam', metrics=['accuracy'])
print(model.summary())
```

Model: "sequential\_3"

Layer (type)	Output Shape	Param #
embedding_3 (Embedding)	(None, 400, 32)	160032
lstm_4 (LSTM)	(None, 50)	16600
dense_3 (Dense)	(None, 1)	51

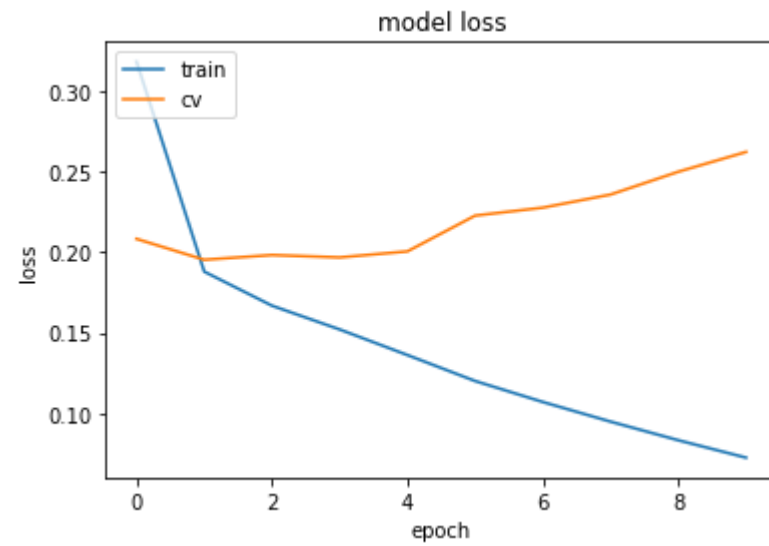
Total params: 176,683  
Trainable params: 176,683  
Non-trainable params: 0

None

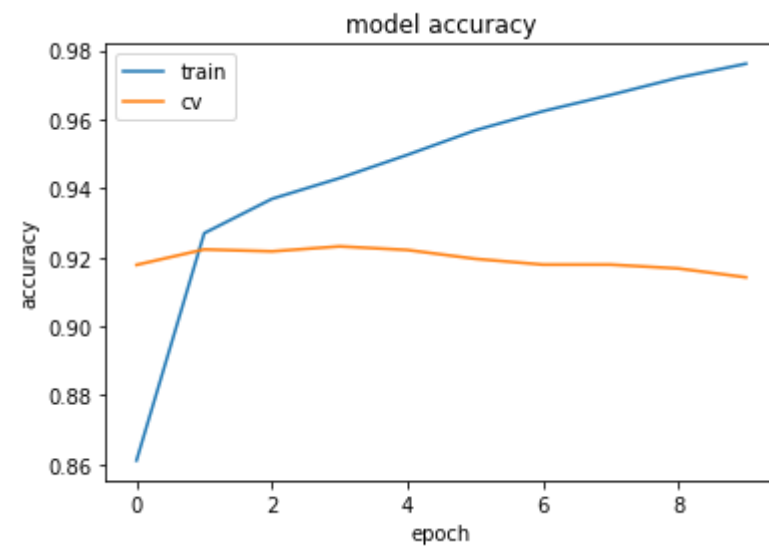
```
In [43]: history = model.fit(X_train, y_train, nb_epoch=10, batch_size=128,
                             validation_data=(X_cv, y_cv), verbose=2)
```

Train on 58320 samples, validate on 12497 samples  
Epoch 1/10  
- 248s - loss: 0.3186 - acc: 0.8611 - val\_loss: 0.2083 - val\_acc: 0.9178  
Epoch 2/10  
- 244s - loss: 0.1880 - acc: 0.9270 - val\_loss: 0.1954 - val\_acc: 0.9223  
Epoch 3/10  
- 249s - loss: 0.1668 - acc: 0.9370 - val\_loss: 0.1983 - val\_acc: 0.9217  
Epoch 4/10  
- 252s - loss: 0.1520 - acc: 0.9430 - val\_loss: 0.1968 - val\_acc: 0.9232  
Epoch 5/10  
- 248s - loss: 0.1361 - acc: 0.9497 - val\_loss: 0.2006 - val\_acc: 0.9221  
Epoch 6/10  
- 249s - loss: 0.1200 - acc: 0.9568 - val\_loss: 0.2228 - val\_acc: 0.9196  
Epoch 7/10  
- 250s - loss: 0.1069 - acc: 0.9623 - val\_loss: 0.2278 - val\_acc: 0.9179  
Epoch 8/10  
- 247s - loss: 0.0947 - acc: 0.9671 - val\_loss: 0.2359 - val\_acc: 0.9179  
Epoch 9/10  
- 252s - loss: 0.0831 - acc: 0.9721 - val\_loss: 0.2501 - val\_acc: 0.9168  
Epoch 10/10  
- 257s - loss: 0.0723 - acc: 0.9761 - val\_loss: 0.2624 - val\_acc: 0.9142

```
In [44]: # This is for plotting the model loss
plt.plot(history.history['loss'])
plt.plot(history.history['val_loss'])
plt.title('model loss')
plt.ylabel('loss')
plt.xlabel('epoch')
plt.legend(['train', 'cv'], loc='upper left')
plt.show()
```



```
In [45]: # This is for plotting the model accuracy
plt.plot(history.history['acc'])
plt.plot(history.history['val_acc'])
plt.title('model accuracy')
plt.ylabel('accuracy')
plt.xlabel('epoch')
plt.legend(['train', 'cv'], loc='upper left')
plt.show()
```



```
In [47]: # Final evaluation of the model
scores = model.evaluate(X_test, y_test, verbose=0)
print("Accuracy: %.2f%%" % (scores[1]*100))
print("Loss : %.2f%%" % (scores[0]))
```

Accuracy: 91.65%  
Loss : 0.26%

```
In [0]: table.add_row([32, 'LSTM(50)-Dense', 'Train: 97.6% Test:91.6%',
                        'Train: 0.07 Test: 0.26'])
```

In [0]:

In [0]: *# Model 4*

```
In [52]: # create the model
embedding_vecor_length = 32
model = Sequential()
model.add(Embedding(vocabulary_size+1, embedding_vecor_length,
                    input_length=max_review_length))
model.add(LSTM(32, activation='tanh', use_bias=True,
               kernel_initializer='glorot_uniform', dropout=0.4))
model.add(Dense(1, activation='sigmoid'))
model.compile(loss='binary_crossentropy',
              optimizer='adam', metrics=['accuracy'])
print(model.summary())
```

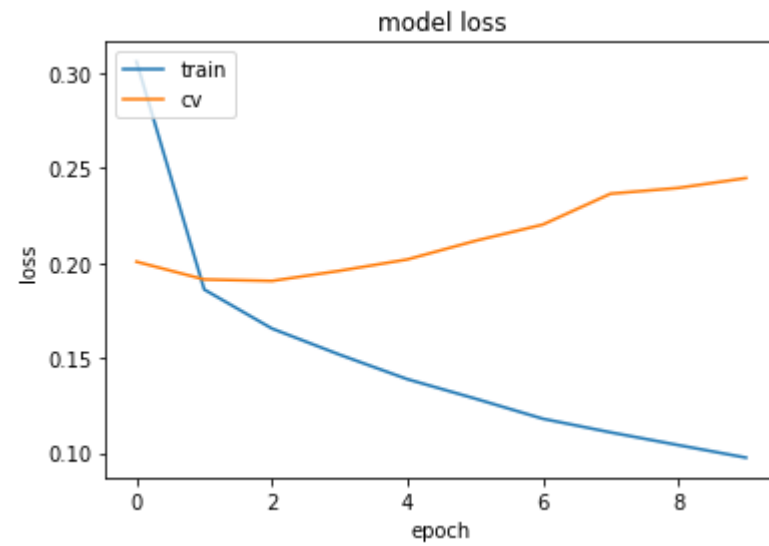
Model: "sequential\_4"

Layer (type)	Output Shape	Param #
=====		
embedding_4 (Embedding)	(None, 400, 32)	160032
-----		
lstm_5 (LSTM)	(None, 32)	8320
-----		
dense_4 (Dense)	(None, 1)	33
=====		
Total params: 168,385		
Trainable params: 168,385		
Non-trainable params: 0		
-----		
None		

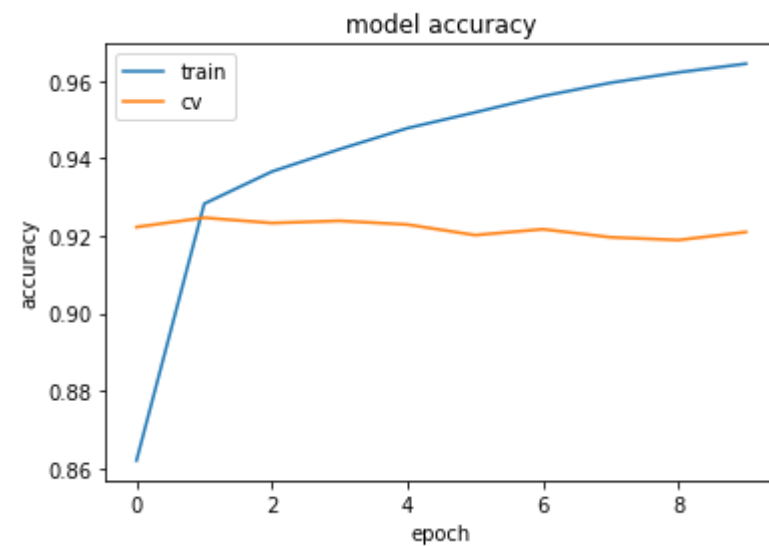
```
In [53]: history = model.fit(X_train, y_train, nb_epoch=10, batch_size=128,
                             validation_data=(X_cv, y_cv), verbose=2)
```

Train on 58320 samples, validate on 12497 samples  
Epoch 1/10  
- 213s - loss: 0.3061 - acc: 0.8620 - val\_loss: 0.2007 - val\_acc: 0.9222  
Epoch 2/10  
- 212s - loss: 0.1861 - acc: 0.9282 - val\_loss: 0.1914 - val\_acc: 0.9246  
Epoch 3/10  
- 209s - loss: 0.1656 - acc: 0.9365 - val\_loss: 0.1906 - val\_acc: 0.9233  
Epoch 4/10  
- 207s - loss: 0.1518 - acc: 0.9423 - val\_loss: 0.1960 - val\_acc: 0.9238  
Epoch 5/10  
- 211s - loss: 0.1389 - acc: 0.9477 - val\_loss: 0.2019 - val\_acc: 0.9229  
Epoch 6/10  
- 209s - loss: 0.1287 - acc: 0.9518 - val\_loss: 0.2117 - val\_acc: 0.9201  
Epoch 7/10  
- 209s - loss: 0.1181 - acc: 0.9560 - val\_loss: 0.2203 - val\_acc: 0.9217  
Epoch 8/10  
- 209s - loss: 0.1109 - acc: 0.9594 - val\_loss: 0.2365 - val\_acc: 0.9196  
Epoch 9/10  
- 210s - loss: 0.1042 - acc: 0.9621 - val\_loss: 0.2396 - val\_acc: 0.9189  
Epoch 10/10  
- 212s - loss: 0.0976 - acc: 0.9644 - val\_loss: 0.2447 - val\_acc: 0.9209

```
In [54]: # This is for plotting the model loss
plt.plot(history.history['loss'])
plt.plot(history.history['val_loss'])
plt.title('model loss')
plt.ylabel('loss')
plt.xlabel('epoch')
plt.legend(['train', 'cv'], loc='upper left')
plt.show()
```



```
In [55]: # This is for plotting the model accuracy
plt.plot(history.history['acc'])
plt.plot(history.history['val_acc'])
plt.title('model accuracy')
plt.ylabel('accuracy')
plt.xlabel('epoch')
plt.legend(['train', 'cv'], loc='upper left')
plt.show()
```



```
In [56]: # Final evaluation of the model
scores = model.evaluate(X_test, y_test, verbose=0)
print("Accuracy: %.2f%%" % (scores[1]*100))
print("Loss : %.2f%%" % (scores[0]))
```

Accuracy: 91.77%  
Loss : 0.25%

```
In [0]: table.add_row([32, 'LSTM(32)-Dense', 'Train: 96.4% Test:91.7%',  
                      'Train: 0.09 Test: 0.25'])
```

In [0]:

In [0]:

# Model 5

In [58]:

```
# create the model
embedding_vecor_length = 32
model = Sequential()
model.add(Embedding(vocabulary_size+1, embedding_vecor_length,
                    input_length=max_review_length))
model.add(LSTM(10, dropout=0.5))
model.add(Dense(1, activation='sigmoid'))
model.compile(loss='binary_crossentropy',
              optimizer='adam', metrics=['accuracy'])
print(model.summary())
```

Model: "sequential\_5"

Layer (type)	Output Shape	Param #
=====		
embedding_5 (Embedding)	(None, 400, 32)	160032
-----		
lstm_6 (LSTM)	(None, 10)	1720
-----		
dense_5 (Dense)	(None, 1)	11
=====		
Total params: 161,763		
Trainable params: 161,763		
Non-trainable params: 0		
-----		
None		

In [59]:

history = model.fit(X\_train, y\_train, nb\_epoch=10, batch\_size=128,
 validation\_data=(X\_cv, y\_cv), verbose=2)

Train on 58320 samples, validate on 12497 samples

Epoch 1/10

- 167s - loss: 0.3602 - acc: 0.8461 - val\_loss: 0.2259 - val\_acc: 0.9115

Epoch 2/10

- 163s - loss: 0.2076 - acc: 0.9194 - val\_loss: 0.2027 - val\_acc: 0.9218

Epoch 3/10

- 164s - loss: 0.1817 - acc: 0.9320 - val\_loss: 0.1995 - val\_acc: 0.9213

Epoch 4/10

- 163s - loss: 0.1664 - acc: 0.9368 - val\_loss: 0.1986 - val\_acc: 0.9232

Epoch 5/10

- 162s - loss: 0.1547 - acc: 0.9425 - val\_loss: 0.1982 - val\_acc: 0.9246

Epoch 6/10

- 162s - loss: 0.1453 - acc: 0.9457 - val\_loss: 0.2010 - val\_acc: 0.9233

Epoch 7/10

- 163s - loss: 0.1366 - acc: 0.9493 - val\_loss: 0.2044 - val\_acc: 0.9221

Epoch 8/10

- 162s - loss: 0.1298 - acc: 0.9520 - val\_loss: 0.2157 - val\_acc: 0.9218

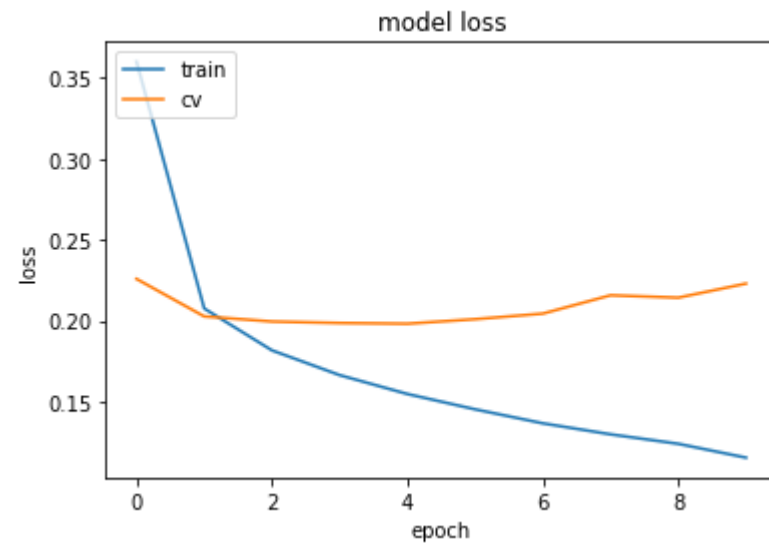
Epoch 9/10

- 163s - loss: 0.1239 - acc: 0.9544 - val\_loss: 0.2143 - val\_acc: 0.9213

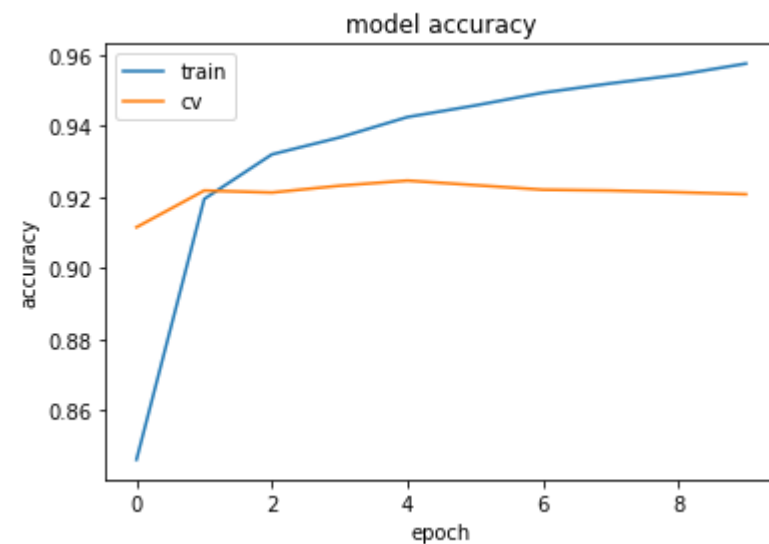
Epoch 10/10

- 163s - loss: 0.1154 - acc: 0.9575 - val\_loss: 0.2230 - val\_acc: 0.9208

```
In [60]: # This is for plotting the model loss
plt.plot(history.history['loss'])
plt.plot(history.history['val_loss'])
plt.title('model loss')
plt.ylabel('loss')
plt.xlabel('epoch')
plt.legend(['train', 'cv'], loc='upper left')
plt.show()
```



```
In [61]: # This is for plotting the model accuracy
plt.plot(history.history['acc'])
plt.plot(history.history['val_acc'])
plt.title('model accuracy')
plt.ylabel('accuracy')
plt.xlabel('epoch')
plt.legend(['train', 'cv'], loc='upper left')
plt.show()
```



```
In [62]: # Final evaluation of the model
scores = model.evaluate(X_test, y_test, verbose=0)
print("Accuracy: %.2f%%" % (scores[1]*100))
print("Loss : %.2f%%" % (scores[0]))
```

Accuracy: 92.16%  
Loss : 0.22%

```
In [0]: table.add_row([32, 'LSTM(10)-Dense', 'Train: 95.7% Test:92.1%',
                        'Train: 0.11 Test: 0.22'])
```



```
In [64]: print(table)
```

Embedding Len	Architechture	Accuracy		Loss	
32	LSTM(50)-Dense	Train: 97%	Test:91%	Train: 0.06	Test: 0.27
64	LSTM(32)-LSTM(16)-Dense	Train: 97.6%	Test:91.8%	Train: 0.06	Test: 0.28
32	LSTM(50)-Dense	Train: 97.6%	Test:91.6%	Train: 0.07	Test: 0.26
32	LSTM(32)-Dense	Train: 96.4%	Test:91.7%	Train: 0.09	Test: 0.25
32	LSTM(10)-Dense	Train: 95.7%	Test:92.1%	Train: 0.11	Test: 0.22

```
In [0]: # Clearly we can see that the initial models are having a pretty good accuracy
# on the test data but are clearly showing some sign of overfitting a little bit.
# Towards the last model we are able to compensate this issue to some extent
# by training on an extremly simplified model having very few LSTM units.
```