ex8_sol

July 6, 2018

1 Exercise 8 - Recurrent Neural networks

This exercise is based on https://github.com/leriomaggio/deep-learning-keras-tensorflow and https://github.com/keras-team/keras/blob/master/examples/imdb_lstm.py and https://machinelearningmastery.com/sequence-classification-lstm-recurrent-neural-networks-python-keras/

A recurrent neural network (RNN) is a class of artificial neural network where connections between units form a directed cycle. This creates an internal state of the network which allows it to exhibit dynamic temporal behavior.

```
keras.layers.recurrent.SimpleRNN(units, activation='tanh', use_bias=True,
                                 kernel_initializer='glorot_uniform',
                                 recurrent_initializer='orthogonal',
                                 bias_initializer='zeros',
                                 kernel_regularizer=None,
                                 recurrent_regularizer=None,
                                 bias_regularizer=None,
                                 activity_regularizer=None,
                                 kernel_constraint=None, recurrent_constraint=None,
                                 bias_constraint=None, dropout=0.0, recurrent_dropout=0.0)
```

Arguments: units: Positive integer, dimensionality of the output space.

activation: Activation function to use (see activations). If you pass None, no activation is applied (ie. "linear" activation: a(x) = x).

use_bias: Boolean, whether the layer uses a bias vector.

kernel_initializer: Initializer for the kernel weights matrix, used for the linear transformation of the inputs. (see initializers).

recurrent_initializer: Initializer for the recurrent_kernel weights matrix, used for the linear transformation of the recurrent state. (see initializers).

bias_initializer: Initializer for the bias vector (see initializers).

kernel_regularizer: Regularizer function applied to the kernel weights matrix (see regularizer).

recurrent_regularizer: Regularizer function applied to the recurrent_kernel weights matrix (see regularizer).

bias_regularizer: Regularizer function applied to the bias vector (see regularizer).

activity_regularizer: Regularizer function applied to the output of the layer (its "activation"). (see regularizer).

kernel_constraint: Constraint function applied to the kernel weights matrix (see constraints).

recurrent_constraint: Constraint function applied to the recurrent_kernel weights matrix (see constraints).

bias_constraint: Constraint function applied to the bias vector (see constraints).

dropout: Float between 0 and 1. Fraction of the units to drop for the linear transformation of the inputs.

recurrent_dropout: Float between 0 and 1. Fraction of the units to drop for the linear transformation of the recurrent state.

Backprop Through time Contrary to feed-forward neural networks, the RNN is characterized by the ability of encoding longer past information, thus very suitable for sequential models. The BPTT extends the ordinary BP algorithm to suit the recurrent neural architecture.

Reference: Backpropagation through Time

1.1 IMDB sentiment classification task

The problem that we will use to demonstrate sequence learning in this tutorial is the IMDB movie review sentiment classification problem. Each movie review is a variable sequence of words and the sentiment of each movie review must be classified.

The Large Movie Review Dataset (often referred to as the IMDB dataset) contains 25,000 highly-polar movie reviews (good or bad) for training and the same amount again for testing. The problem is to determine whether a given movie review has a positive or negative sentiment. http://ai.stanford.edu/~amaas/data/sentiment/

The data was collected by Stanford researchers and was used in a 2011 paper (http://ai.stanford.edu/~amaas/papers/wvSent_acl2011.pdf) where a split of 50-50 of the data was used for training and test. An accuracy of 88.89% was achieved.

Keras provides access to the IMDB dataset built-in. The imdb.load_data() function allows you to load the dataset in a format that is ready for use in neural network and deep learning models.

The words have been replaced by integers that indicate the ordered frequency of each word in the dataset. The sentences in each review are therefore comprised of a sequence of integers.

1.1.1 Word Embedding

We will map each movie review into a real vector domain, a popular technique when working with text called word embedding. This is a technique where words are encoded as real-valued vectors in a high dimensional space, where the similarity between words in terms of meaning translates to closeness in the vector space.

Keras provides a convenient way to convert positive integer representations of words into a word embedding by an Embedding layer.

We will map each word onto a 32 length real valued vector. We will also limit the total number of words that we are interested in modeling to the 5000 most frequent words, and zero out the rest. Finally, the sequence length (number of words) in each review varies, so we will constrain each review to be 500 words, truncating long reviews and pad the shorter reviews with zero values.

Now that we have defined our problem and how the data will be prepared and modeled, we are ready to develop an LSTM model to classify the sentiment of movie reviews.

1.1.2 Data Preparation - IMDB

In [1]:
```
import numpy
from keras.datasets import imdb
from keras.models import Sequential
from keras.layers import Dense, Dropout
from keras.layers import LSTM, SimpleRNN
from keras.layers.embeddings import Embedding
from keras.preprocessing import sequence

from sklearn.model_selection import train_test_split

# fix random seed for reproducibility
numpy.random.seed(42)
```

```
/media/nackenho/Data/programs/ML/anaconda2/lib/python2.7/site-packages/h5py/__init__.py:34: Futu
  from ._conv import register_converters as _register_converters
Using TensorFlow backend.
```

We need to load the IMDB dataset. We are constraining the dataset to the top 5,000 words. We also split the dataset into train (70%) and validation (30%) sets.

In [2]:
```
# load the dataset but only keep the top n words, zero the rest
top_words = 5000
print("Loading data...")
(X_train, y_train), (X_test, y_test) = imdb.load_data(num_words=top_words)

X_train, X_val, y_train, y_val = train_test_split(X_train, y_train, test_size=0.3, rando

print(len(X_test), 'test sequences')
print(len(X_train), 'train sequences')
print(len(X_val), 'validation sequences')
print('Example:')
print(X_train[:1])
```

```
Loading data...
(25000, 'test sequences')
(17500, 'train sequences')
(7500, 'validation sequences')
Example:
[list([1, 416, 9, 35, 576, 73, 93, 248, 201, 44, 49, 84, 15, 26, 416, 23, 35, 1111, 225, 38, 111
```

Next, we need to truncate and pad the input sequences so that they are all the same length for modeling. The model will learn the zero values carry no information so indeed the sequences are not the same length in terms of content, but same length vectors is required to perform the computation in Keras.

```python
In [3]: # truncate and pad input sequences
        max_review_length = 500
        X_train = sequence.pad_sequences(X_train, maxlen=max_review_length)
        X_test = sequence.pad_sequences(X_test, maxlen=max_review_length)
        X_val = sequence.pad_sequences(X_val, maxlen=max_review_length)
        print('Example:')
        print(X_train[:1])
```

```
Example:
[[   0    0    0    0    0    0    0    0    0    0    0    0    0    0
     0    0    0    0    0    0    0    0    0    0    0    0    0    0
     0    0    0    0    0    0    0    0    0    0    0    0    0    0
     0    0    0    0    0    0    0    0    0    0    0    0    0    0
     0    0    0    0    0    0    0    0    0    0    0    0    0    0
     0    0    0    0    0    0    0    0    0    0    0    0    0    0
     0    0    0    0    0    0    0    0    0    0    0    0    0    0
     0    0    0    0    0    0    0    0    0    0    0    0    0    0
     0    0    0    0    0    0    0    0    0    0    0    0    0    0
     0    0    0    0    0    0    0    0    0    0    0    0    0    0
     0    0    0    0    0    0    0    0    0    0    0    0    0    0
     0    0    0    0    0    0    0    0    0    0    0    0    0    0
     0    0    0    0    0    0    0    0    0    0    0    0    0    0
     0    0    0    0    0    0    0    0    0    0    0    0    0    0
     0    0    0    0    0    0    0    0    0    0    0    0    0    0
     0    0    0    0    0    0    0    0    0    0    0    0    0    0
     0    0    0    0    0    0    0    0    0    0    0    0    0    0
     0    0    0    0    0    0    0    0    0    0    0    0    0    0
     0    0    0    0    0    0    0    0    0    0    0    0    0    0
     0    0    0    0    0    0    0    0    0    0    0    0    0    0
     0    0    0    0    0    0    0    0    0    0    0    0    0    0
     0    0    0    0    0    0    0    0    0    0    0    0    0    0
     0    0    0    0    0    0    1  416    9   35  576   73   93  248
   201   44   49   84   15   26  416   23   35 1111  225   38  111 1299
     5  505   15   25  191   66 1197   37  129 1640  109    9   31  786
    94   90   95   29  127  142   38  240    2   95    2   44    8   81
   142   38    2    4    2   95  836 3861   56    5   43   17   25   26
    44    8    2    4  390  630    5  129   40    2   38   25   28    8
   858    6  226 1269   99   67    4  375  390   21   12    9  290    4
   858  836  206  883 1285   94  188   12   32  972   39    4 4245  539
    21 1584   52   17   12  817   15   25   70  165    2   23    4   65
    53    5   65    9   51   14    9   32   44   38   48   25   40    6
    52   65    5   40  836   14    9    6   52   31  190 3333   13  104
     9  242  128   13   28    6  733   23   15   99   15   25  100  808
    12   46   13   62  202  416    6   52  709   46    7  158 1424   88
    94   38    2   25  115  124   51   80  593  375]]
```

1.2 A simple RNN model

In [4]:
```
print('Build model...')
# create the model
embedding_vecor_length = 32
model = Sequential()
model.add(Embedding(top_words, embedding_vecor_length, input_length=max_review_length))
model.add(Dropout(0.4))
model.add(SimpleRNN(128))
model.add(Dropout(0.4))
model.add(Dense(1, activation='sigmoid'))
model.compile(loss='binary_crossentropy', optimizer='adam', metrics=['accuracy'])
print(model.summary())
```

```
Build model...
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
embedding_1 (Embedding)      (None, 500, 32)           160000
_________________________________________________________________
dropout_1 (Dropout)          (None, 500, 32)           0
_________________________________________________________________
simple_rnn_1 (SimpleRNN)     (None, 128)               20608
_________________________________________________________________
dropout_2 (Dropout)          (None, 128)               0
_________________________________________________________________
dense_1 (Dense)              (None, 1)                 129
=================================================================
Total params: 180,737
Trainable params: 180,737
Non-trainable params: 0
_________________________________________________________________
None
```

1.2.1 Training

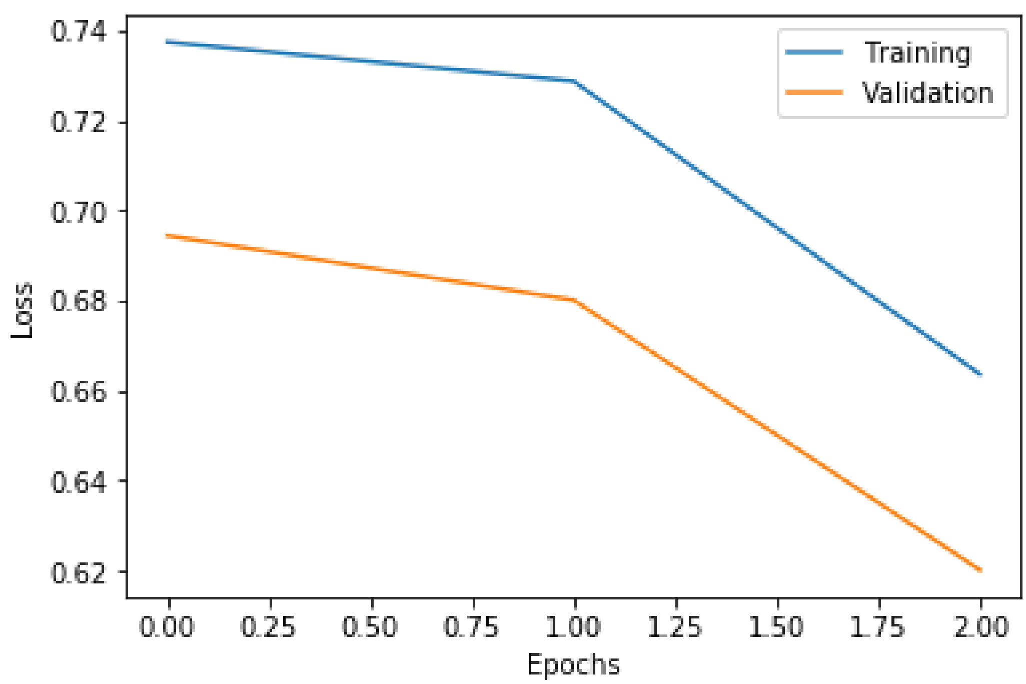
In [5]:
```
history = model.fit(X_train, y_train, validation_data=(X_val, y_val), epochs=3, batch_si
```

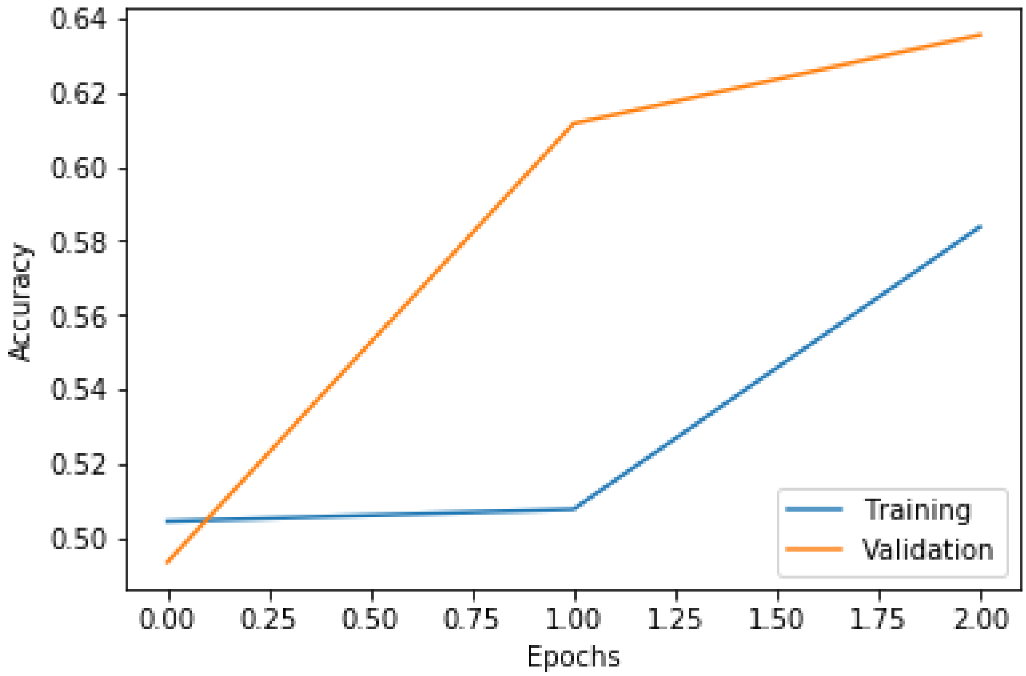
```
Train on 17500 samples, validate on 7500 samples
Epoch 1/3
17500/17500 [==============================] - 73s 4ms/step - loss: 0.7373 - acc: 0.5044 - val_l
Epoch 2/3
17500/17500 [==============================] - 76s 4ms/step - loss: 0.7287 - acc: 0.5077 - val_l
Epoch 3/3
17500/17500 [==============================] - 73s 4ms/step - loss: 0.6636 - acc: 0.5838 - val_l
```

In [6]:
```
%matplotlib inline
from matplotlib import pyplot as plt
```

```
def plot_history(network_history):
    plt.figure()
    plt.xlabel('Epochs')
    plt.ylabel('Loss')
    plt.plot(network_history.history['loss'])
    plt.plot(network_history.history['val_loss'])
    plt.legend(['Training', 'Validation'])

    plt.figure()
    plt.xlabel('Epochs')
    plt.ylabel('Accuracy')
    plt.plot(network_history.history['acc'])
    plt.plot(network_history.history['val_acc'])
    plt.legend(['Training', 'Validation'], loc='lower right')
    plt.show()
```

```
In [7]: plot_history(history)
```





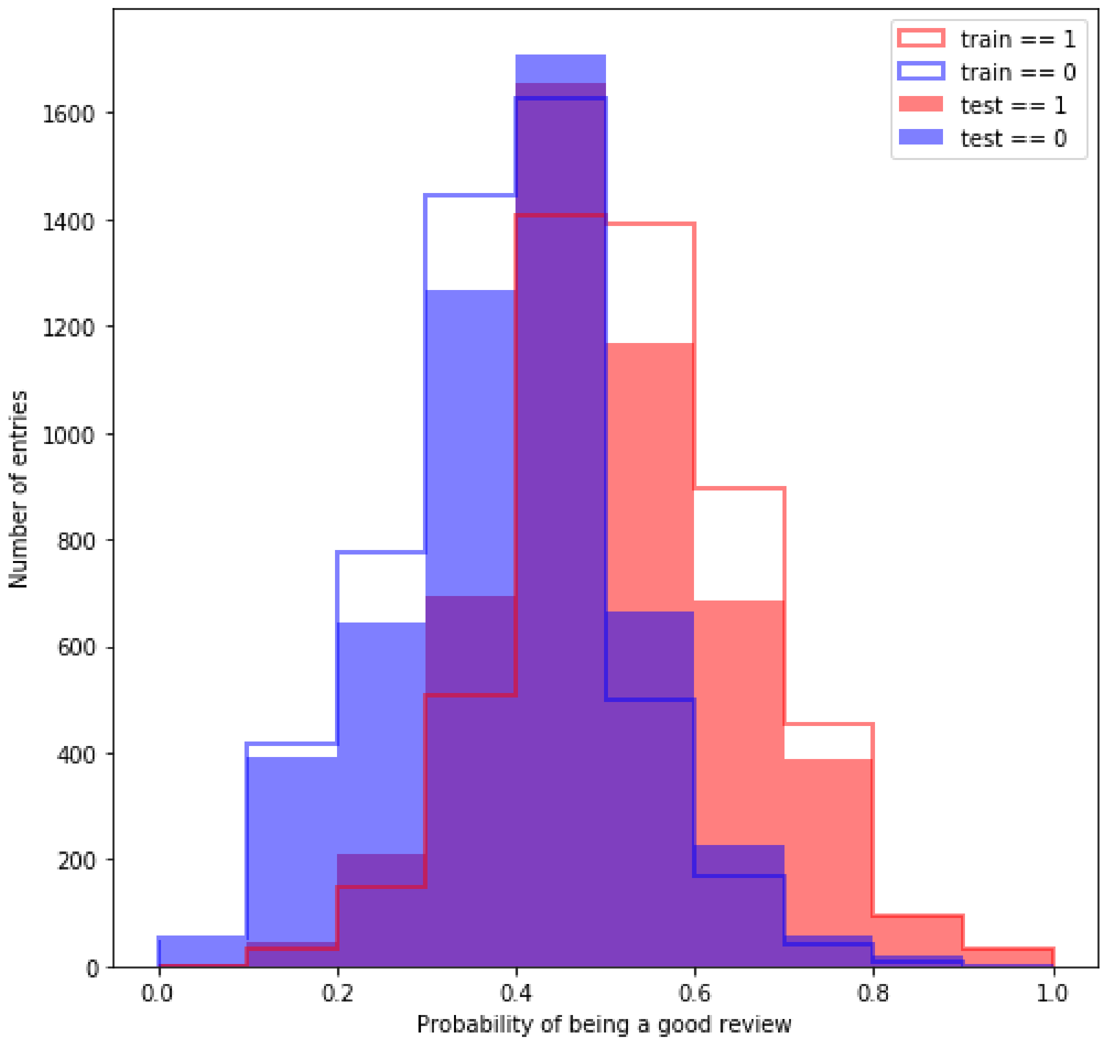
1.2.2 Evaluation

In [8]:
```
from sklearn.metrics import accuracy_score, precision_score, recall_score, classificatio

def evaluate(X_test, Y_test, X_train, Y_train, model):

    ##Evaluate loss and metrics and predict & classes
    loss, accuracy = model.evaluate(X_test, Y_test, verbose=0)
    Y_pred = model.predict(X_test, batch_size=1)
    Y_cls  = model.predict_classes(X_test, batch_size=1)

    print('Test Loss:', loss)
    print('Accuracy: %.2f' % accuracy_score(Y_test, Y_cls))
    print("Precision: %.2f" % precision_score(Y_test, Y_cls, average='weighted'))
    print("Recall: %.2f" % recall_score(Y_test, Y_cls, average='weighted'))
    print 'Classification Report:\n', classification_report(Y_test, Y_cls)


    ## Plot 0 probability including overtraining test
    plt.figure(figsize=(8,8))

    label=1
    #Test prediction
    plt.hist(Y_pred[Y_test == label], alpha=0.5, color='red', range=[0, 1], bins=10)
```

```
            plt.hist(Y_pred[Y_test != label], alpha=0.5, color='blue', range=[0, 1], bins=10)

            #Train prediction
            Y_train_pred = model.predict(X_train)
            plt.hist(Y_train_pred[Y_train == label], alpha=0.5, color='red', range=[0, 1], bins=
            plt.hist(Y_train_pred[Y_train != label], alpha=0.5, color='blue', range=[0, 1], bins

            plt.legend(['train == 1', 'train == 0', 'test == 1', 'test == 0'], loc='upper right'
            plt.xlabel('Probability of being a good review')
            plt.ylabel('Number of entries')
            plt.show()
```

In [9]:
```
evaluate(X_test[:10000], y_test[:10000],X_train[:10000], y_train[:10000], model)
```

```
('Test Loss:', 0.6246966641426086)
Accuracy: 0.64
Precision: 0.66
Recall: 0.64
Classification Report:
             precision    recall  f1-score   support

          0       0.61      0.81      0.69      5027
          1       0.71      0.48      0.57      4973

avg / total       0.66      0.64      0.63     10000
```



1.3 LSTM model

A LSTM network is an artificial neural network that contains LSTM blocks instead of, or in addition to, regular network units. A LSTM block may be described as a "smart" network unit that can remember a value for an arbitrary length of time.

Unlike traditional RNNs, an Long short-term memory network is well-suited to learn from experience to classify, process and predict time series when there are very long time lags of unknown size between important events.

```
keras.layers.recurrent.LSTM(units, activation='tanh', recurrent_activation='hard_sigmoid', use_b
                            kernel_initializer='glorot_uniform', recurrent_initializer='orthogon
                            bias_initializer='zeros', unit_forget_bias=True, kernel_regularizer=
                            recurrent_regularizer=None, bias_regularizer=None, activity_regulari
                            kernel_constraint=None, recurrent_constraint=None, bias_constraint=N
                            dropout=0.0, recurrent_dropout=0.0)
```

Arguments units: Positive integer, dimensionality of the output space.

activation: Activation function to use If you pass None, no activation is applied (ie. "linear" activation: a(x) = x).

recurrent_activation: Activation function to use for the recurrent step.

use_bias: Boolean, whether the layer uses a bias vector.

kernel_initializer: Initializer for the kernel weights matrix, used for the linear transformation of the inputs.

recurrent_initializer: Initializer for the recurrent_kernel weights matrix, used for the linear transformation of the recurrent state.

bias_initializer: Initializer for the bias vector.

unit_forget_bias: Boolean. If True, add 1 to the bias of the forget gate at initialization. Setting it to true will also force bias_initializer="zeros". This is recommended in Jozefowicz et al.

kernel_regularizer: Regularizer function applied to the kernel weights matrix.

recurrent_regularizer: Regularizer function applied to the recurrent_kernel weights matrix.

bias_regularizer: Regularizer function applied to the bias vector.

activity_regularizer: Regularizer function applied to the output of the layer (its "activation").

kernel_constraint: Constraint function applied to the kernel weights matrix.

recurrent_constraint: Constraint function applied to the recurrent_kernel weights matrix.

bias_constraint: Constraint function applied to the bias vector.

dropout: Float between 0 and 1. Fraction of the units to drop for the linear transformation of the inputs.

recurrent_dropout: Float between 0 and 1. Fraction of the units to drop for the linear transformation of the recurrent state.

1.4 Task 1: Train and evaluate an LSTM model

- Build a model using again one embedding layer and one dense output node but with an LSTM layer with 128 units instead of the RNN layer
- Use a dropout layer between the embedding and LSTM layer and between the LSTM and the dense layer
- Train the model and plot the loss and accuracy over epochs
- Evaluate the performance of the model and compare it with the RNN model

We can now define, compile and fit our LSTM model.

The first layer is the Embedded layer that uses 32 length vectors to represent each word. The next layer is the LSTM layer with 128 memory units (smart neurons). Finally, because this is a classification problem we use a Dense output layer with a single neuron and a sigmoid activation function to make 0 or 1 predictions for the two classes (good and bad) in the problem.

Because it is a binary classification problem, log loss is used as the loss function (binary_crossentropy in Keras). The efficient ADAM optimization algorithm is used. The model is fit for only 2 epochs because it quickly overfits the problem. A large batch size of 64 reviews is used to space out weight updates.

```
In [10]: print('Build model...')
         # create the model
         embedding_vecor_length = 32
         model = Sequential()
         model.add(Embedding(top_words, embedding_vecor_length, input_length=max_review_length))
```

```
model.add(Dropout(0.4))
model.add(LSTM(128))
model.add(Dropout(0.4))
model.add(Dense(1, activation='sigmoid'))
model.compile(loss='binary_crossentropy', optimizer='adam', metrics=['accuracy'])
print(model.summary())
```

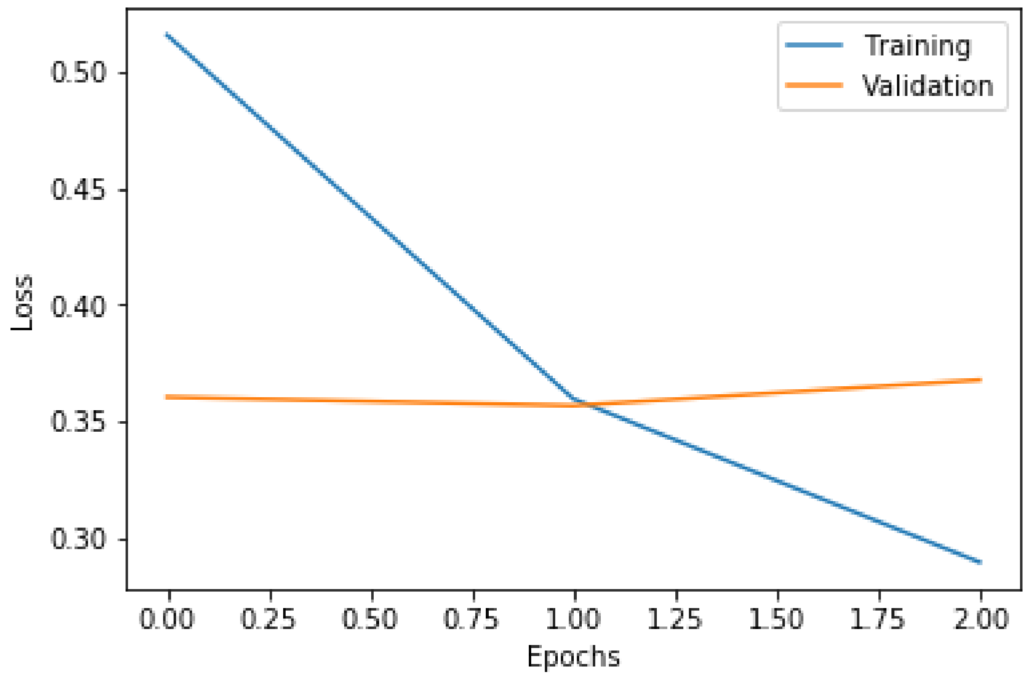
```
Build model...
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
embedding_2 (Embedding)      (None, 500, 32)           160000
_________________________________________________________________
dropout_3 (Dropout)          (None, 500, 32)           0
_________________________________________________________________
lstm_1 (LSTM)                (None, 128)               82432
_________________________________________________________________
dropout_4 (Dropout)          (None, 128)               0
_________________________________________________________________
dense_2 (Dense)              (None, 1)                 129
=================================================================
Total params: 242,561
Trainable params: 242,561
Non-trainable params: 0
_________________________________________________________________
None
```

1.4.1 Training

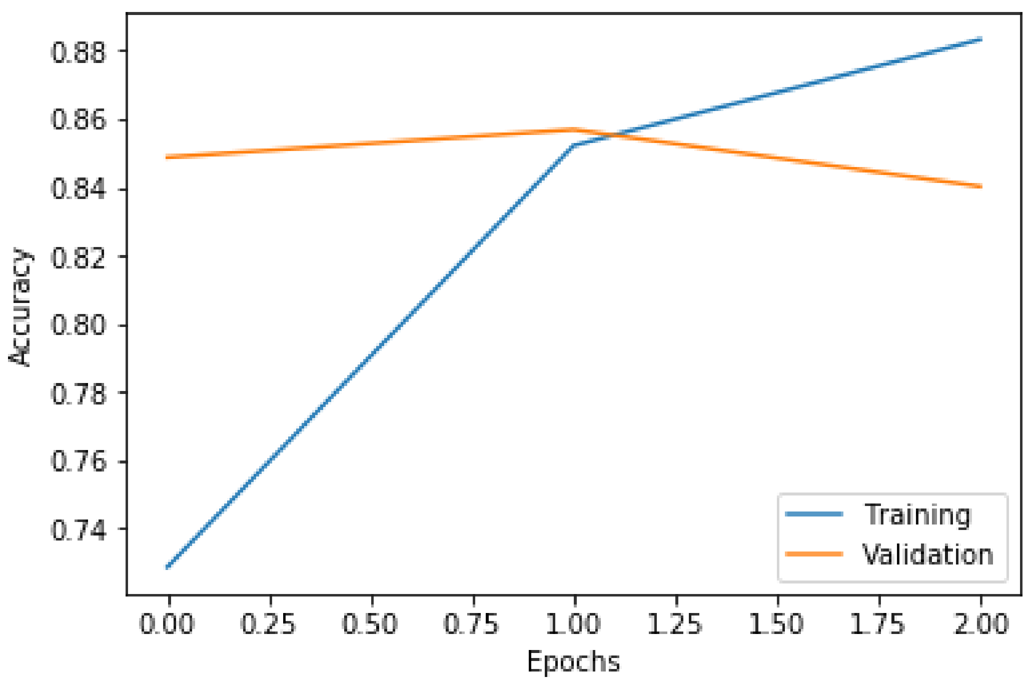
```
In [11]: history = model.fit(X_train, y_train, validation_data=(X_val, y_val), epochs=3, batch_s
```

```
Train on 17500 samples, validate on 7500 samples
Epoch 1/3
17500/17500 [==============================] - 202s 12ms/step - loss: 0.5156 - acc: 0.7287 - val
Epoch 2/3
17500/17500 [==============================] - 198s 11ms/step - loss: 0.3594 - acc: 0.8522 - val
Epoch 3/3
17500/17500 [==============================] - 197s 11ms/step - loss: 0.2893 - acc: 0.8833 - val
```

```
In [12]: plot_history(history)
```



Training
Validation
0.50
0.45
0.40
0.35
0.30
Loss
0.00
0.25
0.50
0.75
1.00
1.25
1.50
1.75
2.00
Epochs

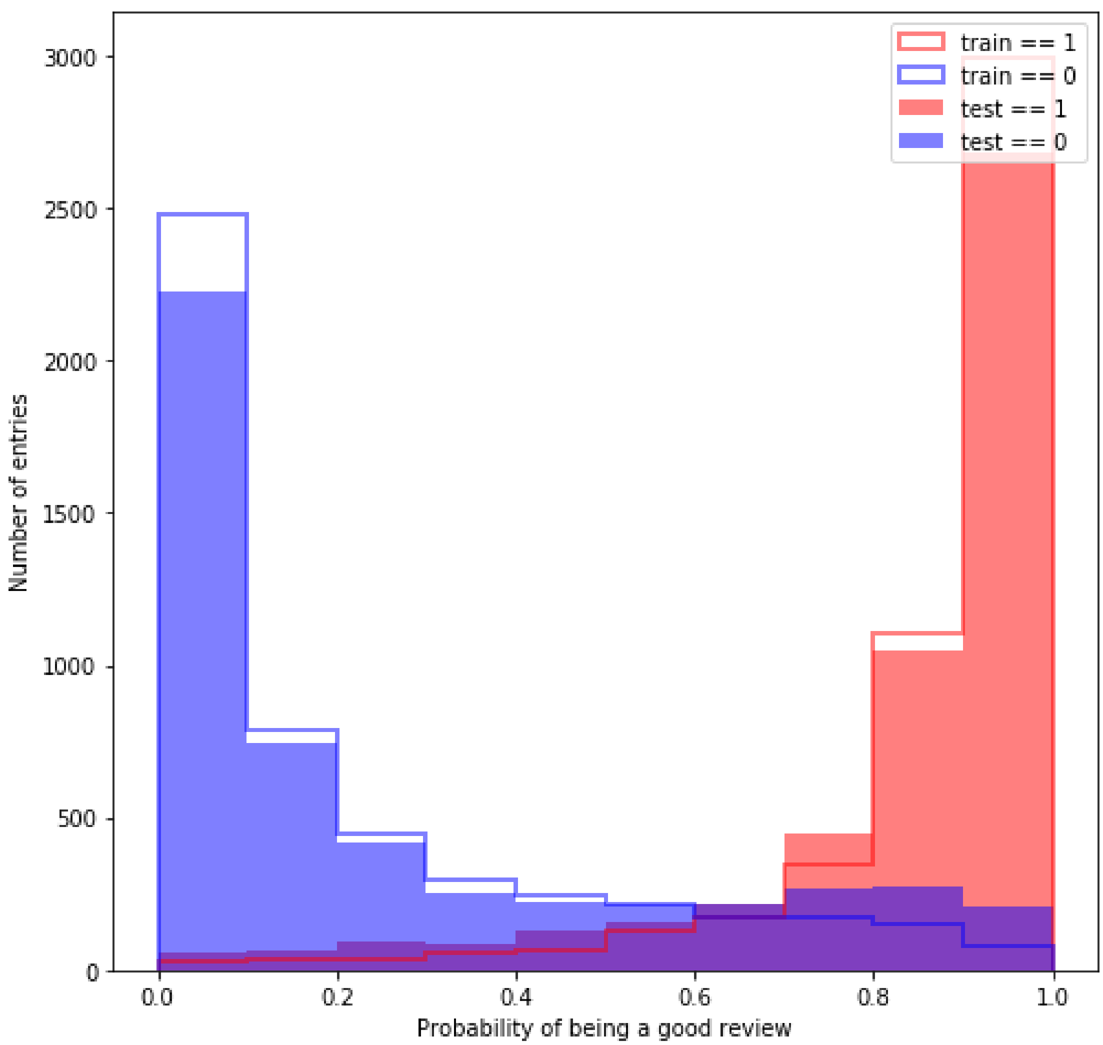


0.88
0.86
0.84
0.82
0.80
0.78
0.76
0.74
Accuracy
Training
Validation
0.00
0.25
0.50
0.75
1.00
1.25
1.50
1.75
2.00
Epochs

1.4.2 Evaluation

```
In [13]: evaluate(X_test[:10000], y_test[:10000],X_train[:10000], y_train[:10000], model)
```

```
('Test Loss:', 0.3655299718618393)
Accuracy: 0.84
Precision: 0.85
Recall: 0.84
Classification Report:
             precision    recall  f1-score   support

          0       0.90      0.77      0.83      5027
          1       0.80      0.91      0.85      4973

avg / total       0.85      0.84      0.84     10000
```



1.5 LSTM with dropout

Recurrent Neural networks like LSTM generally have the problem of overfitting.

Dropout can be applied between layers using the Dropout Keras layer. We have done this easily by adding new Dropout layers between the Embedding and LSTM layers and the LSTM and Dense output layers.

Alternately, dropout can be applied to the input and recurrent connections of the memory units with the LSTM precisely and separately. Keras provides this capability with parameters on the LSTM layer, the dropout for configuring the input dropout and recurrent_dropout for configuring the recurrent dropout. For example, we can modify the first example to add dropout to the input and recurrent connections as follows:

```
model.add(LSTM(128, dropout=0.2, recurrent_dropout=0.2))
```

1.6 Task 2: Train and evaluate an LSTM model with dropout

- Instead of using two dropout layers, apply dropout to the input and recurrent connections of the LSTM model
- Train the model and plot the loss and accuracy over epochs
- Evaluate the performance of the model and compare it with the previous models

In [14]:
```python
# create the model
embedding_vecor_length = 32
model = Sequential()
model.add(Embedding(top_words, embedding_vecor_length, input_length=max_review_length))
model.add(LSTM(128, dropout=0.4, recurrent_dropout=0.4))
model.add(Dense(1, activation='sigmoid'))
model.compile(loss='binary_crossentropy', optimizer='adam', metrics=['accuracy'])
print(model.summary())
```

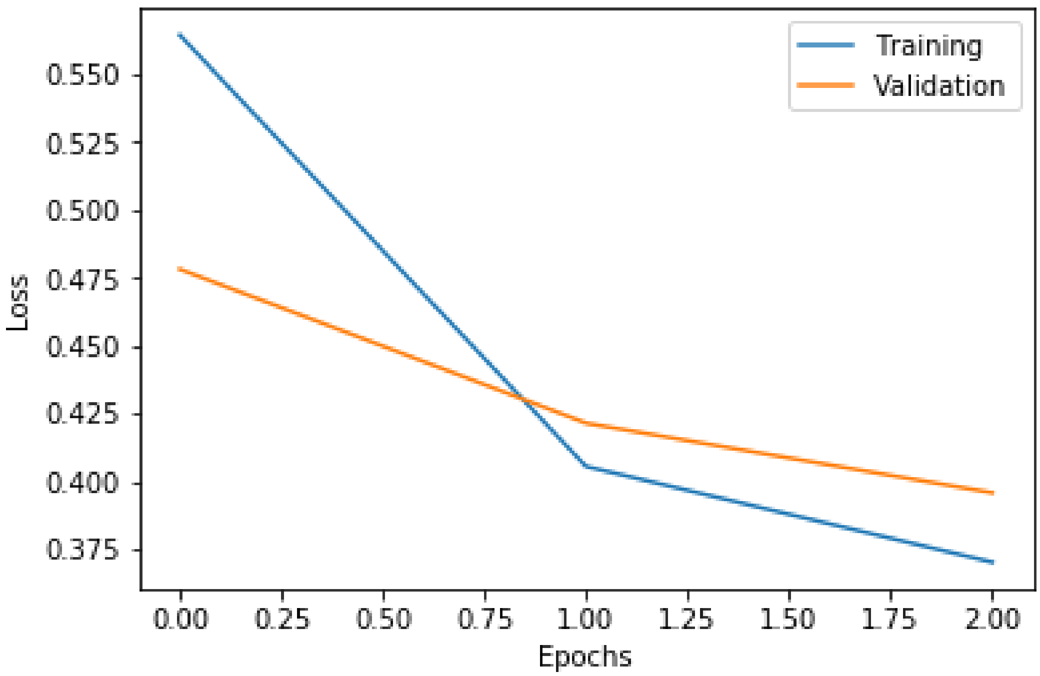
```
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
embedding_3 (Embedding)      (None, 500, 32)           160000
_________________________________________________________________
lstm_2 (LSTM)                (None, 128)               82432
_________________________________________________________________
dense_3 (Dense)              (None, 1)                 129
=================================================================
Total params: 242,561
Trainable params: 242,561
Non-trainable params: 0
_________________________________________________________________
None
```

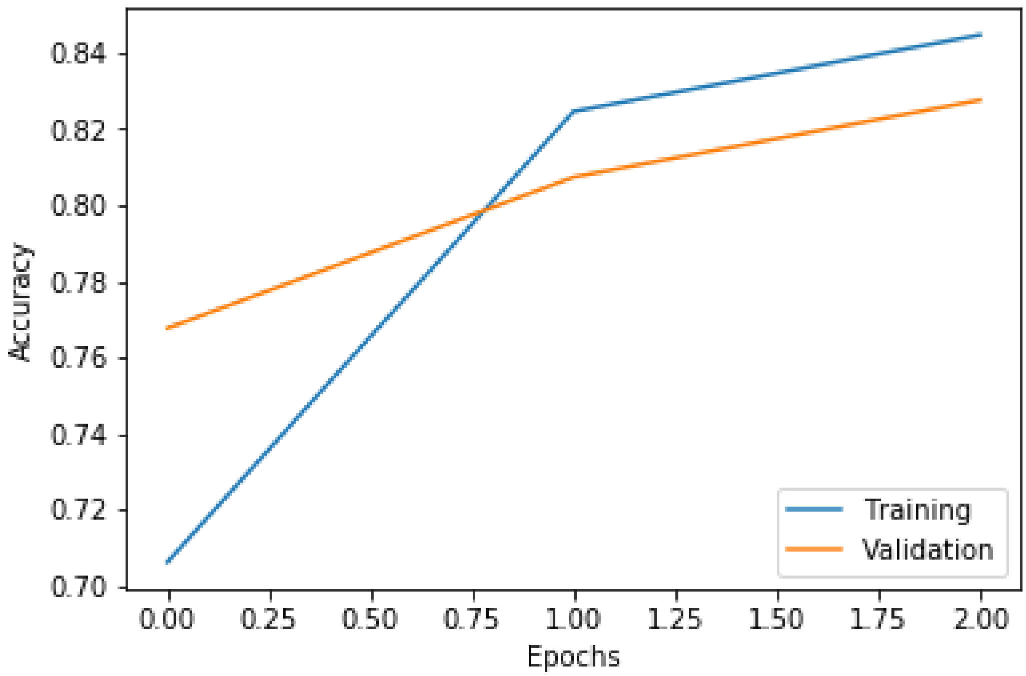
1.6.1 Training

In [15]:
```
history = model.fit(X_train, y_train, validation_data=(X_val, y_val), epochs=3, batch_s
```

```
Train on 17500 samples, validate on 7500 samples
Epoch 1/3
17500/17500 [==============================] - 225s 13ms/step - loss: 0.5642 - acc: 0.7061 - val
Epoch 2/3
17500/17500 [==============================] - 217s 12ms/step - loss: 0.4055 - acc: 0.8246 - val
Epoch 3/3
17500/17500 [==============================] - 228s 13ms/step - loss: 0.3703 - acc: 0.8447 - val
```

In [16]:
```
plot_history(history)
```

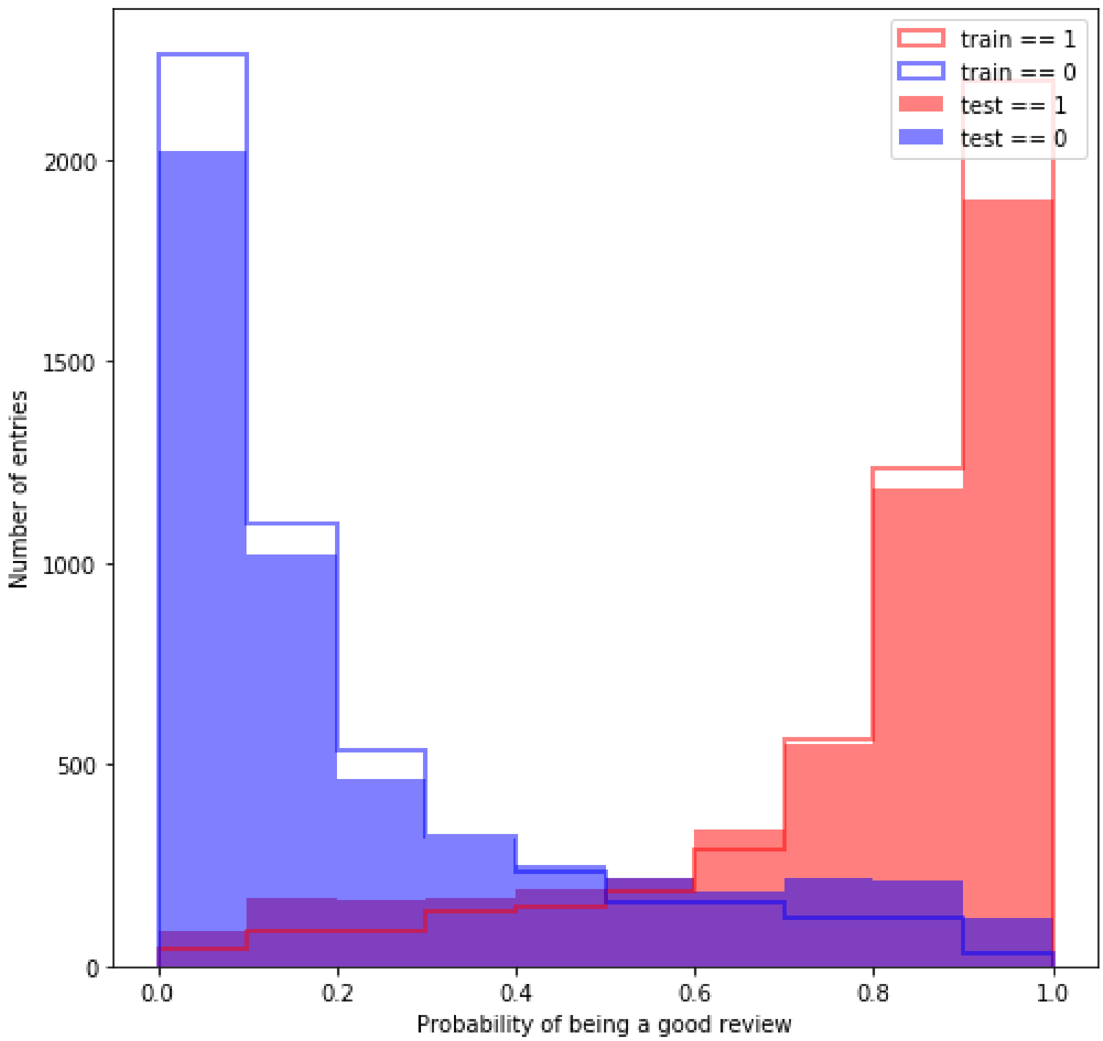




1.6.2 Evaluation

```
In [17]: evaluate(X_test[:10000], y_test[:10000],X_train[:10000], y_train[:10000], model)
```

```
('Test Loss:', 0.3926689309597015)
Accuracy: 0.83
Precision: 0.83
Recall: 0.83
Classification Report:
             precision    recall  f1-score   support

          0       0.84      0.81      0.83      5027
          1       0.82      0.84      0.83      4973

avg / total       0.83      0.83      0.83     10000
```



We can see that the LSTM specific dropout has a more pronounced effect on the convergence of the network than the layer-wise dropout. As above, the number of epochs was kept constant and could be increased to see if the skill of the model can be further lifted.

Dropout is a powerful technique for combating overfitting in your LSTM models and it is a good idea to try both methods, but you may bet better results with the gate-specific dropout provided in Keras.

1.7 Convolutional LSTM

Convolutional neural networks excel at learning the spatial structure in input data.

The IMDB review data does have a one-dimensional spatial structure in the sequence of words in reviews and the CNN may be able to pick out invariant features for good and bad sentiment. This learned spatial features may then be learned as sequences by an LSTM layer.

We can easily add a one-dimensional CNN and max pooling layers after the Embedding layer which then feed the consolidated features to the LSTM. We can use a smallish set of 32 features with a small filter length of 3. The pooling layer can use the standard length of 2 to halve the feature map size.

1.8 Task 3: Train and evaluate an LSTM model with a convolutional layer

- Add one convolutional layer and one maxpooling layer before the LSTM layer
- Train the model and plot the loss and accuracy over epochs
- Evaluate the performance of the model and compare it with the previous models

In [18]:
```
from keras.layers.convolutional import Conv1D,MaxPooling1D
# create the model
embedding_vecor_length = 32
model = Sequential()
model.add(Embedding(top_words, embedding_vecor_length, input_length=max_review_length))
model.add(Conv1D(filters=32, kernel_size=3, padding='same', activation='relu'))
model.add(MaxPooling1D(pool_size=2))
model.add(LSTM(128, dropout=0.4, recurrent_dropout=0.4))
model.add(Dense(1, activation='sigmoid'))
model.compile(loss='binary_crossentropy', optimizer='adam', metrics=['accuracy'])
print(model.summary())
```

```
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
embedding_4 (Embedding)      (None, 500, 32)           160000
_________________________________________________________________
conv1d_1 (Conv1D)            (None, 500, 32)           3104
_________________________________________________________________
max_pooling1d_1 (MaxPooling1 (None, 250, 32)           0
_________________________________________________________________
lstm_3 (LSTM)                (None, 128)               82432
_________________________________________________________________
dense_4 (Dense)              (None, 1)                 129
=================================================================
Total params: 245,665
Trainable params: 245,665
Non-trainable params: 0
_________________________________________________________________
None
```

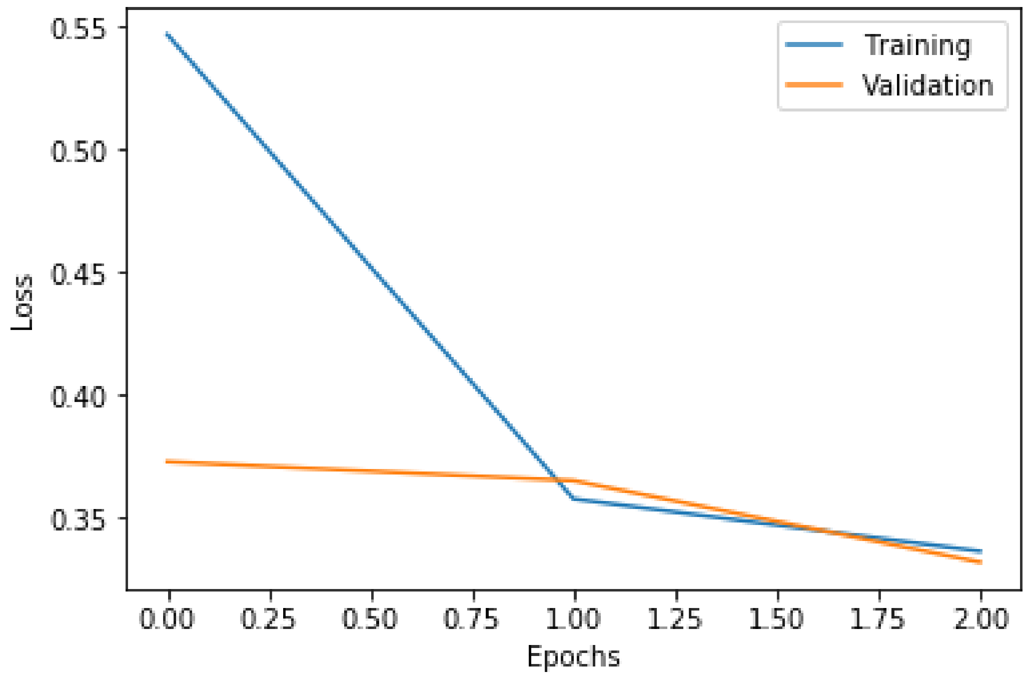
1.8.1 Training

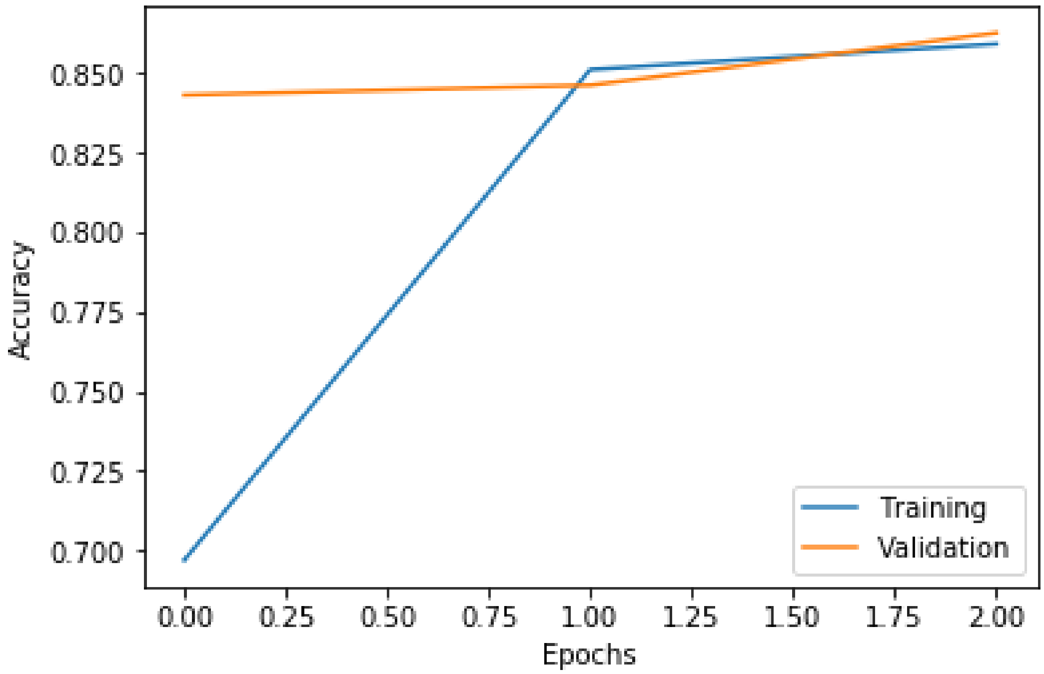
In [19]:
```
history = model.fit(X_train, y_train, validation_data=(X_val, y_val), epochs=3, batch_s
```

```
Train on 17500 samples, validate on 7500 samples
Epoch 1/3
17500/17500 [==============================] - 123s 7ms/step - loss: 0.5468 - acc: 0.6969 - val_
Epoch 2/3
```

```
17500/17500 [==============================] - 122s 7ms/step - loss: 0.3579 - acc: 0.8512 - val_
Epoch 3/3
17500/17500 [==============================] - 119s 7ms/step - loss: 0.3366 - acc: 0.8592 - val_
```

```
In [20]: plot_history(history)
```

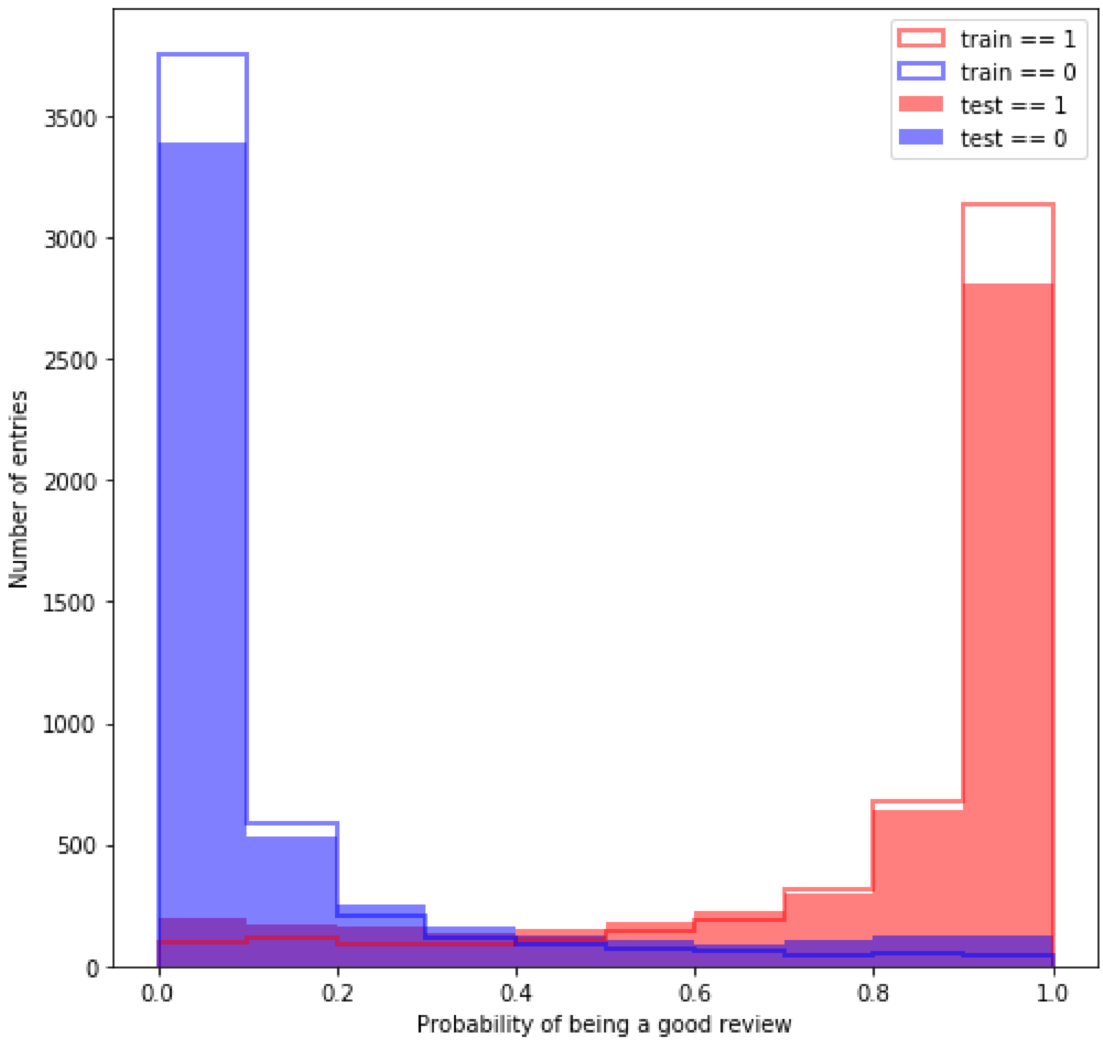




1.8.2 Evaluation

```
In [21]: evaluate(X_test[:10000], y_test[:10000],X_train[:10000], y_train[:10000], model)
```

```
('Test Loss:', 0.3300702913761139)
Accuracy: 0.86
Precision: 0.86
Recall: 0.86
Classification Report:
             precision    recall  f1-score   support

          0       0.85      0.89      0.87      5027
          1       0.88      0.84      0.86      4973

avg / total       0.86      0.86      0.86     10000
```



1.9 Bonus: LSTM with convolutional input & recurrent transformation

Convolutional LSTM Network: A Machine Learning Approach for Precipitation Nowcasting

Based on https://github.com/keras-team/keras/blob/master/examples/conv_lstm.py

This network is used to predict the next frame of an artificially generated movie which contains moving squares.

Artificial Data Generation Generate movies with 3 to 7 moving squares inside.

The squares are of shape 1×1 or 2×2 pixels, which move linearly over time.

For convenience we first create movies with bigger width and height (`80x80`) and at the end we select a 40×40 window.

In [22]:
```
# Artificial Data Generation
def generate_movies(n_samples=1200, n_frames=15):
    row = 80
    col = 80
    noisy_movies = np.zeros((n_samples, n_frames, row, col, 1), dtype=np.float)
    shifted_movies = np.zeros((n_samples, n_frames, row, col, 1),
                              dtype=np.float)

    for i in range(n_samples):
        # Add 3 to 7 moving squares
        n = np.random.randint(3, 8)

        for j in range(n):
            # Initial position
            xstart = np.random.randint(20, 60)
            ystart = np.random.randint(20, 60)
            # Direction of motion
            directionx = np.random.randint(0, 3) - 1
            directiony = np.random.randint(0, 3) - 1

            # Size of the square
            w = np.random.randint(2, 4)

            for t in range(n_frames):
                x_shift = xstart + directionx * t
                y_shift = ystart + directiony * t
                noisy_movies[i, t, x_shift - w: x_shift + w,
                             y_shift - w: y_shift + w, 0] += 1

                # Make it more robust by adding noise.
                # The idea is that if during inference,
                # the value of the pixel is not exactly one,
                # we need to train the network to be robust and still
                # consider it as a pixel belonging to a square.
                if np.random.randint(0, 2):
                    noise_f = (-1)**np.random.randint(0, 2)
                    noisy_movies[i, t,
                                 x_shift - w - 1: x_shift + w + 1,
                                 y_shift - w - 1: y_shift + w + 1,
                                 0] += noise_f * 0.1

                # Shift the ground truth by 1
                x_shift = xstart + directionx * (t + 1)
                y_shift = ystart + directiony * (t + 1)
                shifted_movies[i, t, x_shift - w: x_shift + w,
                               y_shift - w: y_shift + w, 0] += 1

    # Cut to a 40x40 window
```

```
        noisy_movies = noisy_movies[::, ::, 20:60, 20:60, ::]
        shifted_movies = shifted_movies[::, ::, 20:60, 20:60, ::]
        noisy_movies[noisy_movies >= 1] = 1
        shifted_movies[shifted_movies >= 1] = 1
        return noisy_movies, shifted_movies
```

1.9.1 Model

```
In [23]: from keras.models import Sequential
         from keras.layers.convolutional import Conv3D
         from keras.layers.convolutional_recurrent import ConvLSTM2D
         from keras.layers.normalization import BatchNormalization
         import numpy as np
         from matplotlib import pyplot as plt

         %matplotlib inline
```

We create a layer which take as input movies of shape (n_frames, width, height, channels) and returns a movie of identical shape.

```
In [24]: seq = Sequential()
         seq.add(ConvLSTM2D(filters=40, kernel_size=(3, 3),
                            input_shape=(None, 40, 40, 1),
                            padding='same', return_sequences=True))
         seq.add(BatchNormalization())

         seq.add(ConvLSTM2D(filters=40, kernel_size=(3, 3),
                            padding='same', return_sequences=True))
         seq.add(BatchNormalization())

         seq.add(ConvLSTM2D(filters=40, kernel_size=(3, 3),
                            padding='same', return_sequences=True))
         seq.add(BatchNormalization())

         seq.add(ConvLSTM2D(filters=40, kernel_size=(3, 3),
                            padding='same', return_sequences=True))
         seq.add(BatchNormalization())

         seq.add(Conv3D(filters=1, kernel_size=(3, 3, 3),
                        activation='sigmoid',
                        padding='same', data_format='channels_last'))
         seq.compile(loss='binary_crossentropy', optimizer='adadelta')
```

1.9.2 Train the Network

Beware: This takes time

```
In [25]: # Train the network
         noisy_movies, shifted_movies = generate_movies(n_samples=1200)
```

```
seq.fit(noisy_movies[:1000], shifted_movies[:1000], batch_size=10,
        epochs=20, validation_split=0.05)
```

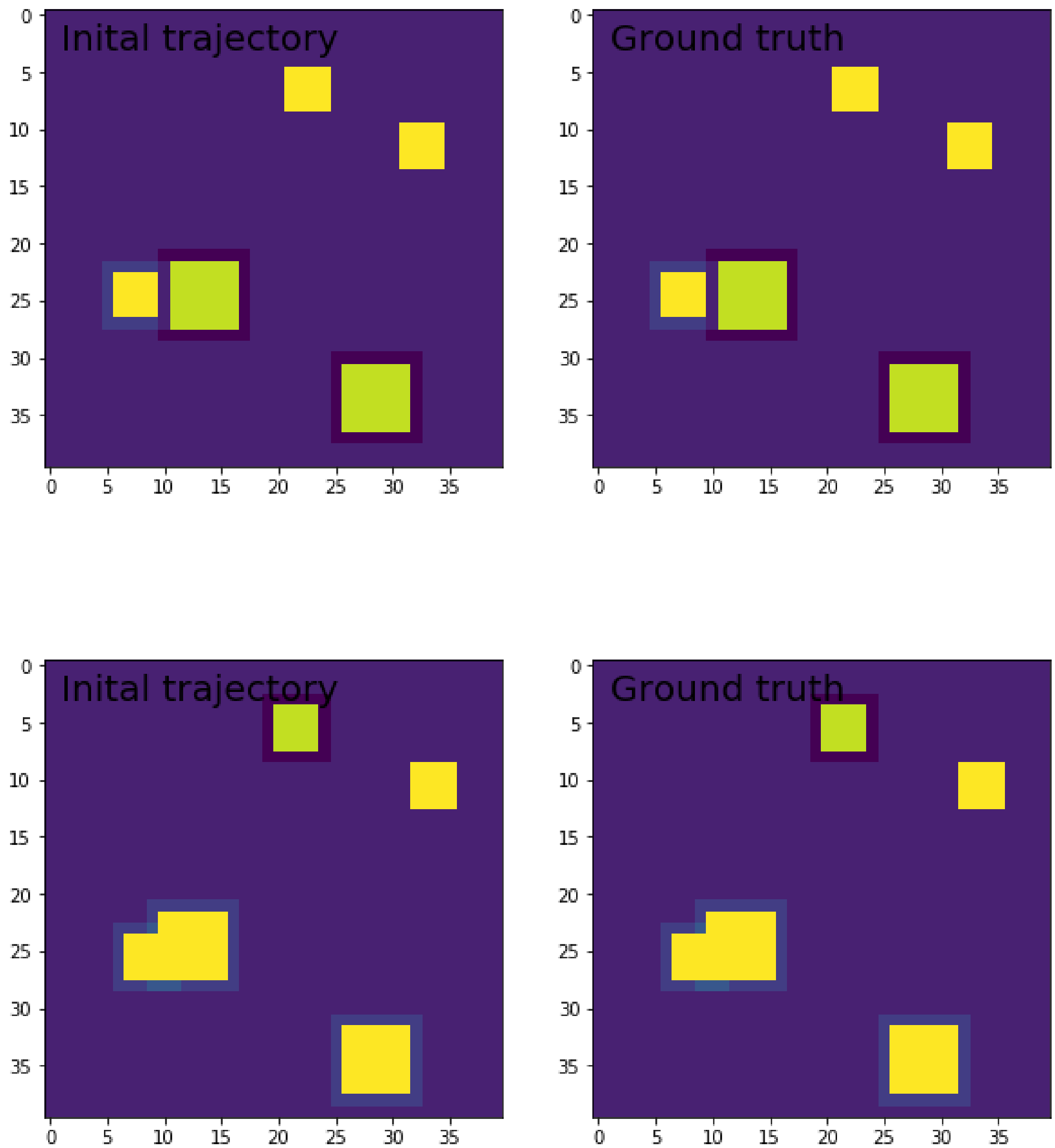
```
Train on 950 samples, validate on 50 samples
Epoch 1/20
950/950 [==============================] - 2051s 2s/step - loss: 0.2899 - val_loss: 0.0970
Epoch 2/20
950/950 [==============================] - 2050s 2s/step - loss: 0.0295 - val_loss: 0.0134
Epoch 3/20
950/950 [==============================] - 2029s 2s/step - loss: 0.0175 - val_loss: 0.0336
Epoch 4/20
950/950 [==============================] - 2033s 2s/step - loss: 0.0039 - val_loss: 0.0029
Epoch 5/20
950/950 [==============================] - 2028s 2s/step - loss: 0.0016 - val_loss: 0.0012
Epoch 6/20
950/950 [==============================] - 2004s 2s/step - loss: 8.6522e-04 - val_loss: 7.6514e-
Epoch 7/20
950/950 [==============================] - 1988s 2s/step - loss: 6.2943e-04 - val_loss: 6.0122e-
Epoch 8/20
950/950 [==============================] - 1981s 2s/step - loss: 5.1458e-04 - val_loss: 5.2007e-
Epoch 9/20
950/950 [==============================] - 1966s 2s/step - loss: 4.4904e-04 - val_loss: 4.5834e-
Epoch 10/20
950/950 [==============================] - 1963s 2s/step - loss: 4.0121e-04 - val_loss: 4.4027e-
Epoch 11/20
950/950 [==============================] - 1967s 2s/step - loss: 3.6737e-04 - val_loss: 4.1293e-
Epoch 12/20
950/950 [==============================] - 1942s 2s/step - loss: 3.3867e-04 - val_loss: 3.7608e-
Epoch 13/20
950/950 [==============================] - 1932s 2s/step - loss: 3.1483e-04 - val_loss: 3.6869e-
Epoch 14/20
950/950 [==============================] - 1942s 2s/step - loss: 2.9349e-04 - val_loss: 3.4511e-
Epoch 15/20
950/950 [==============================] - 1938s 2s/step - loss: 2.7652e-04 - val_loss: 3.2635e-
Epoch 16/20
950/950 [==============================] - 1914s 2s/step - loss: 2.5790e-04 - val_loss: 3.2990e-
Epoch 17/20
950/950 [==============================] - 1894s 2s/step - loss: 2.4624e-04 - val_loss: 3.4290e-
Epoch 18/20
950/950 [==============================] - 1889s 2s/step - loss: 2.3411e-04 - val_loss: 3.0872e-
Epoch 19/20
950/950 [==============================] - 1883s 2s/step - loss: 2.2149e-04 - val_loss: 3.1227e-
Epoch 20/20
950/950 [==============================] - 1884s 2s/step - loss: 2.1072e-04 - val_loss: 3.0010e-
```

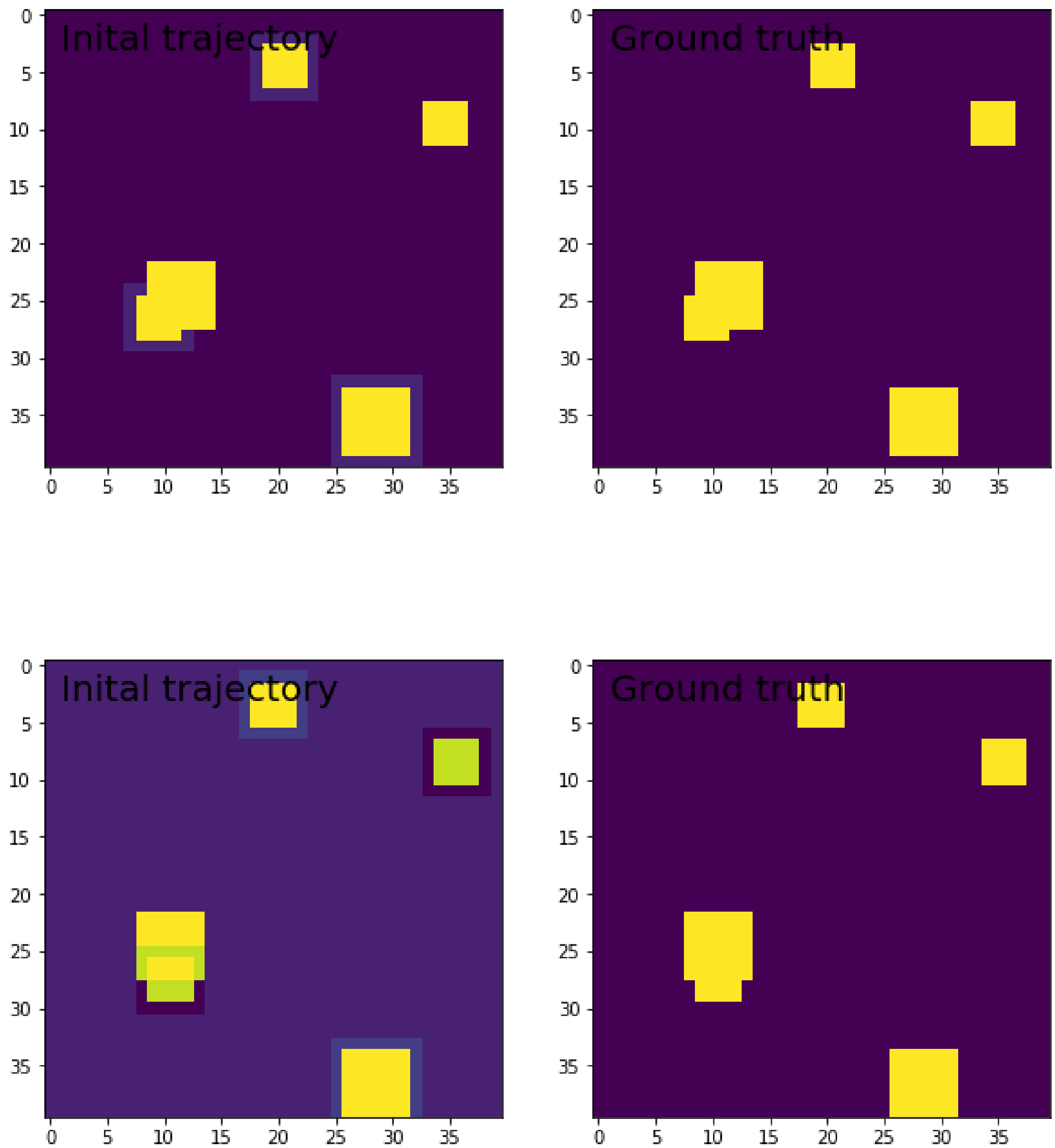
```
Out[25]: <keras.callbacks.History at 0x7f2431ebc090>
```

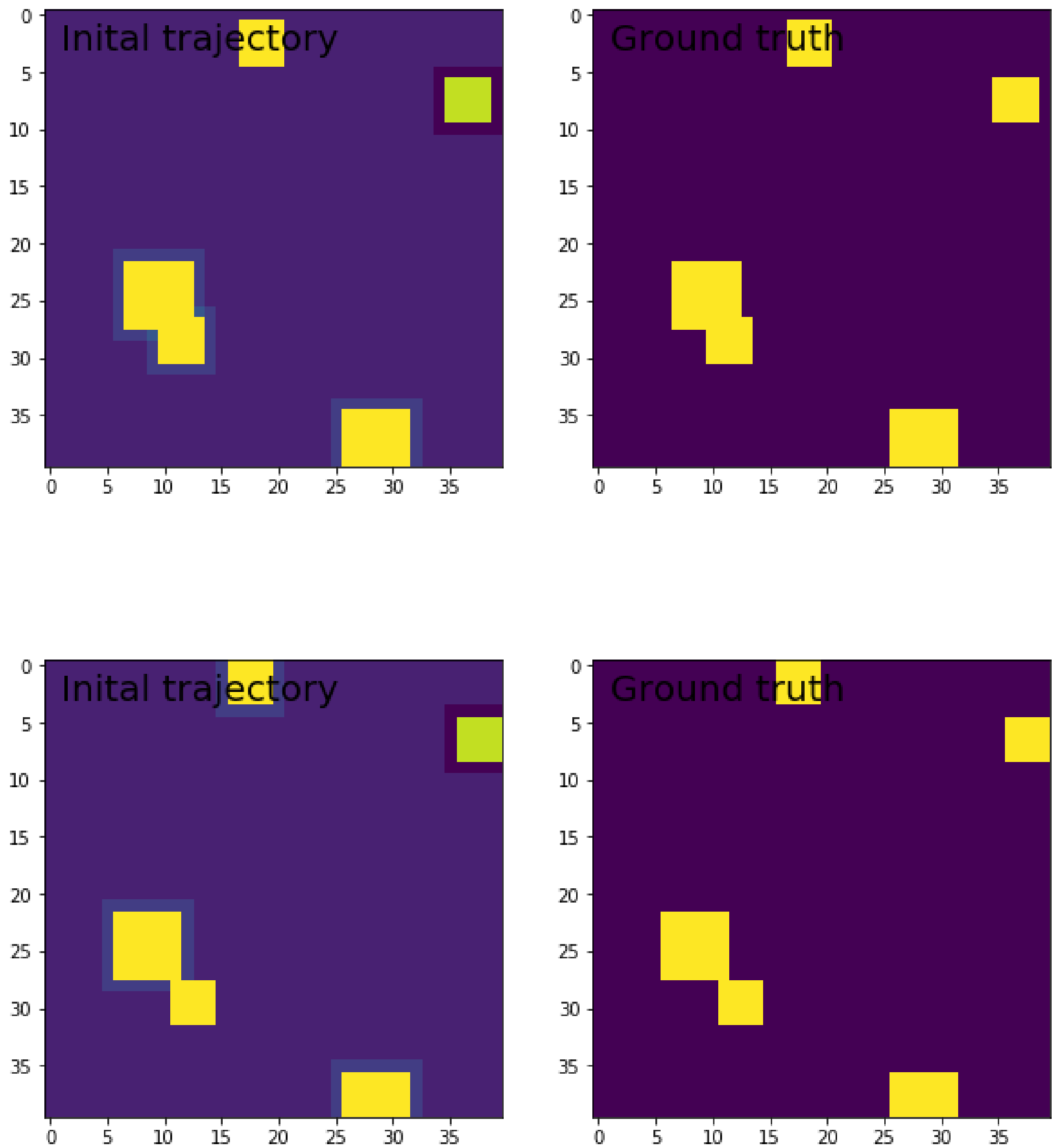
1.9.3 Test the Network

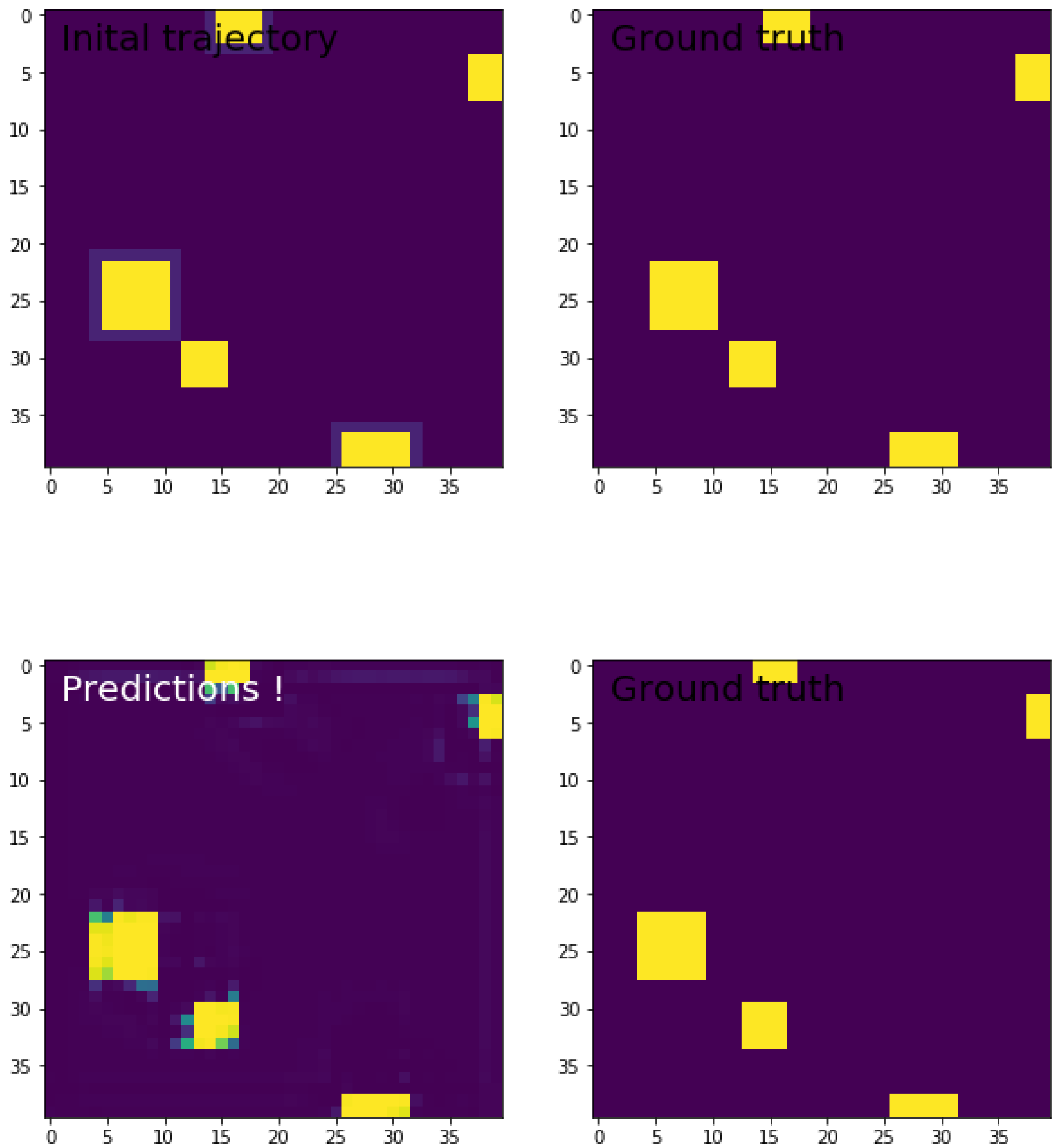
In [26]:
```
# Testing the network on one movie
# feed it with the first 7 positions and then
# predict the new positions
which = 1004
track = noisy_movies[which][:7, ::, ::, ::]

for j in range(16):
    new_pos = seq.predict(track[np.newaxis, ::, ::, ::, ::])
    new = new_pos[::, -1, ::, ::, ::]
    track = np.concatenate((track, new), axis=0)
```

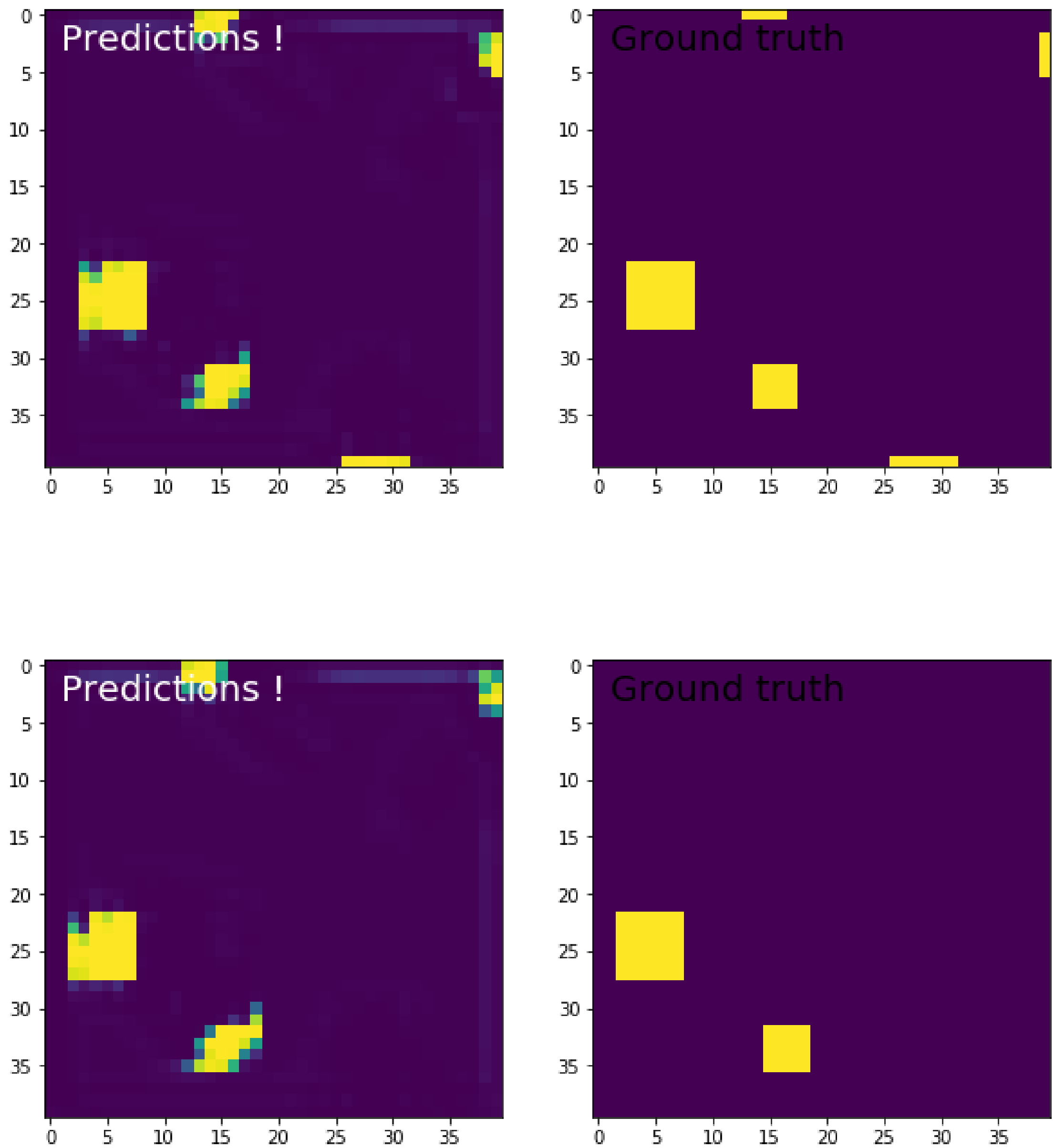
In [27]:
```
# And then compare the predictions
# to the ground truth
track2 = noisy_movies[which][::, ::, ::, ::]
for i in range(15):
    fig = plt.figure(figsize=(10, 5))

    ax = fig.add_subplot(121)

    if i >= 7:
        ax.text(1, 3, 'Predictions !', fontsize=20, color='w')
    else:
        ax.text(1, 3, 'Inital trajectory', fontsize=20)

    toplot = track[i, ::, ::, 0]

    plt.imshow(toplot)
    ax = fig.add_subplot(122)
    plt.text(1, 3, 'Ground truth', fontsize=20)

    toplot = track2[i, ::, ::, 0]
    if i >= 2:
        toplot = shifted_movies[which][i - 1, ::, ::, 0]

    plt.imshow(toplot)
    plt.savefig('%i_animate.png' % (i + 1))
```

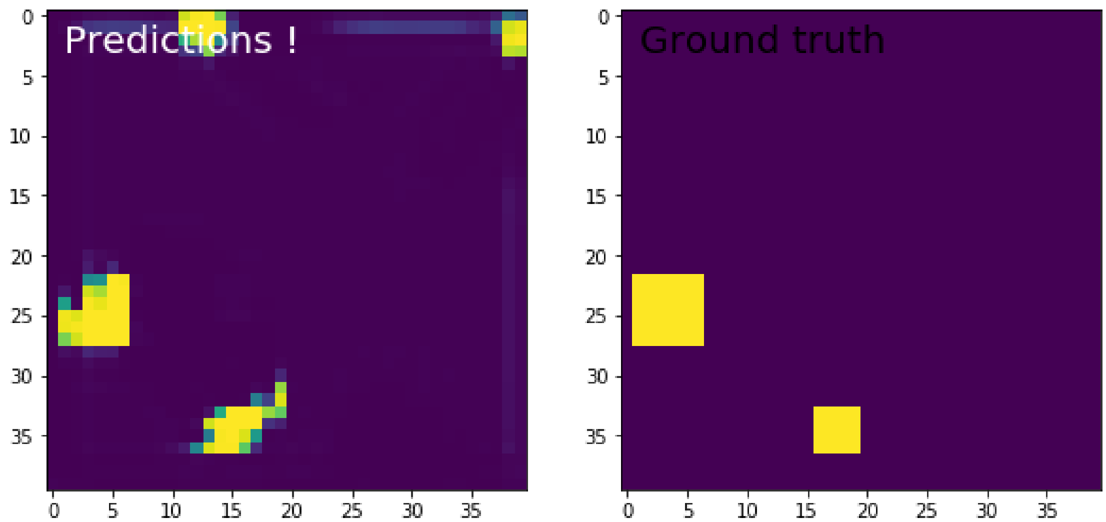

Inital trajectory
Ground truth
Inital trajectory
Ground truth

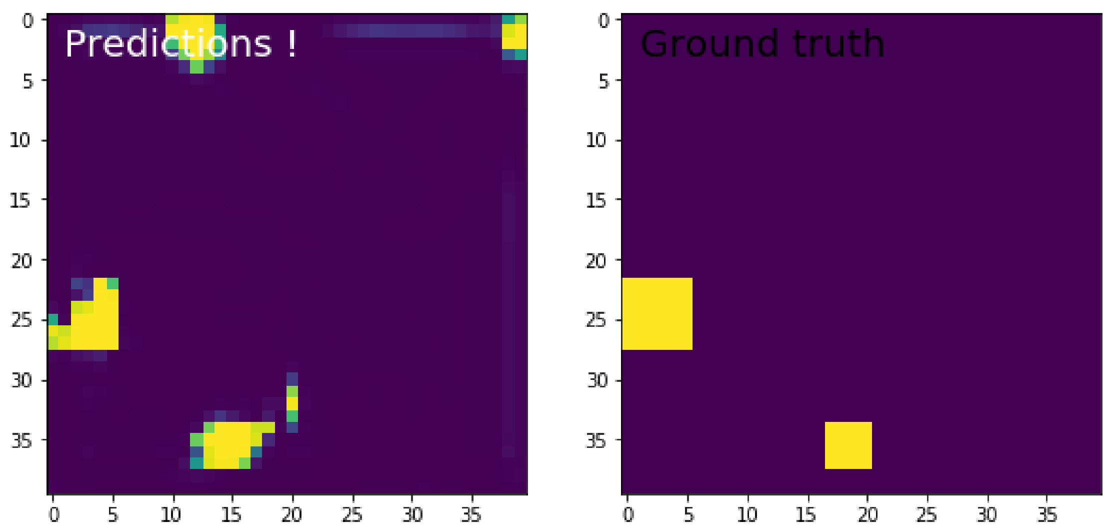

Inital trajectory
Ground truth
Inital trajectory
Ground truth

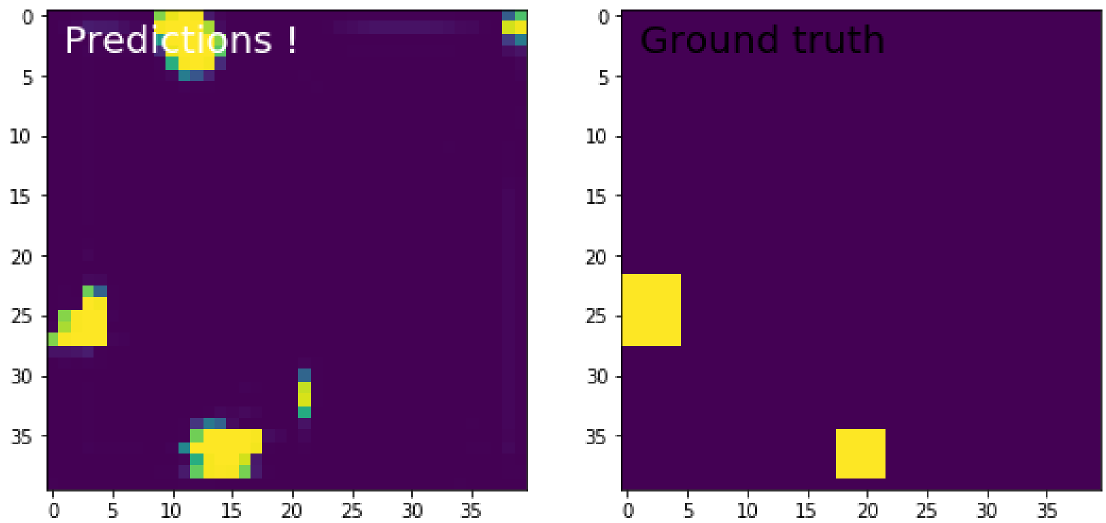

Inital trajectory
Ground truth
Inital trajectory
Ground truth
0 5 10 15 20 25 30 35

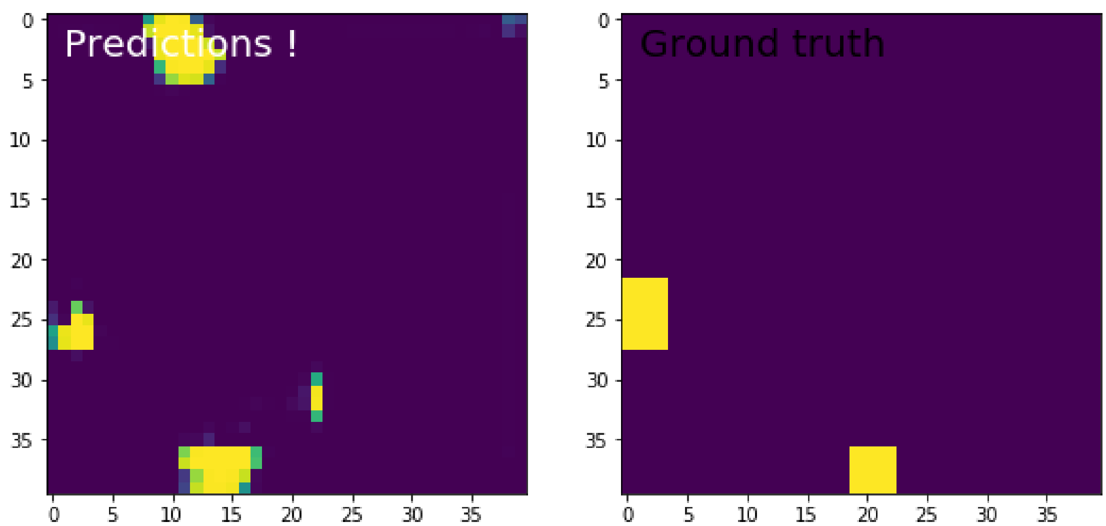

Inital trajectory
Ground truth
Predictions !
Ground truth

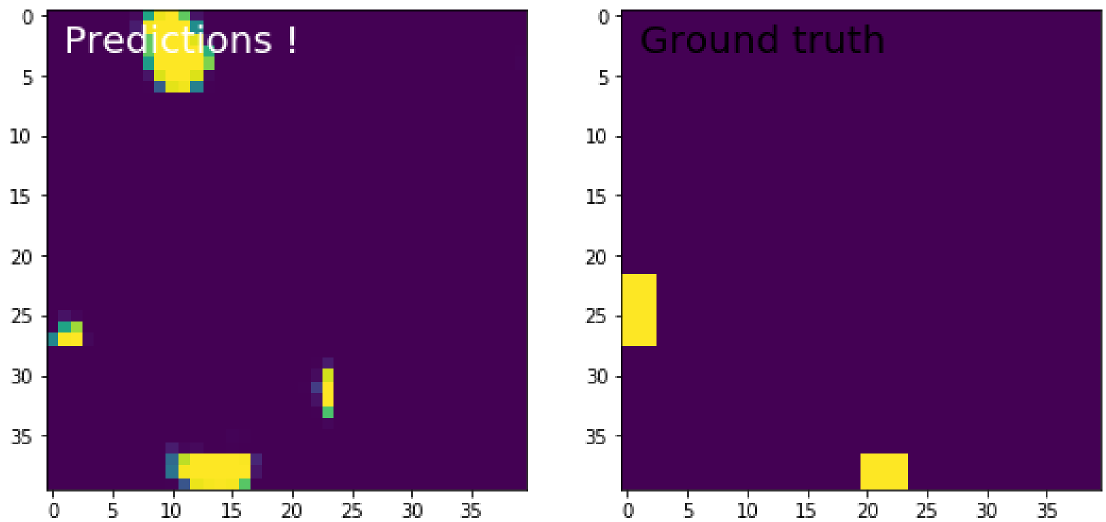

Predictions !
Ground truth
Predictions !
Ground truth
0
5
10
15
20
25
30
35


Predictions !
Ground truth


Predictions !
Ground truth


Predictions !
Ground truth


Predictions !
Ground truth


Predictions !
Ground truth
0
5
10
15
20
25
30
35