Homework 2

May 14, 2019

```
In [1]: import pandas as pd
        from keras.preprocessing.text import Tokenizer
        from keras.preprocessing.sequence import pad_sequences
        from keras.utils import to_categorical
Using TensorFlow backend.
   1. Import the data and tokenize to use with Keras.
In [35]: train_df = pd.read_csv('data/congress_train.csv', encoding='ISO-8859-1')
         valid df = pd.read csv('data/congress val.csv', encoding='ISO-8859-1')
         test_df = pd.read_csv('data/congress_test.csv', encoding='ISO-8859-1')
In [50]: train words = []
         valid_words = []
         test_words = []
         for title in list(train_df['Title']):
             train_words.append(str(title))
         for title in list(valid_df['Title']):
             valid_words.append(str(title))
         for title in list(valid_df['Title']):
             test_words.append(str(title))
In [51]: train_y = to_categorical(list(train_df['Major']))
         valid y = to categorical(list(valid df['Major']))
         test_y = to_categorical(list(valid_df['Major']))
In [52]: #Keep only the 10000 most frequent words
         tokenizer = Tokenizer(num_words=10000)
         tokenizer.fit_on_texts(train_words)
In [53]: #Limit each bill's title to a maximum length of 100 words
         #Pad each sequence to be of length 100
         train_seq = tokenizer.texts_to_sequences(train_words)
         test seq = tokenizer.texts to sequences(test words)
         valid_seq = tokenizer.texts_to_sequences(valid_words)
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In [54]: train_x = pad_sequences(train_seq, maxlen=100)
   test_x = pad_sequences(test_seq, maxlen=100)
   valid_x = pad_sequences(valid_seq, maxlen=100)
 2. Use a task-specific embedding layer with an appropriate number of output dimensions
 3. Estimate a basic feed-forward network
In [40]: from keras.layers import Embedding, Flatten, Dense
   from keras.models import Sequential
In [81]: ffn = Sequential()
   ffn.add(Embedding(10000, 25, input_length=100))
   ffn.add(Flatten())
   ffn.add(Dense(24, activation='softmax'))
   ffn.compile(optimizer='rmsprop', loss='categorical_crossentropy', metrics=['accuracy']
   result_ffn = ffn.fit(train_x, train_y, validation_data=(valid_x,valid_y), epochs=50,
Train on 278612 samples, validate on 69649 samples
Epoch 1/50
Epoch 2/50
Epoch 3/50
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Epoch 50/50
4. Estimate a recurrent neural network (RNN) with a layer_simple_rnn
In [57]: from keras.layers import SimpleRNN
In [59]: rnn = Sequential()
  rnn.add(Embedding(10000, 25, input_length=100))
  rnn.add(SimpleRNN(25))
  rnn.add(Dense(24, activation='softmax'))
  rnn.compile(optimizer='rmsprop', loss='categorical_crossentropy', metrics=['accuracy']
  result_rnn = rnn.fit(train_x, train_y, validation_data=(valid_x,valid_y), epochs=50,
Train on 278612 samples, validate on 69649 samples
Epoch 1/50
Epoch 2/50
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5. Estimate an RNN with an LSTM layer

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In [60]: from keras.layers import LSTM

lstm = Sequential()
   lstm.add(Embedding(10000, 25, input_length=100))
   lstm.add(LSTM(25))
   lstm.add(Dense(24, activation='softmax'))
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lstm.compile(optimizer='rmsprop', loss='categorical_crossentropy', metrics=['accuracy
result_lstm = lstm.fit(train_x, train_y, validation_data=(valid_x,valid_y), epochs=50

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Train on 278612 samples, validate on 69649 samples
Epoch 1/50
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Epoch 33/50				_				
	[]	-	76s	274us/step	- loss:	0.3653	- acc:	0.8969 -
Epoch 34/50								
	[=====]	-	76s	274us/step	- loss:	0.3627	- acc:	0.8974 -
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	[======]	-	76s	271us/step	- loss:	0.3595	- acc:	0.8982 -
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	[=====]	-	73s	263us/step	- loss:	0.3569	- acc:	0.8992 -
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-	[=====]	_	73s	263us/step	- loss:	0.3391	- acc:	0.9039 -
Epoch 44/50			• -	2000	<u>-</u>	V • = - ·		V.L.
-	[=====]	_	74s	267us/step	- loss:	0.3367	- acc:	0.9048 -
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Epoch 46/50								
278612/278612	[=====]	-	75s	269us/step	- loss:	0.3324	- acc:	0.9062 -

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Epoch 47/50
Epoch 48/50
Epoch 49/50
Epoch 50/50
6. Estimate an RNN with a GRU layer
In [61]: from keras.layers import GRU
  gru = Sequential()
  gru.add(Embedding(10000, 25, input_length=100))
  gru.add(GRU(25))
  gru.add(Dense(24, activation='softmax'))
  gru.compile(optimizer='rmsprop', loss='categorical_crossentropy', metrics=['accuracy']
  result_gru = gru.fit(train_x, train_y, validation_data=(valid_x,valid_y), epochs=50,
Train on 278612 samples, validate on 69649 samples
Epoch 1/50
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Epoch 15/50				-				I
•	[======]	-	75s	269us/step -	loss:	0.4635	- acc:	0.8720 -
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Epoch 19/50	-					4		
	[=====]	-	64s	231us/step -	loss:	0.4274	- acc:	0.8808 -
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	[=====]	-	66s	235us/step -	loss:	0.4198	- acc:	0.8828 -
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	[======]	-	64s	230us/step -	loss:	0.4129	- acc:	0.8847 -
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•	[=====]	-	62s	222us/step -	loss:	0.3743	- acc:	0.8951 -
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	[]	-	63s	225us/step -	loss:	0.3699	- acc:	0.8964 -
Epoch 30/50	_							ļ
	[======]	-	64s	231us/step -	loss:	0.3659	- acc:	0.8978 -
Epoch 31/50			- 4	· · -				5300
	[=====]	-	64s	230us/step -	loss:	0.3612	- acc:	0.8989 -
Epoch 32/50	1		30 -	/ .	-	- 0570		- 2222
	[]	-	62s	222us/step -	loss:	0.3570	- acc:	0.9000 -
Epoch 33/50	51		60 a	202 /-+		0.0500		0 0011
	[]	-	63s	226us/step -	loss:	0.3533	- acc:	0.9011 -
Epoch 34/50	·1		204	200 -/-+	7	2 2405		0.0010 -
	[======]	-	ნ∠ნ	223us/step -	loss:	0.3495	- acc:	0.9019 -
Epoch 35/50	「·]	_	4E 4	024	7.22.	0 34E8	2001	0 0024 -
	[]	-	400	234us/step =	1055.	U.3400	- acc.	0.9034
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Epoch 37/50	[======================================		ಎ೧೧	230us/ step	1055.	U.3424	- acc.	U.9U4Z
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Epoch 50/50
7. Estimate five additional neural network models with different configurations of hyperparameters
In [63]: model1 = Sequential()
   model1.add(Embedding(10000, 25, input_length=100))
   model1.add(SimpleRNN(25, return_sequences=True))
   model1.add(SimpleRNN(25))
   model1.add(Dense(24, activation='softmax'))
   model1.compile(optimizer='rmsprop', loss='categorical_crossentropy', metrics=['accura
   result_model1 = model1.fit(train_x, train_y, validation_data=(valid_x,valid_y), epoch
Train on 278612 samples, validate on 69649 samples
Epoch 1/25
Epoch 2/25
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Epoch 3/25

Epoch 4/25

Epoch 5/25

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Epoch 24/25
Epoch 25/25
In [68]: model2 = Sequential()
 model2.add(Embedding(10000, 25, input_length=100))
 model2.add(LSTM(25, return_sequences=True))
 model2.add(LSTM(25))
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model2.add(Dense(24, activation='softmax'))

```
model2.compile(optimizer='rmsprop', loss='categorical_crossentropy', metrics=['accura
result_model2 = model2.fit(train_x, train_y, validation_data=(valid_x,valid_y), epoch
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Train on 278612 samples, validate on 69649 samples
Epoch 1/25
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Epoch 21/25
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Epoch 23/25
Epoch 24/25
Epoch 25/25
In [71]: model3 = Sequential()
  model3.add(Embedding(10000, 25, input_length=100))
  model3.add(SimpleRNN(25, dropout=0.3))
  model3.add(Dense(24, activation='softmax'))
  model3.compile(optimizer='rmsprop', loss='categorical_crossentropy', metrics=['accura
  result_model3 = model3.fit(train_x, train_y, validation_data=(valid_x,valid_y), epoch
Train on 278612 samples, validate on 69649 samples
Epoch 1/25
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Epoch 3/25
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Epoch 18/25
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Epoch 23/25
Epoch 24/25
Epoch 25/25
In [73]: model4 = Sequential()
  model4.add(Embedding(10000, 25, input_length=100))
  model4.add(LSTM(25, dropout=0.3))
  model4.add(Dense(24, activation='softmax'))
  model4.compile(optimizer='rmsprop', loss='categorical_crossentropy', metrics=['accura
  result_model4 = model4.fit(train_x, train_y, validation_data=(valid_x,valid_y), epoch
Train on 278612 samples, validate on 69649 samples
Epoch 1/25
Epoch 2/25
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Epoch 17/25

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Epoch 24/25
Epoch 25/25
In [75]: model5 = Sequential()
  model5.add(Embedding(10000, 25, input_length=100))
  model5.add(GRU(25, dropout=0.3))
  model5.add(Dense(24, activation='softmax'))
  model5.compile(optimizer='rmsprop', loss='categorical_crossentropy', metrics=['accura
  result_model5 = model5.fit(train_x, train_y, validation_data=(valid_x,valid_y), epoch
Train on 278612 samples, validate on 69649 samples
Epoch 1/25
Epoch 2/25
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Epoch 23/25
Epoch 24/25
Epoch 25/25
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8. For each model, plot the validation loss and accuracy over each epoch.

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In [77]: import matplotlib.pyplot as plt
In [82]: models_list = [result_ffn, result_rnn, result_lstm, result_gru, result_model1, result_
```

```
for model in models_list:
    plt.plot(model.history['val_loss'])

plt.legend(['ffn', 'rnn', 'lstm', 'gru', 'model1', 'model2', 'model3', 'model4', 'model1', 'model2', 'model4', 'model1', 'model2', 'model4', 'model1', 'mo
```

Validation loss over epochs ffn 2.0 mn Istm 1.8 gru model1 1.6 model2 1.4 model3 model4 1.2 model5 1.0 0.8 0.6

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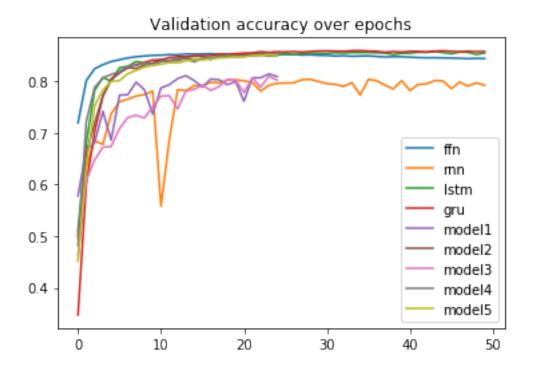
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9. Select the best performing model based on the validation set and evaluate its performance using the test set. Assume that with hand-coding we can achieve a 95% accuracy rate. Would your neural network perform better or worse than hand-coding?

From above two plots we can see that, the best performing model is the model with GRU layer because it seems to have the highest validation accuracy and lowest validation loss.

Out [84]: [0.5703272305414112, 0.8573848870826176]

The test accuracy rate using GRU model is 85.7%, it performs worse than hand-coding.

In []: