變更於 幾秒前

♡ 讚賞

♣ 已訂閱 ~ 口 收藏

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## HW5: Fake News Detection 2

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## 1. Data Preprocessing

1. 將 train.csv \ test.csv 和 sample\_submission.csv 的資料(id, text, label)提取出 來,並消除 HTML tag 及 stop words (利用 spacy 提供的停頓詞列表)。

```
import pandas as pd
     import spacy
     spacy.load('en_core_web_sm')
     spacy_stopwords = spacy.lang.en.stop_words.STOP_WORDS
     def data_preprocess(data_path, mode, stop_words):
 8
         def rm_tags_stops(text, stop_words):
 9
             # remove tags
10
             re_tag = re.compile(r'<[^>]+>')
11
             out_text = re_tag.sub(' ', text.lower())
             # remove stop words
14
             out_text = (" ").join([word for word in out_text.split(' ') if not wor
15
16
             return out_text
17
18
         # read data
19
         fp = open(f'{data_path}{mode}.csv')
20
         data_lines = fp.readlines()
21
22
         fp.close()
23
24
         # data preprocess
         data_df = pd.DataFrame([], columns=['id', 'text', 'label'])
25
26
         avg_text_len = 0
         if mode == 'train':
27
28
             for i, l_i in enumerate(data_lines):
                 if i == 0:
29
30
                     continue
31
                 try:
                     dict_i = {}
32
                     text_i, label = l_i.split('\t')
33
34
                     text_i = rm_tags_stops(text_i.strip(), stop_words)
                     avg_text_len += len(text_i.split(' '))
35
36
                     dict_i['id'] = [str(i)]
37
38
                     dict_i['text'] = [text_i]
                     dict_i['label'] = [int(label.strip())]
39
                     data_df = pd.concat([data_df, pd.DataFrame.from_dict(dict_i, o
40
                 except:
41
42
                     pass
43
         else:
             label_data = pd.read_csv(f'{data_path}sample_submission.csv')
44
45
             for i, (test_li, label_i) in enumerate(zip(data_lines, label_data['lab
46
                 if i == 0:
47
                     continue
48
49
                 dict_i = {}
                 id, text_i = test_li.split('\t')
50
                 text_i = rm_tags_stops(text_i.strip(), stop_words)
51
52
                 avg_text_len += len(text_i.split(' '))
53
54
                 dict_i['id'] = [id.strip()]
                 dict_i['text'] = [text_i]
55
                 dict_i['label'] = [int(label_i)]
                 data_df = pd.concat([data_df, pd.DataFrame.from_dict(dict_i, orien
57
         print(f'{mode} avg text len: {avg_text_len / len(data_df)}')
58
```

2. 使用 Tokenizer 模組建立 token,建立一個 3800(hyper\_params['dict\_len'])字的字典: 讀取所有訓練文檔資料之後,會依照每個英文字在資料出現的次數進行排序,並將前 3800 名 的英文單字加進字典中。

return data\_df['text'], np.array(data\_df['label'].values)

- 3. 透過 texts\_to\_sequences 可以將訓練和測試集資料中的文檔轉換為數字列表。
- 4. 每一篇影評文字字數不固定,但後續進行深度學習模型訓練時長度必須固定,因此需要截長補 短 sequence.pad\_sequences :長度小於 380 (hyper\_params['content\_len'])的,前面的 數字補 0;長度大於 380 的,截去前面的數字

```
from keras.preprocessing import sequence
from keras.preprocessing.text import Tokenizer
# create token
token = Tokenizer(num_words=hyper_params['dict_len'])
token.fit_on_texts(text_train.values)
x_train = token.texts_to_sequences(text_train.values)
x_train = sequence.pad_sequences(x_train, maxlen=hyper_params['content_len'])
x_test = token.texts_to_sequences(text_test.values)
x_test = sequence.pad_sequences(x_test, maxlen=hyper_params['content_len'])
```

## 2. Model Training

59

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- 訓練兩種模型 SimpleRNN 和 LSTM ,並將每個 Epoch 的 training loss \ training accuracy 和 testing accuracy 記錄下來。
- Hyperparameters epoch: 100
  - batch size: 4987 drop out: 0.7

  - optimizer: Adam (learning rate: 1e-3)

```
import keras
     from keras.models import Sequential
     from keras.layers.core import Dense, Dropout
     from keras.layers.embeddings import Embedding
     from keras.layers.recurrent import SimpleRNN, LSTM
 6
    hyper_params = {'epoch': 100, 'batch_size': 4987, 'drop_out': 0.7,
                     'dict_len': 3800, 'content_len': 380}
 8
 9
    def train(target_path, model_type, params, x_train, y_train, x_test, y_test):
         # set up model
11
         model = Sequential()
12
         model.add(Embedding(output_dim=128,
13
                             input_dim=params['dict_len'],
14
                             input_length=params['content_len']))
15
         model.add(Dropout(params['drop_out']))
16
         if model_type == 'RNN':
17
18
             model.add(SimpleRNN(units=128))
19
         else:
20
             model.add(LSTM(units=128))
         model.add(Dense(units=128, activation='relu'))
21
22
         model.add(Dropout(params['drop_out']))
23
         model.add(Dense(units=1, activation='sigmoid'))
24
         model.summary()
25
26
         # define model
         model.compile(loss='binary_crossentropy',
27
                       optimizer=keras.optimizers.Adam(learning_rate=1e-3),
28
                       metrics=['accuracy'])
29
30
         # training
         fp_train_loss = open(f'{target_path}{model_type}_train_loss.txt', 'w')
32
         fp_train_acc = open(f'{target_path}{model_type}_train_acc.txt', 'w')
33
         fp_test_acc = open(f'{target_path}{model_type}_test_acc.txt', 'w')
34
35
36
         for epoch_i in range(1, params['epoch'] + 1):
37
             train_history = model.fit(x_train, y_train,
38
                                       epochs=1, batch_size=params['batch_size'],
39
                                       shuffle=True, workers=12,
                                       verbose=0)
40
             train_loss = train_history.history["loss"][0]
41
             train_acc = train_history.history["accuracy"][0]
42
             print(f'\nEpoch {epoch_i}/{params["epoch"]}')
43
             print(f'Loss: {train_loss}, Accuracy: {train_acc}')
44
             fp_train_loss.write(f'{train_loss}\n')
45
             fp_train_acc.write(f'{train_acc}\n')
46
47
             score = model.evaluate(x_test, y_test, verbose=0, workers=12)
48
49
             print(f'Testing accuracy: {score[1]}')
             fp_test_acc.write(f'{score[1]}\n')
50
51
52
         fp_train_loss.close()
53
         fp_train_acc.close()
54
         fp_test_acc.close()
```

## 3. Results

最後雖然兩種模型 training accuracy 都有提升至將近百分百、 loss 也都趨近 0,但 testing accuracy 都維持在 50% 左右,有 overfitting 的現象。

• RNN

Accuracy

```
Accuarcy
                                                                          Training Loss
                                                       0.7
Test
                                                       0.6
                                                       0.5
                                                       0.4
                                                       0.3
                                                       0.2 -
                                                       0.1
                                                                    20
```

**Test** 

51.52%

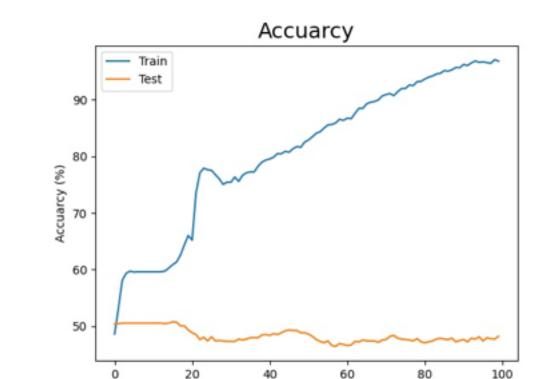
Train

99.16%

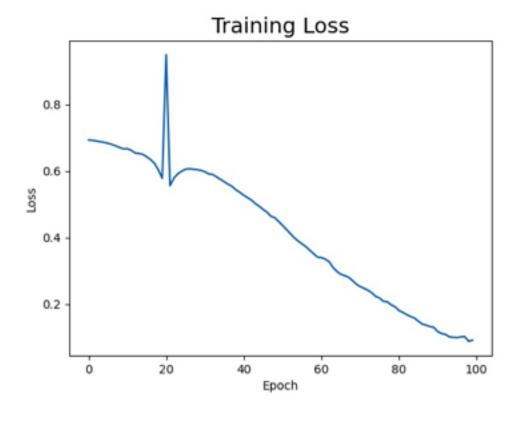
• LSTM

	Train	Test
Accuracy	97.03%	50.80%

Epoch



Epoch



Epoch