Artificial Intelligence In Medical Applications and Services Homework3 Report

1. Score Result

```
1 flscore
0.4258144301165879
```

2. Process

As the TA mentioned, we can seperate the whole project into 2 parts which are **Preprocessing** and **Model_Training**.

1. Preprocessing

First we use **loadInputFile** function to load the data given by TA (SampleData_deid.txt).

```
1  def loadInputFile(path):
2    trainingset = list() # store trainingset [content, content,...]
3    position = list() # store position [article_id, start_pos, end
4    mentions = dict() # store mentions[mention] = Type
5    with open(file_path, 'r', encoding='utf8') as f:
6        file_text=f.read().encode('utf-8').decode('utf-8-sig')
7    datas=file_text.split('\n\n-----\n\n')[:-1]
8    for data in datas:
9        data=data.split('\n')
10        content=data[0]
11        trainingset.append(content)
12        annotations=data[1:]
13        for annot in annotations[1:]:
14             annot=annot.split('\t') #annot= article_id, start_pos,
15             position.extend(annot)
16             mentions[annot[3]]=annot[4]
17
18        return trainingset, position, mentions
```

Then use CRFFormatData to change the input data into a corresponding format (clear the space, adding 'B' 'O' 'I' label)

```
def CRFFormatData(trainingset, position, path):
    if (os.path.isfile(path)):
        os.remove(path)
    outputfile = open(path, 'a', encoding= 'utf-8')
    count = 0 # annotation counts in each content
tagged = list()
     for article_id in range(len(trainingset)):
        trainingset_split = list(trainingset[article_id])
while '' or ' ' in trainingset_split:
    if '' in trainingset_split:
                 trainingset_split.remove('')
            else:
    trainingset_split.remove(' ')
        start_tmp = 0
        for position_idx in range(0,len(position),5):
             if int(position[position_idx]) == article_id:
                 count +
                     start_pos = int(position[position_idx+1])
                      end pos = int(position[position idx+2])
                      entity_type=position[position_idx+4]
                      if start pos == 0:
                          token = list(trainingset[article_id][start_pos:end_pos])
                          whole_token = trainingset[article_id][start_pos:end_pos]
                           for token_idx in range(len(token)):
                               if len(token[token_idx].replace(' ','')) == 0:
                               if token idx == 0:
                                   label = 'B-'+entity_type
                                   label = 'I-'+entity_type
```

2. Model_Training

Create a model to fit and predict, and don't forget to flatten to get final f1score and print the prediction result

```
def CRF(x train, y train, x test, y test):
    crf = sklearn_crfsuite.CRF(
        algorithm='lbfgs',
        cl=0.1,
        cz=0.1,
        max_iterations=100,
        all_possible_transitions=True
    )
    crf.fit(x_train, y_train)
    # print(crf)
    y_pred = crf.predict(x_test)
    y_pred_mar = crf.predict_marginals(x_test)
    # print(y_pred_mar)
    labels = list(crf.classes_)
    labels.remove('0')
    flscore = metrics.flat_fl_score(y_test, y_pred, average='weighted', labels=labels)
    sorted_labels = sorted(labels,key=lambda name: (name[1:], name[0])) # group B and I results
    print(flat_classification_report(y_test, y_pred, labels=sorted_labels, digits=3))
    return y_pred, y_pred_mar, flscore
```

This part is very important. We need to prepare a pretrained word vector file to let it find corresponding key value of the token that get from input data.

The first two tokens are the parameters which are vocabulary_size and it's dimension. And keep the rest tokens into **vec** array in float type, and return word_vecs dictionary.

```
# load pretrained word vectors
# get a dict of tokens (key) and their pretrained word vectors (value)
# pretrained word2vec CBOW word vector: https://fgc.stpi.narl.org.tw/activity/videoDoddim = 0

word_vecs= {}
# open pretrained word vector file
with open('/content/drive/MyDrive/Colab Notebooks/NER/glove.42B.300d.txt') as f:
for line in f:
tokens = line.strip().split()

# there 2 integers in the first line: vocabulary_size, word_vector_dim
if len(tokens) == 2:
    dim = int(tokens[1])
    continue

word = tokens[0]
vec = np.array([ float(t) for t in tokens[1:] ])
word_vecs[word] = vec

# get a dict of tokens (value)
https://fgc.stpi.narl.org.tw/activity/videoDod
https:/
```

Prepare dataset and split them into training_set and testing_set with test_size = 0.33

Use the pretrained word vector that we just imported as embedding_dict to find the input data_list's corresponding value with three for loops and keep them as a list.

```
def Word2Vector(data_list, embedding_dict):
    embedding_list = list()

# No Match Word (unknown word) Vector in Embedding
unk_vector=np.random.rand(*(list(embedding_dict.values())[0].shape))

for idx_list in range(len(data_list)):
    embedding_list_tmp = list()
    for idx_tuple in range(len(data_list[idx_list])):
        key = data_list[idx_list][idx_tuple][0] # token

# print(str(idx_tuple) + key)

if key in embedding_dict:
    value = embedding_dict(key)

else:
    value = unk_vector
    embedding_list_tmp.append(value)
    embedding_list.append(embedding_list_tmp)
return embedding_list
```

Extract all the features of embedding_list and keep also(three loops go through 3 dimension of embed_list)

```
# input features: pretrained word vectors of each token
# return a list of feature dicts, each feature dict corresponding to each token

def Feature(embed_list):
    feature_list = list()
    for idx_list in range(len(embed_list)):
        feature_list_tmp = list()
        for idx_tuple in range(len(embed_list[idx_list])):
            feature_dict = dict()
            for idx_vec in range(len(embed_list[idx_list][idx_tuple])):
            feature_dict['dim_' + str(idx_vec+1)] = embed_list[idx_list][idx_tuple][idx_vec]

feature_list_tmp.append(feature_dict)

feature_list_append(feature_list_tmp)
return feature_list
```

This is how embed_list[idx_list][idx_tuple][idx_vec] looks like:

```
0.6180830816584256
0.23310316349906202
0.7140401709909245
0.19546616359681368
0.8567940396548351
0.7400688220122569
```

Prepare a Label list by set the third dimension of data_list to 1

```
1  # get the labels of each tokens in train.data
2  # return a list of lists of labels
3  def Preprocess(data_list):
4     label_list = list()
5     for idx_list in range(len(data_list)):
6         label_list_tmp = list()
7         for idx_tuple in range(len(data_list[idx_list])):
8         label_list_tmp.append(data_list[idx_list][idx_tuple][1])
9     label_list.append(label_list_tmp)
10     return label_list
```

Call the functions

```
1  # Load Word Embedding
2  trainembed_list = Word2Vector(traindata_list, word_vecs)
3  testembed_list = Word2Vector(testdata_list, word_vecs)
4
5  # CRF - Train Data (Augmentation Data)
6  x_train = Feature(trainembed_list)
7  y_train = Preprocess(traindata_list)
8
9  # CRF - Test Data (Golden Standard)
10  x_test = Feature(testembed_list)
11  y_test = Preprocess(testdata_list)
```

Fit and predict

```
1 y_pred, y_pred_mar, f1score = CRF(x_train, y_train, x_test, y_test)
```

Result

	precision	recall	fl-score	support
B-location	0.000	0.000	0.000	15
I-location	0.000	0.000	0.000	41
B-med exam	0.200	0.030	0.053	33
I-med_exam	1.000	0.075	0.140	80
B-money	0.364	0.333	0.348	12
I-money	0.353	0.171	0.231	35
B-name	0.500	0.143	0.222	7
I-name	0.333	0.100	0.154	10
B-time	0.667	0.450	0.538	111
I-time	0.825	0.532	0.647	265
micro avg	0.714	0.345	0.465	609
macro avg	0.424	0.184	0.233	609
weighted avg	0.661	0.345	0.426	609

F1Score

```
1 flscore
0.4258144301165879
```

Change the output format and save into output.tsv file Here we show the entity text's id, start_position, ending_position, content and type.

```
output="article_id\tstart_position\tend_position\tentity_text\tentity_type\n"
for test_id in range(len(y_pred)):
    pos=0

start_pos=None
end_pos=None
entity_text=None
entity_type=None
for pred_id in range(len(y_pred[test_id])):
    if y_pred[test_id][pred_id][0]=='B':
        start_pos=pos
    entity_type=y_pred[test_id][pred_id][2:]
elif start_pos_is not None and y_pred[test_id][pred_id][0]=='I' and y_pred[test_id][pred_id+1][0]=='0':
    end_pos=pos
entity_text=''.join([testdata_list[test_id][position][0] for position in range(start_pos,end_pos+1)])
line=str(testdata_article_id_list[test_id])+'\t\t'+str(start_pos)+'\t\t'+str(end_pos+1)+'\t\t'+entity_type
output+=line+'\n'
pos==1
```

article id	start position	end position	entity text	entity_type
8	52	54	前天	time
8	68	70	昨天	time
8	189	193	二十分鐘	time
8	293	295	五年	time
8	540	544	兩個禮拜	time
8	726	728	前天	time
8	730	732	前天	time
8	858	860	前天	time
8	898	900	前天	time
8	1549	1551	五天	time
8	1622	1626	五天禮拜	time
8	2352	2354	去喬	time
8	2560	2563	兩個月	time
16	51	55	九、十點	time
16	60	64	九、十點	time
16	122	124	三年	time
16	130	132	三年	time
16	247	249	三年	time
0	1268	1271	8公分	med_exam
0	1358	1362	三多路上	time
0	2576	2578	五天	time

3. Features

這裡原本我是只使用助教給的抓取data_list的第一個([0])也就是token內容去比對 embedding dict的key value 作為features

```
for idx_tuple in range(len(data_list[idx_list])):
    key = data_list[idx_list][idx_tuple][0] # token
    # print(str(idx_tuple) + key)
    if key in embedding_dict:
        value = embedding_dict[key]
    else:
        value = unk_vector
```

This is how embed_list[idx_list][idx_tuple][idx_vec] looks like:

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0.7400688220122569
```

- 1. 後來有試着先做了加入word_length的features, 平均f1score有比較微微的上升(比原本的0.35~0.41), 固定維持在0.4以上
- 2. 再來是加入word_position(start_pos), 我這裡是選擇給start_pos, 因為給end_pos的效果其實沒什麼影響, 給了start pos後只加了一點點
- 3. 再來是對於features的組織是要通過word2vector和features這兩個function後才能作成x_train, x_test的,我發現其實我的word2vector有成功把我想要的features加入到embedding_dict中並且return吐出,但是由於時間的關係我在features的dict中沒有成功整合,所以model其實沒有吃到我加入的features。不過就上述情況而言,我已經成功了解如果要訓練一個NER-CRF的模型的大概流程是怎麼樣的了。

```
else:
    # print('Row:' + row)
    row = row.strip('\n').split(' ')
    data_tuple = (row[0], row[1], row[2], row[3])
    # print(data_tuple)
```

4. Experience

- From this homework, I had learned what are NER and CRF model, and how computer learn a high-level human language.
- As we know, f1score show our model performance, but the point is how to get higher score! This is definitely different to the typical ML model, because it is not only the input_data but also how we processing the input_data into tokens and label is decisively important!
- There is no so much parameters to let you adjust to get better model performance, so a great processing_data and completely pretrained word vector file will help your model to become better!
- Interesting topic for us to explore how great ML is in this generation.
- 雖然由於時間的關係我在features的dict中沒有成功整合不過就上述情況而言,我 已經成功了解如果要訓練一個NER-CRF的模型的大概流程是怎麼樣的了。
- Thanks for Prof and TA!:)