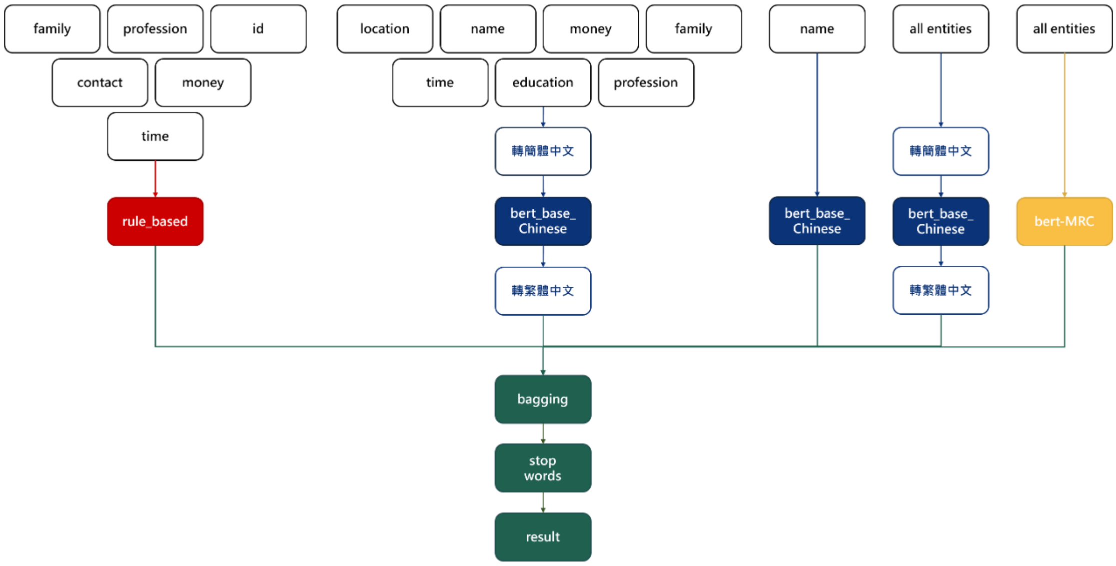
醫病訊息決策與對話語料分析競賽 - 秋季賽：醫病資料去識別化

隊名：HHH-LKT

一、系統架構



圖一、系統架構圖

(一) Rule-based

將較明確的特徵利用 Rule-based 的方式辨認，若有規律的組合會利用 Regular Expression 的方法辨認，例如身份證為一個英文字母配上九個數字，錢為數字後加上「元」或「塊」等。若較不規律的組合則是會用比對字串的方式，再給予該特徵相對應的標記，例如爸爸、媽媽標記為家人，而老師則標記為職業別等。

(二) Bert base Chinese

將各個類別分別利用 bert-base-chinese 訓練，也就是一次只訓練一個類別。由於上傳的結果顯示簡體中文的預測表現比繁體中文的還要好，因此，我們先將所有資料轉成簡體中文，得到結果後，再轉為繁體中文。提及名字類別，因為該繁體中文特徵表現較佳，所以，將其納入 Bagging 特徵之一。最後，我們也將所有類別一起訓練，將其結果納入 Bagging 特徵。

(三) Bert MRC

除了上述方法之外，本系統也嘗試利用閱讀理解方法(MRC)來達成此任務。首先，對一句話，建構數個不同的類別，接著，將每個類別與句子進行拼接，最後，得到多個不同 Bert 的輸入數據。其預測起始位置、結束位置以及哪個類型的機率，將最高的機率類型及位置之特徵輸出為結果。

(四) Bagging

本系統將上述所有結果，合併於一個檔案，其程序包含設定合併次序及清除相同特徵。首先，依照各個檔案的表現，由高到低設定合併的次序，較後面才合併的資料，會與前者比對，若有相同或重疊的特徵，將會移除。以此方法，將所有結果 Bagging 成總結果。

(五) Stop words

分析每份結果之詞頻，將不合理於某類別之詞類，進行字串比對後清除，輸出最終的預測結果。

二、程式碼

(一) Rule based

<table>
<tr><th>功能</th><th>程式碼</th><th>註記</th></tr>
<tr><td>抓取特徵</td><td>regex =
r'A\d{9,10}|B\d{9,10}|C\d{9,10}|D\d{9,10}|E\d{9,10}|F\d{9,10}|G\d{9,10}|
H\d{9,10}|I\d{9,10}|J\d{9,10}|K\d{9,10}|L\d{9,10}|M\d{9,10}|N\d{9,10}|O\
d{9,10}|P\d{9,10}|Q\d{9,10}|R\d{9,10}|S\d{9,10}|T\d{9,10}|U\d{9,10}|V\d{
9,10}|W\d{9,10}|X\d{9,10}|Y\d{9,10}|Z\d{9,10}'
regex_phone = r'09\d{8}|line|LINE|Line|ＬＩＮＥ
|EMAIL|MAIL|email|mail|FB|臉書|ＦＢ|Grindr|Hornet|Tinder|tinder|wootalk'
regex_time = r'去年\d+月\d+號|去年\d+月|去年\d+號|去年|明年|正午|清晨|
明天|昨天|今天|一個月|兩個月|三個月|一個禮拜|一個星期|兩個禮拜|兩個
星期|三個禮拜|三個星期|早上|中午|下午|晚上|一天|兩天|三天|四天|五天|六
天|\d+天|\d+月\d+號|\d+月\d+日|\d+個月|\d+年|聖誕節|清明節|情人節|感恩
節|端午節|[一二三四五六七八九十]月[一三四五六七八九][日號]'
regex_family = r'我姊姊|我姐姐|我妹妹|我老婆|我太太|我先生|我丈夫|我老
公|你爺爺|你姊姊|你姐姐|你妹妹|你老婆|你太太|你先生|你丈夫|你老公|你
奶奶|你爸爸|你叔叔|你嬸嬸|你舅舅|你阿姨|你姑姑|你大姑|你二姑|你外婆|
你婆婆|你姊|你姐|你妹|你爺|你奶|你爸|你叔|你舅|你嬸|你姨|你姑|你婆|你
大女兒|你二女兒|你三女兒|你小女兒|你小女|你大兒子|你二兒子|你三兒子
|你小兒子|你兒子|你犬子|我爺爺|我奶奶|我爸爸|我叔叔|我嬸嬸|我舅舅|我
阿姨|我姑姑|我大姑|我二姑|我外婆|我婆婆|我爺|我奶|我爸|你姊|你姐|你妹|
我叔|我舅|我嬸|我姨|我姑|我婆|我大女兒|我二女兒|我三女兒|我小女兒|我
小女|我女兒|我大兒子|我二兒子|我三兒子|我小兒子|我兒子|我犬子|爺爺|
奶奶|爸爸|爸|叔叔|阿姨|嬸嬸|嬸|姑姑|大姑|二姑|姑|外婆|姊姊|姐姐|妹妹|老
婆|太太|先生|丈夫|老公|婆|老大|老二|老三|大女兒|二女兒|三女兒|小女兒|
小女|女兒|大兒子|二兒子|三兒子|小兒子|兒子|犬子'
regex_profession = r'Google'
regex_money = r'\d+塊|\d+元'

df_for_test['ID']=df_for_test['words'].apply(lambda x:re.findall(regex, x))
df_for_test['contact']=df_for_test['words'].apply(lambda
x:re.findall(regex_phone, x))
df_for_test['time']=df_for_test['words'].apply(lambda x:re.findall(regex_time,
x))
df_for_test['profession']=df_for_test['words'].apply(lambda
x:re.findall(regex_profession, x))
df_for_test['money']=df_for_test['words'].apply(lambda
x:re.findall(regex_money, x))
df_for_test['family']=df_for_test['words'].apply(lambda
x:re.findall(regex_family, x))</td><td>利用 Regular Expression 的方式將身分證、電話、時間、家人、職業別、金錢方式進行標記。</td></tr>
</table>

(二) Bert base Chinese

1. 按照各類別做訓練

<table>
<tr><th>功能</th><th>程式碼</th><th>註記</th></tr>
<tr><td>資料
前處理</td><td>

```
def split_conser_label(input_list):
    # input word_list
    convers = []
    label = []
    for i in input_list:
        j = i.split('\n', 1)
        if len(j[0]) > 0:
            convers.append(j[0])
        if len(j[1].split('\n\n')[0]):
            label.append(j[1].split('\n\n')[0])
    return convers, label

def label_to_dict(input_label_list):
    # input label
    dict_label = {}
    for i in range(len(input_label_list)):
        total_label = input_label_list[i].split('\n')
        dict_label.update({i : dict()})
        for j in range(len(total_label)-1):
            each_row = total_label[j+1].split('\t')
            duration = (int(each_row[2]) - int(each_row[1]))
            for q in range(duration):
                # origin_label = each_row[4].lower()
                # chinese_label = my_map[origin_label]
                dict_label[i].update({int(each_row[1])+q : each_row[4]})
    return dict_label
def fit_ner_form(input_con, input_label_dict):
    #input convers dict_label
    list_sentence_id = []
    list_words = []
    list_labels = []

    for i in range(len(input_con)):
        now = input_con[i]
        for j in range(len(now)):
            if j in input_label_dict[i].keys():
                list_sentence_id.append(i)
                list_words.append(now[j])
                list_labels.append(input_label_dict[i][j])
            else:
                list_sentence_id.append(i)
                list_words.append(now[j])
                list_labels.append('O')
    return list_sentence_id, list_words, list_labels
```

</td><td>將對話及標記資料切割，建立類別索引，並將資料建構成 NER 的格式。</td></tr>
<tr><td>句子切割</td><td>

```
def split_sentence(row):
    global count__, word_len, list_warn
    word_len+=1
    if row.words in ['。','？','！','，'] and word_len > 20:
        list_warn.append(word_len)
        if word_len > 128:
            print(count__)
        count__+=1
        word_len = 0
        return (count__ -1)
    else:
        return count__
```

</td><td>以標點符號分割句子，並設定句子長度 20 字以上。</td></tr>
<tr><td>轉簡體字</td><td>

```
train_df['sentence_id'] = train_df.apply(split_sentence, 1)
cc = OpenCC('t2s')
train_df['words'] = train_df['words'].apply(lambda x: cc.convert(x))
```

</td><td>利用 Opencc 將繁體中文轉為簡體中文。</td></tr>
</table>

建立模型

```
def train_and_predict(only_label, train_data):
    model = NERModel('bert', f'bert-base-chinese',
        labels=label_list, args={'train_batch_size':16,
'overwrite_output_dir': True, 'output_dir':'output/ner/bert_sim/{only_label}',
'reprocess_input_data': True, 'num_train_epochs': 15})
    model.train_model(train_data)
    g = open('test.txt', 'r')
    words = g.read()
    word_list = words.split('--------------------\n\n')
    def test_file_form(test_input):
        id_ = []
        string_ = []
        num = 0
        for i in test_input:
            if len(i) > 0:
                sequence = i.split('\n')[1]
                whole_split_sent = re.split('(。|？|！|，)', sequence)
                for j in range(len(whole_split_sent)):
                    if whole_split_sent[j] not in ['。','？','！','，']:
                        if len(whole_split_sent[j])>0:
                            id_.append(i.split('\n')[0].split(' ')[1])
                            string_.append(' '.join(whole_split_sent[j]))
                            num+=1
                    else:
                        string_[num-1] += f' {whole_split_sent[j]}'
        return id_, string_
    id_, string_ = test_file_form(word_list)
    test_df = pd.DataFrame({'sentence_id':id_, 'words':string_})
    print(test_df.head())
    print(f'len test_df : {len(test_df)}')
    temp_id = []
    temp_sent = []
    trans_id = []
    trans_sent = []
    for i in range(len(test_df)):
        if len(temp_id)==0 and len(temp_sent)==0:
            if len(test_df.iloc[i]['words']) > 20:
                trans_id.append(test_df.iloc[i]['sentence_id'])
                trans_sent.append(test_df.iloc[i]['words'])
            else:
                temp_id.append(test_df.iloc[i]['sentence_id'])
                temp_sent.append(test_df.iloc[i]['words'])
        else:
            if temp_id[0] == test_df.iloc[i]['sentence_id']:
                now_sent = temp_sent[0] +' '+ test_df.iloc[i]['words']
                if len(now_sent) > 20:
                    trans_id.append(test_df.iloc[i]['sentence_id'])
                    trans_sent.append(now_sent)
                    temp_id = []
                    temp_sent = []
                    now_sent = ''
                else:
                    temp_sent = [now_sent]
            else:
                trans_id.append(temp_id[0])
                trans_sent.append(temp_sent[0])
                temp_id = [test_df.iloc[i]['sentence_id']]
                temp_sent = [test_df.iloc[i]['words']]
    if len(temp_id)>0 and len(temp_sent)>0:
        trans_id.append(temp_id[0])
        trans_sent.append(temp_sent[0])
    test_df = pd.DataFrame({'sentence_id':trans_id, 'words':trans_sent})
    test_df['words'] = test_df['words'].apply(lambda x: cc.convert(x))
    print(test_df.head())
    print(f'len test_df : {len(test_df)}')
    predictions, raw_outputs = model.predict(test_df.words.values)
    test_df['predict'] = predictions
    test_df['raw_outputs'] = raw_outputs
    return test_df
```

利用 simple transformer 的 NER 訓練方式，以 bert-base-chinese 作為 pre-trained model，並產生預測資料。

預測結果	``` for i in whole_label: train_data_each = train_df.copy() train_data_each['labels'] = train_data_each['labels'].apply(trans_label, args=(i), 1) if len(list(set(train_data_each['labels'].values))) > 1: df = train_and_predict(i, train_data_each) print(df.head()) num = 0 sentence_id = [] words = [] predictions = [] for i in range(len(df)): if i==0: sentence_id.append(df.iloc[i]['sentence_id']) words.append(df.iloc[i]['words']) predictions.append(eval(df.iloc[i]['predict'])) else: if df.iloc[i]['sentence_id'] == sentence_id[num]: words[num]+= ' '+ df.iloc[i]['words'] #print(words[num]) #print(predictions[num]) predictions[num].extend((eval(df.iloc[i]['predict']))) else: sentence_id.append(df.iloc[i]['sentence_id']) words.append(df.iloc[i]['words']) predictions.append(eval(df.iloc[i]['predict'])) num+=1 df = pd.DataFrame({'sentence_id':sentence_id, 'words':words, 'predictions':predictions}) print(len(df)) art_id = [] order_ = [] word_ = [] label_ = [] for i in range(len(df)): now = df.iloc[i]['predictions'] for j in range(len(now)): if 'O' not in now[j].values(): art_id.append(i) order_.append(j) for k, v in now[j].items(): word_.append(k) label_.append(v) #label_.append(v.split('-')[1]) print(len(pd.DataFrame({'art_id':art_id, 'order_':order_, 'word_':word_, 'label_':label_}))) total = len(art_id) i = 0 j = 0 article_id = [] start_position = [] end_position = [] entity_text = [] entity_type = [] while i<total: if i == 0: article_id.append(art_id[i]) start_position.append(int(order_[i])) end_position.append(int(order_[i])+1) entity_text.append(word_[i]) entity_type.append(label_[i]) i+=1 else: if article_id[j] == art_id[i] and end_position[j] == int(order_[i]) and entity_type[j] == label_[i]: end_position[j] = int(order_[i])+1 entity_text[j] += word_[i] i+=1 ```	將訓練資料切割成各類別之特徵，進行預測後，轉換成比賽單位之格式，輸出檔案。

<table>
<tr>
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```python
                else:
                    article_id.append(art_id[i])
                    start_position.append(int(order_[i]))
                    end_position.append(int(order_[i])+1)
                    entity_text.append(word_[i])
                    entity_type.append(label_[i])
                    i+=1
                    j+=1
            df = pd.DataFrame({'article_id':article_id,
                'start_position':start_position, 'end_position':end_position,
                'entity_text':entity_text, 'entity_type':entity_type})
cc = OpenCC('s2t')
df['entity_text'] = df['entity_text'].apply(lambda x: cc.convert(x))
df.to_csv('to_aidea/simplified_bert/bert_Simplified_{only_label}.tsv', sep =
'\t', index=None)
        else:
            pass
```

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</table>

2. 全部類別訓練

<table>
<tr>
<th>功能</th>
<th>程式碼</th>
<th>註記</th>
</tr>
<tr>
<td>資料
前處理</td>
<td>

```python
def split_conser_label(input_list):
    # input word_list
    convers = []
    label = []
    for i in input_list:
        j = i.split('\n', 1)
        if len(j[0]) > 0:
            convers.append(j[0])
        if len(j[1].split('\n\n')[0]):
            label.append(j[1].split('\n\n')[0])
    return convers, label
def label_to_dict(input_label_list):
    # input label
    dict_label = {}
    for i in range(len(input_label_list)):
        total_label = input_label_list[i].split('\n')
        dict_label.update({i : dict()})
        for j in range(len(total_label)-1):
            each_row = total_label[j+1].split('\t')
            duration = (int(each_row[2]) - int(each_row[1]))
            for q in range(duration):
                dict_label[i].update({int(each_row[1])+q : each_row[4]})
    return dict_label
def fit_ner_form(input_con, input_label_dict):
    list_sentence_id = []
    list_words = []
    list_labels = []
    for i in range(len(input_con)):
        now = input_con[i]
        for j in range(len(now)):
            if j in input_label_dict[i].keys():
                list_sentence_id.append(i)
                list_words.append(now[j])
                list_labels.append(input_label_dict[i][j])
            else:
                list_sentence_id.append(i)
                list_words.append(now[j])
                list_labels.append('O')
    return list_sentence_id, list_words, list_labels
```

</td>
<td>將對話及標記資料切割，建立類別索引，並將資料建構成 NER 的格式。</td>
</tr>
</table>

句子切割	<pre>def split_sentence(row): global count__, word_len, list_warn word_len+=1 if row.words in ['。', '？', '！', '，'] and word_len > 20: list_warn.append(word_len) if word_len > 128: print(count__) count__+=1 word_len = 0 return (count__ -1) else: return count__</pre>	以標點符號分割句子，並設定句子長度 20 字以上。
建立模型	<pre>model = NERModel('bert', 'bert-base-chinese', labels=label_list, args={'train_batch_size':16, 'overwrite_output_dir': True, 'output_dir':'output/ner/bert_Simplified', 'reprocess_input_data': True, 'num_train_epochs': 15}) model.train_model(train_df)</pre>	利用 simple transformer 的 NER 訓練方式，以 bert-base-chinese 作為 pre-trained model。
預測結果	<pre>def test_file_form(test_input): # word_list id_ = [] string_ = [] num = 0 for i in test_input: #print(i) if len(i) > 0: #print('test',i) sequence = i.split('\n')[1] #print(sequence) whole_split_sent = re.split('(。|？|！|，)', sequence) for j in range(len(whole_split_sent)): if whole_split_sent[j] not in ['。','？','！','，']: if len(whole_split_sent[j])>0: id_.append(i.split('\n')[0].split(' ')[1]) string_.append(' '.join(whole_split_sent[j])) num+=1 else: string_[num-1] += f' {whole_split_sent[j]}' return id_, string_ id_, string_ = test_file_form(word_list) test_df = pd.DataFrame({'sentence_id':id_, 'words':string_}) print(test_df.head()) print(f'len test_df : {len(test_df)}') temp_id = [] temp_sent = [] trans_id = [] trans_sent = [] for i in range(len(test_df)): if len(temp_id)==0 and len(temp_sent)==0: if len(test_df.iloc[i]['words']) > 20: trans_id.append(test_df.iloc[i]['sentence_id']) trans_sent.append(test_df.iloc[i]['words']) else: temp_id.append(test_df.iloc[i]['sentence_id']) temp_sent.append(test_df.iloc[i]['words'])</pre>	將測試資料處理為與訓練資料相同格式後，預測出結果。

<table>
<tr><td></td><td><pre>
        else:
                if temp_id[0] == test_df.iloc[i]['sentence_id']:
                        now_sent = temp_sent[0] +' '+ test_df.iloc[i]['words']
                        if len(now_sent) > 20:
                                trans_id.append(test_df.iloc[i]['sentence_id'])
                                trans_sent.append(now_sent)
                                temp_id = []
                                temp_sent = []
                                now_sent = ''
                        else:
                                temp_sent = [now_sent]
                else:
                        trans_id.append(temp_id[0])
                        trans_sent.append(temp_sent[0])
                        temp_id = [test_df.iloc[i]['sentence_id']]
                        temp_sent = [test_df.iloc[i]['words']]
if len(temp_id)>0 and len(temp_sent)>0:
        trans_id.append(temp_id[0])
        trans_sent.append(temp_sent[0])
test_df = pd.DataFrame({'sentence_id':trans_id, 'words':trans_sent})
test_df['words'] = test_df['words'].apply(lambda x: cc.convert(x))
print(test_df.head())
print(f'len test_df : {len(test_df)}')
predictions, raw_outputs = model.predict(test_df.words.values)
</pre></td><td></td></tr>
<tr><td>資料
後處理</td><td><pre>
while i<total:
        if i == 0:
                article_id.append(art_id[i])
                start_position.append(int(order_[i]))
                end_position.append(int(order_[i])+1)
                entity_text.append(word_[i])
                entity_type.append(label_[i])
                i+=1
        else:
                if article_id[j] == art_id[i] and end_position[j] == int(order_[i]) and
entity_type[j] == label_[i]:
                        end_position[j] = int(order_[i])+1
                        entity_text[j] += word_[i]
                        i+=1
                else:
                        article_id.append(art_id[i])
                        start_position.append(int(order_[i]))
                        end_position.append(int(order_[i])+1)
                        entity_text.append(word_[i])
                        entity_type.append(label_[i])
                        i+=1
                        j+=1
df = pd.DataFrame({'article_id':article_id, 'start_position':start_position,
'end_position':end_position,
                                'entity_text':entity_text, 'entity_type':entity_type})
cc = OpenCC('s2t')
df['entity_text'] = df['entity_text'].apply(lambda x: cc.convert(x))
df.to_csv('to_aidea/simplified_bert/bert_Simplified_{only_label}.tsv', sep =
'\t', index=None)
</pre></td><td>將結果轉換成與比賽單位相符之格式。</td></tr>
</table>

(三) Bert MRC

<table>
<tr><th>功能</th><th>程式碼</th><th>註記</th></tr>
<tr><td>建立模型</td><td>

```
class BertLabeling(pl.LightningModule):
    def __init__(
        self,
        args: argparse.Namespace):
        super().__init__()
        if isinstance(args, argparse.Namespace):
            self.save_hyperparameters(args)
            self.args = args
        else:
            TmpArgs = namedtuple("tmp_args",
                                 field_names=list(args.keys()))
            self.args = args = TmpArgs(**args)

        self.bert_dir = args.bert_config_dir
        self.data_dir = self.args.data_dir

        bert_config =
            BertQueryNerConfig.from_pretrained(args.bert_config_dir,
            hidden_dropout_prob=args.bert_dropout,
            attention_probs_dropout_prob=args.bert_dropout,
            mrc_dropout=args.mrc_dropout)

        self.model = BertQueryNER.from_pretrained(args.bert_config_dir,
                                                  config=bert_config)
        logging.info(str(args.__dict__ if isinstance(args,
                         argparse.ArgumentParser) else args))
        self.loss_type = args.loss_type
        if self.loss_type == "bce":
            self.bce_loss = BCEWithLogitsLoss(reduction="none")
        else:
            self.dice_loss = DiceLoss(with_logits=True,
                                      smooth=args.dice_smooth)
        weight_sum = args.weight_start + args.weight_end +
        args.weight_span
        self.weight_start = args.weight_start / weight_sum
        self.weight_end = args.weight_end / weight_sum
        self.weight_span = args.weight_span / weight_sum
        self.flat_ner = args.flat
        self.span_f1 = QuerySpanF1(flat=self.flat_ner)
        self.chinese = args.chinese
        self.optimizer = args.optimizer
        self.span_loss_candidates = args.span_loss_candidates

    @staticmethod
    def add_model_specific_args(parent_parser):
        parser = argparse.ArgumentParser(parents=[parent_parser],
        add_help=False)
        parser.add_argument("--mrc_dropout", type=float, default=0.1,
                            help="mrc dropout rate")
        parser.add_argument("--bert_dropout", type=float, default=0.1,
                            help="bert dropout rate")
        parser.add_argument("--weight_start", type=float, default=1.0)
        parser.add_argument("--weight_end", type=float, default=1.0)
        parser.add_argument("--weight_span", type=float, default=1.0)
        parser.add_argument("--flat", action="store_true", help="is flat
        ner")
        parser.add_argument("--span_loss_candidates", choices=["all",
        "pred_and_gold", "gold"],
        default="all", help="Candidates used to compute span loss")
        parser.add_argument("--chinese", action="store_true",
                            help="is chinese dataset")
        parser.add_argument("--loss_type", choices=["bce", "dice"],
        default="bce", help="loss type")
        parser.add_argument("--optimizer", choices=["adamw", "sgd"],
        default="adamw", help="loss type")
```

</td><td>產生 MRC 模型，其包含資料讀取、建立 Loss function、參數設定等。</td></tr>
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```
        parser.add_argument("--dice_smooth", type=float, default=1e-8,
                            help="smooth value of dice loss")
        parser.add_argument("--final_div_factor", type=float, default=1e4,
                            help="final div factor of linear decay
                            scheduler")
        return parser

    def configure_optimizers(self):
        no_decay = ["bias", "LayerNorm.weight"]
        optimizer_grouped_parameters = [{"params": [p for n, p in
        self.model.named_parameters() if not any(nd in n for nd in
        no_decay)], "weight_decay": self.args.weight_decay,},
        { "params": [p for n, p in self.model.named_parameters() if any(nd
        in n for nd in no_decay)],    "weight_decay": 0.0, },]
        if self.optimizer == "adamw":
            optimizer = AdamW(optimizer_grouped_parameters,
            betas=(0.9, 0.98),    # according to RoBERTa paper
            lr=self.args.lr, eps=self.args.adam_epsilon,)
        else:
            optimizer = SGD(optimizer_grouped_parameters,
lr=self.args.lr, momentum=0.9)
        num_gpus = len([x for x in str(self.args.gpus).split(",") if x.strip()])
        t_total = (len(self.train_dataloader())//
(self.args.accumulate_grad_batches * num_gpus) + 1) * self.args.max_epochs
        scheduler=
        torch.optim.lr_scheduler.ReduceLROnPlateau(optimizer,
factor=0.8, mode='min', patience=1000, min_lr=1e-6)
        return [optimizer], [{"scheduler": scheduler, "interval": "step"}]

    def forward(self, input_ids, attention_mask, token_type_ids):
              return self.model(input_ids,
attention_mask=attention_mask, token_type_ids=token_type_ids)

    def compute_loss(self, start_logits, end_logits, span_logits,
                     start_labels, end_labels, match_labels,
                     start_label_mask, end_label_mask):
        batch_size, seq_len = start_logits.size()

        start_float_label_mask = start_label_mask.view(-1).float()
        end_float_label_mask = end_label_mask.view(-1).float()
        match_label_row_mask = start_label_mask.bool().
                               unsqueeze(-1).expand(-1, -1, seq_len)
        match_label_col_mask = end_label_mask.bool().
                               unsqueeze(-2).expand(-1, seq_len, -1)
        match_label_mask = match_label_row_mask &
                               match_label_col_mask
        match_label_mask = torch.triu(match_label_mask, 0)
        if self.span_loss_candidates == "all":
            float_match_label_mask = match_label_mask.view(batch_size,
                                                           -1).float()
        else:
            start_preds = start_logits > 0
            end_preds = end_logits > 0
            if self.span_loss_candidates == "gold":
                match_candidates = ((start_labels.unsqueeze(-1).expand
                (-1, -1, seq_len) > 0) & (end_labels.unsqueeze
                                  (-2).expand(-1, seq_len, -1) > 0))
            else:
                match_candidates =
                torch.logical_or((start_preds.unsqueeze(-1).expand(-1, -1,
                seq_len) & end_preds.unsqueeze(-2).expand(-1, seq_len, -
                1)), (start_labels.unsqueeze(-1).expand(-1, -1, seq_len)&
                end_labels.unsqueeze(-2).expand(-1, seq_len, -1)))
            match_label_mask = match_label_mask & match_candidates
            float_match_label_mask = match_label_mask.view(batch_size,
                                                      -1).float()
        if self.loss_type == "bce":
            start_loss = self.bce_loss(start_logits.view(-1),
                                  start_labels.view(-1).float())
```

	<pre>start_loss = (start_loss * start_float_label_mask).sum() / start_float_label_mask.sum() end_loss = self.bce_loss(end_logits.view(-1), end_labels.view(-1).float()) end_loss = (end_loss * end_float_label_mask).sum() / end_float_label_mask.sum() match_loss = self.bce_loss(span_logits.view(batch_size, -1), match_labels.view(batch_size, -1).float()) match_loss = match_loss * float_match_label_mask match_loss = match_loss.sum() / (float_match_label_mask.sum() + 1e-10) else: start_loss = self.dice_loss(start_logits, start_labels.float(), start_float_label_mask) end_loss = self.dice_loss(end_logits, end_labels.float(), end_float_label_mask) match_loss = self.dice_loss(span_logits, match_labels.float(), float_match_label_mask) return start_loss, end_loss, match_loss def training_step(self, batch, batch_idx): tf_board_logs = { "lr": self.trainer.optimizers[0].param_groups[0]['lr'] } tokens, token_type_ids, start_labels, end_labels, start_label_mask, end_label_mask, match_labels, sample_idx, label_idx = batch attention_mask = (tokens != 0).long() start_logits, end_logits, span_logits = self(tokens, attention_mask, token_type_ids) start_loss, end_loss, match_loss = self.compute_loss(start_logits=start_logits, end_logits=end_logits, span_logits=span_logits, start_labels=start_labels, end_labels=end_labels, match_labels=match_labels, start_label_mask=start_label_mask, end_label_mask=end_label_mask) total_loss = self.weight_start * start_loss + self.weight_end * end_loss + self.weight_span * match_loss tf_board_logs[f"train_loss"] = total_loss tf_board_logs[f"start_loss"] = start_loss tf_board_logs[f"end_loss"] = end_loss tf_board_logs[f"match_loss"] = match_loss return {'loss': total_loss, 'log': tf_board_logs} def validation_step(self, batch, batch_idx): output = {} tokens, token_type_ids, start_labels, end_labels, start_label_mask, end_label_mask, match_labels, sample_idx, label_idx = batch attention_mask = (tokens != 0).long() start_logits, end_logits, span_logits = self(tokens, attention_mask, token_type_ids) start_loss, end_loss, match_loss = self.compute_loss(start_logits=start_logits, end_logits=end_logits, span_logits=span_logits, start_labels=start_labels, end_labels=end_labels, match_labels=match_labels, start_label_mask=start_label_mask, end_label_mask=end_label_mask) total_loss = self.weight_start * start_loss + self.weight_end * end_loss + self.weight_span * match_loss output[f"val_loss"] = total_loss output[f"start_loss"] = start_loss</pre>	

```
        output[f"end_loss"] = end_loss
        output[f"match_loss"] = match_loss
        start_preds, end_preds = start_logits > 0, end_logits > 0
        span_f1_stats = self.span_f1(start_preds=start_preds,
        end_preds=end_preds, match_logits=span_logits,
        start_label_mask=start_label_mask,
        end_label_mask=end_label_mask,
        match_labels=match_labels)
        output["span_f1_stats"] = span_f1_stats
        return output
    def validation_epoch_end(self, outputs):
        avg_loss = torch.stack([x['val_loss'] for x in outputs]).mean()
        tensorboard_logs = {'val_loss': avg_loss}
        all_counts = torch.stack([x[f'span_f1_stats'] for x in
                                                        outputs]).sum(0)
        span_tp, span_fp, span_fn = all_counts
        span_recall = span_tp / (span_tp + span_fn + 1e-10)
        span_precision = span_tp / (span_tp + span_fp + 1e-10)
        span_f1 = span_precision * span_recall * 2 / (span_recall +
                                                        span_precision + 1e-10)
        tensorboard_logs[f"span_precision"] = span_precision
        tensorboard_logs[f"span_recall"] = span_recall
        tensorboard_logs[f"span_f1"] = span_f1
        return {'val_loss': avg_loss, 'log': tensorboard_logs}

    def test_step(self, batch, batch_idx):
        return self.validation_step(batch, batch_idx)
    def test_epoch_end(self,outputs) -> Dict[str, Dict[str, Tensor]]:
        return self.validation_epoch_end(outputs)
    def train_dataloader(self) -> DataLoader:
        return self.get_dataloader("train")
    def val_dataloader(self):
        return self.get_dataloader("dev")
    def test_dataloader(self):
        return self.get_dataloader("test")
    def get_dataloader(self, prefix="train", limit: int = None) -> DataLoader:
        json_path = os.path.join(self.data_dir, f"mrc-ner.{prefix}")
        vocab_path = os.path.join(self.bert_dir, "vocab.txt")
        dataset = MRCNERDataset(json_path=json_path,
                    tokenizer=BertWordPieceTokenizer(vocab_path),
                    max_length=self.args.max_length,
                    is_chinese=self.chinese,
                    pad_to_maxlen=False)
        if limit is not None:
            dataset = TruncateDataset(dataset, limit)
        dataloader = DataLoader(
            dataset=dataset,
            batch_size=self.args.batch_size,
            num_workers=self.args.workers,
            shuffle=True if prefix == "train" else False,
            collate_fn=collate_to_max_length)
        return dataloader
```

(四) Bagging

功能	程式碼	註記
過濾 相同特徵	deleteIndex = [] count = 0 for i in range(len(addedFile)): for j in range(count, len(baseFile)): if addedID[i] == baseID[j] and addedSP[i] == baseSP[j] and addedEP[i] == baseEP[j]: deleteIndex.append(i) count += 1 break; filterFile = addedFile.drop(index = deleteIndex).copy() print(filterFile)	將文章編號、起始位置、結束位置、文字相同的特徵於疊加的檔案刪除。
過濾 重疊特徵	deleteIndex = [] count = 0 for i in filterFile.index: for j in range(count, len(baseFile)): if addedSP[i] >= baseSP[j] and addedEP[i] <= baseEP[j] and addedSP[i] < baseEP[j]: if addedTxt[i] in baseTxt[j]: deleteIndex.append(i) count += 1 break doubleFilterFile = filterFile.drop(index = deleteIndex).copy() print(doubleFilterFile) deleteIndex = [] count = 0 for i in doubleFilterFile.index: for j in range(count, len(baseFile)): if baseSP[j] >= addedSP[i] and baseEP[j] <= addedEP[i] and baseSP[j] < addedEP[i]: if baseTxt[j] in addedTxt[i]: deleteIndex.append(i) count += 1 break tripleFilterFile = doubleFilterFile.drop(index = deleteIndex).copy() print(tripleFilterFile)	將文章編號、起始位置、結束位置、文字重疊之特徵於疊加的檔案刪除。
合併檔案	mergeFile = pd.concat([baseFile, tripleFilterFile]) mergeFile = mergeFile.sort_values(['article_id','start_position']) mergeFile = mergeFile[['article_id', 'start_position', 'end_position', 'entity_text', 'entity_type']].reset_index(drop=True) print(mergeFile)	將原本的檔案與過濾特徵後之檔案合併。

(五) Stop words

功能	程式碼	註記
刪除 停止詞	def lenless1(row): if row in ['禮拜', '一萬三左', '百塊','眼前','HELL','UANG', 'ok', 'ＯＫ', 'Ok', '前二後二','國外原','0 點','現在冬天', '2 次','百七']: return False else: return True mergeFile['split'] = mergeFile['entity_text'].apply(lenless1, 1) mergeFile = mergeFile[mergeFile['split']] mergeFile = mergeFile[['article_id', 'start_position', 'end_position', 'entity_text', 'entity_type']]	將不合理於正常字串的特徵，進行比對後移除。

三、結果分析

(一) 最佳結果

本系統利用上述方法，使其 F1-score 於 Public Leaderboard 達到 76.60%，Precision 及 Recall 分別為 71.63%、82.30%，而 F1-score 於 Private Leaderboard 達到 78.11%。

(二) 詞頻分析

	word	label_count	total_count	百分比
0	今天	171	450	38%
1	昨天	21	37	56%
2	明天	16	33	48%
3	後天	11	19	57%
4	前天	28	30	93%
5	早上	96	153	62%
6	中午	12	25	48%
7	晚上	27	105	25%
8	凌晨	1	1	100%

圖二、時間特徵詞頻分析結果

在實施本專案時，發現原始資料標記定義不一，以上述為例，在時間類別中，「今天」一詞於訓練資料出現了 450 次，有被標記的只有 171 筆，由於不清楚標記的定義為何，因此，我們嘗試各種方法，讓預測結果的表現更符合訓練資料的詞頻分布。

(三) 嘗試方法

1. 更換特徵

本專案曾嘗試將類別標記加入 LMR，也就是除了判斷類型，也會判斷開頭字、中間字、結尾字，可惜其並未提升表現。此外，我們也曾利用全部類別進行訓練，發現 Recall 較 Precision 低，因此，將各個類別分別進行訓練，再將預測結果合併，以提升 Recall 的數值。

2. 更換模型

除了使用 Bert、MRC 模型之外，我們曾嘗試使用 Crf，利用 Unigram、Bigram 方法擷取特徵，其方法之 Precision 達到 82%，其 Recall 卻只有 40-50%。此外，我們還嘗試使用 Bi-lstm 加上 Crf，其表現並未比 Bert 模型高。

3. 更換簡體中文

由於看到文獻結果分析，在 bert-base-chinese 的 Pre-trained 模型下，簡體中文的效能較繁體中文好，因此，我們將所有使用 Bert 所跑的模型，將其資料皆轉為簡體中文，輸出結果後，再轉回繁體中文，其 F1-score 提升了 2-3%。

4. 更換 Bagging 方式

在我們嘗試上述方法的過程中發現，若是增加特徵，通常會改善 Recall；但若是更換模型，通常會改善 Precision，因此，我們決定將所有預測出來的結果，利用簡單的演算法進行合併。我們曾嘗試將兩份資料格式改為 article id、position、text、type，例如今天會攤平成：[0, 0, 今天, 時間]、[0, 1, 今天, 時間]、[0, 2, 今天, 時間]，共三筆，接著比對兩份資料完全相同的特徵刪除於其中一份資料，再合併檔案。然而，該方法會有刪除不完全的問題等，因此，改為本專案提及上述之方法，完成 Bagging 程序。