

Machine Learning HW5 Report

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(1%) 請說明你實作之 RNN 模型架構及使用的 word embedding 方法，回報模型的正確率並繪出訓練曲線*。

RNN 模型主要使用兩層的雙向 LSTM+DNN 實現，最終輸入層的維度為 300，序列長度為 120，具體結構見下圖：

Layer (type)	Output Shape	Param #
embedding_1 (Embedding)	(None, 120, 300)	5249400
bidirectional_1 (Bidirection	(None, 120, 256)	439296
bidirectional_2 (Bidirection	(None, 128)	164352
batch_normalization_1 (Batch	(None, 128)	512
dense_1 (Dense)	(None, 64)	8256
dropout_1 (Dropout)	(None, 64)	0
dense_2 (Dense)	(None, 32)	2080
dropout_2 (Dropout)	(None, 32)	0
dense_3 (Dense)	(None, 2)	66

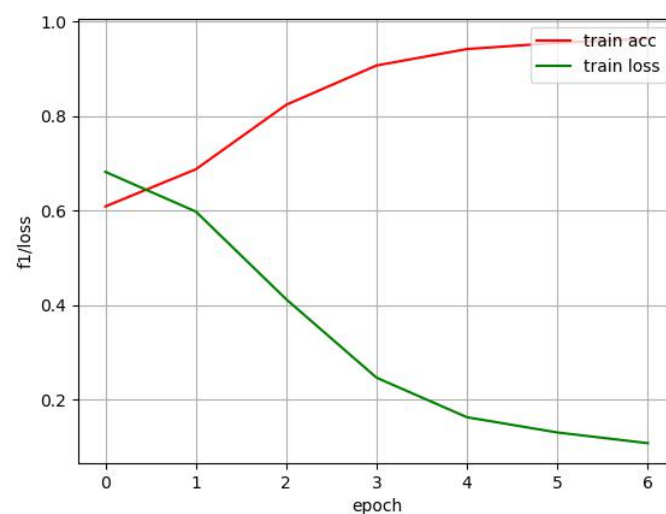
Word embedding 部分使用 `gensim.models.Word2Vec`，維度取 300，具體參數見下圖：

```
# train
w2v_model = gensim.models.Word2Vec(data, size=300, window=5, min_count=0, workers=8)
w2v_model.save('./wordEmbed')
```

F1_score:

Private : 0.83488 Public: 0.77674

訓練曲線:



(1%) 請實作 BOW+DNN 模型，敘述你的模型架構，回報模型的正確率並繪出訓練曲線*。

BOW+DNN 模型我取了頻率最高的 20000 個詞進行 one_hot_encode，DNN 部分具體架構見下圖：

```
Warning:tensorflow:Instructions that this TensorFlow binary was not compiled to use: AVX2
```

Model: "sequential_1"

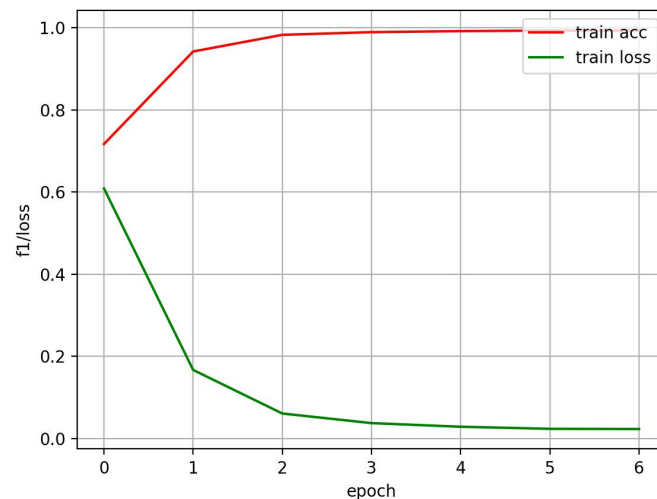
Layer (type)	Output Shape	Param #
dense_1 (Dense)	(None, 1024)	20481024
batch_normalization_1 (Batch Normalization)	(None, 1024)	4096
dense_2 (Dense)	(None, 256)	262400
batch_normalization_2 (Batch Normalization)	(None, 256)	1024
dense_3 (Dense)	(None, 64)	16448
dense_4 (Dense)	(None, 2)	130

Total params: 20,765,130

F1_score:

Private: 0.81162 Public: 0.73953

訓練曲線：



(1%) 請敘述你如何 improve performance (preprocess, embedding, 架構等)，並解釋為何這些做法可以使模型進步。

Preprocess:

數據清洗部分我先解析了 emoji，然後使用 spacy 的處理，去除標點符號，空格和停用詞（具體見下圖）。解析 emoji 可以保留跟多信息，去除標點符號，空格和停用詞，可以去

除文本的多餘無用信息。

```
data = pd.read_csv(data_path)['comment'].values
data = [emoji.demojize(seg) for seg in data]
data = [seg.replace('@user', ' ') for seg in data]
nlp = spacy.load('en_core_web_sm')
```

```
if (not token or not token.string.strip() or
    token.is_stop or token.is_punct):
    return False
```

Embedding:

embedding 部分使用 `gensim.models.Word2Vec`，主要通過使用不同的參數檢測結果的分數。最終使用了 (1) 中的參數。

架構:

RNN 部分我最早使用的是單向的 LSTM，後面改為雙向的 LSTM，獲得了較好的改進。

使用雙向的 LSTM 能使模型對前後語義理解更充分，結果也會獲得比較大的提升。

(1%) 請比較不做斷詞 (e.g.,用空白分開) 與有做斷詞，兩種方法實作出來的效果差異，並解釋為何有此差別。

空格分開: public f1_score: 0.75418

Spacy('en_core_web_sm')斷詞: public f1_score: 0.77906

使用套件斷詞會使結果好一些，原因可能是套件在斷詞時會去掉一些無用的語氣詞，使數據的無用信息進一步減少。進而提升結果的分數。

(1%) 請比較 RNN 與 BOW 兩種不同 model 對於 "Today is hot, but I am happy."與"I am happy, but today is hot." 這兩句話的分數 (model output)，並討論造成差異的原因。

RNN 分數:

```
[[0.8983901 0.10160995]
 [0.7675597 0.23244028]]
```

BOW 分數:

```
[[9.9828124e-01 1.7187380e-03]
 [9.9978095e-01 2.1904591e-04]]
```

可以看出當使用 BOW model 時，兩個句子的得分基本沒有差別。

但使用 RNN 時，這兩個不同句子就出現了差別。

說明 RNN 可以識別句子中單詞的順序，這個順序會對 model 的結果產生影響。但 BOW 則只能識別單詞，雖然單詞順序不同，但只要單詞相同，output 的結果就一樣。

$$1. \quad t=1: \quad z = wx + b = 3 \quad g(z) = g(3) = 3$$

$$z^i = w_i x + b = 90 \quad f(z^i) = f(90) = 1$$

$$z^f = wf x + b = 10 \quad f(z^f) = f(10) = 1$$

$$c = c f(z^f) + f(z^i) \cdot g(z)$$

$$= 0 \times 1 + 1 \times 3 = 3$$

$$z^o = w_o x + b = -10 \quad f(z^o) = f(-10) = 0$$

$$h(c) = h(3) = 3$$

$$y = h(c) \cdot f(z^o) = 3 \times 0 = 0$$

$$\text{thus } t=1 \quad y=0 \quad \text{now } c=3$$

$$t=2: \quad z = wx + b = -2 \quad g(z) = g(-2) = -2$$

$$z^i = w_i x + b = 90 \quad f(z^i) = f(90) = 1$$

$$z^f = wf x + b = 10 \quad f(z^f) = f(10) = 1$$

$$c = (f(z^f) + f(z^i) \cdot g(z))$$

$$= 3 \times 1 - 2 \times 1 = 1$$

$$z^o = w_o x + b = 90 \quad f(z^o) = f(90) = 1$$

$$h(c) = h(1) = 1$$

$$y = h(c) \cdot f(z^o) = 1 \quad \text{now } c=1$$

$$t=3: \quad z = wx + b = 4 \quad g(z) = g(4) = 4$$

$$z^i = w_i x + b = 90 \quad f(z^i) = f(90) = 1$$

$$z^f = wf x + b = -90 \quad f(z^f) = f(-90) = 0$$

$$c = (f(z^f) + f(z^i) \cdot g(z))$$

$$= 1 \times 0 + 4 \times 1 = 4$$

$$z^o = w_o x + b = 90 \quad f(z^o) = f(90) = 1$$

$$h(c) = h(4) = 4$$

$$y = h(c) \cdot f(z^o) = 4 \quad \text{now } c=4$$

$$t=4: \quad z = wx + b = 0 \quad g(z) = g(0) = 0$$

$$z^i = w_i x + b = 90 \quad f(z^i) = f(90) = 1$$

$$z^f = w_f x + b = -10 \quad f(z^f) = f(-10) = 0$$

$$c = (f(z^f) + f(z^i)) \cdot g(z)$$

$$= 4 \times 0 + 0 \times 1 = 0$$

$$z^o = w_o x + b = 90 \quad f(z^o) = f(90) = 1$$

$$h(c) = h(0) = 0$$

$$y = h(c) \cdot f(z^o) = 0 \quad \text{now } c = 0$$

$$t=5: \quad z = wx + b = 2 \quad g(z) = g(2) = 2$$

$$z^i = w_i x + b = 90 \quad f(z^i) = f(90) = 1$$

$$z^f = w_f x + b = 10 \quad f(z^f) = f(10) = 1$$

$$c = (f(z^f) + f(z^i)) \cdot g(z)$$

$$= 0 \times 1 + 1 \times 2 = 2$$

$$z^o = w_o x + b = -10 \quad f(z^o) = f(-10) = 0$$

$$h(c) = h(2) = 2$$

$$y = h(c) \cdot f(z^o) = 0 \quad \text{now } c = 2$$

$$t=6: \quad z = wx + b = -4 \quad g(z) = g(-2) = -4$$

$$z^i = w_i x + b = -10 \quad f(z^i) = f(-10) = 0$$

$$z^f = w_f x + b = 10 \quad f(z^f) = f(10) = 1$$

$$c = (f(z^f) + f(z^i)) \cdot g(z)$$

$$= 2 \times 1 - 4 \times 0 = 2$$

$$z^o = w_o x + b = 90 \quad f(z^o) = f(90) = 1$$

$$h(c) = h(1) = 1$$

$$y = h(c) \cdot f(z^o) = 2 \quad \text{now } c = 2$$

$$\begin{aligned}
 t=7: \quad z &= wx+b = 1 & g(z) &= g(1) = 1 \\
 z^i &= w_i x + b = 90 & f(z^i) &= f(90) = 1 \\
 z^f &= w_f x + b = -90 & f(z^f) &= f(-90) = 0 \\
 c &= (f(z^f) + f(z^i)) \cdot g(z) \\
 &= 2 \times 0 + 1 \times 1 = 1 \\
 z^o &= w_o x + b = 90 & f(z^o) &= f(90) = 1 \\
 h(c) &= h(1) = 1 \\
 y &= h(c) \cdot f(z^o) = 1 \quad \text{now } c = 1
 \end{aligned}$$

$$\begin{aligned}
 t=8: \quad z &= wx+b = 2 & g(z) &= g(2) = 2 \\
 z^i &= w_i x + b = 90 & f(z^i) &= f(90) = 1 \\
 z^f &= w_f x + b = 10 & f(z^f) &= f(10) = 1 \\
 c &= (f(z^f) + f(z^i)) \cdot g(z) \\
 &= 1 \times 1 + 2 \times 1 = 3 \\
 z^o &= w_o x + b = 90 & f(z^o) &= f(90) = 1 \\
 h(c) &= h(1) = 1 \\
 y &= h(c) \cdot f(z^o) = 3 \quad \text{now } c = 3
 \end{aligned}$$

thus: $y: 0 \ 1 \ 4 \ 0 \ 0 \ 2 \ 1 \ 3$

2. Word Embedding

↓ next page:

$$L = -\log \prod_{c=1}^C \frac{\exp(u_{c,j^*})}{\sum_{j=1}^V \exp(u_{c,j})}$$

$$= -\sum_{c=1}^C u_{c,j^*} + \sum_{c=1}^C \log \sum_{j=1}^V \exp(u_{c,j})$$

$$\frac{\partial L}{\partial w_{ij}} = \sum_{k=1}^V \sum_{c=1}^C \frac{\partial L}{\partial u_{c,k}} \frac{\partial u_{c,k}}{\partial w_{ij}}$$

$$\frac{\partial L}{\partial w_{ij}} = \sum_{k=1}^V \sum_{c=1}^C \frac{\partial L}{\partial u_{c,k}} \frac{\partial u_{c,k}}{\partial w_{ij}}$$

$$\frac{\partial L}{\partial u_{c,j}} = -\delta_{jj_c^*} + y_{c,j}$$

$$\text{thus: } \frac{\partial L}{\partial w_{ij}} = \sum_{k=1}^V \sum_{c=1}^C \frac{\partial L}{\partial u_{c,k}} \frac{\partial u_{c,k}}{\partial w_{ij}} = \sum_{c=1}^C \frac{\partial L}{\partial u_{c,j}} \frac{\partial u_{c,j}}{\partial w_{ij}}$$

$$= \sum_{c=1}^C (-\delta_{jj_c^*} + y_{c,j}) \left(\sum_{k=1}^V w_{ki} x_k \right)$$

$$\text{thus: } \frac{\partial L}{\partial w_{ij}} = \sum_{k=1}^V \sum_{c=1}^C \frac{\partial L}{\partial u_{c,k}} \frac{\partial}{\partial w_{ij}} \left(\sum_{m=1}^N \sum_{l=1}^V w_{mk} w_{lm} x_l \right)$$

$$= \sum_{k=1}^V \sum_{c=1}^C (-\delta_{jj_c^*} + y_{c,j}) \left(\sum_{k=1}^V w_{ki} x_k \right)$$