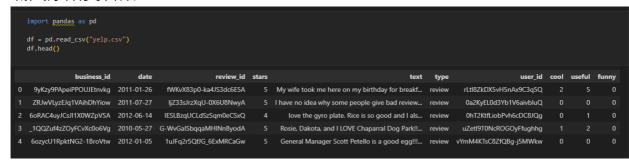
Yelp Reviews - Sentiment Analysis

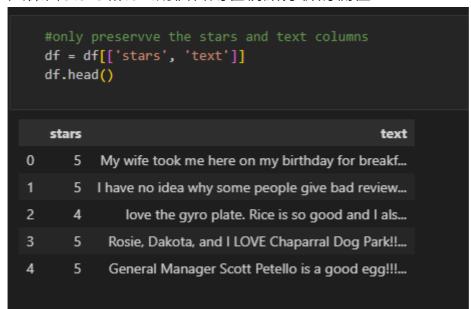
312706034 資管碩二 張棨翔

1. 資料前處理

• 載入原始資料集



只保留stars和text兩個會用在情緒分析的欄位



• 將stars欄位當中的值,以大於等於4作為標準進行binary數值的轉換

```
#switch the stars to binary (1 for positive, 0 for negative sentiment)

df['stars'] = df['stars'].apply(lambda x: 1 if x >= 4 else 0)

df.head()

stars

text

1 My wife took me here on my birthday for breakf...

1 I have no idea why some people give bad review...

2 1 love the gyro plate. Rice is so good and I als...

3 1 Rosie, Dakota, and I LOVE Chaparral Dog Park!!...

4 1 General Manager Scott Petello is a good egg!!!...
```

• 將text欄位內的文字內容轉換成串列

```
#use separator to split the text into words

df['text'] = df['text'].str.split()

df.head()

stars

text

1 [My, wife, took, me, here, on, my, birthday, f...

1 [I, have, no, idea, why, some, people, give, b...

2 1 [love, the, gyro, plate., Rice, is, so, good, ...

3 1 [Rosie,, Dakota,, and, I, LOVE, Chaparral, Dog...

4 1 [General, Manager, Scott, Petello, is, a, good...
```

• 載入nltk套件並且下載stopwords的資料

• 將text欄位中的停頓詞(stopwords)去除

將text欄位當中的串列值轉換回字串

用tf-idf的技術將text欄位當中的字串轉換成向量(vector)

 將資料進行分割,以80%/20%的比例分成訓練集和測試集,並且再把80%的 訓練集再分成75%的訓練集和25%的驗證集

```
#split the data into training and testing sets
from sklearn.model selection import train_test_split
X_train, X_test, y_train, y_test = train_test_split(tfidf_matrix, df['stars'], test_size=0.2, random_state=42)
#split the training data into training and validation sets
X_train, X_val, y_train, y_val = train_test_split(X_train, y_train, test_size=0.25, random_state=42)
```

2. CNN模型

卷積神經網路(CNN, Convolutional Neural Network)是一種常用於圖像處理和 其他類型的數據分析的深度學習模型

- 1.卷積層 (Convolutional Layer)
 - 這是CNN的核心,負責提取圖像中的特徵。卷積層使用卷積運算將filter (又稱為kernel)應用於輸入圖像,生成特徵圖(Feature Map)
 - 卷積運算可以幫助模型識別圖像中的邊緣、形狀和其他基本特徵
- 2.激活函數 (Activation Function)

- 通常在卷積層後面會使用激活函數(如ReLU)來引入非線性,使得網絡 能夠學習更複雜的特徵
- 激活函數的作用是將卷積層的輸出轉換為更有用的數值範圍
- 3.池化層 (Pooling Layer)
 - 池化層常用來縮小特徵圖的尺寸(降維),常見的池化方式有最大池化 (Max Pooling)和平均池化(Average Pooling)
 - 池化層有助於減少計算量,降低overfitting的風險,並且使得特徵具有平 移不變性
- 4.全連接層 (Fully Connected Layer)
 - 在CNN的最後,通常會有一層或多層全連接層,用來將提取到的特徵映 射到最終的輸出類別(如圖片分類結果)
 - 全連接層中的每一個神經元都與前一層的所有神經元相連
- 5.輸出層(Output Layer)
 - 輸出層的神經元數量等於分類的類別數。對於二分類問題,通常會使用 sigmoid激活函數;對於多分類問題,則會使用softmax激活函數
- 6.優化器(Optimizer)和損失函數(Loss Function)
 - 優化器(如Adam、SGD)用來更新網路中的權重,目的是最小化損失函數
 - 損失函數衡量預測值與實際值之間的誤差,通過反向傳播來調整網絡權重,達到更好的預測效果

CNN的特點:

- 特徵自動提取: CNN不需要手動提取特徵,它能夠自動學習和提取圖像中的關鍵特徵
- 局部連接:每個神經元只與上一層的一部分神經元相連,這有助於減少參數數量
- 權重共享:卷積層中的filter在整個圖像中共享權重,進一步減少了參數的數量

程式碼截圖

• 建立結構簡單的CNN模型用來訓練情緒分析的能力

• 印出所建構出的CNN模型的架構

```
#show CNN model structure
print(model.summary())

Model: "sequential"
```

Layer (type)	Output Shape	Param #
embedding (Embedding)	(None, 29183, 128)	3,735,424
conv1d (Conv1D)	(None, 29181, 128)	49,280
max_pooling1d (MaxPooling1D)	(None, 5836, 128)	0
conv1d_1 (Conv1D)	(None, 5834, 64)	24,640
max_pooling1d_1 (MaxPooling1D)	(None, 2917, 64)	0
flatten (Flatten)	(None, 186688)	0
dense (Dense)	(None, 64)	11,948,096
dropout (Dropout)	(None, 64)	0
dense_1 (Dense)	(None, 1)	65

```
Total params: 47,272,517 (180.33 MB)
```

Trainable params: 15,757,505 (60.11 MB)

Non-trainable params: 0 (0.00 B)

Optimizer params: 31,515,012 (120.22 MB)

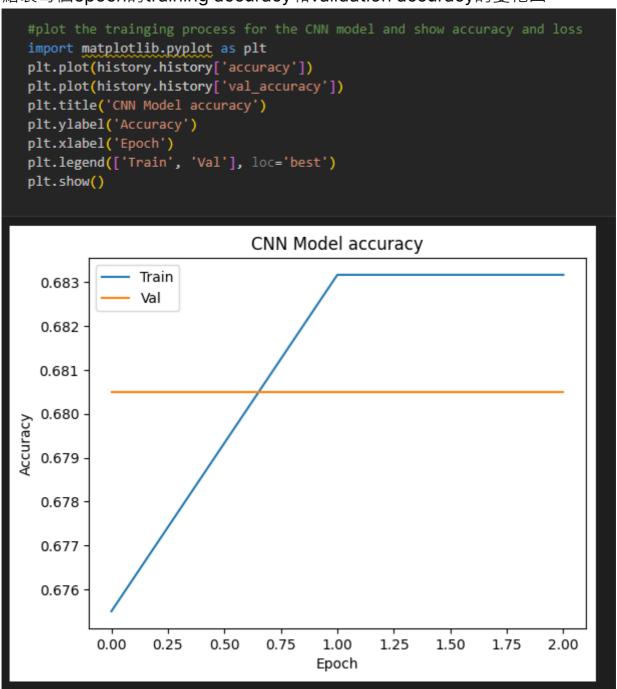
None

• 用建立完的CNN模型以切割出的訓練集和測試集進行訓練

```
#train the model
history = model.fit(X_train, y_train, epochs=3, batch_size=32, validation_data=(X_val, y_val))

Epoch 1/3
188/188 — 299s 2s/step - accuracy: 0.6676 - loss: 0.6978 - val_accuracy: 0.6805 - val_loss: 0.6339
Epoch 2/3
188/188 — 296s 2s/step - accuracy: 0.6740 - loss: 0.6587 - val_accuracy: 0.6805 - val_loss: 0.6310
Epoch 3/3
188/188 — 297s 2s/step - accuracy: 0.6758 - loss: 0.6460 - val_accuracy: 0.6805 - val_loss: 0.6287
```

• 繪製每個epoch的training accuracy和validation accuracy的變化圖



• 繪製每個epoch的training loss和validation loss的變化圖

```
#plot the trainging process for the CNN model and show accuracy and loss
 plt.plot(history.history['loss'])
 plt.plot(history.history['val_loss'])
 plt.title('CNN Model loss')
 plt.ylabel('Loss')
 plt.xlabel('Epoch')
 plt.legend(['Train', 'Val'], loc='best')
 plt.show()
                                CNN Model loss
                                                                    Train
  0.67
                                                                    Val
  0.66
S 0.65
  0.64
  0.63
         0.00
                 0.25
                        0.50
                               0.75
                                       1.00
                                               1.25
                                                      1.50
                                                              1.75
                                                                     2.00
                                      Epoch
```

• 用測試集的資料評估訓練出的CNN模型在情緒分析任務上的表現

3.LSTM模型

長短期記憶網路(LSTM, Long Short-Term Memory)是一種特殊的循環神經網絡(RNN),用於處理和預測序列數據,特別擅長解決傳統RNN在長期依賴問題中的局限

• 1.LSTM的基本結構

- LSTM包含一組特殊的記憶單元(memory cell),每個記憶單元都有三個主要的閘控結構:輸入閘(Input Gate)、遺忘閘(Forget Gate)和輸出閘(Output Gate)
- 這些閘控決定了信息的傳遞方式,控制哪些資訊被記住、丟棄或傳遞給下 一層

• 2.遺忘閘 (Forget Gate)

• 遺忘閘決定哪些資訊從單元的記憶中丟棄。它會根據當前輸入和前一狀態的輸出生成一個0到1之間的值,這個值用來乘以記憶單元的狀態,表示 丟棄多少資訊

• 3.輸入閘 (Input Gate)

輸入閘控制哪些新資訊將被加入到單元的記憶中。它同樣生成一個0到1 之間的值,並將其與當前的輸入進行加權後,更新記憶單元的狀態

• 4.輸出閘 (Output Gate)

輸出閘決定了記憶單元的哪些部分將被用來產生當前的輸出。它會根據當前的輸入和內部狀態生成一個0到1之間的值,這個值用來調節記憶單元狀態的輸出

• 5.記憶單元狀態更新

- 記憶單元的狀態是LSTM的關鍵,它會結合遺忘閘的操作(丟棄部分舊資訊)和輸入閘的操作(加入新的資訊)進行更新,從而使得LSTM能夠記住關鍵的長期資訊
- 6.避免梯度消失(Gradient Vanishing)與梯度爆炸(Gradient Exploding)問題
 - 傳統的RNN在處理長序列時會遇到梯度消失或梯度爆炸的問題,而LSTM 通過引入記憶單元和閘控結構,有效地解決了這些問題,使得LSTM可以 學習長期依賴的關係

LSTM的特點:

• 1.長期依賴

 LSTM能夠記住長期依賴關係,特別適合處理長序列數據,如語音識別、 語言建模等

• 2. 閘控結構

- LSTM的閘控結構使得它可以動態地選擇性地儲存或遺忘資訊,從而更靈活地捕捉數據中的時間依賴性
- 3.避免RNN的缺陷

相比傳統RNN,LSTM能夠更好地處理長期依賴問題,避免了梯度消失或 爆炸的問題

程式碼截圖

• 建立結構簡單的LSTM模型用來訓練情緒分析的能力

```
#build the LSTM model
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Embedding, LSTM, Dense
from tensorflow.keras.layers import SpatialDropoutID

model_lstm = Sequential()
model_lstm.add(Smbedding(input_dim=tfidf_matrix.shape[1], output_dim=128, input_length=tfidf_matrix.shape[1]))
model_lstm.add(SpatialDropoutID(0.7))
model_lstm.add(SpatialDropoutID(0.7))
model_lstm.add(Dense(1, activation='sigmoid'))
model_lstm.add(Dense(1, activation='sigmoid'))

model_lstm.compile(optimizer='adam', loss='binary_crossentropy', metrics=['accuracy'])

c:\Users\a0905\AppData\Local\Programs\Python\Python\12\Lib\site-packages\keras\src\layers\core\embedding_py:90: UserWarning: Argument `input_length` is deprecated. Just remove it.
warnings.warn(
```

• 印出所建構出的LSTM模型的架構

```
#show LSTM model structure
print(model_lstm.summary())
```

Model: "sequential_1"

Layer (type)	Output Shape	Param #
embedding_1 (Embedding)	(None, 29183, 128)	3,735,424
spatial_dropout1d (SpatialDropout1D)	(None, 29183, 128)	ø
lstm (LSTM)	(None, 64)	49,408
dense_2 (Dense)	(None, 1)	65

```
Total params: 11,354,693 (43.31 MB)
```

Trainable params: 3,784,897 (14.44 MB)

Non-trainable params: 0 (0.00 B)

Optimizer params: 7,569,796 (28.88 MB)

None

用建立完的LSTM模型以切割出的訓練集和測試集進行訓練

```
history_lstm = model_lstm.fit(X_train, y_train, epochs=3, batch_size=32, validation_data=(X_val, y_val))
Epoch 1/3
188/188
                             14560s 77s/step - accuracy: 0.6876 - loss: 0.6310 - val_accuracy: 0.6805 - val_loss: 0.6265
Epoch 2/3
188/188
                             14386s 77s/step - accuracy: 0.6787 - loss: 0.6302 - val_accuracy: 0.6805 - val_loss: 0.6347
Epoch 3/3
188/188
                             14502s 77s/step - accuracy: 0.6909 - loss: 0.6207 - val_accuracy: 0.6805 - val_loss: 0.6265
```

```
繪製每個epoch的training accuracy和validation accuracy的變化圖
    #plot the trainging process for the LSTM model and show accuracy and loss
    import matplotlib.pyplot as plt
    plt.plot(history_lstm.history['accuracy'])
    plt.plot(history_lstm.history['val_accuracy'])
    plt.title('LSTM Model accuracy')
    plt.ylabel('Accuracy')
    plt.xlabel('Epoch')
    plt.legend(['Train', 'Val'], loc='upper left')
    plt.show()
                                 LSTM Model accuracy
                    Train
      0.6830
                    Val
      0.6825
   Accuracy
      0.6820
      0.6815
      0.6810
      0.6805
```

0.75

0.00

0.25

0.50

1.00

Epoch

1.25

1.50

1.75

2.00

• 繪製每個epoch的training loss和validation loss的變化圖

```
#plot the trainging process for the LSTM model and show accuracy and loss
plt.plot(history_lstm.history['loss'])
plt.plot(history_lstm.history['val_loss'])
plt.title('LSTM Model loss')
plt.ylabel('Loss')
plt.xlabel('Epoch')
plt.legend(['Train', 'Val'], loc='upper left')
plt.show()
                                LSTM Model loss
 0.635
               Train
               Val
 0.634
 0.633
 0.632
 0.631
 0.630
 0.629
 0.628
 0.627
         0.00
                0.25
                        0.50
                                0.75
                                       1.00
                                              1.25
                                                      1.50
                                                              1.75
                                                                     2.00
                                      Epoch
```

• 用測試集的資料評估訓練出的LSTM模型在情緒分析任務上的表現

• 建立結構簡單但unit更大的LSTM模型用來訓練情緒分析的能力

```
#build the LSTM model
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Embedding, LSTM, Dense
from tensorflow.keras.layers import SpatialDropoutID

(variable) model_lstm: Any | _t_dim=tfidf_matrix.shape[1], output_dim=128, input_length=tfidf_matrix.shape[1]))
model_lstm.add(SpatialDropoutID(0.7))
model_lstm.add(LSTM(128, dropouta-0.2, recurrent_dropout=0.2))
model_lstm.add(Dense(1, activation='sigmoid'))
model_lstm.compile(optimizer='adam', loss='binary_crossentropy', metrics=['accuracy'])

c:\Users\a0905\App@ata\local\Programs\Python\Python312\Lib\site-packages\keras\src\layers\core\embedding.py:90: UserWarning: Argument `input_length` is deprecated. Just remove it.
warnings.warn(
```

• 印出所建構出的LSTM模型的架構

```
#show LSTM model structure

print(model_lstm.summary())
```

Model: "sequential_2"

Layer (type)	Output Shape	Param #
embedding_2 (Embedding)	(None, 29183, 128)	3,735,424
spatial_dropout1d_1 (SpatialDropout1D)	(None, 29183, 128)	0
lstm_1 (LSTM)	(None, 128)	131,584
dense_3 (Dense)	(None, 1)	129

Total params: 11,601,413 (44.26 MB)

Trainable params: 3,867,137 (14.75 MB)

Non-trainable params: 0 (0.00 B)

Optimizer params: 7,734,276 (29.50 MB)

None

用建立完的LSTM模型以切割出的訓練集和測試集進行訓練

```
history_lstm = model_lstm.fit(X_train, y_train, epochs=3, batch_size=32, validation_data=(X_val, y_val))
Epoch 1/3
188/188
                             9814s 52s/step - accuracy: 0.6604 - loss: 0.6382 - val_accuracy: 0.6805 - val_loss: 0.6270
Epoch 2/3
188/188
                            9748s 52s/step - accuracy: 0.6877 - loss: 0.6235 - val_accuracy: 0.6805 - val_loss: 0.6270
Epoch 3/3
188/188
                            9758s 52s/step - accuracy: 0.6792 - loss: 0.6311 - val_accuracy: 0.6805 - val_loss: 0.6265
```

```
繪製每個epoch的training accuracy和validation accuracy的變化圖
    #plot the trainging process for the LSTM model and show accuracy and loss
    import matplotlib.pyplot as plt
    plt.plot(history_lstm.history['accuracy'])
    plt.plot(history_lstm.history['val_accuracy'])
    plt.title('LSTM Model accuracy')
    plt.ylabel('Accuracy')
    plt.xlabel('Epoch')
    plt.legend(['Train', 'Val'], loc='upper left')
    plt.show()
                                  LSTM Model accuracy
                    Train
      0.6830
                    Val
      0.6825
      0.6820
   Accuracy
      0.6815
      0.6810
      0.6805
      0.6800
              0.00
                     0.25
                             0.50
                                    0.75
                                            1.00
                                                   1.25
                                                          1.50
                                                                  1.75
                                                                         2.00
                                           Epoch
```

• 繪製每個epoch的training loss和validation loss的變化圖

```
#plot the trainging process for the LSTM model and show accuracy and loss
 plt.plot(history_lstm.history['loss'])
 plt.plot(history_lstm.history['val_loss'])
 plt.title('LSTM Model loss')
 plt.ylabel('Loss')
 plt.xlabel('Epoch')
 plt.legend(['Train', 'Val'], loc='upper left')
 plt.show()
                                 LSTM Model loss
                Train
                Val
  0.630
  0.629
Loss
  0.628
  0.627
          0.00
                 0.25
                         0.50
                                 0.75
                                        1.00
                                                1.25
                                                       1.50
                                                               1.75
                                                                      2.00
                                       Epoch
```

• 用測試集的資料評估訓練出的LSTM模型在情緒分析任務上的表現