IMDB - Embedding with DNN

NLP(Natural Language Processing)

```
import warnings
warnings.filterwarnings('ignore')
```

Import Keras

Keras Version 확인

```
import keras
keras.__version__
'2.4.3'
```

I. IMDB Data_Set Load & Review

→ 1) Load IMDB Data_Set

- · Word to Vector
- 전체 데이터 내에서 단어의 사용빈도에 따라 인덱스화
- 정수 인덱스 '11'은 11번째로 자주 사용된 단어를 나타냄
- num_words = 10000 : 인덱스 값 10000 이하의 단어만 추출
- 단어 인덱스 값이 10000을 넘지 않는 단어만 분석에 사용

```
from keras.datasets import imdb

(X_train, y_train), (X_test, y_test) = imdb.load_data(num_words = 10000)
```

2) Visualization & Frequency(Optional)

• x - Histogram(리뷰 길이)

```
import matplotlib.pyplot as plt

print('리뷰 최대 길이 :', max(len(L) for L in X_train))
print('리뷰 평균 길이 :', sum(map(len, X_train))/len(X_train))

plt.figure(figsize = (9, 6))
plt.hist([len(L) for L in X_train], bins = 50)
plt.xlabel('Length of X_train')
plt.ylabel('Number of X_train')
plt.show()
```

• y - Frequency(0:부정, 1:긍정)

```
import numpy as np

unique_elements, counts_elements = np.unique(y_train, return_counts = True)

print('Label 빈도수:')
print(np.asarray((unique_elements, counts_elements)))

Label 빈도수:
[[ 0 1]
[12500 12500]]
```

II. Tensor Transformation

- → 1) X_train & X_test: (25000, 10000)
 - vectorization
 - (25000, 10000)

```
from keras import preprocessing

X_train = preprocessing.sequence.pad_sequences(X_train, maxlen = 10000)

X_test = preprocessing.sequence.pad_sequences(X_test, maxlen = 10000)

X_train.shape, X_test.shape

((25000, 10000), (25000, 10000))
```

Transformation Check

```
print(X_train[0][:21])
print(X_train[0][9979:])
```

```
print(X_test[0][:21])
print(X_test[0][9979:])
   [ 226
         65
            16
               38 1334
                     88
                          12
                                       16 4472
                                            113
     32
         15
            16 5345
                   19 178
                         32]
   14 286 170
                8 157
                      46
                          5
                             27 239
                                    16 179
                                              38
                                                 32
     25 7944 451 202
                   14
                       6 717]
```

→ 2) y_train & y_test

```
y_train = np.asarray(y_train).astype(float)
y_test = np.asarray(y_test).astype(float)

print(y_train[:21])
print(y_test[:21])

[1. 0. 0. 1. 0. 0. 1. 0. 1. 0. 1. 0. 0. 0. 0. 1. 1. 0. 1. 0.]
[0. 1. 1. 0. 1. 1. 1. 0. 0. 1. 1. 0. 0. 0. 1. 0. 1. 0. 0. 0. 1.]
```

III. Keras Embedding Modeling

→ 1) Model Define

- 모델 신경망 구조 정의
 - Embedding Dimension: 32

```
from keras import models
from keras import layers

imdb = models.Sequential()

imdb.add(layers.Embedding(10000, 32, input_length = 10000))

imdb.add(layers.Flatten())

imdb.add(layers.Dense(16))
imdb.add(layers.Dropout(0.5))
imdb.add(layers.Dense(1, activation = 'sigmoid'))
```

• 모델 구조 확인

```
imdb.summary()
```

Model: "sequential"

Layer (type)	Output Shape	Param #
embedding (Embedding)	(None, 10000, 32)	320000
flatten (Flatten)	(None, 320000)	0
dense (Dense)	(None, 16)	5120016
dropout (Dropout)	(None, 16)	0
dense_1 (Dense)	(None, 1)	17

Total params: 5,440,033 Trainable params: 5,440,033 Non-trainable params: 0

→ 2) Model Compile

• 모델 학습방법 설정

→ 3) Model Fit

약 20분

```
%%time
Hist_imdb = imdb.fit(X_train, y_train,
                     epochs = 50,
                     batch_size = 512,
                     validation_data = (X_test, y_test))
     בטיטוו בטיטע
     49/49 [=====
                                    ======] - 20s 408ms/step - loss: 0.0042 - accuracy: 1.0000
     Epoch 24/50
     49/49 [=====
                                      =====] - 20s 407ms/step - loss: 0.0035 - accuracy: 1.0000
     Epoch 25/50
     49/49 [=====
                                    ======] - 20s 407ms/step - loss: 0.0035 - accuracy: 1.0000
     Epoch 26/50
                                   ======] - 20s 409ms/step - loss: 0.0032 - accuracy: 1.0000
     49/49 [=====
     Epoch 27/50
     49/49 [====
                                      =====] - 20s 407ms/step - loss: 0.0027 - accuracy: 1.0000
     Epoch 28/50
     49/49 [==
                                        ====] - 20s 406ms/step - loss: 0.0028 - accuracy: 1.0000
     Epoch 29/50
```

```
49/49 [====
                                 =====] - 20s 407ms/step - loss: 0.0021 - accuracy: 1.0000
Epoch 30/50
49/49 [====
                                  ====] - 20s 408ms/step - Ioss: 0.0022 - accuracy: 0.9999
Epoch 31/50
                                   ==] - 20s 406ms/step - loss: 0.0019 - accuracy: 1.0000
49/49 [====
Epoch 32/50
49/49 [=====
                                =====] - 20s 406ms/step - loss: 0.0018 - accuracy: 1.0000
Epoch 33/50
49/49 [====
                                 =====] - 20s 406ms/step - loss: 0.0017 - accuracy: 1.0000
Epoch 34/50
49/49 [==
                                   ===] - 20s 408ms/step - loss: 0.0018 - accuracy: 1.0000
Epoch 35/50
49/49 [==
                                   ==] - 20s 409ms/step - loss: 0.0017 - accuracy: 1.0000
Epoch 36/50
49/49 [==
                                   ===] - 20s 409ms/step - loss: 0.0015 - accuracy: 1.0000
Epoch 37/50
49/49 [===
                                ====] - 20s 409ms/step - loss: 0.0014 - accuracy: 1.0000
Epoch 38/50
49/49 [====
                                 =====] - 20s 409ms/step - loss: 0.0013 - accuracy: 1.0000
Epoch 39/50
                                =====] - 20s 414ms/step - loss: 0.0013 - accuracy: 1.0000
49/49 [====
Epoch 40/50
49/49 [====
                                 ====] - 20s 405ms/step - loss: 0.0012 - accuracy: 1.0000
Epoch 41/50
49/49 [====
                                  ====] - 20s 406ms/step - loss: 0.0013 - accuracy: 1.0000
Epoch 42/50
49/49 [====
                                 ====] - 20s 409ms/step - loss: 9.3620e-04 - accuracy: 1.C
Epoch 43/50
49/49 [==
                                   ===] - 20s 405ms/step - loss: 0.0010 - accuracy: 1.0000
Epoch 44/50
49/49 [====
                                  ===] - 20s 407ms/step - loss: 9.9379e-04 - accuracy: 1.C
Epoch 45/50
49/49 [=====
                            =======] - 20s 405ms/step - loss: 9.0731e-04 - accuracy: 1.C
Epoch 46/50
49/49 [====
                               =====] - 20s 408ms/step - loss: 9.1410e-04 - accuracy: 1.C
Epoch 47/50
49/49 [==
                                   ==] - 20s 406ms/step - loss: 8.2664e-04 - accuracy: 1.C
Epoch 48/50
49/49 [=====
                          =======] - 20s 406ms/step - loss: 7.7742e-04 - accuracy: 1.C
Epoch 49/50
49/49 [=====
                         ========] - 20s 406ms/step - loss: 7.1441e-04 - accuracy: 1.C
Epoch 50/50
                      =======] - 20s 407ms/step - loss: 7.4424e-04 - accuracy: 1.C
CPU times: user 16min 1s, sys: 25 s, total: 16min 26s
```

▼ 4) 학습 결과 시각화

Wall time: 16min 37s

Loss Visualization

```
import matplotlib.pyplot as plt
epochs = range(1, len(Hist_imdb.history['loss']) + 1)
```

```
plt.figure(figsize = (9, 6))
plt.plot(epochs, Hist_imdb.history['loss'])
plt.plot(epochs, Hist_imdb.history['val_loss'])
plt.title('Training & Validation Loss')
plt.xlabel('Epochs')
plt.ylabel('Loss')
plt.legend(['Training Loss', 'Validation Loss'])
plt.grid()
plt.show()
```

Accuracy Visualization

```
import matplotlib.pyplot as plt

epochs = range(1, len(Hist_imdb.history['accuracy']) + 1)

plt.figure(figsize = (9, 6))
plt.plot(epochs, Hist_imdb.history['accuracy'])
plt.plot(epochs, Hist_imdb.history['val_accuracy'])
plt.title('Training & Validation Accuracy')
plt.xlabel('Epochs')
plt.ylabel('Accuracy')
plt.legend(['Training Accuracy', 'Validation Accuracy'])
plt.grid()
plt.show()
```

▼ 5) Model Evaluate

Loss & Accuracy

The End

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2021. 3. 31.

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