

문혜지

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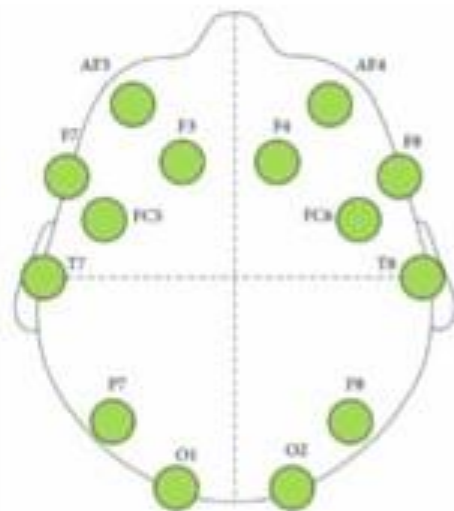
Content

- Introduction
- Algorithm & Result
- Conclusion

Introduction



- 뇌파 분류 경진대회
- emotiv사의 EPOC 장비 이용하여 14개 채널로 각 뇌파를 받음
- 10초동안 '정지(0)', '왼쪽으로 이동(1)', '오른쪽으로 이동(2)' 의 뇌파를 받음
- 뇌파를 받은 사람은 subjectA, subjectB, subjectC, subjectD, 총 4명



DATA

- 결측치 확인

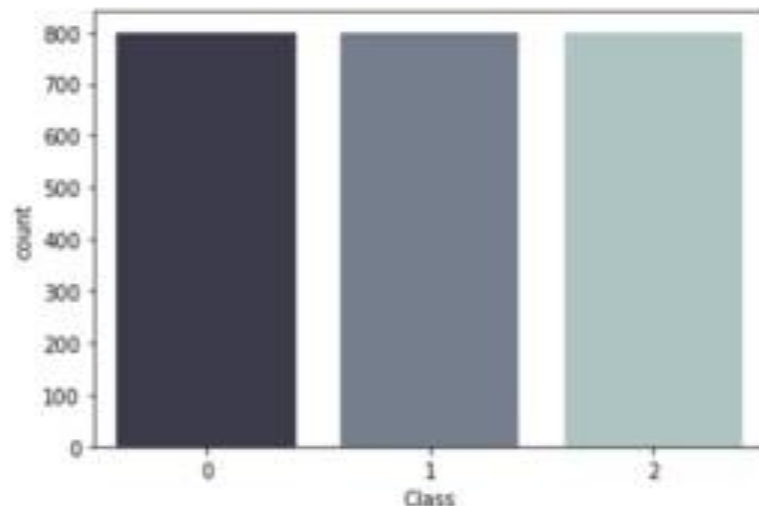
```
a = df_train.isnull().sum()
a[a > 0]
```

```
Series([], dtype: int64)
```

- 종속변수(Y) 확인

```
subject[target].value_counts()
```

```
0    800
2    800
1    800
Name: Class, dtype: int64
```



- 데이터 확인

	Class	AF3 delta std	AF3 delta m	AF3 theta std	AF3 theta m	AF3 alpha std	AF3 alpha m	AF3 beta std	AF3 beta m	F7 delta std
0	1	3574.0	2068.0	1.334961	2.294922	0.742188	2.052734	3.605469	4.855469	3576.0
1	1	3570.0	2064.0	1.639648	2.572266	1.096680	2.677734	2.314453	4.726562	3574.0
2	1	3570.0	2064.0	0.706543	2.613281	1.086914	2.222656	2.410156	4.937500	3574.0
3	1	3570.0	2066.0	0.939941	2.564453	0.836426	2.152344	2.611111	4.726562	3574.0
4	1	3568.0	2064.0	0.961914	2.373047	1.046875	1.783203	2.411111	4.726562	3574.0

	F8 beta std	F8 beta m	AF4 delta std	AF4 delta m	AF4 theta std	AF4 theta m	AF4 alpha std	AF4 alpha m	AF4 beta std	AF4 beta m
0	3.625000	8.859375	3522.0	2045.0	0.750488	2.169922	1.372070	2.099609	2.417969	3.884756
1	3.917969	7.472656	3526.0	2048.0	0.799805	2.408203	1.110352	2.154297	2.048828	4.238281
2	4.355469	8.320312	3532.0	2050.0	1.411133	2.642578	1.518555	1.738281	1.457031	3.861328
3	3.683594	5.964844	3530.0	2050.0	1.221680	3.437500	1.272461	2.111328	1.679688	3.505859
4	3.498047	6.484375	3520.0	2044.0	1.796875	3.386719	0.770996	3.505859	1.477539	3.687500

DATA

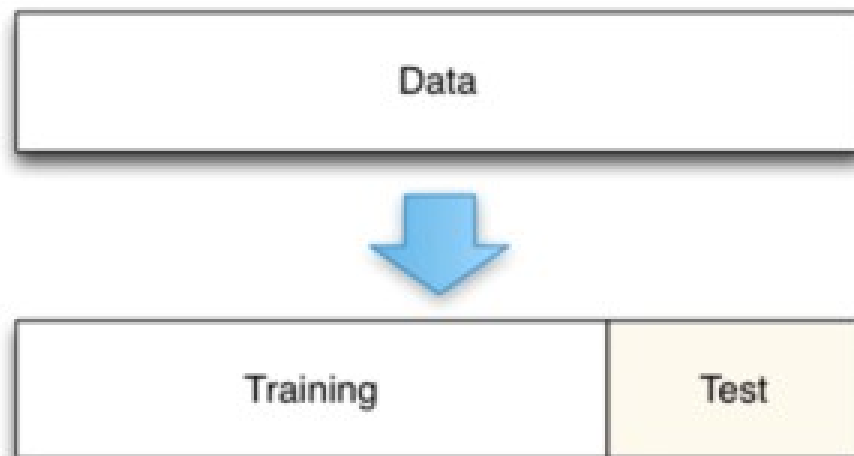
- 정규화(normalization)

각 데이터의 스케일을 맞추기 위해 진행

$$x_{i_new} = \frac{x_i - \text{mean}(x)}{\text{std}(x)}$$

- TRAIN TEST 분리

TRAIN 7 : TEST 3로 지정

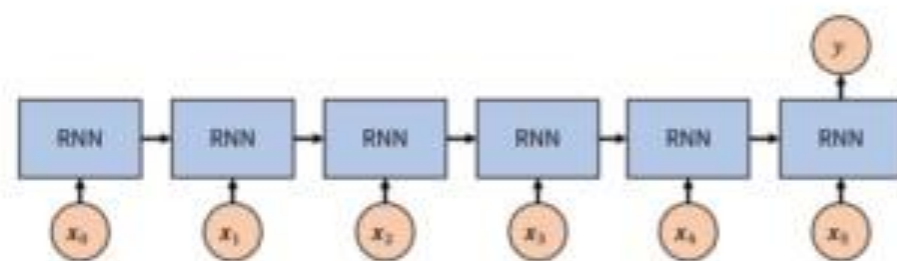
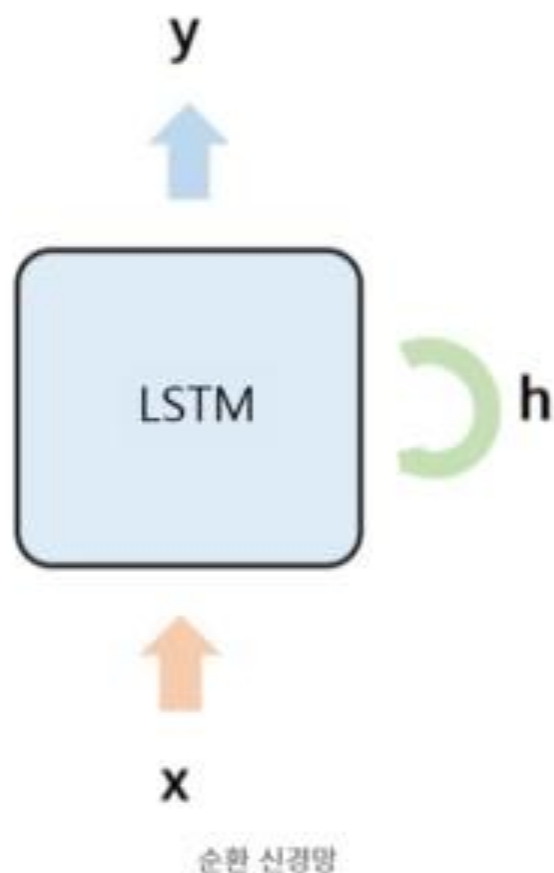




Algorithm & Result

LSTM

- LSTM 은 Long Short Term Memory의 약자
- 주로 시계열 처리나 자연어 처리를 사용하는 데 사용
- X가 Input으로 들어가 여러 번의 순환을 거쳐 output인 y가 나오는 구조.
이때 h(hidden state)는 그 중간다리 역할을 함.
- 최종적으로 y값이 나오는 데는 hidden state와 연속적인 x의 입력에 의해 결정



Subject A의 과정

```
Epoch 1/100
53/53 [-----] - 5s 17ms/step - loss: 0.5262 - accuracy: 0.4585
Epoch 2/100
53/53 [-----] - 1s 17ms/step - loss: 0.1496 - accuracy: 0.6025
Epoch 3/100
53/53 [-----] - 1s 17ms/step - loss: 0.0730 - accuracy: 0.6851
Epoch 4/100
53/53 [-----] - 1s 17ms/step - loss: 0.0311 - accuracy: 0.6712 0s - loss: 0.0338
Epoch 5/100
53/53 [-----] - 1s 17ms/step - loss: 0.0219 - accuracy: 0.6730
Epoch 6/100
53/53 [-----] - 1s 17ms/step - loss: 0.0175 - accuracy: 0.6742
Epoch 7/100
53/53 [-----] - 1s 17ms/step - loss: 0.0163 - accuracy: 0.6730
Epoch 00007: early stopping
```

LSTM

Subject_A Subject A 정확도 : 63.0%

```
LSTM train
[[571  0  0]
 [223 337  0]
 [ 1 353 188]]
```

```
LSTM test
[[227  2  0]
 [ 88 142  0]
 [ 2 175 81]]
```

Subject_C Subject A 정확도 : 66.0%

```
LSTM train
[[556  0  0]
 [205 348  0]
 [ 0 200 364]]
```

```
LSTM test
[[239  5  0]
 [ 90 147  0]
 [ 0 133 103]]
```

Subject_B Subject B 정확도 : 67.0%

```
LSTM train
[[555  0  0]
 [271 292  0]
 [ 0 363 192]]
```

```
LSTM test
[[245  0  0]
 [110 127  0]
 [ 1 151 83]]
```

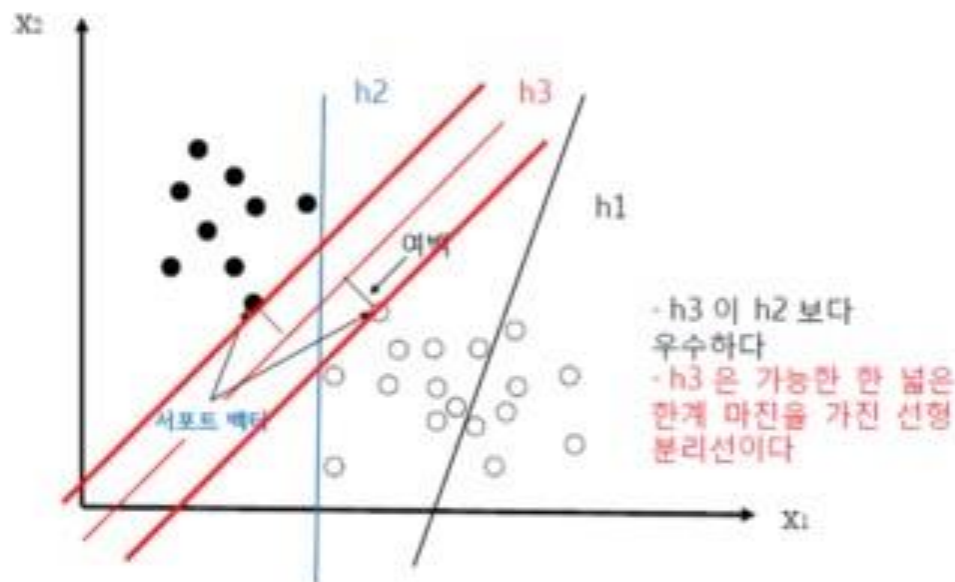
Subject_D Subject D 정확도 : 65.0%

```
LSTM train
[[545  0  0]
 [412 164  0]
 [ 0 389 163]]
```

```
LSTM test
[[254  1  0]
 [152  62  0]
 [ 0 186 62]]
```


SVM

- 서포트 벡터 머신(support vector machine)의 약자
- SVM은 기계 학습의 분야 중 하나로 패턴 인식, 자료 분석을 위한 지도 학습 모델이며, 주로 분류와 회귀 분석을 위해 사용됨.
- 분류된 두 범주 사이에서 해당 범주에 속하는 데이터의 분류 오차를 줄이면서 여백(margin)을 최대화하는 결정 경계(decision boundary)를 찾는 방법
- 두 범주 사이에 여러 경계가 존재할 수 있지만, 여백을 최대화하는 경계를 최대 마진 분류기라 함



```
> a_final_svm_model
Workflow [trained]
Preprocessor: Recipe
Model: svm_rbf()

Preprocessor
1 Recipe Step

step_normalize()

Model
Support Vector Machine object of class "ksvm"

SV type: C-svc (classification)
parameter : cost C = 13.4494875098975

Gaussian Radial Basis kernel function.
Hyperparameter : sigma = 0.00767386792870953

Number of Support Vectors : 1674

Objective Function Value : -1580.792 -1699.441 -2087.19
Training error : 0.001667
Probability model included.
```

SVM

Subject_A Subject A 정확도 : 87.6%

```
A SVM train
[[496 37 23]
 [ 32 478 45]
 [ 23 48 586]]

A SVM test
[[285 17 22]
 [ 28 191 42]
 [ 21 21 181]]
```

Subject_C Subject C 정확도 : 82.1%

```
C SVM train
[[469 38 51]
 [ 45 459 45]
 [ 44 78 451]]

C SVM test
[[153 38 51]
 [ 48 168 43]
 [ 51 58 118]]
```

Subject_B Subject B 정확도 : 94.9%

```
B SVM train
[[534 14 17]
 [ 6 531 12]
 [ 7 29 538]]

B SVM test
[[198 17 28]
 [ 11 238 18]
 [ 15 27 192]]
```

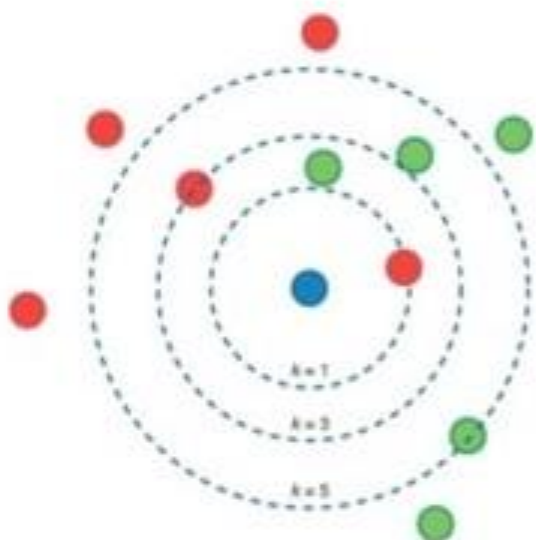
Subject_D Subject D 정확도 : 90.7%

```
D SVM train
[[515 22 33]
 [ 21 519 23]
 [ 28 38 489]]

D SVM test
[[176 24 38]
 [ 21 192 24]
 [ 28 36 189]]
```

KNN

- k-Nearest Neighbor 모델의 약자
- 새로운 데이터가 어느 그룹에 속해있는지를 판단하기 위해서, 인접한 학습데이터의 개수를 기준으로 판단
- 이때 인접한 학습데이터의 개수가 바로 kNN의 'k'가 됨

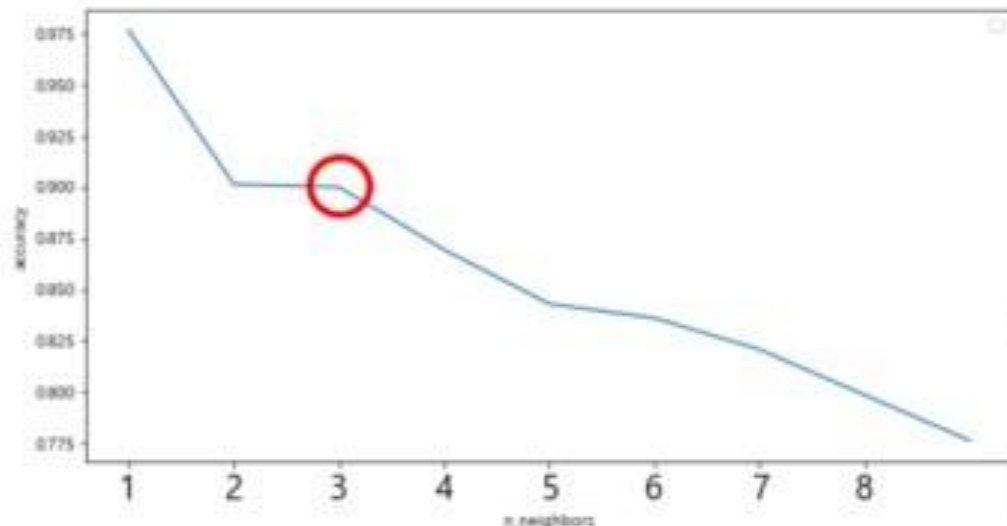


빨간색과 녹색은 학습된 데이터이고 파란색은 새로운 데이터

k=1이면 빨간색
k=3이면 빨간색
k=5이면 녹색

```
from sklearn.neighbors import KNeighborsClassifier  
  
knn = KNeighborsClassifier(n_neighbors=3)  
knn.fit(x_train, y_train)  
knn_train_pred = knn.predict(x_train)  
knn_test_pred = knn.predict(x_test)
```

k=3 으로 사용



KNN

Subject_A Subject A 정확도 : 96.6%

```
KNN train
[[535  7  9]
 [ 8 550  8]
 [12 13 538]]
```

```
KNN test
[[215 17 17]
 [15 208 11]
 [14 23 200]]
```

Subject_C Subject A 정확도 : 89.7%

```
D KNN train
[[539  3  1]
 [ 2 560  5]
 [ 6  2 562]]
```

```
D KNN test
[[241  6 10]
 [11 214  8]
 [13 10 207]]
```

Subject_B Subject B 정확도 : 98.6%

```
B KNN train
[[571  1  3]
 [ 4 533  6]
 [ 5  5 552]]
```

```
B KNN test
[[212  7  6]
 [19 220 18]
 [15  4 219]]
```

Subject_D Subject D 정확도 : 98.9%

```
C KNN train
[[509 19 22]
 [30 508 25]
 [49 28 490]]
```

```
C KNN test
[[190 33 27]
 [41 172 24]
 [50 24 159]]
```



Conclusion

Conclusion

Algorithm	LSTM	SVM	KNN
Subject A의 정확도	63.0%	87.6%	96.0%
Subject B의 정확도	67.0%	94.9%	98.6%
Subject C의 정확도	66.0%	82.1%	89.7%
Subject D의 정확도	65.0%	90.7%	98.9%

LSTM

Subject_A, B, C, D 예측값 error

```
model.predict(x_test)

>>> outputs = call_fn(inputs, *args, **kwargs)
>>>
>>> File "C:\Users\yhg31\Anaconda3\lib\site-packages\keras\utils\traceback_utils.py", line 92, in error_handler
>>>     return fn(*args, **kwargs)
>>>
>>> File "C:\Users\yhg31\Anaconda3\lib\site-packages\keras\layers\recurrent_v2.py", line 1254, in call
>>>     runtime) = lstm_with_backend_selection(**normal_lstm_kwargs)
>>>
>>> File "C:\Users\yhg31\Anaconda3\lib\site-packages\keras\layers\recurrent_v2.py", line 1649, in lstm_with_backend_selection
>>>     last_output, outputs, new_h, new_c, runtime = defun_standard_lstm(**params)
>>>
>>> File "C:\Users\yhg31\Anaconda3\lib\site-packages\keras\layers\recurrent_v2.py", line 1380, in standard_lstm
>>>     last_output, outputs, new_states = backend.rnn(
>>>
>>> File "C:\Users\yhg31\Anaconda3\lib\site-packages\keras\backend.py", line 4654, in rnn
>>>     final_outputs = tf.compat.v1.WhileLoop(
>>>
>>> File "C:\Users\yhg31\Anaconda3\lib\site-packages\keras\backend.py", line 4638, in _step
>>>     current_input = tuple(ta.read(time) for ta in input_ta)
>>>
>>> File "C:\Users\yhg31\Anaconda3\lib\site-packages\keras\backend.py", line 4638, in <genexpr>
>>>     current_input = tuple(ta.read(time) for ta in input_ta)
```

SVM

Subject_A

Class	0	1	2
예측값	195	160	125

Subject_C

Class	0	1	2
예측값	243	139	98

Subject_B

Class	0	1	2
예측값	228	168	84

Subject_D

Class	0	1	2
예측값	223	151	106

KNN

Subject_A

Class	0	1	2
예측값	209	146	125

Subject_C

Class	0	1	2
예측값	226	132	122

Subject_B

Class	0	1	2
예측값	192	172	116

Subject_D

Class	0	1	2
예측값	195	149	136

Thanks!

