머신러닝 – 기말 프로젝트(자유)

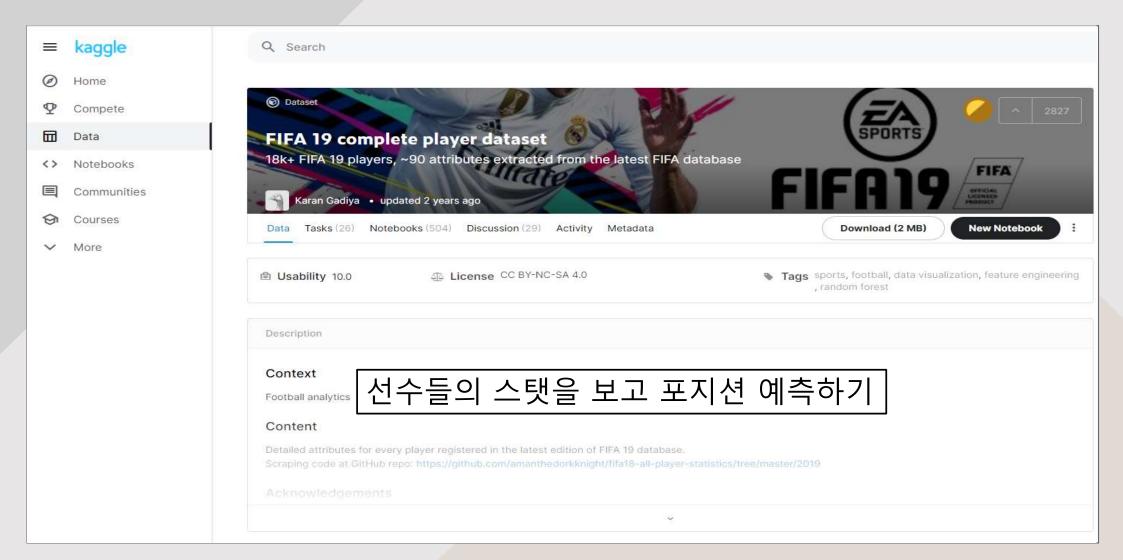
20165517 오기용

콘텐츠 IT학과 20165517 오기용

목차



데이터 소개



데이터 소개

ID	Name	Age	Photo	Nationalit	Flag	Overall	Potenti	al Club	Club Log	c Value	Wage	Special	Preferred	Internati	or Weak Fo	o Skill Mo	ve Work Rate	Body Type	Real Face	Position	Jersey Nu	r Joined	Loaned Fr	Contract	\ Height
158023	L. Messi		31 https://co	r Argentina	https://cdr	94	l	94 FC Barcel	https://co	dr €110.5M	€565K	220	2 Left		5	4	4 Medium/	Messi	Yes	RF	10	01-Jul-04	,	202	1 5'7
20801	Cristiano	F	33 https://co	r Portugal	https://cdr	94	l	94 Juventus	https://co	dr€77M	€405K	222	8 Right		5	4	5 High/ Low	C. Ronaldo	Yes	ST	7	7 10-Jul-18	i	202	2 6'2
190871	Neymar Jr		26 https://co	r Brazil	https://cdr	9)	93 Paris Sain	https://co	dr €118.5M	€290K	214	3 Right		5	5	5 High/ Med	Neymar	Yes	LW	10) ######		202	2 5'9
Weight		ST	RS	LW	LF	CF	RF	RW	LAM	CAM	RAM	LM	LCM	CM	RCM	RM	LWB	LDM	CDM	RDM	RWB	LB	LCB	СВ	RCB
159lbs	88+2	88+2	88+2	92+2	93+2	93+2	93 + 2	92+2	93+2	93+2	93 + 2	91+2	84+2	84+2	84+2	91+2	64+2	61+2	61+2	61+2	64+2	59+2	47+2	47+2	47+2
133103	00+2	00+2	00+2	JZTZ	33+2	33+2	33 T Z	JZTZ	3372	3312	3312	3112	OTIZ	0112	UTIL	J1.2	UTIL	0112	UIIL	OTTE	OTIL	55.2	11 12	11.5	7/1/
183lbs	91+3	91+3	91+3	89+3	90+3	90+3	90+3	89+3	88+3	88+3	88+3	88+3	81+3	81+3	81+3	88+3			61+3	61+3	65+3			53+3	53+3

RB	Crossing	Finishing	HeadingA Sh	ortPassi Volleys	D	ribbling Curve	F	KAccurac Lon	gPassii Bal	Contrc Acc	celeratic Spi	rintSpec Agilit	y F	Reactions Balance	S	ShotPowe Jumping	Stamina	Strength	LongShot	Aggressior In	terceptic Po	sitionin Vis	sion
59+2	84	95	70	90	86	97	93	94	87	96	91	86	91	95	95	85 68	72	59	94	48	22	94	94
61+3	84	94	89	81	87	88	81	76	77	94	89	91	87	96	70	95 95	88	79	93	63	29	95	82
60+3	79	87	62	84	84	96	88	87	78	95	94	90	96	94	84	80 61	81	49	82	56	36	89	87

Penalties	Composur	Marking	StandingT	SlidingTac	GKDiving	GKHandlir	GKKicking	GKPosition	GKReflexe	Release Clause
75	96	33	28	26	6	11	15	14	8	€226.5M
85	95	28	31	23	7	11	15	14	11	€127.1M
81	94	27	24	33	9	9	15	15	11	€228.1M



행 : 18207개 열 : 89개

데이터 소개

데이터 소개

```
# 사용할 모듈 불러오기
import pandas as pd
import numpy as np
import pickle
import seaborn as sns
%matplotlib inline
import matplotlib.pyplot as plt
```

피파 데이터 읽기

fifa_data = pd.read_csv("C:/Users/multi050/fifa_data.csv")

데이터 내용보기 fifa_data.head()

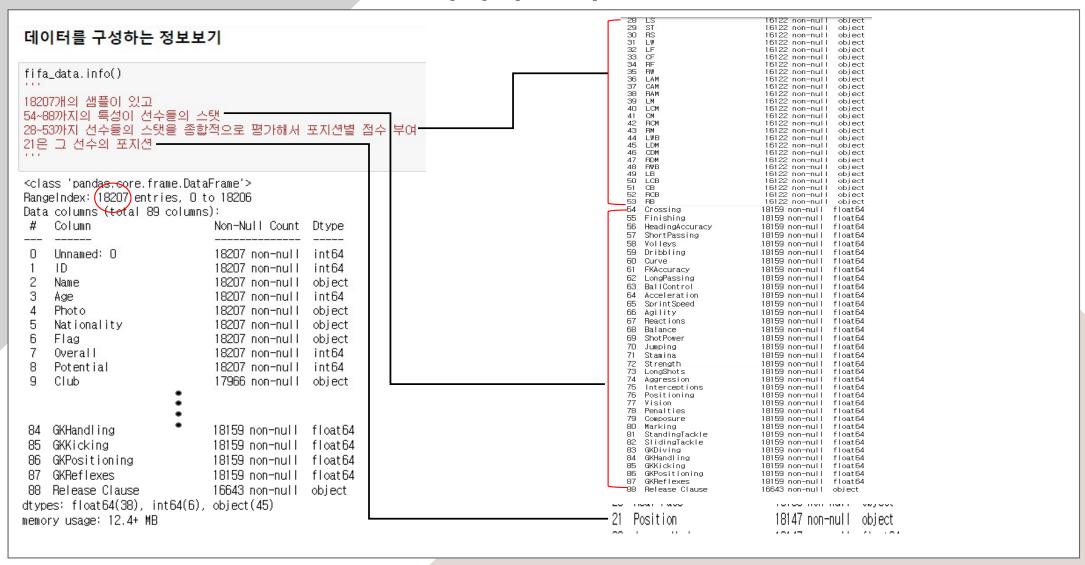
88+1개 특성

	Unnamed: 0	ID	Name	Age	Photo	Nationality	Flag	Overall	Potential	Club	
0	0	158023	L. Messi	31	https://cdn.sofifa.org/players/4/19/158023.png	Argentina	https://cdn.sofifa.org/flags/52.png	94	94	FC Barcelona	
1	1	20801	Cristiano Ronaldo	33	https://cdn.sofifa.org/players/4/19/20801.png	Portugal	https://cdn.sofifa.org/flags/38.png	94	94	Juventus	
2	2	190871	Neymar Jr	26	https://cdn.sofifa.org/players/4/19/190871.png	Brazil	https://cdn.sofifa.org/flags/54.png	92	93	Paris Saint- Germain	
3	3	193080	De Gea	27	https://cdn.sofifa.org/players/4/19/193080.png	Spain	https://cdn.sofifa.org/flags/45.png	91	93	Manchester United	
4	4	192985	K. De Bruyne	27	https://cdn.sofifa.org/players/4/19/192985.png	Belgium	https://cdn.sofifa.org/flags/7.png	91	92	Manchester City	

18206+1개의 샘플

5 rows x 89 columns

데이터 분석



데이터 분석

위에서 언급한 선수의 포지션, 포지션별 점수, 스탯을 보여줌
player_position = pd.DataFrame({'Name': fifa_data.Name, 'Position':fifa_data.Position,}) # 선수 이름, 포지션
player_Stat = fifa_data.iloc[:,54:88] # 스탯
player_information = pd.concat([player_position,player_Stat],axis=1)
player_information

→ 필요한 특성 (포지션, 스탯)만 사용

	Name	Position	Crossing	Finishing	HeadingAccuracy	ShortPassing	Volleys	Dribbling	Curve	FKAccuracy	Penalties	Composure	Marking	StandingTackle	SlidingTackle	GKDiving	GKHandling	GKKicking	GKPositioning	GKReflexes
0	L. Messi	RF	84.0	95.0	70.0	90.0	86.0	97.0	93.0	94.0	75.0	96.0	33.0	28.0	26.0	6.0	11.0	15.0	14.0	8.0
1	Cristiano Ronaldo	ST	84.0	94.0	89.0	81.0	87.0	88.0	81.0	76.0	85.0	95.0	28.0	31.0	23.0	7.0	11.0	15.0	14.0	11.0
2	Neymar Jr	LW	79.0	87.0	62.0	84.0	84.0	96.0	88.0	87.0	81.0	94.0	27.0	24.0	33.0	9.0	9.0	15.0	15.0	11.0
3	De Gea	GK	17.0	13.0	21.0	50.0	13.0	18.0	21.0	19.0	40.0	68.0	15.0	21.0	13.0	90.0	85.0	87.0	88.0	94.0
4	K. De Bruyne	RCM	93.0	82.0	55.0	92.0	82.0	86.0	85.0	83.0	79.0	88.0	68.0	58.0	51.0	15.0	13.0	5.0	10.0	13.0
		100	2000	***														127		
18202	J. Lundstram	CM	34.0	38.0	40.0	49.0	25.0	42.0	30.0	34.0	43.0	45.0	40.0	48.0	47.0	10.0	13.0	7.0	8.0	9.0
18203	N. Christoffersson	ST	23.0	52.0	52.0	43.0	36.0	39.0	32.0	20.0	43.0	42.0	22.0	15.0	19.0	10.0	9.0	9.0	5.0	12.0
18204	B. Worman	ST	25.0	40.0	46.0	38.0	38.0	45.0	38.0	27.0	55.0	41.0	32.0	13.0	11.0	6.0	5.0	10.0	6.0	13.0
18205	D. Walker-Rice	RW	44.0	50.0	39.0	42.0	40.0	51.0	34.0	32.0	50.0	46.0	20.0	25.0	27.0	14.0	6.0	14.0	8.0	9.0
18206	G. Nugent	CM	41.0	34.0	46.0	48.0	30.0	43.0	40.0	34.0	33.0	43.0	40.0	43.0	50.0	10.0	15.0	9.0	12.0	9.0

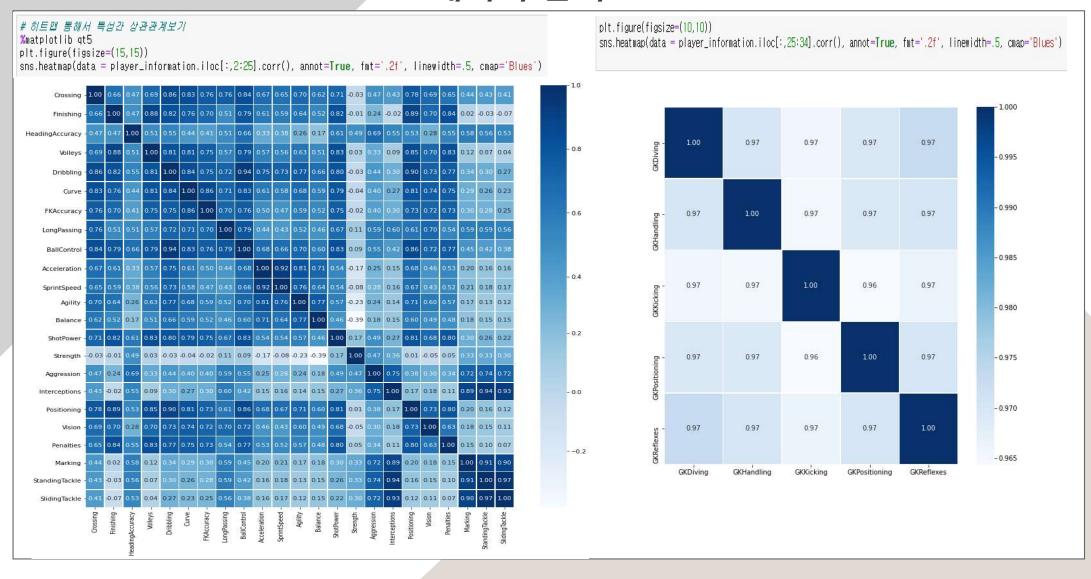
18207 rows × 36 columns

fifa_data.iloc[:,28:53] # 포지션별 점수

	LS	ST	RS	LW	LF	CF	RF	RW	LAM	CAM	 RM	LWB	LDM	CDM	RDM	RWB	LB	LCB	СВ	RCB
0	88+2	88+2	88+2	92+2	93+2	93+2	93+2	92+2	93+2	93+2	 91+2	64+2	61+2	61+2	61+2	64+2	59+2	47+2	47+2	47+2
1	91+3	91+3	91+3	89+3	90+3	90+3	90+3	89+3	88+3	88+3	 88+3	65+3	61+3	61+3	61+3	65+3	61+3	53+3	53+3	53+3
2	84+3	84+3	84+3	89+3	89+3	89+3	89+3	89+3	89+3	89+3	 88+3	65+3	60+3	60+3	60+3	65+3	60+3	47+3	47+3	47+3
3	NaN	 NaN	NaN																	
4	82+3	82+3	82+3	87+3	87+3	87+3	87+3	87+3	88+3	88+3	 88+3	77+3	77+3	77+3	77+3	77+3	73+3	66+3	66+3	66+3
											 	000		000	-					
18202	42+2	42+2	42+2	44+2	44+2	44+2	44+2	44+2	45+2	45+2	 44+2	44+2	45+2	45+2	45+2	44+2	45+2	45+2	45+2	45+2
18203	45+2	45+2	45+2	39+2	42+2	42+2	42+2	39+2	40+2	40+2	 38+2	30+2	31+2	31+2	31+2	30+2	29+2	32+2	32+2	32+2
18204	45+2	45+2	45+2	45+2	46+2	46+2	46+2	45+2	44+2	44+2	 44+2	34+2	30+2	30+2	30+2	34+2	33+2	28+2	28+2	28+2
18205	47+2	47+2	47+2	47+2	46+2	46+2	46+2	47+2	45+2	45+2	 46+2	36+2	32+2	32+2	32+2	36+2	35+2	31+2	31+2	31+2
18206	43+2	43+2	43+2	45+2	44+2	44+2	44+2	45+2	45+2	45+2	 46+2	46+2	46+2	46+2	46+2	46+2	46+2	47+2	47+2	47+2

18207 rows x 25 columns

데이터 분석



데이터 수정

- 1. 특성(스탯) 중에서 분류에 영향을 주지않는 특성 제거→ 포지션 별로 스탯을 비교했을 때 차이가 거의 없는 경우 삭제
- 2. 비슷한 영역의 포지션을 하나의 포지션으로 합쳐서 데이터 수 늘리기

Ex) LB(왼쪽 수비수), RB(오른쪽 수비수), LCB(왼쪽 중앙 수비수), RCB(오른쪽 중앙 수비수)

↓
CB(중앙 수비수)

3. NULL값 들어간 데이터 삭제

```
#null값 존재해서 null값 제거
print("제거 전: ", len(player_information))
player_information = player_information.dropna()
print("제거 후: ", len(player_information))

제거 전: 18207
제거 후: 18147
```

4. 훈련set, 시험,set 나누기

대표 포지션 3개(공격, 수비, 미드필더)의 스탯 비교

ST=player_information.loc[player_information['Position']=='ST',:] ST=ST[0:1000]

0,	٠.	LO.	
ST			

	Name	Position	Crossing	Finishing	HeadingAccuracy	ShortPassing	Volleys	Drit
1	Cristiano Ronaldo	ST	84.0	94.0	89.0	81.0	87.0	
10	R. Lewandowski	ST	62.0	91.0	85.0	83.0	89.0	
16	H. Kane	ST	75.0	94.0	85.0	80.0	84.0	
23	S. Agüero	ST	70.0	93.0	77.0	81.0	85.0	
36	G. Bale	ST	87.0	86.0	84.0	85.0	85.0	
	12			7.2.				
9064	S. Davies	ST	65.0	64.0	70.0	60.0	65.0	
9073	S. Brandstetter	ST	49.0	65.0	65.0	58.0	58.0	
9075	D. Samuel	ST	49.0	65.0	67.0	60.0	57.0	
9084	Stéfano Pinho	ST	64.0	67.0	52.0	56.0	57.0	
9099	A. Baclet	ST	57.0	61.0	71.0	61.0	61.0	

1000 rows x 36 columns

CB=player_information.loc[player_information['Position']=='CB',:] CB=CB[0:1000] CB

Name	Position	Crossing	Finishing	HeadingAccuracy	Shor

	Name	Position	Crossing	i illisilling	neadingAccuracy	Shortrassing	volleys	DII
12	D. Godín	СВ	55.0	42.0	92.0	79.0	47.0	
42	S. Umtiti	СВ	69.0	51.0	79.0	81.0	70.0	
73	M. Benatia	СВ	45.0	47.0	83.0	65.0	44.0	
89	N. Otamendi	СВ	52.0	54.0	85.0	75.0	57.0	
102	Naldo	СВ	45.0	57.0	94.0	76.0	60.0	
				***	***	***		
11623	Kim Jungya	СВ	29.0	47.0	64.0	60.0	31.0	
11640	V. Selimović	СВ	32.0	21.0	65.0	54.0	26.0	
11643	C. Shaughnessy	СВ	41.0	31.0	64.0	64.0	40.0	
11665	E. Wahlström	СВ	43.0	31.0	61.0	50.0	22.0	
11674	M. Fontaine	СВ	62.0	26.0	71.0	64.0	11.0	

1000 rows x 36 columns

CM=player_information.loc[player_information['Position']=='CM',:]

	Name	Position	Crossing	Finishing	HeadingAccuracy	ShortPassing	Volleys	Dribb
67	Thiago	CM	72.0	69.0	54.0	90.0	90.0	
78	S. Milinković- Savić	СМ	64.0	80.0	86.0	85.0	74.0	
121	Jorginho	CM	75.0	57.0	56.0	89.0	71.0	
136	I. Gündoğan	СМ	74.0	73.0	50.0	88.0	75.0	,
161	N. Keïta	CM	62.0	74.0	42.0	88.0	71.0	3

15244	P. Mbodji	CM	38.0	54.0	48.0	64.0	27.0	
15253	H. Heath	CM	50.0	39.0	54.0	66.0	45.0	
15256	T. Domgjoni	СМ	36.0	39.0	58.0	61.0	38.0	
15267	K. Monlouis	СМ	45.0	36.0	61.0	74.0	45.0	1
15273	N. Husin	CM	59.0	55.0	44.0	63.0	44.0	

1000 rows × 36 columns

st_score=ST.iloc[:,2:].sum()
st_score

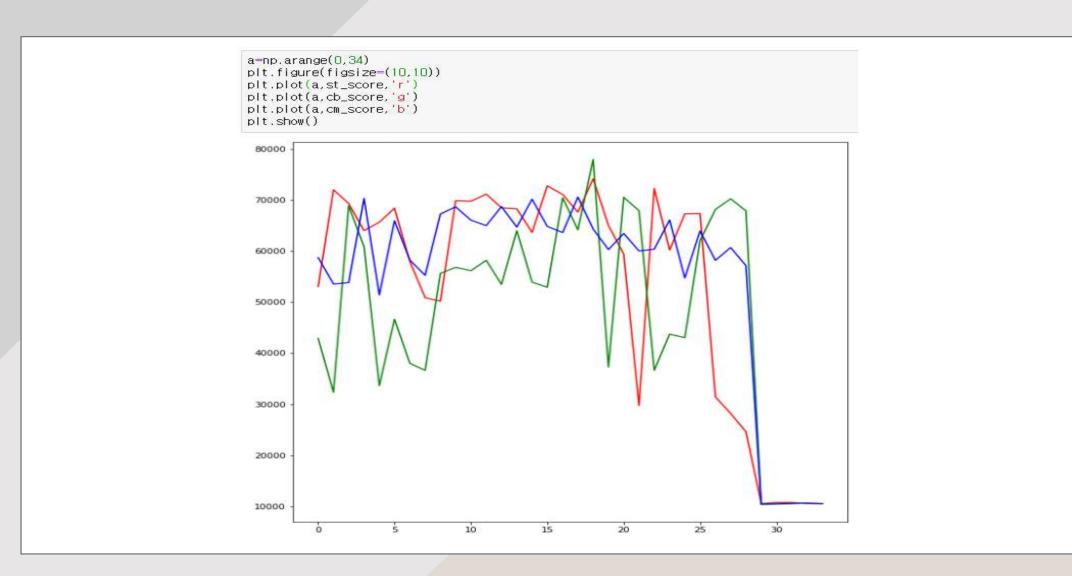
Crossing 53056.0 72022.0 Finishing HeadingAccuracy 69315.0 Short Passing 64010.0 Volleys 65661.0 Dribbling 68409.0 Curve 57955.0 FKAccuracy 50886.0 LongPassing 50200.0 BallControl 69878.0 Acceleration 69755.0 SprintSpeed 71157.0 Agility 68471.0 React ions 68271.0 Balance 63652.0 Shot Power 72787.0 Jumping 71094.0 Stamina 67632.0 Strength 74172.0 LongShots 65026.0 Aggression 59417.0 Interceptions 29741.0 Positioning 72281.0 Vision 60203.0 Penalties 67313.0 Composure 67358.0 Marking 31441.0 StandingTackle 28220.0 24638.0 SlidingTackle GKDiving 10591.0 GKHandling. 10781.0 GKKicking 10793.0 GKPositioning 10560.0 GKRef Lexes 10578.0 dtype: float64

cb_score=CB.iloc[:,2:].sum()
cb_score

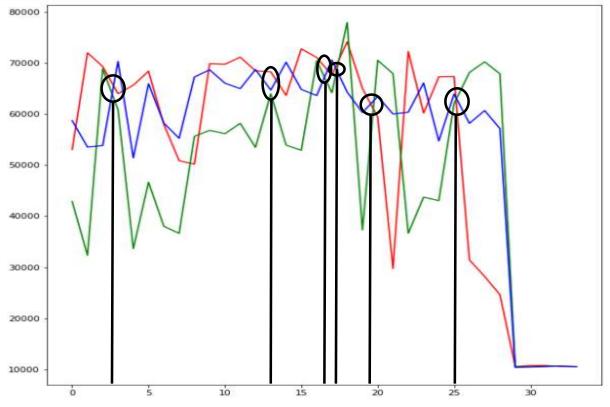
Crossing 42896.0 32337.0 Finishing HeadingAccuracy 68895.0 60850.0 Short Passing Volleys 33652.0 Dribbling 46671.0 Curve 38030.0 **FKAccuracy** 36643.0 LongPassing 55647.0 BallControl 56827.0 Acceleration 56169.0 SprintSpeed 58199.0 Agility 53482.0 Reactions 63999.0 Balance 53931.0 52913.0 Shot Power Jumping 70437.0 Stamina 64159.0 Strength 77946. D 37305.0 LongShots Aggression 70544.0 Interceptions 67903.0 Positioning 36658.0 Vision 43737.0 43071.0 Penalties Composure 62079.0 Marking 68152.0 StandingTackle 70247.0 SlidingTackle 67874.0 GKDiving 10591.0 GKHandling. 10507.0 10629.0 GKKicking GKPositioning 10669.0 GKReflexes 10555.0 dtype: float64

cm_score=CM.iloc[:,2:].sum()
cm score

Crossing 58731.0 53550.0 Finishing HeadingAccuracy 53846.0 Short Passing 70328.0 Volleys 51412.0 Dribbling 65959.0 Curve 58236.0 FKAccuracy 55260.0 LongPassing 67274.0 BallControl 68671.0 66054.0 Acceleration SprintSpeed 64996.0 Agility 68729.0 Reactions 64707.0 Balance 70175.0 Shot Power 64838.0 Jumping 63627.0 Stamina 70600.0 64317.0 Strength 60303.0 LongShots Aggression 63452.0 60028.0 Interceptions Positioning 60371.0 Vision 66104.0 Penalties 54729.0 63944.0 Composure Marking 58184.0 StandingTackle 60701.0 SlidingTackle 57163.0 GKDiving 10388.0 GKHandling. 10469.0 GKKicking 10561.0 GKPositioning 10665.0 GKReflexes. 10567.0 dtype: float64



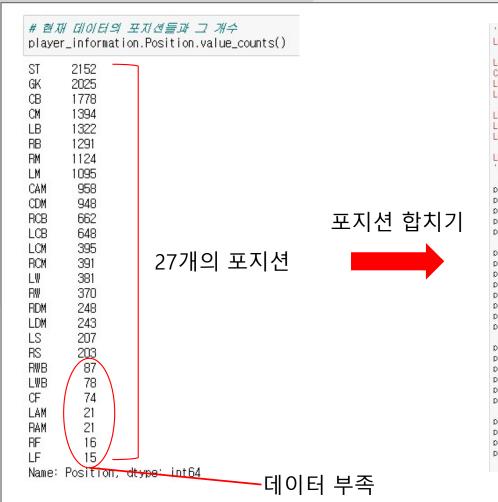




dtype='object')

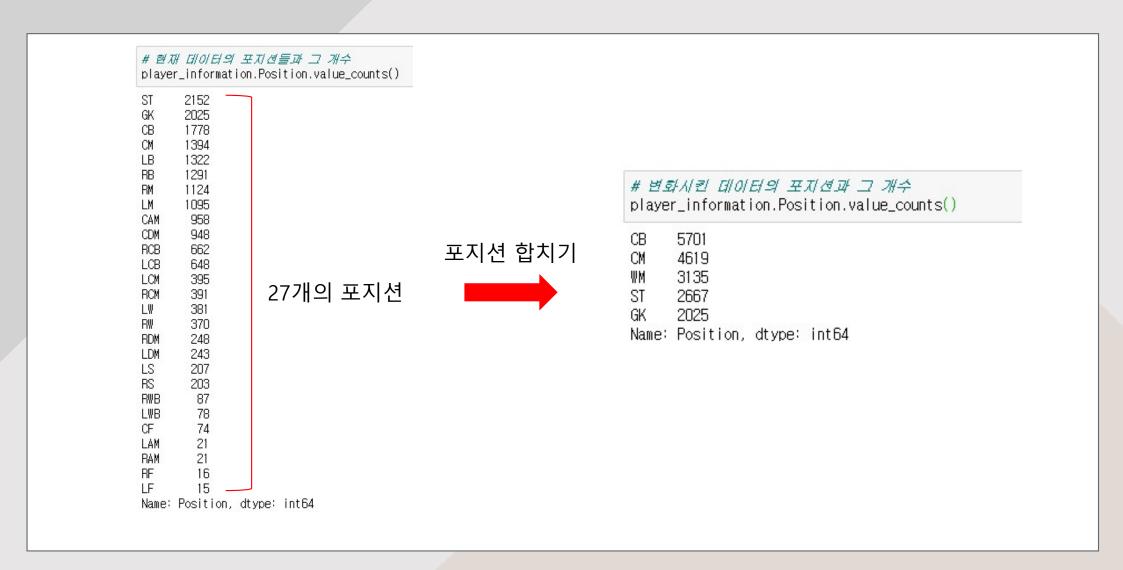
```
mean=(st_score+cb_score+cm_score)/3
var=((st_score-mean)**2*(cb_score-mean)**2*(cm_score-mean)**2)/3
std=var**(1/2)
std
plt.figure(figsize=(10,10))
plt.plot(a,std,'r')
plt.show()
17500
15000
12500
 10000
 7500
 5000
 2500
                                                                 30
```

타켓 줄이고 데이터 늘리기



```
LF(왼쪽 공격수), RF(오른쪽 공격수), CF(중앙 공격수), LS(왼쪽 스트라이커), RS(오른쪽 스트라이커) → ST(스트라이커)
LAM(왼쪽 공격형 미드필터), RAM(오른쪽 공격형 미드필터), 
ightarrow CM(중앙 미드필터)
CAM(중앙 공격형 미드필터), CDM(중앙 수비형 미드필터) → CM(중앙 미드필터)
LDM(왼쪽 수비형 미드필터), RDM(오른쪽 수비형 미드필터) <math>\rightarrow CM(중앙 미드필터)
LCM(왼쪽 중앙 미드필터), RCM(오른쪽 중앙 미드필터) → CM(중앙 미드필터)
L₩(왼쪽 윙어), R₩(오른쪽 윙어) → ₩M(윙 미드필터)
LWB(좌측 원백), RWB(무촉 원백) → WM(원 미드필터)
LM(왼쪽 미드필터), RM(오른쪽 미드필터) → WM(윙 미드필터)
LB(왼쪽 수비수), RB(오른쪽 수비수), LCB(왼쪽 중앙 수비수), RCB(오른쪽 중앙 수비수) → CB(중앙 수비수)
player_information.loc[player_information['Position'] == 'LF', ['Position']] = 'ST'
player_information.loc[player_information['Position'] == 'RF', ['Position']] = 'ST'
                                                                              스트라이커
player_information.loc[player_information['Position'] == 'CF', ['Position']] = 'ST'
player_information.loc[player_information['Position'] == 'LS', ['Position']] = 'ST'
player_information.loc[player_information['Position'] == 'RS', ['Position']] = 'ST'
player_information.loc[player_information['Position'] == 'LAM', ['Position']] = 'CM
player_information.loc[player_information['Position'] == 'RAM', ['Position']] = 'CM'
player_information.loc[player_information['Position']=='CAM', ['Position']] = 'CM'
player_information.loc[player_information['Position']=='CDM', ['Position']] = 'CM'
                                                                             중앙 미드필더
player_information.loc[player_information['Position'] == 'LDM', ['Position']] = 'CM'
player_information.loc[player_information['Position'] == 'RDM', ['Position']] = 'CM
player_information.loc[player_information['Position'] == 'LCM', ['Position']] = 'CM'
player_information.loc[player_information['Position'] == 'RCM', ['Position']] = 'CM'
player_information.loc[player_information['Position'] == 'LW', ['Position']] = 'WM'
player_information.loc[player_information['Position']=='RW', ['Position']] = 'WM'
player_information.loc[player_information['Position'] == 'LWB', ['Position']] = 'WM'
                                                                              윙 미드필더
player_information.loc[player_information['Position'] == 'RWB', ['Position']] = 'WM'
player_information.loc[player_information['Position'] == 'LM', ['Position']] = 'WM'
player information.loc[player information['Position'] == 'RM', ['Position']] = 'WM'
player_information.loc[player_information['Position'] == 'LB', ['Position']] = 'CB'
                                                                              중앙 수비수
player_information.loc[player_information['Position']=='RB', ['Position']] = 'CB'
player_information.loc[player_information['Position'] == 'LCB', ['Position']] = 'CB'
player_information.loc[player_information['Position']=='RCB', ['Position']] = 'CB'
```

타켓 줄이고 데이터 늘리기



훈련SET, 시험SET 나누기

```
# 데이터 나눌 때 유용한 모듈
from sklearn.model_selection import train_test_split

# 훈련데이터 80%, 시험데이터 20%로 나눌
train, test = train_test_split(player_information, test_size=0.2)
print("총 개수: ", len(player_information))
print("훈련set 개수: ",len(train))
print("시험set 개수: ",len(test))
```

총 개수 : 18147 훈련set 개수 : 14517 시험set 개수 : 3630

```
X_train = train.iloc[:,2:34]: y_train = train[['Position']].values.ravel() # 훈련데이터에 사용될 특징(스탯)과 예측 값(포지션)
X_test = test.iloc[: 2:34]: v_test = test[['Position']] # 시험데이터에 사용될 특징(스탯)과 예측 값(포지션)
```

사용할 특징(스탯) 범위 ↓ 이름, 포지션 값 제외

훈련(모델 선택)

RandomForest 사용

```
from sklearn.ensemble import RandomForestClassifier

forest_clf = RandomForestClassifier(n_estimators=100, random_state=42)
forest_clf.fit(X_train, y_train) #values.ravel()로 1차원 배열로 한돌로 만들
```

RandomForestClassifier(random_state=42)

```
#훈련데이터에 대한 정확도
forest_tr=format(forest_clf.score(X_train,y_train));
forest_tr
```

10.99993111524419641

#시설데이터에 대한 정확도 forest_te=format(forest_clf.score(X_test,y_test)); forest_te

10.8592286501377411

SVM 사용

```
from sklearn.svm import SVC

svm_clf = SVC(C=10, gamma=0.0001, kernel='rbf')
svm_clf.fit(X_train, y_train)

SVC(C=10, gamma=0.0001)

#훈련데이터에 대한 정확도
svm_tr=format(svm_clf.score(X_train,y_train));
svm_tr

'0.8857890748777295'

#시험데이터에 대한 정확도
svm_te=format(svm_clf.score(X_test,y_test));
svm_te

'0.865564738292011'
```

RandomForest < SVM

모델 세부 튜닝 - 배깅

한 모델로 데이터 중복을 허용하여 샘플링

모델 세부 튜닝 - 배깅사용-

```
#훈련데이터에 대한 정확도
bag_tr=format(bag_clf.score(X_train,y_train));
bag_tr
```

10.86409037679961421

```
#시컬데이터에 대한 정확도
bag_te=format(bag_clf.score(X_test,y_test));
bag_te
```

'0.8672176308539945' <mark>큰 차이는 안남</mark>

```
# 설제값과 예측값이 어떻게 다른지 비교
comparison = pd.DataFrame({'실제 값':y_test.values.ravel(),'예측 값':bag_clf.predict(X_test)})
comparison
```

결과 보기

실제값과 예측값이 어떻게 다른지 비교 comparison = pd.DataFrame({'실제 값':y_test.values.ravel(),'예측 값':bag_clf.predict(X_test)}) comparison[:50]

	실제 값	예측 값	
0	WM	СМ	
1	СВ	СВ	
2	WM	WM	
3	СВ	СВ	
4	СВ	СВ	
5	CM	WM	
6	CM	CM	
7	ST	ST	
8	WM	WM	
9	ST	ST	
10	ST	WM	
11	GK	GK	
12	CM	CM	
13	WM	CM	
14	CM	CM	
15	ST	ST	
16	GK	GK	
17	GK	GK	
18	ST	ST	
19	СВ	СВ	
20	СВ	СВ	
21	CM	CM	
22	WM	WM	
23	СВ	CM	
24	ST	ST	
25	CM	CM	

26	СВ	СВ
27	СВ	СВ
28	CM	СВ
29	СВ	СВ
30	GK	GK
31	GK	GK
32	СВ	СВ
33	CM	CM
34	GK	GK
35	ST	ST
36	WM	WM
37	CM	CM
38	GK	GK
39	GK	GK
40	CM	СВ
41	ST	ST
42	WM	WM
43	CM	ST
44	CM	CM
45	WM	СВ
46	ST	ST
47	СВ	СВ
48	СВ	СВ
49	ST	ST