

▼ Data Preprocessing

- I. Missing Value
- II. apply()
- III. Filtering
- IV. 데이터프레임 합치기
- V. 그룹 연산
- VI. Multi-Index
- VII. pivot_table()

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

▼ I. Missing Value(결측치)

▼ 1) 실습용 'titanic' 데이터셋

- 'age' 및 'deck' 열(Column)에서 결측치(NaN) 확인

```
import seaborn as sns
DF = sns.load_dataset('titanic')

DF.head(10)
```

	survived	pclass	sex	age	sibsp	parch	fare	embarked	class	who	a
0	0	3	male	22.0	1	0	7.2500	S	Third	man	
1	1	1	female	38.0	1	0	71.2833	C	First	woman	
2	1	3	female	26.0	0	0	7.9250	S	Third	woman	
3	1	1	female	35.0	1	0	53.1000	S	First	woman	
4	0	3	male	35.0	0	0	8.0500	S	Third	man	
5	0	3	male	NaN	0	0	8.4583	Q	Third	man	
6	0	1	male	54.0	0	0	51.8625	S	First	man	
7	0	3	male	2.0	3	1	21.0750	S	Third	child	
8	1	3	female	27.0	0	2	11.1333	S	Third	woman	
9	1	2	female	14.0	1	0	30.0708	C	Second	child	

- 'titanic' Dataset Information

```
DF.shape
```

```
(891, 15)
```

```
DF.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 891 entries, 0 to 890
Data columns (total 15 columns):
 #   Column                Non-Null Count  Dtype
---  -
 0   survived              891 non-null    int64
 1   pclass                891 non-null    int64
 2   sex                   891 non-null    object
 3   age                   714 non-null    float64
 4   sibsp                 891 non-null    int64
 5   parch                 891 non-null    int64
 6   fare                  891 non-null    float64
 7   embarked              889 non-null    object
 8   class                 891 non-null    category
 9   who                   891 non-null    object
10   adult_male            891 non-null    bool
11   deck                  203 non-null    category
12   embark_town           889 non-null    object
13   alive                 891 non-null    object
14   alone                 891 non-null    bool
dtypes: bool(2), category(2), float64(2), int64(4), object(5)
memory usage: 80.6+ KB
```

▼ 2) 결측치 확인

- `.value_counts(dropna = False)`
 - 결측치(NaN)를 포함하여 결과 출력

```
DF['deck'].value_counts(dropna = False)
```

```
NaN    688
C       59
B       47
D       33
E       32
A       15
F       13
G        4
Name: deck, dtype: int64
```

- `.isnull()`
 - 결측치(NaN)를 'True'로 출력

```
DF.head(10).isnull()
```

	survived	pclass	sex	age	sibsp	parch	fare	embarked	class	who	adult_m
0	False	False	False	False	False	False	False	False	False	False	F
1	False	False	False	False	False	False	False	False	False	False	F
2	False	False	False	False	False	False	False	False	False	False	F
3	False	False	False	False	False	False	False	False	False	False	F
4	False	False	False	False	False	False	False	False	False	False	F
5	False	False	False	True	False	False	False	False	False	False	F
6	False	False	False	False	False	False	False	False	False	False	F
7	False	False	False	False	False	False	False	False	False	False	F
8	False	False	False	False	False	False	False	False	False	False	F
9	False	False	False	False	False	False	False	False	False	False	F

- 각 열(Column)별로 결측치 개수 확인
- `.isnull().sum(axis = 0)`
 - `axis = 0` : 행(Row) 방향
 - `axis = 1` : 열(Column) 방향

```
DF.isnull().sum(axis = 0)
```

```
survived      0
pclass        0
sex           0
age          177
sibsp         0
parch         0
fare          0
embarked      2
class         0
who           0
adult_male    0
deck         688
embark_town   2
alive         0
alone         0
dtype: int64
```

- `.notnull()`
 - 결측치(NaN)를 'False'로 출력

```
DF.head(10).notnull()
```

	survived	pclass	sex	age	sibsp	parch	fare	embarked	class	who	adult_ma
0	True	True	True	True	True	True	True	True	True	True	True
1	True	True	True	True	True	True	True	True	True	True	True
2	True	True	True	True	True	True	True	True	True	True	True
3	True	True	True	True	True	True	True	True	True	True	True
4	True	True	True	True	True	True	True	True	True	True	True
5	True	True	True	False	True	True	True	True	True	True	True
6	True	True	True	True	True	True	True	True	True	True	True

3) 결측치 삭제

- 각 열(Column)별로 결측치 개수 확인

```
DF.isnull().sum(axis = 0)
```

```
survived      0
pclass        0
sex            0
age          177
sibsp         0
parch         0
fare          0
embarked      2
class         0
who           0
adult_male    0
deck         688
embark_town    2
alive         0
alone         0
dtype: int64
```

- 결측치가 300개 이상인 열(Column) 삭제
 - `.dropna(thresh = 300, axis = 1)`
 - 'deck' 열 삭제

```
DF.dropna(thresh = 300, axis = 1).shape
```

```
(891, 14)
```

- 결측치가 한 개라도 있는 행(Row) 삭제
 - `.dropna(subset = ['age'], how = 'any', axis = 0)`

```
DF.shape
```

```
(891, 15)
```

```
DF.dropna(subset = ['age'], how = 'any', axis = 0).shape
```

```
(714, 15)
```

4) 결측치 치환

- 연속형 데이터 치환
 - 'age'의 결측치를 평균값으로 치환
 - `.fillna(int(DF['age'].mean(axis = 0)), inplace = True)`

```
DF['age'].head(10)
```

```
0    22.0
1    38.0
2    26.0
3    35.0
4    35.0
5     NaN
6    54.0
7     2.0
8    27.0
9    14.0
Name: age, dtype: float64
```

```
DF['age'].fillna(int(DF['age'].mean(axis = 0)), inplace = True)
```

```
DF['age'].head(10)
```

```
0    22.0
1    38.0
2    26.0
3    35.0
4    35.0
5    29.0
6    54.0
7     2.0
8    27.0
9    14.0
Name: age, dtype: float64
```

- 명목형 데이터 치환
 - 'embark_town'의 결측치를 최빈값으로 치환
 - `.fillna(most_freq, inplace = True)`

```
DF['embark_town'][825:830]
```

```
825    Queenstown
826    Southampton
```

```

827      Cherbourg
828      Queenstown
829      NaN
Name: embark_town, dtype: object

```

```

most_freq = DF['embark_town'].value_counts(dropna = True).idxmax()

most_freq

```

```
'Southampton'
```

```
DF['embark_town'].fillna(most_freq, inplace = True)
```

```
DF['embark_town'][825:830]
```

```

825      Queenstown
826      Southampton
827      Cherbourg
828      Queenstown
829      Southampton
Name: embark_town, dtype: object

```

- 결측치 치환 with 'ffill'
 - 이전 데이터포인트로 치환
 - `.fillna(method = 'ffill', inplace = True)`

```
DF = sns.load_dataset('titanic')
```

```
DF['embark_town'][828:831]
```

```

828      Queenstown
829      NaN
830      Cherbourg
Name: embark_town, dtype: object

```

```
DF['embark_town'].fillna(method = 'ffill', inplace = True)
```

```
DF['embark_town'][828:831]
```

```

828      Queenstown
829      Queenstown
830      Cherbourg
Name: embark_town, dtype: object

```

- 결측치 치환 with 'bfill'
 - 다음 데이터포인트로 치환
 - `.fillna(method = 'bfill', inplace = True)`

```
DF = sns.load_dataset('titanic')
```

```
DF['embark_town'][828:831]
```

```
828    Queenstown
829           NaN
830    Cherbourg
Name: embark_town, dtype: object
```

```
DF['embark_town'].fillna(method = 'bfill', inplace = True)
```

```
DF['embark_town'][828:831]
```

```
828    Queenstown
829    Cherbourg
830    Cherbourg
Name: embark_town, dtype: object
```

▼ II. apply()

- 시리즈(Series)나 데이터프레임(DataFrame) 구조에 함수를 매핑

▼ 1) 실습용 'titanic' 데이터셋

```
import seaborn as sns
titanic = sns.load_dataset('titanic')

DF = titanic.loc[:, ['age', 'fare']].head(5)

DF
```

	age	fare
0	22.0	7.2500
1	38.0	71.2833
2	26.0	7.9250
3	35.0	53.1000
4	35.0	8.0500

▼ 2) apply(axis = 0)

- sum() 함수를 행(Row) 방향으로 매핑
 - Column Wise

```
DF.apply(sum, axis = 0)
```

```
age      156.0000
fare     147.6083
dtype: float64
```

▼ 3) apply(axis = 1)

- sum() 함수를 열(Column) 방향으로 매핑
 - Row Wise

```
DF.apply(sum, axis = 1)
```

```
0      29.2500
1     109.2833
2      33.9250
3      88.1000
4      43.0500
dtype: float64
```

▼ III. Filtering(필터링)

▼ 1) 실습용 'titanic' 데이터셋

```
import seaborn as sns
titanic = sns.load_dataset('titanic')

titanic.head(3)
```

	survived	pclass	sex	age	sibsp	parch	fare	embarked	class	who	ad
0	0	3	male	22.0	1	0	7.2500	S	Third	man	
1	1	1	female	38.0	1	0	71.2833	C	First	woman	
2	1	3	female	26.0	0	0	7.9250	S	Third	woman	

▼ 2) 'age'가 10살 이상이면서 20살 미만

```
Filter_1 = (titanic.age >= 10) & (titanic.age < 20)

titanic.loc[Filter_1, :].head()
```


	survived	pclass	sex	age	sibsp	parch	fare	embarked	class	who
9	1	2	female	14.0	1	0	30.0708	C	Second	child
14	0	3	female	14.0	0	0	7.8542	S	Third	child
22	1	2	female	15.0	0	0	26.0000	C	Third	child

▼ 3) 'age'가 10살 미만이면 'sex'이 여자

```
Filter_2 = titanic[titanic['age'] < 10 & titanic['sex'] == 'female']
```

```
Filter_2 = (titanic.age < 10) & (titanic.sex == 'female')
```

```
titanic.loc[Filter_2, :].head()
```

	survived	pclass	sex	age	sibsp	parch	fare	embarked	class	who	alone
10	1	3	female	4.0	1	1	16.7000	S	Third	child	
24	0	3	female	8.0	3	1	21.0750	S	Third	child	
43	1	2	female	3.0	1	2	41.5792	C	Second	child	
58	1	2	female	5.0	1	2	27.7500	S	Second	child	
119	0	3	female	2.0	4	2	31.2750	S	Third	child	

▼ 4) 'age'가 10살 미만 또는 60살 이상

- 'age', 'sex', 'alone' 열만 출력

```
Filter_3 = (titanic.age < 10) | (titanic.age >= 60)
```

```
titanic.loc[Filter_3, ['age', 'sex', 'alone']].head()
```

	age	sex	alone
7	2.0	male	False
10	4.0	female	False
16	2.0	male	False
24	8.0	female	False
33	66.0	male	True

▼ 5) isin()

- 'sibsp'에 3 또는 4 또는 5를 포함
 - 'sibsp == 3 | sibsp == 4 | sibsp == 5'

```
Filter_isin = titanic['sibsp'].isin([3, 4, 5])
```

```
titanic[Filter_isin].head(6)
```

	survived	pclass	sex	age	sibsp	parch	fare	embarked	class	who	ad
7	0	3	male	2.0	3	1	21.0750	S	Third	child	
16	0	3	male	2.0	4	1	29.1250	Q	Third	child	
24	0	3	female	8.0	3	1	21.0750	S	Third	child	
27	0	1	male	19.0	3	2	263.0000	S	First	man	
50	0	3	male	7.0	4	1	39.6875	S	Third	child	
59	0	3	male	11.0	5	2	46.9000	S	Third	child	

▼ IV. 데이터프레임 합치기

▼ 1) 데이터프레임 DF1, DF2 생성

```
import pandas as pd
```

```
DF1 = pd.DataFrame({'HP': ['hp0', 'hp1', 'hp2', 'hp3'],
                    'IBM': ['ibm0', 'ibm1', 'ibm2', 'ibm3'],
                    'DELL': ['dell0', 'dell1', 'dell2', 'dell3']},
                    index = [0, 1, 2, 3])
```

DF1

	HP	IBM	DELL
0	hp0	ibm0	dell0
1	hp1	ibm1	dell1
2	hp2	ibm2	dell2
3	hp3	ibm3	dell3

```
DF2 = pd.DataFrame({'HP': ['hp2', 'hp3', 'hp4', 'hp5'],
                    'IBM': ['ibm2', 'ibm3', 'ibm4', 'ibm5'],
                    'DELL': ['dell2', 'dell3', 'dell4', 'dell5'],
                    'ASUS': ['asus2', 'asus3', 'asus4', 'asus5']},
                    index = [2, 3, 4, 5])
```

DF2

	HP	IBM	DELL	ASUS
2	hp2	ibm2	dell2	asus2
3	hp3	ibm3	dell3	asus3

▼ 2) concat()

- 행기준 : axis = 0

```
pd.concat([DF1, DF2], axis = 0)
```

	HP	IBM	DELL	ASUS
0	hp0	ibm0	dell0	NaN
1	hp1	ibm1	dell1	NaN
2	hp2	ibm2	dell2	NaN
3	hp3	ibm3	dell3	NaN
2	hp2	ibm2	dell2	asus2
3	hp3	ibm3	dell3	asus3
4	hp4	ibm4	dell4	asus4
5	hp5	ibm5	dell5	asus5

- ignore_index = True

```
pd.concat([DF1, DF2], axis = 0, ignore_index = True)
```

	HP	IBM	DELL	ASUS
0	hp0	ibm0	dell0	NaN
1	hp1	ibm1	dell1	NaN
2	hp2	ibm2	dell2	NaN
3	hp3	ibm3	dell3	NaN
4	hp2	ibm2	dell2	asus2
5	hp3	ibm3	dell3	asus3
6	hp4	ibm4	dell4	asus4
7	hp5	ibm5	dell5	asus5

- 열기준 : axis = 1, join = 'inner'
 - 'inner' : Intersection

```
pd.concat([DF1, DF2], axis = 1, join = 'inner')
```

	HP	IBM	DELL	HP	IBM	DELL	ASUS
2	hp2	ibm2	dell2	hp2	ibm2	dell2	asus2
3	hp3	ibm3	dell3	hp3	ibm3	dell3	asus3

- 열기준 : axis = 1, join = 'outer'
 - 'outer' : Union

```
pd.concat([DF1, DF2], axis = 1, join = 'outer')
```

	HP	IBM	DELL	HP	IBM	DELL	ASUS
0	hp0	ibm0	dell0	NaN	NaN	NaN	NaN
1	hp1	ibm1	dell1	NaN	NaN	NaN	NaN
2	hp2	ibm2	dell2	hp2	ibm2	dell2	asus2
3	hp3	ibm3	dell3	hp3	ibm3	dell3	asus3
4	NaN	NaN	NaN	hp4	ibm4	dell4	asus4
5	NaN	NaN	NaN	hp5	ibm5	dell5	asus5

▼ 3) merge()

- how = 'inner'

```
pd.merge(DF1, DF2)
```

	HP	IBM	DELL	ASUS
0	hp2	ibm2	dell2	asus2
1	hp3	ibm3	dell3	asus3

- how = 'outer'

```
pd.merge(DF1, DF2, how = 'outer')
```

	HP	IBM	DELL	ASUS
0	hp0	ibm0	dell0	NaN

- how = 'left'

- 왼쪽 데이터프레임의 키(Key)만 사용 'left-outer'

```
3 hp3 ibm3 dell3 asus3
```

```
pd.merge(DF1, DF2, how = 'left')
```

	HP	IBM	DELL	ASUS
0	hp0	ibm0	dell0	NaN
1	hp1	ibm1	dell1	NaN
2	hp2	ibm2	dell2	asus2
3	hp3	ibm3	dell3	asus3

- how = 'right'

- 오른쪽 데이터프레임의 키(Key)만 사용 'right-outer'

```
pd.merge(DF1, DF2, how = 'right')
```

	HP	IBM	DELL	ASUS
0	hp2	ibm2	dell2	asus2
1	hp3	ibm3	dell3	asus3
2	hp4	ibm4	dell4	asus4
3	hp5	ibm5	dell5	asus5

▼ V. 그룹 연산

▼ 1) 실습용 'titanic' 데이터셋

```
import seaborn as sns
titanic = sns.load_dataset('titanic')

DF = titanic.loc[:, ['age', 'sex', 'class', 'fare', 'survived']]

DF.head()
```

	age	sex	class	fare	survived
0	22.0	male	Third	7.2500	0
1	38.0	female	First	71.2833	1
2	26.0	female	Third	7.9250	1

2) groupby()

- 'class' 기준의 DataFrameGroupBy 객체 생성

```
grouped = DF.groupby(['class'])
```

```
grouped
```

```
<pandas.core.groupby.generic.DataFrameGroupBy object at 0x7f3d7ee4ecc0>
```

- groupby 결과 확인(3개 그룹)
 - 'First', 'Second', 'Third' 키별 3줄씩 출력
 - .get_group('Key_Name')

```
for key in ['First', 'Second', 'Third']:
    print(grouped.get_group(key).head(3))
    print('\n')
```

	age	sex	class	fare	survived
1	38.0	female	First	71.2833	1
3	35.0	female	First	53.1000	1
6	54.0	male	First	51.8625	0

	age	sex	class	fare	survived
9	14.0	female	Second	30.0708	1
15	55.0	female	Second	16.0000	1
17	NaN	male	Second	13.0000	1

	age	sex	class	fare	survived
0	22.0	male	Third	7.250	0
2	26.0	female	Third	7.925	1
4	35.0	male	Third	8.050	0

- 3개 그룹별 평균('age', 'fare', 'survived')

```
grouped.mean()
```

	age	fare	survived
class			
First	38.233441	84.154687	0.629630
Second	29.877630	20.662183	0.472826

- 'Third' 키 그룹 정보 확인
 - `.get_group('Third')`

```
grouped.get_group('Third').head(3)
```

	age	sex	class	fare	survived
0	22.0	male	Third	7.250	0
2	26.0	female	Third	7.925	1
4	35.0	male	Third	8.050	0

- 두 개 키(Key) 사용하여 DataFrameGroupBy 객체 생성
 - 'class', 'sex' 키 적용

```
grouped_TWO = DF.groupby(['class', 'sex'])
```

```
grouped_TWO
```

```
<pandas.core.groupby.generic.DataFrameGroupBy object at 0x7f3d7e5de7b8>
```

- `groupby` 결과 확인(6개 그룹)

```
for key, group in grouped_TWO:
    print('* key :', key)
    print('* number :', len(group))
    print(group.head(3))
    print('Wn')
```

```
* key : ('First', 'female')
* number : 94
   age  sex  class  fare  survived
1  38.0 female First  71.2833         1
3  35.0 female First  53.1000         1
11 58.0 female First  26.5500         1
```

```
* key : ('First', 'male')
* number : 122
   age  sex  class  fare  survived
6  54.0 male First  51.8625         0
23 28.0 male First  35.5000         1
27 19.0 male First 263.0000         0
```

```
* key : ('Second', 'female')
* number : 76
   age    sex    class    fare  survived
9   14.0  female Second   30.0708        1
15  55.0  female Second   16.0000        1
41  27.0  female Second   21.0000        0
```

```
* key : ('Second', 'male')
* number : 108
   age    sex    class    fare  survived
17   NaN  male  Second   13.0        1
20  35.0  male  Second   26.0        0
21  34.0  male  Second   13.0        1
```

```
* key : ('Third', 'female')
* number : 144
   age    sex    class    fare  survived
2   26.0  female Third    7.9250        1
8   27.0  female Third   11.1333        1
10   4.0  female Third   16.7000        1
```

```
* key : ('Third', 'male')
* number : 347
   age    sex    class    fare  survived
0   22.0  male  Third    7.2500        0
4   35.0  male  Third    8.0500        0
5    NaN  male  Third    8.4583        0
```

- 6개 그룹별 평균('age', 'fare', 'survived')

```
grouped_TWO.mean()
```

		age	fare	survived
class	sex			
First	female	34.611765	106.125798	0.968085
	male	41.281386	67.226127	0.368852
Second	female	28.722973	21.970121	0.921053
	male	30.740707	19.741782	0.157407
Third	female	21.750000	16.118810	0.500000
	male	26.507589	12.661633	0.135447

- ('First', 'female') 키 그룹 정보 확인
 - .get_group(('First', 'female'))


```
grouped_TWO.get_group(('First', 'female')).head(3)
```

	age	sex	class	fare	survived
1	38.0	female	First	71.2833	1
3	35.0	female	First	53.1000	1
11	58.0	female	First	26.5500	1

3) agg()

- Aggregation : 여러개의 함수를 groupby 객체에 적용
 - 그룹별로 연산 결과를 집계하여 반환

```
grouped.agg(['mean', 'std'])
```

	age		fare		survived	
	mean	std	mean	std	mean	std
class						
First	38.233441	14.802856	84.154687	78.380373	0.629630	0.484026
Second	29.877630	14.001077	20.662183	13.417399	0.472826	0.500623
Third	25.140620	12.495398	13.675550	11.778142	0.242363	0.428949

```
grouped_TWO.agg(['mean', 'std'])
```

		age		fare		survived	
		mean	std	mean	std	mean	std
class	sex						
First	female	34.611765	13.612052	106.125798	74.259988	0.968085	0.176716
	male	41.281386	15.139570	67.226127	77.548021	0.368852	0.484484
Second	female	28.722973	12.872702	21.970121	10.891796	0.921053	0.271448
	male	30.740707	14.793894	19.741782	14.922235	0.157407	0.365882
Third	female	21.750000	12.729964	16.118810	11.690314	0.500000	0.501745
	male	26.507589	12.159514	12.661633	11.681696	0.135447	0.342694

```
grouped.fare.agg(['min', 'max'])
```

```

        min      max
class

```

```
grouped.agg({'fare' : ['min', 'max'], 'age' : ['mean', 'std']})
```

```

        fare      age
        min  max    mean    std
class
First    0.0  512.3292  38.233441  14.802856
Second  0.0   73.5000  29.877630  14.001077
Third   0.0   69.5500  25.140620  12.495398

```

▼ 4) transform()

- 그룹별로 함수를 적용하여 각 원소의 행과 열을 기준으로 연산 결과를 반환
 - 데이터프레임에 'z_score' 열(Column)을 추가
- 원본 DF

```
DF.head(3)
```

```

      age  sex  class  fare  survived
0  22.0  male  Third   7.2500         0
1  38.0  female  First  71.2833         1
2  26.0  female  Third   7.9250         1

```

- z_score() 표준화 함수 정의

```
def z_score(x) :
    return (x - x.mean()) / x.std()
```

- DF에 transform() 함수를 적용하여 'z_score' 열 추가
 - 3개 그룹별 'age' 변수에 대한 표준화 변수('z_score') 계산

```
DF['z_score'] = grouped.age.transform(z_score)
```

- 추가된 'z_score' 열 확인

```
DF.head(3)
```

```
df.head(3)
```

	age	sex	class	fare	survived	z_score
0	22.0	male	Third	7.2500	0	-0.251342
1	38.0	female	First	71.2833	1	-0.015770
2	26.0	female	Third	7.9250	1	0.068776

5) filter()

- 데이터 개수가 200개 이상인 그룹의 결과만 필터링
 - 'First', 'Third'

```
grouped.filter(lambda x : len(x) >= 200).head(3)
```

	age	sex	class	fare	survived	z_score
0	22.0	male	Third	7.2500	0	-0.251342
1	38.0	female	First	71.2833	1	-0.015770
2	26.0	female	Third	7.9250	1	0.068776

- 그룹별 데이터 개수

```
grouped.apply(len)
```

```
class
First    216
Second   184
Third    491
dtype: int64
```

- 'age' 열 평균이 30보다 작은 그룹의 결과만 필터링
 - 'Second', 'Third'

```
grouped.filter(lambda x: x.age.mean() < 30 ).tail(3)
```

	age	sex	class	fare	survived	z_score
886	27.0	male	Second	13.00	0	-0.205529
888	NaN	female	Third	23.45	0	NaN
890	32.0	male	Third	7.75	0	0.548953

- 그룹별 'age' 열의 평균

```
grouped.age.mean()
```

```
class
First    38.233441
Second   29.877630
Third     25.140620
Name: age, dtype: float64
```

▼ 6) apply()

- 각 그룹별 describe() 함수 적용

```
grouped.apply(lambda x: x.describe())
```

age fare survived z_score

class

- 각 그룹별 'age' 열의 평균값이 30보다 작은지 평가

```
grouped.apply(lambda x : x.age.mean() < 30)
```

```
class
First    False
Second   True
Third    True
dtype: bool
```

▼ VI. 멀티 인덱스

- 'class' 및 'sex' 기준의 DataFrameGroupBy 객체 생성

```
mean    29.811630    20.062185    0.412820   -1.043178e-11
```

```
grouped_M1 = DF.groupby(['class', 'sex'])
```

```
min    0.670000    0.000000    0.000000    0.000000e+00
```

- 6개 그룹별 mean() 함수 적용

```
grouped_M1.mean()
```

		age	fare	survived	z_score
class sex					
First	female	34.611765	106.125798	0.968085	-0.244661
	male	41.281386	67.226127	0.368852	0.205903
Second	female	28.722973	21.970121	0.921053	-0.082469
	male	30.740707	19.741782	0.157407	0.061644
Third	female	21.750000	16.118810	0.500000	-0.271349
	male	26.507589	12.661633	0.135447	0.109398

▼ 1) .xs('First', level = 'class')

```
grouped_M1.mean().xs('First', level = 'class')
```

	age	fare	survived	z_score
sex				
female	34.611765	106.125798	0.968085	-0.244661
male	41.281386	67.226127	0.368852	0.205903

▼ 2) .xs('female', level = 'sex')

```
grouped_MI.mean().xs('female', level = 'sex')
```

	age	fare	survived	z_score
class				
First	34.611765	106.125798	0.968085	-0.244661
Second	28.722973	21.970121	0.921053	-0.082469
Third	21.750000	16.118810	0.500000	-0.271349

▼ 3) .xs(['First', 'male'], level = ['class', 'sex'])

```
grouped_MI.mean().xs(['First', 'male'], level = ['class', 'sex'])
```

		age	fare	survived	z_score
class	sex				
First	male	41.281386	67.226127	0.368852	0.205903

▼ VII. pivot_table()

▼ 1) 실습용 'titanic' 데이터셋

```
import seaborn as sns
titanic = sns.load_dataset('titanic')

DF = titanic.loc[:, ['age', 'sex', 'class', 'fare', 'survived']]

DF.head(3)
```

	age	sex	class	fare	survived
0	22.0	male	Third	7.2500	0
1	38.0	female	First	71.2833	1
2	26.0	female	Third	7.9250	1

▼ 2) pivot_table() 구성요소

- index : 행 인덱스
- column : 열 인덱스
- values : 데이터
- aggfunc : 적용 함수

```
DF_1 = pd.pivot_table(DF,
                        index = 'class',
                        columns = 'sex',
                        values = 'age',
                        aggfunc = 'mean')
```

DF_1

	sex	female	male
class			
First		34.611765	41.281386
Second		28.722973	30.740707
Third		21.750000	26.507589

▼ 3) 두개의 적용 함수

```
DF_2 = pd.pivot_table(DF,
                        index = 'class',
                        columns = 'sex',
                        values = 'survived',
                        aggfunc = ['mean', 'sum'])
```

DF_2

	mean		sum	
sex	female	male	female	male
class				
First	0.968085	0.368852	91	45
Second	0.921053	0.157407	70	17
Third	0.500000	0.135447	72	47

▼ 4) 다중 인덱스, 다중 데이터, 다중 함수

```
DF_3 = pd.pivot_table(DF,
                        index = ['class', 'sex'],
```

```
columns = 'survived',
values = ['age', 'fare'],
aggfunc = ['mean', 'max'])
```

DF_3

		mean				max			
		age		fare		age		fare	
	survived	0	1	0	1	0	1	0	1
class	sex								
First	female	25.666667	34.939024	110.604167	105.978159	50.0	63.0	151.55	512.3
	male	44.581967	36.248000	62.894910	74.637320	71.0	80.0	263.00	512.3
Second	female	36.000000	28.080882	18.250000	22.288989	57.0	55.0	26.00	65.0
	male	33.369048	16.022000	19.488965	21.095100	70.0	62.0	73.50	39.0
Third	female	23.818182	19.329787	19.773093	12.464526	48.0	63.0	69.55	31.3
	male	27.255814	22.274211	12.204469	15.579696	74.0	45.0	69.55	56.4

5) 멀티 인덱스

- 행 : 멀티 인덱스

DF_3.index

```
MultiIndex([( 'First', 'female'),
            ( 'First', 'male'),
            ( 'Second', 'female'),
            ( 'Second', 'male'),
            ( 'Third', 'female'),
            ( 'Third', 'male')],
            names=['class', 'sex'])
```

- 열 : 멀티 인덱스

DF_3.columns

```
MultiIndex([('mean', 'age', 0),
            ('mean', 'age', 1),
            ('mean', 'fare', 0),
            ('mean', 'fare', 1),
            ('max', 'age', 0),
            ('max', 'age', 1),
            ('max', 'fare', 0),
            ('max', 'fare', 1)],
            names=[None, None, 'survived'])
```

- 행 멀티인덱스 : 'First'


```
DF_3.xs('First', axis = 0)
```

		mean				max			
		age		fare		age		fare	
survived	0	1	0	1	0	1	0	1	
sex									
female	25.666667	34.939024	110.604167	105.978159	50.0	63.0	151.55	512.3292	
male	44.581967	36.248000	62.894910	74.637320	71.0	80.0	263.00	512.3292	

- 행 멀티인덱스 : ('First','female')

```
DF_3.xs(('First','female'), axis = 0)
```

```

mean  age  0      25.666667
       1      34.939024
      fare 0      110.604167
          1      105.978159
max    age 0      50.000000
       1      63.000000
      fare 0      151.550000
          1      512.329200
Name: (First, female), dtype: float64
```

- 행 멀티인덱스 : 성별이 남자
 - names = ['class', 'sex']

```
DF_3.xs('male', level = 'sex', axis = 0)
```

		mean				max			
		age		fare		age		fare	
survived	0	1	0	1	0	1	0	1	
class									
First	44.581967	36.248000	62.894910	74.637320	71.0	80.0	263.00	512.3292	
Second	33.369048	16.022000	19.488965	21.095100	70.0	62.0	73.50	39.0000	
Third	27.255814	22.274211	12.204469	15.579696	74.0	45.0	69.55	56.4958	

- 행 멀티인덱스 : 객실등급이 일등실이면서 성별이 남자

```
DF_3.xs(('First', 'male'), level = ['class', 'sex'], axis = 0)
```

		mean				max			
		age		fare		age		fare	
survived		0	1	0	1	0	1	0	1
class	sex								

- 열 멀티인덱스 : 'mean'

```
DF_3.xs('mean', axis = 1)
```

		age		fare	
survived		0	1	0	1
class	sex				
First	female	25.666667	34.939024	110.604167	105.978159
	male	44.581967	36.248000	62.894910	74.637320
Second	female	36.000000	28.080882	18.250000	22.288989
	male	33.369048	16.022000	19.488965	21.095100
Third	female	23.818182	19.329787	19.773093	12.464526
	male	27.255814	22.274211	12.204469	15.579696

- 열 멀티인덱스 : ('mean', 'fare')

```
DF_3.xs(('mean', 'fare'), axis = 1)
```

		survived	
		0	1
class	sex		
First	female	110.604167	105.978159
	male	62.894910	74.637320
Second	female	18.250000	22.288989
	male	19.488965	21.095100
Third	female	19.773093	12.464526
	male	12.204469	15.579696

- 열 멀티인덱스 : 사망자의 최대 나이
 - names = [None, None, 'survived']

```
DF_3.xs(('max', 'age', 0), level = [0, 1, 'survived'], axis = 1)
```

		max
		age
survived		0
class	sex	
First	female	50.0
	male	71.0
Second	female	57.0
	male	70.0
Third	female	48.0
	male	71.0

- 열 멀티인덱스 : 생존자 정보

```
DF_3.xs(1, level = 'survived', axis = 1)
```

		mean		max	
		age	fare	age	fare
class	sex				
First	female	34.939024	105.978159	63.0	512.3292
	male	36.248000	74.637320	80.0	512.3292
Second	female	28.080882	22.288989	55.0	65.0000
	male	16.022000	21.095100	62.0	39.0000
Third	female	19.329787	12.464526	63.0	31.3875
	male	22.274211	15.579696	45.0	56.4958

#

The End

#

