Pandas 3
Data Preprocessing and Calculation

Data analysis process

Data Understanding	•Descriptive statistics •Types of data (numerical/categorical)
Data Preprocessing	•Subset selection •Data consolidation •Missing data handling
Calculation (Modeling)	•Derived variables •Data aggregation
Data Visualization	•Univariate chart •Bivariate chart •Multivariate chart

Outline

- Missing data handling
  - Pandas missing values
  - Detect missing values
  - Drop missing values
  - Fill in missing values
- Derived variables
- Data aggregation
  - Groupby
  - Pivot_table
  - Crosstab

Missing data

- Many real-world datasets may contain missing data (or missing values). Missing data may either be data that does not exist or that exists but not available.

- Examples:
  - Marketing survey or CRM system (Customer Relationship Management):
    - Customers choose not to answer some questions.
    - The customer did not complete the survey.
  - Clinical data:
    - Patient did not continue treatment.
    - No access to information for privacy reasons.
  - Database:
    - Data could not be fully collected due to connectivity issues or sensor failure.

Missing data in Pandas

- None is a Python object that is used for missing data.

```
x = None
type(x)
```

```
NoneType
```

- Pandas uses NaN (Not-a-Number) to represent missing values in numerical data types, and it often uses None to represent missing values in object data type.

```
s1 = pd.Series([1,2, None, 4])
s1
```

```
0    1.0
1    2.0
2    NaN
3    4.0
dtype: float64
```

```
type(s1[2])
```

```
numpy.float64
```

```
s2 = pd.Series(["A", "B", None, "D"])
s2
```

```
0       A
1       B
2    None
3       D
dtype: object
```

- NaN is a special floating-point value in the numpy package and is used to represent missing values in pandas.

Dataset with missing data

```
fashion_df = pd.read_csv("../dataset/fashion.csv")
fashion_df.head(15)
```

	Date	Amanda_Christensen	Calvin_Klein	Eton	J_Lindeberg	Lacoste	Levi_s	Oscar_Jacobson	Ray_Ban	Tiger_of_Sweden
0	2014-07-01	5744.000000	29976.0000	78835.127273	89833.846154	65226.40000	63884.8	18971.813333	NaN	287420.566400
1	2014-08-01	7372.800000	33969.0000	98835.054545	153530.892308	43368.68000	57153.6	48796.800000	NaN	322481.827200
2	2014-09-01	8881.000000	28602.0000	70640.000000	146138.461538	26553.20000	47048.0	37864.266667	NaN	263211.054400
3	2014-10-01	10693.215000	23257.0000	70230.181818	151481.846154	37045.60000	33032.0	23762.000000	NaN	295135.536000
4	2014-11-01	17121.800000	29817.0000	96073.745455	180756.000000	35666.80000	25476.0	41173.600000	NaN	328531.016000
5	2014-12-01	34321.600000	43738.5000	143256.363636	144416.615385	33796.40000	25960.8	47829.466667	NaN	519894.808000
6	2015-01-01	7085.200000	28526.5000	120765.818182	182552.492308	31064.80000	55235.2	30837.733333	NaN	300741.560000
7	2015-02-01	7233.600000	27148.4658	82245.672727	134998.584492	29403.62392	30020.8	21506.095840	19107.20000	270403.424000
8	2015-03-01	7635.205680	48290.5000	81373.939491	189940.558031	62399.68420	302.4	66656.124907	67636.40000	260036.051003
9	2015-04-01	8710.552920	30567.9132	80840.245018	136470.398400	73999.01736	NaN	52975.765947	57623.21312	200100.461966
10	2015-05-01	17661.463395	39250.6262	116184.852655	179055.8					
11	2015-06-01	12468.388200	56983.3720	87637.331418	122439.3					
12	2015-07-01	6179.535600	42632.2670	135494.885091	153376.0					
13	2015-08-01	13285.157680	40665.5152	154798.000145	138074.2					
14	2015-09-01	12214.492200	53042.9611	90523.556436	233688.1					

Open csv file in Notepad++

```
Date,Amanda_Christensen,Calvin_Klein,Eton,J_Lindeberg,Lacoste,Levi_s,Oscar_Jacobson,Ray_Ban,Tiger_of_Sweden
2014-07-01,5744,29976,78835.1272727272,89833.8461538462,65226.4,63884.8,18971.8133333333,,287420.566400001
2014-08-01,7372.8,33969,98835.0545454545,153530.892307692,43368.6799999999,57153.6,48796.8,,322481.827200001
2014-09-01,8881,28602,70639.9999999999,146138.461538462,26553.1999999999,47048,37864.2666666667,,263211.0544
2014-10-01,10693.215,23257,70230.1818181817,151481.846153846,37045.5999999999,33032,23762,,295135.536000001
2014-11-01,17121.8,29817,96073.7454545454,180756.000000001,35666.8,25476,41173.6,,328531.016000001
2014-12-01,34321.5999999999,43738.5,143256.363636364,144416.615384615,33796.4,25960.8,47829.4666666667,,519894.808000004
2015-01-01,7085.2,28526.5,120765.818181818,182552.492307693,31064.7999999999,55235.2,30837.7333333333,,300741.560000001
2015-02-01,7233.6,27148.4658,82245.6727272726,134998.584492308,29403.62392,30020.8,21506.09584,19107.2,270403.424
```

https://pandas.pydata.org/pandas-docs/dev/user_guide/missing_data.html

Non-null count

- Use `info()` to see the number of non-missing values in each column.

```
fashion_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 51 entries, 0 to 50
Data columns (total 10 columns):
 #   Column              Non-Null Count  Dtype
---  ------              --------------  -----
 0   Date                51 non-null     object
 1   Amanda_Christensen  51 non-null     float64
 2   Calvin_Klein        51 non-null     float64
 3   Eton                51 non-null     float64
 4   J_Lindeberg         51 non-null     float64
 5   Lacoste             51 non-null     float64
 6   Levi_s              22 non-null     float64
 7   Oscar_Jacobson      51 non-null     float64
 8   Ray_Ban             44 non-null     float64
 9   Tiger_of_Sweden     51 non-null     float64
dtypes: float64(9), object(1)
memory usage: 4.1+ KB
```

Handling missing data

- A list of methods for missing data.

Method	Description
`isna`	Return Boolean values indicating which values are missing.
`notna`	Negation of isna.
`dropna`	Filter out missing data.
`fillna`	Fill in missing data with some value or using an interpolation method such as ‘ffill’ or ‘bfill’

isna

- Use `isna()` to detect if the value is missing.

	Q1	Q2	Q3	Q4
A	176.0	214.0	78.0	219.0
B	132.0	180.0	232.0	158.0
C	157.0	230.0	218.0	188.0
D	NaN	NaN	NaN	NaN
E	135.0	185.0	175.0	203.0
F	108.0	123.0	188.0	163.0
G	NaN	213.0	129.0	NaN
H	191.0	143.0	NaN	189.0
I	191.0	245.0	80.0	242.0
J	136.0	213.0	71.0	204.0

```
sales_df.isna()
```

	Q1	Q2	Q3	Q4
A	False	False	False	False
B	False	False	False	False
C	False	False	False	False
D	True	True	True	True
E	False	False	False	False
F	False	False	False	False
G	True	False	False	True
H	False	False	True	False
I	False	False	False	False
J	False	False	False	False

By default, the `sum()` function sums values across rows (axis =0).

True = 1
False = 0

```
sales_df.isna().sum()
```

```
Q1    2
Q2    1
Q3    2
Q4    2
dtype: int64
```

The number of missing values for each column.

```
sales_df.isna().sum(axis = 1)
```

```
A    0
B    0
C    0
D    4
E    0
F    0
G    2
H    1
I    0
J    0
dtype: int64
```

The number of missing values for each row.

https://pandas.pydata.org/docs/reference/api/pandas.DataFrame.isnull.html

isna

- Use `isna()` to filter data.

	Q1	Q2	Q3	Q4
A	176.0	214.0	78.0	219.0
B	132.0	180.0	232.0	158.0
C	157.0	230.0	218.0	188.0
D	NaN	NaN	NaN	NaN
E	135.0	185.0	175.0	203.0
F	108.0	123.0	188.0	163.0
G	NaN	213.0	129.0	NaN
H	191.0	143.0	NaN	189.0
I	191.0	245.0	80.0	242.0
J	136.0	213.0	71.0	204.0

```
sales_df.Q1.isna()
```

```
A    False
B    False
C    False
D     True
E    False
F    False
G     True
H    False
I    False
J    False
Name: Q1, dtype: bool
```

Boolean array

```
sales_df[sales_df.Q1.isna()]
```

	Q1	Q2	Q3	Q4
D	NaN	NaN	NaN	NaN
G	NaN	213.0	129.0	NaN

Select rows with missing Q1 data

dropna – (1) drop rows

- Use `dropna(how="any")` to remove the rows containing any NaNs.

	Q1	Q2	Q3	Q4	
A	176.0	214.0	78.0	219.0	
B	132.0	180.0	232.0	158.0	
C	157.0	230.0	218.0	188.0	
D	NaN	NaN	NaN	NaN	✘
E	135.0	185.0	175.0	203.0	
F	108.0	123.0	188.0	163.0	
G	NaN	213.0	129.0	NaN	✘
H	191.0	143.0	NaN	189.0	✘
I	191.0	245.0	80.0	242.0	
J	136.0	213.0	71.0	204.0	

10 rows

```
sales_df.dropna()
```

By default, how="any"

	Q1	Q2	Q3	Q4
A	176.0	214.0	78.0	219.0
B	132.0	180.0	232.0	158.0
C	157.0	230.0	218.0	188.0
E	135.0	185.0	175.0	203.0
F	108.0	123.0	188.0	163.0
I	191.0	245.0	80.0	242.0
J	136.0	213.0	71.0	204.0

7 rows

https://pandas.pydata.org/docs/reference/api/pandas.DataFrame.dropna.html

dropna – (1) drop rows

- Use `dropna(how="all")` to remove the rows that are all NaN.

	Q1	Q2	Q3	Q4
A	176.0	214.0	78.0	219.0
B	132.0	180.0	232.0	158.0
C	157.0	230.0	218.0	188.0
D	NaN	NaN	NaN	NaN
E	135.0	185.0	175.0	203.0
F	108.0	123.0	188.0	163.0
G	NaN	213.0	129.0	NaN
H	191.0	143.0	NaN	189.0
I	191.0	245.0	80.0	242.0
J	136.0	213.0	71.0	204.0

10 rows

```
sales_df.dropna(how = "all")
```

	Q1	Q2	Q3	Q4
A	176.0	214.0	78.0	219.0
B	132.0	180.0	232.0	158.0
C	157.0	230.0	218.0	188.0
E	135.0	185.0	175.0	203.0
F	108.0	123.0	188.0	163.0
G	NaN	213.0	129.0	NaN
H	191.0	143.0	NaN	189.0
I	191.0	245.0	80.0	242.0
J	136.0	213.0	71.0	204.0

9 rows

Exercise

Exercise A

(A.1) The results of three exams for 8 students are recorded in the following dataframe. Shows the number of students who were absent for each exam.

Hint: Count the number of missing values in each column.

```
score_df = pd.DataFrame({"Exam1": [7.5, 9, None, 6, 8.5, 8, None, 7],
                         "Exam2": [6, None, 8.5, None, 9.5, 7, None, 8],
                         "Exam3": [8.5, 7.5, 6, 6.5, 9, 7.5, None, 9]} )
score_df
```

	Exam1	Exam2	Exam3
0	7.5	6.0	8.5
1	9.0	NaN	7.5
2	NaN	8.5	6.0
3	6.0	NaN	6.5
4	8.5	9.5	9.0
5	8.0	7.0	7.5
6	NaN	NaN	NaN
7	7.0	8.0	9.0

(A.2) Delete the data for students who were absent from all three exams and print out the dimensions of the updated dataframe.

dropna – (1) drop rows

- Define in which columns to look for missing values.

	Q1	Q2	Q3	Q4
A	176.0	214.0	78.0	219.0
B	132.0	180.0	232.0	158.0
C	157.0	230.0	218.0	188.0
D	NaN	NaN	NaN	NaN
E	135.0	185.0	175.0	203.0
F	108.0	123.0	188.0	163.0
G	NaN	213.0	129.0	NaN
H	191.0	143.0	NaN	189.0
I	191.0	245.0	80.0	242.0
J	136.0	213.0	71.0	204.0

10 rows

```
sales_df.dropna(subset = ['Q1', 'Q3'], how = "all")
```

	Q1	Q2	Q3	Q4
A	176.0	214.0	78.0	219.0
B	132.0	180.0	232.0	158.0
C	157.0	230.0	218.0	188.0
E	135.0	185.0	175.0	203.0
F	108.0	123.0	188.0	163.0
G	NaN	213.0	129.0	NaN
H	191.0	143.0	NaN	189.0
I	191.0	245.0	80.0	242.0
J	136.0	213.0	71.0	204.0

9 rows

dropna – (2) drop columns

- To drop the columns in the same way, pass `axis=1`.

	Q1	Q2	Q3	Q4
A	176	214	78.0	219.0
B	132	180	232.0	158.0
C	157	230	218.0	NaN
D	212	192	NaN	NaN
E	135	185	175.0	203.0
F	108	123	188.0	163.0
G	151	213	129.0	NaN
H	191	143	NaN	189.0
I	191	245	80.0	242.0
J	136	213	71.0	204.0

4 columns

```
sales_df2.dropna(axis = 1)
```

	Q1	Q2
A	176	214
B	132	180
C	157	230
D	212	192
E	135	185
F	108	123
G	151	213
H	191	143
I	191	245
J	136	213

2 columns

fillna – (1) constant value

- Replace all missing values in the entire dataframe with a constant value.

	Month	Oslo	Bergen
0	Jan	266.0	198.0
1	Feb	145.9	154.2
2	Mar	183.1	177.3
3	Apr	NaN	NaN
4	May	180.3	160.9
5	Jun	168.5	188.7
6	Jul	231.8	191.0
7	Aug	NaN	207.4
8	Sep	192.8	NaN
9	Oct	122.9	168.3
10	Nov	203.4	179.6
11	Dec	211.7	180.2

```
month_sales_df.fillna(0)
```

	Month	Oslo	Bergen
0	Jan	266.0	198.0
1	Feb	145.9	154.2
2	Mar	183.1	177.3
3	Apr	0.0	0.0
4	May	180.3	160.9
5	Jun	168.5	188.7
6	Jul	231.8	191.0
7	Aug	0.0	207.4
8	Sep	192.8	0.0
9	Oct	122.9	168.3
10	Nov	203.4	179.6
11	Dec	211.7	180.2

- Replace missing values in a specific column with a constant value.

```
month_sales_df.Oslo.fillna(0)
```

```
0     266.0
1     145.9
2     183.1
3       0.0
4     180.3
5     168.5
6     231.8
7       0.0
8     192.8
9     122.9
10    203.4
11    211.7
Name: Oslo, dtype: float64
```

https://pandas.pydata.org/pandas-docs/stable/reference/api/pandas.DataFrame.fillna.html

fillna – (2) forward

- Replace missing values with the last valid observation.

```
month_sales_df
```

	Month	Oslo	Bergen
0	Jan	266.0	198.0
1	Feb	145.9	154.2
2	Mar	183.1	177.3
3	Apr	NaN	NaN
4	May	180.3	160.9
5	Jun	168.5	188.7
6	Jul	231.8	191.0
7	Aug	NaN	207.4
8	Sep	192.8	NaN
9	Oct	122.9	168.3
10	Nov	203.4	179.6
11	Dec	211.7	180.2

```
month_sales_df.fillna(method = "ffill")
```

	Month	Oslo	Bergen
0	Jan	266.0	198.0
1	Feb	145.9	154.2
2	Mar	183.1	177.3
3	Apr	183.1	177.3
4	May	180.3	160.9
5	Jun	168.5	188.7
6	Jul	231.8	191.0
7	Aug	231.8	207.4
8	Sep	192.8	207.4
9	Oct	122.9	168.3
10	Nov	203.4	179.6
11	Dec	211.7	180.2

fillna – (3) backward

- Replace missing values with the next valid observation.

```
month_sales_df
```

	Month	Oslo	Bergen
0	Jan	266.0	198.0
1	Feb	145.9	154.2
2	Mar	183.1	177.3
3	Apr	NaN	NaN
4	May	180.3	160.9
5	Jun	168.5	188.7
6	Jul	231.8	191.0
7	Aug	NaN	207.4
8	Sep	192.8	NaN
9	Oct	122.9	168.3
10	Nov	203.4	179.6
11	Dec	211.7	180.2

```
month_sales_df.fillna(method = "bfill")
```

	Month	Oslo	Bergen
0	Jan	266.0	198.0
1	Feb	145.9	154.2
2	Mar	183.1	177.3
3	Apr	180.3	160.9
4	May	180.3	160.9
5	Jun	168.5	188.7
6	Jul	231.8	191.0
7	Aug	192.8	207.4
8	Sep	192.8	168.3
9	Oct	122.9	168.3
10	Nov	203.4	179.6
11	Dec	211.7	180.2

Exercise

Exercise.B

(B.1) Import the dataset `melbourne.csv`. Calculate the number of missing value in each columns.

(B.2) Use the dataframe in (B.1). The `Car` column records the number of parking spaces for each property. What is the average number of parking spaces in this dataset?
Hint: `df.column.mean()`

(B.3) Use the dataframe in (B.1). Fill the missing values in the `Car` column with 0 and apply this change directly to the data frame. What is the average number of parking space?

Derived variables

Derived variables

- Create a new column derived from existing columns
  - Example-1: Calculate the sum of all the values over the column axis.

	grocery	transportation	dining out	entertainment
Jan	3050	1050	1200	1250
Feb	2800	900	1950	1050
Mar	2750	1150	1350	2500
Apr	2300	1850	3250	3150
May	3150	1250	1050	2000
Jun	2900	950	2800	1050

```
df_expense["total_expense"] = df_expense.sum(axis = 1)
df_expense
```

	grocery	transportation	dining out	entertainment	total_expense
Jan	3050	1050	1200	1250	6550
Feb	2800	900	1950	1050	6700
Mar	2750	1150	1350	2500	7750
Apr	2300	1850	3250	3150	10550
May	3150	1250	1050	2000	7450
Jun	2900	950	2800	1050	7700

Other methods: `mean()`, `max()`, `min()`

Derived variables

- Example-2: Calculate the sum of the values of two columns

```
df_expense['necessary_expense']  = df_expense.grocery + df_expense.transportation
df_expense
```

	grocery	transportation	dining out	entertainment	total_expense	necessary_expense
Jan	3050	1050	1200	1250	6550	4100
Feb	2800	900	1950	1050	6700	3700
Mar	2750	1150	1350	2500	7750	3900
Apr	2300	1850	3250	3150	10550	4150
May	3150	1250	1050	2000	7450	4400
Jun	2900	950	2800	1050	7700	3850

Derived variables

- Example 3: Calculate the percentage

```
df_expense['necessary_expense(%)'] =  round((df_expense.necessary_expense/ df_expense.total_expense)*100,2)
df_expense
```

	grocery	transportation	dining out	entertainment	total_expense	necessary_expense	necessary_expense(%)
Jan	3050	1050	1200	1250	6550	4100	62.60
Feb	2800	900	1950	1050	6700	3700	55.22
Mar	2750	1150	1350	2500	7750	3900	50.32
Apr	2300	1850	3250	3150	10550	4150	39.34
May	3150	1250	1050	2000	7450	4400	59.06
Jun	2900	950	2800	1050	7700	3850	50.00

$$\frac{4100}{6550} \times 100 = 62.60$$

Derived variables

- Example-4: Convert numerical data to categorical data
  - Use `cut()` to segment and sort continuous data into bins.

Points	Grade
75-100	A
65-74	B
55-64	C
45-54	D
35-44	E
0-34	F

bin edges for the segmentation

```
score_df["grade"] = pd.cut(score_df.score, bins = [0,34,44,54,64,74,100],
                           labels = ["F","E","D","C","B","A"],
                           include_lowest= True)
score_df
```

	score
0	75
1	60
2	40
3	100
4	85
5	55
6	65
7	20
8	70
9	0

	score	grade
0	75	A
1	60	C
2	40	E
3	100	A
4	85	A
5	55	C
6	65	B
7	20	F
8	70	B
9	0	F

By default, bins include the rightmost edge (`right = True`)

- include_lowerst = True ➔ [0,34]
- include_lowerst = False ➔ (0,34]

https://pandas.pydata.org/docs/reference/api/pandas.cut.html

Exercise

	Q1	Q2	Q3	Q4
A	124	132	150	128
B	148	131	142	138
C	126	125	157	128
D	102	150	133	126
E	116	119	152	159

Exercise.C

(C.1) Given the dataframe `product_df` above, each column represents quarterly sales, and the index is the product name. Caculate the annual sales of each product.

Expected output:

	Q1	Q2	Q3	Q4	Annual
A	124	132	150	128	534
B	...	...	...	...	...
C	...	...	...	...	...

(C.2) For each product, calculate first-half sales as a percentage of annual sales. Round numbers to two decimal places.

Expected output:

	Q1	Q2	Q3	Q4	Annual	H1(%)
A	124	132	150	128	534	47.94
B	...	...	...	...	...	...
C	...	...	...	...	...	...

$$H1(\%) = \frac{Q1 + Q2}{Annual} \times 100$$

Data aggregation

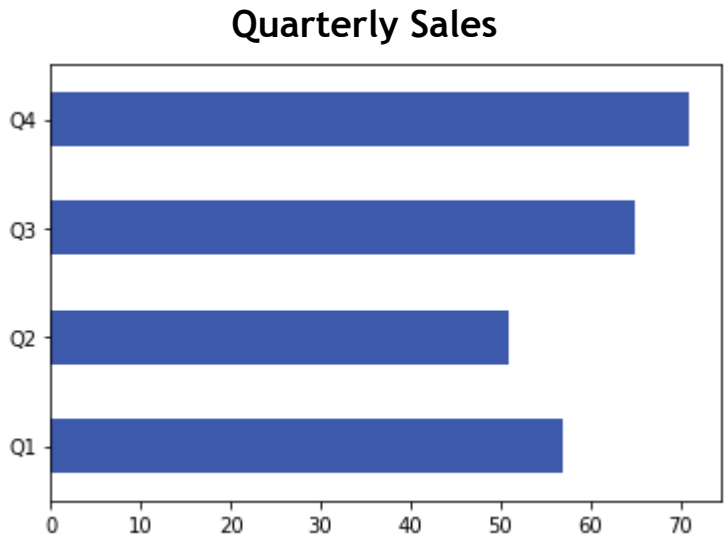
Data aggregation

- In some cases, you may need to compute group statistics for reporting or visualization purposes.

Quarter	Month	Sales
Q1	1	20
Q1	2	16
Q1	3	21
Q2	4	15
Q2	5	14
Q2	6	22
Q3	7	27
Q3	8	15
Q3	9	23
Q4	10	25
Q4	11	22
Q4	12	24

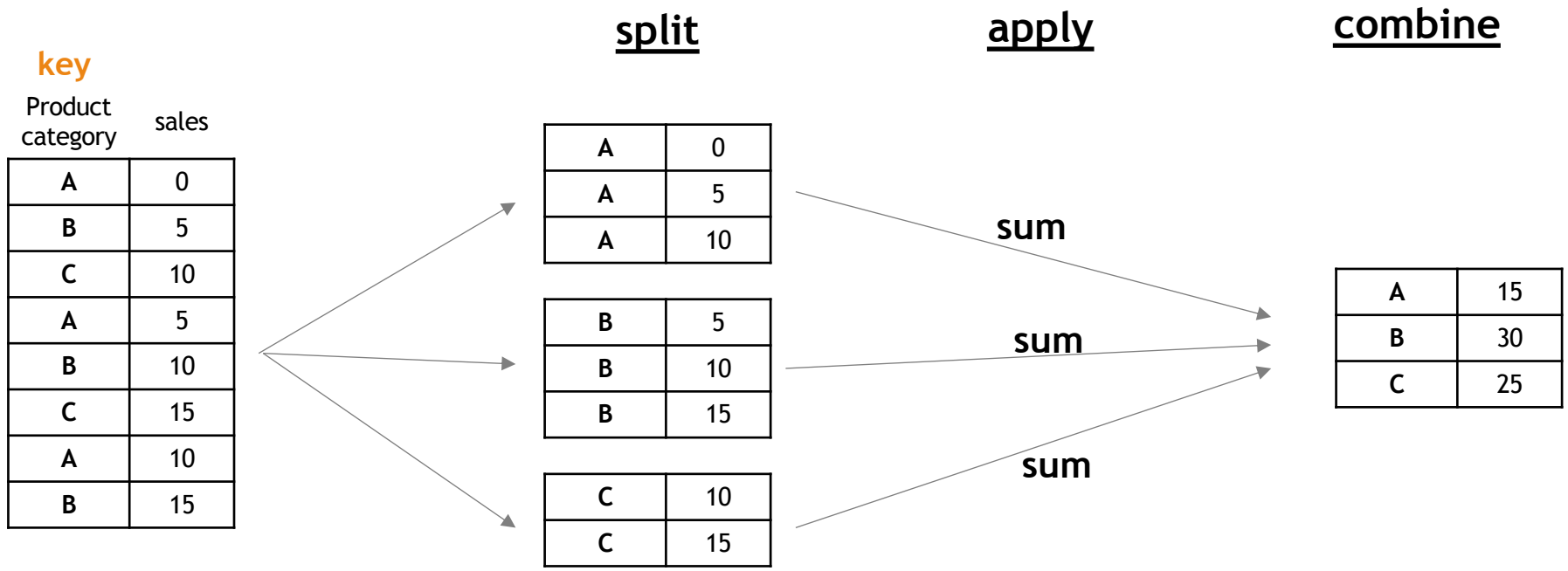
20+16+21 = 57

Quarter	Sales
Q1	57
Q2	51
Q3	65
Q4	71



Group by: split-apply-combine

- "Group by" means a process involving the following steps:
  - Splitting the data into groups based on key(s).
  - Applying a function to each group independently.
  - Combining the results into a data structure.



GroupBy object

- Use `groupby()` to group the data according to the keys and apply a function to the groups.
- The method `groupby()` returns a `GroupBy` object.

	Product	Quarter	Month	Sales
0	A	Q1	Jan	67
1	A	Q1	Feb	57
2	A	Q1	Mar	87
3	A	Q2	Apr	50
4	A	Q2	May	97
5	A	Q2	Jun	68
6	B	Q1	Jan	78
7	B	Q1	Feb	102
8	B	Q1	Mar	113
9	B	Q2	Apr	98
10	B	Q2	May	80
11	B	Q2	Jun	84

```
sales_gb_product = sales_df.groupby("Product")
type(sales_gb_product)
```

```
pandas.core.groupby.generic.DataFrameGroupBy
```

```
sales_gb_product.groups
```

```
{'A': [0, 1, 2, 3, 4, 5], 'B': [6, 7, 8, 9, 10, 11]}
```

https://pandas.pydata.org/docs/reference/groupby.html

GroupBy object - statistics

- The **GroupBy object** has all of the information needed to then apply some operation to each of the groups.

	Product	Quarter	Month	Sales
0	A	Q1	Jan	67
1	A	Q1	Feb	57
2	A	Q1	Mar	87
3	A	Q2	Apr	50
4	A	Q2	May	97
5	A	Q2	Jun	68
6	B	Q1	Jan	78
7	B	Q1	Feb	102
8	B	Q1	Mar	113
9	B	Q2	Apr	98
10	B	Q2	May	80
11	B	Q2	Jun	84

```
sales_gb_product.size()
```

```
Product
A    6
B    6
dtype: int64
```

```
sales_gb_product.Sales.mean()
```

```
Product
A    71.0
B    92.5
Name: Sales, dtype: float64
```

Calculate the average of a numeric column

Other methods: `mean()`, `max()`, `min()`

GroupBy object - statistics

- Use `agg()` to aggregate more operations.

	Product	Quarter	Month	Sales
0	A	Q1	Jan	67
1	A	Q1	Feb	57
2	A	Q1	Mar	87
3	A	Q2	Apr	50
4	A	Q2	May	97
5	A	Q2	Jun	68
6	B	Q1	Jan	78
7	B	Q1	Feb	102
8	B	Q1	Mar	113
9	B	Q2	Apr	98
10	B	Q2	May	80
11	B	Q2	Jun	84

```
sales_gb_product.Sales.agg(['mean','min','max'])
```

Product	mean	min	max
A	71.0	50	97
B	92.5	78	113

Exercise

Exercise D

(D.1) Given the following data frame. What is the highest score in Exam1 and the highest score in Exam2?

```
exam_df = pd.DataFrame({"ID":["S01","S02","S03","S04","S01","S02","S03","S04"],
                        "Exam":["Exam1","Exam1","Exam1","Exam1","Exam2","Exam2","Exam2","Exam2"],
                        "Score":[79, 56, 75, 93, 73, 73, 65, 87]})
exam_df
```

	ID	Exam	Score
0	S01	Exam1	79
1	S02	Exam1	56
2	S03	Exam1	75
3	S04	Exam1	93
4	S01	Exam2	73
5	S02	Exam2	73
6	S03	Exam2	65
7	S04	Exam2	87

```
Exam
Exam1    93
Exam2    87
Name: Score, dtype: int64
```

(D.2) The final score is calculated from the average of Exam1 and Exam2. Calculate final score for all students.

```
ID
S01    76.0
S02    64.5
S03    70.0
S04    90.0
Name: Score, dtype: float64
```

GroupBy object – two keys

- Grouping the data according to a list of keys.

	Product	Quarter	Month	Sales
0	A	Q1	Jan	67
1	A	Q1	Feb	57
2	A	Q1	Mar	87
3	A	Q2	Apr	50
4	A	Q2	May	97
5	A	Q2	Jun	68
6	B	Q1	Jan	78
7	B	Q1	Feb	102
8	B	Q1	Mar	113
9	B	Q2	Apr	98
10	B	Q2	May	80
11	B	Q2	Jun	84

```
sales_gb_product_Q = sales_df.groupby(['Product','Quarter'])
```

```
sales_gb_product_Q.groups
```

```
{('A', 'Q1'): [0, 1, 2], ('A', 'Q2'): [3, 4, 5], ('B', 'Q1'): [6, 7, 8], ('B', 'Q2'): [9, 10, 11]}
```

2 products × 2 quarters = 4 groups

GroupBy object – two keys

- Statistics

	Product	Quarter	Month	Sales
0	A	Q1	Jan	67
1	A	Q1	Feb	57
2	A	Q1	Mar	87
3	A	Q2	Apr	50
4	A	Q2	May	97
5	A	Q2	Jun	68
6	B	Q1	Jan	78
7	B	Q1	Feb	102
8	B	Q1	Mar	113
9	B	Q2	Apr	98
10	B	Q2	May	80
11	B	Q2	Jun	84

```
sales_gb_product_Q.Sales.sum()
```

```
Product  Quarter
A        Q1         211
         Q2         215
B        Q1         293
         Q2         262
Name: Sales, dtype: int64
```

Total sales of each product per quarter

- MultiIndex https://pandas.pydata.org/docs/user_guide/advanced.html

Other methods: (1) pivot_table

- Use method `pivot_table()` to get a spreadsheet-style pivot table from a DataFrame.

	Product	Quarter	Month	Sales
0	A	Q1	Jan	67
1	A	Q1	Feb	57
2	A	Q1	Mar	87
3	A	Q2	Apr	50
4	A	Q2	May	97
5	A	Q2	Jun	68
6	B	Q1	Jan	78
7	B	Q1	Feb	102
8	B	Q1	Mar	113
9	B	Q2	Apr	98
10	B	Q2	May	80
11	B	Q2	Jun	84

```
sales_df.pivot_table(index = "Product",
                     columns = "Quarter",
                     values = "Sales",
                     aggfunc = sum)
```

Quarter	Q1	Q2
Product		
A	211	215
B	293	262

https://pandas.pydata.org/docs/reference/api/pandas.pivot_table.html

Other methods: (2) crosstab

- Use the pandas function `crosstab()` to compute a crosstab of two (or more) categorical columns.

	Product	Quarter	Month	Sales
0	A	Q1	Jan	67
1	A	Q1	Feb	57
2	A	Q1	Mar	87
3	A	Q2	Apr	50
4	A	Q2	May	97
5	A	Q2	Jun	68
6	B	Q1	Jan	78
7	B	Q1	Feb	102
8	B	Q1	Mar	113
9	B	Q2	Apr	98
10	B	Q2	May	80
11	B	Q2	Jun	84

```
pd.crosstab(index = sales_df.Product,
            columns = sales_df.Quarter,
            values = sales_df.Sales,
            aggfunc = sum)
```

Quarter	Q1	Q2
Product		
A	211	215
B	293	262

https://pandas.pydata.org/docs/reference/api/pandas.crosstab.html

Exercise

Exercise.E

(E.1) The data below records quarterly sales for two stores in Bergen and Oslo. What are the total annual sales in 2019 and 2020?

```
product_df
```

	Year	Quarter	Location	Sales
0	2019	Q1	Oslo	136
1	2019	Q2	Oslo	146
2	2019	Q3	Oslo	147
3	2019	Q4	Oslo	214
4	2019	Q1	Bergen	178
5	2019	Q2	Bergen	188
6	2019	Q3	Bergen	210
7	2019	Q4	Bergen	111
8	2020	Q1	Oslo	203
9	2020	Q2	Oslo	100
10	2020	Q3	Oslo	144
11	2020	Q4	Oslo	197
12	2020	Q1	Bergen	177
13	2020	Q2	Bergen	100
14	2020	Q3	Bergen	189
15	2020	Q4	Bergen	194

(E.2) What are the annual sales of the two stores in 2019 and 2020?

```
Year
2019    1330
2020    1304
Name: Sales, dtype: int64
```

```
Year  Location
2019  Bergen      687
      Oslo        643
2020  Bergen      660
      Oslo        644
Name: Sales, dtype: int64
```

More on data aggregation

- `crosstab()` is often used to build contingency tables for categorical data to understand the frequency of combinations of values.

	ID	age_group	vaccinated
0	101	<18	No
1	102	18-64	No
2	103	18-64	Yes
3	104	18-64	No
4	105	18-64	Yes
5	106	<18	No
6	107	18-64	No
7	108	18-64	Yes
8	109	>65	Yes
9	110	<18	Yes

```
pd.crosstab(df_covid.age_group, df_covid.vaccinated)
```

vaccinated	No	Yes
age_group		
18-64	3	3
<18	2	1
>65	0	1

A contingency table displays the frequency of occurrence of two or more categorical variables.

More on data aggregation

- Use `pivot_table` to calculate various statistics on different columns.

	Day	Hour	Temperature	Humidity
0	1	01-08	5	0.75
1	1	09-18	11	0.53
2	1	17-24	8	0.74
3	2	01-08	5	0.35
4	2	09-18	9	0.57
5	2	17-24	12	0.63
6	3	01-08	4	0.84
7	3	09-18	11	0.82
8	3	17-24	8	0.89
9	4	01-08	6	0.45
10	4	09-18	13	0.10
11	4	17-24	11	0.41
12	5	01-08	5	0.78
13	5	09-18	12	0.14
14	5	17-24	10	0.62

```
weather_df.pivot_table(index = "Day",
                       values = ["Temperature", "Humidity"],
                       aggfunc = {"Temperature":["min", "max"], "Humidity":["mean"]}).round(2)
```

	Humidity	Temperature	
	mean	max	min
Day			
1	0.67	11	5
2	0.52	12	5
3	0.85	11	4
4	0.32	13	6
5	0.51	12	5

Recall: Python variables and memory allocation

- If one variable is assigned to another variable, both variables point to the same memory address.

```
x = [1,2,3]
```

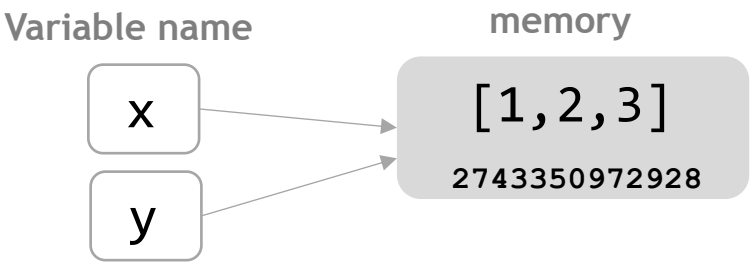
```
id(x)
```

```
2743350972928
```

```
y = x
```

```
id(y)
```

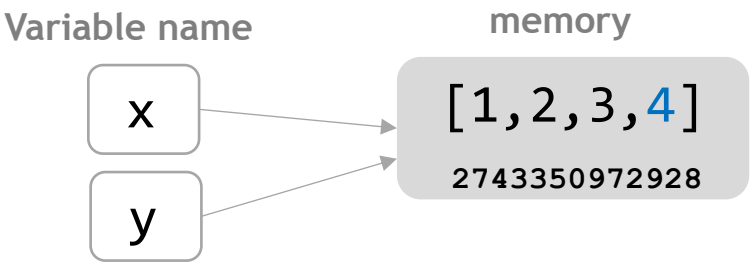
```
2743350972928
```



- If two variables point to the same address, changing the value of one variable will change the value of the other variable.

```
y.append(4)
print(x)
print(y)
```

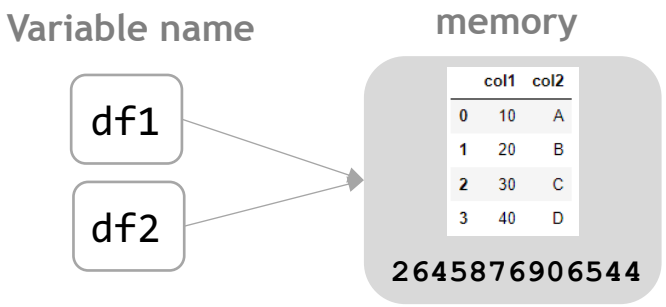
```
[1, 2, 3, 4]
[1, 2, 3, 4]
```



Create a copy of a DataFrame

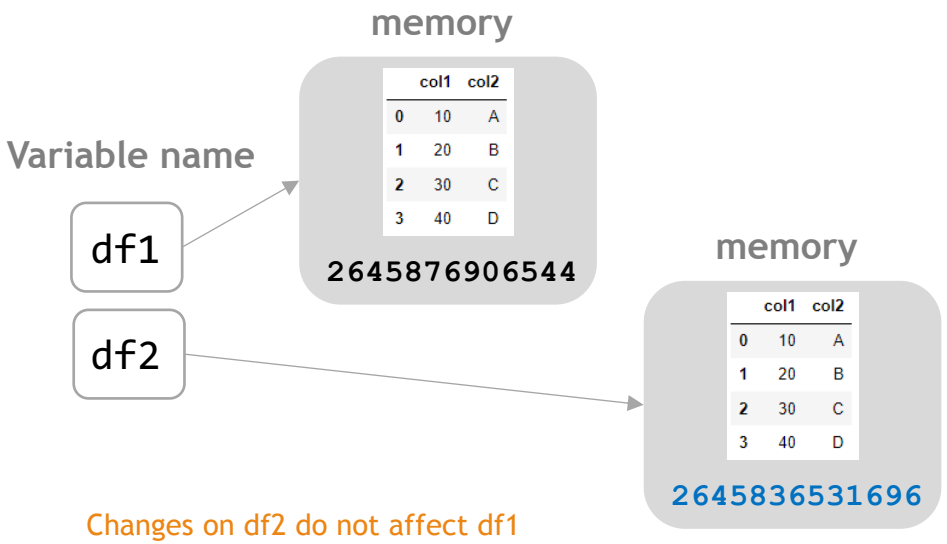
- To avoid modifying the source DataFrame when manipulating the data, you can use copy() to create a copied DataFrame in advance.

```
df2 = df1
```



Changes on df2 also affect df1.

```
df2 = df1.copy()
```



Changes on df2 do not affect df1