DSC510: Introduction to Data Science and Analytics
Lab 2: Data Handling

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Data science project workflow

1. **Problem definition** – understand the business/research question.
2. **Data collection** – gather data from files, databases, APIs
3. **Exploratory Data Analysis (EDA)** – explore structure, summarize with statistics, visualize patterns, detect anomalies. – LAB2, LAB3
   - EDA is iterative: usually do a first pass on raw data (before data preparation) to understand issues, then clean, then explore again more reliably
4. **Data preparation** – fix/clean missing values, inconsistencies, errors, perform basic transformations. – LAB4, LAB5
5. **Modeling** – build and evaluate machine learning models. – LAB 6, LAB7, LAB8
6. **Deployment & monitoring/maintenance** – put the model into production, track performance and provide maintenance.

Can EDA be performed before data cleaning?

- EDA can be performed before and after data cleaning.

- Practical approach in projects
  - Initial (dirty) EDA → inspect raw data as is to spot problems.
  - Data cleaning & preprocessing → fix missing values, errors, outliers.
  - Refined EDA → redo visualizations and statistics on the cleaned dataset.

- EDA is iterative. We usually do a first pass on raw data to understand issues, then clean, then explore again more reliably.

What is Exploratory Data Analysis (EDA)?

- EDA is the process of exploring and understanding a dataset before formal modeling.
- It combines summary statistics and visualizations.
- Main goals:
  - Provides the first understanding of the dataset
  - Discover patterns and relationships between variables
  - Detect anomalies or missing data
  - Test initial hypotheses
    - look for evidences (numerical / visual) that either confirm or contradict your early ideas
  - Guides the choice of appropriate methods and algorithms

Python Libraries for Data Science

Many popular Python toolboxes/libraries:

Data Manipulation and Pre-processing (Labs 2, 4, 5)

- NumPy
- SciPy
- **Pandas**

Data Visualization (Lab 3)

- **matplotlib**
- **seaborn**

Machine Learning (Labs 6-11)

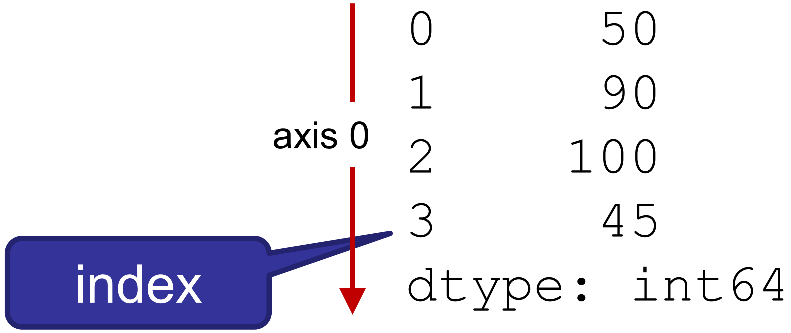
- **SciKit-Learn**

Introduction to Pandas

- Pre-installed in Anaconda
  - No need to install it separately
  - import it to a notebook using: `import pandas as pd`
    - pd is the de facto abbreviation for Pandas used by the data science community
- Primary data structures in Pandas:
  - Series
  - DataFrames

Pandas: Series & DataFrames Examples

- A **Series** is a one-dimensional array with axis labels

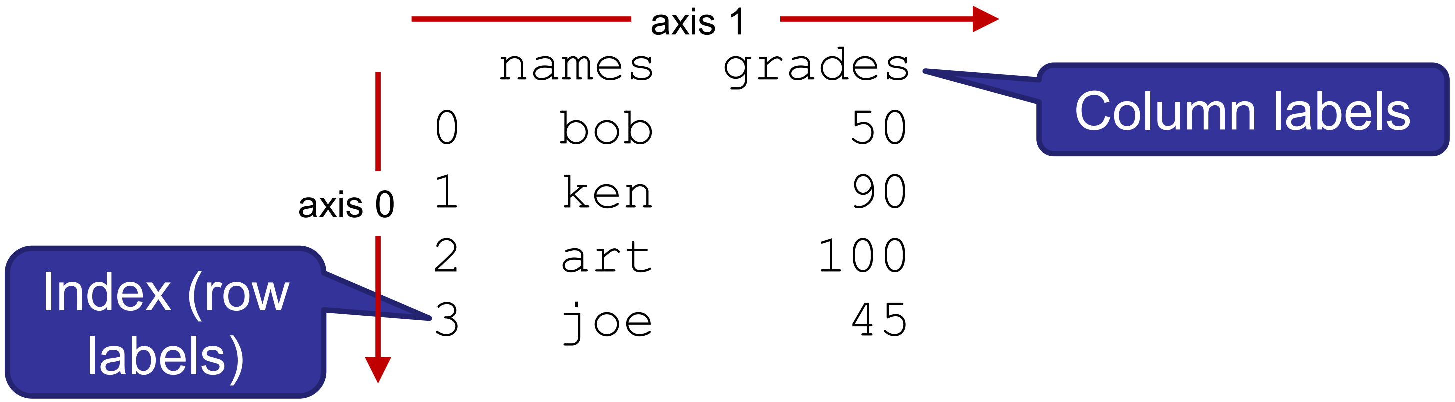


```
0      50
1      90
2     100
3      45
dtype: int64
```

Axis labels are stored in the index. Series support both integer-based and string-based indexing. The default, if index is not set, is integer-based starting from 0.

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

- A **DataFrame** is a two-dimensional tabular dataset with labeled axes



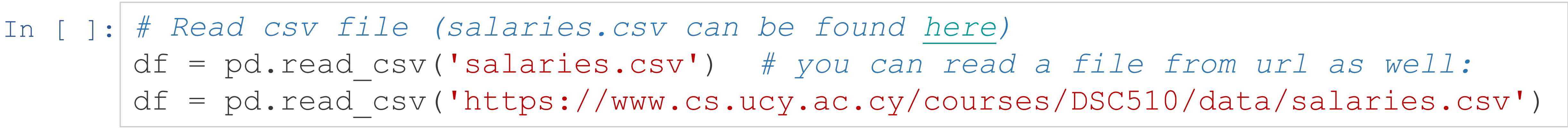
```
  names  grades
0   bob      50
1   ken      90
2   art     100
3   joe      45
```

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

Pandas: Create Dataframes

- Pandas DataFrames can be created using various inputs like:
  - List
  - Dictionary
  - Series
  - Another DataFrame
  - Files (e.g. csv / json)
  - Databases (e.g SQLite, MySQL, PostgreSQL)

Read data using Pandas



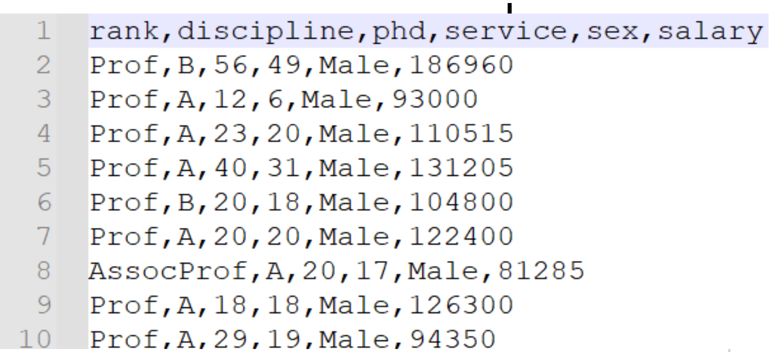
```
In [ ]: # Read csv file (salaries.csv can be found here)
        df = pd.read_csv('salaries.csv')   # you can read a file from url as well:
        df = pd.read_csv('https://www.cs.ucy.ac.cy/courses/DSC510/data/salaries.csv')
```

Note: read_csv command has many optional arguments to fine-tune the data import process.

- There is a number of pandas functions to read other data formats:

```
# Read json file

pd.read_json('myfile.json')

# Read excel file

pd.read_excel('myfile.xlsx',sheet_name='Sheet1', index_col=None, na_values=['NA'])

# Read xml file

pd.read_xml('myfile.xml')

# Read from database (connection to database must be established in advance)

pd.read_sql_query('select * from iris', conn)

...
```

Read data using Pandas: Example



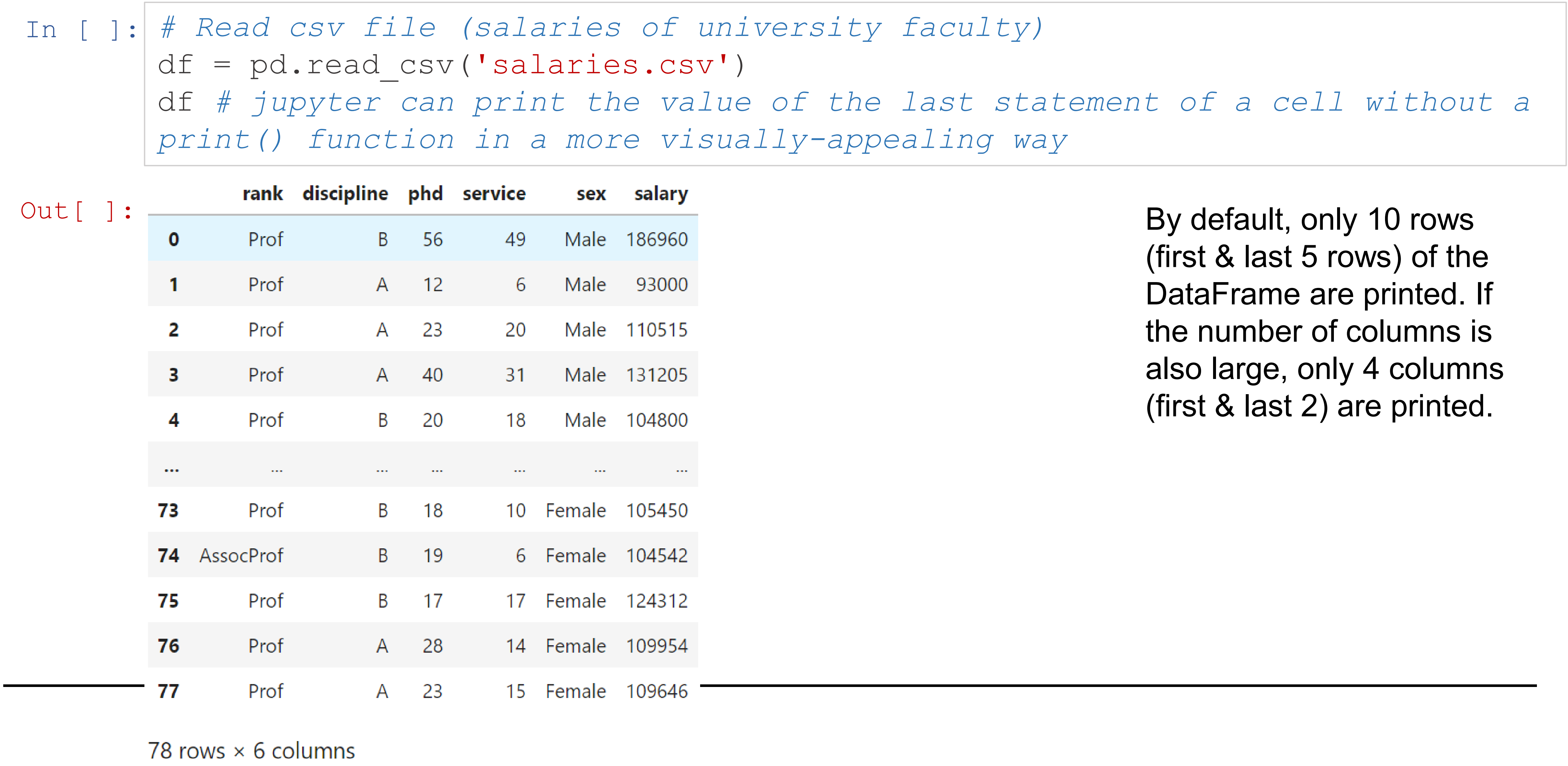
```
rank,discipline,phd,service,sex,salary
Prof,B,56,49,Male,186960
Prof,A,12,6,Male,93000
Prof,A,23,20,Male,110515
Prof,A,40,31,Male,131205
Prof,B,20,18,Male,104800
Prof,A,20,20,Male,122400
AssocProf,A,20,17,Male,81285
Prof,A,18,18,Male,126300
Prof,A,29,19,Male,94350
```

```
In [ ]: # Read csv file (salaries of university faculty)
        df = pd.read_csv('salaries.csv')
        print(df)
```

```
Out[ ]:       rank discipline  phd  service     sex  salary
        0       Prof          B   56       49    Male  186960
        1       Prof          A   12        6    Male   93000
        2       Prof          A   23       20    Male  110515
        3       Prof          A   40       31    Male  131205
        4       Prof          B   20       18    Male  104800
        ..       ...        ...  ...      ...     ...     ...
        73      Prof          B   18       10  Female  105450
        74 AssocProf          B   19        6  Female  104542
        75      Prof          B   17       17  Female  124312
        76      Prof          A   28       14  Female  109954
        77      Prof          A   23       15  Female  109646
```

By default, only 10 rows (first & last 5 rows) of the DataFrame are printed. If the number of columns is also large, only 4 columns (first & last 2) are printed.

Read data using Pandas: Example



```
In [ ]: # Read csv file (salaries of university faculty)
        df = pd.read_csv('salaries.csv')
        df # jupyter can print the value of the last statement of a cell without a
        print() function in a more visually-appealing way
```

Out[ ]:

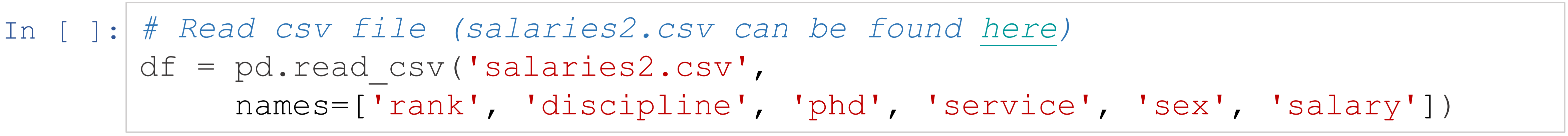
	rank	discipline	phd	service	sex	salary
0	Prof	B	56	49	Male	186960
1	Prof	A	12	6	Male	93000
2	Prof	A	23	20	Male	110515
3	Prof	A	40	31	Male	131205
4	Prof	B	20	18	Male	104800
...	...	...	...	...	...	...
73	Prof	B	18	10	Female	105450
74	AssocProf	B	19	6	Female	104542
75	Prof	B	17	17	Female	124312
76	Prof	A	28	14	Female	109954
77	Prof	A	23	15	Female	109646

78 rows × 6 columns

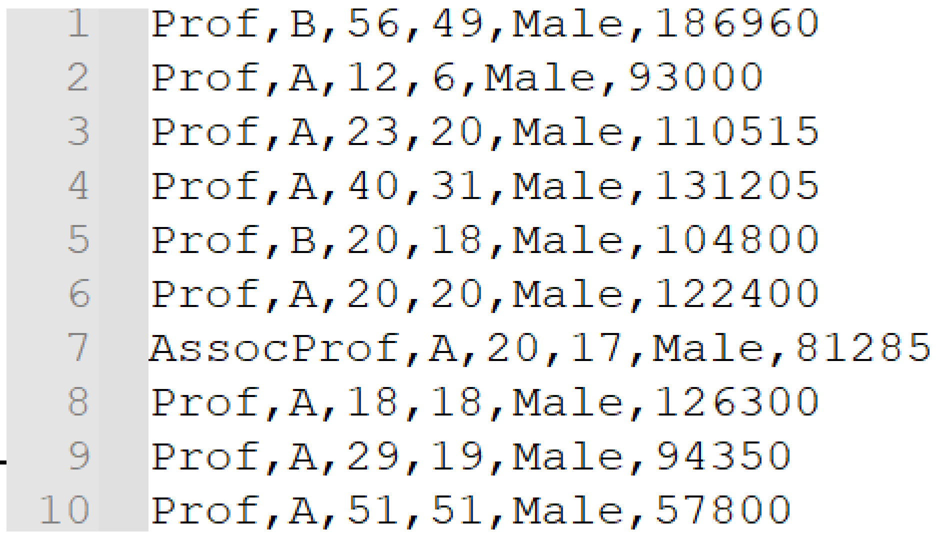
By default, only 10 rows (first & last 5 rows) of the DataFrame are printed. If the number of columns is also large, only 4 columns (first & last 2) are printed.

A bit more reading

- A file may not always have a header row (column titles)
  - pandas assigns default (but not informative) column names (a list of integers)
  - can be implicitly specified while reading data file



```
In [ ]: # Read csv file (salaries2.csv can be found here)
        df = pd.read_csv('salaries2.csv',
                names=['rank', 'discipline', 'phd', 'service', 'sex', 'salary'])
```



```
Prof,B,56,49,Male,186960
Prof,A,12,6,Male,93000
Prof,A,23,20,Male,110515
Prof,A,40,31,Male,131205
Prof,B,20,18,Male,104800
Prof,A,20,20,Male,122400
AssocProf,A,20,17,Male,81285
Prof,A,18,18,Male,126300
Prof,A,29,19,Male,94350
Prof,A,51,51,Male,57800
```

Explore DataFrames

```
In [ ]: #List first 5 records (rows)
        df.head()
```

```
Out[ ]:    rank discipline  phd  service   sex  salary
        0  Prof          B   56       49  Male  186960
        1  Prof          A   12        6  Male   93000
        2  Prof          A   23       20  Male  110515
        3  Prof          A   40       31  Male  131205
        4  Prof          B   20       18  Male  104800
```

```
#List first 15 records
df.head(15)
```

```
#List last 5 records
df.tail()
```

Data Frame data types

```
In [ ]: #Check data types for all columns
        df.dtypes
```

```
Out[ ]: rank              object
        discipline        object
        phd                int64
        service            int64
        sex               object
        salary             int64
        dtype: object
```

The most general dtype. Will be assigned to your column if column has strings or mixed types (numbers and strings)

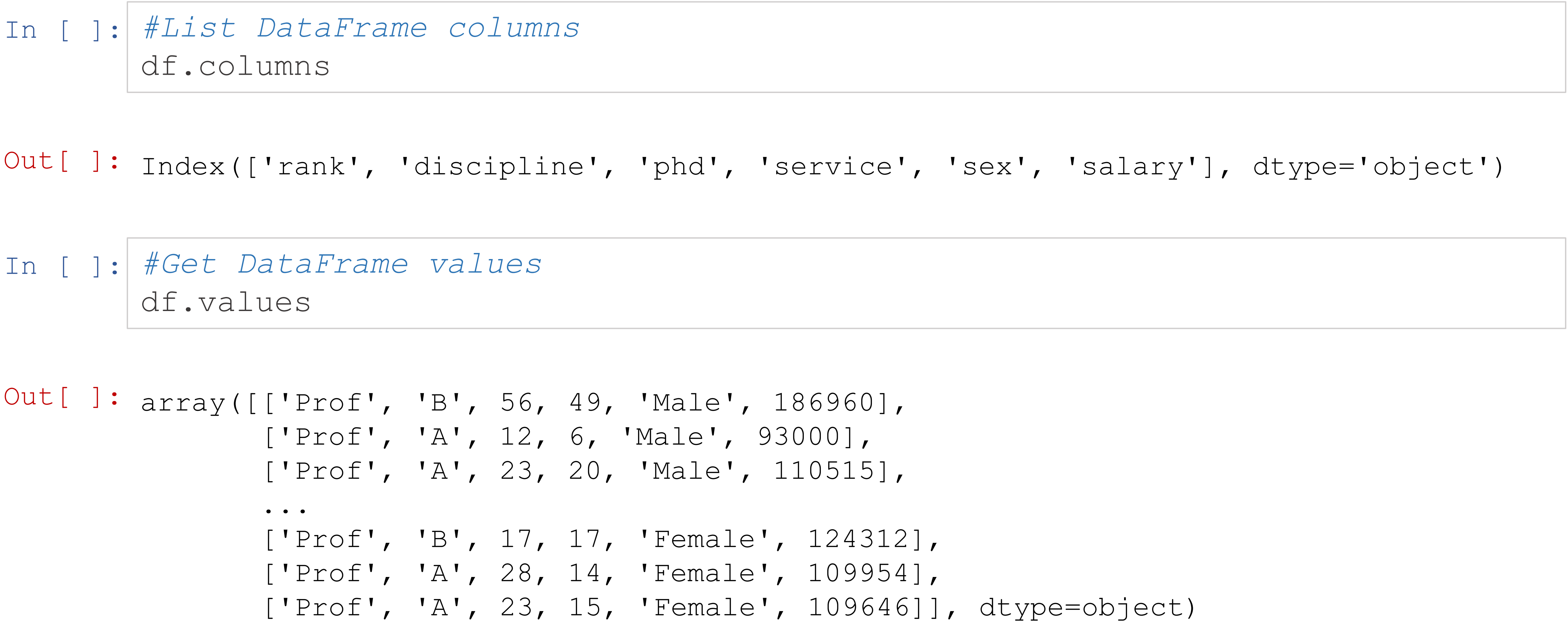
Numeric characters. 64 refers to the memory allocated (in bits) to hold each value of the given column

Data Frames attributes

Pandas **DataFrames** have *attributes* and *methods*. See some attributes below.

df.attribute	description
dtypes	list the types of the columns
columns	list the column names
axes	list the row labels and column names
ndim	number of dimensions
size	number of elements (number of all values)
shape	return a tuple representing the dimensionality (rows, columns)
values	numpy representation of the data as a 2D array without index and column names

Explore DataFrames



```
In [ ]: #List DataFrame columns
        df.columns
```

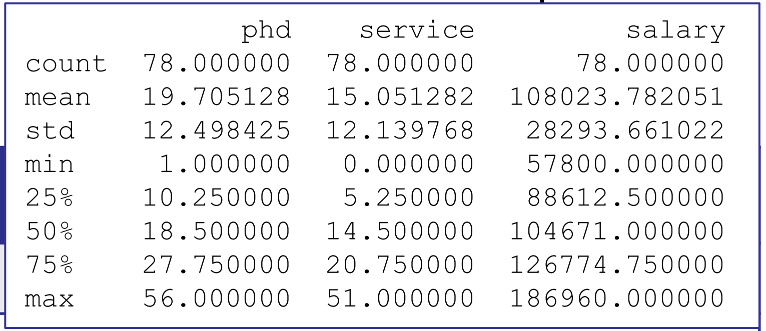
```
Out[ ]: Index(['rank', 'discipline', 'phd', 'service', 'sex', 'salary'], dtype='object')
```

```
In [ ]: #Get DataFrame values
        df.values
```

```
Out[ ]: array([['Prof', 'B', 56, 49, 'Male', 186960],
               ['Prof', 'A', 12, 6, 'Male', 93000],
               ['Prof', 'A', 23, 20, 'Male', 110515],
               ...
               ['Prof', 'B', 17, 17, 'Female', 124312],
               ['Prof', 'A', 28, 14, 'Female', 109954],
               ['Prof', 'A', 23, 15, 'Female', 109646]], dtype=object)
```

Data Frames methods

Unlike attributes, methods have *parentheses*. See some methods below.
All attributes and methods can be listed with a *dir()* function: `dir(df)`



```
             phd    service         salary
count  78.000000  78.000000      78.000000
mean   19.705128  15.051282  108023.782051
std    12.498425  12.139768   28293.661022
min     1.000000   0.000000   57800.000000
25%    10.250000   5.250000   88612.500000
50%    18.500000  14.500000  104671.000000
75%    27.750000  20.750000  126774.750000
max    56.000000  51.000000  186960.000000
```

df.method()	description
head([n]), tail([n])	first/last n rows
describe()	generate summary statistics (for numeric columns only)
max(), min()	return max/min values. Select all numeric columns using `numeric_only=True`
sum()	return the sum of values. Select all numeric columns using `numeric_only=True`
mean(), median(), std()	return mean/median/standard deviation. Select all numeric columns using `numeric_only=True`
dropna()	drop all rows with at least one missing value (set axis param to 1 to drop columns)
drop()	drop specified rows or columns
count()	count non-NA cells
value_counts()	returns counts of unique values in descending order so that the first element is the most frequently-occurring element
apply()	applies a function along an axis of the DataFrame
replace()	replaces values with other values
cut()	bin (group) values into discrete intervals
astype(type)	casts to a specified data type (e.g. astype(int))

Select a column in a Data Frame

Method 1: Use the column name in square brackets:

```
df['sex']
```

Can be used to select more than one column:

```
df[['salary', 'sex']]
```

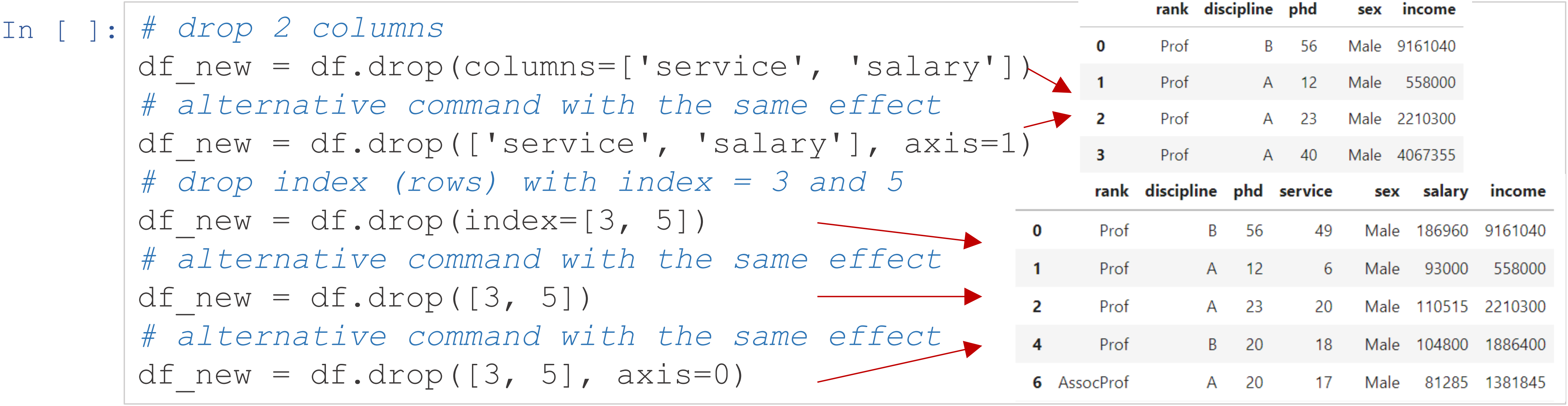
Method 2: Use the column name as an attribute:

```
df.sex
```

Note: there is an attribute *rank* for pandas data frames, so to select a column with a name "rank" we should use method 1.

Drop rows / columns

- `drop()` method can be used to remove index (rows) or columns by specifying label names and corresponding axis, or by specifying directly index or column names
  - Drops rows if `axis = 0` or `'index'` (default), drops columns of `axis = 1` or `'columns'`
  - Returns a new DataFrame without the removed rows or columns (original dataframe remains intact)



```
In [ ]: # drop 2 columns
        df_new = df.drop(columns=['service', 'salary'])
        # alternative command with the same effect
        df_new = df.drop(['service', 'salary'], axis=1)
        # drop index (rows) with index = 3 and 5
        df_new = df.drop(index=[3, 5])
        # alternative command with the same effect
        df_new = df.drop([3, 5])
        # alternative command with the same effect
        df_new = df.drop([3, 5], axis=0)
```

	rank	discipline	phd	sex	income
0	Prof	B	56	Male	9161040
1	Prof	A	12	Male	558000
2	Prof	A	23	Male	2210300
3	Prof	A	40	Male	4067355

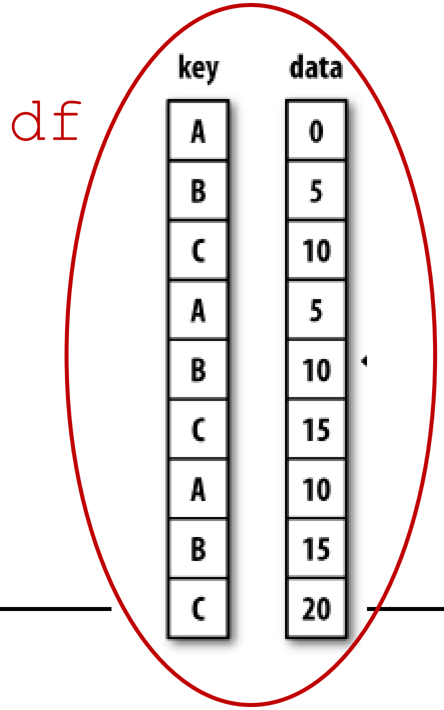
	rank	discipline	phd	service	sex	salary	income
0	Prof	B	56	49	Male	186960	9161040
1	Prof	A	12	6	Male	93000	558000
2	Prof	A	23	20	Male	110515	2210300
4	Prof	B	20	18	Male	104800	1886400
6	AssocProf	A	20	17	Male	81285	1381845

Dataframe processing operations

- Group-by method
  - splits data into groups by a categorical col, e.g. group faculty members by rank or gender
- Aggregate (or agg) method
  - an aggregation method is one which takes multiple individual values and returns a summary; in most of the cases, this summary is a single value
  - apply multiple aggregation methods on one or more columns or groups
- Splitting (binning) operation
  - bins (groups) values into discrete intervals; convert numerical to categorical, e.g. split faculty member into categorical groups based on their age: 25-39 young, 40-59 middle, 60+ old
- Filtering operation
  - selects a subset of data based on one or more conditions
- Slicing operation
  - selects a subset of data by row or column position/label
- Sorting operation
  - sorts data by the values of one or more column(s)

Grouping data using groupby()

- Using "group by" method we can:
  - Split the data into groups based on some criteria (e.g. the values of a column)
  - Once a groupby object is created, we can run aggregation methods (e.g. sum, mean) on each group and combine the results into a data structure

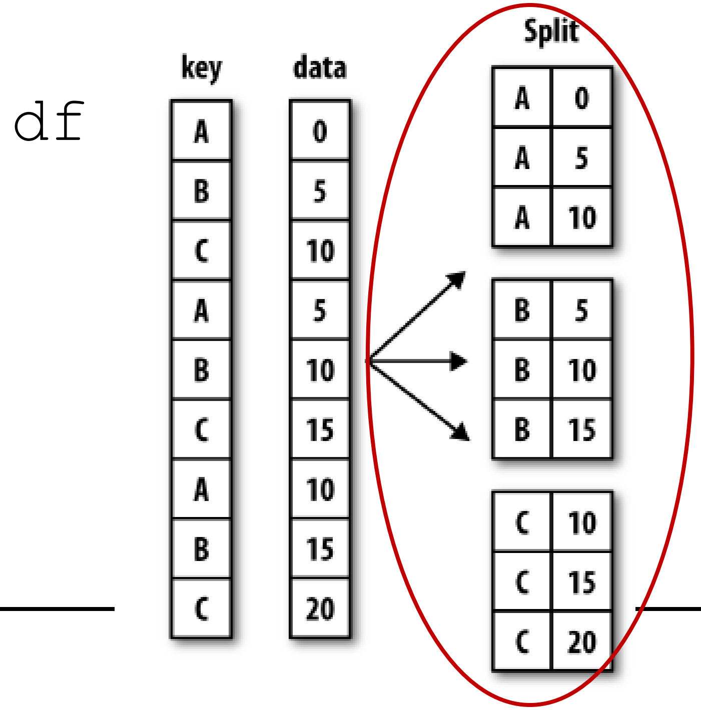


key	data
A	0
B	5
C	10
A	5
B	10
C	15
A	10
B	15
C	20

Grouping data using groupby()

- Using "group by" method we can:
  - Split the data into groups based on some criteria (e.g. the values of a column)
  - Once a groupby object is created, we can run aggregation methods (e.g. sum, mean) on each group and combine the results into a data structure

```
df.groupby('key')
```



df

key	data
A	0
B	5
C	10
A	5
B	10
C	15
A	10
B	15
C	20

Split

A	0
A	5
A	10

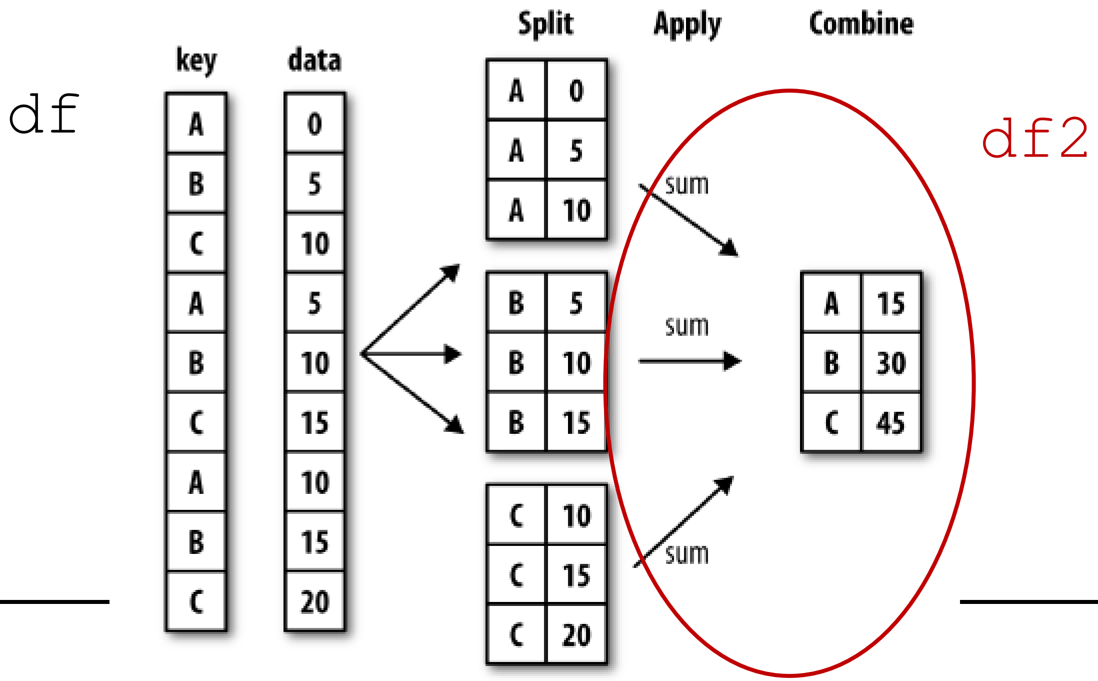
B	5
B	10
B	15

C	10
C	15
C	20

Grouping data using groupby()

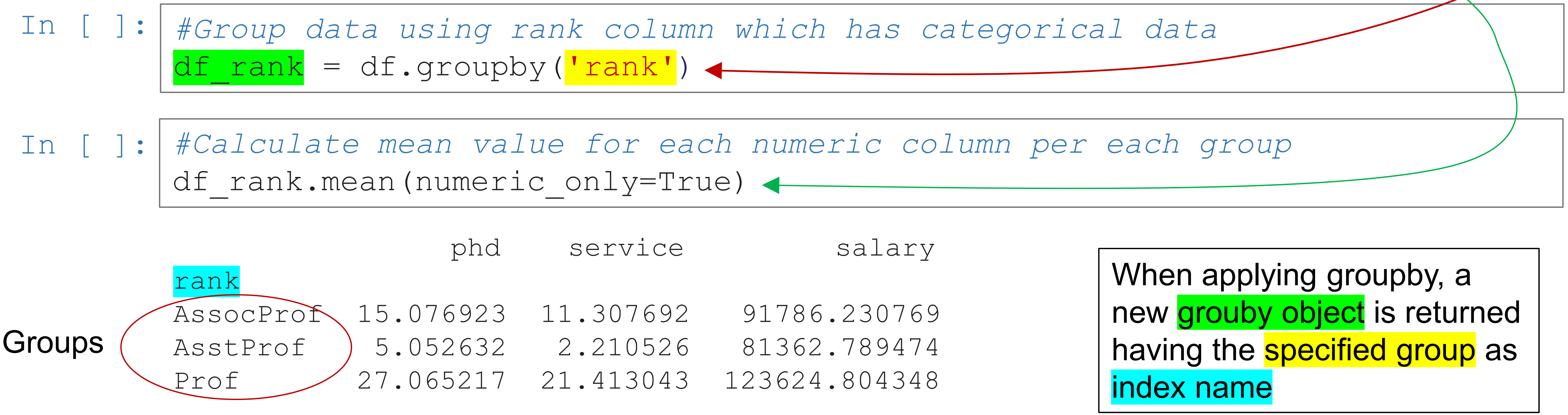
- Using "group by" method we can:
  - Split the data into groups based on some criteria (e.g. the values of a column)
  - Once a groupby object is created, we can run aggregation methods (e.g. sum, mean) on each group and combine the results into a data structure

```
df2 = df.groupby('key').sum()
```



Grouping data using groupby(): Example

- Using "group by" method we can:
  - Split the data into groups based on some criteria (e.g. the values of a column)
  - Once a groupby object is created, we can run aggregation methods (e.g. sum, mean) on each group and combine the results into a data structure



```
In [ ]:  #Group data using rank column which has categorical data
         df_rank = df.groupby('rank')
```

```
In [ ]:  #Calculate mean value for each numeric column per each group
         df_rank.mean(numeric_only=True)
```

```
                 phd    service         salary
rank
AssocProf  15.076923  11.307692   91786.230769
AsstProf    5.052632   2.210526   81362.789474
Prof       27.065217  21.413043  123624.804348
```

Groups

When applying groupby, a new grouby object is returned having the specified group as index name

Grouping data using groupby()

- On the groupby object we can first isolate column(s) and then run aggregation functions (statistics) for each group:

```
In [ ]:  # Isolate salary and calculate mean value for each rank:
         df_rank['salary'].mean(numeric_only=True)
```

```
Out[ ]:  rank
         AssocProf     91786.230769
         AsstProf      81362.789474
         Prof         123624.804348
         Name: salary, dtype: float64
```

Group names

Note: If **single brackets** are used to select the column (e.g. ['salary'] instead of [['salary']]), then the output is **Pandas Series** object. When **double brackets** are used the output is a **DataFrame**.

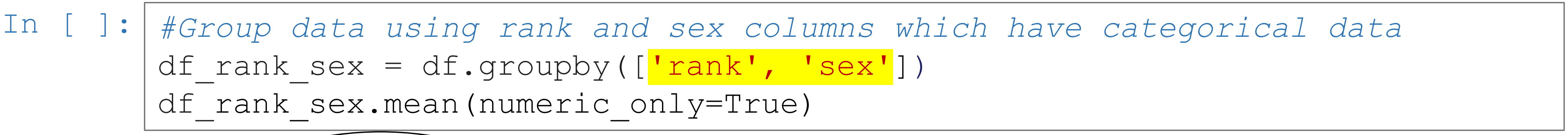
```
In [ ]:  # Isolate salary and calculate mean value for each rank:
         df_rank[['salary']].mean(numeric_only=True)
```

```
Out[ ]:                      salary
         rank
         AssocProf     91786.230769
         AsstProf      81362.789474
         Prof         123624.804348
```

Although some operations may overlap, many operations (methods) applied on **Series** and **DataFrames** differ due to the structural differences between the 2 data structures.

Grouping data using groupby()

- `groupby()` can be performed on multiple columns

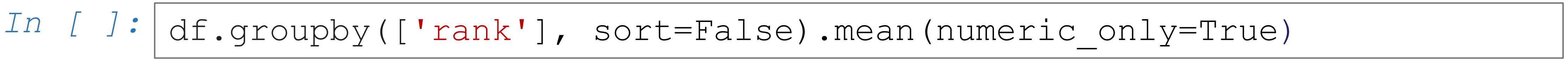


```
In [ ]: #Group data using rank and sex columns which have categorical data
        df_rank_sex = df.groupby(['rank', 'sex'])
        df_rank_sex.mean(numeric_only=True)
```

```
                          phd         service        salary
     rank        sex
     AssocProf   Female   15.500000   11.500000      88512.800000
                 Male     13.666667   10.666667      102697.666667
     AsstProf    Female   5.636364    2.545455       78049.909091
                 Male     4.250000    1.750000       85918.000000
     Prof        Female   23.722222   17.111111      121967.611111
                 Male     29.214286   24.178571      124690.142857
```

Multi-index: multi-level index

- `groupby()` performance notes:
  - by default, the group names are sorted during the groupby operation. You may want to pass `sort=False` for potential speedup:



```
In [ ]: df.groupby(['rank'], sort=False).mean(numeric_only=True)
```

Aggregations on multiple columns or groups

- `agg()` method allows applying multiple aggregation methods on one or more columns or groups
- `agg()` on applying aggregation methods **on column(s)**:

```
In [ ]: df = pd.read_csv('salaries.csv')
        # get numeric columns
        df_numeric = df[['phd', 'service', 'salary']]
        # get mean values: the same as df_numeric.mean() - returns a Series
        df_numeric.agg('mean')
```

```
Out[ ]: phd              19.705128
        service          15.051282
        salary       108023.782051
        dtype: float64
```

```
df_numeric.agg(['mean']) #returns a DataFrame
              phd    service          salary
mean    19.705128  15.051282   108023.782051
```

```
In [ ]: # multiple aggregations for all columns - returns a DataFrame
        df_numeric.agg(['max','mean','std'])
```

```
Out[ ]:
                 phd     service          salary
        max    56.000000  51.000000  186960.000000
        mean   19.705128  15.051282  108023.782051
        std    12.498425  12.139768   28293.661022
```

Aggregations on multiple columns or groups

```
In [ ]: # multiple statistics on specific columns
        df_numeric[['service','salary']].agg(['max','mean','std'])
```

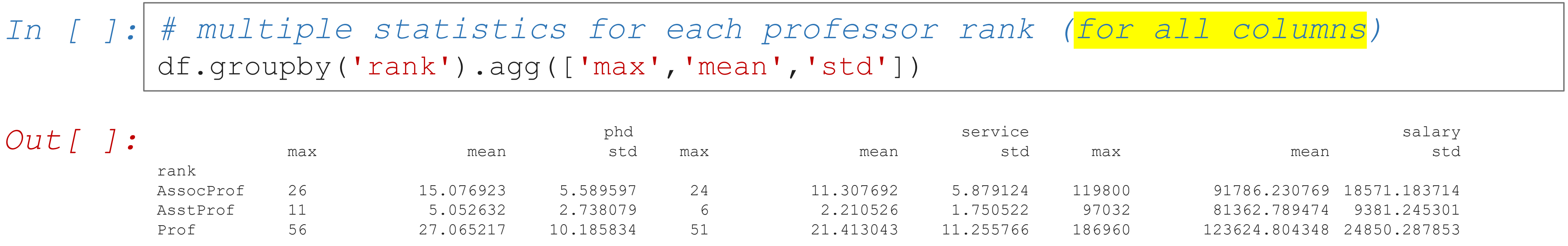
```
Out[ ]:        service          salary
        max   51.000000  186960.000000
        mean  15.051282  108023.782051
        std   12.139768   28293.661022
```

```
In [ ]: # multiple different aggregations for each selected column(s)
        df_numeric.agg({'phd': ['max','mean','std'], 'service': ['count', 'mean']})
```

```
Out[ ]:              phd       service
        max    56.000000          NaN
        mean   19.705128    15.051282
        std    12.498425          NaN
        count        NaN    78.000000
```

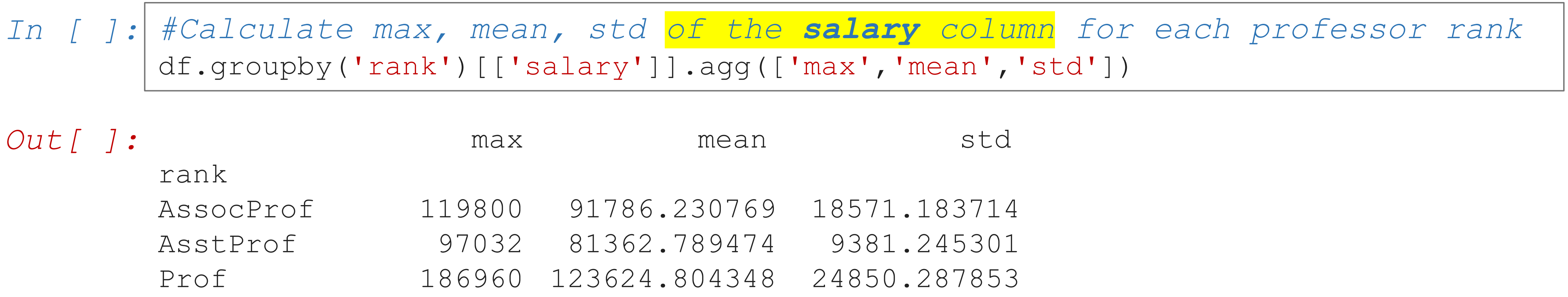
Aggregations on multiple columns or groups

- `agg()` on applying aggregation methods **on groups (groupby)**



```
In [ ]: # multiple statistics for each professor rank (for all columns)
        df.groupby('rank').agg(['max','mean','std'])
```

```
Out[ ]:                                  phd                                    service                                    salary
                max       mean        std   max       mean       std     max          mean          std
        rank
        AssocProf  26  15.076923   5.589597    24  11.307692   5.879124  119800   91786.230769  18571.183714
        AsstProf   11   5.052632   2.738079     6   2.210526   1.750522   97032   81362.789474   9381.245301
        Prof       56  27.065217  10.185834    51  21.413043  11.255766  186960  123624.804348  24850.287853
```



```
In [ ]: #Calculate max, mean, std of the salary column for each professor rank
        df.groupby('rank')[['salary']].agg(['max','mean','std'])
```

```
Out[ ]:                  max          mean           std
        rank
        AssocProf     119800   91786.230769  18571.183714
        AsstProf       97032   81362.789474   9381.245301
        Prof          186960  123624.804348  24850.287853
```

Split data values into bins (groups)

- `cut()` method bins (groups) numerical values into discrete intervals
- Useful for going from a numerical (continuous) variable to a discrete (categorical) variable
  - For example, cut() could convert ages to groups of age ranges e.g. (0-12] → child, (12-18] → teenager, (18-60] → adult, (60-∞] → elder)
- Supports binning into equal-sized bins, or a pre-specified array of bins
- Returns an array-like object representing the respective bin for each value of the column to be split

Split data values into bins (groups)

- Example 1: Split faculty members by their salary into 3 equal-sized bins (all bins have the same number of faculty members)

```
In [ ]: df['salary_bin'] = pd.cut(df.salary, bins=3)
        df['salary_bin']
```

```
Out[ ]: 0         (143906.667, 186960.0]
        1         (57670.84, 100853.333]
        2       (100853.333, 143906.667]
        3       (100853.333, 143906.667]
        4       (100853.333, 143906.667]
                          ...
        73      (100853.333, 143906.667]
        74      (100853.333, 143906.667]
        75      (100853.333, 143906.667]
        76      (100853.333, 143906.667]
        77      (100853.333, 143906.667]
        Name: salary, Length: 78, dtype: category
        Categories (3, interval[float64, right]): [(57670.84, 100853.333] < (100853.333,
        143906.667] < (143906.667, 186960.0]]
```

belongs to the third bin

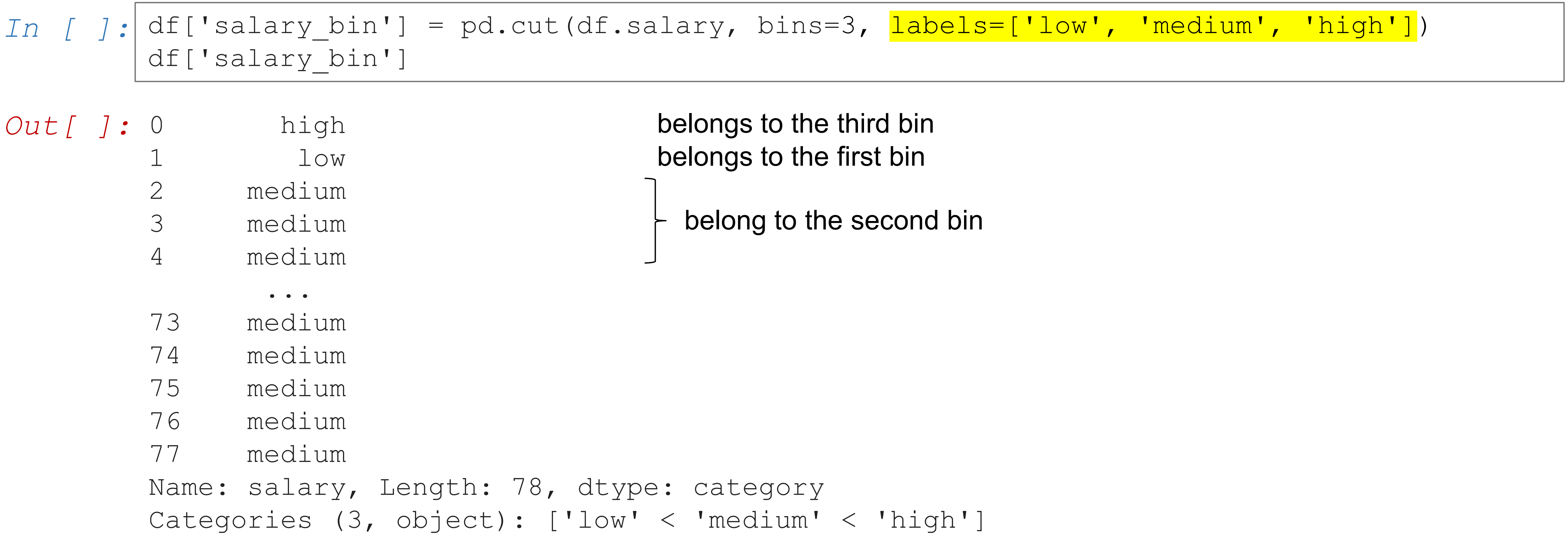
belongs to the first bin

belong to the second bin

The result of the cut method is a new column that shows the bin each faculty member belongs to according to his/her salary

Split data values into bins (groups)

- Example 1: Split faculty members by their salary into 3 equal-sized bins (a label for each split can be defined)



```
In [ ]: df['salary_bin'] = pd.cut(df.salary, bins=3, labels=['low', 'medium', 'high'])
        df['salary_bin']
```

```
Out[ ]: 0         high
        1          low
        2       medium
        3       medium
        4       medium
                 ...
        73      medium
        74      medium
        75      medium
        76      medium
        77      medium
        Name: salary, Length: 78, dtype: category
        Categories (3, object): ['low' < 'medium' < 'high']
```

belongs to the third bin

belongs to the first bin

belong to the second bin

Split data values into bins (groups)

- Example 2: Split faculty members by their salary into 3 pre-specified array of bins

```
In [ ]: df['salary_bin'] = pd.cut(df.salary, bins=[0, 100000, 150000, np.inf], labels=['low',
        'medium', 'high'])
        df['salary_bin']
```

```
Out[ ]: 0        high
        1         low
        2      medium
        3      medium
        4      medium
                ...
        73     medium
        74     medium
        75     medium
        76     medium
        77     medium
        Name: salary, Length: 78, dtype: category
        Categories (3, object): ['low' < 'medium' < 'high']
```

0 high: belongs to the third bin

1 low: belongs to the first bin

2–4 medium: belong to the second bin

Salaries are split into 3 ranges:
`0-100,000` → **low**
`100,001-150,000` → **medium**
`>150,000` → **high**

Data Frame: Filtering

- In order to filter data we can apply Boolean indexing. For example, if we want to filter rows in which the salary value is greater than $120K:

```
In [ ]: #Select only those that earn more than 12000:
        df_sub = df[ df['salary'] > 120000 ]
```

```
0        True
1       False
2       False
3        True
4       False
         ...
73      False
74      False
75       True
76      False
77      False
Name: salary, Length:
78, dtype: bool
```

Any Boolean operator can be used to subset the data:
>   greater;   >= greater or equal;
<   less;   <= less or equal;
== equal;   != not equal;

```
In [ ]: #Select only those rows that contain female professors:
        df_f = df[ df['sex'] == 'Female' ]
```

Data Frame: Filtering

- Symbol & refers to AND condition which means meeting both the criteria:

```
df_1 = df[ (df['sex'] == 'Female') & (df['service'] > 20) ]
```

- Symbol | refers to OR condition which means meeting any of the criteria:

```
df_2 = df[ (df['sex'] == 'Female') | (df['service'] > 20) ]
```

Data Frame: Filtering

- Select rows which a specific column involves specific values

```
df_3 = df[ df['phd'].isin([5,10,15]) ]
```

- Select rows which a specific column contains a specific letter

```
df_4 = df[ df['rank'].str.contains('f')]
```

- Select rows with NaN values in specific column

```
df_5 = df[ df['service'].isnull() ]
```

- Select rows with NaN values in any column

```
df_6 = df[ df.isnull().any(axis=1) ]
```

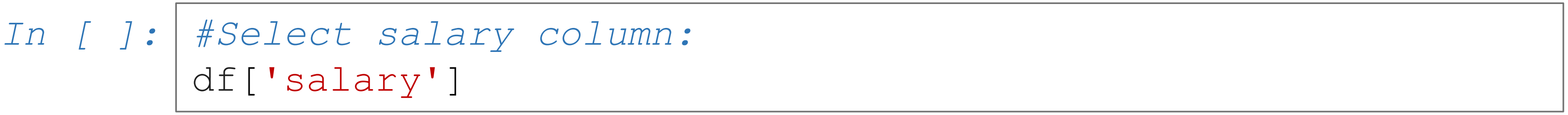
Data Frames: Slicing

- There is a number of ways to get a slice of the DataFrame:
  - select one or more columns
  - select one or more rows
  - select a subset of rows and columns

- Rows and columns can be selected by their position or label

Data Frames: Slicing (selecting columns)

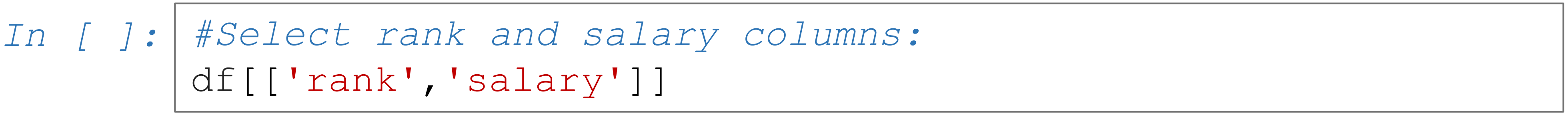
- When selecting one column, it is possible to use single set of brackets, but the resulting object will be a Series (not a DataFrame):



In [ ]:

```
#Select salary column:
df['salary']
```

- When we need to select more than one columns and/or make the output to be a DataFrame, we must use double brackets:

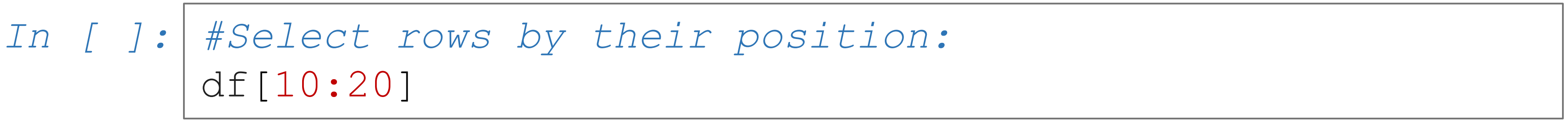


In [ ]:

```
#Select rank and salary columns:
df[['rank','salary']]
```

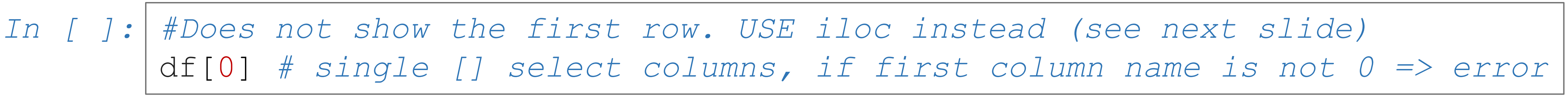
Data Frames: Slicing (selecting rows)

- If we need to select a subset of rows, we can specify the range using :



```
In [ ]: #Select rows by their position:
        df[10:20]
```

- The first row has a position 0, and the last value in the range is not returned:
  - So for 0:10 range the first 10 rows are returned with the positions starting with 0 and ending with 9
- BUT (*):

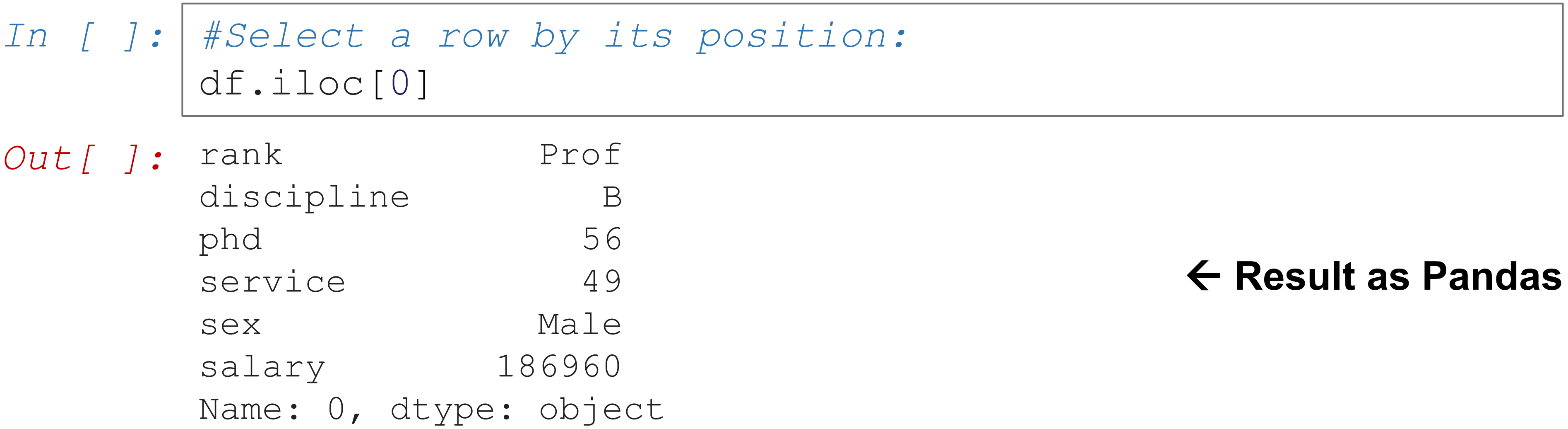


```
In [ ]: #Does not show the first row. USE iloc instead (see next slide)
        df[0] # single [] select columns, if first column name is not 0 => error
```

(*) The primary purpose of the DataFrame indexing operator, [] is to select columns.

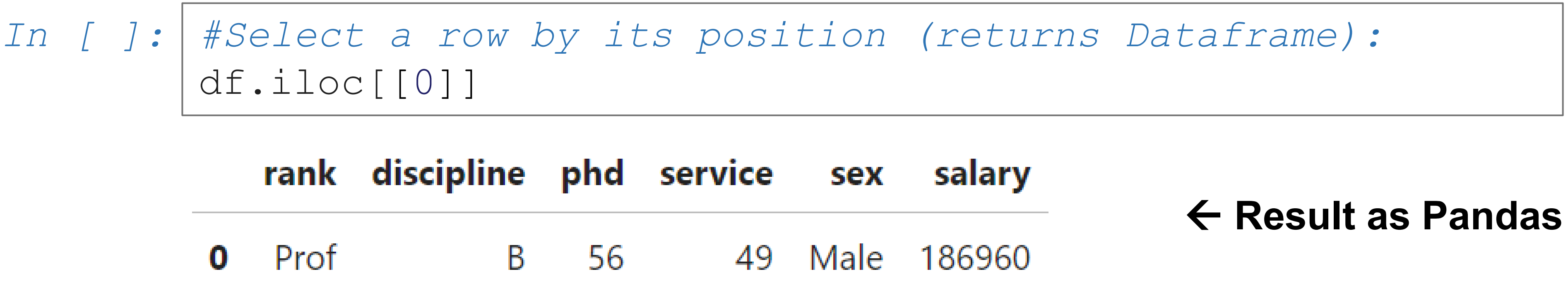
Data Frames: method iloc

- If we need to select a single **row using its integer position** we can use the method iloc:



```
In [ ]:  #Select a row by its position:
         df.iloc[0]

Out[ ]:  rank                Prof
         discipline             B
         phd                   56
         service               49
         sex                 Male
         salary            186960
         Name: 0, dtype: object
```

← **Result as Pandas Series**



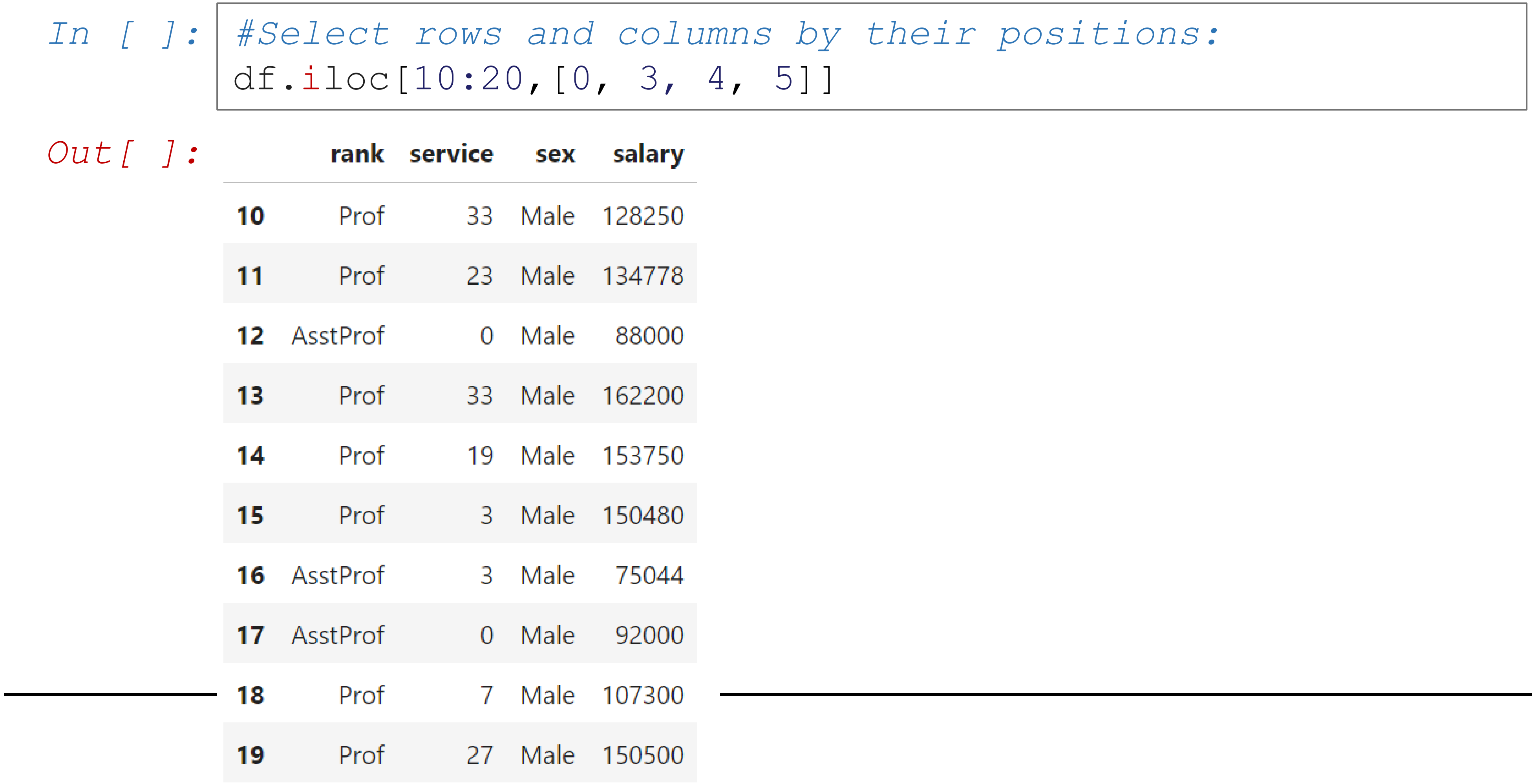
```
In [ ]:  #Select a row by its position (returns Dataframe):
         df.iloc[[0]]
```

	rank	discipline	phd	service	sex	salary
0	Prof	B	56	49	Male	186960

← **Result as Pandas DataFrame**

Data Frames: method iloc

- If we need to select a range of rows and/or columns, **using their** (integer) **positions** we can use method iloc:



In [ ]:

```
#Select rows and columns by their positions:
df.iloc[10:20,[0, 3, 4, 5]]
```

Out[ ]:

	rank	service	sex	salary
10	Prof	33	Male	128250
11	Prof	23	Male	134778
12	AsstProf	0	Male	88000
13	Prof	33	Male	162200
14	Prof	19	Male	153750
15	Prof	3	Male	150480
16	AsstProf	3	Male	75044
17	AsstProf	0	Male	92000
18	Prof	7	Male	107300
19	Prof	27	Male	150500

Data Frames: method iloc (summary)

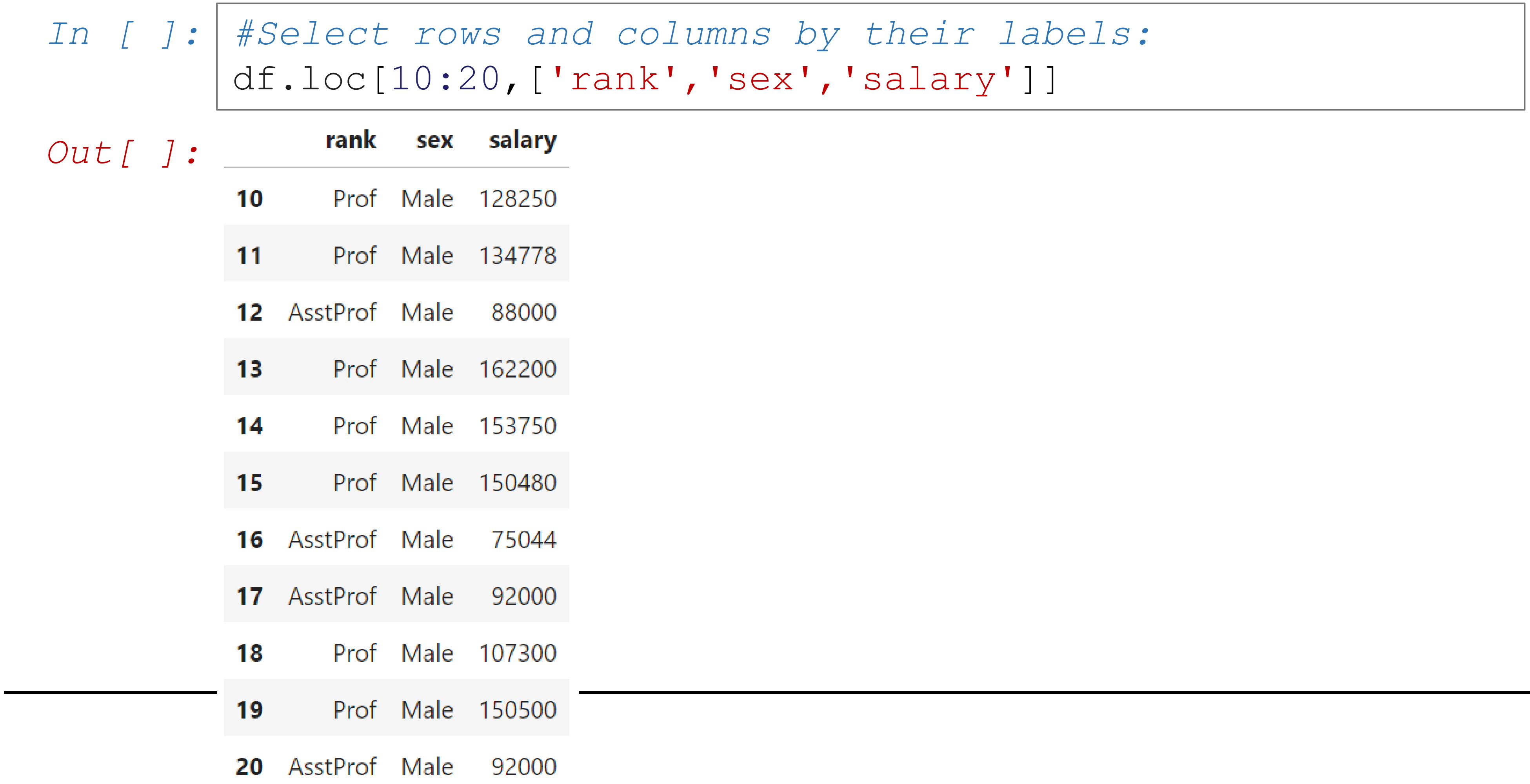
```
df.iloc[0]   # First row of a data frame
df.iloc[i]   # (i+1)th row
df.iloc[-1]  # Last row
```

```
df.iloc[:, 0]   # All rows of the first column
df.iloc[:, -1]  # All rows of the last column
```

```
df.iloc[0:7]          # First 7 rows
df.iloc[:, 0:2]       # All rows of the first 2 columns
df.iloc[1:3, 0:2]     # Second through third rows and first 2 columns
df.iloc[[0,5], [1,3]]   # 1st and 6th rows and 2nd and 4th columns
```

Data Frames: method loc

- If we need to select a range of rows and/or columns, **using their labels** we can use method loc:



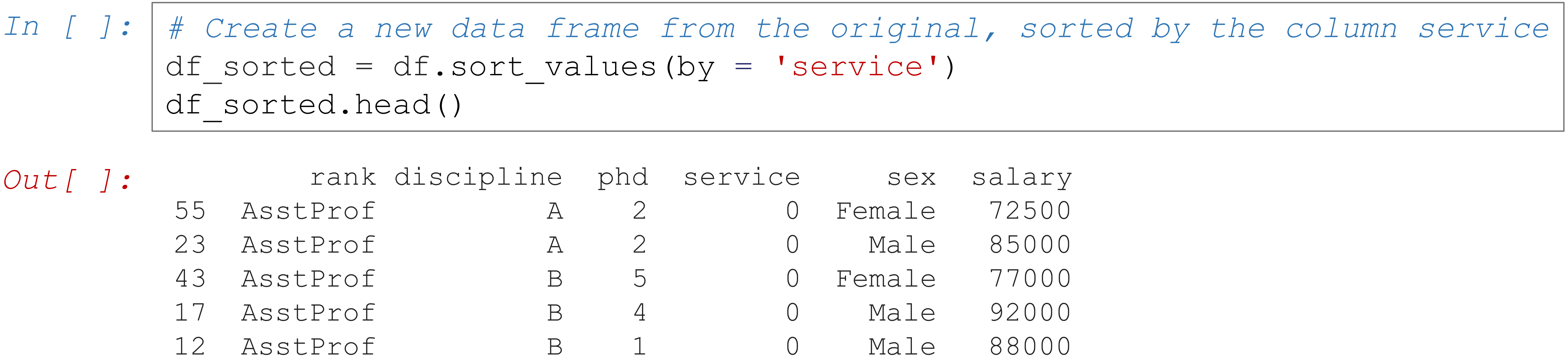
```
In [ ]:  #Select rows and columns by their labels:
         df.loc[10:20,['rank','sex','salary']]
```

Out[ ]:

	rank	sex	salary
10	Prof	Male	128250
11	Prof	Male	134778
12	AsstProf	Male	88000
13	Prof	Male	162200
14	Prof	Male	153750
15	Prof	Male	150480
16	AsstProf	Male	75044
17	AsstProf	Male	92000
18	Prof	Male	107300
19	Prof	Male	150500
20	AsstProf	Male	92000

Data Frames: Sorting

- We can sort the data by the values of a specified column. By default, the sorting will occur in ascending order (change using ascending Boolean parameter) and a new dataframe is returned.

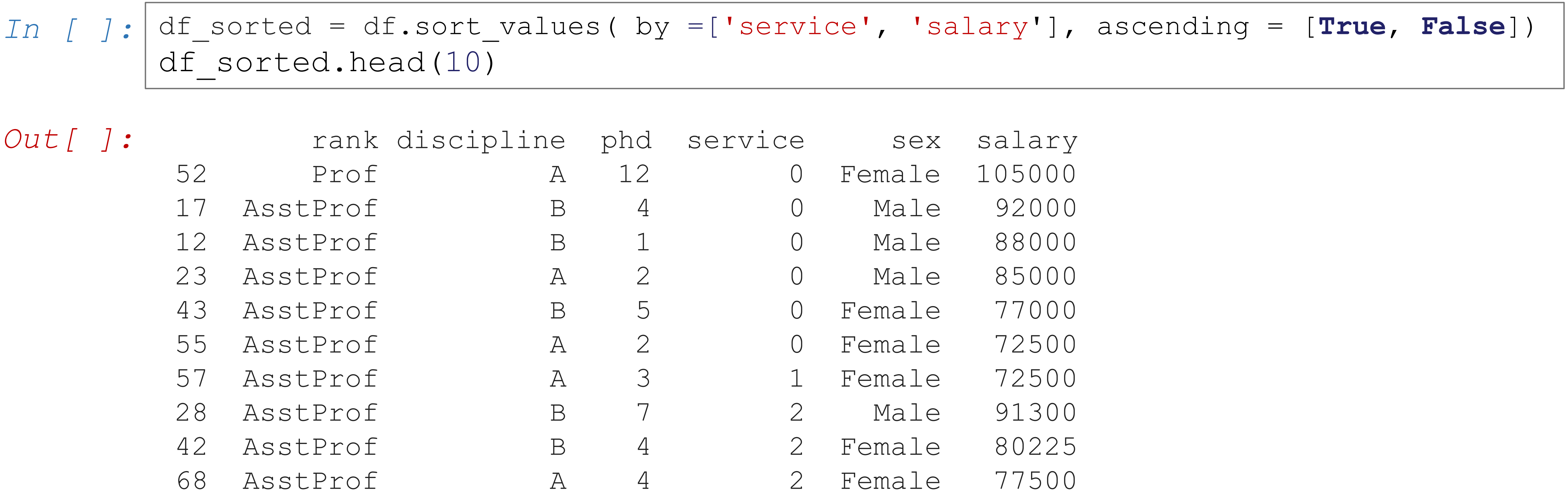


```
In [ ]:  # Create a new data frame from the original, sorted by the column service
         df_sorted = df.sort_values(by = 'service')
         df_sorted.head()
```

```
Out[ ]:           rank discipline  phd  service     sex  salary
         55  AsstProf          A    2        0  Female   72500
         23  AsstProf          A    2        0    Male   85000
         43  AsstProf          B    5        0  Female   77000
         17  AsstProf          B    4        0    Male   92000
         12  AsstProf          B    1        0    Male   88000
```

Data Frames: Sorting

- We can sort the data using 2 or more columns:



```
In [ ]: df_sorted = df.sort_values( by =['service', 'salary'], ascending = [True, False])
        df_sorted.head(10)
```

```
Out[ ]:
            rank discipline  phd  service     sex  salary
     52     Prof          A   12        0  Female  105000
     17 AsstProf          B    4        0    Male   92000
     12 AsstProf          B    1        0    Male   88000
     23 AsstProf          A    2        0    Male   85000
     43 AsstProf          B    5        0  Female   77000
     55 AsstProf          A    2        0  Female   72500
     57 AsstProf          A    3        1  Female   72500
     28 AsstProf          B    7        2    Male   91300
     42 AsstProf          B    4        2  Female   80225
     68 AsstProf          A    4        2  Female   77500
```