# Dataset join, aggregation and pivot table

Contents this week:

- Final project instruction I
- Data Join
- Web scrapping (If we have time)

Last week, we introduce `pd.concat` function to append different data vertically or horizontally. This week, we consider how to merge data based on some common columns.

In [ ]:
```
import numpy as np
import pandas as pd
```

In [ ]:
```
# DataFrame 1
df1 = pd.DataFrame({
    'ID': [2, 1, 3, 4],
    'Name': ['Bob', 'Alice', 'Charlie', 'David'],
    'Score': [90, 85, None, 88]
})

# DataFrame 2
df2 = pd.DataFrame({
    'ID': [1, 2, 3, 5],
    'Name': ['Alice', 'Bob', 'Charlie', 'Eve'],
    'Grade': ['A', 'B', None, 'C']
})

df1
```

Out[ ]:

| | ID | Name | Score |
|---|---|---|---|
| **0** | 2 | Bob | 90.0 |
| **1** | 1 | Alice | 85.0 |
| **2** | 3 | Charlie | NaN |
| **3** | 4 | David | 88.0 |

In [ ]:
```
df2
```

Out[ ]:

| | ID | Name | Grade |
|---|---|---|---|
| **0** | 1 | Alice | A |
| **1** | 2 | Bob | B |
| **2** | 3 | Charlie | None |
| **3** | 5 | Eve | C |

In [ ]:
```
pd.concat([df1,df2])
```

Out[ ]:

| | ID | Name | Score | Grade |
|---|---|---|---|---|
| **0** | 2 | Bob | 90.0 | NaN |
| **1** | 1 | Alice | 85.0 | NaN |
| **2** | 3 | Charlie | NaN | NaN |
| **3** | 4 | David | 88.0 | NaN |
| **0** | 1 | Alice | NaN | A |
| **1** | 2 | Bob | NaN | B |
| **2** | 3 | Charlie | NaN | None |
| **3** | 5 | Eve | NaN | C |

In [ ]:
```
pd.concat([df1,df2], axis = 1, join ='outer')
```

Out[ ]:

| | employee | group | employee | hire_date |
|---|---|---|---|---|
| **0** | Bob | Accounting | Lisa | 2004 |
| **1** | Jake | Engineering | Bob | 2008 |
| **2** | Lisa | Engineering | Jake | 2012 |
| **3** | Sue | HR | Sue | 2014 |

Data join:

`pd.concat()` : Stack or concatenate DataFrames along an axis, useful when you just need to append or combine them without needing a key.

`df.merge()` : SQL-style join based on key columns, useful when combining DataFrames with relational data.

In [ ]:
```
# Merging based on the 'ID' column, performing an outer join
result = df1.merge(df2, on=['ID','Name'], how='outer')
```

```
# on = [keys]

result
```

```
---------------------------------------------------------------------------
KeyError                                  Traceback (most recent call last)
/var/folders/nw/5zcrqdxs7c57b12ptv8284p80000gn/T/ipykernel_17339/4259199408.
py in ?()
      1 # Merging based on the 'ID' column, performing an outer join
----> 2 result = df1.merge(df2, on=['ID','Name'], how='outer')
      3
      4 # on = [keys]
      5

~/Library/Python/3.12/lib/python/site-packages/pandas/core/frame.py in ?(sel
f, right, how, on, left_on, right_on, left_index, right_index, sort, suffixe
s, copy, indicator, validate)
  10483         validate: MergeValidate | None = None,
  10484     ) -> DataFrame:
  10485         from pandas.core.reshape.merge import merge
  10486
> 10487         return merge(
  10488             self,
  10489             right,
  10490             how=how,

~/Library/Python/3.12/lib/python/site-packages/pandas/core/reshape/merge.py
in ?(left, right, how, on, left_on, right_on, left_index, right_index, sort,
suffixes, copy, indicator, validate)
    165             validate=validate,
    166             copy=copy,
    167         )
    168     else:
--> 169         op = _MergeOperation(
    170             left_df,
    171             right_df,
    172             how=how,

~/Library/Python/3.12/lib/python/site-packages/pandas/core/reshape/merge.py
in ?(self, left, right, how, on, left_on, right_on, left_index, right_index,
sort, suffixes, indicator, validate)
    787             self.right_join_keys,
    788             self.join_names,
    789             left_drop,
    790             right_drop,
--> 791         ) = self._get_merge_keys()
    792
    793         if left_drop:
    794             self.left = self.left._drop_labels_or_levels(left_drop)

~/Library/Python/3.12/lib/python/site-packages/pandas/core/reshape/merge.py
in ?(self)
```

```
   1265                         # Then we're either Hashable or a wrong-leng
th arraylike,
   1266                         #  the latter of which will raise
   1267                         rk = cast(Hashable, rk)
   1268                         if rk is not None:
-> 1269                             right_keys.append(right._get_label_or_le
vel_values(rk))
   1270                         else:
   1271                             # work-around for merge_asof(right_index
=True)
   1272                             right_keys.append(right.index._values)

~/Library/Python/3.12/lib/python/site-packages/pandas/core/generic.py in ?(s
elf, key, axis)
   1840             values = self.xs(key, axis=other_axes[0])._values
   1841         elif self._is_level_reference(key, axis=axis):
   1842             values = self.axes[axis].get_level_values(key)._values
   1843         else:
-> 1844             raise KeyError(key)
   1845
   1846         # Check for duplicates
   1847         if values.ndim > 1:

KeyError: 'ID'
```

## `merge`

When using `pd.merge`, we look for one or more matching column names between the two inputs, and uses this as the key.

In [ ]:
```
df1 = pd.DataFrame({'employee': ['Bob', 'Jake', 'Lisa', 'Sue'],
                    'group': ['Accounting', 'Engineering','Engineering', 'H
df2 = pd.DataFrame({'employee': ['Lisa', 'Bob', 'Jake', 'Sue'], 'hire_date'
```

In [ ]:
```
df1
```

Out[ ]:

| | employee | group |
|---|---|---|
| **0** | Bob | Accounting |
| **1** | Jake | Engineering |
| **2** | Lisa | Engineering |
| **3** | Sue | HR |

In [ ]:
```
df2
```

Out[ ]:

| | employee | hire_date |
|---|---|---|
| 0 | Lisa | 2004 |
| 1 | Bob | 2008 |
| 2 | Jake | 2012 |
| 3 | Sue | 2014 |

In [ ]:
```
df3 = pd.merge(df1, df2)
df3
```

Out[ ]:

| | employee | group | hire_date |
|---|---|---|---|
| 0 | Bob | Accounting | 2008 |
| 1 | Jake | Engineering | 2012 |
| 2 | Lisa | Engineering | 2004 |
| 3 | Sue | HR | 2014 |

In [ ]:
```
df4 = pd.DataFrame({'group': ['Accounting', 'Engineering', 'HR'], 'supervis
pd.merge(df3, df4)
```

Out[ ]:

| | employee | group | hire_date | supervisor |
|---|---|---|---|---|
| 0 | Bob | Accounting | 2008 | Carly |
| 1 | Jake | Engineering | 2012 | Guido |
| 2 | Lisa | Engineering | 2004 | Guido |
| 3 | Sue | HR | 2014 | Steve |

In [ ]:
```
df5 = pd.DataFrame({'group': ['Accounting', 'Accounting','Engineering', 'En
                    'skills': ['math', 'spreadsheets', 'software', 'math','
df5
```

Out[ ]:

| | group | skills |
|---|---|---|
| 0 | Accounting | math |
| 1 | Accounting | spreadsheets |
| 2 | Engineering | software |
| 3 | Engineering | math |
| 4 | HR | spreadsheets |
| 5 | HR | organization |

In [ ]:
```
df1
```

Out[ ]:

| | employee | group |
|---|---|---|
| **0** | Bob | Accounting |
| **1** | Jake | Engineering |
| **2** | Lisa | Engineering |
| **3** | Sue | HR |

In [ ]:
```
pd.merge(df1, df5)
```

Out[ ]:

| | employee | group | skills |
|---|---|---|---|
| **0** | Bob | Accounting | math |
| **1** | Bob | Accounting | spreadsheets |
| **2** | Jake | Engineering | software |
| **3** | Jake | Engineering | math |
| **4** | Lisa | Engineering | software |
| **5** | Lisa | Engineering | math |
| **6** | Sue | HR | spreadsheets |
| **7** | Sue | HR | organization |

In [ ]:
```

```

Specify key columns

In [ ]:
```
df1
```

Out[ ]:

| | employee | group |
|---|---|---|
| **0** | Bob | Accounting |
| **1** | Jake | Engineering |
| **2** | Lisa | Engineering |
| **3** | Sue | HR |

In [ ]:
```
df2
```

Out[ ]:

| | employee | hire_date |
|---|---|---|
| 0 | Lisa | 2004 |
| 1 | Bob | 2008 |
| 2 | Mary | 2012 |
| 3 | Peter | 2014 |

In [ ]:
```
# when key column has the same column name
pd.merge(df1, df2, on="employee")
```

Out[ ]:

| | employee | group | hire_date |
|---|---|---|---|
| 0 | Bob | Accounting | 2008 |
| 1 | Lisa | Engineering | 2004 |

In [ ]:
```
# different column names
df1.columns = ["name", "group"]
df1
```

Out[ ]:

| | name | group |
|---|---|---|
| 0 | Bob | Accounting |
| 1 | Jake | Engineering |
| 2 | Lisa | Engineering |
| 3 | Sue | HR |

In [ ]:
```
pd.merge(df1, df2, left_on="name", right_on="employee")
```

Out[ ]:

| | name | group | employee | hire_date |
|---|---|---|---|---|
| 0 | Bob | Accounting | Bob | 2008 |
| 1 | Lisa | Engineering | Lisa | 2004 |

In [ ]:
```
pd.merge(df1, df2, left_on="name", right_on="employee").drop("employee", ax
```

Out[ ]:

| | name | group | hire_date |
|---|---|---|---|
| 0 | Bob | Accounting | 2008 |
| 1 | Lisa | Engineering | 2004 |

In [ ]:
```

```

In [ ]:
```
df1.columns = ["employee", "group"]
df1a = df1.set_index("employee")
df1a
```

Out[ ]:

| employee | group |
|---|---|
| **Bob** | Accounting |
| **Jake** | Engineering |
| **Lisa** | Engineering |
| **Sue** | HR |

In [ ]:
```
df2a = df2.set_index("employee")
df2a
```

Out[ ]:

| employee | hire_date |
|---|---|
| **Lisa** | 2004 |
| **Bob** | 2008 |
| **Mary** | 2012 |
| **Peter** | 2014 |

In [ ]:
```
pd.merge(df1a, df2a, left_index=True, right_index=True)
```

Out[ ]:

| employee | group | hire_date |
|---|---|---|
| **Bob** | Accounting | 2008 |
| **Lisa** | Engineering | 2004 |

In [ ]:
```

```

Different types of merge

In [ ]:
```
df1
```

Out[ ]:

| | employee | group |
|---|---|---|
| 0 | Bob | Accounting |
| 1 | Jake | Engineering |
| 2 | Lisa | Engineering |
| 3 | Sue | HR |

In [ ]:
```
df2 = pd.DataFrame({"employee": ["Lisa", "Bob", "Mary", "Peter"], "hire_dat
df2
```

Out[ ]:

| | employee | hire_date |
|---|---|---|
| 0 | Lisa | 2004 |
| 1 | Bob | 2008 |
| 2 | Mary | 2012 |
| 3 | Peter | 2014 |

In [ ]:
```
pd.merge(df1, df2)
```

Out[ ]:

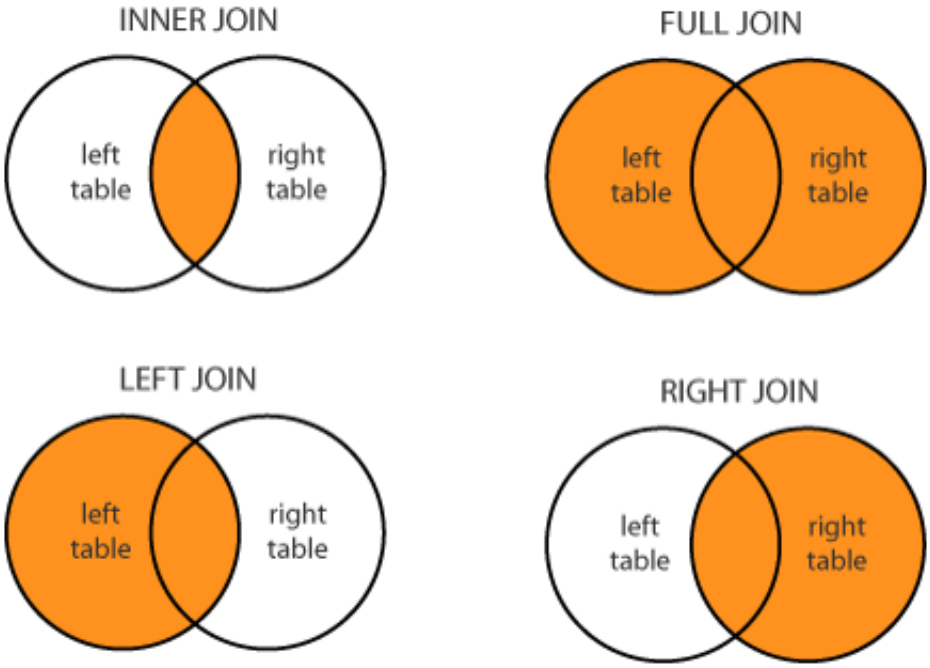
| | employee | group | hire_date |
|---|---|---|---|
| 0 | Bob | Accounting | 2008 |
| 1 | Lisa | Engineering | 2004 |

In [ ]:
```
pd.merge(df1, df2, how="inner")
```

Out[ ]:

| | employee | group | hire_date |
|---|---|---|---|
| 0 | Bob | Accounting | 2008 |
| 1 | Lisa | Engineering | 2004 |

Other options for the `how` keyword are `outer`, `left`, and `right`.




In [ ]:

In [ ]:
```
pd.merge(df1, df2, how="outer")
```

Out[ ]:

| | employee | group | hire_date |
|---|---|---|---|
| **0** | Bob | Accounting | 2008.0 |
| **1** | Jake | Engineering | NaN |
| **2** | Lisa | Engineering | 2004.0 |
| **3** | Sue | HR | NaN |
| **4** | Mary | NaN | 2012.0 |
| **5** | Peter | NaN | 2014.0 |

In [ ]:
```
pd.merge(df1, df2, how="left")
```

Out[ ]:

| | employee | group | hire_date |
|---|---|---|---|
| **0** | Bob | Accounting | 2008.0 |
| **1** | Jake | Engineering | NaN |
| **2** | Lisa | Engineering | 2004.0 |
| **3** | Sue | HR | NaN |

In [ ]:
```
pd.merge(df1, df2, how="right")
```

Out[ ]:

| | employee | group | hire_date |
|---|---|---|---|
| **0** | Lisa | Engineering | 2004 |
| **1** | Bob | Accounting | 2008 |
| **2** | Mary | NaN | 2012 |
| **3** | Peter | NaN | 2014 |

In [ ]:

In [ ]:

In [ ]:

# Aggregation

In [ ]:
```
df = pd.read_csv("iris.csv")
df
```

Out[ ]:

| | sepal_length | sepal_width | petal_length | petal_width | species |
|---|---|---|---|---|---|
| **0** | 5.1 | 3.5 | 1.4 | 0.2 | setosa |
| **1** | 4.9 | 3.0 | 1.4 | 0.2 | setosa |
| **2** | 4.7 | 3.2 | 1.3 | 0.2 | setosa |
| **3** | 4.6 | 3.1 | 1.5 | 0.2 | setosa |
| **4** | 5.0 | 3.6 | 1.4 | 0.2 | setosa |
| **...** | ... | ... | ... | ... | ... |
| **145** | 6.7 | 3.0 | 5.2 | 2.3 | virginica |
| **146** | 6.3 | 2.5 | 5.0 | 1.9 | virginica |
| **147** | 6.5 | 3.0 | 5.2 | 2.0 | virginica |
| **148** | 6.2 | 3.4 | 5.4 | 2.3 | virginica |
| **149** | 5.9 | 3.0 | 5.1 | 1.8 | virginica |

150 rows × 5 columns

In [ ]:
```
df.mean(numeric_only = True)
```

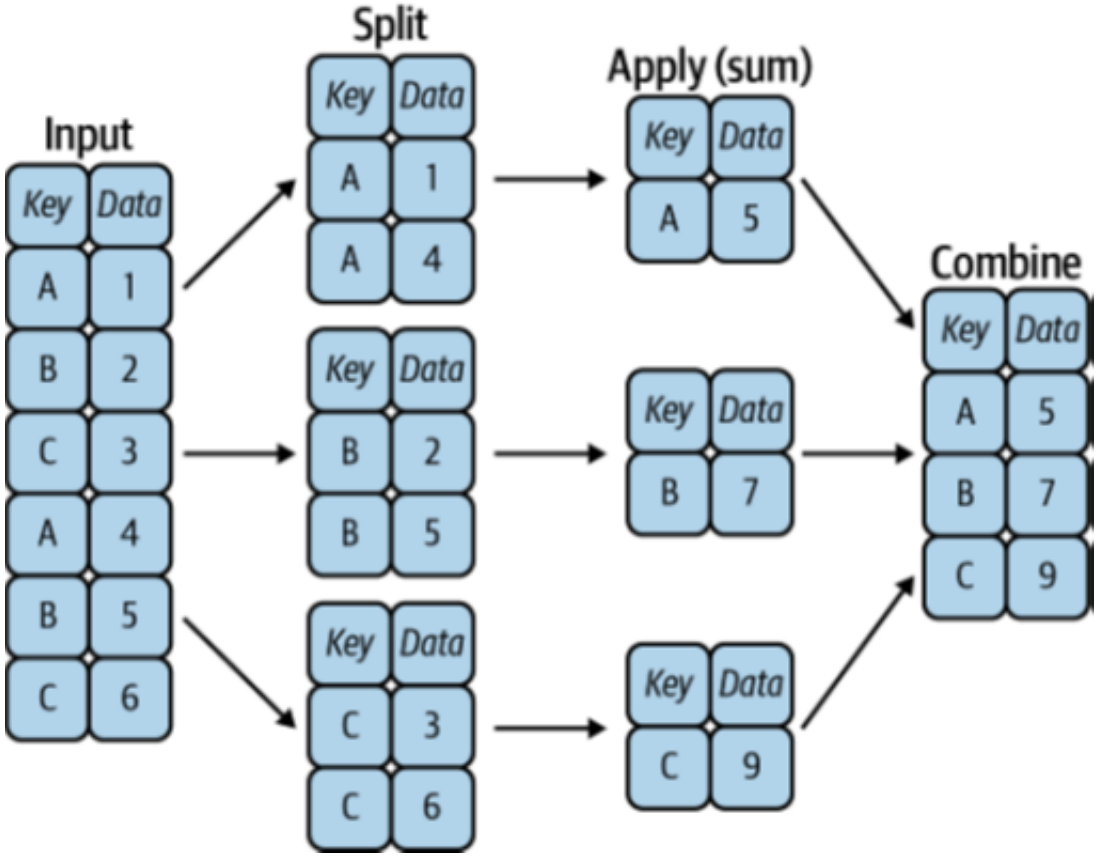
Out[ ]:
```
sepal_length    5.843333
sepal_width     3.057333
petal_length    3.758000
petal_width     1.199333
dtype: float64
```

In [ ]:
```
df.mean(axis=1, numeric_only = True)
```

Out[ ]:
```
0      2.550
1      2.375
2      2.350
3      2.350
4      2.550
       ...
145    4.300
146    3.925
147    4.175
148    4.325
149    3.950
Length: 150, dtype: float64
```

## Groupby: split, apply, combine

- `split` breaks up and groups a DataFrame depending on the value of the specified key.
- `apply` computes some function, usually an aggregate, transformation, or filtering, within the individual groups.
- `combine` merges the results of these operations into an output array.




In [ ]:

In [ ]:
```
df.groupby("species").sum()
```

Out[ ]:

| species | sepal_length | sepal_width | petal_length | petal_width |
|---|---|---|---|---|
| **setosa** | 250.3 | 171.4 | 73.1 | 12.3 |
| **versicolor** | 296.8 | 138.5 | 213.0 | 66.3 |
| **virginica** | 329.4 | 148.7 | 277.6 | 101.3 |

In [ ]:
```
df.groupby("species")["petal_width"].mean(numeric_only = True)
```

Out[ ]:
```
species
setosa        0.246
versicolor    1.326
virginica     2.026
Name: petal_width, dtype: float64
```

In [ ]:
```
df.groupby("species")["petal_width"].median()
```

Out[ ]:
```
species
setosa        0.2
versicolor    1.3
virginica     2.0
Name: petal_width, dtype: float64
```

In [ ]:
```
df.groupby("species").aggregate(["min", "median", "max", 'count'])
```

Out[ ]:

| | sepal_length | | | | sepal_width | | | | petal_l | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | min | median | max | count | min | median | max | count | min | median | max |
| species | | | | | | | | | | | |
| setosa | 4.3 | 5.0 | 5.8 | 50 | 2.3 | 3.4 | 4.4 | 50 | 1.0 | 1.50 | 1.9 |
| versicolor | 4.9 | 5.9 | 7.0 | 50 | 2.0 | 2.8 | 3.4 | 50 | 3.0 | 4.35 | 5.1 |
| virginica | 4.9 | 6.5 | 7.9 | 50 | 2.2 | 3.0 | 3.8 | 50 | 4.5 | 5.55 | 6.9 |

In [ ]:
```
df.groupby('species').describe()
```

Out[ ]:

| | sepal_length | | | | | | | | sepal_width | | ... |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | count | mean | std | min | 25% | 50% | 75% | max | count | mean | ... |
| species | | | | | | | | | | | |
| setosa | 50.0 | 5.006 | 0.352490 | 4.3 | 4.800 | 5.0 | 5.2 | 5.8 | 50.0 | 3.428 | ... |
| versicolor | 50.0 | 5.936 | 0.516171 | 4.9 | 5.600 | 5.9 | 6.3 | 7.0 | 50.0 | 2.770 | ... |
| virginica | 50.0 | 6.588 | 0.635880 | 4.9 | 6.225 | 6.5 | 6.9 | 7.9 | 50.0 | 2.974 | ... |

3 rows × 32 columns

In [ ]:
```
df.groupby('species').aggregate({'sepal_length': ['min', 'max'],'sepal_widt
```

Out[ ]:

| | sepal_length | | sepal_width |
|---|---|---|---|
| | min | max | mean |
| species | | | |
| setosa | 4.3 | 5.8 | 3.428 |
| versicolor | 4.9 | 7.0 | 2.770 |
| virginica | 4.9 | 7.9 | 2.974 |

In [ ]:
```
df.groupby('species').filter(lambda x: x["sepal_length"].mean() > 6)
```

Out[ ]:

| | sepal_length | sepal_width | petal_length | petal_width | species |
|---|---|---|---|---|---|

| | | | | | |
|---|---|---|---|---|---|
| **100** | 6.3 | 3.3 | 6.0 | 2.5 | virginica |
| **101** | 5.8 | 2.7 | 5.1 | 1.9 | virginica |
| **102** | 7.1 | 3.0 | 5.9 | 2.1 | virginica |
| **103** | 6.3 | 2.9 | 5.6 | 1.8 | virginica |
| **104** | 6.5 | 3.0 | 5.8 | 2.2 | virginica |
| **105** | 7.6 | 3.0 | 6.6 | 2.1 | virginica |
| **106** | 4.9 | 2.5 | 4.5 | 1.7 | virginica |
| **107** | 7.3 | 2.9 | 6.3 | 1.8 | virginica |
| **108** | 6.7 | 2.5 | 5.8 | 1.8 | virginica |
| **109** | 7.2 | 3.6 | 6.1 | 2.5 | virginica |
| **110** | 6.5 | 3.2 | 5.1 | 2.0 | virginica |
| **111** | 6.4 | 2.7 | 5.3 | 1.9 | virginica |
| **112** | 6.8 | 3.0 | 5.5 | 2.1 | virginica |
| **113** | 5.7 | 2.5 | 5.0 | 2.0 | virginica |
| **114** | 5.8 | 2.8 | 5.1 | 2.4 | virginica |
| **115** | 6.4 | 3.2 | 5.3 | 2.3 | virginica |
| **116** | 6.5 | 3.0 | 5.5 | 1.8 | virginica |
| **117** | 7.7 | 3.8 | 6.7 | 2.2 | virginica |
| **118** | 7.7 | 2.6 | 6.9 | 2.3 | virginica |
| **119** | 6.0 | 2.2 | 5.0 | 1.5 | virginica |
| **120** | 6.9 | 3.2 | 5.7 | 2.3 | virginica |
| **121** | 5.6 | 2.8 | 4.9 | 2.0 | virginica |
| **122** | 7.7 | 2.8 | 6.7 | 2.0 | virginica |
| **123** | 6.3 | 2.7 | 4.9 | 1.8 | virginica |
| **124** | 6.7 | 3.3 | 5.7 | 2.1 | virginica |
| **125** | 7.2 | 3.2 | 6.0 | 1.8 | virginica |
| **126** | 6.2 | 2.8 | 4.8 | 1.8 | virginica |
| **127** | 6.1 | 3.0 | 4.9 | 1.8 | virginica |
| **128** | 6.4 | 2.8 | 5.6 | 2.1 | virginica |
| **129** | 7.2 | 3.0 | 5.8 | 1.6 | virginica |
| **130** | 7.4 | 2.8 | 6.1 | 1.9 | virginica |

| | | | | | |
|---|---|---|---|---|---|
| **131** | 7.9 | 3.8 | 6.4 | 2.0 | virginica |
| **132** | 6.4 | 2.8 | 5.6 | 2.2 | virginica |
| **133** | 6.3 | 2.8 | 5.1 | 1.5 | virginica |
| **134** | 6.1 | 2.6 | 5.6 | 1.4 | virginica |
| **135** | 7.7 | 3.0 | 6.1 | 2.3 | virginica |
| **136** | 6.3 | 3.4 | 5.6 | 2.4 | virginica |
| **137** | 6.4 | 3.1 | 5.5 | 1.8 | virginica |
| **138** | 6.0 | 3.0 | 4.8 | 1.8 | virginica |
| **139** | 6.9 | 3.1 | 5.4 | 2.1 | virginica |
| **140** | 6.7 | 3.1 | 5.6 | 2.4 | virginica |
| **141** | 6.9 | 3.1 | 5.1 | 2.3 | virginica |
| **142** | 5.8 | 2.7 | 5.1 | 1.9 | virginica |
| **143** | 6.8 | 3.2 | 5.9 | 2.3 | virginica |
| **144** | 6.7 | 3.3 | 5.7 | 2.5 | virginica |
| **145** | 6.7 | 3.0 | 5.2 | 2.3 | virginica |
| **146** | 6.3 | 2.5 | 5.0 | 1.9 | virginica |
| **147** | 6.5 | 3.0 | 5.2 | 2.0 | virginica |
| **148** | 6.2 | 3.4 | 5.4 | 2.3 | virginica |
| **149** | 5.9 | 3.0 | 5.1 | 1.8 | virginica |

In [ ]:

In [ ]:
```
df.groupby("species").transform("mean") # makes every value the mean
```

Out[ ]:

| | sepal_length | sepal_width | petal_length | petal_width |
|---|---|---|---|---|
| **0** | 5.006 | 3.428 | 1.462 | 0.246 |
| **1** | 5.006 | 3.428 | 1.462 | 0.246 |
| **2** | 5.006 | 3.428 | 1.462 | 0.246 |
| **3** | 5.006 | 3.428 | 1.462 | 0.246 |
| **4** | 5.006 | 3.428 | 1.462 | 0.246 |
| **...** | ... | ... | ... | ... |
| **145** | 6.588 | 2.974 | 5.552 | 2.026 |
| **146** | 6.588 | 2.974 | 5.552 | 2.026 |
| **147** | 6.588 | 2.974 | 5.552 | 2.026 |
| **148** | 6.588 | 2.974 | 5.552 | 2.026 |
| **149** | 6.588 | 2.974 | 5.552 | 2.026 |

150 rows × 4 columns

In [ ]:
```
df.groupby("species").transform(lambda x: x-x.mean())
```

Out[ ]:

| | sepal_length | sepal_width | petal_length | petal_width |
|---|---|---|---|---|
| **0** | 0.094 | 0.072 | -0.062 | -0.046 |
| **1** | -0.106 | -0.428 | -0.062 | -0.046 |
| **2** | -0.306 | -0.228 | -0.162 | -0.046 |
| **3** | -0.406 | -0.328 | 0.038 | -0.046 |
| **4** | -0.006 | 0.172 | -0.062 | -0.046 |
| **...** | ... | ... | ... | ... |
| **145** | 0.112 | 0.026 | -0.352 | 0.274 |
| **146** | -0.288 | -0.474 | -0.552 | -0.126 |
| **147** | -0.088 | 0.026 | -0.352 | -0.026 |
| **148** | -0.388 | 0.426 | -0.152 | 0.274 |
| **149** | -0.688 | 0.026 | -0.452 | -0.226 |

150 rows × 4 columns

In [ ]:
```

```

In [ ]:
```
df.groupby("species").apply(np.mean)
```

Out[ ]:
```
species
setosa        2.5355
versicolor    3.5730
virginica     4.2850
dtype: float64
```

In [ ]:
```
df.groupby("species").apply(lambda x:x["sepal_length"]/x["sepal_length"].ma
```

Out[ ]:
```
species
setosa     0      0.879310
           1      0.844828
           2      0.810345
           3      0.793103
           4      0.862069
                    ...
virginica  145    0.848101
           146    0.797468
           147    0.822785
           148    0.784810
           149    0.746835
Name: sepal_length, Length: 150, dtype: float64
```

In [ ]:
```
df.groupby("species")["sepal_length"].apply(lambda x: x/x.max())
```

Out[ ]:
```
species
setosa     0      0.879310
           1      0.844828
           2      0.810345
           3      0.793103
           4      0.862069
                    ...
virginica  145    0.848101
           146    0.797468
           147    0.822785
           148    0.784810
           149    0.746835
Name: sepal_length, Length: 150, dtype: float64
```

In [ ]:
```

```

# Pivot table

In [ ]:
```
df = pd.read_csv("titanic.csv")
df
```

Out[ ]:

| | survived | pclass | sex | age | sibsp | parch | fare | embarked | class | wh |
|---|---|---|---|---|---|---|---|---|---|---|
| **0** | 0 | 3 | male | 22.0 | 1 | 0 | 7.2500 | S | Third | ma |
| **1** | 1 | 1 | female | 38.0 | 1 | 0 | 71.2833 | C | First | woma |
| **2** | 1 | 3 | female | 26.0 | 0 | 0 | 7.9250 | S | Third | woma |
| **3** | 1 | 1 | female | 35.0 | 1 | 0 | 53.1000 | S | First | woma |
| **4** | 0 | 3 | male | 35.0 | 0 | 0 | 8.0500 | S | Third | ma |
| **...** | ... | ... | ... | ... | ... | ... | ... | ... | ... | |
| **886** | 0 | 2 | male | 27.0 | 0 | 0 | 13.0000 | S | Second | ma |
| **887** | 1 | 1 | female | 19.0 | 0 | 0 | 30.0000 | S | First | woma |
| **888** | 0 | 3 | female | NaN | 1 | 2 | 23.4500 | S | Third | woma |
| **889** | 1 | 1 | male | 26.0 | 0 | 0 | 30.0000 | C | First | ma |
| **890** | 0 | 3 | male | 32.0 | 0 | 0 | 7.7500 | Q | Third | ma |

891 rows × 15 columns

In [ ]:
```
df.groupby(['sex', 'pclass'])['survived'].aggregate('mean')
```

Out[ ]:
```
sex     pclass
female  1         0.968085
        2         0.921053
        3         0.500000
male    1         0.368852
        2         0.157407
        3         0.135447
Name: survived, dtype: float64
```

In [ ]:
```
df.groupby(['sex', 'pclass'])['survived'].aggregate('mean').unstack()
# unstack <- giving multi index function, turns one of the indecies into co
```

Out[ ]:

| pclass | 1 | 2 | 3 |
|---|---|---|---|
| **sex** | | | |
| **female** | 0.968085 | 0.921053 | 0.500000 |
| **male** | 0.368852 | 0.157407 | 0.135447 |

In [ ]:
```
df.pivot_table('survived', index='sex', columns='pclass', aggfunc='mean')
```

Out[ ]:

| pclass | 1 | 2 | 3 |
|---|---|---|---|
| sex | | | |
| female | 0.968085 | 0.921053 | 0.500000 |
| male | 0.368852 | 0.157407 | 0.135447 |

In [ ]:
```
age = pd.cut(df['age'], [0, 18, 80], labels = ["young", "adult"])
df.pivot_table('survived', ['sex', age], 'pclass', observed=False)
```

Out[ ]:

| | pclass | 1 | 2 | 3 |
|---|---|---|---|---|
| sex | age | | | |
| female | young | 0.909091 | 1.000000 | 0.511628 |
| | adult | 0.972973 | 0.900000 | 0.423729 |
| male | young | 0.800000 | 0.600000 | 0.215686 |
| | adult | 0.375000 | 0.071429 | 0.133663 |

In [ ]:
```
fare = pd.qcut(df['fare'], 3) # qcut = intervals with same # of observation
df.pivot_table('survived', ['sex', age], [fare, 'pclass'])
```

Out[ ]:

| | fare | (-0.001, 8.662] | | (8.662, 26.0] | | | (26.0, 512.329] | | |
|---|---|---|---|---|---|---|---|---|---|
| | pclass | 1 | 3 | 1 | 2 | 3 | 1 | 2 | 3 |
| sex | age | | | | | | | | |
| female | young | NaN | 0.700000 | NaN | 1.000000 | 0.583333 | 0.909091 | 1.0 | 0.111111 |
| | adult | NaN | 0.523810 | 1.0 | 0.877551 | 0.433333 | 0.972222 | 1.0 | 0.125000 |
| male | young | NaN | 0.166667 | NaN | 0.500000 | 0.500000 | 0.800000 | 0.8 | 0.052632 |
| | adult | 0.0 | 0.127389 | 0.0 | 0.086957 | 0.102564 | 0.400000 | 0.0 | 0.500000 |

In [ ]:
```
df.pivot_table('survived', ['sex'], ['pclass'], margins=True)
```

Out[ ]:

| pclass | 1 | 2 | 3 | All |
|---|---|---|---|---|
| sex | | | | |
| female | 0.968085 | 0.921053 | 0.500000 | 0.742038 |
| male | 0.368852 | 0.157407 | 0.135447 | 0.188908 |
| All | 0.629630 | 0.472826 | 0.242363 | 0.383838 |

In [ ]:

In [ ]:

# In-class activity:

You are provided with three tables: a `Class Table`, an `Enrollment Table`, and a `Student Table`.

Solve two subproblems:

- 1. Calculate the **average class size** for each student, based on the courses they are enrolled in.
- 2. Calculate the **average GPA** of students for each instructor, considering that one instructor may teach multiple courses.

In [ ]:
```
# Class Table
class_df = pd.DataFrame({
    'Course_ID': ['STOR101', 'STOR102', 'STOR103', 'STOR104', 'STOR105'],
    'Instructor': ['Dr. Smith', 'Dr. Jones', 'Dr. Adams', 'Dr. Brown', 'Dr.
    'Class_Size': [30, 25, 20, 15, 50]
})
class_df
```

Out[ ]:

| | Course_ID | Instructor | Class_Size |
|---|---|---|---|
| **0** | STOR101 | Dr. Smith | 30 |
| **1** | STOR102 | Dr. Jones | 25 |
| **2** | STOR103 | Dr. Adams | 20 |
| **3** | STOR104 | Dr. Brown | 15 |
| **4** | STOR105 | Dr. Smith | 50 |

In [ ]:
```
# Enrollment Table
enroll_df = pd.DataFrame({
    'Student_ID': [101, 102, 103, 101, 104, 105, 106, 102],
    'Course_ID': ['STOR101', 'STOR101', 'STOR102', 'STOR102', 'STOR103', 'S
})
enroll_df
```

Out[ ]:

| | Student_ID | Course_ID |
|---|---|---|
| **0** | 101 | STOR101 |
| **1** | 102 | STOR101 |
| **2** | 103 | STOR102 |
| **3** | 101 | STOR102 |
| **4** | 104 | STOR103 |
| **5** | 105 | STOR104 |
| **6** | 106 | STOR105 |
| **7** | 102 | STOR104 |

In [ ]:
```
# Student Table (with GPA)
student_gpa_df = pd.DataFrame({
    'Student_ID': [101, 102, 103, 104, 105, 106],
    'GPA': [3.5, 3.2, 3.8, 3.7, 3.0, 3.6]
})
student_gpa_df
```

Out[ ]:

| | Student_ID | GPA |
|---|---|---|
| **0** | 101 | 3.5 |
| **1** | 102 | 3.2 |
| **2** | 103 | 3.8 |
| **3** | 104 | 3.7 |
| **4** | 105 | 3.0 |
| **5** | 106 | 3.6 |

In [ ]:
```
# merge student_gpa_df and enroll_df
gpa_enroll_df = pd.merge(enroll_df, student_gpa_df, how="left")
gpa_enroll_df
```

Out[ ]:

| | Student_ID | Course_ID | GPA |
|---|---|---|---|
| **0** | 101 | STOR101 | 3.5 |
| **1** | 102 | STOR101 | 3.2 |
| **2** | 103 | STOR102 | 3.8 |
| **3** | 101 | STOR102 | 3.5 |
| **4** | 104 | STOR103 | 3.7 |
| **5** | 105 | STOR104 | 3.0 |
| **6** | 106 | STOR105 | 3.6 |
| **7** | 102 | STOR104 | 3.2 |

In [ ]:
```
# connect course info to course ids
df = pd.merge(gpa_enroll_df, class_df, how="left")
df
```

Out[ ]:

| | Student_ID | Course_ID | GPA | Instructor | Class_Size |
|---|---|---|---|---|---|
| **0** | 101 | STOR101 | 3.5 | Dr. Smith | 30 |
| **1** | 102 | STOR101 | 3.2 | Dr. Smith | 30 |
| **2** | 103 | STOR102 | 3.8 | Dr. Jones | 25 |
| **3** | 101 | STOR102 | 3.5 | Dr. Jones | 25 |
| **4** | 104 | STOR103 | 3.7 | Dr. Adams | 20 |
| **5** | 105 | STOR104 | 3.0 | Dr. Brown | 15 |
| **6** | 106 | STOR105 | 3.6 | Dr. Smith | 50 |
| **7** | 102 | STOR104 | 3.2 | Dr. Brown | 15 |

In [ ]:
```
df.groupby("Student_ID").mean(numeric_only=True)
```

Out[ ]:

| Student_ID | GPA | Class_Size |
|---|---|---|
| **101** | 3.5 | 27.5 |
| **102** | 3.2 | 22.5 |
| **103** | 3.8 | 25.0 |
| **104** | 3.7 | 20.0 |
| **105** | 3.0 | 15.0 |
| **106** | 3.6 | 50.0 |

In [ ]:
```
df.groupby("Instructor").mean(numeric_only=True)
```

Out[ ]:

| Instructor | Student_ID | GPA | Class_Size |
|---|---|---|---|
| **Dr. Adams** | 104.0 | 3.700000 | 20.000000 |
| **Dr. Brown** | 103.5 | 3.100000 | 15.000000 |
| **Dr. Jones** | 102.0 | 3.650000 | 25.000000 |
| **Dr. Smith** | 103.0 | 3.433333 | 36.666667 |

# Calculate the range of iris data for each feature per species, display as pivot table

In [ ]:
```
import pandas as pd
```

In [ ]:
```
df = pd.read_csv("iris.csv")
```

Out[ ]:

| | sepal_length | sepal_width | petal_length | petal_width | species |
|---|---|---|---|---|---|
| **0** | 5.1 | 3.5 | 1.4 | 0.2 | setosa |
| **1** | 4.9 | 3.0 | 1.4 | 0.2 | setosa |
| **2** | 4.7 | 3.2 | 1.3 | 0.2 | setosa |
| **3** | 4.6 | 3.1 | 1.5 | 0.2 | setosa |
| **4** | 5.0 | 3.6 | 1.4 | 0.2 | setosa |
| **...** | ... | ... | ... | ... | ... |
| **145** | 6.7 | 3.0 | 5.2 | 2.3 | virginica |
| **146** | 6.3 | 2.5 | 5.0 | 1.9 | virginica |
| **147** | 6.5 | 3.0 | 5.2 | 2.0 | virginica |
| **148** | 6.2 | 3.4 | 5.4 | 2.3 | virginica |
| **149** | 5.9 | 3.0 | 5.1 | 1.8 | virginica |

150 rows × 5 columns

In [ ]:
```
colnames = df.columns[0:4]
df.pivot_table(values=colnames, index="species", aggfunc = lambda x: x.max(
```

Out[ ]:

| species | petal_length | petal_width | sepal_length | sepal_width |
|---|---|---|---|---|
| **setosa** | 0.9 | 0.5 | 1.5 | 2.1 |
| **versicolor** | 2.1 | 0.8 | 2.1 | 1.4 |
| **virginica** | 2.4 | 1.1 | 3.0 | 1.6 |

In [ ]:
```

```