Lecture 1 Introduction to Python Packages

May 10, 2022

1 PANDAS WORKBOOK

We start by importing our libraries and label them with the namespace alias.

[1]:
```
import numpy as np
import pandas as pd
```

1.1 1. Creating Dataframes

The core of Pandas is the dataframe. So let's see how we can create a Pandas dataframe from a Series or NumPy array.

[2]:
```
sample_series = pd.Series([1,2,3,4,np.nan,6,7,8])
print('Sample series is: \n', sample_series)
```

```
Sample series is:
 0    1.0
1    2.0
2    3.0
3    4.0
4    NaN
5    6.0
6    7.0
7    8.0
dtype: float64
```

[6]:
```
sample_df = pd.DataFrame(np.random.randn(12, 4), columns=["A","B","C","D"])
 ↪#["A","B","C","D"]
print('Sample dataframe is: \n', sample_df)
```

```
Sample dataframe is:
            A         B         C         D
0   0.383964 -0.401091  1.484901 -0.285452
1   0.882779  0.261930  1.268670 -0.535812
2   1.643004 -0.788867 -0.467345  0.265282
3  -0.429295 -0.713140  0.003509  0.279888
4   0.664636  0.842189  1.277506  0.195862
5   1.203121  2.128217 -0.095578  0.107313
```

```
6   -1.291218 -1.180055 -0.398511  0.530923
7   -0.702030 -0.515842 -0.432594 -2.442934
8    1.602506 -0.578821 -0.386948  0.517119
9    0.377802 -1.499028 -1.494981  0.756031
10   0.607319 -0.474547  0.396957  0.178727
11  -0.813245 -1.183351  0.416621  0.394159
```

[7]:
```
pd.DataFrame?
```

Remember what I said about Pandas DataFrame being 2D. Let's see what it actually looks like with the example below. Here we are creating a Pandas dataframe from a dictionary object.

[8]:
```
sample_dictionary = { "A": 1.0,
                      "B": pd.Timestamp("20130102"),
                      "C": pd.Series(1, index=list(range(4)), dtype="float32"),
                      "D": np.array([3] * 4, dtype="int32"),
                      "E": pd.Categorical(["test", "train", "test", "train"]),
                      "F": "foo",
                    }
```

[9]:
```
type(sample_dictionary)
```

[9]:
```
dict
```

[10]:
```
sample_dictionary
```

[10]:
```
{'A': 1.0,
 'B': Timestamp('2013-01-02 00:00:00'),
 'C': 0    1.0
 1    1.0
 2    1.0
 3    1.0
 dtype: float32,
 'D': array([3, 3, 3, 3], dtype=int32),
 'E': ['test', 'train', 'test', 'train']
 Categories (2, object): ['test', 'train'],
 'F': 'foo'}
```

[11]:
```
sample_dataframe = pd.DataFrame(sample_dictionary)
```

[12]:
```
type(sample_dataframe)
```

[12]:
```
pandas.core.frame.DataFrame
```

[13]:
```
sample_dataframe
```

[13]:

```
     A          B    C  D      E    F
0  1.0 2013-01-02  1.0  3   test  foo
1  1.0 2013-01-02  1.0  3  train  foo
2  1.0 2013-01-02  1.0  3   test  foo
3  1.0 2013-01-02  1.0  3  train  foo
```

See how the shape changes. Which one is computationally faster?

1.1.1 Displaying DataFrame

Another way to display dataframe is .head() and .tail() functions.

[14]:

```python
sample_df.head()
```

[14]:

```
          A         B         C         D
0  0.383964 -0.401091  1.484901 -0.285452
1  0.882779  0.261930  1.268670 -0.535812
2  1.643004 -0.788867 -0.467345  0.265282
3 -0.429295 -0.713140  0.003509  0.279888
4  0.664636  0.842189  1.277506  0.195862
```

[17]:

```python
sample_df.tail(n=3)
```

[17]:

```
           A         B         C         D
9   0.377802 -1.499028 -1.494981  0.756031
10  0.607319 -0.474547  0.396957  0.178727
11 -0.813245 -1.183351  0.416621  0.394159
```

Try printing out only a few rows from the end.

[18]:

```python
sample_df.tail(2)
```

[18]:

```
           A         B         C         D
10  0.607319 -0.474547  0.396957  0.178727
11 -0.813245 -1.183351  0.416621  0.394159
```

We can also explore the dataframe with the .describe() function.

[19]:

```python
sample_df.describe()
```

[19]:

```
               A          B          C          D
count  12.000000  12.000000  12.000000  12.000000
mean    0.344112  -0.341867   0.131017  -0.003241
std     0.961997   1.002847   0.880591   0.844401
min    -1.291218  -1.499028  -1.494981  -2.442934
25%    -0.497479  -0.886664  -0.407032   0.009121
50%     0.495641  -0.547331  -0.046035   0.230572
75%     0.962865  -0.235336   0.629633   0.424899
```

```
max      1.643004   2.128217   1.484901   0.756031
```

We can also display the column and index elements separately.

[20]:
```
sample_df.columns
```

[20]:
```
Index(['A', 'B', 'C', 'D'], dtype='object')
```

[21]:
```
sample_df.rows
```

```
---------------------------------------------------------------------------
AttributeError                            Traceback (most recent call last)
Input In [21], in <cell line: 1>()
----> 1 sample_df.rows

File ~/Library/Python/3.8/lib/python/site-packages/pandas/core/generic.py:5583,
 ↪in NDFrame.__getattr__(self, name)
   5576 if (
   5577     name not in self._internal_names_set
   5578     and name not in self._metadata
   5579     and name not in self._accessors
   5580     and self._info_axis._can_hold_identifiers_and_holds_name(name)
   5581 ):
   5582     return self[name]
-> 5583 return object.__getattribute__(self, name)

AttributeError: 'DataFrame' object has no attribute 'rows'
```

[22]:
```
sample_df.index
```

[22]:
```
RangeIndex(start=0, stop=12, step=1)
```

1.2 2. Sorting and Selection

1.2.1 Sorting

We can sort a dataframe object using an axis or values.

[23]:
```
sample_df.head()
```

[23]:

	A	B	C	D
0	0.383964	-0.401091	1.484901	-0.285452
1	0.882779	0.261930	1.268670	-0.535812
2	1.643004	-0.788867	-0.467345	0.265282
3	-0.429295	-0.713140	0.003509	0.279888
4	0.664636	0.842189	1.277506	0.195862

[24]:
```
sample_df.sort_index(axis=1, ascending=False)
```

[24]:

	D	C	B	A
0	-0.285452	1.484901	-0.401091	0.383964
1	-0.535812	1.268670	0.261930	0.882779
2	0.265282	-0.467345	-0.788867	1.643004
3	0.279888	0.003509	-0.713140	-0.429295
4	0.195862	1.277506	0.842189	0.664636
5	0.107313	-0.095578	2.128217	1.203121
6	0.530923	-0.398511	-1.180055	-1.291218
7	-2.442934	-0.432594	-0.515842	-0.702030
8	0.517119	-0.386948	-0.578821	1.602506
9	0.756031	-1.494981	-1.499028	0.377802
10	0.178727	0.396957	-0.474547	0.607319
11	0.394159	0.416621	-1.183351	-0.813245

[25]:
```
sample_df.sort_values(by='B')
```

[25]:

	A	B	C	D
9	0.377802	-1.499028	-1.494981	0.756031
11	-0.813245	-1.183351	0.416621	0.394159
6	-1.291218	-1.180055	-0.398511	0.530923
2	1.643004	-0.788867	-0.467345	0.265282
3	-0.429295	-0.713140	0.003509	0.279888
8	1.602506	-0.578821	-0.386948	0.517119
7	-0.702030	-0.515842	-0.432594	-2.442934
10	0.607319	-0.474547	0.396957	0.178727
0	0.383964	-0.401091	1.484901	-0.285452
1	0.882779	0.261930	1.268670	-0.535812
4	0.664636	0.842189	1.277506	0.195862
5	1.203121	2.128217	-0.095578	0.107313

1.2.2 Selection

There are various ways to make selections with a Pandas dataframe. First, let's look at selection of an entire column.

[26]:
```
sample_df_column_a = sample_df["A"]
print('This is the A column of the sample_df: \n', sample_df_column_a)
```

```
This is the A column of the sample_df:
 0    0.383964
1     0.882779
2     1.643004
3    -0.429295
4     0.664636
5     1.203121
6    -1.291218
```

```
7    -0.702030
8     1.602506
9     0.377802
10    0.607319
11   -0.813245
Name: A, dtype: float64
```

[27]:
```
print('This is the A column of the sample_df: \n', sample_df.A) #A.min "A bike"
```

```
This is the A column of the sample_df:
 0     0.383964
1     0.882779
2     1.643004
3    -0.429295
4     0.664636
5     1.203121
6    -1.291218
7    -0.702030
8     1.602506
9     0.377802
10    0.607319
11   -0.813245
Name: A, dtype: float64
```

[28]:
```
print('This is the A column of the sample_df: \n', sample_df.loc[:,["A"]])
```

```
This is the A column of the sample_df:
            A
0   0.383964
1   0.882779
2   1.643004
3  -0.429295
4   0.664636
5   1.203121
6  -1.291218
7  -0.702030
8   1.602506
9   0.377802
10  0.607319
11 -0.813245
```

Now let's see how we can make selections of a subset of elements based on location or values.

[30]:
```
sample_df.loc[3:5, ["A", "B"]]
```

[30]:

	A	B
3	-0.429295	-0.713140
4	0.664636	0.842189

```
5  1.203121  2.128217
```

.loc and .iloc are different locators. While '.loc' returns rows and columns with specific labels, '.iloc' returns rows and columns at specific integer locations.

[31]:
```python
sample_df.iloc[3:5]
```

[31]:
```
          A         B         C         D
3 -0.429295 -0.713140  0.003509  0.279888
4  0.664636  0.842189  1.277506  0.195862
```

[32]:
```python
sample_df.iloc[3:5, ["A", "B"]]
```

```
---------------------------------------------------------------------------
IndexError                                Traceback (most recent call last)
Input In [32], in <cell line: 1>()
----> 1 sample_df.iloc[3:5, ["A", "B"]]

File ~/Library/Python/3.8/lib/python/site-packages/pandas/core/indexing.py:961,
 ↪in _LocationIndexer.__getitem__(self, key)
    959     if self._is_scalar_access(key):
    960         return self.obj._get_value(*key, takeable=self._takeable)
--> 961     return self._getitem_tuple(key)
    962 else:
    963     # we by definition only have the 0th axis
    964     axis = self.axis or 0

File ~/Library/Python/3.8/lib/python/site-packages/pandas/core/indexing.py:1458
 ↪in _iLocIndexer._getitem_tuple(self, tup)
   1456 def _getitem_tuple(self, tup: tuple):
-> 1458     tup = self._validate_tuple_indexer(tup)
   1459     with suppress(IndexingError):
   1460         return self._getitem_lowerdim(tup)

File ~/Library/Python/3.8/lib/python/site-packages/pandas/core/indexing.py:769,
 ↪in _LocationIndexer._validate_tuple_indexer(self, key)
    767 for i, k in enumerate(key):
    768     try:
--> 769         self._validate_key(k, i)
    770     except ValueError as err:
    771         raise ValueError(
    772             "Location based indexing can only have "
    773             f"[{self._valid_types}] types"
    774         ) from err

File ~/Library/Python/3.8/lib/python/site-packages/pandas/core/indexing.py:1372
 ↪in _iLocIndexer._validate_key(self, key, axis)
```

```
   1370 # check that the key has a numeric dtype
   1371 if not is_numeric_dtype(arr.dtype):
-> 1372     raise IndexError(f".iloc requires numeric indexers, got {arr}")
   1374 # check that the key does not exceed the maximum size of the index
   1375 if len(arr) and (arr.max() >= len_axis or arr.min() < -len_axis):

IndexError: .iloc requires numeric indexers, got ['A' 'B']
```

[34]:
```
sample_df.A
```

[34]:
```
0     0.383964
1     0.882779
2     1.643004
3    -0.429295
4     0.664636
5     1.203121
6    -1.291218
7    -0.702030
8     1.602506
9     0.377802
10    0.607319
11   -0.813245
Name: A, dtype: float64
```

[33]:
```
sample_df["A"] > 0
```

[33]:
```
0      True
1      True
2      True
3     False
4      True
5      True
6     False
7     False
8      True
9      True
10     True
11    False
Name: A, dtype: bool
```

[35]:
```
sample_df[sample_df["A"] > 0]
```

[35]:
```
           A         B         C         D
0   0.383964 -0.401091  1.484901 -0.285452
1   0.882779  0.261930  1.268670 -0.535812
2   1.643004 -0.788867 -0.467345  0.265282
4   0.664636  0.842189  1.277506  0.195862
```

```
5   1.203121  2.128217 -0.095578  0.107313
8   1.602506 -0.578821 -0.386948  0.517119
9   0.377802 -1.499028 -1.494981  0.756031
10  0.607319 -0.474547  0.396957  0.178727
```

1.3 3. Handling Missing Data

We need to come up with a way to deal with our missing data points. Here are a few tricks to find and mark them.

[56]:
```
# First we need to add some missing data to our sample_df dataframe.
sample_df2 = sample_df[sample_df > -1.0]
```

[57]:
```
sample_df
```

[57]:
```
           A         B         C         D
0   0.383964 -0.401091  1.484901 -0.285452
1   0.882779  0.261930  1.268670 -0.535812
2   1.643004 -0.788867 -0.467345  0.265282
3  -0.429295 -0.713140  0.003509  0.279888
4   0.664636  0.842189  1.277506  0.195862
5   1.203121  2.128217 -0.095578  0.107313
6  -1.291218 -1.180055 -0.398511  0.530923
7  -0.702030 -0.515842 -0.432594 -2.442934
8   1.602506 -0.578821 -0.386948  0.517119
9   0.377802 -1.499028 -1.494981  0.756031
10  0.607319 -0.474547  0.396957  0.178727
11 -0.813245 -1.183351  0.416621  0.394159
```

[58]:
```
sample_df2
```

[58]:
```
           A         B         C         D
0   0.383964 -0.401091  1.484901 -0.285452
1   0.882779  0.261930  1.268670 -0.535812
2   1.643004 -0.788867 -0.467345  0.265282
3  -0.429295 -0.713140  0.003509  0.279888
4   0.664636  0.842189  1.277506  0.195862
5   1.203121  2.128217 -0.095578  0.107313
6        NaN       NaN -0.398511  0.530923
7  -0.702030 -0.515842 -0.432594       NaN
8   1.602506 -0.578821 -0.386948  0.517119
9   0.377802       NaN       NaN  0.756031
10  0.607319 -0.474547  0.396957  0.178727
11 -0.813245       NaN  0.416621  0.394159
```

[40]:
```
sample_df2.head()
```

[40]:

	A	B	C	D
0	0.383964	-0.401091	1.484901	-0.285452
1	0.882779	0.261930	1.268670	-0.535812
2	1.643004	-0.788867	-0.467345	0.265282
3	-0.429295	-0.713140	0.003509	0.279888
4	0.664636	0.842189	1.277506	0.195862

[41]:
```
sample_df2.describe()
```

[41]:

	A	B	C	D
count	11.000000	9.000000	11.000000	11.000000
mean	0.492778	-0.026664	0.278835	0.218549
std	0.852197	0.962995	0.751373	0.367416
min	-0.813245	-0.788867	-0.467345	-0.535812
25%	-0.025747	-0.578821	-0.392730	0.143020
50%	0.607319	-0.474547	0.003509	0.265282
75%	1.042950	0.261930	0.842645	0.455639
max	1.643004	2.128217	1.484901	0.756031

1.3.1 Dropping the NaN values.

We can use .dropna() command to drop values with NaN.

[42]:
```
sample_df2.dropna()
```

[42]:

	A	B	C	D
0	0.383964	-0.401091	1.484901	-0.285452
1	0.882779	0.261930	1.268670	-0.535812
2	1.643004	-0.788867	-0.467345	0.265282
3	-0.429295	-0.713140	0.003509	0.279888
4	0.664636	0.842189	1.277506	0.195862
5	1.203121	2.128217	-0.095578	0.107313
8	1.602506	-0.578821	-0.386948	0.517119
10	0.607319	-0.474547	0.396957	0.178727

1.3.2 Filling the NaN values.

We can use .fillna() command to drop values with NaN.

[43]:
```
sample_df2.fillna(value='Missing')
```

[43]:

	A	B	C	D
0	0.383964	-0.401091	1.484901	-0.285452
1	0.882779	0.26193	1.26867	-0.535812
2	1.643004	-0.788867	-0.467345	0.265282
3	-0.429295	-0.71314	0.003509	0.279888
4	0.664636	0.842189	1.277506	0.195862
5	1.203121	2.128217	-0.095578	0.107313

```
6    Missing   Missing -0.398511  0.530923
7   -0.70203 -0.515842 -0.432594   Missing
8   1.602506 -0.578821 -0.386948  0.517119
9   0.377802   Missing   Missing  0.756031
10  0.607319 -0.474547  0.396957  0.178727
11 -0.813245   Missing  0.416621  0.394159
```

[44]:
```
sample_df2.fillna(value=2)
```

[44]:

	A	B	C	D
0	0.383964	-0.401091	1.484901	-0.285452
1	0.882779	0.261930	1.268670	-0.535812
2	1.643004	-0.788867	-0.467345	0.265282
3	-0.429295	-0.713140	0.003509	0.279888
4	0.664636	0.842189	1.277506	0.195862
5	1.203121	2.128217	-0.095578	0.107313
6	2.000000	2.000000	-0.398511	0.530923
7	-0.702030	-0.515842	-0.432594	2.000000
8	1.602506	-0.578821	-0.386948	0.517119
9	0.377802	2.000000	2.000000	0.756031
10	0.607319	-0.474547	0.396957	0.178727
11	-0.813245	2.000000	0.416621	0.394159

Let's see how our dataframe looks like now:

[46]:
```
sample_df2
```

[46]:

	A	B	C	D
0	0.383964	-0.401091	1.484901	-0.285452
1	0.882779	0.261930	1.268670	-0.535812
2	1.643004	-0.788867	-0.467345	0.265282
3	-0.429295	-0.713140	0.003509	0.279888
4	0.664636	0.842189	1.277506	0.195862
5	1.203121	2.128217	-0.095578	0.107313
6	NaN	NaN	-0.398511	0.530923
7	-0.702030	-0.515842	-0.432594	NaN
8	1.602506	-0.578821	-0.386948	0.517119
9	0.377802	NaN	NaN	0.756031
10	0.607319	-0.474547	0.396957	0.178727
11	-0.813245	NaN	0.416621	0.394159

[49]:
```
sample_df3 = sample_df2.fillna(value=2)
```

[50]:
```
sample_df3
```

[50]:

	A	B	C	D
0	0.383964	-0.401091	1.484901	-0.285452

```
1   0.882779  0.261930  1.268670 -0.535812
2   1.643004 -0.788867 -0.467345  0.265282
3  -0.429295 -0.713140  0.003509  0.279888
4   0.664636  0.842189  1.277506  0.195862
5   1.203121  2.128217 -0.095578  0.107313
6   2.000000  2.000000 -0.398511  0.530923
7  -0.702030 -0.515842 -0.432594  2.000000
8   1.602506 -0.578821 -0.386948  0.517119
9   0.377802  2.000000  2.000000  0.756031
10  0.607319 -0.474547  0.396957  0.178727
11 -0.813245  2.000000  0.416621  0.394159
```

[62]:
```python
sample_df2.fillna(value=0, inplace=True)
```

[63]:
```python
sample_df2
```

[63]:
```
           A         B         C         D
0   0.383964 -0.401091  1.484901 -0.285452
1   0.882779  0.261930  1.268670 -0.535812
2   1.643004 -0.788867 -0.467345  0.265282
3  -0.429295 -0.713140  0.003509  0.279888
4   0.664636  0.842189  1.277506  0.195862
5   1.203121  2.128217 -0.095578  0.107313
6   0.000000  0.000000 -0.398511  0.530923
7  -0.702030 -0.515842 -0.432594  0.000000
8   1.602506 -0.578821 -0.386948  0.517119
9   0.377802  0.000000  0.000000  0.756031
10  0.607319 -0.474547  0.396957  0.178727
11 -0.813245  0.000000  0.416621  0.394159
```

Why didn't it change?

1.3.3 Dummy Variables

This is a handy dataframe tool to convert categorical variables into dummy/indicator variables. Let's add some categorical variables to sample_df2.

[54]:
```python
import pandas as pd
pd.options.mode.chained_assignment = None  # default='warn'
```

[55]:
```python
categorical_df = sample_df2
```

[59]:
```python
positive_index = sample_df2.B[sample_df2.B > 0].index
negative_index = sample_df2.B[sample_df2.B < 0].index
```

[60]:
```python
categorical_df.B[positive_index] = 'Positive'
categorical_df.B[negative_index] = 'Negative'
```

[61]:
```
categorical_df
```

[61]:
```
           A         B         C         D
0   0.383964  Negative  1.484901 -0.285452
1   0.882779  Positive  1.268670 -0.535812
2   1.643004  Negative -0.467345  0.265282
3  -0.429295  Negative  0.003509  0.279888
4   0.664636  Positive  1.277506  0.195862
5   1.203121  Positive -0.095578  0.107313
6   2.000000       2.0 -0.398511  0.530923
7  -0.702030  Negative -0.432594  2.000000
8   1.602506  Negative -0.386948  0.517119
9   0.377802       2.0  2.000000  0.756031
10  0.607319  Negative  0.396957  0.178727
11 -0.813245       2.0  0.416621  0.394159
```

[64]:
```
categorical_df = categorical_df.fillna(0)
```

[65]:
```
categorical_df.head()
```

[65]:
```
          A         B         C         D
0  0.383964  Negative  1.484901 -0.285452
1  0.882779  Positive  1.268670 -0.535812
2  1.643004  Negative -0.467345  0.265282
3 -0.429295  Negative  0.003509  0.279888
4  0.664636  Positive  1.277506  0.195862
```

[66]:
```
pd.get_dummies( categorical_df, columns=['B'] ).head()
```

[66]:
```
          A         C         D  B_2.0  B_Negative  B_Positive
0  0.383964  1.484901 -0.285452      0           1           0
1  0.882779  1.268670 -0.535812      0           0           1
2  1.643004 -0.467345  0.265282      0           1           0
3 -0.429295  0.003509  0.279888      0           1           0
4  0.664636  1.277506  0.195862      0           0           1
```

[67]:
```
categorical_df = pd.get_dummies( categorical_df, columns=['B'] )
```

1.4 4. Pandas Operations

We can perform basic descriptive statistics using .mean(), .min(), .max() or .describe(). When you see a homework question starting with "Describe your data set", it is good practice to first run the .describe() command.

[68]:
```
sample_df2.mean() #A.mean
```

[68]:
```
A    0.451713
B   -0.019998
C    0.255599
D    0.200337
dtype: float64
```

[69]:
```
sample_df2.min()
```

[69]:
```
A   -0.813245
B   -0.788867
C   -0.467345
D   -0.535812
dtype: float64
```

[70]:
```
sample_df2.max()
```

[70]:
```
A    1.643004
B    2.128217
C    1.484901
D    0.756031
dtype: float64
```

[71]:
```
sample_df2.describe()
```

[71]:

	A	B	C	D
count	12.000000	12.000000	12.000000	12.000000
mean	0.451713	-0.019998	0.255599	0.200337
std	0.824896	0.821333	0.720914	0.355953
min	-0.813245	-0.788867	-0.467345	-0.535812
25%	-0.107324	-0.531587	-0.389839	0.080484
50%	0.495641	-0.200546	0.001754	0.230572
75%	0.962865	0.065483	0.629633	0.424899
max	1.643004	2.128217	1.484901	0.756031

1.5 5. Dataframe Merging

Because life is difficult, you will end up merging various data set in preparation to an ML application. Merging is never easy, always messy, seldom successful at first try.

1.5.1 Concatenating dataframes

[72]:
```
sample_df
```

[72]:

	A	B	C	D
0	0.383964	-0.401091	1.484901	-0.285452
1	0.882779	0.261930	1.268670	-0.535812
2	1.643004	-0.788867	-0.467345	0.265282

```
3  -0.429295 -0.713140  0.003509  0.279888
4   0.664636  0.842189  1.277506  0.195862
5   1.203121  2.128217 -0.095578  0.107313
6  -1.291218 -1.180055 -0.398511  0.530923
7  -0.702030 -0.515842 -0.432594 -2.442934
8   1.602506 -0.578821 -0.386948  0.517119
9   0.377802 -1.499028 -1.494981  0.756031
10  0.607319 -0.474547  0.396957  0.178727
11 -0.813245 -1.183351  0.416621  0.394159
```

[73]:
```
pd.concat?
```

[74]:
```
new_df = pd.concat(sample_df, sample_df2)
```

```
/var/folders/d0/xtw4cvdd52nfnnxn7pz_jdfw0000gn/T/ipykernel_16675/945766093.py:1:
FutureWarning: In a future version of pandas all arguments of concat except for
the argument 'objs' will be keyword-only.
  new_df = pd.concat(sample_df, sample_df2)
```

```
---------------------------------------------------------------------------
TypeError                                 Traceback (most recent call last)
Input In [74], in <cell line: 1>()
----> 1 new_df = pd.concat(sample_df, sample_df2)

File ~/Library/Python/3.8/lib/python/site-packages/pandas/util/_decorators.py:
↪311, in deprecate_nonkeyword_arguments.<locals>.decorate.<locals>.
↪wrapper(*args, **kwargs)
    305 if len(args) > num_allow_args:
    306     warnings.warn(
    307         msg.format(arguments=arguments),
    308         FutureWarning,
    309         stacklevel=stacklevel,
    310     )
--> 311 return func(*args, **kwargs)

File ~/Library/Python/3.8/lib/python/site-packages/pandas/core/reshape/concat.py:
↪346, in concat(objs, axis, join, ignore_index, keys, levels, names,␣
↪verify_integrity, sort, copy)
    142 @deprecate_nonkeyword_arguments(version=None, allowed_args=["objs"])
    143 def concat(
    144     objs: Iterable[NDFrame] | Mapping[Hashable, NDFrame],
   (…)
    153     copy: bool = True,
    154 ) -> DataFrame | Series:
    155     """
    156     Concatenate pandas objects along a particular axis with optional set␣
↪logic
    157     along the other axes.
```

```
    (…)
    344     ValueError: Indexes have overlapping values: ['a']
    345     """
--> 346     op = _Concatenator(
    347         objs,
    348         axis=axis,
    349         ignore_index=ignore_index,
    350         join=join,
    351         keys=keys,
    352         levels=levels,
    353         names=names,
    354         verify_integrity=verify_integrity,
    355         copy=copy,
    356         sort=sort,
    357     )
    359     return op.get_result()

File ~/Library/Python/3.8/lib/python/site-packages/pandas/core/reshape/concat.py:
 ↪381, in _Concatenator.__init__(self, objs, axis, join, keys, levels, names,␣
 ↪ignore_index, verify_integrity, copy, sort)
    367 def __init__(
    368     self,
    369     objs: Iterable[NDFrame] | Mapping[Hashable, NDFrame],
    (…)
    378     sort=False,
    379 ):
    380     if isinstance(objs, (ABCSeries, ABCDataFrame, str)):
--> 381         raise TypeError(
    382             "first argument must be an iterable of pandas "
    383             f'objects, you passed an object of type "{type(objs).
 ↪__name__}"'
    384         )
    386     if join == "outer":
    387         self.intersect = False

TypeError: first argument must be an iterable of pandas objects, you passed an␣
 ↪object of type "DataFrame"
```

I told you never easy!

[76]:
```
new_df = pd.concat([sample_df, sample_df2])
```

[77]:
```
new_df.head()
```

[77]:

	A	B	C	D
0	0.383964	-0.401091	1.484901	-0.285452
1	0.882779	0.261930	1.268670	-0.535812

```
2  1.643004 -0.788867 -0.467345  0.265282
3 -0.429295 -0.713140  0.003509  0.279888
4  0.664636  0.842189  1.277506  0.195862
```

[78]:
```python
sample_df2.head()
```

[78]:
```
          A         B         C         D
0  0.383964 -0.401091  1.484901 -0.285452
1  0.882779  0.261930  1.268670 -0.535812
2  1.643004 -0.788867 -0.467345  0.265282
3 -0.429295 -0.713140  0.003509  0.279888
4  0.664636  0.842189  1.277506  0.195862
```

[79]:
```python
sample_df.head()
```

[79]:
```
          A         B         C         D
0  0.383964 -0.401091  1.484901 -0.285452
1  0.882779  0.261930  1.268670 -0.535812
2  1.643004 -0.788867 -0.467345  0.265282
3 -0.429295 -0.713140  0.003509  0.279888
4  0.664636  0.842189  1.277506  0.195862
```

[81]:
```python
sample_df2.tail()
```

[81]:
```
           A         B         C         D
7  -0.702030 -0.515842 -0.432594  0.000000
8   1.602506 -0.578821 -0.386948  0.517119
9   0.377802  0.000000  0.000000  0.756031
10  0.607319 -0.474547  0.396957  0.178727
11 -0.813245  0.000000  0.416621  0.394159
```

[84]:
```python
new_df.head() == sample_df2.head()
```

[84]:
```
      A     B     C     D
0  True  True  True  True
1  True  True  True  True
2  True  True  True  True
3  True  True  True  True
4  True  True  True  True
```

What did concat do?

1.5.2 Merging the dataframes

Merging is a directional way of combining data frames.

[85]:
```python
left = pd.DataFrame({"key": ["val", "val"], "left_val": [1, 2]})
```

[86]:
```
left
```

[86]:
```
   key  left_val
0  val         1
1  val         2
```

[87]:
```
right = pd.DataFrame({"key": ["val", "val"], "right_val": [3, 4]})
```

[88]:
```
right
```

[88]:
```
   key  right_val
0  val          3
1  val          4
```

[89]:
```
pd.merge(left, right, on="key")
```

[89]:
```
   key  left_val  right_val
0  val         1          3
1  val         1          4
2  val         2          3
3  val         2          4
```

[90]:
```
left = pd.DataFrame({"key": ["val1", "val2"], "left_val": [1, 2]})
```

[91]:
```
left
```

[91]:
```
    key  left_val
0  val1         1
1  val2         2
```

[92]:
```
right = pd.DataFrame({"key": ["val1", "val2"], "right_val": [3, 4]})
```

[93]:
```
right
```

[93]:
```
    key  right_val
0  val1          3
1  val2          4
```

[94]:
```
pd.merge(left, right, on="key")
```

[94]:
```
    key  left_val  right_val
0  val1         1          3
1  val2         2          4
```

Logical right? Let's see what concat would do?

[95]:
```
pd.concat([left,right])
```

[95]:
```
     key  left_val  right_val
0   val1       1.0        NaN
1   val2       2.0        NaN
0   val1       NaN        3.0
1   val2       NaN        4.0
```

#nevereasy #alwaysmessy #seldomsuccessful.

1.6 6. Dataframe Grouping

One of the best features of pandas dataframes is the dataframe grouping.

[96]:
```
sample_df3 = df = pd.DataFrame({
                                "A": ["foo", "bar", "foo", "bar", "foo", "bar",␣
 ↪"foo", "foo"],
                                "B": ["one", "one", "two", "three", "two",␣
 ↪"two", "one", "three"],
                                "C": np.random.randn(8),
                                "D": np.random.randn(8),
                                }
                               )
```

[98]:
```
sample_df3
```

[98]:
```
     A      B         C         D
0  foo    one -0.746668 -2.433648
1  bar    one  0.434697  0.325568
2  foo    two  1.556932 -0.108870
3  bar  three  0.642019  1.102126
4  foo    two -0.128129  0.225443
5  bar    two  2.083353  1.420522
6  foo    one -0.237136  0.560903
7  foo  three  0.463496 -1.019963
```

[97]:
```
sample_df3.groupby("A").median()
```

[97]:
```
            C         D
A
bar  0.642019  1.102126
foo -0.128129 -0.108870
```

[100]:
```
sample_df3.describe?
```

[101]:
```
sample_df3.groupby("A").sum()
```

[101]:
```
            C         D
A
bar  3.160069  2.848215
```

```
foo  0.908495 -2.776135
```

[102]:
```
sample_df3.groupby(["A","B"]).sum()
```

[102]:
```
                  C         D
A   B
bar one     0.434697  0.325568
    three   0.642019  1.102126
    two     2.083353  1.420522
foo one    -0.983804 -1.872744
    three   0.463496 -1.019963
    two     1.428802  0.116573
```

1.7 7. Pandas with a Real Data Set

[103]:
```
# Read the iris dataset from a CSV file
iris_df = pd.read_csv('./iris.csv')

# Print data type for df
print( type(iris_df) )
```

```
<class 'pandas.core.frame.DataFrame'>
```

Let's further explore what is in this data set.

[104]:
```
iris_df.head()
```

[104]:
```
   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
```

[105]:
```
iris_df.shape
```

[105]:
```
(150, 5)
```

[106]:
```
iris_df.min()
```

[106]:
```
sepal_length       4.3
sepal_width        2.0
petal_length       1.0
petal_width        0.1
species         setosa
dtype: object
```

[107]:
```
iris_df.max()
```

[107]:
```
sepal_length           7.9
sepal_width            4.4
petal_length           6.9
petal_width            2.5
species          virginica
dtype: object
```

[111]:
```
iris_df.describe(include='all')
```

[111]:

	sepal_length	sepal_width	petal_length	petal_width	species
count	150.000000	150.000000	150.000000	150.000000	150
unique	NaN	NaN	NaN	NaN	3
top	NaN	NaN	NaN	NaN	setosa
freq	NaN	NaN	NaN	NaN	50
mean	5.843333	3.057333	3.758000	1.199333	NaN
std	0.828066	0.435866	1.765298	0.762238	NaN
min	4.300000	2.000000	1.000000	0.100000	NaN
25%	5.100000	2.800000	1.600000	0.300000	NaN
50%	5.800000	3.000000	4.350000	1.300000	NaN
75%	6.400000	3.300000	5.100000	1.800000	NaN
max	7.900000	4.400000	6.900000	2.500000	NaN

[112]:
```
# First 5 values of petal length
print(iris_df.petal_length.head())
```

```
0    1.4
1    1.4
2    1.3
3    1.5
4    1.4
Name: petal_length, dtype: float64
```

[113]:
```
# Create new petal area feature
iris_df['sepal_area'] = iris_df.sepal_width * iris_df.sepal_length
```

[114]:
```
iris_df['sepal_area'].head()
```

[114]:
```
0    17.85
1    14.70
2    15.04
3    14.26
4    18.00
Name: sepal_area, dtype: float64
```

1.7.1 Filtering, Segmentation and Aggregation

Let's create a mask.

[115]:
```python
sepal_width_mask = iris_df.sepal_width>3.
```

[116]:
```python
iris_df[sepal_width_mask]
```

[116]:
```
     sepal_length  sepal_width  petal_length  petal_width    species  \
0             5.1          3.5           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
5             5.4          3.9           1.7          0.4     setosa
..            …            …             …            …        …
140           6.7          3.1           5.6          2.4  virginica
141           6.9          3.1           5.1          2.3  virginica
143           6.8          3.2           5.9          2.3  virginica
144           6.7          3.3           5.7          2.5  virginica
148           6.2          3.4           5.4          2.3  virginica

     sepal_area
0         17.85
2         15.04
3         14.26
4         18.00
5         21.06
..          …
140       20.77
141       21.39
143       21.76
144       22.11
148       21.08

[67 rows x 6 columns]
```

[117]:
```python
iris_df[sepal_width_mask].min()
```

[117]:
```
sepal_length       4.4
sepal_width        3.1
petal_length       1.0
petal_width        0.1
species         setosa
sepal_area       14.08
dtype: object
```

[118]:
```python
iris_df.groupby('species').median()
```

[118]:
```
            sepal_length  sepal_width  petal_length  petal_width  sepal_area
species
setosa               5.0          3.4          1.50          0.2      17.170
```

versicolor	5.9	2.8	4.35	1.3	16.385
virginica	6.5	3.0	5.55	2.0	20.060

[ ]:

2 Seaborn Workbook

Welcome to the Seaborn Workbook. Let's start with importing the required libraries.

[1]:
```
import numpy as np
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt
```

[2]:
```
sns.__version__, np.__version__, pd.__version__
```

[2]:
```
('0.11.0', '1.22.2', '1.4.0')
```

[9]:
```
%matplotlib inline
```

Are you ready to prepare the best plots EVER? Let's start with working on real data.

[4]:
```
# Read the iris dataset from a CSV file
iris_df = pd.read_csv('./iris.csv')

# Print data type for df
print( type(iris_df) )
```

```
<class 'pandas.core.frame.DataFrame'>
```

[5]:
```
iris_df.head()
```

[5]:

	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

If you want to explore different data sets, seaborn comes with default examples.

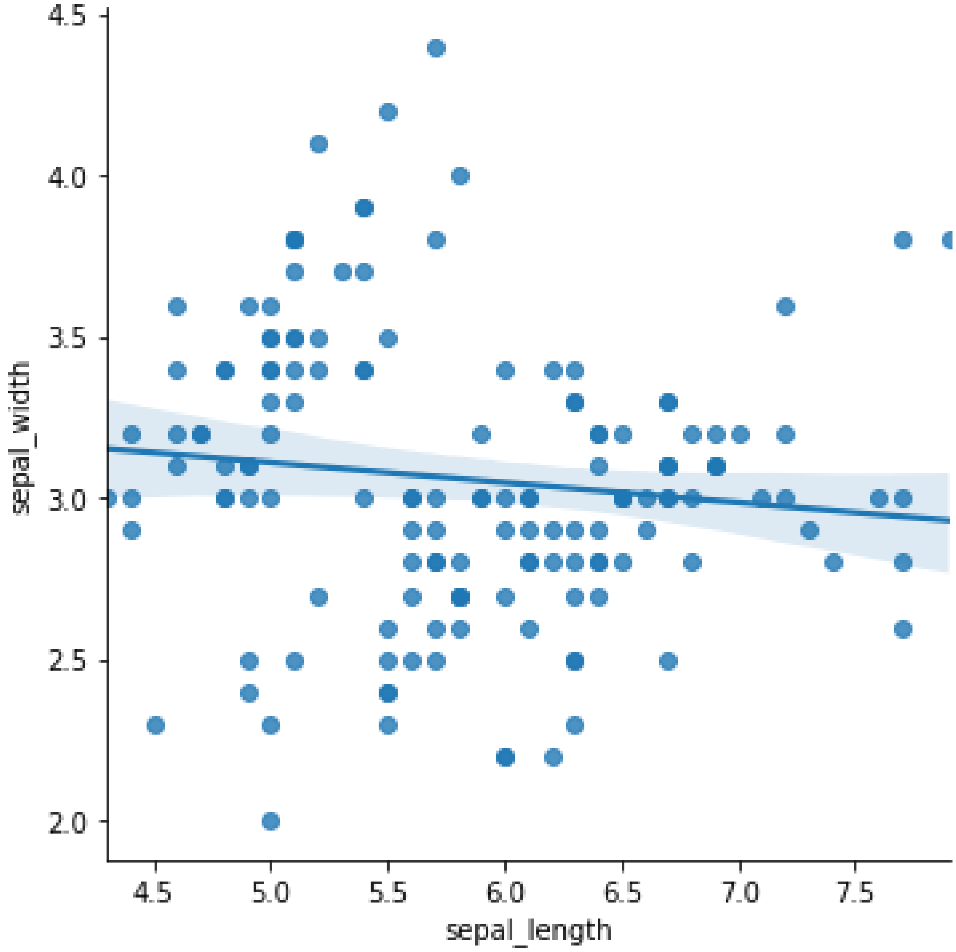
[6]:
```
iris_df = sns.load_dataset?
```

[7]:
```
iris_df = sns.load_dataset("iris")
```

2.0.1 Lmplot and Regplot

These are the most simple plotting options for regression.

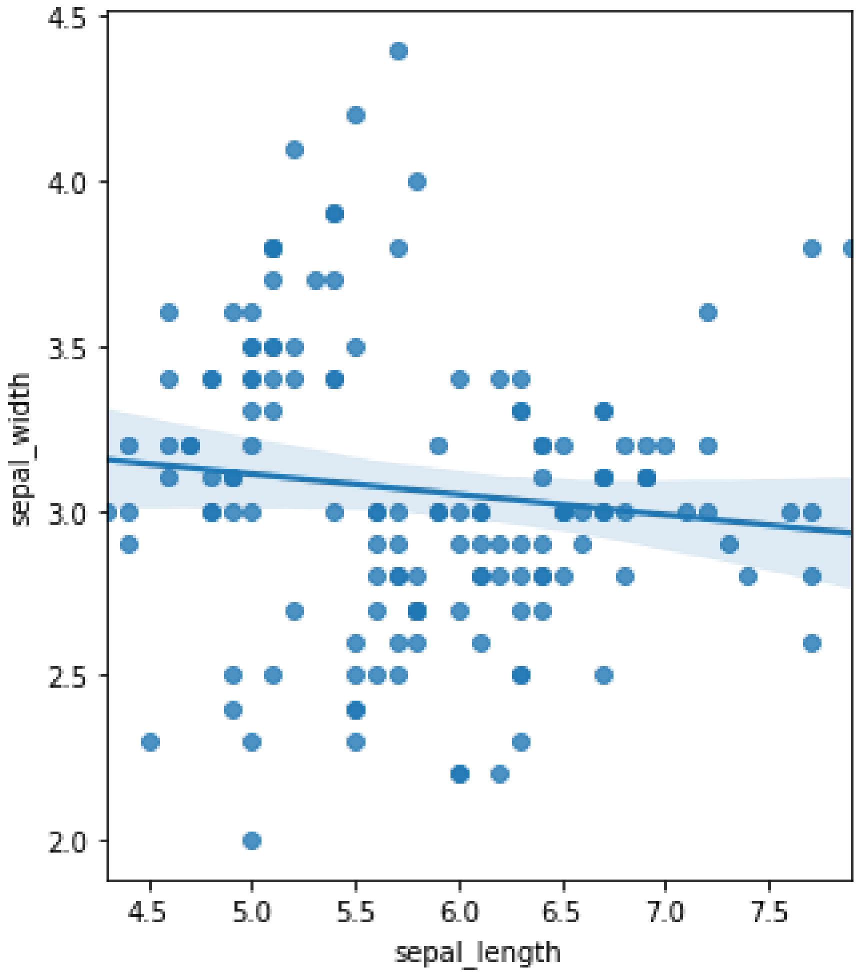
[10]:
```
sns.lmplot(x='sepal_length', y='sepal_width', data=iris_df)
plt.show()
```



However, if you want to control the size and shape of the plot, you need to use regplot.

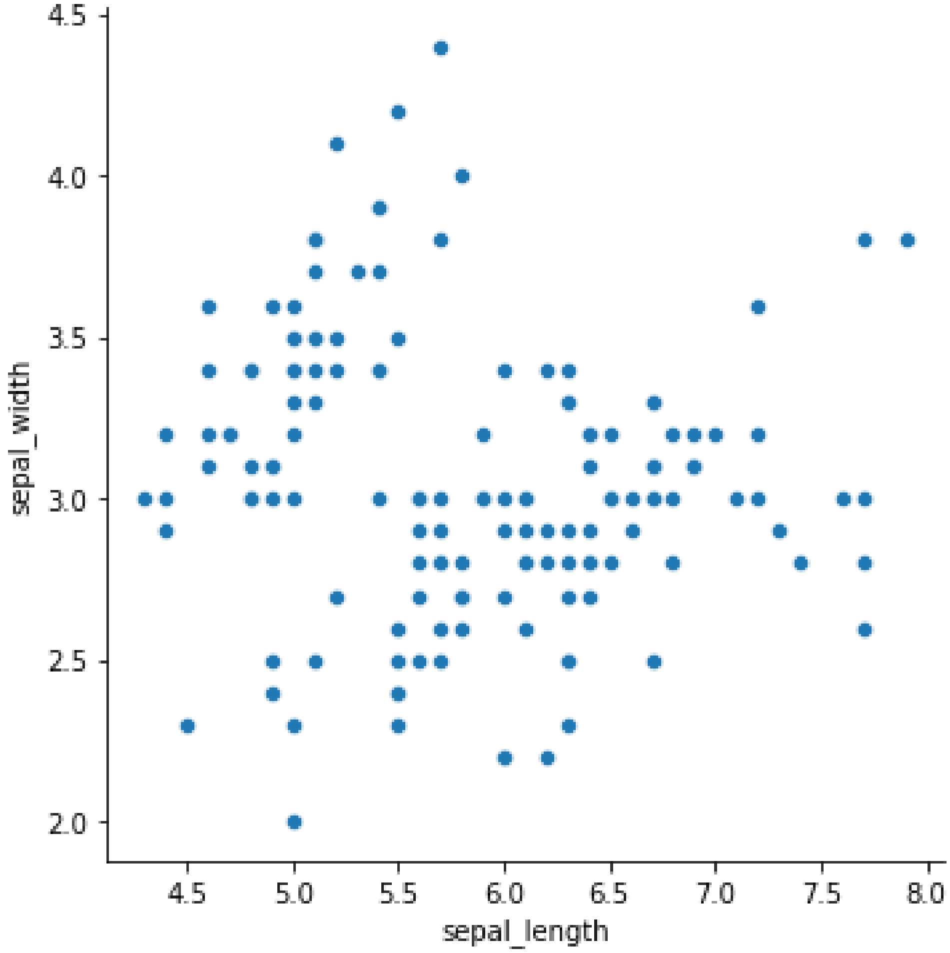
[11]:
```
fig, ax = plt.subplots(figsize=(5,6))
sns.regplot(x="sepal_length", y="sepal_width", data=iris_df, ax=ax)
```

[11]: <AxesSubplot:xlabel='sepal_length', ylabel='sepal_width'>

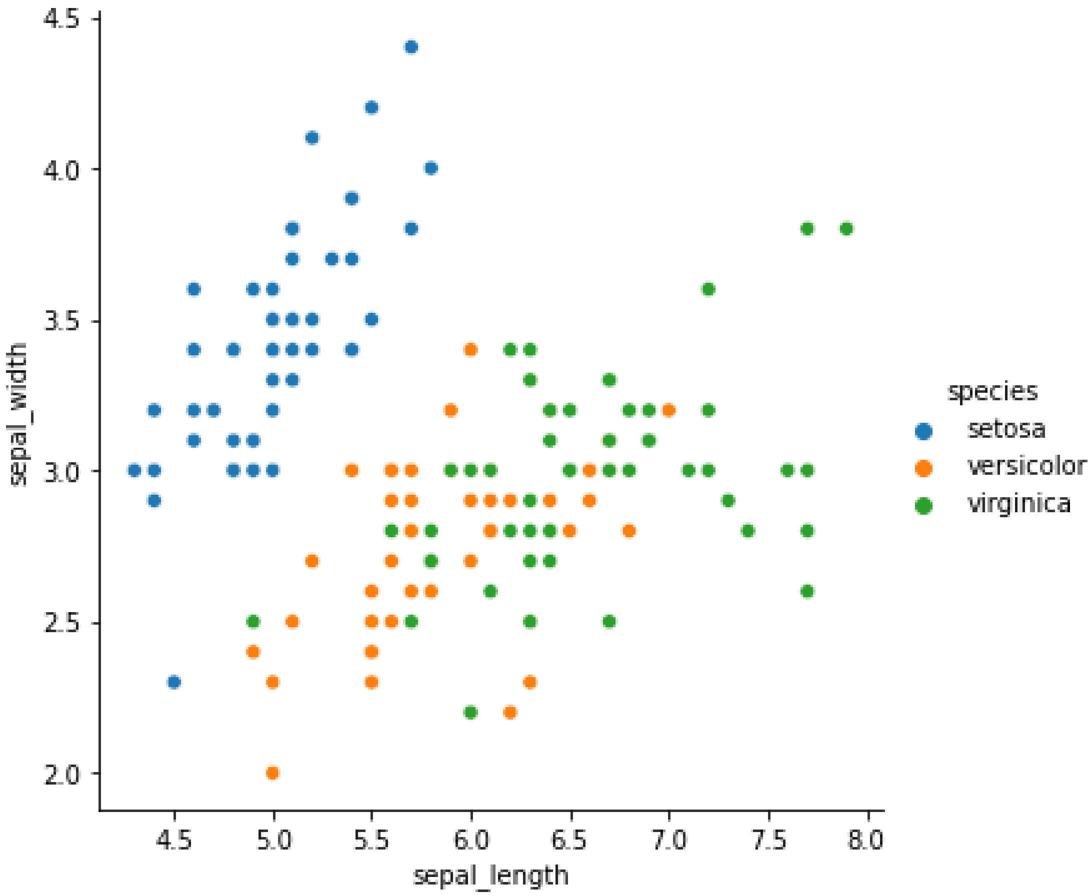


2.0.2 Relplot

[12]:
```
fig = sns.relplot(data=iris_df, x="sepal_length", y="sepal_width")
plt.show()
```

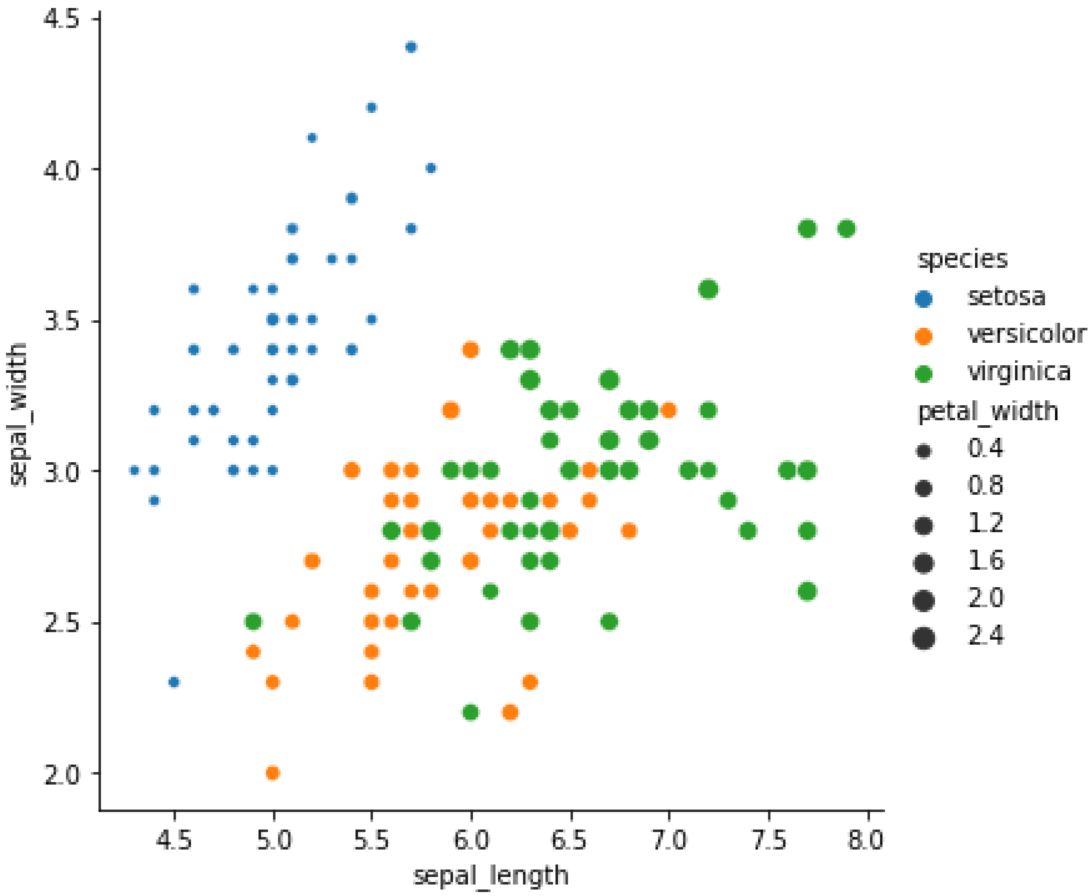


[13]:
```
sns.relplot(data=iris_df, x="sepal_length", y="sepal_width", hue='species')
plt.show()
```



[14]:

```
sns.relplot(data=iris_df, x="sepal_length", y="sepal_width", hue='species',␣
    ↪size="petal_width")
plt.show()
```



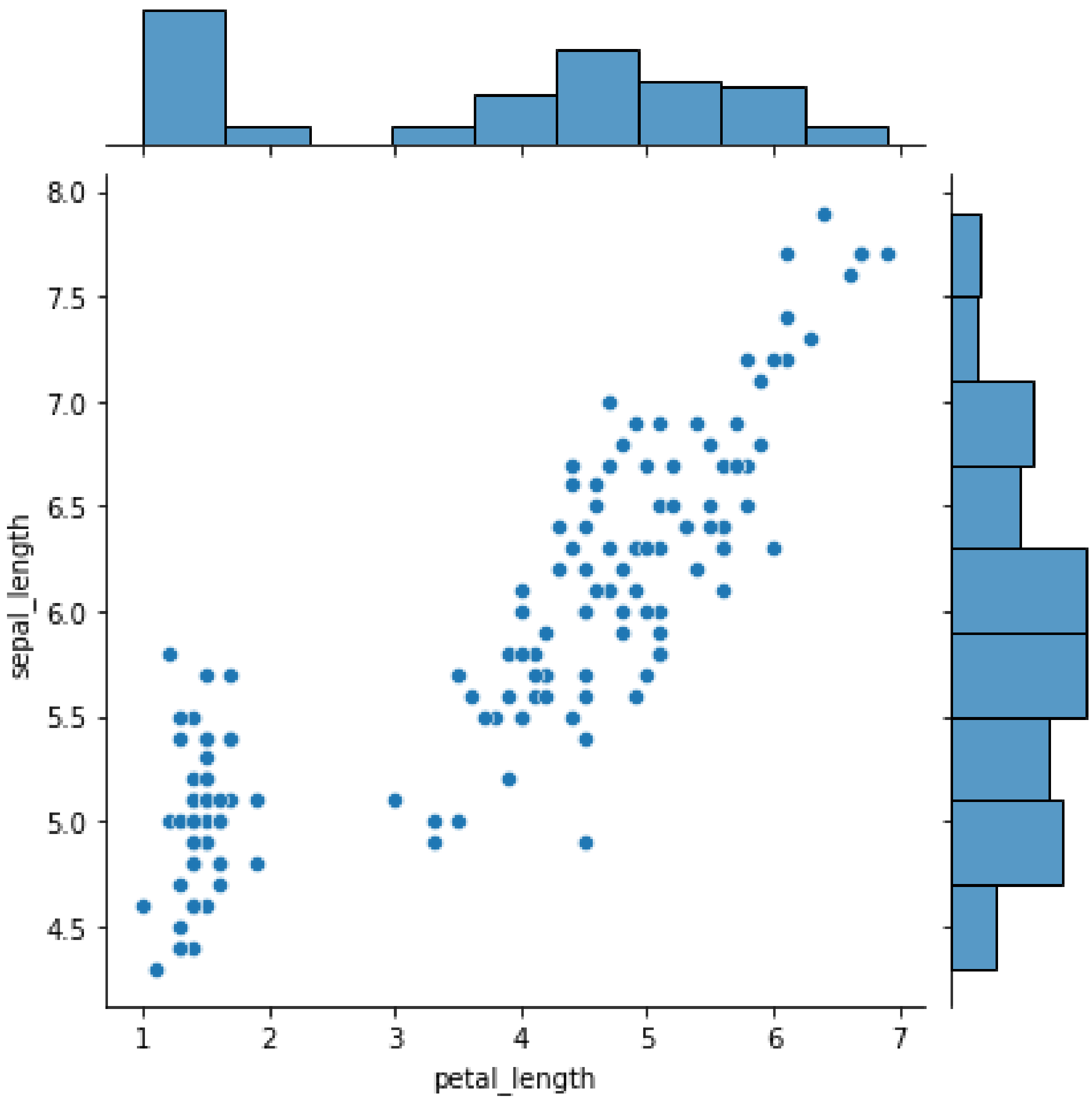
What can you tell me about these species?

2.0.3 Jointplot

This plot type is used to plot two variables with bivariate and univariate graphs.

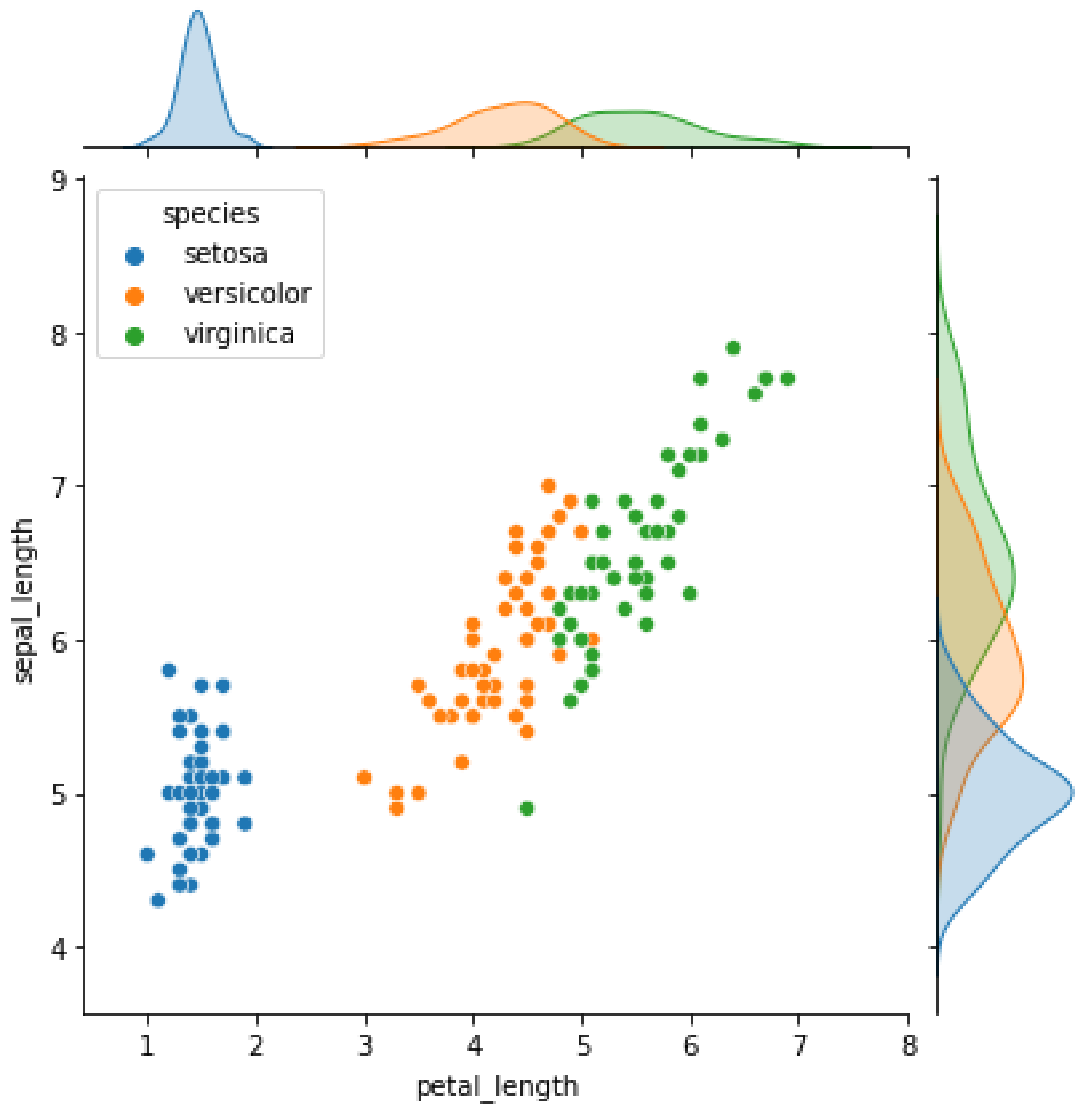
[15]:
```
sns.jointplot(data=iris_df, x="petal_length", y="sepal_length")
```

[15]:
```
<seaborn.axisgrid.JointGrid at 0x135cc28b0>
```



[16]:
```
sns.jointplot(data=iris_df, x="petal_length", y="sepal_length", hue="species")
```

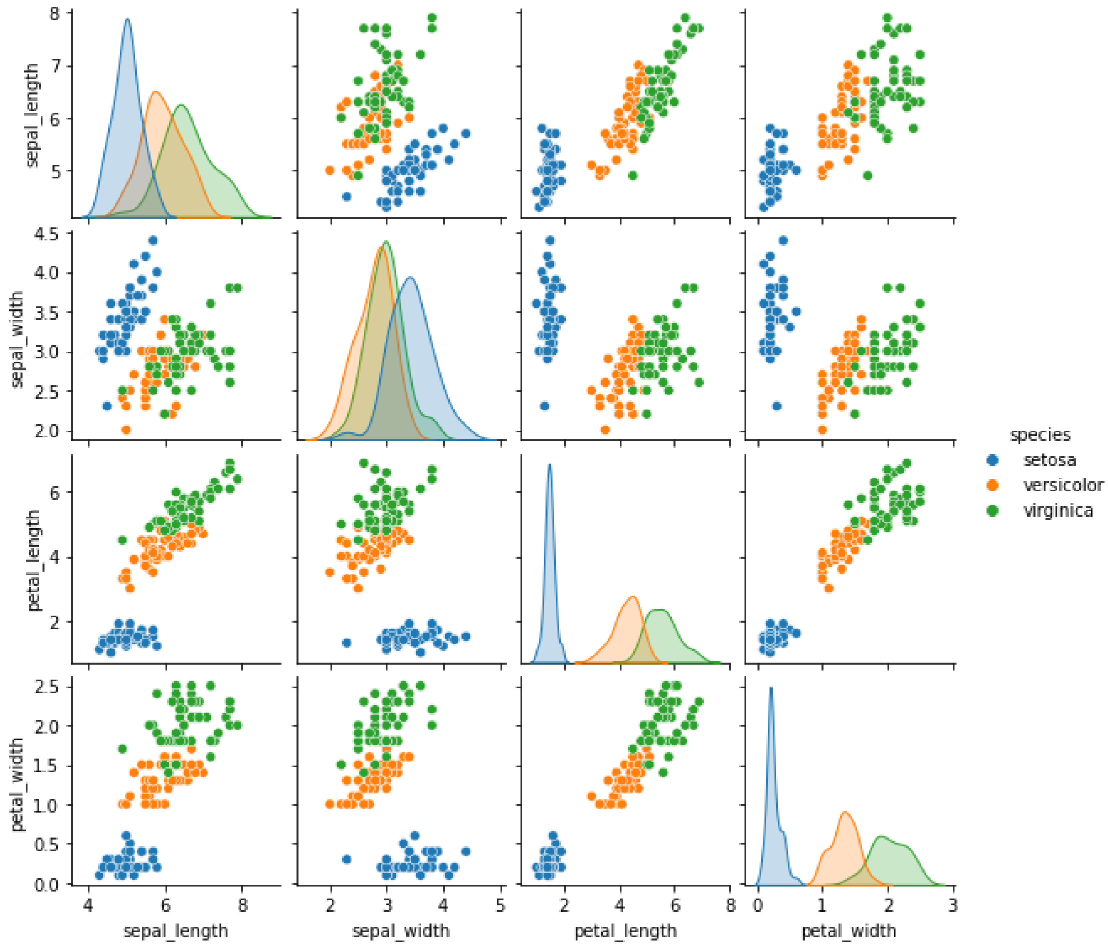
[16]: <seaborn.axisgrid.JointGrid at 0x136019fa0>



2.0.4 Pairplot

It explores the pairwise relationship of the whole data set.

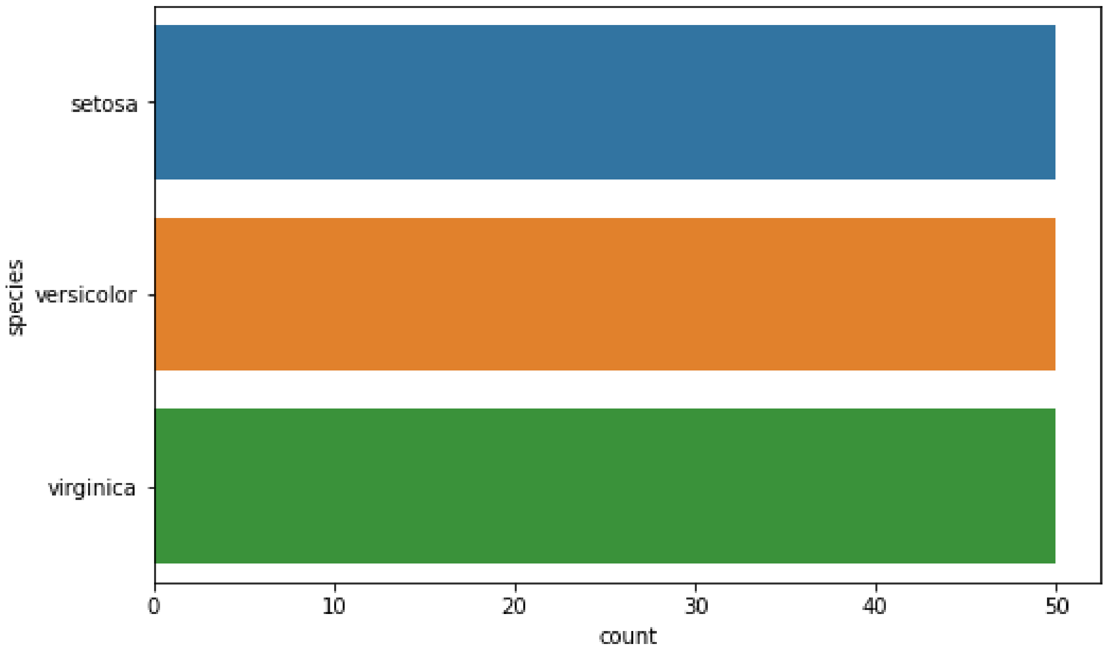
[17]:
```
sns.pairplot(data=iris_df, hue="species", height=2.)
plt.show()
```



2.0.5 Countplot

Countplot is like a simple bar plot that shows the counts of observations in each category.

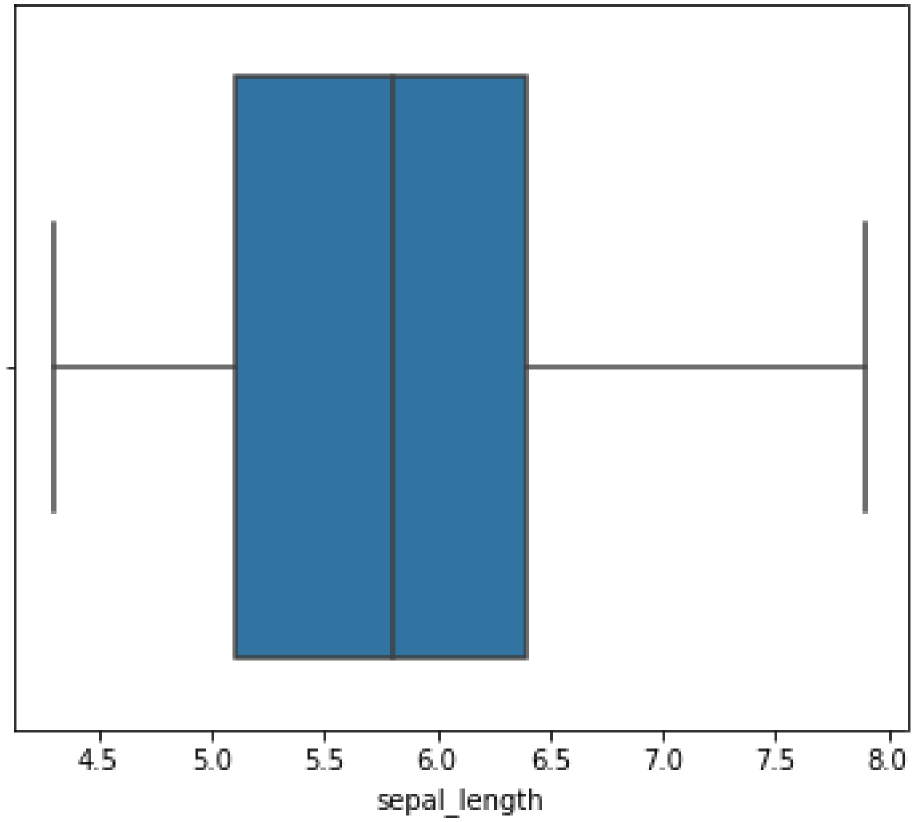
[18]:
```
fig, ax = plt.subplots(figsize=(8,5))
sns.countplot(y='species', data=iris_df)
plt.show()
```



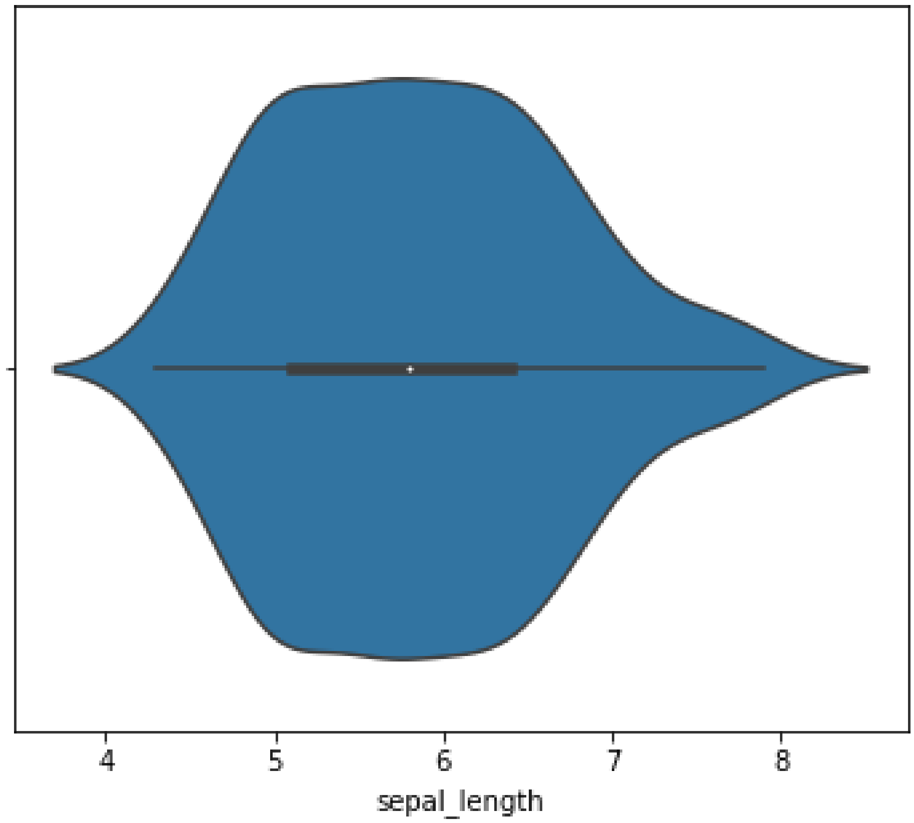
2.0.6 Boxplot and Violinplot

Boxplot shows the distributions with respect to categories as a box plot. Violinplot is a combination of boxplot and densities of categories.

[19]:
```
fig, ax = plt.subplots(figsize=(6,5))
sns.boxplot(x='sepal_length', data=iris_df)
plt.show()
```



[20]:
```
fig, ax = plt.subplots(figsize=(6,5))
sns.violinplot(x='sepal_length', data=iris_df)
plt.show()
```



2.0.7 Heatmap

A personal favourite, the heatmap is a rectangular matrix like demonstration of values.

[21]:
```
corr = iris_df.corr()
```

[22]:
```
corr
```

[22]:

	sepal_length	sepal_width	petal_length	petal_width
sepal_length	1.000000	-0.117570	0.871754	0.817941
sepal_width	-0.117570	1.000000	-0.428440	-0.366126
petal_length	0.871754	-0.428440	1.000000	0.962865
petal_width	0.817941	-0.366126	0.962865	1.000000

[23]:
```
# Draw a heatmap with the numeric values in each cell
f, ax = plt.subplots(figsize=(9, 6))
sns.heatmap(corr*100, annot=True, fmt="2.1f", linewidths=.5, ax=ax, vmin=-100)
plt.show()
```


sepal_length
sepal_width
petal_length
petal_width
100.0
-11.8
87.2
81.8
-11.8
100.0
-42.8
-36.6
87.2
-42.8
100.0
96.3
81.8
-36.6
96.3
100.0
100
75
50
25
0
−25
−50
−75
−100

```
[ ]:
```