Introduction to data manipulation in Python with Pandas and visulization with plotnine

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Who am I ?

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Over the last few years, Python has gained an immense amount of popularity thanks to its numerous libraries in the field of machine learning, statistical data analysis, and bioinformatics. While a few years ago, it was often necessary to go back to R for performing routine data manipulation and analysis tasks, nowadays Python has a vast ecosystem of libraries for doing just that.

Today, we will do a quick introduction of the most popular libraries for data analysis:

- **pandas**, for reading and manipulation tabular data
- **plotnine**, the Python clone of ggplot2

Overview:

- 0 - Foreword, working in a jupyter environment
- 1 - Loading required libraries
- 2 - Foreword on Pandas
- 3 - Reading data with Pandas
- 4 - Dealing with missing data
- 5 - Computing basic statistics
- 6 - Filtering
- 8 - GroupBy operations
- 9 - Joining different tables
- 10 - Visualization with Plotnine

This is a markdown cell

With some features of the markdown syntax, such as:

- **bold** `**bold**`
- *italic* `*italic*`
- `inline code`

  ```
  `inline code`
  ```

- links `[links](https://www.google.com/)`
- Images

  `![](https://maximeborry.com/authors/maxime/avatar_hu4dc3c23d5a8c195732bbca11d7ce61be_114670_`
- Latex code $y = ax + b$
  `$y = ax + b$`

```python
print("This is a code cell in Python")
```

```
This is a code cell in Python
```

```bash
! echo "This is code cell in bash"
```

```
This is code cell in bash
```

```
%%bash

echo "This a multiline code cell"
echo "in bash"
```

```
This a multiline code cell
in bash
```

1 - Loading required libraries

```python
import pandas as pd
import numpy as np
from plotnine import *
```

```python
pd.__version__
```

```
'1.4.3'
```

```python
np.__version__
```

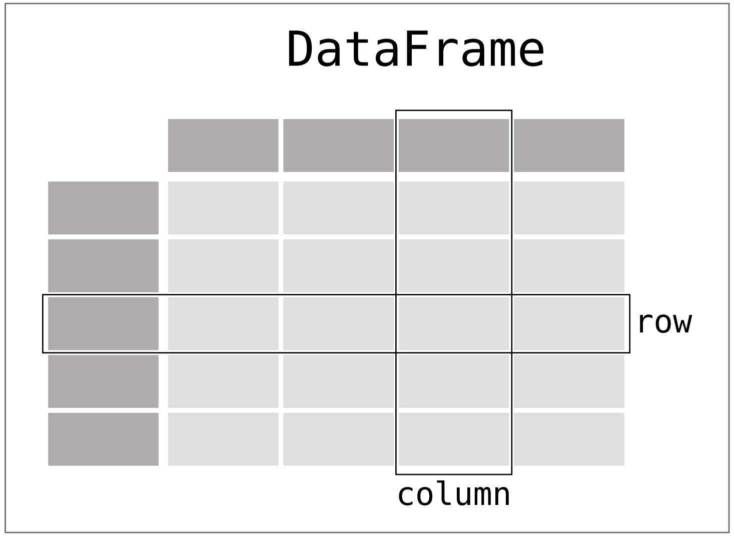
```
'1.23.1'
```

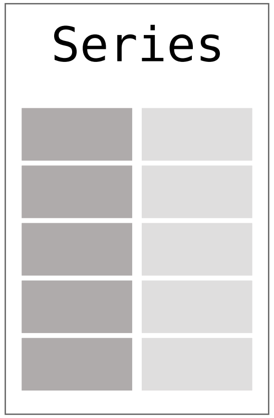
```python
! conda list | grep plotnine
```

```
plotnine                  0.9.0              pyhd8ed1ab_0    conda-forge
```

2 - Foreword on Pandas

Pandas terminology





The pandas getting started tutorial: **pandas.pydata.org/docs/getting_started**

3 - Reading data with Pandas

```
sample_table_url = "https://raw.githubusercontent.com/SPAAM-community/AncientMetagenomeDir/b187df6ebd23dfeb42935fd5020cb615ead3f164/ancie
library_table_url = "https://raw.githubusercontent.com/SPAAM-community/AncientMetagenomeDir/b187df6ebd23dfeb42935fd5020cb615ead3f164/anci
```

Getting help in Python

```
help(pd.read_csv)
```

```
Help on function read_csv in module pandas.io.parsers.readers:

read_csv(filepath_or_buffer: 'FilePath | ReadCsvBuffer[bytes] | ReadCsvBuffer[str]', sep=<no_default>, delimiter=N
one, header='infer', names=<no_default>, index_col=None, usecols=None, squeeze=None, prefix=<no_default>, mangle_d
upe_cols=True, dtype: 'DtypeArg | None' = None, engine: 'CSVEngine | None' = None, converters=None, true_values=No
ne, false_values=None, skipinitialspace=False, skiprows=None, skipfooter=0, nrows=None, na_values=None, keep_defau
lt_na=True, na_filter=True, verbose=False, skip_blank_lines=True, parse_dates=None, infer_datetime_format=False, k
eep_date_col=False, date_parser=None, dayfirst=False, cache_dates=True, iterator=False, chunksize=None, compressio
n: 'CompressionOptions' = 'infer', thousands=None, decimal: 'str' = '.', lineterminator=None, quotechar='"', quoti
ng=0, doublequote=True, escapechar=None, comment=None, encoding=None, encoding_errors: 'str | None' = 'strict', di
alect=None, error_bad_lines=None, warn_bad_lines=None, on_bad_lines=None, delim_whitespace=False, low_memory=True,
memory_map=False, float_precision=None, storage_options: 'StorageOptions' = None)
    Read a comma-separated values (csv) file into DataFrame.

    Also supports optionally iterating or breaking of the file
    into chunks.

    Additional help can be found in the online docs for
    `IO Tools <https://pandas.pydata.org/pandas-docs/stable/user_guide/io.html>`_.

    Parameters
    ----------
    filepath_or_buffer : str, path object or file-like object
        Any valid string path is acceptable. The string could be a URL. Valid
        URL schemes include http, ftp, s3, gs, and file. For file URLs, a host is
        expected. A local file could be: file://localhost/path/to/table.csv.

        If you want to pass in a path object, pandas accepts any ``os.PathLike``.

        By file-like object, we refer to objects with a ``read()`` method, such as
        a file handle (e.g. via builtin ``open`` function) or ``StringIO``.
    sep : str, default ','
        Delimiter to use. If sep is None, the C engine cannot automatically detect
        the separator, but the Python parsing engine can, meaning the latter will
        be used and automatically detect the separator by Python's builtin sniffer
        tool, ``csv.Sniffer``. In addition, separators longer than 1 character and
        different from ``'\s+'`` will be interpreted as regular expressions and
        will also force the use of the Python parsing engine. Note that regex
        delimiters are prone to ignoring quoted data. Regex example: ``'\r\t'``.
    delimiter : str, default ``None``
        Alias for sep.
    header : int, list of int, None, default 'infer'
        Row number(s) to use as the column names, and the start of the
```

```
    data.  Default behavior is to infer the column names: if no names
    are passed the behavior is identical to ``header=0`` and column
    names are inferred from the first line of the file, if column
    names are passed explicitly then the behavior is identical to
    ``header=None``. Explicitly pass ``header=0`` to be able to
    replace existing names. The header can be a list of integers that
    specify row locations for a multi-index on the columns
    e.g. [0,1,3]. Intervening rows that are not specified will be
    skipped (e.g. 2 in this example is skipped). Note that this
    parameter ignores commented lines and empty lines if
    ``skip_blank_lines=True``, so ``header=0`` denotes the first line of
    data rather than the first line of the file.
names : array-like, optional
    List of column names to use. If the file contains a header row,
    then you should explicitly pass ``header=0`` to override the column names.
    Duplicates in this list are not allowed.
index_col : int, str, sequence of int / str, or False, optional, default ``None``
  Column(s) to use as the row labels of the ``DataFrame``, either given as
  string name or column index. If a sequence of int / str is given, a
  MultiIndex is used.

  Note: ``index_col=False`` can be used to force pandas to *not* use the first
  column as the index, e.g. when you have a malformed file with delimiters at
  the end of each line.
usecols : list-like or callable, optional
    Return a subset of the columns. If list-like, all elements must either
    be positional (i.e. integer indices into the document columns) or strings
    that correspond to column names provided either by the user in `names` or
    inferred from the document header row(s). If ``names`` are given, the document
    header row(s) are not taken into account. For example, a valid list-like
    `usecols` parameter would be ``[0, 1, 2]`` or ``['foo', 'bar', 'baz']``.
    Element order is ignored, so ``usecols=[0, 1]`` is the same as ``[1, 0]``.
    To instantiate a DataFrame from ``data`` with element order preserved use
    ``pd.read_csv(data, usecols=['foo', 'bar'])[['foo', 'bar']]`` for columns
    in ``['foo', 'bar']`` order or
    ``pd.read_csv(data, usecols=['foo', 'bar'])[['bar', 'foo']]``
    for ``['bar', 'foo']`` order.

    If callable, the callable function will be evaluated against the column
    names, returning names where the callable function evaluates to True. An
    example of a valid callable argument would be ``lambda x: x.upper() in
    ['AAA', 'BBB', 'DDD']``. Using this parameter results in much faster
    parsing time and lower memory usage.
squeeze : bool, default False
    If the parsed data only contains one column then return a Series.

    .. deprecated:: 1.4.0
        Append ``.squeeze("columns")`` to the call to ``read_csv`` to squeeze
        the data.
prefix : str, optional
    Prefix to add to column numbers when no header, e.g. 'X' for X0, X1, ...
```

```
    .. deprecated:: 1.4.0
       Use a list comprehension on the DataFrame's columns after calling ``read_csv``.
mangle_dupe_cols : bool, default True
    Duplicate columns will be specified as 'X', 'X.1', ...'X.N', rather than
    'X'...'X'. Passing in False will cause data to be overwritten if there
    are duplicate names in the columns.
dtype : Type name or dict of column -> type, optional
    Data type for data or columns. E.g. {'a': np.float64, 'b': np.int32,
    'c': 'Int64'}
    Use `str` or `object` together with suitable `na_values` settings
    to preserve and not interpret dtype.
    If converters are specified, they will be applied INSTEAD
    of dtype conversion.
engine : {'c', 'python', 'pyarrow'}, optional
    Parser engine to use. The C and pyarrow engines are faster, while the python engine
    is currently more feature-complete. Multithreading is currently only supported by
    the pyarrow engine.

    .. versionadded:: 1.4.0

        The "pyarrow" engine was added as an *experimental* engine, and some features
        are unsupported, or may not work correctly, with this engine.
converters : dict, optional
    Dict of functions for converting values in certain columns. Keys can either
    be integers or column labels.
true_values : list, optional
    Values to consider as True.
false_values : list, optional
    Values to consider as False.
skipinitialspace : bool, default False
    Skip spaces after delimiter.
skiprows : list-like, int or callable, optional
    Line numbers to skip (0-indexed) or number of lines to skip (int)
    at the start of the file.

    If callable, the callable function will be evaluated against the row
    indices, returning True if the row should be skipped and False otherwise.
    An example of a valid callable argument would be ``lambda x: x in [0, 2]``.
skipfooter : int, default 0
    Number of lines at bottom of file to skip (Unsupported with engine='c').
nrows : int, optional
    Number of rows of file to read. Useful for reading pieces of large files.
na_values : scalar, str, list-like, or dict, optional
    Additional strings to recognize as NA/NaN. If dict passed, specific
    per-column NA values.  By default the following values are interpreted as
    NaN: '', '#N/A', '#N/A N/A', '#NA', '-1.#IND', '-1.#QNAN', '-NaN', '-nan',
    '1.#IND', '1.#QNAN', '<NA>', 'N/A', 'NA', 'NULL', 'NaN', 'n/a',
    'nan', 'null'.
keep_default_na : bool, default True
    Whether or not to include the default NaN values when parsing the data.
    Depending on whether `na_values` is passed in, the behavior is as follows:
```

```
        * If `keep_default_na` is True, and `na_values` are specified, `na_values`
          is appended to the default NaN values used for parsing.
        * If `keep_default_na` is True, and `na_values` are not specified, only
          the default NaN values are used for parsing.
        * If `keep_default_na` is False, and `na_values` are specified, only
          the NaN values specified `na_values` are used for parsing.
        * If `keep_default_na` is False, and `na_values` are not specified, no
          strings will be parsed as NaN.

        Note that if `na_filter` is passed in as False, the `keep_default_na` and
        `na_values` parameters will be ignored.
    na_filter : bool, default True
        Detect missing value markers (empty strings and the value of na_values). In
        data without any NAs, passing na_filter=False can improve the performance
        of reading a large file.
    verbose : bool, default False
        Indicate number of NA values placed in non-numeric columns.
    skip_blank_lines : bool, default True
        If True, skip over blank lines rather than interpreting as NaN values.
    parse_dates : bool or list of int or names or list of lists or dict, default False
        The behavior is as follows:

        * boolean. If True -> try parsing the index.
        * list of int or names. e.g. If [1, 2, 3] -> try parsing columns 1, 2, 3
          each as a separate date column.
        * list of lists. e.g.  If [[1, 3]] -> combine columns 1 and 3 and parse as
          a single date column.
        * dict, e.g. {'foo' : [1, 3]} -> parse columns 1, 3 as date and call
          result 'foo'

        If a column or index cannot be represented as an array of datetimes,
        say because of an unparsable value or a mixture of timezones, the column
        or index will be returned unaltered as an object data type. For
        non-standard datetime parsing, use ``pd.to_datetime`` after
        ``pd.read_csv``. To parse an index or column with a mixture of timezones,
        specify ``date_parser`` to be a partially-applied
        :func:`pandas.to_datetime` with ``utc=True``. See
        :ref:`io.csv.mixed_timezones` for more.

        Note: A fast-path exists for iso8601-formatted dates.
    infer_datetime_format : bool, default False
        If True and `parse_dates` is enabled, pandas will attempt to infer the
        format of the datetime strings in the columns, and if it can be inferred,
        switch to a faster method of parsing them. In some cases this can increase
        the parsing speed by 5-10x.
    keep_date_col : bool, default False
        If True and `parse_dates` specifies combining multiple columns then
        keep the original columns.
    date_parser : function, optional
        Function to use for converting a sequence of string columns to an array of
        datetime instances. The default uses ``dateutil.parser.parser`` to do the
        conversion. Pandas will try to call `date_parser` in three different ways,
```

```
    advancing to the next if an exception occurs: 1) Pass one or more arrays
    (as defined by `parse_dates`) as arguments; 2) concatenate (row-wise) the
    string values from the columns defined by `parse_dates` into a single array
    and pass that; and 3) call `date_parser` once for each row using one or
    more strings (corresponding to the columns defined by `parse_dates`) as
    arguments.
dayfirst : bool, default False
    DD/MM format dates, international and European format.
cache_dates : bool, default True
    If True, use a cache of unique, converted dates to apply the datetime
    conversion. May produce significant speed-up when parsing duplicate
    date strings, especially ones with timezone offsets.

    .. versionadded:: 0.25.0
iterator : bool, default False
    Return TextFileReader object for iteration or getting chunks with
    ``get_chunk()``.

    .. versionchanged:: 1.2

       ``TextFileReader`` is a context manager.
chunksize : int, optional
    Return TextFileReader object for iteration.
    See the `IO Tools docs
    <https://pandas.pydata.org/pandas-docs/stable/io.html#io-chunking>`_
    for more information on ``iterator`` and ``chunksize``.

    .. versionchanged:: 1.2

       ``TextFileReader`` is a context manager.
compression : str or dict, default 'infer'
    For on-the-fly decompression of on-disk data. If 'infer' and '%s' is
    path-like, then detect compression from the following extensions: '.gz',
    '.bz2', '.zip', '.xz', or '.zst' (otherwise no compression). If using
    'zip', the ZIP file must contain only one data file to be read in. Set to
    ``None`` for no decompression. Can also be a dict with key ``'method'`` set
    to one of {``'zip'``, ``'gzip'``, ``'bz2'``, ``'zstd'``} and other
    key-value pairs are forwarded to ``zipfile.ZipFile``, ``gzip.GzipFile``,
    ``bz2.BZ2File``, or ``zstandard.ZstdDecompressor``, respectively. As an
    example, the following could be passed for Zstandard decompression using a
    custom compression dictionary:
    ``compression={'method': 'zstd', 'dict_data': my_compression_dict}``.

    .. versionchanged:: 1.4.0 Zstandard support.

thousands : str, optional
    Thousands separator.
decimal : str, default '.'
    Character to recognize as decimal point (e.g. use ',' for European data).
lineterminator : str (length 1), optional
    Character to break file into lines. Only valid with C parser.
quotechar : str (length 1), optional
```

```
    The character used to denote the start and end of a quoted item. Quoted
    items can include the delimiter and it will be ignored.
quoting : int or csv.QUOTE_* instance, default 0
    Control field quoting behavior per ``csv.QUOTE_*`` constants. Use one of
    QUOTE_MINIMAL (0), QUOTE_ALL (1), QUOTE_NONNUMERIC (2) or QUOTE_NONE (3).
doublequote : bool, default ``True``
   When quotechar is specified and quoting is not ``QUOTE_NONE``, indicate
   whether or not to interpret two consecutive quotechar elements INSIDE a
   field as a single ``quotechar`` element.
escapechar : str (length 1), optional
    One-character string used to escape other characters.
comment : str, optional
    Indicates remainder of line should not be parsed. If found at the beginning
    of a line, the line will be ignored altogether. This parameter must be a
    single character. Like empty lines (as long as ``skip_blank_lines=True``),
    fully commented lines are ignored by the parameter `header` but not by
    `skiprows`. For example, if ``comment='#'``, parsing
    ``#empty\na,b,c\n1,2,3`` with ``header=0`` will result in 'a,b,c' being
    treated as the header.
encoding : str, optional
    Encoding to use for UTF when reading/writing (ex. 'utf-8'). `List of Python
    standard encodings
    <https://docs.python.org/3/library/codecs.html#standard-encodings>`_ .

    .. versionchanged:: 1.2

       When ``encoding`` is ``None``, ``errors="replace"`` is passed to
       ``open()``. Otherwise, ``errors="strict"`` is passed to ``open()``.
       This behavior was previously only the case for ``engine="python"``.

    .. versionchanged:: 1.3.0

       ``encoding_errors`` is a new argument. ``encoding`` has no longer an
       influence on how encoding errors are handled.

encoding_errors : str, optional, default "strict"
    How encoding errors are treated. `List of possible values
    <https://docs.python.org/3/library/codecs.html#error-handlers>`_ .

    .. versionadded:: 1.3.0

dialect : str or csv.Dialect, optional
    If provided, this parameter will override values (default or not) for the
    following parameters: `delimiter`, `doublequote`, `escapechar`,
    `skipinitialspace`, `quotechar`, and `quoting`. If it is necessary to
    override values, a ParserWarning will be issued. See csv.Dialect
    documentation for more details.
error_bad_lines : bool, optional, default ``None``
    Lines with too many fields (e.g. a csv line with too many commas) will by
    default cause an exception to be raised, and no DataFrame will be returned.
    If False, then these "bad lines" will be dropped from the DataFrame that is
    returned.
```

```
    .. deprecated:: 1.3.0
       The ``on_bad_lines`` parameter should be used instead to specify behavior upon
       encountering a bad line instead.
warn_bad_lines : bool, optional, default ``None``
    If error_bad_lines is False, and warn_bad_lines is True, a warning for each
    "bad line" will be output.

    .. deprecated:: 1.3.0
       The ``on_bad_lines`` parameter should be used instead to specify behavior upon
       encountering a bad line instead.
on_bad_lines : {'error', 'warn', 'skip'} or callable, default 'error'
    Specifies what to do upon encountering a bad line (a line with too many fields).
    Allowed values are :

        - 'error', raise an Exception when a bad line is encountered.
        - 'warn', raise a warning when a bad line is encountered and skip that line.
        - 'skip', skip bad lines without raising or warning when they are encountered.

    .. versionadded:: 1.3.0

        - callable, function with signature
          ``(bad_line: list[str]) -> list[str] | None`` that will process a single
          bad line. ``bad_line`` is a list of strings split by the ``sep``.
          If the function returns ``None``, the bad line will be ignored.
          If the function returns a new list of strings with more elements than
          expected, a ``ParserWarning`` will be emitted while dropping extra elements.
          Only supported when ``engine="python"``

    .. versionadded:: 1.4.0

delim_whitespace : bool, default False
    Specifies whether or not whitespace (e.g. ``' '`` or ``'    '``) will be
    used as the sep. Equivalent to setting ``sep='\s+'``. If this option
    is set to True, nothing should be passed in for the ``delimiter``
    parameter.
low_memory : bool, default True
    Internally process the file in chunks, resulting in lower memory use
    while parsing, but possibly mixed type inference.  To ensure no mixed
    types either set False, or specify the type with the `dtype` parameter.
    Note that the entire file is read into a single DataFrame regardless,
    use the `chunksize` or `iterator` parameter to return the data in chunks.
    (Only valid with C parser).
memory_map : bool, default False
    If a filepath is provided for `filepath_or_buffer`, map the file object
    directly onto memory and access the data directly from there. Using this
    option can improve performance because there is no longer any I/O overhead.
float_precision : str, optional
    Specifies which converter the C engine should use for floating-point
    values. The options are ``None`` or 'high' for the ordinary converter,
    'legacy' for the original lower precision pandas converter, and
    'round_trip' for the round-trip converter.
```

```
    .. versionchanged:: 1.2

storage_options : dict, optional
    Extra options that make sense for a particular storage connection, e.g.
    host, port, username, password, etc. For HTTP(S) URLs the key-value pairs
    are forwarded to ``urllib`` as header options. For other URLs (e.g.
    starting with "s3://", and "gcs://") the key-value pairs are forwarded to
    ``fsspec``. Please see ``fsspec`` and ``urllib`` for more details.

    .. versionadded:: 1.2

Returns
-------
DataFrame or TextParser
    A comma-separated values (csv) file is returned as two-dimensional
    data structure with labeled axes.

See Also
--------
DataFrame.to_csv : Write DataFrame to a comma-separated values (csv) file.
read_csv : Read a comma-separated values (csv) file into DataFrame.
read_fwf : Read a table of fixed-width formatted lines into DataFrame.

Examples
--------
>>> pd.read_csv('data.csv')  # doctest: +SKIP
```

```python
sample_df = pd.read_csv(sample_table_url, sep="\t")
library_df = pd.read_csv(library_table_url, sep="\t")
```

```python
sample_df.project_name.nunique()
```

```
45
```

```python
library_df.project_name.nunique()
```

```
43
```

Listing the columns of the sample dataframe

```
sample_df.columns
```

```
Index(['project_name', 'publication_year', 'publication_doi', 'site_name',
       'latitude', 'longitude', 'geo_loc_name', 'sample_name', 'sample_host',
       'sample_age', 'sample_age_doi', 'community_type', 'material', 'archive',
       'archive_project', 'archive_accession'],
      dtype='object')
```

Looking at the data type of the sample dataframe

```
sample_df.dtypes
```

```
project_name           object
publication_year        int64
publication_doi        object
site_name              object
latitude              float64
longitude             float64
geo_loc_name           object
sample_name            object
sample_host            object
sample_age              int64
sample_age_doi         object
community_type         object
material               object
archive                object
archive_project        object
archive_accession      object
dtype: object
```

- `int64` is for integers
- `floating64` is for floating point precision numbers, also known as double in some other programing languages
- `object` is a general type in pandas for everything that is not a number, interval, categorical, or date

Let’s inspect our data

What is the size of our dataframe ?

```
sample_df.shape
```

```
(1060, 16)
```

This dataframe has **1060** rows, and **16** columns

Let's look at the first 5 rows

```
sample_df.head()
```

	project_name	publication_year	publication_doi	site_name	latitude	longitude	geo_loc_name	sample_name	sample_host
0	Warinner2014	2014	10.1038/ng.2906	Dalheim	51.565	8.840	Germany	B61	Homo sapiens
1	Warinner2014	2014	10.1038/ng.2906	Dalheim	51.565	8.840	Germany	G12	Homo sapiens
2	Weyrich2017	2017	10.1038/nature21674	Gola Forest	7.657	-10.841	Sierra Leone	Chimp	Pan troglodytes
3	Weyrich2017	2017	10.1038/nature21674	El Sidrón Cave	43.386	-5.328	Spain	ElSidron1	Homo sapiens neanderthalensis
4	Weyrich2017	2017	10.1038/nature21674	El Sidrón Cave	43.386	-5.329	Spain	ElSidron2	Homo sapiens neanderthalensis

Unlike R, Python is `0` based language, meaning the first element is of index `0`, not like R where it is `1`.

Let's look at the last 5 rows

```
sample_df.tail()
```

	project_name	publication_year	publication_doi	site_name	latitude	longitude	geo_loc_name	sample_name	samp
1055	Kazarina2021b	2021	10.1016/j.jasrep.2021.103213	St. Gertrude's Church, Riga	56.958	24.121	Latvia	T2	sa
1056	Kazarina2021b	2021	10.1016/j.jasrep.2021.103213	St. Gertrude's Church, Riga	56.958	24.121	Latvia	T3	sa
1057	Kazarina2021b	2021	10.1016/j.jasrep.2021.103213	St. Gertrude's Church, Riga	56.958	24.121	Latvia	T9	sa
1058	Kazarina2021b	2021	10.1016/j.jasrep.2021.103213	Dom Square, Riga	56.949	24.104	Latvia	TZA3	sa
1059	Kazarina2021b	2021	10.1016/j.jasrep.2021.103213	St. Peter's Church, Riga	56.947	24.109	Latvia	TZA4	sa

Let's randomly inspect 5 rows

```
sample_df.sample(n=5)
```

	project_name	publication_year	publication_doi	site_name	latitude	longitude	geo_loc_name	sample_name	sample_ho
413	Neukamm2020	2020	10.1186/s12915-020-00839-8	Abusir el-Meleq	29.240	31.100	Egypt	Abusir1576	Homo sapien
754	Rampelli2021	2021	10.1038/s42003-021-01689-y	El Salt	38.687	-0.508	Spain	V3	Homo sapien neanderthalensi
436	Neukamm2020	2020	10.1186/s12915-020-00839-8	Abusir el-Meleq	29.240	31.100	Egypt	Abusir1606	Homo sapien
474	Neukamm2020	2020	10.1186/s12915-020-00839-8	Abusir el-Meleq	29.240	31.100	Egypt	Abusir1654	Homo sapien
573	Philips2017	2017	10.1186/s12864-020-06810-9	Kowalewko	52.699	17.605	Poland	PCA0040	Homo sapien

Accessing the data by index/columns

The are different way of selecting of subset of a dataframe

Selecting by the row index

```
# selecting the 10th row, and all columns
sample_df.iloc[9, :]
```

```
project_name                          Weyrich2017
publication_year                             2017
publication_doi            10.1038/nature21674
site_name               Stuttgart-Mühlhausen I
latitude                                   48.839
longitude                                   9.227
geo_loc_name                              Germany
sample_name                              EuroLBK1
sample_host                          Homo sapiens
sample_age                                   7400
sample_age_doi             10.1038/nature21674
community_type                               oral
material                          dental calculus
archive                                       SRA
archive_project                       PRJNA685265
archive_accession                      SRS7890488
Name: 9, dtype: object
```

```python
# selecting the 10th to 12th row, and all columns
sample_df.iloc[9:12, :]
```

	project_name	publication_year	publication_doi	site_name	latitude	longitude	geo_loc_name	sample_name	sample_host	san
9	Weyrich2017	2017	10.1038/nature21674	Stuttgart-Mühlhausen I	48.839	9.227	Germany	EuroLBK1	Homo sapiens	
10	Weyrich2017	2017	10.1038/nature21674	Stuttgart-Mühlhausen I	48.839	9.227	Germany	EuroLBK2	Homo sapiens	
11	Weyrich2017	2017	10.1038/nature21674	Stuttgart-Mühlhausen I	48.839	9.227	Germany	EuroLBK3	Homo sapiens	

```python
# selecting the 10th to 12th row, and the first to the 4th column
sample_df.iloc[9:12, 0:4]
```

	project_name	publication_year	publication_doi	site_name
9	Weyrich2017	2017	10.1038/nature21674	Stuttgart-Mühlhausen I
10	Weyrich2017	2017	10.1038/nature21674	Stuttgart-Mühlhausen I
11	Weyrich2017	2017	10.1038/nature21674	Stuttgart-Mühlhausen I

```python
# selecting the column site_name
sample_df['site_name']
```

```
0                           Dalheim
1                           Dalheim
2                       Gola Forest
3                    El Sidrón Cave
4                    El Sidrón Cave
                   ...
1055    St. Gertrude’s Church, Riga
1056    St. Gertrude’s Church, Riga
1057    St. Gertrude’s Church, Riga
1058              Dom Square, Riga
1059       St. Peter’s Church, Riga
Name: site_name, Length: 1060, dtype: object
```

```python
# Also valid, but less preferred
sample_df.site_name
```

```
0                            Dalheim
1                            Dalheim
2                        Gola Forest
3                     El Sidrón Cave
4                     El Sidrón Cave
                   ...              
1055    St. Gertrude’s Church, Riga
1056    St. Gertrude’s Church, Riga
1057    St. Gertrude’s Church, Riga
1058               Dom Square, Riga
1059       St. Peter’s Church, Riga
Name: site_name, Length: 1060, dtype: object
```

```
# Removing a row
sample_df.drop(0)
```

	project_name	publication_year	publication_doi	site_name	latitude	longitude	geo_loc_name	sample_name	
1	Warinner2014	2014	10.1038/ng.2906	Dalheim	51.565	8.840	Germany	G12	H
2	Weyrich2017	2017	10.1038/nature21674	Gola Forest	7.657	-10.841	Sierra Leone	Chimp	Pa
3	Weyrich2017	2017	10.1038/nature21674	El Sidrón Cave	43.386	-5.328	Spain	ElSidron1	H nea
4	Weyrich2017	2017	10.1038/nature21674	El Sidrón Cave	43.386	-5.329	Spain	ElSidron2	H nea
5	Weyrich2017	2017	10.1038/nature21674	Spy Cave	50.480	4.674	Belgium	Spy1	H nea
...	...	...	...	...	...	...	...	...	
1055	Kazarina2021b	2021	10.1016/j.jasrep.2021.103213	St. Gertrude's Church, Riga	56.958	24.121	Latvia	T2	H
1056	Kazarina2021b	2021	10.1016/j.jasrep.2021.103213	St. Gertrude's Church, Riga	56.958	24.121	Latvia	T3	H
1057	Kazarina2021b	2021	10.1016/j.jasrep.2021.103213	St. Gertrude's Church, Riga	56.958	24.121	Latvia	T9	H
1058	Kazarina2021b	2021	10.1016/j.jasrep.2021.103213	Dom Square, Riga	56.949	24.104	Latvia	TZA3	H

	project_name	publication_year	publication_doi	site_name	latitude	longitude	geo_loc_name	sample_name
1059	Kazarina2021b	2021	10.1016/j.jasrep.2021.103213	St. Peter's Church, Riga	56.947	24.109	Latvia	TZA4

1059 rows × 16 columns

```python
# Removing a columm
sample_df.drop('project_name', axis=1)
```

	publication_year	publication_doi	site_name	latitude	longitude	geo_loc_name	sample_name	sample_host	sa
0	2014	10.1038/ng.2906	Dalheim	51.565	8.840	Germany	B61	Homo sapiens	
1	2014	10.1038/ng.2906	Dalheim	51.565	8.840	Germany	G12	Homo sapiens	
2	2017	10.1038/nature21674	Gola Forest	7.657	-10.841	Sierra Leone	Chimp	Pan troglodytes	
3	2017	10.1038/nature21674	El Sidrón Cave	43.386	-5.328	Spain	ElSidron1	Homo sapiens neanderthalensis	
4	2017	10.1038/nature21674	El Sidrón Cave	43.386	-5.329	Spain	ElSidron2	Homo sapiens neanderthalensis	
...	...	...	...	...	...	...	...	...	
1055	2021	10.1016/j.jasrep.2021.103213	St. Gertrude's Church, Riga	56.958	24.121	Latvia	T2	Homo sapiens	
1056	2021	10.1016/j.jasrep.2021.103213	St. Gertrude's Church, Riga	56.958	24.121	Latvia	T3	Homo sapiens	
1057	2021	10.1016/j.jasrep.2021.103213	St. Gertrude's Church, Riga	56.958	24.121	Latvia	T9	Homo sapiens	
1058	2021	10.1016/j.jasrep.2021.103213	Dom Square, Riga	56.949	24.104	Latvia	TZA3	Homo sapiens	

	publication_year	publication_doi	site_name	latitude	longitude	geo_loc_name	sample_name	sample_host	sa
1059	2021	10.1016/j.jasrep.2021.103213	St. Peter's Church, Riga	56.947	24.109	Latvia	TZA4	Homo sapiens	

1060 rows × 15 columns

4 - Dealing with missing data

Checking is some entries if the table have missing data (NA or NaN)

```
sample_df.isna()
```

	project_name	publication_year	publication_doi	site_name	latitude	longitude	geo_loc_name	sample_name	sample_host	sample_age	sample_a
0	False	False	False	False	False	False	False	False	False	False	
1	False	False	False	False	False	False	False	False	False	False	
2	False	False	False	False	False	False	False	False	False	False	
3	False	False	False	False	False	False	False	False	False	False	
4	False	False	False	False	False	False	False	False	False	False	
...	...	...	...	...	...	...	...	...	...	...	
1055	False	False	False	False	False	False	False	False	False	False	
1056	False	False	False	False	False	False	False	False	False	False	
1057	False	False	False	False	False	False	False	False	False	False	
1058	False	False	False	False	False	False	False	False	False	False	
1059	False	False	False	False	False	False	False	False	False	False	

1060 rows × 16 columns

```python
# making the sum by row - axis=1
sample_df.isna().sum(axis=1)
```

```
0       0
1       0
2       0
3       0
4       0
       ..
1055    0
1056    0
1057    0
1058    0
1059    0
Length: 1060, dtype: int64
```

Sorting by decreasing order to check which rows have missing values

```
sample_df.isna().sum(axis=1).sort_values(ascending=False)
```

```
800     2
962     2
992     2
801     2
802     2
       ..
362     0
363     0
364     0
365     0
1059    0
Length: 1060, dtype: int64
```

```python
sample_df.iloc[800,:]
```

```
project_name                          FellowsYates2021
publication_year                                  2021
publication_doi             10.1073/pnas.2021655118
site_name                                Not specified
latitude                                           NaN
longitude                                          NaN
geo_loc_name         Democratic Republic of the Congo
sample_name                                  GDC002.A
sample_host                    Gorilla gorilla gorilla
sample_age                                         200
sample_age_doi              10.1073/pnas.2021655118
community_type                                    oral
material                              dental calculus
archive                                            ENA
archive_project                             PRJEB34569
archive_accession                           ERS3774403
Name: 800, dtype: object
```

What to do now ? The ideal scenario would be to correct or impute the data.
However, sometimes, the only thing we can do is remove the row with missing data, with the `.dropna() function.`
Here, we're just going to ignore them, and deal with it individually if necessary

5 - Computing basic statistics

TLDR: use the `describe()` function, the equivalent of `summarize` in R

```
sample_df.describe()
```

	publication_year	latitude	longitude	sample_age
count	1060.000000	1021.000000	1021.000000	1060.000000
mean	2019.377358	40.600493	3.749624	3588.443396
std	1.633877	18.469421	43.790316	9862.416855
min	2014.000000	-34.030000	-121.800000	100.000000
25%	2018.000000	29.240000	-1.257000	200.000000
50%	2020.000000	45.450000	14.381000	1000.000000
75%	2021.000000	52.699000	23.892000	2200.000000
max	2021.000000	79.000000	159.346000	102000.000000

Let's look at various individual summary statistics We can run them on the whole dataframe (for `int` or `float` columns), or on a subset of columns

```
sample_df.mean()
```

```
/var/folders/1c/l1qb09f15jddsh65f6xv1n_r0000gp/T/ipykernel_69168/2260452167.py:1: FutureWarning: Dropping of nuisa
nce columns in DataFrame reductions (with 'numeric_only=None') is deprecated; in a future version this will raise
TypeError.  Select only valid columns before calling the reduction.
```

```
publication_year    2019.377358
latitude              40.600493
longitude              3.749624
sample_age          3588.443396
dtype: float64
```

```python
sample_df['publication_year'].describe()
```

```
count    1060.000000
mean     2019.377358
std         1.633877
min      2014.000000
25%      2018.000000
50%      2020.000000
75%      2021.000000
max      2021.000000
Name: publication_year, dtype: float64
```

```python
# The average publication year
sample_df['publication_year'].mean()
```

```
2019.377358490566
```

```python
# The median publication year
sample_df['publication_year'].median()
```

```
2020.0
```

```python
# The minimum, or oldest publication year
sample_df['publication_year'].min()
```

```
2014
```

```python
# The maximum, or most recent publication year
sample_df['publication_year'].max()
```

```
2021
```

```python
# The number of sites
sample_df['site_name'].nunique()
```

246

```python
# The number of samples from the different hosts
sample_df['sample_host'].value_counts()
```

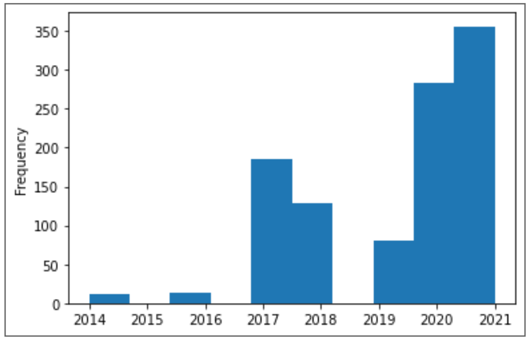
```
Homo sapiens                     741
Ursus arctos                      85
Ambrosia artemisiifolia           46
Arabidopsis thaliana              34
Homo sapiens neanderthalensis     32
Pan troglodytes schweinfurthii    26
Gorilla beringei beringei         15
Canis lupus                       12
Gorilla gorilla gorilla            8
Mammuthus primigenius              8
Pan troglodytes verus              7
Rangifer tarandus                  6
Gorilla beringei graueri           6
Pan troglodytes ellioti            6
Papio hamadryas                    5
Alouatta palliata                  5
Conepatus chinga                   4
Gerbilliscus boehmi                4
Strigocuscus celebensis            4
Papio anubis                       2
Gorilla beringei                   2
Papio sp.                          1
Pan troglodytes                    1
Name: sample_host, dtype: int64
```

```python
# The quantile of the publication years
sample_df['publication_year'].quantile(np.arange(0,1,0.1))
```

```
0.0    2014.0
0.1    2017.0
0.2    2018.0
0.3    2018.0
0.4    2020.0
0.5    2020.0
0.6    2020.0
0.7    2021.0
0.8    2021.0
0.9    2021.0
Name: publication_year, dtype: float64
```

```python
# We can also visualize it with built-in plot functions of pandas
sample_df['publication_year'].plot.hist()
```

```
<AxesSubplot:ylabel='Frequency'>
```



6 - Filtering

There are different ways of filtering data with Pandas:

- The **classic** method with bracket indexing/subsetting
- The `query()` method

The classic method

```
# Getting all the publications before 2015
sample_df[sample_df['publication_year']  < 2015 ]
```

	project_name	publication_year	publication_doi	site_name	latitude	longitude	geo_loc_name	sample_name
0	Warinner2014	2014	10.1038/ng.2906	Dalheim	51.565	8.84	Germany	B61
1	Warinner2014	2014	10.1038/ng.2906	Dalheim	51.565	8.84	Germany	G12
272	Campana2014	2014	10.1186/1756-0500-7-111	Teposcolula Yucundaa	17.490	-97.46	Mexico	TP4
273	Campana2014	2014	10.1186/1756-0500-7-111	Teposcolula Yucundaa	17.490	-97.46	Mexico	TP10
274	Campana2014	2014	10.1186/1756-0500-7-111	Teposcolula Yucundaa	17.490	-97.46	Mexico	TP18
275	Campana2014	2014	10.1186/1756-0500-7-111	Teposcolula Yucundaa	17.490	-97.46	Mexico	TP37
276	Campana2014	2014	10.1186/1756-0500-7-111	Teposcolula Yucundaa	17.490	-97.46	Mexico	TP9
277	Campana2014	2014	10.1186/1756-0500-7-111	Teposcolula Yucundaa	17.490	-97.46	Mexico	TP48
278	Campana2014	2014	10.1186/1756-0500-7-111	Teposcolula Yucundaa	17.490	-97.46	Mexico	TP02,TP10,TP15,TP26
279	Campana2014	2014	10.1186/1756-0500-7-111	Teposcolula Yucundaa	17.490	-97.46	Mexico	TP32,TP42,TP45,TP48
500	Appelt2014	2014	10.1128/AEM.03242-13	Place d'Armes, Namur	50.460	4.86	Belgium	4.453

```python
# Getting all the publications before 2015, only in the Northern hemisphere
sample_df[(sample_df['publication_year']  < 2015) & (sample_df['longitude'] > 0)]
```

	project_name	publication_year	publication_doi	site_name	latitude	longitude	geo_loc_name	sample_name	sample_host	sampl
0	Warinner2014	2014	10.1038/ng.2906	Dalheim	51.565	8.84	Germany	B61	Homo sapiens	
1	Warinner2014	2014	10.1038/ng.2906	Dalheim	51.565	8.84	Germany	G12	Homo sapiens	
500	Appelt2014	2014	10.1128/AEM.03242-13	Place d'Armes, Namur	50.460	4.86	Belgium	4.453	Homo sapiens	

This syntax can rapidly become quite cumbersome, which is why we can also use the `query()` method

```
# Getting all the publications before 2015
sample_df.query("publication_year < 2015")
```

	project_name	publication_year	publication_doi	site_name	latitude	longitude	geo_loc_name	sample_name
0	Warinner2014	2014	10.1038/ng.2906	Dalheim	51.565	8.84	Germany	B61
1	Warinner2014	2014	10.1038/ng.2906	Dalheim	51.565	8.84	Germany	G12
272	Campana2014	2014	10.1186/1756-0500-7-111	Teposcolula Yucundaa	17.490	-97.46	Mexico	TP4
273	Campana2014	2014	10.1186/1756-0500-7-111	Teposcolula Yucundaa	17.490	-97.46	Mexico	TP10
274	Campana2014	2014	10.1186/1756-0500-7-111	Teposcolula Yucundaa	17.490	-97.46	Mexico	TP18
275	Campana2014	2014	10.1186/1756-0500-7-111	Teposcolula Yucundaa	17.490	-97.46	Mexico	TP37
276	Campana2014	2014	10.1186/1756-0500-7-111	Teposcolula Yucundaa	17.490	-97.46	Mexico	TP9
277	Campana2014	2014	10.1186/1756-0500-7-111	Teposcolula Yucundaa	17.490	-97.46	Mexico	TP48
278	Campana2014	2014	10.1186/1756-0500-7-111	Teposcolula Yucundaa	17.490	-97.46	Mexico	TP02,TP10,TP15,TP26
279	Campana2014	2014	10.1186/1756-0500-7-111	Teposcolula Yucundaa	17.490	-97.46	Mexico	TP32,TP42,TP45,TP48
500	Appelt2014	2014	10.1128/AEM.03242-13	Place d'Armes, Namur	50.460	4.86	Belgium	4.453

```python
# Getting all the publications before 2015, only the Northern hemisphere
sample_df.query("publication_year < 2015 and longitude > 0 ")
```

	project_name	publication_year	publication_doi	site_name	latitude	longitude	geo_loc_name	sample_name	sample_host	sampl
0	Warinner2014	2014	10.1038/ng.2906	Dalheim	51.565	8.84	Germany	B61	Homo sapiens	
1	Warinner2014	2014	10.1038/ng.2906	Dalheim	51.565	8.84	Germany	G12	Homo sapiens	
500	Appelt2014	2014	10.1128/AEM.03242-13	Place d'Armes, Namur	50.460	4.86	Belgium	4.453	Homo sapiens	

7 - GroupBy operations, and computing statistics on grouped values

The "groupBy" operation, as the name suggests, allows us to group values by a grouping key, and perform a groupwise operation.
For example, we can group by the `sample_host` and get the age of the **youngest** sample in each group

```
sample_df.groupby("sample_host")['sample_age'].min()
```

```
sample_host
Alouatta palliata                  200
Ambrosia artemisiifolia            100
Arabidopsis thaliana               100
Canis lupus                        400
Conepatus chinga                   100
Gerbilliscus boehmi                100
Gorilla beringei                   100
Gorilla beringei beringei          200
Gorilla beringei graueri           200
Gorilla gorilla gorilla            200
Homo sapiens                       100
Homo sapiens neanderthalensis    35800
Mammuthus primigenius            41800
Pan troglodytes                    100
Pan troglodytes ellioti            200
Pan troglodytes schweinfurthii     100
Pan troglodytes verus              200
Papio anubis                       100
Papio hamadryas                    100
Papio sp.                          100
Rangifer tarandus                  100
Strigocuscus celebensis            100
Ursus arctos                       100
Name: sample_age, dtype: int64
```

Here `min()` is a so-called aggregation function

Notice that `.value_counts()` is actually a special case of `.groupby()`

```
sample_df.groupby("sample_host")["sample_host"].count()
```

```
sample_host
Alouatta palliata                   5
Ambrosia artemisiifolia            46
Arabidopsis thaliana               34
Canis lupus                        12
Conepatus chinga                    4
Gerbilliscus boehmi                 4
Gorilla beringei                    2
Gorilla beringei beringei          15
Gorilla beringei graueri            6
Gorilla gorilla gorilla             8
Homo sapiens                      741
Homo sapiens neanderthalensis      32
Mammuthus primigenius               8
Pan troglodytes                     1
Pan troglodytes ellioti             6
Pan troglodytes schweinfurthii     26
Pan troglodytes verus               7
Papio anubis                        2
Papio hamadryas                     5
Papio sp.                           1
Rangifer tarandus                   6
Strigocuscus celebensis             4
Ursus arctos                       85
Name: sample_host, dtype: int64
```

8 - Reshaping data, from wide to long and back

Wide data format

A	B	C
1.1	4.2	5.6
1.0	4.5	5.8

Tidy data format

Condition	Value
A	1.1
A	1.0
B	4.2
B	4.5
C	5.6
C	5.8

From wide to long/tidy

The tidy format, or long format idea is that one column = one kind of data.
Unfortunately for this tutorial, the AncientMetagenomeDir tables are already in the tidy format (good), so we'll see an example or the wide format just below

	individual	1991	1992	1993	1994
0	John	150	155	157	160
1	Jack	149	153	154	155

In this hypothetic dataframe, we have the years as column, the individual as index, and their height as value.
We'll reformat to the tidy/long format using the `.melt()` function

```python
tidy_df = wide_df.melt(id_vars='individual', var_name='birthyear', value_name='height')
tidy_df
```

	individual	birthyear	height
0	John	1991	150
1	Jack	1991	149
2	John	1992	155
3	Jack	1992	153
4	John	1993	157
5	Jack	1993	154
6	John	1994	160
7	Jack	1994	155

Bonus

How to deal with a dataframe with the kind of data indicated in the column name, typically like so

	individual	year-1991	year-1992	year-1993	year-1994
0	John	150	155	157	160
1	Jack	149	153	154	155

```python
pd.wide_to_long(wide_df, ['year'], i='individual', j='birthyear', sep="-").rename(columns={'year':'height'})
```

		height
individual	**birthyear**	
John	**1991**	150
Jack	**1991**	149
John	**1992**	155
Jack	**1992**	153
John	**1993**	157
Jack	**1993**	154
John	**1994**	160
Jack	**1994**	155

From long/tidy to wide format using the `.pivot()` function.

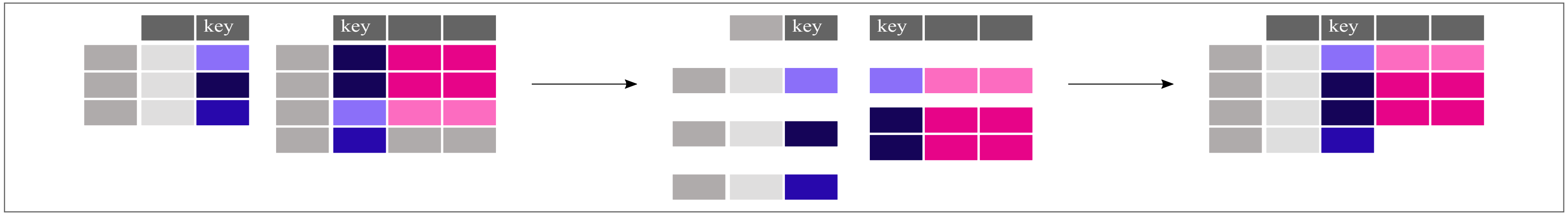
```
tidy_df.pivot(index='individual', columns='birthyear', values='height')
```

```
/Users/maxime/mambaforge/envs/intro-data/lib/python3.10/site-packages/pandas/core/algorithms.py:798: FutureWarnin
g: In a future version, the Index constructor will not infer numeric dtypes when passed object-dtype sequences (ma
tching Series behavior)
```

birthyear	**1991**	**1992**	**1993**	**1994**
individual				
Jack	149	153	154	155
John	150	155	157	160

9 - Joining two different tables

In AncientMetagenomeDir, the information about each sample is located in sample table, and about the library in the library table.
To match these two together, we need to join the tables together.
To do so, we need a column in common between the two tables, the so-called **joining key** (this key can be the index)



For the samples and libraries dataframe, the joining key is the column `sample_name`

```
sample_df.merge(library_df, on='sample_name').columns
```

```
Index(['project_name_x', 'publication_year_x', 'publication_doi', 'site_name',
       'latitude', 'longitude', 'geo_loc_name', 'sample_name', 'sample_host',
       'sample_age', 'sample_age_doi', 'community_type', 'material',
       'archive_x', 'archive_project_x', 'archive_accession', 'project_name_y',
       'publication_year_y', 'data_publication_doi', 'archive_y',
       'archive_project_y', 'archive_sample_accession', 'library_name',
       'strand_type', 'library_polymerase', 'library_treatment',
       'library_concentration', 'instrument_model', 'library_layout',
       'library_strategy', 'read_count', 'archive_data_accession',
       'download_links', 'download_md5s', 'download_sizes'],
      dtype='object')
```

We have some duplicate columns that we can get rid of:

```
merged_df = sample_df.merge(library_df.drop(['project_name', 'publication_year', 'archive_project', 'archive'], axis=1), on='sample_name'
merged_df
```

	project_name	publication_year	publication_doi	site_name	latitude	longitude	geo_loc_name	sample_name	sam
0	Warinner2014	2014	10.1038/ng.2906	Dalheim	51.565	8.84	Germany	B61	s
1	Warinner2014	2014	10.1038/ng.2906	Dalheim	51.565	8.84	Germany	B61	s
2	Warinner2014	2014	10.1038/ng.2906	Dalheim	51.565	8.84	Germany	B61	s
3	Warinner2014	2014	10.1038/ng.2906	Dalheim	51.565	8.84	Germany	B61	s
4	Warinner2014	2014	10.1038/ng.2906	Dalheim	51.565	8.84	Germany	G12	s
...	...	...	...	...	...	...	...	...	
1802	Maixner2021	2021	10.1016/j.cub.2021.09.031	Edlersbergwerk - oben, Hallstatt	47.560	13.63	Austria	2612	s
1803	Maixner2021	2021	10.1016/j.cub.2021.09.031	Edlersbergwerk - oben, Hallstatt	47.560	13.63	Austria	2612	s
1804	Maixner2021	2021	10.1016/j.cub.2021.09.031	Edlersbergwerk - oben, Hallstatt	47.560	13.63	Austria	2612	s
1805	Maixner2021	2021	10.1016/j.cub.2021.09.031	Edlersbergwerk - oben, Hallstatt	47.560	13.63	Austria	2612	s
1806	Maixner2021	2021	10.1016/j.cub.2021.09.031	Edlersbergwerk - oben, Hallstatt	47.560	13.63	Austria	2612	s

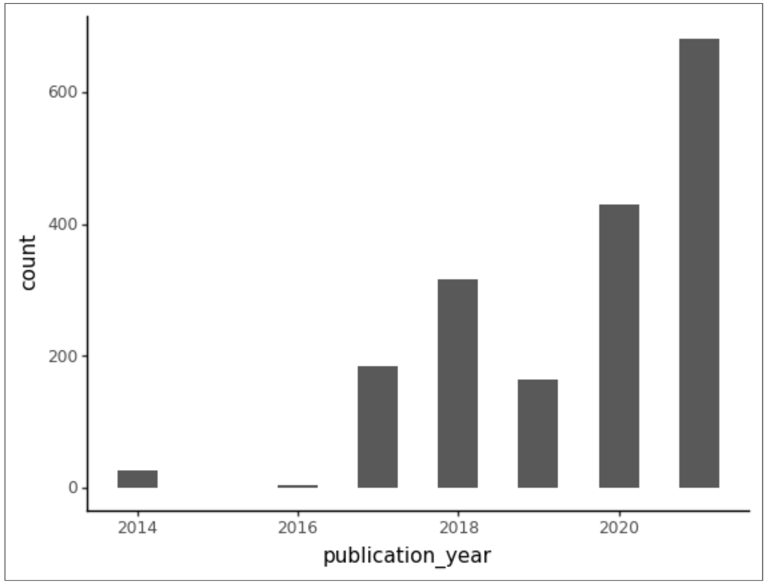
1807 rows × 31 columns

10 - Visualizing some of the results with Plotnine

Plotnine is the Python clone of ggplot2, the syntax is identical, which makes it great if you're working with data in tidy/long format, and are already familiar with the ggplot2 syntax

```
ggplot(merged_df, aes(x='publication_year')) + geom_histogram() + theme_classic()
```

```
/Users/maxime/mambaforge/envs/intro-data/lib/python3.10/site-packages/plotnine/stats/stat_bin.py:95: PlotnineWarni
ng: 'stat_bin()' using 'bins = 15'. Pick better value with 'binwidth'.
```

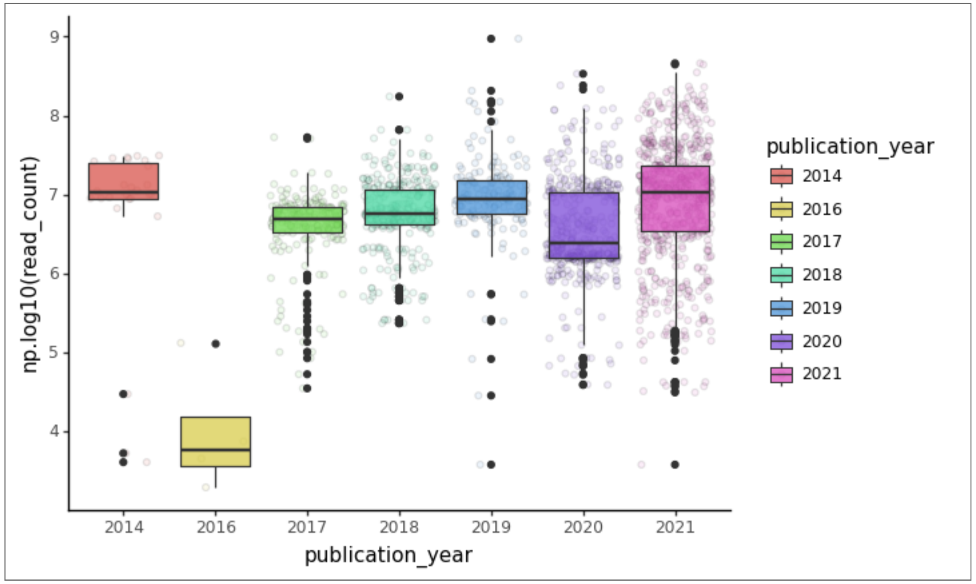



```
<ggplot: (366051178)>
```

We can start to ask some questions, for example, is the sequencing depth increasing with the years ?

```
merged_df['publication_year'] = merged_df['publication_year'].astype('category')
```

```
ggplot(merged_df, aes(x='publication_year', y='np.log10(read_count)', fill='publication_year')) + geom_jitter(alpha=0.1) + geom_boxplot(a
```



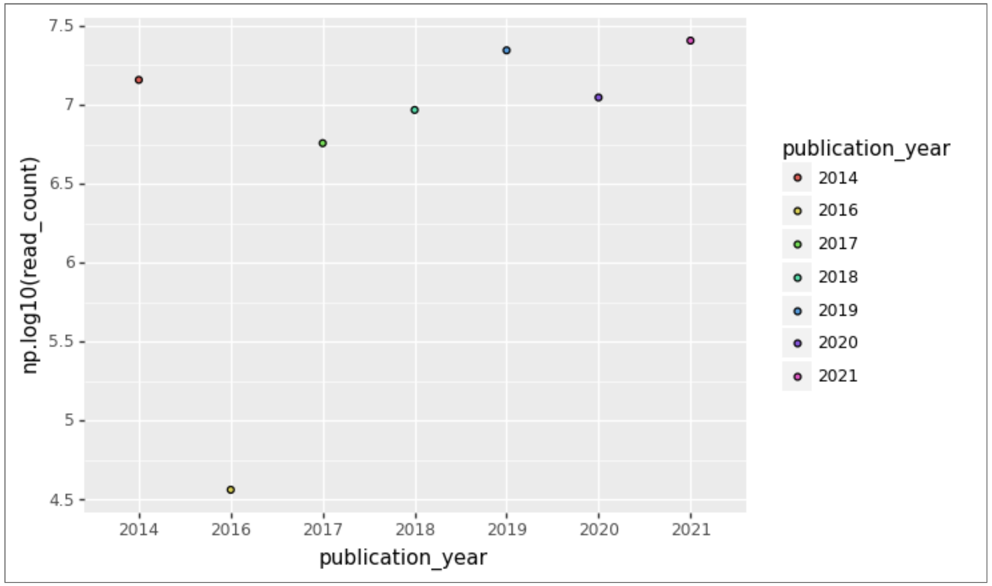

```
<ggplot: (366112582)>
```

We could ask the same question, but first grouping the samples by publication year

```
avg_read_count_by_year = merged_df.groupby('publication_year')['read_count'].mean().to_frame().reset_index()
avg_read_count_by_year
```

	publication_year	read_count
0	2014	1.437173e+07
1	2016	3.653450e+04
2	2017	5.712598e+06
3	2018	9.273287e+06
4	2019	2.211632e+07
5	2020	1.111819e+07
6	2021	2.547655e+07

```
ggplot(avg_read_count_by_year, aes(x='publication_year', y='np.log10(read_count)', fill='publication_year')) + geom_point()
```




```
<ggplot: (366206706)>
```

Your turn ! Make a plot to investigate the relation between the type of library treatment throughout the publication years

11 - Bonus, dealing with ill-formatted columns

Sometimes, colums can contains entries which could be split in multiple columns, typically values separated by a comma. In AncientMetagenomeDir, this is the case with the archive accession column.

Here is how we would solve it with pandas

```
sample_df.assign(archive_accession = sample_df.archive_accession.str.split(",")).explode('archive_accession')
```

	project_name	publication_year	publication_doi	site_name	latitude	longitude	geo_loc_name	sample_name	samp
0	Warinner2014	2014	10.1038/ng.2906	Dalheim	51.565	8.840	Germany	B61	sa
0	Warinner2014	2014	10.1038/ng.2906	Dalheim	51.565	8.840	Germany	B61	sa
0	Warinner2014	2014	10.1038/ng.2906	Dalheim	51.565	8.840	Germany	B61	sa
0	Warinner2014	2014	10.1038/ng.2906	Dalheim	51.565	8.840	Germany	B61	sa
1	Warinner2014	2014	10.1038/ng.2906	Dalheim	51.565	8.840	Germany	G12	sa
...	...	...	...	...	...	...	...	...	
1057	Kazarina2021b	2021	10.1016/j.jasrep.2021.103213	St. Gertrude's Church, Riga	56.958	24.121	Latvia	T9	sa
1058	Kazarina2021b	2021	10.1016/j.jasrep.2021.103213	Dom Square, Riga	56.949	24.104	Latvia	TZA3	sa
1058	Kazarina2021b	2021	10.1016/j.jasrep.2021.103213	Dom Square, Riga	56.949	24.104	Latvia	TZA3	sa
1059	Kazarina2021b	2021	10.1016/j.jasrep.2021.103213	St. Peter's Church, Riga	56.947	24.109	Latvia	TZA4	sa

	project_name	publication_year	publication_doi	site_name	latitude	longitude	geo_loc_name	sample_name	samp
1059	Kazarina2021b	2021	10.1016/j.jasrep.2021.103213	St. Peter's Church, Riga	56.947	24.109	Latvia	TZA4	sa

1262 rows × 16 columns