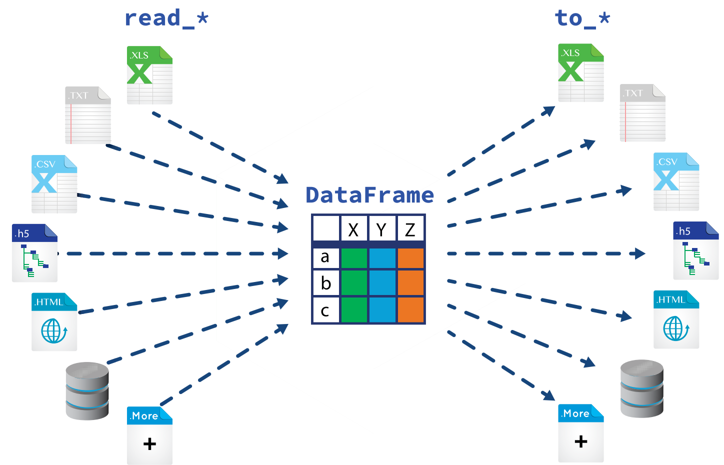
1 Reading and Writing Data with Pandas

pandas



Functions to read data are all named **`pd.read_*`** where `*` is the file type. Series and DataFrames can be saved to disk using their **`to_*`** method.

Usage Patterns

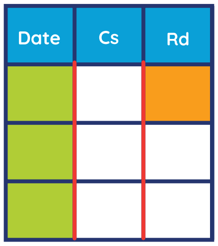
Use **`pd.read_clipboard()`** for one-off data extractions.
Use the other **`pd.read_*`** methods in scripts for repeatable analyses.

Reading Text Files into a DataFrame

Colors highlight how different arguments map from the data file to a DataFrame.

```
# Historical_data.csv
Date, Cs, Rd
2005-01-03, 64.78, -
2005-01-04, 63.79, 201.4
2005-01-05, 64.46, 193.45
...
Data from Lab Z.
  Recorded by Agent E
```

```
>>> read_csv(
        'historical_data.csv',
         sep=',',
         header=1,
         skiprows=1,
         skipfooter=2,
         index_col=0,
         parse_dates=True,
         na_values=['-'])
```

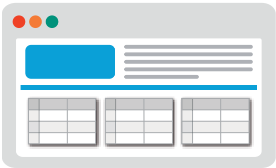


Other arguments:

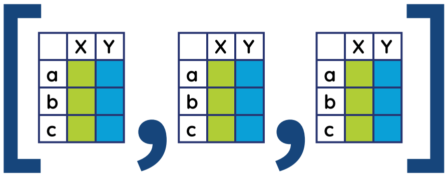
- **`names`**: Set or override column names
- **`parse_dates`**: Accepts multiple argument types
- **`converters`**: Manually process each element in a column
- **`comment`**: Character indicating commented line
- **`chunksize`**: Read only a certain number of rows each time

Possible values of **`parse_dates`:**
`[0, 2]`: Parse columns 0 and 2 as separate dates
`[[0, 2]]`: Group columns 0 and 2 and parse as single date
`{'Date': [0, 2]}`: Group columns 0 and 2, parse as single date in a column named Date
Dates are parsed after the converters have been applied.

Parsing Tables from the Web



```
>>> df_list = read_html(url)
```



Writing Data Structures to Disk

Write data structures to disk:

```
>>> s_df.to_csv(filename)
>>> s_df.to_excel(filename)
```

Write multiple DataFrames to single Excel file:

```
>>> writer = pd.ExcelWriter(filename)
>>> df1.to_excel(writer, sheet_name='First')
>>> df2.to_excel(writer, sheet_name='Second')
>>> writer.save()
```

Writing Data Structures from and to a Database

Read, using SQLAlchemy. Supports multiple databases:

```
>>> from sqlalchemy import create_engine
>>> engine = create_engine(database_url)
>>> conn = engine.connect()
>>> df = pd.read_sql(query_str_or_table_name, conn)
```

Write:

```
>>> df.to_sql(table_name, conn)
```

2 Pandas Data Structures: Series and DataFrames

pandas

Within Pandas, there are two primary data structures: Series (s) and DataFrames (df).

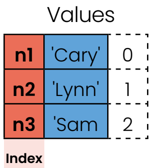
s A Series, which maps an index to values. It can be thought of as an ordered dictionary or a Numpy array with row labels and a name.

df A DataFrame, which maps index and column labels to values. It is like a dictionary of Series (columns) sharing the same index, or like a 2D Numpy array with row and column labels.

s_df Applies to both Series and DataFrames.

Manipulations of Pandas objects usually return copies.

Creating Series and DataFrames

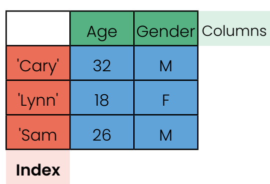


Series

```
>>> pd.Series(values, index=index, name=name)
>>> pd.Series({'idx1' : val1,'idx2' : val2})
```

Where values, index, and name are sequences or arrays.

DataFrame




```
>>> pd.DataFrame(values,
    index=index, columns=col_names)
>>> pd.DataFrame({'col1' :
    series1_or _seq,
  'col2': series2_or _seq})
```

Where **values** is a sequence of sequences or a 2D array.

Manipulating Series and DataFrames

Manipulating **Columns**

`df.rename(columns={old_name:new_name})`	Renames column
`df.drop(name_or_names, axis='columns')`	Drops column name

Manipulating **Index**

`s_df.reindex(new_index)`	Conform to new index
`s_df.drop(labels_to_drop)`	Drops index labels
`s_df.rename (index={old_label: new_label})`	Renames index labels
`s_df.sort_index()`	Sorts index labels
`df.set_index(column_name_or_names)`	
`s_df.reset_index()`	Inserts index into columns, resets index to default integer index

Manipulating **Values**

All row values and the index will follow:

```
df.sort_values(col_name, ascending=True)
df.sort_values(['X','Y'], ascending=[False, True])
```

Important Attributes and Methods

`s_df.index`	Array-like row labels
`df.columns`	Array-like column labels
`s_df.values`	Numpy array, data
`s_df.shape`	(n_rows, n_cols)
`s.dtype, df.dtypes`	Type of Series or of each column
`len(s_df)`	Number of rows
`s_df.head()` and **`s_df.tail()`**	First/last rows
`s.unique()`	Series of unique values
`s_df.describ`	Summary stats
`df.info()`	Memory usage

Indexing and Slicing

Use these attributes on Series and DataFrames for indexing, slicing, and assignments:

`s_df.loc[ ]`	Refers only to the index labels
`s_df.iloc[ ]`	Refers only to the integer location, similar to lists or Numpy arrays
`s_df.xs(key, level=L)`	Select rows with label key in level L of an object with MultiIndex.

Masking and Boolean Indexing

Create masks with comparisons:

`mask = df['X'] < 0`

Or **isin**, for membership mask:

`mask = df['X'].isin(list_of_valid_values)`

Use masks for indexing:

`df.loc[mask] = 0`

Combine multiple masks with bitwise operators — and (**&**), or (**|**), or (**^**), not (**~**) — and group them with parentheses:

`mask = (df['X'] < 0) & (df['Y'] == 0)`

Common Indexing and Slicing Patterns

rows and **cols** can be values, lists, Series, or masks.

`s_df.loc[rows]`	Some rows (all columns in a DataFrame)
`df.loc[:, cols_list]`	All rows, some columns
`df.loc[rows, cols]`	Subset of rows and columns
`s_df.loc[mask]`	Boolean mask of rows (all columns)
`df.loc[mask, cols]`	Boolean mask of rows, some columns

Using [ ] on Series and DataFrames

On Series, **[]** refers to the index labels, or to a slice:

`s['a']`	Value
`s[:2]`	Series, first two rows

On DataFrames, **[]** refers to columns labels:

`df['X']`	Series
`df[['X', 'Y']]`	DataFrame

`df['new_or_old_col'] = series_or_array`

Except with a slice or mask, as shown below:

`df[:2]`	DataFrame, first two rows
`df[mask]`	DataFrame, rows where mask is True

Never chain brackets

NO `>>> df[mask]['X'] = 1`
`SettingWithCopyWarning`

YES `>>> df.loc[mask, 'X'] = 1`

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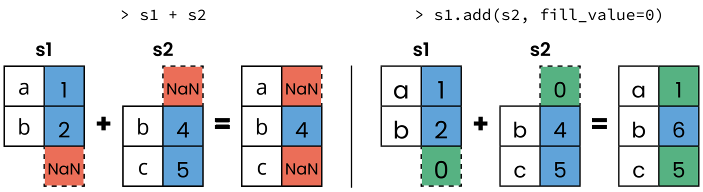
3 Computation with Series and DataFrames

pandas

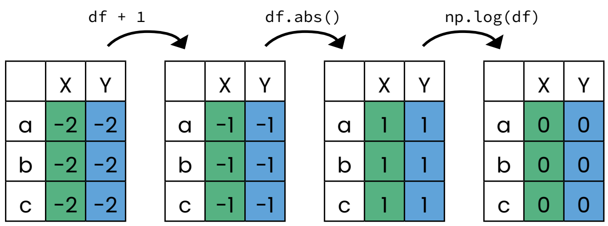
Pandas objects do not behave exactly like Numpy arrays. They follow three main rules of binary operations.

Rule 1: Operations between multiple Pandas objects implement auto-alignment based on index first.

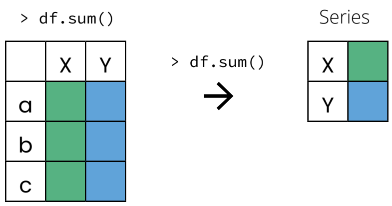


Use **add**, **sub**, **mul**, and **div**, to set fill value.

Rule 2: Mathematical operators (+ - * / exp, log, ...) apply element by element on the values.



Rule 3: Reduction operations (mean, std, skew, kurt, sum, prod, ...) are applied column by column by default.



Operates across rows by default (**axis=0**, or **axis='rows'**).
Operate across columns with **axis=1** or **axis='columns'**.

Differences Between Pandas Objects and Numpy Arrays

When it comes to Pandas objects and Numpy arrays, aligning objects on the index (or columns) before calculations might be the most important difference. There are built-in methods for most common statistical operations, such as **mean** or **sum**, and they apply across one-dimension at a time. To apply custom functions, use one of three methods to do tablewise (**pipe**), row or column-wise (**apply**), or elementwise (**applymap**) operations.

Apply a Function to Each Value

Apply a function to each value in a Series or DataFrame:

s.apply(value_to_value)	→	Series
df.applymap(value_to_value)	→	DataFrame

Apply a Function to Each Series

Apply series_to_* function to every column by default (across rows):

df.apply(series_to_value)	→	Series
df.apply(series_to_series)	→	DataFrame

To apply the function to every row (across columns), set **axis=1**:
df.apply(series_to_series, axis=1)

Apply a Function to a DataFrame

Apply a function that receives a DataFrame and returns a Series, a DataFrame, or a single value:

df.pipe(df_to_series)	→	Series
df.pipe(df_to_df)	→	DataFrame
df.pipe(df_to_value)	→	Value

What Happens with Missing Values?

Missing values are represented by **NaN** (not a number) or **NaT** (not a time).

- They propagate in operations across Pandas objects (**1 + NaN → NaN**).
- They are ignored in a "sensible" way in computations; They equal 0 in sum, they're ignored in **mean**, etc.
- They stay **NaN** with mathematical operations such as **np.log(NaN) → NaN**.

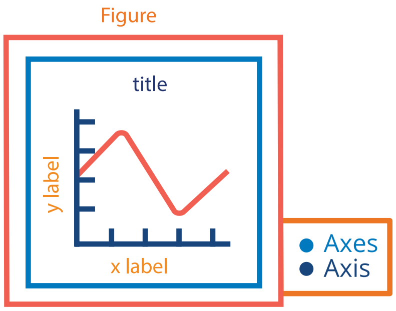
count:	Number of non-null observations
sum:	Sum of values
mean:	Mean of values
mad:	Mean absolute deviation
median:	Arithmetic median of values
min:	Minimum
max:	Maximum
mode:	Mode
prod:	Product of values
std:	Bessel-corrected sample standard deviation
var:	Unbiased variance
sem:	Standard error of the mean
skew:	Sample skewness (3rd moment)
kurt:	Sample kurtosis (4th moment)
quartile:	Sample quantile (Value at %)
value_counts:	Count of unique values

4 Plotting with Pandas Series and DataFrames

Pandas uses Matplotlib to generate figures. Once a figure is generated with Pandas, all of Matplotlib's functions can be used to modify the title, labels, legend, etc. In a Jupyter notebook, all plotting calls for a given plot should be in the same cell.

Parts of a Figure

An Axes object is what we think of as a "plot". It has a title and two Axis objects that define data limits. Each Axis can have a label. There can be multiple Axes objects in a Figure.



Setup

Import packages:

```
>>> import pandas as pd
>>> import matplotlib.pyplot as plt
```

Execute this at IPython prompt to display figures in new windows:

```
>>> %matplotlib
```

Use this in Jupyter notebooks to display static images inline:

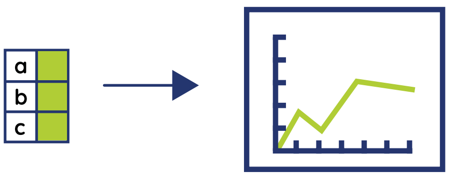
```
>>> %matplotlib inline
```

Use this in Jupyter notebooks to display zoomable images inline:

```
> %matplotlib notebook
```

Plotting with Pandas Objects

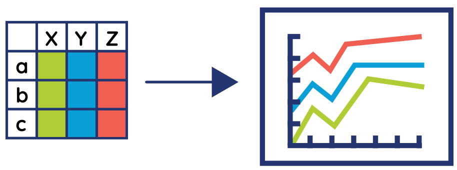
Series



With a Series, Pandas plots values against the index:

```
>>> ax = s.plot()
```

DataFrame

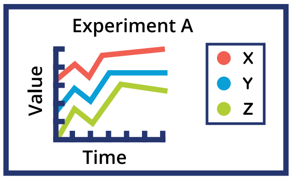


With a DataFrame, Pandas creates one line per column:

```
>>> ax = df.plot()
```

Note: When plotting the results of complex manipulations with **`groupby`**, it's often useful to **`stack`**/**`unstack`** the resulting DataFrame to fit the one-line-per-column assumption.

Labels



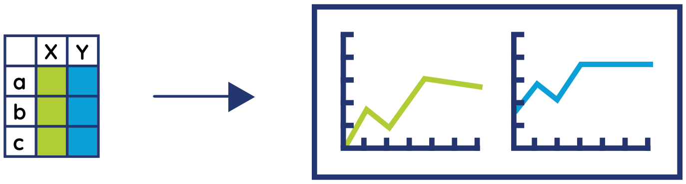
Use Matplotlib to override or add annotations:

```
>>> ax.set_xlabel('Time')
>>> ax.set_ylabel('Value')
>>> ax.set_title('Experiment A')
```

Pass labels if you want to override the column names and set the legend location:

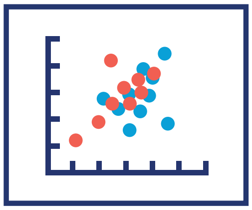
```
>>> ax.legend(labels, loc='best')
```

Useful Arguments to Plot

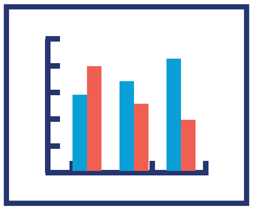


- **`subplots=True`**: One subplot per column, instead of one line
- **`figsize`**: Set figure size, in inches
- **`x`** and **`y`**: Plot one column against another

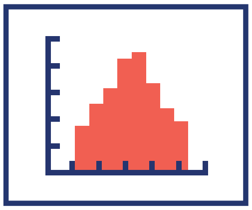
Kinds of Plots



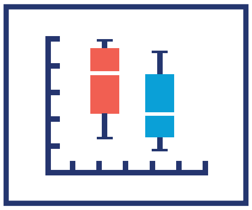
`df.plot.scatter(x, y)`



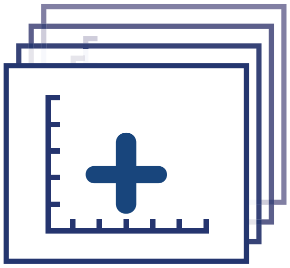
`df.plot.bar()`



`df.plot.hist()`



`df.plot.box()`



5 Manipulating Dates and Times

pandas

Use a Datetime index for easy time-based indexing and slicing, as well as for powerful resampling and data alignment. Pandas makes a distinction between timestamps, called **`Datetime`** objects, and time spans, called **`Period`** objects.

Converting Objects to Time Objects

Convert different types like strings, lists, or arrays to Datetime with:

```
>>> pd.to_datetime(value)
```

Convert timestamps to time spans and set the period "duration" with frequency offset.

```
>>> date_obj.to_period(freq=freq_offset)
```

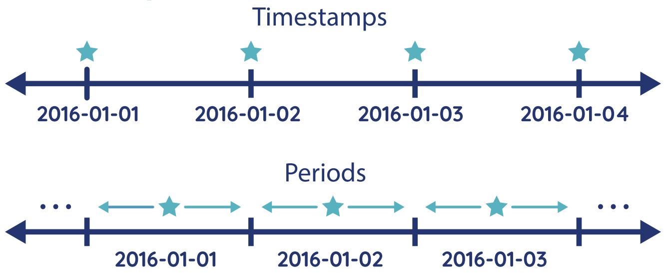
Frequency Offsets

Used by **`date_range`**, **`period_range`** and **`resample`**:

- B: Business day
- D: Calendar day
- W: Weekly
- M: Month end
- MS: Month start
- BM: Business month end
- Q: Quarter end
- A: Year end
- AS: Year start
- H: Hourly
- S: Secondly
- L, ms: Milliseconds
- U, us: Microseconds
- N: Nanoseconds

For more, look up "Pandas Offset Aliases" or check out the **`pandas.tseries.offsets`** and **`pandas.tseries.holiday`** modules.

Timestamps vs Periods



Creating Ranges of Timestamps

```
>>> pd.date_range(start=None, end=None,
                  periods=None, freq=offset,
                  tz='Europe/London')
```

Specify either a start or end date, or both. Set number of "steps" with **`periods`**. Set "step size" with **`freq`**. Specify time zones with **`tz`**.

Save Yourself Some Pain: Use ISO 8601 Format

To be consistent and minimize the risk of error or confusion, use ISO format YYYY-MM-DD when entering dates:

```
NO   >>> pd.to_datetime('12/01/2000') # 1st December
       Timestamp('2000-12-01 00:00:00')
NO   >>> pd.to_datetime('13/01/2000') # 13th January!
       Timestamp('2000-01-13 00:00:00')
YES  >>> pd.to_datetime('2000-01-13') # 13th January
       Timestamp('2000-01-13 00:00:00')
```

Creating Ranges of Periods

```
>>> pd.period_range(start=None, end=None,
                    periods=None, freq=offset)
```

Resampling

```
>>> s_df.resample(freq_offset).mean()
```

`resample` returns a groupby-like object that must be aggregated with **`mean`**, **`sum`**, **`std`**, **`apply`**, etc. (See also the Split-Apply-Combine cheatsheet.)

VECTORIZED STRING OPERATIONS

Pandas implements vectorized string operations named after Python's string methods. Access them through the str attribute of string Series.

Some String Methods

```
>>> s.str.lower()
>>> s.str.isupper()
>>> s.str.len()
>>> s.str.strip()
>>> s.str.normalize()
```

Index by character position:

```
>>> s.str[0]
```

True if a regular expression pattern or string is in a Series:

```
>>> s.str.contains(str_or_pattern)
```

Splitting and Replacing

Split returns a Series of lists:

```
>>> s.str.split()
```

Access an element of each list with get:

```
>>> s.str.split(char).str.get(1)
```

Return a DataFrame instead of a list:

```
>>> s.str.split(expand=True)
```

Find and replace with string or regular expressions:

```
>>> s.str.replace(str_or_regex, new)
>>> s.str.extract(regex)
>>> s.str.findall(regex)
```

6 Combining DataFrames

pandas

There are numerous tools for combining Series and DataFrames together, with SQL-type joins and concatenation. Use **`join`** if merging on indices, otherwise use **`merge`**.

Merge on Column Values

`>>> pd.merge(left, right, how='inner', on='id')`

Ignores index, unless **`on=None`**. See the section on the **`how`** keyword.

Use **`on`** if merging on same column in both DataFrames, otherwise use **`left_on`**, **`right_on`**.

Join on Index

`>>> df.join(other)`

`Merge` DataFrames on indexes. Set **`on=columns`** to join on index of **`other`** and on columns of **`df.join`** uses **`pd.merge`** under the covers.

Concatenating DataFrames

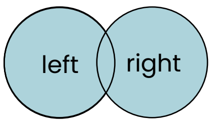
`>>> pd.concat(df_list)`

"Stacks" DataFrames on top of each other.

Set **`ignore_index=True`** to replace index with **`RangeIndex`**.

Note: Faster than repeated **`df.append(other_df)`**.

MERGE TYPES: THE HOW KEYWORD



how="outer"

left

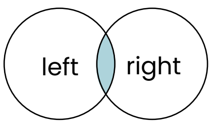
	LONG	X
0	aaaa	a
1	bbbb	b

left_on='X' right_on='Y'

	LONG	X	Y	SHORT
0	aaaa	a	—	—
1	bbbb	b	b	bb
2	—	—	c	cc

right

	Y	SHORT
0	b	bb
1	c	cc

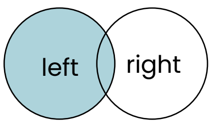


how="inner"

	LONG	X
0	aaaa	a
1	bbbb	b

	LONG	X	Y	SHORT
0	bbbb	b	b	bb

	Y	SHORT
0	b	bb
1	c	cc

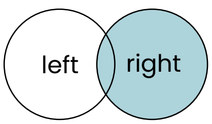


how="left"

	LONG	X
0	aaaa	a
1	bbbb	b

	LONG	X	Y	SHORT
0	aaaa	a	—	—
1	bbbb	b	b	bb

	Y	SHORT
0	b	bb
1	c	cc



how="right"

	LONG	X
0	aaaa	a
1	bbbb	b

	LONG	X	Y	SHORT
0	bbbb	b	b	bb
1	—	—	c	cc

	Y	SHORT
0	b	bb
1	c	ctc

CLEANING DATA WITH MISSING VALUES

Pandas represents missing values as **`NaN`** (Not a Number), which comes from Numpy and is of type **`float64`**. To find and replace these missing values, you can use any number of methods.

To find missing values, use:

`>>> s_df.isnull()` or **`>>> pd.isnull(obj)`**

`>>> s_df.notnull()` or **`>>> pd.notnull(obj)`**

To replace missing values, use:

`s_df.loc[s_df.isnull()] = 0`	Use mask to replace NaN
`s_df.interpolate(method='linear')`	Interpolate using different methods
`s_df.fillna(method='ffill')`	Fill forward (last valid value)
`s_df.fillna(method='bfill')`	Or backward (next valid value)
`s_df.dropna(how='any')`	Drop rows if any value is NaN
`s_df.dropna(how='all')`	Drop rows if all values are NaN
`s_df.dropna(how='all', axis=1)`	Drop across columns instead of rows

7 Split / Apply / Combine with DataFrames

pandas

1. Split the data based on some criteria.
2. Apply a function to each group to aggregate, transform, or filter.
3. Combine the results.

The apply and combine steps are typically done together in Pandas.

Split: Group By

Group by a single column:

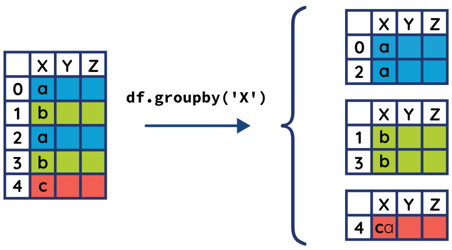
```
>>> g = df.groupby(col_name)
```

Grouping with list of column names creates a DataFrame with a MultiIndex:

```
>>> g = df.groupby(list_col_names)
```

Pass a function to group based on the index:

```
>>> g = df.groupby(function)
```



Apply/Combine: General Tool: apply

apply is more general than **agg**, **transform**, and **filter**. It can aggregate, transform or filter. The resulting dimensions can change, for example:

```
>>> g.apply(lambda x: x.describe())
```

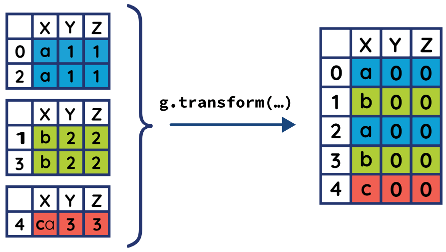
Apply/Combine: Transformation

The shape and the index do not change.

```
>>> g.transform(df_to_df)
```

Example, normalization:

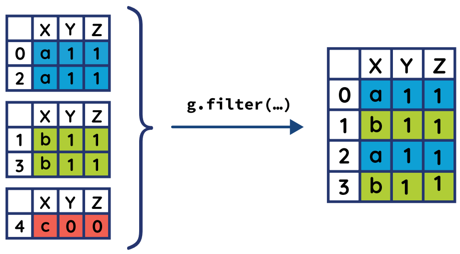
```
>>> def normalize(grp):
...     return (
...         (grp - grp.mean())
...         / grp.var()
...     )

>>> def normalize(grp):
...     return ((grp - grp.mean())
...         / grp.var())
```



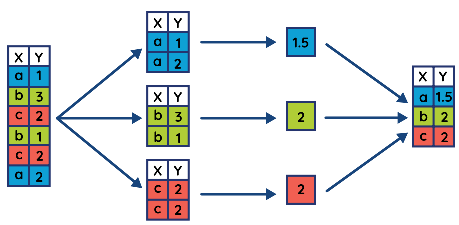
Apply/Combine: Filtering

Returns a group only if condition is true.

```
>>> g.filter(lambda x: len(x)>1)
```



Split/Apply/Combine



Split	Apply	Combine
• Groupby • Window Functions	• Apply • Group-specific transformations • Aggregation • Group-specific Filtering	

Split: What's a GroupBy Object?

It keeps track of which rows are part of which group.

>>> g.groups → Dictionary, where keys are group names, and values are indices of rows in a given group.

It is iterable:

```
>>> for group, sub_df in g:
...     ...
```

Apply/Combine: Aggregation

Perform computations on each group. The shape changes; the categories in the grouping columns become the index. Can use built-in aggregation methods: **mean**, **sum**, **size**, **count**, **std**, **var**, **sem**, **describe**, **first**, **last**, **nth**, **min**, **max**, for example:

```
>>> g.mean()
```

… or aggregate using custom function:

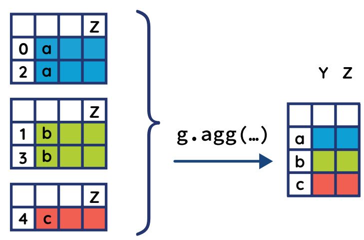
```
>>> g.agg(series_to_value)
```

… or aggregate with multiple functions at once:

```
>>> g.agg([s_to_v1, s_to_v2])
```

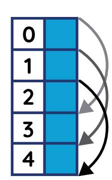
… or use different functions on different columns:

```
>>> g.agg({'Y': s_to_v1,
...        'Z': s_to_v2})
```



Other Groupby-Like Operations: Window Functions

- **resample**, **rolling**, and **ewm** (exponential weighted function) methods behave like GroupBy objects. They keep track of which row is in which "group." Results must be aggregated with **sum**, **mean**, **count**, etc.
- **resample** is often used before **rolling**, **expanding**, and **ewm** when using a DateTime index.



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8 Reshaping DataFrames and Pivot Tables

pandas

Let's explore some **tools for reshaping DataFrames from the wide to the long format and back**. The long format can be tidy, which means that each variable is a column, each observation is a row. It is easier to filter, aggregate, transform, sort, and pivot. Reshaping operations often produces multi-level indices or columns, which can be sliced and indexed.

MultiIndex: A Multi-Level Hierarchical Index

Often created as a result of:

```
>>> df.groupby(list_of_columns)
>>> df.set_index(list_of_columns)
```

Contiguous labels are displayed together but apply to each row. The concept is similar to multi-level columns.

A **MultiIndex** allows indexing and slicing one or multiple levels at once. Using the Long example from the right:

`long.loc[1900]`	All 1900 rows
`long.loc[(1900, 'March')]`	Value **2**
`long.xs('March', level='Month')`	All March rows

Simpler than using boolean indexing, for example:

```
>>> long[long.Month == 'March']
```

Pivot Tables

```
>>> pd.pivot_table(df,
...     index=cols,          keys to group by for index
...     columns=cols2,       keys to group by for columns
...     values=cols3,        columns to aggregate
...     aggfunc='mean')      what to do with repeated values
```

Omitting **index**, **columns**, or **values** will use all remaining columns of **df**. You can "pivot" a table manually using **groupby**, **stack**, and **unstack**.

Index

Columns

0	Recently updated	Number of stations	Continent code
1	FALSE	1	EU
2	FALSE	1	EU
3	FALSE	1	EU
4	TRUE	1	EU
5	FALSE	1	AN
6	TRUE	1	AN
7	TRUE	1	AN

Continent code / Recently updated	AN	EU
FALSE	1	3
TRUE	2	1

```
pd.pivot_table(df,
        index="Recently updated",
        columns="continent code",
        values="Number of Stations",
        aggfunc=np.sum)
```

df.pivot() vs pd.pivot_table

`df.pivot()`	Does not deal with repeated values in index. It's a declarative form of **stack** and **unstack**.
`pd.pivot_table()`	Use if you have repeated values in index (specify **aggfunc** argument).

Long to Wide Format and Back with stack() and unstack()

Pivot column level to index, i.e. "stacking the columns" (wide to long):

```
>>> df.stack()
```

Pivot index level to columns, "unstack the columns" (long to wide):

```
>>> df.unstack()
```

If there are multiple indices or column levels, use level number or name to stack/unstack:

`>>> df.unstack(1)` or `>>> df.unstack('Month')`

A common use case for unstacking, plotting group data vs index after groupby:

```
>>> (df.groupby(['A', 'B])['relevant'].mean()
...      .unstack().plot())
```

Wide

Year	Jan.	Feb.	Mar.
1900	1	7	2
2000	4	3	9

Stack →

← Unstack

Long

Year	Month	Value
1900	Jan.	1
	Feb	7
	Mar.	2
2000	Jan.	4
	Feb	3
	Mar.	9

From Wide to Long with melt

Specify which columns are identifiers (**id_vars**, values will be repeated for each row) and which are "measured variables" (**value_vars**, will become values in variable column. All remaining columns by default).

```
>>> pd.melt(df, id_vars=id_cols, value_vars=value_columns)
>>> pd.melt(team, id_vars=['Color'],
...          value_vars=['A', 'B', 'C'],
...          var_name='Team',
...          value_name='Score')
```

Team

	Color	A	B	C
0	Red	1	3	4
1	Blue	2	-	6

Melt →

	Color	Team	Score
0	Red	A	1
1	Blue	A	2
2	Red	B	3
3	Blue	B	-
4	Red	C	4
5	Blue	C	6