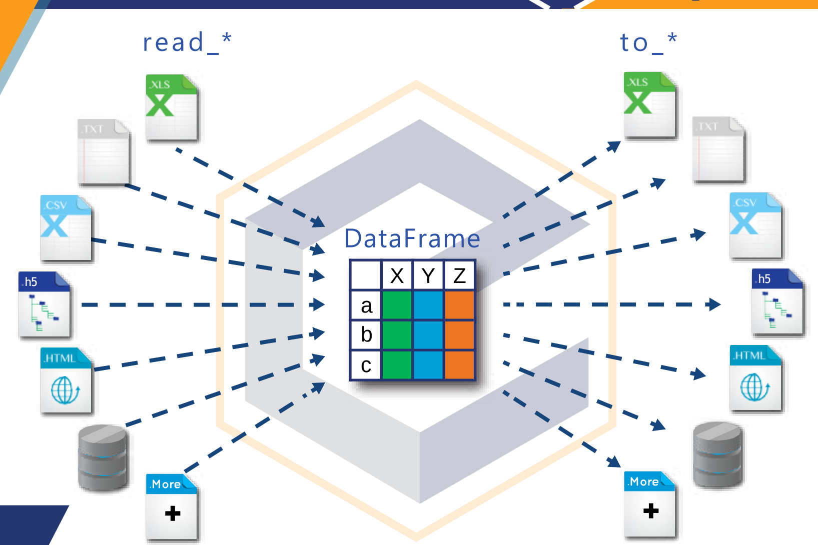
Reading and Writing Data with Pandas

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

Other arguments:

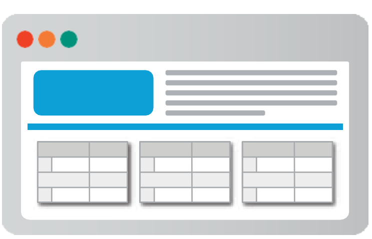
- names: set or override column names
- `parse_dates`: accepts multiple argument types, see on the right
- `converters`: manually process each element in a column
- comment: character indicating commented line
- `chunksize`: read only a certain number of rows each time

Possible values of `parse_dates`:

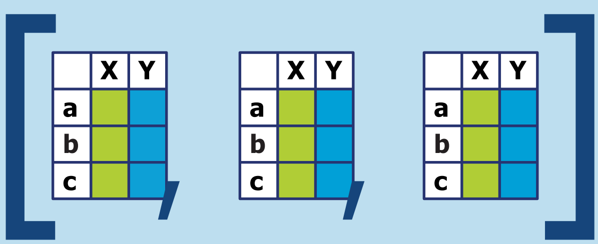
- `[0, 2]`: Parse columns 0 and 2 as separate dates
- `[[0, 2]]`: Group columns 0 and 2 and parse as single date
- `{'Date': [0, 2]}`: Group columns 0 and 2, parse as single date in a column named Date.

Dates are parsed *after* the `converters` have been applied.

Parsing Tables from the Web



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



Writing Data Structures to Disk

Writing 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()
```

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)
```

Pandas Data Structures: Series and DataFrames

A Series, `s`, maps an index to values. It is:
- **Like an ordered dictionary**
- **A Numpy array with row labels and a name**

A DataFrame, `df`, maps index and column labels to values. It is:
- **Like a dictionary of Series (columns) sharing the same index**
- **A 2D Numpy array with row and column labels**

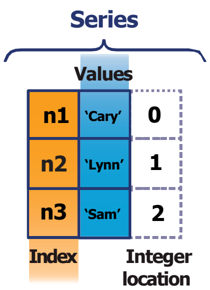
`s_df` applies to both Series and DataFrames.
Assume that manipulations of Pandas object return copies.

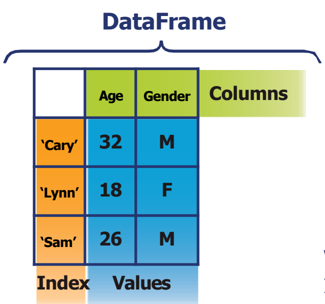
Creating Series and DataFrames

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, m_cols)
`s.dtype, df.dtypes`	Type of `Series`, 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.describe()`	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)`	Select rows with label `key` in level `level` of an object with MultiIndex.

Masking and Boolean Indexing

Create masks with, for example, comparisons

`mask = df['X'] ◂ 0`

Or `isin`, for membership mask

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

Use masks for indexing (must use `loc`)

`df.loc[mask] = 0`

Combine multiple masks with bitwise operators (and (ß), or (|), xor (^), not (~)) and group them with parentheses:

`mask = (df['X'] ◂ 0) ß (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 2 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.

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

NEVER CHAIN BRACKETS!

✗ `> df[mask]['X'] = 1`
`SettingWithCopyWarning`

✓ `> df.loc[mask , 'X'] = 1`

Computation with Series and DataFrames

Pandas objects do not behave exactly like Numpy arrays. They follow three main rules (see on the right). 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.**

The **3 Rules** of Binary Operations

Rule 1:

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

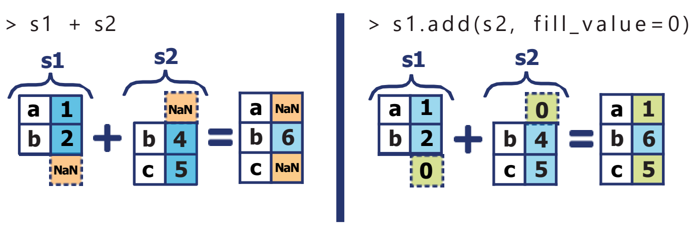
Rule 2:

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

Rule 3:

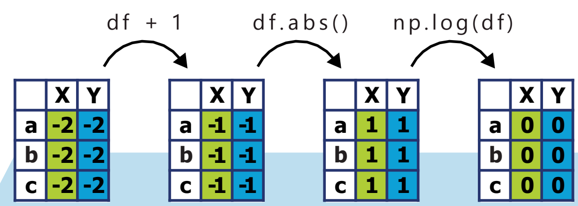
Reduction operations (mean, std, skew, kurt, sum, prod, ...) are applied column by column by default.

Rule 1: Alignment First



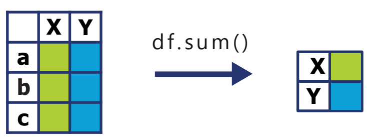
Use add, sub, mul, div, to set fill value.

Rule 2: Element-By-Element Mathematical Operations



Rule 3: Reduction Operations

`>>> df.sum()` → Series



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

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)
quantile:	Sample quantile (Value at %)
value_counts:	Count of unique values

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_series)` → DataFrame
`df.apply(series_to_value)` → Series

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 DataFrame, a Series, or a single value:

`df.pipe(df_to_df)` → DataFrame
`df.pipe(df_to_series)` → Series
`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).

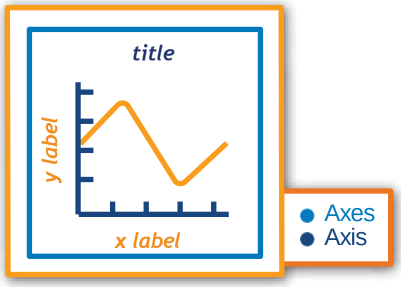
- They propagate in operations across Pandas objects (1 + NaN → NaN).
- They are ignored in a "sensible" way in computations, they equal 0 in sum, they're ignored in mean, etc.
- They stay NaN with mathematical operations (np.log(NaN) → NaN).

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:

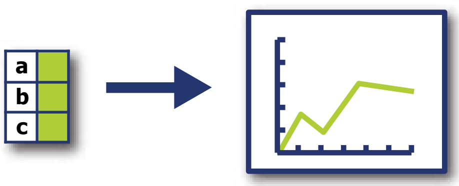
```
> %matplotlib inline
```

Use this in Jupyter notebooks to display zoom-able images inline:

```
> %matplotlib notebook
```

Plotting with Pandas Objects

Series



With a Series, Pandas plots values against the index:

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

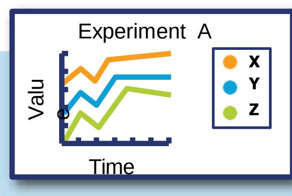
Dataframe

With a DataFrame, Pandas creates one line per column:

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

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 (see Data Structures cheatsheet).

Labels



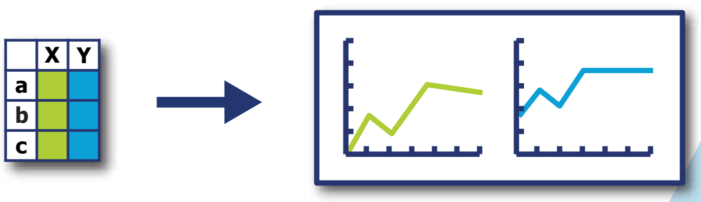
Use Matplotlib to override or add annotations:

```
> 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:

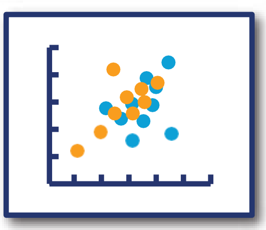
```
> ax.legend(labels, loc='best')
```

Useful Arguments to plot

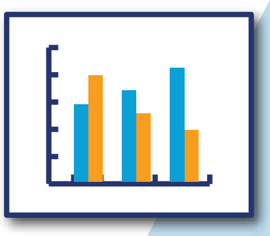


- `subplots=True`: one subplot per column, instead of one line
- `figsize`: set figure size, in inches
- `x` and `y`: plot one column against another

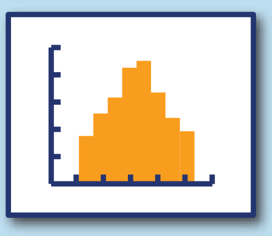
Kinds of Plots



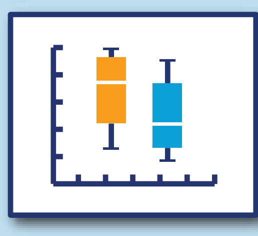
`df.plot.scatter(x, y)`



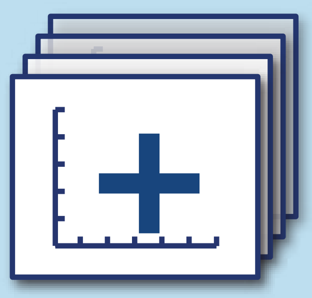
`df.plot.bar()`



`df.plot.hist()`



`df.plot.box()`



Manipulating Dates and Times

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, for example strings, lists, or arrays to Datetime with:

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

Convert timestamps to time spans: set period "duration" with frequency offset (see below).

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

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`; see "Frequency offsets" for acceptable values. Specify time zones with `tz`.

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
- T, min: Minutely
- S: Secondly
- L, ms: Milliseconds
- U, us: Microseconds
- N: Nanoseconds

For more:

Lookup "Pandas Offset Aliases" or check out `pandas.tseries.offsets`, and `pandas.tseries.holiday` modules.

Timestamps vs Periods

Timestamps

Periods

Save Yourself Some Pain: Use ISO 8601 Format

When entering dates, to be consistent and to lower the risk of error or confusion, use ISO format YYYY-MM-DD:

```
✗ >>> pd.to_datetime('12/01/2000')    # 1st December
  Timestamp('2000-12-01 00:00:00')
✗ >>> pd.to_datetime('13/01/2000')    # 13th January!
  Timestamp('2000-01-13 00:00:00')
✓ >>> pd.to_datetime('2000-01-13')    # 13th January
  Timestamp('2000-01-13 00:00:00')
```

Creating Ranges or 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 cheat sheet.)

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

and more...

Index by character position:

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

`True` if regular expression pattern or string in 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)
```

ENTHOUGHT

Combining DataFrames

Tools for combining Series and DataFrames together, with SQL-type joins and concatenation. Use join if merging on indices, otherwise use merge.

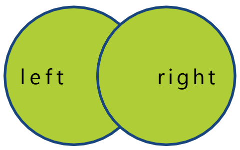
Merge on Column Values

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

Ignores index, unless on=None. See value of how below.
Use on if merging on same column in both DataFrames, otherwise use left_on, right_on.

Merge Types: The how Keyword

left_on='X' right_on='Y'



how="outer"

left

	long	X
0	aaaa	a
1	bbbb	b

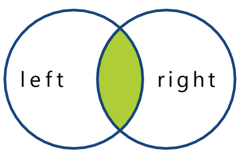
→

	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"

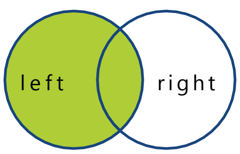
	long	X
0	aaaa	a
1	bbbb	b

→

	long	X	Y	short
0	bbbb	b	b	bb

←

	Y	short
0	b	bb
1	c	cc



how="left"

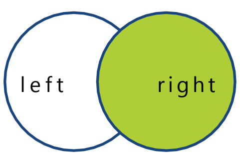
	long	X
0	aaaa	a
1	bbbb	b

→

	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

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).

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.

Cleaning Data with Missing Values

Pandas represents missing values as NaN (Not a Number). It comes from Numpy and is of type floatC4. Pandas has many methods to find and replace missing values.

Find Missing Values

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

Replacing Missing Values

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

ENTHOUGHT

Split / Apply / Combine with DataFrames

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:

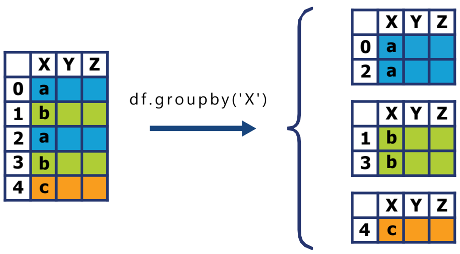
```
> g = df.groupby(col_name)
```

Grouping with list of column names creates DataFrame with MultiIndex. (see “Reshaping DataFrames and Pivot Tables” cheatsheet):

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

Pass a function to group based on the index:

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



Apply/Combine: General Tool: apply

More general than agg, transform, and filter. Can aggregate, transform or filter. The resulting dimensions can change, for example:

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

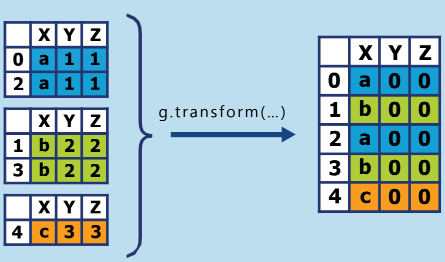
Apply/Combine: Transformation

The shape and the index do not change.

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

Example, normalization:

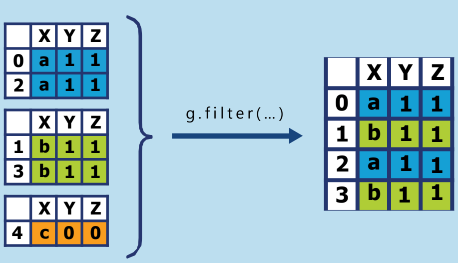
```
> def normalize(grp):
.      return (grp - grp.mean()) / grp.var()
> g.transform(normalize)
```



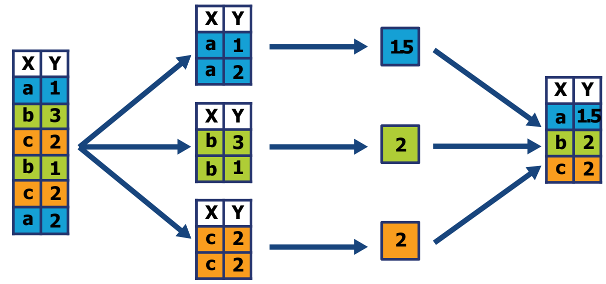
Apply/Combine: Filtering

Returns a group only if condition is true.

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



Split/Apply/Combine



Split
- Groupby
- Window Functions

Apply / **Combine**
- 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:

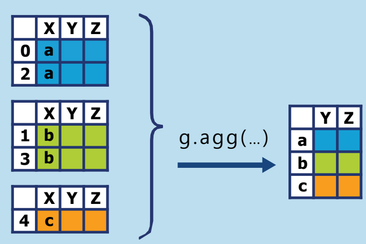
```
> g.agg(series_to_value)
```

... or aggregate with multiple functions at once:

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

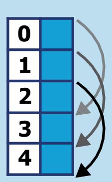
... or use different functions on different columns.

```
> 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. (see Aggregation).
- resample is often used before rolling, expanding, and ewm when using a DateTime index.



ENTHOUGHT

Reshaping DataFrames and Pivot Tables

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"[1]. Tidy data is easier to filter, aggregate, transform, sort, and pivot. Reshaping operations often produce multi-level indices or columns, which can be sliced and indexed.

1 Hadley Wickham (2014) "Tidy Data", http://dx.doi.org/10.18637/jss.v059.i10

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']
```

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 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

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	AN	EU
Recently updated		
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).

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