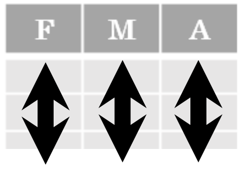
# برگه تقلب پانداس

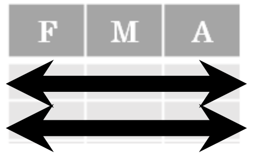
## Data Wrangling

# Tidy Data – A foundation for wrangling in pandas

In a tidy data set:

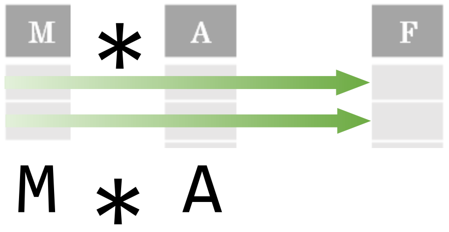


Each **variable** is saved in its own **column**



Each **observation** is saved in its own **row**

Tidy data complements pandas's **vectorized operations**. pandas will automatically preserve observations as you manipulate variables. No other format works as intuitively with pandas.



# Creating DataFrames

|   | a | b | c |
|---|---|---|---|
| 1 | 4 | 7 | 10 |
| 2 | 5 | 8 | 11 |
| 3 | 6 | 9 | 12 |

```
df = pd.DataFrame(
        {"a" : [4, 5, 6],
         "b" : [7, 8, 9],
         "c" : [10, 11, 12]},
       index = [1, 2, 3])
```

Specify values for each column.

```
df = pd.DataFrame(
     [[4, 7, 10],
      [5, 8, 11],
      [6, 9, 12]],
     index=[1, 2, 3],
     columns=['a', 'b', 'c'])
```

Specify values for each row.

|   |   | a | b | c |
|---|---|---|---|---|
| N | v |   |   |   |
| D | 1 | 4 | 7 | 10 |
|   | 2 | 5 | 8 | 11 |
| e | 2 | 6 | 9 | 12 |

```
df = pd.DataFrame(
        {"a" : [4 ,5, 6],
         "b" : [7, 8, 9],
         "c" : [10, 11, 12]},
index = pd.MultiIndex.from_tuples(
       [('d', 1), ('d', 2),
        ('e', 2)], names=['n', 'v']))
```

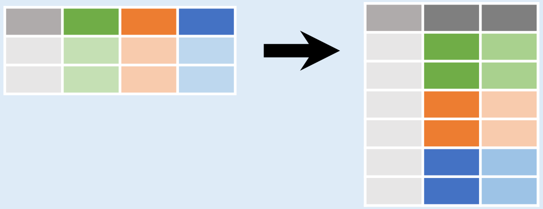
Create DataFrame with a MultiIndex

# Method Chaining

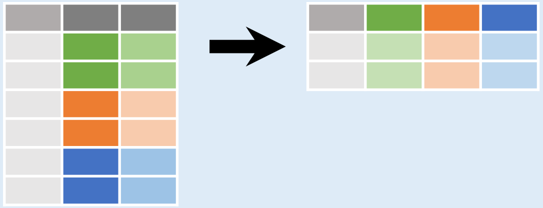
Most pandas methods return a DataFrame so that another pandas method can be applied to the result. This improves readability of code.

```
df = (pd.melt(df)
        .rename(columns={
                'variable':'var',
                'value':'val'})
        .query('val >= 200')
     )
```

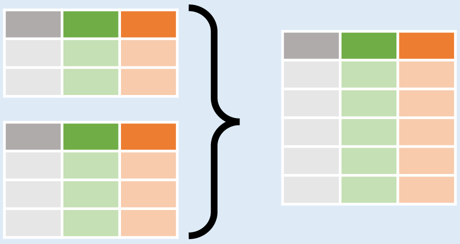
# Reshaping Data – Change layout, sorting, reindexing, renaming



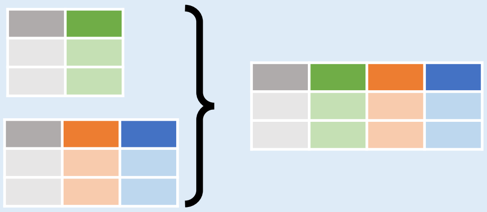
`pd.melt(df)`
Gather columns into rows.



`df.pivot(columns='var', values='val')`
Spread rows into columns.



`pd.concat([df1,df2])`
Append rows of DataFrames



`pd.concat([df1,df2], axis=1)`
Append columns of DataFrames

`df.sort_values('mpg')`
Order rows by values of a column (low to high).

`df.sort_values('mpg', ascending=False)`
Order rows by values of a column (high to low).

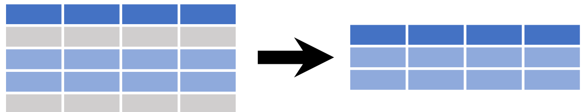
`df.rename(columns = {'y':'year'})`
Rename the columns of a DataFrame

`df.sort_index()`
Sort the index of a DataFrame

`df.reset_index()`
Reset index of DataFrame to row numbers, moving index to columns.

`df.drop(columns=['Length', 'Height'])`
Drop columns from DataFrame

# Subset Observations - rows



`df[df.Length > 7]`
Extract rows that meet logical criteria.

`df.drop_duplicates()`
Remove duplicate rows (only considers columns).

`df.sample(frac=0.5)`
Randomly select fraction of rows.

`df.sample(n=10)` Randomly select n rows.

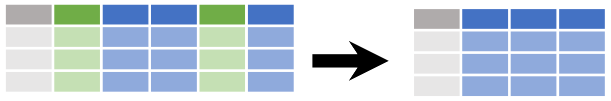
`df.nlargest(n, 'value')`
Select and order top n entries.

`df.nsmallest(n, 'value')`
Select and order bottom n entries.

`df.head(n)`
Select first n rows.

`df.tail(n)`
Select last n rows.

# Subset Variables - columns



`df[['width', 'length', 'species']]`
Select multiple columns with specific names.

`df['width']` *or* `df.width`
Select single column with specific name.

`df.filter(regex='regex')`
Select columns whose name matches regular expression *regex*.

# Using query

query() allows Boolean expressions for filtering rows.

```
df.query('Length > 7')
df.query('Length > 7 and Width < 8')
df.query('Name.str.startswith("abc")',
                 engine="python")
```

# Subsets - rows and columns

Use **df.loc[]** and **df.iloc[]** to select only rows, only columns or both.
Use **df.at[]** and **df.iat[]** to access a single value by row and column.
First index selects rows, second index columns.

`df.iloc[10:20]`
Select rows 10-20.

`df.iloc[:, [1, 2, 5]]`
Select columns in positions 1, 2 and 5 (first column is 0).

`df.loc[:, 'x2':'x4']`
Select all columns between x2 and x4 (inclusive).

`df.loc[df['a'] > 10, ['a', 'c']]`
Select rows meeting logical condition, and only the specific columns .

`df.iat[1, 2]` Access single value by index

`df.at[4, 'A']` Access single value by label

| Logic in Python (and pandas) | | | |
|---|---|---|---|
| < | Less than | != | Not equal to |
| > | Greater than | df.column.isin(*values*) | Group membership |
| == | Equals | pd.isnull(*obj*) | Is NaN |
| <= | Less than or equals | pd.notnull(*obj*) | Is not NaN |
| >= | Greater than or equals | &,\|,~,^,df.any(),df.all() | Logical and, or, not, xor, any, all |

| regex (Regular Expressions) Examples | |
|---|---|
| '\.' | Matches strings containing a period '.' |
| 'Length$' | Matches strings ending with word 'Length' |
| '^Sepal' | Matches strings beginning with the word 'Sepal' |
| '^x[1-5]$' | Matches strings beginning with 'x' and ending with 1,2,3,4,5 |
| '^(?!Species$).*' | Matches strings except the string 'Species' |

# Summarize Data

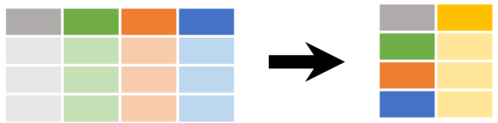
```
df['w'].value_counts()
```
Count number of rows with each unique value of variable

```
len(df)
```
# of rows in DataFrame.

```
df.shape
```
Tuple of # of rows, # of columns in DataFrame.

```
df['w'].nunique()
```
# of distinct values in a column.

```
df.describe()
```
Basic descriptive and statistics for each column (or GroupBy).



pandas provides a large set of **summary functions** that operate on different kinds of pandas objects (DataFrame columns, Series, GroupBy, Expanding and Rolling (see below)) and produce single values for each of the groups. When applied to a DataFrame, the result is returned as a pandas Series for each column. Examples:

`sum()`
Sum values of each object.

`count()`
Count non-NA/null values of each object.

`median()`
Median value of each object.

`quantile([0.25,0.75])`
Quantiles of each object.

`apply(`*`function`*`)`
Apply function to each object.

`min()`
Minimum value in each object.

`max()`
Maximum value in each object.

`mean()`
Mean value of each object.

`var()`
Variance of each object.

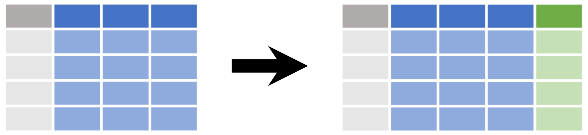
`std()`
Standard deviation of each object.

# Handling Missing Data

```
df.dropna()
```
Drop rows with any column having NA/null data.

```
df.fillna(value)
```
Replace all NA/null data with value.

# Make New Columns



```
df.assign(Area=lambda df: df.Length*df.Height)
```
Compute and append one or more new columns.

```
df['Volume'] = df.Length*df.Height*df.Depth
```
Add single column.

```
pd.qcut(df.col, n, labels=False)
```
Bin column into n buckets.

Vector function
Vector function

pandas provides a large set of **vector functions** that operate on all columns of a DataFrame or a single selected column (a pandas Series). These functions produce vectors of values for each of the columns, or a single Series for the individual Series. Examples:

`max(axis=1)`
Element-wise max.

`clip(lower=-10,upper=10)`
Trim values at input thresholds

`min(axis=1)`
Element-wise min.

`abs()`
Absolute value.

# Group Data

```
df.groupby(by="col")
```
Return a GroupBy object, grouped by values in column named "col".

```
df.groupby(level="ind")
```
Return a GroupBy object, grouped by values in index level named "ind".

All of the summary functions listed above can be applied to a group. Additional GroupBy functions:

`size()`
Size of each group.

`agg(`*`function`*`)`
Aggregate group using function.

The examples below can also be applied to groups. In this case, the function is applied on a per-group basis, and the returned vectors are of the length of the original DataFrame.

`shift(1)`
Copy with values shifted by 1.

`rank(method='dense')`
Ranks with no gaps.

`rank(method='min')`
Ranks. Ties get min rank.

`rank(pct=True)`
Ranks rescaled to interval [0, 1].

`rank(method='first')`
Ranks. Ties go to first value.

`shift(-1)`
Copy with values lagged by 1.

`cumsum()`
Cumulative sum.

`cummax()`
Cumulative max.

`cummin()`
Cumulative min.

`cumprod()`
Cumulative product.

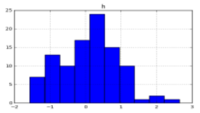
# Windows

```
df.expanding()
```
Return an Expanding object allowing summary functions to be applied cumulatively.

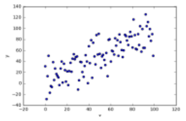
```
df.rolling(n)
```
Return a Rolling object allowing summary functions to be applied to windows of length n.

# Plotting

```
df.plot.hist()
```
Histogram for each column



```
df.plot.scatter(x='w',y='h')
```
Scatter chart using pairs of points



# Combine Data Sets

adf

| x1 | x2 |
|---|---|
| A | 1 |
| B | 2 |
| C | 3 |

+

bdf

| x1 | x3 |
|---|---|
| A | T |
| B | F |
| D | T |

=

Standard Joins

| x1 | x2 | x3 |
|---|---|---|
| A | 1 | T |
| B | 2 | F |
| C | 3 | NaN |

```
pd.merge(adf, bdf,
         how='left', on='x1')
```
Join matching rows from bdf to adf.

| x1 | x2 | x3 |
|---|---|---|
| A | 1.0 | T |
| B | 2.0 | F |
| D | NaN | T |

```
pd.merge(adf, bdf,
         how='right', on='x1')
```
Join matching rows from adf to bdf.

| x1 | x2 | x3 |
|---|---|---|
| A | 1 | T |
| B | 2 | F |

```
pd.merge(adf, bdf,
         how='inner', on='x1')
```
Join data. Retain only rows in both sets.

| x1 | x2 | x3 |
|---|---|---|
| A | 1 | T |
| B | 2 | F |
| C | 3 | NaN |
| D | NaN | T |

```
pd.merge(adf, bdf,
         how='outer', on='x1')
```
Join data. Retain all values, all rows.

Filtering Joins

| x1 | x2 |
|---|---|
| A | 1 |
| B | 2 |

```
adf[adf.x1.isin(bdf.x1)]
```
All rows in adf that have a match in bdf.

| x1 | x2 |
|---|---|
| C | 3 |

```
adf[~adf.x1.isin(bdf.x1)]
```
All rows in adf that do not have a match in bdf.

ydf

| x1 | x2 |
|---|---|
| A | 1 |
| B | 2 |
| C | 3 |

+

zdf

| x1 | x2 |
|---|---|
| B | 2 |
| C | 3 |
| D | 4 |

=

Set-like Operations

| x1 | x2 |
|---|---|
| B | 2 |
| C | 3 |

```
pd.merge(ydf, zdf)
```
Rows that appear in both ydf and zdf (Intersection).

| x1 | x2 |
|---|---|
| A | 1 |
| B | 2 |
| C | 3 |
| D | 4 |

```
pd.merge(ydf, zdf, how='outer')
```
Rows that appear in either or both ydf and zdf (Union).

| x1 | x2 |
|---|---|
| A | 1 |

```
pd.merge(ydf, zdf, how='outer',
         indicator=True)
.query('_merge == "left_only"')
.drop(columns=['_merge'])
```
Rows that appear in ydf but not zdf (Setdiff).