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```
sex
Female     87
Male      157
dtype: int64
```

Notice that in the pandas code we used *size()* and not *count()*. This is because *count()* applies the function to each column, returning the number of `not null` records within each.

```
In [19]: tips.groupby('sex').count()
Out[19]:
        total_bill  tip  smoker  day  time  size
sex
Female          87   87      87   87    87    87
Male           157  157     157  157   157   157
```

Alternatively, we could have applied the *count()* method to an individual column:

```
In [20]: tips.groupby('sex')['total_bill'].count()
Out[20]:
sex
Female     87
Male      157
Name: total_bill, dtype: int64
```

Multiple functions can also be applied at once. For instance, say we'd like to see how tip amount differs by day of the week - `agg()` allows you to pass a dictionary to your grouped DataFrame, indicating which functions to apply to specific columns.

```
SELECT day, AVG(tip), COUNT(*)
FROM tips
GROUP BY day;
/*
Fri   2.734737   19
Sat   2.993103   87
Sun   3.255132   76
Thur  2.771452   62
*/
```

```
In [21]: tips.groupby('day').agg({'tip': np.mean, 'day': np.size})
Out[21]:
           tip  day
day
Fri   2.734737   19
Sat   2.993103   87
Sun   3.255132   76
Thur  2.771452   62
```

Grouping by more than one column is done by passing a list of columns to the *groupby()* method.

```
SELECT smoker, day, COUNT(*), AVG(tip)
FROM tips
GROUP BY smoker, day;
/*
smoker day
No     Fri      4  2.812500
       Sat     45  3.102889
```

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```
        Sun      57  3.167895
        Thur     45  2.673778
Yes     Fri      15  2.714000
        Sat      42  2.875476
        Sun      19  3.516842
        Thur     17  3.030000
*/
```

```
In [22]: tips.groupby(['smoker', 'day']).agg({'tip': [np.size, np.mean]})
Out[22]:
              tip
             size      mean
smoker day
No     Fri    4.0  2.812500
       Sat   45.0  3.102889
       Sun   57.0  3.167895
       Thur  45.0  2.673778
Yes    Fri   15.0  2.714000
       Sat   42.0  2.875476
       Sun   19.0  3.516842
       Thur  17.0  3.030000
```

JOIN

JOINs can be performed with `join()` or `merge()`. By default, `join()` will join the DataFrames on their indices. Each method has parameters allowing you to specify the type of join to perform (LEFT, RIGHT, INNER, FULL) or the columns to join on (column names or indices).

```
In [23]: df1 = pd.DataFrame({'key': ['A', 'B', 'C', 'D'],
   ....:                     'value': np.random.randn(4)})
   ....:

In [24]: df2 = pd.DataFrame({'key': ['B', 'D', 'D', 'E'],
   ....:                     'value': np.random.randn(4)})
   ....:
```

Assume we have two database tables of the same name and structure as our DataFrames.

Now let's go over the various types of JOINs.

INNER JOIN

```
SELECT *
FROM df1
INNER JOIN df2
  ON df1.key = df2.key;
```

```
# merge performs an INNER JOIN by default
In [25]: pd.merge(df1, df2, on='key')
Out[25]:
  key   value_x   value_y
0   B -0.282863  1.212112
```

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```
1    D -1.135632 -0.173215
2    D -1.135632  0.119209
```

`merge()` also offers parameters for cases when you'd like to join one DataFrame's column with another DataFrame's index.

```
In [26]: indexed_df2 = df2.set_index('key')

In [27]: pd.merge(df1, indexed_df2, left_on='key', right_index=True)
Out[27]:
  key   value_x   value_y
1   B -0.282863  1.212112
3   D -1.135632 -0.173215
3   D -1.135632  0.119209
```

LEFT OUTER JOIN

```
-- show all records from df1
SELECT *
FROM df1
LEFT OUTER JOIN df2
  ON df1.key = df2.key;
```

```
# show all records from df1
In [28]: pd.merge(df1, df2, on='key', how='left')
Out[28]:
  key   value_x   value_y
0   A  0.469112       NaN
1   B -0.282863  1.212112
2   C -1.509059       NaN
3   D -1.135632 -0.173215
4   D -1.135632  0.119209
```

RIGHT JOIN

```
-- show all records from df2
SELECT *
FROM df1
RIGHT OUTER JOIN df2
  ON df1.key = df2.key;
```

```
# show all records from df2
In [29]: pd.merge(df1, df2, on='key', how='right')
Out[29]:
  key   value_x   value_y
0   B -0.282863  1.212112
1   D -1.135632 -0.173215
2   D -1.135632  0.119209
3   E       NaN -1.044236
```

FULL JOIN

pandas also allows for FULL JOINs, which display both sides of the dataset, whether or not the joined columns find a match. As of writing, FULL JOINs are not supported in all RDBMS (MySQL).

```
-- show all records from both tables
SELECT *
FROM df1
FULL OUTER JOIN df2
  ON df1.key = df2.key;
```

```
# show all records from both frames
In [30]: pd.merge(df1, df2, on='key', how='outer')
Out[30]:
  key   value_x   value_y
0   A  0.469112       NaN
1   B -0.282863  1.212112
2   C -1.509059       NaN
3   D -1.135632 -0.173215
4   D -1.135632  0.119209
5   E       NaN -1.044236
```

UNION

UNION ALL can be performed using `concat()`.

```
In [31]: df1 = pd.DataFrame({'city': ['Chicago', 'San Francisco', 'New York City'],
   ....:                     'rank': range(1, 4)})
   ....:

In [32]: df2 = pd.DataFrame({'city': ['Chicago', 'Boston', 'Los Angeles'],
   ....:                     'rank': [1, 4, 5]})
   ....:
```

```
SELECT city, rank
FROM df1
UNION ALL
SELECT city, rank
FROM df2;
/*
         city  rank
      Chicago     1
San Francisco     2
New York City     3
      Chicago     1
       Boston     4
  Los Angeles     5
*/
```

```
In [33]: pd.concat([df1, df2])
Out[33]:
            city  rank
0        Chicago     1
1  San Francisco     2
```

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```
2  New York City     3
0        Chicago     1
1         Boston     4
2    Los Angeles     5
```

SQL's UNION is similar to UNION ALL, however UNION will remove duplicate rows.

```
SELECT city, rank
FROM df1
UNION
SELECT city, rank
FROM df2;
-- notice that there is only one Chicago record this time
/*
         city  rank
      Chicago     1
San Francisco     2
New York City     3
       Boston     4
  Los Angeles     5
*/
```

In pandas, you can use `concat()` in conjunction with `drop_duplicates()`.

```
In [34]: pd.concat([df1, df2]).drop_duplicates()
Out[34]:
            city  rank
0        Chicago     1
1  San Francisco     2
2  New York City     3
1         Boston     4
2    Los Angeles     5
```

Pandas equivalents for some SQL analytic and aggregate functions

Top N rows with offset

```
-- MySQL
SELECT * FROM tips
ORDER BY tip DESC
LIMIT 10 OFFSET 5;
```

```
In [35]: tips.nlargest(10 + 5, columns='tip').tail(10)
Out[35]:
     total_bill   tip     sex smoker   day    time  size
183       23.17  6.50    Male    Yes   Sun  Dinner     4
214       28.17  6.50  Female    Yes   Sat  Dinner     3
47        32.40  6.00    Male     No   Sun  Dinner     4
239       29.03  5.92    Male     No   Sat  Dinner     3
88        24.71  5.85    Male     No  Thur   Lunch     2
181       23.33  5.65    Male    Yes   Sun  Dinner     2
44        30.40  5.60    Male     No   Sun  Dinner     4
52        34.81  5.20  Female     No   Sun  Dinner     4
```

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```
85          34.83  5.17  Female     No  Thur   Lunch     4
211         25.89  5.16    Male    Yes   Sat  Dinner     4
```

Top N rows per group

```
-- Oracle's ROW_NUMBER() analytic function
SELECT * FROM (
  SELECT
    t.*,
    ROW_NUMBER() OVER(PARTITION BY day ORDER BY total_bill DESC) AS rn
  FROM tips t
)
WHERE rn < 3
ORDER BY day, rn;
```

```
In [36]: (tips.assign(rn=tips.sort_values(['total_bill'], ascending=False)
   ....:                     .groupby(['day'])
   ....:                     .cumcount() + 1)
   ....:      .query('rn < 3')
   ....:      .sort_values(['day', 'rn']))
   ....:
Out[36]:
     total_bill    tip     sex smoker   day    time  size  rn
95        40.17   4.73    Male    Yes   Fri  Dinner     4   1
90        28.97   3.00    Male    Yes   Fri  Dinner     2   2
170       50.81  10.00    Male    Yes   Sat  Dinner     3   1
212       48.33   9.00    Male     No   Sat  Dinner     4   2
156       48.17   5.00    Male     No   Sun  Dinner     6   1
182       45.35   3.50    Male    Yes   Sun  Dinner     3   2
197       43.11   5.00  Female    Yes  Thur   Lunch     4   1
142       41.19   5.00    Male     No  Thur   Lunch     5   2
```

the same using *rank(method='first')* function

```
In [37]: (tips.assign(rnk=tips.groupby(['day'])['total_bill']
   ....:                      .rank(method='first', ascending=False))
   ....:      .query('rnk < 3')
   ....:      .sort_values(['day', 'rnk']))
   ....:
Out[37]:
     total_bill    tip     sex smoker   day    time  size  rnk
95        40.17   4.73    Male    Yes   Fri  Dinner     4  1.0
90        28.97   3.00    Male    Yes   Fri  Dinner     2  2.0
170       50.81  10.00    Male    Yes   Sat  Dinner     3  1.0
212       48.33   9.00    Male     No   Sat  Dinner     4  2.0
156       48.17   5.00    Male     No   Sun  Dinner     6  1.0
182       45.35   3.50    Male    Yes   Sun  Dinner     3  2.0
197       43.11   5.00  Female    Yes  Thur   Lunch     4  1.0
142       41.19   5.00    Male     No  Thur   Lunch     5  2.0
```

```
-- Oracle's RANK() analytic function
SELECT * FROM (
  SELECT
    t.*,
```

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```
    RANK() OVER(PARTITION BY sex ORDER BY tip) AS rnk
  FROM tips t
  WHERE tip < 2
)
WHERE rnk < 3
ORDER BY sex, rnk;
```

Let's find tips with (rank < 3) per gender group for (tips < 2). Notice that when using `rank(method='min')` function *rnk_min* remains the same for the same *tip* (as Oracle's RANK() function)

```
In [38]: (tips[tips['tip'] < 2]
   ....:     .assign(rnk_min=tips.groupby(['sex'])['tip']
   ....:                         .rank(method='min'))
   ....:     .query('rnk_min < 3')
   ....:     .sort_values(['sex', 'rnk_min']))
   ....:
Out[38]:
     total_bill   tip     sex smoker  day    time  size  rnk_min
67         3.07  1.00  Female    Yes  Sat  Dinner     1      1.0
92         5.75  1.00  Female    Yes  Fri  Dinner     2      1.0
111        7.25  1.00  Female     No  Sat  Dinner     1      1.0
236       12.60  1.00    Male    Yes  Sat  Dinner     2      1.0
237       32.83  1.17    Male    Yes  Sat  Dinner     2      2.0
```

UPDATE

```
UPDATE tips
SET tip = tip*2
WHERE tip < 2;
```

```
In [39]: tips.loc[tips['tip'] < 2, 'tip'] *= 2
```

DELETE

```
DELETE FROM tips
WHERE tip > 9;
```

In pandas we select the rows that should remain, instead of deleting them

```
In [40]: tips = tips.loc[tips['tip'] <= 9]
```

Comparison with SAS

For potential users coming from SAS this page is meant to demonstrate how different SAS operations would be performed in pandas.

If you're new to pandas, you might want to first read through *10 Minutes to pandas* to familiarize yourself with the library.

As is customary, we import pandas and NumPy as follows:

```
In [1]: import pandas as pd

In [2]: import numpy as np
```

Note: Throughout this tutorial, the pandas `DataFrame` will be displayed by calling `df.head()`, which displays the first N (default 5) rows of the `DataFrame`. This is often used in interactive work (e.g. Jupyter notebook or terminal) - the equivalent in SAS would be:

```
proc print data=df(obs=5);
run;
```

Data structures

General terminology translation

pandas	SAS
`DataFrame`	data set
column	variable
row	observation
groupby	BY-group
`NaN`	.

`DataFrame` / `Series`

A `DataFrame` in pandas is analogous to a SAS data set - a two-dimensional data source with labeled columns that can be of different types. As will be shown in this document, almost any operation that can be applied to a data set using SAS's `DATA` step, can also be accomplished in pandas.

A `Series` is the data structure that represents one column of a `DataFrame`. SAS doesn't have a separate data structure for a single column, but in general, working with a `Series` is analogous to referencing a column in the `DATA` step.

Index

Every DataFrame and Series has an Index - which are labels on the *rows* of the data. SAS does not have an exactly analogous concept. A data set's rows are essentially unlabeled, other than an implicit integer index that can be accessed during the DATA step (_N_).

In pandas, if no index is specified, an integer index is also used by default (first row = 0, second row = 1, and so on). While using a labeled Index or MultiIndex can enable sophisticated analyses and is ultimately an important part of pandas to understand, for this comparison we will essentially ignore the Index and just treat the DataFrame as a collection of columns. Please see the *indexing documentation* for much more on how to use an Index effectively.

Data input / output

Constructing a DataFrame from values

A SAS data set can be built from specified values by placing the data after a datalines statement and specifying the column names.

```
data df;
    input x y;
    datalines;
    1 2
    3 4
    5 6
    ;
run;
```

A pandas DataFrame can be constructed in many different ways, but for a small number of values, it is often convenient to specify it as a Python dictionary, where the keys are the column names and the values are the data.

```
In [3]: df = pd.DataFrame({'x': [1, 3, 5], 'y': [2, 4, 6]})

In [4]: df
Out[4]:
   x  y
0  1  2
1  3  4
2  5  6
```

Reading external data

Like SAS, pandas provides utilities for reading in data from many formats. The tips dataset, found within the pandas tests (csv) will be used in many of the following examples.

SAS provides PROC IMPORT to read csv data into a data set.

```
proc import datafile='tips.csv' dbms=csv out=tips replace;
    getnames=yes;
run;
```

The pandas method is *read_csv()*, which works similarly.

```
In [5]: url = ('https://raw.github.com/pandas-dev/'
   ...:        'pandas/master/pandas/tests/io/data/csv/tips.csv')
   ...:

In [6]: tips = pd.read_csv(url)

In [7]: tips.head()
Out[7]:
   total_bill   tip     sex smoker  day    time  size
0       16.99  1.01  Female     No  Sun  Dinner     2
1       10.34  1.66    Male     No  Sun  Dinner     3
2       21.01  3.50    Male     No  Sun  Dinner     3
3       23.68  3.31    Male     No  Sun  Dinner     2
4       24.59  3.61  Female     No  Sun  Dinner     4
```

Like `PROC IMPORT`, `read_csv` can take a number of parameters to specify how the data should be parsed. For example, if the data was instead tab delimited, and did not have column names, the pandas command would be:

```
tips = pd.read_csv('tips.csv', sep='\t', header=None)

# alternatively, read_table is an alias to read_csv with tab delimiter
tips = pd.read_table('tips.csv', header=None)
```

In addition to text/csv, pandas supports a variety of other data formats such as Excel, HDF5, and SQL databases. These are all read via a `pd.read_*` function. See the *IO documentation* for more details.

Exporting data

The inverse of `PROC IMPORT` in SAS is `PROC EXPORT`

```
proc export data=tips outfile='tips2.csv' dbms=csv;
run;
```

Similarly in pandas, the opposite of `read_csv` is `to_csv()`, and other data formats follow a similar api.

```
tips.to_csv('tips2.csv')
```

Data operations

Operations on columns

In the `DATA` step, arbitrary math expressions can be used on new or existing columns.

```
data tips;
    set tips;
    total_bill = total_bill - 2;
    new_bill = total_bill / 2;
run;
```

pandas provides similar vectorized operations by specifying the individual `Series` in the `DataFrame`. New columns can be assigned in the same way.

```
In [8]: tips['total_bill'] = tips['total_bill'] - 2

In [9]: tips['new_bill'] = tips['total_bill'] / 2.0

In [10]: tips.head()
Out[10]:
   total_bill   tip     sex smoker  day    time  size  new_bill
0       14.99  1.01  Female     No  Sun  Dinner     2     7.495
1        8.34  1.66    Male     No  Sun  Dinner     3     4.170
2       19.01  3.50    Male     No  Sun  Dinner     3     9.505
3       21.68  3.31    Male     No  Sun  Dinner     2    10.840
4       22.59  3.61  Female     No  Sun  Dinner     4    11.295
```

Filtering

Filtering in SAS is done with an `if` or `where` statement, on one or more columns.

```
data tips;
    set tips;
    if total_bill > 10;
run;

data tips;
    set tips;
    where total_bill > 10;
    /* equivalent in this case - where happens before the
       DATA step begins and can also be used in PROC statements */
run;
```

DataFrames can be filtered in multiple ways; the most intuitive of which is using *boolean indexing*

```
In [11]: tips[tips['total_bill'] > 10].head()
Out[11]:
   total_bill   tip     sex smoker  day    time  size
0       14.99  1.01  Female     No  Sun  Dinner     2
2       19.01  3.50    Male     No  Sun  Dinner     3
3       21.68  3.31    Male     No  Sun  Dinner     2
4       22.59  3.61  Female     No  Sun  Dinner     4
5       23.29  4.71    Male     No  Sun  Dinner     4
```

If/then logic

In SAS, if/then logic can be used to create new columns.

```
data tips;
    set tips;
    format bucket $4.;

    if total_bill < 10 then bucket = 'low';
    else bucket = 'high';
run;
```

The same operation in pandas can be accomplished using the `where` method from `numpy`.

```
In [12]: tips['bucket'] = np.where(tips['total_bill'] < 10, 'low', 'high')

In [13]: tips.head()
Out[13]:
   total_bill   tip     sex smoker  day    time  size bucket
0       14.99  1.01  Female     No  Sun  Dinner     2   high
1        8.34  1.66    Male     No  Sun  Dinner     3    low
2       19.01  3.50    Male     No  Sun  Dinner     3   high
3       21.68  3.31    Male     No  Sun  Dinner     2   high
4       22.59  3.61  Female     No  Sun  Dinner     4   high
```

Date functionality

SAS provides a variety of functions to do operations on date/datetime columns.

```
data tips;
    set tips;
    format date1 date2 date1_plusmonth mmddyy10.;
    date1 = mdy(1, 15, 2013);
    date2 = mdy(2, 15, 2015);
    date1_year = year(date1);
    date2_month = month(date2);
    * shift date to beginning of next interval;
    date1_next = intnx('MONTH', date1, 1);
    * count intervals between dates;
    months_between = intck('MONTH', date1, date2);
run;
```

The equivalent pandas operations are shown below. In addition to these functions pandas supports other Time Series features not available in Base SAS (such as resampling and custom offsets) - see the *timeseries documentation* for more details.

```
In [14]: tips['date1'] = pd.Timestamp('2013-01-15')

In [15]: tips['date2'] = pd.Timestamp('2015-02-15')

In [16]: tips['date1_year'] = tips['date1'].dt.year

In [17]: tips['date2_month'] = tips['date2'].dt.month

In [18]: tips['date1_next'] = tips['date1'] + pd.offsets.MonthBegin()

In [19]: tips['months_between'] = (
   ....:     tips['date2'].dt.to_period('M') - tips['date1'].dt.to_period('M'))
   ....:

In [20]: tips[['date1', 'date2', 'date1_year', 'date2_month',
   ....:       'date1_next', 'months_between']].head()
   ....:
Out[20]:
       date1      date2  date1_year  date2_month date1_next    months_between
0 2013-01-15 2015-02-15        2013            2 2013-02-01  <25 * MonthEnds>
1 2013-01-15 2015-02-15        2013            2 2013-02-01  <25 * MonthEnds>
2 2013-01-15 2015-02-15        2013            2 2013-02-01  <25 * MonthEnds>
3 2013-01-15 2015-02-15        2013            2 2013-02-01  <25 * MonthEnds>
4 2013-01-15 2015-02-15        2013            2 2013-02-01  <25 * MonthEnds>
```

Selection of columns

SAS provides keywords in the `DATA` step to select, drop, and rename columns.

```
data tips;
    set tips;
    keep sex total_bill tip;
run;

data tips;
    set tips;
    drop sex;
run;

data tips;
    set tips;
    rename total_bill=total_bill_2;
run;
```

The same operations are expressed in pandas below.

```
# keep
In [21]: tips[['sex', 'total_bill', 'tip']].head()
Out[21]:
      sex  total_bill   tip
0  Female       14.99  1.01
1    Male        8.34  1.66
2    Male       19.01  3.50
3    Male       21.68  3.31
4  Female       22.59  3.61

# drop
In [22]: tips.drop('sex', axis=1).head()
Out[22]:
   total_bill   tip smoker  day    time  size
0       14.99  1.01     No  Sun  Dinner     2
1        8.34  1.66     No  Sun  Dinner     3
2       19.01  3.50     No  Sun  Dinner     3
3       21.68  3.31     No  Sun  Dinner     2
4       22.59  3.61     No  Sun  Dinner     4

# rename
In [23]: tips.rename(columns={'total_bill': 'total_bill_2'}).head()
Out[23]:
   total_bill_2   tip     sex smoker  day    time  size
0         14.99  1.01  Female     No  Sun  Dinner     2
1          8.34  1.66    Male     No  Sun  Dinner     3
2         19.01  3.50    Male     No  Sun  Dinner     3
3         21.68  3.31    Male     No  Sun  Dinner     2
4         22.59  3.61  Female     No  Sun  Dinner     4
```

Sorting by values

Sorting in SAS is accomplished via PROC SORT

```
proc sort data=tips;
    by sex total_bill;
run;
```

pandas objects have a *sort_values()* method, which takes a list of columns to sort by.

```
In [24]: tips = tips.sort_values(['sex', 'total_bill'])

In [25]: tips.head()
Out[25]:
     total_bill   tip     sex smoker   day    time  size
67         1.07  1.00  Female    Yes   Sat  Dinner     1
92         3.75  1.00  Female    Yes   Fri  Dinner     2
111        5.25  1.00  Female     No   Sat  Dinner     1
145        6.35  1.50  Female     No  Thur   Lunch     2
135        6.51  1.25  Female     No  Thur   Lunch     2
```

String processing

Length

SAS determines the length of a character string with the LENGTHN and LENGTHC functions. LENGTHN excludes trailing blanks and LENGTHC includes trailing blanks.

```
data _null_;
set tips;
put(LENGTHN(time));
put(LENGTHC(time));
run;
```

Python determines the length of a character string with the len function. len includes trailing blanks. Use len and rstrip to exclude trailing blanks.

```
In [26]: tips['time'].str.len().head()
Out[26]:
67     6
92     6
111    6
145    5
135    5
Name: time, dtype: int64

In [27]: tips['time'].str.rstrip().str.len().head()
Out[27]:
67     6
92     6
111    6
145    5
135    5
Name: time, dtype: int64
```

Find

SAS determines the position of a character in a string with the FINDW function. `FINDW` takes the string defined by the first argument and searches for the first position of the substring you supply as the second argument.

```
data _null_;
set tips;
put(FINDW(sex,'ale'));
run;
```

Python determines the position of a character in a string with the `find` function. `find` searches for the first position of the substring. If the substring is found, the function returns its position. Keep in mind that Python indexes are zero-based and the function will return -1 if it fails to find the substring.

```
In [28]: tips['sex'].str.find("ale").head()
Out[28]:
67     3
92     3
111    3
145    3
135    3
Name: sex, dtype: int64
```

Substring

SAS extracts a substring from a string based on its position with the SUBSTR function.

```
data _null_;
set tips;
put(substr(sex,1,1));
run;
```

With pandas you can use `[]` notation to extract a substring from a string by position locations. Keep in mind that Python indexes are zero-based.

```
In [29]: tips['sex'].str[0:1].head()
Out[29]:
67     F
92     F
111    F
145    F
135    F
Name: sex, dtype: object
```

Scan

The SAS SCAN function returns the nth word from a string. The first argument is the string you want to parse and the second argument specifies which word you want to extract.

```
data firstlast;
input String $60.;
First_Name = scan(string, 1);
Last_Name = scan(string, -1);
```

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```
datalines2;
John Smith;
Jane Cook;
;;;
run;
```

Python extracts a substring from a string based on its text by using regular expressions. There are much more powerful approaches, but this just shows a simple approach.

```
In [30]: firstlast = pd.DataFrame({'String': ['John Smith', 'Jane Cook']})

In [31]: firstlast['First_Name'] = firstlast['String'].str.split(" ", expand=True)[0]

In [32]: firstlast['Last_Name'] = firstlast['String'].str.rsplit(" ", expand=True)[0]

In [33]: firstlast
Out[33]: 
       String First_Name Last_Name
0  John Smith       John      John
1   Jane Cook       Jane      Jane
```

Upcase, lowcase, and propcase

The SAS UPCASE LOWCASE and PROPCASE functions change the case of the argument.

```
data firstlast;
input String $60.;
string_up = UPCASE(string);
string_low = LOWCASE(string);
string_prop = PROPCASE(string);
datalines2;
John Smith;
Jane Cook;
;;;
run;
```

The equivalent Python functions are `upper`, `lower`, and `title`.

```
In [34]: firstlast = pd.DataFrame({'String': ['John Smith', 'Jane Cook']})

In [35]: firstlast['string_up'] = firstlast['String'].str.upper()

In [36]: firstlast['string_low'] = firstlast['String'].str.lower()

In [37]: firstlast['string_prop'] = firstlast['String'].str.title()

In [38]: firstlast
Out[38]: 
       String   string_up  string_low string_prop
0  John Smith  JOHN SMITH  john smith  John Smith
1   Jane Cook   JANE COOK   jane cook   Jane Cook
```

Merging

The following tables will be used in the merge examples

```
In [39]: df1 = pd.DataFrame({'key': ['A', 'B', 'C', 'D'],
   ....:                     'value': np.random.randn(4)})
   ....:

In [40]: df1
Out[40]:
  key     value
0   A  0.469112
1   B -0.282863
2   C -1.509059
3   D -1.135632

In [41]: df2 = pd.DataFrame({'key': ['B', 'D', 'D', 'E'],
   ....:                     'value': np.random.randn(4)})
   ....:

In [42]: df2
Out[42]:
  key     value
0   B  1.212112
1   D -0.173215
2   D  0.119209
3   E -1.044236
```

In SAS, data must be explicitly sorted before merging. Different types of joins are accomplished using the `in=` dummy variables to track whether a match was found in one or both input frames.

```
proc sort data=df1;
    by key;
run;

proc sort data=df2;
    by key;
run;

data left_join inner_join right_join outer_join;
    merge df1(in=a) df2(in=b);

    if a and b then output inner_join;
    if a then output left_join;
    if b then output right_join;
    if a or b then output outer_join;
run;
```

pandas DataFrames have a *merge()* method, which provides similar functionality. Note that the data does not have to be sorted ahead of time, and different join types are accomplished via the `how` keyword.

```
In [43]: inner_join = df1.merge(df2, on=['key'], how='inner')

In [44]: inner_join
Out[44]:
  key   value_x   value_y
0   B -0.282863  1.212112
```

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```
1   D -1.135632 -0.173215
2   D -1.135632  0.119209

In [45]: left_join = df1.merge(df2, on=['key'], how='left')

In [46]: left_join
Out[46]:
  key   value_x   value_y
0   A  0.469112       NaN
1   B -0.282863  1.212112
2   C -1.509059       NaN
3   D -1.135632 -0.173215
4   D -1.135632  0.119209

In [47]: right_join = df1.merge(df2, on=['key'], how='right')

In [48]: right_join
Out[48]:
  key   value_x   value_y
0   B -0.282863  1.212112
1   D -1.135632 -0.173215
2   D -1.135632  0.119209
3   E       NaN -1.044236

In [49]: outer_join = df1.merge(df2, on=['key'], how='outer')

In [50]: outer_join
Out[50]:
  key   value_x   value_y
0   A  0.469112       NaN
1   B -0.282863  1.212112
2   C -1.509059       NaN
3   D -1.135632 -0.173215
4   D -1.135632  0.119209
5   E       NaN -1.044236
```

Missing data

Like SAS, pandas has a representation for missing data - which is the special float value `NaN` (not a number). Many of the semantics are the same, for example missing data propagates through numeric operations, and is ignored by default for aggregations.

```
In [51]: outer_join
Out[51]:
  key   value_x   value_y
0   A  0.469112       NaN
1   B -0.282863  1.212112
2   C -1.509059       NaN
3   D -1.135632 -0.173215
4   D -1.135632  0.119209
5   E       NaN -1.044236

In [52]: outer_join['value_x'] + outer_join['value_y']
Out[52]:
0         NaN
```

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```
1    0.929249
2         NaN
3   -1.308847
4   -1.016424
5         NaN
dtype: float64

In [53]: outer_join['value_x'].sum()
Out[53]: -3.5940742896293765
```

One difference is that missing data cannot be compared to its sentinel value. For example, in SAS you could do this to filter missing values.

```
data outer_join_nulls;
    set outer_join;
    if value_x = .;
run;

data outer_join_no_nulls;
    set outer_join;
    if value_x ^= .;
run;
```

Which doesn't work in pandas. Instead, the `pd.isna` or `pd.notna` functions should be used for comparisons.

```
In [54]: outer_join[pd.isna(outer_join['value_x'])]
Out[54]:
  key  value_x   value_y
5   E      NaN -1.044236

In [55]: outer_join[pd.notna(outer_join['value_x'])]
Out[55]:
  key   value_x   value_y
0   A  0.469112       NaN
1   B -0.282863  1.212112
2   C -1.509059       NaN
3   D -1.135632 -0.173215
4   D -1.135632  0.119209
```

pandas also provides a variety of methods to work with missing data - some of which would be challenging to express in SAS. For example, there are methods to drop all rows with any missing values, replacing missing values with a specified value, like the mean, or forward filling from previous rows. See the *missing data documentation* for more.

```
In [56]: outer_join.dropna()
Out[56]:
  key   value_x   value_y
1   B -0.282863  1.212112
3   D -1.135632 -0.173215
4   D -1.135632  0.119209

In [57]: outer_join.fillna(method='ffill')
Out[57]:
  key   value_x   value_y
0   A  0.469112       NaN
1   B -0.282863  1.212112
2   C -1.509059  1.212112
```

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```
3   D -1.135632 -0.173215
4   D -1.135632  0.119209
5   E -1.135632 -1.044236

In [58]: outer_join['value_x'].fillna(outer_join['value_x'].mean())
Out[58]:
0    0.469112
1   -0.282863
2   -1.509059
3   -1.135632
4   -1.135632
5   -0.718815
Name: value_x, dtype: float64
```

GroupBy

Aggregation

SAS's PROC SUMMARY can be used to group by one or more key variables and compute aggregations on numeric columns.

```
proc summary data=tips nway;
    class sex smoker;
    var total_bill tip;
    output out=tips_summed sum=;
run;
```

pandas provides a flexible `groupby` mechanism that allows similar aggregations. See the *groupby documentation* for more details and examples.

```
In [59]: tips_summed = tips.groupby(['sex', 'smoker'])[['total_bill', 'tip']].sum()

In [60]: tips_summed.head()
Out[60]:
               total_bill     tip
sex    smoker
Female No          869.68  149.77
       Yes         527.27   96.74
Male   No         1725.75  302.00
       Yes        1217.07  183.07
```

Transformation

In SAS, if the group aggregations need to be used with the original frame, it must be merged back together. For example, to subtract the mean for each observation by smoker group.

```
proc summary data=tips missing nway;
    class smoker;
    var total_bill;
    output out=smoker_means mean(total_bill)=group_bill;
run;
```

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```
proc sort data=tips;
    by smoker;
run;

data tips;
    merge tips(in=a) smoker_means(in=b);
    by smoker;
    adj_total_bill = total_bill - group_bill;
    if a and b;
run;
```

pandas `groupby` provides a `transform` mechanism that allows these type of operations to be succinctly expressed in one operation.

```
In [61]: gb = tips.groupby('smoker')['total_bill']

In [62]: tips['adj_total_bill'] = tips['total_bill'] - gb.transform('mean')

In [63]: tips.head()
Out[63]:
     total_bill   tip     sex smoker   day    time  size  adj_total_bill
67         1.07  1.00  Female    Yes   Sat  Dinner     1      -17.686344
92         3.75  1.00  Female    Yes   Fri  Dinner     2      -15.006344
111        5.25  1.00  Female     No   Sat  Dinner     1      -11.938278
145        6.35  1.50  Female     No  Thur   Lunch     2      -10.838278
135        6.51  1.25  Female     No  Thur   Lunch     2      -10.678278
```

By group processing

In addition to aggregation, pandas `groupby` can be used to replicate most other by group processing from SAS. For example, this `DATA` step reads the data by sex/smoker group and filters to the first entry for each.

```
proc sort data=tips;
   by sex smoker;
run;

data tips_first;
    set tips;
    by sex smoker;
    if FIRST.sex or FIRST.smoker then output;
run;
```

In pandas this would be written as:

```
In [64]: tips.groupby(['sex', 'smoker']).first()
Out[64]:
               total_bill   tip   day    time  size  adj_total_bill
sex    smoker
Female No            5.25  1.00   Sat  Dinner     1      -11.938278
       Yes           1.07  1.00   Sat  Dinner     1      -17.686344
Male   No            5.51  2.00  Thur   Lunch     2      -11.678278
       Yes           5.25  5.15   Sun  Dinner     2      -13.506344
```

Other Considerations

Disk vs memory

pandas operates exclusively in memory, where a SAS data set exists on disk. This means that the size of data able to be loaded in pandas is limited by your machine's memory, but also that the operations on that data may be faster.

If out of core processing is needed, one possibility is the dask.dataframe library (currently in development) which provides a subset of pandas functionality for an on-disk DataFrame

Data interop

pandas provides a *read_sas()* method that can read SAS data saved in the XPORT or SAS7BDAT binary format.

```
libname xportout xport 'transport-file.xpt';
data xportout.tips;
    set tips(rename=(total_bill=tbill));
    * xport variable names limited to 6 characters;
run;
```

```
df = pd.read_sas('transport-file.xpt')
df = pd.read_sas('binary-file.sas7bdat')
```

You can also specify the file format directly. By default, pandas will try to infer the file format based on its extension.

```
df = pd.read_sas('transport-file.xpt', format='xport')
df = pd.read_sas('binary-file.sas7bdat', format='sas7bdat')
```

XPORT is a relatively limited format and the parsing of it is not as optimized as some of the other pandas readers. An alternative way to interop data between SAS and pandas is to serialize to csv.

```
# version 0.17, 10M rows

In [8]: %time df = pd.read_sas('big.xpt')
Wall time: 14.6 s

In [9]: %time df = pd.read_csv('big.csv')
Wall time: 4.86 s
```

Comparison with Stata

For potential users coming from Stata this page is meant to demonstrate how different Stata operations would be performed in pandas.

If you're new to pandas, you might want to first read through *10 Minutes to pandas* to familiarize yourself with the library.

As is customary, we import pandas and NumPy as follows. This means that we can refer to the libraries as pd and np, respectively, for the rest of the document.

```
In [1]: import pandas as pd

In [2]: import numpy as np
```

Note: Throughout this tutorial, the pandas `DataFrame` will be displayed by calling `df.head()`, which displays the first N (default 5) rows of the `DataFrame`. This is often used in interactive work (e.g. Jupyter notebook or terminal) – the equivalent in Stata would be:

```
list in 1/5
```

Data structures

General terminology translation

pandas	Stata
`DataFrame`	data set
column	variable
row	observation
groupby	bysort
`NaN`	.

`DataFrame` / `Series`

A `DataFrame` in pandas is analogous to a Stata data set – a two-dimensional data source with labeled columns that can be of different types. As will be shown in this document, almost any operation that can be applied to a data set in Stata can also be accomplished in pandas.

A `Series` is the data structure that represents one column of a `DataFrame`. Stata doesn't have a separate data structure for a single column, but in general, working with a `Series` is analogous to referencing a column of a data set in Stata.

`Index`

Every `DataFrame` and `Series` has an `Index` – labels on the *rows* of the data. Stata does not have an exactly analogous concept. In Stata, a data set's rows are essentially unlabeled, other than an implicit integer index that can be accessed with `_n`.

In pandas, if no index is specified, an integer index is also used by default (first row = 0, second row = 1, and so on). While using a labeled `Index` or `MultiIndex` can enable sophisticated analyses and is ultimately an important part of pandas to understand, for this comparison we will essentially ignore the `Index` and just treat the `DataFrame` as a collection of columns. Please see the *indexing documentation* for much more on how to use an `Index` effectively.

Data input / output

Constructing a DataFrame from values

A Stata data set can be built from specified values by placing the data after an `input` statement and specifying the column names.

```
input x y
1 2
3 4
5 6
end
```

A pandas `DataFrame` can be constructed in many different ways, but for a small number of values, it is often convenient to specify it as a Python dictionary, where the keys are the column names and the values are the data.

```
In [3]: df = pd.DataFrame({'x': [1, 3, 5], 'y': [2, 4, 6]})

In [4]: df
Out[4]:
   x  y
0  1  2
1  3  4
2  5  6
```

Reading external data

Like Stata, pandas provides utilities for reading in data from many formats. The `tips` data set, found within the pandas tests (csv) will be used in many of the following examples.

Stata provides `import delimited` to read csv data into a data set in memory. If the `tips.csv` file is in the current working directory, we can import it as follows.

```
import delimited tips.csv
```

The pandas method is *read_csv()*, which works similarly. Additionally, it will automatically download the data set if presented with a url.

```
In [5]: url = ('https://raw.github.com/pandas-dev'
   ...:        '/pandas/master/pandas/tests/io/data/csv/tips.csv')
   ...:

In [6]: tips = pd.read_csv(url)

In [7]: tips.head()
Out[7]:
   total_bill   tip     sex smoker  day    time  size
0       16.99  1.01  Female     No  Sun  Dinner     2
1       10.34  1.66    Male     No  Sun  Dinner     3
2       21.01  3.50    Male     No  Sun  Dinner     3
3       23.68  3.31    Male     No  Sun  Dinner     2
4       24.59  3.61  Female     No  Sun  Dinner     4
```

Like `import delimited`, *read_csv()* can take a number of parameters to specify how the data should be parsed. For example, if the data were instead tab delimited, did not have column names, and existed in the current working directory, the pandas command would be:

```
tips = pd.read_csv('tips.csv', sep='\t', header=None)

# alternatively, read_table is an alias to read_csv with tab delimiter
tips = pd.read_table('tips.csv', header=None)
```

Pandas can also read Stata data sets in `.dta` format with the *read_stata()* function.

```
df = pd.read_stata('data.dta')
```

In addition to text/csv and Stata files, pandas supports a variety of other data formats such as Excel, SAS, HDF5, Parquet, and SQL databases. These are all read via a `pd.read_*` function. See the *IO documentation* for more details.

Exporting data

The inverse of `import delimited` in Stata is `export delimited`

```
export delimited tips2.csv
```

Similarly in pandas, the opposite of `read_csv` is *DataFrame.to_csv()*.

```
tips.to_csv('tips2.csv')
```

Pandas can also export to Stata file format with the *DataFrame.to_stata()* method.

```
tips.to_stata('tips2.dta')
```

Data operations

Operations on columns

In Stata, arbitrary math expressions can be used with the `generate` and `replace` commands on new or existing columns. The `drop` command drops the column from the data set.

```
replace total_bill = total_bill - 2
generate new_bill = total_bill / 2
drop new_bill
```

pandas provides similar vectorized operations by specifying the individual `Series` in the `DataFrame`. New columns can be assigned in the same way. The *DataFrame.drop()* method drops a column from the `DataFrame`.

```
In [8]: tips['total_bill'] = tips['total_bill'] - 2

In [9]: tips['new_bill'] = tips['total_bill'] / 2

In [10]: tips.head()
Out[10]: 
   total_bill   tip     sex smoker  day    time  size  new_bill
0       14.99  1.01  Female     No  Sun  Dinner     2     7.495
1        8.34  1.66    Male     No  Sun  Dinner     3     4.170
2       19.01  3.50    Male     No  Sun  Dinner     3     9.505
3       21.68  3.31    Male     No  Sun  Dinner     2    10.840
4       22.59  3.61  Female     No  Sun  Dinner     4    11.295
```

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