Cheat Sheet: The Pandas DataFrame Object

Preliminaries

Start by importing these Python modules

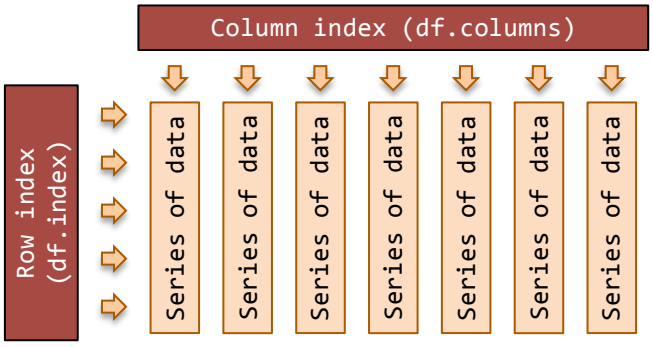
```
import numpy as np                  # required
import pandas as pd                 # required
from pandas import DataFrame, Series # useful
```

The conceptual model

Series object: an ordered, one-dimensional array of data with an index. All the data in a Series is of the same data type. Series arithmetic is vectorised after first aligning the Series index for each of the operands.

```
s1 = Series(range(0,4))  # --> 0, 1, 2, 3
s2 = Series(range(1,5))  # --> 1, 2, 3, 4
s3 = s1 + s2             # --> 1, 3, 5, 7
s4 = Series(['a','b'])*3 # --> 'aaa', 'bbb'
```

DataFrame object: a two-dimensional table of data with column and row indexes. The columns are made up of pandas Series objects.



Get your data into a DataFrame

Data in Series then combine into a DataFrame

```
# Exmaple 1 ...
s1 = Series(range(6))
s2 = s1 * s1
s2.index = s2.index + 2 # misaligned indexes
df = pd.concat([s1, s2], axis=1)

# Exmaple 2 ...
s3 = Series({'Tom':1, 'Dick':4, 'Harry':9})
s4 = Series({'Tom':3, 'Dick':2, 'Mary':11})
df = pd.concat({'A': s3, 'B': s4 }, axis=1)
```

Note: 1st method has in integer column labels
Note: 2nd method does not guarantee col order
Note: index alignment on DataFrame creation

Load a DataFrame from a CSV file

```
df = pd.read_csv('file.csv')
```

Load a DataFrame from a Microsoft Excel file

```
# put each Excel workbook in a dictionary
workbook = pd.ExcelFile('file.xls')
d = {}
for name in workbook.sheet_names:
    df = workbook.parse(name)
    d[name] = df
```

Load a DataFrame from a MySQL database

```
import MySQLdb as db
import pandas.io.sql as ps
cx = db.connect('localhost', 'username',
                'password', 'database')
df = ps.frame_query('SELECT * FROM data', cx)
```

Get a DataFrame from a Python dictionary

```
# default – assume your data in columns
df = DataFrame({
        'col0' : [1.0, 2.0, 3.0, 4.0],
        'col1' : [100, 200, 300, 400]
    })

# use helper method for data in rows
df = DataFrame.from_dict({ # data by row
        'row0' : {'col0':0, 'col1':'A'},
        'row1' : {'col0':1, 'col1':'B'}
    }, orient='index')

df = DataFrame.from_dict({ # data by row
        'row0' : [1, 1+1j, 'A'],
        'row1' : [2, 2+2j, 'B']
    }, orient='index')
```

Create play data (useful for testing)

```
# created from a 2D numpy array (of randoms)
df = DataFrame(np.random.randn(26,5),
    columns=['col'+str(i) for i in range(5)],
    index=list("ABCDEFGHIJKLMNOPQRSTUVWXYZ"))
df['cat'] = list('aaaabbbccddef' * 2)
```

Saving a DataFrame

Writing DataFrames to CSV

```
df.to_csv('filename.csv', encoding='utf-8')
```

Writing DataFrames to Excel

```
from pandas import ExcelWriter
writer = ExcelWriter('filename.xlsx')
df1.to_excel(writer,'Sheet1')
df2.to_excel(writer,'Sheet2')
writer.save()
```

Writing DataFrames to MySQL

```
import MySQLdb as db
cx = db.connect('localhost', 'username',
                'password', 'database')
df.to_sql(name='tablename', con=cx,
    flavour='mysql', if_exists='replace')
```

Note: if_exists – 'fail', 'replace', 'append'

Working with row and column indexes

DataFrames have two Indexes
Typically, the column index (df.columns) is a list of strings (observed variable names) or (less commonly) integers. The row index (df.index) might be:

- Integers - for case or row numbers (default is numbered from 0 to length-1)
- Strings – for case names
- DatetimeIndex or PeriodIndex – for time series data (more on these indexes below)

Get column index and labels

```
idx = df.columns               # get col index
label = df.columns[0]          # 1st col label
lst = df.columns.tolist()      # get as a list
```

Change column labels

```
df.rename(columns={'old':'new'},inplace=True)
df = df.rename(columns = {'a':'a1','b':'b2'})
```

Get the row index and labels

```
idx = df.index                 # get row index
label = df.index[0]            # 1st row label
lst = df.index.tolist()        # get as a list
```

Change the (row) index

```
df.index = idx             # new ad hoc index
df.index = range(len(df))  # set with list
df = df.reset_index() # replace old with new
     # note: old index stored as a col in df
df = df.reindex(index=range(len(df)))
df = df.set_index(keys=['col1','col2','etc'])
df.rename(index={'old':'new'}, inplace=True)
```

Get the integer position of a row index label

```
i = df.index.get_loc('label') # also columns
```

Sort DataFrame by its row or column index

```
df.sort_index(inplace=True) # sort by rows
df = df.sort_index(axis=1)  # sort by cols
```

Test if the index values are unique/monotonic

```
if df.index.is_unique: pass # do something
if df.columns.is_unique: pass # do something
if df.index.is_monotonic: pass # do something
if df.columns.is_monotonic: pass # something
```

For a monotonic index, each element is greater than or equal to the previous element

Drop duplicates in the row index

```
df['index'] = df.index     # 1 create new col
df = df.drop_duplicates(cols='index',
        take_last=True)    # 2 use new col
del df['index']            # 3 del the col
df.sort_index(inplace=True)# 4 tidy up
```

Test if two DataFrames/Series have same index

```
len(a) == len(b) and all(a.index == b.index)
```

Working with columns of data (axis=1)

A DataFrame column is a pandas Series object

Selecting columns

```
s = df['colName']     # select column by name
df = df[['a','b']]    # select 2 or more cols
df = df[['c','a','b']]# change column order
s = df[df.columns[0]] # select column by num
```

Selecting columns with Python attributes

```
s = df.a              # same as s = df['a']
df.existing_col = df.a / df.b
# cannot create new columns by attribute ...
df['new_col'] = df.a / df.b
```

Trap: column names must be valid identifiers.

Adding new columns to a DataFrame

```
df['new_col'] = range(len(df))
df['new_col'] = np.repeat(np.nan, len(df))
df['random'] = np.random.rand(len(df))
df['index_as_col'] = df.index
df1[['b','c']] = df2[['e','f']]   # multi add
df3 = df1.append(other=df2)       # multi add
```

Swap column contents

```
df[['B', 'A']] = df[['A', 'B']]
```

Dropping columns (by label)

```
df = df.drop('col1', axis=1)
df.drop('col1', axis=1, inplace=True)
df = df.drop(['col1','col2'], axis=1) # multi
s = df.pop('col') # get col; drop from frame
del df['col']     # even classic python works
```

Selecting columns with .loc, .iloc and .ix

```
df = df.loc[:, 'col1':'col2'] #inclusive "to"
df = df.iloc[:, 0:2]          #exclusive "to"
```

A slice of columns can be selected by label (using df.loc[rows, cols]); by integer position (using df.iloc[rows, cols]); or a hybrid of the two (using df.ix[rows, cols])
Note: the row slice object : copies all rows
Note: For .loc, the indexes can be:

- A single label (eg. 'A')
- A list/array of labels (eg. ['A', 'B'])
- A slice object of labels (eg. 'A':'C')
- A Boolean array

Note: For .iloc, the indexes can be

- A single integer (eg. 27)
- A list/array of integers (eg. [1, 2, 6])
- A slice object with integers (eg. 1:9)

Vectorised arithmetic on columns

```
df['proportion'] = df['count'] / df['total']
df['percent'] = df['proportion'] * 100.0
```

Apply numpy mathematical functions to columns

```
df['log_data'] = np.log(df['col1'])
df['rounded'] = np.round(df['col2'], 2)
```

Columns value set based on criteria

```
# Option 1: using a mask
df['new'] = 0
df[df['c'] > 0]['new'] = df['c']
# Option 2: using the where statement
df['new'] = df['c'].where(df['c']>0, other=0)
```

Note: Multiple conditions can be combined using & and | with conditions in parentheses.
Note: where other can be a Series or a scalar
Note: ~ the boolean not operator for pandas

Iterating over the Dataframe cols

```
for (column, series) in df.iteritems():
    # do something ...
```

Where column is the label and series is a pandas Series that contains the column data.

Common column-wide methods/attributes

```
value = df['col1'].dtype     # type of data
value = df['col1'].size      # col dimensions
value = df['col1'].count()   # non-NA count
value = df['col1'].sum()
value = df['col1'].prod()
value = df['col1'].min()
value = df['col1'].max()
value = df['col1'].mean()
value = df['col1'].median()
value = df['col1'].cov(df['col2'])
s =     df['col1'].describe()
s =     df['col1'].value_counts()
```

Find index for min/max values in column

```
value =  df['col1'].idxmin() # returns label
value =  df['col1'].idxmax() # returns label
```

Common column element-wise methods

```
s = df['col'].to_datetime()
s = df['col1'].isnull()
s = df['col1'].notnull() # not isnull()
s = df['col1'].astype('float') # type convert
s = df['col1'].round(decimals=0)
s = df['col1'].diff(periods=1)
s = df['col1'].shift(periods=1)
s = df['col1'].fillna(0) # replace NaN with 0
s = df['col1']. pct_change(periods=4)
s = df['c'].rolling_min(periods=4, window=4)
s = df['c'].rolling_max(periods=4, window=4)
s = df['c'].rolling_sum(periods=4, window=4)
```

Append a column of row totals to a DataFrame

```
df['Total'] = df.sum(axis=1)
```

Note: can do row means, mins, maxs, etc. in a similar manner.

Group by a column

```
s = df.groupby('cat')['col1'].sum()
dfg = df.groupby('cat').sum()
```

Group by a row index (non-hierarchical index)

```
df = df.set_index(keys='cat')
s = df.groupby(level=0)['col1'].sum()
dfg = df.groupby(level=0).sum()
```

Working with rows (axis=0)

Adding rows

```
df = original_df.append(more_rows_in_df)
```

Hint: convert to a DataFrame and then append. Both DataFrames should have same col labels.

Dropping rows (by name)

```
df = df.drop('row_label')
df = df.drop(['row1','row2'])     # multi-row
```

Boolean row selection by values in a column

```
df = df[df['col2'] >= 0.0]
df = df[(df['col3']>=1.0) | (df['col1']<0.0)]
df = df[df['col'].isin([1,2,5,7,11])]
df = df[~df['col'].isin([1,2,5,7,11])] # not
df = df[df['col'].str.contains('hello')]
```

Trap: bitwise "or" and "and" co-opted to be Boolean operators on a Series of Boolean --> also note parentheses around comparisons.

Select a slice of rows by integer position
[inclusive-from : exclusive-to]
[inclusive-from : exclusive-to : step]
default start is 0; default end is len(df)

```
df = df[:]       # copy DataFrame
df = df[0:2]     # rows 0 and 1
df = df[-1:]     # the last row
df = df[2:3]     # row 2 (the third row)
df = df[:-1]     # all but the last row
df = df[::2]     # every 2nd row (0 2 ..)
```

Trap: a single integer without a colon is a column index for numbered columns.

Select a slice of rows by label/index
[inclusive-from : inclusive-to [: step]]

```
df = df['a':'c'] # rows 'a' through 'c'
```

Trap: doesn't work on integer labelled rows

Append a row of column totals to a DataFrame

```
# Option 1: using a dictionary comprehension
sums = {col: df[col].sum() for col in df}
sums_df = DataFrame(sums, index=['Total'])
df = df.append(sums_df)
# Option 2: All done with pandas
df = df.append(DataFrame(df.sum(),
     columns=['Total']).T) # .T is transpose
```

Iterating over DataFrame rows

```
for (index, row) in df.iterrows():
```

Trap: row data type may be coerced.

Sorting DataFrame rows by column values

```
df = df.sort(df.columns[0], ascending=False)
df.sort(['col1', 'col2'], inplace=True)
```

Remember!

```
w = df['label']          # a selected column
x = df[['L1', 'L2']]     # selected columns
y = df['label':'label']  # selected rows
z = df[i:j] # where i & j are ints, → rows
```

Working with cells

Selecting a cell by row and column labels

```
value = df.at['row', 'col']
value = df.loc['row', 'col']
value = df['col']['row']              # tricky
```

Note: .at[] fastest label based scalar lookup

Setting a cell by row and column labels

```
df.at['row, 'col'] = value
df.loc['row, 'col'] = value
df['col']['row'] = value              # tricky
```

Selecting and slicing on labels

```
df = df.loc['row1':'row3', 'col1':'col3']
```

Note: the "to" on this slice is inclusive.

Setting a cross-section by labels

```
df.loc['A':'C', 'col1':'col3'] = np.nan
df.loc[1:2, 'col1':'col2'] = np.zeros((2,2))
df.loc[1:2, 'A':'C'] = other.loc[1:2,'A':'C']
```

Remember: inclusive from:to in the slice

Selecting a cell by integer position

```
value = df.iat[9, 3]              # [row, col]
value = df.iloc[0, 0]             # [row, col]
value = df.iloc[len(df)-1, len(df.columns)-1]
```

Selecting a range of cells by int position

```
df = df.iloc[2:4, 2:4]# a subset of the df
df = df.iloc[:5, :5]  # top left corner
s = df.iloc[5, :]     # returns row as Series
df = df.iloc[5:6, :]  # returns row as a row
```

Note: exclusive "to" – same as list slicing.

Setting cell by integer position

```
df.iloc[0, 0] = value             # [row, col]
df.iat[7, 8] = value
```

Setting cell range by integer position

```
df.iloc[0:3, 0:5] = value
df.iloc[1:3, 1:4] = np.ones((2,3))
```

Remember: exclusive from:to in the slice

Operate on the whole DataFrame

```
# replace np.nan with 0
df.fillna(0, inplace=True)
# replace white space with np.nan
df = df.replace(r'\s+', np.nan, regex=True)
```

Views and copies

From the manual: The rules about when a view on the data is returned are dependent on NumPy. Whenever an array of labels or a boolean vector are involved in the indexing operation, the result will be a copy. A single label/scalar indexing & slicing, e.g. df.ix[3:6] or df.ix[:, 'A'], returns a view.

Joining/Combining DataFrames

Three ways to join two DataFrames:

- merge (a database/SQL-like join operation)
- concat (stack side by side or stack one on top of the other)
- combine_first (splice the two togther, choosing values from one over the other)

Merge on indexes

```
df_new = pd.merge(left=df1, right=df2,
  how='outer', left_index=True,
  right_index=True)
```

How: 'left', 'right', 'outer', 'inner'
How: outer=union/all; inner=intersection

Merge on columns

```
df_new = pd.merge(left=df1, right=df2,
how='left', left_on='col1', right_on='col2')
```

Trap: When joining on columns, the indexes on the passed DataFrames are ignored.
Trap: many-to-many merges on a column can result in an explosion of associated data.

Join on indexes (another way of merging)

```
df_new = df1.join(other=df2, on='col1',
                  how='outer')
df_new = df1.join(other=df2, on=['a', 'b'],
                  how='outer')
```

Note: DataFrame.join() joins on indexes by default. DataFrame.merge() joins on common columns by default.

Simple concatenation is often the best

```
df=pd.concat([df1,df2],axis=0) # top/bottom
df = df1.append([df2, df3])    # top/bottom
df=pd.concat([df1,df2],axis=1) # left/right
```

Trap: can end up with duplicate rows or cols
Note: concat has an ignore_index parameter

Combine_first

```
df = df1.combine_first(other=df2)
df = reduce(lambda x, y: x.combine_first(y),
       [df1, df2, df3, df4, df5])
```

Uses the non-null values from df1. The index of the combined DataFrame will be the union of the indexes from df1 and df2.

Working with the whole DataFrame

Peek at the DataFrame

```
summary_df = df.describe()
head_df = df.head(); tail_df = df.tail()
top_left_corner_df = df.iloc[:5, :5]
```

Other useful

```
df = df.T         # transpose rows and columns
df2 = df.copy()   # copy a DataFrame
```

Working with dates, times and their indexes

Dates and time – points and spans

With its focus on time-series data, pandas provides a suite of tools for managing dates and time: either as a point in time (a Timestamp) or as a span of time (a Period).

```
timestamp = pd.Timestamp('2013-01-01')
period = pd.Period('2013-01-01', freq='M')
```

Dates and time – stamps and spans as indexes

An index of Timestamps is a DatetimeIndex; and an index of Periods is a PeriodIndex. These can be constructed as follows:

```
date_strs = ('2013-10-01', '2013-11-01',
             '2013-12-01', '2014-01-01')
tstamp = pd.to_datetime(pd.Series(date_strs))
dt_idx = pd.DatetimeIndex(tstamp, freq='MS')
prd_idx = pd.PeriodIndex(tstamp, freq='M')
spi = Series([1,2,3,4], index=prd_idx)
sdi = Series([1,2,3,4], index=dt_idx)
# Also: index changed through its attribute
spi.index = dt_idx # change to time stamps
spi.index = range(len(spi)) # to integers
```

From DatetimeIndex and PeriodIndex and back

```
spi = sdi.to_period(freq='M')# to PeriodIndex
sdi = spi.to_timestamp()   # to DatetimeIndex
```

Note: from period to timestamp defaults to the point in time at the start of the period.

Frequency constants (not a complete list)

Name	Description
U	Microsecond
L	Millisecond
S	Second
T	Minute
H	Hour
D	Calendar day
B	Business day
W-{MON, TUE, …}	Week ending on …
MS	Calendar start of month
M	Calendar end of month
QS-{JAN, FEB, …}	Quarter start with year starting (QS – December)
Q-{JAN, FEB, …}	Quarter end with year ending (Q – December)
AS-{JAN, FEB, …}	Year start (AS - December)
A-{JAN, FEB, …}	Year end (A - December)

More examples on working with dates/times

```
d = pd.to_datetime(['04-01-2012'],
      dayfirst=True) # Australian date format
t = pd.to_datetime(['2013-04-01 15:14:13.1'])
```

DatetimeIndex can be converted to an array of Python native datetime.datetime objects using the to_pydatetime() method.

Error handling with dates

```
# first example returns string not Timestamp
s = pd.to_datetime('2014-02-30')
# second example returns NaT (not a time)
n = pd.to_datetime('2014-02-30', coerce=True)
# NaT is like NaN ... tests True for isnull()
b = pd.isnull(n) # --> True
```

Creating date/period indexes from scratch

```
dt_idx = pd.DatetimeIndex(pd.date_range(
    start='1/1/2011',  periods=12, freq='M'))
p_idx = pd.period_range('1960-01-01',
      '2010-12-31', freq='M')
```

Row selection with a time-series index

```
# play data ... start with play data above
idx = pd.period_range('2013-01',
      periods=len(df), freq='M')
df.index = idx

february_selector = (df.index.month == 2)
february_data = df[february_selector]

q1_data = df[(df.index.month >= 1) &
   (df.index.month <= 3)] # note: & not "and"

mayornov_data = df[(df.index.month == 5) |
   (df.index.month == 11)] # note: | not "or"

annual_tot = df.groupby(df.index.year).sum()
```

Also: year, month, day [of month], hour, minute, second, dayofweek [Mon=0 .. Sun=6], weekofmonth, weekofyear [numbered from 1], week starts on Monday], dayofyear [from 1], …
Note: this method works with both Series and DataFrame objects.

The tail of a time-series DataFrame

```
df = df.last("5M")     # the last five months
```

Working with strings

Working with strings

```
# assume that df['col'] is series of strings
s = df['col'].str.lower()
s = df['col'].str.upper()
s = df['col'].str.len()
df['col'] += 'suffix' # add text to each row
df['col'] *= 2        # repeat text
s = df['col1'] + df['col2'] # concatenate
```

Most python string functions are replicated in the pandas DataFrame and Series objects.

Regular expressions

```
s = df['col'].str.contains('regex')
s = df['col'].str.startswith('regex')
s = df['col'].str.endswith('regex')
s = df['col'].str.replace('old', 'new')
```

Note: pandas has many more regex methods

Working with missing and non-finite data

Working with missing data
Pandas uses the not-a-number construct (np.nan and float('nan')) to indicate missing data. The Python None can arise in data as well. It is also treated as missing data; as is the pandas not-a-time (pd.NaT) construct.

Missing data in a Series

```
s = pd.Series([8,None,float('nan'),np.nan])
# -->             [8,     NaN,  NaN,   NaN]
s.isnull() # --> [False, True, True,  True]
s.notnull()# --> [True, False, False, False]
```

Missing data in a DataFrame

```
df = df.dropna()  # drop all rows with a NaN
df = df.dropna(axis=1) # as above for cols
df=df.dropna(how='all') # only if all in row
df=df.dropna(thresh=2) # at least 2 NaN in r
# only drop row if NaN in a specified 'col'
df = df.dropna(df['col'].notnull())
```

Non-finite numbers
With floating point numbers, pandas provides for positive and negative infinity.

```
s = Series([float('inf'), float('-inf'),
     np.inf, -np.inf]) # inf, -inf, inf, -inf
```

Pandas treats integer comparisons with plus or minus infinity as expected.

Testing for finite numbers
(using the data from the previous example)

```
np.isfinite(s) # False, False, False, False
```

Working with Categorical Data

Categorical data
The pandas Series has an R factors-like data type for encoding categorical data into integers.

```
c = pd.Categorical.from_array(list)
c.levels   # --> the coding frame
c.labels   # --> the encoded integer array
c.describe # --> the values and levels
```

Indexing categorical data
The categorical data can be indexed in a manner conceptually similar to that for Series.iloc[] above:

```
listy = ['a', 'b', 'a', 'b', 'b', 'c']
c = pd.Categorical.from_array(listy)
c.levels       # --> ['a', 'b', 'c']
c.labels       # --> [0, 1, 0, 1, 1, 2]
x = c[1]       # --> 'b'
x = c[[0,1]]   # --> ['a', 'b']
x = c[0:2]     # --> ['a', 'b']
```

Categorical into DataFrame
You can put a column of encoded Categorical data in the DataFrame, but in the process the factor information will be lost; so you will need to hold this factor information outside of the DataFrame.

```
factor = pd.Categorical.from_array(df['cat'])
df['labels'] = factor.labels # integers only
df['cat2'] = factor # converts back to string
```

Basic Statistics

Summary statistics

```
s = df['col1'].describe()
df1 = df.describe()
```

Value counts

```
s = df['col1'].value_counts()
```

Cross-tabulation (frequency count)

```
ct = pd.crosstab(index=df['a'], cols=df['b'])
```

Quantiles and ranking

```
q = df.quantile(q=[0.05,0.25,0.5,0.75,0.95])
r = df.rank()
```

Histogram binning

```
count, bins = np.histogram(df['col1'])
count, bins = np.histogram(df['col'], bins=5)
count, bins = np.histogram(df['col1'],
                  bins=[-3,-2,-1,0,1,2,3,4])
```

Correlation and covariance

```
df_cm = df.corr()
df_cv = df.cov()
```

Regression

```
import statsmodels.formula.api as sm
result = sm.ols(formula="col1 ~ col2 + col3",
                  data=df).fit()
print (result.params)
print (result.summary())
```

Smoothing example using rolling_apply

```
k3x5 = np.array([1,2,3,3,3,2,1]) / 15.0
s = pd.rolling_apply(df['col1'], window=7,
         func=lambda x: (x * k3x5).sum(),
          min_periods=7, center=True)
```

Cautionary note

This cheat sheet was cobbled together by bots roaming the dark recesses of the Internet seeking ursine and pythonic myths. There is no guarantee the narratives were captured and transcribed accurately. You use these notes at your own risk. You have been warned.