Fast Data Mining with pandas and PyTables

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To begin with: What is Data Mining?

"The overall goal of the data mining process is to extract knowledge from an existing data set and transform it into a human-understandable structure for further use. Besides the raw analysis step, it involves database and data management aspects, data preprocessing, model and inference considerations, interestingness metrics, complexity considerations, post-processing of found structures, visualization, and online updating."[1]

[1] Source: http://en.wikipedia.org/wiki/Data_mining

Why Data Mining at all?

- Available data from public, commercial and in-house sources increases exponentially over time
- To make profound strategic, operational and financial decisions, corporations must increasingly rely on diligent data mining
- Therefore, efficient data management and analysis, i.e. data mining, becomes paramount in many industries, like financial services, utilities
- From a more general point of view, efficient data management and analysis is essential in almost any area of software development and deployment
- In addition, the majorty of reasearch fields nowadays requires the managememt and analysis of large data sets, like in physics or finance

Data management is a huge industry, driven by ever increasing data volumes

Corporations invest huge amounts of money to manage data:[2]

- 100.000.000.000 bn USD spent in 2011 on data center infrastructure/hardware
- 24.000.000.000 bn USD spent in 2011 on database technology/software
- "The world's No. 1 provider of data center real estate, Digital Realty Trust, is buying three properties near London for $1.1 billion."[3]

[2] Source: Gartner Group; as reported in Bloomberg Businessweek, 2 July 2012, "Data Centers – Revenge of the Nerdiest Nerds"

[3] Source: Bloomberg Businessweek, 2 July 2012, "Bid & Ask"

Fast Data Mining =

Rapid Implementation

+ Quick Execution

In practice, what we talk about could somehow look like this

- Recent **question in client project**: “How beneficial are costly guarantees in unit-linked insurance polices from a policy holder perspective?”
- **Reframed question**: “How often would a policy holder would have lost money with 10-/15-/20-years straight and mixed savings plans in popular stock indices?”
- **Solution**: Concise `Python` script—using mainly `pandas`—to efficiently analyze the question for different parametrizations and with real, i.e. historic, financial market data.
- **Effort** (for first prototype): Approximately **one hour** coding and testing (= playing); **one hour** for preparing a brief presentation with selected results (text + graphics).

Major problems in data management and analysis

- **sources**: data typically comes from different sources, like from the Web, from in-house databases or it is generated in-memory
- **formats**: data typically comes in different formats, like `SQL` databases/tables, `Excel` files, `CSV` files, `NumPy` arrays
- **structure**: data typically comes differently structured, like unstructured, simply indexed, hierarchically indexed, in table form, in matrix form, in multidimensional arrays
- **completeness**: real-world data typically comes in an incomplete form, i.e. there is missing data (e.g. along an index)
- **convention**: for some types of data there a many conventions with regard to formatting, like for dates and time
- **interpretation**: some data sets typically contain information that can be intelligently interpreted, like a time index
- **performance**: reading, streamlining, aligning, analyzing (large) data sets might be slow

What this talk is about

We will talk mainly about two libraries

- `pandas`: a library that conveniently enhances `Python's` data management and analysis capabilities; its major focus are in-memory operations
- `PyTables`: a popular database which optimizes writing, reading and analyzing large data sets out-of-memory, i.e. on disk

We will illustrate their use mainly be the means of examples

- Introductory `pandas` Example—illustration of some fundamental `pandas` classes and their methods
- **Financial Data Mining in Action**—simple, but real world, example
- **High-Frequency Financial Data**—reading and analyzing high-frequency financial data with `pandas`
- Introductory `PyTables` Example—illustration of some fundamental `pandas` classes and their methods
- **Out-Of-Memory Monte Carlo Simulation**—implementing a Monte Carlo simulation with `PyTables` out-of-memory

Throughout the talk: Results matter more than Style

Bruce Lee—The Tao of Jeet Kune Do:

"There is no mystery about my style. My movements are simple, direct and non-classical. The extraordinary part of it lies in its simplicity. Every movement in Jeet Kune Do is being so of itself. There is nothing artificial about it. I always believe that the easy way is the right way."

The Tao of **My** Python:

"There is no mystery about my style. My lines of code are simple, direct and non-classical. The extraordinary part of it lies in its simplicity. Every line of code in my Python is being so of itself. There is nothing artificial about it. I always believe that the easy way is the right way."

A fundamental class in pandas is the Series class (I)

- The Series class is explicitly designed to handle indexed (time) series[4]
- If s is a Series object, s.index gives its index
- A simple example is s=Series([1,2,3,4,5],index=['a','b','c','d','e'])

```
In [16]: s=Series([1,2,3,4,5],index=['a','b','c','d','e'])

In [17]: s
Out[17]:
a     1
b     2
c     3
d     4
e     5

In [18]: s.index
Out[18]: Index([a, b, c, d, e], dtype=object)

In [19]: s.mean()
Out[19]: 3.0

In [20]:
```

There are lots of useful methods in the Series class ...

[4] The major pandas source is http://pandas.sourceforge.net

A fundamental class in pandas is the Series class (II)

- A major strength of pandas is the handling of time series data, i.e. data indexed by dates and times
- An simple example using the DateRange function shall illustrate the time series management

```
In [3]: x=standard_normal(250)

In [4]: index=DateRange('01/01/2012',periods=len(x))

In [5]: s=Series(x,index=index)

In [6]: s
Out[6]:
2012-01-02    1.06959238875
2012-01-03    0.794515407245
2012-01-04    -1.01590534404
2012-01-05    -0.751618588824
...
```

The offset parameter of the DateRange function allows flexible, automatic indexing

```
In [33]: datetools.
datetools.bday               datetools.Minute
datetools.BDay               datetools.monthEnd
datetools.bmonthEnd          datetools.MonthEnd
datetools.BMonthEnd          datetools.normalize_date
datetools.bquarterEnd        datetools.ole2datetime
datetools.BQuarterEnd        datetools.OLE_TIME_ZERO
datetools.businessDay        datetools.parser
datetools.businessMonthEnd   datetools.relativedelta
datetools.byearEnd           datetools.Second
datetools.BYearEnd           datetools.thisBMonthEnd
datetools.CacheableOffset    datetools.thisBQuarterEnd
datetools.calendar           datetools.thisMonthEnd
datetools.DateOffset         datetools.thisYearBegin
datetools.datetime           datetools.thisYearEnd
datetools.day                datetools.Tick
datetools.format             datetools.timedelta
datetools.getOffset          datetools.to_datetime
datetools.getOffsetName      datetools.v
datetools.hasOffsetName      datetools.week
datetools.Hour               datetools.Week
datetools.i                  datetools.weekday
datetools.inferTimeRule      datetools.WeekOfMonth
datetools.isBMonthEnd        datetools.yearBegin
datetools.isBusinessDay      datetools.YearBegin
datetools.isMonthEnd         datetools.yearEnd
datetools.k                  datetools.YearEnd

In [33]: index=DateRange('01/01/2012',periods=len(x),offset=datetools.DateOffset(2))
```

Another fundamental class in pandas is DataFrame

- This class's intellectual father is the `data.frame` class from the statistical language/package R
- The `DataFrame` class is explicitly designed to handle **multiple**, maybe **hierarchically indexed** (time) series
- The following example illustrates some convenient features of the `DataFrame` class, i.e. data alignment and handling of missing data

```
In [35]: s=Series(standard_normal(4),index=['1','2','3','5'])

In [36]: t=Series(standard_normal(4),index=['1','2','3','4'])

In [37]: df=DataFrame({'s':s,'t':t})

In [38]: df['SUM']=df['s']+df['t']

In [39]: print df.to_string()
          s         t       SUM
1 -0.125697  0.016357 -0.109340
2  0.135457 -0.907421 -0.771964
3  1.549149 -0.599659  0.949491
4       NaN  0.734753       NaN
5 -1.236310       NaN       NaN

In [40]: df['SUM'].mean()
Out[40]: 0.022728863312009556
```

The two main pandas classes have methods for easy plotting

- The Series and DataFrame classes have methods to easily generate plots
- The two major methods are plot and hist
- Again, an example shall illustrate the usage of the methods

```
In [54]: index=DateRange(start='1/1/2013',periods=250)

In [55]: x=standard_normal(250)

In [56]: y=standard_normal(250)

In [57]: df=DataFrame({'x':x,'y':y},index=index)

In [58]: df.cumsum().plot()
Out[58]: <matplotlib.axes.AxesSubplot at 0x3082c10>

In [59]: df['x'].hist()
Out[59]: <matplotlib.axes.AxesSubplot at 0x3468190>

In [60]:
```

The results of which can then be saved for further use

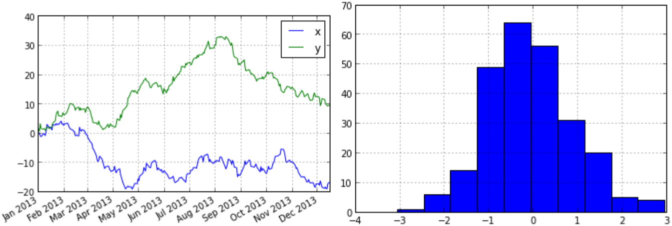


Figure: Some example plots with pandas

The first 'real' example should give an impression of the efficiency of working with `pandas`

1. **data gathering**: read historical quotes of the Apple stock (ticker `AAPL`) beginning with 01 January 2006 from `finance.yahoo.com` and store it in a `pandas` `DataFrame` object
2. **data analysis**: calculate the daily log returns (use the `shift` method of the `pandas` `Series` object) and generate a new column with the log returns in the `DataFrame` object
3. **plotting**: plot the log returns together with the daily Apple quotes into a single figure
4. **simulation**: simulate the Apple stock price developement using the last Close quote as starting value and the historical yearly volatility of the Apple stock (short rate 2.5%)—the difference equation is given, for $s = t - \Delta t$ and z_t standard normal, by
$$S_t = S_s \cdot \exp((r - \sigma^2/2)\Delta t + \sigma\sqrt{\Delta t} z_t)$$
5. **option valuation**: calculate the value of a European call option with strike of 110% of the last Close quote and time-to-maturity of 1 year
6. **data storage**: save the `pandas` `Data Frame` to a `PyTables/HDF5` database (use the `HDFStore` function)

1. Data Gathering

```
#
# Rapid Financial Engineerung
# with pandas and PyTables
# RFE.py
#
# (c) Visixion GmbH
# Script for Illustration Purposes Only.
#
from pylab import *

# 1. Data Gathering

from pandas.io.data import *

AAPL=DataReader('AAPL', 'yahoo', start='01/01/2006')
```

2. Data Analysis (I)

```python
# 2. Data Analysis

from pandas import *

AAPL['Ret']=log(AAPL['Close']/AAPL['Close'].shift(1))
```

2. Data Analysis[5]

```
Python 2.7.3 (default, Apr 20 2012, 22:39:59)
[GCC 4.6.3] on linux2
Type "copyright", "credits" or "license()" for more information.
>>> ================================ RESTART ================================
>>>
Call Value   88.336
>>> print AAPL[-10:].to_string()
              Open    High     Low   Close    Volume  Adj Close       Ret
Date
2012-06-11  587.72  588.50  570.63  571.17  21094900     571.17 -0.015893
2012-06-12  574.46  576.62  566.70  576.16  15549300     576.16  0.008699
2012-06-13  574.52  578.48  570.38  572.16  10485000     572.16 -0.006967
2012-06-14  571.24  573.50  567.26  571.53  12341900     571.53 -0.001102
2012-06-15  571.00  574.62  569.55  574.13  11954200     574.13  0.004539
2012-06-18  570.96  587.89  570.37  585.78  15708100     585.78  0.020088
2012-06-19  583.40  590.00  583.10  587.41  12896200     587.41  0.002779
2012-06-20  588.21  589.25  580.80  585.74  12819400     585.74 -0.002847
2012-06-21  585.44  588.22  577.44  577.67  11655400     577.67 -0.013873
2012-06-22  579.04  582.19  575.42  582.10  10159700     582.10  0.007639
>>>
```

[5] Quelle: http://finance.yahoo.com, 24. June 2012

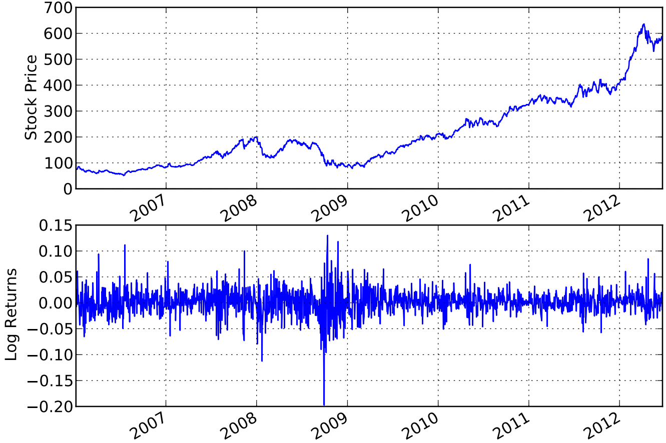
3. Plotting (I)

```
# 3. Plotting

subplot(211)
AAPL['Close'].plot()
ylabel('Index Level')

subplot(212)
AAPL['Ret'].plot()
ylabel('Log Returns')
```

3. Plotting (II)[6]



[6] Quelle: `http://finance.yahoo.com`, 24. June 2012

4. Monte Carlo Simulation

```
# 4. Monte Carlo Simulation

## Market Parameters
S0=AAPL['Close'][-1] # End Value = Starting Value
vol=std(AAPL['Ret'])*sqrt(252) # Historical Volatility
r=0.025  # Constant Short Rate
## Option Parameters
K=S0*1.1 # 10% OTM Call Option
T=1.0    # Maturity 1 Year
## Simulation Parameters
M=50;dt=T/M # Time Steps
I=10000     # Simulation Paths

# Simulation
S=zeros((M+1,I));S[0,:]=S0
for t in range(1,M+1):
    ran=standard_normal(I)
    S[t,:]=S[t-1,:]*exp((r-vol**2/2)*dt+vol*sqrt(dt)*ran)
```

5. Option Valuation

```python
# 5. Option Valuation
V0=exp(-r*T)*sum(maximum(S[-1]-K,0))/I
print "Call Value %8.3f" %V0
```

5. Data Storage (in HDF5 format)

```python
# 5. Data Storage
h5file=HDFStore('AAPL.h5')
h5file['AAPL']=AAPL
h5file.close()
```

The whole Python script

```
...
from pylab import *
# 1. Data Gathering
from pandas.io.data import *
AAPL=DataReader('AAPL', 'yahoo', start='01/01/2006')

# 2. Data Analysis
from pandas import *
AAPL['Ret']=log(AAPL['Close']/AAPL['Close'].shift(1))

# 3. Plotting
subplot(211)
AAPL['Close'].plot(); ylabel('Index Level')
subplot(212)
AAPL['Ret'].plot(); ylabel('Log Returns')

# 4. Monte Carlo Simulation
S0=AAPL['Close'][-1]
vol=std(AAPL['Ret'])*sqrt(252)
r=0.025; K=S0*1.1; T=1.0; M=50; dt=T/M; I=10000
S=zeros((M+1,I));S[0,:]=S0
for t in range(1,M+1):
    ran=standard_normal(I)
    S[t,:]=S[t-1,:]*exp((r-vol**2/2)*dt+vol*sqrt(dt)*ran)

# 5. Option Valuation
V0=exp(-r*T)*sum(maximum(S[-1]-K,0))/I
print "Call Value %8.3f" %V0

# 6. Data Storage
h5file=HDFStore('AAPL.h5');h5file['AAPL']=AAPL;h5file.close()
```

This example is about high-frequency stock data

- In this example, we are going to analyze intraday stock price data for Apple (ticker `AAPL`) and Google (ticker `GOOG`)
- Intraday data for US stocks is available from Netfonds (`http://www.netfonds.no`), a Norwegian online stock broker
- We retrieve intraday data for both stocks for 22 June 2012 as a CSV file
- The Apple stock price data file contains 16,465 rows; the Google stock price data file only 7,937 rows

In the following, we will implement 8 typical data mining tasks

1. **data gathering**: retrieve data for Apple and Google from Web source and save as CSV file
2. **data reading**: read data from CSV files into two `pandas` `DataFrame` objects
3. **data pre-processing**: delete such rows with double time entries and use time data to generate time index for `DataFrame` objects
4. **data merging**: merge the bid quotes of both Apple and Google into a single `DataFrame` object
5. **data cleaning**: delete all quotes before 10 am on 22 June 2012
6. **data output**: print selected data for the new `DataFrame` object and plot the stock quotes
7. **data aggregation**: aggregate the tick data to average hourly quotes for both Apple and Google; print and plot the results
8. **data analysis**: get some statistics for tick data and hourly data (e.g. mean, min, max, correlation)

1. Data Gathering (I)

```
#
# Analyzing High-Frequency Stock Data
# with pandas
#
# (c) Visixion GmbH
# Script for illustration purposes only.
#
from pylab import *
from pandas import *
from urllib import urlretrieve

# 1. Data Gathering
url='http://hopey.netfonds.no/posdump.php?date=20120622&\
paper=%s.O&csv_format=csv'

urlretrieve(url %'AAPL','AAPL.csv')
urlretrieve(url %'GOOG','GOOG.csv')
```

1. Data Gathering (II)

Raw CSV data for Apple stock quotes:

```
time,bid,bid_depth,bid_depth_total,offer,offer_depth,offer_depth_total
...
20120622T100201,577.33,400,400,579.71,300,300
20120622T100231,577.33,400,400,579.71,400,400
20120622T100233,577.33,400,400,579.71,300,300
20120622T100236,577.33,400,400,579.71,400,400
20120622T100257,577.33,400,400,579.71,300,300
20120622T100258,577.33,400,400,579.71,400,400
20120622T100301,577.71,400,400,579.71,400,400
20120622T100316,577.71,400,400,579.71,300,300
20120622T100318,577.71,400,400,579.71,400,400
20120622T100334,578.11,400,400,579.71,400,400
20120622T100439,578.11,400,400,579.71,300,300
20120622T100445,578.11,400,400,579.71,400,400
20120622T100513,578.26,400,400,579.71,400,400
20120622T100533,578.26,300,300,579.71,400,400
20120622T100536,578.26,400,400,579.71,400,400
20120622T100540,578.26,300,300,579.71,400,400
20120622T100557,578.26,400,400,579.71,400,400
...
```

2. Data Reading

```
# 2. Data Reading
AAPL = read_csv('AAPL.csv')
GOOG = read_csv('GOOG.csv')
```

3. Data Pre-Processing (I)

```
# 3. Data Pre-Processing
AAPL=AAPL.drop_duplicates(cols='time')
GOOG=GOOG.drop_duplicates(cols='time')
for i in AAPL.index:
    AAPL['time'][i]=datetime.strptime(AAPL['time'][i],'%Y%m%dT%H%M%S')
AAPL.index=AAPL['time']; del AAPL['time']
for i in GOOG.index:
    GOOG['time'][i]=datetime.strptime(GOOG['time'][i],'%Y%m%dT%H%M%S')
GOOG.index=GOOG['time']; del GOOG['time']
```

3. Data Pre-Processing (II)

```
print AAPL[['bid','offer']].ix[1000:1015].to_string()
                       bid   offer
time
2012-06-22 13:57:09  578.71  579.50
2012-06-22 13:57:16  578.71  579.48
2012-06-22 13:57:22  578.72  579.48
2012-06-22 13:57:47  578.73  579.48
2012-06-22 13:57:51  578.74  579.48
2012-06-22 13:57:52  578.75  579.48
2012-06-22 13:57:56  578.51  579.48
2012-06-22 13:57:57  578.53  579.48
2012-06-22 13:57:59  578.51  579.48
2012-06-22 13:58:20  578.51  579.46
2012-06-22 13:58:33  578.75  579.46
2012-06-22 13:58:36  578.76  579.46
2012-06-22 13:58:37  578.75  579.46
2012-06-22 13:58:51  578.76  579.46
2012-06-22 13:59:29  578.76  579.46
```

4. Data Merging

```
# 4. Data Merging
DATA = DataFrame({'AAPL': AAPL['bid'],'GOOG': GOOG['bid']})
```

5. Data Cleaning

```
# 5. Data Cleaning
DATA = DATA[DATA.index > datetime(2012,06,22,9,59,0)]
```

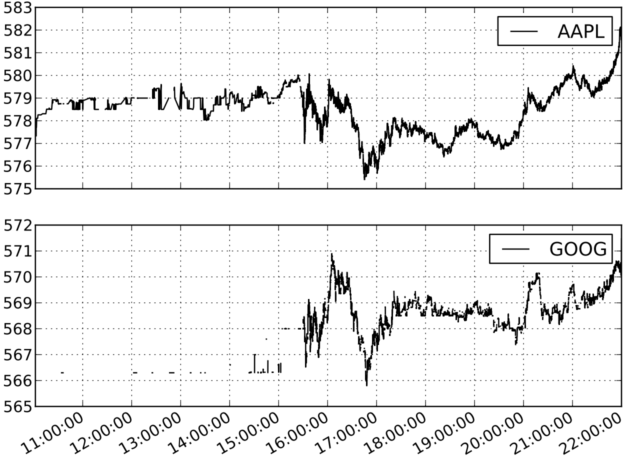
6. Data Output (I)

```
# 6. Data Output
print DATA.ix[:20].to_string()
DATA.plot(subplots=True)
```

6. Data Output (II)

```
print AAPL[['bid','offer']].ix[1000:1015].to_string()
                       AAPL    GOOG
2012-06-22 10:02:01  577.33  566.3
2012-06-22 10:02:31  577.33    NaN
2012-06-22 10:02:33  577.33    NaN
2012-06-22 10:02:36  577.33    NaN
2012-06-22 10:02:57  577.33    NaN
2012-06-22 10:02:58  577.33    NaN
2012-06-22 10:03:01  577.71    NaN
2012-06-22 10:03:16  577.71    NaN
2012-06-22 10:03:18  577.71    NaN
2012-06-22 10:03:34  578.11    NaN
2012-06-22 10:04:39  578.11    NaN
2012-06-22 10:04:45  578.11    NaN
2012-06-22 10:05:13  578.26    NaN
2012-06-22 10:05:33  578.26    NaN
2012-06-22 10:05:36  578.26    NaN
2012-06-22 10:05:40  578.26    NaN
2012-06-22 10:05:57  578.26    NaN
2012-06-22 10:06:00  578.26    NaN
2012-06-22 10:06:07  578.26    NaN
2012-06-22 10:06:12  578.26    NaN
```

6. Data Output (III)[7]



[7] Quelle: `http://finance.yahoo.com`, 24. June 2012

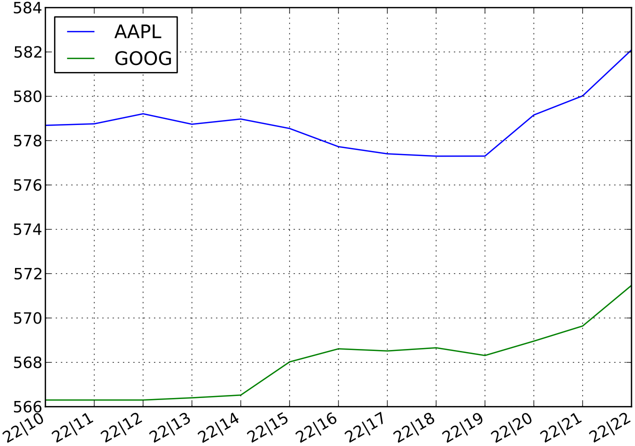
7. Data Aggregation (I)

```
# 7. Data Aggregation
by = lambda x: lambda y: getattr(y, x)
D = DATA.groupby([by('day'), by('hour')]).mean()
print D; D.plot()
```

7. Data Aggregation (II)

```
                  AAPL        GOOG
key_0 key_1
22    10    578.688760  566.300000
      11    578.758111  566.300000
      12    579.211250  566.300000
      13    578.739874  566.400000
      14    578.973806  566.521786
      15    578.547614  568.020159
      16    577.727252  568.609922
      17    577.405185  568.513652
      18    577.299690  568.655632
      19    577.302453  568.308739
      20    579.156171  568.956426
      21    580.020014  569.639033
      22    582.090000  571.470000
```

7. Data Aggregation (III)



8. Data Analysis (I)

```
# 8. Data Analysis
print "\n\nSummary Statistics for Tick Data\n",DATA.describe()
print "\nCorrelation for Tick Data\n",DATA.corr()

print "\n\nSummary Statistics for Hourly Data\n",D.describe()
print "\nCorrelation for Hourly Data\n",D.corr()
```

8. Data Analysis (II)

```
Summary Statistics for Tick Data
                AAPL          GOOG
count  14104.000000  7595.000000
mean     578.320379   568.682132
std        1.191263     0.907999
min      575.410000   565.800000
25%      577.380000   568.180000
50%      578.400000   568.640000
75%      579.190000   569.220000
max      582.130000   571.470000

Correlation for Tick Data
           AAPL      GOOG
AAPL  1.000000  0.735884
GOOG  0.735884  1.000000
```

8. Data Analysis (III)

```
Summary Statistics for Hourly Data
              AAPL        GOOG
count    13.000000   13.000000
mean    578.763091  567.999642
std       1.300395    1.586889
min     577.299690  566.300000
25%     577.727252  566.400000
50%     578.739874  568.308739
75%     579.156171  568.655632
max     582.090000  571.470000

Correlation for Hourly Data
           AAPL      GOOG
AAPL  1.000000  0.417359
GOOG  0.417359  1.000000
```

Major benefits and characteristics of `PyTables`

- **hierarchy**: structure your data in a hierarchical fashion (as with directories) and add user-specific data to each group/node
- **main objects**: `PyTables` knows **tables** as well as `NumPy` **arrays**; however, tables may also contain arrays
- **speed**: `PyTables` is optimized for I/O speed
- **operations**: it is ideally suited to do mathematical operations on your data
- **file**: it is file based and can be used on any notebook/desktop
- **concurrency**: only for reading operations, not really for writing
- **integration**: it integrates seamlessly with all kinds of `Python` applications
- **syntax**: the syntax is really `Pythonic` and quite close to standard `NumPy` syntax, e.g. with respect to indexing/slicing
- **relational database**: `PyTables` is NOT a replacement for a relational database (e.g. `MySQL`); it is a complementary work horse for computationally demanding tasks

Some of the most important PyTables functions/methods

- openFile: create new file or open existing file, like in h5=openFile('data.h5','w'); 'r'=read only, 'a'=read/write
- .close(): close database, like in h5.close()
- h5.createGroup: create a new group, as in group=h5.createGroup(root,'Name')
- IsDescription: class for column descriptions of tables, used as in:

```
class Row(IsDescription):
   name = StringCol(20,pos=1)
   data = FloatCol(pos=2)
```

- h5.createTable: create new table, as in tab=h5.createTable(group,'Name',Row)
- tab.iterrows(): iterate over table rows
- tab.where('condition'): SQL-like queries with flexible conditions
- tab.row: return current/last row of table, used as in r=tab.row
- row.append(): append row to table, as in r.append()
- tab.flush(): flush table buffer to disk/file
- h5.createArray: create an array, as in arr=h5.createArray(group,'Name',zeros((10,5)))

Let's start with a simple example (I)

```
In [59]: from tables import *

In [60]: h5=openFile('Test_Data.h5','w')

In [61]: class Row(IsDescription):
   ....:     number = FloatCol(pos=1)
   ....:     sqrt   = FloatCol(pos=2)
   ....:

In [62]: tab=h5.createTable(h5.root,'Numbers',Row)

In [63]: tab
Out[63]:
/Numbers (Table(0,)) ''
  description := {
  "number": Float64Col(shape=(), dflt=0.0, pos=0),
  "sqrt": Float64Col(shape=(), dflt=0.0, pos=1)}
  byteorder := 'little'
  chunkshape := (512,)

In [64]: r=tab.row

In [65]: for x in range(1000):
   ....:     r['number']=x
   ....:     r['sqrt']=sqrt(x)
   ....:     r.append()
   ....:
```

Let's start with a simple example (II)

```
In [66]: tab
Out[66]:
/Numbers (Table(0,)) ''
  description := {
  "number": Float64Col(shape=(), dflt=0.0, pos=0),
  "sqrt": Float64Col(shape=(), dflt=0.0, pos=1)}
  byteorder := 'little'
  chunkshape := (512,)

In [67]: tab.flush()

In [68]: tab
Out[68]:
/Numbers (Table(1000,)) ''
  description := {
  "number": Float64Col(shape=(), dflt=0.0, pos=0),
  "sqrt": Float64Col(shape=(), dflt=0.0, pos=1)}
  byteorder := 'little'
  chunkshape := (512,)
In [69]: tab[:5]
Out[69]:
array([(0.0, 0.0), (1.0, 1.0), (2.0, 1.4142135623730951),
       (3.0, 1.7320508075688772), (4.0, 2.0)],
      dtype=[('number', '<f8'), ('sqrt', '<f8')])

In [70]:
```

Let's start with a simple example (III)

```
In [7]: h5=openFile('Test_Data.h5','a')

In [8]: h5
Out[8]:
File(filename=Test_Data.h5, title='', mode='a', rootUEP='/', filters=Filters(complevel=0,
shuffle=False, fletcher32=False))
/ (RootGroup) ''
/Numbers (Table(1000,)) ''
  description := {
  "number": Float64Col(shape=(), dflt=0.0, pos=0),
  "sqrt": Float64Col(shape=(), dflt=0.0, pos=1)}
  byteorder := 'little'
  chunkshape := (512,)


In [9]: tab=h5.root.Numbers

In [10]: tab[:5]['sqrt']
Out[10]: array([ 0.        ,  1.        ,  1.41421356,  1.73205081,  2.        ])

In [11]: from pylab import *

In [12]: plot(tab[:]['sqrt'])
Out[12]: [<matplotlib.lines.Line2D at 0x7fe65cf12d10>]

In [13]: show()
```

You can also inspect the database graphically with ViTables

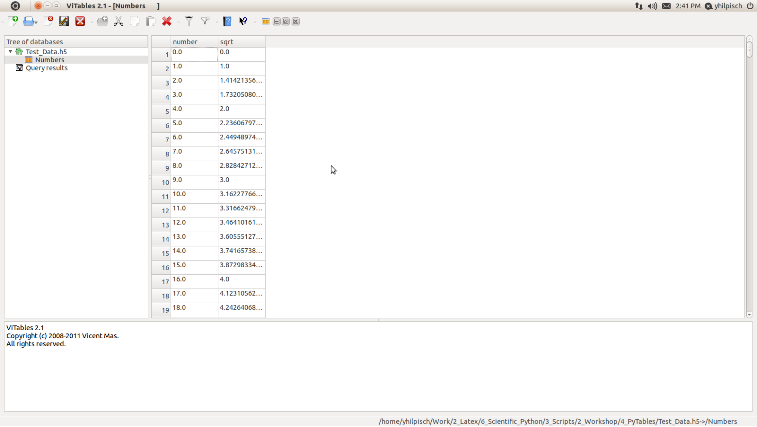


Figure: ViTables—a graphical interface to PyTables files[8]

[8] You find it under http://vitables.berlios.de

To illustrate PyTables's math capabilities consider the following Python script (I)

```
#
# Monte Carlo with Normal Arrays
# American Option with Least-Squares MCS
# LSM_Memory.py
#
from pylab import *
from time import *
t0=time()
# Option Parameters
S0=36.;K=40.;r=0.06;T=1.0;vol=0.2
# MCS Parameters
M=200;I=400000;dt=T/M
# Arrays
ran=standard_normal((M+1,I))
S=zeros_like(ran)
V=zeros_like(ran)
```

To illustrate PyTables's math capabilities consider the following Python script (II)

```
# Simulation
S[0]=S0
for t in range(1,M+1):
        S[t]=S[t-1]*exp((r-0.5*(vol**2))*dt+vol*sqrt(dt)*ran[t])
# Valuation
df=exp(-r*dt)
h=maximum(K-S,0)
V[-1,:]=h[-1,:]
for t in range(M-1,0,-1):
        rg = polyfit(S[t,:],V[t+1,:]*df,3)
        C = polyval(rg,S[t,:])
        V[t,:] = where(h[t,:]>C,h[t,:],V[t+1,:]*df)
V0=df*sum(V[1,:])/I
# Output
t1=time()
print "Option Value is %7.3f" %V0
print "Time in Seconds %7.3f" %(t1-t0)
```

With PyTables you can use database objects like NumPy arrays (I)

```
#
# Monte Carlo with PyTables Arrays -- Writing and Reading
# American Option with Least-Squares MCS
# LSM_PyTab.py
#
from pylab import *
from tables import *
from time import *
t0=time()
# Open HDF5 file for Array Storage
data=openFile('LSM_Data.h5','w')
# Option Parameters
S0=36.;K=40.;r=0.06;T=1.0;vol=0.2
# MCS Parameters
M=200;I=400000;dt=T/M
# Arrays
ran=data.createArray('/','ran',zeros((M+1,I),'f'),\
                     'Random Numbers')
for t in range(M+1):
    ran[t]=standard_normal(I)
S=data.createArray('/','S',zeros((M+1,I),'d'),'Index Levels')
h=data.createArray('/','h',zeros((M+1,I),'d'),'Inner Values')
V=data.createArray('/','V',zeros((M+1,I),'d'),'Option Values')
C=data.createArray('/','C',zeros((I),'d'),'Continuation Values')
```

With PyTables you can use database objects like NumPy arrays (II)

```
# Simulation
S[0]=S0
for t in range(1,M+1):
        S[t]=S[t-1]*exp((r-0.5*(vol**2))*dt+vol*sqrt(dt)*ran[t])
# Valuation
df=exp(-r*dt)
h=maximum(K-S[:,:],0)
V[-1,:]=h[-1,:]
for t in range(M-1,0,-1):
        rg = polyfit(S[t,:],V[t+1,:]*df,3)
        C = polyval(rg,S[t,:])
        V[t,:] = where(h[t,:]>C,h[t,:],V[t+1,:]*df)
V0=df*sum(V[1,:])/I
# Output
data.close();t1=time()
print "Option Value is %7.3f" %V0
print "Time in Seconds %7.3f" %(t1-t0)
```

If you only read from a PyTables database, computations are quite fast

```
#
# Monte Carlo with PyTables Array -- Reading from File
# American Option with Least-Squares MCS
# LSM_PyTab_RO.py
#
from pylab import *
from tables import *
from time import *
from LSM_PyTab import K,r,T,M,I,dt,df
t0=time()
# Open HDF5 file for Array Reading
data=openFile('LSM_Data.h5','a')
S=data.root.S
h=data.root.h
V=data.root.V
C=data.root.C
# Valuation
for t in range(M-1,0,-1):
        rg = polyfit(S[t,:],V[t+1,:]*df,3)
        C = polyval(rg,S[t,:])
        V[t,:] = where(h[t,:]>C,h[t,:],V[t+1,:]*df)
V0=df*sum(V[1,:])/I
# Output
data.close();t1=time()
print "Option Value is %7.3f" %V0
print "Time in Seconds %7.3f" %(t1-t0)
```

In addition, recent versions of `PyTables` support improved math capabilities

- **NumPy**: fast in-memory array manipulations and operations
- **numexpr**: (memory) improved array operations for faster execution
- **tables.Expr**: combining the strengths of `numexpr` with `PyTables'` I/O capabilities

A simple script illustrates how to apply the three alternatives

```python
#
# Evaluating Complex Expressions
# Expr_Comparison.py
#
from pylab import *
from numexpr import *
from tables import *
# Assumption and Input Data
expr='0.3*x**3+2.0*x**2+log(abs(x))-3'
new=True
size=10E5
x=standard_normal(size)
if new == True:
    h5=openFile('expr.h5','w')
    h5.createArray(h5.root,'x',x)
    h5.close()
# Three Evaluation Routines
def num_py():
    y=eval(expr)
    return y
def num_ex():
    y=evaluate(expr)
    return y
def tab_ex():
    h5=openFile('expr.h5','r')
    x=h5.root.x
    ex=Expr(expr)
    y=ex.eval()
    h5.close()
    return y
```

Interestingly, reading from HDF5 file and using Expr is faster than pure NumPy

```
In [43]: %run Expr_Comparison.py

In [44]: %timeit num_py()
10 loops, best of 3: 177 ms per loop

In [45]: %timeit num_ex()
100 loops, best of 3: 12.6 ms per loop

In [46]: %timeit tab_ex()
10 loops, best of 3: 33.3 ms per loop

In [47]: size
Out[47]: 1000000.0

In [48]:
```

Visixion's experience with Python

- **DEXISION**: full-fledged Derivatives Analytics suite implemented in Python and delivered On Demand (since 2006, www.dexision.com)
- **research**: Python used to implement a number of numerical research projects (see www.visixion.com)
- **trainings**: Python trainings with focus on Finance for clients from the financial services industry
- **client projects**: Python used to implement client specific financial applications
- **teaching**: Python used to implement and illustrate financial models in derivatives course at Saarland University (see Course Web Site)
- **talks**: we have given a number of talks at Python conferences about the use of Python for Finance
- **book**: Python used to illustrate financial models in our recent book"Derivatives Analytics with Python—Market-Based Valuation of European and American Stock Index Options"

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