PHYS4038/MLiS and ASI/MPAGS

Scientific Programming in



mpags-python.github.io

Steven Bamford



An introduction to scientific programming with



Session 6: Data handling

- Python has tools for accessing most (all?) databases
 - e.g. MySQL, SQLite, MongoDB, Postgres, ...
- Allow one to work with huge datasets
- Data can be at remote locations
- Robust and fast

- May require knowledge of DB-specific language
- But often provide Pythonic interface

- SQLite
 - Lightweight
 - No server
 - Just uses files (convenient, but less powerful)
 - Standard python module: sqlite3

- MariaDB (MySQL)
 - Widely used
 - Need MySQL server installed
 - Official: mariadb
 - SQLAlchemy, mysqlclient, pymysql, MySQLdb

- MongoDB
 - NoSQL database
 - Documents rather than tables
 - Need Mongo database server
 - Official: pymongo

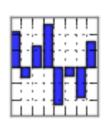
- Python has tools for accessing most (all?) databases
 - e.g. MySQL, SQLite, MongoDB, Postgres, ...
- Allow one to work with huge datasets
- Data can be at remote locations
- Fast random read and write
- Atomic transactions
- Concurrent connections

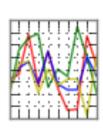
DB pros and cons

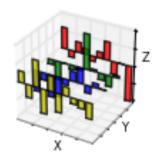
- Allow one to work with huge datasets
- Data can be at remote locations
- Fast random read and write
- Concurrent, atomic transactions

- However, most databases are designed for webserver use
 - typically not optimised for data analysis
 - write once, multiple sequential reads

$\mathsf{pandas}_{y_{it}=\beta'x_{it}+\mu_i+\epsilon_{it}}$







- Python Data Analysis Library
 - http://pandas.pydata.org
- Easy-to-use data structures
 - DataFrame (more friendly recarray)
 - Handles missing data (more friendly masked array)
 - read and write various data formats
 - data-alignment
 - tries to be helpful, though not always intuitive
 - Easy to combine data tables
 - Surprisingly fast!

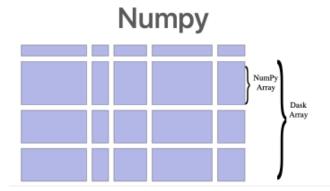
Notebook demo...

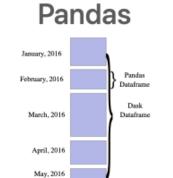
Dask



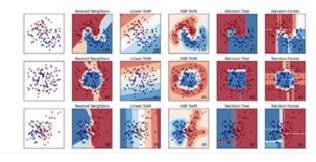
```
# Dataframes implement the Pandas API
import dask.dataframe as dd
df = dd.read_csv('s3://.../2018-*-*.csv')
df.groupby(df.account_id).balance.sum()
```

```
# Dask-ML implements the Scikit-Learn API
from dask_ml.linear_model \
  import LogisticRegression
lr = LogisticRegression()
lr.fit(train, test)
```





Scikit-Learn



PySpark



- typically for dealing with very large datasets
- distributed computing on a cluster
- need to setup infrastructure

PyTables / h5py

- http://pytables.github.io
- For creating, storing and analysing datasets
 - from simple, small tables to complex, huge datasets
 - standard HDF5 file format
 - incredibly fast even faster with indexing
 - uses on the fly block compression
 - designed for modern systems
 - fast multi-code CPU; large, slow memory
 - "in-kernel" data and algorithm are sent to CPU in optimal way
 - "out-of-core" avoids loading whole dataset into memory



PyTables / h5py

- Can store many things in one HDF5 file (like FITS)
- Tree structure
- Everything in a group (starting with root group, '/')
- Data stored in leaves
- Arrays (e.g. n-dimensional images)

```
>>> from tables import *
>>> h5file = openFile("test.h5", mode = "w")
>>> x = h5file.createArray("/", "x", arange(1000))
>>> y = h5file.createArray("/", "y", sqrt(arange(1000)))
>>> h5file.close()
```

PyTables

- Tables (columns with different formats) better to use Pandas!
 - described by a class
 - accessed by a row iterator

```
>>> class MyTable(IsDescription):
    z = Float32Col()
>>> table = h5file.createTable("/", "mytable", MyTable)
>>> row = table.row
>>> for i in xrange(1000):
    row["z"] = i**(3.0/2.0)
    row.append()
>>> table.flush()
>>> z = table.cols.z
```

PyTables Expr

• **Expr** enables in-kernel & out-of-core operations

```
>>> r = h5file.createArray("/", "r", np.zeros(1000))
>>> xyz = Expr("x*y*z")
>>> xyz.setOutput(r)
>>> xyz.eval()
/r (Array(1000,)) ''
 atom := Float64Atom(shape=(), dflt=0.0)
 maindim := 0
 flavor := 'numpy'
 byteorder := 'little'
 chunkshape := None
>>> r.read(0, 10)
array([ 0. , 1. , 7.99999986, 26.9999989,
      64. , 124.99999917, 216.00000085, 343.00001259,
      511.99999124, 729. ])
```

PyTables Expr

• where enables in-kernel selections

There is also a where in Expr

Multiprocessing

- Python includes modules for writing "parallel" programs:
 - threaded limited by the Global Interpreter Lock
 - multiprocessing generally more useful

```
from multiprocessing import Pool

def f(x):
    return x*x

pool = Pool(processes=4)  # start 4 worker processes

z = range(10)
print pool.map(f, z)  # apply f to each element of z in parallel
```

Multiprocessing

```
from multiprocessing import Process
from time import sleep
def f(name):
   print('Hello {}, I am going to sleep now'.format(name))
   sleep(3)
   print('OK, finished sleeping')
if ___name__ == '___main___':
   p = Process(target=f, args=(lock, 'Steven'))
   p.start() # start additional process
   sleep(1) # carry on doing stuff
   print 'Wow, how lazy is that function!'
   p.join() # wait for process to complete
```

```
$ python thinking.py
Hello Steven, I am going to sleep now
Wow, how lazy is that function!
OK, finished sleeping
```

(Really, should use a lock
 to avoid writing output
 to screen at same time)

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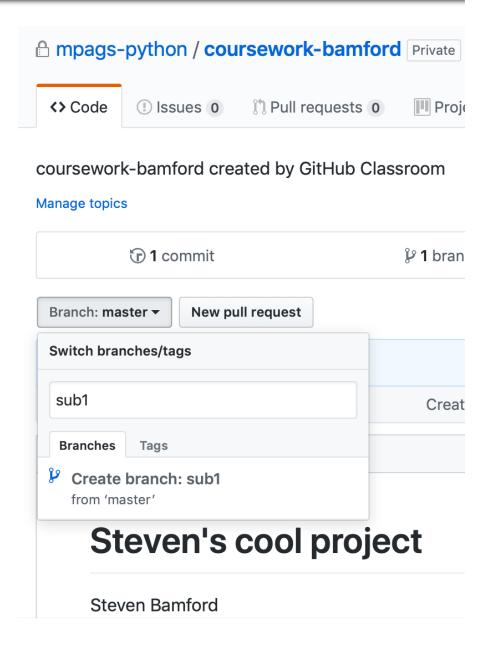
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Coursework submission

- Ongoing work
 - preliminary version
 - Incomplete / with bugs
 - roughly working
 - understandable
 - problems to be solved
 - questions
- Submission and feedback via your GitHub repository
- Mandatory for MLiS, optional for MPAGS
- Create a branch called sub2



Questions and exercises

Any questions?

- ask on the Slack channel (@Steven Bamford)
- email steven.bamford@nottingham.ac.uk
- ask in the next synchronous session