Using Python for Analytics

"Batteries Included"

MarginHound
hound@marginhound.com
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The Analyst Role (and its discontents)

- Theoretical Purpose of The Analyst – Guide other members of the team through developing rigorous solutions to business questions, using deep expertise in statistics, finance, etc….
- How it really works:
  - In retrospect, the answer to most "valuable" questions becomes obvious if you have access to the correct data
  - Corollary: If we had the data, we would have already solved it.
  - Your job is to figure out how to hack together the right dataset
    - From stuff we haven't used before…
    - And make sure it's right…
    - By noon tomorrow…

Why Python?

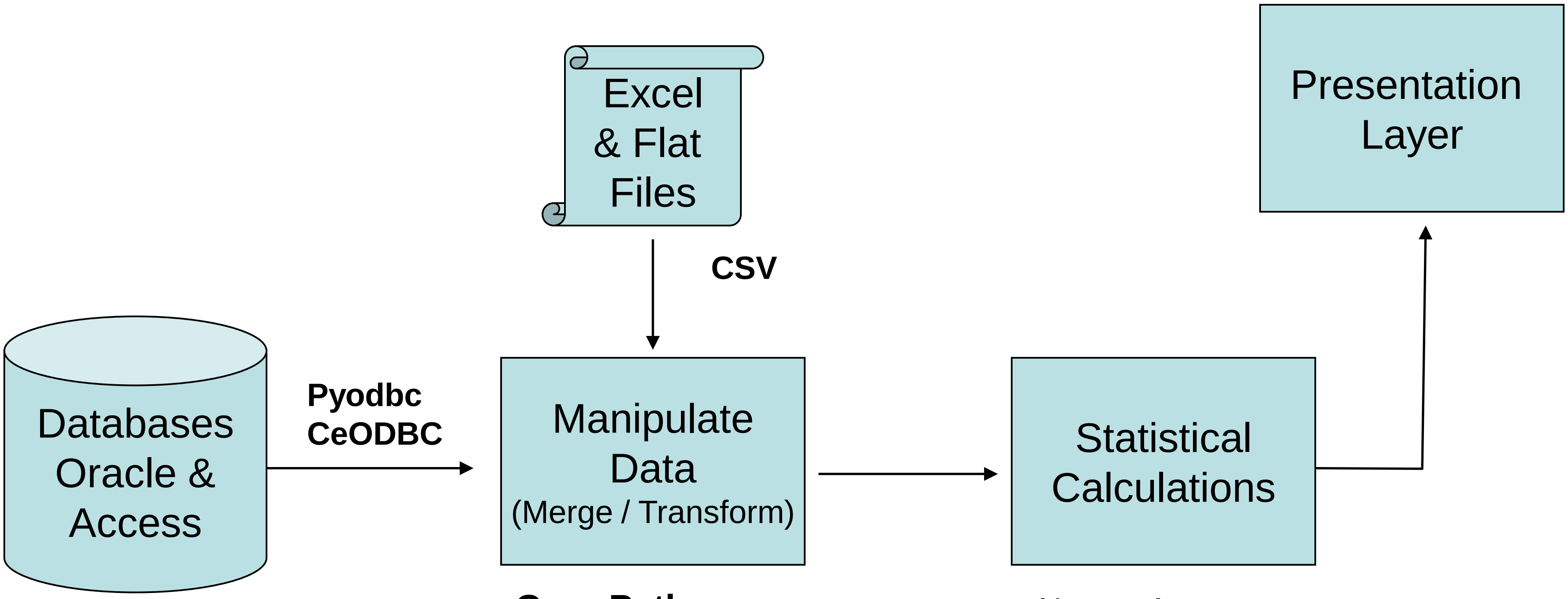
- Ad-hoc analysis usually requires three “layers” in your tool box:
  - Data Extraction => SQL or a query builder
  - Transformation & Analysis => Scripting Language
  - Presentation => Excel / PowerPoint / Access

- Python handles the middle layer well:
  - Succinct, Powerful Code – Duck Typing, First Class Functions
  - More expressive than databases (SQL), MS Office, statistics applications
  - Large library of built-in modules / data-types for common chores
  - Easy access to higher speed options (Numpy, Cython, JIT compilers)
  - Interpreter – often have to “doodle” with data / functions to identify trends
  - Readability Counts…

Hypothetical Problem (For Main Examples)

- You manage a kitchen
- Every day, you purchase food – you keep a record of this
- You would like to know:
  - What you are buying?
  - How much variation in prices exists?
- You intend to ask for a discount but…
  - Your customers are very sensitive to certain items – so you need to make sure you don't lose those suppliers…
- Naturally, as a trained analyst, you want to use statistics which aren't easily available in most entry-level database programs…

Typical Process Flow



Core Python

- List Comprehensions
- Itertools

Numpy

- Matplotlib

- Numpy Array
- Scipy Library

Python ODBC Connections

- Simplifies Access to Databases
  - Script refresh / download processes (eliminates boring work)
  - Save "snapshots" of data sets for future review / justification
  - Can directly export your results to DB/Access/Excel
- Requires you to learn SQL but..
  - Enables you to shift some of your processing to the larger machine; increases calculation speed and reduces volume of data to retrieve
  - High end databases will often have a nice analytics library
- Python has a database API specification (v 2.0); many libraries exist (mix of free and commercial). Two good ones:
  - pyodbc http://code.google.com/p/pyodbc/ (supports 2.x)
  - ceODBC http://ceodbc.sourceforge.net/ (supports 3.1)

Python ODBC Connections

High Level Activities

- Establish a connection to the database
- Set up a cursor
- Generate SQL & feed it to the cursor
- Cursor returns an iterable object for you to work with
- If writing, remember to commit
- Close connection when done – risks locking the database / table

Read Example

```
conn = pyodbc.connect('DSN=‘Main DW’;
              UID=SPAM;PWD=EGGS)
cursor = conn.cursor()

sql = "Select food, amount from po_list”
cursor.execute (sql)

Results = [ [row.food, row. amount)] for
                    row in cursor]
```

Write Example

```
<continues read example>

sql="Insert into po_list (food, amount)
    values (‘Milk’, 1)”


cursor.execute(sql)
conn.commit()
conn.close()
```

Databases – Simplifying your life

- Analytics SQL is often verbose, repetitive, and tedious to debug:
    - 80% of your queries request the same data (invoices, shipments, etc)
    - A solution – build templates, customize at runtime (search/replace)
    - Use external template files so you can share within your team
- Multi-step queries are frequently simpler / faster / more transparent:
    - Run an initial query to get current database status (update dates, etc.)
    - Complete calculation of query parameters in your script
    - Update the main query template(s) with the results of your work
    - Often much easier to test, may execute quicker as well
- Also worth automating “data type conversion” when using the results:
    - Cursor object has a “description” attribute – data type, size, etc.
    - Write introspective code to identify data types (for array, table creation)
    - Also useful for: date conversions, management of null values

Manipulating Data – Core Python

Can get a lot done using simple fundamentals:

- Data Structures
  - Obvious Choices - List of Lists (aka Nested Lists), Dictionaries
  - Specialized Options: Deque, Array, Tuples, Named Tuples
- Useful tools for slicing and dicing
  - List comprehensions
    - Select / Filter data, apply functions to results
    - Use nested and multi-step list comps for advanced operations
    - enumerate() – useful for ranking, updating a nested list in place
  - If-Else Expressions (X if X>0 Else 0)
  - Lambda and Map
  - Operator.Itemgetter() - allows you to select subset of elements from a list
  - Itertools: Group By, Cycles, Calculate Permutations
- Constantly making tradeoffs within this universe:
  - Remembering Data Structure Layout (Field1, Field2, Field3)
  - Additional complexity of manipulating data structures other than lists / tuples
  - Processing Performance impacts

Manipulating Data – List of Lists Examples

We will start manipulating the purchase order data for our main example:

Each record consists of:

1 – food
2 – uom
3 – amount
4 - unit_cost
5 - buy_date

- Example 1 – calculate total cost for each PO (item 2 x item 3)

```
dataset= [item + [item[2]*item[3]]
                    for item in dataset]
```

- Example 2 – rank my purchase orders by total cost

```
dataset = [[i+1] + item for i, item in
      enumerate(
            sorted(dataset, key=operator.itemgetter(5),
                  reverse = True))]
```

Manipulating Data – More Complex

Want to replicate functionality delivered by a SQL “Group By” Statement and aggregate statistical calculations, with the following twists:

- Define your own aggregate statistics (Python, Numpy, custom code)
- Incorporate data from outside your original database
- Wants to be able to recycle code within your script (similar reports)

The Specific Request (using our kitchen example):

- Group purchase orders by item purchased (spam, eggs, beer, etc.)
- Check to see if there are special notes for the item
- Calculate list of aggregate statistics (total qty, total cost, best cost, etc.)

Solution Components (using some “helper” functions):

- Group records using itertools.groupby
- Use dictionary “get” method to append notes to the keys
- Use list comprehension to calculate statistics for each group

Manipulating Data – More Complex

First Helper - set up the group by statement

The Function:

```
def group_my_list(dataset, my_key):
        return itertools.groupby(sorted(dataset, key=my_key),
                key=my_key)
```

The Function Call:

group_my_list(dataset, operator.itemgetter(0))]

Explanation:

- Returns a “configured” group by iterator with less repetitive code
- Dataset needs to be sorted by your key
- Key is actually a comparison function
  - Use operator.itemgetter to select specific list element
  - Could rewrite this to pass the list element vs. a function

Manipulating Data – More Complex

Second Helper – Process List of Statistics For Each Group

The Function:

```
def run_stats(record_set, stats_list):

    return [stat(map(operator.itemgetter(ref), record_set))
                       for stat, ref in stats_list]
```

The Function Call:

```
PO_Stats = ((sum,2),(sum,5),(min,2),(max,2),(min,3),(max,3), (np.median, 3))
run_stats(list(g),PO_Stats)
```

Explanation:

- Called with a list of grouped records and a list of function / element pairs
- Returns a list of aggregate statistics (one per pair on function list)
- For each pair in the list of the function / element pairs:
  - Use map and operator.itemgetter to select a list of that element (eg. all prices)
  - Use the function piece of the pair to reduce that list to a single value
  - Append that value to your result list

Manipulating Data – More Complex

Bringing It all Together…. (doing the dictionary check in-line)

Generating The List of Aggregate Statistics:

```
prod_agg = [[k + special_prefs.get(k,””)] +
                    run_stats(list(g),PO_Stats)
                      for k, g in
                        group_my_list(dataset, operator.itemgetter(0))]
```

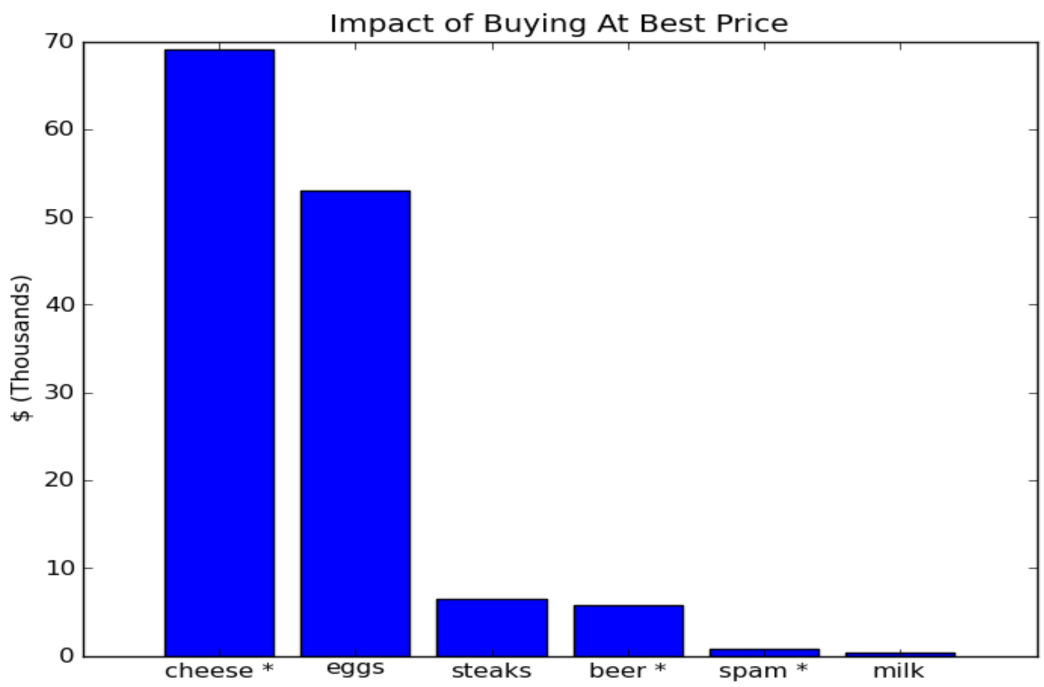
Explanation:

- Use a list comprehension to iterate across the sets of grouped records
- For each set of grouped records, construct a “result list” by joining:
  - The key plus any notes (Single Element List)
    - For each key, use the get method of the dictionary “special prefs” to return any notes; get lets you define a default value (in this case, ””)
  - The aggregate statistics for that group
    - Calculated using our run_stats function

Manipulating Data – Demonstration

<Slide Added To Summarize The Program Used In The Demonstration>

- **Generated table of product level statistics using our group by statement**
- **Calculated a potential savings number (cost @ best price vs. actual cost)**
- **Ranked categories by potential savings**
- **And generated the following graph (using matplotlib.pyplot's plot function):**



Looks like we need to visit the cheese shop….

Manipulating Data – Numpy

Numpy Array:

- Wraps a very fast low level array for performing calculations
- Supported by set of built-in function optimized for numpy
  - Some of these functions can also be use on Python lists
- Large base of supporting statistical/numeric libraries in Scipy
- The price: must define data type in advance, one type per array
- But…may significant boost performance (with minor changes)

Analyzing 5MM subsets of series: 600 -> 150 CPU seconds

Structured Array:

- Variant of the numpy array but can access “columns” of data using string references (eg. “price”, “cost”, “part number”)
- Similar to data sets / frames in R, SAS, and other languages
- Significantly More Readable – certain operations may be slower
- Can mix data types (at the column level)
- Very good for exploratory analysis

Manipulating Data – Matplotlib

- Plotting Library for Scipy / Numpy
  - Mlab module has utilities for managing datasets / structured arrays
- Some useful functions

• Rec_summarize	Create New Field by Applying a Function
• Rec_GroupBy	Aggregate Stats for Subset of Records
• Rec_Append_Fields	Create New Field from like-sized array

- Other useful functions

• Rec_join	Match datasets
• Drop_fields	Simplify datasets
• Rec2CSV, CSV2REC	Load / Unload datasets (auto-typing)

Manipulating Data – Numpy Example

Some sample applications:

Example 1 – Calculating a field using other fields

```
dataset = ml.rec_append_fields(dataset, "gross_cost",
                 [item['amount']*item['unit_cost'] for item in dataset])
```

List comprehensions Very Useful Here

Example 2a - Create New Field using dict lookup

```
lookup = (('food', lambda x:[item+special_prefs.get(item,"")
                            for item in x],
                                'food_groups'),)
prod_agg = ml.rec_summarize (prod_agg,lookup)
```

Works When New Field Derived From Single Element

Manipulating Data – Numpy Example

Example 2b – Group By With Aggregate Statistics

```
stats_list = (("amount",np.sum,"qty_sum"),
              ("gross_cost",np.sum,"cost_sum"),
              ("amount",np.min,"qty_min"),
              ("amount",np.max,"qty_max"),
              ("unit_cost",np.min,"uc_min"),
              ("unit_cost",np.max,"uc_max"),
              ("unit_cost",np.median,"uc_median"),)

prod_agg = ml.rec_groupby(dataset,(("food"),),stats_list)
```

Cleaner, More Readable Than Prior Version

“The Hack”

These functions appear to work with any function which:

- Rec_Summarize accepts a list and returns a list of the same size/order
- Rec_GroupBy accepts a list and reduces it to a single value

Which enables you to execute a wide range of calculations and transformations with some creative use of list comprehensions and other methods.

Summation

- Several ways to do it – the “obvious one” depends on tradeoffs
  - How much does your data structure change?
  - Is the data fundamentally static (eg. financial markets data)
  - Developer Speed vs. Processing Power
- Don’t underestimate the value of freedom
  - Create / Extend your own analytical functions
  - Develop your own frameworks / helper libraries
  - Can view / fork source code for key modules
  - Active online support community
- Makes the analyst role more interesting
  - Can ask questions faster, streamline repetitive tasks
  - Transparency -> Quality -> Less Stress
  - More time to think of interesting ways to transform your data