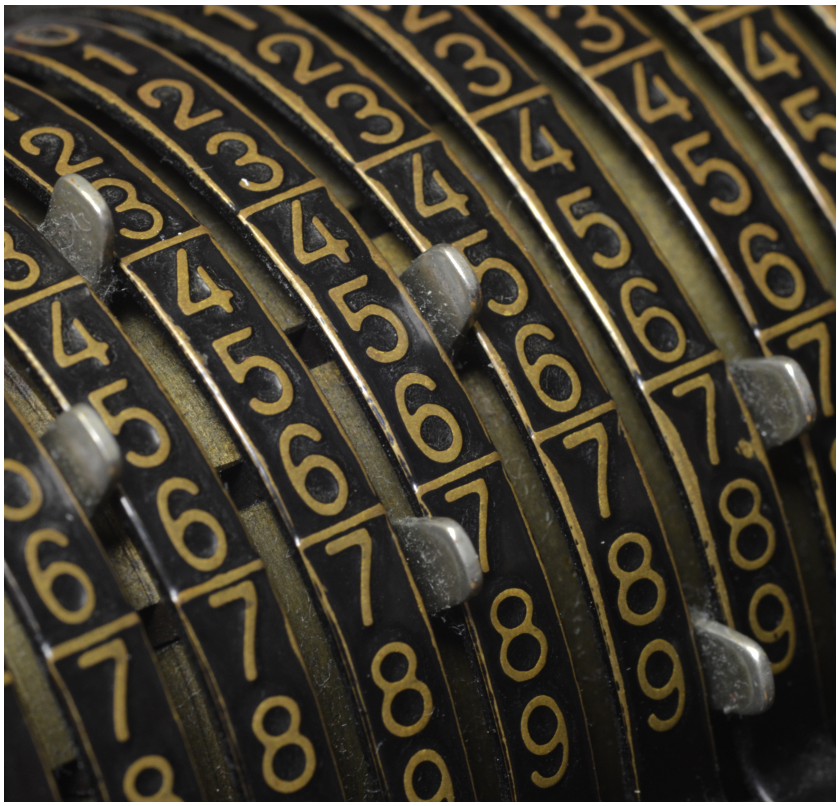
Expertmaker Accelerator

User's Reference



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Glossary

automata	a script run by urd dispatching or recalling jobs
chain	a one-directional list of datasets
dataset	efficient storage of data
job	a running or completed method
jobid	a link to a successfully completed method
method	main source file of program to be executed by framework
package	a location where methods are stored
urd	dispatcher and job database
workdir	a location where job data and metadata is stored

Chapter 1

Introduction

The Accelerator is a very efficient environment for running and scheduling big data tasks. It has been in continuous development since 2012, and has been used in seven different projects, of which three has been live to customers, and the other four was data analysis and insight projects.

Due to its minimalistic implementation, the Accelerator is capable of working at high speed with terabytes of data with billions of lines on a single computer. Two things stand out: first, all jobs are bookkeeped in a novel way; and second, data is represented and accessed with close to zero overhead. The end result is a globally optimised data processing machine with a wide spectrum of uses.

Some Accelerator features

- **Data integration** - The Accelerator has been used in several projects with different customers and data, and has thereby adopted to a number of formats and cases.
- **Efficient Data Access** - Data is streamed through jobs using low level operating- and filesystem primitives.
- **Simple job tracking** - Easy to find source data, easy to use results from other users.
- **Transparency** - Total context for all jobs ever run is stored and straightforward to retreive. Any job could be retrieved or replayed.

Chapter 2

Overview

2.1 Introduction

The Accelerator platform is a complete environment designed for high performance parallel computing on large sets of data. On a high level, the platform is composed of two parts: a server providing a set of features for efficient parallel processing of large amounts of data, and a client that dispatches jobs on the server and provides a lookup of all data in a project.

A user of the platform may use or write two kinds of programs, denoted *methods* and *automatas*. Methods are parallel programs executed on the server, and automatas are high level scripts used to control flow and parameters to and from the methods running on the server. Programs are written in the Python programming language[1]. In theory, any language may be used, and critical parts of the internals of the Accelerator are written in the C programming language.

Methods that are running or have completed running are called jobs. The server stores results and parameters from all jobs in a database that is partitioned into what is called workdirs. The client, on the other hand, keeps a log, called the *Urd log*, which is bookkeeping all dispatched jobs and associated parameters and dependencies. Interestingly, data is also stored in jobs, so retrieving data is no different from retrieving jobs.

Here is a very simple example

```
# a_helloworld.py:
def analysis(sliceno):
  print("Hello, world: %d" % (sliceno,))

# automata.py:
def main(urd):
  urd.begin('test')
  urd.build('helloworld')
```

The program is executed by calling

```
% automatarunner.py
```

This example will print the string `Hello, world:` plus a digit for each slice a number of times to standard out. In more detail, the automata is dispatching the

2.2 Dispatch, Dependencies, and Jobids

The framework is basically a job dispatcher and dependency tracker. Input to a job is parameters and source code, called method. When a job is run, a directory is created in the workdir. A pointer to this directory, called a jobid, is returned upon finished execution. Inside the directory, everything needed to run the job is stored, for example input parameters, as well as all results created during execution.

The framework keeps information for each job that has been successfully completed for dependency tracking. Dependency tracking is used for two things: first, it avoids re-execution of jobs that have been run before; and second, it permits jobs to depend on already finished jobs.

Re-execution is avoided if a job is issued with exactly the same source code and input options. If source code is not equal, or if any input to the job is different, the job will be executed again. All successful runs of a job will be kept.

A job may have reference to other jobs as input. If these references are valid, the running job will have access to all information from the reference jobs.

2.3 Datasets and Chaining

A particularly efficient way to store data is by using the dataset. Datasets reside inside jobs, abstracting databases to jobs containing data. Data is stored so that it can be retrieved row by row at a very high pace and requesting from one to any number of columns.

Data in a dataset is separated into slices, where on a single server, the number of slices is close to the number of actual CPU cores for best performance.

A dataset may be hashed on one of its columns. Hashing means that each slice contains a mutually exclusive set of column data.

[1] Both Python 2 and Python 3 are supported.

Typically, a dataset is created for each file that is imported. When several files are imported, the jobids may be chained, that is, each new jobid contains a pointer to the previous job. Using the previous-pointers, datasets could be iterated one after another without interruption.

2.4 Job Bookkeeping

A prominent feature of both the client and the server is the ability to immediately recall instead of recompute previously executed jobs. Any job that has been successfully executed may be recalled, provided that the job is submitted again with exactly the same input and source code. The framework uses a hash of the method's source code to decide if it has changed or not.

The combination of bookkeeping and the client/server architecture provides a very powerful environment for accessing and depending on previous result. Not only can a user's own results be recalled, but also those from another user or from the "production" user in a live environment. In a typical application, this dramatically increases performance while minimizing the probability of errors. It also allows for a high level of transparency. Past jobs could be replayed in a controlled manner, and the complete context with respect to input arguments of any job could be retrieved and used to answer "what-if"-scenarios.

2.5 Workdirs

A workdir is where results are stored. One can think of it as a directory populated with jobid-directories. Workdirs are specified with absolute paths in the server filesystem. A workdir has a fixed slicing, and all workdirs in a project need to have the same number of slices.

2.6 Method

Code is executed on the framework is written in methods. Methods allow for parallel execution and more.

2.7 Urd

Urd provides a scripting environment for running and recalling jobs. It has a transaction-log database that stores information about jobs that have been run and their inter-dependencies. Since data is also stored in jobs, another of Urd's purposes is to provide lookups to all data in a project.

2.8 Automata

An automata is a script run by urd, in which jobs and data are recalled, and new jobs may be dispatched.

Chapter 3

High Level Control: Urd

3.1 Introduction to Urd

Urd is the key controller in the framework. It is the primary job dispatcher as well as the bookkeeper of all jobs executed. Events in urd are quantified into what is called *sessions*, and the core of urd is a transaction log database storing these sessions together with meta information. The result is a server providing lookups for all jobs executed together with their context.

The Urd database is partitioned into what is called *lists*. Each user, human or agent, owns one or more lists where information about executed jobs are stored. Lists are globally readable, but writing is limited using authentication, so that, for example, only the production user may publish a model to go live.

With the exception of experimental work, all work initiated by urd is run in closed sessions, with well defined starting and ending points. The input dependencies to these sessions are recorded, together with the resulting output.

3.2 Urd sessions

Here is an example of a minimal urd session

```
def main(urd):
  urd.begin('test')
  ...
  urd.finish('test', '20161025')
```

Everything dispatched between `begin` and `finish` will be appended to the `test` urd list with timestamp 20161025, as log as the `finish` function is called, since it is responsible for updating the urd transaction log. Before `finish`, noting is stored, and it is perfectly ok to omit `finish` during development work.

There are a number of options associated with a session, as shown here,

```
  urd.begin(path, timestamp=None, caption=None, update=False)
  urd.finish(path, timestamp=None, caption=None)
```

and the following rules apply to these options:

- the same `path` must be specified in both `begin` and `finish`.
- `timestamp` is mandatory, but could be set in either `begin` or `finish`. `finish` overrides `begin`.
- `caption` is mandatory, but could be set in either `begin` or `finish`. `finish` overrides `begin`.

There is also an `update` option that will be discussed in section **??**.

Timestamp resolution

Timestamps may be specified in various resolution depending on the application. The following examples cover the available formats

```
   '20161025'              day resolution
   '20161025 15'           hour resolution
   '20161025 1525'         minute resolution
   '20161025 152500'       second resolution
```

Aborting an Urd Session

When a session is initiated, a new session cannot start until the current has finished. A session may be aborted, however,

```
  urd.begin('test')
  urd.abort()
```

and aborted sessions are not stored in the urd transaction log.

3.3 Building jobs

Jobs are dispatched in session using the `build` function. The syntax is as follows

```
jobid = urd.build('method1', options={}, datasets={}, jobids={}, ...)
```

where `options`, `datasets`, and `jobids` are optional, depending on the method to be dispatched. In addition, a name and a caption may optionally be specified too

```
jobid = urd.build('method1', name='myjob', caption='looking for something')
```

The name will replace the method name in the joblist, in this case, this job will now be referred to as `myjob` (default was `method1`). A jobid to the finished job is returned upon successful completion.

3.3.1 Building chained jobs

It is also possible to build chained jobs implicitly using the `build_chained` function

```
jobid = urd.build_chained('method1', name='myjob')
```

which takes the same options as the standard `build` method, with the exception that name is mandatory, since it is used to find the previous job of matching type.

3.3.2 Debug: Why build

By specifying the flag `why_build` to the automatarunner it is possible to see the reasons for building a job. For example

```
print(urd.build('method3', jobids=dict(firstjob=jid2, secondjob=jid2), name='knut'))
# Would have built from:
# ======================
# {
#     "caption": "fsm_method3",
#     "method": "method3",
#     "params": {
#         "method3": {
#             "datasets": {},
#             "jobids": {
#                 "firstjob": "test-59_0",
#                 "secondjob": "test-59_0"
#             },
#             "options": {}
#         }
#     },
#     "why_build": "on_build"
# }
# Could have avoided build if:
# ============================
# {
#     "method3": {
#         "test-60_0": {
#             "jobids": {
#                 "firstjob": "test-56_0"
#             }
#         }
#     }
# }
```

A more machine-friendly output is possible by specifying `why_build=True` in the `build`-request (and not specifying it to the automatarunner).

3.4 Sessions with dependency

A job may have dependencies, such as other jobs or datasets. These dependencies are input to the job using the corresponding arguments to the `build` function. Locating these jobs or datasets, however, is exactly a design goal of Urd. Urd implements a `get` function that looks up jobids and dependencies from a key that is composed of a urd list name and a timestamp. There are also, for convenience, `first` and `latest` functions to get the first and latest job in an urd list.

Here is an example. Assume that a method, `method1`, uses some kind of imported transaction logs, called `tlog`. When dispatching `method1`, it should be using the latest available `tlog`. The example shows how the function `latest` is used for this

```
def main(urd):
  urd.begin('test')
  latest_tlog = urd.latest('tlog').joblist.jobid
  urd.build('method1', datasets=dict(tlog=latest_tlog))
  urd.finish('test', '20161025')
```

Two things have happened here. First, urd has provided a jobid link to the latest available `tlog`. Second, the dependency of exactly this version of `tlog` to `method1` is recorded in the urd list `test` for timestamp 20161025. So, if there is a question in the future which version of the `tlog` database that was used on that date for the `method1` function, it is immediately available from urd.

The more general form is `get`, which is shown below together with its derived convenience-functions

```
  urd.get('test', '20161001')
  urd.latest('test')
  urd.first('test')
```

And here is an example of running `method1` on `tlog` data from previous month

```
def main(urd):
  urd.begin('test')
  tlog = urd.get('tlog', '20160925').joblist.jobid
  urd.build('method1', datasets=dict(tlog=tlog))
  urd.finish('test', '20161025')
```

3.5 Avoiding recording dependency

Dependency-recording will be activated on use of the `get`, `latest`, and `first` functions. If, for some reason, the point is to just have a look at the database to see what is in there, it can be done using the peek-versions, as presented below:

```
  urd.peek('test', '20161025')
  urd.peek_latest('test')
  urd.peek_first('test')
```

3.6 More on Finding Items in Urd

There is a `list` function that returns what lists are recorded in the database:

```
print(urd.list())
# ['ab/test', 'ab/live']
```

And there is also a `since` function that returns a list of all timestamps after the input argument

```
print(urd.since('20161005'))
# ["20161006", "20161007", "20161008", "20161009"]
```

The `since` is rather relaxed with respect to the resolution of the input. The input timestamp may be truncated from the right down to only one digits. An input of zero is also valid.

```
print(urd.since('0'))
# ["20160101", "20161004", "20161005", "20161006", "20161007", "20161008"]
print(urd.since('2016'))
# ["20160101", "20161004", "20161005", "20161006", "20161007", "20161008"]
print(urd.since('20161'))
# ["20161004", "20161005", "20161006", "20161007", "20161008"]

print(urd.since('2016105'))
# ["20161006", "20161007", "20161008"]
...
print(urd.since('2016105 000000'))
# ["20161006", "20161007", "20161008"]
```

3.7 Truncating and Updating

Urd will always keep a consistent history of all events taken place. Sometimes, however, it makes sense to re-run events from the past. There are two means to achieve this, update and truncate.

update

The begin-function takes an optional argument update

```
urd.begin('test', '20161025', update=True)
```

If update is True, the entry in the test list at '20161025' will be updated, unless there has been no change.

Truncate

The truncate() class member is used to rollback an arbitrary amount of an urd list.

```
urd.truncate('test', '20160930')
```

This will rollback everything that has happened in the test list back to '20160930'. Internally, urd stores the complete history, however.

3.8 More on Joblist and Jobtuple

Urd is using the type joblist to keep track of successfully executed jobs. Each item in the joblist is of type jobtuple. This section will start by describing jobtuple first and then joblist.

Jobtuple

The `JobTuple` type is used to group method names and corresponding jobids. It is basically a tuple with some extra properties, such as a conversion of a jobtuple to `str`, which happens for example when printing it, returns the jobid as a string.

```
>>> jt = JobTuple('imprt', 'jid-0_0')

>>> jt
('imprt', 'jid-0_0')
```

as expected, and

```
>>> jt.method
'imprt'

>>> jt.jobid
'jid-0_0'
```

but note that

```
>>> print(jt)  # str and encode return jobid only
jid-0_0
```

JobList

The `JobList` is a list with add-ons for bookkeeping and finding jobs. It stores instances of `JobTuple`. Here is an example. First, define a `JobTuple`

```
>>> jt = JobTuple('imprt', 'jid-0_0')
```

then define a joblist initiated with the same tuple. Then append some more jobs directly using the `append` method.

```
>>> jl = JobList(jt)
>>> jl.append('learn', 'lrn-0_0')
>>> jl.append('imprt', 'imp-1_0')
```

Let's see how and what is stored in the `JobList`. The `pretty` method is quite useful, but note that just printing the object will show the last jobid only.

```
>>> print(jl.pretty)
JobList(
   [  0]  imprt : jid-0_0
   [  1]  learn : lrn-0_0
   [  2]  imprt : imp-1_0
)

>>>  print(jl)  # jobid of latest appended JobTuple
imp-1_0
```

It is easy to retrieve the last job with a particular `method` name, either by lookup or by using `find`.

```
>>> jl['imprt']          # latest jobid with name 'imprt'
('imprt', 'imp-1_0')

>>> print(jl['imprt'])   # jl['imprt'] is JobTuple
imp-1_0
```

The Find method returns a `JobList`. Slicing also returns `JobLists`

```
>>> jl.find('imprt')
JobList([('imprt', 'jid-0_0'), ('imprt', 'imp-1_0')])

>>> jl[:2]
JobList([('imprt', 'jid-0_0'), ('learn', 'lrn-0_0')])
```

Looking up by index returns `JobTuple`.

```
>>> jl[0]
('imprt', 'jid-0_0')
```

These conveniences are also supported

```
>>> jl.all              # list of all jobids
'jid-0_0,lrn-0_0,imp-1_0'

>>> jl.method           # last method
'import'

>>> jl.jobid            # last jobid
'imp-1_0'
```

3.9 Urd HTTP_API

In some situations it is convenient to make calls to urd directly without using the framework. Urd will react to HTTP requests.

```
% curl http://localhost:8833/list
["ab/test"]

% curl http://localhost:8833/ab/test/latest
{"caption": "", "automata": "test", "user": "ab", "deps": {},
  "timestamp": "20161025", "joblist": [["method1", "test-56_0"],
  ["method2", "test-59_0"], ["method3", "test-60_0"]]}

% curl http://localhost:8833/ab/test/first
{"caption": "", "automata": "test", "user": "ab", "deps": {},
  "timestamp": "20161025", "joblist": [["method1", "test-56_0"],
  ["method2", "test-59_0"], ["method3", "test-60_0"]]}

% curl http://localhost:8833/ab/test/20161025
{"caption": "", "automata": "test", "user": "ab", "deps": {},
  "timestamp": "20161025", "joblist": [["method1", "test-56_0"],
  ["method2", "test-59_0"], ["method3", "test-60_0"]]}

% curl http://localhost:8833/ab/test/since/201610024
["20161025"]
% curl http://localhost:8833/ab/test/since/20161026
[]
```

Chapter 4

Method

4.1 Methods

Methods are source files executed by the framework. The nomenclature is that methods turn into jobs when they are assigned input arguments and get executed by the framework. A method may be dispatched by urd, or by another method as a subjob.

4.2 Packages and Source code

Methods are stored in directories, called packages, in the main framework directory. A package needs to be present in the main configuration file, and the package directory has to contain the file `__init__.py` for Python to see it.

There are two limitations, that apply to methods, designed to avoid accidental execution of the wrong source code. For a method file to be accepted by the framework, the filename has to start with the prefix "`a_`". Furthermore, the method name, without this prefix must be present on a separate line in the `methods.conf` file for the package.

4.3 Recall and Method Hashing

The framework is applying a hash function to the method source code to determine if a job may be recalled or re-executed. Changing the method source code in an unique way causes a new job to be built from the method code.

A method may use code located in other files, and in that case it is possible to ensure that jobs are dispatched if any of those files change. This is specified in the method using the `depend_extra` list, as for example:

```
import generic_params
depend_extra = (generic_params, 'mystuff.data',)
```

You can specify a module object or a filename relative to the module source.

A different scenario is when the method source code needs to be modified, but the change does not alter past behavior, i.e. remake of jobs should be actively avoided. There is an `equivalent_hashes` dict for that, as shown

```
  equivalent_hashes = {'verifier': ('0c573685f713ac6500a6eda7df1a7b3f',)}
```

The verifier string is a hash that depends on everything in the method except the equivalent_hashes block. It is there to avoid the scenario where you forget the method has equivalent_hashes and make changes. When the verifier is wrong (as it will be after editing the method) you will be informed what the correct verifier would be, so you can use that or discard the equivalent_hashes block, as appropriate. The tuple on the right can contain any number of old hashes.

4.4 Method Inputs

When a method is dispatched as a job, it will be provided with input from the dispatcher. There are three kinds of input to a method: `jobids`, `datasets`, and `options`. These are specified early in the method source code, such as for example

```
jobids = ('accumulated_costs',)
datasets = ('transaction_log',)
options = dict(length=4)
```

The `jobids` argument is used to input pointers to other finished jobs, `datasets` is used to input other datasets, and `options` is used to input any other type of parameters specifying running behavior of the method. Note that `jobids` and `datasets` are tuples (and a single entry has to be followed by a comma), while `options` is a dictionary. Each will be described in more detail next

4.4.1 Input Jobids

The `jobids` argument is a tuple of jobids linking this job to other jobs. Inside the running method, a jobid from the `jobids` tuple is simply a string that can be passed to various helper functions in order to use results from the corresponding jobs.

4.4.2 Input Datasets

The `datasets` argument is the way to communicate datasets from automata to job. In the running method, the `datasets` variable is a tuple of dataset objects ready to use. The dataset class is described in a dedicated chapter.

4.4.3 Input Options

The `options` argument is of type `dict` and used to pass various information from the dispatcher (typically Urd or a method) to a method. Information could be integers, strings, enumerations, sets, lists, and dicts in a recursive fashion. Options may have a default value.

Options are defined in a method like this

```
options = dict( ... )  # or
options = { ... }
```

Options are easiest described by examples, and such will be presented in the following sections. The remaining of this section is dedicated to describe the formal rules for option typing and assignment.

- an input value is required to be of the correct type.
- An input may be left unassigned, unless
  - typing is RequiredOptions(), or
  - OptionEnum without default
- Typing may be specified using the class name (i.e. int), or as a value that will construct into such a class object (i.e. the number 3).
- If typing is specified as a value, this is the default value if left unspecified.
- If typing is specified as a class name, default is None.
- Values are accepted if they are valid input to the type's constructor, i.e. 3 and '3' are valid input for an integer.
- None is a valid input unless
  - RequiredOptions() and not none_ok set
  - OptionEnum() and not none_ok set
- All containers can be specified as empty (?)
- Complex types (like dicts, dicts of lists of dicts, ...) never enforce specific keys, only types. ({'a': 'b'} is a valid value for {'foo': 'bar'}) (?)
- containers with a type in the values default to empty containers (otherwise the specified values are the default contents)

Typing and default values are presented in the following sections. Default values are assigned if there is no input. Note that definition of type is that the constructor must accept the value provided, for example the string `'3'` is a valid input for the `int` constructor.

Unspecifieds

An option with no typing may be specified by assigning `None`.

```
options = dict(length=None)
# accepts anything, default is None
```

Here, `length` could be set to anything.

Scalars

Scalars are either explicitly typed, as

```
options = dict(length=int)
# Requires an intable value or None
```

or implicitly with default value like

```
options = dict(length=3)
# Requires an intable value, default is 3 if left unassigned
```

In these examples, intable means that the value provided should be valid input to the `int` constructor, for example the number 3 or the string `'3'` both yield the integer number 3.

Strings

A (possibly empty) string with default value `None` is typed as

```
# requires string or None, defaults to None
options = dict(name=str)
```

A default value may be specified as follows

```
# requires string or None, provides default value
options = dict(name='foo')
```

And a string required to be specified and none-empty as

```
# requires non-empty string
options = dict(name=OptionString)
```

In some situations, an example string is convenient

```
# Requires string, provides example (NOT default value)
options = dict(name=OptionString('bar')
```

Note that 'bar' is not default, it just gives the programmer a way to express what is expected.

Enums

Enumerations are convenient in a number of situations. They are typed as follows

```
# Requires one of the strings 'a', 'b' or 'c'
options = dict(foo=OptionEnum('a b c'))
```

A default value may be specified like this

```
 # Requires one of the strings 'a', 'b' or 'c', defaults to 'b'
options = dict(foo=OptionEnum('a b c').b
```

or, like this, accepting `None`

```
# Requires one of the strings 'a', 'b', or 'c'; or None
options = dict(foo=OptionEnum('a b c', none_ok=True))
```

The `none_ok` flag may be combined with a default value too.
Furthermore, the asterisk-wildcard may be used too

```
# Requires one of the strings 'a', 'b', or any string starting with 'c'
options = dict(foo=OptionEnum('a b c*'))
```

Lists and Sets

Lists and sets are specified like this

```
# Requires list of intable, defaults to empty list
options=dict(foo=[int])
```

and

```
# Requires set of intable, defaults to empty set
options=dict(foo={int})
```

More complex stuff

It is possible to have more complex types, such as dictionaries of dictionaries and so on, for example

```
  # Requires dict of string to string
  options = dict(foo={str: str})
```

or another example

```
  # Requires dict of string to dict of string to int
  options = dict(foo={str: {str: int}})
```

Containers with a type in the values default to empty containers. Otherwise, the specified values are the default contents.

Date and Time

The following date and time related types are supported: `datetime`, `date`, `time`, and `timedelta`. A typical usecase is as follows

```
  # a datetime object if input, or None
  options = dict(ts=datetime)
```

and with a default assignment

```
  #  a datetime object if input, defaults to a datetime(2014, 1, 1) object
  options = dict(ts=datetime(2014, 1, 1))
```

JobWithFile

Any file residing in a jobdir may be input to a method like this

```
  options = dict(usefile=JobWithFile(jid, 'user.txt')
```

There are two additional arguments, `sliced` and `extras`. The `extras` argument is used to pass any information that is helpful in using the specified file, and `sliced` tells that the file is stored in parallel slices.

```
options = dict(usefile=JobWithFile(jid, 'user.txt', sliced=True, extras={'uid': 37}))
```

In the method, the `JobWithFile` object has these members

```
  usefile.jobid
  usefile.filename
  usefile.sliced
  usefile.extras
```

Where the full filename of the file is available through

```
from extras import full_filename
print full_filename(filename, '')
```

The mandatory string (which is empty in this case, is a filename extension. **Will be changed!**)

4.5 Code Flow: `prepare`, `analysis`, and `synthesis`

There are three pre-defined functions in a method, `prepare`, `analysis`, and `synthesis`, and they are always run in that order. `prepare` and `synthesis` are single threaded, while `analysis` provides parallel execution.

The following combinations are valid and are of practical use

- `synthesis`-only, used for a single threaded program
- `analysis`-only, used for completely parallel tasks
- `prepare` + `analysis`, setup and run a parallel job
- `analysis` + `synthesis`, run a parallel job and combine outputs
- `prepare` + `analysis` + `synthesis`, setup, run, and combine a parallel task.

All the three functions take `options`, `jobids`, and `datasets` as optional arguments. The `analysis` function takes a required argument `sliceno`, which is an integer between zero and the total number of slices minus one. This is the unique identity indicator for the `analysis` process.

Return values may be passed from one function to another. What is returned from prepare is called `prepare_res`, and may be used as input argument to `analysis` and `synthesis`. The return values from `analysis` is available as `analysis_res` in `synthesis`. The return value from `synthesis` is stored permanently in the jobdir. A complete example may look like

```
options = dict(length=4)
datasets = ('transaction_log')

def prepare(options):
  return options.length * 2

def analysis(sliceno, prepare_res):
  return set(
    u for u in datasets.transaction_log.iterate(sliceno, 'user')
  )

def synthesis(analysis_res, prepare_res):
   return analyses_res.merge_auto()
```

4.5.1 The `params` Variable

The `params` variable contain all input and initialization parameters for a job, such as the caption

```
def synthesis(params):
  print params.caption
# urd_dispatched_method1
```

The `params` variable contains lots of information that is typically not required in a regular method. For a method developer, the most important members are

```
params.package     # which package the method source code is stored in
params.slices      # number of slices for the workdirs in use
params.caption     # may be specified when building a job
params.seed        # seed to initialize a random number generator
params.starttime   # execution start in epoch time
```

but params does also contain all options, jobids, and datasets inputs.

4.5.2 Accessing Another Job's `params` using `job_params`

The `params` data structure contains all input and initialization data for a job. To access another job's `params` variable, just feed the job's jobid into the `job_params` function.

```
from extras import job_params

jobids = ('anotherjob',)

def synthesis():
  print jobids.anotherjob
  # will print something like 'jid-0_0'
  print job_params(jobids.anotherjob).options
  # will print something like {length: 3}
```

4.6 More on Intermediate and Result Files

4.6.1 Sharing Data Inside a Job

Data is easily shared between `prepare`, `analysis`, and `synthesis` as follows.

- what is returned in `prepare` is available as `prepare_res` in `analysis` and `synthesis`
- what is returned in `analysis` is available as `analysis_res` in `synthesis`. `analysis_res` is an iterator.
- what is returned in `synthesis` is a persistent file in the job catalog referenced by `result`.

The blob module

The simplest way to share intra job data is using the blob module.

```
import blob
def synthesis()
  blob.load('filename')
```

saving data is as follows

```
  blob.save(data, filename, sliceno=None, temp=None)
```

`sliceno` and `temp` are optional. If `sliceno` is set, data is stored in a sliced file. This is typically used in `analysis`, where each thread will save its own file. The argument `temp` is used for file persistence. By default, files are stored permanently when a job terminates successfully. Setting `temp` to `True` removes them upon completion of the job. Temporary files are useful when communicating data between the functions in the method (and not using the res-files) or in debugging.

4.6.2 debug help

There is also a more advanced debug functionality relating to temp.

```
from extras import Temp
def analysis(sliceno):
  ...
  blob.save(data, filename, sliceno=sliceno, temp=Temp.DEBUG)
  # or
  blob.save(data, filename, sliceno=sliceno, temp=Temp.DEBUGTEMP)
```

where the first only stores when `-debug` is specified, and the other always stores but removes unless `-debug` is set.

4.7 Subjobs

Jobs may launch subjobs. If the jobs are already built, they will be immediately linked in. The syntax is as follows, assuming we build the jobs in
prepare:

```
import subjob

def prepare():
  subjob.build('count_items', options=dict(length=3))
```

The `subjob.build` uses the same syntax as `urd.build` described elsewhere, so `options`, `datasets`, `jobids`, and `caption` are available. Similarly, subjob jobid is returned.

If there are datasets built in a subjob, these will not be explicitly available to Urd. Instead, the dataset definition may be copied to the launching method like this

```
from Dataset import dataset

def synthesis():
  jid = subjob.build('create_dataset')
  Dataset(jid).link_to_here(name='thename')
```

the `name` argument is optional, the name `default` is used if left empty, corresponding to the default dataset.

Chapter 5

Dataset

5.1 Introduction

The dataset is the prefered way to store large amounts of data. The dataset is the container for fast and simple access to data. Data in a dataset are stored as a matrix in rows and columns. Using the dataset, data is simple to access and at a very high performance.

Datasets are created in methods, and any job may contain zero, one, or more datasets. The most obvious use of a dataset is the cvsimport method that creates a dataset from an input file.

A job may contain more than one dataset. This allows for efficient storage and access of data in some common practical situations. For example, a filtering job may split the input dataset in two or more output datasets that can be accessed independently.

For performance reasons, datasets are typically split into several slices, where each data line exists in exactly one of the slices. The actual slicing may be carried out in any fashion, like round robin, or even random, but an interesting approach is to slice according to the hash value of a certain column. Slicing according to a hashed column ensures that all lines with a certain hash column value ends up in the same slice.

This chapter covers ... chaining, where datasets grows in number of lines, and column appending, where datasets grow in number of columns.

5.2 Dataset access

In a running job, datasets are represented by objects from the Dataset class. These objects are immediately available from the datasets-tuple. For example

```
datasets = ('tlog',)

def synthesis(datasets):
  print(datasets.tlog.filename)
```

Most common dataset operations are available as member functions to the dataset class.

A dataset may also be instantiated using jobids. like this

```
from dataset import Dataset
d = Dataset('foo-0_0')
```

In this case, d will be an object based on the default dataset residing at jobid foo-0_0. If there are more datasets in a jobid, or the dataset is stored by a different name, it may be accessed like this

```
d = Dataset('foo-0_0/foo')
# or
d = Dataset(('foo-0_0', 'foo'))
```

where the latter is more general in that it uses parameters for both jobid and name.

5.3 Dataset properties

The dataset class has a number of member functions and attributes that is intended to make it simple to work with datasets.

Column names

Consider the following example, which shows how to find the available columns in the dataset

```
datasets = ('source',)

def synthesis():
  print(datasets.source.columns.keys())
  # ['GTIN', 'date', 'locale', 'subsource']
```

Column properties

For each column, the name, type, and if applicable, the min and max values are accessible like this

```
# each key, i.e. column, has a number of properties, of which the
# most important ones are shown below
print(datasets.source.columns['locale'].type)
# ascii
print(datasets.source.columns['locale'].name)
# locale
print(datasets.source.columns['locale'].min)
# 3
print(datasets.source.columns['locale'].max)
# 9
```

Lines per slice

It may be interesting to see how many lines there are per slice in a dataset. This information is available as a list, for example

```
print(datasets.source.lines)
# [5771, 6939, 6212, 6312, 6702, 6341, 5988, 6195,
#  6741, 6587, 6518, 5840, 6327, 5933, 6745, 6673,
#  6536, 6405, 6259, 6455, 6036, 6088, 6937, 6245,
#  6418, 6437, 6360, 6106, 6878]
```

From an efficiency perspective, the variance of the numbers in this list should be low, so that all slices will contain about the same amount of data.

Dataset shape (i.e. number of columns and total number of lines

The shape if the dataset, i.e. the number of columns times the total number of lines, is available from the shape attribute

```
print(datasets.source.shape)
# (4, 184984)
```

the second number is exactly the sum of the number of lines for each slice from above.

hashlabel

If the dataset is hashed on a particular column, this column is stored in the hashlabel attribute

```
print(datasets.source.hashlabel)
# GTIN
```

Filename, caption, hashlabel

The dataset may have a filename associated to it. This makes sense in situations for example where the dataset is created from an input datafile. The filename is accessable like this

```
print(datasets.source.filename)
# /data/incoming/raw_repository_5391.gz
```

Furthermore, it is possible to set a caption when creating a dataset. The caption is entirely user-defined, an accessible like this

```
print(datasets.source.caption)
# flattening
```

Chains

When a dataset is created, it is possible to input an optional parameter previous which is a link to another dataset. This has effect on the dataset iterators, which may continue to iterate over dataset boundaries when one dataset is exhausted and continue to the next.

This will be described in another section in more detail. The previous dataset is available as an attribute

```
print(datasets.source.previous)
# neu4-4893_0/default
```

5.4 Column Typing

The dataset columns are typed. The following types are available

number	float or int
float64	64 bit double float
float32	32 bit float
int64	64 bit signed integer
int32	32 bit integer
bool	True or False
date	date
time	time
datetime	complete date and time object
bytes	raw input, avoid
ascii	ascii is faster in python2, otherwise unicode
unicode	use for strings
parsed:number	int, float or string parsing to int or float
parsed:float64	and so on...
parsed:float32	
parsed:int64	
parsed:sint32	
json	a datastructure that is jsonable
parsed:json	string containing parseable json

Table 5.1: Available dataset column types.

To be completed.

5.5 Create New Dataset

Datasets are either created in prepare + analysis, or in just synthesis.

5.5.1 Create in prepare + analysis

A simple example writing three columns to the default dataset is presented next. Note that the example creates a dataset chain, linking the currently created dataset to the dataset that is input with the name previous.

```
from dataset import DatasetWriter
datasets = ('previous',)

def prepare():
  dw = DatasetWriter(
    hashlabel = 'X',
    previous = datasets.previous,
  )
  dw.add('X', number)
  dw.add('Y', number)
  dw.add('Z', number)
  return dw

def analysis(sliceno, prepare_res):
  dw = prepare_res
  ...
  for x, y, z in data:
    dw.write(x, y, z)
```

Note that the order of the variables in the dw.write function call is the same as the order of the add calls in prepare[1].

DatasetWriter takes a number of optional arguments such as caption and filename. The argument "name" specifies the name of the dataset, which is set to be "default" when unassigned. Several datasets can be created in the same method using more than one datasetwriter instance with different "name"s.

There is some flexibility in the way the write function may be called

```
  dw.write_dict({column: value})
  dw.write_list([value, value, ...])
  dw.write(value, value, ...)
  # or even
  dw.writers[name].write(value)  # return True if hashed to correct slice
```

5.5.2 Creating Hashed datasets

If hashlabel is set, one can use dw.hashcheck(value) to check if value belongs to the slice. It is also possible to just call the writer since it will discard anything not belonging to the correct slice.

5.5.3 Create in synthesis

There are two options if the dataset is to be created in synthesis. One in to set the slice number first

```
  dw.set_slice(sliceno)
```

while the other is to use one of these functions

```
  dw.get_split_write_dict()({column: value})
  dw.get_split_write_list()([value, value, ...])
  dw.get_split_write()(value, value, ...)
```

that will assign the data to the correct slice automatically.

5.5.4 Placeholder: Creating datasets more manually

[1] in case write is called with a dict, the order is unknown, but then names are looked up using the dict keys.

5.6 Appending new columns to an existing Dataset

With minimal overhead, the dataset supports adding new columns to an existing dataset. This is implemented by storing the new column data together with a pointer to the dataset

Appending new columns work exactly the same way as creating a dataset, with the exception that a link to a dataset that is to be appended to is input to the writer constructor. The following example appends one column to an existing dataset while maintaining the chain. Note that appending does only apply to one dataset, and not to the complete chain.

```
datasets = ("source", "previous",)

def prepare():
  dw = dataset.DatasetWriter(
    parent=datasets.source,
    previous=datasets.previous,
    caption="flattening_attempt_1"
  )
  dw.add(name, type)
  return dw

def analysis(sliceno, prepare_res):
  dw = prepare_res
  ...
  dw.write(value)
```

Note that an error is issued if the total number of appended lines does not match the number of lines in the parent dataset.

Chapter 6

Iterator

6.1 Dataset Iterators

Iterators are used to stream dataset data one line at a time into a method. Data may be streamed from a single dataset, or from a chain of datasets, one dataset at a time.

6.1.1 Basic Iteration

The iterator iterates over specified data columns. The output will be one line at a time, formatted as a tuple.

A Simple Parallel Iterator Invocation

Read variables X and Y in all slices in parallel

```
def analysis(sliceno):
    h = defaultdict(set)
    for user, item in datasets.source.iterate_chain(sliceno, columns=('user', 'item',)):
        h[user].add(item)
```

data is iterated over all rows and all datasets in the chain, running in increasing jobid direction.

Iterate over all data in synthesis

It is possible to iterate over all slices in a single loop by specifying sliceno=None as follows

```
def synthesis():
    for user, item in datasets.source.iterate_chain(None, columns=('user', 'item',)):
        h[user].add(item)
```

slices will be iterated one at at time in increasing order.

6.1.2 Special cases, iterating over all or a singe column

If column names are omitted, the iterator will produce a tuple of data including all columns.

```
for items in iterate_datasets(sliceno, None, jobids):
    print(items)  # is a tuple of all columns
```

Also, if only one column is specified, it is possible to have the iterator produce a scalar directly

```
# alternative 1, use lists/tuples always
for user in iterate_datasets(sliceno, ('USER',), jobids):
    userset.add(user[0])  # user is a tuple

# alternative 2, target is tuple
for user, in iterate_datasets(sliceno, ('USER',), jobids):
    userset.add(user)

# alternative 3, input is string, not list
for user in iterate_datasets(sliceno, 'USER', jobids):
    userset.add(user)
```

Both styles are supported by filters and translators.

6.1.3 Halting Iteration

Iteration over a dataset chain will continue until all data is exhausted. Sometimes, one wish to limit the number of iterations. There are several mechanisms for that, and they may be combined in the same expression. If so, iteration will be over the shortest range of the conditions.

Halting using length

```
for user, item in datasets.source.iterate_chain(
    sliceno,
    columns=('user', 'item',),
    length = options.length):
```

This will iterate for options.length number of datasets. Note that a length of -1 iterates without bounds and is the default.

Halting using stop_jobid

```
for user, item in datasets.source.iterate_chain(
    sliceno,
    columns=('user', 'item',),
    stop_jobid = datasets.stopjob):
```

A more advanced, but very useful, method is to stop at a dataset that is input to another job

Halting using another job's input parameters

```
for user, item in datasets.source.iterate_chain(
    sliceno,
    columns=('user', 'item',),
    stop_jobid = {jobids.preprocess: 'source',}):
```

this will iterate until reaching end or the dataset job_params(jobids.preprocess).datasets.source.

It is also possible to iterate over a specified data range. This works for datasets that are sorted on the column of choice.

Iterating over a data range

```
for user, item in datasets.source.iterate_chain(
    sliceno,
    columns=('user', 'item',),
    range={timestamp, ('2016-01-01', '2016-01-31'),}):
```

this will limit the iterator to exactly the range of lines that fulfill the range condition. It is relatively costly to filter each line, and there is a speed advantage by specifying sloppy_range, which will iterate over all datasets that contain part of the range.

6.1.4 Iterating in the reverse direction

It is possible to iterate the dataset chain in the backwards direction by specifying reverse=True, but note that iteration is always in the forward direction within each dataset.

```
for user, item in datasets.source.iterate_chain(
    sliceno,
    columns=('user', 'item',),
    reverse=True):
```

@@@ HASHLABEL FOR AVOIDING MISTAKES!!!

6.1.5 iterate_list

PLACEHOLDER

6.1.6 Translators

Translators transform data values. A translator is either a callable or a `dict`. Translators are similar to `filters`, and always executed before filtering.

The idea behind translators and filters is that they provide a way to modify code behavior by supplying functions as iterator options. In this way, it is possible to write re-useable simple methods that still could be altered significantly in behavior.

Callable Translator

A translator function is called with a tuple and is expected to return a tuple of the same length. Using translator functions it is possible to mix different columns with each other before sending them to the iterator output. Here is an example

```
def merger(user, item):
    return "%s:%s" % (user, item), None
for merge, _ in iterate_datasetchain(None, ('user', 'item',), tip_jobid=jobid,
                                     translator=merger):
    ...
```

The purpose of this translator is to convert each `(user, item)` tuple to a string `user:item`. This is the first output of the translator and iterator and is stored in the `merge` variable. The second output variable is not used in this application, but a variable still has to be assigned.

Translator dict

One or more columns may be translated independently using a translator dictionary, specified as `{name: translation}`. A translation may be either a `dict` or a callable. Examples of both kinds are shown below.

First an example illustrating the use of a translation `dict`. Here, integers are translated into more comprehensible strings.

```
mapper = {2: 'HUMANLIKE', 4: 'LABRADOR', 5: 'STARFISH',}
for animal in iterate_datasetchain(None, 'NUM_LEGS', tip_jobid=jobid,
                                   translator={'NUM_LEGS': mapper,}):
    ...
```

Items missing in a translation-`dict` yield `None`.

Second, an example of a translation callable. In this example, each user string is output from the iterator reads backwards.

```
def reverse(x):
    return x[::-1]
for resu, item in iterate_datasetchain(None, ('USER', 'ITEM',), tip_jobid=jobid,
                                       translator={'USER': reverse,}):
    ...
```

6.1.7 Filters

Filters are run *after* translators.

Filters decide which rows to pass to the iterator output. A filter is either a callable or a `dict`.

Callable Filter

Callable filters receive the iterator tuple as input. The output must be `True` for the tuple to be output from the iterator, otherwise the iterator continues reading the next line.

The following two examples, of which the first uses a callable filter, are functionally equivalent

```
# Ex1.  filter users that are bearded and longhaired
filter=lambda line: line[1] and line[2]
for user, beard, hair in iterate_datasetchain(None, ('user', 'bearded', 'longhaired'),
                                       tip_jobid=jobid, filters=filter):
    ...

# Ex2.  filter users that are bearded and longhaired
for user, beard, hair in iterate_datasetchain(None, ('user', 'bearded', 'longhaired'),
                                       tip_jobid=jobid):
    if beard and hair:
        ...
```

Filter Dict

It is possible to filter on one or more columns independently using a `dict`. All filters must be `True` for a line to be output from the iterator. Here are two examples. The first example will remove all lines except the ones with valid users. The second example will only keep lines with movie items. (The fact that book is false is redundant — missing keys will result in discarded lines.)

```
# keep valid users only
validusers={'user1', 'user2', 'user3'}
filters={'user': validusers.__contains__}

# keep valid users with movie items
validitems={'movie': True, 'book': False}
filters={'user': validusers.__contains__, 'item': validitems.get}
```

Filter by Column Values

Column values could also be used directly, i.e. the values get evaluated by Python. For example, assume there is a column `hasbeard` with values being boolean integers, i.e. `1` or `0`. Bearded users may be collected by

```
for user, beard in iterate_datasetchain(None, ('user', 'bearded',), tip_jobid=jobid,
                                        filters={'bearded': None}):
    bearded.add(user)
```

This may seem strange at first, but it works because the key for the `bearded` column exists, and the value is `None`, and not a callable nor a `dict`.

6.1.8 Callback

It is also possible to inject callback functions, either before or after each dataset is loaded. If `sliceno=None`, i.e. iteration runs over all slices of all datasets, it is even possible to have callback between slice change.

The example below will print dataset `jobid` for each dataset prior to iterating over it.

```
# pre_callback once per dataset
def prefun(jobid):
    print(jobid)
for user, item in iterate_datasetchain(sliceno, ('user', 'item',), tip_jobid=jobid,
                                       pre_callback=prefun):
    ...
```

Next is an example of an iterator running over all slices. The callback function is executed before each new slice is iterated. Note the difference between this example and the previous. The callback function in this example takes two arguments, while the previous takes only one.

```
# callback once per slice
def prefun(jobid, sliceno):
    print(sliceno, jobid)
for user, item in iterate_datasetchain(None, ('user', 'item',), tip_jobid=jobid,
                                       pre_callback=prefun):
    ...
```

Post-callback is defined similarly.

Skipping Datasets and Slices from Callbacks

It is possible to skip iterations by raising exceptions, as follows

```
# Raise this in pre_callback to skip iterating the coming slice
# (if your callback doesn't want sliceno, this is the same as SkipJob)
raise SkipSlice

# Raise this in pre_callback to skip iterating the coing job
raise SkipJob

# Raise this to quit iterating, but with the side effect that
# post_callback will not run.
# @@@ TO BE DEFINED
raise StopIteration
```

Chapter 7

standard methods

To cover: csvimport, csvexport, dataset_type, dataset_sort, dataset_rehash, and more.