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dispel4py: A Python Framework for Data-Intensive Scientific Computing

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Abstract

This paper presents `dispel4py`, a new Python framework for describing abstract stream-based workflows for distributed data-intensive applications. These combine the familiarity of Python programming with the scalability of workflows. Data streaming is used to gain performance, rapid prototyping and applicability to live observations. `dispel4py` enables scientists to focus on their scientific goals, avoiding distracting details and retaining flexibility over the computing infrastructure they use. The implementation, therefore, has to map `dispel4py` abstract workflows optimally onto target platforms chosen dynamically. We present four `dispel4py` mappings: Apache Storm, MPI, multi-threading and sequential, showing two major benefits: *a*) smooth transitions from local development on a laptop to scalable execution for production work, and *b*) scalable enactment on significantly different distributed computing infrastructures. Three application domains are reported and measurements on multiple infrastructures show the optimisations achieved; they have provided demanding real applications and helped us develop effective training. The `dispel4py.org` is an open-source project to which we invite participation. The effective mapping of `dispel4py` onto multiple target infrastructures demonstrates exploitation of data-intensive and HPC architectures and consistent scalability.

Keywords— Data-intensive computing, e-Infrastructures, data streaming, scientific workflows, programming frameworks

1 Introduction

During recent years there has been a widespread and increasing requirement for data-intensive computation in science, engineering, medicine, government and many other fields [1]. The term “data-intensive” is used to characterise computation that either requires or generates large volumes of data, or has complex data access patterns due to algorithmic or infrastructural reasons. Most of the research reported in that book proceeded by gathering the required data and organising it for one kind of use in one administrative context. Data exploitation was then conducted by teams that included domain scientists, data-analysis specialists and computer scientists. Similar data exploitation preparations and localisation are typical in many other contexts, such as those reported in [2, 3, 4].

Many domains of science use live data or large volumes of data archived for multiple purposes, so that a dynamic approach is needed. We have developed `dispel4py` to address these needs based on three key requirements.

1. Scientists can develop and experiment with encodings of their scientific methods entirely in a familiar Python environment, using their preferred program-development environments, their familiar scientific, statistical and visualization libraries and established data-analysis tools.

2. Scientists can complete the work entirely themselves or draw on experts in data-analysis or data-intensive engineering [5].
3. The resulting encoded methods will transfer *unchanged* into production and live-streaming deployments and adapt automatically to the data scale, data rates and computational infrastructure encountered.

Nowadays Python is probably the programming language of choice (besides R, Matlab, C++) for scientists [7]. This is due to its succinct style, its rich handling of data types, convenient interfaces to legacy code, a very substantial supply of relevant libraries and excellent development tools. It runs on every computer we encounter and is already installed in most cases. Therefore, Python was a preferred choice for encoding `dispel4py`. In the future it would be worthwhile having a flexible framework that works well with multiple languages. Our geoscience collaborators were already adept at Python. They have to handle primary data streams as well as data from institutional and global archives. Their live data flows from global and local networks of digital seismometers, and streams from many other digital instruments *e.g.* when observing volcanoes. They employ the usual two-stage handling of data – established initial collection with quality monitoring [8], then an open ended exploration of data and simulation models where researchers are responsible for the design of methods and the interpretation of results. These researchers may want to ‘re-cook’ relevant primary data according to their own needs. Their research context has the added complexity of delivering services, such as hazard assessments and event, *e.g.* earthquake, detection and categorisation, which may trigger support actions for emergency responders [9]. They therefore have the aspiration to move innovative methods into service contexts easily.

Data-streaming is essential to enable users such as geoscientists to move developed methods between live and archived data applications, and to address long-term performance goals. The growing volumes of scientific data, the increased focus on data-driven science and the achievable storage density doubling every 14 months (Kryder’s Law [10]), severely stresses the available disk I/O – or more generally the bandwidth between RAM and external devices. This is driving increased adoption of data-streaming interconnections between workflow stages, as these avoid a write out to disk followed by reading in, or double that I/O load if files have to be moved. As long as stages can process a succession of data units and pass derived data units to subsequent stages, the code in the stages can remain resident, and the coupling can use in-RAM, local or inter-site communication mechanisms¹. As with disk-mediated communication, moving data reduction to as early a stage as is logically possible and employing lossless compression has benefits [11]. Significantly reducing the cost of data movement between stages makes it economic to compose very simple stages, *e.g.* format changes, which potentially intermingle with much more demanding stages.

Each stage of a `dispel4py` encoded method is represented as a Python object that takes data from zero or more input streams and emits data on zero or more output streams. Typically it applies a function to units of data taken from the input streams and emits units of data on its output streams. Where the function only uses a small number of data units per function application and where the data units are of modest size the stage can work with a limited memory footprint. Such near linear stages predominate once the combined expertise has transformed the method into an appropriate form. The connections between stages are also set up in the Python program. When the program is run, a graph is produced, which consists of nodes that perform the operations on data and arcs along which data streams between nodes. That graph is interpreted during development, when processing rates are not usually a priority, and is transformed, optimised and mapped for production runs. That is, if the enactment is local, the normal case during development, the processes in each node, corresponding to stages in the method, are set running, data is streamed into the inputs, consumed and passed along communication channels to the next stage(s), eventually reaching the output stages. The complete graph is choreographed by flow control along the channels [12]. Termination occurs for one of three reasons: *a)* the incoming streams terminate, and the ‘end-of-stream’ propagates through the nodes and reaches the final outputs; *b)* a ‘no-longer-interested’ signal propagates back through the graph – this may save much computation when a user recognises that an output stream is erroneous, or *c)* a signal to stop is sent to the control software that deployed the graph, *e.g.* when expected termination hasn’t occurred.

When production runs are anticipated the enactment is targeted at a distributed computational infrastructure (DCI). Those handled at present are: Apache Storm clusters², MPI [13] powered clusters, and shared-memory multi-core machines using Multiprocessing (a multi-threading Python package). In these cases, once the graph has been produced

¹Of course, capture or viewing of intermediary streams needs to be supported for diagnostics during experiments and development.

²<https://storm.incubator.apache.org/>

it is transformed to match the target DCI, *e.g.* parallel streaming is introduced. The revised graph is then mapped to the target DCI and all nodes are started. The data flow to the input streams is then released and processing continues until one of the above termination conditions applies. After this, the control software verifies the clean up of the deployed graph has released all resources. The third termination condition and this final check are the only moments of orchestrated coordination.

The `dispel4py` evaluation shows that it can achieve good scalability results on the different DCI, with medium and large scale applications, parallelising and adapting itself automatically to the number of cores available, without modifying the workflow. The evaluations also show that an application’s best-performance depends on a combination of two factors: `dispel4py` mapping and the DCI selected.

The primary use of `dispel4py` is in e-Science contexts, most notably in *Seismology*. Recently it has been used in two other domains: *Astrophysics* and *Social Computing*.

The rest of the paper is structured as follows. Section 2 presents relevant background. Section 3 introduces and defines `dispel4py` concepts. Section 4 discusses four `dispel4py` supported mappings. Section 5 presents three eScience domains, *Seismology*, *Astrophysics* and *Social Computing*, with `dispel4py` workflows. Section 6 presents a `dispel4py` workflow required by seismologists, which is used in this paper to evaluate the `dispel4py` mappings. We conclude with a summary of achievements and outline some future work.

2 Background

There are many scientific workflow systems, including: Pegasus [14], Kepler [15], Swift [16], KNIME [17, 18], Taverna [19], Galaxy [20], Trident [21] and Triana [22]. These are task oriented, that is their predominant model has stages that correspond to tasks, and they organise their enactment on a wide range of distributed computing infrastructures (DCI) [23], normally arranging data transfer between stages using files [24]. These systems have achieved substantial progress in handling data-intensive scientific computations; *e.g.* in astrophysics [26, 27, 28], in climate physics and meteorology [29], in biochemistry [31], in geosciences and ge-oengineering [32] and in environmental sciences [33, 34].

Despite the undoubted success of the task-oriented scientific workflow systems, `dispel4py` adopts a data-streaming approach for reasons given above. This mirrors the shared-nothing composition of operators in database queries and in distributed query processing [35] that has been developed and refined in the database context [36]. Data streaming was latent in the auto-iteration of Taverna [37], has been developed as an option for Kepler [38], is the model used by Meandre [39], and by Swift (which supports the data-object-based operation using its own data structure). Data streaming pervaded the design of Dispel [40]. Dispel [41] was proposed as a means of enabling the specification of scientific methods assuming a stream-based conceptual model that allows users to define abstract, machine-agnostic, fine-grained data-intensive workflows. The `dispel4py` system implements many of the original Dispel concepts, but presents them as Python constructs.

Bobolang, a relative new workflow system based on data streaming, has linguistic forms based on C++ and focuses on automatic parallelisation [42]. It also supports multiple inputs and outputs, meaning that a single node can have as many inputs or outputs as a user requires. Currently, it does not support automatic mapping to different DCIs.

A data-streaming system, such as `dispel4py`, typically passes small data units along its streams compared with the volume of each data unit (file) passed between stages in task-oriented workflows. In principle, at least, the units passed in a data stream can be arbitrarily large, *e.g.* multi-dimensional arrays denoting successive states in a finite element model (FEM) of a dynamic system [43], though they are typically time-stamped tuples often encoding time and a small number of scalars in a highly compressed form. The data-streaming model can also pass file names in its data units and thereby draw on the facilities task-oriented systems use.

The optimisation of data-streaming workflows has been investigated recently [44, 45, 46, 47]. This has addressed the substantial challenges of task distribution, data dependencies, and inter-task data movement at large scale, since they can become a bottleneck, as Wozniak reports [48].

Mechanisms to improve sharing and reuse of workflows have proved important in the task-oriented context, *e.g.* `myExperiment` [49], `Wf4Ever` [50], and `Neuroimaging workflow reuse` [51]. It is unclear whether these will need extension to accommodate data-streaming workflows [52]. For example, the properties of data handled, *i.e.* where very large volumes of simulation output data, large curated repositories of archived data *e.g.* many seismic traces over

long periods, or data where the owner asks users not to make copies, precludes simple bundling of data with workflows to ensure reproducibility. Whereas this is appropriate for computationally intensive task-oriented workflows [53].

3 Vision and `dispel4py` concepts

The `dispel4py` data-streaming workflow library is part of a greater vision for the future of formalising and automating both data-intensive and computational scientific methods. We posit that workflow tools and languages will play increasingly significant roles due to their inherent modularity, user-friendly properties, accommodation of the full range from rapid prototyping to optimised production, and intuitive visualisation properties – graphs appear to be a natural way to visualise logical sequences. Data streaming is a technological discipline and abstraction which will have a significant impact in the ways scientists think and carry out their computational and data-analysis tasks, due to its natural divide-and-conquer properties. Easy-to-use data-streaming workflow technologies, such as `dispel4py`, allow scientists to express their requirements in abstractions closer to their needs and further from implementation and infrastructural details.

The Dispel workflow specification language for data-intensive applications [41] was designed with the above goals in mind. The `dispel4py` system built on this and aligned more closely with the requirements of scientists than of infrastructure providers. In addition to its modelling and programming constructs, `dispel4py` needs to be part of an eScience infrastructure that facilitates sharing and collaboration. It does this via registries of workflow and other components³. The registry and collections of observations of previous enactments provide input to optimising execution on dynamically changing environments. The registry also supports strong data provenance by identifying workflows and sub-workflows. These identities are used by tools for exploring provenance and for validating and replicating scientific results [54]. The tools present intuitive and helpful user interfaces [55].

In the vision sketched above `dispel4py` has a central role as a user-friendly, streaming workflow library and engine which enables scientists to describe data-intensive applications and to execute them in a scalable manner on a variety of platforms. We now present a summary of the main `dispel4py` concepts and terminology:

- A processing element (PE) is a computational activity, corresponding to a stage in a scientific method or a data-transforming operator, that encapsulates an algorithm or a service. PEs represent the basic computational blocks of any `dispel4py` workflow, at an abstract level – they are instantiated as nodes in a workflow graph. They may be constructed as a Python class, or may be a composite processing element. `dispel4py` offers a variety of base classes for PEs to be extended: `GenericPE`, `IterativePE`, `ConsumerPE`, `SimpleFunctionPE` and `CompositePE`. The primary differences between them are the number of inputs that they accept and how users express their computational activities. `GenericPE` represents the basic interface and accepts a configurable number of inputs and outputs, whereas `IterativePE` declares exactly one input and one output and usually encapsulates a simple iterative computational step such as a filter or a transformation. A `ConsumerPE` has one input and no outputs, representing a leaf in the workflow tree and accordingly, a `ProducerPE` has no inputs and one output and serves as a data producer or root.
- An instance is the executable copy of a PE with its input and output ports that runs in a process as a node in the data-streaming graph. During enactment and prior to execution each PE is translated into one or more instances. Multiple instances may occur because the same action is required in more than one part of the encoded method or to parallelise to increase data throughput.
- A connection streams data from one output of a PE instance to one or more input ports on other PE instances. The rate of data consumption and production depends on the behaviour of the source and destination PEs. Consequently a connection needs to provide adequate buffering. Distributed choreography is thereby achieved: when a buffer is full the data generating processes pauses, and when the buffer is empty the consuming processes suspend themselves. Connections also provide signalling pathways to achieve the first two forms of termination (see Section 1).

³A `dispel4py` reference registry can be found at <https://github.com/iaklampanos/dj-vercereg>

- A composite processing element is a PE that wraps a `dispel4py` sub-workflow. Composite processing elements allow for synthesis of increasingly complex workflows by composing previously defined sub-workflows.
- A partition is a number of PEs wrapped together and executed within the same process. This is a new feature of `dispel4py` that was not included in Dispel. It is used to explicitly co-locate PEs that have relatively low CPU and RAM demands, but high data-flows between them. This corresponds to task-clustering in the task-oriented workflow systems, and will also occur automatically in `dispel4py`, but users like to specify that a group of PEs should normally go together.
- A graph defines the ways in which PEs are connected and hence the paths taken by data, *i.e.* the topology of the workflow. There are no limitations on the type of graphs that can be designed with `dispel4py`. Figure 1 is an example graph involving four PEs. PE-1 produces random words (output-1) and numbers (output-2) as outputs, and sends each output to a different PE, PE-2 and PE-3. PE-2 counts the number of words, and PE-3 calculates the average of the numbers. The output of those PEs are then merged in PE-4, which prints out the number of words and the final average. More graph examples can be found in the `dispel4py` documentation⁴.
- A grouping specifies for an input connection the communication pattern between PEs. There are four different groupings available: shuffle, group-by, one-to-all, all-to-one. Each grouping arranges that there are a set of receiving PE instances. The shuffle grouping randomly distributes data units to the instances, whereas group by ensures that each value that occurs in the specified elements of each data unit is received by the same instance. In this case, the effect is that an instance receives all of the data units with its particular value. one to all means that all PE instances send copies of their output data to all the connected instances and all to one means that all data is received by a single instance.

To construct `dispel4py` workflows, users only have to use available PEs from the `dispel4py` libraries and registry, or implement PEs (in Python) if they require new ones. They connect them as they desire in graphs. We show the code for creating the Split and Merge `dispel4py` workflow represented in Figure 1. In the code listing below, we assume that the logic within PEs is already implemented.

```
1 from dispel4py.workflow_graph import WorkflowGraph
2
3 pe1 = WordNumber() # create instances of the PEs
4 pe2 = CountWord()
5 pe3 = Average()
6 pe4 = Reduce()
7
8 graph = WorkflowGraph() # start a new graph
9 graph.connect(pe1, 'output1', pe2, 'input') # establish connections between instances
10 graph.connect(pe1, 'output2', pe3, 'input') # along which data units flow
11 graph.connect(pe2, 'output', pe4, 'input1')
12 graph.connect(pe3, 'output', pe4, 'input2')
```

Listing 1: Python script defining split-and-merge `dispel4py` graph.

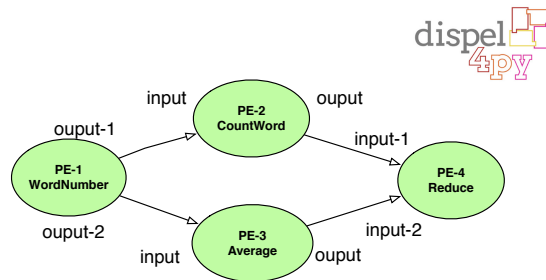


Figure 1: Split and Merge `dispel4py` workflow generated by the Python script above.

⁴http://dispel4py.org/api/dispel4py.examples.graph_testing.html

Once the `dispel4py` workflow has been built, it can be automatically executed in several distributed computing infrastructures thanks to the mappings that are explained in the next section. Hence `dispel4py` workflows can be executed anywhere Python is available and without any adaptation by users. If a `dispel4py` workflow is executed using MPI or Multiprocess with several processes, then the processes are equally distributed among the PEs, except for the first PE, which is assigned one process by default. If users want to change the default topology, they only need to write the following instruction in the script before connecting their PEs in the graphs.

```
<name_of_PE>. numprocesses = Number
```

If the number of processes is not specified the enactment system attempts to allocate an optimal number.

4 `dispel4py` mappings

One of `dispel4py`'s strengths is a level of abstraction that allows the creation and refinement of workflows without knowledge of the hardware or middleware context in which they will be executed. Users can therefore focus on designing their workflows at an abstract level, describing actions, input and output streams, and how they are connected. The `dispel4py` system then maps these descriptions to the selected enactment platforms. Since the abstract workflows are independent from the underlying communication mechanism these workflows are portable among different computing resources without any migration cost imposed on users, *i.e.* users do not need to make any changes to run in a different context.

The `dispel4py` system currently implements mappings for Apache Storm, MPI and Multiprocessing DCIs, as well as a Sequential mapping for development and small applications. However, for understanding them better, we need first to pay attention (see Figure 2) to the main modules that compose `dispel4py`:

- The `core` module defines the base class `GenericPE` which all PE implementations must extend.
- The `base` module makes available the utility PE classes described in the previous section, notably `IterativePE`, `ConsumerPE` and `CompositePE`.
- The module `workflow_graph` constructs the graph representation, building on the Python package `networkx`⁵. It also provides other utilities, for example visualisation of the `dispel4py` graph using `Graphviz` dot⁶.
- The mapping modules `mpi_process` (MPI), `multi_process` (Multiprocessing) and `simple_process` for sequential mapping are described in the following subsections. They are based on the shared `processor` module containing methods applicable to all platforms, for example `create_partitioned` method creates the partitions to group the workflow's PEs), `assign_and_connect` method reads the number of processes to run the workflow and then assigns the instances to execute each PE and `load_graph_and_inputs` method loads the workflow (graph) and its initial inputs. The `processor` is responsible for calling the appropriate mapping module based on a user's command-line argument. Each mapping module has its own implementation for creating the PE's instances and for streaming data from one PE instance to another (*e.g.* MPI asynchronous calls for MPI mapping or multiprocessing. Queues objects for Multiprocessing mapping).
- The Apache Storm mapping has its own package with various modules that translate a `dispel4py` workflow to a Storm topology and submit it to a cluster.

Descriptions of Sequential, Multiprocessing, Apache Storm, MPI, and Spark mappings follow.

⁵<https://networkx.github.io/>

⁶<http://www.graphviz.org/>

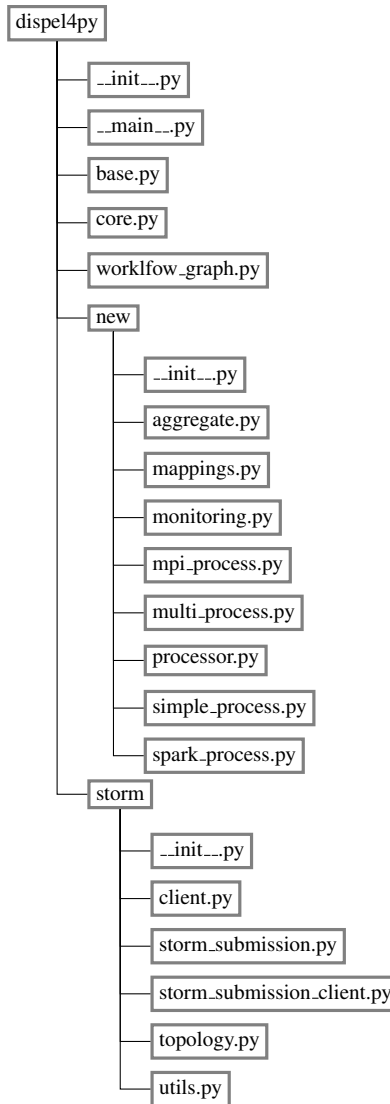


Figure 2: The file structure of the `dispel4py` project

4.1 Sequential mode

The sequential mode (simple) is a simple standalone mode that is ideal for testing workflow execution during development. It executes a `dispel4py` graph in sequence within a single process without optimisation. When executing a `dispel4py` graph in sequential mode, the dependencies of each PE are determined and the PEs in the graph are executed in a depth-first fashion starting from the roots of the graph (data sources). The source PEs process a number of iterations as specified by the user. All data is processed and messages are passed in-memory within a single process.

```
dispel4py simple split_and_merge
```

4.2 Multiprocessing

The Python library `multiprocessing` is a package that supports spawning subprocesses to leverage multicore shared-memory resources. It is available as part of standard Python distributions on many platforms without further dependencies, and hence is ideal for small jobs on desktop machines. The Multiprocessing mapping of `dispel4py`

creates a pool of processes and assigns each PE instance to its own process. Messages are passed between PEs using multiprocessing.Queue objects.

As in the MPI mapping, `dispel4py` maps PEs to a collection of processes. Each PE instance reads from its own private input queue on which its input data units arrive. Each data unit triggers the execution of the `process()` method which may or may not produce data units to be output. Output from a PE is distributed to the connected PEs depending on the grouping pattern that the destination PE has requested. The distribution of data is managed by a Communication class for each connection. The default is `ShuffleCommunication` which implements a round-robin pattern; the use case below also uses `GroupByCommunication` which groups the output by certain attributes.

The Multiprocessing mapping also allows partitioning of the graph to support gathering several PEs together in one process. Users can specify partitions of the graph and the mapping distributes these across processes in the same way as single PEs. The following shows the command to execute the Split and Merge `dispel4py` graph, using Multiprocessing mapping:

```
dispel4py multi -n <number processes> split_and_merge
```

4.3 Apache Storm

The `dispel4py` system was initially designed to use Apache Storm. This was motivated by similarities between `dispel4py`'s and Storm's streaming models, and because Storm delivered dynamic scaling and was well proven reliability in the context of Twitter.

Apache Storm executes graphs, called *topologies*, that are like workflows; they consume and process streams of data units when data arrive, typically running continuously until killed. The Storm system handles load balancing and recovers from failures of worker nodes by restarting crucial services. Workers can be added to the cluster at runtime, building on the Apache Zookeeper technology⁷. However, Storm is not normally deployed on HPC resources, on which most large-scale scientific computing runs. Instead, it is normally installed on a dedicated cluster.

The `dispel4py` system maps to Storm by translating its graph description to a Storm topology. As `dispel4py` allows its users to define data types for each PE in a workflow graph, types are deduced and propagated from the data sources throughout the graph when the topology is created. Each Python PE is mapped to either a Storm bolt or spout, depending on whether the PE has inputs (a bolt), i.e. is an internal stage, or is a data source (a spout), i.e. is a point where data flows into the graph from external sources. The data streams in the `dispel4py` graph are mapped to Storm streams. The `dispel4py` PEs may declare how a data stream is partitioned across processing instances. By default these instructions map directly to built-in Storm stream groupings. The source code of all mappings can be found at⁸.

There are two execution modes for Storm: a topology can be executed in local mode using a multi-threaded framework (development and testing), or it can be submitted to a production run. The user chooses the mode when submitting a `dispel4py` graph in Storm. Both modes require the availability of the Storm package on the client machine. The following command submits the Split and Merge `dispel4py` graph (Figure 1) as a Storm topology in local mode or to a remote cluster depending on the `-m` option.

```
dispel4py storm split_and_merge -m <local|remote>
```

4.4 MPI

MPI is a standard, portable message-passing system for parallel programming, whose goals are high performance, scalability and portability [13]. MPI, in contrast to Storm, is very well known and widely supported in HPC environments. For this mapping, `dispel4py` uses `mpi4py`⁹, which is a full-featured Python binding for MPI based on the MPI-2 standard. The `dispel4py` system maps PEs to a collection of MPI processes. Depending on the number of targeted processes, which the user specifies when submitting the mapping, multiple instances of each PE are created to make use of all available processes. Input PEs, i.e. at the root of the `dispel4py` graph, only ever execute in one instance to avoid the generation of duplicate data units.

⁷<http://zookeeper.apache.org>

⁸<https://github.com/dispel4py/dispel4py/>

⁹<http://mpi4py.scipy.org/>

Data units to be shipped along streams are converted into generic pickle-based Python objects and transferred using MPI asynchronous calls. Groupings are mapped to communication patterns, which assign the destination of a stream according to the grouping (*e.g.* shuffle grouping is mapped to a round-robin pattern, for group-by the hash of the data block determines the destination).

To use the MPI mapping, `mpi4py`, and any MPI interface, such as `mpich`¹⁰ or `openmpi`¹¹ need to have been installed. To submit the Split and Merge `dispel4py` graph by using MPI mapping, a user would issue the following command:

```
mpiexec -n <number mpi_processes> dispel4py mpi split_and_merge
```

4.5 Apache Spark

Currently, we are prototyping¹² a new mapping to Apache Spark¹³, which is a popular platform that leverages Hadoop YARN and HDFS taking advantage of many properties such as dynamic scaling and fault tolerance. It has also been used on HPC platforms by distributing Spark worker nodes at runtime to the available processors of a job in an HPC cluster and managing Spark tasks. The Spark mapping is targeted at users who are not familiar with the Hadoop/MapReduce environment but would like to take advantage of the rich libraries and scalability that platform provides. The `dispel4py` system maps to Spark by translating a graph description to PySpark actions and transformations on Spark’s resilient distributed datasets (RDDs). RDDs can be created from any storage source supported by Hadoop, such as text files in HDFS, HBase tables, or Hadoop sequence files. Root PEs in the `dispel4py` graph are mapped to RDD creators, and each PE with inputs is mapped to an action or a transformation of an RDD. At the leaves of the `dispel4py` graph a call to `foreach()` is inserted in order to trigger the execution of a complete pipeline of actions. In the future we envisage mapping a set of reserved PE names (possibly supported by the registry) to available actions and transformations in Spark to take full advantage of the optimizations available on that platform.

```
dispel4py spark split_and_merge
```

5 dispel4py workflows

The following subsections describe `dispel4py` workflows with examples from three domains: Seismology, Astrophysics and Social Computing [56]. Using these we will show how `dispel4py` enables scientists to describe data-intensive applications using a familiar notation, and to execute them in a scalable manner on a variety of platforms without modifying their code.

5.1 Seismic ambient noise cross-correlation

Earthquakes and volcanic eruptions are often preceded or accompanied by changes in the geophysical properties of the Earth, such as seismic wave velocities or event rates. The development of reliable risk assessment methods for these hazards requires real-time analysis of seismic data and truly prospective forecasting and testing to reduce bias. However, potential techniques, including seismic interferometry and earthquake “repeater” analysis, require a large number of waveform cross-correlations, which is computationally intensive, and is particularly challenging in real-time. With `dispel4py` we have developed the *Seismic Ambient Noise Cross-Correlation* workflow (also called the `xcorr` workflow) as part of the VERCE¹⁴ project [57], which preprocesses and cross-correlates traces from several stations in real-time.

Seismic Ambient Noise can be used for surface wave tomography [58]. The first two phases described in this paper have been designed and implemented as a workflow in `dispel4py`. During Phase 1, each continuous time series from a given seismic station (called a “*trace*”), is subject to a series of treatments. The processing of each trace is independent from any other, making this phase embarrassingly parallel (complexity $O(n)$, where n is the number of stations). Phase 2 pairs all of the stations and calculates the cross-correlation for each pair (complexity $O(n^2)$).

¹⁰<http://www.mpich.org/>

¹¹<http://www.open-mpi.org/>

¹²As the Spark mapping is currently a prototype, its evaluation is not available in this paper.

¹³<http://spark.apache.org>

¹⁴<http://www.verce.eu>

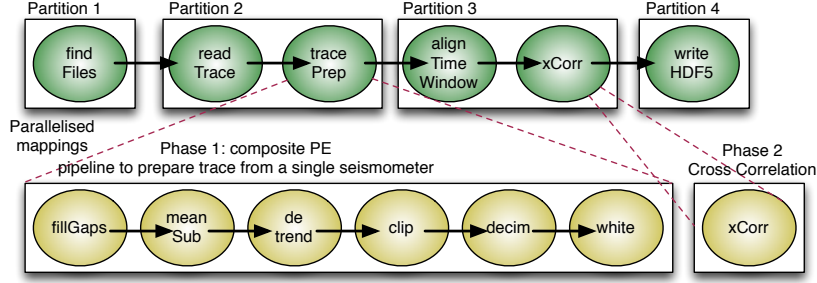


Figure 3: A simplified abstract workflow for seismic cross-correlation using `dispel4py`

Figure 3 shows the `dispel4py` `xcorr` workflow, which has six PEs. Note that the `tracePrep` PE is a compositePE, where data preparation takes place. Each of those PEs, from `decim` to `calc.fft`, performs processing on the data stream.

Raw data is recorded continuously by seismic networks, over periods of a few months for temporary deployments to decades. Each network is composed of hundreds of stations, each of which records three spatial components at sampling rates that range from a few to hundreds of Hz. Raw data volumes range from a few TBs to hundreds of TBs. The main attributes characterising a trace are the name of the network, the station, the component or channel, and the start and end times. Traces are available in several formats, such as miniSEED [59] or SAC¹⁵. They are obtained from public archives, (e.g. EIDA-Orfeus¹⁶ or IRIS¹⁷). Often each file corresponds to a single channel of a single station on a given network for a single day. The metadata describing the trace are recorded in the header of the file.

The design and formalisation of the scientific method (the composition PE and the cross-correlation function) can be easily modified by seismologists to meet revised goals, by changing the order of PEs and their parameters, or by altering or adding PEs, coded as simple Python functions. They can draw on Python’s rich scientific libraries, or those specific to seismology, such as ObsPy [60], wrap legacy code using Python’s embedding of other languages, or call on experts to develop advanced functions. The scientists do not worry about how to parallelise the workflow nor choose on which platform it will run because `dispel4py` performs the parallelisation automatically. The source code of the PE implementations in the example above is 350 lines of Python, while the definition of the graph is only 60 lines long. The modularity and abstraction level of the PEs enhances reusability, allowing scientists to compose new workflow graphs using their own or other scientists’ previously written and shared PEs.

Two test loads were used for measurements: *a*) cross-correlation of two seismic traces, using data accumulated over 90 and 180 days, denoted as X_2^{90d} and X_2^{180d} ; and *b*) cross-correlation of up to 1000 seismic traces, using a sampling period of 1 hour, denoted as X_{1000}^{1h} .

The input data size for X_2^{180d} is 3.5GB, and the size of the results is 25MB (X_2^{90d}) and 51MB (X_2^{180d}). The input data for X_{1000}^{1h} was 150MB producing 39GB of results.

5.2 Astrophysics: Internal Extinction of Galaxies

One of the current challenges in Astronomy is the efficient exploitation of the huge volume of data currently available. The scientific workflows are becoming a useful tool to approach this challenge since on the one hand they enable the scientist to share and reuse their scientific methods, thereby avoiding duplication and improving reproducibility, and on the other hand empowering scientists to take the most of the available computational and data infrastructures, without being distracted or deterred by the complexity of the target technology.

The Virtual Observatory (VO)¹⁸ is a network of tools and services implementing the standards published by the International Virtual Observatory Alliance (IVOA)¹⁹ to provide transparent access to multiple archives of astronomical data. The *ASTRONET Infrastructure Roadmap* [61] stated that the development of the VO was expected to merge

¹⁵http://www.iris.edu/files/sac-manual/manual/file_format.html

¹⁶<http://www.orfeus-eu.org>

¹⁷<http://www.iris.edu/hq>

¹⁸Not to be confused with VO meaning Virtual Organisation.

¹⁹<http://www.ivoa.es>

into the standard practices for the delivery of astronomical data by 2008. IVOA confirmed in 2014 that this was achieved and that the architecture of the Virtual Observatory (VO) system was now well established with a set of core standards²⁰. VO services are used in Astronomy for data sharing and serve as the main data access point for astronomical workflows in many cases. This is the case of the workflow presented here, which calculates the *Internal Extinction of the Galaxies* from the AMIGA catalogue²¹. This property represents the dust extinction within the galaxies and is a correction coefficient needed to calculate the optical luminosity of a galaxy. The implementation of this workflow (also called `int_ext` workflow) with `dispel4py` shows that it can use VO services, as a first step to supporting more complex workflows in this field.

Figure 4 shows the `dispel4py` `int_ext` workflow with four PEs. The first PE reads an input file (`coordinates.txt` size 19KB) that contains the right ascension (Ra) and declination (Dec) values for 1051 galaxies. The second PE queries a VO service for each galaxy in the input file using the Ra and Dec values. The results of these queries are filtered by `filterColumns` PE, which selects only the values that correspond to the morphological type (Mtype) and the apparent flattening (`logr25`) features of the galaxies. Their internal extinction is calculated by the `internalExtinction` PE.

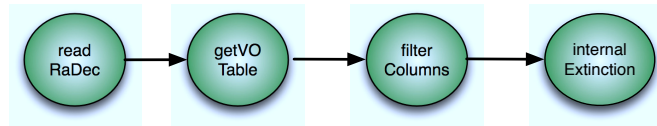


Figure 4: Workflow for calculating the internal extinction of galaxies using `dispel4py`

The `int_ext` workflow was previously implemented using Taverna, which, as well as the VO service query and the python script, includes two services belonging to the Astrotaverna plugin [62]²² to manage the data format of VOTables. For this work, we re-implemented it by using `dispel4py` and compared against the Taverna's implementation.

5.3 Social Computing: Twitter Sentiment Analysis

Today, social media such as *Facebook* and *Twitter* are driving new forms of social interaction, dialogue, exchange and collaboration. It enables users to exchange ideas, post updates and comments, or participate in activities and events while sharing their views and interests. Researchers can use this data to study language variation and change, to detect various real-world events, or to perform text mining and sentiment analysis. However, the amount and variety of social media data is huge and grows at increasingly high rates every year. Therefore, tools that enable scientists to process and analyse large-scale social data are needed.

With over 500 million tweets per day²³ and 240 million active users who post opinions about people, events, products or services, *Twitter* has become an interesting resource for sentiment analysis [63]. In this case study, we investigate the benefits of `dispel4py` for analysing *Twitter* data by implementing a basic *Sentiment Analysis* workflow, called `sentiment`. `dispel4py` has been specifically designed for implementing streaming and data-intensive workflows, which fits the data stream model followed by *Twitter*. The aim of sentiment analysis (also referred to as opinion mining) is to determine the attitude of the author with respect to the subject of the text, which is typically quantified in a polarity: positive, negative or neutral. There are two main approaches [64] to the problem, the lexical approach and the machine learning approach. The lexical approach uses lexicon-based methods that rely on emotional dictionaries. Emotional lexical items from the dictionary are searched in the text, their sentiment weights are calculated, and some aggregated weight function is applied to compute a final score. In the machine learning approach, the task of the sentiment analysis algorithm is reduced to the common problem of text classification and can be solved by training a classifier on a labeled text collection.

We focus on how `dispel4py` manages the frequency of tweets for performing two basic sentiment analyses by using the lexical approach and by applying the AFINN and SentiWordNet lexicons [65]. AFINN [66] is a dataset of

²⁰http://www.astronet-eu.org/IMG/pdf/ASTRONET_IR_final_pdf_1.pdf

²¹<http://amiga.iaa.es>

²²<http://myexperiment.org/workflows/2920.html>

²³<http://www.internetlivestats.com/twitter-statistics/>

2477 English words and phrases that are frequently used in microblogging services and each word is associated with an integer between minus five (negative) to plus five (positive). SentiWordNet (SWN3) [67]²⁴ is a fine-grained, exhaustive lexicon with 155,287 English words and 117,659 synsets, which are sets of synonyms that represent cognitive synonyms. It distinguishes between nouns, verbs, adjectives and adverbs, and each synset is automatically annotated according to positivity, negativity and neutrality.

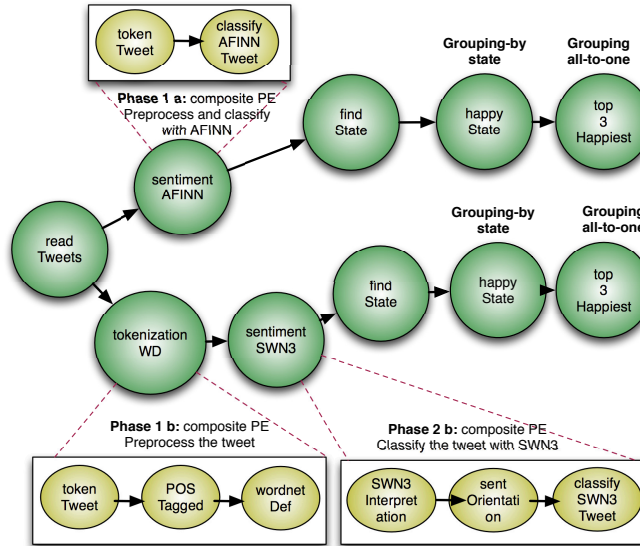


Figure 5: Workflow for calculating *Twitter* sentiment analysis and the top three happiest U.S. states using `dispel4py`.

The original code used for building the sentiment workflow can be found at²⁵. Figure 5 shows the sentiment workflow, which first scans the tweets preprocessing the words they contain, and then classifies each tweet based on the total counts for positive and negative words. As the sentiment workflow applies two analyses, different preprocessing and classification tasks need to be performed. To classify each tweet with the AFINN lexicon (see Phase 1a in Figure 5), the `sentimentAFINN` PE tokenises each tweet “text” word, and then a very rudimentary sentiment score for the tweet is calculated by adding the score of each word. After determining the sentiments of all tweets, they are sent to the `findState` PE, which searches the US state from which the tweet originated, and discards tweets which are not sent from the US. The `HappyState` PE applies a grouping by based on the state and aggregates the sentiment scores of tweets from the same state, which are sent to the `top3Happiest` PE. This PE applies all-to-one grouping and determines which are the top three happiest states.

The sentiment workflow also calculates tweet sentiment in parallel using the SWN3 lexicon. The `tokenizationWD` PE is a composite PE, where tweet tokenisation and tagging takes place (see Phase 1b in Figure 5): the `tokenTweet` PE splits the tweet text into tokens, the `POSTagged` PE produces a part-of-speech (POS) tag as an annotation based on the role of each word (*e.g.* noun, verb, adverb) and the `wordnetDef` PE determines the meaning of each word by selecting the synset that best represents the word in its context. After pre-processing each tweet, the second phase of the analysis is performed by the `sentiment SWN3` composite PE (see Phase 2b in Figure 5): the `SWN3 Interpretation` PE searches the sentiment score associated with each synset in the SWN3 lexicon, the `sentimentOrientation` PE gets the positives, negatives and average scores of each term found in a tweet and the `classifySWN3Tweet` PE determines the sentiment of the tweet. After the classification, the same procedure as before is applied to each tweet, to know which are the three happiest states.

With `dispel4py` we could run the sentiment workflow for computing the top three “happiest” US states and the sentiment analysis results as the tweets are produced. However, to study the performance of the workflow under

²⁴<http://sentiwordnet.isti.cnr.it/>

²⁵https://github.com/linkTDP/BigDataAnalysis_TweetSentiment

different DCIs and mappings, 126,826 tweets (500MB) were downloaded into a file in March 2015, and used as a test set for all the experiments. For this reason, the first PE, readTweets PE, reads each tweet from the file, and streams them out.

6 Evaluation

To evaluate `dispel4py` we performed two types of experiment: *Scalability* and *Performance*. *Scalability* experiments compare the scalability of the `dispel4py` mappings on different DCIs while using the same Seismic Ambient Noise Cross-Correlation workflow and while varying the number of cores and the input data (X_2^{90d} , X_2^{180d} and X_{1000}^{1h}). *Performance* experiments show the maximum performance for each workflow described in Section 5 using the maximum number of cores available to us for each DCI.

As introduced in Section 4, given a workflow and a number of processes in which to execute it, `dispel4py` automatically scales by creating multiple instances of each PE, with the exception of the Sequential mapping. Input PEs, *i.e.* at the root of the `dispel4py` graph, only ever execute in one instance to avoid the generation of duplicate data units. However, for the rest of PEs, `dispel4py` creates as many instances as the number of processes divided by the number of PEs. `dispel4py` includes also a mechanism to override the number of instances per PE. The number of processes for executing a workflow can not be lower than the number of PEs; an exception is raised in such a situation.

6.1 Experiments

Five platforms have been used for our experiments: Terracorelator, the SuperMUC cluster (LRZ – Munich), Amazon EC2, the Open Science Data Cloud cluster (OSDC sullivan), and the Edinburgh Data-Intensive Machine (EDIM1); these are described below and summarised in Table 6.

The Terracorelator²⁶ is configured for massive data assimilation in environmental sciences at the University of Edinburgh. The machine has four nodes, each with 32 cores. Two nodes are Dell R910 servers with 4 Intel Xeon E7-4830 8 processors, each with 2TB RAM, 12TB SAS storage and 8Gbps fibre-channel to storage arrays. We used one 32-core node for our measurements.

SuperMUC²⁷ is a supercomputer at the Leibniz Supercomputing Centre (LRZ) in Munich, with 155,656 processor cores in 9,400 nodes. SuperMUC has greater than 300 TB RAM and infiniband FDR10 interconnect. SuperMUC is based on the Intel Xeon architecture consisting of 18 Thin Node Islands and one Fat Node Island. We used two Thin (Sandy Bridge) Nodes, each with 16 cores and 32 GB of memory, for the measurements.

On the Amazon EC2 the Storm deployment used an 18-worker node setup. We chose Amazon’s T2.medium instances²⁸, provisioned with 2 vCPUs and 4GB of RAM. Amazon instances are built on Intel Xeon processors operating at 2.5GHz, with Turbo up to 3.3GHz. The MPI measurements on Amazon EC2 used the same resources.

OSDC sullivan²⁹ is an OpenStack cluster with GlusterFS. Each node is an m1.xlarge with 8 vCPUS, 20GB VM disk, and 16GB RAM. Four nodes were used, providing 32 cores, for our measurements.

EDIM1³⁰ is an Open Nebula³¹ linux cloud designed for data-intensive workloads. Backend nodes use mini ITX motherboards with low-powered Intel Atom processors with 3x 2TB SATA disk and 1x 250GB SSD per backend node. Our experiments on EDIM1 used a 15-node Apache Storm cluster, on a one-to-one setup with the hosting nodes. Each VM in our cluster had 4 virtual cores – using the processor’s hyperthreading mode, 3GB of RAM and 2.1TB of disk space on 3 local disks. Data were streamed to and from a virtual cluster with the same specifications and number of nodes, implementing Hadoop HDFS.

As Storm could not be installed on all resources the set of measurements vary with target DCI as shown in Table 1.

²⁶<http://gtr.rcuk.ac.uk/project/F8C52878-0385-42E1-820D-D0463968B3C0>

²⁷<http://www.lrz.de/services/compute/supermuc/systemdescription/>

²⁸<http://aws.amazon.com/ec2/instance-types/>

²⁹<https://www.opensciencedatacloud.org/>

³⁰<https://www.wiki.ed.ac.uk/display/DIRC>

³¹<http://opennebula.org>

	Measurement platform				
	Terracorelator	SuperMUC	Amazon EC2	OSDC sullivan	EDIM1
DCI type	shared-memory	cluster	cloud	cloud	cloud
Enactment systems	MPI, multi	MPI, multi	MPI, Storm, multi	MPI, multi	MPI, Storm, multi
Nodes	1	16	18	4	14
Cores per Node	32	16	2	8	4
Total Cores	32	256	36	32	14
Memory	2,048 GB	32 GB	4 GB	20 GB	3 GB
Workflows	xcorr, int_ext, sentiment	xcorr, sentiment	xcorr	xcorr	xcorr, int_ext, sentiment

Table 1: Coverage of target computational and data infrastructures

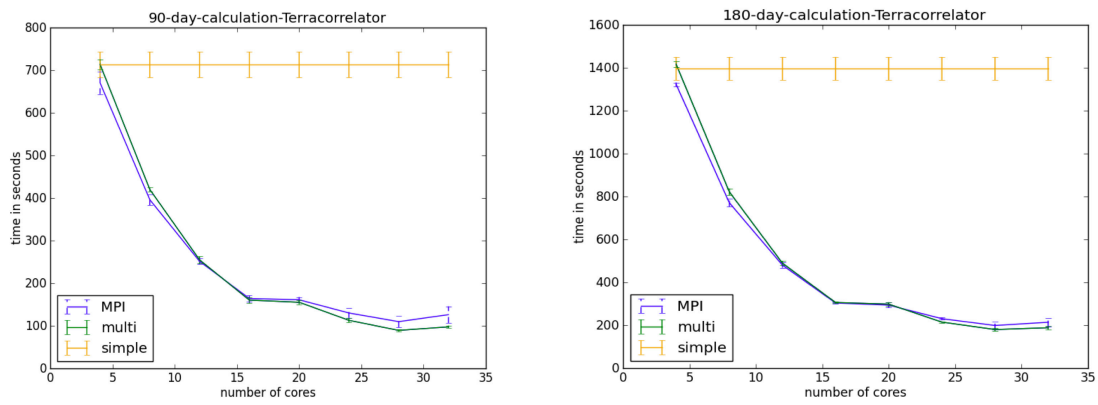


Figure 6: Cross-correlation experiments running `dispel4py` on the Terracorelator cluster.

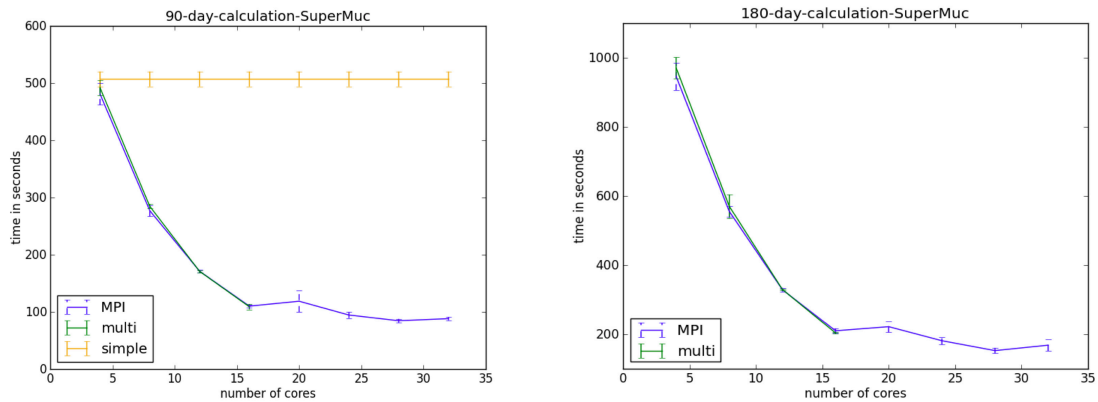


Figure 7: Cross-correlation experiments running `dispel4py` on part of the SuperMUC cluster.

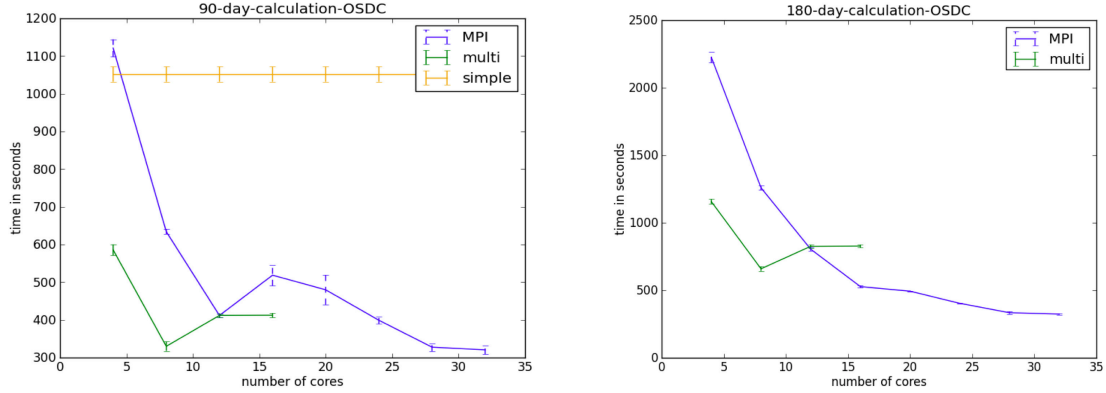


Figure 8: Cross-correlation experiments running `dispel4py` on an OSDC cluster.

6.2 Scalability experiments

For each measurement we varied the number of cores, except for simple mapping, which always uses one core to run a `dispel4py` workflow. In Table 2 we show a summary of the Scalability experiments that we have performed with different testbeds, DCI and mappings.

Load	Measurement platform		
	Terracorelator	SuperMUC	OSDC sullivan
X_2^{180d}	MPI, multiprocessing & simple	MPI, & multiprocessing	MPI, & multiprocessing
X_{1000}^{1h}		MPI	

Table 2: Coverage of Scalability experiments by using `xcorr` workflow

Firstly, we present the scalability results for both X_2^{90d} and X_2^{180d} . Figure 6 (Terracorelator) shows that MPI and Multiprocess mappings scale well when the number of cores is increased in both cases (X_2^{90d} and X_2^{180d}). As the Terracorelator is a shared memory machine, the Multiprocess mapping slightly outperforms MPI.

Figure 7 shows that the MPI and the Multiprocess mappings scale well on SuperMUC, which is very fast, so our mappings perform extremely well. The MPI implementation used is optimised to a degree that it performs as fast as the multiprocessing library within shared memory. As the number of cores per node is 16, we only tested the Multiprocess mapping up to that number, because as we have shown in Figure 8, that this mapping does not improve when there are more processes than cores.

Figure 8 (OSDC cloud) shows that the Multiprocess mapping scales for 8 cores, but then levels off for more as it only has 8 cores per node. However, for the MPI mapping, it scales well for X_2^{180d} , but shows some variation for X_2^{90d} , probably due to the increase of messages for the same input data.

The sequential mapping simple keeps all of the intermediate data in memory and does not make use of multiple cores, which explains its constant performance regardless of the number of cores allocated. As an HPC platform, SuperMUC shows better performance than the others for simple. Only Terracorelator had sufficient RAM per node for X_2^{180d} using the simple mode.

Finally, we present the scalability results for the X_{1000}^{1h} . The number of cross-correlations for this use case is $(1000 \times 999) / 2 = 499500$. The measurements on SuperMUC with 16, 32, 64, 128, and 256 cores (which means 1, 2, 4, 8 and 16 nodes), are shown in Figure 9. They demonstrate the effectiveness of scalability for those experiments, showing that the performance of *MPI* mapping gains by increasing the number of cores and nodes.

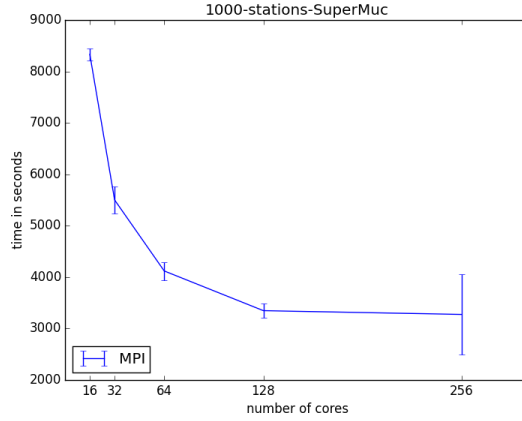


Figure 9: dispel4py Cross-correlation of 1000 stations by using SuperMUC machine and MPI mapping.

6.3 Performance experiments

6.3.1 Performance: *Seismic Ambient Noise Cross-Correlation*

To obtain an exhaustive performance evaluation of dispel4py’s parallel mappings (MPI, multi, and Storm), we used the X_{1000}^{1h} use case on three DCIs, which differ significantly, while using two mappings for each platform. SuperMUC was chosen because it offers a high-level of computational power from 256 cores (16 nodes with 16 cores per node) using the MPI mapping. Terracorelator was selected because it is an example of a shared memory (SMP) DCI, allowing us to test Multi and MPI mappings with up to 32 cores. For popularity, flexibility and freedom to tweak the environment with our needs, we chose Amazon EC2 Cloud and we installed Storm and MPI enactment systems. Note, that the Storm mapping has not been tested on the Terracorelator or SuperMUC DCI, because that would have required us to setup a Storm Cluster on Grid Engine based clusters, which was beyond our rights on both platforms. We included EDIM1, because we have a better control of this DCI in terms of exclusive use, and we had the same freedom as for Amazon EC2 for testing Storm and MPI. However, the resources (processor and network speed) that EDIM1 offers are the weakest.

The measurements on SuperMUC, Terracorelator, Amazon EC2, and EDIM1 have been performed with the maximum number of cores available to us in each DCI: 256 cores for SuperMUC, 32 cores for Terracorelator, 36 cores for Amazon EC2, and 14 cores for EDIM1, because we wanted to evaluate the performance of each mapping under the best conditions for each DCI.

Measurements were run several times for each mapping and DCI, and the results reported in Table 3 are the average, except for Amazon EC2, the measures for which are shown as the fastest, because the EC2 performance suffers from variations ($>$ a factor of 5) which depends on external factors [68] for our solution (e.g. instance, network and CPU).

The results show that the performance for X_{1000}^{1h} (see Table 3) not only depends on which DCI is selected for running the application, but also on which mapping is chosen. For example, the best results in terms of performance were achieved on the SuperMUC machine with MPI followed by the Terracorelator machine with both MPI and multi mappings. The Storm mapping has proved to be the least suitable in terms of performance (see Table 3) for this use case on both of the DCI where it has been tested. However, it is the best mapping in terms of fault-tolerance, for any use case and DCI. Storm offers auto fault recovery and reliability, but as a trade-off, those features make it the slowest mapping. For example, if an application submitted with MPI or multi mapping fails at any point (e.g. an operation causing an invalid floating point number), then the whole application will crash immediately. But, with the Storm mapping, it will recover from the error and continue running the application. Finally, the difference in times between EC2 and EDIM1 are due the EDIM1 resource limitations: fewer cores, poorer processors, and lowest bandwidth network.

To illustrate the way a scientist would use Simple_process to develop a workflow for X_{1000}^{1h} we obtained timings for

Mode	Measurement platform			
	Terracorrelator	Amazon EC2	EDIM1	SuperMUC
MPI	3,066	16,863	38,657	1,093
multi	3,144			
Storm		27,899	120,077	

Table 3: Elapsed time (in seconds) for X_{1000}^{1h} on four DCI using the maximum number of cores available

X_5^{1h} ; these are 88 seconds by a Mac OS X 10.9.5 laptop, with processor 1.7GHz Intel Core i5 and 8GB RAM using release 2.7 of the Python system³².

6.3.2 Performance: *Internal Extinction of Galaxies*

Initially, we compared the time-to-complete for both implementations (Taverna vs dispel4py), performing a set of executions using the same desktop machine, with 4 GB RAM, an Intel Core 2 Duo 2.66GHz processor, and ensuring the same network conditions, checking that the VO service is running, and executing them in the same time slot. The number of jobs executed concurrently was set to 10 in the Taverna workflow, since after several tests, we verified this was its optimal configuration. dispel4py was configured to use the multi mapping and 4 processes. The difference in elapsed time is considerable. While the Taverna execution takes approximately 9.5 minutes, dispel4py takes 1.7 minutes.

Mode	Measurement platform	
	Terracorrelator	EDIM1
MPI	32	96
multi	14	101
Storm		30

Table 4: Elapsed times (seconds) for 1,050 galaxies on two DCIs with the maximum number of cores available

Further evaluations were performed using the Terracorrelator and EDIM1 DCIs, and the results show (see Table 4) that the lowest elapsed time for this workflow was achieved using the multi mapping on the Terracorrelator, followed by Storm on EDIM1. For those evaluations we used the maximum number of cores available in each DCI (see Table 1). The performance differences for the MPI and multi mappings between Terracorrelator and EDIM are due to the number and features of the cores available in each DCI. We used 14 cores for the MPI mapping and 4 cores for the multi mapping on EDIM1, and 32 cores for both mappings on the Terracorrelator.

6.3.3 Performance: *Twitter Sentiment Analysis*

The results shown in Table 5 demonstrate that dispel4py is able to map to diverse DCIs and enactment systems, adapting automatically to their variations, and show that the performance depends on the DCI selected and that the same use case can run faster or slower depending on the selection of DCI and dispel4py mapping made.

Mode	Measurement platform		
	Terracorrelator	EDIM1	SuperMUC
MPI	925	32,396	2,058
multi	971		3,955

Table 5: Elapsed times (seconds) for 126,826 tweets on three DCIs with the maximum number of cores available

³²When comparing this with times in Table 3 note that correlation is of $O(n^2)$, where n is the number of sources (subscript in the notation X_5^{1h}).

6.4 Analysis of measurements

The major features of the measured results are summarized in Table 6.

Load	Measurement platform					
	Mode	Terracorelator	SuperMUC	Amazon EC2	OSDC sullivan	EDIM1
X_2^{180d}	simple	1,420				
	MPI	242	173		613	
	multi	218	203		325	
X_{1000}^{1h}	MPI	3,066	1,093	16,863		38,657
	multi	3,144				
	Storm			27,898		120,077
int_ext	MPI	32				96
	multi	14				101
	Storm					30
twitter	MPI	952	2,058			32,396
	multi	971	3,955			

Table 6: Highlights as best average elapsed times for various loads on multiple DCIs

Machine	X_2^{90d}	X_2^{180d}
Terracorelator	0.44	0.52
SuperMUC	0.67	0.64
OSDC	0.43	0.84

Table 7: Parallelization efficiency values for MPI mapping for two sample loads on three DCI.

To assess `dispel4py`'s automatic parallelisation, we calculated the efficiency of the MPI mapping by using the `xcorr` workflow and assessed its parallelisation efficiency using Equation (1) below, as this is an established method in HPC for measuring scalability of an application. As shown in Table 7, for large datasets the efficiency is at over 40% on all platforms.

$$\frac{\text{Time_4processes}}{\text{Time_32processes} * \frac{32}{4}} \quad (1)$$

The results overall show that: *a)* the *same* `dispel4py` workflow can be used unchanged with different mappings, *b)* the scalability achieved demonstrates the power of data streaming for data-intensive workloads, *c)* that the `dispel4py` Python library provides access to this power for scientists, both when they are developing and when they are running in production mode their automated scientific methods, and *d)* mapping to different target DCIs is essential to handle the variety of workloads—exploiting effectively the features of the target DCIs.

The strategy of depending solely on the Python environment during development and early tests pays off because users can install this on their computer very easily and without the need for technical help. This effectively lowers the intellectual barrier to getting started, particularly for those already adept and using Python. Though the Python information is well crafted and the Python community very helpful if a would be `dispel4py` user is not familiar with Python. The automated mapping to other target computing infrastructures smooths the path to more demanding evaluations and eventual production deployment. Hence the application of innovations developed in `dispel4py` is accelerated and can be achieved by practitioners who don't have local experts to solve system issues and to optimize their methods for particular target computing infrastructures. In most cases those target infrastructures will be on shared clusters. Consequently, the data-intensive frameworks and libraries will have to be set up by the system's administrators to comply with security policies.

The present repertoire of supported mappings (with Apache Spark being prototyped) satisfies a large number of applications. The current mappings are remarkably efficient even though they do not analyze past performance to estimate costs more accurately. Such an upgrade to the mappings is also being prototyped. The strategy of avoiding

(disk) IO clearly pays off in contexts where fast inter-process communication is well supported (in memory or fast interconnect). That gain is lost when, in contexts such as Storm, data is being preserved for recovery. Coupling such data preservation for recovery into the abstract graph could reduce this effect by being selective and strategic in the choice of locations for recovery – trading potential work lost against recovery overhead. Today, it is possible for the author of a `dispel4py` workflow to do this, but it requires care and effort. A PE library and a tool that supported such recovery strategies would be worthwhile, and the graphs produced could then be mapped to the highly developed frameworks for data-intensive work, such as Storm and Spark. This would get the best of both worlds.

7 Conclusions and future work

Section 1 identified three demanding requirements that should be met by `dispel4py`, a novel Python library for automating data-intensive research methods. We have demonstrated that all three requirements are met. The users of `dispel4py` have been able to express their computations and data handling as fine-grained abstract workflows. They have been able to use development environments, and tools such as `iPython` to create and refine sophisticated data-intensive methods. They have been able to complete this work themselves or integrate developments produced by other experts via the standard Python library mechanisms. The automatic mapping of their workflows *without modification* to a wide range of computing and data infrastructures empowers researchers with smooth transitions between development and production. This is achieved because the workflow *source definition* is unchanged. As a consequence transitions from the lightweight development context are not delayed waiting for expert help to insert optimizations and details specific to the target, the user just submits the workflow to a different target. Similarly, if a user retrieves a copy of a production workflow to refine a method or develop a related method, that user is not confused by those inserted details and does not need to reverse the changes.

We argue that data-streaming has long-term value in lightweight coupling of the stages of research methods, in handling live data streams, and in achieving high-performance data-intensive processing. Three realistic scenarios were illustrated from the fields of seismology, astrophysics and social computation. These were used to measure the performance and scalability achieved when `dispel4py` workflows are mapped to the MPI, Multiprocessing, Storm and Sequential modes running on five different distributed computing infrastructures. It is clear that the underlying differences in technology are exploited effectively and that impressive speedups and delivered performance is achieved. Table 6 illustrates this well, showing the best performance achieved on each target platform with different data-intensive frameworks. Significant differences appear. Some are explained by the properties of the underlying hardware. But the TerraCorrelator, designed for data-intensive work with moderate cost and energy consumption compared with SuperMUC, shows consistently reasonable elapsed times, outperforming SuperMUC in some cases. The target data-intensive framework also has a significant effect, with Storm significantly slower than MPI on the two infrastructures on which we measured them both. User communities will often choose a platform because of their application domain’s shared provision, or because they have entitlement on their project’s or institution’s resources. The efficient accommodation of multiple target mappings means that their needs and constraints can usually be met quite easily.

The next stages of the `dispel4py` open-source project’s development will include: *a)* providing a registry system to assist in the description and sharing of PEs and re-usable workflow fragments, *b)* developing additional diagnostic tools, including graph visualisation and user-controlled monitoring, *c)* expanding the existing system of provenance collecting and provenance-driven tools, *d)* developing a planner that can select the best target DCIs and enactment modes automatically, building on systematically garnered and analysed data about previous enactments, and *e)* extending the community of developers and users to improve `dispel4py`’s future sustainability. We seek to deploy and evaluate `dispel4py` in a wide range of scientific and commercial domains. It is an open source project and we would welcome collaborators in steering its development. Our aim will remain delivering products, tools and technologies, to practitioners in many application disciplines to empower them to develop and conduct their own data-intensive research. We will be happy to help but we should not be needed.

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