

Gene expression data analysis for cancer diagnosis

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to which an entity belongs is specified at the time of entity creation and cannot be

implemented, such as name, unique identifier, and state. Whereas the name can be freely assigned, the identifier is generated by Aneka, and it represents a globally unique identifier (GUID) in its string form rather than an integer. Properties such as IsBackground, Priority, and IsThreadPoolThread have been provided for interface compatibility but actually do not have any effect on thread scheduling. Other properties concerning the state of the thread, such as IsAlive and IsRunning, exhibit the expected behavior, whereas a slightly different behavior has been implemented for the ThreadState property that is mapped to the State property. The remaining methods of the System.Threading.Thread class (.NET 2.0) are not supported.

Finally, it is important to note differences in thread creation. Local threads implicitly belong to the hosting process and their range of action is limited by the process boundaries. To create local threads it is only necessary to provide a pointer to a method to execute in the form of the ThreadStart or ParameterizedThreadStart delegates. Aneka threads live in the context of a distributed application, and

multiple distributed applications can be managed within a single process; for this reason, thread creation also requires the specification of the reference to the application to which the thread belongs.

Interface compatibility between Aneka threading APIs and the base class library allow quick porting of most of the local multithreaded applications to Aneka by simply replacing the class names and modifying the thread constructors.

Distinction based on Thread life cycle

Since Aneka threads live and execute in a distributed environment, their life cycle is necessarily different from the life cycle of local threads. For this reason, it is not possible to directly map the state values of a local thread to those exposed by Aneka threads. Figure below provides a comparative view of the two life cycles.

The white balloons in the figure indicate states that do not have a corresponding mapping on the other life cycle; the shaded balloons indicate the common states. Moreover, in local threads most of the state transitions are controlled by the developer, who actually triggers the state transition by invoking methods on the thread instance, whereas in Aneka threads, many of the state transitions are controlled by the middleware. As depicted in Figure, Aneka threads exhibit more states than local threads because Aneka threads support file staging and they are scheduled by the middleware, which can queue them for a considerable amount of time. As Aneka supports the reservation of nodes for execution of thread related to a specific application, an explicit state indicating execution failure due to missing reservation credential has been introduced. This occurs when a thread is sent to an execution node in a time window where only nodes with specific reservation credentials can be executed.

An Aneka thread is initially found in the Unstarted state. Once the Start() method is called, the thread transits to the Started state, from which it is possible to move to the StagingIn state if there are files to upload for its execution or directly to the Queued state. If there is any error while uploading files, the thread fails and it ends its execution with the Failed state, which can also be reached for any exception that occurred while invoking Start().

Another outcome might be the Rejected state that occurs if the thread is started with an invalid reservation token. This is a final state and implies execution failure due to lack of rights. Once the thread is in the queue, if there is a free node where to execute it, the middleware moves all the object data and depending files to the remote node and starts its execution, thus changing the state into Running. If the thread generates an exception or does not produce the expected output files, the execution is considered failed and the final state of the thread is set to Failed. If the execution is successful, the final state is set to Completed. If there are output files to retrieve, the thread state is set to StagingOut while files are collected and sent to their final destination, and then it transits to Completed. At any point, if the developer stops the execution of the application or directly calls the Abort() method, the thread is aborted and its final state is set to Aborted.

In most cases, the normal state transition will resemble the one occurring for local threads: Unstarted-[Started]-[Queued]-Running-Completed/Aborted/Failed

a. System.Threading.Thread life cycle.

b. Aneka.Threading.AnekaThread life cycle.

other cases, it might be necessary to implement the ISerializable interface and provide appropriate constructors for the type. This is not a strong limitation, since there are very few cases in which types cannot be defined as serializable. For example, local threads, network connections, and streams are not serializable since they directly access local resources that cannot be implicitly moved onto a different node.

for which the scalar product is defined.

 The number of columns in the first matrix must match the number of rows of the second matrix.

Given these conditions, the resulting matrix will have the number of rows of the first matrix and the number of columns of the second matrix, and each element will be computed as described by the preceding equation.

It is evident that the repetitive operation is the computation of each of the elements of the resulting matrix. These are subject to the same formula, and the computation does not depend on values that have been obtained by the computation of other elements of the resulting matrix. Hence, the problem is embarrassingly parallel, and we can logically organize the multithreaded program in the following steps:

- Define a function that performs the computation of the single element of the resulting matrix by implementing the previous equation.
- Create a double for loop (the first index iterates over the rows of the first matrix and the second over the columns of the second matrix) that spawns a thread to compute the elements of the resulting matrix.
- Join all the threads for completion and compose the resulting matrix.

Functional Decomposition

Functional decomposition is the process of identifying functionally distinct but independent computations. The focus here is on the type of computation rather than on the data manipulated by the computation. This kind of decomposition is less common and does not lead to the creation of many threads, since the different computations that are performed by a single program are limited.

Functional decomposition leads to a natural decomposition of the problem in separate units of work because it does not involve partitioning the dataset, but the separation among them is clearly defined by distinct logic operations. Figure below provides a pictorial view of how decomposition operates and allows parallelization.

composing the images taken from different telescopes or points of view into a coherent image. The toolkit provides several applications for manipulating images and composing them together; some of the applications perform background reprojection, perspective transformation, and brightness and color correction. The workflow depicted here describes the general process for composing a mosaic; the labels on the right describe the different tasks that have to be performed to compose a mosaic. In the case presented in the diagram, a mosaic is composed of seven images. The entire process can take advantage of a distributed infrastructure for its execution, since there are several operations that can be performed in parallel. For each of the image files, the following process has to be performed: image file transfer, reprojection, calculation of the difference, and common plane placement. Therefore, each of the images can be processed in parallel for these tasks. Here is where a distributed infrastructure helps in executing workflows.

There might be another reason for executing workflows on a distributed infrastructure: It might be convenient to move the computation on a specific node because of data locality issues. For example, if an operation needs to access specific resources that are only available on a specific node, that operation cannot be performed elsewhere, whereas the rest of the operations might not have the same requirements. A scientific experiment might involve the use of several problem solving components that might require the use of specific instrumentation; in this case all the tasks that have these constraints need to be executed where the instrumentation is available, thus creating a distributed execution of a process that is not parallel in principle.

among components from the coordination logic that is used to execute workflow. Thus, for the same workflow, Kepler supports different models, such as synchronous and asynchronous models. The workflow specification is expressed using a proprietary XML language.

DAGMan (Directed Acyclic Graph Manager), part of the Condor project, constitutes an extension to the Condor scheduler to handle job interdependencies. Condor finds machines for the execution of programs but does not support the scheduling of jobs in a specific sequence. Therefore, DAGMan acts as a metascheduler for Condor by submitting the jobs to the scheduler in the appropriate order. The input of DAGMan is a simple text file that contains the information about the jobs, pointers to their job submission files, and the dependencies among jobs.

Cloudbus Workflow Management System (WfMS) is a middleware platform built for managing large application workflows on distributed computing platforms such as grids and clouds. It comprises software tools that help end users compose, schedule, execute, and monitor workflow applications through a Web-based portal. The portal provides the capability of uploading workflows or defining new ones with a graphical editor. To execute workflows, WfMS relies on the Gridbus Broker, a grid/cloud resource broker that supports the execution of applications with quality-ofservice (QoS) attributes over a heterogeneous distributed computing infrastructure, including Linux-based clusters, Globus, and Amazon EC2. WfMS uses a proprietary XML language for the specification of workflows.

Offspring has a different perspective, which offers a programming-based approach to developing workflows. Users can develop strategies and plug them into the environment, which will execute them by leveraging a specific distribution engine. The advantage provided by Offspring over other solutions is the ability to define dynamic workflows. This strategy represents a semistructured workflow that can change its behavior at runtime according to the execution of specific tasks. This allows developers to dynamically control the dependencies of tasks at runtime rather than statically defining them. Offspring supports integration with any distributed computing middleware that can manage a simple bag-of-tasks application. It provides a native integration with Aneka and supports a simulated distribution engine for testing strategies during development. Because Offspring allows the definition of workflows in the form of plug-ins, it does not use any XML specification.

Any distributed computing framework that provides support for embarrassingly parallel applications can also support the execution of parameter sweep applications, since the tasks composing the application can be executed independently of each other. The only difference is that the tasks that will be executed are generated by iterating over all the possible and admissible combinations of parameters. This operation can be performed by frameworks natively or tools that are part of the distributed computing middleware. For example, Nimrod/G is natively designed to support the execution of parameter sweep applications, and Aneka provides client-based tools for visually composing a template task, defining parameters, and iterating over all the possible combinations of such parameters.

A plethora of applications fall into this category. Mostly they come from the scientific computing domain: evolutionary optimization algorithms, weather-forecasting models, computational fluid dynamics applications, Monte Carlo methods, and many others. For example, in the case of evolutionary algorithms it is possible to identify the domain of the applications as a combination of the relevant parameters of the algorithm. For genetic algorithms these might be the number of individuals of the population used by the optimizer and the number of generations for which to run the optimizer.

MPI applications

Message Passing Interface (MPI) is a specification for developing parallel programs that communicate by exchanging messages. Compared to earlier models, MPI introduces the constraint of communication that involves MPI tasks that need to run at the same time. MPI has originated as an attempt to create common ground from the several distributed shared memory and messagepassing infrastructures available for distributed computing. Nowadays, MPI has become a de facto standard for developing portable and efficient message-passing HPC applications. Interface specifications have been defined and implemented for C/C11 and Fortran.

MPI provides developers with a set of routines that:

- Manage the distributed environment where MPI programs are executed
- Provide facilities for point-to-point communication
- Provide facilities for group communication
- Provide support for data structure definition and memory allocation
- Provide basic support for synchronization with blocking calls

information elements that is relevant to one or more applications. Datasets are often

maintained in repositories, which are infrastructures supporting the storage, retrieval, and indexing of large amounts of information. To facilitate the classification and search, relevant bits of information, called metadata, are attached to datasets.

Data-intensive computations occur in many application domains. Computational science is one of the most popular ones. People conducting scientific simulations and experiments are often keen to produce, analyze, and process huge volumes of data. Hundreds of gigabytes of data are produced every second by telescopes mapping the sky; the collection of images of the sky easily reaches the scale of petabytes over a year. Bioinformatics applications mine databases that may end up containing terabytes of data. Earthquake simulators process a massive amount of data, which is produced as a result of recording the vibrations of the Earth across the entire globe.

Data-intensive applications not only deal with huge volumes of data but, very often, also exhibit compute-intensive properties. Data-intensive applications handle datasets on the scale of multiple terabytes and petabytes. Datasets are commonly persisted in several formats and distributed across different locations. Such applications process data in multistep analytical pipelines, including transformation and fusion stages. The processing requirements scale almost linearly with the data size, and they can be easily processed in parallel. They also need efficient mechanisms for data management, filtering and fusion, and efficient querying and distribution.

Challenges:

- 1. Scalable algorithms that can search and process massive datasets
- 2. New metadata management technologies that can scale to handle complex, heterogeneous, and distributed data sources
- 3. Advances in high-performance computing platforms aimed at providing a better support for accessing in-memory multiterabyte data structures
- 4. High-performance, highly reliable, petascale distributed file systems
- 5. Data signature-generation techniques for data reduction and rapid processing
- 6. New approaches to software mobility for delivering algorithms that are able to move the computation to where the data are located
- 7. Specialized hybrid interconnection architectures that provide better support for filtering multigigabyte datastreams coming from high-speed networks and scientific instruments
- 8. Flexible and high-performance software integration techniques that facilitate the combination of software modules running on different platforms to quickly form analytical pipelines