

MG7: Configurable and scalable 16S data analysis

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ABSTRACT

As part of the Cambrian explosion of omics data, metagenomics brings to the table a specific, defining trait: its social essence. The *meta* prefix exerts its influence, with multitudes manifesting themselves everywhere; from samples to data analysis, from actors involved to (present and future) applications. Of these dimensions, data analysis is where needs lay further from what current tools provide. Key features are, among others, scalability, reproducibility, data provenance and distribution, process identity and versioning. These are the goals guiding our work in MG7, a 16S metagenomics data analysis system. The basic principle is a new approach to data analysis, where configuration, processes, or data locations are static, type-checked and subject to the standard evolution of a well-maintained software project. Cloud computing, in its Amazon Web Services incarnation, when coupled with these ideas, produces a robust, safely configurable, scalable tool. Processes, data, machine behaviors and their dependencies are expressed using a set of libraries which bring as much as possible checking and validation to the type level, without sacrificing expressiveness. Together they form a toolkit for defining scalable cloud-based workflows composed of stateless computations, with a static reproducible specification of dependencies, behavior and wiring of all steps. The modeling of taxonomy data is done using Bio4j, where the new paradigm of graph databases allows for both a simple expression of taxonomic assignment tasks and the calculation of taxa abundance values considering the hierarchic structure of the taxonomy tree. MG7 includes a new 16S reference database, *16S-DB7*, built with a flexible and sustainable update system, and the possibility of project-driven personalization.

Keywords: Metagenomics, 16S, taxonomic profiling, Bio4j, Graph databases, Cloud computing, NGS, Genomics, big data, Microbiome, Environmental, 16S Database

INTRODUCTION

During the past decade, metagenomics data analysis is growing exponentially. Some of the reasons behind this are the increasing throughput of massively parallel sequencing technologies (with the derived decrease in sequencing costs), and the wide impact of metagenomics studies (Oulas et al., 2015), especially in human health (diagnostics, treatments, drug response or prevention) (Bikel et al., 2015). We should also mention what could be called the microbiome explosion: all kind of microbiomes (gut, mouth, skin, urinary tract, airway, milk, bladder) are now routinely sequenced in different conditions of health and disease, or after different treatments. The impact of microbiome analysis is also being felt in environmental sciences (Ufarté et al., 2015), crop sciences, the agrifood sector (Coughlan et al., 2015), bioenergy (Yang et al., 2016), and biotechnology in general (Cowan et al., 2015) (Kodzius and Gojbori, 2015). These new possibilities for exploring the diversity of micro-organisms in the most varied environments are opening new research areas, and drastically changing the existing ones.

As a consequence, the challenge is thus moving (as in other fields) from data acquisition to data analysis: the amount of data is expected to be overwhelming in a very short time (Stephens et al., 2015).

Genome researchers have raised the alarm over big data in the past (Hayden, 2015), but even a more serious challenge might be faced with the metagenomics boom. If we compare metagenomics data with other genomics data used in clinical genotyping we find a differential feature: the key role of time. Thus, for example, in some longitudinal studies, serial sampling from the same patient (Faust et al., 2015) along several weeks (or years) is being used for the follow up of some intestinal pathologies,

for studying the evolution of the gut microbiome after antibiotic treatment, or for colon cancer early detection (Zeller et al., 2014) (Garrett, 2015). This need of sampling across time adds more complexity to metagenomics data storage and demands adapted algorithms to detect state variations across time as well as idiosyncratic commonalities of the microbiome of each individual (Franzosa et al., 2015). In addition to the intra-individual sampling-time dependence, metagenomic clinical test results vary depending on the specific region of extraction of the clinical specimen. This local variability adds complexity to the analysis since different localizations (different tissues, different anatomical regions, healthy or tumor tissues) are required to have a sufficiently complete landscape of the human microbiome. Moreover, re-analysis of old samples using new tools and better reference databases might be also demanded from time to time.

Other disciplines such as astronomy or particle physics have faced the big data challenge before. A key difference is the existence of standards for data processing (Stephens et al., 2015); in metagenomics global standards for converting raw sequence data into processed data are not yet well defined, and there are shortcomings derived from the fact that most bioinformatics methodologies used for metagenomics data analysis were designed for scenarios very different from the current one. These are some of the aspects that have suffered crucial changes and advances with a direct impact in metagenomics data analysis:

1. **Sequence data:** the reads are larger, the sequencing depth and the number of samples of each project are considerably bigger. The first metagenomics studies were very local projects, while nowadays the most fruitful studies are done at a global level (international, continental, national). This kind of global studies has yielded the discovery of clinical biomarkers for diseases of the importance of cancer, obesity or inflammatory bowel diseases and has allowed exploring the biodiversity of varied earth environments.
2. **The genomics explosion:** its effect being felt in this case in the reference sequences. The immense amount of sequences available in public repositories demands new strategies for curation, update and storage of metagenomics reference databases: current models will (already) have problems to face the future avalanche of metagenomic sequence data.
3. **Cloud computing:** the appearance of new models for massive computation and storage such as the cloud-based platforms, or the widespread adoption of programming methodologies like functional programming, or, more speculatively, dependently typed programming. The new possibilities that these advances offer must have a direct impact in metagenomics data analysis.
4. **Open science:** the new social manner to do science, particularly so in genomics, brings its own set of requirements. Metagenomics evolves in a social and global scenario following a science democratization trend in which many small research groups from distant countries share a common big metagenomics project; this global cooperation demands systems allowing for reproducible data analysis, data interoperability, and tools and practices for asynchronous collaboration between different groups.

RESULTS

Overview

Considering the current new metagenomics scenario and to tackle the challenges posed by metagenomics big data analysis outlined in the Introduction we have designed a new open source methodology for analyzing metagenomics data. It exploits the new possibilities that cloud computing offers to get a system robust, programmatically configurable, modular, distributed, flexible, scalable and traceable in which the biological databases of reference sequences can be easily updated and/or frequently substituted by new ones or by databases specifically designed for focused projects.

These are some of the more innovative MG7 features:

- Static reproducible specification of dependencies and behavior of the different components using *Statika* and *Datasets*
- Parallelization and distributed analysis based on AWS, with on-demand infrastructure as the basic paradigm
- Definition of complex workflows using *Loquat*, a composable system for scaling/parallelizing stateless computations especially designed for AWS

- A new approach to data analysis specification, management and specification based on working with it in exactly the same way as for a software project, together with the extensive use of compile-time structures and checks
- Modeling of the taxonomy tree using the new paradigm of graph databases (Bio4j, (Pareja-Tobes et al., 2015)). It facilitates the taxonomic assignment tasks and the calculation of the taxa abundance values considering the hierarchic structure of taxonomy tree
- Exhaustive per-read taxonomic assignment using two complementary assignment algorithms Lowest Common Ancestor and Best BLAST Hit
- Using a new 16S database of reference sequences (16S-DB7) with a flexible and sustainable system of updating and project-driven customization

Libraries and resources

In this section we describe the resources and libraries developed by the authors on top of which MG7 is built. All MG7 code is written in [Scala](#), a hybrid object-functional programming language. Scala was chosen based on the possibility of using certain advanced programming styles, and Java interoperability, which let us build on the vast number of existing Java libraries; we take advantage of this when using Bio4j as an API for the NCBI taxonomy. It has support for type-level programming, type-dependent types (through type members) and singleton types, which permits a restricted form of dependent types where types can depend essentially on values determined at compile time (through their corresponding singleton types). Conversely, through implicits one can retrieve the value corresponding to a singleton type.

Statika: machine configuration and behavior

[Statika](#) is a Scala library developed by AA and EPT which serves as a way of defining and composing machine behaviors statically. The main component are **bundles**. Each bundle declares a sequence of computations (its behavior) which will be executed in an **environment**. A bundle can *depend* on other bundles, and when being executed by an environment, its DAG (Directed Acyclic Graph) of dependencies is linearized and run in sequence. In our use, bundles correspond to what an EC2 instance should do and an environment to an AMI (Amazon Machine Image) which prepares the basic configuration, downloads the Scala code and runs it.

Datasets: a mini-language for data

[Datasets](#) is a Scala library developed by AA and EPT with the goal of being a Scala-embedded mini-language for datasets and their locations. **Data** is represented as type-indexed fields: keys are modeled as singleton types, and values correspond to what could be called a denotation of the key: a value of type `Location` tagged with the key type. Then a **Dataset** is essentially a collection of data, which are guaranteed statically to be different through type-level predicates, making use of the value–type correspondence which can be established through singleton types and implicits. A dataset location is then just a list of locations formed by locations of each dataset key. All this is based on what could be described as an embedding in Scala of an extensible record system with concatenation on disjoint labels, in the spirit of (Harper and Pierce, 1990) (Harper and Pierce, 1991). For that *Datasets* uses the [ohnosequences/cosas](#) library.

Data keys can further have a reference to a **data type**, which, as the name hints at, can help in providing information about the type of data we are working with. For example, when declaring Illumina reads as a data, a data type containing information about the read length, insert size or end type (single or paired) is used.

A **location** can be, for example, an S3 object or a local file; by leaving the location type used to denote particular data free we can work with different “physical” representations, while keeping track of to which logical data they are a representation of. Thus, a process can generate locally a `.fastq` file representing the merged reads, while another can put it in S3 with the fact that they all correspond to the “same” merged reads is always present, as the data that those “physical” representations denote.

Loquat: Parallel data processing with AWS

[Loquat](#) is a library developed by AA, EK and EPT designed for the execution of embarrassingly parallel tasks using S3, SQS and EC2 Amazon services.

A *loquat* executes a process with explicit input and output datasets (declared using the *Datasets* library described above). Workers (EC2 instances) read from an SQS queue the S3 locations for both input and

149 output data; then they download the input to local files, and pass these file locations to the process to be
150 executed. The output is then put in the corresponding S3 locations.

151 A manager instance is used to monitor workers, provide initial data to be put in the SQS queue and
152 optionally release resources depending on a set of configurable conditions.

153 Both worker and manager instances are *Statika* bundles. The worker can declare any dependencies
154 needed to perform its task: other tools, libraries, or data.

155 All configuration such as the number of workers or the instance types is declared statically, the
156 specification of a loquat being ultimately a Scala object. Deploy and resource management methods make
157 easy to use an existing loquat either as a library or from (for example) a Scala REPL.

158 The input and output (and their locations) being defined statically has several critical advantages.
159 First, composing different loquats is easy and safe; just use the output types and locations of the first one
160 as input for the second one. Second, data and their types help in not mixing different resources when
161 implementing a process, while serving as a safe and convenient mechanism for writing generic processing
162 tasks. For example, merging paired-end Illumina reads generically is easy as the data type includes the
163 relevant information (insert size, read length, etc) to pass to a tool such as FLASH.

164 **Type-safe eDSLs for BLAST and FLASH**

165 We developed our own Scala-based type-safe eDSLs (embedded Domain Specific Languages) for **FLASH**
166 ([Magoč and Salzberg, 2011](#)) and **BLAST** ([Camacho et al., 2009](#)) expressions and their execution.

167 In the case of BLAST we use a model where we can guarantee for each BLAST command expression
168 at compile time that

- 169 • all required arguments are provided
- 170 • only valid options are provided
- 171 • correct types for each option value
- 172 • valid output record specification

173 Generic type-safe parsers returning a heterogeneous record of BLAST output fields are also available,
174 together with output data defined using *Datasets* which have a reference to the exact BLAST command
175 options which yielded that output. This lets us provide generic parsers for BLAST output which are
176 guaranteed to be correct.

177 In the same spirit as for BLAST, we implemented a type-safe eDSL for FLASH expressions and their
178 execution, supporting features equivalent to those outlined for the BLAST eDSL.

179 **Bio4j and Graph Databases**

180 Bio4j ([Pareja-Tobes et al., 2015](#)) is a data platform integrating data from different resources such as
181 UniProt, the NCBI taxonomy, or GO, in a graph data paradigm. In the assignment phase we use a
182 subgraph containing the NCBI Taxonomy, wrapping in Scala its Java API in a tree algebraic data type.

183 **16S-DB7 Reference Database Construction**

184 The starting point for our 16S reference database is RNA Central ([Consortium et al., 2014](#)), [version 5](#).
185 RNAcentral was chosen being the most up to date, comprehensive RNA sequence repository, including
186 among others all RNA data from Silva, GreenGenes, RDP, ENA, and RefSeq. First we take those
187 sequences which

- 188 1. are annotated as being of rRNA type¹
- 189 2. their length is at least 1300²
- 190 3. have at least one taxonomic assignment to a descendant of *Bacteria* or *Archaea*
- 191 4. their lineage does not contain a set of taxa deemed uninformative³

192 After this first step, we drop redundant assignments: if sequences $S_1 \subseteq S_2$ share an assignment T ,
193 it gets dropped from S_1 ; sequences which as a result of this process end up having no assignments are
194 removed.

¹We are aware of the existence of a gene annotation corresponding to 16S in RNAcentral, that we are **not using** due to a significant amount of 16S sequences lacking it

²Note that 16S sequences are sometimes part of an entry corresponding to whole small subunits; that's why we do not set a maximum length threshold

³for example: "unclassified Bacteria (miscellaneous)" or "unclassified". Assigning a read to an "unclassified" taxon defeats the first and foremost goal of taxonomic profiling: *classification*.

195 Once we have a non-redundant set of ribosomal RNA sequences (containing all those corresponding
196 to 16S), we can apply our procedure for checking internal consistency of taxonomic assignments. We run
197 MG7 using this set of sequences as query, with reference all but the one we are trying to assign. Under
198 the (reasonable) assumption of 16S sequence similarity being correlated with the taxonomy tree topology,
199 the resulting MG7 taxonomic assignment should either

- 200 1. be a taxon *close* to the original assignment, if there are sequences similar enough in the reference
201 database; what we consider as close is: the parent of the MG7 assignment should be contained in
202 the lineage of the original assignment.
- 203 2. be empty, due to this sequence having no similar sequences in the reference database, thus making
204 impossible to do any taxonomic assignment.

205 In any other case, under our assumptions, this assignment should be discarded.

206 All these steps are automated, and integrated with every release of our reference database. The whole
207 process can be repeated and adapted to other subsets of RNACentral; we do this for an 18S reference
208 database.

209 **Workflow Description**

210 The MG7 analysis workflow is summarized in Figure 1. The input files for MG7 are the FASTQ files
211 resulting from a paired-end NGS sequencing experiment.

212 ***Joining reads of each pair using FLASH***

213 In the first step the paired-end reads, designed with an insert size that yields pairs of reads with an
214 overlapping region between them, are assembled using FLASH (Magoč and Salzberg, 2011). FLASH is
215 designed to merge pairs of reads when the original DNA fragments are shorter than twice the length of
216 reads. Thus, the sequence obtained after joining the 2 reads of each pair is larger and has better quality
217 since the sequence at the ends of the reads is refined merging both ends in the assembly. To have a
218 larger and improved sequence is crucial to do more precise the inference of the bacterial origin based on
219 similarity with reference sequences.

220 ***Parallelized BLASTN of each read against the 16S-DB7***

221 The second step is to search for similar 16S sequences in our 16S-DB7 database. The taxonomic
222 assignment for each read is based on BLASTN of each read against the 16S database. Assignment based
223 on direct similarity of each read one by one compared against a sufficiently wide database is considered in
224 different reviews of metagenomics analysis methodologies (Segata et al., 2013) (Morgan and Huttenhower,
225 2012) as a very exhaustive method for assignment. Some methods of assignment compare the sequences
226 only against the 16S genes from available complete bacterial genomes or avoid computational cost
227 clustering or binning the sequences first, and then doing the assignments only for the representative
228 sequence of each cluster. MG7 carries out an exhaustive comparison of all the reads under analysis and
229 it does not apply any binning strategy. Every read is specifically compared with all the sequences of
230 the 16S database. We select the best BLAST hits (10 hits by default) obtained for each read to do the
231 taxonomic assignment.

232 ***Taxonomic Assignment Algorithms***

233 All the reads are assigned under two different algorithms of assignment: i. Lowest Common Ancestor
234 based taxonomic assignment (LCA) and ii. Best BLAST Hit based taxonomic assignment (BBH). Figure
235 2 displays schematically the LCA algorithm applied sensu stricto (left panel) and the called ‘in line’
236 exception (right panel) designed in order to gain specificity in the assignments in the cases in which the
237 topology of the taxonomical nodes corresponding to the BLAST hits support sufficiently the assignment
238 to the most specific taxon.

239 **Lowest Common Ancestor based Taxonomic Assignment** For each read, first, we select the BEST
240 BLAST HITS (by default 10 Hits) over a threshold of similarity. To evaluate similarity for this first
241 filtering of hits we use the Expect value (by default $value \leq e^{-15}$) that describes the number of hits one
242 can “expect” to see by chance when searching a database of a particular size. In a second filtering step we
243 filter those hits that are not sufficiently good comparing them with the best one. We select the best HSP
244 (High Similarity Pair) per reference sequence and then choose the best HSP (that with lowest E-value)



Figure 1. MG7 analysis workflow. The paired reads in fastq format are merged resulting in only one sequence per read pair. The next step is a parallelized BLASTN of every merged sequence against the 16S reference database 16S-DB7. Then, the mapping of the detected similar sequences in the database to the taxonomy node to which they belong is carried out. This is done using Bio4j that includes a module with all the NCBI taxonomy in a graph connected with the Gene Ontology, Uniprot, and RefSeq graphs. Then the taxonomic assignment is done for each sequence following two different approaches: LCA and BBH, and finally the abundances corresponding to direct and cumulative assignments for each node in percentage and absolute counts are provided for each assignment mode.



Figure 2. Lowest Common Ancestor algorithm for taxonomic assignment. The Left panel displays an example of the application of LCA algorithm in a *sensu stricto* mode. A, B, C and D represent taxonomy tree nodes with assigned reads. Right panel displays the *in line* mode of assignment which is an exception for the *sensu stricto* mode of application of LCA algorithm. The *in line* mode is used when all the nodes are located in a line without bifurcations. In that case the taxon assigned is the most specific (the most distant from the root).

245 between all the selected ones. The bitscore of this best HSP (called S) is used as reference to filter the rest
 246 of HSPs. All the HSPs with bitscore below the product pS are filtered. p is a coefficient fixed by the user
 247 to define the bitscore required, e.g. if $p = 0.9$ and $S = 700$ the required bitscore threshold would be 630.
 248 Once we have the definitive HSPs selected, we obtain their corresponding taxonomic nodes using the
 249 taxonomic assignments that NCBI provides for all the nt database sequences. Now we have to analyze
 250 the topological distribution of these nodes in the taxonomy tree: i. If all the nodes forms a line in the
 251 taxonomy tree (are located in a not branched lineage to the tree root) we should choose the most specific
 252 taxID as the final assignment for that read. We call to this kind of assignment the ‘in line’ exception (see
 253 Figure 2 right panel). ii. If not, we should search for the *sensu stricto* Lowest Common Ancestor (LCA) of
 254 all the selected taxonomic nodes (See Figure 2 left panel). In this approach we decided to use the bitscore
 255 for evaluating the similarity because it is a value that increases when similarity is higher and depends a lot
 256 on the length of the HSP. Some reads could not find sequences with enough similarity in the database and
 257 then they would be classified as reads with no hits. Advanced metagenomics analysis approaches (Huson
 258 and Weber, 2012) have adopted LCA-based assignment algorithms because it provides fine and trusted
 259 taxonomical assignment.

260 **Best BLAST hit taxonomic assignment** We decided to maintain the simpler method of Best BLAST
 261 Hit (BBH) for taxonomic assignment because, in some cases, it can provide information about the
 262 sequences that adds information to that obtained using the LCA algorithm. With the LCA algorithm, when
 263 some reference sequences with BLAST alignments over the required thresholds map to a not sufficiently
 264 specific taxID, the read can be assigned to an unspecific taxon near to the root of the taxonomy tree. If the
 265 BBH reference sequence maps to more specific taxa, this method, in that case, gives us useful information.

266 **Output for LCA and BBH assignments**

267 MG7 provides independent results for the 2 different approaches, LCA and BBH. The output files
 268 include, for each taxonomy node (with some read assigned), abundance values for direct assignment
 269 and cumulative assignment. The abundances are provided in counts (absolute values) and in percentage
 270 normalized to the number of reads of each sample. Direct assignments are calculated counting reads
 271 specifically assigned to a taxonomic node, not including the reads assigned to the descendant nodes in
 272 the taxonomy tree. Cumulative assignments are calculated including the direct assignments and also the
 273 assignments of the descendant nodes. For each sample MG7 provides 8 kinds of abundance values: LCA
 274 direct counts, LCA cumu. counts, LCA direct %, LCA cumu. %, BBH direct counts, BBH cumu. counts,
 275 BBH direct % and BBH cumu. %.

Data analysis as a software project

The MG7 16S data analysis workflow is indeed a set of tasks, all of them based in *Loquat*. For each task, a set of inputs and outputs as well as configuration parameters must be statically defined. The user is also free to leave the reasonable defaults for configuration, needing only to define the input and output of the whole workflow. The definition of this configuration is Scala code and the way of starting an MG7 analysis is compiling the project code and launching it from the Scala interactive console.

Code compilation prior to launching any analysis assures that no AWS resources are launched if the analysis is not well-defined, avoiding expenses not leading to any analysis. Besides compile-time checks, runtime checks are made before launch to ensure existence of input data and availability of resources.

An MG7 analysis is then a Scala project where the user only needs to set certain variables at the code level (input, output and parameters), compile the code and run it. To facilitate the process of setting up the Scala project, a template with sensible defaults is provided.

In order to be able to exploit AWS infrastructure for the MG7 analysis, the user needs to set up an AWS account with certain IAM (Identity and Access Management) permission policies that will grant access to the resources used in the workflow.

Availability

MG7 is open source, available at <https://github.com/ohnosequences/mg7> under an [AGPLv3](#) license.

DISCUSSION

We could summarize the most innovative ideas and developments in MG7:

1. Treating data analysis as a software project. This makes for radical improvements in *reproducibility*, *reuse*, *versioning*, *safety*, *automation* and *expressiveness*
2. Checking at compile-time: input and output data, their locations and type are expressible and checked at compile-time using *Datasets*
3. Management of dependencies and machine configurations using *Statika*
4. Automation of AWS cloud resources and processes, including distribution and parallelization through the use of *Loquat*
5. Taxonomic data and related operations are treated natively as what they are: graphs, through the use of *Bio4j*
6. MG7 provides a sustainable model for taxonomic assignment, appropriate to face the challenging amount of data that high throughput sequencing technologies generate

We will expand on each item in the following sections.

A new approach to data analysis: data analysis as a software project and checking at compile-time

MG7 proposes to define and work with a particular data analysis task as a software project, using Scala. The idea is that *everything*: data description, their location, configuration parameters and the infrastructure used should be expressed as Scala code, and treated in the same way as any (well-managed) software project. This includes, among other things, using version control systems (*git* in our case), writing tests, making stable releases following [semantic versioning](#) or publishing artifacts to a repository.

What we see as key advantages of this approach (when coupled with compile-time specification and checking), are

- **Reproducibility** the same analysis can be run again with exactly the same configuration in a trivial way.
- **Versioning** as in any software project, there can be different versions, stable releases, etc.
- **Reuse** we can build standard configurations on top of this and reuse them for subsequent data analysis. A particular data analysis *task* can be used as a *library* in further analysis.
- **Decoupling** We can start working on the analysis specification, without any need for available data in a much easier way.
- **Documentation** We can take advantage of all the effort put into software documentation tools and practices, such as in our case Scaladoc or literate programming. As documentation, analysis processes and data specification live together in the files, it is much easier to keep coherence between them.

- **Expresiveness and safety** For example in our case we can choose only from valid illumina read types, and then build a default FLASH command based on that. The output locations, being declared statically, are also available for use in further analysis.

Input and output data declaration

An important aspect of the MG7 workflow is the way it deals with data resources. All the data that is going to be used in the analysis or produced as an output is described as Scala code using rich types from the *Datasets* language. This allows the user to specify information about types of data, information that can then be utilized by tools analyzing this data. For example, we can specify that, for the first part of the MG7 workflow, running FLASH in parallel requires illumina paired end reads and produces joined reads.

On one hand, specification of the input data allows us to restrict its type and force users to be conscious about what they pass as an input. On the other hand, specification of the output data helps to build a workflow as a *composition* of several parts: we can ensure on the Scala code type level that the output of one component fits as an input for the next component. This is crucial as, obviously, the way a data analysis task works depends a lot on the particular structure of the data. For instance, in the MG7 workflow, using BLAST eDSL, we can precisely describe which format will have the output of the BLAST step, which information it will include, and then in the next step we can reuse this description to parse BLAST output and retrieve the part of the information needed for the taxonomy assignment analysis. Having the data structure described statically as Scala code allows us to be sure that we will not have parsing problems or other issues with incompatible data passed between workflow components.

All this does not compromise flexibility in how the user works with data in MG7: having static data declarations as a part of the configuration allows the user to reuse analysis components, or modify them according to particular needs. Besides that, an important advantage of the type-level control is the added protection from the execution (and deployment) of a wrongly configured analysis task, which may lead to significant costs in both time and money.

Tools, data, dependencies and automated deployment

Bioinformatics software often has a complicated installation process and requires various dependencies with unclear versions. This makes the deployment of the bioinformatics tools an involved task and resolving it manually is not a solution in the context of cloud computations. To face this problem, one needs an automated system of managing tools and resources, which will allow an expressive way for describing dependencies between parts of a pipeline and provide a reproducible procedure of its deployment. We have developed *Statika* for this purpose and successfully used it in MG7.

Every external tool involved in the workflow is represented as a *Statika* bundle, which is essentially a Scala project describing the installation process of this tool and declaring dependencies on other bundles which will be installed prior to the considered tool itself. Describing relationships between bundles on the code level allows us to track the directed acyclic graph of their dependencies and linearize them to automatically install them sequentially in the right order. Meanwhile, describing the installation process on the code level allows the user to utilize the wide range of available Scala and Java APIs and tools, making installation a well-defined sequence of steps rather than an unreliable script, dependent on a certain environment. *Statika* offers an easy path towards making deployment an automated, reproducible process.

Besides bioinformatics tools like BLAST and FLASH, *Statika* bundles are used for wrapping data dependencies and all inner components of the system that require cloud deployment. In particular, all components of *Loquat* are bundles; the user can then define which components are needed for the parallel processing on each computation unit in an expressive way, declaring them as bundle dependencies of the loquat “worker” bundle. This modularization is also important for the matter of making components of the system reusable for different projects and liberating the user from most of the tasks related to their deployment.

Parallel computations in the cloud

The MG7 workflow consists of certain steps, each of which performs some work in parallel, using the cloud infrastructure managed by *Loquat*. It is important to notice the horizontal scalability of this approach. Irrespectively of how much data needs to be processed, MG7 will handle it, by splitting data into chunks and performing the analysis on multiple computation units. The Amazon Elastic Compute Cloud (EC2) service provides a transparent way of managing computation infrastructure, called autoscaling

380 groups. The User can set MG7 configuration parameters, adjusting for each task the amount and hardware
381 characteristics of the EC2 instances they want to use for it. But it is important to note that, as each
382 workflow step is not very resource demanding, it is not needed to hire EC2 instances with some advanced
383 hardware. Instead, an average type will work and you can reduce execution time by simply scaling out the
384 number of instances.

385 **Taxonomy and Bio4j**

386 The hierarchic structure of the taxonomy of the living organisms is a tree, and, hence, is also a graph in
387 which each node, with the exception of the root node, has a unique parent node. It led us to model the
388 taxonomy tree as a graph using the graph database paradigm. Previously we developed Bio4j ([Pareja-
389 Tobes et al., 2015](#)), a platform for the integration of semantically rich biological data using typed graph
390 models. It integrates most publicly available data linked with sequences into a set of interdependent
391 graphs to be used for bioinformatics analysis and especially for biological data. MG7 works based on the
392 Bio4j taxonomy module, which contains all the NCBI taxonomy data. It opens the possibility to connect
393 the taxonomic profiling data obtained with MG7 to all the biological knowledge associated to each taxon.
394 Using the information available in Bio4j for all the proteins assigned to each taxon we are connected to
395 all the functional data available in Uniprot related with it.

396 **Future developments**

397 ***Shotgun metagenomics***

398 It is certainly possible to adapt MG7 to work with shotgun metagenomics data. Simply changing the
399 reference database to include whole genome sequence data could yield interesting results. This could also
400 be refined by restricting reference sequences according to all sort of criteria, like biological function or
401 taxonomy. Bio4j would be an invaluable tool here, thanks to its ability to express complex predicates on
402 sequences using all the information linked with them (GO annotations, UniProt data, NCBI taxonomy,
403 etc).

404 ***Comparing groups of samples***

405 The comparison of the taxonomic profiles between different groups of samples is a need for many
406 metagenomics studies. Tasks related with this group-based analysis, such as the extraction of the minimal
407 tree with all the taxa with some direct or accumulated assignment, will be part of a new MG7 module,
408 already in development.

409 ***Interactive visualizations based on Biographika***

410 New visualization tools for metagenomics results are undoubtedly needed. Interactivity is a especially
411 interesting feature for metagenomics data visualization, since the expert needs to explore the results in a
412 knowledge-driven way. The majority of the available metagenomics data visualizations are static. We are
413 working in the *Biographika* project ([Tobes et al., 2015](#)), to provide interactive rich visualizations on the
414 web for Bio4j data. The development of visualizations specific for MG7 is one of Biographika current
415 goals. Biographika is based on D3.js, the de-facto standard JavaScript data visualization library, and is
416 open source.

417 **MATERIALS AND METHODS**

418 **Amazon Web Services**

419 MG7 uses the following Amazon Web Services:

- 420 • **EC2** (Elastic Compute Cloud) autoscaling groups for launching and managing computation units
- 421 • **S3** (Simple Storage Service) for storing input and output data
- 422 • **SQS** (Simple Queue Service) for communication between different components of the system
- 423 • **SNS** (Simple Notification Service) for e-mail notifications

424 These services are used through a Scala wrapper of the official [AWS Java SDK v1.9.25](#): [ohnosequences/aws-
425 scala-tools v0.13.2](#).

426 **Scala**

427 MG7 itself and all the libraries used are written in Scala v2.11.

428 **Statika**
429 MG7 uses [ohnosequences/statika v2.0.0](#) for specifying the configuration and behavior of EC2 instances.

430 **Datasets**
431 MG7 uses [ohnosequences/datasets v0.2.0](#) for specifying input and output data, their type and their location.

432 **Loquat**
433 MG7 uses [ohnosequences/loquat v2.0.0](#) for the specification of data processing tasks and their execution
434 using AWS resources.

435 **BLAST eDSL**
436 MG7 uses [ohnosequences/blast v0.2.0](#). The BLAST version used is v2.2.31+.

437 **FLASH eDSL**
438 MG7 uses [ohnosequences/flash v0.1.0](#). The FLASH version used is v1.2.11.

439 **Bio4j**
440 MG7 uses [bio4j/bio4j v0.12.0-RC3](#) and [bio4j/bio4j-titan v0.4.0-RC2](#) as an API for the NCBI taxonomy.

441 **DISCLOSURE/CONFLICT-OF-INTEREST STATEMENT**

442 All authors work at the *Oh no sequences!* research group, part of Era7 Bioinformatics. Era7 offers
443 metagenomics data analysis services based on MG7. MG7 is open source, available under the OSI-
444 approved AGPLv3 license.

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446 **AUTHOR CONTRIBUTIONS**

- 447 • **AA** developed *MG7*, *Loquat*, *Statika*, *Datasets*, and *aws-scala-tools*; wrote the paper;
- 448 • **EK** developed *nispero* (a prototype for *Loquat* ([Kovach et al., 2014](#))) and *aws-scala-tools*.
- 449 • **MM** *MG7* workflow design; curation and design of the *16S-DB7* reference database; wrote the
450 paper.
- 451 • **PPT** design and development of the first *MG7* prototype
- 452 • **EP** *MG7* workflow design; wrote the paper.
- 453 • **RT** *MG7* workflow design, assignment strategy; curation and design of the *16S-DB7* reference
454 database; wrote the paper.
- 455 • **EPT** developed *MG7*, *Statika*, *Datasets*, *FLASH/BLAST eDSLs*; data analysis approach and design;
456 reference database automated curation and filtering; wrote the paper.

457 All authors have read and approved the final manuscript.

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