

1 What the Phage: A scalable workflow for 2 the identification and analysis of phage 3 sequences

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15 Abstract

16 Phages are among the most abundant and diverse biological entities on earth. Identification
17 from sequence data is a crucial first step to understand their impact on the environment. A
18 variety of bacteriophage identification tools have been developed over the years. They differ
19 in algorithmic approach, results and ease of use. We, therefore, developed “What the
20 Phage” (WtP), an easy-to-use and parallel multitool approach for phage identification
21 combined with an annotation and classification downstream strategy, thus, supporting the
22 user’s decision-making process when the phage identification tools are not in agreement to
23 each other. WtP is reproducible and scales to thousands of datasets through the use of a

24 workflow manager (Nextflow). WtP is freely available under a GPL-3.0 license
25 (https://github.com/replikation/What_the_Phage).

26 Introduction

27 Bacteriophages (phages) are viruses that infect prokaryotes and replicate by utilizing the
28 metabolism of the host (1). They are among the most abundant and diverse organisms on the
29 planet and inhabit almost every environment (2). Phages drive and maintain bacterial diversity
30 by perpetuating the coevolutionary interactions with their bacterial prey, facilitating horizontal
31 gene transfer, and nutrient turnover through continuous cycles of predation and coevolution
32 (3,4). They have a direct impact on the microbiome e.g. the human gut and can influence
33 human health (5). However, despite having considerable impacts on microbial ecosystems
34 such as the human gut, they remain one of the least understood members of complex
35 communities (6).

36 The sequencing of the entire DNA of environmental samples (metagenomics) is an essential
37 approach to gain insights into the microbiome and functional properties. It should be noted
38 that due to the small genome size of phages (5 kbp to 300 kbp) (7), their entire genome can
39 be sequenced assembly-free via long-read technologies (e.g., Oxford Nanopore
40 Technologies or PacBio) (8). This facilitates phage genome recovery in their natural habitat,
41 without the need to culture their hosts to isolate the phages (2). However, the identification
42 of phages from metagenomes in general and their differentiation from prophages remains a
43 challenge as there is no established computational gold standard (9).

44 Existing identification tools rely on direct comparison of sequence similarity (10,11), sequence
45 composition (12,13), and models based on these features derived through learning algorithms
46 (10,11,14,15).

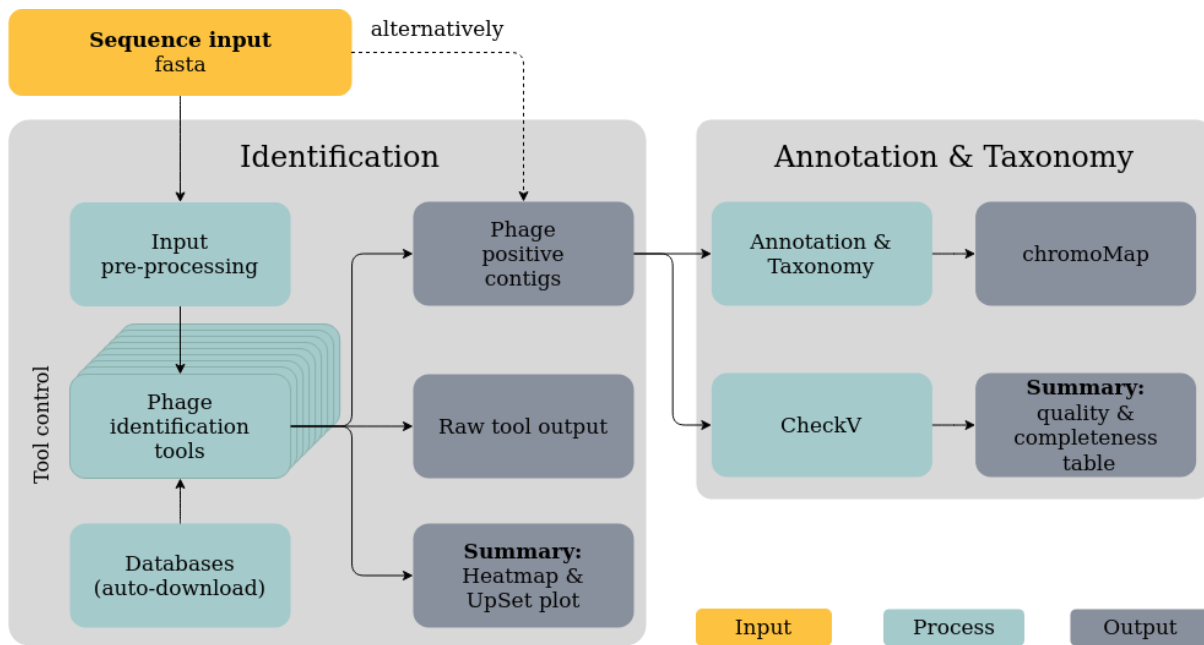
47 The performance of each identification method varies greatly depending on the sample type
48 or material, the sequencing technology, and the assembly method, which makes the correct
49 choice for any given sample difficult without having to install and test several tools.

50 To further complicate matters, the user can choose from many tools based on different
51 calculation strategies and based on different software dependencies and databases. While
52 working with these phage identification tools, we observed various installation issues and
53 conflicts making a multi-tool screening approach unnecessary complex and time-consuming.
54 To overcome these obstacles and issues we developed “What the Phage” (WtP), a
55 reproducible, accessible and scalable workflow utilizing the advantages of multiple
56 identification tools in parallel to detect and annotate phages.

57 Design and Implementation

58 WtP was implemented in Nextflow, a portable, scalable, and parallelizable workflow manager
59 (16). At the time of writing, twelve different approaches to identify phage sequences are
60 included in WtP besides other programs for further annotation and classification. WtP uses
61 so-called containers (Docker or Singularity) for an installation-free workflow execution without
62 dependency or operating system conflicts for each of the currently over 21 programs included.
63 All containers are pre-build, version-controlled, online available at dockerhub.com and
64 automatically downloaded if used. Additionally, all nine different databases/datasets used by
65 the workflow are automatically managed. The modular code structure and functionalities of
66 Nextflow and Docker/Singularity allow easy integration of other phage prediction tools and
67 additional analysis steps in future releases of the pipeline. The workflow consists of two main
68 steps which are executed subsequently or, if specified, individually (see Figure 1):

- 69 1. Identification: The identification of putative phage sequences
- 70 2. Annotation & Taxonomy: The gene annotation and taxonomic classification of phage
71 sequences



72

73 Figure 1: Simplified DAG chart of the “What the Phage” workflow. Sequence input (yellow) can
74 either be first-run through the “Identification” and subsequently “Annotation & Taxonomy” as
75 a whole or used directly as an input for the “Annotation & Taxonomy” only. Each of the multiple
76 phage identification tools can be individually controlled if needed (tool control).

77 Identification and Visualization

78 The first step takes a multi fasta file as input (e.g. a metagenome assembly), formats it to the
79 demands of each tool and filters sequences below a user-defined length threshold (1,500 bp
80 by default) via SeqKit v0.10.1 (17). Sequences which are too small usually generate false-
81 positive hits as observed by Gregory *et al.* (18). The phage identification process is performed
82 by nine different tools in parallel: VirFinder v1.1 (13), PPR-Meta v1.1 (15), VirSorter v1.0.6
83 (with and without virome mode) (11), DeepVirFinder v1.0 (19), Metaphinder with no release
84 version (using default database and own database) (20), MARVEL v0.2 (14), sourmash v2.0.1
85 (12), Vibrant v1.2.1 (with and without virome mode) (10), and VirNet v0.1 (21). Positive
86 identifications are collected, filtered by adjustable parameters (Table 1), and the results are
87 summarized via a detailed heat map (Figure 3 A) that serves as a general identification
88 performance overview of each input sample. In addition, and because standard Venn and

89 Euler diagrams are an inadequate solution for quantitative visualization of multiple ($n > 4$)
 90 intersections, we used an R package to generate UpSet plots (22) as a scalable alternative
 91 for visualizing intersecting sets and their properties (Figure 2).

92

93 Table 1: Overview of the default criteria for “What the Phage” to determine a phage positive
 94 contig by the raw output results of each tool. VirSorter and Vibrant are executed in default and
 95 virome mode. MetaPhinder is executed with the default database and an own database based
 96 on Zheng *et al.* (23).

Tool	Criteria	Filter
MARVEL	probability according to Random Forest algorithm	> 75 %
VirFinder	p-value	> 0.9
PPR-Meta	contig classification	“Phage”
VirSorter & VirSorter_virome	Category of detection (1, 2 or 3: intact, incomplete or questionable)	Category 1 & 2
MetaPhinder & MetaPhinder-own-DB	A) contig classification & B) average nucleotide identity %	A) Phage & B) > 50
DeepVirFinder	p-value	> 0.9
Vibrant & Vibrant_virome	contig classification	Virus
Virnet	p-value (as median across all hits per contig)	> 0.5
Sourmash	Similarity score	> 0.5

97

98 Annotation & Taxonomy

99 For this step, phage positive contigs are used and either automatically retrieved from the
100 identification step or directly via user input. Prodigal v2.6.3-1 (22) is used in metagenome
101 mode to predict ORFs and HMMER v3.3 (24) to identify homologs via the pVOG-database
102 (25). All annotations are summarized in an interactive HTML file via chromoMap (26) (see
103 Figure 3 B). Additionally, WtP classifies positive matches via sourmash and thus provides a
104 taxonomic classification of already known phages.

105 Other features

106 All mandatory databases and containers are automatically downloaded when the workflow is
107 started and stored for following executions. Additionally, the workflow can be pre-setup in
108 order to subsequently analyse sequences offline. To support a transparent and reproducible
109 mode of operation, the raw output of each tool is provided. Maximum execution stability is
110 ensured by automatically excluding phage identification tools that cannot analyse the input
111 data without failing the workflow (e.g. file too large, not the scope of an individual tool).

112 Dependencies and version control

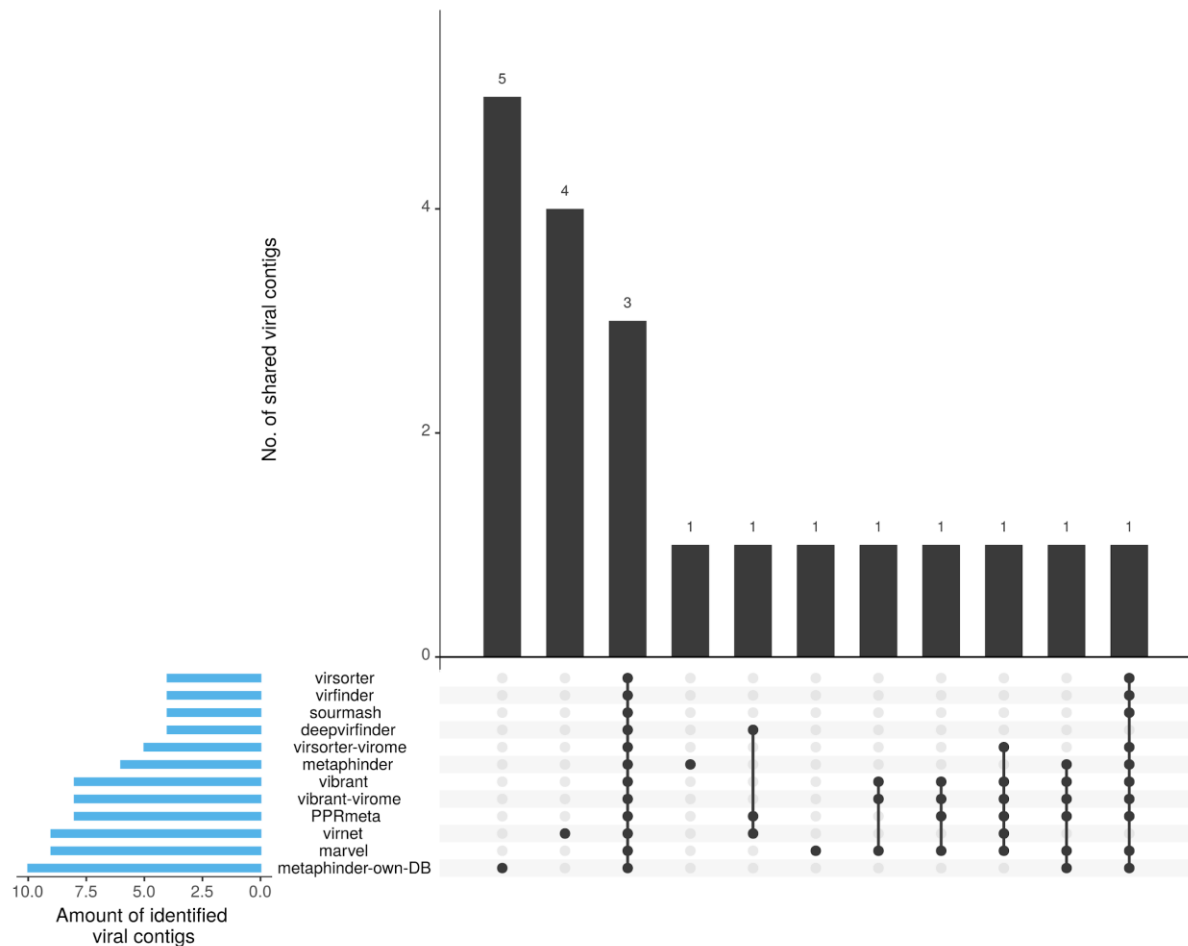
113 WtP requires only the workflow management software Nextflow (16) and either Docker or
114 Singularity (27) installed and configured on the system. The pipeline was tested on Ubuntu
115 16.04 LTS, Ubuntu 18.04 LTS and Windows 10 (via Windows Subsystem for Linux 2 using
116 Docker). The installation process is described in detail at
117 https://github.com/replikation/What_the_Phage. Each workflow release specifies the Nextflow
118 version the code was tested on to avoid any version conflicts between the workflow code and
119 the workflow manager at any time. A specific Nextflow version can always be directly
120 downloaded as an executable file from <https://github.com/nextflow-io/nextflow/releases>.

121 Additionally, each container used in the workflow is tagged by the accompanying tool version,
122 pre-build and stored on hub.docker.com.

123 Results

124 To demonstrate the utility and performance of WtP, we analysed a described metagenome
125 data set (ENA Study PRJEB6941) using a local desktop machine (24 threads, 60 GB RAM,
126 Ubuntu 18.04.4 LTS) and WtP release v0.8.0. In this study (28), Kleiner *et al.* sequenced an
127 artificial microbiome sample which was produced via bacteria and phage cultures in mice
128 faeces (germ-free C57BL/6 J mice). The samples contained six different phages: P22, T3, T7,
129 $\phi 6$, M13 and ϕ VPE25.

130 The raw read data set composed of eight samples was downloaded from the ENA server and
131 individually assembled via metaSPAdes v3.14 using the default settings (29). The resulting
132 eight assembly files (available at [https://github.com/mult1fractal/WtP_test-](https://github.com/mult1fractal/WtP_test-data/tree/master/01.Phage_assemblies)
133 [data/tree/master/01.Phage_assemblies](https://github.com/mult1fractal/WtP_test-data/tree/master/01.Phage_assemblies)) were analysed with WtP (release v0.8.0, default
134 settings). As WtP uses multiple tools for phage identification, an UpSet plot summarizes for
135 each sample the performance of all approaches executed successfully (see Figure 2 for
136 sample ERR575692 and Supplementary Dataset for all samples).



137

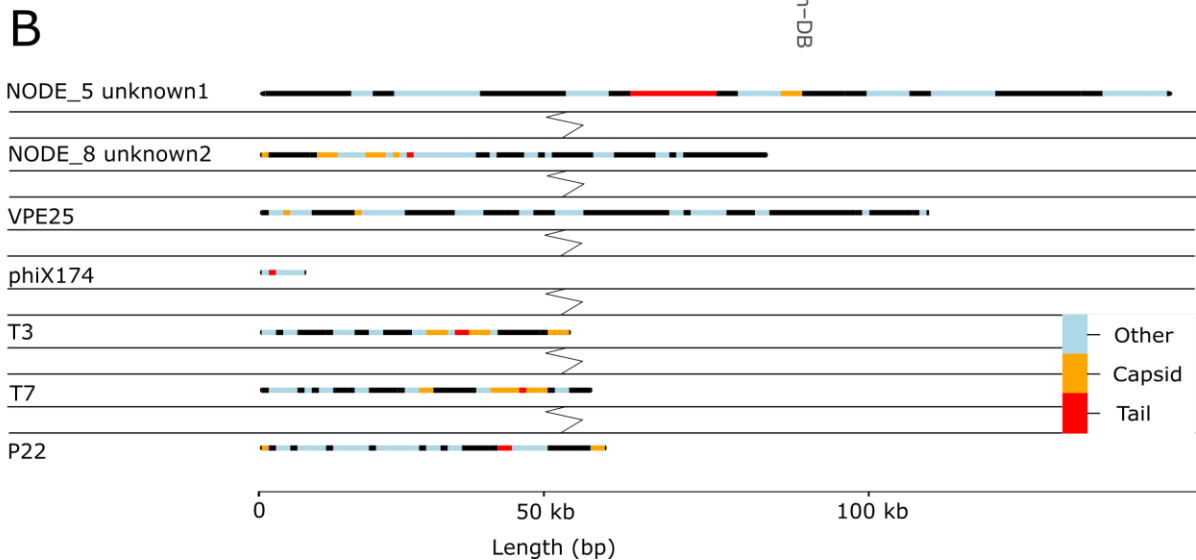
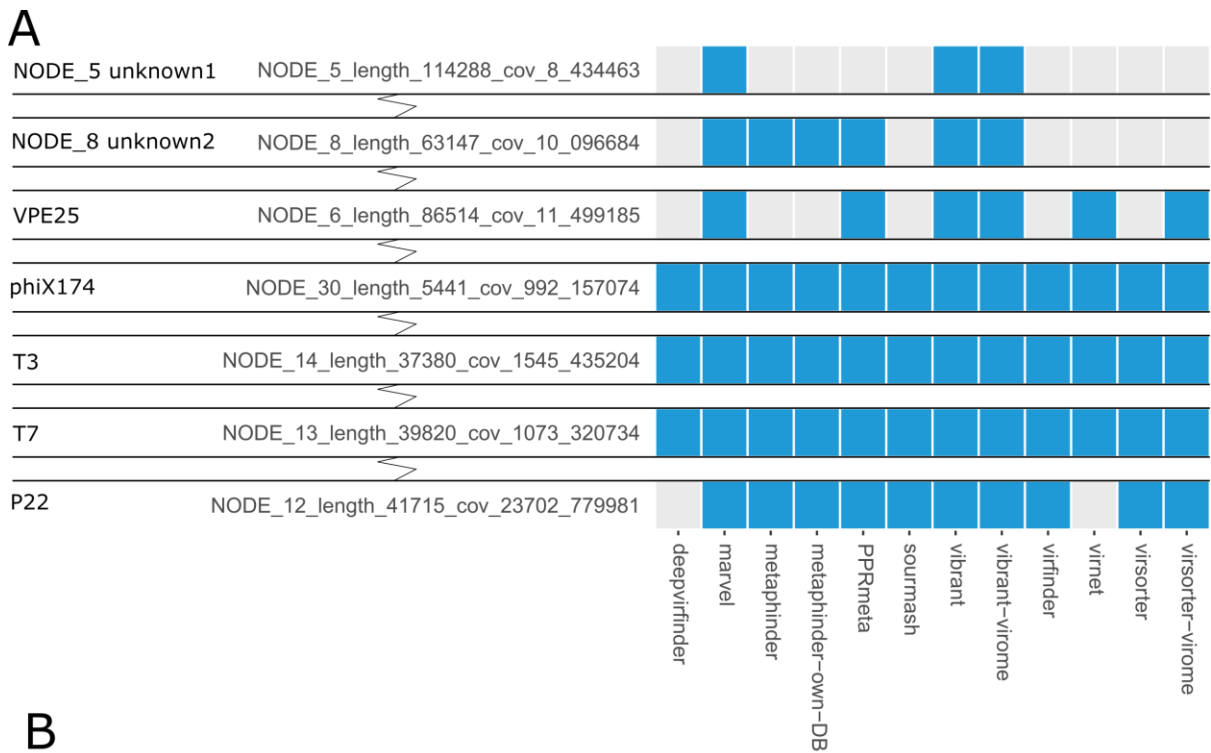
138 *Figure 2: UpSet plot summarizing the identification performance of each tool for the sample*
 139 *ERR575692. The total amount of identified phage-contigs per tool is shown in blue bars on*
 140 *the left. Black bars visualize the number of contigs that each tool or tool combination has*
 141 *uniquely identified. Each tool combination is shown below the barplot as a dot matrix.*

142

143 The workflow was able to detect contigs that correspond to the phages P22, T3, T7 and VPE25
 144 in all eight samples. In addition, the phage for the internal Illumina control (phiX174) was also
 145 identified. The M13 phage (27) could not be identified as it was not assembled via
 146 metaSPAdes due to the low read-abundance and low coverages (below 0.55x, determined by
 147 Kleiner *et. al* (27)). The same applies to phage $\phi 6$ which was not detectable by Kleiner *et. al*
 148 (27).

149 Unknown or novel phages, false-positive hits and tool disagreements are all plausible results
 150 during the phage identification step. Therefore, WtP generates for each positive contig a visual

151 plot highlighting the identified phage genes and additionally a heatmap to visualize tool
 152 agreements for each contig. While for some contigs all tools agreed, in many cases, only a
 153 handful (e.g. 6 out of 12 in case of VPE25) could identify the phage positive contig (Figure 3
 154 A). VPE25 was initially not taxonomically classified by WtP as it was not represented in the
 155 taxonomic database at this time, however, the corresponding positive contig was annotated
 156 with multiple different essential phage genes (Figure 3 B). Therefore, this unclassified but
 157 positive contig was compared via blastn and matched against the genome sequence of VPE25
 158 (PRJEB13004).
 159



160

161 *Figure 3: (A) Modified heatmap for assembly ERR575692 visualising the tool agreements per*
162 *phage positive contig and (B) a visual annotation of phage contigs and annotated protein-*
163 *coding genes via chromoMap. Annotations are coloured based on the categories of capsid*
164 *genes (orange), tail genes (red) and other phage genes (blue). Other contigs without either*
165 *capsid or tail genes have been removed for better readability. All unedited figures for each*
166 *sample can be found in the Supplementary Dataset.*

167

168 WtP streamlines the detection of phage sequences across multiple tools and thus balancing
169 some drawbacks of tools (e.g. relying on updated databases, only identifying known phages).

170 This issue is best highlighted in Figure 3 A: P22 could not be identified by either VirNet or
171 DeepVirFinder and VPE25 could not be identified by DeepVirFinder, MetaPhinder (both
172 databases), sourmash, VirFinder and VirSorter without the virome option. However, besides
173 other phage genes (e.g. DNA ligase, helicase), capsid and tail genes could be clearly
174 annotated for both (Figure 3 B: P22 and VPE25). Furthermore, CheckV determined a phage
175 completeness score of over 99.99 for both P22 and VPE25 (Table 2).

176 In addition to the above-mentioned phages, WtP identified two more large contigs with capsid
177 and tail annotations and a taxonomic assignment pointing to a phage of *Salmonella enterica*
178 (contig NODE_5 and NODE_8). However, both contigs are labelled as prophages via CheckV
179 with an estimated completeness of over 99.99 %. These phage positive contigs match to
180 prophages *Salmonella enterica* (additionally confirmed via blastn search on NCBI) and they
181 were identified in six out of eight samples.

182

183 Table 2: Summary of the CheckV output for the sample ERR575692. All contigs with a
184 completeness > 10 % and a length > 5,000 bp are shown.

185

Phage name	Contig_id	Gene count	CheckV quality	Completeness	contig length [bp]
unknown1	NODE_5	107	Complete	100.0	114,288
unknown2	NODE_8	71	High-quality	100.0	63,147
VPE25	NODE_6	137	High-quality	99.99	86,514
phiX174	NODE_30	8	Medium-quality	89.31	5,441
T3	NODE_14	43	High-quality	93.36	37,380
T7	NODE_13	53	Complete	99.46	39,820
P22	NODE_12	67	Complete	100.0	41,715

186

187 Some limitations must be noted. No specialised phage assembly strategy or any cleanup step
188 were included during the assembly step. Therefore, some smaller mice host contigs (below
189 5,000 bp) produced false positive hits. However, these contigs were clearly distinguishable
190 after the “Annotation & Taxonomy” step both in CheckV and due to the lack of typical genes
191 related to e.g. capsid or tail proteins, showing the application of WtP also for contaminated
192 datasets

193 Conclusion

194 With the rise of metagenomics and the application of machine learning principles for virus
195 detection, several phage identification tools have been released over the last few years. All
196 these tools utilize different identification approaches, all with advantages and limitations. The
197 choice of the user of a certain tool often depends strongly on its usability and less on its
198 performance. While some tools already come with a packaging system such as Conda or a
199 containerized environment, there exists no general framework for their execution and
200 different filter parameters, database dependencies, and installation issues prevent many

201 potential users from using certain tools. At least one multitool approach was implemented
202 on a smaller scale by Ann C. Gregory *et al.* (comprising only VirFinder and VirSorter) (20).
203 The overarching goal of WtP is to identify positive phage sequences via a comprehensive
204 and extendable multitool approach that is easy to use across different platforms. After a WtP
205 run, the user is provided with sufficient processed data (such as tool performance
206 comparisons, taxonomic assessments, and annotation maps) to reliably work with the
207 identified sequences. The results support the decision-making process of the user if different
208 identification tools are not in agreement with each other (e.g.: see reported results for VPE25
209 phage). Thus, WtP streamlines the identification of phage sequence recognition across
210 multiple tools in a reproducible and scalable workflow to allow researchers to concentrate on
211 their scientific questions instead of software implementations.

212 Future directions

213 WtP is a workflow project that will be improved and extended as the modular approach and
214 containerisation simplify the integration of new tools. Besides the intended main application of
215 the workflow - the identification of phages - the workflow can be used to benchmark current
216 and novel virus detection tools in a continuous manner. The predictive scope of WtP can be
217 extended to other viruses (such as RNA viruses) and prophages by including future tools
218 specifically designed for such use cases and by adjusting filter and annotation steps.
219 Furthermore, we plan to support the input of raw long reads as an alternative to assemblies.
220 The versioning of WtP represents a well-functioning approach with tested and up-to-date
221 versions of the workflow. Thus, the correct functioning of the workflow is always guaranteed
222 and allows a reliable and fast identification of phage sequences.

223 Declarations

224 Availability

225 Source code: https://github.com/replikation/What_the_Phage

226
227 Supplementary Dataset: https://github.com/mult1fractal/WtP_test_profile_results
228
229 Sequence data used in this work is available at: https://github.com/mult1fractal/WtP_test-
230 data

231 Competing interest

232 None to declare.

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238 based HPC with Singularity.

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