

Identifying contamination with advanced visualization and analysis practices: metagenomic approaches for eukaryotic genome assemblies

Tom O Delmont, A. Murat Eren

High-throughput sequencing provides a fast and cost effective mean to recover genomes of organisms from all domains of life. However, adequate curation of the assembly results against potential contamination of non-target organisms requires advanced bioinformatics approaches and practices. Here, we re-analyzed the sequencing data generated for the tardigrade *Hypsibius dujardini* using approaches routinely employed by microbial ecologists who reconstruct bacterial and archaeal genomes from metagenomic data. We created a holistic display of the eukaryotic genome assembly using DNA data originating from two groups and eleven sequencing libraries. By using bacterial single-copy genes, k-mer frequencies, and coverage values of scaffolds we could identify and characterize multiple near-complete bacterial genomes, and curate a 182 Mbp draft genome for *H. dujardini* supported by RNA-Seq data. Our results indicate that most contaminant scaffolds were assembled from Moleculo long-read libraries, and most of these contaminants have differed between library preparations. Our re-analysis shows that visualization and curation of eukaryotic genome assemblies can benefit from tools designed to address the needs of today's microbiologists, who are constantly challenged by the difficulties associated with the identification of distinct microbial genomes in complex environmental metagenomes.

1 Identifying contamination with advanced
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5 Tom O. Delmont¹ and A. Murat Eren^{1,2}

6 ¹Department of Medicine, The University of Chicago, Chicago, IL , United States.

7 ²Josephine Bay Paul Center, Marine Biological Laboratory, Woods Hole, MA , United States.

8 Corresponding Author:

9 A. Murat Eren¹

10 *Knapp Center for Biomedical Discovery,*
11 *900 E. 57th St., MB 9, RM 9118, Chicago, IL 60637 USA*

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13 Email address: meren@uchicago.edu

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16 Abstract

17 High-throughput sequencing provides a fast and cost effective mean to recover genomes of
18 organisms from all domains of life. However, adequate curation of the assembly results
19 against potential contamination of non-target organisms requires advanced bioinformatics
20 approaches and practices. Here, we re-analyzed the sequencing data generated for the
21 tardigrade *Hypsibius dujardini* using approaches routinely employed by microbial
22 ecologists who reconstruct bacterial and archaeal genomes from metagenomic data. We
23 created a holistic display of the eukaryotic genome assembly using DNA data originating
24 from two groups and eleven sequencing libraries. By using bacterial single-copy genes, k-
25 mer frequencies, and coverage values of scaffolds we could identify and characterize
26 multiple near-complete bacterial genomes, and curate a 182 Mbp draft genome for *H.*
27 *dujardini* supported by RNA-Seq data. Our results indicate that most contaminant scaffolds
28 were assembled from Moleculo long-read libraries, and most of these contaminants have
29 differed between library preparations. Our re-analysis shows that visualization and
30 curation of eukaryotic genome assemblies can benefit from tools designed to address the
31 needs of today's microbiologists, who are constantly challenged by the difficulties
32 associated with the identification of distinct microbial genomes in complex environmental
33 metagenomes.

34 **Key words:** genomics, assembly, curation, visualization, contamination, anvi'o, HGT

35 Introduction

36 Advances in high-throughput sequencing technologies are revolutionizing the field of
37 genomics by allowing researchers to generate large amount of data in a short period of
38 time (Loman & Pallen 2015). These technologies, combined with advances in
39 computational approaches, help us understand the diversity and functioning of life at
40 different scales by facilitating the rapid recovery of bacterial, archaeal, and eukaryotic
41 genomes (Venter et al. 2001; Brown et al. 2015; Schleper et al. 2005). Yet, the recovery of
42 genomes is not straightforward, and reconstructing bacterial and archaeal versus
43 eukaryotic genomes present researchers with distinct pitfalls and challenges that result in
44 different molecular and computational workflows.

45 For instance, difficulties associated with the cultivation of bacterial and archaeal organisms
46 (Schloss & Handelsman 2003) have persuaded microbiologists to reconstruct genomes
47 directly from the environment through assembly-based metagenomics workflows and
48 genome binning. This workflow commonly entails (1) whole sequencing of environmental
49 genetic material, (2) assembly of short reads into contiguous DNA segments (contigs), and
50 (3) identification of draft genomes by binning contigs that originate from the same
51 organism. Due to the extensive diversity of bacteria and archaea in most environmental
52 samples (Gans et al. 2005; Rusch et al. 2007), the field of metagenomics has rapidly evolved
53 to accurately delineate genomes in assembly results. Today, microbiologists often exploit
54 two essential properties of bacterial and archaeal genomes to improve the "binning" step:
55 (1) k-mer frequencies that are somewhat preserved throughout a single microbial genome

56 (Pride et al. 2003), to identify contigs that likely originate from the same genome (Teeling
57 et al. 2004), and (2) a set of genes that occur in the vast majority of bacterial genomes as a
58 single copy, to estimate the level of completion and contamination of genome bins (Wu &
59 Eisen 2008; Campbell et al. 2013; Parks et al. 2015). These properties, along with
60 differential coverage of contigs across multiple samples when such data exist, are routinely
61 used to identify coherent microbial draft genomes in metagenomic assemblies (Albertsen
62 et al. 2013; Alneberg et al. 2014; Kang et al. 2015; Eren et al. 2015).

63

64 On the other hand, researchers who study eukaryotic genomes generally focus on the
65 recovery of a single organism, which, in most cases, simplifies the identification of the
66 target genome in assembly results. However, sequences of bacterial origin can contaminate
67 eukaryotic genome assembly results due to their occurrence in samples (Chapman et al.
68 2010; Artamonova & Mushegian 2013), DNA extraction kits (Salter et al. 2014), or
69 laboratory environments (Laurence et al. 2014; Strong et al. 2014). One of the major
70 challenges of working with eukaryotic genomes is the extent of repeat regions that
71 complicate the assembly process (Richard et al. 2008). To optimize the assembly,
72 researchers often employ multiple library preparations for sequencing (Ekblom & Wolf
73 2014; Gnerre et al. 2010), which may increase the potential sources of post-DNA extraction
74 contamination. Contaminants in assembly results can eventually contaminate public
75 databases (Merchant et al. 2014), and impair scientific findings (Artamonova et al. 2015).
76 The detection and removal of contaminants poses a major bioinformatics challenge. To
77 identify undesired contigs in a genomic assembly, scientists can simply compare their
78 assembly results to public sequence databases for positive hits to unexpected taxa (Ekblom
79 & Wolf 2014), use k-mer coverage plots to identify distinct genomes (Percudani 2013), or
80 employ scatter plots to partition contigs based on their GC-content and coverage (Kumar et
81 al. 2013). However, advanced solutions developed for accurate identification of microbial
82 genomes in complex metagenomic assemblies can leverage these approaches further, and
83 offer enhanced curation options for eukaryotic assemblies.

84

85 The first release of a tardigrade genome by Boothby et al. (2015) demonstrates a striking
86 example of the importance of careful screening for contaminants in eukaryotic genome
87 assemblies. Tardigrades are microscopic animals occurring in a wide range of ecosystems
88 and they exhibit extended capabilities to survive in harsh conditions that would be fatal to
89 most animals (Ramløv & Westh 2001; Jönsson et al. 2005, 2008; Horikawa et al. 2013).
90 Boothby and his colleagues generated a composite DNA sequencing dataset from a culture
91 of the tardigrade *Hypsibius dujardini* by exploiting some of the best practices of high-
92 throughput sequencing available today (Boothby et al. 2015). In their assembled tardigrade
93 genome, the authors detected a large number of genes originating from bacteria, making up
94 approximately one-sixth of the gene pool, and suggested that horizontal gene transfers
95 (HGTs) could explain the unique ability of tardigrades to withstand extreme ranges of
96 temperature, pressure, and radiation. However, Koutsovoulos et al.'s subsequent analysis
97 of Boothby et al.'s assembly suggested that it contained extensive bacterial contamination,
98 casting doubt on the extended HGT hypothesis (Koutsovoulos et al. 2015). By applying two-
99 dimensional scatterplots on their own assembly results (which were also contaminated
100 with bacterial sequences), Koutsovoulos et al. reported a curated draft genome of *H.*
101 *dujardini*.

102 Here we re-analyzed the raw sequencing data generated by Boothby et al. (2015) and
103 Koutsovoulos et al. (2015) using *anvi'o*, an analysis and visualization platform originally
104 designed for the identification and assessment of bacterial genomes in metagenomic
105 assemblies (Eren et al. 2015). In our analysis, we relied on bacterial single-copy genes to
106 assess the occurrence of bacterial genomes in assembly results, used k-mer frequencies to
107 organize contigs, combined all sequencing data for each library preparation method from
108 both groups into a single display, and overlaid RNA-Seq data (courtesy of Itai Yanai) over
109 contigs to confirm the origin of contigs.

110 **Material and methods**

111 **Genome assemblies, and raw sequencing data for DNA and RNA.** Boothby et al.
112 constructed three paired-end Illumina libraries (insert sizes of 0.3, 0.5 and 0.8 kbp) for 2 x
113 100 paired-end sequencing on a HiSeq2000 and six single-end long-read libraries (five
114 Illumina Moleculo libraries sequenced by the Illumina “long read” DNA sequencing service,
115 and one PacBio SMRT library sequenced using the P6-C4 chemistry and a 1 X 240 movie),
116 which altogether provided a co-assembly of 252.5 Mbp (Boothby et al. 2015). The
117 tardigrade genome released by Boothby et al. (2015), along with the nine sequencing data
118 used for its assembly, are available at http://weatherby.genetics.utah.edu/seq_transf.
119 Independently, Koutsovoulos et al. generated a 0.3 kbp insert library and a 1.1 kbp insert
120 mate-pair library for 2 x 100 paired end sequencing on a HiSeq2000 that provided a co-
121 assembly of 185.8 Mbp (Koutsovoulos et al. 2015). These authors subsequently curated a
122 135 Mbp draft genome by removing potential bacterial contamination (Koutsovoulos et al.
123 2015). The tardigrade raw assembly and curated draft genome released by Koutsovoulos et
124 al. (2015) are available at http://badger.bio.ed.ac.uk/H_dujardini, and their two
125 sequencing datasets are available from the ENA, under study accession PRJEB11910.
126 Itai Yanai (Technion - Israel Institute of Technology, <http://yanailab.technion.ac.il/>)
127 graciously provided RNA-seq data generated from a *H. dujardini* culture, which will be
128 available under the accession ID accession GSE70185 upon their publication.

129 **Quality filtering and read mapping.** We used *illumina-utils* (Eren et al. 2013) (available
130 from <http://github.com/meren/illumina-utils>) for quality filtering of short Illumina reads
131 using ‘*iu-filter-quality-minoche*’ script with default parameters, which implements the
132 quality filtering described by Minoche et al. (Minoche et al. 2011). *Bowtie2* v2.2.4
133 (Langmead & Salzberg 2012) with default parameters mapped all reads to assemblies. We
134 used *samtools* v1.2 (Li et al. 2009) to generate BAM files from mapping results.

135 **Processing of contigs, visualization and genome binning.** We processed BAM files and
136 raw genome assemblies using *anvi'o* v1.2.2 (available from
137 <http://github.com/meren/anvio>), generated *anvi'o* contig databases, profiled BAM files,
138 and merged resulting profiles using default parameters and following the metagenomic
139 workflow outlined in Eren et al (2015). In addition, we mapped and profiled the RNA-seq
140 data to identify scaffolds with transcriptomic activity, and exported the table for
141 proportion of each scaffold covered by transcripts using *anvi'o* script ‘*get-db-table-as-*
142 *matrix*’. We used the supplementary material published by Boothby et al. (2015) (“Dataset

143 S1" in the original publication) to identify scaffolds with proposed HGTs. We included the
144 RNA-seq results and scaffolds with HGTs into our visualization as an additional data file.
145 The URL <http://merenlab.org/data/> reports anvi'o files to regenerate Figure 1 and Figure
146 2, our curation of the tardigrade genome from Boothby et al.'s assembly (which is also
147 available in NCBI via the bioproject ID PRJNA309530), and the FASTA files for bacterial
148 genomes we identified in the Boothby et al. and Koutsovoulos et al. assemblies. To finalize
149 the anvi'o generated SVG files for publication, we used Inkscape v0.91 (available from
150 <https://inkscape.org/>).

151
152 **Predicting number of bacterial genomes.** To estimate the number of bacterial genomes
153 in a given collection of scaffolds in a raw assembly or in a curated genome bin, and to
154 visualize the distribution of HMM hits for each bacterial single-copy gene, we used the
155 anvi'o script 'gen-stats-for-single-copy-genes', which reports the most frequent number in
156 the list of number of hits per single-copy gene as the estimated number of bacterial
157 genomes in a collection of scaffolds. The script uses HMMer v3.1b2 (Eddy 2011) to search
158 for Hidden Markov Profiles (HMMs) of 139 bacterial single-copy genes identified by
159 Campbell et al (2013), and the R library 'ggplot' v1.0.0 (R Development Core Team 2011;
160 Ginstet 2011) to plot results.

161 **Taxonomical and functional annotation of bacterial genomes.** After binning, we
162 uploaded bacterial draft genomes recovered from the assembly into the RAST server (Aziz
163 et al. 2008), and used the RAST best taxonomic hits and FigFams to infer the taxonomy of
164 genome bins and functions they harbor.

165 Results and Discussion

166 Boothby et al. generated sequencing data from a tardigrade culture using three short read
167 (Illumina) and six long read (Moleculo and PacBio) libraries, which altogether provided a
168 co-assembly of 252.5 Mbp (Boothby et al. 2015). Using this assembly without any curation,
169 authors suggested that 6,663 genes were entered into the tardigrade genome through
170 HGTs. Independently, Koutsovoulos et al. generated sequencing data from another
171 tardigrade culture using two short read Illumina libraries that provided a co-assembly of
172 185.8 Mbp, from which they could curate a 135 Mbp tardigrade draft genome by removing
173 potential bacterial contamination using two-dimensional scatterplots of scaffolds with
174 respect to their GC-content and coverage (Koutsovoulos et al. 2015).

175 A holistic view of the data

176 The use of multiple library preparations and sequencing strategies is likely to result in
177 more optimal assembly results (Gnerre et al. 2010). Hence, we focused on the scaffolds
178 generated by Boothby et al. (2015) as a foundation to maximize the recovery of the
179 tardigrade genome. To provide a holistic understanding of the composite sequencing data
180 generated by the two teams, we mapped the raw data from the nine DNA sequencing
181 libraries from Boothby et al., and the two Illumina libraries from Koutsovoulos et al. (2015)
182 on this assembly. Anvi'o generated a hierarchical clustering of scaffolds by combining the

183 tetra-nucleotide frequency and coverage of each scaffold across the 11 DNA sequencing
184 libraries (Eren et al. 2015). Besides visualizing the coverage of each scaffold in each sample,
185 we highlighted scaffolds with HGTs identified by Boothby et al. on the resulting
186 organization of scaffolds, and visualized RNA-seq mapping results. Figure 1 displays the
187 anvi'o merged profile that represents all this information in a single display.

188 **A larger draft genome for *H. dujardini***

189 Through the anvi'o interactive interface we selected 14,961 scaffolds from the Boothby et
190 al. assembly that recruited large number of short-reads in a consistent manner (Fig. 1).
191 This 182.2 Mbp selection with consistent coverage (#1 in Fig. 1) represents our curation of
192 the tardigrade draft genome from Boothby et al.'s assembly. The remaining 7,535 scaffolds,
193 which total about 70 Mbp of the assembly, harbored 96.1% of HGTs identified by Boothby
194 et al. These scaffolds recruited only 0.05% of the reads from the RNA-Seq data, highlighting
195 the extent of contamination in the original assembly. This finding is in agreement with
196 Koutsovoulos et al.'s findings; however, our curated draft genome is 47 Mbp larger than the
197 draft genome released by Koutsovoulos et al. (2015). The portion of scaffolds covered by
198 RNA-Seq data suggests that the additional 47 Mbp still originate from the tardigrade
199 genome. Thus, our selection is likely to be a more complete draft genome for *H. dujardini*
200 than that of Koutsovoulos et al., most probably due to Boothby et al.'s inclusion of longer
201 reads.

202 **The origin of bacterial contamination**

203 Our mapping results indicate the presence of non-target sequences in the assembly that
204 recruit reads only from long-read libraries. One interpretation could be that most of the
205 contamination in Boothby et al.'s assembly originated from Moleculo libraries, post DNA-
206 extraction (Fig. 1). However, a recent study shows that the majority of long reads from
207 Moleculo libraries originated from low-abundance organisms in samples (Sharon et al.
208 2015), while another study suggests relatively more sequencing bias in Moleculo library
209 preparation results (Kuleshov et al. 2015). Therefore another interpretation of the
210 mapping results can be that the bacterial contaminants were present in the sample in low
211 abundances pre-DNA extraction, and individual Moleculo library preparations resulted in
212 long reads originating from different parts of this rare community. Regardless, long reads
213 considerably improved Boothby et al.'s assembly, which resulted in a larger tardigrade
214 genome following the removal of non-target sequences. While these results reiterate that
215 the use of long-read libraries is essential to generate more comprehensive assemblies, they
216 also suggest that extra care should be taken to better mitigate the presence of non-target
217 sequences in assembly results when long-read libraries are used for sequencing.

218 We identified three near-complete bacterial genomes affiliated to *Chitinophaga* and
219 *Thermosinus* in Boothby et al.'s assembly (Fig. 1). Surprisingly, Boothby et al. identified only
220 a small portion of these complete bacterial genomes as sources of HGTs while applying a
221 metric specifically designed to detect foreign DNA in eukaryotic genomes. For instance,
222 none of the 4,459 genes in bacterial draft genome #2 (selection #3 in Fig. 1) were reported
223 in Boothby et al.'s findings as HGTs. Although this falls outside of the scope of our study,

224 this oddity may indicate a potential flaw in metrics commonly used to quantify foreign DNA
225 in eukaryotic genomes. We also processed and visualized the raw assembly from
226 Koutsovoulos et al. (2015) using *anvi'o* (Figure S1) and recovered eight bacterial genomes,
227 however, we found no taxonomical overlap between high-completion bacterial genomes
228 from the two sequencing projects (Table S1).

229
230 Interestingly, one bacterial genome (selection #2 in Fig. 1) was detected in DNA libraries
231 from both groups, as well as in the RNA-seq data, suggesting that the related bacterial
232 population was in all samples prior to the DNA/RNA extraction step. This genome is
233 affiliated to *Chitinophaga*, and harbors genes coding for chitin degradation and utilization
234 (Table S2). Chitin occurs naturally in the feeding apparatus of tardigrades (Guidetti et al.
235 2015), and might be a source of carbon for its microbial inhabitants. The genome also
236 harbors genes coding for the biosynthesis of tryptophan, an essential amino acid for
237 animals (Crawford 1989; Zelante et al. 2013), proteorhodopsin, host invasion and
238 intracellular resistance, dormancy and sporulation, and oxidative stress. Although this
239 genome may belong to a tardigrade symbiont, the generation of the data does not allow us
240 to rule out the possibility that it may be associated with the food source. Nevertheless, this
241 finding suggests that there may be cases where non-target genomes in an assembly can
242 provide clues about the lifestyle of a given host.

243 **Best practices to assess bacterial contamination**

244 Initial assessment of the occurrence of bacterial single-copy genes in eukaryotic assemblies
245 can provide a quick estimation of the number of bacterial genomes that occur in assembly
246 results. The use of bacterial single-copy genes can give much more accurate representation
247 of potential bacterial contamination than screening for 16S rRNA genes alone, as they are
248 less likely to be found in co-assembly results (Miller et al. 2011; Delmont et al. 2015).
249 Although Boothby et al. reported the lack of 16S rRNA genes in their assembly (Boothby et
250 al. 2015), *anvi'o* estimated that it contained at least 10 complete bacterial genomes (Fig. 2)
251 using a bacterial single-copy gene collection (Campbell et al. 2013). This simple yet
252 powerful step could identify cases of extensive contamination, and alert researchers to be
253 diligent in identifying scaffolds originating from bacterial organisms. Figure 2 also
254 summarizes the HMM hits in scaffolds found in curated tardigrade genomes from our
255 analysis and Koutsovoulos et al.'s study. We observed that the average significance score
256 for the remaining HMM hits for bacterial single-copy genes in curated genomes was 4.2
257 times lower in average compared to the HMM hits in assembly results (Table S3). The
258 decrease in the significance scores, and the very similar patterns of occurrence of HMM hits
259 between the two curation efforts suggest that some of the HMM profiles may not be specific
260 enough to be identified only in bacteria.

261 Two-dimensional scatterplots have a long history of identifying distinct genomes in
262 assembly results (Tyson et al. 2004) and continue to be used for delineating microbial
263 genomes in metagenomic assemblies (Albertsen et al. 2013; Cantor et al. 2015), as well as
264 detecting contamination in eukaryotic assembly results (Kumar et al. 2013). Although
265 scatterplots can describe the organization of contigs in assembly results, they suffer from
266 limited number of dimensions they can display, and their inability to depict complex

267 supporting data that can improve the identification of individual genomes. These
268 limitations are particularly problematic in sequencing projects covering multiple
269 sequencing libraries, where displaying mapping results from each library can help
270 detecting sources of contaminants. Despite their successful applications, two dimensional
271 scatter plots limit researchers to the use of simple characteristics of the data that can be
272 represented on an axis (such as GC-content). In contrast, clustering scaffolds, and
273 overlaying multiple layers of independent information produce more comprehensive
274 visualizations that display multiple aspects of the data.

275 **Conclusions**

276 The field of genomics requires advanced computational approaches to take best advantage
277 of constantly evolving ways to generate sequencing data. The need for *de novo*
278 reconstruction of microbial genomes from environmental samples through shotgun
279 metagenomics data has given raise to advanced techniques and software platforms that can
280 make sense of complex assemblies (Wu et al. 2014; Dick et al. 2009; Alneberg et al. 2014;
281 Kang et al. 2015; Eren et al. 2015). Our study demonstrates that these approaches can be
282 effectively used in eukaryotic assembly projects for curation purposes.

283 **Acknowledgments**

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289 **Figure and table legends**

290 Figure 1. Holistic assessment of the tardigrade genome release from Boothby et al. (2015).
291 Dendrogram in the center organizes scaffolds based on sequence composition and
292 coverage values in data from 11 DNA libraries. Scaffolds larger than 40 kbp were split into
293 sections of 20 kbp for visualization purposes. Splits are displayed in the first inner circle
294 and GC-content (0-71%) in the second circle. In the following 11 layers, each bar
295 represents the portion of scaffolds covered by short reads in a given sample. The next layer
296 shows the same information for RNA-Seq data. Scaffolds harboring genes used by Boothby
297 et al. to support the expended HGT hypothesis is shown in the next layer. Finally, the
298 outermost layer shows our selections of scaffolds as draft genome bins: the curated
299 tardigrade genome (selection #1), as well as three near-complete bacterial genomes
300 originating from various contamination sources (selection #2, #3, and #4).

301 Figure 2. Figure 2: Occurrence of the 139 bacterial single-copy genes reported by Campbell
302 et al. (2013) across scaffold collections. The top two plots display the frequency and

303 distribution of single-copy genes in the raw tardigrade genomic assembly generated by
304 Boothby et al. (2015), and Koutsovoulos et al. (2015), respectively. The bottom two plots
305 display the same information for each of the curated tardigrade genomes. Each bar
306 represents the squared-root normalized number of significant hits per single-copy gene.
307 The same information is visualized as box-plots on the left side of each plot.

308 Figure S1. Visualization and curation of the raw tardigrade genome assembly from
309 Koutsovoulos et al. (2015). In the left panel (curation step I), 24,841 scaffolds that were
310 longer than 1 kbp from the raw assembly were clustered based on sequence composition
311 and coverage values in data from the two Illumina sequencing libraries (the inner
312 dendrogram). Scaffolds longer than 40 kbp were split into sections of 20 kbp for
313 visualization purposes. The second layer shows the GC-content for each scaffold. The next
314 two view layers represent the log-normalized mean coverage values for scaffolds in the two
315 sequencing datasets. Finally, our scaffold selections (tardigrade draft 01 and six bacterial
316 draft genomes) are displayed in the outer layer. In the right panel (curation step II), the
317 15,839 scaffolds from the tardigrade selection from step I were clustered based on
318 sequence composition only for more precise curation. Additional scaffold selections
319 (tardigrade draft 02 and two bacterial draft genomes) are displayed in the outer layer.

320 Table S1. Summary of *H. dujardini* and bacterial genomes identified from the raw assembly
321 results of Boothby et al. (2015) and Koutsovoulos et al. (2015). * Inferred from Boothby et
322 al. (2015) and Koutsovoulos et al. (2015) publications. ** Scores were calculated using
323 bacterial single copy genes from Campbell et al. (2013) and are only used to assess
324 bacterial contamination levels in the eukaryotic assembly results.

325 Table S2. Summary of functions identified by RAST in the bacterial draft genome #2
326 (selection #3 in Fig. 1).

327 Table S3. Summary of HMM hits for each bacterial single-copy gene (collection of 139 from
328 Campbell et al. (2013)) identified in 1) the raw assembly by Boothby et al. (2015), 2) the
329 raw assembly by Koutsovoulos et al. (2015), 3) the curated draft genome of *Hypsibius*
330 *dujardini* from Boothby et al. assembly in this study, and 4) the curated draft genome of *H.*
331 *dujardini* from Koutsovoulos et al. (2015).

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333

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Holistic assessment of the tardigrade genome release from Boothby et al. (2015).

Dendrogram in the center organizes scaffolds based on sequence composition and coverage values in data from 11 DNA libraries. Scaffolds larger than 40 kbp were split into sections of 20 kbp for visualization purposes. Splits are displayed in the first inner circle and GC-content (0-71%) in the second circle. In the following 11 layers, each bar represents the portion of scaffolds covered by short reads in a given sample. The next layer shows the same information for RNA-Seq data. Scaffolds harboring genes used by Boothby et al. to support the expanded HGT hypothesis is shown in the next layer. Finally, the outermost layer shows our selections of scaffolds as draft genome bins: the curated tardigrade genome (selection #1), as well as three near-complete bacterial genomes originating from various contamination sources (selection #2, #3, and #4).



