

Dual RNA-Seq meta-analysis in *Plasmodium* infection

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Abstract

Dual RNA-Seq is the simultaneous analysis of host and parasite transcriptomes. This approach can identify host-parasite interactions by correlated gene expression. Co-expression might highlight interlinked signaling, metabolic or gene regulatory pathways in addition to potentially physically interacting proteins. Numerous studies have used gene expression data to investigate *Plasmodium* infection causing malaria. Usually such studies focus on one organism – either the host or the parasite – and the other is considered “contaminant”. Dual RNA-Seq, in contrast, follows the rationale that cross-species interactions determine not only virulence of the parasite but also tolerance, resistance or susceptibility of the host.

Here we propose a meta-analysis approach for dual RNA-Seq. We screened malaria transcriptome experiments for studies providing gene expression data from both *Plasmodium* and its host. Out of 105 malaria studies in *Homo sapiens*, *Macaca mulatta* and *Mus musculus*, we identified 56 studies with the potential to provide host and parasite data. While 15 studies (1935 total samples) of these 56 explicitly aimed to generate dual RNA-Seq data, 41 (1129 samples) had an original focus on either the host or the parasite. We show that a total of up to 2530 samples are suitable for dual RNA-Seq analysis providing an unexplored potential for meta analysis.

19 We argue that the multitude of variations in experimental conditions found in the
20 selected studies should help narrow down a conserved core of cross-species interactions.
21 Different hosts used as laboratory models for human malaria infection are infected by
22 evolutionarily diverse species of genus *Plasmodium*. We propose that a conserved core of
23 interacting pathways and co-regulated genes might be identified using overlying interaction
24 networks of different host-parasite species pairs based on orthologous genes. Our approach
25 might also provide the opportunity to gauge the applicability of model systems for different
26 pathways in malaria studies.

Introduction

Transcriptomes are often analysed in a first attempt to understand cellular and organismic events, because a comprehensive profile of RNA expression can be obtained at reasonable cost and with high technical accuracy [1]. Microarrays dominated transcriptomics for over ten years since 1995 [2–4]. Microarrays quantify gene expression based on hybridisation of a target sequence to an immobilised probe of known sequence. Technical difficulties associated with microarrays lie in probe selection, cross-hybridization, and design cost of custom chips [5]. RNA sequencing (RNA-Seq) eliminates these difficulties and provides deep and accurate expression estimates for all RNAs in a sample. RNA-Seq has thus replaced microarrays as the predominant tool for transcriptomics [1,6]. RNA-Seq assesses host and parasite transcriptomes simultaneously, if RNA of both organisms is contained in a sample. Virulence of infectious disease is often a result of interlinked processes of both host and pathogen (“host-pathogen interactions”) and it has been proposed to analyse transcriptomes of both organisms involved in an infection to obtain a more complete understanding of disease [5–7]. This approach is called dual RNA-Seq.

In case of malaria, unlike in bacterial infections, both the pathogen and the host are eukaryotic organisms with similar transcriptomes. Host and parasite mRNA is selected simultaneously when poly-dT priming is used to amplify polyadenylated transcripts [5,6]. This makes most malaria transcriptome datasets potentially suitable for dual RNA-Seq analysis. Malaria research, especially transcriptomics, is traditionally designed to target one organism, either the host or the parasite. Expression of mRNA, for example, can be compared between different time points in the life cycle of *Plasmodium* or between different drug treatment conditions. In the mammalian intermediate host, *Plasmodium* invades first liver and then red blood cells (RBCs) for development and asexual expansion. While the nuclear machinery of cells from both host and parasite produces mRNA in the liver, RBCs are enucleated and transcriptionally inactive in mammalian host. In blood infections leukocytes are thus the source of host mRNA. Researchers conducting a targeted experiment might regard transcripts from the non-target organism as “contamination”. Nevertheless, expression of those transcripts potentially responds to stimuli during the investigation. Additionally, some recent studies on malaria make intentional use dual RNA-Seq. Malaria is the most thoroughly investigated disease caused by an eukaryotic organism and accumulation of these two kinds of studies, RNA-Seq with “contaminants”

59 and intentional dual RNA-Seq, provides a rich resource for meta-analysis.

60 Such a meta analysis can use co-regulated gene expression to infer host-parasite inter-
61 actions. Correlation of mRNA expression can be indicative of different kinds of biological
62 “interactions”: On one hand, protein products could be directly involved in the forma-
63 tion of complexes and might therefore be produced at quantities varying similarly under
64 altered conditions. On the other, involvement in the same biological pathways can re-
65 sult in co-regulated gene expression without physical interaction. This broad concept of
66 interaction has long been exploited in single organisms (e.g. [?, 8–10]). We (and others
67 before [11]) propose to extrapolate this to interactions between the host and pathogen. It
68 can be expected that a stimulus presented by the parasite to a host causes host immune
69 response and the parasite in turn tries to evade this response, creating a cascade of genes
70 co-regulated at different time points or under different conditions.

71 In this paper we explore first steps in a comparative meta-analysis of dual RNA-Seq
72 transcriptomes. Existing raw read datasets collectively present an unexplored potential to
73 answer questions that have not been investigated by individual studies. Meta-analysis in-
74 creases the number of observations and statistical power and helps eliminate false positives
75 and true negatives which may otherwise conceal important biological inferences [12–14].
76 Since mice- and macaque-malaria are often used as laboratory models for human malaria,
77 we analyse the availability and suitability of mRNA sequencing data from three evolution-
78 arily close hosts - *Homo sapiens*, *Macaca mulatta* and *Mus musculus* - and their associated
79 *Plasmodium* parasites. We summarize available data, challenges and approaches to obtain
80 host-parasite interactions and discuss orthology across different host-parasite systems as
81 a means to enrich information.

82 Data review and curation of potentially suitable 83 studies

84 Sequence data generated in biological experiments is submitted to one of the three mirror-
85 ing databases of the International Nucleotide Sequence Database Collaboration (INSDC):
86 NCBI Sequence Read Archive (SRA), EBI Sequence Read Archive (ERA) and DDBJ Se-
87 quence Read Archive (DRA). Comprehensive query tools to access these databases via
88 web interfaces and programmatically via scriptable languages exist (for example, SRADB,

89 ENAbrowseR). In these databases, all experiments submitted under a single accession are
90 given a single “study accession number” and are collectively referred to as a “study” here
91 onwards.

92 We used SRADB [15], a Bioconductor/R package [16,17], to query SRA [18,19] for
93 malaria RNA-Seq studies with the potential to provide host and *Plasmodium* reads for
94 our meta-analysis. We first selected studies with “library_strategy” given as “RNA-Seq”
95 and “Plasmodium” in study title, abstract or sample attributes using the “dbGetQuery”
96 function. Then we used the “getSRA” function with the query “(malaria OR Plasmodium)
97 AND RNA-Seq”. This function searches all fields. We manually curated the combined
98 results and added studies based on a literature review using the terms described for
99 the “getSRA” function in SRA, PubMed and Google Scholar. During this search, we
100 disregarded 91 studies, all of which provide data from vectors and non-target hosts (e.g.
101 avian malaria). 49 more studies were excluded because their gene expression data was
102 derived from *Plasmodium* spp cultures in erythrocytes, blood or RPMI and thus can be
103 expected to be devoid of host mRNA. We then used the SRADB Bioconductor/R package,
104 and the prefetch and fastq-dump functions from SRAtoolkit, to download all replicate
105 samples (called “runs” in the databases) of the selected studies. The curation of studies
106 and the download was performed on 21 January, 2019.

107 In total we found 56 potentially suitable studies in this database and literature review.
108 The host organism for 22 studies was *Homo sapiens*, for 24, *Mus musculus* and for 10,
109 *Macaca mulatta*. The corresponding infecting parasites were *P. falciparum*, *P. vivax* and
110 *P. berghei* in human studies (including four artificial infections of human liver cell culture
111 with *P. berghei*), *P. yoelii*, *P. chabaudi* and *P. berghei* in mouse studies and *P. cynomolgi*
112 and *P. coatneyi* in macaque studies(table 1).

113 We note that 20 of the 56 studies depleted (or enriched, respectively) specific classes of
114 cells from their samples. Some studies, for example, targeted the parasite using vaccines
115 derived from sporozoites during liver infection [20–22]. Such infection is physiologically
116 asymptomatic and a low number of parasites cells [23] makes it difficult to study *Plas-*
117 *modium* transcriptomes in this stage. To reduce overwhelming host RNA levels, 3 out of
118 10 liver studies sorted infected hepatoma cells from uninfected cells. Similarly, 17 other
119 studies have depleted or enriched host WBCs (leukocytes) to focus expression analysis on
120 *Plasmodium* or the host immune system, respectively. In all these scenarios, we suspect
121 depletion to be imperfect and thus the samples to potentially include mRNA of both or-

122 organisms. We note, however, that host gene-expression for WBC-depleted samples might
123 be problematic as incomplete depletion might affect different types of WBCs differentially
124 and hence bias the detectable host mRNA expression in the direction of less-depleted cell
125 types. For the similar reasons, parasite depletion might be challenging to control for.

126 For 15 out of the 56 studies the authors state that they intended to simultaneously
127 study host and parasite transcriptomes (“dual RNA-Seq”). This includes 8 studies from
128 MaHPIC (Malaria Host-Pathogen Interaction Center), based at Emory University, that
129 made extensive omics measurements in macaque malaria. The original focus of the re-
130 maining 41 studies was on the parasite in 20 and on the host in 21 cases.

131 *Plasmodium* parasites sequester in bone marrow, adipose tissue, lung, spleen and brain
132 (the latter causing cerebral malaria) [24, 25]. To study a comprehensive spectrum of
133 host-parasite interactions it would be optimal to have data from these different tissues.
134 Our collection of studies represent data derived from blood and liver for all three host
135 organisms. In addition, we have seven spleen studies ([26–32]) and two studies of cerebral
136 malaria ([33, 34]) from mice. MaHPIC offers a collection of blood and bone marrow studies
137 in macaques.

138 Experiments performed on mouse blood focus on the parasite instead of the host (11
139 vs. 0). Studies on human blood infection focus more often on the host immune response
140 than on the parasite (9 vs. 5). Liver and spleen studies focus on host and parasite almost
141 equally as often, with sources for host tissue in this case being either mice (*in vivo*) or
142 hepatoma cell cultures (*in vitro*). We, here, argue that small clusters of genes co-expressed
143 across several of such diverse conditions might help to point towards potentially novel core
144 host-parasite interactions.

145 Dual RNA-Seq suitability analysis

146 A sample (experimental replicate or “run” in the jargon of sequencing databases) suitable
147 for dual RNA-Seq analysis must provide “sufficient” gene expression from both host and
148 parasite. To assess the proportion for host and parasite RNA sequencing reads in each
149 study and sample we mapped sequencing reads onto concatenated host and parasite ref-
150 erence genomes using STAR [35, 36]. Simultaneous mapping against both genomes should
151 avoid non-specific mapping of reads in regions conserved between host and parasites. We
152 quantified the sequencing reads mapped to exons using the “countOverlaps” function of

153 the GenomicRanges package [37] and calculated the proportion of reads mapping to host
154 and parasite genes.

155 The proportions of host and parasite reads for each run does not always reflect the
156 original focus of a study (fig. 1a). Studies using no depletion or enrichment give us an idea
157 how skewed overall RNA expression is towards one organism under native conditions: in
158 studies on blood stage infections, the original focus is mostly on immune gene expression
159 from leukocytes. In the respective samples the number of host reads is often overwhelming
160 unless parasitemia is very high, like in studies originally designed to use a dual RNA-Seq
161 approach on blood stages. Samples with lower parasitemia are mostly not suitable for
162 dual RNA-Seq analysis (table 1).

163 Many studies using depletion or enrichment prior to RNA sequencing (“enriched/depleted”
164 in fig. 1a) show considerable expression of the non-target organism. Studies on liver infec-
165 tion, for example, [38] and [39], comprise several runs with balanced proportions of host
166 and parasite reads. This is a result of infected liver cells being sorted from uninfected cells
167 in culture. While the parasite has been the original target organism in most studies they
168 provide data suitable for dual RNA-Seq. Studies depleting whole blood from leukocytes
169 to focus on parasite transcriptomes still show considerable host gene expression and pro-
170 vide principally suitable runs for the analysis of blood infection at lower intensities. The
171 latter comes with the caveat that host expression might be biased by unequal depletion
172 of particular cell types.

173 To establish suitability thresholds for inclusion of individual samples (runs) in further
174 analysis we plotted the number of host and parasite reads against the number of host
175 and parasite genes expressed (fig. 1b and fig. 1c). For runs with high sequencing depth
176 the total number of expressed genes of the host and parasite approaches the number of
177 annotated genes: around 30000 for the mammalian host and around 4500 for *Plasmodium*.
178 When sequencing depth is lower, the number of genes detected as expressed is lower and
179 a decrease in sensitivity can be expected to prevent analysis of lowly expressed genes. We
180 propose four parameters for suitability thresholds in dual RNA-Seq analysis: the number
181 reads mapping to host (1) and (2) parasite genes and the number of genes these reads map
182 to (expressed genes) in host and parasite (3, 4). In table 1, we give the number of runs
183 considered suitable for three different combinations of thresholding. Without claiming a
184 particular thresholds to be ideal we propose to use thresholds to avoid uninformative runs
185 in further processing to reduce the computational burden of co-expression analysis.

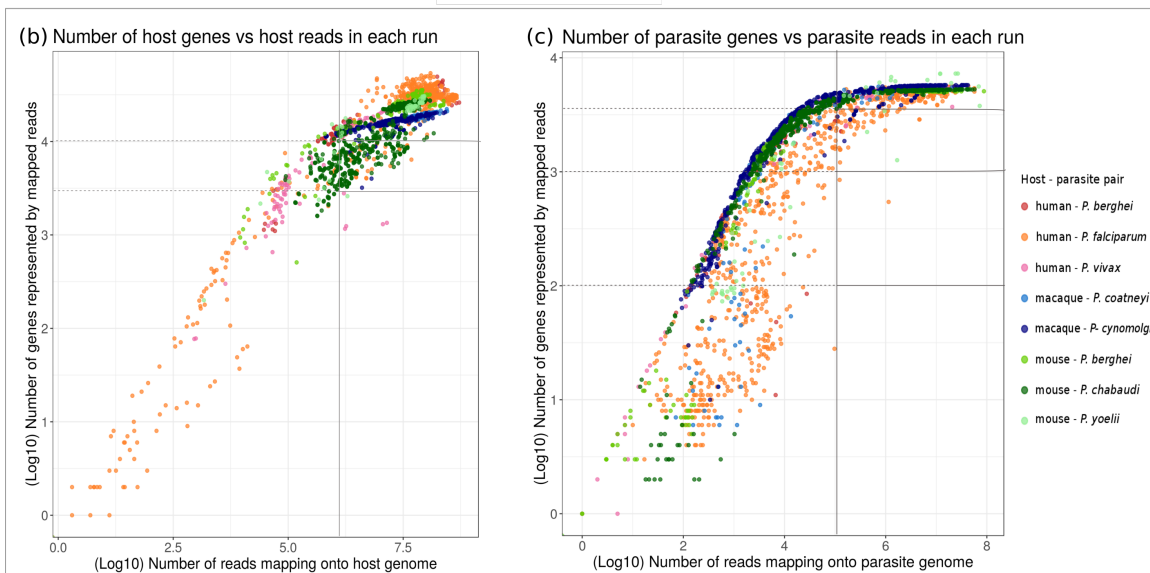
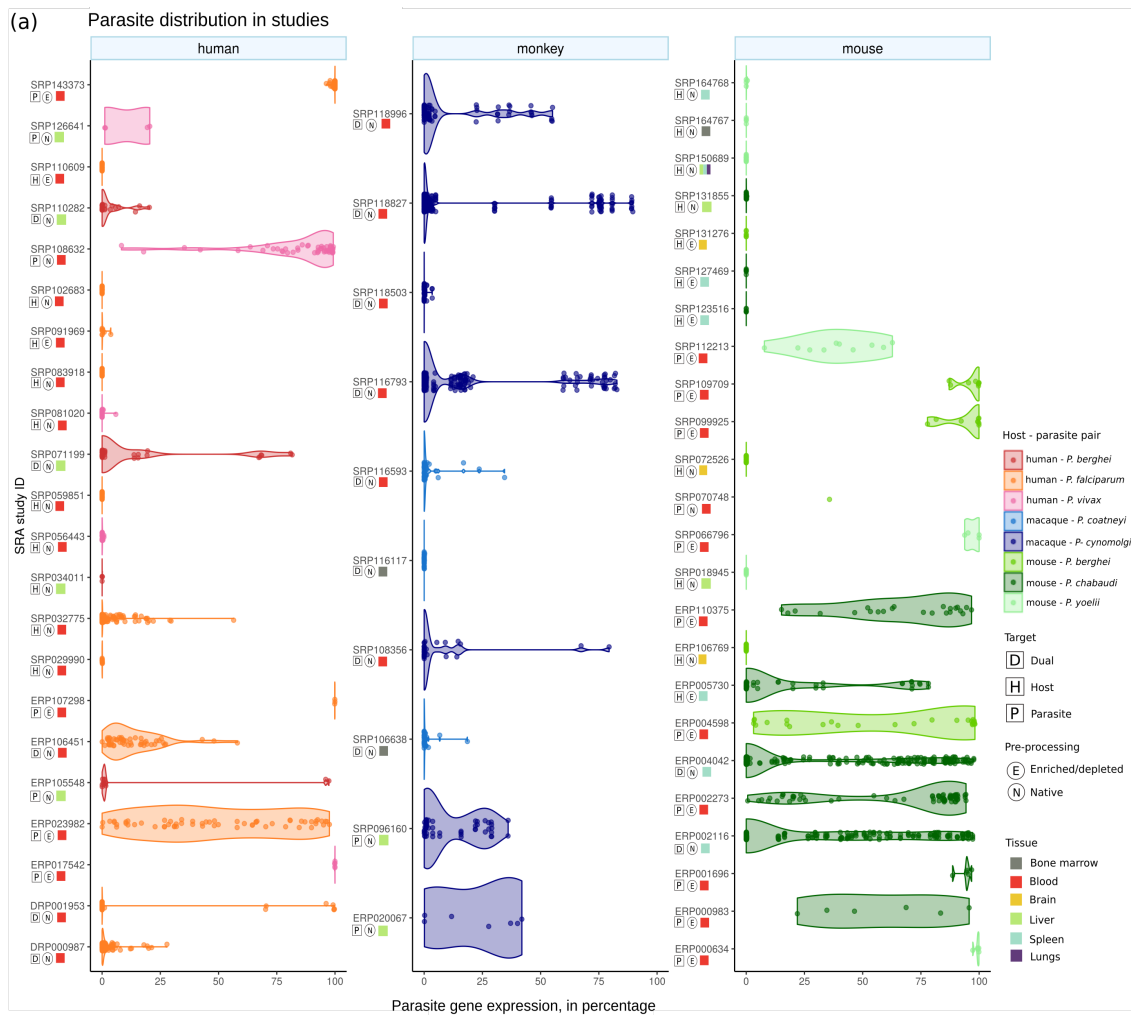


Figure 1: Proportion and number of sequencing reads and expressed genes from parasite and host in selected malaria RNA-Seq studies. We mapped sequencing reads from studies selected for their potential to provide both host and parasite gene expression data (studies N=56, total runs n=3064) mapped against appropriate host and parasite genomes. (a) The percentage of parasite reads (x-axis) is plotted for runs in each study. The studies are categorised according to the host organisms and labeled “enriched/depleted” to indicate enrichment of infected hepatocytes or depletion of leukocytes from blood. Studies labeled “dual” were originally intended to simultaneously assess host and parasite transcriptomes. We also plot the number of reads mapped against the number of expressed genes for host (a) and parasite (b). The number of expressed genes increases with sequencing depth towards the maximum of all annotated genes for the respective organism. The vertical lines indicate a threshold of 1,000,000 and 100,000 reads for host and parasite, respectively. The horizontal lines correspond to thresholds on the number of expressed genes at 10,000 and 3,000 for host and at 1,000 and 100 for the parasite. At such exemplary thresholds data could be considered sufficient for dual RNA-Seq analysis on both organisms.

Table 1: Number of studies for each host-parasite pair and suitability analysis of their runs.

Host	Parasite	# total studies	# total runs	# depletion studies	# depletion runs	Run suitability analysis from all studies							
						# host genes	# parasite genes	# studies	no threshold on read count	# studies	# runs	prc ^a >= 10 ⁵ hrc ^b >= 10 ⁶	# studies
Human	<i>P. falciparum</i>	13	840	5	216	3000	100	11	523	6	270	6	270
						3000	1000	11	362	6	268	6	268
						10000	3000	7	219	5	207	5	207
Human	<i>P. berghei</i>	4	77	4	77	3000	100	3	60	2	16	2	16
						3000	1000	3	42	2	16	2	16
						10000	3000	3	25	2	16	2	16
Human	<i>P. vivax</i>	5	135	1	5	3000	100	3	39	1	1	1	1
						3000	1000	3	36	1	1	1	1
						10000	3000	2	4	1	1	1	1
Mouse	<i>P. berghei</i>	7	128	4	50	3000	100	6	74	4	23	4	23
						3000	1000	6	54	4	23	4	23
						10000	3000	4	24	4	22	4	22
Mouse	<i>P. chabaudi</i>	10	926	7	174	3000	100	8	869	7	341	7	341
						3000	1000	7	801	7	341	7	341
						10000	3000	7	252	6	109	6	109
Mouse	<i>P. yoelii</i>	7	65	3	19	3000	100	7	34	2	8	2	8
						3000	1000	6	21	2	8	2	8
						10000	3000	2	7	2	6	2	6
Macaque	<i>P. coatneyi</i>	3	70	0	0	3000	100	3	74	3	26	3	26
						3000	1000	3	53	3	26	3	26
						10000	3000	3	33	3	26	3	26
Macaque	<i>P. cynomolgi</i>	7	849	0	0	3000	100	7	857	7	375	7	375
						3000	1000	7	706	7	357	7	357
						10000	3000	7	514	7	365	7	365

^aprc: parasite read count

^bhrc: host read count

186 Suitable runs at the thresholds chosen here are identified from human-*P. falciparum*,
187 monkey-*P. cynomolgi*, human-*P. berghei* and mouse-*P. berghei* systems. Unfortunately,
188 with current thresholds and currently available data, we highly under-represent human-
189 *P. vivax* and human-*P. berghei* systems, the two liver *in vitro* models. This outcome
190 is understandable owing to the low parasitemia in liver cultures [40]. We note that the
191 thresholds could further be made lenient enough to include more runs for these systems
192 at the cost of analysing only the most highly expressed parasite genes. An alternative
193 approach relies on depleted/enriched samples for these systems. For further analysis,
194 however, we it could prove challenging to include depleted/enriched samples as discussed
195 before. Analysis approaches such as multilayer networks (see below) might help to gauge
196 problems with such runs for the inference of co-expression in further steps of analysis.

197 Identification of co-expressed genes via correlation 198 techniques

199 Some genes are likely to show almost uniform expression under different experimental con-
200 ditions (“housekeeping genes”). Naive assessments of correlation could, however, identify
201 pairs of such genes as highly correlated. An analysis of co-expression can deal with this
202 challenge in two different ways:

203 Firstly, the most variable genes within and across studies can be selected and other
204 genes discarded. While requiring little computational time and resources, exclusion of
205 genes with too little variance in expression from downstream analysis should be per-
206 formed with caution, as seemingly small variations might result in a suitable signal over
207 a large set of runs. To select only variable genes, one option is to compute their variance
208 across all samples (in one or multiple studies). Genes with variance below a threshold
209 may then be excluded from further analysis. As variance increases with the mean for
210 gene expression data, the Biological Coefficient of Variation (BCV) [41,42] may provide a
211 more robust threshold. Secondly, one can compute empirical correlation indices, similar
212 to p-values, for any gene-pair. Empirical p-values are a robust way to estimate whether
213 gene-pairs are correlated because of specific events (treatment condition, time point) and
214 not by chance (e.g., housekeeping genes) [43, 44]. These methods construct a null dis-
215 tribution using permutations of the given data instead of assuming a null distribution

216 in advance. Since host and parasite genomes total nearly 30,000 genes, the number of
217 permutations has to be around 1.6×10^9 to be suitable for corrections for multiple-testing.
218 Alternatively, as computational costs for these permutations can be expected to be too
219 high for datasets with thousands of samples, non-corrected “p-values” may be consid-
220 ered a ranking for host-parasite gene correlation, following the suggestion of Reid and
221 Berriman [11]. Nevertheless, reliance on empirical computation of p-values without prior
222 variance/BCV filtering might become impracticable for very large datasets in the proposed
223 meta- analysis.

224 We consider partial correlation as an additional approach that could be combined with
225 the above methods. Partial correlation can control pairwise correlations for the influence
226 of other genes [45]. In transcriptomic applications full-conditioned partial correlation is
227 computationally very expensive. Some studies therefore resort to second-order partial
228 correlation (relationship between two genes independent of two other genes) [46–48]. A
229 suitable pipeline might first use (zero-order partial, that is “regular”) correlation with
230 empirical p-values to remove constitutively expressed gene-pairs. For all correlations with
231 an empirical “p-value” below a certain threshold, one could compute e.g. first-order partial
232 correlations reducing the number of computations. Iterations of such an approach with
233 higher-order partial correlations are then possible.

234 **Across different studies; across different host-parasite** 235 **systems**

236 *Gene × gene* matrices obtained from correlation analysis can be visualised and analysed
237 as interaction networks. We have identified different but interlinked workflows to recon-
238 struct a consensus network of expression correlation (fig. 2). A first approach (fig. 2(a))
239 integrates data from different studies of one host-parasite system by simply appending
240 expression profiles of their runs.

241 Knowledge of 1:1 orthologs [49] between different host and different parasite species
242 can be used in the next steps to integrate across different host-parasite systems. Humans
243 and macaques share 18179 1:1 orthologous genes, humans and mice share 17089 ortholo-
244 gous genes and 14776 genes are 1:1:1 orthologs among all three species. Similarly, 7760
245 groups of orthologous genes exist among the *Plasmodium* species. A simple approach

246 to combine data across host-parasite systems could again append those orthologs in the
 247 original datasets before correlations of gene expression.

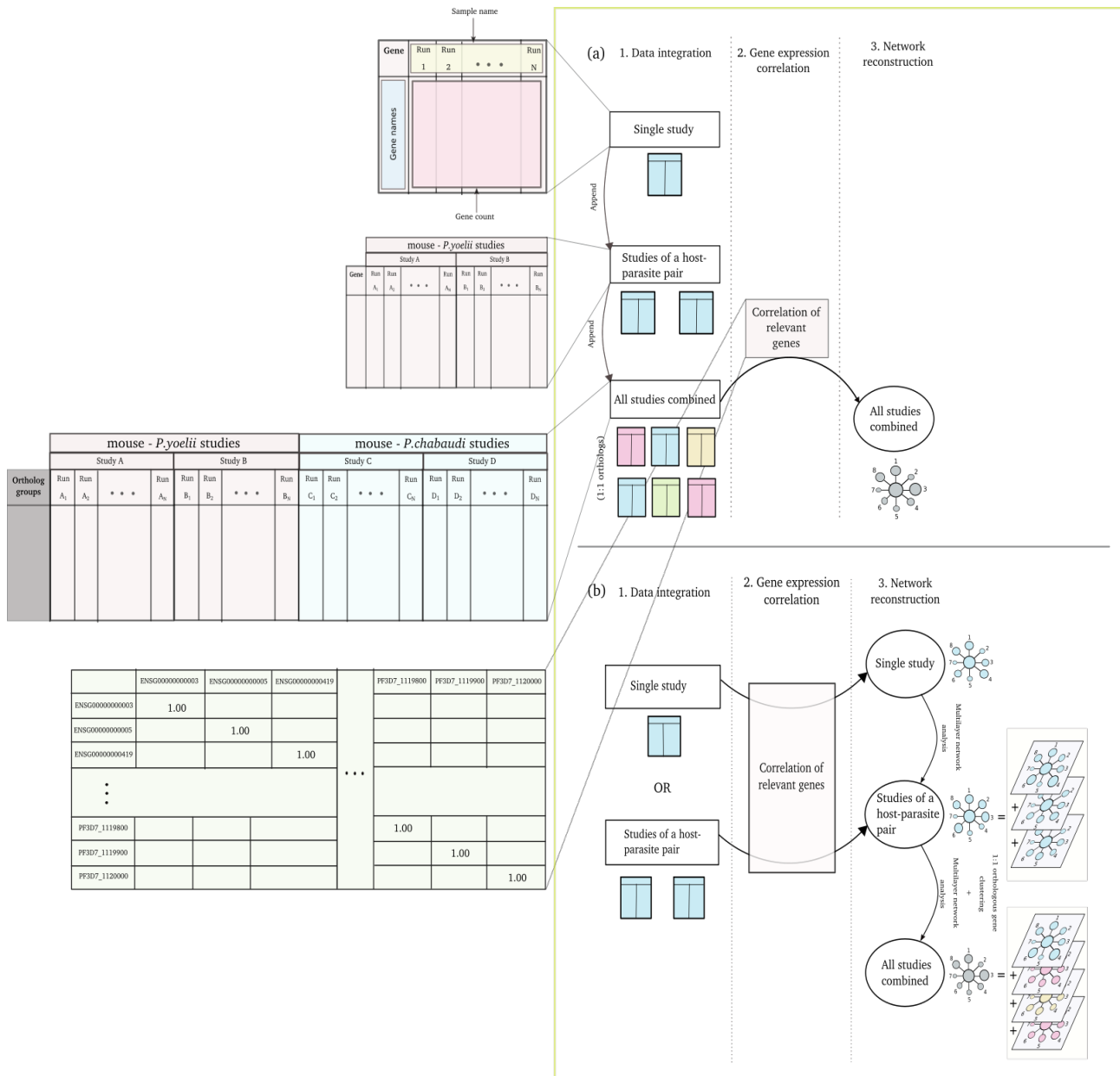


Figure 2: Two strategies identified to reconstruct host-parasite interaction networks from SRA. We identified two approaches to obtain a consensus network involving multiple hosts and multiple parasites. We selected appropriate studies from SRA for this analysis. The aim is to find a set of important interactions in malaria using co-regulated gene expression and visualising this information as a biological network. Using the first approach (figure (a)), we form single networks from single RNA-seq datasets or single networks from all studies of a host-parasite system appended one after the other, using cross-species gene correlation. To obtain a consensus network for all hosts and all parasites, we use 1:1 orthologous genes names for all hosts and all parasites, rename these genes to show their equivalency and append them to form one big dataset. Next we perform pairwise correlation of genes and finally, a network that will represent the direct interactions among orthologous genes. In (b), the second approach, we implement multi-layered network analysis to obtain a consensus network from several layers of individual networks. In this approach, we make single networks for individual RNA-seq datasets. To obtain a network for a host-parasite system, we either append all datasets of the host-parasite system with each other and form a network, or we apply multi-layered network analysis on single networks to get the consensus. To reconstruct a network involving multiple host-parasite systems, we rename orthologous genes in each layer and then look for overlapping communities.

248 Alternatively, to construct a consensus network involving all hosts and parasites, a
 249 multi-layer network analysis could align networks by orthologous genes. This approach

250 can offer more control when looking for similar correlation in different layers representing
251 different host-parasite systems. Similarly, more insight could be possible when correlations
252 from different types of tissues are combined as multilayer networks. This would only
253 require the construction of networks for a single host-parasite system and multi-layered
254 network analysis on networks from single studies of the same host-parasite system.

255 We hope correlation between host and parasite transcript expression to highlight host-
256 parasite interactions worth scrutiny of further focussed research. As a second goal, meta-
257 analysis involving different host-parasite systems could give insights into how easily other
258 insights obtained in malaria models can be translated to human malaria. If e.g. certain
259 groups of pathways show lower evolutionary conservation in host-parasite co-expression
260 networks, one could expect results on those to be harder to translate between systems.
261 Finally, one can ask whether expression correlation between host and parasite species is
262 more or less evolutionarily conserved than within host species [50–52].

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