

vConTACT: an iVirus tool to classify viruses that infect *Archaea* and *Bacteria*

Benjamin Bolduc¹, **Ho Bin Jang**¹, **Guilhem Doucier**², **Zhi-Qiang You**³, **Simon Roux**¹, **Matthew B Sullivan**

Corresp. ^{1, 4}

¹ Department of Microbiology, Ohio State University, Columbus, Ohio, United States

² Department of Biology École Normale Supérieure, PSL Research University, Paris, France

³ Department of Chemistry and Biochemistry, Ohio State University, Columbus, Ohio, United States

⁴ Department of Civil, Environmental and Geodetic Engineering, Ohio State University, Columbus, Ohio, United States

Corresponding Author: Matthew B Sullivan

Email address: mbsulli@gmail.com

Taxonomic classification of archaeal and bacterial viruses is challenging, yet also fundamental for developing a predictive understanding of microbial ecosystems. Recent identification of hundreds of thousands of new viral genomes and genome fragments, whose hosts remain unknown, require a paradigm shift away from traditional classification approaches and towards the use of genomes for taxonomy. Here we revisited the use of genomes and their protein content as a means for developing a viral taxonomy for bacterial and archaeal viruses. A network-based analytic was optimized and benchmarked against authority-accepted taxonomic assignments and found to be largely concordant. Exceptions were manually examined and found to represent areas of viral genome 'sequence space' that are under-sampled or prone to excessive gene flow. While both cases are poorly resolved by genome-based taxonomic approaches, the former will improve as viral sequence space is better sampled and the latter are uncommon. Finally, given the largely robust taxonomic capabilities of this approach, we sought to enable researchers to easily and systematically classify new viruses. Thus, we established a tool, vConTACT, as an app at iVirus, where it operates as a fast, highly scalable, user-friendly app within the free and powerful CyVerse cyberinfrastructure.

1 **vConTACT: an iVirus tool to classify viruses that infect *Archaea* and *Bacteria***

2 Benjamin Bolduc^{1&}, Ho Bin Jang^{1&}, Guilhem Doucier^{3,4}, Zhi-Qiang You⁵, Simon Roux¹ &
3 Matthew B. Sullivan^{*1,2}

4 ¹Department of Microbiology, The Ohio State University, Columbus, OH 43210

5 ²Department of Civil, Environmental and Geodetic Engineering, The Ohio State University,
6 Columbus, OH 43210

7 ³École normale supérieure, PSL Research University, IBENS, F-75005, Paris, France.

8 ⁴ESPCI, PSL Research University, CBI, F-75005, Paris, France.

9 ⁵Department of Chemistry and Biochemistry, The Ohio State University, Columbus, OH 43210

10 & These authors contributed equally to this work.

11

12 Corresponding Author:

13 Matthew B. Sullivan^{1,2}

14 Riffe Building Rm 914, 496 W 12th Ave Columbus, OH 43210, USA

15 Email address: mbsulli@gmail.com

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18 Abstract.

19 Taxonomic classification of archaeal and bacterial viruses is challenging, yet also
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22 hosts remain unknown, require a paradigm shift away from traditional classification approaches
23 and towards the use of genomes for taxonomy. Here we revisited the use of genomes and their
24 protein content as a means for developing a viral taxonomy for bacterial and archaeal viruses. A
25 network-based analytic was optimized and benchmarked against authority-accepted taxonomic
26 assignments and found to be largely concordant. Exceptions were manually examined and found
27 to represent areas of viral genome ‘sequence space’ that are under-sampled or prone to excessive
28 gene flow. While both cases are poorly resolved by genome-based taxonomic approaches, the
29 former will improve as viral sequence space is better sampled and the latter are uncommon.
30 Finally, given the largely robust taxonomic capabilities of this approach, we sought to enable
31 researchers to easily and systematically classify new viruses. Thus, we established a tool,
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34

35 Introduction.

36 Classification of viruses that infect Archaea and Bacteria remains challenging in
37 virology. Official viral taxonomy is handled by the International Committee for the Taxonomy of
38 Viruses (ICTV) and organizes viruses into order, family, subfamily, genus and species.
39 Historically, this organization derives from numerous viral features, such as morphology,

40 genome composition, segmentation, replication strategies and amino- and nucleic-acid
41 similarities – all of which is thought to roughly organize viruses according to their evolutionary
42 histories (Simmonds, 2015). As of 2015, the latest report issued, the ICTV has classified 7
43 orders, 111 families, 27 subfamilies, 609 genera and 3704 species
44 (<http://ictvonline.org/virusTaxInfo.asp>).

45 Problematically, however, current ICTV classification procedures cannot keep pace with
46 viral discovery and may need revision where viruses are not brought into culture. For example,
47 of the 4400 viral isolate genomes deposited into National Center for Biotechnology information
48 (NCBI) viral RefSeq, only 43% had been ICTV-classified by 2015. This is because the lengthy
49 ‘proposal’ processes lags deposition of new viral genomes, in some cases for years (Fauquet &
50 Fargette, 2005). Concurrently, new computational approaches are providing access to viral
51 genomes and large genome fragments at unprecedented rates. One approach mines microbial
52 genomic datasets to provide virus sequences where the host is known – already adding 12,498
53 new prophages from publicly available bacterial and archaeal microbial genomes (Roux et al.,
54 2015a) and 89 (69 and 20, respectively) new virus sequences from single cell amplified genome
55 sequencing projects (Roux et al., 2014; Labonté et al., 2015). A second approach assembles viral
56 genomes and large genome fragments from metagenomics datasets. These studies have added
57 15,222 and 125,842 new virus sequences from oceanic viral metagenomes (Tara Oceans Virome,
58 or TOV (Brum et al., 2015b) and Global Oceans Virome, or GOV (Roux et al., 2016)), and from
59 microbial and viral metagenomes from a diversity of ecosystems (Paez-Espino et al., 2016),
60 respectively. A third approach leverages large-insert cloning and sequencing approaches to
61 identify new viral sequences – with 208 from a single seawater sample (Mizuno et al., 2013).
62 Such new virus genomes and large genome fragments will keep coming for the foreseeable

63 future and represent an incredible resource for viral ecology, but they also represent a daunting
64 challenge for taxonomy.

65 Currently such rapidly expanding genomic databases of the virosphere remain
66 unclassified and challenging to integrate into a systematic framework for three reasons. First,
67 viruses lack a universal marker gene, which prevents the taxonomic starting place that is so
68 valuable for microbes (Woese, Kandler & Wheelis, 1990). Second, though genomes and large
69 genome fragments are now much more readily available, researchers are reticent to use genomes
70 as a basis for taxonomy as a paradigm has emerged whereby viruses are rampantly mosaic and
71 therefore must exist as part of a genomic continuum such that any clustering in ‘sequence space’
72 is an artifact of sampling. This is most well studied in the many genomes of mycobacteriophages
73 (Pope et al., 2015), but is contrasted by observations in cyanophages where efforts have been
74 made to more deeply sample variability in a single site with findings suggesting clear population
75 structure for naturally-occurring cyanophages (Deng et al., 2014) and that cyanophage
76 populations appear to fit a population genetics-based species definition (Marston & Amrich,
77 2009; Gregory et al., 2016). It is possible that gene flow in fast evolving RNA and ssDNA
78 viruses is rampant, but that slower evolving dsDNA viruses, particularly if obligately lytic rather
79 than temperate, could evolve into relatively stable populations that could be the basis of
80 taxonomy. Thus, it remains unclear whether viral genomes can serve as the sole basis for
81 taxonomy, or whether exploration of available data could help identify areas of viral genome
82 sequence space that are amenable to taxonomic ‘rules’ and others that are not.

83 Despite these challenges, numerous reference-independent, automated, genome-based
84 classification schemes have been proposed. An early effort recognized that more genes are
85 shared within related virus groups than between them (Lawrence, Hatfull & Hendrix, 2002),

86 which led to virologists grappling with natural diversity to use translated genomes as the basis of
87 whole genome phylogenomic tree classifications – e.g., the Phage Proteomic Tree (Edwards &
88 Rohwer 2002). Simulations showed this method to be very accurate for assigning fragmented
89 reads to the correct genomes (Edwards & Rohwer, 2005) but it suffers from the availability of
90 phage genomes. A second approach that has emerged for relatively well-studied virus groups, is
91 to use pairwise distances between aligned sequences to identify discontinuities that can indicate
92 classification thresholds. Two tools – Pairwise Sequence Comparison (PASC; Bao 2014) and
93 DEmARC (Lauber & Gorbalenya, 2012a) – are available to align the sequences either in context
94 of previous knowledge of the taxonomic affiliations (PASC) or naively using pairwise
95 distributions (DEmARC). These tools have worked well for several virus families, such as the
96 *Picornaviridae* (Lauber & Gorbalenya, 2012a) and *Filoviridae* (Lauber & Gorbalenya, 2012b)
97 for DEmARC, and *Bornaviridae* and arenavirus for PASC (Kuhn et al., 2014; Radoshitzky et al.,
98 2015). However, DEmARC and PASC suffer from several issues: (i) they are not generalizable
99 to the coming deluge of environmental viral genome sequences as they require *a priori* expert
100 knowledge to impose similarity thresholds at each level, (ii) ICTV subcommittees have
101 established varied sequence similarity thresholds across viral groups (Simmonds, 2015), which
102 would require a sliding threshold, and (iii) the methods can only classify sequences that are
103 similar to database references (Zanotto et al., 1996), which for the oceans at least represents <1%
104 of the viral genomes recovered (Brum et al., 2015a).

105 Complementarily, two network-based approaches have been utilized to organize virus
106 genome sequence space in a manner that enables classification without *a priori* knowledge. The
107 first, a gene sharing network (Lima-Mendez et al., 2008), predicts viral genes in all the genomes,
108 translates them into proteins, organizes these proteins into MCL-based protein families (protein

109 clusters, “PCs”), evaluates the number of shared protein clusters pairwise throughout the dataset
110 to establish a protein profile, and then represents this information as a weighted graph, with
111 nodes representing viral genomes and edges the similarity score of their shared protein content.
112 Given the 306 bacterial viruses (phages) known at the time, this method was precise as it
113 correctly placed 92% and 95% of these phages into their correct ICTV genus or family,
114 respectively (Lima-Mendez et al., 2008). The second, a bipartite network (Iranzo, Krupovic &
115 Koonin, 2016), incorporates both gene sharing as above and genomic similarity. In this work, all
116 dsDNA viruses along with mobile genetic elements were analyzed, which revealed a module-
117 based structure to the dsDNA virosphere. These two studies imply that even very distantly
118 related viruses can be organized into discrete populations by genomes alone and that there may
119 be hope for automated, genome-based viral taxonomy, at least for dsDNA viruses.

120 Here we optimize gene sharing networks and re-evaluate their efficacy for recapitulating
121 ICTV-based classifications using an expanded dataset of 2,010 bacterial and archaeal virus
122 genomes (available as of RefSeq v75), while also deeply exploring where network-based
123 methods have lower resolution and/or yield discontinuities with currently established
124 taxonomies. Further, we make these approaches accessible to researchers by developing a tool,
125 vConTACT (Viral CONTigs Automatic Clustering and Taxonomy), and deploy it as part of the
126 iVirus ecosystem of apps that leverages the CyVerse cyberinfrastructure (Bolduc et al., 2016).

127

128 **Materials and Methods.**

129 **Terminology.** Network topological parameters, their definitions and abbreviations are
130 available in Table 1.

131 **Reference datasets.** To test this methodology, we downloaded the entire NCBI viral
132 reference dataset (“ViralRefSeq”, version 75, containing 5539 viruses) and removed eukaryotic
133 viruses by filtering against tables downloaded on NCBI’s ViralRefSeq viral genome page
134 (<http://www.ncbi.nlm.nih.gov/genomes/GenomesGroup.cgi?taxid=10239>). The resulting file
135 (“Bacterial and Archaeal viruses”; BAV) contained 2010 total viruses; 1905 dsDNA, 88 ssDNA,
136 5 dsRNA and 12 ssRNA. All viruses contained taxonomic affiliation information, though not all
137 viruses had affiliations associated with each level of the taxonomy (i.e. not all viruses have a
138 “sub-family” designation). To improve taxonomic assignments, the ICTV taxonomy was also
139 retrieved (<https://talk.ictvonline.org/files/master-species-lists/>) and the ICTV affiliations were
140 used to supplement the NCBI version.

141 **Building protein cluster profiles.** To generate sequence profiles – with information
142 about the presence or absence of a sequence within one or more protein clusters (described
143 previously as protein *families* (Lima-Mendez et al., 2008)), proteins from each sequence were
144 first extracted from the ViralRefSeq proteins file. BLASTP (Altschul et al., 1997) was used to
145 compare all proteins (198,102) from the sequences in an all-verses-all pairwise comparison.
146 Protein clusters were subsequently identified using the Markov clustering algorithm (MCL) with
147 an inflation value of 2, resulting in 23,022 protein clusters (“PCs”). Finally, we generated protein
148 cluster profiles for each genome such that the presence of a gene within a protein cluster of a
149 viral genome was given a value of “1” and the absence “0”. This resulted in a large 2,010 x
150 23,022 matrix.

151 **Generating the similarity network.** The similarity network is a graph where the nodes
152 (i.e. reference sequences) are linked by edges when the similarity between their pc-profiles is
153 considered significant. In other words, the network represents the overall similarity between

154 sequences based on the number of shared protein clusters. To calculate the similarity between the
 155 profiles of two sequences (sequence A and sequence B), the hypergeometric formula was used to
 156 estimate the probability that at least c protein clusters would be in common:

$$157 \quad P(X \geq c) = \sum_{i=c}^{\min(a,b)} \frac{C_a^i C_{n-a}^{b-i}}{C_n^b} \quad (1)$$

158 Simply stated, the hypergeometric formula is the probability that genomes A and B would have c
 159 protein clusters in common by chance. The probability can be converted to an expectation value
 160 (E ; for false positives) by multiplying the probability (P) by the total number of comparisons (T).
 161 The expectation value can then be converted into a significance score:

$$162 \quad S(A,B) = -\log(E) = -\log(P \times T) \quad (2)$$

163 Genome pairs with significance scores greater than 1 (i.e. E -value < 0.1) are considered
 164 sufficiently similar (see permutation test, below) and were joined by an edge in the similarity
 165 network with a weight equal to their significance score. We refer to sequences within the
 166 network as *nodes*, the relationships connecting them, *edges* and the strength of that relationship,
 167 edge *weight*.

168 After generating the similarity network, groups of similar sequences (referred to as viral
 169 clusters, “VCs”) were clustered by applying MCL with an inflation of 2.

170 **Measuring the proportion of shared genes between genomes.** Given that genome
 171 sizes between pairs can differ greatly, this can lead to large differences in the proportion of the
 172 shared genes (Ågren et al., 2012). To counter this, we characterized the proportion of shared PCs
 173 between two genomes using the geometric index (G) as a symmetric index:

$$174 \quad G_{AB} = \frac{|N(A) \cap N(B)|}{|N(A)| \times |N(B)|} \quad (3)$$

175 where $N(A)$ and $N(B)$ indicate the numbers of protein clusters (PCs) in the genomes of A and B,
 176 respectively.

177 **Permutation test.** The stringency of the significant score was evaluated through
 178 randomization of the original matrix where rows present viral genomes and columns PCs or
 179 singletons that are not shared with any other protein sequences (Leplae et al., 2004). Briefly,
 180 with an in-house R script, 1,000 matrices were generated by randomly rearranging PCs and/or
 181 singletons within pairs of genomes having the significant score ≤ 1 (a negative control) and
 182 calculated a new significant score each time. None of the genome pairs in this negative control
 183 produced significant scores >1 , indicating values above this significance threshold did not occur
 184 by chance (Lima-Mendez et al., 2008).

185 **Affiliating sequence clusters with taxonomic groups.** To assign (in the case of
 186 unknown sequences) or compare nodes (genomes) within clusters to their reference counterparts,
 187 we first defined *membership* of a node c to a cluster k $B(c,k)$ according to two methods,
 188 conservative and permissive. The conservative method 4) directly takes the result from the MCL
 189 clustering to assign a node to a cluster:

$$190 \quad B(c,k) = \begin{cases} 1 & \text{if Contig } c \in \text{Cluster } k, \\ 0 & \text{otherwise} \end{cases} \quad (4)$$

191 while the permissive method takes the sum of all edge weights w linking the node to nodes of the
 192 cluster, with the node becoming a member of its maximal membership cluster (5):

$$193 \quad B'(c,k) = \frac{\sum_{i \in k} w_{c,i}}{\sum_{p \in \{\text{Clusters}\}} \sum_{j \in p} w_{g,j}} \quad (5)$$

194 The precision $P(k,t)$ of the taxonomic class t with respect to a cluster k as its membership of
 195 nodes of the class t in the memberships of reference nodes in the cluster k .

196
$$P(k,t) = \frac{\sum_{vi \in \{\text{sequence of class } t\}} B(i,k)}{\sum_{vj \in \{\text{reference sequence}\}} B(j,k)} \quad (6)$$

197 A cluster and all its node members are then affiliated with its maximal precision class. For the
 198 conservative method, the cluster is affiliated with the taxonomic class associated with the
 199 majority of its members (i.e. $\geq 50\%$). In cases where clusters do not contain at least half
 200 reference sequences, the entire cluster will be unaffiliated.

201 **Measuring the connectivity of genomes to clusters.** The connection strength of a node
 202 g to cluster c was calculated as the average edge weight linking it to nodes of cluster c :

203
$$W_{g,c} = \frac{1}{k} \sum_{i=1}^k w_{g,i} \quad (7)$$

204 where k and w are the number and total weight of edges of the node g in the cluster c ,
 205 respectively. We refer to the average edge weight for node g to the cluster it belongs to as its in-
 206 VC average weight, and to other clusters within the network as out-VC average weight.

207 **Identifying sub-clusters.** To further subdivide heterogeneous clusters (those comprising
 208 ≥ 2 taxa), cluster-wise module profiles (i.e. a module profile only including viruses previously
 209 identified as belonging to the same viral cluster) were hierarchically clustered using UPGMA
 210 with pairwise distances calculated using Euclidean distance implemented in Scipy.

211 **Statistical calculations.** All calculations, statistics, network statistical analyses were
 212 performed using in-house python scripts, with the Numpy, Scipy, Biopython and Pandas python-
 213 packages. vConTACT is implemented in python with the same dependencies. The tool is
 214 available at <https://bitbucket.org/MAVERICLab/vcontact>. Scripts used in the generational and
 215 calculations of data are available at <https://bitbucket.org/MAVERICLab/vcontact-SI>.

216 **Network visualization and analysis.** The network was visualized with Cytoscape
217 (version 3.1.1; <http://cytoscape.org/>), using an edge-weighted spring embedded model, which
218 places the genomes or fragments sharing more PCs closer to each other. Topological properties
219 were estimated using a combination of python and the Network Analyzer 2.7 Cytoscape plug-in
220 (Assenov et al., 2008).

221

222 **Results and Discussion.**

223 ***vConTACT analytical workflow and terminology:*** The vConTACT analyses are based
224 on previously established gene sharing network methods (Lima-Mendez 2008). Briefly, PCs are
225 established across all genomes in the dataset; with vConTACT doing this by default using MCL
226 clustering from all-verses-all BLASTP comparisons (though user-specified clusters can also be
227 used). *PC profiles* of genomes or genome fragments (herein ‘genome’) are then calculated,
228 where the presence and absence of PCs (from the entire PC dataset) along a genome are
229 established and then compared pairwise between genomes (Fig. 1). The pairwise genome
230 comparisons are then mathematically adjusted (using the hypergeometric similarity formula) to
231 establish a probability that any genome pair would share n PCs, given the total number of all
232 PCs. This probability is log-transformed (in similar fashion to BLAST E-values) into a
233 significance score and applied as a *weight* to an edge between the two paired genomes in a
234 similarity network. High significance scores represent a low probability that two genomes would
235 share n PCs by chance, which can be interpreted as evidence of gene-sharing and presumably
236 evolutionary relatedness between the paired genomes. After evaluating all pairings in the dataset,
237 significance scores ≥ 1 are retained, and a network of the remaining genome pairs is constructed.
238 MCL is subsequently applied to identify structure in the gene sharing network, but now the

239 clusters represent groups or related genomes and are termed *viral* clusters (“VCs”). MCL is also
240 applied against the network of PCs, whose members can be similar to members of other PCs.
241 This effectively organizes the PCs into a higher-order structure known as a protein module. The
242 relationship information identified from the genomes (organized into VCs) and PCs (organized
243 into protein modules) are used to create a *module profile*, which can then be mined for
244 taxonomic identification, functional profiling, etc.

245 **Benchmarking network-based taxonomy:** To benchmark the ability of network-based
246 taxonomy to capture ‘known’ viral relationships, we evaluated how vConTACT “re-classified”
247 viral sequences at various taxonomic levels using 2,010 bacterial and archaeal viral genomes
248 from VirRefSeq (v75). Of these reference genomes, ICTV-classifications were only available for
249 a subset; 654 viruses from 2 orders, 738 viruses from 19 families, 152 viruses from 11
250 subfamilies, and 562 viruses from 158 genera. The network was then decomposed into VCs
251 (described above) and a permutation test was used to establish significance score thresholds to
252 prevent random relationships from entering the network. This analysis used the initial network’s
253 edge information to construct a matrix between genome pairs, and then permuted the edges 1,000
254 times. No edges were found to be significant during these tests, suggesting that relationships seen
255 within the network did not arise by chance and could be confidently used to establish taxonomic
256 groupings (see Materials and Methods, Table S1).

257 The resulting network, consisting of 1,964 viruses (nodes) and 65,393 relationships
258 (edges) between them (Fig. 2A), was then used as a basis for comparison to the ICTV-based
259 classifications. A total of 211 VCs were identified, spread among 46 components (unconnected
260 subnetworks), which more than doubles the 17 connected components identified previously
261 (Lima-Mendez et al., 2008). Of the 46 components, 38 included 1,891 phages representing 194

262 VCs (left, Fig. 2A), and 8 components included 73 archaeal viruses representing 17 VCs (right,
263 Fig. 2A). Most (87%) of the 1,891 phages belonged to the order *Caudovirales*, and comprised
264 the largest connected component (LCC) in the analysis (top left, Fig. 2A). At the VC level, the
265 network clustering performed well with average (across each taxonomic level) recall / precision
266 percentages of 100% / 100%, 90% / 86%, and 80% / 80% at the order, family and genus levels,
267 respectively (Fig. 2B). Of the 211 VCs resolved by the network, 76.4% contained a single ICTV-
268 accepted genus, suggesting concordance between the network VCs and accepted taxonomy,
269 whereas 15.1% and 8.5% of the VCs contained two and 3 or more genera, respectively (Fig. 2A
270 and C). Thus, roughly 4 out of 5 of the VCs correspond to ICTV genera.

271 Mechanistically, these discrepancies between network clustering and the ICTV
272 classification could derive from: (i) undersampling such that VCs with fewer members may not
273 represent the naturally-occurring diversity of that viral group, or (ii) gene flow between viral
274 genomes that ameliorates taxonomic boundaries by providing excessive access to genes outside
275 the VC's gene pool. While much of abundant viral genome sequence space is recently being
276 mapped (Paez-Espino et al., 2016; Roux et al., 2016), there remains contrasting paradigms about
277 the role of gene flow in structuring mycobacteriophage ("mycophages") vs cyanophage
278 populations (Gregory et al., 2016).

279 To discriminate between these possibilities, we identified these "ICTV-discordant" areas
280 of the network containing 2 or more ICTV genera (which we define as *heterogeneous VCs*),
281 focusing on three of the more well-populated (many member genomes) heterogeneous VCs, and
282 the archaeal virus heterogeneous VCs, which are among the least well-sampled taxa. Of the well-
283 sampled VCs, VCs containing the 2nd, 3rd, and 4th most members (i.e. genomes), included the
284 following: (i) VC1 contains the 8 genera belonging to the *Tevenvirinae* subfamily (*T4virus*,

285 *Cc31virus*, *Js98virus*, *Rb49virus*, *Rb69virus*, *Sl6virus*, *Sp18virus*, and *Schizot4virus*) and a
286 genus of the *Eucamylvirinae* (*Cp8virus*), as well as the *Tg1virus* and *Secunda5virus* that are not
287 assigned to a particular subfamily, (ii) VC2 contains three genera (*Biseptimavirus*, *Phietavirus*,
288 and *Triavirus*), and (iii) VC3 contains four genera (*Kayvirus*, *Silviavirus*, *Twortvirus*, and
289 *P100virus*) belonging to the *Spounavirinae* and the six *Bacillus* virus genera (*Agatevirus*,
290 *B4virus*, *Bc431virus*, *Bastillevirus*, *Nit1virus*, and *Wphvirus*). Finally, among the 73 archaeal
291 viruses, only the *Fuselloviridae* were accurately classified at the genus level, while most (63%)
292 archaeal viruses were incorrectly classified at the genus level.

293 ***Gene content analyses suggest ICTV classifications, not VC-based classifications***

294 ***should be revised:*** A total of 23.6% of the VCs contained genomes from more than one ICTV-
295 recognized genus, which suggests ‘lumping’ by the network analyses (via MCL) or ‘splitting’
296 during ICTV classification. To assess this, we computed the fraction of PCs that were shared
297 both within an ICTV genus and between the multiple ICTV genera found in each heterogeneous
298 VC and represented them as the percentage of intragenus similarity and intergenera similarity,
299 respectively. Of the 25 VCs, intragenus similarities of all but one (VC9) suggested they shared
300 more than 40% of their PCs (Fig. 3A, Table S2), which is consistent with the threshold
301 commonly used to define a new dsDNA viral genus (Lavigne et al., 2009). In contrast, the
302 intergenera similarities varied widely – some VCs (VCs 1-3, 9-11, 17, 20, 25, 33, 58, 91, 95)
303 shared 20-40% of their PCs (subfamily level), whereas others shared more than ~40% (VCs 12,
304 14, 24, 26, 37, 44, and 51) or less than ~20% (VCs 39, 55, 63, 74, and 77) of their PCs. Where
305 intergenera similarities are high (>40% of the PCs are shared), there may be a case to be made
306 for merging the currently recognized ICTV genera. Consistent with this, all 6 of these highly
307 (>40%) similar VCs (12, 14, 24, 26, 37 and 51) are suggested to be in need of revision, as these

308 include *G7Cvirus*, *N4virus*, *T1virus*, *HP34virus*, and *PhiKMVvirus* (Wittmann et al., 2015;
309 Eriksson et al., 2015; Niu et al., 2014; Krupovic et al., 2016). Additionally, we found that in
310 VC44, the phage CAjan, belonging to the *Seuratvirus*, shared 41.6-42.7% of its genes with three
311 phages (JenP1 and 2 and JenK1 of the *Nongavirus* (Table S2)). Where intergenera similarities
312 are lower (<20%, or 20-40% of the PCs are shared), the appropriate taxonomic assignment may
313 require deeper sampling of viral genome sequence space and/or further network analytic
314 development.

315 To further assess these cases, we next examined four VCs (1-3, 14) that contained more
316 than 4 ICTV-recognized genera using hierarchical clustering of PC presence-absence data for
317 each genome (Fig. 3B). In parallel, we computed the actual connectivity of the genomes within
318 these heterogeneous VCs according to the average weight of edges that (i) are between genomes
319 of the same VC (in-VC avg. weight) and (ii) between the genomes of other VCs (out-VC avg.
320 weight) (Table S3; Materials and Methods). For example, within VC1, 8 genera of the
321 *Tevenvirinae* (*SI6virus*, *Cc31virus*, *T4virus*, *Rb69virus*, *Sp18virus*, *Js98virus*, *Rb49virus* and
322 *Schizotvirus*) and their relatives (*Tg1virus* and *Secunda5virus*) share, on average, 61% and 38%
323 of their total PCs, respectively, and 39% between all 10 genera (Table S2). Outside VC1, they
324 share ~11.2% of genes with other viral groups (Table S2). We found that the 10 genera within
325 VC1 are more tightly interconnected than those of the 210 VCs overall, with average in-cluster
326 values of 223.7 and 131.9 and average out-cluster values of 13.1 and 9.0, respectively (Table
327 S3). These observations indicate that higher cross-similarities of 10 genera can be attributed to a
328 large fraction of their shared genes, whereas only a small fraction of gene shared by other groups
329 can hold them together.

330 Upon closer inspection, some of this ‘lumping’ appeared to be due to poorly sampled
331 regions of sequence space. For example, VC1 also contained the *Cp8virus* of the subfamily
332 *Eucampyvirinae*, which is odd to be placed alongside the *Tevevirinae*, given that other ICTV-
333 recognized genus (*Cp220virus*) of the *Eucampyvirinae* is grouped into the separate cluster (VC
334 87). Since both genera (*Cp8virus* and *Cp220virus*) are distantly related to the *Tevenvirinae*
335 (Javed et al., 2014), containing only ~11% the shared genes to (an average weight of 18.5) and
336 ~6% (11.8) , respectively (Tables S2 and S3), these groupings might be driven by the lack of
337 diversity among the *Cp220virus* where only 2 reference genomes (i.e., *Campylobacter* phages
338 CPX and NCTC12673) available in our ViralRefSeq dataset. To test this, we computationally
339 doubled the number of the genomes for this group while holding the number and weight of their
340 connections constant, finding that the *Cp220virus* genomes clearly separated from VC1 and
341 instead were correctly placed alongside VC 87 (Table S4). Consistently, among the
342 heterogeneous VCs 39, 55, 63, 74, and 77 showing < ~20% intergenera similarities (Figs. 3A and
343 S1), increasing the genome numbers of poorly-sampled ICTV genera led to clustering of
344 members of those genera into their correct VCs (Table S4). Together these findings suggest that
345 additional sampling in poorly sampled areas of viral sequence space will be required to most
346 accurately establish genome-based taxonomy – issues that parallel those presented by long
347 branch attraction for phylogenies (Bergsten, 2005).

348 Similar structure emerged from hierarchical clustering of PC presence / absence data
349 from the 3 other well-represented heterogeneous VCs. In VC2, the three known subgroups of the
350 *Phietavirus* (Gutiérrez et al., 2014) were resolved, sharing 44.9% of their PCs, and separate from
351 two other subgroups – the *Biseptimavirus* and *Triavirus*, which shared 22.3% of their PCs (Fig.
352 3B, Table S2). In VC3, containing the *Spounavirinae* (Krupovic et al., 2016), each sub-cluster

353 has a corresponding ICTV genus with largely overlapping sets of genes while also showing a
354 clearly distinct set(s) of genes. Of these, the six *Bacillus* virus genera (*Wphvirus*, *Bastillevirus*,
355 *B4virus*, *Bc431virus*, *Agatevirus*, and *Nit1virus*) appear to be closely related to the
356 *Spounavirinae*, with ~20% of total PCs in common (Fig. 3B, Table S2). Finally, VC14 produced
357 a clear division of the *Tunavirinae* (Krupovic et al., 2016), in which the *Escherichia* virus Jk06 is
358 placed in a separate branch due to its less shared common genes (~56%) to the other
359 *Rogue1virus* members (~82%); their highly-overlapped genes between genera above the genus
360 boundary (40%) are associated with “taxonomic lumping” as described above (Niu et al., 2014;
361 Krupovic et al., 2016).

362 We next evaluated three phage groups which were poorly represented in the S277
363 network (Lima-Mendez et al 2008) and also represent some of the most abundant, widespread,
364 and/or extensively studied phage groups (Grose & Casjens, 2014; Pope et al., 2015; Roux et al.,
365 2015b)) – the mycobacteriophages, *Teveniviriae*, *Autographivirinae* and the archaeal viruses.

366 ***Mycobacterium* phages.** The largest viral group covering 16.1% of the total population of
367 the LCC (mostly *Caudovirales*, top left Fig. 1A) includes phages infecting *Mycobacteria*. The
368 318 mycophage genomes were assigned to 14 VCs (Fig. 4A), 13 of which were composed of
369 reference genomes belonging to a single ICTV-recognized genus for each VC. The 14th
370 mycophage VC, VC25, contained three ICTV-recognized genera – the *Bignuzvirus*,
371 *Charlievirus*, and *Che9cvirus*. Although the module-based approach discerned the structure in
372 this VC, which would group them into the known genera (Fig. S1), this “lumping” into a single
373 VC reflects (i) their undersampling (i.e., each genus has 1 to at most 3 viruses) and/or (ii) highly-
374 overlapped genes between genera. Indeed, of the 3 phages belonging to the *Che9cvirus*, phages
375 Babsiella and Che9c shared 45% of their genes, but also shared 35% and 36% of their genes with

376 the *Bignuzvirus* and 28% and 32% with the *Charlievirus*, respectively (Table S2), which results
377 in higher connectivity between three genera than other viral groups to which they linked (Table
378 S3). These findings contrast those in the rest of the network, and suggest that some phage groups
379 (e.g., mycophages) may more frequently exchange genes than others.

380 To quantify this, we next examined features of the network. For example, many VC59
381 mycophages were broadly linked to nine VCs that contain other mycophages and phages from
382 diverse hosts (Fig. 4A). To characterize this further, we analyzed the topological properties using
383 the betweenness centrality (BC), as it can identify the node residing in the shortest path between
384 other nodes (Halary et al., 2009). Specifically, in the shared-gene network, high-betweenness
385 nodes (phages) can act as bridges between phages that would remain disconnected, due to their
386 mosaic content of genes (Lima-Mendez et al., 2008). Indeed, these eight VC 59 phages had 42-
387 fold higher average BC than those of other mycophages and their relatives (0.04 vs. 9.45E-04)
388 (Fig. S2), strongly indicating they may be prone to increased gene flow and thus exceptionally
389 ‘mosaic’ genomes (Halary et al., 2009; Pope et al., 2015a).

390 ***The Tevenvirinae*** As the second-largest group, containing 94 viruses in the
391 heterogeneous VC1, which were further connected to 74 distant relatives and taxonomically
392 unclassified myo-/siphoviruse(s), appeared to be restricted to a densely interconnected region
393 (Fig. 4). A subsequent hierarchical clustering within VC1 grouped these 168 viral genomes into
394 5 subgroups (Fig. S3). Interestingly, three phages infecting cyanobacteria (P-SSM2, P-SSM4,
395 and S-PM2) and T4-like phages that were initially found in a single cluster (Lima-Mendez et al.,
396 2008) are separated into two clusters of the Exo T-evens (VC_8) and T-evens/Pseudo/Schizo T-
397 evens (VC_1), respectively (Filee, 2006) (upper in Fig. 4B; Fig. S3). This network grouping can
398 identify the Exo T-evens including cyano- and pelagiphages, which the literature suggests to be

399 only distantly related to other T4 superfamily viruses (Comeau & Krisch, 2008; Roux et al.,
400 2015b).

401 ***The Autographivirinae*** We further identified 8 VCs associated with the
402 *Autographivirinae*. Of four genera defined by the NCBI and/or ICTV, the *T7virus*, *SP6virus*,
403 *Kp34virus* were found in VCs 4, 28, and 37, respectively, whereas the *PhiKMVvirus* were spread
404 across VCs 13 and 37 (Fig. 4B; also Fig. S4). Notably, a previous phylogenetic study based on
405 three conserved proteins (i.e., RNA polymerase, head-tail connector and the DNA maturase B)
406 showed considerable diversity of the *phiKMVvirus* (Eriksson et al., 2015). We also observed
407 distinct patterns of PC sharing between the PhiKMV-related genome(s) and other viruses in each
408 cluster (Fig. S4), suggesting that the *PhiKMVvirus* should likely be divided into two new
409 subgroups.

410 In addition, as the recently emerged groups, nine *Acinetobacter* phages (Huang et al.,
411 2013), as well as phage vB_CsaP_GAP227 (Abbasifar et al., 2013) and its close relatives were
412 found in VCs 54 and 93, respectively (Fig. S4); all of them encode T7-specific RNA polymerase
413 (Lavigne et al., 2009), which suggest that they fall within the *Autographivirinae* subfamily.

414 Finally, many viruses are now thought to co-opt host genes to improve viral fitness;
415 these stolen ‘auxiliary metabolic genes’ are known from cyanophage genomes (photosynthesis
416 genes; (Sullivan et al., 2006; Millard et al., 2009; Labrie et al., 2013), but also from ocean viral
417 metagenomes where viruses are now shown to contain genes involved in central carbon
418 metabolism (Hurwitz, Hallam & Sullivan, 2013) and nitrogen and sulfur cycling (Roux et al.,
419 2016) in ways that likely drive niche differentiation (Hurwitz, Brum & Sullivan, 2014). Thus it is
420 striking that VC22 in our network, which contains 19 cyanopodoviruses, had many linkages to
421 taxonomically disparate *Tevenvirinae*, which turned out to be driven by photosynthesis genes

422 shared across these viral taxa (Fig. 4B). Such “host” genes in viruses can bring taxonomically
423 disparate viral groups closer together, and the network can thus help identify such niche defining
424 viral genes for viruses infecting well studied hosts.

425 **The Archaeal Viruses.** Of the 72 archaeal viruses, 66 were associated with 18 VCs,
426 while 6 viruses (Haloviruses HHTV-1 and VNH-1, Hyperthermophilic Archaeal Virus 1 & 2,
427 Pyrococcus abyssi virus 1, and His 1 virus) were not included in the network, due to lack of
428 statistically significant similarity to any other virus. Of the 25 heterogeneous VCs, archaeal
429 viruses comprise 3 of them (VCs 51, 74 and 77), likely owing to their gene products showing
430 little similarity to published viruses outside of other archaeal viruses (Prangishvili, Garrett &
431 Koonin, 2006). All 3 VCs show considerable sharing of PCs within each VC (61.3 %, 50.2 %
432 and 67.6 %, respectively). VCs 74 and 77, each consisting of 2 genera
433 (*Gammalipothrixvirus/Rudivirus* and *Betalipothrixvirus/Deltalipothrixvirus*) unify the entire
434 *Ligamenvirales* order (2 families). Though the genera are distinguished mainly by their virion
435 morphology (Prangishvili & Krupovič, 2012), it can be argued that some lipothrixviruses share
436 as much similarity within the *Lipothrixviridae* family as to the rudiviruses, exemplified by the 10
437 genes shared between AFV-1 (a lipothrixvirus) and SIRV1 (a rudivirus) (Prangishvili &
438 Krupovič, 2012) and that they likely derive from a common ancestor (Goulet et al., 2009). In
439 addition to the number of PCs shared between AFV-1 and the rudivirus in VC74 (Fig. S1), the
440 more “distal” position between AFV-2 (*Deltalipothrixvirus*) and the other VC77 members
441 (*Betalipothrixvirus*) (Fig. S1), the order-level separation is easily seen in the overall network
442 (Fig. 2). VC55 (*Alphafusellovirus/Betafusellovirus*) consists of all known *Fuselloviridae*
443 members. Like VCs 74 and 77, their genera are separated mainly through virion morphology,
444 with Alphafusellovirus lemon-shaped and Betafusellovirus pleomorphic, and also through their

445 attachment structures (Redder et al., 2009). The large number of “core” genes (13) shared among
446 all family members argues for frequent recombination events, with even distant fuselloviruses
447 potentially capable of recombination during integration. Furthermore, some fuselloviruses
448 exhibit regions >70% pairwise identity on the nucleotide level, including ASV-1
449 (*Betafusellovirus*) and SSV-K1 (*Alphafusellovirus*) (Redder et al., 2009). Despite shared non-
450 core regions between the *fuselloviridae*, the high similarity between the two genera is also
451 revealed in the network through unification into a single VC. The most recently identified
452 member of the *Fuselloviridae*, *Sulfolobales* Mexican fusellovirus 1 (SMF1) has no official ICTV
453 classification between family, though clustering within the VC shows clear association with the
454 *Betafusellovirus*. It is remarkable that nearly all known archaeal viruses not only fall within the
455 network, but that most of their VCs follow a genus-level affiliation.

456 **vConTACT, an iVirus tool for network-based viral taxonomy:** Given the strong and
457 robust performance of these network classification methods (Lima-Mendez et al., 2008) to
458 largely capture known viral taxonomy from genomes alone, we sought to democratize the
459 analytical capability. To this end, we developed a tool named “vContact” (overview of its logic
460 in Fig. 1) and integrated it into iVirus, a virus ecology-focused set of tools also known as “apps”
461 and databases (Bolduc et al., 2016). Such implementation at iVirus enables any user to run the
462 application simply by inputting viral sequences with all compute, storage and data repository
463 happening via the CyVerse cyberinfrastructure (formerly the iPlant Collaborative (Goff et al.,
464 2011).

465

466 **Conclusions**

467 Network-based approaches have been widely used to explore mathematical, statistical,
468 biological, and structural properties of a set of entities (nodes) and the connections between them
469 (edges) in a variety of biological and social systems (Dagan, 2011; Barberán et al., 2012). Such
470 approaches are invaluable for developing a quantitative framework to evaluate if and where
471 taxonomically meaningful classifications can be made in viral sequence space (Simmonds et al.,
472 2016). By expanding upon prior large-scale analyses (Lima-Mendez et al., 2008; Koonin,
473 Krupovic & Yutin, 2015; Roux et al., 2015a) we sought here to quantitatively evaluate when and
474 where such network-based classifications will perform poorly. These findings suggest that under
475 sampled viral sequence space and some phage groups with exceptionally high gene flow (e.g.,
476 mosaic genomes of the mycophages) are currently challenging and represent about 1 in 4
477 publicly-available, dsDNA viral genomes. While these problematic viral genomes await
478 improved representation of viral sequence space and/or improvements in network analytics to
479 best resolve their taxonomy, the remaining $\frac{3}{4}$ of viral genomes appear ready for gene sharing
480 network-based viral taxonomy. To this end, we present vConTACT as a publicly-available tool
481 for researchers to effectively enable large-scale, automated virus classification. Given the scale
482 of thousands of new virus genomes and genome fragments discovered through increasingly used
483 metagenomics approaches (Roux 2016 and Paez et al 2016), such step-wise progress towards an
484 automated taxonomic classifier will be foundational to most rapidly integrate viruses into models
485 that seek to make predictions in ecosystems ranging from the oceans and soils to bioreactors and
486 humans.

487

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493

494 **References**

- 495 Abbasifar R., Kropinski AM., Sabour PM., Ackermann H-W., Alanis Villa A., Abbasifar A.,
496 Griffiths MW. 2013. The Genome of Cronobacter sakazakii Bacteriophage
497 vB_CsaP_GAP227 Suggests a New Genus within the Autographivirinae. *Genome*
498 *Announcements* 1:e00122-12-e00122-12. DOI: 10.1128/genomeA.00122-12.
- 499 Ågren J., Sundström A., Håfström T., Segerman B. 2012. Gegenees: Fragmented alignment of
500 multiple genomes for determining phylogenomic distances and genetic signatures unique
501 for specified target groups. *PLoS ONE* 7. DOI: 10.1371/journal.pone.0039107.
- 502 Altschul SF., Madden TL., Schäffer AA., Zhang J., Zhang Z., Miller W., Lipman DJ. 1997.
503 Gapped BLAST and PSI-BLAST: a new generation of protein database search programs.
504 *Nucleic Acids Research* 25:3389–3402.
- 505 Assenov Y., Ramirez F., Schelhorn S-E., Lengauer T., Albrecht M. 2008. Computing topological
506 parameters of biological networks. *Bioinformatics* 24:282–284. DOI:
507 10.1093/bioinformatics/btm554.
- 508 Barberán A., Bates ST., Casamayor EO., Fierer N. 2012. Using network analysis to explore co-
509 occurrence patterns in soil microbial communities. *The ISME Journal* 6:343–351.
- 510 Bergsten J. 2005. A review of long-branch attraction. *Cladistics* 21:163–193. DOI:
511 10.1111/j.1096-0031.2005.00059.x.
- 512 Bolduc B., Youens-Clark K., Roux S., Hurwitz BL., Sullivan MB. 2016. iVirus: facilitating new
513 insights in viral ecology with software and community data sets imbedded in a
514 cyberinfrastructure. *The ISME Journal*:1–8. DOI: 10.1038/ismej.2016.89.

- 515 Brum JR., Ignacio-Espinoza JC., Roux S., Doulcier G., Acinas SG., Alberti A., Chaffron S.,
516 Cruaud C., de Vargas C., Gasol JM., Gorsky G., Gregory AC., Guidi L., Hingamp P.,
517 Iudicone D., Not F., Ogata H., Pesant S., Poulos BT., Schwenck SM., Speich S., Dimier C.,
518 Kandels-Lewis S., Picheral M., Searson S., Tara Oceans Coordinators., Bork P., Bowler C.,
519 Sunagawa S., Wincker P., Karsenti E., Sullivan MB. 2015a. Ocean plankton. Patterns and
520 ecological drivers of ocean viral communities. *Science (New York, N.Y.)* 348:1261498. DOI:
521 10.1126/science.1261498.
- 522 Brum JR., Ignacio-Espinoza JC., Roux S., Doulcier G., Acinas SG., Alberti A., Chaffron S.,
523 Cruaud C., de Vargas C., Gasol JM., Gorsky G., Gregory AC., Guidi L., Hingamp P.,
524 Iudicone D., Not F., Ogata H., Pesant S., Poulos BT., Schwenck SM., Speich S., Dimier C.,
525 Kandels-Lewis S., Picheral M., Searson S., Bork P., Bowler C., Sunagawa S., Wincker P.,
526 Karsenti E., Sullivan MB. 2015b. Patterns and ecological drivers of ocean viral
527 communities. *Science* 348:1261498–1261498. DOI: 10.1126/science.1261498.
- 528 Comeau AM., Krisch HM. 2008. The Capsid of the T4 Phage Superfamily: The Evolution,
529 Diversity, and Structure of Some of the Most Prevalent Proteins in the Biosphere.
530 *Molecular Biology and Evolution* 25:1321–1332. DOI: 10.1093/molbev/msn080.
- 531 Dagan T. 2011. Phylogenomic networks. *Trends in Microbiology* 19:483–491. DOI:
532 10.1016/j.tim.2011.07.001.
- 533 Deng L., Ignacio-Espinoza JC., Gregory AC., Poulos BT., Weitz JS., Hugenholtz P., Sullivan
534 MB. 2014. Viral tagging reveals discrete populations in *Synechococcus* viral genome
535 sequence space. *Nature* advance on. DOI: 10.1038/nature13459.
- 536 Edwards RA., Rohwer F. 2005. Viral metagenomics. *Nature Reviews Microbiology* 3:504–510.
- 537 Eriksson H., Maciejewska B., Latka A., Majkowska-Skrobek G., Hellstrand M., Melefors Ö.,
538 Wang JT., Kropinski AM., Drulis-Kawa Z., Nilsson AS. 2015. A suggested new
539 bacteriophage genus, “Kp34likevirus”, within the Autographivirinae subfamily of
540 podoviridae. *Viruses* 7:1804–1822. DOI: 10.3390/v7041804.
- 541 Fauquet CM., Fargette D. 2005. International Committee on Taxonomy of Viruses and the 3,142
542 unassigned species. *Virology journal* 2:64. DOI: 10.1186/1743-422X-2-64.

- 543 Filee J. 2006. A Selective Barrier to Horizontal Gene Transfer in the T4-Type Bacteriophages
544 That Has Preserved a Core Genome with the Viral Replication and Structural Genes.
545 *Molecular Biology and Evolution* 23:1688–1696. DOI: 10.1093/molbev/msl036.
- 546 Goff S a., Vaughn M., McKay S., Lyons E., Stapleton AE., Gessler D., Matasci N., Wang L.,
547 Hanlon M., Lenards A., Muir A., Merchant N., Lowry S., Mock S., Helmke M., Kubach A.,
548 Narro M., Hopkins N., Micklos D., Hilgert U., Gonzales M., Jordan C., Skidmore E.,
549 Dooley R., Cazes J., McLay R., Lu Z., Pasternak S., Koesterke L., Piel WH., Grene R.,
550 Noutsos C., Gendler K., Feng X., Tang C., Lent M., Kim S-J., Kvilekval K., Manjunath
551 BS., Tannen V., Stamatakis A., Sanderson M., Welch SM., Cranston K a., Soltis P., Soltis
552 D., O’Meara B., Ane C., Brutnell T., Kleibenstein DJ., White JW., Leebens-Mack J.,
553 Donoghue MJ., Spalding EP., Vision TJ., Myers CR., Lowenthal D., Enquist BJ., Boyle B.,
554 Akoglu A., Andrews G., Ram S., Ware D., Stein L., Stanzione D. 2011. The iPlant
555 Collaborative: Cyberinfrastructure for Plant Biology. *Frontiers in Plant Science* 2:1–16.
556 DOI: 10.3389/fpls.2011.00034.
- 557 Goulet A., Blangy S., Redder P., Prangishvili D., Felisberto-Rodrigues C., Forterre P.,
558 Campanacci V., Cambillau C. 2009. Acidianus filamentous virus 1 coat proteins display a
559 helical fold spanning the filamentous archaeal viruses lineage. *Proceedings of the National*
560 *Academy of Sciences* 106:21155–21160.
- 561 Gregory AC., Solonenko SA., Ignacio-Espinoza JC., LaButti K., Copeland A., Sudek S.,
562 Maitland A., Chittick L., dos Santos F., Weitz JS., Worden AZ., Woyke T., Sullivan MB.
563 2016. Genomic differentiation among wild cyanophages despite widespread horizontal gene
564 transfer. *BMC Genomics* 17:930. DOI: 10.1186/s12864-016-3286-x.
- 565 Grose JH., Casjens SR. 2014. Understanding the enormous diversity of bacteriophages: The
566 tailed phages that infect the bacterial family Enterobacteriaceae. *Virology* 468:421–443.
567 DOI: 10.1016/j.virol.2014.08.024.
- 568 Halary S., Leigh JW., Cheaib B., Lopez P., Baptiste E. 2009. Network analyses structure genetic
569 diversity in independent genetic worlds. *Proceedings of the National Academy of Sciences*
570 107:127–132. DOI: 10.1073/pnas.0908978107.
- 571 Huang G., Le S., Peng Y., Zhao Y., Yin S., Zhang L., Yao X., Tan Y., Li M., Hu F. 2013.

- 572 Characterization and genome sequencing of phage Abp1, a new phiKMV-like virus
573 infecting multidrug-resistant acinetobacter baumannii. *Current Microbiology* 66:535–543.
574 DOI: 10.1007/s00284-013-0308-7.
- 575 Hurwitz BL., Brum JR., Sullivan MB. 2014. Depth-stratified functional and taxonomic niche
576 specialization in the “core” and “flexible” Pacific Ocean Virome. *The ISME journal*:1–13.
577 DOI: 10.1038/ismej.2014.143.
- 578 Hurwitz BL., Hallam SJ., Sullivan MB. 2013. Metabolic reprogramming by viruses in the sunlit
579 and dark ocean. *Genome Biology* 14:R123. DOI: 10.1186/gb-2013-14-11-r123.
- 580 Iranzo J., Krupovic M., Koonin E V. 2016. The Double-Stranded DNA Virophere as a Modular
581 Hierarchical Network of Gene Sharing. *mBio* 7:e00978-16. DOI: 10.1128/mBio.00978-16.
- 582 Koonin E V., Krupovic M., Yutin N. 2015. Evolution of double-stranded DNA viruses of
583 eukaryotes: from bacteriophages to transposons to giant viruses. *Annals of the New York*
584 *Academy of Sciences*:n/a-n/a. DOI: 10.1111/nyas.12728.
- 585 Krupovic M., Dutilh BE., Adriaenssens EM., Wittmann J., Vogensen FK., Sullivan MB.,
586 Rumnieks J., Prangishvili D., Lavigne R., Kropinski AM., Klumpp J., Gillis A., Enault F.,
587 Edwards RA., Duffy S., Clokie MRC., Barylski J., Ackermann H-W., Kuhn JH. 2016.
588 Taxonomy of prokaryotic viruses: update from the ICTV bacterial and archaeal viruses
589 subcommittee. *Archives of Virology* 161:1095–1099. DOI: 10.1007/s00705-015-2728-0.
- 590 Kuhn JH., Dürrwald R., Bào Y., Briesse T., Carbone K., Clawson AN., deRisi JL., Garten W.,
591 Jahrling PB., Kolodziejek J., Rubbenstroth D., Schwemmler M., Stenglein M., Tomonaga
592 K., Weissenböck H., Nowotny N. 2014. Taxonomic reorganization of the family
593 Bornaviridae. *Archives of Virology* 160:621–632. DOI: 10.1007/s00705-014-2276-z.
- 594 Labonté JM., Swan BK., Poulos B., Luo H., Koren S., Hallam SJ., Sullivan MB., Woyke T., Eric
595 Wommack K., Stepanauskas R. 2015. Single-cell genomics-based analysis of virus–host
596 interactions in marine surface bacterioplankton. *The ISME Journal* 9:2386–2399. DOI:
597 10.1038/ismej.2015.48.
- 598 Labrie SJ., Frois-Moniz K., Osburne MS., Kelly L., Roggensack SE., Sullivan MB., Gearin G.,
599 Zeng Q., Fitzgerald M., Henn MR., Chisholm SW. 2013. Genomes of marine

- 600 cyanopodoviruses reveal multiple origins of diversity. *Environmental Microbiology*
601 15:1356–1376. DOI: 10.1111/1462-2920.12053.
- 602 Lauber C., Gorbalenya AE. 2012a. Partitioning the Genetic Diversity of a Virus Family:
603 Approach and Evaluation through a Case Study of Picornaviruses. *Journal of virology*
604 86:3890–3904.
- 605 Lauber C., Gorbalenya AE. 2012b. Genetics-based classification of filoviruses calls for
606 expanded sampling of genomic sequences. *Viruses* 4:1425–1437. DOI: 10.3390/v4091425.
- 607 Lavigne R., Darius P., Summer EJ., Seto D., Mahadevan P., Nilsson AS., Ackermann HW.,
608 Kropinski AM. 2009. Classification of Myoviridae bacteriophages using protein sequence
609 similarity. *BMC Microbiology* 9:224. DOI: 10.1186/1471-2180-9-224.
- 610 Lawrence JG., Hatfull GF., Hendrix RW. 2002. Imbrolios of Viral Taxonomy: Genetic
611 Exchange and Failings of Phenetic Approaches. *Journal of Bacteriology* 184:4891–4905.
612 DOI: 10.1128/JB.184.17.4891-4905.2002.
- 613 Leplae R., Hebrant A., Wodak SJ., Toussaint A. 2004. ACLAME: a CLAssification of Mobile
614 genetic Elements. *Nucleic acids research* 32:D45-9. DOI: 10.1093/nar/gkh084.
- 615 Lima-Mendez G., Van Helden J., Toussaint A., Leplae R. 2008. Reticulate representation of
616 evolutionary and functional relationships between phage genomes. *Molecular Biology and*
617 *Evolution* 25:762–777. DOI: 10.1093/molbev/msn023.
- 618 Marston MF., Amrich CG. 2009. Recombination and microdiversity in coastal marine
619 cyanophages. *Environmental Microbiology* 11:2893–2903. DOI: 10.1111/j.1462-
620 2920.2009.02037.x.
- 621 Millard AD., Zwirgmaier K., Downey MJ., Mann NH., Scanlan DJ. 2009. Comparative
622 genomics of marine cyanomyoviruses reveals the widespread occurrence of *Synechococcus*
623 host genes localized to a hyperplastic region: Implications for mechanisms of cyanophage
624 evolution. *Environmental Microbiology* 11:2370–2387. DOI: 10.1111/j.1462-
625 2920.2009.01966.x.
- 626 Mizuno CM., Rodriguez-Valera F., Kimes NE., Ghai R. 2013. Expanding the Marine Virosphere
627 Using Metagenomics. *PLoS Genetics* 9. DOI: 10.1371/journal.pgen.1003987.

- 628 Niu YD., McAllister TA., Nash JHE., Kropinski AM., Stanford K. 2014. Four Escherichia coli
629 O157:H7 Phages: A New Bacteriophage Genus and Taxonomic Classification of T1-Like
630 Phages. *PLoS ONE* 9:e100426. DOI: 10.1371/journal.pone.0100426.
- 631 Paez-Espino D., Eloie-Fadrosh EA., Pavlopoulos GA., Thomas AD., Huntemann M., Mikhailova
632 N., Rubin E., Ivanova NN., Kyrpides NC. 2016. Uncovering Earth's virome. *Nature*
633 536:425–430. DOI: 10.1038/nature19094.
- 634 Pope WH., Bowman C a., Russell D a., Jacobs-Sera D., Asai DJ., Cresawn SG., Jacobs WR.,
635 Hendrix RW., Lawrence JG., Hatfull GF. 2015. Whole genome comparison of a large
636 collection of mycobacteriophages reveals a continuum of phage genetic diversity. *eLife*
637 4:e06416. DOI: 10.7554/eLife.06416.
- 638 Prangishvili D., Garrett RA., Koonin E V. 2006. Evolutionary genomics of archaeal viruses:
639 Unique viral genomes in the third domain of life. *Virus Research* 117:52–67.
- 640 Prangishvili D., Krupovič M. 2012. A new proposed taxon for double-stranded DNA viruses, the
641 order “Ligamenvirales.” *Archives of Virology* 157:791–795.
- 642 Radoshitzky SR., Bào Y., Buchmeier MJ., Charrel RN., Clawson AN., Clegg CS., DeRisi JL.,
643 Emonet S., Gonzalez JP., Kuhn JH., Lukashevich IS., Peters CJ., Romanowski V., Salvato
644 MS., Stenglein MD., de la Torre JC arlos. 2015. Past, present, and future of arenavirus
645 taxonomy. *Archives of virology* 160:1851–1874. DOI: 10.1007/s00705-015-2418-y.
- 646 Redder P., Peng X., Brugger K., Shah SA., Roesch F., Greve B., She Q., Schleper C., Forterre P.,
647 Garrett RA., Prangishvili D. 2009. Four newly isolated fuselloviruses from extreme
648 geothermal environments reveal unusual morphologies and a possible interviral
649 recombination mechanism. *Environmental Microbiology* 11:2849–2862.
- 650 Roux S., Hawley AK., Torres Beltran M., Scofield M., Schwientek P., Stepanauskas R., Woyke
651 T., Hallam SJ., Sullivan MB. 2014. Ecology and evolution of viruses infecting uncultivated
652 SUP05 bacteria as revealed by single-cell- and meta- genomics. *eLife*:e03125. DOI:
653 10.7554/eLife.03125.
- 654 Roux S., Hallam SJ., Woyke T., Sullivan MB. 2015a. Viral dark matter and virus-host
655 interactions resolved from publicly available microbial genomes. *eLife* 4:e08490. DOI:

656 10.7554/eLife.08490.

657 Roux S., Enault F., Ravet V., Pereira O., Sullivan MB. 2015b. Genomic characteristics and
658 environmental distributions of the uncultivated Far-T4 phages. *Frontiers in microbiology*
659 6:199. DOI: 10.3389/fmicb.2015.00199.

660 Roux S., Brum JR., Dutilh BE., Sunagawa S., Duhaime MB., Loy A., Poulos BT., Solonenko N.,
661 Lara E., Poulain J., Pesant S., Kandels-Lewis S., Dimier C., Picheral M., Searson S., Cruaud
662 C., Alberti A., Duarte CM., Gasol JM., Vaqué D., Bork P., Acinas SG., Wincker P.,
663 Sullivan MB. 2016. Ecogenomics and potential biogeochemical impacts of globally
664 abundant ocean viruses. *Nature* 537:689–693. DOI: 10.1038/nature19366.

665 Simmonds P. 2015. Methods for virus classification and the challenge of incorporating
666 metagenomic sequence data. *Journal of General Virology* 96:1193–1206. DOI:
667 10.1099/vir.0.000016.

668 Sullivan MB., Lindell D., Lee J a., Thompson LR., Bielawski JP., Chisholm SW. 2006.
669 Prevalence and evolution of core photosystem II genes in marine cyanobacterial viruses and
670 their hosts. *PLoS Biology* 4:1344–1357. DOI: 10.1371/journal.pbio.0040234.

671 Woese CR., Kandler O., Wheelis ML. 1990. Towards a natural system of organisms: proposal
672 for the domains Archaea, Bacteria, and Eucarya. *Proceedings of the National Academy of*
673 *Sciences* 87:4576–4579.

674 Zanotto PM de., Gibbs MJ., Gould EA., Holmes EC. 1996. A reevaluation of the higher
675 taxonomy of viruses based on RNA polymerases. *Journal of virology* 70:6083–6096.

676

Table 1 (on next page)

Terminology used.

1

Terminology	Definition
Nodes	Also known as <i>vertices</i> , these are points within a network. In this work, they are viral genomes.
Edges	Also known as <i>arcs</i> , these lines connect nodes in the network. In this work, edges have a property called <i>weight</i> , which represents the strength (as measured by significance score) between two genomes.
Betweenness centrality (BC)	Measure of how influential a node is within a network, measured by the number of shortest paths that pass through the node from all other nodes.
Connected component	A subgraph in which any two nodes are connected to each other directly (to each other) or indirectly (through other nodes).
Largest connected component (LCC)	The connected component with the greatest number of nodes.
Viral cluster (VC)	A group of viral sequences sharing a significant number of genes.
Protein cluster (PC)	A group of highly similar and related proteins, defined in this work using MCL on BLAST E-values between proteins.
Module Profile	A table-like representation of the presence/absence data between groups of protein clusters (modules) and groups of genomes (viral clusters).
Precision (P)	Also known as the <i>positive predictive value</i> , is a measure of how many true positives are identified.
Recall (R)	Also known as <i>sensitivity</i> , is a measure of how many of the total positives are identified.

2

Figure 1

Overview of the vContact processing pipeline.

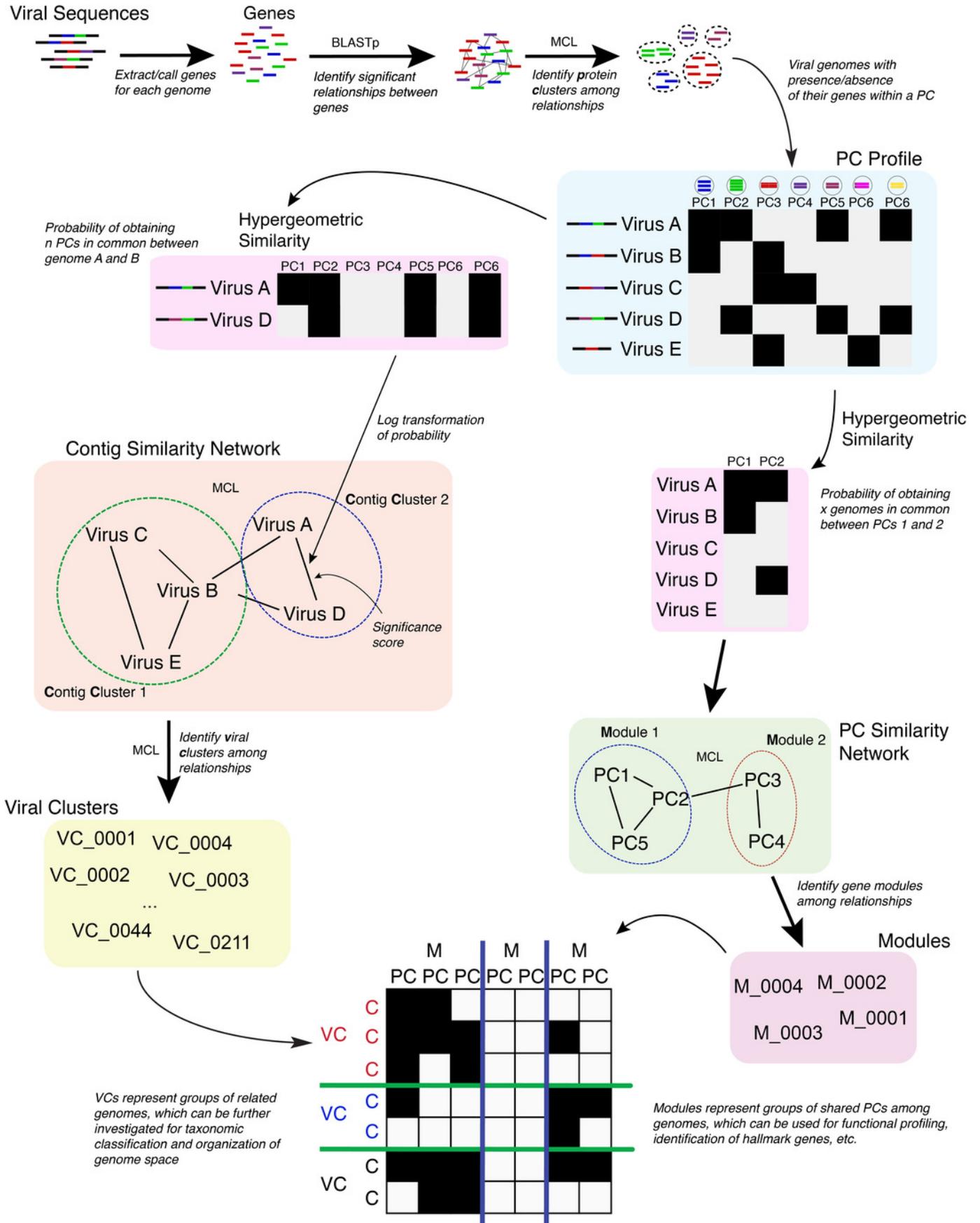
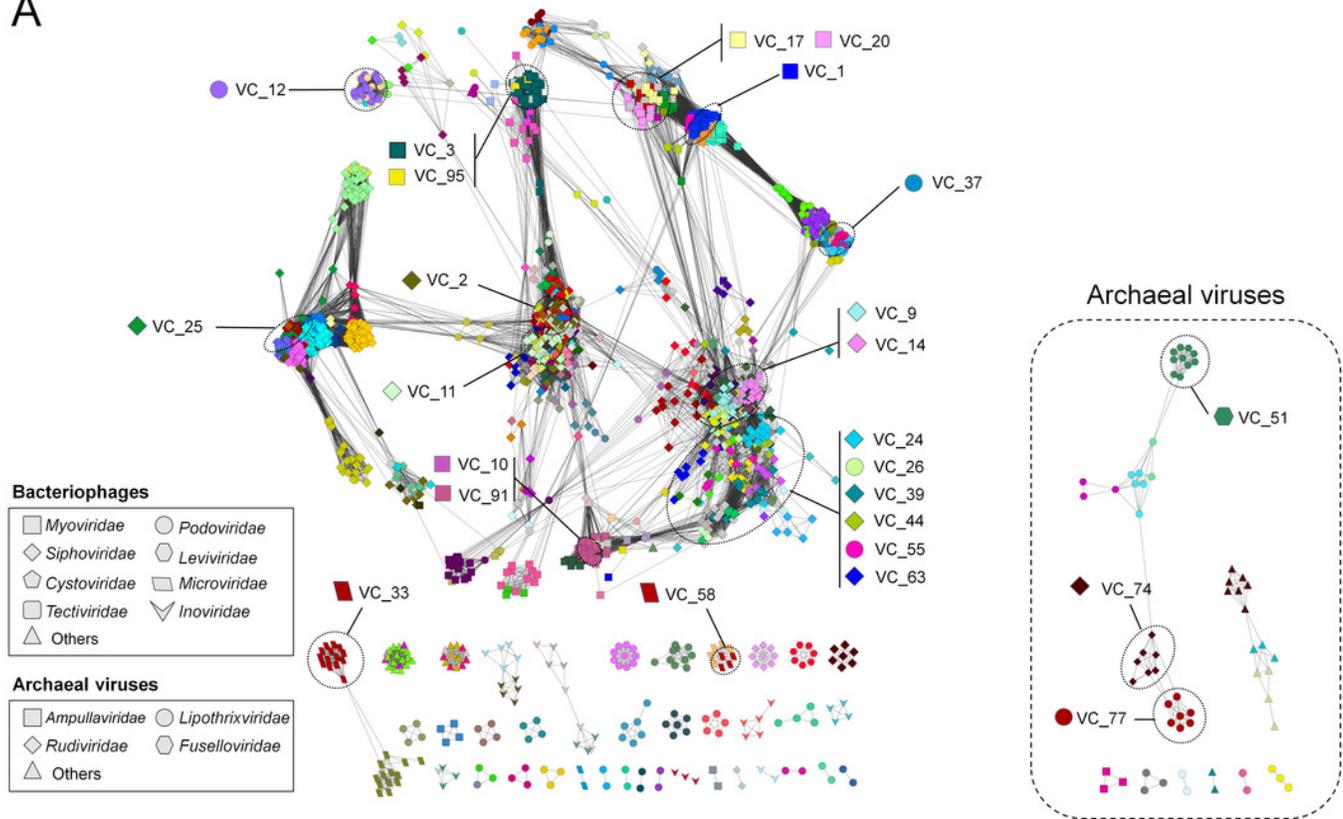


Figure 2

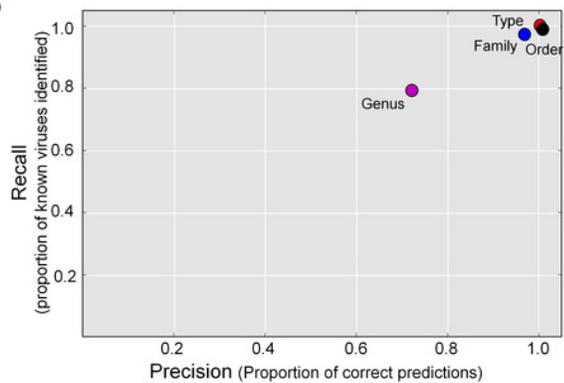
Protein-sharing network.

Protein-sharing network for 1,964 archaeal and bacterial virus genomes benchmarked against ICTV-accepted viral taxonomy. (A) Each node represents a viral genome from RefSeq, with its shape representing the viral family (as indicated in the legend) and each distinct color the node's viral cluster (VC). Edges between nodes indicate a statistically significant relationship between the protein profiles of their viral genomes, with edge colors (darker = more significant) corresponding to their weighted similarity scores (threshold of ≥ 1). VCs within the network are discriminated using the MCL algorithm (Materials and Methods) and denoted as separate colors. The position of 26 heterogeneous VCs that contain 2 or more genera is indicated. (B) Precision and recall of network-based assignments as compared to ICTV assignments for each taxonomic level (genus, family, order, and type). (C) Percentage (Y-axis) of VCs that contain the number (X-axis) of each ICTV taxonomic level (genus, family, and order).

A



B



C

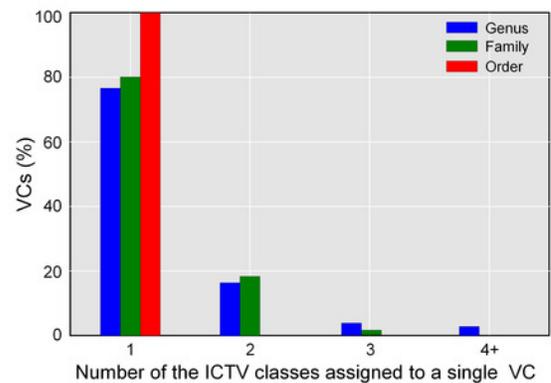


Figure 3

Detailed view of three major viral groups with relatives.

A detailed view of network regions containing three major viral groups and their relatives. Viruses (nodes) are grouped by the MCL clustering. The different shapes and colors of the nodes represent different viral families (Figure 2) and viral clusters (VCs, legends), respectively. The location of viral groups is indicated for illustrative purpose.

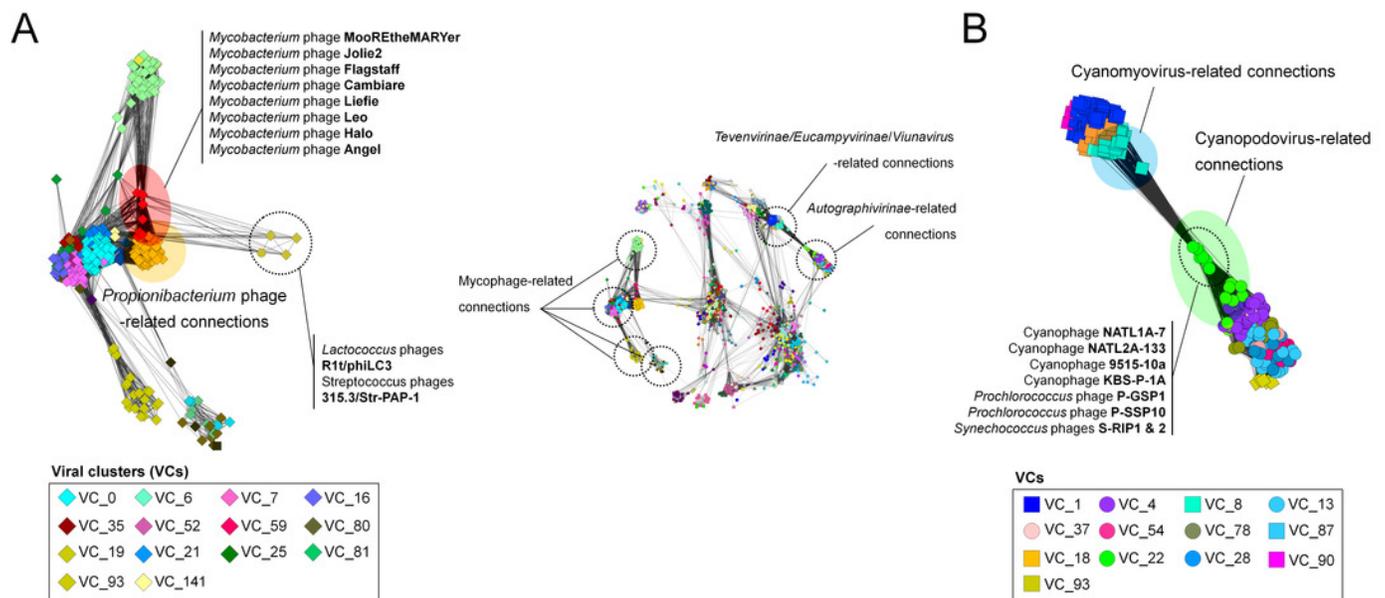


Figure 4

Heterogeneous VCs

Evaluation of VCs which contained taxon representatives from more than one ICTV genus. (A) Box plots show the percent inter- and intra-genus proteome similarities in the heterogeneous VCs. Dotted lines indicate the cut-off values of 20% and 40% proteome similarities to define the subfamily and genus, respectively, which have been ratified by the ICTV Bacterial and Archaeal Viruses Subcommittee. (B) Module profiles showing the presence and absence of PCs across genomes. Presence (dark box) denotes a gene that is present within a protein cluster. Genes from related genomes often cluster into the same PC, with alignments of highly related genomes showing large groups of PCs. Genomes are further partitioned using hierarchical clustering (see materials and methods).

