Manual resolution of virome dark matter uncovers hundreds of viral families in the infant gut

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Abstract

The gut microbiome (GM) is shaped through infancy and plays a major role in determining susceptibility to chronic diseases later in life. Bacteriophages (phage) are known to modulate bacterial populations in numerous ecosystems, including the gut. However, virome data is difficult to analyse because it mostly consists of unknown viruses, i.e. viral dark matter. Here, we manually resolved the viral dark matter in the largest human virome study published to date. Fecal viromes from a cohort of 647 infants at 1 year of age were deeply sequenced and analysed through successive rounds of clustering and curation. This uncovered more than ten thousand viral species distributed over 248 viral families falling within 17 viral order-level clusters. Most of the defined viral families and orders were novel and belonged to the *Caudoviricetes* viral class. Bacterial hosts were predicted for 79% of the viral species using CRISPR spacers in metagenomes from the same fecal samples. While *Bacteroides*-infecting Crassphages were present, novel viral families were more predominant, including phages infecting Clostridiales and *Bifidobacterium*. Phage lifestyles were determined for more than three thousand caudoviral species. Lifestyles were homogeneous at the family level for 149 caudiviral families. 32 families were found to be virulent, while 117 families were temperate. Virulent phage families were more abundant but temperate phage families were more diverse and widespread. Together, the viral families found in this study represent a major expansion of current bacteriophage taxonomy, and the sequences have been put online for use and validation by the community.

Introduction

The establishment of the gut microbiome (GM) during the first years of life plays a pivotal role in the maturation of the infant immune system[1,2]. Early-life GM dysbiosis has been linked to a series of chronic diseases occurring later in life, indicative of an immune system thrown off balance[3–6]. Most existing research has been on the bacterial component of the GM but in recent years it has become evident that other microbes and especially viruses are prominent GM members. They populate the gut during the first months of life following a patterned trajectory resembling the establishment of gut bacteria[7–10].

Bacteriophages (phages) are viruses that infect bacteria in a host specific manner. Virulent phages multiply by killing their host bacteria. Temperate phages can integrate into the bacterial chromosome as prophages, thereby postponing an attack on the host until conditions are favourable. Some phages also cause chronic infections leading to continuous shedding of viral particles[11]. Bacteria will defend themselves using defence systems such as Clustered Regularly Interspaced Palindromic Repeats (CRISPR), an adaptive immune mechanism where records of past infections saved on the chromosome help combat any future attacks[12].

Lately, it has become clear that phages are not only abundant in the gut, but also possess the ability to alter GM composition and function[8,13]. Moreover, the reported interactions between phage proteins and the host immune response[14–16] suggest a tripartite interaction

that may modulate host health. The first report on the viral metagenome (virome) composition in the infant gut dates back more than a decade[17], and it has recently been shown to be influenced by caesarian section[18]. Nevertheless large-scale studies establishing the early-life virome composition and structure are sparse, and human virome studies in general have been severely challenged by the viral "dark matter" problem[19].

The dark matter problem is a phenomenon where only a small fraction of sequences can be traced back to any known virus because sequence databases underrepresent the diversity of viruses in natural environments. Attempts at *de novo* virus discovery directly from the virome data have been limited by the lack of universal viral marker genes, which makes it difficult to distinguish viral sequences from contaminating DNA. In addition, *de novo* classification of novel viruses has been held back by the lack of reproducible classification criteria and methods. Although much progress has been made in recent years[20–22], virome studies are still catching up. The dark matter problem has prevented researchers from getting the most out of their viromes, perhaps thereby missing biologically meaningful associations in their data.

Traditionally, the definition of new viral taxa has required the laboratory isolation of the virus along with its host and its subsequent characterization[23], but recently the International Committee for the Taxonomy of Viruses (ICTV) opened up the possibility for defining viral taxa based on sequence information alone. This move is due to have major implications for our understanding of bacteriophages, and tailed phages (or caudoviruses) in particular, as their diversity is the greatest and has been misrepresented in existing taxonomy[24]. As an example, the ICTV established the complete taxonomy of the *Herelleviridae* caudoviral family, demonstrating the proper definition of viral subfamilies and genera under the new paradigm[25]. Subsequently, three new caudoviral families were found in human gut metagenome data[26], and recently the well-known human gut phage family *Crassviridae*[27], was upgraded into a viral order *Crassvirales*[28], belonging to the viral class *Caudoviricetes* which itself is proposed to encompass caudoviruses[29] in general.

In line with these developments, here we present the fecal virome characterization of 647 infants at one year of age enrolled in the COPSAC2010 cohort. The viral dark matter was exhaustively resolved by manual curation. This enabled the identification of over ten thousand curated viral species, more than half of which were completely sequenced. Hierarchical clustering of the viruses based on encoded protein similarity enabled the *de novo* definition of novel viral genera, subfamilies and families. In total, we identified 248 viral families that have been tentatively grouped into seventeen viral order-level clusters. Most of the novel families belonged to *Caudoviricetes*, representing a major expansion of known caudoviral diversity. We also predicted the hosts of the viral species by matching spacer sequences from bacterial CRISPRs and found that members of the *Bacteroides*-infecting *Crassvirales* - otherwise abundant in adult gut viromes - were outnumbered by novel phage families infecting numerous gut bacteria such as Clostridiales and *Bifidobacterium*. Temperate phages were the most widespread and diverse while virulent phages were more abundant. Our manually confirmed viral set was also used for benchmarking the performance of several metagenome virus discovery tools. All viral sequences found in the study have been made available online in an interface for browsing their genome contents along with their viral taxonomy, host and lifestyle predictions (http://copsac.com/earlyvir/f1y/fig1.svg).

Results

Study population

COPSAC2010 is a population-based birth cohort of 700 children recruited in pregnancy where we study the causes for chronic disease. The children are monitored by clinicians who diagnose eventual conditions, and multi-omics data is collected routinely to shed light on disease mechanisms. A total of 647 children had a fecal sample obtained at 1 year of age where the virome was characterised, and deep metagenomes for the samples were sequenced in parallel[30].

Identifying the viruses and resolving their taxonomies

Virome extractions are known to contain large amounts of bacterial contaminating DNA[31] and the virome dark matter problem[19] makes it difficult to discern novel viruses from contaminants. We decided to resolve the virome dark matter by assembly, clustering and successive rounds of manual curation.

Assembly of all samples resulted in 1.5M contigs that fell within 8050 broad decontamination clusters based on remote protein similarity. After ranking the clusters by prevalence and CRISPR targeting, they were visualised and inspected manually. 255 of them were deemed viral (Figure S1). In parallel, we deduplicated all contigs at the species level, (95% average nucleotide identity or ANI), resulting in 363k operational taxonomic units (OTUs) (Table 1). Of these, 16,746 belonged to the 255 viral decontamination clusters and were thus termed viral OTUs (vOTUs).

The vOTUs were pooled with 7.7k reference phage species[91] before gene calling. Protein alignments were then used for defining viral ortholog gene clusters (VOGs) *de novo* and for constructing an aggregate protein similarity (APS) tree (methods). The tree was rooted and cut at the levels reproducing published taxonomy for Herelleviridae[25], thus yielding viral families, subfamilies and genera covering all vOTUs and reference phages. An additional order-level cutoff was based on the newly proposed caudoviral *Crassvirales* order[28] (Table 2).

All family-level clusters were validated by visualising (Figure S2) and inspecting their gene contents and any weak clusters were removed in the process (methods, Figure S1). The minimum complete genome size cutoff for the validated families was determined manually (methods). Next, each vOTU within each family was curated individually to remove small fragments, putative satellites and MGEs (Table 1).

The final curated set consisted of 248 viral families, grouped into 17 order-level clusters (Table 1), representing a major expansion of current bacteriophage taxonomy. The 232 novel viral families were named after the infants that produced the fecal samples (Figure 1). The 12 novel order-level clusters were named after influential microbiologists and features of member viruses. In total the 248 curated families harboured 10021 manually confirmed species-level vOTUs, 5608 of which were complete or near-complete. Genome maps of vOTUs in each family have been made available online (Figure S2) along with DNA

sequences, all of which is accessible via the interactive version of Figure 1 on http://copsac.com/earlyvir/f1y/fig1.svg.

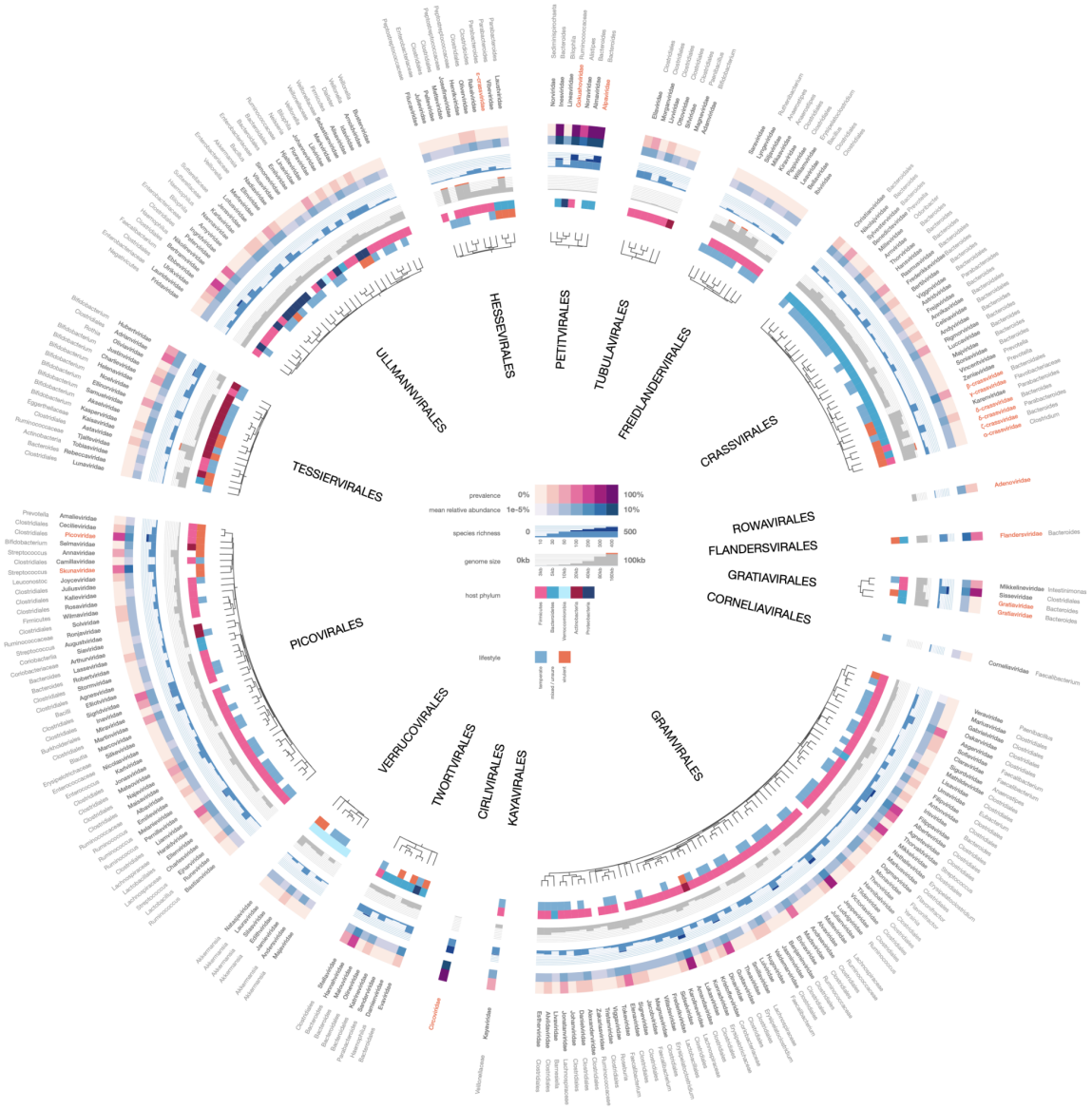


Figure 1: **An atlas of infant gut DNA virus diversity**. Fecal viromes from 647 infants at age 1 year were deeply sequenced, assembled and curated, resulting in the identification of 10,021 viruses falling within 248 viral families. The 232 novel families were named after the infants. Host ranges for each family are given, and the families have been grouped into 17 order-level clusters. Trees show how families are interrelated within each order-level cluster. The 16 previously defined families are highlighted in red. Interactive version with expandable families: http://copsac.com/earlyvir/f1y/fig1.svg

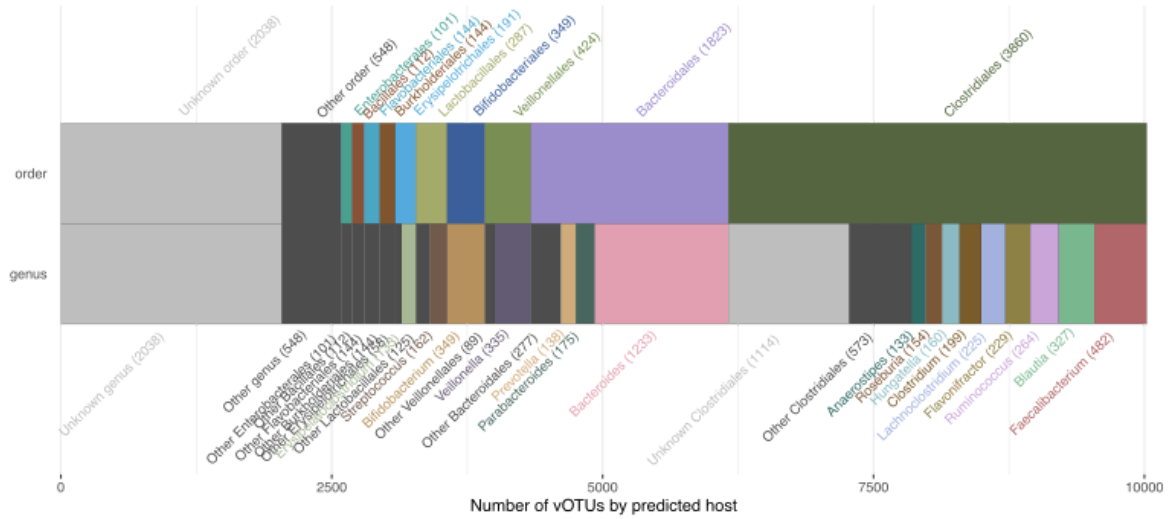
Table 1: Distribution of vOTUs and mapped reads over different curated categories. Viral OTUs recruited half of the mapped reads. Non-viral OTUs recruited the other half despite being much more numerous than the vOTUs. Caudoviruses accounted for a majority of mapped viral reads, although ssDNA viruses were more abundant after normalising for genome length.

	OTUs	mean length	mapped reads	proportion
all	362668	4.37 kb	1532152367	100 %
vOTUs	16746	19.4 kb	748493386	49 %
viruses	**10646**	**25.0 kb**	**712219234**	**47 %**
satellites or fragments	4999	10.0 kb	33208298	2.4 %
MGEs	452	11.8 kb	2315098	< 0.1%
others	649	3.6 kb	750756	< 0.1%
non-vOTUs	346k	3.6 kb	783658981	51 %
Bacteria (viromeQC)				44 %
remaining dark matter				7 %
curated vOTUs	10021	24.8 kb	684273808	100 %
Caudoviruses	**7387**	**32.0 kb**	**439625597**	**64 %**
Microviruses	1424	5.7 kb	223341210	33 %
Circoviruses	970	3.0 kb	11929988	1.7 %
Adenoviruses	5	32.5 kb	5531399	0.8 %
Inoviruses	235	6.8 kb	3845613	0.6 %

vOTU host distributions mimic the bacterial composition

Bacterial hosts for the vOTUs were predicted using 318k CRISPR spacers from our metagenome assembled genomes[30], CRISPRopenDB[32] and WIsH[33], and the three predictions were integrated by taking the last common ancestor (LCA). 63% of the vOTUs yielded host predictions at the bacterial genus-level, while 77% were covered at the bacterial order-level (Figure 2A) and 79% at the phylum level. *Bacteroides* was by far the most common bacterial host genus followed by *Faecalibacterium* and *Bifidobacterium*. At the order level though, more than half of all vOTUs had Clostridiales as hosts, with Bacteroidales covering just 20% (Figure 2A). This difference mirrors the corresponding pattern for the bacteria found in the metagenome, where *Bacteroides* are abundant while Clostridiales are diverse (Figure 2B).

A


order
genus
Unknown order (2038)
Other order (548)
Enterobacteriales (101)
Bacillales (112)
Flavobacteriales (144)
Burkholderiales (144)
Erysipelotrichiales (191)
Lactobacillales (287)
Bifidobacteriales (349)
Veillonellales (424)
Bacteroidales (1823)
Clostridiales (3860)
Unknown genus (2038)
Other genus (548)
Other Enterobacteriales (101)
Other Bacillales (112)
Other Flavobacteriales (144)
Other Burkholderiales (144)
Other Erysipelotrichiales (191)
Other Lactobacillales (287)
Streptococcus (162)
Bifidobacterium (349)
Other Veillonellales (89)
Veillonella (335)
Other Bacteroidales (277)
Prevotella (138)
Parabacteroides (175)
Bacteroides (1233)
Unknown Clostridiales (1114)
Other Clostridiales (573)
Anaerostipes (133)
Roseburia (154)
Hungatella (160)
Clostridium (199)
Lachnoclostridium (225)
Flavonifractor (229)
Ruminococcus (264)
Blautia (327)
Faecalibacterium (482)
0
2500
5000
7500
10000
Number of vOTUs by predicted host

B

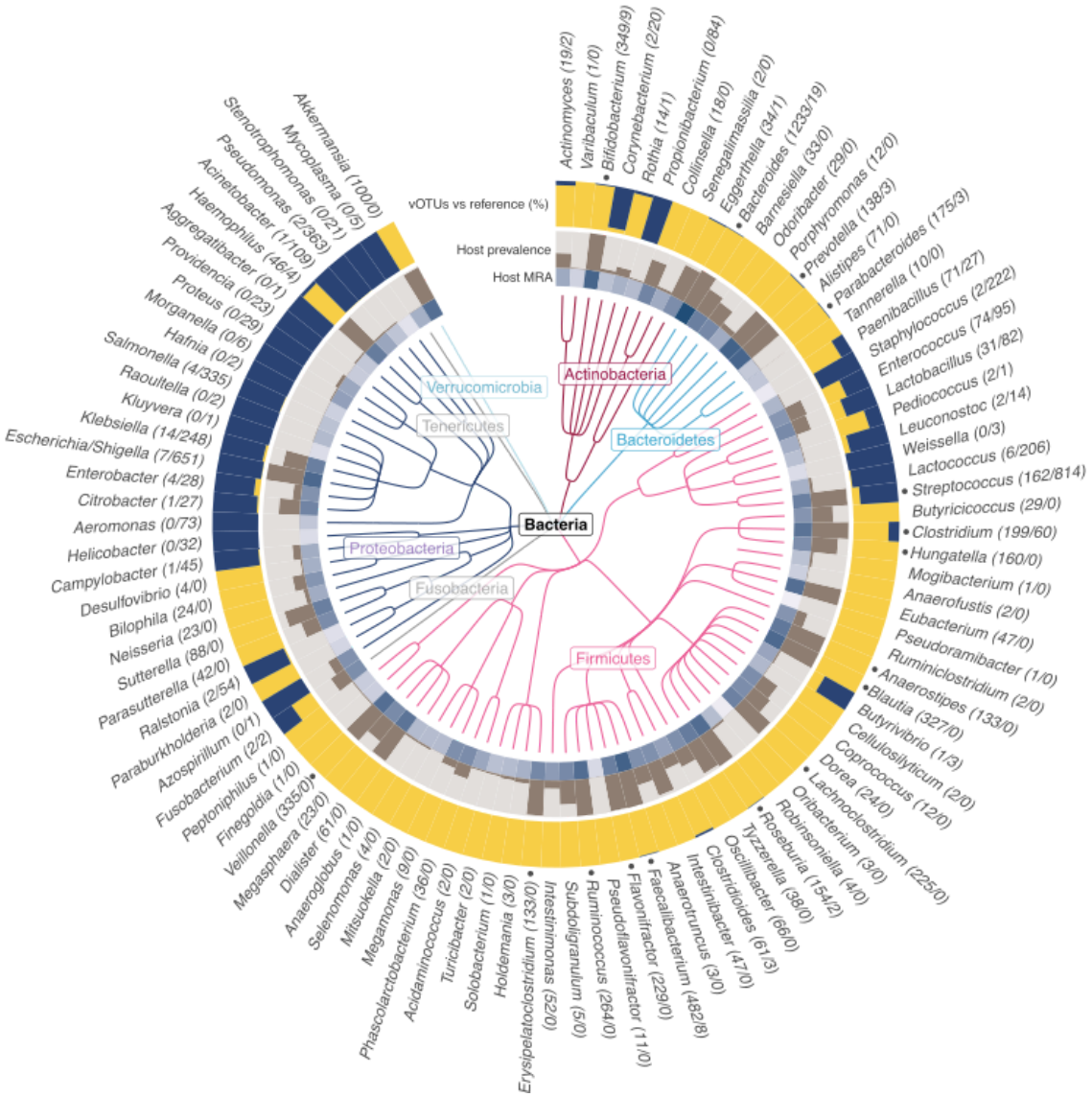

vOTUs vs reference (%)
Host prevalence
Host MRA
Bacteria
Actinobacteria
Bacteroidetes
Firmicutes
Verrucomicrobia
Tenericutes
Proteobacteria
Fusobacteria
Actinomyces (19/2)
Varibaculum (1/0)
Bifidobacterium (349/9)
Corynebacterium (2/20)
Rothia (14/1)
Propionibacterium (0/84)
Collinsella (18/0)
Senegalimassilia (2/0)
Eggerthella (34/1)
Bacteroides (1233/19)
Barnesiella (33/0)
Odoribacter (29/0)
Porphyromonas (12/0)
Prevotella (138/3)
Alistipes (71/0)
Parabacteroides (175/3)
Tannerella (10/0)
Paenibacillus (71/27)
Staphylococcus (2/222)
Enterococcus (74/95)
Lactobacillus (31/82)
Pediococcus (2/1)
Leuconostoc (2/14)
Weissella (0/3)
Lactococcus (6/206)
Streptococcus (162/814)
Butyricicoccus (29/0)
Clostridium (199/60)
Hungatella (160/0)
Mogibacterium (1/0)
Anaerofustis (2/0)
Eubacterium (47/0)
Pseudoramibacter (1/0)
Ruminiclostridium (2/0)
Anaerostipes (133/0)
Blautia (327/0)
Butyrivibrio (1/3)
Cellulosilyticum (2/0)
Coprococcus (12/0)
Dorea (24/0)
Lachnoclostridium (225/0)
Oribacterium (3/0)
Robinsoniella (4/0)
Roseburia (154/2)
Tyzzerella (38/0)
Oscillibacter (66/0)
Clostridioides (61/3)
Intestinibacter (47/0)
Anaerotruncus (3/0)
Faecalibacterium (482/8)
Flavonifractor (229/0)
Pseudoflavonifractor (11/0)
Ruminococcus (264/0)
Subdoligranulum (5/0)
Intestinimonas (52/0)
Erysipelatoclostridium (133/0)
Holdemania (3/0)
Solobacterium (1/0)
Turicibacter (2/0)
Acidaminococcus (2/0)
Phascolarctobacterium (36/0)
Megamonas (9/0)
Mitsuokella (2/0)
Selenomonas (4/0)
Anaeroglobus (1/0)
Dialister (61/0)
Megasphaera (23/0)
Veillonella (335/0)
Finegoldia (1/0)
Peptoniphilus (1/0)
Fusobacterium (2/2)
Azospirillum (0/1)
Paraburkholderia (2/0)
Ralstonia (2/54)
Parasutterella (42/0)
Sutterella (88/0)
Neisseria (23/0)
Bilophila (24/0)
Desulfovibrio (4/0)
Campylobacter (1/45)
Helicobacter (0/32)
Aeromonas (0/73)
Citrobacter (1/27)
Enterobacter (4/28)
Escherichia/Shigella (7/651)
Klebsiella (14/248)
Kluyvera (0/1)
Raoultella (0/2)
Salmonella (4/335)
Hafnia (0/2)
Morganella (0/6)
Proteus (0/29)
Providencia (0/23)
Aggregatibacter (0/1)
Haemophilus (46/4)
Acinetobacter (1/109)
Pseudomonas (2/363)
Stenotrophomonas (0/21)
Mycoplasma (0/5)
Akkermansia (100/0)

Figure 2: Prediction of bacterial hosts for the 10021 viruses found in the infant gut virome shows that *Bacteroides*, *Faecalibacterium* and *Bifodobacterium* are the three most prominent host genera A) Distribution of virus host predictions collapsed to bacterial order and genus levels, respectively. Numbers in parentheses denote the number of vOTUs with a given host genus or order. B) The top 100 gut bacterial genera found in gut metagenomes from the same infants, as represented by a taxonomic tree. The mean relative abundance (MRA) of each bacterial genus is shown in the blue heatmap, while the prevalence is shown with the brown histogram. For each host bacterium, the yellow bars show the proportion of viral species found in this study relative to those in the reference phage species set[91] shown in dark blue. Numbers behind each genus name denote the total number of vOTU vs. reference phage species per bacterial host genus. The 15 major host genera from panel A are indicated by a dot in front of their names in panel B.

Quantification of viruses and bacterial contamination

In order to gauge the quality of the virome extractions we estimated the virus particle concentration for a subset of the samples using epifluorescence microscopy. The mean virus-like particle (VLP) concentration obtained was 1.0×10^9 VLPs/g of feces, ranging from 3×10^8 to 3×10^9 VLPs/g for the 18 samples tested.

Before library preparation we used multiple-displacement amplification (MDA) because it enables detection of ssDNA viruses. MDA, however, can introduce compositional biases[34,35] that favour ssDNA viruses over dsDNA viruses. To control the bias we kept the MDA step brief, at 30 minutes, instead of the 2 hours recommended by protocol. After sequencing and assembly, vOTU abundances were estimated by read mapping and normalising for mapping depth and contig length. ssDNA virus counts made up more than half of the mean relative abundance (MRA) across all samples. To investigate if the MDA had affected whether caudoviral counts were quantitative we compared counts of plaque forming units (PFUs) of different coliphages isolated from the same samples[36] against their corresponding vOTU abundances. Phages that were present in amounts lower than 25000 PFU/g of feces were undetected, limited most likely by sequencing depth. However, phages with PFU counts above this limit showed perfectly quantitative abundances (Figure S3). This confirmed that the virome abundances were quantitative for caudoviruses internally, allowing for valid comparisons of dsDNA abundances across different vOTUs and samples.

The 16,746 vOTUs recruited roughly half of the reads despite making up a minor fraction of all OTUs (Table 1). The remaining half of the read mappings were spread over the 346k non-vOTUs. Since ViromeQC[37] estimated a mean bacterial contamination rate of 44%, we infer that most non-vOTUs must be bacterial (Table 1). After subtracting viral and bacterial reads, only 7% of the reads were left over, comprising unaccounted dark matter.

Viral family prevalence, richness and abundance

In order to identify the most important of the 248 viral families, we ranked them by both species richness, prevalence across samples, and MRA (Figure 3). All three rankings gave similar results because the three estimates were highly correlated (Figure 1). The correlation between such seemingly independent measures is predicted by neutral theory which has

already been shown to explain bacterial community structures quite accurately[38,39]. Human-infecting ssDNA circoviruses and bacterial ssDNA microviruses were the most abundant followed by the major caudoviral families (Figure 3). The major caudoviral families were defined as the ten most abundant ones. Of these, four were already known while the remaining six were novel.

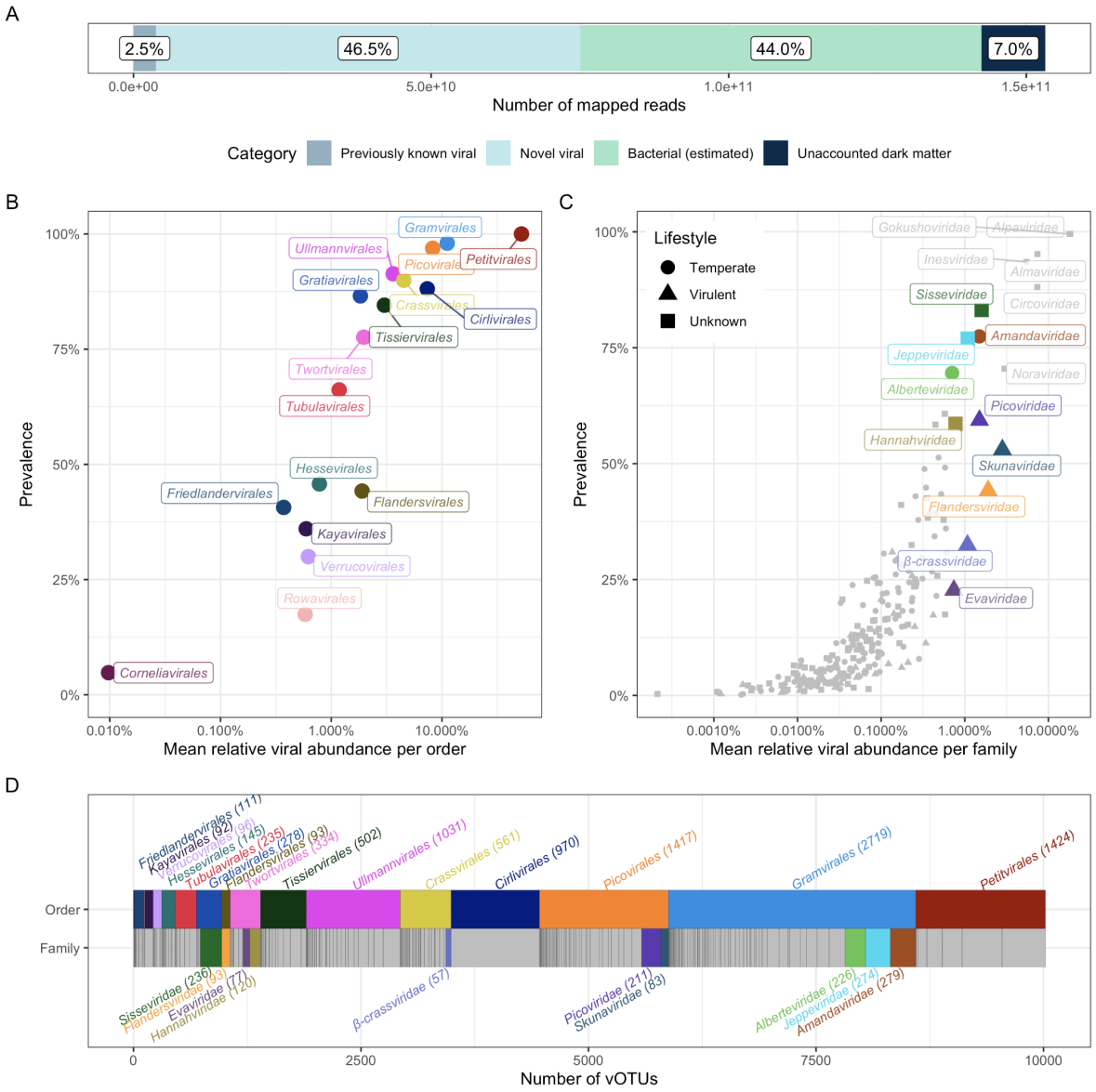


Figure 3: **Abundance, prevalence and richness of the novel families in the infant gut.** A) illustration of the virome dark matter for samples of this study B) the 17 viral order-level clusters and their prevalence and MRA across samples C) the 248 viral families in terms of prevalence and MRA. The major caudoviral families are colored and labelled. Minor families as well as ssDNA families are left grey. Virulent and temperate caudoviral families are indicated by different shapes D) orders and families scaled by species richness, ordered by MRA. The viral families are represented underneath the order they belong to. The major families and novel orders are present in most samples while also making up a majority of the viruses in the data in terms of both richness and abundance.

Virulent vs. temperate *Caudoviricetes* families

While examining the major caudoviral families we noticed how most of them showed a distinct lack of any encoded integrases, otherwise widespread throughout the remaining families in the data. Since integrases are an indicator of a temperate lifestyle, we went on to investigate systematically whether a virulent lifestyle was linked to higher abundances overall. Using the manually determined minimum complete size limit per viral family, 3398 complete and near-complete caudoviral vOTUs from 230 caudoviral families were screened for the presence of integrase VOGs. Using this information 117 of the caudoviral families were deemed temperate, while only 32 were found to be virulent. The remaining 81 caudoviral families exhibited either a mixed lifestyle pattern or were uncertain due to an insufficient number of complete genomes.

On its own, abundance was not significantly linked to phage lifestyle (Figure 4A), but temperate families were significantly more prevalent than virulent families (Figure 4B). Temperate phages are known to be genetically more diverse than their virulent counterparts[40], so we decided to test this by comparing genus richness normalised for overall family size. Indeed temperate caudoviral families were significantly more genetically diverse than virulent families (Figure 4C). As for the predicted bacterial hosts, especially *Clostridiales* were enriched in temperate viral families, whereas most virulent families had *Bacteroidales* as hosts (Figure 1). Using the CRISPR spacer mappings we found, in line with other studies[22,41], that some vOTUs appeared to infect multiple host species, genera or even families of bacteria. We decided to check whether the CRISPR-Cas system targeted virulent phages more often than temperate phages, or whether virulence was associated with a broader host range. This was not the case. Both temperate and virulent families exhibited similar mean host ranges and number of targeting spacers (Figure 4DE).

Plotting the abundance and prevalence of the virulent and temperate families against each other (Fig. 4F) resurfaced our initial suspicion that virulence was the more abundant, albeit less prevalent lifestyle. Thus we decided to test this hypothesis systematically by using the neutral community model (Fig 4G), which describes the typical relationship seen between abundance and prevalence, as the baseline assumption[42]. After fitting the model on all of our family abundances, temperate families had significantly higher residuals against it than virulent families (Fig. 4H), confirming that they were more prevalent while also being less abundant than virulent phage families.

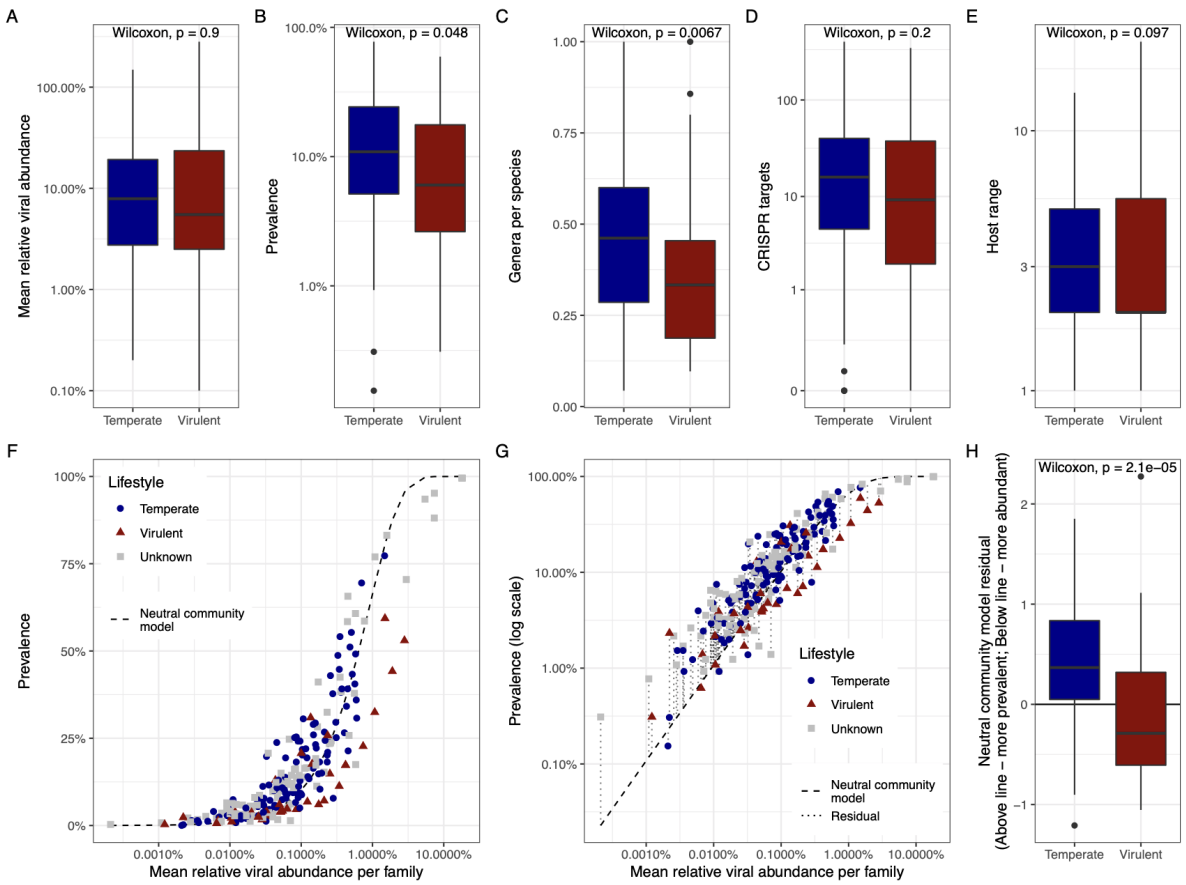


Figure 4: Characteristics of temperate vs. virulent families in the data in terms of A) MRA; B) prevalance; C) genus richness for family size; D) number of metagenomic CRISPR spacer matches; E) host range (number of host species); F) Fit of the neutral community model on the viral families from Fig 3C, with families coloured by lifestyle, G) Deriving neutral community model residuals from the log-transformed prevalences; and H) Comparison of neutral community model residuals, showing that temperate families tend to have positive residuals, whereas virulent families tend towards negative residuals.

ssDNA viruses in the infant gut

ssDNA vOTUs collectively recruited around a third of the sequencing reads, but after normalising for their short genome sizes, they accounted for 60% of the MRA. Although MDA may have inflated the counts for ssDNA viruses, both their prevalence and richness were in line with their high abundance. The ssDNA virus families display canonical positioning along the neutral community model (figures 3C, 4F) indicating that any inflation should have been limited. ssDNA viruses in our data fell within three separate classes, *Malgrandeviricetes*, *Arfaviricites* and *Faserviricetes*, harboring a single viral order each.

Respectively, microviruses of the *Petitvirales* viral order (and *Malgrandeviricetes* class) were both the most prevalent and abundant group of viruses found in our viromes, making up 52% of the MRA. Further, 21 % of the CRISPR spacer matches from the metagenome target microviruses, and this exceeds their richness which accounts for 16% of the bacterial viruses in our data, or 1424 vOTUs in total. vOTUs from the two major families, *Gokushoviridae* and *Alpaviridae* (currently known as *Gokushovirinae* and *Alpavirinae*) in our data infect

Clostridiales and Bacteroidales respectively, but other minor and novel families were also detected.

Circoviridae, also referred to as anelloviruses, are small 3kb ssDNA viruses that infect animal tissue. They are known to cause chronic asymptomatic infections in humans, displaying elevated titers in individuals with weak or developing immune systems[43]. The immature immunity of the infants could be a reason that *Circoviridae* were so abundant in our data, making up 7% MRA and comprising by far the richest single family with 970 species-level vOTUs. Unsurprisingly, no CRISPR spacer matches were found targeting any *Circoviridae* vOTUs.

Inoviruses from the *Tubulavirales* order are small ssDNA filamentous bacteriophages recently found to be ubiquitous and diverse[44]. Some of them can integrate into their hosts using encoded integrases while others cause chronic non-lethal infections that are neither lytic, nor lysogenic, but cause continuous shedding of new virus particles[11]. Although they were diverse in our data, split into 7 distinct families, like the *Petitvirales*, their species richness was much lower at 235 vOTUs, and abundances were correspondingly lower at 1% MRA. Most of the inoviral families found, infected *Clostridiales*, although a single family, *Adamviridae*, infected *Bifidobacterium* exclusively.

Summarising the major *Caudoviricites* families

As explained previously, viral families were defined by cutting the APS tree at the branch uniting *Herelleviridae*[25], and the validity of this cutoff was confirmed independently later because we obtained family-level clusters reproducing the expected Crassphage families defined just recently[28]. Ranking the 230 obtained caudoviral families by MRA, the virulent *Skunaviridae* was the most abundant caudoviral family in the children, comprising 2.7% MRA overall or 6.3% when counting only caudoviruses, and disregarding ssDNA viruses. Widely known as 936-group phages with numerous reference sequences originating from *Lactococcus* dairy cultures, in our data the *Skunaviridae* vOTUs were predicted to infect *Streptococcus*. *Flandersviridae*, a recently described family of gut phages[26] that infects *Bacteroides*, was the second most abundant caudoviral family at just under 5.9% caudoviral MRA. Consistent with earlier speculation[26], we predicted this family to be virulent, which is supported by its high abundance in the children. Next, at 3.9% caudoviral MRA was our first novel viral family, *Sisseviridae*. It was also the most prevalent caudoviral family, found in more than 80% of the children. This family included the recently discovered *Faecalibacterium* phage Oengus[45], also known to be highly prevalent. Being a large family composed of 236 vOTUs infecting mainly Clostridiales hosts, it displayed a mixed lifestyle with some subfamilies being virulent and others temperate. Next, *Picoviridae*, at 3.8% caudoviral MRA, comprises a virulent family of podoviruses including reference phages belonging to the *Picovirinae* subfamily like *Bacillus* phage phi29. The vOTUs belonging to this family were split between those infecting Actinobacteria such as *Bifidobacterium* and *Eggerthella*, or Clostridiales hosts like *Erysipelatoclostridium* and *Hungatella*. At 3.5% caudoviral MRA, our most abundant Crassphage family, *β-crassviridae*, was not the same as the *α-crassviridae* most commonly found in adults[46]. The latter was only present at 0.2% caudoviral MRA. The predicted hosts for *β-crassviridae* included both *Clostridium* and *Bacteroides*. Next, *Amandaviridae* and *Jeppeviridae* at 3.2 and 2.7% caudoviral MRA comprise two related and large temperate families hosting almost three hundred vOTUs

each, infecting Clostridiales host genera such as *Ruminococcus*, *Blautia*, *Anaerostipes* and *Hungatella*. Both families share the interesting characteristic of terminase shuffling, where the most conserved caudoviral gene, *terL*, is subject to frequent horizontal gene transfer (HGT), while the remainder of the genome is held constant. The related family *Alberteviridae* exhibits a similar characteristic. Finally, *Evaviridae* and *Hannahviridae* at 2.4 and 2.3% caudoviral MRA, respectively, comprise two related novel families of *Bacteroides*-infecting phage. The former was predicted to be virulent while the latter was mixed containing two major subfamilies each with its own lifestyle. *Hannahviridae* includes the recently described *Bacteroides* Hankyphage[47], and has been extensively described in our parallel provirome study performed on the same children[92].

Expanding the view to order-level taxa

Cutting the APS tree at the branch unifying the recently defined *Crassvirales* viral order reproduced all other known viral orders in the virome, including *Petitvirales* (microviruses), *Tubulavirales* (inoviruses), *Cirilvirales* (circoviruses) and *Rowavirales* (adenoviruses). In addition to the known orders, the cutoff predicted the existence of 12 novel viral orders all of which were caudoviral (Table 2), unifying our families into broader groups of related families. *Gramvirales*, the most diverse, prevalent and abundant cluster at 27% caudoviral MRA, encompassed 67 novel viral families that were overwhelmingly temperate, infecting Clostridiales host bacteria. *Gramvirales* includes the major families *Jeppeviridae*, *Amandaviridae* and *Alberteviridae* described above. Interestingly, terminase shuffling was a feature that seemed to pervade the entire order. Two major TerL clades are prevalent throughout most of the order, and they are often exchanged even between species of the same genus. Some caudoviral families were so distantly related to any other family that they formed their own singleton orders. *Flandersvirales* is a notable example but we found others as well, like *Kayavirales*, composed of a single novel family *Kayaviridae* that infects mostly *Veillonella*. Our *Crassvirales* cluster includes the four original crassphage families[48] plus the recent *ζ-crassviridae*, which were all predicted to be virulent. In addition, 24 mostly temperate families, infecting mainly *Bacteroides*, were also found to be part of the same order. However, *ε-crassviridae* belongs to a different order-level cluster, *Hessevirales*, consisting of multiple families with exceptionally long genomes. The *Crassvirales* cluster as a whole covers 15% of the caudoviral MRA, with the currently proposed families making up 6%. Other caudoviral families overshadow Crassphage families in our data, and *Crassvirales* as an order is less prevalent than the novel *Gramvirales*, *Picovirales* and *Ullmannvirales*.

Table 2: The 10,021 viral species belonging to the 248 viral families found in the study were grouped into viral order-level clusters. The clusters are sorted by total richness and novel orders are indicated in bold. Caudoviral MRAs (cMRA) are shown for the caudoviral orders. For each order, the number of families, subfamilies and genera are also given along with their most frequent hosts.

order-level cluster	cMRA	families	subfams	genera	species	major host
Gramvirales	24%	67	531	1163	2719	Clostridiales
Petitvirales	-	7	67	154	1424	*Bacteroides*

Picovirales	19%	45	315	618	1417	Clostridiales
Ullmannvirales	9%	30	171	358	1031	Veillonellaceae
Cirlivirales	-	1	21	268	970	human
Crassvirales	15%	30	114	214	561	Bacteroidales
Tissiervirales	7%	17	64	149	502	*Bifidobacterium*
Twortvirales	6%	8	47	108	334	Bacteroidales
Gratiavirales	5%	4	27	75	278	Clostridiales
Tubulavirales	-	7	50	78	235	Clostridiales
Hessevirales	2%	11	37	61	145	Clostridiales
Friedlandervirales	1%	10	38	61	111	Clostridiales
Verrucovirales	1%	7	19	31	96	*Akkermansia*
Flandersvirales	6%	1	4	10	93	*Bacteroides*
Kayavirales	1%	1	3	4	92	Veillonellaceae
Corneliavirales	0.05%	1	3	6	8	*Faecalibacterium*
Rowavirales	-	1	1	2	5	human

Benchmarking of virome decontamination software

A series of virus discovery and decontamination tools have been published recently[21,37,49–55] and they have already seen widespread application by the viromics community for decontaminating viromes and prediction of viral sequences in published metagenomes. Entire databases have been released that were built on predictions from such tools[22,35], yet little is known about their sensitivities to novel viral clades, or their ability to weed out virome-contaminating DNA.

The manually curated nature of our virome data set makes it well suited as a gold standard for training and testing prediction software. Thus we decided to use it for benchmarking the above tools. A purely random prediction was generated for comparison. A naive length cutoff of +20kb was also used for comparison, since non-vOTUs were distinctly short in our data (Table 1).

CheckV[49], VIBRANT[21] and viralVerify[51] sported the best performances (Table 3). VIRSorter[54] also worked well. With a specificity of 97.5%, the length cutoff did a better job than VIRSorter2[50]. DeepVirFinder[55] PPR-Meta[53] and Seeker[52], all of which were “alignment free”, yielded performances that were close to random. VIRSorter and VIBRANT when run in virome decontamination mode improved sensitivity at the cost of greatly reduced specificity. For our data, VIRSorter performed better when used in “db2” mode.

ViromeQC estimates the proportion of bacterial contamination in viromes[37] and we found it estimated around half of the reads in our samples to comprise contamination. We compared its estimate to two independent measures that we were able to generate using the manual curation and our coupled metagenome samples, namely 1) the proportion of mapped reads to non-vOTUs and 2) the depletion of bacterial core genes in the virome reads compared to cognate metagenomes. Although all three estimates were in strong agreement on average, there was considerable sample to sample variation (Figure S4). Importantly, our metagenome-normalised core gene depletion did not perform better than ViromeQC when comparing against the non-vOTU standard, confirming that ViromeQC performs well.

Table 3: Benchmarking statistics from various metagenomic virus discovery methods against 10021 vOTUs in the manually curated viral set from a total of 362,668 OTUs. The skewed nature of the data set, with non-vOTUs far outnumbering vOTUs, inflates the specificity metric, which is 0.965 for a random prediction. The Kappa performance metric was included because it is robust against skews. Prediction methods that provided a confidence score were cut conservatively so the number of positive predictions reasonably matched the manual set. The performances of VIRSorter and VIBRANT were also checked in the alternate modes (bottom portion).

method	predictions	cutoff	sensitivity	specificity	kappa
CheckV	9393	>= medium qual	0.71161	0.99359	0.7273
viralVerify	10921	> 15	0.69873	0.98889	0.6589
VIBRANT	5843	>= medium qual	0.44696	0.99613	0.5556
VIRSorter	14366	cat. 1 + 2	0.69335	0.97896	0.5553
Length + 20kb	13452	> 20kb	0.48548	0.97565	0.3954
VIRSorter2	18638	virus maxscore = 1	0.50983	0.96164	0.3325
DeepVirFinder	10192	q < 0.05	0.058078	0.972749	0.0306
PPR Meta	17222	score > 0.95	0.060772	0.952891	0.0101
random	12500	w/o replacement	0.0330306	0.9654924	-0.0013
Seeker	13520	>= 0.9	0.0263447	0.9624100	-0.0096
VIRSorter virome	30736	cat. 1 + 2	0.83155	0.93647	0.3832
VIRSorter db2	13298	cat. 1 + 2	0.70971	0.98246	0.5973
VIBRANT virome	6181	>= medium qual	0.45395	0.99537	0.5521

Discussion

We have presented here the largest human virome study published to date, covering fecal samples from 647 1-year-old infants where DNA viromes were sequenced to an average depth of 3 Gb. This study represents three major advances for descriptive viromics. Firstly, to our knowledge, this has been the first exhaustive attempt at resolving virome dark matter. Doing this we learned that accounting for all detected viral and bacterial DNA leaves little dark matter left. Secondly, the study represents the first attempt at comprehensive taxonomic resolution of a virome data set. This led to the definition of 232 novel viral families suggesting a major expansion of current bacteriophage taxonomy. Lastly, our study represents the first systematic view on phage lifestyles at the community level. The analysis shows clear evidence that the bulk of phage diversity in the human gut is made up by temperate phages, even if less diverse virulent phages can be more abundant.

In our samples, bacterial contaminating DNA made up just under half of the sequenced reads, which is within the typical range[37]. After assembly and species-level deduplication, the number of non-viral OTUs resulting from the bacterial contamination was 20 times greater than our total number of viral OTUs. vOTUs were generally longer and more prevalent than contaminating bacterial non-vOTUs which tended to be sample-specific. This supports an explanation where small broken bits of bacterial DNA became copurified along with the viral particles. Contaminant DNA species were not conserved between samples due to their random nature, and thus made up the majority of the overall sequence diversity despite being shorter and less prevalent than the viruses.

Skunaviridae, the most abundant caudoviral family in our data, comprised only 8 complete vOTUs, and this is atypical considering the hundreds of vOTUs in most of our other abundant viral families. All reference phages belonging to the family infect *Lactococcus* while our vOTUs were predicted to infect *Streptococcus*, but this could be an artefact caused by the lack of lactococcal CRISPR spacers in our host prediction database. *Streptococcus*, although very prevalent in the children, may not be abundant enough to support the high counts of *Skunaviridae* that we found, and we also did not find any strong (anti)correlation between *Streptococcus* and *Skunaviridae* counts in the data. Thus it remains an interesting possibility that these phages were ingested as dairy products and survived the digestive tract to end up as the most abundant viral family in our study. Unlikely as it may sound, the notion does receive support from our epifluorescence VLP counts, which place gut viruses at a billion per gram of feces, or at least an order of magnitude lower than most estimates for bacteria. Our estimates are consistent with other estimates in both adults and infants[8,56], and such scarcity of phages in the gut, would make it all the more likely for fecal virome extractions to occasionally become flooded by ingested VLPs over proliferating ones.

In our previous study on *E. coli* phages isolated from the same samples[36], we found that virulent coliphages were found less frequently, but were more abundant and had broader host ranges, at least at the strain level. Temperates on the contrary, were frequently isolated, but had limited host ranges. In this study we found a very similar pattern albeit on a much larger scale. Virulent phage families were more abundant but less prevalent than temperate phage families. Although we did not see a difference in host range, we did find that the temperate phage families were more genetically diverse compared to the virulent phage

families. Such behavior within intestinal viromes likely reflects a frequent tendency for lysogenic gut bacterial strains to induce their prophages, as shown repeatedly in mouse models[57–59], where the induced virions do not necessarily infect new hosts and multiply. This would generate a background of temperate phage virions on top of which the entry of any virulent phage (through fermented food or water), would generate sporadic phage blooms. As for the differences in genetic diversity we saw, higher rates of HGT have previously been documented for temperate phage genomes[40]. One proven mechanism is that temperate phages actively carry enzymes that help them recombine with related prophages in the same host[60], but additional passive mechanisms could also be at play. The number of replication cycles temperate phages spend as integrated prophages could provide more opportunities for genome evolution. Virulent phages, on the other hand, depend on successful infections with every replication, multiplying clonally in the process, so they may have much fewer chances for evolving freely.

For resolving the taxonomy of our vOTUs into genera, subfamilies, families and order-level clusters we used an AAI-based phylogenomic approach and applied global cutoffs after rooting. Although it has been argued that global cutoffs are not suitable for virus classification[23] we do find that they work, and come with the key advantage of reproducibility. The current guideline for defining new phage families[25] involves manual inspection of gene-sharing networks[20], and a more reproducible alternative is needed in order to avoid contradictions during the imminent overhaul of bacteriophage taxonomy. Phylogenomics with global cutoffs do provide such reproducibility. One might argue that clustering phages based on the proportion of shared proteins could lead to co-clustering phages sharing accessory rather than core genes. Still, as of today, it has proven a robust method for phage classification, as it resists the formidable capacity of phages to exchange genetic material, including TerL as discussed below.

The large terminase subunit (TerL) is the most conserved protein shared by all caudoviruses, but we found it was subject to frequent exchange such that even members of the same viral genus would carry completely different TerL VOGs (Figure S5). Notable examples of this phenomenon are found in *Gramvirales* of this study. Thus, when using TerL phylogeny to supervise the definition of caudoviral families, as is becoming common practice[26,28], results can become confusing. As shown by Yutin et al.[28], *Crassvirales* is not TerL monophyletic and non-Crass phages often harbour TerLs that wind up in the middle of the Crass TerL tree. The recent introduction of *ε-crassviridae* into *Crassvirales*[28] likely illustrates this problem.

Finally, we found that the latest generation of metagenome virus discovery tools such as CheckV, viralVerify and VIBRANT complete within hours the task that has taken us years to undertake. The data (Table 1) demonstrates that the tools, in conjunction with ViromeQC, should be enough to account for most sequences in one's virome data. This recent development begins to question the continued relevance of the viral dark matter problem for DNA viromics at least. Although sensitivities never got close to 100%, most of the sequences missed by the best tools were simply too short to pass the quality thresholds that we imposed. Thus we consider their predictions close to perfect, and certainly much easier to obtain than manual curation. That said, we cannot recommend the use of the alignment-free methods, as their performances appear to be very close to random. Although the prospect of detecting truly novel viruses is commendable, nucleotide-level motifs do not appear to carry enough information to distinguish viruses from their abundant hosts.

Conclusion

As part of the largest human virome study performed to date, we deeply sequenced 647 infant gut viromes and tackled the viral dark matter by manual curation. The approach enabled complete taxonomic resolution of all viruses found, uncovering 248 viral families in total, 232 of which were novel, and most of which were caudoviral. After determining lifestyles for thousands of phages we found that temperate phages dominate the infant gut virome, while Crassphage is a minor player overshadowed by several larger novel viral orders. We used our manual data set to benchmark a series of recent virus discovery tools, and found that the latest generation of tools feature almost perfect performance, rendering the dark problem practically resolved for DNA viromes. Our deep annotations of the infant gut viromes provide a framework for making biologically meaningful statistical analyses against cohort clinical phenotypes for upcoming translational viromics research efforts. In the meantime we urge researchers to browse our data online to use it and validate it.

Methods

The study was embedded in the Danish population-based COPSAC2010 prospective mother-child cohort of 736 women and their children followed from week 24 of pregnancy, with the aim of studying the mechanisms underlying chronic disease[61]. 660 participants delivered a fecal sample 1-year after birth. Each fecal sample was mixed with 10% vol/vol glycerol broth and stored at -80°C until DNA extraction for metagenomes[30], and virome extraction. Extraction and sequencing of virions was done using a previously described protocol[62]. Briefly, DNA from fecal filtrates enriched in viral particles was extracted and subjected to brief (30 mins.) MDA amplification and libraries prepared following using manufacturer's procedures for the Illumina Nextera XT kit (FC-131-1096). For epifluorescence VLP estimations 10µL of virome was diluted 100 fold, fixed and deposited on a 0.02 µM filter, dried and stained with cyber-Gold (200X), then visualised in an epifluorescence microscope using a 475 nm laser. VLPs were counted in 8 to 10 fields and multiplied over the remaining filter surface area. Virome libraries were sequenced, paired-end, on the Illumina HiSeq X platform to an average depth of 3 GB per sample with paired end 2x150 bp reads. Satisfactory sequencing results were obtained for 647 samples. Virome reads were quality filtered and trimmed using Fastq Quality Trimmer/Filter (options -Q 33 -t 13 -l 32 -p 90 -q 13), and residual Illumina adapters removed using cutadapt. Trimmed reads were dereplicated using vsearch derep_prefix and then assembled with Spades v3.10.1 using the meta flag and disabling read error correction. Decontamination clusters were generated by first deduplicating the 1.5M contigs into 267k 90% ANI subgenus-level clusters, then calling genes[63] and aligning[64] proteins all-against-all for building an APS tree[65] (supplementary methods). The tree was cut close to the root in order to obtain the decontamination clusters. MAGs[30] were mined for CRISPR spacers using CRISPRdetect[66], and the decontamination clusters were ranked by their extent of CRISPR targeting multiplied by sample prevalence. The protein alignment results were used to define orthologous gene clusters de novo[67], and gene orthology information was used to visualise the gene contents of contigs within each decontamination cluster. The top 400 ranked clusters were inspected visually for two viral signatures, namely conservation of contig sizes and conservation of gene content. Beyond the top 400 mark, returns were diminishing, with very few new viral clusters, and the remaining decontamination clusters were assumed to represent contaminants. Species-level (95% ANI) deduplication of contigs into OTUs was done using BLAT[68]. Decontaminated vOTUs and reference phage species[91] were pooled and the APS tree and gene orthology (VOGs) were recalculated. VOGs were aligned against Pfam[69], CDD[70], COG[71] and TIGRFAMs[72] using HH-suite3[73] to gain functional annotations. The APS tree was cut using treelib.py (https://github.com/agormp/treetool) to reproduce published phage taxonomy[28,74]. The minimum AAI required for two viruses to belong to the same taxonomic level were derived from the cut distances to be 50%, 25%, 8% and 5% for genus, subfamily, family and order-level clusters respectively. Family visualisations (Figure S2) were used to 1) further curate each individual vOTU in order to separate confirmable viruses that had structural VOGs, from vOTUs representing small fragments or various virus-related MGEs that did not encode any structural proteins. 2) The OTU length distribution within each family was inspected manually aided by a histogram with 5kb steps to determine the lower size bound for a complete genome. 3) The family visualisations were also inspected to manually remove families that were dominated by reference phages, so as to avoid interference with ongoing classification efforts. Weak families composed mainly of

MGEs or fragments or having less than five vOTUs or less than two complete vOTUs were also removed. For the final version of the family visualisations available online, VOG annotations were redone against PhROGs[93] because it was more informative. MAG spacers, along with spacers from CRISPRopenDB[32] and WIsH[32] were used to generate separate host predictions for each vOTU. The three predictions were integrated using the LCA of the two most closely matching predictions, as an error-correction strategy, since all three methods would occasionally mispredict. Bacterial contamination was estimated for each virome sample using ViromeQC[37] along with a custom approach where we leveraged the metagenomes cognate to each virome: Reads were mapped from both fractions against 16S DNA[75] and *cpn60*[76] and the degree of contamination was calculated as the ratio between the two fractions. Abundances of vOTUs in each sample were determined by mapping sample reads to sample contigs using bwa mem -a[77], then using msamtools profile to determine depth and length-normalised relative abundances with iterative redistribution of ambiguously mapped reads (https://github.com/arumugamlab/msamtools). The obtained contig abundances were then aggregated at the OTU level in order to obtain vOTU abundances per sample. vOTU abundances were aggregated at the family and order levels using phyloseq[78] to obtain the statistics used for figures 3 and 4. A list of VOGs matching to integrase and recombinase protein families was first curated, then used to judge whether complete vOTUs within viral families were temperate or virulent. Families where fewer than 5% of complete vOTUs carried an integrase were deemed virulent, whereas for temperate families at least 50% of complete or incomplete vOTUs needed to encode an integrase. The versions of virus prediction tools used for benchmarking were DeepVirFinder v1.0, VIBRANT v1.2.1, VIRSorter 1.0.6, VIRSorter2 v2.0 commit 22f6a7d, Seeker commit 9ae1488, PPR-Meta v1.1, and CheckV v.0.7.0. The random prediction was created by randomly sampling the 362k OTUs 12500 times without replacement. The number 12500 was chosen because it was reasonably close to our own positive set and the number of positives generated by most tools.

Supplementary Figures

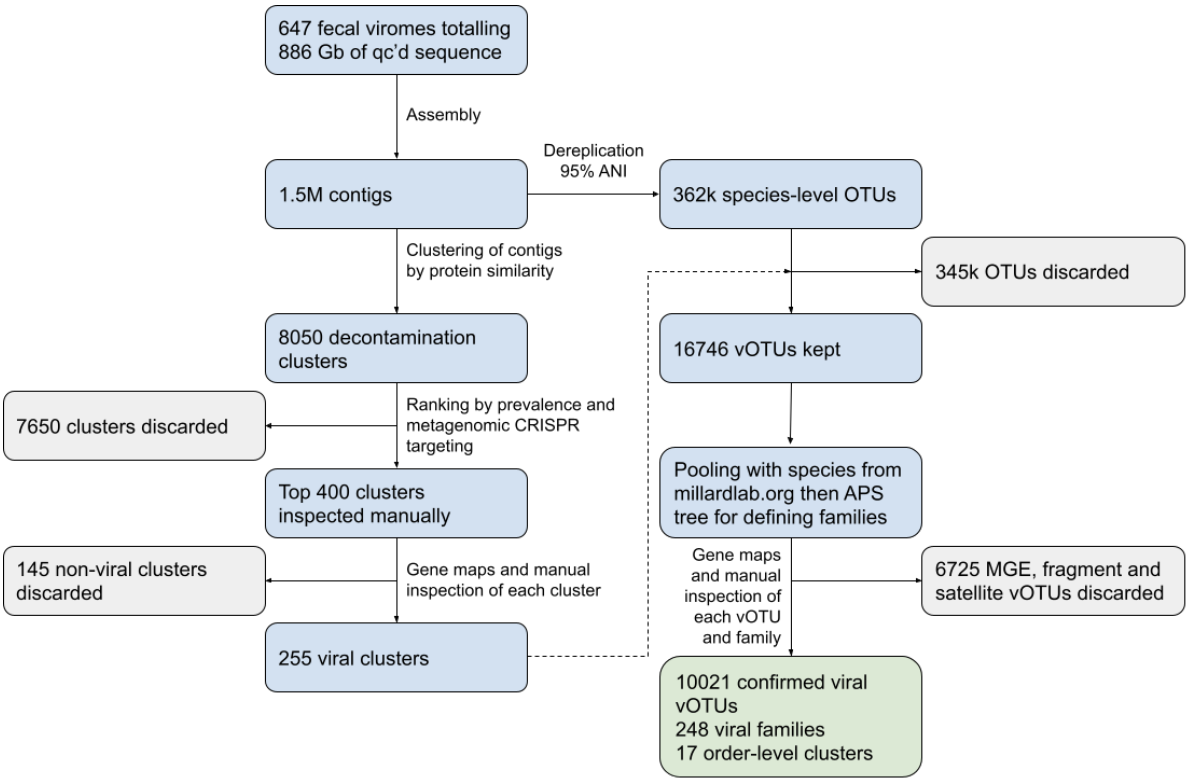
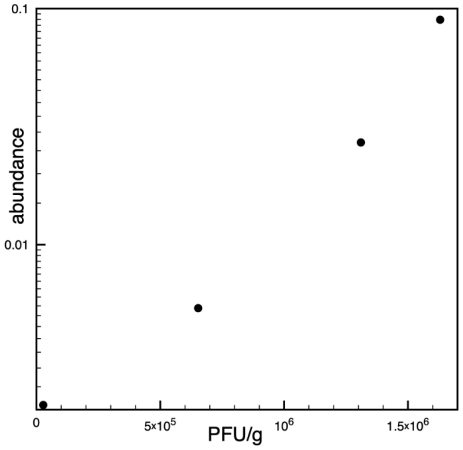


Figure S1: Overview of decontamination and curation procedure

Figure S2: Clickable gene map of vOTUs belonging to Ingridviridae available at http://copsac.com/earlyvir/f1y/families/Ingridviridae.svg along with similar maps for the remaining 247 families. Small vertical gaps between vOTUs denote genus boundaries, while large gaps denote subfamily boundaries. Ordering of the vOTUs follows the order in the APS tree so related vOTUs are closest. ORFs are aligned vertically based on strandedness and colored by VOG affiliation. VOG definitions against the PhROGs database[93] can be looked up by clicking an ORF. ORF gene product (GP) numbers are displayed by mouse-over hovering. GenBank files for each vOTU can be viewed along with virus and host taxonomy by clicking on the OTU name. Caudoviral maps were inverted and zeroed according to the TerL gene, while the GenBank files were not. Reference phages that belong to the same family were also included in the maps and are indicated by GenBank accession numbers.



Phage	PFUs	OTU	abundance
Lambda_ev207	269	OTU_9447	0
Lambda_ev017	301	OTU_8782	0
Lambda_ev087	672	OTU_6450	0
mEp460_ev081	6430	OTU_15409	0
rV5_ev168	10500	OTU_55	0
VpaE1_ev035	27500	OTU_237	0.2 %
T5_ev212	653000	OTU_80	0.5 %
VpaE1_ev078	1310000	OTU_1075	2.7 %
Gluttony_ev152	1630000	OTU_1388	9.0 %

Figure S3: **The MDA amplified viromes were quantitative for dsDNA phages**. The relationship between experimentally determined PFU/g of feces for isolated coliphages and virome abundances for their corresponding vOTUs in the same samples is shown. The agreement between the two estimates supports that the dsDNA virome sequencing was quantitative despite its insensitivity to rare phages.

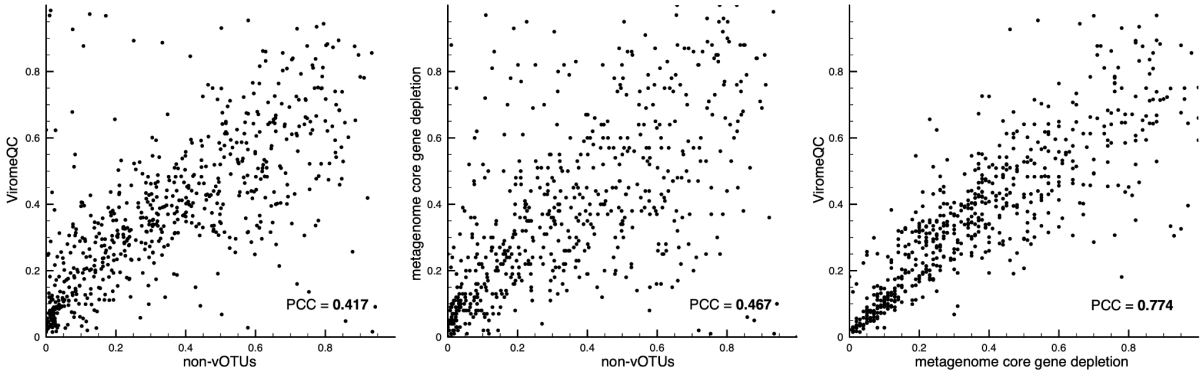


Figure S4: **Three approaches for estimating the proportion of bacterial contamination compared**. Each graph has 647 dots, one for each sample. Axes denote the proportion of bacterial contamination as estimated by the indicated method. Each graph is a pairwise comparison of two different methods. A) non-vOTU mappings vs. ViromeQC B) non-vOTU mappings vs. metagenome core gene depletion C) metagenome core gene depletion vs. ViromeQC. Pearson correlation coefficients are given for all three comparisons.

```
 initn:  42 init1:  42 opt:  42  Z-score: 66.6  bits: 21.5 E(2): 0.13
Smith-Waterman score: 60; 24.8% identity (51.3% similar) in 113 aa overlap (215-323:226-331)

                        190       200       210       220       230       240
OTU_3060_5          KHWEWFTNTMLSRLEENGKIIIIMTRWASDDLAGRAIAHY-TQQGVNVRHITMKALIDKE
                                                        ::  : :   : :: . ....  : ::
OTU_3175_18         QRKMLAAPKGTKLYKNKILGLRGRATGLVFDLQPRNIISLGTAQGFKFERFS--AGLDTA
                      200       210       220       230       240       250

                        250       260       270       280       290       300
OTU_3060_5          KHTMLCPEIL--SYVSYLAKTKAMGVDIASANYQQEPIDLKGRLYDSFKTYTE-LPKDSN
                     ...  :. .  ..:.  :  : . .:  . : ... : :     :  : .:: : :.
OTU_3175_18         -YSQSSPDTIAFTFVGITADRKCVTLDEETYNNRDRQIPLTPS--DIPKIFTEFLEKNRR
                          260       270       280       290       300       310

                            310       320       330       340       350       360
OTU_3060_5          GNSLFEGIYSYTDTADEGDDFLCSIIWGVYMREAYVLDVYFSKANMEITEKETARRHKEF
                      .. . .:   :.::..  . :
OTU_3175_18         LWGFAKDVY--IDSADQATILECQKFKRLSGSLYNFIPAFKKTKIIDRIHLQSAWLAAGD
                                320       330       340       350       360
```

```
initn: 2503 init1: 1900 opt: 2506  Z-score: 1933.2  bits: 367.2 E(2): 1.4e-105
Smith-Waterman score: 2506; 76.9% identity (90.4% similar) in 490 aa overlap (3-492:5-491)

                             10        20        30        40        50
OTU_3060_4            MKIGERFKSMIQNWLNIVPAANQSVVLQELLPREIEVLRSQLWYRGDATELRQFFHQI
                        :::. ..:. ::::: ::..:. ::..    ..:..::::::: :: ::..:.
OTU_3175_17         MKFDIGEKVRQMFLNWLNIVPASEQTFVLNERTGLMADILRARKLWYRGDAYELSQFFKQL
                             10        20        30        40        50        60

                     60        70        80        90       100       110
OTU_3060_4           GDGSGSFWASVPNKNNIRKIHSGLPAIIADTLAYIVYSDMDKIKVTGEKENSIFESVSKA
                     : :..:::.:::.....::::::::::::::::::::::: : : :::    ::..:.
OTU_3175_17          GCGTNSFWGSVPDNEKVRKIHSGLPAIIADTLAYIVYSDMDDIAVEGEKGRVAFEDISQN
                             70        80        90       100       110       120

                    120       130       140       150       160       170
OTU_3060_4           VDFNELVGKAVVDTLVSGDGAFKISVDMTENSVSDVPIVEFWSADKVEYRYIRGVLKEVV
                     .::. :::::.::::: ::::::::::   ...: .:::::: .:::.::::.::::.::.
OTU_3175_17          TDFTALVGKAIVDTLVEGDGAFKISVD---DTLSLTPIVEFVGADKIEYRYLRGVLSEVI
                            130       140       150       160       170

                    180       190       200       210       220       230
OTU_3060_4           FRSEHKEGDRLYHLEECYGKGYIESRLYDNSGHEVRLDSVPCLSGIETRTIFDGDYIMAV
                     ::: :..:.:.:.::: ::.::::::::.::::: :::::::.::: :. :  ::::::
OTU_3175_17          FRSAHEDGNRIYQLEEHYGRGYIESRLYDHSGHEVSLDSVPCLAGIEPRVEFARDYIMAV
                     180       190       200       210       220       230

                    240       250       260       270       280       290
OTU_3060_4           PLKFYASKKYPNRGKSIFDGGKSDCFDALDEVISQWWDAIRAGRVTKYIPSDKIPRSPEN
                     ::::::::::::.::::::::::::::::::::::::::::: ::: .::::. :::. ::
OTU_3175_17          PLKFYASKKYPGRGKSIFDGGKSDCFDALDEVISQWWDAIRMGRVKQYIPDNMIPRNAEN
                     240       250       260       270       280       290

                    300       310       320       330       340       350
OTU_3060_4           GALQRVNSFGNEFIEIASSLGDERSSQIQVVQPDIKYDAFVSSYTNCLLMCLQGLVSPAT
                     :.. ..:.::::..:: :.. : :  .  .:.::::::::::::::::::::::::::::
OTU_3175_17          GSVGKLNQFGNNYITTSQPILQEGVTPKIEVVQPDIKYDAFVSSYTNCLLMCLQGLVSPAT
                     300       310       320       330       340       350

                    360       370       380       390       400       410
OTU_3060_4           LGIDVGKMSSADAQREKKDVTGNTRNTITTALEKALPELVSAVLKTYDNMQGKAPEEYEV
                     ::::::::.::::::::::::::::::::::::::::::::::::::::::::::::::
OTU_3175_17          LGIDVGKMQSADAQREKKDVTGNTRNTITTALEKALPELVSAVLKTYDNMQGKAPEEYEV
                     360       370       380       390       400       410

                    420       430       440       450       460       470
OTU_3060_4           SVDFGEYGAPDFDSRVETVGKASTYGIMSVETQVEELWGSSKEDEWKAGEVKRIMQEKGL
                     ::::::::::::::::::::::::::::::::::::::::::::::::::::::::::::
OTU_3175_17          SVDFGEYGAPDFDSRVETVGKASTYGIMSVETQVEELWGSSKEDEWKAGEVKRIMQEKGL
                     420       430       440       450       460       470

                    480       490
OTU_3060_4           ADGTTPAVGDELA*
                     :::.: ::::::::
OTU_3175_17          ADGATSAVGDELA*
                     480       490
```

Figure S5: Alignments of TerL and the portal protein for two viruses belonging to the same genus within Jeppeviridae. The 75% amino acid identity for the portal protein alignment is within the expected range for viruses of the same genus, whereas the terminase proteins are so disparate that horizontal gene transfer is the most likely explanation.

Supplementary Methods

The COPSAC2010 birth cohort

The study was embedded in the Danish population-based COPSAC2010 prospective mother-child cohort of 736 women and their children followed from week 24 of pregnancy, with the primary clinical endpoint persistent wheeze or asthma[79].

Fecal sample collection, transport, storage

Of the 700 children part of the COPSAC2010 cohort, 647 delivered a fecal sample 1-year after birth. Fecal samples were collected either at the research clinic or by parents at home using detailed instructions. Upon arrival, each fecal sample was mixed with 10% vol/vol glycerol broth and stored at -80°C until virome extraction.

Virome extraction and library preparation

Preparation of fecal samples, and extraction and sequencing of virions was done using a previously described protocol[62]. Briefly, viral-associated DNA was subjected to brief MDA amplification and libraries prepared following using manufacturer's procedures for the Illumina Nextera XT kit (FC-131-1096). Libraries were sequenced, paired-end, on the Illumina HiSeq X platform.

VLP counts by epifluorescence.

10µL of virome was diluted 100 fold in SM buffer, fixed with 0.5% glutaraldehyde, and frozen in liquid nitrogen. The sample was thawed, deposited on a 0.02 µM pore size membrane (Anodisc 25, Anopore, Whatman) using a filtering device. Next, the filter was dried, incubated on a 70 µL drop of cyber-Gold (200X) in the dark for 15 minutes, dried, and mounted on a microscope slide, together with fluoromount and antifade. VLP dots were visualized using an epifluorescence microscope equipped with an ORCA camera, and a 475 nm excitation laser. Eight to ten fields (1344x1024 pixels) were imaged and fluorescent dots counted. VLP count on the total filter surface was deduced by multiplying the average field count by the number of fields over the total membrane surface (60 493).

Read qc and virome assembly

Virome libraries were sequenced to an average depth of 3 GB per sample with paired end 2x150 bp reads. Satisfactory sequencing results were obtained for 647 samples out of a total 648. Virome reads were first quality filtered and trimmed using Fastq Quality Trimmer/Filter (options -Q 33 -t 13 -l 32 -p 90 -q 13), and residual Illumina adapters were subsequently removed using cutadapt. The resulting trimmed reads were dereplicated using vsearch derep_prefix and then assembled with metaSpades v3.10.1 using the meta flag and disabling read error correction.

Species-level deduplication

Species-level deduplication was necessary because the same viruses from different samples had been assembled into separate contigs, since assemblies were carried out separately per sample. These had to be merged into a single representative or OTU. In order to account for incomplete assemblies in samples where the virus was present in amounts too low to yield a complete assembly, we needed to select the longest version as the OTU. However, we also found that the longest version of a species was sometimes a chimeric assembly, where two closely related viruses had been merged into a long contig e.g. containing two copies of each gene. To avoid selection of chimeras as OTUs, all contigs with more than 110% self-similarity (judging from self-alignment score over length) were flagged as potentially repetitive so they would not become selected as OTUs. In such cases the next-longest representative was selected as the OTU. A variety of tools were tested for deduplication of contigs into OTUs at a specified ANI level, including cd-hit-est[80], BB dedupe[81] and nucmer[82]. The most consistent results were obtained using BLAT[68] and setting a cutoff on the alignment score. This was done by requiring a score of 90% of what the shorter sequence obtained against itself, while aligned against a longer sequence, in which case the two were merged. The 90% score would correspond on average to 95% identity at 95% coverage, but at extremes in either direction could also occasionally include 100% identity at 90% coverage or 90% identity at 100% coverage. This flexibility was a compromise offset by the superior accuracy of BLAT vs. other tools tested. Using the same rationale, the 90% ANI clustering used for decontamination was obtained by requiring an 80% BLAT score. The clustering step itself was carried out with a perl one-liner applied on top of an all against all BLAT output, where all assembly contigs had been used as input.

The aggregate protein similarity (APS) tree

Sharing features with DICE[83] and VIPtree[84], the APS tree methodology was first developed in 2013 for systematic and automated classification of prokaryotic defence systems and mobile genetic elements that were traditionally classified by manual inspection. The tree was found to reproduce existing manual classes and sub-classes when cutting it with global cutoffs[65,85]. The tree also predicted deeper relationships between classes that were experimentally validated later[86]. The method uses as input, an all-against-all protein alignment search, preferably with sensitive alignment software like FASTA[64], although BLASTP or DIAMOND also work. For all viruses being compared, all constituent viral proteins are searched against each other. Next, virus to virus similarity scores are tallied by aggregating the alignment scores for all their constituent proteins. Next, using the bray-curtis dissimilarity[87], a distance matrix is constructed between all viruses, which is used as input for a neighbour joining tree. After manually rooting the tree, it can be cut at fixed distances from the root to reproduce classes at required levels. Using more sensitive alignment software generates more reliable distant alignments, making deeper cuts less noisy. In this study we found that cuts down to the viral order-level were reproducing existing and proposed taxonomy, making such cuts useful for defining novel taxa as well.

Protein annotation, clustering and visualisation

Protein coding genes for vOTUs and reference phages were predicted using Prodigal[63]. All protein sequences were subject to an all-against-all sequence alignment using FASTA[64].

Protein alignment scores aggregated at the contig-level were used to compute the APS tree using the bray-curtis distance[87] and RapidNJ (https://github.com/somme89/rapidNJ). The APS tree was rooted and cut at specified distances from the root using TreeLib, an in-house developed python library for manipulation and exploration of large phylogenetic trees. VOGs were defined denovo using a previously described orthology detection pipeline involving protein alignment coverage cutoffs[67] and Markov Clustering[88]. Multiple sequence alignments (MSAs) and phylogenetic trees were constructed[89] from the protein sequences corresponding to each VOG. MSAs were used for profile-profile alignments against the Pfam, COG, CDD, TIGRFAMs and PhROGs databases using HHblits[73] in order to annotate them and determine their functions. Gene contents of the contigs were visualised along with other contigs belonging to the same family-level cluster by coloring genes by orthology and hyperlinking profile-profile results in SVG graphics. SVG files were generated using a custom bash script. The graphics were browsed manually during manual decontamination, species curation and family curation steps (Figure S2).

Manual decontamination

The 1.5M assembled contigs were first clustered at the 90% ANI level, resulting in 267k OTUs that were subject to gene calling using Prodigal[63]. All proteins from all OTUs were then subject to an all-against-all FASTA[64] search that was used for defining orthologous gene clusters using a published algorithm[67]. The search results were also used to construct an APS tree that was cut close to the root in order to yield 8050 decontamination clusters of OTUs. SVG graphics were generated for each decontamination cluster by visualising each individual OTU within it. This was done by using the gene orthology information generated earlier to color rectangles corresponding to encoded genes. The decontamination clusters were then ranked by their sample prevalence and extent of CRISPR targeting from our MAGs[30]. SVG graphics for the first 400 ranked decontamination clusters were manually inspected and the 255 clusters resembling viral families were flagged. Viral clusters were recognised by having conserved genome sizes with the majority of the genes and synteny being largely conserved between most members in the cluster. Plasmid clusters were often heterogeneous in size and extremely variable with regard to gene content, and would encode mobilisation proteins, relaxases or Type IV secretion systems. Bacterial contaminant clusters were made up of short contigs sharing one or two genes, with any remaining genes being disparate. Clusters ranking lower than the top 400 were not inspected further due diminishing returns, as most additionally inspected clusters at this point resembled bacterial contamination. For the 255 flagged viral clusters, contigs smaller than 10kb were discarded unless the apparent complete genome size for that cluster was shorter, as e.g. for *Petitvirales*. A total of 8327 OTUs belonged to the 255 viral clusters.

treelib.py for exploring and cutting the APS tree

Treelib.py (https://github.com/agormp/treelib) is a Python library developed in-house for manipulating or extracting information from phylogenetic trees. In this study we used treelib.py via its command line front-end treetool.py (https://github.com/agormp/treetool). After constructing the APS tree it was visually inspected in FigTree (https://github.com/rambaut/figtree/) to find a suitable ourgroup. Suitable outgroups comprised branches originating directly from the stem of the tree. The stem was easily

visible due to the diversity sequences used to construct the APS tree. Next, treetool.py was used with the --root option to root the APS tree based on the selected outgroup. Next, a list of accession numbers was made containing all members of Herelleviridae, along with separate lists for members of different subfamilies and genera within Herelleviridae. Another list was made containing all known crassphages at the time. Then treetool.py was used with the --cladeinfo option to retrieve the distances from the root to the clades in the lists. Next, treetool.py's --clustcut option was used to cut the tree at the specified distances in order to obtain clusters of vOTUs and reference phages belonging to the same orders, families, subfamilies and genera. The minimum AAI required for two viruses to belong to the same cluster were derived from the cut distances to be 50%, 25%, 8% and 8% for genus, subfamily, family and order-level clusters respectively.

Species-level curation

To find viral species corresponding to the flagged viral decontamination clusters, a new species-level deduplication was generated using all 1.5M contigs at 95% ANI, resulting in 362k OTUs. The 8327 viral sequences from the decontamination step were aligned against 95% ANI vOTUs requiring a 50% BLAT score (~75% ANI). The 16,746 95% ANI vOTUs recruited in this manner were pooled with 95% dereplicated reference phages from millardlab.org. Protein coding genes were annotated for all sequences and subject to an all-against-all FASTA search. The de novo VOGs and APS tree were recomputed. The tree was rooted manually using TreeLib, and the Herelleviridae family-level root distance was measured using TreeLib's CladeInfo function. The tree was cut at that distance yielding 1259 viral family-level clusters. In order to make sure that the large number of families was not a result of accidental recruitment of additional contaminant contigs during the construction of the 95% ANI vOTU data set, each vOTU and reference phage within each family-level cluster was visualised using the VOG information as seen in Figure S2. Next, each individual vOTU was manually flagged as belonging to either one of the categories virus, putative satellite, putative MGE or unknown contaminants using the following guidelines. To be considered viral, a vOTU needed to encode at least one structural protein along with an additional viral protein. vOTUs that did not live up to these criteria were considered MGEs if they encoded at least one protein indicative of a mobile lifestyle (e.g. integrases or replication proteins), or if they were conserved in size and gene content across multiple samples. The rationale for the latter was that random segments of contaminating DNA should not be conserved in size and gene content, while any mobile DNA would be expected to do so. Unknown viruses that encoded novel structural proteins could thus end up in the MGE class. MGEs that co-clustered within viral family-level clusters, or contained two or more viral non-structural proteins were classed as putative satellites. vOTUs that did not live up to any criteria were classed unknown. A class of non-coding sequence was particularly prevalent in the unknown group and were flagged separately.

Final family curation

All 1259 family-level clusters were manually inspected to make sure that they looked like true families instead of being artefacts of the methods employed. The majority of the family-level clusters consisted of singleton vOTUs or reference phages, and these were discarded. Additionally, families consisting mostly of reference phages were discarded to

avoid interference with independent classification efforts. An exception was made for families dominated by Streptococcus or Lactococcus reference phages, because there was already expertise on such phages within the group. Finally, families that looked unconvincing because they consisted of mostly MGEs, satellites, or genome fragments were also removed, leaving 248 curated families in the end. For each curated family, a histogram of vOTU length was made using a bin width of 5kb. The minimum genome completion size for each family was determined by inspecting each histogram manually, and choosing the 5kb bin immediately preceding the rightmost peak. This size cutoff was used subsequently to select all complete and near-complete vOTUs from each family. Families that did not have enough vOTUs to yield a convincing genome size peak were flagged as having an unknown completion size.

Host prediction

As part of a separate effort[30], metagenomes from the same samples had been assembled and binned into MAGs that had taxonomies predicted using GTDB-tk. CRISPR arrays were predicted on each MAG using CRISPRdetect[66], and the spacers were pooled and used as a host prediction database, alongside the CRISPR spacer database[32]. The host prediction algorithm from the CRISPR spacer database was used to predict hosts for each vOTU using either spacer database. A final host prediction was also made using WIsH v1.0[33], against a database of complete bacterial genomes with null-models calibrated against all reference phage sequences on millardlab.org. The best maximum-likelihood WIsH prediction per vOTU having a P-value under 0.05 was used. Host predictions from all three methods were translated into NCBI taxonomy identifiers and integrated by taking the last common ancestor of the two closest genus-level predictions. I.e. if WIsH predicted *Bacteroides*, public spacers Clostridium and metagenome spacers Faecalibacterium, then the host was set to order clostridiales, being the last common ancestor of the two most closely matching predictions. The rationale for this approach was to absorb occasional false positives stemming from either of the three methods, as all three methods had been seen to make false predictions on separate occasions. However, most predictions were unanimous at the genus-level.

Quantification of bacterial contamination

Two approaches were used for quantifying the amount of bacterial contamination in the virome samples. In the first approach, ViromeQC was run on the QC'd virome reads, and the proportion of bacterial contamination per sample was determined by taking the inverse of the "virus enrichment ratio" as reported by ViromeQC.

In the other approach, we wanted to take advantage of our coupled metagenomes for each virome sample, hoping to gain a more accurate estimate than ViromeQC, which does not utilise such additional information. We did this by first searching reads from the virome with the Rfam 16S rDNA model (RF00177). Then the same was done for reads from cognate metagenomes. The ratio between the proportion of reads mapping to RF00177 in the virome over the same proportion for the metagenome was counted as the estimated bacterial contamination ratio by 16S content. In parallel, reads from both the viromes and metagenomes were mapped against a database of the bacterial *cpn60* core gene, cpnDB[76], using bowtie2[90]. As for the 16S-based contamination estimate, the proportion of reads

mapping to this database in the virome over the metagenome for each sample was counted as the estimated bacterial contamination ratio by *cpn60* content. Although the two estimates, by 16S and *cpn60* content respectively, were in general agreement, they also sometimes differed. The mean between the two estimates was used as the "metagenome core gene depletion" contamination-estimate used in Figure S4.

Estimating sample vOTU abundances

vOTU counts were generated by mapping the reads of each sample against only the assembled contigs from that particular sample. Mapping was performed using the `bwa mem -a` flag[77]. Contig counts were generated with `msamtools profile` (https://github.com/arumugamlab/msamtools), which computes relative abundances of each contig, normalising by contig length and mapping depth while iteratively redistributing non-uniquely mapping reads. Abundances of contigs corresponding to vOTUs were aggregated by leveraging the 95% ANI dereplication cluster membership information computed previously. Counts for contigs that did not correspond to any vOTU were assumed to represent contaminant DNA and gathered as an independent contamination estimate. The vOTU to sample relative abundance matrix, or OTU table, was loaded into a phyloseq object in R, along with the APS tree to compute the weighted unifrac sample-sample distance matrix used for PERMANOVA analyses. The OTU table was agglomerated at the viral family and order-levels to compute the statistics used in Figures 3 and 4.

Prediction tool benchmarking

The versions of virus prediction tools used were DeepVirFinder v1.0, VIBRANT v1.2.1, VIRSorter 1.0.6, VIRSorter2 commit 22f6a7d, Seeker commit 9ae1488, PPR-Meta v1.1, and CheckV v.0.7.0. Some of these tools are designed for virus discovery in metagenomes, while others meant for virome decontamination, but the two problems are related given the high amount of bacterial contamination in most viromes published to date[37]. In spite of ours being a virome study, the vast majority of our OTUs were bacterial contamination rather than viral, and this would apply for metagenomes as well. For this reason no distinction was made between the two types of tools. For the tools that required cutoffs, we used typical cutoffs used by the research community, or if such information was not available, we tried to set a cutoff that would generate a number of positive predictions that reasonably matched our own positive set. Since our data set is so skewed, with 10.021 positive viral sequences versus over thirty times more negatives, performance measures can be biased, which is why we included the "kappa" metric, designed to address this issue, as well as a random prediction for comparison. The random prediction was created by randomly subsampling the 360k OTUs 12500 times without replacement. The number 12500 was chosen because it was reasonably close to our own positive set and the number of positives generated by most tools.

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