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Predictive ger	nomics for the bacterial pathogen Escherichia	6 7
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¹ Abstract	1
Background: Predictive genomics is the translation of raw genome sequence data into an assessment of the phenotypes exhibited by the organism. For bacterial ⁴ pathogens, these phenotypes can range from environmental survivability, to the ⁵ severity of human disease associated with them. Significant progress has been made in the development of generic tools for genomic analyses that are broadly applicable to analyze genomic data in the context of organism-specific phenotypic knowledge, which has been accumulated from decades of research and can provide a meaningful	6
Results: In this study, we present SuperPhy, an online predictive genomics platform 11 (http://lfz.corefacility.ca/superphy/) for <i>Escherichia coli</i> . The platform integrates the 12 analyses tools and genome sequence data for all publicly available <i>E. coli</i> genomes and 13 facilitates the upload of new genome sequences from users under public or private 14 settings. SuperPhy provides real-time analyses of thousands of genome sequences with 15 results that are understandable and useful to a wide community, including those in the 16 fields of clinical medicine, epidemiology, ecology, and evolution. SuperPhy includes 16 identification of: 1) virulence and antimicrobial resistance determinants 2) statistical 17 associations between genotypes, biomarkers, geospatial distribution, host, source, and 18 phylogenetic clade; 3) the identification of biomarkers for groups of genomes on the 19 based presence / absence of specific genomic regions and single-nucleotide 20 polymorphisms and 4) <i>in silico</i> Shiga-toxin subtype. 21 Conclusions: SuperPhy is a predictive genomics platform that attempts to provide an 22 essential link between the vast amounts of genome information currently being 23 generated and phenotypic knowledge in an organism-specific context.	13 14 15 16 17
	25 26
Whole-genome sequencing (WGS) of bacterial isolates generates the complete DNA sequence of each organism. WGS provides the greatest possible resolution of any typing method, the sequence is easily transferable, and its analyses can reveal important phenotypic insights such as the presence of virulence factors or anti-microbial resistance determinants. Current benchtop sequencers such as the Illumina MiSeq	28 29 30 31

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<sup>1</sup>as was recently seen in the 2014 Ebola outbreak, and in managing a hospital out-
^{2}break of Salmonella [1, 2, 3, 4].
<sup>3</sup> WGS will likely replace current typing and sub-typing methods due to its low
 <sup>4</sup>cost, high information content, portability, and speed of analyses. It is now being <sup>4</sup>
 <sup>5</sup>used in real-time for: the identification of the source of foodborne outbreaks [5], <sup>5</sup>
<sup>6</sup>surveillance [6, 7], epidemiological investigations [7], industrial applications [8, 9], <sup>6</sup>
<sup>7</sup>population studies [10, 11], routine typing [12], regulation [13], providing point-of-
<sup>8</sup>care insight for clinicians [14, 15], informing veterinary practice [16], and helping
<sup>9</sup>inform public-health decisions [17].
   WGS is now the de\ facto standard for bacterial strain analyses and the global ^{10}
11 community is coming together to help store and best utilize this rapid in-
<sup>12</sup> flux of information under the Global Microbial Identifier network (http://www.
globalmicrobialidentifier.org/). This international effort currently involves
<sup>14</sup>32 countries, many of which have their own national or regional programs to <sup>14</sup>
best utilize WGS data in public health, epidemiological and research contexts, <sup>15</sup>
such as the GenomeTrakR initiative of the Food and Drug Administration in the 16
United States of America (http://www.fda.gov/Food/FoodScienceResearch/17
WholeGenomeSequencingProgramWGS/), the Integrated Rapid Infectious Disease
Analysis (IRIDA) platform in Canada (http://www.irida.ca/), and the Patho-
NGen-Trace project within the European Union (http://patho-ngen-trace.eu/20
project/).
   Recently, several platforms have emerged that attempt to provide additional con-
 text in addition to the raw WGS data. For instance PATRIC provides pre-computed ^{23}
 analyses for public genomes, including annotation, protein families, antibiotic re-
 sistance identification and comparative pathway analysis [18]. MicroScope provides
 an expert-guided annotation pipeline, as well as comparative analyses based on
 shared gene content [19]. The Integrated Microbial Genomes (IMG) project is also
 a combined genome annotation and analysis platform, that additionally allows for
 genomic data submissions by the user [20]. BIGSdb allows local comparisons among
 genomes using a multi-locus sequence typing approach, and allows phenotypic data
 to be stored along with the genomic information [21]. The Harvest suite of tools
 allows for fast core-genome alignments and interactive visualizations for thousands
 of genomes [22]. Other platforms focus on a specific organism, such as Sybil, a plat-
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form for the comparative analyses of <i>Streptococcus pneumoniae</i> based on BLASTP ¹
² searches [23].
3 The large initiatives that generate and collect the tens- and hundreds-of thousands 3
4 of genome sequences, and the platforms that host and analyze the public data pro- 4
$^5{\rm vide}$ an enormous benefit. Even though WGS and basic comparative analyses is 5
6 commonplace, meaningful interpretation of the raw data in a phenotypic context, 6
$^7 {\rm also}$ known as predictive genomics, lags considerably behind [24]. Microbiologists of 7
$^8\mathrm{ten}$ have organism-specific knowledge that can meaningfully inform the WGS data, 8
$^9\mathrm{but}$ which is not incorporated into a generic analysis. The ability to interactively 9
$^{10}\mathrm{explore}$ species-specific data that contains organism-specific knowledge from experts 10
$^{11}\mathrm{in}$ the field is of tremendous value. A recent study on outbreak investigations using 12
$^{12}\mathrm{WGS}$ also listed a main obstacle of routine adoption as 'a paucity of user-friendly 12
$^{13}{\rm and}$ clinically focused bioinformatics platforms' [25]. While some components nec- $^{13}{\rm cm}$
$^{14}\mathrm{essary}$ for phenotypic prediction based on WGS data have been developed, there is $^{14}\mathrm{essary}$
$^{15}\mathrm{currently}$ no single integrated platform built to provide predictive genomic analyses 15
for organism-specific end-users.
17 Here we present SuperPhy, a predictive genomics platform that brings organism- 17
18 specific knowledge to comparative genomic analyses. SuperPhy incorporates knowledge 18
edge from research on the pathogenesis and epidemiology of $E.\ coli,$ as well as the
20 tremendous amount of genotypic and phenotypic data that have previously been
generated. This knowledge is used within SuperPhy to discover relationships among ²¹
and about sub-groups. It allows non-bioinformaticians to quickly analyze new data ²²
against the background of other sequenced $E.\ coli$, facilitating novel insights.
We have previously developed Panseq, software that performs comparative ge-
25 nomics in a pan-genome context, identifying differences in the accessory genome and 25
single nucleotide variations within the core genome [26]. SuperPhy utilizes the pan-
genomic output from Panseq to identify: 1) virulence and antimicrobial resistance
determinants 2) epidemiological associations between specific genotypes, biomark-
ers, geospatial distribution, host, source, and other metadata in an interactive and
30 explorable setting; 3) statistically significant clade-specific genome markers (pres- 30
31 ence / absence of specific genomic regions, and single-nucleotide polymorphisms) 32
for bacterial populations; and 4) $in\ silico\ $ Shiga-toxin subtyping for genomes that
33 possess stx genes.

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1 SuperPhy allows the submission of genomes in a private or public context and is 1
$^2{\rm continually}$ updated with the influx of public $E.~coli$ data from GenBank, allow- 2
$^3\mathrm{ing}$ researchers to quickly analyze and compare new genomes with other $\mathrm{publicly}^3$
$^4{\rm available~sequenced}~E.~coli~{\rm strains.}$ Predictive genomics provides an essential link be- 4
$^5{\rm tween}$ the vast numbers of genomes currently being generated and organism-specific 5
⁶ phenotypic knowledge.
7
*1 Platform Features *
⁹ 1.1 Navigation and Overview
The layout of the SuperPhy website (https://lfz.corefacility.ca/superphy)
provides universal and quick access to the major components of the platform: 'Group
¹² Analyses' provides an interactive environment for comparing groups of strains based
on metadata types or user-created strain-groupings, and determining statistically
$^{14}{\rm significant}$ biomarkers (both the presence / absence of genomic regions and SNPs) $^{14}{\rm cm}$
$^{15} \mathrm{for}$ these groups; 'VF and AMR' provides an ontology of both virulence genes and 15
¹⁶ AMR determinants, and the ability to select groups of genomes and factors based ¹⁶
17 on the provided ontologies. Output includes a summary of the presence $/$ absence 17
¹⁸ of selected VF and AMR factors among the strains of interest; 'Group Browse', ¹⁸
provides an interface to examine groups of strains, and their distribution in both
²⁰ a geospatial and phylogenetic context simultaneously; 'My Data' provides an inter-
21 face for uploading and modifying user-submitted genomes that are available only to 21
the user; 'Home' provides a landing page and an overview of the features of the site. ²²
²³ Additionally, an in-depth examination and report on an individual strain, including
²⁴ all known metadata, Shiga-toxin subtype (if applicable), phylogenetic and geospa-
²⁵ tial information, and a summary of virulence factor and anti-microbial resistance
determinants can be accessed by selecting 'detailed information' from any genome ²⁶
in the platform.
28 28
²⁹ 1.2 Strain Selection
SuperPhy provides three methods of selecting $E.\ coli$ genomes for analyses, that
are consistent across the site: list-, tree-, and map-based selections. The platform
is based heavily on metadata, and as such provides a unified metadata $control^{32}$
33 nanel that displays the metadata fields and their associated values for each genome

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¹ across each of the three views. The metadata control panel also allows filtering and ¹
2 selecting genomes that match given metadata criteria.
3 1) List-based selection provides a table-based interface to the genomes and their 3
4 metadata, with private and public genome sets afforded their own sections.
$^5~~2)$ Tree-based selection provides an interactive phylogeny that can be manipulated 5
$^6\mathrm{to}$ expand / contract clades, and from which clade and individual genome selection 6
$^7\mathrm{can}$ be made. Metadata is appended to each leaf node of the tree, and $\mathrm{branches}^7$
$^8\mathrm{containing}$ more than one genome have the metadata for the entire branch sum- 8
$^9\mathrm{marized}$ as an interactive bar-chart that displays the frequency of values within 9
10 selected metadata categories. This summary is an excellent way to visually discern 1
11 clade differences, and allows an effective representation of thousands of genomes in 1
12 tree form that would otherwise be intractable. An example of the phylogenetic tree 1
¹³ with metadata clusters is shown in Figure 1.
¹⁴ 3) Map-based selection provides a Google Maps interface to geospatial genome ¹
15 selection, along with a table-view of the metadata for the genomes in the map. 1
16 Just as in the list-based view, the displayed metadata fields for each genome can 1
17 be changed, and used to filter the displayed genomes. As an example, we show the 1
¹⁸ map when a user searches for 'United Kingdom' in Figure 2.
19
201.3 Website Usage Tutorials
$_{21}\mathrm{Every}$ page of the SuperPhy platform includes a guided tutorial introduction using $_2$
the IntroJS plugin (https://usablica.github.io/intro.js/). This tutorial pro-
$_{23} {\rm vides}$ a walk-through of all the major features and how to use them, and is activated $_2$
by clicking the large red 'Introduction' button located on each page.
²⁵ 2 Implementation
206 2.1 Webserver Application and Database
Genome data and analyses are administered using a PostgreSQL 9.3 database with
a schema adapted from the Generic Model Organism Database (GMOD) Chado
schema [27]. The Chado relational database schema uses a flexible, ontology-centric
approach to organizing biological entities, relationships, properties and analyses.
Entries in generic tables are assigned types using a mutable, controlled vocabulary.
By not defining entity types directly into the relational layer, the database can be
highly adaptable and can grow to add new analyses or biological data.

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The application layer for the SuperPhy website is build using the Model-View-
² Controller (MVC) Perl CGI::Application framework (http://www.cgi-app.org/). ²
$^3\mathrm{The}$ phylogenetic tree display and interaction is built on top of the Data Driven Doc- 3
⁴ uments (D3) JavaScript library (http://d3js.org/). Geospatial views are built us- ⁴
⁵ ing the Google Maps JavaScript API v3 (https://developers.google.com/maps/ ⁵
$^6 \\ \text{documentation/javascript/}).$ Group comparisons are processed and displayed us- 6
7 ing the RS tudio Shiny web application framework for R [28].
8 The webserver application code base, database schema and public data are hosted 8
on Github at https://github.com/superphy/version-1.
11
122.1.1 Access to Uploaded Data
13Users can upload genomes and metadata and choose between three access levels to 1
14govern their use: 'public' information is available to all users; 'private' information 14
15is only available for the genome uploader and additional users they select; and 15
16'private until a specified date' data is released to 'public' data after a specified of
17date. Users may also designate other registered users for whom the data will be 1
18available. Private data is accessible only to designated users, but can be combined 18
19with public data for user-specific analyses. Users can create custom genome-groups 19
20that can be saved, and all results may be downloaded for offline analyses.
²¹ Uploaded data undergo a series of checks to ensure the quality of the data. Data ²¹
22 are rejected if any of the following conditions are met: 1) Greater than 1000 con- 22
$^{23}{\rm tigs;}~2)$ Genome size less than 3 Mbp or greater than 7.5 Mbp; 3) Invalid nucleotide $^{23}{\rm tigs;}~2)$
24 characters (all IUPAC characters are valid); 4) The MD5 checksum of the concate- 24
²⁵ nated contigs already exists in the database; 5) The SNP string for the pan-genome ²⁶
²⁶ alignment is identical to another strain in the database.
Uploaded genomes undergo two checks to ensure the data are of a minimum ²
quality, and that the genomes being uploaded belong to the species $E.\ coli.$ We
initially identified genomic regions present in at least 70% of the genomes, referred
to as the 'conserved core'. All genomes are considered to be $E.\ coli\ { m if:}\ 1)$ they
contain at least 1500 conserved core regions, and 2) The presence of at least three 31
32 E. coli species-specific regions. The derivation of these markers is presented in the
33 'Pan-genome' subsection of the 'Example analyses'

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1 ¹2.2 Acquisition of public *Escherichia coli* genomes ²SuperPhy is continually and automatically updated with closed and draft genomes ² ³of Escherichia coli from GenBank using the script https://github.com/superphy/³ ⁴version-1/Sequences/ncbi_downloader.pl. All metadata present in the Gen-⁴ ⁵Bank submissions are extracted automatically using the script https://github. ⁵ ⁶com/superphy/version-1/Sequences/genbank_to_genodo.pl. For the initial⁶ ⁷bulk upload, a second phase of manual curation was carried out to ensure all ⁷ ⁸available metadata was included, even if it was stored in a non-standard way dur-⁸ ⁹ing the initial submission. The complete list of 1641 public E. coli genomes present⁹ ¹⁰in the SuperPhy database at the time of manuscript preparation, along with all ¹⁰ ¹¹extracted metadata is available at (https://github.com/superphy/version-1/¹¹ ¹²Data/metadata_table.csv). A summary of the metadata fields used in Super-¹² ¹³Phy, as well as the percentage of the public genomes containing information for a¹³ ¹⁴particular metadata category is presented in Table 1. 15 162.3 Comparative Genomic Analyses ₁₇Our pan-genomic analyses tool, Panseq is used for the background comparative, analyses [26]. It iteratively adds new genomic sequences, and compares them to 18 those already stored in the platform. This computational approach allows a contin-20 uous influx of new sequence data without large time or memory requirements. In 20 21 this way, the complete pan-genome of all sequences in the database is determined. 22 Annotations for these regions are determined by querying the GenBank NR protein 23database via BLASTx. Differences in the accessory genome and the single nucleotide variation in the core $_{25}$ genome are obtained and used by SuperPhy in downstream applications including $_{25}$ $_{26}$ the construction of discriminatory and robust phylogenies, and in the pre-computed $_{26}$ 27data for bio-marker identification among groups of genomes. 28 2.3.1 Tree Construction $^{29}\mathrm{SuperPhy}$ provides a dynamic maximum-likelihood phylogenetic tree that is continuously updated to include all $E.\ coli$ genomes currently in the database, as likeli- 31 hood approaches to phylogenetic reconstruction have been shown to be superior to distance and parsimony approaches [29]. An initial phylogenetic tree for SuperPhy was constructed using conserved genomic regions from the 1641 E. coli genomes

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$^{1}\mathrm{obtained}$ from GenBank. The conserved regions were aligned using Muscle $\left[30,31\right]^{1}$
$^2{\rm and}$ input into FastTreeMP to build a minimum-evolution tree [32]. To achieve suf- 2
$^3 {\rm ficient}$ resolution in branch lengths to disambiguate strains, the double-precision 3
⁴ version of FastTree was used [32]. As new genomes are uploaded to SuperPhy, they ⁴
$^5\mathrm{are}$ incorporated into the multiple sequence alignment and a new tree is rebuilt, 5
6 which becomes the tree used for all analyses within the SuperPhy platform.
7
₈ 2.3.2 Virulence and Anti-microbial Resistance Markers
$_{9}\mathrm{The~presence}$ / absence of virulence and AMR genes are computed using Panseq. $_{9}$
$_{10}\mathrm{The}$ non-redundant query set of AMR genes from the Comprehensive Antibiotic $_{10}$
$_{11}\mathrm{Resistance~Database}$ (CARD) [33] is used for $in~silico$ AMR determinant screen- $_{11}$
$_{12}{\rm ing.}$ All AMR genes are organized and stored in the database according to their $_{12}$
$_{13}\mathrm{CARD}\text{-}\mathrm{assigned}$ Antibiotic Resistance Ontology annotation to aid in identifying $_{13}$
$_{14} {\rm the~presence~of~different~antimicrobial~resistance~mechanisms}$. The virulence ${\rm gene}_{14}$
$_{15}\mathrm{database}$ was constructed by obtaining all gene alleles of known virulence factors $_{15}$
$_{16} {\rm for}\ E.\ coli$ from the Virulence Factor Database [34], supplemented with additional $_{16}$
$_{17}$ virulence factors from ' $Escherichia\ coli\colon$ Pathotypes and Principles of Pathogen- $_{17}$
$_{18}\mathrm{esis},\ 2\mathrm{nd}\ \mathrm{Ed.'}\ [35],\ \mathrm{and}\ \mathrm{additional}\ \mathrm{published}\ \mathrm{literature},\ \mathrm{which}\ \mathrm{effectively}\ \mathrm{doubled}_{18}$
$_{19} \mathrm{the}$ number of virulence factors in the database. To avoid duplication of factors, $_{19}$
$_{20}\mathrm{all}$ AMR and virulence factor sequences were clustered based on similarity using $_{20}$
$_{21}\mathrm{BLAST}$ clust with default settings; the longest allele was selected for each gene, ex- $_{21}$
$_{22}\mathrm{cept}$ in cases where sequence similarity was less than 90%, in which case multiple $_{22}$
23 alleles were included [36].
$_{24}$ $$ In addition to providing the presence / absence of virulence and AMR factors, Su- $_{24}$
$_{25}\mathrm{perPhy}$ stores the sequence of the individual alleles for each genome, and $\mathrm{constructs}_{25}$
$_{26}\mathrm{a}$ phylogeny based on each single gene. This allows one to compare the relationships $_{26}$
$_{27}$ among genomes based on a single virulence or AMR attribute and to examine the $_{27}$
$_{28} \rm sequence$ variation of the gene at the individual base level, as the multiple $\rm sequence_{28}$
$_{29}$ alignment (MSA) can also be displayed, as shown in Figure 3 $$
2.3.3 Group Comparisons
The statistical identification of markers that differ between groups based on both ³¹
1 he statistical identification of markers that differ between groups based on both 32 single nucleotide polymorphisms and the presence / absence of genomic loci is imple-
single nucleotide polymorphisms and the presence / absence of genomic foci is imple- 33 mented using a two stage approach: 1) The 'approximate' vectorized Fisher's Exact

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¹Test (FET) from the R corpora package is calculated (http://cran.r-project.¹ ²org/web/packages/corpora/index.html), and the 100 most-significant results are ² ³then subject to the FET from the base R statistical package [37]. All single-³ ⁴nucleotide polymorphisms and genomic presence / absence data reside in the ⁴ ⁵database, and require only the retrieval and P-value computation for the strains⁵ ⁶of interest for the real time analysis of genome markers. ⁷ The R Shiny interface is used for group creation and all metadata fields are pre-⁷ ⁸populated for all strains in the database. This makes comparing, for example, all⁸ ⁹human and non-human strains of a given serotype as simple as selecting groups⁹ ¹⁰based on the serotype and host metadata fields, and clicking the compare button. ¹⁰ ¹¹Additionally, custom groups of any genomes can be created and saved to a user-¹¹ ¹²profile so they become available whenever the user is logged in. These custom groups ¹² ¹³can include private genomes available only to the logged-in user, in addition to any ¹³ ¹⁴public genomes. 15 162.4 Stx Typing ₁₇Shiga-toxin (Stx) subtype assignment, when a strain possesses a copy of one or ₁₇ $_{18}$ more of stx1 or stx2, is calculated based on a phylogenetic tree generated from $_{4}$ or concatenated and aligned a and b subunits for each of Stx1 and Stx2. Clades specific 20 to a Shiga-toxin subtype were identified based on the scheme presented by Scheutz 20 21 et al. (2012) [38]. Membership in these pre-defined clades is used to identify the 22 subtype of the toxin gene; those strains that fall outside of known sub-type clades 22 ₂₃ are marked as unknown. Multiple sequence alignments of the Stx genes are stored 24 in the database for reference and comparison. 24 ²⁵2.5 Geospatial Visualization $^{\mathbf{26}}$ The geospatial visualizations provide an interactive map interface for selecting and and searching genomes and groups of genomes. SuperPhy leverages Google Maps along with the companion Javascript library, Google Maps API (V3). Genome location data is geocoded for latitude and longitude during the process 30 of adding a new strain to the platform. To reduce the computational overhead in rendering thousands of genome map markers, the marker clustering algorithm MarkerClusterPlus for Google Maps V3 http://google-maps-utility-library-v3. googlecode.com/svn/trunk/markerclustererplus/docs/reference.html was

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$^{1}\mathrm{implemented}.$ Locations within a distance of 60 pixels on the map are clustered 1
$^2\mathrm{into}$ a single marker rendered at the geometric center of the cluster, and a count of^2
3 the number of genomes is displayed. 3
$^4~$ All geospatial views are accompanied by a dynamic and sortable table of genome^4
$^5\mathrm{metadata}$ that is by default sorted by country. Users also have the option of sorting 5
$^6\mathrm{by}$ province, state and city. The table is dynamic and updates to display informa- 6
$^7\mathrm{tion}$ for the genomes visible on the map. Locations for each $\it E.~coli$ strain can be 7
$^8 {\rm downloaded}$ for offline manipulation.
9
102.6 Continuous Integration
The user community is able to provide feedback as the platform evolves in the form $_{11}$
$_{12}$ of feature requests and bug reports using the 'Issues' section at https://github. $_{12}$
₁₃ com/superphy/version-1/issues. This will ensure the platform evolves in a way
that is most beneficial to those who use it.
¹⁵ 3 Results and Discussion
3.1 Pan-genome
At the time of writing, 2324 publicly available <i>E. coli</i> genomes from GenBank 17
had been analyzed for incorporation into the SuperPhy platform [39]. E. coli is
a ubiquitous, gram-negative bacterial species found in the intestines of healthy
mammals, with only a small subset causing disease in humans or animals [40]. The
population structure of $E.\ coli$ was initially described as being broadly distributed
222 among four large and two smaller phylogenetic groups [41, 42]. Recent studies have
found that the species has an open pan-genome, meaning that the addition of new 23
genomes is likely to add additional genes to the pool [43]. The pan-genome of $E.\ coli$
is highly variable, with around 80% of an individual genome comprised of accessory
genes and the remainder from the shared core genome [44]; a stable proportion of
approximately 4000 genes are present in at least 50% of the genomes [45].
The pan-genome distribution of these 2324 $E.\ coli$ genomes as 1000 bp genomic
segments is presented in Figure 4. As can be seen, the majority (29.7 Mbp) of the
30 37.44 Mbp pan-genome is present in fewer than 100 genomes, with the core genome
size (present in at least 2300 genomes) observed to be 1.86 Mbp. Only $5.84~\mathrm{Mbp}^{31}$
of the pan-genome was found in greater than 100 genomes, but fewer than 2300
genomes. Based on these results, we selected a 'conserved core' of 3598 genomic

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<sup>1</sup>regions, defined as those present in at least 70% of the 2324 genomes. The conserved
<sup>2</sup>core is used within SuperPhy to identify SNPs that are used in phylogenetic tree<sup>2</sup>
<sup>3</sup>building, as well as in the quality filtering of uploaded genomes.
   Additionally, we endeavored to identify genomic regions that were specific to the
<sup>5</sup>species E. coli. To achieve this we screened the 'conserved core' against genomes <sup>5</sup>
<sup>6</sup> from a subset of E. coli and other bacterial species, the results of which are presented
<sup>7</sup>in Table 2. The E. coli genomes contained more of the 'conserved core' regions than <sup>7</sup>
<sup>8</sup> any of the other genomes examined, although genomes from Shigella spp. contained
<sup>9</sup> nearly as many, which is not surprising given that Shigella spp. has long been known <sup>9</sup>
<sup>10</sup>to be very similar to E. coli [46]. Recent work using the analyses of whole genome <sup>10</sup>
<sup>11</sup>sequence data of both Shiqella spp. and E. coli showed Shiqella spp. to form three <sup>11</sup>
<sup>12</sup> separate monophyletic clades within the E. coli species [47], and that there was a <sup>12</sup>
mixing of traditional Shiqella spp. within these clades. The analyses performed in 13
<sup>14</sup>this study to find E. coli specific regions treated Shigella spp. as distinct from E. <sup>14</sup>
<sup>15</sup> coli; had they been considered as sub-groups within E. coli, the number of species-<sup>15</sup>
<sup>16</sup> specific markers would likely have increased.
   The results shown in Table 2 were filtered based on the distribution among these ^{17}
18 genomes to identify genomic regions present in only the E. coli genomes, re-
sulting in 33 candidates; the raw data table is available at https://github. 19
20 com/superphy/version-1/Sequences/genome_content_panseq/binary_table. 20
<sup>21</sup>txt. These 33 candidates were screened against the GenBank 'nr' and 'WGS', <sup>21</sup>
^{22} databases using the 'bacteria' taxid to limit the search; the raw BLAST re-^{22}
sults are available at https://github.com/superphy/version-1/Sequences/23
24 genome_content_panseq/UBOHWGTR015-Alignment.xml and https://github. 24
25 com/superphy/version-1/Sequences/genome_content_panseq/UD4GVA26015-Alignment.
<sup>26</sup> xml. Based on these queries using a 90% total sequence identity threshold, we re-
moved all putative species-specific regions that were identified in genomes from
bacteria other than E. coli, and were left with the ten species-specific regions pre-
sented in Table 3.
   The correlation between the species-specific regions and the 'conserved core' re-
  gions among the 2324 E. coli genomes is presented in Figure 5. As can be seen, not
 all species-specific markers were found in all strains; however, most E. coli genomes
 contained at least 8 of the markers and all contained at least 3 given the quality
```

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'checks for assembled genomes previously described. A general trend was observed'
$^2\mathrm{where}$ genomes with higher ratios of 'Genome size' / 'No. contigs' contained both 2
3 more 'conserved core' regions and species-specific regions, indicating that the qual- 3
4 ity of genome assembly affects the number of genomic regions that can be identified 4
⁵ at a given sequence identity threshold. Based on these results, any genome in the ⁵
6 SuperPhy database is defined as $E.\ coli$ if it possesses at least three of the species 6
⁷ specific markers and at least 1500 of the conserved core genomic regions.
8 Of the 2324 genomes examined, only 1641 had metadata beyond the name of the 8
⁹ strain. As such, the initial SuperPhy database contained only these 1641 genomes
¹⁰ to facilitate a metadata driven approach to genomic analysis.
11
¹² 3.2 Predictive Markers for Sub-groups
$^{13}\mathrm{A}$ 'group' of bacteria can be defined in numerous ways, from spatially or temporally 13
14 co-located strains, to those sharing biochemical utilization patterns, or those that 14
$^{15}{\rm occupy}$ a clade of a phylogenetic tree. Regardless of how a group is defined, users 18
¹⁶ are generally interested in defining characteristics that are predictive of the group, ¹⁶
17 and can be used to discriminate its members from those of other related genomes. 17
$^{18}\mathrm{SuperPhy}$ utilizes both the presence / absence of genomic regions, and SNPs within 18
shared regions to define markers statistically predictive of a group. These identified 19
$^{20}{\rm biomarkers}$ have potential downstream application in $\it in~silico$ diagnostics or simple $^{20}{\rm biomarkers}$
²¹ wet-lab tests for the identified markers.
As an example, we utilized the 'Group Analyses' feature of SuperPhy to identify
23 SNPs that were statistically predictive for <i>E. coli</i> of serotype O157:H7 with respect 23
to those of all other $E.\ coli.$ This is demonstrated in Figure 6, where the SNPs 24
25 are ranked from most- to least-significant. The marker ID for each SNP, the poly- 25
morphism being examined, the p-value, the false discovery rate adjusted p-value,
and the presence / absence of each SNP for the two groups being examined are 27
displayed. The marker ID provides a link to a 'SNP Information' page (Figure 7),
which identifies the pan-genome region the SNP is found in, the allele frequency
of SNPs for all genomes in the database, the putative function of the region given
by the top BLAST hit, and an option to download detailed SNP information for
each genome. The download includes the genomic location, allele, and upstream $/$
downstream sequences for all genomes in the database.

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In addition to providing groups based on metadata categories such as serotype, ¹ ²and providing group vs. non-group comparisons, SuperPhy allows multi-way group ² ³vs. group comparisons, as shown in the example of Figure 8, where 'isolation host'³ ⁴is selected and the categories 'Bos taurus (cow)', 'Homo sapiens (human)', and ⁴ ⁵'Environmental source' are used to generate comparisons between all combinations ⁵ ⁶of the categories. This facilitates more rapid identification of group and sub-group ⁶ ⁷predictive markers for the genomes being examined. 3.3 Distribution of the eae gene Within the species E. coli, there are a subset of strains that attach to human intesti-11 nal epithelial cells via an attaching and effacing mechanism, the requisite apparatus 12 for which is encoded in a genomic island known as the locus of enterocyte effacement ₁₃(LEE) [48]. As an example of the 'VF and AMR' functionality within SuperPhy, we ₁₄identified the distribution of the LEE gene eae among the 1641 public genomes in ₁₄ the SuperPhy database. All virulence factors are stored using controlled ontologies, 15 ₁₆ which facilitate easy addition and retrieval of related data. The ontological category ₁₆ ₁₇'LEE-encoded TTSS effector' provided the eae alleles, and they were selected, along, $_{18}$ with all 1641 public genomes. The results are presented in an interactive matrix of $_{10}$ ₁₀gene presence / absence, as well as allele copy number (Figure 9). Within the 1641₁₀ ₂₀genomes examined, 662 possessed the eae gene. Additionally, SuperPhy provides a₂₀ 21 table of the results for download, where subsequent offline manipulation is possible. 21 ²²3.4 Analyses of Geographical and Phylogenetic Clusters 22 23 The 'Group Browse' section of SuperPhy provides a means for selecting, filtering and exploring groups of genomes utilizing the three modes of genome selection, namely 25 the tree, map and list views. These allows users to view geographical clusters in 26 terms of their corresponding position in a phylogenetic tree. For example, using the map view, and the hierarchical listing of locations, all genomes with the isolation ²⁸ location of Santa Clara, California, United States were selected and their corresponding positions on the phylogenetic tree automatically highlighted, as shown in $^{30}\mathrm{Figure}\ 10$. Here it is evident that although all six genomes were isolated from Santa $^{31}\mathrm{Clara},\,\mathrm{California}$ on the same day, the genomes do not form their own cluster on the phylogenetic tree. On the tree, all nodes that contain a selected genome are shown as blue-filled squares, while those that do not are white-filled squares. Similarly, all

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¹selected genomes appear on the tree as blue-filled circles, and those not selected as ¹ ²white-filled circles. All six selected genomes from Santa Clara are not visible on the ² ³tree at once, as they are not all closely related and the tree needed to be zoomed in ³ ⁴for readability. Genomes CS02 and CS06 are both visible, on separate branches of ⁴ ⁵the tree, indicating they are less related to each other, and the other four genomes ⁶from Santa Clara, than the genomes with which they group most closely. This ability to quickly examine geographical strain clusters in a phylogenetic context would prove extremely useful in determining if a group of genomes from the same time and place originated from a single bacterial clone, as in an outbreak situation or in the routine surveillance of a location such as a food-processing plant, to determine whether bacterial isolates were that of a persistent strain. Conversely, within SuperPhy one can also select a phylogenetic clade and have the geographical locations of all strains shown. The ability to break apart a cluster of strains that are related at the genome level into geographical and metadata categories has use in source tracking of strains, and in determining the geographical dissemination of bacterial clones over time. As an example, genomes from the serotype O104:H4 outbreak that occurred in Germany in 2011 were chosen. This outbreak was the first caused by strains of O104:H4 that were found to have acquired the stx2 gene through lateral gene transfer, which is thought to have been the contributing factor that led to the high rates of acute illness in healthy adults observed throughout the outbreak [49]. As can be seen in Figure 11, the O104:H4 strains containing the stx2 gene are nearly identical on the phylogenetic tree; however, the source of isolation of these bacteria, visible on the map, shows the dissemination of the bacterial clone from the German epicenter to countries such as Denmark, the United Kingdom, Canada, and the United states, which were determined to be travel-acquired infections. 28 28 Conclusions Predictive genomics and platforms that easily facilitate it are poised to become the translation layer between the vast amounts of sequence data and biological knowledge in a specific domain that is needed to test hypotheses. SuperPhy allows users to make some of these genotype / phenotype correlations, and platforms like

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it will become increasingly important in transforming raw genome data into useful	. 1
² knowledge.	2
3 Current work involves the addition of previously published in $silico$ serotyping	,3
⁴ schemes to SuperPhy, and the expansion of the platform to include the bacterial	4
⁵ pathogens Salmonella enterica and Campylobacter jejuni. Lastly, a representational	5
⁶ state transfer (REST) application programming interface (API) is being designed	6
⁷ to allow programmatic interaction with the SuperPhy platform, which will help	7
⁸ ensure that SuperPhy does not become a data silo but can instead contribute to a	8
⁹ dynamic and growing web of biological knowledge.	9
10	10
11Availability and Requirements	11
Project name: Superphy Project home page: https://lfz.corefacility.ca/superphy Operating system(s): Platform 12 independent (modern web-browser; the most recent Firefox or Chrome for best experience) Programming 13languages: Perl, Coffeescript / Javascript, R License: Apache2	12
14List of abbreviations	1/1
WGS: whole-genome sequencing DNA: deoxyribonucleic acid GMOD: generic model organism database Stx:	14
¹⁵ Shiga-toxin AMR : anti-microbial resistance CARD : comprehensive antibiotic resistance database SNP: ₁₆ single-nucleotide polymorphism	16
17 Availability of supporting data	17
The project is entirely open source under the Apache 2 license https://www.apache.org/licenses/LICENSE-2.0.	18
18All code and any additional files referenced in the manuscript are available at the GitHub repository 19 https://github.com/superphy/version-1.	
Competing interests	19
The authors declare that they have no competing interests.	20
21 Author's contributions	21
22Designed the project: VPJG, CRL, MDW	22
Coded the platform: MDW, AM, JM, CRL, PK 23 Wrote the manuscript: CRL, MDW, AM, VPJG	23
	24
25 Ac knowledgements	25
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	28
¹ Laboratory for Foodborne Zoonoses, Public Health Agency of Canada, Twp Rd 9-1, T1J 3Z4 Lethbridge, Canada.	20
²⁹ Laboratory for Foodborne Zoonoses, Public Health Agency of Canada, Twp Rd 9-1, T1J 3Z4 Lethbridge, Canada.	29
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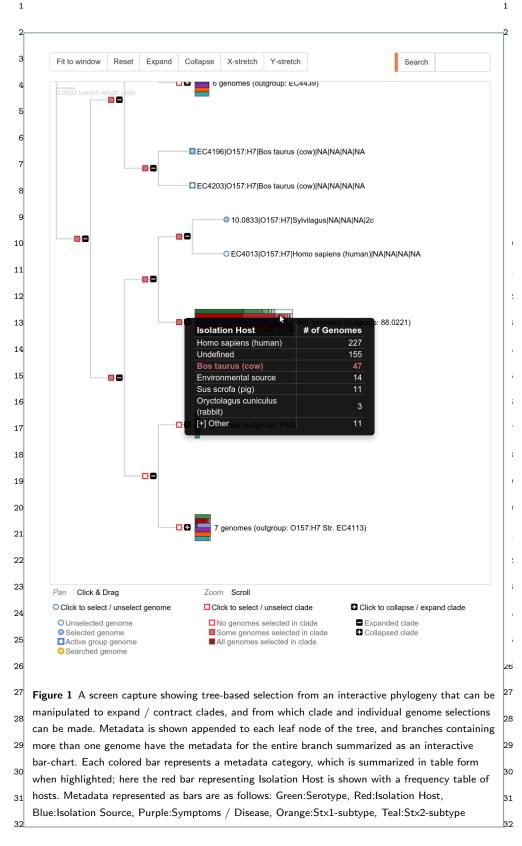
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	fast core-genome multi-aligner, and Gingr, a dynamic visual platform. Combined they provide interactive	
16	core-genome alignments, variant calls, recombination detection, and phylogenetic trees. Using simulated and	16
17	real data we demonstrate that our approach exhibits unrivaled speed while maintaining the accuracy of existing	~17
		g - ·
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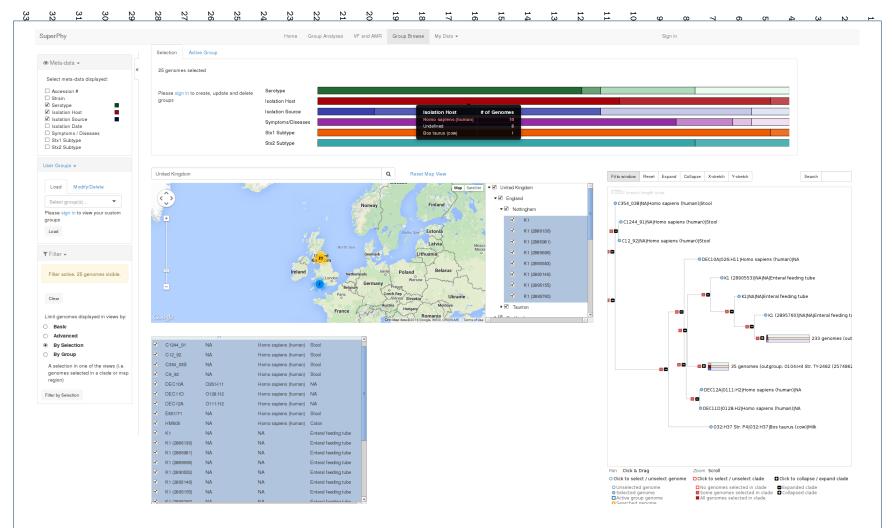
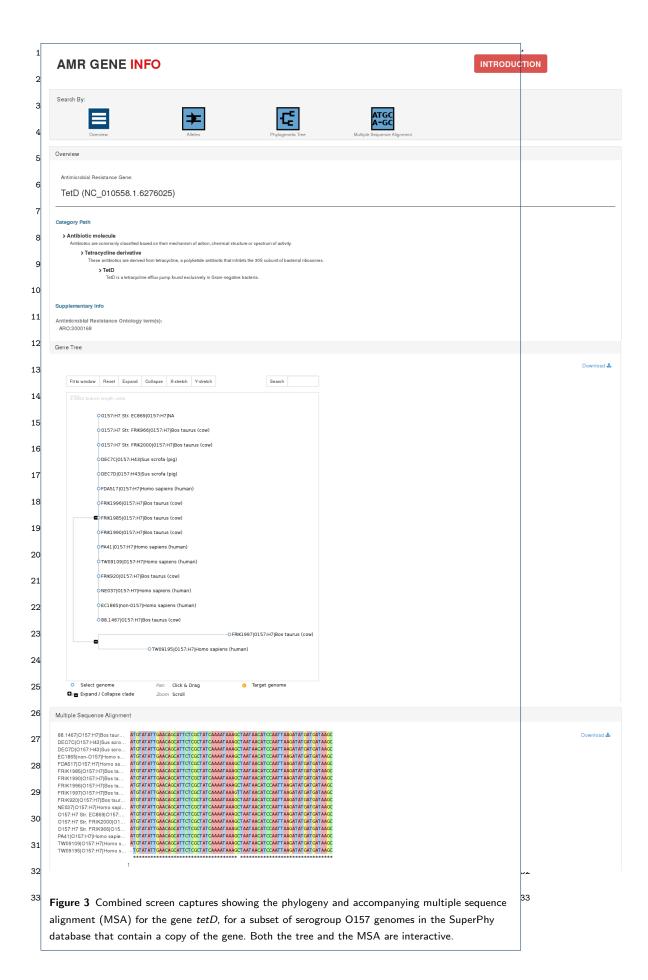
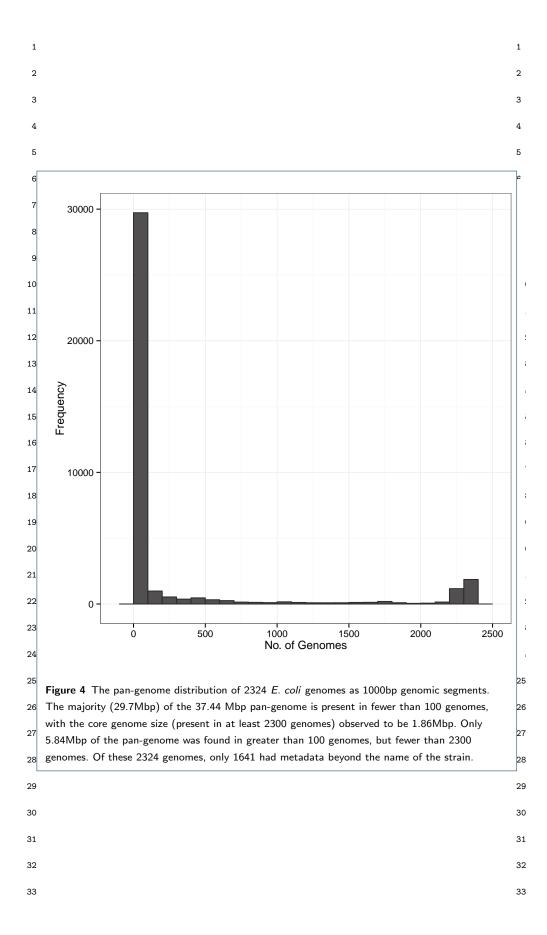


Figure 2 A screen capture showing selection of a group of genomes based on the map interface. In this example, the search term 'United Kingdom' has been used to focus the map on the respective world region, which displays a hierarchical view of regions and subregions visible in the map. Here, the 'United Kingdom' checkbox has been used to select all subregions and genomes below it in the hierarchy eg. 'Nottingham' and the genomes from that region. The three views (tree, map, and list) have been filtered to display only the genomes from the 'United Kingdom', and the top of the page displays a metadata breakdown of the currently selected genomes for all metadata, where each colour represents a metadata category, shades of that colour represent separate values, and the size of the shaded bar represents the percentage of the total genomes with that value. The display is interactive, and hovering over a metadata category presents a summary table, as shown here for 'Isolation Host'.

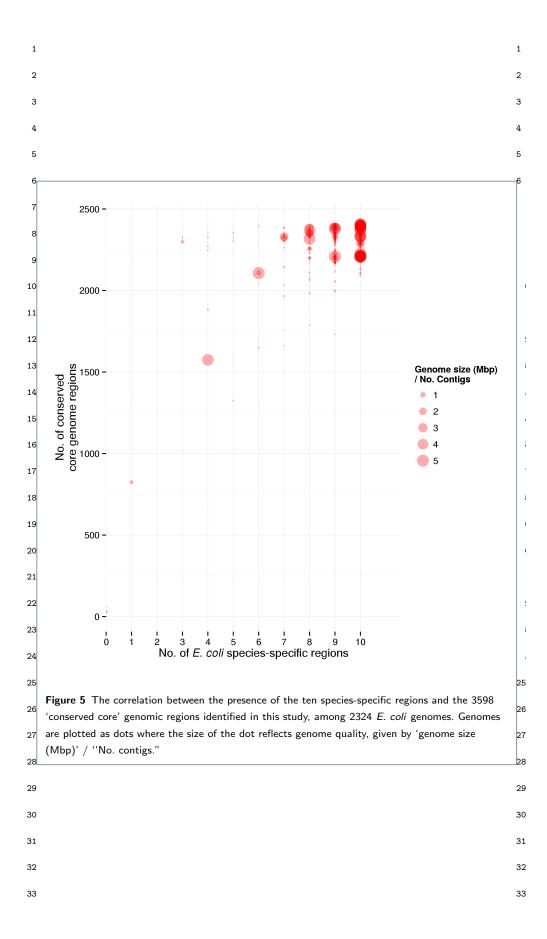
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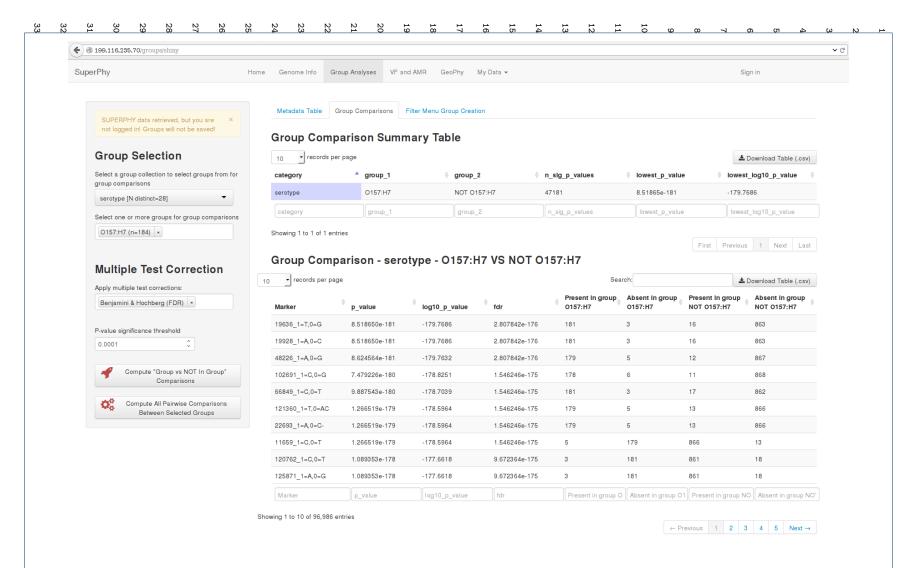


Figure 6 A screen capture demonstrating the 'Group Analyses' functionality of SuperPhy. In this example, all genomes of serotype O157:H7 are compared to all other genomes, and SNPs in the shared regions are ranked by p-value, from most statistically predictive of the group to least, with false discovery rate multiple testing correction. The results table is interactive and the complete dataset can be downloaded as a .csv file for offline analyses.

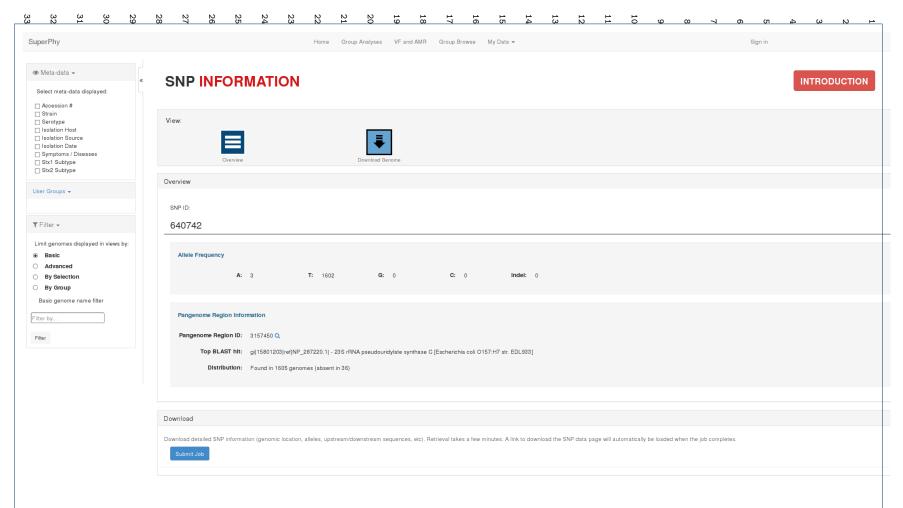


Figure 7 A screen capture demonstrating the 'SNP Information' page, where a SNP of interest can be more fully examined. The page identifies the pan-genome region the SNP is found in, the allele frequency of SNPs for all genomes in the database, the putative function of the region given by the top BLAST hit, and an option to download detailed SNP information for each genome. The download includes the genomic location, allele, and upstream / downstream sequences for all genomes in the database.

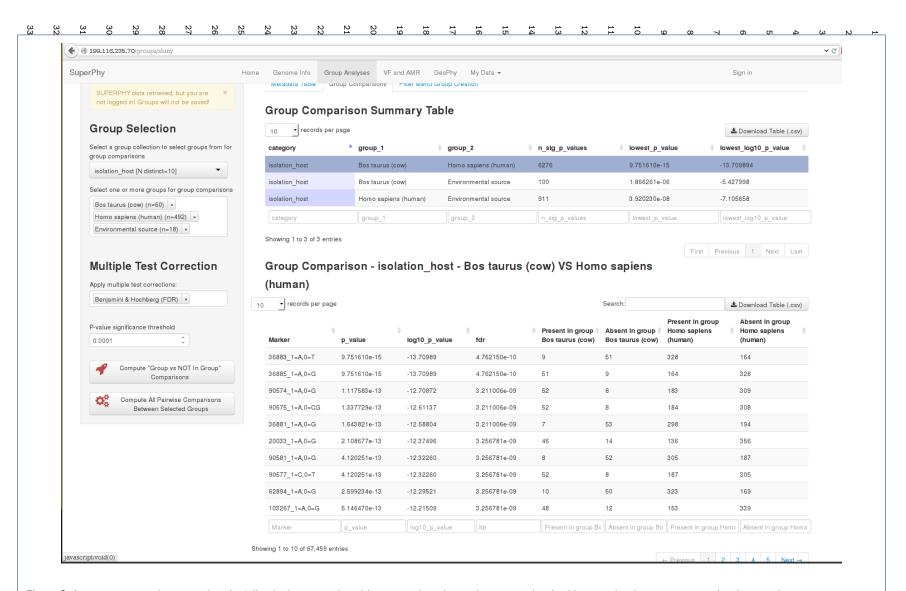
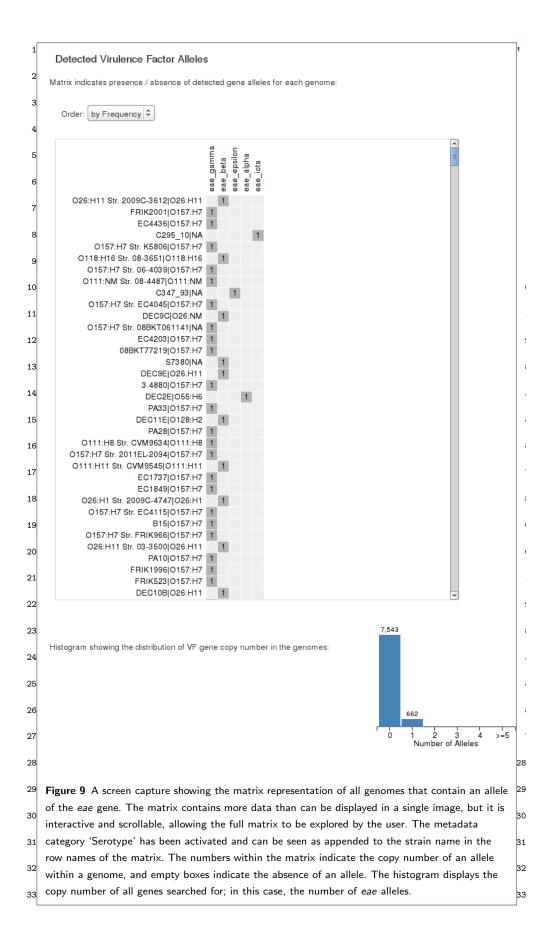


Figure 8 A screen capture demonstrating the 'all pairwise comparisons' between selected metadata categories. In this example, those genomes under the metadata category 'Isolation Host' are compared pairwise in all possible combinations for the categories 'Bos taurus (cow)', 'Homo sapiens (human)', and 'Environmental source'. The resulting SNPs in the shared regions for each comparison are ranked by p-value, from most statistically predictive of the group to least, with false discovery rate multiple testing correction. The results table is interactive and the complete dataset can be downloaded as a .csv file for offline analyses.

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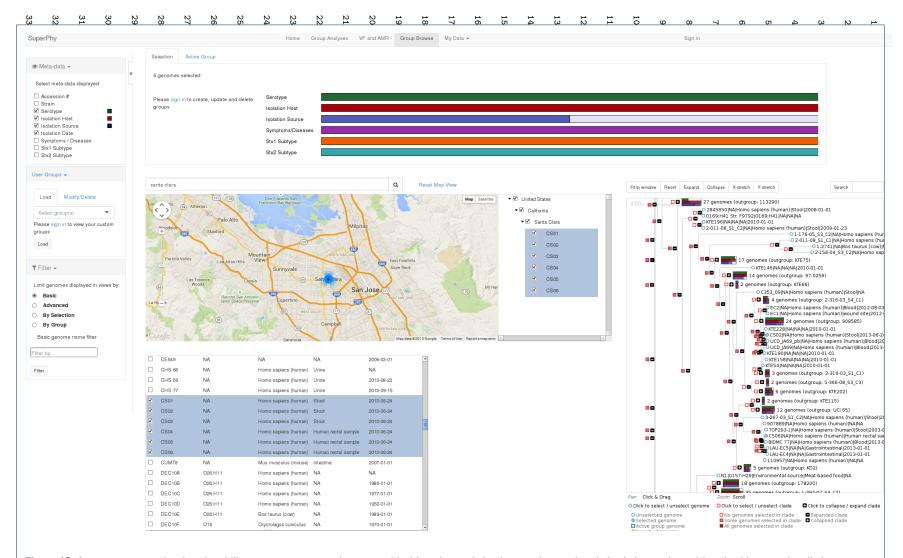


Figure 10 A screen capture showing the ability to group genomes by geographical location and simultaneously examine their phylogenetic position. In this example, all six genomes from Santa Clara, California, United States are selected and highlighted in the map, tree and list views. The available metadata shows that all six genomes were isolated from human sources on the same day; however, their phylogenetic positioning indicates that they are not all from a clonal source. On the tree, all nodes that contain a selected genome are shown as blue-filled squares, while those that do not are white filled squares. Similarly, all selected genomes appear on the tree as blue-filled circles, and those not selected as white-filled circles.

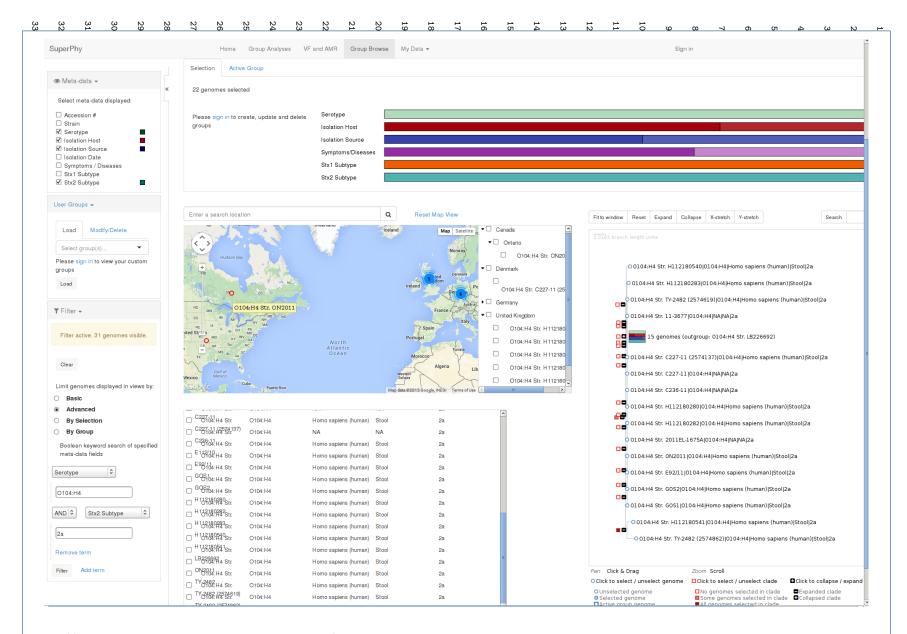


Figure 11 A screen capture showing genomes from the *E. coli* O104:H4 outbreak that occurred in Germany in 2011. The phylogeny of the outbreak strains shows their clonality, and the metadata, visible on the map, shows the dissemination of the bacterial clone from the German epicenter to countries such as Denmark, the United Kingdom, Canada, and the United States, which were determined to be travel-acquired infections.

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¹ Tables				1
² Table 1 The percentage of geno	omes that contain met	adata for each of t	he metadata fields in the	2
initial public data set of 1641 <i>E</i> .	Metadata field	Percentage		3
4	Location	85		4
5	Host	79		5
3	Date of Isolation	63		3
6	Source	52		6
7	Serotype	44		7
_	Stx2 subtype	23		
8	Stx1 subtype Disease syndrome	18 6		8
9	Disease sylluloille			9
10				10
11				11
12				12
13				13
14				14
15				15
16				16
17				17
18				18
19				19
20				20
21				21
22				22
23				23
24				24
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26				26
27				27
28				28
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30				30
31				31
32				32
33				33

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Table 2 The number of conserved core genomic regions present in 19 selected bacterial genomes, from the total 3598 conserved core genomic regions found in at least 70% of the 2324 *E. coli* ²genomes examined.

2

Genome	No.	'conserved core'	genes 3
E. coli O103:H2,12009		3563	
E. coli O157:H7, EDL933		3557	4
E. coli K-12, MG1655		3550	5
E. coli, UMN026		3483	
E. coli O7:K1, CE10		3448	6
E. coli 083:H1, NRG 857C		3289	7
Shigella sonnei, 53G		3259	
Shigella flexneri 2002017		3148	8
Shigella boydii, CDC 3083-94		2965	9
Snigelia dysenteriae, 1017		2683	9
Escherichia fergusonii ATCC 35469		1619	10
Salmonella enterica subsp. Enterica serovar Typhimurium str. 14028S		95	
Citrobacter rodentium, ICC168		77	11
Klebsiella oxytoca, E718		50	12
Klebsiella pneumoniae subsp. Pneumoniae, 1084		50	
Klebsiella variicola, At-22		46	13
Escherichia blattae, DSM 4481		27	4.
Staphylococcus aureus, 04-02981		0	14
Listeria monocytogenes, 07PF0776		0	15
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₁**Table 3** The ten *E. coli* species-specific genomic regions identified in this study based on a total sequence identity of 90%, their location in the K12 reference genome MG1655, the number out of ²²³²⁴ *E. coli* genomes each region was found in, and their putative function based on the top scoring ² BLASTx hit.

3_						3
_	Region ID	Start bp	Stop bp	No. Genomes	Putative function	
4	3160548	347258	346259	2238	Propionate catabolism operon regulatory p	orote⁴n PrpR
5	3160296	537566	536567	2256	2-hydroxy-3-oxopropionate reductase	5
	3160113	538566	537567	2248	Allantoin permease	
6	3159571	541565	540567	2275	Purine permease ybbY	6
7	3159389	542566	541567	2268	Glycerate kinase	7
	3158844	545665	544666	2261	Allantoate amidohydrolase	•
8		546665	545666	2272	Ureidoglycolate dehydrogenase	8
	3159808	1588200	1587201	2171	FimH protein	9
9	3160196	4411062	4410063	2261	Hypothetical protein	
10_	3158082	4456632	4457631	2074	Mur ligase family, glutamate ligase domain	n protein
11						11
12						12
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