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**Bystro: rapid online variant annotation and natural-language filtering at whole-genome
scale**

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21 **Abstract**

22 Accurately selecting relevant alleles in large sequencing experiments remains
23 technically challenging. Bystro (<https://bystro.io/>) is the first online, cloud-based application that
24 makes variant annotation and filtering accessible to all researchers for terabyte-sized whole-
25 genome experiments containing thousands of samples. Its key innovation is a general-purpose,
26 natural-language search engine that enables users to identify and export alleles and samples of
27 interest in milliseconds. The search engine dramatically simplifies complex filtering tasks that
28 previously required programming experience or specialty command-line programs. Critically,
29 Bystro's annotation and filtering capabilities are orders of magnitude faster than previous
30 solutions, saving weeks of processing time for large experiments.

31

32 **Keywords**

33 Natural-language search, genomics, bioinformatics, annotation, filtering, web, online,
34 cloud, big data

35

36 **Background**

37 While genome-wide association studies (GWAS) and whole-exome sequencing (WES)
38 remain important components of human disease research, the future lies in whole-genome
39 sequencing (WGS), as it inarguably provides more complete data. The central challenge posed
40 by WGS is one of scale. Genetic disease studies require thousands of samples to obtain
41 adequate power, and the resulting WGS datasets are hundreds of gigabytes in size and contain
42 tens of millions of variants. Manipulating data at this scale is difficult. To find the alleles that
43 contribute to traits of interest, two steps must occur. First, the variants identified in a sequencing
44 experiment need to be described in a process called annotation, and second, the relevant
45 alleles need to be selected based on those descriptions in a procedure called variant filtering.

46 Annotating and filtering large numbers of variant alleles requires specialty software.
47 Existing annotators, such as ANNOVAR[1], SeqAnt[2], VEP[3], and GEMINI[4] have played an
48 important research role, and are sufficient for small to medium experiments (e.g., 10s to 100s of
49 WES samples). However, they require significant computer science training to use in offline,
50 distributed computing environments, and have substantial restrictions in terms of performance
51 and the maximum size of the data they will annotate online. Existing variant filtering solutions
52 are even more limited, with most analyses requiring researchers to program custom scripts,
53 which can result in errors that impact reproducibility[5]. Therefore, annotation and filtering are
54 not readily accessible to most scientists, and even bioinformaticians face challenges of
55 performance, cost and complexity.

56 Here we introduce an application called Bystro that significantly simplifies variant
57 annotation and filtering, while also improving performance by orders of magnitude and saving
58 weeks of processing time on large data sets. It is the first program capable of handling
59 sequencing experiments on the scale of thousands of whole-genome samples and tens of
60 millions of variants online in a web browser, and integrates the first, to our knowledge, publicly-
61 available, online natural-language search engine for filtering variants and samples from these
62 experiments. The search engine enables real-time (sub-second), nuanced variant filtering, both
63 across all samples and per sample, using simple phrases and interactive, web-based filters.
64 Bystro makes it possible to efficiently find alleles of interest in any sequencing experiment
65 without computer science training, improving reproducibility while reducing annotation and
66 filtering costs.

67

68 **Results**

69 To compare Bystro's capabilities with other recent programs, we submitted 1000
70 Genomes[6] Phase 1 and Phase 3 VCF files for annotation and filtering (Figure 1). Phase 1
71 contains 39.4 million variants from 1,092 WGS samples, while Phase 3 includes 84.9 million

72 alleles from 2,504 WGS samples. We first evaluated the online capabilities of the web-based
73 versions of Bystro, wANNOVAR[7], VEP, and GEMINI (running on the Galaxy[8] platform).
74 Bystro was the only program able to complete either 1000 Genomes Phase 1 or Phase 3 online,
75 and was also the only application to handle a 6×10^6 variant subset of Phase 3, a size
76 representative of modest whole-genome experiments. When tested with $5 \times 10^4 - 1 \times 10^6$ variant
77 subsets of 1000 Genomes Phase 3, Bystro was approximately 144 – 212x faster than
78 GEMINI/Galaxy in generating a downloadable annotation and searchable result database, and
79 was significantly easier to use, as it did not require a separate annotation step (Figure 2). When
80 tested on a small trio data set, Bystro was able to identify *de novo* variants without any
81 additional software, and was 45x faster than GEMINI's *de_novo* tool (Additional file 1: Table
82 S1). Bystro and GEMINI/Galaxy produced similarly detailed outputs, with Bystro offering fewer,
83 but more complete and recent sources, as well as more detailed annotations for some classes
84 of data (Additional file 1: Table S2 ; Additional file 2). Notably GEMINI was found to work only
85 with the hg19 human genome assembly, whereas Bystro supports hg19, hg38, and a variety of
86 model organisms.

Figure 1 | Using Bystro online to find alleles of interest in sequencing experiments. A)

After logging in (<https://bystro.io/>), users upload one or more VCF or SNP-format files - containing alleles from a sequencing experiment - from a computer or a connected Amazon S3 bucket. Datasets of over 890GB, containing thousands of samples and tens of millions of variants are supported. The data is rapidly annotated in the cloud, using descriptions from public sources (e.g. RefSeq, dbSNP, Clinvar, and others). The annotated results can be filtered using Bystro's natural-language search engine, and any search results can be saved as new annotations. Annotated experiments and saved results can be viewed online, downloaded as tab-delimited text, or uploaded back to linked Amazon S3 buckets. **B)** An example of using Bystro's natural-language search engine to filter 1000 Genomes Phase 3 (<https://bystro.io/public>). To do so, users may type natural phrases, specific terms, numerical ranges, or apply filters on any annotated field. Queries are flexible, allowing misspelled terms such as "earl-onset" to accurately match. Complex tasks, such as identifying *de novo* variants can be achieved by using Boolean operators (AND, OR, NOT, +, -), exact-match filters, and user-defined terms. For instance, after labeling the "proband" and their "parents", the user could simply search *proband -parents*, or combine with additional parameters for more refined queries, i.e. *proband -parents missingness < .1 gnomad.exomes.af_nfe < .001*.

Figure 2 | Online performance comparison of Bystro, VEP, wANNOVAR, and GEMINI.

Bystro, wANNOVAR, VEP, and GEMINI (running on Galaxy) we run under similar conditions. Total processing time was recorded for 1000 Genomes Phase 3 WGS VCF files, containing either the full data set (2,504 samples, 8.49×10^7 variant sites), or subsets (2,504 samples and 5×10^4 , 3×10^5 , 1×10^6 , and 6×10^6 variants). Only Bystro successfully processed more than 1×10^6 variants online: wANNOVAR (not shown) could not complete the smallest 5×10^4 variant subset; VEP could not complete more than 5×10^4 variants; and GEMINI/Galaxy could not complete more than 1×10^6 variants. Online, VEP outputted a restricted subset of annotation data compared to its offline version. GEMINI and Bystro (but not VEP) outputted whole-genome CADD scores, while only Bystro also returned whole-genome PhyloP and PhastCons conservation scores. Bystro was faster than GEMINI/Galaxy by 144x-212x across all time points.

88

89 We next tested offline performance on identical servers to gauge performance in the
90 absence of web-related file-size and networking limitations. Bystro was 113x faster than
91 ANNOVAR and up to 790x faster than VEP, annotating all 8.5×10^7 variants and 2,504 samples
92 from Phase 3 in less than 3 hours (Table 1). Furthermore, ANNOVAR was unable to finish
93 either Phase 1 or Phase 3 annotations due to memory requirements (exceeding 60GB of RAM),
94 and VEP annotated Phase 3 at a rate of 10 variants per second, indicating that it would need at
95 least 98 days to complete. Critically, Bystro's run time grew linearly with the number of
96 submitted genotypes, suggesting that it could handle even hundreds of thousands of samples
97 within days.

98 While offering significantly faster performance, Bystro also provided 3.5x the number of
99 annotation output fields as ANNOVAR and 5.6x that of VEP (Additional file 3). Notably, unlike
100 ANNOVAR or VEP, Bystro annotated each sample relative to its genotype, reporting
101 homozygosity, heterozygosity, missingness, sample minor allele frequency, and labeling each

102 sample as homozygous, heterozygous, or missing. In contrast, ANNOVAR provided only
103 sample minor allele frequency, while VEP reported no sample-level data. We note that VEP is
104 capable of providing per-sample annotations (heterozygosity/homozygosity status), but we were
105 unable to use this feature for performance reasons. A detailed comparison of the exact settings
106 used is given (Additional file 2 ; Additional file 3).

107 To investigate annotation accuracy, we next compared Bystro with ANNOVAR and VEP
108 on a previously-analyzed synthetic dataset[9]. Overall, excellent concordance between all
109 methods was noted (Additional files 4, 5, and 6). For instance, in comparison with ANNOVAR,
110 allele position (>98%), allele identity (100%), and variant effects (>99%) were highly consistent
111 across all classes of variation, for sites that Bystro did not exclude for quality reasons
112 (Additional file 4).

113 In cases where the annotators disagreed, Bystro gave the more correct interpretations.
114 For instance, Bystro and VEP excluded reference sites (ALT: "."), while ANNOVAR annotated
115 such loci as "synonymous SNV"; it is of course incorrect to call reference sites variant
116 (Additional file 4 ; Additional file 5). In cases of insertions and deletions, which are often
117 ambiguously represented in VCF files due to the format's padding requirements, Bystro always
118 provided the parsimonious left-shifted representation, while ANNOVAR and VEP occasionally
119 right-shifted variants (Additional file 4 ; Additional file 5). This is evident at
120 chr15:42680000CA>CAA, where both ANNOVAR and VEP called the insertion as occurring after
121 the first "A", with 2 bases of padding, rather than the simpler option after the first base, "C", with
122 1 base of padding (Additional file 1: Table S3). Similar results were found at multiallelic loci with
123 complex indels (Additional file 1: Table S4).

124 Similarly, in cases where Bystro and ANNOVAR or VEP disagreed on variant
125 consequences, Bystro always appeared correct relative to the underlying transcript set. For
126 example, in the case of the simple insertion chr19:41123094G>GG, Bystro correctly identified
127 all three overlapping transcripts (NM_003573;NM_001042544;NM_001042545), and noted the

128 variant as coding (exonic) relative to all three. In contrast, ANNOVAR called the allele as
129 disrupting a splice site, despite the fact that the nearest intron, and therefore splice site, was
130 37bp downstream (Additional file 1: Figure S1).

131 Additionally, Bystro's strict VCF quality control measures substantially improved
132 annotation accuracy. This is evident in the case of gnomAD, a VCF-format dataset that
133 represents the largest experiment on human genetic variation. While Bystro and ANNOVAR
134 provided identical gnomAD data for 93.7% of tested alleles, the remaining 6.3% were low-
135 quality gnomAD results that were included in ANNOVAR and excluded from Bystro (Additional
136 file 4). For instance, in the case of chr16:2103394C>T, ANNOVAR reported rs760688660,
137 which failed gnomAD's random forest qc step. We note that a 6.3% false-positive rate is similar
138 to the frequency of common variation, and significantly larger than the frequency of rare
139 variants, making ANNOVAR's gnomAD annotations a potentially unreliable source of data for
140 both common and rare variant filtering.

141

Table 1 | **Bystro, VEP, ANNOVAR offline command-line performance.**

Software	Dataset	Samples	Variants	Variants/s	Bystro vs
Bystro	1000G Phase 3 chr1	2504	1x10 ⁶	8156 ± 195	-
	1000G Phase 3 chr1	2504	2x10 ⁶	8484 ± 67.9	-
	1000G Phase 3 chr1	2504	4x10 ⁶	8516 ± 57.2	-
	1000G Phase 3 chr1	2504	6.5x10 ⁶	7779 ± 21.8	-
	1000G Phase 1	1092	3.9x10 ⁷	5417 ± 76.8	-
	1000G Phase 3	2504	8.5x10 ⁷	7904 ± 15.9	-
VEP	1000G Phase 1	1092	3.9x10 ⁷	18.67 ± 0.58	290x
	1000G Phase 3	2504	8.5x10 ⁷	10.00 ± 0.00	790x
ANNOVAR	1000G Phase 3 chr1	2504	1x10 ⁶	74.67 ± 0.21	109x
	1000G Phase 3 chr1	2504	2x10 ⁶	75.32 ± 0.06	113x
	1000G Phase 3 chr1	2504	4x10 ⁶	75.15 ± 0.39	113x
	1000G Phase 3 chr1	2504	6.5x10 ⁶	NA	NA
	1000G Phase 1	1092	3.9x10 ⁷	NA	NA
	1000G Phase 3	2504	8.5x10 ⁷	NA	NA

Bystro, VEP, and ANNOVAR were similarly configured with 8 threads on Amazon i3.2xlarge servers. “Dataset” refers to the VCF file used. “Variants/s” is the average of three trials. VEP performance was recorded after 2x10⁵ sites in consideration of time. In runs of 1x10⁶ or more annotated sites, VEP performance did not deviate from the 2x10⁵ value. ANNOVAR could not complete the full Phase 1, Phase 3, or Phase 3 chromosome 1 datasets due to memory limitations. Thus, ANNOVAR was compared to Bystro on subsets of 1000 Genomes Phase 3 chromosome 1. Bystro run times included time taken to compress outputs. 1000 Genomes Phase 1 performance reflects IO limitations.

142 Next, we explored the Bystro search engine’s ability to filter the 84.9 million annotated
 143 Phase 3 variants. Bystro’s search engine was unique in its natural-language capabilities, and no
 144 other tested online program could handle the full Phase 3 dataset, or subsets as large as 6x10⁶
 145 variants (Figure 2). First, we used Bystro’s search engine to find all alleles in exonic regions by
 146 entering the term “exonic” (933,343 alleles, 0.030 ± .001 seconds, Table 2). The search engine
 147 calculated a transition to transversion ratio of 2.96 for the query, consistent with previously
 148 observed values in coding regions. To refine results to rare, predicted deleterious alleles, we
 149 queried “cadd > 20 maf < .001 pathogenic expert review missense” (65 alleles, 0.029 ± 0.025s,

150 Table 2). This search query could be written using partial words (“pathogen”), possessive nouns
 151 (“expert’s”), different tenses (“reviews”), and synonyms (“nonsynonymous”) without changing
 152 the results.

Table 2 | Online comparison of Bystro and recent programs in filtering 8.49×10^7 variants from 1000 Genomes

Group	Search query	Time (s)	Variants	Tr:Tv
1	exonic	0.030 ± 0.030	993,343	2.96
2 (a)	cadd > 20 maf < .001 pathogenic expert review missense	0.029 ± 0.009	65	1.71
2 (b)	cadd > 20 maf < .001 pathogenic expert’s review non-synonymous	0.036 ± 0.019	65	1.71
2 (c)	cadd > 20 maf < .001 pathogen expert-reviewed nonsynonymous	0.044 ± 0.025	65	1.71
3 (a)	early onset breast cancer	0.046 ± 0.029	4,335	2.51
3 (b)	early-onset breast cancer	0.037 ± 0.020	4,335	2.51
3 (c)	Early onset breast cancers	0.033 ± 0.015	4,335	2.51
4 (a)	Pathogenic nonsense Ehlers-Danlos	0.038 ± 0.027	1	NA
4 (b)	pathogenic nonsense E.D.S	0.078 ± 0.087	1	NA
4 (c)	pathogenic stopgain eds	0.040 ± 0.022	1	NA

The full 1000 Genomes Phase 3 VCF file (853GB, 8.49×10^7 variants, 2,504 samples) was filtered in the publicly-available Bystro web application using the Bystro natural-language search engine. VEP, GEMINI, and wANNOVAR (not shown) were also tested, but were unable to annotate this data set or filter it. Bystro’s search engine uses a natural language parser that allows for unstructured queries: queries in groups 2, 3, and 4 show phrasing variations that did not affect results returned, as would be expected for a search engine that could handle normal language variation. “Tr:Tv” is the transition to transversion ratio automatically calculated for each query by the search engine. The transition to transversion ratio of 2.96 for the “exonic” query is close to the ~2.8-3.0 ratio expected in coding regions, suggesting that the search engine accurately identified exonic (coding) variants.

153 To test the search engine's ability to accurately match variants from full-text disease
154 queries, we first searched "early-onset breast cancer", returning the expected alleles in *BRCA1*
155 and *BRCA2* (4,335 variants, $.037 \pm .020s$, Table 2). Notably, the queried phrase "early-onset
156 breast cancer" did not exist within the annotation, and instead matched closely-related RefSeq
157 transcript names, such as "Homo sapiens breast cancer 2, early onset (BRCA2), mRNA." We
158 next explored Bystro's ability to handle synonyms and acronyms. To test the hypothesis that
159 Bystro could interpret common ontologies, we queried "pathogenic nonsense E.D.S", where
160 "nonsense" is a common synonym for "stopGain" (a term annotated by the Bystro annotation
161 engine), and "E.D.S" is an acronym for "Ehlers-Danlos Syndrome". Bystro successfully parsed
162 this query, returning a single *PLOD1* variant found in 1000 Genomes Phase 3 that introduces an
163 early stop codon in all three of its overlapping transcripts, and which has been reported in
164 Clinvar as "pathogenic" for "Ehlers-Danlos syndrome, type 4" (1 variant, $.038s \pm .027s$, Table 2).

165 Since no other tested program could load or filter the 1000 Genomes Phase 3 VCF file
166 online, we next compared Bystro to GEMINI (running on the Galaxy platform) on subsets of
167 1000 Genomes Phase 3. In contrast with GEMINI's structured SQL queries, Bystro enabled
168 shorter and more flexible searches. For instance, to return all missense, rare variants with
169 CADD Phred scores larger than 15, GEMINI required a 162 character SQL query, while Bystro
170 needed only 36 characters. Bystro also demonstrated synonym support, returning identical
171 results for "missense" and "nonsynonymous" queries. Critically, Bystro's search engine enabled
172 real-time (sub-second) filtering, performing approximately four orders of magnitude faster than
173 GEMINI on Galaxy while searching and returning similar volumes of data (Table 3).

174 To test the accuracy of Bystro's search engine relative to the underlying annotation, we
175 first compared Bystro's natural-language queries with Bystro's "Filters", which provide a
176 complimentary, exact-match filtering option. All results were identical between the two methods
177 (Additional file 1: Table S5). To control for the possibility that Bystro's "Filters" were biased, we
178 created separate Perl filtering scripts that searched for exact matches within the underlying tab-

179 delimited text annotation. Again, results were completely concordant (Additional file 1: Table
180 S5). Finally, to control for the possibility that both Bystro's "Filters" and the Perl scripts were
181 biased due to the programmer, we compared Bystro's natural-language queries with Excel
182 filters on a smaller dataset that could be manually examined. The queries were found
183 completely specific in this comparison as well (Additional file 1: Table S6; Additional file 7).

Table 3 | Online comparison of Bystro and GEMINI/Galaxy in filtering 1×10^6 variants

#	Program	Query	Time (s)	Variants	Ts/Tv
1	Bystro	cadd > 15 alt:(a c t g)	.004 ± 0	28,099	2.512
1	GEMINI	SELECT * FROM variants JOIN variant_impacts ON variants.variant_id = variant_impacts.variant_id WHERE cadd_scaled > 15	442 ± 87	22,063	NA
2	Bystro	gnomad.exomes.af < .001 cadd > 15 missense	.007 ± .003	6,840	3.083
2	GEMINI	SELECT * FROM variants JOIN variant_impacts ON variants.variant_id = variant_impacts.variant_id WHERE cadd_scaled > 15 AND aaf_exac_all < .001 AND variant_impacts.impact = 'missense_variant'	77.6 ± 18.6	5,160	NA
3	Bystro	gnomad.exomes.af < .001 cadd > 15 nonsynonymous	.006 ± .001	6,840	3.083
3	GEMINI	SELECT * FROM variants JOIN variant_impacts ON variants.variant_id = variant_impacts.variant_id WHERE cadd_scaled > 15 AND aaf_exac_all < .001 AND variant_impacts.impact = 'nonsynonymous_variant'	NA	0	NA

Bystro was compared to the latest hosted version of GEMINI (v0.8.1, on the Galaxy platform) in filtering the 1×10^6 variant subset of 1000 Genomes Phase 3, which was the largest tested file that GEMINI/Galaxy could process. GEMINI requires structured SQL queries, while Bystro allows for shorter, unstructured search. In query #1, Bystro searched for CADD scores only within single-nucleotide polymorphisms (using alt:(a || c || t || g), or equivalently the regex query alt:[actg]/), to normalize results with GEMINI, which provides no CADD data for insertions and deletions. In queries #2 and #3, Bystro's search engine returned identical results for the synonymous terms "missense" and "nonsynonymous", despite annotating such sites only as "nonsynonymous". In contrast, GEMINI required the specific term 'missense_variant'. GEMINI/Galaxy and Bystro returned different results because the latest version of GEMINI on Galaxy (0.8.1) uses outdated annotation sources. Comparisons between Bystro and GEMINI/Galaxy are further limited as GEMINI doesn't provide a natural-language parser, annotation field filters, an interactive result browser, per-query statistics, or the ability to filter saved search results. Notably, Bystro also performed substantially faster, returning all results in less than 1 second.

185

186 **Discussion**

187 The Bystro annotation and filtering capabilities are primarily exposed through a public
188 web application (<https://bystro.io/>), and are also available for custom, offline installation. To
189 ensure data safety, Bystro follows industry recommendations for password management, in-
190 transit data security, and at-rest data security. Input and output files are encrypted at rest on
191 Amazon EFS file systems, using AES 256-bit encryption, and every request for annotation or
192 search data is authenticated by the web server using short-lived identity tokens. To further
193 protect user data, annotation and search services are not directly open to the Internet, but
194 require routing and authentication through the web server. Furthermore, all web traffic is
195 encrypted using TLS (HTTPS), and password hashing follows the National Institute of
196 Standards and Technology (NIST) recommended PBKDF2-HMAC-SHA512 strategy.

197 Creating an annotation online is as simple as selecting the genome and assembly used
198 to make the variant call format (VCF)[10] or SNP[11] format files, and uploading these files from
199 a computer or Amazon S3 bucket, which can be easily linked to the web application. Annotation
200 occurs in the cloud, where distributed instances of the Bystro annotation engine process the
201 data and send the results back to the web application for storage and display (Figure 1).

202 The Bystro annotation engine is open source, and supports diverse model organisms
203 including *Homo sapiens* (hg19, hg38), *M. musculus* (mm9, mm10), *R. macaque* (rheMac8), *R.*
204 *norvegicus* (rn6), *D. melanogaster* (dm6), *C. elegans* (ce11), *S. cerevisiae* (sacCer3). To
205 annotate, it rapidly matches alleles from users' submitted files to descriptions from RefSeq[12],
206 dbSNP[13], PhyloP[14], PhastCons[14], Combined Annotation-Dependent Depletion (CADD),
207 Clinvar[15], and gnomAD[16]. For custom installations, Bystro supports Ensembl, RefSeq, or
208 UCSC Known Genes transcript sets, and can be flexibly configured include annotations from
209 any files in genePredExt, wigFix, BED, or VCF formats.

210 The annotation engine is aware of alternate splicing, and annotates all variants relative
211 to each alternate transcript. When provided sample information, Bystro also annotates all
212 variants relative to all sample genotypes. In such cases, at every site it labels each sample as
213 homozygous, heterozygous, or missing, and also calculates the heterozygosity, homozygosity,
214 missingness, and sample minor allele frequency. Furthermore, in contrast with current programs
215 that require substantial VCF file pre-processing, Bystro automatically removing low-quality sites,
216 normalizes variant representations, splits multi-allelic variants, and checks the reference allele
217 against the genome assembly. Critically, Bystro's algorithm guarantees parsimonious (left-
218 shifted) variant representations, even for multi-allelic sites containing complex insertions and
219 deletions.

220 The Bystro annotation engine is designed to scale to any size experiment, offering the
221 speed of distributed computing solutions such as Hail[17], but with less complexity. Current well-
222 performing annotators - such as ANNOVAR and SeqAnt - load significant amounts of data into
223 memory to improve performance. However, when these programs use multiple threads to take
224 advantage of multicore CPUs they may exceed available memory (in some cases over 60GB),
225 resulting in a sharp drop in performance or system crash. To solve this, Bystro annotates
226 directly from an efficient memory-mapped database (LMDB), using only a few megabytes per
227 thread, and because memory-mapped databases naturally lend themselves to the caching
228 frequently accessed data, Bystro achieves most of the benefits of in-memory solutions, but
229 without the per-thread penalties. This approach allows Bystro to take excellent advantage of
230 multicore CPUs, while also enabling it to perform well on inexpensive, low-memory machines.
231 Critically, when multiple files are submitted to it simultaneously, the Bystro annotation engine
232 can automatically distribute the work throughout the cloud (or a user-configured computer
233 cluster), gaining additional performance by processing the files on multiple computers (Figure
234 1). Furthermore, in reflection of the large sizes of both input sequencing experiments and the
235 corresponding annotation outputs - on the order of terabytes for modern whole-genome

236 experiments - Bystro accepts compressed input files, and directly writes compressed outputs.

237 This ability to directly write compressed annotations with no uncompressed intermediate is

238 critical given the rapid growth in sequencing experiment size.

239 When the web application receives a completed annotation, it saves the data and

240 creates a permanent results page. Detailed information about the annotation, such as the

241 database version used for the annotation is stored in a log file that the user may download.

242 Users may then explore several quality control metrics, including the transition to transversion

243 ratio on a per-sample or per-experiment basis. They may also download the results as tab-

244 delimited text to their computer, or upload them to any connected Amazon S3 bucket. In parallel

245 with the completion of an annotation, the Bystro search engine automatically begins indexing

246 the results. Once finished, a search bar is revealed in the results page, allowing users to filter

247 their variants using the search engine (Figure 1).

248 Unlike existing filtering solutions, Bystro's Elasticsearch-based natural-language search

249 engine accepts unstructured, "full-text" queries, and relies on a sophisticated language parser to

250 match annotated variants. This allows it to offer the flexibility of modern search engines like

251 Google and Bing, while remaining specific enough for the precise identification of alleles

252 relevant to the research question. The Bystro search engine matches terms regardless of

253 capitalization, punctuation, or word tense, and accurately finds partial terms within long

254 annotation values. Like the annotation engine, the search engine is also exceptionally fast,

255 automatically distributing indexed annotations throughout the cloud, enabling users to sift

256 through millions of variants from large whole-genome sequencing experiments in milliseconds.

257 In order to provide flexible, but specific matches without relying on structured SQL

258 queries, the search engine identifies the data type of every value in the annotation. Text

259 undergoes stemming and lemmatization, which reduces the influence of grammatical variation,

260 and is then tokenized into left-edge n-grams, which allows for flexible matching. Numerical data

261 is stored in the smallest integer or float format that can accommodate it, allowing for rapid and

262 accurate range queries. For complex queries, the search engine supports Boolean operators
263 (AND, OR), regular expressions, and Levenshtein-edit distance fuzzy matches. It also has a
264 built-in dictionary of synonyms, for instance equating “stopgain” and “nonsense”.

265 In some cases, text will match accurately, but not specifically; this most often happens
266 with short, generic terms. For instance, querying “intergenic” alone may match the word
267 “intergenic” in “long intergenic non-protein coding RNA” in refSeq’s description field, as well as
268 “intergenic” in the refSeq’s siteType field. To help improve accuracy in such cases, Bystro
269 provides three, closely related features: 1) “Aggregations” allows users to see the top 200
270 values for any text field, or equivalently the min, max, mean, standard deviation (and other
271 similar statistics) for any numerical field. This allows users to quickly and precisely understand
272 the composition of search results, as well as to generate summary statistics. 2) “Filters” allows
273 users to refine queries, by forcing the inclusion or exclusion of any values found in any field. For
274 instance, rather than query “intergenic”, it may be easier and more precise to simply click on the
275 “refSeq.siteType” filter, and select the “intergenic” value. Any number of “Filters” may be
276 combined with any natural-language query, containing up to 1 million words. 3) Bystro allows
277 field names within a natural-language query for added specificity. For example, rather than
278 searching for “intergenic”, the user could type “refSeq.siteType:intergenic”, to indicate that they
279 wished to match “intergenic” specifically in the refSeq.siteType annotation field.

280 Bystro’s search engine also includes several features to increase flexibility beyond the
281 contents of the annotation: 1) “Custom Synonyms” allows users to define their own terms and
282 annotations. Among other uses, this make it is possible to label trios, which can be used to
283 easily identify *de novo* variants and test allele transmission models. 2) “Search Tools” are small
284 programs, accessible by a single mouse click, that dynamically modify any query to generate
285 complex result summaries. Some of their functions include identifying compound heterozygotes.
286 3) “Statistical Filters” dynamically perform statistical tests on the variants returned from any

287 query. For instance, the “HWE” filter allows users to exclude variants out of Hardy-Weinberg
288 Equilibrium. This is an often-needed quality control step.

289 Most importantly, there is no limit to the number of query terms and “Filters” that can be
290 combined, and users can save and download the results of any search query, which enables
291 recursive filtering on a single dataset. The saved results are indexed for search, and hyperlinked
292 to the annotations that they were generated from, forming permanent records that can be used
293 to reproduce complex analyses. This multi-step filtering provides functionality similar to custom
294 command-line filtering script pipelines, but is significantly faster, less error prone, and
295 accessible to researchers without programming experience.

296
297 While Bystro’s annotation and filtering performance is currently unparalleled by any other
298 approach, other software (such as Hail[17]) could achieve similar performance by implementing
299 distributed computing algorithms like MapReduce[18], and spreading annotation workloads
300 across many servers. Bystro demonstrates that these workarounds are unnecessary to achieve
301 reasonable run-times for large datasets online or offline. Additionally, while Bystro’s natural-
302 language search engine significantly reduces the difficulty of variant filtering, it does not handle
303 language idiosyncrasies as robustly as more mature solutions like Google’s, and may return
304 unexpected results when search queries are very short and non-specific, since such queries
305 may have multiple correct matches. This is easily avoided by using longer phrases, by using
306 “Custom Synonyms” to define more specific terms, by examining the composition of results
307 using “Aggregations”, or by applying “Filters” to precisely filter results. Such considerations and
308 options are well-documented in Bystro’s online user guide (<https://bystrio.io/help>).

309

310 **Conclusions**

311 To date, identifying alleles of interest in sequencing experiments has been time-
312 consuming and technically challenging, especially for whole-genome sequencing experiments.

313 Bystro increases performance by orders of magnitude and improves ease of use through three
314 key innovations: 1) a low-memory, high-performance, multithreaded variant annotator that
315 automatically distributes work in cloud or clustered environments; 2) an online architecture that
316 handles significantly larger sequencing experiments than previous solutions; and 3) the first
317 publicly-available, general-purpose, natural-language search engine for variant filtering in
318 individual research experiments. Bystro annotates large experiments in minutes, and its search
319 engine is capable of matching variants within whole-genome datasets in milliseconds, enabling
320 real-time data analysis. Bystro's features enable practically any researcher – regardless of their
321 computational experience - to analyze large sequencing experiments (e.g. thousands of whole-
322 genome samples) within less than a day, and small ones (e.g. hundreds of whole-exome
323 samples) in seconds. As genome sequencing continues the march toward ever-larger datasets
324 and becomes more frequently used in diverse research settings, Bystro's combination of
325 performance and ease of use will prove invaluable for reproducible, rapid research.

326

327 **Methods**

328

329 **Accessing Bystro**

330 For most users, we recommend the Bystro web application (<https://bystro.io>), as it gives
331 full functionality, supports arbitrarily large datasets, and provides a convenient interface to the
332 natural-language search engine. Users with computational experience can download the Bystro
333 open-source package (<https://github.com/akotlar/bystro>). Using the provided installation script or
334 Amazon AMI image, Bystro can be easily deployed on an individual computer, computational
335 cluster, or any Amazon Web Services (AWS) EC2 instance. Bystro has very low memory and
336 CPU requirements, but benefits from fast SSD drives. As such we recommend at AWS
337 instances with provisioned I/O EBS drives, RAID 0 non-provisioned EBS, or i2/i3-class EC2
338 instances.

339

340 Detailed documentation on Bystro's use, as well as example search queries can be
341 found at <https://bystro.io/help>.

342

343 **Bystro comparisons with ANNOVAR, wANNOVAR, VEP, and GEMINI/Galaxy**

344

345 **Bystro Database**

346 Bystro databases were created using the open-source package
347 (<https://github.com/akotlar/bystro>). The hg19 and hg38 databases contains RefSeq, dbSNP,
348 PhyloP, PhastCons, Combined Annotation-Dependent Depletion (CADD), and Clinvar fields, as
349 well as custom annotations (Additional file 8). A complete listing of the original source data is
350 enumerated in the Git repository (<https://github.com/akotlar/bystro/tree/master/config>). Other
351 organism databases contain a subset of these sources, based on availability. Pre-built, up-to-
352 date versions of these databases are publicly available (<https://github.com/akotlar/bystro>).

353

354 **WGS Datasets**

355 Phase 1 and Phase 3 autosome and chromosome X VCF files were downloaded from
356 <http://www.internationalgenome.org/data/>. Phase 1 files were concatenated using bcftools[19]
357 "concat" function. Phase 3 files were concatenated using a custom Perl script
358 (<https://github.com/wingolab-org/GenPro/blob/master/bin/mergeSnpFiles>). The Phase 1 VCF file
359 was 895GB (139GB compressed), and the Phase 3 data was 853GB (15.6GB compressed).
360 The larger size of Phase 1 can be attributed to the inclusion of extra genotype information (the
361 genotype likelihood). The full Phase 3 chromosome 1 VCF file (6.4×10^6 variants, 1.2GB
362 compressed), and 5×10^4 - 4×10^6 variant allele subsets (8-655MB compressed) were also tested.
363 All Phase 1 and Phase 3 data correspond to the GRCh37/hg19 human genome assembly. All
364 data used are available (Additional file 9).

365

366 **Online annotation comparisons**

367 For online comparisons, the latest online versions offered at time of writing were used.
368 Bystro beta10 (September 2017), wANNOVAR (April 2017), VEP (April 2017), and GEMINI
369 (Galaxy version 0.8.1, released February 2016, latest as of October 2017) were tested online
370 with the full 1000 Genomes Phase 1 and Phase 3 VCF files, unless they were unable to upload
371 the files due to file size restrictions (Additional file 2). Bystro was found to be the only program
372 capable of uploading and processing the full Phase 1 and Phase 3 data sets, or subsets of
373 Phase 3 larger than 1×10^6 variants.

374

375 To conduct Bystro online annotations, a new user was registered within the public Bystro
376 web application (<https://bystro.io/>). Phase 1 and Phase 3 files were submitted in triplicate, one
377 replicate at a time, using the default database configuration (Additional file 2). Indexing was
378 automatically performed by Bystro upon completion of each annotation. The Phase 3 annotation
379 is publicly available to be tested (<https://bistro.io/public>).

380

381 The public Bystro server was configured on an Amazon i3.2xlarge EC2 instance. The
382 server supported 8 simultaneous users. Throughout the duration of each experiment, multiple
383 users had concurrent access to this server, increasing experiment variance, and limiting
384 observed performance.

385

386 Online Variant Effect Predictor (VEP) submissions were done using the VEP web
387 application (<http://www.ensembl.org/info/docs/tools/vep/index.html>). VEP has a 50MB
388 (compressed) file size limit. Due to gateway timeout issues and this file size limit, data sets
389 larger than 5×10^4 variants failed to complete (Additional file 2).

390

391 Online ANNOVAR submissions were handled using the wANNOVAR web application.

392 wANNOVAR could not accept the smallest tested file, the 5×10^4 variant subset of Phase 3

393 chromosome 1 (8MB compressed) due to file size restrictions (Additional file 2).

394 Galaxy submission was made using the public Galaxy servers. Galaxy provides

395 ANNOVAR, but its version of this software failed to complete any annotations, with the error

396 “unknown option: vcfinput”. Annotations on Galaxy were therefore performed using GEMINI,

397 which provides annotations similar to Bystro’s. Galaxy has a total storage allocation of 250GB

398 (after requisite decompression), and both Phase 1 and Phase 3 exceed this size. Galaxy was

399 therefore tested with the full 6.4×10^6 variant Phase 3 chromosome 1 VCF file. Galaxy’s FTP

400 server was able to upload the file; however, Galaxy was unable to load the data into GEMINI,

401 terminating after running for 36 hours, with the message “This job was terminated because it ran

402 longer than the maximum allowed job run time” (Additional file 2). Subsets of Phase 3

403 chromosome 1 containing 5×10^4 , 3×10^5 , and 1×10^6 variants were therefore tested. Three

404 repetitions of the 5×10^4 variant submission were made. In consideration of the duration of

405 execution, two repetitions were made of the 3×10^5 and 1×10^6 variants submissions. Since

406 Galaxy does not record completion time, QuickTime was used to record each submission.

407

408 Bystro, VEP, and GEMINI online annotation times included the time to generate both a user-

409 readable tab-delimited text annotation and a searchable database. GEMINI required an extra

410 step to do so, using the query `SELECT * FROM variants JOIN variant_impacts ON`

411 `variants.name = variant_impacts.name.`

412 **Variant filtering comparisons**

413 After Bystro completed each annotation, it automatically indexed the results for search.

414 The time taken to index this data was recorded. Once this was completed, the Bystro web

415 application’s search bar was used to filter the annotated sequencing experiments. The query

416 time, as well as the number of results and the transition to transversion ratio for each query,

417 were automatically generated by the search engine and recorded. Query time did not take into
418 account network latency between the search server and the web server. All queries were run six
419 times and averaged. The public search engine, which processed all queries, was hosted on a
420 single Amazon i3.2xlarge EC2 instance.

421

422 Since VEP, wANNOVAR, and Galaxy/GEMINI could not complete Phase 1 or Phase 3
423 annotations, variant filtering on these data sets could not be attempted. For small experiments
424 VEP and GEMINI can filter based on exact matches, while wANNOVAR provides only pre-
425 configured phenotype and disease model filters. VEP could annotate and filter at most only
426 5×10^4 variants and was therefore excluded from query comparisons.

427 Galaxy/GEMINI was tested with subsets of 1000 Genomes Phase 3 of 1×10^6 variants
428 (the largest tested data set that Galaxy could handle), with the described settings (Additional file
429 2). In all GEMINI queries a JOIN operation on the variant_impacts table was used to return all
430 variant consequences, and all affected transcripts, as Bystro does by default. Similarly, Bystro's
431 CADD query was restricted to single nucleotide polymorphisms (using alt:(A || C || T || G)), as its
432 behavior diverges from GEMINI's at insertions and deletions: Bystro returns all possible CADD
433 Phred scores at such sites, whereas GEMINI returns a missing value. Bystro returns all values
434 to give users added flexibility: its search engine can accurately search within arrays (lists) of
435 data. Furthermore, as GEMINI on Galaxy only provided the Ensembl transcript set, for all query
436 comparisons with GEMINI, Bystro was configured to use Ensembl 90, which was the latest
437 version available at time of revision. It is important to note that the latest version of GEMINI on
438 Galaxy (0.8.1) dates to February 2016, and its databases are several years older: CADD (v1.0,
439 2014), Ensembl (v75, February 2014), ExAc (v0.3, October 2014), whereas Bystro uses up-to-
440 date resources. As a result of searching more up to date Ensembl (v90), population allele
441 frequency (gnomAD 2.0.1, the successor to ExAc 1.0), and CADD (v1.3) data, Bystro's queries
442 returned more data.

443 Since Galaxy does not report run times, QuickTime software was used to record each
444 run, and the query time was calculated as the difference between the time the search
445 submission entered the Galaxy queue, to the time that it was marked completed.
446 Galaxy/GEMINI queries were each run more than 6 times. Because run times varied by more
447 than 17x, the fastest consecutive 6 runs were averaged to minimize the influence of Galaxy
448 server load.

449

450 All comparisons with the Bystro search engine are limited, because no other existing
451 method provides natural-language parsing, and either rely on built-in scripts or require the user
452 to learn a specific language (SQL).

453

454 **Filtering accuracy comparison**

455 The latest version of Bystro (beta 10, September 2017) was used. For the 1000
456 Genomes query accuracy checks, the same underlying Ensembl-based Bystro annotation and
457 search index was used as in the Bystro/GEMINI filtering comparison. Direct comparison to
458 GEMINI were not made, in reflection of the age of the latest GEMINI Galaxy version (v0.8.1,
459 with database sources dating to 2014). All Bystro queries from that comparison were saved,
460 downloaded, and compared with Bystro “Filters”, which are exact-match alternatives to Bystro’s
461 natural-language queries, as well as custom Perl filtering scripts that also require exact
462 matches. A second query accuracy step was conducted, on the Yen et al 2017[9] VCF file. This
463 file was annotated using the standard RefSeq Bystro database. The same queries used in the
464 Bystro/GEMINI comparison were re-created on this smaller annotation, saved, downloaded, and
465 compared with Bystro “Filters” and Excel filters. Excel filters were created in Excel 2016 (Mac),
466 and required exact matches. All Excel-filtered and all Bystro query results were manually
467 inspected for concordance (Additional file 7). All scripts generated and used in the comparison
468 may be found at <https://github.com/akotlar/bystro-paper>.

469

470 **Offline annotation comparisons**

471 To generate offline performance data, the latest versions of each program available at
472 time of writing were used. Bystro beta10 (September 2017), VEP 86 (March 2017), and
473 ANNOVAR (March 2017) were each run on separate, dedicated Amazon i3.2xlarge EC2
474 instances (Additional file 3). All programs' databases were updated to the latest versions
475 available as of March 2017 (VEP, ANNOVAR), or September 2017 (Bystro). All programs were
476 configured to use the RefSeq transcript set.

477

478 Each instance contained 4 CPU cores (8 threads), 60GB RAM, and a 1920GB NVMe
479 SSD. Each instance was identically configured. All programs were configured to as closely
480 match Bystro's output as possible, although Bystro output more total annotation fields
481 (Additional file 3). Each data set tested was run 3 times. The annotation time for each run was
482 recorded, and averaged to generate the mean variant per second (variant/s) performance.
483 Submissions were recorded using the terminal recorder asciinema, and both memory and cpu
484 usage were recorded using the **free** and **top** commands set to a 30 second timeout.

485

486 VEP was configured to use 8 threads and to run in "offline" mode to maximize
487 performance, as recommended[3]. In each of three recorded trials, VEP was set to annotate
488 from RefSeq and CADD, and to check the reference assembly (Additional file 3). Based on
489 VEP's observed performance, adding PhastCons annotations was not attempted. VEP's
490 performance was measured by reading the program's log, which records variant/second
491 performance every 5×10^3 annotated sites. In consideration of time, VEP was stopped after at
492 least 2×10^5 variants were completed, and the 2×10^5 variants performance was recorded.

493

494 ANNOVAR was configured to annotate RefSeq, CADD, PhastCons 100way, PhyloP
495 100way, Clinvar, avSNP, and ExAc version 0.3 (Additional file 3). ANNOVAR's avSNP database
496 was used in place of dbSNP, as recommended. We configured ANNOVAR to report allele
497 frequencies from ExAc, because it does not do so from either avSNP or dbSNP databases.
498 When annotating Phase 1, Phase 3, or Phase 3 chromosome 1, ANNOVAR crashed by
499 exceeding the available 60GB of memory. It was therefore tested with the subsets of Phase 3
500 chromosome 1 that contained $1 \times 10^6 - 4 \times 10^6$ variants.

501

502 Bystro was configured to annotate descriptions from RefSeq, dbSNP 147, CADD,
503 PhastCons 100way, PhyloP 100way, Clinvar, and to check the reference for each submitted
504 genomic position (Additional file 3).

505

506 **Annotation accuracy comparison**

507 The latest version of Bystro (beta 10, September 2017), ANNOVAR (July 2017), and
508 VEP (version 90) at the time of revision submission were used. All programs' databases were
509 updated to the latest version available. RefSeq-based databases were downloaded using each
510 program's database builder. All programs were compared on the Yen et al 2017 VCF file [9] for
511 position, variant call, and variant effects, based on each programs' respective RefSeq database.
512 The Yen et al VCF file *fileformat* header line was modified to "VCFv4.1" to allow programs to
513 recognize it as a valid VCF file. This modified file is available: [https://github.com/akotlar/bystro-](https://github.com/akotlar/bystro-paper)
514 [paper](https://github.com/akotlar/bystro-paper). For the SnpEff comparison, annotations were adapted from Additional File 1 of Yen et al
515 2017[9]. ANNOVAR was additionally configured with gnomAD genomes, gnomAD exomes, and
516 CADD 1.3, and compared to Bystro on the corresponding values.

517

518 **Additional Files**

519 Additional file 1: This file contains 1) a feature comparison of tested programs, 2) investigation
520 of annotation concordance between tested programs, 3) investigation of Bystro query accuracy
521 (.docx, 1.4MB)

522 Additional file 2: Description of online comparison settings (.xlsx, 859KB)

523 Additional file 3: Description of online comparison settings (.xlsx, 40KB)

524 Additional file 4: Bystro vs ANNOVAR annotation comparison details (.xlsx, 87KB)

525 Additional file 5: Bystro vs VEP annotation comparison details (.xlsx, 701KB)

526 Additional file 6: Bystro vs SnpEff annotation comparison details (.xlsx, 63KB)

527 Additional file 7: Bystro queries vs Excel filters concordance details (.xlsx, 166KB)

528 Additional file 8: Species supported at time of writing, and their configurations (.xlsx, 36KB)

529 Additional file 9: URLs of 1000 Genomes Phase 1, 1000 Genomes Phase 3, and Yen et al 2017
530 VCF files used (.xlsx, 47KB)

531

532 **Declarations**

533 ***Availability of data and materials***

534 The Bystro web application is freely accessible at <https://bystro.io/>, and features detailed
535 interface documentation (<https://bystro.io/help>). The Bystro annotator, search indexer,
536 distributed queue servers, and database builder source code is freely available on GitHub
537 (<https://github.com/akotlar/bystro>) and Zenodo (doi: [10.5281/zenodo.1012417](https://doi.org/10.5281/zenodo.1012417)), under the
538 Apache 2 open-source license [20]. The software is written in Perl and Go programming
539 languages and runs on Linux and Mac operating systems. Detailed documentation for Bystro
540 software is provided at <https://github.com/akotlar/bystro/blob/master/README.md>. The datasets
541 generated during and/or analyzed during the current study are available in the GitHub
542 repository, <https://github.com/akotlar/bystro-paper> [6],[9].

543

544 ***Author contributions***

545 A.V.K designed, wrote, and tested Bystro and performed experiments. C.E.T wrote
546 Bystro documentation and performed quality control. M.E.Z and D.J.C. contributed to the design
547 of Bystro and experiments. T.S.W. designed and wrote Bystro and designed and performed
548 experiments. A.V.K. and T.S.W. wrote the manuscript with contributions from all authors.

549

550 ***Acknowledgements***

551 We thank Kelly Shaw and Katherine Squires for beta testing and design suggestions. We thank
552 Viren Patel and the Emory Integrated Genomics Core (EIGC) for technical support.

553

554 ***Funding***

555 This work was supported by the AWS Cloud Credits for Research program, the Molecules to
556 Mankind program (a project of the Burroughs Wellcome Fund and the Laney Graduate School
557 at Emory University), Veterans Health Administration (BX001820), and the National Institutes of
558 Health (AG025688, MH101720, NS091859).

559

560 ***Competing interests***

561 The authors have no competing interests to declare.

562

563 ***Ethics approval and consent to participate***

564 Not applicable

565

566 **References**

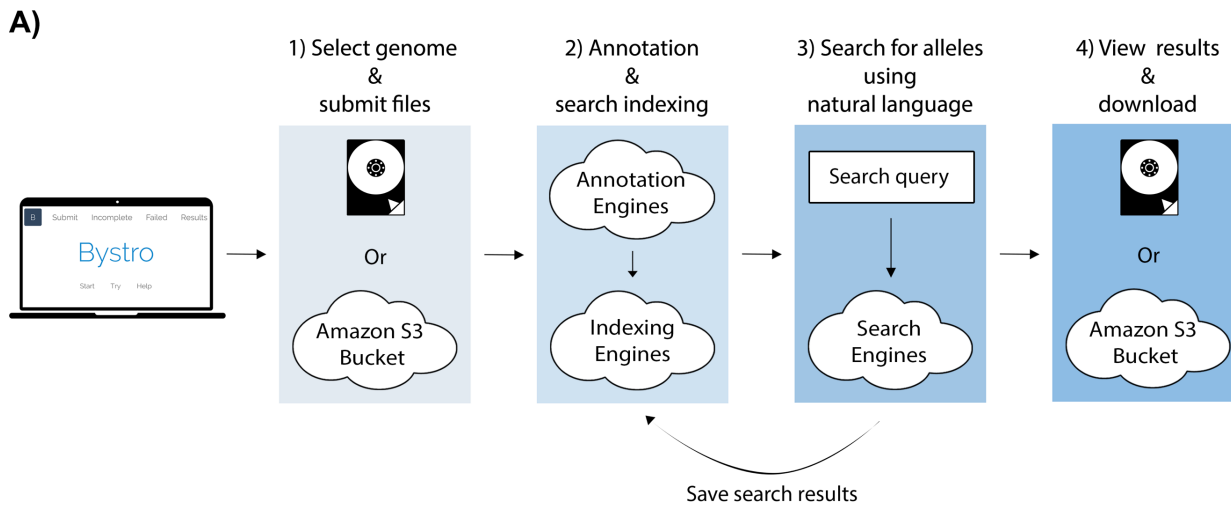
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624

Figure 1



B)

phase3.vcf (completed)
Created on: Jun 25, 2017 4:25:45 PM
Notes: (Click to add a note)

[Search this file](#)
earl-onset pathogenic breast cancer

Sort ▾ Tools ▾ Size ▾

Search Results Summary

Found **278 results** in **0.027s**
Showing page 1 (10 results per page)

Transitions & Transversions [Ⓢ]

Tr:Tv Ratio: **2.366**
Transitions: **194**
Transversions: **82**

Filter Search Results

- Genes ▾
- Exonic Allele Function ▾
- RefSeq Site Type ▾
- Chromosome ▾

Expand all

BRCA2

chr13 : 32,929,053

E2355*

Cadd: 43 PhyloP: 1.17 PhastCons: 0.97

Less ▲ Detail

RefSeq Transcripts [Ⓢ]

Name: **NM_000059**
spDisplayID: **BRCA2_HUMAN**
spID: **P51587**
mRNA: **NM_000059**
protAcc: **NP_000050**
Site Type: **exonic**
Description: **Homo sapiens breast cancer 2, early onset (BRCA2), mRNA.**
Strand: **+**
Function: **stopGain**
Codon Number: **2355**

Figure 2

1000 Genomes Phase 3 Online Processing Time

