# Standardised and efficient querying of GWAS summary statistics by adapting the VCF format

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## Abstract

## Introduction

The genome-wide association study (GWAS) is a powerful tool for identifying genetic loci associated with traits, diseases and molecular phenotypes such as gene expression and biomarker concentration[1]. Sharing of non-identifiable test summary statistics (i.e. variant, effect size, standard error, p-value etc) has enabled a range of important secondary research applications including gene prioritization[2], causal inference (Mendelian randomization; MR)[3], risk prediction[1], genetic correlation[4] and heritability estimation[5]. However, data requirements for downstream analysis can vary widely, for example gene prioritization is undertaken with loci and trait association P-value while MR additionally demands allele and standard error information which is often unavailable. Even when the required data are present, existing tools have a plethora of input formats making analyses cumbersome and error prone. Storage and distribution of essential meta-data with summary statistics is also rarely practiced and can lead to errors if there is misinterpretation of the genome build, allele coding of the effect allele, or the trait and effect sizes units.

Lack of a common standard has led to GWAS analysis tools outputting results in different formats (e.g. plink[6], GCTA[7], BOLT-LMM[8], GEMMA[9] and meta-analysis tools e.g. METAL[10]). During secondary analyses various processing issues are typically encountered: ambiguity in which allele relates to the effect size estimate, different field names and information, slow and unscalable queries. Some proposals have been made for standard formats. The EBI-NHGRI GWAS catalog developed a text format with standardized column names[11]. The SMR tool[12] proposed a way to store GWAS summary data in a binary format for rapid querying of quantitative trait loci. Learning from these examples and considering future needs i.e. GWAS of rare variants using genome sequencing we have identified a set of requirements for a suitable universal format (Table 1).

We determined that adapting the widely used variant call format (VCF) [13], [14] was a convenient and constructive approach to meet these requirements. Here we outline the implementation, explain how it meets these requirements, describe existing and new software that creates and connects to the data format, and show results of query performance. Finally, we provide access to over 10,000 complete GWAS summary datasets that have been converted to this format as part of the IEU GWAS database, and are freely available for download: <https://gwas.mrcieu.ac.uk>.

## Method

### Implementation

The VCF format is organized into three units: flexible file header containing meta-data (lines beginning with ‘#’), variant information (one locus per row) and sample information (one sample per column). We adapt the format such that each sample data column represents GWAS of a single trait (Figure 1).

Meta-data define important characteristics of the GWAS: trait description and units, genome build, number of variants, type of trait (continuous or case/control), sample size and study identifier. The VCF header is also mandatory for defining fields used in the file body including variable description, value requirements (i.e. number of values permitted and null values) and data type (i.e. string, number and boolean).

Each row of the file body contains a single variant position including contig (chromosome) name, base-pair position, variant identifier (i.e. dbSNP identifier), reference (major/non-effect allele) and alternative (minor/effect allele) alleles. The sample column is used to store allele-trait association metrics: marker identifier, allele frequency, regression coefficient, standard error and association P-value.

The full specification provides detailed information including reserved keys: <https://github.com/MRCIEU/gwas_vcf_spec>.

### Query performance simulation

Densely imputed summary statistics (13,791,467 variants) for a large GWAS of body mass index data were obtained from MR Base [15]. The data were mapped to VCF using our tool (gwas2vcf; Table 2) and processed using bcftools [16] to remove multiallelic variants or records with missing dbSNP identifiers. The VCF was indexed using tabix [16] and rsidx [17] which enable rapid queries by genomic position and dbSNP identifier, respectively. A tabular (unindexed) file was prepared from the VCF to replicate a typical storage format currently used by the community. Runtime performance of a range of queries was evaluated: single variant selection using dbSNP identifier or chromosome position, multi-variant selection by association P value or 1 Mb genomic interval . Testing was undertaken with five repetitions using VCF or unindexed text formats with and without GZIP compression on an Ubuntu v18.04 server with Intel Xeon(R) 2.0 Ghz processor.

Implementation code are available from: <https://github.com/MRCIEU/gwas-vcf-performance>

## Results

### How this format meets the specification

*Human readable and easy to parse*

The plain text file format can be easily read with any text viewer. Open-source parsing libraries are available in C (HTSLIB[18]) and Java (HTSJDK[18]) which can be implemented in most modern programming languages. Bcftools[16] provides user-friendly functionality accessible from the command line.

*Unambiguous interpretation of the data*

Data field descriptions and value types are required and defined in the file header. File validity is enforced during each read/write.

*Unambiguous representation of bi-allelic, multi-allelic and insertion-deletion variants*

Each locus (row) has capacity to store multiple alternative alleles as required. GWAS effect sizes are stored one per alternative allele allowing for bi/multi-allelic and insertion-deletion variants. HTSLIB[18] and HTSJDK[18] parsing libraries have routines for handling complex variants. Using this approach alternative allele(s) are always the effect allele allowing consistency between studies for ease of comparison.

*Genomic information can be validated*

The file header contains genome build, contig identifiers and sequence length. Reference alleles must match the specified reference FASTA. GATK[19] ValidateVariants can be used to verify file validity.

*Flexibility on which GWAS fields are recorded and enforcement of essential fields*

All fields are defined in the file header and can be set optional or required as desired. Our specification implements essential fields and reserved keys.

*Capacity to store meta-data about the study or studies*

Each GWAS trait has a row in the file header to store trait description and units, number of variants, study type (case/control or continuous) and unique identifier.

*Allows multiple studies to be stored together*

The sample column was chosen to store GWAS association metrics to allow for multiple traits in a single file enabling distribution of related phenotypes or individually as desired.

*Rapid querying by dbSNP identifier, genomic position range or GWAS summary data values*

The file is sorted karyotypically and indexed to allow rapid queries by genomic position. Refer to query performance section for comparison with standard UNIX tools.

*File compression*

VCF files may be compressed with block GZIP[16] or converted to a binary call file which is a binary VCF companion format [16].

*Readable by existing open-source tools*

A large number of tools support VCF files including: GATK[19], Picard[20], bcftools[16], bedtools[21], vcftools[14] and plink[6]. Bcftools[16] can also provide a tabular extract for use with non-compatible tools.

*Amenable to cloud-based streaming and database storage*

Genomic intervals may be extracted over a network using range-requests which allows for file segments to be read without transferring the whole file. This is enables rapid streaming of queries over the internet.

For high-throughput storage and querying, VCF files can be easily imported into GenomicsDB[22].

## Query performance simulation

We evaluated the runtime performance of querying GWAS summary statistics in VCF and unindexed text through simulation studies with five repetitions using a range of common operations. The fastest mean runtime to extract a variant by dbSNP identifier (Figure 2) was 0.09 seconds (95% CI 0.09, 0.10) for compressed VCF indexed with rsidx [17]. The second-best performer was 0.78 seconds (95% 0.68, 0.89) using UNIX grep on uncompressed plain text representing an 8.5-fold increase in runtime over VCF. VCF was also quickest to retrieve a single record by chromosome position (Figure 3; mean runtime 0.08 seconds [95% CI 0.07, 0.08]) compared with the second-best performer using UNIX grep on uncompressed plain text ().

: extracting a single variant by dbSNP identifier (Figure 2) of chromosome position (Figure 3), extracting a range of variants by genomic interval (Figure 4) or trait association P value (Figure 5).

## Discussion

We have developed open-source tools for mapping summary statistics to and reading from VCF according to our specification (Table 2). We encourage users to provide feedback via the issue pages.

## Conclusion

The VCF format is a robust solution to storing and distributing GWAS summary statistics. We find the query performance to be around ten times faster than reading the whole dataset with standard UNIX tools. To facilitate adoption, we have developed tools for mapping data from tabular data to VCF and reading using R or Python.

## Specification

Available from: <https://github.com/MRCIEU/gwas_vcf_spec>

## Data availability

Full summary statistics for over 10,000 GWAS in VCF format available from the IEU GWAS Database (<https://gwas.mrcieu.ac.uk>)

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Table 1. List of requirements for summary statistics storage format

|  |  |
| --- | --- |
| # | Requirement |
| 1 | Human readable and easy to parse |
| 2 | Unambiguous interpretation of the data |
| 3 | Unambiguous representation of bi-allelic, multi-allelic and insertion-deletion variants |
| 4 | Genomic information can be validated |
| 5 | Flexibility on which GWAS fields are recorded and enforcement of essential fields |
| 6 | Capacity to store meta-data about the study or studies |
| 7 | Allows multiple studies to be stored together |
| 8 | Rapid querying by dbSNP identifier, genomic position range or GWAS summary data values |
| 9 | File compression |
| 10 | Readable by existing open-source tools |
| 11 | Amenable to cloud-based streaming and database storage |

GWAS, genome-wide association study. dbSNP, database of single-nucleotide polymorphisms.

Table 2. Open-source tools for working with the summary statistics VCF format

|  |  |  |  |
| --- | --- | --- | --- |
| Program | Purpose | Implementation | Source code link |
| gwas2vcf | Mapping tab separated GWAS summary statistics and EBI format to VCF | Python3 (Docker) | <https://github.com/mrcieu/gwas2vcf> |
| gwas2vcfweb (<http://64.227.44.193:8400/>) | Front-end and queue schedular for gwas2vcf | Python3, Cromwell[23]  (Docker) | <https://github.com/mrcieu/gwas2vcfweb> |
| R/gwasvcf | Library for querying and reading GWAS VCF files | R | <https://github.com/mrcieu/gwasvcf> |
| pygwasvcf | Library for querying and reading GWAS VCF files | Python3 | <https://github.com/mrcieu/pygwasvcf> |
| R/gwasglue | Library for processing GWAS summary statistics ready for secondary analysis | R | <https://github.com/mrcieu/gwasglue> |
| LD Score Regression[4] | Estimating genetic correlation and heritability | Python | <http://github.com/explodecomputer/ldsc> |

GWAS, genome-wide association study. LD, linkage disequilibrium. VCF, variant call format. EBI, European Bioinformatics Institute.

Figure 1. VCF format adapted to store GWAS summary statistics

A screenshot of a social media post

Description automatically generated

Variant call file format for storing GWAS summary statistics. The file contains metadata, variant-level content and variant-trait association statistics. Each field is defined in the metadata including variable type and number. The format can accommodate multiple traits/studies or one per file as required.

Figure 2. Performance comparison for querying summary statistics in plain text and VCF format using dbSNP identifier

A close up of a piece of paper

Description automatically generated

Mean query time (seconds; repetitions n=5) for extracting a single variant using the dbSNP identifier from summary statistics stored in tab-separated text or VCF. AWK, grep, bcftools [16] and rsidx [17] were evaluated using uncompressed and GZIP/BGZIP [16] compressed files. Error bars represent the 95% confidence interval.

Figure 3. Performance comparison for querying summary statistics in plain text and VCF format using chromosome position

A screenshot of a cell phone

Description automatically generated

Mean query time (seconds; repetitions n=5) for extracting a single variant using chromosome position from summary statistics stored in tab-separated text or VCF. AWK, grep, and bcftools [16] were evaluated using uncompressed and GZIP/BGZIP [16] compressed files. Error bars represent the 95% confidence interval.

Figure 4. Performance comparison for querying summary statistics in plain text and VCF format using genomic interval

A close up of a piece of paper

Description automatically generated

Mean query time (seconds; repetitions n=5) for extracting variants within a genomic interval using chromosome position from summary statistics stored in tab-separated text or VCF. AWK and bcftools [16] were evaluated using uncompressed and GZIP/BGZIP [16] compressed files. Error bars represent the 95% confidence interval.

Figure 5. Performance comparison for querying summary statistics in plain text and VCF format using trait association P value threshold

A screenshot of a cell phone

Description automatically generated

Mean query time (seconds; repetitions n=5) for extracting variants by trait association P value from summary statistics stored in tab-separated text or VCF. AWK and bcftools [16] were evaluated using uncompressed and GZIP/BGZIP [16] compressed files. Error bars represent the 95% confidence interval.