# Supplementary Materials for 'GLANET: Genomic Loci ANnotation and Enrichment Tool'

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### 1 Overview of Available Tools

There are various tools that provide enrichment and/or annotation analysis on given genomic intervals. In Supplementary Table 1, we compare some of the available tools.



Supplementary Table 1. Available tools including GLANET are compared with respect to their input type, annotation and enrichment options, libraries utilized and statistical tests carried out. **Supplementary Table 1.** Available tools including GLANET are compared with respect to their input type, annotation and enrichment options, libraries utilized and statistical tests carried out.

## 2 Random Interval Sampling Procedure

To perform enrichment analysis, GLANET generates a null distribution of the test statistics by first sampling random intervals and calculating these intervals' overlap with the annotation library element intervals. The random intervals are generated such that they match properties of the each member of the input interval set as opposed to the average properties of these intervals. The algorithm for generating random intervals is outlined in Algorithm 1. Note that, we do not include the relaxation steps of the thresholds for sake of clarity. Here we provide the details of this random interval generation scheme.

The input interval set may contain overlapping intervals. In such cases, GLANET preprocesses the input by merging overlapping intervals into a single interval to avoid dependency within them. Similarly, the random intervals for an input interval set are always selected such that they do not overlap. GLANET provides four main parameters for random interval generation: with GC (wGC) , with Mappability (wM), with GC and Mappability (wGCM), and without GC and Mappability (woGCM). GLANET random interval generation can also be run with Isochore Family (wIF) and without Isochore Family (woIF) (as explained in the main text). Regardless of which option is selected, for each input interval a corresponding random interval of the same length from the same chromosome is sampled. When the given interval's length is greater than 100, 000 bps, GLANET does not generate random intervals by accounting for GC content and/or mappability even one of these options ( $\forall G\mathcal{C},\forall M,\forall G\mathcal{C}$ ) is on. Since for very large intervals, GC content and mappabilty values are not meaningful. In case of **wGC, wM**, or **wGCM** options are selected in addition to the length and chromosome of given interval, GLANET also matches given interval's GC, mappability, or both GC and mappability, respectively as follows:

- GC Option or Mappability Option Selected: If one of the wGC or wM option is selected, GLANET tries to match the GC content or mappability value of the given interval. Same procedure applies for matching GC or mappability values. GLANET first generates a random interval and calculates its GC content or mappability depending on which option is selected. This random interval is accepted if its value is close to the corresponding value of input interval within a pre-defined threshold. Otherwise, GLANET generates a new random interval until an acceptable random interval is obtained. If after a certain number of attempts, no random interval can be found because it is not within the threshold distance to the GC or mappability of the input interval, then the threshold for the acceptable match is increased by a small increment. Again, after a certain amount of trials, if relaxing this threshold does not help, GLANET chooses the random interval with the minimum difference in GC content or mappability up to that point.
- GC and Mappability Option Selected: If wGCM option is on, GLANET selects a random interval with close GC content and mappability values to the input interval. A random interval is considered acceptable if its GC content and mappability values are within a pre-defined distance to the input interval's values. If the random interval values do not match, a new interval is sampled until an acceptable random interval is obtained. If after a certain number of attempts, no random interval can be generated because it is not within the threshold distance to the GC or mappability of the input interval, the threshold for the acceptable match is increased by a small increment. If relaxing this threshold does not help, GLANET chooses the random interval with the minimum sum of the differences in GC content and mappability up to that point.

GC and Mappability Calculation: In order to calculate the GC content and mappability of given intervals, GLANET pre-computes GC content and mappability values of genomic regions and stores them in the disk. The GC content of the genomic regions are calculated at various lengths such as 1 bp, 100 bps, 1000 bps, 10, 000 bps and 100, 000 bps. In runtime GLANET constructs a GC interval tree from one of these pre-computed GC content values based on the mode of the input interval lengths. Specifically, the shorter the input intervals are, the more precise the GC calculation is. If mode of given intervals' lengths is short  $\left(\leq 100 \text{ bps long}\right)$ , GLANET calculates GC content of the given intervals at one base resolution and stores them in a byte list. Otherwise, GLANET stores GC contents of 100 bps, 1000 bps and 10000 bps long intervals in interval trees. When the mode is between ( $> 100$  and  $\leq 1000$ ) GLANET calculates GC content at 100 base resolution, if the mode is  $(>1000 \text{ and } < 10,000)$  GLANET calculates at 1000 base resolution. For cases between  $(> 10,000 \text{ and } \leq 100,000)$  at 10,000 base resolution and when mode gets longer than  $(100,000 \text{ bps})$ then GLANET does not calculate GC content for intervals longer than (100, 000 bps) but only for intervals shorter than (100, 000 bps) at 10, 000 base resolution. Mappabilities of genomic intervals are obtained from ENCODE, the source files are listed in Supplementary Table 2. A query interval can be part of a single interval or overlap with multiple intervals with different mappability values as provided in the original source. In either case, its mappability is estimated by calculating the weighted average, where the weights are the proportions of the query interval lengths that overlap with the source mappability interval.

GLANET also offers matching isochore family of the given interval: The genome is divided into five regions that are characterized by similar GC content composition. These regions are called isochores and are named as L1, L2, H1, H2, and H3 in accordance with increasing GC levels, <38%, 38–42%, 42–47%, 47–52%, >52%, respectively as defined in [\[1,](#page-35-0) [2\]](#page-35-1). Finally, each chromosome is divided into 100, 000 bps long intervals and each such interval is tagged with its appropriate isochore family. When  $\bf{wIF}$  option is selected, initially, input interval's isochore family is calculated and a random interval of 100, 000 bps long is selected from the appropriate isochore family pool of that chromosome. Subsequently, a random interval of input interval's length is sampled from this 100, 000 bps long interval.

Algorithm 1: Generating a random sample for a given set of genomic intervals.

```
1 Function: Generate Random Genomic Intervals (S, wGC, wM, wGCM, wIF);Input : S: Set of n input intervals.
             wIF: If true, isochore family pools will be used in random interval generation.
             t_M: Threshold to match mappability within this value.
             t_{GC}: Threshold to match GC content within this value.
             t_{Value}: Stands for t_M or t_{GC}.
             LMAX: Maximum interval length GC and mappability will be accounted for (Default is 100,000 bps).
2 for each chromosome chr<sub>i</sub> do
      S_i \leftarrowsubset of intervals in S that are on chr<sub>i</sub>
      if S_i \neq \emptyset then
          for each sampling b in \{1, \ldots, B\} do
              S_i^{(b)} \leftarrow \emptysetfor each given interval g in S_i do
                  gLen \leftarrow length(g)if qLen \leq LMAX then
                      if wGCM then
                          gGC \leftarrow calculateGC(g)gM \leftarrow calculateMappingibility(g)do
                             do
                                 if wIF then
                                     gIF \leftarrow findIsochoreFamily(g)r \leftarrow getAR and o mInterval (chr_i, gLen, gIF)else
                                     r \leftarrow getAR and omInterval(chr_i, gLen)end
                              while r overlaps with an already generated interval in S_i^{(b)};
                             rGC \leftarrow calculateGC(r)rM \leftarrow calculateMappingibility(r)while (|rGC - gGC| > t_{GC}) or (|rM - gM| > t_M);else
                         if wGC or wM then
                              qValue \leftarrow calculateGC(q) or calculateMapability(q)do
                                 do
                                     if wIF then
                                         gIF \leftarrow findIsochoreFamily(q)r \leftarrow getAR and omInterval(chr_i, gLen, gIF)else
                                         r \leftarrow getAR and omInterval(chr_i, gLen)end
                                  while r overlaps with an already generated interval in S_i^{(b)};
                                 rValue \leftarrow calculateGC(r) or calculateMapability(r)while \langle |rValue - qValue| > t_{Value} \rangle;
                          end
                     end
                  end
                  if qLen > LMAX or woGCM then
                     do
                          r \leftarrow getAR and omInterval(chr_i, gLen)while r overlaps with an already generated interval in S_i^{(b)};
                  end
                  S_i^{(b)} \leftarrow S_i^{(b)} \cup rend
          end
      end
3 end
```
# 3 GLANET Data Sources

Data sources are provided in Supplementary Table 2.



Supplementary Table 2. GLANET data sources and their download dates.

# 4 GLANET Library Representation

An interval tree is a red-black tree in which each node x stores the low and high endpoints,  $t_1$  and  $t_2$ , of an interval and an integer value max which is the maximum high endpoint stored in the subtree rooted at this node  $x$  [\[3\]](#page-35-2). On each node of the tree, we also store the genomic annotations associated with the interval stored on that node. For each element type in the annotation library, e.g., genomic elements representing all transcription factor binding regions across all cell lines, chromosome-specific interval trees are constructed (Supplementary Figure 1). Then, for annotation and enrichment analysis the appropriate interval trees are searched for query intervals using the interval tree search algorithm as described in [\[3\]](#page-35-2).



Supplementary Figure 1. Genomic intervals are represented in interval trees [\[3\]](#page-35-2). A separate interval tree is constructed for each chromosome and genomic element type, e.g. for transcription factor binding annotations. Each node contains the low and high endpoints of the genomic interval, the color of the node (red or black), the maximum high endpoint stored in the subtree rooted at this node and the genomic elements annotated with this particular genomic interval.

# 5 GLANET Regulatory Sequence Analysis

Specific to SNP inputs, GLANET offers regulatory sequence analysis (RSA). Regulatory sequence analysis takes advantage of the available ENCODE transcription factor binding regions in the default GLANET annotation library. This analysis can be conducted after an annotation analysis that involves transcription factor elements. GLANET performs regulatory sequence analysis in three main steps (depicted in Supplementary Figure 2):

In the first step, SNP and TF pairs for which SNP resides in the binding region of the TF are found. This is accomplished by overlapping the positions of the SNPs with transcription factor binding sites provided in the annotation library.

In the second step, GLANET generates three subsequences around the SNP site: reference, SNP and extended sequences. These sequences are used to statistically assess whether the SNP can alter the transcription factor binding. Reference and SNP sequences are 41 bps long and they are created by taking  $\pm 20$  bps upstream and downstream sequences around SNP locus. Extended sequence is obtained by taking ±200 bps upstream and downstream sequences around SNP locus and is used to check if the SNP site is actually the most likely binding site in the vicinity of the SNP.

In the third step, GLANET scans the subsequences for a matching motif site in each of the sequences (Reference, SNP, Extended) and evaluate the statistical significance of the match using RSAT [\[4\]](#page-35-3). For this, the position frequency matrices (PFMs) for the annotated TFs are obtained from Jaspar Core and Encode motifs [\[5,](#page-35-4) [6\]](#page-35-5). This step results with three *p*-values:  $p_{ref}$ ,  $p_{sup}$  and  $p_{extended}$ .



Supplementary Figure 2. Three main steps of regulatory sequence analysis in GLANET.

# 6 Data-driven Computational Experiments Results

In this section, we provide the results of data-driven computational experiments for all GLANET parameter settings under different experiment settings. Results for activator elements are displayed in Supplementary Figures 3-10 and results for repressor elements are listed in Supplementary Tables 3-6.

- Data-driven Computational Experiment Settings: We conduct experiments in two cell lines, GM12878 and K562, with expressed genes under Top5 and Top20 and non-expressed genes under CompletelyDiscard and TakeTheLongest settings. Type-I error and power are reported for each activator and repressor element for all GLANET parameter settings at significance levels of  $\alpha = 0.05$  and  $\alpha = 0.001$ .
- GLANET Parameter Settings: For each data-driven computational experiment setting, GLANET is run with all possible parameter combinations. We present data-driven computational experiment results for two different association measures: Existence of Overlap (EOO) and Number of Overlapping Bases (NOOB), for four different null distribution generation modes: with GC (wGC), with Mappability (wM), with GC and Mappability (wGCM) and without GC and Mappability (woGCM), and finally for two different isochore family options: with Isochore Family (wIF) and without Isochore Family (woIF).

#### 6.1 Data-driven Computational Experiments Results for Activator Elements

#### 6.1.1 K562 NonExpressed (CompletelyDiscard), Expressed (Top5),  $\alpha = 0.05$



Supplementary Figure 3. Assessment of GLANET Type-I error and power with data-driven computational experiments. Results for the two association statistics - existence of overlap (EOO) and the number of overlapping bases (NOOB) - together with - with GC (wGC), with Mappability (wM), with GC and Mappability (wGCM), and without GC and mappability (woGCM) null distribution generation modes are displayed. Histone marks with ambiguous activator roles are marked with ∗. (a, b) Type-I error and power estimated with Isochore Family (wIF) heuristic using K562, (Nonexpressed Genes,CompletelyDiscard) and (Expressed Genes,Top5) results, for significance level of 0.05. (c, d) Type-I error and power estimated without Isochore Family (woIF) heuristic using K562, (Non-expressed Genes,CompletelyDiscard) and (Expressed Genes,Top5) results, for significance level of 0.05.



Supplementary Figure 4. Assessment of GLANET Type-I error and power with data-driven computational experiments. Results for the two association statistics - existence of overlap (EOO) and the number of overlapping bases (NOOB) - together with - with GC (wGC), with Mappability (wM), with GC and Mappability (wGCM), and without GC and mappability (woGCM) null distribution generation modes are displayed. Histone marks with ambiguous activator roles are marked with ∗. (a, b) Type-I error and power estimated with Isochore Family (wIF) heuristic using K562, (Non-expressed Genes,TakeTheLongest) and (Expressed Genes,Top20) results, for significance level of 0.05. (c, d) Type-I error and power estimated without Isochore Family (woIF) heuristic using K562, (Non-expressed Genes,TakeTheLongest) and (Expressed Genes,Top20) results, for significance level of 0.05.



Supplementary Figure 5. Assessment of GLANET Type-I error and power with data-driven computational experiments. Results for the two association statistics - existence of overlap (EOO) and the number of overlapping bases (NOOB) - together with - with GC (wGC), with Mappability (wM), with GC and Mappability (wGCM), and without GC and mappability (woGCM) null distribution generation modes are displayed. Histone marks with ambiguous activator roles are marked with ∗. (a, b) Type-I error and power estimated with Isochore Family (wIF) heuristic using K562, (Non-expressed Genes,CompletelyDiscard) and (Expressed Genes,Top5) results, for significance level of 0.001. (c, d) Type-I error and power estimated without Isochore Family (woIF) heuristic using K562, (Non-expressed Genes,CompletelyDiscard) and (Expressed Genes,Top5) results, for significance level of 0.001.



Supplementary Figure 6. Assessment of GLANET Type-I error and power with data-driven computational experiments. Results for the two association statistics - existence of overlap (EOO) and the number of overlapping bases (NOOB) - together with - with GC (wGC), with Mappability (wM), with GC and Mappability (wGCM), and without GC and mappability (woGCM) null distribution generation modes are displayed. Histone marks with ambiguous activator roles are marked with ∗. (a, b) Type-I error and power estimated with Isochore Family (wIF) heuristic using K562, (Non-expressed Genes,TakeTheLongest) and (Expressed Genes,Top20) results, for significance level of 0.001. (c, d) Type-I error and power estimated without Isochore Family (woIF) heuristic using K562, (Non-expressed Genes,TakeTheLongest) and (Expressed Genes,Top20) results, for significance level of 0.001.



Supplementary Figure 7. Assessment of GLANET Type-I error rate and statistical power with data-driven computational experiments. Results for the two association statistics - existence of overlap (EOO) and the number of overlapping bases (NOOB) - together with GC (wGC), with Mappability (wM), with GC and Mappability (wGCM), and without GC and mappability (woGCM) null distribution generation modes are displayed. Histone marks with ambiguous activator roles are marked with ∗. (a, b) Type-I error and power estimated with Isochore Family (wIF) heuristic using GM12878, (Non-expressed Genes,CompletelyDiscard) and (Expressed Genes,Top5) results, for significance level of 0.05. (c, d) Type-I error and power estimated without Isochore Family (woIF) heuristic using GM12878, (Non-expressed Genes,CompletelyDiscard) and (Expressed Genes,Top5) results, for significance level of 0.05.



Supplementary Figure 8. Assessment of GLANET Type-I error and power with data-driven computational experiments. Results for the two association statistics - existence of overlap (EOO) and the number of overlapping bases (NOOB) - together with - with GC (wGC), with Mappability (wM), with GC and Mappability (wGCM), and without GC and mappability (woGCM) null distribution generation modes are displayed. Histone marks with ambiguous activator roles are marked with ∗. (a, b) Type-I error and power estimated with Isochore Family (wIF) heuristic using GM12878, (Non-expressed Genes,TakeTheLongest) and (Expressed Genes,Top20) results, for significance level of 0.05. (c, d) Type-I error and power estimated without Isochore Family (woIF) heuristic using GM12878, (Non-expressed Genes,TakeTheLongest) and (Expressed Genes,Top20) results, for significance level of 0.05.



Supplementary Figure 9. Assessment of GLANET Type-I error and power with data-driven computational experiments. Results for the two association statistics - existence of overlap (EOO) and the number of overlapping bases (NOOB) - together with - with GC (wGC), with Mappability (wM), with GC and Mappability (wGCM), and without GC and mappability (woGCM) null distribution generation modes are displayed. Histone marks with ambiguous activator roles are marked with ∗. (a, b) Type-I error and power estimated with Isochore Family (wIF) heuristic using GM12878, (Non-expressed Genes,CompletelyDiscard) and (Expressed Genes,Top5) results, for significance level of 0.001. (c, d) Type-I error and power estimated without Isochore Family (woIF) heuristic using GM12878, (Non-expressed Genes,CompletelyDiscard) and (Expressed Genes,Top5) results, for significance level of 0.001.



Supplementary Figure 10. Assessment of GLANET Type-I error and power with data-driven computational experiments. Results for the two association statistics - existence of overlap (EOO) and the number of overlapping bases (NOOB) - together with - with GC (wGC), with Mappability (wM), with GC and Mappability (wGCM), and without GC and mappability (woGCM) null distribution generation modes are displayed. Histone marks with ambiguous activator roles are marked with ∗. (a, b) Type-I error and power estimated with Isochore Family (wIF) heuristic using GM12878, (Non-expressed Genes,TakeTheLongest) and (Expressed Genes,Top20) results, for significance level of 0.001. (c, d) Type-I error and power estimated without Isochore Family (woIF) heuristic using GM12878, (Non-expressed Genes,TakeTheLongest) and (Expressed Genes,Top20) results, for significance level of 0.001.

#### 6.2 Data-driven Computational Experiments Results for Repressor Elements

			Type-I Error, $\alpha = 0.05$							
			wIF				woIF			
	<b>Expressed Genes</b>		WGC	wM	wGCM	woGCM	WGC	wM	wGCM	woGCM
	Top <sub>5</sub>	EOO	$\Omega$	$\Omega$	$\Omega$	$\Omega$	$\Omega$	$\Omega$	$\Omega$	$\Omega$
H3K27me3	Top20	EOO	0.001	$\Omega$	$\theta$	0.001	0.002	0.001	$\Omega$	0.006
GM12878	Top <sub>5</sub>	<b>NOOB</b>	$\Omega$	$\Omega$	$\theta$	$\Omega$	$\Omega$	$\theta$	$\theta$	$\Omega$
	Top20	<b>NOOB</b>	$\Omega$	$\Omega$	$\theta$	0.001	0.001	0.001	$\Omega$	0.008
	Top5	<b>EOO</b>	$\Omega$	$\Omega$	$\Omega$	$\theta$	$\Omega$	$\theta$	$\Omega$	$\Omega$
H3K27me3	Top20	<b>EOO</b>	$\Omega$	$\Omega$	$\theta$	$\theta$	$\Omega$	$\theta$	$\theta$	$\Omega$
K562	$\overline{\text{Top5}}$	<b>NOOB</b>	$\Omega$	$\Omega$	$\theta$	$\theta$	$\theta$	$\theta$	$\theta$	$\Omega$
	Top20	<b>NOOB</b>	$\Omega$	$\Omega$	$\theta$	$\theta$	$\theta$	$\theta$	$\theta$	$\theta$
	$\overline{\text{Top5}}$	<b>EOO</b>	$\Omega$	$\theta$	$\Omega$	$\overline{0}$	$\theta$	$\theta$	$\theta$	$\theta$
H3K9me3	Top20	<b>EOO</b>	$\Omega$	$\Omega$	$\theta$	$\theta$	$\Omega$	$\theta$	$\theta$	$\Omega$
GM12878	Top5	<b>NOOB</b>	$\Omega$	$\Omega$	$\Omega$	$\theta$	$\Omega$	$\theta$	$\Omega$	$\Omega$
	Top20	<b>NOOB</b>	$\Omega$	$\Omega$	$\theta$	$\theta$	$\theta$	$\theta$	$\Omega$	$\Omega$
	$\overline{\text{Top5}}$	<b>EOO</b>	$\Omega$	$\Omega$	$\Omega$	$\Omega$	$\Omega$	$\theta$	$\Omega$	$\Omega$
H3K9me3	$\overline{\text{Top}}20$	<b>EOO</b>	0.079	0.051	0.052	0.083	0.103	0.081	0.066	0.126
K562	$\overline{\text{Top5}}$	<b>NOOB</b>	$\Omega$	$\Omega$	$\Omega$	$\Omega$	$\Omega$	$\Omega$	$\Omega$	$\Omega$
	$\text{Top}20$	<b>NOOB</b>	0.042	0.023	0.025	0.041	0.06	0.039	0.035	0.085

Supplementary Table 3. Type-I error rates calculated in data-driven experiments conducted with repressor elements, H3K27me3 and H3K9me3, in GM12878 and K562 cell lines for  $\alpha = 0.05$ .



Supplementary Table 4. Type-I error rates calculated in data-driven experiments conducted with repressor elements, H3K27me3 and H3K9me3, in GM12878 and K562 cell lines for  $\alpha = 0.001$ .



Supplementary Table 5. Power calculated in data-driven experiments conducted with repressor elements, H3K27me3 and H3K9me3, in GM12878 and K562 cell lines for  $\alpha=0.05.$ 



Supplementary Table 6. Power calculated in data-driven experiments conducted with repressor elements, H3K27me3 and H3K9me3, in GM12878 and K562 cell lines for  $\alpha = 0.001$ .

# 7 Assessing best GLANET parameter settings through Data-driven Computational Experiments Results



Supplementary Figure 11. Violin plots for (a) GC of randomly sampled intervals from human genome, GC of intervals of K562 non-expressed genes and expressed genes. (b) Mappability of randomly sampled intervals from human genome, mappability of intervals from non-expressed and expressed gene-sets of K562.

Kolmogorov-Smirnov Test Results						
<b>Property</b>	<b>Interval Set</b>	Maximum				
		<b>Distance</b>				
GC	Non-expressed $(\overline{\text{GM12878}})$	0.1454				
GC	Expressed (GM12878)	0.1462				
GC	Non-expressed (K562)	0.1241				
GC	Expressed (K562)	0.1897				
Mappability	Non-expressed (GM12878)	0.0794				
Mappability	Expressed $\overline{\text{GM12878}}$	0.1693				
Mappability	Non-expressed (K562)	0.0898				
Mappability	Expressed (K562)	0.1585				

Supplementary Table 7. Kolmogorov-Smirnov test results. Null hypothesis states that the distribution of GC content or mappability values calculated for 50, 000 randomly sampled intervals from human genome and the corresponding interval set are not different. Each row corresponds to Kolmogorov-Smirnov testing of this null hypothesis. In all tests, the null hypothesis is rejected  $(p-value < 2.2e-16)$ . The first column lists the property of the genome in question, the second column lists the distribution that is compared with the genome, finally the last column lists the maximum distance between the two distributions.

## 8 Wilcoxon Signed Rank Test Results

To assess the different parameter settings, we carried out one-sided paired Wilcoxon signed rank tests and we compared the distribution of Type-I errors generated under these different parameters. The null states there is no difference in the mean of the ranks of the two distributions whereas alternative hypothesis is that the first distribution has lower mean of ranks than the second one.

The distribution generated under the GLANET parameter setting specified in the row is tested against the Type I error distribution generated under the parameter setting specified in the column. A p-value less than or equal to the value in the cell indicates that setting in the corresponding row has a lower mean of ranks in Type-I error distribution than the setting in the corresponding column.

We pooled the Type-I errors of parameter setting results to compare wIF and woIF. Results indicate wIF achieves lower Type-I errors than woIF (Supplementary Table 8). Similarly, we pooled simulation results to compare NOOB with **EOO**, we observed that **NOOB** provides lower Type-I errors than **EOO** (Supplementary Table 9).



Supplementary Table 8. Wilcoxon Signed Rank test results that compares Type I error distribution of all simulations generated under (woIF) setting against the Type-I errors generated under (wIF) setting. A  $p$ -value less than or equal to the value in the cell indicates that setting in the corresponding row has a lower mean of ranks in Type-I error distribution than the setting in the corresponding column.



Supplementary Table 9. Wilcoxon Signed Rank test results that compares Type I error distribution of all simulations generated under (EOO) setting against the Type-I errors generated under (NOOB) setting. A p-value less than or equal to the value in the cell indicates that setting in the corresponding row has a lower mean of ranks in Type-I error distribution than the setting in the corresponding column.

# 9 ROC Curves for Assessing GLANET's Different Parameter Settings and GAT's Performance

To compare quantitatively how GLANET parameters affect the enrichment performance, we also analyzed ROC curves. To compare GLANET's performance with GAT, we also include GAT results in the ROC curves. To plot a single ROC curve per an element in cell line, simulation results that are conducted under the same parameter setting for expressed and non-expressed genes are combined. While drawing element-based ROC curves, we label each activator element as "enriched" in expressed gene scenario and "not enriched" in non-expressed genes scenarios. Similarly, the true label for each repressor element as "not-enriched" and "enriched" under expressed and non-expressed genes simulations, respectively.

We compared the difference in AUC of two ROC curves with each other using pROC R package [\[7\]](#page-35-6). We utilized "delong" method and count the number of wins, ties and losses. A win is registered whenever the first ROC curve is found to be higher than the second tested ROC curve at 0.05 significance level. A lose registers the reverse scenario; the first curve is found to be below the second one, and a tie indicates that there is no statistically significant difference between the two compared curves. We accumulate the number of wins, ties and losses across different histone modification elements and POL2 and cell line to summarize the results. The results are summarized in Supplementary Tables 10-17.



Supplementary Table 10. ROC curves of different parameter settings where (EOO,woIF) setting is on are compared. A Win indicates a case where the ROC curve obtained with settings specified in the row is statistically significantly above the ROC curve obtained with the settings specified in the column at significance level 0.05. A lose indicates the opposite, while a tie indicates that there is no statistically significant difference between the two compared curves. The counts indicate the number of times win/tie/lose cases occur when the results for different elements, cell lines and other experimental conditions are compared.



Supplementary Table 11. ROC curves of different parameter settings where (E00,wIF) setting is on are compared. A Win indicates a case where the ROC curve obtained with settings specified in the row is statistically significantly above the ROC curve obtained with the settings specified in the column at significance level 0.05. A lose indicates the opposite, while a tie indicates that there is no statistically significant difference between the two compared curves. The counts indicate the number of times win/tie/lose cases occur when the results for different elements, cell lines and other experimental conditions are compared.



Supplementary Table 12. ROC curves of different parameter settings where (NOOB,woIF) setting is on are compared. A Win indicates a case where the ROC curve obtained with settings specified in the row is statistically significantly above the ROC curve obtained with the settings specified in the column at significance level 0.05. A lose indicates the opposite, while a tie indicates that there is no statistically significant difference between the two compared curves. The counts indicate the number of times win/tie/lose cases occur when the results for different elements, cell lines and other experimental conditions are compared.



Supplementary Table 13. ROC curves of different parameter settings where (NOOB, wIF) setting is on are compared. A Win indicates a case where the ROC curve obtained with settings specified in the row is statistically significantly above the ROC curve obtained with the settings specified in the column at significance level 0.05. A lose indicates the opposite, while a tie indicates that there is no statistically significant difference between the two compared curves. The counts indicate the number of times win/tie/lose cases occur when the results for different elements, cell lines and other experimental conditions are compared.



Supplementary Table 14. Winner settings from Supplementary Tables 10-13 are compared with each other. A Win indicates a case where the ROC curve obtained with settings specified in the row is statistically significantly above the ROC curve obtained with the settings specified in the column at significance level 0.05. A lose indicates the opposite, while a tie indicates that there is no statistically significant difference between the two compared curves. The counts indicate the number of times win/tie/lose cases occur when the results for different elements, cell lines and other experimental conditions are compared.



Supplementary Table 15. ROC curves of different parameter settings where (woIF) setting is on are compared. A Win indicates a case where the ROC curve obtained with settings specified in the row is statistically significantly above the ROC curve obtained with the settings specified in the column at significance level 0.05. A lose indicates the opposite, while a tie indicates that there is no statistically significant difference between the two compared curves. The counts indicate the number of times win/tie/lose cases occur when the results for different elements, cell lines and other experimental conditions are compared.



Supplementary Table 16. ROC curves of different parameter settings where (wIF) setting is on are compared. A Win indicates a case where the ROC curve obtained with settings specified in the row is statistically significantly above the ROC curve obtained with the settings specified in the column at significance level 0.05. A lose indicates the opposite, while a tie indicates that there is no statistically significant difference between the two compared curves. The counts indicate the number of times win/tie/lose cases occur when the results for different elements, cell lines and other experimental conditions are compared.

All Pooles	GAT (woGCM)	<b>GLANET</b> (woGCM)	<b>GLANET</b> (wGC)	<b>GLANET</b> $(\text{wM})$	<b>GLANET</b> (wGCM)	-ot Wins	of Ties	Number Number Number Ωf Losses
GAT(woGCM)	0/0/0	9/167/24	13/157/30	13/155/32	15/154/31	50	633	117
GLANET(woGCM)	24/167/9	0/0/0	17/164/19	17/160/23	17/160/23	75	651	74
GLANET(wGC)	30/157/13	19/164/17	0/0/0	17/167/16	19/165/16	85	653	62
GLANET(wM)	32/155/13	23/160/17	16/167/17	0/0/0	17/173/10	88	655	57
GLANET(wGCM)	31/154/15	23/160/17	16/165/19	10/173/17	0/0/0	80	652	68

Supplementary Table 17. ROC curves of different "Generate Random Data Options" are compared. A Win indicates a case where the ROC curve obtained with settings specified in the row is statistically significantly above the ROC curve obtained with the settings specified in the column at significance level 0.05. A lose indicates the opposite, while a tie indicates that there is no statistically significant difference between the two compared curves. The counts indicate the number of times win/tie/lose cases occur when the results for different elements, cell lines and other experimental conditions are compared.

#### 10 GLANET GAT Comparison

- 10.1 GLANET GAT Comparison Results for Activator and Repressor Elements through Data-driven Computational Experiments
- 10.1.1 NonExpressed (CompletelyDiscard), Expressed (Top5),  $\alpha = 0.05$



Supplementary Figure 12. Comparison of GLANET and GAT with respect to data-driven computational experiments in terms of Type-I Error and Power for significance level of 0.05. GLANET(wIF, wGC) and GAT(wIF) parameter settings results are used. Results for the two association statistics - existence of overlap (EOO) and the number of overlapping bases (NOOB) are displayed. (a, b) Type-I error and power of activator elements in (Non-expressed Genes,CompletelyDiscard) and (Expressed Genes,Top5) experiment settings, respectively. GLANET attains lower Type-I error for H3K4me1 and higher power for H3K36me3 and H4K20me1 elements than GAT. (c, d) Type-I error and power of repressor elements in (Expressed Genes,Top5) and (Non-expressed Genes,CompletelyDiscard) experiment settings, respectively. GLANET achieves higher power for H3K9me3 than GAT.



Supplementary Figure 13. Comparison of GLANET and GAT with respect to data-driven computational experiments in terms of Type-I Error and Power for significance level of 0.05. GLANET(wIF, wGC) and GAT(wIF) parameter settings results are used. Results for the two association statistics - existence of overlap (EOO) and the number of overlapping bases (NOOB) are displayed. (a, b) Type-I error and power of activator elements in (Non-expressed Genes,TakeTheLongest) and (Expressed Genes,Top20) experiment settings, respectively. (c, d) Type-I error and power of repressor elements in (Expressed Genes,Top20) and (Non-expressed Genes,TakeTheLongest) experiment settings, respectively.



Supplementary Figure 14. Comparison of GLANET and GAT with respect to data-driven computational experiments in terms of Type-I Error and Power for significance level of 0.001. GLANET(wIF, wGC) and GAT(wIF) parameter settings results are used. Results for the two association statistics - existence of overlap (EOO) and the number of overlapping bases (NOOB) are displayed. (a, b) Type-I error and power of activator elements in (Non-expressed Genes,CompletelyDiscard) and (Expressed Genes,Top5) experiment settings, respectively. (c, d) Type-I error and power of repressor elements in (Expressed Genes,Top5) and (Non-expressed Genes,CompletelyDiscard) experiment settings, respectively.



Supplementary Figure 15. Comparison of GLANET and GAT with respect to data-driven computational experiments in terms of Type-I Error and Power for significance level of 0.001. GLANET(wIF, wGC) and GAT(wIF) parameter settings results are used. Results for the two association statistics - existence of overlap (EOO) and the number of overlapping bases (NOOB) are displayed. (a, b) Type-I error and power of activator elements in (Non-expressed Genes,TakeTheLongest) and (Expressed Genes,Top20) experiment settings, respectively. (c, d) Type-I error and power of repressor elements in (Expressed Genes,Top20) and (Non-expressed Genes,TakeTheLongest) experiment settings, respectively.

#### 10.2 Results for Additional GAT Experiments

We repeated the experiments provided in the GAT supplementary website [\[8\]](#page-35-7) with GLANET. The detailed results for these additional experiments are provided in Supplementary Tables 18-21. Results for GAT runs are obtained from the GAT tutorial (<http://gat.readthedocs.org/en/latest/tutorialIntervalOverlap.html>). For each experiment, GLANET results are computed in sixteen different parameter settings. GLANET is run with different modes of random data generation (wGC,wM,wGCM,woGCM), isochore family (woIF,wIF) and association measure (EOO,NOOB). In each of the Supplementary Tables 18-21, Observed column shows the association measure value calculated between the given sets, set1 and set2. Expected and StdDev columns show the mean and standard deviation of association measure values of samplings, respectively. Fold change is one plus Observed divided by one plus Expected. Enrichment result is provided by the p-value column.



Supplementary Table 18. Experiment1: Intervals of transcriptor factor Srf in Jurkat cell line are overlapped with DNaseI hypersensitive sites in Jurkat cell line. Both GAT and GLANET find enrichment of DNaseI(Jurkat) for Srf(Jurkat).



Supplementary Table 19. Experiment2: Intervals of transcriptor factor Srf in Jurkat cell line are overlapped with DNaseI hypersensitive sites in HepG2 cell line. Both GAT and GLANET find enrichment of DNaseI(HepG2) for Srf(Jurkat).

Experiment3 Set1: DNaseI(HepG2) Set2: DNaseI(Jurkat)									
Tool	<b>Parameter Settings</b>	<b>Observed</b>	Expected	<b>StdDev</b>	FoldChange	pValue			
GAT	$(NOOB, \overline{w}GCM, \overline{w}oIF)$	6163503	456928.2770	8119.7800	13.4890	$1.0e-03$			
<b>GLANET</b>	EOO, wGC, woIF	37863	4486.2310	63.3604	8.4381	$\Omega$			
<b>GLANET</b>	EOO, wM, woIF	37863	4729.1280	62.8720	8.0048	$\Omega$			
<b>GLANET</b>	EOO, wGCM, woIF	37863	4980.2900	63.7331	7.6012	$\Omega$			
<b>GLANET</b>	EOO,woGCM,woIF)	37863	4021.9370	61.3296	9.4120	$\theta$			
<b>GLANET</b>	EOO, wGC, wIF)	37863	4779.9930	62.7600	7.9196	$\Omega$			
<b>GLANET</b>	EOO, wM, wIF	37863	5330.1410	66.3065	7.1024	$\theta$			
<b>GLANET</b>	EOO, wGCM, wIF	37863	5304.6820	67.4277	7.1365	$\overline{0}$			
<b>GLANET</b>	$(EOO, \text{woGCM}, \text{wIF})$	37863	4679.8590	62.3539	8.0891	$\theta$			
<b>GLANET</b>	(NOOB, wGC, woIF)	6163503	514669.0700	8361.7736	11.9756	$\Omega$			
<b>GLANET</b>	(NOOB, wM, woIF)	6163503	542634.9810	8866.3420	11.3584	$\theta$			
<b>GLANET</b>	(NOOB, wGCM, wolF)	6163503	577794.1580	9186.0057	10.6672	$\Omega$			
<b>GLANET</b>	(NOOB, woGCM, wolF)	6163503	457457.8130	7800.8096	13.4733	$\Omega$			
<b>GLANET</b>	(NOOB, wGC, wIF)	6163503	548311.7080	8391.4861	11.2408	$\Omega$			
<b>GLANET</b>	(NOOB, wM, wIF)	6163503	616187.0040	9160.8373	10.0026	$\Omega$			
<b>GLANET</b>	(NOOB, wGCM, wIF)	6163503	614923.7840	8718.6997	10.0231	$\theta$			
<b>GLANET</b>	(NOOB, woGCM, wIF)	6163503	536616.5930	8472.0299	11.4858	$\theta$			

Supplementary Table 20. Experiment3: DNaseI hypersensitive sites in HepG2 cell line are overlapped with DNaseI hypersensitive sites in Jurkat cell line. Both GAT and GLANET find enrichment of DNaseI(Jurkat) for DNaseI(HepG2).



Supplementary Table 21. Experiment4: Intervals of transcriptor factor Srf in Jurkat cell line are overlapped with DNaseI hypersensitive sites in HepG2-Unique cell line. Both GAT and GLANET find no enrichment of DNaseI(HepG2- Unique) for Srf(Jurkat).

Here, we provide command line arguments for one of the GLANET runs of Experiment1 in Supplementary Table 18. The input is the genomic intervals of Srf in Jurkat cell line and annotation/enrichment is conducted with respect to DNaseI hypersensitive sites of Jurkat cell line using GLANET's user-defined library feature. The enrichment analysis is conducted with 10,000 samplings. In this run, GLANET parameter setting is as follows,  $(NOOB, wGCM, wIF)$ . This run took 5 minutes on Intel(R) Core i7-3630QM CPU, 2.40 GHz with 16GB RAM.

```
java -Xms8G -Xmx8G -jar "path/to/GLANET.jar" -c -g "path/to/GLANET Folder/" -i
"path/to/GLANET Folder/Data/demo_input_data/GAT_Comparison_Data/srf.hg19.bed"
-fbed -udl -udldf0exc -udlinput
"path/to/GLANET Folder/Data/demo_input_data/GAT_Comparison_Data/GAT_UDL_InputFile_jurkat.txt"
-e -noob -wgcm -wif -s 10000 -se 10000 -l -j "GLANET_SRF_JURKAT_NOOB_wGCM_wIF"
```
We supply another command line arguments for one of the GLANET runs of Experiment3 in Supplementary Table 20. The input is the genomic intervals of DNaseI hypersensitive sites of HepG2 cell line and annotation/enrichment is conducted with respect to DNaseI hypersensitive sites of Jurkat cell line using GLANET's user-defined library feature. The enrichment analysis is conducted with 1000 samplings. In this run, GLANET parameter setting is as follows, (EOO,wM,woIF). This run took 7 minutes on Intel(R) Core i7-3630QM CPU, 2.40 GHz with 16GB RAM.

java -Xms16G -Xmx16G -jar "path/to/GLANET.jar" -c -g "path/to/GLANET Folder/" -i "path/to/GLANET Folder/Data/demo\_input\_data/GAT\_Comparison\_Data/hepg2.hg19.dhs.bed" -fbed -udl -udldf0exc -udlinput "path/to/GLANET Folder/Data/demo\_input\_data/GAT\_Comparison\_Data/GAT\_UDL\_InputFile\_jurkat.txt" -e -eoo -wm -woif -s 1000 -se 1000 -l -j "GLANET\_HEPG2\_JURKAT\_EOO\_wM\_woIF"

# 11 GLANET Runtime Comparison

We compare GLANET against GAT and GREAT with respect to run-time. GLANET and GAT are compared based on genomic interval enrichment, as GAT does not offer gene set enrichment. GREAT comparisons were on the basis of gene set enrichment, as GREAT only offers enrichment based on annotations of nearby genes. All GAT and GLANET run were run on the following system configuration: CPU: Intel(R) Xeon(R) CPU E7-4850 v3 @ 2.20GHz CPU. Memory: 1TB. Operating system: Ubuntu 16.04.2 LTS.

#### 11.1 Comparison with GAT

We compare GAT and GLANET in two different experimental settings. For the first comparison setting, we used the genomic intervals randomly selected from promoter regions of non-expressing genes in GM12878 cell line as input. We conducted two different experiments with this input. In the first one the enrichment analysis of two different genomic element sets, in the first one the entire ENCODE transcription factor and histone modification elements in various cell lines were included (568 files). In the second analysis only the subset of ENCODE elements are checked, these included the 12 histone modification elements and POL2 in cell line GM12878 that are used in the data driven experiment as described in manuscript Section 2.7 (13 files). It's worth noticing that increasing the library size did not increase the runtime that much. We varied the number of intervals and the number of samplings. The resulting runtimes are provided in Supplementary Table 22.



Supplementary Table 22. Elapsed CPU times (in seconds) for GLANET and GAT runs for a given input query are provided. Input intervals are randomly selected sets from the promoter regions of non-expressing genes in GM12878 cell line from (Non-Expressing,CompletelyDiscard), where each interval is 601 bps long. All ENCODE checks the enrichment of all ENCODE elements in the GLANET library which encompass histone modifications, transcription factor sites, and DNase I hypersensitive sites for all cell lines. ENCODE subset only include 12 histone modifications and POL2 as described in Section 2.6 of the main manuscript. Both GLANET and GAT are run under the parameter setting (NOOB,wIF,woGCM). Results for 1,000 and 10,000 samplings are averaged over 10 runs. For 100,000 samplings, each run time in the table denotes the average run-time from 5 individual runs.



Supplementary Table 23. CPU time in seconds spent for GLANET and GAT runs given the input query specified. For 1,000 and 10,000 samplings, run time is the average of 10 runs. For 100,000 samplings, each run time shows the average run-time from 5 individual runs.

In the second comparison setting, we used data provided in GAT readthedocs web page as described in the Section 3.3 of the manuscript. Srf(Jurkat) is the transcription binding sites of 556 intervals each 51 bps long from Jurkat cell line.

DNaseI(Jurkat) and DNaseI(HepG2) comprised of DNaseI hypersensitive sites in Jurkat and HepG2 cell line, respectively. DNaseI(HepG2Unique) consists of DNaseI hypersensitive sites in HepG2 but not in Jurkat cell line. For your information, DNaseI(Jurkat) have 159,613 intervals each 151 bps long. DNaseI(HepG2) have 144,171 intervals of average 360 bps long. DNaseI(HepG2Unique) have 106,308 intervals of average 275 bps long. The results are listed in Supplementary Table 23.

All the running time results for GLANET and GAT are shown in terms of CPU time in seconds. This is the actual time that one CPU would need to complete its process. Thus, these running times are the sum of the times taken in each thread for a run if multithreading is available (time command in Unix). Since GLANET is a multi-threaded java application, as the same runs are conducted with a larger number of threads, the elapsed time for an individual run would decrease accordingly. During these runs, GLANET and GAT 16GB of memory is reserved, except for DNaseI(Hepg2)-DNaseI(Jurkat) runs of 100,000 samplings, GLANET required 64GB of memory.

#### 11.2 Comparison with GREAT



Supplementary Table 24. CPU time in seconds spent for GLANET runs given the input query specified. For 1,000 and 10,000 samplings, each run time is the average of 10 individual runs.

We compared GREAT on the basis of GO term gene set enrichment. The input was GATA2 transcription bindings sites in K562 cell line and their enrichment is checked against gene sets derived from GO terms as described in Section 3.4.3 in the main text. The input included 7407 intervals of average 256 bps long. Supplementary Table 24 includes the results. GREAT is not available as a stand-alone command line application, thus, the results are obtained from the online web service. Nevertheless, when run on from the server, GREAT was very fast, it completed one analysis in less than 1 minute, as its enrichment procedure does not do include sampling but instead assumes a parametric distribution. Since we do not know how each GREAT run is parallelized in their server, we do not know the actual CPU hour. Therefore, it is not possible for us to compare the running times in terms of CPU hours and we do not have information on the actual memory used for the GREAT analysis.

### 12 Enrichment Analysis of OCD GWAS SNPs

The GLANET command line arguments to replicate GLANET run for OCD GWAS SNPs is provided below. Input query is the set of SNPs found to be associated with OCD. These SNPs are overlapped with the intervals in default annotation library of GLANET. The enrichment analysis included 10, 000 samplings and were conducted with respect to the GLANET default annotation library that included all ENCODE data (DNaseI hypersensitive sites, transcription factor binding sites and histone modification sites in all cell lines), RefSeq Genes, KEGG pathways, joint TF KEGG pathways (cell line pooled). The complete analysis took 19 minutes on Intel(R) Core i7-3630QM CPU, 2.40 GHz with 16GB RAM.

```
java -Xms16G -Xmx16G jar "path/to/GLANET.jar" -c -g "path/to/GLANET Folder/"
-i "path/to/GLANET Folder/Data/demo_input_data/OCD_GWAS_chrNumber_1Based_GRCh37_p13_Coordinates.txt"
-f1 -dnase -histone -tf -gene -kegg -tfkegg
-e -noob -wgcm -wif -s 10000 -se 10000 -l -j "GLANET_OCD_GWAS_SNPs_NOOB_wGCM_wIF"
```
## 13 Regulatory Sequence Analysis of OCD GWAS SNPs

For a transcription factor, there can be more than one position frequency matrices (PFMs) available. We scan the sequences with all of the PFMs of that TF. RSAT returns the subsequence that achieves the smallest  $p$ -value along with the PFM that leads to that p-value.

RSAT's best matching motif might not contain the SNP locus. If that is the case, GLANET finds the subsequence containing the SNP with the smallest p-value among the remaining results. Therefore, as it can be seen in the provided RSA results of rs1891215 (STAT1) and rs10946279 (MAX), we have two results line for each sequence. RSA results of STAT1 and MAX are shown in Supplementary Table 25 and 26.



Supplementary Table 25. Regulatory sequence analysis result for rs1891215 and transcription factor, STAT1. For each of the subsequences, the best matching motif site is provided together with the position frequency matrix that leads to that result and the source of the matrix. The direction column indicates whether the match is within the forward (D) or the reverse (R) strand. rs1891215 is an enhancer SNP for transcription factor STAT1 because nucleotide change at SNP locus, from A to G increases STAT1's binding affinity.  $p_{snp}$  is 6.10e-05 while  $p_{ref}$  is 1.10e-03. Last column lists  $\log(p_{ref}/p_{snp})$  value where  $p_{ref}$  is the p-value of reference sequence containing SNP position and  $p_{snp}$  is the p-value of the match for the altered SNP sequence containing SNP position.



Supplementary Table 26. Regulatory sequence analysis result for rs10946279 and transcription factor, MAX. For each of the subsequences, the best matching motif site is provided together with the position frequency matrix that lead to that result and the source of the matrix. The direction column indicates whether the match is within the forward (D) or reverse (R) strand. rs10946279 acts as a repressor SNP for transcription factor MAX, since nucleotide change at SNP locus, from C to T decreases the TF's binding affinity.  $p_{ref}$  is 6.10e-05 where as  $p_{snp}$  is 1.50e-03. Last column lists  $\log(p_{ref}/p_{snp})$  value where  $p_{ref}$  is the p-value of reference sequence containing SNP position and  $p_{snp}$  is the p-value of the match for the altered SNP sequence containing SNP position..

java -Xms4G -Xmx4G -jar "path/to/GLANET.jar" -c -g "path/to/GLANET Folder/" -i "path/to/GLANET Folder/Data/demo\_input\_data/OCD\_GWAS\_chrNumber\_1Based\_GRCh37\_p13\_Coordinates.txt" -f1 -tf -rsa -l -j "GLANET\_OCD\_GWAS\_SNPs\_RSA"

# 14 Analysis with User-Defined Gene Sets: Gene Ontology Enrichment Analysis for GATA2 Binding Regions

We ran GLANET with genomic intervals of GATA2 in K562 cell line as input query and loaded the GO terms in the library using the user-defined gene set feature of GLANET. Annotation and enrichment of the input with respect to the new library is conducted. The enrichment analysis is conducted with 10, 000 samplings. The analysis can be repeated with the with the command line arguments below:

```
java -Xms16G -Xmx16G -jar "path/to/GLANET.jar" -c -g "path/to/GLANET Folder/" -i
"path/to/GLANET Folder/Data/demo_input_data/RDA2/
spp.optimal.wgEncodeSydhTfbsK562bGata2UcdAlnRep0_VS_wgEncodeSydhTfbsK562bInputUcdAlnRep1.narrowPeak"
-fbed -udgs -udgsinput
"path/to/GLANET Folder/Data/demo_input_data/UserDefinedGeneSet/GO/GO_gene_associations_human_ref.txt"
-genesym -udgsname "GO" -udgsdfile
"path/to/GLANET Folder/Data/demo_input_data/UserDefinedGeneSet/GO/GO_ids2terms.txt"
-e -noob -wgcm -wif -s 10000 -se 1000 -l -j "GLANET_SydhGATA2K562_GoTerms_NOOB_wGCM_wIF"
```
## 15 Additional Supplementary Tables

Supplementary Table 27: OCD GWAS SNPs that overlap with genes of glutamatergic synapse pathway (hsa04724) in the regulation based analysis. The table lists the locations of SNPs and genes, which region of the gene the SNP resides in. Excel file: SupplementaryTable27.xlsx

Supplementary Table 28: OCD GWAS SNP list enrichment analysis with GLANET default library. Results include enriched DNaseI hypersensitive sites, transcription factor binding sites, modification regions for multiple histones across all cell lines available in ENCODE, RefSeq genes, KEGG pathways, TF-KEGG pathway pairs. KEGG pathway enrichment analyses are conducted in three modes: exon, regulation and all-based. Excel file: SupplementaryTable28.xlsx

Supplementary Table 29: List of interesting SNP and transcription factor pairs where SNP allele potentially affects the transcription factor binding event. Excel file: SupplementaryTable29.xlsx

Supplementary Table 30: Output of GLANET enrichment analysis for the user-defined gene set option. Gene ontology (GO) enrichment analysis for GATA2 binding regions in K562 cell line conducted in three modes: exon-based, regulation-based and all-based. Excel file: SupplementaryTable30.xlsx

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