

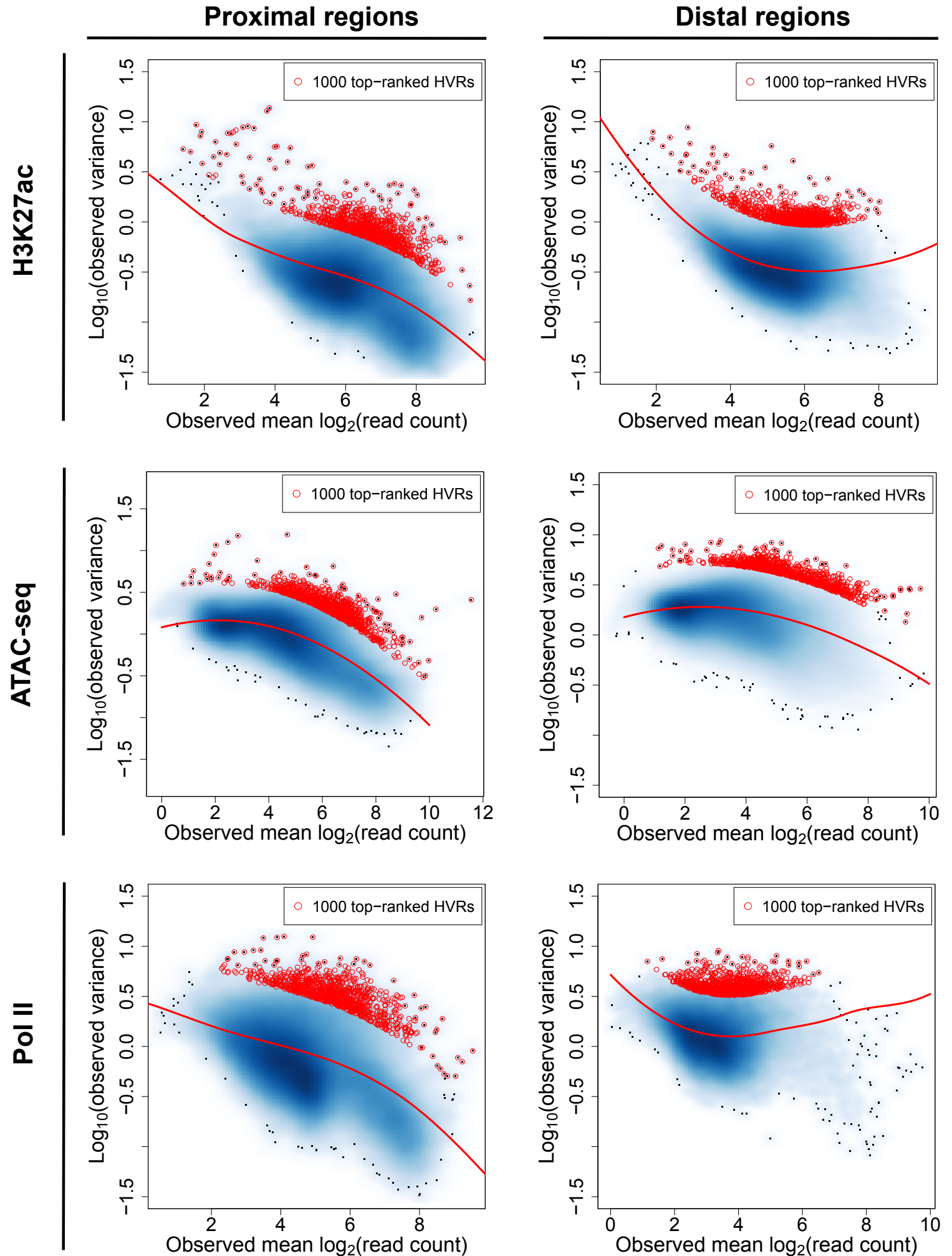
Fig. S1

Figure S1. Scatter plots showing various mean-variance trends associated with different data sets. Variance is shown at the \log_{10} scale. Red lines depict the corresponding MVCs. Red points mark the 1000 regions with the largest scaled variances.

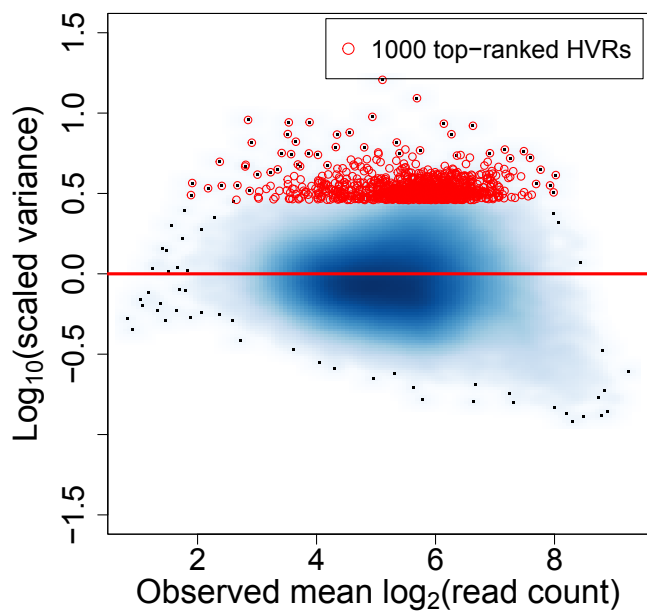
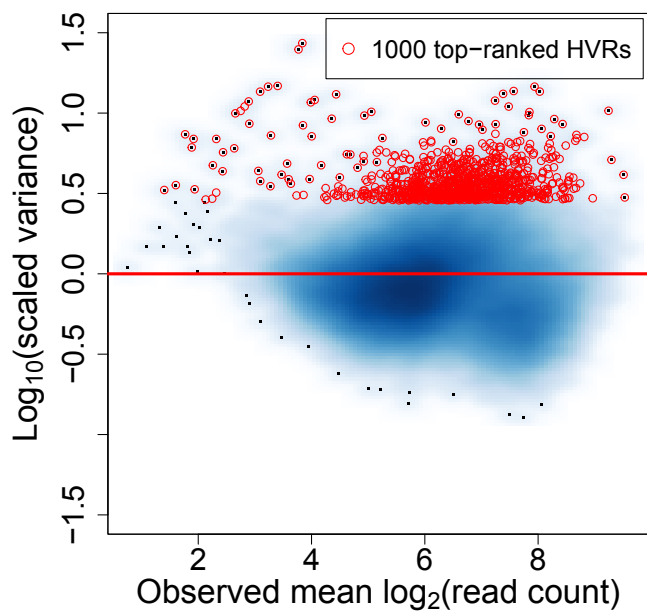
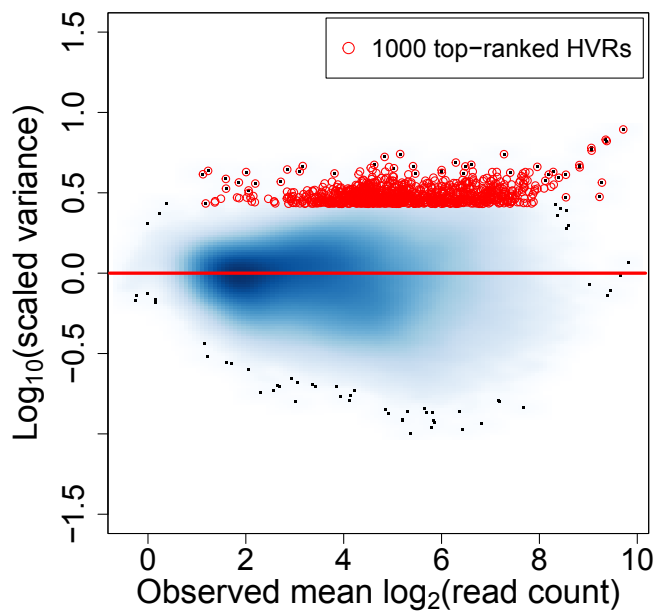
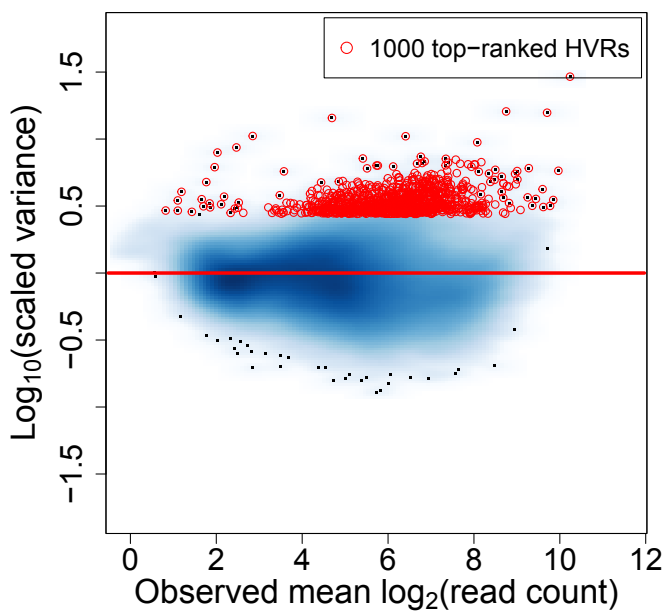
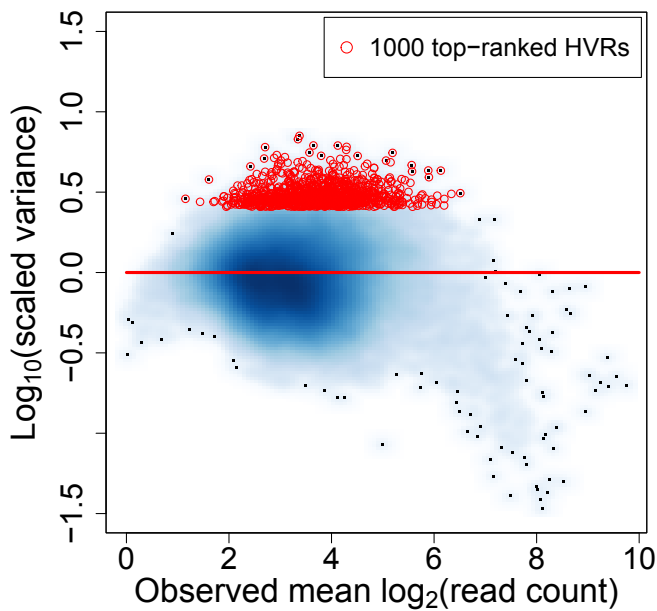
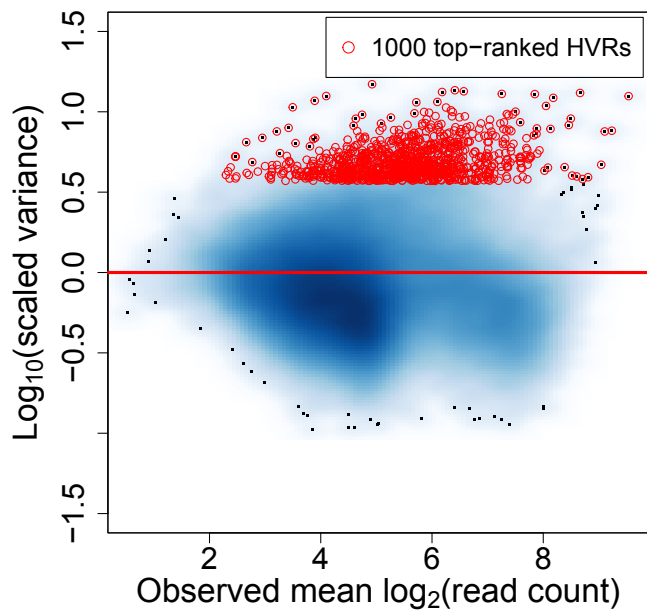
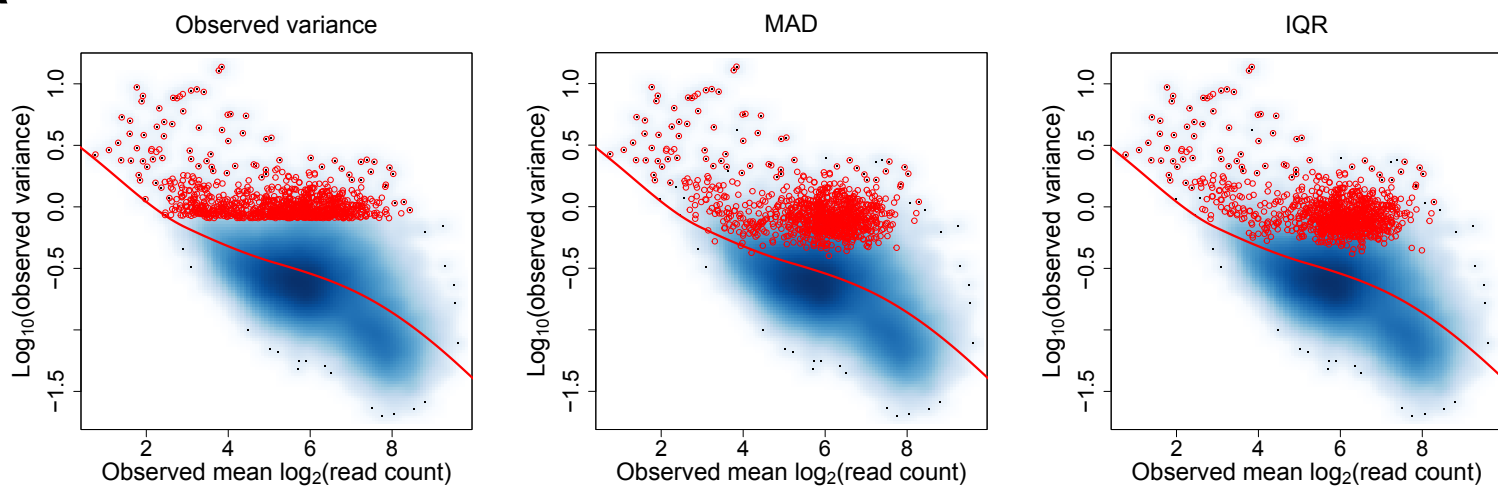
Fig. S2**Proximal regions****Distal regions****H3K27ac****ATAC-seq****PoI II**

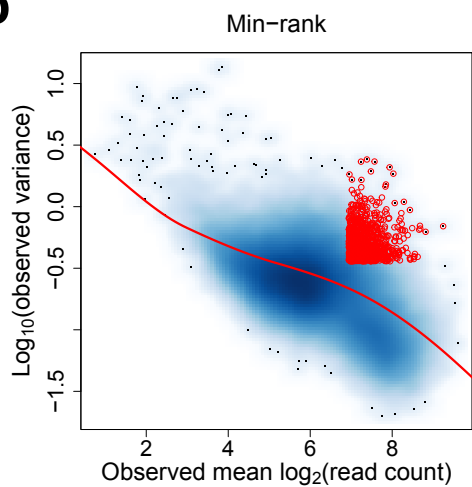
Figure S2. Scatter plots of \log_{10} scaled variances against observed mean signal intensities for different data sets. Red points mark the 1000 regions with the largest scaled variances.

Fig. S3

a



b



c

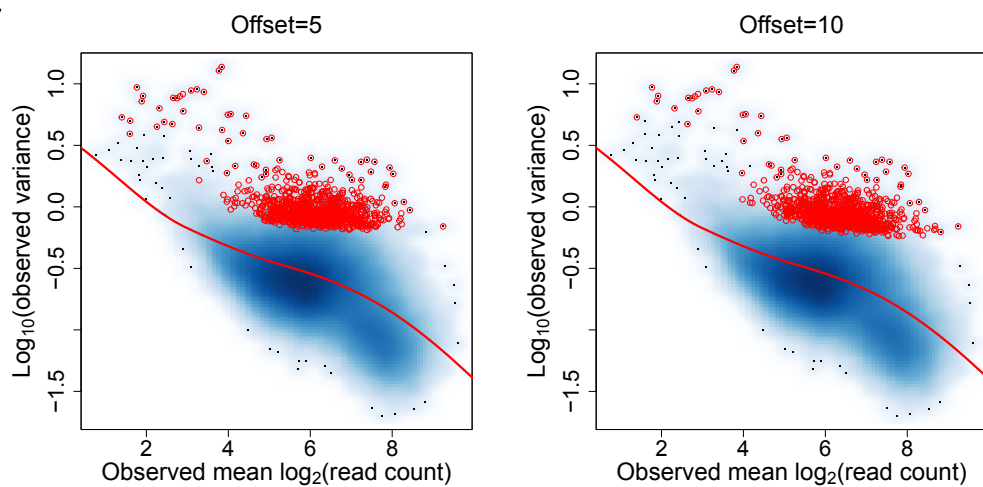


Figure S3. Applying other methods for ranking genomic regions and selecting HVRs. (a-c) Scatter plots showing the mean-variance trend (at proximal regions) associated with the H3K27ac ChIP-seq data set as well as the regions that are ranked in the top 1000 HVRs by each method (marked by red points). MAD, median absolute deviation; IQR, interquartile range.

Fig. S4

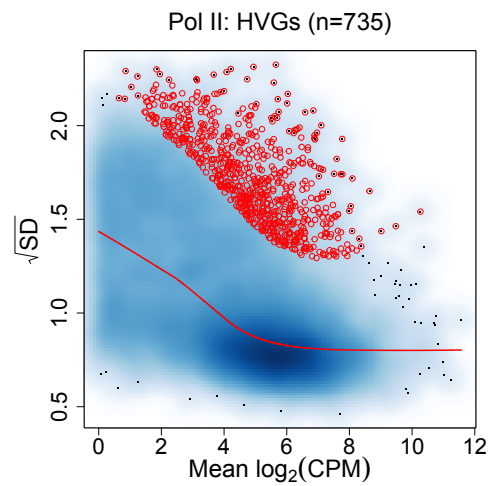
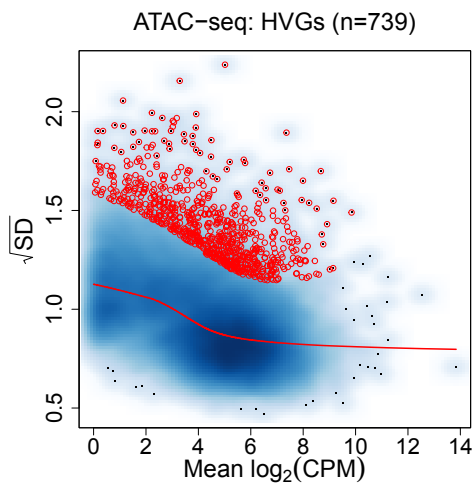
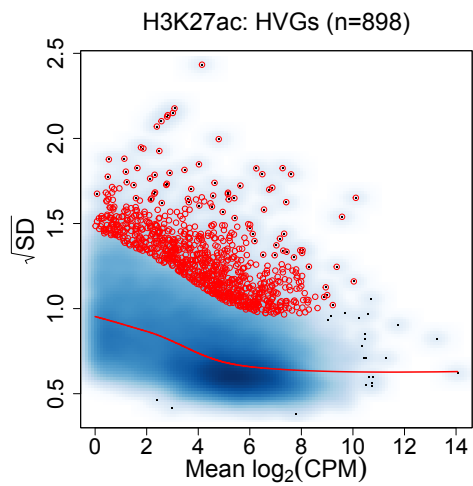


Figure S4. Identifying HVGs. We have separately identified HVGs for each data set in Table 1, by applying limma-trend to the corresponding RNA-seq data (see Methods in the main text for details). Scatter plots shown here demonstrate the modeling of the mean-variance relationships by limma-trend. Red points in each plot mark the identified HVGs. CPM, count per million; SD, standard deviation.

Fig. S5

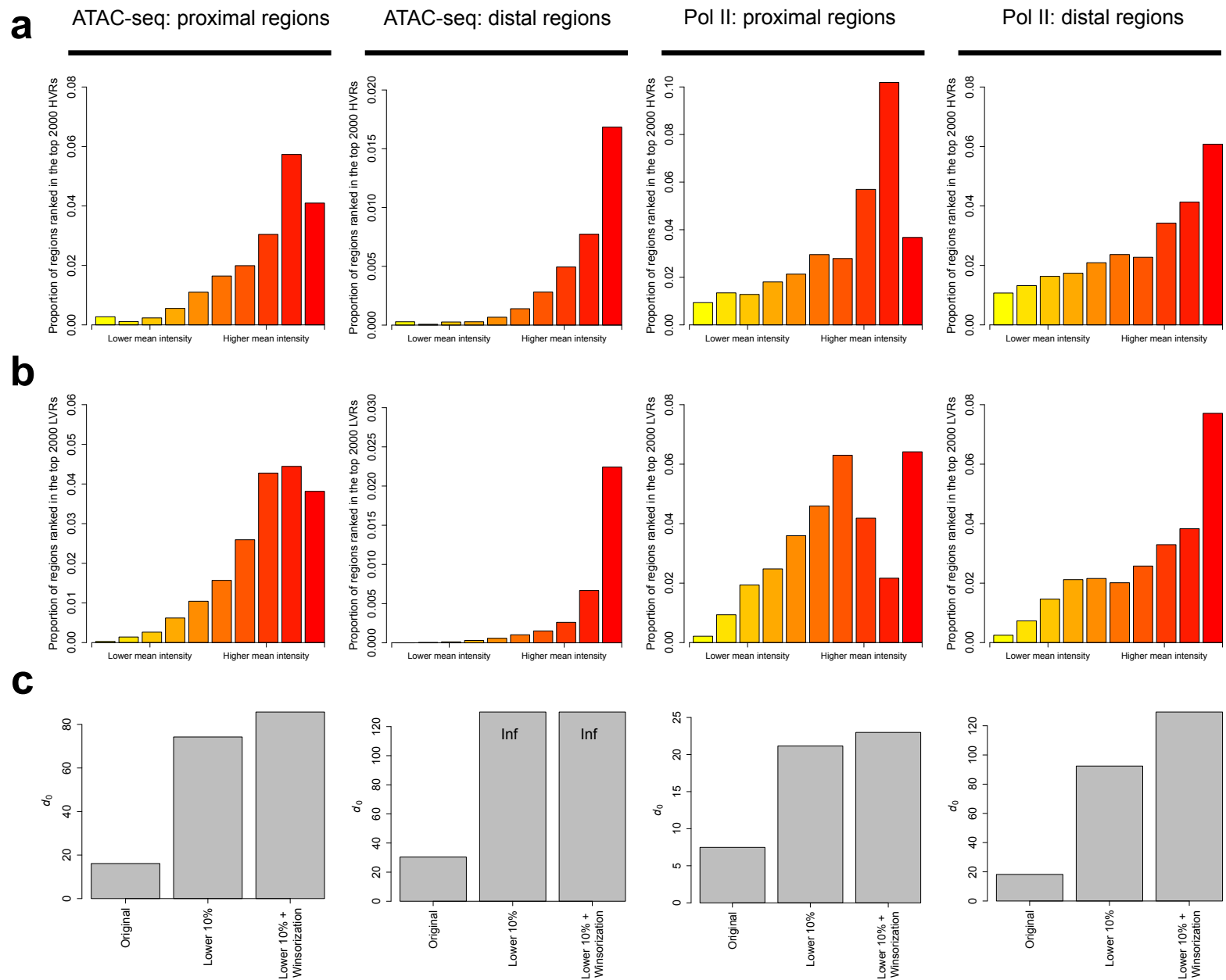


Figure S5. Selecting a subset of genomic regions and using Winsorization for parameter estimation. **(a)** For the ATAC-seq and Pol II ChIP-seq data sets, bar plots showing the distributions of top-ranked proximal/distal HVRs along the range of mean intensities. For each data set, proximal and distal regions have been separately divided into 10 equally-sized groups based on the observed mean signal intensities. **(b)** Bar plots showing the distributions of top-ranked proximal/distal LVRs along the range of mean intensities. **(c)** d_0 estimates resulting from different parameter estimation methods. Inf refers to positive infinity.

Fig. S6

Pol II: proximal regions

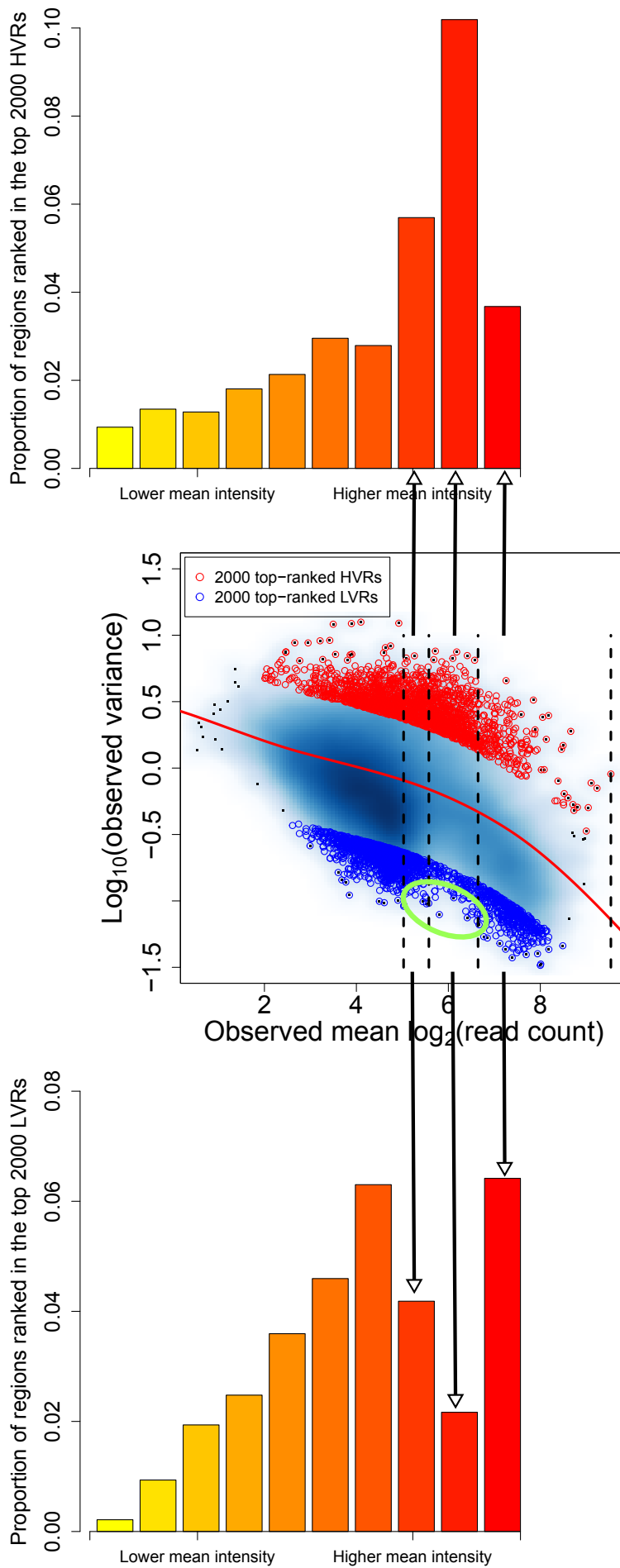


Figure S6. The distributions of top-ranked proximal HVRs and LVRs associated with the Pol II ChIP-seq data set. The top-ranked LVRs form two clusters that are somewhat separated from one another in the mean-variance scatter plot, owing to a gap (indicated by the area circled in green) largely corresponding to the 70th to 90th percentile of mean intensities. As a result, the proportion of the LVRs dips at the corresponding two groups of regions, leading to a bimodal distribution profile as well as a rise in the HVR proportion that is more dramatic compared to the other two data sets.

Fig. S7

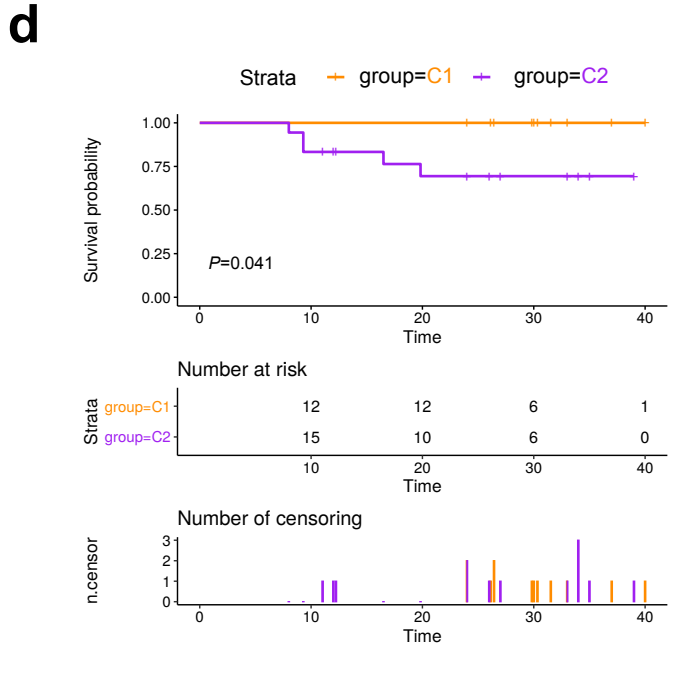
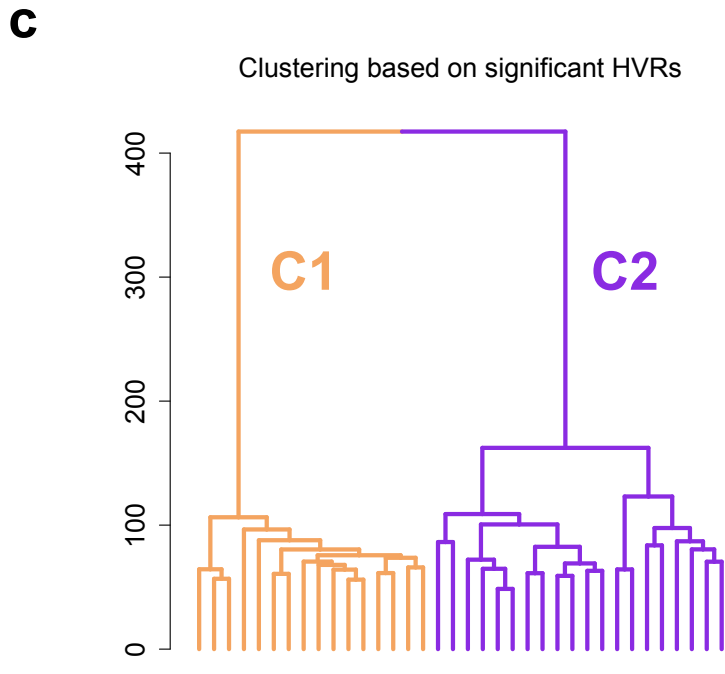
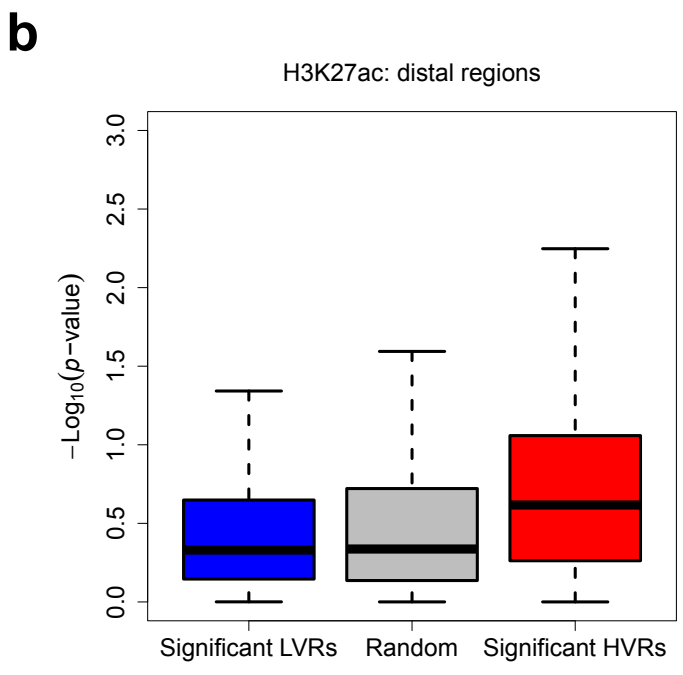
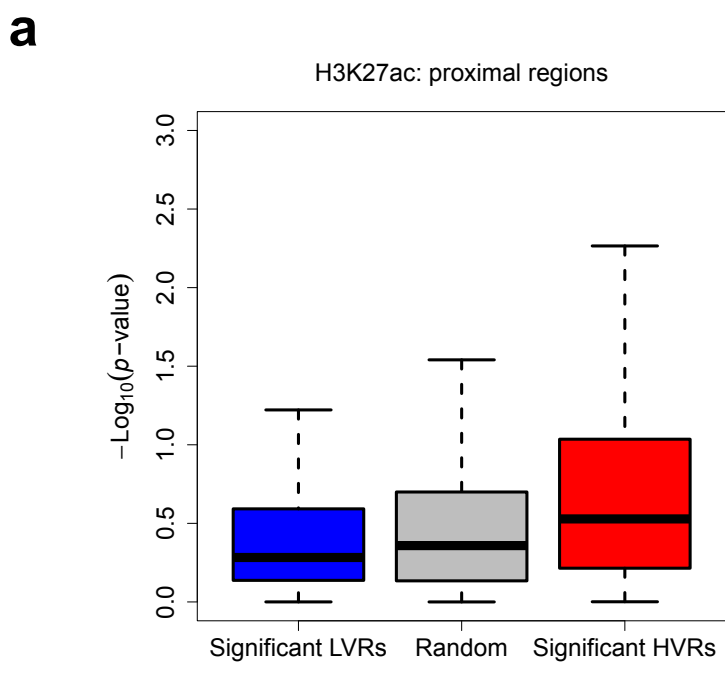
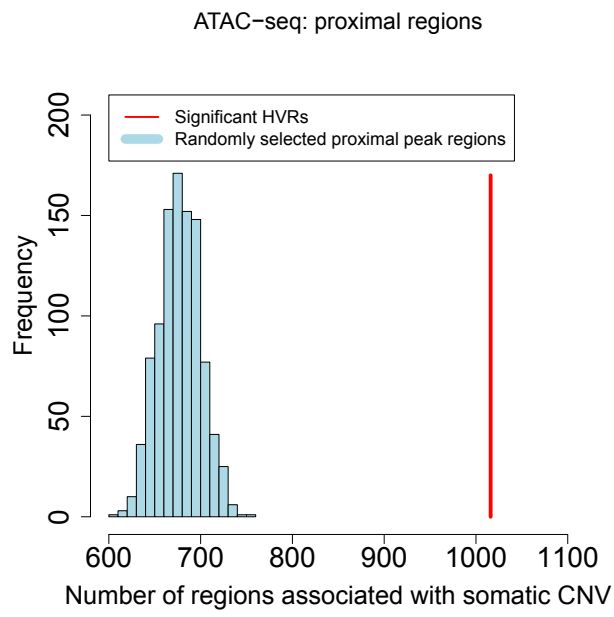


Figure S7. Evaluating the prognostic associations of different genomic regions. (a, b) Proximal/distal HVRs are more significantly associated with the survival time of patients than proximal/distal LVRs and randomly selected proximal/distal peak regions. Results shown here are based on the H3K27ac ChIP-seq data set. The p -values are derived by separately performing a Cox regression on the H3K27ac level in each region. (c) Dendrogram showing the hierarchical clustering of the patients based on the proximal and distal HVRs. The patients are classified into two sub-groups, labeled C1 and C2. (d) There is a significant survival difference between C1 and C2.

Fig. S8

a



b

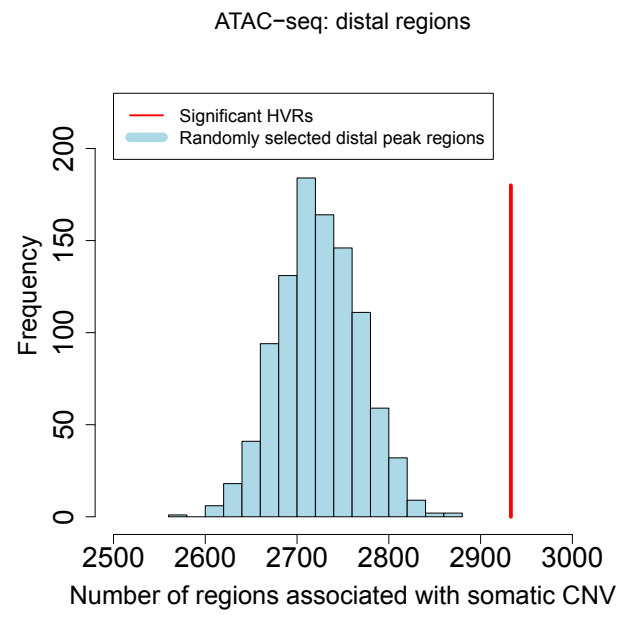
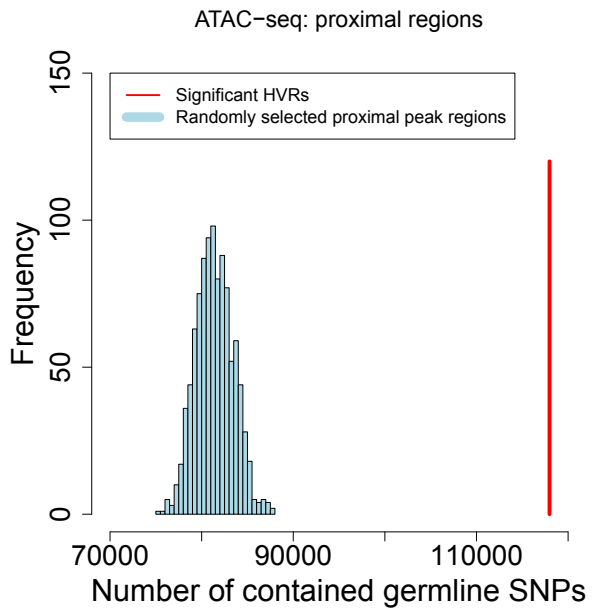


Figure S8. HVRs have a significant association with somatic copy number variation (CNV). (a, b) Proximal/distal HVRs are more likely to be associated with somatic CNV than randomly selected proximal/distal peak regions. Results shown here are based on the ATAC-seq data set. For this data set, the genomic segments with somatic CNV in at least one patient together occupied almost the whole genome (>95%). We therefore considered a region as associated with somatic CNV only if it overlapped CNV segments in more than 5 patients. 1,000 random simulations were performed separately for proximal and distal peak regions. In each time, we randomly selected the same number of proximal/distal peak regions as that of the proximal/distal HVRs.

Fig. S9

a



b

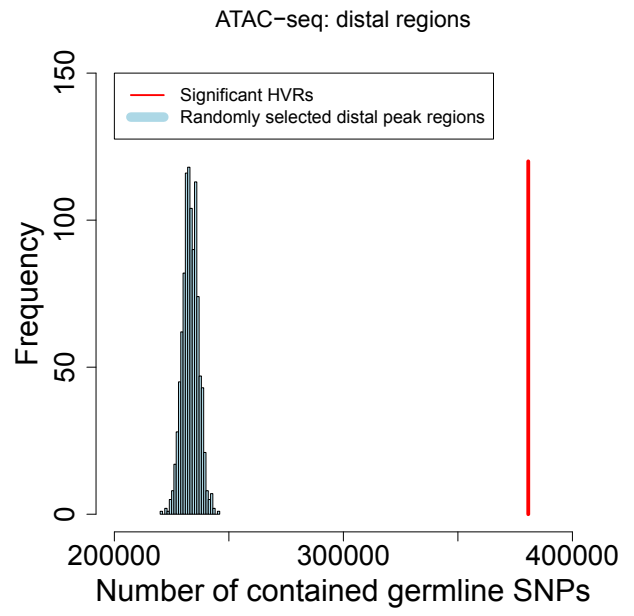


Figure S9. HVRs contain significantly more germline SNPs than by chance. (a) Proximal HVRs identified for the ATAC-seq data set are enriched with germline SNPs. We have performed 1,000 times of random simulation. In each time, a set of proximal peak regions matching the number of the HVRs has been randomly selected. **(b)** Distal HVRs are enriched with germline SNPs as well.

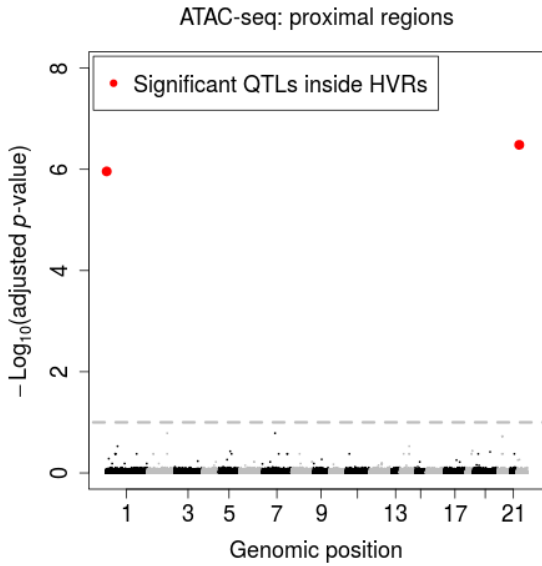
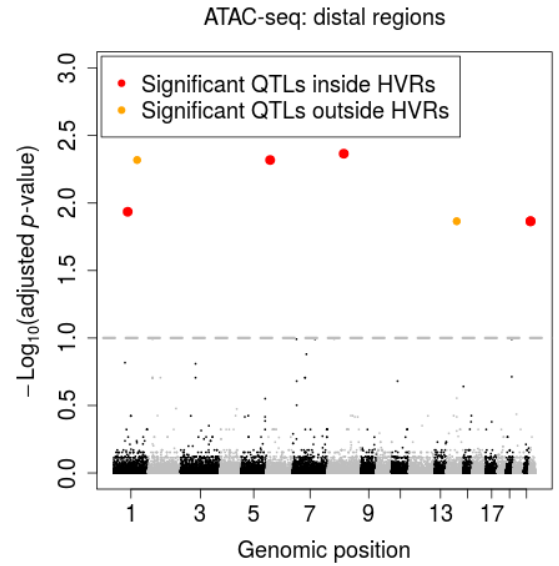
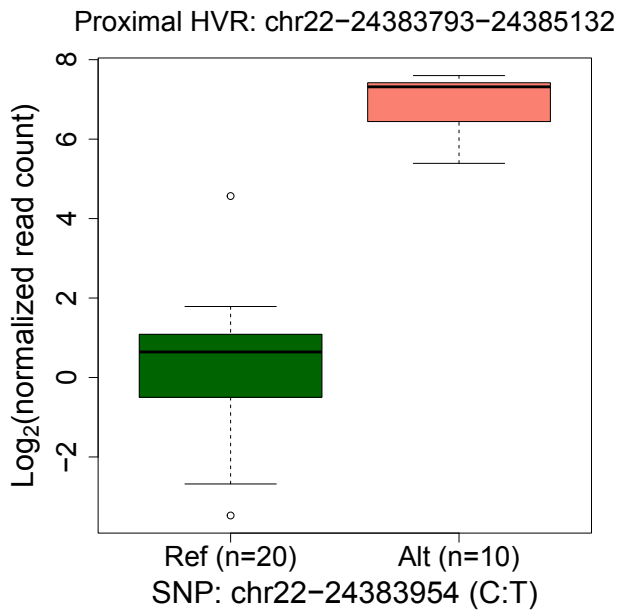
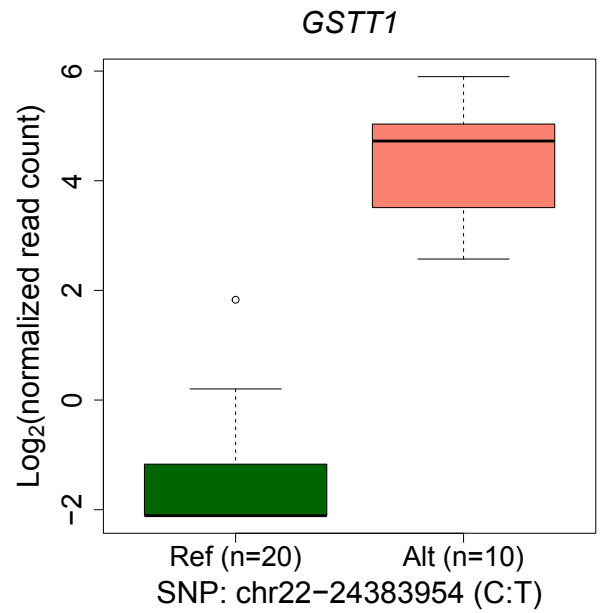
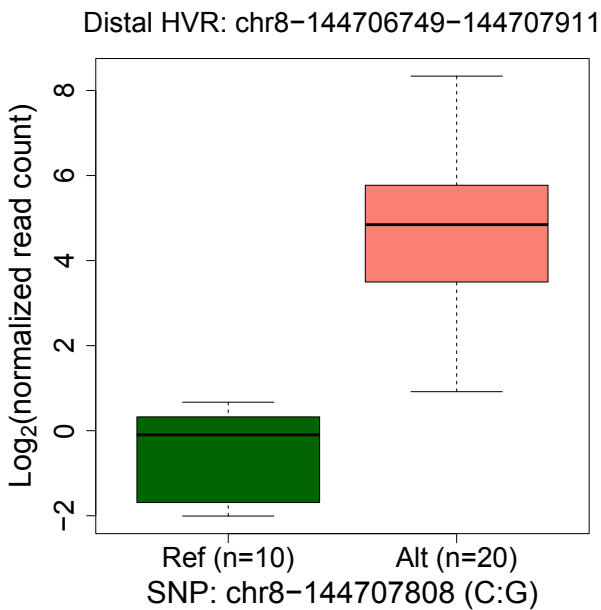
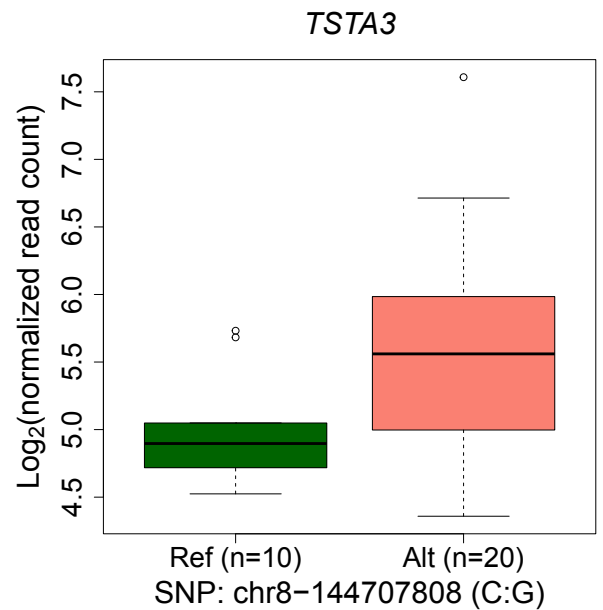
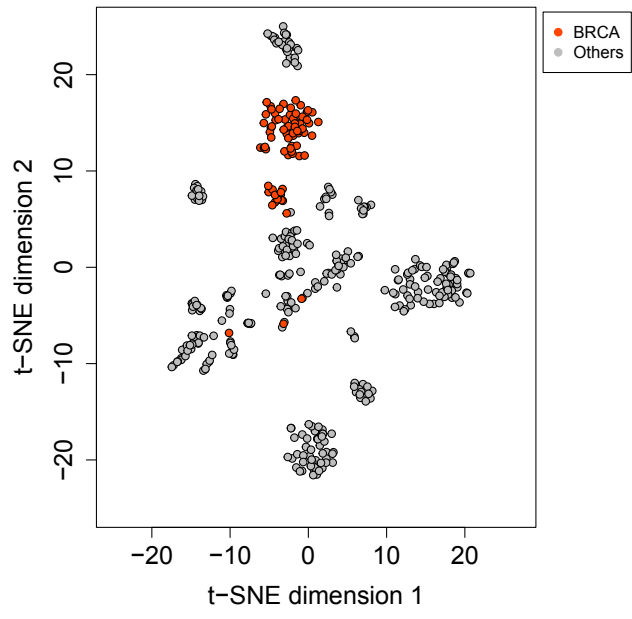
Fig. S10**a****b****c****d****e****f**

Figure S10. Association between QTLs and HVRs. (a, b) Identifying QTLs among the germline SNPs located within ATAC-seq peak regions. Each (BH-adjusted) p -value assesses the statistical significance of the association between the genotype of a SNP and the ATAC-seq signal in the peak region containing it. (c) Box plots showing the ATAC-seq signals associated with different genotypes of the most significant QTL, which is located within a proximal HVR. Ref and Alt refer to the reference genotype and the alternative one, respectively. (d) Box plots showing the RNA-seq signals of the downstream gene of the proximal HVR. (e) Box plots showing the ATAC-seq signals associated with different genotypes of the most significant distal QTL, which is also located within an HVR. (f) Box plots showing the RNA-seq signals of the gene nearest to the distal HVR.

Fig. S11

a



b

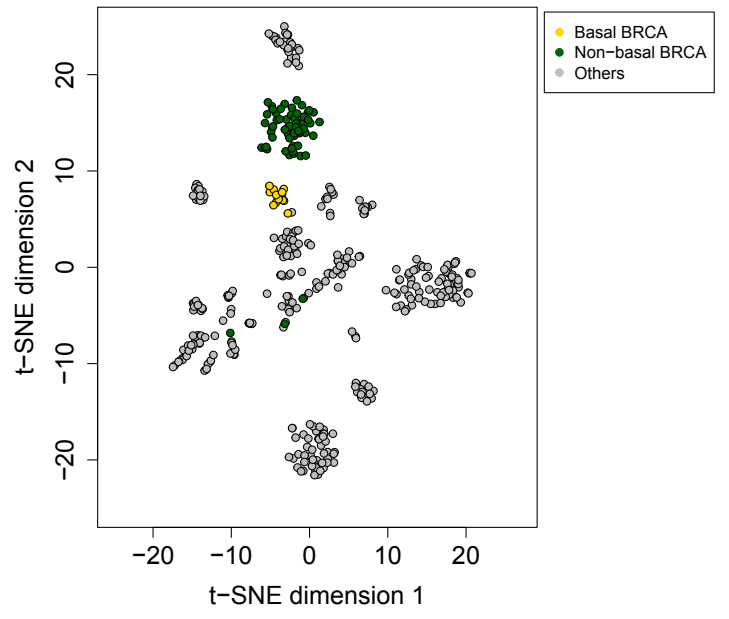


Figure S11. For the TCGA pan-cancer ATAC-seq data set, two-dimensional t-SNE plots showing the distribution of BRCA patients. These patients are comprised of 14 basal and 61 non-basal cases.

Fig. S12

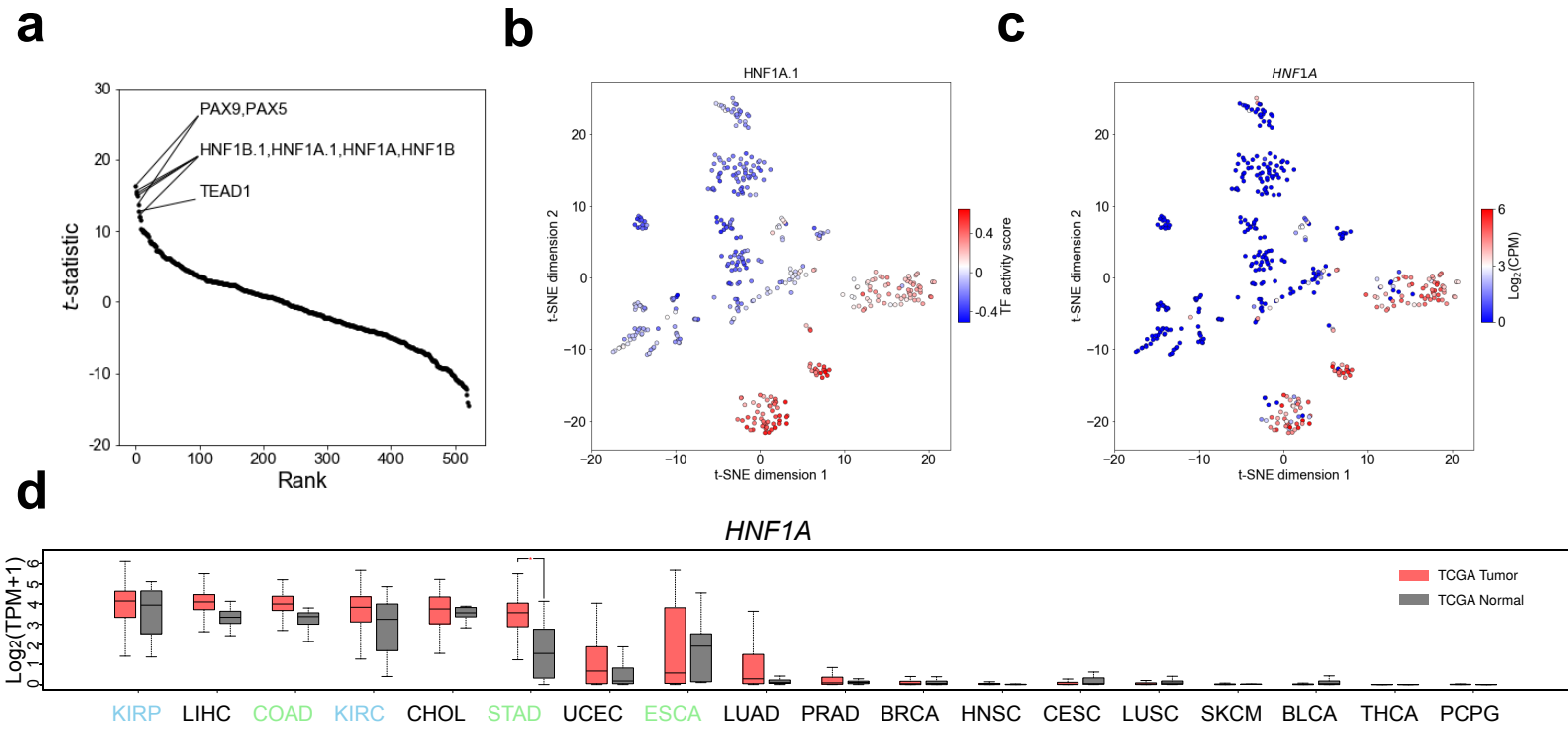


Figure S12. *HNF1A* is identified as a top-ranked TF for the kidney carcinoma class. (a) Plotting the *t*-statistics of all motifs against their rankings in the identification of TFs specific to the kidney carcinoma class. (b) Mapping the TF activity scores associated with the HNF1A.1 motif to the t-SNE plot. (c) Mapping the expression levels of the *HNF1A* gene to the t-SNE plot. (d) Box plots showing the expression of *HNF1A* in a larger TCGA cohort of patients. TPM, transcripts per million.

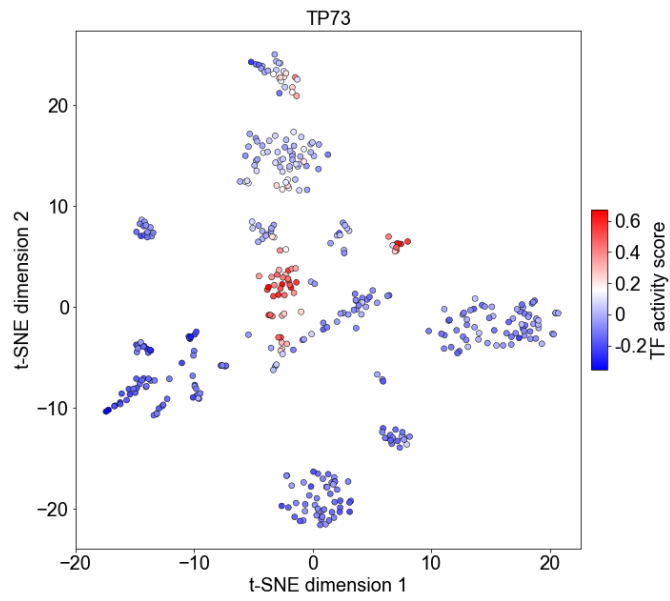
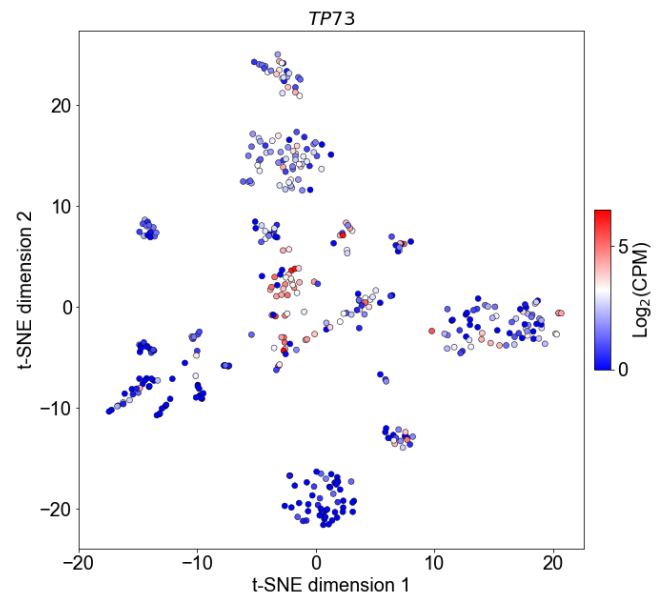
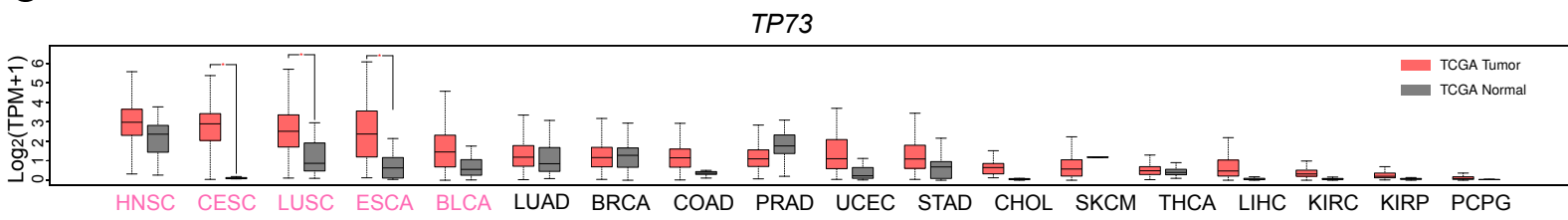
Fig. S13**a****b****c**

Figure S13. *TP73* is identified as a top-ranked TF for the SC class. (a) Mapping the TF activity scores associated with the TP73 motif to the t-SNE plot. **(b)** Mapping the expression levels of the *TP73* gene to the t-SNE plot. **(c)** Box plots showing the expression of *TP73* in the larger TCGA cohort.

Fig. S14

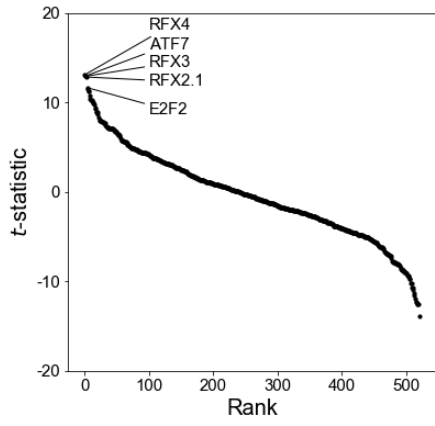
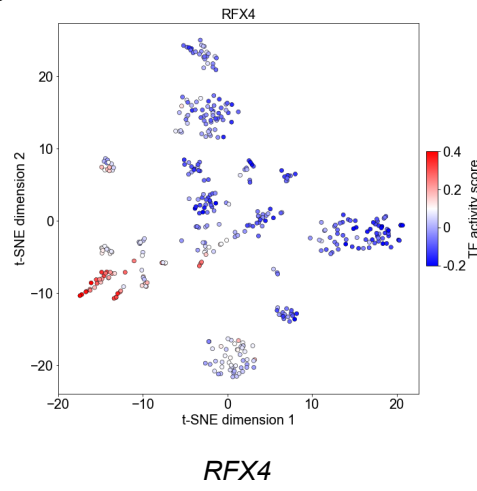
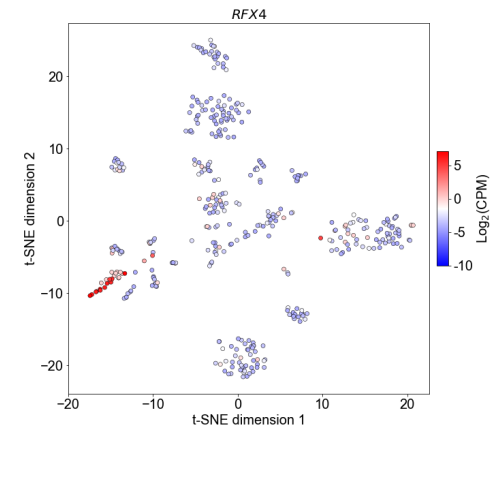
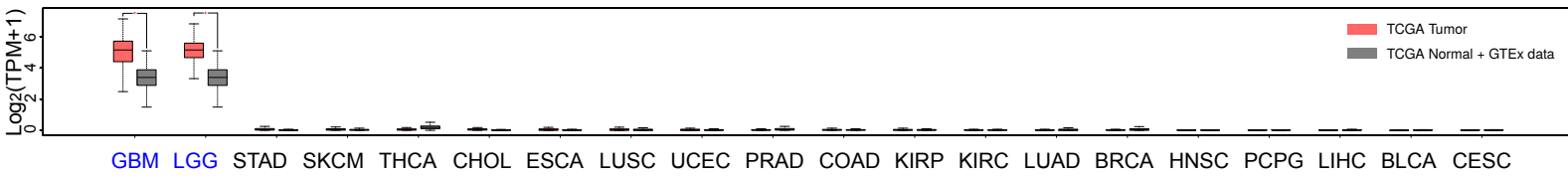
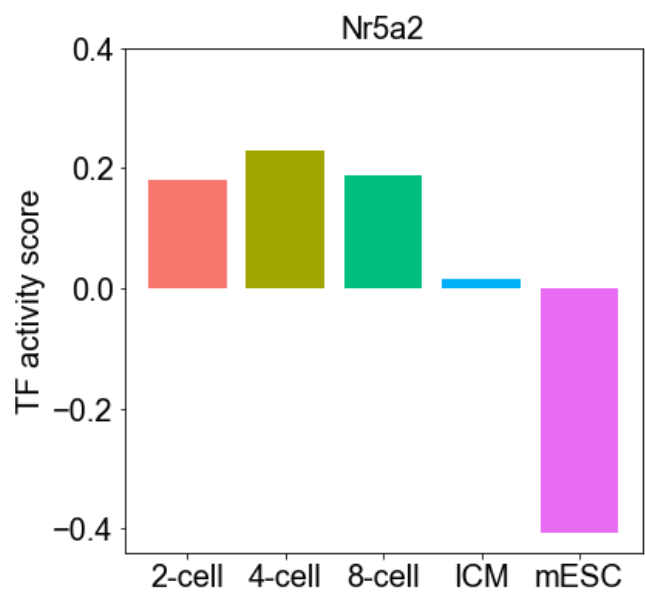
a**b****c****d**

Figure S14. *RFX4* ranks first among the brain cancer class-specific TFs. (a) Plotting the *t*-statistics of all motifs against their rankings in the identification of TFs specific to the brain cancer class. (b) Mapping the TF activity scores associated with the *RFX4* motif to the t-SNE plot. (c) Mapping the expression levels of the *RFX4* gene to the t-SNE plot. (d) Box plots showing the expression of *RFX4* in the larger TCGA cohort as well as in 3,006 RNA-seq samples of normal individuals provided by the GTEx (Genotype-Tissue Expression) project (<https://gtexportal.org/home/>). We involved the GTEx data because RNA-seq samples for matched normal tissues of GBM and LGG were missing in the TCGA program.

Fig. S15

a



b

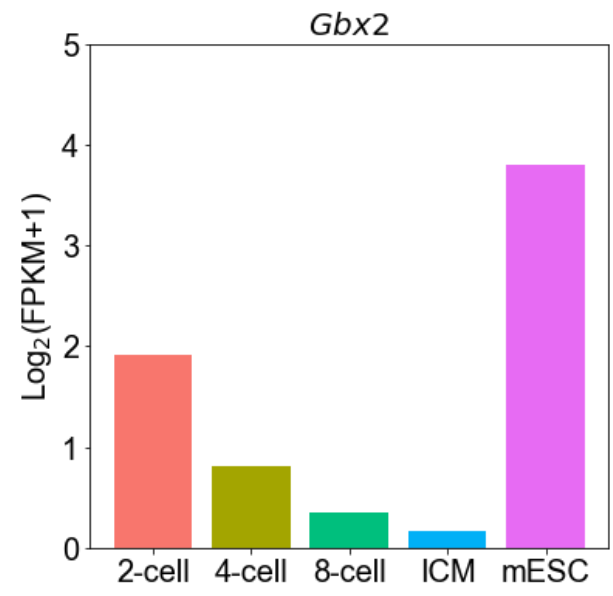
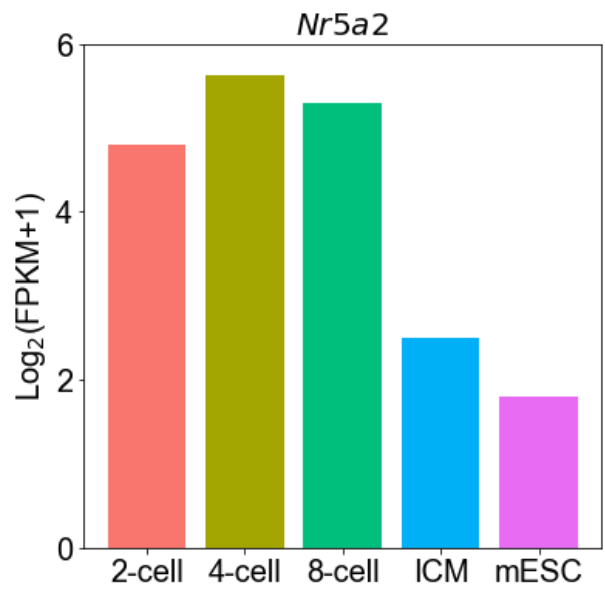
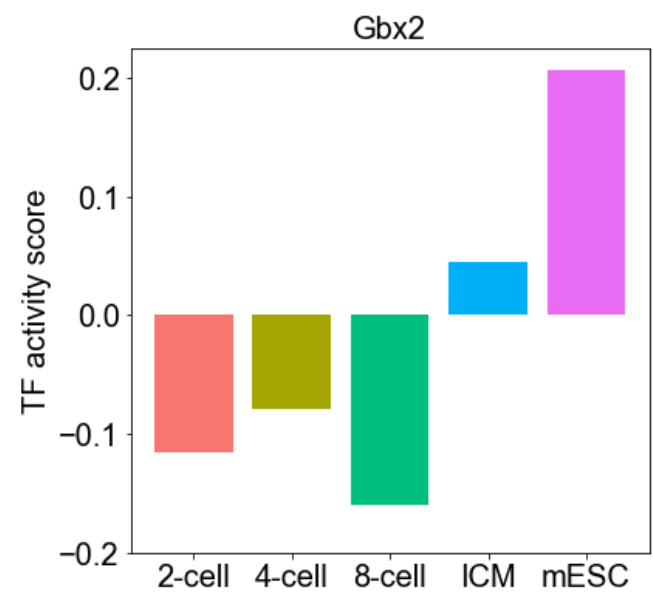
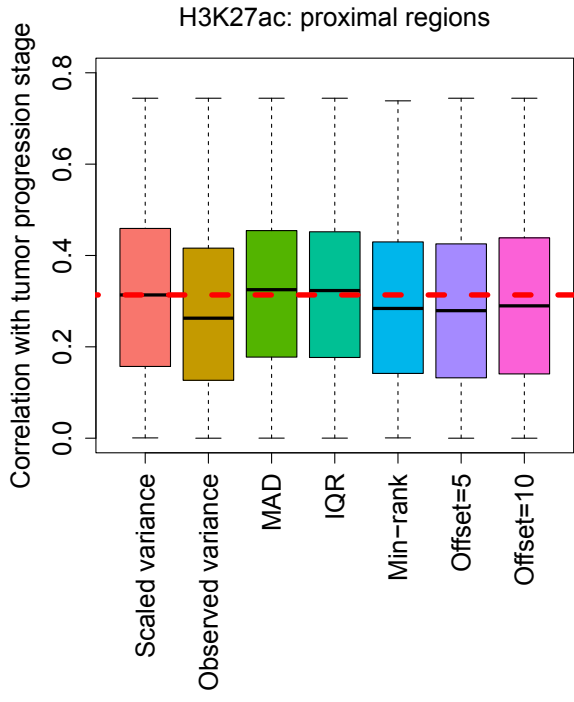


Figure S15. Examples of stage-specific regulators identified from the mouse ATAC-seq data set. (a, b) Bar plots showing the TF activity scores and expression levels of (a) *Nr5a2* and (b) *Gbx2*, which are top-ranked TFs associated with the early and late stages, respectively. TF activity scores have been averaged across biological replicates for each individual cell stage.

Fig. S16

a



b

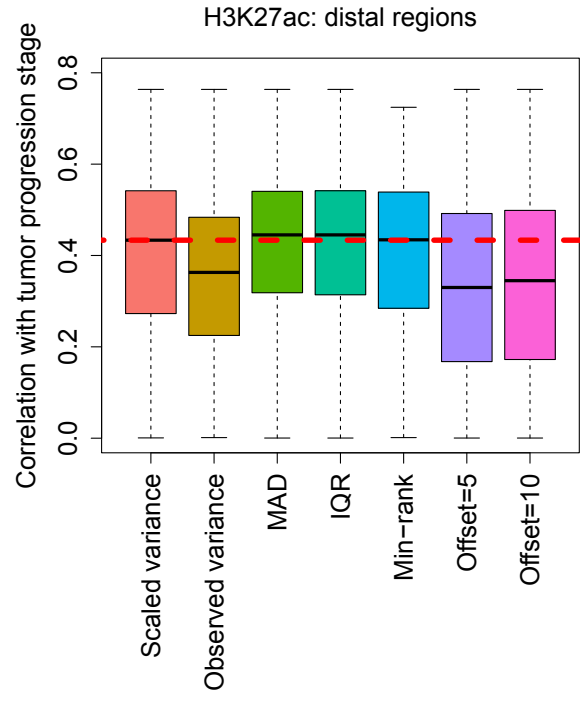
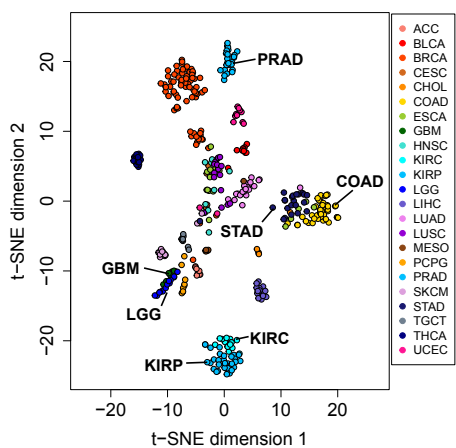


Figure S16. Evaluating the correlations of HVRs identified by different methods with tumor progression stage. (a, b) Results shown here are based on the LUAD H3K27ac CHIP-seq data set. For each method, the same number of top-ranked proximal/distal HVRs as identified by HyperChIP are selected. The red dotted line in each plot indicates the median correlation of the HVRs identified by HyperChIP.

Fig. S17

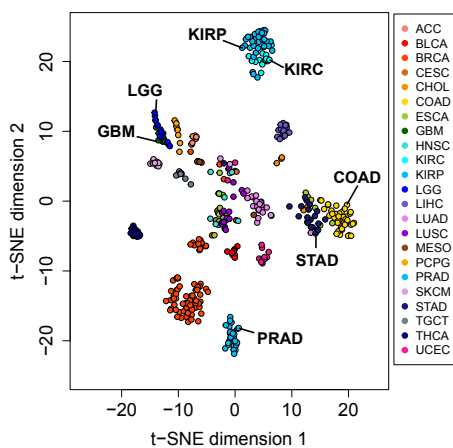
a

Scaled variance



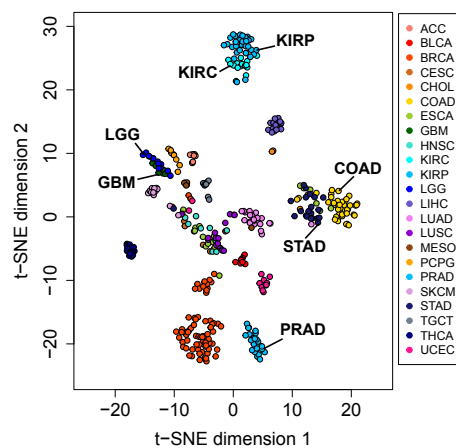
b

Observed variance



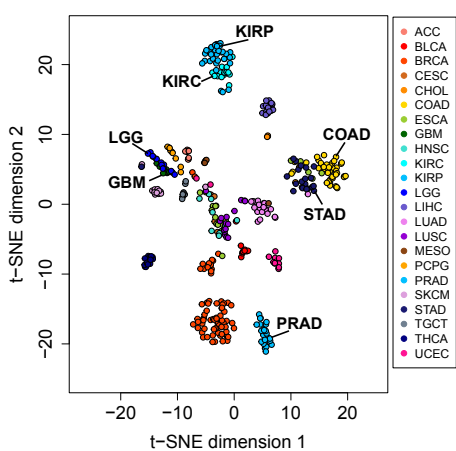
c

MAD



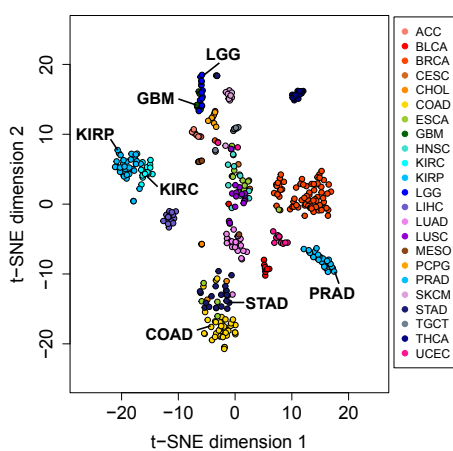
d

IQR



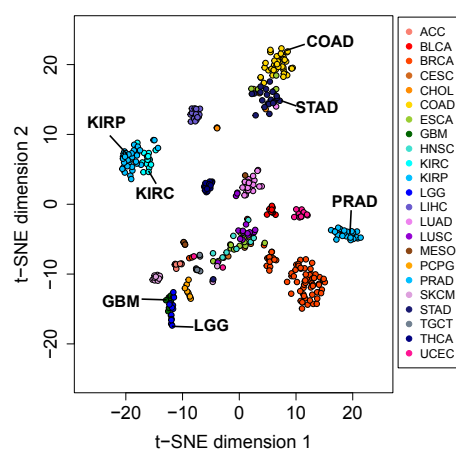
e

Min-rank



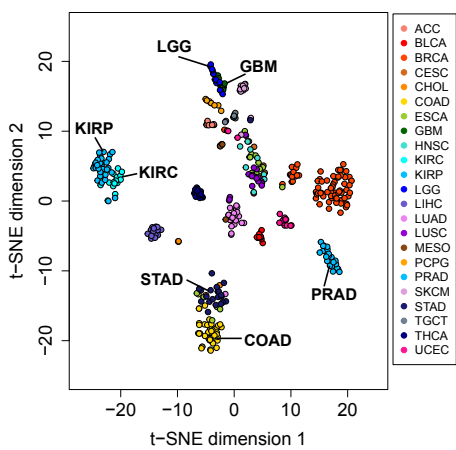
f

Offset=5



g

Offset=10



h

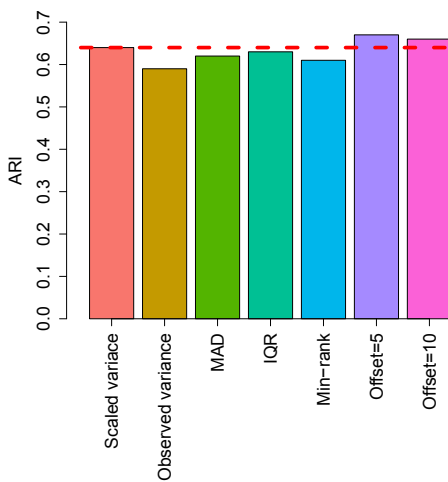


Figure S17. Applying different methods to the pan-cancer ATAC-seq data set. (a-g) Two-dimensional t-SNE plots generated by different methods. For each method, the same number of top-ranked proximal/distal HVRs as identified by HyperChIP were used for the downstream PCA and t-SNE analysis (see Methods in the main text). **(h)** Bar plot showing the ARI values achieved by different methods in classifying all samples. For each method, we performed a hierarchical clustering of all samples based on the same principal components as used in the t-SNE analysis. The samples were then classified into 23 sub-groups based on the resulting hierarchical tree, and the corresponding ARI assessed the agreement of this classification with the cancer type labels. The red dotted line indicates the ARI value achieved by HyperChIP.

Fig. S18

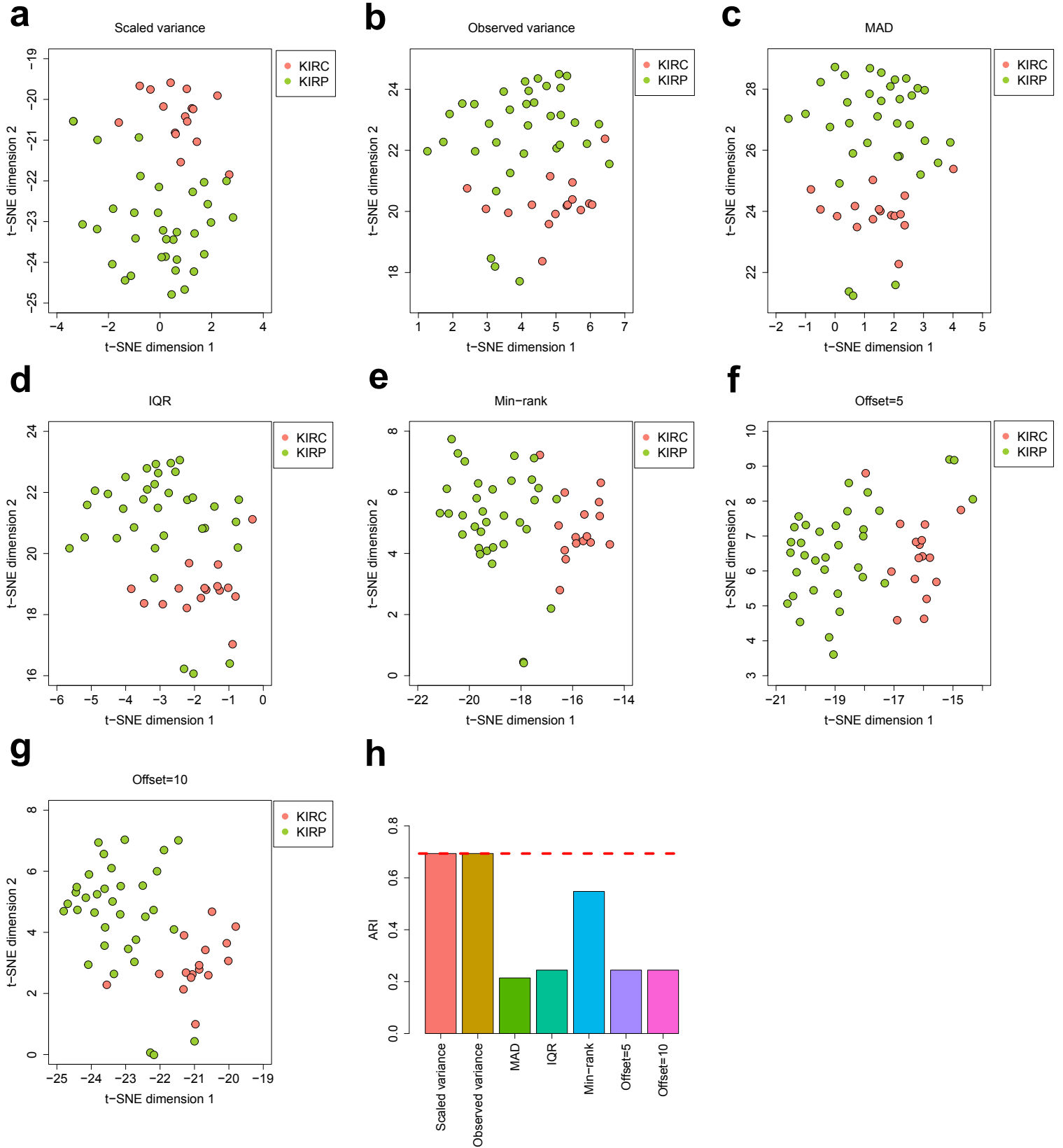
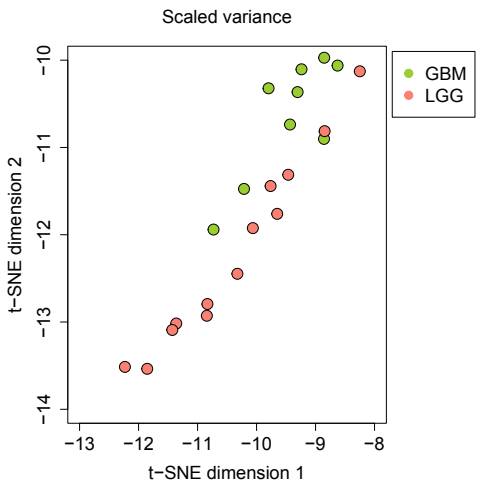


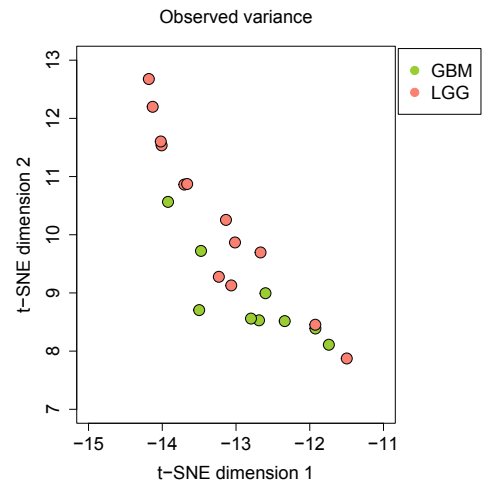
Figure S18. Evaluating the ability of different methods to distinguish between the KIRC and KIRP cancer types. (a-g) Zooming in on the t-SNE plots to more clearly present the distributions of KIRC and KIRP samples. **(h)** Bar plot showing the ARI values achieved by different methods in classifying KIRC and KIRP samples. For each method, we performed a hierarchical clustering of KIRC and KIRP samples and classified them into two sub-groups based on the resulting hierarchical tree.

Fig. S19

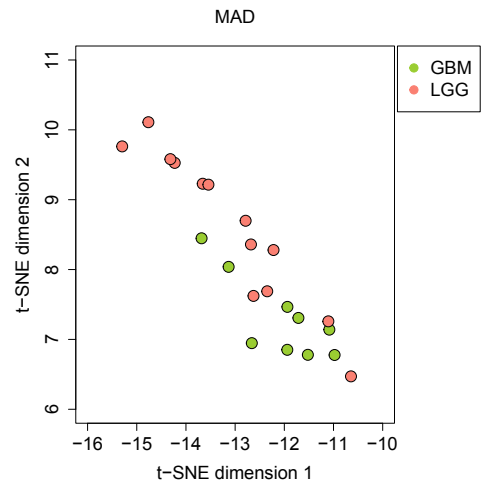
a



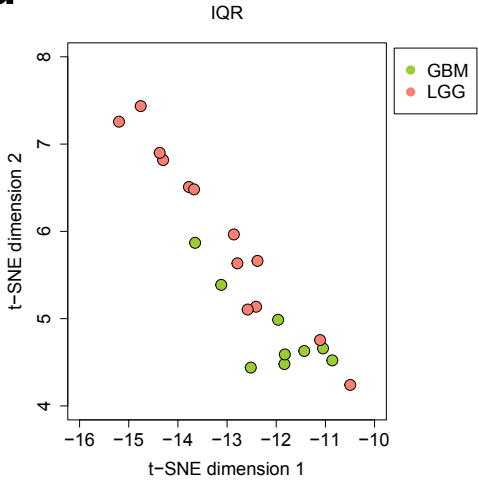
b



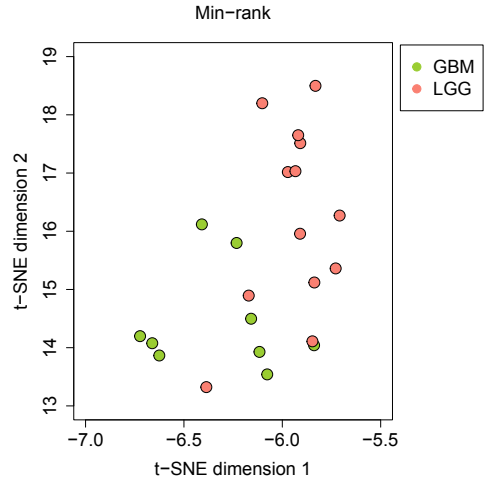
c



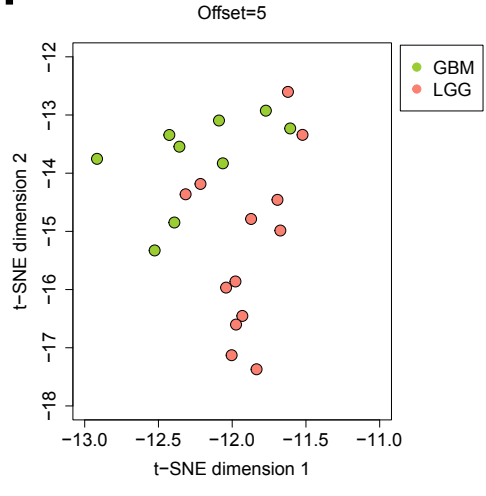
d



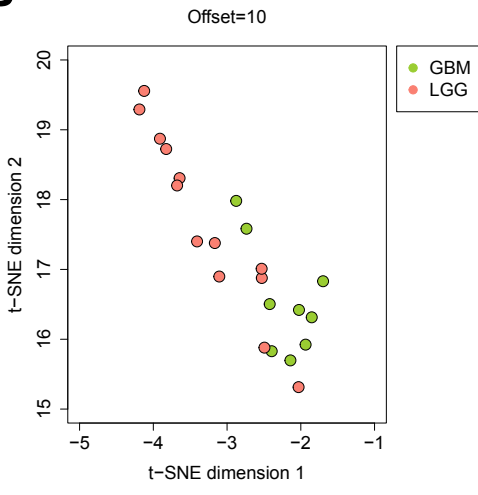
e



f



g



h

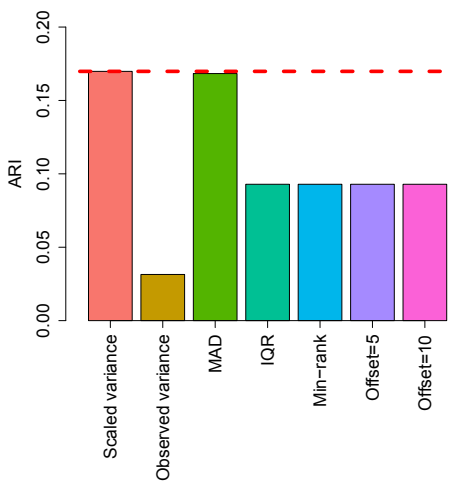


Figure S19. Evaluating the ability of different methods to distinguish between the GBM and LGG cancer types. (a-g) Zooming in on the t-SNE plots to more clearly present the distributions of GBM and LGG samples. **(h)** Bar plot showing the ARI values achieved by different methods in classifying GBM and LGG samples. For each method, we performed a hierarchical clustering of GBM and LGG samples and classified them into two sub-groups based on the resulting hierarchical tree.

Fig. S20

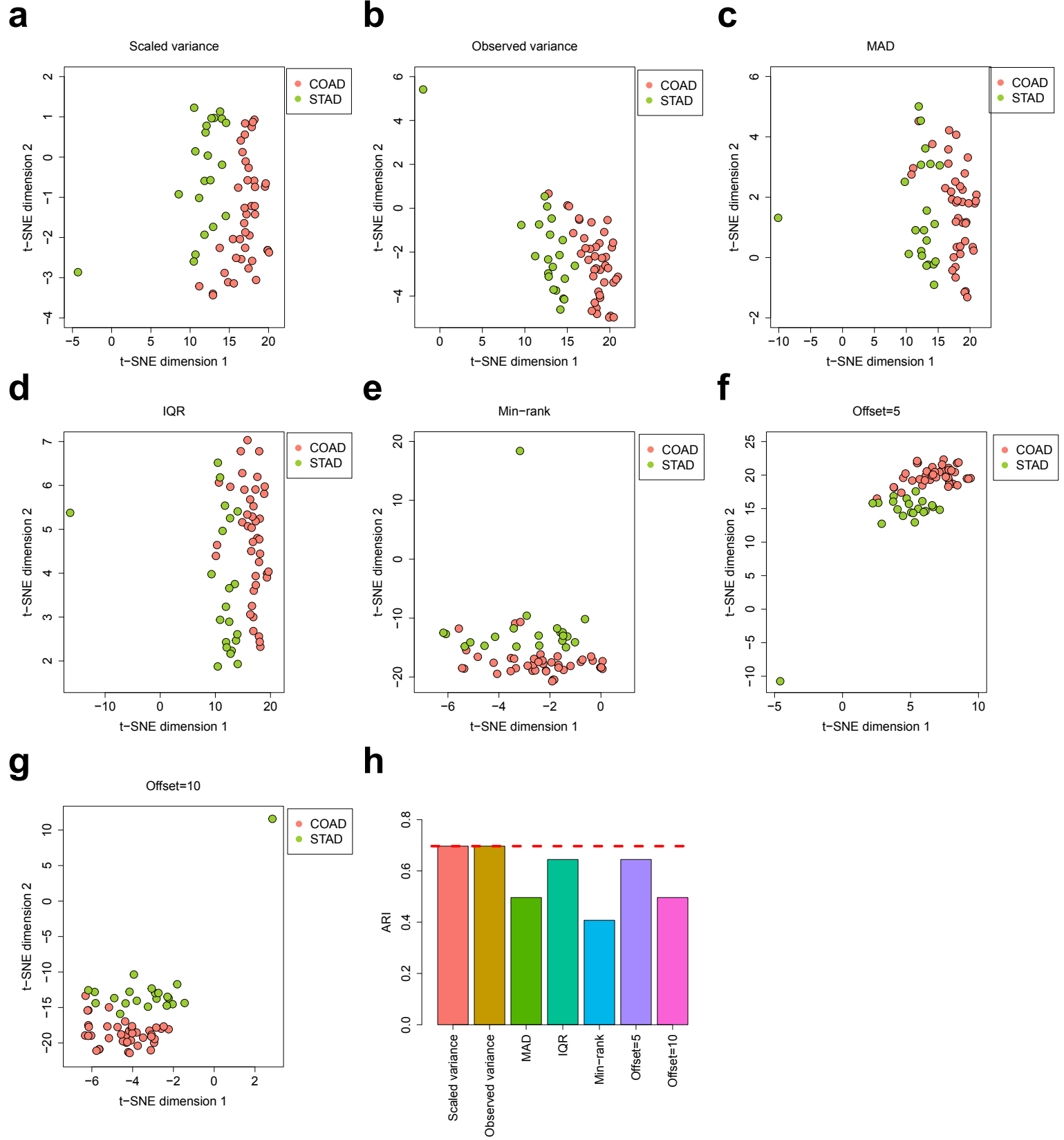


Figure S20. Evaluating the ability of different methods to distinguish between the COAD and STAD cancer types. (a-g) Zooming in on the t-SNE plots to more clearly present the distributions of COAD and STAD samples. **(h)** Bar plot showing the ARI values achieved by different methods in classifying COAD and STAD samples. For each method, we performed a hierarchical clustering of COAD and STAD samples and classified them into two sub-groups based on the resulting hierarchical tree.