

Supplementary Materials

Revealing global regulatory perturbations across human cancers

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Supplemental Procedures

In what follows, we provide a detailed description of the methods used in this study. The iPAGE software along with a minitutorial and other results from this study (both experimental and computational) are available online at <http://tavazoielab.princeton.edu/iPAGE/>. Our approach, described here, involves the discovery of the informative *cis*-regulatory elements and cellular pathways from gene expression datasets; a subsequent analysis recovers the pathways that are likely regulated by the identified putative binding sites. A schematic of the FIRE/iPAGE framework is presented in Figure 1 and Figure S12.

Pre-processing of input datasets

All cancer microarray datasets used in this study were downloaded from GEO (<http://www.ncbi.nlm.nih.gov/projects/geo/>). Each cancer versus normal dataset was converted into continuous or discrete gene expression profiles, as follows.

In the continuous case (i.e., urinary bladder cancer), each gene was associated with a continuous expression value based on the following equation:

$$(1) \quad v = s(1 - p),$$

where p is a p -value calculated by performing a Student's t -test between the cancer samples and the normal controls. s is the sign of the difference between the average values in these two sets. Thus, v indicates the extent to which a gene is up-regulated or down-regulated in the cancer state with maximal and minimal values of 1 and -1 respectively.

In the discrete case, genes were first clustered into $\sim \sqrt{N}$ groups (N is the total number of genes) based on their expression values in the normal and tumor samples, using the k -means unsupervised clustering approach. Then the clusters whose average expressions did not differ between the normal and cancer samples (nominal p -value from t -test > 0.05 , where the t -test is performed on the expression profiles in each cluster) were combined into a single background cluster. Subsequently, each gene was associated with the cluster index of the cluster to which it belongs.

FIRE: De novo discovery of informative regulatory elements

FIRE was used with default settings, as described in Elemento et al, 2007.

iPAGE: A detailed explanation of the algorithm

Expression profile

An *expression profile* is defined across N genes, where each gene is associated with a unique expression measure. Expression measures, discrete or continuous, can be obtained from a variety of gene-level measurements or analyses. For example, cluster indices from a partitioning process or the ranks obtained from sorting are discrete measures; whereas, results from a single microarray or any continuous-type statistic (e.g., p -values) are continuous values. In this study we have demonstrated this unifying capacity of iPAGE; e.g., in the bladder carcinoma we have used a continuous statistic derived from Student's t -test while in the BL vs DLBCL case we employed discrete indices obtained from clustering of gene expression values across all the samples. From here forward, we refer to these lists of input values as *expression profiles*. Schematized continuous and discrete expression profiles are shown in Figure S13.

Pathway Profile

Each gene can be associated with a subset of M known pathways (e.g. from the Gene Ontology annotations). For each pathway, the *pathway profile* is defined as a binary vector with N elements, one for each gene. In this profile, “1” indicates that the gene belongs to the pathway and “0” indicates that it does not. A schematized pathway profile is shown in Figure S13.

Quantizing continuous expression profiles

Although the concept of mutual information is defined for both discrete and continuous random variables, in practice, continuous data are discretized before calculating the mutual information (MI) values. Our quantization procedure is based on the maximum entropy principle (so as to make the least assumptions about the underlying data distribution), and involves using equally populated “expression bins”. Thus, the discretization step only requires a single parameter, i.e., the number of genes in each bin. In the default iPAGE settings, the number of bins (N_e) is determined by:

$$(2) \quad N_e \cdot N_m = N/50$$

where N_m is the number of bins in the pathway profile (here $N_m=2$). Although determining N_e values from Eqn. (2) allows a reliable calculation of mutual information (Slonim et al., 2005), other values can also be explored by the user. In this study, we used the continuous mode in one of the datasets and variations in the number of bins did not significantly change the results. Indeed, when we ran FIRE and iPAGE on the bladder carcinoma dataset with various numbers of bins (10, 50, 100 and 250), the identified seeds (k-mers) largely overlapped, with hypergeometric p -values always less than $1e-53$ (down to $1e-281$ in some comparisons). We made the same observation for the number of iPAGE-identified pathways, with hypergeometric p -values always less than $1e-20$ (down to $1e-83$).

Calculating the mutual information values

Given a *pathway profile* and an *expression profile* with N_e bins (or clusters), we create a table C of dimensions $2 \times N_e$, in which $C(1, j)$ represents the number of genes that are contained in the j^{th} expression bin and are also present in the given pathway. $C(2, j)$, on the other hand, contains the number of genes that are in the j^{th} expression bin but are not assigned to the pathway. Given this table, we calculate the empirical mutual information as follows:

$$(3) \quad I(\text{candidate pathway; expression}) = \sum_{i=1}^2 \sum_{j=1}^{N_e} P(i, j) \log \frac{P(i, j)}{P(i)P(j)},$$

where $P(i, j) = C(i, j)/N$, $P(i) = \sum_{j=1}^{N_e} P(i, j)$ and $P(j) = \sum_{i=1}^2 P(i, j)$.

Randomization-based statistical testing

To assess the statistical significance of the calculated MI values, we use a non-parametric randomization-based statistical test. Given I as the real MI value and keeping the pathway profile unaltered, the expression profile is shuffled 10,000 times and the corresponding MI values I_{random} are calculated. A pathway is accepted only if I is larger than $(1 - \max_p)$ of the I_{random} values (\max_p is set to 0.005 by default). This corresponds to a p -value < 0.005 . In iPAGE, pathways are first sorted by information (from informative to non-informative). Starting from the most informative pathway, the statistical test described above is applied to each pathway, and pathways that pass the test are returned (provided they also pass the conditional information test described below). When k contiguous pathways in the sorted list do not pass the test, the procedure is stopped (k is set to 20 by default).

Removing redundantly informative pathways

Due to the hierarchical and nested nature of pathway annotations (e.g. Gene Ontology), many pathways display some level of redundancy, i.e., two pathways may be represented by very similar sets of genes (e.g. GO:0006511, ubiquitin dependent protein catabolic process and GO:0019941, modification dependent protein catabolic process). To discover representative pathways and remove redundant ones, we require that each returned pathway be highly informative about the expression profile, but also bring a significant amount of new information compared to all other significantly informative pathways as calculated by conditional mutual information (Cover and Thomas, 2006). To achieve this, we require that each candidate pathway fulfills

$$(4) \quad \frac{I(\text{candidate pathway}; \text{expression} \mid \text{accepted pathways})}{I(\text{candidate pathway}; \text{accepted pathway})} > r$$

for all already accepted pathways, i.e., all pathways that have already passed the statistical and conditional information tests. An identical criterion was used in FIRE (Elemento et al., 2007). In iPAGE, r is set to 5 by default and only the pathways satisfying the above equation are presented in the graphical output; however, the list of all significant pathways is also created and stored as a text file.

Pathway over- and under-representation

Informative pathways are generally over-represented or under-represented in certain expression clusters/bins. To quantify the level of over- and under-representation, the hypergeometric distribution is used to calculate two distinct p -values:

$$(5) \quad p_{\text{over}}(X \geq x) = \sum_{i=x}^N \frac{\binom{m}{i} \binom{N-m}{n-i}}{\binom{N}{n}} \text{ for over-representation}$$

and

$$(6) \quad p_{\text{under}}(X \leq x) = \sum_{i=0}^x \frac{\binom{m}{i} \binom{N-m}{n-i}}{\binom{N}{n}} \text{ for under-representation,}$$

where x equals the number of genes in the given expression bin/cluster which are also assigned to the given pathway. m is the number of genes assigned to the pathway, n is the number of genes in the expression bin and N is the total number of genes. If $p_{\text{over}} < p_{\text{under}}$, we consider the pathway to be over-represented in the expression bin/cluster; otherwise, it is under-represented.

iPAGE graphical output

The over- and under-representation p -values described in the previous section are used to draw a heatmap, i.e., a graphical representation of pathway over- and under-representation across all expression bins/clusters. In this heatmap, the rows represent the significantly informative pathways and the columns are the expression bins/clusters. Colors indicate over- or under-representation levels. The red color-map indicates (in \log_{10}) the over-representation p -values; whereas, the blue color-map shows under-representation.

Additional iPAGE output files

In addition to the graphical heatmap, iPAGE generates files containing the actual $\log(p\text{-values})$ for over- and under-representations, and the list of removed redundant pathways.

False Discovery Rate (FDR)

In order to measure the FDR of our method, we randomly shuffled the gene labels of the gene expression profile and counted the number of pathways discovered compared to the non-shuffled data. We have tabulated the results in Table S1, for the BL vs DLBCL and bladder cancer expression datasets (continuous and clustered profiles).

iPAGE command line

The basic command line syntax for iPAGE is :

```
perl page.pl --expfile=<inp> --species=<sp> --exptype=<type>
```

where <inp> indicates the input expression profile (a two-column tab-delimited text file with gene names in the first column and expression measures in the second), <sp> indicates the species, and <type> indicates whether the expression profile is discrete (e.g., cluster indices) or continuous (e.g., expression values obtained from a single microarray experiment). We have prepackaged pathway annotations for many species, ranging from bacteria to human.

For example, the following command line will run iPAGE on a continuous *E. coli* expression profile :

```
perl page.pl --expfile=./TEST/continuous.exp --species=human_go --exptype=continuous
```

iPAGE creates an expfile_PAGE directory where the results are saved to (./TEST/continuous.exp_PAGE in this case).

Pathway-Regulatory Interaction Map Generator (PRMG)

Motif definition

As described in (Elemento et al., 2007), regulatory elements (motifs) are defined as *regular expressions* and can only consist of the following characters: A, C, G, T, [AC], [AG], [AT], [CG], [CT], [GT], [ACG], [ACT], [AGT], [CGT], and N (equivalent to [ACGT]).

Motif profile

We look for motifs both in 5' upstream (DNA motifs) and in 3'UTR sequences (RNA motifs). Given a motif, the *motif profile* is defined as a binary vector with N elements, where for each gene, “+1” indicates the presence and “0” indicates the absence of the motif in the corresponding promoter (or 3'UTR). “1” indicates that at least one match of the regular expression is present in the sequences (see Figure S14). For 5' sequences both strands are searched; whereas, in 3' UTR sequences only the transcribed strand is considered.

We used a generic definition of *active motif profile* (Elemento et al., 2007) to build the pathway-regulatory map; i.e., we only count the motif occurrences that are in expression cluster/bins in which the motif is over-represented. This approach filters out motif occurrences that are unlikely to be functional.

Pathway Profiles

For each pathway, the *pathway profile* is defined the same as in iPAGE.

Creating pathway-regulatory interaction maps

In the first step, we calculate the mutual information between the *motif profile* and *pathway profile* for each pair of motifs and pathways. We then assess the significance of these associations through 1,000 random shuffles of the motif profile and recalculating the MI values. By default, a category is accepted only if the real MI is larger than 995 of the random values. The associations that pass this test are deemed significant and their under- or over-representation *p*-values are calculated using equations (5) and (6).

Graphical output

We build a matrix with motifs as columns and pathways as rows where the non-zero elements represent the $-\log_{10}(p\text{-value})$ in case of over-representations and $\log_{10}(p\text{-value})$ otherwise. This matrix is then visualized as a blue-red heatmap with red and blue elements representing positive and negative associations respectively. A schematic representation of this method is shown in Figure S14.

PRMG command line

The PRMG script (prmg.pl) is part of the iPAGE package and is located in the PAGEvx.x directory; however, it also relies on FIRE outputs to run (FIRE is available at <http://tavazoilab.princeton.edu/FIRE/>):

```
export FIREDIR=/path/to/FIRE
export PAGEDIR=/path/to/iPAGE
perl prmg.pl --expfile=<inp> --species=<sp>
```

where <inp> indicates the input expression profile, <sp> indicates the species. The script does not work on *expfile* itself, but uses it to locate iPAGE and FIRE summary files (in expfile_PAGE and expfile_FIRE directories).

For example, the following command line will run PRMG on a continuous expression profile:

```
perl prmg.pl --expfile=./TEST/continuous.exp --species=human_go
```

The results are written to a motif_cat.cdt file and the graphical representations are created in the motif_cat.eps and motif_cat.pdf files. In order to run this program you also need to install the cluster 3.0 perl binder at <http://bonsai.ims.u-tokyo.ac.jp/~mdehoon/software/cluster/software.htm> and define a global variable termed USRDIR pointing to the directory where this binder is installed:

```
export USRDIR=/path/to/cluster3
```

Experimental validation of the discovered regulatory associations

Transfection of siRNAs targeting Elk1 and NFYA transcription factors

ON-Target^{plus}TM (Dharmacon) set of siRNAs for each TF were transfected into MDA-MB-231 cells (grown in D10F medium) using LipofectamineTM 2000 (Invitrogen). 72 hours after transfection, RNA samples were extracted from the cells (mirVanaTM miRNA Isolation Kit) and were subjected to cDNA synthesis (SuperScript[®] III RTS First-Strand cDNA Synthesis Kit from Invitrogen). mRNA knock-down in each sample was verified using SYBRE Green qPCR reactions (Universal ProbeLibrary Assay Design Center, Roche Applied Science). For each TF, we selected two of the successfully knocked-down transfections and extracted their total RNA along with mock-transfected cells as controls. We then differentially labeled the RNA samples with Cy3 and Cy5 dyes and hybridized them to Agilent human gene expression arrays (4×44k). The genes with significant discordant changes between the two biological replicates were filtered out and for the rest, the Cy3/Cy5 values were

averaged and combined into a single dataset as log of ratios. The expression profiles are available at <http://tavazoilab.princeton.edu/iPAGE/>.

Transfection of decoy and scrambled oligonucleotide sequences

For the validation experiments, we chose two of the genes implicated by FIRE to have a version of AAAA[ATG]TT (NM_000337 and NM_001024660). For each gene, we then synthesized a 19bp sequence containing the AAAA[ATG]TT motif. These sequences were also randomly shuffled to create scrambled sequences as controls. The resulting sequences were synthesized as double stranded oligonucleotides: Decoy1: caattGAAATTTTGagcaa, Scrambled1: gtTtATAcAcTaaaGaTGa, Decoy2: gctggAAAAAATTTaagac, Scrambled2: aagATTgctAgAAgAaATc. We then transfected these oligonucleotides into MDA-MB-231 cells grown in D10F medium at a concentration of 1 μ M (TransIT®-Express Transfection Reagent). 72 hours post-transfection, we extracted RNA and differentially labeled the samples with Cy3 or Cy5 dyes. The samples were then hybridized to Agilent human gene expression arrays (4 \times 44k). The Cy3/Cy5 ratios from the two sets were then averaged, filtered and combined in a single dataset as log of ratios. In this step, we filtered out ~2000 genes that showed significantly discordant expression level changes in the two biological replicates. The expression profile is available at <http://tavazoilab.princeton.edu/iPAGE/>.

Supplemental Results

iPAGE and Gene-set Enrichment Analysis

As mentioned in the main text, a variety of powerful approaches have been developed for gene-set enrichment analysis (e.g., Sinha et al., 2008; Subramanian et al., 2005). These computational methods rely on different statistical tests to assess the non-random distribution of pathway-membership across the expression values. For examples, Sinha et al. (2008) use the hypergeometric distribution to calculate the overlap between gene-expression clusters and pathway-memberships. Subramanian et al. (2005), on the other hand, use a rank-based approach to discover non-random patterns. These approaches are well-defined, powerful and tested; however, in a setting where a large number of statistical tests are performed, sensitivity is reduced mainly because of multiple-testing corrections.

In iPAGE, we employ mutual information to tackle this problem. Although iPAGE is only one component in our broader approach, it provides major advantages over the previous methodologies:

1. In comparison with the hypergeometric distribution, using a mutual information-based method notably decreases the number of statistical tests necessary (by the number of clusters/bins), resulting in a higher sensitivity at the same false discovery rate.
2. Mutual information also enables iPAGE to analyze both discrete and continuous inputs making it a universal approach for analyzing any type of data without the need for any upstream analysis. This is particularly important in this study where we analyze different whole-genome datasets.
3. iPAGE is also capable of discovering non-monotonic associations, a category that is masked in rank-based methods. In these associations, different components of a pathway may show opposite expression patterns relative to each other. For example, a number of metabolic pathways include both biosynthetic and catabolic genes and an increase in the final product typically requires the simultaneous down-regulation of the catabolic genes and up-regulation of the biosynthetic genes.
4. In iPAGE, we use conditional information to substantially reduce the redundancy, which in turn results in a concise and manageable graphical output.
5. We have been extra careful in limiting the computational expenses and our package is relatively fast. Also, we have attempted to make iPAGE as user-friendly as possible. In addition to the complete command-line version, we have developed Graphical User Interfaces for both Mac OS X and windows users for rapid and every-day use of the application by non-experts.

The Regulatory Network of Bladder Carcinoma

The general method for meta-analysis of bladder cancer vs normal dataset used in the main text (Dyrskjot et al., 2004) reveals the most prominent signatures of a cancer state: in this case, a faster cell cycle and a repressed immune response through the regulatory effects of E2F and SEF1/E47 transcription factors respectively. We also identified a range of significant *cis*-regulatory elements, including a putative 3'UTR element, NUNGNUGU (seed UAGAUGU/TAGATGT) (Figure 2B, main text). Our approach also reveals that several of these motifs co-occur in promoters or 3'UTRs of the same genes (Figure S1A), thus suggesting possible cooperations between the regulatory factors that bind them. In order to provide additional evidence for these predicted cooperations, we used the approach described in Pilpel et al. (2001) to compare the extent to which two of the novel motifs (one DNA and one RNA) cooperate with the Elk-1 motif in co-regulating their target genes. First, we selected 1000 random pairs of genes and used Pearson correlation to calculate the correlation coefficient (R) between the expression levels of each pair across the bladder carcinoma dataset (Dyrskjot et al., 2004). We then repeated the same procedure, this time on the set of genes harboring an

Elk1 motif in their upstream sequence. As it is shown in Figure S1B, the distribution of the resulting R-values from Elk1 target genes is shifted to the right compared to the random background values (p -value $<1e-14$). The genes harboring the DNA motif [ACG]ACGT[CT][CGT][AG][CGT] (seed ACGTCGG), show a distribution similar to that of Elk1 (p -value $<1e-15$) and focusing on the genes that harbor both of the motifs results in an even larger shift towards higher R-values (p -value $<1e-15$). The p -values reported in each case have been calculated using Mann-Whitney test, comparing each distribution to that of the background. Repeating this procedure for [ACU]U[ACU]G[ACG]UGU (seed UAGAUGU/TAGATGT), resulted in comparable distributions (Figure S1B). These observations further highlight the biological relevance of the discovered novel motifs and provide additional support for the predicted motif interactions.

While the continuous analysis of bladder carcinoma signatures apparently captures a global picture of deregulations, it does not take into account intra-cancer variations and may hide pathways that are deregulated in different subsets of samples. In order to increase our sensitivity in capturing a broader range of pathway deregulations, we first clustered the genes based on their expression across normal and tumor samples and then combined the clusters with low average differences between normal and tumor into a single background cluster. The informative pathways that iPAGE discovered from this discrete input data were generally similar to the pathways obtained when analyzing the continuous profile, as described in the main text. However, iPAGE also identified NF- κ B, PI3-K and Rho signaling pathways as globally up-regulated in the tumor samples (Figure S15). Genes involved in “Negative regulation of apoptosis” also show a substantial increase in their expression compared to normal samples (Figure S15).

The identification of additional pathways without an increase in FDR (Table S1) suggests that using a cluster-based approach, which takes into account the intra-cancer variability, may increase sensitivity and reveal additional pathways. Interestingly, the benefits of using this approach become even more apparent when we search for *cis*-regulatory elements. We identified 128 significantly informative motifs, a summarized version of which is presented in Figure S16. The sequence motifs discovered in the continuous analysis are included among the new set of motifs (e.g. E2F and SEF-1); however, this analysis reveals many new known and novel regulatory elements including p53, Elk-1, Sp1, NF-Y and CRE-BP1 (Figure S16).

Among the known regulatory elements, Elk-1, Sp1, NF-Y and E2F show a significant association with “DNA replication” compared to E2F alone in the continuous method. E47 and SEF-1 are associated with the “immune response” pathways (Figure S17). In addition to these, we also captured the role of STAT3 transcription factor in cell cycle regulation. The signal transducers and activators of transcription (STATs) are a family of proteins with key roles in cellular differentiation and proliferation. Among these, STAT3 is known to be involved in coordinating G1-S transition (Fukada et al., 1998).

In the pathway-regulatory interaction map (Figure S17), up-regulation in the “protein folding” genes is associated with HSF (Heat Shock Factor). In higher eukaryotes, HSF binds the heat shock element (HSE) located in the promoters of heat shock genes to activate their transcription as part of the unfolded protein response (Amin et al., 1988). In addition to its apparent role in protein folding, HSF is also believed to participate in general immune response (Singh and Aballay, 2006) potentially explaining its association with this pathway in our analysis (Figure S17).

Besides the abovementioned transcription factors, we should also highlight the role of SRF in regulating the “cell junction” pathway. Assembly and disassembly of cell-cell junctions comprise a number of key events during physiological and pathological processes. The role of serum receptor

factor (SRF) as a potential regulator of this process has been previously established by *in vivo* observation of the deficiencies in mutant backgrounds (Busche et al., 2008). As highlighted in our results (Figure S17), deregulation in the activity of this transcription factor may be crucial for tumor metastasis (*i.e.* benign to malignant transition).

A substantial fraction of *cis*-regulatory elements discovered in this study correspond to the binding sites of known transcription factors. The expression of these transcription factors can be viewed in the context of this dataset or other independent whole-genome datasets. This would enable us to compare the presence or absence of a given transcription factor to the expression of its putative downstream genes. Such analysis can act as a validation step for both the discovered motifs and the functions associated with them through the “pathway-regulatory interaction map”. For example, here, we have focused on two transcription factors from the bladder carcinoma dataset: Elk1 and TFDP1 (a protein that binds E2F and promotes its DNA binding affinity; Crosby et al., 2007). Elk1, which was associated with mitosis, RNA splicing and ribosome biogenesis in our study (Figure 2C, main text), shows a significant anti-correlation with these genes, suggesting that it functions as a repressor (Figure S2). Similarly, TFDP1, which is a partner in E2F complexes, is significantly correlated with the expression of the genes in the E2F associated functions, namely DNA replication, microtubule biogenesis and mitotic cell cycle (Figure S3). We have also included the same analysis for AhR and its predicted association with Ub-dependent protein catabolic process (Figure S4).

In addition to GO pathways, we also used the MSigDB c2 gene-sets to re-analyze the bladder cancer dataset in its continuous format (as presented in the main text). The iPAGE results are presented in Figure S18. Up-regulation of many cancer-related genes and cell-cycle pathways along with a down-regulation of immune response pathways (e.g. cytokine pathway, IL and TNF mediated inflammatory responses) match the results presented based on the GO pathways in the main text. We have also included the pathway-regulatory interaction map obtained from these gene-sets (Figure S19).

Comparative analysis of cancer sub-types (BL vs. DLBCL)

Due to space limitations, for this analysis, we only included a limited number of deregulated pathways in the figures of the main paper. Here, however, we have presented the iPAGE and FIRE outputs with the complete list of the deregulated pathways and informative sequence motifs (Figure S5A and B). Some of the matrices presented here and in the next section are too large to be legibly fit in a page; however, the figures are vector graphics and can be enlarged when viewed electronically.

Similar to the Elk1 and TFDP1 analysis for the bladder carcinoma dataset, in Figure S6, we have included the expression of NF-Y (as the average expression of NFYB and NFYC genes) and SP1 in comparison with the expression of their associated downstream pathways. NF-Y, associated with cell cycle and chromatin biogenesis, is highly correlated with the genes in these pathways (p -value < $1e-30$). Sp1 shows a similar correlation with cell cycle and secretory pathways (p -value < $1e-12$).

Building a regulatory map of cancer deregulation

Next, we studied regulatory perturbations across many cancer types to capture both globally deregulated and more cancer-specific pathways. We compiled a compendium of 46 cancer versus normal gene expression microarray datasets (see Table S2). We then processed the samples and used iPAGE to build a cancer pathway map (Figure S7 and Figure 5 in the main text). This systematic iPAGE analysis of cancer datasets allowed us to compare the corresponding cancers based on their pathway-level perturbations. In order to do so, we used hierarchical clustering to cluster the cancers based on their informative pathways (listed in Figure 5, main text). The clustering results and the correlation matrix are shown in Figure S20. The hierarchical clustering tree in Figure S20 shows that independent cancer datasets of similar types are also similar in terms of their informative (and

therefore deregulated) pathways. For example, in this figure, all non-small cell lung datasets are grouped together in one cluster (Beer et al., 2002; Bhattacharjee et al., 2001; Stearman et al., 2005) distinguishing them from the single small cell carcinoma (SMCL) dataset (Bhattacharjee et al., 2001). Among all the cancers, two samples in particular show a highly negative correlation with others: a melanoma dataset (Hoek et al., 2006) and a chronic lymphocytic leukemia (CML) dataset (Alizadeh et al., 2000). This anti-correlation largely results from a lower expression of cell cycle related genes in both of these tumors (Figure 5, main text). As Alizadeh et al. (2000) noted, CML is a slowly progressing disease with a low proliferation rate. Similarly, despite being highly metastatic, a cohort of melanoma samples in this dataset has been shown to have a low proliferation rate (Hoek et al., 2006) thus explaining the lower expression of mitotic genes in this cancer.

We also used FIRE on our compendium to build a cancer regulatory map. In essence, sequence motifs whose associated genes show significant deregulation in the tumor samples are identified and compiled to form this regulatory map (Figure S8). Apart from their independent occurrences in multiple datasets, most of these motifs also have high network-level conservation scores (Figure S9). Figure S9 also includes the *cis*-regulatory elements identified in the bladder carcinoma and lymphoma datasets.

Subsequently, using an information-theoretical approach, we associated the discovered *cis*-regulatory elements with the deregulated pathways to build a cancer pathway-regulatory interaction map (Figure S10). In Table S3, we list a number of novel and significant associations from this map, representing an unknown regulatory protein (or miRNA) potentially regulating the associated pathway through recognition of the corresponding sequence motif. In some cases, we have predicted novel associations for known transcription factors (or miRNAs). In Figure S11, we have used the NCI-60 gene expression panel to test some of these novel associations. For example, we have predicted Lmo2-complex as a direct regulator of PI3K signaling and cell migration. The members of these pathways that harbor an Lmo2 binding site are highly correlated with the expression of this transcription factor (Figure S11). We observed similar correlations between TCF3 (E47 complex) and the inflammatory response pathway and miR-203 and protein degradation pathway (Figure S11).

Here, we have also included the cancer pathway map built from MSigDB c2 gene-sets in Figure S21. The procedure is the same as above, with the exception that we have used MDigDB c2 gene-sets instead of GO terms (biological processes).

The discovered motifs are informative of gene expression patterns across independent datasets

We used the human gene-expression atlas (Su et al., 2004) and NCI-60 gene expression panel (Ross et al., 2000) to further test the functional relevance of our discovered elements. We clustered the genes in these two datasets into 70 clusters using the *k*-means approach, and then used FIRE in non-discovery mode (a mode in which the motif discovery is skipped and all the steps are performed on a set of input motifs) to test whether our 104 identified motifs show a significant non-random pattern across these datasets. As shown in Figure S22 and Figure S23, 74 of these motifs have significant mutual information values with the expression clusters further strengthening the evidence for the role of these elements in regulating gene expression.

FIRE analysis of experimentally tested associations

As shown in Figure S24, we used FIRE to also analyze our gene expression profiles from both decoy vs. scrambled dataset and TF knock-down datasets. In the AAAA[ATG]TT dataset, in addition to ATA[AT][GT][CT]T[AT] (which resembles the reverse complement of AAAA[ATG]TT), we also discovered Elk4 and another novel motif (Figure S24B). The observed deregulation in the Elk4 downstream genes explains the up-regulation in the cell cycle genes, as this TF is a known modulator

of mitosis. Similarly, we observed an up-regulation in the genes harboring the CCAAT motif in the NFYA knock-down dataset (Figure S24C).

Legends

Figure S1. Measuring co-regulation in the downstream genes of novel motifs. (A) The regulatory interaction matrix for the bladder carcinoma *cis*-regulatory elements. (B) 1000 gene pairs are selected from bladder carcinoma dataset (Dyrskjot et al., 2004) and the distribution of their Pearson correlation coefficients is plotted. The background set includes all the genes in the dataset; whereas ‘Elk1’ is limited to the genes harboring Elk1 motifs in their upstream sequences. Similarly, TAGATGT plot represents the genes harboring [ACU]U[ACU]G[ACG]UGU (a novel 3’ UTR element). We have also included this distribution for the simultaneous occurrence of these two motifs. Similarly, the distribution of R-values are shown for Elk1 and ACGTCGG (a upstream element [ACG]ACGT[CT][CGT][AG][CGT]) and their simultaneous presence.

Figure S2. Elk1 expression across the bladder carcinoma samples and its comparison with target genes within the associated pathways. The expression of each pathway is calculated as the average normalized expression of the genes listed. A regression test is then used to calculate the correlation coefficients and their associated *p*-values.

Figure S3. TFDP1 (E2F associated protein) expression and its comparison with E2F associated pathways across the bladder carcinoma samples.

Figure S4. The correlation of transcription factor AhR with Ub-dependent protein catabolic process.

Figure S5. The complete iPAGE (A) and FIRE (B) outputs for the BL vs DLBCL dataset. While Figure 2A and B contain a summarized version of these results, here we have included the complete outputs.

Figure S6. The normalized expression of NF-Y and Sp1 across the BL vs. DLBCL samples along with the expression of their target genes.

Figure S7. The complete cancer pathway map without redundancy removal.

Figure S8. Cancer regulatory map. The level of significance by which the genes harboring a given putative *cis*-regulatory element are up or down regulated is depicted here. This matrix is formatted to include only the known motifs and those that are significantly associated with more than 3 cancers.

Figure S9. Network-level conservation scores. This figure shows our discovered motifs and their network-level conservation scores with respect to the chicken genome (Elemento and Tavazoie, 2005). Values range from 0 to 1, with 1 being most conserved.

Figure S10. The complete cancer pathway-regulatory interaction map.

Figure S11. The expression level of Lmo2, TCF3 and miR-203 modules across the NCI-60 panel.

Figure S12. Conceptual schematic of our computational framework. We start from a gene expression dataset and use iPAGE and FIRE to discover the deregulated pathways and *cis*-regulatory elements that are informative of gene expression patterns. We then use pathway-regulatory interaction map (PRM) analysis to functionally annotate the identified motifs through associating them with their potential downstream pathways.

Figure S13. iPAGE schematic. Two exemplary expression profiles are shown: discrete (*e.g.* cluster indices from co-expression clustering) and continuous (*e.g.* log of fold change in expression level in the tumor sample compared to normal). Mutual information is then used to assess the level by which given pathway profiles are informative of these expression profiles.

Figure S14. Pathway-Regulatory Interaction Map Generator. The discovered informative pathways (from iPAGE) and putative *cis*-regulatory elements (from FIRE) are combined in this approach to associate regulatory proteins with their target pathways.

Figure S15. Bladder carcinoma versus normal samples (discrete mode). The informative pathways discovered by iPAGE that are deregulated in tumor samples compared to normal controls. The top panel shows the normalized average expression of each cluster in Bladder carcinoma and normal samples.

Figure S16. Discovering putative *cis*-regulatory elements driving bladder cancer deregulation. We used FIRE to identify putative DNA/RNA motifs whose downstream/upstream genes show significant deregulation in the tumor samples compared to normal controls. The top panel shows the normalized average expression of each cluster in Bladder carcinoma and normal samples.

Figure S17. The pathway-regulatory interaction map of bladder cancer. The discovered *cis*-regulatory elements (Figure S16) are positively or negatively associated with the significantly informative pathways (Figure S15).

Figure S18. iPAGE output for the bladder cancer dataset (continuous) using MSigDB c2 gene-sets.

Figure S19. The pathway-regulatory interaction map of bladder cancer using the MSigDB gene sets. The gene-sets discovered in Figure S18 are associated with *cis*-regulatory elements in Figure 2A (main text).

Figure S20. Correlation matrix calculated from our cancer pathway map. All the cancer samples are clustered based on their deregulations across different pathways. Each element in this matrix represents a pair-wise correlation value. On the right, the tree representing the hierarchical clustering is presented.

Figure S21. The complete cancer pathway map for MSigDB c2 gene-sets (without redundancy removal).

Figure S22. The discovered *cis*-regulatory elements in the cancer regulatory map are informative of gene expression clusters in the NCI-60 dataset.

Figure S23. The discovered *cis*-regulatory elements are informative of gene expression clusters in the human gene expression atlas.

Figure S24. FIRE analysis of experimentally tested associations. (A) The motifs that are most informative of the decoy AAAA[ATG]TT vs scrambled microarray experiment. (B) Knocking down Elk1 results in the upregulation of genes harboring Sp1, Elk1 and MEF-2 binding sites. (C) Knocking down NFYA results in upregulation of genes harboring the NF-Y binding site.

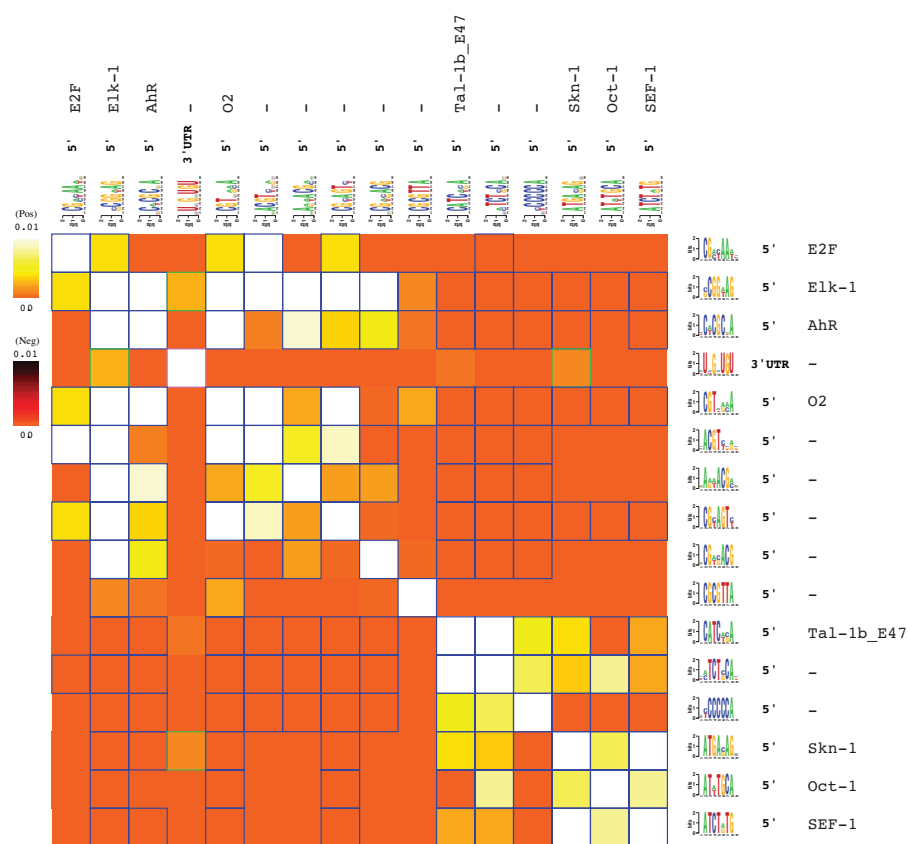
Table S1. The number of pathways discovered by iPAGE in 3 datasets studied in the main text in comparison with the number of pathways obtained from the same but randomly shuffled datasets.

Table S2. The list, tissue and references of the cancer gene expression studies used to compile our initial dataset.

Table S3. A list of predictions based on the associations in the Cancer Pathway-Regulatory Interaction Map.

Supplemental Figures

(A)



(B)

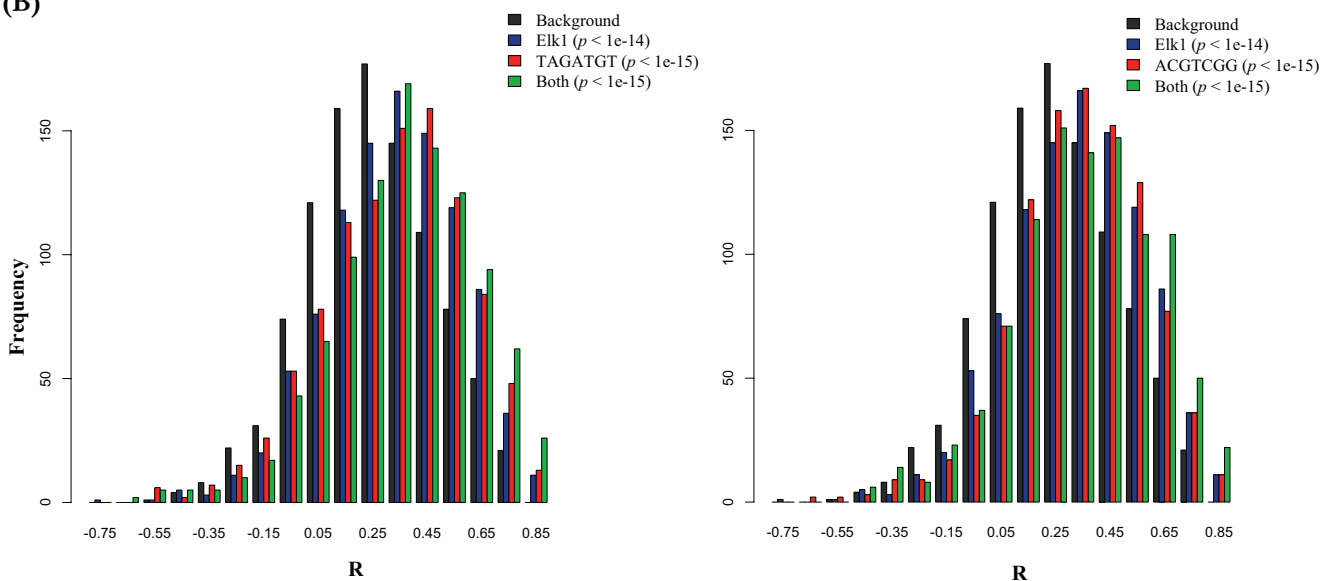
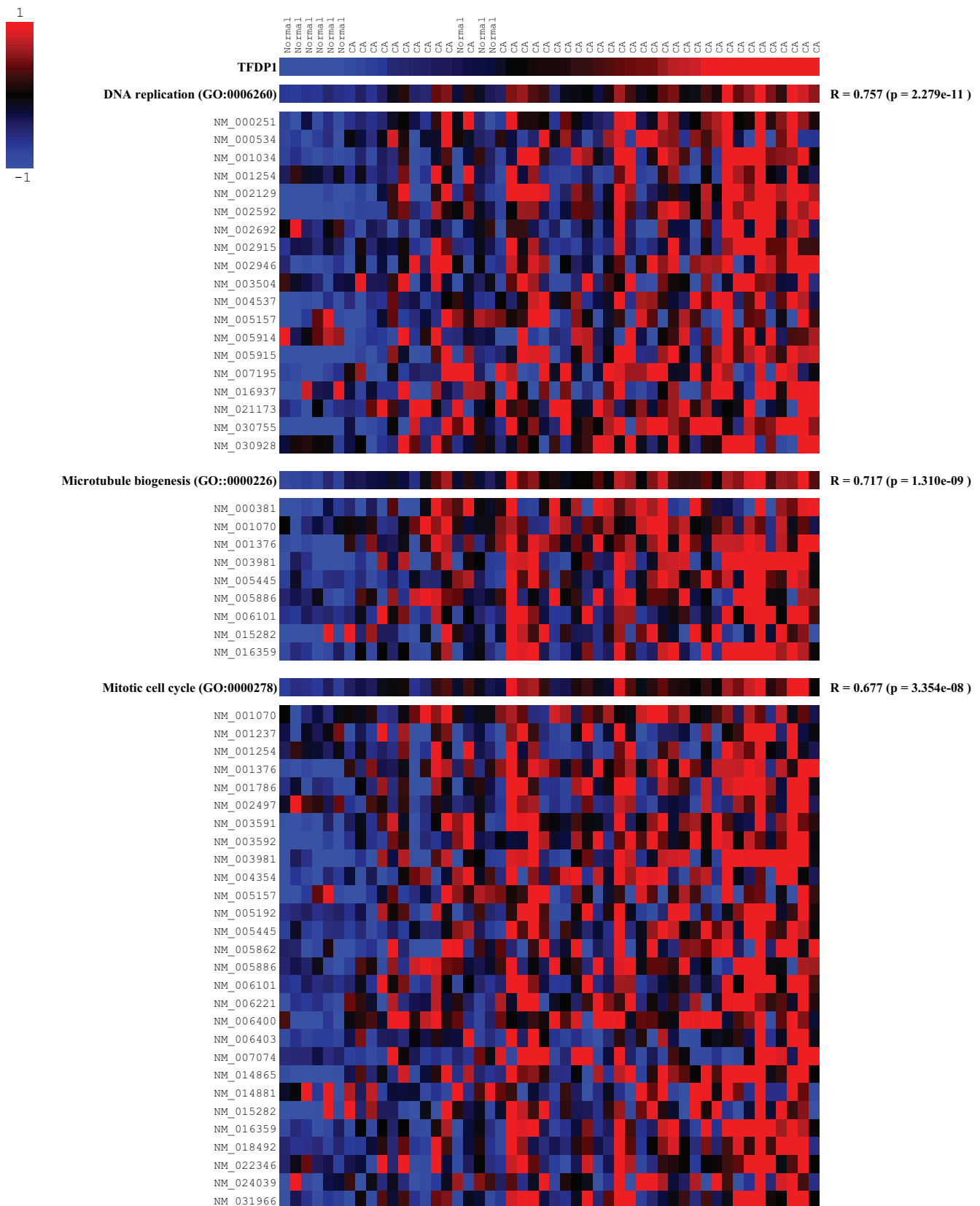
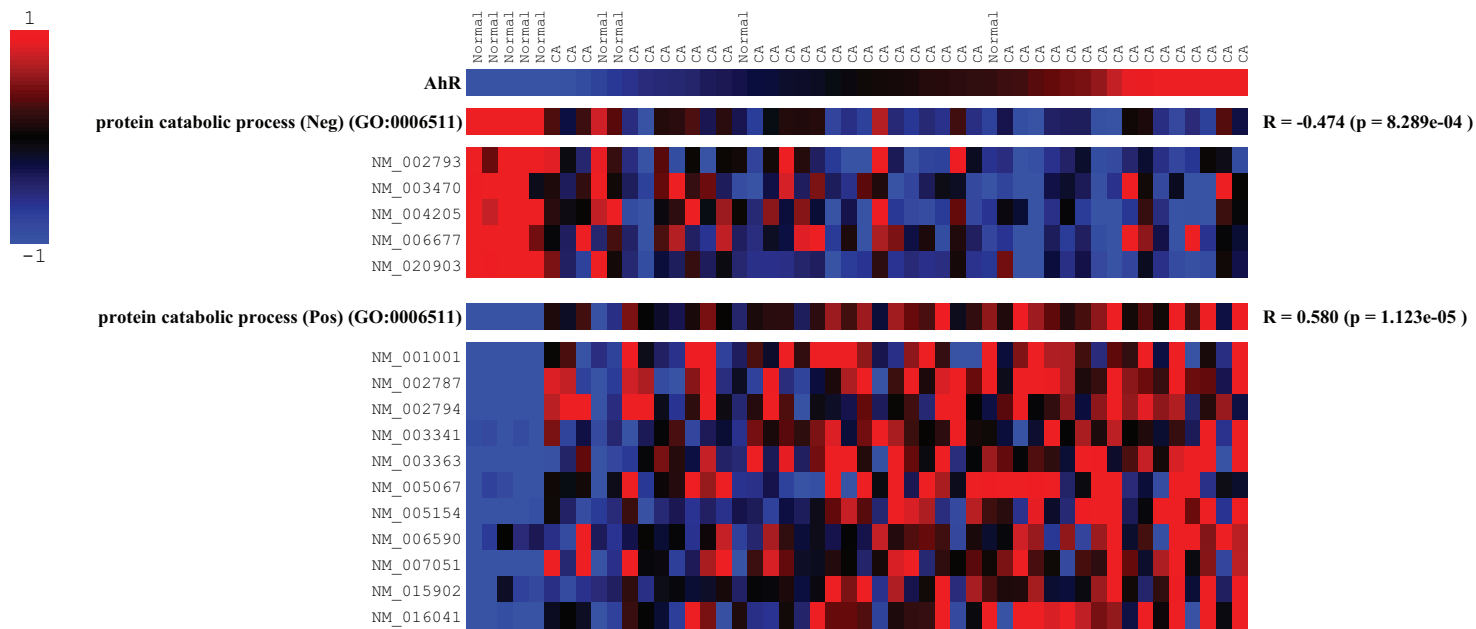


Figure S1





(A)

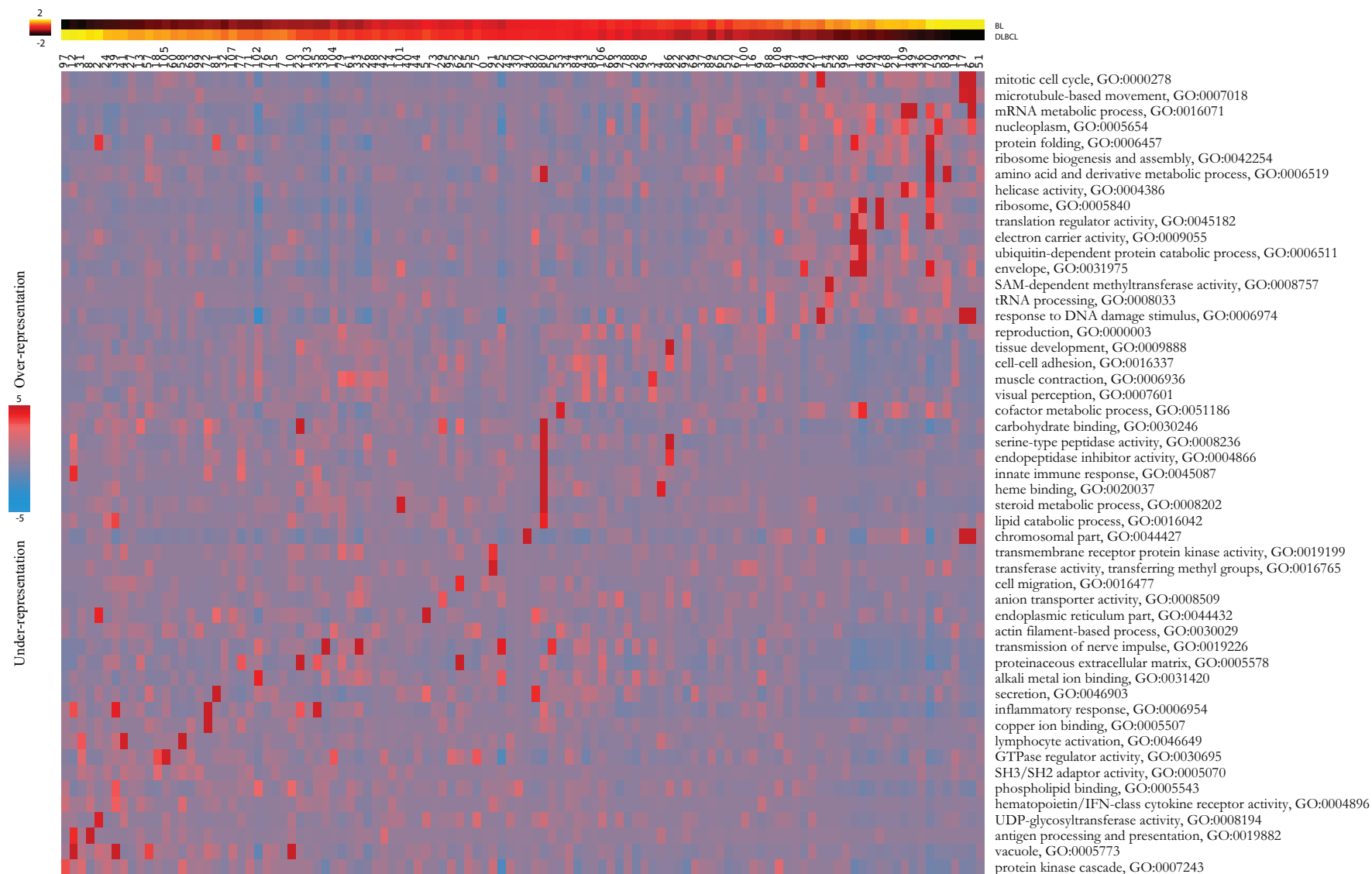


Figure S5A

(B)

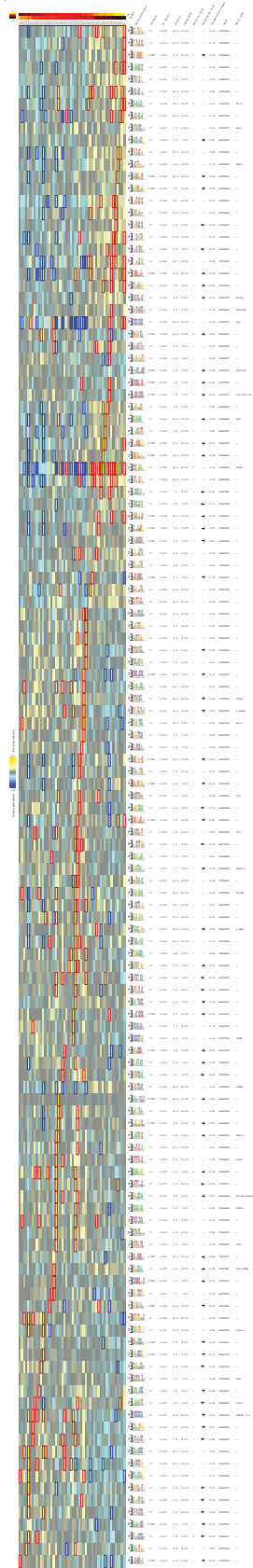


Figure S5B

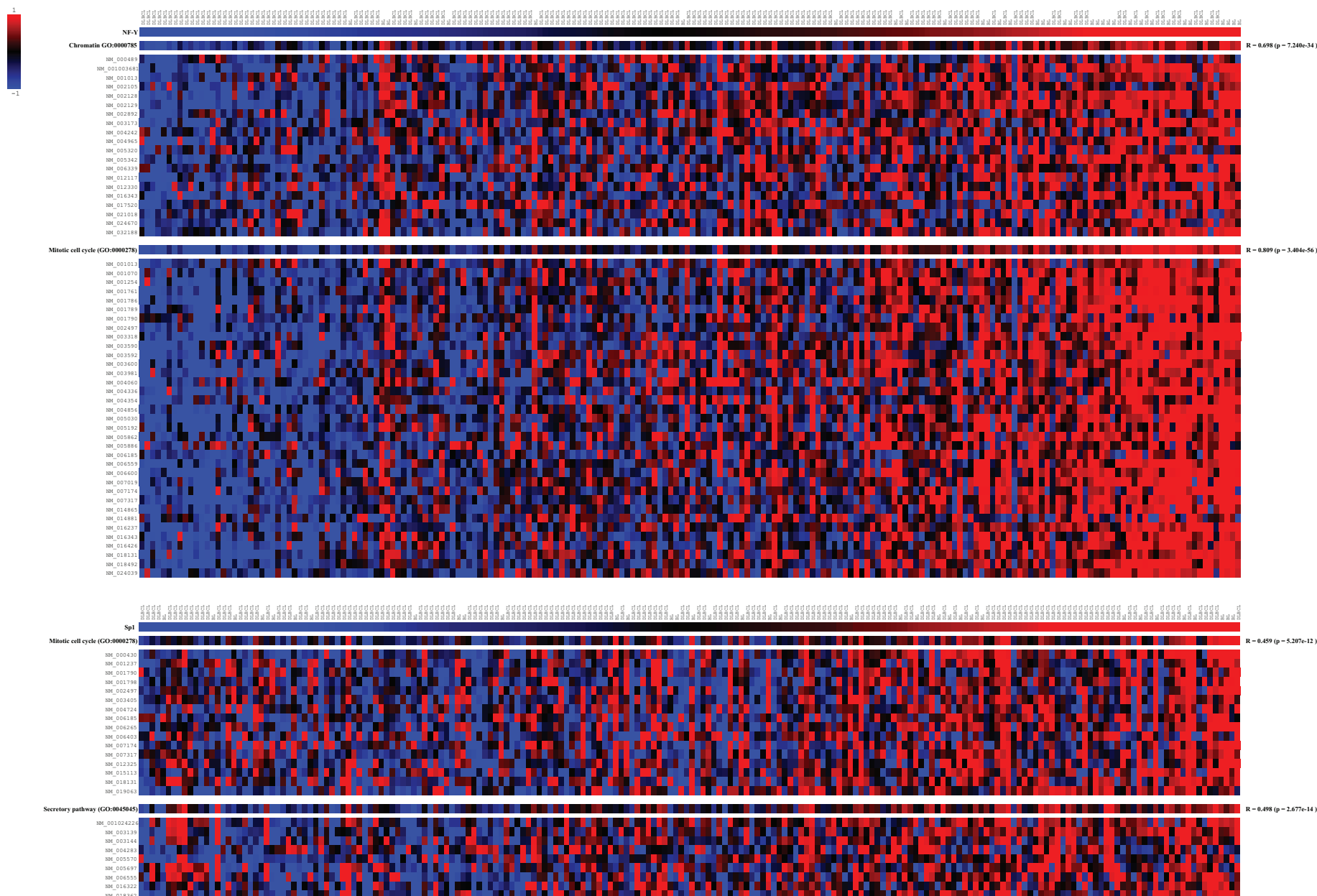


Figure S6



Cancer Regulatory Motifs

[illegible]

24

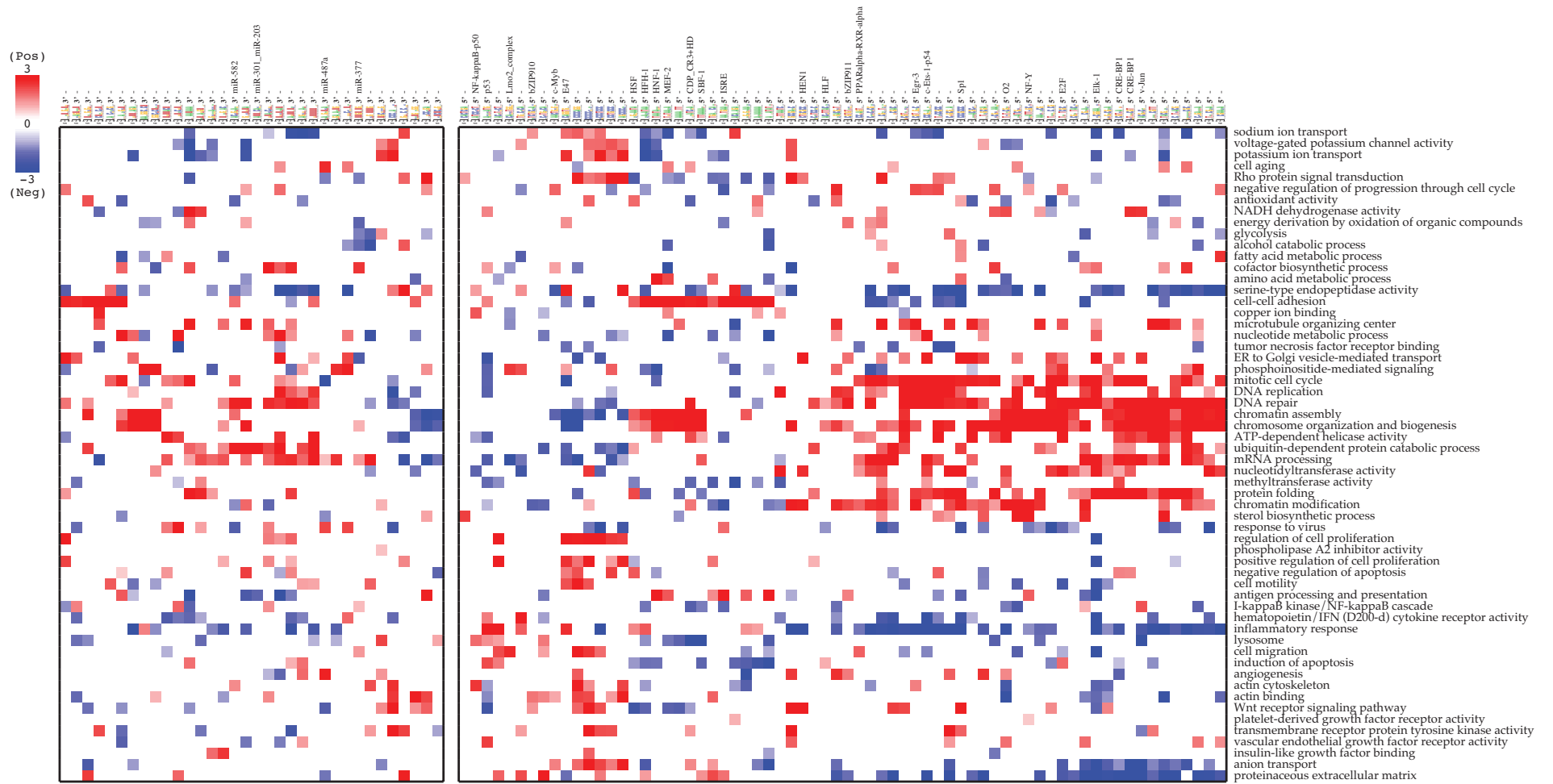
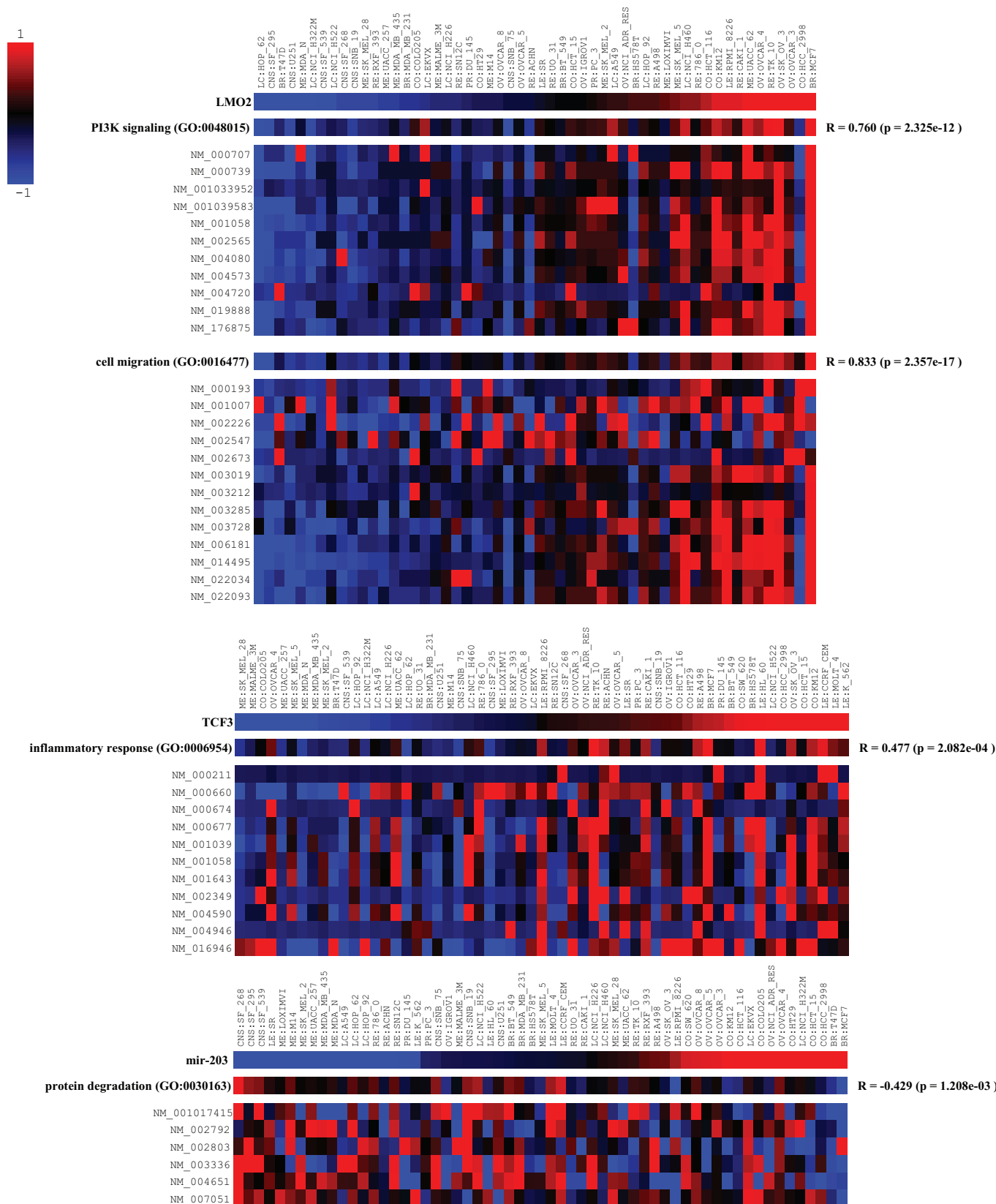


Figure S10



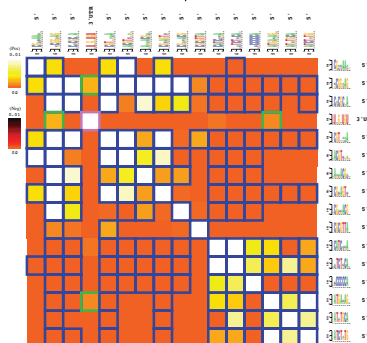
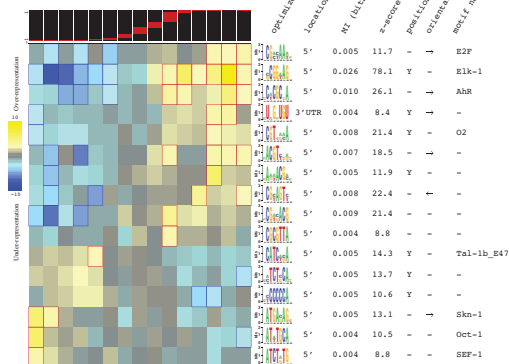


Figure S12

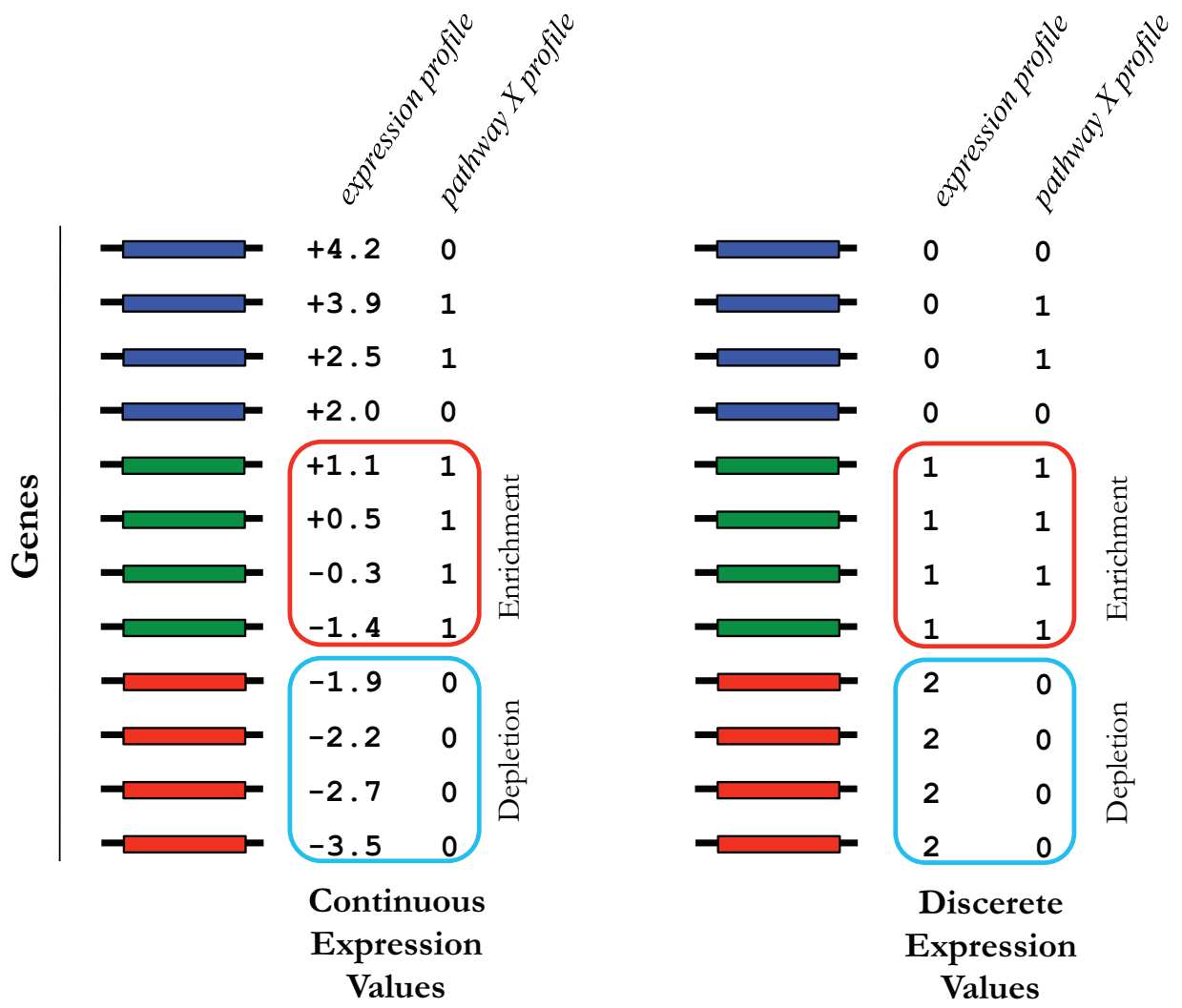


Figure S13

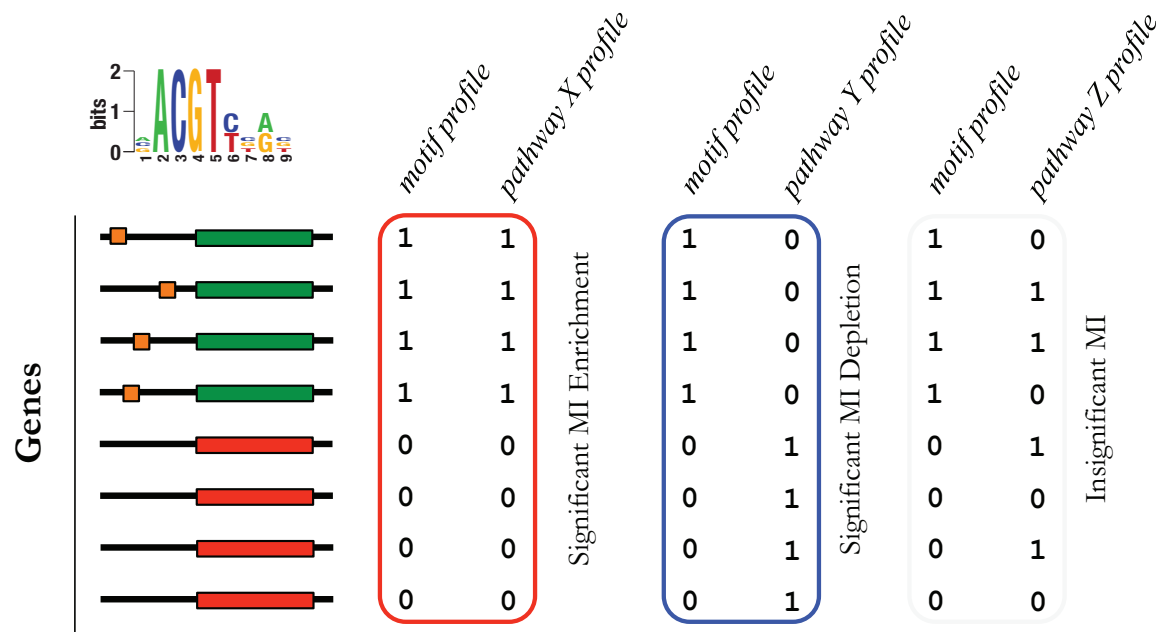


Figure S14

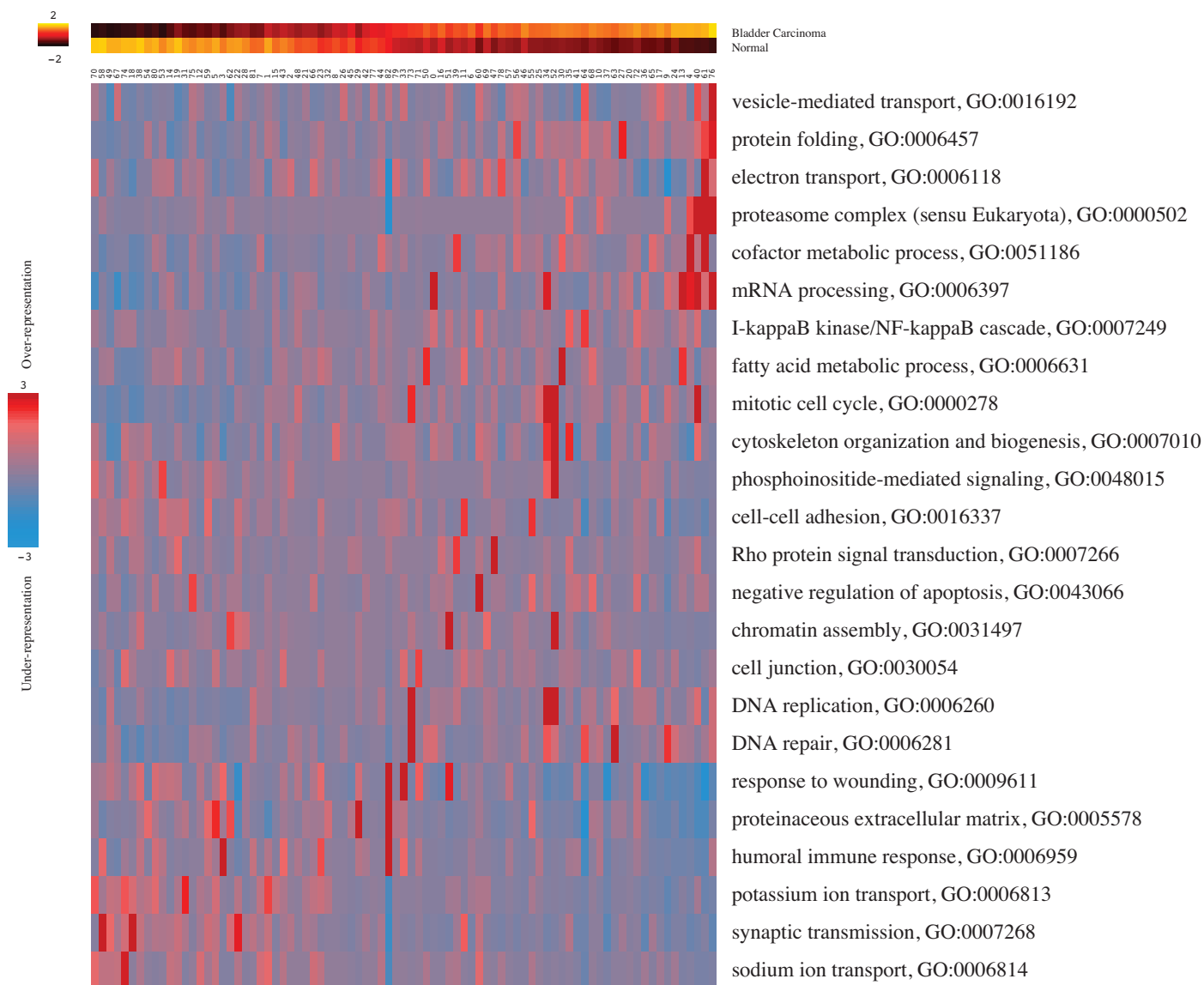


Figure S15

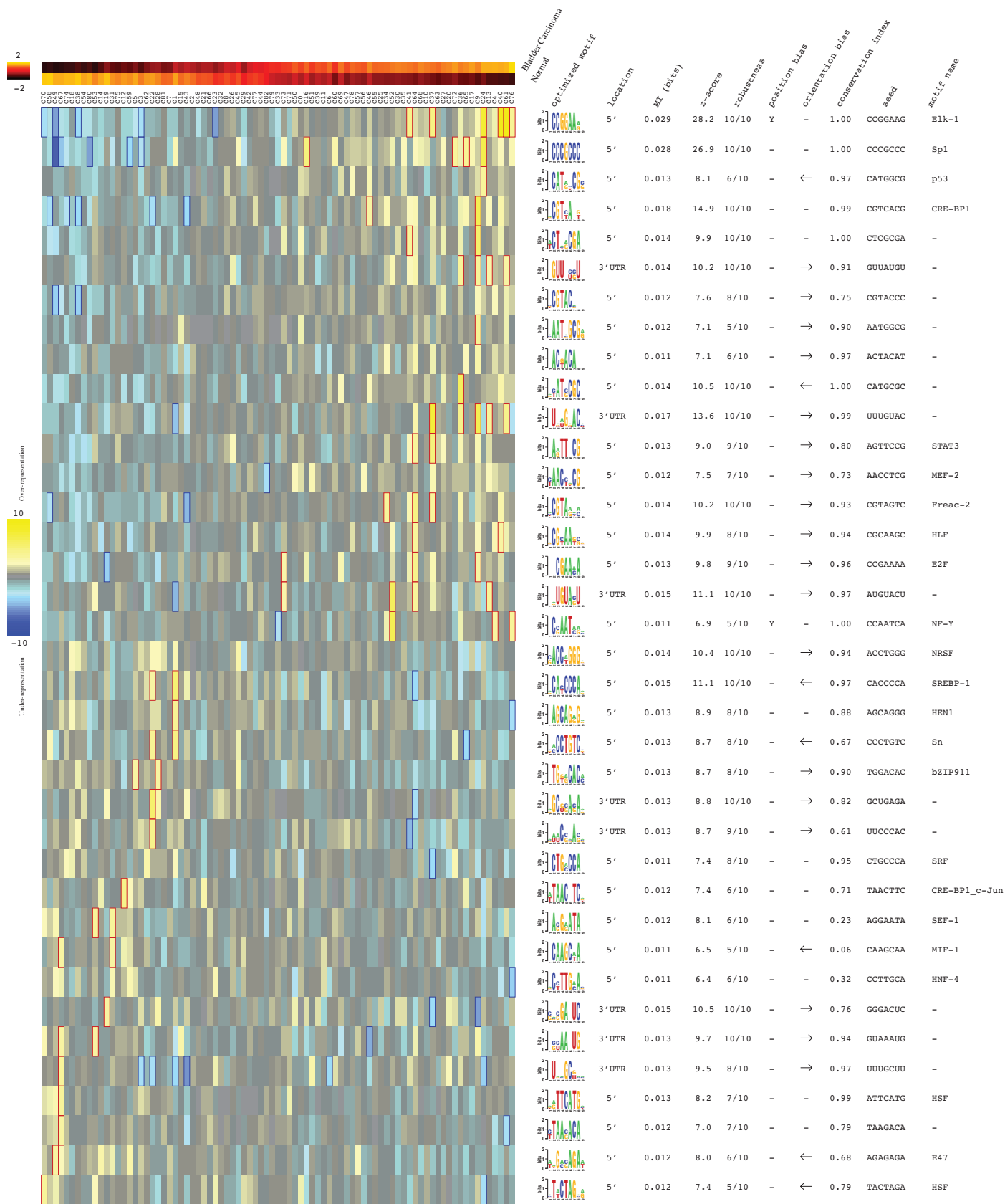


Figure S16

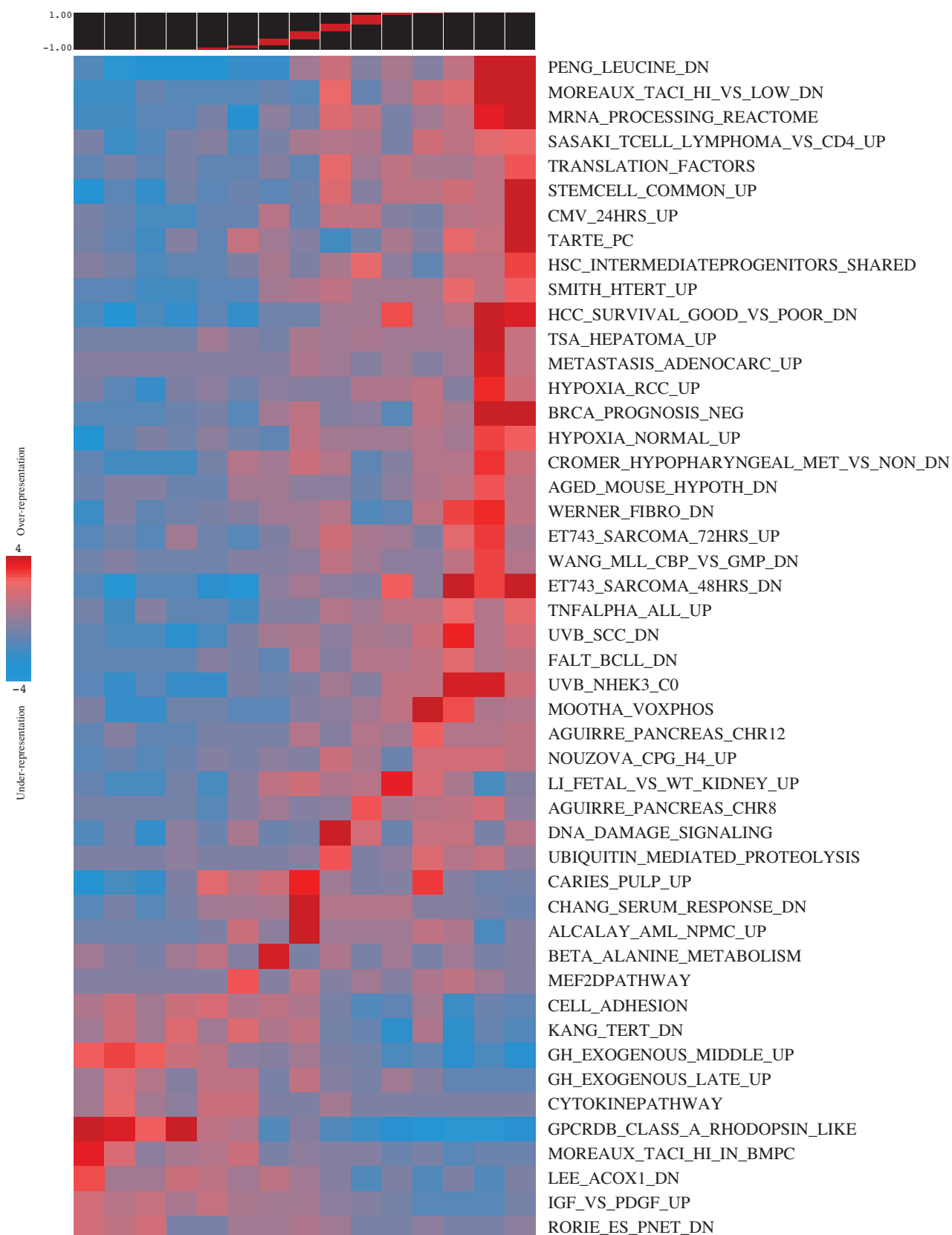


Figure S18

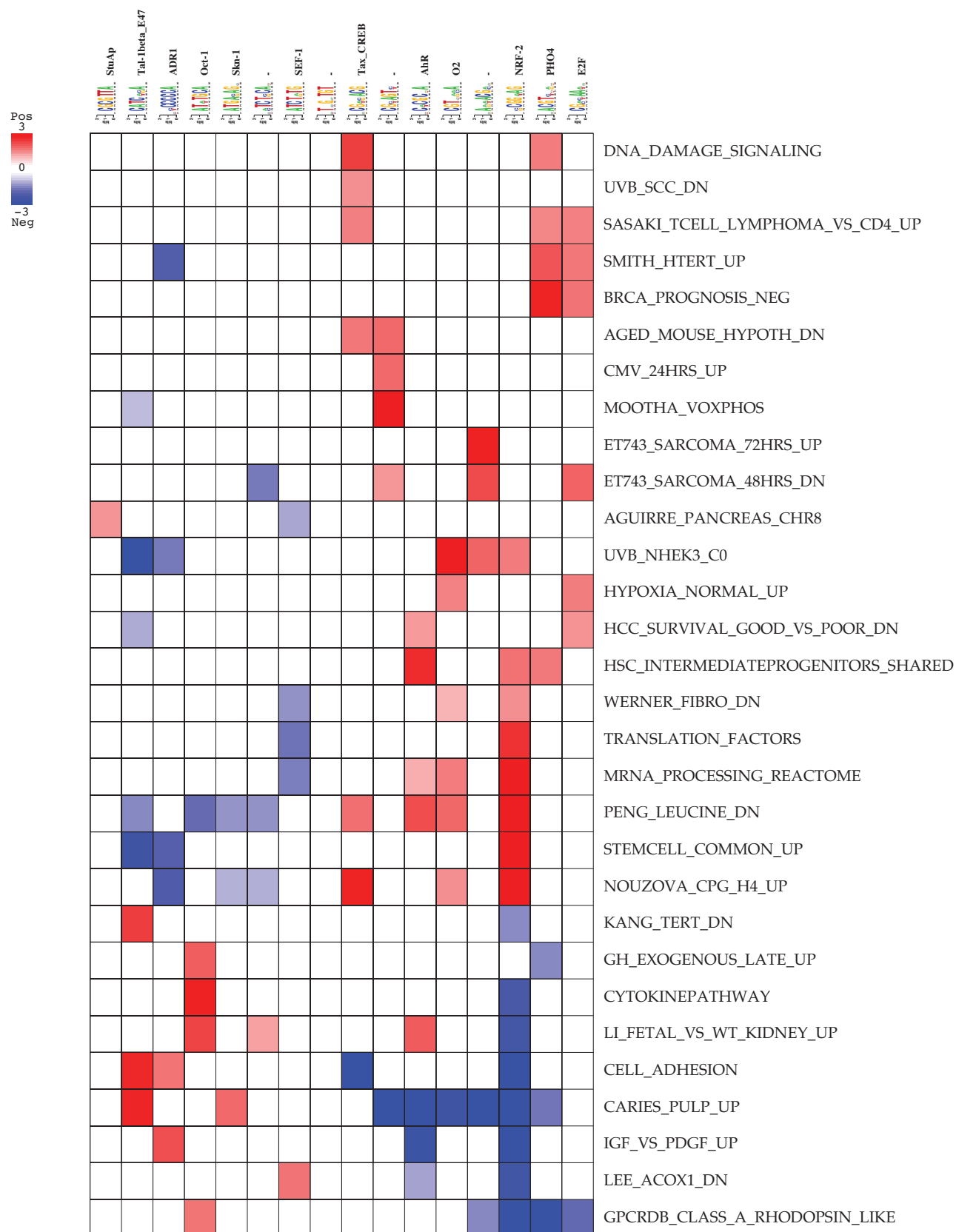


Figure S19

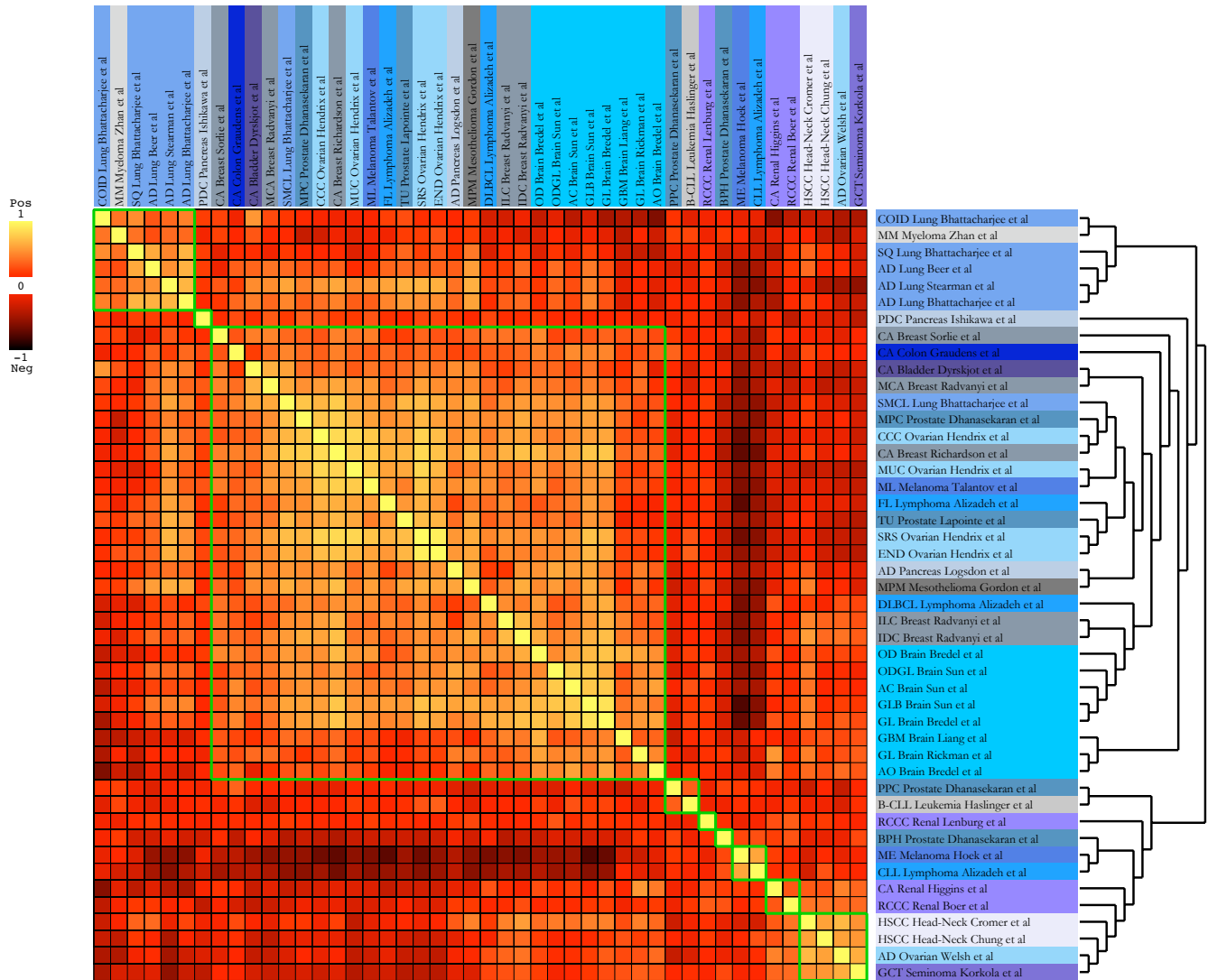


Figure S20



Figure S21

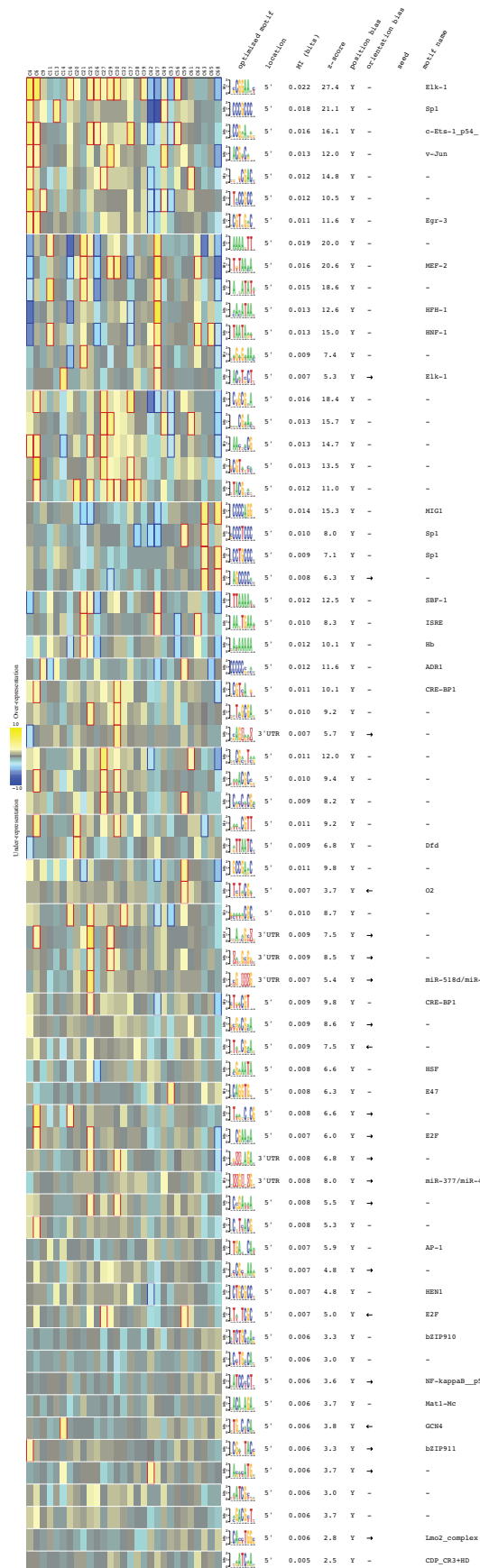


Figure S22

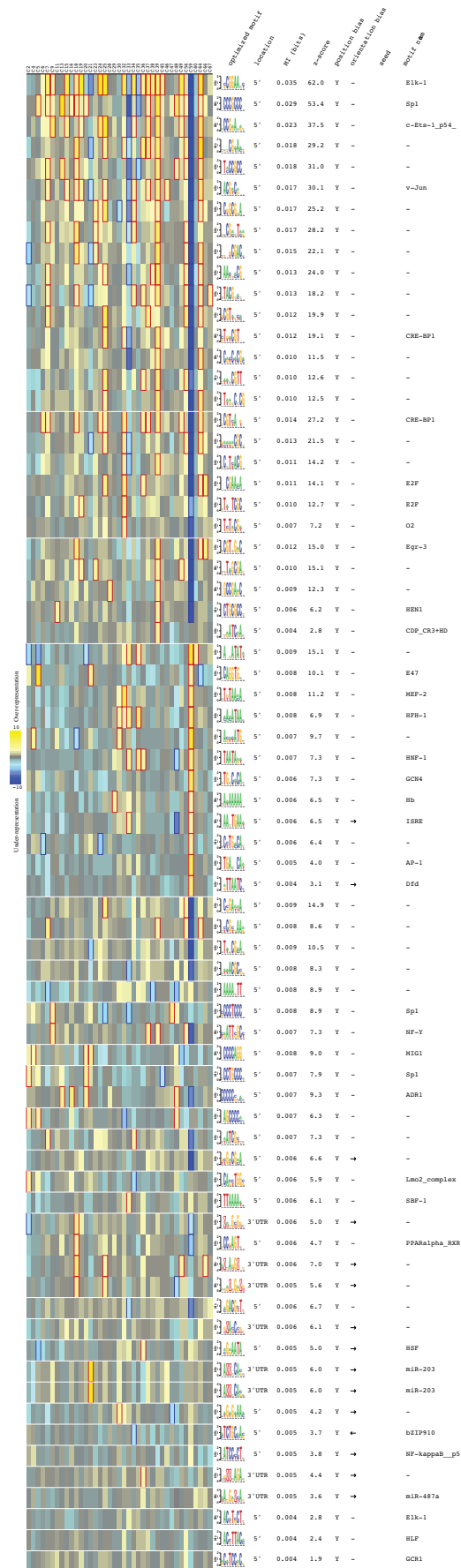
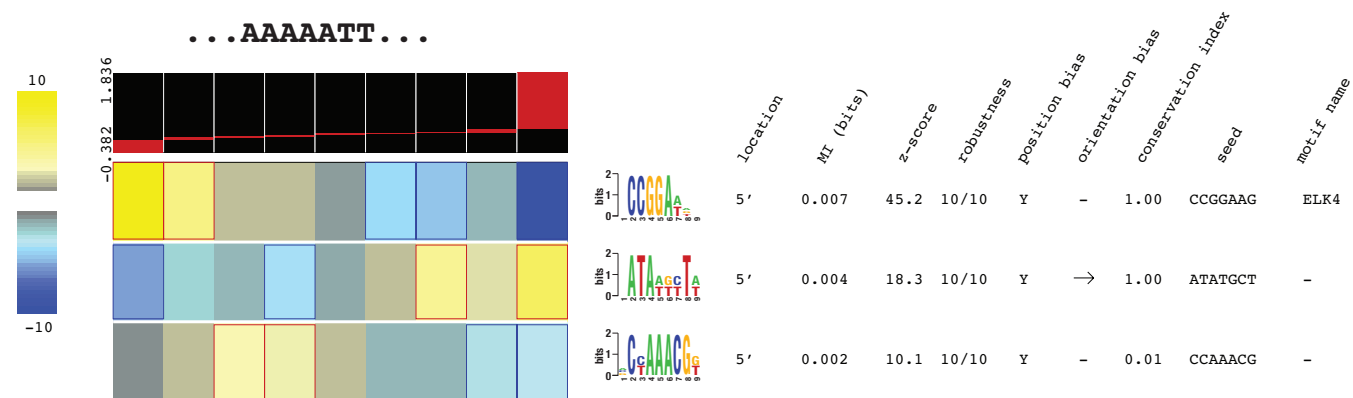
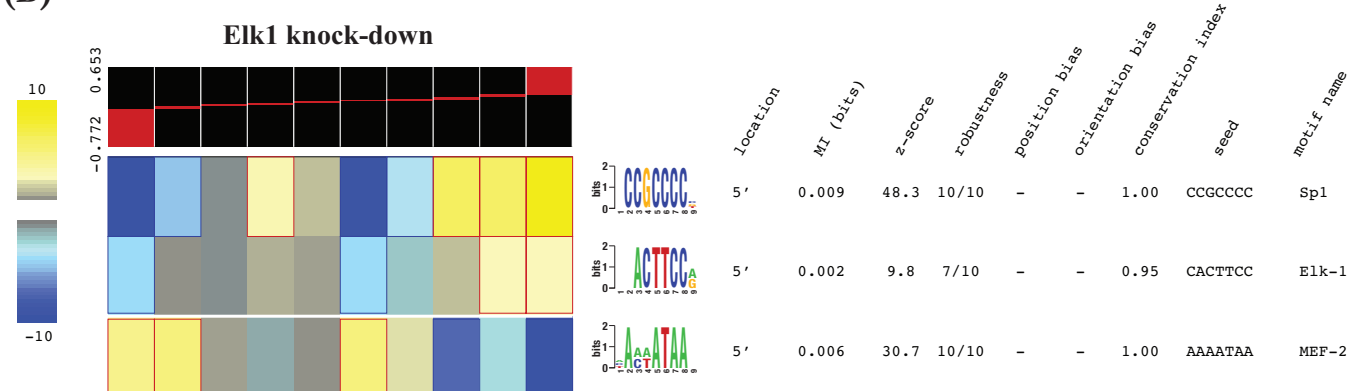


Figure S23

(A)



(B)



(C)

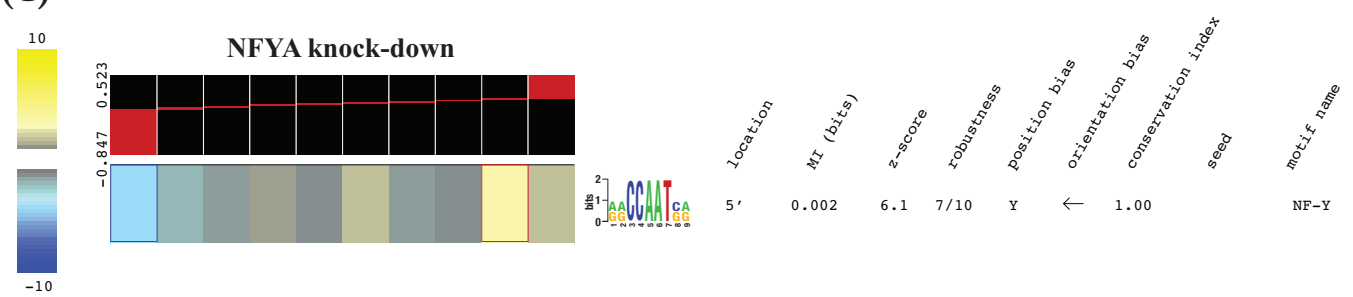


Figure S24

Supplemental Table

Table S1

	Real Data	Random Data I	Random Data II
BL vs DLBCL	525	1	1
Bladder Carcinoma (cont)	224	4	5
Bladder Carcinoma (disc)	248	1	1

Table S2

Tissue	Sample Name	Sample
Bladder	CA Bladder Dyrskjot et al	Carcinoma (Dyrskjot et al., 2004)
Brain	GBM Brain Liang et al	Glioblastoma Multiforme (Liang et al., 2005)
	OD Brain Bredel et al	Oligodendroglioma (Bredel et al., 2005)
	GL Brain Bredel et al	Glioblastoma (Bredel et al., 2005)
	AO Brain Bredel et al	Anaplastic Oligoastrocytoma (Bredel et al., 2005)
	GL Brain Rickman et al	Glioma (Rickman et al., 2001)
	ODGL Brain Sun et al	Oligodendroglioma (Sun et al., 2006)
	AC Brain Sun et al	Astrocytoma (Sun et al., 2006)
	GLB Brain Sun et al	Glioblastoma (Sun et al., 2006)
Breast	CA Breast Sorlie et al	Carcinoma (Sorlie et al., 2001)
	CA Breast Richardson et al	Carcinoma (Richardson et al., 2006)
	MCA Breast Radvanyi et al	Metastatic Breast Carcinoma (Radvanyi et al., 2005)
	ILC Breast Radvanyi et al	Invasive Lobular Carcinoma (Radvanyi et al., 2005)
	IDC Breast Radvanyi et al	Invasive Ductal Carcinoma (Radvanyi et al., 2005)
Colon	CA Colon Graudens et al	Carcinoma (Graudens et al., 2006)
Head-neck	HSCC Head-Neck Cromer et al	Head-Neck Squamous Cell Carcinoma (Cromer et al., 2004)
	HSCC Head-Neck Chung et al	Head-Neck Squamous Cell Carcinoma (Chung et al., 2004)
Leukemia	B-CLL Leukemia Haslinger et al	Chronic Lymphocytic Leukemia (Haslinger et al., 2004)
Lung	AD Lung Beer et al	Adenocarcinoma (Beer et al., 2002)
	AD Lung Bhattacharjee et al	Adenocarcinoma (Bhattacharjee et al., 2001)
	COID Lung Bhattacharjee et al	Carcinoid (Bhattacharjee et al., 2001)
	SQ Lung Bhattacharjee et al	Squamous Cell Lung Carcinoma (Bhattacharjee et al., 2001)
	SMCL Lung Bhattacharjee et al	Small Cell Lung Cancer (Bhattacharjee et al., 2001)
	AD Lung Stearman et al	Adenocarcinoma (Stearman et al., 2005)
Lymphoma	FL Lymphoma Alizadeh et al	Follicular Lymphoma (Alizadeh et al., 2000)
	DLBCL Lymphoma Alizadeh et al	Diffuse Large B-Cell Lymphoma (Alizadeh et al., 2000)
	CLL Lymphoma Alizadeh et al	Chronic Lymphocytic Leukemia (Alizadeh et al., 2000)
Melanoma	ML Melanoma Talantov et al	Cutaneous melanoma (Hoek et al., 2006)
	ME Melanoma Hoek et al	Melanoma (Talantov et al., 2005)
Mesothelioma	MPM Mesothelioma Gordon et al	Malignant Mesothelioma (Gordon et al., 2005)
Myeloma	MM Myeloma Zhan et al	Multiple Myeloma (Zhan et al., 2002)
Ovarian	AD Ovarian Welsh et al	Adenocarcinoma (Welsh et al., 2001)
	CCC Ovarian Hendrix et al	Clear Cell Carcinoma (Hendrix et al., 2006)
	MUC Ovarian Hendrix et al	Mucinous Adenocarcinoma (Hendrix et al., 2006)
	SRS Ovarian Hendrix et al	Serous Adenocarcinoma (Hendrix et al., 2006)
	END Ovarian Hendrix et al	Endometrioid Adenocarcinoma (Hendrix et al., 2006)
Pancreas	PDC Pancreas Ishikawa et al	Pancreatic Ductal Carcinoma (Ishikawa et al., 2005)
	AD Pancreas Logsdon et al	Adenocarcinoma (Logsdon et al., 2003)
Prostate	MPC Prostate Dhanasekaran et al	Metastatic Prostate Cancer (Dhanasekaran et al., 2001)
	PPC Prostate Dhanasekaran et al	Primary Prostate Cancer (Dhanasekaran et al., 2001)
	BPH Prostate Dhanasekaran et al	Benign Prostatic Hyperplasia (Dhanasekaran et al., 2001)
	TU Prostate Lapointe et al	Primary Tumor (Lapointe et al., 2004)
Renal	CA Renal Higgins et al	Carcinoma (Higgins et al., 2003)
	RCCC Renal Boer et al	Clear Cell Renal Cell Carcinoma (Boer et al., 2001)
	RCCC Renal Lenburg et al	Clear Cell Renal Cell Carcinoma (Lenburg et al., 2003)
Seminoma	GCT Seminoma Korkola et al	Germ Cell Tumor (Korkola et al., 2006)

Table S3

GO terms	Motifs	Significance
chromatin assembly	3'	$p < 1e-86.7$
DNA packaging	3'	$p < 1e-32.5$
chromosome organization and biogenesis	5'	$p < 1e-11.1$
ribonucleoprotein complex	5'	$p < 1e-8.7$
DNA packaging	5'	$p < 1e-8.4$
DNA repair	5'	$p < 1e-7.7$
mRNA processing	3'	$p < 1e-7$
cell-cell adhesion	3'	$p < 1e-6.9$
cell-cell adhesion	3'	$p < 1e-6.7$
ubiquitin-protein ligase activity	3'	$p < 1e-6.4$
protein-tyrosine kinase activity	3'	$p < 1e-6.3$
Golgi vesicle transport	5'	$p < 1e-6.3$
cytoskeletal protein binding	3'	$p < 1e-6.2$
GPI anchor binding	3'	$p < 1e-6.2$
DNA repair	3'	$p < 1e-6$
humoral immune response	5'	$p < 1e-6$
phosphoinositide-mediated signaling	3'	$p < 1e-6$
mitotic cell cycle	5'	$p < 1e-5.9$
mitosis	5'	$p < 1e-5.5$
response to wounding	5'	$p < 1e-5.4$
response to wounding	5'	$p < 1e-5.3$
cell-cell adhesion	5'	$p < 1e-5.2$
mRNA metabolic process	5'	$p < 1e-5.1$
small GTPase mediated signal transduction	5'	$p < 1e-5$
Wnt receptor signaling pathway	5'	$p < 1e-4.8$

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