

## Supplemental Data

### A Universal Framework

### for Regulatory Element Discovery

### across All Genomes and Data Types

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## Supplemental Results

In what follows, we present additional information about the motifs obtained when applying FIRE to the yeast and human clustering partitions (stress and tissue expression datasets). Then, we describe the results obtained when applying FIRE to several additional datasets: a large compendium of gene expression profiles in *C. elegans*, and pre-specified groups of genes in *D. melanogaster*, including groups of genes with similar spatio-temporal patterns of gene expression revealed by *in situ* hybridization. The ability to analyze such groups of genes is important, as it is common practice to simply specify a relatively small set of presumably co-expressed genes, using some *ad hoc* criteria, and to attempt to elucidate the regulatory elements responsible for this assumed co-expression.

### Additional results for yeast and human gene clustering partitions

#### Expression variance explained by the yeast predicted motifs

As shown in Figure 3, the motifs predicted by FIRE are in general highly over-represented in a small set of co-expression clusters. To further evaluate the significance of the motifs discovered by FIRE, we consider the percentage of genes that have a given motif both in clusters where the motif is significantly over-represented (denoted “active” clusters – such clusters are shown with a red frame in Figure 3) and in the remaining clusters (“non-active” clusters). These two fractions, shown in Table S2, for the 23 yeast motifs presented in Figure 3, indicate the level of variance in the expression data that can be explained by the discovered motifs. For example, the top motif (PAC) in Figure 3 has active occurrences in 47% of promoters associated with 5 different clusters (marked by red frames in the first row in Figure 3), and additional non-active occurrences in only 7% of the promoters associated with other clusters. Table S2 shows that, in general, the percentage of the motif's non-active occurrences is relatively low, suggesting that indeed much of the variance in the expression data can be explained by the predicted motifs.

#### Comparison with conservation-based motif discovery approaches

To further validate our predictions, we have undertaken a systematic comparison between our predicted motifs and the motifs predicted using alignment-based phylogenetic footprinting in yeast (Kellis et al., 2003) and mammals (Xie et al., 2005).

Motif comparisons were performed using CompareACE (Hughes et al., 2000). Two motifs were considered equivalent if their CompareACE score was greater than 0.7. At this threshold, in yeast, 3/12 (DNA) and 1/2 (RNA) of the FIRE-predicted motifs that match a known (experimentally verified) motif do not match any motif predicted in Kellis *et al.* In addition, 1/5 (DNA) and 3/4 (RNA) of the novel FIRE-predicted motifs do not match any motif reported in (Kellis et al., 2003).

Moreover, the ability of FIRE to detect entirely novel motifs is fully revealed in mammals. In particular, for the human tissue expression data, although many of the FIRE-predicted motifs that match known motifs in TRANSFAC or JASPAR also match conserved motifs discovered in (Xie et al., 2005), when we examine FIRE-predicted motifs that do not match known motifs in these databases, we observe the opposite trend. Specifically, among these FIRE-predicted motifs, 32/52 (DNA) and 21/36 (RNA) do not match any motif in (Xie et al., 2005). We therefore conclude that FIRE predicts many motifs that were not already predicted by prior comparative analysis. More generally, we believe that FIRE analyses should be seen as complementary to comparative genomics methods, providing additional support for conserved motifs, and further pointing out less conserved, possibly species-specific motifs that are relevant to the expression data under analysis.

### **On the sensitivity/specificity tradeoff**

The tradeoff between specificity and sensitivity is a fundamental issue that must be addressed when designing motif prediction approaches. In FIRE, we have chosen to favor specificity over sensitivity. Thus, the output of FIRE typically consists of a small, experimentally tractable set of high confidence motifs. We believe that this emphasis on specificity represents an important distinction between FIRE and previously described motif discovery methods that will play a significant role in making FIRE the tool of choice for motif discovery.

However, it is possible (and straightforward) to decrease the default stringency level in FIRE, and thus to increase the number of predicted motifs (at the possible cost of reducing specificity). The simplest way is to use a less stringent robustness index threshold. Figure S15 shows the number of predicted motifs for the yeast dataset of Gasch *et al.*, at different robustness index thresholds (from 0 to 10; 6 is the default value). Clearly, lower thresholds increase the number of predicted motifs. Importantly, several of the lower scoring motifs are supported by GO enrichments of their target genes and/or match known (experimentally validated) yeast motifs, suggesting that many of the predicted “weaker” motifs are also true positives. We note that the ability of FIRE to detect weak motifs is possibly due to the fact that several clusters (or expression bins for

continuous data) may contribute to the mutual information. Thus, a motif does not strictly need to be highly over-represented in a single cluster to be detected by FIRE (as opposed to other cluster-based approaches).

## **Application to *C. elegans***

We examined a dataset containing 551 *C. elegans* expression microarrays reported in (Kim et al., 2001) and focused on the 11,562 genes with reported expression levels in at least 400 microarrays. Following precisely the same analysis discussed above for yeast data, we clustered the 11,562 genes into 108 non-overlapping clusters using Iclust. With default parameters, FIRE predicts 61 DNA motifs and 33 RNA motifs (Figure S16) that are highly informative about the corresponding clustering partition, versus an average of 0.06 DNA “motifs” and 0.09 RNA “motifs” when applied to 100 randomly shuffled partitions. Figure S17 shows how much information each seed initially conveys and how much additional information is gained through optimization. The predicted motifs are further partitioned into 46 modules, many of which contain both DNA and RNA motifs (Figure S18), suggesting that cooperation between transcriptional and post-transcriptional regulatory mechanisms plays an important role in shaping the worm transcriptome.

Overall, 13 predicted DNA motifs closely match 13 distinct known motifs in TRANSFAC (Matys et al., 2006) or JASPAR (Vlieghe et al., 2006), and 3 predicted RNA motifs match the 5' extremity of known worm miRNAs (Chan et al., 2005; Lewis et al., 2005), suggesting that they are targeted by these miRNAs. Independent conservation analysis with respect to the *C. briggsae* genome further supports our predictions: nearly half (47%) of the predicted motifs are highly conserved, with a conservation index  $\geq 0.95$ .

A subset of the predicted motifs is presented in Figure S19. The first module is relatively large with 10 motifs, two of which are shown in Figure S19. The most informative motif is a highly conserved C-rich RNA motif, [CU]N[ACU]CCCC, that is over-represented in several clusters, two of which are associated with regulation of growth (c100,  $p < 1e-14$ ) and DNA replication (c68,  $p < 1e-07$ ).

The second module consists of two motifs that match two different GATA-factor binding sites in TRANSFAC, and are found to be preferentially located close to the TSS. While it is possible that both motifs match binding sites for the same GATA-factor, we note that their over-representation patterns are slightly different (Figure 8). Our analysis also suggests that one of these motifs, [CGT]CTTATC[AT], may be involved in regulating the expression of several enzymes with oxidoreductase activity ( $p < 1e-04$ ).

The third module consists of one RNA motif and one DNA motif, [ACT][AC]CGTG[AG][AC][AC], with a remarkable position bias towards the TSS (Figure S20). This motif strongly resembles an E-box, bound by bHLH transcription factors, and its target genes are associated in general with protein modification ( $p < 1e-27$ ),

and more specifically with kinase ( $p < 1e-19$ ) and phosphatase activity ( $p < 1e-12$ ). In fact, 17% of the worm genes with protein kinase activity and 29% of genes coding for protein phosphatases have this motif in their 1kb 5' upstream, suggesting some common regulatory control for these activities. This is intriguing as kinases and phosphatases are typically thought to be involved in a multitude of independent biological processes. Further analyses will be needed to understand the involvement of this motif in the transcriptional regulation related to these post-translational modification processes.

A fourth module contains five predicted motifs, two of which are presented in Figure S19; a DNA motif that resembles the binding site for Cut-like homeobox protein in mammals (Andres et al., 1992) and the DNA-replication element in *Drosophila* (Matsukage et al., 1995), and a U-rich highly conserved RNA motif, previously detected based on independent conservation analysis (Chan et al., 2005). The target genes of these two motifs are highly enriched for protein biosynthesis ( $p < 1e-08$  and  $p < 1e-30$ , respectively).

Another predicted RNA motif, [CGU]UGUANAU[ACU], matches almost perfectly the yeast Puf3 binding site (Gerber et al., 2004) and thus might be bound by one (or several) of the PUF proteins in worm (Wickens et al., 2002). Two other predicted RNA motifs, [ACU][AGU]CGGGU and [CU][AU]UAUCN[ACU][ACU], match with high specificity the 5' extremity of known worm miRNAs (Figure S19); both motifs were also reported in (Chan et al., 2005) based on an independent network-level conservation analysis. Two additional predicted RNA motifs, AA[AG]UAAA and UUGUUGA[ACU], are both highly conserved and show a position bias towards the stop codon. GO analysis shows that the former, which resembles a poly-adenylation sequence, is enriched in the 3'UTRs of mRNAs that code for components of the cuticle ( $p < 1e-24$ ), while the latter is enriched in 3'UTRs of mRNAs that code for components of the ribosome ( $p < 1e-11$ ).

Our analysis further detects pairs of motifs for which the relative distance is significantly informative about the cluster indices. For example, as depicted in Figure S21, the two DNA motifs, [ACG]AA[ACG]CGAG and [CGT]ACCGTA[CG][ACT], are jointly present in 130 upstream promoters, 9 of which are associated with cluster c63 (over representation of  $p < 1e-8$ ); in 8 out of their 130 joint occurrences, these two motifs are located exactly 3 nucleotides one after another, in the same relative order towards the TSS, where 6 of these 8 cases are again within promoters associated with c63 ( $p < 1e-6$ ), and all 6 are ribosomal genes ( $p < 1e-9$ ). Although the numbers involved here are small, we speculate that co-regulation of these genes requires both motifs in the proper spatial arrangement. It is also possible that the two motifs are part of a single larger motif. We note, that for all 6 genes, almost identical motifs with an identical arrangement are observed in the promoters of their *C. briggsae* orthologs (data not shown).

Finally, we also applied FIRE to each of the 551 expression arrays independently. These complementary results are available at our Web site.

## **Analyzing a pre-specified set of genes: examples from *Drosophila***

The scenarios described so far involve applying FIRE to whole genome expression data that had been processed through subsequent analyses, *e.g.*, describing periodic expression in terms of phase values or finding gene clustering partitions. It is however common practice to simply specify a relatively small set of presumably co-expressed genes, using some *ad hoc* criteria, and to attempt to elucidate the regulatory elements responsible for this assumed co-expression. In essence, this simply represents a special case of categorical data with only two categories: the pre-specified set of genes versus all remaining genes. Thus, FIRE is directly applicable to these scenarios as well, as we demonstrate in the following two examples.

### ***Drosophila* early embryonic enhancers**

Transcriptional regulation during early development of *Drosophila* embryos involves regulatory elements concentrated within particular DNA regions, termed enhancer sequences (see (Arnosti and Kulkarni, 2005) for a recent review). In the following, we use 124 early embryonic fly enhancer sequences collected from the literature (D. Papatsenko, <https://webfiles.berkeley.edu/~dap5/>), of which 20 are known to be bound by the Bicoid morphogen (Driever and Nusslein-Volhard, 1989; Struhl et al., 1989), giving rise to a simple two-category partition: the 20 Bicoid bound enhancers, versus the remaining 104. Given these data, FIRE predicts a single motif (Table S3) that matches well the previously reported Bicoid binding site (Driever and Nusslein-Volhard, 1989) and is present in 95% of the Bicoid-bound enhancers, but only in 25% of the remaining enhancers. Applying AlignACE to the same data yields a somewhat similar motif (Table S3), but apparently less discriminative: it is present in 80% of the Bicoid-bound enhancers and in 28% of the remaining enhancers (when using ScanACE (Hughes et al., 2000) with default parameters). We further applied a simple leave-one-out test, in which each enhancer was withdrawn and the remaining 123 were analyzed by FIRE to extract a maximally informative motif that was then used to predict whether the withdrawn enhancer is bound by Bicoid or not; the high performance reported in Table S3 supports the robustness of our results in this example. Applying the same analysis to the 20 enhancers bound by Dorsal, another fly morphogen, yielded similar results (see our Web site).

### ***Drosophila in situ* hybridization database**

Spatial patterns of gene expression, for example during different developmental stages, can be determined using RNA *in situ* hybridization. In this section, we present the results of the analysis of a large-scale *in situ* hybridization study during *D. melanogaster* embryogenesis (Tomancak et al., 2002). Fifty-five groups of genes were analyzed, where each group corresponds to a set of genes with a similar spatio-temporal expression pattern during embryogenesis (*e.g.*, embryonic midgut during stages 13-16) (Tomancak et al., 2002). Altogether, these groups cover ~2,000 genes, with some genes associated with more than one group. We applied FIRE to each of these 55 groups independently,

where in each case, genes within the group constitute one category while the remaining genes constitute the other category. Given these data, FIRE predicts a total of 28 DNA motifs and 11 RNA motifs, versus an average of 2.4 and 4.5 DNA and RNA “motifs”, respectively, when applied 10 times to the same data after random shuffling. A selection of the obtained motifs is presented in Figure S22, and the complete results are available at our Web site.

Several motifs shown in Figure S22 have been previously described in the literature. For example, the ATCGATA motif matches the DNA replication-related element (DRE) (Matsukage et al., 1995). Our results indicate that this motif is highly enriched upstream of maternal genes, *i.e.*, genes whose mRNAs are deposited into the egg by the mother, and therefore are detected in stage 1-3 embryos. In addition, our analysis shows that this motif tends to be located close to the TSS (Figure S23). The DRE has previously been associated with genes involved in cell proliferation and DNA replication (Matsukage et al., 1995). Cell divisions in stages 1-3 embryos are likely dependent on the products of many of these genes. However, the mRNAs for these genes must be supplied maternally as the embryonic genome is transcriptionally silent (for the most part) during these early stages. Thus, the predicted motif may be involved in transcribing cell proliferation genes within the maternal nurse cells. The corresponding mRNAs would then be selectively shuttled into the oocyte. Another motif, [GT]C[AG]GGT[AT]G[ATG], is found mainly upstream of genes with a non-uniform expression pattern during stages 4-6 (‘subset’ category). This motif matches the consensus CAGGTAG element that was recently shown experimentally to enhance transcription of early zygotic genes (De Renzis et al., 2007). Other predicted motifs may intervene in later stages. For example, the [CG][ACG]CGATA[AG] motif is found in upstream regions of 35% of the 376 genes expressed in the embryonic midgut during stages 13-16, but only in 18% of promoters of the remaining 1620 genes ( $p < 1e-11$ ). Its sequence suggests that it is bound by a GATA-factor transcriptional regulator. Indeed, previous reports argue that GATA factors play a major role in *Drosophila* endodermal midgut specification (see (Murakami et al., 2005) for review).

## Supplemental Experimental Procedures

In what follows, we discuss the FIRE methodology, algorithms, and features in more detail. Information regarding the gene expression data and sequence data analyzed in this work are available at the end of this document. The complete results, as well as all the relevant source code and software, can be downloaded at the FIRE web site at <http://tavazoielab.princeton.edu/FIRE/>.

### Motif and expression profiles

#### Motif definition

In the current FIRE implementation, motifs are defined through *regular expressions* and using the standard degenerate code. Thus, a motif 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]). As an example, the motif A[CG]T has A at the first position, C or G at the second position, and T at the third position. Using regular expressions for defining motifs allows for a highly efficient search through motif-space. In addition, determining whether a motif is present within a given promoter is straightforward and requires no arbitrary thresholds.

### **Motif profile**

In the following, we assume that we examine  $N$  genes where each one is associated with a single expression measurement (see below). In addition, for each of these genes, our data include its 5' upstream and 3'UTR sequences. For brevity, we focus here on 5' upstream regions, but the same applies to 3'UTRs. Given a motif, represented as a regular expression, the *motif profile* is defined as a binary vector with  $N$  elements, where for each gene, "1" indicates that the motif is present in the corresponding promoter and "0" indicates that it is absent. A motif is considered present in a promoter if the promoter contains at least one exact match to its regular expression. For DNA sequences, we consider occurrences of the motif on either strand. For RNA sequences, we only consider the transcribed strand.

### **Expression profiles**

The *expression profile* is also defined as a vector with  $N$  elements. Each element corresponds to a gene, and indicates the associated expression value for that gene. The expression profile can be discrete or continuous. For example, a *discrete* expression profile can be obtained using the following procedure: we cluster the  $N$  genes based on multiple microarray data, associate an index to each cluster, and assign each gene to the index of the cluster it belongs to. A *continuous* expression profile may consist of the results of a single microarray experiment, where each gene is associated with a single expression value (*e.g.*, raw intensity value or log-ratio of intensities). Note that a continuous expression profile does not necessarily contain gene expression levels. For example, in the analysis of the *Plasmodium falciparum* data, the continuous expression profile indicates the "phase" of each gene, corresponding to a time point during the developmental cycle where the expression of this gene peaks (Llinas and DeRisi, 2004). Likewise, a discrete expression profile does not necessarily contain gene expression clusters defined from microarrays conditions. For example, it may often contain two categories, where one category consists of a set of genes of interest (*e.g.*, genes sharing the same spatio-temporal pattern of activity, as measured using *in situ* hybridization or genes defined using any *ad hoc* criteria), and the other consists of all remaining genes.

### **Quantizing continuous expression profiles**

The concept of mutual information is well defined, both for continuous and for discrete random variables (Cover and Thomas, 2006). Nonetheless, in practice, estimating the information when continuous variables are involved requires quantizing their values. In this study, we quantize continuous expression profiles into equally populated bins, as described in (Slonim et al., 2005). In FIRE (by default), the number of bins,  $N_e$ , is determined using  $N_e \cdot N_m \approx 50 \cdot N$ , where  $N_m$  is the number of bins used in the motif profile, *i.e.*,  $N_m=2$ , and  $N$  is the total number of genes. This implies that the expected count within each entry of the joint-counts table created for the motif and the expression profiles (see below) is approximately 50, allowing for a relatively reliable estimation of the mutual information (Slonim et al., 2005).

### Removing promoters and 3'UTRs of recently duplicated genes

Recently duplicated members of gene families or transposons (*e.g.*, Ty transposons in yeast) often share a significant amount of sequence identity in their promoters (and in their 3'UTRs). Their recently duplicated sequences also tend to cross-hybridize on certain high-throughput expression assays (*e.g.*, microarrays), and therefore often appear as co-expressed. When this occurs, multiple conserved sequences within the promoter of these genes will appear as highly correlated with the expression, constituting spurious motif predictions, as we observed in a preliminary yeast analysis. To address this issue (which is in fact relevant for all expression-based motif finding approaches), FIRE applies, by default, a simple duplicate removal procedure, which guarantees that within each expression category/bin, no pair of promoters and no pair of 3'UTRs will have a MegaBlast local alignment with E-value  $< 1e-10$ . In addition, prior to duplicate removal, repeats and low-complexity sequences are systematically masked using RepeatMasker (<http://www.repeatmasker.org>) and the appropriate species-specific repeat library from RepBase (Jurka et al., 2005).

## Motif-expression information

### Estimating the mutual information

In FIRE, we generally seek to evaluate whether a candidate motif is informative about the expression profile at hand. Given a motif profile (with two possible values, corresponding to presence and absence) and the expression profile (with  $N_e$  possible values), we first generate a joint-counts table, denoted as  $C$ , with 2 rows and  $N_e$  columns.  $C(1,j)$  indicates the number of promoters which contain the motif and are associated with the  $j^{\text{th}}$  category/bin;  $C(2,j)$  indicates the number of promoters which do not contain the motif and are associated with the  $j^{\text{th}}$  category/bin. The empirical mutual information between the presence/absence of the motif in a promoter and the expression of the corresponding gene, when averaging across all genes, is given by

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



where  $P(i, j) = C(i, j) / N$ ,  $P(i) = \sum_{j=1}^{N_e} P(i, j)$ , and  $P(j) = \sum_{i=1}^2 P(i, j)$  (Cover and Thomas, 2006).

## Evaluating the information significance via randomization tests

To estimate the statistical significance of observed empirical information values, non-parametric randomization tests are applied. Specifically, let  $I$  denote the obtained empirical mutual information, *e.g.*, between a given motif profile and the expression profile. Next, we randomly shuffle the expression profile and calculate the information value between the unchanged motif profile and the shuffled expression profile. We repeat the same procedure  $N_r$  times to obtain  $N_r$  random information values, and consider the original empirical information,  $I$ , as statistically significant (with  $p < (1/N_r)$ ), if and only if it is greater than *all*  $N_r$  random information values. As detailed below, different  $N_r$  values are used by default, depending on the context and on the number of hypotheses tested. In addition, a corresponding Z-score is reported, defined as  $Z = (I - \langle I_{random} \rangle) / \sigma_{random}$  where  $\langle I_{random} \rangle$  is the average random information value and  $\sigma_{random}$  is the corresponding standard deviation. This Z-score is often useful in comparing motifs that pass the randomization test, as it reflects how far the empirical information is, in number of standard deviations, from the average random information. However, we do not use Z-scores directly to determine the significance of mutual information values as the underlying distribution of random information values is not a normal distribution.

## Evaluating the information robustness

Another important non-parametric statistical significance test incorporated in FIRE is based on jack-knife re-sampling (Efron, 1979). Specifically, for each predicted motif,  $N_j$  jack-knife trials are applied where in each trial a substantial fraction (one third by default) of the genes is randomly removed from the data. An information value is recalculated based on the remaining data, and its statistical significance is evaluated using the randomization test described above (with  $N_r=10,000$  repeats, by default). The *robustness* score of the motif indicates in how many of these jack-knife trials the motif information was found to be statistically significant. By default, we use  $N_j=10$ , hence the robustness scores range from 0/10 up to 10/10.

## Revealing highly informative motifs

### Detecting motif seeds

Finding motifs whose profiles are highly informative about a given expression profile can be approached through different search strategies. The two-step procedure currently implemented in FIRE is reminiscent of procedures used by other motif finding techniques (*e.g.*, (Foat et al., 2005)). Nonetheless, it is used here to optimize an entirely different target function, namely the information between the predicted motifs and expression. The first step amounts to scoring an exhaustive list of simple motif definitions in the form of

$k$ -mers (non-degenerate sequences of  $k$  nucleotides), where by default  $k$  is set to 7; thus, all 7-mers are examined, resulting in a coarse-grained, yet exhaustive exploration of motif space.

When searching for DNA motifs (typically in upstream promoters), reverse complements are removed from the list of all 7-mers as FIRE considers both matches to a motif and to its reverse complement; therefore, effectively, 8,192 7-mers are examined. When searching for RNA motifs (typically in 3'UTRs), FIRE examines all 16,384 7-mers. For each 7-mer, the mutual information between its profile and the expression profile is evaluated. All 7-mers are then sorted based on their information values and a simple and efficient algorithm is used to search for the first 10 consecutive 7-mers whose information is *not* significant, within the sorted list. All 7-mers sorted above these 10 are retained for further analysis, and are henceforth termed motif *seeds*. Recall, that the information associated with a particular 7-mer is considered significant if and only if it passes the randomization test, *i.e.*, if it is greater than all  $N_r$  random information values obtained for this 7-mer profile over  $N_r$  randomly shuffled expression profiles. To correct for multiple hypothesis testing,  $N_r$  is set by default to the number of  $k$ -mers initially examined, *i.e.*,  $N_r = 8,192$  when searching for DNA motifs and  $N_r = 16,384$  when searching for RNA motifs.

### **Optimizing seeds into more informative motifs**

It is now fully established that DNA- and RNA-binding proteins typically can bind (with different affinities) to multiple slightly distinct sites. Therefore, motif definitions that can capture multiple sites simultaneously are likely to more accurately represent binding sites for these proteins. As mentioned above, to address this problem, motifs are represented in FIRE using the standard degenerate code. The second search stage in FIRE consists of an optimization process that gradually converts the seeds obtained at the previous stage into longer and potentially degenerate motifs that convey more information about the expression profile.

All seeds obtained in the previous stage are sorted based on their information values, and are examined one after the other, starting with the most informative one. If a seed corresponds to a variant of a motif obtained from optimizing previous – more informative – seeds, it is discarded (see below). Otherwise, it is optimized using the following procedure. First (by default), a single position is added to each side of the seed, initialized to the non-informative N character. Thus, the examined motif is now 9 nucleotides long. A single position among these 9 is chosen at random, and all characters of the degenerate code that are consistent with the seed's initial character at that position are tested. For example, if the seed has an A at that position, a new character is selected from [AC], [AG], [AT], [ACG], [ACT], [AGT], and N. Each of these 7 alternatives induces a possibly different motif profile with corresponding information over the expression profile. Among the permitted alternatives (see below) the one that results in a maximally informative motif is selected. This procedure is repeated until convergence, namely, until no further improvements are possible, at all 9 positions. Due to its greedy nature, this process may converge to a local maximum of the information. Thus, the entire

optimization is repeated 10 times per motif, ending up with possibly 10 (slightly) different motifs, of which the most informative one is retained.

### **Avoiding redundant/degenerate output**

As mentioned above, multiple seeds may often represent different variations over the binding site of a single protein. To avoid redundant output, FIRE requires that each reported motif provides some novel information over the expression profile while being relatively independent of motifs obtained from optimizing previous seeds. Formally, this is implemented by 1) avoiding the optimization of some seeds and discarding these seeds from the list of predicted motifs, and 2) when optimizing a seed, distinguishing between permitted versus non-permitted characters at each optimization step. 1) and 2) are implemented using the same mechanism. Each time a new motif is considered (either a seed is considered for optimization, or a new character at a given position is considered during optimization), it is accepted for further consideration if and only if it satisfies:

$$I(\text{motif}; \text{expression} \mid \text{prev\_motif}) / I(\text{motif}; \text{prev\_motif}) > r,$$

where  $I(\text{motif}; \text{expression} \mid \text{prev\_motif})$  is the *conditional information* (Cover and Thomas, 2006) conveyed by this motif profile over the expression profile, given the profile of a previous motif denoted  $\text{prev\_motif}$ ;  $I(\text{motif}; \text{prev\_motif})$  is the information between the motif profile and the profile of the previous motif; and  $r$  is a tradeoff parameter. Importantly, this inequality must be satisfied with respect to *all* motifs obtained from optimizing previous seeds, suggesting that the considered motif provides some novel information over expression (*i.e.*,  $I(\text{motif}; \text{expression} \mid \text{prev\_motif})$  is not too low), while, at the same time, showing relatively little dependency with previous motifs (*i.e.*,  $I(\text{motif}; \text{prev\_motif})$  is not too high). The tradeoff parameter,  $r$ , can be seen as a “knob” that controls the level of output redundancy. Since seeds not satisfying this inequality (with respect to all previous motifs) are discarded, high  $r$  values will typically result in very few motifs that are clearly different from one another, while low  $r$  values will typically result in a larger number of predicted motifs and greater redundancy. In practice, it is recommended to explore different  $r$  values. However, in order to avoid over-fitting our data, we used a single value ( $r=5$ ) in all the FIRE runs reported in this manuscript, chosen based on preliminary tests in yeast.

### **Reporting only significant and robust motifs**

After optimization, each motif is subjected to a randomization test with  $N_r=10,000$  and motifs that do not pass this test are discarded. In addition, each motif is assigned a robustness score, calculated as explained above using  $N_j=10$  and  $N_r=10,000$ . By default, FIRE only reports motifs with a robustness score of at least 6/10, but exploring other values is also recommended. For example, in the analysis of the *Drosophila in situ* hybridization data, only motifs with a robustness score of at least 8/10 are reported.

## Post-processing: characterization of predicted motifs

### Predicting orientation bias

Given a predicted motif, FIRE further examines two binary profiles, each with  $N$  elements, termed here the *transcribed strand motif profile* and the *non-transcribed strand motif profile*. In the former, “1” indicates that the motif is present in the promoter on the transcribed strand (*i.e.*, the same strand as the transcribed gene) and “0” indicates otherwise; in the latter, “1” indicates that the motif is present in the promoter on the non-transcribed strand and “0” indicates otherwise. FIRE evaluates the information conveyed by each of these two profiles over the expression profile, assesses their significance using  $N_r=10,000$  randomization tests, and reports an *orientation bias* if and only if only one of these two information values is found to be statistically significant. As RNA motifs can only be on the transcribed strand, the default FIRE setting is to report an RNA motif only if it has a significant orientation bias in the right direction, *i.e.*, only if the transcribed strand motif profile is significantly informative over the expression profile, while the non-transcribed profile is not. This requirement may prevent contaminations from downstream DNA motifs which are less likely to have an orientation bias. Nonetheless, in many cases (*e.g.* for the yeast gene clustering partition), we have observed that all or most RNA motifs predicted by FIRE have a highly significant orientation bias.

### Patterns of motif over- and under-representation

Highly informative motifs are generally over- or under-represented in the promoters associated with certain categories/bins. We quantify this using the binomial distribution. Specifically, let  $N$  be the total number of promoters (or genes),  $n$  the total number of promoters in which the given motif is present,  $K$  the number of promoters within a particular category/bin, and  $x$  the overlap, namely the number of promoters in this category/bin in which the given motif is present. Then, the probability of observing  $x$  genes (or more) with the motif in that category/bin, under the null hypothesis that the motif is distributed across promoters independently of the expression profile, is given by

$$P(X \geq x) = \sum_{t=x}^K \binom{K}{t} f^t (1-f)^{K-t}$$

where  $f=n/N$ . We consider that the motif is *over-represented* in this category/bin if and only if  $P(X \geq x) < 0.05/N_e$ , where  $N_e$  is the number of categories/bins in the expression profile, used as a Bonferroni correction for multiple hypothesis testing. We consider that the motif is *under-represented* in that category/bin if and only if  $P(0 \leq X \leq x) < 0.05/N_e$ , where  $P(0 \leq X \leq x)$  is calculated using the same formula as above.

In many of the tests described below, it is useful to distinguish between motif occurrences that are more likely to represent functional binding sites versus occurrences that are more likely to represent non-functional sites (*e.g.*, due to being located in non-

accessible DNA regions or due to any other reason). To address that, we henceforth refer to motif occurrences in categories/bins in which the motif is over-represented as *active*, and to all other occurrences as *non-active*.

### **Predicting position bias**

For each predicted motif, FIRE examines the subset of promoters in which it is present. Assuming there are  $n_m$  such promoters in our data, FIRE generates a *position profile* for this motif with  $n_m$  elements, each indicating (for each of these promoters) the average distance between all motif occurrences and the TSS. This position profile is quantized into  $N_b$  equally populated bins and FIRE evaluates the empirical information between the quantized profile and a binary version of the original expression profile with the same  $n_m$  genes (termed *binary expression profile*), defined as “1” for categories/bins in which the motif is over-represented, and “0” otherwise. Thus, the obtained information quantifies how informative the motif’s relative position in the promoter is, regarding the distinction between its “active” versus its “non-active” occurrences. A randomization test (as described above) with  $N_r=10,000$  randomizations of the binary expression profile is applied to determine the significance of this information. This is repeated for  $N_b=2,3,4,5$ , and a *position bias* is reported if and only if, in at least one of these four trials, the obtained information is ranked in the top percentile of the 10,000 random information values. This significance test is less stringent than the one used to predict motifs, as it merely serves to point out possibly interesting trends in the motif relative position. Also, notice that Data Processing Inequality (Cover and Thomas, 2006) implies that, if the relative position of the motif is informative about the binary expression profile, it is also informative about the original expression profile.

### **Predicting functional interactions**

Putative functional interactions between pairs of motifs are predicted by FIRE by asking whether the presence of one motif in a promoter is informative about the presence of another motif. Given two predicted motifs, FIRE generates a filtered version of each of their profiles where promoters with “non active” motif occurrences (*i.e.*, not in categories/bins where the motif is over-represented) are assigned a “0” instead of a “1”. The mutual information between the resulting filtered motif profiles, termed here the *interaction information*, is evaluated, and a randomization test with  $N_r=10,000$  repeats is used to determine its significance. An interaction is predicted if and only if the interaction information is greater than all 10,000 random information values. Note that this information may be significant also due to a negative correlation between the two motifs, namely, when the presence of one motif implies the absence of the other. These cases are reported as well, but are distinguished from the positive correlation cases in the FIRE interaction heat-map (see below).

Modules of predicted motifs are generated as follows. All motifs are sorted based on the significance of their information values over the expression profile, *i.e.*, based on their Z-scores, and are partitioned into *assigned* versus *non-assigned* motifs, where originally the set of assigned motifs is empty while the set of non-assigned motifs consist of all

predicted motifs. Next, the most significant motif in the non-assigned set is picked as the core of a new module and is moved to the assigned set. All motifs in the non-assigned set are examined in the order of their  $Z$ -scores, and a motif is added to the new module (and correspondingly moved to the assigned set) if and only if it has significant interaction information due to a positive correlation with each and every motif already present in that module. This is repeated until the non-assigned set is empty. By construction, in each of the resulting modules, all motifs are significantly informative about one another due to a positive correlation.

### **Predicting motif co-localization**

If the interaction information between two predicted motifs is found to be significant due to a positive correlation, FIRE further examines whether these two motifs tend to co-localize when both are present within the same promoter. Specifically, given all promoters in which both motifs are present, the *intersection expression profile* is defined as “1” if both motifs have “active” occurrences within the promoter, and “0” otherwise. The *co-localization profile* is defined as a continuous profile that indicates the minimal distance between both motif occurrences within each promoter in which both are present. This profile is then quantized into  $N_b$  equally populated bins and the information between the quantized profile and the intersection expression profile is evaluated. Intuitively, this information quantifies how informative the minimal distance between the two motifs is over the distinction between promoters where both motif occurrences are “active” versus the remaining promoters. A randomization test with  $N_r=10,000$  repeats is applied to determine the significance of this information. This is repeated for  $N_b=2,3,4,5$ , and a *co-localization* is reported if and only if the obtained information is ranked in the top percentile of the 10,000 random information values in at least one of these four trials.

### **Gene Ontology analysis**

We define the *target genes* of a predicted motif as all genes whose promoter contain the motif and are associated with a category/bin where the motif is over-represented. In other words, these are the genes whose promoters contain the “active” motif occurrences. For the species discussed in this article, for each predicted motif, FIRE automatically determines whether its target genes significantly overlap with any Gene Ontology (GO) category, as significant overlaps may hint at the biological role of this motif. The overlap significance is determined using the hyper-geometric distribution (Tavazoie et al., 1999), and a motif is defined as enriched with a particular GO category if and only if the associated  $p$ -value is smaller than 0.05, after correcting for multiple hypothesis testing (using the number of GO categories tested as a Bonferroni correction). The results are reported through an automatically generated table (e.g., Table S1). A similar analysis is done for each category/bin of genes within the expression profile, and is reported on top of each column in the FIRE  $p$ -value heat-map (e.g., Figure 3).

### **Assessing motif conservation**

For the species discussed in this article, FIRE automatically determines a *conservation index* for each predicted motif. First, the network-level conservation score of a predicted motif is calculated with respect to a different related genome, as described in (Elemento and Tavazoie, 2005; Pritsker et al., 2004). Briefly, only genes with non-ambiguous orthologs in both species are considered; the sets of genes, in each species, bearing the motif in their promoter region (or 3'UTR) are determined, and the conservation score is defined as the negative logarithm of the hyper-geometric  $p$ -value for the overlap between these two sets (see (Elemento and Tavazoie, 2005) for more details). This score is compared to the scores obtained for all 7-mers (8,192 for promoters, 16,384 for 3'UTRs), and the motif conservation index is defined as the fraction of these 7-mers with a smaller conservation score. Thus, a conservation index of 1.0 implies that the motif is more conserved than all 7-mers, according to this evaluation procedure.

### **Comparing predicted motifs to known regulatory elements**

Motifs predicted by FIRE are systematically compared to known regulatory elements, when relevant data are available. While analyzing yeast data, predicted motifs are compared to a database compiled from diverse sources (literature, high-quality CHIP-chip assays, etc.), originally used in (Pritsker et al., 2004). While analyzing data for worm, fly, mouse, and human, predicted motifs are compared to TRANSFAC (Matys et al., 2006) (release 4) and JASPAR (Vlieghe et al., 2006). To assess whether a predicted motif matches a known regulatory element, we use CompareACE (Hughes et al., 2000) to find the Pearson correlation between weights of the position weight matrix associated with each regulatory element in these databases, and the position weight matrix representing the predicted motif (where A is converted to [1,0,0,0], [AG] to [0.5,0,0.5,0], etc.). The name of the known regulatory element that is most similar to the predicted motif is reported, assuming that their similarity, *i.e.*, their Pearson correlation, is greater than the stringent cutoff score of 0.8.

### **Comparing predicted RNA motifs to miRNA targets**

It is now widely assumed that metazoan miRNAs typically bind their target 3'UTRs through exact or near-exact complementarity between their 5' extremity and the 3'UTRs. Therefore, in FIRE, predicted metazoan RNA motifs are systematically compared to the 5' extremity of known miRNA sequences within the corresponding species. Similar to what CompareACE does, we try to find a 7-nucleotide (or more) exact match between the motif and the reverse complement of the first 8-nucleotides within the miRNAs. For each motif, we count the number of miRNAs that the motif matches. However, as motifs predicted by FIRE may be highly degenerate and match a large number of miRNAs we further apply a simple control where we shuffle the miRNA sequences 100 times and repeat the analysis. A motif is reported to match miRNAs only when it matches significantly more real miRNAs than randomized miRNAs, *i.e.*, if the number of matched real miRNAs is greater than 3 standard deviations above the average number of matched randomized miRNAs.

## Automatically generated FIRE figures

### FIRE *p*-value heat-map and FIRE density heat-map

The FIRE *p*-value heat-map is automatically generated and summarizes the most important results in a graphical concise manner. An example for yeast is given in Figure 3. The rows in this heat-map correspond to all predicted motifs while the columns correspond to expression categories/bins (gene expression clusters in Figure 3). By default, only categories/bins in which at least one motif was found to be over- or under-represented are shown. Motifs are partitioned into modules as described above, and modules are separated by white horizontal bars. For each category/bin of genes, the most highly enriched GO annotation is reported. The yellow color-map indicates (in a log<sub>10</sub> scale) the over-representation *p*-value (after Bonferroni correction) of a motif in a category/bin where significant events ( $p < 0.05$ ) are marked by red frames. For presentation purposes, *p*-values smaller than  $1e-20$  are set to  $1e-20$ . The blue color-map indicates (in a log<sub>10</sub> scale) under-representation *p*-values (after Bonferroni correction) and significant events ( $p < 0.05$ ) are marked by blue frames, where again  $p < 1e-20$  values are set to  $1e-20$ . Motif logos are used to represent the predicted motifs (after regular expressions are turned into weight matrices, as described above). For each motif, its mutual information, Z-score, robustness, conservation index, the most similar known motif, and the seed that gave rise to it, are also indicated. In addition, predicted position biases are indicated by “Y” and orientation biases in favor of the transcribed or the non-transcribed strand are indicated by “→” or “←”, respectively. The FIRE density heat-map (e.g., Figure S4) has the same format, but instead of reporting *p*-values of over/under-representation, indicates the actual fraction of promoters within each category/bin that contain each motif.

### FIRE interaction heat-map

The FIRE interaction heat-map (e.g., Figure 4) is automatically generated to highlight putative functional relations between predicted motifs. The light (yellow) color map indicates the interaction information between each pair of motifs when this information is due to a positive correlation. The dark (red) color-map indicates the interaction information between each pair of motifs when this information is due to a negative correlation. Putative functional modules are separated by black lines. Significant interaction information values ( $p < 1e-4$ ) that involve two DNA motifs and two RNA motifs are marked by blue and pink frames, respectively. Significant interactions that involve a DNA motif and an RNA motif are marked by green frames. Significant co-localization events are marked by “+”.

### FIRE motif maps

When a position bias or an orientation bias is observed for a predicted motif, FIRE automatically generates a corresponding motif map figure that highlights the nature of the observed bias (e.g., Figure S6). This figure depicts all promoters (or 3'UTRs) in which the motif is present and all occurrences of the motif within each of these promoters.



Genes in the expression bin/category where the motif is most over-represented are shown at the top of the figure. Other bins/categories are subsequently shown in descending order of over-representation significance. Motif maps are also generated for pairs of motifs which avoid being in the same promoters (*e.g.*, Figure S10), or which co-occur. The latter includes cases where motifs co-localize on the DNA or the RNA (*e.g.*, Figure S21).

### **FIRE text report files**

In addition to the above figures, FIRE also generates by default text files that are aimed at facilitating experimental follow-ups. In particular, all occurrences of each predicted motif are reported, along with the corresponding gene, sequence context, position within the promoter/3'UTR, strand (for DNA motifs), *etc.* Promoters in which the predicted motif is present are sorted according to a combined 'putative functionality' score that reflects whether the motif is over-represented within the expression category/bin the gene belongs to, and whether it is located on the preferred strand and/or at the preferred distance from the TSS (or stop codon for RNA motifs).

## **Modular implementation and command lines**

### **A modular implementation**

The relevant FIRE software is implemented via several modules than can be used independently. For example, given expression data and a set of predicted motifs *not* obtained by FIRE analysis, but rather from any other source (*e.g.*, experimentally validated motifs), it is straightforward to generate figures like the FIRE *p*-value heat-map or the FIRE interaction heat-map, in order to highlight various aspects related to these motifs in the context of the available expression data. See the FIRE Web site for more details.

### **Executing FIRE**

For all the species discussed in this article, executing FIRE with default parameters involves a simple command line:

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

where <sp> indicates the species, <inp> indicates the input expression profile (see below), 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). For example, the following command line will reproduce our results for the yeast clustering partition (yeast\_gasch\_IclustPos.txt is available on our Web site):

```
perl fire.pl --species=yeast --expfile=yeast_gasch_IclustPos.txt --exptyspe=discrete
```

The FIRE program, documentation and all results presented in this article can be downloaded from <http://tavazoielab.princeton.edu/FIRE/>. A preliminary Web interface to FIRE is also available at <http://quantbio-tools.princeton.edu/cgi-bin/FIRE/form.pl>.

## Captions for Supplemental Figures

### **Figure S1: Informative co-occurrence and co-avoidance.**

Mutual information is also used to characterize the level of interaction between predicted motifs. A functional interaction between motifs is predicted when the presence of one motif in the promoter implies the presence of the other motif (left panel), leading to a significant information signal between the two motif profiles. However, mutual information can also capture other dependencies, *e.g.*, scenarios when the presence of one motif implies the absence of another motif (right panel). In addition, the same concept can be used to capture dependencies between DNA motifs and RNA motifs, pointing to possible interactions between transcriptional and post transcriptional processes.

### **Figure S2: Informative co-localization.**

The concept of mutual information is further used to capture significant co-localization of pairs of motifs. Specifically, if the combination of two motifs is functional only when both are located in the same vicinity, we expect that the minimal distance between the two motifs will convey significant information over the expression data being analyzed. In the depicted example, the two motifs tend to co-localize among promoters of genes within cluster 2.

### **Figure S3: Schematic overview of the optimization procedure.**

Starting from a candidate motif (seed), our optimization procedure uses a greedy algorithm to explore the surrounding motif space, in search for a more informative and possibly more general motif representation. This optimization is constrained in order to avoid being attracted to highly informative motifs obtained by optimizing previous seeds. Specifically, at each optimization step, we require that the examined motif provides a significant amount of novel information over the expression, given all already optimized motifs at this point. See the Supplementary Methods Section for more details.

### **Figure S4: Density heat map for motifs predicted for yeast gene clustering partition.**

The format of this figure is identical to the format of Figure 3. However, this heat map represents motif densities within each cluster. The density is defined as the fraction of promoters in each cluster in which the motif is present at least once. Significant over- and under-representation events detected through p-value estimation (Figure 3) are highlighted using red and blue frames, respectively.

**Figure S5: Gaining information through optimization – results for yeast.**

This figure depicts the information initially conveyed by each seed (darker colors), and the additional information gained through optimizing this seed (lighter colors). DNA motifs are depicted in red color, while RNA motifs are depicted in green.

**Figure S6: Motif map for the predicted yeast motif matching PAC.**

Position and orientation of the predicted motif that matches the PAC binding site are presented for all *S. cerevisiae* 600bp upstream regions in clusters c66 and c8, in which this motif is most over-represented, and in other clusters (below the thick black line), in which the motif is not over-represented. The position bias detected by FIRE reflects a strong tendency of this motif to be located towards the beginning of the gene (the ATG codon). The full motif map, with all occurrences of this motif, is available at our Web site and illustrates how this tendency is much more dominant in clusters in which the motif is over-represented, leading to a significant information signal between motif positions and cluster indices.

**Figure S7: Motif map for the predicted yeast motif matching RRPE.**

Position and orientation of the predicted motif that matches the RRPE binding site are presented for all *S. cerevisiae* 600bp upstream regions in clusters c66 and c8, in which this motif is most over-represented, and in other clusters (below the thick black line), in which the motif is not over-represented. The position bias detected by FIRE reflects a strong tendency of this motif to be located towards the beginning of the gene (the ATG codon), although not as close as the motif matching PAC (Figure S6). The full motif map, with all occurrences of this motif, is available at our Web site and illustrates how this tendency is much more dominant in clusters in which the motif is over-represented.

**Figure S8: Motif map for the predicted yeast motif matching Rap1 binding site.**

Position and orientation of the predicted motif that matches the Rap1 binding site are presented for all *S. cerevisiae* 600bp upstream regions in cluster c9 and in several other clusters. The motif is over-represented in c9 but not in the other clusters. The position bias detected by FIRE is different from the position biases of the motifs matching PAC (Figure S6) and RRPE (Figure S7). Indeed, this motif seem to be preferentially located in an interval ranging from -200bp to -500bp. This preferential location, and in particular its dominance in cluster c9, is reflected by a statistically significant information between motif position and cluster indices.

**Figure S9: Motif map for the predicted yeast motif matching Puf3 binding site.**

Position and orientation of the predicted RNA motif that matches the Puf3 binding site are presented for all *S. cerevisiae* 300nt 3'UTRs in clusters c53 and c70, in which this motif is most over-represented, and in other clusters (below the thick black line), in which the motif is not over-represented. The position bias detected by FIRE reflects a strong tendency of this motif to be located close to the stop codon. Notice, however that a position bias observed for an RNA motif may also reflect a correlation between the actual 3'UTR length and expression, as opposed to a biophysical constraint over motif location.

**Figure S10: Combined motif map for the predicted yeast motifs matching PAC and Msn2/4 binding sites.**

Position and orientation of the predicted motifs that match PAC and Msn2/4 binding sites are presented for all *S. cerevisiae* 600bp upstream regions in clusters c8, c43, and c66. PAC is most over-represented in c8 and c66, while Msn2/4 is most over-represented in c43. As detected by FIRE, both motifs are typically not found within the same promoter, leading to statistically significant information, where the presence of one motif implies the absence of the other.

**Figure S11: All predicted DNA and RNA motifs for the human genes clustering partition.**

17,390 human genes were clustered based on the human tissue expression data in (Su et al., 2004) and the obtained clustering partition was analyzed by FIRE. All predicted motifs are presented in the figure. The format of this figure is identical to the format of Figure 3. Motif names are based on the closest motif in JASPAR or TRANSFAC (with compareACE score > 0.8). MiRNAs whose 5' extremity matches 3'UTR elements with high specificity are also reported (see Supplementary Methods).

**Figure S12: Predicted interactions among predicted human motifs.**

17,390 human genes were clustered based on the human tissue expression data in (Su et al., 2004) and the obtained clustering partition was analyzed by FIRE. The interactions between all predicted motifs are presented in the figure. The format of this figure is identical to the format of Figure 4.

**Figure S13: Motif map for the predicted human motif matching the NF-Y binding site.**

Position and orientation of a predicted motif matching the NF-Y binding site are presented for all human 1000bp upstream regions in cluster c114, in which this motif is

most over-represented, and in other clusters (below the thick black line), in which the motif is not over-represented. The position bias detected by FIRE reflects a strong tendency of this motif to be located close to the TSS.

**Figure S14: Average expression patterns of human genes in tissue specific clusters.**

Genes within cluster c0 are highly expressed almost exclusively in adult and fetal liver. Genes within cluster c112 are highly expressed in heart, skeletal muscle, and tongue tissues. Motifs associated with these two clusters are described in the main text.

**Figure S15: number of predicted motifs by FIRE (DNA+RNA) when analyzing the Gasch *et al.* yeast stress dataset, at different robustness index thresholds.**

The figure also shows the number of motifs supported by GO functional categories (red), the number of motifs matching known motifs (green), and the expected number of false positives calculated from 100 shuffled clustering partitions (blue).

**Figure S16: All predicted DNA and RNA motifs for worm genes clustering partition.**

11,562 worm genes were clustered based on the expression data in (Kim et al., 2001) and the obtained clustering partition was analyzed by FIRE. All predicted motifs are presented in the figure. The format of this figure is identical to the format of Figure 3. Motif names are based on the closest motif in JASPAR or TRANSFAC (with compareACE score > 0.8). MiRNAs whose 5' extremity matches 3'UTR elements with high specificity are also reported (see Supplementary Methods).

**Figure S17: Gaining information through optimization – results for worm.**

This figure depicts the information initially conveyed by each seed (darker colors), and the additional information gained through optimizing this seed (lighter colors). DNA motifs are depicted in red color, while RNA motifs are depicted in green.

**Figure S18: Predicted interactions among all predicted worm motifs.**

11,562 worm genes were clustered based on the expression data in (Kim et al., 2001) and the obtained clustering partition was analyzed by FIRE. The interactions between all predicted motifs are presented in the figure. The format of this figure is identical to the format of Figure 4.

**Figure S19: Predicted DNA and RNA motifs for worm genes clustering partition.**

11,562 worm genes were clustered based on the expression data in (Kim et al., 2001). The format of this figure is identical to the format of Figure 3. Due to space limitations, only a selection of the predicted motifs is presented. The complete figure is given as Figure S15. DNA motif names are reported based on the closest known motif in JASPAR or TRANSFAC, with compareACE score > 0.8. MiRNAs whose 5' extremity matches 3'UTR elements with high specificity are also reported (see Supplementary Methods).

**Figure S20: Motif map for a predicted E-box-like worm motif.**

Position and orientation of a predicted E-box like motif are presented for all *C. elegans* 1000bp upstream regions in clusters c30 and c103, in which this motif is most over-represented, and in other clusters (below the thick black line), in which the motif is not over-represented. The position bias detected by FIRE reflects a strong tendency of this motif towards the TSS.

**Figure S21: Combined motif map for two predicted co-localizing worm motifs.**

Position and orientation of two predicted motifs within *C. elegans* 1000bp upstream regions in which both motifs are present. In c63, where both motifs are over-represented, their minimal distance is almost always exactly 3 nucleotides, leading to statistically significant information between this minimal distance and the cluster indices, detected by FIRE.

**Figure S22: Predicted motifs for *Drosophila in situ* hybridizations data.**

FIRE was applied independently to 55 binary expression profiles, which describe whether genes are expressed (or not) in a specific tissue and at a specific stage during *Drosophila* embryogenesis. All motifs predicted within these 55 runs were clustered based on their pairwise CompareACE scores, and the motif with the maximal Z-score within each cluster was chosen as the cluster representative. A selection of these representatives is shown in the figure that indicates the information robustness scores obtained for these motifs for 8 different spatio-temporal expression profiles.

**Figure S23: Motif map for the predicted fly motif matching the DRE element.**

Position and orientation of the predicted motif that matches the DRE element are presented for all *D. melanogaster* 1000bp upstream regions in clusters c1 and c0. The expression profile analyzed here only contains two clusters, with genes in c1 showing a relatively uniform expression during stages 1-3 in the embryo (implying these are maternal genes). Expression of genes in c0 is not detected at stages 1-3. The position bias

detected by FIRE reflects a strong tendency of this motif to be located towards the TSS, especially for genes in c1.



Figure S1

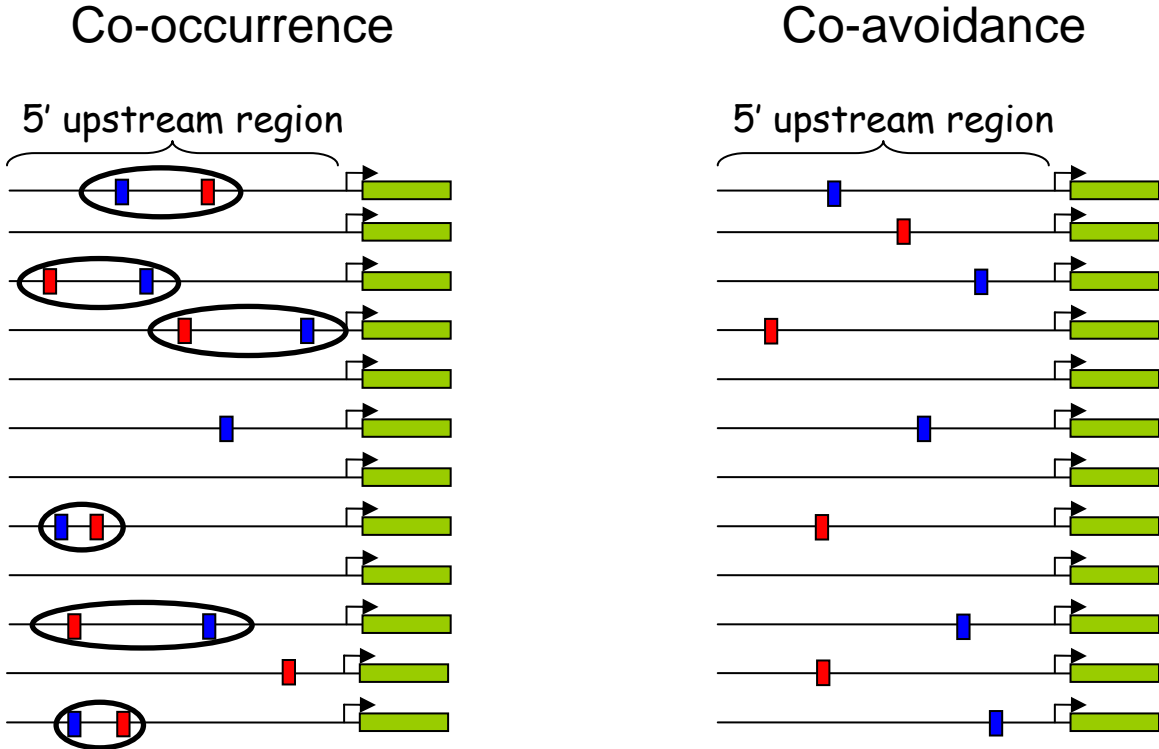


Figure S2

# Co-localization

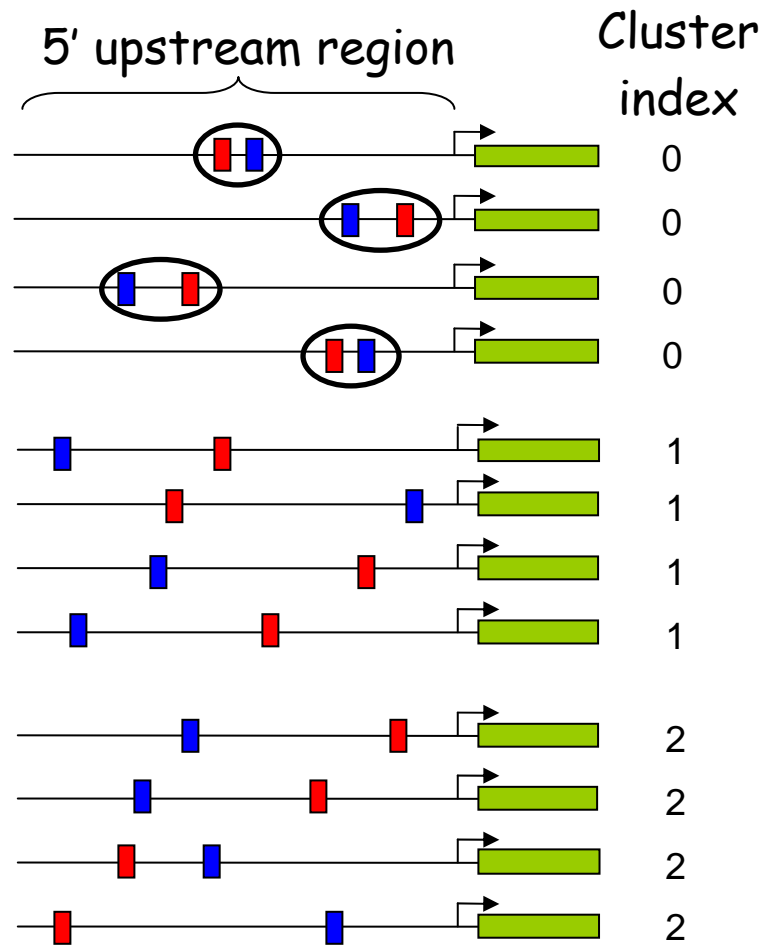
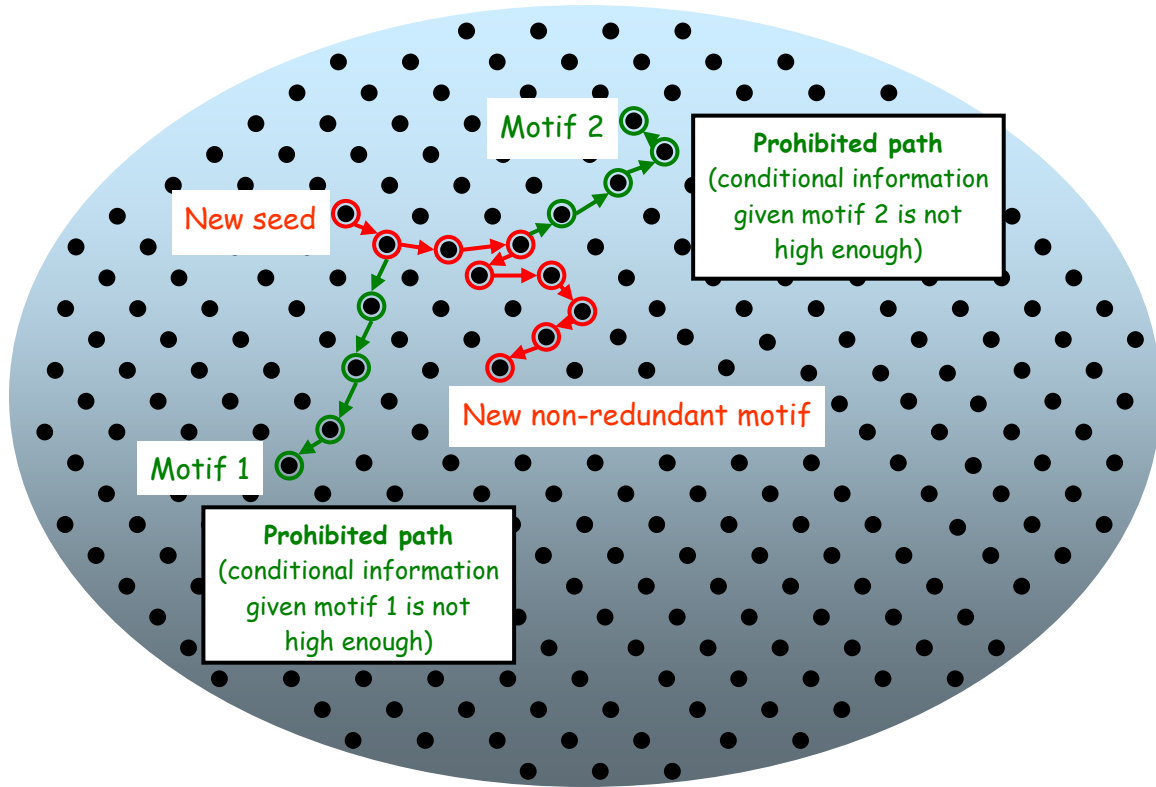


Figure S3



# Figure S4



# Figure S5

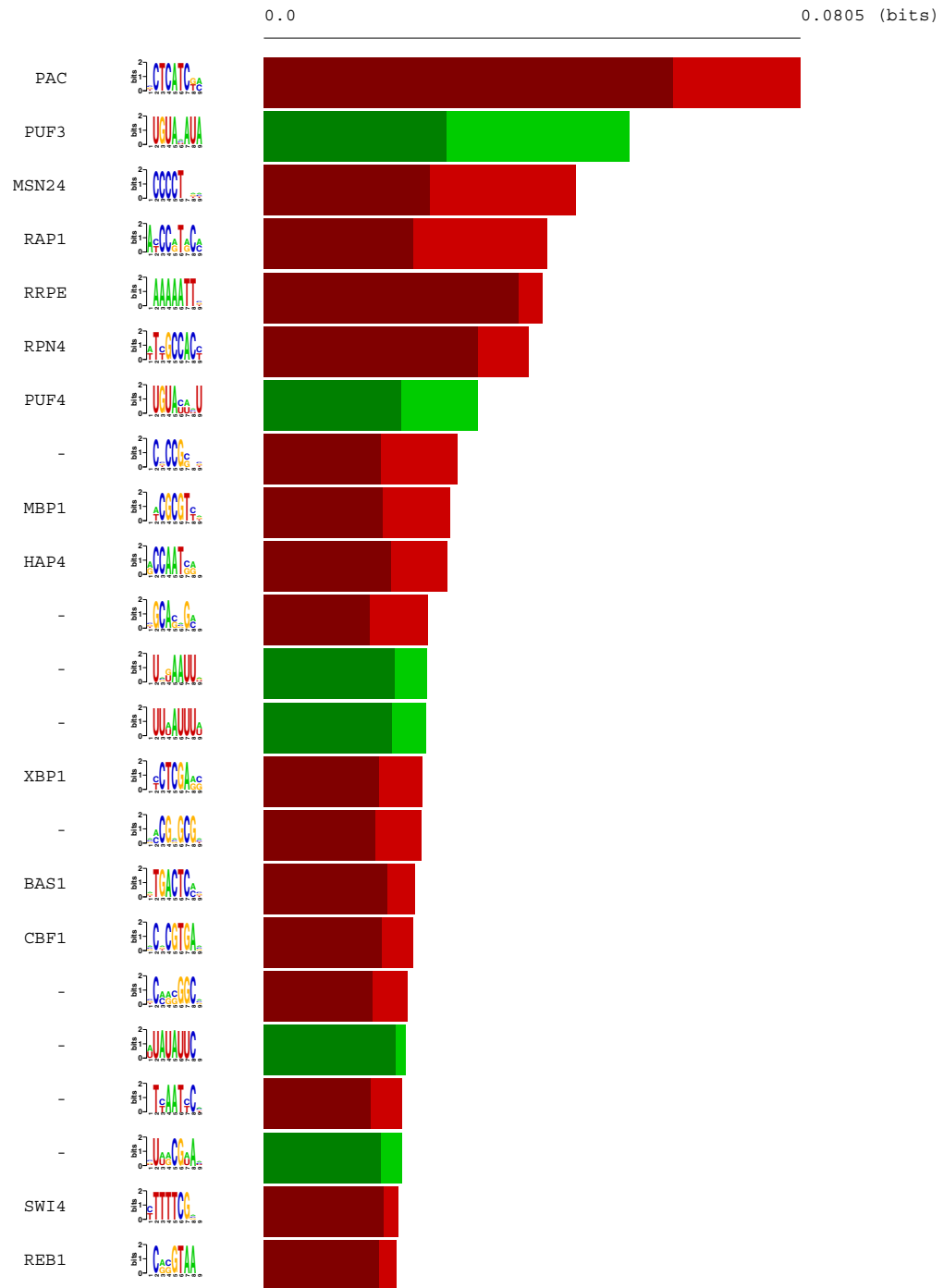






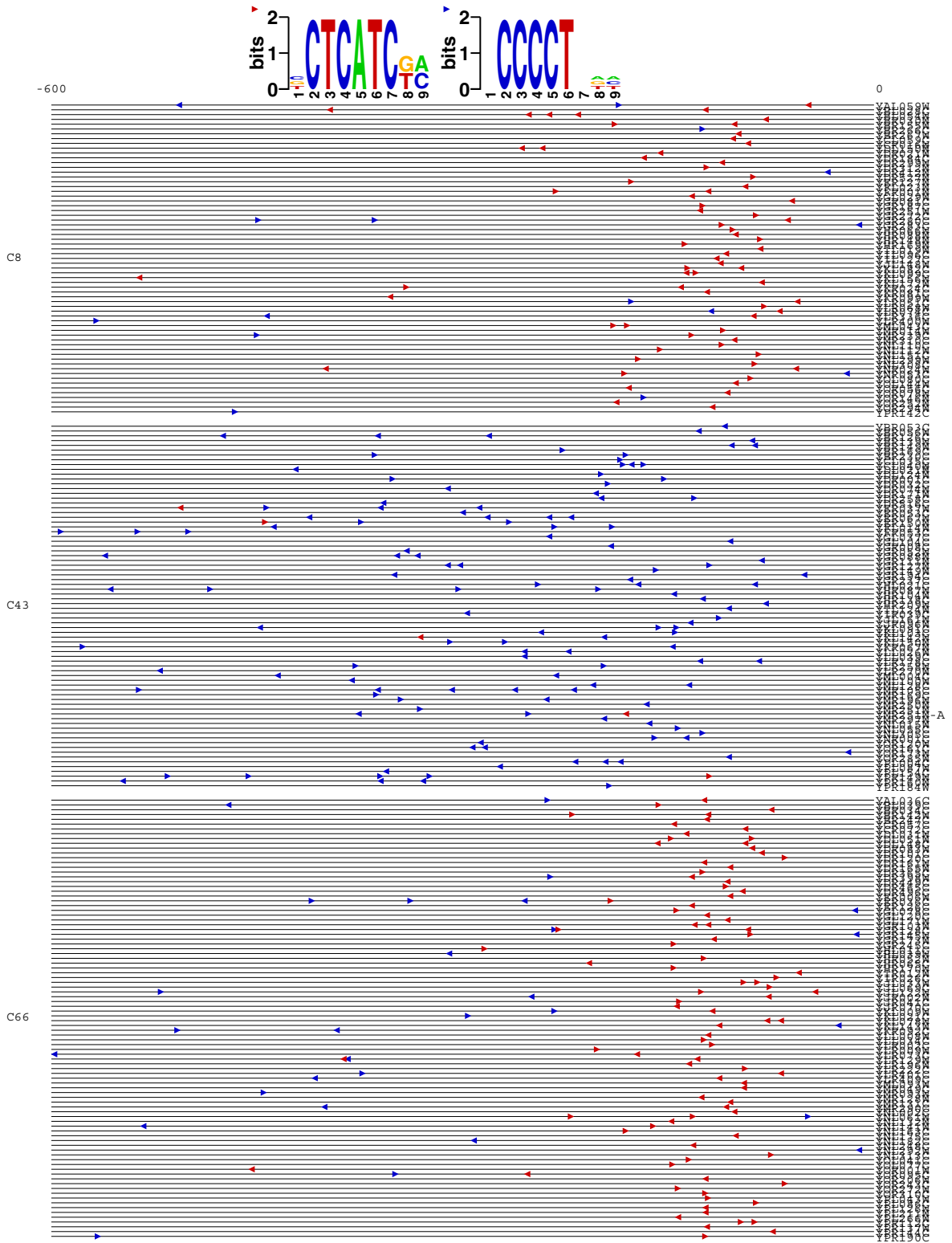




Figure S9



Figure S10



# Figure S11

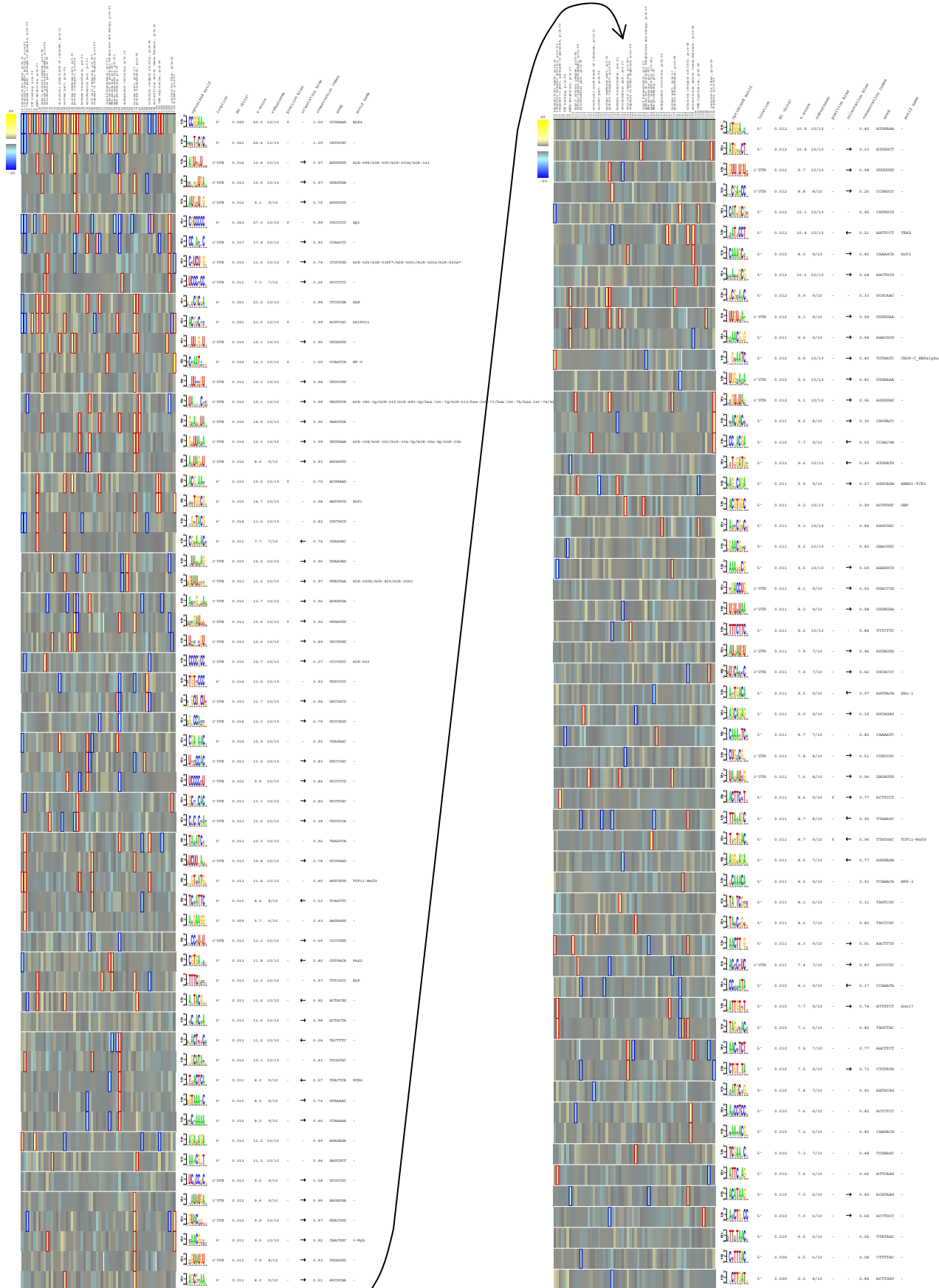
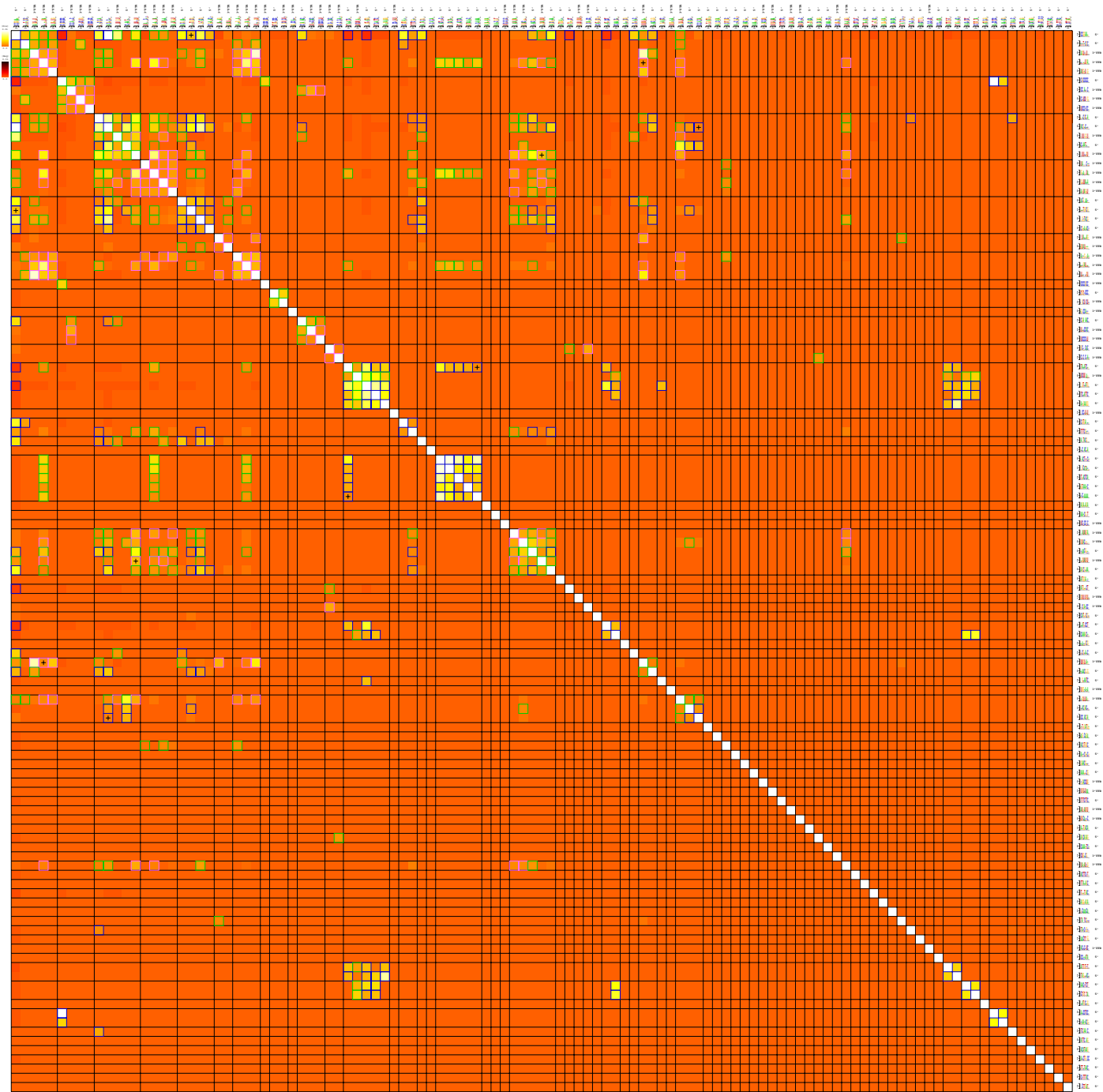
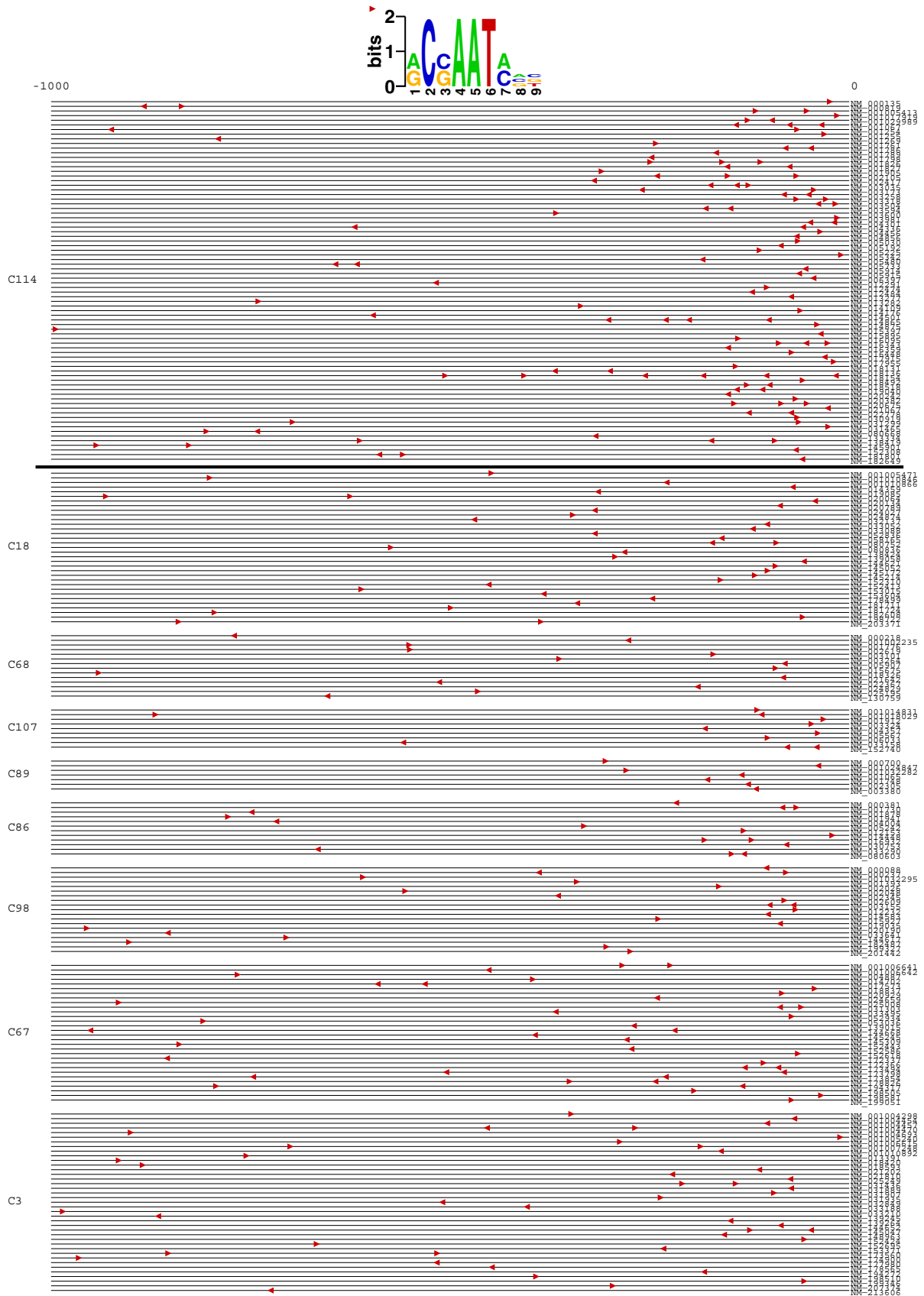


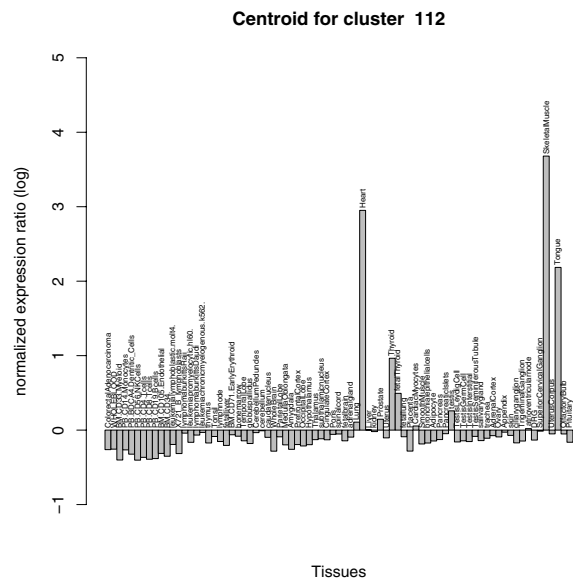
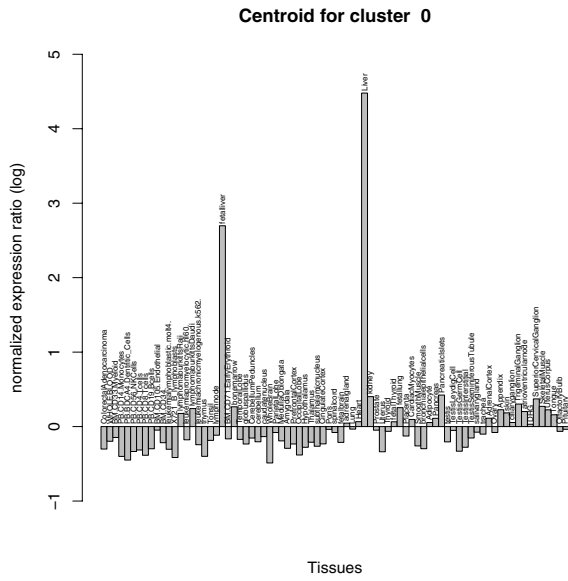
Figure S12



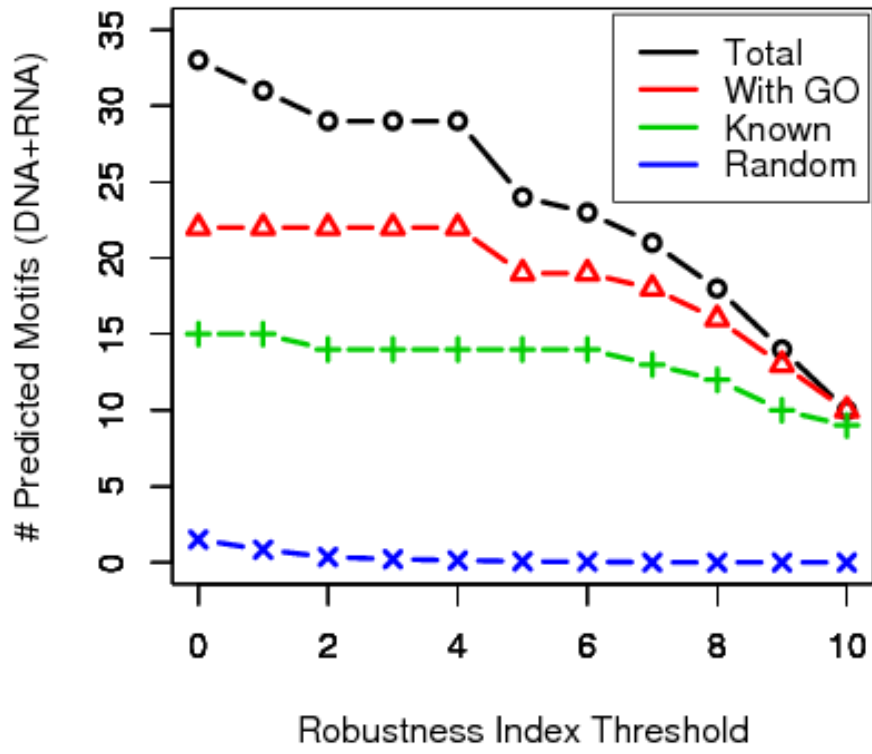
# Figure S13



# Figure S14



**Figure S15**







# Figure S17

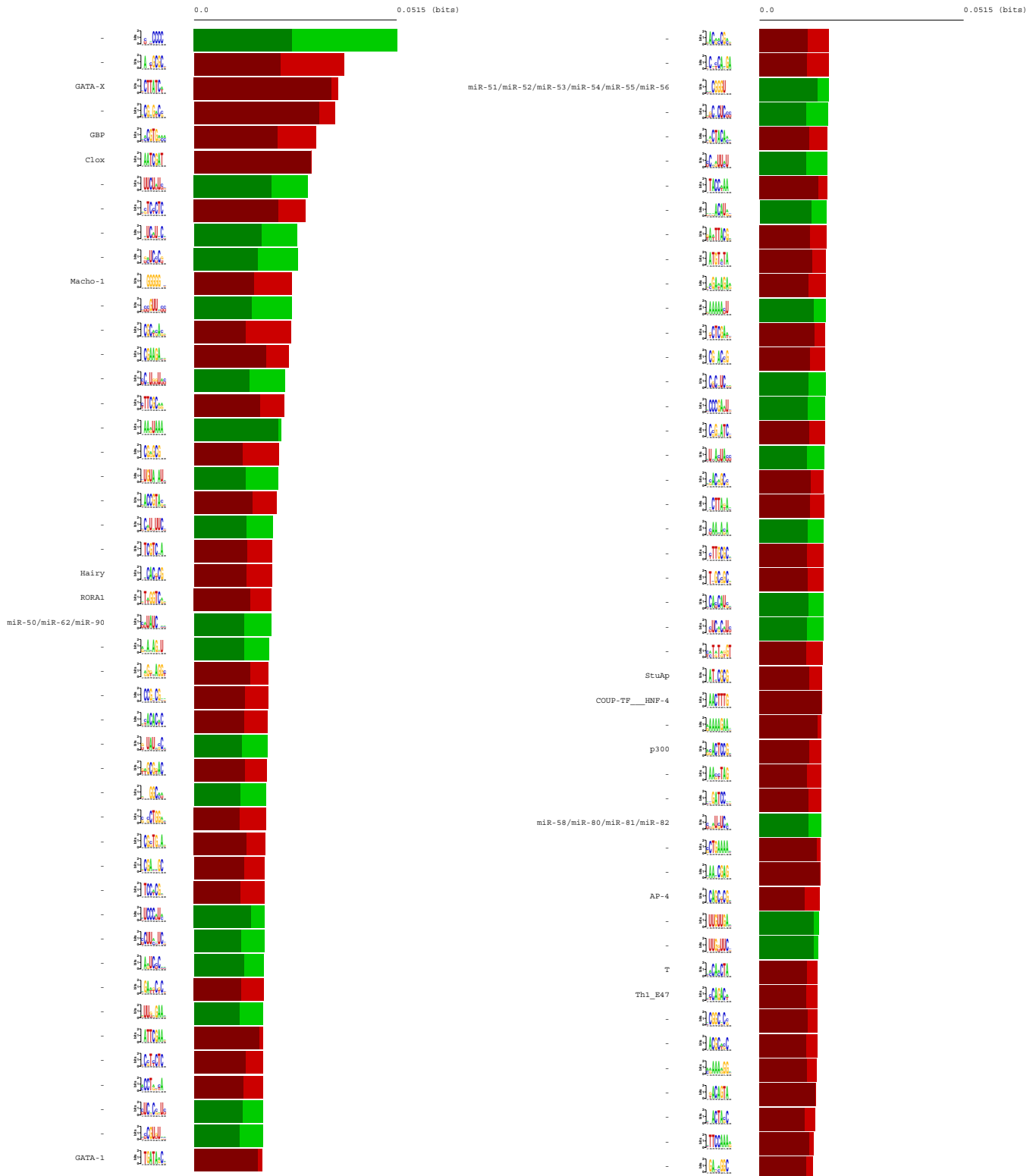
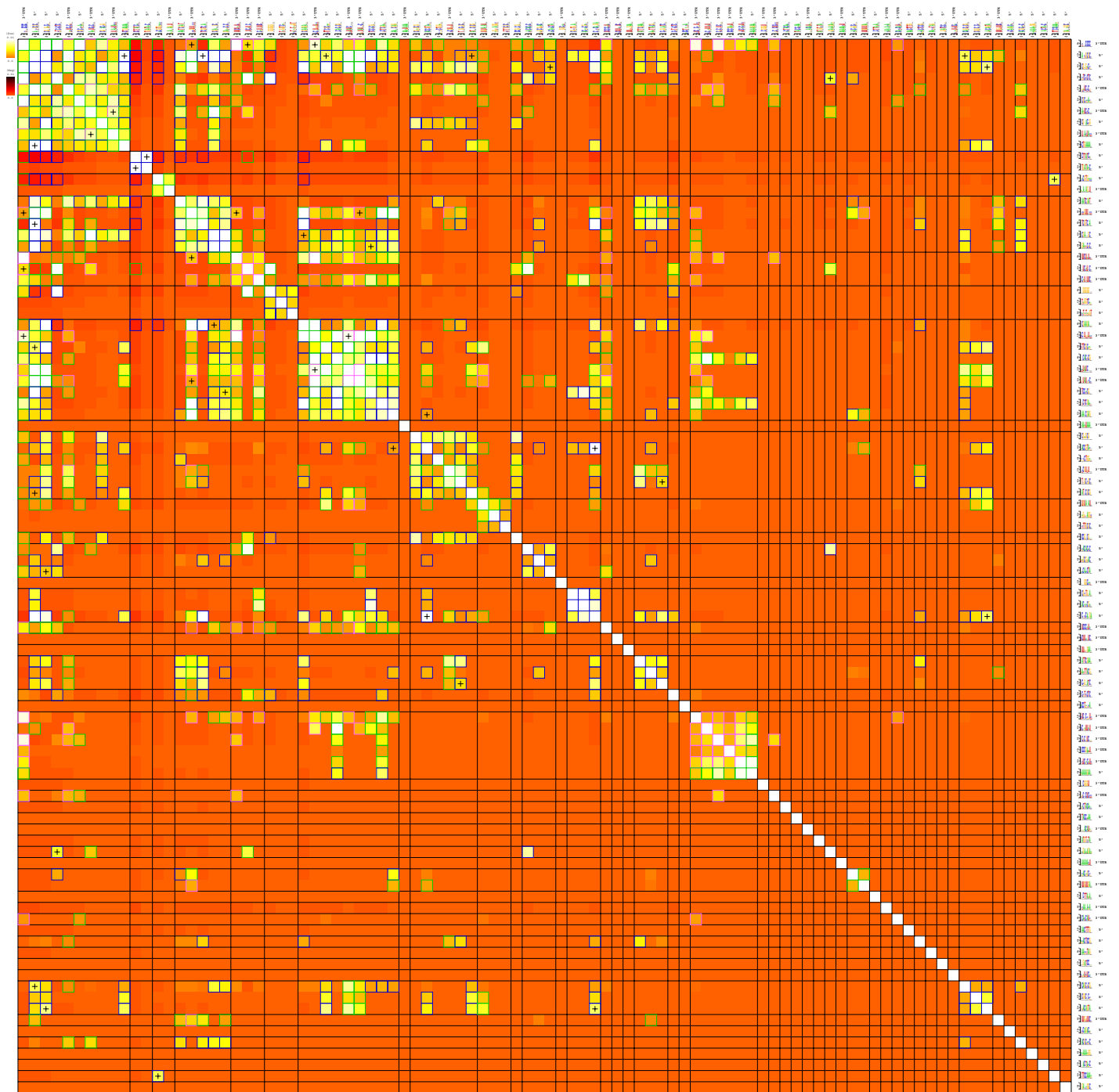


Figure S18



# Figure S19

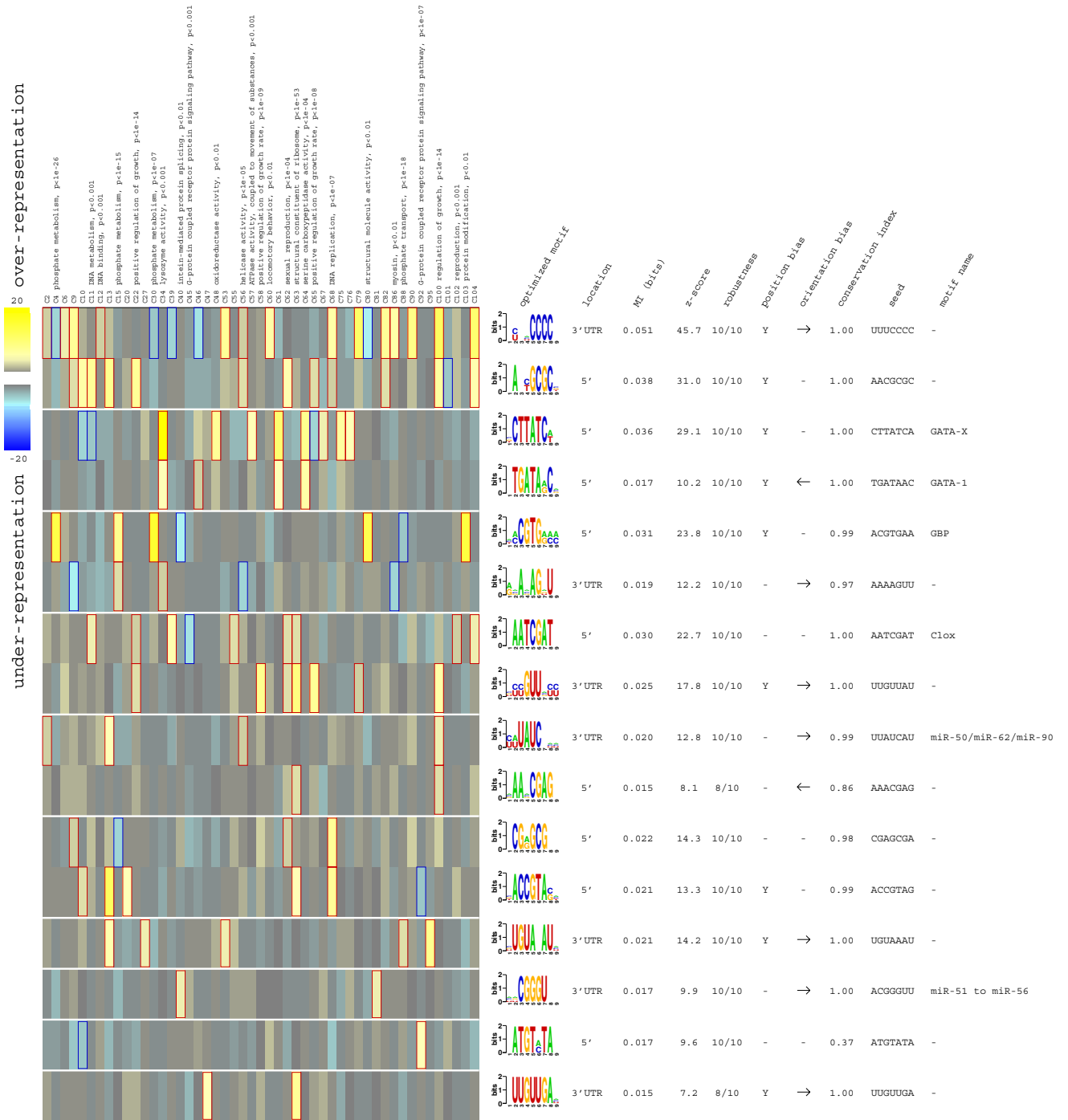


Figure S20





# Figure S22

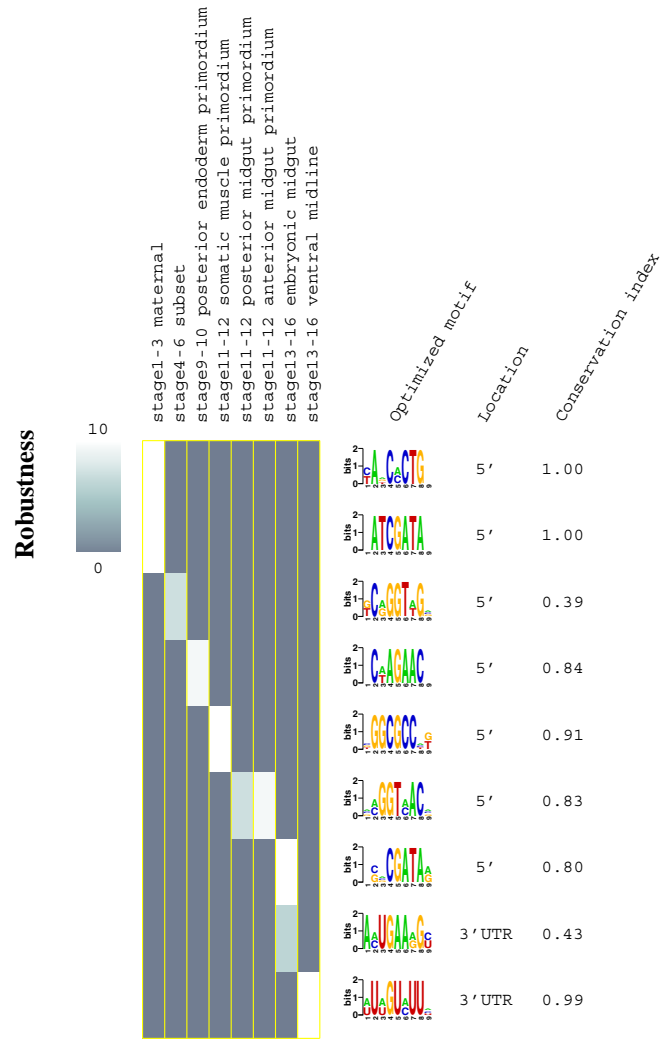
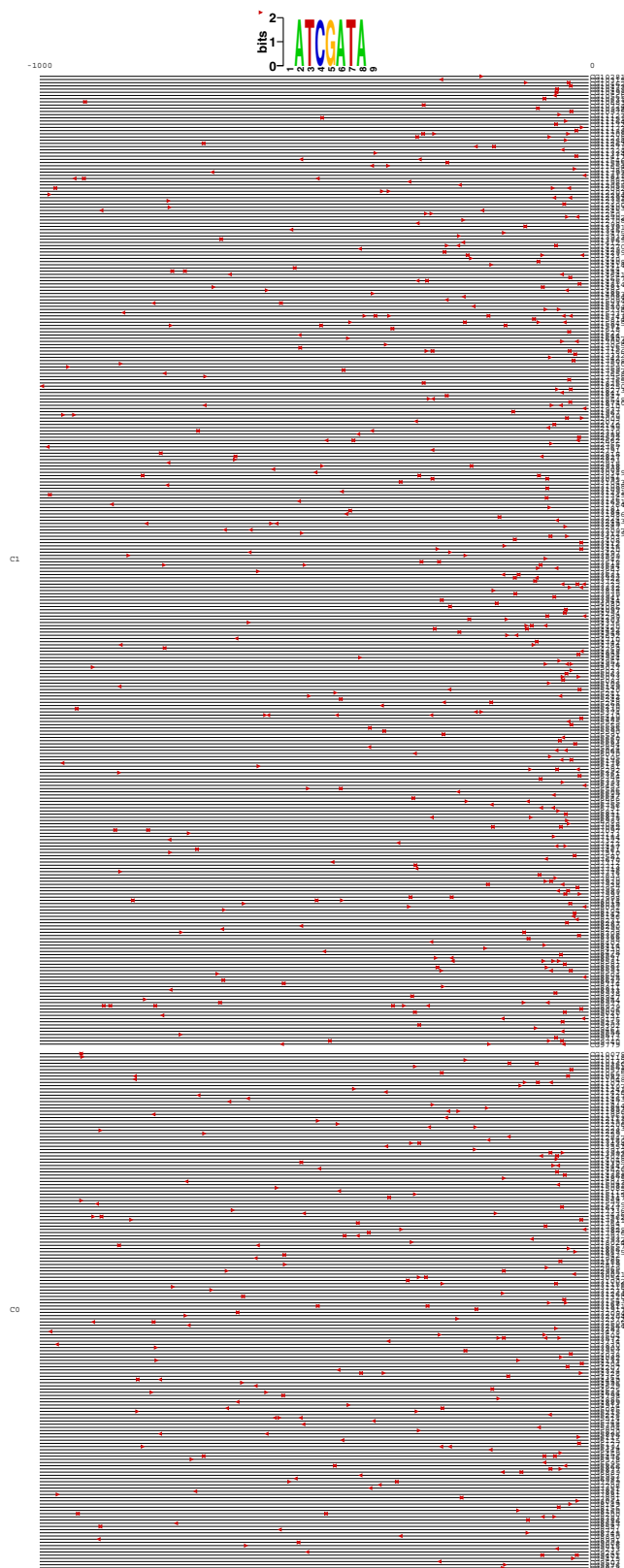


Figure S23



## Captions for Supplemental Tables

### **Table S1: Most significant Gene Ontology enrichments for all predicted yeast motifs.**

The target genes of each predicted motif are defined as genes whose promoter contain the motif and are associated with clusters in which the motif is over-represented. Enrichment of the target genes of each motif is determined with respect to Gene Ontology (GO) categories using the hypergeometric distribution, and the most significant GO category is indicated in this table along with its p-value after correcting for multiple hypotheses testing using a Bonferroni correction.

### **Table S2: Fraction of genes that have a given FIRE motif both in clusters where the motif is significantly over-represented (“active” clusters) and in the remaining clusters (non-active clusters).**




















These two fractions provide an indication of the amount of variance in the expression data that can be explained by the discovered motifs. This table shows that, in general, the percentage of the motif's non-active occurrences is relatively low, suggesting that much of the variance in the expression data is explained by the predicted motifs.

### **Table S3: Motif discovery from *Drosophila* enhancer data.**

FIRE was applied to 124 early embryonic *Drosophila* enhancer sequences collected from the literature (D. Papatsenko, <https://webfiles.berkeley.edu/~dap5/>) of which 20 are known to be bound by the Bicoid morphogen. The predicted motif (on the left) matches well the previously reported Bicoid binding site and is more discriminative between Bicoid-bound enhancers and other enhancers compared to the somewhat similar motif obtained by applying AlignACE (on the right) to the same data. In a leave-one-out test, each enhancer was withdrawn and the remaining 123 were analyzed by FIRE to extract a maximally informative motif that was then used to predict whether the withdrawn enhancer is bound by Bicoid or not. The success rate (SR), sensitivity (SE) and specificity (SP) are shown.





# Table S1

Motif	Location	Most significant functional enrichment
	5'	ribosome biogenesis, $p < 1e-09$
	5'	cytoplasm organization and biogenesis, $p < 1e-09$
	3'UTR	cytoplasm organization and biogenesis, $p < 1e-42$
	3'UTR	organellar ribosome, $p < 1e-71$
	5'	carbohydrate metabolism, $p < 1e-06$
	5'	oxidative phosphorylation, $p < 1e-17$
	5'	cytosolic ribosome (sensu Eukaryota), $p < 1e-10$
	3'UTR	cytosolic ribosome (sensu Eukaryota), $p < 1e-54$
	3'UTR	cytosolic ribosome (sensu Eukaryota), $p < 1e-48$
	5'	proteasome complex (sensu Eukaryota), $p < 1e-44$
	5'	modification-dependent macromolecule catabolism, $p < 1e-12$
	5'	DNA replication, $p < 1e-07$
	5'	oxidative phosphorylation, $p < 1e-38$
	5'	oxidative phosphorylation, $p < 0.001$
	5'	oxidative phosphorylation, $p < 1e-05$
	5'	protein folding, $p < 0.01$
	5'	amino acid metabolism, $p < 1e-14$
	5'	sulfur utilization, $p < 1e-05$
	3'UTR	oxidative phosphorylation, $p < 1e-22$

## Table S2

Motif	# active clusters	Fraction in active clusters	Fraction in non-active clusters
[CGT]CTCATC[GT][AC]	5	0.47	0.07
.AAAAATT[CGT]	5	0.63	0.30
.UGUA[CU][AU][ACU]U	4	0.41	0.20
.UGUA[ACU]AUA	2	0.86	0.13
.CCCCT.[AGT][ACT]	6	0.51	0.23
.C[CGT]CCG[CG].[CGT]	4	0.45	0.23
[CGT]GCA[CG][ACG]G[AC].	4	0.44	0.24
A[CT]CC[AG]T[AG]C[AC]	1	0.55	0.05
.U[ACG][GU]AAUU[AGU]	2	0.39	0.20
.UU[AU]AUUU[AU]	2	0.47	0.23
[AT]T[CT]GCCAC[CT]	3	0.32	0.04
.C[AG][CG]GTAA.	3	0.40	0.22
.[AT]CGCGT[CT][AGT]	2	0.31	0.09
[AG]CCAAT[CG][AG].	1	0.59	0.11
[ACG][AC]CG[ACG]GCG[ACT]	2	0.18	0.04
[CGT]C[AC][AG][CG]GGC[ACG]	2	0.27	0.10
.[CT]CTCGA[AG][CG]	2	0.29	0.10
[AGT]TGACTC[AC][CGT]	1	0.53	0.04
[ACG]C[AGT]CGTGA[ACG]	1	0.30	0.04
[AU]UAUAUUC.	1	0.34	0.06
.T[CT]AAT[CT]C[ACT]	1	0.46	0.26
[CGU]U[AU][AG]CG[AU]A[ACU]	1	0.22	0.09

# Table S3

	FIRE motif	FIRE cross-val			AlignACE motif
		SR	SE	SP	
Bicoid		69%	50%	73%	

## Data Sources

<b><i>S. cerevisiae</i> (FIRE species name: yeast)</b>	
Expression dataset	173 microarrays that measure mRNA levels in response to different environmental stress conditions, originally published in (Gasch et al., 2000); downloaded from SMD ( <a href="http://genome-www5.stanford.edu/">http://genome-www5.stanford.edu/</a> ).
Sequence data	Genome sequence (SGD1) downloaded from Ensembl ( <a href="http://www.ensembl.org/index.html">http://www.ensembl.org/index.html</a> ) on Aug 16 <sup>th</sup> 2006.
Gene annotation	Downloaded from Ensembl on Aug 16 <sup>th</sup> 2006.
Gene Identifiers	ORF names (e.g., YAL001C)
Upstream regions	600bp upstream of ATG.
3'UTRs	300nt downstream of Stop codon.
Gene Ontology	Downloaded from <a href="http://www.geneontology.org">http://www.geneontology.org</a> on Sep 19 <sup>th</sup> 2006.
Comparative genomics	Comparisons were made with <i>S. bayanus</i> 600bp upstream regions and 300nt 3'UTRs, downloaded from SGD on Aug 16 <sup>th</sup> 2006. Protein sequences downloaded from Ensembl ( <i>S. cerevisiae</i> ) and SGD ( <i>S. bayanus</i> ).
Known motifs	A list of yeast motifs manually compiled by M. Beer, used previously in (Pritsker et al., 2004); two 3'UTR motifs were added to this list based on (Gerber et al., 2004).

<b><i>P. falciparum</i> (FIRE species name: malaria)</b>	
Expression dataset	46 microarrays that measure mRNA levels at different time points during the parasite developmental cycle, along with gene "phase" values, originally published in (Bozdech et al., 2003); downloaded from <a href="http://malaria.ucsf.edu/supplementaldata/Datasets/Overview_Dataset.txt">http://malaria.ucsf.edu/supplementaldata/Datasets/Overview_Dataset.txt</a> .
Sequence data	Genome sequence downloaded from PlasmoDB ( <a href="http://www.plasmodb.org/plasmo/home.jsp">http://www.plasmodb.org/plasmo/home.jsp</a> ) on June 15 <sup>th</sup> 2006.
Gene annotation	Downloaded from PlasmoDB on June 15 <sup>th</sup> 2006.
Gene Identifiers	ORF names (e.g., PFB0245c)
Upstream regions	1kb upstream of ATG.
3'UTRs	1kb downstream of Stop codon.
Gene Ontology	Downloaded from <a href="http://www.geneontology.org">http://www.geneontology.org</a> on Sep 22 <sup>nd</sup> 2006.
Comparative genomics	Comparisons were made with <i>P. yoelli</i> . Genome sequence, downloaded from PlasmoDB on Dec 2 <sup>nd</sup> 2005. Since no gene annotation was available at that time, we annotated the genome using the <i>P. falciparum</i> protein sequences and an

	(unpublished) annotation script based on Blast and Genewise (Birney et al., 2004). 1kb upstream regions and 3'UTRs were then extracted.
Known motifs	NA.

<b><i>C. elegans</i> (FIRE species name: worm)</b>	
Expression dataset	551 microarrays, originally published in (Kim et al., 2001); downloaded from <a href="http://cmgm.stanford.edu/~kimlab/topomap/kimbig">http://cmgm.stanford.edu/~kimlab/topomap/kimbig</a>
Sequence data	Genome sequence downloaded from Ensembl on Aug 3 <sup>rd</sup> 2006.
Gene annotation	Downloaded from Ensembl on Aug 3 <sup>rd</sup> 2006.
Gene Identifiers	ORF names (e.g., 2L52.1)
Upstream regions	1kb upstream of TSS; if several TSSs are annotated, the farthest upstream one was used.
3'UTRs	300nt downstream of stop codon. If several stop codons are annotated, the farthest downstream one was used.
Gene Ontology	Downloaded from <a href="http://www.geneontology.org">http://www.geneontology.org</a> on Aug 4 <sup>th</sup> 2006
Comparative genomics	Comparisons were made with <i>C. briggsae</i> . Genome, gene annotation, and protein sequences were downloaded from <a href="ftp://ftp.sanger.ac.uk/pub/wormbase/cbriggsae/cb25.agp8">ftp://ftp.sanger.ac.uk/pub/wormbase/cbriggsae/cb25.agp8</a> on Sep 19 <sup>th</sup> 2006. 1kb upstream regions and 300nt 3'UTRs were then extracted from the genomic sequence.
Known motifs	Compiled from TRANSFAC Release 4.0 ( <a href="http://www.genome.jp/dbget-bin/show_tfmatrix">http://www.genome.jp/dbget-bin/show_tfmatrix</a> ) and JASPAR, Dec 2006 ( <a href="http://mordor.cgb.ki.se/cgi-bin/jaspar2005/jaspar_db.pl">http://mordor.cgb.ki.se/cgi-bin/jaspar2005/jaspar_db.pl</a> ).
miRNAs	117 miRNA sequences, downloaded from miRBase (Griffiths-Jones, 2004) on Oct 20 <sup>th</sup> 2006.

<b><i>D. melanogaster</i> (FIRE species name: drosophila)</b>	
Expression dataset	<i>In situ</i> hybridization data, originally published in (Tomancak et al., 2002) downloaded from <a href="http://www.fruitfly.org/cgi-bin/ex/insitu.pl">http://www.fruitfly.org/cgi-bin/ex/insitu.pl</a> ; 124 early embryonic enhancer sequences downloaded from <a href="https://webfiles.berkeley.edu/~dap5/">https://webfiles.berkeley.edu/~dap5/</a> .
Sequence data	Genome sequence (BDGP 4.3) downloaded from Ensembl on Sep 5 <sup>th</sup> 2006.
Gene annotation	Downloaded from Ensembl on Sep 5 <sup>th</sup> 2006.
Gene Identifiers	CG identifiers (e.g., CG2986).
Upstream regions	1kb upstream of TSS; if several TSSs are annotated, the farthest upstream one was used.

3'UTRs	300nt downstream of stop codon. If several stop codons are annotated, the farthest downstream one was used.
Gene Ontology	Downloaded from <a href="http://www.geneontology.org">http://www.geneontology.org</a> on Oct 9 <sup>th</sup> 2006.
Comparative genomics	Comparisons were made with <i>D. pseudoobscura</i> . Genome, gene annotation, and protein sequences were downloaded from Flybase on Jan 12 <sup>th</sup> 2007. 1kb upstream regions and 300nt 3'UTRs were then extracted from the genomic sequence.
Known motifs	Same as for worm.
miRNAs	73 miRNA sequences, downloaded from miRBase (Griffiths-Jones, 2004) on Oct 19 <sup>th</sup> 2006.

<b><i>M. musculus</i> (FIRE species name: mouse)</b>	
Expression dataset	62 microarrays that measure mRNA levels in different mouse tissues (each array represents the average of two repeats), originally published in (Su et al., 2004); downloaded from <a href="http://wombat.gnf.org/index.html">http://wombat.gnf.org/index.html</a> .
Sequence data	Genome sequence was downloaded from UCSC Genome Browser on Nov 5 <sup>th</sup> 2006 (chromFaMasked.tar.gz).
Gene annotation	Downloaded from UCSC on Nov 5 <sup>th</sup> 2006 (refGene.txt).
Gene Identifiers	RefSeq identifiers (e.g., NM_144958).
Upstream regions	1kb upstream of TSS; if several TSSs are annotated, the farthest upstream one was used.
3'UTRs	300nt downstream of stop codon. If several stop codons are annotated, the farthest downstream one was used.
Gene Ontology	Downloaded from <a href="http://www.geneontology.org">http://www.geneontology.org</a> on Nov 7 <sup>th</sup> 2006.
Comparative genomics	Comparisons were made with <i>G. gallus</i> . Genome, gene annotation, and protein sequences were downloaded from Ensembl on Nov 11 <sup>th</sup> 2006. 1kb upstream regions and 300nt 3'UTRs were then extracted from the genomic sequence.
Known motifs	Same as for worm and fly.
miRNAs	375 miRNA sequences, downloaded from miRBase (Griffiths-Jones, 2004) on Jan 8 <sup>th</sup> 2007.

<b><i>H. sapiens</i> (FIRE species name: human)</b>	
Expression dataset	79 microarrays that measure mRNA levels in different human tissues (each array represents the average of two repeats), originally published in (Su et al., 2004); downloaded from <a href="http://wombat.gnf.org/index.html">http://wombat.gnf.org/index.html</a> .
Sequence data	Genome sequence was downloaded from UCSC Genome Browser on Oct 1 <sup>st</sup> 2006 (chromFaMasked.tar.gz).
Gene annotation	Downloaded from UCSC on Oct 1 <sup>st</sup> 2006 (refGene.txt).

Gene Identifiers	RefSeq identifiers ( <i>e.g.</i> , NM_018117).
Upstream regions	1kb upstream of TSS; if several TSSs are annotated, the farthest upstream one was used.
3'UTRs	300nt downstream of stop codon. If several stop codons are annotated, the farthest downstream one was used.
Gene Ontology	Downloaded from <a href="http://www.geneontology.org">http://www.geneontology.org</a> on July 3 <sup>rd</sup> 2006.
Comparative genomics	Comparisons were made with <i>G. gallus</i> . Genome, gene annotation, and protein sequences were downloaded from Ensembl on Nov 11 <sup>th</sup> 2006. 1kb upstream regions and 300nt 3'UTRs were then extracted from the genomic sequence.
Known motifs	Same as for worm, fly, and mouse.
miRNAs	420 miRNA sequences, downloaded from miRBase (Griffiths-Jones, 2004) on Oct 19 <sup>th</sup> 2006.

## Supplemental References

Andres, V., Nadal-Ginard, B., and Mahdavi, V. (1992). Clox, a mammalian homeobox gene related to *Drosophila cut*, encodes DNA-binding regulatory proteins differentially expressed during development. *Development* *116*, 321-334.

Arnosti, D. N., and Kulkarni, M. M. (2005). Transcriptional enhancers: Intelligent enhanceosomes or flexible billboards? *J Cell Biochem* *94*, 890-898.

Birney, E., Clamp, M., and Durbin, R. (2004). GeneWise and Genomewise. *Genome Res* *14*, 988-995.

Bozdech, Z., Llinas, M., Pulliam, B. L., Wong, E. D., Zhu, J., and DeRisi, J. L. (2003). The transcriptome of the intraerythrocytic developmental cycle of *Plasmodium falciparum*. *PLoS Biol* *1*, E5.

Chan, C. S., Elemento, O., and Tavazoie, S. (2005). Revealing posttranscriptional regulatory elements through network-level conservation. *PLoS Comput Biol* *1*, e69.

Cover, T., and Thomas, J. (2006). *Elements of Information Theory*, 2nd edn (Hoboken, NJ, Wiley-Interscience).

De Renzis, S., Elemento, O., Tavazoie, S., and Wieschaus, E. (2007). Unmasking Activation of the Zygotic Genome Using Chromosomal Deletions in the *Drosophila* Embryo. *PLoS Biol* (in press).

Driever, W., and Nusslein-Volhard, C. (1989). The bicoid protein is a positive regulator of hunchback transcription in the early *Drosophila* embryo. *Nature* *337*, 138-143.

Efron, B. (1979). Bootstrap Methods: Another Look at the Jackknife. *The annals of statistics* *7*, 1-26.

Elemento, O., and Tavazoie, S. (2005). Fast and systematic genome-wide discovery of conserved regulatory elements using a non-alignment based approach. *Genome Biol* *6*, R18.

Foat, B. C., Houshmandi, S. S., Olivas, W. M., and Bussemaker, H. J. (2005). Profiling condition-specific, genome-wide regulation of mRNA stability in yeast. *Proc Natl Acad Sci U S A* *102*, 17675-17680.

Gasch, A. P., Spellman, P. T., Kao, C. M., Carmel-Harel, O., Eisen, M. B., Storz, G., Botstein, D., and Brown, P. O. (2000). Genomic expression programs in the response of yeast cells to environmental changes. *Mol Biol Cell* *11*, 4241-4257.



Gerber, A., Herschlag, D., and Brown, P. (2004). Extensive association of functionally and cytologically related mRNAs with Puf family RNA-binding proteins in yeast. *PLoS Biol* 2, E79.

Griffiths-Jones, S. (2004). The microRNA Registry. *Nucleic Acids Res* 32 *Database issue*, D109-111.

Hughes, J. D., Estep, P. W., Tavazoie, S., and Church, G. M. (2000). Computational identification of cis-regulatory elements associated with groups of functionally related genes in *Saccharomyces cerevisiae*. *J Mol Biol* 296, 1205-1214.

Jurka, J., Kapitonov, V. V., Pavlicek, A., Klonowski, P., Kohany, O., and Walichiewicz, J. (2005). Repbase Update, a database of eukaryotic repetitive elements. *Cytogenet Genome Res* 110, 462-467.

Kellis, M., Patterson, N., Endrizzi, M., Birren, B., and Lander, E. S. (2003). Sequencing and comparison of yeast species to identify genes and regulatory elements. *423*, 241-254.

Kim, S. K., Lund, J., Kiraly, M., Duke, K., Jiang, M., Stuart, J. M., Eizinger, A., Wylie, B. N., and Davidson, G. S. (2001). A gene expression map for *Caenorhabditis elegans*. *Science* 293, 2087-2092.

Lewis, B., Burge, C., and Bartel, D. (2005). Conserved seed pairing, often flanked by adenosines, indicates that thousands of human genes are microRNA targets. *Cell* 120, 15-20.

Llinas, M., and DeRisi, J. L. (2004). Pernicious plans revealed: *Plasmodium falciparum* genome wide expression analysis. *Curr Opin Microbiol* 7, 382-387.

Matsukage, A., Hirose, F., Hayashi, Y., Hamada, K., and Yamaguchi, M. (1995). The DRE sequence TATCGATA, a putative promoter-activating element for *Drosophila melanogaster* cell-proliferation-related genes. *Gene* 166, 233-236.

Matys, V., Kel-Margoulis, O. V., Fricke, E., Liebich, I., Land, S., Barre-Dirrie, A., Reuter, I., Chekmenev, D., Krull, M., Hornischer, K., *et al.* (2006). TRANSFAC and its module TRANSCompel: transcriptional gene regulation in eukaryotes. *Nucleic Acids Res* 34, D108-110.

Murakami, R., Okumura, T., and Uchiyama, H. (2005). GATA factors as key regulatory molecules in the development of *Drosophila* endoderm. *Dev Growth Differ* 47, 581-589.

Pritsker, M., Liu, Y., Beer, M., and Tavazoie, S. (2004). Whole-genome discovery of transcription factor binding sites by network-level conservation. *Genome Res* 14, 99-108.

Slonim, N., Atwal, G., Tkacik, G., and Bialek, W. (2005). Estimating mutual information and multi-information in large networks.

Struhl, G., Struhl, K., and Macdonald, P. M. (1989). The gradient morphogen bicoid is a concentration-dependent transcriptional activator. *Cell* 57, 1259-1273.

Su, A. I., Wiltshire, T., Batalov, S., Lapp, H., Ching, K. A., Block, D., Zhang, J., Soden, R., Hayakawa, M., Kreiman, G., *et al.* (2004). A gene atlas of the mouse and human protein-encoding transcriptomes. *Proc Natl Acad Sci U S A* 101, 6062-6067.

Tavazoie, S., Hughes, J., Campbell, M., Cho, R., and Church, G. (1999). Systematic determination of genetic network architecture. *Nat Genet* 22, 281-285.

Tomancak, P., Beaton, A., Weiszmann, R., Kwan, E., Shu, S., Lewis, S. E., Richards, S., Ashburner, M., Hartenstein, V., Celniker, S. E., and Rubin, G. M. (2002). Systematic determination of patterns of gene expression during *Drosophila* embryogenesis. *Genome Biol* 3, R88.

Vlieghe, D., Sandelin, A., De Bleser, P. J., Vleminckx, K., Wasserman, W. W., van Roy, F., and Lenhard, B. (2006). A new generation of JASPAR, the open-access repository for transcription factor binding site profiles. *Nucleic Acids Res* 34, D95-97.

Wickens, M., Bernstein, D., Kimble, J., and Parker, R. (2002). A PUF family portrait: 3'UTR regulation as a way of life. *Trends Genet* 18, 150-157.

Xie, X., Lu, J., Kulbokas, E., Golub, T., Mootha, V., Lindblad-Toh, K., Lander, E., and Kellis, M. (2005). Systematic discovery of regulatory motifs in human promoters and 3' UTRs by comparison of several mammals. *Nature* 434, 338-345.