Systematic identification of mammalian regulatory motifs' target

genes and functions

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Note: Supplementary Table 3 is available on the Nature Methods website.

Supplementary Figure 1: PhylCRM scoring scheme for a single motif (**a**) *g* represents the sequence being searched for CRMs and *a¹* and *a²* are sequences from another organism aligned to it. *L* represents the length of the sequence, $H_{0,\bullet}$ =g, $H_{i,\bullet}$ =a⁽ⁱ⁾, and $H_{\bullet,j}$ denotes the alignment column at position *j*. (**b**) Tree indicating the phylogeny of g , a^1 , and a^2 . (**c**) Scoring motif matches using the MEHB model. Here, the probability that a given nucleotide *a* turns into *b* during time *t* is given by a matrix exponential, for a suitably chosen rate-matrix *R*. This probability is then used to compute the probability of observing the set of nucleotides *H* , *^j* under both the MEHB rate-matrix and the neutral matrix. The score of the motif φ is then taken to be the log-likelihood of the ratio of these probabilities. (**d**) Graphical image of scores for a motif *M* along *g*, where the height of the bars is φ/m . These scores are stored in an array ξ and the score of a window w_i (represented by $E(w_i)$) is then given by summing ξ in w_i . (e) When there is no alignable sequence at a given position (or if there is no motif match there), the branch containing that sequence is removed and the pruned tree is used to compute φ .

Supplementary Figure 2. Comparisons between the empirical and the fitted mixture of Delta, Uniform and Gamma distributions.

(a) Upper panel shows empirical cumulative distribution function (CDF) for MRF (in blue) and the corresponding CDF for the fitted mixture model (in red).

(a) Lower panel shows empirical output score for MRF (in blue) and the corresponding output score for the fitted mixture model (in red).

(b) Upper panel shows empirical CDF for MEF2 (in blue) and the corresponding CDF for the fitted mixture model (in red).

(b) Lower panel shows empirical output score for MEF2 (in blue) and the corresponding output score for the fitted mixture model (in red);

(c) Upper panel shows empirical CDF for SRF (in blue) and the corresponding CDF for the fitted mixture model (in red).

(c) Lower panel shows empirical output score for SRF (in blue) and the corresponding output score for the fitted mixture model (in red).

(d) Upper panel shows empirical CDF for TEAD (in blue) and the corresponding CDF for the fitted mixture model (in red).

(d) Lower panel shows empirical output score for TEAD (in blue) and the corresponding output score for the fitted mixture model (in red).

Supplementary Figure 3: Schema of scoring scheme for PhylCRM, for case of multiple motifs. (**a**) For two potentially overlapping motifs with positional scores ¹ and 2, a de-overlapping step is performed (see text) where *ⁱ* (*j*) =0 if $\hat{g}(j) \neq \max\{\xi_1(j),\ \xi_2(j)\},\ i{\in}\{1,2\}.$ This step prevents motif-matches from being double-counted. (**b**) A restrictively-defined tail for the joint distribution of window scores $P(E_1, E_2)$. Here, a window can receive a good score (i.e., low $P(E_1, E_2)$) if it is enriched for either of the motifs, and thus this tail can be interpreted as an OR. (c) A generously-defined tail for the joint distribution of window scores $P(E_1, E_2)$. Here, a window must be enriched for both motifs in order to score well, and thus this tail can be interpreted as an AND. (**d**) A tail that is analogous to an "AND NOT" Boolean combination. Here, a window must be enriched for motif 1, but not enriched for motif 2 in order to score highly (i.e., low $P(\Xi_1, \Xi_2)$).

Supplementary Figure 4: Evaluation of PhylCRM and the effect of phylogeny

(**a**) Phylogenetic tree of 11 vertebrates utilized in this study. (**b**) Sensitivity and specificity of PhylCRM on a collection of 27 sequences of length 75 kb containing a CRM, as compared to a collection of length-matched sequences. Sequences were scanned with the OR combination of MRF, Mef2, SRF and Tead, and using only human sequence. (**c**) Similar to (**b**) but using all 11 vertebrate genomes. (**d**) AUC values when using progressively larger phylogenies. H=Human, C=Chimpanzee, Q=Macaque, M=Mouse, R=Rat, D=Dog, W=Cow, O= Opposum, K=Chicken, P=Pufferfish, Z=Zebrafish. (**e**) Sensitivity and specificity when using the phylogeny HCQMRDWO and a permuted form of these motifs.

Supplementary Figure 5: Lever screen of time course of human skeletal muscle differentiation. (**a**) Median arcsinh value (relative to –48 hrs) of each considered expression cluster or combination of clusters. (**b**) AUC values for each TF binding site motif combination and gene set (GM-pair). (**c**) FDR qvalue for each GM pair computed by Lever using a permutation test.

Supplementary Figure 6: Lever screen of 101 myogenic gene sets using Boolean combinations of MRF/Mef2/SRF/Tead myogenic motifs.

(**a**) Median signal intensity throughout the time-course of gene expression profiling for each of the 101 gene sets derived from GO categories and expression clusters.

(**b**) AUC values for each GM-pair using 75-kb regions surrounding transcription start.

(**c**) FDR Q-value for each GM- pair.

(**d**) Bar graphs indicating the maximum AUCs across all considered

Boolean combinations of the motifs for these gene sets

(**e**) Sensitivity vs. specificity curves for the MRF AND MEF2 combination on the sarcomere gene set.

TF binding sites: MRF Mef2 SRF **T**ead

Known binding sites

Supplementary Figure 7. Schematic display of comptutationally predicted human CRMs and control sequences. Previously described CRMs were used as positive controls in ChIP assays; see Supplementary Methods for full descriptions of the known and candidate CRMs. Negative control regions used in ChIP assays were chosen to not contain matches to the MRF AND Mef2 motif combinations, and to also not be enriched for the other binding sites under consideration (MRF = blue, Mef2 = red, SRF = cyan, Tead = gold), where stars indicate known binding sites. The PhylCRM score of the degree of enrichment for MRF AND Mef2 is shown (see Supplementary Methods for a description of the PhylCRM scoring scheme). Locations of sequence windows in relation to transcriptional start (if upstream or intronic) or stop (if downstream) are shown. We note that the region labeled "PDLIM3/SORBS2" was located between the PDLIM and SORBS2 genes. Also, we note that "ACTA 1 (prom)" refers to a previously

Supplementary Figure 8 - Verification of transcription upregulation during 8 muscle differentiation. Total RNA from primary human cells was extracted and processed as described in **Supplementary Methods.** The following sets of transcripts were normalized to *RPS18*: (**a**) muscle transcription factors, (**b**) genes regulated by positive control CRMs, (**c**) genes associated with predicted CRMs.

Hours relative to addition of differentiation medium

⁹ Supplementary Figure 9: Western blots to detect levels of muscle transcription factors.

(**a**) Western blots were performed as described in **Supplementary Methods** to detect known muscle transcription factors. A lamin B1 antibody was used as normalization control. (**b**) Quantitation of bands in panel **a** was performed using lamin B1 for normalization relative to 0 hours.

Supplementary Figure 10: Western blot analyses after RNAi knockdown. An antibody against Lamin B1 was used to control for gel loading.

Supplementary Figure 11: Luciferase reporter assays of predicted CRMs after shRNA knockdown. (a-c) C2C12 myoblasts were infected with lentivirus encoding shRNAs directed against known myogenic TFs. In all experiments, lentivirus encoding shRNA against $HNF4\alpha$, a liver-specific TF, was used as a negative control. Experimental knockdowns were directed against (a) Myogenin, (b) MEF2D, and (c) SRF. In (a-c), $*$ indicates $P < 0.05$, while vertically stacked double asterisks indicate $P < 0.005$, comparing luciferase activity in the experimental knockdown versus the HNF4α knockdown.

catgatgcattcacctcccaccaggccccaccttcaacattggggattacagttcaaaatgaggtttggtggggacacagatccaaaccatatca ACTTGTAGGGGCAGAAAGACGTCACCTTTACTTGAATTGCAACCCTTACCTTTTCATCGCAGGCTGTAGGAG

>MGLL - ligated with MRF/Mef2/MRF sites

catgatgcattcacctcccaccaggccccaccttcaacattggggCAGCTGgttcaaaatgaggtttggtggggacacagatccaaaccatatca ACTTGTAGGGGCAGAACTAAAAATAGTTTACTTGAATTGCAACCCTTACCTTTTCATCGCAGGCTGCAGCTG

Supplementary Figure 12: Luciferase reporter assays for a synthetic CRM containing binding sites for MRF AND Mef2. Putative and control CRMs were cloned either upstream (BgIII) or downstream (BamHI) of the luciferase reporter gene of the pGL3-Promoter vector (Promega) in order to reflect the genomic location of the CRM. As positive controls, we used an SV40 enhancer, one of the five previously known muscle CRMs used in our ChIPs (DMD), and a novel CRM that we verified previously CRM (ACTA1, Fig 6). As a negative control we used a human noncoding genomic region (MGLL) not enriched for matches to the four known myogenic motifs. As described in Supplementary Methods, we created variants of a shorter 167-bp MGLL negative control region by ligating segments of the original MGLL region (MGLL - ligated) or by ligating segments of the MGLL region that have two consensus MRF sites (shown in blue) and one consensus Mef2 site (shown in red). C2C12 cells were cultured in 6-well plates (9.4 cm² per well) 24 hours prior to transfection at 3 x 10⁴ cells per well for myoblasts or 1.5 x 10⁵ cells per well for myotubes. The cells were then cotransfected in triplicate with 1 µg of experimental vector (pGL3-P with or without inserted region) and 50 ng of the normalization vector (pRL-TK) using FuGENE 6 transfection reagent (Roche) according to the manufacturer's protocols. Cell extracts were obtained from an aliquot of the proliferating myoblasts 24 hours after transfection. The remaining cell cultures were then switched to differentiation medium, and cell extracts were obtained after 96 hours in differentiation medium. Luciferase reporter assays were performed using the Dual-Luciferase® Reporter Assay System (Promega) according to the manufacturer's protocols. Firefly luminescence intensities were normalized by the luminescence intensities of the internal Renilla control.

Supplementary Table 1: Gene names and expression clusters

Supplementry Table 2 GO attributes by cluster


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4 4.10E-06 0.003 0006936: muscle contraction
             4 3.00E-05 0.013 0005583: fibrillar collagen
4 6.50E-05 0.05 0000323: lytic vacuole
4 6.50E-05 0.05 0005764: lysosome
5 2.20E-05 0.007 0016126: sterol biosynthesis
5 2.30E-05 0.031 0008970: phospholipase A1 activity
5 4.20E-05 0.045 0008610: lipid biosynthesis
5 4.30E-05 0.045 0006694: steroid biosynthesis/steroidogenesis
6 0.05 0006325: establishment and/or maintenance of chromatin architecture
7 7.50E-11 <0.001 0043231: intracellular membrane-bound organelle
7 7.50E-11 <0.001 0043227: membrane-bound organelle
7 1.50E-10 <0.001 0005737: cytoplasm
7 4.60E-09 <0.001 0005622: intracellular/protoplasm
7 1.80E-08 <0.001 0043226: organelle
7 1.80E-08 <0.001 0043229: intracellular organelle
7 4.00E-07 <0.001 0005654: nucleoplasm
7 6.20E-07 <0.001 0015980:energy deriv. by oxidation of org. compounds/chemoorganotrophy
7 7.00E-06 0.002 0044262: cellular carbohydrate metabolism
7 1.00E-05 0.003 0006006: glucose metabolism
7 1.10E-05 0.004 0044237: cellular metabolism
7 1.20E-05 0.005 0006092: main pathways of carbohydrate metabolism
7 1.40E-05 0.005 0000910: cytokinesis/cell division
7 1.40E-05 0.005 0051301: cell division
             7 1.70E-05 0.005 0044238: primary metabolism
7 3.00E-05 0.012 0019318: hexose metabolism
7 3.70E-05 0.019 0005996: monosaccharide metabolism
7 6.20E-05 0.03 0005739: mitochondrion
7 7.10E-05 0.03 0043283: biopolymer metabolism
7 0.0001 0.05 0006007: glucose catabolism
8 1.20E-07 <0.001 0005730: nucleolus
8 2.20E-06 0.002 0009127: purine nucleoside monophosphate biosynthesis
8 2.20E-06 0.002 0009168: purine ribonucleoside monophosphate biosynthesis
8 2.20E-06 0.002 0009167: purine ribonucleoside monophosphate metabolism
8 2.20E-06 0.002 0009126: purine nucleoside monophosphate metabolism
8 4.70E-06 0.006 0006396: RNA processing
8 6.40E-06 0.006 0016072: rRNA metabolism
8 6.60E-06 0.006 0009161: ribonucleoside monophosphate metabolism
8 6.60E-06 0.006 0009156: ribonucleoside monophosphate biosynthesis
8 1.10E-05 0.011 0009124: nucleoside monophosphate biosynthesis
8 1.10E-05 0.011 0009123: nucleoside monophosphate metabolism
8 1.30E-05 0.011 0016070: RNA metabolism
8 2.30E-05 0.016 0007046: ribosome biogenesis
8 3.40E-05 0.024 0046037: GMP metabolism
8 3.40E-05 0.024 0006177: GMP biosynthesis
8 5.40E-05 0.039 0006364: rRNA processing
9 2.40E-07 0.001 0000279: M phase/M-phase
9 6.60E-06 0.003 0006950: response to stress
9 1.50E-05 0.011 0003684: damaged DNA binding
9 1.60E-05 0.011 0007049: cell cycle/cell-division cycle
9 2.10E-05 0.015 0006281: DNA repair
9 2.90E-05 0.019 0000278: mitotic cell cycle
9 4.10E-05 0.046 0006974: response to DNA damage stimulus
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10 3.50E-17 <0.001 0007049: cell cycle/cell-division cycle
10 1.60E-16 <0.001 0005694: chromosome
10 9.10E-15 <0.001 0000278: mitotic cell cycle
10 3.20E-14 <0.001 0006259: DNA metabolism
10 5.30E-13 <0.001 0000279: M phase/M-phase
10 3.50E-12 <0.001 0006260: DNA replication/DNA biosynthesis/DNA synthesis
10 3.90E-12 <0.001 0006261: DNA-dependent DNA replication
10 5.90E-12 <0.001 0007067: mitosis
10 7.10E-12 <0.001 0000087: M phase of mitotic cell cycle/M-phase of mitotic cell cycle
10 9.10E-11 <0.001 0000074: regulation of cell cycle/cell cycle control
10 1.90E-09 <0.001 0000910: cytokinesis/cell division
10 1.90E-09 <0.001 0051301: cell division
10 1.00E-08 <0.001 0005660: delta-DNA polymerase cofactor complex
10 1.80E-08 <0.001 0008283: cell proliferation
10 2.40E-08 <0.001 0005659: delta DNA polymerase complex
10 3.60E-08 <0.001 0000775: chromosome, pericentric region/centromere
10 8.70E-08 <0.001 0042575: DNA polymerase complex
10 1.80E-07 <0.001 0000086: G2/M transition of mitotic cell cycle
10 2.10E-07 <0.001 0030894: replisome
10 2.40E-07 <0.001 0051329: interphase of mitotic cell cycle
10 2.40E-07 <0.001 0051325: interphase/karyostasis/resting phase
10 2.60E-07 <0.001 0005657: replication fork/replication focus
10 3.50E-07 <0.001 0051338: regulation of transferase activity/transferase regulator
10 3.50E-07 <0.001 0045859: regulation of protein kinase activity
10 3.90E-07 <0.001 0043283: biopolymer metabolism
10 1.20E-06 <0.001 0000785: chromatin
10 1.40E-06 0.001 0050790: regulation of enzyme activity
               10 1.60E-06 0.001 0000075: cell cycle checkpoint
10 1.60E-06 0.002 0000776: kinetochore
10 1.80E-06 0.002 0000079: regul. of cyclin dep. protein kinase activity/regul. of CDK activ
               10 3.20E-06 0.003 0043228: non-membrane-bound organelle
10 3.20E-06 0.003 0043232: intracellular non-membrane-bound organelle
10 4.80E-06 0.004 0006271: DNA strand elongation/DNA replication elongation
10 7.60E-06 0.006 0008094: DNA-dep ATPase activity/DNA dep ATPase activity
10 7.70E-06 0.006 0005634: nucleus
10 9.60E-06 0.008 0006270: DNA replication initiation
               10 1.10E-05 0.008 0000082: G1/S transition of mitotic cell cycle
10 1.40E-05 0.009 0006139: nucleobase, nucleoside, nucleotide and nucleic acid metabolism
10 2.00E-05 0.013 0031497: 
10 2.60E-05 0.015 0051052: regulation of DNA metabolism
10 2.90E-05 0.028 0007093: mitotic checkpoint
10 3.10E-05 0.028 0005819: spindle
10 3.80E-05 0.036 0005663: DNA replication factor C complex
10 4.60E-05 0.037 0000786: nucleosome
10 5.00E-05 0.039 0007088: regulation of mitosis
10 6.00E-05 0.042 0006275: regulation of DNA replication
10 7.20E-05 0.046 0048519: negative regulation of biological process
11 1.20E-20 <0.001 0007049: cell cycle/cell-division cycle
11 3.60E-20 <0.001 0000279: M phase/M-phase
11 1.90E-19 <0.001 0000278: mitotic cell cycle
11 3.20E-19 <0.001 0007067: mitosis
11 4.20E-19 <0.001 0000087: M phase of mitotic cell cycle/M-phase of mitotic cell cycle
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11 1.60E-16 <0.001 0000910: cytokinesis/cell division
11 1.60E-16 <0.001 0051301: cell division
11 1.00E-15 <0.001 0000074: regulation of cell cycle/cell cycle control
11 1.30E-14 <0.001 0006259: DNA metabolism
11 3.40E-11 <0.001 0006261: DNA-dependent DNA replication
11 6.10E-11 <0.001 0005694: chromosome
11 1.10E-10 <0.001 0006260: DNA replication/DNA biosynthesis/DNA synthesis
11 4.60E-10 <0.001 0000075: cell cycle checkpoint
11 2.60E-09 <0.001 0000086: G2/M transition of mitotic cell cycle
11 6.80E-09 <0.001 0005660: delta-DNA polymerase cofactor complex
11 1.60E-08 <0.001 0005659: delta DNA polymerase complex
11 2.80E-08 <0.001 0008283: cell proliferation
11 5.60E-08 <0.001 0042575: DNA polymerase complex
11 6.50E-08 <0.001 0043283: biopolymer metabolism
11 1.20E-07 <0.001 0051329: interphase of mitotic cell cycle
11 1.20E-07 <0.001 0051325: interphase/karyostasis/resting phase
11 2.20E-07 0.001 0007093: mitotic checkpoint
11 5.70E-07 0.001 0005634: nucleus
11 1.00E-06 0.003 0007088: regulation of mitosis
11 1.00E-06 0.003 0000079: regul. of cyclin dep. protein kinase activ./regul. of CDK activity
11 6.30E-06 0.01 0006270: DNA replication initiation
11 6.30E-06 0.01 0030894: replisome
11 6.50E-06 0.01 0000082: G1/S transition of mitotic cell cycle
11 7.40E-06 0.01 0005657: replication fork/replication focus
11 7.90E-06 0.01 0050794: regulation of cellular process
11 9.60E-06 0.013 0006139: nucleobase, nucleoside, nucleotide and nucleic acid metabolism
11 1.10E-05 0.013 0043228: non-membrane-bound organelle
               11 1.10E-05 0.013 0043232: intracellular non-membrane-bound organelle
11 1.70E-05 0.015 0051052: regulation of DNA metabolism
11 1.80E-05 0.015 0005819: spindle
11 1.90E-05 0.015 0050789: regulation of biological process/regulation
11 1.90E-05 0.015 0051244: regulation of cellular physiological process
11 2.10E-05 0.016 0007052: mitotic spindle organization and biogenesis
11 2.10E-05 0.016 0007051: spindle organization and biogenesis
11 2.30E-05 0.028 0008284: positive regulation of cell proliferation
11 2.50E-05 0.028 0000786: nucleosome
11 2.80E-05 0.028 0005663: DNA replication factor C complex
11 3.00E-05 0.03 0051338: regulation of transferase activity/transferase regulator
11 3.00E-05 0.03 0045859: regulation of protein kinase activity
11 3.40E-05 0.03 0000785: chromatin
11 4.20E-05 0.036 0050791: regulation of physiological process
11 4.40E-05 0.038 0006275: regulation of DNA replication
11 4.80E-05 0.038 0042127: regulation of cell proliferation
11 6.10E-05 0.04 0006334: nucleosome assembly
12 6.70E-16 <0.001 0007049: cell cycle/cell-division cycle
12 1.50E-14 <0.001 0000278: mitotic cell cycle
12 6.60E-14 <0.001 0000279: M phase/M-phase
12 9.40E-13 <0.001 0000074: regulation of cell cycle/cell cycle control
12 9.50E-13 <0.001 0007067: mitosis
12 1.20E-12 <0.001 0000087: M phase of mitotic cell cycle/M-phase of mitotic cell cycle
12 2.80E-12 <0.001 0006259: DNA metabolism
12 2.60E-11 <0.001 0000910: cytokinesis/cell division
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12 2.60E-11 <0.001 0051301: cell division
12 4.80E-11 <0.001 0000086: G2/M transition of mitotic cell cycle
12 3.10E-10 <0.001 0008283: cell proliferation
12 3.90E-10 <0.001 0000075: cell cycle checkpoint
12 4.00E-09 <0.001 0051329: interphase of mitotic cell cycle
12 4.00E-09 <0.001 0051325: interphase/karyostasis/resting phase
12 1.70E-08 <0.001 0006261: DNA-dependent DNA replication
12 2.30E-08 <0.001 0000079: regul. of cyclin dep. protein kinase activ./regul. of CDK activity
12 7.90E-08 <0.001 0043283: biopolymer metabolism
12 8.70E-08 <0.001 0008284: positive regulation of cell proliferation
12 1.10E-07 <0.001 0006260: DNA replication/DNA biosynthesis/DNA synthesis
12 1.90E-07 <0.001 0050794: regulation of cellular process
12 2.00E-07 <0.001 0007093: mitotic checkpoint
12 2.20E-07 <0.001 0000082: G1/S transition of mitotic cell cycle
12 3.00E-07 <0.001 0005694: chromosome
12 5.30E-07 <0.001 0050789: regulation of biological process/regulation
12 5.80E-07 <0.001 0042127: regulation of cell proliferation
12 9.30E-07 <0.001 0007088: regulation of mitosis
12 1.50E-06 <0.001 0051244: regulation of cellular physiological process
12 3.50E-06 0.001 0050791: regulation of physiological process
12 4.80E-06 0.001 0006139: nucleobase, nucleoside, nucleotide and nucleic acid metabolism
12 5.40E-06 0.001 0006950: response to stress
12 5.70E-06 0.002 0006270: DNA replication initiation
12 1.20E-05 0.006 0051242: positive regulation of cellular physiological process
               12 1.40E-05 0.008 0048522: positive regulation of cellular process
12 1.50E-05 0.009 0051052: regulation of DNA metabolism
12 1.70E-05 0.009 0043119: positive regulation of physiological process
12 2.60E-05 0.018 0051338: regulation of transferase activity/transferase regulator
12 2.60E-05 0.018 0045859: regulation of protein kinase activity
12 2.70E-05 0.018 0005634: nucleus
               12 4.10E-05 0.027 0006275: regulation of DNA replication
12 4.50E-05 0.027 0006793: phosphorus metabolism
12 4.50E-05 0.027 0006796: phosphate metabolism
12 5.90E-05 0.03 0008083: growth factor activity
13 1.00E-05 0.005 0008283: cell proliferation
13 1.60E-05 0.008 0007267: cell-cell signaling/cell-cell signalling
13 2.80E-05 0.012 0005576: extracellular region/extracellular
13 4.00E-05 0.017 0005102: receptor binding/receptor ligand
13 4.50E-05 0.018 0005125: cytokine activity
13 4.50E-05 0.018 0042221: response to chemical substance
13 6.00E-05 0.02 0042127: regulation of cell proliferation
13 8.10E-05 0.02 0005615: extracellular space/intercellular space
13 0.00021 0.041 0009628: response to abiotic stimulus
13 0.00022 0.041 0016477: cell migration
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Supplementary Table 4: Predicted and Tested CRM Regions

Supplementary Methods

Supplementary Information is available on the Nature Methods website and on our lab website, http://the_brain.bwh.harvard.edu/.

A. Construction of length-matched background sets against which foreground gene sets are evaluated in Lever

The following procedure is similar to the procedure we described previously in a *Drosophila* context¹. We first ordered the search regions in each gene set by length. We defined the "foreground regions" to be those regions upstream and downstream of the genes that belong to a given foreground Gene Set, and we defined the "non-foreground regions" to be the collection of all other regions (i.e., regions not upstream or downstream of genes that belong to a given foreground Gene Set). For each foreground region, we took the 2 non-foreground regions occurring directly above and below it in the length-based ranking as background regions. In the event that two or more foreground regions did not have background regions ranked between them, we continued to extend above and below them in the ranking so that the center of this local collection of background regions was the same as the center of their associated foreground regions. Hence, for each foreground region, we were able to initially associate 2 length-matched background regions. We measured the AUC statistic for the lengths of the foreground and the background gene regions accumulated thus far and repeated the procedure of adding more non-foreground regions to the background set of gene regions until this AUC was close to 0.5, and until the background set was at least 10 times as large (and up to 40 times as large) as the foreground set, so that the distribution of the lengths of the foreground set of gene regions is similar to that of the background set of gene regions. The "PhylCRM_preprocess" program that generates the length-matched background sets of gene regions has a user-defined tolerance for what "close" means; in this study, we employed a tolerance of \pm 0.02, i.e., for all foreground and background gene sets

considered in this paper, we required an AUC between 0.48 and 0.52 when ranking the foreground and background genes according to their lengths $(AUC = 0.5$ implies no difference between the distribution of lengths of foreground genes and that of the background genes).

B. Description of PhylCRM scoring scheme

The increasing number of sequenced genomes provides the opportunity for improved identification of regulatory regions by scanning for noncoding loci under negative selective pressure. To accomplish this, the evolutionary conservation must be scored in a way that the evolutionary history of the organisms is appropriately quantified; conservation of a locus between species sharing a recent ancestor should be weighted less than conservation between species that diverged long ago.

1. Scoring scheme and algorithm, one motif

In this section, we develop the scoring scheme for the case of only of one motif; in Section 2 we extend the scoring scheme to incorporate multiple motifs.

We begin with some notation. Given a base sequence *g* of length *L* from the genome being searched for TF binding site motif matches, let $a^{(i)}$, $i \in \{1, ..., n\}$ denote the sequences aligned to *g* from each of the *n* organisms under consideration. We use $(g_j...g_{j+k-1})$ to denote the subsequence of g beginning at position j and of length k , and we use $\left(a^{(i)}_{j}\ldots a^{(i)}_{j+k-1}\right)$ $a_j^{(i)} \dots a_{j+k-1}^{(i)}$ to denote the corresponding subsequence in the *i*'th alignment to *g*. Similarly, let *H* denote the $(n + 1) \times |L|$ -dimensional matrix storing both *g* and the $a^{(i)}$; thus, $H_{0,\bullet} = g$, $H_{i,\bullet} = a^{(i)}$, and $H_{\bullet,j}$ denotes the alignment column at position *j* (note that the • is used here to denote the collection of all values for that index position; see **Supplementary Fig. 1a** online). Finally, let *T* be the tree indicating the phylogeny of *g* and the $a^{(i)}$, let $\{v_\delta\}$ denote the ancestral vertices in *T*, and let $\{\tau_\epsilon\}$ denote the branch lengths (see **Supplementary Fig. 1b** online).

For a given TF binding site motif of length *m*, let $M(\alpha, j)$ be the 4×*m* matrix indicating the probability of observing the letter $\alpha \in \{A, C, G, T\}$ at position $j = 1,...,m$ of the motif (i.e., *M* is the frequency-derived probability matrix²), and let $Q(\alpha)$ denote the genomic frequency of letter α . For each position $j \in \{1, \ldots, L\}$ of *g*, we evaluate the degree to which $(g_j, \ldots g_{j+m-l})$ matches *M* with the quantity²:

Eqn. 1)
$$
\lambda(j) = \sum_{k=j}^{j+m-1} \log_2 \left(\frac{M(g_k, k)}{Q(g_k)} \right)
$$

This quantity is the commonly used position weight matrix score². If $\lambda(j)$ is greater than a user-specified cutoff *c*, which is usually set to 1 or 2 standard deviations below the motif mean for the standard likelihood ratio score of the PWM model *M* and the genomic frequencies given by *Q*, we evaluate the degree to which this motif match is conserved throughout the phylogeny using an evolutionary model first suggested by Halpern and Bruno³ and developed by Moses, Eisen and colleagues^{4,5} (henceforth referred to as the MEHB model). In their approach, the degree of evolutionary conservation for the match to the TF binding site motif is scored by taking the log-likelihood ratio of observing the given collection of sequences throughout the phylogeny under the MEHB model as compared to a neutral model of evolutionary change:

Eqn. 2)
$$
\varphi(j) = \sum_{k=j}^{j+m-1} \log_2 \left(\frac{P_{\text{MEHB}}(H_{\bullet,k} | T, M, Q)}{P_{\text{neutral}}(H_{\bullet,k} | T, Q)} \right) - c
$$

Here, $P_{MEHB} (H_{\bullet,k} | T, M, Q)$ represents the probability of observing $H_{\bullet,k}$ under the evolutionary model where nucleotide substitutions occur along *T* with a frequency specified by the MEHB proportionality (i.e., with fewer changes expected at the most conserved positions of the motif; see **Supplementary Fig. 1c** online), and $P_{neutral} (H_{\bullet,k} | T, Q)$ represents the probability of observing $H_{\bullet,k}$ under a neutral evolutionary model (either Jukes-Cantor⁶ or Hasegawa-Kishino-Yano⁷). We have schematized how these probabilities are computed for a small phylogenetic tree in **Supplementary Fig. 1c** online.

Let ξ be an array of length *L* (i.e., the same length as *g*) and initialized so that, for all *j*, $\xi(j) = 0$. When a match to the motif *M* is made (i.e., $\lambda(j) > c$) in *g* beginning at position *j*, then, for $k = j, \ldots, j+m-1$, ξ is updated according to:

Eqn. 3)
$$
\xi(k) = \max(\varphi(j)/m, \xi(k))
$$

Here, the max is taken so that, in the event of overlapping motif matches, both matches contribute to the score, but there is no double-counting of scores. This rationale is schematized in **Supplementary Fig. 1d** online, where ξ*(j)* is schematized for a sequence *g* and motif *M*. Note that we shall refer to quantity $\xi(i)$ as the "positional score for *M*" at *j*.

We wish to find sub-windows of the base sequence *g* that have a statistically significant over-representation of high-scoring matches to *M*. We do this by deriving the probability distribution function of the sub-windows of a fixed size within an *a priori* specified size range that best fits our data. We then use this probability distribution function in order to evaluate the enrichment of better scoring sub-windows of this size as compared to a given query sub-window under consideration. We also use the derived probability distribution

functions in order to combine the scores from several motifs of interest in the Fuzzy Boolean logic framework (see Section **3.** below).

Specifically, for each window size we derive the shape and the parameters of the null distribution. This is done by fitting a mixture model of three probability distribution functions – Delta, Uniform and Gamma – on a collection of sequences g_b of total length L_b that are believed not to be enriched for matches to motif *M* (we henceforth refer to this as the "background" sequence). Briefly, the Delta function is used to model the jump in score that occurs when a window of genomic sequence contains the initial portion of a motif at its left-most or right-most edge; the Uniform distribution is used to model the increase in score that occurs as the window contains an increasingly greater portion of the motif at either of its edges; finally, the Gamma distribution is then used for the bulk of the distribution to model an increasing number of binding sites and their evolutionary conservation.

Let w_i be a window of sequence in g of length $|w|$ and beginning at position *j*; we wish to evaluate whether this window is enriched for instances of *M*.Consider the following quantity:

Eqn. 4)
$$
\Xi(w_j) = \sum_{j=j}^{j+|w|-1} \xi(j^j)
$$

For a motif *M* and fixed *a priori* window size |w|, we wish to model the distribution of scores $\Xi(w_j) = \sum_{j+|w|-1}^{j+|w|-1} \xi(j)$ = $\Xi(w_{_I})$ = 1 '' *wj j*'= *j* w_j = $\sum \xi(j)$ under the null hypothesis of no motif enrichment. We shall refer to $\Xi(w_j)$ as the "window score" of w_j and, for a given window w_j , we shall determine

whether $\Xi(w_i)$ is statistically significantly large by estimating the p-value with respect to the modeled distribution at Ξ(*wj*).

In order to see how well the window scores $E(w_i)$ are modeled by this mixture of three distributions, we considered the four motifs utilized in this paper: MRF, MEF2, SRF and Tead (see **Supplementary Fig. 2** online). For this analysis we utilized the foreground and background 75-kb regions shown in **Supplementary Fig. 4** online, where the foreground sequences contain a collection of 27 CRMs known to drive expression in muscle and background regions are a collection of 1,080 75-kb regions surrounding genes that were not up- or down-regulated during our time-course analysis of myogenesis. In **Supplementary Fig. 2** online, we have plotted the empirical distribution of $\Xi(w_{100})$ (blue curve) for each of these four motifs, as well as the fitted mixture model (red curve). As can be seen, the match between the fitted and empirical curves is very precise (we note that the fit for Tead is somewhat worse, as it is an infrequently occurring motif, and there are thus very few windows of genomic sequence comprising the right tail of the empirical distribution).

We then define the "output score" for the window to be the negative-log of its corresponding p-value:

Eqn. 5) output score = $-\log_{10}P(\Xi(w))$.

In **Supplementary Fig. 2** online, we have plotted the empirical output score (blue curve) for each of the four motifs mentioned above, as well as the output score from the fitted mixture model (red curve).

Finally, there are two related technical issues that must be addressed in building the array of positional scores ξ. First, due to the difficulties in aligning distant genomes, as well as the presence of sequencing gaps resulting from a genome being incompletely sequenced, there may not be any alignment to g at position *j* in genome $a^{(i)}$. Thus, it is not clear how to evaluate **Eqn. 2** in the presence of such missing data. Second, there is the possibility that a binding site may be truly present in *g* but lost (due to evolution) in $a^{(i)}$, particularly if $a^{(i)}$ and g are greatly diverged. In such a situation, it is possible that the quantity φ of **Eqn. 2** will be negative, which is undesirable since it is reasonable to assume that observing the presence of a motif match in a window w_i should increase (not decrease) the window score $E(w_i)$, even if this match is not well-conserved. We handle these issues in a similar fashion by restricting to an appropriate sub-tree of the original tree. In the first scenario, the branches corresponding to genomes with missing alignments are removed; in the second scenario, any binding sites not scoring above the user-specified cutoff for determining a motif match are removed (**Supplementary Fig. 1e** online). We note, however, that for the second scenario it is also possible to run the program so that the entire phylogeny for which alignments are available is considered, even if there is not a motif match in some genomes (such a mode might be used, for example, in attempting to identify exclusively those TF binding sites conserved throughout the phylogeny, as was done in the original work by Moses et al.⁵).

2. Flexible scoring scheme and algorithm, multiple motifs

In this section, we assume the case of multiple motifs M_n , $n=1,...,N$. Let $\zeta_n(j)$ hold the positional scores of motif *Mn*. We desire a means of measuring whether a given window w_i is enriched for motif matches. We allow flexibility in the scoring scheme by allowing the user to address the situation of potentially overlapping motifs (refer to the "- DEOVERLAP" option in the algorithms). A naïve approach would be to first define the array:

Eqn. 6
$$
\hat{\xi}(j) = \max_{n} {\xi_n(j)}.
$$

The score for a window w_i could then be obtained by calculating the significance of:

Eqn. 7)
$$
\hat{\Xi}(w_j) = \sum_{j=j}^{j+|w|-1} \hat{\xi}(j').
$$

This method has the advantage of appropriately handling overlapping motifs. Unfortunately, it has the disadvantage that the behavior of the score is dominated by the degree of enrichment for the most frequently occurring motifs. For example, assuming similar degrees of degeneracy, a motif of width 6 occurs more than twice as frequently as a motif of width 12, but the contribution of each match of the 6-mer motif to $\hat{\Xi}$ is half that of the motif of width 12.

Therefore, we describe an alternative means of scoring multiple motifs when the "- DEOVERLAP" option is specified (which is the option we employed in our Warner *et al.* manuscript). First, define:

Eqn. 8)
$$
\widetilde{\xi}_n(j) = \begin{cases} \xi_n(j) & \text{if } \xi_n(j) = \max_{n'} \{\xi_{n'}(j)\} \\ 0 & \text{otherwise} \end{cases}
$$

Similar to the case of one motif, this step removes the possibility that the score for different motifs could be double-counted at position *j*, but also ensures that each position receives the score of the motif that best matches it. We shall refer to the $\tilde{\xi}_n$ as the "deoverlapped" positional score; this de-overlapping step is schematized in **Supplementary Fig. 3a** online. The de-overlapping step is also performed for the background sequences *gb*.

From now on, let $\tilde{\Xi}_n(w_i)$ be the window score of w_j (with or without the "-DEOVERLAP" option specified), and let $\gamma_n(\tilde{\Xi}_n; |w|)$ be the corresponding mixture distribution of scores $\tilde{\Xi}_n$ (see **Eqn. 7**) for a motif M_n for a given window length $|w|$ under the null hypothesis of no enrichment.

3. Combinations of several motifs in Fuzzy logic framework

We wish to utilize the mixture distributions $\gamma_n(\tilde{\Xi}_n; |w|)$ for a motif M_n in order to determine the statistical significance of observing a given degree of clustering and evolutionary conservation for the set of motifs. In the case of one motif, this computation was straightforward, as the statistical significance was directly obtainable from the tail of the appropriate mixture of Delta, Uniform and Gamma distributions. For many motifs we have developed a rich vocabulary of scoring schemes, in order to model the combinatorial interactions between the TFs under consideration.

For simplicity, take the case of two motifs M_n and M_m . It is possible to calculate statistical significance using a "restrictively-defined tail" (**Supplementary Fig. 3b** online):

Eqn. 9)
$$
P(\widetilde{\Xi}_n, \widetilde{\Xi}_m) = P_n(\widetilde{\Xi}_n) P_m(\widetilde{\Xi}_m) = \left(\int_{\widetilde{\Xi}_n}^{\infty} \gamma_n(\Xi; |w|) d\Xi\right) \left(\int_{\widetilde{\Xi}_m}^{\infty} \gamma_m(\Xi; |w|) d\Xi\right)
$$

(note: $P(\tilde{\Xi}_n, \tilde{\Xi}_m)$ does not refer to the joint distribution of the random variables $\tilde{\Xi}_n$ and $\widetilde{\Xi}_m$).

We take the "output score" to be $-\log(P_n(\tilde{\Xi}_n) P_m(\tilde{\Xi}_m)) = -\log(P_n(\tilde{\Xi}_n)) - \log(P_m(\tilde{\Xi}_m))$, and so the output score is additive in the number of motifs. Hence, a given window can achieve significance if it is greatly enriched for matches to *either* motif one or motif two (OR combination).

Conversely, it is also possible to calculate statistical significance of a combination of distributions using a "generously defined tail" (**Supplementary Fig. 3c** online):

Eqn. 10)
$$
P(\widetilde{\Xi}_n, \widetilde{\Xi}_m) = 1 - \left(\int_0^{\widetilde{\Xi}_n} \gamma_n(\Xi; |w|) d\Xi \right) \left(\int_0^{\widetilde{\Xi}_m} \gamma_m(\Xi; |w|) d\Xi \right)
$$

$$
= P_n(\widetilde{\Xi}_n) + P_m(\widetilde{\Xi}_m) - P_n(\widetilde{\Xi}_n) P_m(\widetilde{\Xi}_m)
$$

Here, if $\tilde{\Xi}_n = 0$ (the window score is zero), then $P_n(\tilde{\Xi}_n) = 1$ and so $P(\tilde{\Xi}_n, \tilde{\Xi}_m) = 1$ and so the window score $-\log (P(\tilde{\Xi}_n, \tilde{\Xi}_m)) = 0$ (and similarly for the case where $\tilde{\Xi}_m = 0$). Thus, using this tail, a window must be enriched for *both* motifs (AND combination) under consideration in order to be statistically significant.

Finally, it is possible to define the combination of the distributions in more complicated ways. For example, the following combination would assign a high score to windows of sequence that are enriched for the first motif but specifically not enriched for the second (NOT combination; **Supplementary Fig. 3d** online):

Eqn. 11

$$
P(\widetilde{\Xi}_n, \widetilde{\Xi}_m) = 1 - \left(\int_0^{\widetilde{\Xi}_n} \gamma_n(\Xi; |w|) d\Xi \right) \left(\int_{\widetilde{\Xi}_m}^{\infty} \gamma_m(\Xi; |w|) d\Xi \right)
$$

$$
= 1 - P_m(\widetilde{\Xi}_m) + P_n(\widetilde{\Xi}_n) P_m(\widetilde{\Xi}_m)
$$

The cases we have described, Eqns. 9-11, can be thought of as Fuzzy logic rules for the discrete Boolean logical functions $(M_n \text{ OR } M_m)$, $(M_n \text{ AND } M_m)$, and $(M_n \text{ AND NOT } M_m)$. In general, we define the "output score" for a Fuzzy logic combination of multiple motifs to be the negative-log of the corresponding *P* (see Eqns 9-11):

Eqn. 12) output score =
$$
-\log_{10}(P(\widetilde{\Xi}_n, \widetilde{\Xi}_m))
$$
.

We have implemented PhylCRM so that a variety of different tails are possible, in order to allow the evaluation of a more nuanced view of *cis* regulatory logic. A summary of all Fuzzy logic combinations considered is listed below:

- a. OR combinations of arbitrarily many motifs
- b. AND combinations of arbitrarily many motifs
- c. The following four classes of compound combinations involving up to 4 motifs:
	- 1) $(M_1 \text{ AND NOT } M_2)$ (two motifs)
	- 2) ((*M1* AND *M2*) OR *M3*) (three motifs)
	- 3) ((*M1* OR *M2*) AND *M3*) (three motifs)

4) $((M_1 \text{ AND } M_2) \text{ AND NOT } M_3)$ (three motifs)

5) $((M_1 \text{ AND } M_2 \text{ AND } M_3) \text{ AND NOT } M_4)$ (four motifs)

Thus, if one would like to find CRMs enriched for any subset of the motifs under consideration, the OR mode is more appropriate; conversely, if one wishes to specifically identify CRMs enriched for matches to all the motifs under consideration, the AND mode is more appropriate.

C. Evaluation of ability of PhylCRM to identify CRMs

We obtained a phylogenetic tree of 11 vertebrate genomes from the ENCODE multiple sequence alignment working group⁸ (**Supplementary Figure 4a** online) and a set of 27 CRMs previously compiled by Wasserman *et al.*⁹ that are known to drive expression in muscle and to be regulated by at least one of the four well known myogenic TFs: a) MEF2, b) Serum Response Factor (SRF), c) Tead, and d) the myogenic regulatory factors (MRFs) MyoD, Myogenin, Myf5 and Myf6 (note that the motifs for the MRFs are currently indistinguishable and thus are encompassed by a single, general MRF motif)⁹. Here, we examined windows ranging between 50 and 500 bp (increment size of 50 bp), and utilized the phylogenetic tree derived by the ENCODE multiple sequence alignment working group⁸. The tree is input to PhylCRM in Newick format:

(((((((human:0.006690,chimp:0.007571):0.024272,

macaque:0.059256):0.107134,(mouse:0.077017,rat:0.081728):0.252613):0.023026,(dog: 0.147731,cow:0.159182):0.03945):0.262899,opossum:0.371073):0.189124,chicken:0.454 691):0.279364,(fugu:0.732855,zebrafish:0.782561):0.156067)

The versions of the genomes that we used are:

- human (hg 17)
- chimp (Nov 2003, panTro1)
- macaque (Jan 2006, rheMac2)
- mouse (May 2004, mm7)
- rat (Jun 2003, rn3)
- dog (May 2005, canFam2)
- cow (Mar 2005, bosTau2)
- opossum (Jun 2005, monDom2)
- chicken (Feb 2004, galGal2)
- zebrafish (May 2005, danRer3)
- Fugu (Aug 2002, fr1)

We compiled a "foreground" human gene set consisting of the 75-kb sequence regions surrounding each of these 27 known CRMs, and also a length-matched random "background" set of genomic regions not believed to contain muscle CRMs. We first masked out any coding regions and repetitive elements, and then searched the foreground and background gene sets with PhylCRM in order to identify windows of sequence significantly enriched for clusters of high-scoring, evolutionarily conserved matches to these four myogenic motifs. We assigned to each foreground and background region the score of its highest scoring PhylCRM window ranging between 10 bp and 500 bp, and then determined whether the foreground gene set scored higher than the background gene set by evaluating the AUC.

Without the use of phylogenetic conservation, we observed statistically significant enrichment for these motifs within this positive control foreground gene set $(AUC = 0.64$ \pm 0.05; *P* < 0.01 calculated by the Wilcoxon-Mann-Whitney¹⁰ (WMW) statistic; **Supplementary Figure 4b** online). When utilizing all 11 available vertebrate genomes, the degree of foreground enrichment increased significantly (AUC = 0.81 ± 0.05 ; $P < 10^{-7}$) by WMW; **Supplementary Figure 4c** online), demonstrating that the use of evolutionary conservation can increase discriminatory power.

Next, we evaluated whether the use of a subset of species in PhylCRM might yield higher foreground enrichment than the use of all available vertebrate genomes for this positive control set of myogenic CRMs. To evaluate such subsets, we systematically added those branches extending from each preceding common ancestor of human (**Supplementary**

Figure 4d online). We observed the greatest degree of enrichment when using all available vertebrate genomes except those of chicken, pufferfish and zebrafish (AUC = 0.82 ± 0.05 ; $P \le 10^{-8}$ by WMW), indicating that a judicious choice of sub-tree could yield improved performance. Finally, as a negative control we scanned the foreground and background regions with a permuted form of the four considered motifs and observed no enrichment (AUC = 0.41 ± 0.06 ; *P* > 0.05 by WMW; **Supplementary Figure 4e** online).

From this analysis, we concluded that PhylCRM can detect enrichment of motifs within 75-kb regions of genomic sequence within an appropriate gene set, and that the utilization of many aligned genomes increases the power of PhylCRM.

D. Comparison of PhylCRM to other CRM prediction methods

There are many available computational tools for CRM identification, and a full comparison of PhylCRM against each of them is beyond the scope of this present study. Therefore, we have selected two computational tools against which to compare PhylCRM, as they have similar goals of taking as input a collection of TF binding site motifs and outputting target CRMs.

We compared the performance of PhylCRM to two other algorithms: Comet (which utilizes a hidden Markov model (HMM) based approach and does not utilize information on the evolutionary conservation of the TF binding site motifs) and Stubb (which also utilizes an HMM-based approach and incorporates information on evolutionary conservation across up to two species of interest – one base genome plus one alignment genome). We selected two data sets for comparison: 1) the collection of 27 known muscle CRMs previously compiled by Wasserman *et al.*⁹ (the results of PhylCRM analysis for this collection of CRMs is shown in **Supplementary Fig. 4** online), and 2) the collection of "sarcomeric genes" from **Fig. 4** and **Supplementary Fig. 6** of the manuscript. Thus, these were the two sequence sets that were most carefully examined in our manuscript.

First, we took as a "foreground" set of sequences the 27 75-kb regions containing each of the known muscle CRMs (i.e., we considered the 75-kb regions within which the CRMs were located) as well as a length-matched background set of sequences (data #1). Next, we took as a "foreground" set of sequences the set of the 75-kb regions around

transcription start of the 46 known sarcomeric genes, as well as a length-matched set of background sequences (data #2). Because of computational limitations of the Stubb algorithm in handling large amounts of sequence, we had to reduce the size of the background data sets from what we used to generate the results shown in the main body of our manuscript (in this comparison, we used the same background to evaluate the results from all three programs – PhylCRM, Comet, and Stubb – in order to ensure that they were compared in a fair and systematic way). Consequently, the performance of PhylCRM shown below is slightly different from the results shown in **Supplementary Figure 4** online.

We ran the three programs by varying the input parameters in order to obtain the best performance from each program. We compared Comet, PhylCRM and Stubb by utilizing the same measure of performance as that utilized in the main text, namely, the AUC statistic that indicates the degree to which foreground sequences are ranked higher than background sequences (see the table below for a summary of the results). First, we observed that when no phylogeny was utilized the performance of PhylCRM on data #1 was AUC = 0.70 ± 0.06 (error represents 1 standard deviation determined by applying bootstrap) $(P < 10^{-3})$; this is within the margin of error of the performance observed for Comet (AUC = 0.70 ± 0.05 , $P < 10^{-4}$) and for Stubb (AUC = 0.68 ± 0.05 , $P < 10^{-3}$) on data #1. On the sarcomeric gene set (data #2), without utilizing phylogeny, PhylCRM (AUC = 0.64 ± 0.05 , $P < 10^{-2}$) was within the margin of error of Comet (AUC = 0.60 ± 10^{-2}) 0.05, $P > 0.01$), but better than Stubb (AUC = 0.49 ± 0.05 , $P > 0.1$).

We then examined how PhylCRM compares with Stubb in the case when information on the evolutionary conservation of the binding sites is utilized. We note that Stubb currently can consider conservation between only two species, while PhylCRM can utilize arbitrarily many genomes. On data #1, using the phylogenetic tree: Human/Chimp/Macaque/Mouse/Rat/Dog/Cow/Opossum, the performance of PhylCRM (AUC = 0.81 ± 0.06 , $P < 10^{-6}$) was within the margin of error of Stubb when using human and mouse (AUC = 0.80 ± 0.05 , $P < 10^{-6}$). We note that many of the CRMs in data set #1 were originally discovered in mouse and other non-human species¹¹, and this bias in the creation of this positive control data set may have resulted in their being better conserved in mouse. Using the same phylogenetic tree (Human/Chimp/Macaque/Mouse/ Rat/Dog/Cow/Opossum) but now considering the Sarcomeric gene set (data #2), PhylCRM (AUC = 0.74 ± 0.05 , $P < 10^{-6}$) performed significantly better than Stubb (AUC $= 0.59 \pm 0.04$, $P > 0.01$) when Stubb was run utilizing human and mouse.

From these comparisons we conclude that that PhylCRM performs comparably to the other algorithms on the collection of 27 known CRMs, and better on the Sarcomeric gene

set. Additionally, PhylCRM has the added feature of being able to score CRMs using a rich vocabulary of Fuzzy Boolean logic rules in order to discover nuanced *cis* regulatory codes (in the preceding comparisons, we utilized the OR combination for simplicity, although the performance could possibly be improved with a different combination of TF binding site motifs but would have complicated a direct comparison with the other algorithms). We show that in all of the datasets considered, using phylogeny information helps to improve the performance (this is also shown in **Supplementary Figure 4** online). Also, we expect that the performance of PhylCRM will continue to improve on these data sets (and other data sets) as more mammalian genomes are sequenced.
E. Lever

The statistical framework of Lever is based upon principles used by other groups for gene set enrichment analysis $12,13$ and utilizes permutation-based corrections for multiple hypothesis testing¹⁴. However, in contrast to gene set enrichment analysis^{12,13}, in the Lever framework genes are ranked by a sequence-based, rather than an expression-based, scoring function, and each combination of motifs gives rise to a distinct scoring function. For each gene set and scoring function, the ranking power of the function is statistically assessed by calculating the enrichment for highly scoring genes within the gene set. Thus, Lever simultaneously calculates and assesses the enrichment for many gene sets across many motif combinations (i.e., GM-pairs).

1. Statistical assessment for enrichment

Let g_1, g_2, \ldots, g_G be a collection of *G* genes whose upstream/downstream/intronic regions are being searched for CRMs, and let GS_1 , GS_2 ,..., GS_N be a collection of subsets of these genes. Within each subset GS_i , the genes g_i which are elements of it will be labeled as either being "foreground" or "background". To denote this labeling, we use the matrix *Y* where:

Eqn. 1)
$$
Y_{i,j} = \begin{cases} 1 & \text{if } g_i \text{ is a foreground gene in set } GS_j \\ 0 & \text{if } g_i \text{ is a background gene in set } GS_j \\ 0 & \text{if } g_i \notin GS_j \end{cases}
$$

The final value (•) of the above equation serves as a set membership indicator, which is used for efficient processing in order to assemble all of the required sets of genes. Specifically, information on set membership is required in a later permutation-based approach for evaluation of statistical significance, during which the assignment of genes

to the various gene sets changes. Let $F_{S_i} \subset GS_j$ and $B_{S_i} \subset GS_j$ be the sets of all foreground and background genes, respectively, within *GS_i*, and let $|F_{GS_i}|$ and $|B_{GS_i}|$ be the number of foreground and background genes, respectively, within *GSj*. Finally, let MC_k , $k = 1, \dots, M$ denote a given collection of combinations of motifs, and let the matrix $X=(X_{i,k})$, $i=1,..,G$, $k=1,..,M$, where $X_{i,k}$ denote the PhylCRM score (see **Supplementary Figures 1-4** online) of the maximum scoring window within the flanking sequence of g_i when scanning it with a motif combination MC_k .

Our goal is to determine which combinations of motifs MC_k are significantly enriched within the various gene sets GS_i . We consider the ranked PhylCRM scores for each combination of motifs and utilize the AUC statistic of the ranked scores in order to evaluate this enrichment. The AUC statistic is broadly applied for bipartite ranking problems and for comparisons of performance of binary classifiers¹⁵:

Eqn. 2)
$$
AUC(GS_j, MC_k) = \left(\frac{1}{\left|F_{GS_j}\right|B_{GS_j}\right|}\right)\left(\sum_{i: Y_{i,j}=1}\sum_{i: Y_{i,j}=0}I_{[X_{i,k}>X_{i',k}]} + \frac{1}{2}I_{[X_{i,k}=X_{i',k}]} \right)
$$

where I is the indicator function taking the value of "1" if the statement in brackets is true and "0" otherwise. The AUC of a ranking function takes values in the range [0,1], and is the probability that a randomly chosen positive instance (a member of the foreground set) will rank higher than a randomly chosen negative instance (a member of the background). It will take the value "1" if all of the genes in the foreground rank higher than genes in the background, the value "0" if all of the genes in the foreground rank lower than genes

in the background, and a value close to 0.5 if the ordering of foreground genes is not biased toward higher or lower ranks.

2. Adjustment for multiple hypothesis testing

An explicit goal of Lever is to evaluate many pairings of gene sets and motifs or motif combinations simultaneously, in order to identify motif combinations exhibiting statistically significant enrichment in specific gene sets (we refer to a matching of a gene set and a motif combination (GS_i, MC_k) as a GM-pair). The evaluation of so many GMpairs, however, necessitates a mechanism to correct for multiple hypothesis testing. Observe that AUC scores of distinct pairings (GS_i, MC_k) and (GS_i, MC_k) are not independent under the null hypothesis of no enrichment, since GS_i and $GS_{i'}$ may contain common genes and MC_k and MC_k [,] may contain common motifs. Consequently, a simple Bonferroni correction for multiple hypothesis testing is overly conservative and would cause many biologically relevant pairings (GS_i, MC_k) to be missed. Therefore, we applied a permutation-based approach for evaluation of statistical significance that takes into account the non-independence of the hypotheses.

For a given gene g_i let $\overline{Y}_i = (Y_{i,1}, Y_{i,2}, \dots Y_{i,S-1}, Y_{i,N})$ be the row vector of *Y* indicating membership of g_i in each of the sets GS_i , $j = 1,...,N$ and let

 $\overline{X}_i = (X_{i,1}, X_{i,2}, \dots X_{i,M-1}, X_{i,M})$ be the row vector of *X* indicating the PhylCRM score of g_i for each combination of motifs $MC_k k = 1,...,M$. Let π be a fixed permutation of *{1,..,G}* (where *G* is the total number of genes).

Next, let:

Eqn. 3)
$$
AUC\big|_{(GS_j,MC_k, \pi)\bigg} = \left(\frac{1}{\left|F_{GS_j}\right|B_{GS_j}\right|}\left(\sum_{i:Y_{i,j}=1}\sum_{i:Y_{i',j}=0}I_{[X_{\pi(i),k}>X_{\pi(i')\!,k}]} + \frac{1}{2}I_{[X_{\pi(i),k}=X_{\pi(i')\!,k}]} \right)
$$

This is the AUC computed for the GM-pair (GS_i, MC_k) when the class labels are permuted. Observe that, as desired, the definition of this permutation preserves all correlations in values of AUC statistics between pairings (*GSj*, *MCk*) and (*GSj'*, *MCk'*) resulting from genes being elements of both GS_j and GS_k and motifs being elements of both MC_k and $MC_{k'}$.

We use the permutation approach in order to evaluate the significance of the values $AUC(GS_i, MC_k)$ when controlling for false discovery rate (FDR) and family-wise error rate for multiple comparisons. Let $\{\pi_i\}^P$ π ^{*l*}_{$i=1$} be a collection of *P* randomly chosen permutations over the gene labels. Because different gene sets GS_i , $j = 1,..,N$ contain different numbers of genes, and because different motif combinations can result in more or fewer ties in PhylCRM scores between distinct genes (for example, AND combinations involving many motifs may result in many genes having a PhylCRM score of "0"), the variance of $AUC(GS_i, MC_k)$ is not constant across pairings (GS_i, MC_k) . Let:

Eqns. 4 and 5)

$$
\mu_{j,k} = \frac{1}{P} \sum_{l=1}^{P} AUC\big(GS_j, MC_k, \pi_l\big)
$$

$$
\sigma_{j,k} = \left(\frac{1}{P-1} \sum_{l=1}^{P} \big(AUC\big(GS_j, MC_k, \pi_l\big) - \mu_{j,k}\big)^2\right)^{1/2}
$$

We normalize the $AUC(GS_i, MC_k)$ value by applying the *z*-transformation:

Eqn. 6)
$$
AUC\big(GS_j, MC_k\big)' = \frac{AUC\big(GS_j, MC_k\big) - \mu_{j,k}}{\sigma_{j,k}}
$$

Following the method of Subramanian *et al.*¹³, for family-wise error rate estimation of significance for each value $AUC(GS_i, MC_k)'$, we take the maximum of the normalized AUC statistics across all gene set and motif combination pairings within a given permutation:

Eqn. 7)
$$
U_{\pi_l} = \max_{j,k} \{ AUC\big(GS_j, MC_k, \pi_l \big) \}
$$

The family-wise error rate estimate of statistical significance of a specific value $AUC(GS_i, MC_k)'$ is then given by:

Eqn. 8)
$$
P\bigg[AUC\big(GS_j, MC_k \big)^{\prime} \bigg]_{FWER} = percentage \ of \ (l) \ s.t. \ U_{\pi_l} \ge AUC\big(GS_j, MC_k \big)
$$

Similarly, the FDR estimate of statistical significance is obtained by utilizing the entire distribution of $AUC(GS_i, MC_k, \pi_l)'$ values and by calculating the FDR *Q*-values, denoted as *Q* in the main text and in the figures:

Eqn. 9)
$$
Q\left[AU\left(GS_j, MC_k\right)^{\prime}\right] = \frac{\text{percentagef}(j^*,k^*,l)\text{ s.t. } AU\left(GC_j^*, MS_k^*, \pi_l\right) \geq AU\left(GS_j, MC_k\right)}{\text{percentagef}(j^*,k^*)\text{ s.t. } AU\left(GC_j^*, MS_k^*\right) \geq AU\left(GS_j, MC_k\right)}
$$

In this paper, we report AUCs along with an error term that corresponds to one standard deviation of the bootstrap confidence interval 14 .

3. Correction for AT/GC-rich motifs

We have observed that many genes of interest have G/C-rich flanking sequences; consequently, many gene sets will show artificially high enrichment for G/C-rich motifs. For the Lever screens shown in **Figure 4** and **Supplementary Figures 5-6**, we controlled for this by first generating many permuted forms of each motif (50 for analyses involving the Xie *et al.*¹⁶ motifs, and 100 for analyses involving the four motifs MRF/MEF2/SRF/Tead). For each gene of interest, we scored its 75-kb flanking noncoding sequence with permuted forms of the motifs. For each gene and each motif or combination of motifs, we *z*-transformed the PhylCRM scores (similarly to **Eqns. 4** and **5**) after calculating the mean and variance from the permuted forms of the motifs. This approach showed reduction of the artifacts described above.

PhylCRM and Lever software parameter settings

For all runs and all motifs considered in this study, as the threshold cutoff used by Lever and PhylCRM for calling a motif match, we used 2 standard deviations (SDs) below the motif average¹⁷ and the "-THRESHOLD" setting in both of these programs. For the PhylCRM results shown in **Supplementary Figure 4**, we used the "-DEOVERLAP" option for the OR combination of the MRF/MEF2/SRF/Tead motifs. We observed very similar trends without the "-DEOVERLAP" option, *i.e.* without removing the overlaps between different motifs. In the rest of this study, we applied PhylCRM and Lever without the "-DEOVERLAP" option. For PhylCRM and Lever runs involving the MRF/MEF2/SRF/Tead motifs, we used windows ranging between 10 and 500 bp, and for runs involving the Xie *et al.*16 motifs we used a window range of 25 to 500 bp since some of those motifs can be wider than 10 bp.

Gene sets examined in this study

For the Lever scans shown in **Supplementary Figure 5**, we examined each of the *k*means expression clusters as an input library of foreground gene sets (we excluded cluster **C13** because it contained only 12 genes). For those shown in **Supplementary Figures 6 and Figure 4,** we added to this collection by additionally considering gene sets based upon shared GO annotation terms (we considered the Biological Process, Molecular Function and Cellular Component terms). Specifically, significantly overrepresented GO categories among the up- and down-regulated genes were determined using FuncAssociate²⁹. Only the significantly (FDR \leq 0.05) up- or down-regulated genes belonging to each of those GO categories were considered in constructing the corresponding reduced GO category gene sets. Nonredundant gene lists were created by matching Refseq sequences to common gene names using $DAVID³⁰$ and removing redundancies. Finally, we considered only those gene sets that contained at least 15 members. Also, if two gene sets were found to contain identical genes, one of the gene sets was dropped.

We noticed that numerous sarcomere-related GO categories, such as actin cytoskeleton, contractile fiber, structural constituent of muscle, muscle contraction, and muscle development, were enriched among the up-regulated genes. Sarcomeric genes might be especially likely to be co-regulated, as they are all components of a single protein complex utilized in muscle. However, the GO category "sarcomere" contained only 12 genes observed to be up-regulated in our study. Therefore, knowing that GO annotation of mammalian genes can be quite incomplete, we manually compiled from the literature a list of 46 sarcomeric genes that were up-regulated during the differentiation of myoblasts

into myotubes. This list of 46 genes included two genes (*ACTA1* and *CSRP3*) for which probes were not included on the microarrays utilized studying gene expression profiling, but for which RT-PCR experiments confirmed their up-regulation (**Supplementary Figure 8**).

F. Further discussion of interpretation of CRM enrichment results from Lever

We note that Lever identifies CRM enrichment within a given gene set. Of the six tested CRMs, the four that showed significant binding by MEF2, MyoD, and myogenin were the ones that are located next to genes involved in sarcomeric function, whereas the two that did not show significant binding by these factors are not. The MEF2 AND MRF motif combination within the up-regulated sarcomeric gene set was one of our top 10 GM-pairs in terms of AUC and *Q*-value from our Lever screen of 101 myogenic gene sets and the four known myogenic motifs MRF, MEF2, SRF and Tead (data provided in **Supplementary Table 3c**). Ranking by AUC values, the top 10 GM-pairs from that

screen were:

FDR Q-

For experimental validation, we chose to examine simple Boolean motif combinations instead of compound Boolean combinations, because simple Boolean motif combinations would be easier to test in subsequent construction and analysis of synthetic CRMs. We also expected an AND motif combination to confer greater specificity of gene expression regulation than an OR motif combination. The MRF AND MEF2 motif combination for

the sarcomere up gene set (FDR 0, AUC 0.822) scored slightly less well than the MRF AND MEF2 motif combination for the CONTRACTILE FIBER_up gene set (FDR *Q*value = 0, AUC = 0.857). One of our positive control CRMs was for the gene $ACTAI$, which belongs to the sarcomere up gene set and not to the CONTRACTILE FIBER up gene set, and we were interested to see if there might be more than 1 functional CRM per gene at a given time point in a given cell type. It would be interesting to see if the predicted CRMs containing the MRF AND MEF2 motif combination for the CONTRACTILE FIBER_up gene set work with just as high a success rate.

To try to estimate what the anticipated CRM success rate might be for a given gene set, consider the following example. The figure below shows the degree to which all 46 sarcomeric genes are enriched for the MRF AND MEF2 TF binding site motif combination, as compared to a background set of 1840 ($= 46*40$) length-matched background genes that were not observed to be up- or down-regulated in this cell-type:

In looking at this figure, we see that at a given PhylCRM score threshold where 20% of background genes have a positive hit (i.e., a maximum-scoring window that we predict as being a CRM) somewhere within their 75 kb regions around transcription start (80% specificity), 70% of sarcomeric genes (foreground) have such a positive hit within their 75 kb regions (i.e., 70% sensitivity). We note that sensitivity values for any given specificity can immediately be read off of the ROC curve, although for simplicity we use the 80% specificity / 70% sensitivity point for the following discussion. At this threshold, we can compile the following table of summary statistics indicating the fraction of true positives (TP), true negatives (TN), false positives (FP) and false negatives (FN), and also the positive predictive value (PPV) and misclassification error:

Using the cutoff mentioned above, 20% of the background genes have a positive PhylCRM hit (i.e., predicted CRM) somewhere within 75 kb of transcription start, and 30% of the foreground genes do not have a predicted CRM, giving a misclassification error of 20% and positive predictive value (PPV) of 8%. We see three possible explanations for these results. First, some background genes containing a PhylCRM hit might be located close to a gene that is expressed in muscle and regulated by MRF AND MEF2; such PhylCRM hits would correspond to *bona fide* myogenic CRMs that were incorrectly placed into the background. Second, many of these PhylCRM hits might

represent CRMs that are targeted by TFs binding to the MRF AND MEF2 motifs but that do not drive expression in muscle. For example, MEF2 is known to regulate gene expression in the brain, and there are several bHLH TFs that are crucial for neuronal cell fate specification and are likely to have a binding site motif similar to the MRF motif bound by the myogenic bHLH TFs (MyoD, myogenin); thus, many of these hits could be true CRMs that drive expression in the brain rather than the muscle. Finally, it is possible that many of the PhylCRM hits are simply false predictions and are not actually CRMs. We have given this issue extensive thought, and we do not presently see a reliable means of estimating what fraction of MRF AND MEF2 hits adjacent to background genes fall into each of these three potential classes. We expect that prioritizing for experimental testing those significant PhylCRM hits that contain MRF AND MEF2 motifs and that are directly adjacent to sarcomeric genes, will lead to a greatly increased success rate in experimental validation of predicted CRMs functional in myogenic differentiation. In general, we believe that the results of Lever can be used to prioritize predicted CRMs for experimental testing, by picking for testing those candidate CRMs which lie next to genes that belong to significant scoring GM-pairs.

G. Position Weight Matrices utilized in this study:

We obtained from the supplementary data of Wasserman *et al.*⁹ DNA binding site sequences corresponding to these 4 motifs from the supplementary data of that study, although we added additional myogenic MEF2 sites obtained from a SELEX $experiment¹⁸$.

MRF:

MEF2:

SRF:

Tead:

H. Detailed experimental protocols, including primer sequences Cell culture

Adult human skeletal myoblasts (Cambrex) were grown in SkGM2 medium (Cambrex) for optimal growth and differentiation potential. Myogenic differentiation was stimulated by switching the culture medium to DMEM with 2% horse serum (Sigma) when the cells reached about 70% confluence. All time points referred to in this study are with respect to the time of switching to differentiation medium. Mouse C2C12 cells (ATCC), mouse 3T3 cells (ATCC), and human lens epithelial cells (gift from Amy Donner) were cultured in DMEM (Invitrogen) with 10% fetal bovine serum (Sigma), respectively. HEK293T cells were a gift from Karen Cichowski.

RNA purification

Total RNA was isolated from primary human skeletal muscle cells using TRIzol reagent (Invitrogen) according to the manufacturer's protocols. For microarray experiments, total RNA was further purified with RNeasy columns (Qiagen).

Gene expression profiling microarray experiments

Microarrays were synthesized and hybridized by the Harvard Partners Center for Genetics and Genomics. Briefly, each glass slide was spotted with the Human $OligoLibraryTM Release 1.0 that was designed by Compugen, Inc. and manufactured by$ Sigma-Genosys, Inc. This oligonucleotide library consists of 18,864 60-mers representing 18,664 unique genes. We extracted mRNA at 6 time points (–48 hrs, –24 hrs, 0 hrs, 12 hrs, 24 hrs, and 48 hrs relative to serum withdrawal). These time points were selected since prior studies in a related cell type (mouse C2C12 cells) demonstrated their

effectiveness for capturing key transcriptional events during myogenic differentiation $19,20$. For each time point, four hybridizations, consisting of duplicate hybridizations with Cy3 and Cy5 dye-reversal, were performed essentially as described previously²¹.

Preprocessing and clustering of gene expression microarray data

Scanned TIF images were quantified with GenePix software (Axon Instruments). For each feature, the median pixel intensity of the local background was subtracted from the spot's median pixel intensity. We then applied variance stabilizing normalization²² to normalize all single channels to each other. False discovery rates (FDRs) were calculated using Significance Analysis of Microarrays²³ (one class time-series and slope parameters) on the four replicate arrays. The arcsinh values of the four replicate arrays for each time point were then combined by taking the arithmetic mean and expressed as the foldchange relative to the first time point (–24 hrs). Changes in arcsinh values correspond to the following approximate ratios (arcsinh = linear): $0 = 1/1$; $1 = 2.7/1$; $2 = 7.5/1$; $3 = 20/1$, $4 = 55/1$; $5 = 155/1$, $6 = 405/1$. Genes that were differentially expressed at a 5% FDR were clustered using *k*-means clustering by de Hoon's Cluster 3.0 software²⁴ (http://bonsai.ims.u-tokyo.ac.jp/~mdehoon/software/cluster/software.htm#ctv). Our choice of 14 clusters was determined empirically.

Western blotting

Cell nuclei extracts and cytoplasmic extracts were obtained from human skeletal myoblasts at -48 , -24 , 0, $+24$, and $+48$ hours with respect to stimulation of differentiation, according to standard protocols. Equal protein amounts were subjected to standard SDS-PAGE. Western Blots were performed using SuperSignal West Femto Maximum Sensitivity Substrate (Pierce) according to the manufacturer's instructions. Blocking solution consisted of 5% nonfat dry milk in TBS-T (Tris Buffered Saline with 0.1% Tween 20) and washing solution was TBS-T.

The following antibodies used in Western blots were purchased from Santa Cruz: Myf5 (sc-302), MyoD (sc-760), Myogenin (sc-576), Myf6 (sc-784), SRF (sc-335), MEF2C (sc-13266), MEF2 (sc-10794), MEF2A (sc-313), and lamin B1 (sc-20682). Tead1 (or Tef-1) antibody was purchased from BD Biosciences Pharmingen (610923). All antibodies were probed at a 1:1,000 dilution in blocking solution, except for the lamin B1 and MEF2C antibodies which were probed at a 1:2,000 dilution. Anti-rabbit and anti-mouse HRPconjugated secondary antibodies (as supplied by Pierce) were diluted 1:3,000 in blocking solution. Anti-goat secondary antibodies (Sigma) were diluted 1:300,000.

The Tead or Tef family of transcription factors are comprised of at least four mammalian members, Tead1 (TEF-1), Tead2 (TEF-4), Tead3 (TEF-5), and Tead4 (TEF-3)²⁵. Tead4 and Tead2 are the only two members detectable in regenerating mouse skeletal muscle^{25,26}. Tead1 is broadly expressed in many different embryonic tissues²⁷, but Tead1 knockout mice have severe cardiac defects suggesting a major role in cardiac d evelopment²⁸. Tead3 is detectable in skeletal and cardiac muscle but is preferentially expressed in the developing placenta^{29,30}. Since the immunogen used to develop the BD Pharmingen is 53% identical and 66% similar to Tead4 protein, it is possible that the antibody is cross-reactive with Tead4 or other Tead family members using a sensitive

Western blot detection system. At the time of submission of this paper, it was believed that Tef1 was the relevant Tead family member for myogenic differentiation¹¹, and BD Biosciences Pharmingen had no data for or against the cross-reactivity of their Tead1 antibody.

ChIP

Chromatin immunoprecipitations were carried out using a modified version of the Farnham protocol (http://mcardle.oncology.wisc.edu/Farnham/protocols/chips.html). 5 x 10⁸ cells fixed at days 0, 1, and 2 of differentiation.

Cells were fixed with 1% formaldehyde at room temperature for 10 minutes with occasional agitation of the plates. 2.5 M glycine was added to the cell media for 5 minutes to stop the crosslinking reaction. The cells were then washed twice with ice-cold PBS and incubated in PBS with 20% trypsin-EDTA (Cambrex) for 10 min at 37ºC. 0.5 ml of FCS was added to inhibit trypsinization. The cells were then scraped and collected into 50-ml conical tubes and kept on ice. Cells were washed once with ice-cold PBS with PMSF (Sigma, 100 μM) and protease inhibitors (20 μl per ml, Sigma P8340), flash frozen in ethanol/dry ice, and kept $@-70^{\circ}\text{C}$ until chromatin immunoprecipitation.

Frozen cells were thawed on ice, resuspended in ice-cold cell lysis buffer (5 mM PIPES pH 8.0, 85 mM KCl, 0.5% NP40, 1:50 protease inhibitor mix [Sigma catalog # P8340]), and incubated on ice for 10 minutes. Nuclei release was aided by dounce homogenization. Nuclei were pelleted by centrifugation and resuspended in room

temperature nuclei lysis buffer (50 mM Tris-Cl pH 8.1, 10 mM EDTA, 1% SDS, 1:50 protease inhibitor mix), followed by incubation on ice for 10 minutes. The nuclei were then sonicated to achieve chromatin fragments with an average length of 1,000 bp. The sonication conditions used were 9 sonications of 15-second pulses separated by 1-minute incubation on ice. Samples were centrifuged at high speed to remove cellular debris. The supernatant containing the sonicated chromatin was transferred to a 50-ml conical tube and diluted 1:10 with ice-cold dilution buffer (0.01% SDS, 1.1% Triton X-100, 1.2 mM EDTA, 16.7 mM Tris-Cl pH 8.1, 167 mM NaCl, 1:50 protease inhibitor mix). Chromatin was precleared by adding 50 μl of Protein A beads/Salmon Sperm DNA (Upstate Protein A/Salmon Sperm DNA, cat# 16-157) per ml and incubating on a rotating platform at 4° C. 3 μg of antibody was used for each immunoprecipitation. The following antibodies were purchased from Santa Cruz: MyoD (sc-760), Myogenin (sc-576), SRF (sc-335), and MEF2 (sc-10794). 60 μl of Protein A/salmon sperm DNA beads were added to each sample and incubated on a rotating platform at 4°C for 1-2 hours. Samples were then microcentrifuged for 1 min and placed into fresh microcentrifuge tubes.

Immunoprecipitates were washed twice with ice-cold wash buffer 1 (20 mM Tris, pH 8.1, 150 mM NaCl, 2 mM EDTA, 0.1 % SDS, 1% Triton X-100), once with wash buffer 2 (20 mM Tris, pH 8.1, 500 mM NaCl, 2 mM EDTA, 0.1 % SDS, 1% Triton X-100), once with wash buffer 3 (10 mM Tris, pH 8.1, 250 mM LiCl, 2 mM EDTA, 1% NP-40, 1% deoxycholate), and once with ice-cold 4 M LiCl/TE. After the last wash and spin, all remaining buffer was carefully removed with a sterile 1-ml pipette. Antibody/protein/DNA complexes were eluted by adding 100 μl of IP elution buffer 1

(1% SDS, 1 mM EDTA, 10 mM Tris, pH 8.1) and incubated $@65^{\circ}$ C for 15 min. Samples were microcentrifuged for 3 minutes. Supernatants were then transferred to fresh microcentrifuge tubes. Samples were then eluted again with 150 μl of elution buffer 2 and incubated at 65°C for 15 min. Samples were then combined and incubated overnight at 65°C to reverse formaldehyde crosslinks.

To each tube, 250 μl TE and 5 μl of proteinase K (20 mg/ml) were added. The tubes were then incubated at 37ºC for 1 hour. To each tube, 55 μl of 4M LiCl was added. The samples were then extracted twice with 500 μl phenol/chloroform/isoamyl alcohol and once with 500 μl of chloroform. Then, 1 μl (10 mg) of glycogen to each sample and the samples were ethanol precipitated. After drying the pellets, the samples were resuspended in 150 μl of 10 mM Tris 8.5. Each IP was performed in triplicate for each individual chromatin sample.

In our ChIP assays, as positive controls we examined five previously described muscle CRMs, and as negative controls we examined two noncoding regions with no significant matches and eight noncoding regions with only a single significant match, to any of these five motifs. The positive control regions were as follows:

CAV3 (0.2 kb upstream of transcriptional start):

• myotube specific promoter; previously confirmed myogenin (MYF) binding site in mouse $C2C12$ cells³¹

COX6A2 (0.3 kb upstream of transcriptional start):

• myotube specific promoter; previously confirmed MRF (E-box) and MEF2 binding sites in mouse Sol8 and C2C12 cells 32

ACTA1 (0.3 kb upstream of transcriptional start):

- promoter region
- 3 previously confirmed SRF sites in primary chicken muscle culture³³
- previously confirmed Tead1 site in rat cardiomyocytes 34

TNNT2 (0.1 kb upstream of transcriptional start):

- conserved Tead1 (M-CAT) site in chicken promoter was previously shown to be important for chicken skeletal muscle³⁵
- MEF2 site was previously shown to be important for rat cardiac muscle expression 36
- CArG boxes (SRF sites) were previously confirmed by footprinting in rat cardiomyocytes³⁶

DMD (6.4 kb into $1st$ introns):

- myotube-specific enhancer
- three MRF sites and one MEF2 site required for activation in myotubes³⁷

Primer sequences:

Quantitative RT-PCR

Total RNA was reverse-transcribed using SuperScript III (Invitrogen) according to the manufacturer's protocols. Quantitative PCRs were performed using iQ^{TM} SYBR® Green Supermix (BioRad) and 0.2 μM primers with an iCycler iQ Real-Time PCR Detection System (BioRad).

Quantitative ChIP-PCR

ChIPs were performed in biological triplicate using a modified version of the Farnham protocol³⁸. The following antibodies were used in ChIPs: $MyoD$ (sc-760), myogenin (sc-576), SRF (sc-335), and MEF2 (sc-10794), all from Santa Cruz Biotechnology, Inc. We included SRF since we observed that several of our predicted CRMs contained SRF motif matches. Tead was not included since a suitable antibody was not available. As positive

controls, we examined five previously described muscle CRMs. Negative control genomic regions were chosen based on their not having any significant PhylCRM hits when considering the MRF, MEF2, SRF, or Tead motifs, and their being adjacent to genes called "present" in the expression microarray data but not up- or down-regulated at a FDR less than 0.1. Quantitative ChIP-PCRs were performed essentially as described above, except using 6 μl of immunoprecipitated DNA.

Luciferase reporter assays

Putative and control CRMs were cloned either upstream (BglII) or downstream (BamHI) of the luciferase reporter gene into pGL3-Promoter vector (Promega) in their native genomic orientation (i.e., upstream versus downstream of transcription, Watson versus Crick strand). As a positive control, we used one of the five previously known muscle CRMs used in our ChIPs. A negative control human noncoding genomic region not enriched for matches to these four motifs was indistinguishable from the corresponding enhancer-less empty vector negative control. C2C12 cells were cultured in 6-well plates (9.4 cm² per well) 24 hours prior to transfection at 3 x 10^4 cells per well for myoblasts or 1.5×10^5 cells per well for myotubes. The cells were then co-transfected in triplicate with 1 μg of experimental vector (pGL3-P with or without inserted region) and 50 ng of the normalization vector (pRL-TK) using FuGENE 6 transfection reagent (Roche) according to the manufacturer's protocols. Cell extracts were obtained from an aliquot of the proliferating myoblasts 24 hours after transfection. The remaining cell cultures were then switched to differentiation medium, and cell extracts were obtained after 96 hours in differentiation medium. Luciferase reporter assays were performed using the DualLuciferase® Reporter Assay System (Promega) according to the manufacturer's protocols. Firefly luminescence intensities were normalized by the luminescence intensities of the internal *Renilla* control. We used C2C12 cells in these assays instead of primary adult human skeletal myoblasts because the primary cells failed to differentiate robustly after transfection.

shRNA knockdowns

Short hairpin RNA (shRNA) constructs directed against mouse RNA transcripts were generated essentially as described previously³⁹. Lentiviral reagents were kindly provided by Karen Cichowski. For lentiviral production, HEK293T cells were transfected with the ∆8.2 lentiviral construct (encoding *gag, pol, rev)*, VSVG, and either empty pLKO.1 vector or the pLKO.1 vector containing a sequence for a shRNA specific for each of the muscle genes *MYOD*, *MYOG*, *MEF2D*, *SRF*, and the liver gene *HNF4*α. Three distinct shRNA constructs were created for each gene in order to control for off-targets effects. Lentivirus was titered by serial dilution followed by colony formation assays in medium containing puromycin. C2C12 cells (7×10^4) were plated on 100-mm plates 24 hours prior to infection. After infection at 5 multiplicities of infection of lentivirus, C2C12 cells were grown in growth media for 24 hours and selected in puromycin for 72 hours. Luciferase reporter assays were then performed as described above, except cells were plated onto 12-well plates and transfected with proportionately less of the reagents. Our MEF2C knockdowns resulted in extensive cell death, and thus could not be utilized here.

Creation of synthetic CRMs

To test the sufficiency of the inferred MRF AND MEF2 *cis* regulatory code for myogenic differentiation, we created a synthetic CRM containing consensus MRF and MEF2 binding sites arranged as in our newly discovered *ACTA1* CRM, but in the context of the *MGLL* negative control flanking sequence. The MGLL negative control region was selected as a template into which to place TF binding sites in order to experimentally test the MRF AND MEF2 *cis* regulatory code for myogenic differentiation. To create synthetic CRMs, we created variants of a shorter 167-bp *MGLL* negative control region by ligating segments of the original *MGLL* region or by ligating modified segments of the *MGLL* region such that the new construct would have two consensus MRF sites and one consensus MEF2 site. The reconstituted *MGLL* region served as a negative control. As positive controls, we used an SV40 enhancer, one of the five previously known muscle CRMs used in our ChIPs (DMD), and a novel CRM that we verified previously CRM (ACTA1, see **Fig. 5** of the manuscript). The TF binding sites were placed in the modified *MGLL* region such that they mimicked the position and orientation of our newly discovered *ACTA1* CRM. The sense (F) and antisense (R) strand of each segment were synthesized as single-stranded DNA oligonucleotides and were then annealed to form double-stranded DNA. The following oligonucleotides were used in the annealing reactions:

CCACCAAACCTC

Segment 1 was designed to have a *SacI*-compatible end and segment 3 a *NheI*-compatible end such that an entire Seg1-Seg2-Seg3 sequence could be ligated into a pGL3-P vector that was previously digested with *NheI* and *SacI* and treated with alkaline phosphatase. The short MGLL sequence was reconstituted by ligating the following double-stranded segments: MGLL_SEG1, MGLL_SEG2, and MGLL_SEG3. The MGLL region with two MRF sites and one MEF2 site was created by ligating MGLL_SEG1_CAGCTG, MGLL_SEG2_ACTA_PMEF2, and MGLL_SEG3_CAGCTG.

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Supplementary Results

A) Lever screen of 4 known myogenic regulatory motifs across 101 myogenic gene sets

As an initial positive control analysis, we applied Lever to systematically analyze the 101 myogenic gene expression clusters and GO categories when considering the four known myogenic motifs MRF, MEF2, SRF and Tead. We found that 41 out of the 101 gene sets showed significant enrichment ($Q \le 0.05$) for at least one Boolean combination of these four motifs (**Supplementary Figure 6** online; **Supplementary Table 3b** online). Nearly all gene sets that showed statistically significant enrichment ($Q \le 0.05$) for combinations of these four motifs were composed of up-regulated genes, consistent with the known functions of the corresponding TFs as transcriptional activators.

B) Experimental validation of CRMs predicted by PhylCRM

We first verified by Q-RT-PCR that these seven genes were up-regulated during differentiation (**Supplementary Figure 8** online). Western blot analyses confirmed that these myogenic TFs were differentially expressed at the protein level during differentiation (**Supplementary Figure 9** online). Next, chromatin immunoprecipitation (ChIP) assays followed by region-specific quantitative PCR (see **Methods**) showed that four of the six candidate CRMs were significantly enriched for binding by MEF2 ($P \leq$ 0.05), MyoD ($P \le 0.05$) and myogenin ($P \le 0.005$) (**Figure 5b**). Positive control CRMs were also significantly enriched for binding by these TFs, while negative control regions were not (**Figure 5b**). Two of these four bound regions were also significantly occupied by SRF ($P \le 0.05$) during differentiation. Interestingly, of the six tested CRMs, the four that showed significant binding by MEF2, MyoD, and myogenin were the ones that are located next to genes involved in sarcomeric function, whereas the two that did not show significant binding by these factors are not. Although this does not tell us what sequence features distinguish the active from the inactive CRMs, it does suggest that the choice of the likely target gene sets is important in predicting CRMs that are active in a given

condition (here, myogenic differentiation).

We performed luciferase assays for the four novel, candidate CRMs that were enriched for *in vivo* TF binding. All four of these candidate CRMs resulted in statistically significant ($P \le 0.05$) activation of luciferase expression during myogenic differentiation (**Figure 5c**). In contrast, these same CRMs did not result in increased luciferase activity in either fibroblasts or lens epithelial cells (**Figure 5c**). To further validate that these four candidate CRMs drive expression specifically in response to myogenic differentiation, we disrupted myogenic differentiation by shRNA knockdown of MEF2D (one of two MEF2 isoforms up-regulated in myotubes), myogenin (the most up-regulated MRF member), or SRF (**Supplementary Figure 10** online). Knockdown of myogenin significantly reduced ($P \leq 0.05$) transcriptional activity of all four predicted human CRMs positive for luciferase reporter activity in C2C12 myotubes (**Supplementary Figure 11a** online), while knockdown of SRF or MEF2D reduced the transcriptional activity of different subsets of these CRMs (**Supplementary Figure 11b,c** online). We note as a caveat that this reduced luciferase activity could potentially have been due to indirect effects involving some other TF under the control of the myogenic regulators knocked down by the shRNAs. In each case the level of luciferase activity was proportional to the amount of TF knockdown for a given shRNA clone (**Supplementary Figures 10 and 11** online).

Finally, we tested the sufficiency of the MRF AND MEF2 motif combination for CRM activity by generating a synthetic CRM containing consensus MRF and MEF2 binding sites arranged as in our newly discovered *ACTA1* CRM, but in the context of the *MGLL* negative control flanking sequence (see **Methods**). This synthetic CRM failed to drive expression in a luciferase reporter construct, suggesting that there are further sequence requirements aside from the MRF and MEF2 motifs (**Supplementary Figure 12** online). We anticipate that further computational analyses with more candidate regulatory motifs, combined with further experimental testing, will help to identify additional sequence features that may be important for CRM activity.