

A Specialized Learner for Inferring

Structured cis-Regulatory Modules

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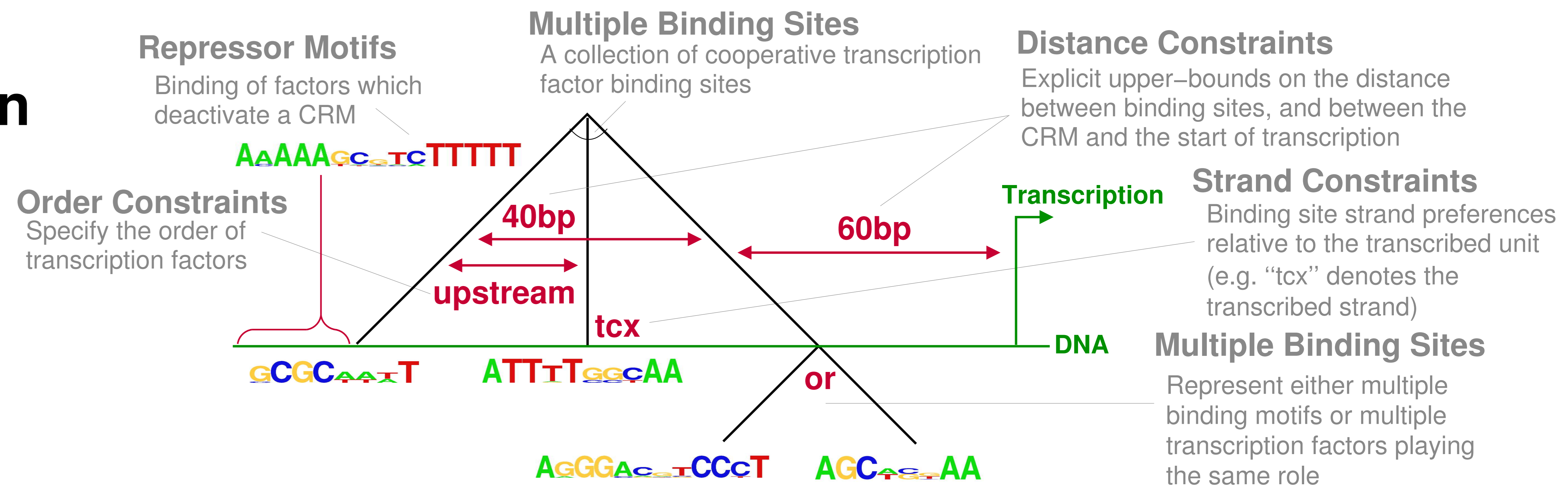
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Abstract

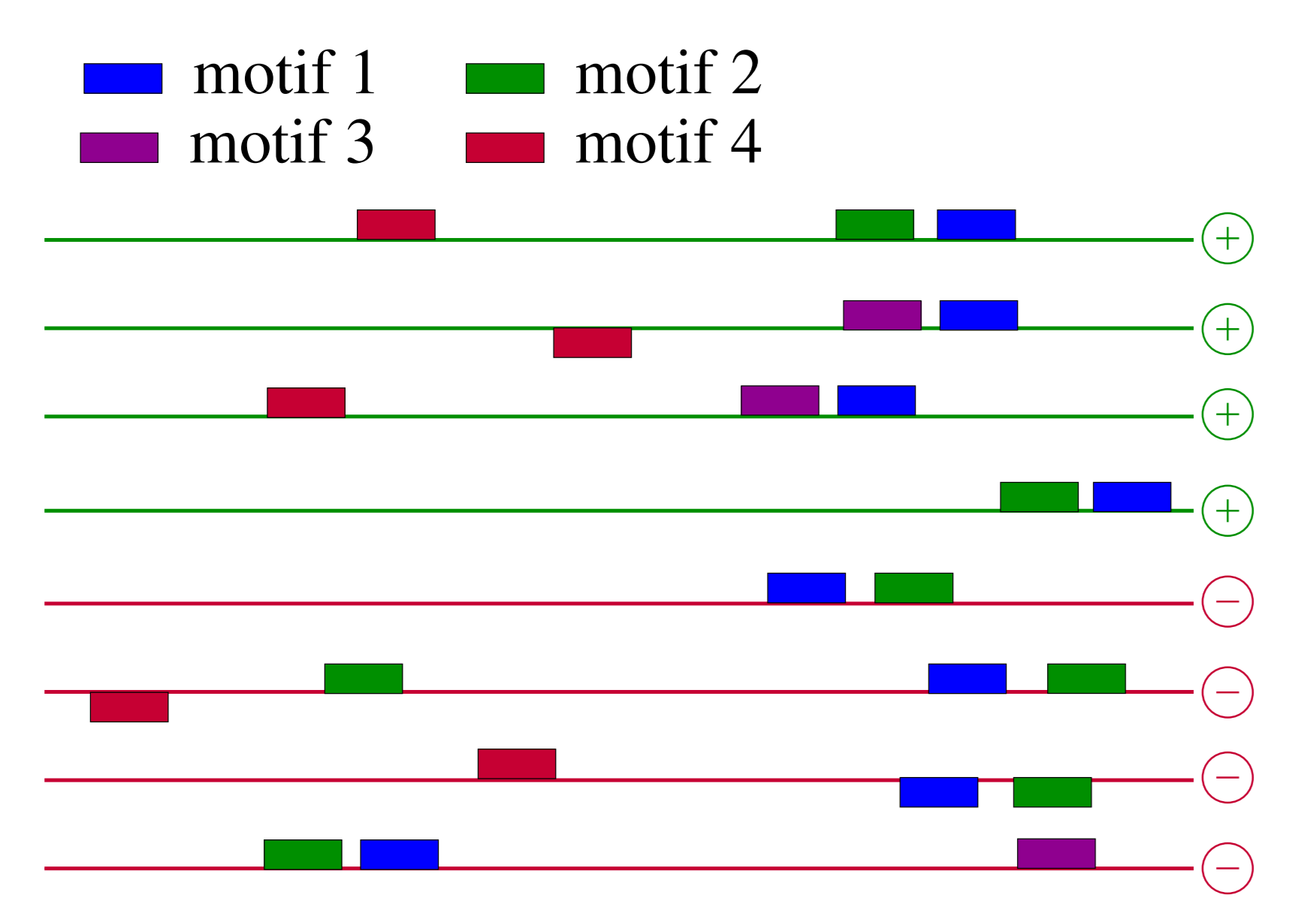
We present an approach to identifying cis-regulatory modules (CRMs) in terms of binding site motifs and the arrangement of their locations relative to the transcriptional start site. It is expressive enough to capture important structural aspects of a CRM, yet the search algorithm is specifically tailored to this context.

1. An Expressive CRM Representation

Transcription factors bind to DNA in specific arrangements and interact with each other. This system is called a cis-regulatory module (CRM). Our work is motivated by the need for more expressive CRM representations which can capture important structural *aspects* (right).

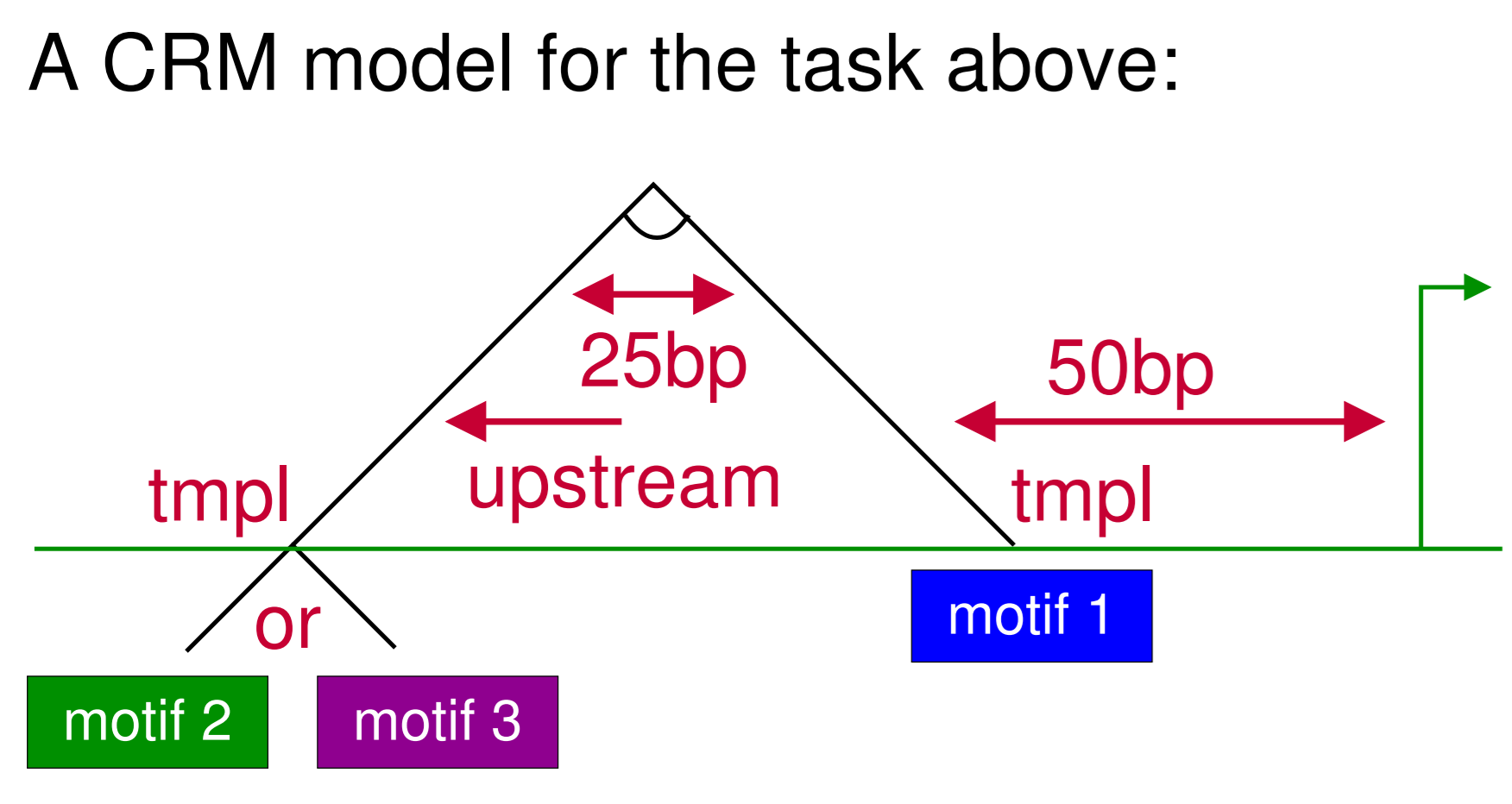


2. Task: Learn a CRM Model from data

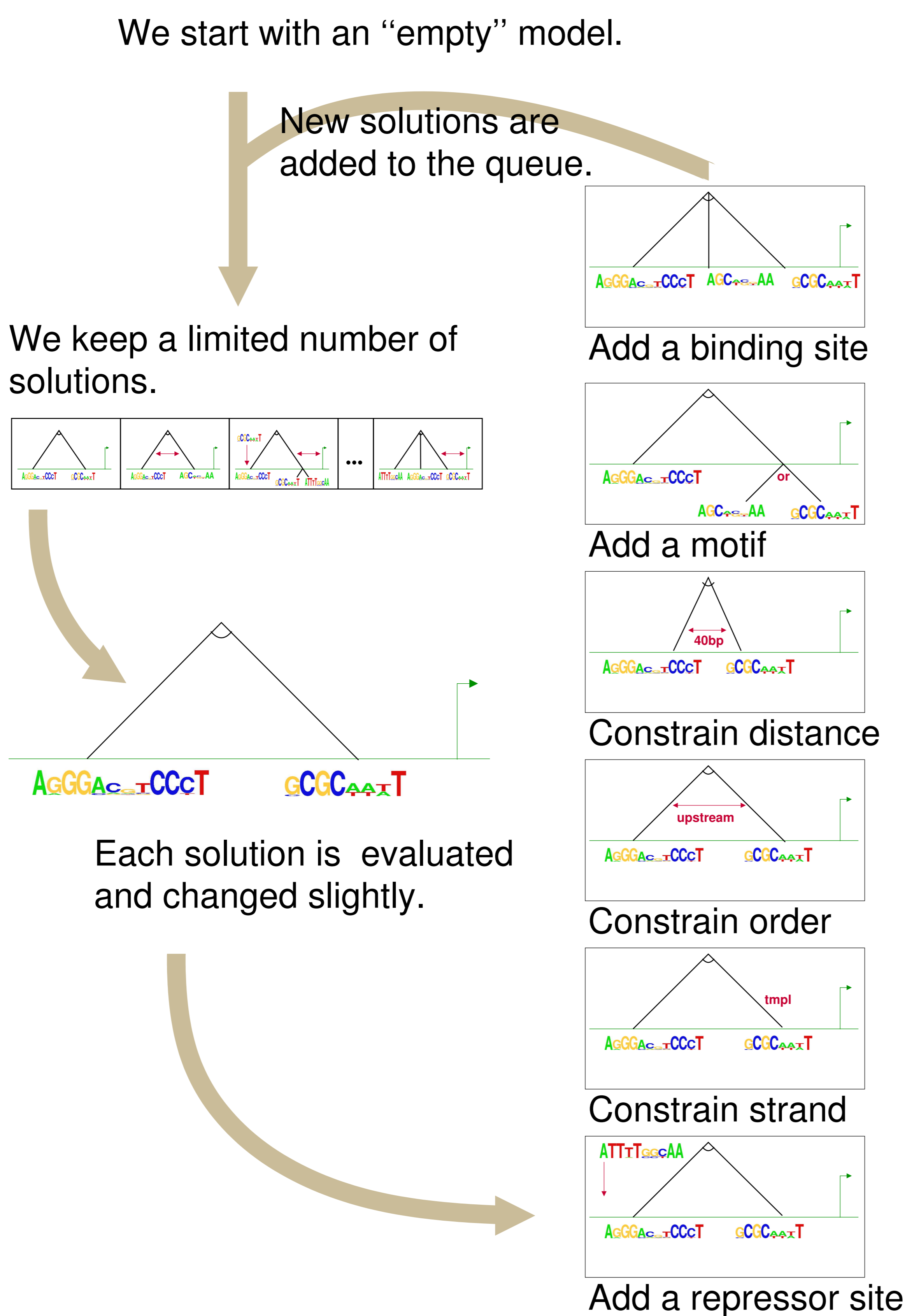


Given: A set of DNA sequences thought to contain a CRM, a set thought not to, and a set of motifs

Do: Learn a CRM model that distinguishes between positive and negative examples

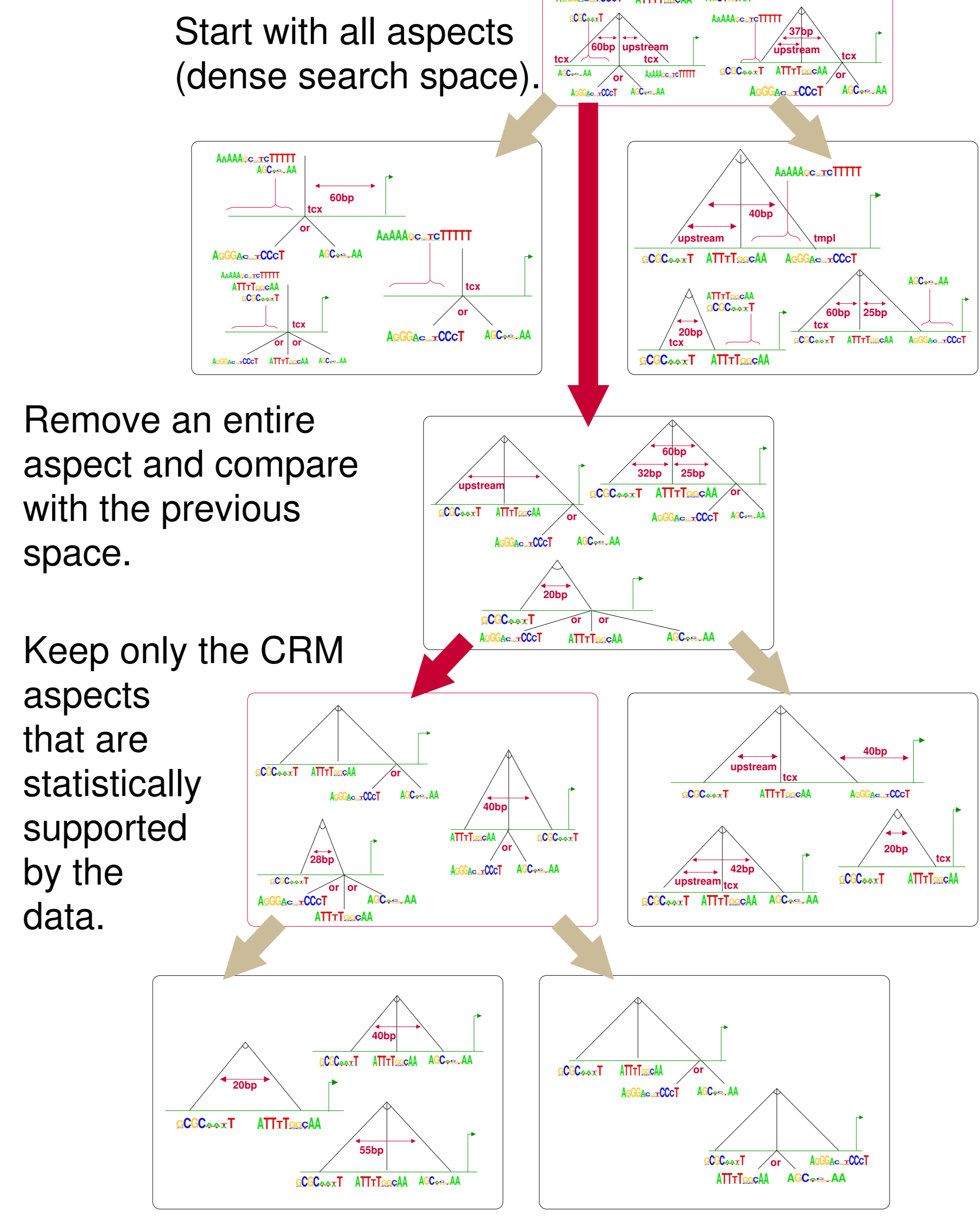


3. Learning a CRM Model



4. Controlling Expressivity

The CRM *aspects* determine the set of possible models. We decide on the set of aspects to employ using a held-aside validation set.



5. Results

We find significant CRMs (test set p-value < 0.01) in 17 of 25 data sets from *Saccharomyces cerevisiae*.

Data set	TP	FP	TN	FN	P	R	F1	p-value	Data set	TP	FP	TN	FN	P	R	F1	p-value
GAT3, RGM1	4	16	84	11	0.200	0.267	0.229	0.246783	GAL4, YAP5	8	2	98	8	0.800	0.500	0.615	7.95E-007
GAT3, PDR1	12	10	90	5	0.545	0.706	0.615	3.27E-007	CIN5, NRG1	14	13	87	4	0.519	0.778	0.622	7.11E-008
RGM1, YAP5	9	3	97	9	0.750	0.500	0.600	9.47E-007	NDI1, SWH4	11	12	88	11	0.478	0.500	0.489	0.000206
SKN7, SWH4	11	60	40	11	0.155	0.500	0.237	0.864014	PHD1, YAP5	11	23	77	12	0.324	0.478	0.386	0.018610
FKH2, SWH4	14	33	67	10	0.298	0.583	0.394	0.020587	PHD1, YAP5	15	25	75	9	0.375	0.625	0.469	0.000692
FHL1, YAP5	15	16	84	10	0.484	0.600	0.536	2.36E-005	FKH2, MCM1	15	16	84	10	0.484	0.600	0.536	2.36E-005
MBP1, NDD1	11	40	60	14	0.216	0.440	0.289	0.442532	ACE2, SWI5	42	17	83	9	0.712	0.824	0.764	4.22E-015
FKH2, MBP1	20	35	62	7	0.364	0.741	0.488	0.000460	MCM1, NDD1	21	20	80	7	0.512	0.750	0.609	1.26E-007
RAP1, YAP5	16	10	90	13	0.615	0.552	0.582	1.03E-006	NRG1, YAP6	16	41	59	14	0.281	0.533	0.368	0.162475
GAT3, YAP5	27	18	82	12	0.600	0.692	0.643	1.79E-008	CIN5, YAP6	25	30	70	15	0.455	0.625	0.526	0.000410
MBP1, SWH4	27	34	66	13	0.443	0.675	0.535	0.000305	SWH4, SWI6	28	63	37	15	0.308	0.651	0.418	0.482183
MBP1, SWI6	40	39	61	4	0.506	0.909	0.650	1.73E-009	FKH2, NDD1	34	77	23	16	0.306	0.680	0.422	0.915385
FHL1, RAP1	94	48	52	20	0.662	0.825	0.734	8.43E-008									

Data sets from Segal and Sharan, *A Discriminative Model for Identifying Spatial cis-Regulatory Modules*, RECOMB 2004.

Precision $P = TP / (TP + FP)$. Recall $R = TP / (TP + FN)$. F1 score = $2PR / (P + R)$.

All CRM aspects have predictive value. Each aspect, when removed from consideration during the search phase (previous section), tends to decrease the accuracy (test set F1 score) of the learned models.

