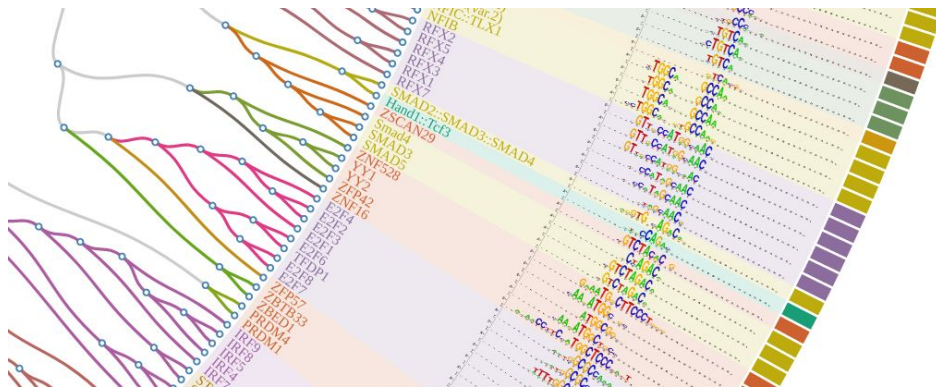


Sequence motifs



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What is a motif ?

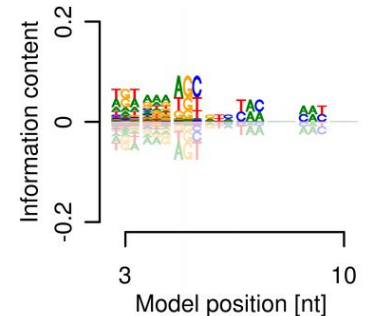
GCTCTTG
GCTTTAA
GTTATAA
GTTGTAA

In genomics, is a pattern found in a set of biological sequences.

G[CT]T[ACTG]T[AT][AG]

- String matching
- Regular expressions
- Consensus sequences
- Position frequency matrices
- Logos
- Complex representations:
 - HMM, deep learning, matrix factorization

GYTNTWR



String matching

- The simplest way to search for a string in a text.
 - In DNA, we have to search in both strands, or the RC of the string pattern.
-
- ✓ Fastest option to search simple (exact) patterns
 - ✗ Does not consider background neither nucleotide frequencies in the string.

Pattern: GTATATA

[illegible]

Pattern: TATATAC (Reverse complement)

[illegible]

Consensus IUPAC - Part 1

- A simple yet informative motif representation considering ambiguity.
 - Regular expression for biological sequences.
-
- ✓ Represents variability/ambiguity in the string
 - ✓ Multiple sequences can be represented in a single expression
 - ✗ Does not consider background probabilities

1	2	3	4	5	6	7
G	C	T	C	T	T	G
G	C	T	T	T	A	A
G	T	T	A	T	A	A
G	T	T	G	T	A	A

↓

GYTNTWR

Symbol	Meaning	Mnemonic
R	A, G	puRine
Y	C, T	pYrimidine
W	A, T	Weak (weaker basepairs, fewer hydrogen bonds)
S	G, C	Strong (stronger basepairs, more hydrogen bonds)
K	G or T	Keto (both have a keto group)
M	A or C	aMine (both have an amine group)
B	C, G, T	not A (B comes after A)
D	A, G, T	not C (D comes after C)
A	A, C, T	not G (H comes after G)
V	A, C, G	not T or U (V comes after T and U)
N	A, C, G, T	aNy base

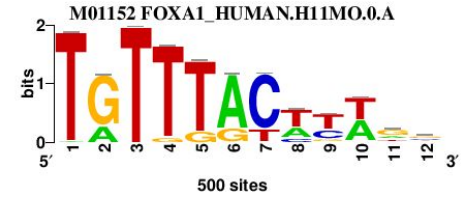
Table 2.1: IUPAC codes for nucleotides. In this table, everywhere that T applies, U applies as well.

Consensus IUPAC - Part 2

- FOXA1

- TGTTTACWYWGS
- SCWRWGTAAACA

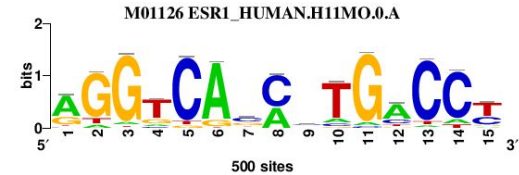
TGTTTAC[AT][CT][AT]G[CG]
[CG]C[AT][AG][AT]GTAAACA



- ESR1

- RGGTCASMSTGACCY
- RGGTCASKSTGACCY

[AG]GGTCA[CG][AC][CG]TGACC[CT]
[AG]GGTCA[CG][GT][CG]TGACC[CT]








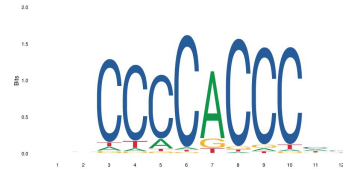
Sequence complexity

- Low complexity sequences
 - Short repetitive elements
 - Many of them with biological function
 - Sequencing artifacts (contamination)
- Complexity is related to the possible number of sequences of a given string
- Confound sequence analysis
- Problematic for genome assembly

$$C_{WF} = \frac{1}{N} \log_D \left(\frac{N!}{n_A! n_C! n_G! n_T!} \right)$$

Wootton-Federhen complexity score






Motif #	Motif Logo	P-value	% of Targets	% of Background	Description
1		1e-621	12.61%	1.15%	Low-complexity (poly-A)
2		1.0E-61	4.34%	1.47%	Low-complexity (poly-G/A)
3		1.0E-44	0.59%	0.02%	Low-complexity (GA-rich)
4		1.0E-35	15.01%	10.30%	Similar to CCAATT-box
5		1.0E-24	6.62%	4.02%	Low-complexity (AT-rich)



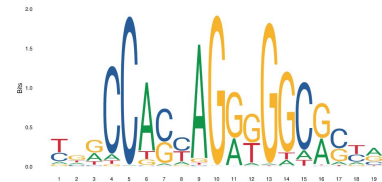
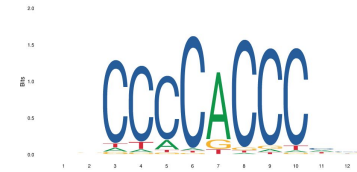
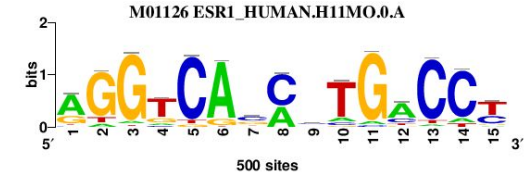
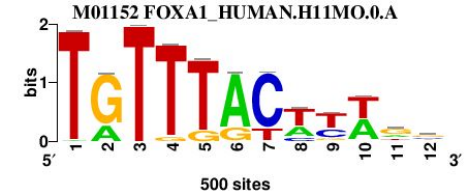
Many TFs (Kruppel-like) bind low-complexity sequences.

Sequence complexity

Name	Sequence	WF
Poly-A	AAAAAAAAA	0.0000000
KLF4	CCCCACCC	0.1875000
GA-rich	GAGAGAGAGA	0.3988640
FOXA1	TGTTTACTTT	0.4745927
ESR1	AGGTCACCCTGACCT	0.7667800
CTCF	TGGCCACCAGGGGGGCGCTA	0.7468272

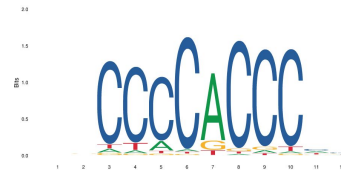
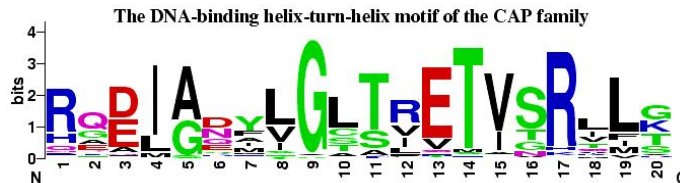
Motif #	Motif Logo	P-value	% of Targets	% of Background	Description
1		1e-621	12.61%	1.15%	Low-complexity (poly-A)
2		1.0E-61	4.34%	1.47%	Low-complexity (poly-G/A)
3		1.0E-44	0.59%	0.02%	Low-complexity (GA-rich)
4		1.0E-35	15.01%	10.30%	Similar to CCAATT-box
5		1.0E-24	6.62%	4.02%	Low-complexity (AT-rich)

$$C_{WF} = \frac{1}{N} \log_D \left(\frac{N!}{n_A! n_C! n_G! n_T!} \right)$$



Position Frequency/Weight Matrices

- The most used model for biological sequences.
 - Probabilistic representation of sequences.
 - A simple matrix representing the nucleotide/aminoacid frequencies along a sequence.
 - Represent TF binding motifs, TSSs, Core-promoter elements, Splice sites, Amino-acid domains, etc.
-
- ✓ Intuitive and simple representation
 - ✓ Allow to integrate background frequencies
 - ✗ Assumes independency among nucleotides/aminoacids.



GCTCTTG
GCTTTAA
GTTATAA
GTTGTAA



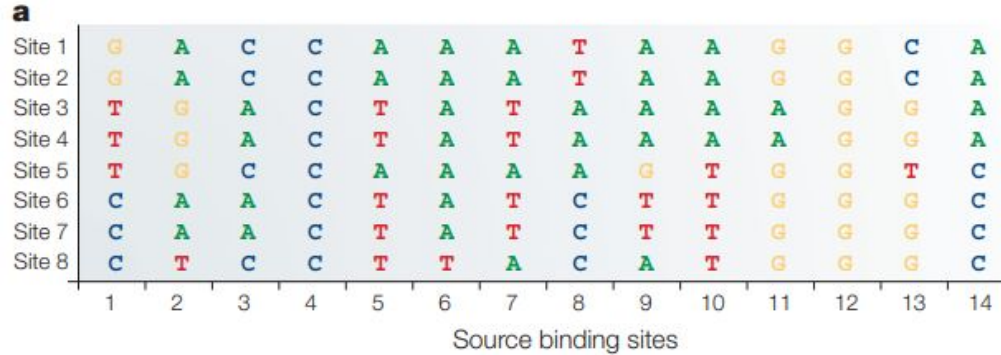
GYTNTWR

G T T AA

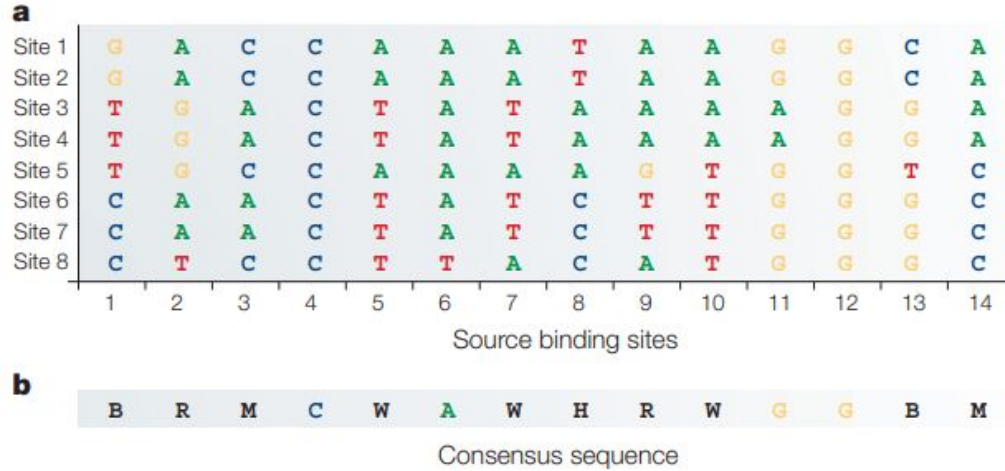
Position Frequency/Weight Matrices

A collection of known sites, aligned and with the same length.

Experimentally validated or predicted.

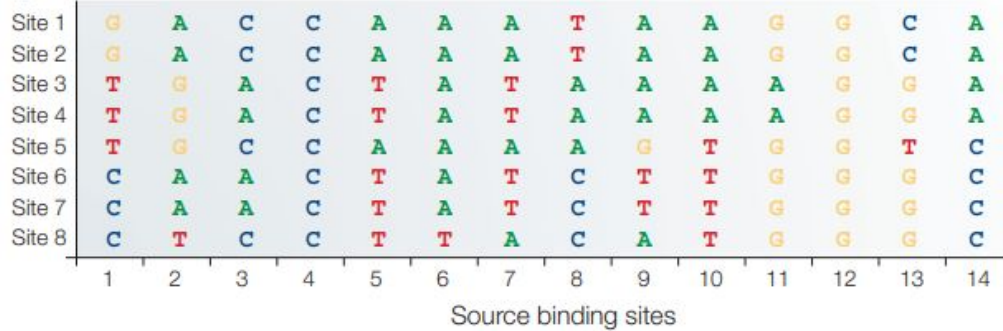


Position Frequency/Weight Matrices

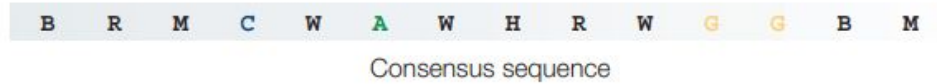


Position Frequency/Weight Matrices

a



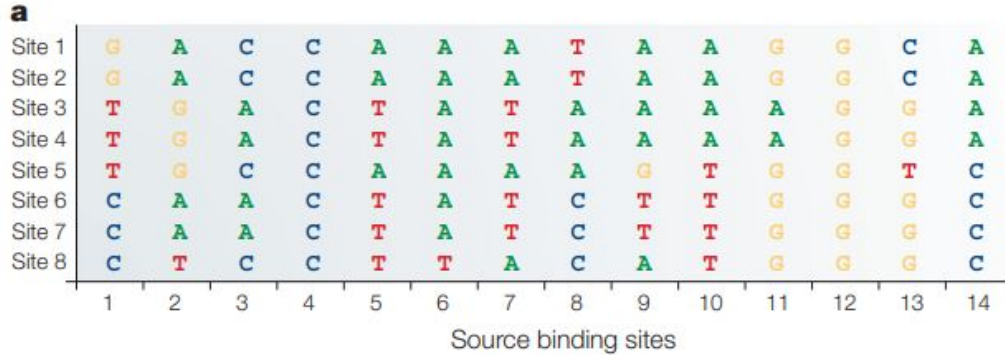
b



c Position frequency matrix (PFM)

	1	2	3	4	5	6	7	8	9	10	11	12	13	14
A	0	4	4	0	3	7	4	3	5	4	2	0	0	4
C	3	0	4	8	0	0	0	3	0	0	0	0	2	4
G	2	3	0	0	0	0	0	0	1	0	6	8	5	0
T	3	1	0	0	5	1	4	2	2	4	0	0	1	0

Position Frequency/Weight Matrices



b

B R M C W A W H R W G G B M

Consensus sequence

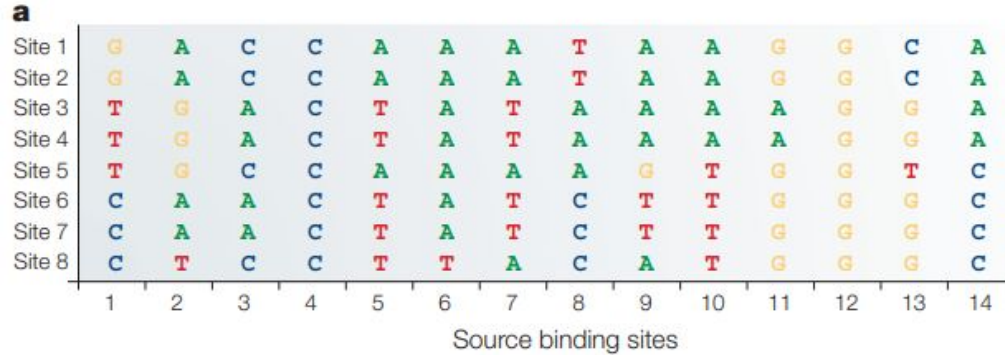
c Position frequency matrix (PFM)

	1	2	3	4	5	6	7	8	9	10	11	12	13	14
A	0	4	4	0	3	7	4	3	5	4	2	0	0	4
C	3	0	4	8	0	0	0	3	0	0	0	0	2	4
G	2	3	0	0	0	0	0	0	1	0	6	8	5	0
T	3	1	0	0	5	1	4	2	2	4	0	0	1	0

PFM databases (for TF binding motifs)



Position Frequency/Weight Matrices



c Position frequency matrix (PFM)

	1	2	3	4	5	6	7	8	9	10	11	12	13	14
A	0	4	4	0	3	7	4	3	5	4	2	0	0	4
C	3	0	4	8	0	0	0	3	0	0	0	0	2	4
G	2	3	0	0	0	0	0	0	1	0	6	8	5	0
T	3	1	0	0	5	1	4	2	2	4	0	0	1	0

d Position weight matrix (PWM)

	1	2	3	4	5	6	7	8	9	10	11	12	13	14
A	-1.93	0.79	0.79	-1.93	0.45	1.50	0.79	0.45	1.07	0.79	0.00	-1.93	-1.93	0.79
C	0.45	-1.93	0.79	1.68	-1.93	-1.93	-1.93	0.45	-1.93	-1.93	-1.93	-1.93	0.00	0.79
G	0.00	0.45	-1.93	-1.93	-1.93	-1.93	-1.93	-1.93	0.66	-1.93	1.30	1.68	1.07	-1.93
T	0.15	0.66	-1.93	-1.93	1.07	0.66	0.79	0.00	0.00	0.79	-1.93	-1.93	-0.66	-1.93

The transition from
Frequencies to
Weights requires a
background.



Background Models

- The expected frequencies of nucleotides/aminoacids.
- Indicates what are the sequences with higher probability to appear by chance.
- The values vary according the sequence context: promoters, exons, CpG islands.
- Can be modeled using markov chains of higher order (di-, tri- , k-nucleotides)

- Human genome (single nucleotide):
 - A: 0.204
 - C: 0.295
 - G: 0.296
 - T : 0.205

Dinucleotides in promoters

pr\suf	a	c	g	t	P_prefix
a	0.28516	0.20576	0.31378	0.19530	0.255
c	0.30680	0.28831	0.08174	0.32316	0.245
g	0.25648	0.24099	0.29096	0.21157	0.247
t	0.17107	0.24799	0.29850	0.28244	0.253

Transition frequencies

Background Models

- Probability of ATACGT

- Single: $(0.204^2) * (0.205^2) * 0.295 * 0.296 = 1.527e-04$

- Dinucleotide : $0.204 * 0.195 * 0.171 * 0.205 * 0.081 * 0.211 = 2.383e-05$
A (AT) (TA) (AC) (CG) (GT)

Human genome (single nucleotide):

- A: 0.204
- C: 0.295
- G: 0.296
- T : 0.205

Dinucleotides in promoters					P_prefix
pr\suf	a	c	g	t	
a	0.28516	0.20576	0.31378	0.19530	0.255
c	0.30680	0.28831	0.08174	0.32316	0.245
g	0.25648	0.24099	0.29096	0.21157	0.247
t	0.17107	0.24799	0.29850	0.28244	0.253

Transition frequencies

Position Frequency/Weight Matrices

a

Site 1	G	A	C	C	A	A	A	T	A	A	G	G	C	A
Site 2	G	A	C	C	A	A	A	T	A	A	G	G	C	A
Site 3	T	G	A	C	T	A	T	A	A	A	A	G	G	A
Site 4	T	G	A	C	T	A	T	A	A	A	A	G	G	A
Site 5	T	G	C	C	A	A	A	A	G	T	G	G	T	C
Site 6	C	A	A	C	T	A	T	C	T	T	G	G	G	C
Site 7	C	A	A	C	T	A	T	C	T	T	G	G	G	C
Site 8	C	T	C	C	T	T	A	C	A	T	G	G	G	C
	1	2	3	4	5	6	7	8	9	10	11	12	13	14

Source binding sites

b

B	R	M	C	W	A	W	H	R	W	G	G	B	M
---	---	---	---	---	---	---	---	---	---	---	---	---	---

Consensus sequence

c Position frequency matrix (PFM)

	1	2	3	4	5	6	7	8	9	10	11	12	13	14
A	0	4	4	0	3	7	4	3	5	4	2	0	0	4
C	3	0	4	8	0	0	0	3	0	0	0	0	2	4
G	2	3	0	0	0	0	0	0	1	0	6	8	5	0
T	3	1	0	0	5	1	4	2	2	4	0	0	1	0

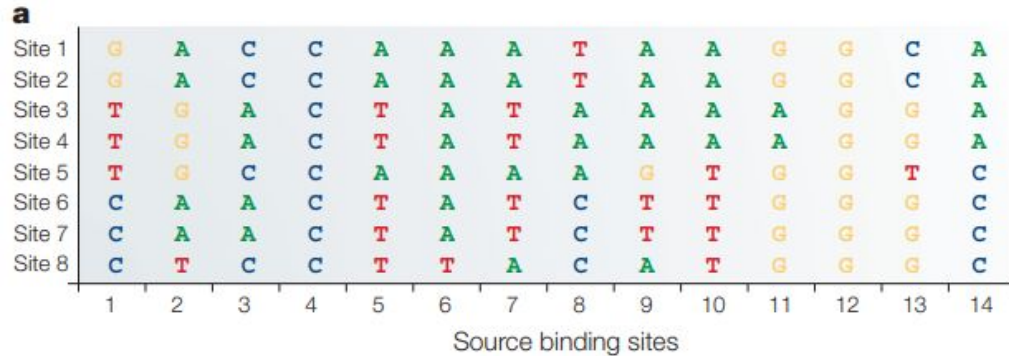
$$W_{i,j} = \ln \left(\frac{f'_{i,j}}{p_i} \right)$$

d Position weight matrix (PWM)

A	-1.93	0.79	0.79	-1.93	0.45	1.50	0.79	0.45	1.07	0.79	0.00	-1.93	-1.93	0.79
C	0.45	-1.93	0.79	1.68	-1.93	-1.93	-1.93	0.45	-1.93	-1.93	-1.93	-1.93	0.00	0.79
G	0.00	0.45	-1.93	-1.93	-1.93	-1.93	-1.93	-1.93	0.66	-1.93	1.30	1.68	1.07	-1.93
T	0.15	0.66	-1.93	-1.93	1.07	0.66	0.79	0.00	0.00	0.79	-1.93	-1.93	-0.66	-1.93

f : probabilities of each nucleotide in the PFM
p : background frequencies

Position Frequency/Weight Matrices

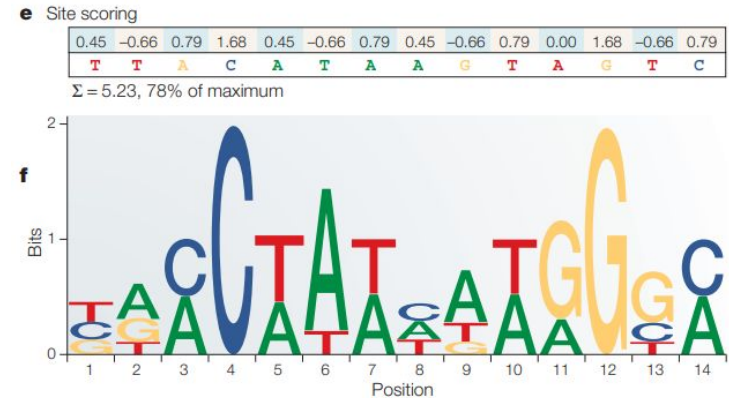


c Position frequency matrix (PFM)

	1	2	3	4	5	6	7	8	9	10	11	12	13	14
A	0	4	4	0	3	7	4	3	5	4	2	0	0	4
C	3	0	4	8	0	0	0	3	0	0	0	0	2	4
G	2	3	0	0	0	0	0	0	1	0	6	8	5	0
T	3	1	0	0	5	1	4	2	2	4	0	0	1	0

d Position weight matrix (PWM)

A	-1.93	0.79	0.79	-1.93	0.45	1.50	0.79	0.45	1.07	0.79	0.00	-1.93	-1.93	0.79
C	0.45	-1.93	0.79	1.68	-1.93	-1.93	-1.93	0.45	-1.93	-1.93	-1.93	-1.93	0.00	0.79
G	0.00	0.45	-1.93	-1.93	-1.93	-1.93	-1.93	-1.93	0.66	-1.93	1.30	1.68	1.07	-1.93
T	0.15	0.66	-1.93	-1.93	1.07	0.66	0.79	0.00	0.00	0.79	-1.93	-1.93	-0.66	-1.93



Position Frequency/Weight Matrices

c Position frequency matrix (PFM)

	1	2	3	4	5	6	7	8	9	10	11	12	13	14
A	0	4	4	0	3	7	4	3	5	4	2	0	0	4
C	3	0	4	8	0	0	0	3	0	0	0	0	2	4
G	2	3	0	0	0	0	0	0	1	0	6	8	5	0
T	3	1	0	0	5	1	4	2	2	4	0	0	1	0

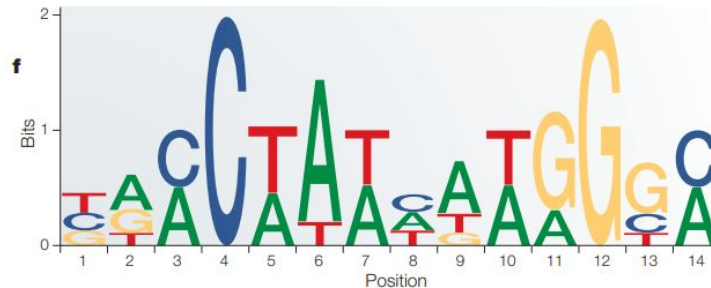
d Position weight matrix (PWM)

A	-1.93	0.79	0.79	-1.93	0.45	1.50	0.79	0.45	1.07	0.79	0.00	-1.93	-1.93	0.79
C	0.45	-1.93	0.79	1.68	-1.93	-1.93	-1.93	0.45	-1.93	-1.93	-1.93	-1.93	0.00	0.79
G	0.00	0.45	-1.93	-1.93	-1.93	-1.93	-1.93	-1.93	0.66	-1.93	1.30	1.68	1.07	-1.93
T	0.15	0.66	-1.93	-1.93	1.07	0.66	0.79	0.00	0.00	0.79	-1.93	-1.93	-0.66	-1.93

e Site scoring

0.45	-0.66	0.79	1.68	0.45	-0.66	0.79	0.45	-0.66	0.79	0.00	1.68	-0.66	0.79
T	T	A	C	A	T	A	A	G	T	A	G	T	C

$\Sigma = 5.23$, 78% of maximum

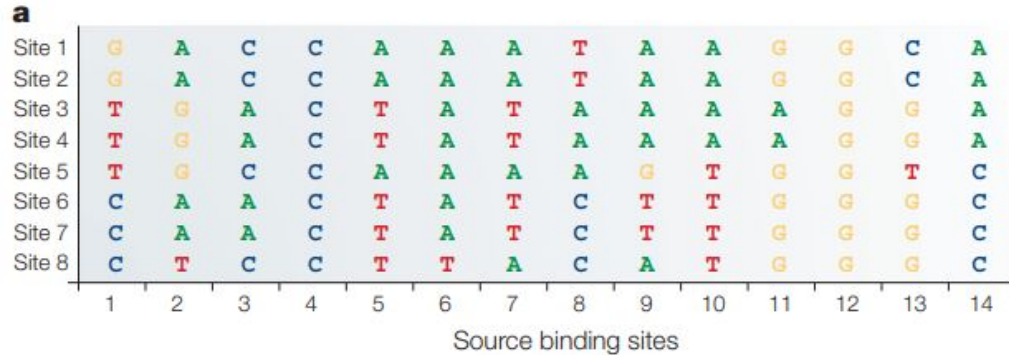


Probability given the Frequency matrix

$$S(x_j) = \log \left(\frac{P(x|M)}{P(x|R)} \right) = \sum_{i=1}^K \log \left(\frac{f_{ix_j[i]}}{p_{x_j[i]}} \right)$$

Probability given the Background model

Position Frequency/Weight Matrices

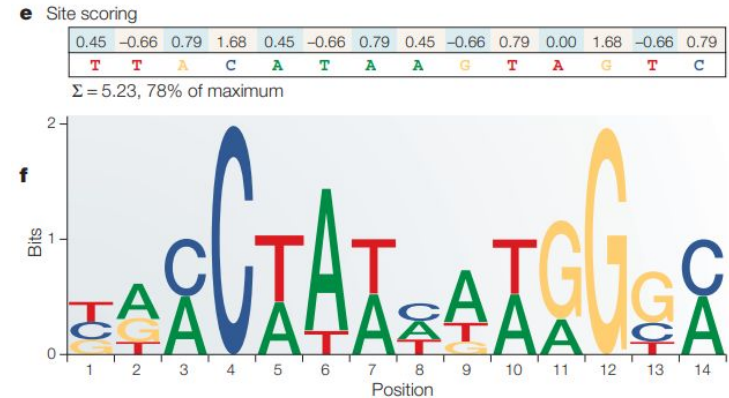


c Position frequency matrix (PFM)

	1	2	3	4	5	6	7	8	9	10	11	12	13	14
A	0	4	4	0	3	7	4	3	5	4	2	0	0	4
C	3	0	4	8	0	0	0	3	0	0	0	0	2	4
G	2	3	0	0	0	0	0	0	1	0	6	8	5	0
T	3	1	0	0	5	1	4	2	2	4	0	0	1	0

d Position weight matrix (PWM)

A	-1.93	0.79	0.79	-1.93	0.45	1.50	0.79	0.45	1.07	0.79	0.00	-1.93	-1.93	0.79
C	0.45	-1.93	0.79	1.68	-1.93	-1.93	-1.93	0.45	-1.93	-1.93	-1.93	-1.93	0.00	0.79
G	0.00	0.45	-1.93	-1.93	-1.93	-1.93	-1.93	-1.93	0.66	-1.93	1.30	1.68	1.07	-1.93
T	0.15	0.66	-1.93	-1.93	1.07	0.66	0.79	0.00	0.00	0.79	-1.93	-1.93	-0.66	-1.93



Sites with $W > 0$ could be potential binding sites

Max score: 14.22

Information Content (IC)

$$H_g = - \sum_{i=1}^A p_i \log_2(p_i)$$

- Shannon entropy is a measure of the uncertainty of a model
- Special cases of uncertainty (for a 4 letter alphabet):
 - **min(H) = 0**
No uncertainty at all: the nucleotide is completely specified (e.g. $p=\{1, 0, 0, 0\}$)
 - **H=1**
Uncertainty between two letters (e.g. $p= \{0.5, 0, 0, 0.5\}$)
 - **max(H) = 2**
Complete uncertainty (e.g. $p= \{0.25, 0.25, 0.25, 0.25\}$)

$$H_{max} = - \left(\frac{1}{4} \log_2 \left(\frac{1}{4} \right) + \frac{1}{4} \log_2 \left(\frac{1}{4} \right) + \frac{1}{4} \log_2 \left(\frac{1}{4} \right) + \frac{1}{4} \log_2 \left(\frac{1}{4} \right) \right)$$

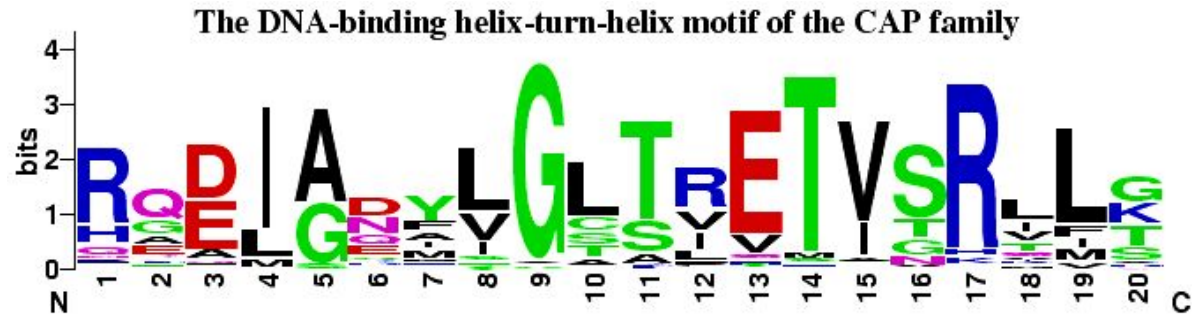
- Information content (IC) of a PFM is the sum of the differences between the Max Entropy and the observed entropy on each column.
 - $IC = H_{max} - H_g$

Information Content (IC)

- Shannon entropy is a measure of the uncertainty of a model
- Special cases of uncertainty (for a 20 letter alphabet, aminoacids):
 - **$\max(H) = 4.32$**

$$H_g = - \sum_{i=1}^A p_i \log_2(p_i)$$

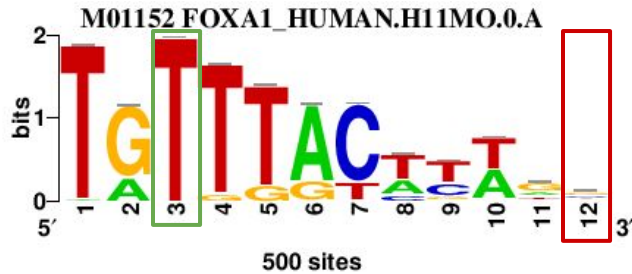
$$H_{\max} = -(1/20 * \log_2(1/20)) * 20$$



Information Content (IC) - Examples

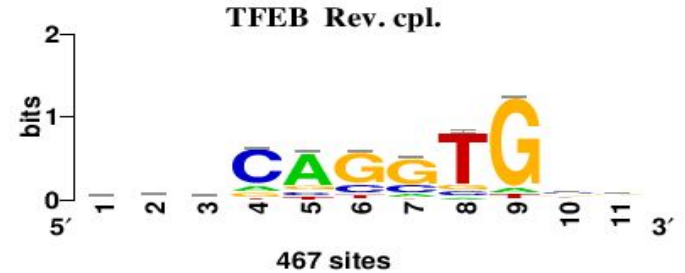
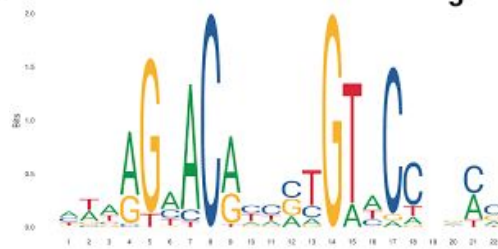
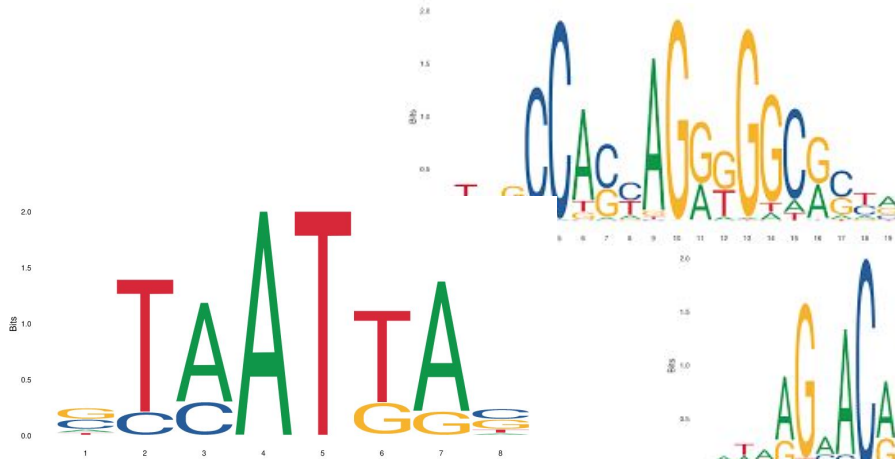
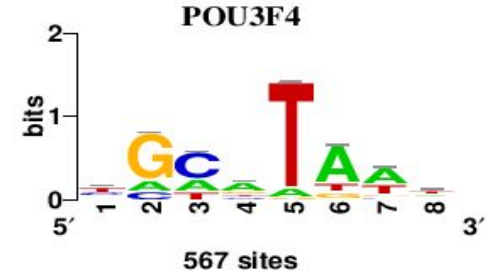
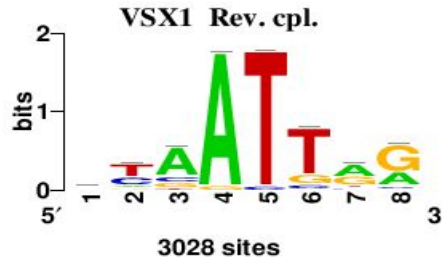
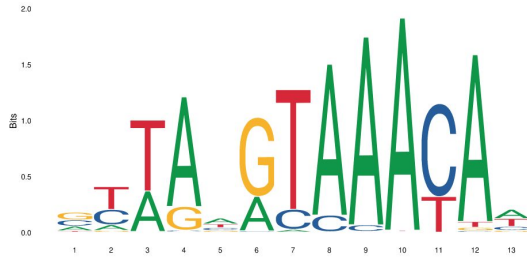
A	8	123	1	2	0	391	4	159	16	232	109	54
C	0	2	0	0	0	0	399	69	157	10	49	130
G	0	375	0	28	72	103	4	2	54	8	247	197
T	492	0	499	470	428	6	93	270	273	250	95	119
	1	2	3	4	5	6	7	8	9	10	11	12

$$H_g = - \sum_{i=1}^A p_i \log_2(p_i)$$



- $IC = H_{\max} - H_g$
- $IC_3: 2 + (1/500 * \log_2(1/500)) + 0 + 0 + (499/500 * \log_2(499/500)) = 1.97$
- $IC_{12}: 2 + (54/500 * \log_2(54/500)) + (130/500 * \log_2(130/500)) + (197/500 * \log_2(197/500)) + (119/500 * \log_2(119/500)) = 0.12$

Information Content (IC) - Examples



Motif analysis algorithms



<https://github.com/daquang/YAMDA>



<http://autosome.ru/ChIPMunk/>



<http://rsat-tagc.univ-mrs.fr/rsat/>



<http://homer.ucsd.edu/homer/motif/>



<https://meme-suite.org/meme/>

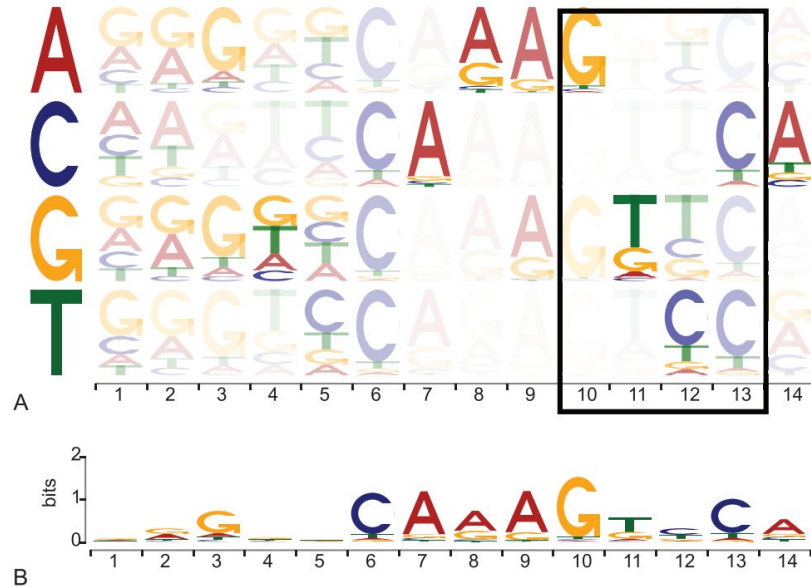
GimmeMotifs

<https://github.com/vanheeringen-lab/gimmemotifs>

Complex representation of motifs

HMM

Mathelier 2013



Nucleotide dependencies are modelled

Complex representation of motifs

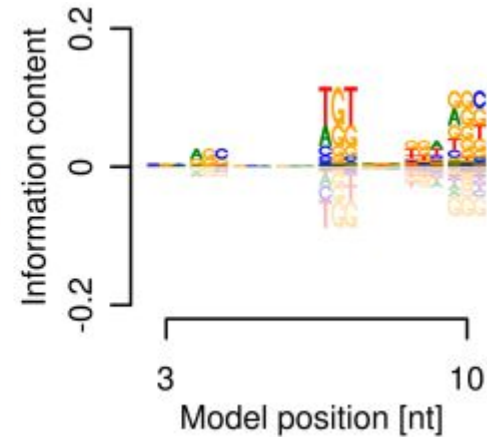
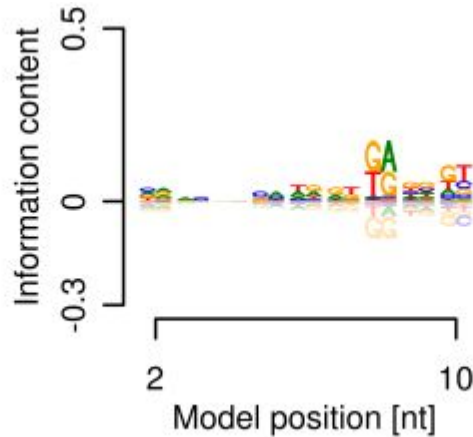
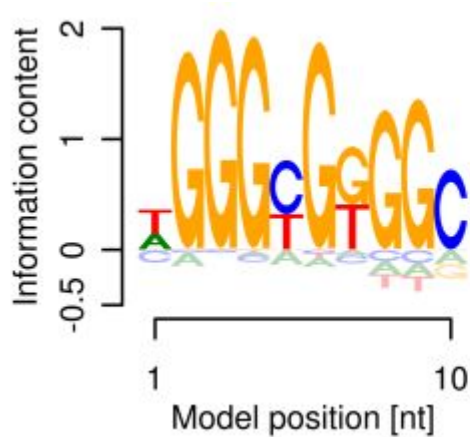
Supports long
k-mers

Bayesian Markov Models

Siebert 2016

$$\begin{aligned}
 & \dots \boxed{\text{A} \text{ T C G C T A}} \dots & p_j^{(0)}(\text{A}) &= \frac{n_j(\text{A}) + \alpha_0 p_{\text{bg}}(\text{A})}{N + \alpha_0} \\
 & \dots \boxed{\text{A} \text{ T C G C T}} \boxed{\text{A}} \dots & p_j^{(1)}(\text{A}|\text{T}) &= \frac{n_j(\text{TA}) + \alpha_1 p_j^{(0)}(\text{A})}{n_{j-1}(\text{T}) + \alpha_1} \\
 & \dots \boxed{\text{A} \text{ T C G C T}} \boxed{\text{A}} \dots & p_j^{(2)}(\text{A}|\text{CT}) &= \frac{n_j(\text{CTA}) + \alpha_2 p_j^{(1)}(\text{A}|\text{T})}{n_{j-1}(\text{CT}) + \alpha_2} \\
 & \dots \boxed{\text{A} \text{ T C G C T}} \boxed{\text{A}} \dots & p_j^{(3)}(\text{A}|\text{GCT}) &= \frac{n_j(\text{GCTA}) + \alpha_3 p_j^{(2)}(\text{A}|\text{CT})}{n_{j-1}(\text{GCT}) + \alpha_3} \\
 & & & \vdots
 \end{aligned}$$

Pseudo-counts



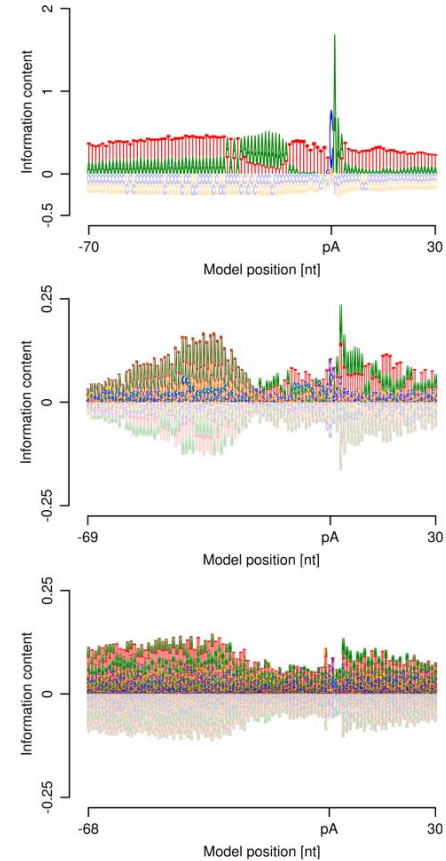
Complex representation of motifs

Bayesian Markov Models

Siebert 2016

Supports long k-mers

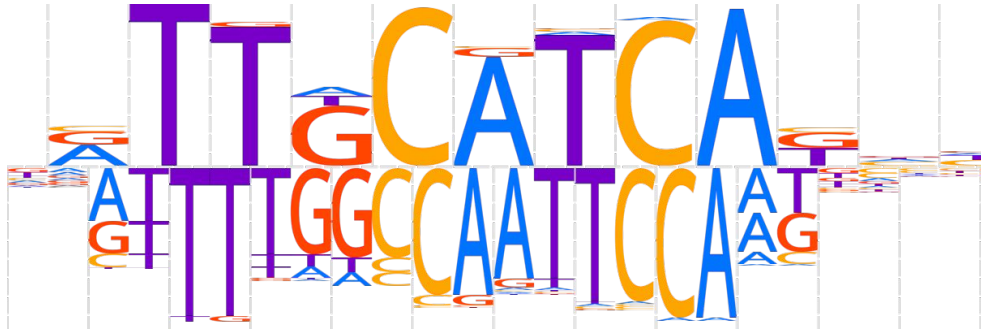
Ideal to visualize dependencies in long sequences, e.g, promoters, poly-A sites



Complex representation of motifs

Dinucleotide PWMs

Kulakovskiy 2018

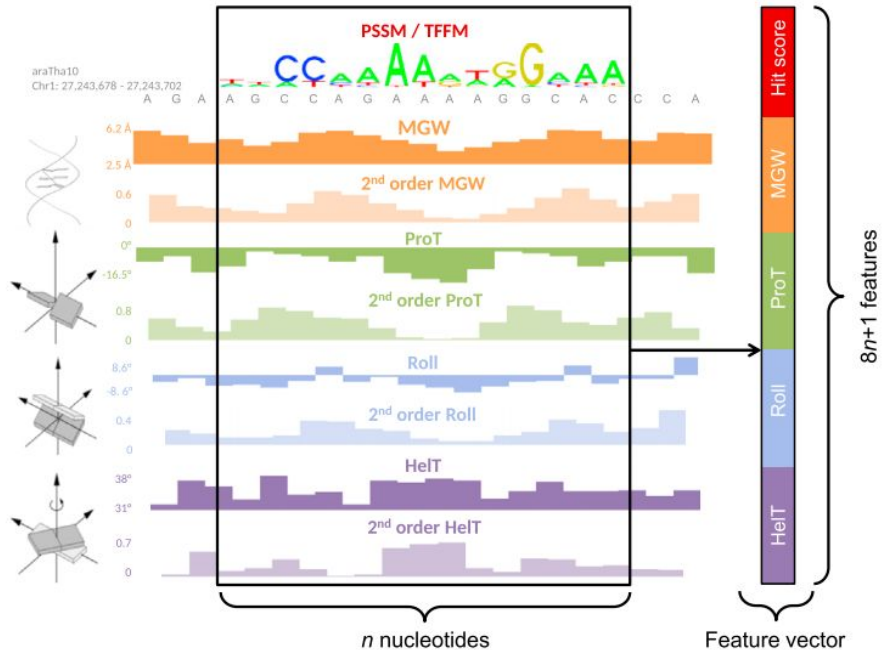


	AA	AC	AG	AT	CA	CC	CG	CT	GA	GC	GG	GT	TA	TC	TG	TT
01	38.0	11.0	44.0	0.0	51.0	15.0	10.0	3.0	86.0	15.0	43.0	3.0	70.0	22.0	53.0	3.0
02	0.0	0.0	0.0	245.0	0.0	0.0	0.0	63.0	0.0	0.0	0.0	150.0	0.0	0.0	0.0	9.0
03	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	17.0	450.0
04	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	8.0	0.0	1.0	8.0	46.0	0.0	354.0	50.0
05	0.0	54.0	0.0	0.0	0.0	0.0	0.0	0.0	1.0	353.0	1.0	0.0	0.0	58.0	0.0	0.0
06	0.0	0.0	1.0	0.0	423.0	5.0	34.0	3.0	0.0	1.0	0.0	0.0	0.0	0.0	0.0	0.0
07	10.0	5.0	4.0	404.0	0.0	0.0	0.0	6.0	0.0	2.0	0.0	33.0	0.0	0.0	0.0	3.0
08	1.0	9.0	0.0	0.0	0.0	7.0	0.0	0.0	0.0	4.0	0.0	0.0	9.0	436.0	0.0	1.0
09	9.0	0.0	1.0	0.0	454.0	0.0	1.0	1.0	0.0	0.0	0.0	0.0	1.0	0.0	0.0	0.0
10	7.0	59.0	186.0	212.0	0.0	0.0	0.0	0.0	0.0	1.0	0.0	1.0	1.0	0.0	0.0	0.0
11	1.0	4.0	1.0	2.0	13.0	28.0	3.0	16.0	62.0	82.0	15.0	27.0	34.0	80.0	50.0	49.0
12	26.0	37.0	16.0	31.0	26.0	85.0	8.0	75.0	13.0	28.0	11.0	17.0	6.0	37.0	16.0	35.0
13	15.0	15.0	27.0	14.0	67.0	48.0	13.0	59.0	17.0	13.0	10.0	11.0	24.0	44.0	38.0	52.0

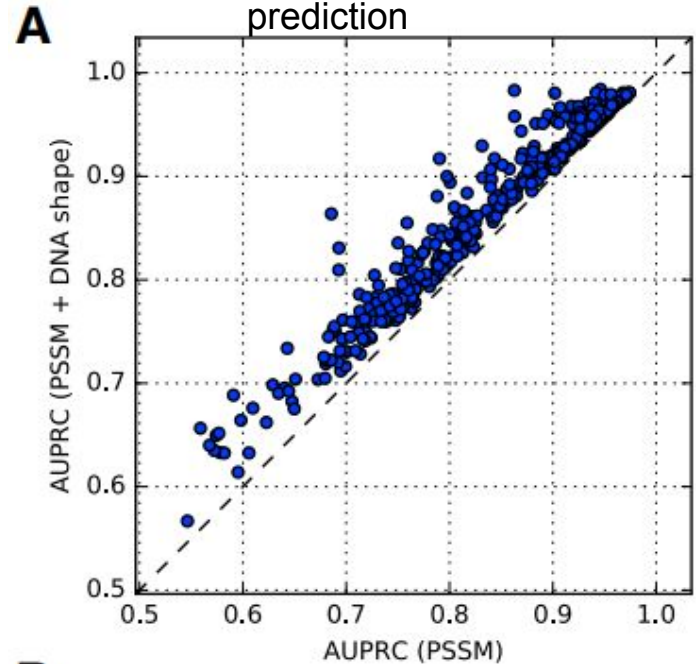
Complex representation of motifs

Combining PFMs + DNashape

Mathelier 2016

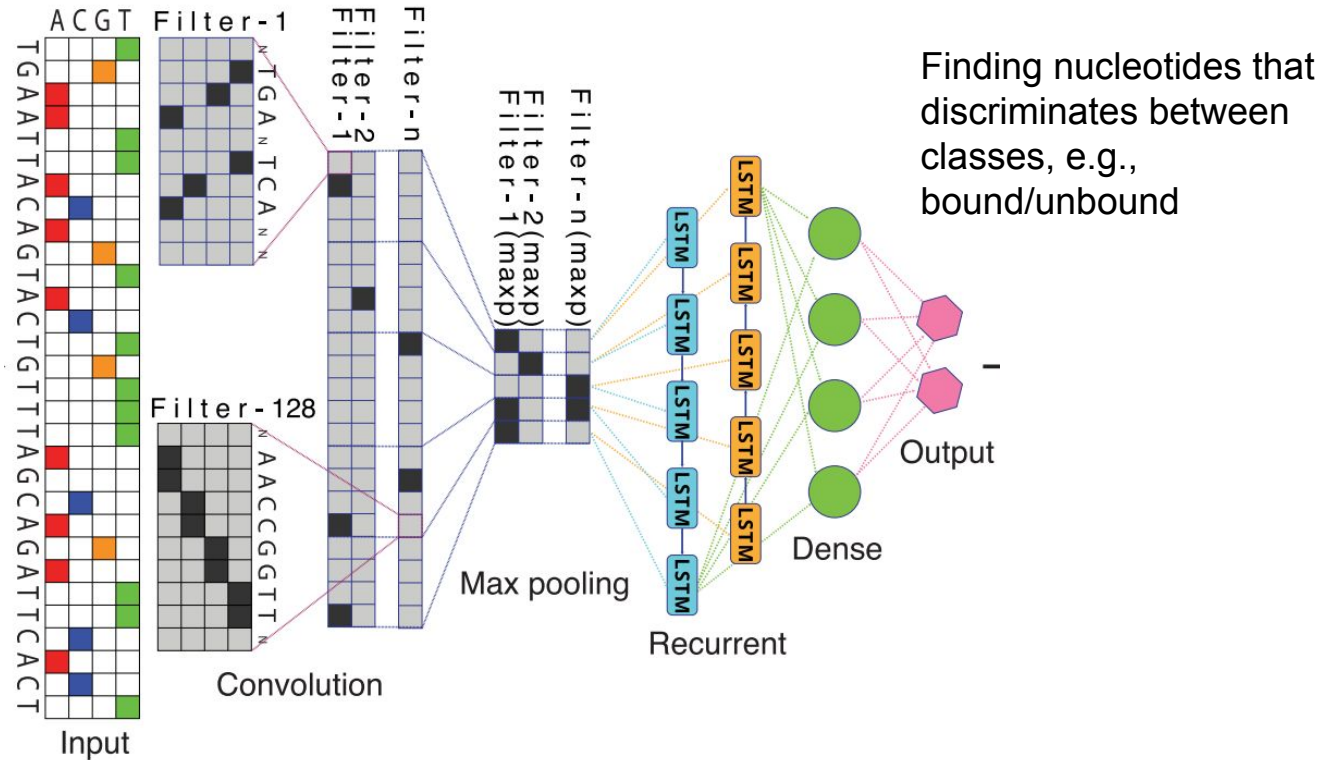


Adding TFBS shape information improves TFBS prediction

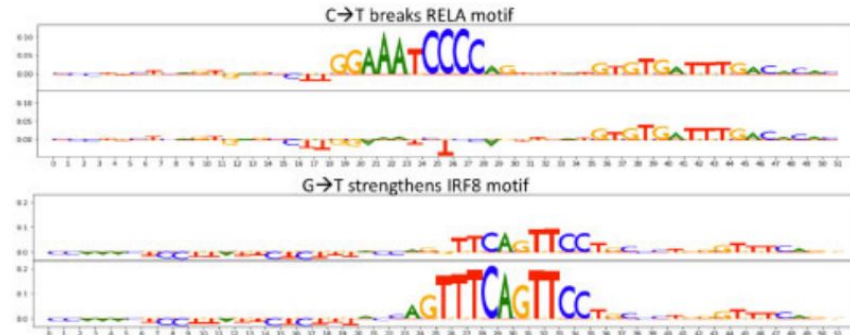
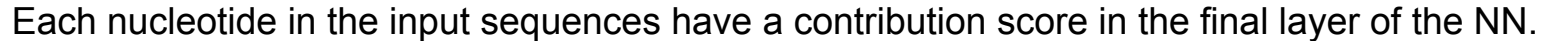


Complex representation of motifs

Motifs derived from deep learning models



Shrikumar 2019



Take-home messages

- Modelling sequences by motifs is an old but still relevant field in bioinformatics (... and it will be always relevant)
- PFMs are still the most used sequence model so far, although more complex alternatives are becoming popular.
- Complex motif representations are not as popular as PFMs, however, they improve TFBSs predictions for particular TF families.
 - No uniform model
 - Many parameters
 - Require large amount of sequences to train
- Methods assessing importance scores allow to detect motif relationship such as motif syntax.
- There is a lot of room for improvement, since many methods were designed to work with the PFMs and not with the more complex models.

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<https://mathelierlab.com/>

