The information content is related to the number of *binary decisions* required to find the information.

The number of binary decisions (= number of questions whose answer is yes/no) required to find the correct element in a set of N elements is:

$$n_q = \log_2 N$$

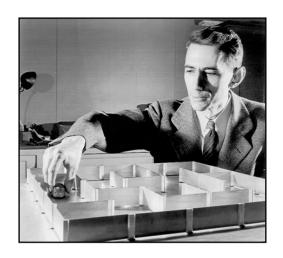
Example: consider the 4 nucleotides, {A,C,G,T}.

John: I have a nucleotide in mind. Guess which one!

Mike: is it A or T?

John: no! Mike: is it G? John: yes!

Thus, $log_2 4 = 2$ questions where necessary to find unambiguously the right nucleotide.



Claude Elwood Shannon (1916-2001)

If we had *N* elements, we first ask if the hidden element is among the N/2 first elements, then in the N/4 left elements, then in N/8 elements, etc, till we reach the 1 correct element. There are thus

$$n_q = 1(N/2?) + 1(N/4?) + 1(N/8?) + ... 1(N/N)$$

= 1(N/2?)+1(N/2²?)+1(N/2³?)+ ... 1 (N/2log₂N)
= log₂N

questions to ask.

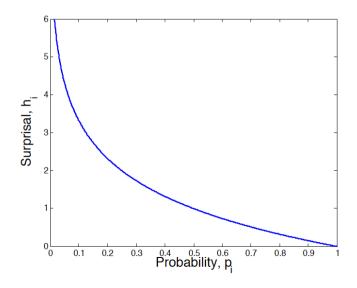
If each element has the same probability, then this probability is p=1/N, and

$$n_q = \log_2 N = -\log_2 p$$

In general the elements are not equally likely; they have different probabilities, p_i .

Tribus (1961) then generalizes the formula here above by introducing the concept of "surprisal" h_i:

$$h_i = -\log_2 p_i$$



Interpretation:

- if p_i approaches 0, then we will be very surprised to see the ith symbol (since it should almost never appear), and the formula says h_i approaches ∞.
- if p_i =1, then we won't be surprised at all to see the ith symbol (because it should always appear) and h_i = 0.

If each element has the same probability, then this probability is p=1/N, and

$$n_q = \log_2 N = -\log_2 p$$

In general the elements are not equally likely; they have different probabilities, p_i .

Tribus (1961) then generalizes the formula here above by introducing the concept of "surprisal" h_i:

$$h_i = -\log_2 p_i$$

On this basis, Shannon introduced the "uncertainty measure" (also called "entropy"), which is the average of all suprisals h_i weighted by their occurrence p_i :

$$H = \sum_{i} p_i h_i = -\sum_{i} p_i \log_2 p_i$$

Special cases of uncertainty (shown here for a 4 letter alphabet, {A,C,G,T})

p={1,0,0,0} H=min(H)=0

No uncertainty at all: the nucleotide is completely specified.

p={0.5,0,0,0.5}

H=1

Uncertainty between two letters

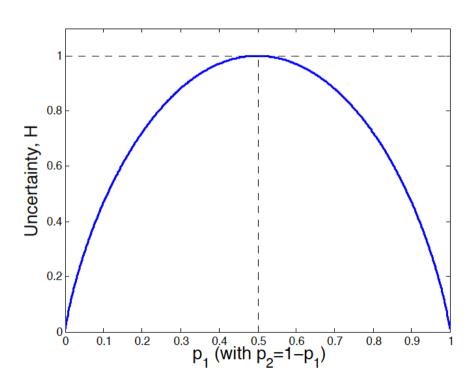
p={0.25,0.25,0.25,0.25}

H=max(H)=2

Complete uncertainty

Case of 2 symbols:

Uncertainty H for the case of 2 symbols, as a function of the probability p_1 of one symbol (with $p_2=1-p_1$).



Exercise

Calculate the uncertainty of the following probability sets:

p={1/2,1/4,1/8,1/8}

p={1/2,1/6,1/6,1/6}

NB: For the second case, you will "certainly" need a computer...

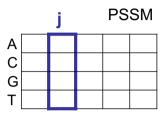
Check that the uncertainty is indeed comprised between 0 and 2 (= maximum uncertainty calculated above).

Shannon uncertainty applied to PSSM

Uncertainty of a column *j* of a PSSM:

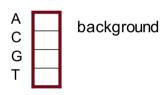
$$H_s(j) = -\sum_{i=1}^{A} f_{i,j} \log_2(f_{i,j})$$

 $H_s(j) = -\sum_{i=1}^{A} f_{i,j} \log_2(f_{i,j})$ A is the number of possible elements (4 letter for DNA, 20 for aa) and f_{ij} is the frequency of letter i in column j.



Uncertainty of the background (e.g. the GC content of a genome):

$$H_g = -\sum_{i=1}^{A} p_i \log_2(p_i)$$
 p_i is the background frequency of letter i.



Schneider (1986) defines an *information content* based on Shannon's uncertainty.

$$R_{seq}(j) = H_g - H_s(j)$$
 for column j

$$R_{seq} = \sum_{j=1}^{w} R_{seq}(j)$$
 for the PSSM

For skewed genomes (i.e. unequal residue probabilities), Schneider recommends an alternative formula for the information content.

$$R_{seq}^*(j) = \sum_{i=1}^{A} f_{ij} \log_2 \left(\frac{f_{ij}}{p_i}\right) \quad \text{for column } j \qquad R_{seq}^* = \sum_{j=1}^{w} R_{seq}^*(j) \quad \text{for the PSSM}$$

$$R_{seq}^* = \sum_{j=1}^w R_{seq}^*(j)$$
 for the PSSM

This is the formula that is nowadays used.

Shannon uncertainty applied to PSSM: example

Count matrix (TRANSFAC matrix F\$PHO4_01)

Residue\position	1	2	3	4	5	6	7	8	9	10	11	12
Α	1	3	2	0	8	0	0	0	0	0	1	2
С	2	2	3	8	0	8	0	0	0	2	0	2
G	1	2	3	0	0	0	8	0	5	4	5	2
T	4	1	0	0	0	0	0	8	3	2	2	2
Sum	8	8	8	8	8	8	8	8	8	8	8	8

Counts

$$f_{i,j} = \frac{n_{i,j}}{\sum_{i=1}^{A} n_{i,j}}$$

 $f_{i,j} = \frac{n_{i,j}}{\sum_{i=1}^{A} n_{i,j}}$ $A \quad alphabet \ size \ (=4)$ $occurrences \ of \ residue \ i \ at \ position \ j$ $p_i \quad prior \ residue \ probability \ for \ residue \ i$ $f_{i,j} \quad relative \ frequency \ of \ residue \ i \ at \ position \ j$ alphabet size (=4)relative frequency of residue i at position j

Pos	1	2	3	4	5	6	7	8	9	10	11	12
Α	0.13	0.38	0.25	0.00	1.00	0.00	0.00	0.00	0.00	0.00	0.13	0.25
С	0.25	0.25	0.38	1.00	0.00	1.00	0.00	0.00	0.00	0.25	0.00	0.25
G	0.13	0.25	0.38	0.00	0.00	0.00	1.00	0.00	0.63	0.50	0.63	0.25
Т	0.50	0.13	0.00	0.00	0.00	0.00	0.00	1.00	0.38	0.25	0.25	0.25
Sum	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00

Frequency

Shannon uncertainty applied to PSSM: example

Pos	1	2	3	4	5	6	7	8	9	10	11	12
Α	0.13	0.38	0.25	0.00	1.00	0.00	0.00	0.00	0.00	0.00	0.13	0.25
С	0.25	0.25	0.38	1.00	0.00	1.00	0.00	0.00	0.00	0.25	0.00	0.25
G	0.13	0.25	0.38	0.00	0.00	0.00	1.00	0.00	0.63	0.50	0.63	0.25
T	0.50	0.13	0.00	0.00	0.00	0.00	0.00	1.00	0.38	0.25	0.25	0.25
Sum	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00

Frequency

1st option: identically distributed pseudo-weight

$$f_{i,j}^{'} = \frac{n_{i,j} + k/A}{\sum_{i=1}^{A} n_{i,j} + k}$$

2nd option: pseudo-weight distributed according to residue priors

$$f'_{i,j} = \frac{n_{i,j} + p_i k}{\sum_{i=1}^{A} n_{i,j} + k}$$

 $A \\ n_{i,j,} \\ p_i \\ f_{i,j} \\ k \\ a$

alphabet size (=4)
occurrences of residue i at position j
prior residue probability for residue i
relative frequency of residue i at position j
pseudo weight (arbitrary, 1 in this case)
corrected frequency of residue i at position j

Pos	1	2	3	4	5	6	7	8	9	10	11	12
Α	0.15	0.37	0.26	0.04	0.93	0.04	0.04	0.04	0.04	0.04	0.15	0.26
С	0.24	0.24	0.35	0.91	0.02	0.91	0.02	0.02	0.02	0.24	0.02	0.24
G	0.13	0.24	0.35	0.02	0.02	0.02	0.91	0.02	0.58	0.46	0.58	0.24
T	0.48	0.15	0.04	0.04	0.04	0.04	0.04	0.93	0.37	0.26	0.26	0.26
Sum	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00

Frequency (+pseudo-counts)

Shannon uncertainty applied to PSSM: example

Pos	1	2	3	4	5	6	7	8	9	10	11	12
Α	0.15	0.37	0.26	0.04	0.93	0.04	0.04	0.04	0.04	0.04	0.15	0.26
С	0.24	0.24	0.35	0.91	0.02	0.91	0.02	0.02	0.02	0.24	0.02	0.24
G	0.13	0.24	0.35	0.02	0.02	0.02	0.91	0.02	0.58	0.46	0.58	0.24
T	0.48	0.15	0.04	0.04	0.04	0.04	0.04	0.93	0.37	0.26	0.26	0.26
Sum	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00

Frequency (+pseudo-counts)

$$f_{i,j}' = \frac{n_{i,j} + p_i k}{\sum_{r=1}^{A} n_{r,j} + k}$$

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

A alphabet size
$$(=4)$$
 $n_{i,j}$, occurrences of residue i at position j
 p_i prior residue probability for residue i
 $f_{i,j}$ relative frequency of residue i at position j
 k pseudo weight (arbitrary, 1 in this case)
 $f_{i,j}$ corrected frequency of residue i at position j
 $W_{i,j}$ weight of residue i at position j

Prior	Pos	1	2	3	4	5	6	7	8	9	10	11	12
0.325	Α	-0.79	0.13	-0.23	-2.20	1.05	-2.20	-2.20	-2.20	-2.20	-2.20	-0.79	-0.23
0.175	С	0.32	0.32	0.70	1.65	-2.20	1.65	-2.20	-2.20	-2.20	0.32	-2.20	0.32
0.175	G	-0.29	0.32	0.70	-2.20	-2.20	-2.20	1.65	-2.20	1.19	0.97	1.19	0.32
0.325	T	0.39	-0.79	-2.20	-2.20	-2.20	-2.20	-2.20	1.05	0.13	-0.23	-0.23	-0.23
1.000	Sum	-0.37	-0.02	-1.02	-4.94	-5.55	-4.94	-4.94	-5.55	-3.08	-1.13	-2.03	0.19

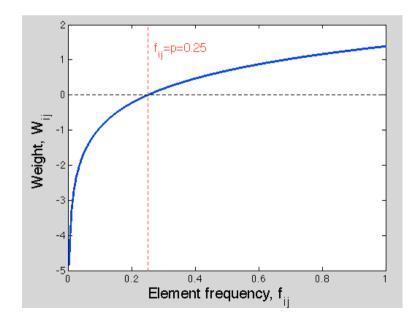
Position-weight matrix

log (frequency / background

Shannon uncertainty applied to PSSM: example

Prior	Pos	1	2	3	4	5	6	7	8	9	10	11	12
0.325	Α	-0.79	0.13	-0.23	-2.20	1.05	-2.20	-2.20	-2.20	-2.20	-2.20	-0.79	-0.23
0.175	С	0.32	0.32	0.70	1.65	-2.20	1.65	-2.20	-2.20	-2.20	0.32	-2.20	0.32
0.175	G	-0.29	0.32	0.70	-2.20	-2.20	-2.20	1.65	-2.20	1.19	0.97	1.19	0.32
0.325	Т	0.39	-0.79	-2.20	-2.20	-2.20	-2.20	-2.20	1.05	0.13	-0.23	-0.23	-0.23
1.000	Sum	-0.37	-0.02	-1.02	-4.94	-5.55	-4.94	-4.94	-5.55	-3.08	-1.13	-2.03	0.19

Positionweight matrix



$$W_{i,j} = \ln\left(\frac{f'_{i,j}}{p_i}\right) \left| f'_{i,j} = \frac{n_{i,j} + p_i k}{\sum_{i=1}^{A} n_{i,j} + k} \right| \qquad \sum_{i=1}^{A} f'_{i,j} = 1$$

The weight W_{ij} is:

- positive when f'_{i,j} > p_i
 (favourable positions for the binding of the transcription factor)
- negative when f'_{i,j} < p_i
 (unfavourable positions)

Shannon uncertainty applied to PSSM: example

Prior	Pos	1	2	3	4	5	6	7	8	9	10	11	12
0.325	Α	-0.79	0.13	-0.23	-2.20	1.05	-2.20	-2.20	-2.20	-2.20	-2.20	-0.79	-0.23
0.175	С	0.32	0.32	0.70	1.65	-2.20	1.65	-2.20	-2.20	-2.20	0.32	-2.20	0.32
0.175	G	-0.29	0.32	0.70	-2.20	-2.20	-2.20	1.65	-2.20	1.19	0.97	1.19	0.32
0.325	Т	0.39	-0.79	-2.20	-2.20	-2.20	-2.20	-2.20	1.05	0.13	-0.23	-0.23	-0.23
1.000	Sum	-0.37	-0.02	-1.02	-4.94	-5.55	-4.94	-4.94	-5.55	-3.08	-1.13	-2.03	0.19

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

Element (i,j) Information Content

$$I_{j} = \sum_{i=1}^{A} I_{i,j}$$

Column (j) Information Content

$$I_{matrix} = \sum_{j=1}^{w} \sum_{i=1}^{A} I_{i,j}$$

PSSM Information Content

Prior	Pos	1	2	3	4	5	6	7	8	9	10	11	12
0.325	Α	-0.12	0.05	-0.06	-0.08	0.97	-0.08	-0.08	-0.08	-0.08	-0.08	-0.12	-0.06
0.175	С	0.08	0.08	0.25	1.50	-0.04	1.50	0.04	-0.04	-0.04	0.08	-0.04	0.08
0.175	G	-0.04	0.08	0.25	-0.04	-0.04	-0.04	1.50	-0.04	0.68	0.45	0.68	0.08
0.325	Т	0.19	-0.12	-0.08	-0.08	-0.08	-0.08	-0.08	0.97	0.05	-0.06	-0.06	-0.06
1.000	Sum	0.11	0.09	0.36	1.29	0.80	1.29	1.29	0.80	0.61	0.39	0.47	0.04

Inform. content

Shannon uncertainty applied to PSSM: example

Prior	Pos	1	2	3	4	5	6	7	8	9	10	11	12
0.325	Α	-0.12	0.05	-0.06	-0.08	0.97	-0.08	-0.08	-0.08	-0.08	-0.08	-0.12	-0.06
0.175	С	0.08	0.08	0.25	1.50	-0.04	1.50	-0.04	-0.04	-0.04	0.08	-0.04	0.08
0.175	G	-0.04	0.08	0.25	-0.04	-0.04	-0.04	1.50	-0.04	0.68	0.45	0.68	0.08
0.325	Т	0.19	-0.12	-0.08	-0.08	-0.08	-0.08	-0.08	0.97	0.05	-0.06	-0.06	-0.06
1.000	Sum	0.11	0.09	0.36	1.29	0.80	1.29	1.29	0.80	0.61	0.39	0.47	0.04

$$f'_{i,j} = \frac{n_{i,j} + p_i k}{\sum_{i=1}^{A} n_{i,j} + k}$$

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

$$I_{j} = \sum_{i=1}^{A} I_{i,j}$$

$$I_{matrix} = \sum_{j=1}^{w} \sum_{i=1}^{A} I_{i,j}$$

A alphabet size (=4)

 $n_{i,j,}$ occurrences of residue i at position j

w matrix width (=12)

p_i prior residue probability for residue i

relative frequency of residue i at position j

k pseudo weight (arbitrary, 1 in this case)

 $f'_{i,i}$ corrected frequency of residue i at position j

 $W_{i,j}$ weight of residue i at position j

 $I_{i,j}$ information of residue i at position j

Reference: Hertz (1999).

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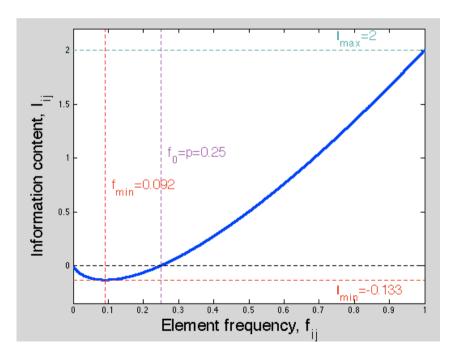
Properties of the information content

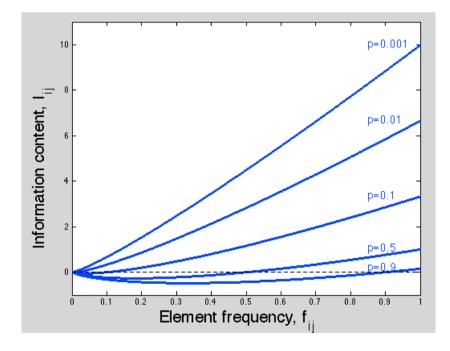
$$I_{i,j} = f'_{i,j} \ln \left(\frac{f'_{i,j}}{p_i} \right)$$

Information content of a given cell (i,j)

For a given cell (i,j) of the matrix:

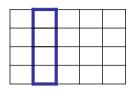
- $I_{ij} > 0$ when $f'_{ij} > p_i$ (i.e. when residue i is more frequent at position j than expected by chance)
- $I_{ij} < 0$ when $f'_{ij} < p_i$ (i.e. when residue i is less frequent at position j than expected by chance)
- I_{ij} tends towards 0 when $f'_{ij} \rightarrow 0$ (because limit x->0 x*ln(x) = 0)





Remark: The upper bound of I_{ij} increases when p_i decreases (I_{ij} -> Inf when p_i -> 0). The information content, as defined by Gerald Hertz, has thus no upper bound.

Properties of the information content



For a given column *j* of the matrix:

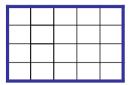
- The information content of the column (I_j) is the sum of information of its cells.
- I_i is always positive $(I_i > 0)$
- I_j is 0 when the frequency of all residues equal their prior probability ($I_i = 0$ if $f_{ij} = p_i$)
- I_j is maximal when the residue with the lowest prior probability has a frequency of 1 (all other residues have a frequency of 0); the pseudo-weight is 0

$$I_{j} = \sum_{i=1}^{A} I_{i,j} = \sum_{i=1}^{A} f_{i,j}^{'} \ln \left(\frac{f_{i,j}^{'}}{p_{i}} \right)$$

Information content of a given column (j)

$$\max(I_j) = 1 * \ln(\frac{1}{p_i}) = -\ln(p_i)$$

Properties of the information content



- The total information content represents the capability of the matrix to make the distinction between a binding site (represented by the matrix) and the background model.
- The information content also allows to estimate an upper limit for the expected frequency of the binding sites in random sequences.
- The pattern discovery program consensus (developed by Jerry Hertz) optimizes the information content in order to detect overrepresented motifs.
- Note that this is not the case of all pattern discovery programs: the *gibbs sampler* algorithm optimizes a log-likelihood.

$$I_{matrix} = \sum_{j=1}^{w} \sum_{i=1}^{A} I_{i,j}$$

Information content of the PSSM

$$P(site) \le e^{-I_{matrix}}$$

Sequences logo based on information content

Schneider (1990) proposes a graphical representation (logo) based on his previous entropy (H) for representing the importance of each residue at each position of an alignment. He provides a new formula for R_{seq} :

$$H_s(j) = -\sum_{i=1}^{A} f_{ij} \log_2(f_{ij})$$

$$R_{seq}(j) = 2 - H_s(j) + e(n)$$

$$h_{ij} = f_{ij}R_{seq}(j)$$



 $H_s(j)$ = uncertainty of column j

 $R_{seq}(j)$ = "information content" of column j (NB: this definition differs from Hertz' information content) e(n) = correction for small samples (pseudo-weight)

Remarks

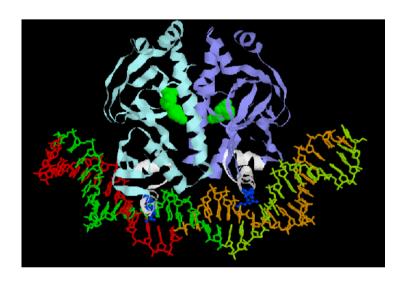
This information content does not include any correction for the prior residue probabilities (p_i) This information content is expressed in bits.

Boundaries

 $min(R_{seq})=0 <=>$ equiprobable residues $max(R_{seq})=2 <=>$ perfect conservation of 1 residue with a pseudo-weight of 0.

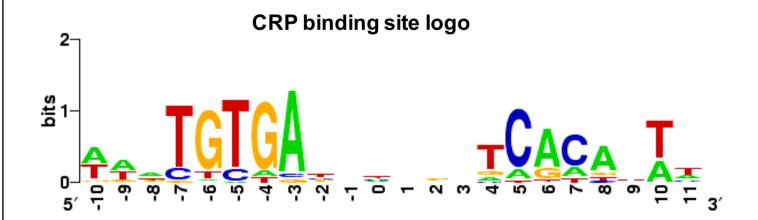
Sequence logos can be generated from aligned sequences on the Weblogo server http://weblogo.berkeley.edu/

Example: CRP binding site.

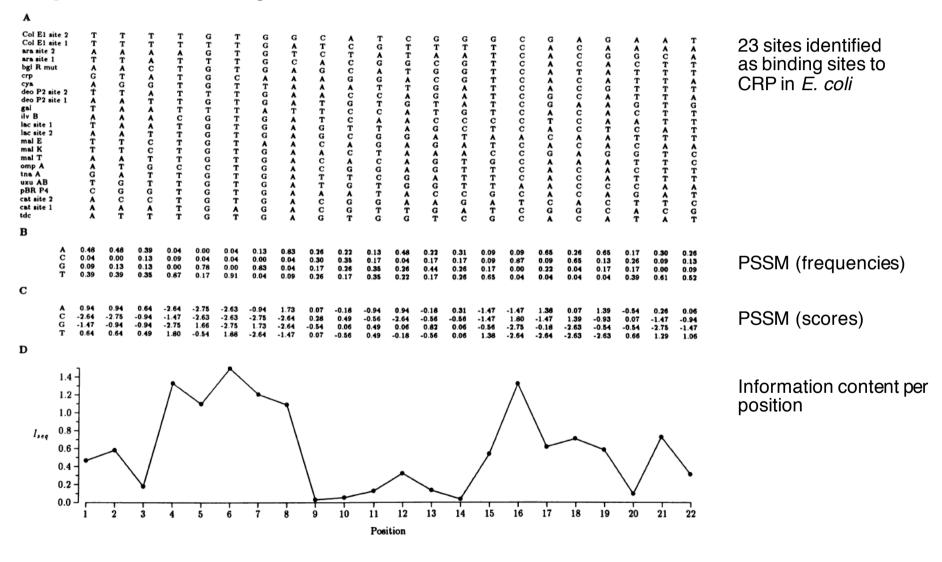


- cAMP Receptor Protein (CRP) is a dimer of two identical subunits.
- cAMP-CRP activates expression of many genes in *E. coli*, by binding to specific sites on the DNA where it directly interacts with RNA Polymerase.
- Nucleotide sequencing and analysis of CRP binding sites established a consensus binding sequence consisting of an imperfect 5 bp palindrome:

TGTGA---N6---TCACA



Example: CRP binding site.



References

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See also:

Schneider TD (2012) *Information Theory Primer*, Lecture notes (available at http://schneider.ncifcrf.gov/)