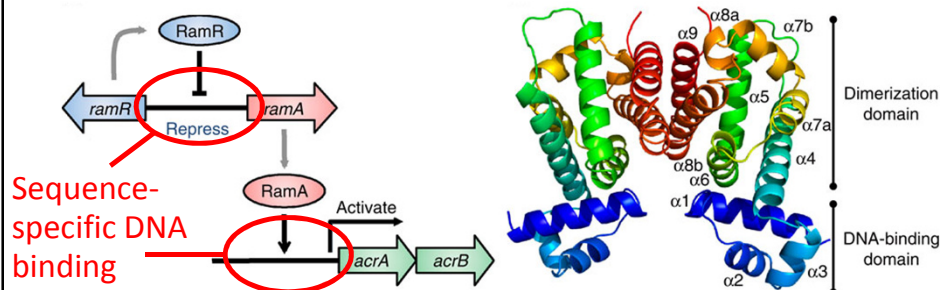


Motifs

BCH394P/364C - Systems Biology / Bioinformatics

Edward Marcotte, Univ of Texas at Austin

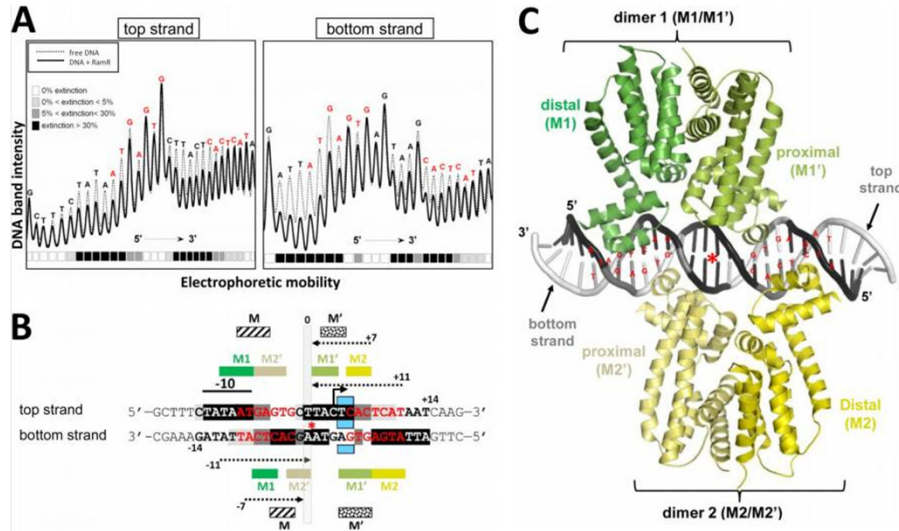
An example transcriptional regulatory cascade Here, controlling *Salmonella* bacteria multidrug resistance



RamR represses the *ramA* gene, which encodes the activator protein for the *acrAB* drug efflux pump genes.

RamR dimer

Historically, DNA and RNA binding sites were defined biochemically (DNase footprinting, gel shift assays, etc.)



Hydroxyl radical footprinting of *ramR-ramA* intergenic region with RamR

Antimicrob Agents Chemother. Feb 2012; 56(2): 942-948.

Historically, DNA and RNA binding sites were defined biochemically (DNase footprinting, gel shift assays, etc.)

Now, many binding motifs are discovered bioinformatically

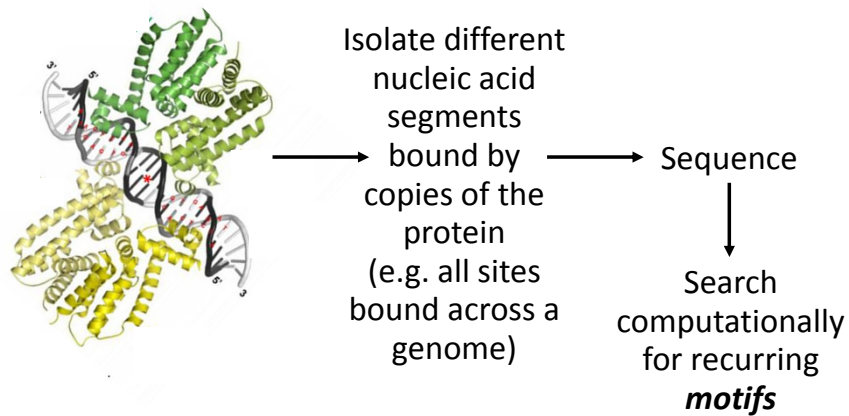
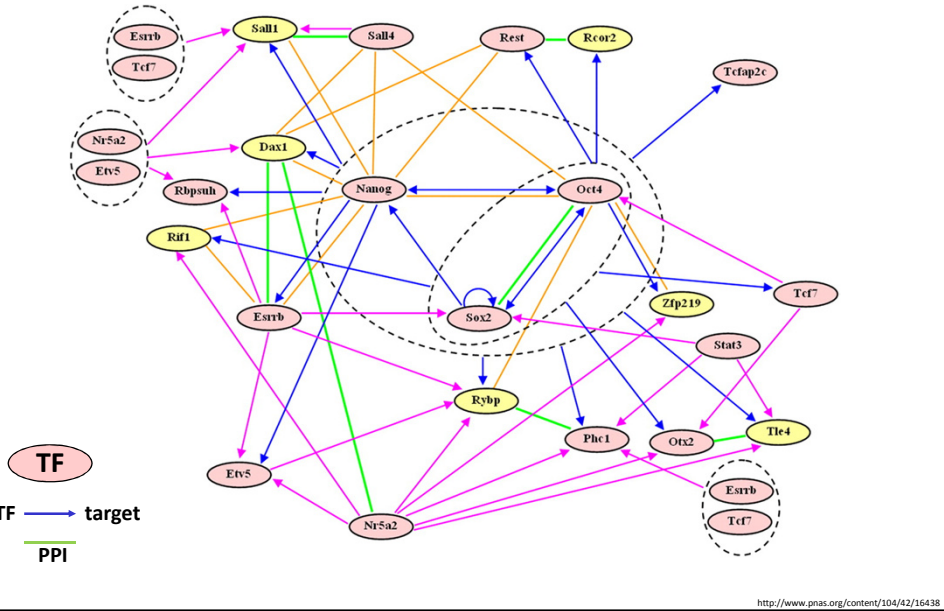


Image: Antimicrob Agents Chemother. Feb 2012; 56(2): 942-948.

Transcription factor regulatory networks can be highly complex, e.g. as for embryonic stem cell regulators



MOTIFS

HEM13 CCCATTGTTCTC
 HEM13 TTTCTGGTTCTC
 HEM13 TCAATTGTTTAG
 ANB1 CTCATTGTTGTC
 ANB1 TCCATTGTTCTC
 ANB1 CCTATTGTTCTC
 ANB1 TCCATTGTTCGT
 ROX1 CCAATTGTTTTG

Binding sites of the transcription factor ROX1

YCHATTGTTCTC

consensus

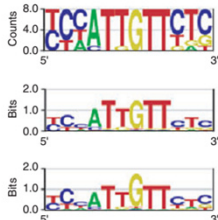
A 002700000010
 C 464100000505
 G 000001800112
 T 422087088261

frequencies

frequency of nuc b at position i

$$I_{seq}(i) = -\sum_b f_{b,i} \log_2 \frac{f_{b,i}}{p_b}$$

freq of nuc b in genome



scaled by information content

So, here's the challenge:

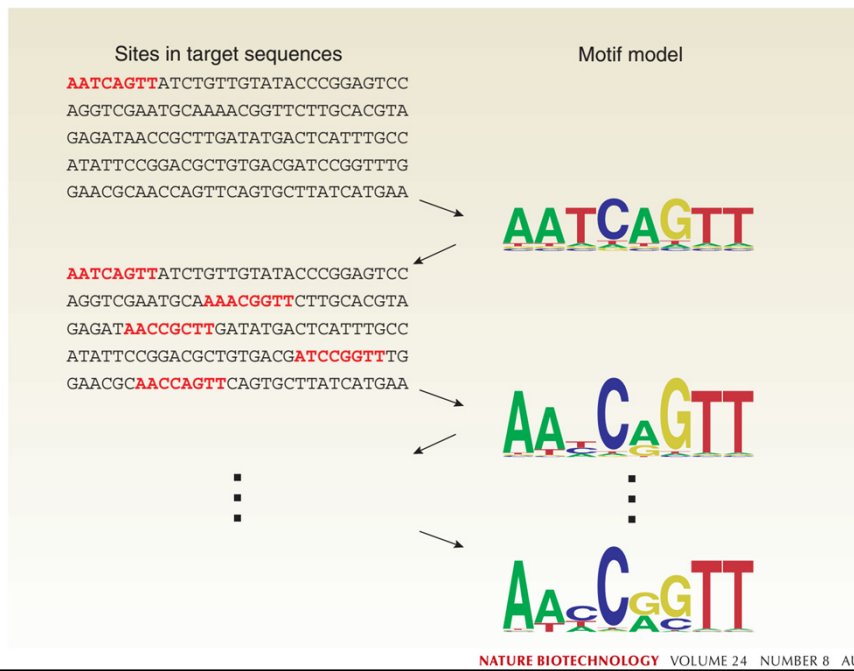
Given a set of DNA sequences that contain a motif (e.g., promoters of co-expressed genes), how do we discover it computationally?

Could we just count all instances of each k -mer?

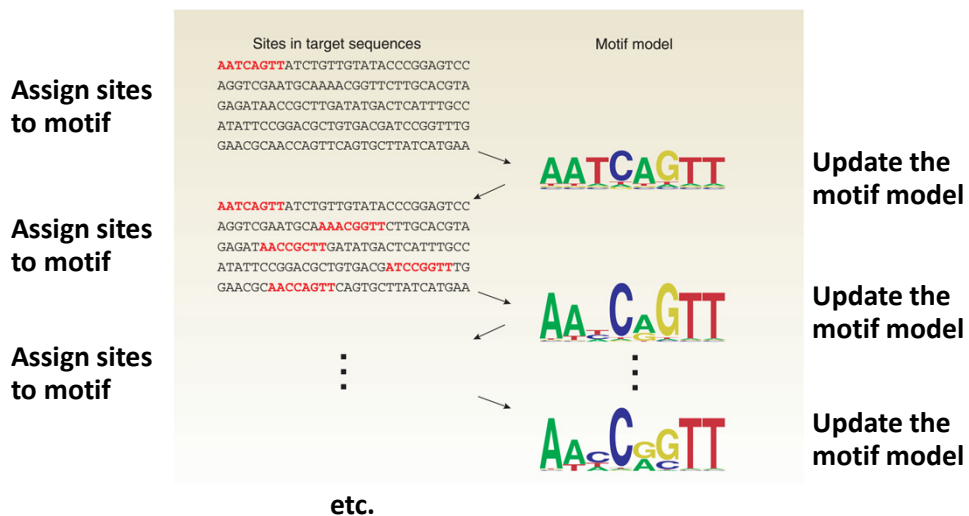
Why or why not?

→ promoters and DNA binding sites are not well conserved

How does motif discovery work?



How does motif discovery work?



How does motif discovery work?

Motif finding often uses expectation-maximization *i.e.* alternating between building/updating a motif model and assigning sequences to that motif model.

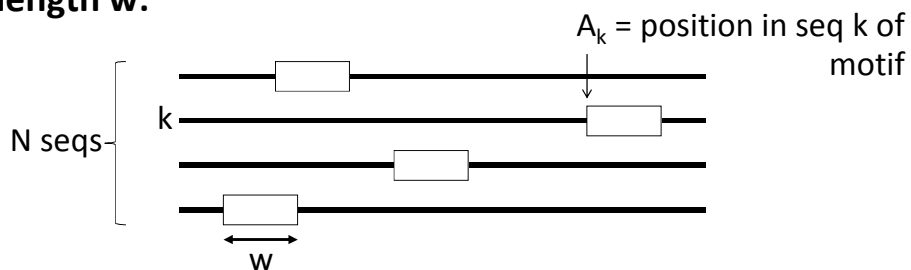
Searches the space of possible motifs for optimal solutions without testing everything.

Most common approach = *Gibbs sampling*

Detecting Subtle Sequence Signals: A Gibbs Sampling Strategy for Multiple Alignment

Charles E. Lawrence, Stephen F. Altschul, Mark S. Boguski, Jun S. Liu, Andrew F. Neuwald, John C. Wootton

We will consider N sequences, each with a motif of length w :



q_{ij} = probability of finding nucleotide (or aa) j at position i in motif
 i ranges from 1 to w
 j ranges across the nucleotides (or aa)

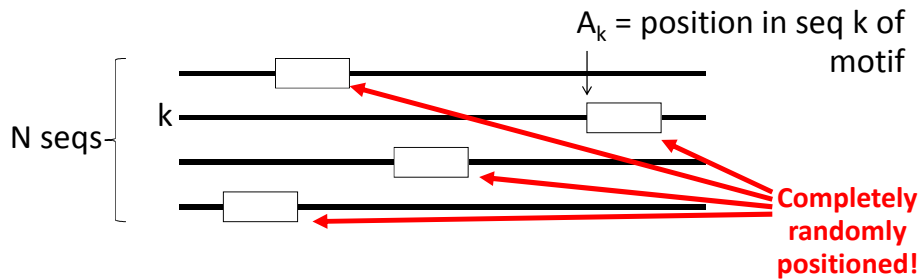
p_j = background probability of finding nucleotide (or aa) j

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NOTE: You won't give any information at all about what or where the motif should be!

Start by choosing w and randomly positioning each motif:



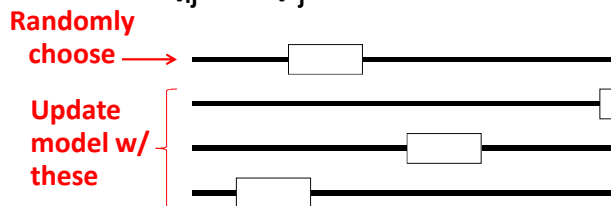
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Predictive update step: Randomly choose one sequence, calculate q_{ij} and p_j from $N-1$ remaining sequences



background frequency of symbol j

count of symbol j at position i

$$q_{i,j} = \frac{c_{i,j} + b_j}{N - 1 + B}$$

Σb_j

q_{ij} = probability of finding nucleotide (or aa) j at position i in motif
 i ranges from 1 to w
 j ranges across the nucleotides (or aa)
 p_j = background probability of finding nucleotide (or aa) j

p_j is calculated similarly from the counts outside the motifs

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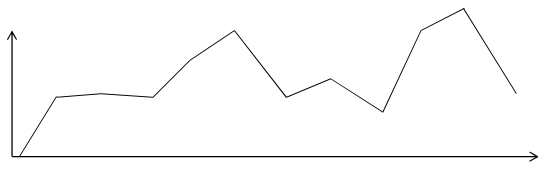
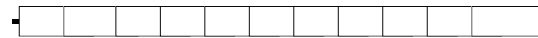
**Detecting Subtle Sequence
Signals: A Gibbs Sampling
Strategy for Multiple Alignment**

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Jun S. Liu, Andrew F. Neuwald, John C. Wootton

Stochastic sampling step: For withheld sequence, slide motif down sequence & calculate agreement with model

**Withheld
sequence** →

Odds ratio of
agreement
with model
vs.
background



$$\frac{\prod(q_{ij})^{c_{xij}}}{\prod(p_j)^{c_{xij}}}$$

(see the paper
for details)

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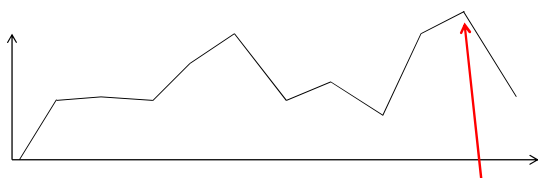
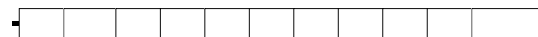
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$$\frac{\prod(q_{ij})^{c_{xij}}}{\prod(p_j)^{c_{xij}}}$$

(see the paper
for details)

**Here's the cool part: DON'T just choose the maximum.
INSTEAD, select a new A_k position proportional to this odds ratio.**

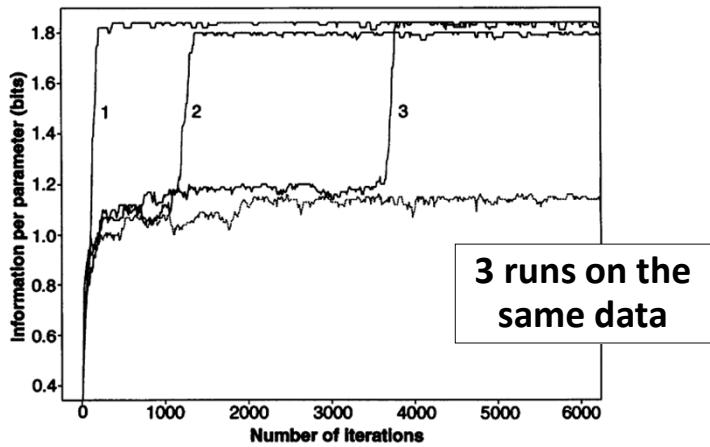
Then, choose a new sequence to withhold, and repeat everything.

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Detecting Subtle Sequence Signals: A Gibbs Sampling Strategy for Multiple Alignment

Charles E. Lawrence, Stephen F. Altschul, Mark S. Boguski, Jun S. Liu, Andrew F. Neuwald, John C. Wootton

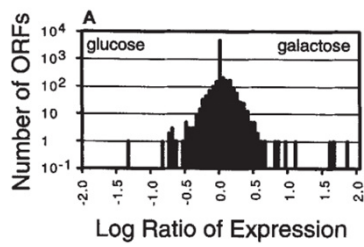
Over many iterations, this magically converges to the most enriched motifs. Note, it's stochastic:



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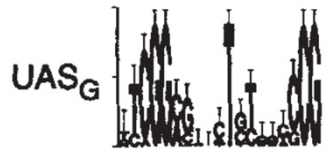
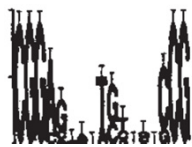
Finding DNA regulatory motifs within unaligned noncoding sequences clustered by whole-genome mRNA quantitation

Frederick P. Roth¹*, Jason D. Hughes²*, Preston W. Estep¹, and George M. Church^{1,2}™



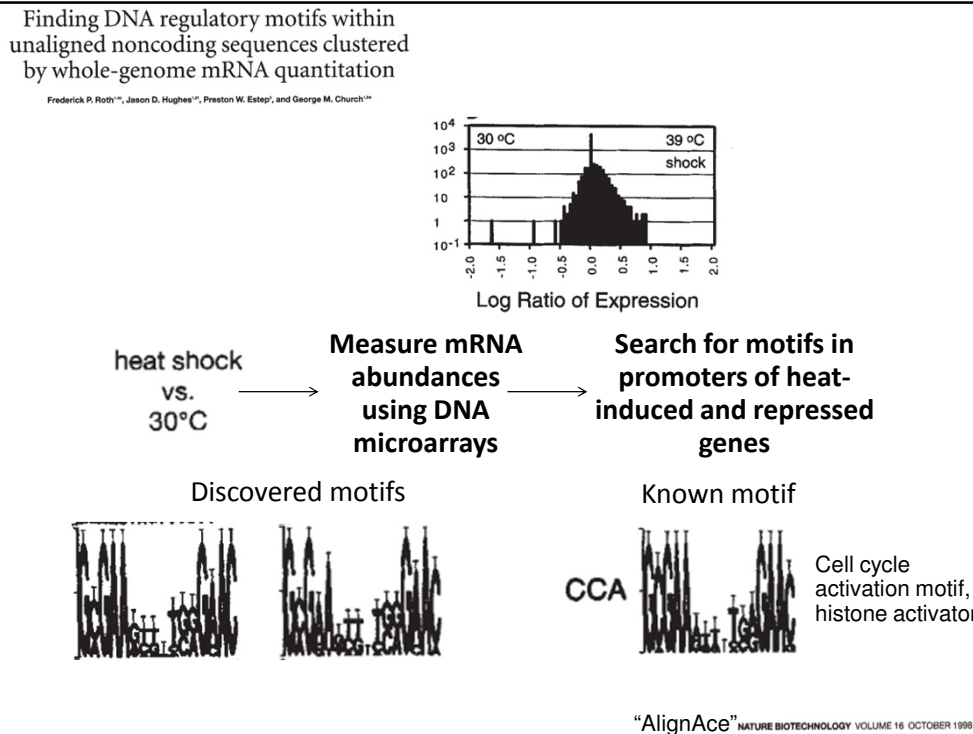
Discovered motifs

Known motif



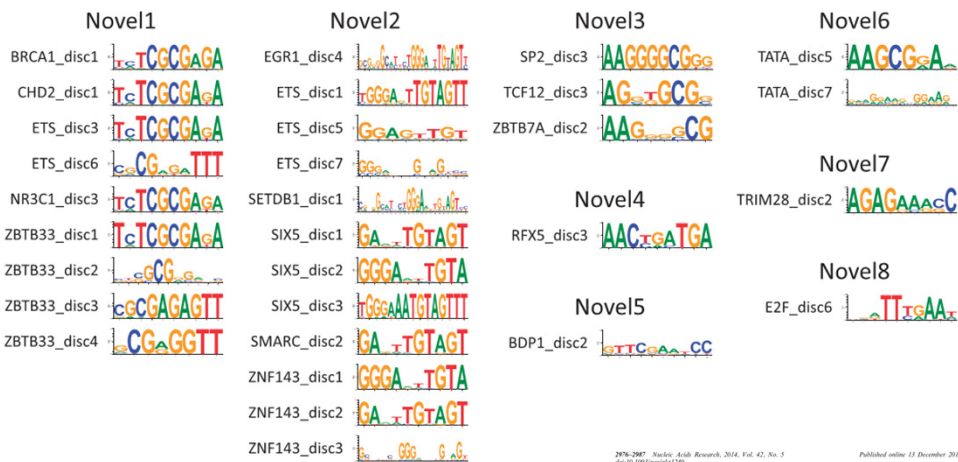
Galactose upstream activation sequence

"AlignAce" NATURE BIOTECHNOLOGY VOLUME 16 OCTOBER 1998



If you need them, we now know the binding motifs for 100's of transcription factors at 1000's of distinct sites in the human genome, including many new motifs.

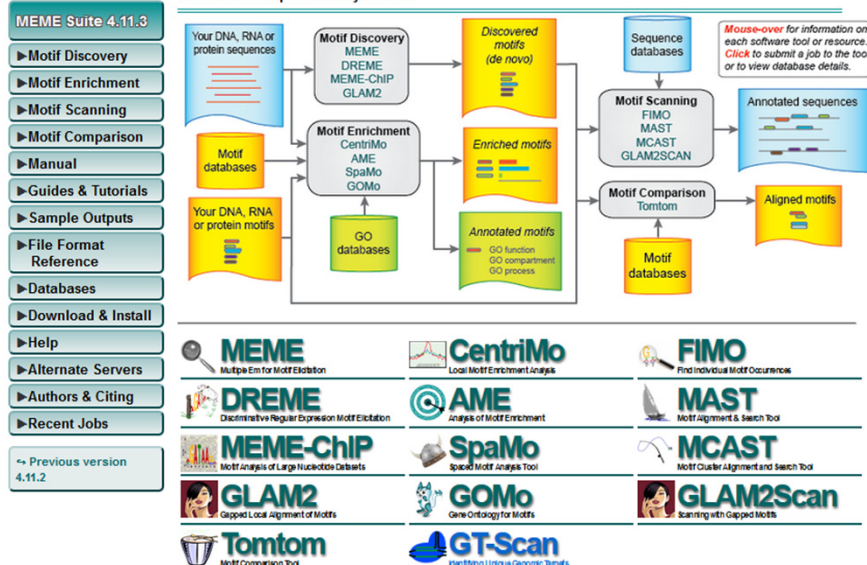
e.g., <http://compbio.mit.edu/encode-motifs/>



Here's a good place to start if you want to do this practically: <http://meme-suite.org/>

The MEME Suite

Motif-based sequence analysis tools



Note: online MEME suite can sometimes be quite laggy. GibbsCluster is a good alternative for peptide motifs:
<http://www.cbs.dtu.dk/services/GibbsCluster/>

DTU Bioinformatics
 Department of Bio and Health Informatics

Home

GibbsCluster-2.0 Server

Simultaneous alignment and clustering of peptide data

View the [version history](#) of this server. All previous versions are available online, for comparison and reference.

GibbsCluster is a server for unsupervised alignment and clustering of peptide sequences. The program takes as input a list of peptide sequences and a matrix. Visit the links on the pink bar below to read instructions and guidelines, see output formats, or download the code.

Update (Nov 2016): Implements deletions and insertions in the sequence alignment.

For very large data sets, you are encouraged to [download](#) a stand-alone version of the program, with full functionality and no parameter limitations.

[Instructions](#) | [Output format](#)

DATA SUBMISSION

Paste peptides in the box:

or submit a file directly from your local disk:

No file chosen

To load some **SAMPLE DATA** click here:

Both can also be installed on your own computer