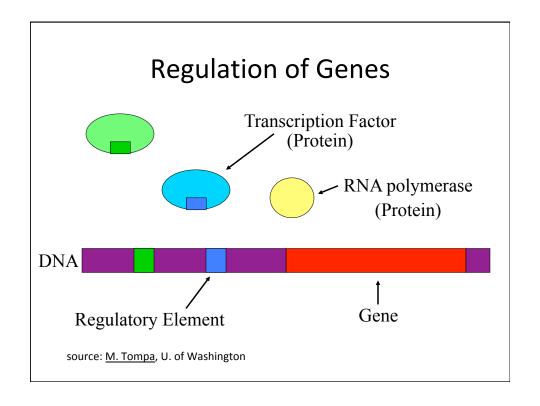
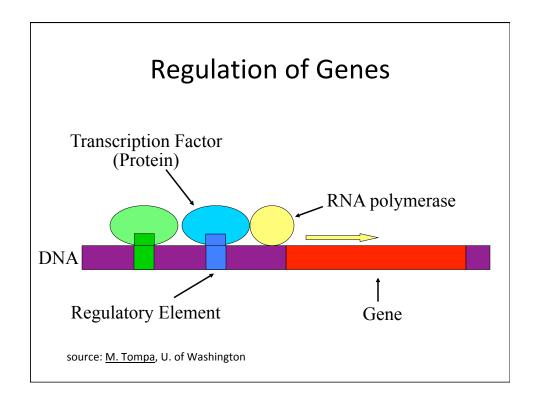
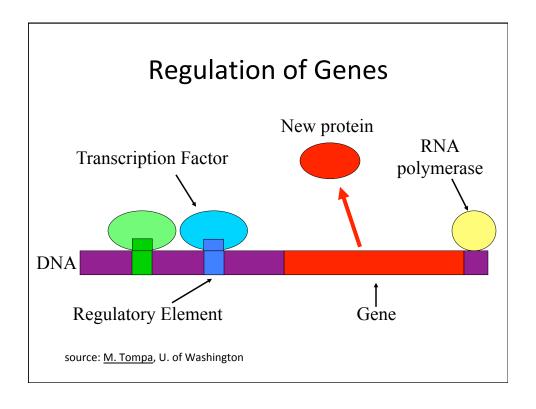
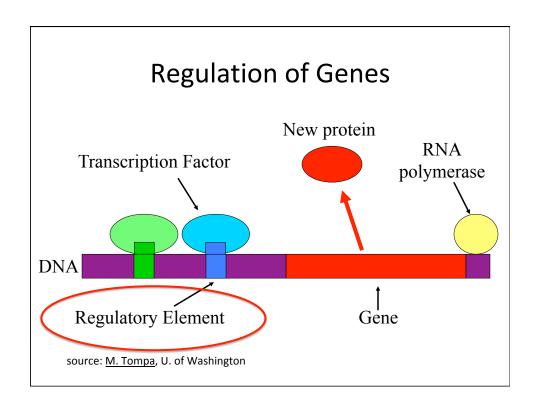
ONE SHOULD NEVER MISTAKE PATTERN FOR MEANING

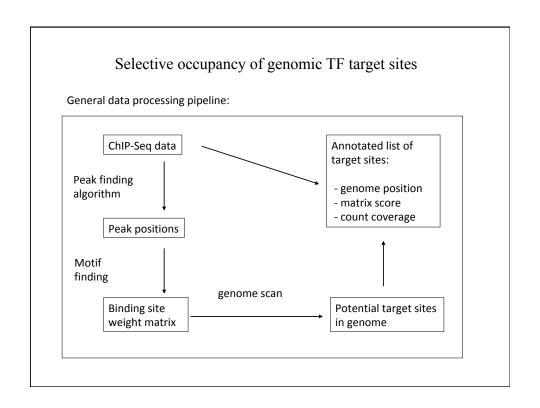
IAIN BANKS







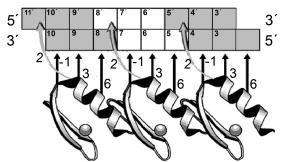




What is a motif?

- A subsequence that occurs in multiple sequences with a biological importance (e.g. at sites of protein binding).
- Motifs can be totally constant (substring) or have variable elements (pattern).
- Protein Motifs often result from structural features.
- DNA Motifs (regulatory elements)
 - Binding sites for proteins
 - Short sequences (5-25 bps)
 - A handful to millions of binding sites in the genome

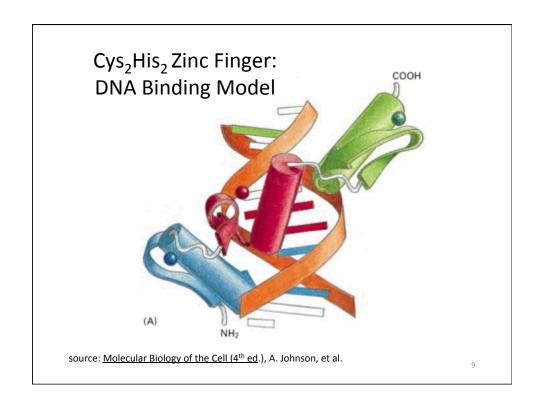
Cys₂His₂ Zinc Finger: Canonical DNA binding model

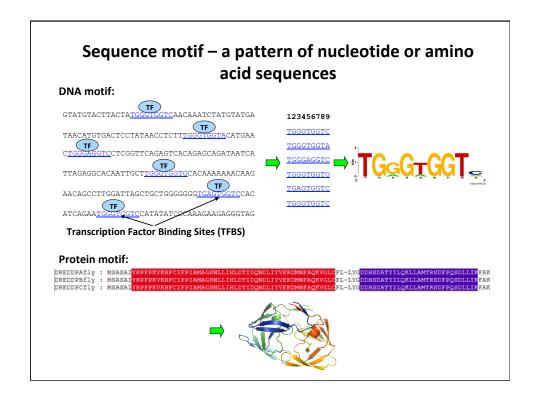


Finger 1 Finger 2 Finger 3

Residues at positions 6, 3, 2, and -1 (relative to the beginning of the a-helix) at each finger interact with adjacent nucleotides in the DNA molecule (interactions shown with arrows).

Kaplan. et al., PLoS Comput Biol, 2005





Motif Representations

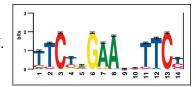
Consensus sequence: a single string with the most likely sequence

TTCTGGAACCTTCT

 Regular expression: a string with wildcards, constrained selection (+/- wildcards & ambiguity)

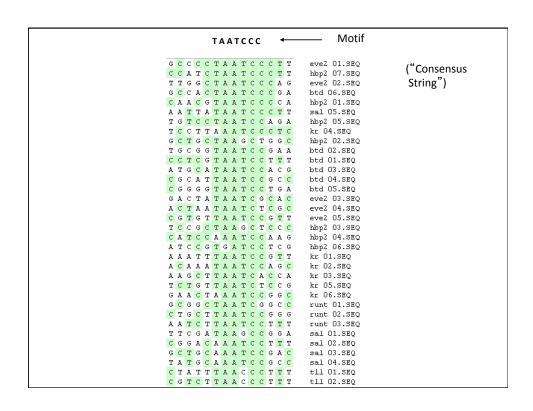
YTCYXGAAXXTTCY

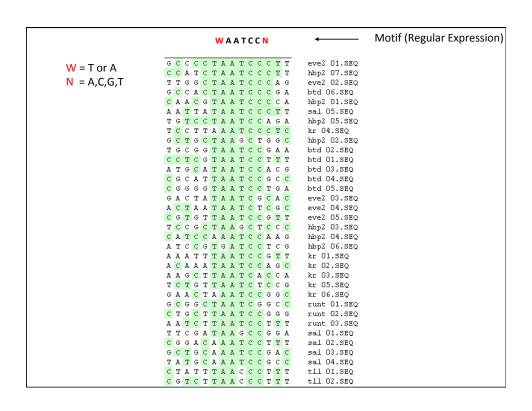
- Profile: a list of the letter frequencies at each position
- Sequence Logo:
 - graphical depiction of a profile
 - conservation of elements in a motif.

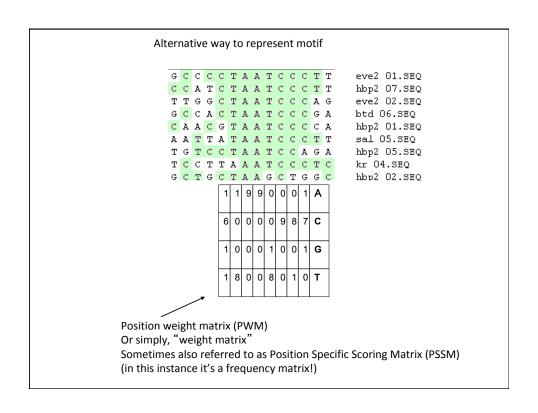


How do we describe a motif? YES! NO Given a multiple sequence alignment, it's trivial

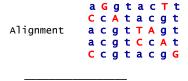
CCTCCTAATCCCTC	Majority
	.mjorroy
10	
GCCCTAATCCCTT	eve2 01.SEQ
CCATCTAATCCCTT	hbp2 07.seq
TTGGCTAATCCCAG	eve2 02.SEQ
GCCACTAATCCCGA	btd 06.seq
CAACGTAATCCCCA	hbp2 01.SEQ
AATTATAATCCCTT	sal O5.SEQ
TGTCCTAATCCAGA	hbp2 O5.SEQ
тсстта а а т с с с т с	kr 04.SEQ
GCTGCTAAGCTGGC	hbp2 02.SEQ
TGCGGTAATCCGAA	btd 02.SEQ
CCTCGTAATCCTTT	btd 01.SEQ
ATGCATAATCCACG	btd 03.seq
CGCATTAATCCGCC	btd 04.seq
CGGGGTAATCCTGA	btd 05.seq
G A C T A T A A T C G C A C	eve2 03.SEQ
астаатаатстсес	eve2 04.SEQ
CGTGTTAATCCGTT	eve2 05.SEQ
TCCGCTAAGCTCCC	hbp2 03.SEQ
CATCCAAATCCAAG	hbp2 04.seQ
ATCCGTGATCCTCG	hbp2 O6.SEQ
AAATTTAATCCGTT	kr 01.SEQ
ACAAATAATCCAGC	kr 02.SEQ
AAGCTTAATCACCA	kr 03.SEQ
TCTGTTAATCTCCG	kr 05.SEQ
GAACTAAATCCGGC	kr 06.seq
GCGGCTAATCGGCC	runt 01.SEQ
CTGCTTAATCCGGG	runt 02.SEQ
AATCTTAATCCTTT	runt 03.SEQ
TTCGATAAGCCGGA	sal 01.SEQ
CGGACAATCCTTT	sal 02.SEQ
GCTGCAAATCCGAC	sal 03.SEQ
TATGCAAATCCGCC	sal 04.SEQ
CTATTAACCCTTT	tll 01.SEQ
CGTCTTAACCCTTT	tll 02.SEQ







Consensus Model

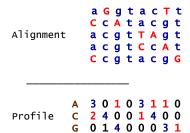


 Line up the patterns by their start indexes

$$\mathbf{s} = (s_1, s_2, ..., s_t)$$

- Profile A 3 0 1 0 3 1 1 0 C 2 4 0 0 1 4 0 0 G 0 1 4 0 0 0 3 1 T 0 0 0 0 5 1 0 1 4
- Construct matrix profile with frequencies of each nucleotide in columns
- Consensus ACGTACGT
- Consensus nucleotide in each position has the highest score in column

PWM Model

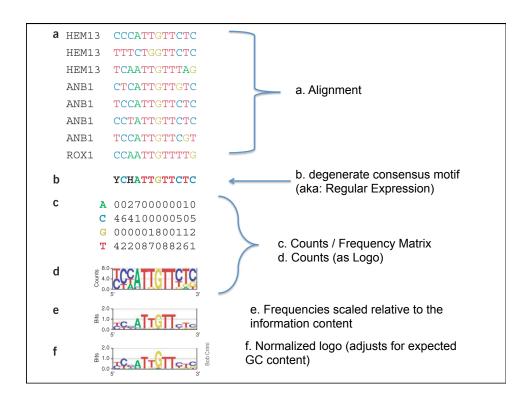


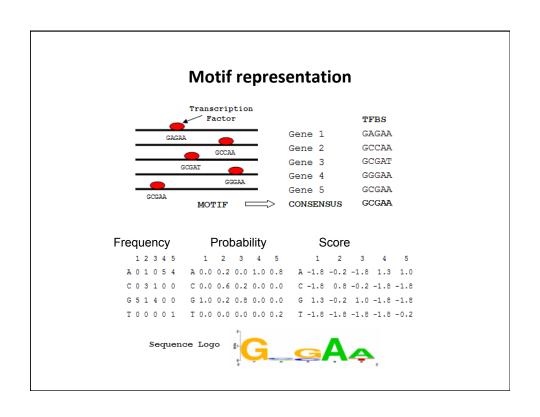
T 0 0 0 5 1 0 1 4

 Line up the patterns by their start indexes

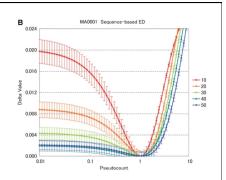
$$\mathbf{s} = (s_1, s_2, ..., s_t)$$

- Construct matrix profile with frequencies of each nucleotide in columns
- Convert the frequency matrix to scores – but how?





To avoid bias due to this small sample size, a certain numeric value, called a pseudocount, is usually allocated for each position, and its fraction according to the background base composition is added to each element.



Avoids division by zero.

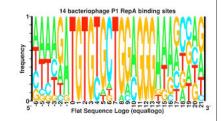
As more data is available, pseudocounts are overwhelmed and have negligible effect.

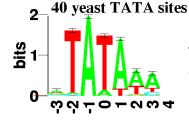
Effectively this is another form of a 'prior'.

Motif Logos

How to create a motif model?

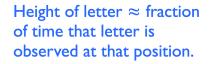
X-axis: position in sequence (assumes position independence)





Y-axis: typically "bits" (occasionally frequency or probability)

assume statistical independence between positions in the pattern



(Height of all the letters in a column ≈ to how conserved the column is)



What is a "bit" in this context?

Each position scaled with the information content of the base frequencies at that position:

$$I_i = 2 + \sum_{b} f_{b,i} \log_2 f_{b,i}$$

Positions are calculated using log likelihoods, the score of a sequence can be calculated by adding (rather than multiplying as is necessary with probabilities).

> Perfect conservation = 2 bits Every base equal = 0 bits

> > Assumes all four bases occur equally likely.

What is a "bit" in this context?

Better measure adjust for background bias:

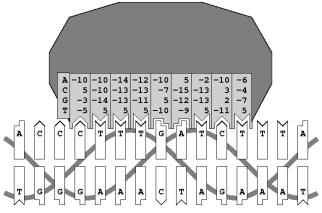
$$I_{seq}(i) = -\sum_{b} f_{b,i} \log_2 \frac{f_{b,i}}{p_b}$$

Aka. "relative entropy"

Notice its equivalent to a log-likelihood ratio!

Play with Logos: Steven Brenner's WebLogo (http://weblogo.berkeley.edu/) enoLOGOS3 (http://biodev.hgen.pitt.edu/enologos)

Physical interpretation of an weight matrix



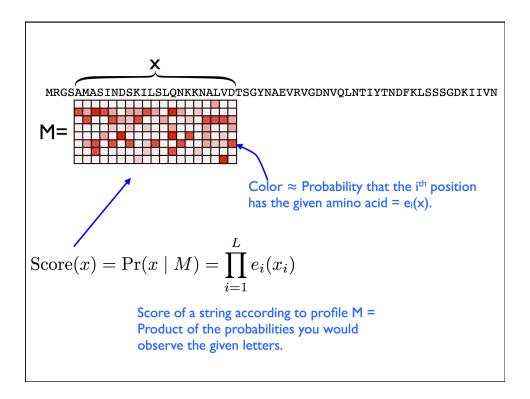
Weight matrix elements represent relative binding energies between DNA base-pairs and protein surface areas (base-pair acceptor sites).

A weight matrix column describes the base preferences of a base-pair acceptor site.

Represents sequence of one strand, though physical interactions may be with other strand.

Motif scanning

- Given a motif (e.g., consensus string, regular expression, or weight matrix), find the binding sites in an input sequence (e.g. a genome)
- For consensus string, problem is trivial
 - For each position in input sequence, check if substring starting at position I matches the motif.
- · For weight matrix, not quite so trivial



For example ···.

- Given a string s of length = 7
- $\bullet \ \mathsf{x} = \mathsf{x}_1 \mathsf{x}_2 ... \mathsf{x}_{\mathsf{l}}$

• Pr(x | M) =
$$\prod_{i=1}^{L} e_i(x_i)$$

• Example: Pr(CTAATCCG) = 0.67 x 0.89 x 1 x 1 x 0.89 x 1 x 0.89 x 0.11

.11	.11	1	1	0	0	0	.11	Α
.67	0	0	0	0	1	.89	.78	С
.11	0	0	0	.11	0	0	.11	G
.11	.89	0	0	.89	0	.11	0	Т

Probability of each base In each column

 $W_{\beta k}$ = probability of base β in column k

Here we are looking at probabilities, so we must multiply!

With normalized "scores," the positions are additive.

	1	2	3	4	5	6	7	8	9
Α	-10	-10	-14	-12	-10	5	-2	-10	-6
С	5	-10	-13	-13	-7	-15	-13	3	-4
G	-3	-14	-13	-11	5	-12	-13	2	-7
Т	-5	5	5	5	-10	-9	5	-11	5

Strong C T T T G A T C T Binding site 5 + 5 + 5 + 5 + 5 + 5 + 5 + 5 + 3 + 5 = 4:

Random A C G T A C G T A Sequence -10 -10 -13 + 5 -10 -15 -13 -11 - 6 = -83

(This is similar to scoring matricies for sequence alignment!)

Binding sites from a weight matrix motif

- Given sequence S (e.g., 1000 base-pairs long)
- For each substring x of S,
 - Compute Pr(x|M)
 - If Pr(x|M) > some threshold, call that a binding site
- · Look at S, as well as its reverse complement

But what threshold?

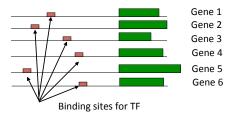
- In reality, every protein binds to every sequence with at least *some* affinity. But poorer matches to matrix are weaker (i.e. less frequent and transient) binding.
- Therefore, cutoff is related to how "strong" a site you are looking for ... depends on protein (TF), its concentration and the question at hand.
- However, empirically 60% of max is often used as a cutoff. This is another arbitrary but commonly used threshold (like 0.05 as a p-value cutoff).

A couple things to ponder ...

- Note how the scoring scheme used for motifs resembles the scoring schemes we discussed for alignment, only now they are position dependent.
- Also notice that a position specific scoring matrix is essentially a very simple HMM.

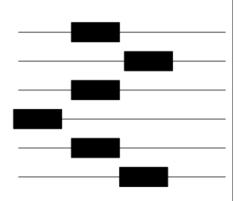
We will leverage "patterns" to identify transcription factor motifs.

- Say a transcription factor (TF) controls six different genes
- Each of the six genes will have binding site(s) for the TF in their promoter region



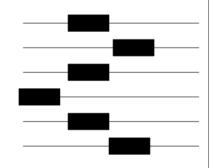
The motif finding problem

- Now suppose we are given the regions of six genes G1, G2, ... G6 identified by ChIP as bound by TF.
- Can we find the binding sites of TF, without knowing about them a priori?
 - Binding sites are similar to each other, but not necessarily identical (e.g. we expect a PWM)

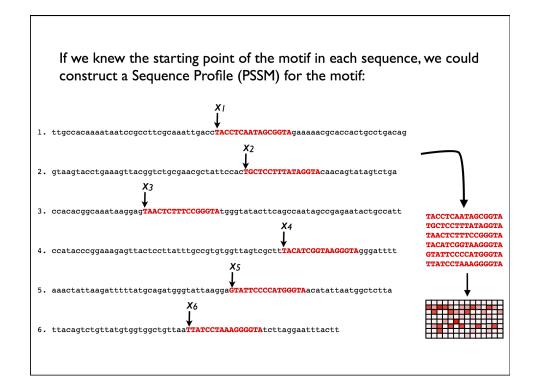


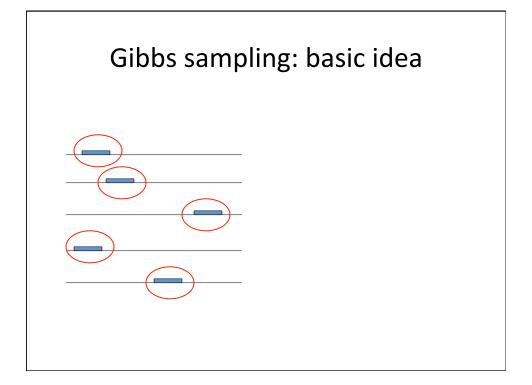
Identifying Motifs: Complications

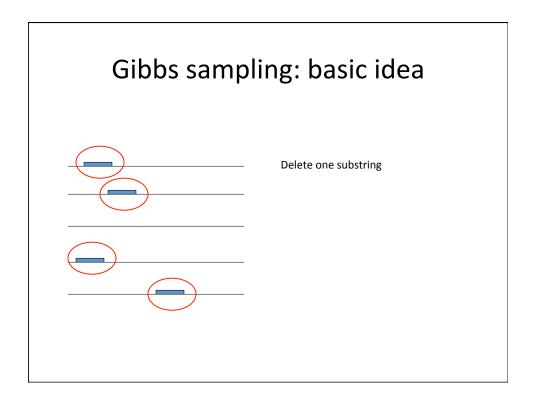
- We do not know the motif sequence
- We do not know where it is located within the sequence fragment

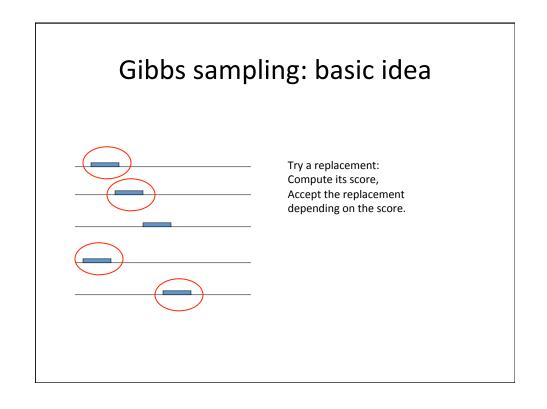


- Motifs can differ slightly from one gene to another
- How to discern it from "random" sequence?

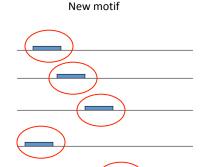








Gibbs sampling: basic idea



Not guaranteed to find "best motif".

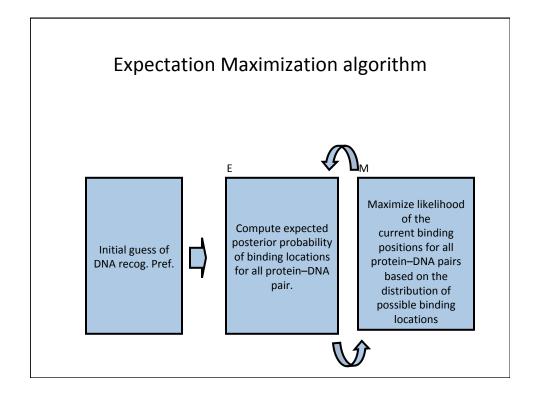
Works well in practice.

Best if you "restart" process many times (resample).

Expectation Maximization

- · Popular algorithm for motif discovery
- Motif model: Position Weight Matrix
- Local search algorithm
 - Move from current choice of motif to a new similar motif, so as to improve the score
 - Keep doing this until no more improvement is obtained : Convergence to local optima

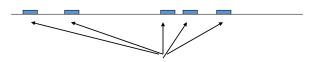
Estimating DNA Recognition Preferences • Apply Expectation Maximization Identify binding locations Optimize recognition preferences



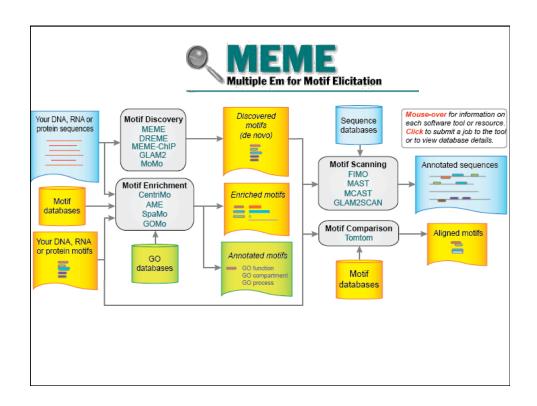
Basic idea of iteration

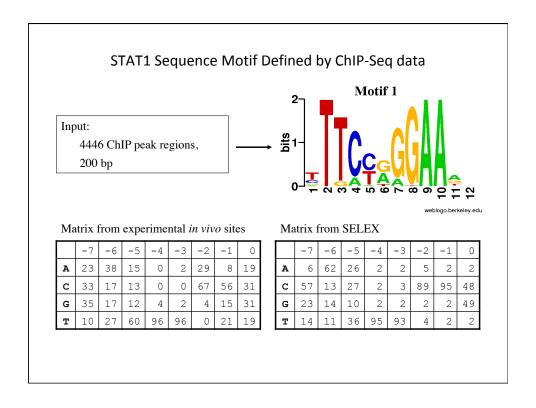
- PWM

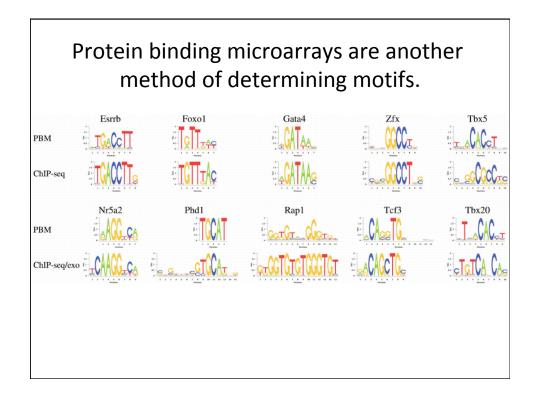
 1. Current motif
- 2. Scan sequence(s) for good matches to the current motif.



3. Build a new PWM out of these matches, and make it the new motif







Motif Databases



TRANSFAC®

Precision of ChIPSeq

- Evaluated against the center of high-scoring canonical motifs.
- 94% of these strong motifs fall within 50bp of the called experimental peak.

