

Regulatory Motif Finding

Lectures 12 – Nov 7, 2011
CSE 527 Computational Biology, Fall 2011
Instructor: Su-In Lee
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Monday & Wednesday 12:00-1:20
Johnson Hall (JHN) 022

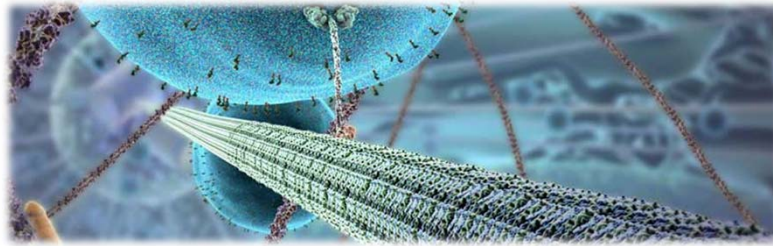
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Outline

- Biology background
- Computational problem
 - Input data
 - Motif representation
- Common methods
 - Enumeration
 - Expectation-Maximization (EM) algorithm
 - Gibbs sampling methods

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Cell = Factory, Proteins = Machines

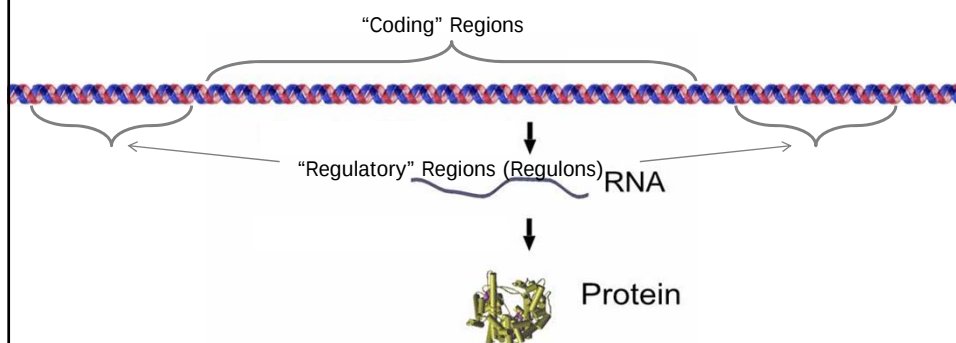


Biovisions, Harvard

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DNA

- Instructions for making the machines



- Instructions for when and where to make them

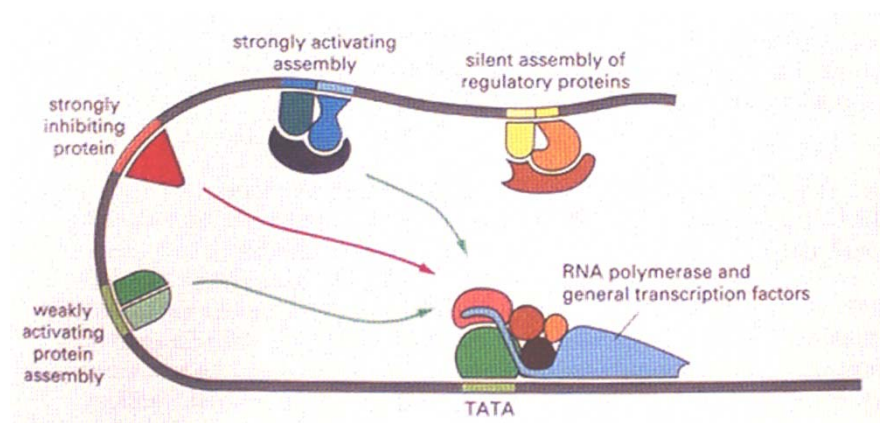
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Transcriptional Regulation

- **Regulatory regions** are comprised of “binding sites”
- **“Binding sites”** attract a special class of proteins, known as “transcription factors”
- A TFBS can be located anywhere within the regulatory region (promoter region)
- Bound transcription factors can also inhibit DNA transcription
 - More realistic picture?

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DNA Regulation

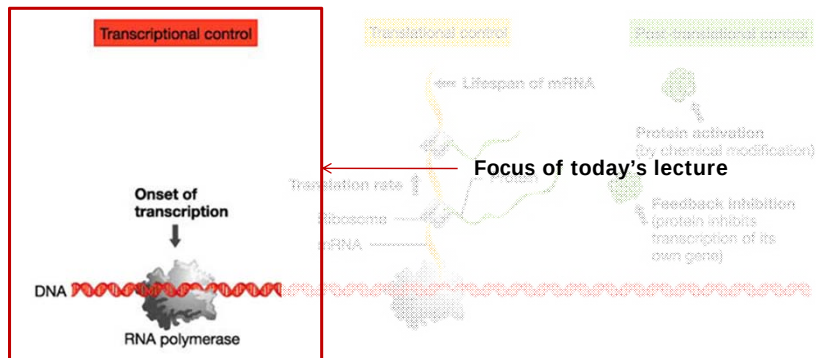


Source: Richardson, University College London

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Gene Regulation

- Transcriptional regulation is one of many regulatory mechanisms in the cell



Source: Mallery, University of Miami

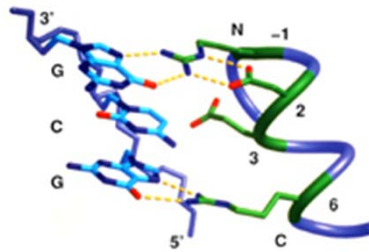
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Transcriptional Regulation of Genes

- **What** turns genes on (producing a protein) and off?
- **When** is a gene turned on or off?
- **Where** (in which cells) is a gene turned on?
- **How many** copies of the gene product are produced?

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Structural Basis of Interaction



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Structural Basis of Interaction

■ Key Feature:

- Transcription factors are not 100% specific when binding DNA because non-essential bases could mutate
- Not one sequence, but family of sequences, with varying affinities

G A C C G	0.54
G A G C G	0.48
G A C T G	0.32
G A C C A	0.25
G G C C G	0.11
G G C T G	0.08

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What is a motif?

- A subsequence (substring) that occurs in multiple sequences with a biological importance.
- Motifs can be totally constant or have variable elements.
- DNA motifs (regulatory elements)
 - Binding sites for proteins
 - Short sequences (5-25)
 - Up to 1000 bp (or farther) from gene
 - Inexactly repeating patterns

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Motif Finding

- **Basic Objective:**
 - Find regions in the genome that transcription factors bind to
- Motivations
 - Understanding which TFs regulate which genes
 - Major part of the gene regulation
- Many classes of algorithms, differ in:
 - Types of input data 
 - Motif representation

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Input Data

- Single sequence

AGCATCAGCAGCACATCATCAGCATACGACTCAGCATAGCCATGGGCTACAGCAGATCGATCGAACAGCAGGGCAGT
AGTCGGGATGCGGATCAGCAGGGAGGGAGCGGACGCTCTATAGAGGAGGACTTAGCAGAGCGATCGACGATTACG
CAGCAGTACGCAGCAAAAAAAAAACGACGTACGTAAGCAGCTGACATCGGACATCTGATCTGTAGCTAGCTACTACACT
CATGACTCAGTCAGTACCGATCAGCAGCTACATGCATGCATGCAGTCACGTAGAG...

- Based on over-representation of short sequences

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Random Sample

atgaccgggatactgataccgtatttggcctaggcgtagacattagataaacgtatgaagtacgttagactcggcgccgccc
acccctattttttagcagatttagtgacctggaaaaaaatttgagtacaaaactttccgaatactgggcataaggtaca
tgagtatccctgggatgacttttgggaacctatagtgtctctccgatttttgaatatgtaggacattcgccaggggtccga
gctgagaattggatgaccttgaagtgtttccacgcaatcggaaccaacgcggaaccaaggcaagaccgataaaggaga
tcccttttgcggtaatgtgcccggaggctggttacgtaggggaagccctaacggacttaatggccacttagtccacttatag
gtcaatcatgttcttgaatggatttttaactgagggcatagaccgcttggcgaccccaaatcagtggtggcgagcgcaa
cggttttggcccttgttagaggcccccgtactgatggaaactttcaattatgagagagctaattctatcgctgctgttcat
aacttgagttggtttcgaaaatgctctggggcacatacaagaggagtcttccctatcagttaatgctgtatgacactatgta
ttggccattggctaaaagcccaacttgacaaatggaagatagaatccttgcatttcaacgtatgccgaaccgaaagggaag
ctggtgagcaacgacagattcttactgtcatttagctcgttccggggatctaatagcacgaagcttctgggtactgatagca

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Implanting Motif AAAAAAAGGGGGG

atgaccgggatactgatAAAAAAAGGGGGGggcggtacacattagataaacgtatgaagtacgttagactcggcgccgcg
acccctatTTTTTgagcagatttagtgacctggaaaaaatttgagtacaaaactTTTccgaataAAAAAAAGGGGGGa
tgagtatccctgggatgacttAAAAAAAGGGGGGtgctctcccgattTTTgaatatgtaggatcattcgccagggtccga
gctgagaattggatgAAAAAAAGGGGGGtccacgcaatcgcaaccaacgcgaccacaaaggcaagaccgataaaggaga
tccctTTTgcggaatgtgccgggaggctggttacgtaggaagccctaacggacttaataAAAAAAAGGGGGGcttatag
gtcaatcatgttcttTgaatggatttAAAAAAAGGGGGGgaccgcttggcgacccaaattcagtggtggcgagcgcaa
cggTTTTggccctgttagaggccccgtAAAAAAAGGGGGGcaattatgagagagctaattctatcgctgctgtttcat
aacttgagttAAAAAAAGGGGGGctggggcacatacaagaggagtcttcttatcagttaatgctgtatgacactatgta
ttggccattggctaaaagcccaacttgacaaatggaagatagaatccttgcatAAAAAAAGGGGGGaccgaaagggaag
ctggtgagcaacgacagattcttactgtcattagctcgttccgggatctaatagcacgaagcttAAAAAAAGGGGGGa

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Where is the Implanted Motif?

atgaccgggatactgataaaaaaagggggggcggtacacattagataaacgtatgaagtacgttagactcggcgccgcg
acccctatTTTTTgagcagatttagtgacctggaaaaaatttgagtacaaaactTTTccgaataaaaaaaggggggga
tgagtatccctgggatgacttaaaaaaaggggggtgctctcccgattTTTgaatatgtaggatcattcgccagggtccga
gctgagaattggatgaaaaaaggggggtccacgcaatcgcaaccaacgcgaccacaaaggcaagaccgataaaggaga
tccctTTTgcggaatgtgccgggaggctggttacgtaggaagccctaacggacttaataaaaaaaggggggcttatag
gtcaatcatgttcttTgaatggatttaaaaaaagggggggaccgcttggcgacccaaattcagtggtggcgagcgcaa
cggTTTTggccctgttagaggccccgtaaaaaaggggggcaattatgagagagctaattctatcgctgctgtttcat
aacttgagttaaaaaaggggggctggggcacatacaagaggagtcttcttatcagttaatgctgtatgacactatgta
ttggccattggctaaaagcccaacttgacaaatggaagatagaatccttgcataaaaaaggggggaccgaaagggaag
ctggtgagcaacgacagattcttactgtcattagctcgttccgggatctaatagcacgaagcttaaaaaaaggggggga

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Implanting Motif AAAAAAGGGGGGGG with Four Mutations – (15,4)-motif

atgaccgggatactgatAgAAgAAAGGttGGGggcggtacacattagataaacgtatgaagtacgttagactcggcgccgcg
 acccctatTTTTTgagcagatttagtgacctggaaaaaaatttaggtacaaaacttttccgaatacAAtAAAAcGGcGGGa
 tgagtatccctgggatgacttAAAAtAAtGGaGtGGtgctctcccgattttgaatatgtaggatcattcgccagggtccga
 gctgagaattggatgcAAAAAAGGGGattGtccacgcaatcgcaaccaacgcggaccctaaaggcaagaccgataaaggaga
 tcccttttgcggtaattgtccgggaggctgggtacgtagggagccctaacggacttaataAAtAAAGGaaGGGcttatag
 gtcaatcatgttcttgtgaatggatttAAcAAtAAGGGctGGgaccgcttggcgacccaaattcagtggtggcgagcgcaa
 cggttttggccctgttagaggccccgttAAACAAAGGaGGGccaattatgagagagctaattctatcgctgctgtttcat
 aacttgagttAAAAAAtAGGGaGccctggggcacatacaagaggagtcttccctatcagttaatgctgtatgacactatgta
 ttggccattggctaaaagcccaacttgacaaatggaagatagaatccttgcatacAAAAAGGaGcGGaccgaaaggaag
 ctggtgagcaacgacagattcttactgtcatttagctcgttccggggatctaatagcacgaagcttActAAAAAGGaGcGGa

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Where is the Motif???

atgaccgggatactgataagaaggttggggggtacacattagataaacgtatgaagtacgttagactcggcgccgcg
 acccctatTTTTTgagcagatttagtgacctggaaaaaaatttaggtacaaaacttttccgaatacaataaaacggcgggga
 tgagtatccctgggatgacttaaaataatggagtgggtgctctcccgattttgaatatgtaggatcattcgccagggtccga
 gctgagaattggatgcaaaaaagggttgcacgcaatcgcaaccaacgcggaccctaaaggcaagaccgataaaggaga
 tcccttttgcggtaattgtccgggaggctgggtacgtagggagccctaacggacttaataataaagggaagggttatag
 gtcaatcatgttcttgtgaatggatttaacaataagggtgggaccgcttggcgacccaaattcagtggtggcgagcgcaa
 cggttttggccctgttagaggccccgtataaacaaggaggccaattatgagagagctaattctatcgctgctgtttcat
 aacttgagttaaaaataggagccctggggcacatacaagaggagtcttccctatcagttaatgctgtatgacactatgta
 ttggccattggctaaaagcccaacttgacaaatggaagatagaatccttgcatactaaaaggagcggaccgaaaggaag
 ctggtgagcaacgacagattcttactgtcatttagctcgttccggggatctaatagcacgaagcttactaaaaaggagcgga

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Why Finding (15,4) Motif is Difficult?

atgacggggatactgatAgAagAAAGGtTGggggtacacattagataaacgtatgaagtacgttagactggcgccggc
acccttattttttgagcagatttagtgacctggaaaaaaatttgagtacaaaacttttcggaatcAatAAAAcGGcGGa
tgagtatccctgggatgactAAATTAATGGAcTGGtctctcccgatttttgaatatgtaggatcattccagggttcga
gtgagaattggatgAAAAAAGGgattGtccacgcaatcggaaccaacggcgaccacaaggcaagacgataaaggaga
tcccttttgcggtaatgtgcggggagctggttacctaggggaagccctaaccgacttaataAATAAAGGaaGGSttatag
gtcaatcatgttcttgtgaatgattTAACAAATAGGGctGGgaccgcttggcgaccaccaaattcagtgtggcgagcgcaa
cggttttggcccttgttagaggcccccgtATAAACAAGGAaGGGcaaatatgagagagctaatactatcgtgctgtgttc
aatctgagttAAAAAATAGGGAaGccctggggcacatacaaggaggtcttccctatcagttaatgctgtatgacactatga
ttggcccatgtggctaaagcccaacttgacaaatggaagatagaatccttgcatActAAAAAGGcGGaccgaaagggaag
ctggtgagcaacgacagattcttacctgcatgtctgcttccggggatctaatagcacgaagctActAAAAAGGAaGcGGA

AgAagAAAGGttGGG
..|.|.|||.|.|.|||
cAAtAAAACGGcGGG

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Challenge Problem

- Find a motif in a sample of
 - 20 “random” sequences (e.g. 600 nt long)
 - each sequence containing an implanted pattern of length 15,
 - each pattern appearing with 4 mismatches as (15,4)-motif.

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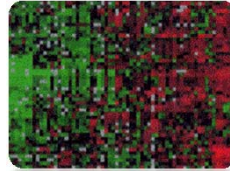
Input Data

- Single sequence

... AGCATCAGCAGCACATCATCAGCATACGACTCAGCATAGCCATGGGCTACAGCAGATCGATCGAACAGCAG...

- Sequence + other data

- Gene expression data
- ChIP-chip
- Others...



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Identifying Motifs

- Genes are turned on or off by regulatory proteins (TFs).
- TFs bind to upstream regulatory regions of genes to either attract or block an RNA polymerase
- So, multiple genes that are regulated by the same TF will have the same motifs in their regulatory regions.
- How do we identify the genes that are regulated by the same TF?

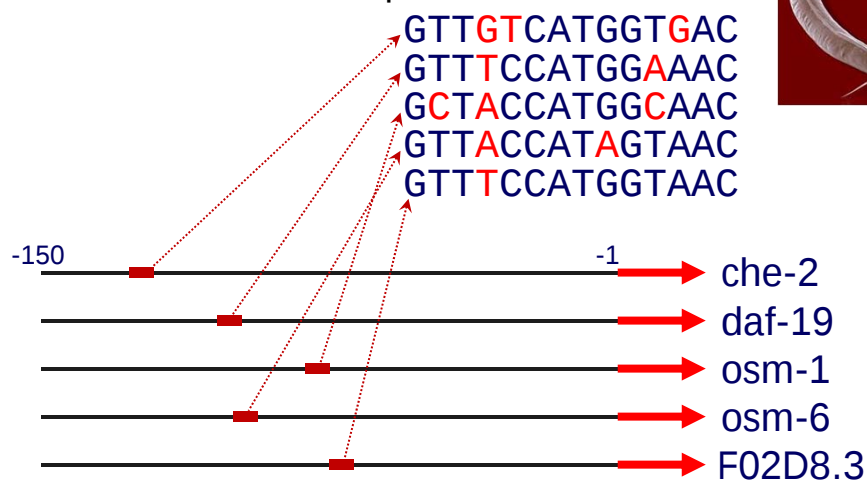
Sequence + Gene Expression Data

- Say that a microarray experiment showed that when gene X is knocked out, 20 other genes are not expressed.
 - How can one gene have such drastic effects?
- Say that 5 different genes are co-expressed across many experiments in a gene expression data.
 - These genes are likely to share the same binding sites.

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daf-19 Binding Sites in *C. elegans*

- Motifs and transcriptional start sites



source: Peter Swoboda

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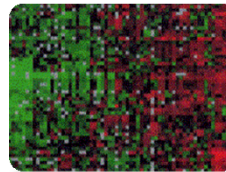
Input Data

- Single sequence

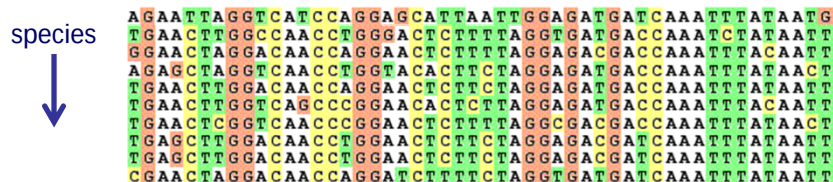
... AGCATCAGCAGCACATCATCAGCATACGACTCAGCATAGCCATGGGCTACAGCAGATCGATCGAACAGCACG...

- Sequence + other data

- Gene expression data
- ChIP-chip
- Others...



- Evolutionarily related set of sequences



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Motif Finding

- **Basic Objective:**

- Find regions in the genome that bind transcription factors

- Motivations

- Understanding which TFs regulate which genes
- Major part of the gene regulation

- Many classes of algorithms, differ in:

- Types of input data
- Motif representation



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Structural Basis of Interaction

- **Key Feature:**

- Transcription factors are not 100% specific when binding DNA

- Not one sequence, but family of sequences, with varying affinities

G	A	C	C	G	0.54
G	A	G	C	G	0.48
G	A	C	T	G	0.32
G	A	C	C	A	0.25
G	G	C	C	G	0.11
G	G	C	T	G	0.08

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Motif Representation

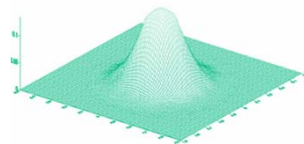
- Structural discussion immediately raises difficulties

- Least expressive: **G A C C G**

- Single sequence

- Most expressive:

- 4^k -dimensional probability distribution
- Independently assign probability for each of the possible k-mers*



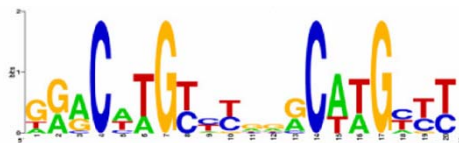
*k-mer refers to a specific n-tuple of nucleic acid or amino acid sequences that can be used to identify certain regions within DNA or protein.

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Motif Representation

- Standard Solution:

- Position-Specific Scoring Matrix (PSSM)
- Assuming independence of positions, assign a probability distribution for each position

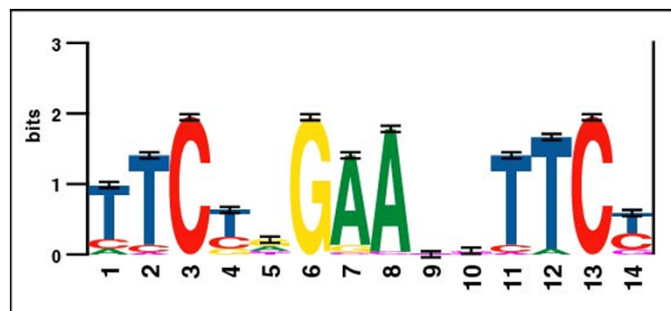


- This is a too simple representation

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Position Weight Matrix (PWM)

- Assign probability to (A,G,C,T) in each position

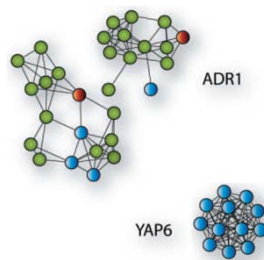


G	0.1	0.01	0	0.1	0.25	1	0.1	0	...
A	0.2	0.99	0	0	0.25	0	0.9	1	...
T	0.6	0.7	0	0.5	0.25	0	0	0	...
C	0.3	0.2	1	0.3	0.25	0	0	0	...

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Oversimplicity of PSSMs

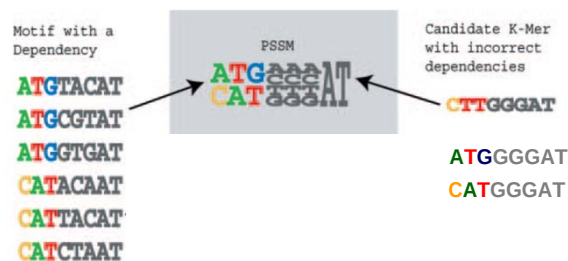
- Assumes independence between positions
- ~25% of TRANSFAC motifs have been shown to violate this assumption
 - Two Examples: ADR1 and YAP6



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Oversimplicity of PSSMs

- Assumes independence between positions
- Generates potentially unseen motifs



- We need to model dependency between positions.
 - Revisit later

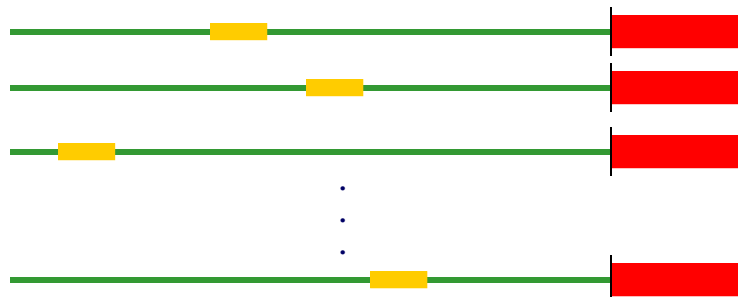
Outline

- Biology background
- Computational problem
 - Input data
 - Motif representation
- Common methods 
 - Enumeration
 - Expectation-Maximization (EM) algorithm
 - Gibbs sampling methods

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Finding Regulatory Motifs

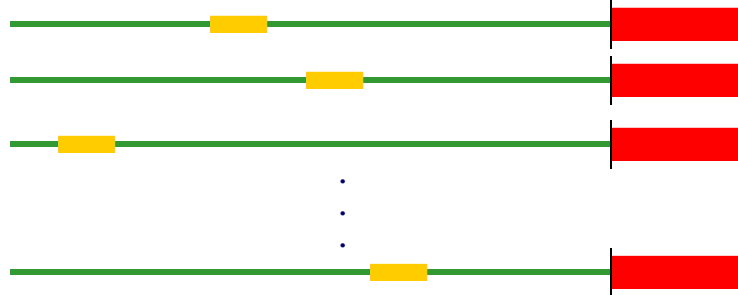
- **Given** a collection of genes that are likely to be regulated by the same TFs,
- **Find** the TF-binding motifs in common



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Identifying Motifs: Complications

- We do not know the motif sequence
- We do not know where it is located relative to the genes start
- Motifs can differ slightly from one gene to another
- How to discern it from “random” motifs?



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Common Methods

- Problem statement:
 - Given a set of n promoters of n co-regulated genes, find a motif common to the promoters
 - Both the PWM (defined in page 30) and the motif sequences are unknown.
- Enumeration (simplest method)
 - Look at the frequency of all k -mers*
- EM algorithm (MEME)
 - Iteratively hone in on the most likely motif model
- Gibbs sampling methods (AlignAce, BioProspector)

* k -mer refers to a specific n -tuple of nucleic acid that can be used to identify certain regions within DNA or proteins.

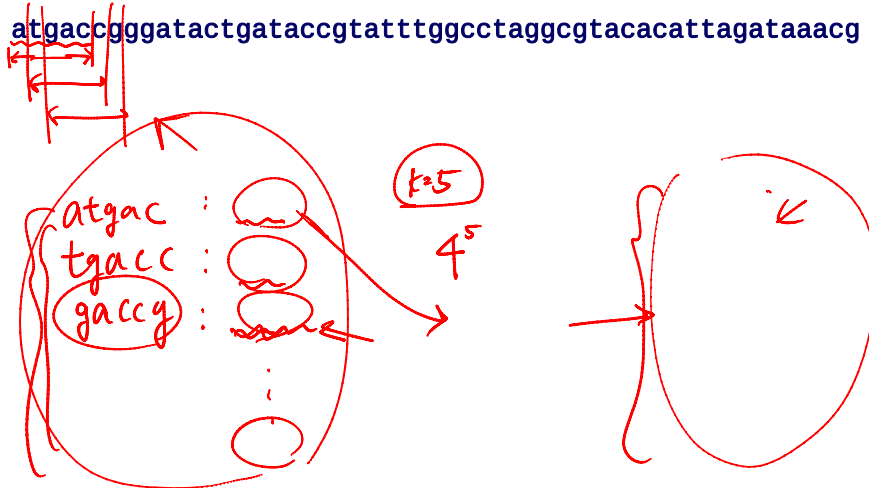
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Generating k-mers

M sequences

- Example: $k=5$

atgaccgggataactgataccgtatttggcctaggcgtacacattagataaacg



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Motif Finding Using EM Algorithm

- MEME (Multiple EM for Motif Elucidation)
 - Bailey and Elkan (1995), Bailey et al. (2006)
 - <http://meme.sdsc.edu/meme/intro.html>
- Expectation-Maximization
 - In each iteration, it learns the PWM model and identifies examples of the matrix (sites in the input sequences)

Identify binding locations for all PWMs



Optimize recognition preferences

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Motif Finding Using EM Algorithm

- MEME works by iteratively refining PWMs and identifying sites for each PWM
 - 1. Estimate motif model (PWM)
 - Start with a k-mer seed (random or specified)
 - Build a PWM by incorporating some of background frequencies
 - 2. Identify examples of the model
 - For every k-mer in the input sequences, identify its probability given the PWM model.
 - 3. Re-estimate the motif model
 - Calculate a new PWM, based on the weighted frequencies of all k-mers in the input sequences
 - 4. Iteratively refine the PWMs and identify sites until convergence.

Example: MEME

- Find a 6-mer motif in 4 sequences

S₁: GGCTATTGCAGATGACGAGATGAGGCCAGACC

S₂: GGATGACAATTATATAAAGGACGATAAGAGATGAC

S₃: CTAGCTCGTAGCTCGTTGAGATGCGCTCCCCGCTC

S₄: GATGACGGAGTATTAAAGACTCGATGAGTTATACGA

- 1. MEME uses an initial EM heuristic to estimate the best starting-point PWM matrix:

G	0.26	0.24	0.18	0.26	0.25	0.26
A	0.24	0.26	0.28	0.24	0.25	0.22
T	0.25	0.23	0.30	0.25	0.25	0.25
C	0.25	0.27	0.24	0.25	0.25	0.27

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- 2. MEME scores the match of all 6-mers to current matrix

G GCTATTG CATATGACGA GATGAG GCCCAGACC

Here, just consider the underlined 6-mers, Although in reality all 6-mers are scored

G GATGAC AATTATATAA AGGACCGT GATAAG AGATTAC

CTAGCTC GTAGCTC GTTGAG ATGCGCT CCCCGCTC

GATGAC GGAGTATTAAAGACTC GATGAG TATACGA

- 3. Re-estimate the PWM based on the **weighted** contribution of all 6-mers.

The height of the bases above corresponds to how much that 6-mer counts in calculating the new matrix

G	0.29	0.24	0.17	0.27	0.24	0.30
A	0.22	0.26	0.27	0.22	0.28	0.18
T	0.24	0.23	0.33	0.23	0.24	0.28
C	0.24	0.27	0.23	0.28	0.24	0.24

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- 4. MEME scores the match of all 6-mers to current matrix

G GCTATTG CATATGACGA GATGAG GCCCAGACC

G GATGAC AATTATATAA AGGACCGT GATAAG AGATTAC

CTAGCTC GTAGCTC GTTGAG ATGCGCT CCCCGCTC

GATGAC GGAGTATTAAAGACTC GATGAG TATACGA

- 5. Re-estimate the PWM based on the **weighted** contribution of all 6-mers.

The height of the bases above corresponds to how much that 6-mer counts in calculating the new matrix

G	0.40	0.20	0.15	0.42	0.24	0.30
A	0.30	0.30	0.20	0.24	0.46	0.18
T	0.15	0.30	0.45	0.16	0.15	0.28
C	0.15	0.20	0.20	0.16	0.15	0.24

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- 6. MEME scores the match of all 6-mers to current matrix

gGCTATTGCATATGACGAGATGAGGCCCAGACC

GGATGACTTATATAAAGGACCGTGATAAGAGATTAC

CTAGCTCGCTAGCTCGTTGAGATGCGCTCCCCGCTC

GATGACGGAGTATTAAAGACTCGATGAGTTATACGA

- Iterations continue until convergence
 - Numbers do not change much between iterations

Final motif

G	0.85	0.05	0.10	0.80	0.20	0.35
A	0.05	0.60	0.10	0.05	0.60	0.10
T	0.05	0.30	0.70	0.05	0.20	0.10
C	0.05	0.05	0.10	0.10	0.10	0.35

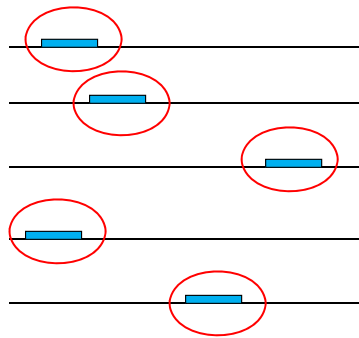
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Gibbs Sampling

- References
 - AlignAce by Hughes et al. 2000
<http://atlas.med.harvard.edu/download/index.html>,
 - BioProspector by Liu et al. 2001
<http://motif.stanford.edu/distributions/r>
- Procedure
 1. Start by randomly choosing sites and creates an initial PWM matrix
 2. Sample other sites
 - Remove some set of matrix examples (sites)
 - Randomly choose other sites and calculate P given matrix
 - If they have a high score to the matrix, keep the new site
 3. Iterate until convergence

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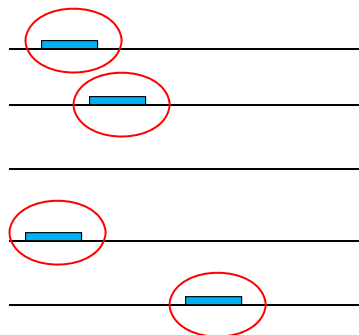
Gibbs Sampling: Basic Idea



Current motif = PWM formed
by circled substrings

Slides generously and unknowingly provided by S. Sinha, Urbana-Champaign CS Dept.

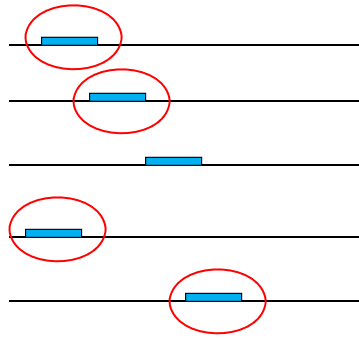
Gibbs Sampling: Basic Idea



Delete one substring

Slides generously and unknowingly provided by S. Sinha, Urbana-Champaign CS Dept.

Gibbs sampling: Basic Idea



Try a replacement:
Compute its score,
Accept the replacement
depending on the score.

Slides generously and unknowingly provided by S. Sinha, Urbana-Champaign CS Dept.

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- Common methods
 - Enumeration
 - Expectation-Maximization (EM) algorithm
 - Gibbs sampling methods