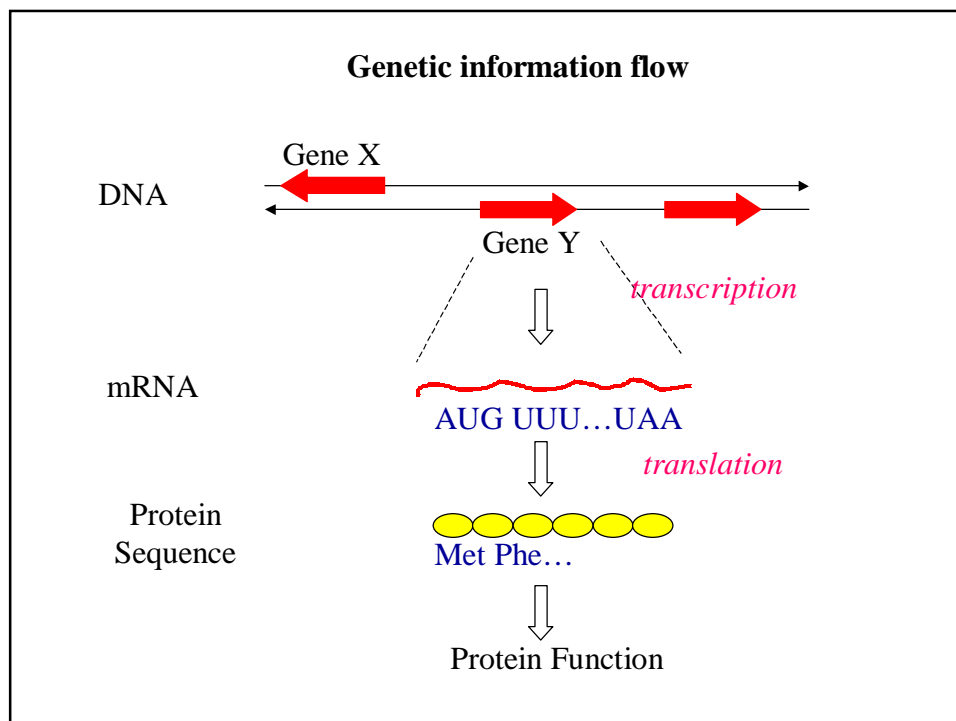


# Introduction to Bioinformatics

KITP, UCSB  
Hao Li, Feb 20, 2003



### Some of the canonical bioinformatics tasks

#### Centered around the processing of genetic information

Finding genes: exons, introns, transcription start site, splicing signal,...

Inferring the function of protein based on sequence

Understanding gene regulation from sequence signal

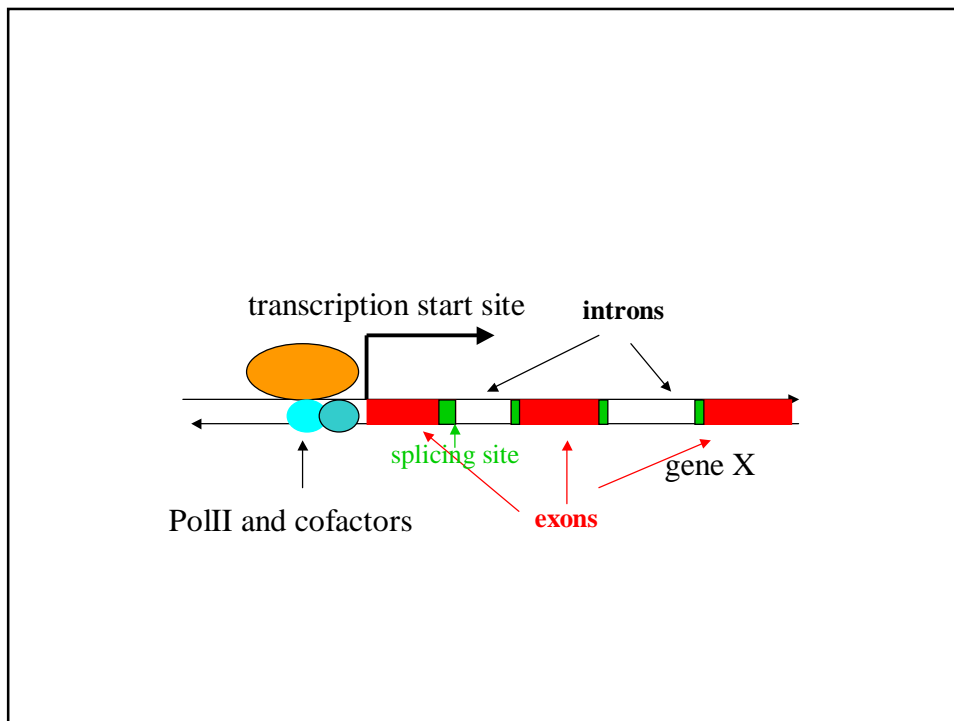
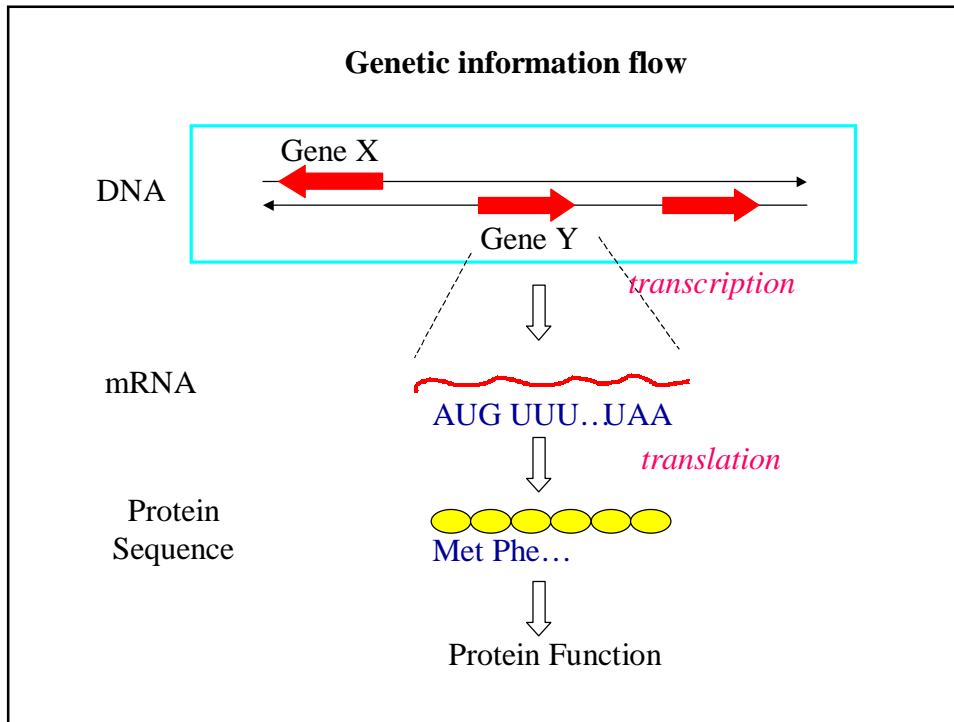
#### Strategy:

Mimic what the cell does

Use statistics cell can not utilize

### Information available

- Primary Sources
  - DNA sequences, [GeneBank](#)
  - Protein sequences and structures, [SwissProt](#), [PDB](#)
- Genome databases for various organisms
- Other more specialized sources, E.g.,
  - Protein families, domains, structure classification, [Pfam](#), [BLOCK](#),..
  - Promoter databases, [EPD](#)
  - Transcription factor binding sites, [TRANSFAC](#)
- Large scale experimental data
  - Gene expression (DNA micro-array, proteomics data), [SMD](#)...
  - Genomic scale functional assay
  - Protein protein interaction data (e.g., two hybrid screen), [DIP](#)...
  - Transcription factor location data (e.g.,CHIP-on-CHIP)



## Gene finding

### Type of signals

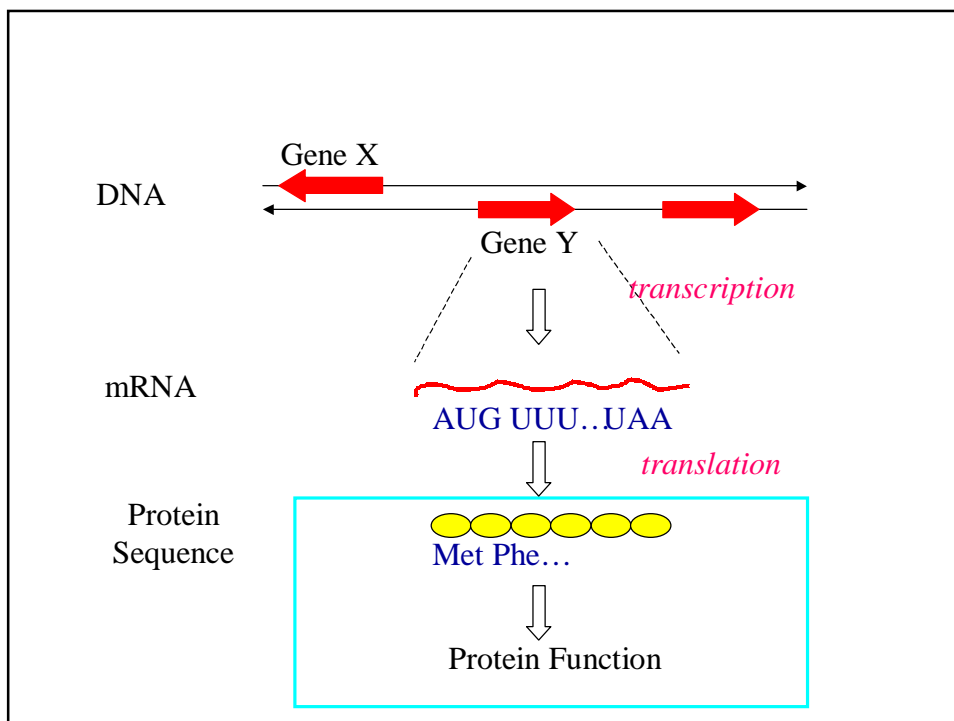
promoter, splicing site, transcription termination, etc  
base frequency at diff. codon positions, 6' mer, etc  
homology to EST, known protein seq.

### Need training set

[a list of gene finding algorithms](#)

[GENSCAN](#) HMM ~90% single bp, ~80% exon

[Grail](#) neural network




## Predicting structure and/or function from sequence

what does it do → function

how → mechanism

can I design a new one with desired  
properties → critical residues,  
structure/function domains etc.

## Predicting function/structure by homology

- 1) find similar sequence with known function/structure  
**Blast/PSI-Blast/Smith-Walterman** form hypothesis  
homology modeling, structure classification etc. 
- 2) Find similar sequences with unknown functions  
Structure information, important residues  
Multiple sequence alignment may give some clue  
**ClustalW**
- 3) No homology detected by sequence alignment  
Try pattern/profile search  
**Prosite, BLOCKS, Pfam etc**

## sequence alignment

```
DALGKTNAVAHKLLVDD
|  | | |      | | | | |
DLLGK--VAQHKLLTAD
```

How to score an alignment

match and mismatch: **scoring (substitution) matrix**

**gap penalty**: opening a gap; extension of a gap

Significance of an alignment

**E value**: expected number by chance

## Substitution matrices

$$s(a, b) = \log \left( \frac{p_{ab}}{q_a q_b} \right)$$

← frequency of aligned pairs  
← frequency of amino acids

PAM (Dayhoff) matrices: derived from the ungapped alignment of very similar proteins, extrapolate to longer evolutionary distance. PAM-x, larger x corresponds to longer distance

BLOSUM matrices: derived from aligned ungapped regions in the block database. BLOSUM-y, smaller y corresponds to longer distance

Recommended matrices and gap costs

Query length	Substitution matrix	Gap costs
<35	PAM-30	(9,1)
35-50	PAM-70	(10,1)
50-85	BLOSUM-80	(10,1)
>85	BLOSUM-62	(11,1)

Sequence alignment algorithms

**Needleman-Wunsch:** global alignment, align two sequences from end to end

**Smith-Walterman:** local alignment, find the alignment of two local pieces that gives highest score.

**Blast:** approximation to Smith-Walterman, heuristic

## Sequence alignment: Blast

NCBI Blast server: <http://www.ncbi.nlm.nih.gov/BLAST>

ftp site: <ftp://ncbi.nlm.nih.gov/blast>

Options:

different databases to search

different versions of the program

program	Probe type	Database type	translate
blastn	n	n	
blastp	p	p	
blastx	n	p	probe
tblastn	p	n	database
tblastx	n	n	probe and database

## Sequence alignment: Blast

Choice of parameters:

scoring matrix

BLOSUM 62 standard for length>85

other matrices for short query seq

effect of gap penalty

Gap open	Gap extension	comment
large	large	Very few ins. Or del
large	small	A few large insertions
small	large	Many small insertions



## Sequence alignment

What is a significant hit

protein: E value  $< 0.001$   
length  $> 80$  AA sequence identity  $> 30\%$

coding DNA: use blastx, tblastx, translate

noncoding DNA: may use small gap penalty

## PSI-Blast

Position Specific Iterated Blast

Using statistically significant hit from Blast  
Convert the alignments into position specific score matrix  
Search database using the matrix  
iterate

Can detect weaker homology

An example

result1 result2

Multiple sequence alignment → structural/evolutionary Relationship (Nature performed mutagenesis for us)

```

sp|P49789|FHIT_HUMAN -----MSFRFGQHLIKPSVVFLKTELSFALVNRKPVVPGHVLVCP
sp|O89106|FHIT_MOUSE -----MSFRFGQHLIKPSVVFLKTELSFALVNRKPVVPGHVLVCP
sp|P49776|APH1_SCHPO -----PKQLYFSKFPVG-SQVFYRTKLSAAFVNLKPILPGHVLVIPQ
sp|P49775|HNT2_YEAST MILSKTKKPKSMNKP IYFSKFLVT-EQVFYKSKYTYALVNLKPIVPGHVLIVPL
sp|Q11066|YHIT_MYCTU -----MPCVFCAIIAGEAPAIRIYEDGGYLAILDIRPFTRGHTLVLPK
sp|Q58276|Y866_METJA -----MCIFCKIINGEIPAKVVYEDEHVLAFLDINPRNKGHTLVVVPK
    
```

Multiple sequence alignment

Generalization of dynamical programming works only for small number (<8) of short sequences

Progressive alignment: practical algorithms for a large number of sequences

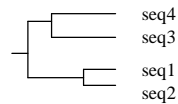
pairwise alignment  
calc. distance matrix



Build guide tree



Progressive alignment  
Align following the tree



## Multiple sequence alignment

### clustalW

sequence weighting according to divergence  
substitution matrix chosen based on expected similarity  
carefully fine tuned gap penalties  
position specific, residue specific

### example

### result

## Searching local profiles

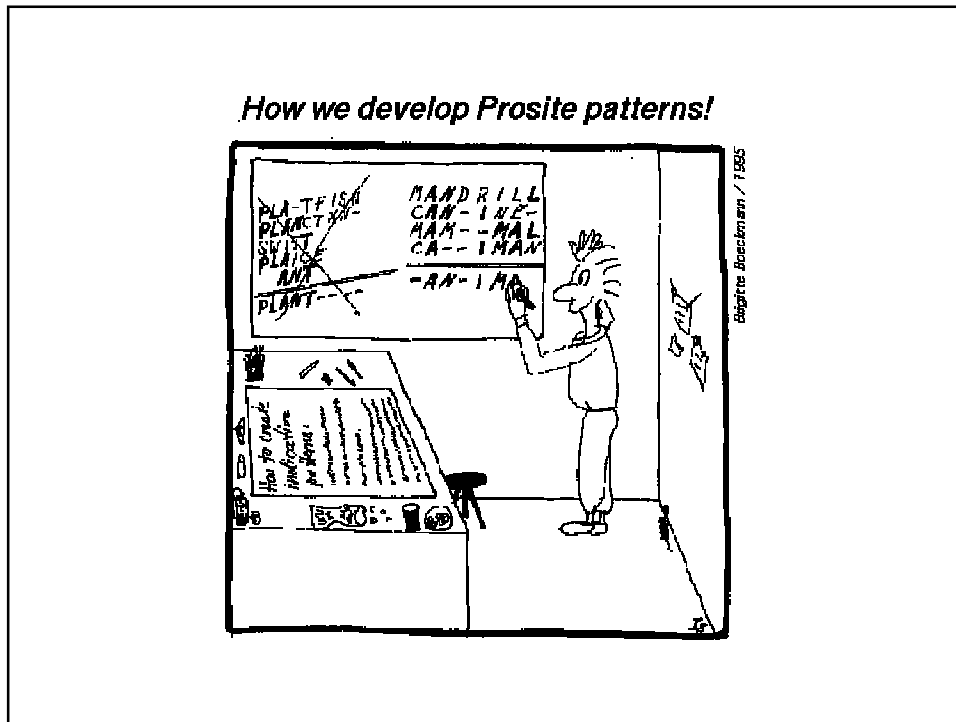
using profile databases

**Prosite:** patterns and profiles from conserved motifs, functional sites  
1580 patterns and profiles (release 17.28 Nov 2002)

**BLOCKS:** based on automatic ungapped alignment, position specific  
scoring matrices  
2101 groups 8656 blocks (version 13.0)

**Pfam:** multiple sequence alignment and profile HMMs  
models for 4832 protein families (Oct, 2002)

Several others



An example of pattern/profile databases

Prosite:

originally only regular expression patterns  
now include profiles  
e.g., build pattern around an active residue

ALRDFATHDDF  
SMTAEATHDSI  
ECDQAATHEAS

CONSENSUS PATTERN ATH[D,E]

BLOCKS:

Construct position specific scoring matrix (PSSM)  
based on gapless blocks of multiply aligned sequences

$$w(x, a) = \sum_b f(x, b) \times s(b, a)$$

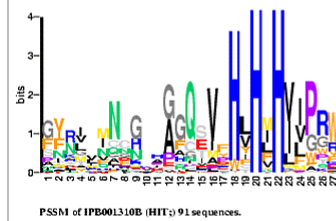
$f(x, b)$  weighted frequency of  $b$  at position  $x$   
 $s(b, a)$  is the scoring matrix. there are more elaborated  
Method based on position dependent pseudo-counts

For example,

... . VGAHA  
... . VNVDE  
... . VEADE  
... . FNANP  
... . IAGAD

$$M(1, a) = 3/5 * s(V, a) + 1/5 * s(F, a) + 1/5 * s(I, a)$$

Example of blocks profile  
Histidine triad  
Zinc binding motif



Predicting structure from sequence

transmembrane helices 80%~95% accuracy

windows of 20 hydrophobic AA, database of known helices

[http://www.ch.embnet.org/software/TMPRED\\_form.html](http://www.ch.embnet.org/software/TMPRED_form.html)

secondary structure prediction 70% ~80%

tertiary structure prediction ?

homology modeling, fold recognition, ab initio

homology modeling:

<http://www.expasy.ch/swissmod/SWISS-MODEL.html>

## Secondary structure prediction

single sequence based

Chou and Fasman helix propensity

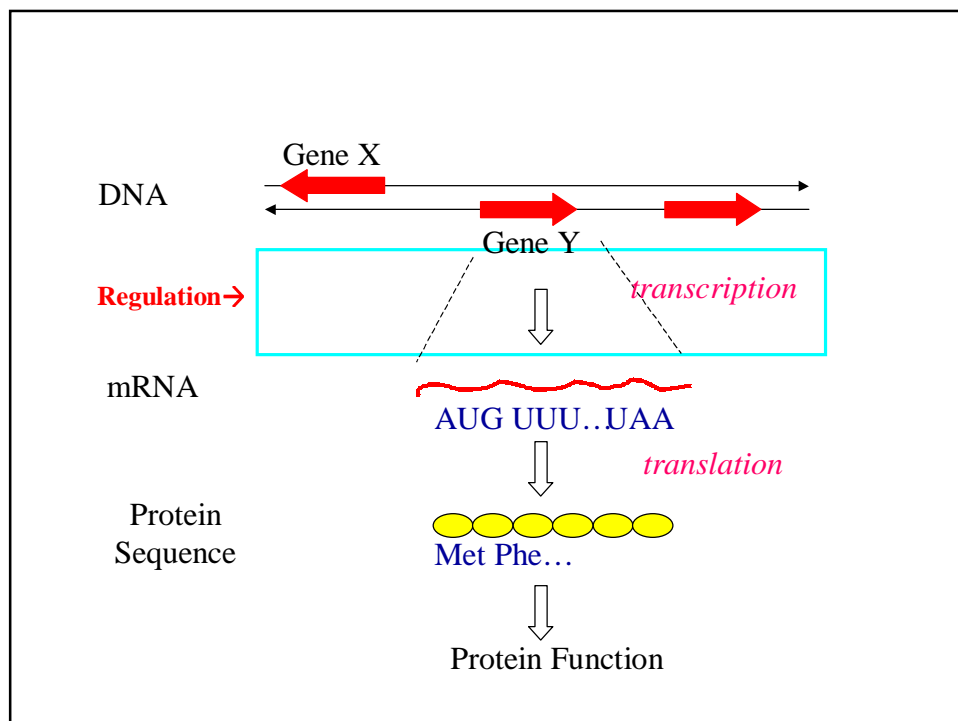
nnpred (Kneller, Cohen, Langridge) neural nets based

....

Algorithms using multiple sequence information

PHD

....



## Gene regulation

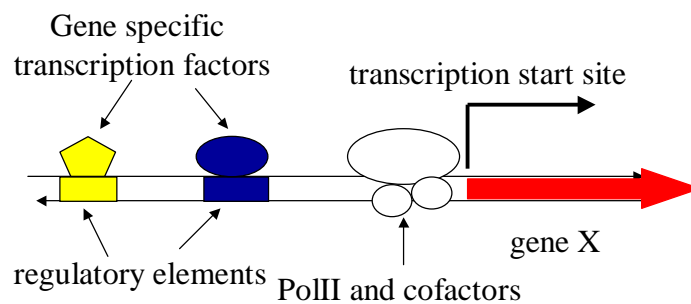
The expression of gene can be controlled in various ways

**transcriptional:** the amount of mRNA synthesized  
translational: the amount of proteins made  
post-translational: modify proteins

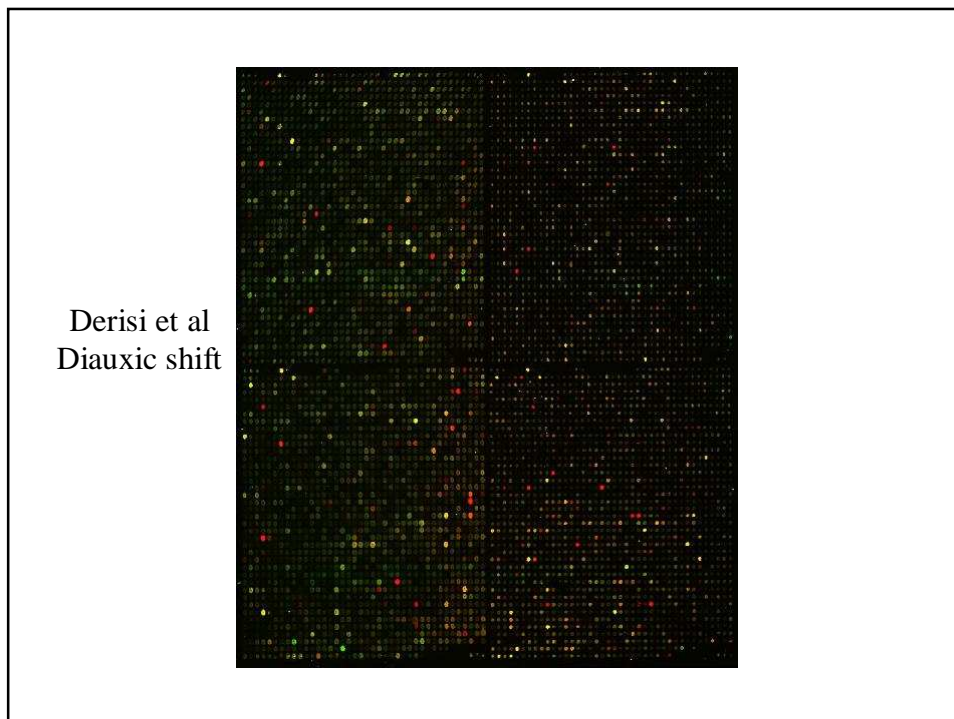
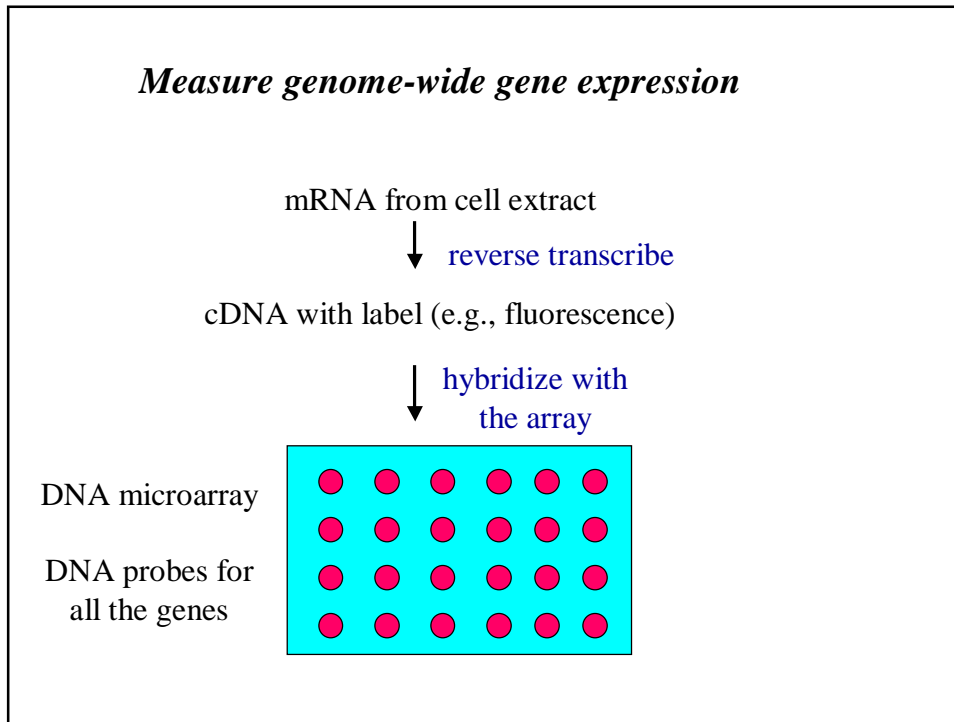
Transcriptional control is a major mechanism for regulation

transcriptional program is encoded in genomic DNA

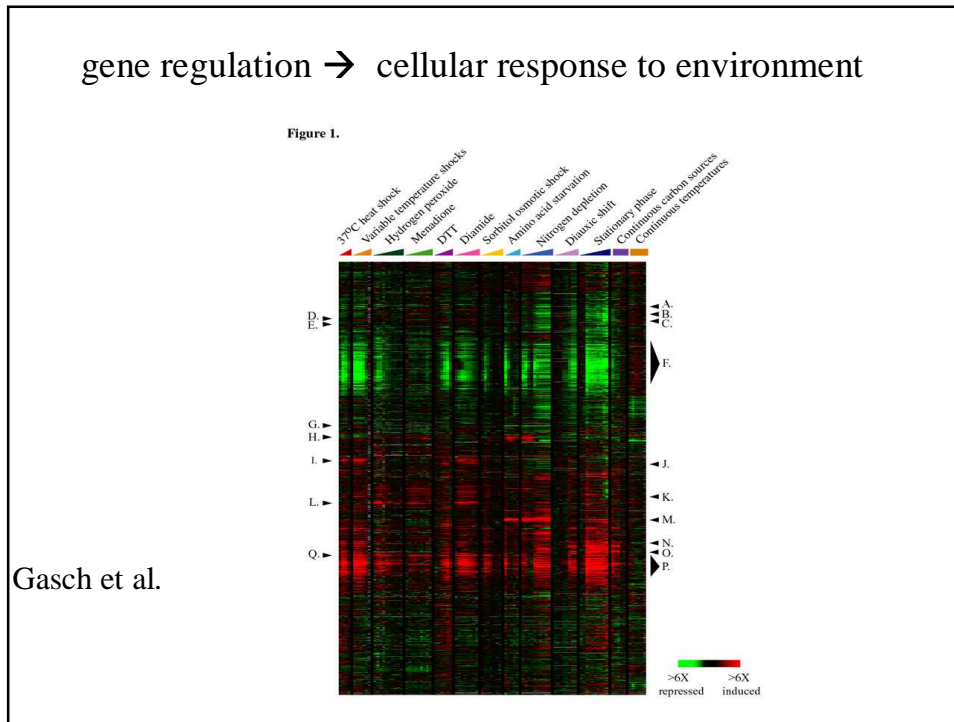
## Transcriptional regulation







gene regulation → cellular response to environment



complete genome sequences



genome-wide expression data  
(e.g., from DNA microarray)



opportunity to decipher a cell's  
regulatory program

## General approaches

### Knowledge based approach

collect examples of known TF binding sites → databases  
build profiles of TF recognition sites → search query seq.

### Discover novel regulatory sites

#### pattern recognition

finding patterns in a group of co-regulated genes  
identifying combinatorial motifs from the whole genome

### knowledge based: Databases of TF binding sites

**TRANSFAC:** The Transcription Factor Database  
a collection of experimentally determined  
transcription factor binding sites

Release IV

site: 8415

gene: 1078

factor: 2785

profiles: 309 matrices

**SCPD:** TF binding sites database for Yeast  
~ 500 sites representing ~100 factors

**E Coli:** Church lab website  
~ 800 sites representing ~ 60 factors

Knowledge based: building TF recognition profiles

Align examples of binding sites for a given TF (MCB)

```

>YDL102W   ACGCGT
>YDL164C   ACGCGT
>YDL164C   ACGCGA
>YJL194W   ACGCGT
>YJL194W   ACGCGA
>YMR199W   CCGCGT
>YMR199W   TCGCGA
>YMR199W   ACGCGT
>YNL102W   ACGCGT
>YNL102W   ACGCGT
>YOR074C   ACGCGT
>YOR074C   ACGCGT
    
```

A	10	0	0	0	0	3
T	1	0	0	0	0	9
G	0	0	12	0	12	0
C	1	12	0	12	0	0

← Alignment matrix

position specific probability matrix

	1	2	3	4	5	6
A	0.84	0.00	0.00	0.00	0.00	0.25
C	0.08	1.00	0.00	1.00	0.00	0.00
G	0.00	0.00	1.00	0.00	1.00	0.00
T	0.08	0.00	0.00	0.00	0.00	0.75

⇐  $f_{i,\sigma}$

probability of certain base occurring in the binding site is given by the above matrix

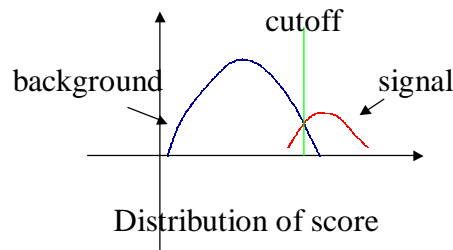
probability of observing certain base not in the binding site is given by the background frequency  $f_{\sigma}^0$

***Predicting new sites using the matrix***

$$w_{i\sigma} = \ln[f_{i\sigma} / f_{\sigma}^0]$$

Score a sequence using the position weight matrix

AGACGT →  $w_{1A} + w_{2C} + w_{3A} + w_{4T} + w_{5G} + w_{6A}$     Log likelihood ratio



**Knowledge based:** searching for known sites in query seq.

Example: his4 histidine biosynthesis

Extract the putative regulatory region for his4, 600bp 5' of the coding region

```

gggctaaagaacgcgaacaattgaaaatgcataacgattcgctcagtaagaatacc
aaaatttgagcaaggaactatTTTgacaaaaccacaagattcctcatcggaagaggtg
gcatccttaacgaaaaaactgaagaggctaataaaaaatcaaacagttggaacagg
ctcaagcacaacagccgtggaatcgttgccaattttcgacccccctgcaccagtcgata
ccacggcaggaagacaacagtggtgtgagcattgcgatac gatgggtcataatacagca
gaatgccccatcacaatcctgacaaccagcagttcttctaggcagtcgaactgactctaat
agtgactccggtaaattagttaattaattgctaaacctgcacagtgactcacgTTTTTtca
gtcattcgatatagaaggtaagaaaaggatatgactatgaacagtagtatactgtgtataat
agatatggaacggtatattcacctccgatgtgtgtgtacatacaaaaaatcatagcaca
ctgcgctgtgtaatagtaataacaatagtttcaaaaTTTTTtctgaata
    
```

Submit the query sequence to TRANSFAC  
Using profile matrices for Fungi to search for  
Putative binding sites of known factors

The result

## **Identify binding sites de novo**

### 1. finding patterns in a group of co-regulated genes

group genes by their similarity (biochem. func., gene  
expression profiles)

extract the putative regulatory regions of the group

search for common sequence patterns (various algorithms)

**Clustering based method**

Focus on a subset of genes  
likely to share a common binding site

Cluster genes based on  
Similarity in their expression profile (DNA microarray)

boosted by the rapid accumulation  
of DNA microarray data

**Deriving co-regulated clusters from  
Gene expression data**

Clustering algorithms

- Hierarchical clustering
- K mean
- self organized map
- Stat. Mech. spin models
- .....

**Hierarchical clustering** (Eisen et. al.)

Define similarity between a pair of genes X and Y

$X_i$ : expression level of X in experiment i

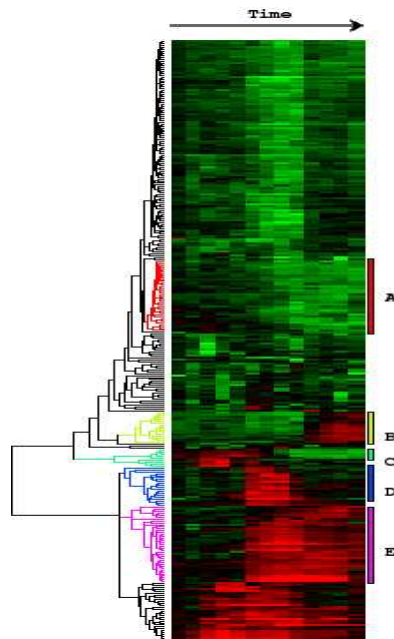
$Y_i$ : expression level of Y in experiment i

$$s(X, Y) = \frac{\sum_i (X_i - \bar{X})(Y_i - \bar{Y})}{N\sigma_X\sigma_Y}$$

Assemble genes into a dendrogram based on the pairwise similarities

Example from Eisen et al.

human fibroblasts  
serum stimulated





Subsets of genes defined by the clusters

**detecting common sequence patterns in  
the regulatory sequences of the subset of genes**

- ❑ frequency count of substrings or regular expression patterns
- ❑ local multiple sequence alignment

Algorithm based on frequency contrast

oligonucleotides frequency contrast

(van Helden, Andre, and Collado-vides)

count the number in the dataset

count the number in a contrast dataset (e.g., whole genome promoters)

use the expected frequency from contrast set to calculate significance of over-representation

An example of van helden algorithm

Find a group of genes involve in  
Methionine synthesise pathway

Extract the upstream 600 bp region

Submit the sequence to the website

<http://www.ucmb.ulb.ac.be/bioinformatics/rsa-tools>

1 seq oligomer sequence  
2 identifier oligomer identifier  
3 expected\_freq expected relative frequency  
4 occ observed occurrences ;  
5 exp\_occ expected occurrences ;  
6 occ\_prb occurrence probability (binomial) ;  
7 occ\_sig occurrence significance (binomial) ;  
8 rank

Seq	identifier	expected_freq	occ	exp_occ	occ_prob	occ_sig	rank
cacgtg	cacgtg cacgtg	0.000117	24	2.23	2.8e-09	5.24	1
acgtga	acgtga tcacgt	0.000166	18	3.16	7.9e-09	4.79	2

Correctly identify the binding site of Cbf1-Met4-Met28 complex

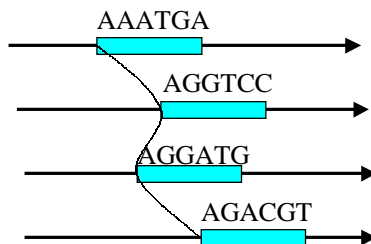
Algorithms based on multiple local alignments

**Consensus** (Hertz and Stormo)

**Gibbs-Sampler** (Lawrence, Liu, Newald et al.)

**MEME** (Baily and Elkan)

*Solving the problem  
A model for the motif*



alignment matrix

	1	2	3	4	5	6
A	4	1	2	1	0	1
C	0	0	0	1	1	1
G	0	3	2	0	2	1
T	0	0	0	2	1	1

position specific frequency matrix

	1	2	3	4	5	6	
A	1.00	0.25	0.50	0.25	0.00	0.25	⇐ $f_{i\sigma}$
C	0.00	0.00	0.00	0.25	0.25	0.25	
G	0.00	0.75	0.50	0.00	0.50	0.25	
T	0.00	0.00	0.00	0.50	0.25	0.25	

↑  
Information 2 bits

$$Information = \sum_{i,\sigma} f_{i\sigma} \ln[f_{i\sigma} / f_{\sigma}^0]$$

Alignment based algorithms  
MEME, Consensus, Gibbs Sampler  
Search for alignment path → optimize information

Statistical Model:

probability of observing certain base inside  
the motif is given by the position-specific prob. matrix

probability of observing certain base outside  
the motif is given by the background frequency

**Maximum likelihood formulation**

Starting positions of the motif unknown  $\bar{x} = (x_1, x_2, \dots, x_N)$

Position specific probability matrix unknown  $f_{i,\sigma}$

need to be inferred from the observed sequence data

$$P(seq | f_{i,\sigma}, \bar{x}) = \prod_{i=1}^N \left( \prod_{j=1}^{x_i-1} f_{\sigma_{ij}}^0 \prod_{j=x_i}^{x_i+w-1} f_{j-x_i+1,\sigma_{ij}} \prod_{j=x_i+w}^L f_{\sigma_{ij}}^0 \right)$$

- $N$  Number of sequences
- $L$  Length of the sequence
- $w$  Width of the motif
- $\sigma_{ij}$  Base of sequence  $i$  at position  $j$

$$P(seq | f_{i,\sigma}, \bar{x}) = const \prod_{j=1}^w \prod_{\sigma} \left( \frac{f_{j,\sigma}}{f_{\sigma}^0} \right)^{n_{j,\sigma}(\bar{x})} \quad \text{likelihood ratio}$$

$n_{j,\sigma}(\bar{x})$  Total number of count for base  $\sigma$  at position  $j$  in the alignment

Maximizing  $P(seq, \bar{x} | f_{i,\sigma})$  w.r.t.  $f_{i,\sigma}$  With  $\bar{x}$  fixed

$$\log P(seq, \bar{x} | \hat{f}_{i,\sigma}) = N \sum_{j=1}^w \hat{f}_{j,\sigma} \log \left( \frac{\hat{f}_{j,\sigma}}{f_{\sigma}^0} \right) \quad \begin{array}{l} \text{log likelihood ratio} \\ \text{relative entropy} \end{array}$$

$$\hat{f}_{j,\sigma} = \frac{n_{j,\sigma}(\bar{x})}{\sum_{\sigma} n_{j,\sigma}(\bar{x})} \quad \begin{array}{l} \text{in reality, this formula is modified} \\ \text{by adding pseudo counts due to} \\ \text{Bayesian estimate} \end{array}$$

Then maximize the above relative entropy w.r.t  $\bar{x}$   
 → Alignment path.

Stormo-Hartzell Algorithm: Consensus

- each of the length  $w$  substrings of the first sequence are aligned against all the substrings of the same length in the second sequence, matrices derived,  $N$  top matrices with highest information contents are saved
- the next sequence on the list is added to the analysis, all the matrices saved previously are paired with the substrings of the added sequence and top  $N$  matrices saved
- repeat the previous step until all the sequences have been processed

Example: 22 genes identified as *pho4* target by microarray, O'shea lab

```
YAR071W:600:-600
\catcaagatgagaaaataaaggatttttcgtctttatcattttctttctcactccgactactcttataatctcttcatcggttcattcatcgtgggtgtcctaagaatttta
atgacagagataaacttgataagctttttatagcgtgtgcacgtatttataaattaccacgttttcgcataacattctgtagttcatgtactaaaaaaaaaaaaaaaa
gaaataggaaaggaaagatgtaaaagttaatagaaaacaagaacacatccctaaacgaagccgcacaactctggcgttcacacgtgggtttaaaaaggcaaatcacag
aatttcagacctgtttaccggaagattccatattccgcacgtcacattgccaaattggcctctcaccagatattataaccgttttggaaatgagcataaacagcgtcgaa
ttgccaaagtaaacgtataaagctcttaccattcagatagattcaagctcagtttcgccttggttgaagtaggaaagaagaagaagaagaaggaacaacaacgcaaa
gagagcaagaacatcatcagaaatacca\
YBR092C:600:-600
\aatcaatgacttctacgactatgctgaaaaagagtagccgactactcctaaaggctgtaacgtcagcagcgtcagtaactctgaattgaccttctactgggac
tggaaactactactaatacaacgccagctattgagacaatagttttgataaactaaataatattggaaactaaatcgaataccgaatttttctaaatttggcgaagatta
aatctcgagatattcgaacaaggtaaatggatgttcaatccctgtagtcagtcaggaaaccatattatatacagattagtcgccgcttagccacgcttattagca
aatcaaaccttaagtgcatacggctataagggaaactcaagaactggcctcgcaaaaatgaaaaaaaggaaagagtaaaaaaaattcaaaagaatttacta
aataatacagtttgggaaatgtaaacagctttgagtgcctatgcaacatataaagtgcttaatttgcctggaatggaagtcattatgcttgattatcaaaaaaata
ctacagtaaaagaggccattccaattacct\
YBR093C:600:-600
\cgtaatagcggcgtgtcgcacgctctttacaggacgccgagaccggcattacaaggatccgaaagtgtattcaacaagaatgcaaatatgtcaacgtattgg
aagtcattttatgtgcgctgctttaatgtttctcatgtaagcggacgtcgtctataaactcaaacgaaaggtaaaaggctcatagcgtttttctttgctgcacaagaatata
tattaaattagcacgttttcgatagaacgcaactgcacaatgccaaaaaaagtataaaagtattaaaaagatttaattgaatagcgaatctctaaatgaatcgataaaccttg
gcactcacacgtgggactagcagactaaattatgattctggctccctgtttcgaagaatcgcacatgccaaattatcaaaattggcacttacttggcaaggcatatc
ccatttgggataaaggtaaacatctttgaattgtcgaatgaaacgtatataagcgtgatgtttgctaaagtcgaggttagtatggcttcatctcatgagaataagaaca
caacaatagagcaagcaaatcgaattacca\
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\gaaatctcggttcacccgcaaaaaagttaaaattcacagatcgcgccacaccgatcacaaaacgcttcaccacaagggtgtgtggctgtgcgatagacctttttctt
ttctgcttttcgtcatccccacgttggccattaatttggtagtgggcccttaaatgtcgaatattgctaaaaattggcccgaatgcaaaaggctttaagaatataaccgtac
aaagggtttatgtaacttaataaattgcataatgacaatgcagcacgtgggagacaaatagtaataactaactatcaatactagatgtcacagccacttggatccttcta
ttatgtaaatcattagattaactcagcgaatgcaatgtttttacaatgtctactgggtggacatctccaaacaattcatgtcactaagcccgttttcgataagaataat
atataaacctgctgaagatgattttacattgaggttattacatgaattgtcagaatgagtgacatagatcaaaagtgagaatactggaagcgtatctaatcgaatcaat
aaacaagattaaagcaaaatg\
```

Consensus output for Pho4 regulated genes

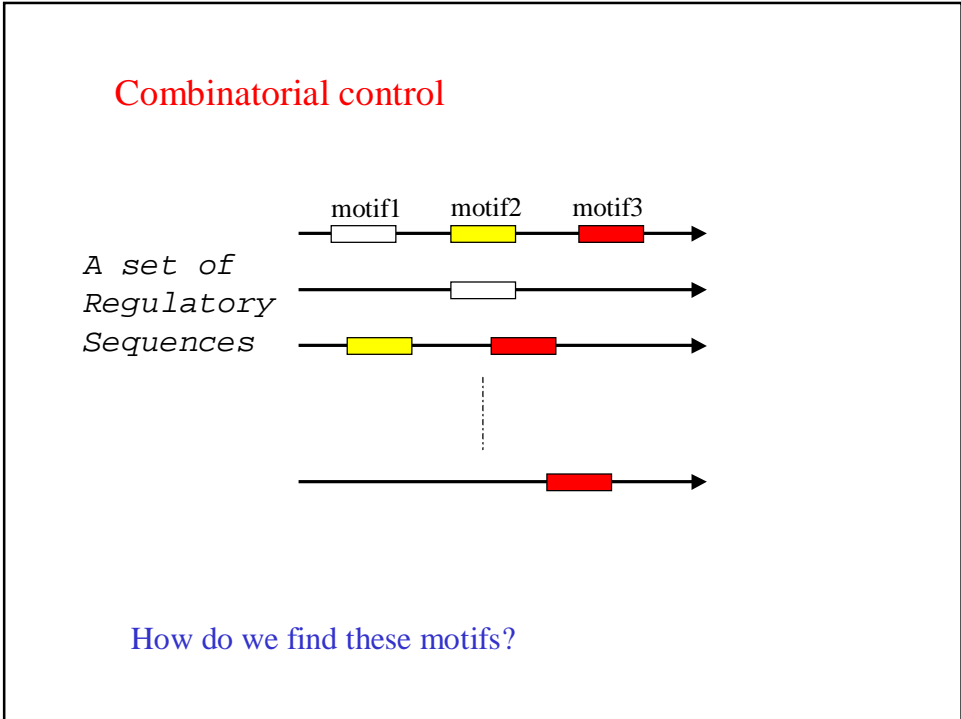
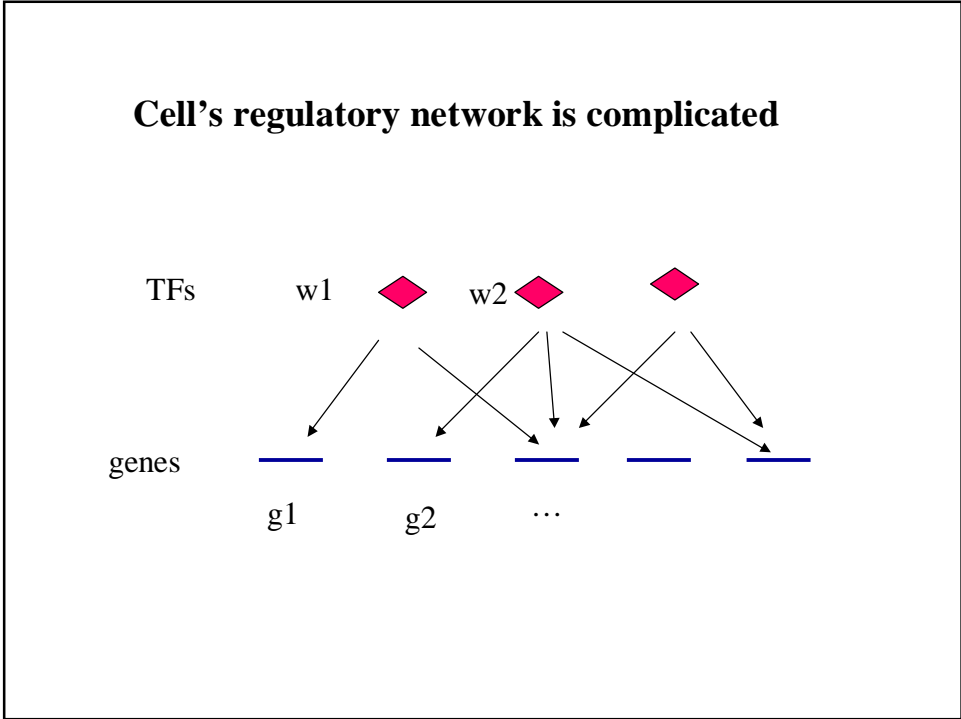
MATRIX 1  
number of sequences = 22  
information = 8.80903  
ln(p-value) = -153.757 p-value = 1.67566E-67  
ln(expected frequency) = -13.357 expected frequency = 1.58165E-06

```
A| 6 5 20 3 0 3 0 0 0 6  
G| 11 0 0 5 22 0 21 15 14 2  
C| 4 17 0 14 0 0 1 2 8 1  
T| 1 0 2 0 0 19 0 5 0 13  
  G C A C G T G G G T
```

```
1|1 : 1/317 ACACGTGGGT  
2|2 : 2/55 AAAGGTCGTG  
3|3 : 3/347 ACACGTGGGA  
4|4 : 4/274 GCACGTGGGA  
5|5 : 5/392 CAACGTGTCT  
6|6 : 6/395 ACAAGTGGGT  
7|7 : 7/321 ACACGTGGGA  
8|8 : 8/536 GCAAGTGGCT  
9|9 : 9/177 GCTGGTGTGT  
10|10 : 10/443 GCACGTGTCT  
11|11 : 11/14 CCAGGTGCCT  
12|12 : 12/502 GAAAGAGGCA  
13|13 : 13/354 GCACGAGGGA  
14|14 : 14/257 GCACGTGCCA  
15|15 : 15/358 TCACGTGTGT  
16|16 : 16/316 ACACGTGGGT  
17|17 : 17/479 GCACGTGGCT  
18|18 : 18/227 GATGGTGGCT  
19|19 : 19/186 GCACGTGGGG  
20|20 : 20/326 GAAGGAGGGG  
21|21 : 21/307 CCACGTGGGC  
22|22 : 22/255 CCACGTGGCT
```

## 2. Identifying combinatorial motifs

dictionary approach: finding words from a scrambled text  
[Mobydick](http://genome.ucsf.edu:8080/mobydick), <http://genome.ucsf.edu:8080/mobydick>





chapterptgpbqdrftezptqtasctmvivwpecjsnisrmbtqlmlfvetl  
loomingsfkicallxjgkmekysjerishmaelplfsomeylqyearstvh  
njbagoaxhjtjcokhvneverpmqpmindhowzrbdljllonggbhqi  
preciselysunpvskepfjdktcgarwtaxybgcvdjfbnohavinglittl  
ezorunozsoyapmoneyyvugsgtsqintmyteixpurseiwfmjwgj  
nyyveqxwftlamnbxkrbkyandrnothingcgparticularwtzao  
qsjtnmtoqsnwvxfiupinterestztimebymonlnshoreggditho  
ughtyxfmxhqixceojzdhwouldsailpcaboutudxsbsnewtpg  
gvjaasxmsvlittleplvcydaowgwlbzizjlnzyxandzolwcudthjd  
osbopxkkfdosxardgcseebbthefzrsskdhmawateryjikzicim  
ypartmofprtheluworlvdtoamfutitazpisagwewayrqbkiosh  
avebojwphiixofprmalungipjdrivingpkuyoikrwxoffodhicb  
nimtheixyucpdzacemspleenqbpcermhwwddyaiwnandada  
bkpgzmpatoregulatingeetheslcirculationvsuctzwvfyxstuzr  
dfwvgygzoejdfmbqescwheneverpitfindmyselfgrowingne  
ostumrydrtrthmjsmgrimcczhjmgbkwczaboutjwbwanbwzq  
thehrjvdrccjgmouthuutwheneveritddfouishlawwphxnae

Moby Dick: CHAPTER 1  
Loomings

Call me Ishmael. Some years ago- never mind how long precisely-having little or no money in my purse, and nothing particular to interest me on shore, I thought I would sail about a little and see the watery part of the world. It is a way I have of driving off the spleen and regulating the circulation. Whenever I find myself growing grim about the mouth; whenever it is a damp, drizzly November in my soul; whenever I find myself involuntarily pausing before coffin warehouses, and bringing up the rear of every funeral I meet; and especially whenever my hypos get such an upper hand of me, that it requires a strong moral principle to prevent me from deliberately stepping into the street, and methodically knocking people' s hats offthen, I account it high time to get to sea as soon as I can.

the Model:

### Probabilistic Segmentation/Maximum likelihood

A probabilistic dictionary  
Words  
probabilities

$$\left. \begin{array}{l} A \rightarrow P_A \\ C \rightarrow P_C \\ G \rightarrow P_G \\ T \rightarrow P_T \\ GC \rightarrow P_{GC} \\ TATAA \rightarrow P_{TATAA} \end{array} \right\}$$

A | G | T | A | T | A | A | G | C  
 A | G | T | A | T | A | A | G | C  
 A | G | T | A | T | A | A | G | C

maximizing  
the likelihood  
function

$$Z = \sum_{Seg} P_{w_1} P_{w_2} P_{w_3} \dots P_{w_n}$$

Dictionary1		Dictionary2		Dictionary3	
e	0.065239	e	0.048730	e	0.042774
t	<b>0.055658</b>	s	0.042589	s	0.040843
a	0.052555	a	0.040539	a	0.038595
o	0.050341	t	<b>0.040442</b>	i	0.036897
n	0.049266	i	0.038550	t	<b>0.036871</b>
i	0.048101	d	0.038547	d	0.036323
s	0.047616	o	0.036486	l	0.035336
h	0.047166	l	0.036300	c	0.034818
r	0.043287	g	0.034509	m	0.034650
l	0.041274	r	0.034496	y	0.034482
d	0.039461	c	0.033916	b	0.034396
u	0.034742	m	0.033724	r	0.034105
m	0.034349	n	0.033321	p	0.034044
g	0.034001	y	0.033227	w	0.033819
w	0.033967	p	0.033156	n	0.033817
c	0.032934	f	0.032863	g	0.033676
f	0.032597	b	0.032780	f	0.033534
y	0.031776	w	0.032009	o	0.033206
p	0.031711	h	0.031494	h	0.033200
b	0.031409	v	0.030727	k	0.032103
v	0.028268	k	0.030445	v	0.031498
k	0.028113	u	0.030379	j	0.031209
j	0.026712	j	0.029268	u	0.031186
q	0.026561	z	0.028905	z	0.031003
z	0.026542	x	0.028404	x	0.030544
x	0.026357	q	0.028123	q	0.030244
		th	<b>0.009954</b>	the	<b>0.005715</b>
		in	0.006408	ing	0.003237
		er	0.004755	and	0.003128
		an	0.004352	in	0.002968
		ou	0.003225	ed	0.002547
		on	0.003180	to	0.002496
		he	0.003108	of	0.002486
		at	0.002851	en	0.001331
		ed	0.002804	an	0.001313
		or	0.002786	th	<b>0.001270</b>
		en	0.002538	er	0.001250
		to	0.002511	es	0.001209
		of	0.002475	at	0.001181
		st	0.002415	it	0.001171
		nd	0.002297	that	0.001165

Words	<Nw>	quality factor
abominate	2.0000	1.0000
achieved	2.0000	1.0000
aemploy	2.0000	1.0000
affrighted	2.0000	1.0000
afternoon	2.0000	1.0000
afterwards	5.0000	1.0000
ahollow	2.0000	1.0000
american	3.0000	1.0000
anxious	2.0000	1.0000
apartment	2.0000	1.0000
appeared	4.0000	1.0000
astonishment	4.0000	1.0000
attention	2.0000	1.0000
avenues	2.0000	1.0000
bashful	2.0000	1.0000
battery	2.0000	1.0000
beefsteaks	2.0000	1.0000
believe	2.0000	1.0000
beloved	2.0000	1.0000
beneath	6.0000	1.0000
between	12.0000	1.0000
boisterous	3.0000	1.0000
botherwise	2.0000	1.0000
bountiful	2.0000	1.0000
bowsprit	2.0000	1.0000
breakfast	5.0000	1.0000
breeding	2.0000	1.0000
bulkington	3.0000	1.0000
bulwarksb	2.0000	1.0000
bumpkin	2.0000	1.0000
business	6.0000	1.0000
carpenters	2.0000	1.0000

### summary

Enormous amount of systematic data

DNA sequence, protein sequence & structure, functional data

Various Databases (general purpose + specialized)

Analysis tools

Tasks driven by known mechanisms

Combine multiple source of data



build mechanistic models



suggest new principle