Statistical modeling of biological sequences

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Hillerød

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#### Is there information in

ACSLPKV0GPCSGKHSYYYFNSAN00CETFVYGGCLGNTNRFATIEECNARC-VCLLPKSAGPCTGFTKKWYFDVDRNRCEEF0YGGCYGTNNRFDSLE0C0GTC-VCAMPPDAGVCTNYTPRWFFNS0TG0CE0FAYGSCGGNENNFFDRNTCERKCM TCSLSPSPGTCGPGVFKYHYNP0T0ECESFEYLGCDGNSNTFASRAECENYCG -CHTEHSSGACPGAVTMFYHDPRTKKCTPFTFLGCGGNSNKFDTRPOCERFCK PCMLPSDKGNC0DILTRWYFDS0KH0CRAFLYSGCRGNANNFLTKTDCRNACM ----RLVGYCSPYLRRYFFNRTTEKCVLFIPERCEKDGNNFPNRKVCMKTCM PCSLKEDYGIGRAYYERWYFNTTTANCTRFIWGGNHKEW00FR------PCK0DLD0GHGKTL0ARYYFNKYAKVCE0FDYRGIDGNRNNFESL0EC000C--CFLKPDEGVGRAILKAFYYNPKNRRCEEFEYGGLGGNENNFETMEKCEEECK -CSOPAASGHGEOYLSRYFYSPEYROCLHFIYSGERGNLNNFESLTDCLETCV LCNLKYDSGVGGEKSDKYFWVPKYTTCMRFSFYGTLGNANNFPNYNSCMATCG ----RGADTIORWYWDTNDLTCRTFKYHGOGGNFNNFGDKOGCLDFC-PCEQAIEEGIGNVLLRRWYFDPATRLCQPFYYKGFKGNQNNFMSFDTCNRACG PCG0PLDRGVGGS0LSRWYWN00S0CCLPFSYCG0KGT0NNFLTK0DCDRTC-VCIOPLESGD-EPSVPRWWYNSATGTCVOFMWDPDTTNANNFRTAEHCESYCR TCVOPTATGP-NPTEPRWWYNSITGMC00FLWDPTASGPNNFRTVEHCESFCR -CD00LMLGVGGASMERFYYDTTDDACLVFNYSGVGGNENNFLTKAEC0IAC-PCSVPLAPGTGNAGLARYYYNPDDR0CLPF0YNGKRGN0NNFEN0ADCERTC-----PESEGVTGAPTSRWYYDOTDMOCKOFTYNGRRGNONNFLTOEDCAATC-ACKMPLSVGIGGAPANRWYYDAAASTCKTFEYNGRKGNONNFISEADCAATC-VCNLPMSTGEGNANLDRFYYD00SKTCRPFVYNGLKGNONNFISLRAC0LSC-ICQQPMAVGTGGATLPRWYYNAQTMQCVQFNYAGRMGNQNNFQSQQACEQTC-PCSLPMFSGEGTGNLTRWYADSCSR0CKSFTYNGSKGN0NNFLTK00CESKCK PCEEEMT0GEGSAALTRFYYDAL0RKCLAFNYLGLKGNRNNF0SKEHCESTC-TCELPMTKGYGNSHLTRWHFDKNLNKCVKFIYSGEGGNQNMFLTQEDCLTVC-TCELTMTKGYGNSHLTRWHFDKNLNKCVKFIYSGEGGNQNMFLTQEDCLSVC-RCHLPPAVGYGKORMRRFYFDWKTDACHELOYSGIGGNENIFMDYEOCERVCR -CMESLDRGSCEAMSNRYYFNKRAROCKGFHYTGCGKSGNNFLTKEECOTKC-PC00PL0RGNCS0RIPLFYYNIHNHKCRKFMYRGCNGNENRFSNRR0C0AKCG

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## There are many data...

- >6,800 completed genome sequencing projects
- doubling every 2-3 years (with increasing rate thanks to new technology)



GOLD data base

• equivalent biological functions based on diverged genomic sequences

statistical analysis allows to discover conserved signals in sequences

## Plan of the lectures

- I. DNA sequence motifs, transcription-factor binding sites and position-specific weight matrices
   [van Nimwegen, BMC Bioinformatics (2007)]
- Direct-coupling analysis: From residue co-evolution in proteins to protein-structure prediction [Morcos et al., PNAS (2011); Juan, Pazos, Valencia, Nature Rev Gen (2013)]
- 3. Aligning biological sequences and detecting sequence similarity [Durbin, Eddy, Krogh, Mitchison, Biological Sequence Analysis, CUP 1998]

# Gene regulation

#### Central dogma of molecular biology: directed information flow



#### BUT

- different cell types from same genome
  - differential gene expression
- precise timing of gene expression during cell cycle
- response to external signals, nutrient availability etc.

# Gene regulation



#### BUT

- different cell types from same genome
  - differential gene expression
- precise timing of gene expression during cell cycle
- response to external signals, nutrient availability etc.

Gene regulation = fundamental process for differential gene expression



## Transcriptional repression vs. activation



## Gene regulation



concentrate on transcriptional regulation

## **Protein-DNA** interactions

#### A. Empirical facts

- 1. Transcription Factors
  - size: ~5nm (10-20 bp)



molecular basis of sequence recognition





→ structure of a TF must place the appropriate amino acids next to the base pairs they contact

- various molecular strategies
  - Helix-Turn-Helix



#### well-known examples in bacteria (note: homodimers)



#### - zinc-finger domain



- leucine zipper



#### beta-sheets





- helix-loop-helix



### 2. DNA binding sequences

typically 10-20 bp in bacteria

protein	target sequence			
lac repressor	5' AATTGTGAGCGGATAACAATT 3' TTAACACTCGCCTATTGTTAA			
CRP	TGTGAGTTAGCTCACT ACACTCAATCGAGTGA			
$\lambda$ repressor	TATCACCGCCAGAGGTA ATAGTGGCGGTCTCCAT			

- lots of sequence variants
- consensus sequence often palindromic
- common to have 2~3 mismatches from the core consensus sequence
   -- "fuzzy" binding motif

ATTCTGTAACAGAGATCACACAAA CCTTTGTGATCGCTTTCACGGAGC AAAACGTGATCAACCCCTCAATTT **AACTTGTGGATAAAATCACGGTCT GTTTTGTTACCTGCCTCTAACTTT** TTAATTTGAAAATTGGAATATCCA AATTTGCGATGCGTCGCGCATTTT TTAATGAGATTCAGATCACATATA AATGTGTGCGGCAATTCACATTTA **GAAACGTGATTTCATGCGTCATTT** AAATGACGCATGAAATCACGTTTC TTGCTGTGACTCGATTCACGAAGT TTTTTGTGGCCTGCTTCAAACTTT GAATTGTGACACAGTGCAAATTCA **ATAATGTTATACATATCACTCTAA** CGATTGTGATTCGATTCACATTTA **GTTTTGTGATGGCTATTAGAAATT** GAACTGTGAAACGAAACATATTTT AATGTGTGTGTAAACGTGAACGCAAT TTTGTGTGATCTCTGTTACAGAAT **GTAATGTGGAGATGCGCACATAAA** TTTTTGCAAGCAACATCACGAAAT TTAATGTGAGTTAGCTCACTCATT **ATTATTTGCACGGCGTCACACTTT** ATTATTTGAACCAGATCGCATTAC TAATTGTGATGTGTATCGAAGTGT .....TGTGA......TCACA.....

#### 3. TF-DNA interaction

- passive (no energy consumption)
- strong electrostatic attraction indept of binding seq e.g., [TF - DNA] > 10 × [TF]<sub>free</sub> for LacI in 0.1M salt
   → non-specific binding: G<sub>ns</sub> - G<sub>cyto</sub> ≈ -15kT ( kT ≈ 0.62 kcal/mole at 37C)
- additional energy gained from hydrogen bonds to preferred sequences



 <u>graded increase</u> in binding energy for sequences with partial match to the preferred sequence relative binding affinity for Mnt



binding energy matrix

			(in unit of kT ≈ 0.6 kcal/mole)						
pos.	10	11	12	13	14	15	16	17	
A	1.8	2.4	1.6	1.0	0	2.1	0.8	1.1	
C	2.4	1.9	4.2	2.1	0.3	0	0	0	
G	0	1.6	0	0	1.2	3.2	1.0	1.2	
T	3.0	0	2.2	2.2	0.6	2.2	0.7	0.3	
(D.S. F	· <sup>•</sup> ields,	Y. He	e, A. A	l-Uzr	i & G	. Stori	no, 19	97)	
(from o	compe	etitive	bind	ing ex	xpts)				

- → weak energetic preference -- weak specificity
- → similar results for other TFs studied (e.g., Lacl,  $\lambda$ -Cl,  $\lambda$ -Cro)
- double mutation: binding energy approx additive

Can we say something generic about the design of TF-DNA interaction from these facts/data?

### CRP / E. coli vs. random genome



one intergenic region with TFBS in position 59

Frequency count: E. coli intergenic vs. randomized genome

for transcription factor CRP

#### CRP / E. coli vs. random genome



From networks of residue coevolution to protein (complex) structure prediction

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# Why is this interesting?

High-throughput sequencing technology:

- >6,800 fully sequenced genomes
- >21,000 incomplete genome sequencing projects
- >42,000,000 protein sequences (500,000 with annotation)
- exponential growth of databases

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Structural databases:

- ~93,000 known protein structures
- linear growth of databases (no high-throughput technology)

...but function relies on structure!

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#### How to close the gap:

- sequences classified into ~14,000 families of homologous proteins
  - common evolutionary origin
  - conserved structure / function but variable sequence
- >4,000 families with >1,000 sequences
- >1,000 of these families without structural representatives

## There is information in

ACSLPKV0GPCSGKHSYYYFNSAN00CETFVYGGCLGNTNRFATIEECNARC-VCLLPKSAGPCTGFTKKWYFDVDRNRCEEF0YGGCYGTNNRFDSLE0C0GTC-VCAMPPDAGVCTNYTPRWFFNS0TG0CE0FAYGSCGGNENNFFDRNTCERKCM TCSLSPSPGTCGPGVFKYHYNPOTOECESFEYLGCDGNSNTFASRAECENYCG -CHTEHSSGACPGAVTMFYHDPRTKKCTPFTFLGCGGNSNKFDTRP0CERFCK PCMLPSDKGNC0DILTRWYFDS0KH0CRAFLYSGCRGNANNFLTKTDCRNACM --RI VGYCSPYI RRYFFNRTTFKCVI FTPFRCFKDGNNFPNRKVCMKTCM PCSLKEDYGIGRAYYERWYFNTTTANC PCKODLDOGHGKTLOARYYFNKYAKVCEOFDYRGIDGNRNNFESLOE -CELKPDEGVGRATI KAEYYNPKNR FFFFYGGL -CSOPAASGHGE0YLSRYFYSPEYR0CL RGMINNE CG I CNI KYDSGVGGE PCEOAIEFGTGNVI I RBWY FKGNONN FDPAT PCGOPI DRGVGGSOT CGOKG VCTOPLESGD-EPS TCVOPTATGP WDP -CD001 MI GVGGASM PCSVPI APGTGNAGI AR ACKMPI SVGT GGA VCNI PMSTOFGNANI DRFYYD IAOTMOCVOENYAGB ICOOPMAVGTGGATL PCSI PMFSGOG PCEEEMTOGEGSAAL ΠΔΙ TCFI PMTKGYGNSH OFDCI SVC-TCEL TMTKGYGNSHLTRWHEDKNLNKCVKETYSGEGGNONME RCHLPPAVGYGKORMRRFYFDWKTDACHELOYSGIGGNENIFMDYEOCERVCR -CMESLDRGSCEAMSNRYYFNKRAROCKGFHYTGCGKSGNNFLTKEECOTKC-PCOOPLORGNCSORIPLFYYNIHNHKCRKFMYRGCNGNENRFSNRROCOAKCG

## Residue contacts induce residue co-evolution



## Residue contacts induce residue co-evolution



#### Inverse question:

► Are sequence correlations indicative for inter-protein residue contacts?

[Gobel et al. '94, Neher '94, Ranganathan et al. '99]

## Sequence statistics and correlations

Multiple sequence alignment (MSA):  $D = \{A_i^m \mid i = 1, ..., L; m = 1, ..., M\}$ 



Mutual information measures pair correlation

$$MI_{ij} = \sum_{A,B} f_{ij}(A,B) \ln \frac{f_{ij}(A,B)}{f_i(A) f_j(B)}$$

Compare to 3D protein structure: Are correlated column pairs in contact?

## Correlations vs. residue contacts



- contact
- no contact

# Correlation is not coupling



- Correlations are generated by network of direct couplings
- disentangle direct and indirect couplings:  $P(A_1, ..., A_L)$
- statistical-physics inspired direct coupling analysis (DCA)

[MW, White, Szurmant, Hoch, Hwa, PNAS '09]

## **Direct coupling analysis**

• model data via global distribution  $P(A_1,...,A_L)$  such that

$$P_{ij}(A_i, A_j) = \sum_{\{A_k | k \neq i, j\}} P(A_1, \dots, A_L) \stackrel{!}{=} f_{ij}(A_i, A_j)$$

• maximum-entropy model:

$$-\sum_{\{A_i\}} P(A_1, ..., A_L) \ln P(A_1, ..., A_L) \to \max$$

disordered 21-states Potts model / Markov random field

$$P(A_1, ..., A_L) \sim \exp\left\{ + \sum_{i < j} e_{ij}(A_i, A_j) + \sum_i h_i(A_i) \right\}$$
  
[MW, White, Szurmant, Hoch, H

MW, White, Szurmant, Hoch, Hwa, PNAS '09] Burger, van Nimwegen, PLoS Comp Biol '10] [Morcos, Pagnani,..., MW, PNAS '11] [Balakrishnan et al., Proteins '11] [Jones et al., Bioinformatics '12]

1

# Direct coupling analysis

- Boltzmann-machine learning:
  - start with initialized fields/couplings
  - calculate

$$P_{ij}(A_i, A_j) = \sum_{\{A_k | k \neq i, j\}} P(A_1, ..., A_L)$$

• update couplings

$$\Delta e_{ij}(A,B) = \varepsilon \left[ f_{ij}(A,B) - P_{ij}(A,B) \right]$$

- iterate until sufficiently precise fitting
- exact calculation requires exponential time ~ 21<sup>L</sup>
   approximations needed

# Direct coupling analysis

- Mean-field approximation:
  - mean-field equation for single-site marginal probabilities

$$P_i(A) \sim \exp\left\{h_i(A) + \sum_{j \neq i} \sum_B e_{ij}(A, B)P_j(B)\right\}$$

• fluctuation-dissipation relation

$$\frac{\partial P_i(A)}{\partial h_j(B)} = C_{ij}(A, B) = P_{ij}(A, B) - P_i(A)P_j(B)$$

leads to explicit equation for couplings

$$e_{ij}(A,B) = \left[C^{-1}\right]_{ij}(A,B)$$

- ightarrow couplings estimated in time  $\mathcal{O}(21^3N^3)$
- more complicated approximations (Bethe-Peierls, Thouless-Anderson-Palmer) do not improve performance on biological sequence data

### Interaction strength and direct information

How to quantify direct interaction by scalar quantity:

➡ consider isolated two-spin system



direct information = mutual information due to direct coupling

$$DI_{ij} = \sum_{A_i, A_j} P_{ij}^{(dir)}(A_i, A_j) \log \frac{P_{ij}^{(dir)}(A_i, A_j)}{f_i(A_i) f_j(A_j)}$$

## Couplings vs. residue contacts



- contact
- no contact

## Couplings vs. residue contacts

Comparison for 131 abundant protein families:  $|i - j| \ge 5$ 



DCA strongly improves contact prediction!

#### Not all contacts co-vary, but...



..can guide protein complex assembly [Schug, MW, Onuchic, Hwa, Szurmant, PNAS '09] [Dago, Schug, Procaccini, Hoch, MW, Szurmant, PNAS '12]

and protein structure prediction

[Marks et al., PLoS ONE '11] [Sadowski et al., Comp Biol Chem '11] [Sulkowska, Morcos, MVV, Hwa, Onuchic, PNAS '12] [Hopf et al., Cell '12] [Nugent, Jones, PNAS '12]

#### From contacts to 3D structure



[Sulkowska, Morcos, MW, Hwa, Onuchic, PNAS '12]

## ...global protein structure defined

#### ab initio protein folding simulations:

molecular-dynamics simulations of structure-based models (Go-models):

$$V = V_{bond} + V_{torsion} + V_{contact}$$
with
$$V_{bond} = k_b \sum_{bonds} (r - r_0)^2$$

$$V_{torsion} = k_a \sum_{angles} (\alpha - \alpha_0)^2 + k_d \sum_{dihedral} [1 - \cos(\tau - \tau_0)] + \frac{1}{2} [1 - \cos 3(\tau - \tau_0)]$$

$$V_{contact} = \varepsilon_c \sum_{contacts} \left[ \left( \frac{\sigma_{ij}}{r_{ij}} \right)^{12} - 2 \left( \frac{\sigma_{ij}}{r_{ij}} \right)^6 \right]$$
use only DCA contacts

[Sulkowska, Morcos, MW, Hwa, Onuchic, PNAS '12]



[Dago, Schug, Procaccini, Hoch, MW, Szurmant, PNAS '12]

## Histidine-kinase auto-phosphorylation complex

Two-component signaling system

• most common signaling system in bacteria



- on average ~20 TCS / bacterial genome
- >13,000 sequences of proteins with HisKA/HATPase domains (back in 2008)

## Histidine-kinase auto-phosphorylation complex



[Marina, Waldburger, Hendrickson, EMBO J. (2005)] [Casino, Rubio, Marina, Cell (2009)] [Bick et al., J. Mol. Biol. (2009)]

# **DCA** results

Rank	Res I	Res 2	d/Å	Domain
I.	388	392	4.6	22
2	268	272	3.2	11
3	268	298	3.2	11
4	365	456	3.7	22
5	385	392	3.9	22
6	310	311	1.3	11
7	311	312	1.3	11
8	303	307	3.0	11
9	261	372	14.5	12
10	420	421	1.3	22
11	272	298	6.9	11
12	369	372	2.9	22
13	375	379	2.7	22
14	310	312	3.2	11
15	429	431	3.9	22
6	251	255	2.9	11
17	257	272	20.5	
18	379	383	2.8	22
19	420	429	3./	22
20	431	432	1.3	22
21	385	388	6.4	22
22	251	252	1.3	
23	250	251	1.3	
24	308	369	8.0	12
25	298	310	14.8	
26	369	455	7.0	22
2/	383	384 420	1.5	22
28	426	429	3.1	22
29	420	431 4FF	3.8	22
30	451	455	2.7	
3   2 1			25.6	
3∠ 22	313 257	407	ס.כ ד כ ו	12
33 24	272	42/ 275	12./	12
34 25	240	575 AEC	J. <del>T</del> ∕/ 7	22
33	207	סכ <del>ד</del> 272	7./	12
				17

First 36 DI-ranking pairs:

- 31 intra-domain pairs
  - 28 in contact
  - 3 distant
  - ▶ >90% TP rate
- 5 inter-domain pairs
  - 2 in contact
  - 3 distant
  - predicted contacts in active structure

# DCA predicts 3 inter-domain contacts for auto-phosphorylation complex



## DCA-guided molecular dynamics simulations



## DCA-guided molecular dynamics simulations





#### inactive protein structure



## Comparison of the active / inactive structure



 major conformational change: ATP close to Histidine residue

## Predicted contact map



- DCA-predicted pairs in stable contact
- represent clusters of contacts
- MD predicts clusters of contacts with helix 3
  - not seen by DCA

#### Experiment: verify contacts with helix 3!

# Repairing hybrid kinases

Bacillus subtilis sporulation kinase: KinA as experimental test system



exchange contact residues in one domain by those in cognate domain

## Substituting contacts helix 3 - HisKA



## Why don't we see these residues in DCA?



Pfam domains did not cover helix 3!

## Improved contact prediction



[Dago, Schug, Procaccini, Hoch, MW, Szurmant, PNAS '12]

## Improved Go-model structure



Prediction with 3 contacts

Prediction with 5 contacts

[Dago, Schug, Procaccini, Hoch, MW, Szurmant, PNAS '12]

## ...and we were just in time

[Wang et al., PLoS Biology '13]:

- crystal structure of His kinase VicK from Streptococcus mutans
- homodimer with



- one monomer in inactive conformation:
   2 inactive DCA predictions at 3.5 3.7 Å
- one monomer in active conformation:
   5 active DCA predictions at 2.6 5.4 Å

## Thanks to

HuGeF Torino: Andrea Pagnani Andrea Procaccini

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Karlsruhe Institute of Technology Alexander Schug

Ecole Normale Supérieure Rémi Monasson Simona Cocco