Gene regulation: From biophysics to evolutionary genetics

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Structure and dynamics of molecular networks





- Structure: Random parts? Functional design?
- Evolution: Pathways? Tempo?

1. Evolution of regulatory DNA

Genomic encoding of network interactions

 Multiple binding sites allow for complex regulation of individual genes in higher organisms:



[Bolouri and Davidson, 2002]

Input-output relation?
Evolutionary dynamics?

Biophysics of transcriptional regulation

- Transcription factor proteins bind to specific DNA sites catalyzing transcription.
- **Binding energy** E(a) can be obtained from
 - low-throughput measurements [Fields et al. 97]
 - position weight matrix of functional sites [Berg and v.Hippel 86]
 - ChIP-chip data [Float et al. 05, Kinney et al. 06]
 - high-throughput measurements [Maerkl and Quake 07].
- E(a) depends on the site sequence $\mathbf{a} = (a_1, \dots, a_k)$:

$$E = \sum_{i=1}^{k} \epsilon_i(a_i) + \text{nonlinear terms?}$$

 E(a) is the molecular phenotype of a site, which quantifies its functionality.



Cis-regulatory elements: from sequence to phenotype

 The binding energy E(a) is the molecular phenotype of a site, which quantifies its functionality.



Cis-regulatory elements: from phenotype to fitness

 For broad-acting transcription factors, high-affinity sites (E < E_b) are statistically overrepresented.

 At stationarity, the ensembles of functional and background sites determine the average fitness landscape F(E) of a site:

$$2NF(E) = \log \frac{Q(E)}{P_0(E)} + \text{const.}$$

 This predicts a moderate fitness effect per functional site:

$$2NF_0 \approx 10$$



Abf1 binding sites in S. cerevisiae

[Berg, Willmann, M.L., BMC Evol. Biol. 2004, Mustonen, M.L., PNAS 2005, Mustonen, Kinney, Callen, M.L., PNAS 2008]

Population genetics

• Selection: sequence state a has fitness

$$F(\mathbf{a}) = \frac{d}{dt} \langle \log N(\mathbf{a}) \rangle_{\mu=0} - \text{const.}$$

Point mutations:

$$\mathbf{a} = (\dots, a, \dots) \rightarrow \mathbf{b} = (\dots, b, \dots)$$

Population genetics

Genetic drift:

Kimura-Ohta substitution rates

$$u_{\mathbf{a} \to \mathbf{b}} = \mu_{\mathbf{a} \to \mathbf{b}} \frac{1 - \exp[-2(F(\mathbf{a}) - F(\mathbf{b}))]}{1 - \exp[-2N(F(\mathbf{a}) - F(\mathbf{b}))]}$$



Ratio of forward and backward rates:

$$\frac{u_{\mathbf{a}\to\mathbf{b}}}{u_{\mathbf{b}\to\mathbf{a}}} = \frac{\mu_{\mathbf{a}\to\mathbf{b}}}{\mu_{\mathbf{b}\to\mathbf{a}}} \exp[2N(F(\mathbf{b}) - F(\mathbf{a}))]$$



Population genetics

• Evolutionary equilibria in sequence space:

Given two families of loci,

- background loci with stationary sequence distribution P₀(a) under neutral evolution
- functional loci with stationary sequence distribution Q(a) under selection

the fitness landscape F(a) for the functional loci is given by

$$Q(\mathbf{a}) = P_0(\mathbf{a}) \exp[2NF(\mathbf{a}) + \text{const.}]$$

N: effective population size.

[J.Berg, S. Willmann, M.L., **BMC Evol. Biol.** (2004)] [V. Mustonen, M.L., **Proc. Natl. Acad. Sci.** (2005)] The inferred fitness landscape quantitatively predicts the evolution of the phenotype E:



Abf1 binding energy differences of sites in S. cerevisiae, S.paradoxus, S. mikatae, S. bayanus [Mustonen, Kinney, Callen, M.L., PNAS 2008]

Pathways of promoter evolution



Conservation of binding sites

 Sequences of conserved sites evolve by compensatory mutations:

$$\Delta E = \sum_{i} \Delta \epsilon_{i}$$
 but $\operatorname{var}(\Delta E) < \sum_{i} \operatorname{var}(\Delta \epsilon_{i})$



 Hence, the energy phenotype is more constrained than the site sequence:





[Mustonen, Kinney, Callen, M.L., PNAS 2008]

divergence time from cer

Loss and gain of function

- Turnover of promoter function determines loss and gain of regulatory interactions:
- Species-specific loss of sites:



Functional turnover rate

 $\gamma_f \sim 0.1 \ \mu$

[J. Kinney, V. Mustonen, C. Callan, M.L., PNAS 2008]



• Natural selection acts on complex systems in a scale-dependent way:



 Laboratory experiments, modeling, and evolutionary genomics address complementary aspects of biological systems:



2. Evolution of the Drosophila genome

- Phenotypic concept of Darwinian selection: newly arising selection and response by adaptation.
- Can we trace the time-dependence of selection in genomic data?

Genome evolution under constant and fluctuating selection



- Allele frequency x(t) evolves under selection, mutations, stochastic fluctuations (genetic drift).
- Constant selection leads to evolutionary equilibrium, p_{eq} (x).
- Fluctuating selection

 $\Delta F(t) = f \chi(t)$ with switching rate γ ,

leads to adaptation: excess number of uphill mutations w/r to equilibrium.

- Substitutions and polymorphism spectra [Glinka et al 2003, Ometto et al 2005] are used to infer a **surplus of beneficial over deleterious substitutions**.
- Adaptation is quantified by a positive fitness flux = (substitution rate) x

(average selection coefficient of substitutions).



[Mustonen and M.L, PNAS 2007]

Fitness seascapes

• What drives the waves?



Nonequilibrium + correlations:

one external change can trigger an avalanche of responses.

Conclusions

- Adaptive evolution should be viewed as a nonequilibrium phenomenon.
- Adaptation can be quantified by the fitness flux in a population over a given time interval.
- The biophysical binding energy is a quantitative molecular phenotype for regulatory sequences in yeast.
- Genomic sequence analysis can be used to infer fitness landscapes for this phenotype.
- In *Drosophila*, fitness seascapes drive adaptive evolution.
- Review articles:

From Biophysics to evolutionary genetics, M.L., BMC Bioinformatics 2007 *From fitness landscapes to seascapes: The dynamics of selection and adaptation,* V. Mustonen and M.L., Trends in Genetics 2009