6.047/6.878/HST.507 Computational Biology: Genomes, Networks, Evolution

Lecture 17

Comparative genomics I:

Genome annotation using evolutionary signatures

Module V: Comparative genomics and evolution

- Today: Whole-genome comparative genomics
 - Evolutionary signatures for systematic genome annotation
- Next week: Phylogenetics and Phylogenomics
 - Distance-based and model-based phylogenetics approaches
 - Gene trees and species trees, reconciliation, coalescence
- Computational foundations:
 - Evolutionary rates and models of evolution
 - Dynamic programming on two-dimensional tree structures
 - Synteny-based alignment, genome assembly

Key goal: Evolution preserves functional elements



Yeast (Kellis et al, Nature 2003), Mammals (Xie, Nature 2005), Fly (Stark et al, Nature 07)

Comparative Genomics



Comparative genomics I: Evolutionary signatures

- Nucleotide conservation: evolutionary constraint
 - Purifying selection, neutral branch length, discovery power
 - Detect constrained elements: nucleotides, windows, HMM
 - Estimate fraction constrained: signal vs. background
- Evolutionary signatures: focus on pattern of change
- Signatures of protein-coding genes
 - Reading-frame conservation, codon-substitution frequency
 - Likelihood ratio framework: Estimating Q_CQ_N, scoring
 - Revise genes, read-through, excess constraint regions
- Signatures of microRNA genes
 - Structural and evolutionary features of microRNAs
 - Combining features: decision trees, random forests
 - Sense/anti-sense miRNAs, mature/star arm cooperation
- Measuring selection within the human lineage

Comparative genomics for genome annotation



© Source unknown. All rights reserved. This content is excluded from our Creative Commons license. For more information, see http://ocw.mit.edu/help/faq-fair-use/.

Compare related species to discover functional elmts

Evolution process: random mutation, natural selection

- Non-functional regions: accumulate mutations, kept
- Functional regions: accumulate mutations, decrease fitness
- Evolutionary time: less fit organisms & their genes thin out

Power of many closely related: total branch length



 $\ensuremath{\mathbb{C}}$ Source unknown. All rights reserved. This content is excluded from our Creative

Commons license. For more information, see http://ocw.mit.edu/help/faq-fair-use/.

More branch length more events more power

- Goal: functional vs. non-functional based on # of mutations
- Very close distances: no mutations in either region
- Sufficient distance: ability to distinguish increases
- Very far distances: functional regions no longer conserved
- Many closely related species >> few distantly related
 - For same total branch length: prefer many close species
 - Functional regions conserved for each pair of species
 - Non-functional regions accumulate noise independently
 - Analogy: recording a concert with multiple microphones

Comparative genomics I: Evolutionary signatures

Nucleotide conservation: evolutionary constraint

- Purifying selection, neutral branch length, discovery power
- Detect constrained elements: nucleotides, windows, HMM
- Estimate fraction constrained: signal vs. background
- Evolutionary signatures: focus on pattern of change
- Signatures of protein-coding genes
 - Reading-frame conservation, codon-substitution frequency
 - Likelihood ratio framework: Estimating Q_CQ_N, scoring
 - Revise genes, read-through, excess constraint regions
- Signatures of microRNA genes
 - Structural and evolutionary features of microRNAs
 - Combining features: decision trees, random forests
 - Sense/anti-sense miRNAs, mature/star arm cooperation

Genome-wide alignments reveal orthologous segments



© Source unknown. All rights reserved. This content is excluded from our Creative Commons license. For more information, see http://ocw.mit.edu/help/faq-fair-use/.

- Genome-wide alignments span entire genome
- Comparative identification of functional elements

Comparative genomics and evolutionary signatures



© Source unknown. All rights reserved. This content is excluded from our Creative Commons license. For more information, see http://ocw.mit.edu/help/faq-fair-use/.

Comparative genomics can reveal functional elements

- For example: exons are deeply conserved to mouse, chicken, fish
- Many other elements are also strongly conserved: exons / regulatory?

Develop methods for estimating the level of constraint

- Count the number of edit operations, number of substitutions and gaps
- Estimate the number of mutations (including estimate of back-mutations)
- Incorporate information about neighborhood: conservation 'windows'
- Estimate the probability of a constrained 'hidden state': HMMs next week
- Use phylogeny to estimate tree mutation rate, or 'rejected substitutions'
- Allow different portions of the tree to have different rates: phylogenetics 10

Detecting rates and patterns of selection (ω/π)

Estimating intensity of constraint (ω):

- Probabilistic model of substitution rate
- Maximum Likelihood (ML) estimation of $\boldsymbol{\omega}$
 - Report rate ω
 - Report log odds score that non-neutral
- Window-based vs. sitewise application

Detect unusual substitution pattern (π):

•Probabilistic model of stationary distribution that is different from background.

- •ML estimator (π) of this vector
 - Report PWM for each k-mer in genome.
 - Report log odds score that non-neutral

Manuel Garber, Or Zuk, Xiaohui Xie



© Source unknown. All rights reserved. This content is excluded from our Creative Commons license. For more information, see http://ocw.mit.edu/help/faq-fair-use/. ¹¹

Measuring constraint at individual nucleotides



© Source unknown. All rights reserved. This content is excluded from our Creative Commons license. For more information, see http://ocw.mit.edu/help/faq-fair-use/.

- Reveal individual transcription factor binding sites
- Within motif instances reveal position-specific bias
- More species: motif consensus directly revealed

Detect SNPs that disrupt conserved regulatory motifs



© Source unknown. All rights reserved. This content is excluded from our Creative Commons license. For more information, see http://ocw.mit.edu/help/fag-fair-use/.

- Functionally-associated SNPs enriched in states, constraint
- Prioritize candidates, increase resolution, disrupted motifs

Comparative genomics I: Evolutionary signatures

Nucleotide conservation: evolutionary constraint

- Purifying selection, neutral branch length, discovery power
- Detect constrained elements: nucleotides, windows, HMM
- Estimate fraction constrained: signal vs. background
- Evolutionary signatures: focus on pattern of change
 - Different functions Characteristic patterns of evolution
- Signatures of protein-coding genes
 - Reading-frame conservation, codon-substitution frequency
 - Likelihood ratio framework: Estimating Q_CQ_N, scoring
 - Revise genes, read-through, excess constraint regions
- Signatures of microRNA genes
 - Structural and evolutionary features of microRNAs
 - Combining features: decision trees, random forests
 - Sense/anti-sense miRNAs, mature/star arm cooperation

14

Estimating portion of the genome under constraint

Constraint calculated over a 50mer



Constraint calculated over a 12mer



© Source unknown. All rights reserved. This content is excluded from our Creative Commons license. For more information, see http://ocw.mit.edu/help/faq-fair-use/.

Or Zuk, Manuel Garber₁₅

Estimating total fraction under constraint



© Source unknown. All rights reserved. This content is excluded from our Creative Commons license. For more information, see http://ocw.mit.edu/help/fag-fair-use/

- Actual distribution of conservation scores (Signal) vs. expected distribution if no constraint (Background).
- At any cutoff: true positives (TP) and false predictions (FP)
- Can't detect all constrained elements since curves overlap
- But we can **estimate** the total amount of excess constraint by integrating over entire area between the two curves

Detection of evolutionarily constrained elements



Excess positive/purifying selection Distribution of constraint¹⁷

Coverage depth higher in functional regions



[©] Source unknown. All rights reserved. This content is excluded from our Creative Commons license. For more information, see http://ocw.mit.edu/help/faq-fair-use/.

Challenges of low-coverage genomes: varying aligment depth Evidence of selection against deletions in functional regions

Increase in power from HMRD to 29 mammals



Estimated / kmers detectable at 5% FDR / base pairs detectable at 5% FDR

Small increase in estimate of genome percentage under constraint Dramatic increase in power to detect small constrained elements

Manuel Garber, Or Zuk 19

Comparative genomics I: Evolutionary signatures

Nucleotide conservation: evolutionary constraint

- Purifying selection, neutral branch length, discovery power
- Detect constrained elements: nucleotides, windows, HMM
- Estimate fraction constrained: signal vs. background
- Evolutionary signatures: focus on pattern of change
 - Different functions Characteristic patterns of evolution
- Signatures of protein-coding genes
 - Reading-frame conservation, codon-substitution frequency
 - Likelihood ratio framework: Estimating Q_CQ_N, scoring
 - Revise genes, read-through, excess constraint regions
- Signatures of microRNA genes
 - Structural and evolutionary features of microRNAs
 - Combining features: decision trees, random forests
 - Sense/anti-sense miRNAs, mature/star arm cooperation

20

Comparative genomics and evolutionary signatures



© Source unknown. All rights reserved. This content is excluded from our Creative Commons license. For more information, see http://ocw.mit.edu/help/faq-fair-use/.

Comparative genomics can reveal functional elements

- For example: exons are deeply conserved to mouse, chicken, fish
- Many other elements are also strongly conserved: exons / regulatory?

• Can we also pinpoint specific functions of each region? Yes!

- Patterns of change distinguish different types of functional elements
- Specific function ⇔ Selective pressures ⇔ Patterns of mutation/inse/del

Develop evolutionary signatures characteristic of each function Stark et al, Nature 2007²¹

Evolutionary signatures for diverse functions



Courtesy of Macmillan Publishers Limited. Used with permission.

Source: Stark, Alexander et al. "Discovery of functional elements in 12 Drosophila genomes using evolutionary signatures." Nature 450, no. 7167 (2007): 219-232.

Protein-coding genes

- Codon Substitution Frequencies
- Reading Frame Conservation

RNA structures

- Compensatory changes
- Silent G-U substitutions

microRNAs

- Shape of conservation profile
- Structural features: loops, pairs
- Relationship with 3'UTR motifs

Regulatory motifs

- Mutations preserve consensus
- Increased Branch Length Score
- Genome-wide conservation Stark et al, Nature 2007

Implications for genome annotation / regulation



Courtesy of Macmillan Publishers Limited. Used with permission.

Source: Stark, Alexander et al. "Discovery of functional elements in 12 Drosophila genomes using evolutionary signatures." Nature 450, no. 7167 (2007): 219-232.

Novel protein-coding genes Revised gene annotations Unusual gene structures

Novel structural families Targeting, editing, stability Riboswitches in mammals

Novel/expanded miR families miR/miR* arm cooperation Sense/anti-sense miR switches

Novel regulatory motifs Regulatory motif instances TF/miRNA regulatory networks Single binding site resolution Stark et al, Nature 2007 23

Comparative genomics I: Evolutionary signatures

- Nucleotide conservation: evolutionary constraint
 - Purifying selection, neutral branch length, discovery power
 - Detect constrained elements: nucleotides, windows, HMM
 - Estimate fraction constrained: signal vs. background
- Evolutionary signatures: focus on pattern of change
 - Different functions Characteristic patterns of evolution
- Signatures of protein-coding genes
 - Reading-frame conservation, codon-substitution frequency
 - Likelihood ratio framework: Estimating Q_CQ_N, scoring
 - Revise genes, read-through, excess constraint regions
- Signatures of microRNA genes
 - Structural and evolutionary features of microRNAs
 - Combining features: decision trees, random forests
 - Sense/anti-sense miRNAs, mature/star arm cooperation

24

Evolutionary signatures for protein-coding genes



Same conservation levels, distinct patterns of divergence

- Gaps are multiples of three (preserve amino acid translation)
- Mutations are largely 3-periodic (silent codon substitutions)
- Specific triplets exchanged more frequently (conservative substs.)
- Conservation boundaries are sharp (pinpoint individual splicing signals)

➔ Evolutionary signatures of protein-coding selection

Evolutionary signatures of protein-coding genes

	the	fat	cat	sat
Δ1	the	atc	ats	at
Δ2	the	tca	tsa	t
Δ3	the	cat	sat	

DNA insertions and deletions can either insert/remove AAs, or totally mangle the remainder of the protein (frameshift).

			Second	d Letter			
		Т	С	A	G		
First Letter	т	TTT } Phe TTC } Phe TTA TTG } Leu	TCT TCC TCA TCG	TAT TAC } Tyr TAA Stop TAG Stop	TGT TGC TGA Stop TGG Trp	TCAG	
	с	CTT CTC CTA CTG	CCT CCC CCA CCG	CAT CAC } His CAA CAA } Gin	CGT CGC CGA CGG	TCAG	Third
	A	ATT ATC ATA ATG Met	ACT ACC ACA ACG	AAT AAC AAA AAA AAG Lys	AGT AGC AGA AGA AGG Arg	T C A G	Letter
	G	GTT GTC GTA GTG	GCT GCC GCA GCG	GAT GAC } Asp GAA GAG } Glu	GGT GGC GGA GGG	TCAG	

Some point mutations to the DNA sequence do not change its protein translation at all.

Natural selection tends to tolerate mutations with little/no effect on the protein.

Protein-coding sequences tolerate distinctive types of change



© Source unknown. All rights reserved. This content is excluded from our Creative Commons license. For more information, see http://ocw.mit.edu/help/faq-fair-use/.

Known genes stand out

Substitution typical of protein-coding regions Substitution typical of intergenic regions



© Source unknown. All rights reserved. This content is excluded from our Creative Commons license. For more information, see http://ocw.mit.edu/help/faq-fair-use/.

Comparative genomics I: Evolutionary signatures

- Nucleotide conservation: evolutionary constraint
 - Purifying selection, neutral branch length, discovery power
 - Detect constrained elements: nucleotides, windows, HMM
 - Estimate fraction constrained: signal vs. background
- Evolutionary signatures: focus on pattern of change
 - Different functions Characteristic patterns of evolution
- Signatures of protein-coding genes
 - Reading-frame conservation, codon-substitution frequency
 - Likelihood ratio framework: Estimating Q_CQ_N, scoring
 - Revise genes, read-through, excess constraint regions
- Signatures of microRNA genes
 - Structural and evolutionary features of microRNAs
 - Combining features: decision trees, random forests
 - Sense/anti-sense miRNAs, mature/star arm cooperation

29

Signature 1: Reading frame conservation



Reading Frame Conservation Test





Revisiting gene content with RFC test

		Accept	Rej	ect		
~4000 named genes		99.9%	0.1%			
~3	00 intergenic regions	1%	99%			
2000 Hypothetical		1500	500			
	High sensitivity and specificity					
Example of a rejected ORF						



Comparative genomics I: Evolutionary signatures

- Nucleotide conservation: evolutionary constraint
 - Purifying selection, neutral branch length, discovery power
 - Detect constrained elements: nucleotides, windows, HMM
 - Estimate fraction constrained: signal vs. background
- Evolutionary signatures: focus on pattern of change
 - Different functions Characteristic patterns of evolution
- Signatures of protein-coding genes
 - Reading-frame conservation, codon-substitution frequency
 - Likelihood ratio framework: Estimating Q_CQ_N, scoring
 - Revise genes, read-through, excess constraint regions
- Signatures of microRNA genes
 - Structural and evolutionary features of microRNAs
 - Combining features: decision trees, random forests
 - Sense/anti-sense miRNAs, mature/star arm cooperation

33



protein-coding exon

conserved non-coding sequence

A method to distinguish these evolutionary signatures should: • Quantify the distinctiveness of all 64² possible codon substitutions

- Synonymous: very frequent in protein-coding sequences
- Nonsense: much more frequent in non-coding than coding regions
- Model the phylogenetic relationship among the species
 - Multiple apparent substitutions may be explained by one evolutionary event
- Tolerate uncertainty in the input
 - Unknown ancestral sequences
 - Alignment gaps, missing data
- Report the [un]certainty of the result
 - Quantify confidence that given alignment is protein-coding
 - Units: p-value, bits, decibans, etc.

Codon evolution can be modeled as a Bayesian network



Conditional probability distribution (CPD) giving, for all codons a & b, $\Pr(dyak = b | Ancestor = a)$ Each site (codon alignment column) is treated independently.

Given the topology and CPDs, we can simulate evolution of an ancestral sequence.

Additionally given extant (leaf) sequences, the ancestral sequences can be inferred.

For *L* leaves, CPDs total about $(2L-2)\cdot 64^2$ parameters.

The Bayes net is parameterized as a continuous-time Markov process



Each CPD is determined by a rate matrix shared throughout the tree and a branch-specific 'time' (branch length):

$$\Pr(\text{child} = b | \text{parent} = a; t) = [e^{\mathbf{Q}t}]_{a,b}$$

<u>Intuition</u>: The branch lengths specify how much 'time' passed between any two nodes. The rate matrix describes the relative frequencies of codon substitutions *per unit branch length*. Synonymous substitutions have high rates and nonsense substitutions have low rates.

We can obtain maximum likelihood estimates of $(2L - 2) + 64^2$ parameters using EM in training data.
Example nucleotide (4x4) rate & substitution matrices

 $\mathbf{Q} = \begin{pmatrix} -4 & 2 & 1 & 1 \\ 2 & -4 & 1 & 1 \\ 1 & 1 & -4 & 2 \\ 1 & 1 & 2 & -4 \end{pmatrix} \Big|_{\mathsf{T}}^{\mathsf{A}} \qquad \operatorname{Pr}(\operatorname{child} = b | \operatorname{parent} = a; t) = [e^{\mathbf{Q}t}]_{a,b}$

 $e^{\mathbf{Q}t} = \sum_{n=0}^{\infty} \frac{t^n}{n!} \mathbf{Q}^n$ is the solution to the system of differential equations describing the Markov process model of evolution.

```
MatrixExp[Q * 0] // MatrixForm
                                                               MatrixExp[Q * 0.1] // MatrixForm // NumberForm[#, 4] &
 1 0 0 0
                                                                 0.692 0.1432 0.08242 0.08242
 0 1 0 0
                                                                 0.1432 0.692 0.08242 0.08242
 0 0 1 0
                                                                0.08242 0.08242 0.692 0.1432
 0 0 0 1
                                                                0.08242 0.08242 0.1432 0.692
MatrixExp[Q * 0.001] // MatrixForm // NumberForm[#, 4] &
                                                               MatrixExp[Q * 1.0 ] // MatrixForm // NumberForm[#, 4] &
   0.996
          0.001993 0.000998 0.000998
                                                                0.2558 0.2533 0.2454 0.2454
 0.001993 0.996 0.000998 0.000998
                                                                0.2533 0.2558 0.2454 0.2454
 0.000998 0.000998 0.996 0.001993
                                                                0.2454 0.2454 0.2558 0.2533
 0.000998 0.000998 0.001993 0.996
                                                                0.2454 0.2454 0.2533 0.2558
MatrixExp[Q * 0.01] // MatrixForm // NumberForm[#, 4] &
                                                               MatrixExp[Q * 10.0] // MatrixForm // NumberForm[#, 4] &
  0.9611 0.01932 0.009803 0.009803
                                                                0.25 0.25 0.25 0.25
          0.9611 0.009803 0.009803
  0.01932
                                                                0.25 0.25 0.25 0.25
 0.009803 0.009803 0.9611
                                                                0.25 0.25 0.25 0.25
                             0.01932
                                                                0.25 0.25 0.25 0.25
 0.009803 0.009803 0.01932
                              0.9611
Analogy: y(t) = e^{qt}
                                 Plot[Exp[-t], (t, 0, 5)]
                                                        Side note: Jukes-Cantor and Kimura models are
  solves the differential equation
                                 0.6
                                                        set up so that the entries of e<sup>Qt</sup> have closed-form
       \frac{dy}{dt} = qy
                                                        solutions.
```

37

The hairy math: how do we estimate **Q**?

- Collect many alignments of <u>known</u> protein-coding sequences (training data)
- Consider the probability of the training data as <u>a function of **Q**</u>

$$\text{Likelihood}(\mathbf{Q}) = \Pr(\text{Training Data}; \mathbf{Q}, \underline{t})$$

Still computed using Felsenstein algorithm

- Choose the Q that maximizes that probability: $\hat{Q} = \underset{Q}{\operatorname{argmax}} (\operatorname{Likelihood}(Q))$ Note: Q represents thousands of parameters
- Maximization strategies: expectation-maximization; gradient ascent; simulated annealing; spectral decomposition; others
- Branch lengths can also be optimized in the same way (simultaneously)
- Non-coding model estimated similarly, with random non-coding regions as training data.

Given this generative model of codon evolution:





Rate matrix (Q)

© Source unknown. All rights reserved. This content is Branch lengths <u>t</u> excluded from our Creative Commons license. For more

information, see http://ocw.mit.edu/help/faq-fair-use/.

We can compute the probability of any given alignment, marginalizing over all possible ancestral sequences, using Felsenstein's pruning algorithm.

ATG AGC TCA TTC CTC ATG GGT TAT CCG CAT GCC CCA CAT CAC GTC CAG AGT CCC ATG TCC ATG GGC AAT GGC CTG GAT dmel ATG AGC **TTT** CTC ATG GGT TAT CCG CAT <mark>GCA</mark> CCA CAT <mark>CAT</mark> GTC CAG AGT CCC ATG TCC ATG GGC AAT GGC dsim atg agc <mark>tet ttt</mark> etc atg ggt tat eeg cat <mark>gea</mark> eea cat <mark>eat</mark> gte cag agt eec atg gge aat gge **ttg ga** dsec atg agc **tct ttt** ctc atg ggt tat ccg cat <mark>gca</mark> cca cat <mark>cat</mark> gtc cag agt ccc atg tcc atg ggc aat ggc dyak atg agc **tct ttt** ctc atg **ggc** tat ccg cat <mark>gct</mark> cca cat <mark>cat gtt caa</mark> agt ccc atg tcc atg ggc aat ggc dere ATG AGC **CT TTT** CTC ATG GGT TAT CCG CAT <mark>GCT</mark> CCA CAT <mark>GAT</mark> CAG AGT CCC ATG TCC ATG GGC AAT <mark>ce</mark> tte ete atg <mark>gge tae eee cae</mark> gee <mark>eeg</mark> eat eae gte eag <mark>age</mark> eee atg tee atg gge aat gge etg gat dana ATG AGC dpse atg age tca ttc ctc atg ggt tat cca gcc cat gcc cat cac gtc cag agt ccc atg tcc atg ggc aat ggc ctg gat dper ATG AGC TCA TTC CTC ATG GGT TAT CA CAT GCC CC CAT CAC GTC CAG AGT CCC ATG TCC ATG GGC AAT GGC CTG GAT dwil atg agc tca ttc ctc atg ggt tat ccg cat gcc cca cat <mark>cat</mark> gtc cag agt ccc atg tcc atg ggc aat <mark>gga ctc</mark> gat dvir atg agc tca ttc ctc atg ggt tat <mark>cca</mark> cat <mark>gcg</mark> cca cat <mark>cat</mark> gtc cag <mark>agc</mark> ccc atg tcc atg <mark>ggt</mark> aat ggc <mark>cta</mark> gat dmo j atg agc tca ttc **cta** atg **ggc** tat <mark>cca</mark> cat <mark>gcg</mark> cca cat <mark>cat</mark> gtc cag <mark>agc</mark> ccc atg tcc atg ggc aat <mark>gga</mark> ctg <mark>gaa</mark> dqri atg agc tca ttc ctc atg ggt tac cca cat gcc ccc cat cac gtc cag agc ccc atg tcc atg ggc aat ggc ctg gat

protein-coding exon

ancestor GTG GCG AGT GCA TTT CCC AGA GGA GTT GAT AGG AGT CTG AAA CTA CTG ATA AAT TGC TTT TTA ATT AGC ACA GAG CAG <mark>seg</mark> tit ccc aga gga <mark>teg</mark> gat <mark>gga ggt</mark> etg <mark>aag</mark> eta etg ata <mark>gat</mark> tge tit ita att age aca <mark>g aat gcg</mark> ttt ccc aga gga <mark>tcg</mark> gat <mark>gga</mark> gg<mark>t</mark> ctg aaa cta ctg ata <mark>gat</mark> tgc ttt tta att agc aca dsim GTG A CAG dsec gtg <mark>aca aat acg</mark> ttt ccc aga gga <mark>fcg</mark> gat <mark>gga ggt</mark> ctg aaa <mark>ctt</mark> ctg ata <mark>gat</mark> tgc ttt tta att agc aca <mark>gca</mark> cag dyak gtg <mark>acg aat</mark> gca ttt <mark>cct agt</mark> gga <mark>tcg gaa gaa ggg</mark> ctg aaa <mark>gta</mark> ctg ata <mark>gat</mark> gtc ttt tta <mark>act</mark> agc aca dere GTG GCA TTT CCT AGA GGA TCC GAT G <mark>gt ggt ttg</mark> aaa <mark>ggg</mark> ctg ata <mark>gat</mark> tgc ttt tta att agc ac*a* CAG dana GTG AT GCA TTT A T AGA CG CAGG T <mark>G CCG</mark> AAA <mark>AAG</mark> CTG <mark>ATG GAT</mark> TGC TTT TTA ATT AGC ACA GAG dpse GTG T T GCA TTT ACC <mark>cgg agg ccc acg</mark> agg agt <mark>ctc cac</mark> gca ctg ata <mark>gat</mark> tgc ttt tta att agc aca gao <mark>gg agg ccc acg</mark> agg agt <mark>ctc cac gca</mark> ctg ata <mark>gat</mark> tgc ttt tta att dwilgereeceaereca AA AGA <mark>AGA</mark> GTT <mark>GAG</mark> <mark>BGT</mark> CTG <mark>ATT</mark> AAT TGC TTT TTA ATT AGC TTT AGT CGA dvir GTG GCG AGT GCA <mark>gt <mark>CGG</mark> caa ctg <mark>ggt tag</mark> ctg ata aat tgc ttt tta att agc</mark> dmoj GTG GCG T GCA TAT GCA GGT CGT GTT G CGG GCT CTC GGT CAG CTG ATG GAT GAC TTT TTA ATT CG GGA TGT GTT GGT CAG CGA CTG CGT TGG CTG ATA AAT GGT TTT TTA ATT AGC dari GTG GCG AGT GCA

conserved non-coding sequence

$$\Pr(\text{Leaves}; \mathbf{Q}, \underline{t}) = rac{1}{10^{275}}$$

Pr(Leaves; $\mathbf{Q}, \underline{t}) = \frac{\mathbf{I}}{10^{117}}$ If I simulate alignments randomly according

If I simulate alignments randomly according to the model, I'll get this <u>exact</u> alignment once every 10¹¹⁷ samples

Now suppose we've estimated two rate matrices:

Q_{C} estimated from known coding regions

 Q_N estimated from noncoding regions

© Source unknown. All rights reserved. This content is excluded from our Creative Commons license. For more information, see http://ocw.mit.edu/help/fag-fair-use/.

ancestor GTG GCG AGT GCA TTT CCC AGA GGA GTT GAT AGG AGT CTG AAA CTA CTG ATA AAT TGC TTT TTA ATT AGC ACA GAG CAG

These specify different rates of codon substitution, which in turn lead to different probabilities of any given alignment:

dmel GTG

ancestor ATG AGC TCA TTC CTC ATG GGT TAT CCG CAT GCC CCA CAT CAC GTC CAG AGT CCC ATG TCC ATG GGC AAT GGC CTG GAT **CT TTT** CTC ATG GGT TAT CCG CAT <mark>GCA</mark> CCA CAT <mark>CAT</mark> GTC CAG AGT CCC ATG TCC ATG GGC AAT GGC dmel ATG AGC dsim atg agc **ict itt** ctc atg ggt tat ccg cat <mark>gca</mark> cca cat <mark>cat</mark> gtc cag agt ccc atg tcc atg ggc aat ggc dsec atg agc **tct ttt** ctc atg ggt tat ccg cat <mark>gca</mark> cca cat <mark>cat</mark> gtc cag agt ccc atg tcc atg ggc aat ggc dyak atg agc **tct itt** ctc atg <mark>ggc</mark> tat ccg cat <mark>gct</mark> cca cat <mark>cat gtt caa</mark> agt ccc atg tcc atg ggc aat ggc dere atg age **tet tet** etc atg ggt tat eeg cat <mark>get</mark> eea cat <mark>cat gtt</mark> eag agt eec atg tee atg gge aat dana ATG AGC TCC TTC CTC ATG GGC TAC CCC CAC GCC CCG CAT CAC GTC CAG AGC CCC ATG TCC ATG GGC AAT GGC CTG GAT dpse atg agc tca ttc ctc atg ggt tat cca gcc cat gcc ccc cat cac gtc cag agt ccc atg tcc atg ggc aat ggc ctg gat dder atg age tea tic etc atg ggt tat <mark>cca</mark> cat gee <mark>ecc</mark> cat cae gte cag agt ecc atg tee atg gge aat gge etg gat dwil atg agc tca ttc ctc atg ggt tat ccg cat gcc cca cat <mark>cat</mark> gtc cag agt ccc atg tcc atg ggc aat <mark>gga ctc</mark> gat dvir atg age tea tte etc atg ggt tat cca cat gcg cca cat cat gte cag age cce atg tee atg ggt aat gge cta gat dmoj atg agc tca ttc **cta** atg <mark>ggc</mark> tat <mark>cca</mark> cat <mark>gcg</mark> cca cat <mark>cat</mark> gtc cag <mark>agc</mark> ccc atg tcc atg ggc aat <mark>gga</mark> ctg <mark>gaa</mark> dqri atg agc tca ttc ctc atg ggt tac cca cat gcc ccc cat cac gtc cag agc ccc atg tcc atg ggc aat ggc ctg gat

$$\Pr(\text{Leaves}; \mathbf{Q}_C, \underline{t}) = \frac{1}{10^{117}}$$
$$\Pr(\text{Leaves}; \mathbf{Q}_N, \underline{t}) = \frac{1}{10^{152}}$$

<mark>seg</mark> tit cee aga gga <mark>teg</mark> gat <mark>gga ggt</mark> etg <mark>aag</mark> eta etg ata <mark>gat</mark> tge tit tta att age aca dsim gtg <mark>acg</mark> aat gcg ttt ccc aga gga <mark>tcg</mark> gat <mark>gca ggt</mark> ctg aaa cta ctg ata <mark>gat</mark> tgc ttt tta att agc aca <mark>gca</mark> cag dsec gtg <mark>aca aat acg</mark> ttt ccc aga gga <mark>teg</mark> gat <mark>gga gge</mark> ctg aaa <mark>ctt</mark> ctg ata <mark>gat</mark> tgc ttt tta att agc aca <mark>gea</mark> cag dyak gtg acg aat gca ttt cct act gga tcg caa caa ggg ctg aaa gta ctg ata gat gtc ttt tta act agc aca gca cag dere GTG ACC AAT GCA TTT CCT AGA GGA TCC GAT GGT GGT TTG AAA GCC CTG ATA GAT TGC TTT TTA ATT AGC ACA dana GTG <mark>ACG AAT</mark> GCA TTT <mark>ACT</mark> AGA <mark>CGA TCT AGC</mark> AGG <mark>TGG CGG</mark> AAA <mark>AAG</mark> CTG <mark>ATG GAT</mark> TGC TTT TTA ATT AGC ACA GAG <mark>g</mark> agg agt <mark>ctc cac</mark> gca</mark> ctg ata <mark>gat</mark> tgc ttt tta att agc aca gag dpse GTG TC CT GCA TTT ACG <mark>CGG</mark> AGG CCC A dper GTG <mark>TCG ACT</mark> GCA TTT <mark>ACG CCG AGG CCC ACG</mark> AGG AGT <mark>CTC CAC</mark> GCA CTG ATA <mark>GAT</mark> TGC TTT TTA ATT AGC ACA GAG <mark>AGA</mark> dwilgtggcgagtgca AAA AGA <mark>ACA</mark> GTT TT AGT <mark>BGT</mark> CTG <mark>ATT</mark> AAT TGC TTT TTA ATT AGC dvir GTG GCG AGT GCA <mark>G CAA</mark> CTG <mark>GGT TAG</mark> CTG ATA AAT TGC TTT TTA ATT AGC CTC GGT CAG CTG ATG GAT GAC TTT TTA ATT AGT ATA GCG CAG dmoj GTG GCG ACT GCA TAT GCA GGT CGT GTT dari GTG GCG AGT GCA T TGG CTG ATA AAT GGT TTT TTA ATT AGC CTA GCG CAG ST CAG CGA CTG

$$\Pr(\text{Leaves}; \mathbf{Q}_C, \underline{t}) = \frac{1}{10^{275}}$$
$$\Pr(\text{Leaves}; \mathbf{Q}_N, \underline{t}) = \frac{1}{10^{254}}$$

CA CAG







$$\frac{\Pr(\text{Leaves}; \mathbf{Q}_{C}, \underline{t}) = \frac{1}{10^{117}}}{\Pr(\text{Leaves}; \mathbf{Q}_{N}, \underline{t}) = \frac{1}{10^{152}}} = 10^{35}$$

This alignment is 10³⁵ times <u>more probable</u> under the coding model than the non-coding model.

ancestor GTG GCG AGT	GCA TTT (CCC AGA	GGA GTT	GAT AGO	G AGT	CTG AAA	CTA	CTG ATA	AAT TO	C TTT	TTA AT	F AGC	ACA GI	IG CAG
dmel GTG <mark>ACG</mark> AAT	GCG TTT (CCC AGA	GGA <mark>TCC</mark>	GAT GG	AGGT	CTG AAC	CTA	CTG ATA	GAT TO	C TTT	TTA AT	F AGC	ACA <mark>G</mark>	A CAG
dsim GTG <mark>ACG</mark> AAT	GCG TTT (CCC AGA	GGA <mark>TCC</mark>	GAT GG	AGGT	CTG AAA	CTA	CTG ATA	GAT TO	C TTT	TTA AT	F AGC	ACA <mark>G</mark>	A CAG
dsec GTG <mark>ACA</mark> AAT	ACG TTT (CCC AGA	GGA TCC	GAT GG	AGGT	CTG AAA	CTT	CTG ATA	GAT TO	C TTT	TTA AT	F AGC	ACA <mark>G</mark>	A CAG
dyak GTG <mark>ACG</mark> AAT	GCA TTT	CCT AGT	GGA TCC	GAA GA	AGGG	CTG AAA	GTA	CTG ATA	GAT <mark>G</mark>	IC TTT	TTA AC	AGC	ACA <mark>G</mark>	CAG
dere GTG <mark>ACG</mark> AAT	GCA TTT	CCT AGA	GGA TCC	GAT GG	TGGT	TTG AAA	GGG	CTG ATA	GAT TO	C TTT	TTA AT	F AGC	ACA <mark>G</mark>	A CAG
dana GTG <mark>ACG</mark> AAT	GCA TTT	ACT AGA	CGA TCT	AGC AGO	G <mark>TGG</mark>	CGG AAA	AAG	CTG <mark>ATG</mark>	GAT TO	C TTT	TTA AT	F AGC	ACA GI	\G <mark>TCG</mark>
dpse GTG <mark>TCG</mark> ACT	GCA TTT	ACG <mark>CGG</mark>	AGG CCC	ACC AGO	G AGT	CTC CAC	GCA	CTG ATA	GAT TO	C TTT	TTA AT	F AGC	ACA GI	AG AGA
dper GTG <mark>TCG</mark> ACT	GCA TTT	ACG <mark>CGG</mark> .	AGG CCC	ACC AGO	G AGT	CTC CAC	GCA	CTG ATA	GAT TO	C TTT	TTA AT	F AGC	ACA GA	IG AGA
dwil GTG GCG AGT	GCA TTA	AAA AGA	<mark>aga</mark> GTT	GAG TT	T AGT	CGA <mark>GAG</mark>	GGT	CTG <mark>ATT</mark>	AAT TO	C TTT	TTA AT	F AGC	ACT A	TAA
dvir GTG GCG AGT	GCA TGT	GCG <mark>GGA</mark>	TGG <mark>CTT</mark>	GGT CGC	<mark>g</mark> caa	CTG GG1	TAG	CTG ATA	AAT TO	C TTT	TTA AT	I AGC	ATA GO	CAG
dmoj GTG GCG <mark>ACT</mark>	GCA TAT	GCA GGT	CGT GTI	GGC CGC	G GCT	CTC GG1	CAG	CTG ATG	GAT GA	AC TTT	TTA AT	T AGT	ATA GO	G CAG
dgri <mark>GTG GCG AGT</mark>	GCA TCT	GCG GGA	TGT GTT	GGT CAC	CGA	CTG CGT	TGG	CTG ATA	AAT	TTTT	TTA AT	T AGC	CTA GO	G CAG

$$\frac{\Pr(\text{Leaves}; \mathbf{Q}_C, \underline{t}) = \frac{1}{10^{275}}}{\Pr(\text{Leaves}; \mathbf{Q}_N, \underline{t}) = \frac{1}{10^{254}}} = 10^{-21}$$

This alignment is 10²¹ times less probable under the coding model than the non-coding model.

This **likelihood ratio** $\frac{\Pr(\text{Leaves}; \mathbf{Q}_{C}, \underline{t})}{\Pr(\text{Leaves}; \mathbf{Q}_{N}, \underline{t})}$ is our measure of confidence that

the alignment is protein-coding.

Comparative genomics I: Evolutionary signatures

- Nucleotide conservation: evolutionary constraint
 - Purifying selection, neutral branch length, discovery power
 - Detect constrained elements: nucleotides, windows, HMM
 - Estimate fraction constrained: signal vs. background
- Evolutionary signatures: focus on pattern of change
 - Different functions Characteristic patterns of evolution
- Signatures of protein-coding genes
 - Reading-frame conservation, codon-substitution frequency
 - Likelihood ratio framework: Estimating Q_CQ_N, scoring
 - Revise genes, read-through, excess constraint regions
- Signatures of microRNA genes
 - Structural and evolutionary features of microRNAs
 - Combining features: decision trees, random forests
 - Sense/anti-sense miRNAs, mature/star arm cooperation ⁴²

Evolutionary signatures can predict new genes and





Evolutionary signatures built into a semi-Markov conditional random field to predict proteincoding exons



Courtesy of Macmillan Publishers Limited. Used with permission. Source: Stark, Alexander et al. "Discovery of functional elements in 12 Drosophila genomes using evolutionary signatures." Nature 450, no. 7167 (2007): 219-232.

New protein-coding genes



Translational read-through in flies and mammals

One of four novel candidates in the human genome: OPRL1 neurotransmitter



New mechanism of post-transcriptional regulation?

- Conserved in both mammals (4 candidates) and flies (350 candidates)
- Strongly enriched for neurotransmitters, brain-expressed proteins, TF regulators
- After correcting for gene length: TF enrichment remains

Evidence suggestive of regulatory control

- Read-through stop codon perfectly conserved in 93% of cases (24% at bkgrnd)
- Upstream bases show increased conservation. Downstream is TGAC.
- GCA triplet repeats
- Increased RNA secondary structure

Lin *et al*, Genome Research 2007 Jungreis *et al*, in preparation ⁴⁵

Discover of translational readthrough genes

SACM1L		100 bases	
Stop 1	Stop 2		
anc_aa R L V Q K E K I D I C V C G K R L G L E 	D S I M Q N W S L Y P A F (((((((), A C N W))))))))))))))))))))))))))))))))))	H I S L R S F X S L)))))) CACATCAGC CTGAGG TCT TTT TAA AGC CTT CACATCAGC CTGAGG TCT TTT TAA AGC CTT CACATCAGC CTGAGG TCT TTT TAA AGC CTT CACATCAGC CTAAGG TCT TTT TAAAGC CTT CACATCAGC CTG AGG TCT TTT TAAAGC CTT C	Stop 2
		UGAAUUU	UGAGGUCUUUU
	Typical of protein-coding genes Typical of no	on-coding regions	
	Synonymous substitution Non-co	onservative substitution	
	Conservative substitution Frame	-shifting indel	
	Frame-preserving indel	Stop codons	

© Source unknown. All rights reserved. This content is excluded from our Creative

Commons license. For more information, see http://ocw.mit.edu/help/faq-fair-use/.

Discovery of 4 readthrough genes, abundant in many animal genomes

Overlapping selection in protein-coding exons



Codon-specific measures of positive selection



Commons license. For more information, see http://ocw.mit.edu/help/faq-fair-use/.

Gene-wide vs. punctate regions of exons positive selection

Comparative genomics I: Evolutionary signatures

- Nucleotide conservation: evolutionary constraint
 - Purifying selection, neutral branch length, discovery power
 - Detect constrained elements: nucleotides, windows, HMM
 - Estimate fraction constrained: signal vs. background
- Evolutionary signatures: focus on pattern of change
 - Different functions Characteristic patterns of evolution
- Signatures of protein-coding genes
 - Reading-frame conservation, codon-substitution frequency
 - Likelihood ratio framework: Estimating Q_CQ_N, scoring
 - Revise genes, read-through, excess constraint regions
- Signatures of microRNA genes
 - Structural and evolutionary features of microRNAs
 - Combining features: decision trees, random forests
 - Sense/anti-sense miRNAs, mature/star arm cooperation

49

New RNA structures and families

	No. of structures	No. of novel structures	No. of families	No. of novel families	EvoFold score	RNAz overlap enrichment (x)	DNAse hypersensitivity overlap (%)	Avg. correlation of tissue-specific expression within families
EvoFold all (no CDS)	27,012	26,643	n/a	n/a	14	13.5	25 (<i>P</i> ≤ 5e–3)	n/a
Unfiltered families	3293	3081	1254	1215	18	17.3	25 (<i>P</i> ≤ 7e−3)	0.14 (<i>P</i> ≤ 1e−3)
Filtered families	725	526	220	181	18	29	32 (<i>P</i> ≤ 4e−3)	0.15 (<i>P</i> ≤ 1e−3)

New structs fall in families, supported by evolut/energy



© Source unknown. All rights reserved. This content is excluded from our Creative Commons license. For more information, see http://ocw.mit.edu/help/faq-fair-use/.

Ex: new struct in XIST long non-coding RNA Known function in X-chromosome inactivation Possible functional domain of XIST?

RNA families: orthologous/paralogous conservation



UCUGGGGUAUGG UAAGUACAGAGAAGCCAUCACCUCAGA GUAGGUACAGAGAAGCCCAAGCUCUGAGA UCCCAGACUUGGOUUGUGAUGUCA-UACAGAGAAGUCACGGC... UCUGAAAGCUGGU GUAGCUACAGAGAAACCAGCUUUUCAGA . GGCCAAGGI -UACAGAAAAACCUUGGGUU....))))))))))))))))))))) abcdefghiklmn nmlki hqfedcba UCUGGGGUAUGGCGUAAGUACAGAGAA GCCAUCACCUCAGA UCUGGGGUAUGGC GUAAGUACAGAGAAGCCAUCGCCUCAGA UCUGAGGUAUGGUGUAAGUACAGAGAAGCCAUCACCUCAGA UCUGGGGGAUGGC GUAAGUACAGAGAAGCCAUCUCCUCAGA UCUGAGGUAUGGC GUAAGUACAGAGAAGCCAUCACCUCAGA U-GGGGGUAUGGCUUAAGUACAGAGAAGCCCUCACCUCAGA UCUGGGGUAUGGUGUAAGUACAGAGAAGCCGUCACCUCAGA UCUGGGGUGUGGC GUGAGUACAGAGAAGCUAUCACCUCAGA U-UGGGACCGGGUGUGAGUACAGAGAAGCCCUUGUCUCAAA UCUAGGCUUGGGCGUAAGUACAGAGUAGCCUUUGCCUU---UCUGAGGCCCGGCGUGGAUACAGAGAAGUCGGGCUUUCAGG UCUGAGGCCCGGCGUGGAUACAGAGAAGUCGGGCUGUCAGG UCUGAGACGCAGCGUGGAUACAGAGAAGCUGUGGUUUCAGA UCUGGAACUCGGC GUGGAUACAGAGAAGCCGAUGUUUCAGA CUUGAGCCUUGGCGUCGGUACAGAAAAGCCGGGAUCUCAAG ***** **))))))))))))))))))))))

20

30

40

10

abcdefghijklm

© Source unknown. All rights reserved. This content is excluded from our Creative Commons license. For more information, see http://ocw.mit.edu/help/faq-fair-use/.

Example of new structural 3'UTR family in MAT2A gene likely role in detecting S-adeosyl-methionic (SAM) level

mlkji hqfedcba

Computational challenge of miRNA discovery



A false positive rate of 0.5% → 3800 spurious hairpins. Need 99.99% specificity (>5,000-fold enrichment)

Evolutionary signatures for microRNA genes



© Source unknown. All rights reserved. This content is excluded from our Creative Commons license. For more information, see http://ocw.mit.edu/help/faq-fair-use/.

miRNAs show characteristic conservation properties

Distinguishing true miRNAs from random hairpins



© Source unknown. All rights reserved. This content is excluded from our Creative Commons license. For more information, see http://ocw.mit.edu/help/faq-fair-use/. 4551

327

19

5

6

39

2.3

1.7

1.4

1.4

3

100

Comparative genomics I: Evolutionary signatures

- Nucleotide conservation: evolutionary constraint
 - Purifying selection, neutral branch length, discovery power
 - Detect constrained elements: nucleotides, windows, HMM
 - Estimate fraction constrained: signal vs. background
- Evolutionary signatures: focus on pattern of change
- Signatures of protein-coding genes
 - Reading-frame conservation, codon-substitution frequency
 - Likelihood ratio framework: Estimating Q_CQ_N, scoring
 - Revise genes, read-through, excess constraint regions
- Signatures of microRNA genes
 - Structural and evolutionary features of microRNAs
 - Combining features: decision trees, random forests
 - Sense/anti-sense miRNAs, mature/star arm cooperation

55

miRNA detection using many decision trees



For each tree:

- Randomly select:
 - Subset of features to base classification on
 - Subset of +/- training examples
 - Remainder of testing examples

Use to train a decision tree classifier:

- Select a feature and cutoff at each level
- Continue with feature/cutoff at next level
- (...)
- Evaluate performance on test set:
 - Push each element down the decision tree
 - Leaf label gives classification decision

To combine trees:

- Average prediction class across trees
- Report class with maximum # of votes

Random Forests: Combine many decision trees



© Source unknown. All rights reserved. This content is excluded from our Creative Commons license. For more information, see http://ocw.mit.edu/help/faq-fair-use/.

Many decision trees:

- Each can select cutoffs and direction of cutoff
- Each feature can be reused multiple times
- Used serially (AND) and in parallel (OR)

Ensemble classifier

- Bagging: model averaging, combines predictions
- Can take median of predictions

Advantages: Robustness, Feature importance

Evidence 1: Novel miRNAs match sequencing reads



Commons license. For more information, see http://ocw.mit.edu/help/faq-fair-use/.

Evidence 2: Genomic properties typical of miRNAs



- Novel miRNAs in introns of known genes
- Preference for + strand, transcription factors



Genomic clustering with novel / known miRNAs

Same family, common origin / same precursor

© Source unknown. All rights reserved. This content is excluded from our Creative Commons license. For more information, see http://ocw.mit.edu/help/faq-fair-use/.

Two 'dubious' protein-coding genes are in fact miRNAs

Two novel miRNAs overlap exons (5'UTR and coding!)



Commons license. For more information, see http://ocw.mit.edu/help/faq-fair-use/.

- Both CG31044 and CG33311 were independently rejected as *dubious* based on their non-protein-coding conservation patterns (Lin *et al.*)
- Novel miRNA genes provide explanation for their transcripts, as their precursor miRNA

Comparative genomics I: Evolutionary signatures

- Nucleotide conservation: evolutionary constraint
 - Purifying selection, neutral branch length, discovery power
 - Detect constrained elements: nucleotides, windows, HMM
 - Estimate fraction constrained: signal vs. background
- Evolutionary signatures: focus on pattern of change
 - Different functions Characteristic patterns of evolution
- Signatures of protein-coding genes
 - Reading-frame conservation, codon-substitution frequency
 - Likelihood ratio framework: Estimating Q_CQ_N, scoring
 - Revise genes, read-through, excess constraint regions
- Signatures of microRNA genes
 - Structural and evolutionary features of microRNAs
 - Combining features: decision trees, random forests
 - Sense/anti-sense miRNAs, mature/star arm cooperation

61

Surprise 1: microRNA & microRNA* function



© Source unknown. All rights reserved. This content is excluded from our Creative Commons license. For more information, see http://ocw.mit.edu/help/faq-fair-use/.

Both hairpin arms of a microRNA can be functional

- High scores, abundant processing, conserved targets
- Hox miRNAs miR-10 and miR-iab-4 as master Hox regulators

Stark et al, Genome Research 2007 62

Evidence of miR-iab-4 anti-sense (AS) function



© Cold Spring Harbor Laboratory Press. All rights reserved. This content is excluded from our Creative Commons license. For more information, see http://ocw.mit.edu/help/faq-fair-use/.

Source: Stark, Alexander et al. "A single Hox locus in Drosophila produces functional microRNAs from opposite DNA strands." Genes & development 22, no. 1 (2008): 8-13.

- A single miRNA locus transcribed from both strands
- The two transcripts show distinct expression domains (mutually exclusive)
- Both processed to mature miRNAs: mir-iab-4, miR-iab-4AS (anti-sense)

miR-iab-4AS leads to homeotic transformations



same magnification C,D,E Note: (

© Cold Spring Harbor Laboratory Press. All rights reserved. This content is excluded from our Creative Commons license. For more information, see http://ocw.mit.edu/help/faq-fair-use/.

Source: Stark, Alexander et al. "A single Hox locus in Drosophila produces functional microRNAs from opposite DNA strands." Genes & development 22, no. 1 (2008): 8-13.

- Mis-expression of mir-iab-4S & AS: alteres \rightarrow wings homeotic transform.
- Stronger phenotype for AS miRNA
- Sense/anti-sense pairs as general building blocks for miRNA regulation
- 10 sense/anti-sense miRNAs in mouse



Stark et al, Genes&Development 2008 64

Comparative genomics I: Evolutionary signatures

- Nucleotide conservation: evolutionary constraint
 - Purifying selection, neutral branch length, discovery power
 - Detect constrained elements: nucleotides, windows, HMM
 - Estimate fraction constrained: signal vs. background
- Evolutionary signatures: focus on pattern of change
- Signatures of protein-coding genes
 - Reading-frame conservation, codon-substitution frequency
 - Likelihood ratio framework: Estimating Q_CQ_N, scoring
 - Revise genes, read-through, excess constraint regions
- Signatures of microRNA genes
 - Structural and evolutionary features of microRNAs
 - Combining features: decision trees, random forests
 - Sense/anti-sense miRNAs, mature/star arm cooperation
- Measuring selection within the human lineage

Mammalian constraint matches Human SNPs

SiPhy p elements **PhastCons** SiPhy ω SiPhy π SiPhy π vector ECU read coverage YRI read coverage JPT read coverage © Source unknown. All rights reserved. This content is excluded from our Creative

Commons license. For more information, see http://ocw.mit.edu/help/faq-fair-use/.

Human SNPs match mammalian-wide twofold constraint

Mammalian constraint matches Human SNPs



© Source unknown. All rights reserved. This content is excluded from our Creative Commons license. For more information, see http://ocw.mit.edu/help/faq-fair-use/.

Genome-wide agreement of selection and polymorphisms

Human constraint outside conserved regions



© Source unknown. All rights reserved. This content is excluded from our Creative Commons license. For more information, see http://ocw.mit.edu/help/faq-fair-use/.



Average diversity (heterozygosity)

Aggregate over the genome

- Non-conserved regions:
 - ENCODE-active regions show reduced diversity
- Lineage-specific constraint in biochemically-active regions

- Conserved regions:
 - Non-ENCODE regions show increased diversity
- ➔ Loss of constraint in human when biochemically-inactive_a

Strongest: motifs, short RNA, Dnase, ChIP, IncRNA

	Feature	ean freque 0.190	ency of de 0.200	rived allel 0.210	^{es} Exten	t Comparison
	Protein coding (ND)	1			3 MB	unconserved genome
	Protein coding (all)				5 MB	unconserved genome
	UTR			-	20 MB	unconserved genome
GENCODE	TSS			-	172 MB	unconserved genome
annotations	ntron				725 MB	unconserved genome
	CDS (fourfold)			+j	1 MB	unconserved genome
	Repeat				680 MB	unconserved genome
	Intergenic				776 MB	unconserved genome
	Bound motifs	I			3 MB	unconserved noncoding
ENCODE	Novel short RNA	I			2 MB	unconserved noncoding
ENCODE	DNAse		I		310 MB	unconserved noncoding
activity	FAIRE				239 MB	unconserved noncoding
	ChIP			_	113 MB	unconserved noncoding
	Novel long RNA				882 MB	unconserved noncoding
	Non-ENCODE			_	466 MB	unconserved noncoding
Chromatin states	Transcribed				302 MB	unconserved noncoding
	Promoter		I	-	47 MB	unconserved noncoding
	Enhancer		1		285 MB	unconserved noncoding
	Insulator			- I	35 MB	unconserved noncoding
	Inactive chromatin				954 MB	unconserved noncoding

© Source unknown. All rights reserved. This content is excluded from our Creative Commons license. For more information, see http://ocw.mit.edu/help/faq-fair-use/.

Significant derived allele depletion in active features ... \bullet

Bound motifs show increased human constraint



© Source unknown. All rights reserved. This content is excluded from our Creative Commons license. For more information, see http://ocw.mit.edu/help/faq-fair-use/.

Position-specific reduction in bound motif heterozygosity Aggregate across thousands of CTCF motif instances 70

Most constrained human-specific enhancer functions



Regulatory genes: Transcription, Chromatin, Signaling. Developmental enhancers: embryo, nerve growth

Comparative genomics I: Evolutionary signatures

- Nucleotide conservation: evolutionary constraint
 - Purifying selection, neutral branch length, discovery power
 - Detect constrained elements: nucleotides, windows, HMM
 - Estimate fraction constrained: signal vs. background
- Evolutionary signatures: focus on pattern of change
- Signatures of protein-coding genes
 - Reading-frame conservation, codon-substitution frequency
 - Likelihood ratio framework: Estimating Q_CQ_N, scoring
 - Revise genes, read-through, excess constraint regions
- Signatures of microRNA genes
 - Structural and evolutionary features of microRNAs
 - Combining features: decision trees, random forests
 - Sense/anti-sense miRNAs, mature/star arm cooperation
- Measuring selection within the human lineage
6.047 / 6.878 / HST.507 Computational Biology Fall 2015

For information about citing these materials or our Terms of Use, visit: http://ocw.mit.edu/terms.