

Human Genome Diversity, Coalescence & Haplotypes



The HapMap Project

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$\bullet \bullet \bullet \bullet \bullet$

ASW	African ancestry in Southwest USA	90
CEU	Northern and Western Europeans (Utah)	180
CHB	Han Chinese in Beijing, China	90
CHD	Chinese in Metropolitan Denver	100
GIH	Gujarati Indians in Houston, Texas	100
JPT	Japanese in Tokyo, Japan	91
LWK	Luhya in Webuye, Kenya	100
MXL	Mexican ancestry in Los Angeles	90
MKK	Maasai in Kinyawa, Kenya	180
TSI	Toscani in Italia	100
YRI	Yoruba in Ibadan, Nigeria	100

а

Chromosome



Genotyping:

Probe a limited number (~1M) of known highly variable positions of the human genome



Linkage Disequilibrium & Haplotype Blocks





intervals where distinct obligate recombination events must have occurred (blue and green indicate adjacent intervals). Stacked intervals represent regions where there are multiple recombination events in the sample history. The bottom plot shows estimated recombination rates, with hotspots shown as red triangles⁴⁶.

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Figure 9 | The distribution of recombination events over the ENCODE regions. Proportion of sequence containing a given fraction of all recombination for the ten ENCODE regions (coloured lines) and combined (black line). For each line, SNP intervals are placed in decreasing order of estimated recombination rate⁶⁶, combined across analysis panels, and the cumulative recombination fraction is plotted against the cumulative proportion of sequence. If recombination rates were constant, each line would lie exactly along the diagonal, and so lines further to the right reveal the fraction of regions where recombination is more strongly locally concentrated.

Proportion of recombination



Population Sequencing – 1000 Genomes Project







Population Sequencing – 1000 Genomes Project









CLN

MXI

PEL

PUR

CDX

CHS

JPT

KHV

CEU

FIN

TSI

BEB GIH

ITU

PJL

STU

Population Sequencing – UK10K



Population Sequencing





Population Sequencing





Population Sequencing

When C is high (>30x),

 $Prob(g_{ij} = g | data) \sim$

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Prob(g_{ij} = g | reads mapping on (i, j))
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fast & easy

When C is low,

Prob(g_{ij} = *g* | data) needs to leverage LD: positions j' ≠ j in all individuals in principle, intractable









HMM-based models

• Li and Stephens 2003

Given m reference haplotypes, and a target sample, Find the most likely path of haplotype pairs m² states, m⁴ transitions per position



Informative Neighbors





 $(\mathsf{R}_{\mathsf{ref}},\,\mathsf{R}_{\mathsf{alt}}) = \Sigma_{\{\mathsf{target},\,\mathsf{nbrs}\}}(\mathsf{r}_{\mathsf{ref}},\,\mathsf{r}_{\mathsf{alt}}) = (20,\,0)$

Informative Neighbors





 $(\mathsf{R}_{\text{ref}}, \, \mathsf{R}_{\text{alt}}) = \Sigma_{\{\text{target, nbrs}\}}(\mathsf{r}_{\text{ref}}, \, \mathsf{r}_{\text{alt}}) = (11, \, 9)$

How to pick k nearest neighbors fast





Correlation Coefficient: $r^2 = (p_{AB} - p_A p_B)^2 / p_A p_B p_a p_b$

Caveat: need genotyping, phasing

Let

S_i = { samples covering minor allele } S_i' = { read counts of minor allele }

$$\begin{split} S_i &= \{1, 2, 3, 10\} \\ S_j &= \{1, 3, 4\} \\ S_i' &= \{1, 2, 3, 3, 3, 10\} \\ S_j' &= \{1, 3, 3, 3, 3, 3, 4, 4\} \end{split}$$

$$\begin{split} & \text{Sim}_{1}(i, j) = (\text{S}_{i} \cap \text{S}_{j}) / (\text{S}_{i} \cup \text{S}_{j}) \\ & \text{Sim}_{2}(i, j) = (\text{S}_{i}' \cap \text{S}_{j}') / (\text{S}_{i}' \cup \text{S}_{j}') \\ & \text{Sim}_{3}(i, j) = ((\text{S}_{i}' \cap \text{S}_{j}') / (\text{S}_{i}' \cup \text{S}_{j}'))^{2} \end{split}$$



Genetic distance between NNs





Reveel: Variant Discovery and Imputation

Reveel:

- 1. Identify candidate polymorphic sites
- 2. Calculate k nearest neighbors
 - Jaccard indices Sim₁, Sim₂, Sim₃
- 3. Initialize G⁽⁰⁾
- 4. Summarization/Maximization $p^{(n+1)}_{ijg} = Prob(g_{ij} = g | G^{(n)}, data)$ $g^{(n+1)}_{ijg} = argmax p^{(n+1)}_{ijg}$
- 5. Recalculate k nearest neighbors
 Approximate Correlation Coefficient (Schaid 2004)
- 6. Summarization/Maximization
- 7. Recalculate k nearest neighbors
 - Approximate CC, Entropy
- 8. Summarization/Maximization



Candidate Polymorphic site

Essentially, pos'n j where some individuals have at least 2 reads with same minor allele







Molecular Evolution and Phylogenetic Tree Reconstruction









Proteins (genes) evolve by both duplication and species divergence



Orthology and Paralogy





Orthologs: Derived by speciation

Paralogs: *Everything else*



Orthology, Paralogy, Inparalogs, Outparalogs



Figure 1. Refinements of homology.



Fig. 1. The definition of inparalogs and outparalogs. (a) Consider an ancient gene inherited in the yeast, worm and human lineages. The gene was duplicated early in the animal lineage, before the human-worm split, into genes A and B. After the human-worm split, the A form was in turn duplicated independently in the human and worm lineages. In this scenario, the yeast gene is orthologous to all worm and human genes, which are all co-orthologous to all genes in the HA* set are co-orthologous to all genes in the HA* set. The genes HA* are hence 'inparalogs' to each other when comparing human to worm. By contrast, the genes HB and HA* are 'outparalogs' when comparing human with worm...However, HB and HA*, and WB and WA* are inparalogs when comparing why yeast, because the animal-yeast split pre-dates the HA*-HB duplication. (b) Real-life example of inparalogs: γ-butyrobetaine hydroxylases. The points of speciation and duplication are easily identifiable. The alignment is a subset of Pfam:PF03322 and the tree was generated by neighborjoining in Belvu. All nodes have a bootstrap support exceeding 95%.

Phylogenetic Trees

- Nodes: species
- Edges: time of independent evolution
- Edge length represents evolution time
 - AKA genetic distance
 - Not necessarily chronological time





Inferring Phylogenetic Trees

Trees can be inferred by several criteria:

- Morphology of the organisms
 - Can lead to mistakes
- Sequence comparison

Example:





Inferring Phylogenetic Trees

- Sequence-based methods
 - Deterministic (Parsimony)
 - Probabilistic (SEMPHY)
- Distance-based methods
 - UPGMA
 - Neighbor-Joining
- Can compute distances from sequences





Basic principle:

Distance proportional to degree of independent sequence evolution

Given sequences xⁱ, x^j,

d_{ij} = distance between the two sequences

One possible definition:

 d_{ij} = fraction f of sites u where $x^{i}[u] \neq x^{j}[u]$

Better scores are derived by modeling evolution as a continuous change process

Modeling sequence substitution:

Consider what happens at a position for time Δt ,

- P(t) = vector of probabilities of {A,C,G,T} at time t
- μ_{AC} = rate of transition from A to C per unit time
- $\mu_A = \mu_{AC} + \mu_{AG} + \mu_{AT}$ rate of transition out of A
- $p_A(t+\Delta t) = p_A(t) p_A(t) \mu_A \Delta t + p_C(t) \mu_{CA} \Delta t + p_G(t) \mu_{GA} \Delta t + p_T(t) \mu_{TA} \Delta t$



In matrix/vector notation, we get

$$\mathsf{P}(\mathsf{t}+\Delta\mathsf{t}) = \mathsf{P}(\mathsf{t}) + \mathsf{Q} \; \mathsf{P}(\mathsf{t}) \; \Delta\mathsf{t}$$

where Q is the substitution rate matrix

$$Q = \begin{pmatrix} -\mu_A & \mu_{GA} & \mu_{CA} & \mu_{TA} \\ \mu_{AG} & -\mu_G & \mu_{CG} & \mu_{TG} \\ \mu_{AC} & \mu_{GC} & -\mu_C & \mu_{TC} \\ \mu_{AT} & \mu_{GT} & \mu_{CT} & -\mu_T \end{pmatrix}$$



• This is a differential equation:

P'(t) = Q P(t)

- Q => prob. distribution over {A,C,G,T} at each position, stationary (equilibrium) frequencies π_A , π_C , π_G , π_T
- Each Q is an evolutionary model
 - Some work better than others

Evolutionary Models

- Jukes-Cantor
- Kimura

• HKY

• Felsenstein

$$Q = \begin{pmatrix} * & \frac{\mu}{4} & \frac{\mu}{4} & \frac{\mu}{4} \\ \frac{\mu}{4} & \frac{\mu}{4} & \frac{\mu}{4} & \frac{\mu}{4} \\ \frac{\mu}{4} & \frac{\mu}{4} & \frac{\mu}{4} & \frac{\mu}{4} & * \end{pmatrix}$$

$$Q = \begin{pmatrix} * & \kappa & 1 & 1 \\ \kappa & * & 1 & 1 \\ 1 & 1 & * & \kappa \\ 1 & 1 & \kappa & * \end{pmatrix}$$

$$Q = \begin{pmatrix} * & \pi_T & \pi_T & \pi_T \\ \pi_C & * & \pi_C & \pi_C \\ \pi_A & \pi_A & * & \pi_A \\ \pi_G & \pi_G & \pi_G & * \end{pmatrix}$$

$$Q = \begin{pmatrix} * & \kappa\pi_T & \pi_T & \pi_T \\ \kappa\pi_C & * & \pi_C & \pi_C \\ \pi_A & \pi_A & * & \kappa\pi_A \\ \pi_G & \pi_G & \kappa\pi_G & * \end{pmatrix}$$





• Solve the differential equation and compute expected evolutionary time given sequences

$$\mathsf{P}'(\mathsf{t}) = \mathsf{Q} \; \mathsf{P}(\mathsf{t})$$

Jukes-Cantor:

Let
$$P_{AA}(t) = P_{CC}(t) = P_{CC}(t) = P_{CC}(t) = r$$

 $P_{AC}(t) = \dots = P_{TG}(t) = s$

Then,

$$\begin{aligned} \mathsf{r}'(t) &= - \frac{3}{4} \, \mathsf{r}(t) \, \mu + \frac{3}{4} \, \mathsf{s}(t) \, \mu \\ \mathsf{s}'(t) &= - \frac{1}{4} \, \mathsf{s}(t) \, \mu + \frac{1}{4} \, \mathsf{r}(t) \, \mu \end{aligned}$$

Which is satisfied by

$$r(t) = \frac{1}{4} (1 + 3e^{-\mu t})$$

s(t) = $\frac{1}{4} (1 - e^{-\mu t})$

Estimating Distances



• Solve the differential equation and compute expected evolutionary time given sequences

$$\mathsf{P}'(t) = \mathsf{Q} \mathsf{P}(t)$$

Jukes-Cantor:

$$P = \begin{pmatrix} \frac{1}{4} + \frac{3}{4}e^{-t\mu} & \frac{1}{4} - \frac{1}{4}e^{-t\mu} & \frac{1}{4} - \frac{1}{4}e^{-t\mu} & \frac{1}{4} - \frac{1}{4}e^{-t\mu} \\\\ \frac{1}{4} - \frac{1}{4}e^{-t\mu} & \frac{1}{4} + \frac{3}{4}e^{-t\mu} & \frac{1}{4} - \frac{1}{4}e^{-t\mu} & \frac{1}{4} - \frac{1}{4}e^{-t\mu} \\\\ \frac{1}{4} - \frac{1}{4}e^{-t\mu} & \frac{1}{4} - \frac{1}{4}e^{-t\mu} & \frac{1}{4} + \frac{3}{4}e^{-t\mu} & \frac{1}{4} - \frac{1}{4}e^{-t\mu} \\\\ \frac{1}{4} - \frac{1}{4}e^{-t\mu} & \frac{1}{4} - \frac{1}{4}e^{-t\mu} & \frac{1}{4} - \frac{1}{4}e^{-t\mu} & \frac{1}{4} - \frac{1}{4}e^{-t\mu} \end{pmatrix}$$

Estimating Distances



- Let p = probability a base is different between two sequences, Solve to find **t**
- Jukes-Cantor $r(t) = 1 p = \frac{1}{4} (1 + 3e^{-\mu t})$

$$p = \frac{3}{4} - \frac{3}{4} e^{-\mu t}$$

$$\frac{3}{4} - p = \frac{3}{4} e^{-\mu t}$$

$$1 - \frac{4p}{3} = e^{-\mu t}$$

Therefore,

$$\mu t = -\ln(1 - 4p/3)$$

Letting

d = ¾ µt, denoting substitutions per site, $d = -\frac{3}{4}\ln(1 - \frac{4}{3}p)$



d: Branch length in terms of substitutions per site

Jukes-Cantor

$$d=-\frac{3}{4}\ln(1-\frac{4}{3}p)$$

Kimura

$$d = -\frac{1}{2}\ln(1 - 2P - Q) - \frac{1}{4}\ln(1 - 2Q)$$



UPGMA (unweighted pair group method using arithmetic averages) Or the **Average Linkage Method**

Given two disjoint clusters C_i, C_i of sequences,

$$d_{ij} = \frac{1}{|C_i| \times |C_j|} \Sigma_{\{p \in Ci, q \in Cj\}} d_{pq}$$

Claim that if $C_k = C_i \cup C_i$, then distance to another cluster C_i is:

 $d_{kl} = \frac{d_{il} |C_i| + d_{jl} |C_j|}{|C_i| + |C_j|}$

Algorithm: Average Linkage

Initialization:

Assign each x_i into its own cluster C_i Define one leaf per sequence, height 0

Iteration:

Find two clusters C_i , C_j s.t. d_{ij} is min Let $C_k = C_i \cup C_j$ Define node connecting C_i , C_j , and place it at height $d_{ij}/2$ Delete C_i , C_j

Termination:

When two clusters i, j remain, place root at height $d_{ij}/2$







Average Linkage Example

	v	w	x	у	z
>	0	6	8	8	8
w		0	8	8	8
x			0	4	4
у				0	2
z					0

	v	W	X	yz
V	0	6	8	8
¥		0	8	8
X			0	4
yz				0

	v	w	xyz
v	0	6	8
w		0	8
xyz			0

	vw	xyz
vw	0	8
xyz		0





Ultrametric Distances and Molecular Clock

Definition:

A distance function d(.,.) is ultrametric if for any three distances $d_{ij} \le d_{ik} \le d_{ij}$, it is true that

$$d_{ij} \le d_{ik} = d_{jk}$$

The Molecular Clock:

The evolutionary distance between species x and y is 2× the Earth time to reach the nearest common ancestor

That is, the molecular clock has constant rate in all species







Average Linkage is guaranteed to reconstruct correctly a binary tree with ultrametric distances

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Proof: Exercise



Molecular clock: all species evolve at the same rate (Earth time)

However, certain species (e.g., mouse, rat) evolve much faster

Example where UPGMA messes up:







Additive Distances





Given a tree, a distance measure is **additive** if the distance between any pair of leaves is the sum of lengths of edges connecting them

Given a tree T & additive distances d_{ii}, can uniquely reconstruct edge lengths:

- Find two neighboring leaves i, j, with common parent k
- Place parent node k at distance $d_{km} = \frac{1}{2} (d_{im} + d_{im} d_{ij})$ from any node m $\neq i, j$

Additive Distances





For any four leaves x, y, z, w, consider the three sums

d(x, y) + d(z, w) d(x, z) + d(y, w)d(x, w) + d(y, z)

One of them is smaller than the other two, which are equal

d(x, y) + d(z, w) < d(x, z) + d(y, w) = d(x, w) + d(y, z)





W











Reconstructing Additive Distances Given T



D ₁				
	а	X	у	z
а	0	11	10	10
X		0	9	15
У			0	14
Z				0





Reconstructing Additive Distances Given T

а

X

У

Ζ



May produce a good tree even when distance is not additive

Guaranteed to produce the correct tree if distance is additive

Step 1: Finding neighboring leaves

Define

$$D_{ij} = (N - 2) d_{ij} - \sum_{k \neq i} d_{ik} - \sum_{k \neq j} d_{jk}$$

<u>Claim</u>: The above "magic trick" ensures that i, j are neighbors if D_{ii} is minimal





Neighbor-Joining



 $\mathsf{D}_{ij} = (\mathsf{N}-2) \; \mathsf{d}_{ij} - \sum_{k \neq i} \; \mathsf{d}_{ik} - \sum_{k \neq j} \; \mathsf{d}_{jk}$





Neighbor-Joining

$$D_{ij} = (N - 2) d_{ij} - \sum_{k \neq i} d_{ik} - \sum_{k \neq j} d_{jk}$$





- All leaf edges appear negatively exactly twice
- All other edges appear negatively once for every path from each of the two leaves i, j, to leaves k ≠ i, j

