

Whole Genome Analysis and Annotation

Adam Siepel

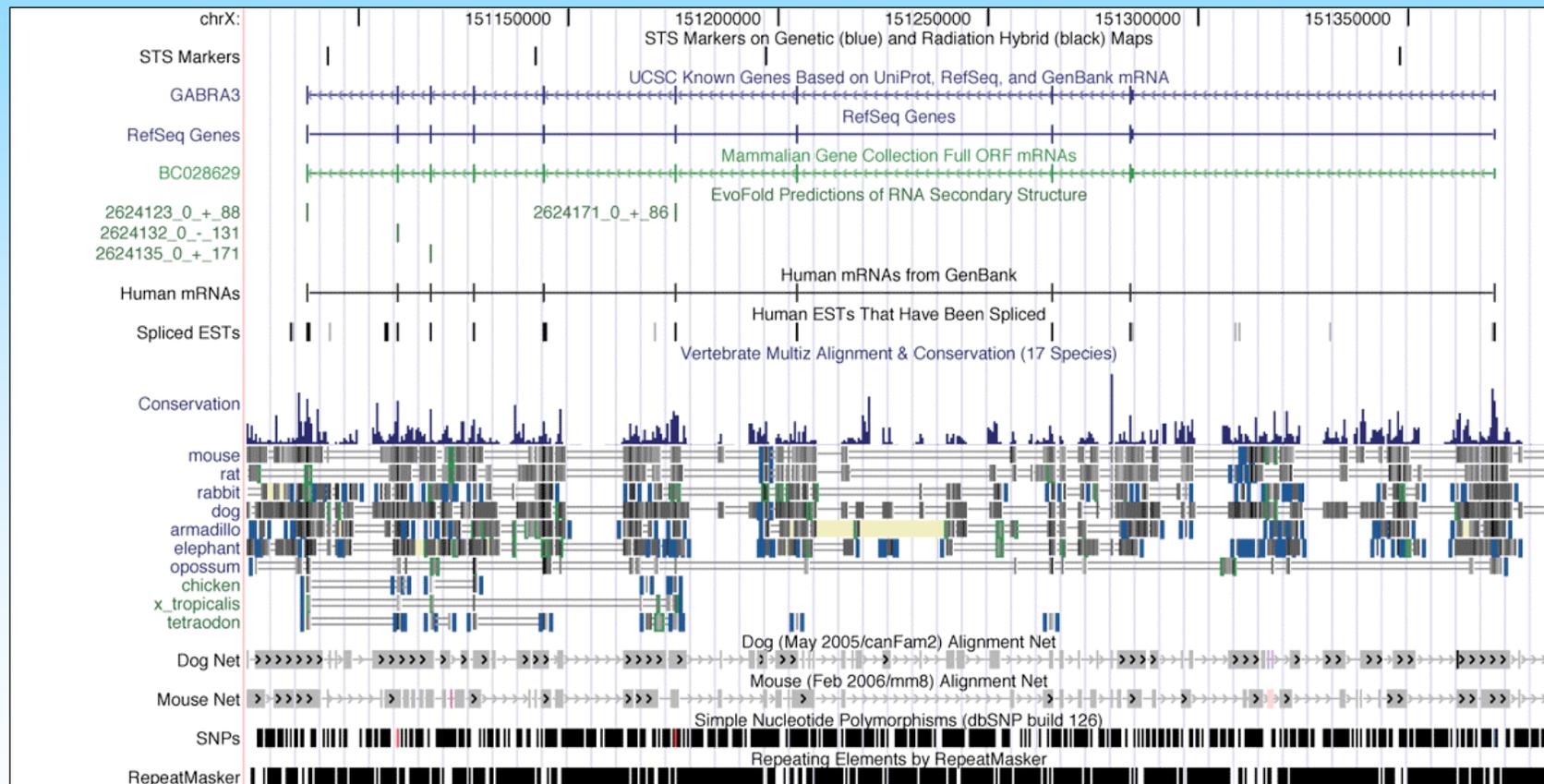
Biological Statistics & Computational Biology
Cornell University

The Challenge



Whole Genome Analysis

Genome Browsers



Human Gene GABRA3 Description and Page Index

http://genome.ucsc.edu/cgi-bin/hgGene?hgg_gene=NM_000808&hgg_prot=GBRA3_HUMAN&hgg_chrom=chrX&hgg_c... Google

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Human Gene GABRA3 Description and Page Index

Description: gamma-aminobutyric acid A receptor, alpha 3
Alternate Gene Symbols: BC028629, S62908
Representative Refseq: [NM_000808](#) **Protein:** [P34903](#) (aka GBRA3_HUMAN or GAA3_HUMAN)
RefSeq Summary: GABA is the major inhibitory neurotransmitter in the mammalian brain where it acts at GABA-A receptors, which are ligand-gated chloride channels. Chloride conductance of these channels can be modulated by agents such as benzodiazepines that bind to the GABA-A receptor. At least 16 distinct subunits of GABA-A receptors have been identified.
Position: chrX:151087188-151370486
Strand: -
Genomic Size: 283299
Exon Count: 10 **CDS Exon Count:** 9

Page Index	Quick Links	UniProt Comments	Sequence	Microarray	RNA Structure
Protein Structure	Other Species	GO Annotations	mRNA Descriptions	Pathways	Methods

Quick Links to Tools and Databases

Genome Browser	Gene Sorter	VisiGene	Proteome Browser	Table Schema	UniProt
Entrez Gene	PubMed	OMIM	GeneLynx	GeneCards	HGNC
CGAP	HPRD	Stanford SOURCE	ExonPrimer	Ensembl	Jackson Labs
H-INV	Allen Brain Atlas				

Comments and Description Text from UniProt (Swiss-Prot/TrEMBL)

ID: [GBRA3_HUMAN](#)

DESCRIPTION: Gamma-aminobutyric-acid receptor alpha-3 subunit precursor (GABA(A) receptor).

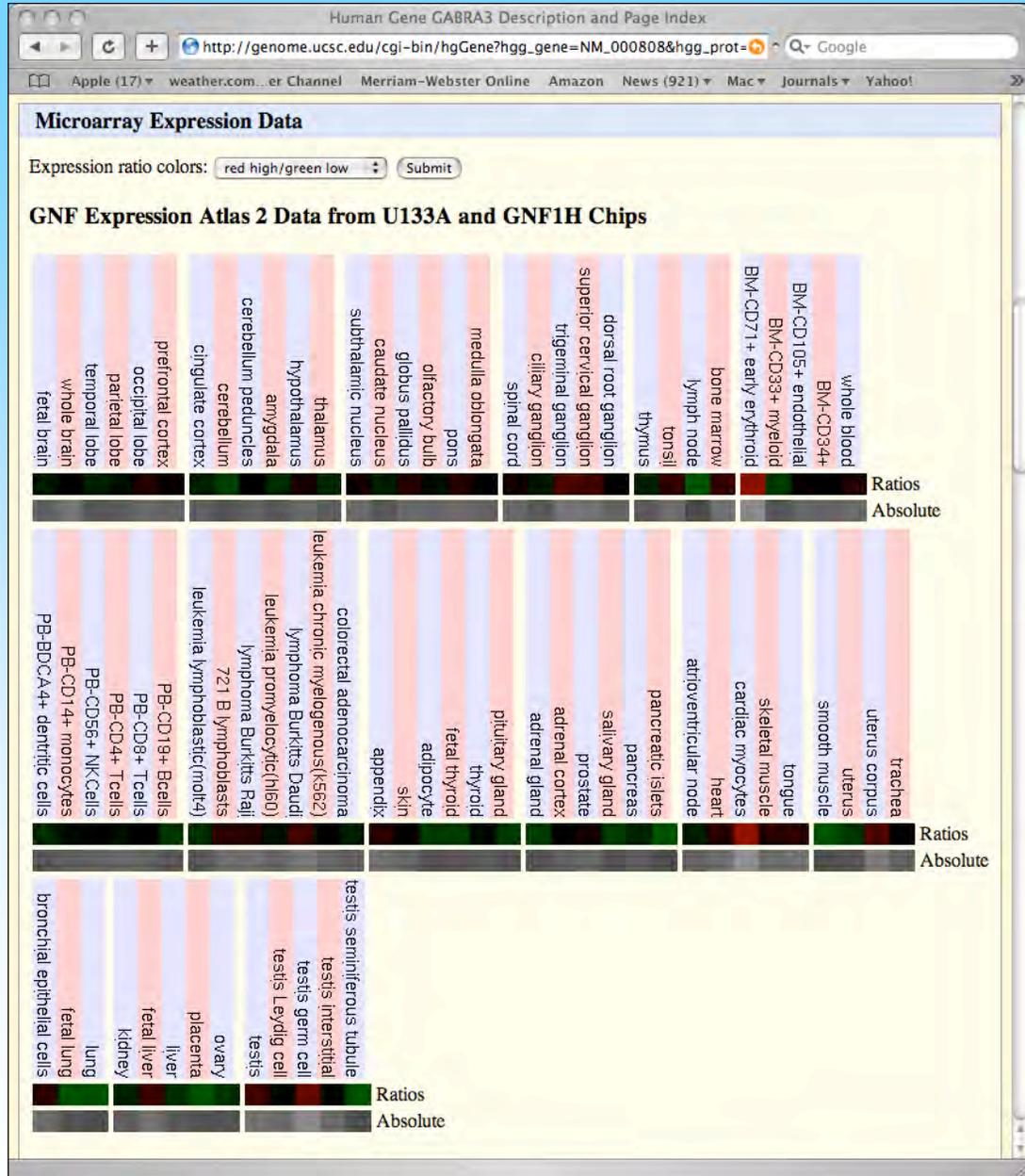
FUNCTION: GABA, the major inhibitory neurotransmitter in the vertebrate brain, mediates neuronal inhibition by binding to the GABA/benzodiazepine receptor and opening an integral chloride channel.

SUBUNIT: Binds UBQLN1 (By similarity). Generally pentameric. There are five types of GABA(A) receptor chains: alpha, beta, gamma, delta, and rho.

SUBCELLULAR LOCATION: Membrane; multi-pass membrane protein.

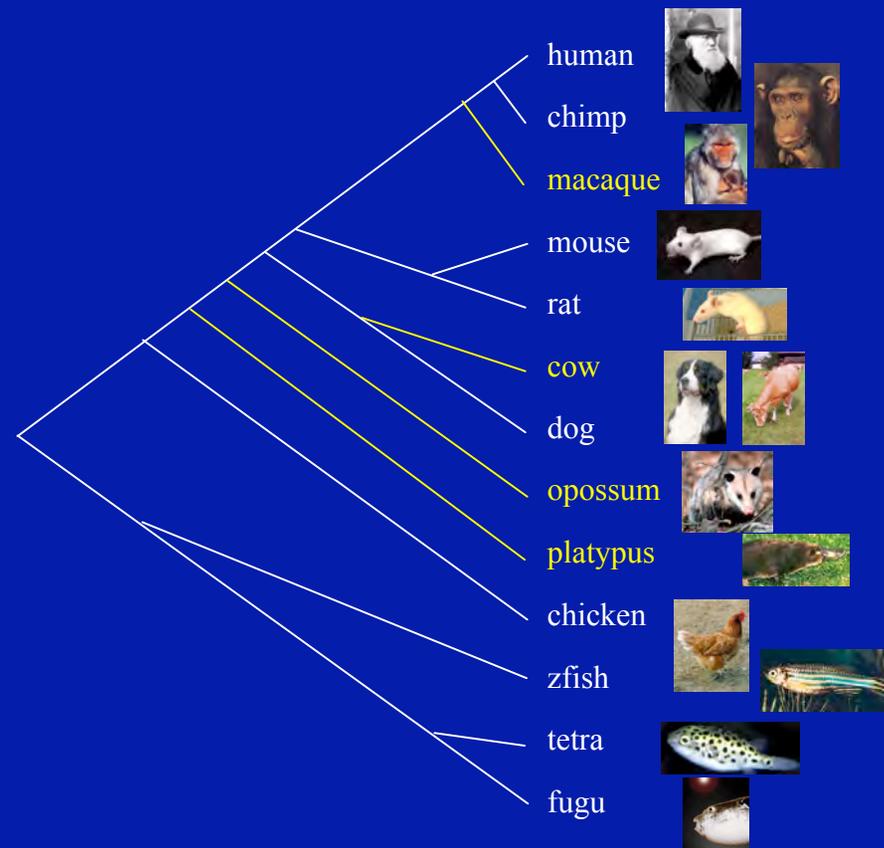
SIMILARITY: Belongs to the ligand-gated ionic channel (TC 1.A.9) family.

DATABASE: NAME=Protein Spotlight; NOTE=Issue 56 of March 2005; WWW="http://www.expasy.org/spotlight/back_issues/splt056.shtml".

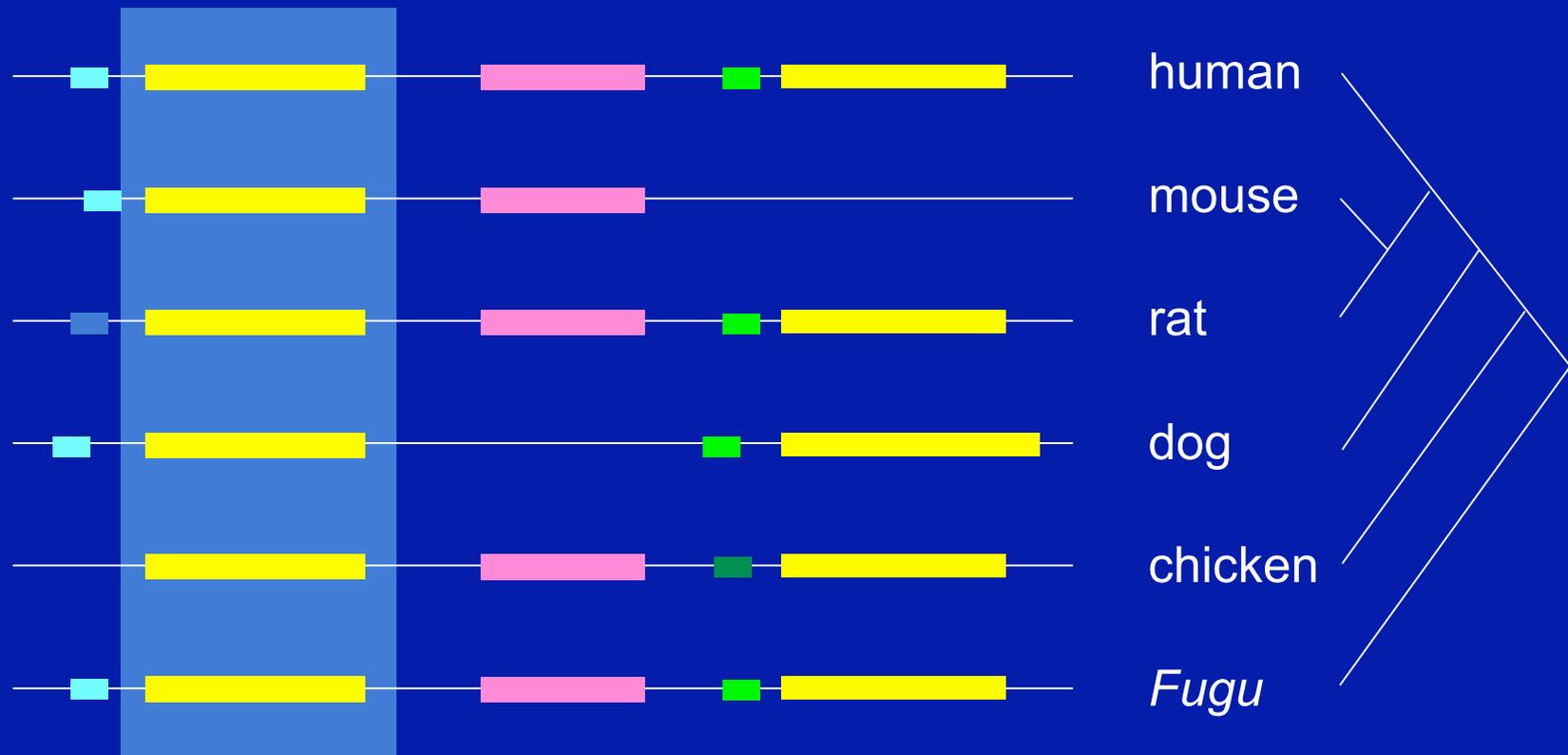


Whole Genome Analysis

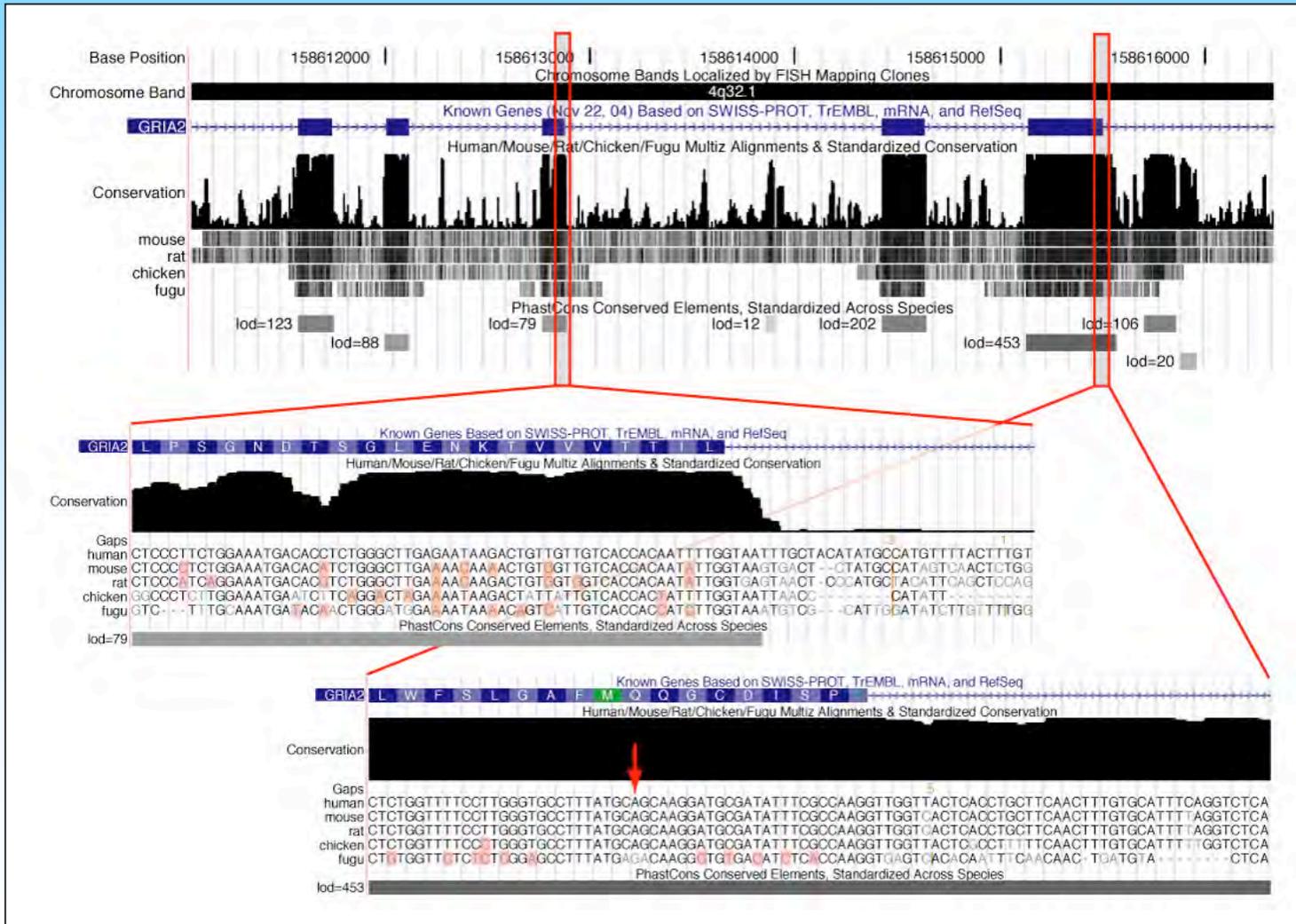
Comparative Analysis of Complete Mammalian Genomes



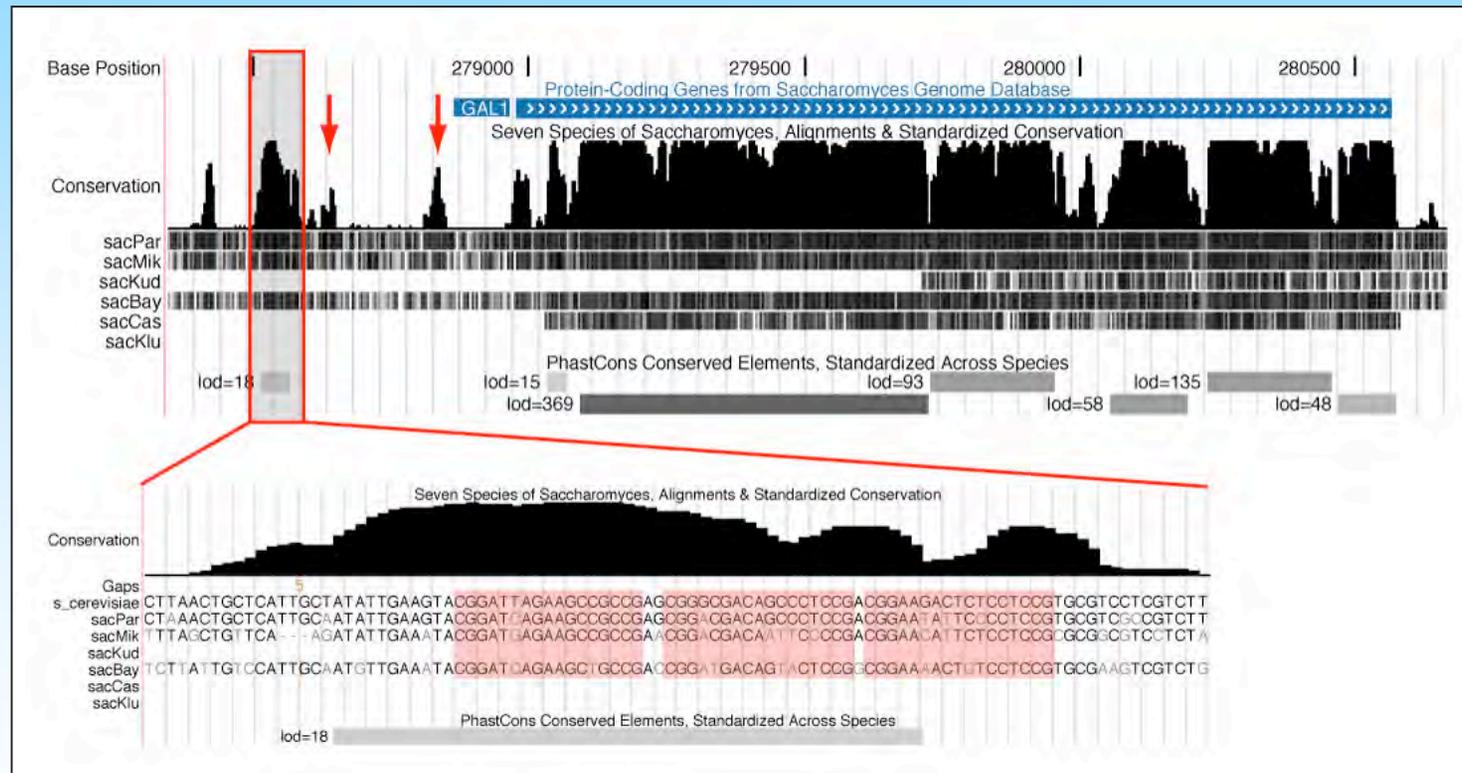
Detection of Functional Elements



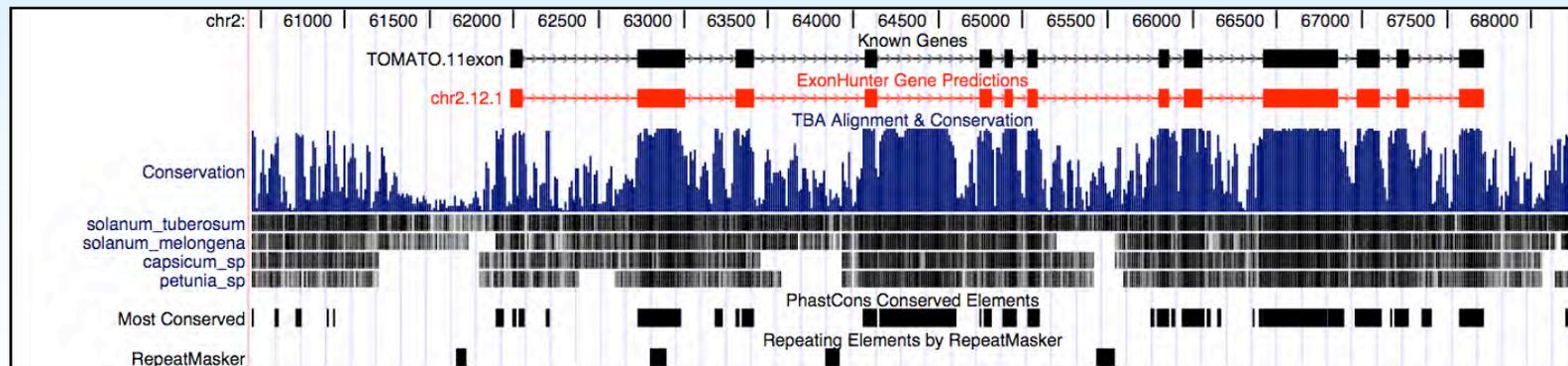
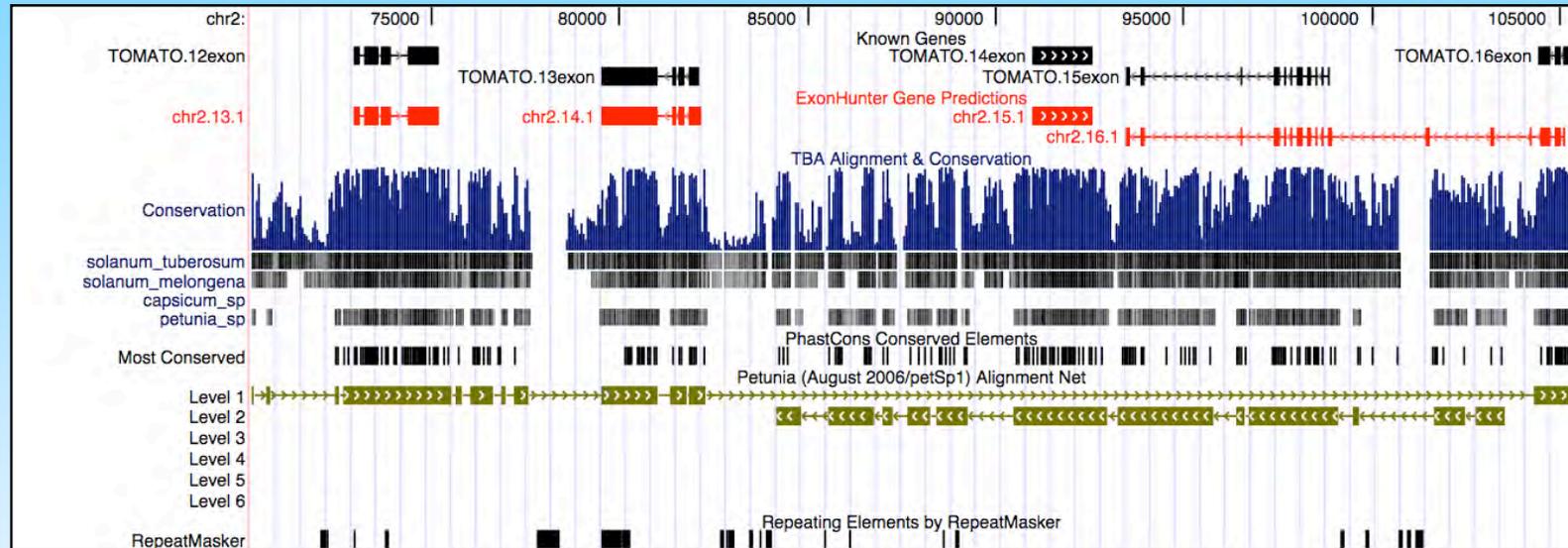
Conservation Track

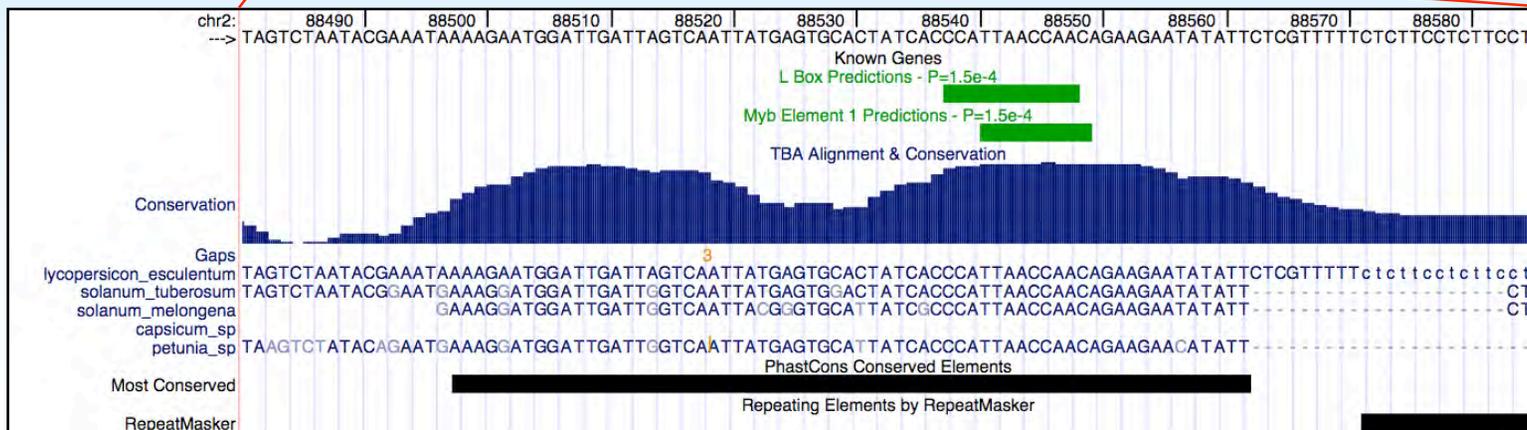
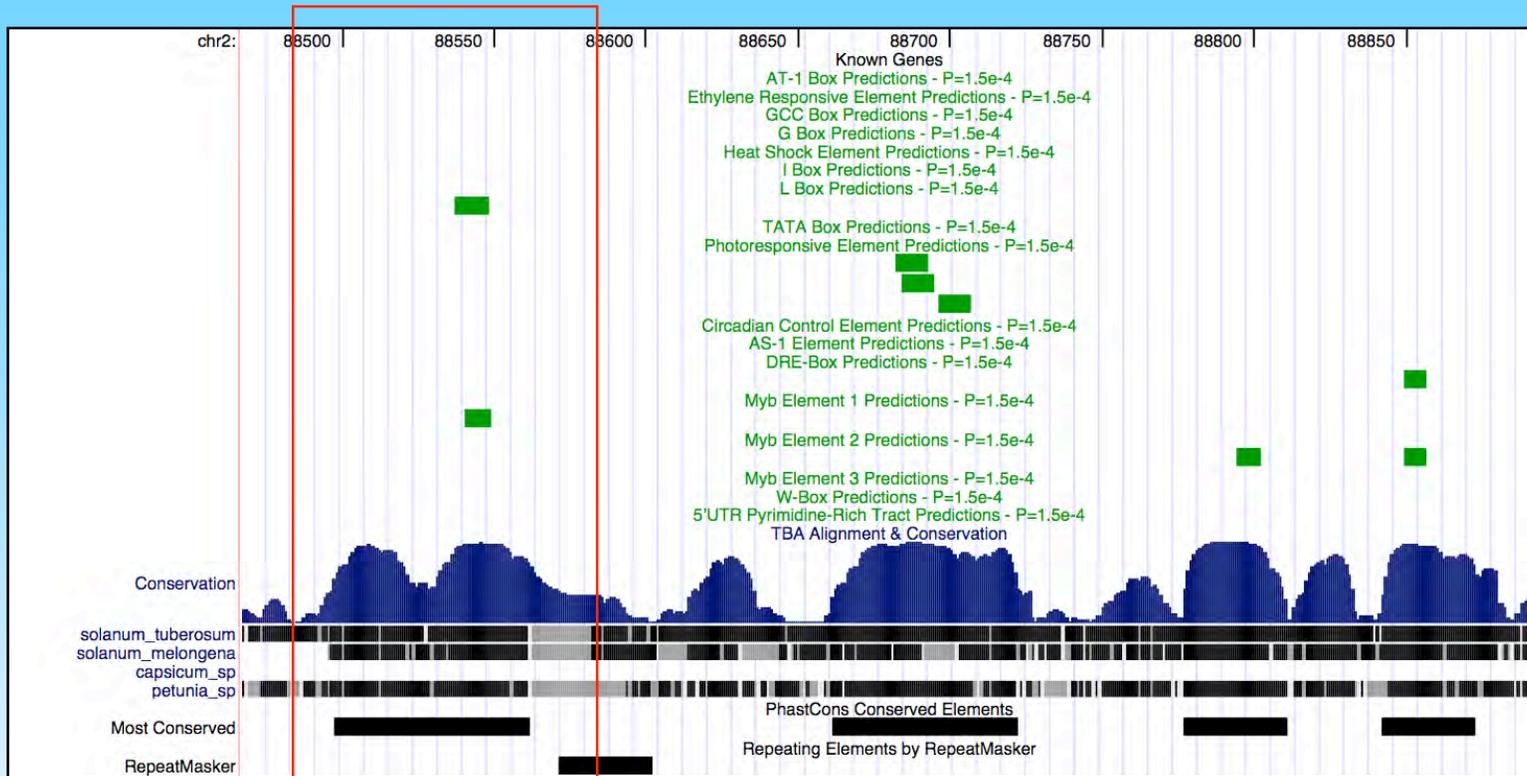


Conservation Track: *GAL1*



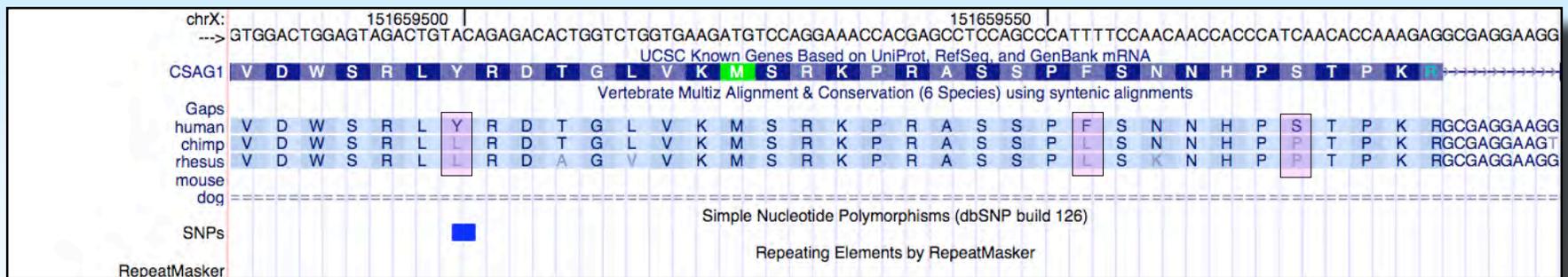
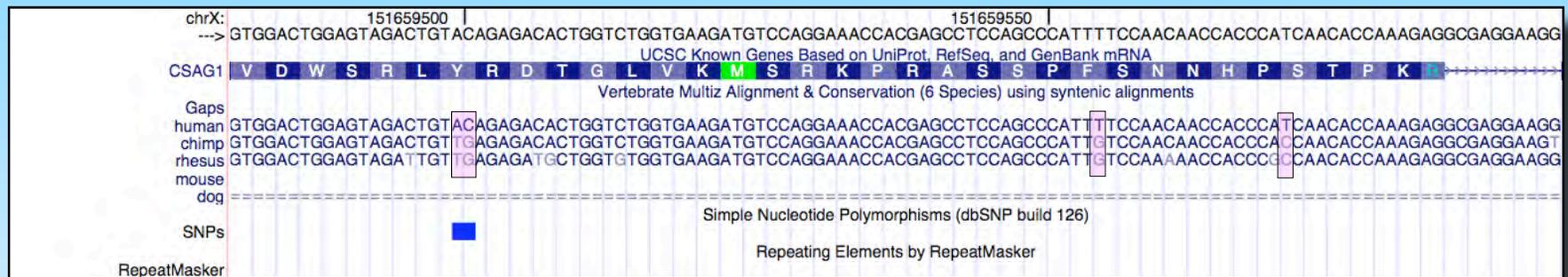
Solanaceae Browser





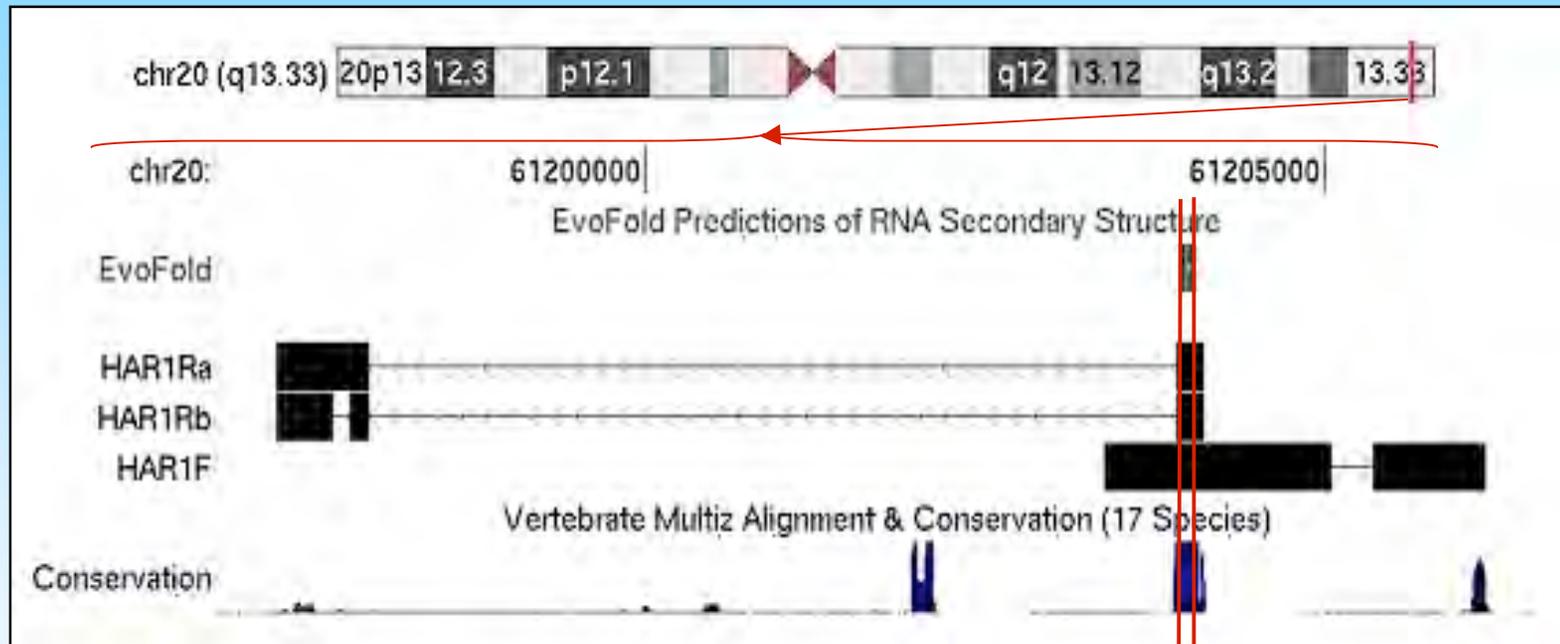
Whole Genome Analysis

Possible Positive Selection



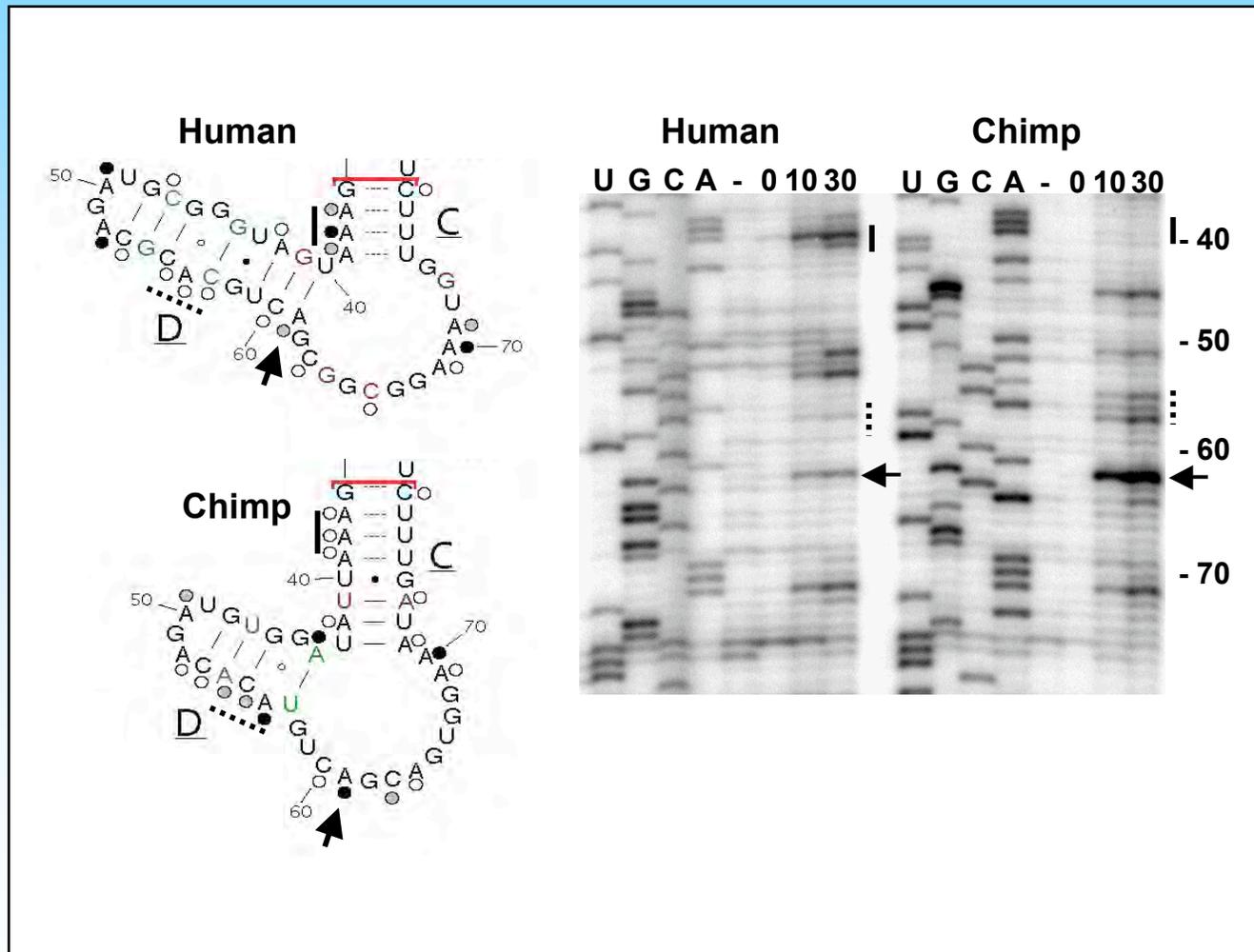
Chondrosarcoma associated gene 1 isoform a

“Human Accelerated Region 1” (HAR1)

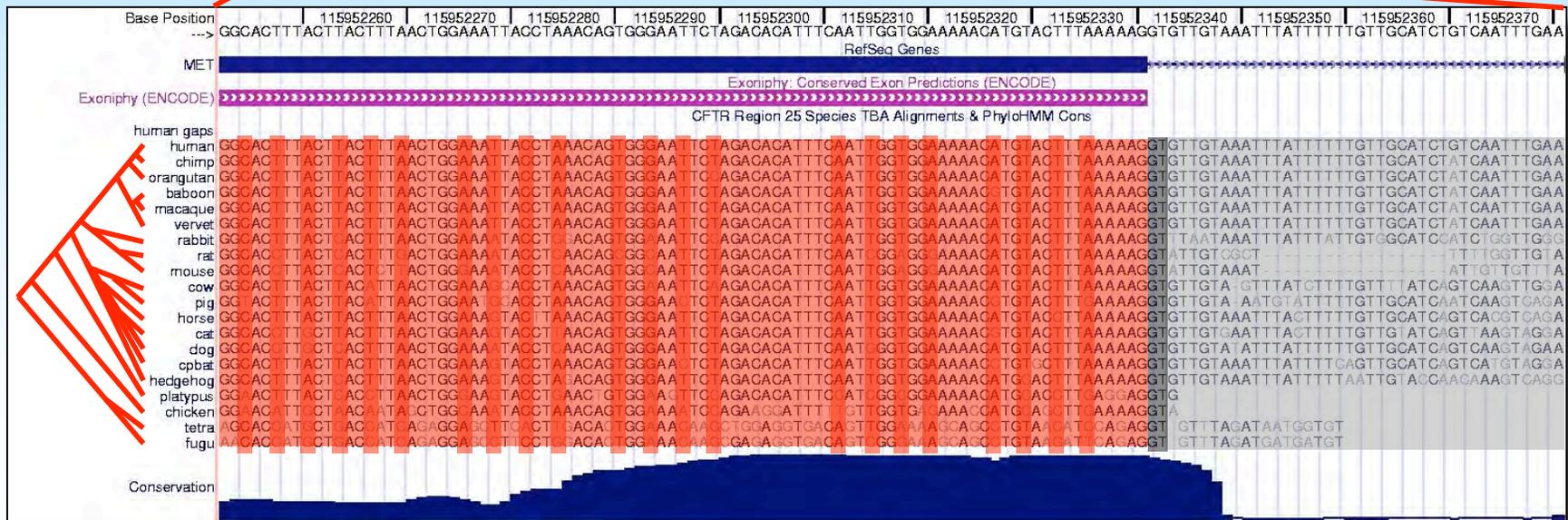
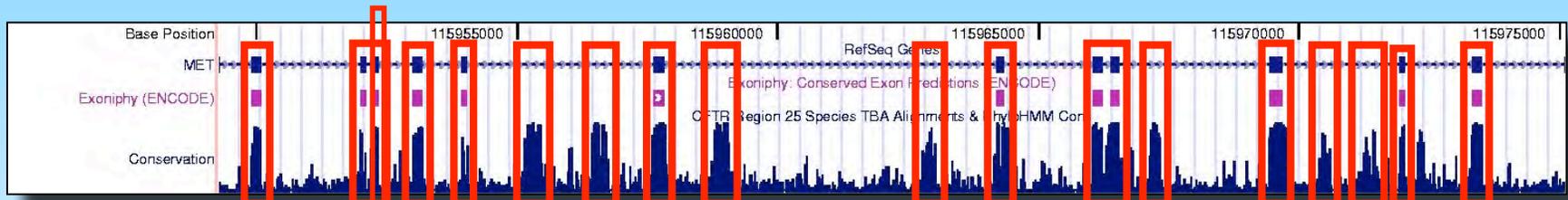


human	T	G	A	T	G	G	G	C	G	T	A	G	A	C	G	C	A	G	T	C	A	G	C	G	G	G	A	A	T	G	G	T	T	C	T	A	T	C	A	A	A	T	G	A	A	G	T	G	T	T	A	G	A	G	A	T	T	T	C	C	T	C	A	A	G	T	T	T	C	A	A	A	T	G	A				
chimp	T	T	A	T	A	G	G	T	G	T	A	G	A	C	A	T	G	T	C	A	G	C	A	G	T	G	G	A	A	T	A	A	G	T	A	T	T	C	T	A	T	C	A	A	A	T	T	A	A	G	T	A	T	T	A	G	A	G	A	T	T	T	C	C	T	C	A	A	T	T	T	C	A	A	A	T	T	A	
dog	T	T	A	T	A	G	G	T	G	T	A	G	A	C	A	T	G	T	C	A	G	C	G	T	G	C	A	A	A	T	A	A	G	T	A	T	T	C	T	A	T	C	A	A	A	T	T	A	A	G	T	A	T	T	A	G	A	G	A	T	T	T	C	C	T	C	A	A	T	T	T	C	A	A	A	T	T	A	
mouse	T	T	A	T	A	G	G	T	G	T	A	G	A	C	A	T	G	T	C	A	G	C	C	G	T	G	G	A	A	T	A	A	G	T	A	T	T	C	T	A	T	C	A	A	A	T	T	A	A	G	T	A	T	T	A	G	A	G	A	T	T	T	C	C	T	C	A	A	T	T	T	C	A	A	A	T	T	A	
rat	T	T	A	T	A	G	G	T	G	T	A	G	A	C	A	T	G	T	C	A	G	C	A	G	T	G	G	A	A	T	A	A	G	T	A	T	T	C	T	A	T	C	A	A	A	T	T	A	A	G	T	A	T	T	A	G	A	G	A	T	T	T	C	C	T	C	A	A	T	T	T	C	A	A	A	T	T	A	
chicken	T	T	A	T	A	G	G	T	G	T	A	G	A	C	A	T	G	T	C	A	G	C	A	G	T	A	G	A	A	A	T	A	A	G	T	A	T	T	C	T	A	T	C	A	A	A	T	T	A	A	G	T	A	T	T	A	G	A	G	A	T	T	T	C	C	T	C	A	A	T	T	T	C	A	A	A	T	T	A

New Human RNA Structure



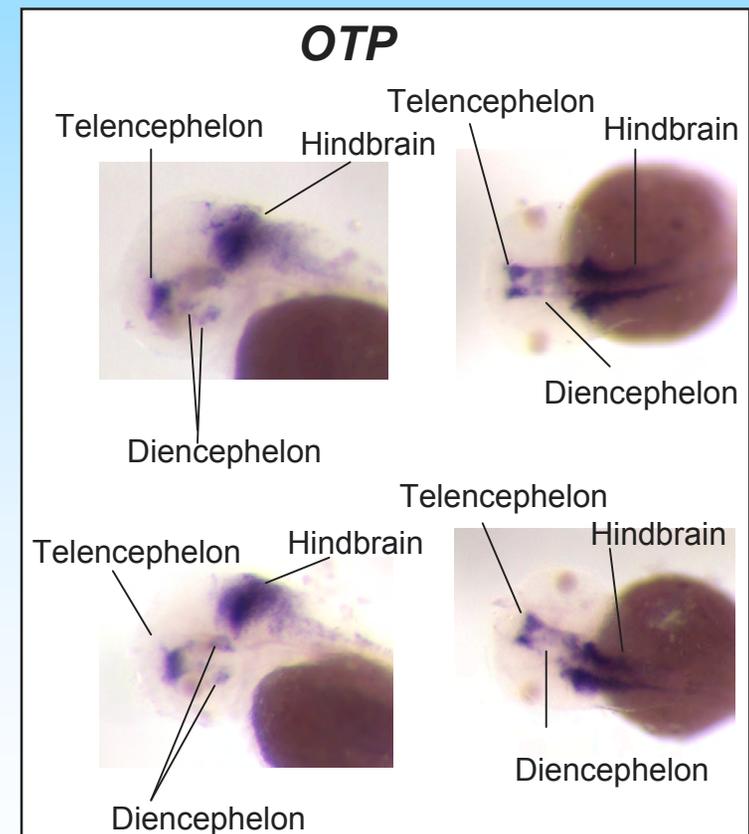
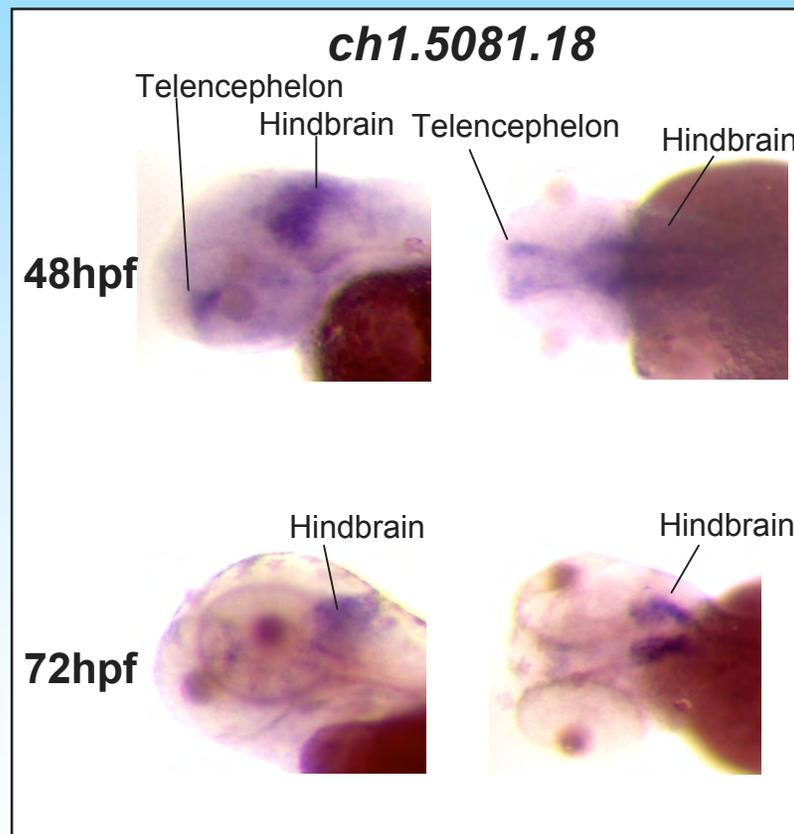
Exon Predictions

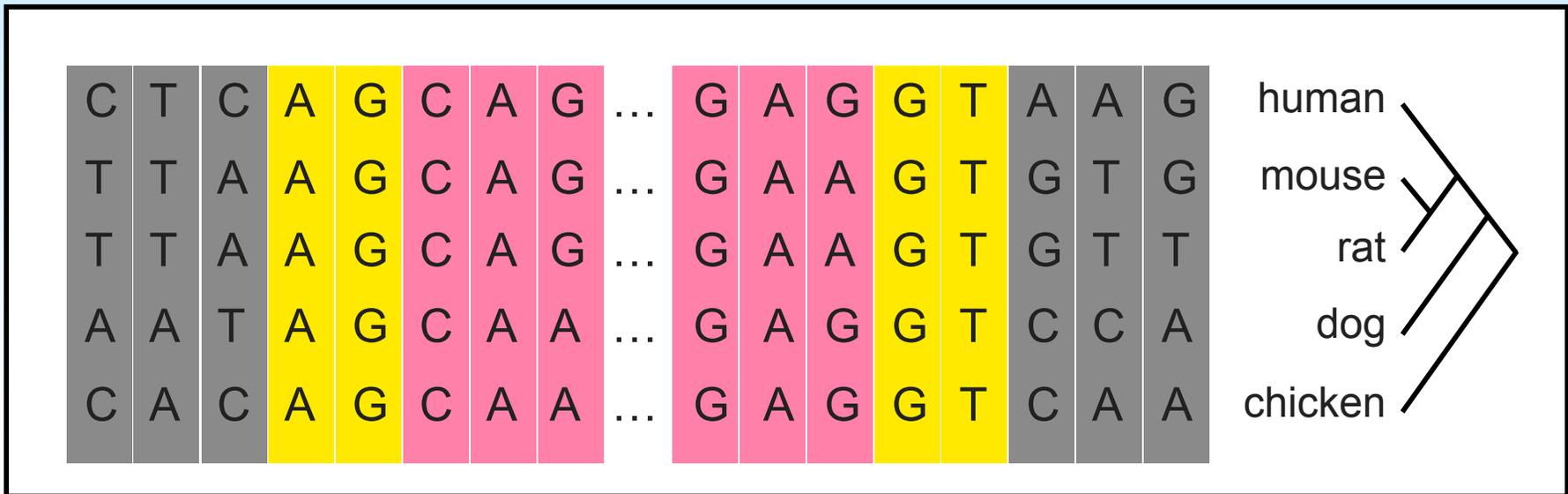
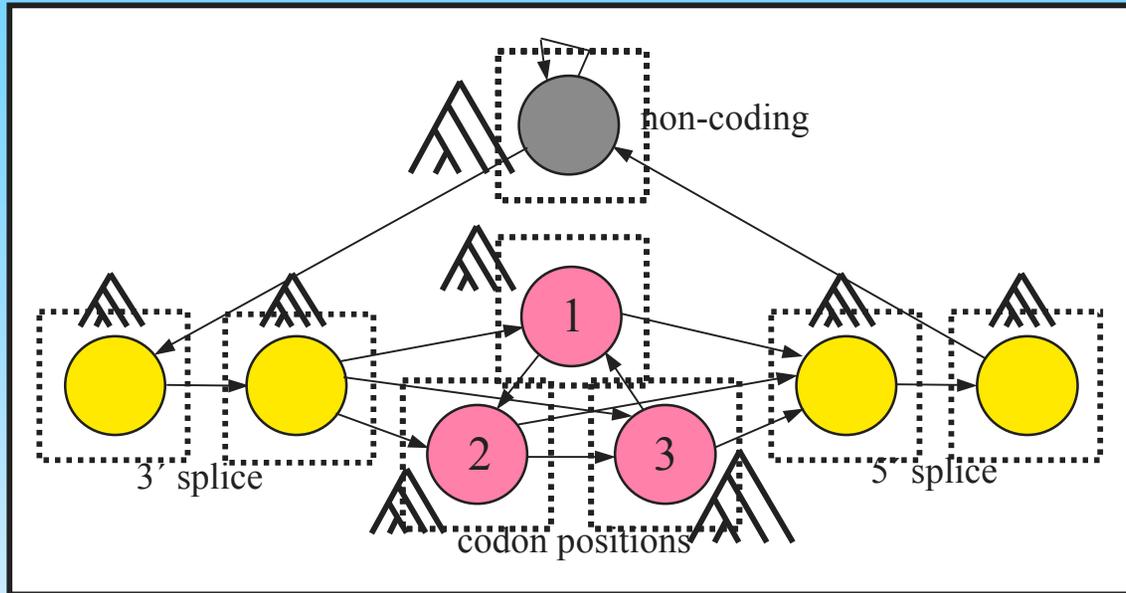


Whole Genome Analysis

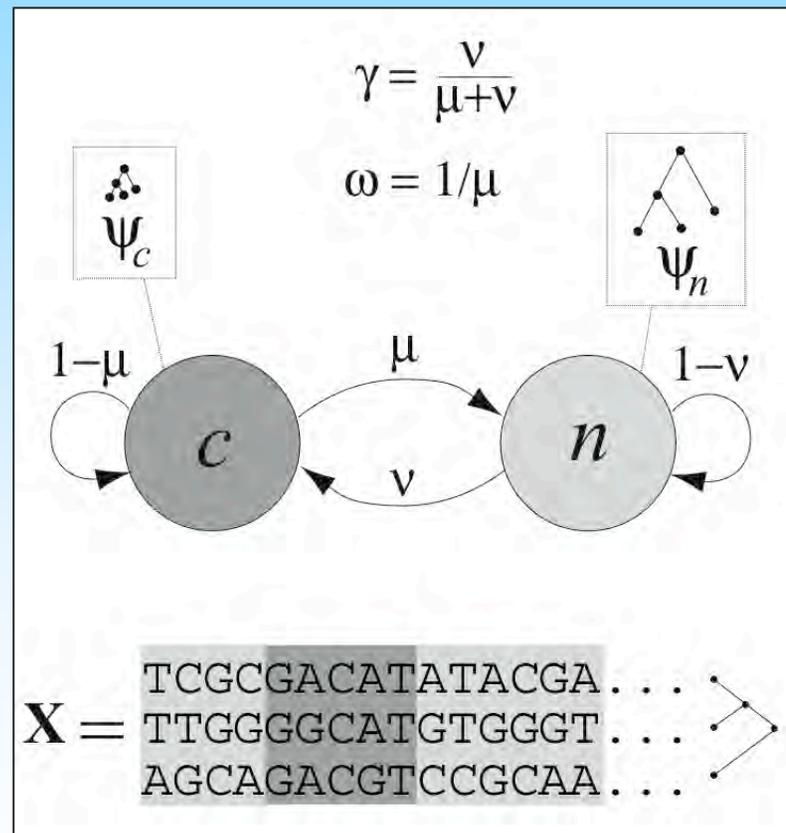
Data from E. Green & colleagues (Thomas et al., *Nature* 2003)

Whole Mount *in situ* Hybridizations to Zebra Fish Embryos





Phylo-HMM Used by PhastCons



Introduction to Hidden Markov Models, Phylogenetic Models, and Phylo-HMMs



A Markov Model (Chain)

- Suppose $\mathbf{Z} = (Z_1, \dots, Z_L)$ is a sequence of cloudy ($Z_i = 0$) or sunny ($Z_i = 1$) days
- We could assume days are iid with probability theta of sun but cloudy and sunny days occur in *runs*
- We can capture the correlation between successive days by assuming a first-order Markov model:

$$P(Z_1, \dots, Z_L) = P(Z_1)P(Z_2|Z_1)P(Z_3|Z_2) \cdots P(Z_L|Z_{L-1})$$

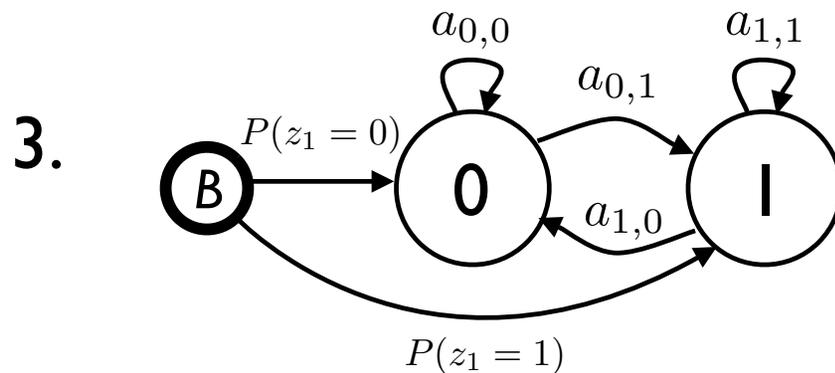
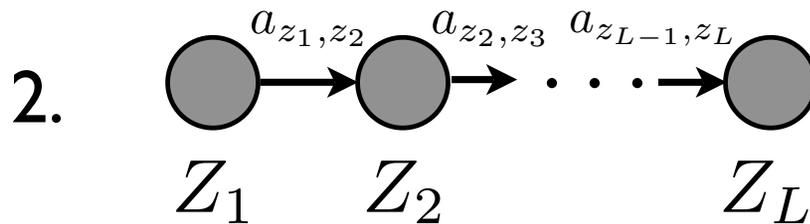
instead of complete independence:

$$P(Z_1, \dots, Z_L) = P(Z_1) \cdots P(Z_L)$$

Three Views

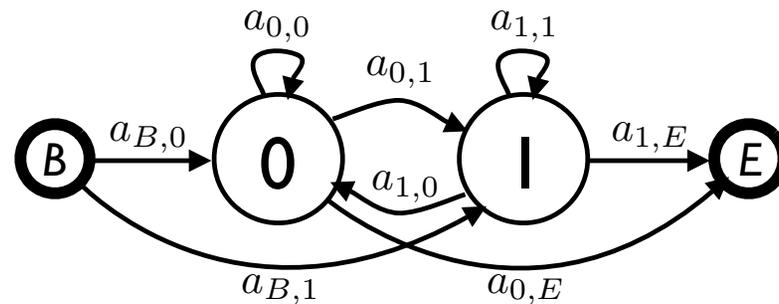
$$1. \quad P(\mathbf{z}) = P(z_1) \prod_{i=2}^L a_{z_{i-1}, z_i}$$

where $a_{c,d} = P(z_i = d | z_{i-1} = c)$



Process Interpretation

- Let's add an *end state* and *cap* the sequence with $z_0 = B, z_{L+1} = E$, e.g. $\mathbf{z} = B000011000E$



- This is a probabilistic machine that generates sequences of any length. It is a stochastic finite state machine and defines a *grammar*.

- We can now simply say: $P(\mathbf{z}) = \prod_{i=0}^L a_{z_i, z_{i+1}}$

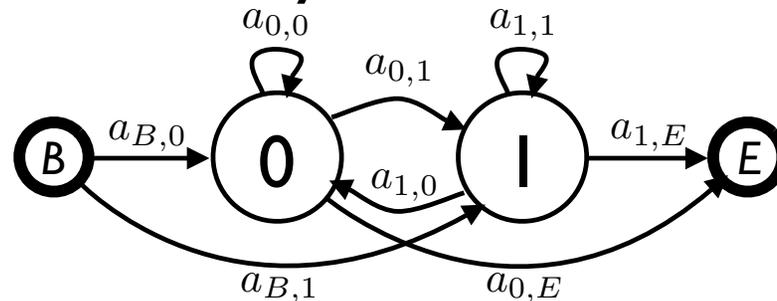
$P(\mathbf{z})$ is a probability distribution over all sequences (for given alphabet).

A Hidden Markov Model

- Let $\mathbf{X} = (X_1, \dots, X_L)$ indicate whether AS bikes on day i ($X_i = 1$) or not ($X_i = 0$)
- Suppose AS bikes on day i with probability $\theta_0 = 0.25$ if it is cloudy ($Z_i = 0$) and with probability $\theta_1 = 0.75$ if it is sunny ($Z_i = 1$)
- Further suppose the Z_i s are *hidden*; we see only $\mathbf{X} = (X_1, \dots, X_L)$
- This *hidden Markov model* is a mixture model in which the Z_i s are correlated
- We call $\mathbf{Z} = (Z_1, \dots, Z_L)$ the *path*

HMM, cont.

- \mathbf{Z} is determined by the Markov chain:

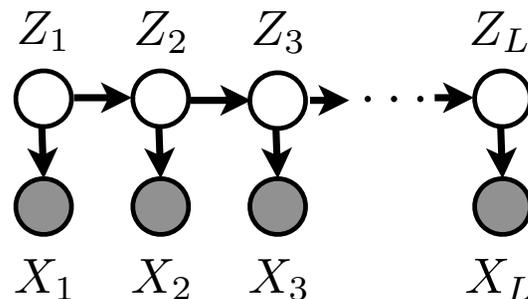


- The joint probability of \mathbf{X} and \mathbf{Z} is:

$$P(\mathbf{x}, \mathbf{z}) = P(\mathbf{z})P(\mathbf{x}|\mathbf{z}) = a_{B,z_1} \prod_{i=1}^L e_{z_i, x_i} a_{z_i, z_{i+1}}$$

where $e_{z_i, x_i} = P(x_i | z_i)$

- The X_i s are *conditionally independent* given the Z_i s



Parameters of the Model

- Transition parameters: a_{s_1, s_2} for all $s_1, s_2 \in S \cup \{B, E\}$
- Emission parameters: $e_{s, x}$ for all $s \in S, x \in \mathcal{A}$
- The transition parameters define conditional distributions for state s_2 at position i given state s_1 at position $i-1$
- The emission parameters define conditional distributions over observation x given state s , both at position i
- The observations can be anything!

Key Questions

- Given the model (parameter values) and a sequence \mathbf{X} , what is the most likely path?

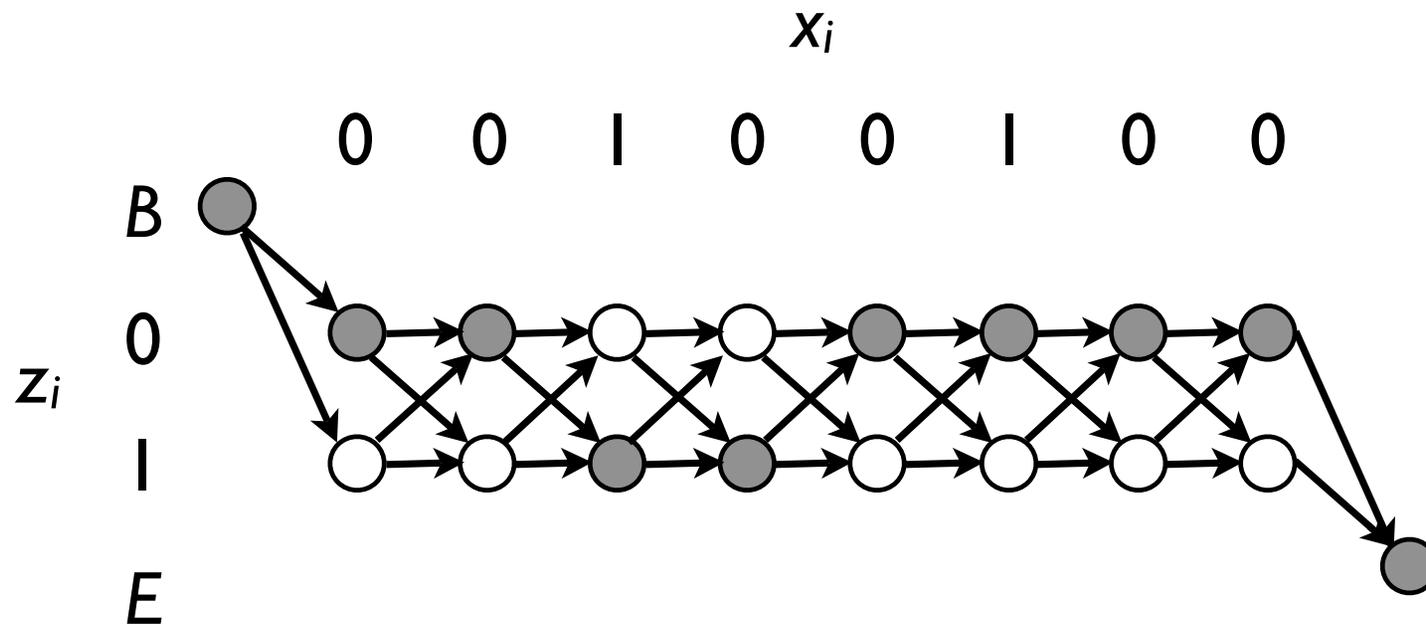
$$\hat{\mathbf{z}} = \operatorname{argmax}_{\mathbf{z}} P(\mathbf{x}, \mathbf{z})$$

- What is the likelihood of the sequence?

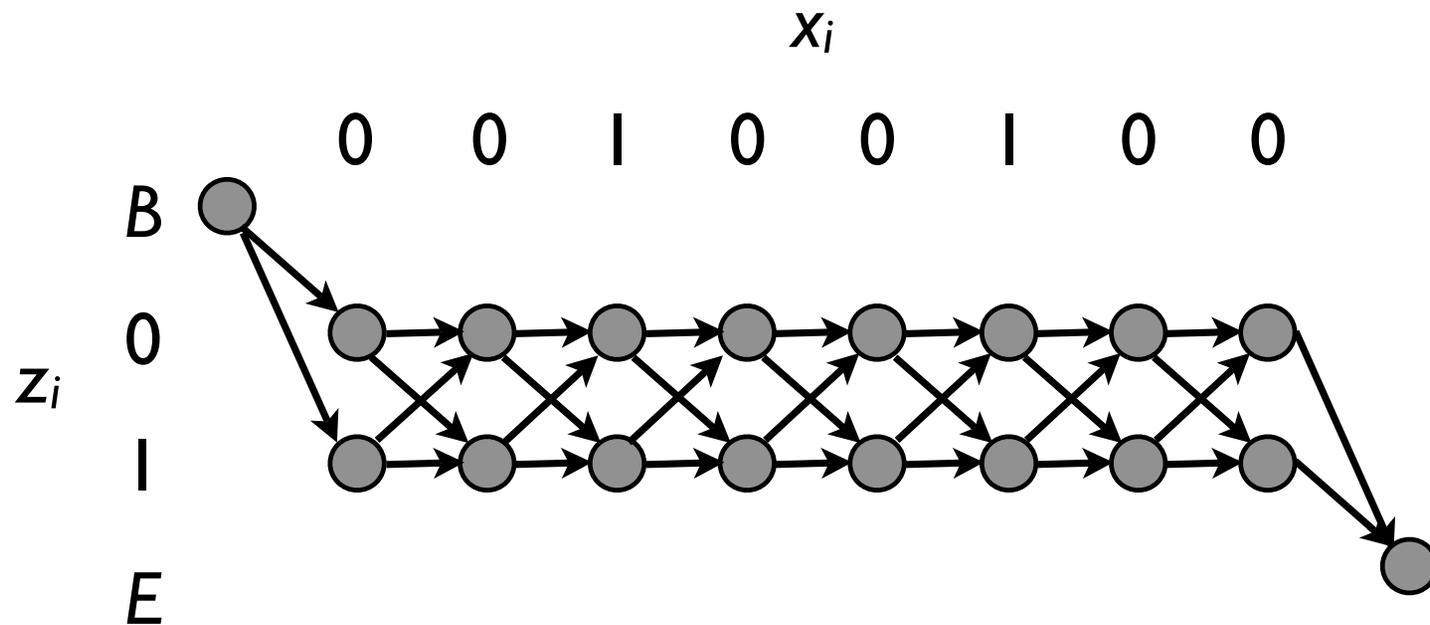
$$P(\mathbf{x}) = \sum_z P(\mathbf{x}, \mathbf{z})$$

- What is the posterior probability of Z_i given \mathbf{X}
- What is the maximum likelihood estimate of all parameters?

Graph Interpretation of Most Likely Path



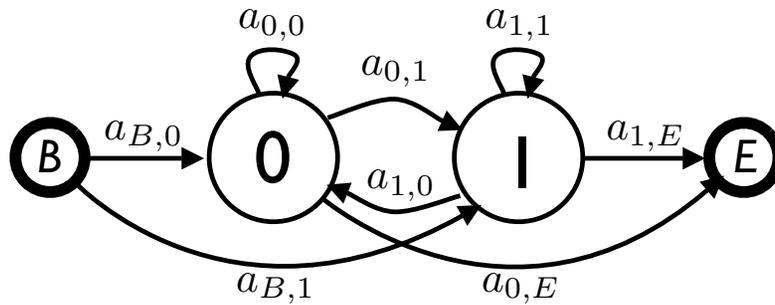
Graph Interpretation of Probability of \mathbf{x}



Viterbi Algorithm for Most Likely Path

- Let v_{ij} be the weight of the most likely path for (x_1, \dots, x_i) that ends in state j
- Base case: $v_{0,B} = 1, v_{i,B} = 0$ for $i > 0$
- Recurrence: $v_{i,j} = e_{x_i,j} \max_k v_{i-1,k} a_{k,j}$
- Termination: $P(\mathbf{x}, \hat{\mathbf{z}}) = \max_k v_{L,k} a_{k,E}$
- Keep back-pointers for traceback, as in alignment
- See Durbin et al. for algorithm

Example



$$P(x_i = 1 | z_i = 0) = 0.25$$

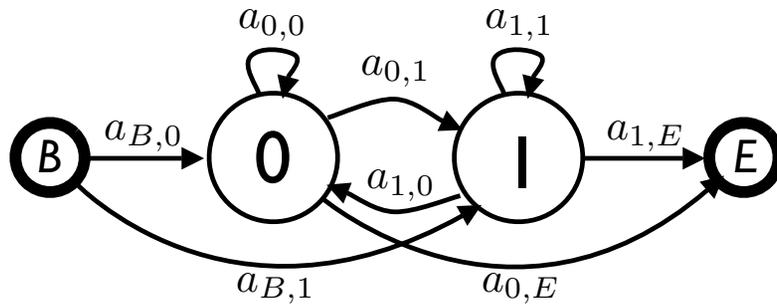
$$P(x_i = 1 | z_i = 1) = 0.75$$

Z = ? ? ? ? ? ? ? ? ? ? ? ?

X = 0 1 0 0 1 1 0 1 0 0 1 0

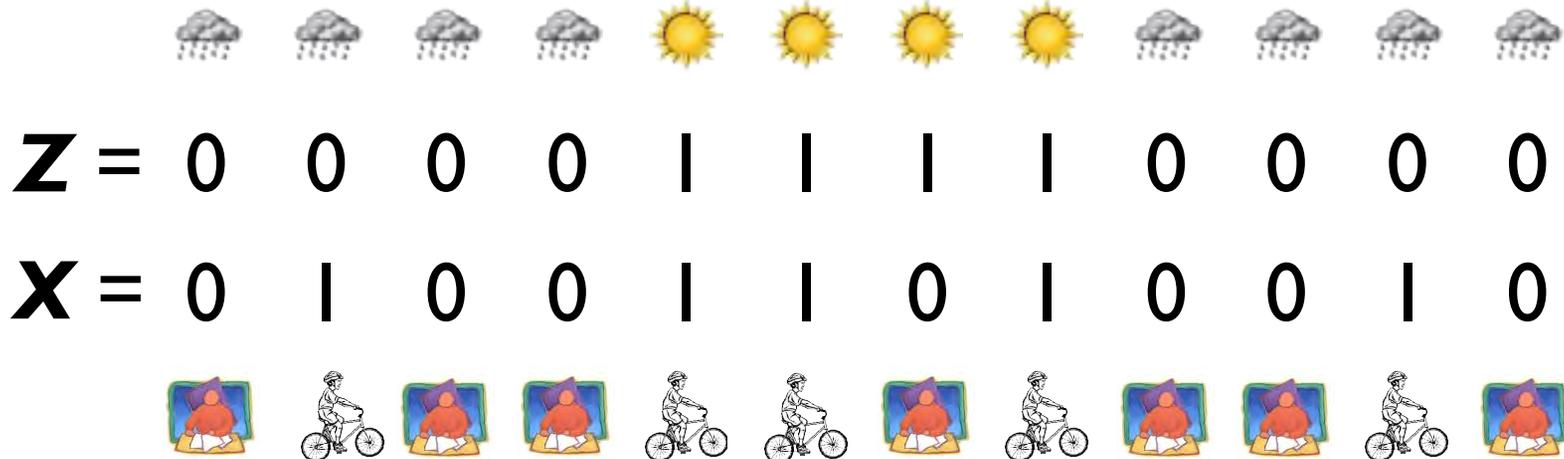


Example



$$P(x_i = 1 | z_i = 0) = 0.25$$

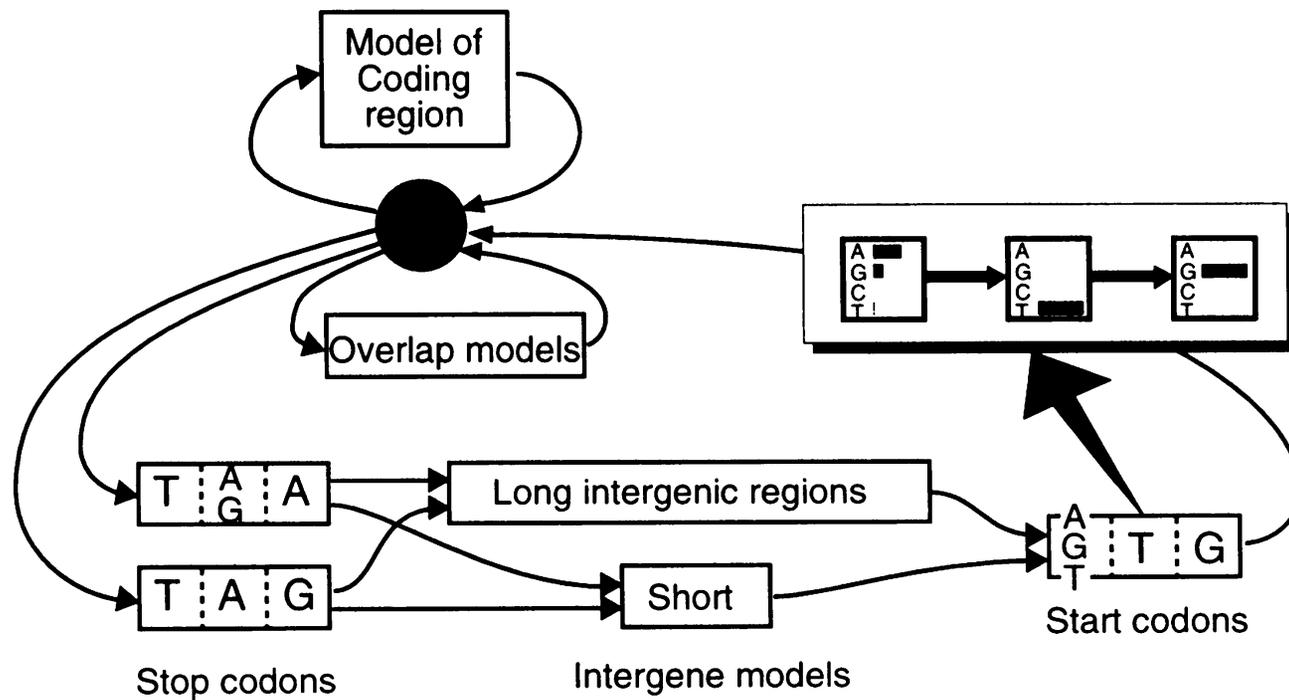
$$P(x_i = 1 | z_i = 1) = 0.75$$

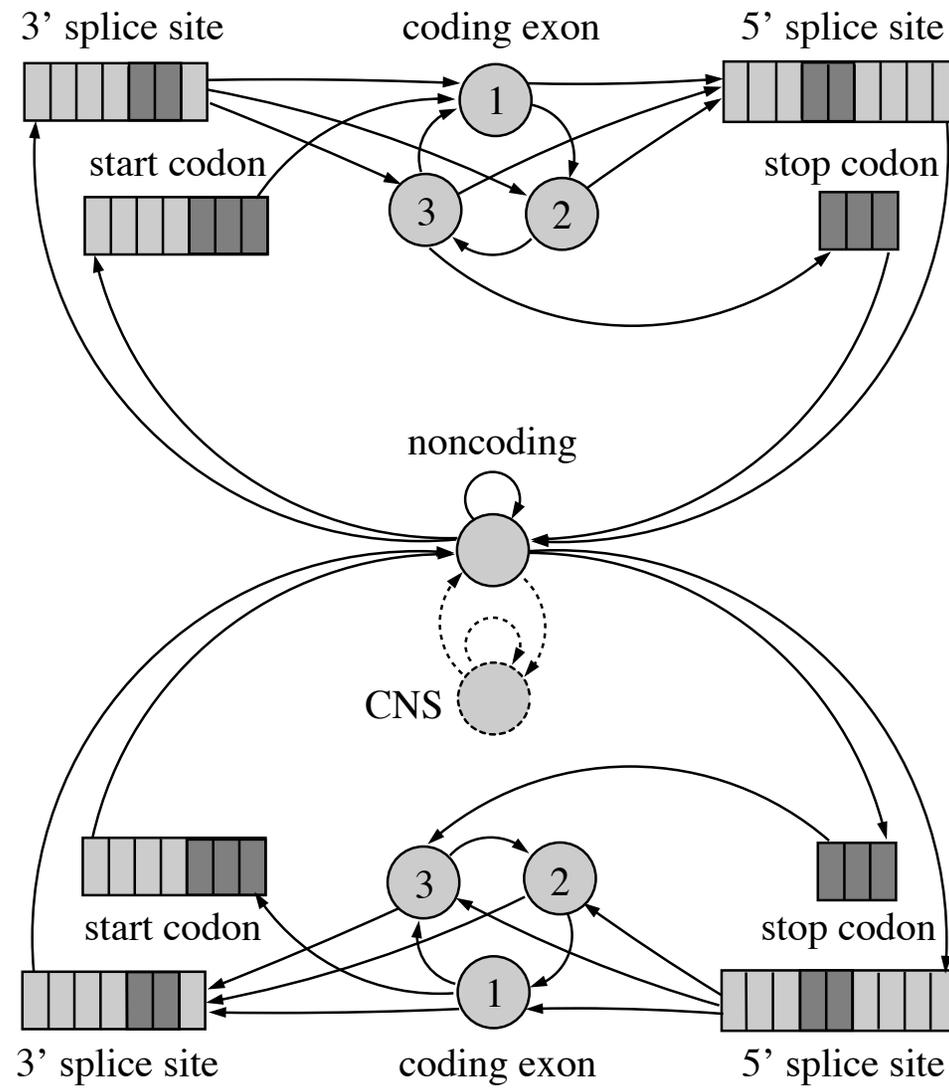


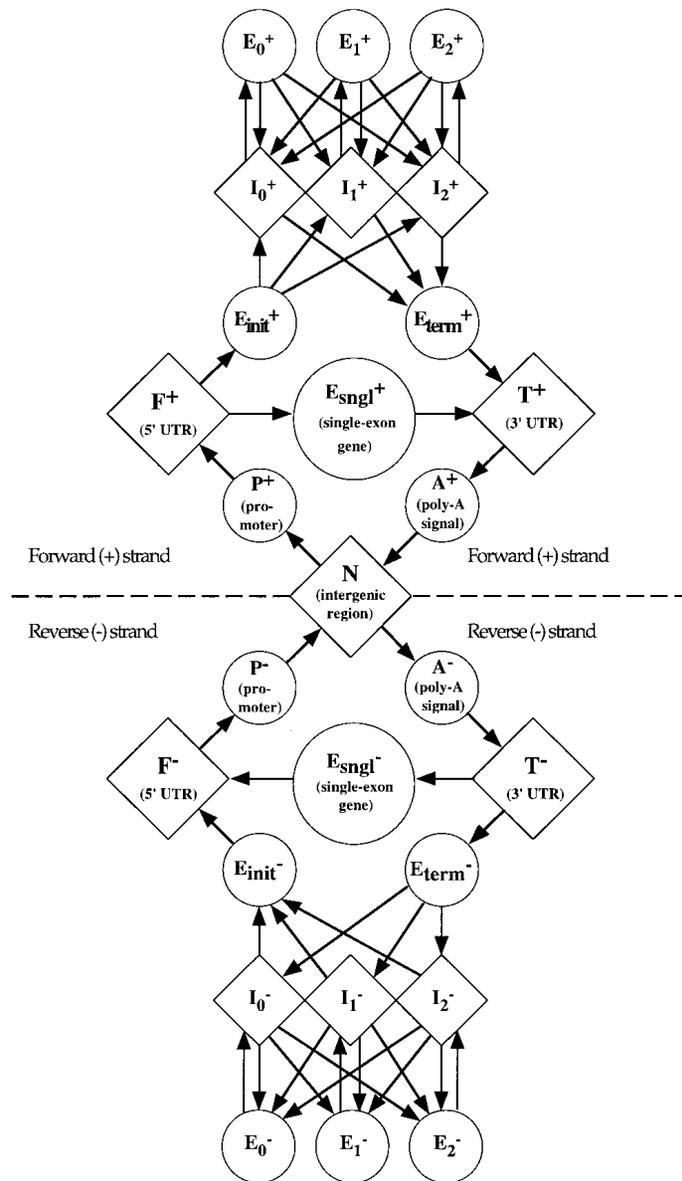
Why HMMs Are Cool

- Extremely general and flexible models for sequence modeling
- Efficient tools for *parsing* sequences
- Also proper probability models: allow maximum likelihood parameter estimation, likelihood ratio tests, etc.
- Inherently *modular*, accommodating of complexity
- In many cases, strike an ideal balance between simplicity and expressiveness

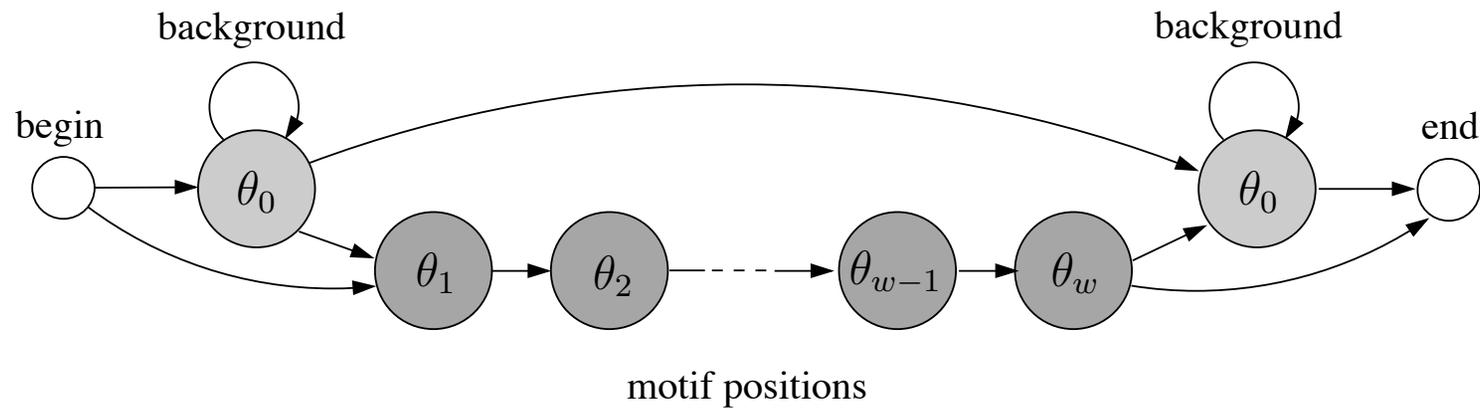
Some Applications In Bioinformatics

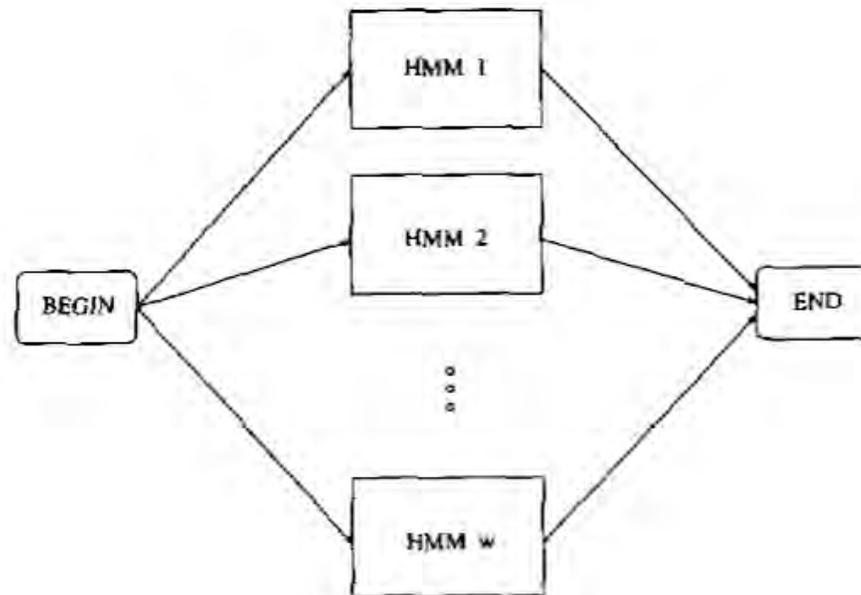
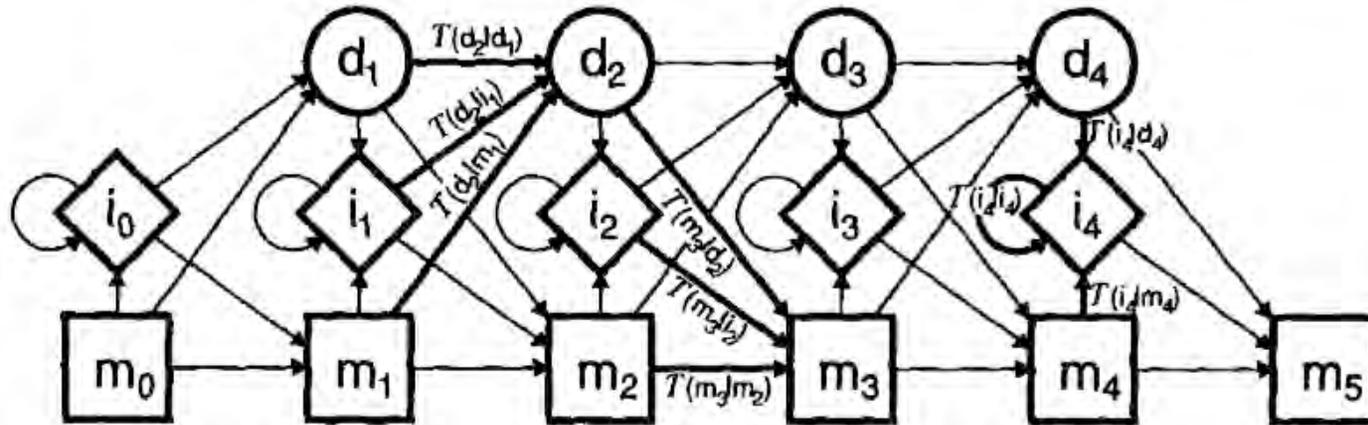




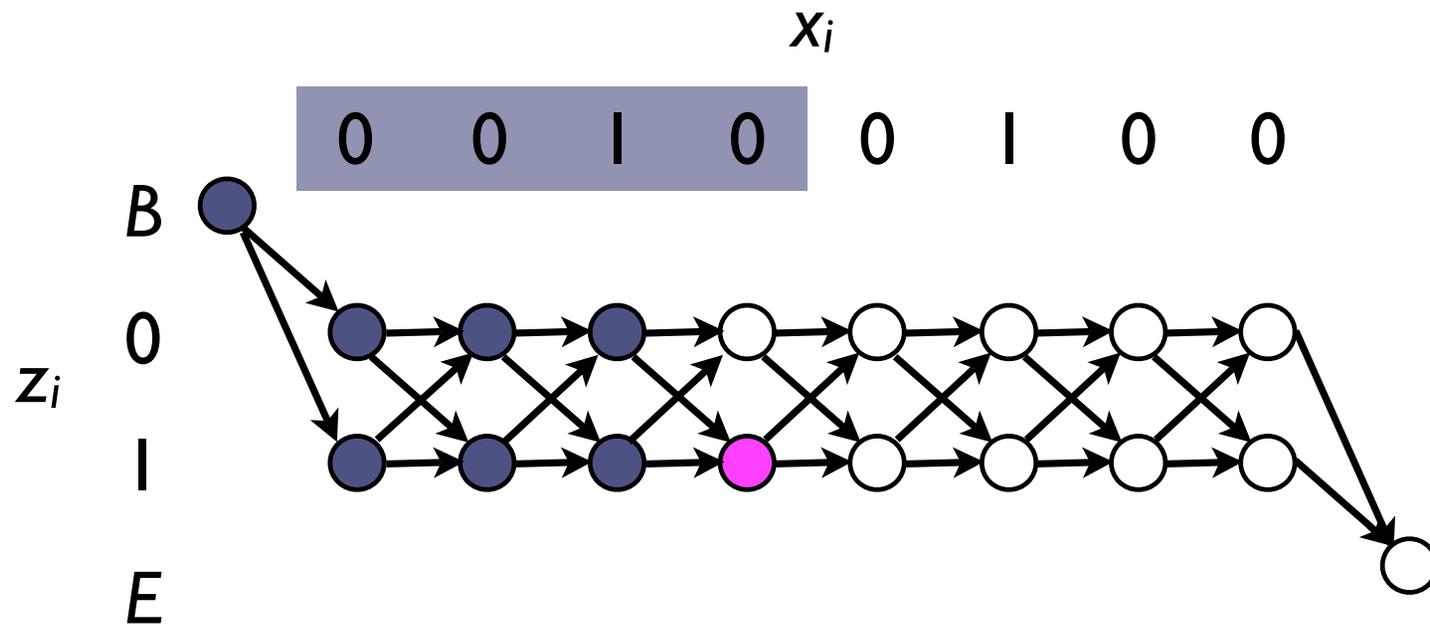


HMMs Generalize Motif Models





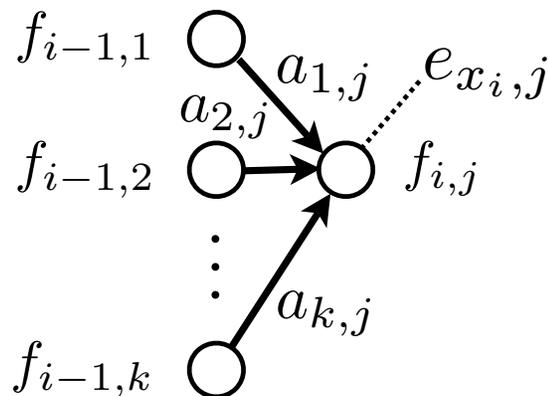
Forward Algorithm



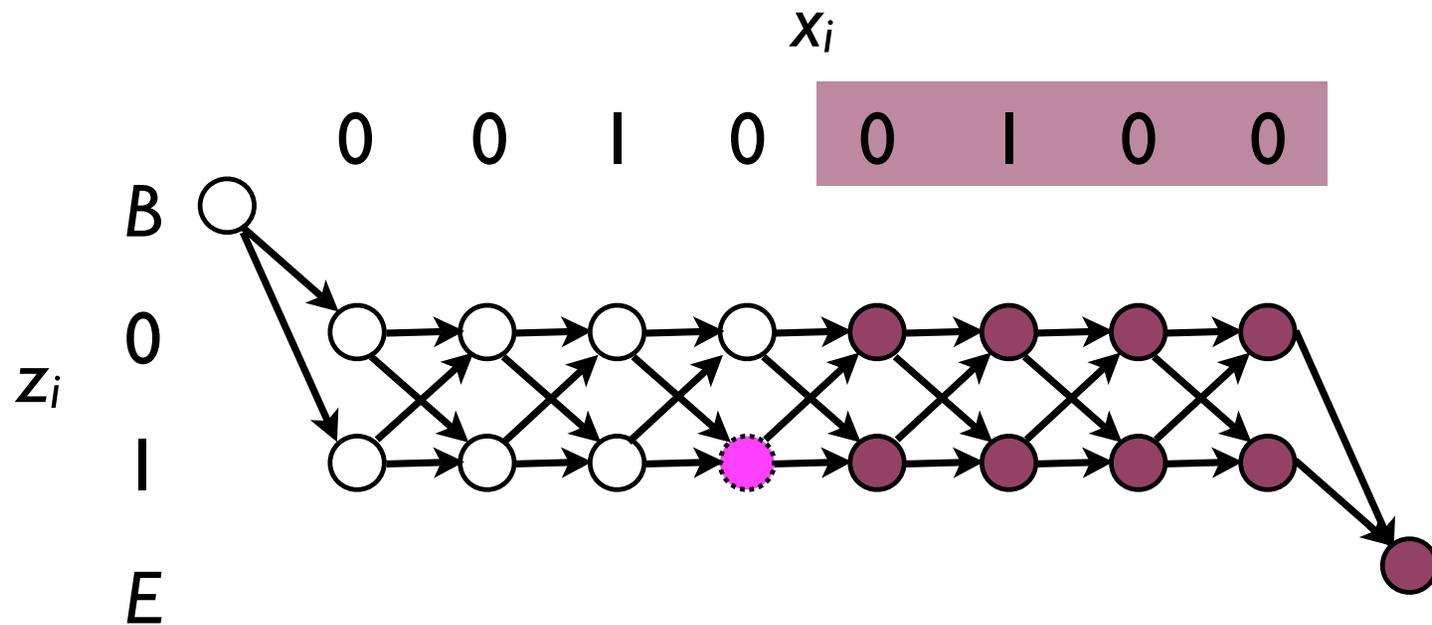
$$f_{4,1} = P(x_1, \dots, x_4, z_4 = 1)$$

Forward Algorithm

- Let $f_{i,j}$ be the (marginal) probability of (x_1, \dots, x_i) and $z_i = j$: $f_{i,j} = P(x_1, \dots, x_i, z_i = j)$
- Base case: $f_{0,B} = 1$, $f_{i,B} = 0$ for $i > 0$
- Recurrence: $f_{i,j} = e_{x_i,j} \sum_k f_{i-1,k} a_{k,j}$
- Termination: $P(\mathbf{x}) = \sum_k f_{L,k} a_{k,E}$



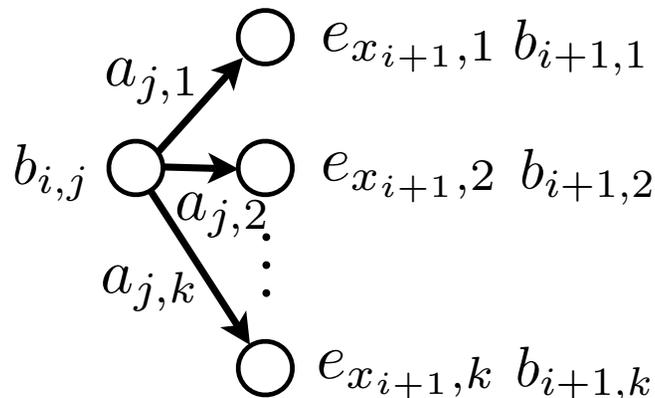
Backward Algorithm



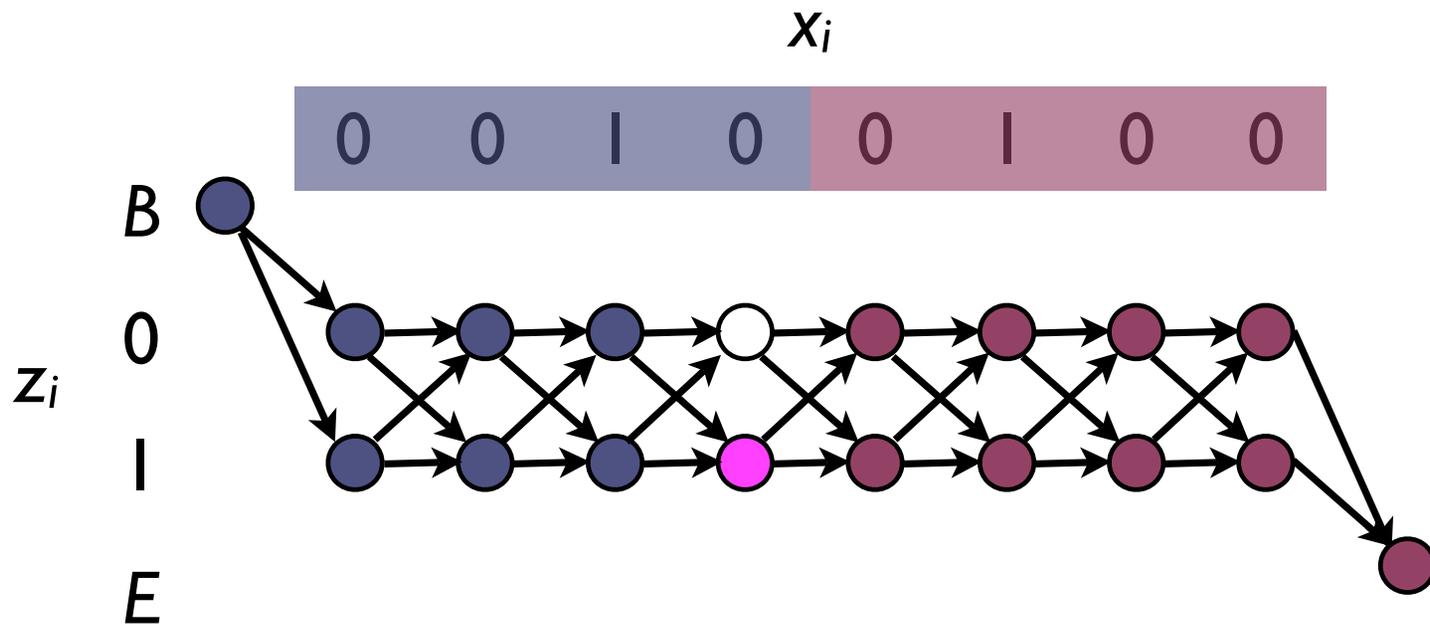
$$b_{4,1} = P(x_5, \dots, x_L | z_4 = 1)$$

Backward Algorithm

- Let $b_{i,j}$ be the (marginal) probability of (x_{i+1}, \dots, x_L) given $z_i = j$: $b_{i,j} = P(x_{i+1}, \dots, x_L | z_i = j)$
- Base case: $b_{L,j} = a_{j,E}$ for all states j
- Recurrence: $b_{i,j} = \sum_k a_{j,k} e_{x_{i+1},k} b_{i+1,k}$
- Termination: $P(\mathbf{x}) = \sum_k a_{B,k} e_{x_1,k} b_{1,k}$

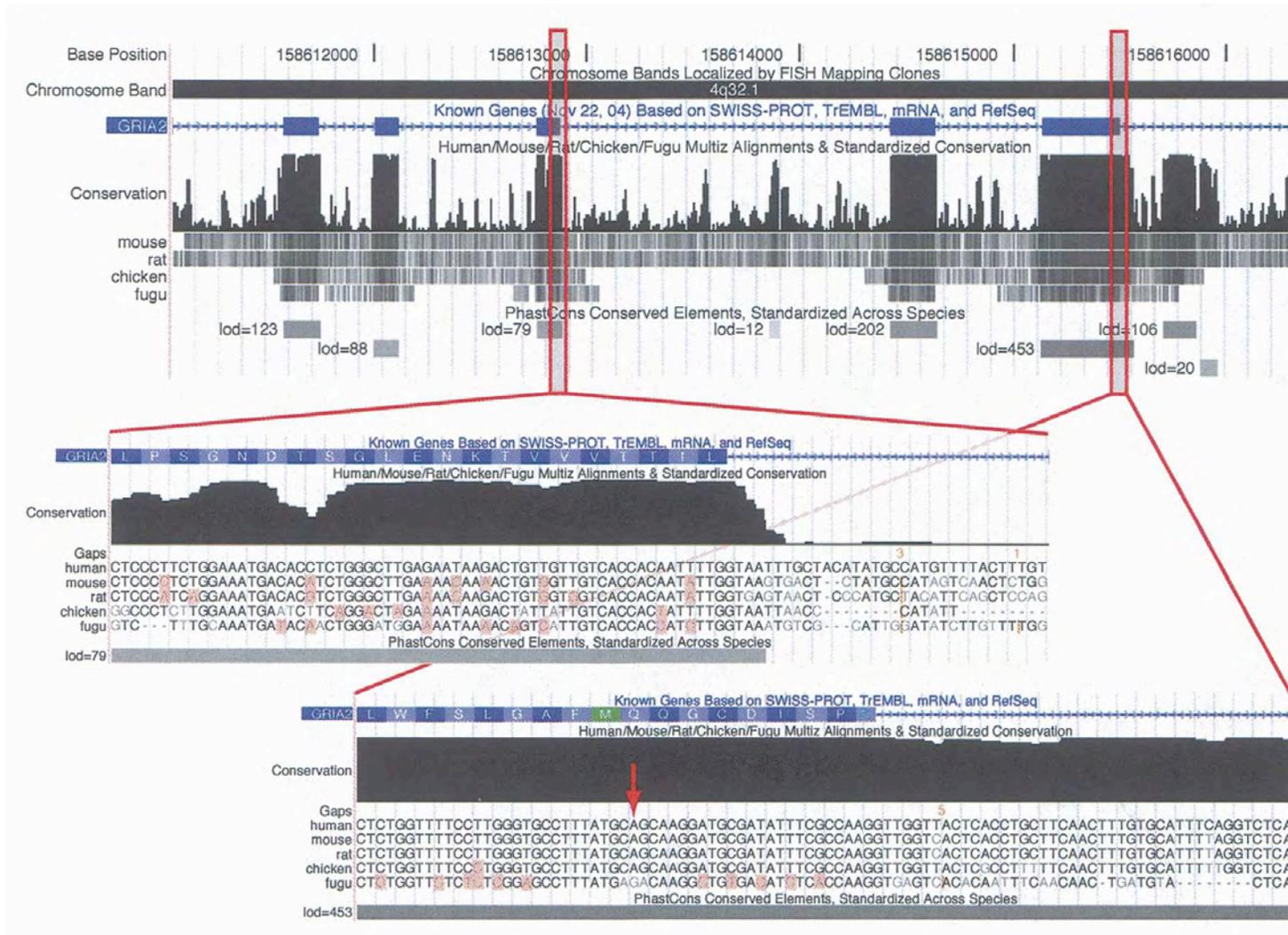


Forward/Backward



$$P(z_4 = 1 | \mathbf{x}) = \frac{P(x_1, \dots, x_4, z_4 = 1) P(x_5, \dots, x_L | z_4 = 1)}{P(\mathbf{x})} = \frac{f_{4,1} b_{4,1}}{P(\mathbf{x})}$$

Real-world Use



Typical Phylogeny

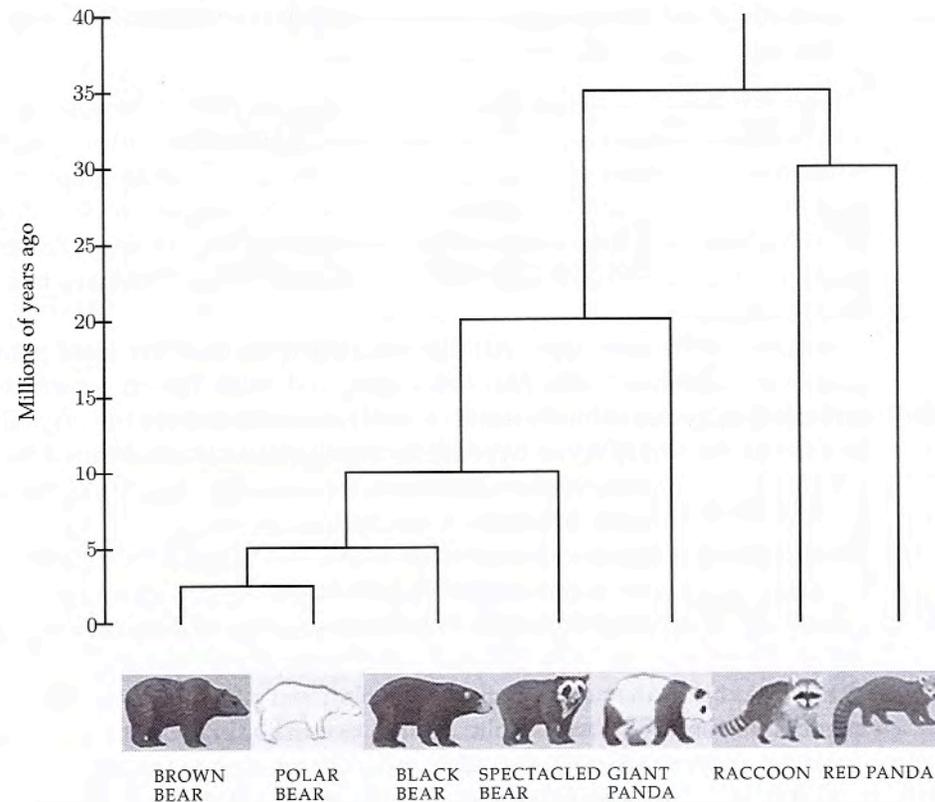
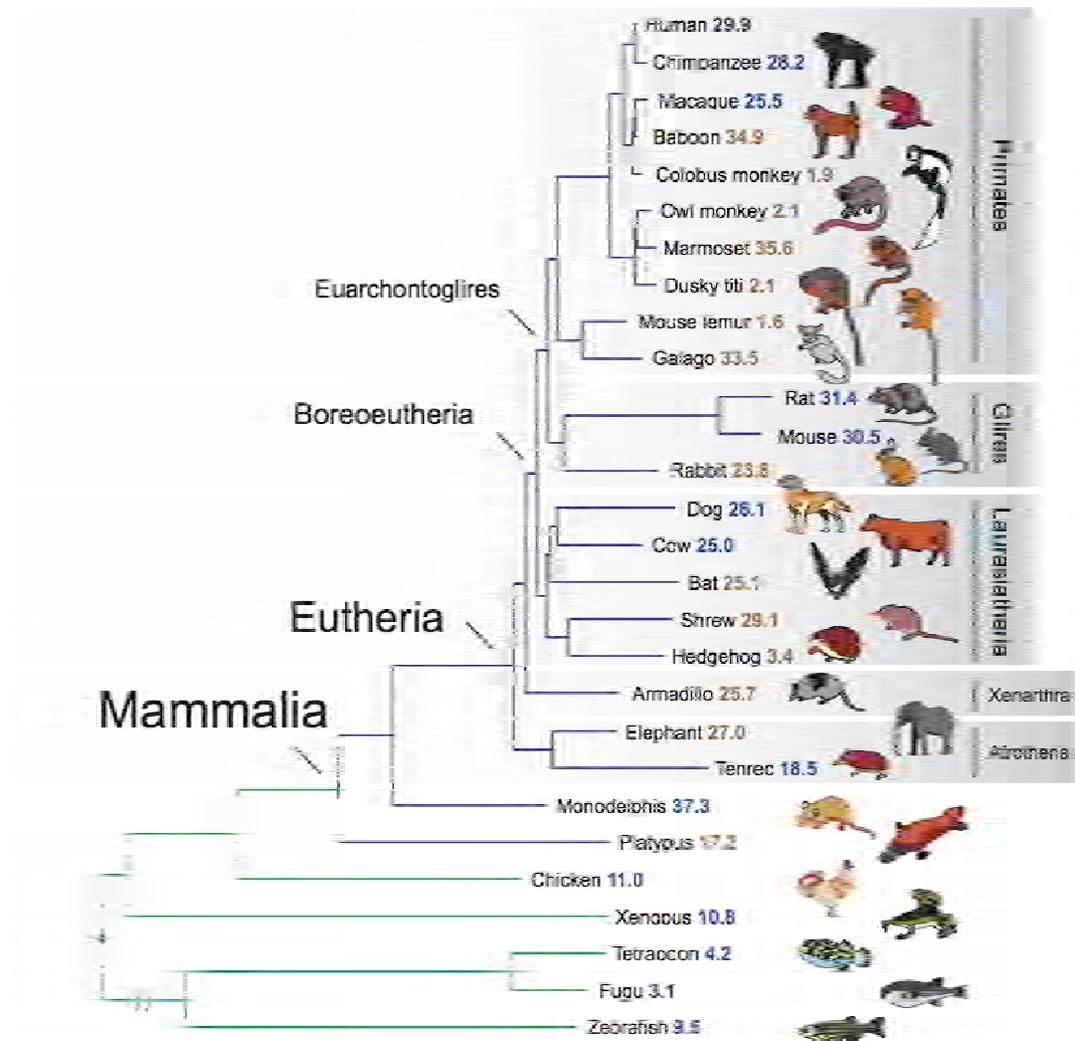


Figure 10.7 An evolutionary tree showing the divergence of raccoons and bears. Despite their difference in size and shape, these two families are closely related.

Recent Vertebrate Phylogeny



Questions

- What is the tree?
- What were the ancestral states (genomes, genes, etc.)?
- When did the divergences occur?
- What is the process?
- Where are the genes?
- ...

The Data

- Originally, morphological “characters” such as number of toes, shape of tooth
- Continuous traits
- DNA or amino acid sequences*
- Gene order or copy number
- Gene expression patterns
- Networks
- ...

General Approaches

- Parsimony: search for tree and ancestral states requiring the fewest events
- Distance matrices: define distance function on taxa, find tree that best approximates matrix of pairwise distances
- Statistical: define probabilistic model, perform ML or Bayesian inference
- Other approaches: compatibility, quartet methods, phylogenetic invariants, Hadamard methods, ...

Parsimony for Sequences

- Given a multiple alignment \mathbf{X} and a tree T , let $U_T(\mathbf{X})$ be the minimum number of changes (substitutions) along the branches of T required to explain \mathbf{X}

- If $U_T(\mathbf{X}_i)$ is the minimum number of changes for column i of \mathbf{X} , then

$$U_T(\mathbf{X}) = \sum_i U_T(\mathbf{X}_i)$$

- We seek the best-scoring tree,

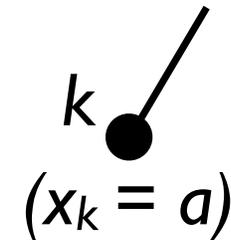
$$\hat{T} = \operatorname{argmin}_T U_T(\mathbf{X})$$

- Ancestral sequences reconstructed in passing

Sankoff's Algorithm

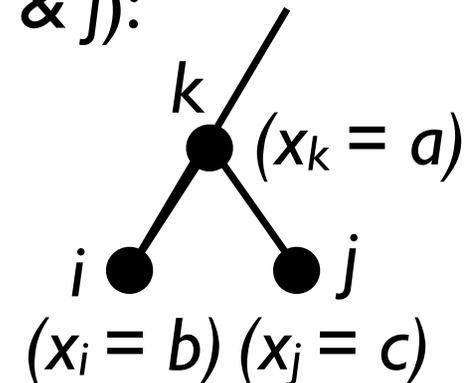
- Let x_k be the base at node k . Let $S_k(a)$ be min. no. changes beneath k , given $x_k = a$
- Base case (leaf k):

$$S_k(a) = \begin{cases} 0 & x_k = a \\ \infty & \text{otherwise} \end{cases}$$



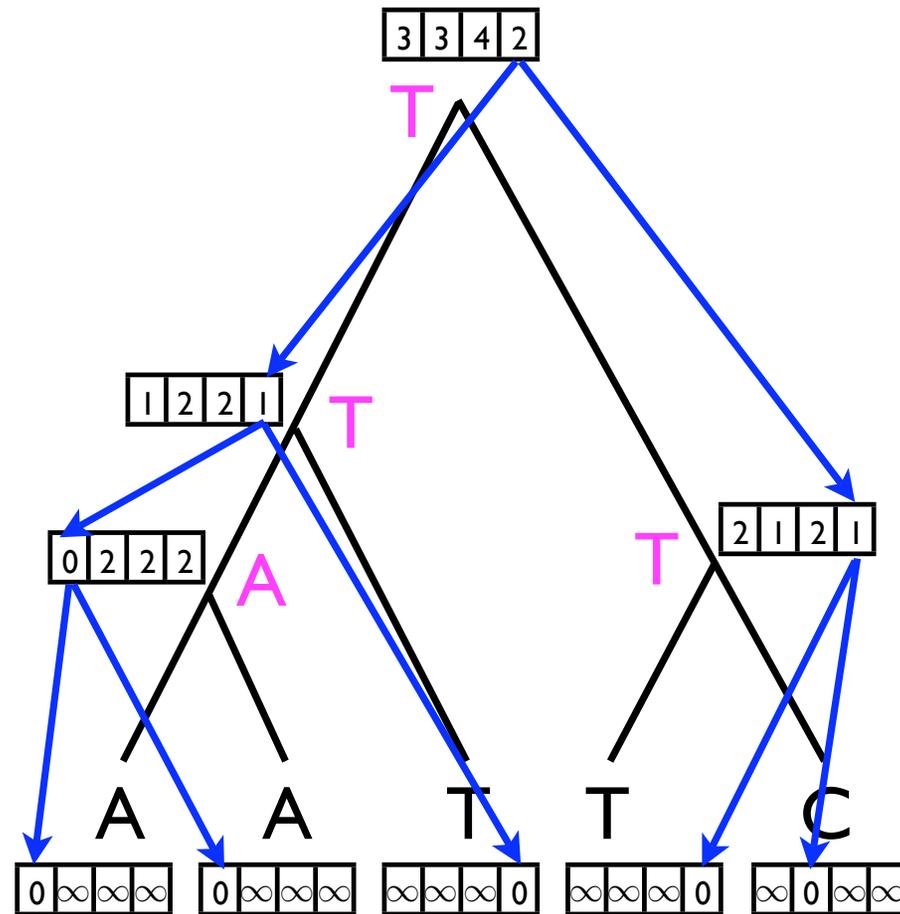
- Recurrence (ancestor k , children i & j):

$$S_k(a) = \min_b (S_i(b) + I(a \neq b)) \\ + \min_c (S_j(c) + I(a \neq c))$$



- Termination: $S_{\text{tree}} = \min_a S_{\text{root}}(a)$

Parsimony Example



Problems with Parsimony

- Incapable of dealing with multiple hits.
Especially a problem with long branches
- Not a natural framework for addressing the correlation between “weights” and branch lengths
- Not consistent!
- We would like a statistical approach

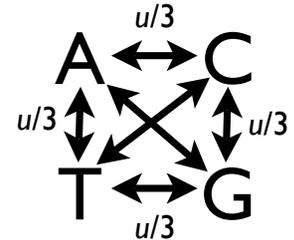
Poisson Processes

- Let $f(x|t)$ denote the probability of x events in an interval of length t
- Suppose $f(x|t)$ obeys the *Poisson postulates*:
 1. $f(1|t) = \lambda t + o(t)$ [$\lambda > 0$, $\lim_{t \rightarrow 0} o(t)/t = 0$]
 2. $\sum_{x=2}^{\infty} f(x|t) = o(t)$
 3. The numbers of events in nonoverlapping intervals are independent
- Then x has a Poisson distribution:

$$f(x|t) = \frac{(\lambda t)^x e^{-\lambda t}}{x!}$$

Jukes-Cantor Model

- Suppose DNA substitutions occur by a Poisson process

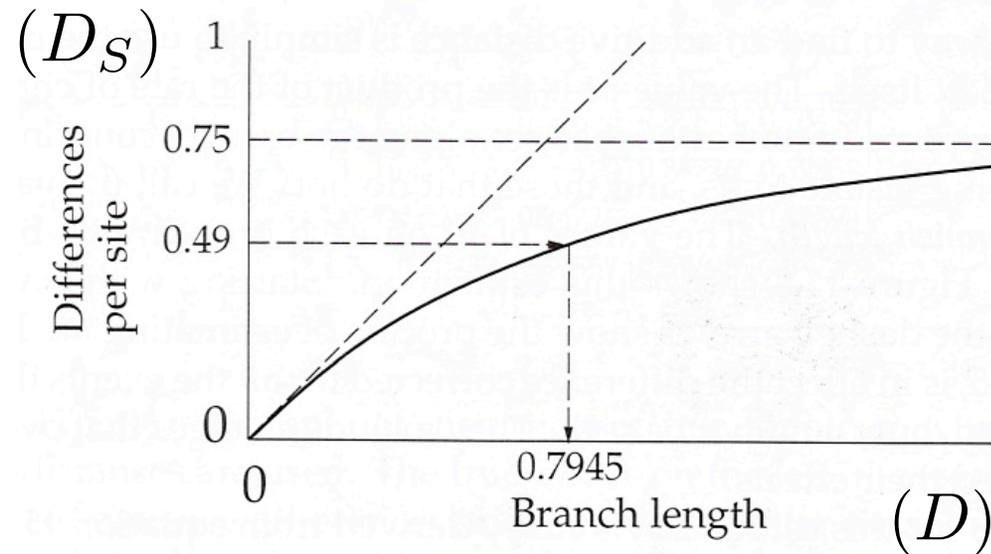


- Some change occurs at rate $4u/3$. A new base is randomly drawn from the four possibilities.
- On a branch of length t , the probability of 0 events is: $e^{-4ut/3}$
- The probability of ≥ 1 events is: $1 - e^{-4ut/3}$
- The probability of $b|a$ is thus:



$$P(b|a, t) = \begin{cases} e^{-4ut/3} + \frac{1}{4}(1 - e^{-4ut/3}) = \frac{1}{4}(1 + 3e^{-4ut/3}) & b = a \\ \frac{1}{4}(1 - e^{-4ut/3}) & b \neq a \end{cases}$$

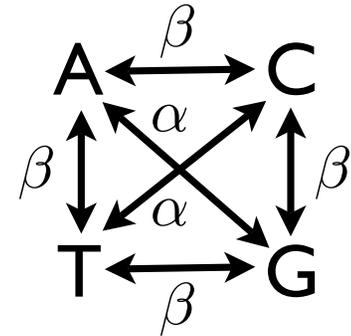
Jukes-Cantor, cont.



$$D = \hat{u}t = -\frac{3}{4} \ln \left(1 - \frac{4}{3} D_S \right)$$

Kimura's Model

- Distinguishes between transitions and transversions
- Scaling constraint: $\alpha + 2\beta = 1$



This implies: $\alpha = \frac{R}{R+1}$, $\beta = \frac{1}{2(R+1)}$ $\left[R = \frac{\alpha}{2\beta} \right]$

- It can be shown that:

$$P(\text{transition}|t) = \frac{1}{4} - \frac{1}{2} \exp\left(-\frac{2R-1}{R+1}t\right) + \frac{1}{4} \exp\left(-\frac{2}{R+1}t\right)$$

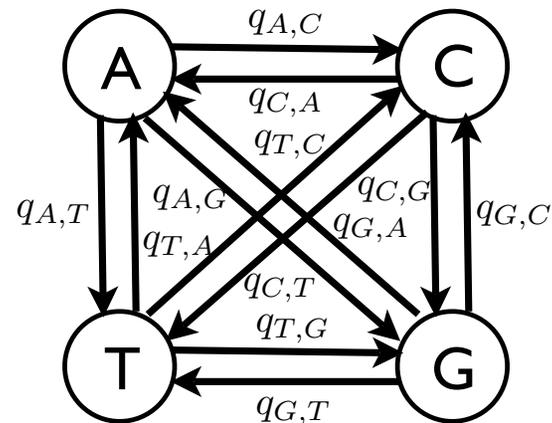
$$P(\text{transversion}|t) = \frac{1}{2} - \frac{1}{2} \exp\left(-\frac{2}{R+1}t\right)$$

- These relationships are also invertible

Some Other (DNA) Models

- Felsenstein, 1981 (F81): Rates proportional to equilibrium frequencies $(\pi_A, \pi_C, \pi_G, \pi_T)$
- Felsenstein, 1984 (F84): Rates proportional to equilibrium frequencies, transition/transversion bias
- Hasegawa-Kishino-Yano, 1985 (HKY85): Similar to F84 but different parameterization
- TN93: Generalizes both F84 & HKY85, allows for unequal A-G and C-T transition biases
- ...

A General Framework



$$Q = \begin{pmatrix} -q_{A,C} - q_{A,G} - q_{A,T} & q_{A,C} & q_{A,G} & q_{A,T} \\ q_{C,A} & -q_{C,A} - q_{C,G} - q_{C,T} & q_{C,G} & q_{C,T} \\ q_{G,A} & q_{G,C} & -q_{G,A} - q_{G,C} - q_{G,T} & q_{G,T} \\ q_{T,A} & q_{T,C} & q_{T,G} & -q_{T,A} - q_{T,C} - q_{T,G} \end{pmatrix}$$

Subject to: $\sum_{a,b:a \neq b} \pi_a q_{a,b} = 1$

Time-Reversibility

- The process is *reversible* if, for all a and b ,

$$\pi_a q_{a,b} = \pi_b q_{b,a}$$

where π_x is the equilibrium frequency of base x

- This is *not* the same as requiring \mathbf{Q} to be symmetric, but it does impose a kind of symmetry on the process
- At equilibrium, the expected numbers of a -to- b and b -to- a substitutions will be equal
- Reversibility has nice mathematical properties and in most cases is not strongly contradicted by real biological data

The REV (GTR) Model

- The most general reversible model is:

$$Q_{\text{REV}} = \begin{pmatrix} - & a\pi_C & b\pi_G & c\pi_T \\ a\pi_A & - & d\pi_G & f\pi_T \\ b\pi_A & d\pi_C & - & g\pi_T \\ c\pi_A & f\pi_C & g\pi_G & - \end{pmatrix}$$

- This model has eight free parameters (accounting for constraints) and a stationary distribution of $\pi = (\pi_A, \pi_C, \pi_G, \pi_T)$
- In practice, π is often taken to be equal to the observed relative frequencies and the other five parameters are estimated by ML

Others are Special Cases

$$\mathbf{Q}_{\text{JC}} = \begin{pmatrix} - & u/3 & u/3 & u/3 \\ u/3 & - & u/3 & u/3 \\ u/3 & u/3 & - & u/3 \\ u/3 & u/3 & u/3 & - \end{pmatrix} \quad \boldsymbol{\pi} = \left(\frac{1}{4}, \frac{1}{4}, \frac{1}{4}, \frac{1}{4} \right)$$

$$\mathbf{Q}_{\text{K2P}} = \begin{pmatrix} - & \beta & \alpha & \beta \\ \beta & - & \beta & \alpha \\ \alpha & \beta & - & \beta \\ \beta & \alpha & \beta & - \end{pmatrix} \quad \boldsymbol{\pi} = \left(\frac{1}{4}, \frac{1}{4}, \frac{1}{4}, \frac{1}{4} \right)$$

$$\mathbf{Q}_{\text{HKY}} = \begin{pmatrix} - & \pi_C & \kappa\pi_G & \pi_T \\ \pi_A & - & \pi_G & \kappa\pi_T \\ \kappa\pi_A & \pi_C & - & \pi_T \\ \pi_A & \kappa\pi_C & \pi_G & - \end{pmatrix} \quad \boldsymbol{\pi} = (\pi_A, \pi_C, \pi_G, \pi_T)$$

Computing Probabilities

- Suppose *discrete* Markov process with transition matrix \mathbf{A}
- Let $\mathbf{P}(k)$ be the matrix of conditional probabilities after k steps. That is, $\mathbf{P}_{a,b}(k) = P(b|a,k)$. Note $\mathbf{P}(0) = \mathbf{I}$
- Recall that $\mathbf{P}(k) = \mathbf{P}(k-1)\mathbf{A}$, so that $\mathbf{P}(k) = \mathbf{A}^k$ (because $P(b|a, k) = \sum_c P(c|a, k-1)a_{c,b}$)
- Therefore:

$$\begin{aligned}\Delta\mathbf{P}(k) &= \mathbf{P}(k) - \mathbf{P}(k-1) \\ &= \mathbf{P}(k-1)\mathbf{A} - \mathbf{P}(k-1) \\ &= \mathbf{P}(k-1)(\mathbf{A} - \mathbf{I})\end{aligned}$$

Continuous Analog

- Suppose each step represents a tiny segment dt of a branch of length t , so $k = t / dt$. What happens as dt approaches 0?
- It can be shown that $\mathbf{P}(t)$ is continuous, and that a differential equation analogous to the above arises:

$$\frac{d}{dt}\mathbf{P}(t) = \mathbf{P}(t)\mathbf{Q}$$

- This equation has solution:

$$\begin{aligned}\mathbf{P}(t) &= e^{\mathbf{Q}t} = \mathbf{I} + \mathbf{Q}t + \frac{\mathbf{Q}^2 t^2}{2} + \frac{\mathbf{Q}^3 t^3}{6} + \dots \\ &= \sum_{n=0}^{\infty} \frac{\mathbf{Q}^n t^n}{n!}\end{aligned}$$

Diagonalization

- In practice, we *diagonalize* \mathbf{Q} :

$$\mathbf{Q} = \mathbf{U}\mathbf{\Lambda}\mathbf{U}^{-1}$$

- Now:

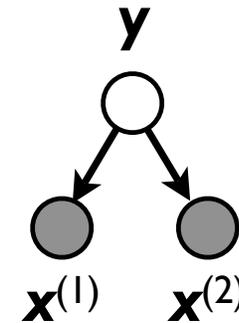
$$\begin{aligned}\mathbf{P}(t) &= \sum_{n=0}^{\infty} \frac{\mathbf{Q}^n t^n}{n!} \\ &= \sum_{n=0}^{\infty} \frac{(\mathbf{U}\mathbf{\Lambda}\mathbf{U}^{-1})^n t^n}{n!} \\ &= \sum_{n=0}^{\infty} \frac{\mathbf{U}\mathbf{\Lambda}^n \mathbf{U}^{-1} t^n}{n!} \\ &= \mathbf{U}e^{\mathbf{\Lambda}t}\mathbf{U}^{-1}\end{aligned}$$

Computing Likelihoods

- Suppose \mathbf{X} is a (gapless) alignment of $\mathbf{x}^{(1)}$ and $\mathbf{x}^{(2)}$, with \mathbf{X}_i as the i th column.

$$\begin{array}{c} \mathbf{X}_i \\ \mathbf{x}^{(1)} = \text{AATCGG} \boxed{\text{T}} \text{ACGA} \dots \\ \mathbf{x}^{(2)} = \text{ATTCAG} \boxed{\text{C}} \text{ACGT} \dots \end{array}$$

- The sequences are derived from an unobserved ancestral sequence \mathbf{y}
- Assuming independence,



$$P(\mathbf{X}|\mathbf{Q}, t, \boldsymbol{\pi}) = \prod_{i=1}^L P(\mathbf{X}_i|\mathbf{Q}, t, \boldsymbol{\pi}) = \prod_{i=1}^L \sum_{y_i} P(x_i^{(1)}, x_i^{(2)}, y_i|\mathbf{Q}, t, \boldsymbol{\pi})$$

- Assuming stationarity,

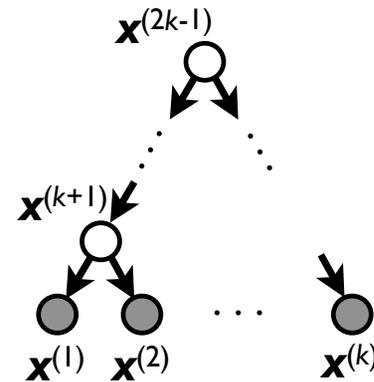
$$P(x_i^{(1)}, x_i^{(2)}, y_i|\mathbf{Q}, t, \boldsymbol{\pi}) = \pi_{y_i} P(x_i^{(1)}|y_i, \mathbf{Q}, t) P(x_i^{(2)}|y_i, \mathbf{Q}, t)$$

Likelihoods, cont.

- Now suppose \mathbf{X} is a *multiple* alignment of sequences related by a (known) phylogeny

\mathbf{X}_i

$\mathbf{x}^{(1)} = \text{AATCGG} \boxed{\text{TACGA}} \dots$
 $\mathbf{x}^{(2)} = \text{ATTCAG} \boxed{\text{CACGT}} \dots$
 \vdots
 $\mathbf{x}^{(k)} = \text{GTTGAC} \boxed{\text{TATGA}} \dots$



- $P(x_i^{(1)}, \dots, x_i^{(2k-1)})$ is a product over branches:

$$P(x_i^{(1)}, \dots, x_i^{(2k-1)}) = \pi_{x_i^{(2k-1)}} \prod_{j=1}^{2k-2} P(x_i^{(j)} | x_i^{\text{parent}(j)}, t_j)$$

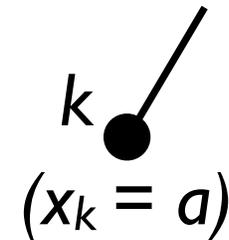
- But we need:

$$P(x_i^{(1)}, \dots, x_i^{(k)}) = \sum_{x_i^{(k+1)}, \dots, x_i^{(2k-1)}} P(x_i^{(1)}, \dots, x_i^{(2k-1)})$$

Recall: Sankoff's Algorithm

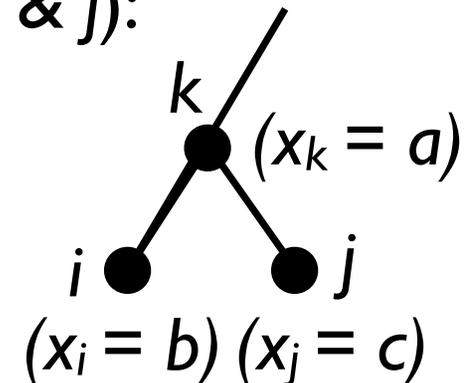
- Let x_k be the base at node k . Let $S_k(a)$ be min. no. changes beneath k , given $x_k = a$
- Base case (leaf k):

$$S_k(a) = \begin{cases} 0 & x_k = a \\ \infty & \text{otherwise} \end{cases}$$



- Recurrence (ancestor k , children i & j):

$$S_k(a) = \min_b (S_i(b) + w(a \rightarrow b)) \\ + \min_c (S_j(c) + w(a \rightarrow c))$$

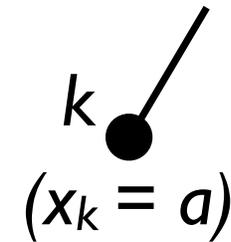


- Termination: $S_{\text{tree}} = \min_a S_{\text{root}}(a)$

Felsenstein's Algorithm

- Let $P(x^{(k)} | x^{(k)} = a)$ be the probability of the *observed bases* beneath node k , given $x^{(k)} = a$
- Base case (leaf k):

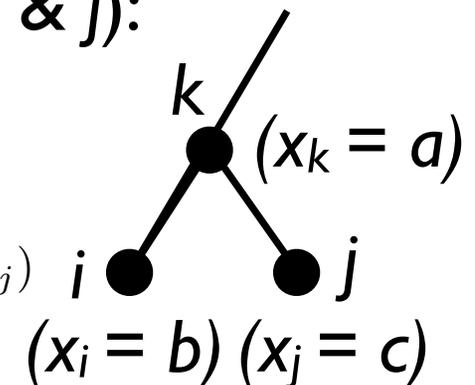
$$P(x^{(k)} | x^{(k)} = a) = \begin{cases} 1 & x^{(k)} = a \\ 0 & \text{otherwise} \end{cases}$$



- Recurrence (ancestor k , children i & j):

$$P(x^{(k)} | x^{(k)} = a) = \sum_b P(x^{(i)} | x^{(i)} = b) P(b|a, t_i)$$

$$\times \sum_c P(x^{(j)} | x^{(j)} = c) P(c|a, t_j)$$



- Termination:

$$P(x^{(1)}, \dots, x^{(k)}) = \sum_a \pi_a P(x^{(2k-1)} | x^{(2k-1)} = a)$$

Estimating Parameters

- We now have an efficient way to compute the likelihood of a given phylogenetic model,

$$P(\mathbf{X}|\mathcal{T}, \mathbf{t}, \boldsymbol{\pi}, \mathbf{Q})$$

- If we fix the tree \mathcal{T} , ML estimation of the other parameters is a standard nonlinear optimization problem:

$$(\hat{\mathbf{t}}, \hat{\boldsymbol{\pi}}, \hat{\mathbf{Q}}) = \arg \max_{\mathbf{t}, \boldsymbol{\pi}, \mathbf{Q}} P(\mathbf{X}|\mathcal{T}, \mathbf{t}, \boldsymbol{\pi}, \mathbf{Q})$$

- It can be solved numerically using well-known algorithms (e.g., quasi-Newton methods)

Finding the Tree

- Unfortunately, finding the tree is still hard.
- Like with parsimony, we use heuristic or branch-and-bound methods to search the space of trees. We compute a likelihood for each tree and keep the best one.
- Unlike with parsimony, we have to solve a nonlinear optimization problem for each tree!
- Divide-and-conquer heuristics can be useful, because the search space for small trees is manageable

Posterior Probabilities

- What is the posterior distribution of bases at the root? By Bayes' rule:

$$P(x^{(2k-1)} = a | x^{(1)}, \dots, x^{(k)}) = \frac{P(x^{(1)}, \dots, x^{(k)} | x^{(2k-1)} = a) \pi_a}{P(x^{(1)}, \dots, x^{(k)})}$$

- We have already computed the numerator and the denominator! (Felsenstein's algorithm)
- With reversibility, we can root the tree at any node and compute the posterior distribution
- Possible to compute simultaneously for all nodes using an "inside/outside" algorithm resembling the forward/backward algorithm

Non-nucleotide Models

- Can define Q in terms of codons, amino acids, paired nucleotides in RNA structures
- Codon models are especially useful. They can be parameterized in terms of a nonsynonymous/synonymous rate ratio ω .
- Estimates of this parameter imply negative selection, positive selection, or neutral evolution
- Likelihood ratio tests for positive selection can be constructed