#### **Pairwise Alignment** (or models and algorithms are your friend)

#### Lecture 2 6.874J/7.90J/6.807

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#### Gene similarities revealed by dot plot

promoter conservation

#### **Dot Plots**

## Align subsequences of *S1* and *S2*; place dot when score is high

## Pairwise Alignment (Global)

Given a query sequence *x*, what is the best alignment to a sequence *y*?

$$y$$
 HEAGAWGME-E  
 $x$  --P-AW-MEAE

Protein (20 letters, X, -)

DNA (A, C, G, T, N, -, W, S, R, Y, K, M, B, D, H, V)RNA (A, C, G, U, -)

 $q_s$  probability of symbol *s* occurring at random in a sequence.

#### Two possible models

- Model R Random– The sequences are unrelated and were generated by coin flips (biased)
- Model M Match The sequences were derived from a common ancestor sequence

#### A Probabilistic Model of Alignment

$$P(x, y \mid R) = \prod_{i} q_{x_i} \prod_{j} q_{y_j}$$

 $P_{ab}$ 

Joint probability that *a* and *b* have been originally derived from some (unknown) ancestor *c* (might be the same as *a* or *b*)

$$P(x, y \mid M) = \prod_{i} P_{x_i y_i}$$

## The Odds Ratio Statistic (No Gaps)

$$\frac{P(x, y \mid M)}{P(x, y \mid R)} = \prod_{i} \frac{P_{x_{i}y_{i}}}{q_{x_{i}}q_{y_{i}}}$$
$$S = \log\left(\frac{P(x, y \mid M)}{P(x, y \mid R)}\right) = \log\prod_{i} \frac{P_{x_{i}y_{i}}}{q_{x_{i}}q_{y_{i}}}$$
$$S = \sum_{i} S(x_{i}, y_{i})$$
$$S(a, b) = \log\frac{P_{ab}}{q_{a}q_{b}}$$

#### Example

$$x_{1} = C \qquad y_{1} = Q$$

$$q_{x_{1}} = \frac{1}{20} \qquad q_{y_{1}} = \frac{1}{20} \qquad q_{x_{1}y_{1}} = \frac{1}{400}$$

$$P_{x_1 y_1} = P_{CQ} = -\frac{1}{800}$$

$$S_{x_1y_1} = S_{CQ} = -3\log_2\left(\frac{\frac{1}{800}}{\frac{1}{400}}\right) =$$

 $3\log_2\left(\frac{1}{2}\right) = -3$ 

#### **Substitution Matrix**

• Logical to think of it in terms of evolutionary time

- **PAM (Point Accepted Mutations)**: Based on substitution data from alignment between similar proteins
  - (1% expected substitutions = 1PAM)
  - PAMn = (1PAM)<sup>n</sup>
- BLOSUM (BLOck Scoring Matrix): Multiple alignment of distantly related proteins
  - BlosumL = Sequences with L% or more of identical residues were clustered to compute log-odds ratio

#### BLOSUM50

#### BLOSUM65

#### **Gap Penalties**

• We can penalize a gap with the function

$$-gd$$

#### where *g* is the length of the gap

- Typical gap penalties in practice for proteins
   d=8 third-bits used in Durbin
- We can also add a fixed penalty for opening a gap

#### Affine gaps

• Assume log odds-ratio of a gap deceases geometrically:

$$f(g) = p(1-p)^{g-1}$$
  

$$\log f(g) = \log p + (g-1)\log(1-p)$$
  

$$d = -\log p$$
  

$$e = -\log(1-p)$$
  

$$\log f(g) = -d - (g-1)e$$
  

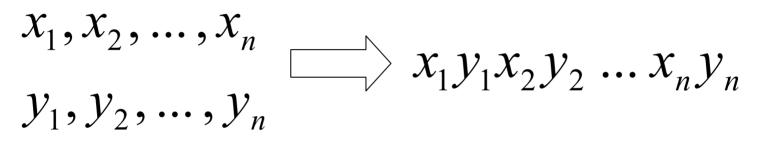
$$s(g) = -d - (g-1)e$$

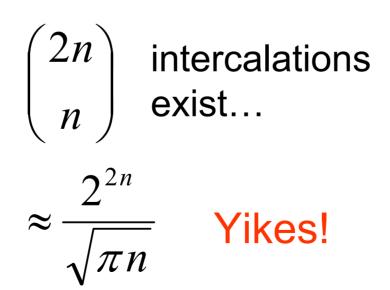
#### Let's find the best alignment

- To do this we will maximize the score, taking into account our ability to incorporate gaps
- We could enumerate all of the possible alignments...

# How many possible alignments exist?

An intercalation of *x* and *y* (discards gaps):





#### Needleman-Wunsch (global)

• F(i,j) = score of best alignment of

$$X_{1...i}$$
 and  $Y_{1...j}$ 

• Suppose F(i-1,j-1), F(i-1,j), F(i,j-1) are known

$$F(0,0) = 0$$

$$F(i,j) = \max \begin{cases} F(i-1,j-1) + s(x_i, y_i), \\ F(i-1,j) - d, \\ F(i,j-1) - d, \end{cases}$$

#### **Example: Needleman-Wunsch**

y HEAGAWGME-E x --P-AW-MEAE

#### **Example: Needleman-Wunsch**

#### Smith-Waterman (Local Alignment)

$$F(0,0) = 0$$

$$F(i,j) = \max \begin{cases} 0, \\ F(i-1,j-1) + s(x_i, y_i), \\ F(i-1,j) - d, \\ F(i,j-1) - d, \\ F(i,j-1) - d \end{cases}$$

- Key idea is to look for best alignment between subsequences
- Expected score of random match must be negative

#### **Example: Smith-Waterman**

#### What does a score mean?

• How can we tell if our match is significant?

 Isn't this related to the size of the query and the database?

## Being Bayesian

- Assume a casino uses a loaded die 1% of the time.
- A loaded die will come up six 50% of the time.
- You pick up a die at the casino and roll it three times, getting three sixes.
- What is the chance the die is loaded?

#### Being Bayesian: II

$$P(X | Y)P(Y) = P(Y | X)P(X)$$

$$P(X | Y) = \frac{P(Y | X)P(X)}{P(Y)}$$

$$P(D_{loaded} | 3 \text{ sixes}) = \frac{P(3 \text{ sixes} | D_{loaded})P(D_{loaded})}{P(3 \text{ sixes})}$$

$$= \frac{(0.5)^3(0.01)}{(0.5)^3(0.01) + (\frac{1}{6})^3(0.99)}$$

= 0.21

#### Comparing Models (Bayesian)

$$P(M \mid x, y) = \frac{P(x, y \mid M)P(M)}{P(x, y)}$$

$$=\frac{P(x, y \mid M)P(M)}{P(x, y \mid M)P(M) + P(x, y \mid R)P(R)}$$

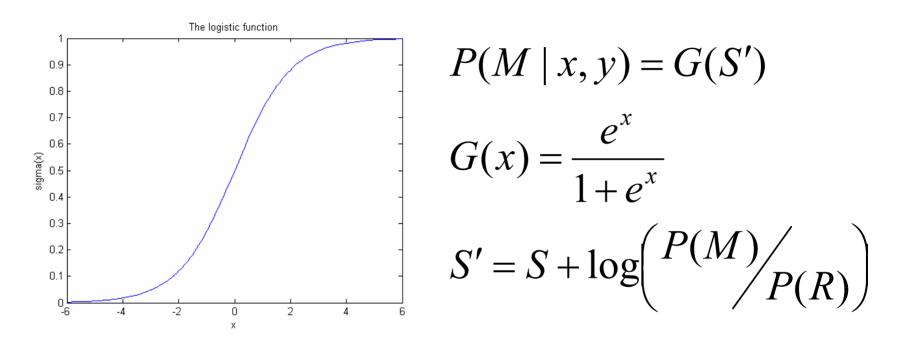
$$= \frac{P(x, y | M)P(M)/P(x, y | R)P(R)}{1 + P(x, y | M)P(M)/P(x, y | R)P(R)}$$

#### Comparing Models (Bayesian)

$$P(M \mid x, y) = \frac{P(x, y \mid M)P(M)/P(x, y \mid R)P(R)}{1 + P(x, y \mid M)P(M)/P(x, y \mid R)P(R)}$$
$$= \frac{e^{S'}}{1 + e^{S'}}$$

where 
$$S' = S + \log \begin{pmatrix} P(M) \\ P(R) \end{pmatrix}$$

## Comparing Models (Bayesian II)



- Global alignment: compare S with log N
- Local alignment: compare S with log MN

#### Classical Approach: Extreme Value Distribution

• Expected number of unrelated matches for a local alignment (*E-value*)

$$E(S) = Kmn2^{-\lambda S}$$

• Used by BLAST

### **Building Phylogenetic Trees**

 Unweighted pair group method using arithmetic averages (UPGMA)

 Clusters sequences based on evolutionary distance

#### Example: UPGMA

Parsimony-based Phylogenetic Trees

• Build all possible trees

 Choose tree that uses <u>fewest</u> number of substitutions

#### **Example:** Parsimony

#### Fin