

# Part 1: Morphological models

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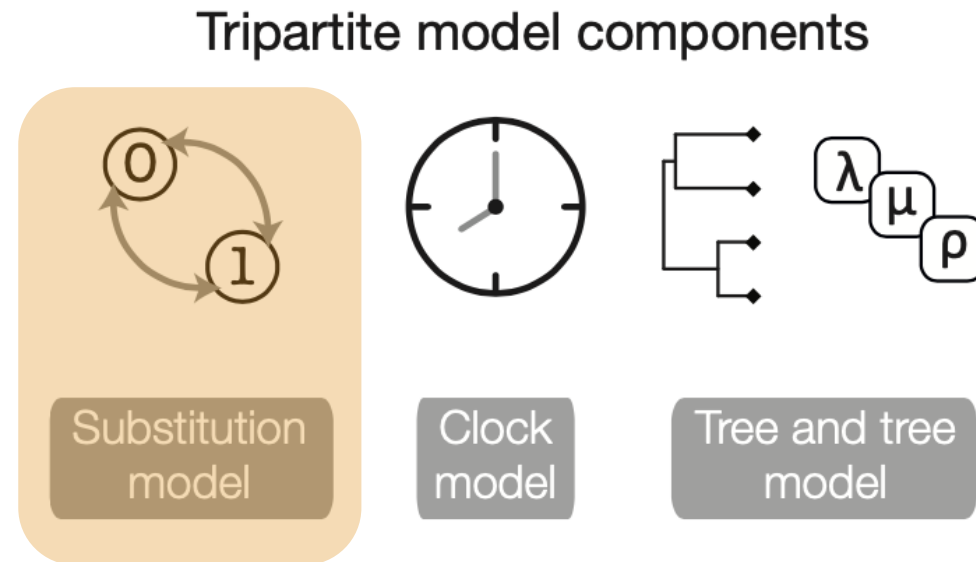
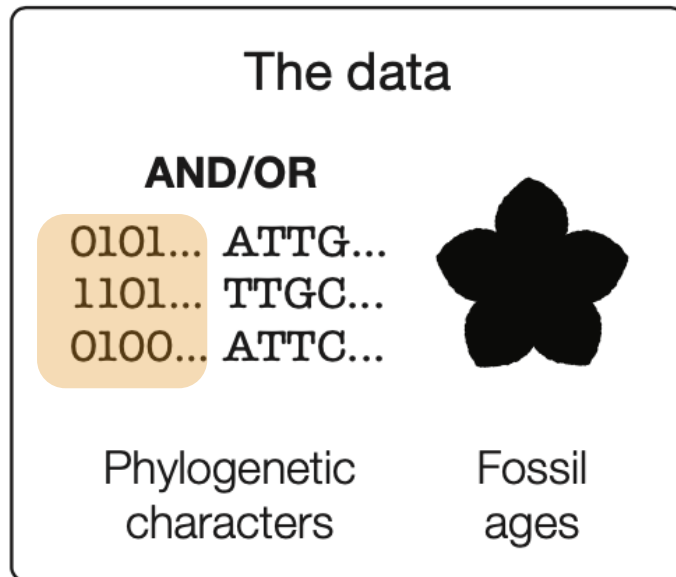
FAU Erlangen-Nürnberg

Wednesday 07.09.22



Friedrich-Alexander-Universität  
Erlangen-Nürnberg





*Warnock & Wright 2020*

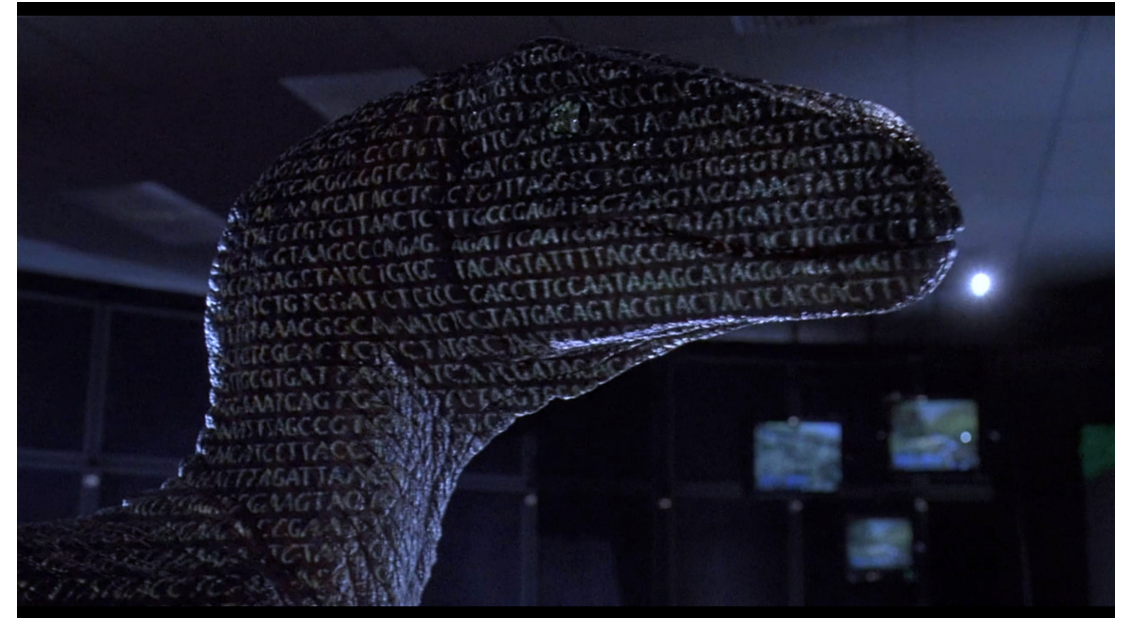
# Already know about substitution models for molecular data

JC substitution model

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

GTR substitution model

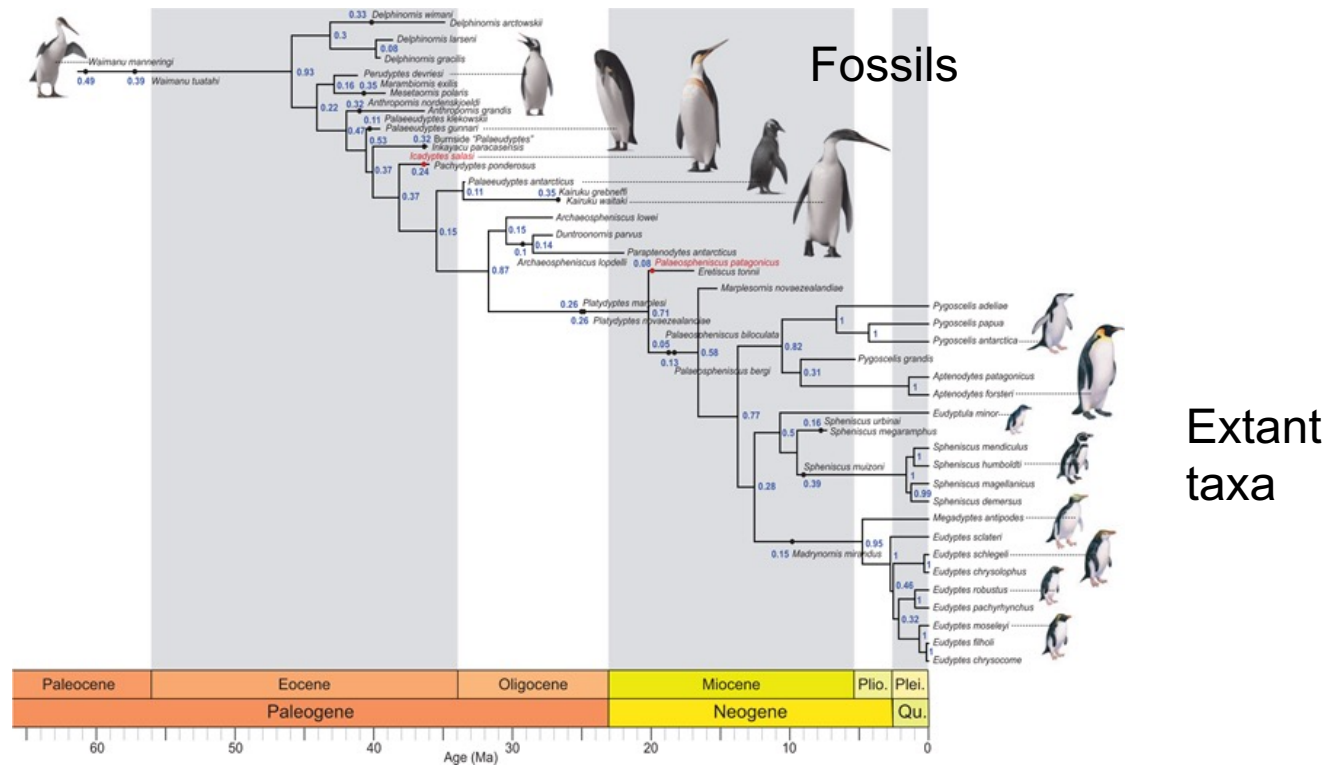
$$Q = \begin{pmatrix} * & \mu_{AG}\pi_G & \mu_{AC}\pi_C & \mu_{AT}\pi_T \\ \mu_{GA}\pi_A & * & \mu_{GC}\pi_C & \mu_{GT}\pi_T \\ \mu_{CA}\pi_A & \mu_{CG}\pi_G & * & \mu_{CT}\pi_T \\ \mu_{TA}\pi_A & \mu_{TG}\pi_G & \mu_{TC}\pi_C & * \end{pmatrix}$$



# Models of discrete character data

For most organisms (essentially of extinct taxa) all we have is morphological data

Important for dating phylogenies,  
ancestral state reconstructing and  
testing evolutionary hypothesis.



*Gavryushkina et al 2016*




001510010?00-100--0000000000  
000500010?200100--0010010000  
002500010?200100--0?10010000  
00?5?0010?200100?-0???010110  
0015000101201000430100011111  
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1005002000101010540?00110020

## Morphological data

*Cambrian stalked echinoderms show  
unexpected plasticity of arm construction  
Zamora & Smith. 2012 Proc B*

# Challenges with Morphological data



Conodonts						
taxa 1	0	1	0	1	2	1
taxa 2	1	2	1	0	1	0
taxa 3	0	0	1	0	0	1
taxa 4	1	1	0	1	0	1



Image from Bryan Shirley

# Challenges with Morphological data




## Conodonts

taxa 1	0	1	0	1	2	1
taxa 2	1	2	1	0	1	0
taxa 3	0	0	1	0	0	1
taxa 4	1	1	0	1	0	1

Often used to indicate presence  
absence data

Image from Bryan Shirley

# Challenges with Morphological data

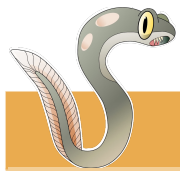


Conodonts						
taxa 1	0	1	0	1	2	1
taxa 2	1	2	1	0	1	0
taxa 3	0	0	1	0	0	1
taxa 4	1	1	0	1	0	1

Multistate characters can be used to represent types of a trait

Image from Bryan Shirley

# Challenges with Morphological data



Conodonts

taxa 1	0	1	0	1	2	1
taxa 2	1	2	1	0	1	0
taxa 3	0	0	1	0	0	1
taxa 4	1	1	0	1	0	1

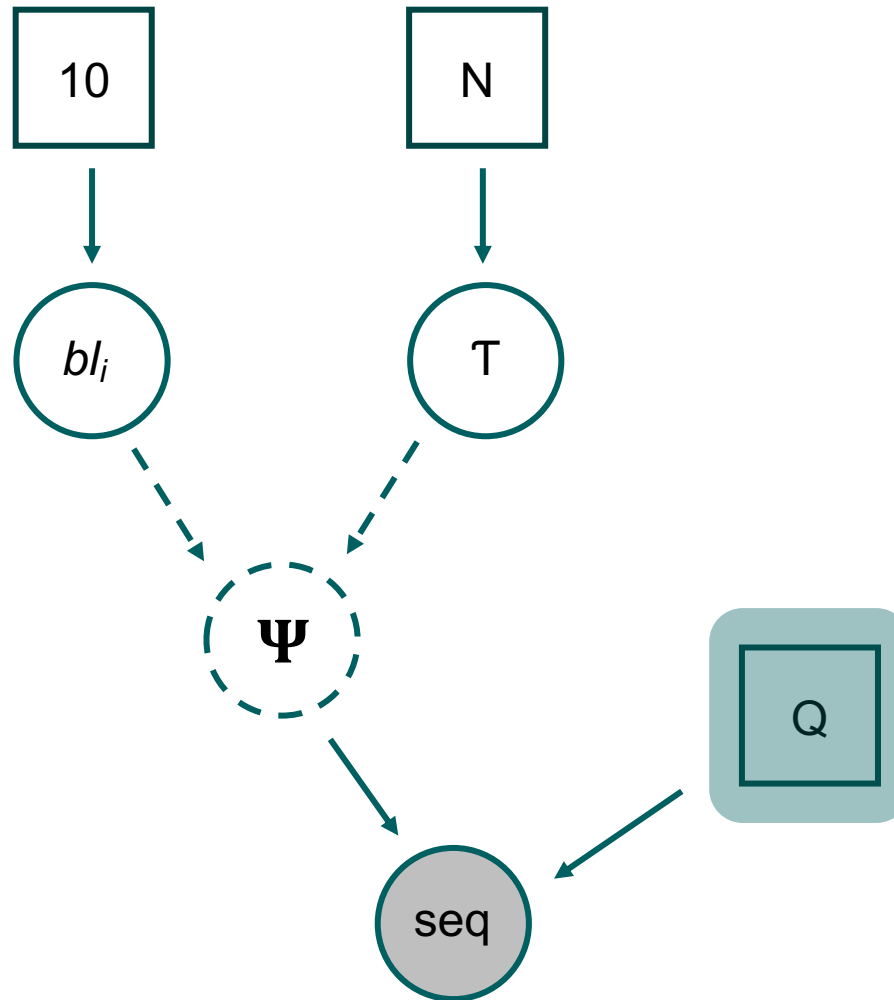
Trait 1		Trait 2
0	≠	0
1	≠	1

Generalising morphological data is much more difficult than molecular

[April Wright has an awesome paper about this stuff!](#)

Image from Bryan Shirley

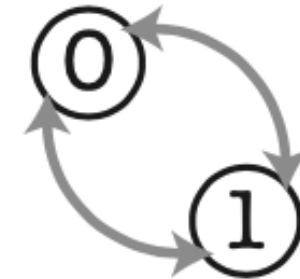
# Mk model – Lewis 2001



Generalised JC 69 model

# Mk model assumptions

It is a symmetric model : probability of changing from 0 to 1 same as 1 to 0

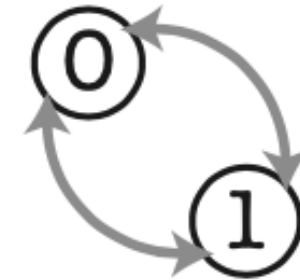




# Mk model assumptions

It is a symmetric model : probability of changing from 0 to 1 same as 1 to 0

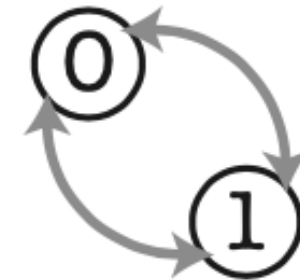
Characters are always in one of k states



# Mk model assumptions

It is a symmetric model : probability of changing from 0 to 1 same as 1 to 0

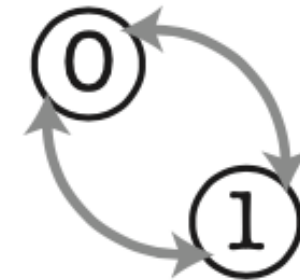
Characters are always in one of k states  
Character change from one state to another is instantaneous along a branch



# Mk model assumptions

It is a symmetric model : probability of changing from 0 to 1 same as 1 to 0

Characters are always in one of k states  
Character change from one state to another is instantaneous along a branch  
Changes are independent of each other



# Mk model assumptions

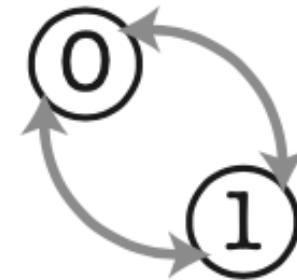
It is a symmetric model : probability of changing from 0 to 1 same as 1 to 0

Characters are always in one of k states

Character change from one state to another is instantaneous along a branch

Changes are independent of each other

No state is a priori ancestral or derived



# Extensions of the Mk model

It is possible to relax some of the assumptions of the MK model.

Extensions are included to account for factors that are considered important in morphological evolution.

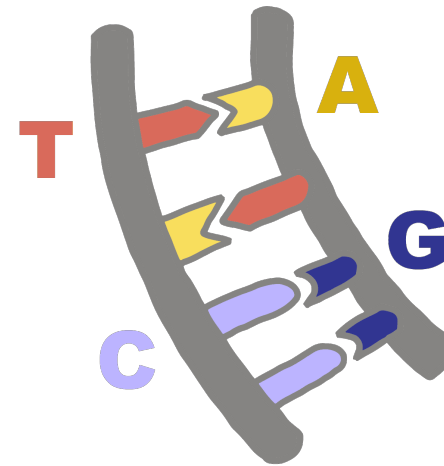
Aim to make the models closer to reality.

# MkV model

$$P(D \mid T, V) = \frac{Pr(D, V \mid T)}{Pr(V \mid T)}$$

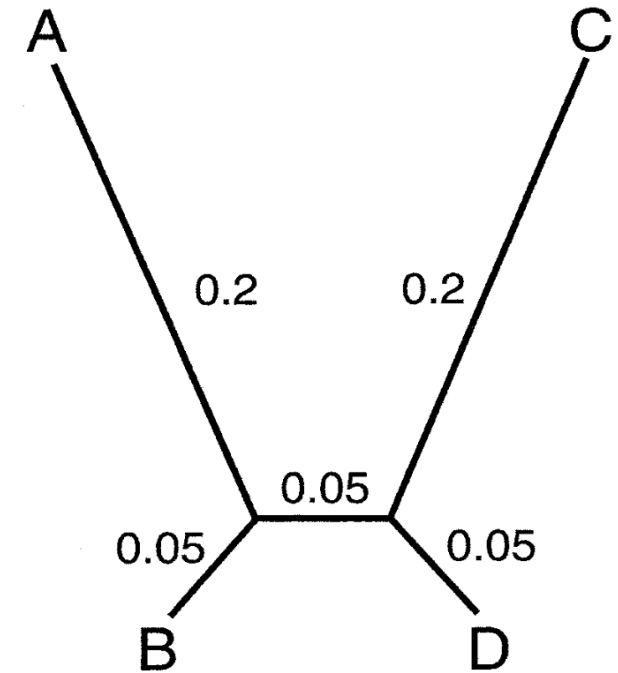


Corrects for the acquisition / ascertainment bias in your data



Lewis 2001

# MkV model



	True branch length	Mk (uncorrected)	Mkv (corrected)
Percent correct	—	74.0	99.8
Branch A	0.2	241,750 ( $\pm 349,100$ )	0.206 ( $\pm 0.060$ )
Branch B	0.05	0.43210 ( $\pm 0.13756$ )	0.050 ( $\pm 0.018$ )
Branch X	0.05	54.646 ( $\pm 1,725.3$ )	0.052 ( $\pm 0.023$ )
Branch C	0.2	143,950 ( $\pm 228,910$ )	0.206 ( $\pm 0.059$ )
Branch D	0.05	0.022 ( $\pm 0.054$ )	0.051 ( $\pm 0.019$ )

*Lewis 2001*

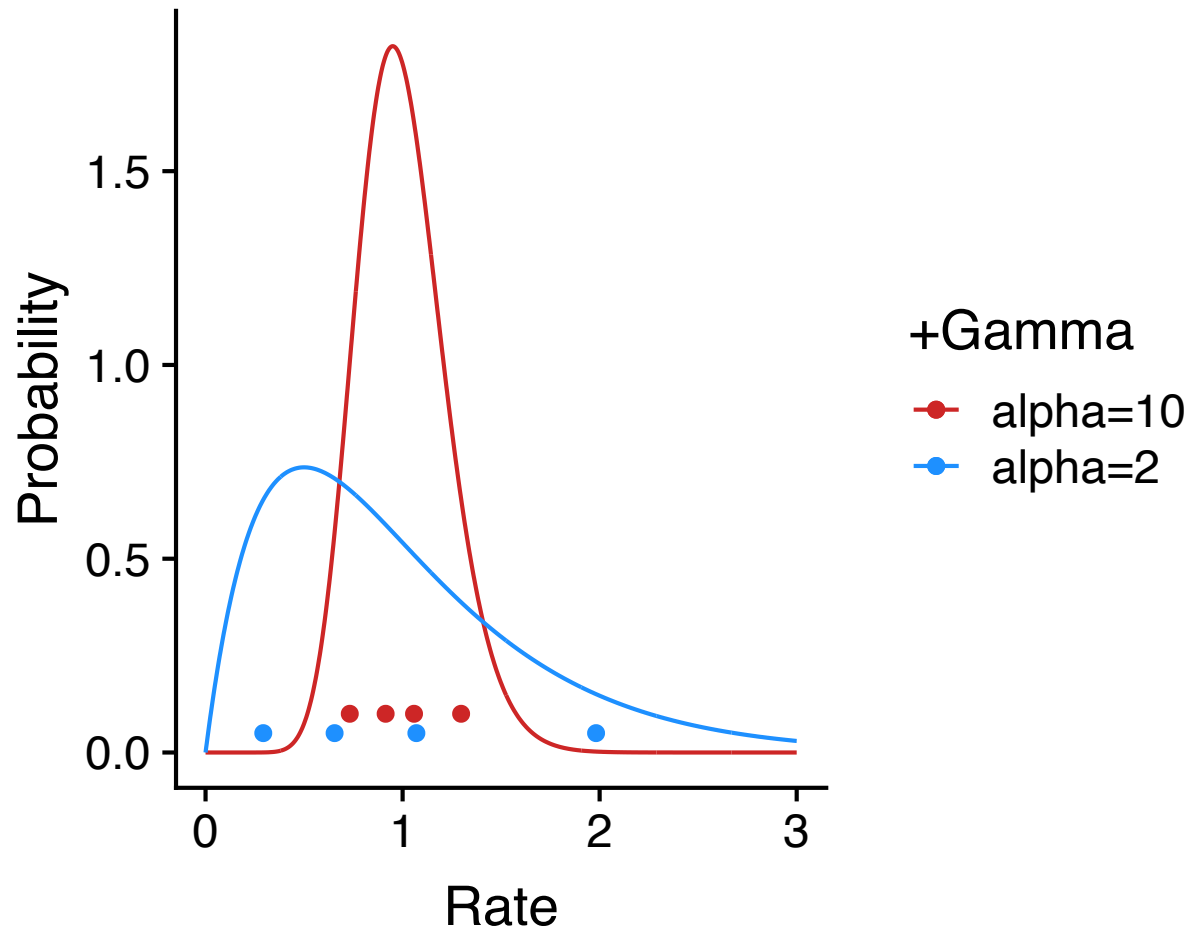


# Rates of morphological evolution

	Conodonts											
taxa 1	0	1	0	1	2	1	0	1	0	1	2	1
taxa 2	1	2	1	0	1	0	0	0	1	0	0	1
taxa 3	0	0	1	0	0	1	1	1	0	1	0	1
taxa 4	1	1	0	1	0	1	0	1	0	1	2	1

Unlikely that all characters evolve under same process

# Across site rate variation



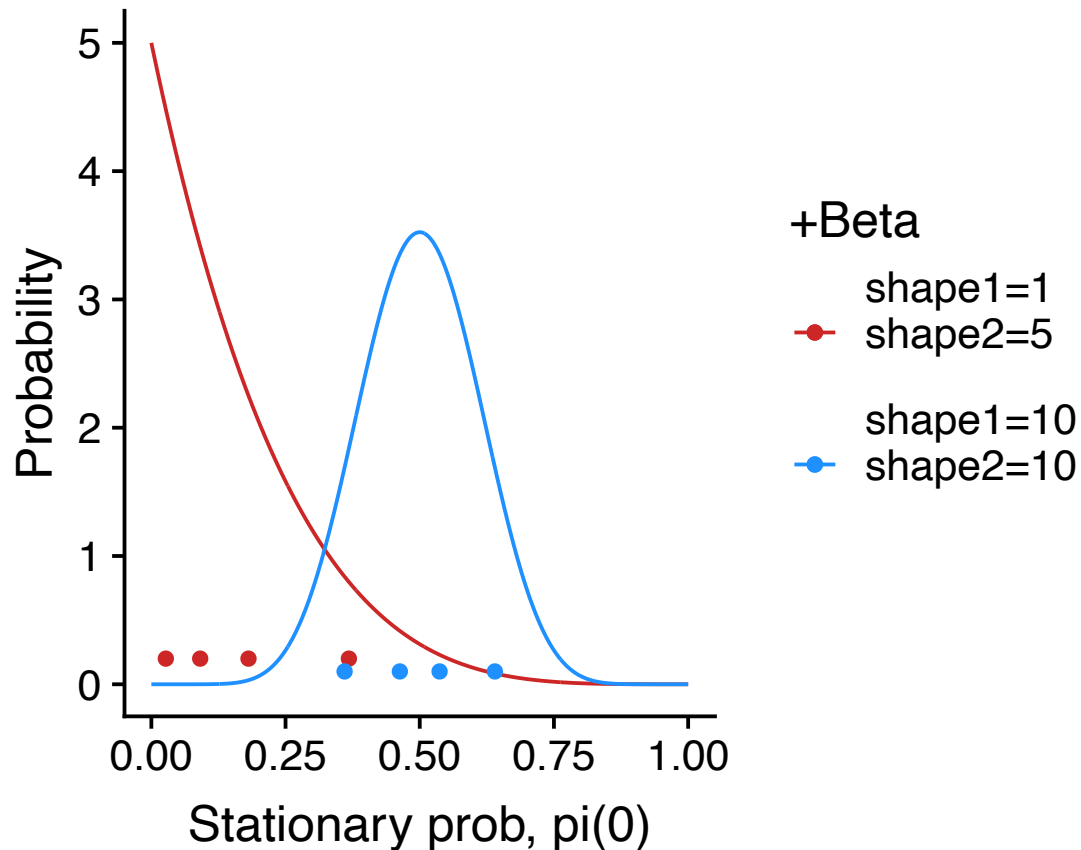
alpha = 10, the rates are similar  
alpha = 2 the rates differ

This approach allows faster evolving sites to evolve according to higher rates and visa versa

[Image](#) from Michael Landis

Yang 1994

# Allowing heterogeneity in character change symmetry



This model allows for unequal transitions between states.

Relaxing the assumption that the probability of changing from 0 to 1 is the same as 1 to 0

Uses state frequencies for transition probabilities – i.e. It may be very likely, in a character, to change from 0 to 1. But if the frequency of 0 is very low, we will still seldom see this change.

[Image](#) from Michael Landis

*Wright et al 2015*

# Partitioning the data

Partitioned analyses allow for different sets of homologous sites to evolve according to different sets of evolutionary parameters

Character sets might share  
number of states  
ancestral/derived polarity  
structure/order  
variability  
ontogeny  
function  
model fit

	Conodonts											
<b>taxa 1</b>	<b>0</b>	<b>1</b>	<b>0</b>	<b>1</b>	<b>2</b>	<b>1</b>	<b>0</b>	<b>1</b>	<b>0</b>	<b>1</b>	<b>2</b>	<b>1</b>
<b>taxa 2</b>	<b>1</b>	<b>2</b>	<b>1</b>	<b>0</b>	<b>1</b>	<b>0</b>	<b>0</b>	<b>0</b>	<b>1</b>	<b>0</b>	<b>0</b>	<b>1</b>
<b>taxa 3</b>	<b>0</b>	<b>0</b>	<b>1</b>	<b>0</b>	<b>0</b>	<b>1</b>	<b>1</b>	<b>1</b>	<b>0</b>	<b>1</b>	<b>0</b>	<b>1</b>
<b>taxa 4</b>	<b>1</b>	<b>1</b>	<b>0</b>	<b>1</b>	<b>0</b>	<b>1</b>	<b>0</b>	<b>1</b>	<b>0</b>	<b>1</b>	<b>2</b>	<b>1</b>

# Partitioning Morphological data sets

	Conodonts											
taxa 1	0	1	0	1	2	1	0	1	0	1	0	1
taxa 2	1	2	1	0	1	0	0	0	1	0	0	1
taxa 3	0	0	1	0	0	1	1	1	0	0	0	1
taxa 4	1	1	0	1	0	1	0	1	0	1	1	1

# Partitioning Morphological data sets

	Conodonts											
taxa 1	0	1	0	1	2	1	0	1	0	1	0	1
taxa 2	1	2	1	0	1	0	0	0	1	0	0	1
taxa 3	0	0	1	0	0	1	1	1	0	0	0	1
taxa 4	1	1	0	1	0	1	0	1	0	1	1	1



Anatomical



Ecological

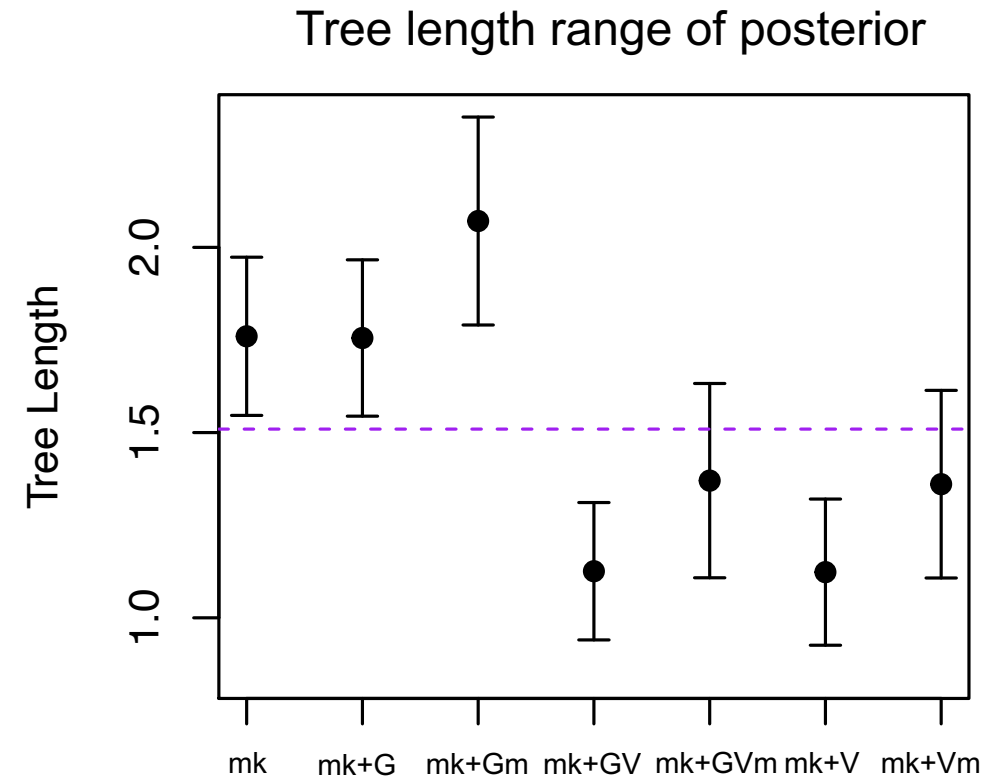
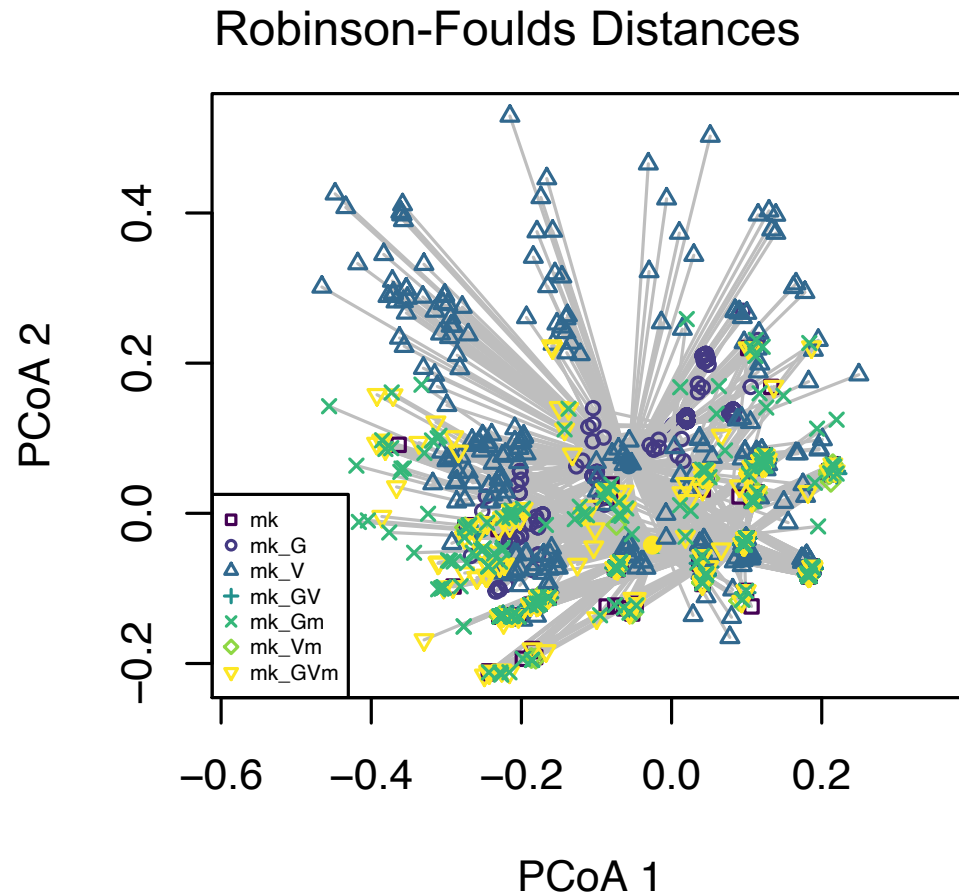


Behavioural

Does changing the substitution model really matter for empirical data?



# Impacts of substitution model on inferred parameters



(Mulvey et al in prep.)



# Exercise 1

Run an MCMC inference using **two** “versions” of the Mk model

