

Molecular Evolution

A Statistical Approach

ZIHENG YANG







Great Clarendon Street, Oxford, OX2 6DP, United Kingdom

Oxford University Press is a department of the University of Oxford. It furthers the University's objective of excellence in research, scholarship, and education by publishing worldwide. Oxford is a registered trade mark of Oxford University Press in the UK and in certain other countries

© Ziheng Yang 2014

The moral rights of the author have been asserted

First Edition published in 2014

Impression: 1

All rights reserved. No part of this publication may be reproduced, stored in a retrieval system, or transmitted, in any form or by any means, without the prior permission in writing of Oxford University Press, or as expressly permitted by law, by licence or under terms agreed with the appropriate reprographics rights organization. Enquiries concerning reproduction outside the scope of the above should be sent to the Rights Department, Oxford University Press, at the address above

You must not circulate this work in any other form and you must impose this same condition on any acquirer

Published in the United States of America by Oxford University Press 198 Madison Avenue, New York, NY 10016, United States of America

British Library Cataloguing in Publication Data

Data available

Library of Congress Control Number: 2013956540

ISBN 978-0-19-960260-5 (hbk.) ISBN 978-0-19-960261-2 (pbk.)

Printed and bound by CPI Group (UK) Ltd, Croydon, CRO 4YY

Links to third party websites are provided by Oxford in good faith and for information only. Oxford disclaims any responsibility for the materials contained in any third party website referenced in this work.

Molecular Evolution

Foreword

Over the last two decades, Ziheng Yang has been a leading architect of the emergent field of computational molecular evolution. His first book, *Computational Molecular Evolution*, was published in 2006 and became an instant classic. The book broke new ground both in terms of its subject matter and expository style. It presented an up-to-date, detailed, and comprehensive account of computational and statistical aspects of molecular evolutionary analysis, while retaining an informal style and pragmatic perspective that made it highly accessible. The book targeted a readership that included both biologists and applied mathematicians, yet it did not oversimplify in catering to biologists by avoiding advanced calculus or linear algebra, or pandering to mathematicians with the usual theorem-proof format. Somehow, this middle-of-the-road approach seems to have worked. Furthermore, despite the book's graduate textbook flavour the chapters were peppered with Yang's original interpretations and suggestions making it part textbook and part research monograph. Even individuals who were already experienced in computational evolutionary analysis will have gained new insights.

Yang's knowledge and practical experience are evident on every page of his new book, Molecular Evolution: A Statistical Approach. What is particularly remarkable is his ability to translate for non-specialists the key developments of this rapidly changing field so effectively. The content represents a significant expansion of his previous book; in particular, the treatment of Bayesian inference is much more extensive. Bayesian inference has become a cornerstone of phylogenetic inference over the last decade, as many programs such as MRBAYES and BEAST are now available which implement Markov chain Monte Carlo (MCMC) simulation methods for this purpose. The book devotes new chapters to the fundamentals of Bayesian inference and MCMC methodologies. Biologists using MCMC programs for molecular evolutionary analyses will benefit from the ground-up approach of these chapters, which introduce the basic principles using motivating examples based on evolutionary processes of obvious practical importance that will be familiar to molecular evolutionists. In this way, remarkably clear explanations are provided for such notoriously difficult concepts as reversible-jump MCMC, Dirichlet processes, Bayes factor calculations for model comparison, and so on. Several excellent books exist on phylogenetic inference, written from either an applied statistical perspective (Felsenstein 2004) or a more rigorous mathematical one (Semple and Steel 2003). However, I am unaware of any book that contains the extensive details found in Yang's book concerning the MCMC implementations (proposal moves, prior distributions, etc.) underlying currently available programs for Bayesian phylogenetic inference.

In this era of cheap next-generation sequencing, multi-locus genomic data are the new norm and therefore the distinction between inference of locus-specific gene trees and multi-locus species trees has become key. *Molecular Evolution: A Statistical Approach* thus contains a new chapter that covers the multi-species coalescent, species tree inference, and species delimitation methods. Yang has been a key contributor to the development of this theory during the last decade and provides one of the clearest explanations of the

vi FOREWORD

multi-species coalescent that I have read. For persons whose research interests include computational molecular evolution and molecular phylogenetics this new book from Ziheng Yang is essential reading.

Bruce Rannala

Davis, California April 2014

Preface

The main objective of this book is to present and explain the statistical methods and computational algorithms developed in molecular evolution, phylogenetics, and phylogeography for the comparative analysis of genetic sequence data. Reconstruction of molecular phylogeny and inference of the molecular evolutionary process are considered problems of statistical inference, and likelihood and Bayesian methods are treated in depth as standard methods of data analysis. Heuristic and approximate methods are discussed from such a viewpoint as well and are often used to introduce the central concepts, because of their simplicity and intuitive appeal. However, the book does not dwell on proofs or mathematical niceties: it emphasizes care but not rigour.

Molecular Evolution: A Statistical Approach represents an expanded and updated treatment of my earlier research monograph Computational Molecular Evolution, published by Oxford University Press in 2006. The major change has been the far more comprehensive and extensive coverage of Bayesian methods, while the target audience has been expanded to include upper level undergraduate as well as graduate students. It can also be read by researchers working in such diverse fields as evolutionary biology, molecular systematics, population genetics, statistical phylogeography, bioinformatics and computational biology, computer science, and computational statistics. It is hoped that biologists who have used software programs to analyse their own data will find the book particularly useful in helping them understand the principles of the methods. For applied mathematicians, molecular studies of evolution are 'a source of novel statistical problems' (Neyman 1971), and this book will provide an accessible summary of the exciting and often unconventional inference problems in the field, some of which are yet unsolved.

Although this new book is written at a similar level of mathematical sophistication as my 2006 work. I have taken care to assist the biologist readers who may find the mathematical arguments challenging. First, every important mathematical result is followed by a verbal rendering, and it is reportedly possible to read the book while skipping the equations, at least at first reading. Second, I have included numerous examples of real data analysis and numerical calculations to illustrate the theory, in addition to the working problems at the end of each chapter. Many biologists find numerical calculations less intimidating than abstract formulae. Example datasets and small C and R programs that implement computational algorithms discussed in the book are posted on the web site for the book: http://abacus.gene.ucl.ac.uk/MESA/. Third, I have prepared a primer on probability and statistics, with an overview of mathematical results used in this book, for biologists who would like to grapple with the mathematical details in the book. This has been used as the pre-course reading material for an advanced workshop on Computational Molecular Evolution (CoME) that runs annually in Hinxton, Cambridge, and Heraklion, Crete, co-organized by Aidan Budd, Nick Goldman, Alexandros Stamatakis, and me. It is available at: http://abacus.gene.ucl.ac.uk/PPS/PrimerProbabilityStatistics.pdf.

The 2006 book was used as a textbook for graduate courses on bioinformatics and computational genomics in Peking University (2010) and in ETH Zurich (2011). I thank the students in those courses for their useful feedback. For instructors, I have found an early

coverage of the simulation chapter to be useful, as afterwards simulation projects can be assigned as homework when other chapters are taught.

I am grateful to a number of colleagues who read earlier drafts of chapters of this book and provided constructive comments and criticisms: Konstantinos Angelis, Mario dos Reis, Ed Susko, Chi Zhang, and Tianqi Zhu. The following colleagues read and commented on Chapter 9: Daniel Dalquen, Adam Leaché, Liang Liu, and Jim Mallet. Needless to say, all errors that remain are mine. (Please report errors and typos you discover to me at z.yang@ucl.ac.uk. Errata will be posted on the book's web site.) Thanks are also due to Helen Eaton, Lucy Nash, and Ian Sherman at Oxford University Press for their support and patience throughout the project.

Ziheng Yang

London
April 2014

Contents

1	Mod	dels of	f nucleotide substitution	1
	1.1	Introd	duction	1
	1.2	Marko	ov models of nucleotide substitution and distance estimation	4
		1.2.1	The JC69 model	4
		1.2.2	The K80 model	7
		1.2.3	HKY85, F84, TN93, etc.	9
		1.2.4	The transition/transversion rate ratio	13
	1.3	Varial	ole substitution rates across sites	15
	1.4	Maxii	num likelihood estimation of distance	17
		1.4.1	The JC69 model	18
		1.4.2	The K80 model	22
		1.4.3	Likelihood ratio test of substitution models	22
		*1.4.4	Profile and integrated likelihood methods	24
	1.5	Marko	ov chains and distance estimation under general models	26
		1.5.1	Markov chains	26
		*1.5.2	Distance under the unrestricted (UNREST) model	27
		*1.5.3	Distance under the general time-reversible model	29
	1.6	Discu	ssions	32
		1.6.1	Distance estimation under different substitution models	32
		1.6.2	Limitations of pairwise comparison	32
	1.7	Proble	ems	33
2	Mod	dels of	amino acid and codon substitution	35
	2.1	Introd	duction	35
	2.2	Mode	ls of amino acid replacement	35
			Empirical models	35
		2.2.2		39
		2.2.3	Among-site heterogeneity	39
	2.3	Estim	ation of distance between two protein sequences	40
		2.3.1	The Poisson model	40
		2.3.2	Empirical models	41
		2.3.3	Gamma distances	41
	2.4	Mode	ls of codon substitution	42
		2.4.1	The basic model	42
		2.4.2	Variations and extensions	44
	2.5	Estim	ation of d_S and d_N	47
		2.5.1	Counting methods	47
		2.5.2	Maximum likelihood method	55

		252	Comparison of methods	57		
		2.5.4	More distances and interpretation of the d_N/d_S ratio	58		
		2.5.5	Estimation of d_S and d_N in comparative genomics	61		
			Distances based on the physical-site definition	63		
			Utility of the distance measures	65		
	*2.6		erical calculation of the transition probability matrix	65		
	2.7	Proble		68		
	2.7	TIODI	elli3	00		
3	Phy	ylogeny reconstruction: overview				
	3.1	Tree c	oncepts	70		
		3.1.1	Terminology	70		
		3.1.2	Species trees and gene trees	79		
		3.1.3	Classification of tree reconstruction methods	81		
	3.2	Exhau	astive and heuristic tree search	82		
		3.2.1	Exhaustive tree search	82		
		3.2.2	Heuristic tree search	82		
		3.2.3	Branch swapping	84		
		3.2.4	Local peaks in the tree space	86		
		3.2.5	Stochastic tree search	88		
	3.3	Distar	nce matrix methods	88		
		3.3.1	Least-squares method	89		
		3.3.2	Minimum evolution method	91		
		3.3.3	Neighbour-joining method	91		
	3.4	Maxir	num parsimony	95		
		3.4.1	Brief history	95		
		3.4.2	Counting the minimum number of changes on a tree	95		
		3.4.3	Weighted parsimony and dynamic programming	96		
		3.4.4	Probabilities of ancestral states	99		
		3.4.5	Long-branch attraction	99		
	And the second	3.4.6	Assumptions of parsimony	100		
	3.5	Proble	ems	101		
4	Max	imum	likelihood methods	102		
	4.1	Introd	luction	102		
	4.2	Likelil	hood calculation on tree	102		
		4.2.1	Data, model, tree, and likelihood	102		
		4.2.2	The pruning algorithm	103		
		4.2.3	Time reversibility, the root of the tree, and the molecular clock	107		
		4.2.4	A numerical example: phylogeny of apes	108		
		4.2.5	Amino acid, codon, and RNA models	110		
		*4.2.6	Missing data, sequence errors, and alignment gaps	110		
	4.3	Likelil	hood calculation under more complex models	114		
		4.3.1	Mixture models for variable rates among sites	114		
		4.3.2	Mixture models for pattern heterogeneity among sites	122		
		4.3.3	Partition models for combined analysis of multiple datasets	123		
		4.3.4	Nonhomogeneous and nonstationary models	125		

xi

	4.4	Reconstruction of ancestral states	125
		4.4.1 Overview	125
		4.4.2 Empirical and hierarchical Bayesian reconstruction	127
		*4.4.3 Discrete morphological characters	130
		4.4.4 Systematic biases in ancestral reconstruction	131
	*4.5	Numerical algorithms for maximum likelihood estimation	133
		*4.5.1 Univariate optimization	134
		*4.5.2 Multivariate optimization	136
	4.6	ML optimization in phylogenetics	138
		4.6.1 Optimization on a fixed tree	138
		4.6.2 Multiple local peaks on the likelihood surface for a fixed tree	139
		4.6.3 Search in the tree space	140
		4.6.4 Approximate likelihood method	143
	4.7	Model selection and robustness	144
		4.7.1 Likelihood ratio test applied to rbcL dataset	144
		4.7.2 Test of goodness of fit and parametric bootstrap	146
		*4.7.3 Diagnostic tests to detect model violations	147
		4.7.4 Akaike information criterion (AIC and AIC $_c$)	148
		4.7.5 Bayesian information criterion	149
		4.7.6 Model adequacy and robustness	150
	4.8	Problems	151
	Con	parison of phylogenetic methods and tests on trees	153
	5.1	Statistical performance of tree reconstruction methods	153
	5.1	5.1.1 Critéria	154
		5.1.2 Performance	156
	5.2	Likelihood	157
	0.2	5.2.1 Contrast with conventional parameter estimation	157
		5.2.2 Consistency	158
		5.2.3 Efficiency	159
		5.2.4 Robustness	163
	5.3	Parsimony	165
		5.3.1 Equivalence with misbehaved likelihood models	165
		5.3.2 Equivalence with well-behaved likelihood models	168
		5.3.3 Assumptions and justifications	169
	5.4	Testing hypotheses concerning trees	171
		5.4.1 Bootstrap	172
		5.4.2 Interior-branch test	177
		5.4.3 K-H test and related tests	178
		5.4.4 Example: phylogeny of apes	179
		5.4.5 Indexes used in parsimony analysis	180
	5.5	Problems	18
5	Ray	esian theory	182
		*	
	6.1	Overview	182
	6.2	The Bayesian paradigm	183

		6.2.1	The Bayes theorem	183
		6.2.2	The Bayes theorem in Bayesian statistics	184
		*6.2.3		189
	6.3	Prior		197
		6.3.1	Methods of prior specification	197
		6.3.2	Conjugate priors	198
		6.3.3	Flat or uniform priors	199
		*6.3.4	The Jeffreys priors	200
			The reference priors	202
	6.4		ods of integration	203
			Laplace approximation	203
		6.4.2	Mid-point and trapezoid methods	204
		6.4.3	Gaussian quadrature	205
		6.4.4	Marginal likelihood calculation for JC69 distance estimation	206
		6.4.5	Monte Carlo integration	210
		6.4.6	Importance sampling	210
	6.5	Proble	ems	212
7	Bay	esian	computation (MCMC)	214
	7.1	Marko	ov chain Monte Carlo	214
		7.1.1	Metropolis algorithm	214
		7.1.2	Asymmetrical moves and proposal ratio	218
		7.1.3	The transition kernel	219
		7.1.4	Single-component Metropolis-Hastings algorithm	220
		7.1.5	Gibbs sampler	221
	7.2	Simpl	e moves and their proposal ratios	221
		7.2.1	Sliding window using the uniform proposal	222
		7.2.2	Sliding window using the normal proposal	223
		7.2.3	Bactrian proposal	223
		7.2.4	Sliding window using the multivariate normal proposal	224
		7.2.5	Proportional scaling	225
		7.2.6	Proportional scaling with bounds	226
	7.3	Conv	ergence, mixing, and summary of MCMC	226
		7.3.1	Convergence and tail behaviour	226
		7.3.2	Mixing efficiency, jump probability, and step length	230
		7.3.3	Validating and diagnosing MCMC algorithms	241
		7.3.4	Potential scale reduction statistic	242
		7.3.5	Summary of MCMC output	243
	7.4	Advar	nced Monte Carlo methods	244
		7.4.1	Parallel tempering (MC ³)	245
		7.4.2	Trans-model and trans-dimensional MCMC	247
		7.4.3	Bayes factor and marginal likelihood	256
	7.5	Proble	ems	260
8	Ray	acian :	phylogenetics	2/2
0				263
	8.1	Overv		263
		8.1.1	Historical background	263

		8.1.2	A sketch MCMC algorithm	264
		8.1.3	The statistical nature of phylogeny estimation	264
	8.2	Model	s and priors in Bayesian phylogenetics	266
		8.2.1	Priors on branch lengths	266
		8.2.2	Priors on parameters in substitution models	269
		8.2.3	Priors on tree topology	276
	8.3	MCMO	C proposals in Bayesian phylogenetics	279
		8.3.1	Within-tree moves	279
		8.3.2	Cross-tree moves	281
		8.3.3	NNI for unrooted trees	284
		8.3.4	SPR for unrooted trees	287
		8.3.5	TBR for unrooted trees	289
		8.3.6	Subtree swapping	291
		8.3.7	NNI for rooted trees	292
		8.3.8	SPR on rooted trees	293
		8.3.9	Node slider	294
	8.4	Summ	arizing MCMC output	295
	8.5	High I	posterior probabilities for trees	296
		8.5.1	High posterior probabilities for trees or splits	296
		8.5.2	Star tree paradox	298
		*8.5.3	Fair coin paradox, fair balance paradox, and Bayesian model selection	300
		8.5.4	Conservative Bayesian phylogenetics	305
	8.6	Proble	ems	306
^			A the amy and enceing type	
9	Coa	lescen	t theory and species trees	308
9	Coa 9.1	lescen Overv		308 308
9		Overv		
9	9.1	Overv	iew	308
9	9.1	Overv The co	iew palescent model for a single species	308 309
9	9.1	Overv The co	iew palescent model for a single species The backward time machine	308 309 309
9	9.1	Overv The co 9.2.1 9.2.2	iew palescent model for a single species The backward time machine Fisher–Wright model and the neutral coalescent	308 309 309 309
9	9.1	Overv The co 9.2.1 9.2.2 9.2.3	iew balescent model for a single species The backward time machine Fisher–Wright model and the neutral coalescent A sample of <i>n</i> genes	308 309 309 309 312
9	9.1	Overv The co 9.2.1 9.2.2 9.2.3 9.2.4 9.2.5	iew coalescent model for a single species The backward time machine Fisher–Wright model and the neutral coalescent A sample of <i>n</i> genes Simulating the coalescent	308 309 309 309 312 315
9	9.1 9.2	Overv The co 9.2.1 9.2.2 9.2.3 9.2.4 9.2.5	tiew coalescent model for a single species The backward time machine Fisher–Wright model and the neutral coalescent A sample of n genes Simulating the coalescent Estimation of θ from a sample of DNA sequences	308 309 309 309 312 315 316
9	9.1 9.2	Overv The co 9.2.1 9.2.2 9.2.3 9.2.4 9.2.5 Popula	tiew balescent model for a single species The backward time machine Fisher–Wright model and the neutral coalescent A sample of n genes Simulating the coalescent Estimation of θ from a sample of DNA sequences ation demographic process	308 309 309 309 312 315 316 320 321 322
9	9.1 9.2	Overv The co 9.2.1 9.2.2 9.2.3 9.2.4 9.2.5 Popula 9.3.1	iew balescent model for a single species The backward time machine Fisher–Wright model and the neutral coalescent A sample of n genes Simulating the coalescent Estimation of θ from a sample of DNA sequences ation demographic process Homogeneous and nonhomogeneous Poisson processes	308 309 309 309 312 315 316 320 321
9	9.1 9.2	Overv The co 9.2.1 9.2.2 9.2.3 9.2.4 9.2.5 Popula 9.3.1 9.3.2 9.3.3	tiew coalescent model for a single species The backward time machine Fisher–Wright model and the neutral coalescent A sample of n genes Simulating the coalescent Estimation of θ from a sample of DNA sequences ation demographic process Homogeneous and nonhomogeneous Poisson processes Deterministic population size change	308 309 309 309 312 315 316 320 321 322
9	9.1 9.2 9.3	Overv The co 9.2.1 9.2.2 9.2.3 9.2.4 9.2.5 Popula 9.3.1 9.3.2 9.3.3	biew balescent model for a single species The backward time machine Fisher–Wright model and the neutral coalescent A sample of n genes Simulating the coalescent Estimation of θ from a sample of DNA sequences ation demographic process Homogeneous and nonhomogeneous Poisson processes Deterministic population size change Nonparametric population demographic models	308 309 309 309 312 315 316 320 321 322 323
9	9.1 9.2 9.3	Overv The co 9.2.1 9.2.2 9.2.3 9.2.4 9.2.5 Popula 9.3.1 9.3.2 9.3.3 Multis	iew balescent model for a single species The backward time machine Fisher–Wright model and the neutral coalescent A sample of n genes Simulating the coalescent Estimation of θ from a sample of DNA sequences ation demographic process Homogeneous and nonhomogeneous Poisson processes Deterministic population size change Nonparametric population demographic models species coalescent, species trees and gene trees	308 309 309 309 312 315 316 320 321 322 323 325 325 331
9	9.1 9.2 9.3	Overv The co 9.2.1 9.2.2 9.2.3 9.2.4 9.2.5 Popula 9.3.1 9.3.2 9.3.3 Multis 9.4.1	iew balescent model for a single species The backward time machine Fisher–Wright model and the neutral coalescent A sample of n genes Simulating the coalescent Estimation of θ from a sample of DNA sequences ation demographic process Homogeneous and nonhomogeneous Poisson processes Deterministic population size change Nonparametric population demographic models species coalescent, species trees and gene trees Multispecies coalescent	308 309 309 309 312 315 316 320 321 322 323 325 325
9	9.1 9.2 9.3	Overv The co 9.2.1 9.2.2 9.2.3 9.2.4 9.2.5 Popula 9.3.1 9.3.2 9.3.3 Multis 9.4.1	palescent model for a single species The backward time machine Fisher–Wright model and the neutral coalescent A sample of n genes Simulating the coalescent Estimation of θ from a sample of DNA sequences ation demographic process Homogeneous and nonhomogeneous Poisson processes Deterministic population size change Nonparametric population demographic models species coalescent, species trees and gene trees Multispecies coalescent Species tree–gene tree conflict	308 309 309 309 312 315 316 320 321 322 323 325 325 331
9	9.1 9.2 9.3	Overv The co 9.2.1 9.2.2 9.2.3 9.2.4 9.2.5 Popula 9.3.1 9.3.2 9.3.3 Multis 9.4.1 9.4.2 9.4.3 9.4.4	palescent model for a single species The backward time machine Fisher–Wright model and the neutral coalescent A sample of n genes Simulating the coalescent Estimation of θ from a sample of DNA sequences ation demographic process Homogeneous and nonhomogeneous Poisson processes Deterministic population size change Nonparametric population demographic models species coalescent, species trees and gene trees Multispecies coalescent Species tree–gene tree conflict Estimation of species trees	308 309 309 309 312 315 316 320 321 322 323 325 325 331 335
9	9.1 9.2 9.3	Overv The co 9.2.1 9.2.2 9.2.3 9.2.4 9.2.5 Popula 9.3.1 9.3.2 9.3.3 Multis 9.4.1 9.4.2 9.4.3 9.4.4	iew balescent model for a single species The backward time machine Fisher–Wright model and the neutral coalescent A sample of n genes Simulating the coalescent Estimation of θ from a sample of DNA sequences ation demographic process Homogeneous and nonhomogeneous Poisson processes Deterministic population size change Nonparametric population demographic models species coalescent, species trees and gene trees Multispecies coalescent Species tree–gene tree conflict Estimation of species trees Migration	308 309 309 312 315 316 320 321 322 323 325 325 331 335 343
9	9.1 9.2 9.3	Overv The co 9.2.1 9.2.2 9.2.3 9.2.4 9.2.5 Popula 9.3.1 9.3.2 9.3.3 Multis 9.4.1 9.4.2 9.4.3 9.4.4 Specie	calescent model for a single species The backward time machine Fisher–Wright model and the neutral coalescent A sample of n genes Simulating the coalescent Estimation of θ from a sample of DNA sequences ation demographic process Homogeneous and nonhomogeneous Poisson processes Deterministic population size change Nonparametric population demographic models species coalescent, species trees and gene trees Multispecies coalescent Species tree–gene tree conflict Estimation of species trees Migration es delimitation	308 309 309 309 312 315 316 320 321 322 323 325 325 331 335 343 349

			The impact of guide tree, prior, and migration	355
		9.5.5	Pros and cons of Bayesian species delimitation	358
	9.6	Proble	ems	359
10	Mole	ecular	clock and estimation of species divergence times	361
	10.1	Overv	iew	361
	10.2	Tests o	of the molecular clock	363
			Relative-rate tests	363
			Likelihood ratio test	364
		10.2.3	Limitations of molecular clock tests	365
		10.2.4	Index of dispersion	366
	10.3	Likelil	nood estimation of divergence times	366
			Global clock model	366
		10.3.2	Local clock model	367
		10.3.3	Heuristic rate-smoothing methods	368
		10.3.4	Uncertainties in calibrations	370
		10.3.5	Dating viral divergences	372
		10.3.6	Dating primate divergences	373
	10.4	Bayesi	an estimation of divergence times	375
		10.4.1	General framework	375
		10.4.2	Approximate calculation of likelihood	376
			Prior on evolutionary rates	377
			Prior on divergence times and fossil calibrations	378
			Uncertainties in time estimates	382
			Dating viral divergences	384
			Application to primate and mammalian divergences	385
		Perspe		388
	10.6	Proble	ems	389
11	Neu	tral ar	nd adaptive protein evolution	390
	11.1	Introd	luction	390
	11.2	The n	eutral theory and tests of neutrality	391
			The neutral and nearly neutral theories	391
			Tajima's D statistic	393
			Fu and Li's D, and Fay and Wu's H statistics	394
			McDonald-Kreitman test and estimation of selective strength	395
		11.2.5	Hudson-Kreitman-Aquade test	397
	11.3	Lineag	ges undergoing adaptive evolution	398
		11.3.1	Heuristic methods	398
		11.3.2	Likelihood method	399
	11.4	Amino	o acid sites undergoing adaptive evolution	400
			Three strategies	400
			Likelihood ratio test of positive selection under random-site models	402
			Identification of sites under positive selection	405
			Positive selection at the human MHC	406

	11.5	Adaptive evolution affecting particular sites and lineages	408
		11.5.1 Branch-site test of positive selection	408
		11.5.2 Other similar models	409
		11.5.3 Adaptive evolution in angiosperm phytochromes	410
	11.6	Assumptions, limitations, and comparisons	411
		11.6.1 Assumptions and limitations of current methods	412
		11.6.2 Comparison of methods for detecting positive selection	413
	11.7	Adaptively evolving genes	414
	11.8	Problems	416
12	Sim	ulating molecular evolution	418
	12.1	Introduction	418
	12.2	Random number generator	418
		Generation of discrete random variables	420
	==	12.3.1 Inversion method for sampling from a general discrete distribution	420
		12.3.2 The alias method for sampling from a discrete distribution	421
		12.3.3 Discrete uniform distribution	422
		12.3.4 Binomial distribution	423
		12.3.5 The multinomial distribution	423
		12.3.6 The Poisson distribution	423
		12.3.7 The composition method for mixture distributions	424
	12.4	Generation of continuous random variables	424
		12.4.1 The inversion method	425
		12.4.2 The transformation method	425
		12.4.3 The rejection method	425
		12.4.4 Generation of a standard normal variate using the polar method	428
		12.4.5 Gamma, beta, and Dirichlet variables	430
	12.5	Simulation of Markov processes	430
		12.5.1 Simulation of the Poisson process	430
		12.5.2 Simulation of the nonhomogeneous Poisson process	431
		12.5.3 Simulation of discrete-time Markov chains	433
		12.5.4 Simulation of continuous-time Markov chains	435
	12.6	Simulating molecular evolution	436
		12.6.1 Simulation of sequences on a fixed tree	436
		12.6.2 Simulation of random trees	439
	12.7	Validation of the simulation program	439
	12.8	Problems	440
Ар	pend	ices	442
	Арре	endix A. Functions of random variables	442
		endix B. The delta technique	446
		endix C. Phylogenetic software	448
Refe	rences		450
	dex		

Reader note: The asterisk next to a heading indicates a more difficult or technical section/problem.

Models of nucleotide substitution

1.1 Introduction

Calculation of the distance between two sequences is perhaps the simplest phylogenetic analysis, yet it is important for two reasons. First, calculation of pairwise distances is the first step in distance matrix methods of phylogeny reconstruction, which use cluster algorithms to convert a distance matrix into a phylogenetic tree. Second, Markov process models of nucleotide substitution used in distance calculation form the basis of likelihood and Bayesian methods of phylogeny reconstruction. Indeed, joint analysis of multiple sequences can be viewed as a natural extension of pairwise distance calculation. Thus, besides discussing distance estimation, this chapter introduces the theory of Markov chains used in modelling nucleotide substitutions in a DNA sequence. It also introduces the method of maximum likelihood (ML). Bayesian estimation of pairwise distances and Bayesian phylogenetics are introduced in Chapters 6–8.

The distance between two sequences is defined as the expected number of nucleotide substitutions per site. If the evolutionary rate is constant over time, the distance will increase linearly with the time of divergence. A simplistic distance measure is the proportion of different sites, sometimes called the p distance. If 10 sites are different between two sequences, each 100 nucleotides long, then p = 10% = 0.1. This raw proportion works fine for very closely related sequences but is otherwise a clear underestimate of the number of substitutions that have occurred. A variable site may result from more than one substitution, and even a constant site, with the same nucleotide observed in the two sequences, may harbour back or parallel substitutions (Figure 1.1). Multiple substitutions at the same site or *multiple hits* cause some changes to be hidden. As a result, p is not a linear function of evolutionary time. Thus the raw proportion p is usable only for highly similar sequences, with p < 5%, say.

To estimate the number of substitutions, we need a probabilistic model to describe changes between nucleotides over evolutionary time. Continuous-time Markov chains are commonly used for this purpose. The nucleotide sites in the sequence are assumed to be evolving independently of each other. Substitutions at any particular site are described by a Markov chain, with the four nucleotides to be the *states* of the chain. The main feature of a Markov chain is that it has no memory: 'given the present, the future does not depend on the past'. In other words, the probability with which the chain jumps into other nucleotide states depends on the current state, but not on how the current state is reached. This is known as the *Markovian property*. Besides this basic assumption, we often place further constraints on substitution rates between nucleotides, leading to

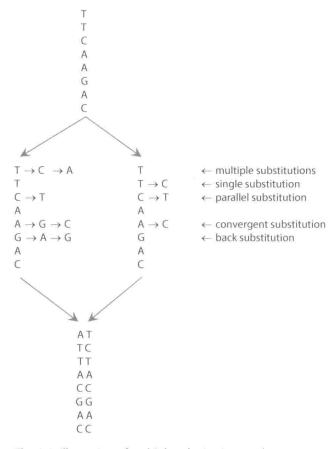


Fig. 1.1 Illustration of multiple substitutions at the same site or multiple hits. An ancestral sequence has diverged into two sequences and has since accumulated nucleotide substitutions independently along the two lineages. Only two differences are observed between the two present-day sequences, so that the proportion of different sites is $\hat{p} = 2/8 = 0.25$, while in fact as many as 10 substitutions (seven on the left lineage and three on the right lineage) occurred so that the true distance is 10/8 = 1.25 substitutions per site. Constructed following Graur and Li (2000).

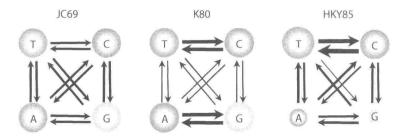


Fig. 1.2 Relative substitution rates between nucleotides under three Markov chain models of nucleotide substitution: JC69, K80, and HKY85. The thickness of the lines represents the substitution rates, while the sizes of the circles represent the steady-state distribution.