

# AUTO

POPULATION SIZE, MIGRATION, DIVERGENCE, ASSIGNMENT, HISTORY

Bayesian inference using the structured coalescent

Migrate-n version 5.0.0a [May-20-2017]

Using Intel AVX (Advanced Vector Extensions)

Compiled for PARALLEL computer architectures

One master and 100 compute nodes are available.

Program started at Sun Aug 13 05:22:37 2017

Program finished at Sun Aug 13 06:46:42 2017 [Runtime:0000:01:24:05]



## Options

Datatype:

DNA sequence data

Inheritance scalers in use for Thetas:

All loci use an inheritance scaler of 1.0

[The locus with a scaler of 1.0 used as reference]

Random number seed:

(with internal timer)

2809592585

Start parameters:

Theta values were generated

Using a percent value of the prior

M values were generated

Using a percent value of the prior

Connection matrix:

m = average (average over a group of Thetas or M,

s = symmetric migration M, S = symmetric 4Nm,

0 = zero, and not estimated,

\* = migration free to vary, Thetas are on diagonal

d = row population split off column population, D = split and then migration

Population 1

1 Romanshorn\_0 \*

Order of parameters:

1  $\Theta_1$

<displayed>

Mutation rate among loci:

Mutation rate is constant for all loci

Analysis strategy:

Bayesian inference

-Population size estimation:

Exponential Distribution

Proposal distributions for parameter

Parameter	Proposal
Theta	Metropolis sampling
M	Metropolis sampling
Divergence	Metropolis sampling
Divergence Spread	Metropolis sampling
Genealogy	Metropolis-Hastings

Prior distribution for parameter

Parameter	Prior	Minimum	Mean	Maximum	Delta	Bins	UpdateFreq
1	Theta -11 Uniform	0.000000	0.050	0.100	0.010	1500	0.20000

[-1 -1 means priors were set globally]

Markov chain settings:

Long chain

Number of chains

1

Recorded steps [a]

50000

Increment (record every x step [b])

200

Number of concurrent chains (replicates) [c]

2

Visited (sampled) parameter values [a\*b\*c]

20000000

Number of discard trees per chain (burn-in)

10000

Multiple Markov chains:

Static heating scheme

4 chains with temperatures

1000000.00

3.00

1.50

1.00

Swapping interval is 1

Print options:

Data file:

infile.1.0

Haplotyping is turned on:

NO

Output file:

outfile\_1.0\_0.5

Posterior distribution raw histogram file:

bayesfile

Raw data from the MCMC run:

bayesallfile\_1.0\_0.5

Print data:

No

Print genealogies [only some for some data type]:

None

## Data summary

Data file: infile.1.0  
 Datatype: Sequence data  
 Number of loci: 100

Mutationmodel:

Locus	Sublocus	Mutationmodel	Mutationmodel parameters
-------	----------	---------------	--------------------------

1	1	Jukes-Cantor	[Basefreq: =0.25]
2	1	Jukes-Cantor	[Basefreq: =0.25]
3	1	Jukes-Cantor	[Basefreq: =0.25]
4	1	Jukes-Cantor	[Basefreq: =0.25]
5	1	Jukes-Cantor	[Basefreq: =0.25]
6	1	Jukes-Cantor	[Basefreq: =0.25]
7	1	Jukes-Cantor	[Basefreq: =0.25]
8	1	Jukes-Cantor	[Basefreq: =0.25]
9	1	Jukes-Cantor	[Basefreq: =0.25]
10	1	Jukes-Cantor	[Basefreq: =0.25]
11	1	Jukes-Cantor	[Basefreq: =0.25]
12	1	Jukes-Cantor	[Basefreq: =0.25]
13	1	Jukes-Cantor	[Basefreq: =0.25]
14	1	Jukes-Cantor	[Basefreq: =0.25]
15	1	Jukes-Cantor	[Basefreq: =0.25]
16	1	Jukes-Cantor	[Basefreq: =0.25]
17	1	Jukes-Cantor	[Basefreq: =0.25]
18	1	Jukes-Cantor	[Basefreq: =0.25]
19	1	Jukes-Cantor	[Basefreq: =0.25]
20	1	Jukes-Cantor	[Basefreq: =0.25]
21	1	Jukes-Cantor	[Basefreq: =0.25]
22	1	Jukes-Cantor	[Basefreq: =0.25]
23	1	Jukes-Cantor	[Basefreq: =0.25]
24	1	Jukes-Cantor	[Basefreq: =0.25]
25	1	Jukes-Cantor	[Basefreq: =0.25]
26	1	Jukes-Cantor	[Basefreq: =0.25]
27	1	Jukes-Cantor	[Basefreq: =0.25]
28	1	Jukes-Cantor	[Basefreq: =0.25]
29	1	Jukes-Cantor	[Basefreq: =0.25]
30	1	Jukes-Cantor	[Basefreq: =0.25]
31	1	Jukes-Cantor	[Basefreq: =0.25]
32	1	Jukes-Cantor	[Basefreq: =0.25]
33	1	Jukes-Cantor	[Basefreq: =0.25]
34	1	Jukes-Cantor	[Basefreq: =0.25]

35	1	Jukes-Cantor	[Basefreq: =0.25]
36	1	Jukes-Cantor	[Basefreq: =0.25]
37	1	Jukes-Cantor	[Basefreq: =0.25]
38	1	Jukes-Cantor	[Basefreq: =0.25]
39	1	Jukes-Cantor	[Basefreq: =0.25]
40	1	Jukes-Cantor	[Basefreq: =0.25]
41	1	Jukes-Cantor	[Basefreq: =0.25]
42	1	Jukes-Cantor	[Basefreq: =0.25]
43	1	Jukes-Cantor	[Basefreq: =0.25]
44	1	Jukes-Cantor	[Basefreq: =0.25]
45	1	Jukes-Cantor	[Basefreq: =0.25]
46	1	Jukes-Cantor	[Basefreq: =0.25]
47	1	Jukes-Cantor	[Basefreq: =0.25]
48	1	Jukes-Cantor	[Basefreq: =0.25]
49	1	Jukes-Cantor	[Basefreq: =0.25]
50	1	Jukes-Cantor	[Basefreq: =0.25]
51	1	Jukes-Cantor	[Basefreq: =0.25]
52	1	Jukes-Cantor	[Basefreq: =0.25]
53	1	Jukes-Cantor	[Basefreq: =0.25]
54	1	Jukes-Cantor	[Basefreq: =0.25]
55	1	Jukes-Cantor	[Basefreq: =0.25]
56	1	Jukes-Cantor	[Basefreq: =0.25]
57	1	Jukes-Cantor	[Basefreq: =0.25]
58	1	Jukes-Cantor	[Basefreq: =0.25]
59	1	Jukes-Cantor	[Basefreq: =0.25]
60	1	Jukes-Cantor	[Basefreq: =0.25]
61	1	Jukes-Cantor	[Basefreq: =0.25]
62	1	Jukes-Cantor	[Basefreq: =0.25]
63	1	Jukes-Cantor	[Basefreq: =0.25]
64	1	Jukes-Cantor	[Basefreq: =0.25]
65	1	Jukes-Cantor	[Basefreq: =0.25]
66	1	Jukes-Cantor	[Basefreq: =0.25]
67	1	Jukes-Cantor	[Basefreq: =0.25]
68	1	Jukes-Cantor	[Basefreq: =0.25]
69	1	Jukes-Cantor	[Basefreq: =0.25]
70	1	Jukes-Cantor	[Basefreq: =0.25]
71	1	Jukes-Cantor	[Basefreq: =0.25]
72	1	Jukes-Cantor	[Basefreq: =0.25]
73	1	Jukes-Cantor	[Basefreq: =0.25]
74	1	Jukes-Cantor	[Basefreq: =0.25]
75	1	Jukes-Cantor	[Basefreq: =0.25]
76	1	Jukes-Cantor	[Basefreq: =0.25]
77	1	Jukes-Cantor	[Basefreq: =0.25]
78	1	Jukes-Cantor	[Basefreq: =0.25]
79	1	Jukes-Cantor	[Basefreq: =0.25]

80	1	Jukes-Cantor	[Basefreq: =0.25]
81	1	Jukes-Cantor	[Basefreq: =0.25]
82	1	Jukes-Cantor	[Basefreq: =0.25]
83	1	Jukes-Cantor	[Basefreq: =0.25]
84	1	Jukes-Cantor	[Basefreq: =0.25]
85	1	Jukes-Cantor	[Basefreq: =0.25]
86	1	Jukes-Cantor	[Basefreq: =0.25]
87	1	Jukes-Cantor	[Basefreq: =0.25]
88	1	Jukes-Cantor	[Basefreq: =0.25]
89	1	Jukes-Cantor	[Basefreq: =0.25]
90	1	Jukes-Cantor	[Basefreq: =0.25]
91	1	Jukes-Cantor	[Basefreq: =0.25]
92	1	Jukes-Cantor	[Basefreq: =0.25]
93	1	Jukes-Cantor	[Basefreq: =0.25]
94	1	Jukes-Cantor	[Basefreq: =0.25]
95	1	Jukes-Cantor	[Basefreq: =0.25]
96	1	Jukes-Cantor	[Basefreq: =0.25]
97	1	Jukes-Cantor	[Basefreq: =0.25]
98	1	Jukes-Cantor	[Basefreq: =0.25]
99	1	Jukes-Cantor	[Basefreq: =0.25]
100	1	Jukes-Cantor	[Basefreq: =0.25]

#### Sites per locus

Locus	Sites
1	10000
2	10000
3	10000
4	10000
5	10000
6	10000
7	10000
8	10000
9	10000
10	10000
11	10000
12	10000
13	10000
14	10000
15	10000
16	10000
17	10000
18	10000
19	10000
20	10000

21	10000
22	10000
23	10000
24	10000
25	10000
26	10000
27	10000
28	10000
29	10000
30	10000
31	10000
32	10000
33	10000
34	10000
35	10000
36	10000
37	10000
38	10000
39	10000
40	10000
41	10000
42	10000
43	10000
44	10000
45	10000
46	10000
47	10000
48	10000
49	10000
50	10000
51	10000
52	10000
53	10000
54	10000
55	10000
56	10000
57	10000
58	10000
59	10000
60	10000
61	10000
62	10000
63	10000
64	10000
65	10000

66	10000
67	10000
68	10000
69	10000
70	10000
71	10000
72	10000
73	10000
74	10000
75	10000
76	10000
77	10000
78	10000
79	10000
80	10000
81	10000
82	10000
83	10000
84	10000
85	10000
86	10000
87	10000
88	10000
89	10000
90	10000
91	10000
92	10000
93	10000
94	10000
95	10000
96	10000
97	10000
98	10000
99	10000
100	10000

Site rate variation and probabilities:

Locus	Sublocus	Region type	Rate of change	Probability	Patch size
-------	----------	-------------	----------------	-------------	------------

1	1	1	1.000	1.000	1.000
2	1	1	1.000	1.000	1.000
3	1	1	1.000	1.000	1.000
4	1	1	1.000	1.000	1.000
5	1	1	1.000	1.000	1.000
6	1	1	1.000	1.000	1.000

7	1	1	1.000	1.000	1.000
8	1	1	1.000	1.000	1.000
9	1	1	1.000	1.000	1.000
10	1	1	1.000	1.000	1.000
11	1	1	1.000	1.000	1.000
12	1	1	1.000	1.000	1.000
13	1	1	1.000	1.000	1.000
14	1	1	1.000	1.000	1.000
15	1	1	1.000	1.000	1.000
16	1	1	1.000	1.000	1.000
17	1	1	1.000	1.000	1.000
18	1	1	1.000	1.000	1.000
19	1	1	1.000	1.000	1.000
20	1	1	1.000	1.000	1.000
21	1	1	1.000	1.000	1.000
22	1	1	1.000	1.000	1.000
23	1	1	1.000	1.000	1.000
24	1	1	1.000	1.000	1.000
25	1	1	1.000	1.000	1.000
26	1	1	1.000	1.000	1.000
27	1	1	1.000	1.000	1.000
28	1	1	1.000	1.000	1.000
29	1	1	1.000	1.000	1.000
30	1	1	1.000	1.000	1.000
31	1	1	1.000	1.000	1.000
32	1	1	1.000	1.000	1.000
33	1	1	1.000	1.000	1.000
34	1	1	1.000	1.000	1.000
35	1	1	1.000	1.000	1.000
36	1	1	1.000	1.000	1.000
37	1	1	1.000	1.000	1.000
38	1	1	1.000	1.000	1.000
39	1	1	1.000	1.000	1.000
40	1	1	1.000	1.000	1.000
41	1	1	1.000	1.000	1.000
42	1	1	1.000	1.000	1.000
43	1	1	1.000	1.000	1.000
44	1	1	1.000	1.000	1.000
45	1	1	1.000	1.000	1.000
46	1	1	1.000	1.000	1.000
47	1	1	1.000	1.000	1.000
48	1	1	1.000	1.000	1.000
49	1	1	1.000	1.000	1.000
50	1	1	1.000	1.000	1.000
51	1	1	1.000	1.000	1.000



52	1	1	1.000	1.000	1.000
53	1	1	1.000	1.000	1.000
54	1	1	1.000	1.000	1.000
55	1	1	1.000	1.000	1.000
56	1	1	1.000	1.000	1.000
57	1	1	1.000	1.000	1.000
58	1	1	1.000	1.000	1.000
59	1	1	1.000	1.000	1.000
60	1	1	1.000	1.000	1.000
61	1	1	1.000	1.000	1.000
62	1	1	1.000	1.000	1.000
63	1	1	1.000	1.000	1.000
64	1	1	1.000	1.000	1.000
65	1	1	1.000	1.000	1.000
66	1	1	1.000	1.000	1.000
67	1	1	1.000	1.000	1.000
68	1	1	1.000	1.000	1.000
69	1	1	1.000	1.000	1.000
70	1	1	1.000	1.000	1.000
71	1	1	1.000	1.000	1.000
72	1	1	1.000	1.000	1.000
73	1	1	1.000	1.000	1.000
74	1	1	1.000	1.000	1.000
75	1	1	1.000	1.000	1.000
76	1	1	1.000	1.000	1.000
77	1	1	1.000	1.000	1.000
78	1	1	1.000	1.000	1.000
79	1	1	1.000	1.000	1.000
80	1	1	1.000	1.000	1.000
81	1	1	1.000	1.000	1.000
82	1	1	1.000	1.000	1.000
83	1	1	1.000	1.000	1.000
84	1	1	1.000	1.000	1.000
85	1	1	1.000	1.000	1.000
86	1	1	1.000	1.000	1.000
87	1	1	1.000	1.000	1.000
88	1	1	1.000	1.000	1.000
89	1	1	1.000	1.000	1.000
90	1	1	1.000	1.000	1.000
91	1	1	1.000	1.000	1.000
92	1	1	1.000	1.000	1.000
93	1	1	1.000	1.000	1.000
94	1	1	1.000	1.000	1.000
95	1	1	1.000	1.000	1.000
96	1	1	1.000	1.000	1.000

97	1	1	1.000	1.000	1.000	
98	1	1	1.000	1.000	1.000	
99	1	1	1.000	1.000	1.000	
100	1	1	1.000	1.000	1.000	
Population			Locus		Gene copies	
1 Romanshorn_0			1		10	
			2		10	
			3		10	
			4		10	
			5		10	
			6		10	
			7		10	
			8		10	
			9		10	
			10		10	
			11		10	
			12		10	
			13		10	
			14		10	
			15		10	
			16		10	
			17		10	
			18		10	
			19		10	
			20		10	
			21		10	
			22		10	
			23		10	
			24		10	
			25		10	
			26		10	
			27		10	
			28		10	
			29		10	
			30		10	
			31		10	
			32		10	
			33		10	
			34		10	
			35		10	
			36		10	
			37		10	
			38		10	
			39		10	
			40		10	

41	10
42	10
43	10
44	10
45	10
46	10
47	10
48	10
49	10
50	10
51	10
52	10
53	10
54	10
55	10
56	10
57	10
58	10
59	10
60	10
61	10
62	10
63	10
64	10
65	10
66	10
67	10
68	10
69	10
70	10
71	10
72	10
73	10
74	10
75	10
76	10
77	10
78	10
79	10
80	10
81	10
82	10
83	10
84	10
85	10

	86	10
	87	10
	88	10
	89	10
	90	10
	91	10
	92	10
	93	10
	94	10
	95	10
	96	10
	97	10
	98	10
	99	10
	100	10
Total of all populations	1	10
	2	10
	3	10
	4	10
	5	10
	6	10
	7	10
	8	10
	9	10
	10	10
	11	10
	12	10
	13	10
	14	10
	15	10
	16	10
	17	10
	18	10
	19	10
	20	10
	21	10
	22	10
	23	10
	24	10
	25	10
	26	10
	27	10
	28	10
	29	10
	30	10

31	10
32	10
33	10
34	10
35	10
36	10
37	10
38	10
39	10
40	10
41	10
42	10
43	10
44	10
45	10
46	10
47	10
48	10
49	10
50	10
51	10
52	10
53	10
54	10
55	10
56	10
57	10
58	10
59	10
60	10
61	10
62	10
63	10
64	10
65	10
66	10
67	10
68	10
69	10
70	10
71	10
72	10
73	10
74	10
75	10

76	10
77	10
78	10
79	10
80	10
81	10
82	10
83	10
84	10
85	10
86	10
87	10
88	10
89	10
90	10
91	10
92	10
93	10
94	10
95	10
96	10
97	10
98	10
99	10
100	10

## *Bayesian Analysis: Posterior distribution table*

Locus	Parameter	2.5%	25.0%	Mode	75.0%	97.5%	Median	Mean
1	$\Theta_1$	0.03300	0.04540	0.04797	0.04960	0.05160	0.04557	0.08627
2	$\Theta_1$	0.03433	0.04533	0.04783	0.04933	0.05173	0.04557	0.08669
3	$\Theta_1$	0.03440	0.04487	0.04797	0.04987	0.05180	0.04603	0.08802
4	$\Theta_1$	0.03527	0.04360	0.04770	0.04987	0.05153	0.04577	0.08760
5	$\Theta_1$	0.03413	0.04447	0.04783	0.04967	0.05153	0.04563	0.08678
6	$\Theta_1$	0.03387	0.04467	0.04783	0.04980	0.05160	0.04583	0.08755
7	$\Theta_1$	0.03433	0.04507	0.04797	0.04987	0.05173	0.04617	0.08803
8	$\Theta_1$	0.03287	0.04407	0.04797	0.04987	0.05153	0.04523	0.08438
9	$\Theta_1$	0.03333	0.04400	0.04777	0.04973	0.05147	0.04517	0.08439
10	$\Theta_1$	0.03400	0.04467	0.04790	0.04993	0.05187	0.04583	0.08874
11	$\Theta_1$	0.03400	0.04573	0.04790	0.04953	0.05153	0.04590	0.08745
12	$\Theta_1$	0.03453	0.04460	0.04777	0.04973	0.05147	0.04577	0.08662
13	$\Theta_1$	0.03507	0.04567	0.04803	0.04953	0.05167	0.04583	0.08712
14	$\Theta_1$	0.03493	0.04447	0.04797	0.04980	0.05153	0.04563	0.08873
15	$\Theta_1$	0.03007	0.04413	0.04790	0.04987	0.05187	0.04530	0.08615
16	$\Theta_1$	0.03333	0.04440	0.04790	0.04960	0.05160	0.04563	0.08666
17	$\Theta_1$	0.03440	0.04433	0.04777	0.04960	0.05147	0.04557	0.08710
18	$\Theta_1$	0.03293	0.04400	0.04783	0.04967	0.05153	0.04523	0.08592

19	$\Theta_1$	0.03180	0.04453	0.04770	0.04927	0.05160	0.04470	0.08352
20	$\Theta_1$	0.03580	0.04513	0.04797	0.04973	0.05167	0.04630	0.08782
21	$\Theta_1$	0.03320	0.04440	0.04783	0.04980	0.05160	0.04557	0.08577
22	$\Theta_1$	0.03307	0.04440	0.04790	0.04993	0.05153	0.04550	0.08573
23	$\Theta_1$	0.03487	0.04480	0.04790	0.04973	0.05173	0.04603	0.08702
24	$\Theta_1$	0.03333	0.04413	0.04783	0.04980	0.05160	0.04523	0.08434
25	$\Theta_1$	0.03587	0.04587	0.04810	0.04953	0.05160	0.04603	0.08772
26	$\Theta_1$	0.03287	0.04433	0.04803	0.04980	0.05180	0.04557	0.08630
27	$\Theta_1$	0.03233	0.04367	0.04790	0.04980	0.05160	0.04483	0.08254
28	$\Theta_1$	0.03447	0.04460	0.04803	0.05000	0.05173	0.04570	0.08705
29	$\Theta_1$	0.03293	0.04440	0.04797	0.05000	0.05153	0.04543	0.08566
30	$\Theta_1$	0.03293	0.04433	0.04797	0.04987	0.05160	0.04550	0.08614
31	$\Theta_1$	0.03400	0.04440	0.04790	0.04973	0.05160	0.04563	0.08612
32	$\Theta_1$	0.03373	0.04240	0.04803	0.05067	0.05173	0.04623	0.08765
33	$\Theta_1$	0.03307	0.04433	0.04790	0.04980	0.05187	0.04550	0.08609
34	$\Theta_1$	0.03333	0.04533	0.04783	0.04953	0.05180	0.04550	0.08634
35	$\Theta_1$	0.03600	0.04613	0.04837	0.05013	0.05160	0.04630	0.08869
36	$\Theta_1$	0.03587	0.04500	0.04803	0.04980	0.05167	0.04617	0.08825
37	$\Theta_1$	0.03507	0.04473	0.04790	0.04973	0.05160	0.04590	0.08716
38	$\Theta_1$	0.03253	0.04513	0.04790	0.04960	0.05160	0.04530	0.08475
39	$\Theta_1$	0.03313	0.04447	0.04790	0.04980	0.05167	0.04563	0.08705
40	$\Theta_1$	0.03440	0.04453	0.04770	0.04967	0.05160	0.04563	0.08660
41	$\Theta_1$	0.03300	0.04433	0.04810	0.04993	0.05167	0.04543	0.08540



Locus	Parameter	2.5%	25.0%	Mode	75.0%	97.5%	Median	Mean
42	$\Theta_1$	0.03560	0.04480	0.04790	0.04980	0.05167	0.04597	0.08797
43	$\Theta_1$	0.03700	0.04500	0.04777	0.04947	0.05153	0.04630	0.08846
44	$\Theta_1$	0.03207	0.04413	0.04790	0.04987	0.05167	0.04530	0.08500
45	$\Theta_1$	0.03400	0.04447	0.04783	0.04947	0.05160	0.04577	0.08807
46	$\Theta_1$	0.03487	0.04480	0.04810	0.04987	0.05167	0.04597	0.08764
47	$\Theta_1$	0.03360	0.04473	0.04803	0.04980	0.05160	0.04543	0.08707
48	$\Theta_1$	0.03273	0.04527	0.04797	0.04973	0.05153	0.04550	0.08465
49	$\Theta_1$	0.03593	0.04507	0.04810	0.04993	0.05167	0.04617	0.08790
50	$\Theta_1$	0.03380	0.04453	0.04797	0.04987	0.05167	0.04570	0.08447
51	$\Theta_1$	0.03420	0.04467	0.04803	0.04980	0.05180	0.04590	0.08696
52	$\Theta_1$	0.03400	0.04453	0.04797	0.04987	0.05167	0.04563	0.08585
53	$\Theta_1$	0.03393	0.04487	0.04797	0.05000	0.05173	0.04597	0.08696
54	$\Theta_1$	0.03333	0.04453	0.04797	0.04980	0.05160	0.04563	0.08602
55	$\Theta_1$	0.03467	0.04493	0.04803	0.05000	0.05167	0.04603	0.08711
56	$\Theta_1$	0.03293	0.04467	0.04797	0.05000	0.05173	0.04577	0.08718
57	$\Theta_1$	0.03340	0.04453	0.04810	0.05000	0.05160	0.04563	0.08616
58	$\Theta_1$	0.03427	0.04473	0.04810	0.05000	0.05160	0.04583	0.08705
59	$\Theta_1$	0.03200	0.04407	0.04797	0.04987	0.05167	0.04523	0.08459
60	$\Theta_1$	0.03393	0.04467	0.04790	0.04987	0.05160	0.04583	0.08749
61	$\Theta_1$	0.03527	0.04493	0.04797	0.05000	0.05173	0.04603	0.08734

62	$\Theta_1$	0.03427	0.04467	0.04783	0.04987	0.05147	0.04577	0.08728
63	$\Theta_1$	0.03567	0.04587	0.04797	0.04953	0.05167	0.04603	0.08669
64	$\Theta_1$	0.03560	0.04520	0.04803	0.04993	0.05167	0.04630	0.08786
65	$\Theta_1$	0.03580	0.04513	0.04817	0.05000	0.05167	0.04623	0.08762
66	$\Theta_1$	0.03347	0.04440	0.04810	0.04987	0.05167	0.04557	0.08673
67	$\Theta_1$	0.03553	0.04467	0.04783	0.04960	0.05153	0.04590	0.08776
68	$\Theta_1$	0.03420	0.04493	0.04797	0.04987	0.05160	0.04603	0.08767
69	$\Theta_1$	0.03453	0.04427	0.04783	0.04967	0.05153	0.04550	0.08667
70	$\Theta_1$	0.03273	0.04420	0.04803	0.04987	0.05180	0.04537	0.08666
71	$\Theta_1$	0.03407	0.04467	0.04797	0.04987	0.05167	0.04583	0.08588
72	$\Theta_1$	0.03507	0.04453	0.04770	0.04960	0.05160	0.04570	0.08743
73	$\Theta_1$	0.03400	0.04460	0.04797	0.05007	0.05167	0.04563	0.08620
74	$\Theta_1$	0.03567	0.04513	0.04810	0.05000	0.05167	0.04623	0.08793
75	$\Theta_1$	0.03680	0.04540	0.04810	0.04987	0.05180	0.04657	0.08790
76	$\Theta_1$	0.03120	0.04553	0.04803	0.04967	0.05193	0.04570	0.08555
77	$\Theta_1$	0.03153	0.04453	0.04783	0.04967	0.05153	0.04470	0.08350
78	$\Theta_1$	0.03460	0.04467	0.04783	0.04980	0.05167	0.04583	0.08732
79	$\Theta_1$	0.03340	0.04407	0.04803	0.04973	0.05173	0.04537	0.08606
80	$\Theta_1$	0.03427	0.04480	0.04810	0.05007	0.05193	0.04590	0.08769
81	$\Theta_1$	0.03420	0.04527	0.04803	0.05013	0.05180	0.04623	0.08780
82	$\Theta_1$	0.03247	0.04420	0.04783	0.04960	0.05167	0.04550	0.08514
83	$\Theta_1$	0.03287	0.04553	0.04810	0.04967	0.05193	0.04570	0.08638
84	$\Theta_1$	0.03447	0.04493	0.04803	0.04980	0.05167	0.04603	0.08702

Locus	Parameter	2.5%	25.0%	Mode	75.0%	97.5%	Median	Mean
85	$\Theta_1$	0.03480	0.04553	0.04783	0.04920	0.05160	0.04570	0.08621
86	$\Theta_1$	0.03413	0.04407	0.04783	0.04960	0.05153	0.04537	0.08716
87	$\Theta_1$	0.03387	0.04427	0.04803	0.04993	0.05153	0.04537	0.08570
88	$\Theta_1$	0.03340	0.04467	0.04803	0.04987	0.05173	0.04577	0.08633
89	$\Theta_1$	0.03527	0.04520	0.04810	0.04993	0.05173	0.04630	0.08866
90	$\Theta_1$	0.03433	0.04467	0.04803	0.04993	0.05160	0.04577	0.08632
91	$\Theta_1$	0.03487	0.04493	0.04790	0.04980	0.05160	0.04603	0.08766
92	$\Theta_1$	0.03360	0.04447	0.04803	0.04993	0.05167	0.04557	0.08584
93	$\Theta_1$	0.03420	0.04513	0.04810	0.04993	0.05160	0.04617	0.08745
94	$\Theta_1$	0.03553	0.04527	0.04797	0.04973	0.05167	0.04643	0.08815
95	$\Theta_1$	0.03440	0.04453	0.04797	0.04973	0.05173	0.04583	0.08798
96	$\Theta_1$	0.03587	0.04513	0.04810	0.05000	0.05153	0.04610	0.08891
97	$\Theta_1$	0.03507	0.04600	0.04810	0.04973	0.05153	0.04617	0.08790
98	$\Theta_1$	0.03413	0.04560	0.04803	0.04967	0.05173	0.04583	0.08631
99	$\Theta_1$	0.03533	0.04420	0.04790	0.04967	0.05160	0.04550	0.08733
100	$\Theta_1$	0.03300	0.04400	0.04777	0.04973	0.05167	0.04523	0.08588
All	$\Theta_1$	0.01333	0.01633	0.01770	0.01967	0.02327	0.01803	0.09980

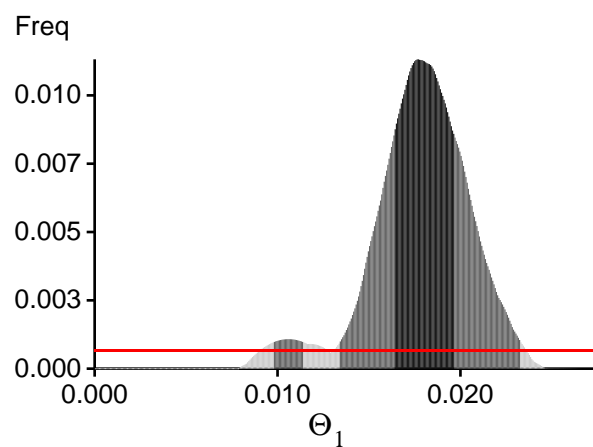
Citation suggestions:

Beerli P., 2006. Comparison of Bayesian and maximum-likelihood inference of population genetic parameters.  
 Bioinformatics 22:341-345

Beerli P., 2007. Estimation of the population scaled mutation rate from microsatellite data,  
 Genetics, 177:1967-1968.

Beerli P., 2009. How to use MIGRATE or why are Markov chain Monte Carlo programs difficult to use?  
 In Population Genetics for Animal Conservation, G. Bertorelle, M. W. Bruford, H. C. Hauffe, A. Rizzoli,  
 and C. Vernesi, eds., vol. 17 of Conservation Biology, Cambridge University Press, Cambridge UK, pp. 42-79.

# *Bayesian Analysis: Posterior distribution over all loci*



## *Log-Probability of the data given the model (marginal likelihood)*

Use this value for Bayes factor calculations:

$BF = \text{Exp}[\ln(\text{Prob}(D \mid \text{thisModel}) - \ln(\text{Prob}(D \mid \text{otherModel}))]$

or as  $LBF = 2 (\ln(\text{Prob}(D \mid \text{thisModel}) - \ln(\text{Prob}(D \mid \text{otherModel})))$

shows the support for thisModel]

Locus	TI(1a)	BTI(1b)	SS(2)	HS(3)
1	-15712.53	-15176.34	-15188.72	-15248.89
2	-17060.79	-15943.60	-15865.89	-15917.20
3	-16979.16	-16057.03	-16024.21	-16071.80
4	-16593.91	-15991.05	-16018.15	-16064.93
5	-16125.40	-15504.18	-15512.91	-15565.09
6	-16200.58	-15523.45	-15528.26	-15574.29
7	-16944.36	-16011.62	-15974.29	-16020.35
8	-16627.61	-15886.71	-15875.14	-15932.90
9	-15887.97	-15073.64	-15036.76	-15093.75
10	-19205.60	-17454.75	-17276.75	-17322.63
11	-16247.39	-15723.68	-15762.26	-15809.61
12	-16245.55	-15483.76	-15469.15	-15524.40
13	-16636.52	-15760.64	-15728.02	-15777.02
14	-17378.69	-16637.22	-16650.57	-16689.82
15	-16135.18	-15479.09	-15483.60	-15536.05
16	-15899.77	-15350.63	-15376.33	-15426.52
17	-16706.28	-15902.13	-15885.15	-15934.46
18	-15754.20	-15334.85	-15381.42	-15430.34
19	-16142.64	-15412.12	-15395.08	-15453.69
20	-17538.34	-16156.11	-16020.56	-16081.15
21	-16532.74	-15647.15	-15607.69	-15661.00
22	-16016.47	-15430.35	-15449.58	-15499.08
23	-15799.38	-15229.75	-15247.39	-15299.76
24	-16316.26	-15349.29	-15284.93	-15343.64
25	-17741.30	-16277.60	-16133.39	-16187.41
26	-16300.22	-15628.43	-15631.56	-15683.70
27	-15210.64	-14730.06	-14749.98	-14811.89
28	-20310.76	-17720.93	-17379.03	-17430.51
29	-15863.76	-15230.69	-15233.80	-15288.60

30	-15127.35	-14825.36	-14886.68	-14940.42
31	-16646.92	-15645.83	-15585.02	-15637.48
32	-15969.34	-15454.90	-15487.92	-15540.40
33	-16218.34	-15716.31	-15752.71	-15800.81
34	-17002.06	-15882.05	-15799.92	-15855.85
35	-19112.79	-17548.81	-17414.77	-17456.62
36	-17602.47	-16312.38	-16207.40	-16251.89
37	-15829.97	-15227.47	-15243.35	-15291.72
38	-15551.55	-14973.35	-14981.09	-15037.55
39	-17588.84	-16461.35	-16388.66	-16439.16
40	-17213.41	-16013.52	-15905.91	-15971.80
41	-15666.82	-15097.21	-15112.19	-15164.88
42	-17022.34	-16095.84	-16053.21	-16107.18
43	-19843.59	-17567.33	-17282.16	-17334.93
44	-15058.11	-14707.67	-14755.27	-14811.12
45	-17546.20	-16378.94	-16288.28	-16346.61
46	-16568.50	-15766.09	-15747.86	-15796.45
47	-16455.55	-15625.84	-15599.76	-15649.79
48	-15708.84	-15283.40	-15327.06	-15381.69
49	-17916.80	-16648.39	-16555.35	-16600.72
50	-15310.07	-14940.99	-14988.85	-15047.87
51	-15788.86	-15242.59	-15267.21	-15316.53
52	-16319.45	-15611.35	-15609.00	-15658.84
53	-17583.02	-16461.34	-16382.18	-16440.11
54	-16847.13	-15948.50	-15912.78	-15964.49
55	-16710.30	-15850.65	-15823.09	-15872.12
56	-17844.54	-16220.16	-16044.20	-16098.50
57	-17585.50	-16479.41	-16403.06	-16457.56
58	-17173.58	-16222.38	-16186.71	-16231.13
59	-16473.03	-15657.19	-15625.47	-15686.70
60	-16259.61	-15551.01	-15550.75	-15597.32
61	-17567.03	-16248.88	-16126.46	-16183.99
62	-16369.04	-15608.57	-15597.40	-15644.84
63	-17235.88	-15917.40	-15799.67	-15852.16
64	-18943.43	-17313.25	-17160.12	-17207.40
65	-15921.30	-15328.62	-15344.60	-15397.42
66	-16859.48	-16074.52	-16060.58	-16109.96
67	-17552.40	-16564.54	-16516.57	-16570.30
68	-15962.42	-15449.69	-15475.89	-15533.61
69	-16143.99	-15445.44	-15442.27	-15494.02
70	-15888.16	-15185.40	-15177.89	-15230.12
71	-15827.62	-15298.92	-15328.61	-15379.34
72	-17999.67	-16535.81	-16396.17	-16447.58
73	-15962.79	-15274.52	-15267.94	-15321.84
74	-17116.36	-16056.13	-15995.08	-16040.85

75	-17201.07	-16448.51	-16451.56	-16497.73
76	-15180.84	-14783.20	-14824.77	-14879.86
77	-15491.19	-15024.28	-15051.93	-15111.41
78	-16240.81	-15497.41	-15481.85	-15534.00
79	-16352.95	-15608.69	-15595.46	-15649.17
80	-18730.53	-17581.92	-17518.45	-17568.92
81	-15851.21	-15308.73	-15335.78	-15382.89
82	-16240.42	-15488.98	-15471.32	-15528.39
83	-16724.09	-15988.77	-15986.91	-16035.29
84	-21601.87	-18206.71	-17716.75	-17767.56
85	-16968.81	-16011.91	-15957.97	-16014.49
86	-17641.36	-16359.66	-16258.26	-16306.42
87	-15771.81	-15298.97	-15334.33	-15387.77
88	-16664.75	-15937.45	-15937.81	-15984.53
89	-18837.81	-17313.18	-17160.26	-17221.46
90	-15926.46	-15368.30	-15389.19	-15441.58
91	-16294.03	-15644.33	-15645.95	-15702.21
92	-15697.20	-15222.94	-15257.95	-15311.41
93	-15996.84	-15556.62	-15604.21	-15650.08
94	-17251.39	-16284.00	-16245.14	-16287.74
95	-17940.79	-16655.76	-16559.67	-16605.41
96	-17194.79	-16167.22	-16114.09	-16164.44
97	-24006.36	-19378.40	-18650.43	-18715.31
98	-15487.78	-14954.19	-14976.18	-15027.72
99	-17917.26	-16915.37	-16876.94	-16919.13
100	-15403.72	-14939.14	-14971.07	-15024.84
All	-1681456.90	-1588603.08	-1584234.14	-1589434.15
(1a) TI: Thermodynamic integration: log(Prob(D Model)): Good approximation with many temperatures				
(1b) BTI: Bezier-approximated Thermodynamic integration: when using few temperatures USE THIS!				
(2) SS: Steppingstone Sampling (Xie et al 2011)				
(3) HS: Harmonic mean approximation: Overestimates the marginal likelihood, poor variance				
[Scaling factor = 167.747460]				
Citation suggestions:				
Beerli P. and M. Palczewski, 2010. Unified framework to evaluate panmixia and migration direction among multiple sampling locations, Genetics, 185: 313-326.				
Palczewski M. and P. Beerli, 2014. Population model comparison using multi-locus datasets. In M.-H. Chen, L. Kuo, and P. O. Lewis, editors, Bayesian Phylogenetics: Methods, Algorithms, and Applications, pages 187-200. CRC Press, 2014.				
Xie W., P. O. Lewis, Y. Fan, L. Kuo, and M.-H. Chen. 2011. Improving marginal likelihood estimation for Bayesian phylogenetic model selection. Systematic Biology, 60(2):150â 160, 2011.				



*Acceptance ratios for all parameters and the genealogies*

Parameter	Accepted changes	Ratio
$\Theta_1$	369806039/399999027	0.92452
Genealogies	72140915/1600000973	0.04509

### *MCMC-Autocorrelation and Effective MCMC Sample Size*

Parameter	Autocorrelation	Effective Sample Size
$\Theta_1$	0.42730	4020878.31
Genealogies	0.47205	3619037.52

## *Average temperatures during the run*

Chain	Temperatures
-------	--------------

1	0.00000
2	0.00000
3	0.00000
4	0.00000

Adaptive heating often fails, if the average temperatures are very close together try to rerun using static heating! If you want to compare models using marginal likelihoods then you **MUST** use static heating

## *Potential Problems*

This section reports potential problems with your run, but such reporting is often not very accurate. With many parameters in a multilocus analysis, it is very common that some parameters for some loci will not be very informative, triggering suggestions (for example to increase the prior range) that are not sensible. This suggestion tool will improve with time, therefore do not blindly follow its suggestions. If some parameters are flagged, inspect the tables carefully and judge whether an action is required. For example, if you run a Bayesian inference with sequence data, for macroscopic species there is rarely the need to increase the prior for Theta beyond 0.1; but if you use microsatellites it is rather common that your prior distribution for Theta should have a range from 0.0 to 100 or more. With many populations (>3) it is also very common that some migration routes are estimated poorly because the data contains little or no information for that route. Increasing the range will not help in such situations, reducing number of parameters may help in such situations.

No warning was recorded during the run