



Chinese Academy of Sciences

bioinformatics
ZHANGroup

生物信息学

单体型组装与推断

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SNP和单体型



多态性

- 人类在DNA水平上有99.9%的相似程度
- 不同个体或种群之间DNA序列的差异称为基因**多态性**
- 基因多态性决定着一些外部特征如绿眼睛和褐眼睛，或直发与弯发等
- 基因变异(Mutation)是主要的一种多态性
- 单体型是研究基因变异与疾病联系的重要工具



单核苷酸多态性(SNP)

- 在单个核苷酸上的差异称为单核苷酸多态性(Single Nucleotide Polymorphism)
- SNP是人类基因组DNA序列变异的主要形式
- SNP是决定人类疾病（尤其是多基因疾病）易感性和药物反应性差异的核心信息
- 90%的多态性都是由单个核苷酸的变异引起的
- 人的SNP密度：平均1000个碱基中含有1个SNP位点
- 在整个人类基因组中大约有300万个单核苷酸多态性存在



SNP的类型

- 大部分SNP都是以双等位基因的形式出现: major (wild type) / minor (mutant type)
- 非同义(Non-Synonymous) SNP是指那些导致编码的氨基酸发生变化的SNP
- 编码序列中的SNP有一半是非同义SNP
- 普通(Common) SNP是指那些minor等位基因出现频率大于5%的SNP



单体型和基因型

- 双倍体生物的染色体总是成对出现的
- 在双倍体生物的每一条染色体的每一个SNP位点上，都会出现两个可能的等位基因中的一个
- 每一条染色体上的所有等位基因按一定顺序排列构成一条**单体型**
- 两条染色体上的对应等位基因组合在一起构成一条**基因型**



例子

来自父方的染色体: ATAGC**C**TATTCC**A**GGAGTCG**A**AGAC

来自母方的染色体: ATAGC**G**TATTCC**C**AGGAGTCG**T**AGAC

单体型 1 → C C A

单体型 2 → G C T

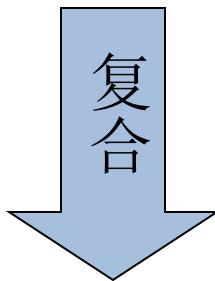
基因型 → {C,G} {C,C} {A,T}



单体型和基因型的表达

0 1 1 1 0 0 1 1 0
1 1 0 1 0 0 1 0 0

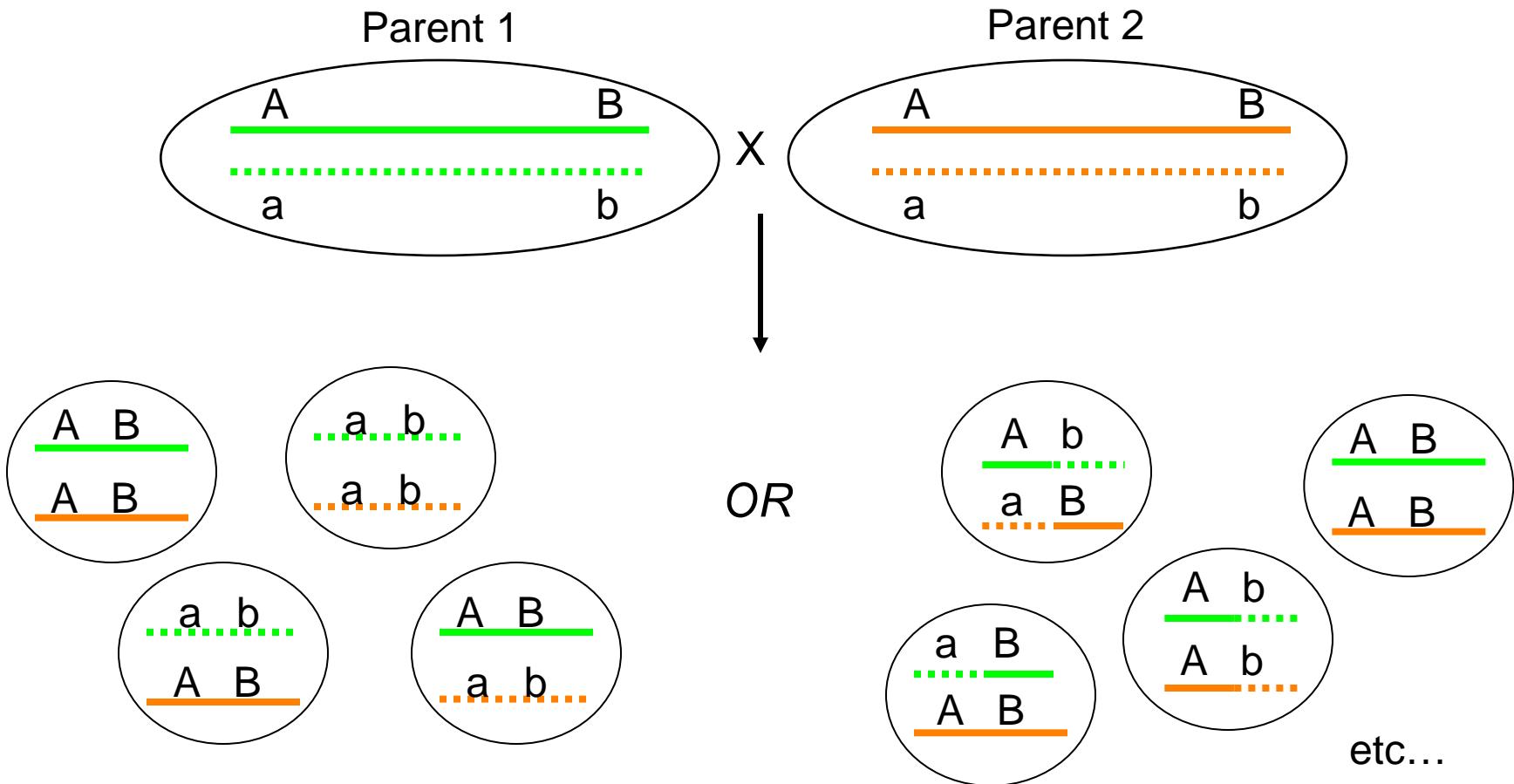
两条单体型



2 1 2 1 0 0 1 2 0

一条基因型

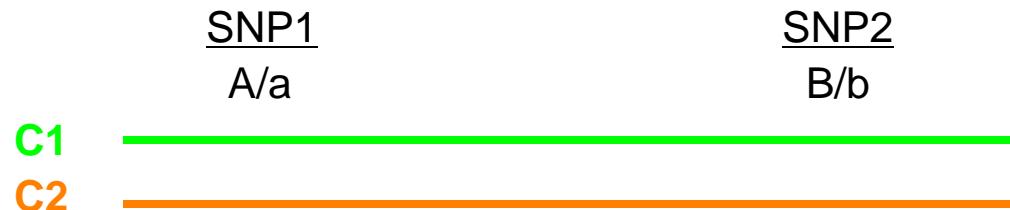
Linkage Disequilibrium



High LD -> No Recombination
($r^2 = 1$) SNP1 “tags” SNP2

Low LD -> Recombination
Many possibilities

alleles:



POP allele freqs:

A (80%)	B (60%)
a (20%)	b (40%)

genotypes:

Person 1

AA

BB

Person 2

AA

Bb

Person 3

Aa

Bb

phased haplotypes (C1/C2):

A C1 B
A C2 B

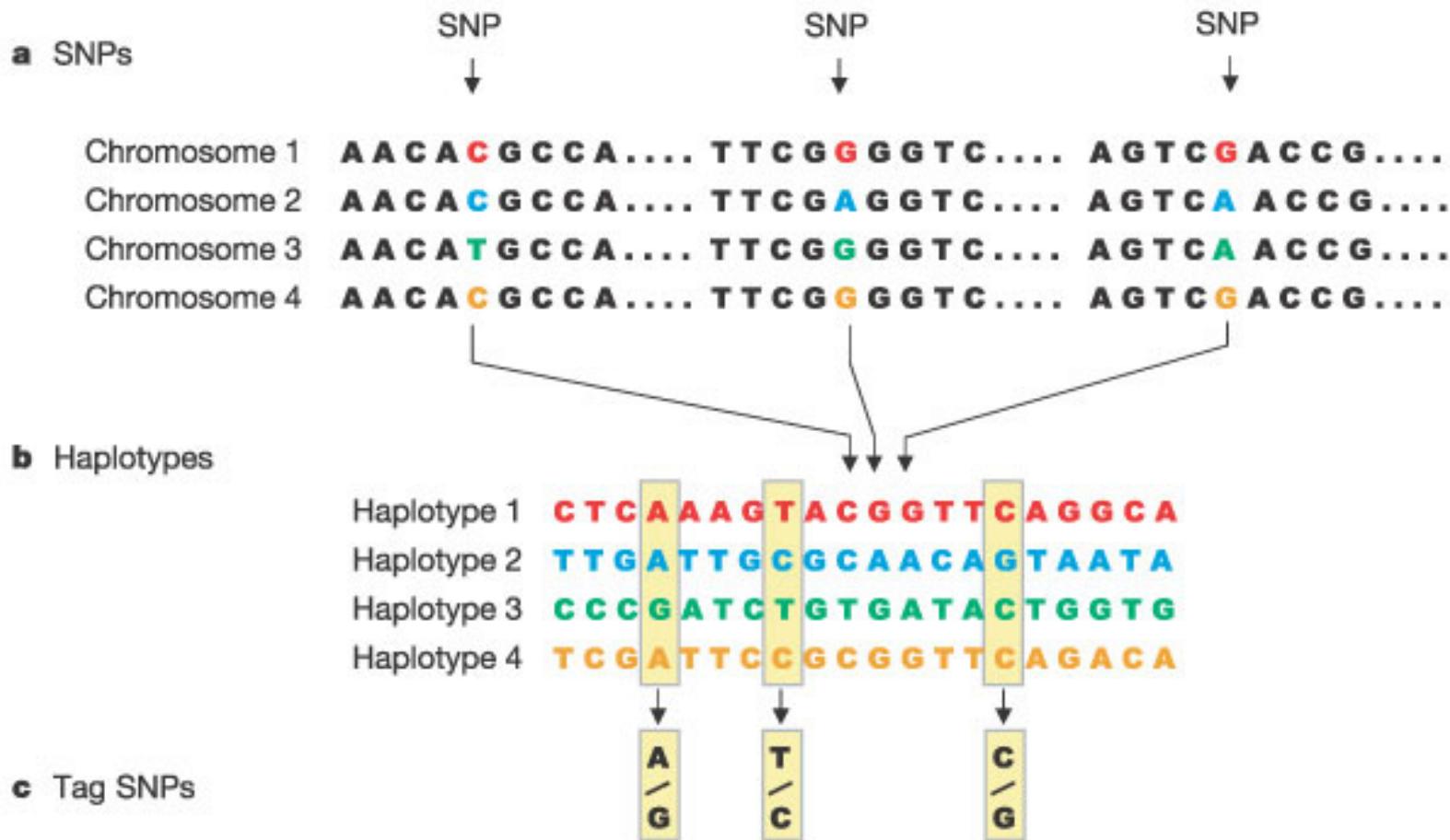
A C1 B
A C2 b

A C1 B
a C2 b

OR

A C1 b
a C2 B

标签SNP





单体型图(HapMap)计划

- 检测染色体上所有的SNPs的费用极其昂贵
- 一些相互邻近的多态位点趋向于在一起共同遗传，这些变异连锁的区域就是单体型
- 在一个特定人群中，55%的人可能拥有同一种单体型，30%的人可能拥有另一种单体型，8%的人可能拥有第三种单体型，而其余的人可能拥有若干种稀有的单体型
- 通过标签SNPs来鉴定一个人的单体型集合
- 定位与重要医学特征相关的基因



单体型检测

- 目前检测单体型的方法主要有两种
- **单体型组装(Haplotype Assembly)**
 - 从较小的SNP片断来组装单体型
 - 优点：比较精确
 - 缺点：技术实现较难、费用昂贵、速度慢
- **单体型推断(Haplotype Inference)**
 - 从群体的基因型来推断单体型
 - 优点：技术实现容易、基因型容易获取
 - 缺点：不精确



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单体型组装问题



单体型组装问题

- Haplotype Assembly
- Haplotyping for individual
- 从Shotgun测序实验得到的序列片断来组装出一对单体型



困难

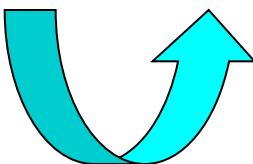
- 序列片断可能来自任何一条染色体
- 片断较短：每个片断可能包含2~3个SNP
- 测序错误
- 杂质污染



SNP矩阵

	s_1	s_2	s_3
f_1	G C A T G		
f_2	G G A T G A A T		
f_3	G C A T G C A T G C A A		
f_4	A T G A A T G C A T G		
f_5		C A T G	

DNA fragments



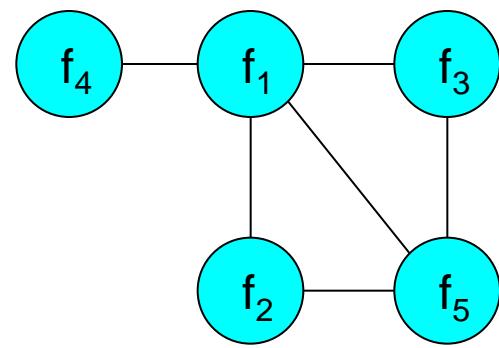
SNP matrix

	s_1	s_2	s_3
f_1	0	—	—
f_2	1	0	—
f_3	0	1	0
f_4	—	0	1
f_5	—	—	1

冲突图

	s_1	s_2	s_3	s_4	s_5	s_6
f_1	0	1	-	0	0	1
f_2	1	0	-	-	1	-
f_3	-	0	1	0	1	0
f_4	-	0	-	-	-	0
f_5	1	-	0	1	0	-

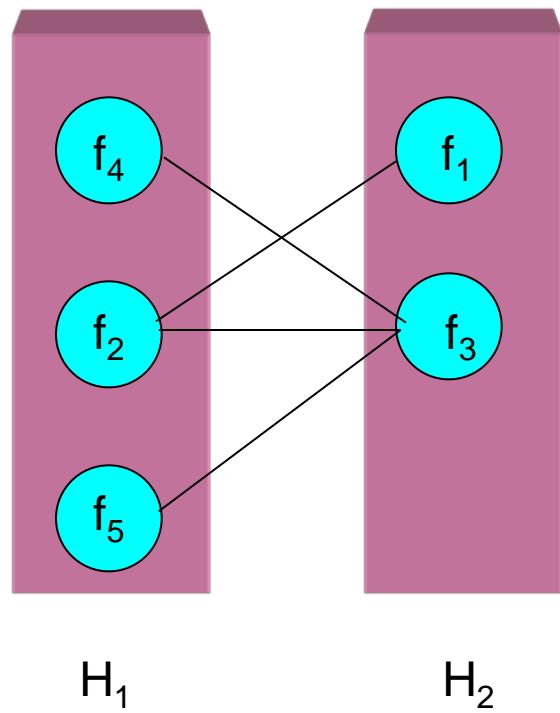
SNP matrix



Fragment conflict
graph G_F



二分图





图的二分化

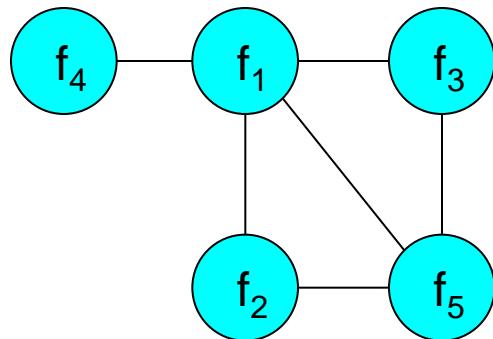
- 可以用Mathematica 5.1中的子程序 *BipartiteQ* 来计算判断一个图是否是一个二分图
- 一个图是否是二分图当且仅当它没有奇圈 (*a cycle with odd number of edges*) (S.Skiena,1990)
- 如何从带有误差的数据中恢复出一对单体型

\Leftrightarrow

如何将一个图合理地变成一个二分图

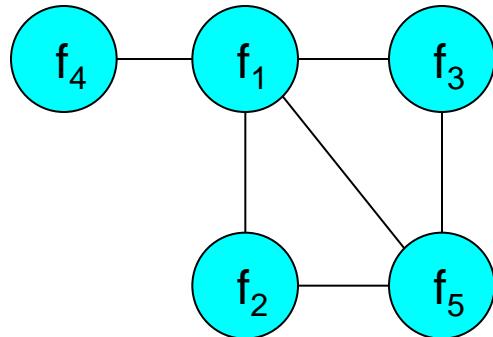
去除顶点

- 去掉一些顶点来得到二分图 (相当于去除一些受污染的片段)



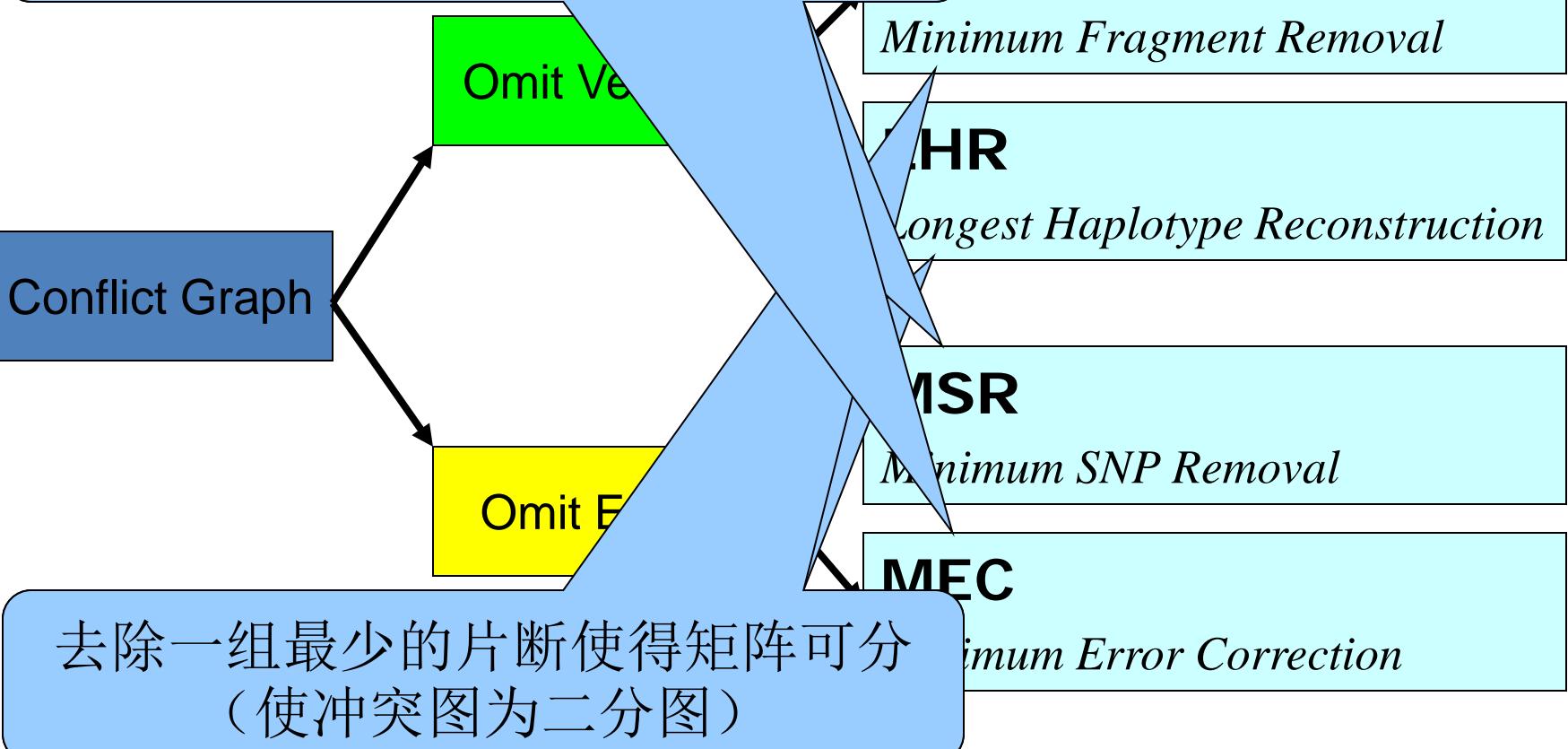
去除边

- 去掉一些边来得到二分图 (相当于去除一些SNP位点或改变某些片段上某些SNP位点的值)

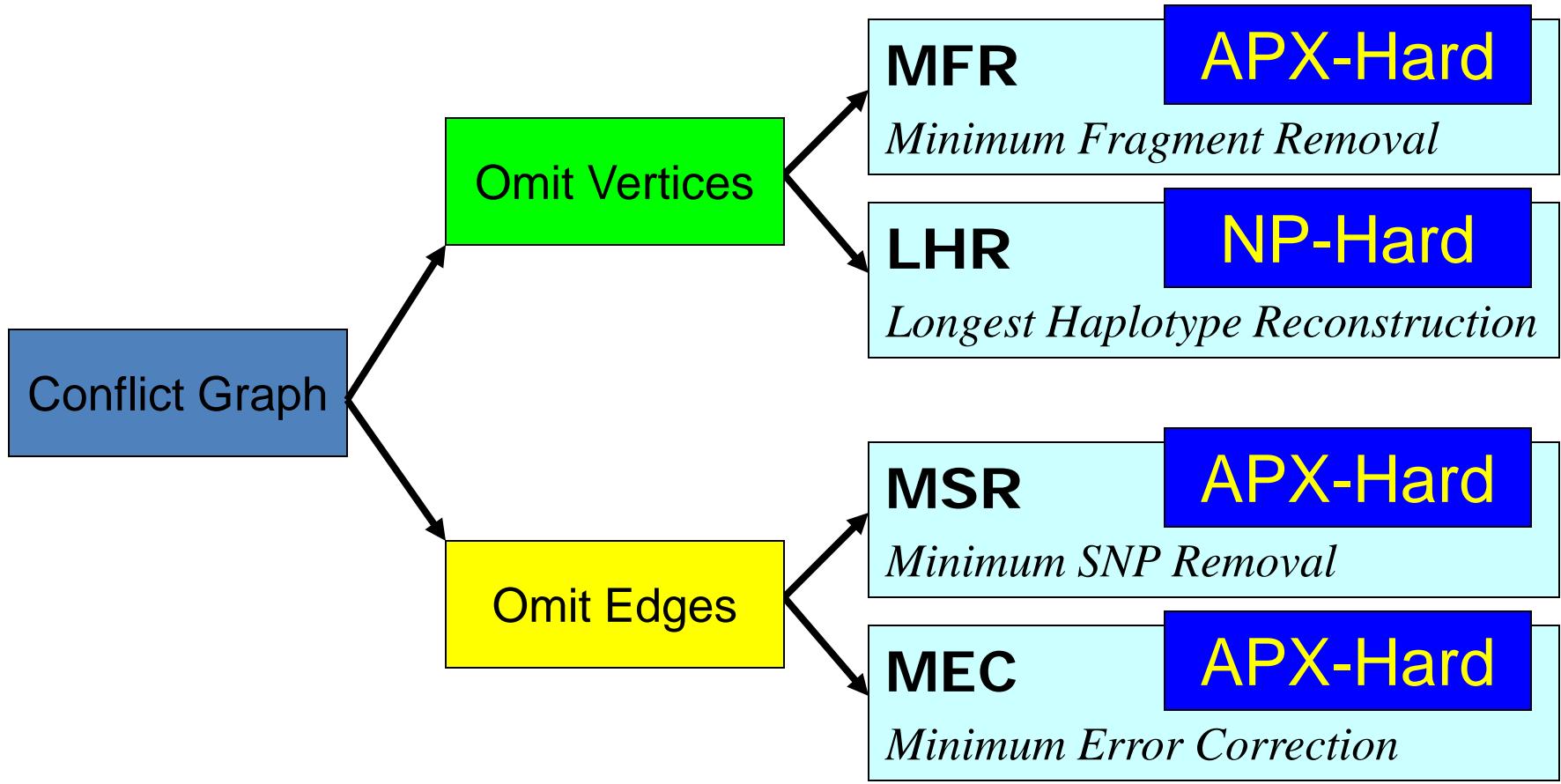


单体型组装模型

改变尽可能少的SNP位点上的值，
使矩阵可分



计算复杂性





MEC的整数规划模型

$$\max \sum_{i=1}^m \sum_{j=1}^n y_{ij}$$

$$x_{il}(r_{ij}y_{ij} - h_{lj}) = 0 \quad \begin{array}{l} i = 1, 2, \dots, m; \\ j = 1, 2, \dots, n; \\ l = 1, 2; \\ r_{ij} \neq 0 \end{array}$$

$$x_{i1} + x_{i2} = 1 \quad i = 1, 2, \dots, m$$

$$x_{il} \in \{0, 1\} \quad i = 1, 2, \dots, m; l = 1, 2$$

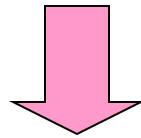
$$y_{ij} \in \{-1, 1\} \quad i = 1, 2, \dots, m; j = 1, 2, \dots, n$$

$$h_{lj} \in \{-1, 1\} \quad l = 1, 2; j = 1, 2, \dots, n$$



线性约束

$$x_{il}(r_{ij}y_{ij} - h_{lj}) = 0 \quad \begin{array}{l} i = 1, 2, \dots, m; \\ j = 1, 2, \dots, n; \\ l = 1, 2; \\ r_{ij} \neq 0 \end{array}$$



$$-2 + x_{il} \leq r_{ij}y_{ij} - h_{lj} \leq 2 - x_{il} \quad \begin{array}{l} i = 1, 2, \dots, m; \\ j = 1, 2, \dots, n; \\ l = 1, 2; \\ r_{ij} \neq 0 \end{array}$$



算法思想

- 将MEC问题转化为分类问题
 - 将SNP片断分为两类: C_1 和 C_2
 - 对每一个分类 C_i , 用最大似然原则迅速求出对应的最优单体型 H_i
(即 C_i 中的SNP片断只需最少的修正次数即可与单体型 H_i 一致)
 - 搜索比较所有可能的分类
- MEC的最优解为满足下式的分类 P^*

$$E(P^*) \leq E(P), \forall P$$



MEC模型算法

- 精确算法
 - 分支定界算法
- 近似算法
 - 动态聚类算法
 - 神经网络算法
 - 遗传算法

MEC模型的扩展

- MEC/GI
 - MEC with Genotype Information
 - 要求组装出的单体型和基因型数据一致

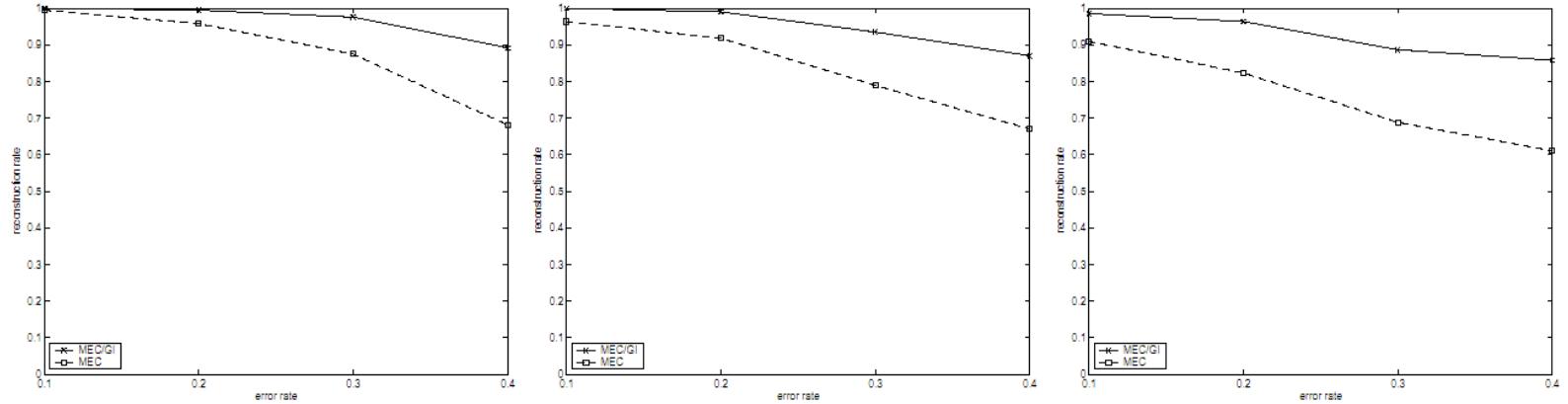


Figure 5: The comparison results of the MEC model and the MEC/GI model on ACE. From left to right, $g = 0.25$, $g = 0.5$, $g = 0.75$.



MEC模型的扩展

- WMEC
 - Weighted MEC
 - DNA测序时每个碱基都有一个置信度
 - 被纠正的SNP的权重之和最小
 - 当所有SNP的权重设为1时，即原始的MEC模型



MEC模型的扩展

- CWMEC
 - Complete Weighted MEC
 - 给定删除比例 R_F 和 R_S , 允许去掉不超过 R_F 比例的片断和 R_S 比例的SNP位点
 - WMEC和MFR、MSR的结合
 - $R_F = 1, R_S = 0$, 即MFR模型
 - $R_F = 0, R_S = 1$, 即MSR模型
 - $R_F = 0, R_S = 0$, 即WMEC模型



图的二分化算法

- Reed B, Smith K, Vetta A. **Finding odd cycle transversals.** *Oper Res Letters* **2004**; 32(4): 299–301.
- Hüffner F. **Algorithm engineering for optimal graph bipartization.** In Proceedings of the 4th International Workshop of Efficient and Experimental Algorithms (WEA). Springer-Verlag **2005**; 240-252.
- Guo J, Gramm J, Hüffner F, Niedermeier R, Wernicke S. **Improved fixed parameter algorithms for two feedback set problems.** In Proceedings of the 9th Workshop on Algorithms and Data Structures (WADS). Springer-Verlag **2005**; 158-168.



评论

- 我们注意到，在 Reed *et al.* 的工作之前，在图论研究中极少有对图的最优二分化的研究，原因是大家知道这是一个NP-难问题。正是由于生物信息学研究的需要，推动图论学家回来研究这一问题并得到好的研究结果。



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单体型推断问题



单体型推断问题

- **Haplotype Inference**
- **Haplotype Phasing**
- **Haplotyping in population**
 - 从一个人群的基因型来推断单体型
 - 给定一个人群的基因型数据
 - 为该人群中的每个人找到最可能的单体型配对
 - 估计在该人群中的单体型出现频率



基因型

- **Genotype (基因型)** 是指每个标签位置（Marker）的无序等位基因对（unordered pair of alleles for each marker）组成的一个序列
- **Homozygous (纯合子)**: 在一个位置上的一对等位基因是相同的
- **Heterozygous (杂合子)**: 在一个位置上的一对等位基因是相异的



例子

来自父方的染色体: ATAGC**C**TATTCCAGGAGTCG**A**AGAC

来自母方的染色体: ATAGC**G**TATTCCAGGAGTCG**T**AGAC

单体型 1 → C C A

单体型 2 → G C T

基因型 → {C,G} {C,C} {A,T}



基因型的解析

- 与基因型一致的一对单体型称为这个基因型的解析 (resolution)
- 一个基因型的杂合子个数为 k , 则对应的不同的解析有 2^{k-1} 个
- 2^{k-1} 个解析中哪种才是正确的、合理的?



例子

Genotype: {A,C}, {G,T}, G, A, {T,A}

Configuration 1:

AGGAT
CTGAA

Configuration 3:

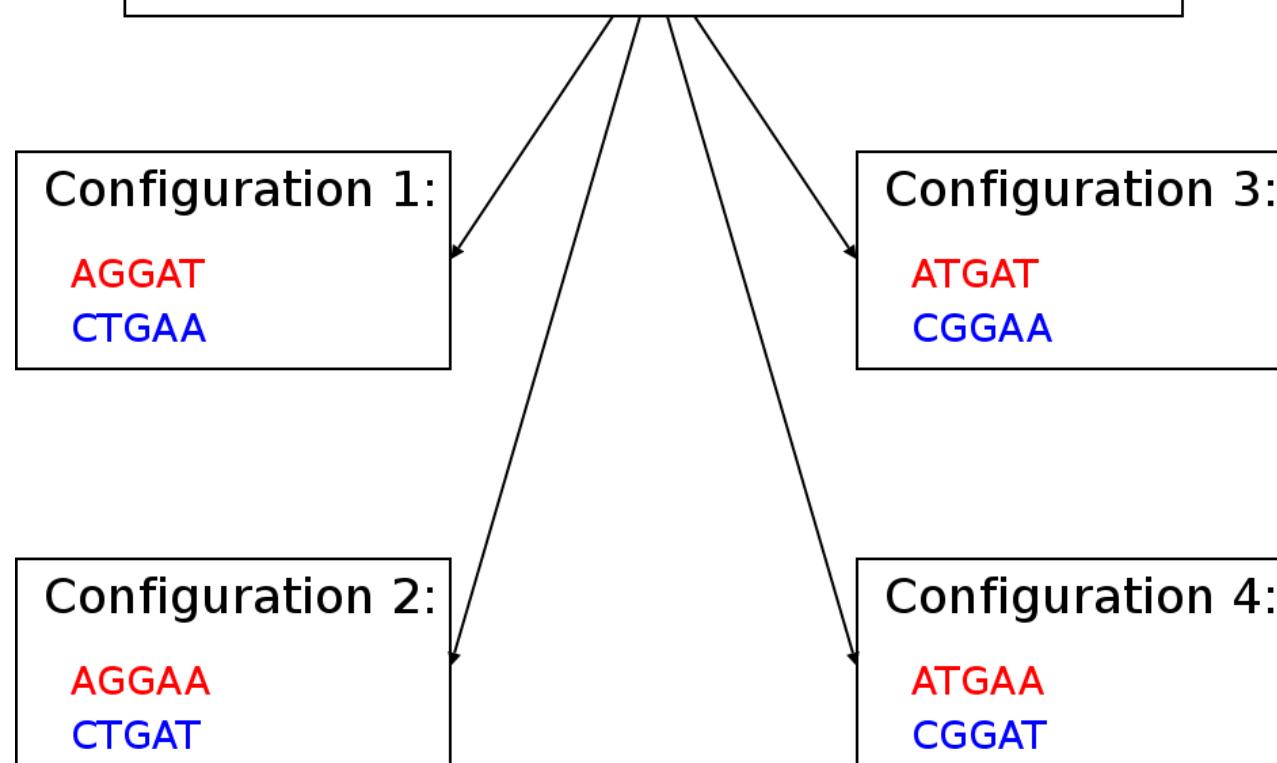
ATGAT
CGGAA

Configuration 2:

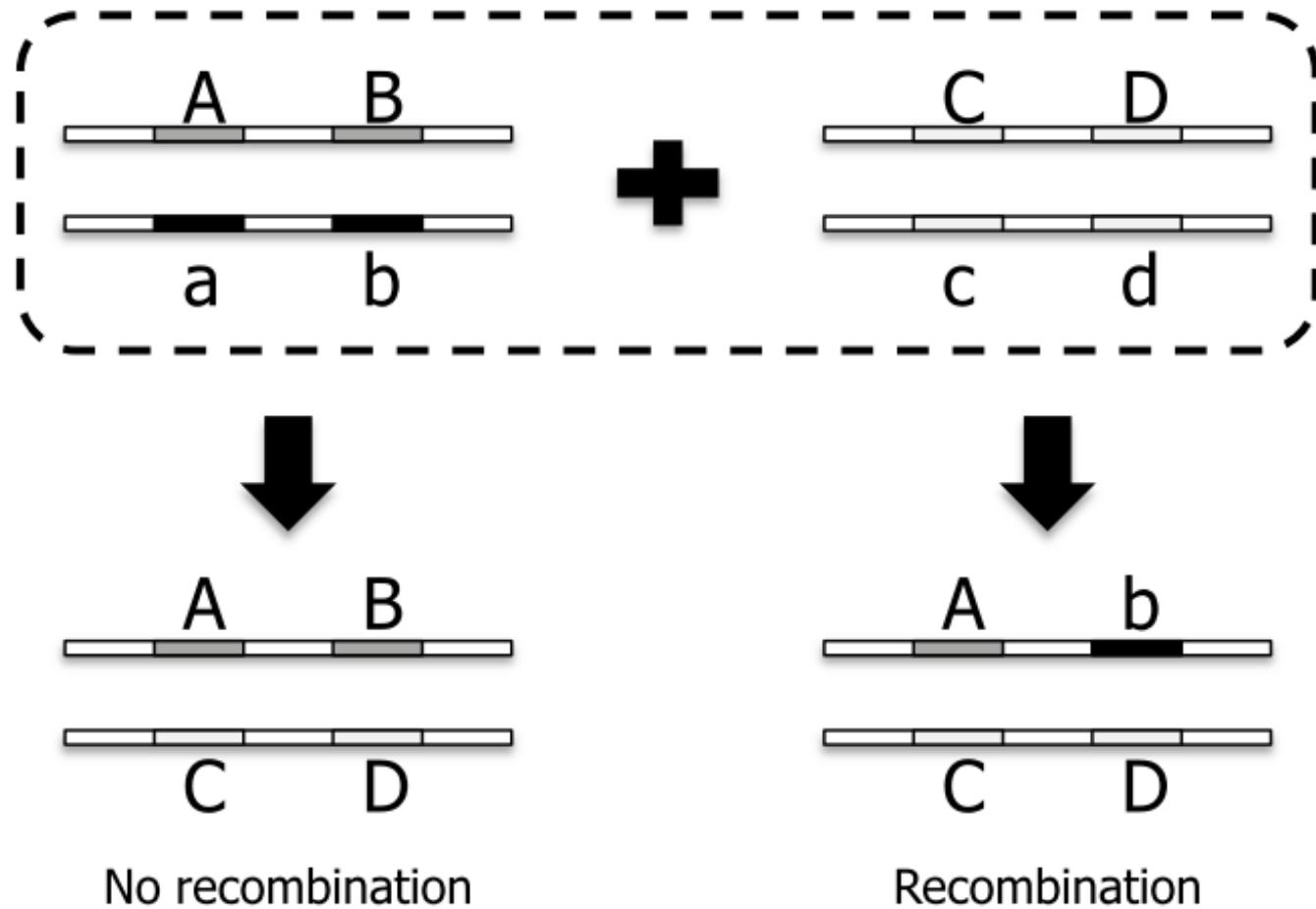
AGGAA
CTGAT

Configuration 4:

ATGAA
CGGAT



基因重组(Recombination)





Pedigree Data

- Assumption
 - Pedigree graph (genetic relationship)
 - Mendelian law (no mutation)
- Difficulty
 - Additional genotyping costs
 - Potential recruiting problems
 - Not all SNP sites can be resolved

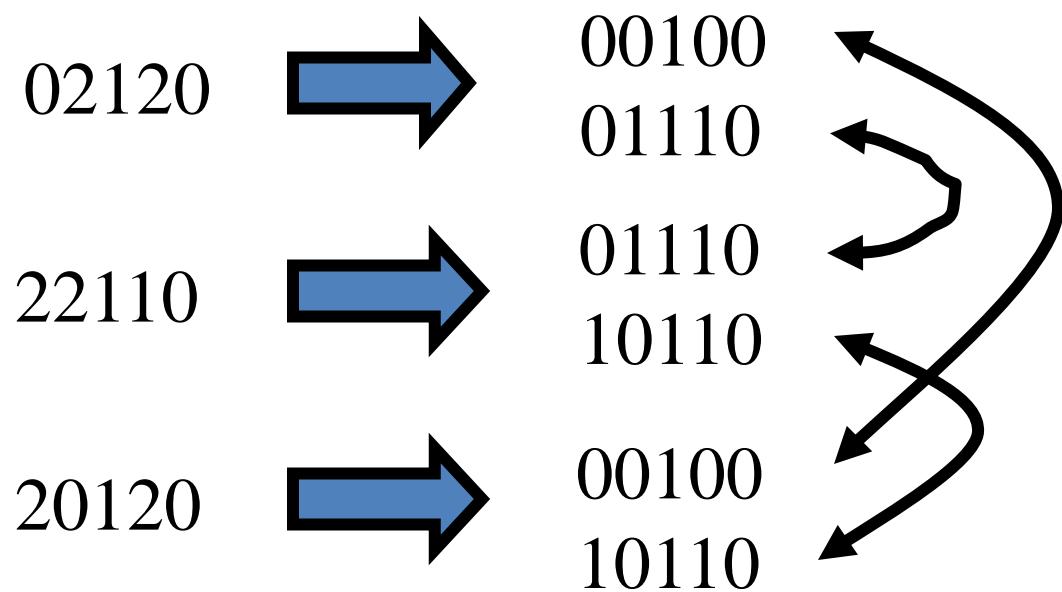


Pedigree Models

- **Minimum Recombination Haplotype Configuration (MRHC)**
 - Pedigree graph: NP-hard (Li and Jiang 2003)
 - Pedigree tree: NP-hard (Doi *et al.* 2003)
- **Zero Recombination Haplotype Configuration (ZRHC)**
 - Polynomial solvable (Li and Jiang 2003)
- **k -Minimum Recombination Haplotype Configuration (k -MRHC)**
 - Pedigree graph: NP-hard ($k \geq 1$) (Chin *et al.* 2005)
 - Pedigree tree: Open



节俭原则





HIPP模型

- **Haplotype Inference by Pure Parsimony**
- The HIPP is APX-hard (*Lancia et al.* 2004)
- Branch and Bound (Wang and Xu 2003)
- Integer Programming (Gusfield 2003, Brown and Harrower 2004, 2006)
- Approximation algorithms (*Lancia et al.* 2004, Huang et al. 2005)
- Heuristic Method (Li et al. 2005)



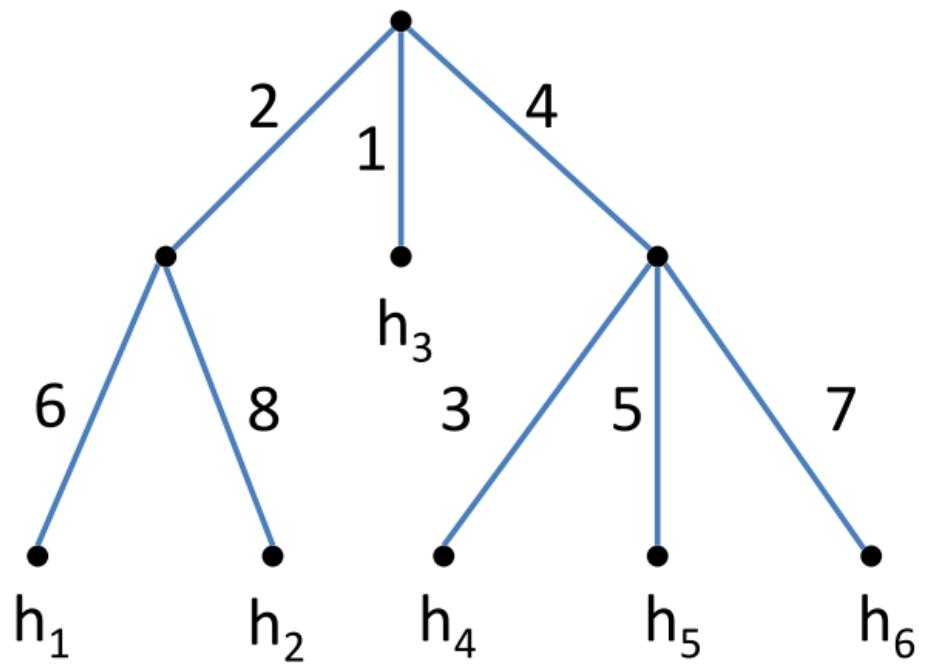
进化树(Phylogeny)

- **Haplotype Perfect Phylogeny**

- Rooted tree
- Each leaf denotes a distinct haplotype
- Each edge represents a SNP site with a mutation from 0 to 1
- Each SNP site is labeled by at most one edge
- For each haplotype labeled by a leaf, the unique path from the root to it specifies all SNP sites with value 1

进化树(Phylogeny)

$$\begin{pmatrix} 0 & 1 & 0 & 0 & 0 & 1 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 & 0 & 0 & 1 \\ 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 1 & 1 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 & 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 & 0 & 1 & 0 \end{pmatrix}$$





PPH模型

- **Perfect Phylogeny Haplotype (PPH)**
 - Graph Realization Problem
 - Polynomial algorithms (Gusfield 2002, Bafna *et al.* 2003, Eskin *et al.* 2003)
- **Minimum Perfect Phylogeny Haplotype**
 - NP-hard (Bafna *et al.* 2004)



Imperfect Phylogeny

- PPH is NP-hard with data missing (Kimmel and Shamir 2005)
- PPH with additional biologically motivated constrains (Gramm et al. 2004)
- Imperfect Phylogeny Haplotype (IPH) (Halperin and Eskin 2004)



统计学假设

- Underlying unknown distribution of haplotype frequencies
- Hardy-Weinber Equilibrium (HWE)

$$\Pr(g) = \sum_{h \oplus \bar{h} = g} \Pr(h) \Pr(\bar{h})$$



统计学模型

- **Haplotype Frequency Estimation**
 - EM (Expectation-Maximization) (Excoffier et al. 1995)
 - PL-EM (Partition-Ligation-Estimation-Maximization) (Niu et al. 2002)
- **Bayesian Haplotype Inference**
 - MCMC (Markov Chain Monte Carlo) (Stephens et al. 2001)
 - PL-MCMC (Niu et al. 2002)
- **Markov Chain Model**
 - PL like method (Eronen et al. 2004)
 - Dynamic Programming (Zhang et al. 2005)



1阶MC模型

$$\Pr(H) \approx \Pr(H(1)) \prod_{i=2,n} \Pr(H(i)|H(i-1))$$

$$\Pr(H) \approx fr(H(1)) \prod_{i=2,n} \frac{fr(H(i-1, i))}{fr(H(i-1))}$$

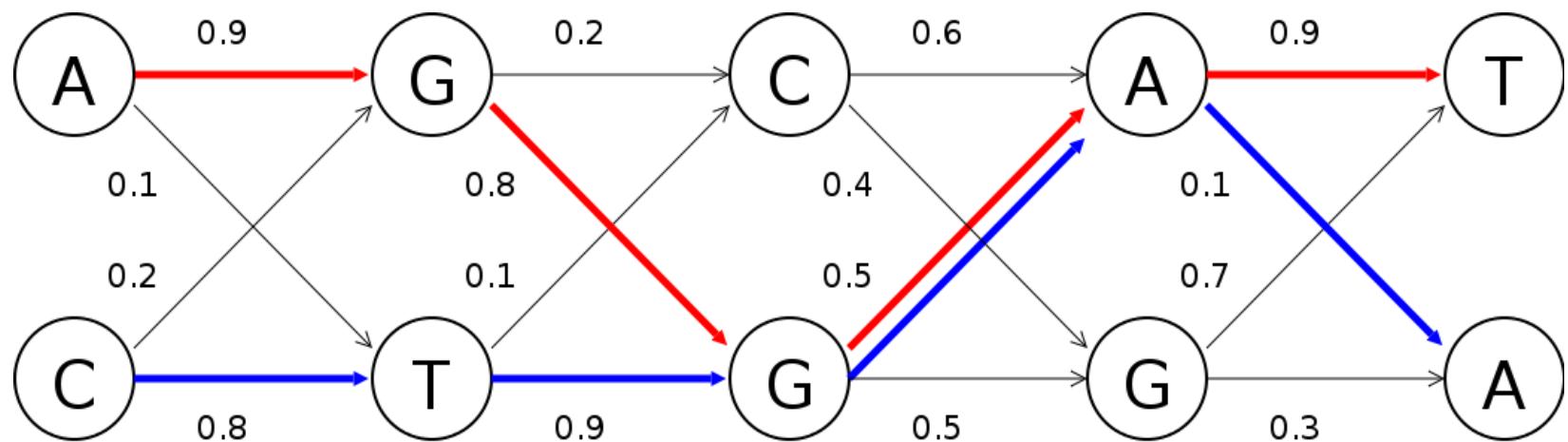


片段频率估计

Suppose that $k_{G(i,j)}$ is the number of heterozygous markers in $G(i,j)$, then the frequency of haplotype fragment $H(i,j)$ is estimated as follows:

$$fr(H(i,j)) = \frac{1}{2|\mathcal{G}|} \sum_{\substack{G \in \mathcal{G}, \\ G \text{ matches } H(i,j)}} 2^{1-k_{G(i,j)}}$$

1阶MC例子



Genotype: {A,C}, {G,T}, G, A, {T,A}

Configuration 1:

AGGAT	0.324
CTGAA	0.036

1阶MC例子

Genotype:

{A,C}, {G,T}, G, A, {T,A}

Configuration 1:

AGGAT 0.324
CTGAA 0.036

0.011664
48.65%

Configuration 3:

ATGAT 0.0405
CGGAA 0.008

0.000324
1.35%

Configuration 2:

AGGAA 0.036
CTGAT 0.324

0.011664
48.65%

Configuration 4:

ATGAA 0.0045
CGGAT 0.072

0.000324
1.35%

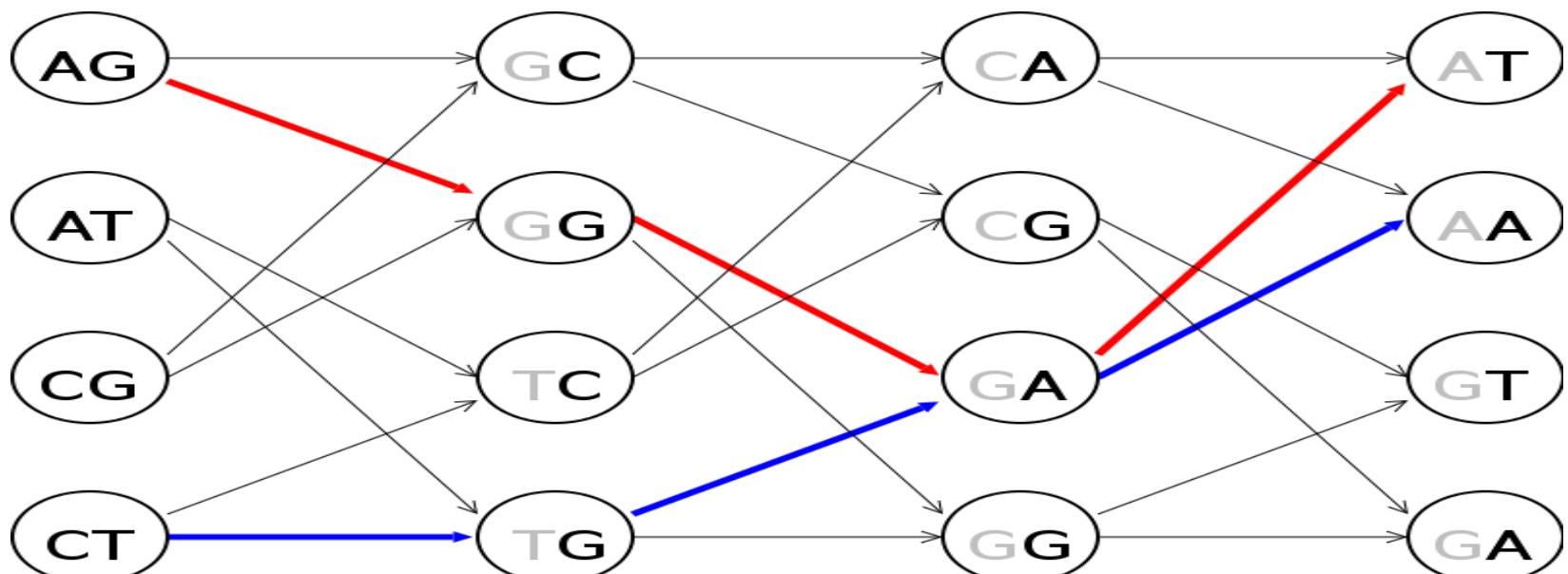


多阶MC模型

$$P(H) \approx P(H(1, d)) \prod_{i=d+1, n} P(H(i)|H(i-d, i-1))$$

$$P(H) \approx fr(H(1, d)) \prod_{i=d+1, n} \frac{fr(H(i - d, i))}{fr(H(i - d, i - 1))}$$

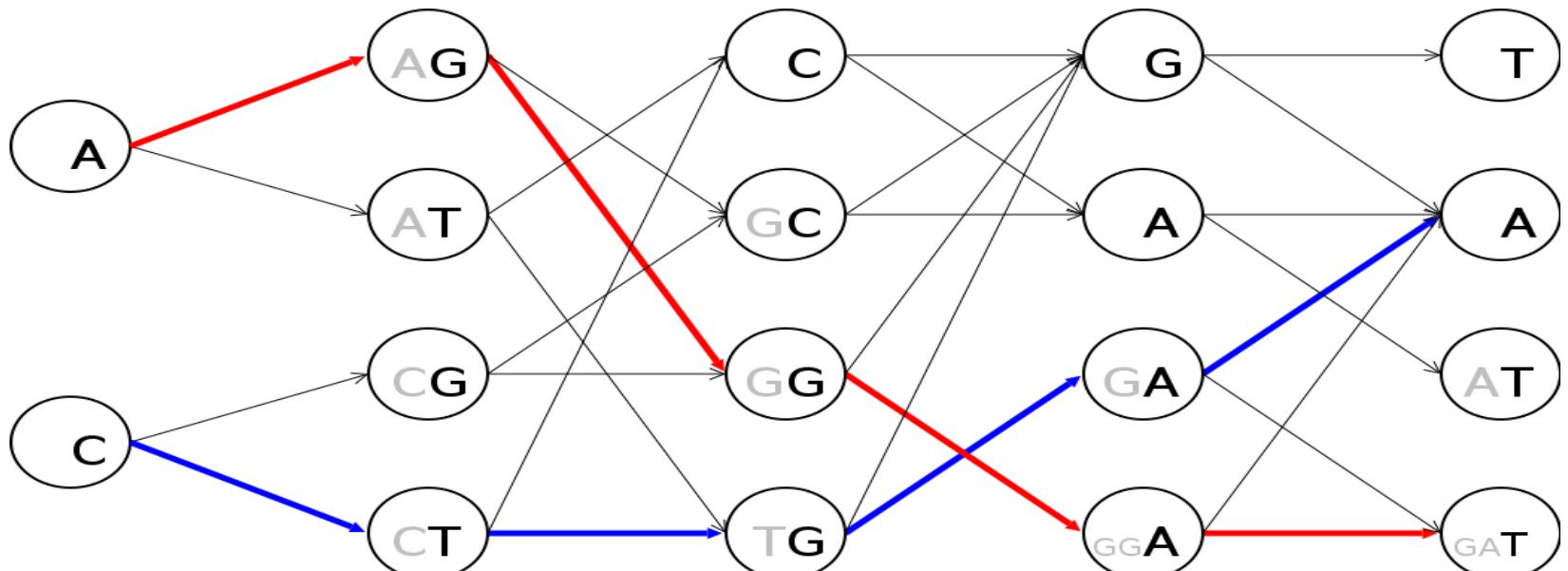
2阶MC例子



Genotype: {A,C}, {G,T}, G, A, {T,A}

Configuration 1:
 AGGAT
 CTGAA

可变阶MC例子



Genotype: {A,C}, {G,T}, G, A, {T,A}

Configuration 1:

AGGAT
CTGAA



片断的长度与频率

- 长的片断
 - 更多的相关信息
 - 较低的频率，不容易估计准确
- 短的片断
 - 较高的频率，估计较准确
 - 较少的相关信息，尤其是长范围的相关信息
- 片断长度与频率之间的tradeoff



最优解

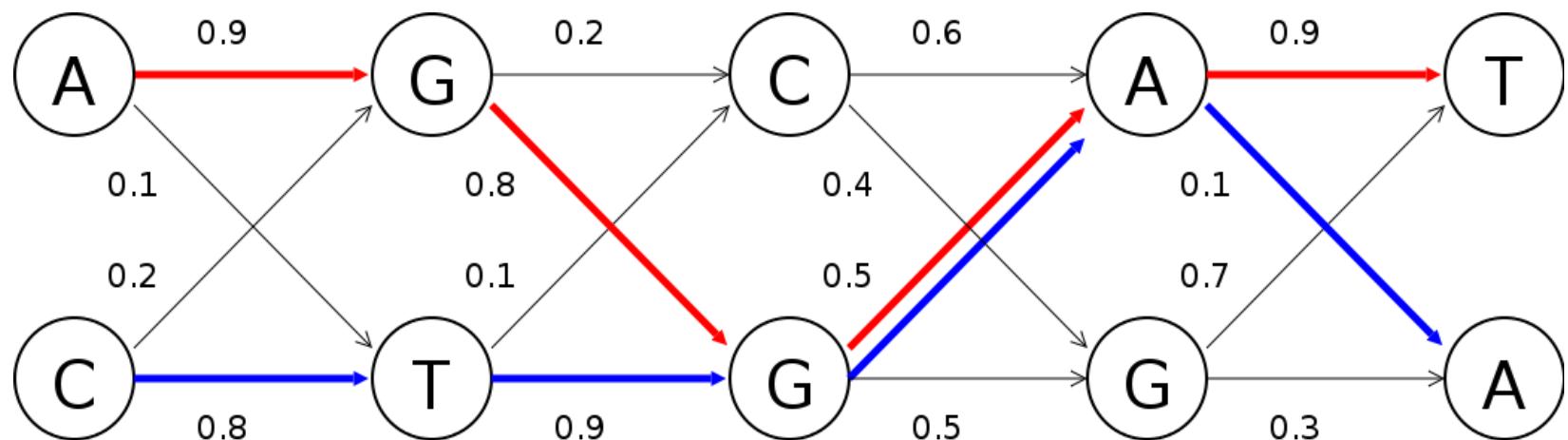
- Given the parameters of Markov chain, how to find the best haplotype pair for each individual?
- The number of possible haplotype configurations for a genotype **grows exponentially** with the number of **heterozygous** markers
- Exhaustive search is **infeasible** for large problem



算法

- Partition-Ligation algorithm
 - Eronen *et al.* 2004
 - Heuristic algorithm
- Dynamic Programming algorithm
 - Exact algorithm
 - Quadratic time complexity (Linear time complexity after improvement) with fixed model parameters
 - Give the condition under which the DP algorithm can be applied to multiple order Markov Chain model

动态规划

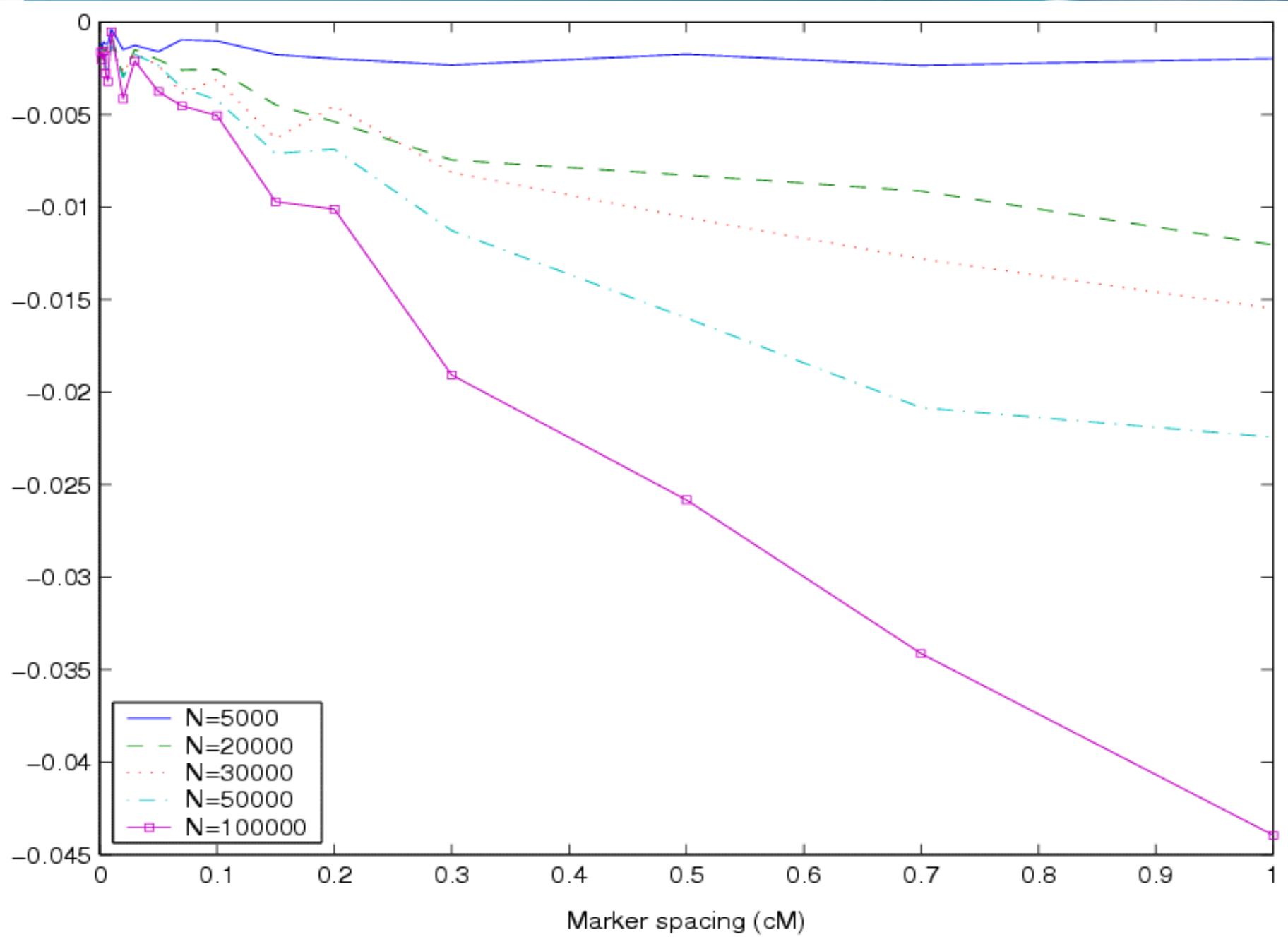


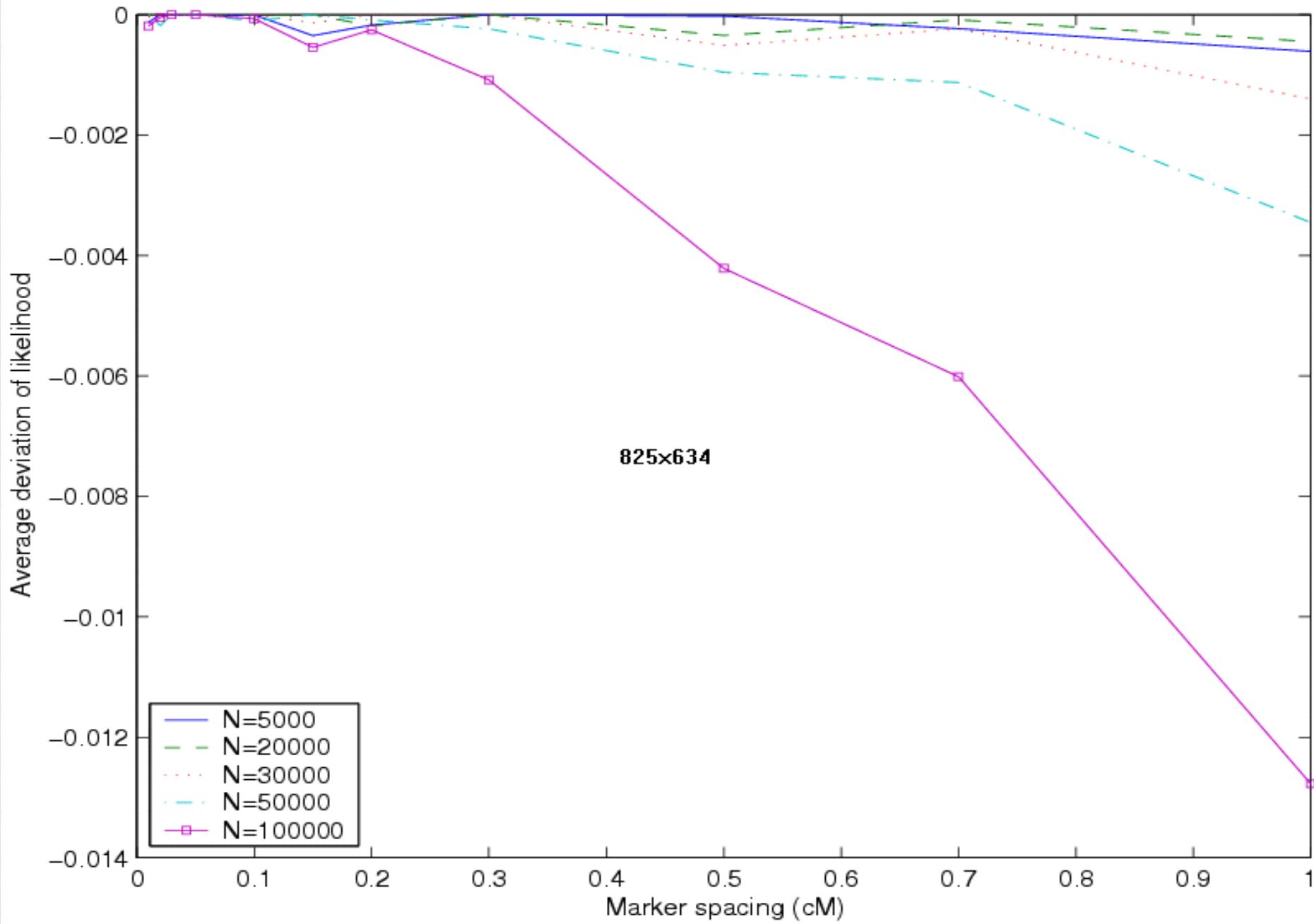
Genotype: {A,C}, {G,T}, G, A, {T,A}

Configuration 1:

AGGAT	0.324
CTGAA	0.036

Average deviation of likelihood





Data	Marker	N=5000		N=20000		N=30000		N=50000		N=100000	
		haplorec	HMC								
A_0.001_2	0.001	0.2974	0.2932	0.0326	0.0298	0.0228	0.0178	0.019	0.0142	0.0146	0.0066
A_0.002_2	0.002	0.3788	0.3776	0.0624	0.0568	0.0404	0.037	0.0264	0.0198	0.0232	0.0152
A_0.003_2	0.003	0.313	0.3074	0.0386	0.035	0.0328	0.0246	0.0272	0.0218	0.022	0.019
A_0.005_2	0.005	0.3862	0.3846	0.0662	0.0574	0.0456	0.0368	0.0366	0.0272	0.0326	0.0192
A_0.007_2	0.007	0.3178	0.3116	0.0702	0.062	0.0492	0.0386	0.0352	0.0262	0.0278	0.0178
A_0.01_2	0.01	0.2708	0.2676	0.0378	0.036	0.0348	0.0286	0.028	0.0224	0.0262	0.0246
A_0.02_2	0.02	0.3876	0.3822	0.0772	0.0664	0.0626	0.0514	0.0584	0.0466	0.0496	0.0382
A_0.03_2	0.03	0.4074	0.406	0.0856	0.0824	0.0662	0.064	0.0718	0.0688	0.0698	0.0704
A_0.05_2	0.05	0.4796	0.471	0.1406	0.1378	0.131	0.132	0.123	0.1276	0.1328	0.139
A_0.07_2	0.07	0.4956	0.4978	0.1826	0.1758	0.1646	0.161	0.1684	0.164	0.1858	0.1804
A_0.10_2	0.1	0.5368	0.5338	0.2496	0.243	0.237	0.2282	0.2362	0.2316	0.2596	0.2588
A_0.15_2	0.15	0.6982	0.6958	0.4026	0.4008	0.3896	0.3944	0.429	0.4322	0.4908	0.4982
A_0.20_2	0.2	0.8682	0.861	0.5694	0.5686	0.5736	0.563	0.616	0.615	0.688	0.6924
A_0.30_2	0.3	1.1264	1.12	0.936	0.9292	0.9428	0.9474	1.0364	1.0418	1.175	1.1912
A_0.50_2	0.5	1.8244	1.8202	1.6996	1.7066	1.771	1.7678	1.881	1.9012	2.0914	2.1368
A_0.70_2	0.7	2.405	2.3994	2.4426	2.4516	2.508	2.53	2.7026	2.7158	2.952	2.9896
A_1.00_2	1	3.0916	3.0902	3.2802	3.3022	3.3964	3.405	3.5722	3.607	3.8634	3.9142

Table 1: Average switch distance of solutions obtained by HMC and haplorec (SNPs)

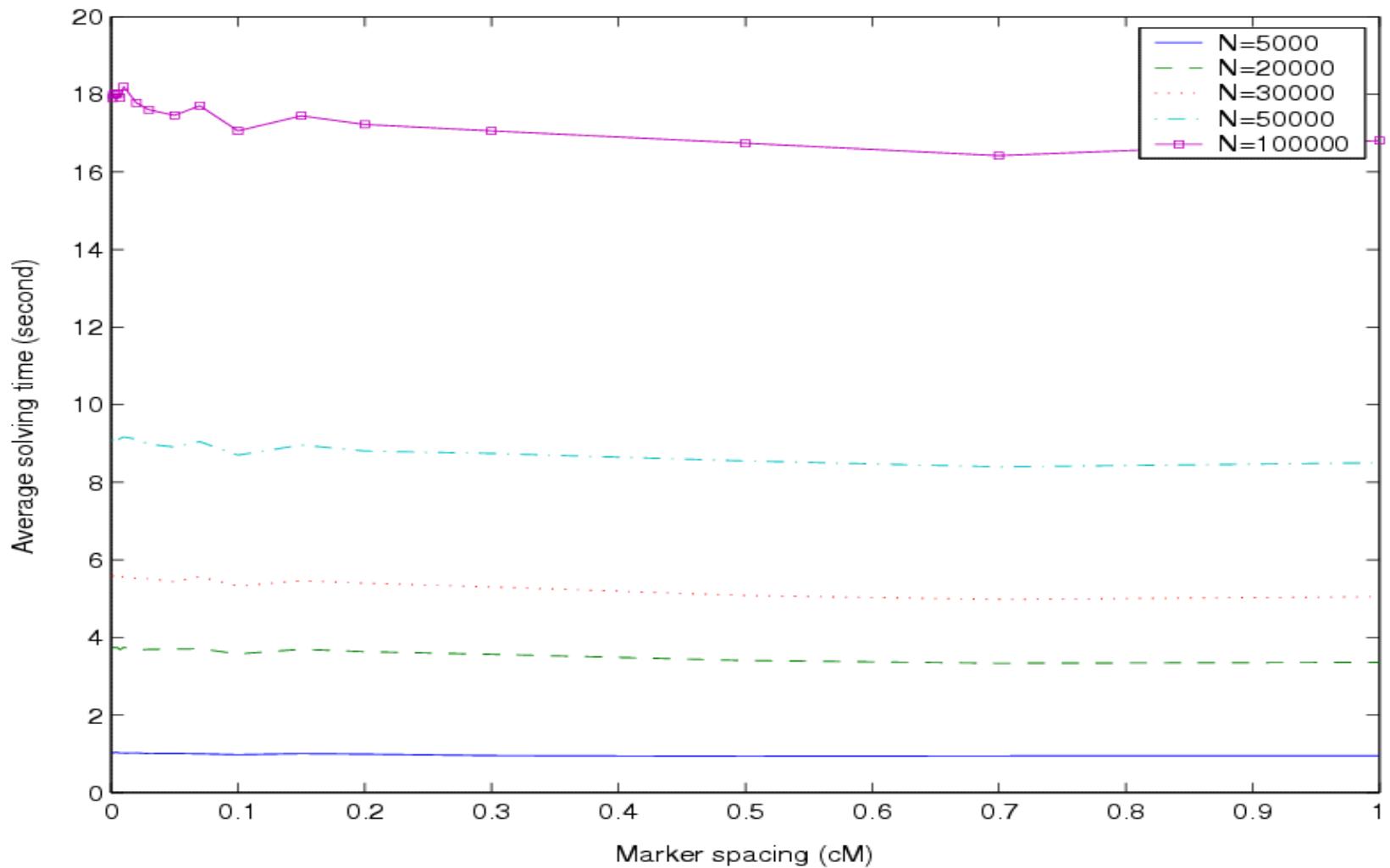
Data name	Marker spacing	N=5000		N=20000		N=30000		N=50000		N=100000	
		haplorec	HMC								
A_0.01_6	0.01	0.0732	0.0746	0.0054	0.0054	0.0056	0.0056	0.0064	0.0064	0.01	0.0086
A_0.02_6	0.02	0.0554	0.0558	0.0094	0.0092	0.0098	0.0092	0.0126	0.0112	0.0092	0.0104
A_0.03_6	0.03	0.0516	0.0516	0.0116	0.0114	0.0104	0.0106	0.0094	0.0094	0.0118	0.0118
A_0.05_6	0.05	0.0758	0.0758	0.0172	0.017	0.02	0.0198	0.0198	0.0194	0.0196	0.0196
A_0.10_6	0.1	0.1184	0.1184	0.0416	0.0424	0.0444	0.0444	0.051	0.0518	0.068	0.0684
A_0.15_6	0.15	0.158	0.1588	0.0796	0.0798	0.0858	0.086	0.096	0.0952	0.1266	0.1298
A_0.20_6	0.2	0.2186	0.2176	0.1286	0.1274	0.129	0.1296	0.1514	0.1524	0.1916	0.1928
A_0.30_6	0.3	0.2968	0.2908	0.2064	0.2076	0.2168	0.215	0.245	0.247	0.3342	0.3392
A_0.50_6	0.5	0.564	0.5604	0.468	0.4702	0.5176	0.5186	0.615	0.6162	0.8426	0.8598
A_0.70_6	0.7	0.8914	0.8874	0.7936	0.7916	0.8824	0.8854	1.0338	1.0404	1.3978	1.42
A_1.00_6	1	1.32	1.3222	1.2942	1.2952	1.4254	1.425	1.6374	1.6528	2.182	2.221

Table 2: Average switch distance of solutions obtained by HMC and haplorec (microsatellites)

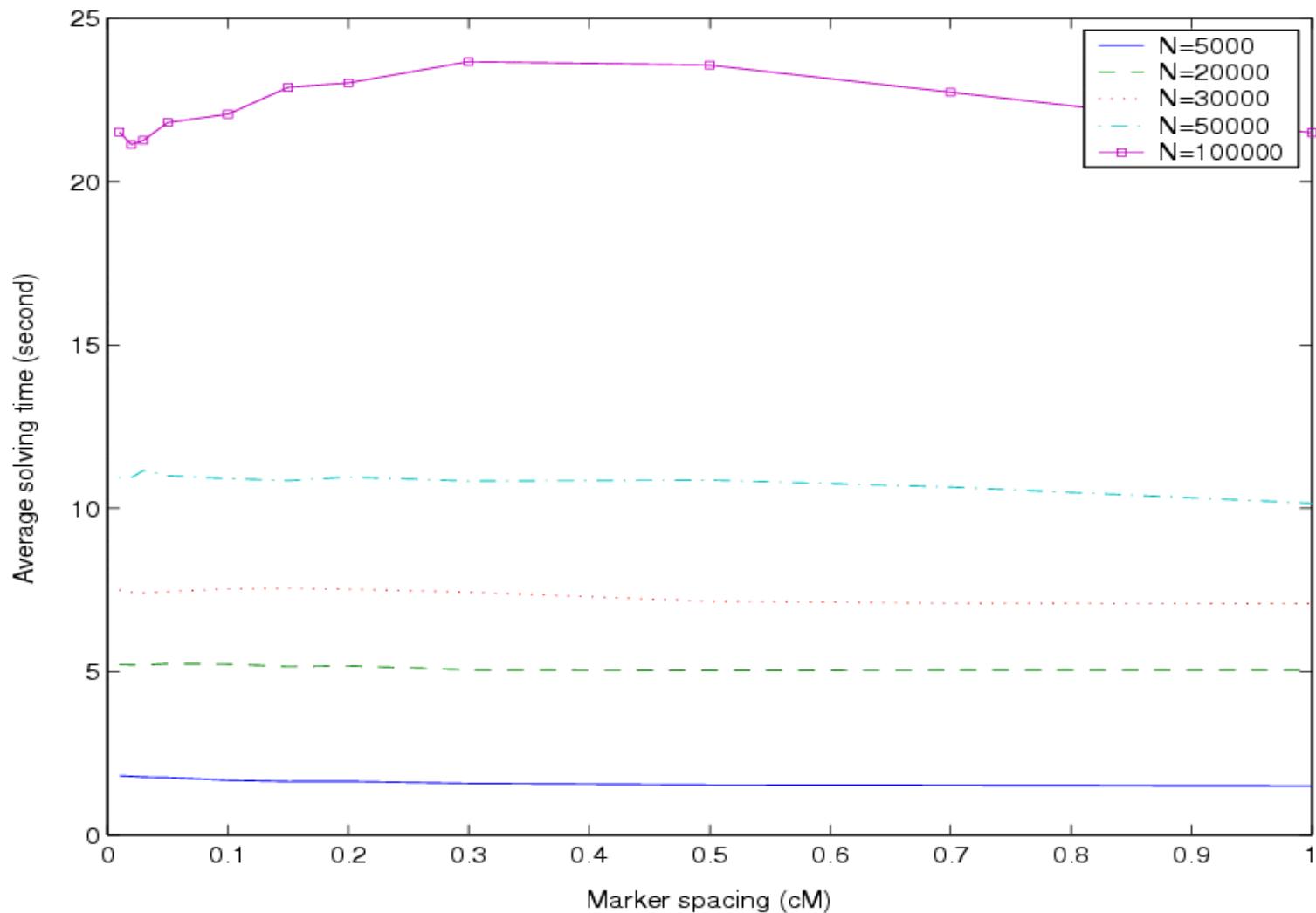
	N=5000		N=20000		N=30000		N=50000		N=100000	
	haplorec	HMC	haplorec	HMC	haplorec	HMC	haplorec	HMC	haplorec	HMC
Switch Distance	1.210884	1.18367	0.938776	0.82313	0.897959	0.81633	0.904762	0.84354	0.979592	0.89116
Accuracy	0.503401	0.489796	0.544218	0.557823	0.537415	0.557823	0.551020	0.557823	0.551020	0.544218

Table 3: Comparison of solutions on the Daly data set

计算时间



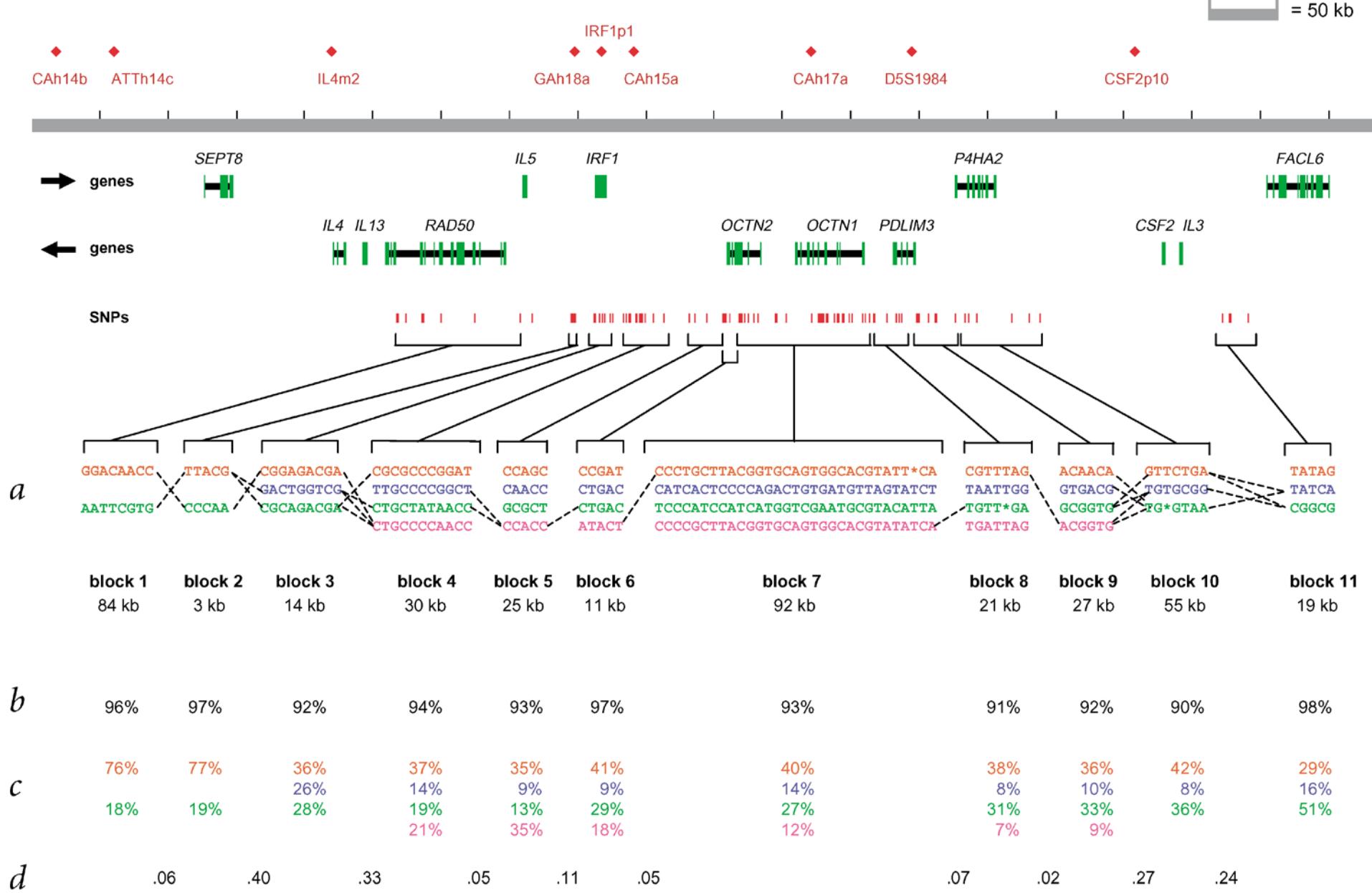
计算时间



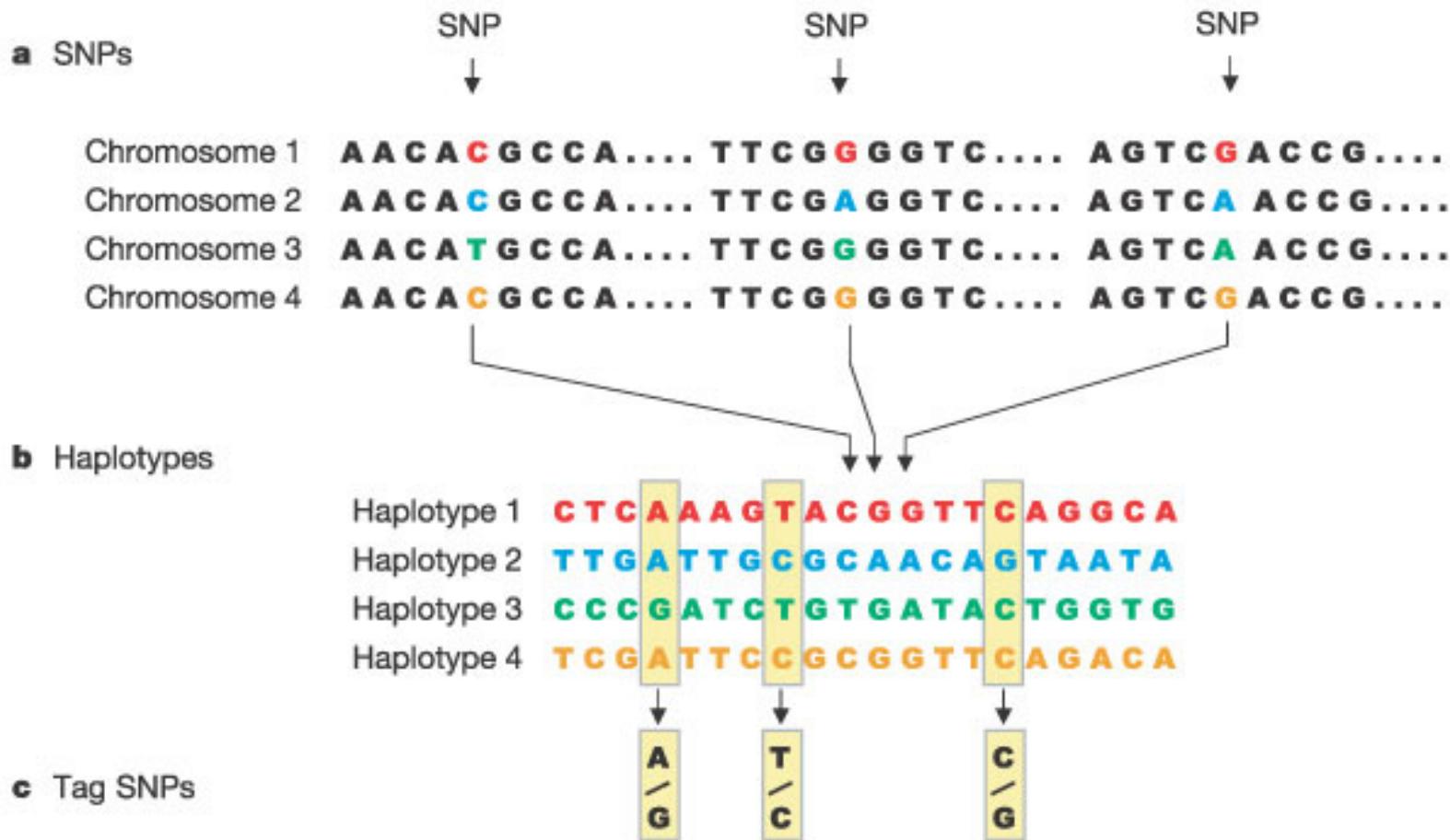


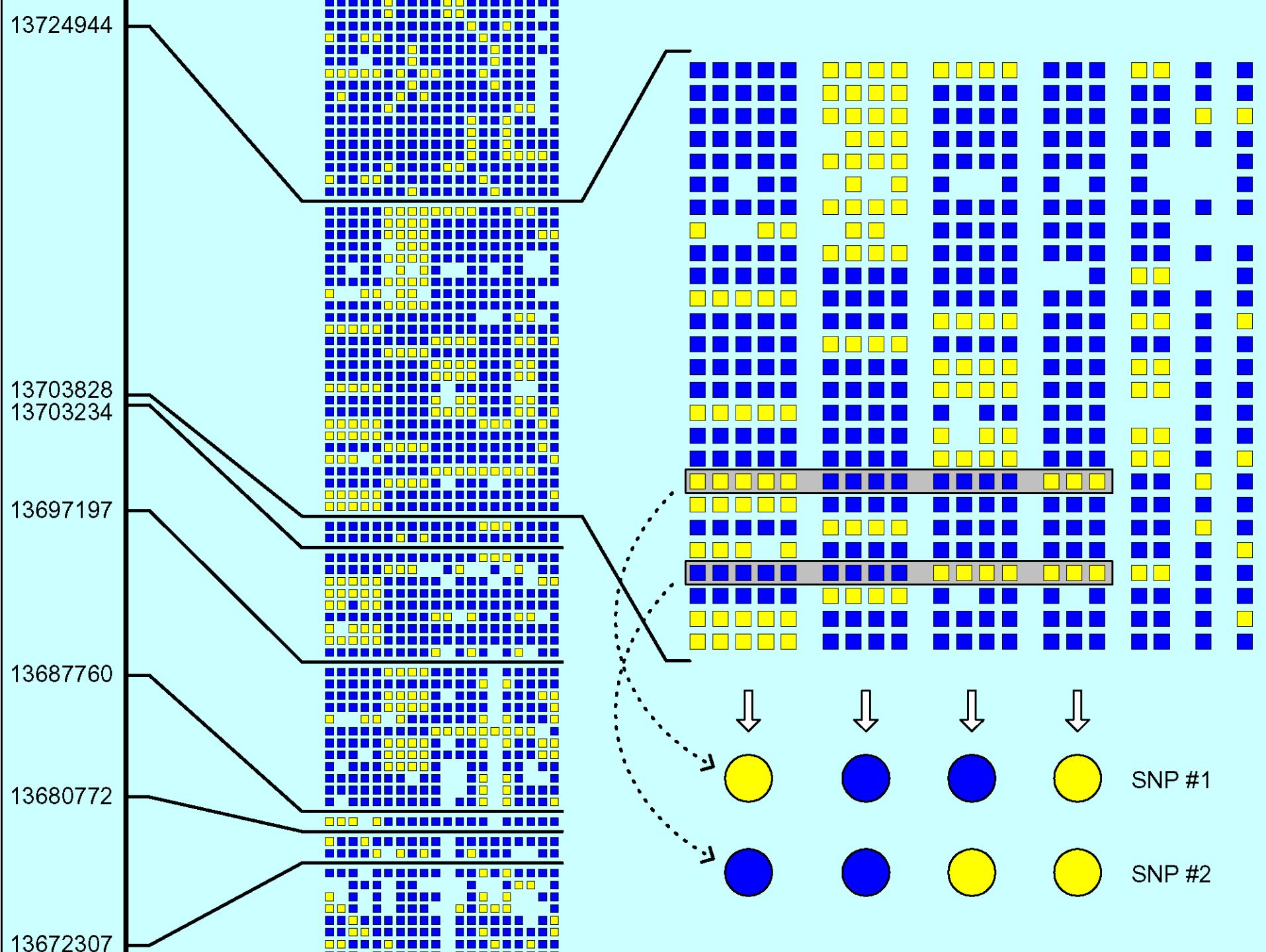
单体型相关问题

- 单体型组装问题
- 单体型推断问题
- 单体型分块问题
- 标签SNP选取问题



标签SNP







标签SNP的定义

- Tag SNPs
 - A small subset of SNPs which is sufficient to distinguish each pair of haplotype patterns
- Robust Tag SNPs
 - A subset of SNPs which can still distinguish all distinct haplotypes **even when some SNPs are missing**



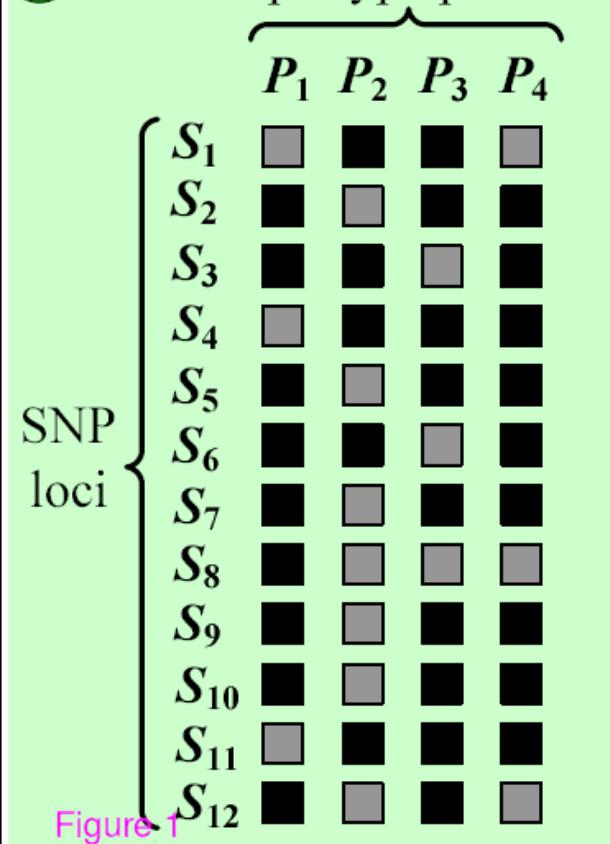
标签SNP选取问题

- Minimum Tag SNPs
 - Find the minimum set of tag SNPs
- Minimum Auxiliary Tag SNPs
 - Find the minimum subset of additional SNPs to resolve the ambiguity caused by missing data
- Minimum Robust Tag SNPs
 - Find the minimum set of robust tag SNPs which are able to tolerate a number of missing SNPs

辅助标签SNPs

A

Haplotype patterns



B

	P_1	P_2	P_3	P_4	h_1
S_1	■	■	■	■	■
S_{12}	■	■	■	■	■

D

	P_1	P_2	P_3	P_4	h_2
S_1	■	■	■	■	■
S_5	■	■	■	■	■
S_{12}	■	■	■	■	□

C

	P_1	P_2	P_3	P_4	h_2	h_3
S_1	■	■	■	■	■	□
S_{12}	■	■	■	■	□	■

Figure 1

■ : Major allele

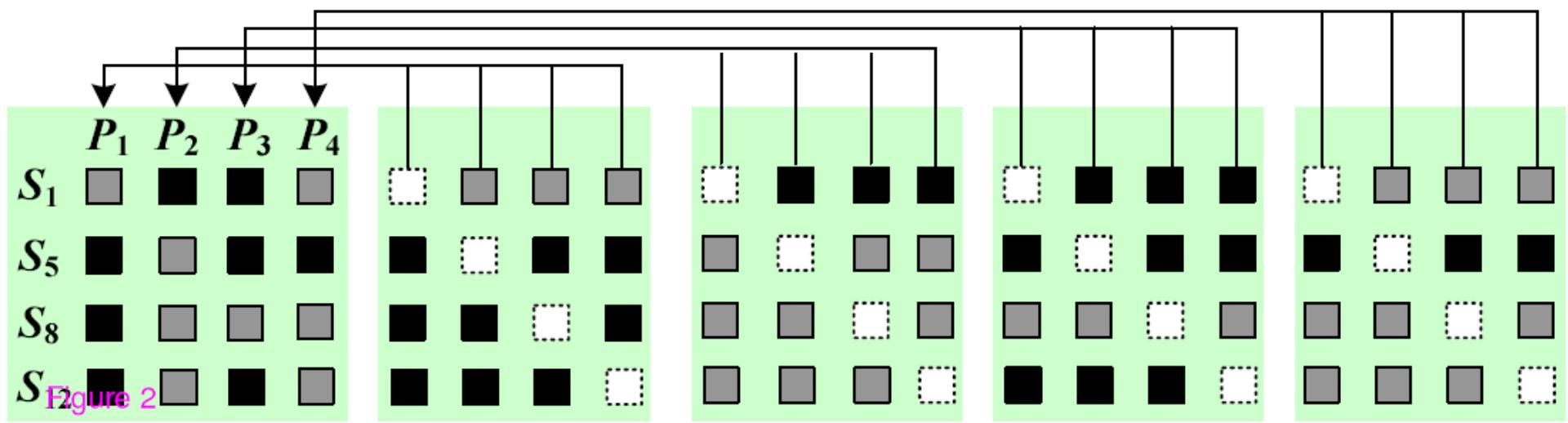
■ : Minor allele

□ : Missing data

E

	P_1	P_2	P_3	P_4	h_3
S_1	■	■	■	■	□
S_8	■	■	■	■	■
S_{12}	■	■	■	■	■

Robust Tag SNPs



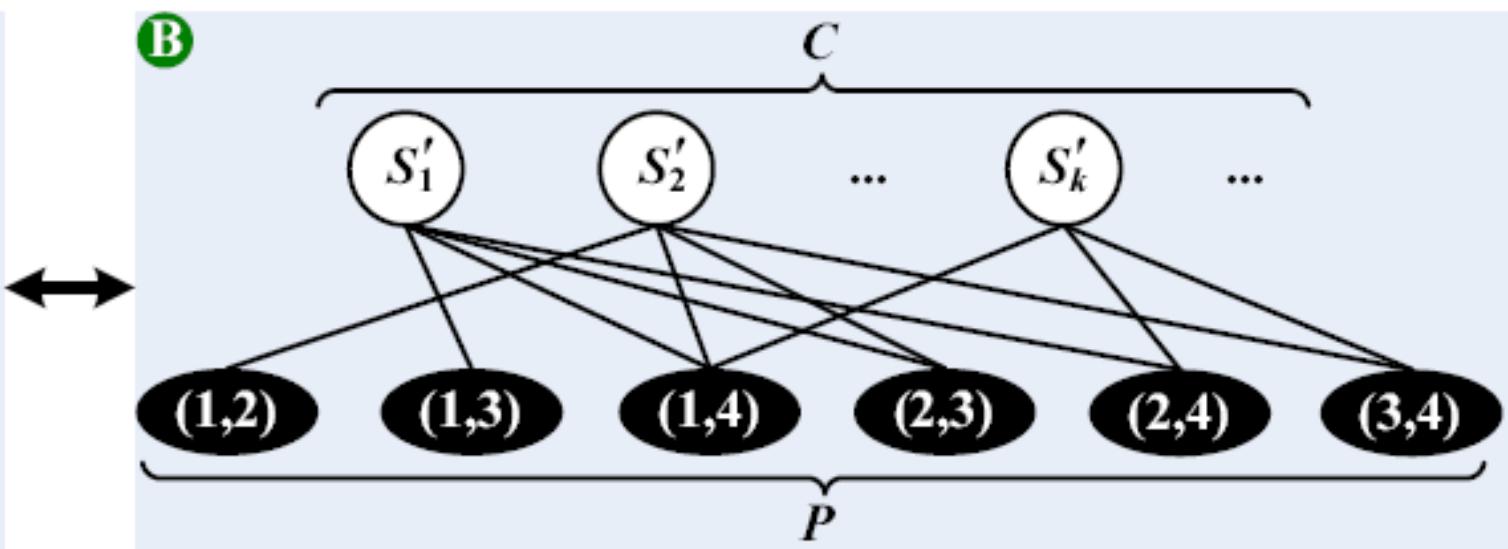
集覆盖问题

A

$$N \left\{ \begin{array}{c} S_1 \\ S_2 \\ \vdots \\ S_k \\ \vdots \end{array} \right. \quad \overbrace{P_1 P_2 P_3 P_4}^{K=4}$$

	P_1	P_2	P_3	P_4
S_1	1	1	2	2
S_2	1	2	1	2
\vdots	\vdots	\vdots	\vdots	\vdots
S_k	1	1	1	2
\vdots	\vdots	\vdots	\vdots	\vdots

Figure 6





计算复杂性

- Minimum Tag SNPs
 - Equivalent to Minimum Set Cover Problem
 - NP-hard
- Minimum Robust Tag SNPs
 - Equivalent to Minimum k -Redundent Coverage
 - NP-hard