Interdisciplinary Research
Cost Function Network for Life Sciences

Simon de Givry

Institut National de Recherche pour l'Agriculture, l'Alimentation et l'Environnement (INRAE)

Laboratoire de Mathématiques et Informatique Appliquées de Toulouse (MIAT), France

Doctoral Program
CP 2022, Haifa, Israel
08/01/2022

Plan

- Case studies
- *Bioinformatics & CFN*
  - Mendelian error detection
  - Computational Protein Design
- *Agronomy & AI*
  - Mixed Fruit-Vegetable Crop Allocation Problem
- Some tips for your thesis

Mendelian error detection in complex pedigree

Simon de Givry, Marti Sanchez, Isabelle Palhière, Zulma Vitezica, and Thomas Schiex

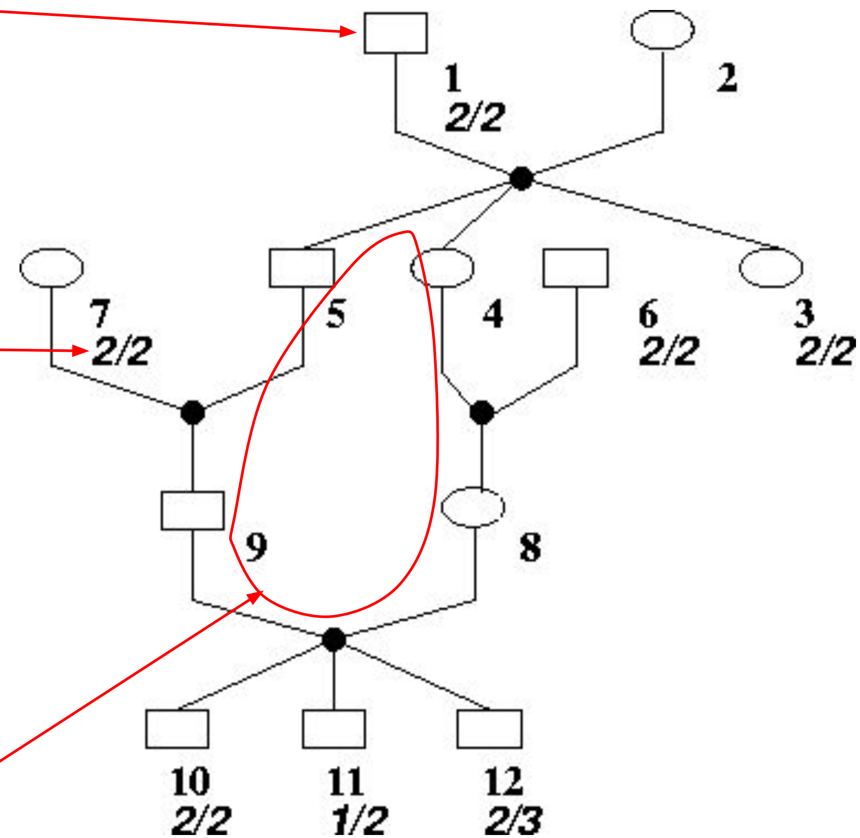
INRAE, Toulouse, France

Cleaning the data

In 2005, about 1% genotyping errors
Today, less than 0.1% (NGS)

Individual
(founder)

Genotype
unordered pair of
alleles
(possibly
unobserved)

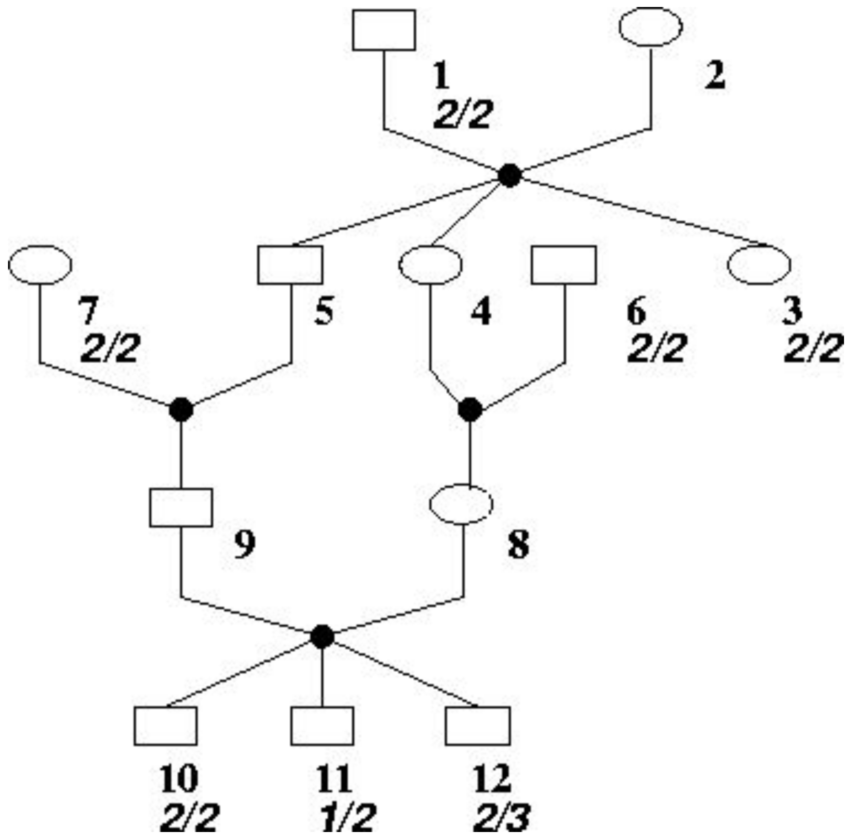


Marriage loop

Task 1: Consistency Checking

- Assuming the pedigree is correct, checks if it exists a complete genotype assignment consistent with the observed genotypes and with the Mendelian laws of inheritance

- Complexity results (Aceto et al., 2003)
  - NP-complete for a pedigree with loops and more than three alleles
  - Polynomial if no loops or just two alleles (SNP)

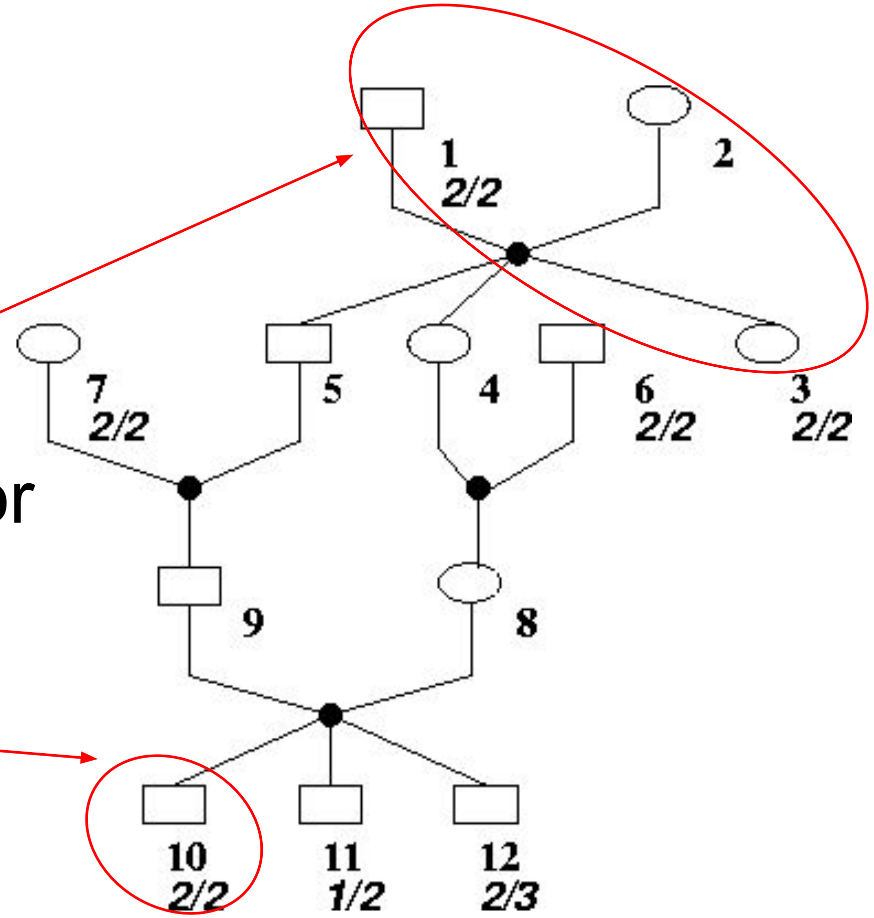


Constraint Satisfaction Problem

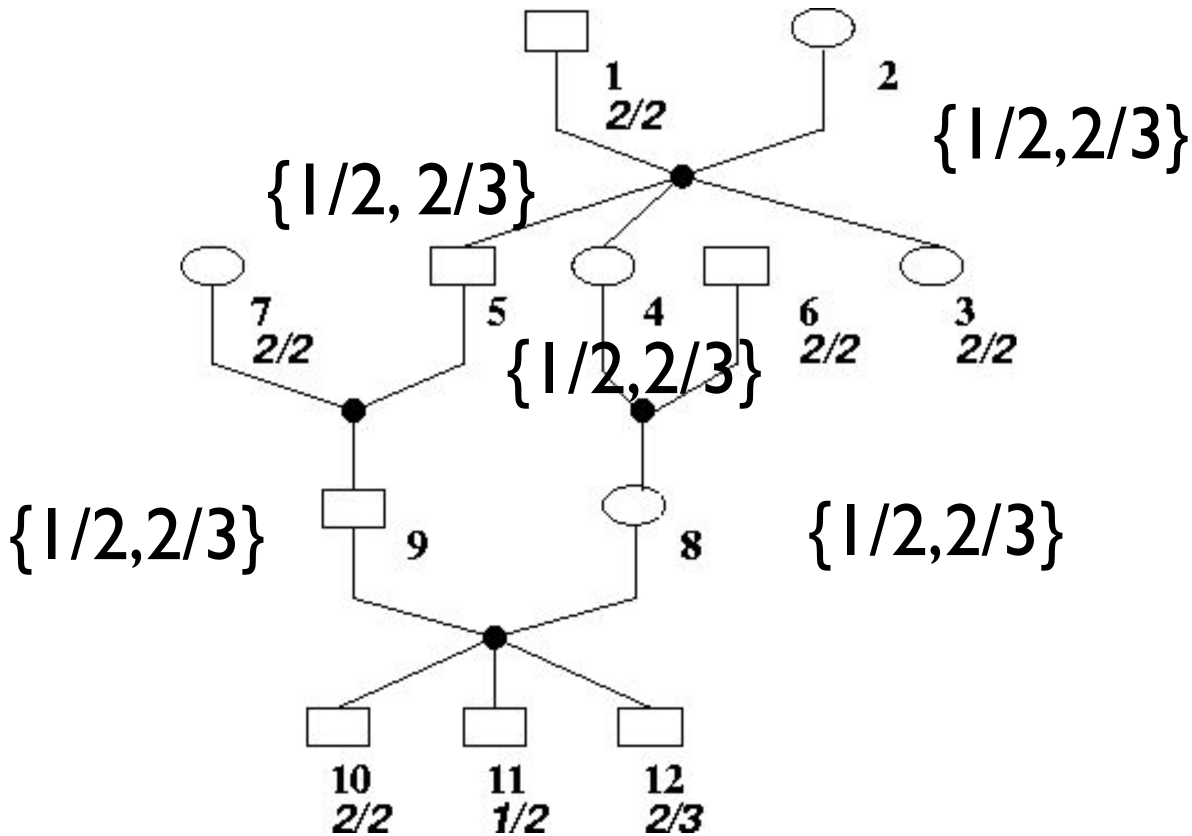
- **X**: one variable per individual
- **D**: domain of every variable is defined as the set of all possible genotypes

{ 1/1, 1/2, 1/3, 2/2, 2/3, 3/3 }

- **C**:
  - Ternary constraints to encode Mendelian laws for any non founder
  - Unary constraints to encode genotyping data



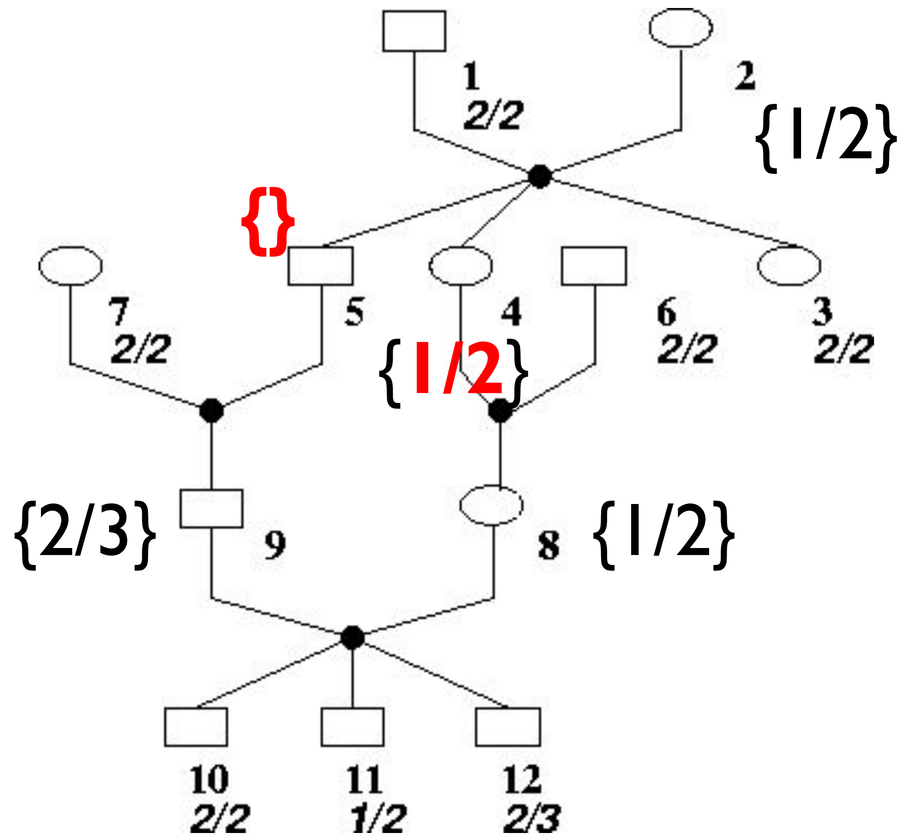
Generalized Arc Consistency



(Mackworth, AIJ 1977)

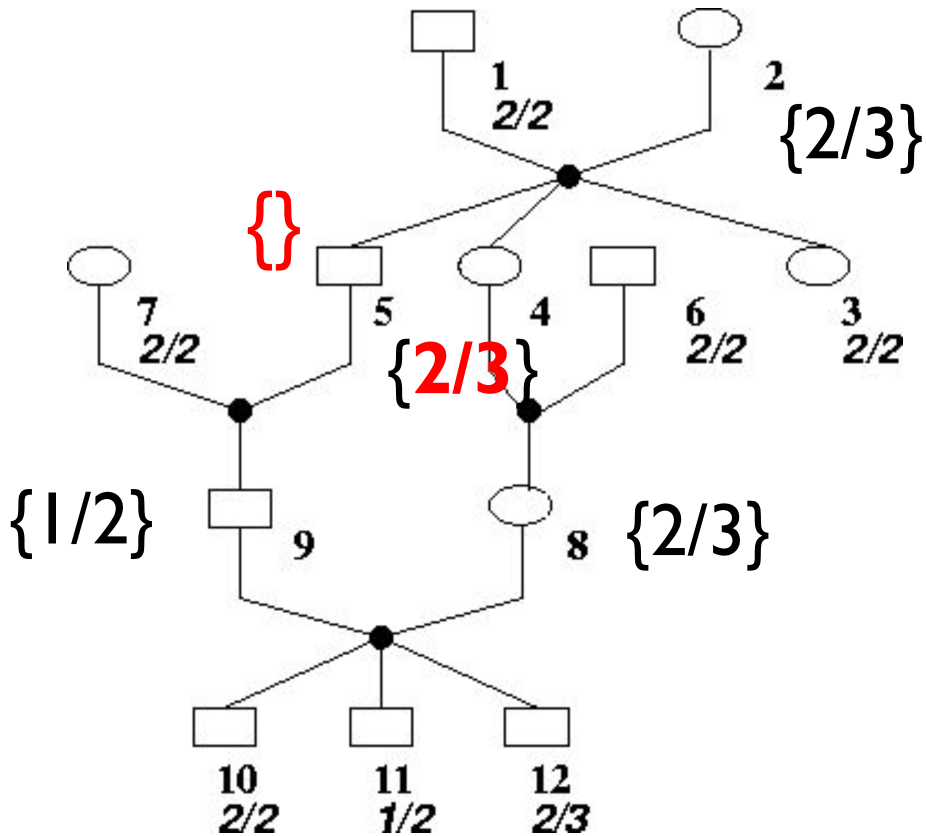
(Lange, Goradia, Am J Hum Genet 1987)

Backtrack search on loop-breaker individuals



(Dechter, AIJ 1990)
(O'Connell, Weeks, Am J Hum Genet 1997)

Backtrack search on loop-breaker individuals

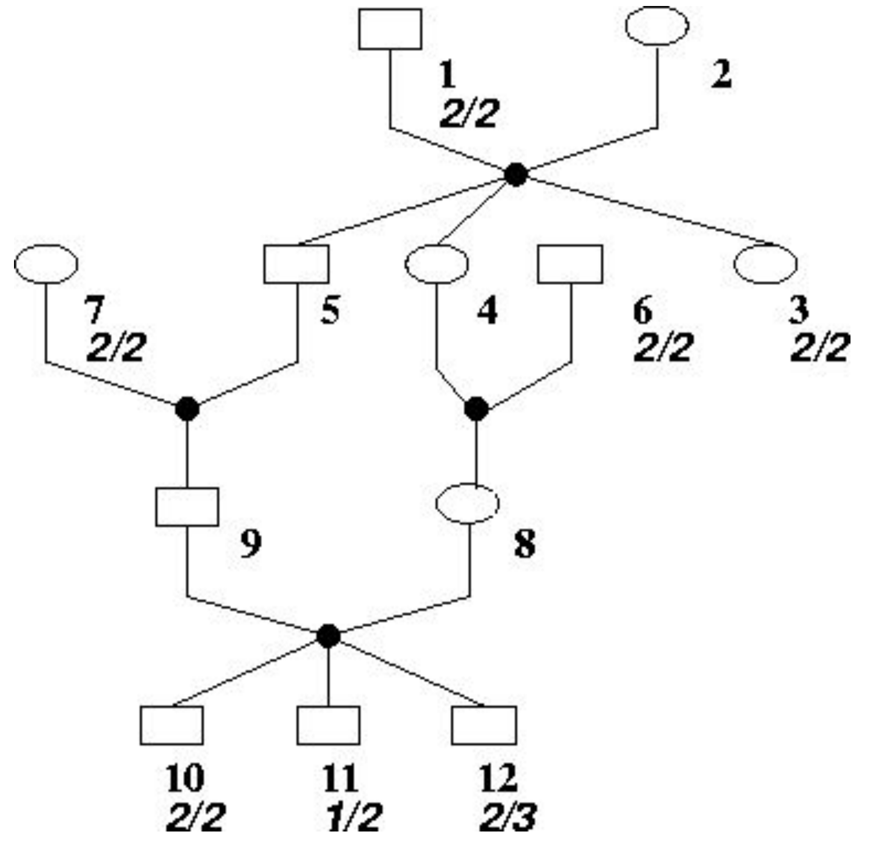


(Dechter, AIJ 1990)
(O'Connell, Weeks, Am J Hum Genet 1997)

Task 2: Error Detection

- Finds a complete assignment with the minimum number of errors

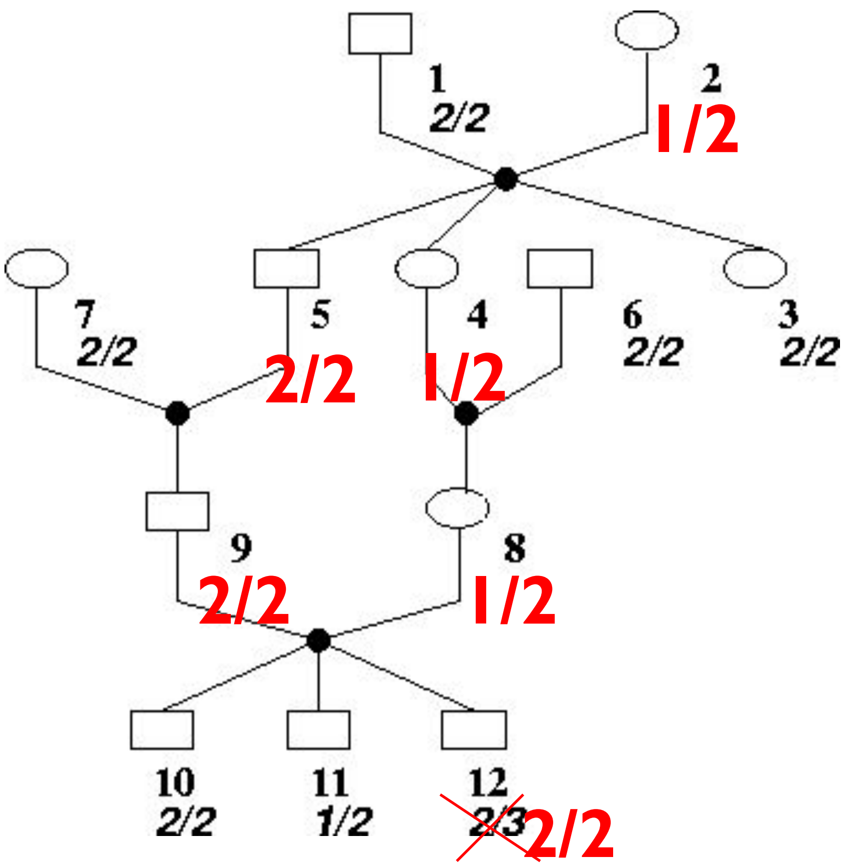
→ parsimony principle



Task 2: Error Detection

- Finds a complete assignment with the minimum number of errors

→ parsimony principle



Cost Function Network

(Shapiro, Haralick, IEEE PAMI 81)
(Freuder, Wallace, AIJ 92)
(Schiex, Fargier, Verfaillie, IJCAI 95)

- (X, D, F)
  - $X=\{X_1,\dots, X_n\}$ ***n*** variables
  - $D=\{D_1,\dots, D_n\}$ ***n*** finite domains of maximum size ***d***
  - $F=\{f_{S1}, \dots, f_{Se}\}$, ***e*** cost functions

  f_{Si} : associates a finite or infinite (***k***) positive integer to each tuple of S_i

- Weighted CSP: find a complete assignment A minimizing

$$\sum_{fS\in F} f_S(A[S])$$

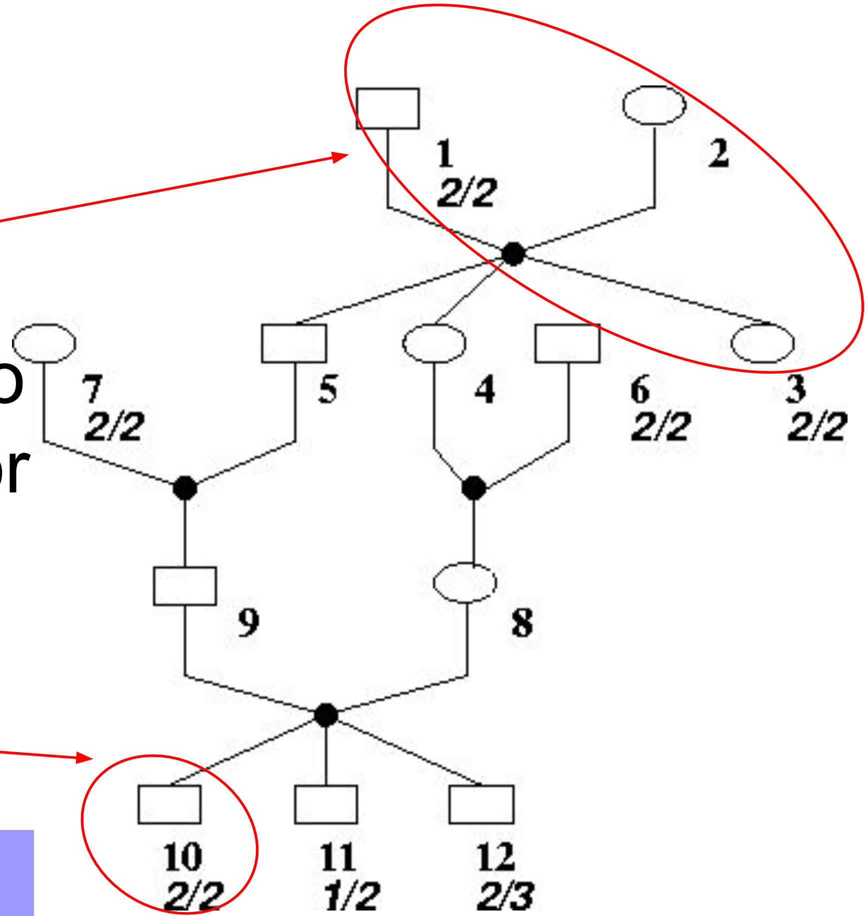
NP-hard problem

Cost Function Network

- **X**: one variable per individual
- **D**: domain of every variable is defined as the set of all possible genotypes

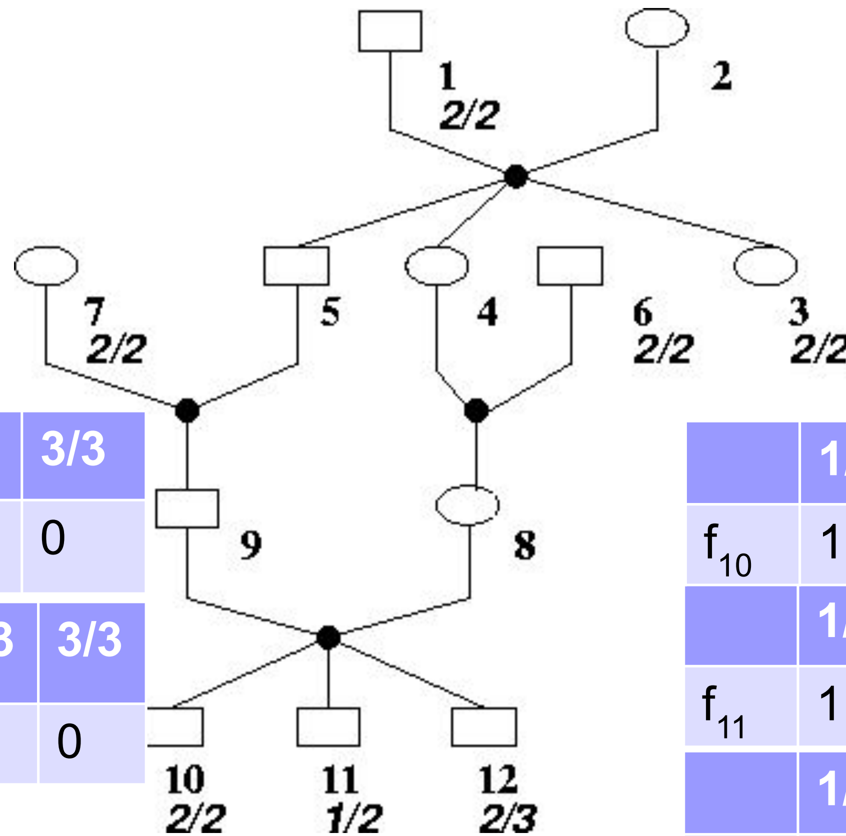
{ 1/1, 1/2, 1/3, 2/2, 2/3, 3/3 }

- **F**:
  - Ternary hard constraints to encode Mendelian laws for any non founder
  - Unary soft constraints to encode genotyping data



	1/1	1/2	1/3	2/2	2/3	3/3
f_{10}	1	1	1	0	1	1

Generalized Soft Arc Consistency



	1/1	1/2	1/3	2/2	2/3	3/3
f_8	0	0	0	0	0	0

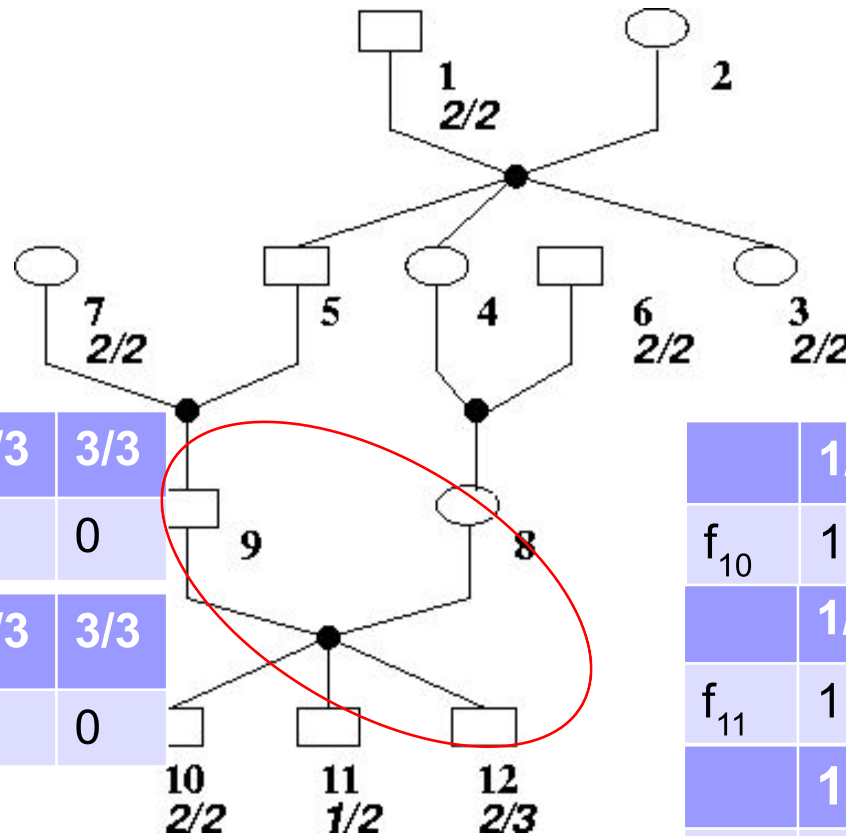
	1/1	1/2	1/3	2/2	2/3	3/3
f_9	0	0	0	0	0	0

	1/1	1/2	1/3	2/2	2/3	3/3
f_{10}	1	1	1	0	1	1

	1/1	1/2	1/3	2/2	2/3	3/3
f_{11}	1	0	1	1	1	1

	1/1	1/2	1/3	2/2	2/3	3/3
f_{12}	1	1	1	1	0	1

Generalized Soft Arc Consistency



	1/1	1/2	1/3	2/2	2/3	3/3
f_8	**1**	0	0	0	0	0

	1/1	1/2	1/3	2/2	2/3	3/3
f_9	0	0	0	0	0	0

	1/1	1/2	1/3	2/2	2/3	3/3
f_{10}	1	1	1	0	1	1

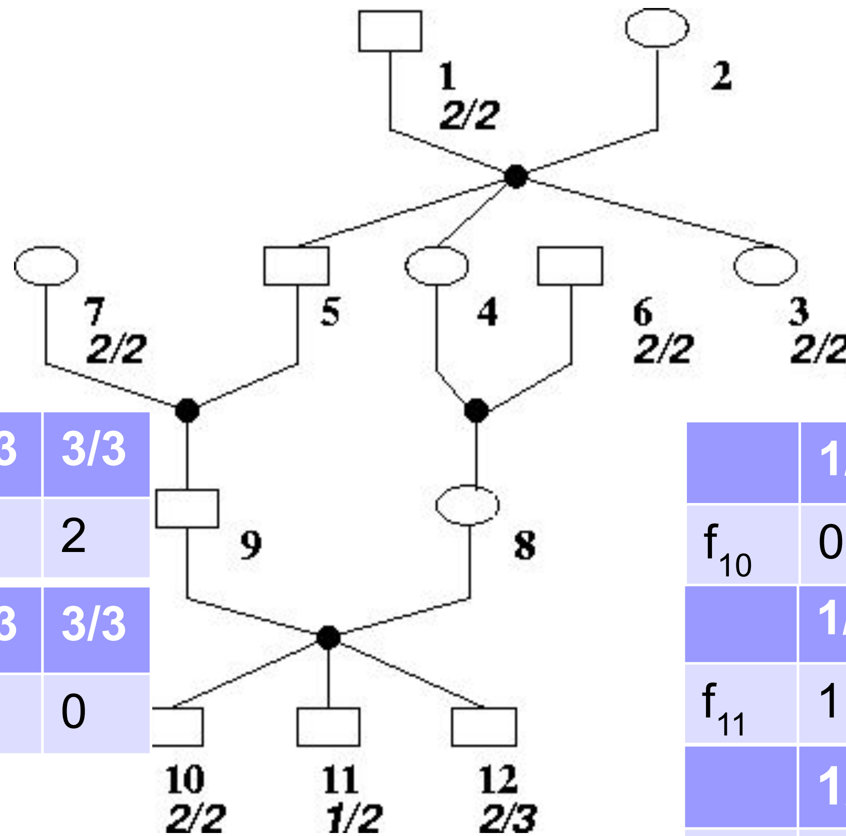
	1/1	1/2	1/3	2/2	2/3	3/3
f_{11}	1	0	1	1	1	1

	1/1	1/2	1/3	2/2	2/3	3/3
f_{12}	**0**	**0**	**0**	1	0	1

Equivalence Preserving Transformation

(Schiex, CP 2000),…

Generalized Soft Arc Consistency

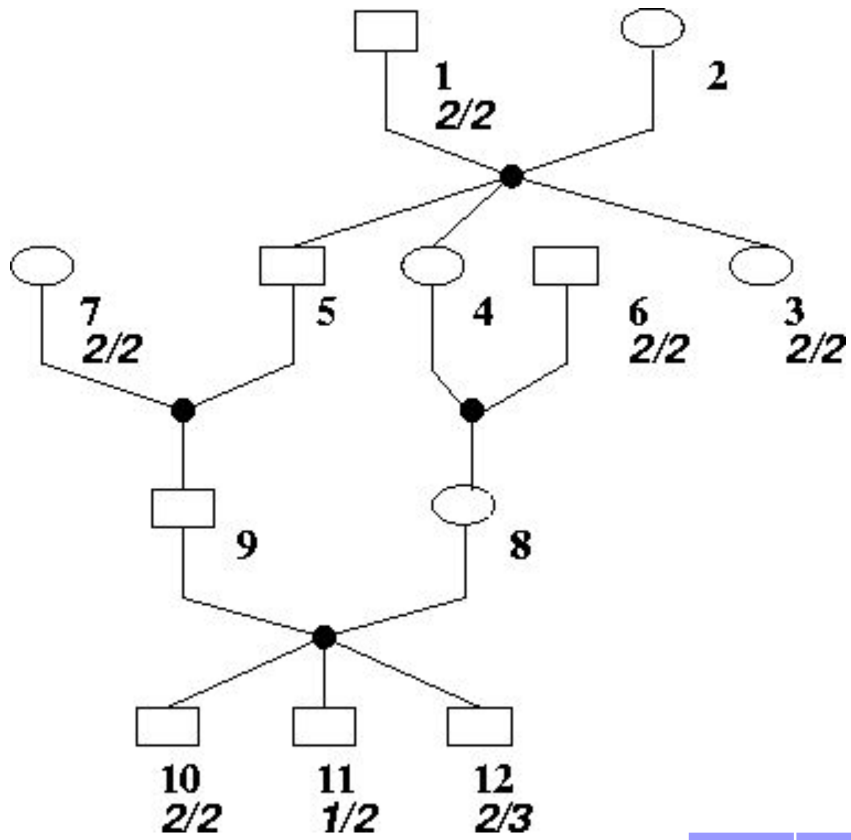


	1/1	1/2	1/3	2/2	2/3	3/3
f_8	2	0	1	0	0	2
f_9	0	0	0	0	0	0
f_{10}	0	0	0	0	0	0
f_{11}	1	0	0	1	0	0
f_{12}	0	0	0	1	0	1

Equivalence Preserving Transformation on trios

(Schiex, CP 2000),…, (Sanchez et al, Constraint 2008)

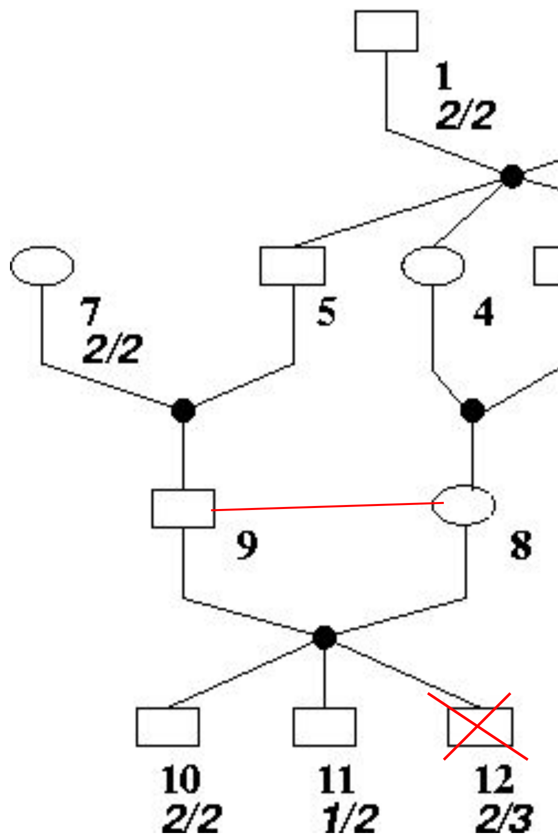
Variable elimination



	1/1	1/2	1/3	2/2	2/3	3/3
f_{12}	1	1	1	1	0	1

(Dechter, AIJ 1999)

Variable elimination



f8,9	1/1	1/2	1/3	2/2	2/3	3/3
1/1	1	1	1	1	1	1
1/2	1	1	0	1	0	0
1/3	1	0	1	0	0	1
2/2	1	1	0	1	0	0
2/3	1	0	0	0	0	0
3/3	1	0	1	0	0	1

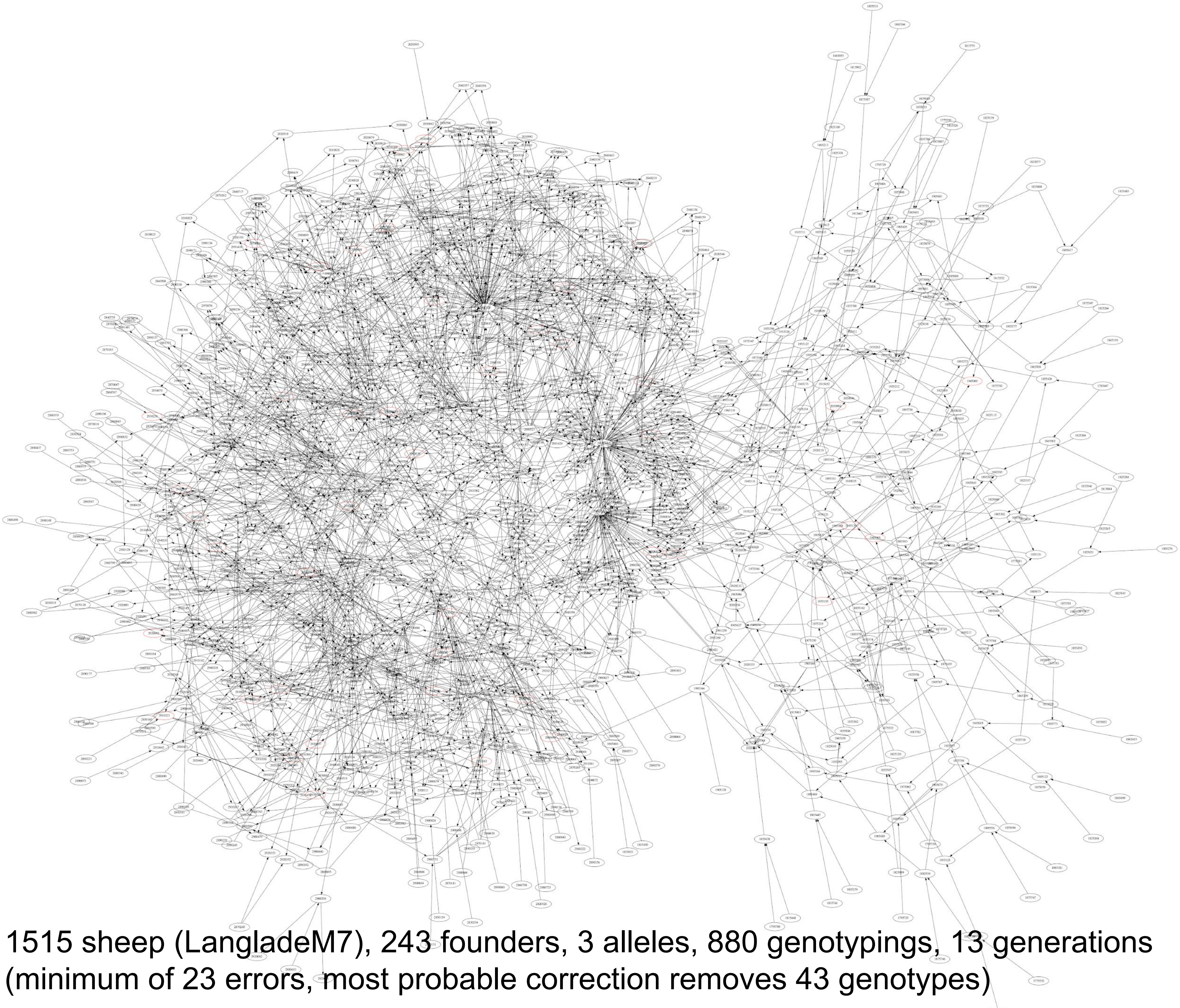
(Dechter, AIJ 1999), (Larrosa, CP 2000)

(Vitezica et al, World Congress on Genetics Applied to Livestock Production 2006)
(Sanchez et al, Constraints 2008)

Real data

CPU time in seconds to find and prove optimality on a linux PC 3 GHz with 16 GB using toulbar2 v0.5

	ind	*vars*	*genotyped*	alleles	*nf*	*ngen*	treewidth ub	B&B-VE(2) errors	B&B-VE(2) time	B&B-VE(2) nodes
eye	36	36	28	6	11	4	2	1	0.02	0
cancer	49	48	37	8	18	5	2	1	0.21	0
parkinson	37	34	13	4	7	7	5	0	0	6
$berrichon_{1nc}$	129516	9947	2448	4	8821	17	262	2	4.73	8805
$berrichon_{1}$	129516	10017	2483	4	8786	17	330	23	5.81	8384
$berrichon_{2nc}$	27255	19337	10215	4	4719	19	-	41	5.89	6170
$berrichon_{2}$	27255	19562	10215	4	2381	19	-	106	17.23	15445
$langlade_{1}$	1355	1209	711	9	298	13	84	38	12.28	391
$langlade_{2}$	1355	1223	715	7	298	13	82	89	60.56	17857
$langlade_{3}$	1355	1258	787	5	298	13	85	39	14.19	6731
$langlade_{4}$	1355	1186	672	8	298	13	83	43	59.7	3520
$moissac_{1}$	283	260	183	2	81	5	6	0	0	5
$moissac_{2}$	283	244	167	7	81	5	6	0	0.51	6
$moissac_{3}$	283	225	151	3	81	5	6	0	0	4
$moissac_{4}$	283	256	179	2	81	5	6	0	0	5
$moissac_{5}$	283	237	161	8	81	5	6	0	1.02	5
$moissac_{6}$	283	201	131	11	81	5	5	0	5.64	6

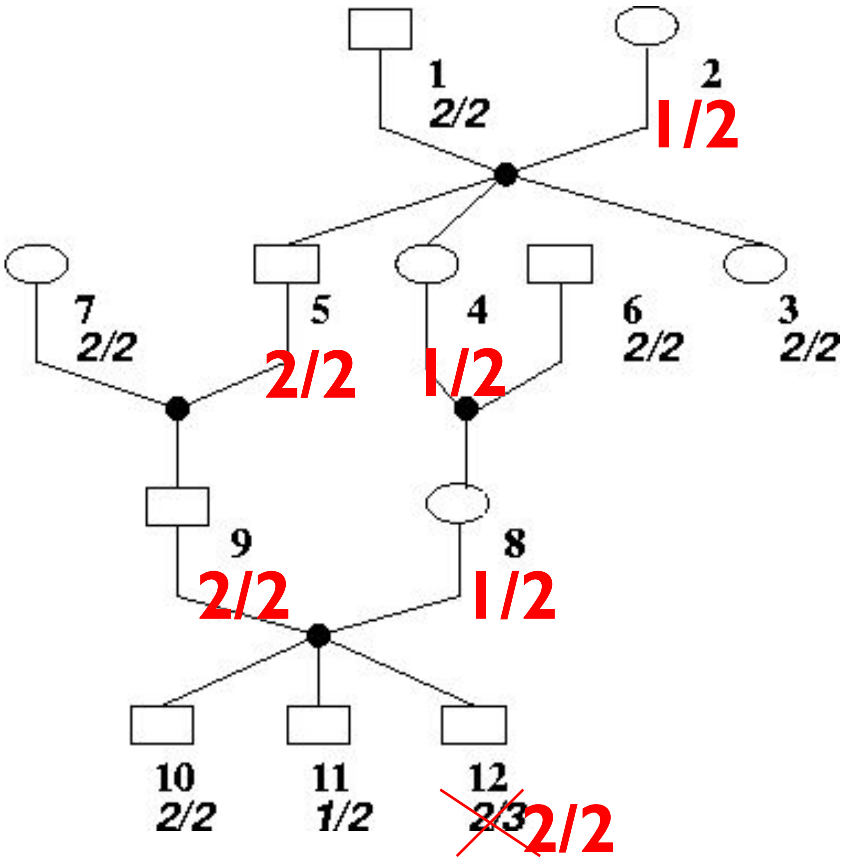


1515 sheep (LangladeM7), 243 founders, 3 alleles, 880 genotypings, 13 generations
(minimum of 23 errors, most probable correction removes 43 genotypes)

Task 3: Error Correction using Probabilistic Model

- Finds a complete assignment with maximum posterior probability

→ Bayesian network

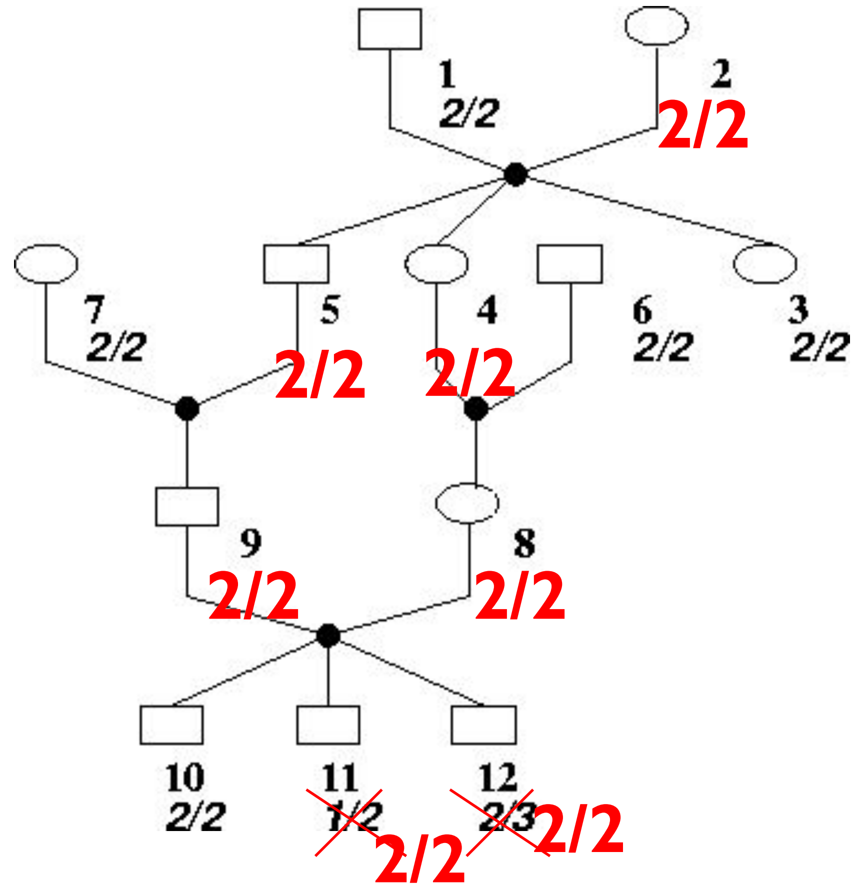


Prior on genotyping error: 1%
(and equifrequent alleles)

Task 3: Error Correction using Probabilistic Model

- Finds a complete assignment with maximum posterior probability

→ Bayesian network

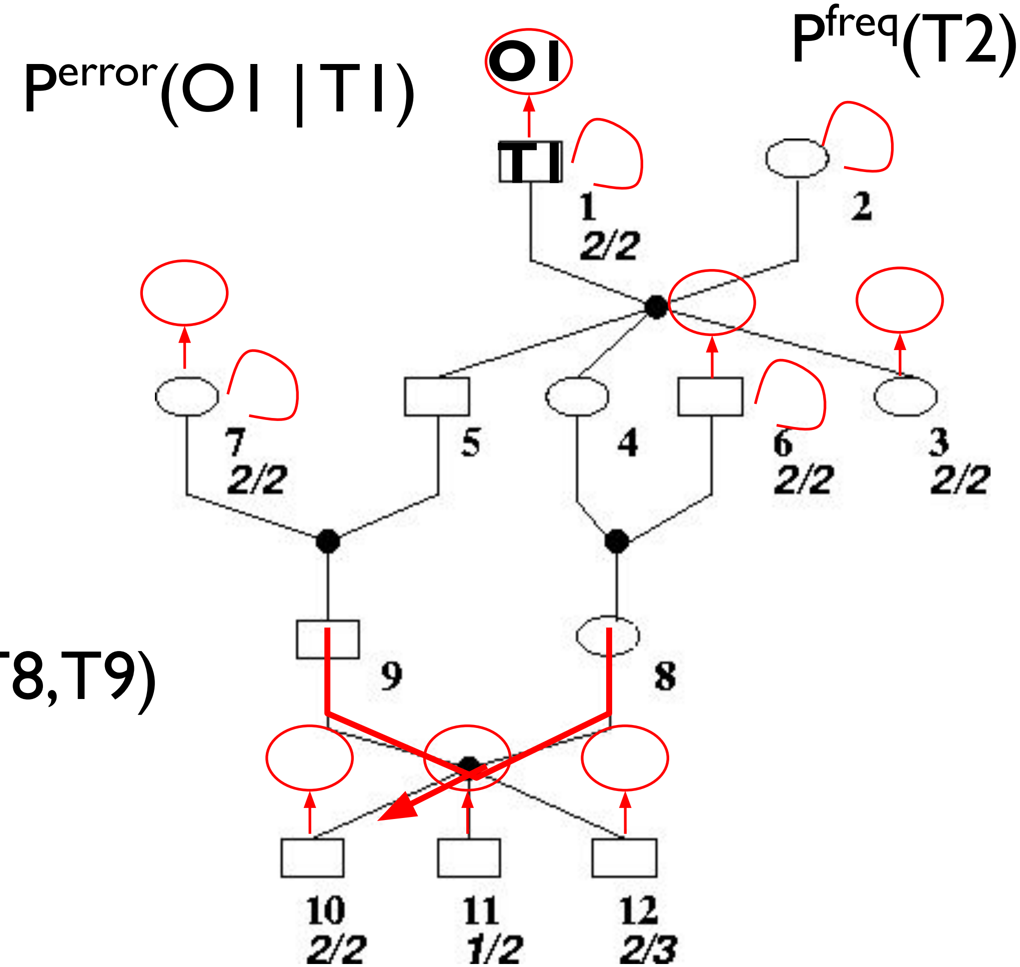


Prior on genotyping error: 10%
(and equifrequent alleles)

Task 3: Error Correction using Probabilistic Model

- Finds a complete assignment with maximum posterior probability

→ Bayesian network

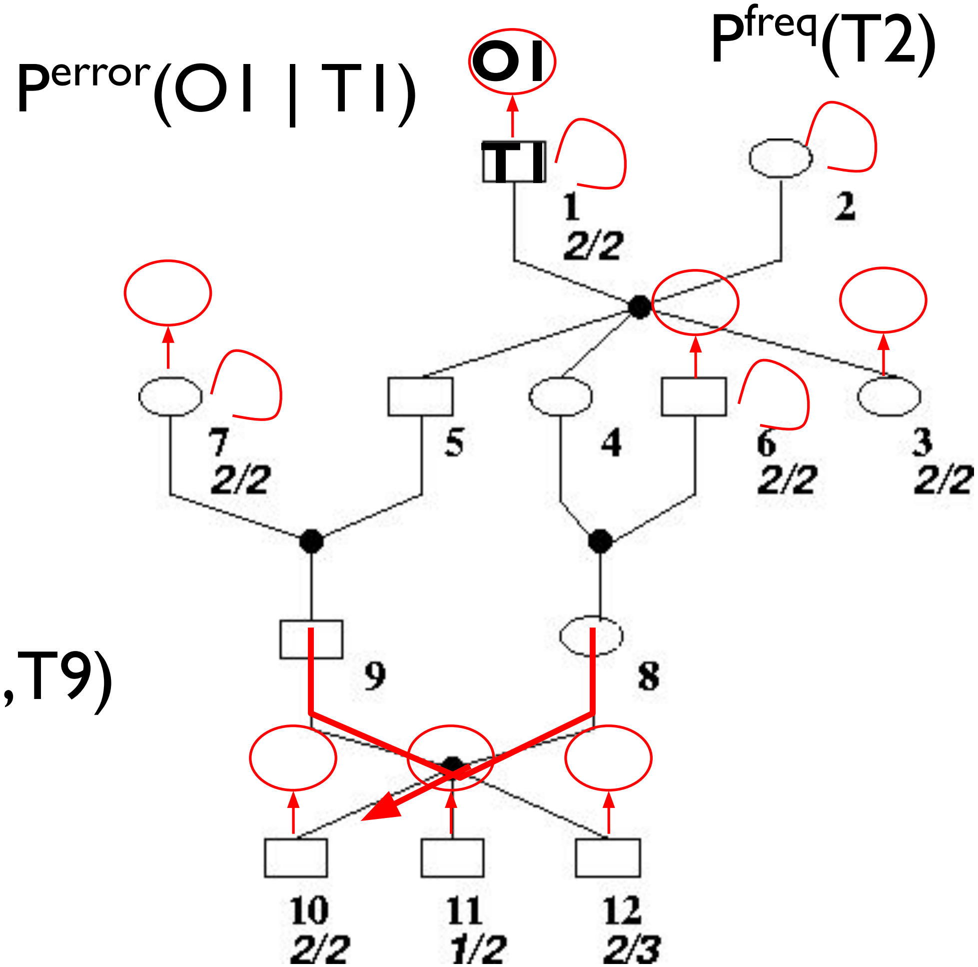


$$P(O, T) = \prod P^{error}(O_i \mid T_i) \times \prod P^{mendel}(T_i \mid parents(i)) \times \prod P^{freq}(T_i)$$

Task 3: Error Correction using Probabilistic Model

- Finds a complete assignment with maximum posterior probability

→ Bayesian network



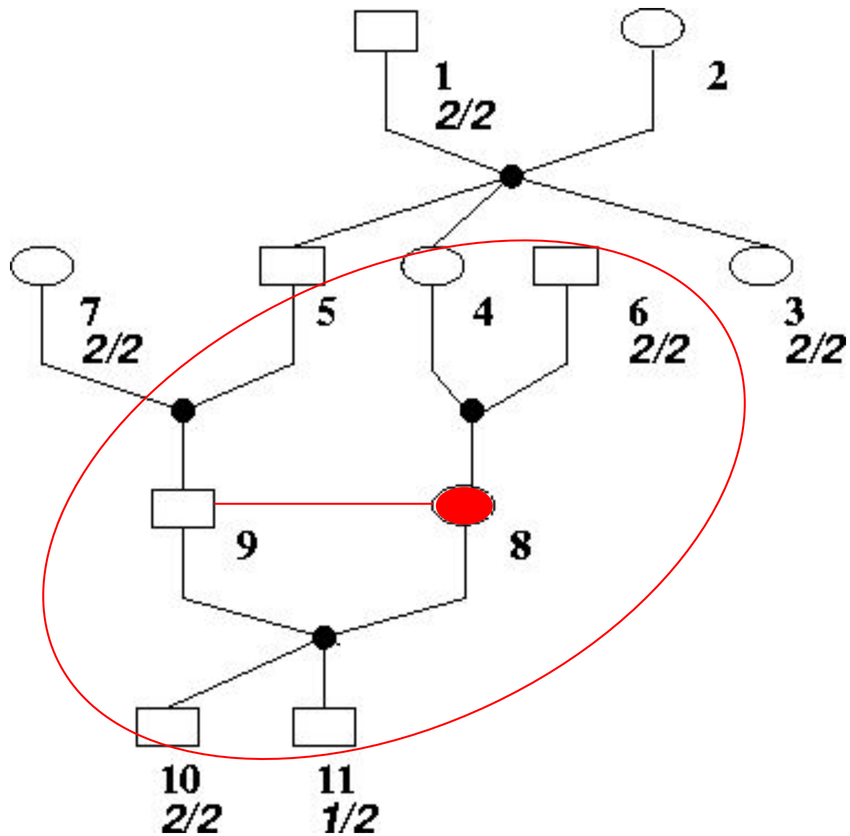
$P^{mendel}(T10 \mid T8,T9)$

$$\cancel{P(O,T)} = \prod P^{error}(O_i \mid T_i) \times \prod P^{mendel}(T_i \mid parents(i)) \times \prod P^{freq}(T_i)$$

-log transform

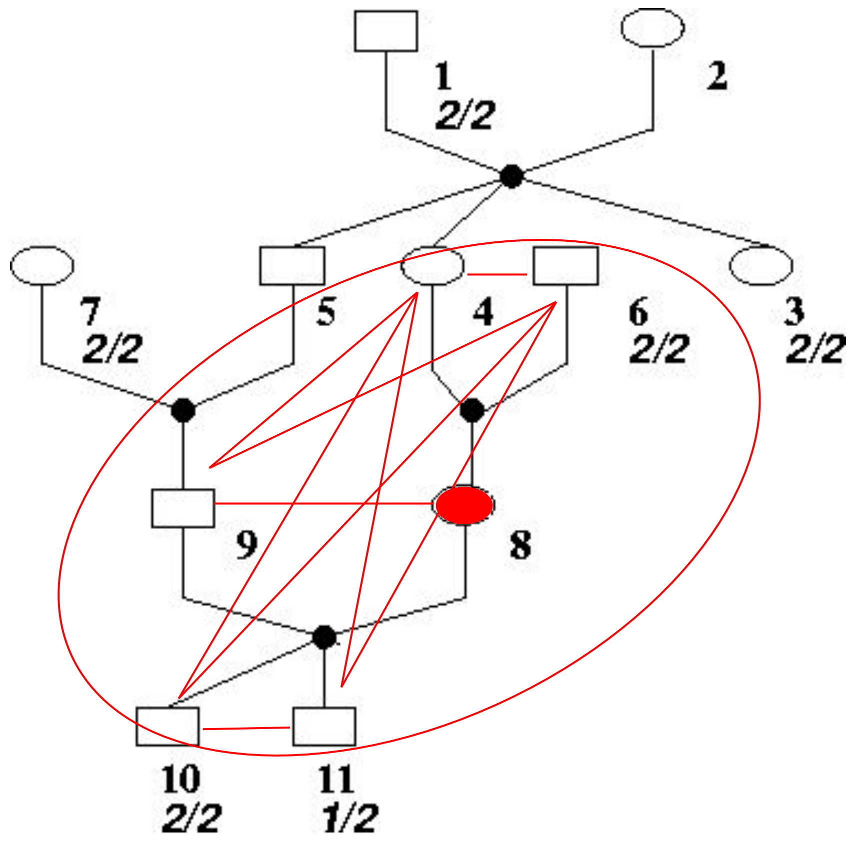
$$\sum_{fS \in F} f_S(A[S])$$

Variable elimination ..continued



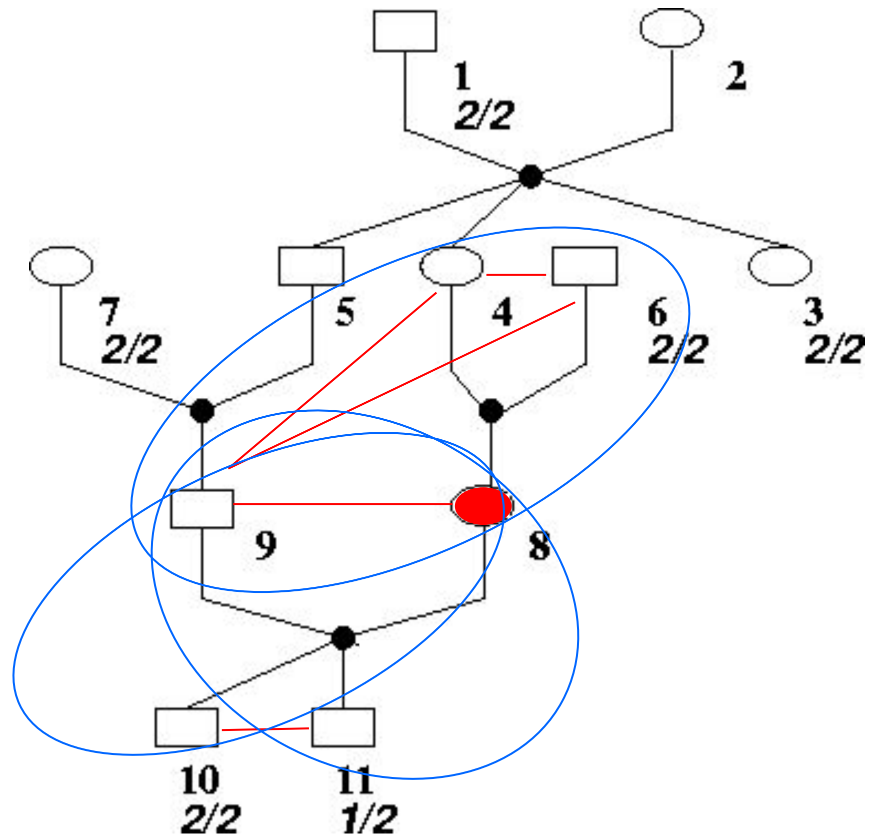
(Dechter, AIJ 1999)

Variable elimination ..continued



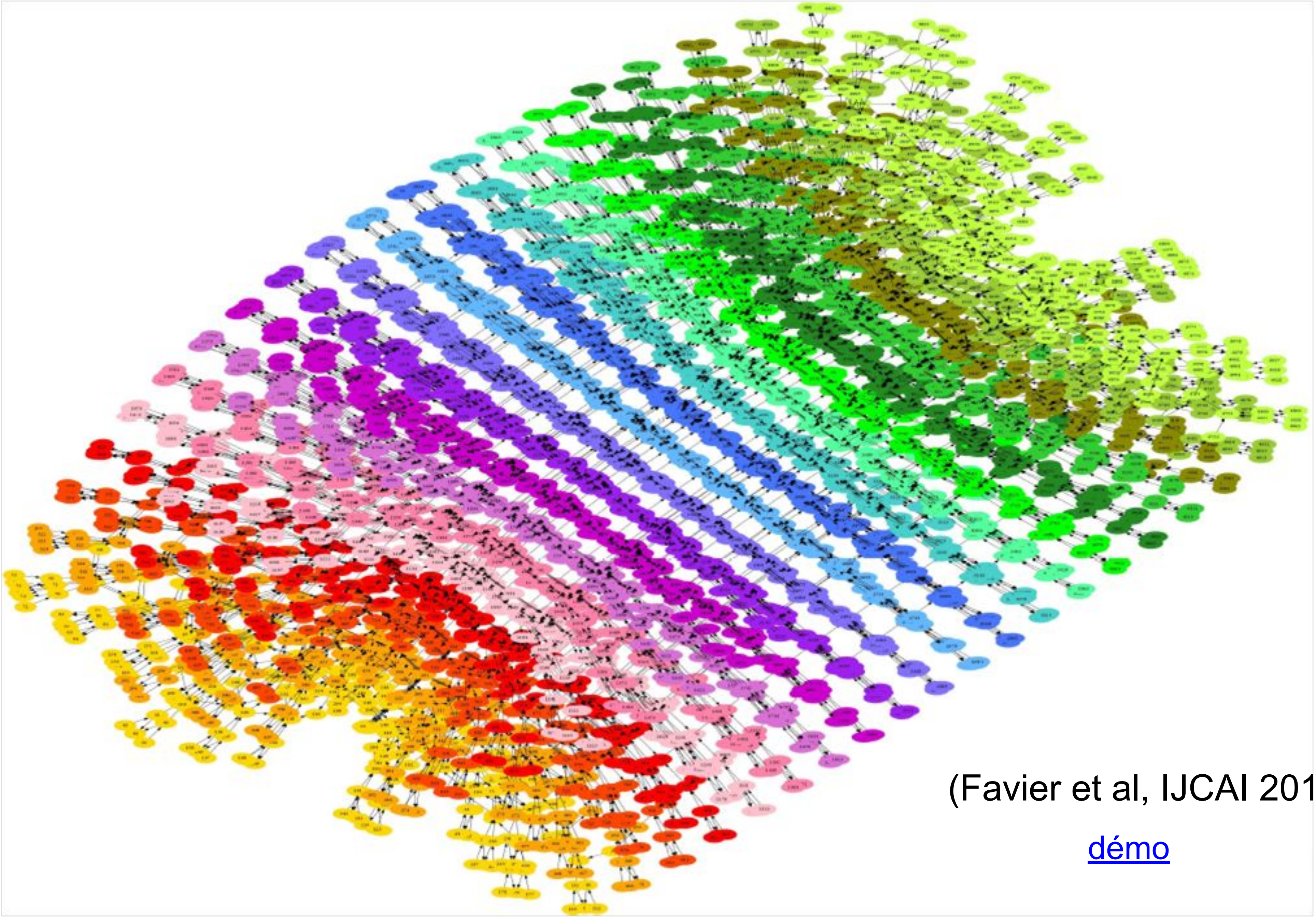
(Dechter, AIJ 1999)

Variable elimination ..continued



Cost function decomposition

(Favier et al, IJCAI 2011)



(Favier et al, IJCAI 2011)

[démo]

Optimal haplotype reconstruction in half-sib families (Legarra et al, WCGALP 2010)

~

Guaranteed Discrete Energy Optimization on Large Protein Design Problems

Guaranteed Discrete Energy Optimization on Large Protein Design Problems. *Journal of chemical theory and computation.*
Fast search algorithms for computational protein design. *Journal of computational chemistry.*

Thomas Schiex (INRA)
D. Simoncini, D. Allouche, S. Barbe (LISBP)

* Slides by T. Schiex

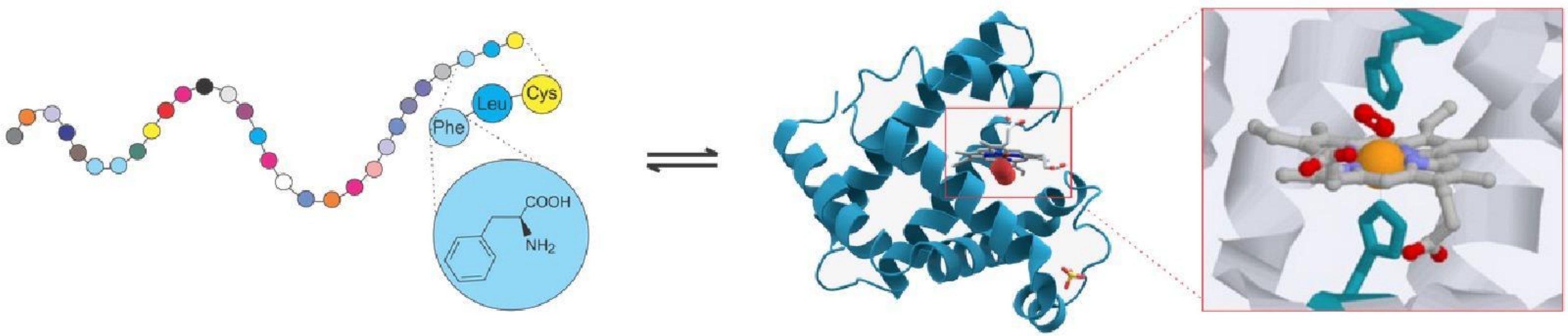
Summer 2016 - US tour

May 2022 – LIPME INRAE

Why should we want to design proteins?

Eco-friendly chemical/structural nano-agents

- New drugs for health (human, animals, plants)
- New catalysts (environment, recycling, biofuels, food and feed, cosmetics...),
- New components for nanotechnologies
- Relying on inexpensive atomic level 3D-printers (bacterias, yeast, ...)



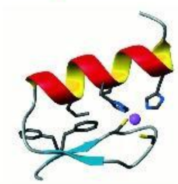
[0] Thanks to the Zhang lab. for this image.

1985

Calmodulin-binding peptide

[DeGrado et al. 1985]

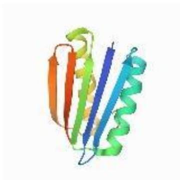
1997



Zinc Finger

[Dehiyat & Mayo 1997]

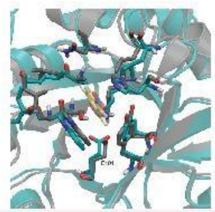
2003



Novel Topology (top7)

[Kuhlman et al. 2003]

2008



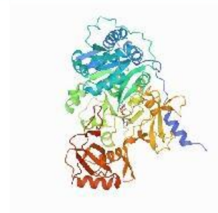
Functional Enzyme

[Rothlisberger et al. 2008]

Enzyme for Multi-Step Reaction

[Jiang et al. 2008]

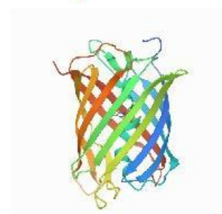
2009



Enzyme activity

[Chen et al. 2009]

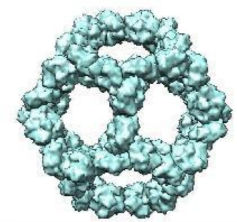
2011



Longer Emission Wave Length Fluorescence

[Chica et al. 2011]

2016



Self-Assembling Nanocage

[Hsia et al. 2016]

2019

Auto-Assembling Symmetrical Protein

[Niguchi et al. 2019]

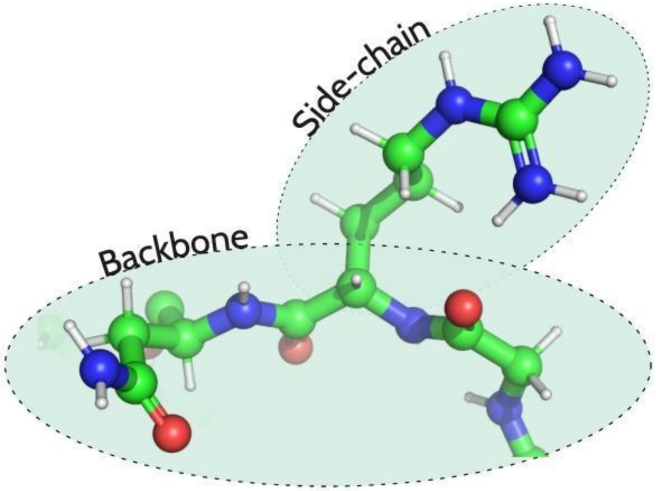
Informal definition (globular proteins)

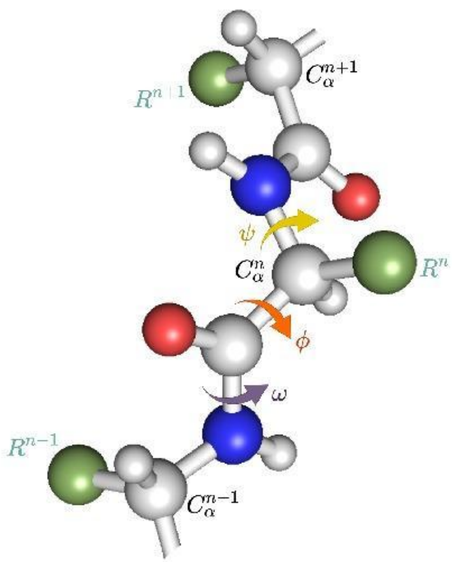
Produce a sequence s of amino-acids that *spontaneously adopts* a conformation X that *performs some function*.

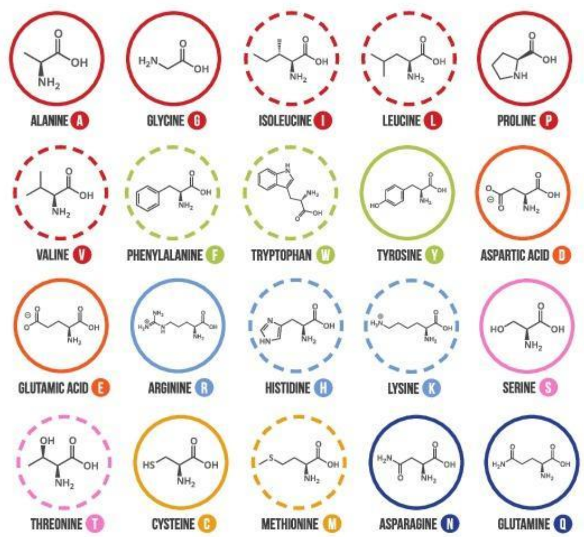
What defines a conformation ?

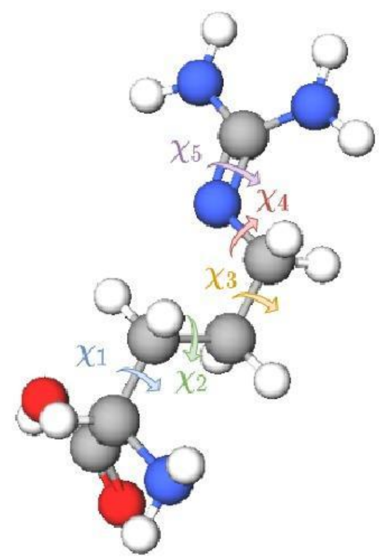
Conformation

- backbone: dihedral angles ϕ_i, ψ_i
- sequence: amino-acid choice s_i
- side-chains: torsion angles χ_{ij}





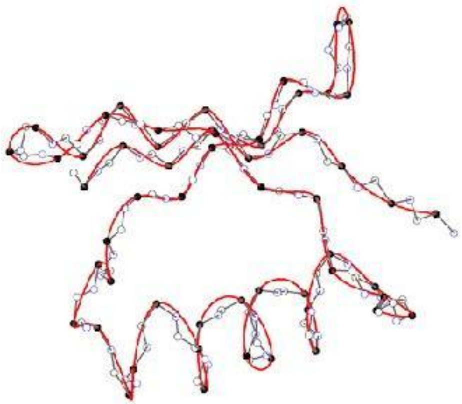


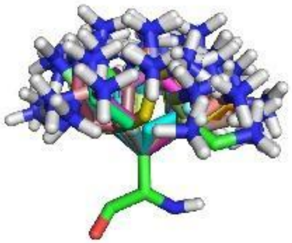


The CPD problem: search space

Rigid backbone design

1. Side-chain flexibility: discretized in rotamers
2. 1 rotamer to choose at each flexible/mutable position





Search Space

1. Fully discrete description, defined by a choice of rotamer (AA $\times$ conformation) for each position.
2. Search space can be $\approx 250^n$ or more (Dunbrack)

Stable = minimum energy (GMEC)

Using Talaris14[20] (pairwise decomposable)

- Bonded (dihedral torsion angles,...)
- van der Waals (attractive+repulsive)
- Electrostatic (statistical)
- Rotamer statistics (Dunbrack)
- Hydrogen bonds
- Implicit solvation
- Cutoff functions

$$E(c) = E_{\varnothing} + \sum_{i=1}^{n} E_i(r) + \sum_{i<j} E_{ij}(r, s)$$

Stable = minimum energy (GMEC)

Using Talaris14[20] (pairwise decomposable)

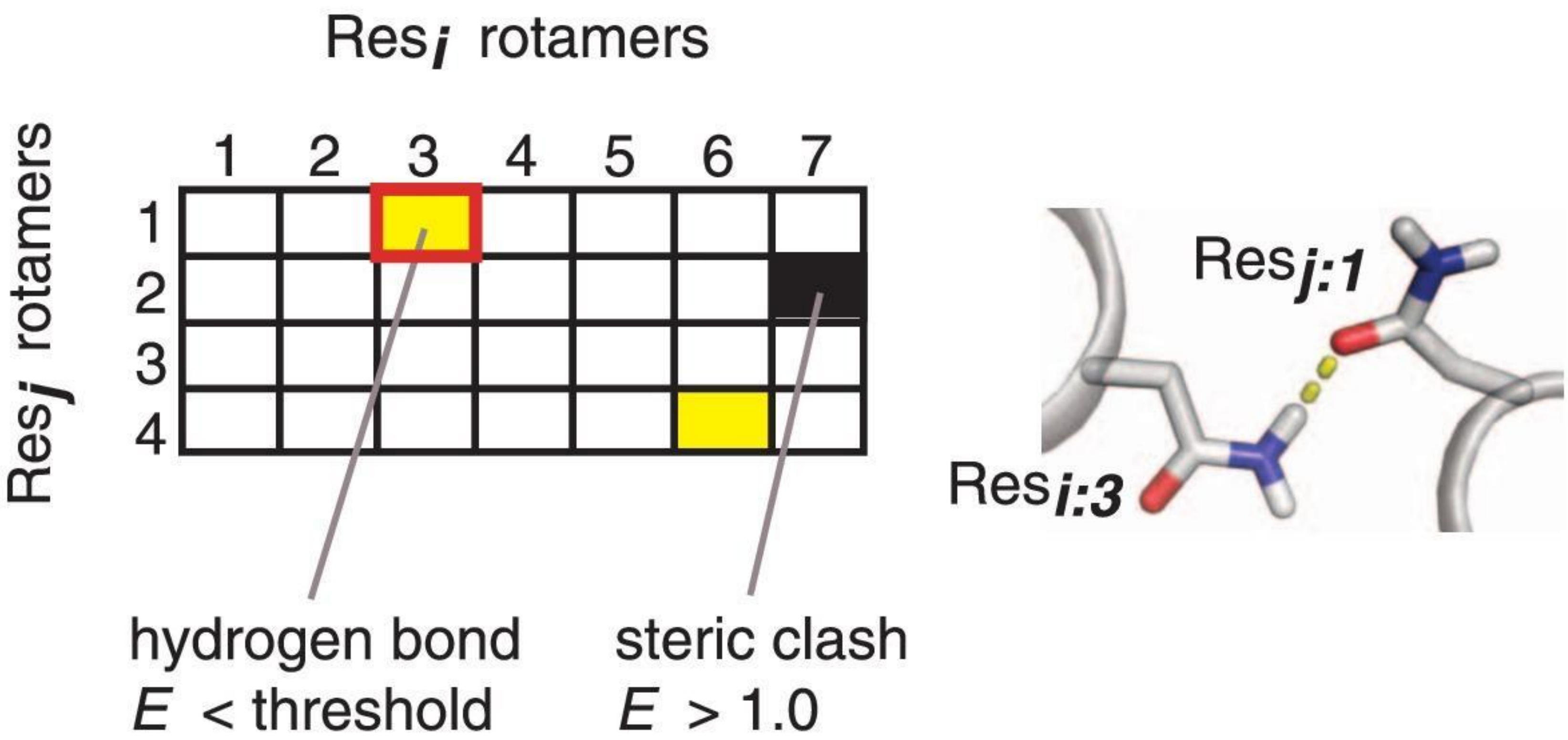
- Bonded (dihedral torsion angles,...)
- van der Waals (attractive+repulsive)
- Electrostatic (statistical)
- Rotamer statistics (Dunbrack)
- Hydrogen bonds
- Implicit solvation
- Cutoff functions

$$E(c) = E_{\varnothing} + \sum_{i=1}^{n} E_i(r) + \sum_{i<j} E_{ij}(r, s)$$

$$\sum_{f_S \in F} f_S(A[S])$$

NP-hard

A cost function

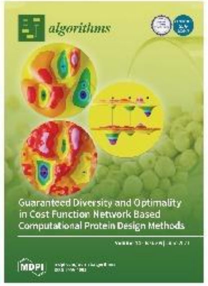


Exact vs. Stochastic search

Large input (> 1GB) **NP-hard problem**

Toulbar2 is able to…

- provide a proven minimum energy solution[25]
- exhaustively enumerate sequences close to it
- provide sequence libraries with guaranteed diversity.[18]
- in sequence-conformation spaces of size $> 10^{400}$



Rosetta's Monte Carlo Simulated Annealer increasingly fails to find the optimal sequence[a]

[a] David Simoncini et al. "Guaranteed Discrete Energy Optimization on Large Protein Design Problems". In: *Journal of Chemical Theory and Computation* 11.12 (2015), pp. 5980–5989. DOI: `10.1021/acs.jctc.5b00594`.

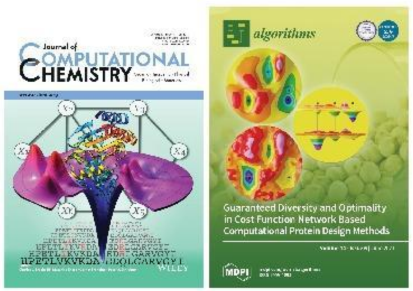
Exact vs. Stochastic search

Clément Viricel's PhD on predicting changes in binding affinity (counting)
(Viricel et al, Bioinformatics 2018)

Large input (> 1GB) | **NP-hard problem**

Toulbar2 is able to…

- provide a proven minimum energy solution[25]
- exhaustively enumerate sequences close to it
- provide sequence libraries with guaranteed diversity.[18]
- in sequence-conformation spaces of size $> 10^{400}$

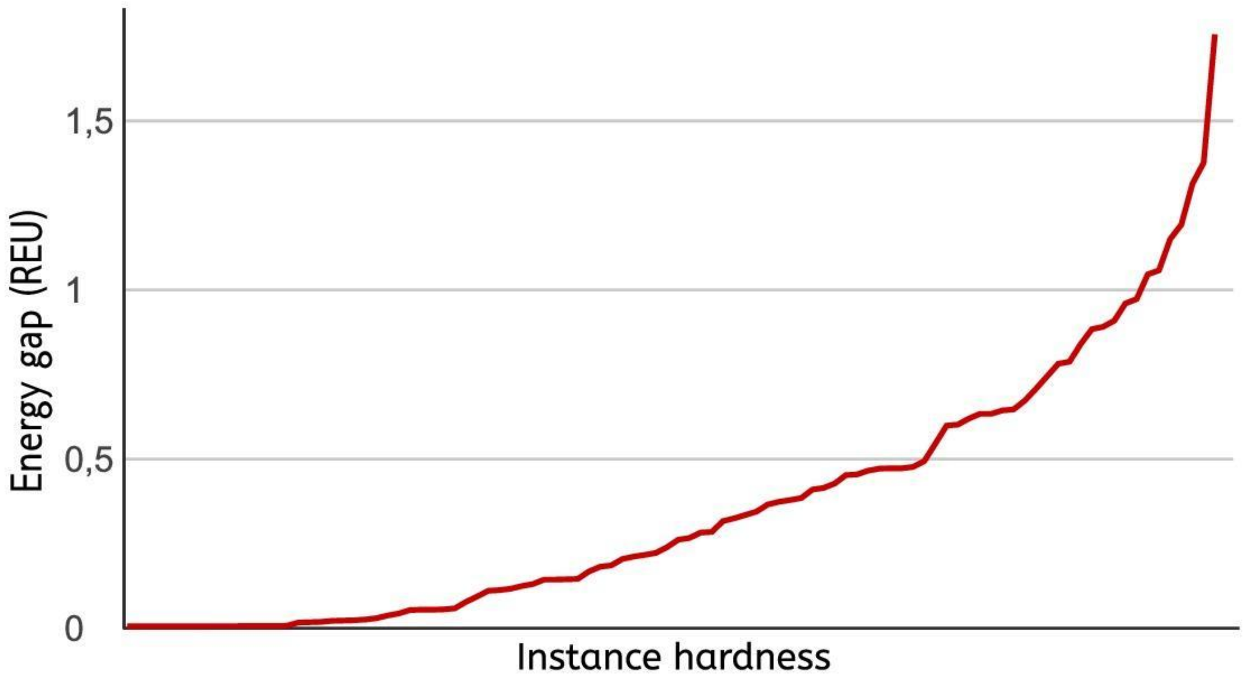


Manon Ruffini's PhD on diversity encoding and negative design
(Ruffini et al, ICTAI 2019, Algorithms 2021)

Rosetta's Monte Carlo Simulated Annealer increasingly fails to find the optimal sequence[a]

[a] David Simoncini et al. "Guaranteed Discrete Energy Optimization on Large Protein Design Problems". In: *Journal of Chemical Theory and Computation* 11.12 (2015), pp. 5980–5989. DOI: 10.1021/acs.jctc.5b00594.

Unbounded error



Asymptote: Size matters!

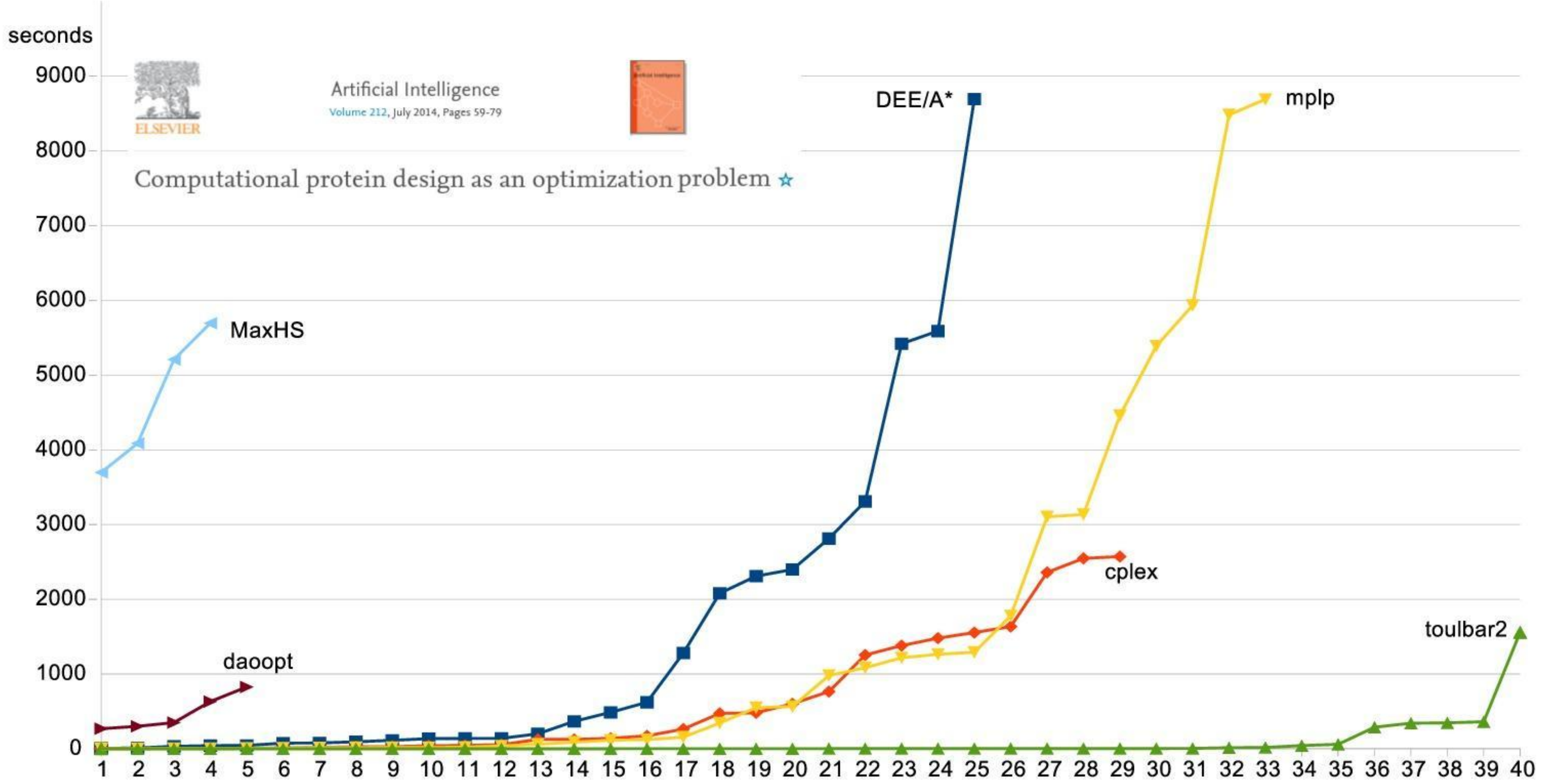
Asymptotic convergence can be arbitrarily slow…

Guaranteed Discrete Energy Optimization on Large Protein Design Problems

David Simoncini[†], David Allouche[†], Simon de Givry[†], Céline Delmas[†], Sophie Barbe[‡§⊥], and Thomas Schiex[*†]

JCTC Journal of Chemical Theory and Computation

Toulbar2 vs. CPLEX, MaxHS…(real instances)

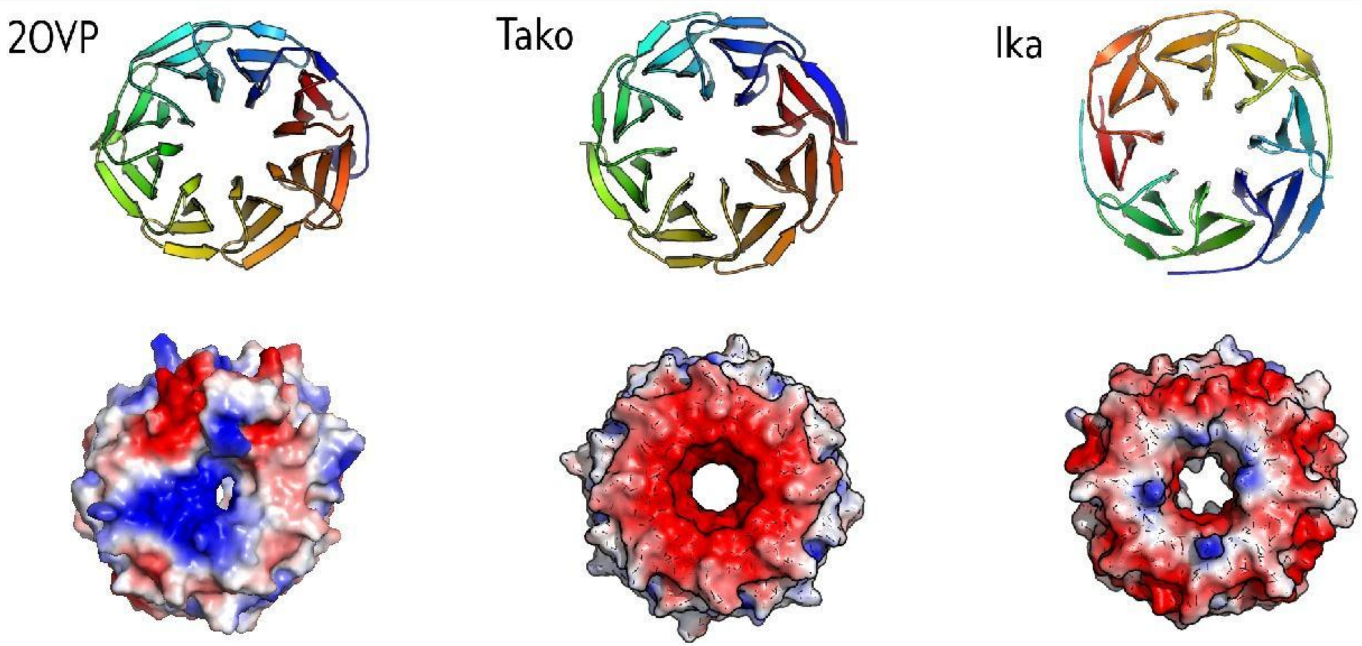


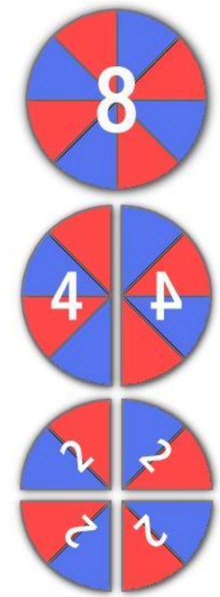
# of instances solved (X) within a per instance cpu-time limit (Y)

Designing a self-assembling β-propeller

Coll. A. Voet (KU Leuven), D. Simoncini[16]

-  Tako: (R)evolution + Rosetta/talaris14 — 8 fold
-  Ika: toulbar2 + talaris14 — 4 fold





A Mixed Integer Programming Reformulation of the Mixed Fruit-Vegetable Crop Allocation Problem

Sara Maqrot [1], Simon De Givry [1], Gauthier Quesnel [1]
Marc Tchamitchian [2] *

[1]UR 875, MIAT-INRA Toulouse France
[2]UR 767, Ecodeveloppement, INRA-Avignon France

June 28th 2017

IEA/AIE 2017, Arras, France

* Jury member of Mahuna Akplogan's PhD on crop allocation problem

Introduction

Fruit cropping

+

Vegetable cropping

=

Mixed fruit-vegetable cropping

Avignon France, 2015

Agriculture's challenges (examples)

- Local market, diversified food.
- Reducing pollution (chemical products).
- Preservation of resources (water, energy).
- Better biodiversity.

Localization in France

Casdar SMART 2014-2016
National Project in France

Introduction

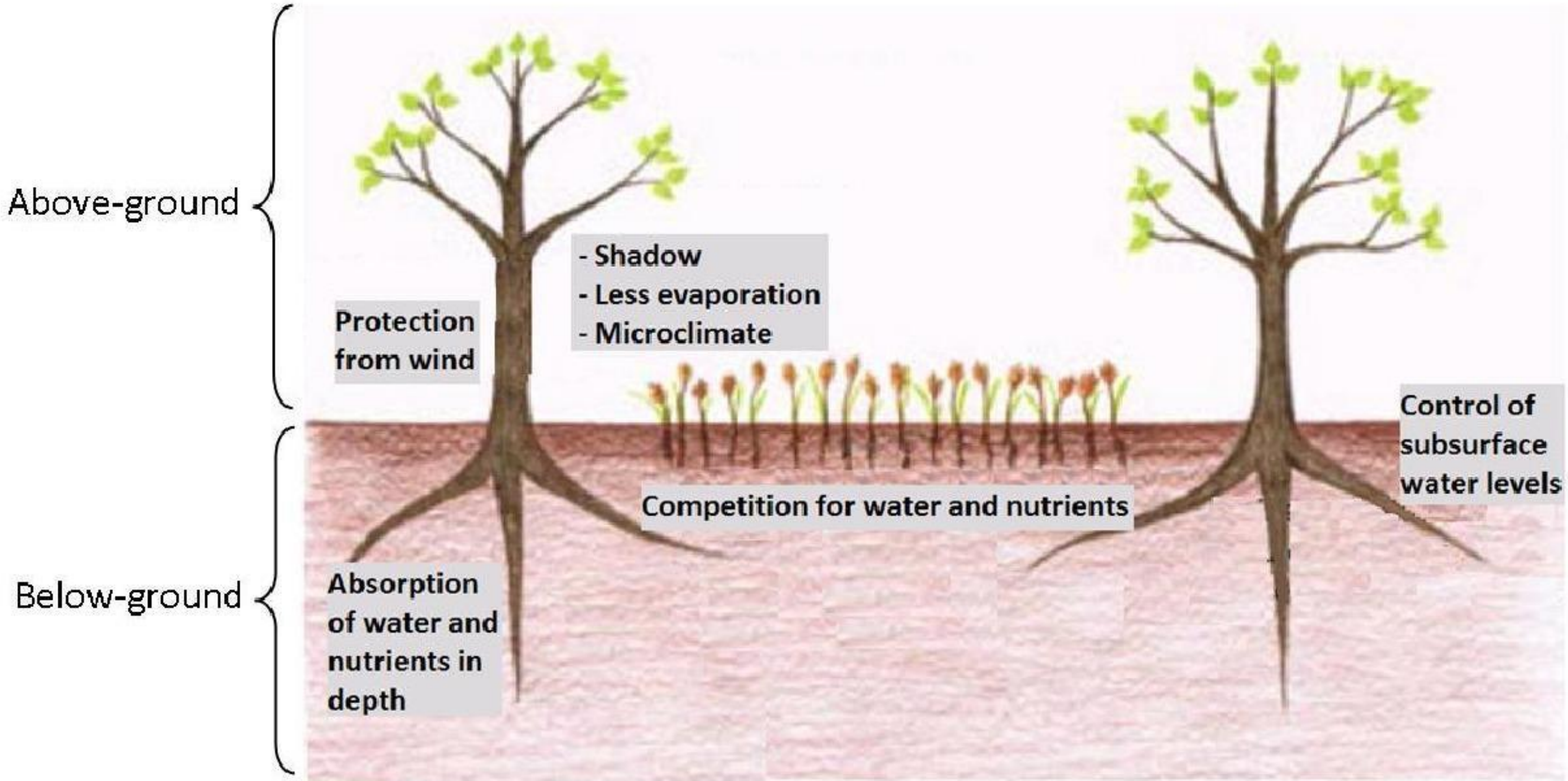
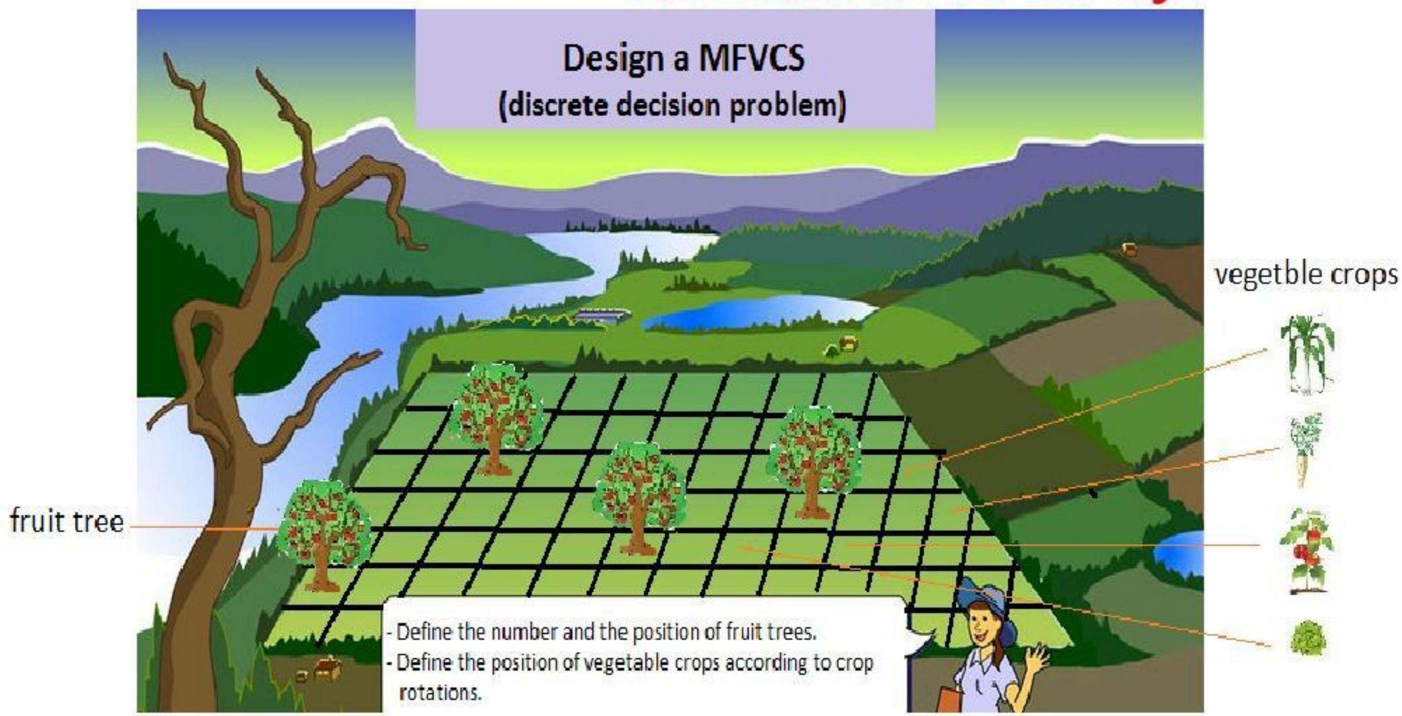


Figure – Example of above- and below-ground interactions between crops and trees [Kaeser et al., 2010]

Introduction

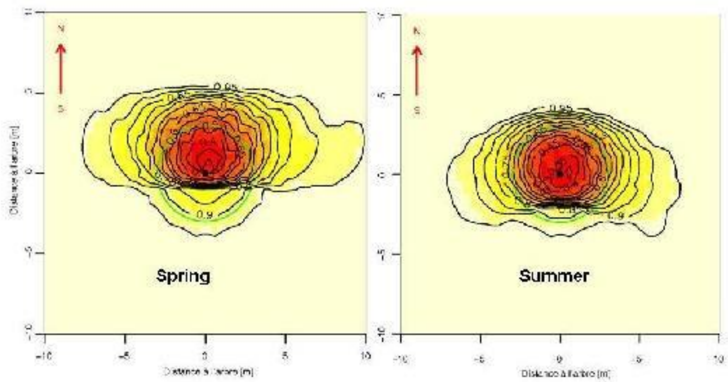
The aim of our study



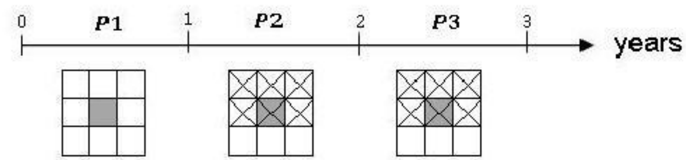
Designing a mixed fruit-vegetable system having diversified production while **optimizing the use of resources** (light, water and nutrients), by exploiting interactions between trees and crops.

Above-ground interactions : shade and micro-climate conditions

Fruit tree



Solar radiation interception simulation of an apple tree
(Source : PSH - INRA Avignon).



Evolution of potential shade in spring and summer (checked cells).

Interactions with vegetable crops

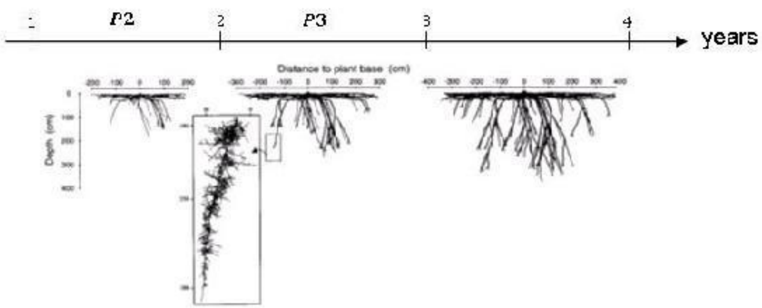
- − : negative effect
- 0 : neutral effect
- + : positive effect

Crop sensitivity to shade.

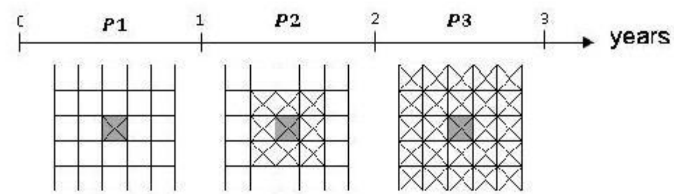
Crops	Shade seasons	
	Spring	Summer
Lettuce	0	+30
Tomato	0	+20
Onion	-10	0
Melon		-10
Carrot		0

Below-ground interactions : root extension dynamics

Fruit tree



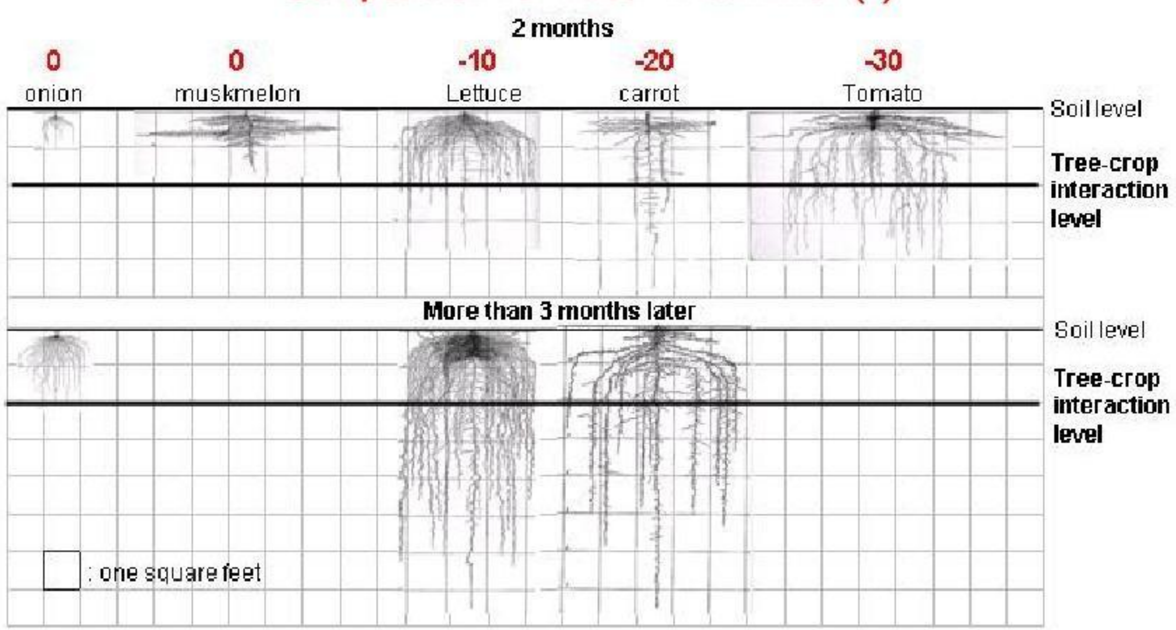
Simulated plum root system [Vercambre et al., 2003]



Surface view of root extensions of an apple tree.

Interactions with vegetable crops

Competition for water in summer (-)



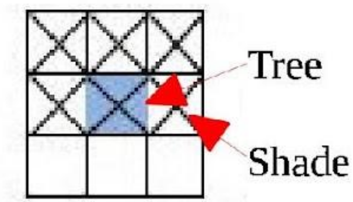
[Weaver and Bruner, 1927]

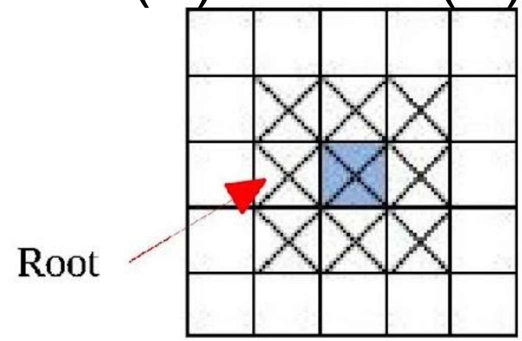
Sharing for water (+)
Absorption of surplus water

winter	spring	summer	autumn
+10	+10		+10

Question

Plants N trees to get the right number of cells with shade(S) or root (R)



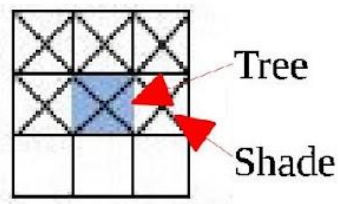


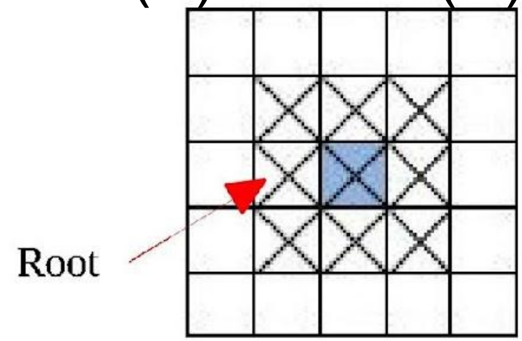
N=2, SR=5, -R=5, --=13

N=2, SR=10, -R=0, --=13

Question

Plants N trees to get the right number of cells with shade(S) or root (R)





N=2, SR=5, -R=5, --=13

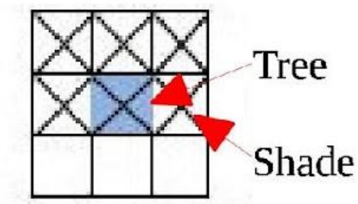
		SR	A	SR
		-R	-R	-R
SR	SR			
A	SR			
-R	-R			

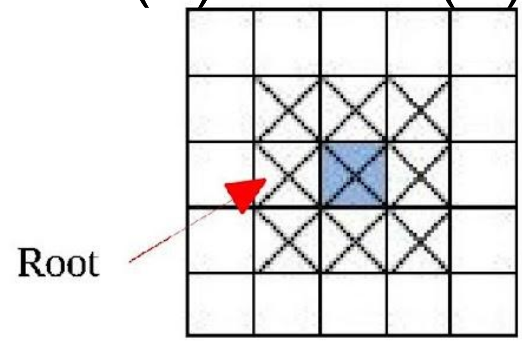
N=2, SR=10, -R=0, --=13

* A: Apple Tree

Question

Plants N trees to get the right number of cells with shade(S) or root (R)





N=2, SR=5, -R=5, --=13

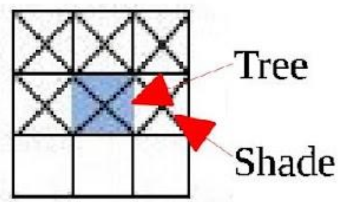
		SR	A	SR
		-R	-R	-R
SR	SR			
A	SR			
-R	-R			

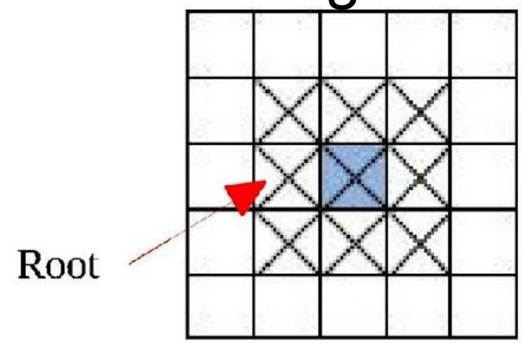
N=2, SR=10, -R=0, --=13

	SR	SR	SR	
	SR	A	SR	
	SR	SR	SR	
	SR	A	SR	

Question

Adds vegetables (each one on 4 or 5 cells) such that it maximizes green situations





N=2, SR=5, -R=5, --=13

		SR	A	SR
		-R	-R	-R
SR	SR			
A	SR			
-R	-R			

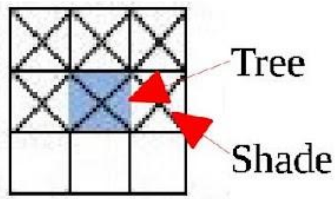
N=2, SR=10, -R=0, --=13

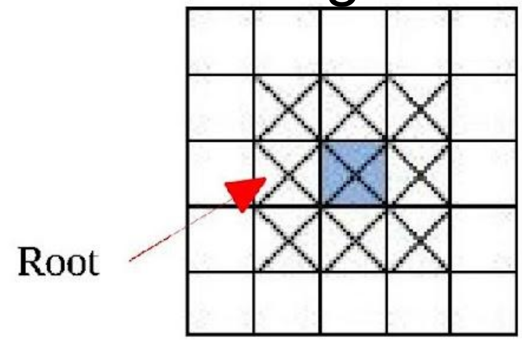
	SR	SR	SR	
	SR	A	SR	
	SR	SR	SR	
	SR	A	SR	

	Shade and root (SR)	Sun and root (-R)	Sun and no root (--)
Lettuce			
Tomato			
Onion			
Melon			
Carrot			

Question

Adds vegetables (each one on 4 or 5 cells) such that it maximizes green situations





N=2, SR=5, -R=5, --=13 Obj=23

T	M	L	A	L
T	T	O	O	O
L	L	M	T	M
A	L	C	C	C
M	O	C	T	C

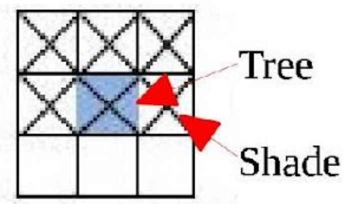
N=2, SR=10, -R=0, --=13

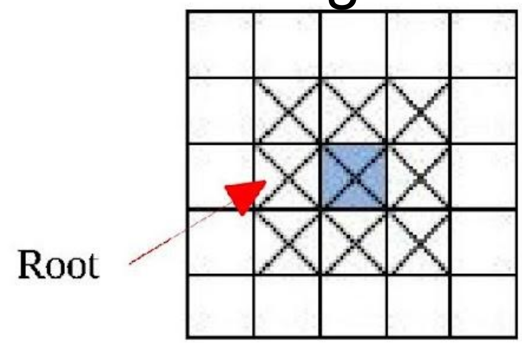
	SR	SR	SR	
	SR	A	SR	
	SR	SR	SR	
	SR	A	SR	

	Shade and root (SR)	Sun and root (-R)	Sun and no root (--)
Lettuce			
Tomato			
Onion			
Melon			
Carrot			

Question

Adds vegetables (each one on 4 or 5 cells) such that it maximizes green situations





N=2, SR=5, -R=5, --=13 Obj=23

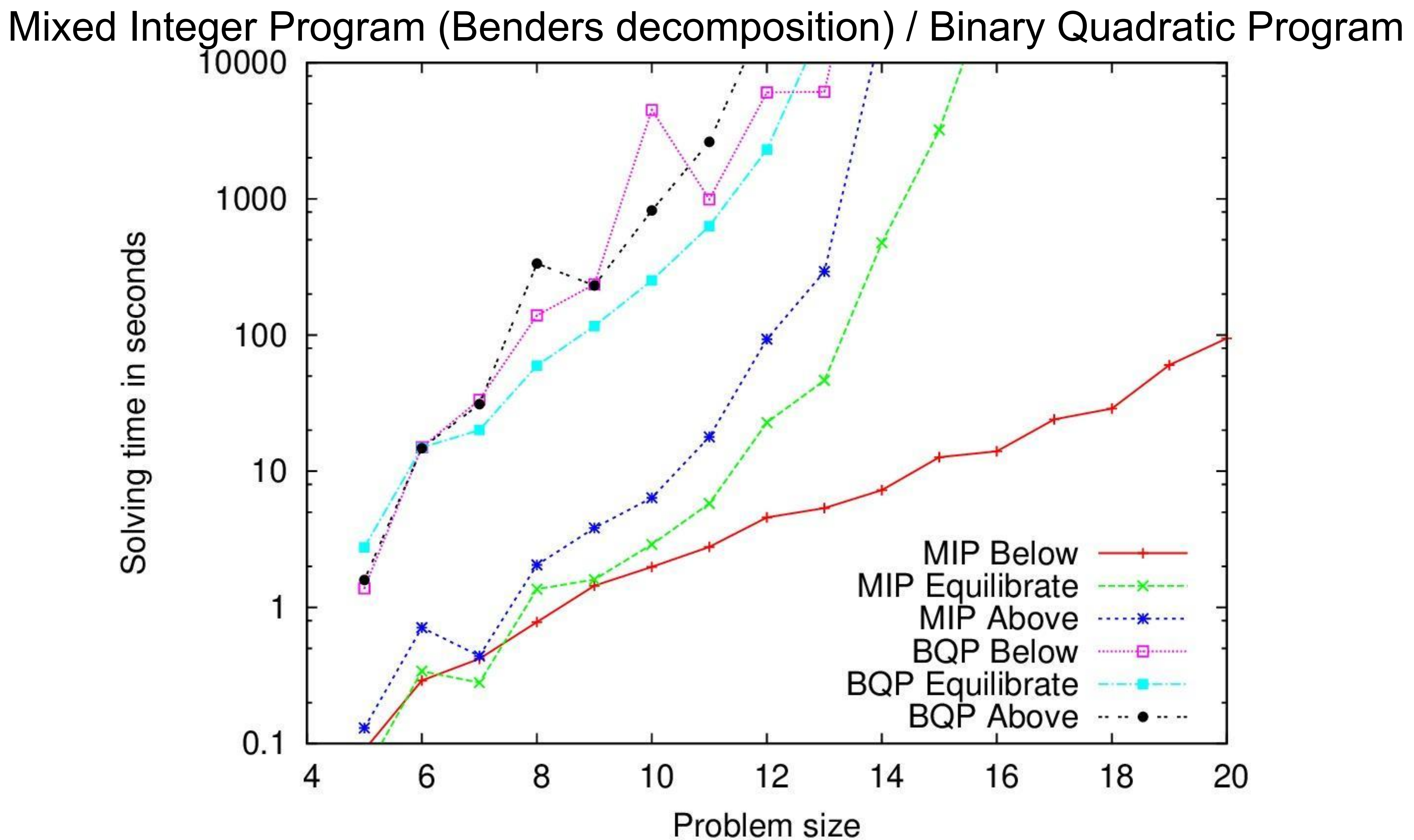
T	M	L	A	L
T	T	O	O	O
L	L	M	T	M
A	L	C	C	C
M	O	C	T	C

N=2, SR=10, -R=0, --=13 Obj=19

M	C	C	M	C
M	L	O	L	T
T	L	A	O	O
C	O	T	L	M
T	L	A	T	M

	Shade and root (SR)	Sun and root (-R)	Sun and no root (--)
Lettuce			
Tomato			
Onion			
Melon			
Carrot			

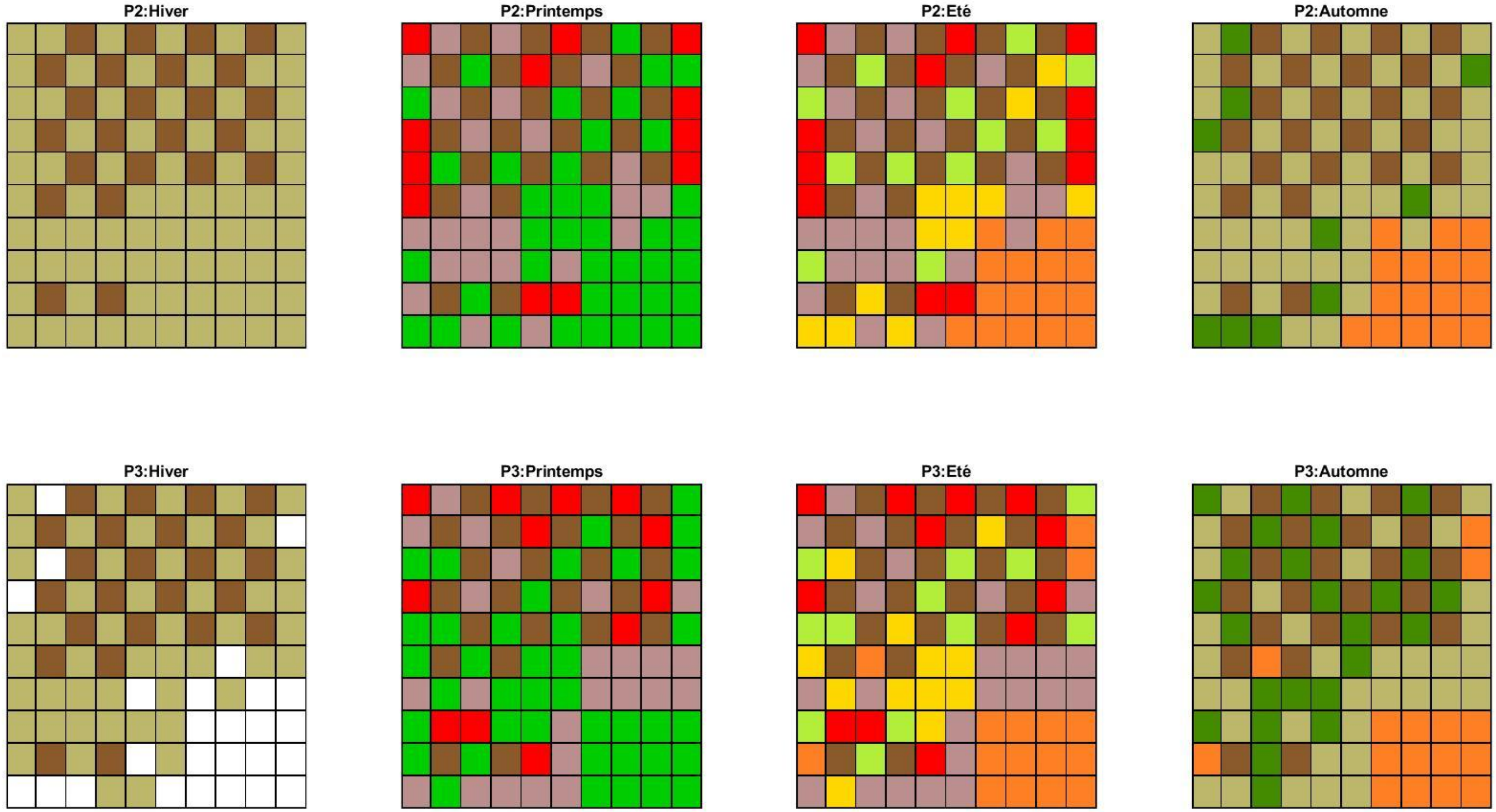
Experimental Results using cplex 12.7

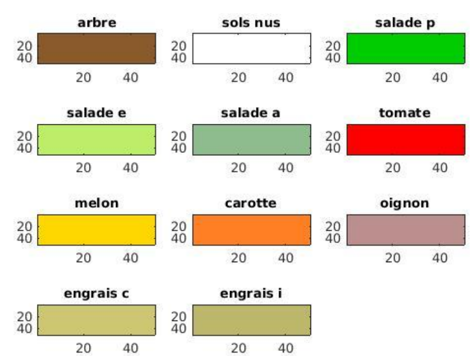


Time to reconstruct a full crop allocation plan from MIP is negligible (greedy algorithm)

Mixed Fruit-Vegetable Crop Allocation Problem

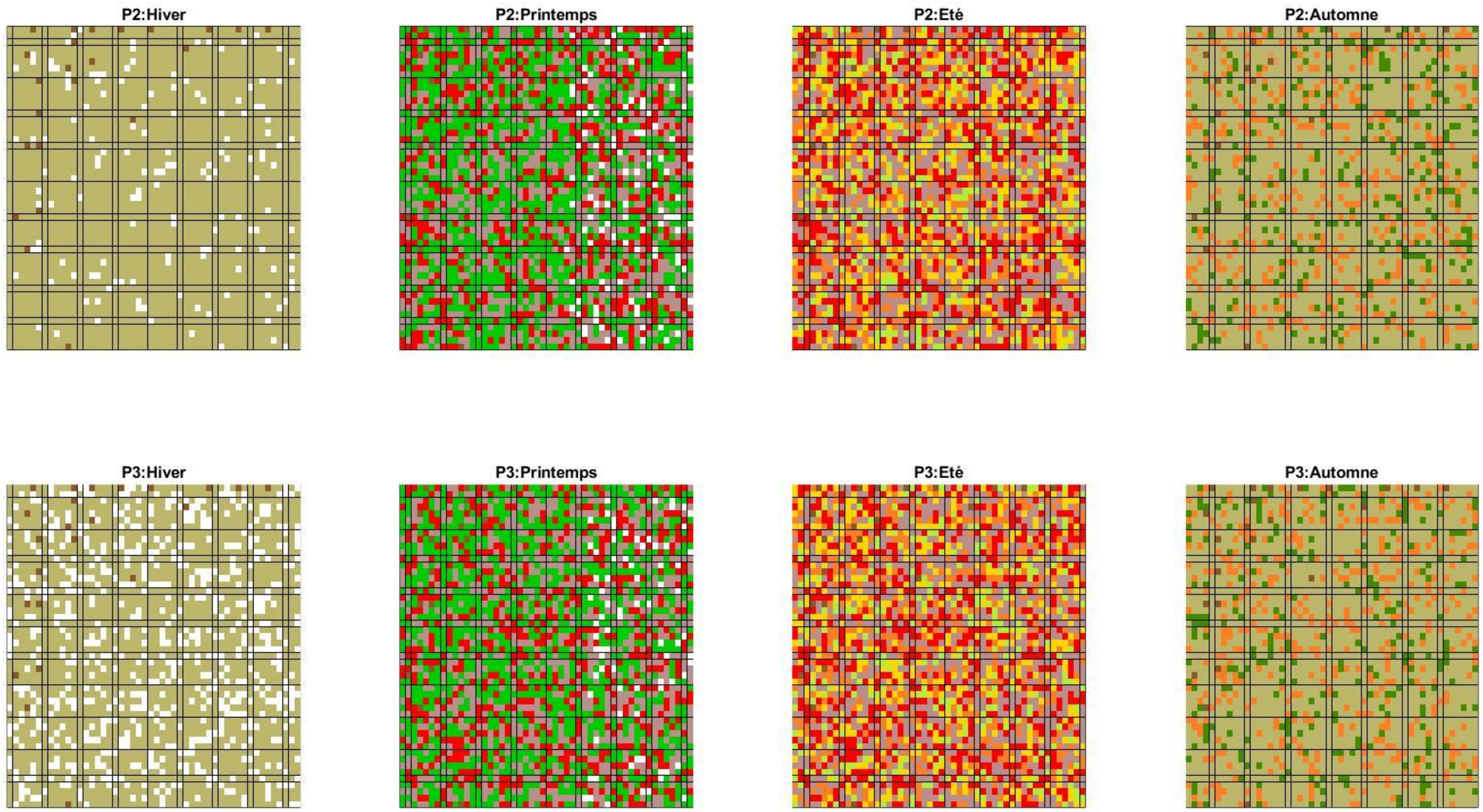
10 x 10





(iEMSs 2016, IEA/AIE 2017)

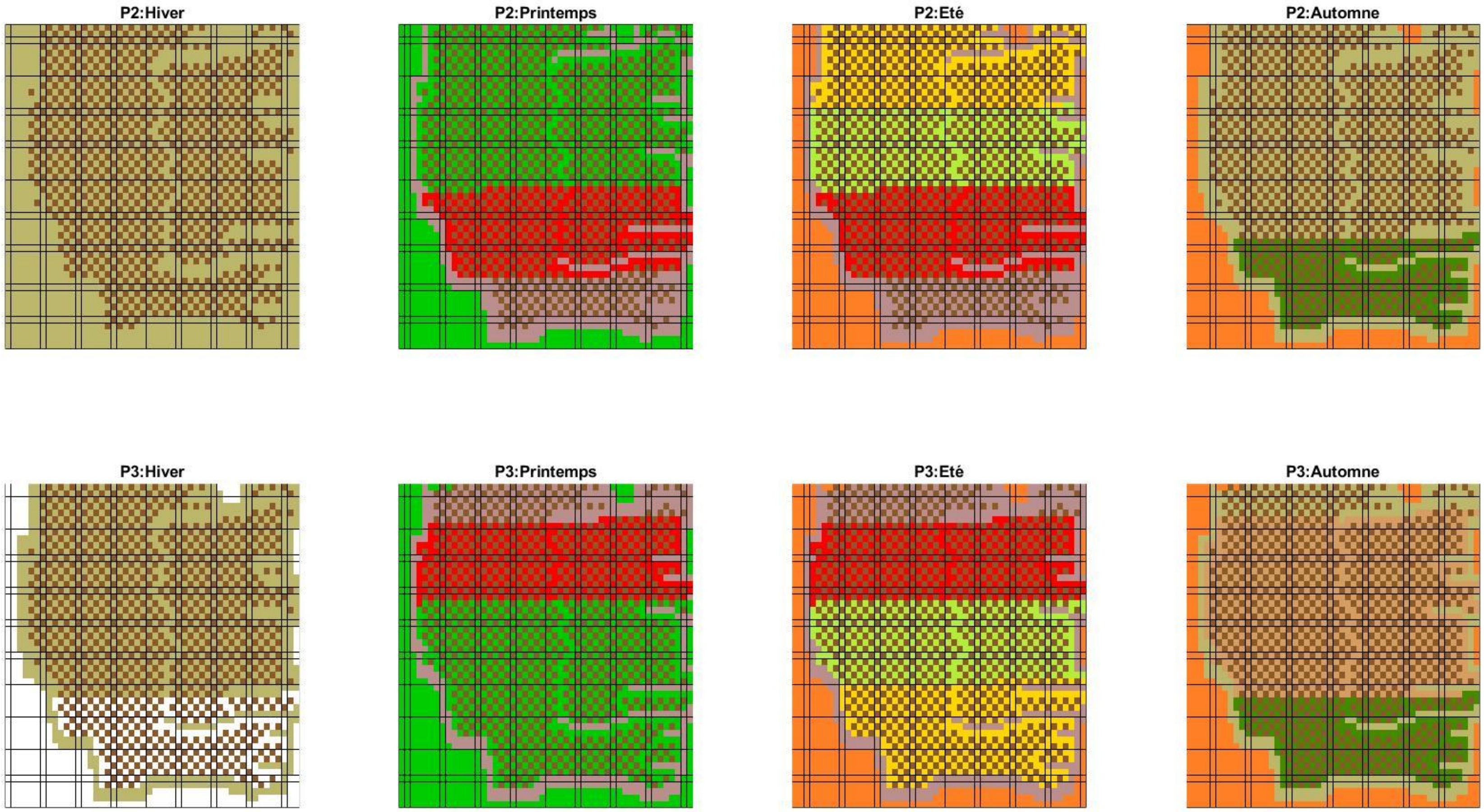
50 x 50



Best solution found by *baryonyx** 0.4 after 1h on 30 cores of AMD Opteron 2.3GHz (01LP-SPP model, 2 million Boolean variables!)

* *https://github.com/quesnel/baryonyx*

50 x 50



MIP best solution found by cplex 12.8 after 1h on 30 cores of AMD Opteron 2.3GHz
(MIP model with 12500 Boolean variables and 276 continuous variables)

Some tips

- Collaborate with researchers from the other discipline
- Get access to (new) real data
- Collect articles, software, contacts to build an overview of the field
- Select journals / (interdisciplinary) conferences to publish
- Validate the results by domain experts
- Enjoy learning a new (complex) discipline!
- PhD subject is a bet! (from your supervisors ;-)

Before the thesis

- How to be recruited
  - Long meeting with the supervisor(s)
  - Master first research experience (technical report)
  - Relevance of your Master courses to the subject (course marks/ranking)
  - Funding (National/European projects are usually more restrictive, already specified, less innovation than University doctoral school funding)
- Building the subject / project
  - A particular story between (at least) two supervisors
  - Better if they have already collaborate in the past
  - Useful for the society ? => complex subjects requiring interdisciplinary approaches
  - Sometimes good subjects need a long time to be mature (between the supervisors)
  - Subject can be revised, it depends on the student interests (eg. more theory vs practical)
  - Associate the student to its construction
  - See as a whole in the student curriculum

During the thesis

- Supervision
  - Diversity of supervisors (at least 2!) => more people, more pressure, more difficult to make choices
  - Identifying all the actors for the thesis and their role
  - Working environment
  - Frequency of meetings (in person), regularity
  - Places for informal meetings
  - Collective agility and flexibility (subject evolution)
  - Anticipate and real-time modifications
  - Strategy of publications: where (conferences/journals), when (deadlines), what (reselling), who (author ordering)

    → it depends on the scientific discipline (computer science, biology,...)

    → doctoral schools usually ask for at least one (two?) selective publication(s)

    → after that you have more freedom!

    → see past Best Dissertation Awards at CP for some good examples
  - Associate the PhD student to the decision process
  - Benevolent attitude, recognition at work

    → for the student: be rigorous, open-mind, be a diplomat

    → for the supervisors: mutual trust, back and forth between freedom and guidance

During the thesis

- Developing skills
  - Which skills? (theory, engineer, relational/meeting, supervision of trainees,...)
  - Recognition, value for the company
  - PhD committee during the thesis (mid-term evaluation)
  - Doctoral school supports (interview, courses)
  - Interdisciplinary conferences
  - Foreign lab visits

After the thesis

- Anticipate after-the-thesis during your thesis!
  - What is your career plan?
    → Inform supervisors of your career plan (academy / industry)
  - List of your skills
  - Career counselor
  - Doctoral school training / workshops (like CP Doctoral Program!)
- Post-doc strategy
  - Social network (of supervisors)
    → supervisors should help
  - Curriculum vitae
  - Publication strategy
  - Doing applied research in your second discipline (being a facilitator, risk taking)
- To be hired
  - Interdisciplinary institutes (University, National Research Institute,…)
  - Raise awareness of the jury members
  - Adapt to the job market (additional training,..)

Professional experiences

- Marti Sanchez, PhD in 2006, postdoc at INRAE (2006-2008) and Barcelona University, tenure track at Universitat Pompeu-Fabra, Barcelona, Spain, in 2022 (work in neuro-robotics)
- Aurélie Favier, PhD in 2011, 2-year postdoc at University College Cork, secondary school teacher in Bordeaux, France since 2014
- Jimmy Vandel, PhD in 2012, postdocs at CEA Grenoble, LIRMM Montpellier and Lille University, permanent research engineer at CNRS, Lille, France since 2020 (work on a bioinformatics and biostatistics platform)
- Mahuna Akplogan, PhD in 2013, recruited in 2012 by a private French company (R&D consultant in optimization, work on nurse scheduling, healthcare and rescue,...)
- Clément Viricel, PhD in 2017, temporary associate professor at Lyon University, freelance data-scientist (work on neural nets)
- Sara Maqrot, PhD in 2019, temporary associate professor at Toulouse University (2018-2020), research engineer at ONERA (2021-2022) and permanent position at Berger Levraut, Toulouse, France since 2022
- Manon Ruffini, PhD in 2021 (My Thesis in 180s), recruited in Aibstract, Albi, France since 2021 (work on automatic music generation)