

Part III - Case studies

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CP'01**Problems and Soft Constraints**

Typical real problems include:

- Hard constraints (physical constraints)
- Preferably satisfied constraints (preferences, eg. deadlines)
- Uncertain constraints (errors, weathers. . .)

All such constraints⇒ unfeasibility No such constraint \Rightarrow many meaningless solutions

Usual approach: ad-hoc heuristic (but often efficient)handling.

RNA secondary structure prediction

RNA is ^a single strand molecule composed of A,U,G,C.

Functional RNA are structured (3d structure). Structure is related to function.

The structure is induced by base pairing: Watson-Crick (A-U,G-C) and Wobble (G-U).

Secondary structure: set of all Watson-Crick andWobble base pairs.

Problem: determine the secondary structure of an RNAmolecule from ^a single sequence.

CP'01**^A transfert RNA**

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RNA secondary structure prediction

Other sources of information:

• thermodynamics.

Zuker's algorithm: DP algorithm that finds an optimal secondary structure. Pb: thermodynamicsis not precise enough.

McCaskill matrix: given an RNA sequence, computes the probability that ^a given base is pairedto another given base (based on thermodynamics).

biological knowledge: one may know/test that ^a given base is paired or not, is paired to ^a givenother base.

CP'01**^A CSP model (C. Gaspin, 1995)**

For a sequence of length $n=$ $(b_1,\ldots b_n)$:

- one variable x_i per base
- domains: $d_i=$ $\{1,\ldots,n\}.$ $b_i=i$ means b_i unpaired.
- constraints: Watson-Crick/Wobble only.

 $x_i=j\Leftrightarrow x_j=i$

No pseudo-knot: for $i < j, k < l, (j,l)$ is forbidden for x_i, x_k $_k$ if $i < k < j < l$ or $k < i < l < j$.

Many other constraints...

Experimental knowledge: ^a base is unpaired, ispaired, with ^a specific base...

Usually too many solutions. Need more information.

Exploiting thermodynamics

McCaskill matrix $P(i,j)$ probability that b_i is paired with b_j .

For algorithmic reasons (satisfaction problem):

- fix a threshold p .
- forbid all pairs $b_i=j$ such that $P(i, j) < p.$

Poor handling of probabilities, Choice of p . . .

Enforce arc consistency, then solve as ^a Max-CSP with unary soft constraints (maximize the number of pairedbases) using ^a maximal clique tree-search algorithm.

Satellite scheduling

- var/dom: ^a set S of pictures. Each picture can be taken at different time points.
- **•** binary constraints: only three instruments are available and each picture requires some instruments with possible transition times forreconfiguration.
- **•** ternary constraints: the data bus bandwidth is limited.
- **e** global constraint: the local memory is limited.

Overconstrained: instanciate a subset of S which maximizes the sum of the weights of the pictures (andsatisfies all constraints).

CP'01**RDS (no global constraint)**

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val ⁼ # of pictures, ∗ ⁼ optimality proof (within 30')

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Satellite scheduling

Beyond RDS, these instances have been tackled byseveral approaches:

- **o** local search: taboo search (M. Vasquez).
- LP + column generation: to provide global lower bounds
- 0/1 LP: as ^a multidimensional Knapsack (MKP01), to provide global lower bounds (M. Vasquez).

The MKP01 model is solved to optimality by CPLEX 7.0 (with float tolerance problems) on most instances (including the global constraint). Cpu-time may reach 5.10^4 sec. on a modern Pentium machine.

Frequency assignment (CELAR)

CP'01**FAP - criteria**

- minimize the maximum frequency used (possibilistic CSP)
- minimize the number of frequencies used (optimisation/global soft constraint)
- minimize the weighted constraint violation (Max-CSP)

Several instances available: from 200 to 916 vars, from1200 to more than 5000 binary constraints. Domainsusually have more than 30 values.

$FAP:$ **results**

Tackled in the CALMA project (1994) and then byindividuals. Most problems solved to optimality. . .

Max-CSP problems are very hard (even for local search). No proof of optimality after CALMA.

- 1997: graph decomposition + RDS proved optimality of Celar06 $(5.10^6$ sec., Sparc 5). PFC-MRDAC $(2.610^5 \text{ sec}, \text{Sparse 2})$.
- 1999: preprocessing (≈ soft AC) + dynamic
programming (subucket elimination) + a lotu programming ([≈] bucket elimination) ⁺ ^a lot more: solves most instances to optimality (Arie Koster, PhD thesis).

Conclusion

Soft constraint technology is still in its enfancy. There is much to do:

- use existing frameworks to build more realistic models for existing problems, that may exploit recent algorithms (eg. bucket elimination, PFC-MRDAC. . .)
- improve algorithms for solving existing models in existing frameworks:
	- **stronger preprocessing**
	- **global soft constraints**
	- **combination of bucket elimination, branching** and local consistency or other preprocessing.

CP'01**Existing implementations (we know. . .)**

■ Con'Flex: Conjunctive fuzzy CSP system with integer, symbolic and numerical constraints

(www.inra.fr/bia/T/conflex).

 $\mathsf{clp}(\mathsf{FD},S)$: semi-ring CLP.

(pauillac.inria.fr/˜georget/clp_fds/clp_fds.html).

LVCSP: Common-Lisp library for Valued CSP withan emphasis on strictly monotonic operators

(ftp.cert.fr/pub/lemaitre/LVCSP).

Choco: ^a claire library for CSP. Existing layers above Choco implements Weighted Max-CSP $\bm{\mathsf{algorithms}}$ (part of LVCSP, $\sf_{\sf{www.choco-constraints.net}}.$

Alessandro Biso, Francesca Rossi, and Alessandro Sperduti. Experimental results onlearning soft constraints. In Anthony G. Cohn, Fausto Giunchiglia, and Bart Selman, editors, KR2000: Principles of Knowledge Representation and Reasoning, pages435–444, San Francisco, 2000. Morgan Kaufmann.

S. Bistarelli, U. Montanari, and F. Rossi. Constraint solving over semirings. In *Proc. of* the 14th IJCAI, Montréal, Canada, August 1995.

S. Bistarelli, U. Montanari, and F. Rossi. Semiring based constraint solving andoptimization. Journal of the ACM, 44(2):201–236, 1997.

S. Bistarelli, H. Fargier, U. Montanari, F. Rossi, T. Schiex, and G. Verfaillie. Semiring-based CSPs and valued CSPs: Frameworks, properties and comparison. Constraints, 4:199–240, 1999.

S. Bistarelli, R Gennari, and F. Rossi. Constraint propagation for soft constraints: generalizationand termination conditions. In *Principles and Practice of Constraint* Programming - CP 2000, volume 1894 of LNCS, pages 83–97, Singapore, September2000.

A. Borning, M. Mahert, A. Martindale, and M. Wilson. Constraint hierarchies and logicprogramming. In *Int. conf. on logic programming*, pages 149–164, 1989.

B. Cabon, S. de Givry, and G. Verfaillie. Anytime lower bounds for constraint violationminimization problems. In *Proc. of the 4th International Conference on Principles and* Practice of Constraint Programming (CP-98), pages 117–131, Pisa, Italy, 1998.

B. Cabon, S. de Givry, L. Lobjois, T. Schiex, and J.P. Warners. Radio link frequencyassignment. *Constraints Journal*, 4:79–89, 1999.

Rina Dechter. Bucket elimination: A unifying framework for reasoning. *Artificial* Intelligence, 113(1–2):41–85, 1999.

D. Dubois, H. Fargier, and H. Prade. The calculus of fuzzy restrictions as ^a basis forflexible constraint satisfaction. In *Proc.* 2 nd *IEEE Conference on Fuzzy Systems*, San Francisco, CA, March 1993.

H. Fargier and J. Lang. Uncertainty in constraint satisfaction problems: ^a probabilisticapproach. In *Proc. of ECSQARU '93, LNCS 747*, pages 97–104, Grenade, Spain, November 1993.

H. Fargier, J. Lang, and T. Schiex. Selecting preferred solutions in Fuzzy Constraint Satisfaction Problems. In *Proc.* of the 1 $^{\mathrm{st}}$ European Congress on Fuzzy and Intelligent Technologies, 1993.

E.C. Freuder and R.J. Wallace. Partial constraint satisfaction. Artificial Intelligence, 58:21–70, December 1992.

Eugene C. Freuder. Partial constraint satisfaction. In *Proc. of the 11th IJCAI*, pages 278–283, Detroit, MI, 1989.

Philippe Galinier and Jin-Kao Hao. Tabu search for maximal constraint satisfactionproblems. In Principles and Practice of Constraint Programming - CP'97, number ¹³³⁰ in LNCS, pages 196–208, 1997.

C. Gaspin and E. Westhof. An interactive framework for RNA secondary structureprediction with ^a dynamical treatment of constraints. Journal of Molecular Biology, 254:163–174, 1995.

L. Kanal and V.Kumar. Search in Intelligence Artificial Intelligence. Springer-Verlag, 1988. ISBN 0-387-96750-8.

J.K. Hao and R. Dorne. Empirical studies of heuristic local search for constraint solving. In International Conference on Principles and Practice of Constraint Programming – CP-96, volume 1118 of LNCS, pages 194–208, Cambridge, MA, 1996. Arie M.C.A Koster. Frequency assignment: Models and Algorithms. PhD thesis, University of Maastricht, The Netherlands, November 1999. Available at www.zib.de/koster/thesis.html.

J. Larrosa and P. Meseguer. Exploiting the use of DAC in max-CSP. In Proc. of CP'96, pages 308–322, Boston (MA), 1996.

J. Larrosa, P. Meseguer, and T. Schiex. Maintaining reversible DAC for Max-CSP. Artificial Intelligence, 107(1):149–163, January 1999.

J. Larrosa. Boosting search with variable elimination. In Principles and Practice of Constraint Programming - CP 2000, volume 1894 of LNCS, pages 291–305, Singapore, September 2000.

T.L. Lau and P.K. Tsang. Guided genetic algorithm and its application to radio linkfrequency assignment problems. Constraints, 6(4):373–398, 2001.

A. Rosenfeld, R. Hummel, and S. Zucker. Scene labeling by relaxation operations. IEEE Trans. on Systems, Man, and Cybernetics, 6(6):173–184, 1976.

Francesca Rossi, and Alessandro Sperduti. Learning solution preferences in constraint problems. Journal of Theoretical and Experimental Artificial Intelligence (JETAI), Vol. 10, 1998, Taylor and Francis publisher.

Zsofia Ruttkay. Fuzzy constraint satisfaction. In *Proc. FUZZ-IEEE'94*, Orlando, Florida, 1994.

T. Schiex, H. Fargier, and G. Verfaillie. Valued constraint satisfaction problems: hardand easy problems. In *Proc. of the 14th IJCAI*, pages 631–637, Montréal, Canada, August 1995.

T. Schiex. Possibilistic constraint satisfaction problems or "How to handle soft constraints ?". In *Proc. of the 8th Int. Conf. on Uncertainty in Artificial Intelligence*, Stanford, CA, July 1992.

T. Schiex. Arc consistency for soft constraints. In *Principles and Practice of Constraint* Programming - CP 2000, volume 1894 of LNCS, pages 411–424, Singapore, September 2000.

L. Shapiro and R. Haralick. Structural descriptions and inexact matching. IEEE Transactions on Pattern Analysis and Machine Intelligence, 3:504–519, 1981.

G. Verfaillie, M. Lemaître, and T. Schiex. Russian doll search. In *Proc. of AAAI'96*, pages 181–187, Portland, OR, 1996.

R. Wallace. Directed arc consistency preprocessing. In M. Meyer, editor, Selectedpapers from the ECAI-94 Workshop on Constraint Processing, number 923 in LNCS, pages 121–137. Springer, Berlin, 1994.

K.C. Wiese and S. D. Goodwin. Keep-best reproduction: A local family competitionselection strategy and the environment it flourishes in. Constraints, 6(4):399–422, 2001.