

Title: Dual Viewpoint Heuristics for  
Binary Constraint Satisfaction Problems  
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Theory and Practice of Constraint Satisfaction  
CSCE 990-05, Fall 1999  
[www.cse.unl.edu/~choueiry/CSE990-05/](http://www.cse.unl.edu/~choueiry/CSE990-05/)

# Contributions

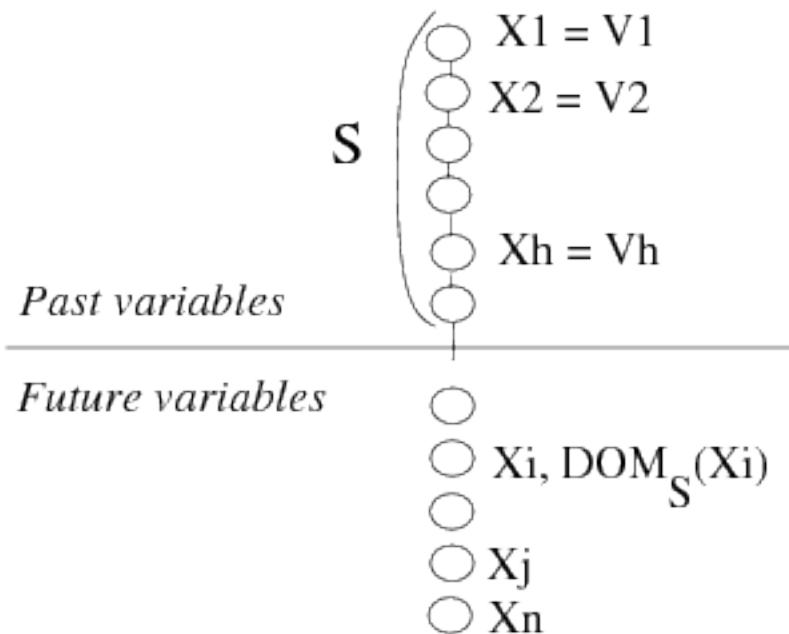
- I- New heuristics for variable & value selection
- II- Double-viewpoint strategy
  - (common in scheduling: [Sadeh '91]  
job vs. resource-centered perspective)
- III- Validation on the  $n$ -Queen problem

# Assumptions

- Binary constraints, finite domains
- Seeking **one** solution (relevant for value ordering)
- Using backtracking (BT) and forward-checking (FC)

## I- Goal of Var/Val orderings in BT

- **avoid constraint violation**
  - select values that do not cause constraint violation
  - most promising value first
- **discover constraint violation quickly**
  - select variables that do not delay constraint violation
  - most constrained variable first (fail first principle)



After forward-checking given  $S$

$$\left\{ \begin{array}{l} \text{DOM}_S(X_i) \\ \vdots \\ \text{DOM}_S(X_j) \\ \text{DOM}_S(X_n) \end{array} \right.$$

For  $X_i = V_i$ , we can separate  $\text{DOM}_S(X_j)$  into two sets in  $\mathcal{O}(a)$ :

- values consistent with  $X_i = V_i$   
→ of size  $\text{LEFT}_S(X_j \mid X_i = V_i)$
- values inconsistent with  $X_i = V_i$   
→ of size  $\text{LOST}_S(X_j \mid X_i = V_i)$

## Value selection for $X_i$

Choose the least constraining value  $V_i$

1. Minimize  $X_j$  future variables

$$\text{Cost}_S(X_i = V_i) = \sum_{X_j \neq i} \text{LOST}_S(X_j \mid X_i = V_i)$$

2. Minimize  $X_j$  future variables

$$\text{Cruciality}_S(X_i = V_i) = \sum_{X_j \neq i} \frac{\text{LOST}_S(X_j \mid X_i = V_i)}{|\text{DOM}_S(X_j)|}$$

3. Maximize  $X_j$  future variables

$$\text{Promise}_S(X_i = V_i) = \prod_{X_j \neq i} \text{LEFT}_S(X_j \mid X_i = V_i)$$

→ number of assignments that  $X_i = V_i$  and can be done such that no constraint on  $X_i$  is violated

- (3) is more discriminating ( $\text{LEFT}_S(X_j \mid X_i = V_i) = 0$ )

## Value selection: example

- Minimize  $X_j$  future variables

$$\text{Cost}_S(X_i = V_i) = \sum_{X_j \neq i} \text{LOST}_S(X_j \mid X_i = V_i)$$

X1	6	6	6	6
X2	6	8	8	6
X3	6	8	8	6
X4	6	6	6	6

- Maximize  $X_j$  future variables

$$\text{Promise}_S(X_i = V_i) = \prod_{X_j \neq i} \text{LEFT}_S(X_j \mid X_i = V_i)$$

X1	8	6	6	8
X2	8	2	2	8
X3	8	2	2	8
X4	8	6	6	8

## Variable selection

Choose the most constrained variable (FFP)  $X_i$

1. Least domain (LD)

2. Maximize

$$V_i \in \text{DOM}_S(X_i)$$

$$\text{Criticality}_S(X_i) =$$

$$\prod_{V_i} \frac{1}{(1 + |\text{DOM}_S(X_i)| + \text{Cruciality}_S(X_i = V_i))}$$

3. Minimize

$$V_i \in \text{DOM}_S(X_i)$$

$$\text{Promise}_S(X_i) = \sum_{V_i} \text{Promise}_S(X_i = V_i)$$

→ number of assignments that can be done  
such that no constraint on  $X_i$  is violated

## Variable selection: example

Minimize:

$$V_i \in \text{DOM}_S(X_i)$$

$$\text{Promise}_S(X_i) = \sum_{V_i} \text{Promise}_S(X_i = V_i)$$

X1	8	6	6	8	28
X2	8	2	2	8	20
X3	8	2	2	8	20
X4	8	6	6	8	28

$X_1, X_4$  promise 28 solutions

$X_2, X_3$  promise 20 solutions, more constraining

Start with  $X_2$  or  $X_3$  (more constraining) and,  
choose columns 1 or 4 (more promising)

# Summary

Most promising value:

- (1) Minimum cost
- (2) Minimum cruciality
- (3) Maximum promise

Most constrained variable:

- Least domain (LD)
- (4) Maximum criticality
- (5) Minimum (false) promise

→ Dynamic variable/value orderings

## Algorithms

Identifier	Choice of Var	Choice of val
LD+1	least domain	Minimum cost
LD+2	—	Min. cruciality
LD+3	—	Max promise
FE+2/4	Max. critical	Min. cruciality
FE+3/5	Min. promise	Max. promise

LD: time  $\mathcal{O}(na^2)$ , space  $\mathcal{O}(na)$

FE: time  $\mathcal{O}(n^2a^2)$ , space  $\mathcal{O}(na)$

Implementation hack: domino effect, saves computations.

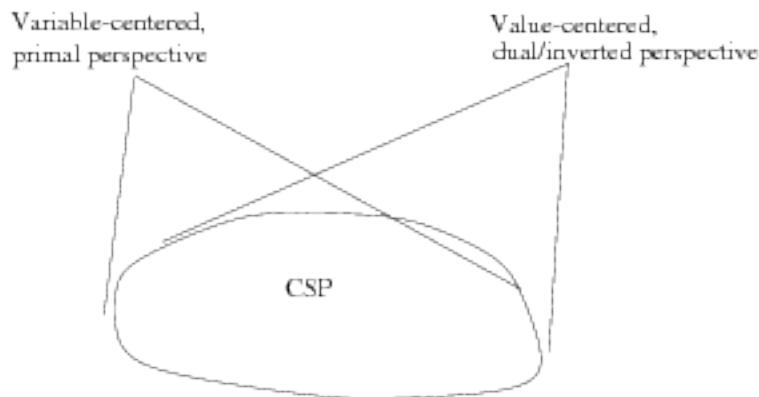
## II- Permutation problems

→  $\left\{ \begin{array}{l} n = a \\ \text{constraint graph is complete} \\ \text{constraints are MUTEX, All-diffs} \end{array} \right.$

→ matching, marriage problem

find one value for every variable and  
exactly one variable for every value

Viewpoints: variable vs. values



→ Which viewpoint to take?

→ How to combine computations in viewpoints?

## Permutation problems (cont'd)

At any point in BT,

$$\# \text{ future variables} = \# \text{ future values}$$

→ choose the most constrained variable in the var-viewpoint, except when the most constrained value in the val-viewpoint is more constrained

## PP: Least domain

X1		2	1
X2	●		
X3		0	1
X4	2		0

## PP: Full evaluation

Introduce:

$$\begin{cases} \text{LEFT}^{inv}(V_i | X_i = V_i) \\ \text{Promise}^{inv}(V_i = X_i) \end{cases}$$
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Combine viewpoints:  $\text{CPromise}(X_i = V_i) \min. \begin{cases} \text{Promise}(X_i = V_i) \\ \text{Promise}^{inv}(V_i = X_i) \end{cases}$

Evaluate vars/vals using:

$$\begin{cases} \text{CPromise}(X_i) = \sum_k \text{CPromise}(X_i = V_k) \\ \text{CPromise}^{inv}(V_i) = \sum_k \text{CPromise}(X_k = V_i) \end{cases}$$

## **Partial permutation problems ( $n \leq a$ )**

- fake a real PP with bogus variables
- extend (3) for PPP

## **III- Experiments**

- 100  $N$ -queen problems:  $4 \leq N \leq 103$
- Comparison criteria
  - average number of backtrack
  - number of backtrack-free solutions
  - maximum number of backtracks
  - number of constraint checks

Algorithms:  $\left\{ \begin{array}{l} \text{LD-1, LD-2, LD-3, LD-1+Dual} \\ \text{FE-2-4, FE-3-5, FE-3-5+Dual} \\ \text{FP-2-4, FP-3-5} \end{array} \right.$

*Include Table from paper*

Dual perspective exhibits dramatic improvements