

Structural Decomposition Methods:

Basic Concepts and Applications in Algorithmic Game Theory



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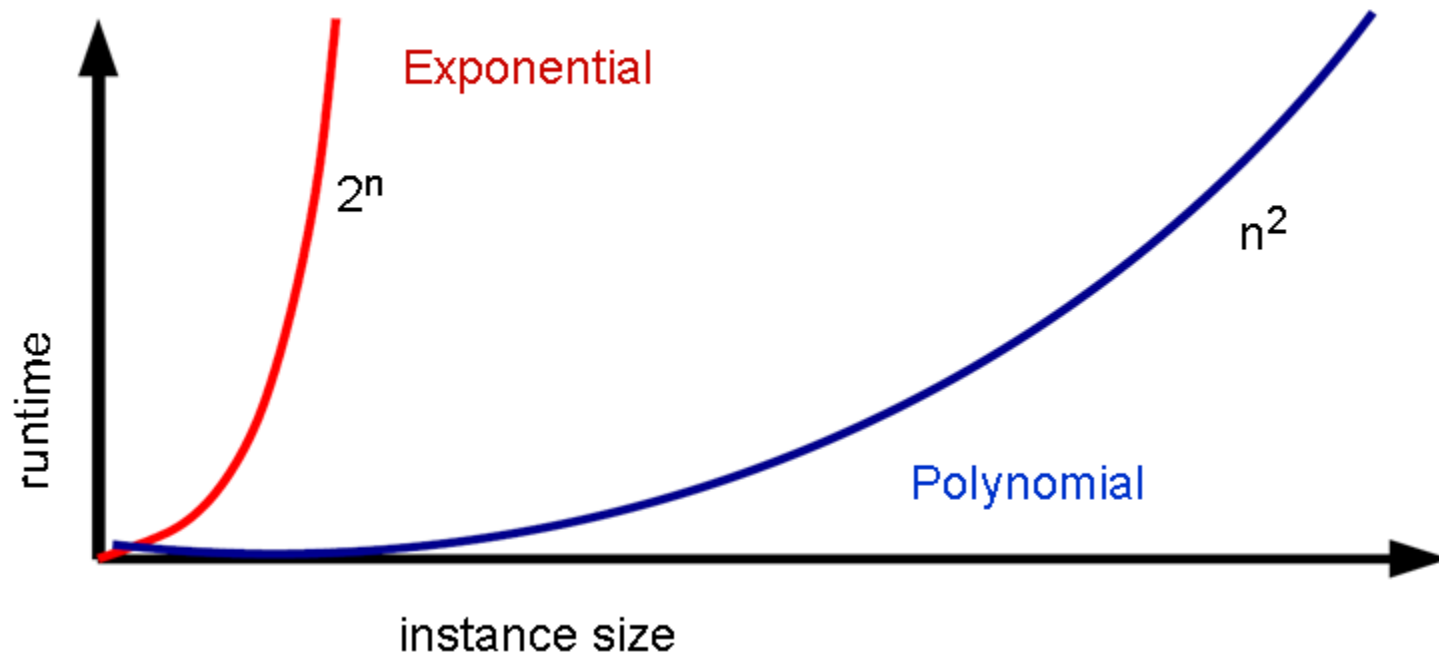
Inherent Problem Complexity

- Problems *decidable* or *undecidable*.
- We concentrate on decidable problems here.
- A problem is as complex as the best possible algorithm which solves it.

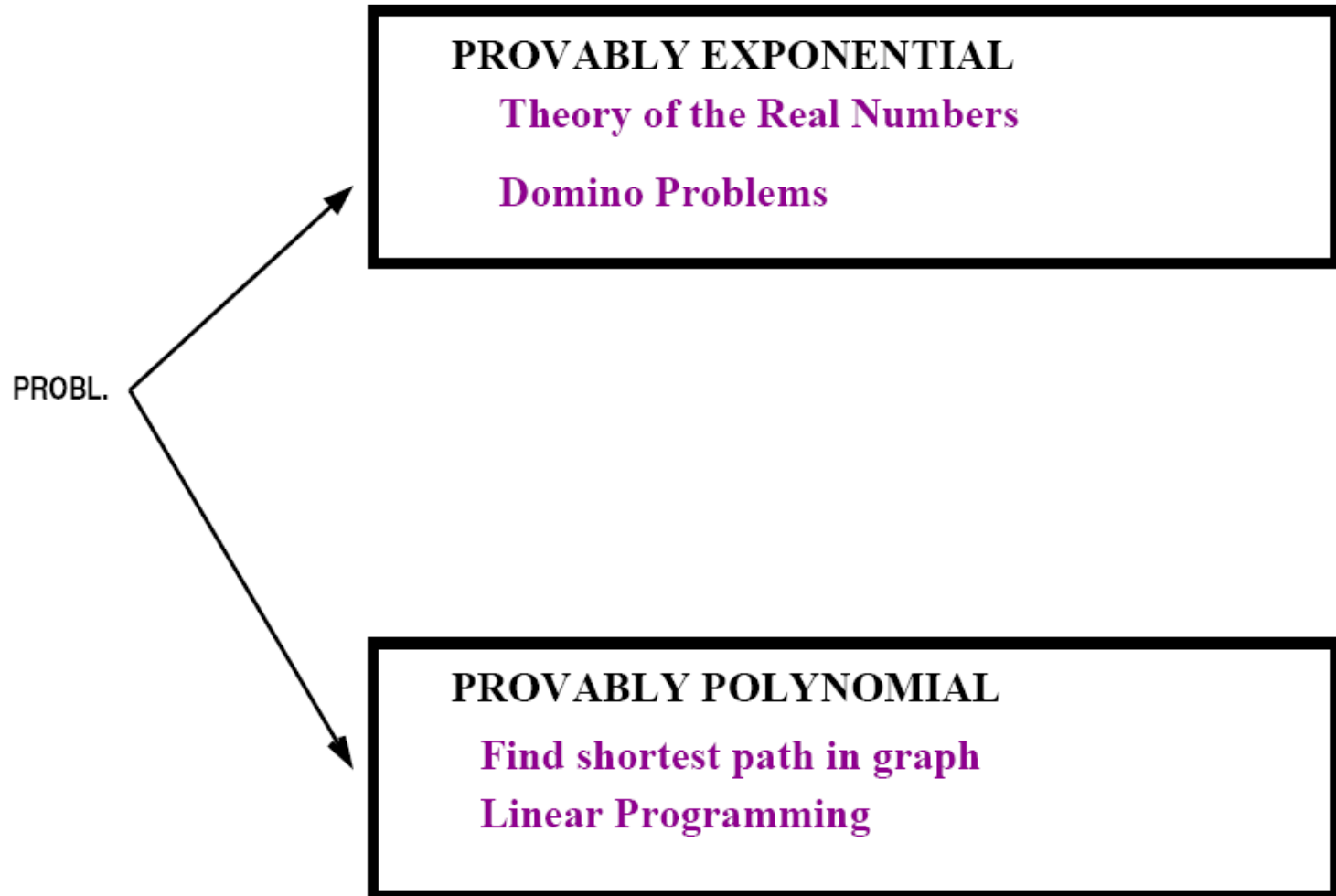
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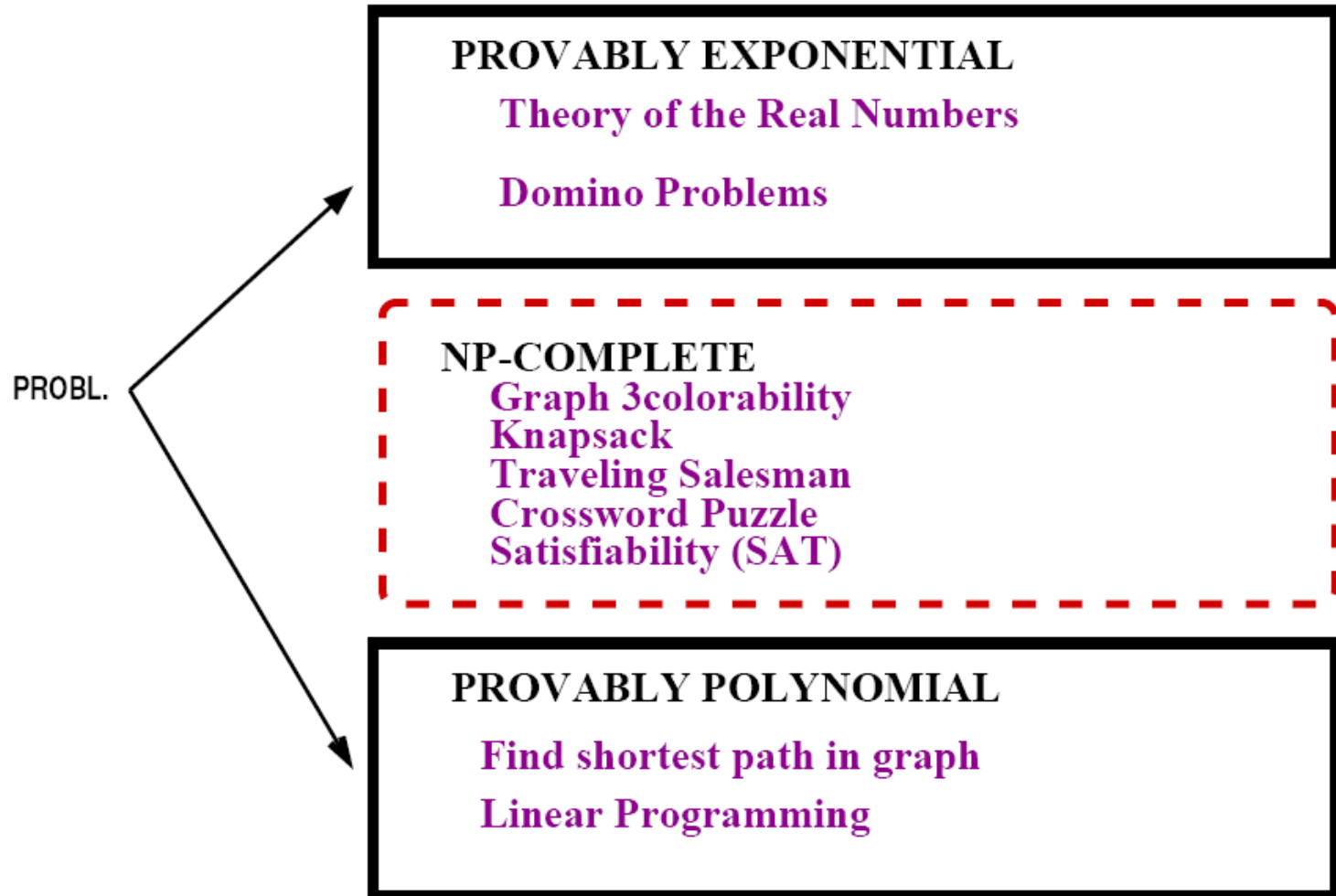
Number of steps it takes for input of size n



Time Complexity



Time Complexity

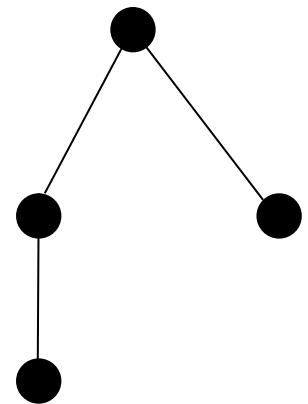
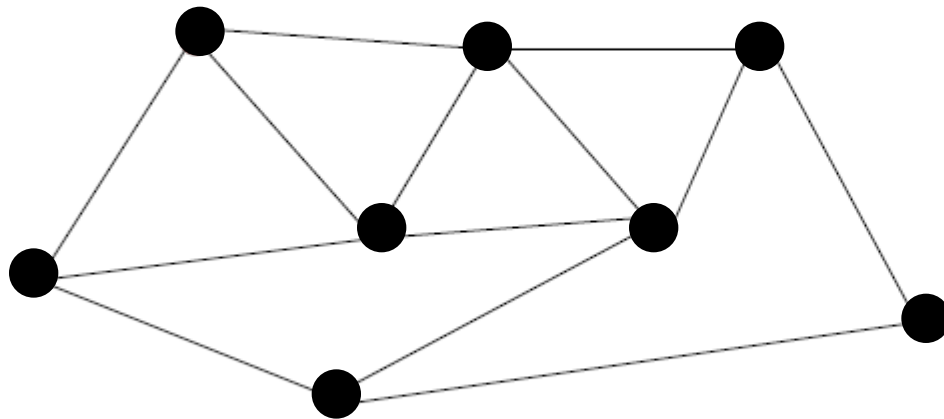


Graph Three-colorability

{ *Instance:* A graph G .

{ *Question:* Is G 3-colorable?

Examples of instances:

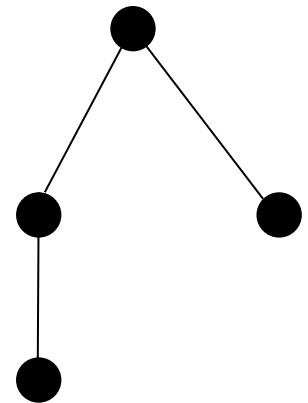
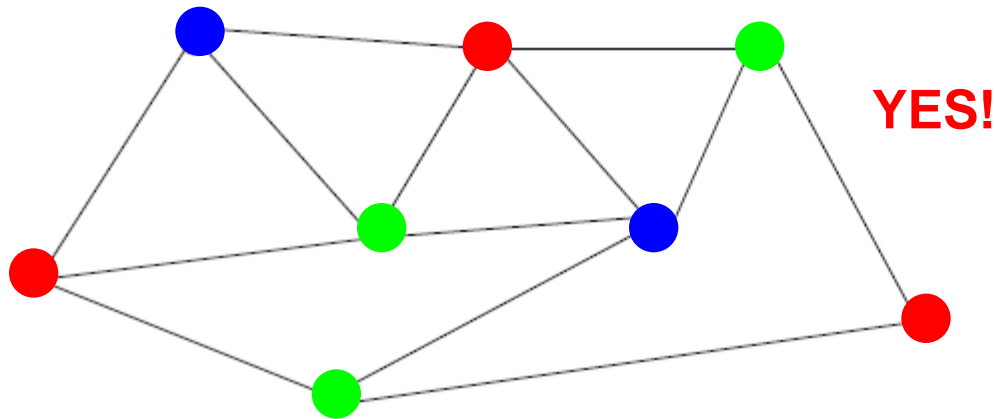


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Examples of instances:



Outline

Identification of “Easy” Classes

Applications of Tree Decompositions

Beyond Tree Decompositions

Decision/Computation Problems

Optimization Problems

Enumeration Problems

Identification of Polynomial Subclasses

- High complexity often arises in “rare” worst case instances
- Worst case instances exhibit intricate structures
- In practice, many input instances have *simple* structures
- Therefore, our goal is to
 - Define polynomially solvable subclasses (possibly, the largest ones)
 - Prove that membership testing is tractable for these classes
 - Develop efficient algorithms for instances in these classes

Problems with a Graph Structure

- With graph-based problems, high complexity is mostly due to *cyclicity*.

Problems restricted to *acyclic* graphs are often trivially solvable (\rightarrow 3COL).

- Moreover, many graph problems are polynomially solvable if restricted to instances of *low cyclicity*.

Problems with a Graph Structure

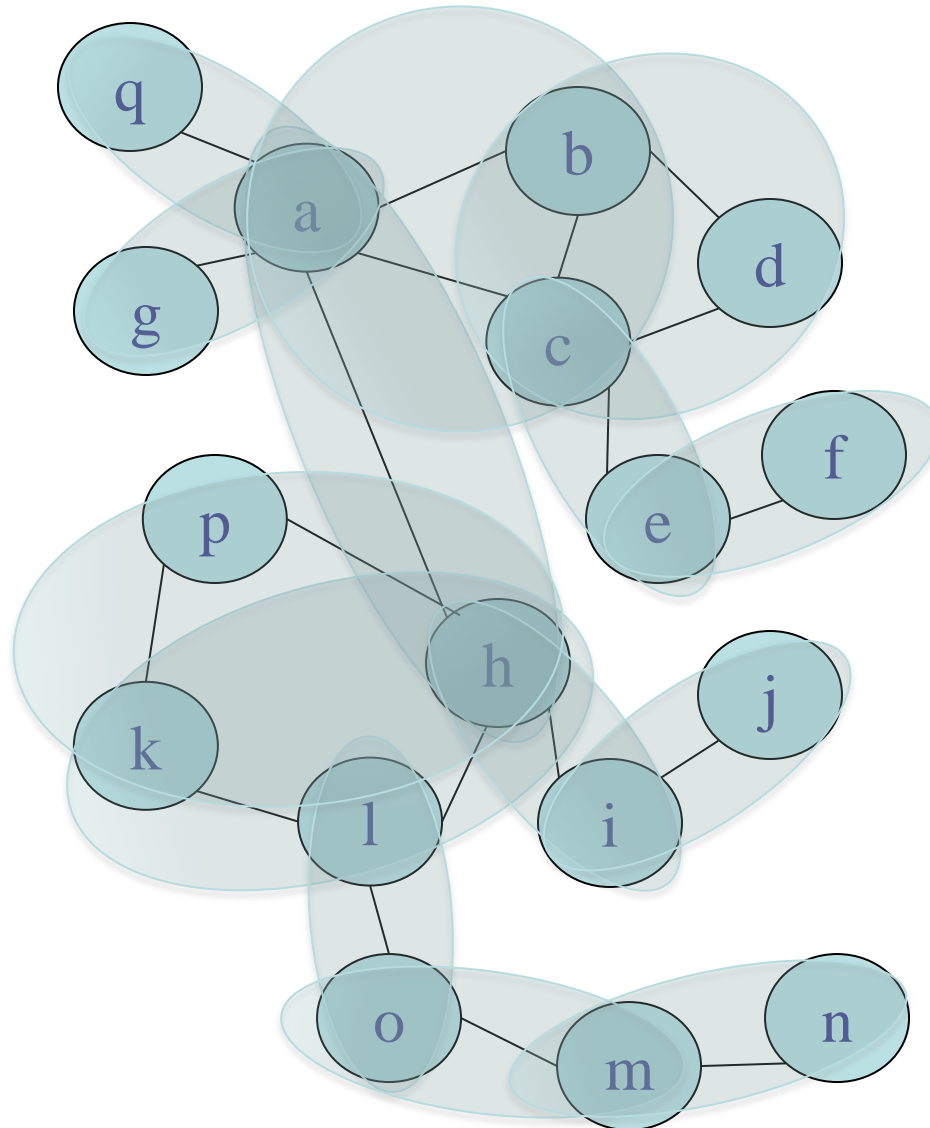
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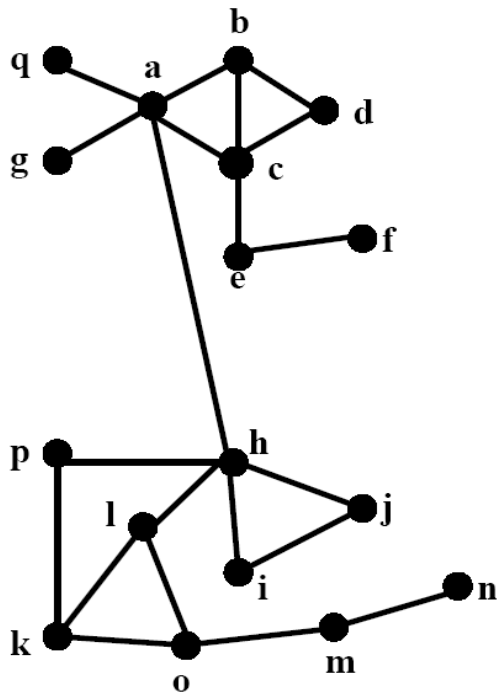
- Moreover, many graph problems are polynomially solvable if restricted to instances of *low cyclicity*.

How can we measure the degree of cyclicity?

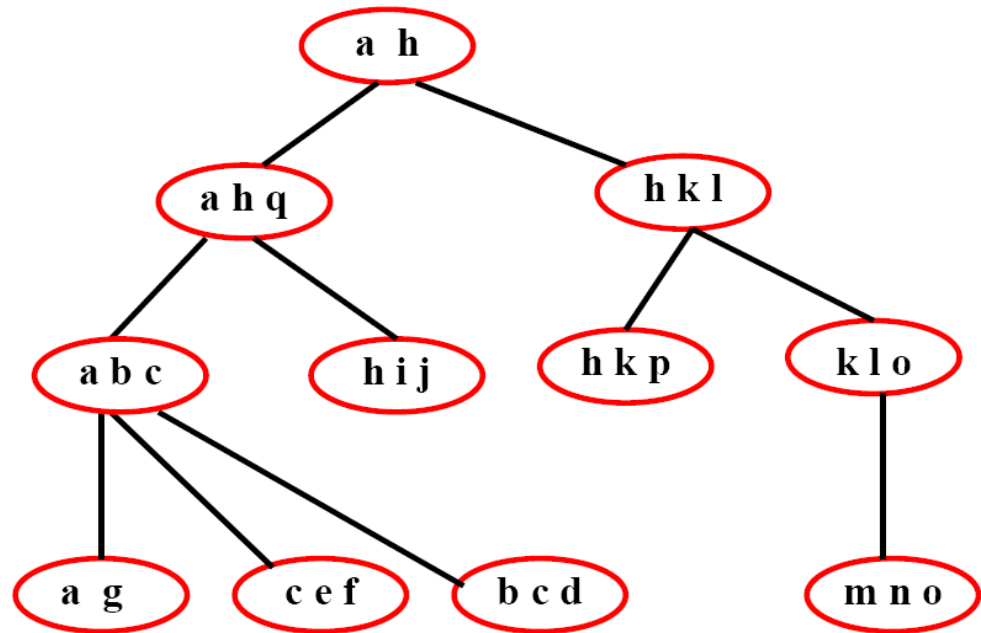
Tree Decompositions [Robertson & Seymour '86]



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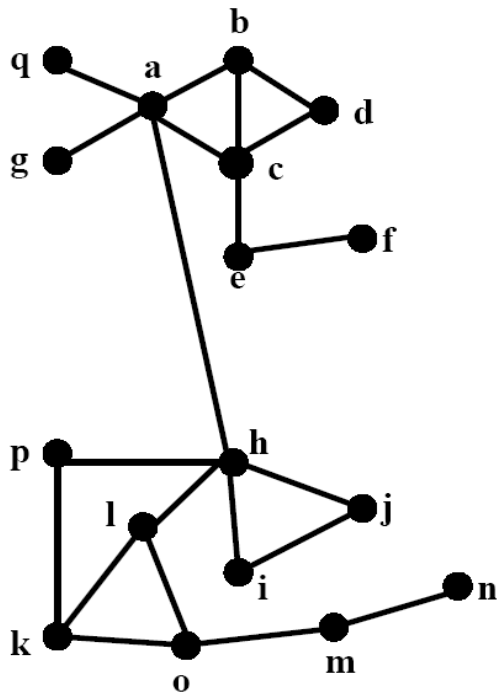


Graph G

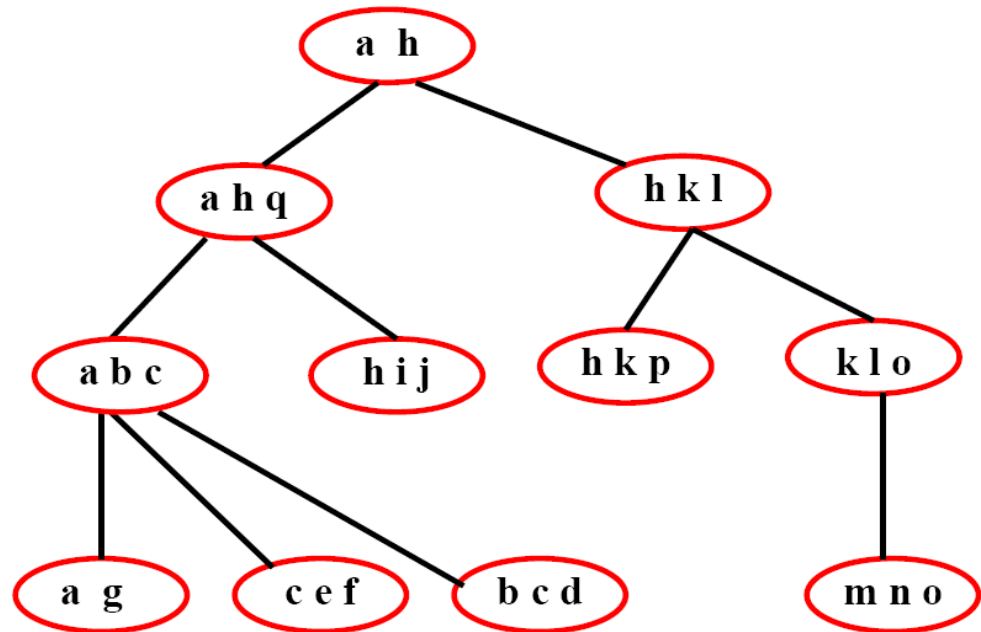


Tree decomposition of width 2 of G

Tree Decompositions [Robertson & Seymour '86]



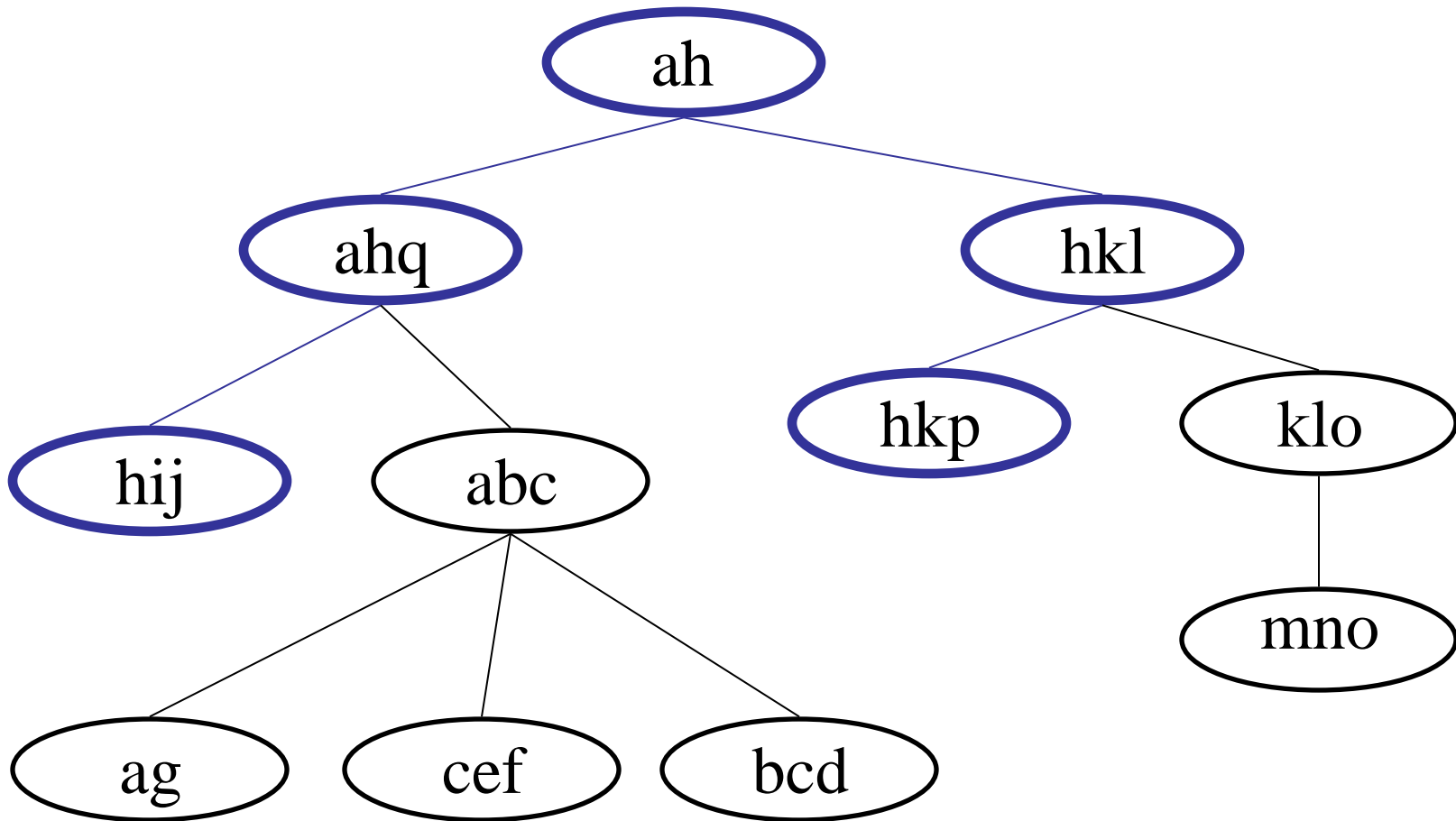
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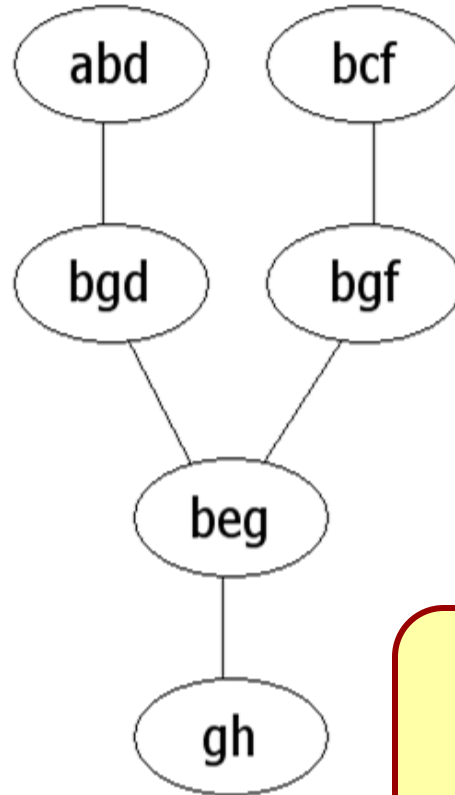
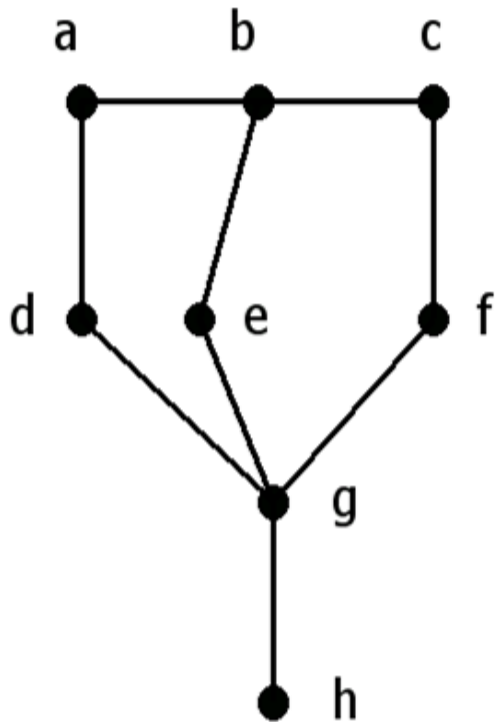
Tree decomposition of width 2 of G

- Every edge realized in some bag
- Connectedness condition

Connectedness condition for h



Tree Decompositions and Treewidth



$$\text{width}(T, X_i) = \max |X_i| - 1$$
$$\text{tw}(G) = \min \text{width}(T, X_i)$$

Properties of Treewidth

- $\text{tw}(\text{acyclic graph})=1$
- $\text{tw}(\text{cycle}) = 2$
- $\text{tw}(G+v) \leq \text{tw}(G)+1$
- $\text{tw}(G+e) \leq \text{tw}(G)+1$
- $\text{tw}(K_n) = n-1$

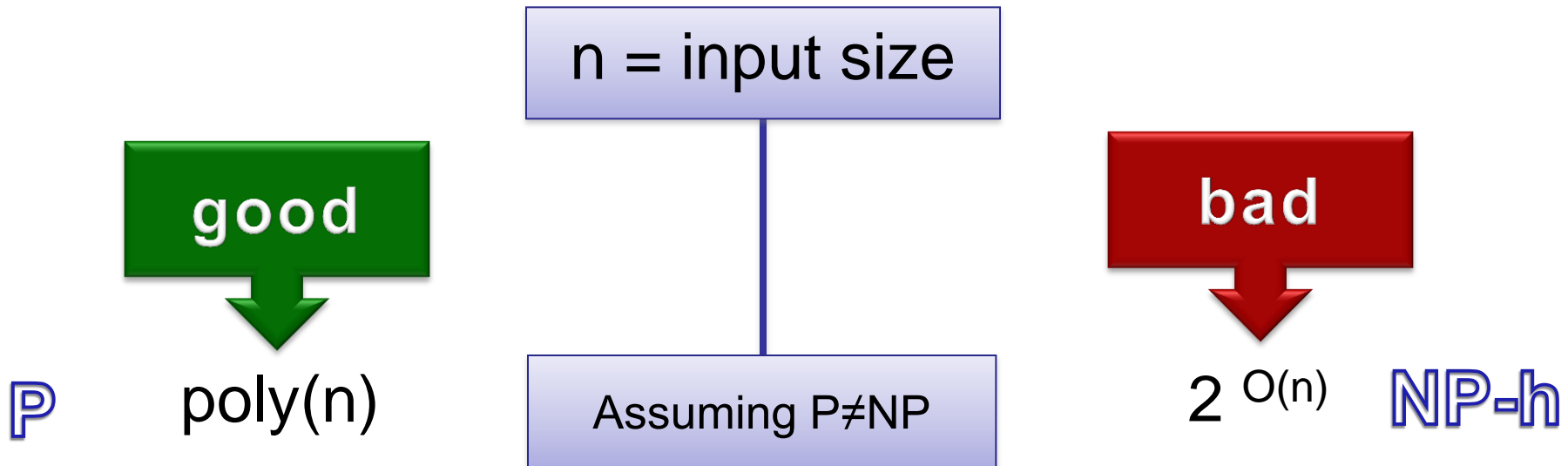
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(1) tw is fixed-parameter tractable (parameter: treewidth)

(2) tw is a key for tractability 

Classical Computational Complexity

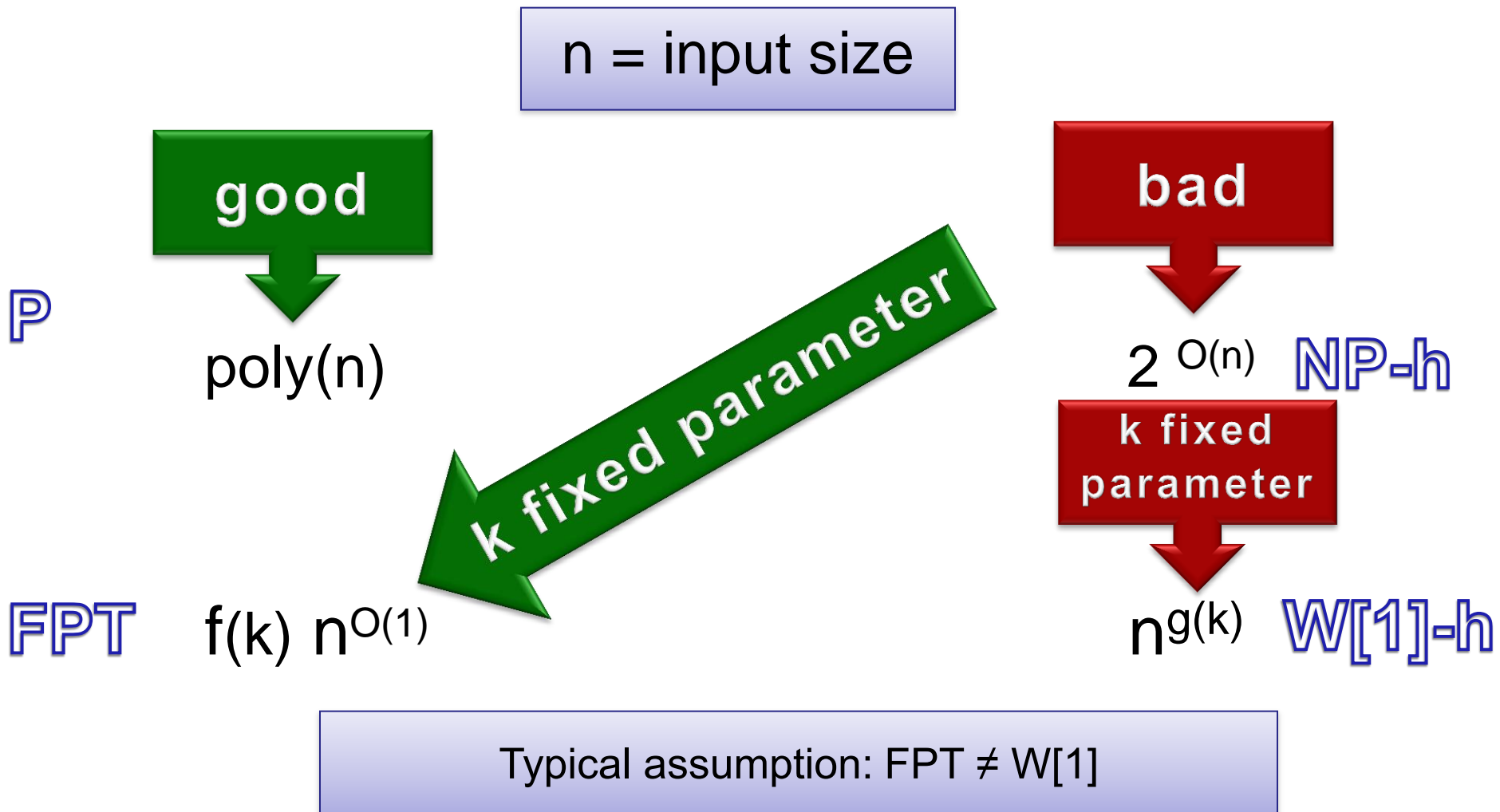


But...

- In many problems there exists some part of the input that are quite small in practical applications
- Natural parameters
- Many NP-hard problems become easy if we fix such parameters (or we assume they are below some fixed threshold)
- Positive examples: k-vertex cover, k-feedback vertex set, k-clique, ...
- Negative examples: k-coloring, k-CNF, ...

Parameterized Complexity

- Initiated by Downey and Fellows, late '80s



W[1]-hard problems: k-clique

- k-clique is hard w.r.t. fixed parameter complexity!

INPUT: A graph $G=(V,E)$

PARAMETER: Natural number k

- Does G have a clique over k vertices?

FPT races

- <http://fpt.wikidot.com/>

Problem	f(k)
Vertex Cover	1.2738^k
Connected Vertex Cover	2^k
Multiway Cut	2^k
Directed Multiway Cut	$2^{O(k^2)}$
Almost-2-SAT (VC-PM)	4^k
Multicut	$2^{O(k^2)}$
Pathwidth One Deletion Set	4.65^k
Undirected Feedback Vertex Set	3.83^k
Undirected Feedback Vertex Set	3^k
Subset Feedback Vertex Set	$2^{O(k \log k)}$
Directed Feedback Vertex Set	$4^k k!$
Odd Cycle Transversal	3^k
Edge Bipartization	2^k
Planar DS	$2^{1.98\sqrt{k}}$
1-Sided Crossing Min	$2^{O(\sqrt{k} \log k)}$
Max Leaf	3.72^k
Directed Max Leaf	3.72^k
Set Splitting	1.8213^k
Nonblocker	2.5154^k
Edge Dominating Set	2.3147^k
k-Path	4^k
k-Path	1.66^k
Convex Recolouring	4^k
VC-max degree 3	1.1616^k
Clique Cover	2^{2^k}
Clique Partition	2^{k^2}
Cluster Editing	1.62^k
Steiner Tree	2^k
3-Hitting Set	2.076^k

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An important Metatheorem

Courcelle's Theorem [1987]

Let P be a problem on graphs that can be formulated in **Monadic Second Order Logic (MSO)**.

Then P can be solved in linear time on graphs of bounded treewidth

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Let P be a problem on graphs that can be formulated in **Monadic Second Order Logic** (MSO).

Then P can be solved in linear time on graphs of bounded treewidth

- **Theorem.** (Fagin): Every NP-property over graphs can be represented by an existential formula of Second Order Logic.

$NP = ESO$

- Monadic SO (MSO): Subclass of SO, only *set variables*, but no relation variables of higher arity.

3-colorability \in MSO.

Three Colorability in MSO

$$\begin{aligned} (\exists R, G, B) \quad [& (\forall x (R(x) \vee G(x) \vee B(x))) \\ & \wedge (\forall x (R(x) \Rightarrow (\neg G(x) \wedge \neg B(x)))) \\ & \wedge \dots \\ & \wedge \dots \\ & \wedge (\forall x, y (E(x, y) \Rightarrow (R(x) \Rightarrow (G(y) \vee B(y))))) \\ & \wedge (\forall x, y (E(x, y) \Rightarrow (G(x) \Rightarrow (R(y) \vee B(y))))) \\ & \wedge (\forall x, y (E(x, y) \Rightarrow (B(x) \Rightarrow (R(y) \vee G(y)))))] \end{aligned}$$

Master Theorems for Treewidth

Arnborg, Lagergren, Seese '91:

Optimization version of Courcelle's Theorem.

Finding an optimal set P such that $G \models \Phi(P)$ is FP-linear over inputs G of bounded treewidth.

Example:

Given a graph $G=(V,E)$

Find a ***smallest*** P such that

$$\forall x \forall y : (E(x,y) \rightarrow (P(x) \neq P(y)))$$

Optimality (More General)

- $G = \langle (N, E), w_N, w_E \rangle$ is a graph weighted on vertices and edges, and ϕ an **MSO**₂ formula
- A solution to ϕ is an interpretation (z_N, z_E) (a pair (set of vertices, set of edges)) such that $(N, E) \models \phi[(z_n, z_E)]$ and its cost is $\sum_{x \in z_N} w_N(x) + \sum_{y \in z_E} w_E(y)$.
- A solution of minimum cost is said optimal

Theorem (simplified from Arnborg et al., 1991)

*Let ϕ be a fixed **MSO**₂ sentence and let $G = \langle (N, E), f_N, f_E \rangle$ be a weighted graph such that $(N, E) \in \mathcal{C}_k$. Then, computing an optimal solution to ϕ over G is feasible in polynomial time (w.r.t. $\|G\|$).*

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Identification of “Easy” Classes

Applications of Tree Decompositions

Beyond Tree Decompositions

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Enumeration Problems

The Model

- Players form *coalitions*
- Each coalition is associated with a *worth*
- A *total worth* has to be distributed

$$\mathcal{G} = \langle N, v \rangle, v : 2^N \mapsto \mathbb{R}$$

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$$\mathcal{G} = \langle N, v \rangle, v : 2^N \mapsto \mathbb{R}$$

- Outcomes belong to the imputation set $X(\mathcal{G})$

$$x \in X(\mathcal{G}) \left\{ \begin{array}{l} \bullet \text{ Efficiency} \\ x(N) = v(N) \\ \bullet \text{ Individual Rationality} \\ x_i \geq v(\{i\}), \quad \forall i \in N \end{array} \right.$$

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- **Solution Concepts** characterize outcomes in terms of
 - Fairness
 - Stability

The Model

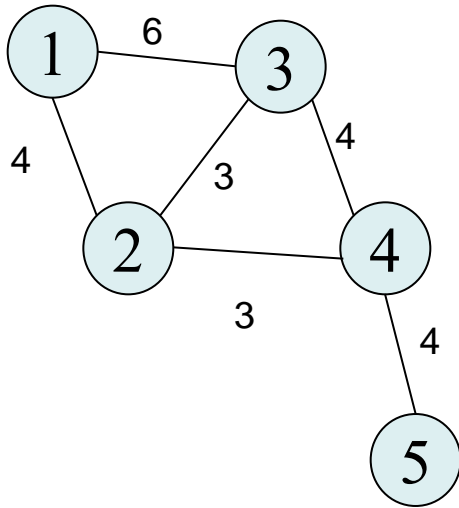
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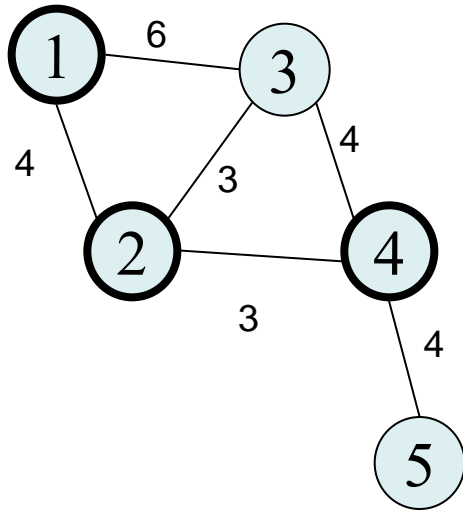
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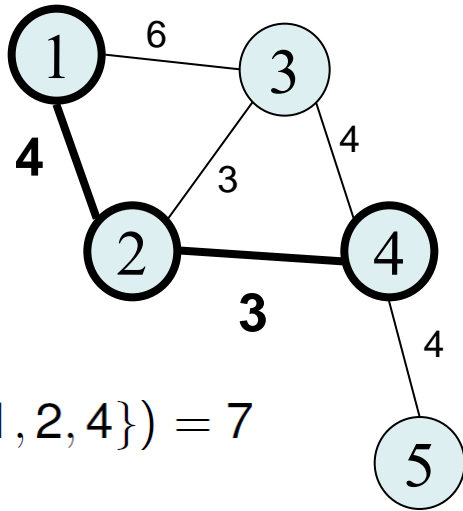
Compact Games



Compact Games

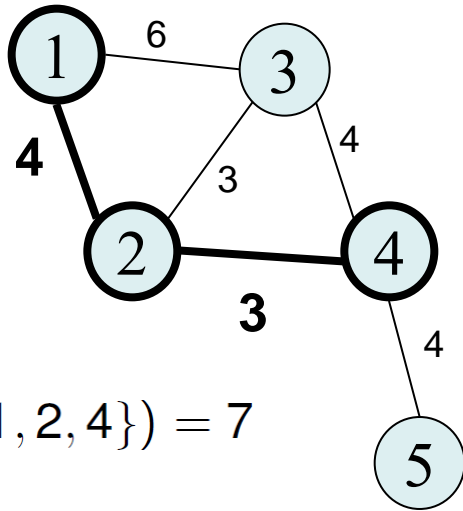


Compact Games



$$v(\{1, 2, 4\}) = 7$$

Compact Games



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- *Graph Games* [Deng and Papadimitriou, 1994]
 - Computational issues of several solution concepts

Membership in the Core on Graph Games

The Core: $\forall S \subseteq N, x(S) \geq v(S);$
 $x(N) = v(N)$

Consider the sentence,

over the graph where N is the set of nodes and E the set of edges :

$$\text{proj}(X, Y) \equiv X \subseteq N \wedge \\ \forall c, c' (Y(c, c') \rightarrow X(c) \wedge x(c')) \wedge \\ \forall c, c' (X(c) \wedge X(c') \wedge E(c, c') \rightarrow Y(c, c'))$$

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...it tells that Y is the set of edges covered by the nodes in X

Membership in the Core on Graph Games

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Let $proj(X, Y)$ be the formula stating that Y is the set of edges covered by the nodes in X

Define the following weights: $w_E(c, c') = -w(c, c')$; $w_N(c) = x_c$



Value of the edge (negated)



Value at the imputation

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Value of the edge (negated) Value at the imputation

Find the “minimum-weight” X and Y such that $proj(X, Y)$ holds

Membership in the Core on Graph Games

The Core: $\forall S \subseteq N, x(S) \geq v(S);$
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$$0 \geq e(S, x) = v(S) - \sum_{i \in S} x_i$$



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Max (value of edges – value of the imputation), i.e., $\max_{S \subseteq N} e(S, x)$

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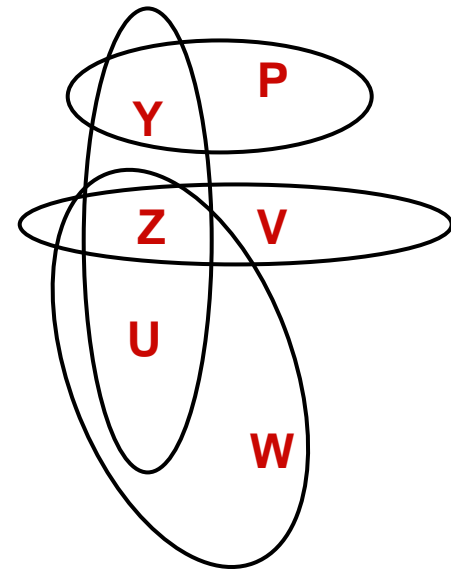
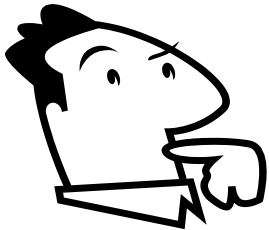
Beyond Treewidth

- Treewidth is currently the most successful measure of graph cyclicity. It subsumes most other methods.
- However, there are “simple” graphs that are heavily cyclic. For example, a clique.

Beyond Treewidth

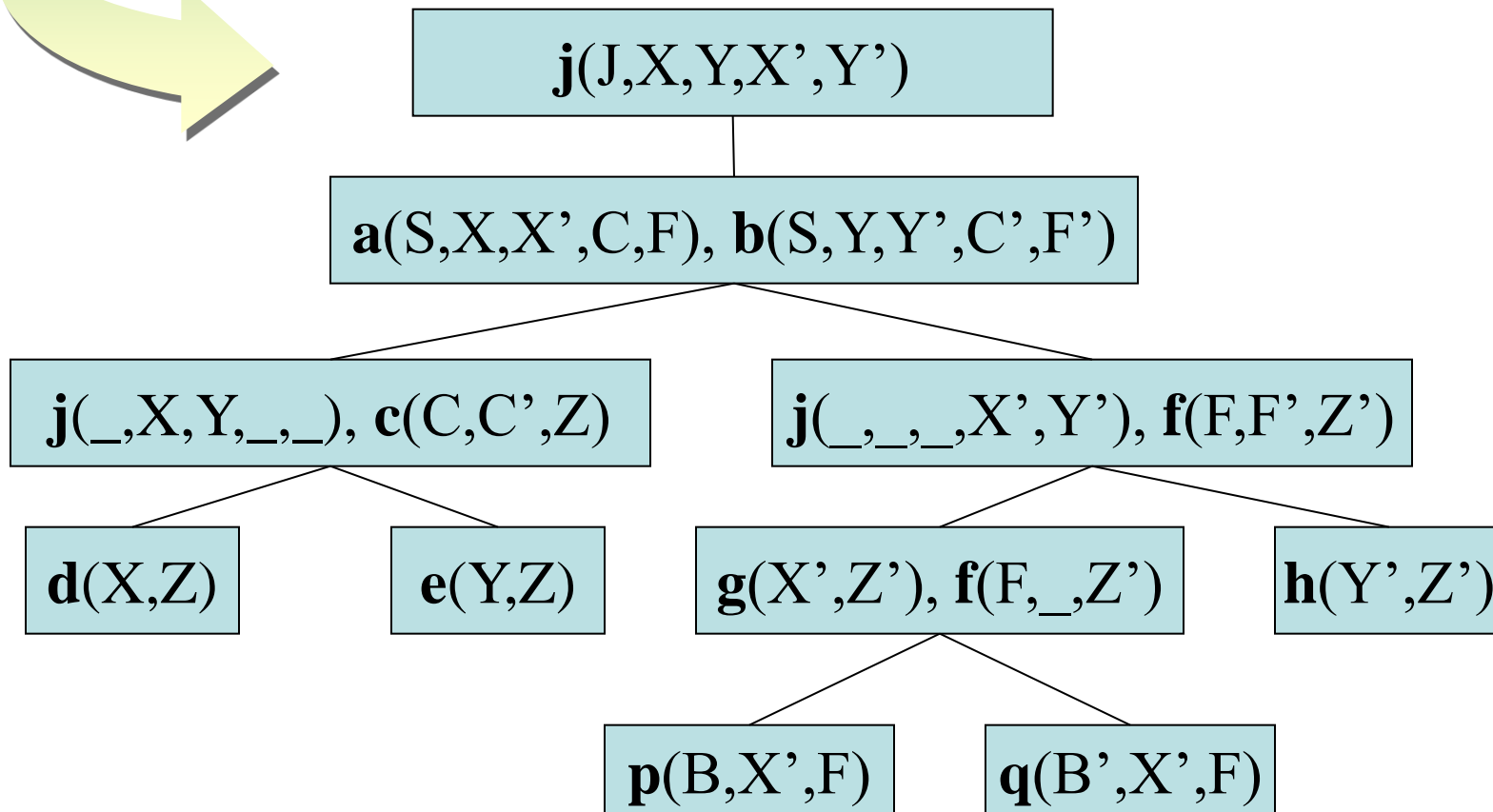
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- However, there are “simple” graphs that are heavily cyclic. For example, a clique.

There are also problems whose structure is better described by **hypergraphs** rather than by graphs...



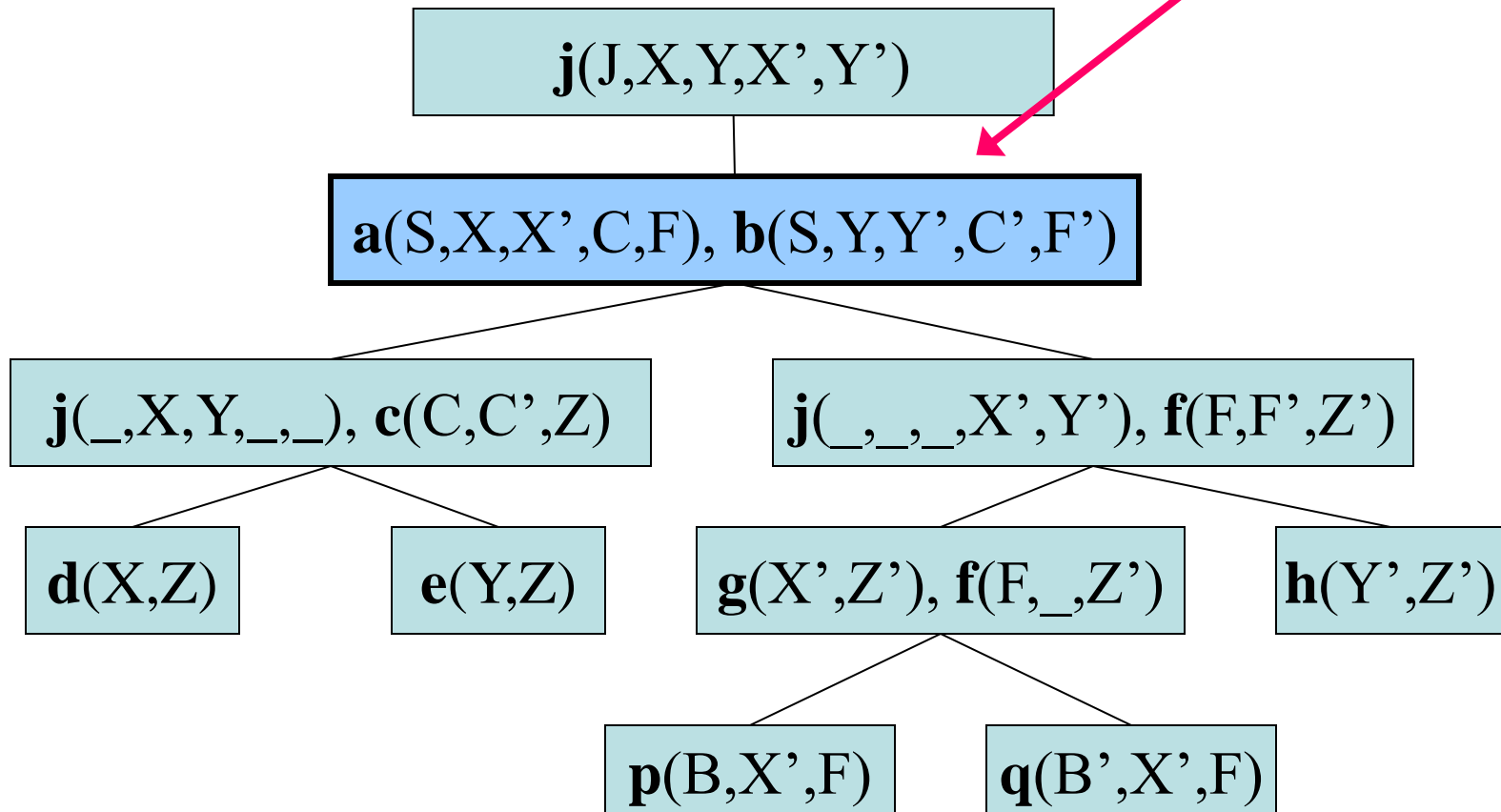
Generalized Hypertree Decompositions

$a(S, X, X', C, F)$ $b(S, Y, Y', C', F')$ $c(C, C', Z)$ $d(X, Z)$
 $e(Y, Z)$ $f(F, F', Z')$ $g(X', Z')$ $h(Y', Z')$
 $j(J, X, Y, X', Y')$ $p(B, X', F)$ $q(B', X', F)$

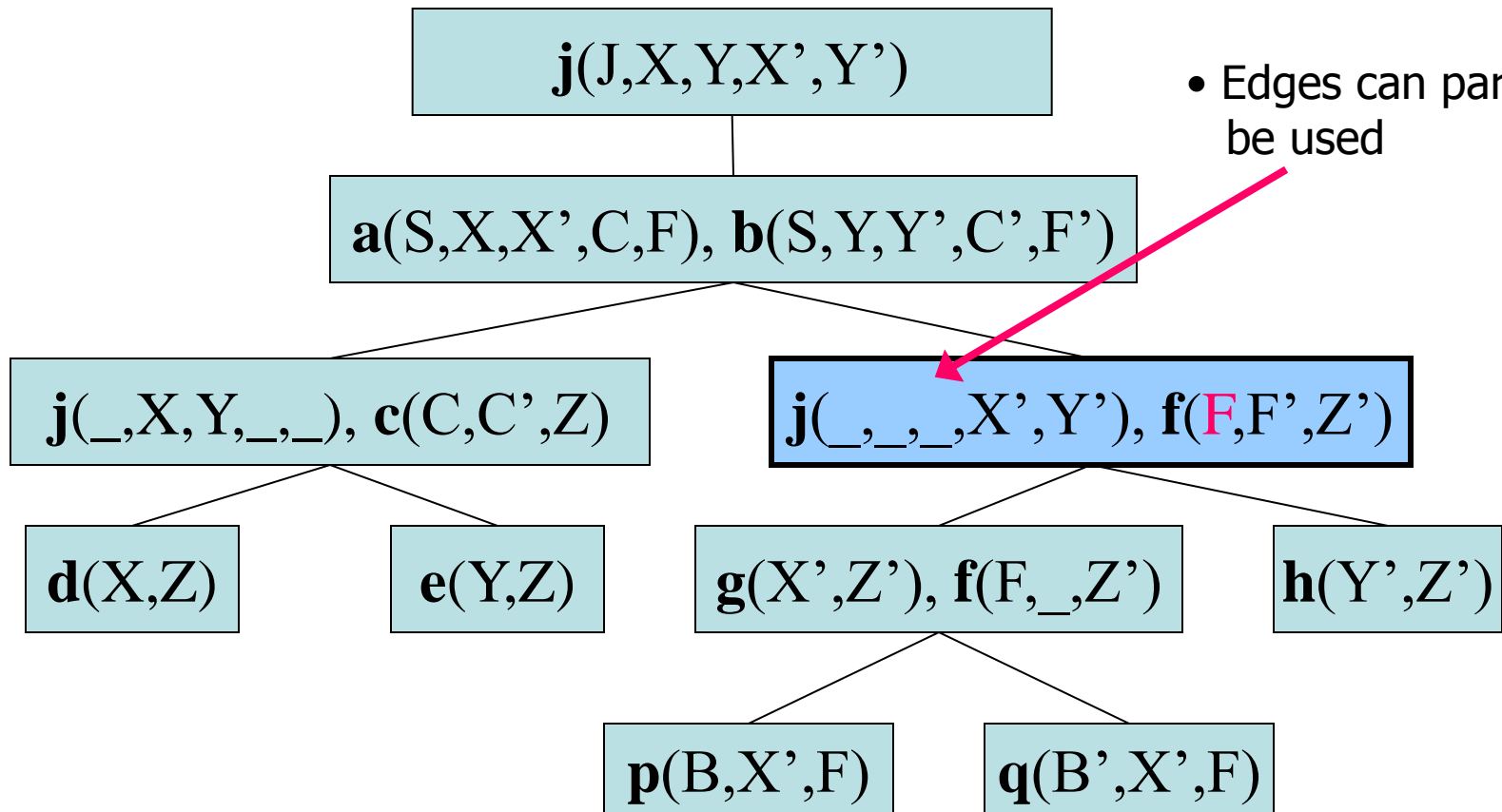


Basic Conditions_(1/2)

- We group edges

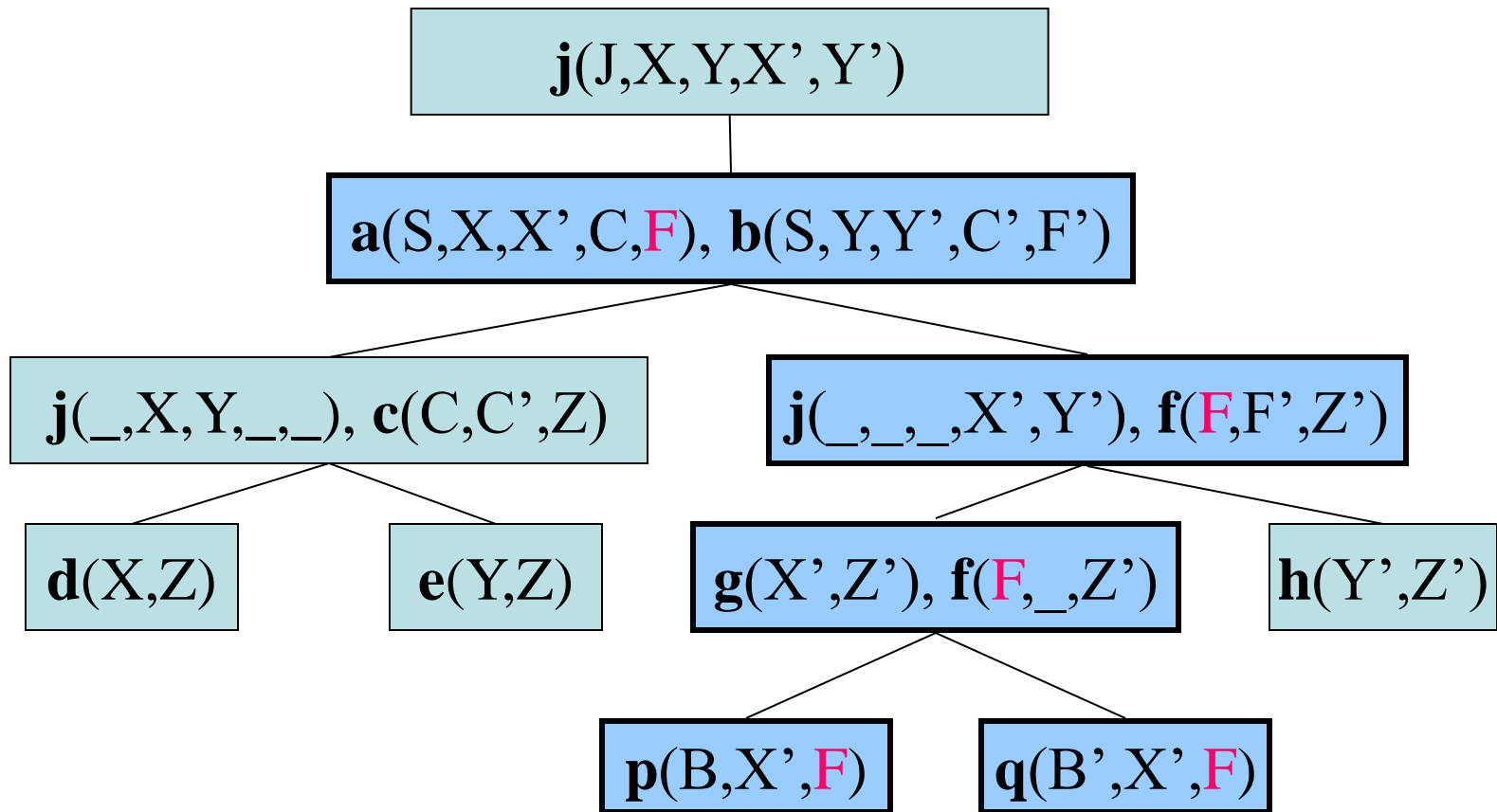


Basic Conditions _(2/2)



- Edges can partially be used

Connectedness Condition

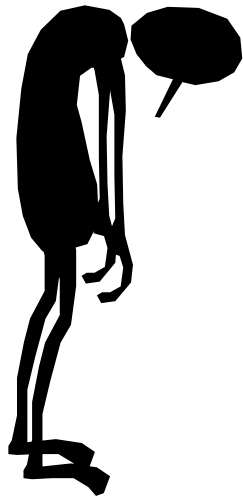


Computational Question

- Can we determine in polynomial time whether $\text{ghw}(H) < k$ for constant k ?

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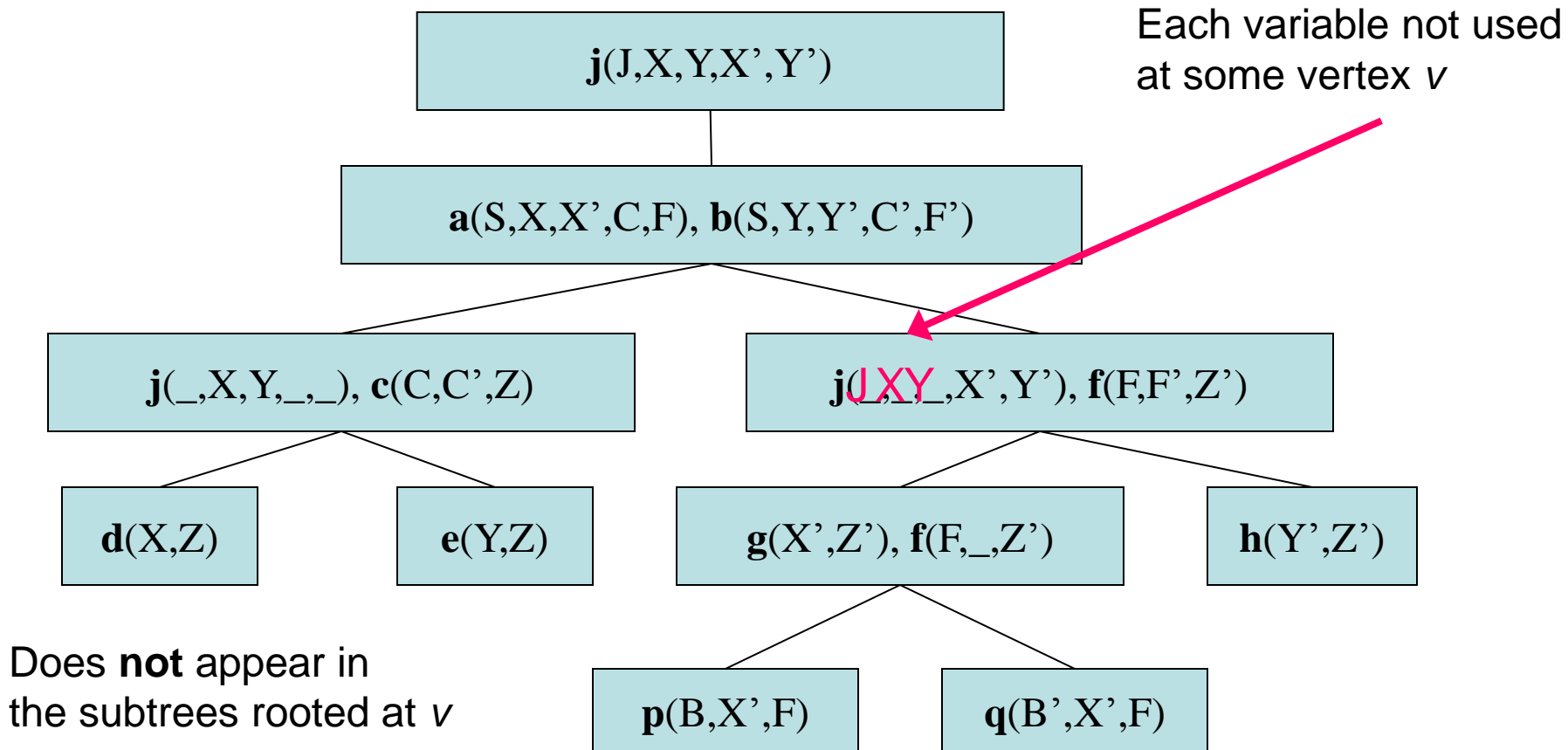


Bad news: $\text{ghw}(H) < 4?$ NP-complete

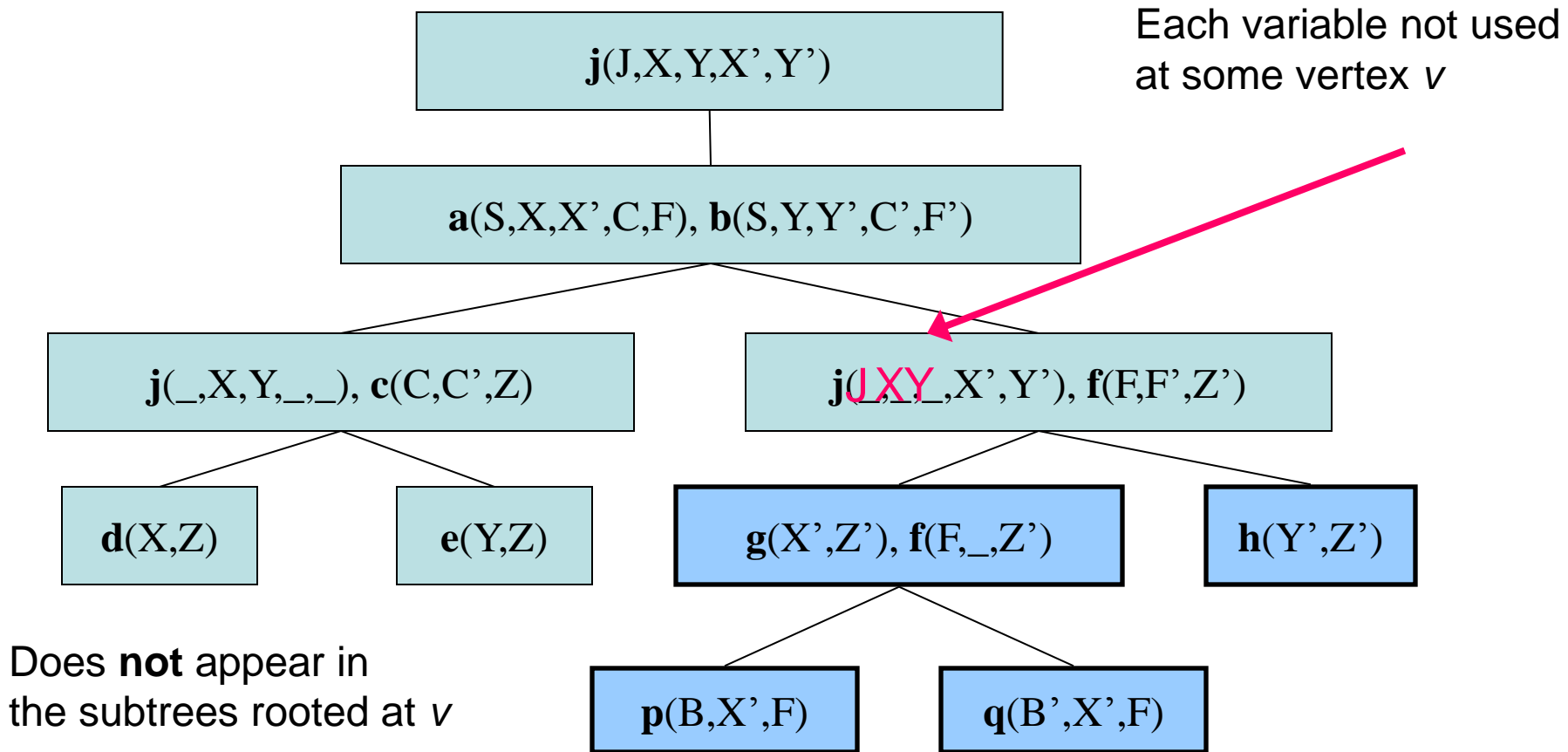
[Schwentick et. al. 06]

Hypertree Decomposition (HTD)

HTD = Generalized HTD + Special Condition

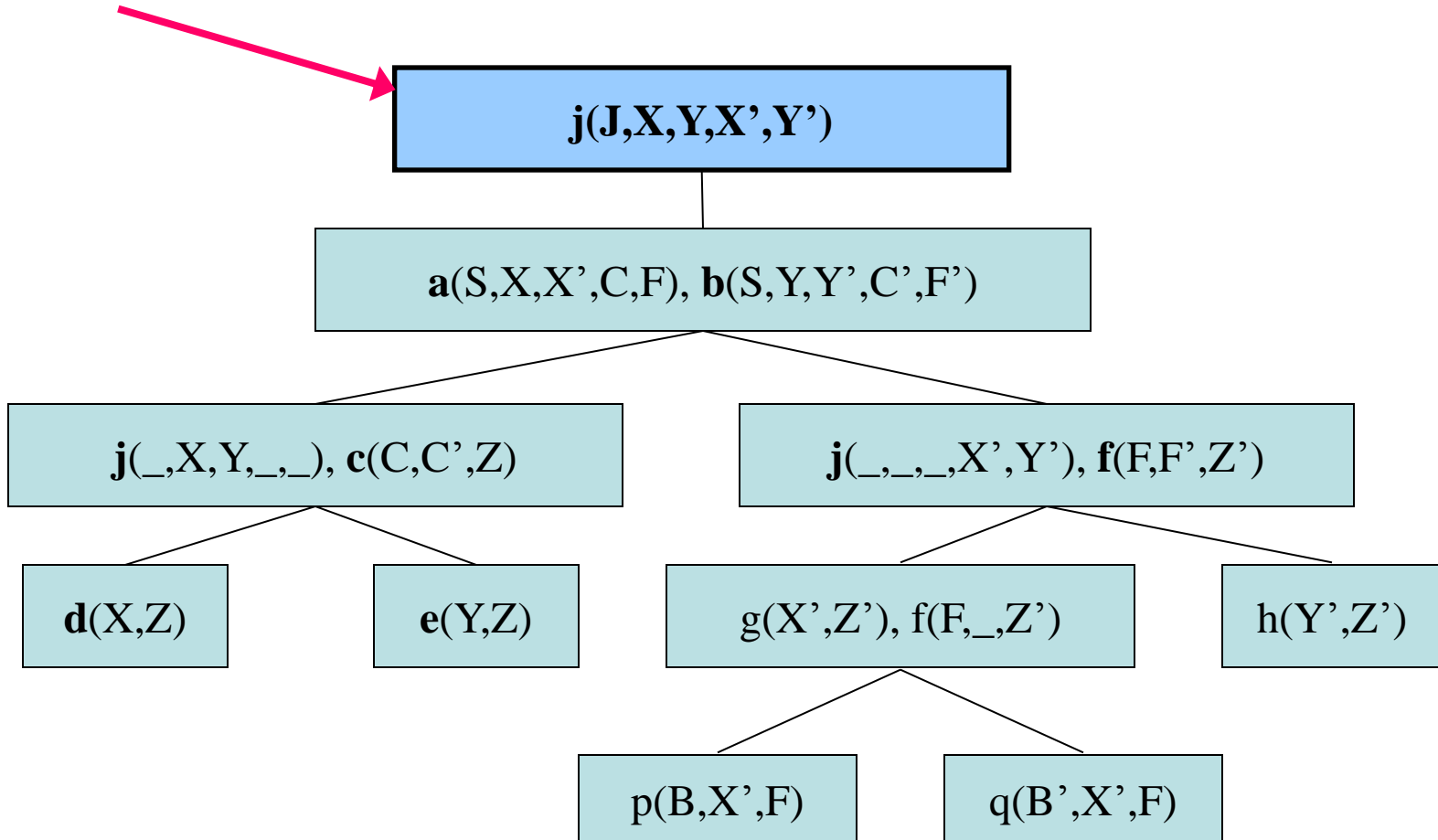


Special Condition



Special Condition

Thus, e.g., all available variables in the root must be used



Positive Results on Hypertree Decompositions

- For fixed k , deciding whether $hw(Q) \leq k$ is in polynomial time (LOGCFL)
- Computing hypertree decompositions is feasible in polynomial time (for fixed k).

But: FP-intractable wrt k : W[2]-hard.

Relationship GHW vs HW

Observation:

$$\text{ghw}(H) = \text{hw}(H^*)$$

where $H^* = H \cup \{E' \mid \exists E \text{ in edges}(H): E' \subseteq E\}$

Exponential!

Approximation Theorem [Adler, Gottlob, Grohe ,05] :

$$\text{ghw}(H) \leq 3\text{hw}(H)+1$$

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Three Problems

HOM: The homomorphism problem

BCQ: Boolean conjunctive query evaluation

CSP: Constraint satisfaction problem

Important problems in different areas.

All these problems are hypergraph based.

The Homomorphism Problem

- Given two relational structures

$$\mathbb{A} = (U, R_1, R_2, \dots, R_k)$$

$$\mathbb{B} = (V, S_1, S_2, \dots, S_k)$$

- Decide whether there exists a *homomorphism* h from \mathbb{A} to \mathbb{B}

$$h: U \longrightarrow V$$

such that $\forall \mathbf{x}, \forall i$

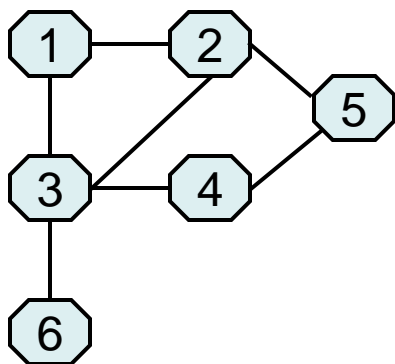
$$\mathbf{x} \in R_i \implies h(\mathbf{x}) \in S_i$$

HOM is NP-complete

(well-known, independently proved in various contexts)

Membership: Obvious, guess h .

Hardness: Transformation from 3COL.



A

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

B

red	green
red	blue
green	red
green	blue
blue	red
blue	green

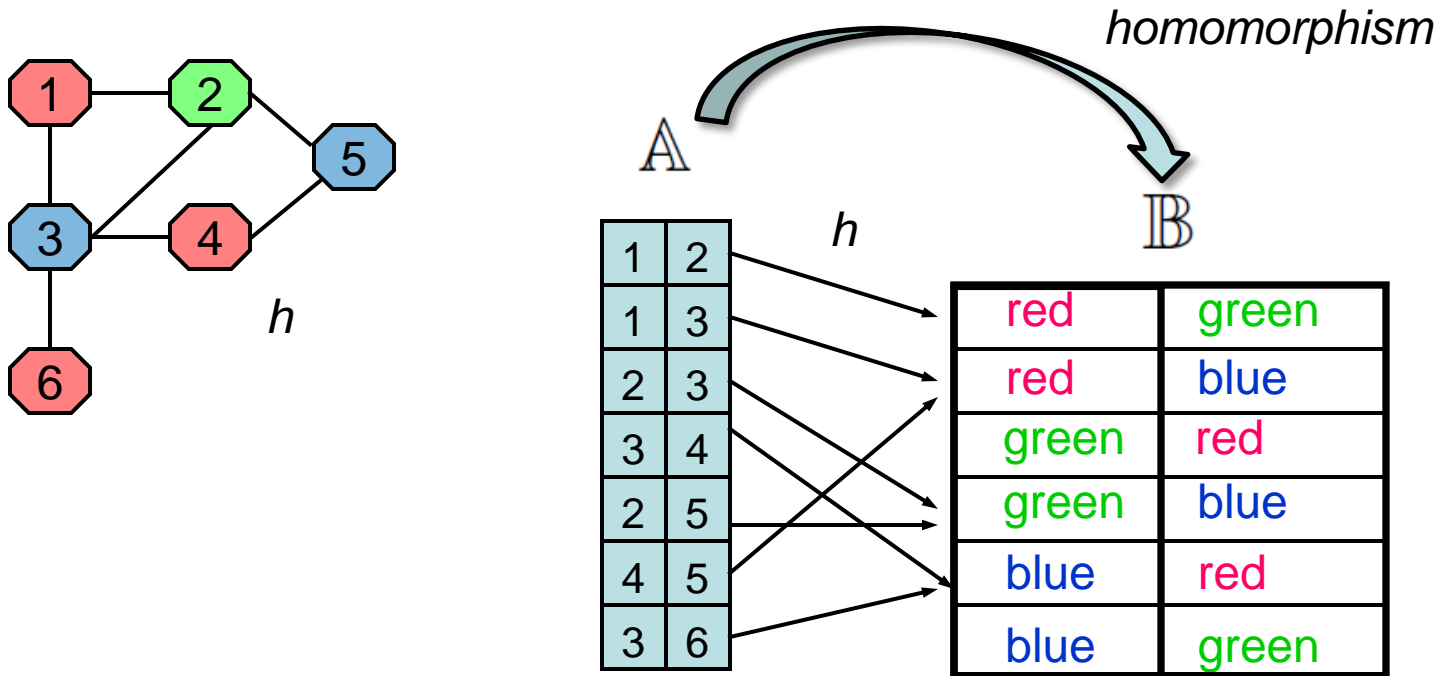
Graph 3-colourable *iff* $\text{HOM}(A,B)$ yes-instance.

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Conjunctive Database Queries

DATABASE:

Enrolled		
John	Algebra	2003
Robert	Logic	2003
Mary	DB	2002
Lisa	DB	2003
.....

Teaches		
McLane	Algebra	March
Verdi	Logic	May
Lausen	DB	June
Rahm	DB	May
.....

Parent	
McLane	Lisa
Verdi	Robert
Rahm	Mary
.....

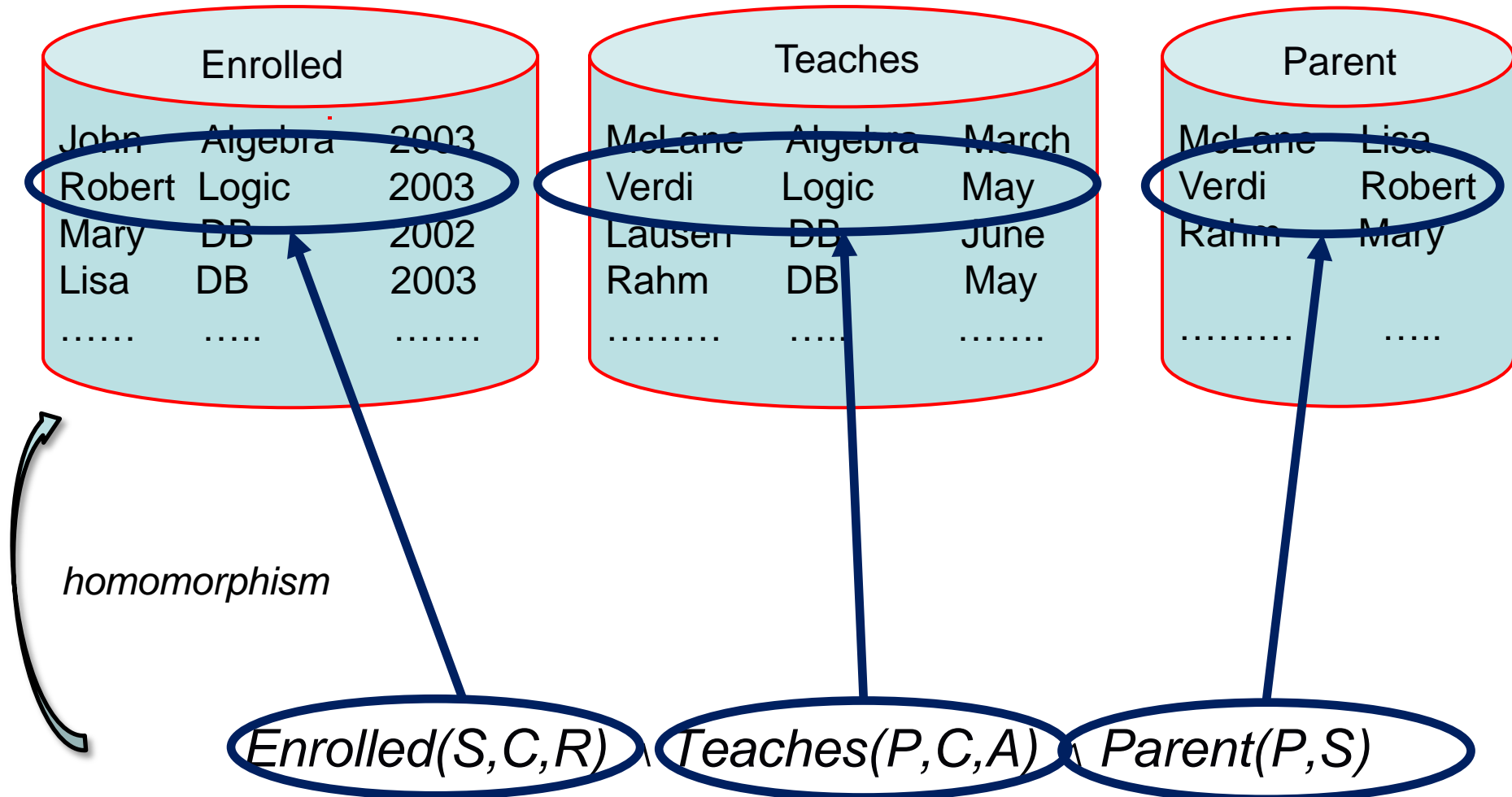
QUERY:

Is there any teacher having a child enrolled in her course?

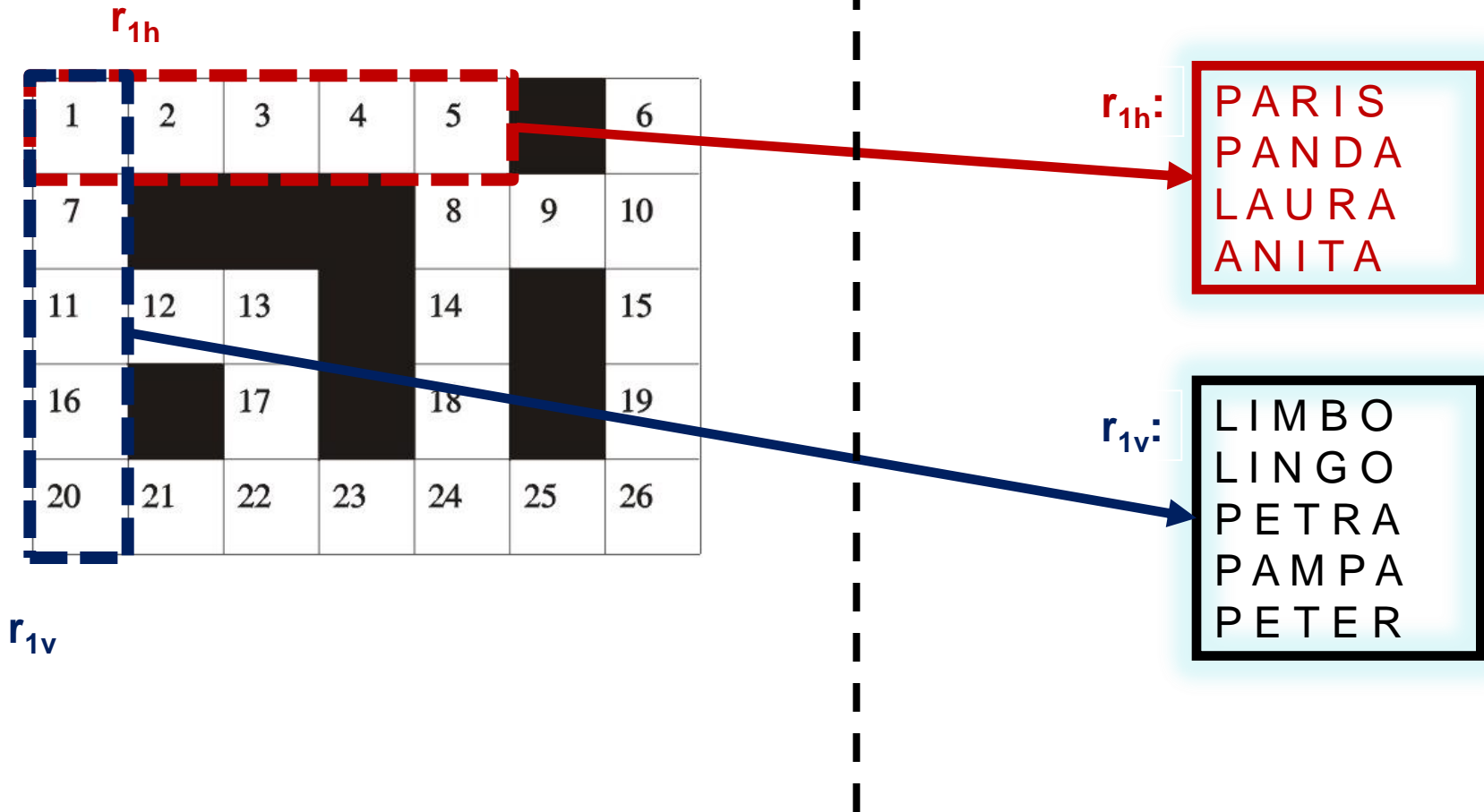
$ans \leftarrow Enrolled(S,C,R) \wedge Teaches(P,C,A) \wedge Parent(P,S)$

Conjunctive Database Queries

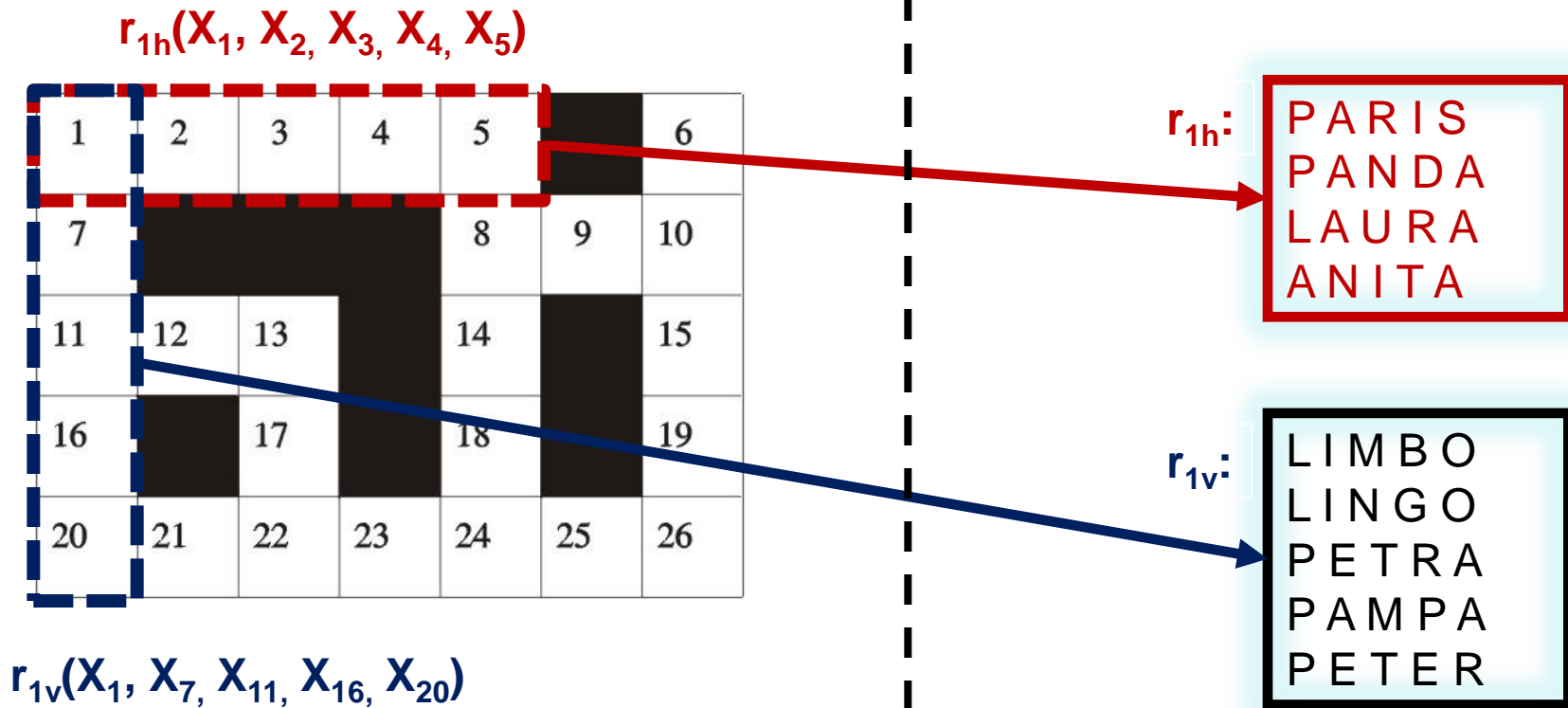
DATABASE:



CSPs as Homomorphism Problems



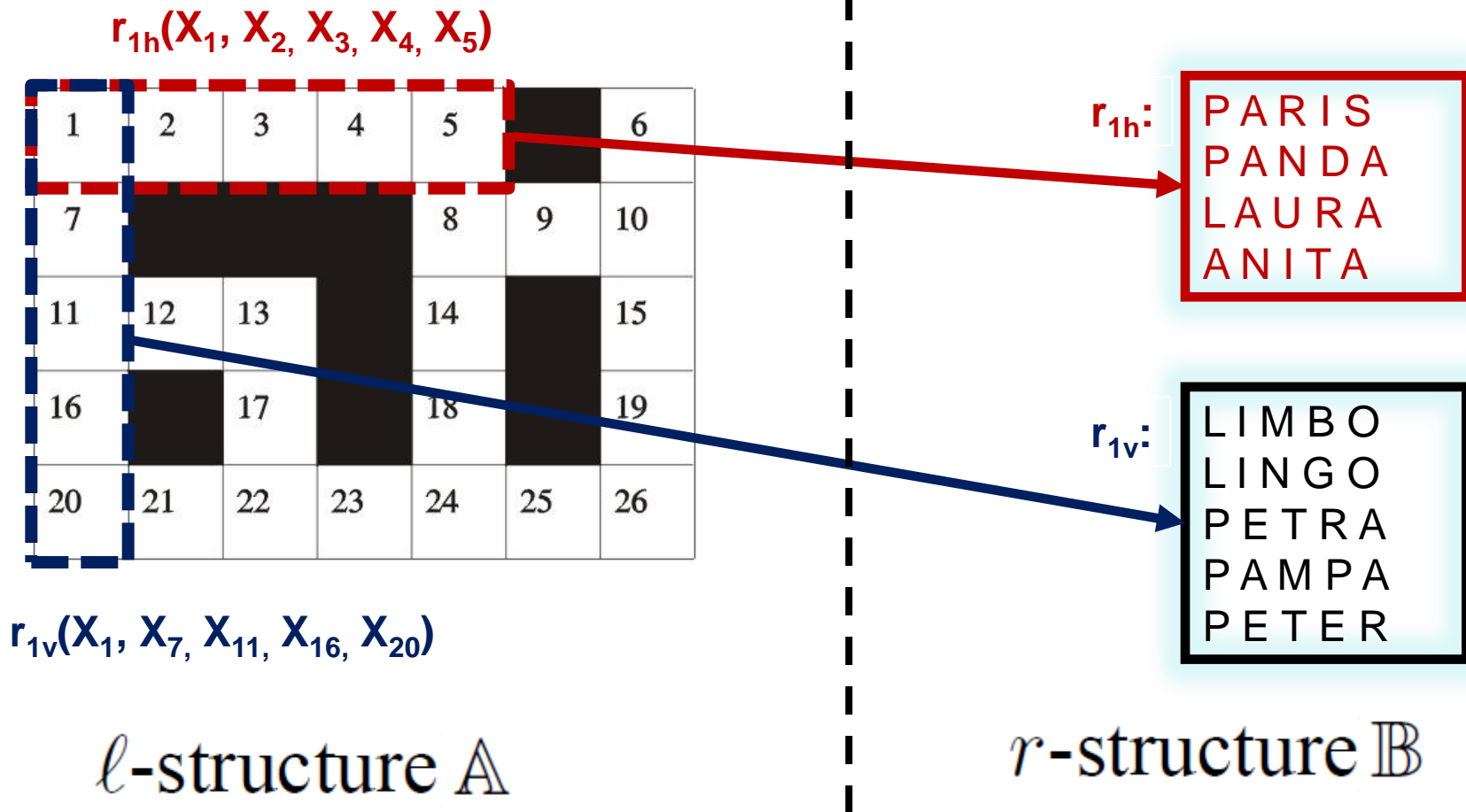
CSPs as Homomorphism Problems



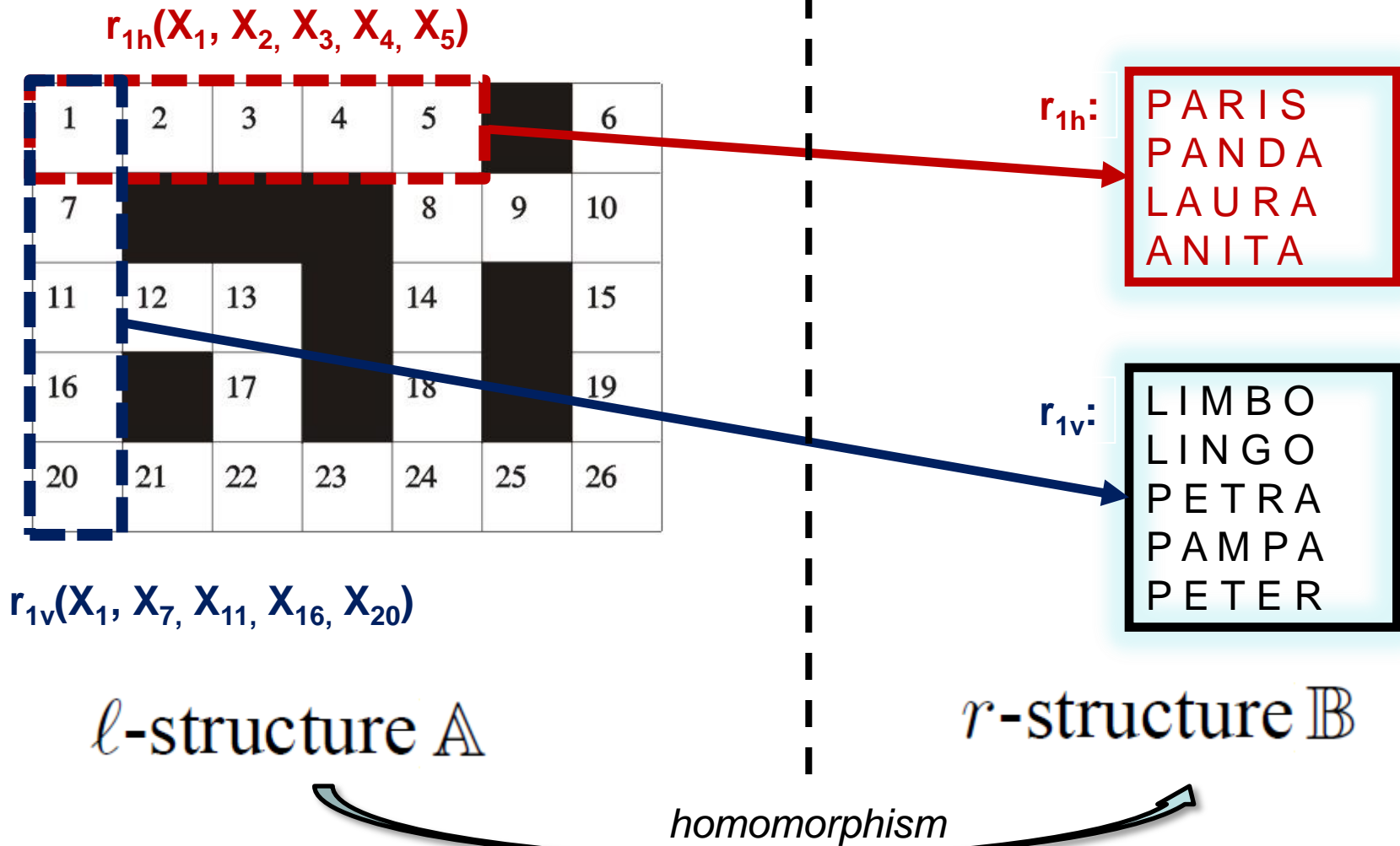
- Set of variables $\{X_1, \dots, X_{26}\}$
- Set of constraint scopes

- Set of constraint relations

CSPs as Homomorphism Problems

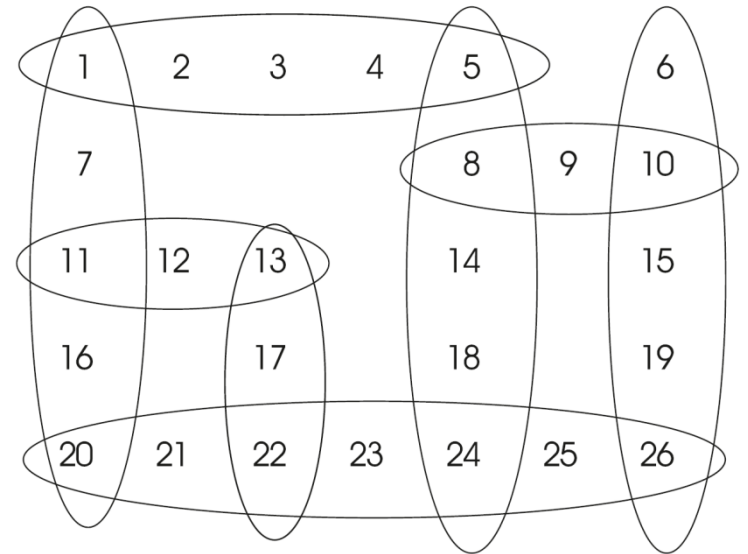


CSPs as Homomorphism Problems



CSPs and Hypergraphs

1	2	3	4	5		6
7				8	9	10
11	12	13		14		15
16		17		18		19
20	21	22	23	24	25	26

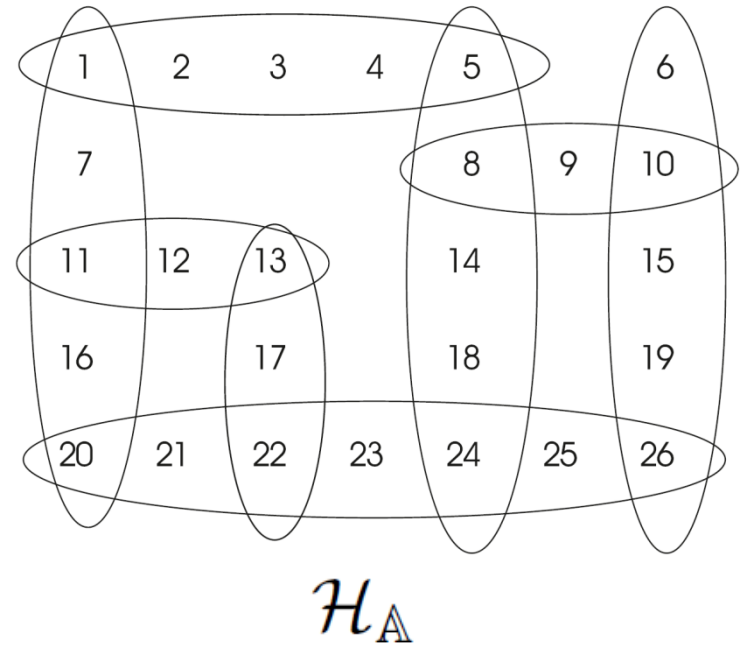


\mathcal{H}_A

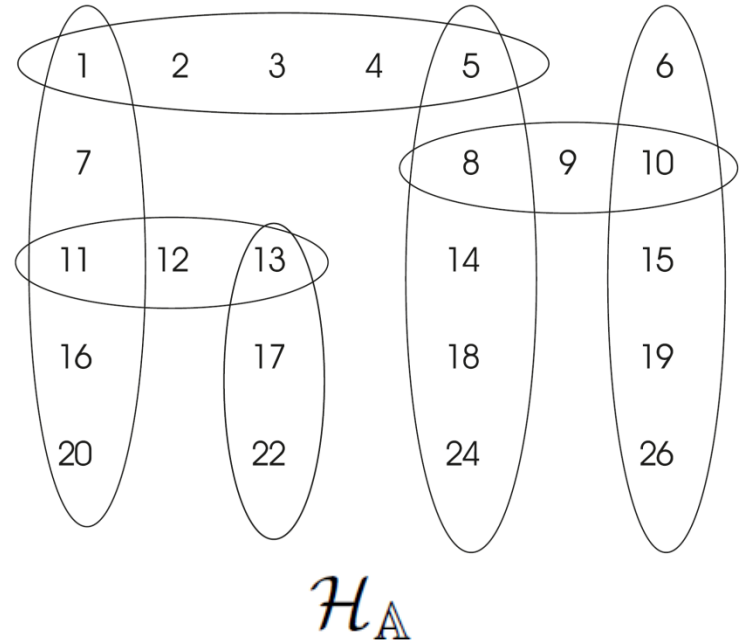
ℓ -structure \mathbb{A}

- Variables map to nodes
- Scopes map to hyperedges

Structurally Restricted CSPs

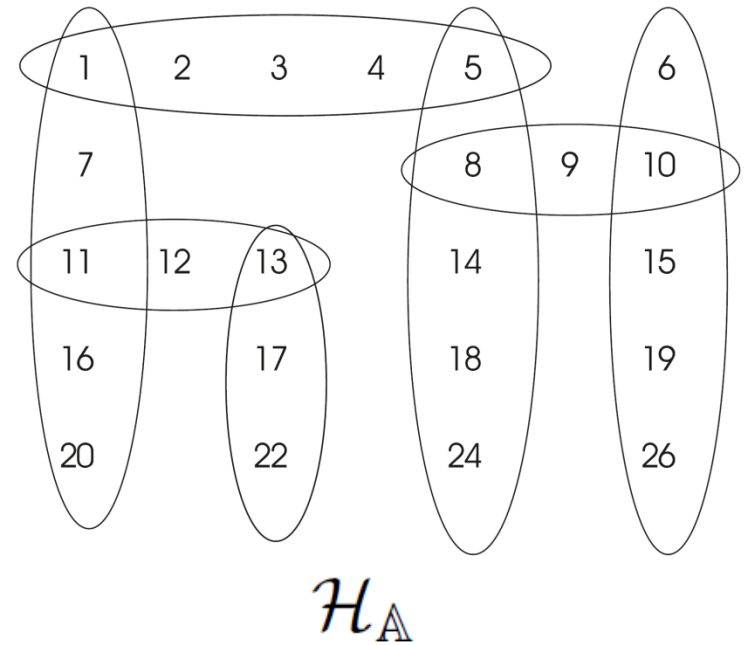


Structurally Restricted CSPs



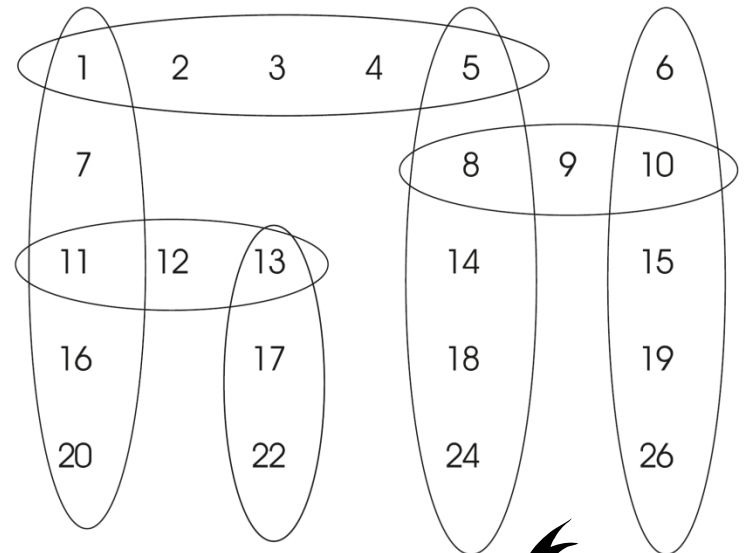
Structurally Restricted CSPs

The hypergraph is acyclic

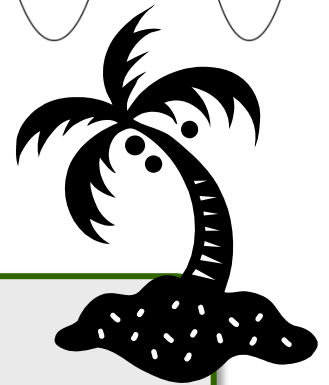


Structurally Restricted CSPs

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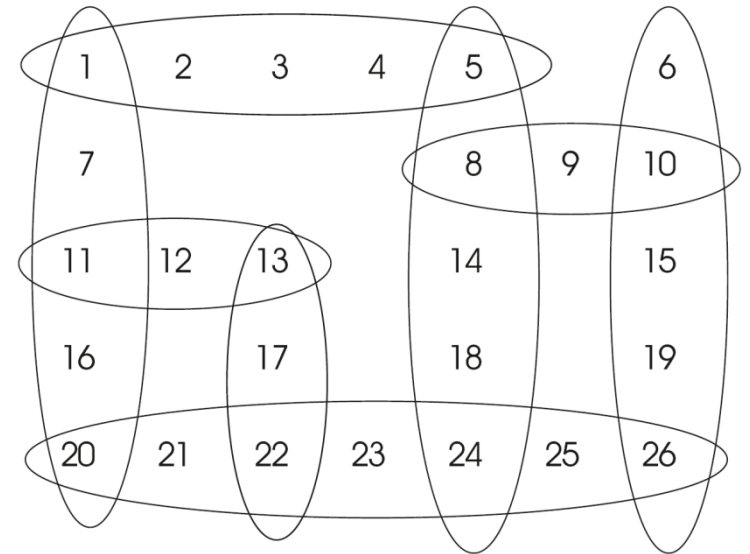


\mathcal{H}_A



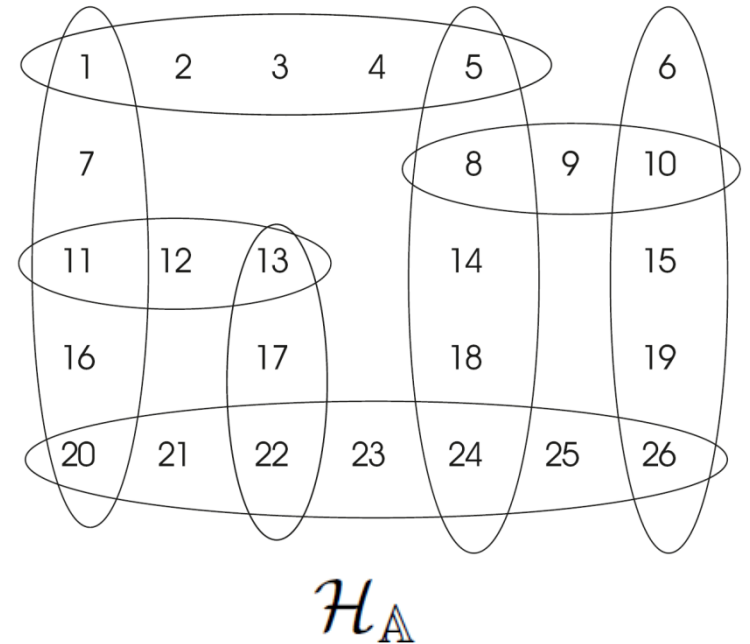
- We have seen that *Acyclicity is efficiently recognizable*
- We shall see that *Acyclic CSPs can be efficiently solved*

Decomposition Methods



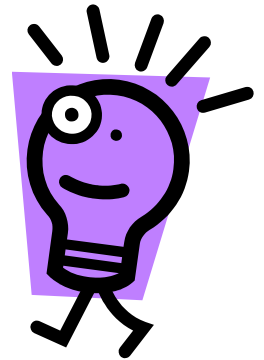
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Decomposition Methods

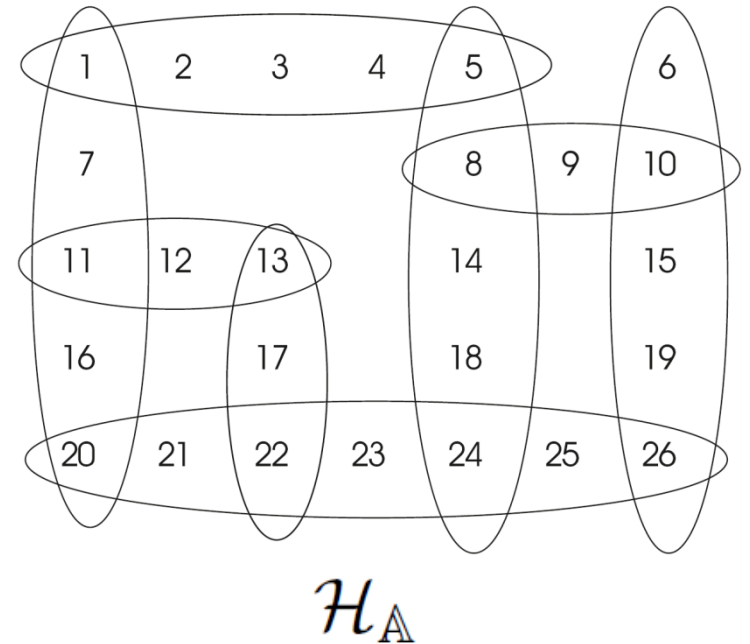
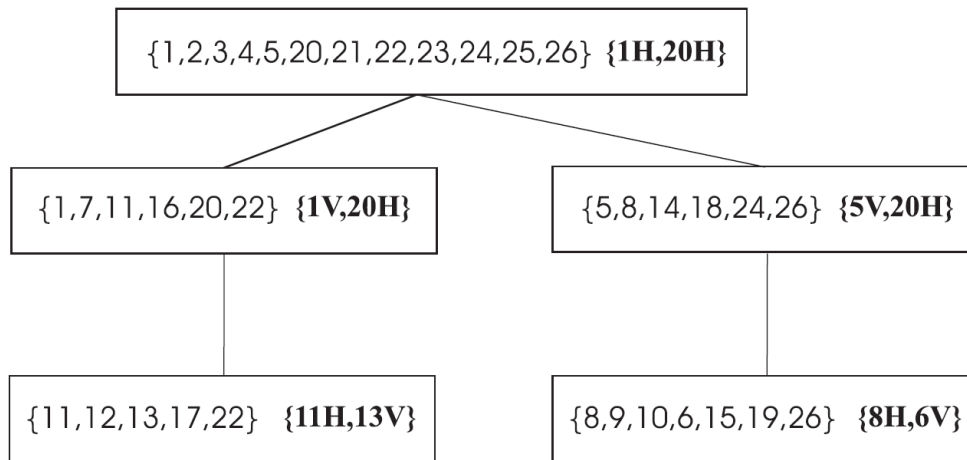


Transform the hypergraph into an acyclic one:

- Organize its edges (or nodes) in clusters
- Arrange the clusters as a tree, by satisfying the connectedness condition

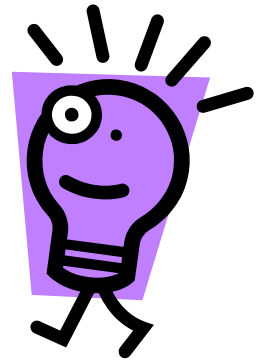


Generalized Hypertree Decompositions

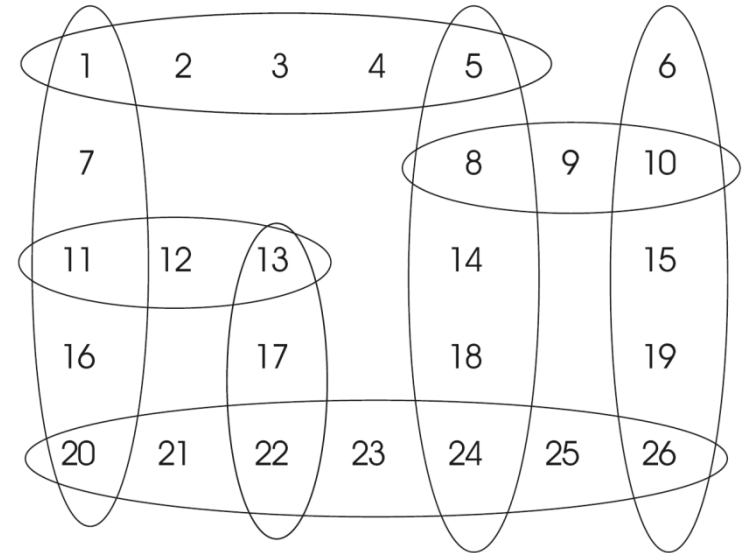
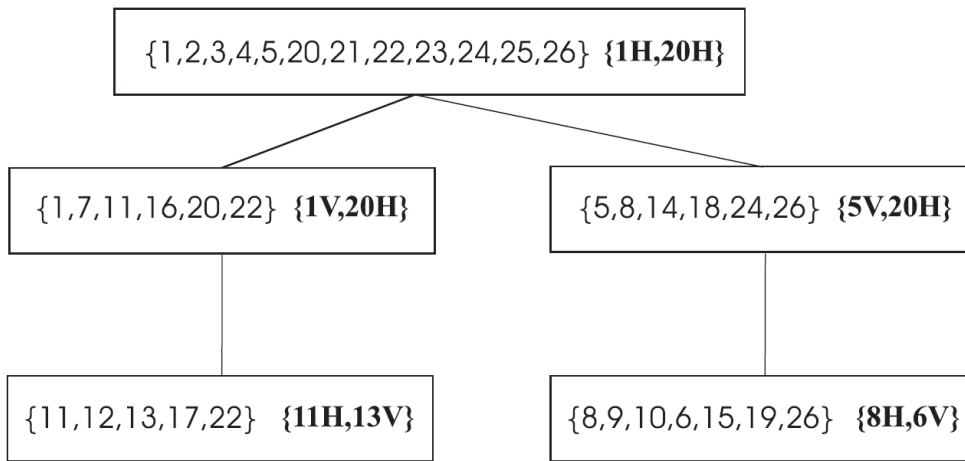


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Generalized Hypertree Decompositions

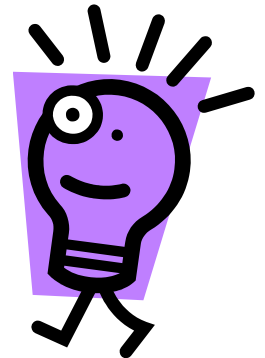


\mathcal{H}_A

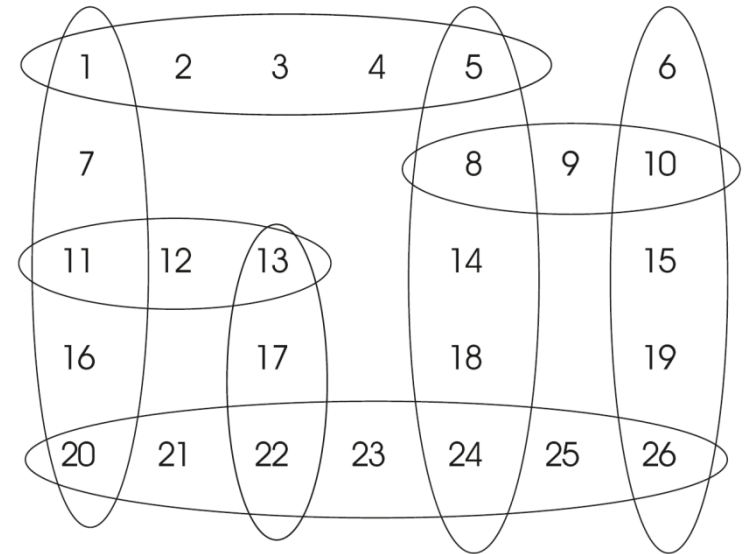
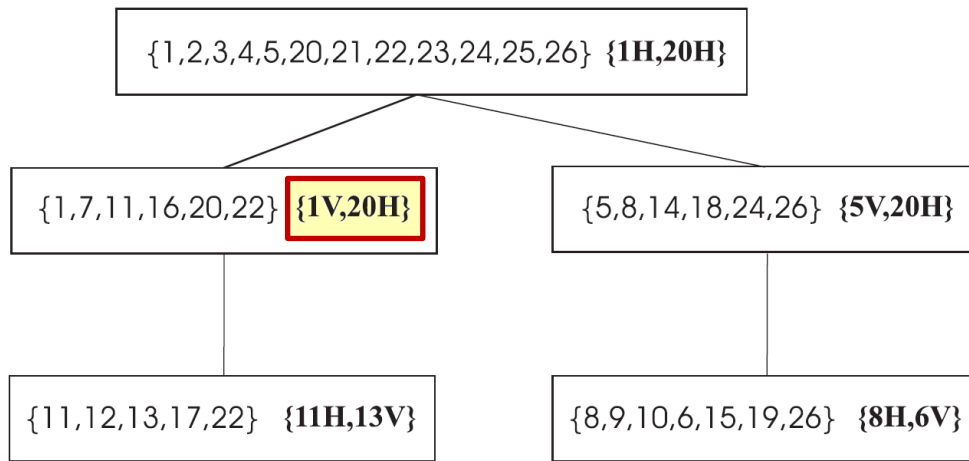
Each cluster can be seen as a **subproblem**

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Generalized Hypertree Decompositions



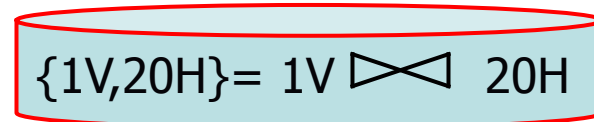
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Relations:



Relations:



Basic Question

INPUT: CSP instance (\mathbb{A}, \mathbb{B})

- Is there a homomorphism from \mathbb{A} to \mathbb{B} ?

Basic Question (on Acyclic Instances)

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- Feasible in polynomial time $O(n^2 \times \log n)$
 - LOGCFL-complete

Basic Question (on Acyclic Instances)

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A Polynomial-time Algorithm

HOM: The homomorphism problem

BCQ: Boolean conjunctive query evaluation

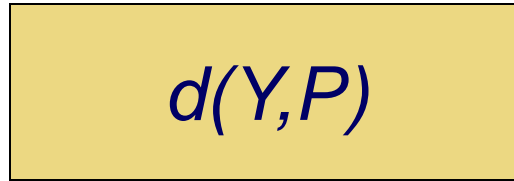
CSP: Constraint satisfaction problem



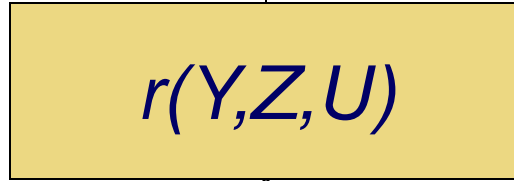
Yannakakis's Algorithm (ABCQs):

Dynamic Programming over a Join Tree

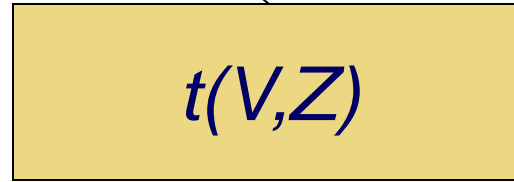
d:
3 8
3 7
5 7
6 7



r:
3 8 9
9 3 8
8 3 8
3 8 4
3 8 3
8 9 4
9 4 7

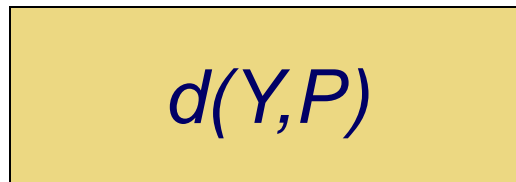


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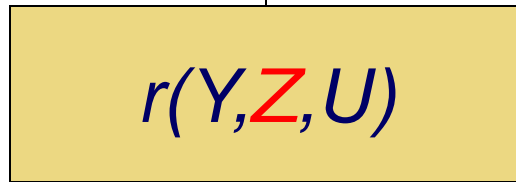


t:
9 8
9 3
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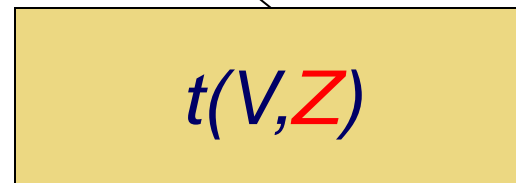
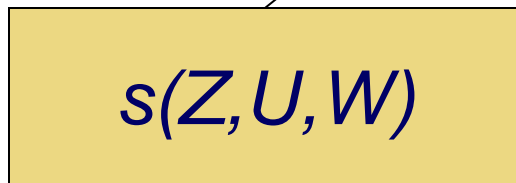
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$d(Y,P)$

r:
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$r(Y,Z,U)$

s:
3 8 9
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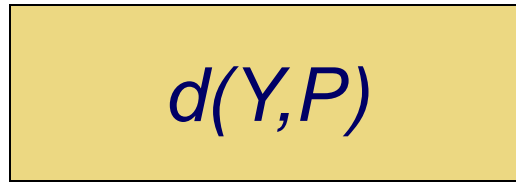
$s(Z,U,W)$

$t(V,Z)$

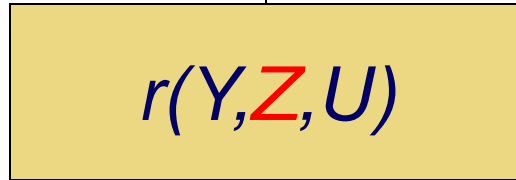
t:
9 8
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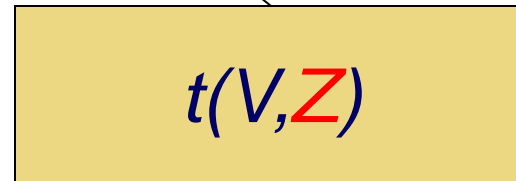
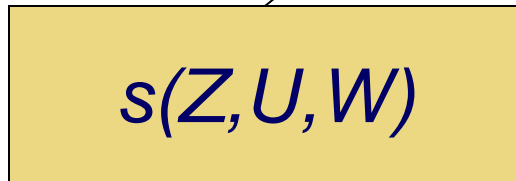
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3 8
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3 8 9
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3 8 9
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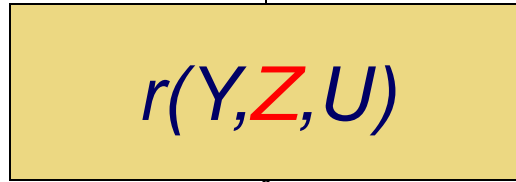
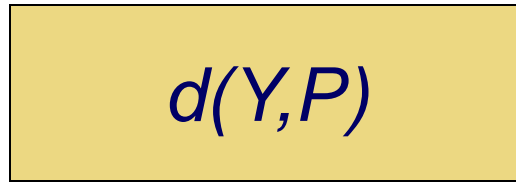
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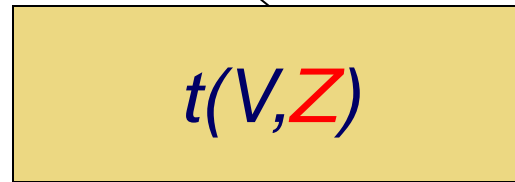
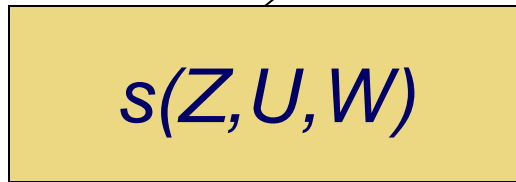
t:
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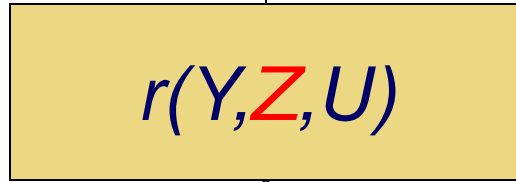
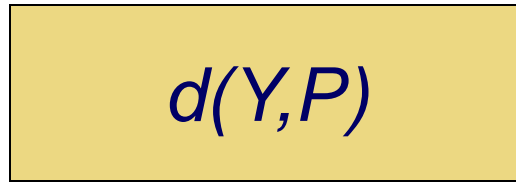
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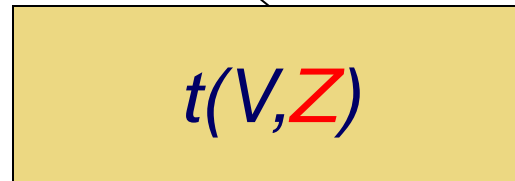
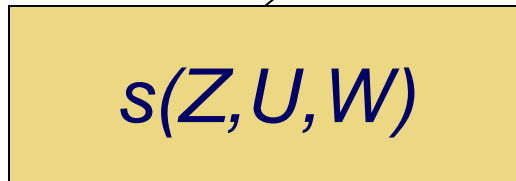
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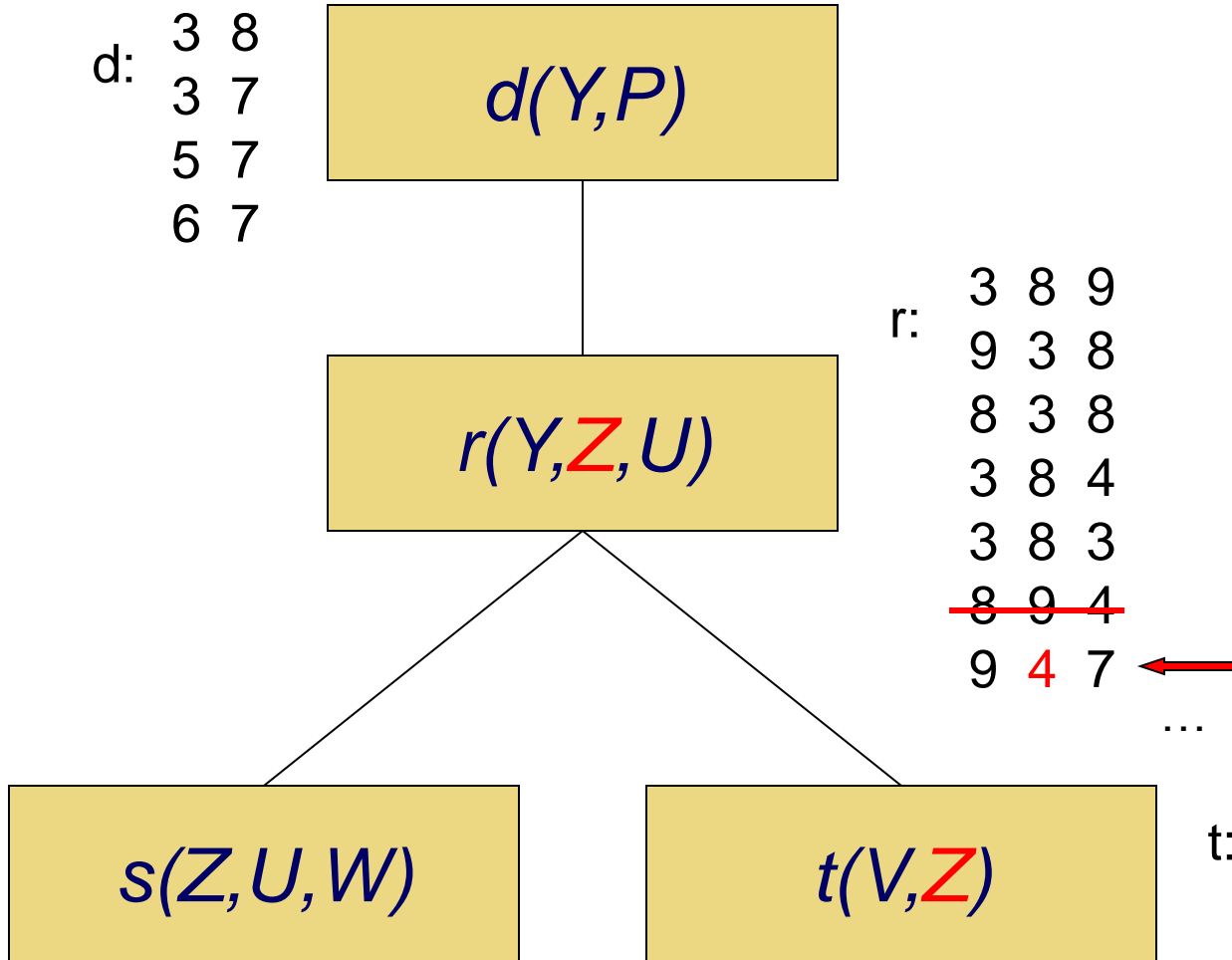
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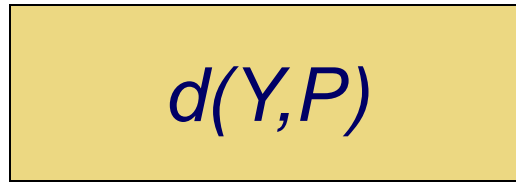
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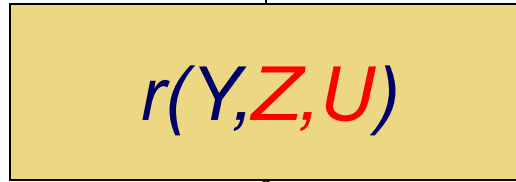
$t(V,Z)$

t:
9 8
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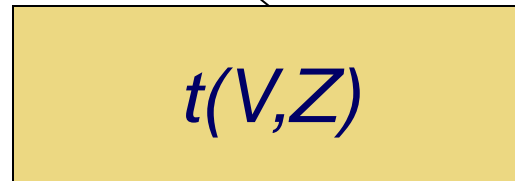
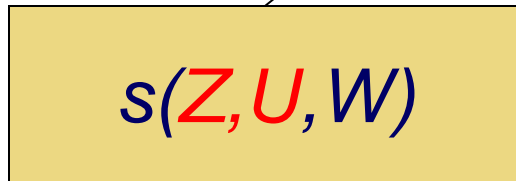
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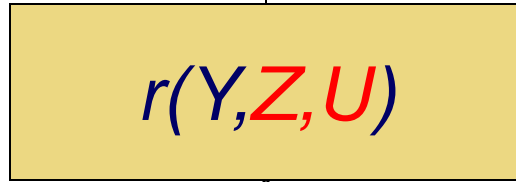
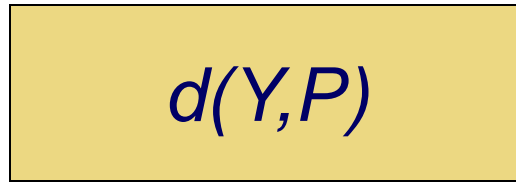


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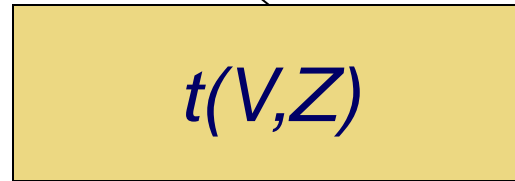
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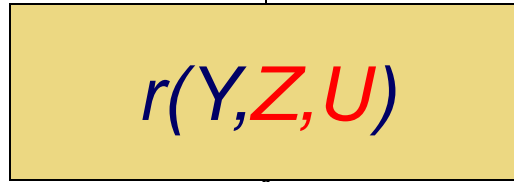
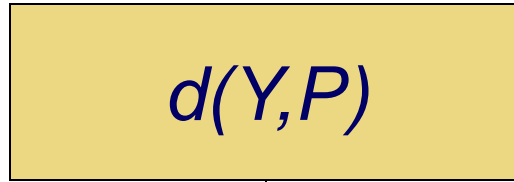
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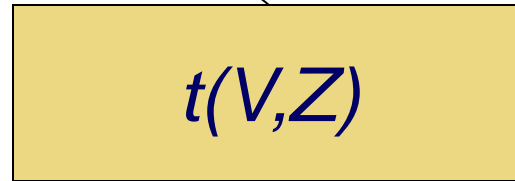
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$r(Y,Z,U)$

r:
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9 3 8 ←
8 3 8
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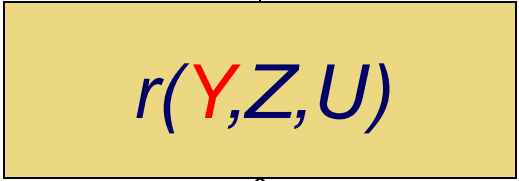
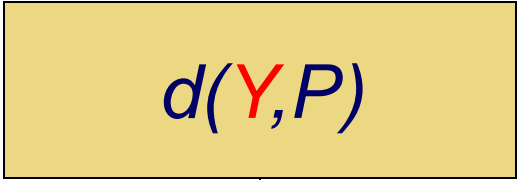
→ s:
3 8 9
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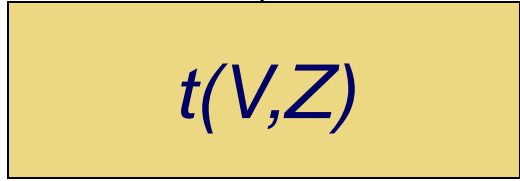
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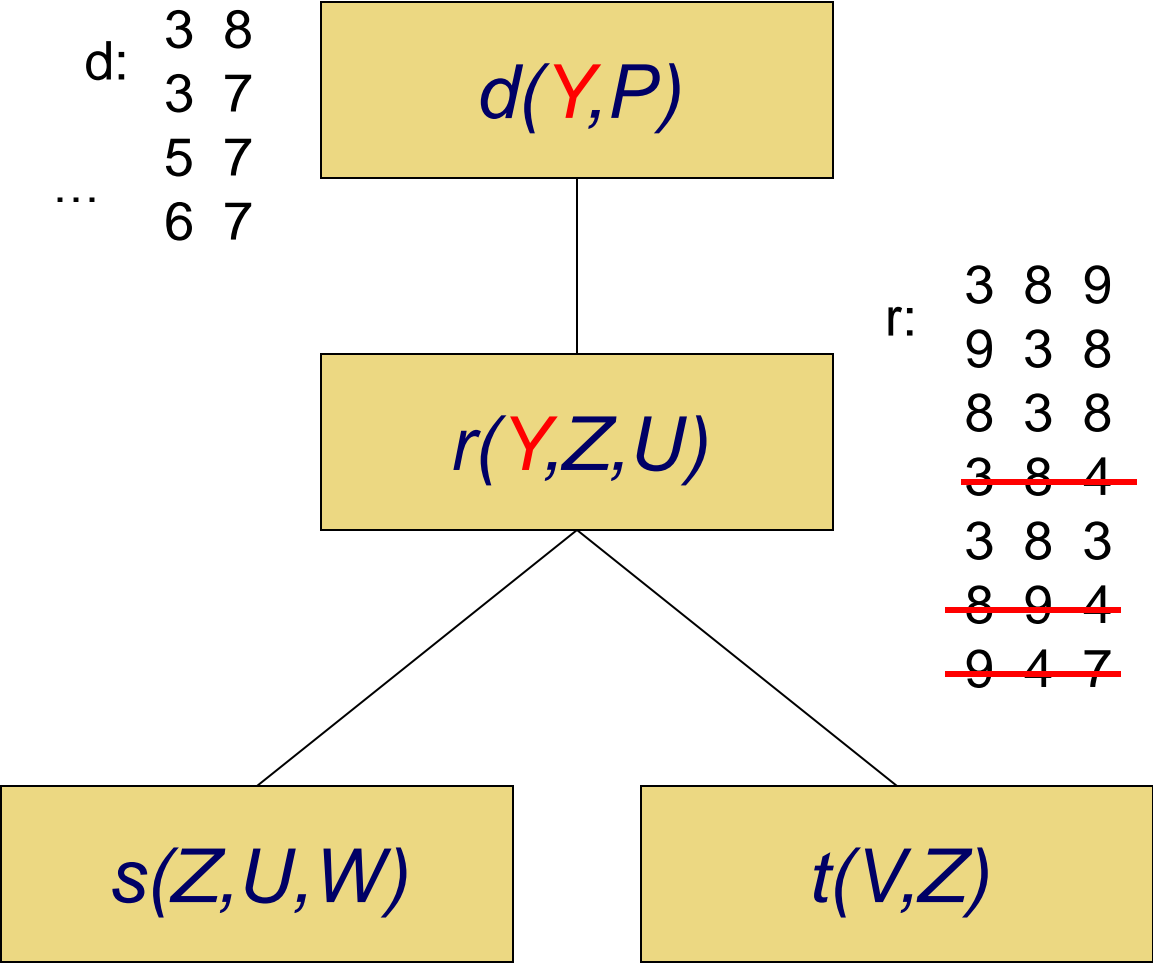


r: 3 8 9
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«Answering» Acyclic Instances

HOM: The homomorphism problem

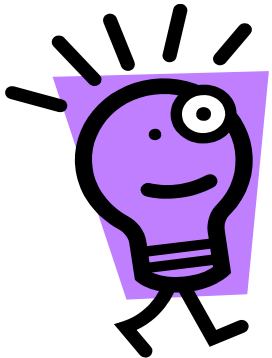
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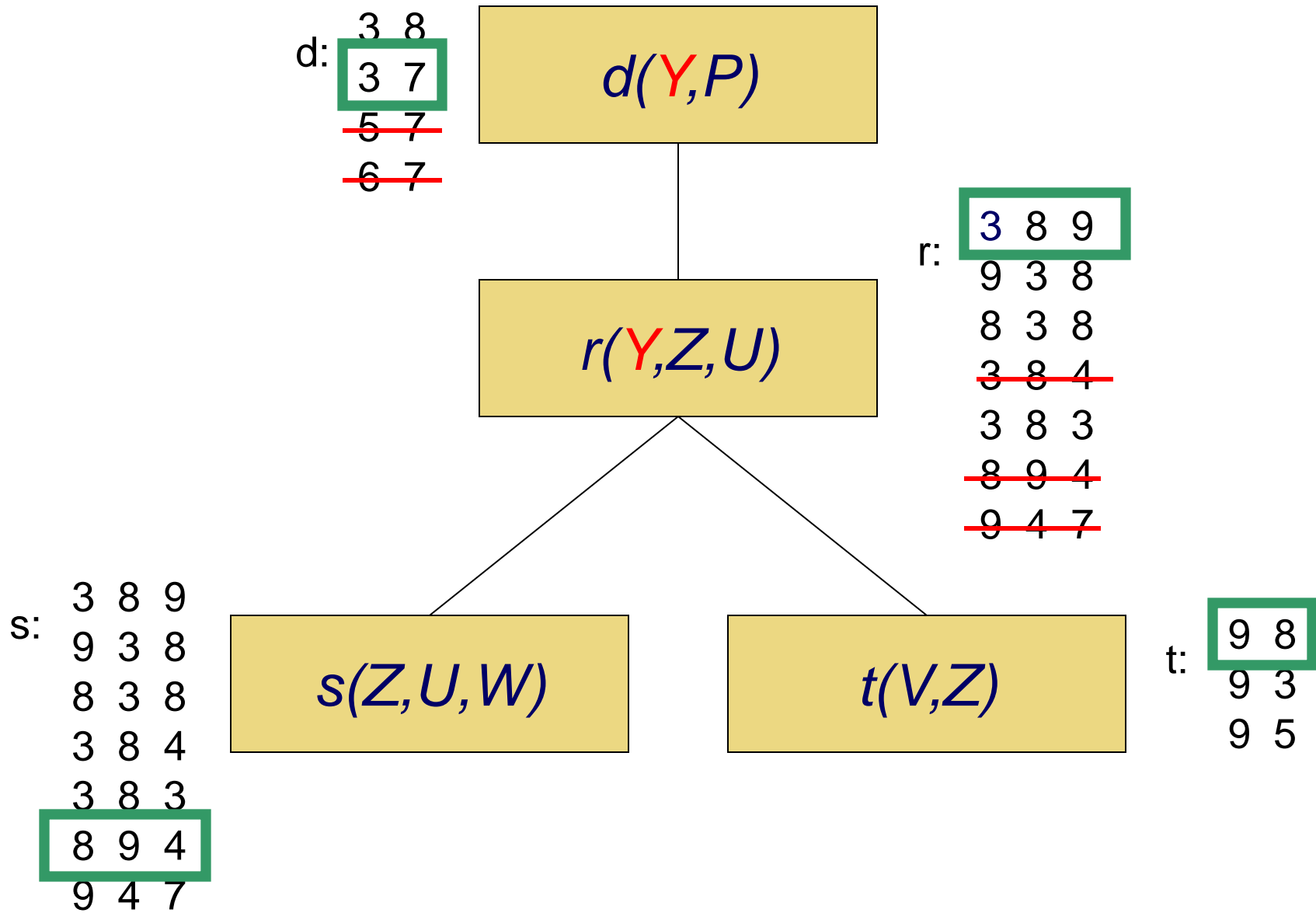


Yannakakis's Algorithm (ABCQs):

Dynamic Programming over a Join Tree



- Answering ACQs can be done adding a top-down phase to Yannakakis' algorithm for ABCQs



A solution: $Y=3, P=7, Z=8, U=9, W=4, V=9$

Example Application: Strategic Games

- Game $G=(P, Neigh, Act, U)$ where
 - P : set of players
 - $Neigh(p)$: neighbors of player p
 - $Act(p)$: actions (strategies) of player p
 - U : utility function $u(p)$, for each player p

Example Application: Strategic Games

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 - $Neigh(p)$: neighbors of player p
 - $Act(p)$: actions (strategies) of player p
 - U : utility function $u(p)$, for each player p

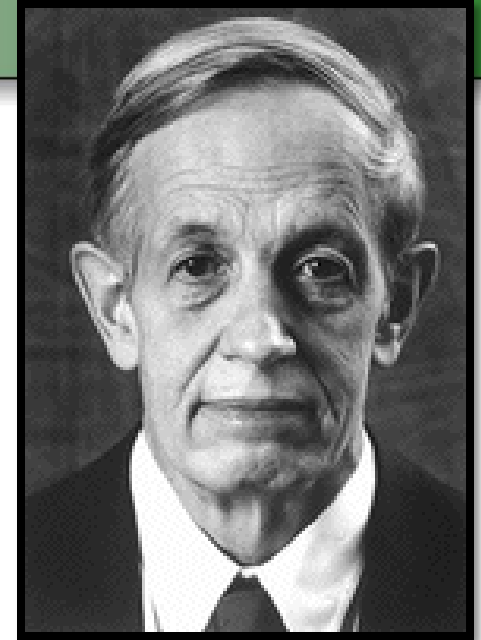
Ex.: Prisoners' Dilemma

- $P = \{P_1, P_2\}$
- $Neigh(P_1) = \{P_2\}$; $Neigh(P_2) = \{P_1\}$;
- $Act(P_1) = Act(P_2) = \{\text{collaborate, defeat}\}$
- Utility functions: listed in the matrix

		P_2	
		Collaborate	Defeat
P_1	Collaborate	(-5,-5)	(-1,-10)
	Defeat	(-10,-1)	(-2,-2)

Nash's theorem

Nash equilibrium: a global strategy, from which no player has an incentive to unilaterally deviate.



Nash's theorem

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		P_2	
		Collaborate	Defeat
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	Defeat	(-10,-1)	(-2,-2)

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Nash's theorem

Nash equilibrium: a global strategy, from which no player has an incentive to unilaterally deviate.

Theorem: Every game admits a *mixed* Nash equilibrium, where players chose their strategies according to probability distributions

P_1

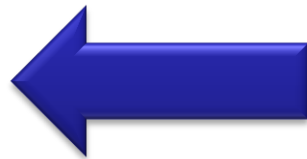
		P_2	
		Collaborate	Defeat
P_1	Collaborate	(-5,-5)	(-1,-10)
	Defeat	(-10,-1)	(-2,-2)

Nash's theorem

Nash equilibrium: a global strategy, from which no player has an incentive to unilaterally deviate.

Theorem: Every game admits a *mixed* Nash equilibrium, where players chose their strategies according to probability distributions

	Collaborate	Defeat
Collaborate	(0,1)	(1,0)
Defeat	(1,0)	(0,1)



P_1

P_2

	Collaborate	Defeat
Collaborate	(-5,-5)	(-1,-10)
Defeat	(-10,-1)	(-2,-2)

Pure Equilibria

- Players:

- Francesco, Paola, Roberto, Giorgio, and Maria

- Choices:

- movie, opera

F	$P_m R_m$	$P_m R_o$	$P_o R_m$	$P_o R_o$
m	2	2	1	0
o	0	2	1	2

G	$P_m F_m$	$P_m F_o$	$P_o F_m$	$P_o F_o$
m	2	0	0	1
o	2	0	0	1

R	F_m	F_o
m	0	1
o	2	0

P	F_m	F_o
m	2	0
o	0	1

M	R_m	R_o
m	1	0
o	0	2

Pure Equilibria

- Players:

- Francesco, Paola, Roberto, Giorgio, and Maria

- Choices:

- movie, opera

F	$P_m R_m$	$P_m R_o$	$P_o R_m$	$P_o R_o$
m	2	2	1	0
o	0	2	1	2

G	$P_m F_m$	$P_m F_o$	$P_o F_m$	$P_o F_o$
m	2	0	0	1
o	2	0	0	1

R	F_m	F_o
m	0	1
o	2	0

P	F_m	F_o
m	2	0
o	0	1

M	R_m	R_o
m	1	0
o	0	2

Pure Equilibria

- Players:

- Francesco, Paola, Roberto, Giorgio, and Maria

- Choices:

- movie, opera

NP-hard !

F	$P_m R_m$	$P_m R_o$	$P_o R_m$	$P_o R_o$
m	2	2	1	0
o	0	2	1	2

G	$P_m F_m$	$P_m F_o$	$P_o F_m$	$P_o F_o$
m	2	0	0	1
o	2	0	0	1

R	F_m	F_o
m	0	1
o	2	0

P	F_m	F_o
m	2	0
o	0	1

M	R_m	R_o
m	1	0
o	0	2

Pure Nash Equilibria and Easy Games

*Nash Equilibrium
Existence*

```
graph TD; A["Nash Equilibrium Existence"] --> B["Constraint Satisfaction Problem"]; B --> C["Solve CSP in polynomial time using known methods"];
```

Constraint Satisfaction Problem

Solve CSP in polynomial time using known methods

Encoding Games in CSPs

F	$P_m R_m$	$P_m R_o$	$P_o R_m$	$P_o R_o$
m	2	2	1	0
o	0	2	1	2

G	$P_m F_m$	$P_m F_o$	$P_o F_m$	$P_o F_o$
m	2	0	0	1
o	2	0	0	1

R	F_m	F_o
m	0	1
o	2	0

P	F_m	F_o
m	2	0
o	0	1

M	R_m	R_o
m	1	0
o	0	2



τ_F :

F	P	R
H	H	H
H	H	o
o	H	o
H	o	H
o	o	H
o	o	o

τ_G :

G	P	F
H	H	H
o	H	H
H	H	o
o	H	o
H	o	H
o	o	H
H	o	o
o	o	o

124

τ_R :

R	F
o	m
H	o

τ_P :

P	F
H	H
o	o

τ_M :

M	R
m	m
o	o

Encoding Games in CSPs

F	$P_m R_m$	$P_m R_o$	$P_o R_m$	$P_o R_o$
m	2	2	1	0
o	0	2	1	2

G	$P_m F_m$	$P_m F_o$	$P_o F_m$	$P_o F_o$
m	2	0	0	1
o	2	0	0	1

R	F_m	F_o
m	0	1
o	2	0

P	F_m	F_o
m	2	0
o	0	1

M	R_m	R_o
m	1	0
o	0	2



τ_F :

F	P	R
H	H	H
H	H	o
o	H	o
H	o	H
o	o	H
o	o	o

τ_G :

G	P	F
H	H	H
o	H	H
H	H	o
o	H	o
H	o	H
o	o	H
H	o	o
o	o	o

125

τ_R :

R	F
o	m
H	o

τ_P :

P	F
H	H
o	o

τ_M :

M	R
m	m
o	o

Encoding Games in CSPs

F	$P_m R_m$	$P_m R_o$	$P_o R_m$	$P_o R_o$
m	2	2	1	0
o	0	2	1	2

G	$P_m F_m$	$P_m F_o$	$P_o F_m$	$P_o F_o$
m	2	0	0	1
o	2	0	0	1

R	F_m	F_o
m	0	1
o	2	0

P	F_m	F_o
m	2	0
o	0	1

M	R_m	R_o
m	1	0
o	0	2



τ_F :

F	P	R
m	m	m
o	m	o
o	o	m
o	o	o

τ_G :

G	P	F
m	m	m
o	m	o
o	o	m
o	o	o

126

τ_R :

R	F
o	m
m	o

τ_P :

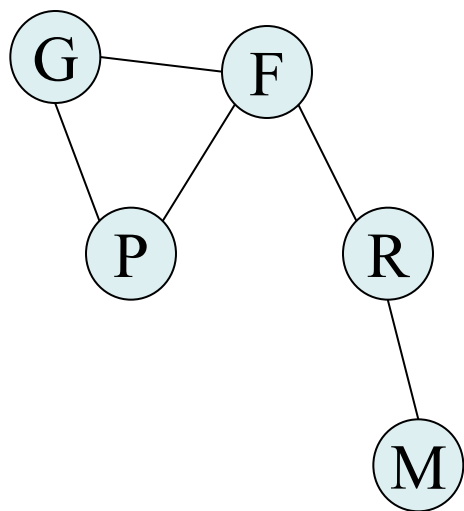
P	F
m	m
o	o

τ_M :

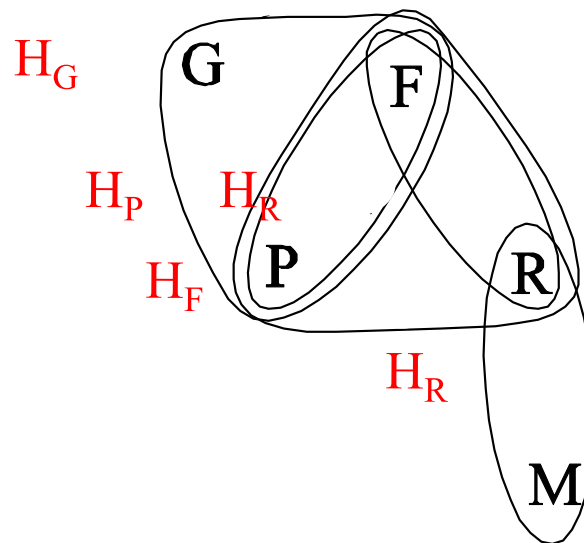
M	R
m	m
o	o

Interaction Among Players: Friends

- The interaction structure of a game G can be represented by:
 - the dependency graph $G(G)$ according to $\text{Neigh}(G)$
 - a hypergraph $H(G)$ with edges: $H(p) = \text{Neigh}(p) \cup \{p\}$



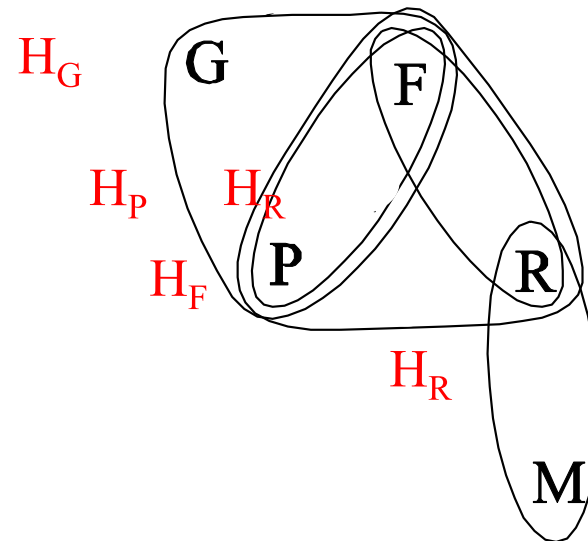
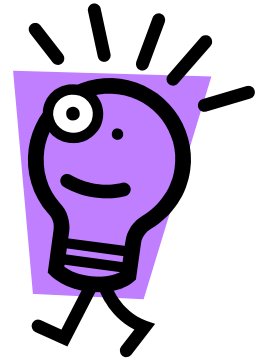
$G(\text{FRIENDS})$



$H(\text{FRIENDS})$

Interaction Among Players: Friends

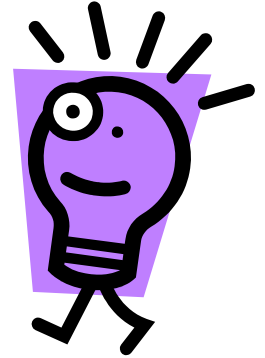
This is the same structure as the one of the associated CSP



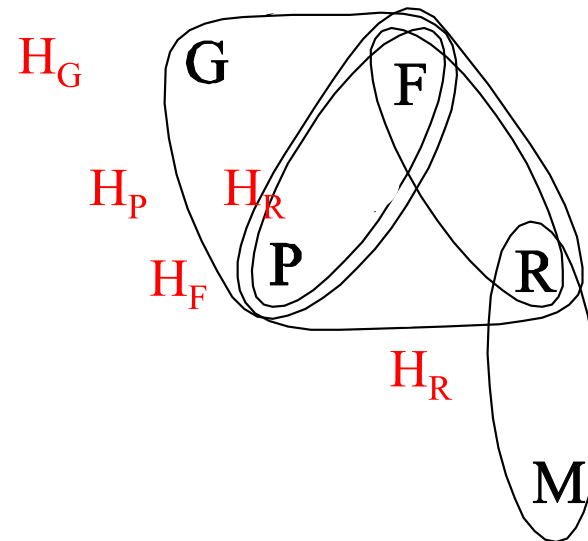
$H(FRIENDS)$

Interaction Among Players: Friends

This is the same structure as the one of the associated CSP



On (nearly)-Acyclic Instances,
Nash equilibria are easy



$H(\text{FRIENDS})$

Outline

Identification of “Easy” Classes

Applications of Tree Decompositions

Beyond Tree Decompositions

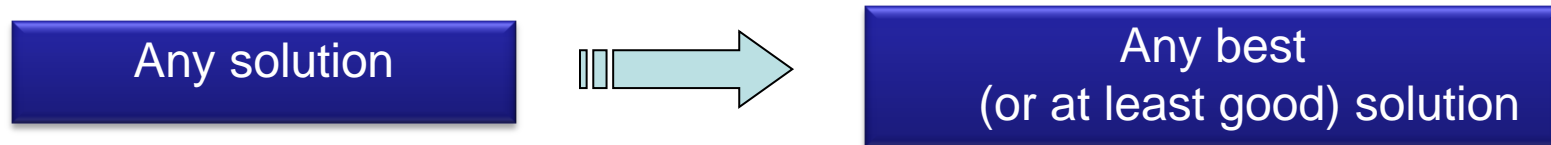
Decision/Computation Problems

Optimization Problems

Enumeration Problems

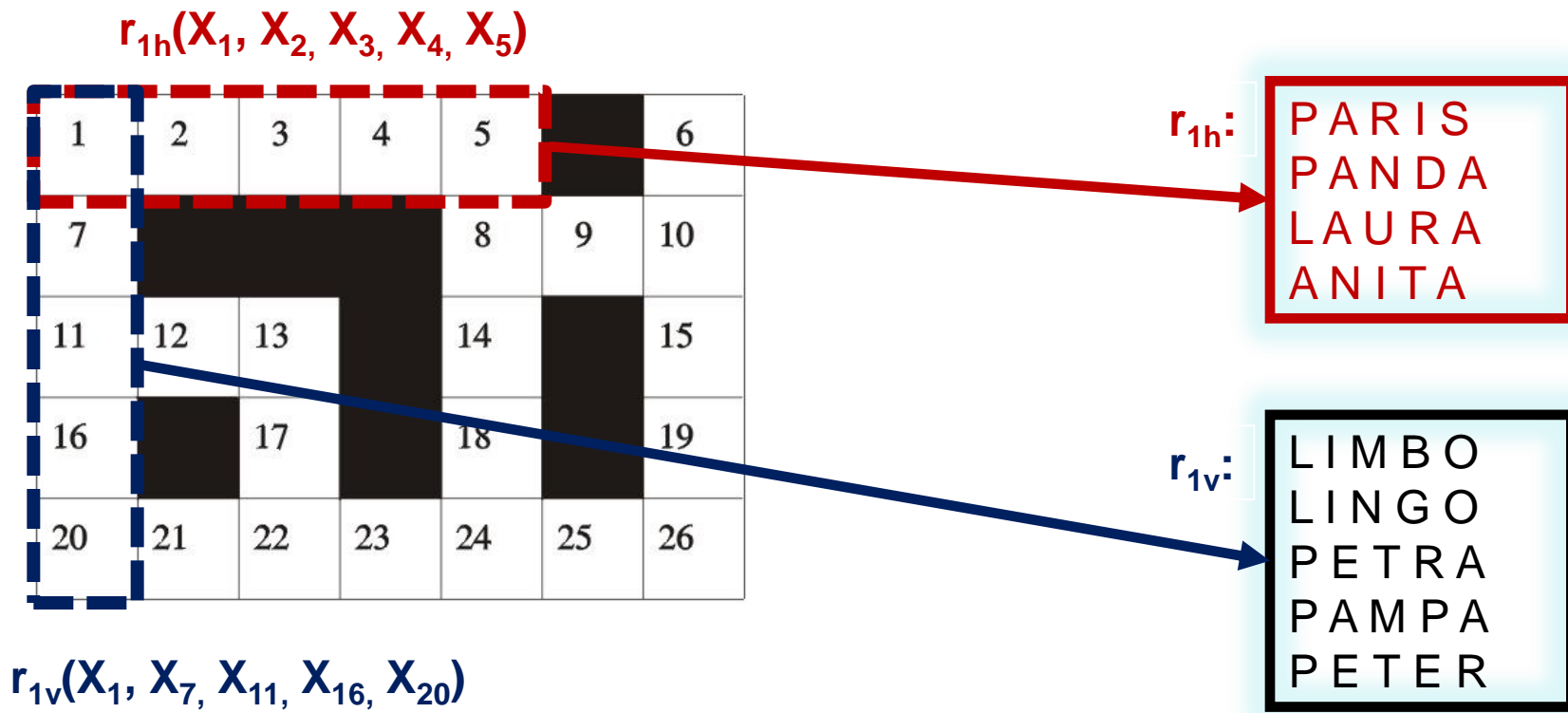
Constraint Optimization Problems

- Classically, CSP: Constraint Satisfaction Problem
- However, sometimes a solution is enough to “satisfy” (constraints), but not enough to make (users) “happy”



- Hence, several variants of the basic CSP framework:
 - E.g., fuzzy, probabilistic, weighted, lexicographic, penalty, valued, semiring-based, ...

Classical CSPs



- Set of variables $\{X_1, \dots, X_{26}\}$
- Set of constraint scopes

- Set of constraint relations

Puzzles for Experts...

1	2	3	4	5		6
7				8	9	10
11	12	13		14		15
16		17		18		19
20	21	22	23	24	25	26

The puzzle in general admits more than one solution...



- E.g., find the solution that **minimizes** the total number of vowels occurring in the words

A Classification for Optimization Problems

CSOP

Each mapping variable-value has a cost.

Then, find an assignment:

- ◆ Satisfying all the constraints, and
- ◆ Having the minimum total cost.

1	2	3	4	5
P	A	R	I	S
P	A	N	D	A
L	A	U	R	A
A	N	I	T	A

A Classification for Optimization Problems

CSOP

Each mapping variable-value has a cost.

Then, find an assignment:

- ◆ Satisfying all the constraints, and
- ◆ Having the minimum total cost.

WCSP

Each tuple has a cost.

Then, find an assignment:

- ◆ Satisfying all the constraints, and
- ◆ Having the minimum total cost.

1	2	3	4	5
P	A	R	I	S
P	A	N	D	A
L	A	U	R	A
A	N	I	T	A

A Classification for Optimization Problems

CSOP

Each mapping variable-value has a cost.

Then, find an assignment:

- ◆ Satisfying all the constraints, and
- ◆ Having the minimum total cost.

WCSP

Each tuple has a cost.

Then, find an assignment:

- ◆ Satisfying all the constraints, and
- ◆ Having the minimum total cost.

MAX-CSP

Each constraint relation has a cost.

Then, find an assignment:

- ◆ Minimizing the cost of violated relations.

1 2 3 4 5

PARIS

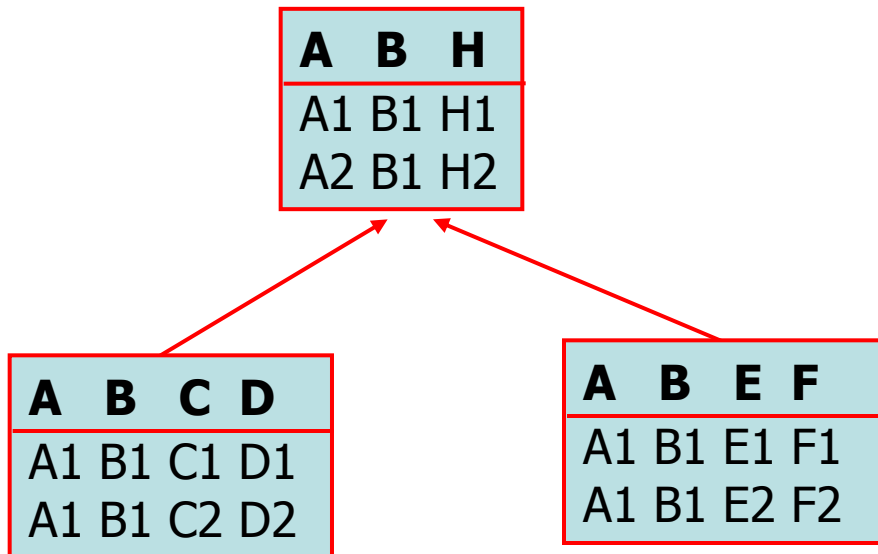
PANDA

LAURA

ANITA

CSOP: Tractability of Acyclic Instances

- Adapt the dynamic programming approach in (Yannakakis'81)

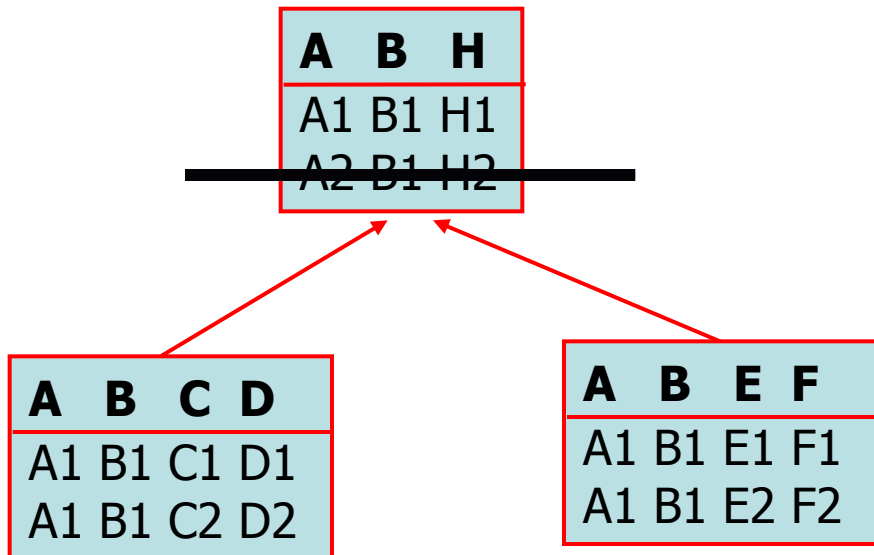


CSOP: Tractability of Acyclic Instances

- Adapt the dynamic programming approach in (Yannakakis'81)

With a bottom-up computation:

- Filter the tuples that do not match

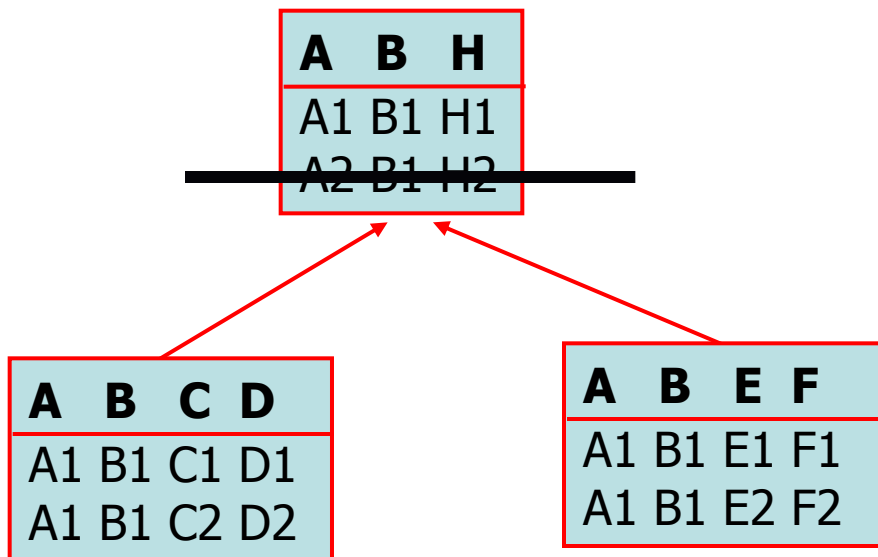


CSOP: Tractability of Acyclic Instances

- Adapt the dynamic programming approach in (Yannakakis'81)

With a bottom-up computation:

- Filter the tuples that do not match
- Compute the cost of the best partial solution, by looking at the children



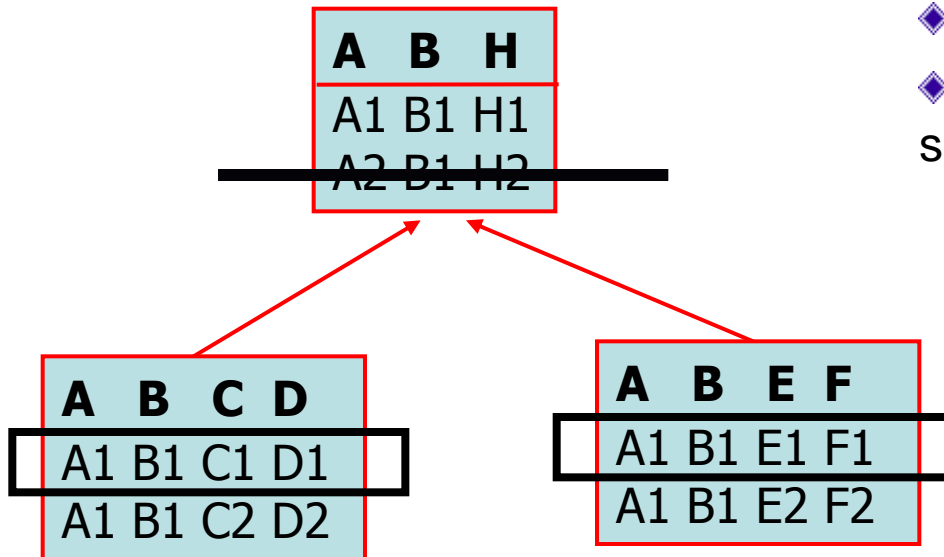
$$\begin{aligned} \text{cost}(C/C1) &= \text{cost}(D/D1) = 0 \\ \text{cost}(C/C2) &= \text{cost}(D/D2) = 1 \\ \text{cost}(E/E1) &= \text{cost}(F/F1) = 0 \\ \text{cost}(E/E2) &= \text{cost}(F/F2) = 1 \end{aligned}$$

CSOP: Tractability of Acyclic Instances

- Adapt the dynamic programming approach in (Yannakakis'81)

With a bottom-up computation:

- Filter the tuples that do not match
- Compute the cost of the best partial solution, by looking at the children



$\text{cost}(C/C1)=\text{cost}(D/D1)=0$
$\text{cost}(C/C2)=\text{cost}(D/D2)=1$
$\text{cost}(E/E1)=\text{cost}(F/F1)=0$
$\text{cost}(E/E2)=\text{cost}(F/F2)=1$

CSOP: Tractability of Acyclic Instances

- Adapt the dynamic programming approach in (Yannakakis'81)

$\left. \begin{array}{l} \text{cost}(A/A1)+ \\ \text{cost}(B/B1)+ \\ \text{cost}(H/H1)+ \\ \text{cost}(C/C1)+ \\ \text{cost}(D/D1)+ \\ \text{cost}(E/E1)+ \\ \text{cost}(F/F1) \end{array} \right\}$

A	B	H
A1	B1	H1
A2	B1	H2

A	B	C	D
A1	B1	C1	D1
A1	B1	C2	D2

A	B	E	F
A1	B1	E1	F1
A1	B1	E2	F2

With a bottom-up computation:

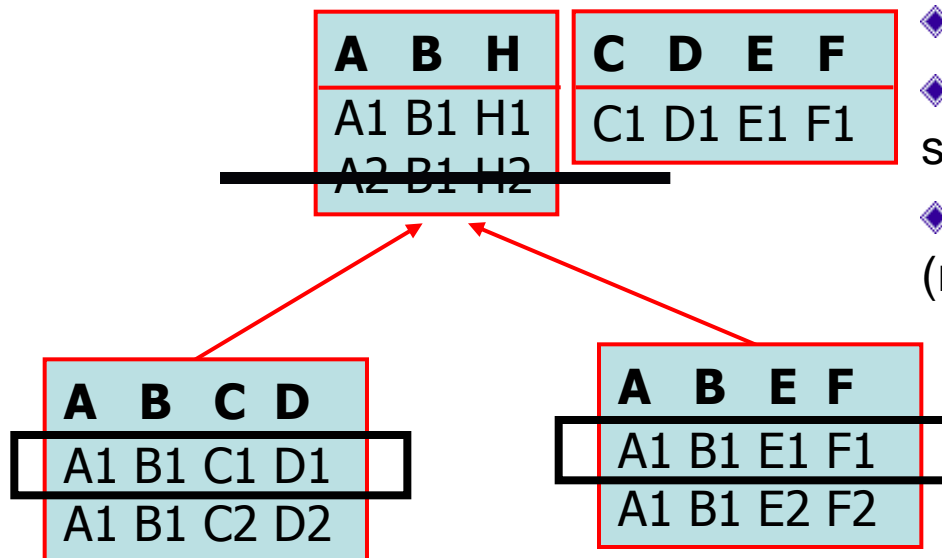
- Filter the tuples that do not match
- Compute the cost of the best partial solution, by looking at the children

$\text{cost}(C/C1)=\text{cost}(D/D1)=0$
 $\text{cost}(C/C2)=\text{cost}(D/D2)=1$
 $\text{cost}(E/E1)=\text{cost}(F/F1)=0$
 $\text{cost}(E/E2)=\text{cost}(F/F2)=1$

CSOP: Tractability of Acyclic Instances

- Adapt the dynamic programming approach in (Yannakakis'81)

With a bottom-up computation:



- Filter the tuples that do not match
- Compute the cost of the best partial solution, by looking at the children
- Propagate the best partial solution (resolving ties arbitrarily)

WCSP: Tractability of Acyclic Instances

1	2	3	4	5
P	A	R	I	S
P	A	N	D	A
L	A	U	R	A
A	N	I	T	A

CSOP



1	2	3	4	5
P	A	R	I	S
P	A	N	D	A
L	A	U	R	A
A	N	I	T	A

WCSP

WCSP: Tractability of Acyclic Instances

1	2	3	4	5	6
PARIS					PARIS
PANDA					PANDA
LAURA					LAURA
ANITA					ANITA

CSOP



1	2	3	4	5
PARIS				
PANDA				
LAURA				
ANITA				

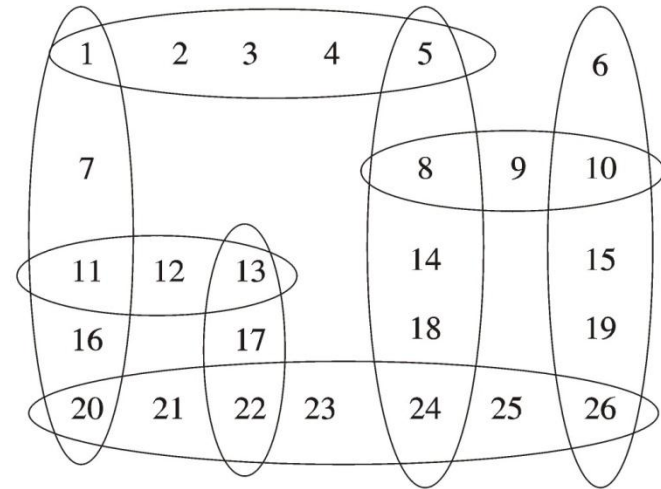
WCSP

- The mapping:
- ◆ Is feasible in linear time
 - ◆ Preserves the solutions
 - ◆ Preserves acyclicity

In-Tractability of MAX-CSP Instances

1	2	3	4	5		6
7				8	9	10
11	12	13		14		15
16		17		18		19
20	21	22	23	24	25	26

- Maximize the number of words placed in the puzzle



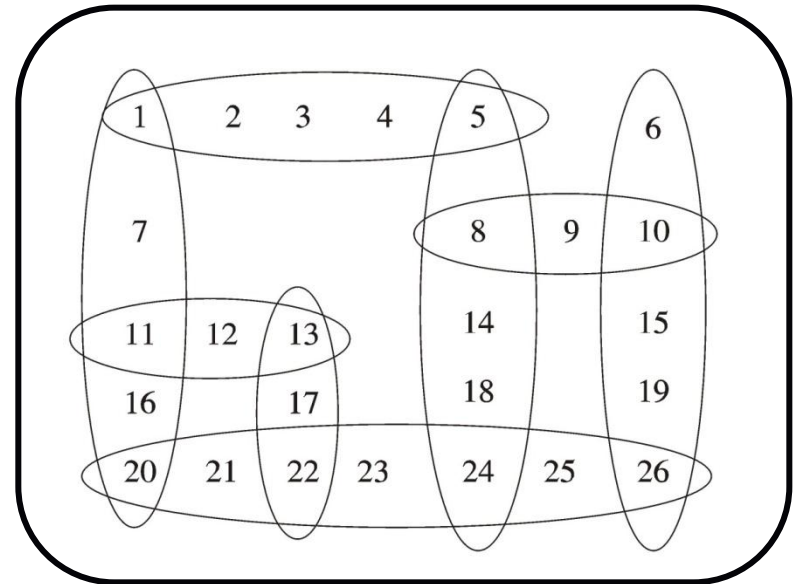
In-Tractability of MAX-CSP Instances

1	2	3	4	5		6
7				8	9	10
11	12	13		14		15
16		17		18		19
20	21	22	23	24	25	26

- Add a “big” constraint with no tuple



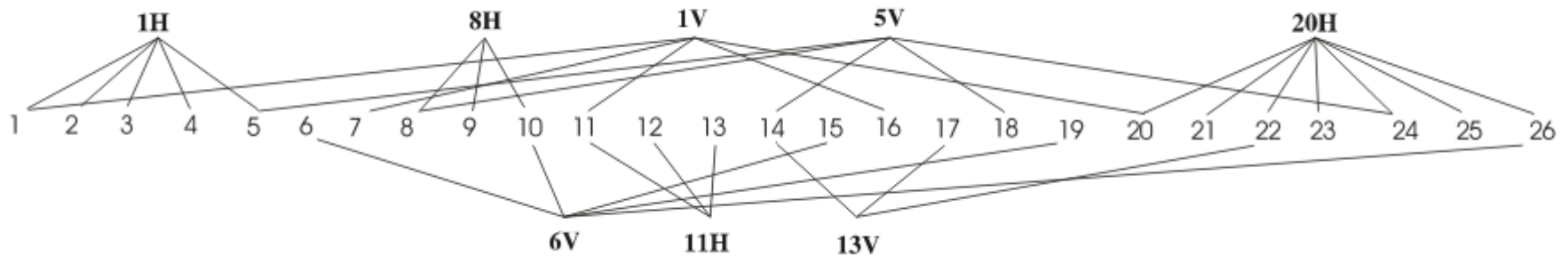
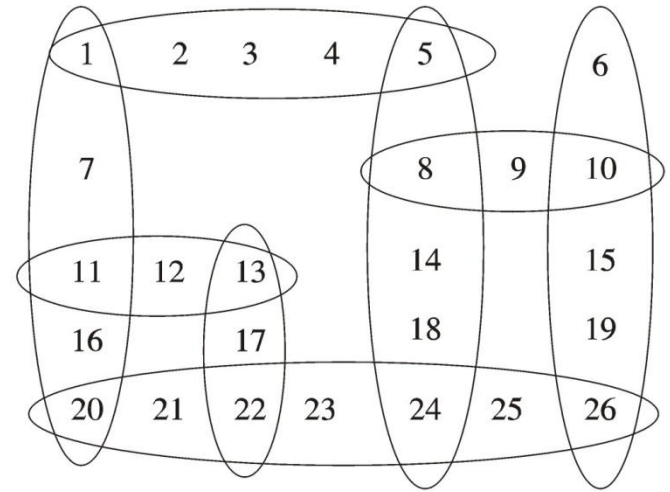
- Maximize the number of words placed in the puzzle



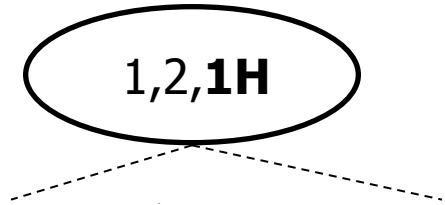
The puzzle is satisfiable \leftrightarrow exactly one constraint is violated in the **acyclic** MAX-CSP

Tractability of MAX-CSP Instances

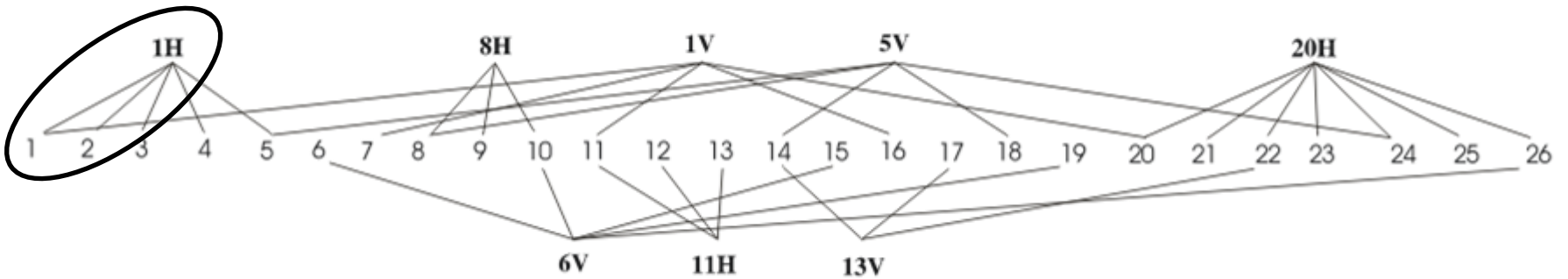
1. Consider the incidence graph
2. Compute a Tree Decomposition



Tractability of MAX-CSP Instances



MAX-CSP



Tractability of MAX-CSP Instances

1 2	1H
P A	PARIS
P A	PANDA
L A	LAURA
A N	ANITA
A A	<i>unsat</i>
A B	<i>unsat</i>
...	<i>unsat</i>

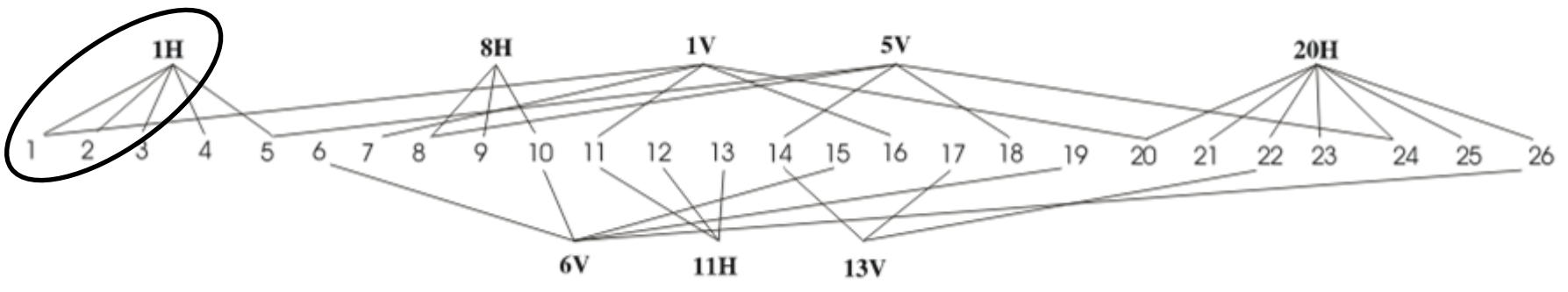


1,2,1H

MAX-CSP

Cost 1,
otherwise cost 0

CSOP



In-Tractability of MAX-CSP Instances

1 2	1H
P A	PARIS
P A	PANDA
L A	LAURA
A N	ANITA
A A	<i>unsat</i>
A B	<i>unsat</i>
...	<i>unsat</i>

CSOP



1,2,1H

MAX-CSP

Cost 1,
otherwise cost 0

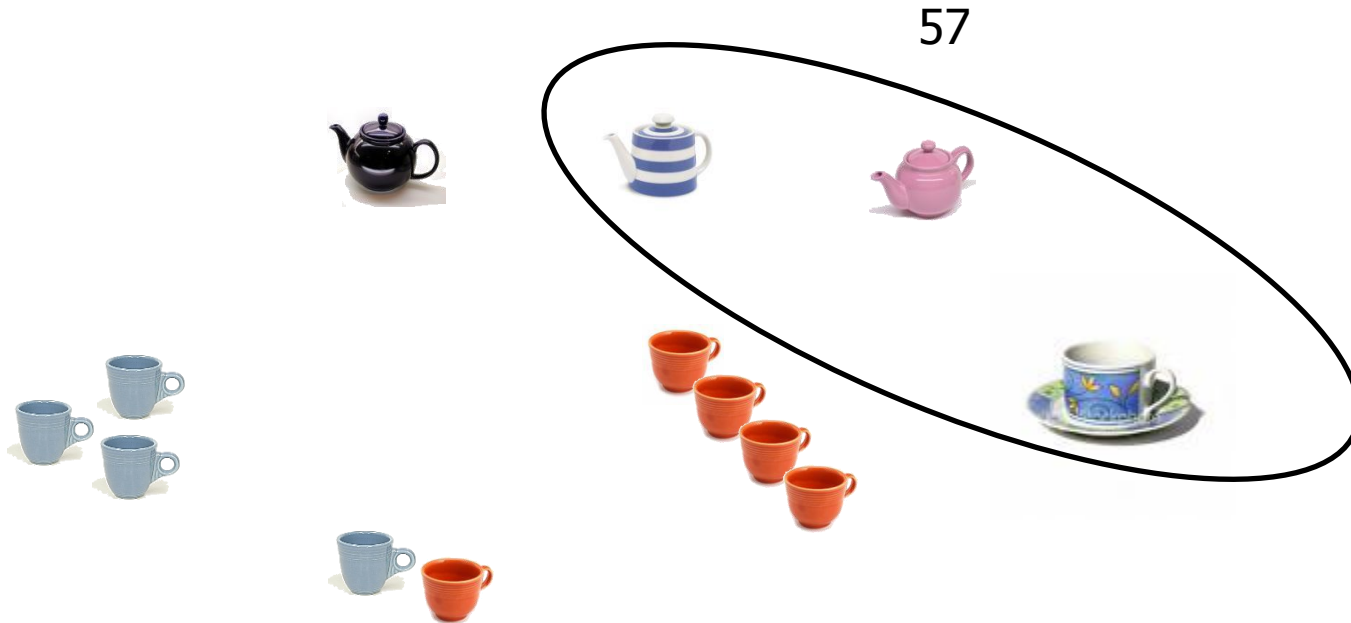
The mapping:

- ◆ Is feasible in time exponential in the width
- ◆ Preserves the solutions
- ◆ Leads to an Acyclic CSOP Instance

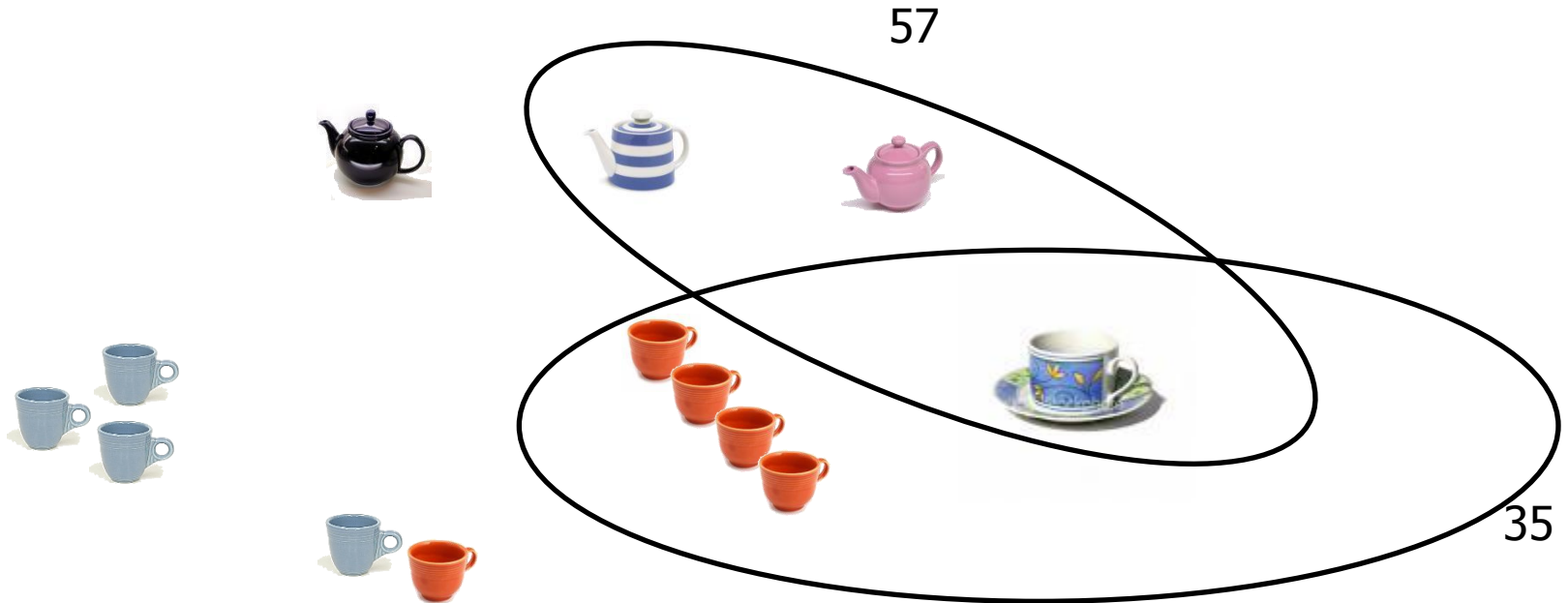
Example Application: Combinatorial Auctions



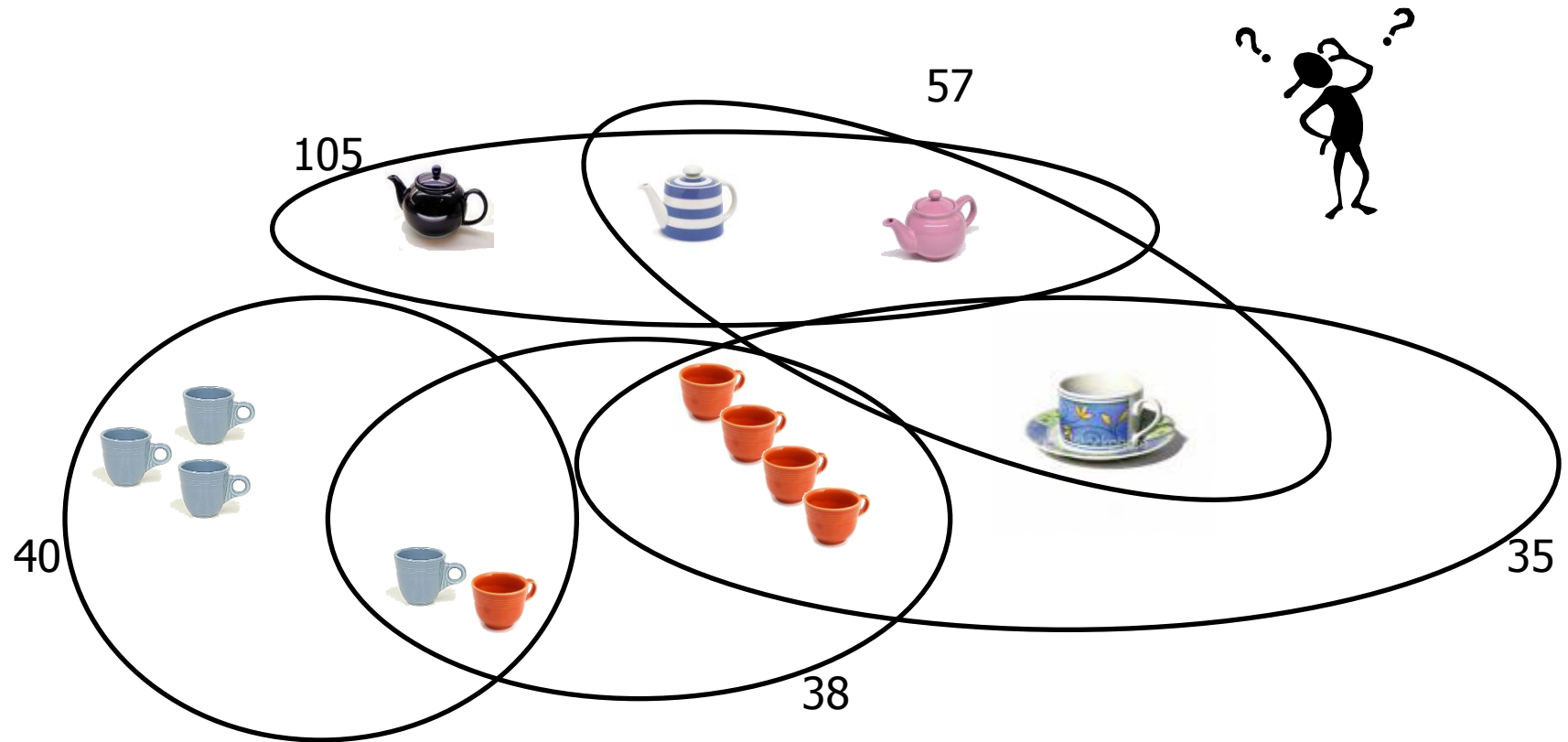
Example Application: Combinatorial Auctions



Example Application: Combinatorial Auctions



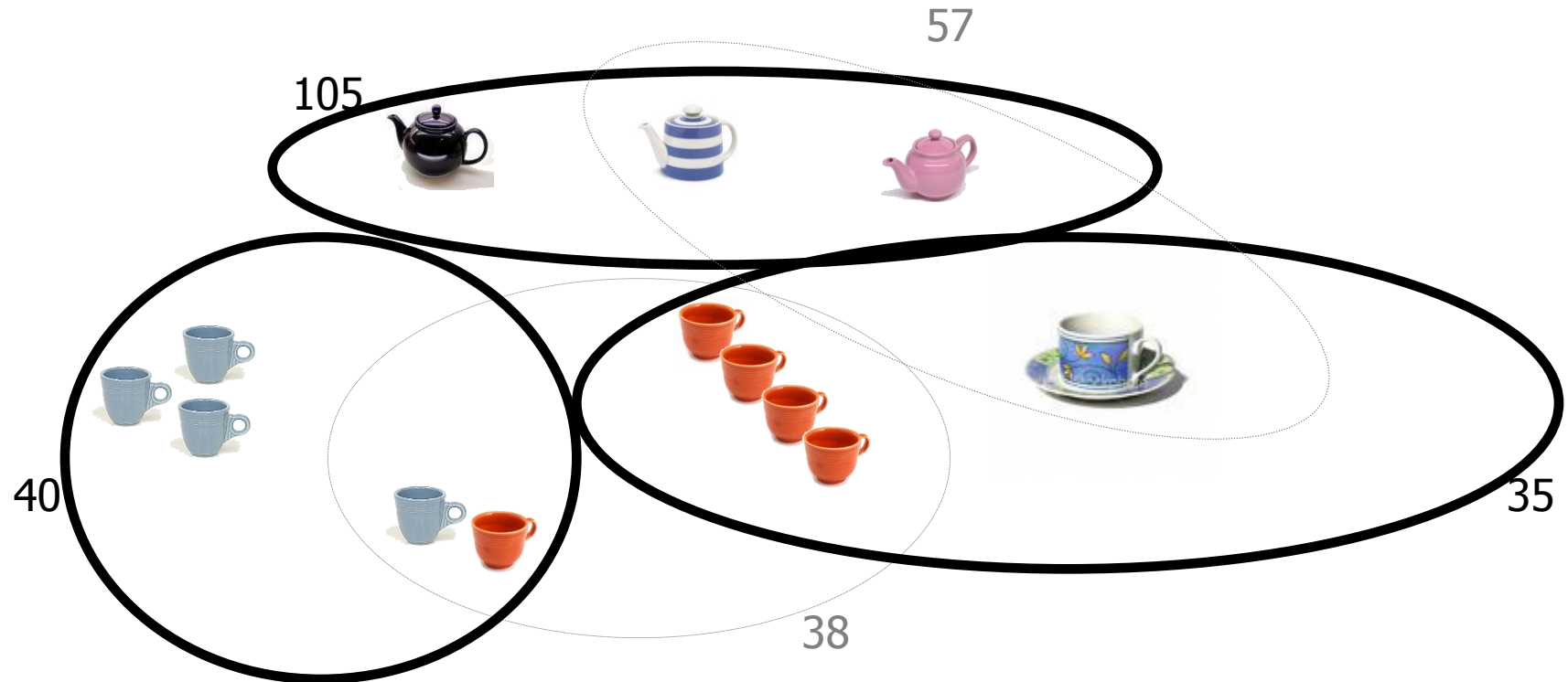
Example Application: Combinatorial Auctions



Winner Determination Problem

- Determine the outcome that maximizes the sum of accepted bid prices

Example Application: Combinatorial Auctions



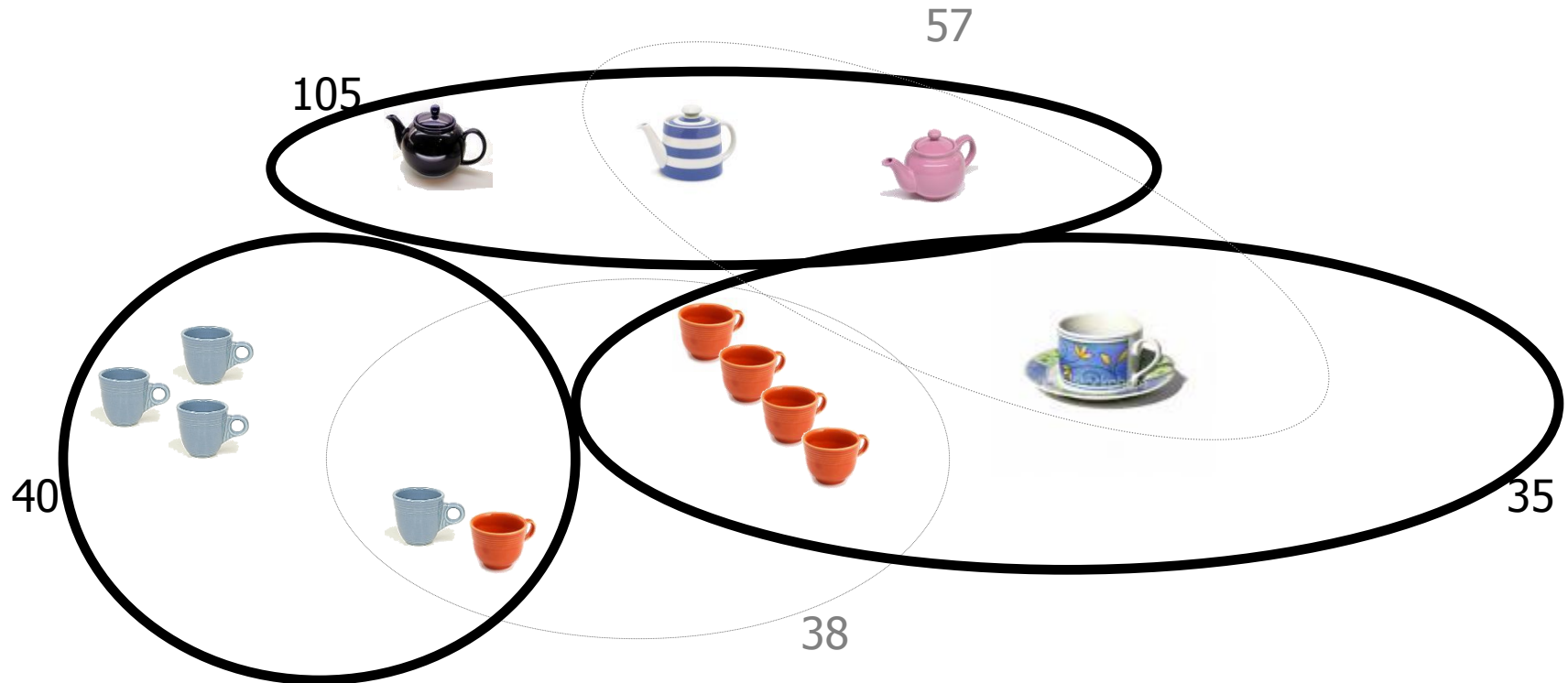
Winner Determination Problem



180

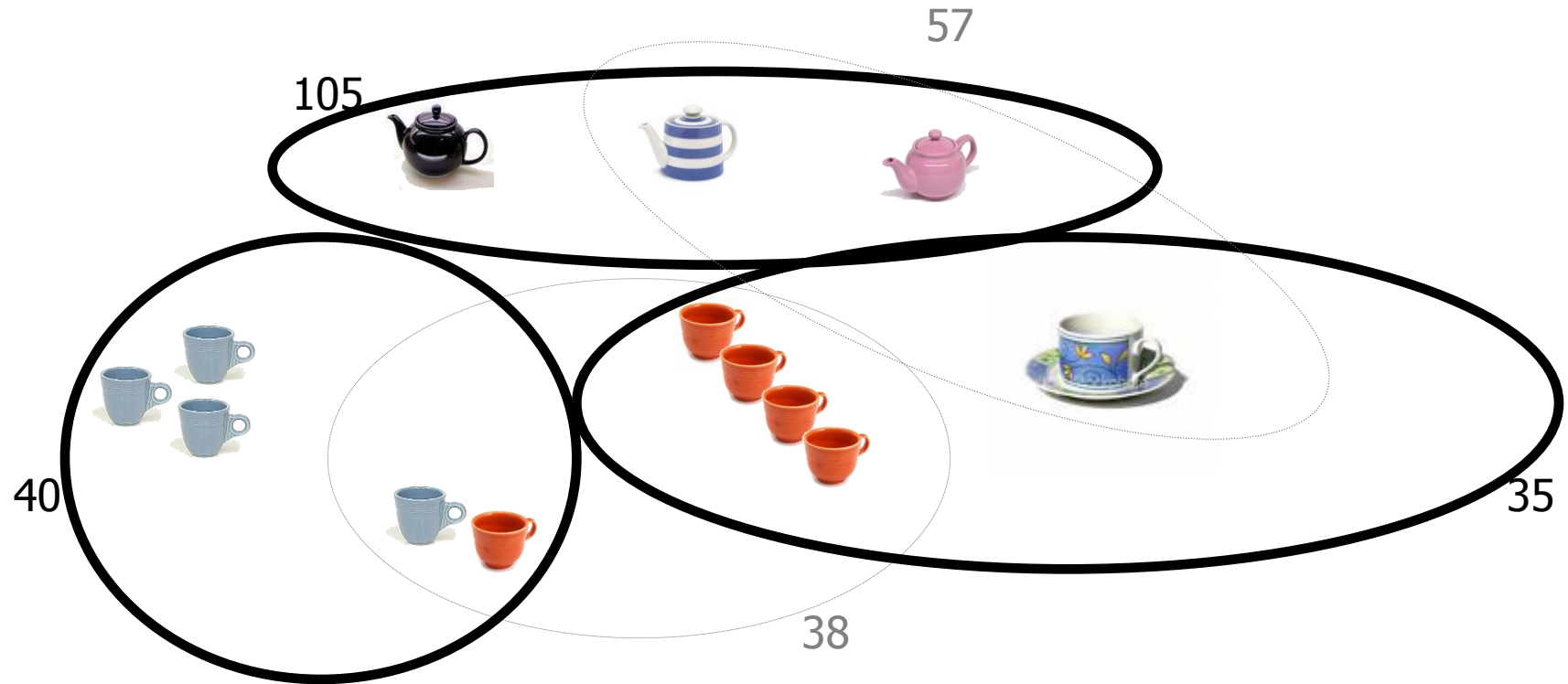
- Determine the outcome that maximizes the sum of accepted bid prices

Example Application: Combinatorial Auctions



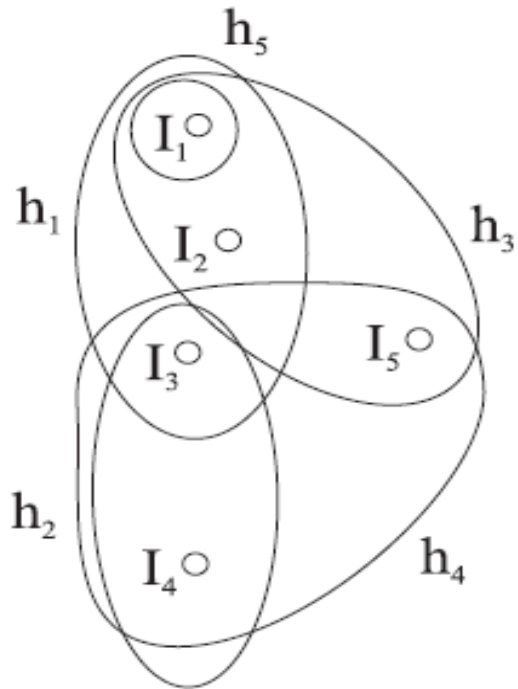
- Other applications [Cramton, Shoham, and Steinberg, '06]
 - airport runway access
 - trucking
 - bus routes
 - industrial procurement

Example Application: Combinatorial Auctions



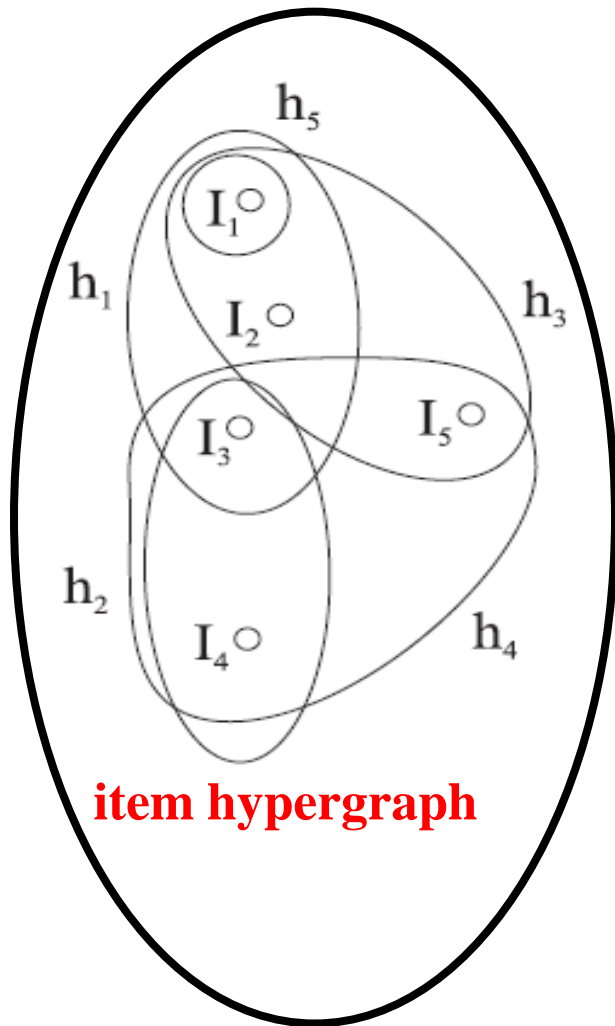
Winner Determination is NP-hard

Structural Properties



item hypergraph

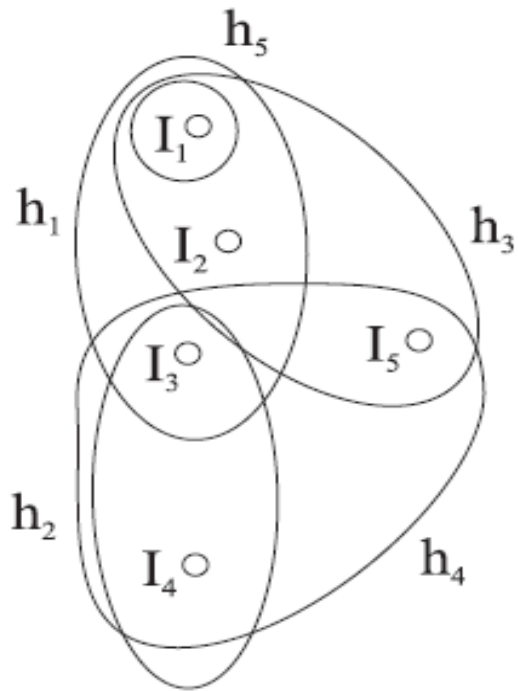
Structural Properties



item hypergraph

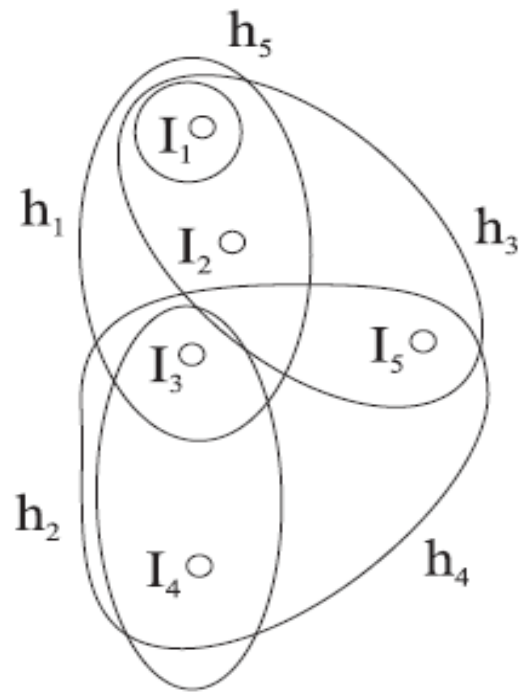
The Winner Determination Problem remains NP-hard even in case of acyclic hypergraphs

Dual Hypergraph

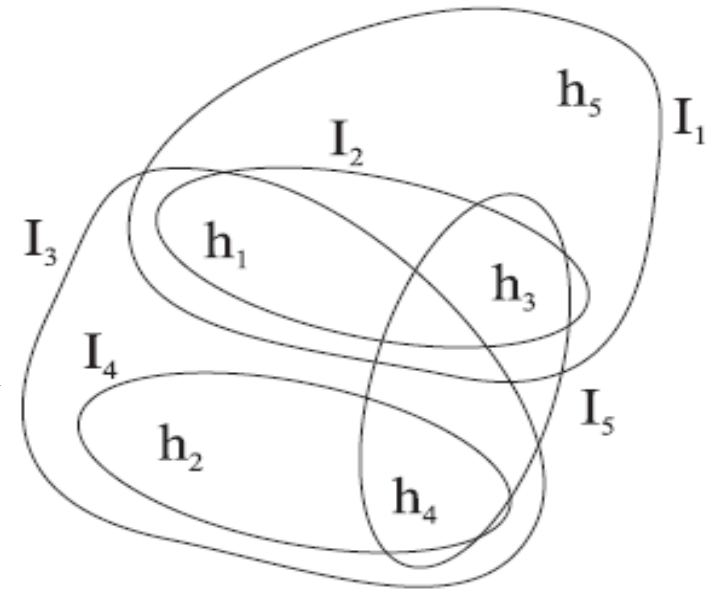


item hypergraph

Dual Hypergraph

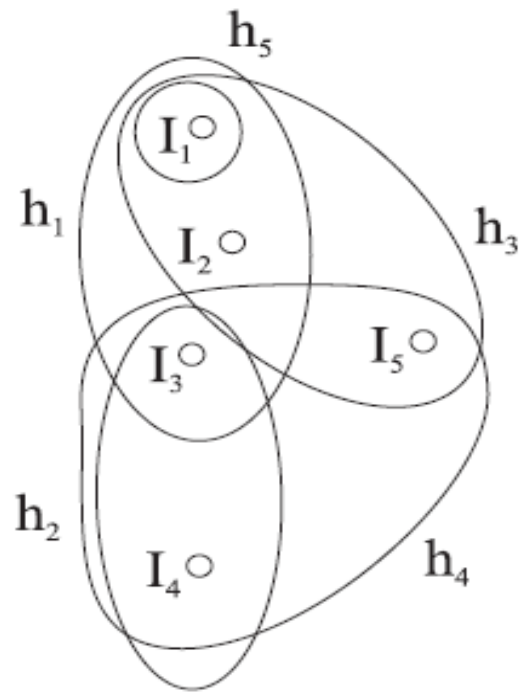


item hypergraph



dual hypergraph

Dual Hypergraph

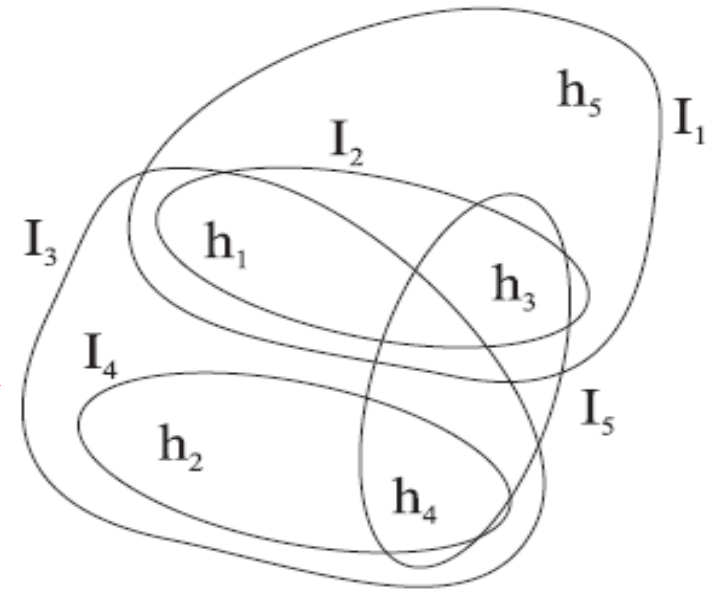


item hypergraph



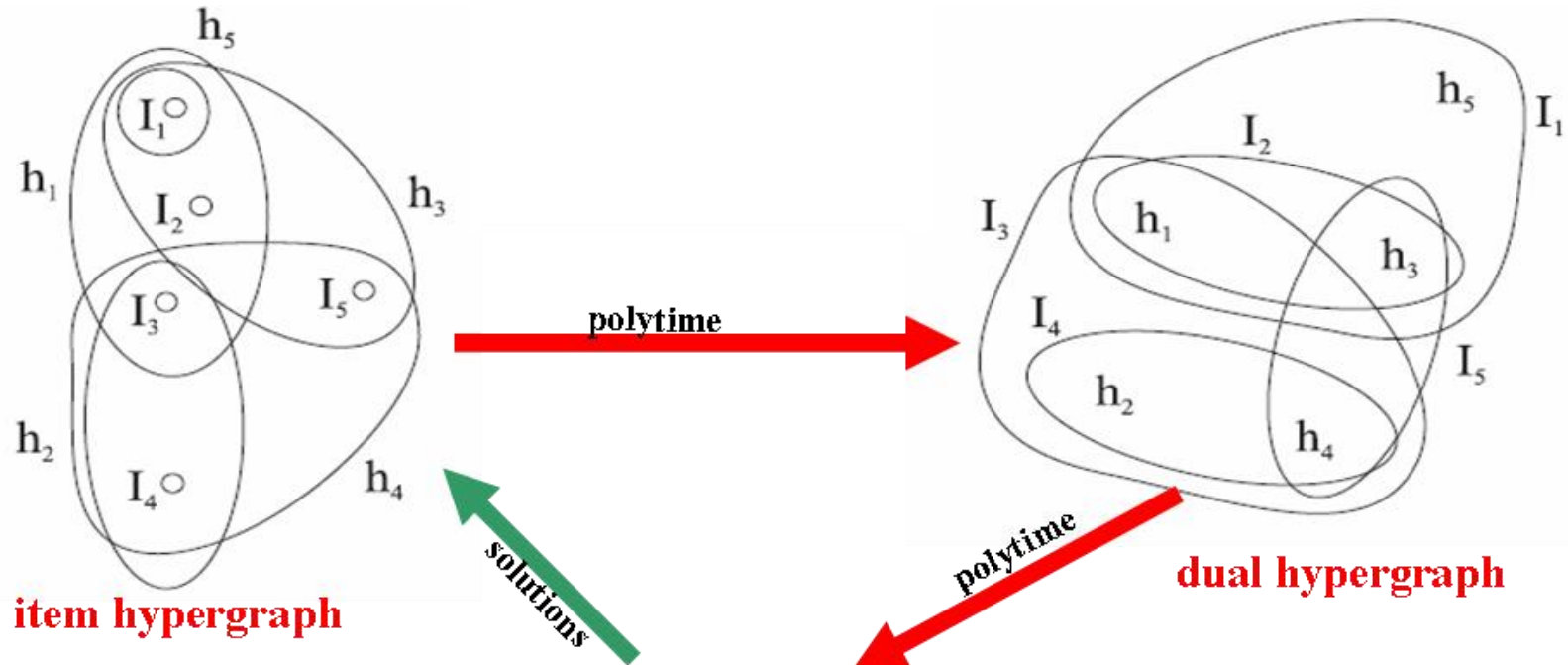
I_1

h_1	h_3	h_5
0	0	0
1	0	0
0	1	0
0	0	1

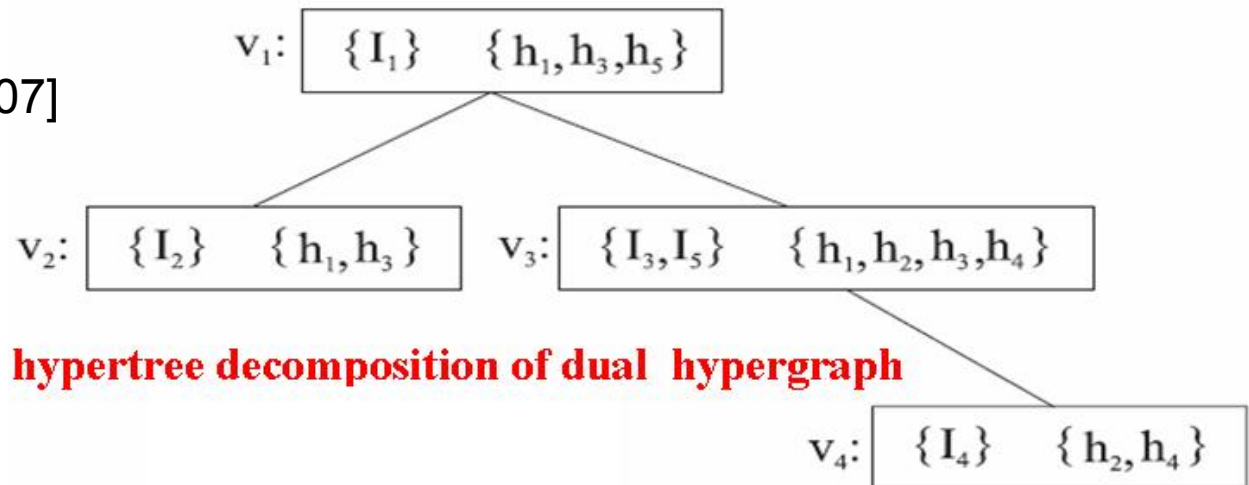


dual hypergraph

The Approach



[Gottlob & Greco, EC'07]



Outline

Identification of “Easy” Classes

Applications of Tree Decompositions

Beyond Tree Decompositions

Decision/Computation Problems

Optimization Problems

Enumeration Problems

Puzzles for «Very» Experts...

1	2	3	4	5		6
7				8	9	10
11	12	13		14		15
16		17		18		19
20	21	22	23	24	25	26

The puzzle in general admits more than one solution...



- Generate all solutions

Puzzles for «Very» Experts...

1	2	3	4	5		6
7				8	9	10
11	12	13		14		15
16		17		18		19
20	21	22	23	24	25	26

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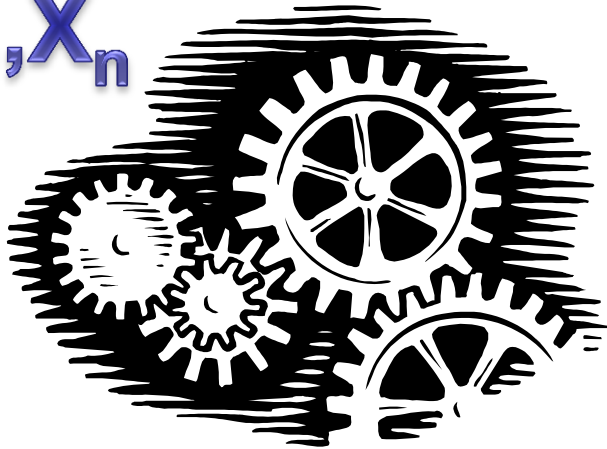
Plain Enumeration

Projection

Problem over Variables X_1, \dots, X_n

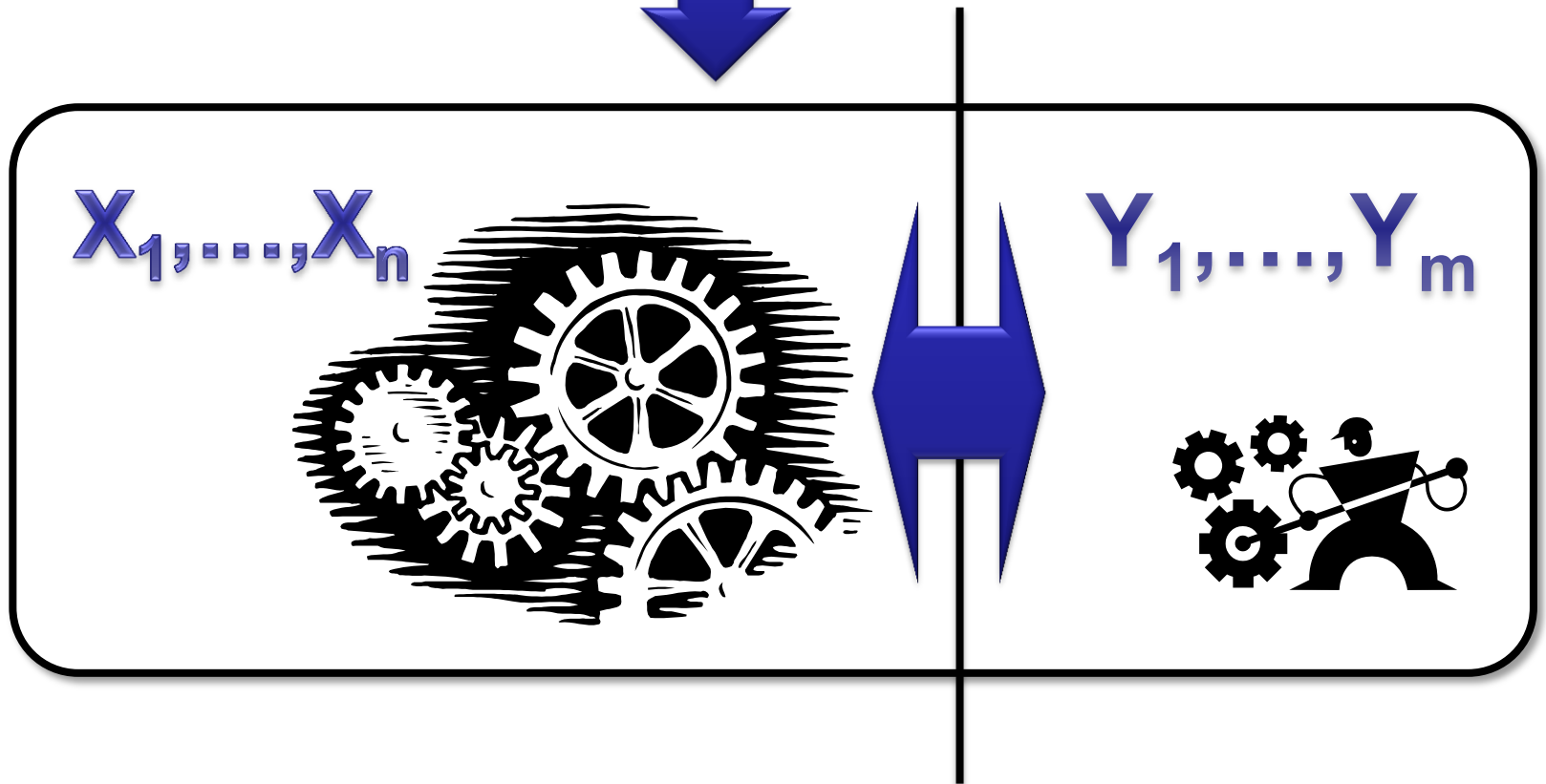


X_1, \dots, X_n



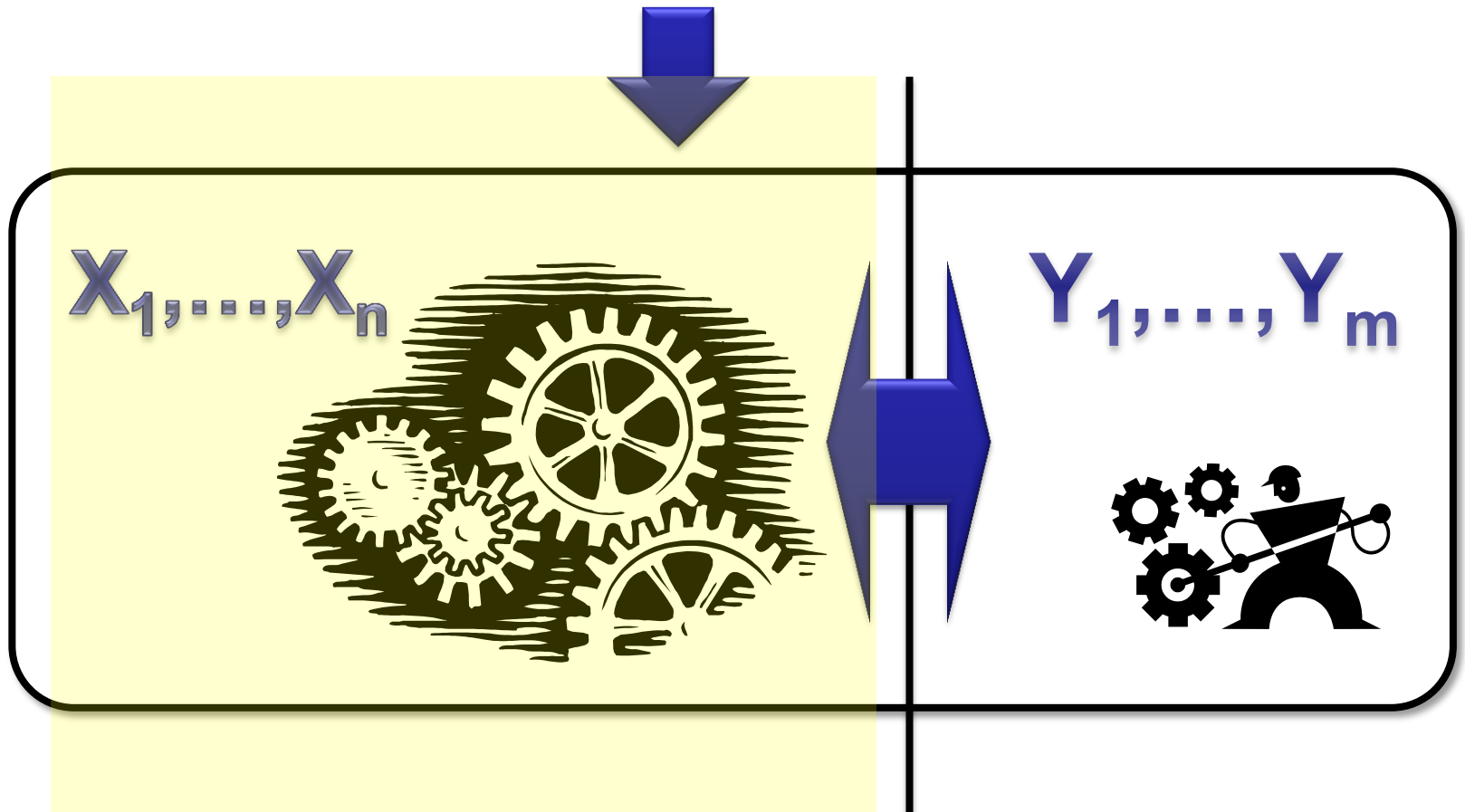
Projection

Problem over Variables X_1, \dots, X_n



Projection

Problem over Variables X_1, \dots, X_n



Questions

INPUT: CSP instance (\mathbb{A}, \mathbb{B})

- Enumerate all the homomorphisms in $\mathbb{A}^{\mathbb{B}}$
- For a set of variables X , enumerate the *projection* $\mathbb{A}^{\mathbb{B}}[X]$

Questions

INPUT: CSP instance (\mathbb{A}, \mathbb{B})

- Enumerate all the homomorphisms in $\mathbb{A}^{\mathbb{B}}$
- For a set of variables X , enumerate the *projection* $\mathbb{A}^{\mathbb{B}}[X]$

What about efficiency here ?



Enumeration With Polynomial Delay

- All the following tasks are in **POLYNOMIAL TIME**
 - Decide whether there is no solution
 - Find the *first* solution
 - Given the current solution, find the *next* one
 - After the last solution, check that there are no further ones

Enumeration With Polynomial Delay

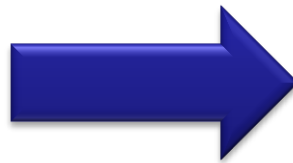
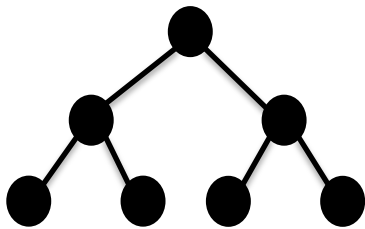
- All the following tasks are in **POLYNOMIAL TIME**
 - Decide whetere there is no solution
 - Find the *first* solution
 - Given the current solution, find the *next* one
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What about the **SPACE** ?



Enumeration With Polynomial Delay

- All the following tasks are in **POLYNOMIAL TIME**
 - Decide whether there is no solution
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 - Given the current solution, find the *next* one
 - After the last solution, check that there are no further ones



*exponential space, but
operations in polynomial time*

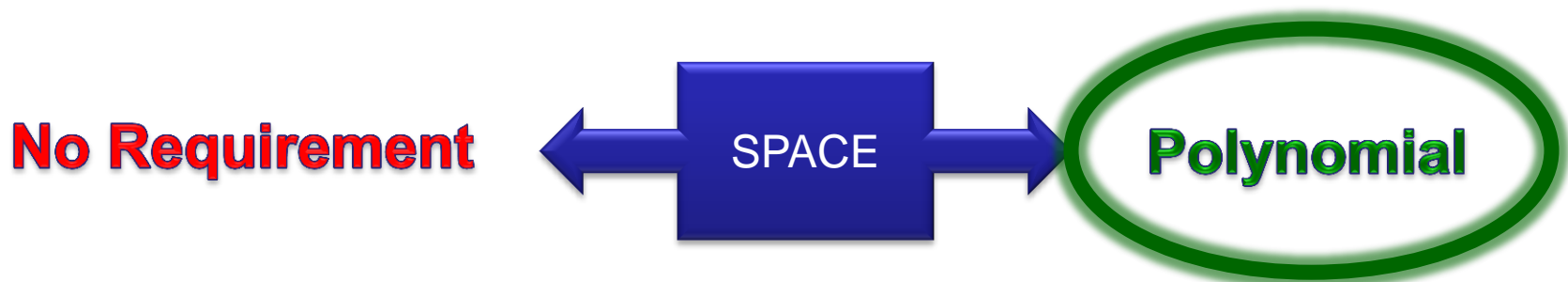
Enumeration With Polynomial Delay

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Enumeration With Polynomial Delay

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 - Decide whether there is no solution
 - Find the *first* solution
 - Given the current solution, find the *next* one
 - After the last solution, check that there are no further ones



d:
3 8
3 7
~~5 7~~
~~6 7~~

$d(Y,P)$

$r(Y,Z,U)$

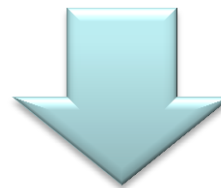
r:
3 8 9
9 3 8
8 3 8
~~3 8 4~~
3 8 3
~~8 9 4~~
~~9 4 7~~

s:
3 8 9
9 3 8
8 3 8
3 8 4
3 8 3
8 9 4
9 4 7

$s(Z,U,W)$

$t(V,Z)$

t:
9 8
9 3
9 5



d:
3 8
3 7
~~5 7~~
~~6 7~~

$d(Y,P)$

$r(Y,Z,U)$

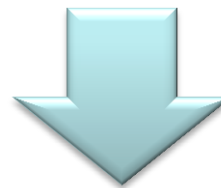
r:
3 8 9
9 3 8
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~~3 8 4~~
3 8 3
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~~9 4 7~~

s:
3 8 9
9 3 8
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$s(Z,U,W)$

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9 8
9 3
9 5



d: 3 8
3 7

$d(Y,P)$

r: 3 8 9
9 3 8
8 3 8
3 8 3

$r(Y,Z,U)$

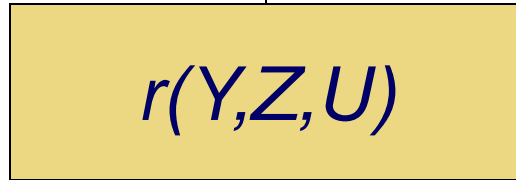
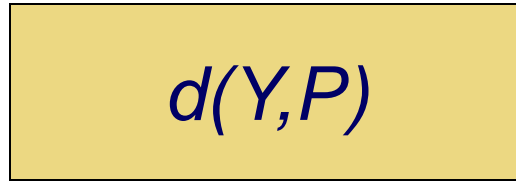
s: 3 8 9
9 3 8
8 3 8
3 8 4
3 8 3
8 9 4
9 4 7

$s(Z,U,W)$

$t(V,Z)$

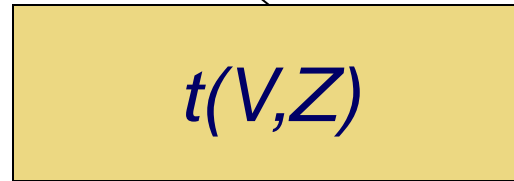
t: 9 8
9 3
9 5

d: 3 8
3 7



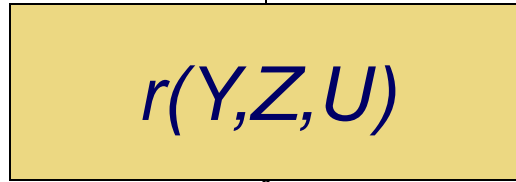
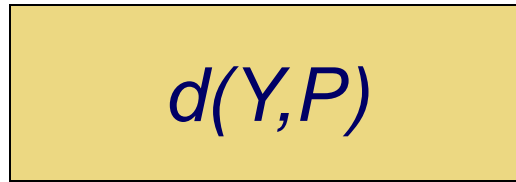
r: 3 8 9
~~9 3 8~~
~~8 3 8~~
3 8 3

s: 3 8 9
9 3 8
8 3 8
3 8 4
3 8 3
8 9 4
9 4 7



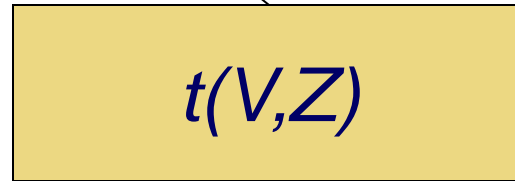
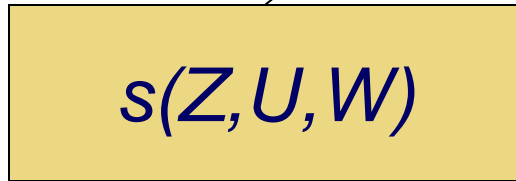
t: 9 8
9 3
9 5

d: 3 8
3 7

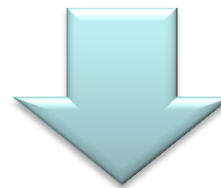


r: 3 8 9
~~9 3 8~~
~~8 3 8~~
3 8 3

s: ~~3 8 9~~
~~9 3 8~~
8 3 8
~~3 8 4~~
~~3 8 3~~
8 9 4
~~9 4 7~~



t: 9 8
~~9 3~~
~~9 5~~



d: 3 8
3 7

$d(Y,P)$

r: 3 8 9

$r(Y,Z,U)$

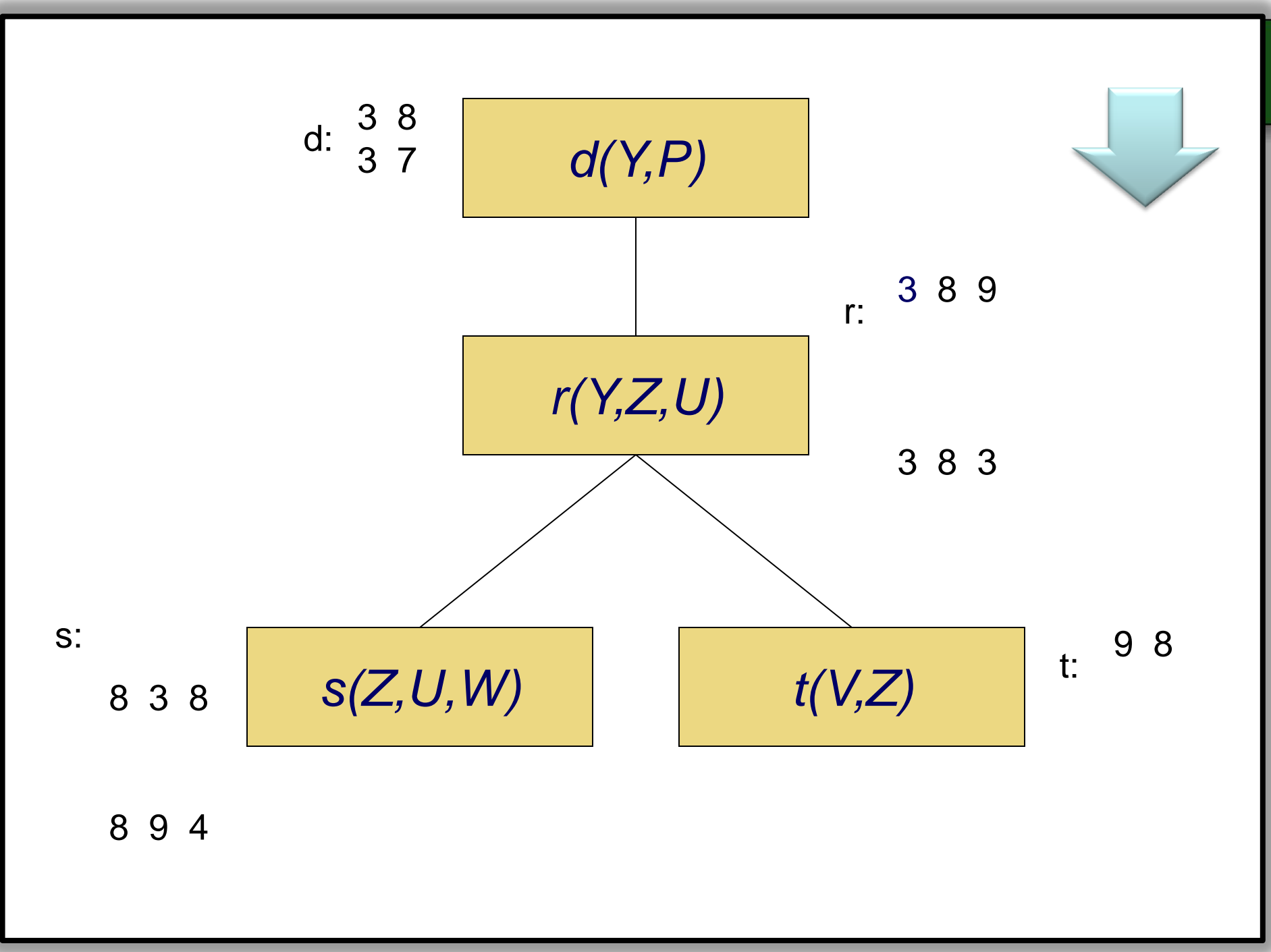
3 8 3

s:
8 3 8
8 9 4

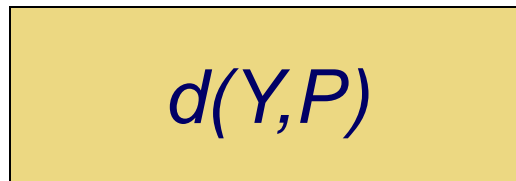
$s(Z,U,W)$

t: 9 8

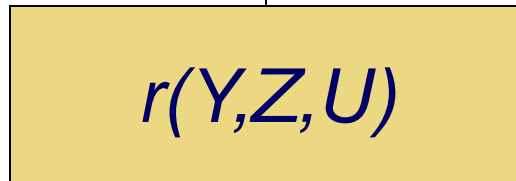
$t(V,Z)$



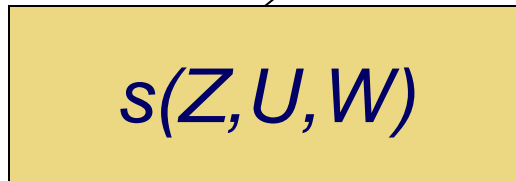
d: 3 8
3 7



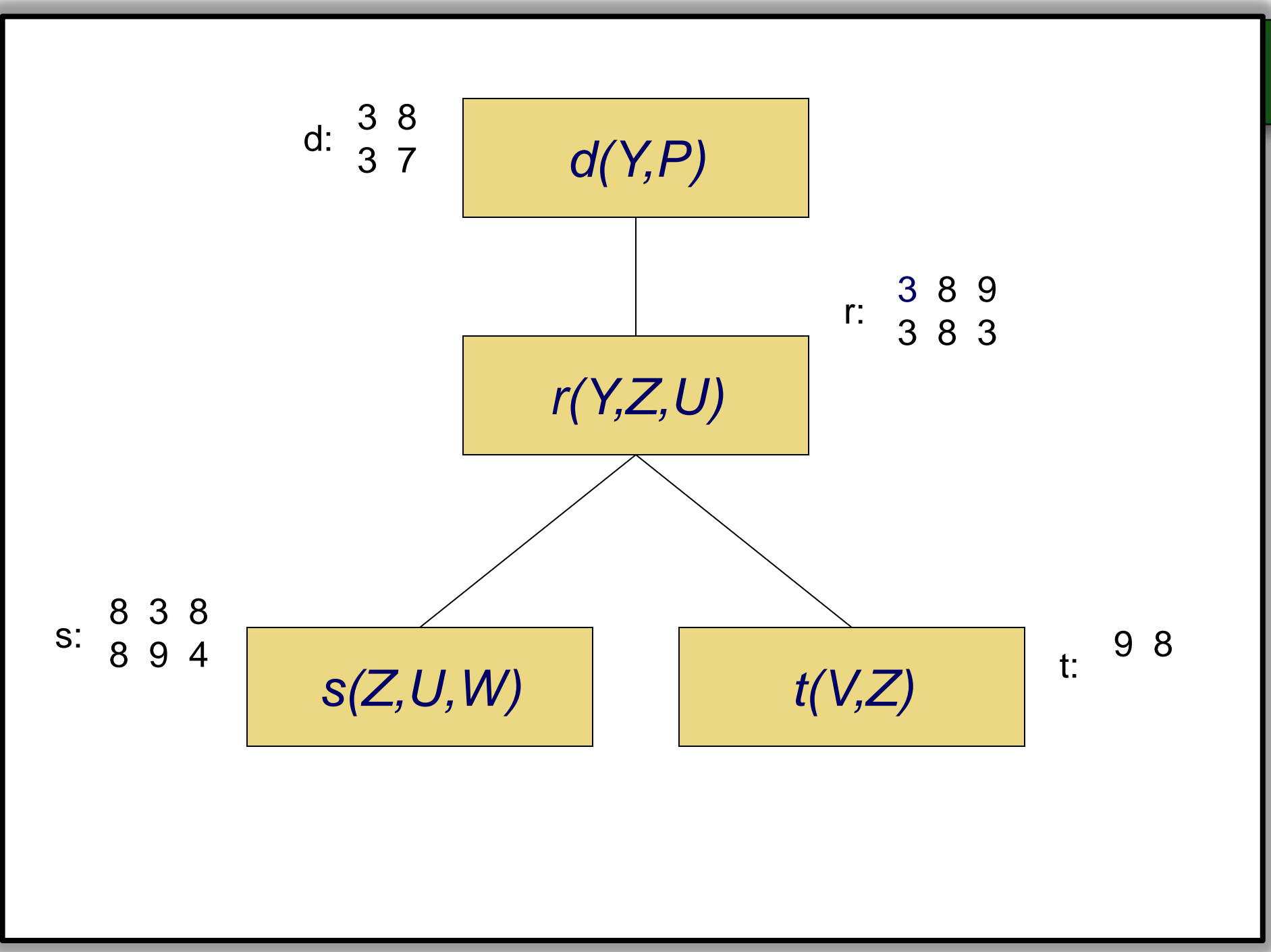
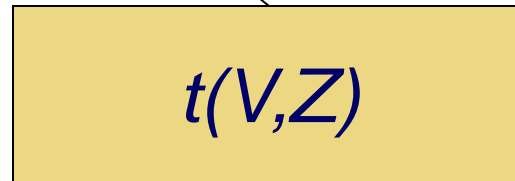
r: 3 8 9
3 8 3



s: 8 3 8
8 9 4



t: 9 8



d: 3 8
3 7

$d(Y, P)$

r: 3 8 9
3 8 3

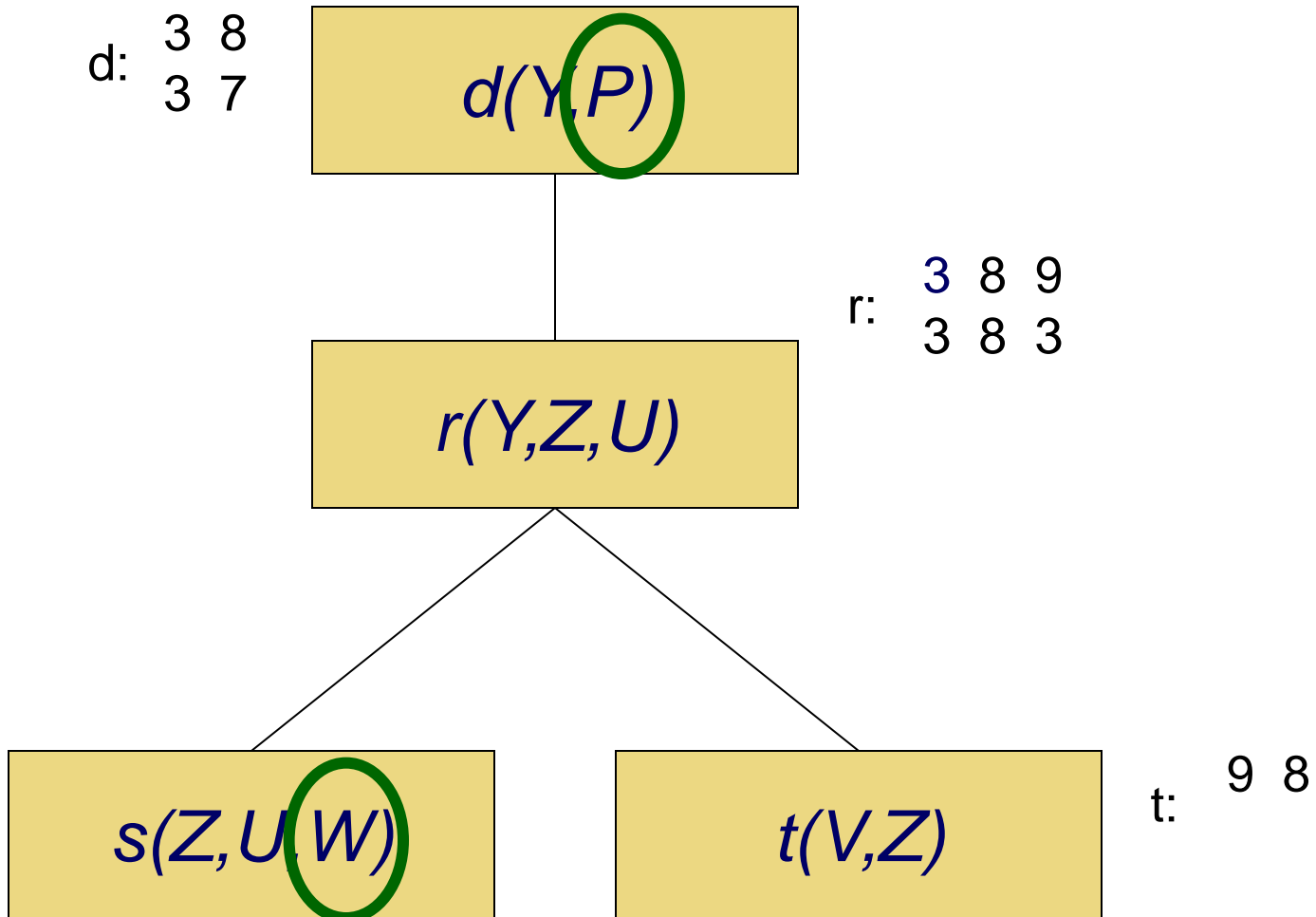
$r(Y, Z, U)$

s: 8 3 8
8 9 4

$s(Z, U, W)$

t: 9 8

$t(V, Z)$



d: 3 8
3 7

$d(Y, P)$

r: 3 8 9
3 8 3

$r(Y, Z, U)$

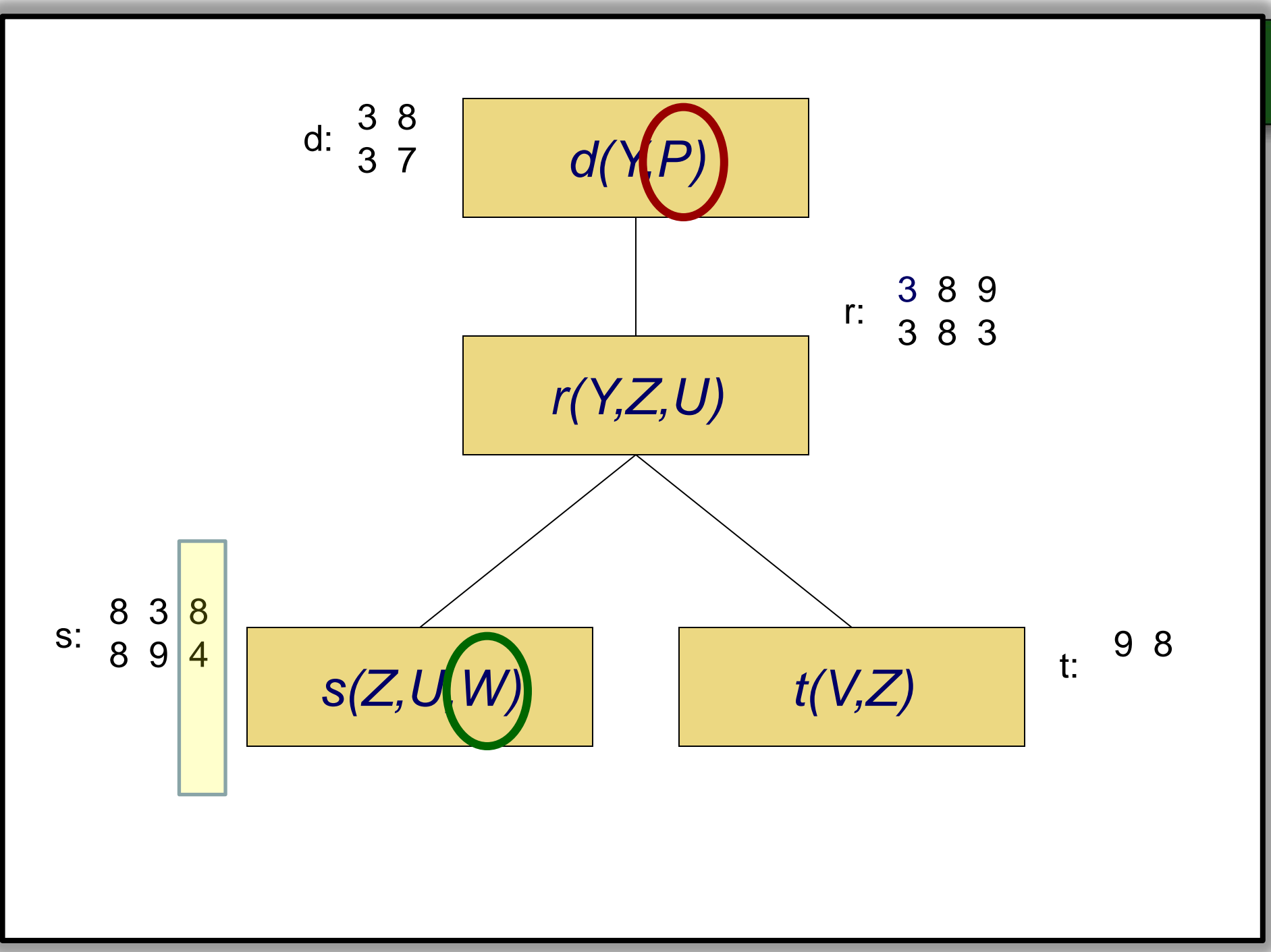
s: 8 3 8
8 9 4

8
4

$s(Z, U, W)$

t: 9 8

$t(V, Z)$



d: 3 8
3 7

$d(Y, P)$

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3 8 3

$r(Y, Z, U)$

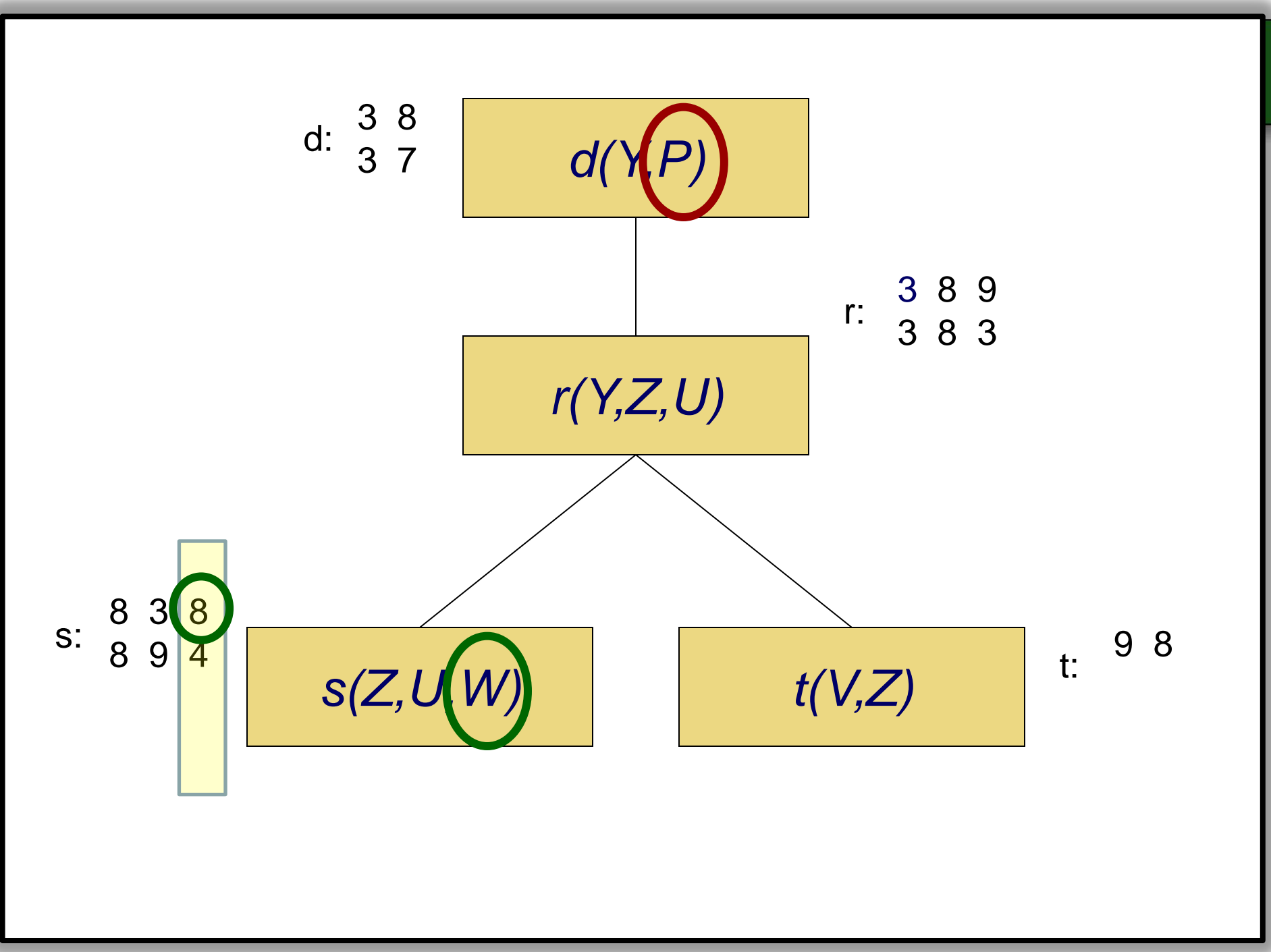
s: 8 3
8 9

8
4

$s(Z, U, W)$

t: 9 8

$t(V, Z)$



d: 3 8
3 7

$d(Y, P)$

r: 3 8 9
3 8 3

$r(Y, Z, U)$

s: 8 3 8
~~8 9 4~~

8

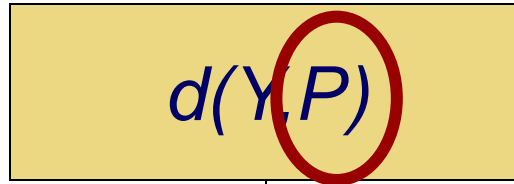
$s(Z, U, W)$

$t(V, Z)$

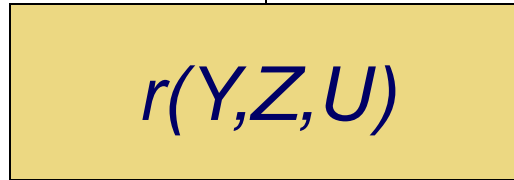
t: 9 8

Fix a value, and propagate

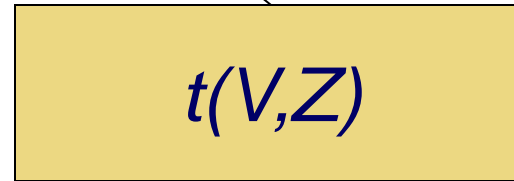
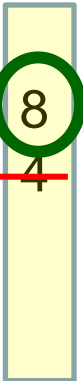
d: 3 8
3 7



r: ~~3 8 9~~
3 8 3



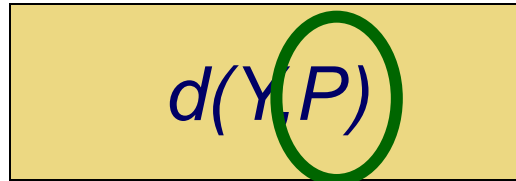
s: 8 3 8
~~8 9 4~~



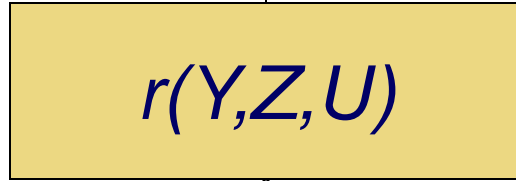
t: 9 8

Fix a value, and propagate

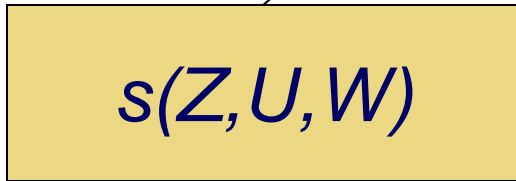
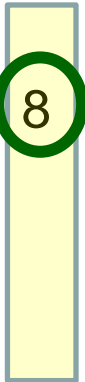
d: 3 8
3 7



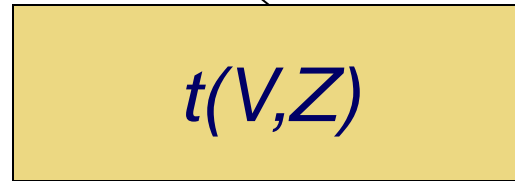
r: 3 8 3



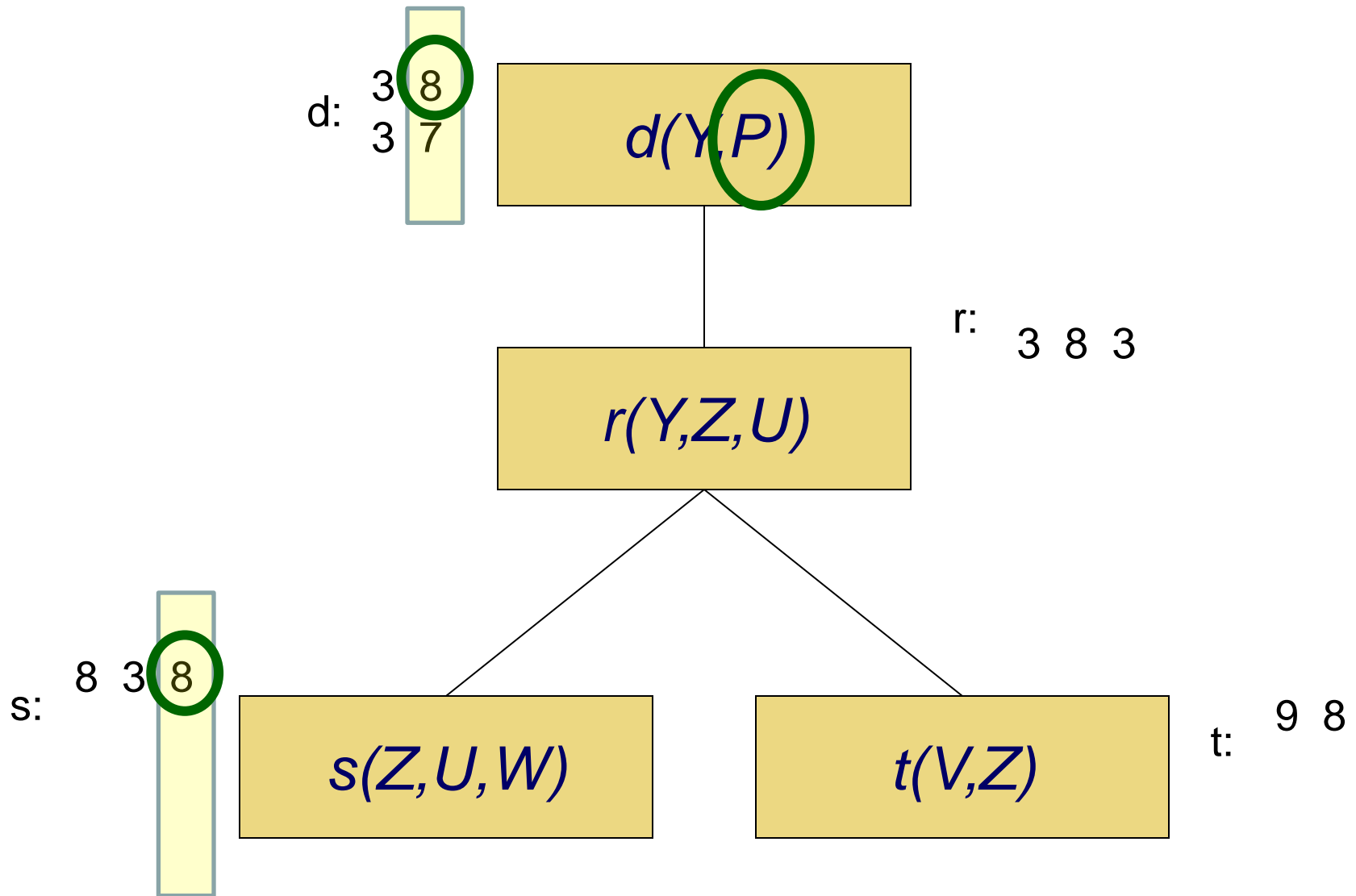
s: 8 3



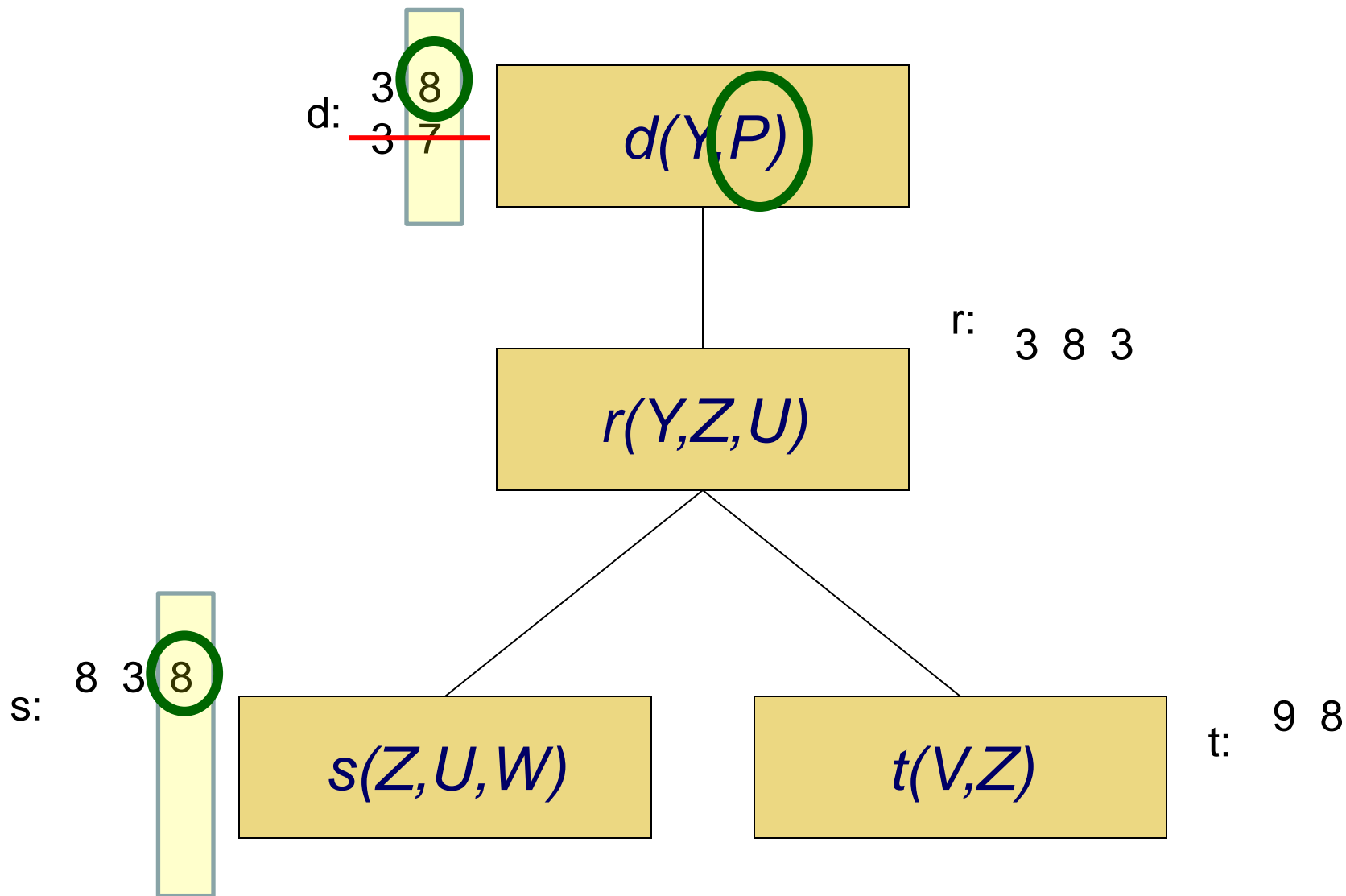
t: 9 8



Focus on the next variable



Fix a value, and propagate



Fix a value, and propagate

d: 3 8
~~3 7~~

$d(Y, P)$

r: 3 8 3

$r(Y, Z, U)$

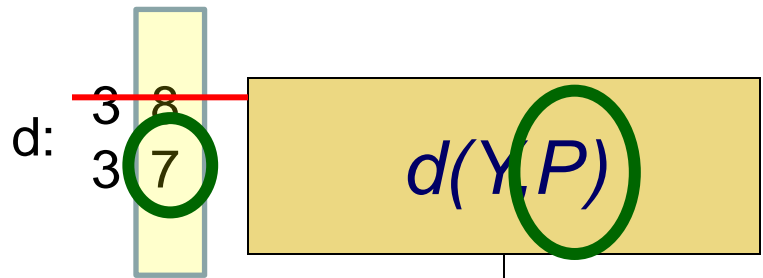
s: 8 3 8

$s(Z, U, W)$

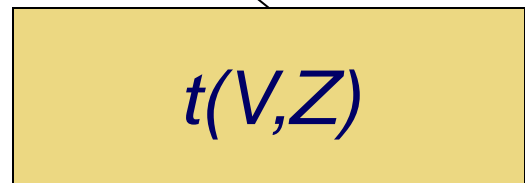
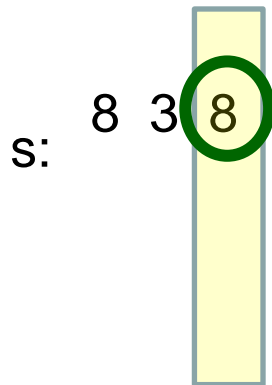
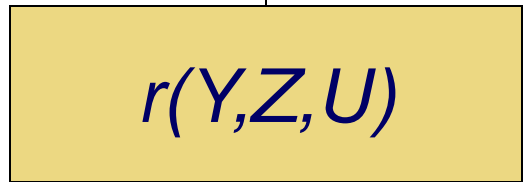
$t(V, Z)$

t: 9 8

Iterate with a different value

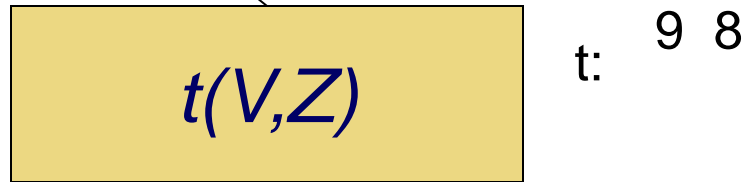
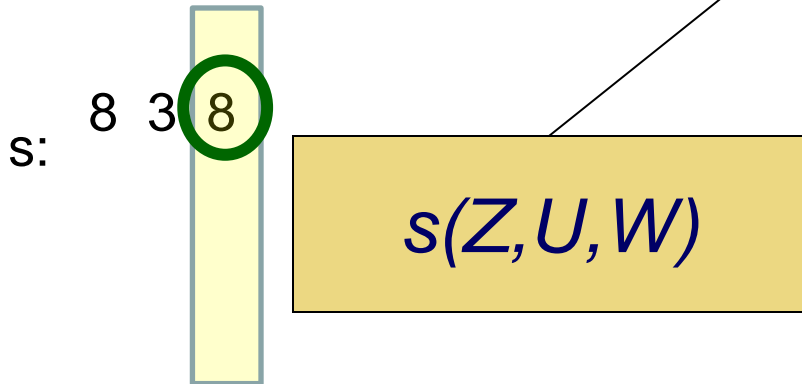
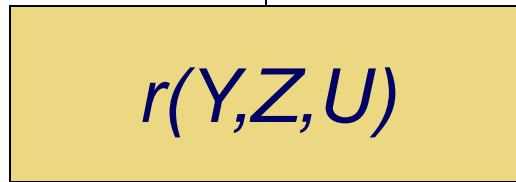
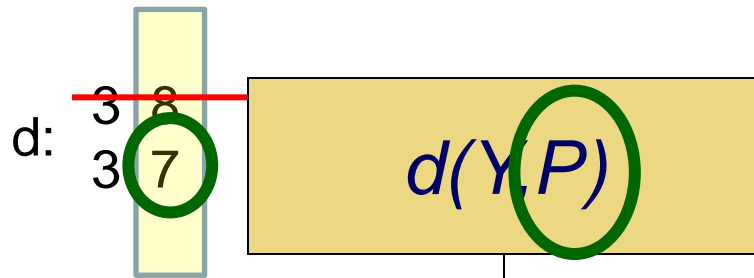


r: 3 8 3



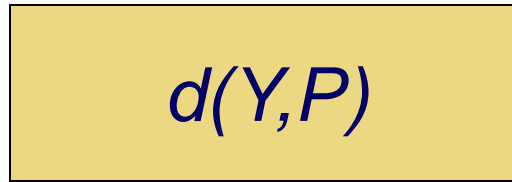
t: 9 8

Iterate with a different value

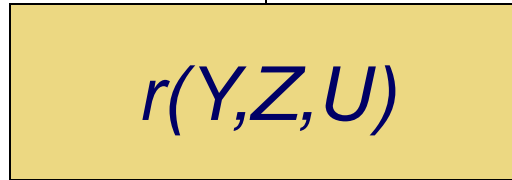


Explore the next value on the previous variable

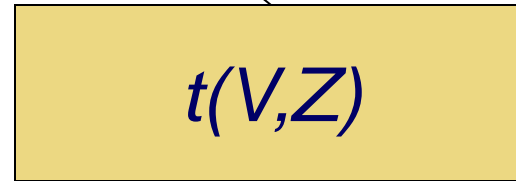
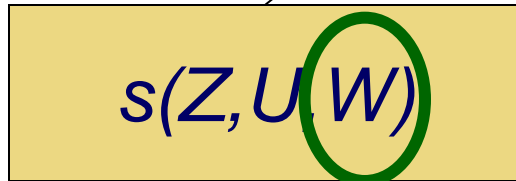
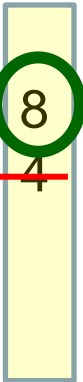
d: 3 8
3 7



r: 3 8 9
3 8 3



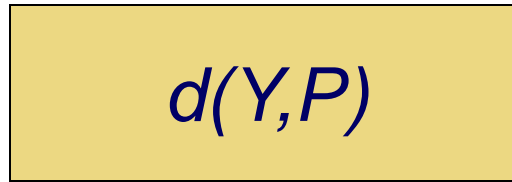
s: 8 3 8
~~8 9 4~~



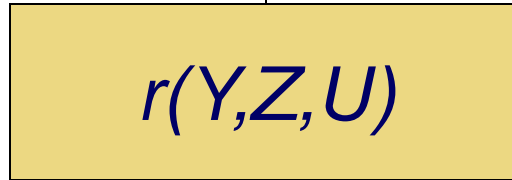
t: 9 8

Explore the next value on the previous variable

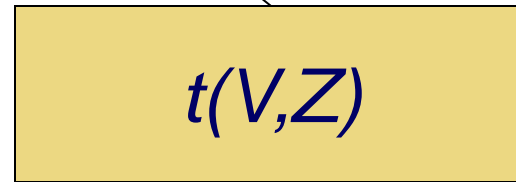
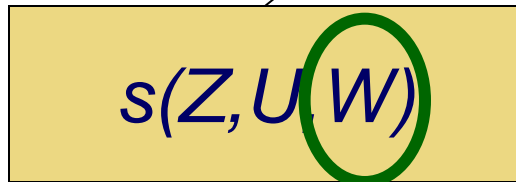
d: 3 8
3 7



r: 3 8 9
3 8 3



s: ~~8 3 8~~
8 9 4



t: 9 8

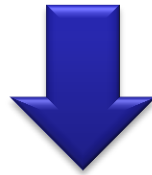
Explore the next value on the previous variable

Putting It All Together

- Bottom-Up + Top-Down propagation
- Fix X_1 to the next value and *propagate*
 - Fix X_2 to the next value and *propagate*
 - ...
 - Fix X_n to the next value and *propagate*

Putting It All Together

- Bottom-Up + Top-Down propagation
- Fix X_1 to the next value and *propagate*
 - Fix X_2 to the next value and *propagate*
 - ...
 - Fix X_n to the next value and *propagate*



Output the given solution

Putting It All Together

- Bottom-Up + Top-Down propagation

- Fix X_1 to the next value and *propagate*

- Fix X_2 to the next value and *propagate*

...

- Fix X_n to the next value and *propagate*



Putting It All Together

- Bottom-Up + Top-Down propagation

- Fix X_1 to the next value and *propagate*

- Fix X_2 to the next value and *propagate*

...

- Fix X_n to the next value and *propagate*



After the propagation phase,
every remaining tuple participates in at least one solution

Putting It All Together

- Bottom-Up + Top-Down propagation

- Fix X_1 to the next value and *propagate*

- Fix X_2 to the next value and *propagate*

...

- Fix X_n to the next value and *propagate*



Backtracking with no wrong choices



Enumeration WPD



Outline

Identification of “Easy” Classes

Applications of Tree Decompositions

Beyond Tree Decompositions

Decision/Computation Problems

Optimization Problems

Enumeration Problems

Appendix: The Frontier of Tractability

The Core

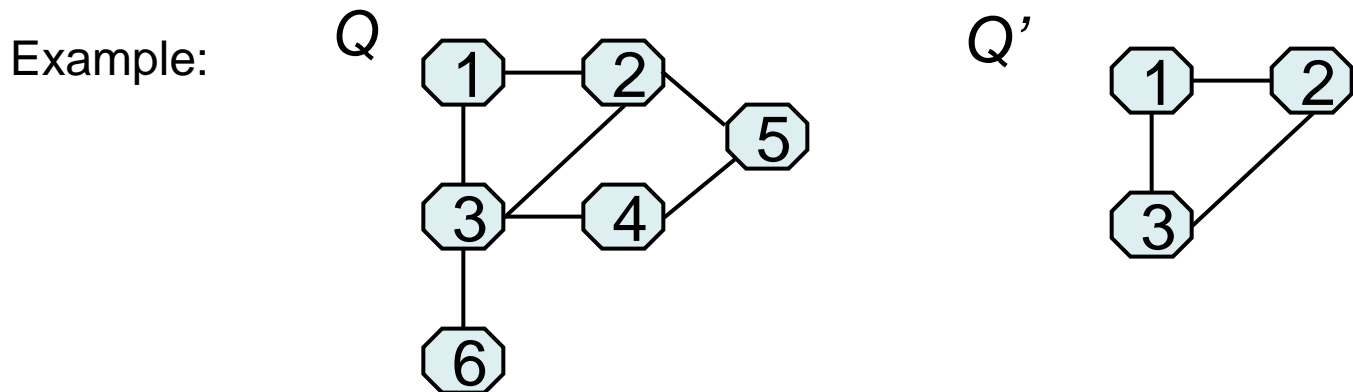
The core of a query Q is a query Q' s.t.:

1. $atoms(Q') \subseteq atoms(Q)$
2. There is a mapping $h: var(Q) \rightarrow var(Q')$
s.t., $\forall r(\mathbf{X}) \in atoms(Q), r(h(\mathbf{X})) \in atoms(Q')$
3. There is no query Q'' satisfying 1 and 2 and such
that $atoms(Q'') \subset atoms(Q')$


The Core

The core of a query Q is a query Q' s.t.:

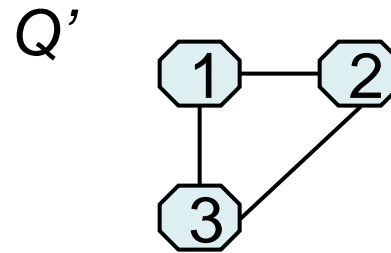
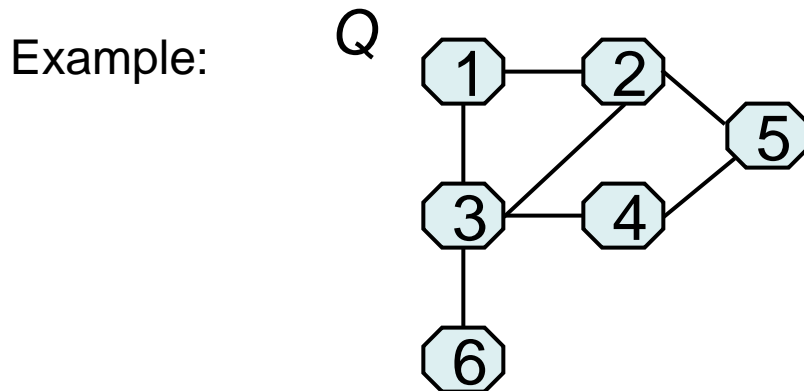
1. $atoms(Q') \subseteq atoms(Q)$
2. There is a mapping $h: var(Q) \rightarrow var(Q')$ s.t., $\forall r(\mathbf{X}) \in atoms(Q), r(h(\mathbf{X})) \in atoms(Q')$
3. There is no query Q'' satisfying 1 and 2 and such that $atoms(Q'') \subset atoms(Q')$



The Core

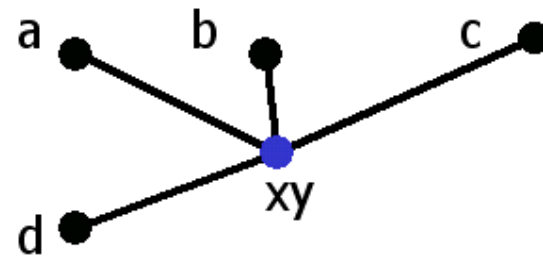
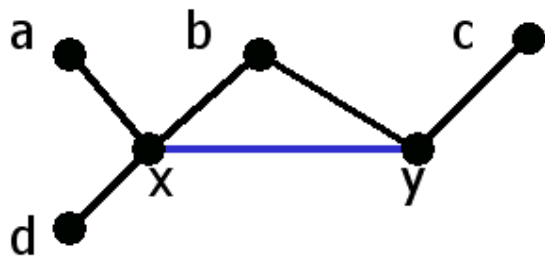
Cores are isomorphic  The “Core”

Cores are equivalent to the query



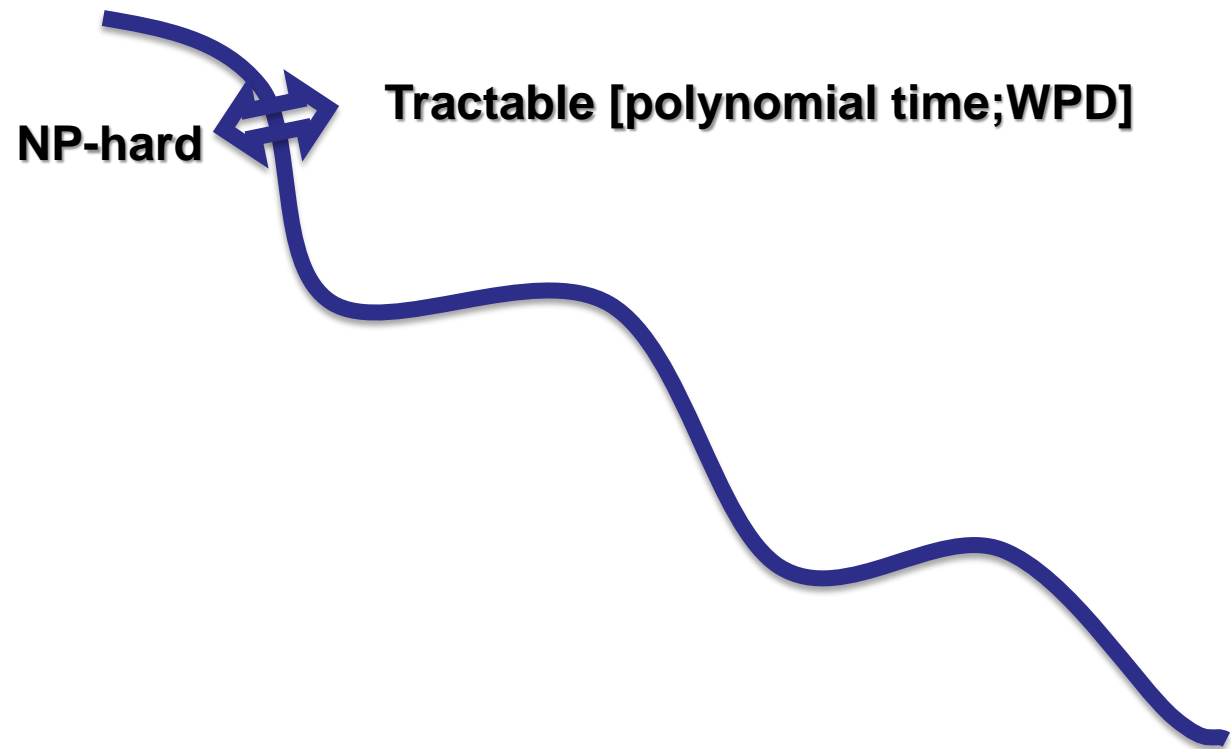
Graph Minors

- H is a minor of G if it can be obtained by repeatedly applying:
 - Edge deletion
 - Vertex deletion
 - Edge contraction



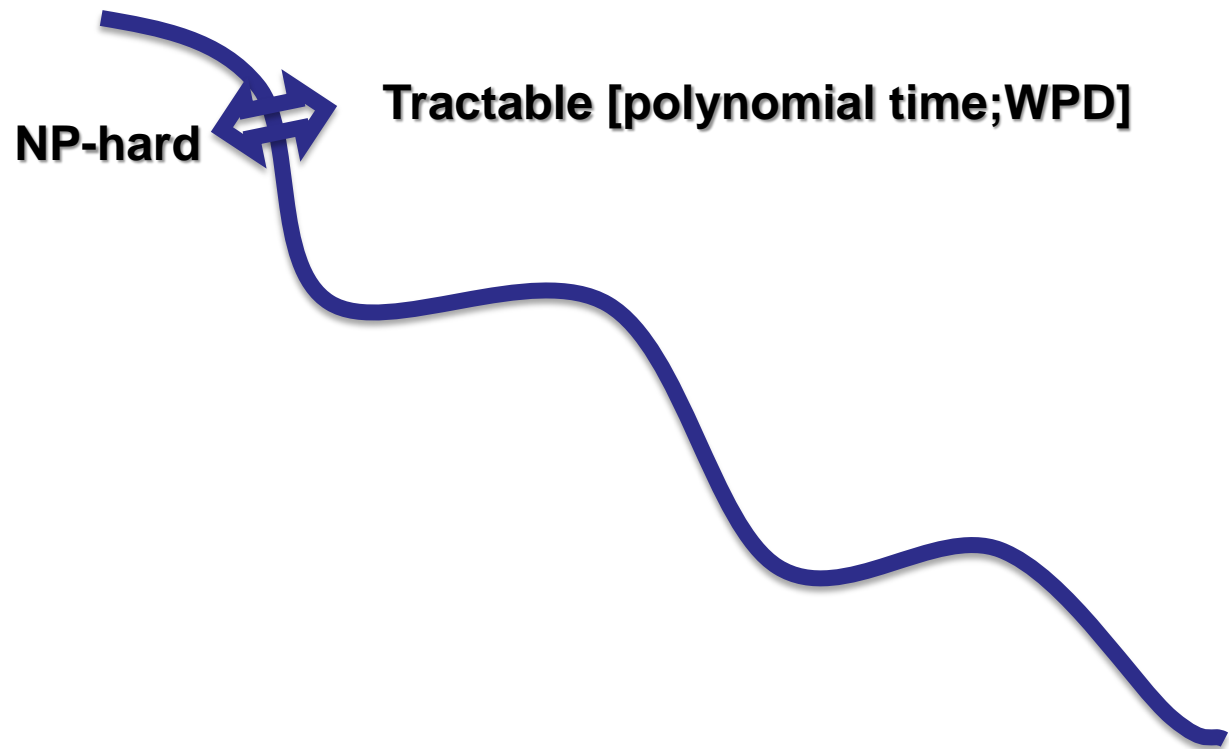
The Frontier of Tractability

- Let **A** be a class of structures:



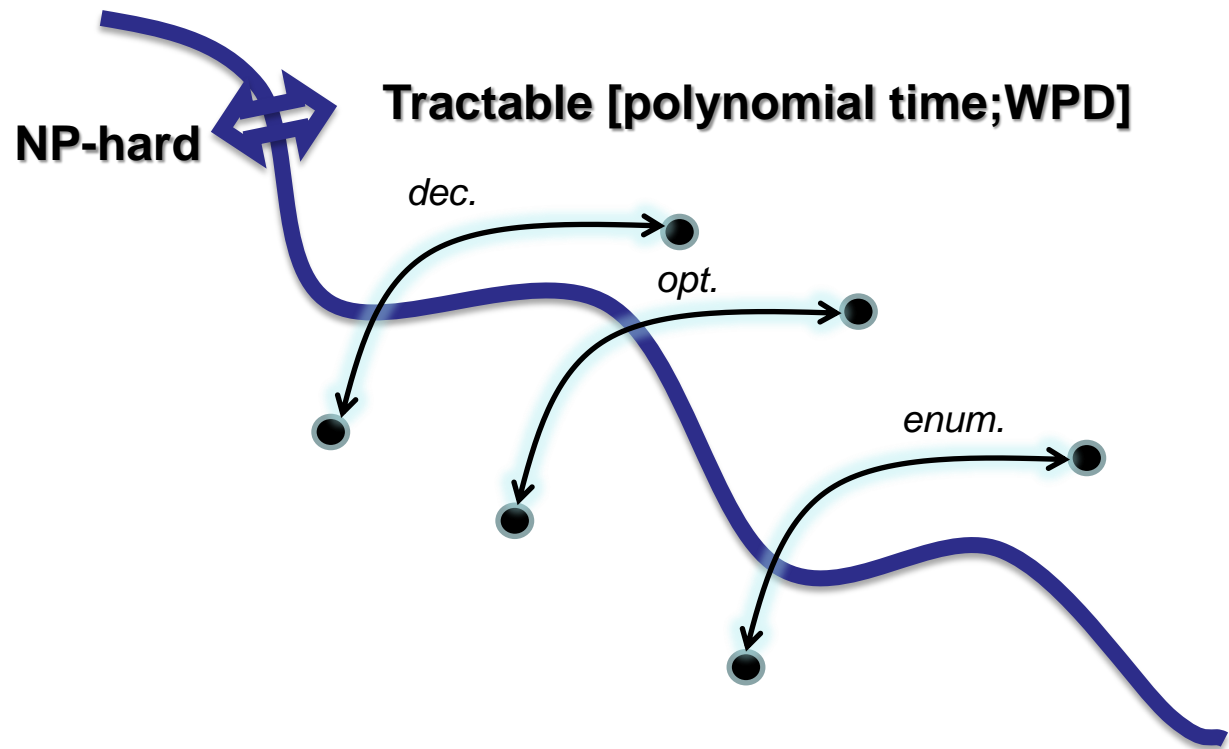
The Frontier of Tractability

- Let **A** be a class of structures:
 - Assume $FPT \neq WP[1]$



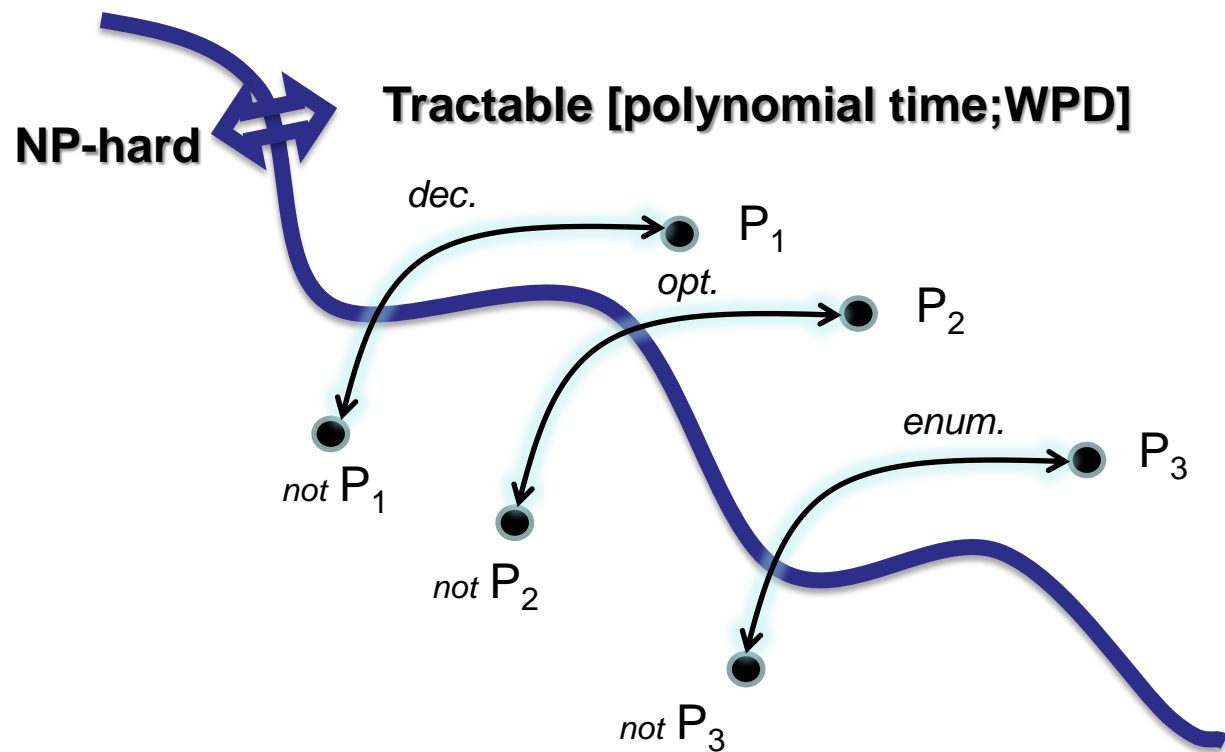
The Frontier of Tractability

- Let **A** be a class of structures:
 - Assume $FPT \neq WP[1]$



The Frontier of Tractability

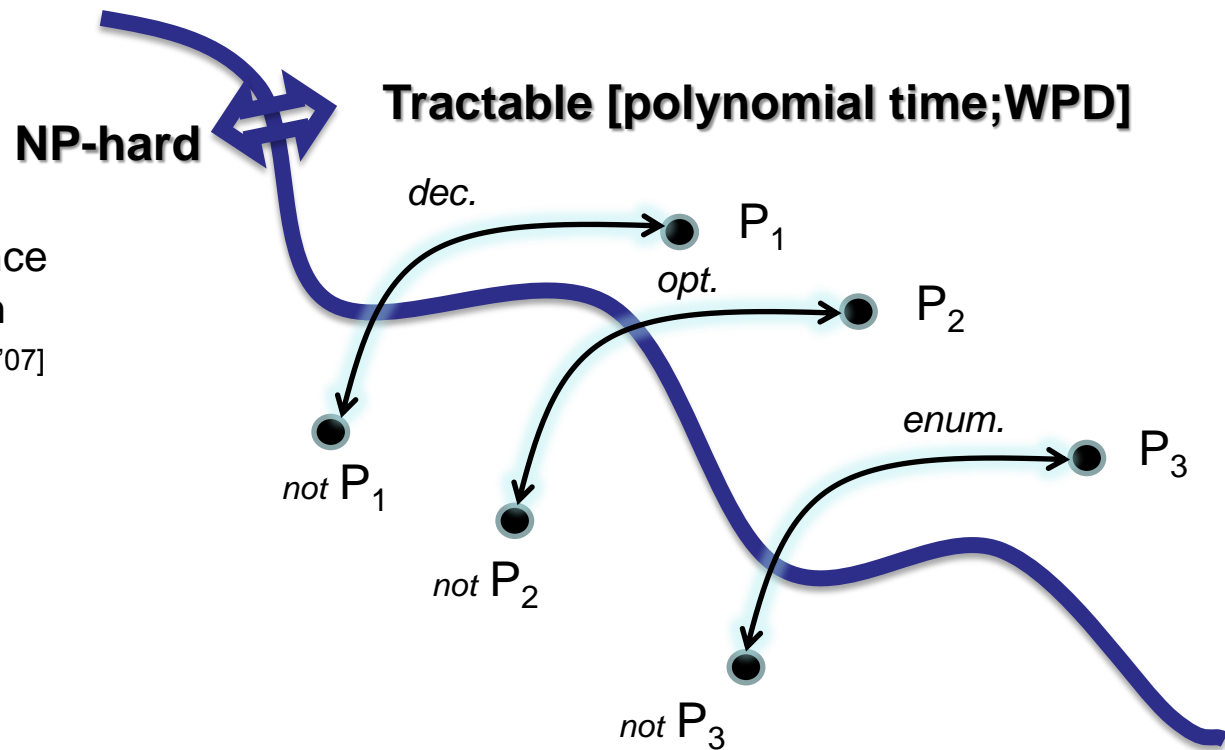
- Let \mathbf{A} be a class of structures:
 - Assume $\text{FPT} \neq \text{WP}[1]$



The Frontier of Tractability

- Let \mathbf{A} be a class of structures:
 - Assume $\text{FPT} \neq \text{WP}[1]$

- \mathbf{P}_1 : The core of each instance in \mathbf{A} has bounded treewidth
[Grohe, '07]

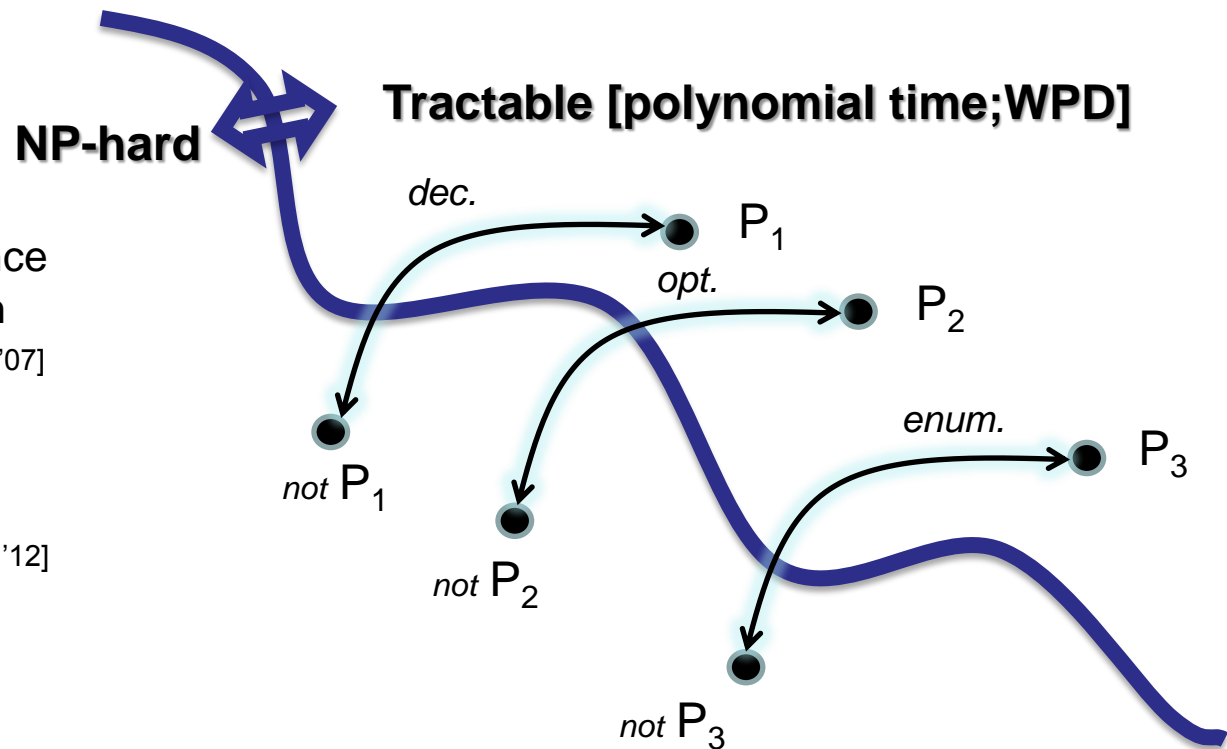


The Frontier of Tractability

- Let \mathbf{A} be a class of structures:
 - Assume $\text{FPT} \neq \text{WP}[1]$

- P_1 : The core of each instance in \mathbf{A} has bounded treewidth
[Grohe, '07]

- P_2 : Each instance in \mathbf{A} has bounded treewidth
[Greco & Scarcello, '12]



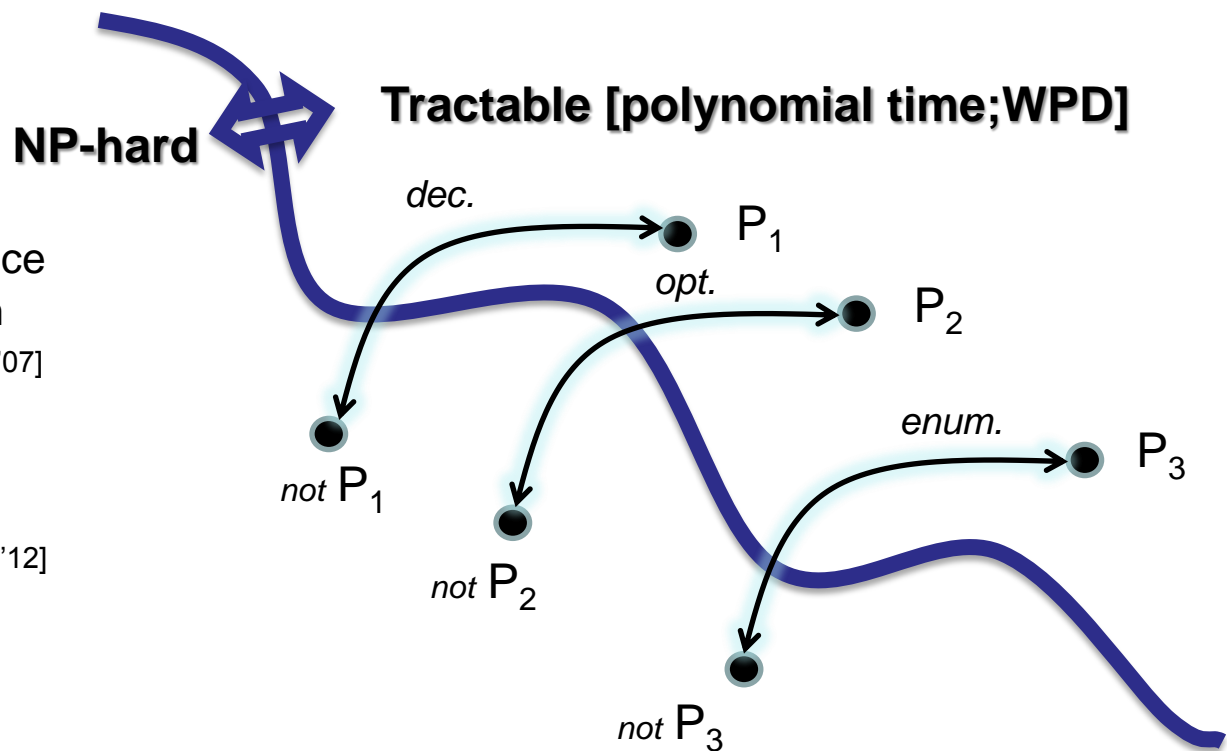
The Frontier of Tractability

- Let **A** be a class of structures:
 - Assume $FPT \neq WP[1]$
- Assume **A** is *closed under taking minors*

- **P₁**: The core of each instance in **A** has bounded treewidth
[Grohe, '07]

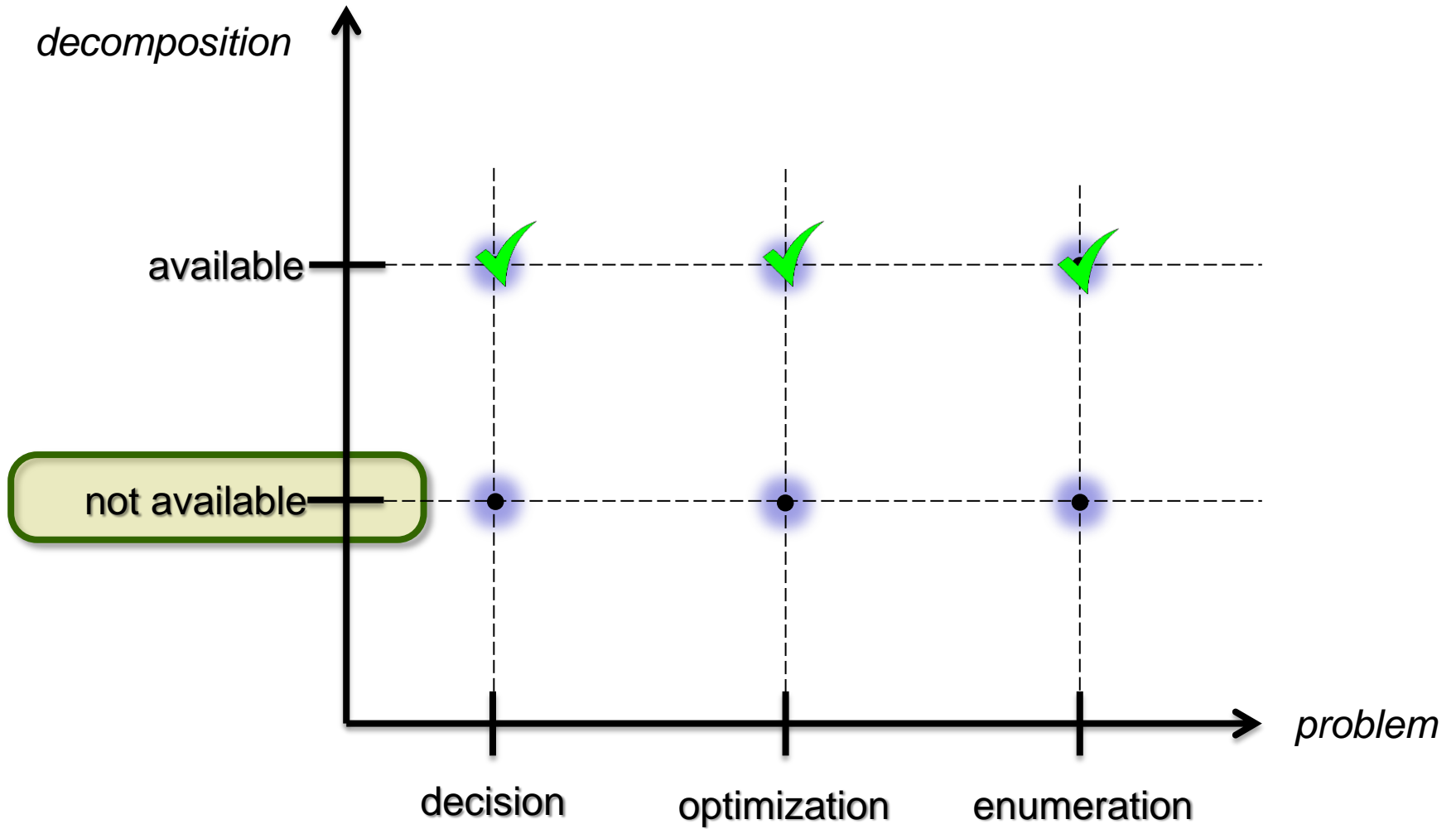
- **P₂**: Each instance in **A** has bounded treewidth
[Greco & Scarcello, '12]

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[Greco & Scarcello, '11]

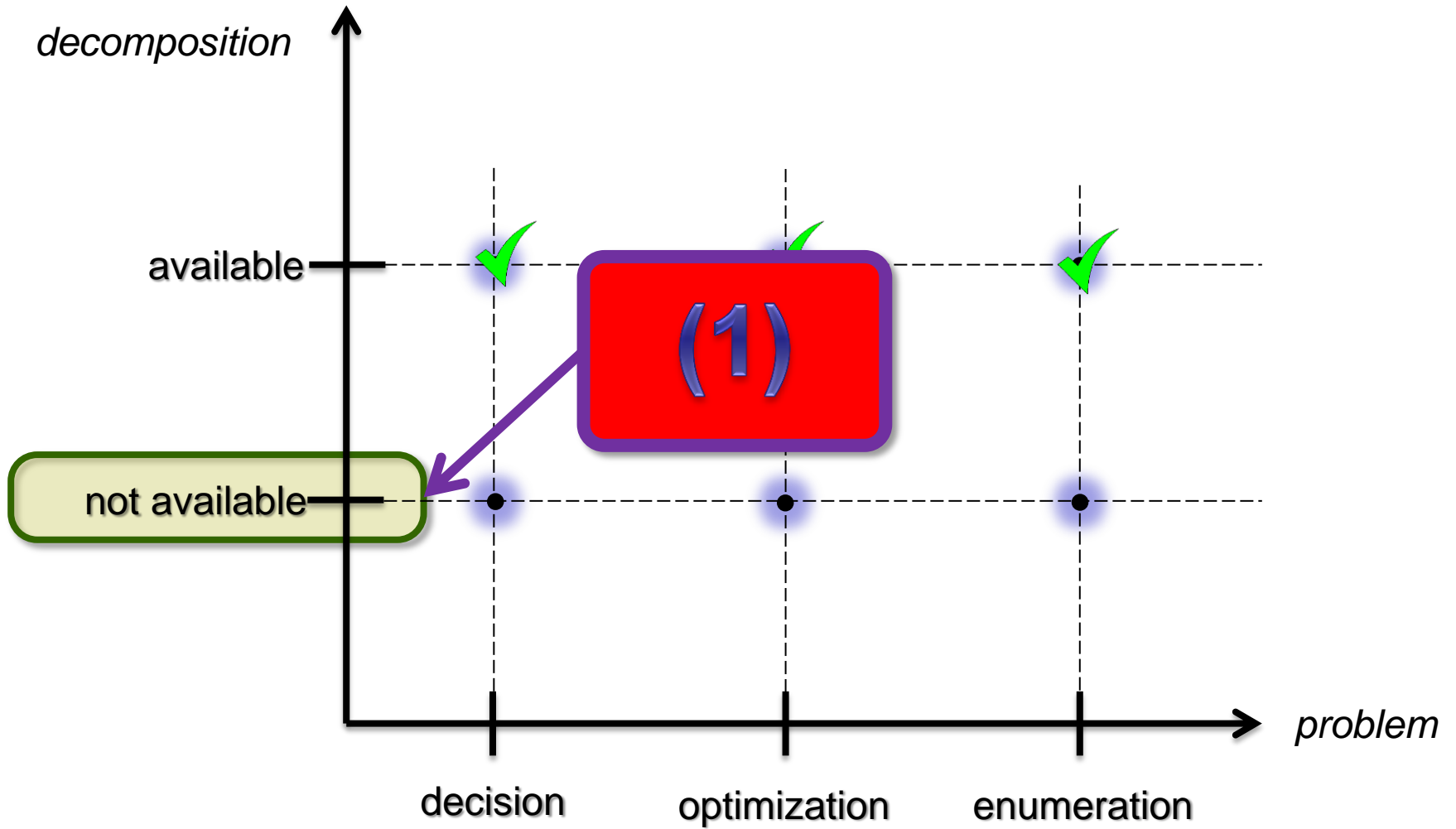


Appendix: Methods without Decompositions

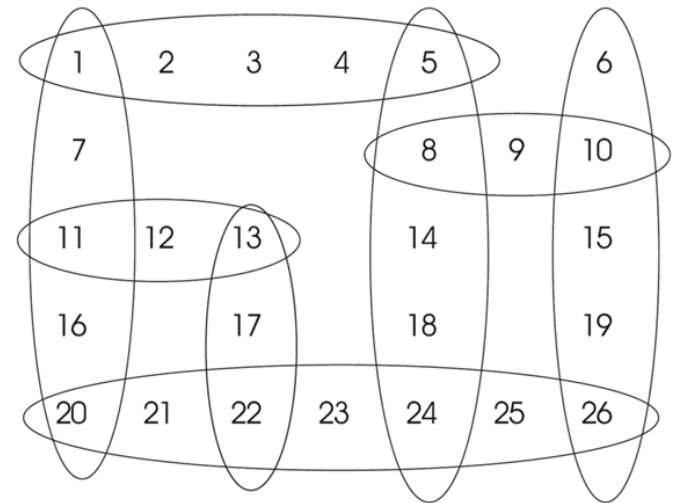
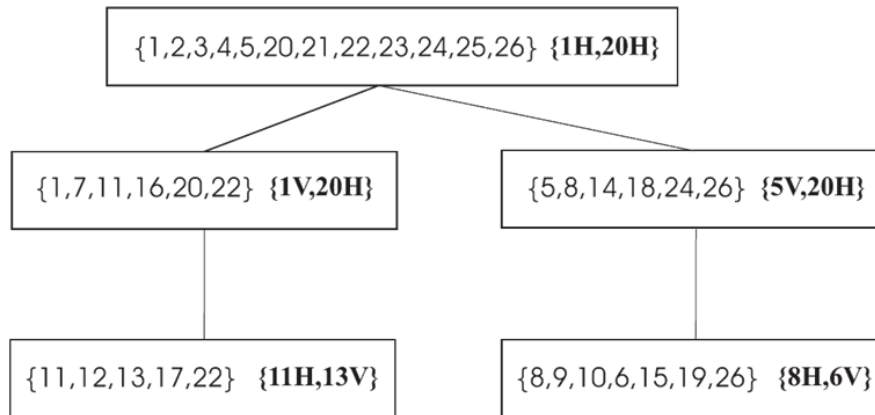
Overview



Overview



Revisiting Decomposition Methods



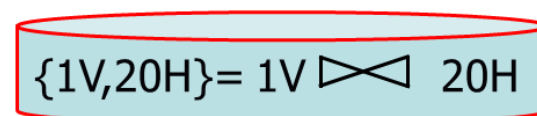
\mathcal{H}_A

Each cluster can be seen as a **subproblem**

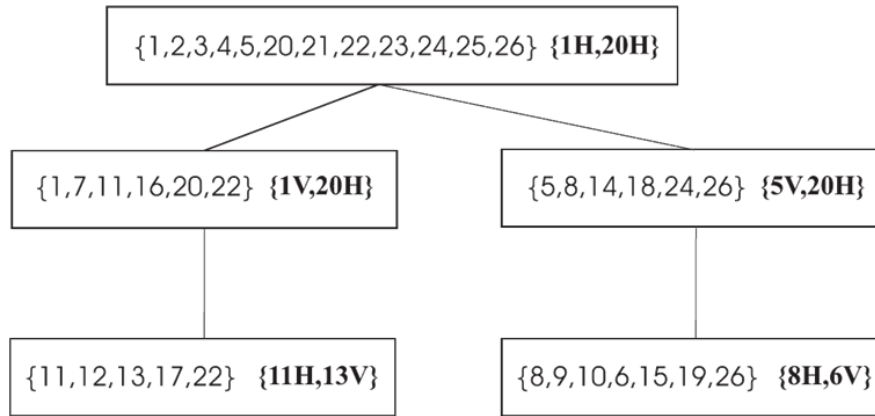
Relations:



Relations:

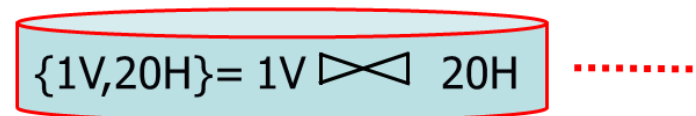


Revisiting Decomposition Methods

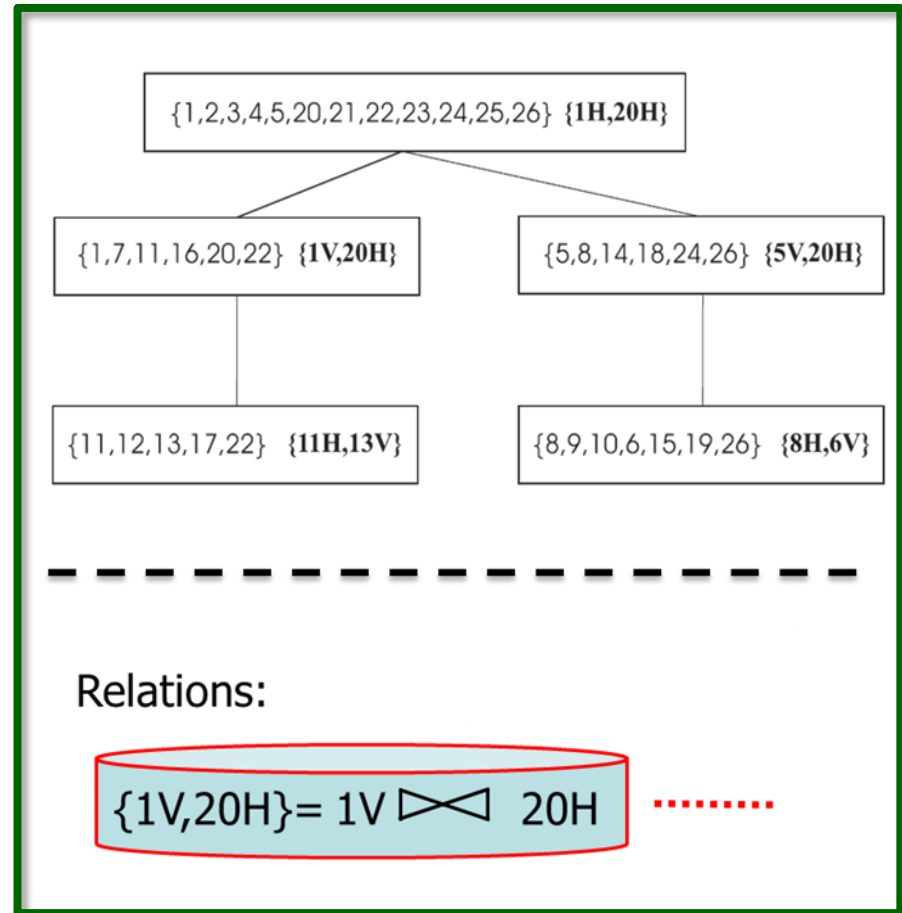


Each cluster can be seen as a **subproblem**

Relations:



Revisiting Decomposition Methods

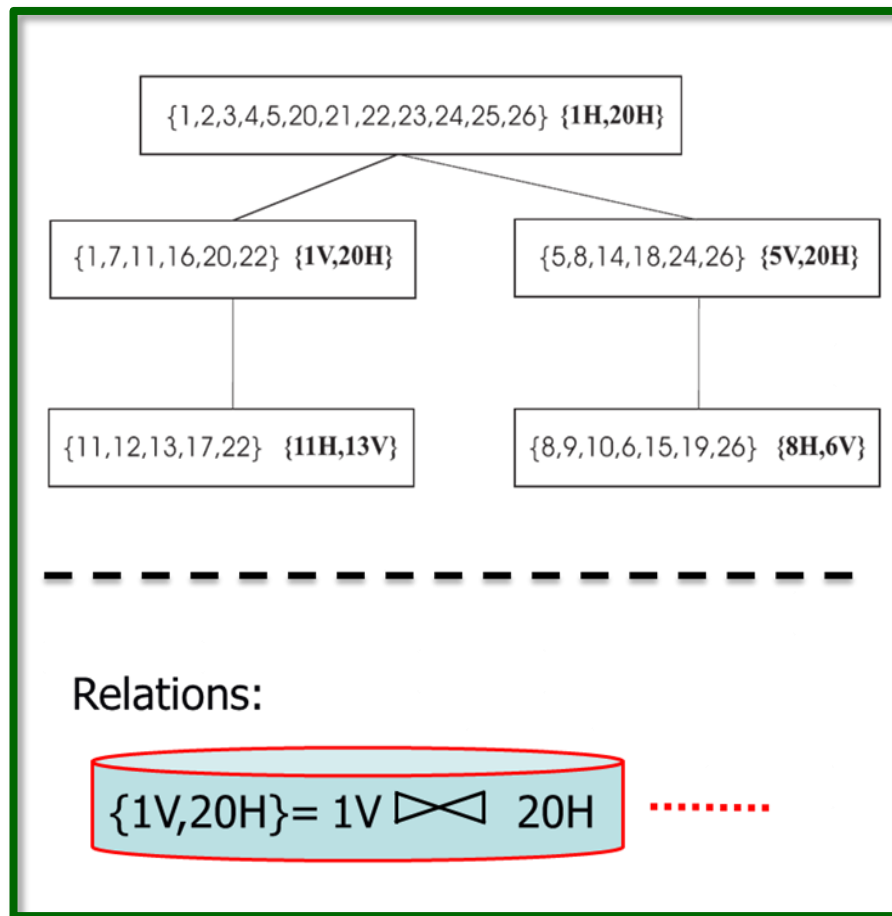


Revisiting Decomposition Methods

CSP instance (A, B)



$$A_{\mathcal{V}} = \ell\text{-DM}(A) \quad \Big| \quad B_{\mathcal{V}} = r\text{-DM}(A, B)$$



Revisiting Decomposition Methods

CSP instance (A, B)

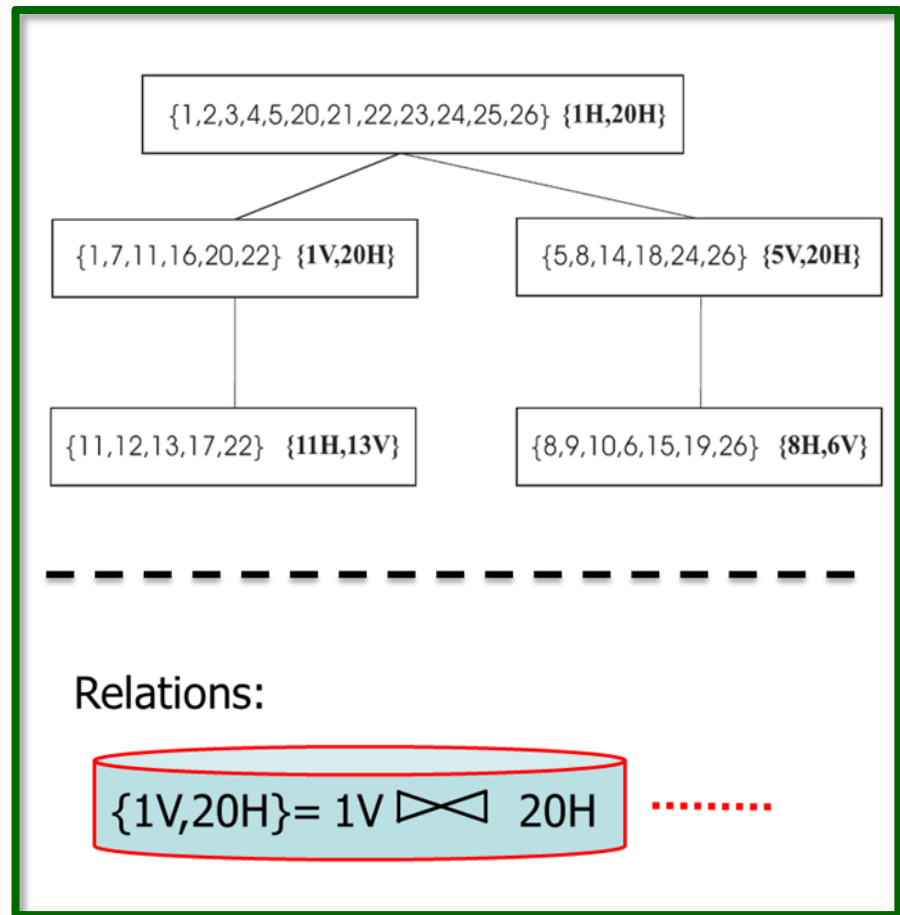


$$A_{\mathcal{V}} = \ell\text{-DM}(A) \quad | \quad B_{\mathcal{V}} = r\text{-DM}(A, B)$$

Scopes

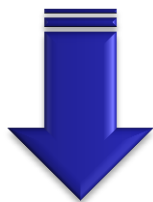
Solutions

Work on subproblems



Revisiting Decomposition Methods

CSP instance (A, B)



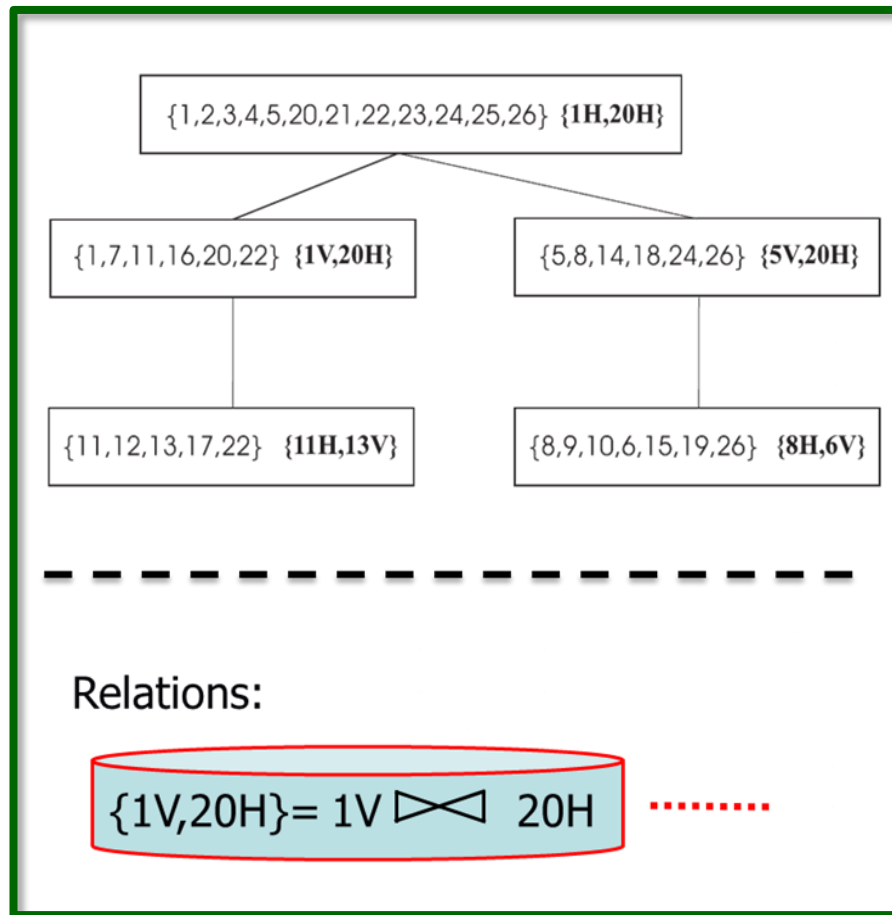
$$A_{\mathcal{V}} = \ell\text{-DM}(A) \quad | \quad B_{\mathcal{V}} = r\text{-DM}(A, B)$$

Scopes

Solutions

Work on subproblems

- Generalized hypertree width: take all views that can be computed by joining at most k atoms (k query views)



Revisiting Decomposition Methods

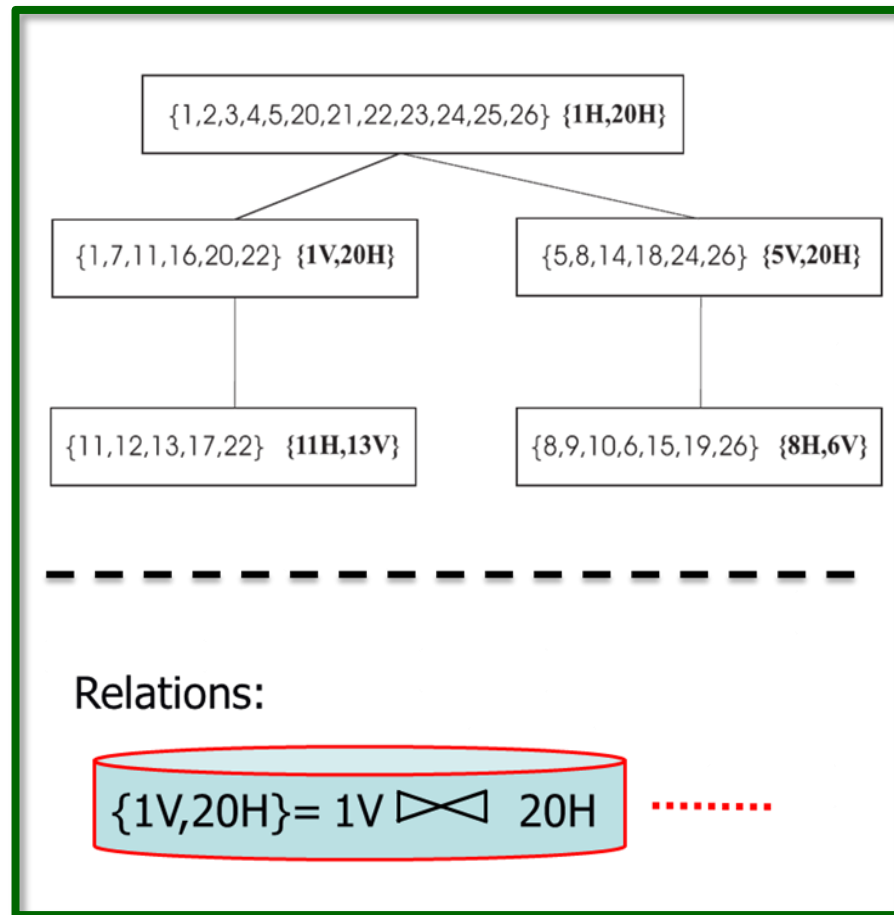
CSP instance (\mathbb{A}, \mathbb{B})



$$\mathbb{A}_V = \ell\text{-DM}(\mathbb{A}) \quad \mathbb{B}_V = r\text{-DM}(\mathbb{A}, \mathbb{B})$$



- *Generalized hypertree width:*
take all views that can be computed by joining at most k atoms (k query views)



Requirements on Subproblem Definition

CSP instance (\mathbb{A}, \mathbb{B})



$$\mathbb{A}_\gamma = \ell\text{-DM}(\mathbb{A}) \quad \mathbb{B}_\gamma = r\text{-DM}(\mathbb{A}, \mathbb{B})$$

1. Every subproblem is not more restrictive than the full problem
2. Every base subproblem is at least restrictive as the corresponding constraint

1. Every constraint is associated with a base subproblem
2. Further subproblems can be defined

Acyclicity in Decomposition Methods

CSP instance (A, B)



$A_{\mathcal{V}} = \ell\text{-DM}(A) \quad \text{---} \quad B_{\mathcal{V}} = r\text{-DM}(A, B)$



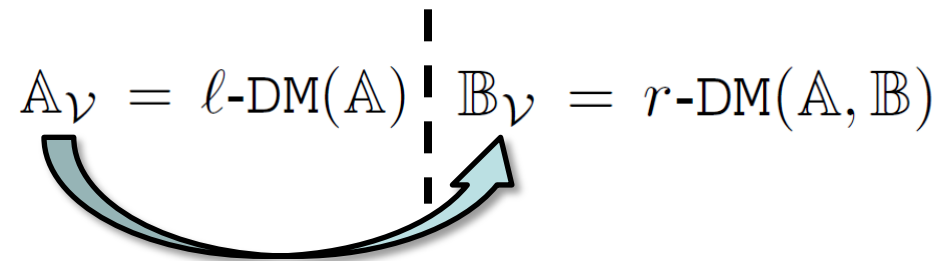
Working on subproblems is not necessarily beneficial...

Acyclicity in Decomposition Methods

CSP instance (\mathbb{A}, \mathbb{B})



Working on subproblems is not necessarily beneficial...



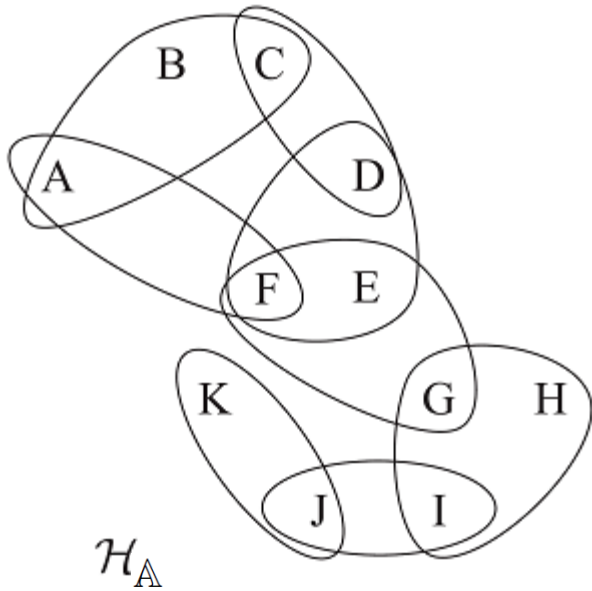
Can some and/or portions of them be selected such that:

- They still cover \mathbb{A} , and
- They can be arranged as a tree



Tree Projections (by Example)

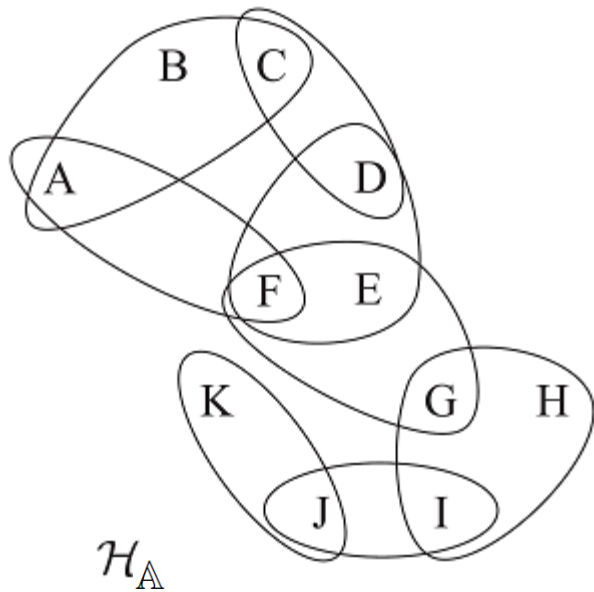
\mathbb{A} : $r_1(A, B, C)$ $r_2(A, F)$ $r_3(C, D)$ $r_4(D, E, F)$
 $r_5(E, F, G)$ $r_6(G, H, I)$ $r_7(I, J)$ $r_8(J, K)$



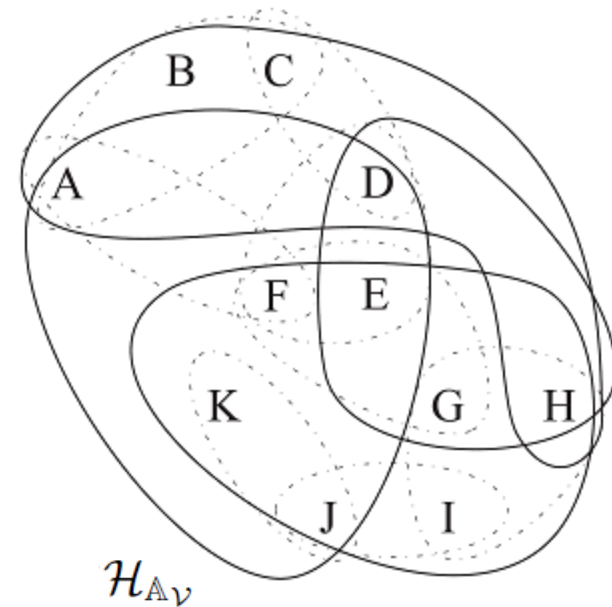
Structure of the CSP

Tree Projections (by Example)

\mathbb{A} : $r_1(A, B, C)$ $r_2(A, F)$ $r_3(C, D)$ $r_4(D, E, F)$
 $r_5(E, F, G)$ $r_6(G, H, I)$ $r_7(I, J)$ $r_8(J, K)$



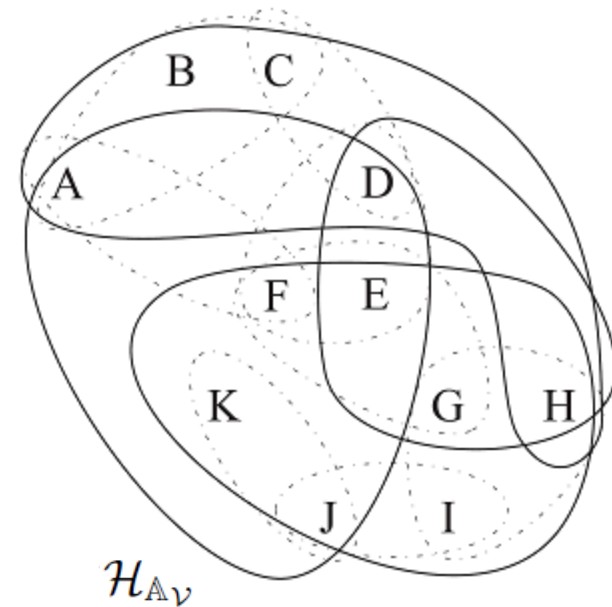
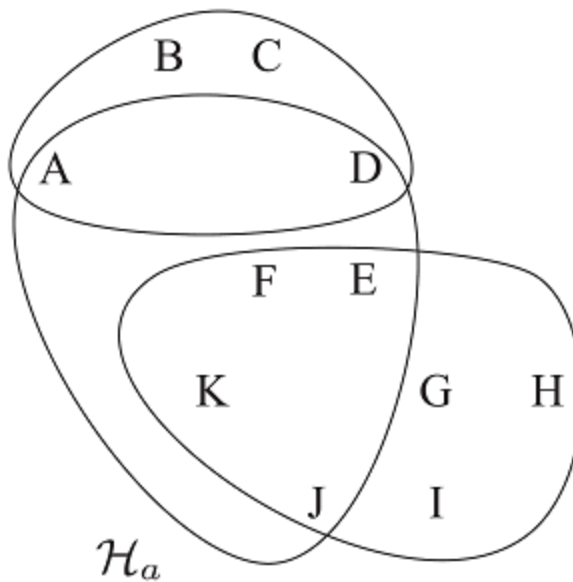
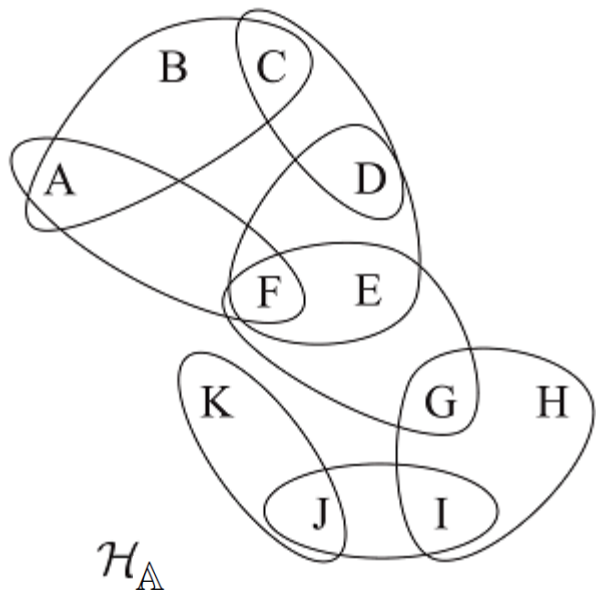
Structure of the CSP



Available Views

Tree Projections (by Example)

\mathbb{A} : $r_1(A, B, C)$ $r_2(A, F)$ $r_3(C, D)$ $r_4(D, E, F)$
 $r_5(E, F, G)$ $r_6(G, H, I)$ $r_7(I, J)$ $r_8(J, K)$



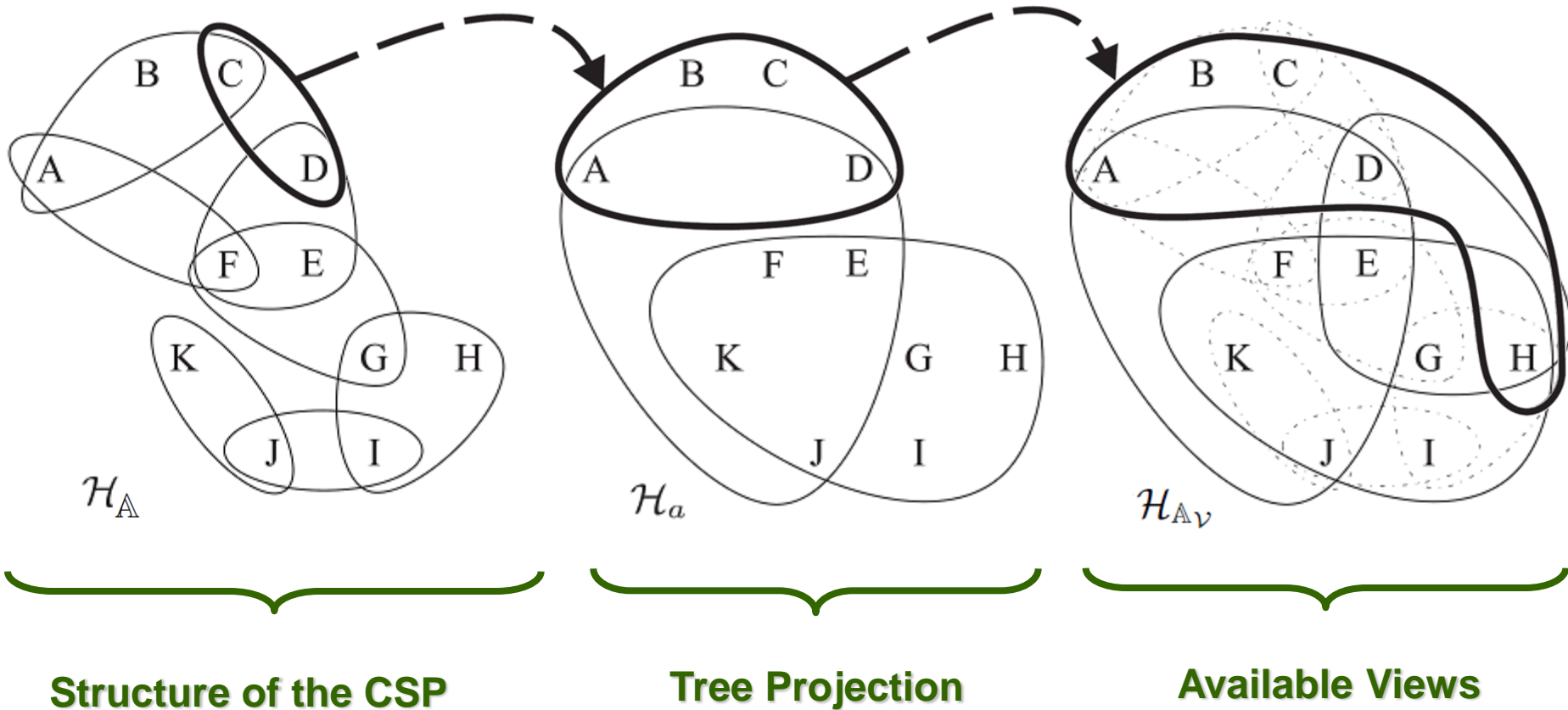
Structure of the CSP

Tree Projection

Available Views

Tree Projections (by Example)

\mathbb{A} : $r_1(A, B, C)$ $r_2(A, F)$ $r_3(C, D)$ $r_4(D, E, F)$
 $r_5(E, F, G)$ $r_6(G, H, I)$ $r_7(I, J)$ $r_8(J, K)$



(Noticeable) Examples

CSP instance (\mathbb{A}, \mathbb{B})

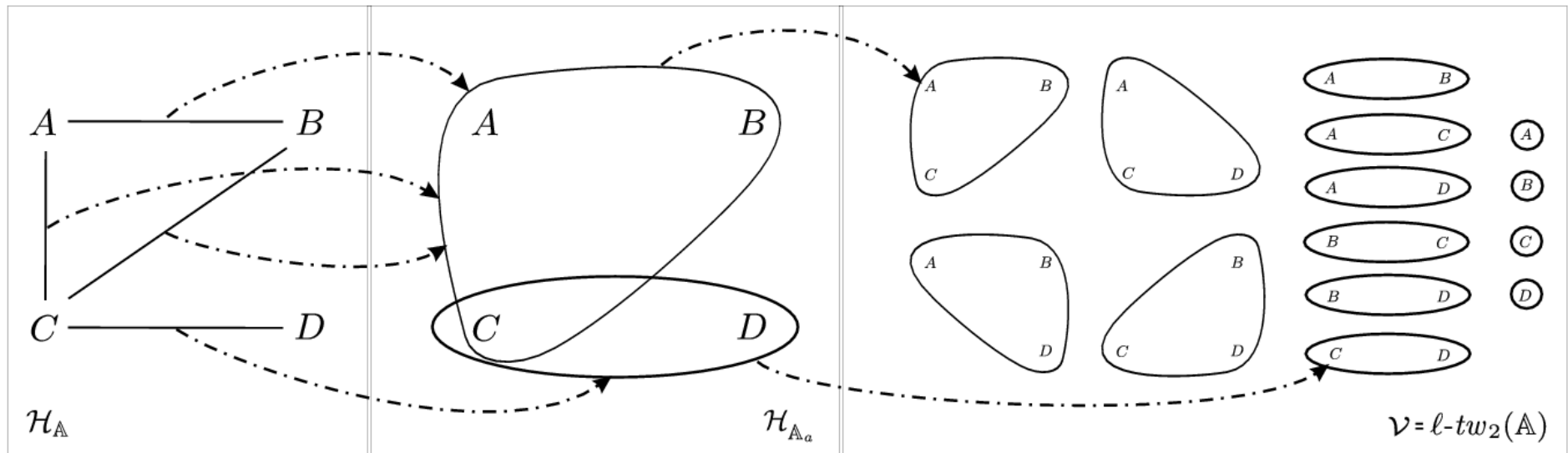


$\mathbb{A}_\mathcal{V} = \ell\text{-DM}(\mathbb{A})$ $\mathbb{B}_\mathcal{V} = r\text{-DM}(\mathbb{A}, \mathbb{B})$



- *Treewidth*: take all views that can be computed with at most k variables
- *Generalized hypertree width*: take all views that can be computed by joining at most k atoms (k query views)
- *Fractional hypertree width*: take all views that can be computed through subproblems having fractional cover at most k (or use Marx's $O(k^3)$ approximation to have polynomially many views)

Tree Decomposition



A General Framework, but

- Decide the existence of a tree projection is **NP-hard**



A General Framework, but

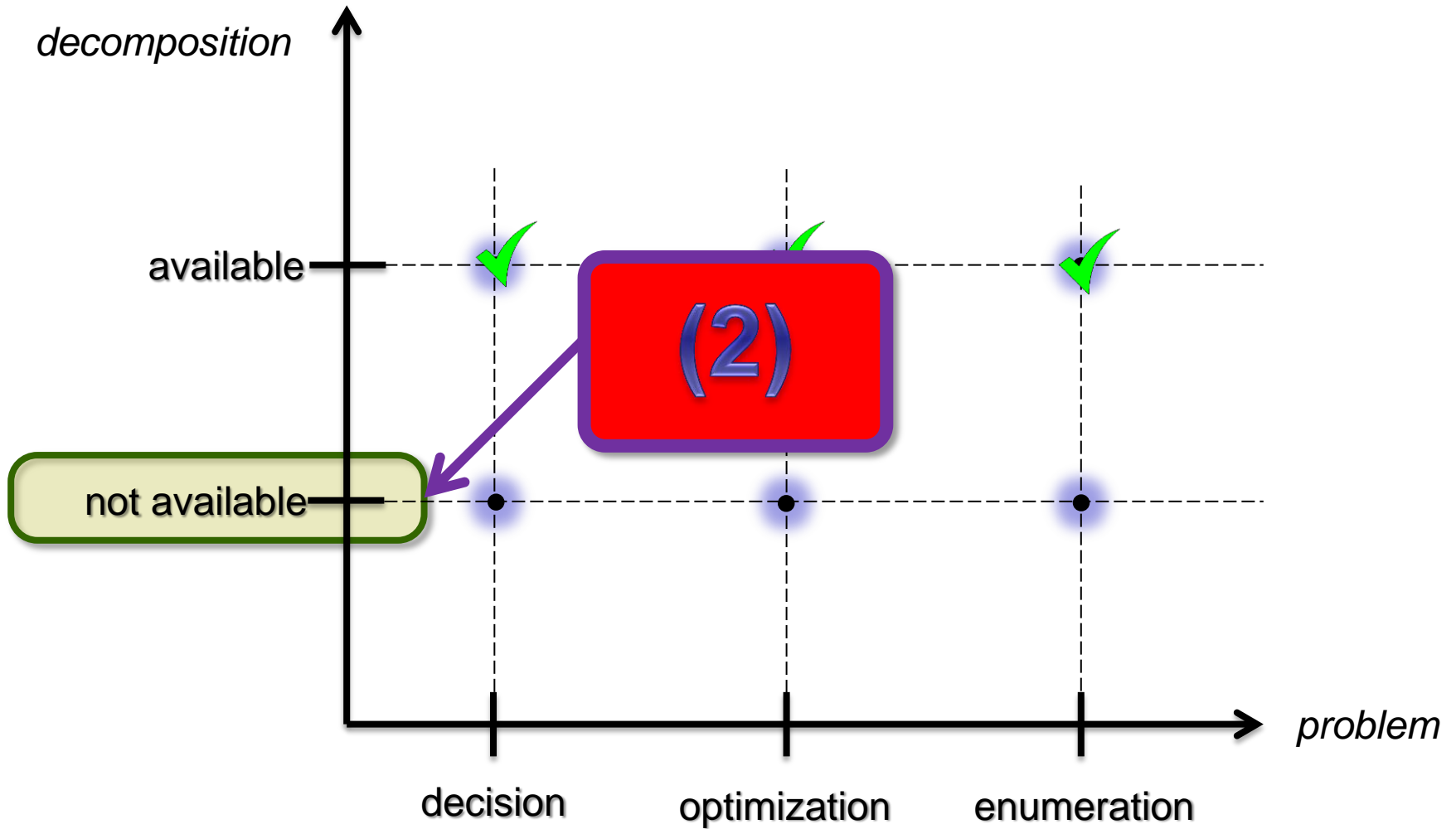
- Decide the existence of a tree projection is **NP-hard**



Hold on generalized hypertree width too.

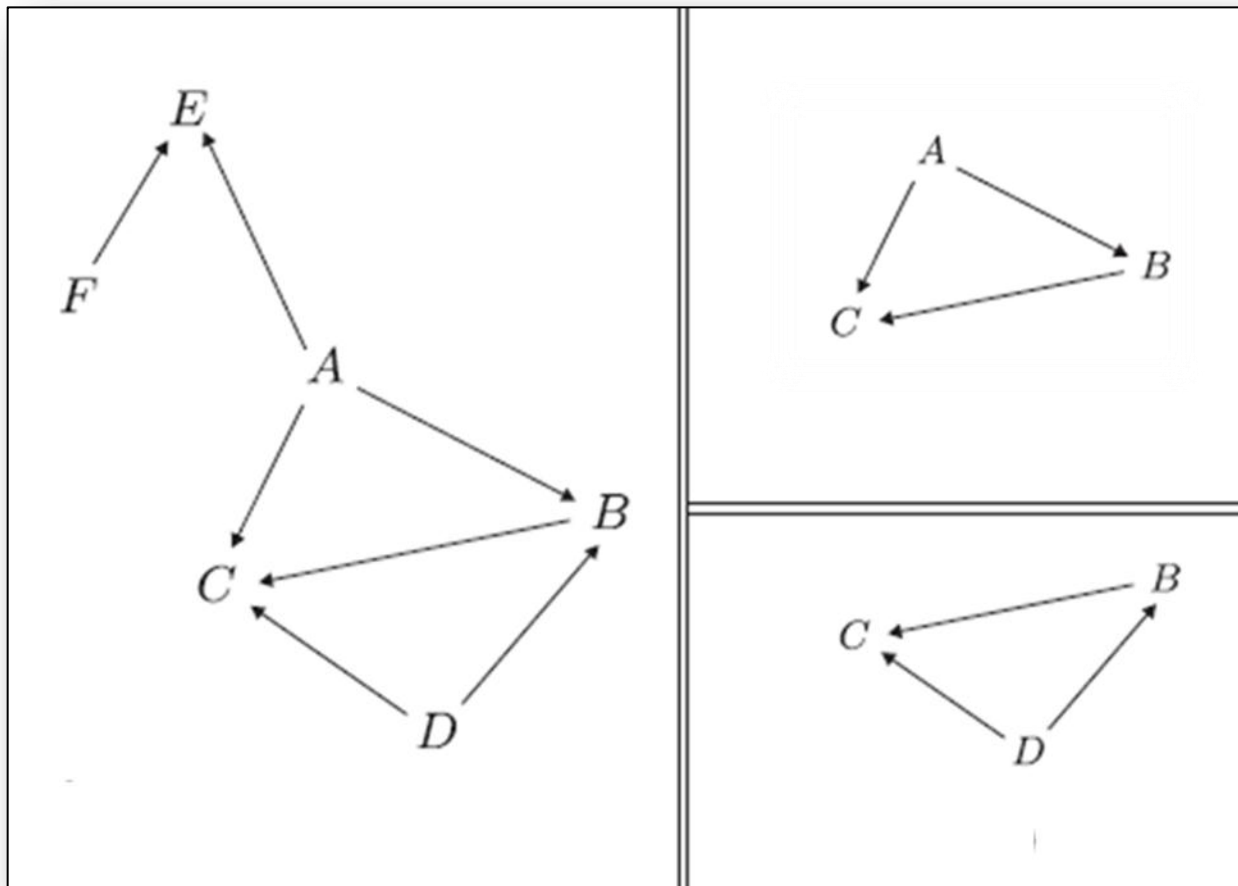


Overview



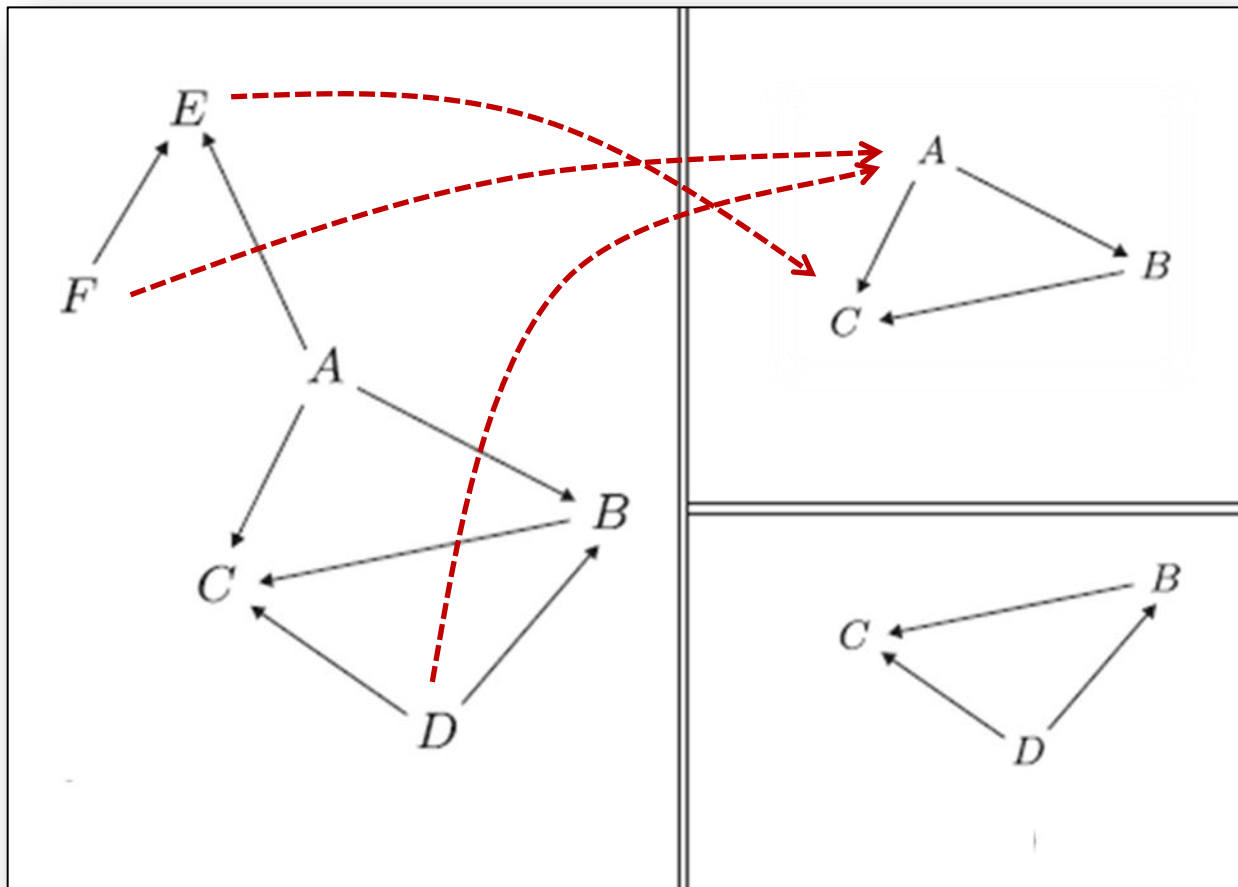
Cores and Tree Projections

Q : $r(A, B) \wedge r(B, C) \wedge r(A, C) \wedge r(D, C) \wedge$
 $r(D, B) \wedge r(A, E) \wedge r(F, E),$

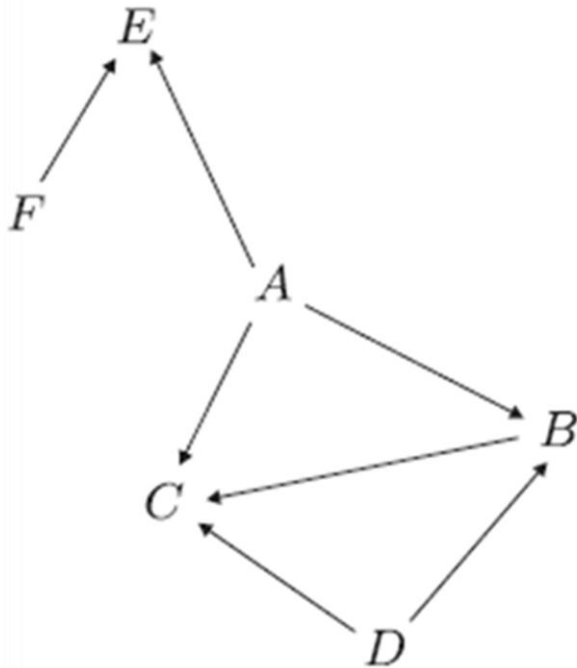


Cores and Tree Projections

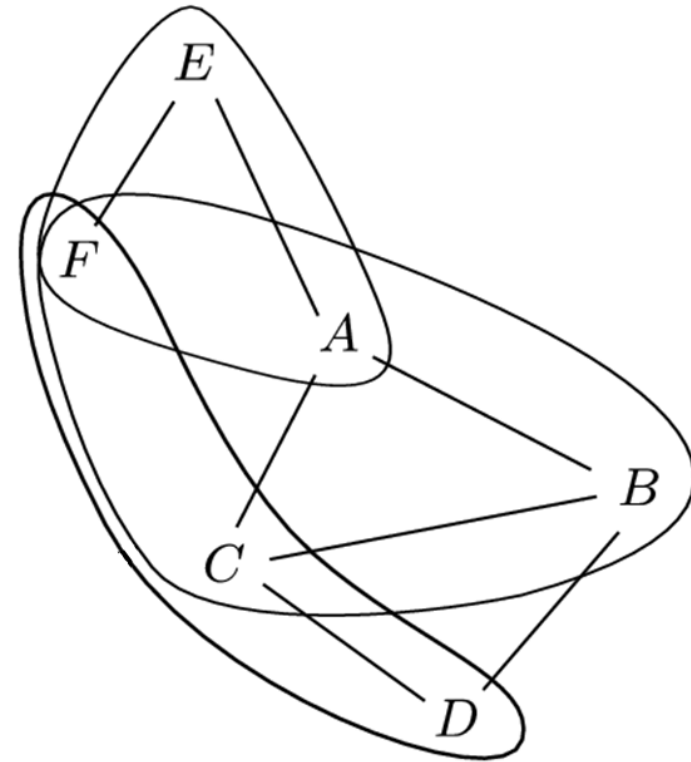
Q : $r(A, B) \wedge r(B, C) \wedge r(A, C) \wedge r(D, C) \wedge$
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Cores and Tree Projections



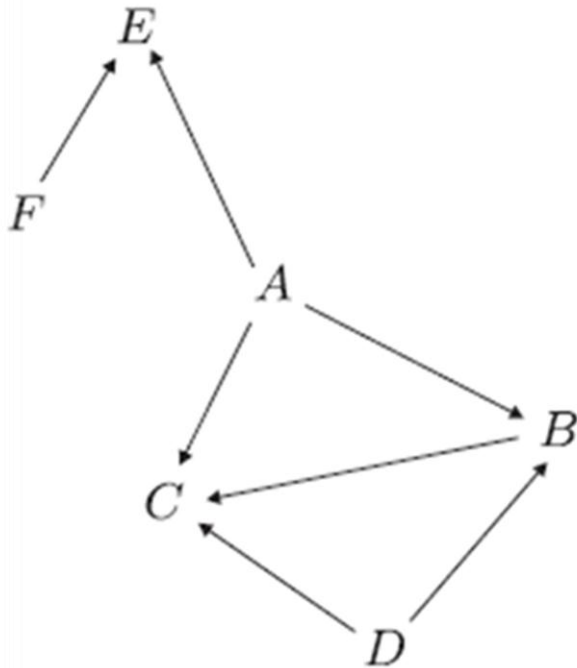
Structure of the CSP



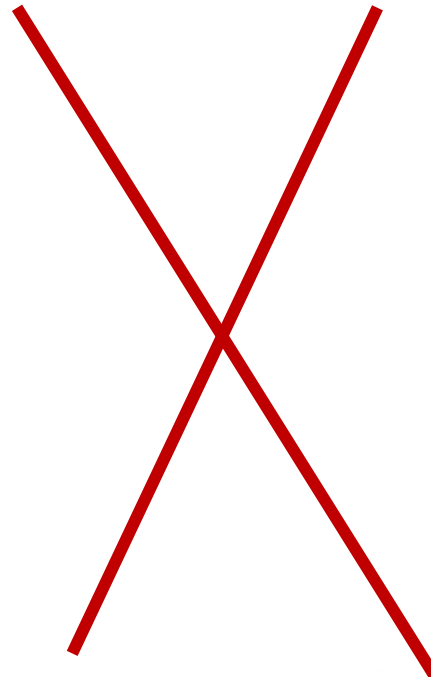
Tree Projection

Available Views

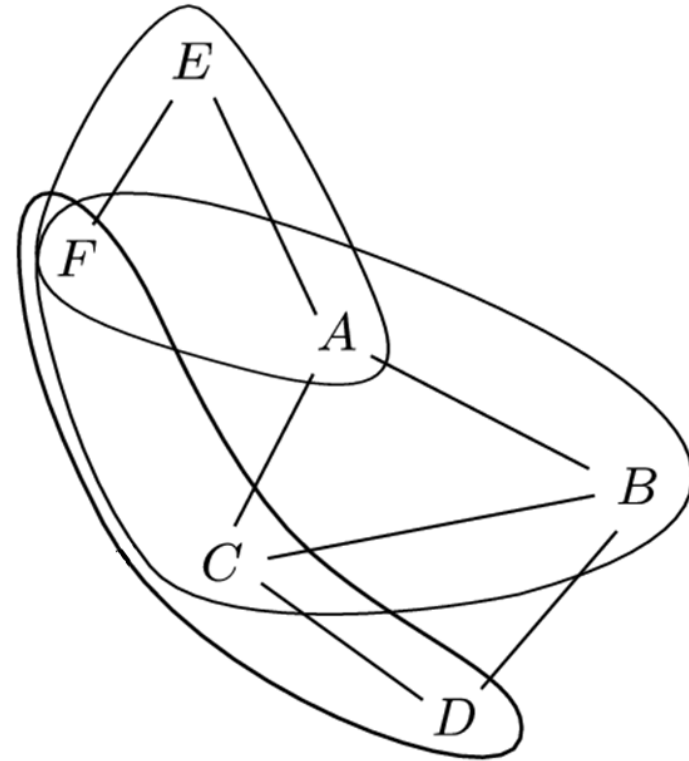
Cores and Tree Projections



Structure of the CSP

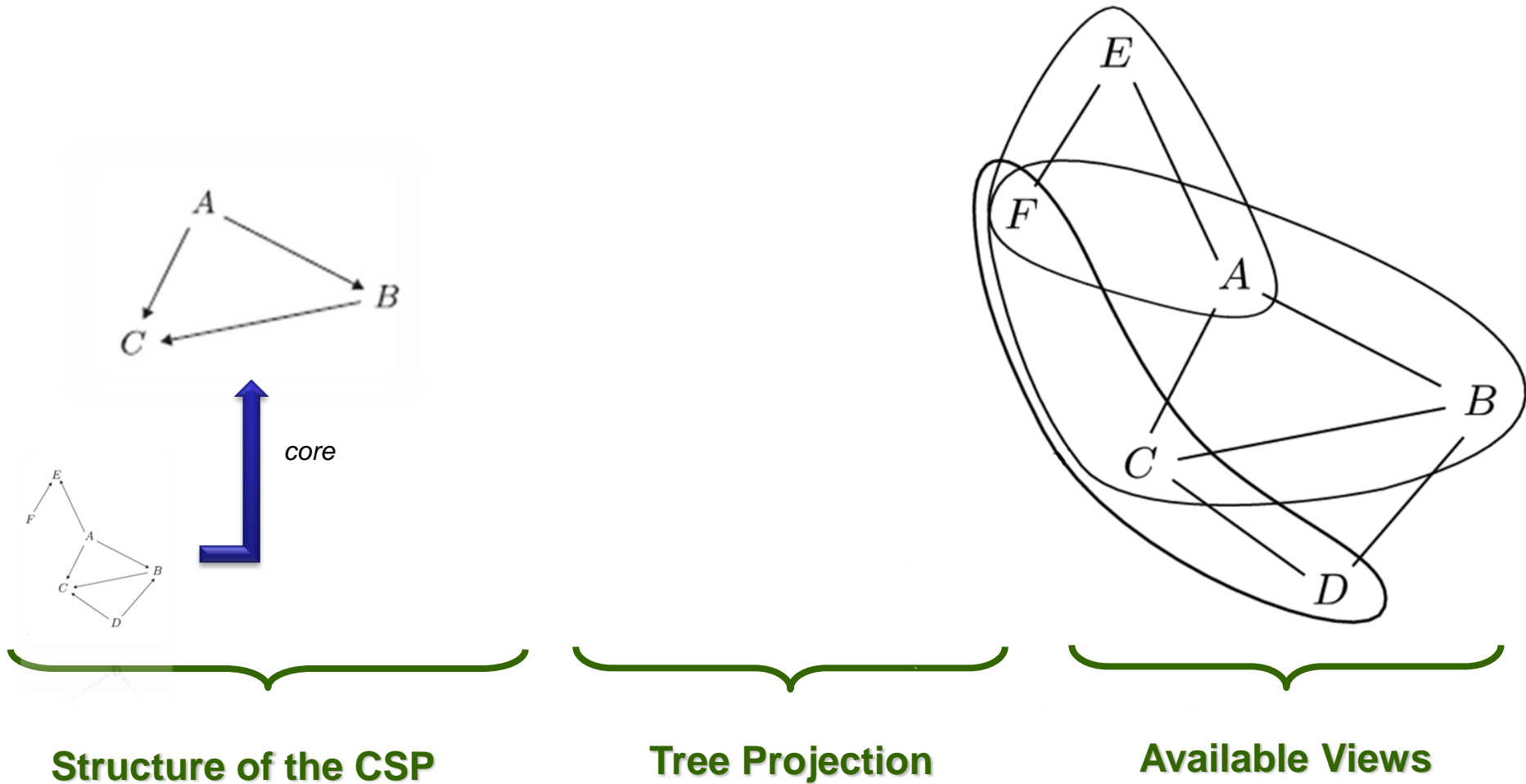


Tree Projection

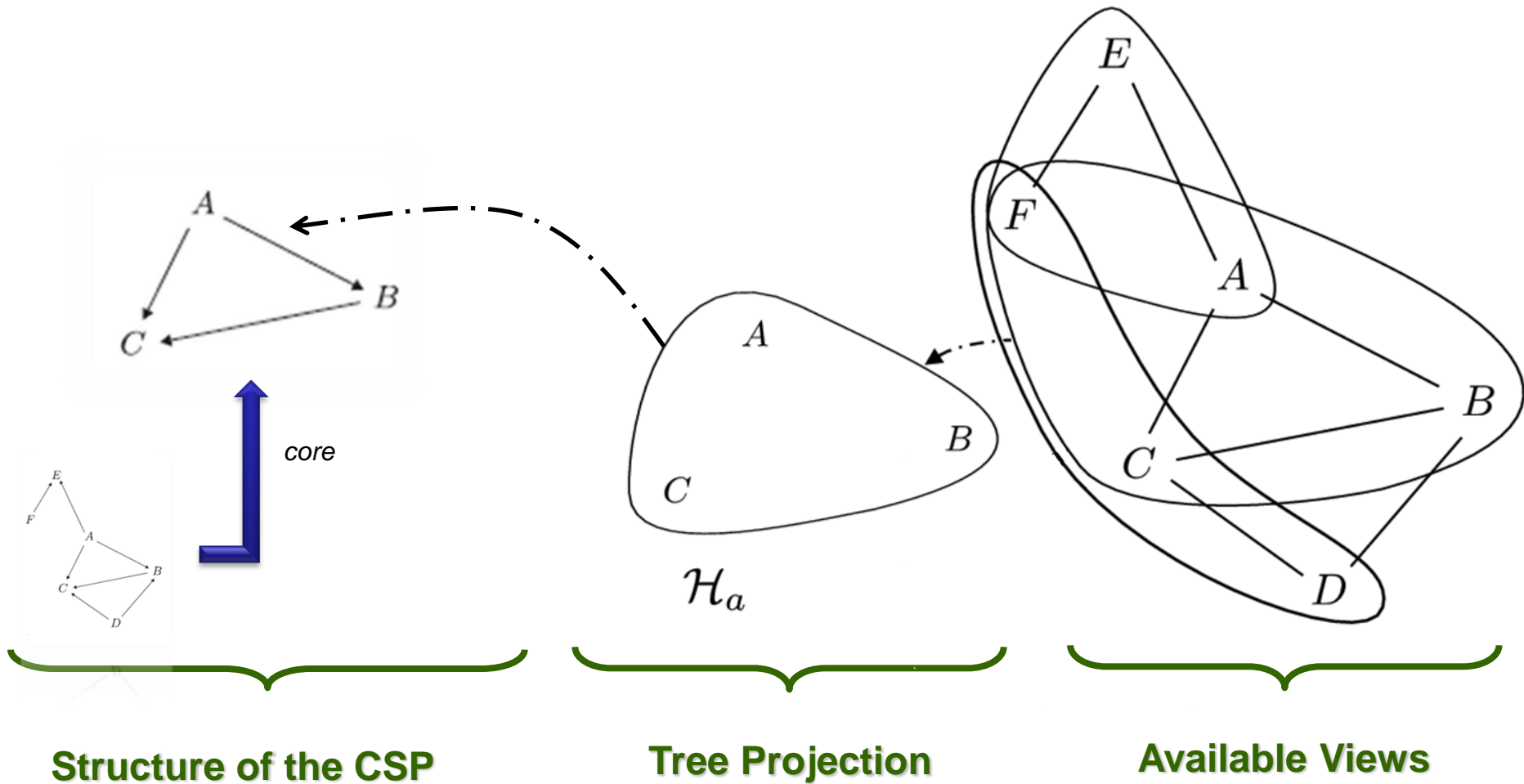


Available Views

Cores and Tree Projections



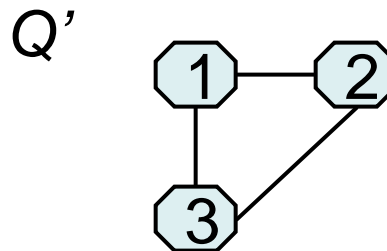
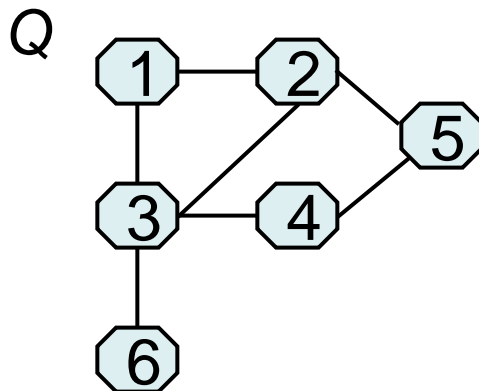
Cores and Tree Projections



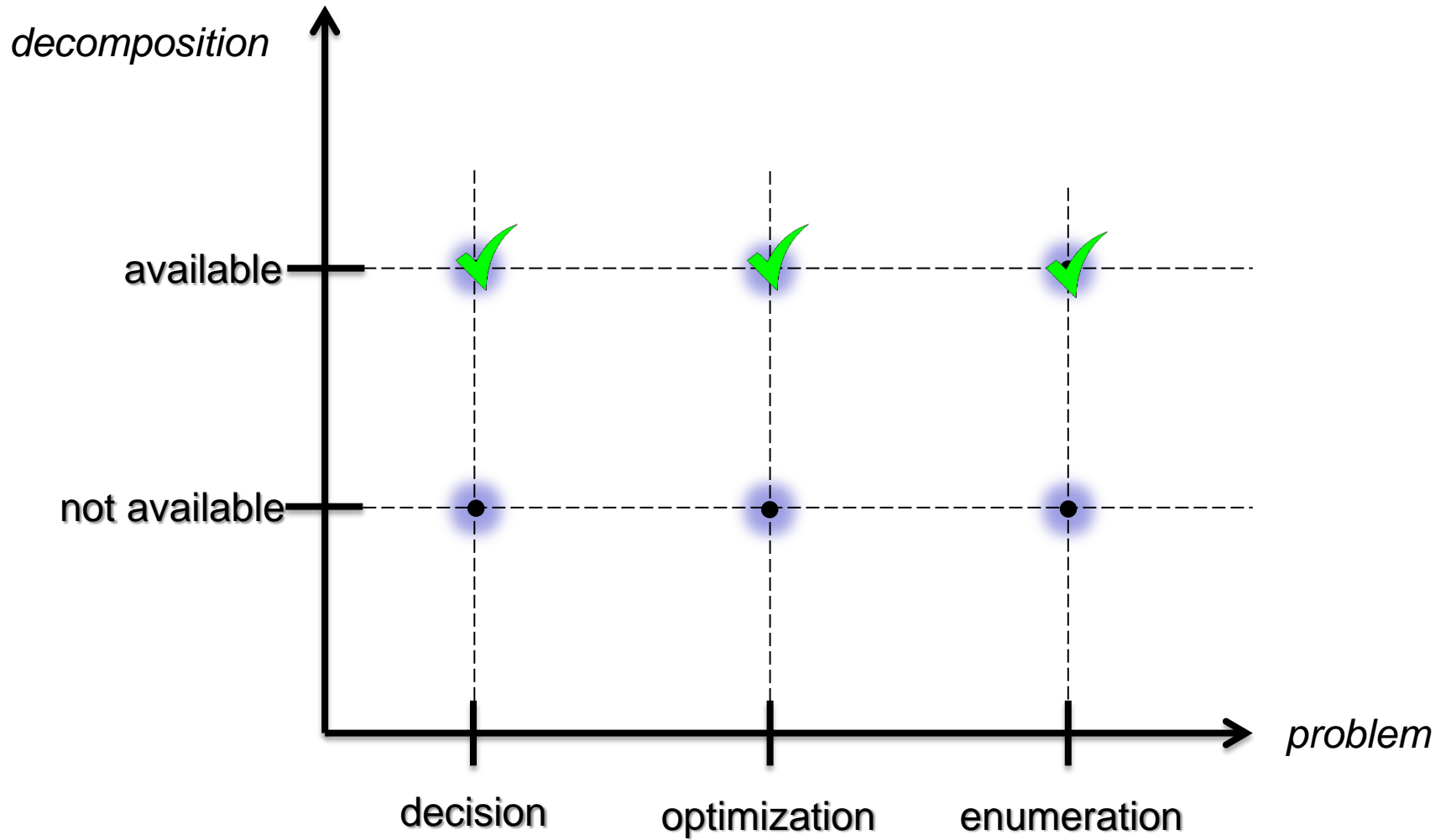
CORE is NP-hard

- Deciding whether Q' is the core of Q is NP-hard
- For instance, let 3COL be the class of all 3-colourable graphs containing a triangle
- Clearly, deciding whether $G \in 3COL$ is NP-hard
- It is easy to see that $G \in 3COL \Leftrightarrow K_3$ is the core of G

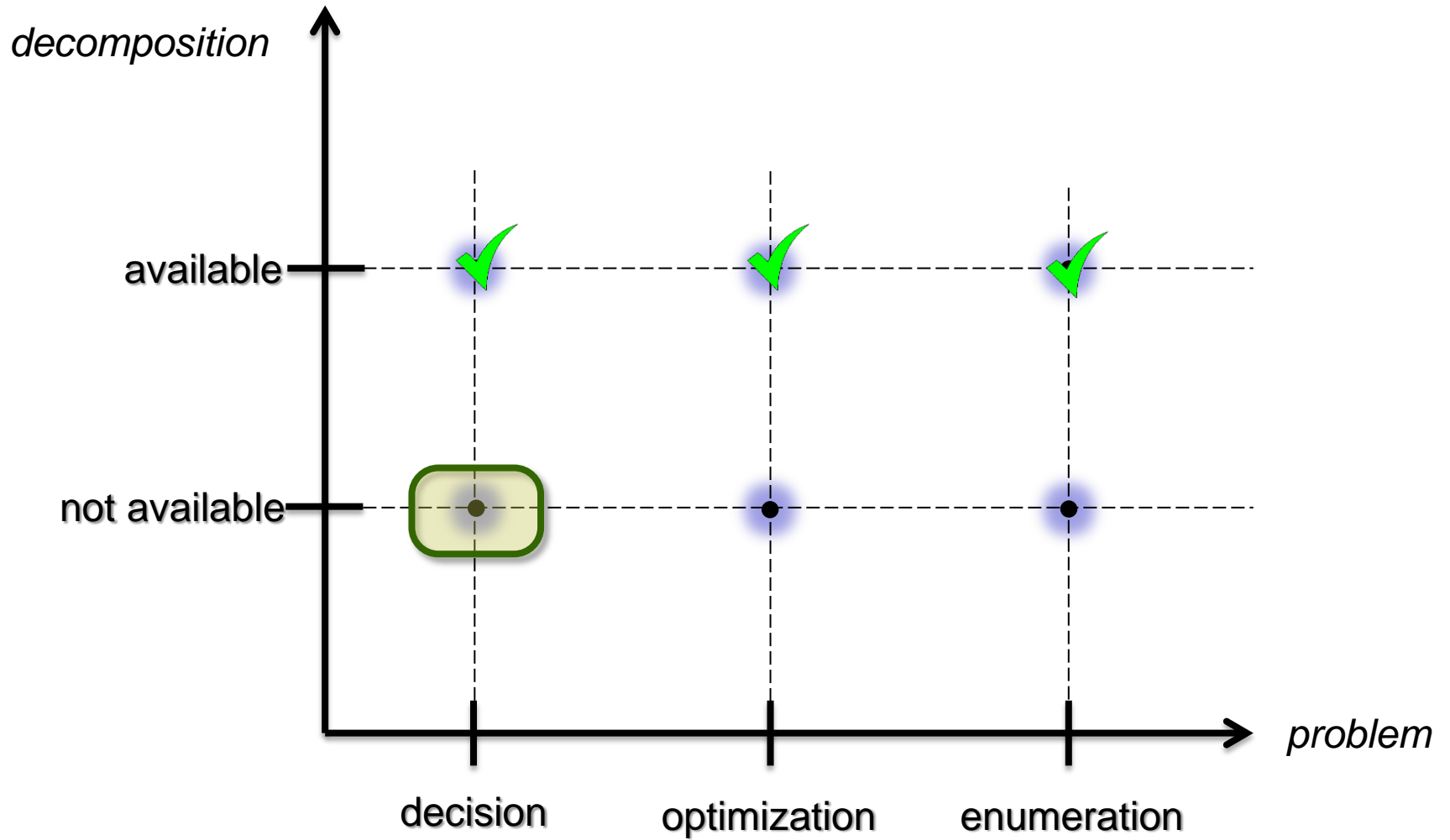
Example:



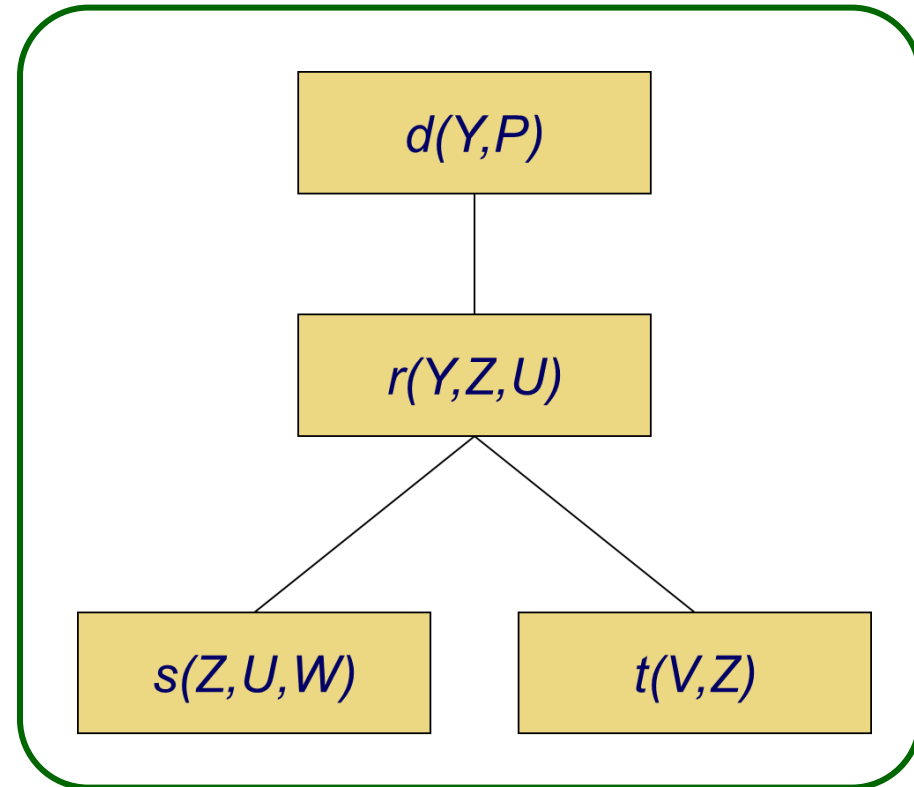
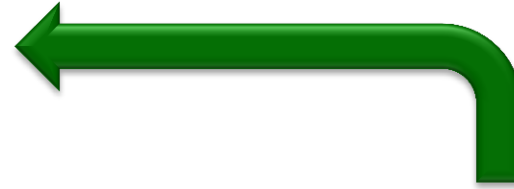
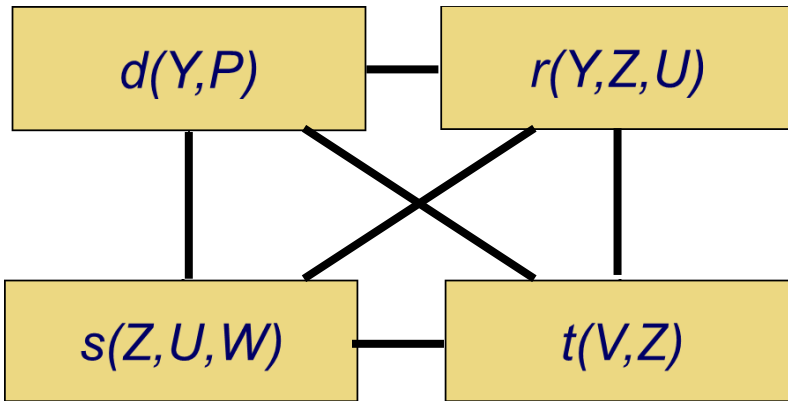
Overview



Overview



Enforcing Local Consistency (Acyclic)



Enforcing Local Consistency (Decomposition)

CSP instance (\mathbb{A}, \mathbb{B})



$\mathbb{A}_\nu = \ell\text{-DM}(\mathbb{A})$ | $\mathbb{B}_\nu = r\text{-DM}(\mathbb{A}, \mathbb{B})$



Enforcing Local Consistency (Decomposition)

CSP instance (\mathbb{A}, \mathbb{B})



$$\mathbb{A}_v = \ell\text{-DM}(\mathbb{A}) \quad \mathbb{B}_v = r\text{-DM}(\mathbb{A}, \mathbb{B})$$



If there is a tree projection, then enforcing local consistency over the views solves the decision problem

Enforcing Local Consistency (Decomposition)

CSP instance (A, B)



Does not need to be computed

$$A_{\mathcal{V}} = l\text{-DM}(A) \quad B_{\mathcal{V}} = r\text{-DM}(A, B)$$



If there is a tree projection, then enforcing local consistency over the views solves the decision problem

Even Better

CSP instance (\mathbb{A}, \mathbb{B})



$\mathbb{A}_\nu = \ell\text{-DM}(\mathbb{A})$ | $\mathbb{B}_\nu = r\text{-DM}(\mathbb{A}, \mathbb{B})$



There is a polynomial-time algorithm that:

- either returns that there is no tree projection,
- or solves the decision problem

Even Better

CSP instance (\mathbb{A}, \mathbb{B})



$\mathbb{A}_\mathcal{T} = \ell\text{-DM}(\mathbb{A}) \quad \mathbb{B}_\mathcal{T} = r\text{-DM}(\mathbb{A}, \mathbb{B})$



just check the
given solution



There is a polynomial-time algorithm that:

- either returns that there is no tree projection,
- or solves the decision problem

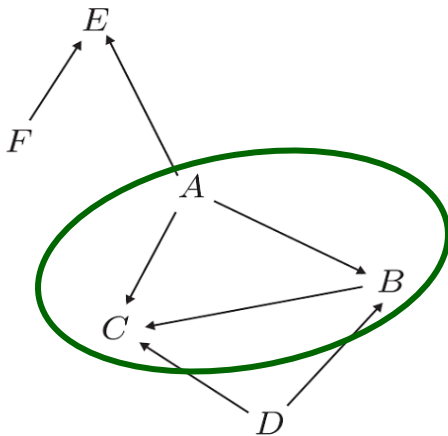
The Precise Power of Local Consistency

- The followings are equivalent:
 - Local consistency solves the decision problem
 - There is *a core* of the query having a tree projection

The Precise Power of Local Consistency

- The followings are equivalent
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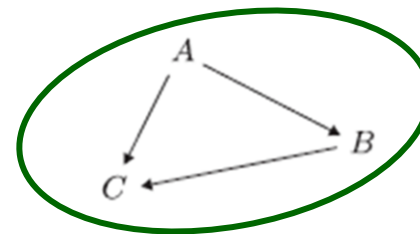
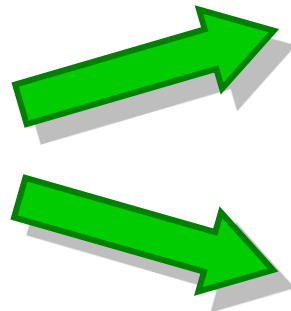
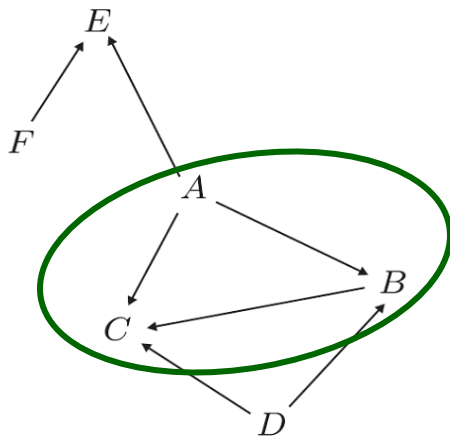
$$Q : r(A, B) \wedge r(B, C) \wedge r(A, C) \wedge r(D, C) \wedge r(D, B) \wedge r(A, E) \wedge r(F, E),$$



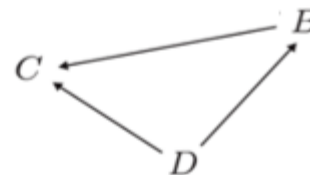
The Precise Power of Local Consistency

- The followings are equivalent
 - Local consistency solves the decision problem
 - There is a *core* of the query having a tree projection

$Q : r(A, B) \wedge r(B, C) \wedge r(A, C) \wedge r(D, C) \wedge$
 $r(D, B) \wedge r(A, E) \wedge r(F, E),$



a core *with* TP



a core *without* TP

A Relevant Specialization (not immediate)

- The followings are equivalent
 - Local consistency solves the decision problem
 - There is a *core* of the query having a tree projection

The CSP has generalized hypertreewidth k at most

Over all union of k atoms

Back on the Result

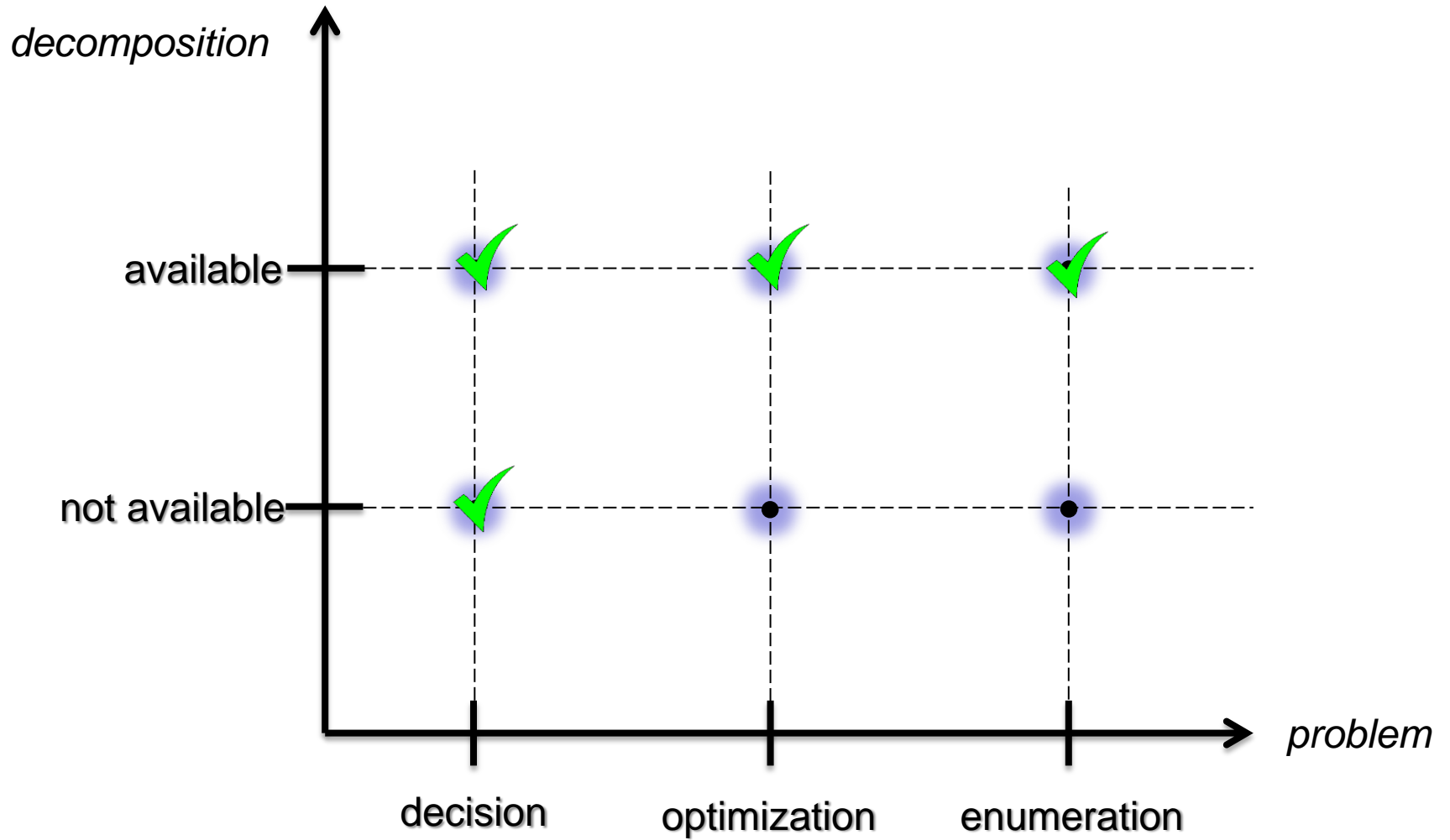
- The followings are equivalent
 - Local consistency solves the decision problem
 - There is a *core* of the query having a tree projection



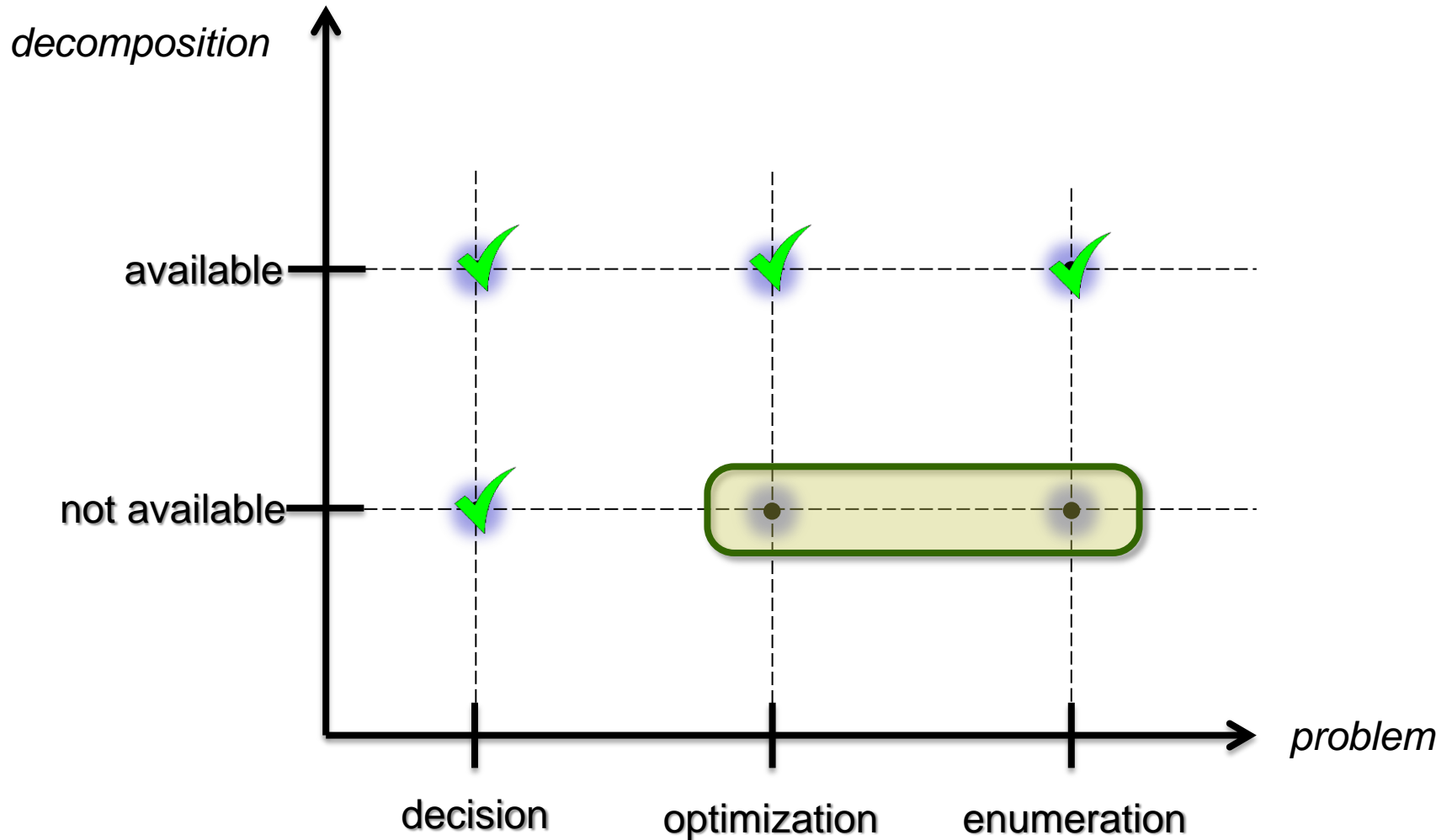
«Promise» tractability

- There is no polynomial time algorithm that
 - either solves the decision problem
 - or disproves the promise

Overview



Overview



[Greco & Scarcello, CP'11]

Recall This Approach

- Bottom-Up + Top-Down propagation

- Fix X_1 to the next value and *propagate*

- Fix X_2 to the next value and *propagate*

...

- Fix X_n to the next value and *propagate*



Backtracking with no wrong choices



Enumeration WPD



Recall This Approach

- Bottom-Up + Top-Down propagation

- Fix X_1 to the next value and *propagate*

- Fix X_2 to the next value and *propagate*

...

- Fix X_n to the next value and *propagate*



If there is a tree projection, then
the algorithm solves the enumeration problem

Recall This Approach

- Bottom-Up + Top-Down propagation
- Fix X_1 to the next value and *propagate*
- Fix X_2 to the next value and *propagate*
- ...
- Fix X_n to the next value and *propagate*

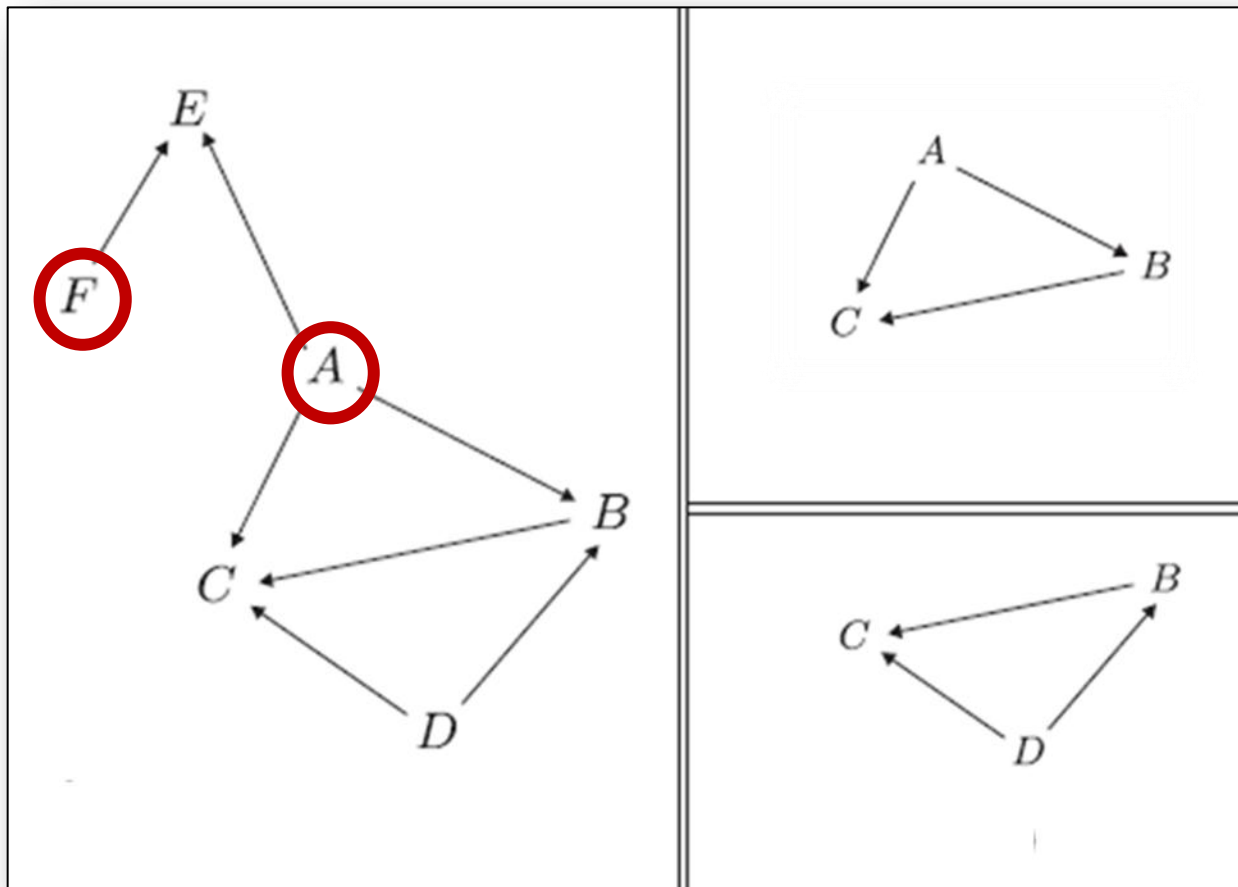


If there is a tree projection, then
the algorithm solves the enumeration problem

but more can be done...

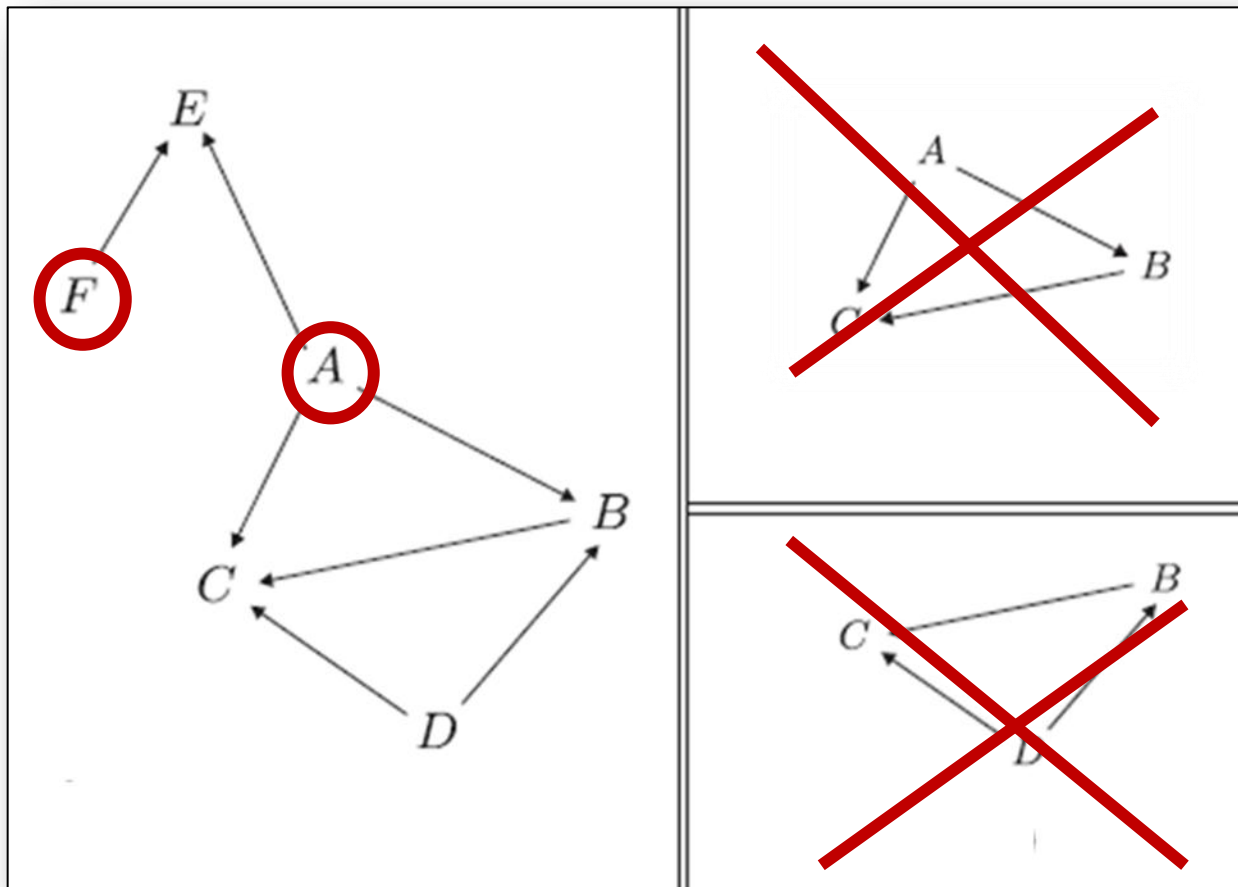
Tp-covered

Q : $r(A, B) \wedge r(B, C) \wedge r(A, C) \wedge r(D, C) \wedge$
 $r(D, B) \wedge r(A, E) \wedge r(F, E),$



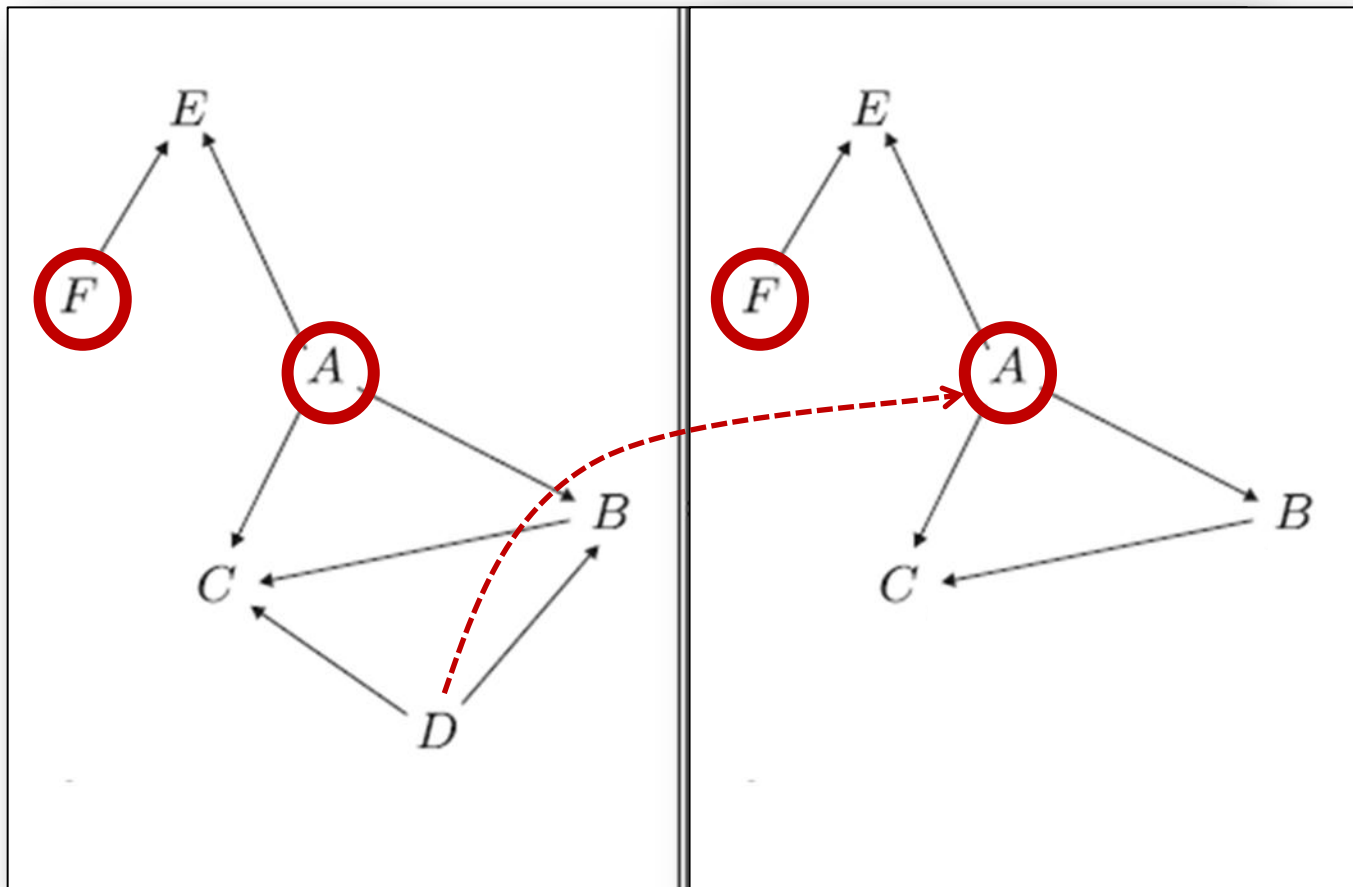
Tp-covered

Q : $r(A, B) \wedge r(B, C) \wedge r(A, C) \wedge r(D, C) \wedge$
 $r(D, B) \wedge r(A, E) \wedge r(F, E),$



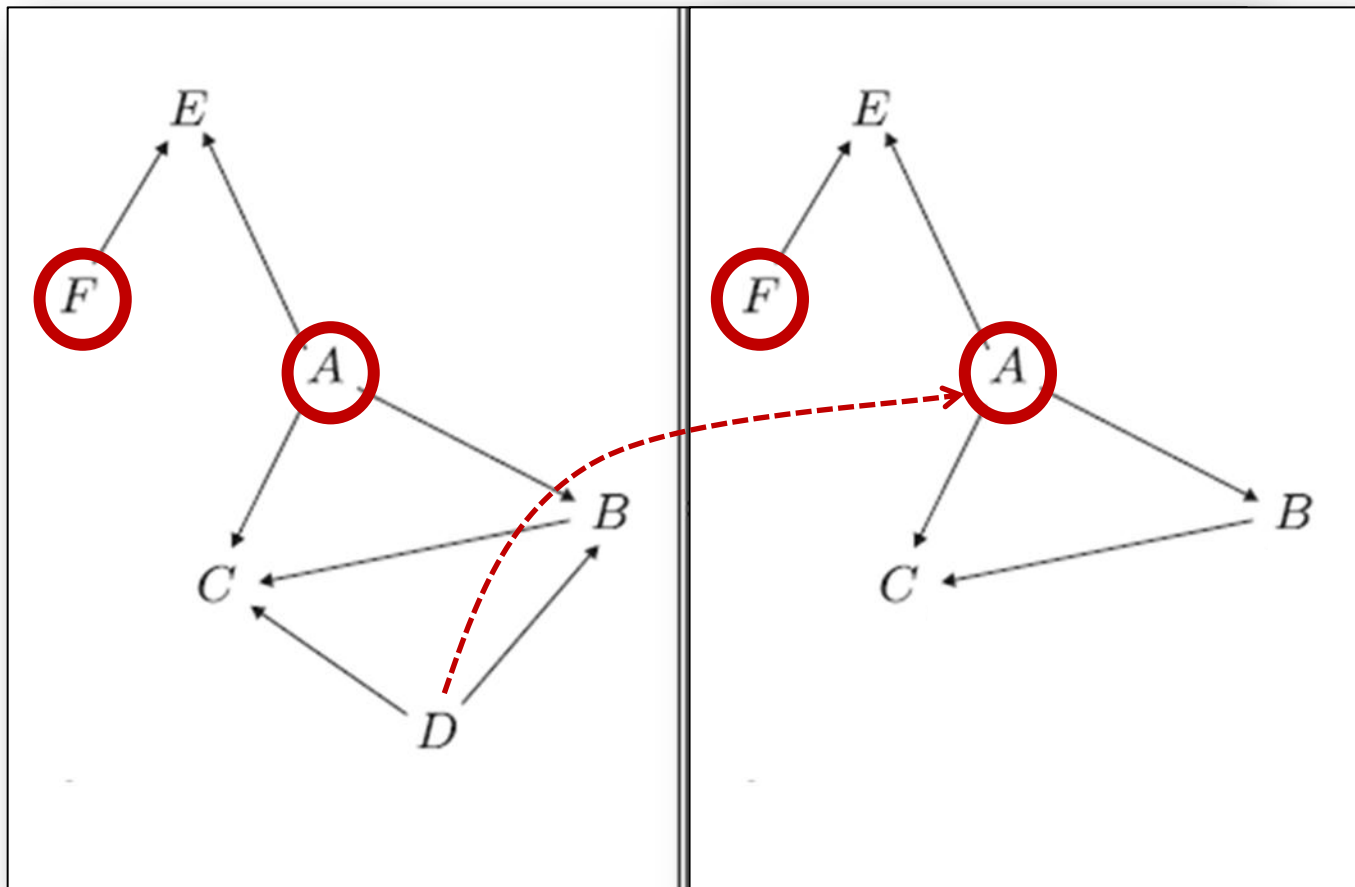
Tp-covered

Q : $r(A, B) \wedge r(B, C) \wedge r(A, C) \wedge r(D, C) \wedge$
 $r(D, B) \wedge r(A, E) \wedge r(F, E),$



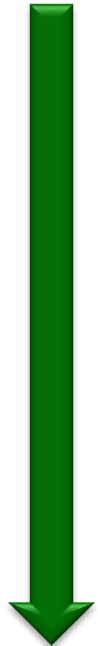
Tp-covered

- $\{F, A\}$ is tp-covered, if there is a tree projection covering an «output»-aware core



Results on Enumeration

There is a tree projection



Enumeration over O is feasible WPD

Results on Enumeration

There is a tree projection

Does not need to be computed

Enumeration over O is feasible WPD

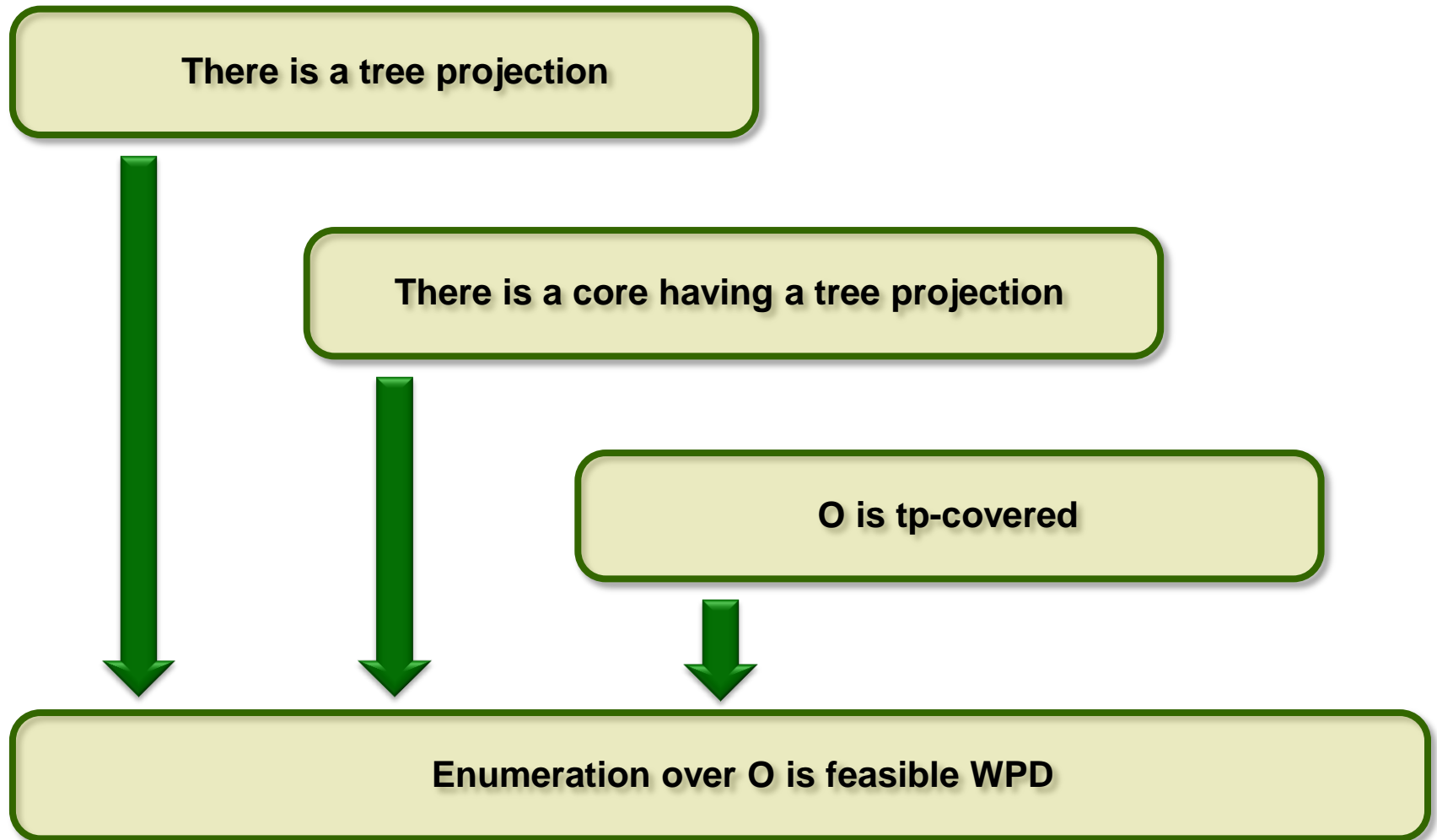
Results on Enumeration

There is a tree projection

There is a core having a tree projection

Enumeration over \mathcal{O} is feasible WPD

Results on Enumeration



Results on Enumeration

There is a tree projection

\mathcal{O} is tp-covered

Results on Enumeration

There is a tree projection



- The algorithm might return FAIL
 - Solutions so far computed are correct
 - There is no tree projection

\mathcal{O} is tp-covered



«Promise» tractability

- There is no polynomial time algorithm that
 - either solves the problem
 - or disproves the promise

Thank you!

Appendix: LCFL Results

Basic Question (on Acyclic Instances)

INPUT: CSP instance (\mathbb{A}, \mathbb{B})

• Is there a homomorphism from \mathbb{A} to \mathbb{B} ?

• Feasible in polynomial time $O(n^2 \times \log n)$

• LOGCFL-complete

LOGCFL

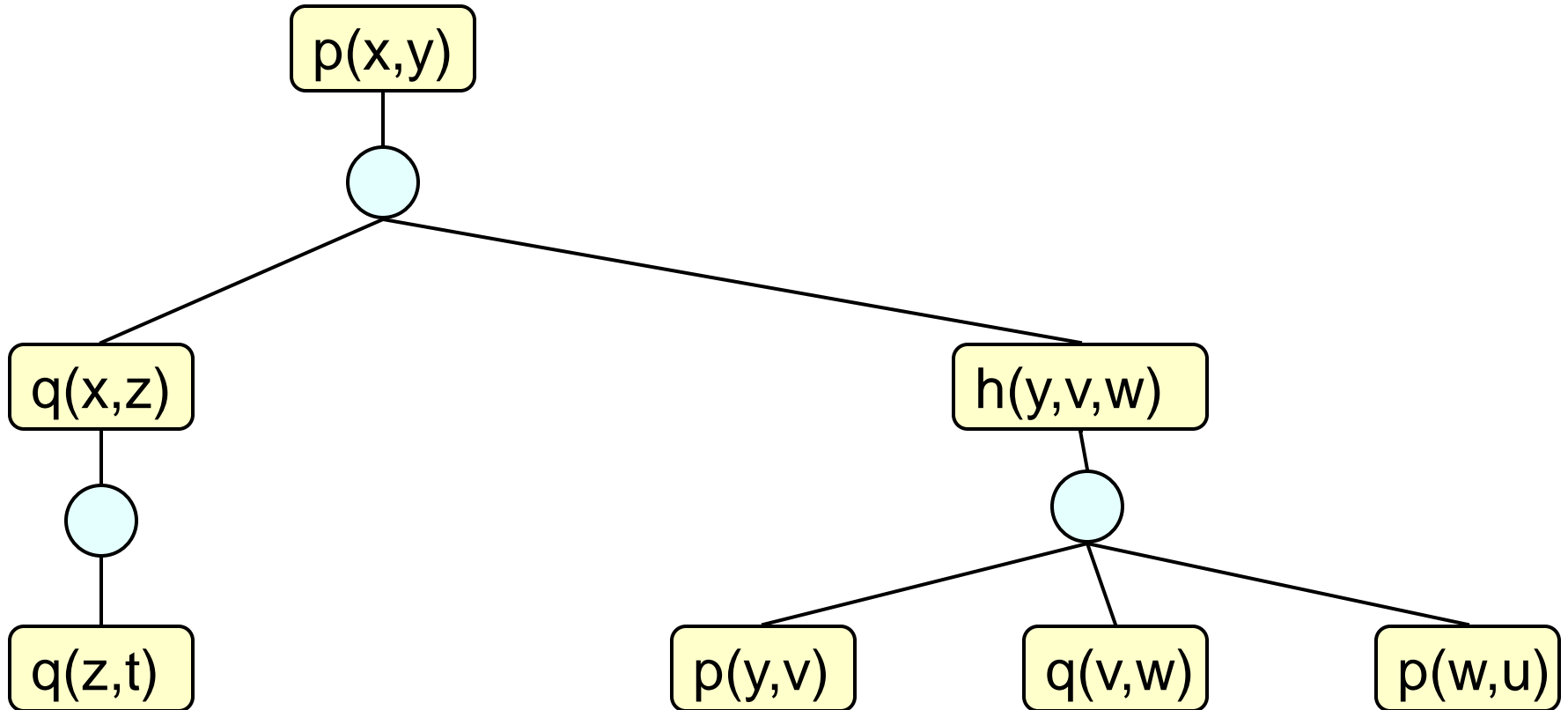
- LOGCFL: class of problems/languages that are logspace-reducible to a CFL
- Admit efficient parallel algorithms

$AC_0 \subseteq NL \subseteq \text{LOGCFL} = SAC_1 \subseteq AC_1 \subseteq NC_2 \subseteq \dots \subseteq NC = AC \subseteq P \subseteq NP$

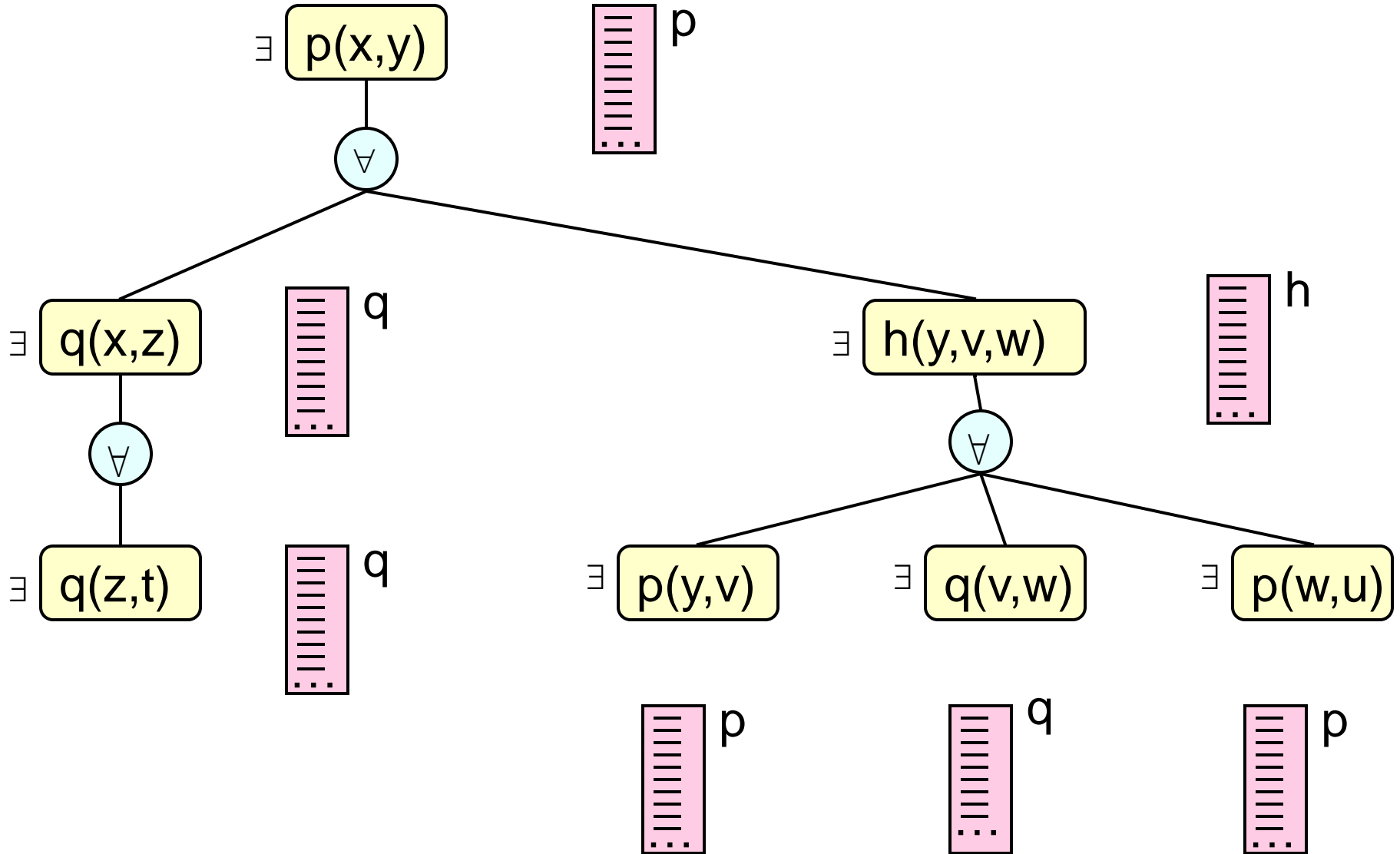
Characterization of LOGCFL [Ruzzo '80]:

LOGCFL = Class of all problems solvable with a logspace ATM
with polynomial tree-size

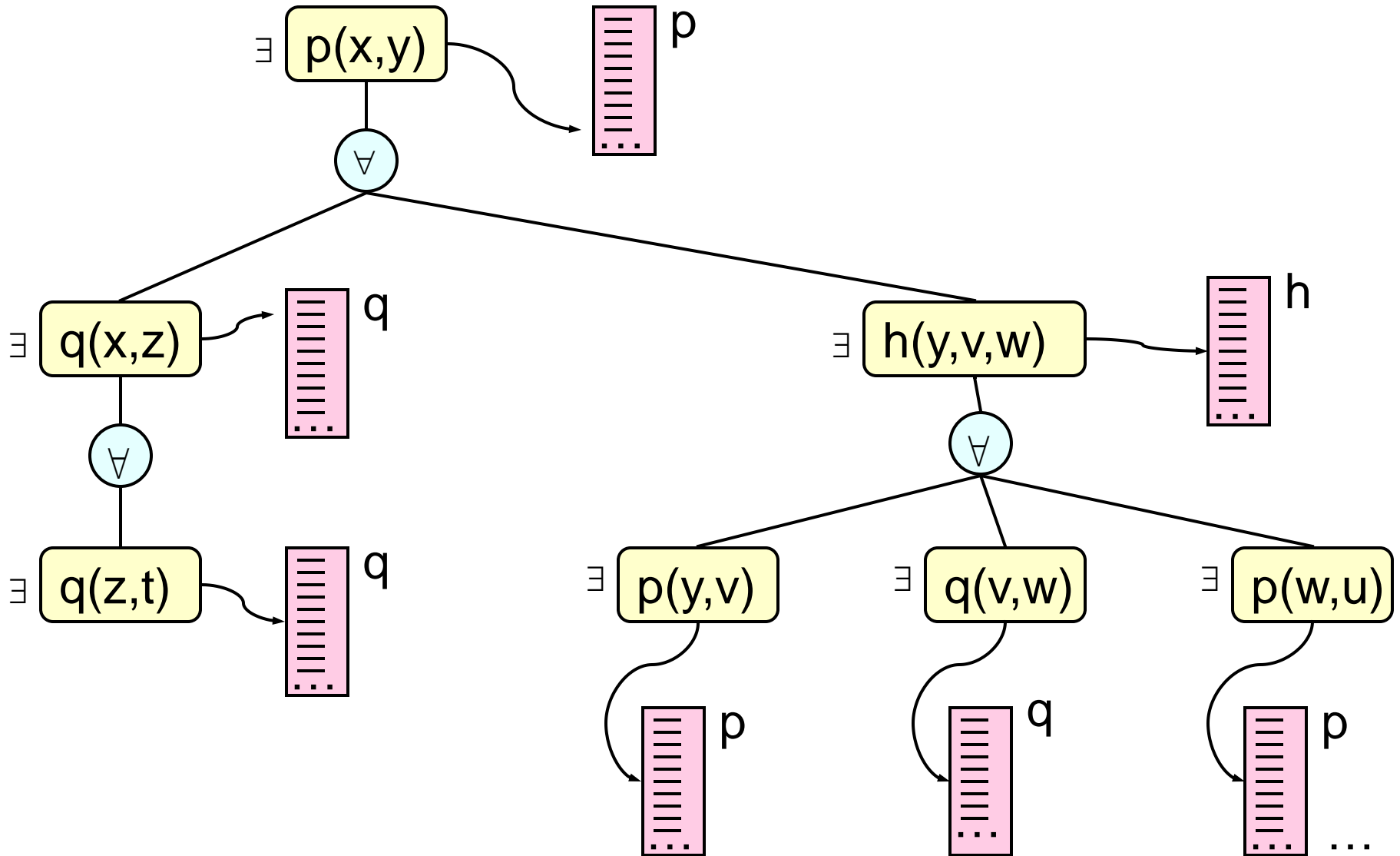
ABCQ is in LOGCFL



ABCQ is in LOGCFL



ABCQ is in LOGCFL



CSOP Extensions: Formal Framework

● Evaluation Functions

- \mathbb{D} domain of values, \succeq a total order over it
- *evaluation function* \mathcal{F} : a tuple $\langle w, \oplus \rangle$ with $w : Var \times \mathcal{U} \mapsto \mathbb{D}$
- \oplus commutative, associative, and closed binary operator with an identity element over \mathbb{D}
- $\mathcal{F}(\theta) = \bigoplus_{X/u \in \theta} w(X, u)$ (with $\mathcal{F}(\emptyset)$ being the identity w.r.t. \oplus)

● Monotone Functions

$$\mathcal{F}(\theta) \succeq \mathcal{F}(\theta') \quad \Rightarrow \quad \mathcal{F}(\theta) \oplus \mathcal{F}(\theta'') \succeq \mathcal{F}(\theta') \oplus \mathcal{F}(\theta''), \quad \forall \theta''$$

CSOP Extensions: Multi-Objective Optimization

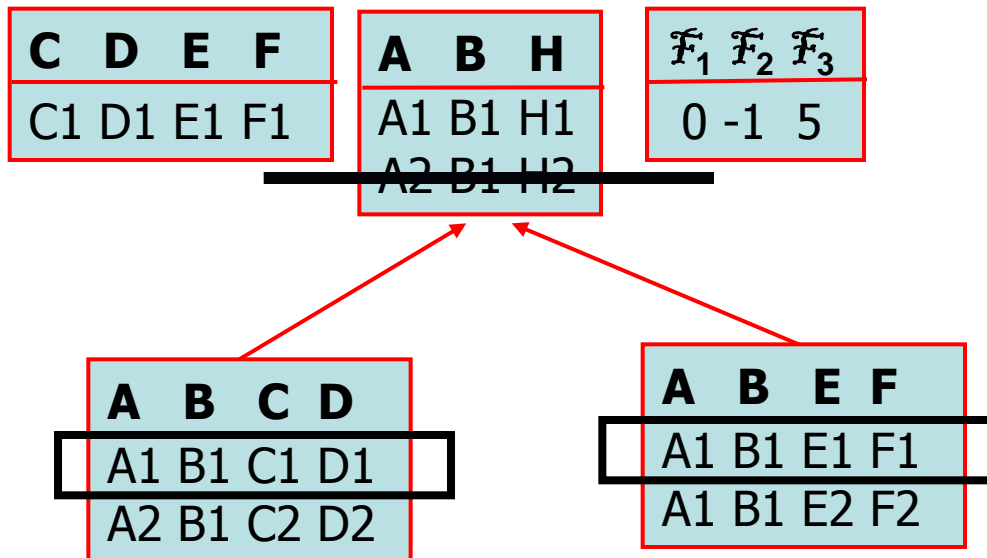
- We often want to express more preferences, e.g.,
 - minimize cost, then minimize total time, or
 - maximize the profit, then minimize the number of different buyers, or transactions
- Formally,
 - $L = [\mathcal{F}_1, \dots, \mathcal{F}_m]$
 - $L(\theta)$ denotes $(\mathcal{F}_1(\theta), \dots, \mathcal{F}_m(\theta)) \in \mathbb{D}_1 \times \dots \times \mathbb{D}_m$
- Compare vectors by the lexicographical precedence relationship (Cascade of preferences)

Linearization (following [Brafman et al'10])

- $\succ_{\mathcal{U}}$ an arbitrary total order defined over \mathcal{U}
- $\ell = [X_1, \dots, X_n]$ a list including all the variables in Var
- Define the total order \succ_L^ℓ
 - ties in \succ_L are resolved according to the lexicographical precedence relationship ℓ over variables and the total order $\succ_{\mathcal{U}}$ over \mathcal{U}
 - \succ_L^ℓ is a refinement of \succ_L

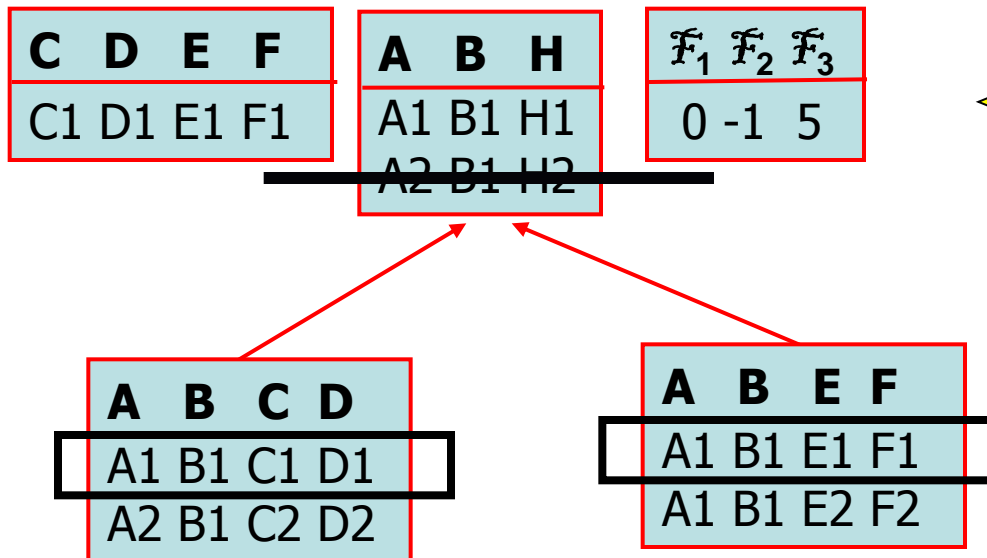
Hints (monotone lists)

- Extend the dynamic programming approach
- Because of linearization we have a total order
- The algorithm exploits an extended list of evaluation functions (still monotone) $[\mathcal{F}_1, \dots, \mathcal{F}_m, \mathcal{F}_\ell]$, $\mathcal{F}_\ell = \langle w_\ell, + \rangle$
- where $w_\ell(X_i, u) = |\mathcal{U}|^{n-i} \times r_{\mathcal{U}}(u)$



Hints (monotone lists)

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- where $w_\ell(X_i, u) = |\mathcal{U}|^{n-i} \times r_{\mathcal{U}}(u)$



For each tuple, manage an Additional vector with the best Values for the m+1 functions

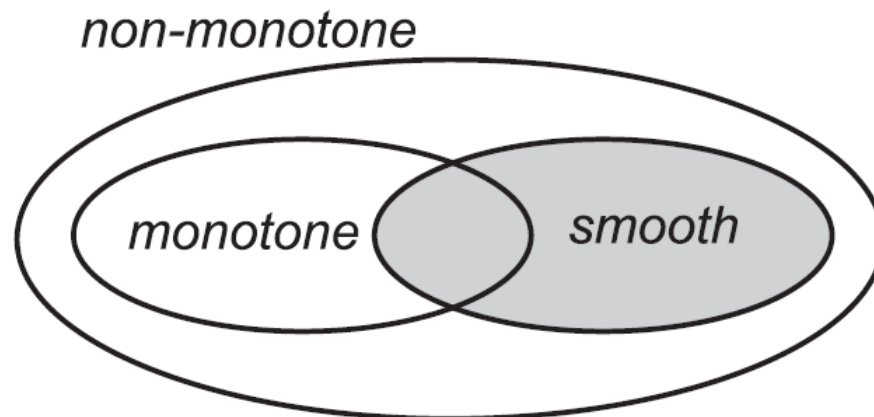
Note that we have no ties, because of the additional function

CSOP Extensions: Smooth Functions

- \mathcal{F} is *smooth* (w.r.t. Φ and DB) if, $\forall \theta$, the value $\mathcal{F}(\theta)$ is polynomially-bounded by the size of Φ , DB, and \mathcal{F}
- a list L of evaluation functions is *smooth* if it consists of a constant number of smooth evaluation functions

CSOP Extensions: Smooth Functions

- Manipulate small (polynomially bounded) values
- Occur in many applications (for instance, in counting-based optimizations)
- May be non-monotonic



Examples of Smooth Functions

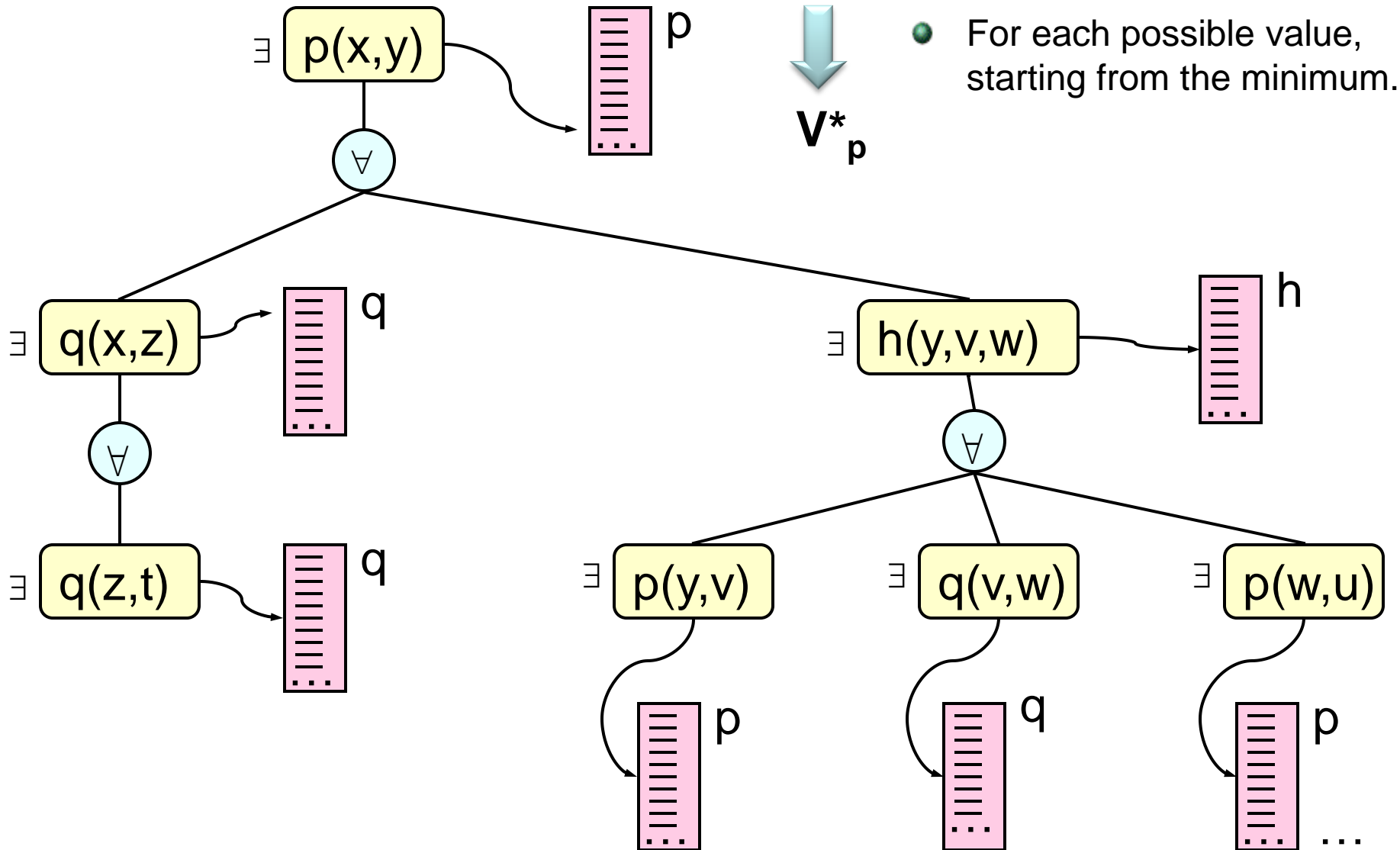
1. Finding solutions minimizing the number of variables mapped to certain domain values
 - It is smooth and monotone
2. Finding solutions with an odd number of variables mapped to certain values (e.g. switch variables)
 - It is smooth and non-monotone
3. $[2,1]$ (or viceversa) is a smooth list of evaluation functions

Tractability of Non-Monotone (smooth) Functions

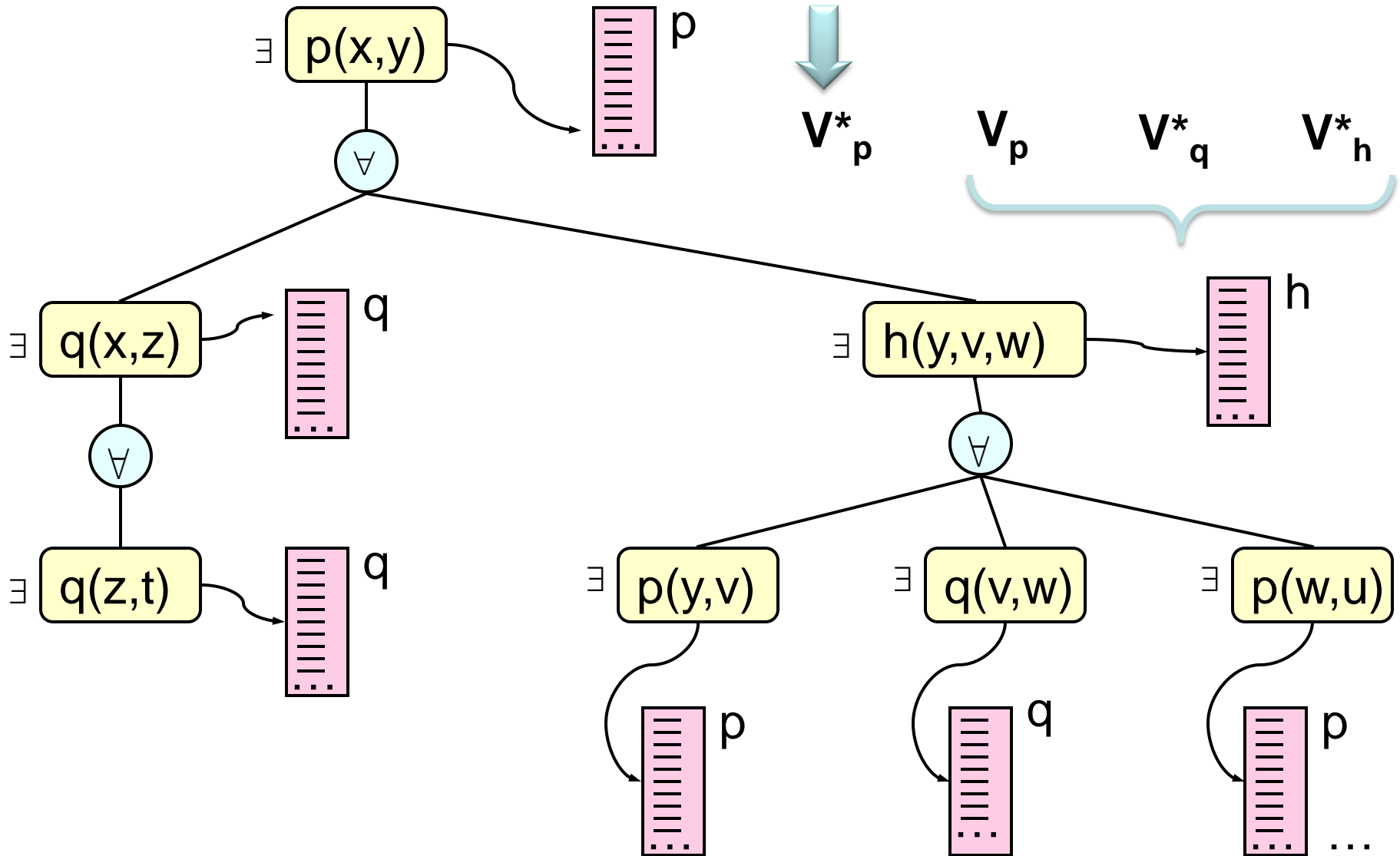
- The classical dynamic programming approach does not work, with non-monotone functions
 - Good (partial) solutions in the subtree may lead to bad final solutions



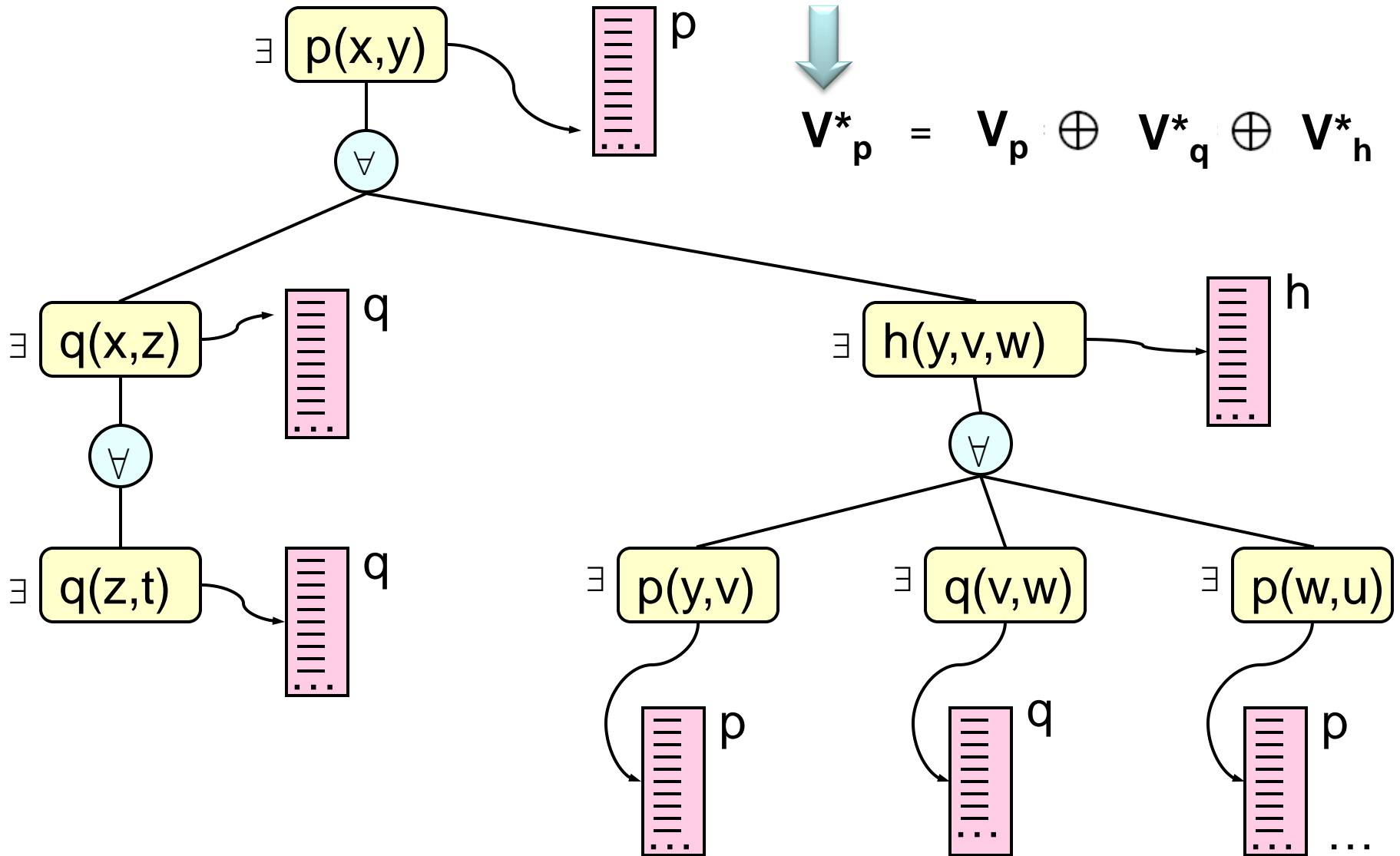
Tractability of Non-Monotone (smooth) Functions



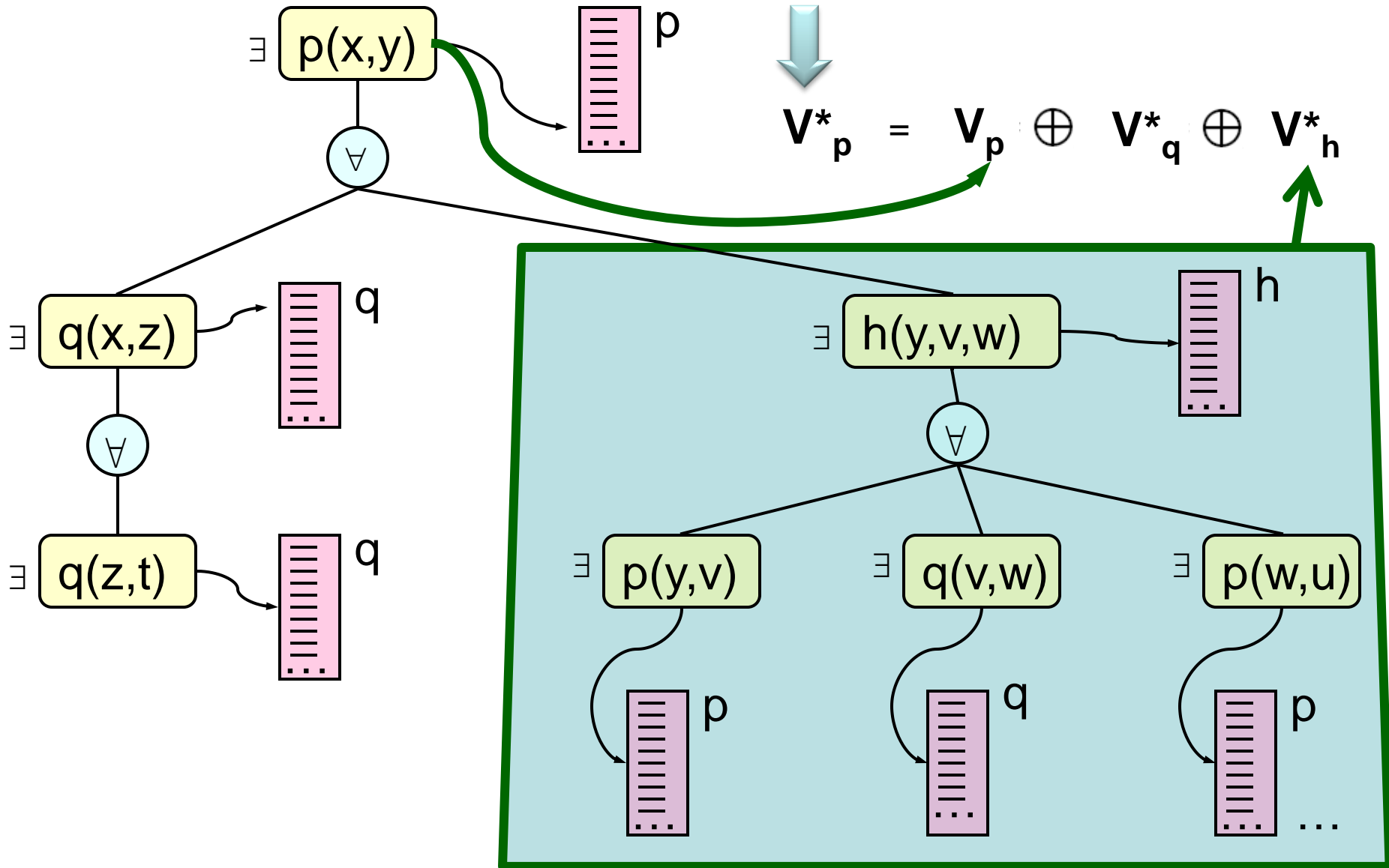
Tractability of Non-Monotone (smooth) Functions



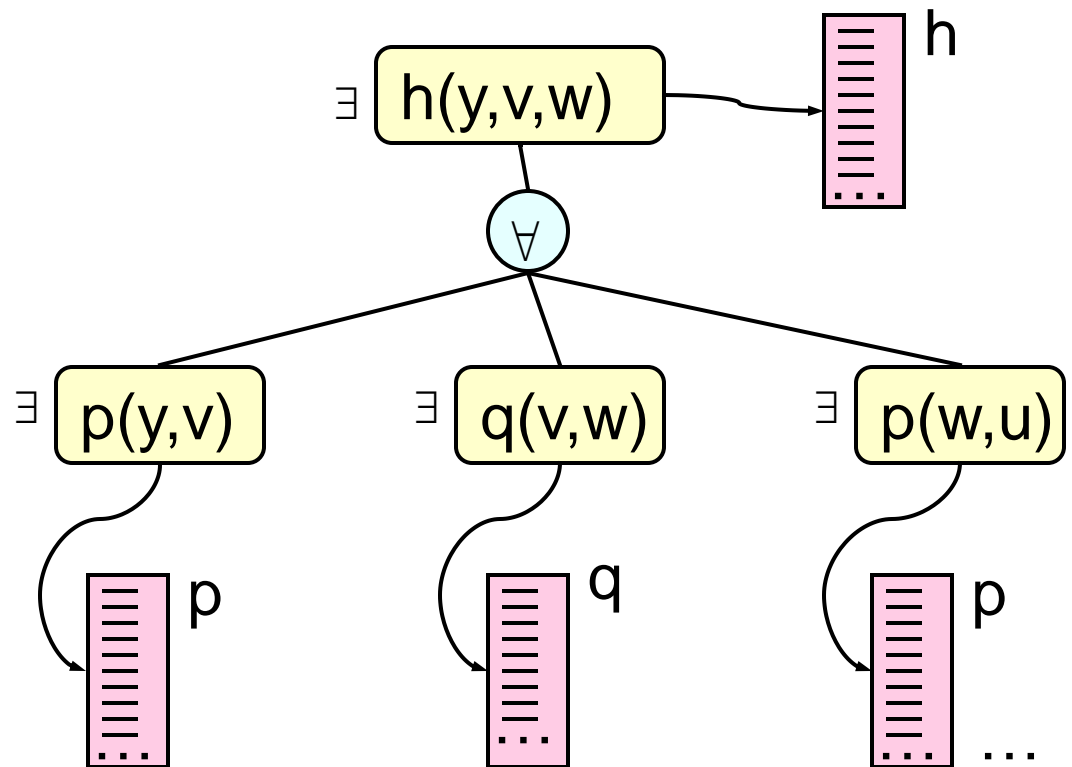
Tractability of Non-Monotone (smooth) Functions



Tractability of Non-Monotone (smooth) Functions

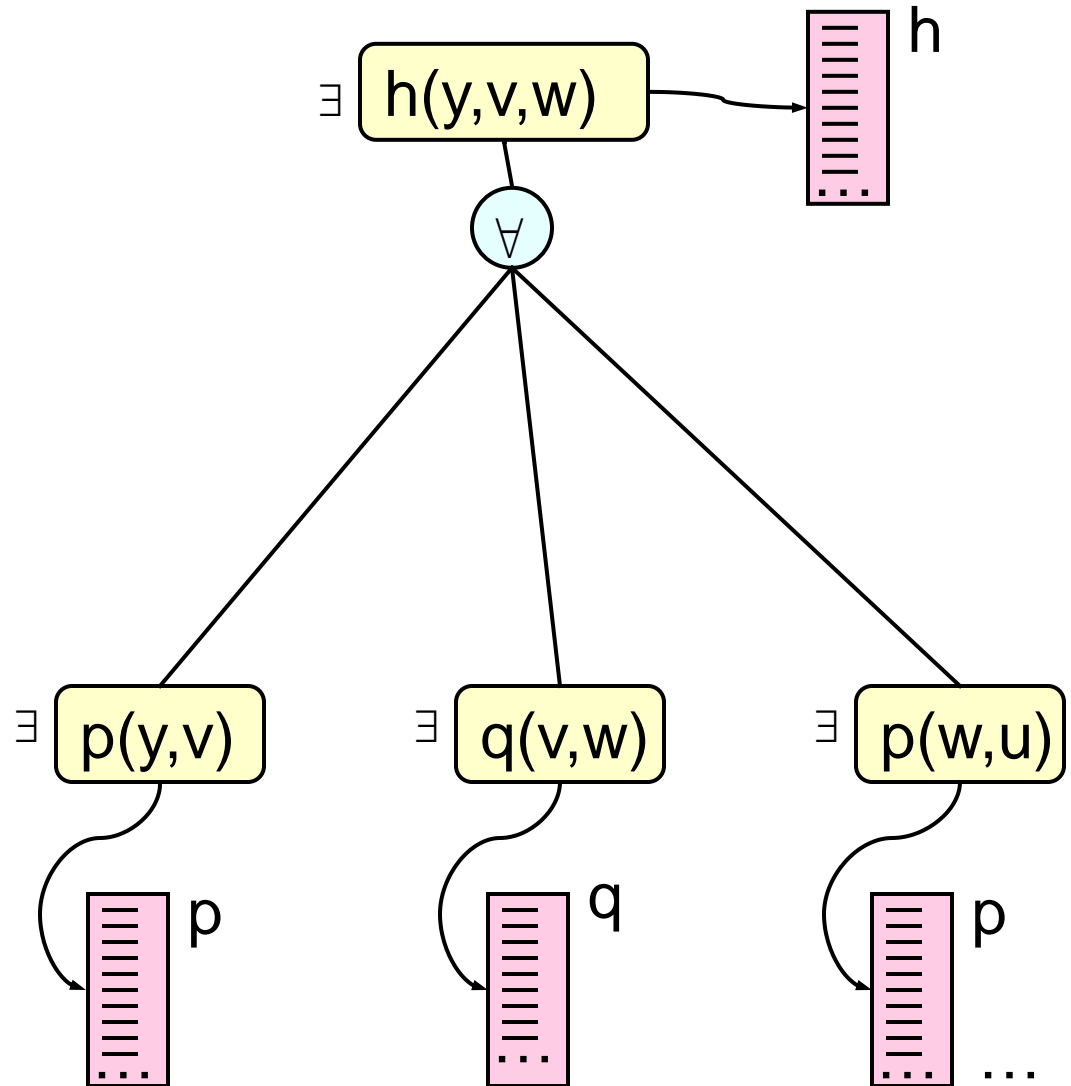


A Subtle Issue



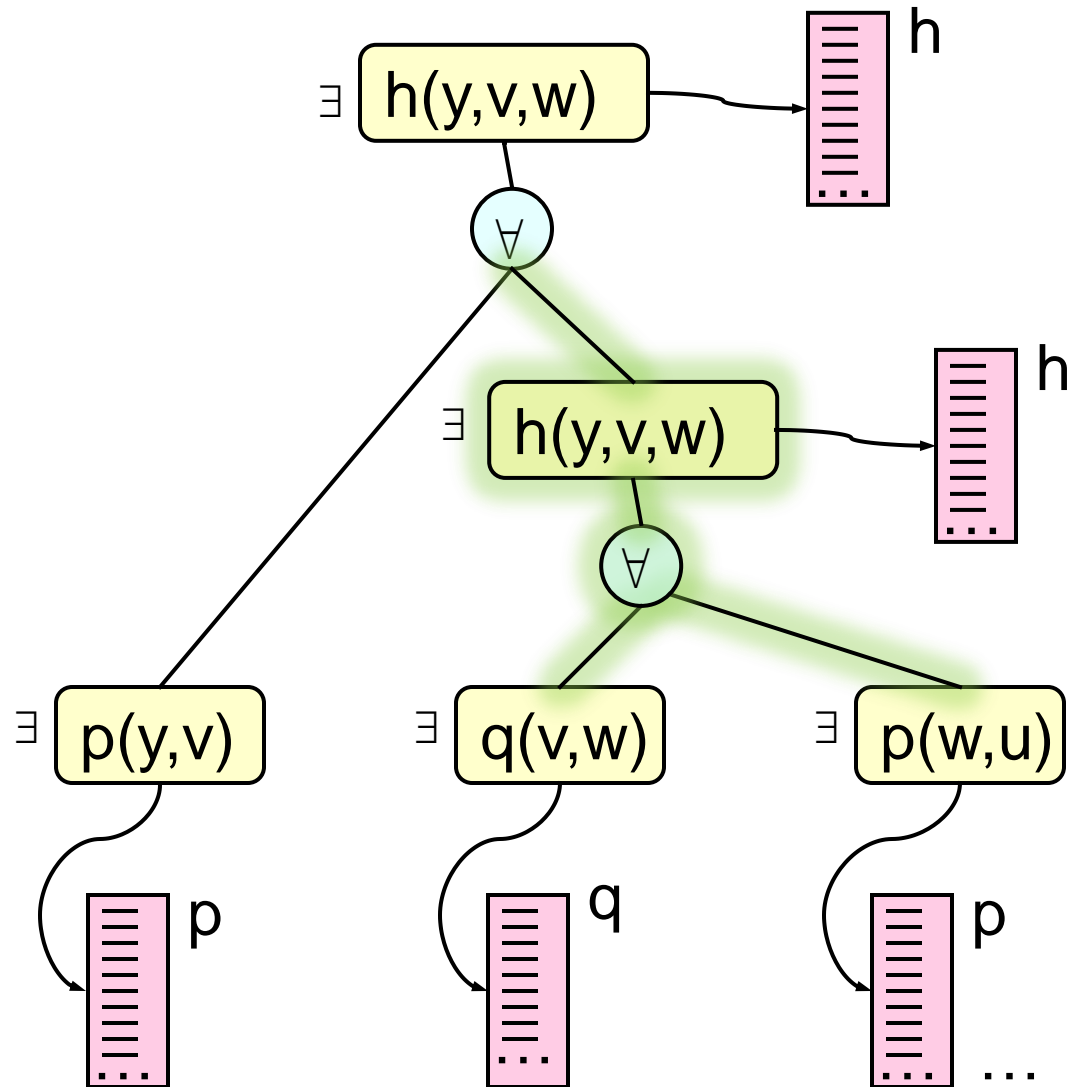
A Subtle Issue

- Binarization



A Subtle Issue

- Binarization



Appendix: TP-coverings