

# CompSci 275, CONSTRAINT Networks

Rina Dechter, Fall 2022

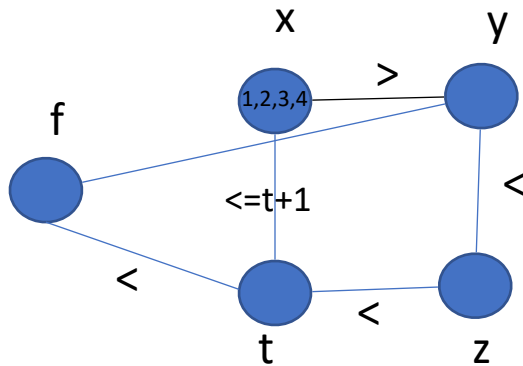
Consistency algorithms, part b  
Chapter 3

# Outline

- Arc-consistency algorithms
- Path-consistency and i-consistency
- Arc-consistency, Generalized arc-consistency, relation arc-consistency
- Global and bound consistency
- Distributed (generalized) arc-consistency
- Consistency operators: join, resolution, Gaussian elimination

# Exercise: make the following network arc-consistent

- Draw the network's primal and dual constraint graph
- Network =
  - Domains  $\{1,2,3,4\}$
  - Constraints:  $y < x$ ,  $z < y$ ,  $t < z$ ,  $f < t$ ,  $x \leq t+1$ ,  $Y < f+2$
  - What is the domain for X in an arc-consistent network?



# Arc-consistency Algorithms

- **AC-1**: brute-force, distributed
- **AC-3**, queue-based
- **AC-4**, context-based, optimal
- **AC-5,6,7,....** Good in special cases
- **Important**: applied at every node of search
- ( $n$  number of variables,  $e$ =#constraints,  $k$ =domain size)
- Mackworth and Freuder (1977,1983), Mohr and Anderson, (1985)
- ...

# Constraint tightness analysis

*t = number of tuples bounding a constraint*

- **AC-1**: brute-force,
- **AC-3**, queue-based
- **AC-4**, context-based, optimal
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- Mackworth and Freuder (1977,1983), Mohr and Anderson, (1985)...

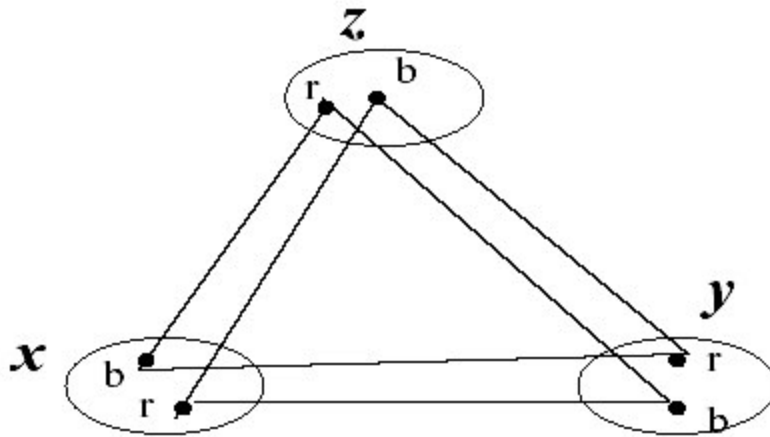
# Is arc-consistency enough?

- Example: a triangle graph-coloring with 2 values.
  - Is it arc-consistent?
  - Is it consistent?
- It is not path, or 3-consistent.

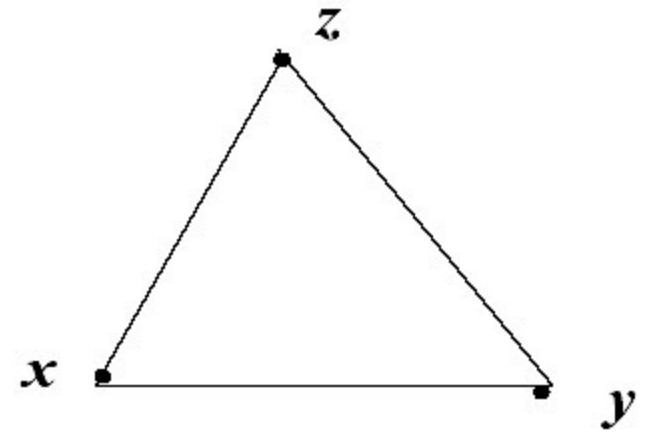
# Outline

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- **Path-consistency and i-consistency**
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# Path-consistency



(a)



(b)

Figure 3.8: (a) The matching diagram of a 2-value graph coloring problem. (b) Graphical picture of path-consistency using the matching diagram.



# Path-consistency (3-consistency)

**Definition 3.3.2 (Path-consistency)** *Given a constraint network  $\mathcal{R} = (X, D, C)$ , a two variable set  $\{x_i, x_j\}$  is path-consistent relative to variable  $x_k$  if and only if for every consistent assignment  $(\langle x_i, a_i \rangle, \langle x_j, a_j \rangle)$  there is a value  $a_k \in D_k$  s.t. the assignment  $(\langle x_i, a_i \rangle, \langle x_k, a_k \rangle)$  is consistent and  $(\langle x_k, a_k \rangle, \langle x_j, a_j \rangle)$  is consistent. Alternatively, a binary constraint  $R_{ij}$  is path-consistent relative to  $x_k$  iff for every pair  $(a_i, a_j) \in R_{ij}$ , where  $a_i$  and  $a_j$  are from their respective domains, there is a value  $a_k \in D_k$  s.t.  $(a_i, a_k) \in R_{ik}$  and  $(a_k, a_j) \in R_{kj}$ . A subnetwork over three variables  $\{x_i, x_j, x_k\}$  is path-consistent iff for any permutation of  $(i, j, k)$ ,  $R_{ij}$  is path consistent relative to  $x_k$ . A network is path-consistent iff for every  $R_{ij}$  (including universal binary relations) and for every  $k \neq i, j$   $R_{ij}$  is path-consistent relative to  $x_k$ .*

# Revise-3

REVISE-3( $(x, y), z$ )

**input:** a three-variable subnetwork over  $(x, y, z)$ ,  $R_{xy}$ ,  $R_{yz}$ ,  $R_{xz}$ .

**output:** revised  $R_{xy}$  path-consistent with  $z$ .

1. **for** each pair  $(a, b) \in R_{xy}$
2.     **if** no value  $c \in D_z$  exists such that  $(a, c) \in R_{xz}$  and  $(b, c) \in R_{yz}$
3.         **then** delete  $(a, b)$  from  $R_{xy}$ .
4.     **endif**
5. **endfor**

Figure 3.9: Revise-3

$$R_{xy} \leftarrow R_{xy} \cap \pi_{xy}(R_{xz} \bowtie D_z \bowtie R_{zy})$$

- Complexity:  $O(k^3)$
- Best-case:  $O(t)$
- Worst-case  $O(tk)$

# Revise3 = join followed by project

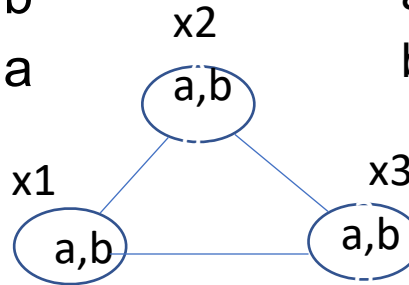
- Join :

$x_1$	$x_2$
a	a
b	b



$x_2$	$x_3$
a	a
a	b
b	a

$x_1$	$x_2$	$x_3$
a	a	a
a	a	b
b	b	a



$$R_{X_1, X_3} = \{(a,a), (a,b), (b,a)\}$$

# PC-1

PC-1( $\mathcal{R}$ )

**input:** a network  $\mathcal{R} = (X, D, C)$ .

**output:** a path consistent network equivalent to  $\mathcal{R}$ .

1. **repeat**
2.     **for**  $k \leftarrow 1$  to  $n$
3.         **for**  $i, j \leftarrow 1$  to  $n$
4.              $R_{ij} \leftarrow R_{ij} \cap \pi_{ij}(R_{ik} \bowtie D_k \bowtie R_{kj})$  /\* *Revise* - 3( $(i, j), k$ )
5.         **endfor**
6.     **endfor**
7. **until** no constraint is changed.

Figure 3.10: Path-consistency-1 (PC-1)

- **Complexity:**

- $O(n^3)$  triplets, each take  $O(k^3)$  steps  $\rightarrow O(n^3 k^3)$

- Max number of loops:  $O(n^2 k^2)$ .

# PC-2

PC-2( $\mathcal{R}$ )

**input:** a network  $\mathcal{R} = (X, D, C)$ .

**output:**  $\mathcal{R}'$  a path consistent network equivalent to  $\mathcal{R}$ .

1.  $Q \leftarrow \{(i, k, j) \mid 1 \leq i < j \leq n, 1 \leq k \leq n, k \neq i, k \neq j\}$
2. **while**  $Q$  is not empty
3.     select and delete a 3-tuple  $(i, k, j)$  from  $Q$
4.      $R_{ij} \leftarrow R_{ij} \cap \pi_{ij}(R_{ik} \bowtie D_k \bowtie R_{kj})$  /\* (Revise-3( $(i, j), k$ ))
5.     **if**  $R_{ij}$  changed then
6.      $Q \leftarrow Q \cup \{(l, i, j), (l, j, i) \mid 1 \leq l \leq n, l \neq i, l \neq j\}$
7. **endwhile**

- Complexity:
- Optimal PC-4:
- (each pair of values deleted may add:  $2n-1$  triplets, number of pairs:  $O(n^2 k^2) \rightarrow$   
size of  $Q$  is  $O(n^3 k^2)$ , processing is  $O(k^3)$  yielding the result)

# Example: before and after path-consistency

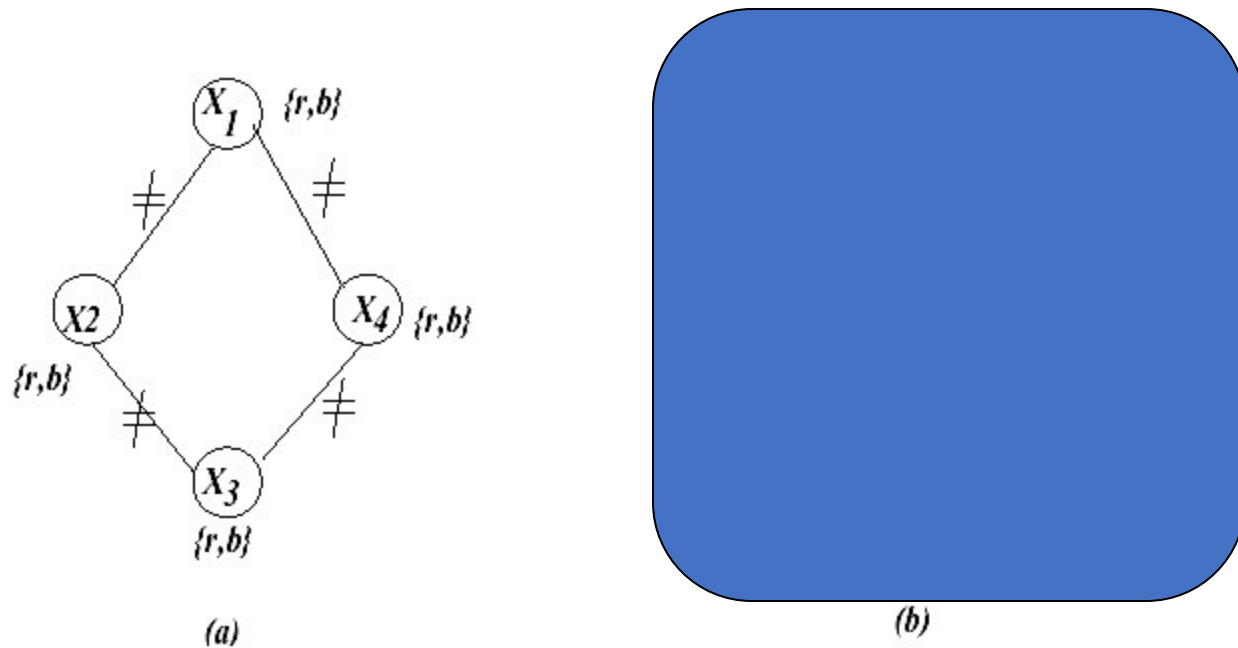


Figure 3.12: A graph-coloring graph (a) before path-consistency (b) after path-consistency

- PC-1 requires 2 processing of each arc while PC-2 may not
- Can we do path-consistency distributedly?

# Example: before and after path-consistency

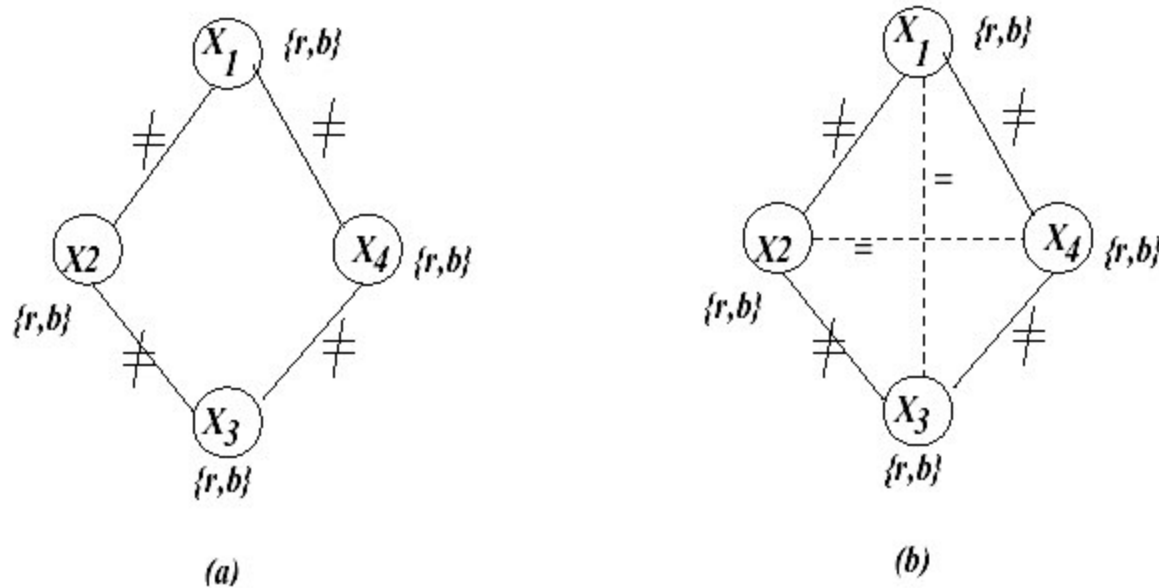


Figure 3.12: A graph-coloring graph (a) before path-consistency (b) after path-consistency

- PC-1 requires 2 processings of each arc while PC-2 may not
- Can we do path-consistency distributedly?

# Path-consistency Algorithms

- Apply Revise-3  $O(k^3)$  until no change

$$R_{ij} \leftarrow R_{ij} \cap \pi_{ij}(R_{ik} \bowtie D_k \bowtie R_{kj})$$

- Path-consistency (3-consistency) adds binary constraints.
- PC-1:
- PC-2:
- PC-4 optimal:



# I-consistency

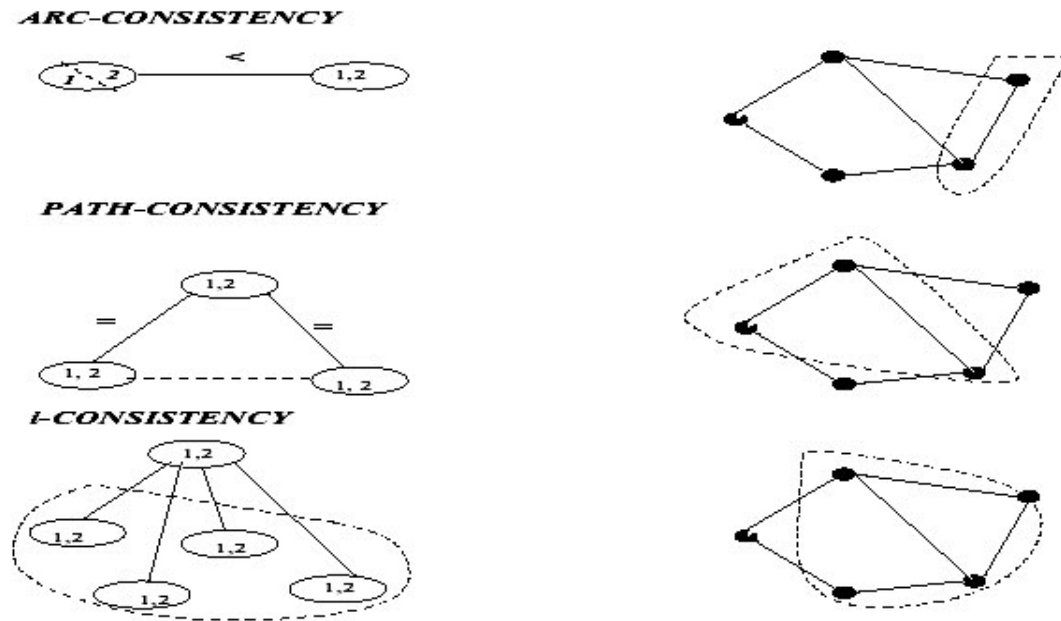


Figure 3.17: The scope of consistency enforcing: (a) arc-consistency, (b) path-consistency, (c) i-consistency

# Higher levels of consistency, global-consistency

Definition:

*t. A network is  $i$ -consistent iff given any consistent instantiation of any  $i - 1$  distinct variables, there exists an instantiation of any  $i$ th variable such that the  $i$  values taken together satisfy all of the constraints among the  $i$  variables. A network is strongly  $i$ -consistent iff it is  $j$ -consistent for all  $j \leq i$ . A strongly  $n$ -consistent network, where  $n$  is the number of variables in the network, is called globally consistent.*

**A Globally consistent network is backtrack-free**

# Revise-i

REVISE- $i$ ( $\{x_1, x_2, \dots, x_{i-1}\}, x_i$ )

**input:** a network  $\mathcal{R} = (X, D, C)$

**output:** a constraint  $R_S$ ,  $S = \{x_1, \dots, x_{i-1}\}$   $i$ -consistent relative to  $x_i$ .

1. **for** each instantiation  $\bar{a}_{i-1} = (\langle x_1, a_1 \rangle, \langle x_2, a_2 \rangle, \dots, \langle x_{i-1}, a_{i-1} \rangle)$  **do**,

2. **if** no value of  $a_i \in D_i$  exists s.t.  $(\bar{a}_{i-1}, a_i)$  is consistent

**then** delete  $\bar{a}_{i-1}$  from  $R_S$

    (Alternatively, let  $\mathcal{S}$  be the set of all subsets of  $\{x_1, \dots, x_i\}$  that contain  $x_i$  and appear as scopes of constraints of  $\mathcal{R}$ , then

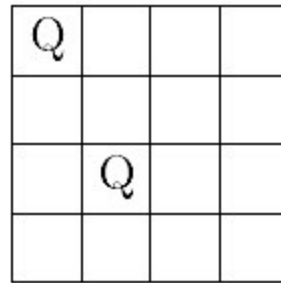
$R_S \leftarrow R_S \cap \pi_S(\bigotimes_{S' \subseteq \mathcal{S}} R_{S'})$ )

3. **endfor**

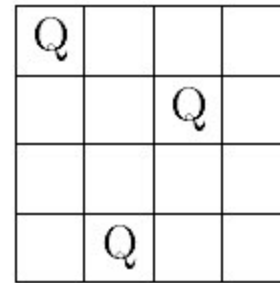
Figure 3.14: Revise-i

- Complexity: for binary constraints  $O(k^i)$
- For arbitrary constraints:
- (because there may be  $O(2^i)$  constraints to test per tuple)

# 4-queen example



(a)



(b)

Figure 3.13: (a) Not 3-consistent; (b) Not 4-consistent

# i-consistency

I-CONSISTENCY( $\mathcal{R}$ )

**input:** a network  $\mathcal{R}$ .

**output:** an i-consistent network equivalent to  $\mathcal{R}$ .

1. **repeat**
2.     **for** every subset  $S \subseteq X$  of size  $i - 1$ , and for every  $x_i$ , do
3.     let  $\mathcal{S}$  be the set of all subsets in of  $\{x_1, \dots, x_i\}$  *scheme*( $\mathcal{R}$ )  
that contain  $x_i$
4.      $R_S \leftarrow R_S \cap \pi_S(\bigotimes_{S' \in \mathcal{S}} R_{S'})$  ( this is Revise-i( $S, x_i$ ))
6.     **endfor**
7. **until** no constraint is changed.

*This S is different it is all subsets of size l  
That includes xi*

Figure 3.15: i-consistency-1

**Theorem 3.4.3 (complexity of i-consistency)** *The time and space complexity of brute-force i-consistency  $O(2^i(nk)^{2i})$  and  $O(n^i k^i)$ , respectively. A lower bound for enforcing i-consistency is  $\Omega(n^i k^i)$ .  $\square$*

# Path-consistency vs 3-consistency

**Example 3.4.4** Suppose a constraint network involves three variables  $x, y, z$  having domains  $\{0, 1\}$  and a single ternary constraint  $R_{xyz} = \{(0, 0, 0)\}$ . Application of the path-consistency algorithm will produce nothing since there are no binary constraints to test; the network is already path-consistent. However, the network is *not* 3-consistent. While we can assign the values  $(\langle x, 1 \rangle, \langle y, 1 \rangle)$  (since there is no constraint), we cannot extend this assignment to  $z$  in a way that satisfies the given ternary constraints. Indeed, if we

apply 3-consistency to this network we will add the constraint  $R_{xy} = \{(\langle x, 0 \rangle \langle y, 0 \rangle)\}$  in addition to the constraint  $R_x = \{(\langle x, 0 \rangle)\}$ .  $\square$

# i-consistency

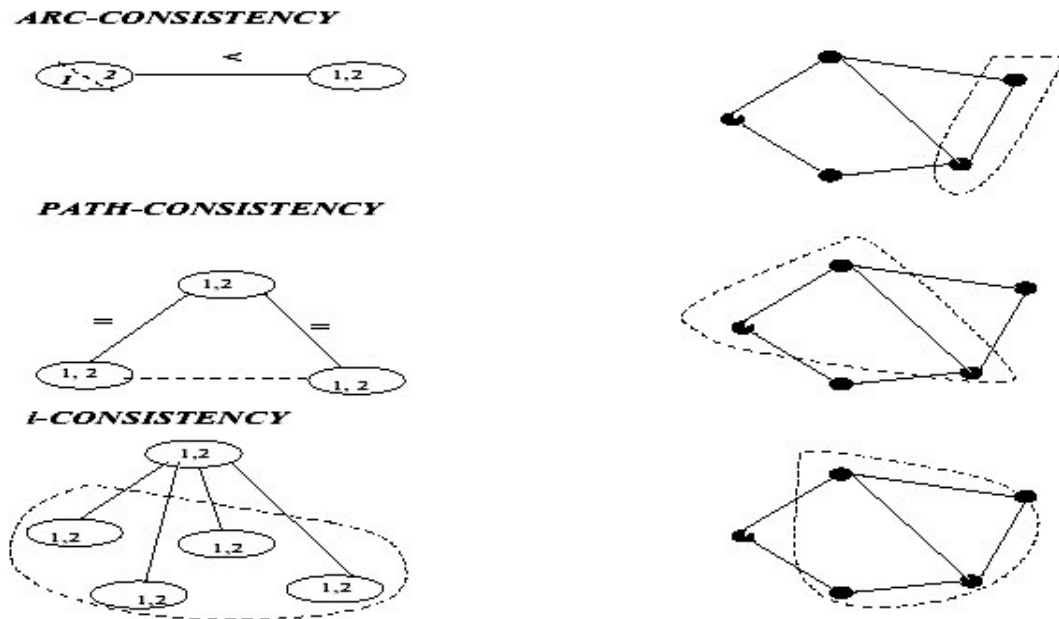


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## Generalized arc-consistency (GAC) for non-binary constraints

**Definition 3.5.1 (generalized arc-consistency)** *Given a constraint network  $\mathcal{R} = (\mathcal{X}, \mathcal{D}, \mathcal{C})$ , with  $R_S \in \mathcal{C}$ , a variable  $x$  is arc-consistent relative to  $R_S$  if and only if for every value  $a \in D_x$  there exists a tuple  $t \in R_S$  such that  $t[x] = a$ .  $t$  can be called a support for  $a$ . The constraint  $R_S$  is called arc-consistent iff it is arc-consistent relative to each of the variables in its scope and a constraint network is arc-consistent if all its constraints are arc-consistent.*

$$D_x \leftarrow D_x \cap \pi_x(R_S \bowtie D_{S-x})$$

Complexity:  $O(t \cdot k)$ ,  $t$  bounds number of tuples.

Relational arc-consistency (different than GAC):

$$R_{S-\{x\}} \leftarrow \pi_{S-\{x\}}(R_S \bowtie D_x).$$

---

### Algorithm 1: AC3 / GAC3

---

```
function Revise3(in  $x_i$ : variable;  $c$ : constraint): Boolean ;
  begin
  1   CHANGE  $\leftarrow$  false;
  2   foreach  $v_i \in D(x_i)$  do
  3     if  $\nexists \tau \in c \cap \pi_{X(c)}(D)$  with  $\tau[x_i] = v_i$  then
  4       remove  $v_i$  from  $D(x_i)$ ;
  5       CHANGE  $\leftarrow$  true;
  6   return CHANGE ;
  end

function AC3/GAC3(in  $X$ : set): Boolean ;
  begin
  /* initialisation */;
  7    $Q \leftarrow \{(x_i, c) \mid c \in C, x_i \in X(c)\}$ ;
  /* propagation */;
  8   while  $Q \neq \emptyset$  do
  9     select and remove  $(x_i, c)$  from  $Q$ ;
  10    if Revise( $x_i, c$ ) then
  11      if  $D(x_i) = \emptyset$  then return false ;
  12      else  $Q \leftarrow Q \cup \{(x_j, c') \mid c' \in C \wedge c' \neq c \wedge x_i, x_j \in X(c') \wedge j \neq i\}$ ;
  13  return true ;
  end
```

---

# Generalized arc-consistency

**Proposition 27 (GAC3).** *GAC3 is a sound and complete algorithm for achieving arc consistency that runs in  $O(er^3d^{r+1})$  time and  $O(er)$  space, where  $r$  is the greatest arity among constraints.*

# Examples of generalized AC and relational AC

- $x+y+z \leq 15$  and  $z \geq 13$  implies



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- $x+y+z \leq 15$  and  $z \geq 13$  implies  
 $x \leq 1, y \leq 1$

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- Example of relational arc-consistency

Here given the 2 top Boolean constraints we infer the 3<sup>rd</sup>.



# Examples: of generalized AC

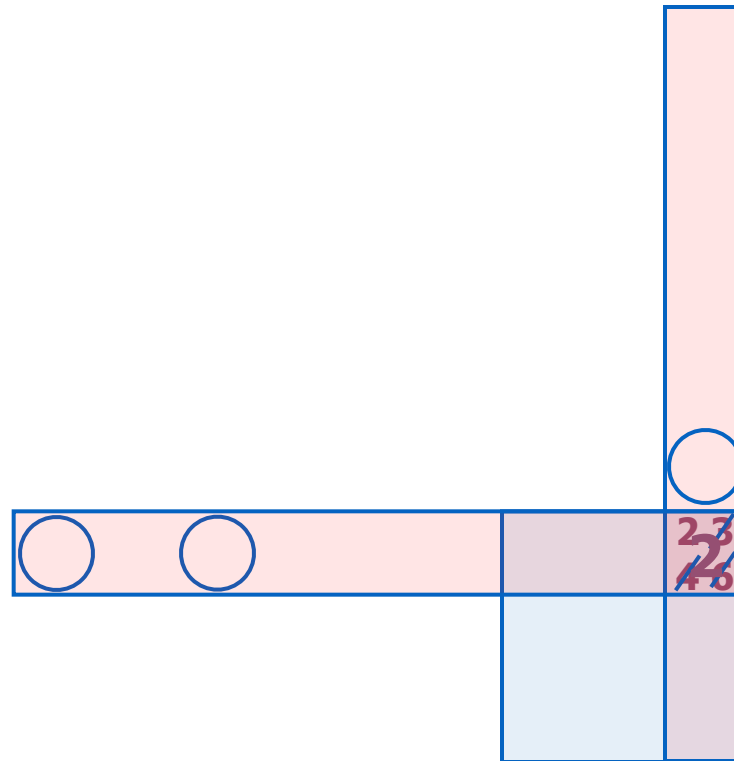
- $x+y+z \leq 15$  and  $z \geq 13$  implies  
 $x \leq 2, y \leq 2$

- Example of relational arc-consistency

Here given the 2 top Boolean constraints we infer the 3<sup>rd</sup>.

# Sudoku

- Constraint Propagation
- Inference



- Variables: empty slots
- Domains =  $\{1,2,3,4,5,6,7,8,9\}$
- Constraints: 27 all-different

Each row, column and major block must be alldifferent

“Well posed” if it has unique solution: 27 constraints



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# More arc-based consistency

- Global constraints: e.g., all-different constraints
  - Special semantic constraints that appears often in practice and a specialized constraint propagation. Used in constraint programming.
- Bounds-consistency: pruning the boundaries of domains

# Global constraints

Constraints of arbitrary scope length defined by expression, a Boolean function

 *Global constraints are classes of constraints defined by a formula of arbitrary arity (see Section 9.2).*

**Example 2.** The constraint  $\text{alldifferent}(x_1, x_2, x_3) \equiv (v_i \neq v_j \wedge v_i \neq v_k \wedge v_j \neq v_k)$  allows the infinite set of 3-tuples in  $\mathbb{Z}^3$  such that all values are different. The constraint  $c(x_1, x_2, x_3) = \{(2, 2, 3), (2, 3, 2), (2, 3, 3), (3, 2, 2), (3, 2, 3), (3, 3, 2)\}$  allows the finite set of 3-tuples containing both values 2 and 3 and only them.

# Global constraints

**Example 86.** The  $\text{alldifferent}(x_1, \dots, x_n)$  global constraint is the class of constraints that are defined on any sequence of  $n$  variables,  $n \geq 2$ , such that  $x_i \neq x_j$  for all  $i, j, 1 \leq i, j \leq n, i \neq j$ . The  $\text{NValue}(y, [x_1, \dots, x_n])$  global constraint is the class of constraints that are defined on any sequence of  $n + 1$  variables,  $n \geq 1$ , such that  $|\{x_i \mid 1 \leq i \leq n\}| = y$  [100, 8].

We need specialized procedures for generalize Arc-consistency because it is too expensive to try and apply the general algorithm (see Bessiere, section 9.2)

We can decompose a global constraint, or use various specialized representation

# Example for alldiff

- $A = \{3,4,5,6\}$
- $B = \{3,4\}$
- $C = \{2,3,4,5\}$
- $D = \{2,3,4\}$
- $E = \{3,4\}$
- $F = \{1,2,3,4,5,6\}$
- Alldiff (A,B,C,D,E)
- Arc-consistency does nothing
- Apply GAC to sol(A,B,C,D,E,F)?
- $\rightarrow A = \{6\}, F = \{1\}....$
- Alg: bipartite matching  $kn^{1.5}$
- (Lopez-Ortiz, et. Al, IJCAI-03 pp 245 (A fast and simple algorithm for bounds consistency of alldifferent constraint))

# Global constraints

- Alldifferent
- Sum constraint (variable equal the sum of others)
- Global cardinality constraint (a value can be assigned a bounded number of times to a set of variables)
- The cumulative constraint (related to scheduling tasks)

*In summary, a global constraint  $C = \{C(i)\}$  is a family of scope-parameterized constraints, (normally  $i \geq 2$ ), where  $C(i)$  is a constraint whose relation is often defined implicitly by either a natural language statement, or as a set of solutions to a subproblem defined by lower arity explicit constraints (e.g., alldifferent). It is associated with one or more specialized propagation algorithms trying to achieve generalized arc-consistency relative to  $C(i)$  (or an approximation of it) in a way that is more efficient than a brute-force approach.*

# Bounds consistency

**Definition 3.5.4 (bounds consistency)** *Given a constraint  $C$  over a scope  $S$  and domain constraints, a variable  $x \in S$  is bounds-consistent relative to  $C$  if the value  $\min\{D_x\}$  (respectively,  $\max\{D_x\}$ ) can be extended to a full tuple  $t$  of  $C$ . We say that  $t$  supports  $\min\{D_x\}$ . A constraint  $C$  is bounds-consistent if each of its variables is bounds-consistent.*

# Bounds consistency

**Example 3.5.5** Consider the constraint problem with variables  $x_1, \dots, x_6$ , each with domains  $1, \dots, 6$ , and constraints:

$$C_1 : x_4 \geq x_1 + 3, \quad C_2 : x_4 \geq x_2 + 3, \quad C_3 : x_5 \geq x_3 + 3, \quad C_4 : x_5 \geq x_4 + 1,$$

$$C_5 : \text{alldifferent}\{x_1, x_2, x_3, x_4, x_5\}$$

The constraints are not bounds consistent. For example, the minimum value 1 in the domain of  $x_4$  does not have support in constraint  $C_1$  as there is no corresponding value for  $x_1$  that satisfies the constraint. Enforcing bounds consistency using constraints  $C_1$  through  $C_4$  reduces the domains of the variables as follows:  $D_1 = \{1, 2\}$ ,  $D_2 = \{1, 2\}$ ,  $D_3 = \{1, 2, 3\}$ ,  $D_4 = \{4, 5\}$  and  $D_5 = \{5, 6\}$ . Subsequently, enforcing bounds consistency using constraints  $C_5$  further reduces the domain of  $C$  to  $D_3 = \{3\}$ . Now constraint  $C_3$  is no longer bound consistent. Reestablishing bounds consistency causes the domain of  $x_5$  to be reduced to  $\{6\}$ . Is the resulting problem already arc-consistent?  $\square$



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- Distributed (generalized) arc-consistency

# Boolean constraint propagation

- $(A \vee \neg B)$  and  $(B)$ 
  - $B$  is arc-consistent relative to  $A$  but not vice-versa
- Arc-consistency by resolution:  
 $\text{res}((A \vee \neg B), B) = A$

Given also  $(B \vee C)$ , path-consistency:

$$\text{res}((A \vee \neg B), (B \vee C)) = (A \vee C)$$

Relational arc-consistency rule = unit-resolution

# Boolean constraint propagation

**Procedure** UNIT-PROPAGATION

**Input:** A cnf theory,  $\varphi$ ,  $d = Q_1, \dots, Q_n$ .

**Output:** An equivalent theory such that every unit clause does not appear in any non-unit clause.

1. queue = all unit clauses.
2. **while** queue is not empty, do.
3.      $T \leftarrow$  next unit clause from Queue.
4.     **for** every clause  $\beta$  containing  $T$  or  $\neg T$
5.         **if**  $\beta$  contains  $T$  delete  $\beta$  (subsumption elimination)
6.         **else**, For each clause  $\gamma = \text{resolve}(\beta, T)$ .
7.             **if**  $\gamma$ , the resolvent, is empty, the theory is unsatisfiable.
8.             **else**, add the resolvent  $\gamma$  to the theory and delete  $\beta$ .
9.             **if**  $\gamma$  is a unit clause, add to Queue.
10.     **endfor**.
11. **endwhile**.

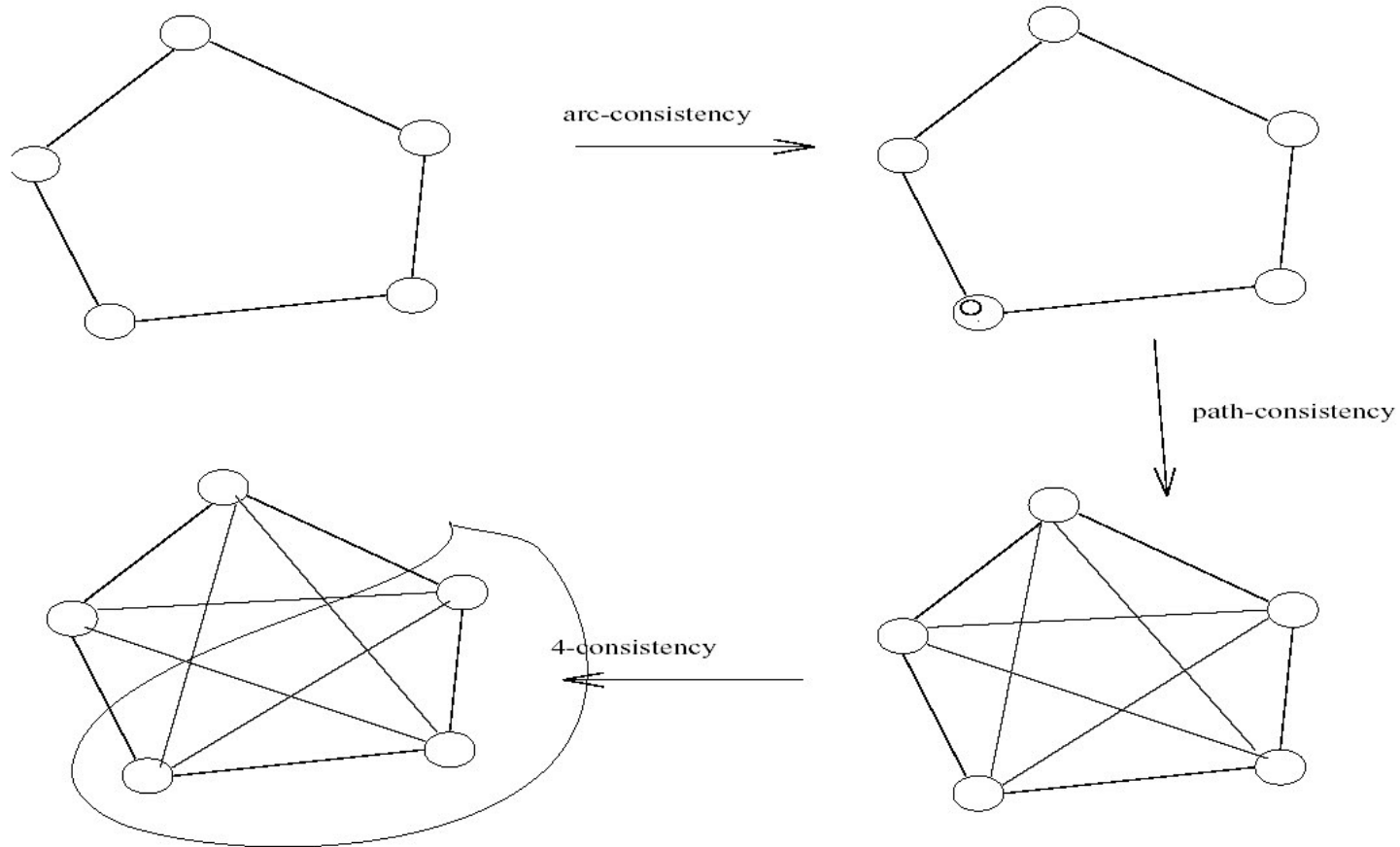
**Theorem 3.6.1** *Algorithm UNIT-PROPAGATION has a linear time complexity.*

# Consistency for numeric constraints (Gaussian elimination)

Gaussian  
elimination of

Gaussian Elimination of:

# Impact on graphs of i-consistency



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- Consistency operators: join, resolution, Gaussian elimination
- **Distributed (generalized) arc-consistency**

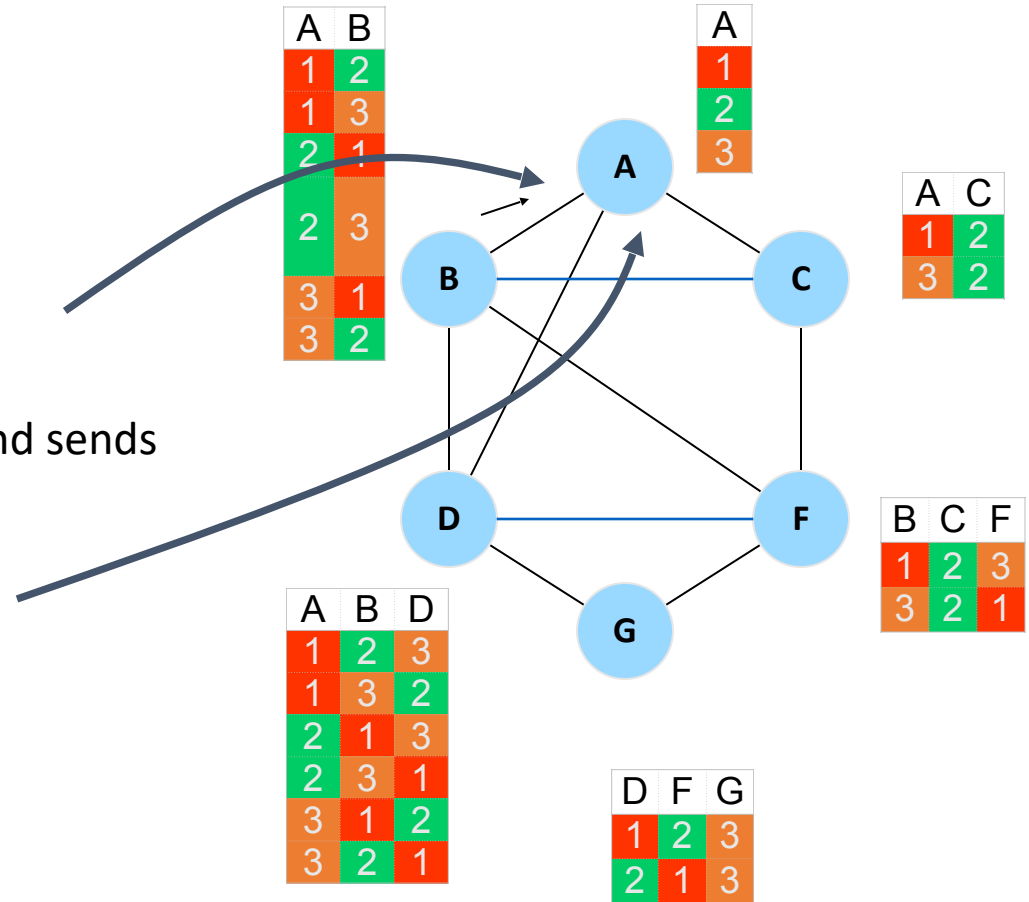
# Distributed arc-consistency (Constraint propagation)

- Implement AC-1 distributedly.
- Node  $x_j$  sends the message to node  $x_i$
- Node  $x_i$  updates its domain:
- Relational and generalized arc-consistency can be implemented distributedly: sending messages between constraints over the dual graph

# Relational Arc-consistency

The message that R2 sends to R1 is

R1 updates its relation and domains and sends messages to neighbors





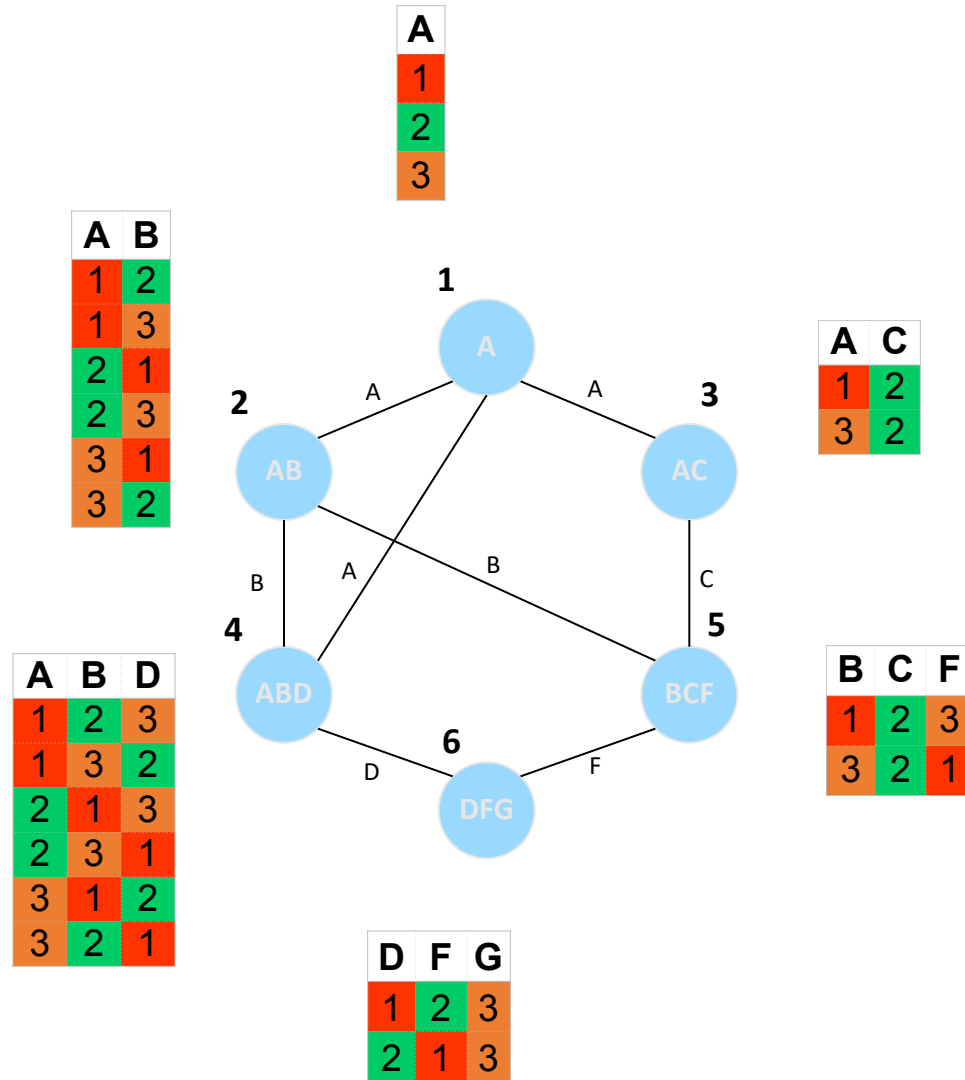
# Distributed Relational Arc-Consistency

- DRAC can be applied to the dual problem of any constraint network:

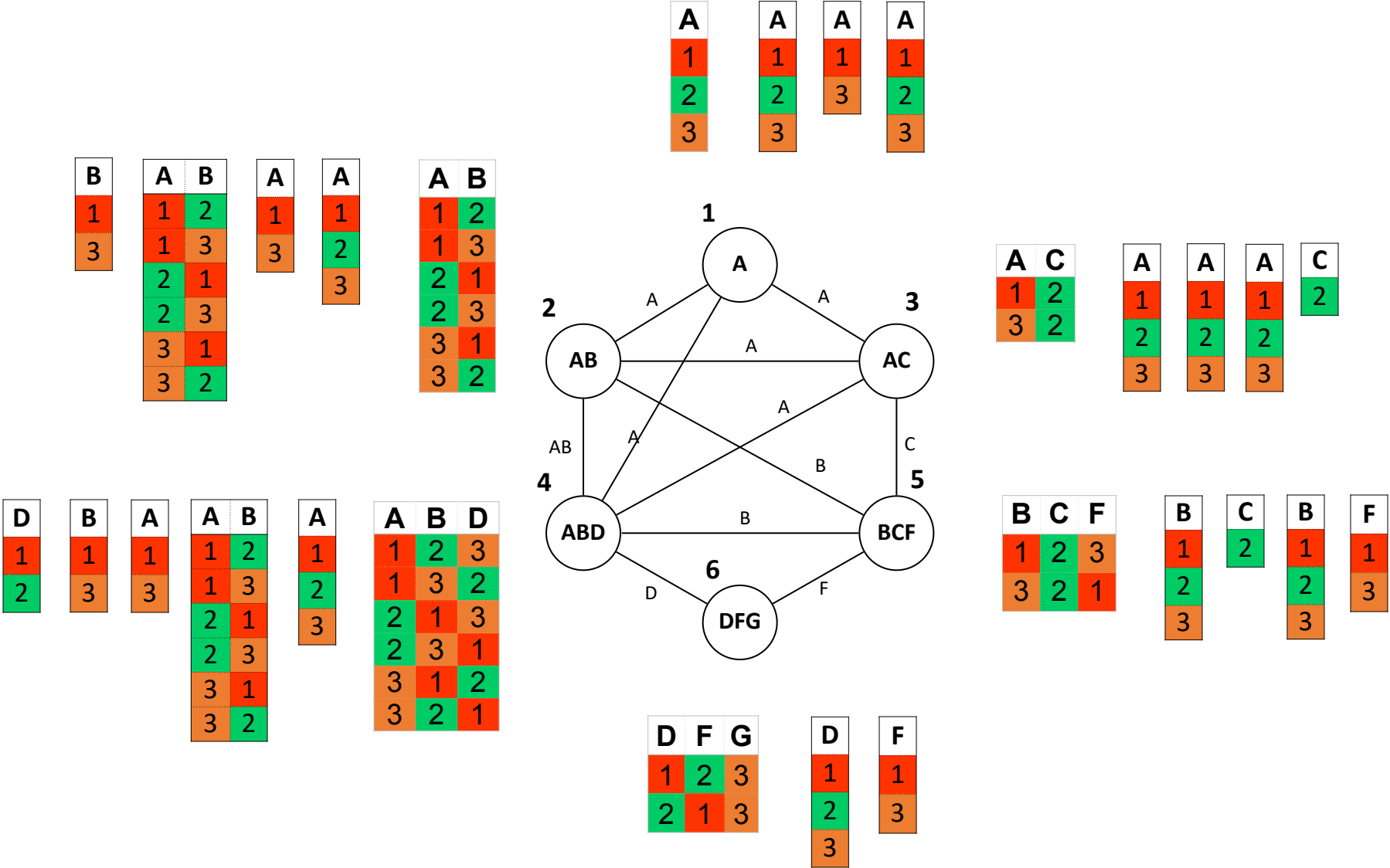
$$h_i^j \leftarrow \pi_{l_{ij}}(R_i \bowtie (\bigotimes_{k \in ne(i)} h_k^i)) \quad (1)$$

$$R_i \leftarrow R_i \cap (\bigotimes_{k \in ne(i)} h_k^i) \quad (2)$$

# DRAC on the dual join-graph

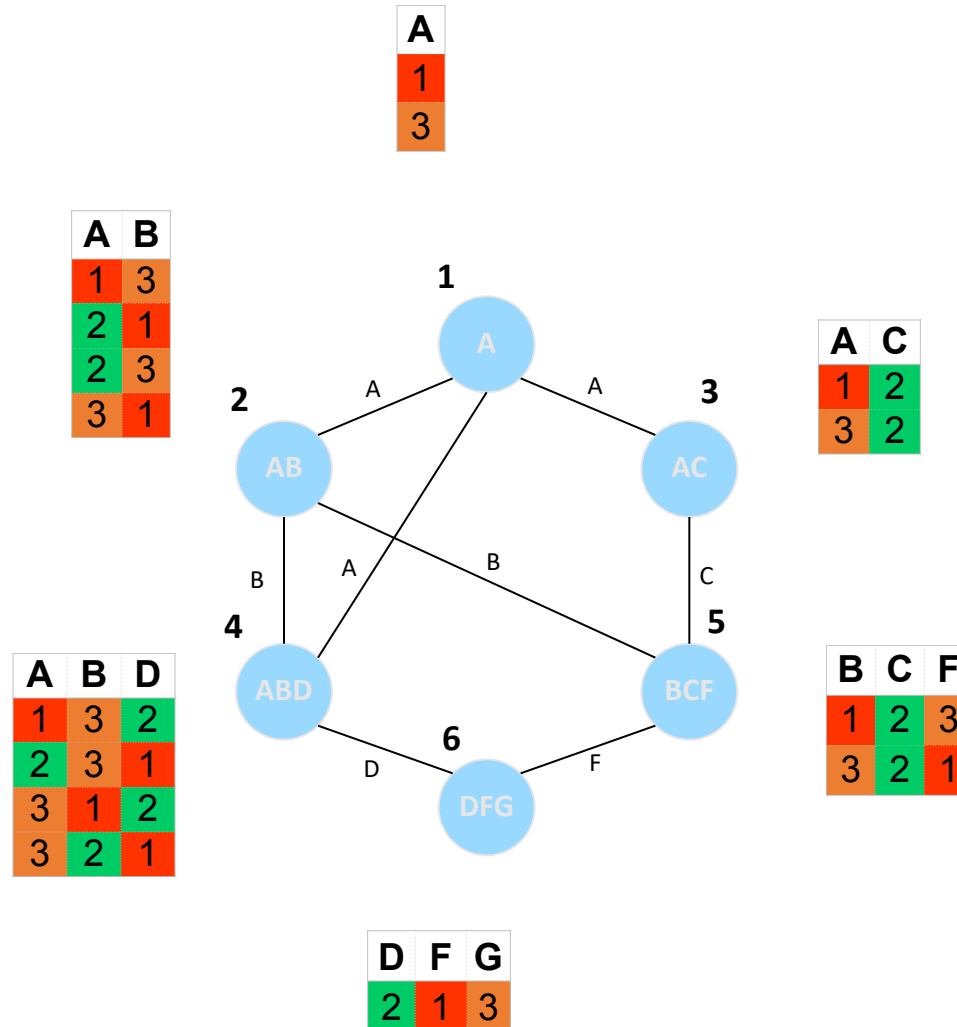


# Iteration 1



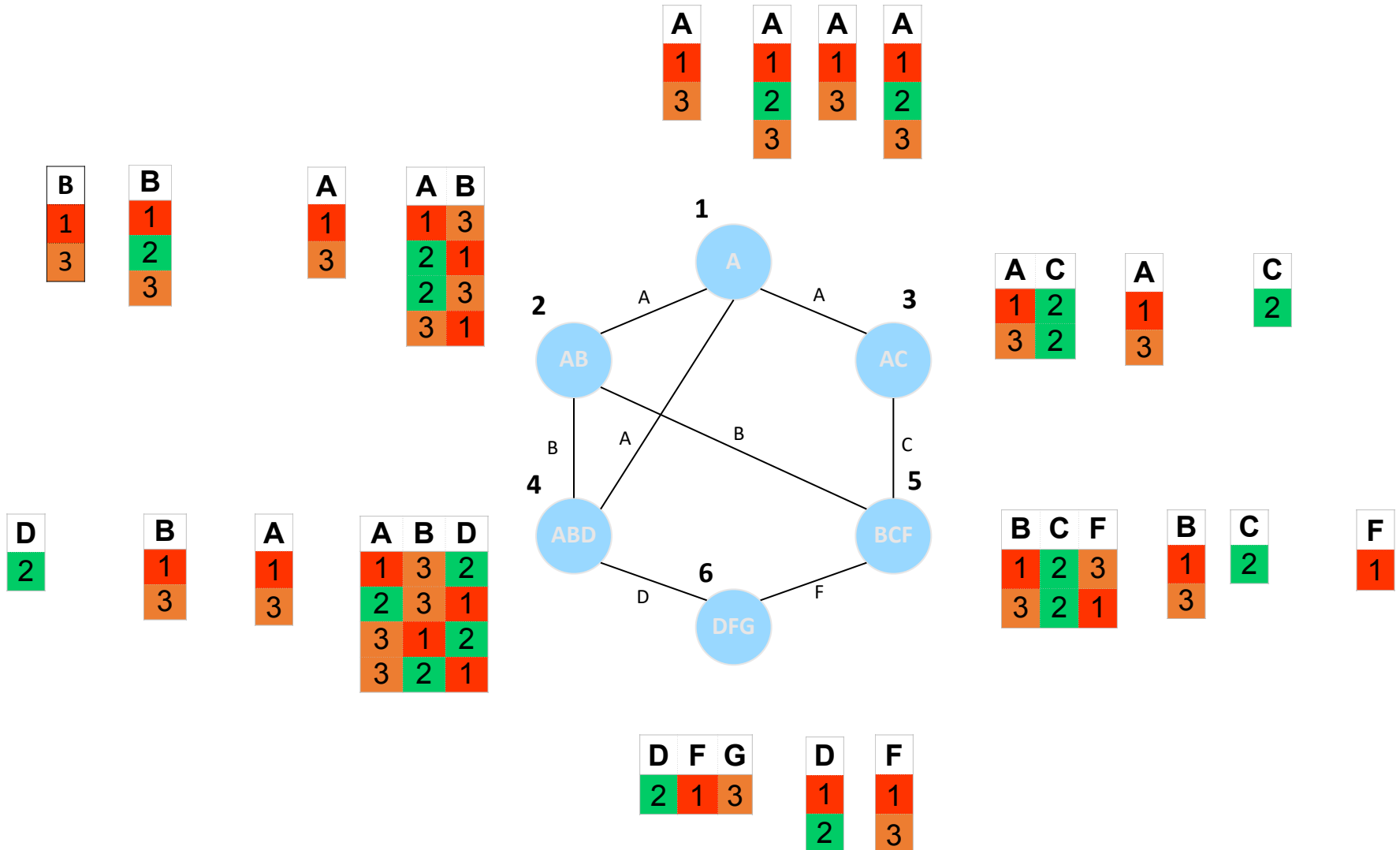
$$R_i \leftarrow R_i \cap \left( \bigwedge_{k \in ne(i)} h_k^i \right) \quad (2)$$

# Iteration 1



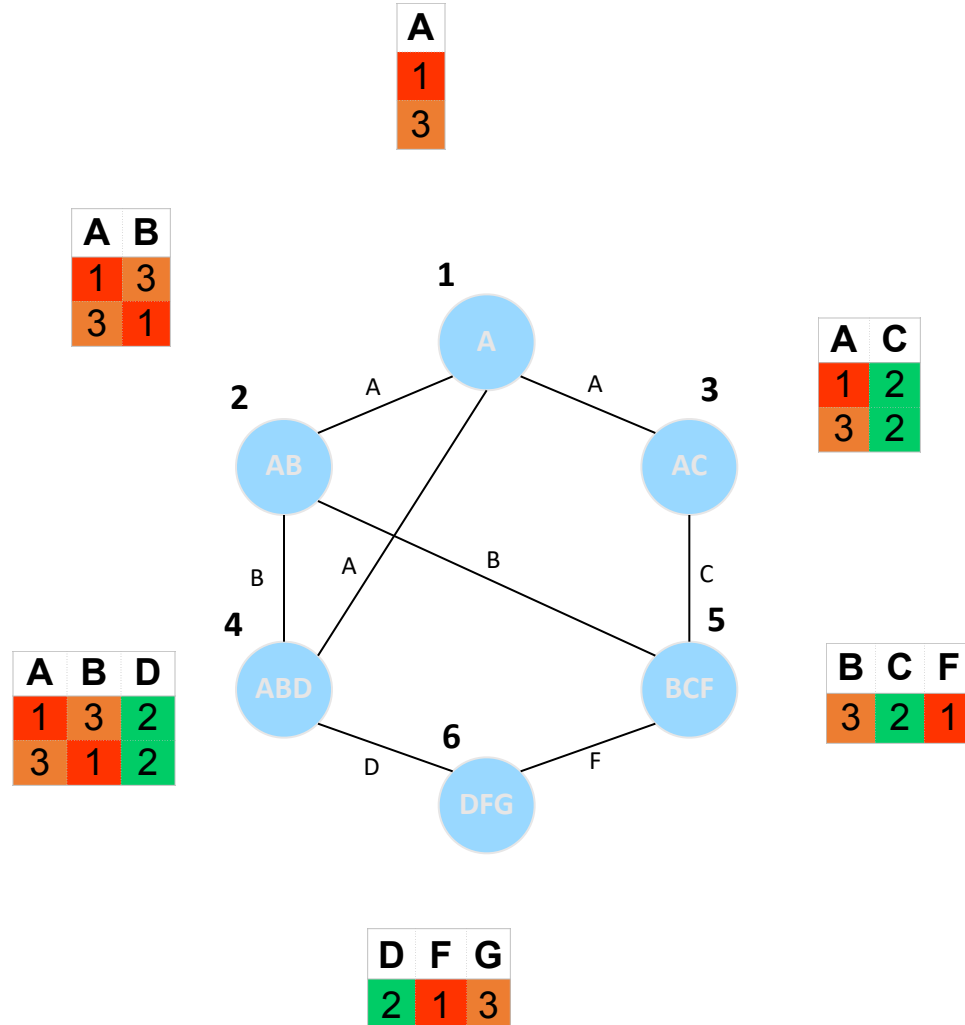
$$h_i^j \leftarrow \pi_{l_{ij}}(R_i \bowtie (\bowtie_{k \in ne(i)} h_k^i)) \quad (1)$$

# Iteration 2



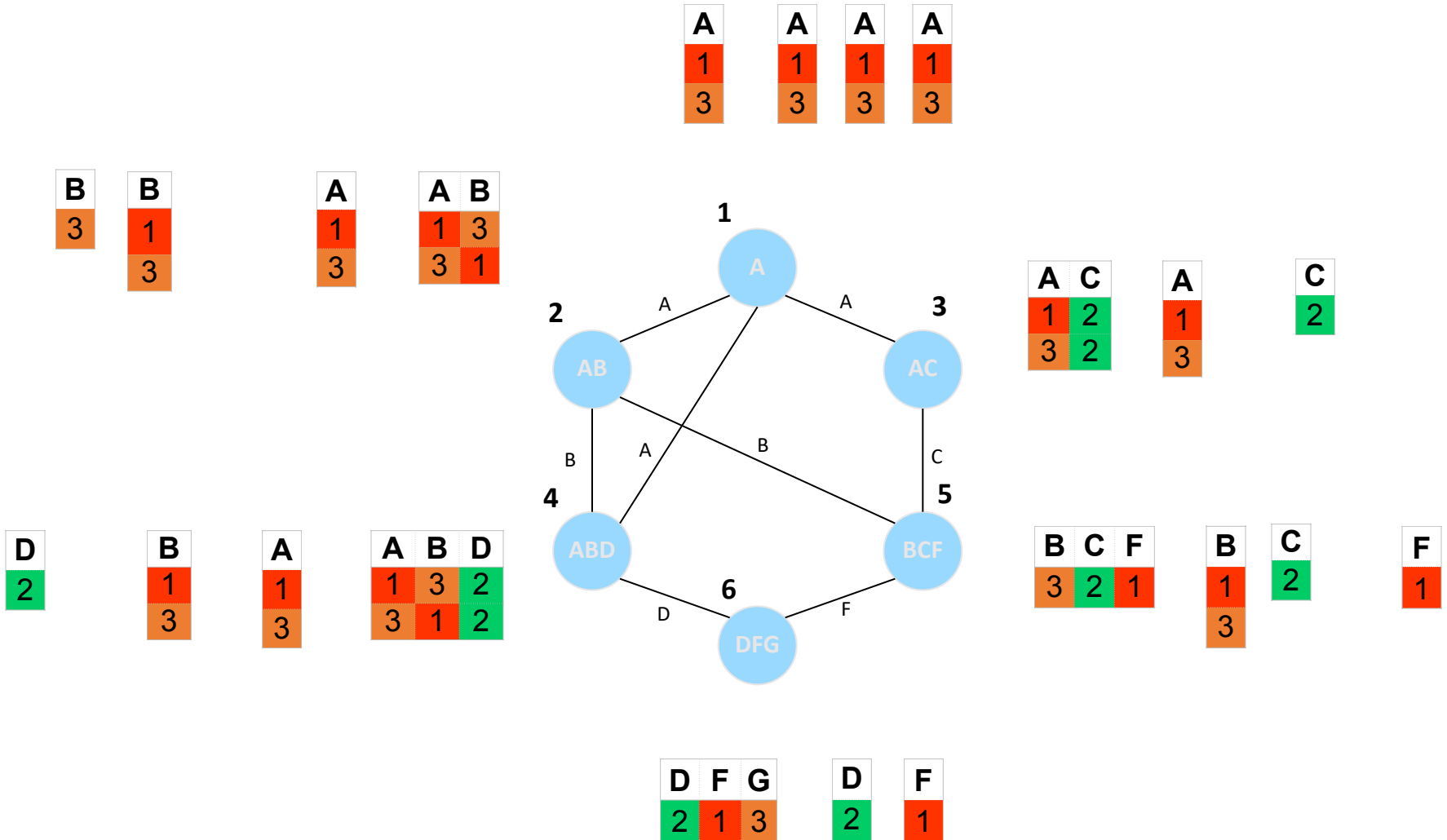
$$R_i \leftarrow R_i \cap \left( \bigwedge_{k \in ne(i)} h_k^i \right) \quad (2)$$

# Iteration 2



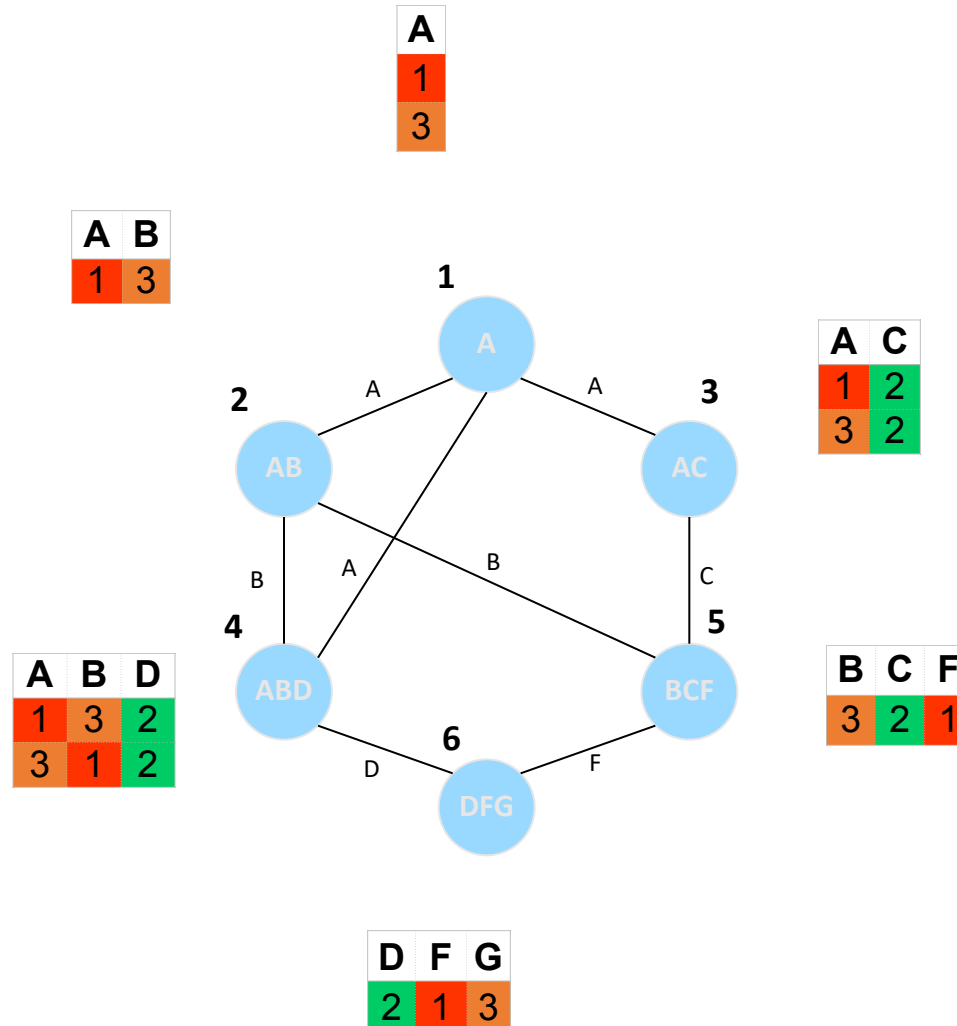
$$h_i^j \leftarrow \pi_{l_{ij}}(R_i \bowtie (\bowtie_{k \in ne(i)} h_k^i)) \quad (1)$$

# Iteration 3



$$R_i \leftarrow R_i \cap \left( \bigwedge_{k \in ne(i)} h_k^i \right) \quad (2)$$

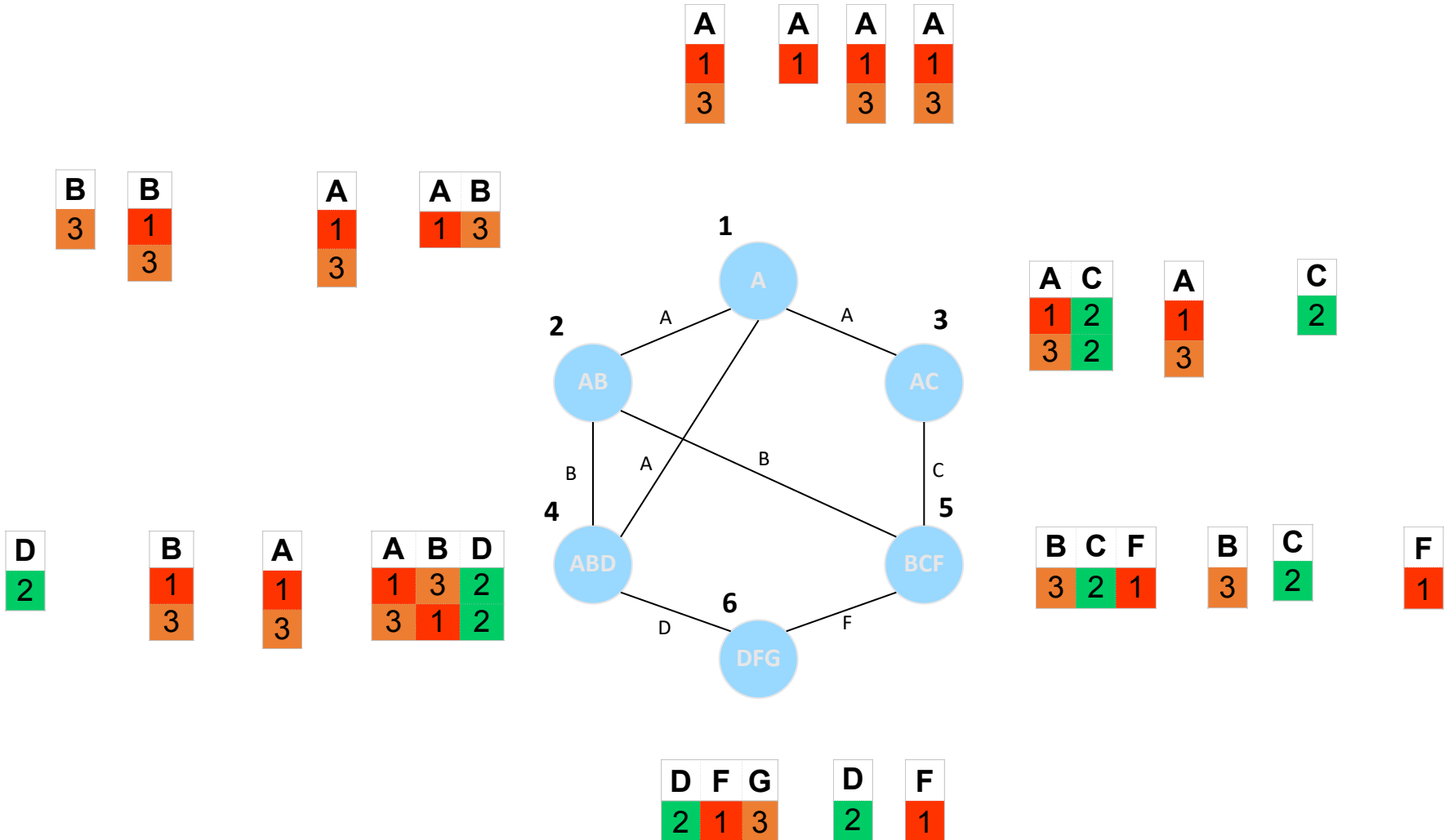
# Iteration 3





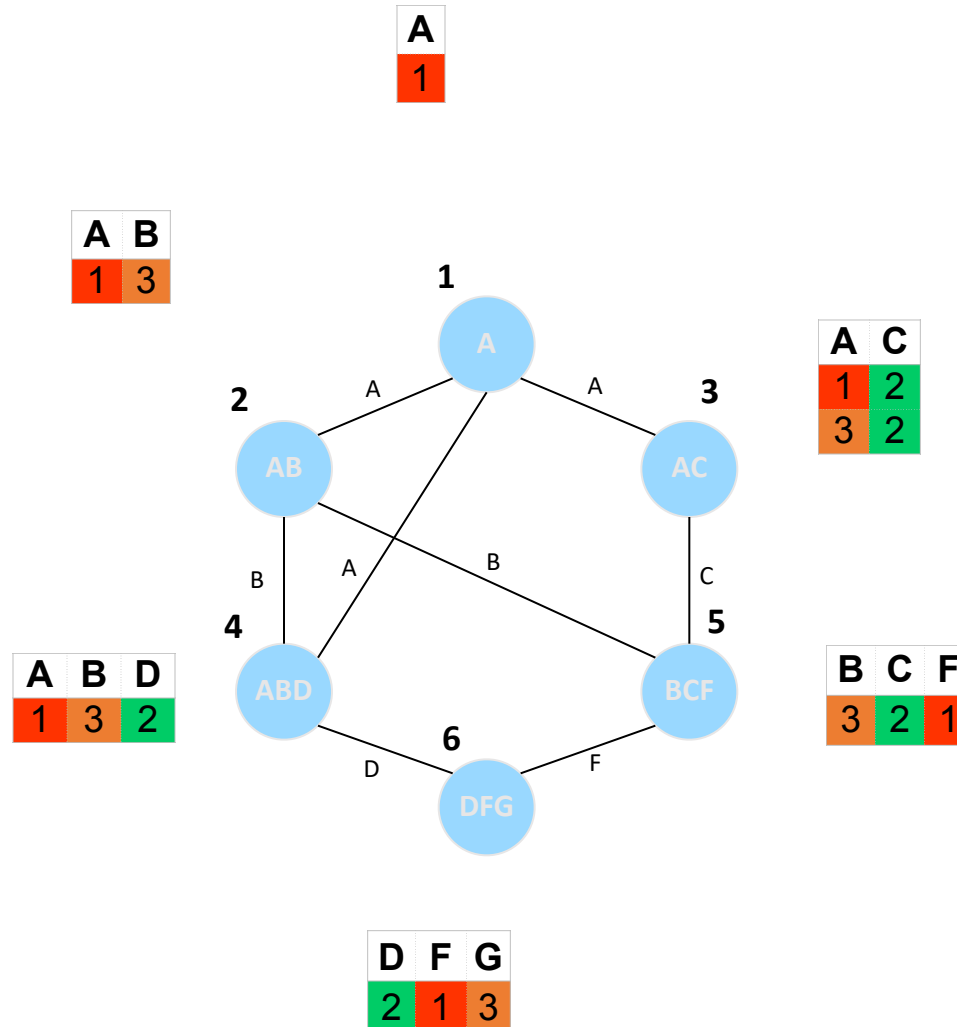
$$h_i^j \leftarrow \pi_{l_{ij}}(R_i \bowtie (\bowtie_{k \in ne(i)} h_k^i)) \quad (1)$$

# Iteration 4



$$R_i \leftarrow R_i \cap \left( \bigwedge_{k \in ne(i)} h_k^i \right) \quad (2)$$

# Iteration 4



$$h_i^j \leftarrow \pi_{l_{ij}}(R_i \bowtie (\bowtie_{k \in ne(i)} h_k^i)) \quad (1)$$

# Iteration 5

A	A	A	A
1	1	1	1

B	B
3	3

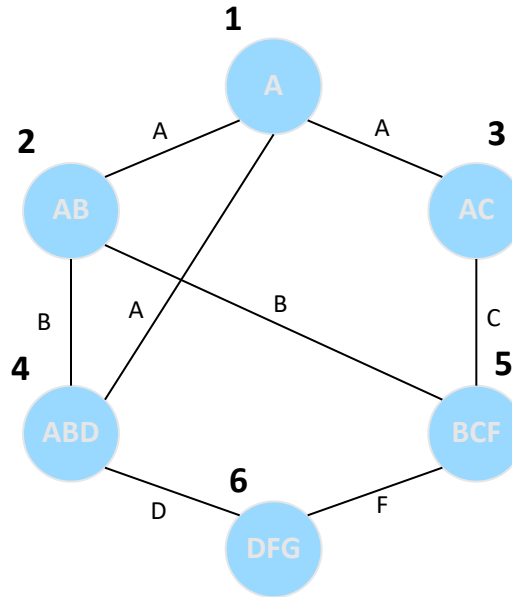
A	A	B
1	1	3

D
2

B
3

A
1

A	B	D
1	3	2



A	C
1	2
3	2

A
1

C
2

B	C	F
3	2	1

B
3

C
2

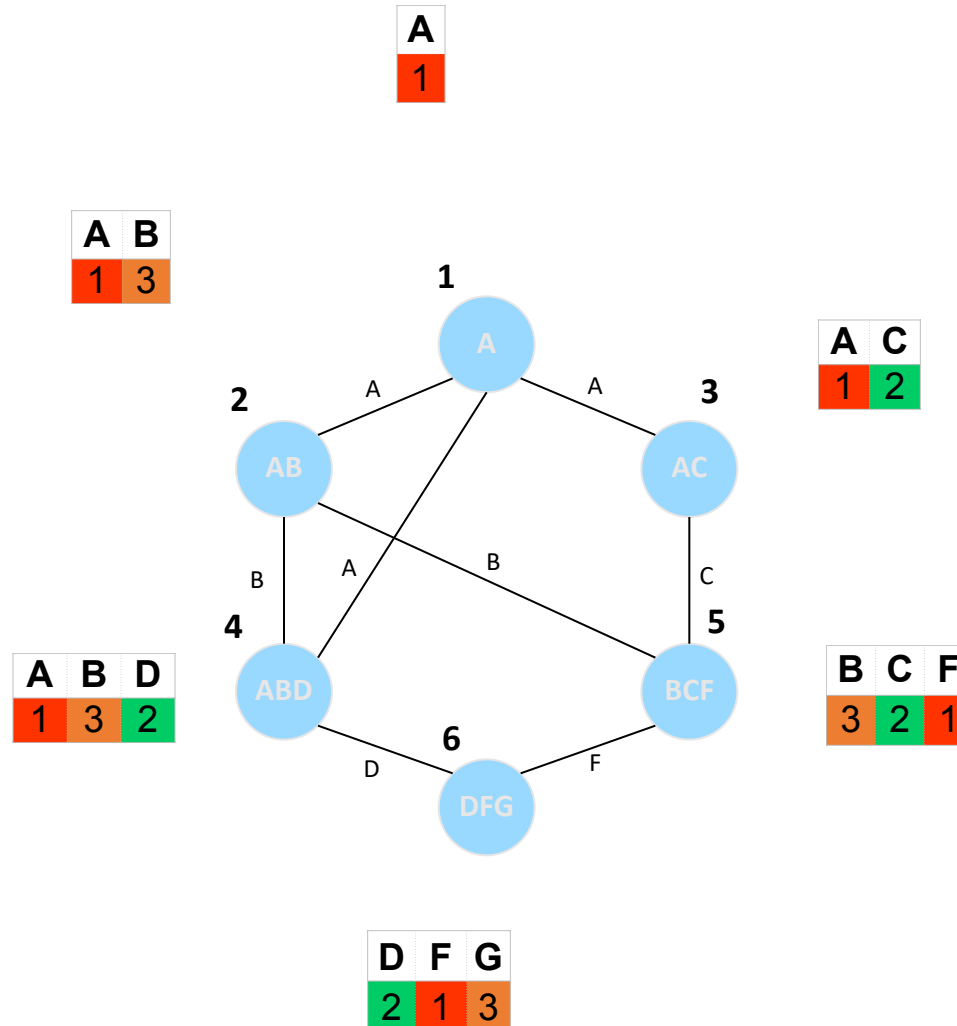
F
1

D	F	G
2	1	3

D	F
2	1

$$R_i \leftarrow R_i \cap \left( \bigwedge_{k \in ne(i)} h_k^i \right) \quad (2)$$

# Iteration 5



# Tractable classes

- Theorem 3.7.1**
- 1. The consistency of binary constraint networks having no cycles can be decided by arc-consistency*
  - 2. The consistency of binary constraint networks with bi-valued domains can be decided by path-consistency,*
  - 3. The consistency of Horn cnf theories can be decided by unit propagation.*

# Outline

- Arc-consistency algorithms
- Path-consistency and i-consistency
- Arc-consistency, Generalized arc-consistency, relation arc-consistency
- Global and bound consistency
- Consistency operators: join, resolution, Gaussian elimination
- Distributed (generalized) arc-consistency