

Scalable Numerical Abstract Domains

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Second Workshop on Analysis and Verification of
Dependable Cyber Physical Software

November 23–24, 2013 – Changsha, China

Motivation

Numerical static analysis:

- ▶ automatic and static discovery of properties on the **numerical** variables of a program

Applications:

- ▶ static verification of programs
- ▶ invariant discovery
- ▶ program optimization

Context: abstract numerical domains

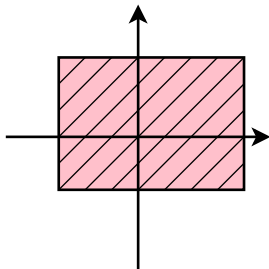
Abstract interpretation [Cousot Cousot 77] defines a formal framework of **sound approximations** of semantics.

A **numerical abstract domain** is:

- ▶ a set $\mathcal{D}_{\mathcal{V}}$ of computer-representable **abstract values**,
- ▶ a concretisation $\llbracket \cdot \rrbracket : \mathcal{D}_{\mathcal{V}} \longrightarrow \mathcal{P}(\mathcal{V} \mapsto \mathbb{Q})$,
- ▶ a comparison algorithm $\sqsubseteq^{\mathcal{D}_{\mathcal{V}}}$ of abstract values,
- ▶ **effective** algorithms to compute **sound** abstractions of the operations: intersection $\sqcap^{\mathcal{D}_{\mathcal{V}}}$, union $\sqcup^{\mathcal{D}_{\mathcal{V}}}$, projection $\exists^{\mathcal{D}_{\mathcal{V}}}$, ...
- ▶ a widening $\nabla^{\mathcal{D}_{\mathcal{V}}}$ to ensure termination, if needed.

Numerical abstract domains: basics

Intervals [Cousot Cousot 76]

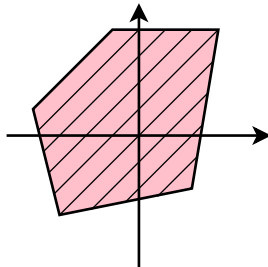


$$\bigwedge_i a_i \leq X_i \leq b_i$$

Non-relational

Linear cost

Polyhedra [Cousot Halbwachs 78]



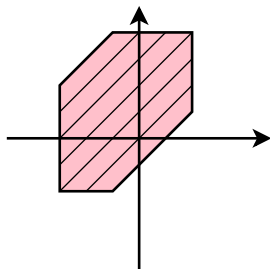
$$\bigwedge_j \sum_i a_{ij} X_i \leq b_j$$

Relational and very precise

Worst-case exponential cost

Weakly relational numerical abstract domains

Zones [Miné 01]



$$\bigwedge_{ij} X_i - X_j \leq c_{ij}$$

Weakly relational
Cubic cost

Octagons [Miné 01]

$$\bigwedge_{ij} \pm X_i \pm X_j \leq c_{ij}$$

Cubic cost

Logahedra [Howe King 09]

$$\bigwedge_{ij} \pm 2^{a_i} X_i \pm 2^{b_j} X_j \leq c_{ij}$$

Cubic cost

TVPI [Simon King Howe 02]

$$\bigwedge_{ij} a_i X_i + b_j X_j \leq c_{ij}$$

Quasi-cubic cost

Octahedra [Clarís Cortadella 07]

$$\bigwedge \sum_i \pm X_i \leq c$$

Worst-case exponential cost

Why abstract domains do not scale up

Execution time of an analysis is roughly the multiplication of:

- ▶ the number of lines of codes,
- ▶ the number of variables (\propto LOC),
- ▶ the number of iterations,
- ▶ the cost of each domain operation,
- ▶ hidden costs (garbage collection, cache database).

When analyzing programs with 10,000+ variables, you need the domain operations to have a linear cost.

Our contribution: TreeKs

- ▶ a domain **functor**
- ▶ applied to linear inequality domains
- ▶ with a **configurable** cost/precision tradeoff

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Outline:

- ▶ the completion operation
- ▶ scaling up with packs
- ▶ application and optimizations for zones/octagons
- ▶ discussion of extensions

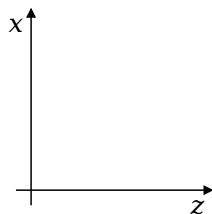
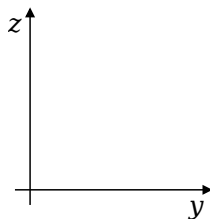
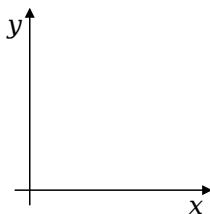
Completion: a key operation

- ▶ Common point of the weakly relational domains
- ▶ Goal: making explicit the implicit relations
- ▶ Done by constraint combination/propagation
- ▶ Needed for the other operations (\sqcup , \sqcap , \sqsubseteq , ...)
- ▶ Dominates the cost of the domain

Closure operation: example

Domain of zones ($\bigwedge_{ij} X_i - X_j \leq b_{ij}$)

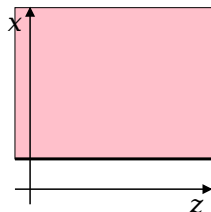
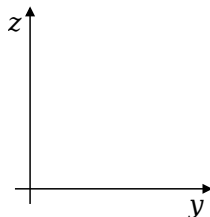
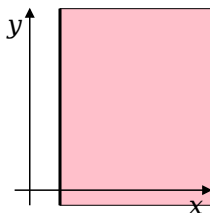
$\mathcal{V} = \{x, y, z\}$



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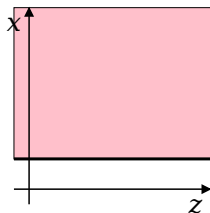
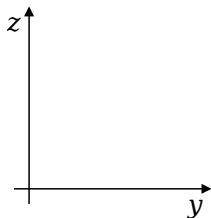
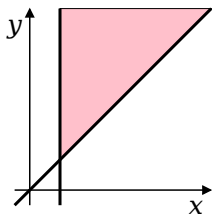


$$-x \leq -1$$

Closure operation: example

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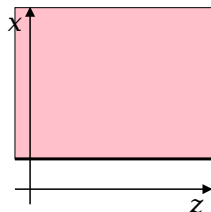
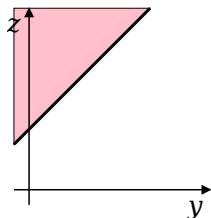
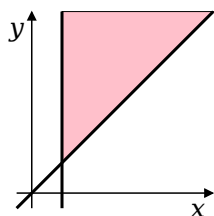


$$\begin{aligned} -x &\leq -1 \\ x - y &\leq 0 \end{aligned}$$

Closure operation: example

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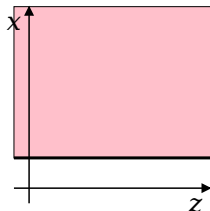
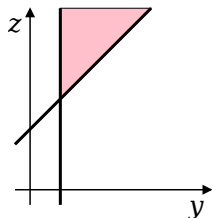
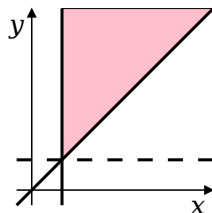
$$x - y \leq 0$$

$$y - z \leq -2$$

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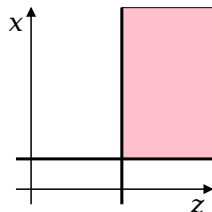
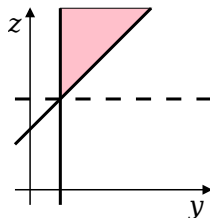
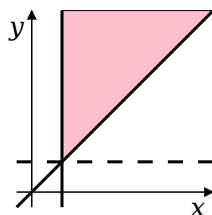
$$y - z \leq -2$$

$$-y \leq -1$$

Closure operation: example

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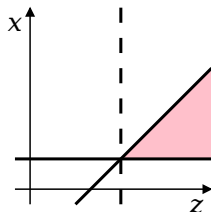
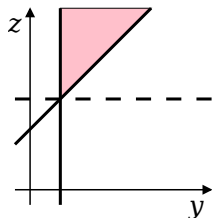
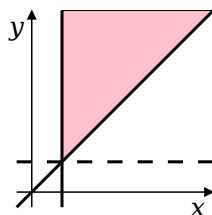
$$-y \leq -1$$

$$-z \leq -3$$

Closure operation: example

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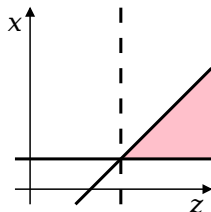
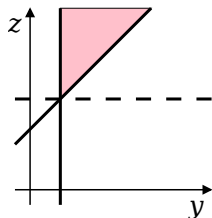
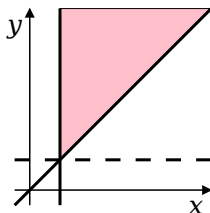
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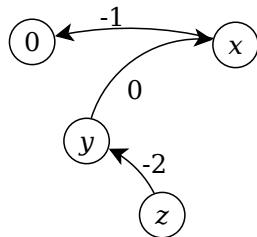
$$-z \leq -3$$

$$x - z \leq -2$$

Done!

Domain of zones: representation

We represent a set of difference constraints between two variables ($X_i - X_j \leq m_{ji}$) by a **potential graph** or by a **DBM** (*Difference Bound Matrix*).



	0	x	y	z
0	0	$+\infty$	$+\infty$	$+\infty$
x	-1	0	$+\infty$	$+\infty$
y	$+\infty$	0	0	$+\infty$
z	$+\infty$	$+\infty$	-2	0

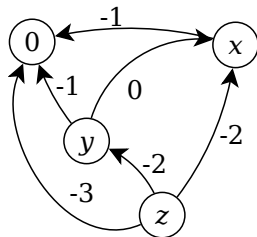
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	0	x	y	z
0	0	$+\infty$	$+\infty$	$+\infty$
x	-1	0	$+\infty$	$+\infty$
y	-1	0	0	$+\infty$
z	-3	-2	-2	0

$$0 - x \leq -1$$

$$x - y \leq 0$$

$$y - z \leq -2$$

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$$x - z \leq -2$$

Domain of zones: completion

In the domain of zones, the completion operation is a **shortest-path closure**.

Floyd-Warshall algorithm $O(n^3)$

```
for  $k \leftarrow 1$  to  $N$  do  
  | for  $i \leftarrow 1$  to  $N$  do  
    | | for  $j \leftarrow 1$  to  $N$  do  
      | | |  $\mathbf{m}_{ij} \leftarrow \min(\mathbf{m}_{ij}, \mathbf{m}_{ik} + \mathbf{m}_{kj})$ 
```

At the end: $\begin{cases} \forall i, j, k, \mathbf{m}_{ij} \leq \mathbf{m}_{ik} + \mathbf{m}_{kj} & \text{if satisfiable} \\ \exists i, \mathbf{m}_{ii} < 0 & \text{if unsatisfiable} \end{cases}$

Domain of zones: operators

After **completion**, operators are pointwise.

Join (best approximation of union):

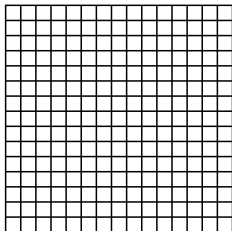
$$(\mathbf{m} \sqcup \mathbf{n})_{ij} = \max(\mathbf{m}_{ij}, \mathbf{n}_{ij})$$

Forget operator (projection):

$$(\exists_{X_k} \mathbf{m})_{ij} = \begin{cases} \mathbf{m}_{ij} & \text{if } i \neq k \text{ and } j \neq k \\ 0 & \text{if } i = j = k \\ +\infty & \text{otherwise} \end{cases}$$

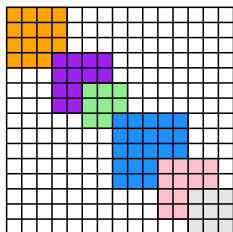
How to scale up: variable packing

- Principle:
- ▶ split variables into packs
 - ▶ use a DBM per pack



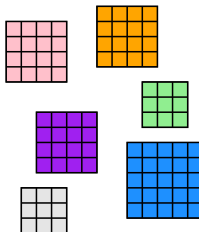
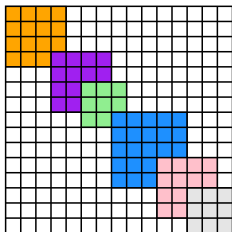
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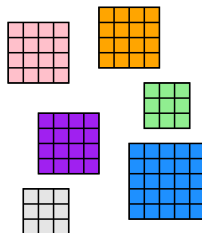
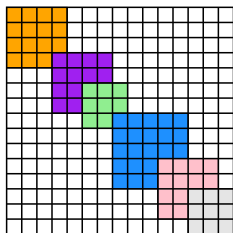
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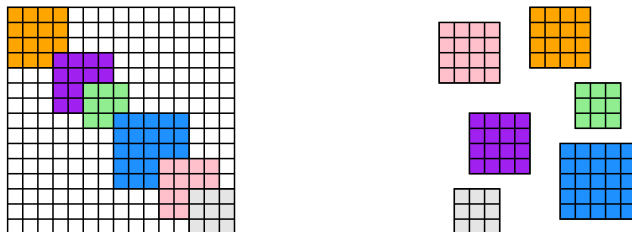
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Cost: **linear** for bounded-size packs

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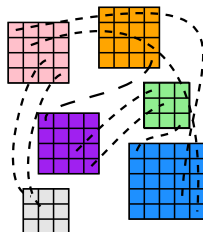
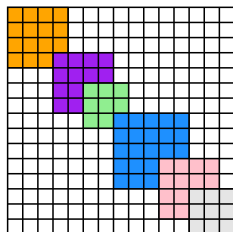


Cost: **linear** for bounded-size packs

Information loss: no communication between packs!

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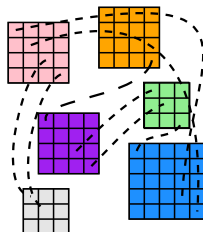
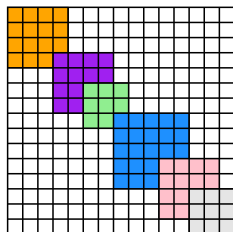
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Not good enough!

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$$P_1 = \{t, x, y\}$$

$$t \leq y$$

$$y \leq x$$

$$P_2 = \{t, x, z\}$$

$$x \leq z$$

$$z \leq t$$

Cost: **linear** for bounded-size packs

Information loss: no communication between packs!

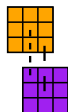
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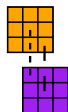
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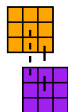
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$$t \leq y$$

$$y \leq x$$

$$t \leq x$$

$$x = t$$

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$$z \leq t$$

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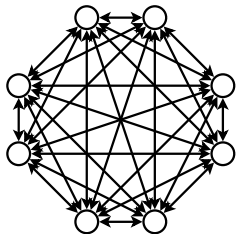
Not good enough!

An idea: a subgraph

Goal: share relational constraints

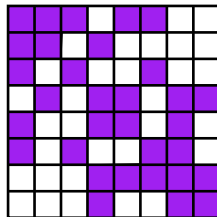
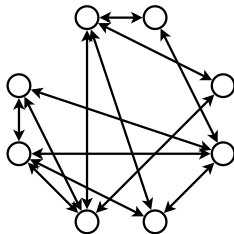
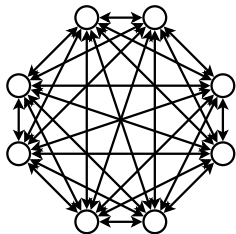
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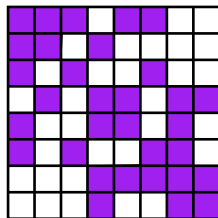
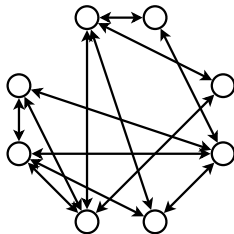
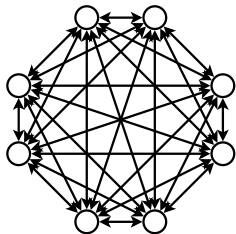
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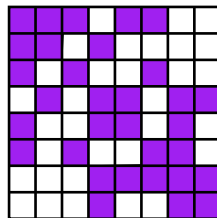
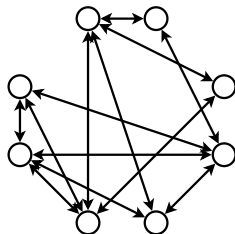
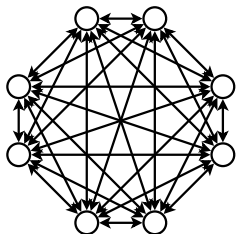
Goal: share relational constraints



Issues: we need to keep

An idea: a subgraph

Goal: share relational constraints



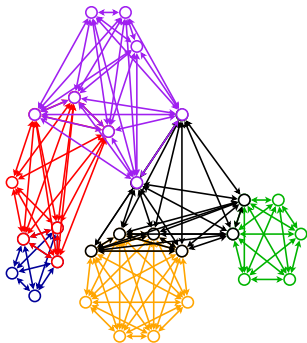
Issues: we need to keep

- ▶ a good expressiveness
- ▶ a structure with packs
- ▶ precise and efficient algorithms

TreeKs: a certain subgraph

Shape:

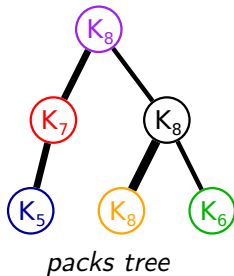
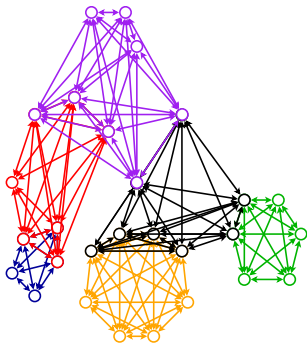
- ▶ a tree of complete graphs (packs)
- ▶ sharing **frontiers**



TreeKs: a certain subgraph

Shape:

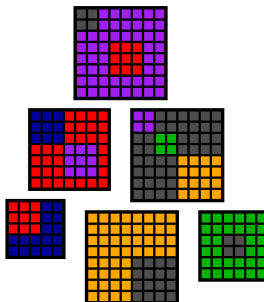
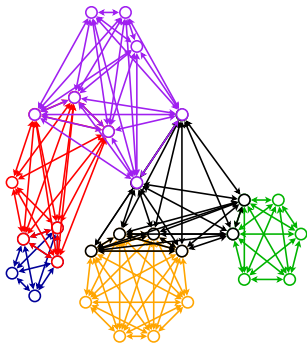
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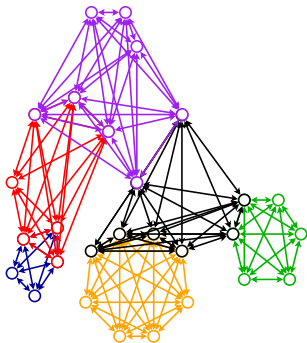


Abstract value: tuple of DBMs

TreeKs: a certain subgraph

Shape:

- ▶ a tree of complete graphs (packs)
- ▶ sharing **frontiers**



Parameters:

- N number of variables
- m number of packs
- p size of a pack
- f size of a frontier
- d diameter of the graph

TreeKs: abstract operators

On **complete** values, all operations can be done pointwisely:

- ▶ inclusion test
- ▶ intersection
- ▶ union

but constraint extraction and addition...

Completion algorithm

Completion algorithm in TreeKs $O(mp^3)$

foreach *pack from the leaves to the root* **do**

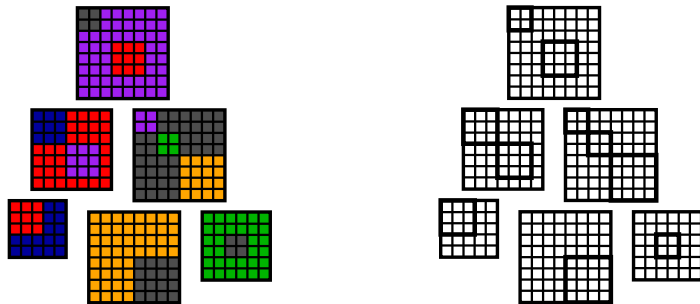
 Apply completion on this pack in the domain of zones

 Pass the new constraints to its father

foreach *pack from the root to the leaves* **do**

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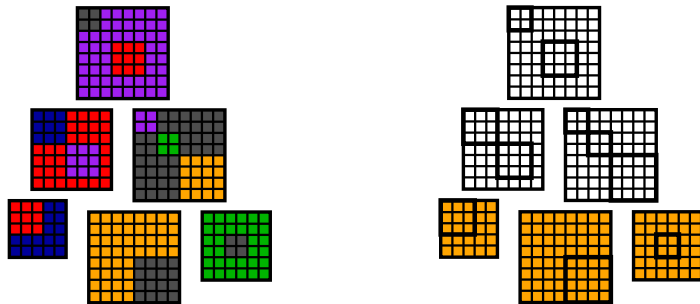
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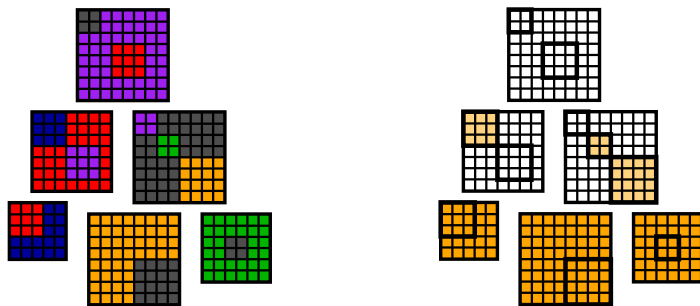
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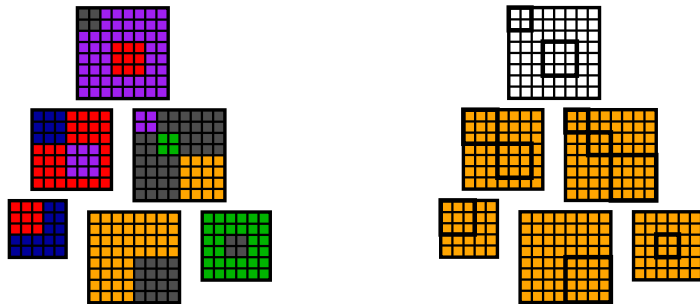
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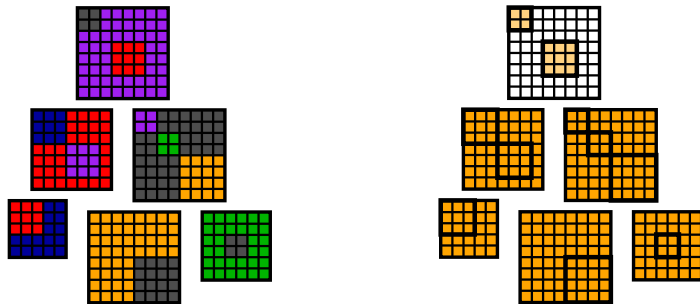
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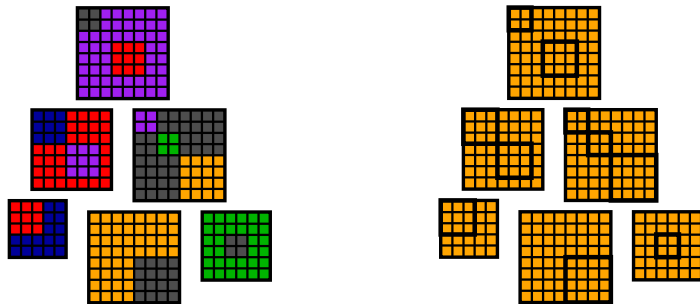
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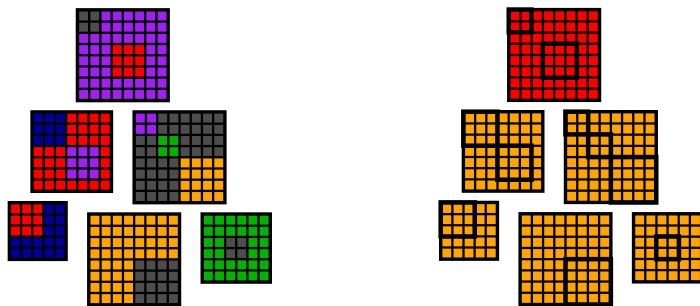
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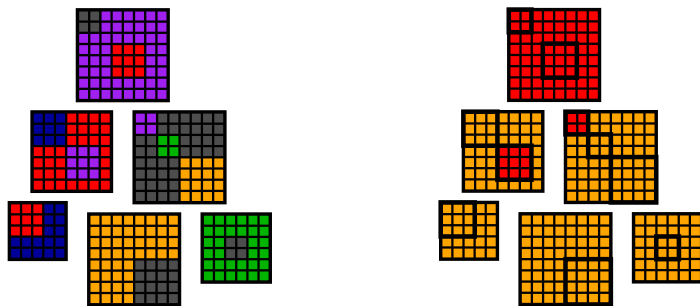
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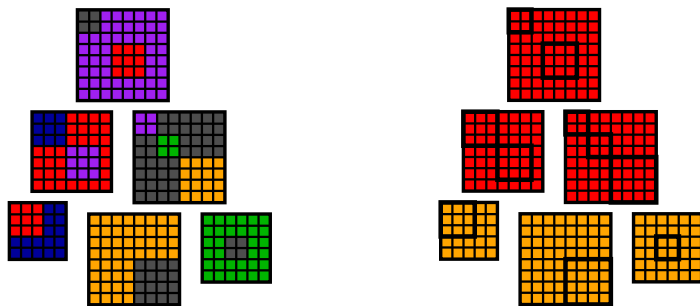
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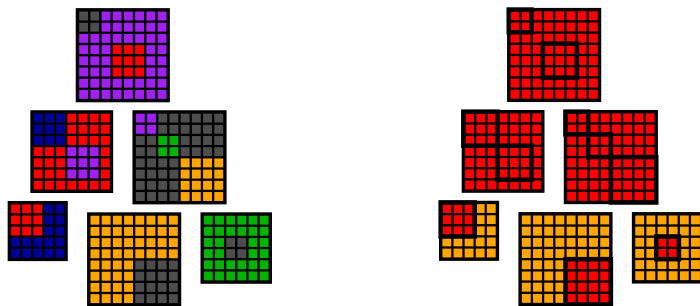
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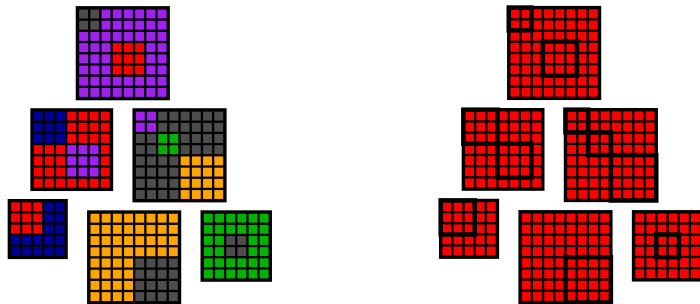
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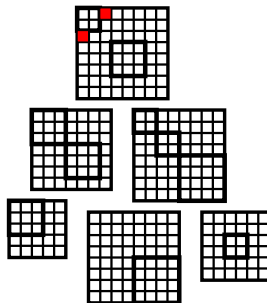
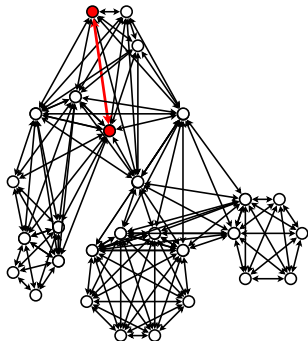
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Constraint extraction

Goal: to bound $X_u - X_v$

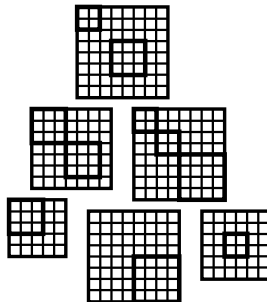
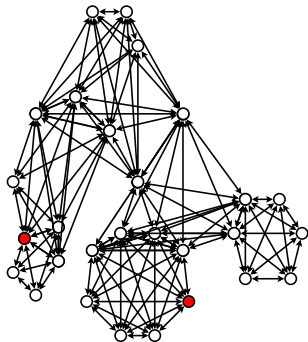
Simple case: X_u and X_v are in the same pack



Constraint extraction

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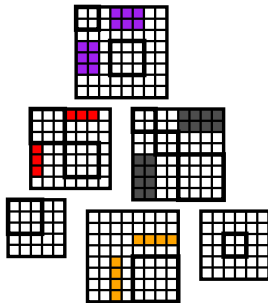
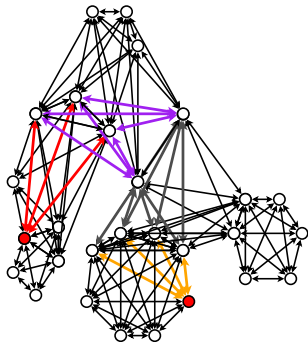
Complex case: X_u and X_v are in different packs



Constraint extraction

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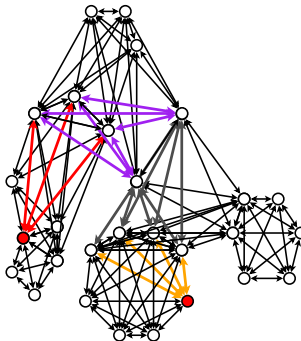
Complex case: X_u and X_v are in different packs



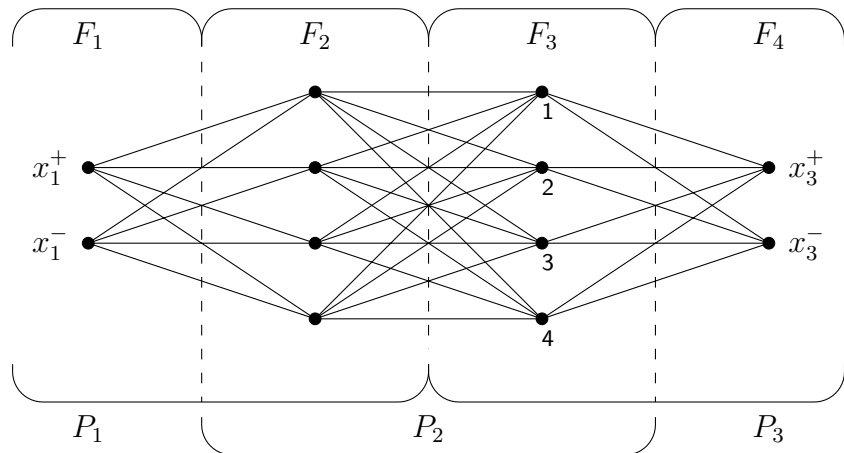
Only constraints in the path between X_v and X_u need to be considered

Constraint extraction (for zones/octagons)

The result is the shortest in a layered graph, which can be solved by dynamic programming, in time $O(df^2)$.



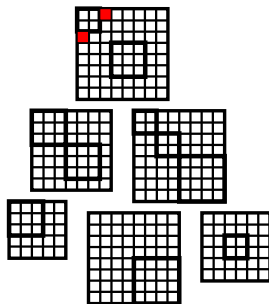
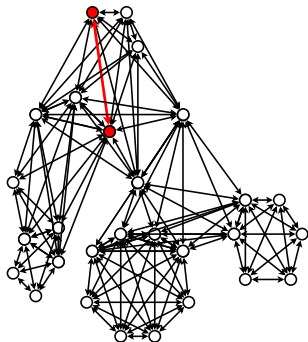
Constraint extraction (for zones/octagons)



Adding constraints

Goal: to add the constraint $X_u - X_v \leq c$

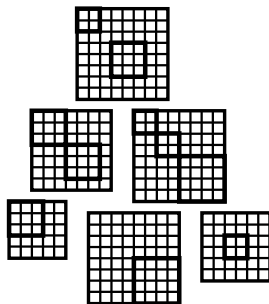
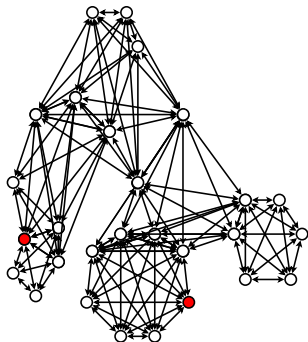
Simple case: X_u and X_v are in the same pack



Adding constraints

Goal: to add the constraint $X_u - X_v \leq c$

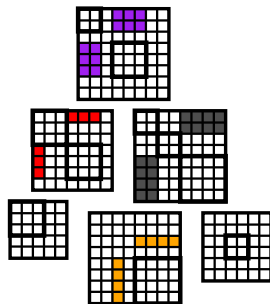
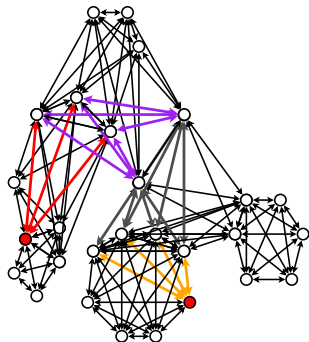
Complex case: X_u and X_v are in different packs



Adding constraints

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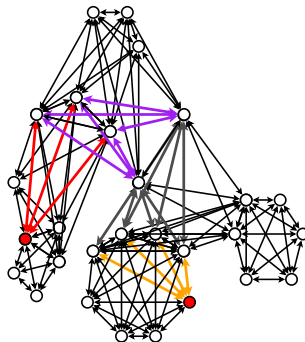
Complex case: X_u and X_v are in different packs



Only constraints in the path between X_v and X_u have to be updated

Adding constraints (for zones/octagons)

Like constraint extraction, shortest paths to successive frontiers help compute the best constraints between X_v and X_u in time $O(df^2)$.



Summary

We showed a method to build new numerical abstract domains:

- ▶ can be applied to many numerical abstract domains (zones, octagons, logahedra, TVPI, octahedra, polyhedra, ...)
- ▶ can be applied to other linear inequality domains to come
- ▶ with **linear cost** completion when pack size is bounded
- ▶ simple, precise, and efficient algorithms

Discussions:

- ▶ application to other convex domains and non-convex domains (e.g. AV domains)
- ▶ pack generation strategies