

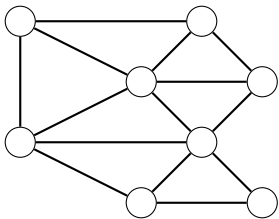
Soft Constraints for Optimisation

Standa Živný
Durham, 02/02/2012

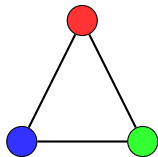


3-Colouring

G

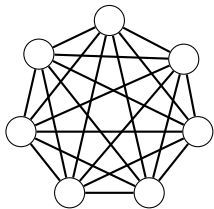


K_3

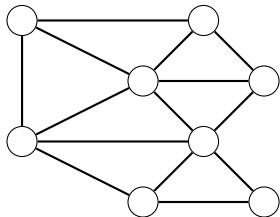


k -Clique

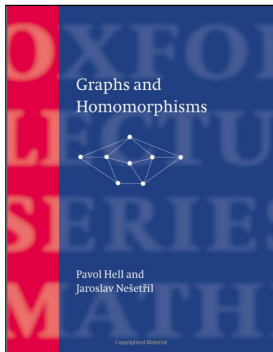
K_k



G



Graph Homomorphisms



[Hell & Nešetřil, OUP'04]

Relational Structures

$$\mathbf{A} \xrightarrow{?} \mathbf{B}$$

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$$\mathbf{A} \xrightarrow{?} \mathbf{B}$$

$$\text{CSP}(\mathcal{A}, \mathcal{B}) = \{(\mathbf{A}, \mathbf{B}) \mid \mathbf{A} \in \mathcal{A}, \mathbf{B} \in \mathcal{B}, \mathbf{A} \rightarrow \mathbf{B}\}$$

$\text{CSP}(\mathcal{A}, \mathcal{B})$

For which classes \mathcal{A} and \mathcal{B} of relational structures is $\text{CSP}(\mathcal{A}, \mathcal{B})$ tractable?

CSP(\mathcal{A}, \mathcal{B})

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- ▶ $\text{CSP}(\mathcal{A}, -)$ = arbitrary right hand side

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CSP($\{\mathbf{A}\}, -$) always tractable

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CSP($\mathcal{A}, -$) P-tractable (bounded arity) \Leftrightarrow bounded $tw(\mathcal{A})$ [Grohe JACM'07]

CSP($\mathcal{A}, -$) FPT-tractable \Leftrightarrow bounded $sub(\mathcal{A})$ [Marx STOC'10]

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- ▶ CSP($\mathcal{A}, -$) = arbitrary right hand side
 - ▶ CSP($-, \mathcal{B}$) = arbitrary left hand side
- CSP($-, \{\mathbf{B}\}$) can be intractable (3-Colouring)

CSP(\mathcal{A}, \mathcal{B})

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$$\text{CSP}(\Gamma) = \text{CSP}(-, \{\Gamma\}), \text{ finite relational structure } \Gamma$$

Complexity of CSP(Γ)

Conjecture [Feder&Vardi'93]

For every finite Γ , CSP(Γ) is either in P or in NP-C.

- ▶ $|D| = 2$ [Schaefer STOC'78]
- ▶ $|D| = 3$ [Bulatov JACM'06]
- ▶ graphs [Hell & Nešetřil JCTB'90]
- ▶ special triads [Barto, Kozik, Maróti, Niven AMS'09]
- ▶ digraphs w/o sources & sinks [Barto, Kozik, Niven SICOMP'09]
- ▶ conservative [Bulatov LICS'03, Barto LICS'11]

Goal

Computational complexity of
optimisation problems

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Computational complexity of optimisation problems

relations \rightarrow cost functions
satisfying all relations \rightarrow minimising the sum of cost functions

VCSP

VCSP instance is triple $\langle V, D, C \rangle$:

- ▶ V : finite set of **variables**
- ▶ D : finite set of **domain values**
- ▶ C : finite set of **constraints** $c = \langle s, \phi \rangle$

$$s = \langle v_1, \dots, v_m \rangle \quad (\text{constraint } \mathbf{scope})$$

$$\phi : D^m \rightarrow \mathbb{Q}_+ \cup \{\infty\} \quad (\text{constraint } \mathbf{cost function})$$

- ▶ **solution** $h : V \rightarrow D$ minimising total sum

$$\min_{h: V \rightarrow D} \sum_{\langle \langle v_1, \dots, v_m \rangle, \phi \rangle \in C} \phi(h(v_1), \dots, h(v_m))$$

Max-Cut as VCSP

Given graph G with $V(G) = \{1, \dots, n\}$:

- ▶ $V = \{v_1, \dots, v_n\}$
- ▶ $D = \{0, 1\}$
- ▶ $C = \{\langle \langle v_i, v_j \rangle, \phi \rangle \mid \{i, j\} \in E(G)\},$

where ϕ is defined as: $\phi(x, y) = \begin{cases} 1 & x = y \\ 0 & x \neq y \end{cases}$

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[Instead of maxim cut we minim non-cut, but for exact solvability the same]

Goal

Computational complexity of
valued CSPs

Why VCSPs?

- ▶ Potts model
- ▶ Gibbs energy
- ▶ locally-defined functions
- ▶ Markov Random Field (MRF)
- ▶ Conditional Markov Field (CRF)
- ▶ pseudo-Boolean minimisation
- ▶ exact inference in graphical models
- ▶ Valued Constraint Satisfaction Problem (VCSP)

VCSP: $\{+, \min\}$

$\{\exists, \wedge, =\}$	CSP	dichotomy conjectured
$\{\exists, \forall, \wedge, =\}$	QCSP	trichotomy conjectured
$\{\exists, \forall, \wedge, \vee\}$	FO=	tetrachotomy [<i>Madelaine & Martin LICS'11</i>] ¹
$\{\times, +\}$	$\#$ CSP	counting, partition functions; several classifications
$\{+, \min\}$	VCSP	several classifications

¹Other fragments of FO, besides CSP and QCSP, uninteresting [*Martin CiE'08*]

Computational complexity of valued CSPs

1. structural restrictions (left-hand side)
2. language restrictions (right-hand side)
3. hybrid restrictions (combination of the above two)

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- language Γ finite set of cost functions $\phi : D^m \rightarrow \overline{\mathbb{Q}}_+$
- VCSP(Γ) class of VCSP instances
with cost functions from Γ

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VCSP(Γ) class of VCSP instances
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For which Γ is VCSP(Γ) in P?

We call such Γ **tractable**.

Submodular Γ

$$\phi : D^m \rightarrow \overline{\mathbb{Q}}_+$$

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$$\phi(\min(\mathbf{x}, \mathbf{y})) + \phi(\max(\mathbf{x}, \mathbf{y})) \leq \phi(\mathbf{x}) + \phi(\mathbf{y})$$

Submodular Γ

$$\phi : D^m \rightarrow \overline{\mathbb{Q}}_+$$

$$\mathbf{x} = (x_1, \dots, x_m)$$

$$x_i \in D$$

$$\min : D \times D \rightarrow D$$

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tractable [Schrijver JCTB'00 & Iwata, Fleischer, Fujishige JACM'01]

(for distributive lattices where $\langle \min, \max \rangle = \{\wedge, \vee\}$)

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Binary Multimorphisms

$$\phi : D^m \rightarrow \overline{\mathbb{Q}}_+$$

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$$y_i \in D$$

$$g : D \times D \rightarrow D$$

$$\phi(f(\mathbf{x}, \mathbf{y})) + \phi(g(\mathbf{x}, \mathbf{y})) \leq \phi(\mathbf{x}) + \phi(\mathbf{y})$$

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$\langle f, g \rangle$ is binary **multimorphism** (mm) of ϕ

$\langle f, g \rangle$ is mm of Γ if $\langle f, g \rangle$ is mm of all $\phi \in \Gamma$

[Cohen, Cooper, Jeavons, Krokhin AIJ'06]

Tractable Γ by Binary Multimorphisms

- ▶ submodular [Schrijver JCTB'00 & Iwata, Fleischer, Fujishige JACM'01]
 - ▶ (symmetric) tournament pair [Cohen, Cooper, Jeavons TCS'08]
 - ▶ bisubmodular on $|D| = 3$ [Fujishige & Iwata SIAM JDM'05]
 - ▶ weak tree-submodular on chains/forks [Kolmogorov MFCS'11]
 - ▶ strong tree-submodular on binary tress [Kolmogorov MFCS'11]
 - ▶ 1-defect [Jonsson, Kuivinen, Thapper CP'11]
-
- ▶ products of binary multimorphisms [Krokhin & Larose SIAM JDM'08]

Classifications of VCSP(Γ)

- ▶ Max-CSPs with $|D| = 2$ [Creignou JCSS'95]
- ▶ Max-CSPs with $|D| = 3$ [Jonsson, Klasson, Krokhin SICOMP'06]
- ▶ Max-CSPs with $|D| = 4$ [Jonsson, Kuivinen, Thapper CP'11]
- ▶ conservative Max-CSPs [Deineko, Jonsson, Klasson, Krokhin JACM'08]
- ▶ Min-Cost-Hom [Takhanov STACS'10]

- ▶ VCSPs with $|D| = 2$ [Cohen, Cooper, Jeavons, Krokhin AIJ'06]
- ▶ conservative VCSPs [Kolmogorov & Ž. SODA'12]

Multimorphisms

- ▶ binary mm $\langle f, g \rangle \rightarrow k$ -ary mm $\langle f_1, \dots, f_k \rangle$
- ▶ tractable Γ by ternary mm [Cohen, Cooper, Jeavons, Krokhin AIJ'06]
- ▶ tractable Γ by binary & ternary mm [Kolmogorov & Ž. SODA'12]

- ▶ algebraic theory of mm [Cohen, Creed, Jeavons, Ž. MFCS'11]
- ▶ algebraic classification of Boolean VCSPs [Creed & Ž. CP'11]

Open Problems on VCSP(Γ)

- ▶ finite-valued languages on $|D| = 3$ (and general-valued)?
 - ▶ bisubmodularity on $|D| > 3$, so-called k -submodularity?
 - ▶ strong tree-submodularity on non-binary trees?
 - ▶ weak tree-submodularity on (even binary) trees?
 - ▶ submodularity on non-distributive lattices?
 - ▶ tractability via binary multimorphisms?
-
- ▶ k -ary multimorphisms needed for $k > 3$?
 - ▶ multimorphisms enough for tractability?

Computational complexity of valued CSPs

1. structural restrictions (left-hand side)
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From Now Onwards...

- ▶ binary VCSPs
- ▶ unbounded domains

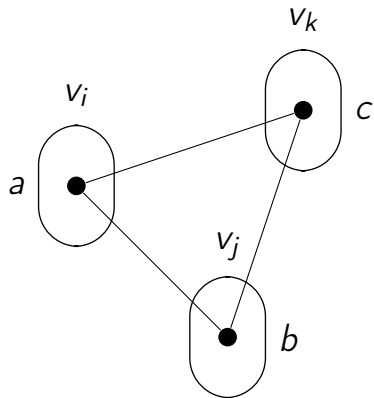
Binary Valued CSPs

- ▶ n variables v_1, \dots, v_n over domains D_1, \dots, D_n
- ▶ cost functions:
 $c_i : D_i \rightarrow \overline{\mathbb{Q}}_+, \quad c_{ij} : D_i \times D_j \rightarrow \overline{\mathbb{Q}}_+$
- ▶ objective:

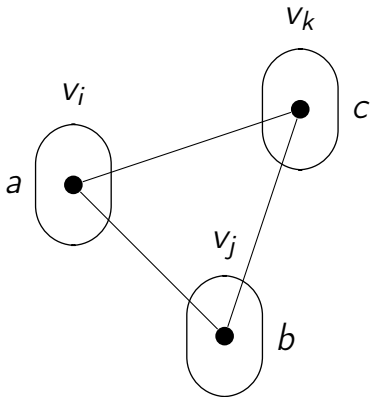
$$\min_{v_1 \in D_1, \dots, v_n \in D_n} \left(\sum_{i=1}^n c_i(v_i) + \sum_{1 \leq i < j \leq n} c_{ij}(v_i, v_j) \right)$$

- ▶ no constraint on scope $\langle v_i, v_j \rangle \Rightarrow c_{ij} = 0$

Triangle



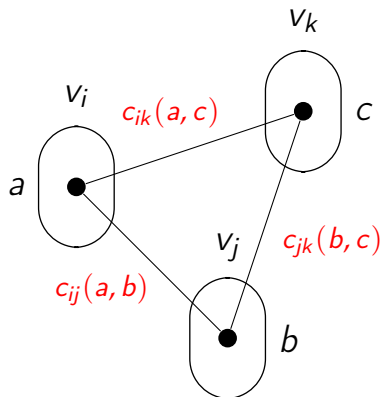
Triangle



$$\{\langle v_i, a \rangle, \langle v_j, b \rangle, \langle v_k, c \rangle\}$$

$$i \neq j \neq k \neq i, a \in D_i, b \in D_j, c \in D_k$$

Costs in a Triangle



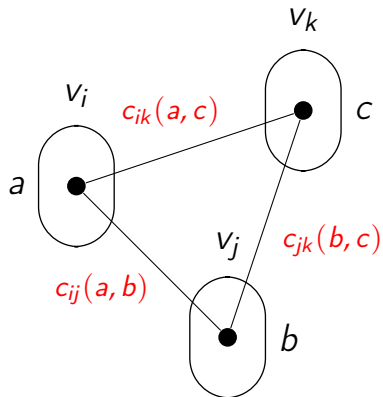
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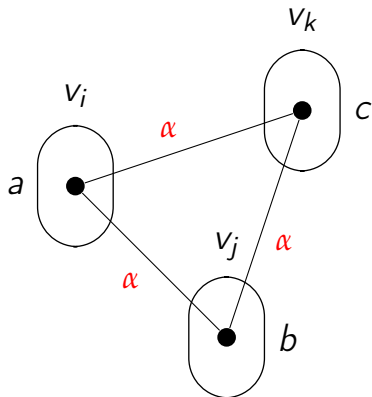
Problem

Computational complexity of problems
with restricted costs in all triangles.

Example: Joint-Winner Property

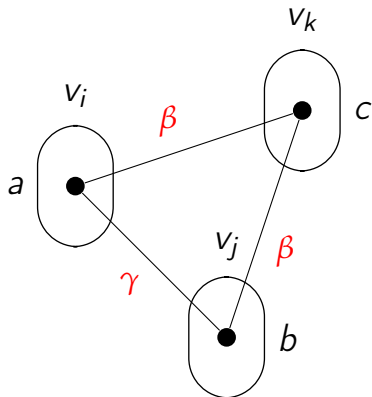


Example: Joint-Winner Property



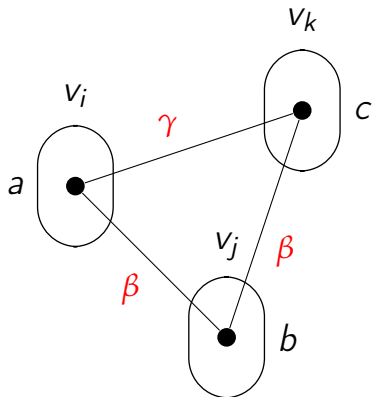
$\forall \Delta : \text{(i) } \{\alpha, \alpha, \alpha\},$

Example: Joint-Winner Property



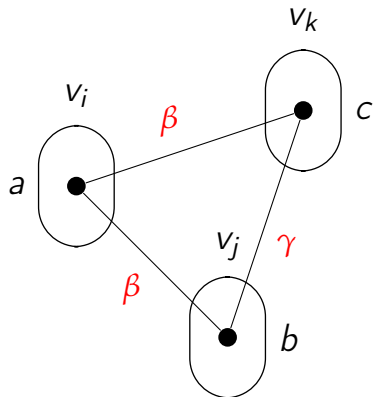
$\forall \Delta : (i) \{ \alpha, \alpha, \alpha \}$, or $(ii) \{ \beta, \beta, \gamma \}$, where $\beta < \gamma$.
(different α, β, γ in different Δ 's)

Example: Joint-Winner Property



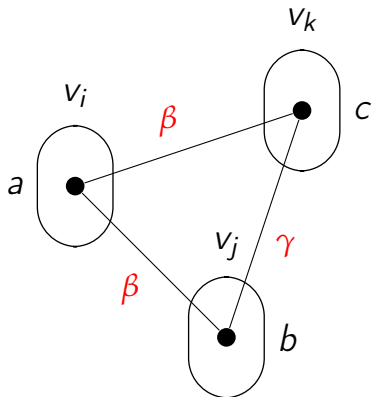
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Example: Joint-Winner Property



$\forall \Delta : (i) \{ \alpha, \alpha, \alpha \}$, or $(ii) \{ \beta, \beta, \gamma \}$, where $\beta < \gamma$.
(different α, β, γ in different Δ 's)

Example: Joint-Winner Property



$\forall \Delta$: no unique strict minimum

Example: Joint-Winner Property, cont'd

- ▶ JWP is tractable
 - ▶ non-trivial algorithm
 - ▶ large class of interesting problems

[Cooper & Ž. AIJ'11]

Example: Joint-Winner Property, cont'd

- ▶ JWP is tractable
 - ▶ non-trivial algorithm
 - ▶ large class of interesting problems

[Cooper & Ž. AIJ'11]

Other tractable classes defined by triangles?

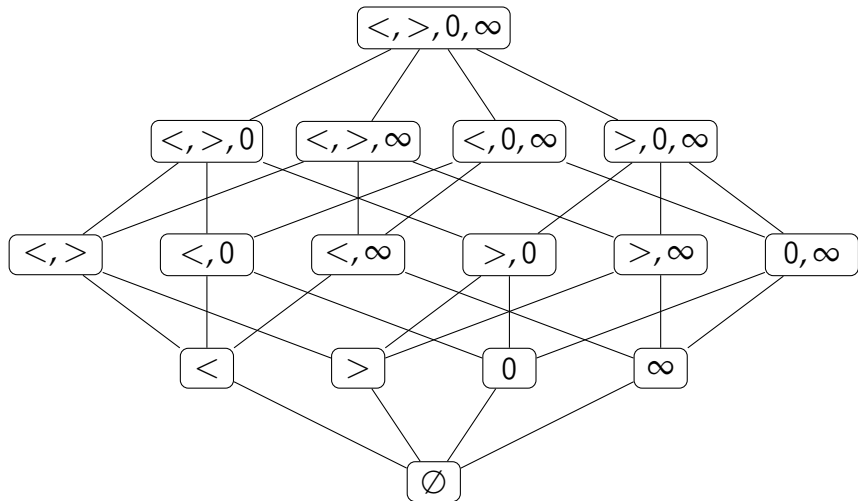
CSP

For CSPs, there are only two possible costs (0 and ∞), thus exactly 4 possible cost types in a triangle:

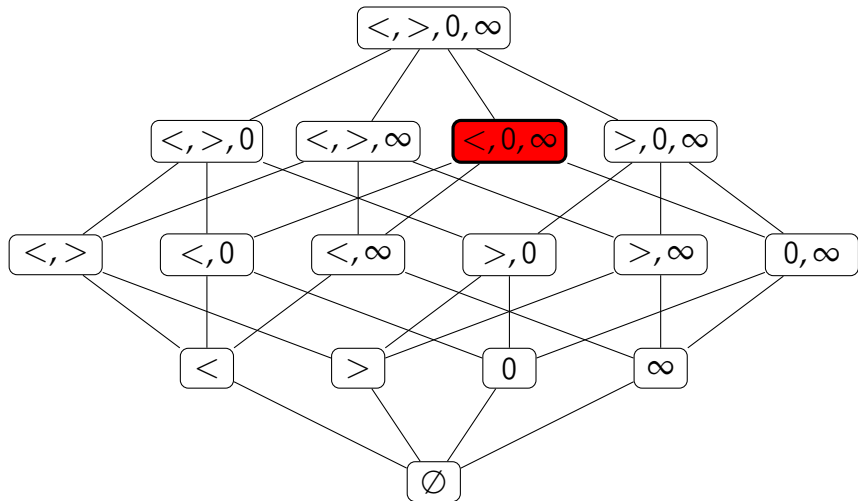
Symbol	Costs
0	$\{0, 0, 0\}$
∞	$\{\infty, \infty, \infty\}$
$<$	$\{0, 0, \infty\}$
$>$	$\{0, \infty, \infty\}$

Hence 16 classes of CSPs defined by allowed cost types.

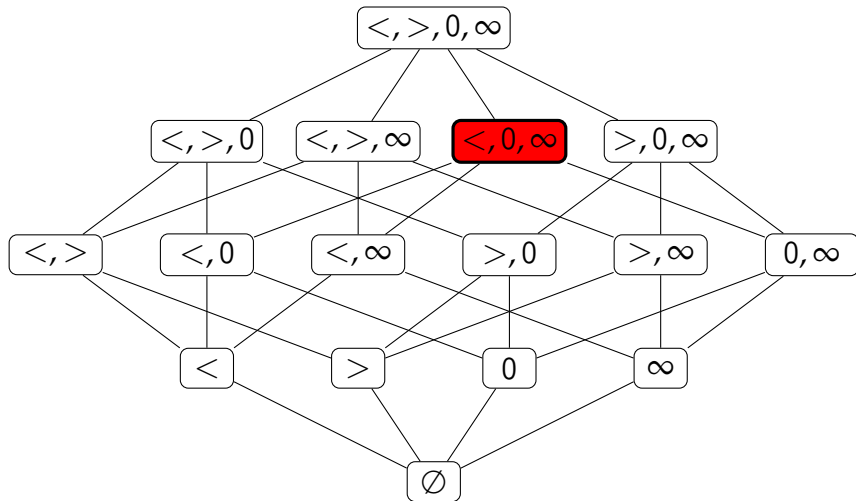
Lattice of CSPs



Lattice of CSPs

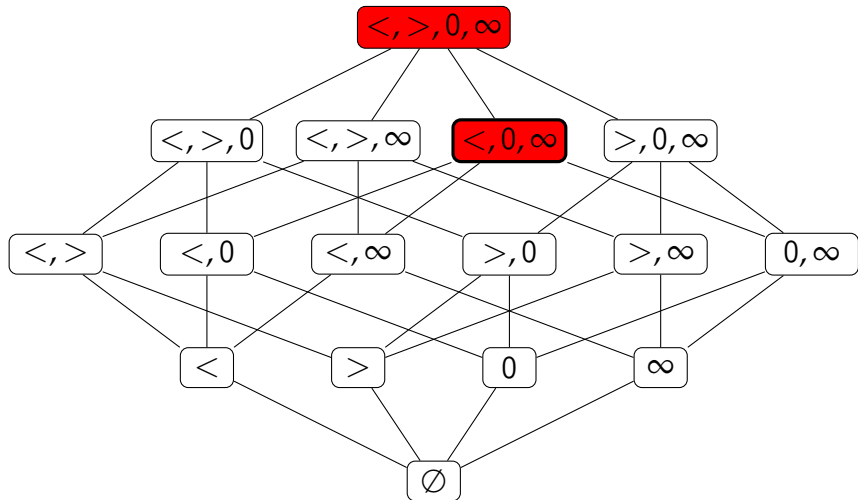


Lattice of CSPs



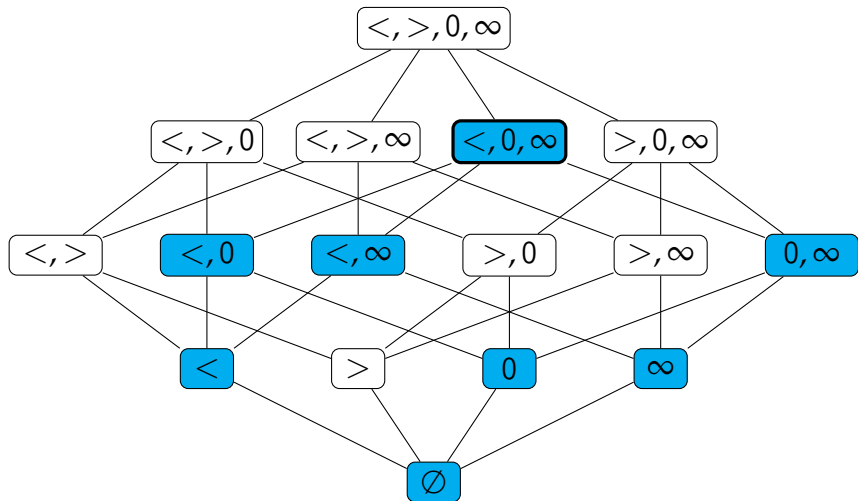
Binary CSPs with Δ : $\{0, 0, \infty\}$, $\{0, 0, 0\}$, $\{\infty, \infty, \infty\}$

Lattice of CSPs



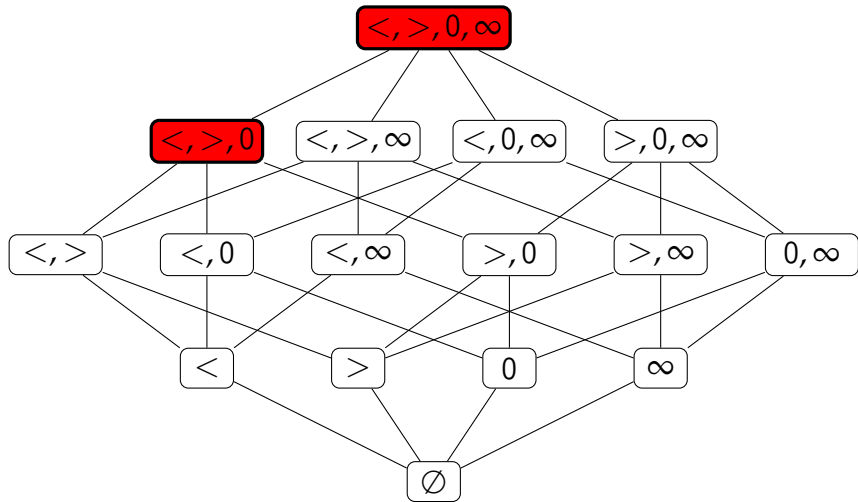
If $\{\langle, 0, \infty\}$ intractable...

Lattice of CSPs



If $\{\langle, 0, \infty\}$ tractable...

CSP Classification



CSP Proofs

- ▶ $\{<, >, 0\}$ NP-hard from 3-Col
- ▶ $\{<, >, \infty\}$ trivially tractable
- ▶ $\{<, 0, \infty\}$ tractable via JWP
- ▶ $\{>, 0, \infty\}$ solved by SAC

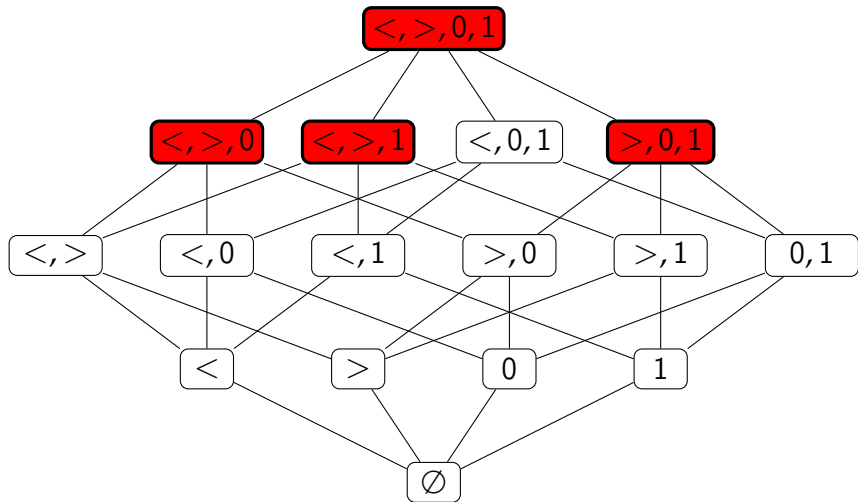
Max-CSP

For unweighted Max-CSPs, there are only two possible costs (0 and 1), thus again 4 cost types in a triangle:

Symbol	Costs
0	{0, 0, 0}
1	{1, 1, 1}
<	{0, 0, 1}
>	{0, 1, 1}

Hence 16 classes of Max-CSPs defined by allowed types.

Max-CSP Classification



Max-CSP Proofs

- ▶ $\{<, >, 0\}$ and $\{<, >, 1\}$ NP-hard from Max-Cut
- ▶ $\{<, 0, 1\}$ tractable via **JWP**
- ▶ $\{<, >\}$ trivially tractable
- ▶ $\{>, 0\}$ tractable (fairly simple)
- ▶ $\{>, 1\}$ tractable via **maximum matching in graphs**
- ▶ $\{>, 0, 1\}$ **NP-hard**

Infinitely many costs, thus infinitely many cost types!

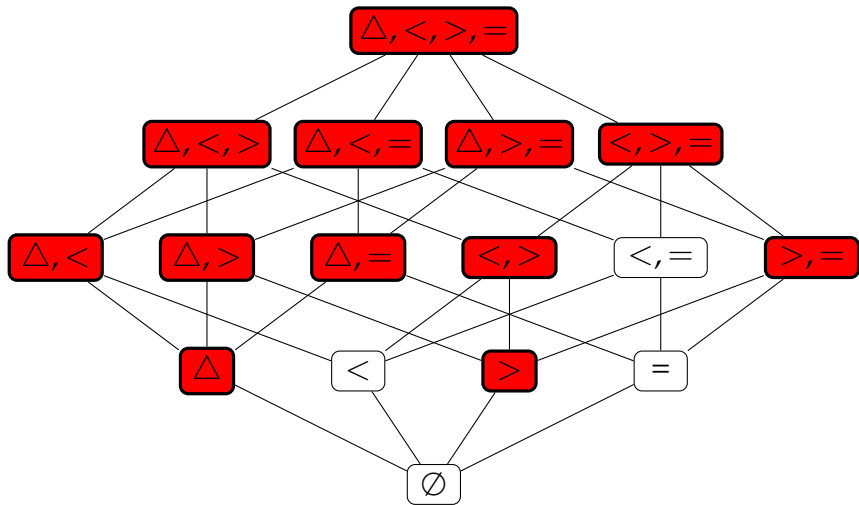
Infinitely many costs, thus infinitely many cost types!

- ▶ classification wrt order
- ▶ classification wrt minimum cost
- ▶ classification wrt maximum cost

VCSP wrt order

Symbol	Costs	Remark
\triangle	$\{\alpha, \beta, \gamma\}$	$\alpha \neq \beta \neq \gamma \neq \alpha$
$<$	$\{\alpha, \alpha, \beta\}$	$\alpha < \beta$
$>$	$\{\alpha, \beta, \beta\}$	$\alpha < \beta$
$=$	$\{\alpha, \alpha, \alpha\}$	

VCSP (order) Classification



VCSP (order) Proofs

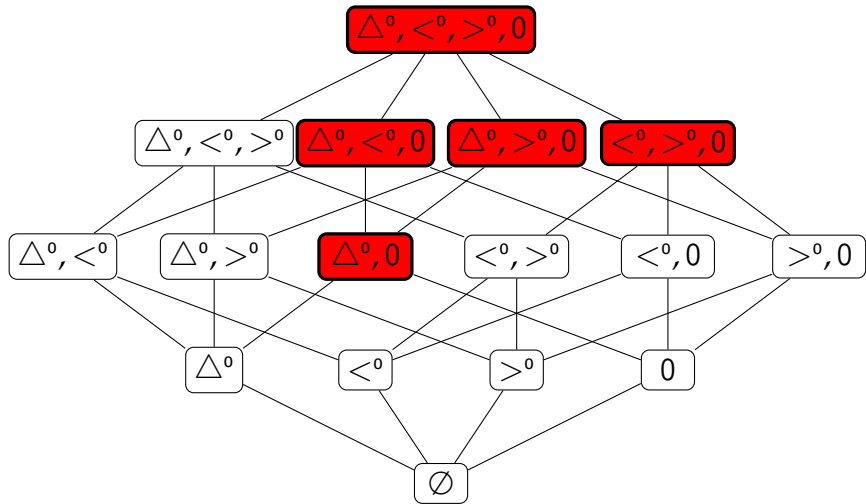
- ▶ $\{<, =\}$ via **JWP**
- ▶ $\{\Delta\}$ NP-hard from Max-Cut
- ▶ $\{>\}$ NP-hard by adapting $\{>, 0, 1\}$

VCSP wrt min

Minimum binary cost: 0

Symbol	Costs	Remark
Δ^0	$\{\alpha, \beta, 0\}$	$\alpha > \beta > 0$
$<^0$	$\{0, 0, \alpha\}$	$\alpha > 0$
$>^0$	$\{\alpha, \alpha, 0\}$	$\alpha > 0$
0	$\{0, 0, 0\}$	

VCSP (min) Classification



VCSP (min) Proofs

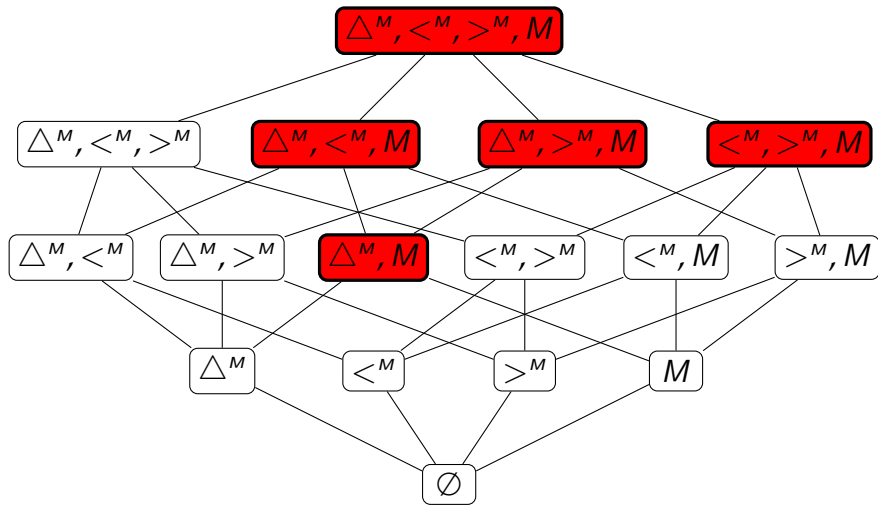
- ▶ $\{>^0, 0\}$ tractable (simple)
- ▶ (the rest easy)

VCSP wrt max

Maximum binary cost: M

Symbol	Costs	Remark
Δ^M	$\{\alpha, \beta, M\}$	$\alpha < \beta < M$
$<^M$	$\{\alpha, \alpha, M\}$	$\alpha < M$
$>^0$	$\{\alpha, M, M\}$	$\alpha < 0$
M	$\{M, M, M\}$	

VCSP (max) Classification



VCSP (max) Proofs

- ▶ $\{>^M, M\}$ tractable via **weighted maximum matching**

Remarks

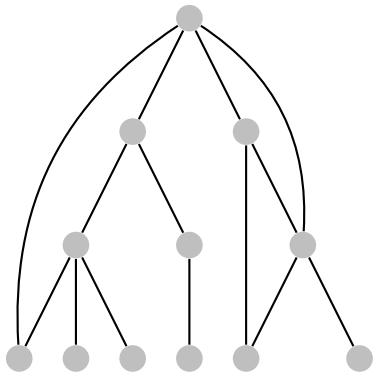
- ▶ $\text{CSP} \sim \text{CSP} + \text{soft unary}$
- ▶ finite-valued VCSP \sim general-valued VCSP
- ▶ all tractability results work with unary constraints
- ▶ NP-hardness results do not require unary constraints
- ▶ NP-hardness results tight wrt domain size

Generalisation of JWP

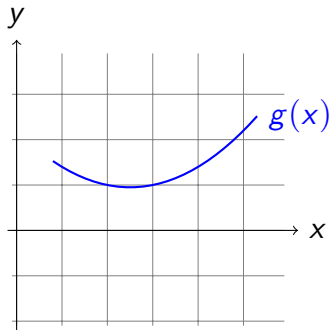
JWP the only tractable class among
VCSPs defined by triangles.

Is there a generalisation to non-binary VCSPs?

Hybrid restrictions



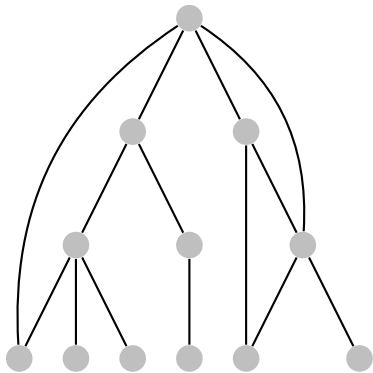
Tree-like structure



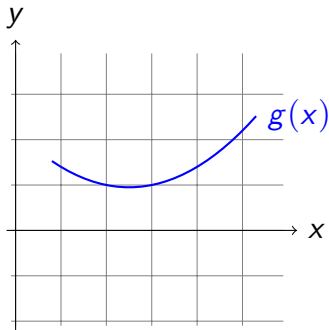
Submodularity

On assignments-sets none is sufficient for tractability!

Hybrid restrictions



Tree-like structure



Submodularity

On assignments-sets none is sufficient for tractability!
Imposing both guarantees tractability!

Laminar Convex VCSPs

Theorem

[Cooper & Ž. CP'11]

Let $\mathcal{A} = \{\langle v_i, a \rangle \mid 1 \leq i \leq n, a \in D_i\}$, and $A_i \subseteq \mathcal{A} (1 \leq i \leq r)$.
Given an objective function of the form:

$$g(\mathbf{x}) = g_1(|\mathbf{x} \cap A_1|) + \dots + g_r(|\mathbf{x} \cap A_r|)$$

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2. A_i laminar \Rightarrow NP-hard
3. A_i laminar and g_i convex \Rightarrow tractable

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Example: $v_1, v_2, v_3, v_4; D = \{0, 1\}$

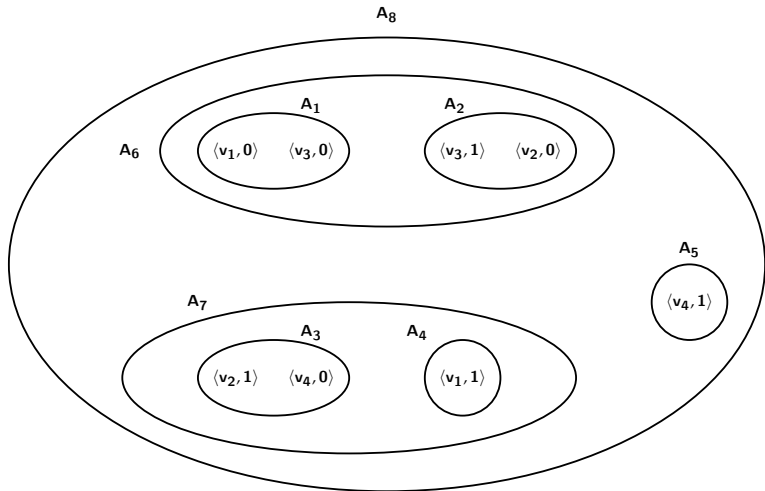
Example: $v_1, v_2, v_3, v_4; D = \{0, 1\}$

$\langle v_1, 0 \rangle$ $\langle v_3, 0 \rangle$ $\langle v_3, 1 \rangle$ $\langle v_2, 0 \rangle$

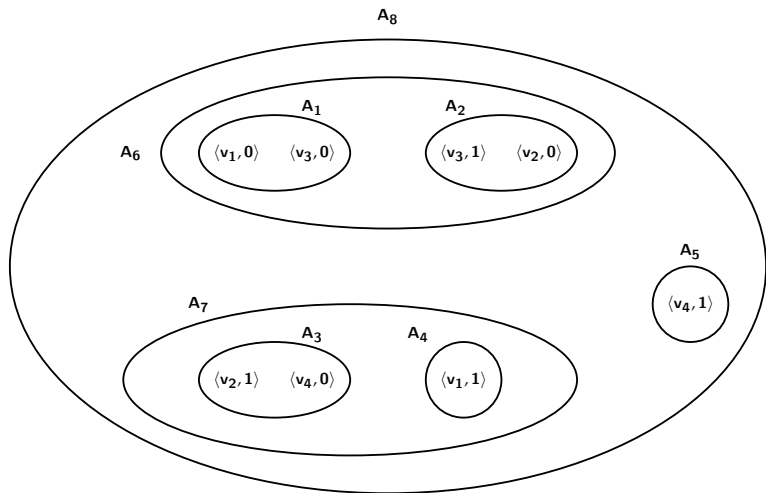
$\langle v_4, 1 \rangle$

$\langle v_2, 1 \rangle$ $\langle v_4, 0 \rangle$ $\langle v_1, 1 \rangle$

Example: $v_1, v_2, v_3, v_4; D = \{0, 1\}$

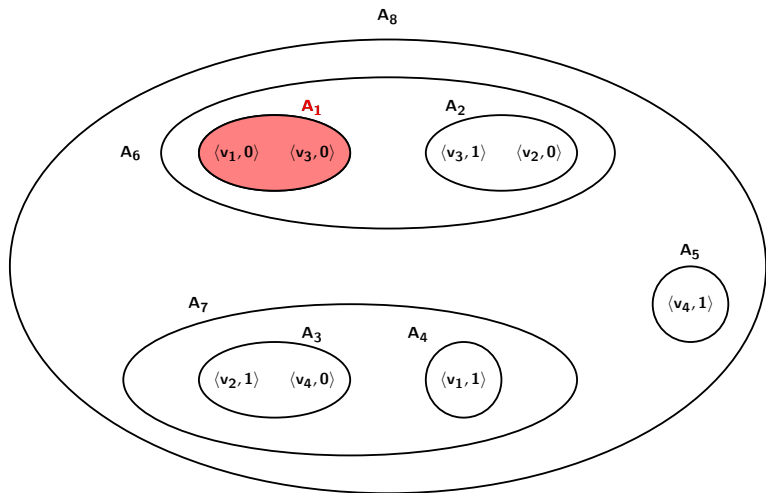


Example: v_1, v_2, v_3, v_4 ; $D = \{0, 1\}$



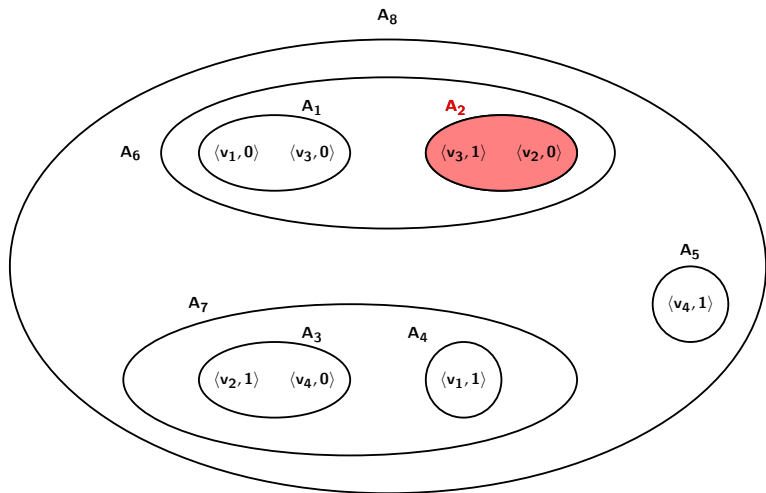
$$g(\mathbf{x}) = g_1(|\mathbf{x} \cap \{\langle v_1, 0 \rangle, \langle v_3, 0 \rangle\}|) + g_2(|\mathbf{x} \cap \{\langle v_3, 1 \rangle, \langle v_2, 0 \rangle\}|) + \dots \\ \dots + g_7(|\mathbf{x} \cap \{\langle v_2, 1 \rangle, \langle v_4, 0 \rangle, \langle v_1, 1 \rangle\}|) + g_8(4)$$

Example: v_1, v_2, v_3, v_4 ; $D = \{0, 1\}$



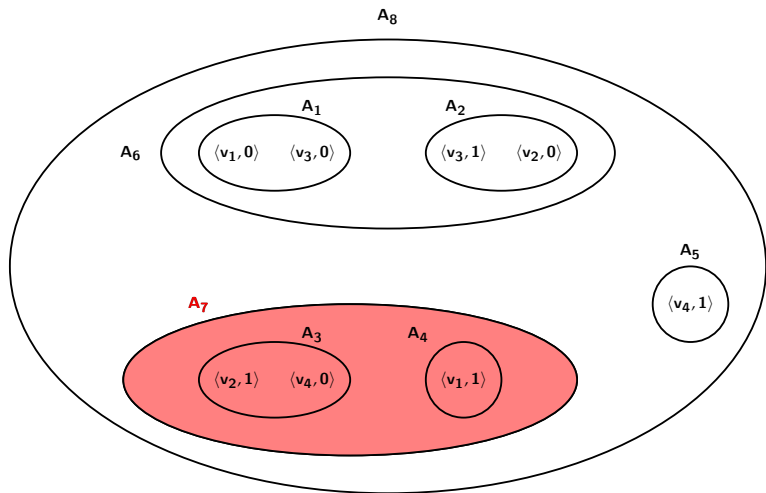
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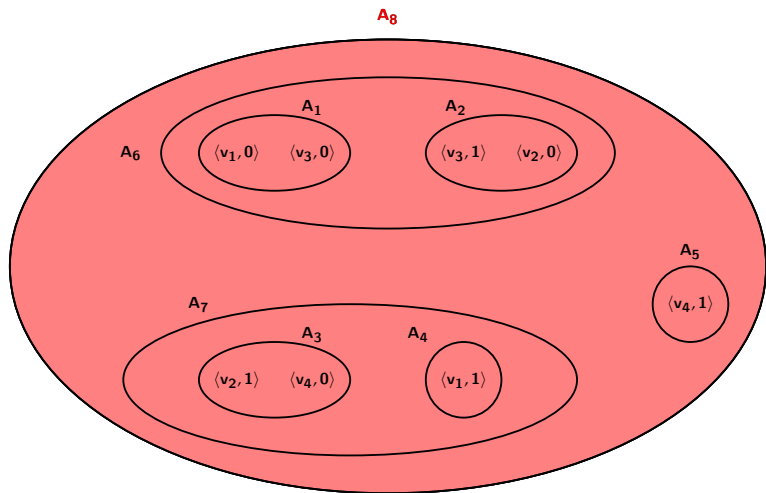
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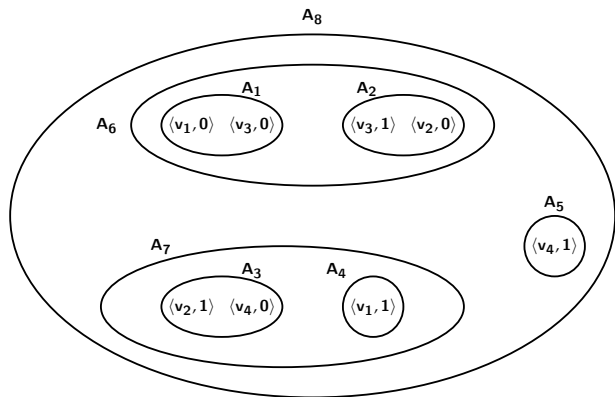
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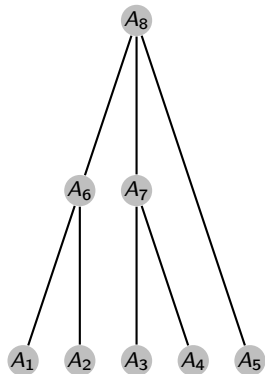
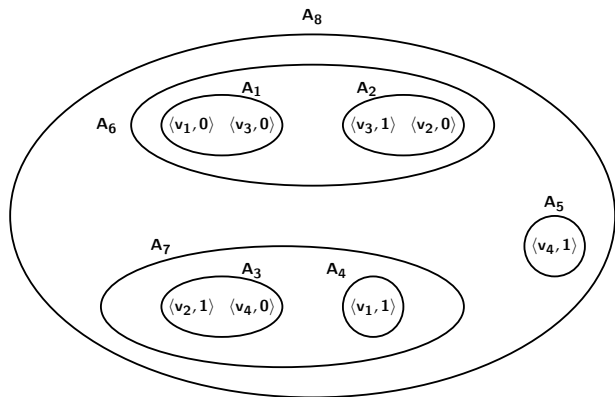


$$g(\mathbf{x}) = g_1(|\mathbf{x} \cap \{\langle v_1, 0 \rangle, \langle v_3, 0 \rangle\}|) + g_2(|\mathbf{x} \cap \{\langle v_3, 1 \rangle, \langle v_2, 0 \rangle\}|) + \dots \\ \dots + g_7(|\mathbf{x} \cap \{\langle v_2, 1 \rangle, \langle v_4, 0 \rangle, \langle v_1, 1 \rangle\}|) + g_8(4)$$

Example: Structure of A-Sets



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Example: Network

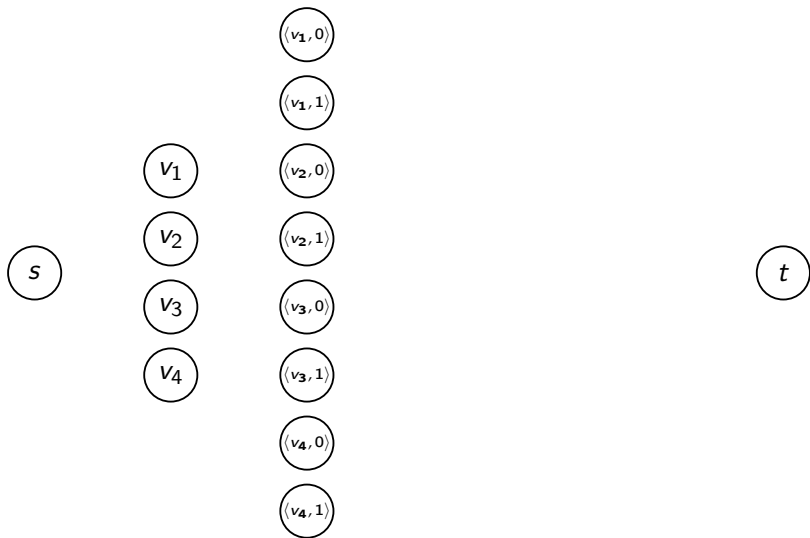
Example: Network



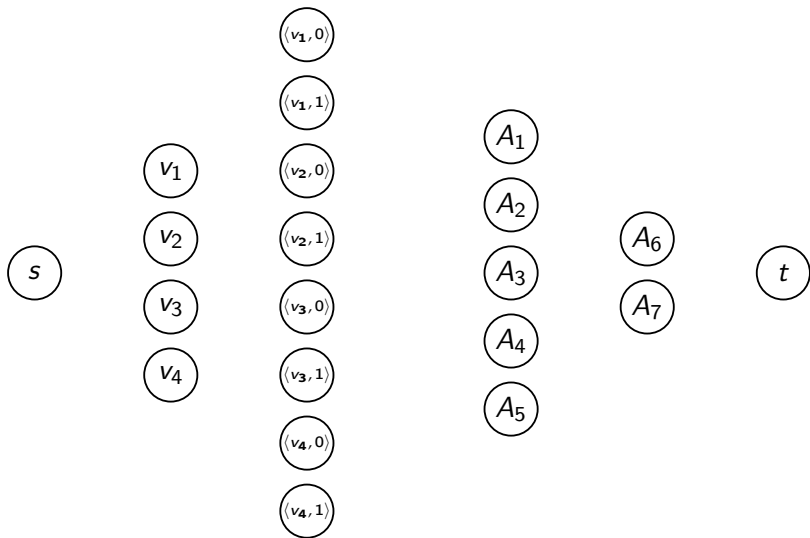
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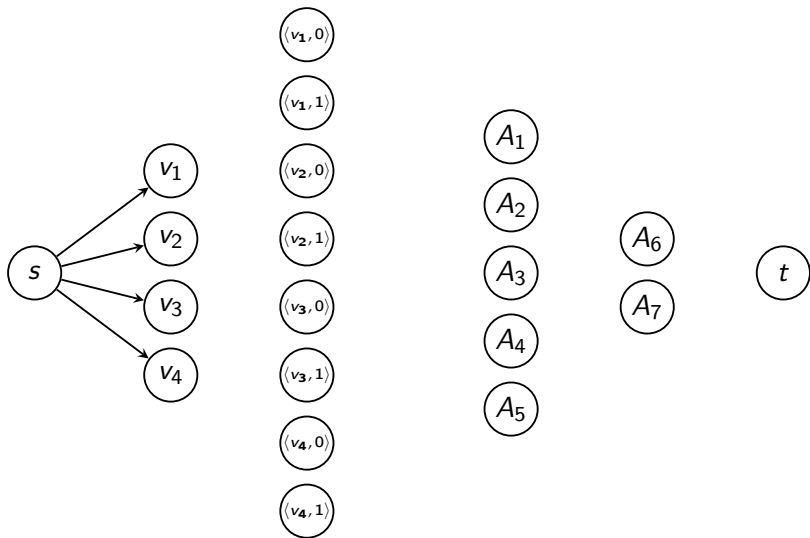
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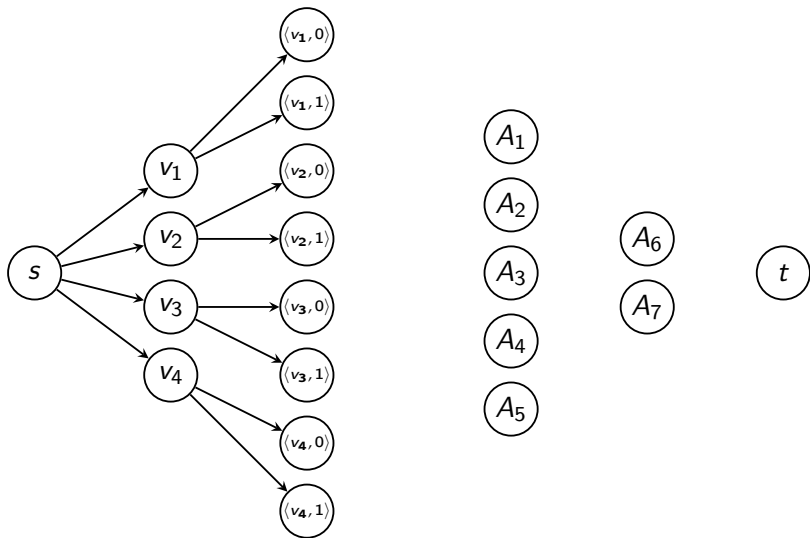
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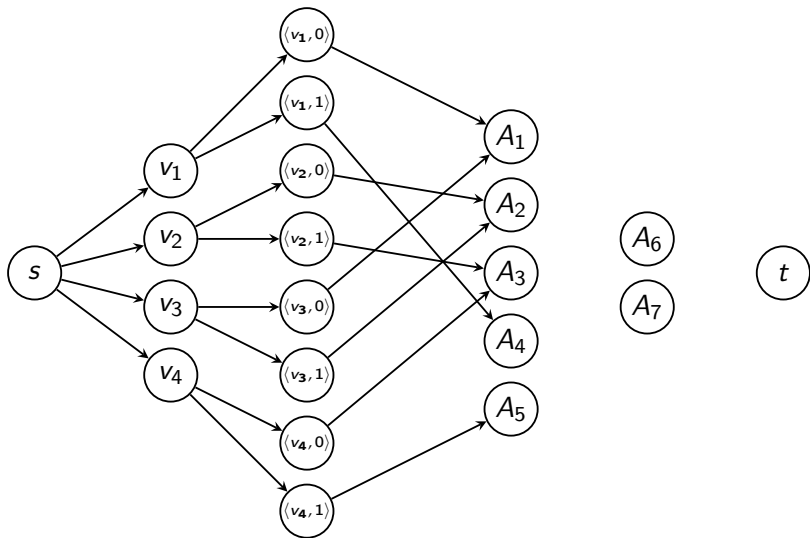
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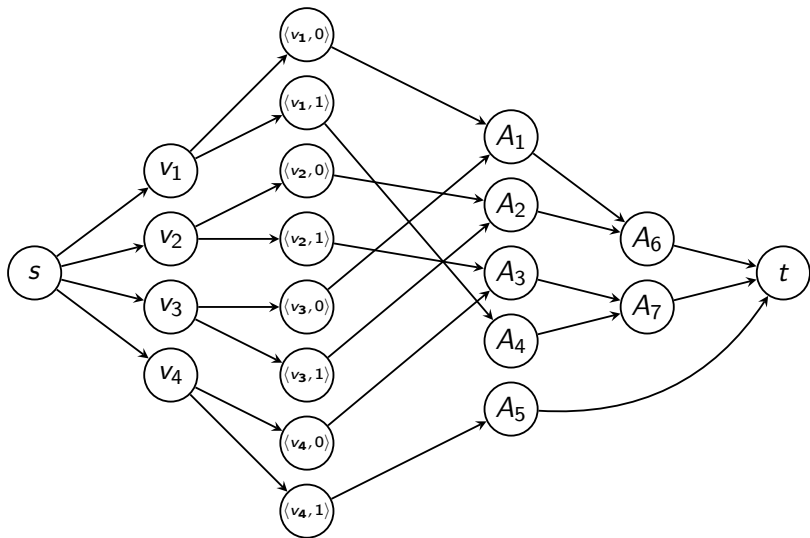
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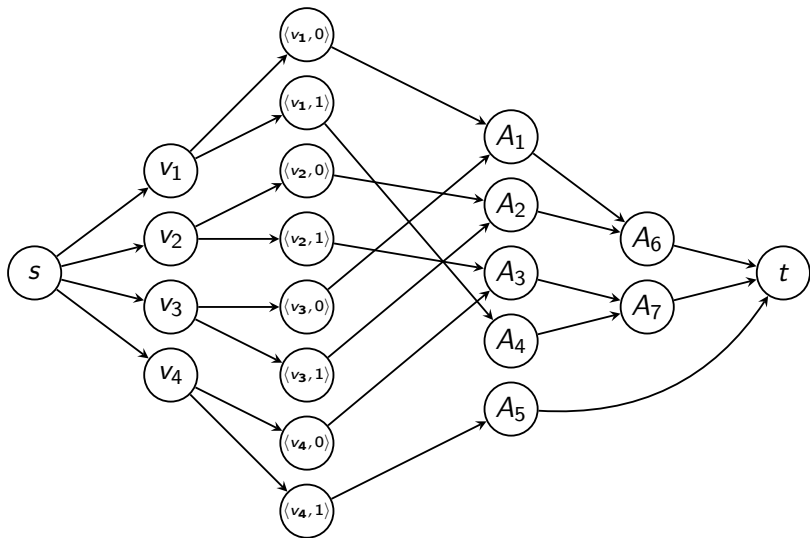


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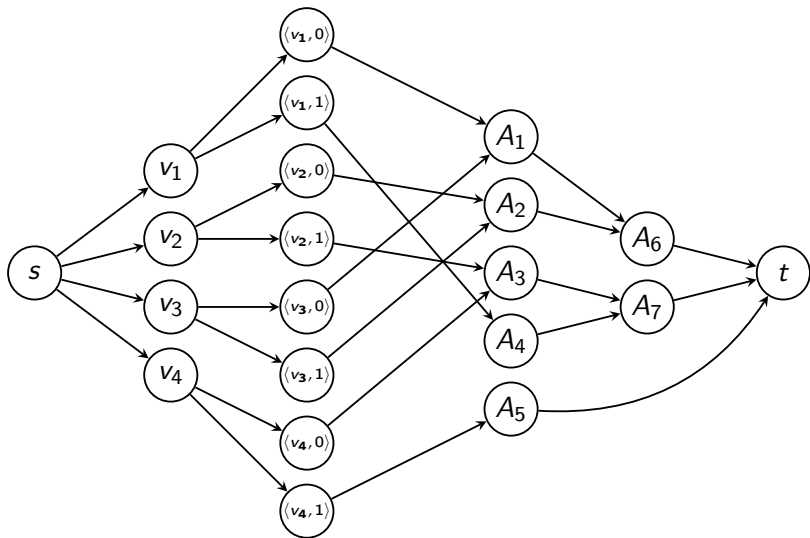
[1,1]



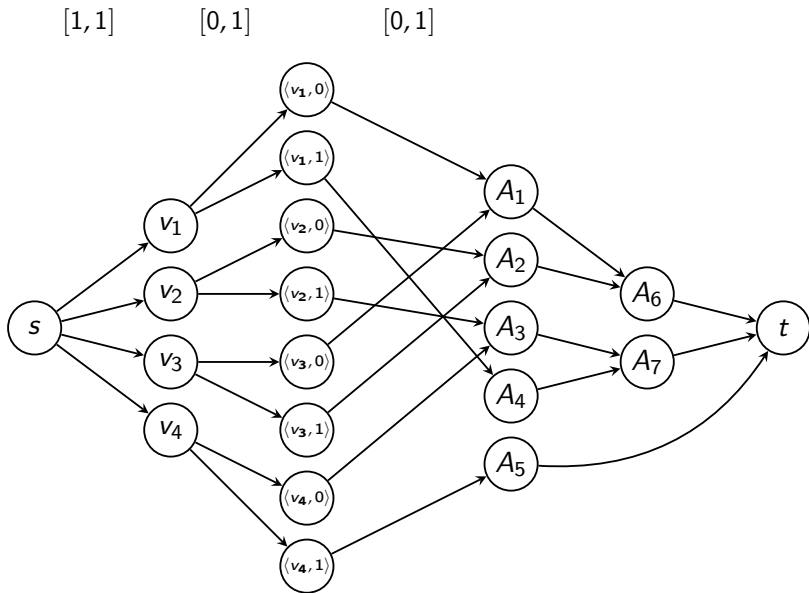
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$[1, 1]$

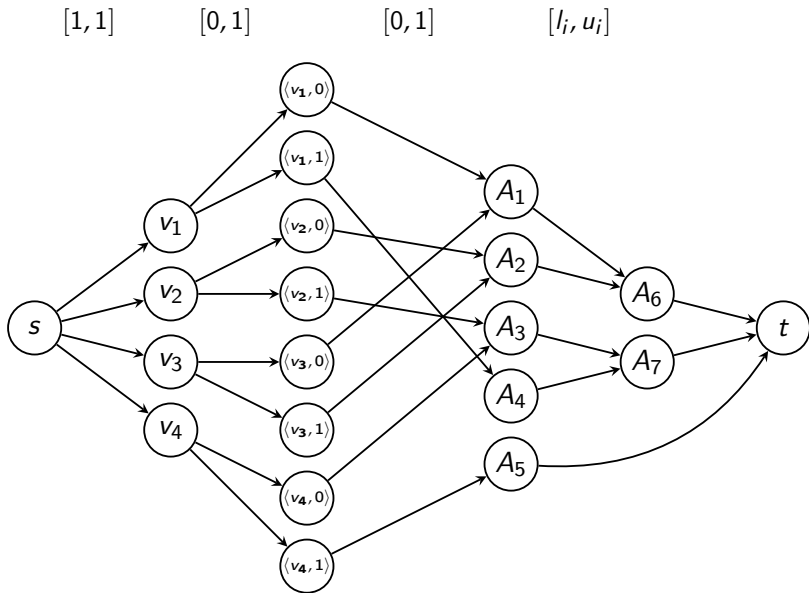
$[0, 1]$



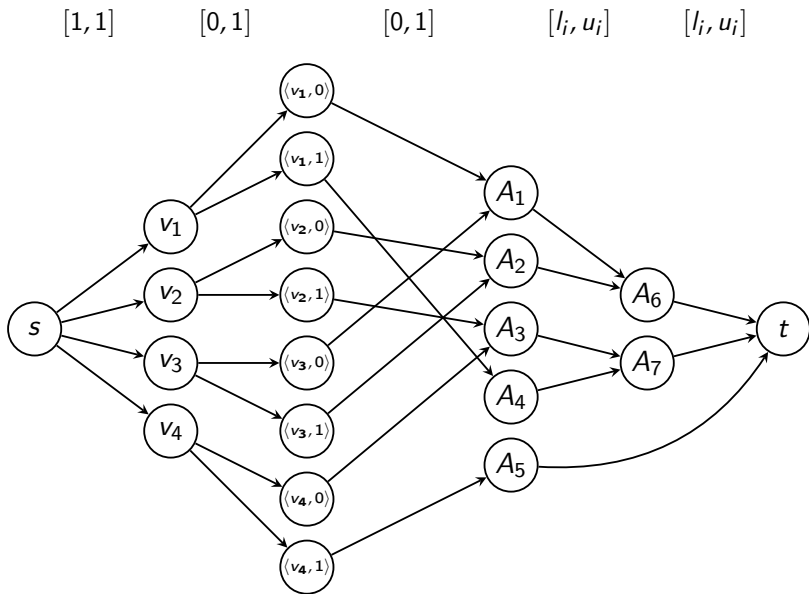
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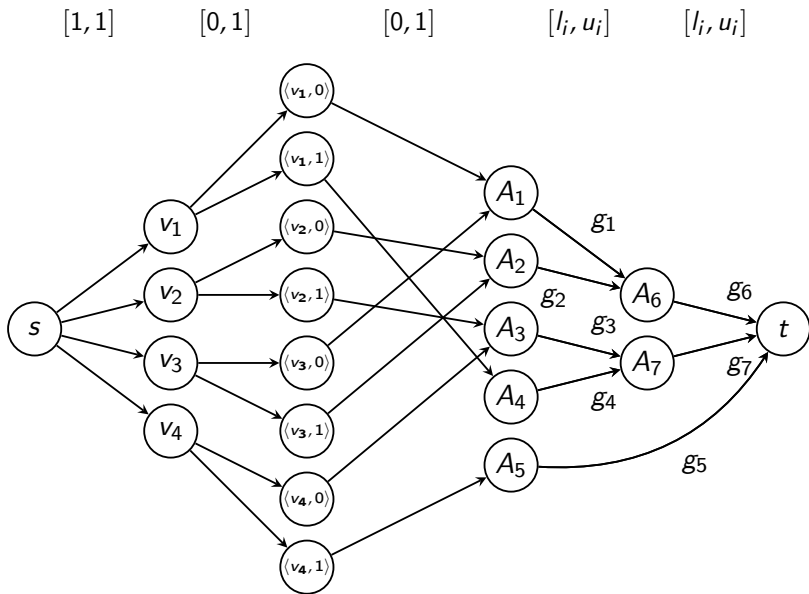
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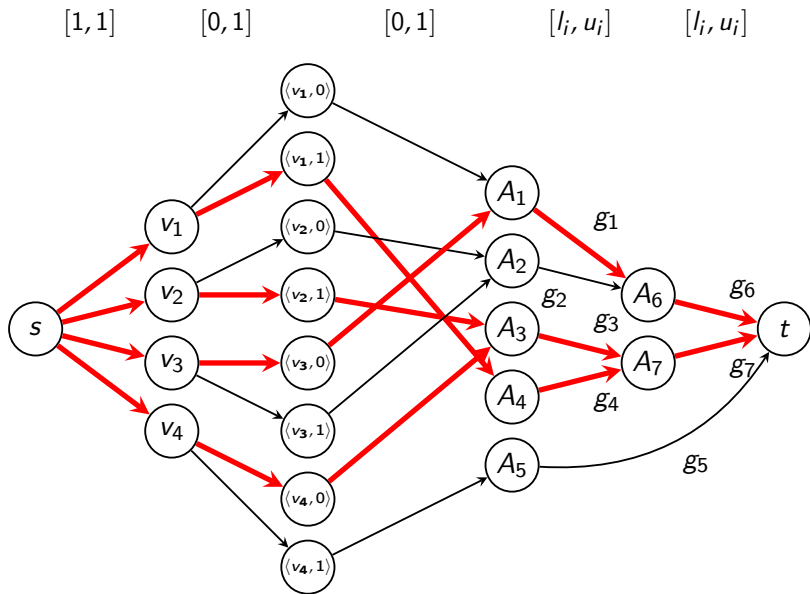
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Laminar Convex VCSPs

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$|A_i| = 2: D = \{0, 1\} \Rightarrow$ bounded treewidth
 $|D| = 3 \Rightarrow$ **open**
 $|D| > 3 \Rightarrow$ equivalent to $|D| = 3$

More on Laminar Convex VCSPs

- ▶ laminar \Rightarrow cross-free
- ▶ renamability over Boolean domains
- ▶ nestedness over variables \Rightarrow bounded treewidth

Open Problems on Hybrid VCSPs

- ▶ more tractable classes!

Conclusions

VCSP

- ▶ tractable languages
- ▶ complexity classifications
- ▶ hybrid tractability

Thank you

Questions?

<http://zivny.cz/>