

Time-Series Constraints

Ekaterina Arafailova, Nicolas Beldiceanu, Mats Carlsson,
Rémi Douence, Pierre Flener, M. Andreína Francisco R.,
Justin Pearson, and Helmut Simonis

8th December 2016



About Me

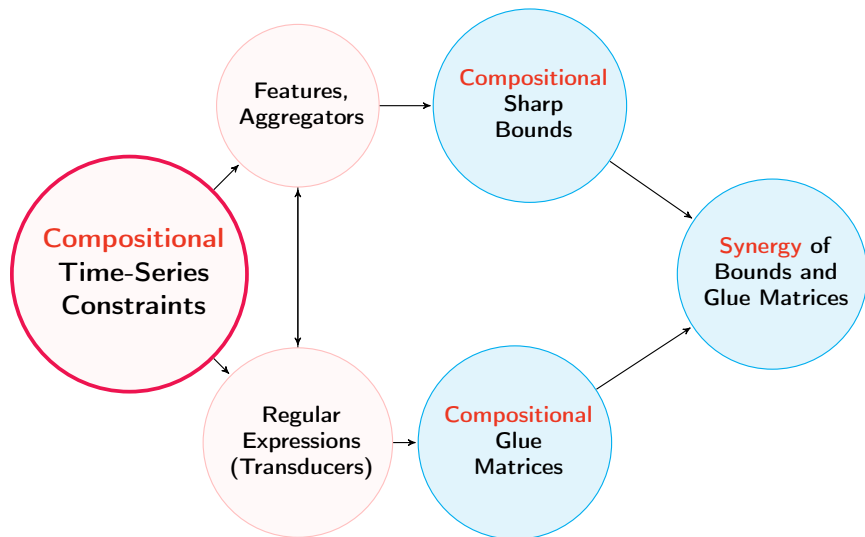
- ▶ Graduated from M2 ORO in 2015.
- ▶ Internship at EMN under supervision of N. Beldiceanu (EMN) and M. Minoux (LIP6).
- ▶ Started a PhD on the 1st of September, 2015.
- ▶ Thesis Director: N. Beldiceanu, Co-Supervisor: R. Douence.
- ▶ GRACeFUL project.

Collaboration

1. GRACeFUL people.
2. Helmut Simonis (University College Cork).
3. Pierre Flener, M. Andreína Francisco R., Justin Pearson (The University of Uppsala).
4. Mats Carlsson (SICS)



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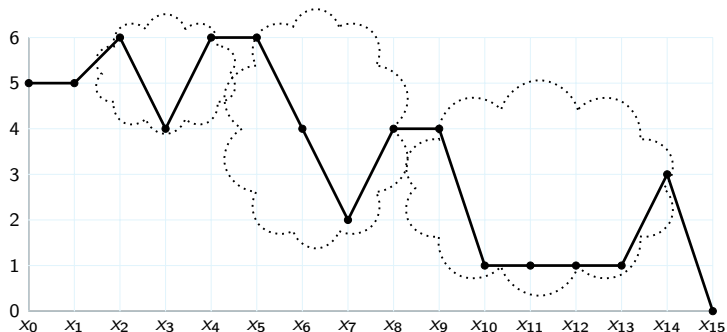


Example of a Time-Series Constraint

Constrain the **maximum** of the **minima** of the **valleys**
in the time series $\langle 5, 5, 6, 4, 6, 6, 4, 2, 4, 4, 1, 1, 1, 1, 3, 0 \rangle$.

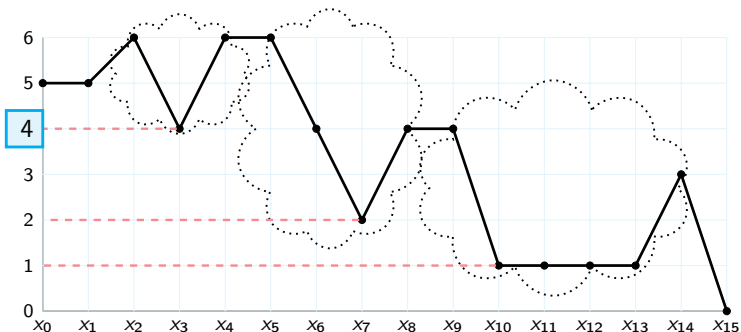
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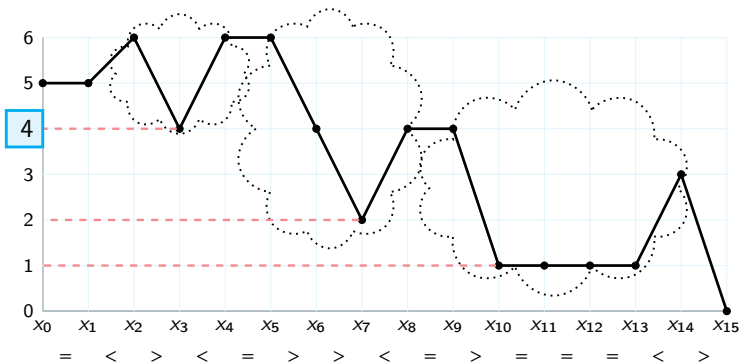
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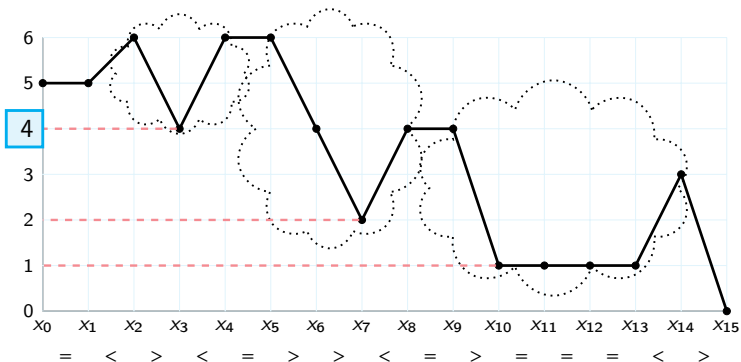
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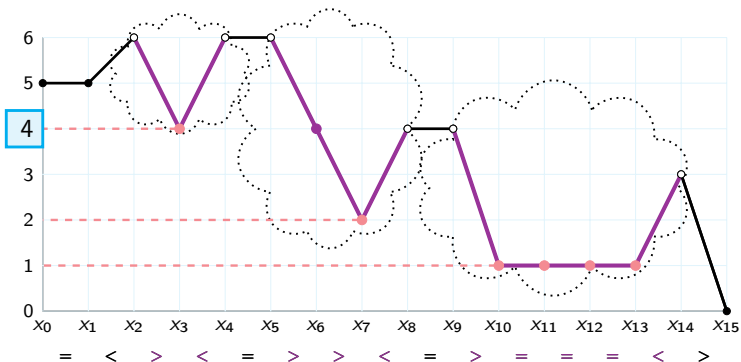
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A subsequence $\langle X_i, \dots, X_j \rangle$ of $\langle X_0, \dots, X_m \rangle$ is a **valley** if the signature of $\langle X_{i-1}, \dots, X_{j+1} \rangle$ is a maximal word matching ' $>(>|=)*(<|=)*<$ '.

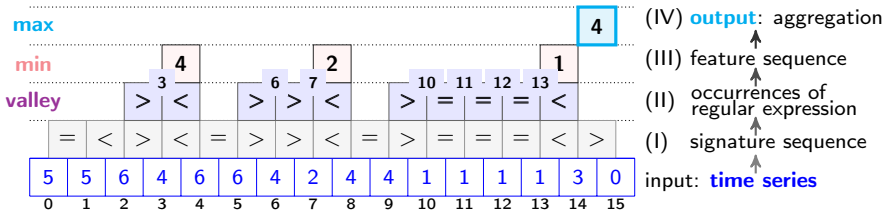
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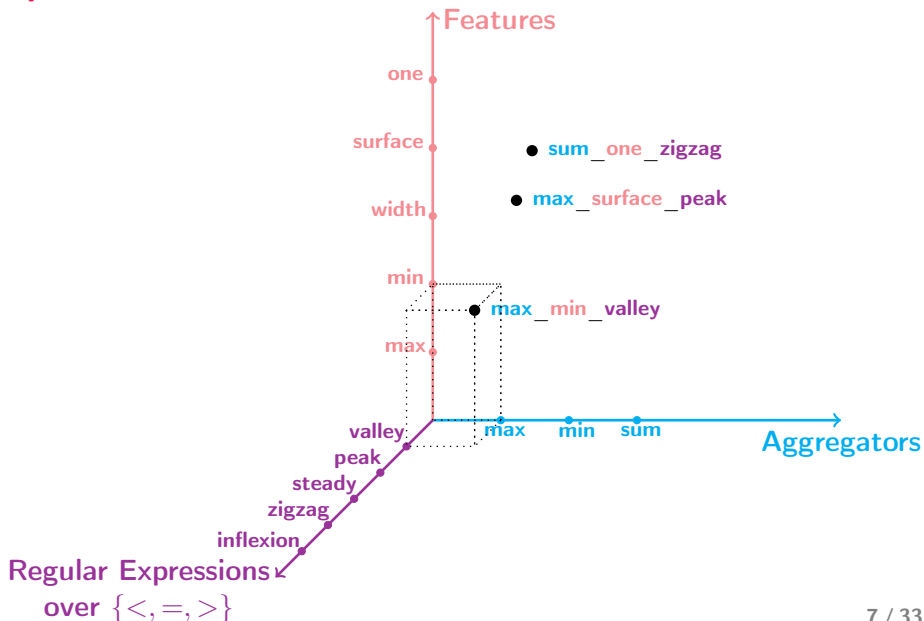
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Compositional Time-Series Definition by Multiple Layers of Functions

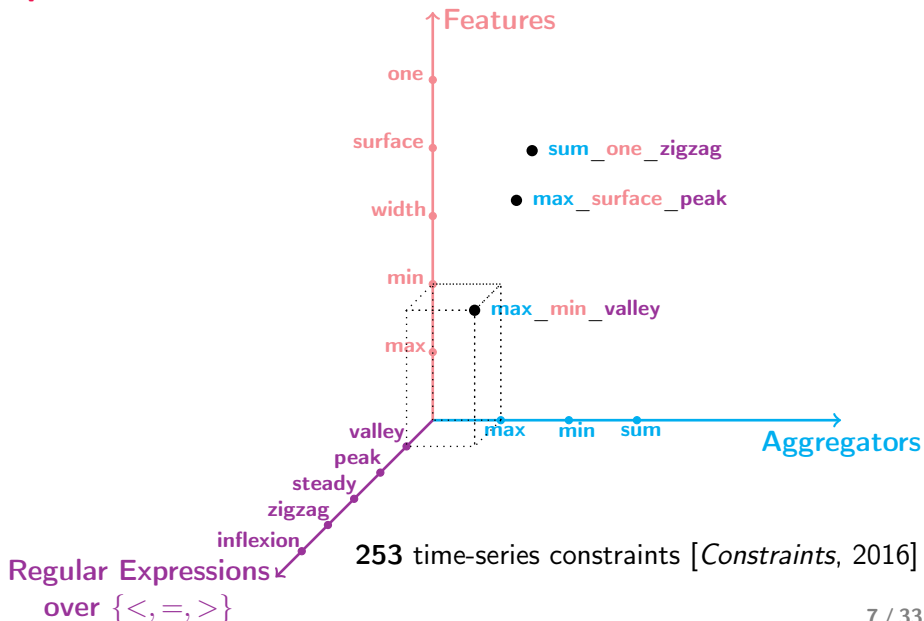


$\text{max_min_valley}(\langle 5, 5, 6, 4, 6, 6, 4, 2, 4, 4, 1, 1, 1, 1, 3, 0 \rangle, 4)$ holds

Space of Time-Series Constraints



Space of Time-Series Constraints



Main Question

How to go from a compositional constraint definition
to **compositional combinatorial objects**
that can be used in different contexts,
such as CP, MIP, local search, and data mining?

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to **compositional combinatorial objects**
that can be used in different contexts,
such as CP, MIP, local search, and data mining?

Time-series constraints are very numerous:
we cannot afford to consider each of them separately.

Applications of Time-Series Constraints

- ▶ Analysis of output of electric power stations over multiple days. [CP 2013]
- ▶ Power management for large-scale-distributed systems. [Computing, 2016]
- ▶ Trace analysis for Internet Service Provider. (CeADAR)
- ▶ Anomaly detection and error correction in building data. (Campus21)

Synthesising Time-Series Constraints

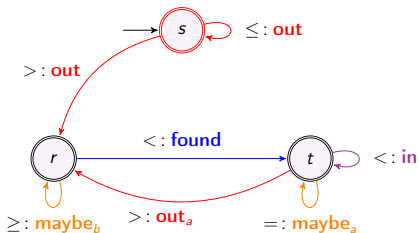
Use a **transducer**: [*Constraints*, 2016]

- ▶ Input sequence: Handle the **matching** aspect
- ▶ Output sequence: Handle the **computational** aspect

Synthesising Time-Series Constraints

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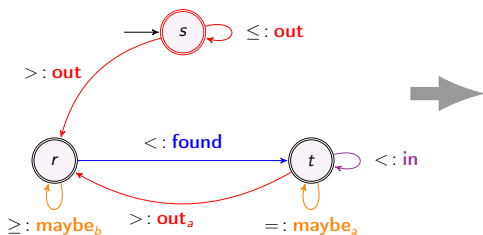


Transducer for **valley**

Synthesising Time-Series Constraints

Use a **transducer**: [Constraints, 2016]

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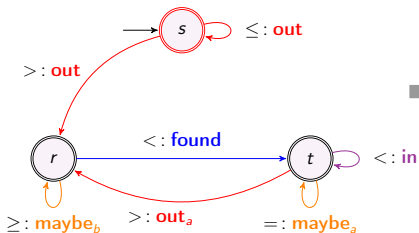
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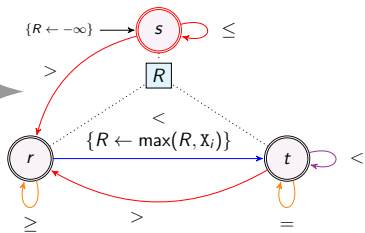
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Transducer for **valley**



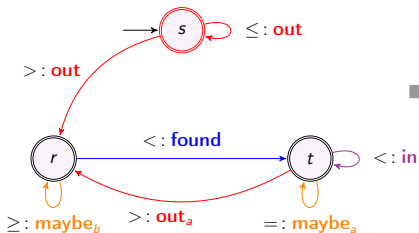
Automaton for **max_min_valley**

Synthesising Time-Series Constraints

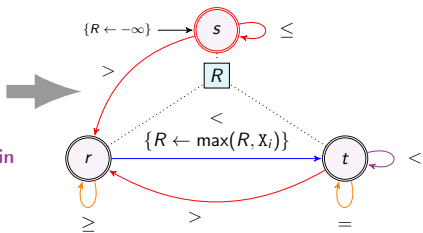
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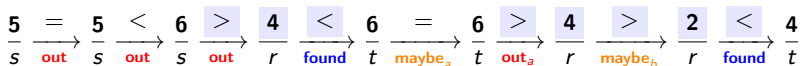
- ▶ Input sequence: Handle the **matching** aspect
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Transducer for **valley**



Automaton for **max_min_valley**



Implementing Time-Series Constraints

- ▶ **CP**: Reformulation of automata with accumulators*
- ▶ **MIP**: Linear reformulation of automata with accumulators**

* [*Constraints*, 2005], ** [*CPAIOR 2016*]

Goal: Address the combinatorial aspect of time-series constraints.

Method: Exploit the **compositional nature** of time-series constraints at the combinatorial level.

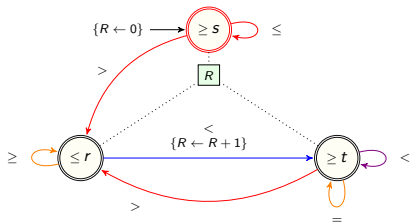
Input

- ▶ Time-series variables X_i with i in $[1, n]$ over their domains $[a_i, b_i]$
- ▶ An automaton with accumulators for a time-series constraint with
 - ▶ a set of states Q ;
 - ▶ an input alphabet Σ ;
 - ▶ an m -tuple of integer accumulators with their initial values

$$I = \langle I_1, \dots, I_m \rangle;$$

- ▶ a transition function $\delta : Q \times Z^m \times \Sigma \rightarrow Q \times Z^m$.

Input: example



Automaton for nb_valley

$$\frac{5}{s} \xrightarrow{=} \frac{5}{s} \xrightarrow{<} \frac{6}{s} \xrightarrow{>} \frac{4}{r} \xrightarrow{<} \frac{6}{t} \xrightarrow{=} \frac{6}{t} \xrightarrow{>} \frac{4}{r} \xrightarrow{>} \frac{2}{r} \xrightarrow{<} \frac{4}{t}$$

$$\frac{5}{0} \xrightarrow{=} \frac{5}{0} \xrightarrow{<} \frac{6}{0} \xrightarrow{>} \frac{4}{0} \xrightarrow{<} \frac{6}{1} \xrightarrow{=} \frac{6}{1} \xrightarrow{>} \frac{4}{1} \xrightarrow{>} \frac{2}{1} \xrightarrow{<} \frac{4}{2}$$

Goal

Our Goal

A way to generate a model for an automaton with linear or linearisable accumulator updates, for example containing min and max.

Linear decomposition of automata without accumulators

Côté, M.C., Gendron, B., Rousseau, L.M.: Modeling the regular constraint with integer programming. In: CPAIOR 2007. LNCS, vol. 4510, pp. 29–43. Springer (2007)

Signature Constraints

Introduced variables: S_i over Σ with $i \in [0, n - 2]$.

What do the values of S_i mean ?

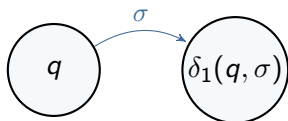
$$S_i = '>' \Leftrightarrow X_i > X_{i+1}, \forall i \in [0, n - 2]$$

$$S_i = '=' \Leftrightarrow X_i = X_{i+1}, \forall i \in [0, n - 2]$$

$$S_i = '<' \Leftrightarrow X_i < X_{i+1}, \forall i \in [0, n - 2]$$

Transition Function Constraints

Introduced variables: Q_i over Q with $i \in [0, n - 1]$; T_i over $Q \times \Sigma$ with $i \in [0, n - 2]$



Each transition constraint has a form:

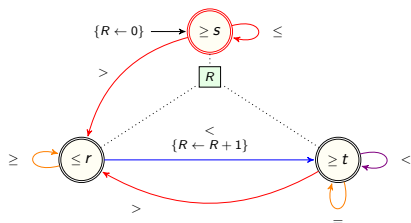
$$Q_i = q \wedge S_i = \sigma \Leftrightarrow Q_{i+1} = \delta_1(q, \sigma) \wedge T_i = \langle q, \sigma \rangle,$$

$$\forall i \in [0, n - 2], \forall q \in Q, \forall \sigma \in \Sigma$$

Initial state is fixed:

$$Q_0 = q_0$$

Accumulator Updates



Accumulator updates

R_i over $[a, b]$ with i in $[0, n - 1]$; T_i over $Q \times \Sigma$ with i in $[0, n - 2]$.

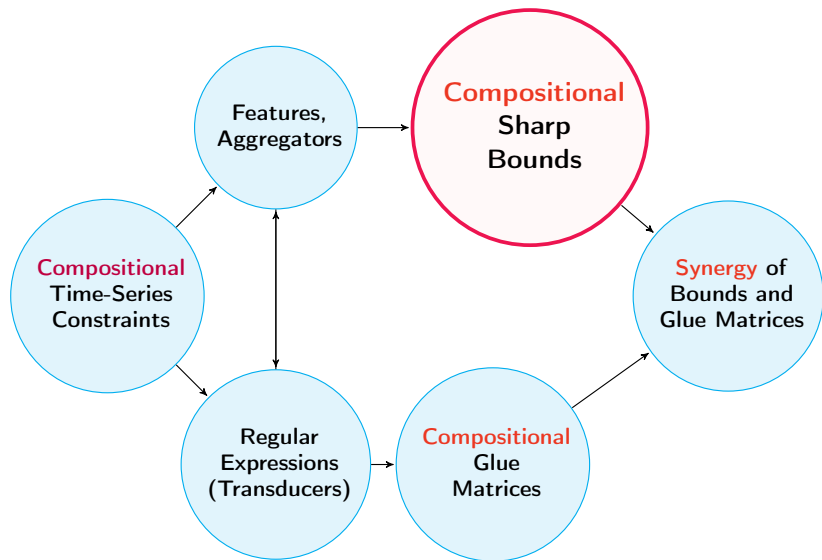
- ▶ $R_0 = 0$
- ▶ $T_i = \langle r, > \rangle \Rightarrow \mathbf{R}_{i+1} = \mathbf{R}_i + \mathbf{1}, \forall i \in [0, n - 2]$
- ▶ $T_i = \langle q, \sigma \rangle \Rightarrow \mathbf{R}_{i+1} = \mathbf{R}_i, \forall i \in [0, n - 2], \forall \langle q, \sigma \rangle \in (Q \times \Sigma) \setminus \langle r, > \rangle$

New Variables for the Linear Model

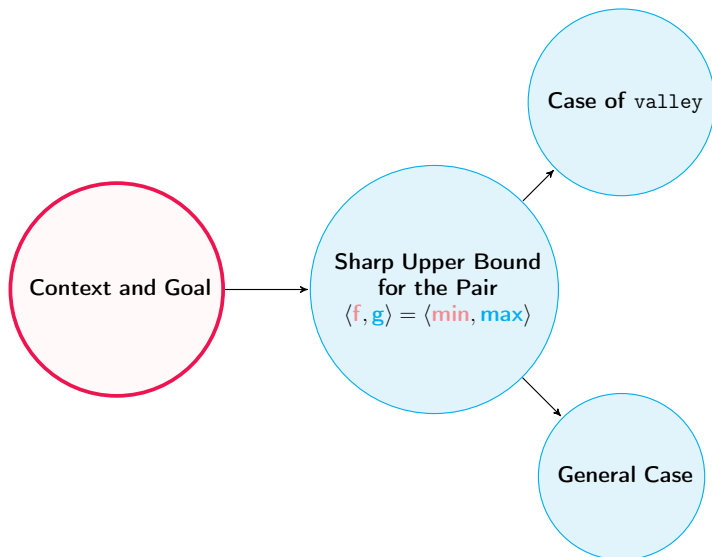
New variables

- ▶ Q_i is replaced by 0-1 variables Q_i^q for all q in Q .
 $Q_i^q = 1 \Leftrightarrow Q_i = q$
 - ▶ New constraint: $\sum_{q \in Q} Q_i^q = 1, \forall i \in [0, \dots, n-1]$
 - ▶ The same procedure for T_i and S_i wrt their domains
 - ▶ X_i and R_i remain integer variables!
-
- ▶ Every constraint of the logical model is made linear by applying some standard techniques
 - ▶ The linear model has $O(n)$ variables and $O(n)$ constraints

Contents



Compositional Sharp Bounds: Contents



Context and Goal

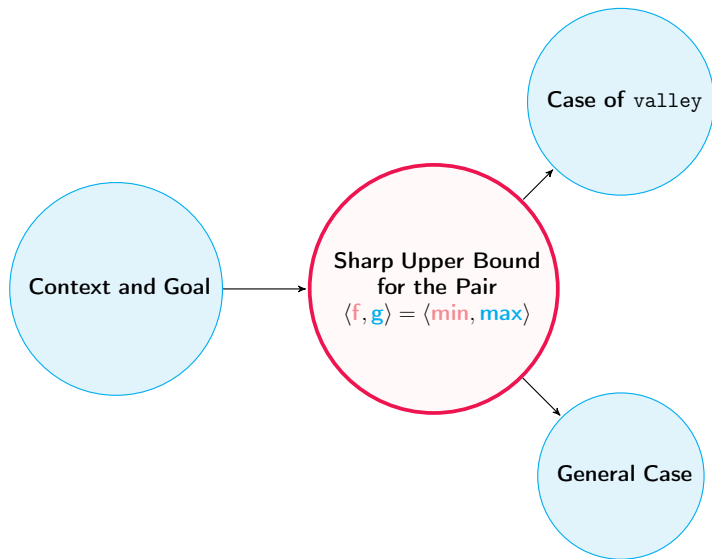
Consider a $g_f_σ(\langle X_0, \dots, X_m \rangle, N)$ time-series constraint, for a regular expression $σ$, a feature f , and an aggregator g , with every X_i ranging over **the same** integer interval $[a, b]$.

Context and Goal

Consider a $\mathbf{g_f_}\sigma(\langle X_0, \dots, X_m \rangle, N)$ time-series constraint, for a regular expression σ , a feature \mathbf{f} , and an aggregator \mathbf{g} , with every X_i ranging over **the same** integer interval $[a, b]$.

Goal: Derive formulae $\beta_{\mathbf{f},\mathbf{g}}^u$ and $\beta_{\mathbf{f},\mathbf{g}}^l$ that are **parametrised by σ** and yield respectively sharp upper and lower bounds on the value of N .

Compositional Sharp Bounds: Contents



Computing a Sharp Upper Bound for the pair $\langle \text{min}, \text{max} \rangle$

Consider a $\text{max_min_}\sigma(\langle X_0, \dots, X_m \rangle, N)$ time-series constraint with every X_i ranging over $[a, b]$.

Goal: Compute a sharp upper bound on the value of N .

Computing a Sharp Upper Bound for the pair $\langle \text{min}, \text{max} \rangle$

Consider a $\text{max_min_}\sigma(\langle X_0, \dots, X_m \rangle, N)$ time-series constraint with every X_i ranging over $[a, b]$.

Goal: Compute a sharp upper bound on the value of N .

Method:

1. Introduce the **characteristics** of a regular expression σ : *the minimal difference between the domain upper bound b and the minima of the subseries*, which is called the **shift** of σ and denoted by Δ_σ .

Computing a Sharp Upper Bound for the pair $\langle \min, \max \rangle$

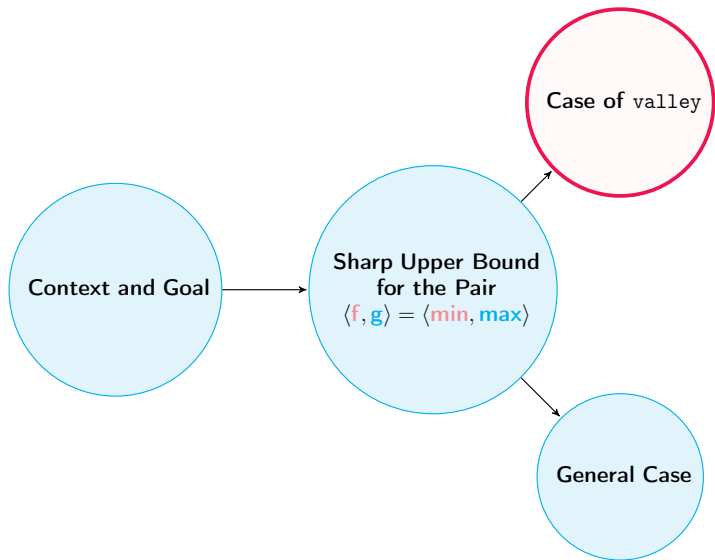
Consider a $\max_min_ \sigma(\langle X_0, \dots, X_m \rangle, N)$ time-series constraint with every X_i ranging over $[a, b]$.

Goal: Compute a sharp upper bound on the value of N .

Method:

1. Introduce the **characteristics** of a regular expression σ : *the minimal difference between the domain upper bound b and the minima of the subseries*, which is called the **shift** of σ and denoted by Δ_σ .
2. Explore the connection between this characteristics and the sharp upper bound on the value of N .

Compositional Sharp Bounds: Contents



Computing a Sharp Upper Bound for `max_min_valley`

Consider the `max_min_valley`($\langle X_0, \dots, X_8 \rangle, N$) time-series constraints with every X_i ranging over $[a, b] = [3, 6]$.

Shift of valley and Its Connection to a Sharp Upper Bound

- ▶ The shift of **valley** is the smallest possible difference between b and the minima of valleys, namely 1 and is reached, for example, for valleys whose signature is ' $><$ '.

Shift of valley and Its Connection to a Sharp Upper Bound

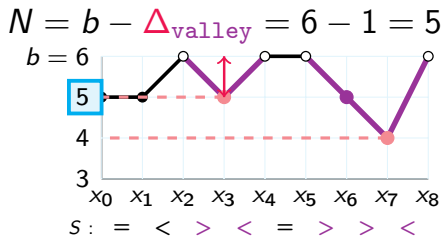
- ▶ The shift of **valley** is the smallest possible difference between b and the minima of valleys, namely 1 and is reached, for example, for valleys whose signature is ' $><$ '.
- ▶ The minimum of **any valley** is at least Δ_{valley} , which is 1, away from b , which is 6, thus $N \leq b - \Delta_{\text{valley}} = 6 - 1 = 5$.

Shift of valley and Its Connection to a Sharp Upper Bound

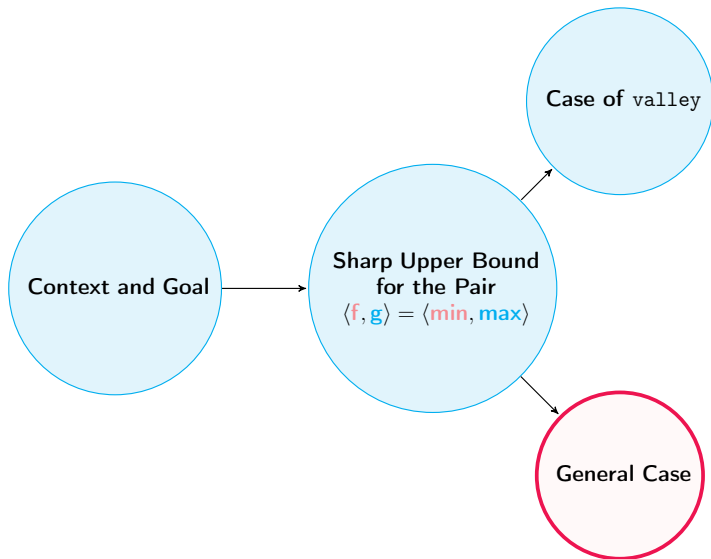
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- ▶ This bound is reached for some ground time series.

Shift of valley and Its Connection to a Sharp Upper Bound

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Compositional Sharp Bounds: Contents



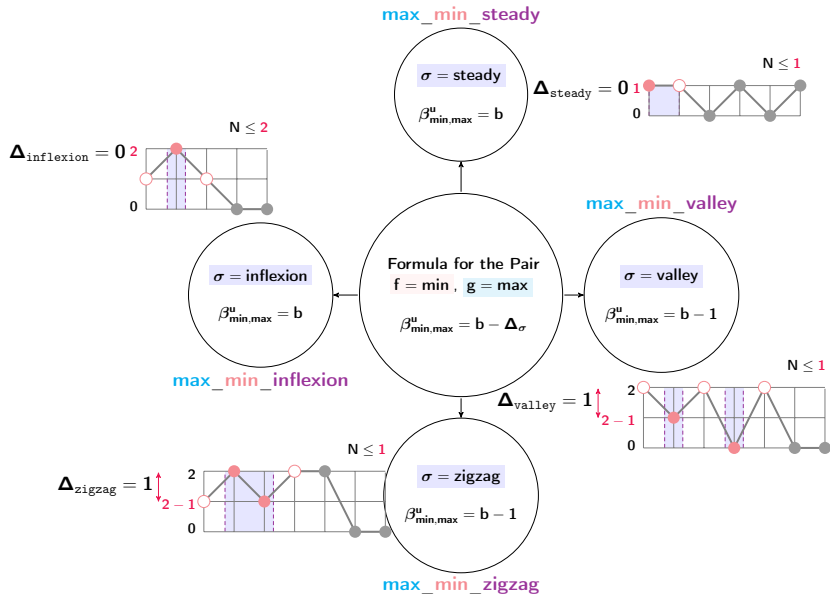
Sharp Upper Bound for the General Case

Theorem

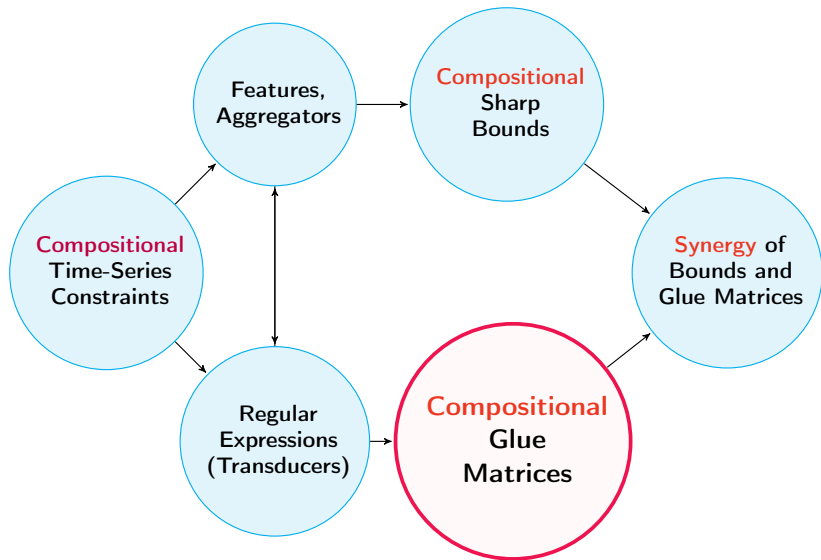
Consider a $\text{max_min_}\sigma(\langle X_0, \dots, X_m \rangle, N)$ time-series constraint, where σ is one of the 22 regular expressions and every X_i ranges over $[a, b]$, then the sharp upper bound on the value of N is

$$\beta_{\text{min,max}}^u = b - \Delta_\sigma$$

Compositional Bounds (Summary)



Contents



Linking the Prefixes and Suffixes of a Sequence

For the ngroup($\langle X_0, \dots, X_m \rangle, \mathcal{S}, N$) constraint, N is the number of maximal subsequences of $\langle X_0, \dots, X_m \rangle$ whose values are all in \mathcal{S} .

Linking the Prefixes and Suffixes of a Sequence

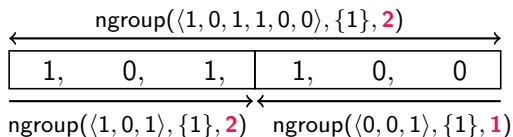
For the $\text{ngroup}(\langle X_0, \dots, X_m \rangle, \mathcal{S}, N)$ constraint, N is the number of maximal subsequences of $\langle X_0, \dots, X_m \rangle$ whose values are all in \mathcal{S} .

The $\text{ngroup}(\langle 1, 0, 1, 1, 0, 0 \rangle, \{1\}, 2)$ constraint holds.

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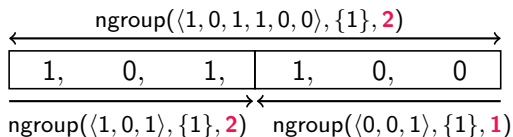
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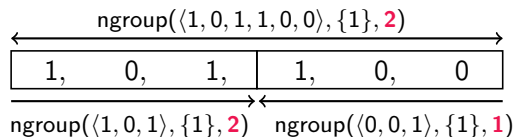


not just a sum ($2 \neq 2 + 1$)...

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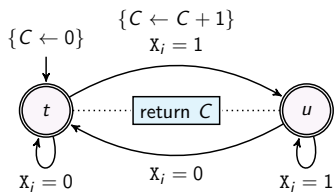
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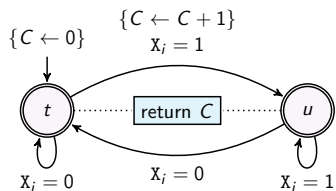
not just a sum ($2 \neq 2 + 1$)...how to compute the correction term -1 ?

Glue Matrix for the ngroup Constraint



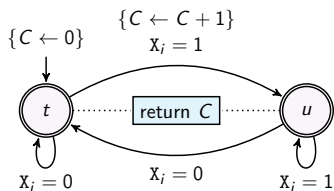
Automaton for **ngroup**

Glue Matrix for the ngroup Constraint



Automaton for **ngroup**

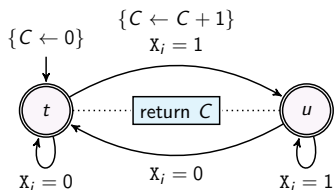
Glue Matrix for the ngroup Constraint

Automaton for **ngroup**

	t	u
t	0	0
u	0	-1

Glue Matrix for **ngroup**

Glue Matrix for the ngroup Constraint

Automaton for **ngroup**

	t	u
t	0	0
u	0	-1

Glue Matrix for **ngroup**

$\text{ngroup}(\langle 1, 0, 1, 1, 0, 0 \rangle, \{1\}, 2)$

1,	0,	1,	1,	1,	0,	0
$t,$	$u,$	$t,$	$u,$	$u,$	$t,$	$t,$
$t,$	$u,$	$t,$	$u,$	$u,$	$t,$	$t,$

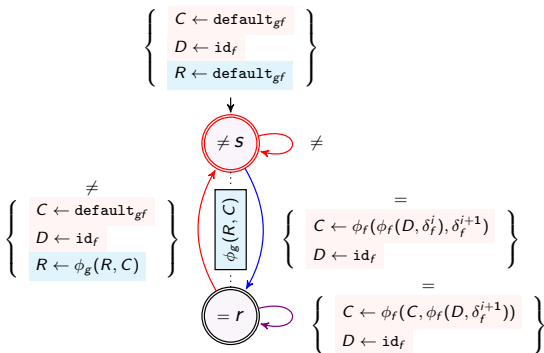
$\text{ngroup}(\langle 1, 0, 1 \rangle, \{1\}, 2)$

$\text{ngroup}(\langle 0, 0, 1 \rangle, \{1\}, 1)$

Compositional Glue Matrices for Time-Series Constraints

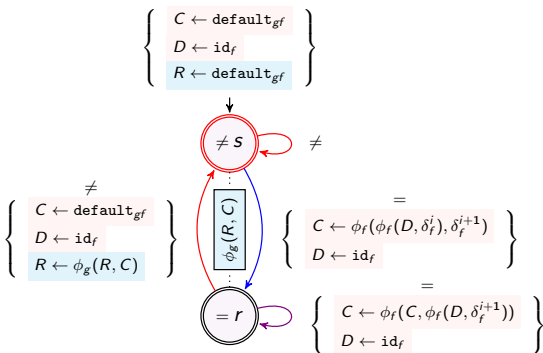
Goal: For a transducer, derive a glue matrix that is **parametrised** by a **feature** and an **aggregator**.

Generic Glue Matrix for steady_sequence = '+'



Generic Automaton for
g_f_steady_sequence

Generic Glue Matrix for `steady_sequence = '='+`

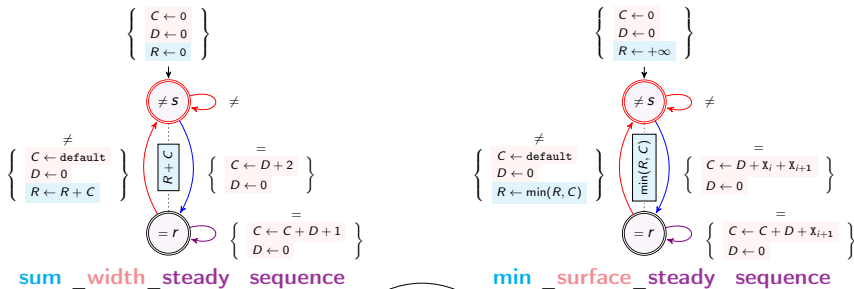


Generic Automaton for
`g_f_steady_sequence`

	s	r
s	$\phi_g(\overrightarrow{C}, \overleftarrow{C})$	$\phi_g(\overrightarrow{C}, \overleftarrow{C})$
r	$\phi_g(\overrightarrow{C}, \overleftarrow{C})$	$\phi_f(\overrightarrow{C}, \overleftarrow{C}, \overrightarrow{D}, \overleftarrow{D}, \delta_f^i)$

Generic Glue Matrix for
`g_f_steady_sequence`

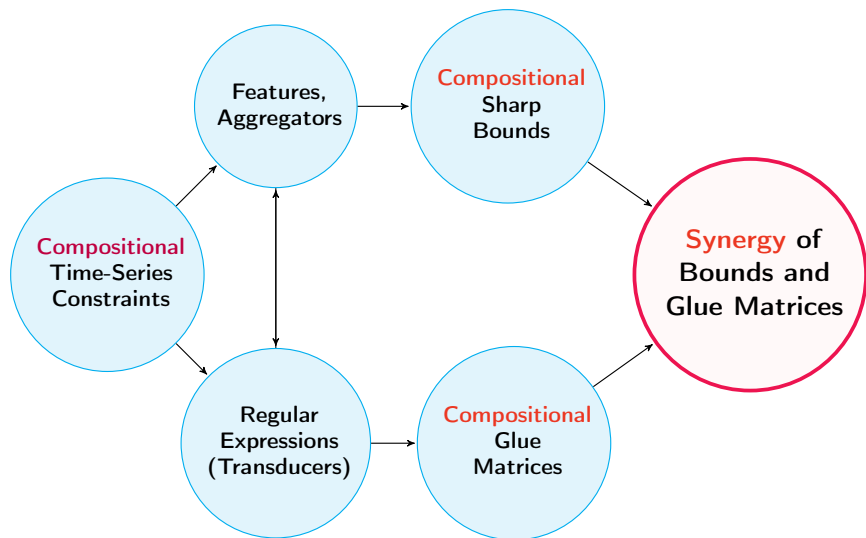
Corresponding Compositional Glue Matrices



	s	r
s	$\overrightarrow{C} + \overleftarrow{C}$	$\overrightarrow{C} + \overleftarrow{C}$
r	$\overrightarrow{C} + \overleftarrow{C}$	$\overrightarrow{C} + \overleftarrow{C} + \overleftarrow{D} + \overleftarrow{D} + 1$

	s	r
s	$\min(\overrightarrow{C}, \overleftarrow{C})$	$\min(\overrightarrow{C}, \overleftarrow{C})$
r	$\min(\overrightarrow{C}, \overleftarrow{C})$	$\overrightarrow{C} + \overleftarrow{C} + \overleftarrow{D} + \overleftarrow{D} + X_i$

Contents



Synergy of Sharp Bounds and Glue Matrices

Consider a $g_f_σ(\langle X_0, \dots, X_m \rangle, N)$ time-series constraint where all X_i range over the same domain.

- ▶ Add **sharp bounds** for **every prefix** and **every reversed suffix** of X_0, \dots, X_m .
- ▶ Impose **glue-matrix implied constraints** on **every prefix** and **every reversed suffix** of X_0, \dots, X_m .

The **combination** of sharp bounds and glue matrices improves propagation.

Conclusion: clear separation between three levels

- ▶ **Language**: compositional description of constraints with aggregator g , feature f , regular expression σ
- ▶ **Abstract Combinatorial Objects** (*transducers and formulae*)
 - ▶ Transducers for each regular expression σ (22)
 - ▶ Parametrised bounds for each pair g, f (20)
 - ▶ Parametrised glue matrices for each regular expression σ (22)
- ▶ **Multiple usages** (*synthesised code: $\text{\LaTeX}(154100)$, Prolog (135267)*)
 - ▶ **CP**: enhanced propagation (*bounds, glue matrices*)
 - ▶ **Local search**: constant time probing (*glue matrices*)
 - ▶ **Data mining**: range of variation of feature (*bounds*)

Separate definition from usage,
be compositional at all levels

MANUAL

SYNTHESISED

Publications on Time-Series Constraints

- ▶ N. Beldiceanu, R. Douence, M. Carlsson, H. Simonis. “Using Finite Transducers for Describing and Synthesising Structural Time-Series Constraints”. Constraints’16.
- ▶ E. Arafailova, N. Beldiceanu, R. Douence, M. A. F. Rodriguez, P. Flener, J. Pearson, H. Simonis. “Time-series constraints: Improvements and application in CP and MIP contexts”. CPAIOR’16.
- ▶ E. Arafailova, N. Beldiceanu, M. Carlsson, M. A. F. Rodriguez, P. Flener, J. Pearson, H. Simonis. “Systematic Derivation of Bounds and Glue Constraints for Time-Series Constraints”. CP’16.
- ▶ E. Arafailova, N. Beldiceanu, R. Douence, M. Carlsson, M. A. F. Rodriguez, P. Flener, J. Pearson, H. Simonis. “Global Constraint Catalog, Volume II, Time-Series Constraints”. CoRR.



Arafailova, Ekaterina et al. (2016). “Time-series constraints: Improvements and application in CP and MIP contexts”. In: *CPAIOR 2016*. Ed. by Claude-Guy Quimper. Vol. 9676. LNCS. Springer, pp. 18–34.



Beldiceanu, Nicolas et al. (2005). “Reformulation of global constraints based on constraints checkers”. In: *Constraints* 10.4, pp. 339–362.



Beldiceanu, Nicolas et al. (2013). “Describing and generating solutions for the EDF unit commitment problem with the ModelSeeker”. In: *CP 2013*. Ed. by Christian Schulte. Vol. 8124. LNCS. Springer, pp. 733–748.



Beldiceanu, Nicolas et al. (2016a). “Towards energy-proportional Clouds partially powered by renewable energy”. In: *Computing*, p. 20. url: <https://hal.inria.fr/hal-01340318>.



Beldiceanu, Nicolas et al. (2016b). “Using finite transducers for describing and synthesising structural time-series constraints”. In: *Constraints* 21.1, pp. 22–40.