

Synthesis of Parametric Hybrid Automata from Time-Series

Miriam García Soto, Thomas A. Henzinger & Christian Schilling
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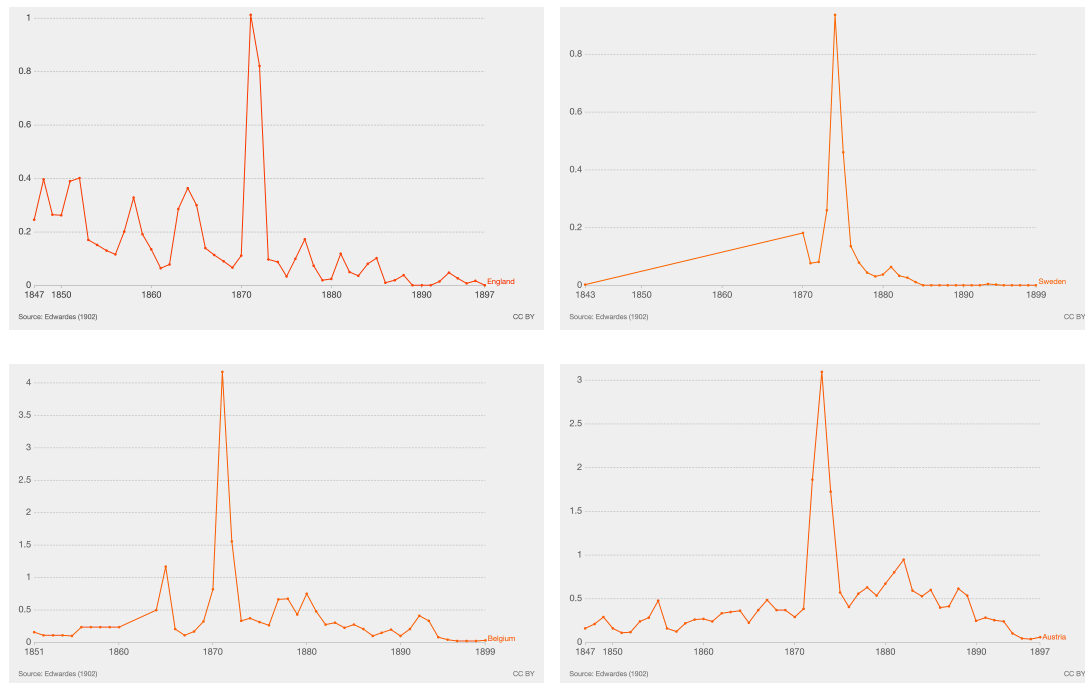
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COMPLUTENSE
M A D R I D



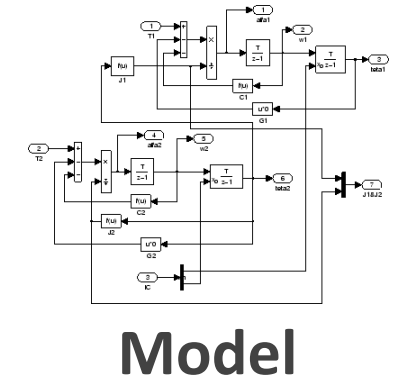
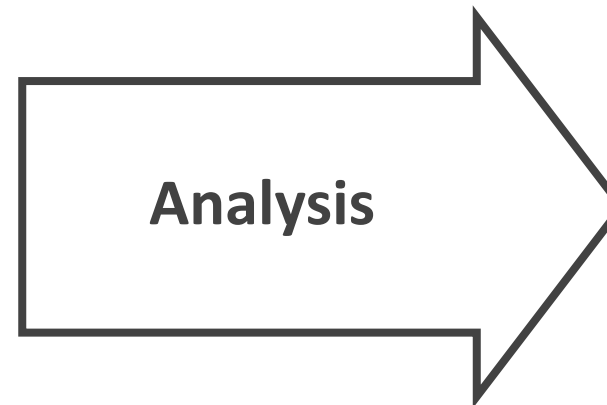
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Motivation

Main goal of many sciences is to create a model from a real system



Experimental data

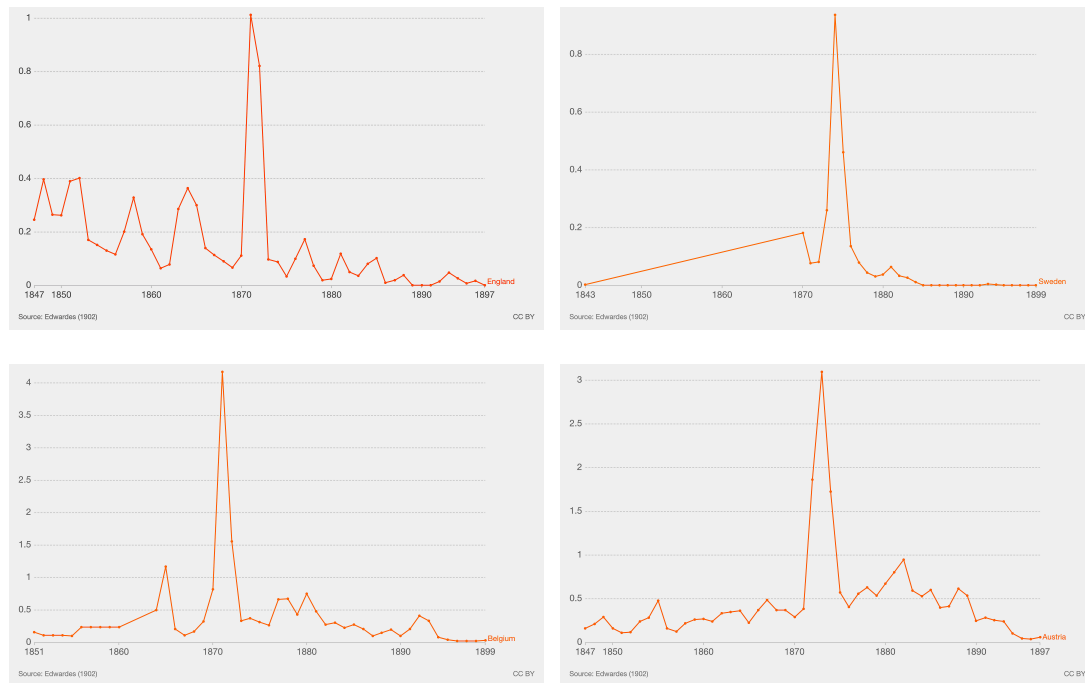


Challenge

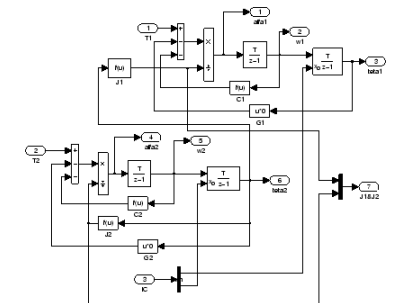
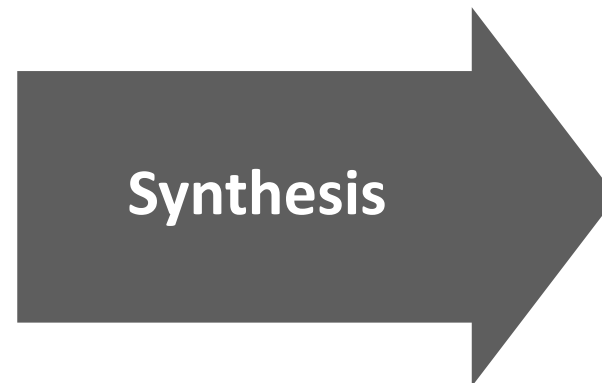
How to automatically create a model?

Motivation

Main goal of many sciences is to create a model from a real system



Experimental data

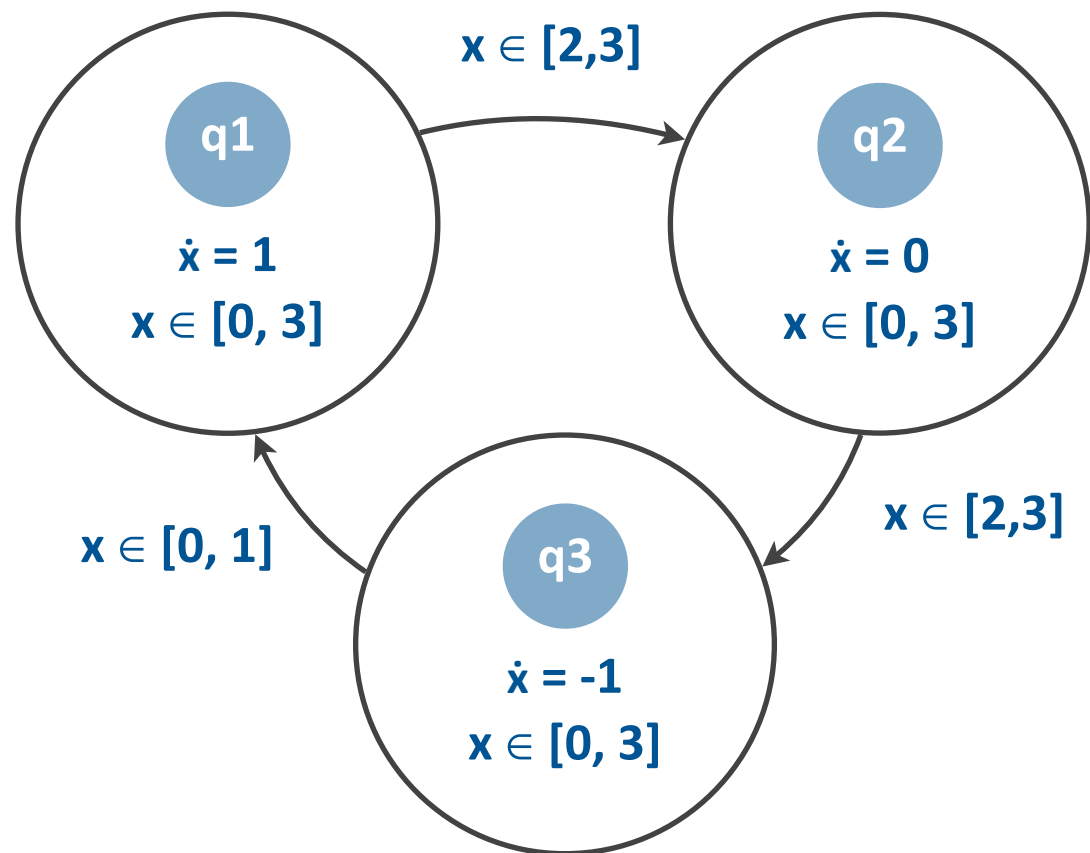


Model

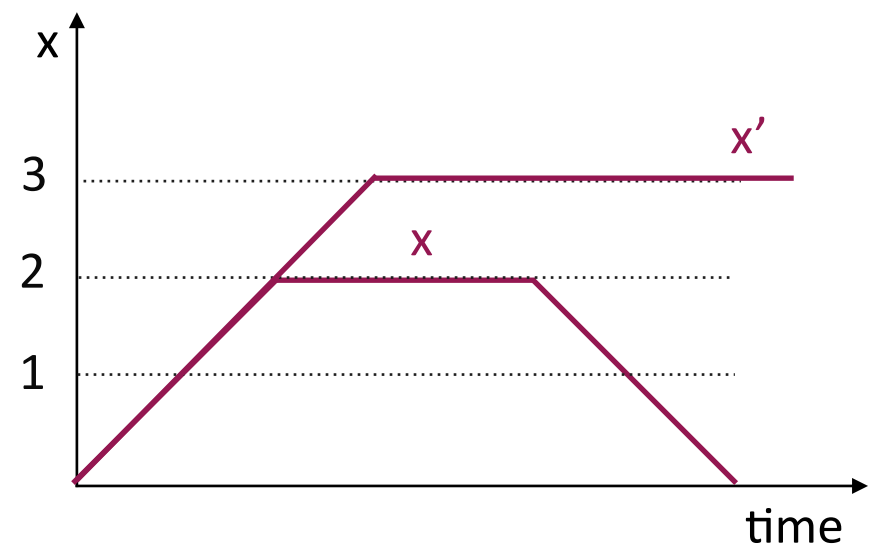
- Correctness **Specifications** - **Time-series** data
- **Synthesis** Algorithm - **Two phases** based on clustering and polyhedral construction
- **Model** - linear **hybrid automaton** with constant dynamics

Hybrid Automata capture the mixed **continuous** and **discrete** behaviour.

Linear hybrid automaton (LHA)



Non deterministic mode changes



Piecewise linear (PWL) function $x(\text{time})$

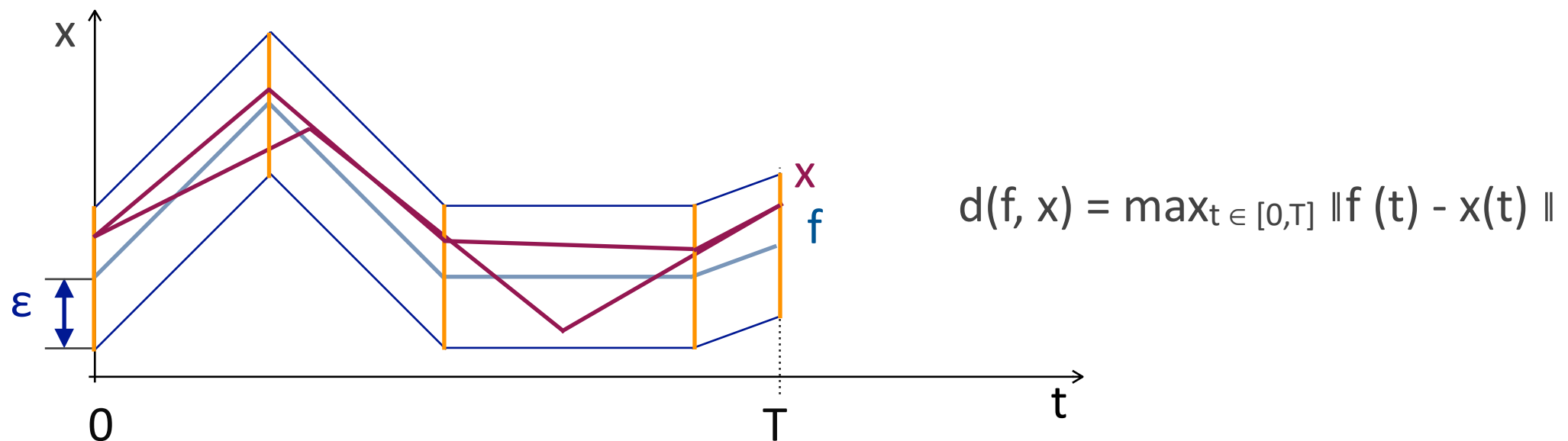
$$x_i(\text{time}) = m_i$$

Problem: find a LHA model that is close to the data

Problem

ϵ -capturing

An LHA H ϵ -captures a PWL function f if there exists an execution x in H with $d(f, x) \leq \epsilon$



Synthesis problem

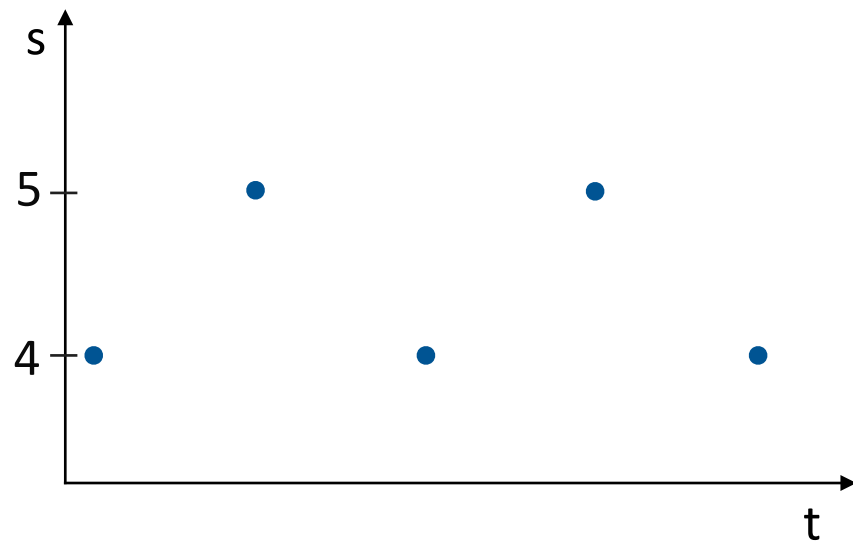
Given a set of PWL functions F and $\epsilon \geq 0$, construct an LHA H that ϵ -captures all $f \in F$

Synchronous time switchings for f and x

Synthesis algorithm

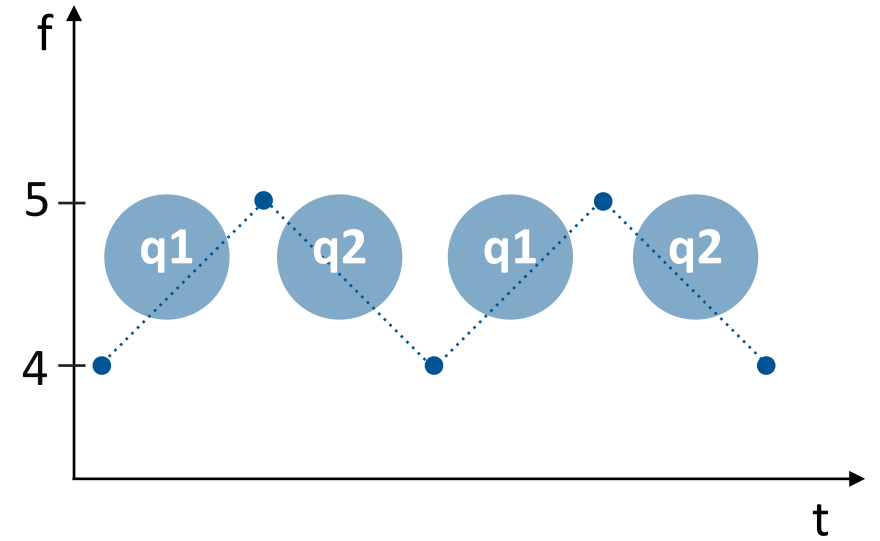
- **Offline** synthesis algorithm
- **Finite** set of time-series
- **Family of** linear hybrid automata **models**
- **Parameter polyhedron** represents all the model solutions
- ϵ is not given but **minimised**

Synthesis algorithm

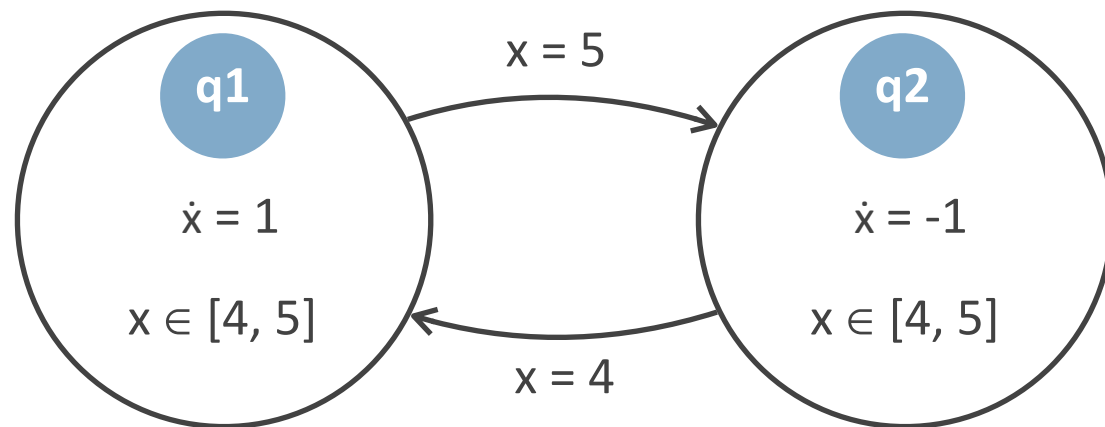


Time-series $s(t)$

Phase I

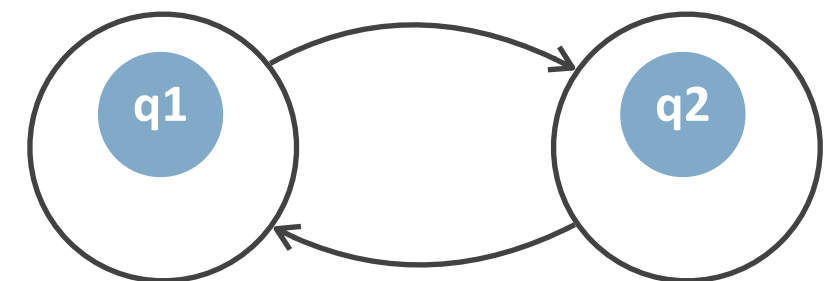


Piecewise linear (PWL) function $f(t)$



Hybrid automaton H

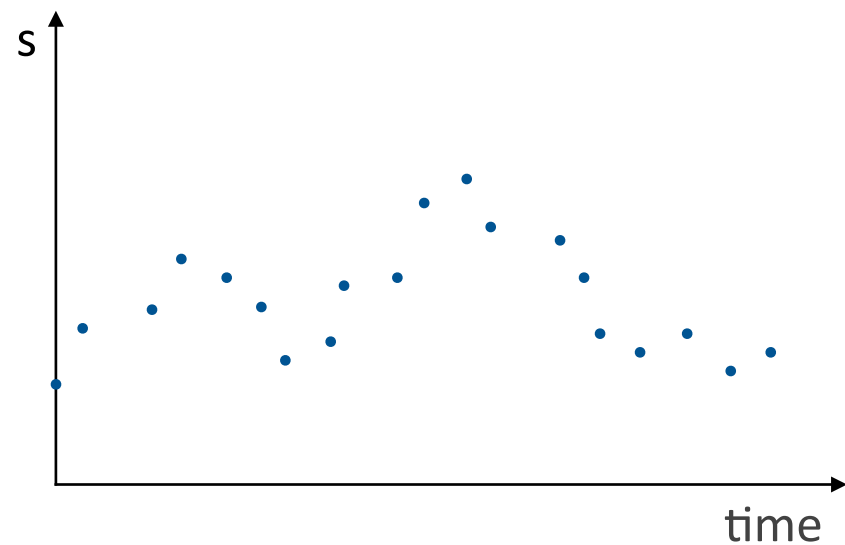
Phase II



Discrete structure H_d

For every **time-series** $s(t)$ there exists an **execution** $x(t)$ in H such that $\text{distance}(s(t), x(t)) \leq \varepsilon$ at every time t

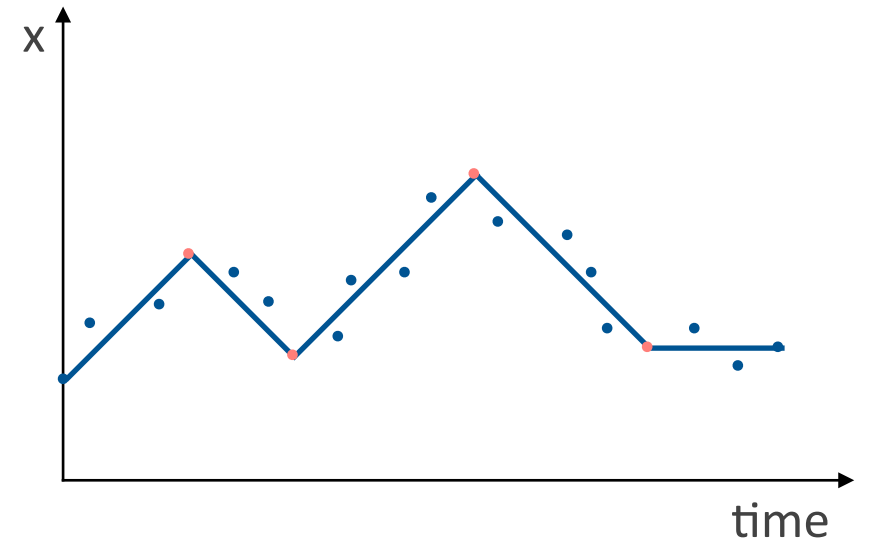
Phase I: time-series to PWL function



Time series $s(t)$

+
 $\delta \geq 0$

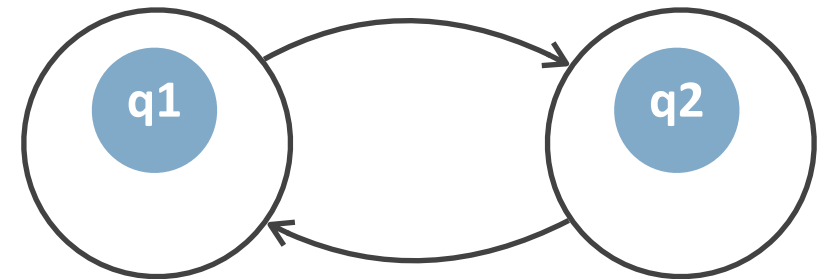
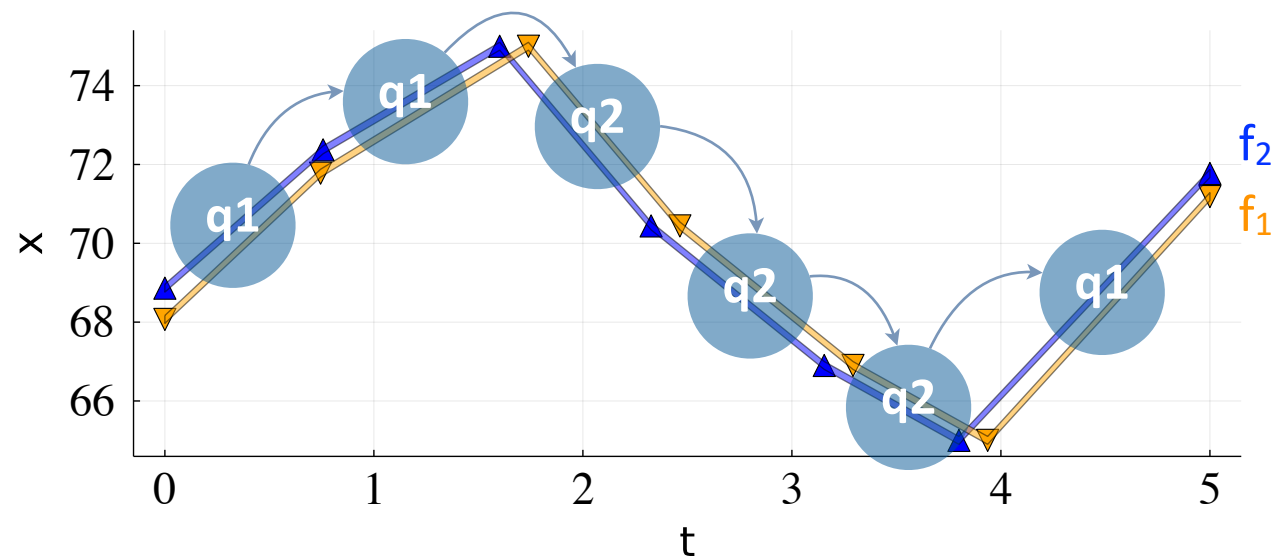
Time series
approximation



Piecewise linear (PWL) function $f(t)$

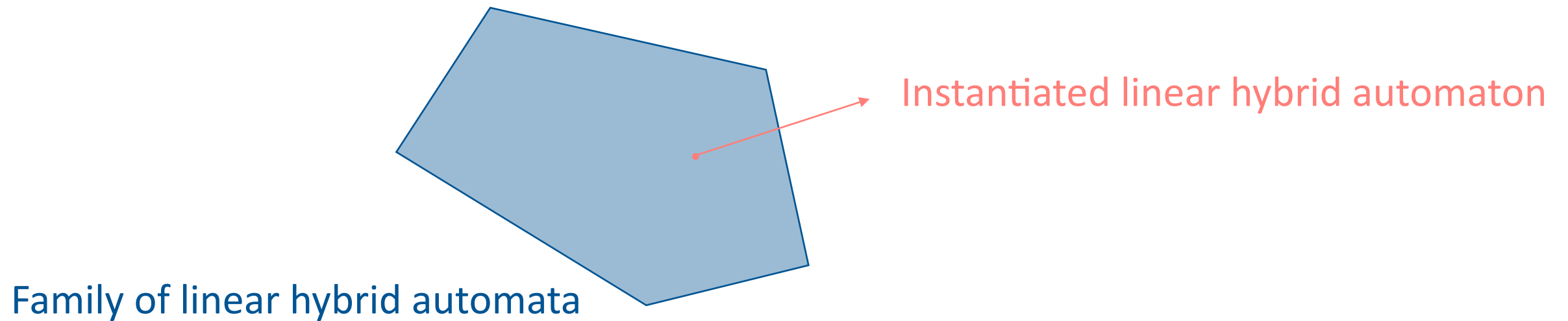
- **Simplification** of time-series
- **Linear interpolation**
- Variant of **Ramer-Douglas-Peucker** algorithm

Phase I: symbolic synthesis



- Send slope vectors of pieces to **clustering algorithm** (k-means)
- Clustering cost for different **numbers of clusters** k , together with relative improvement compared to $k - 1$
- **Mapping** from **pieces** in the PWL function to **clusters**

Phase II: flow polyhedron



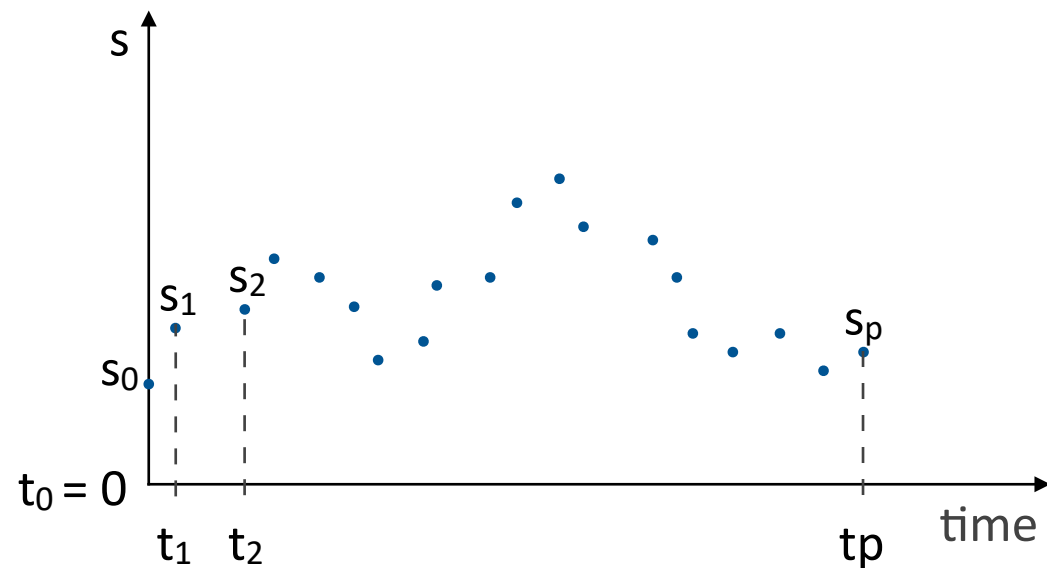
number of symbolic locations number of time-series

$$\lambda \quad n \quad + \quad r \quad n \quad + \quad 1$$

dimension of time series data ϵ value

Intersection of the flow polyhedra for each time-series

Phase II: parameter polyhedron



- time-series $\mathbf{s} = s_0, s_1, \dots, s_p$ with p linear pieces
- with time instants t_0, \dots, t_p
- $\mathbf{m}_1, \dots, \mathbf{m}_\lambda$ as parameters for slopes
- Initial state \mathbf{x}_0 of execution \mathbf{x}
- $M: \{1, \dots, p\} \mapsto \{1, \dots, \lambda\}$

Flow polyhedron for time-series \mathbf{s}

$$P_s = \{(\mathbf{m}_1, \dots, \mathbf{m}_\lambda, \mathbf{x}_0, \varepsilon) \in \mathbb{R}^{\lambda n + rn} \times \mathbb{R}^{\geq 0} \mid \mathbf{x}_0 \in B_\varepsilon(s_0),$$

$$\mathbf{x}_0 + (t_1 - t_0)\mathbf{m}_{M(1)} \in B_\varepsilon(s_1),$$

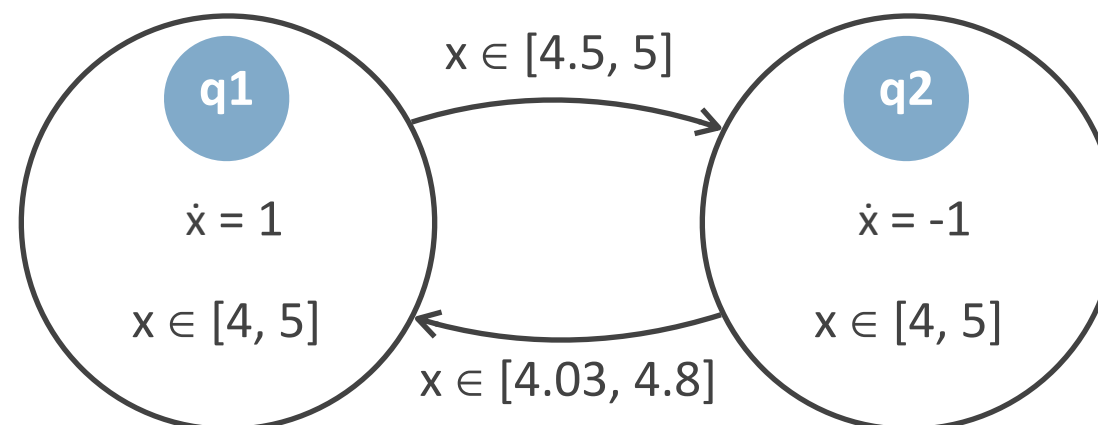
$$\mathbf{x}_0 + (t_1 - t_0)\mathbf{m}_{M(1)} + (t_2 - t_1)\mathbf{m}_{M(2)} \in B_\varepsilon(s_2),$$

$$\mathbf{x}_0 + (t_1 - t_0)\mathbf{m}_{M(1)} + \dots + (t_p - t_{p-1})\mathbf{m}_{M(p)} \in B_\varepsilon(s_p)\}.$$

$$\mathbf{P} = \bigcap_{s \in \text{Data}} P_s$$

Phase II: hybrid automaton model

- Choose a point \mathbf{p} in the parameter polyhedron \mathbf{P}
- **Minimisation** of ϵ provides a point $\mathbf{p} = (\mathbf{m}_1, \dots, \mathbf{m}_\lambda, x_0^{(1)}, \dots, x_0^{(r)}, \epsilon)$
- $\mathbf{m}_1, \dots, \mathbf{m}_\lambda$ define the dynamics for each of the hybrid automaton modes ($\dot{x} = m_i$)
- The **invariant** of each mode is the ϵ -bloated convex hull around all data points associated with the mode
- The **guard** of each transition is the ϵ -bloated convex hull around all data points associated with the transition



Synthesis problem

Given a finite set of time-series and a discrete structure, find the minimal value $\varepsilon \geq 0$ and a hybrid model H with the given discrete structure such that H ε -captures each time-series.

Theorem

Phase II solves problem in polynomial time

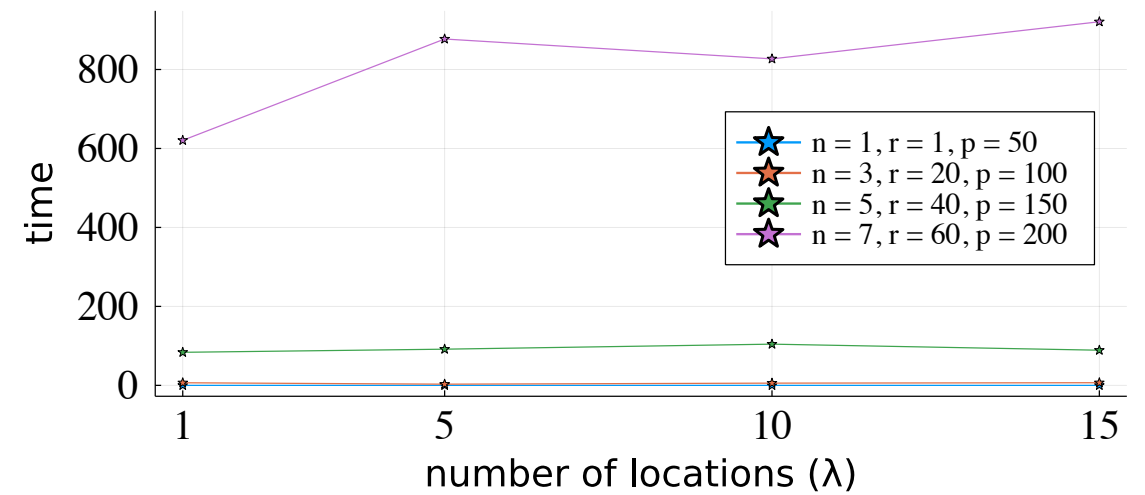
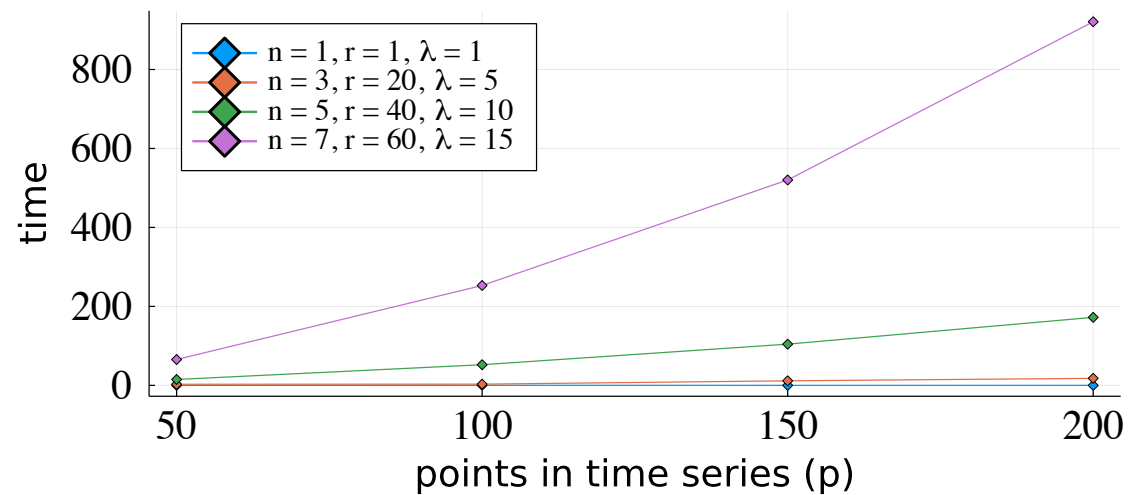
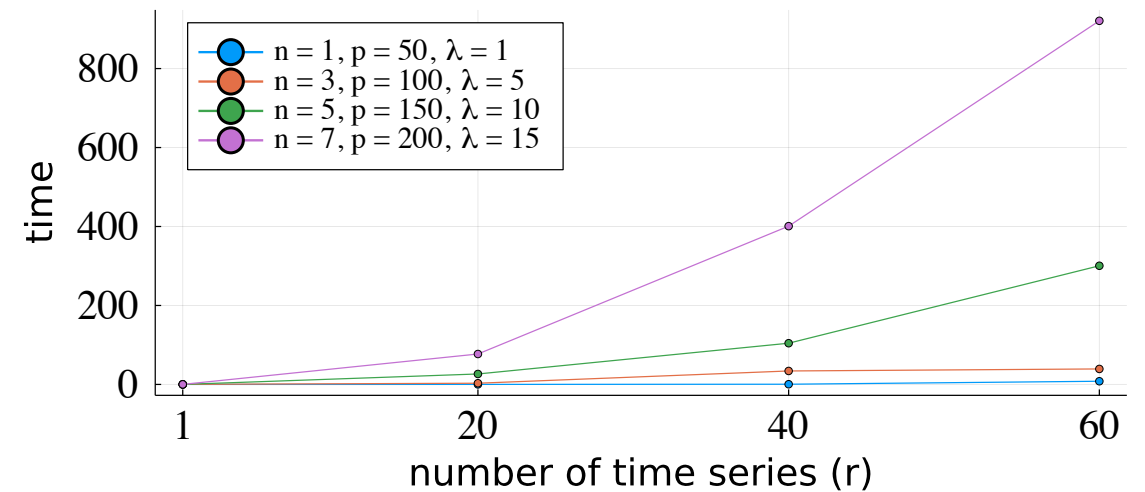
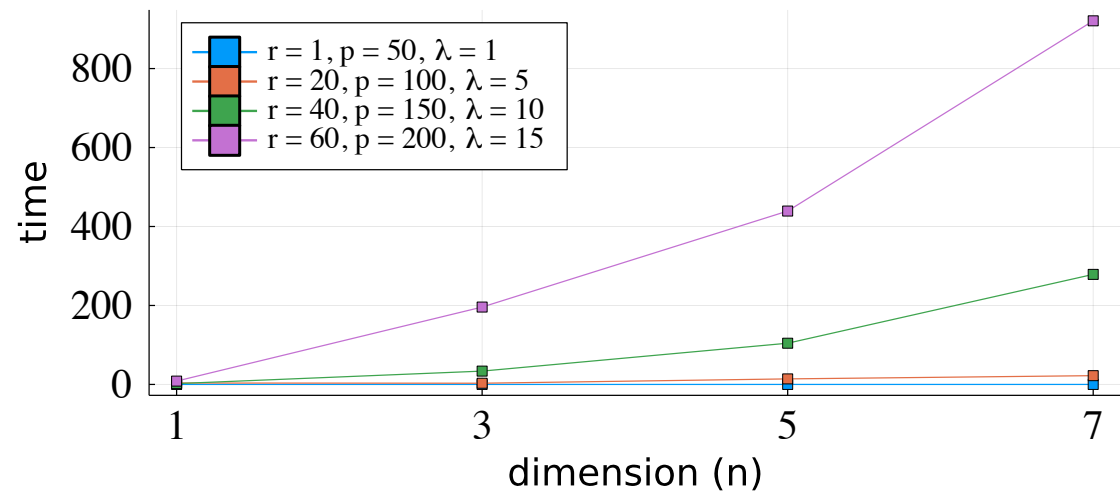
HySynthParametric

- **Julia** programming language
- Evaluation in **two case studies**
- Synthetic data for the **thermostat** and **cell-cycle** models
- **Scalability** evaluation for the thermostat
- **Synthesis** of mammalian cell-cycle from biological model

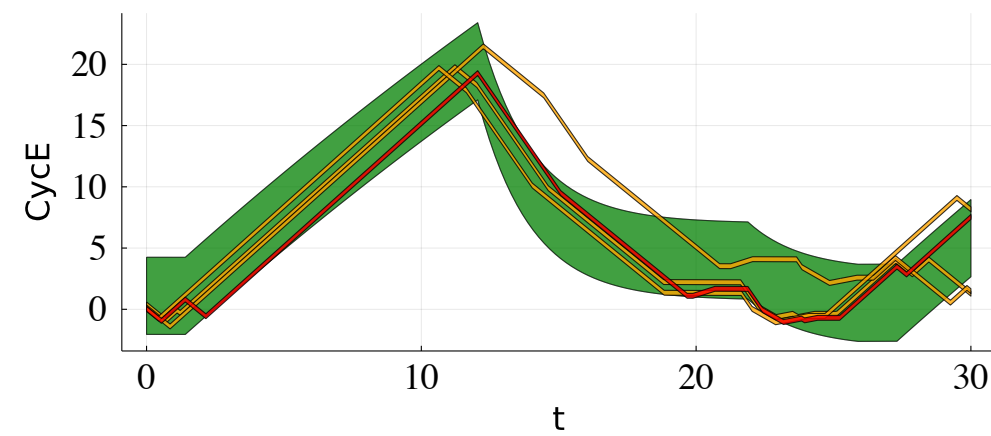
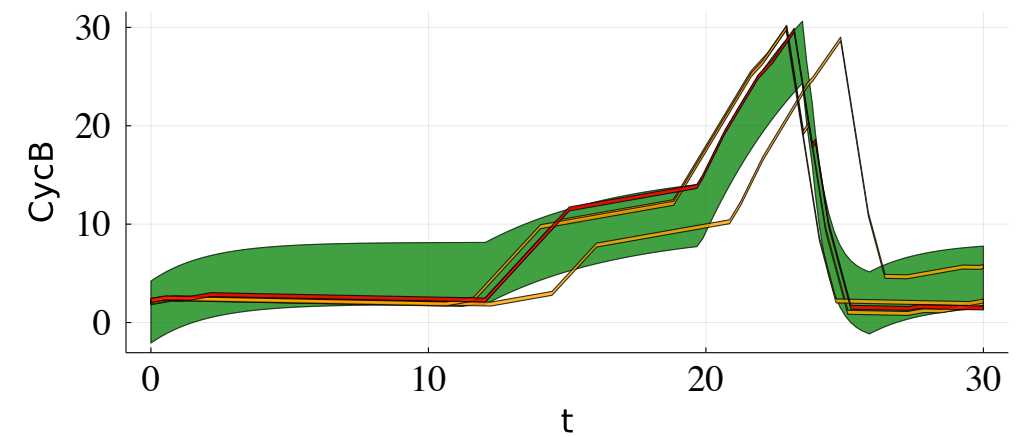
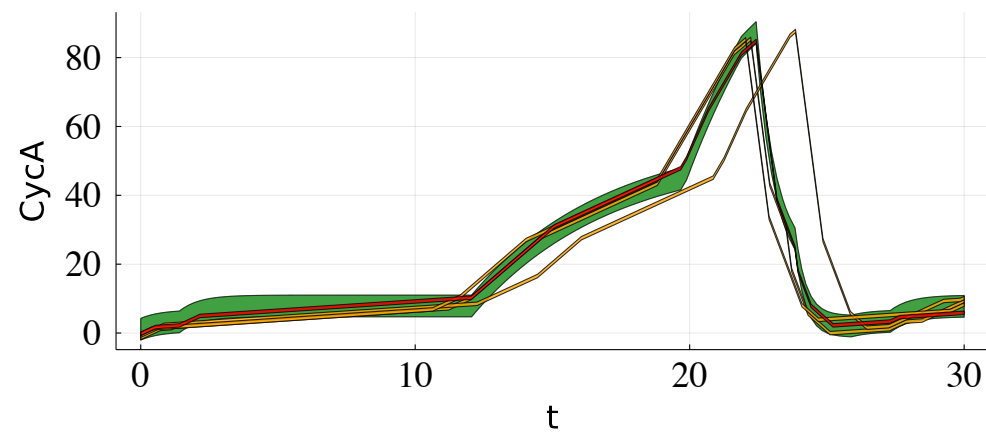
<https://github.com/HySynth/HySynthParametric>

Evaluation: scalability

- r time series with p data points, n dimensions and λ locations



Evaluation: cell cycle regulation



- **Automatic synthesis** of linear hybrid automaton from time-series data
- **Two** algorithmic **phases**
- Phase I: **discrete structure** of the hybrid automaton
- Phase II: **parameter space** of all the possible models
- Selects a model by solving a **linear program**
- The **model** is **ϵ -close** to the time-series
- **ϵ** is **minimal** for the discrete structure chosen in the phase I
- **Algorithm** is **polynomial** and scales to thousands of data points