## PLAYING GENERAL STRUCTURE REWRITING GAMES

Łukasz Kaiser Joint work with Łukasz Stafiniak

Mathematische Grundlagen der Informatik RWTH Aachen

> AGI Lugano, 2010

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#### **Graph Rewriting**

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• OpenCog

• SOAR

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- Hypergraph rewriting with constraints
- Continuous dynamics (by ODE) in the model

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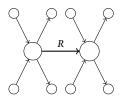
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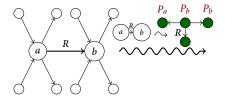
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Why a high-level model? Easier to program, debug, understand Cf. programming languages, regular expressions, databases

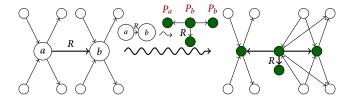
#### **Rewriting Example**



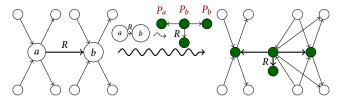
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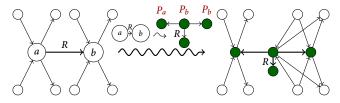


**Embedding**:  $\sigma$  is injective and  $R_i^{\mathfrak{A}}(a_1, \ldots, a_{r_i}) \Leftrightarrow R_i^{\mathfrak{B}}(\sigma(a_1), \ldots, \sigma(a_{r_i}))$ 

$$\sigma : \mathfrak{A} = (A, R_1^{\mathfrak{A}}, R_2^{\mathfrak{A}}, \dots, R_k^{\mathfrak{A}}) \quad \hookrightarrow \quad (B, R_1^{\mathfrak{B}}, R_2^{\mathfrak{B}}, \dots, R_k^{\mathfrak{B}}) = \mathfrak{B}$$

**Rewriting:**  $\mathfrak{B} = \mathfrak{A}[\mathfrak{L} \to \mathfrak{R}/\sigma]$  iff  $B = (A \setminus \sigma(L)) \cup R$  and, for  $M = \{(r, a) \mid a = \sigma(l), r \in P_l^{\mathfrak{R}}$  for some  $l \in L\} \cup \{(a, a) \mid a \in A\},$  $(b_1, \ldots, b_{r_i}) \in R_i^{\mathfrak{B}} \Leftrightarrow (b_1, \ldots, b_{r_i}) \in R_i^{\mathfrak{R}}$  or  $(b_1M \times \ldots \times b_{r_i}M) \cap R_i^{\mathfrak{A}} \neq \emptyset$ . (in the second case at least one  $b_i \notin \mathfrak{A}$ )

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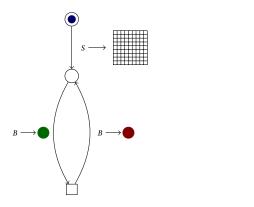


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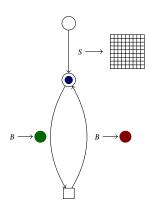
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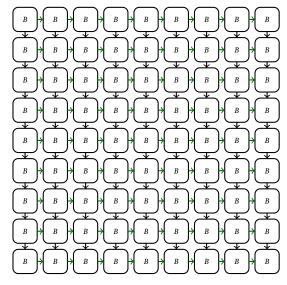
Motivation: many questions naturally defined as structure rewriting games: constraint satisfaction, model checking, graph algorithms, games people play

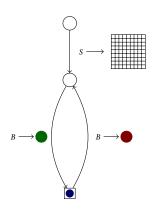


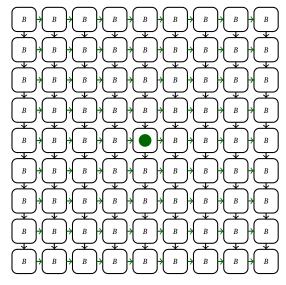


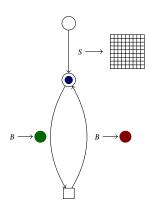
## **Example System: Gomoku (Connect-5)**

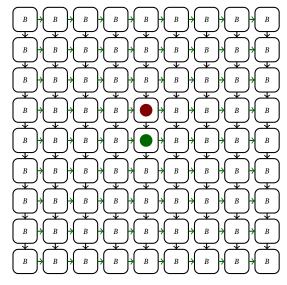


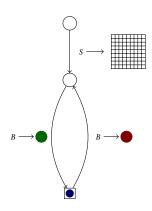


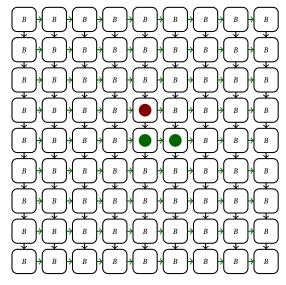


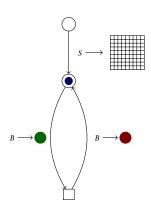


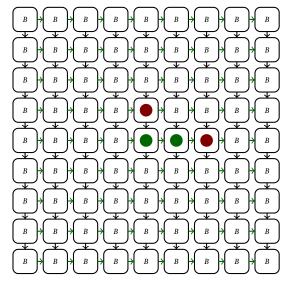




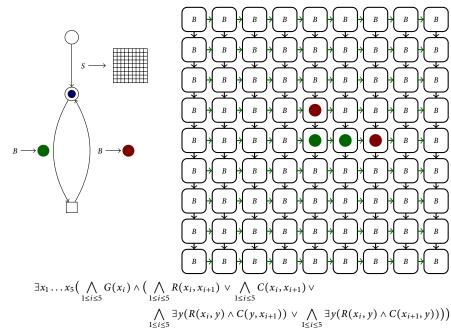








## **Example System: Gomoku (Connect-5)**



#### **CONTINUOUS DYNAMICS**

**R-structures:**  $\mathfrak{A} = (A, R_1, \dots, R_k, f_1, \dots, f_l)$  with  $f_i : A \to \mathbb{R}$ 

#### Additional Parameters to a Rule:

- dynamics: system of ordinary differential equations
- updates: equations assigning values on the right-hand side
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Logic

- Monadic Second-Order Logic (MSO):  $\forall X(x \in X \land (\forall z, v(z \in X \land R(z, v) \rightarrow v \in X)) \rightarrow y \in X)$
- Real-valued terms with counting:  $2 \cdot \chi (\exists y (P(y) \land R(x, y))) + f(x)$
- Real quantification:  $\exists a \in \mathbb{R}(a^2 \cdot f(x) + a 1 = 0) \land (f(x) > 2)$

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- Semantics of Application
- (1) All dynamics applies concurrently
- (2) Rules with **minimal time** fire
- (3) Discrete rewriting after continuous evolution

How do the players play? Monte Carlo with UCT and Learned Playout

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- Calculate the **ratio of wins** of each player

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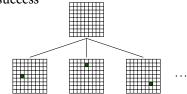
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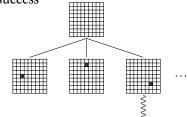
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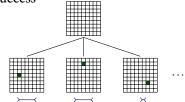
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Pick Max Upper Confidence

$$C \cdot \sqrt{\frac{\ln(n(v)+1)}{n(w)+1}}$$



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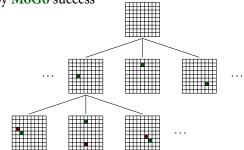
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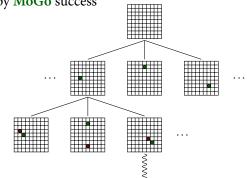
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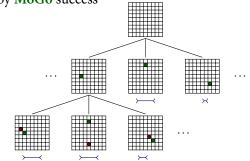
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#### **Evaluation Games**

Improvements vs. UCT with random

- Breakthrough: beat if possible ca. 70% improvement
- Gomoku: play near your stone ca. 80% improvement

$$(0,0) \\ (0,1) \xleftarrow{0.1}{0.7} (1,0) \\ \exists x (P(x) \land M(x)) \\ \neg \exists x (P(x) \land M(x)) \\ (0,1) \xleftarrow{0.2}{0.4} (1,0) \\ \downarrow 0.4 \\ (0,0) \end{cases}$$

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## Thank You