

CLEARING RESTARTING AUTOMATA AND GRAMMATICAL INFERENCE

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Table of Contents

- **Part I:** Introduction,
- **Part II:** Learning Schema,
- **Part III:** Active Learning Example,
- **Part IV:** Hardness Results,
- **Part V:** Concluding Remarks.

Part I: Introduction

- **Restarting Automata:**

- Model for the linguistic technique of *analysis by reduction*.
- Many different types have been defined and studied intensively.

- **Analysis by Reduction:**

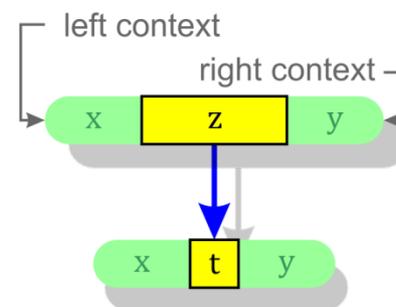
- Method for checking [non-]correctness of a sentence.
- Iterative application of simplifications.
- Until the input cannot be simplified anymore.

- **Restricted Models:**

- *Clearing*, Δ -*Clearing* and Δ^* -*Clearing* Restarting Automata,
- *Subword-Clearing* Restarting Automata.
- Our method is similar to the *delimited string-rewriting systems* [Eyraud et al. (2007)].

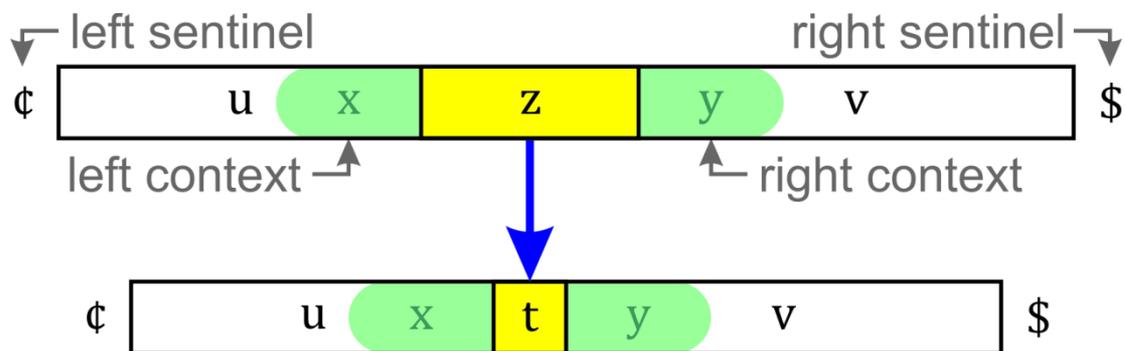
Context Rewriting Systems

- Let k be a *nonnegative integer*.
- k -Context Rewriting System (k -CRS)
- Is a triple $M = (\Sigma, \Gamma, I)$:
 - Σ ... *input alphabet*, $\phi, \$ \notin \Sigma$,
 - Γ ... *working alphabet*, $\Gamma \supseteq \Sigma$,
 - I ... finite set of *instructions* $(x, z \rightarrow t, y)$:
 - $x \in \Gamma^k \cup \{\phi\}, \Gamma^{\leq k-1}$ (**left context**)
 - $y \in \Gamma^k \cup \Gamma^{\leq k-1}, \{\$\}$ (**right context**)
 - $z \in \Gamma^+, z \neq t \in \Gamma^*$.
 - ϕ and $\$$... *sentinels*.
 - The *width of instruction* $i = (x, z \rightarrow t, y)$ is $|i| = |xzty|$.
 - In case $k = 0$ we use $x = y = \lambda$.



Rewriting

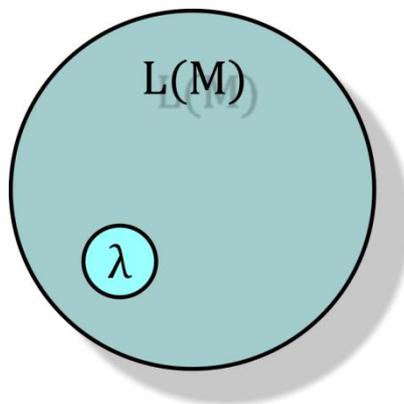
- $uzv \vdash_M utv$ iff $\exists (x, z \rightarrow t, y) \in I$:
- x is a **suffix** of $\$u$ and y is a **prefix** of $v\$$.



- $L(M) = \{w \in \Sigma^* \mid w \vdash_M^* \lambda\}$.
- $L_C(M) = \{w \in \Gamma^* \mid w \vdash_M^* \lambda\}$.

Empty Word

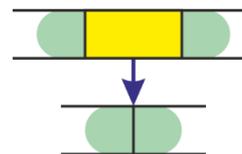
- **Note:** For every k -CRS $M: \lambda \vdash_M^* \lambda$, hence $\lambda \in L(M)$.
- Whenever we say that a k -CRS M recognizes a **language** L , we always mean that $L(M) = L \cup \{\lambda\}$.
- We simply **ignore the empty word** in this setting.



Clearing Restarting Automata

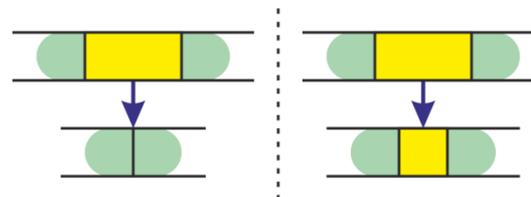
- **k – Clearing Restarting Automaton (k -cl-RA)**

- Is a k -CRS $M = (\Sigma, \Sigma, I)$ such that:
- For each $(\mathbf{x}, z \rightarrow t, \mathbf{y}) \in I$: $z \in \Sigma^+, t = \lambda$.



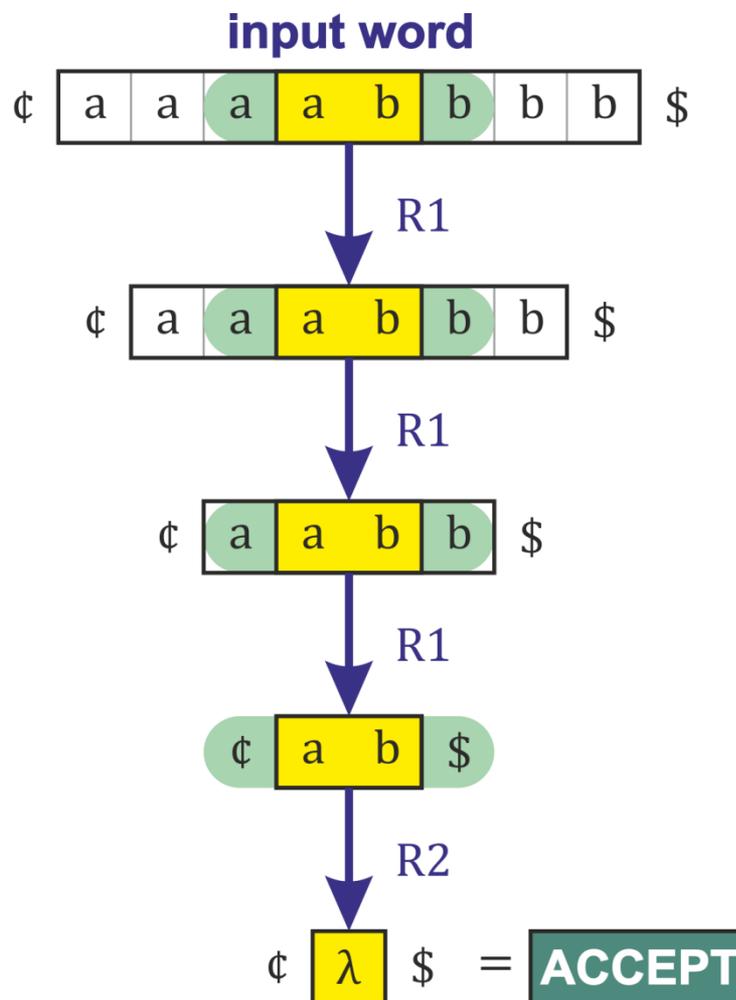
- **k – Subword-Clearing Rest. Automaton (k -scl-RA)**

- Is a k -CRS $M = (\Sigma, \Sigma, I)$ such that:
- For each $(\mathbf{x}, z \rightarrow t, \mathbf{y}) \in I$:
- $z \in \Gamma^+$, t is a **proper subword** of z .



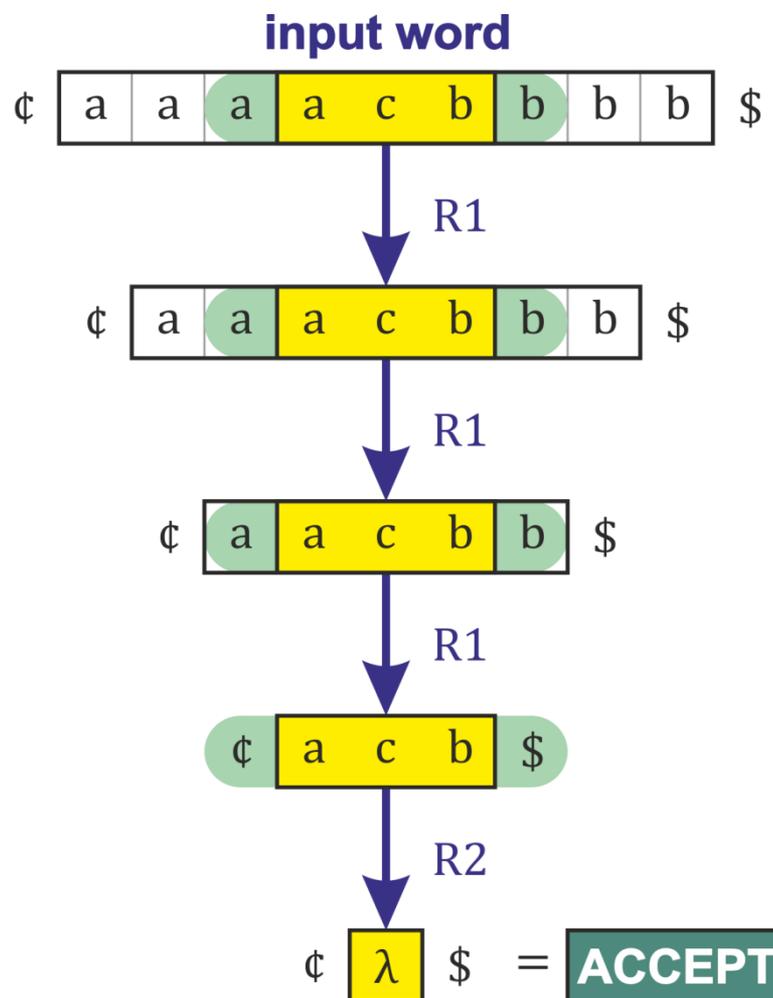
Example 1

- $L_1 = \{a^n b^n \mid n > 0\} \cup \{\lambda\}$:
- 1-cl-RA $M = (\{a, b\}, I)$,
- Instructions I are:
 - $R1 = (a, \underline{ab} \rightarrow \lambda, b)$,
 - $R2 = (\underline{\$}, \underline{ab} \rightarrow \lambda, \$)$.



Example 2

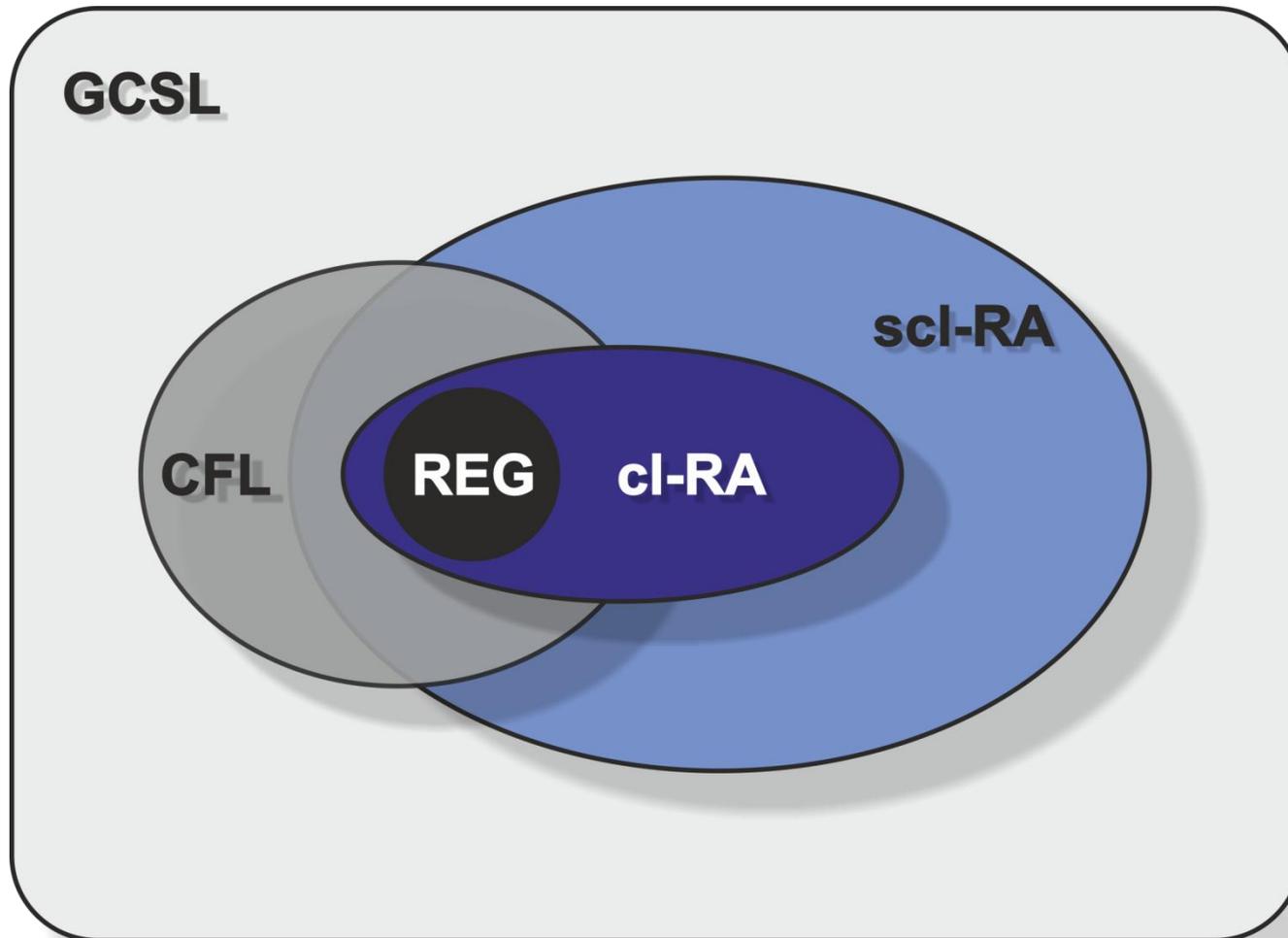
- $L_2 = \{a^n cb^n \mid n > 0\} \cup \{\lambda\}$:
- 1-scl-RA $M = (\{a, b, c\}, I)$,
- Instructions I are:
 - $R1 = (a, \underline{acb} \rightarrow c, b)$,
 - $R2 = (\underbrace{\text{¢}}_a, \underline{acb} \rightarrow \lambda, \underbrace{\text{\$}}_b)$.
- **Note:**
 - The language L_2 cannot
 - be recognized by any *cl-RA*.



Clearing Restarting Automata

- **Clearing Restarting Automata:**
 - Accept **all regular** and even **some non-context-free** languages.
 - They do **not** accept **all context-free** languages ($\{a^n cb^n / n > 0\}$).
- **Subword-Clearing Restarting Automata:**
 - Are **strictly more powerful** than **Clearing Restarting Automata**.
 - They do **not** accept **all context-free** languages ($\{w w^R / w \in \Sigma^*\}$).
- **Upper bound:**
 - **Subword-Clearing Restarting Automata** only accept languages that are **growing context-sensitive** [Dahlhaus, Warmuth].

Hierarchy of Language Classes



Part II: Learning Schema

- **Goal:** *Identify* any *hidden target* automaton *in the limit* from *positive* and *negative* samples.
- **Input:**
 - Set of *positive samples* S^+ ,
 - Set of *negative samples* S^- ,
 - We assume that $S^+ \cap S^- = \emptyset$, and $\lambda \in S^+$.
- **Output:**
 - *Automaton* M such that: $L(M) \subseteq S^+$ and $L(M) \cap S^- = \emptyset$.
 - The term *automaton* = **Clearing** or **Subword-Clearing** Restarting Automaton, or any other *similar model*.

Learning Schema – Restrictions

- **Without further restrictions:**
 - The task becomes *trivial* even for **Clearing Rest. Aut.**
 - Just consider: $I = \{ (\$, w, \$) \mid w \in S^+, w \neq \lambda \}$.
 - Apparently: $L(M) = S^+$, where $M = (\Sigma, \Sigma, I)$.
- **Therefore, we impose:**
 - An *upper limit* $l \geq 1$ on the *width of instructions*,
 - A specific *length of contexts* $k \geq 0$.
- **Note:**
 - We can *effectively enumerate all automata* satisfying these *restrictions*, thus the identification in the limit can be easily deduced from the classical result of **Gold** ...
 - **Nevertheless**, we propose an *algorithm*, which, under certain conditions, works in a polynomial time.

Learning Schema – Algorithm

- **Input:**

- **Positive samples** S^+ , **negative samples** S^- , $S^+ \cap S^- = \emptyset$, $\lambda \in S^+$.
- **Upper limit** $l \geq 1$ on the **width of instructions**,
- A specific **length of contexts** $k \geq 0$.

- **Output:**

- **Automaton** M such that: $L(M) \subseteq S^+$ and $L(M) \cap S^- = \emptyset$, or **Fail**.

```
1  $\Phi \leftarrow \text{Assumptions}(S^+, l, k)$ ;  
2 while  $\exists w_- \in S^-, w_+ \in S^+, \phi \in \Phi : w_- \vdash^{(\phi)} w_+$  do  
3   |  $\Phi \leftarrow \Phi \setminus \{\phi\}$ ;  
4 end  
5  $\Phi \leftarrow \text{Simplify}(\Phi)$ ;  
6 if  $\text{Consistent}(\Phi, S^+, S^-)$  then  
7   | return Automaton with the set of instructions  $\Phi$ ;  
8 end  
9 Fail;
```

Learning Schema – Step 1/4

- **Step 1:**

$\Phi \leftarrow \text{Assumptions}(S^+, l, k);$

- We obtain some set of *instruction candidates*.
- *Note:* We use **only the positive samples** to obtain the instructions.
- Let us **assume**, for a moment, that this set Φ already **contains all instructions** of the *hidden target automaton*.
- Later we will show how to define the function *Assumptions* in such a way that the above assumption can be always satisfied.

Learning Schema – Step 2/4

- **Step 2:**

```
while  $\exists w_- \in S^-, w_+ \in S^+, \phi \in \Phi : w_- \vdash^{(\phi)} w_+$  do  
  |  $\Phi \leftarrow \Phi \setminus \{\phi\}$ ;  
end
```

- We gradually **remove all instructions** that allow a single-step reduction **from a negative sample to a positive sample**.
- Such instructions **violate** the so-called **error-preserving property**.
- It is easy to see, that such instructions **cannot be in our hidden target automaton**.
- *Note:* Here we use **also the negative samples**.

Learning Schema – Step 3/4

- **Step 3:**

$\Phi \leftarrow \text{Simplify}(\Phi);$

- We **remove the redundant instructions**.
- This step is **optional** and **can be omitted** – it does not affect the properties or the correctness of the **Learning Schema**.

- **Possible implementation:**

Input: The set of instructions Φ .

Output: The simplified set of instructions Ψ .

```
1  $\Psi \leftarrow \emptyset;$ 
2 foreach  $\phi = (x, z \rightarrow t, y) \in \Phi$  in some fixed order do
3   |   if  $z \not\models_{\Psi}^* t$  in the context  $(x, y)$  then
4     |   |    $\Psi \leftarrow \Psi \cup \{(x, z \rightarrow t, y)\};$ 
5     |   |   end
6   |   end
7 end
8 return  $\Psi;$ 
```

Learning Schema – Step 4/4

- **Step 4:**

if Consistent(Φ, S^+, S^-) then

 | return Automaton with the set of instructions Φ ;

end

Fail;

- We **check the consistency** of the remaining set of instructions with the given input set of positive and negative samples.
- Concerning the identification in the limit, we can **omit the consistency check** – it does not affect the correctness of the **Learning Schema**. In the limit, we always get a correct solution.

Learning Schema – Complexity

- Time complexity of the **Algorithm** depends on:
 - Time complexity of the **function Assumptions**,
 - Time complexity of the **simplification**,
 - Time complexity of the **consistency check**.
- There are **correct** implementations of the function **Assumptions** that run in a polynomial time.
- If the function Assumptions runs in a polynomial time (Step 1) then also the size of the set Φ is polynomial and then also the cycle (Step 2) runs in a polynomial time.
- It is an open problem, whether the **simplification** and the **consistency check** can be done in a polynomial time. Fortunately, we can omit these steps.

Learning Schema – Assumptions

- We call the *function Assumptions* **correct**, if it is possible to obtain instructions of **any hidden target automaton in the limit** by using this function.
- To be more **precise**:
 - For every *k-cl-RA M* (or *k-scl-RA M*) with the maximal width of instructions bounded from above by $l \geq 1$ there exists a finite set $S_0^+ \subseteq L(M)$ such that for every $S^+ \supseteq S_0^+$ the *Assumptions*(S^+, l, k) contains **all instructions** of some automaton N equivalent to M .

Example – Assumptions_{weak}

- $Assumptions_{weak}(S^+, l, k) :=$ all instructions $(x, z \rightarrow t, y)$:
 - **The length of contexts is k :**
 - $x \in \Sigma^k \cup \{\emptyset\}, \Sigma^{\leq k-1}$ (left context)
 - $y \in \Sigma^k \cup \Sigma^{\leq k-1}, \{\$\}$ (right context)
 - **Our model is a Subword-Clearing Rest. Aut.:**
 - $z \in \Sigma^+$, t is a *proper subword* of z .
 - **The width is bounded by l :**
 - $|xzy| \leq l$.
 - **There are two words $w_1, w_2 \in S^+$ such that:**
 - xzy is a *subword* of $\$ w_1 \$$,
 - xty is a *subword* of $\$ w_2 \$$.
- This function is **correct** and runs in a **polynomial time**.

Example – Assumptions_{weak}

Positive Samples

¢ a+a \$

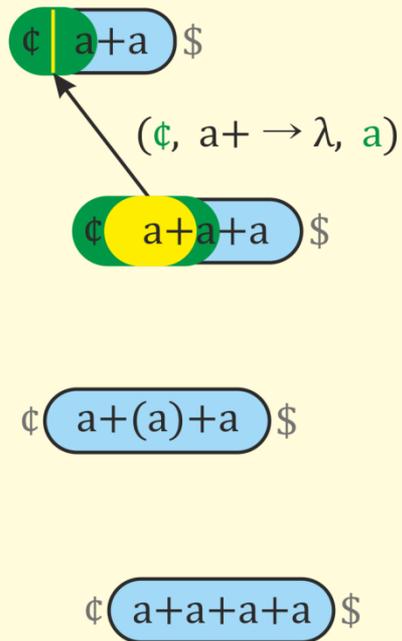
¢ a+a+a \$

¢ a+(a)+a \$

¢ a+a+a+a \$

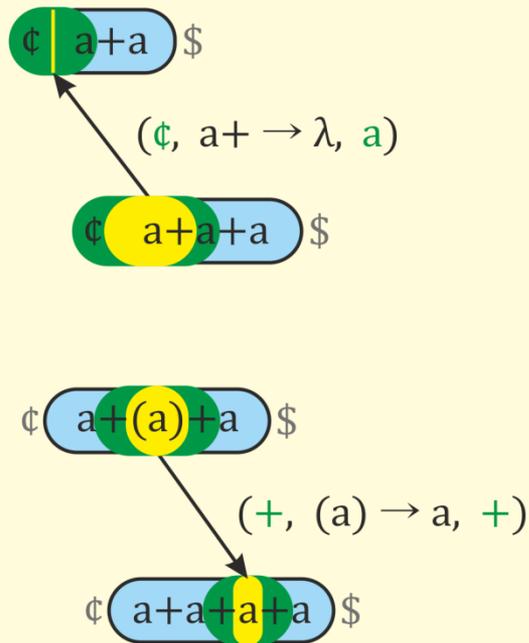
Example – Assumptions_{weak}

Positive Samples



Example – Assumptions_{weak}

Positive Samples



Example – Assumptions_{weak}

Positive Samples

¢ a+a \$

¢ a+a+a \$

¢ a+(a)+a \$

(+, (→ λ, a)

BAD Instruction

¢ a+a+a+a \$

Example – Assumptions_{weak}

Positive Samples

¢ a+a \$

¢ a+a+a \$

¢ a+(a)+a \$



¢ a+a+a+a \$

Part III: Active Learning Example

- **Our goal:**
 - Infer a model of *scl-RA* recognizing the language of *simplified arithmetical expressions* over the alphabet $\Sigma = \{a, +, (,)\}$.
- **Correct** arithmetical expressions:
 - $a + (a + a)$,
 - $(a + a)$,
 - $((a))$, etc.
- **Incorrect** arithmetical expressions:
 - $a +$,
 - $)a$,
 - $(a + a$, etc.
- We fix *maximal width* l to **6**, *length of context* k to **1**.

Active Learning Example

- Initial set of *positive* (S_1^+) and *negative* (S_1^-) samples.

Table 1: The Initial Set of Positive and Negative Samples.

Positive Samples S_1^+			Negative Samples S_1^-				
a	(a)	$((a + a))$	+	$a+$	++	$(+)+$	$+a$
$a + a$	$((a))$	$a + (a + a)$	($a($	$+($	$(())($	$(a$
$a + a + a$	$(a + a)$	$(a + a) + a$)	$a)$	$+$	$()))$	$)a$

Active Learning Example

- $Assumptions_{weak}(S_1^+, l, k)$ gives us **64** instructions.
- After **filtering** bad instructions and after **simplification** we get a consistent automaton M_1 with **21 instructions**:

Table 2: The Instructions of the Resulting Automaton M_1 After Simplification.

$[(, (, a]$	$[\dot{c}, (, (]$	$[+, (, a]$	$[],), \$]$	$[a,),)]$	$[a,), +]$	$[\dot{c}, a, \$]$
$[\dot{c}, ((, a]$	$[\dot{c}, (a \rightarrow a, +]$	$[a,)), \$]$	$[], +a, \$]$	$[a, +a, \$]$	$[a, +a,)]$	$[a, +a, +]$
$[+, a) \rightarrow a, \$]$	$[(, a+, a]$	$[\dot{c}, a+, (]$	$[\dot{c}, a+, a]$	$[+, a+, a]$	$[\dot{c}, (a), \$]$	$[\dot{c}, (a) \rightarrow a, \$]$

Active Learning Example

- All expressions recognized by M_1 up to length 5:

Table 3: The Set of Expressions Recognized by M_1 .

λ	$a + a$	$a + (a$	$a)))$	$(a + a$	$((((a$
a	$((a)$	$((((a$	$a)) + a$	$a + a + a$	$a))))$
(a)	$(a))$	$((a))$	$a + a))$	$a + a)$	$a) + (a$
$((a$	$(a) + a$	$((a + a$	$a + (a$	$((((a$	$(a + (a$
$a))$	$(a + a)$	$a + ((a$	$a) + a$	$(a)))$	$a) + a)$

- There are both **correct** and **incorrect** arithmetical expressions. Note that $(a) + a$ was never seen before.
- Next step:** Add all **incorrect** arithmetical expressions to the set of **negative samples**. (We get: $S_2^+ = S_1^+$ and S_2^-).

Active Learning Example

- We get a consistent automaton M_2 with *16 instructions*.
- **Up to length 5**, the automaton M_2 recognizes **only correct** arithmetical expressions.
- **However**, it recognizes also **some incorrect** arithmetical expressions **beyond this length**, e.g.:
 - $((a + a)$,
 - $(a + a))$,
 - $a + (a + a$,
 - $a + a) + a$.
- Add also these **incorrect** arithmetical expressions to the set of **negative samples**. (We get: $S_3^+ = S_2^+$ and S_3^-).

Active Learning Example

- Now we get a consistent automaton M_3 with **12 instructions** recognizing only **correct** expressions.

Table 4: The Instructions of the Resulting Automaton M_3 After Simplification.

$[\dot{c}, a, \$]$	$], +a, \$]$	$[a, +a, \$]$	$[a, +a,)]$
$[a, +a, +]$	$[(, a+, a]$	$[\dot{c}, a+, (]$	$[\dot{c}, a+, a]$
$[+, a+, a]$	$[(, (a) \rightarrow a,)]$	$[\dot{c}, (a), \$]$	$[\dot{c}, (a) \rightarrow a, \$]$

- The automaton is **not complete** yet.
- It does not recognize e.g. $a + (a + (a))$.
- This time we would need to extend the **positive** samples.

Part III: Hardness Results

- In general, the ***task of finding a consistent Clearing Rest. Aut.*** with the given set of positive and negative samples is ***NP-hard***, provided that we impose an ***upper bound on the width of instructions***.
- This resembles a ***famous result of Gold*** who showed that the question of whether there is a ***finite automaton with at most n states*** consistent with a given list of input/output pairs is ***NP-complete***.
- **Indeed**, for every ***n -state finite automaton***, there is an equivalent ***Clearing Restarting Automaton*** that has the ***width of instructions bounded from above by $O(n)$*** .

Hardness Results

- Let $l \geq 2$ be a *fixed integer*. Consider the following **task**:
- **Input**:
 - Set of *positive samples* S^+ ,
 - Set of *negative samples* S^- ,
 - We assume that $S^+ \cap S^- = \emptyset$, and $\lambda \in S^+$.
- **Output**:
 - *0-cl-RA* M such that:
 1. The *width of instructions* of M is at most l .
 2. $L(M) \subseteq S^+$ and $L(M) \cap S^- = \emptyset$.
- **Theorem**:
 - This task is **NP**-complete.

Hardness Results – Generalization

- Let $k \geq 1$ and $l \geq 4k + 4$ be *fixed integers*. Consider:
- **Input:**
 - Set of *positive samples* S^+ ,
 - Set of *negative samples* S^- ,
 - We assume that $S^+ \cap S^- = \emptyset$, and $\lambda \in S^+$.
- **Output:**
 - *k-cl-RA* M such that:
 1. The *width of instructions* of M is at most l .
 2. $L(M) \subseteq S^+$ and $L(M) \cap S^- = \emptyset$.
- **Theorem:**
 - This task is **NP**-complete for $k = 1$ and **NP**-hard for $k > 1$.

Part V: Concluding Remarks

- We have shown that it is possible to *infer* any *hidden target Clearing* (*Subword-Clearing*) Rest. Aut. *in the limit* from *positive* and *negative* samples.
- However, the *task of finding* a *consistent Clearing* Rest. Aut. with the given set of *positive* and *negative* samples is *NP-hard*, provided that we impose an *upper bound on the width of instructions*.
- If we *do not impose any upper bound* on the maximal *width of instructions*, then the task is trivially decidable in a polynomial time for any $k \geq 0$.

Open Problems

- Do similar *hardness results* hold also for *other* (more powerful) *models* like *Subword-Clearing* Rest. Aut.?
- What is the *time complexity* of the *membership* and *equivalence* queries for these models?

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Thank You!

- The *technical report* is available on:
http://popelka.ms.mff.cuni.cz/cerno/files/cerno_clra_and_gi.pdf
- This *presentation* is available on:
http://popelka.ms.mff.cuni.cz/cerno/files/cerno_clra_and_gi_presentation.pdf
- An *implementation* of the algorithms can be found on:
<http://code.google.com/p/clearing-restarting-automata/>