

One-shot Learning of Context-Sensitive Grammars with Classical Planning

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Abstract

This paper presents a novel approach for learning Context-Sensitive Grammars (CSGs) from a single input string. Our approach is to compile this learning task into a classical planning problem whose solutions are sequences of actions whose prefixes build the CSG and whose post-fixes validate that the built grammar is compliant with the input string. The compilation is flexible to implement the three canonical tasks for CSGs, *grammar generation*, *string production* and *string recognition* within the same classical planning model. Our experimental evaluation shows that the learned CSGs achieve generalization provided that the input strings are long and diverse enough to cover all the grammar rules.

Introduction

A *formal grammar* is a set of symbols and production rules that describe how to form the possible strings of certain formal language. Usually three canonical tasks are defined over formal grammars:

- *Learning*: Given a set of strings, compute a grammar that is compliant with the input strings.
- *Production*: Given a formal grammar, generate strings that belong to the language represented by the grammar.
- *Recognition* (also known as *parsing*): Given a formal grammar and a string, determine whether the string belongs to the language represented by the grammar.

Chomsky defined four types of formal grammars that differ in the form and generative capacity of their rules (Chomsky 2002). Each grammar type generates a different class of formal language that is recognizable with a different kind of automaton: **Type-0** corresponds to the *recursively enumerable* languages that can be recognized with a *Turing machine* automaton. **Type-1** corresponds to the *recursively enumerable* languages that can be recognized with a *Linear-bounded Turing machine* automaton. **Type-2** corresponds to *context-free* languages that are recognizable with a *non-deterministic push-down automaton*. Finally, **type-3** corresponds to *regular* languages that can be recognized with a *Finite state automaton*.

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0. $S \rightarrow aBC$
1. $S \rightarrow aSBC$
2. $CB \rightarrow CZ$
3. $CZ \rightarrow WZ$
4. $WZ \rightarrow WC$
5. $WC \rightarrow BC$
6. $aB \rightarrow ab$
7. $bB \rightarrow bb$
8. $bC \rightarrow bc$
9. $cC \rightarrow cc$

(a)

```
S
aSBC
aaSBCBC
aaaBCBCBC
aaaBCZCBC
aaaBWZCBC
aaaBWCCBC
aaaBBCBC
aaaBBCZC
aaaBBCWC
aaaBBCWC
aaaBBCWC
aaaBBCZC
aaaBBWZC
aaaBBWCC
aaaBBCCC
aaaBBCCC
aaabbCCC
aaabbCCC
aaabbCCC
aaabbCCC
aaabbCCC
aaabbCCC
```

(b)

Figure 1: (a) Example of a context-sensitive grammar; (b) the corresponding *parse tree* for the string *aaabbbccc*.

Figure 1(a) shows an example of a CSG grammar that generates the $\{a^n b^n c^n : n \geq 1\}$ language (*Type-1*). The grammar defines ten production rules, contains three terminal symbols (*a*, *b* and *c*) and five non-terminal symbols (*S*, *B*, *C*, *W* and *Z*). This CSG can generate, for instance, the string *aaabbbccc* by applying the sequence of rules $\langle 1, 1, 0, 2, 3, 4, 5, 2, 3, 4, 5, 2, 3, 4, 5, 6, 7, 7, 8, 9, 9 \rangle$. The *parse tree* in Figure 1(b) exemplifies this rule application and proves that the string *aaabbbccc* belongs to the $\{a^n b^n c^n : n \geq 1\}$ language defined by the CSG grammar.

Previous work showed that a classical planning compilation can implement the three canonical tasks (namely *grammar generation*, *string production* and *string recognition*) for *Type-3* and *Type-2* grammars (Segovia-Aguas, Jiménez, and Jonsson 2017). In this work we show that a novel classical planning compilation implements these three canonical tasks for grammars of the three last types (*Type-3*, *Type-2* and *Type-1*). In addition, this novel compilation has fewer input parameters since it does not require to specify any bound on the number of non-terminal symbols or in the size of the grammar rules. The reported empirical results show that the learned CSGs achieve generalization provided that the input strings *complete*, meaning that they are long

and diverse enough to cover all the grammar rules.

Background

This section defines the formalization of CSGs and the classical planning model that we follow in this work.

Classical planning

Our approach for the one-shot learning of CSGs is compiling this inductive learning task into a classical planning task.

We use F to denote the set of *fluents* (propositional variables) describing a state. A *literal* l is a valuation of a fluent $f \in F$; i.e. either $l = f$ or $l = \neg f$. A set of literals L represents a partial assignment of values to fluents (without loss of generality, we will assume that L does not contain conflicting values). We use $\mathcal{L}(F)$ to denote the set of all literal sets on F ; i.e. all partial assignments of values to fluents.

A *state* s is a full assignment of values to fluents; $|s| = |F|$, so the size of the state space is $2^{|F|}$. Explicitly including negative literals $\neg f$ in states simplifies subsequent definitions but often we will abuse of notation by defining a state s only in terms of the fluents that are true in s , as it is common in STRIPS planning.

A *classical planning frame* is a tuple $\Phi = \langle F, A \rangle$, where F is a set of fluents and A is a set of actions. An action $a \in A$ is defined with *preconditions*, $\text{pre}(a) \subseteq \mathcal{L}(F)$, *positive effects*, $\text{eff}^+(a) \subseteq \mathcal{L}(F)$, and *negative effects* $\text{eff}^-(a) \subseteq \mathcal{L}(F)$. We say that an action $a \in A$ is *applicable* in a state s iff $\text{pre}(a) \subseteq s$. The result of applying a in s is the *successor state* denoted by $\theta(s, a) = \{s \setminus \text{eff}^-(a)\} \cup \text{eff}^+(a)$.

The result of applying action a in state s is the *successor state* $\theta(s, a) = \{s \setminus \text{eff}_c^-(s, a)\} \cup \text{eff}_c^+(s, a)$ where $\text{eff}_c^-(s, a) \subseteq \text{triggered}(s, a)$ and $\text{eff}_c^+(s, a) \subseteq \text{triggered}(s, a)$ are, respectively, the triggered *negative* and *positive* effects.

A *classical planning problem* is a tuple $P = \langle F, A, I, G \rangle$, where I is an initial state and $G \subseteq \mathcal{L}(F)$ is a goal condition. A *plan* for P is an action sequence $\pi = \langle a_1, \dots, a_n \rangle$ that induces the *state trajectory* $\langle s_0, s_1, \dots, s_n \rangle$ such that $s_0 = I$ and a_i ($1 \leq i \leq n$) is applicable in s_{i-1} and generates the successor state $s_i = \theta(s_{i-1}, a_i)$. The *plan length* is denoted with $|\pi| = n$. A plan π *solves* P iff $G \subseteq s_n$; i.e. if the goal condition is satisfied in the last state resulting from the application of the plan π in the initial state I .

Context-Sensitive Grammars

We define a CSGs as a tuple $\mathcal{G} = \langle V, \Sigma, R \rangle$, where:

- V is the finite set of non-terminal symbols, also called variables. With $v_0 \in V$ is the start non-terminal symbol that represents the whole grammar.
- Σ is the finite set of terminal symbols, which are disjoint from the set of non-terminal symbols, i.e. $V \cap \Sigma \neq \emptyset$. The set of terminal symbols is the alphabet of the language defined by \mathcal{G}
- $R : \alpha v \beta \rightarrow \alpha \gamma \beta$ where $v \in V$, $\alpha, \beta \in (V \cup \Sigma)^*$. That is, the left-hand and right-hand sides of any production rules $r \in R$ may be surrounded by a context of terminal and nonterminal symbols.

For any two strings we say that e_1 *directly yields* e_2 , denoted by $e_1 \Rightarrow e_2$, iff e_1 can be written as $e_3 \alpha A \beta e_4$ and e_2 can be written as $e_3 \alpha \gamma \beta e_4$, for some production rule $(\alpha A \beta \rightarrow \alpha \gamma \beta) \in R$, and some context strings $e_3, e_4 \in (V \cup \Sigma)^*$. Furthermore we say e_1 *yields* e_2 , denoted by $e_1 \Rightarrow^* e_2$, iff $\exists k \geq 0$ and $\exists u_1, \dots, u_k$ such that $e_1 = u_1 \Rightarrow u_2 \Rightarrow \dots \Rightarrow u_k = e_2$ for some $k \geq 0$ and some strings $u_1, \dots, u_{k-1} \in (V \cup \Sigma)^*$. That is, the relation \Rightarrow^* is the reflexive transitive closure of the \Rightarrow relation.

For instance, Figure 1(b) shows how the string S yields the string $aaabbbccc$. The language of a CSG, $L(\mathcal{G}) = \{e \in \Sigma^* : v_0 \Rightarrow^* e\}$, is the set of strings that contain only terminal symbols and that can be yielded from the string that contains only the initial non-terminal symbol v_0 (which is denoted by S in the example of Figure 1(b)).

Given a CSG \mathcal{G} and a string $e \in L(\mathcal{G})$ that belongs to its language, we define a *parse tree* $t_{\mathcal{G}, e}$ as an ordered, rooted tree that determines a concrete syntactic structure of e according to the rules in \mathcal{G} :

- Each node in a parse tree $t_{\mathcal{G}, e}$ is either:
 - An *internal node* that corresponds to the application of a rule $r \in R$.
 - A *leaf node* that corresponds to a terminal symbol $\sigma \in \Sigma$ and has no outgoing branches.
- Edges in a parse tree $t_{\mathcal{G}, e}$ connect non-terminal symbols to terminal or non-terminal symbols following the rules R in \mathcal{G} .

Linear-bounded Turing Machines

We define a *Turing machine* as a tuple $M = \langle Q, q_0, Q_\perp, \mathcal{T}, \square, \Sigma, \delta \rangle$, where:

- Q , is a finite and non-empty set of machine states such that $q_0 \in Q$ is the initial state of the machine and $Q_\perp \subseteq Q$ is the subset of terminal states.
- \mathcal{T} is the *tape alphabet*, that is a finite and non-empty set of symbols that includes the blank symbol $\square \in \mathcal{T}$ (the only symbol allowed to occur on the tape infinitely often at any step during the computation).
- Σ is the *input alphabet*, the set of symbols allowed to initially appear in the tape.
- $\delta : (Q \setminus Q_\perp) \times \mathcal{T} \rightarrow Q \times \mathcal{T} \times \{\text{left}, \text{right}\}$ is the *transition function*. If δ is not defined for the current state of the machine and the current tape symbol, then the machine halts.

The most common convention is to represent the transitions defined by the δ function is with a table where table rows, are indexed with the current tape symbol, while table columns, are indexed by the current machine state. For each possible tape symbol and state of the machine there is a table entry that defines: (1) the tape symbol to print at the current position of the header in the tape (2) whether the header is shifted *left* or *right* and (3), the new state of the machine. For instance, the Figure 2 shows the table that represents a *Turing Machine* for recognizing the $\{a^n b^n c^n : n \geq 1\}$ language. In this example the tape alphabet is $\Sigma = \{a, b, c, x, y, z, \square\}$ while the set of possible

	q_0	q_1	q_2	q_3	q_4	q_5
a	x,r,q ₁	a,r,q ₁	-	a,l,q ₃	-	-
b	-	y,r,q ₂	b,r,q ₂	b,l,q ₃	-	-
c	-	-	z,l,q ₃	-	-	-
x	-	-	-	x,r,q ₀	-	-
y	y,r,q ₄	y,r,q ₁	-	y,l,q ₃	y,r,q ₄	-
z	-	-	z,r,q ₂	z,l,q ₃	z,r,q ₄	-
□	-	-	-	-	□,r,q ₅	-

Figure 2: Example of a seven-symbol six-state *Turing Machine* for recognizing the $\{a^n b^n c^n : n \geq 1\}$ language (q_5 is the acceptor state).

machine states is $Q = \{q_0, q_1, q_2, q_3, q_4, q_5\}$ and q_5 is the acceptor state.

A *Turing machine* is an abstract model of computation that operates on an infinite memory tape. An approach to implement in practice a given Turing machine, is to bound the size of its tape. *Linear bounded Turing machines* are acceptors for the class of context-sensitive languages (Hopcroft, Motwani, and Ullman 2001) and present the following three features:

1. Its input alphabet includes two special symbols, serving as left and right endmarkers.
2. Its transitions may not print other symbols over the endmarkers.
3. Its transitions may neither move to the left of the left endmarker nor to the right of the right endmarker.

This means that, instead of having potentially infinite tape on which to compute, computation is restricted to the portion of the tape containing the input plus the two tape squares holding the endmarkers.

Learning Context-Sensitive Grammars

Our approach is to leverage on classical planning to learn an STRIPS action model where each action in the model represents an entry in the table that defines the transitions of a *Linear-bounded Turing Machine* that recognizes the string given as input. First we show how an entry in the table that defines the transitions of a *Linear-bounded Turing Machine* can be modeled as STRIPS action schema. Next we show how classical planning can be effectively used to learn action models of this kind.

Modeling a Linear-bounded Turing Machine with Classical Planning

Given δ the *transition function* of a *Linear-bounded Turing Machine* M , as defined in the previous section. Here we show that this transition can be encoded as a classical planning frame $P = \langle F, A \rangle$.

We assume that fluents F are instantiated from a set of *predicates* Ψ , as in PDDL. Each predicate $p \in \Psi$ has an argument list of arity $ar(p)$. Given a set of *objects* Ω that represent each of the possible cells in the tape of the given Turing Machine M , the set of fluents F is induced by assigning objects in Ω to the arguments of the predicates in Ψ ;

i.e. $F = \{p(\omega) : p \in \Psi, \omega \in \Omega^{ar(p)}\}$, where Ω^k is the k -th Cartesian power of Ω . In more detail the predicates in Ψ are:

- (head ?x) that encodes the current position of the header in the tape.
- (next ?x1 ?x2) that encodes that the cell ?x2 follows cell ?x1 in the tape.
- (symbol- σ ?x) that encodes that the cell ?x in the tape contains the symbol $\sigma \in \Sigma$.
- (state- q) that encodes that $q \in Q$ is the current machine state.

Likewise we assume that actions $a \in A$ are instantiated from STRIPS operator schema. In particular for each transition defined in δ a STRIPS action model is defined such that:

- The name of the schema is rule-id where id uniquely identifies the transition in δ . The parameters of the schema are three tape cells (?xl ?x ?xr)
- The preconditions of the schema include always (head ?x) and (next ?x1 ?x) (next ?x ?xr) to force that the parameters of the schema are the current cell in the tape pointed by the header and its left and right neighbours. Additionally the schema includes the preconditions (symbol- σ ?x) and (state- q) on the current symbol pointed by the header and the current machine state.
- Finally the delete effects delete always the current the current symbol pointed by the header and the current machine state and set the new ones.

To illustrate this, Figure 3 shows the rule $a, q_0 \rightarrow x, r, q_1$ of the Turing Machine defined in Figure 2. The full encoding of the Turing Machine defined in Figure 2 will produce a total of sixteen STRIPS action schema similar to the one of Figure 3.

```
(:action rule1 ;; a,q_0 -> x,r,q_1
:parameters (?xl ?x ?xr)
:precondition (and (head ?x)
                  (next ?xl ?x) (next ?x ?xr)
                  (symbol-a ?x) (state-q_0))
:effect (and (not (head ?x))
             (not (symbol-a ?x))
             (not (state-q_0))
             (symbol-x ?x) (head ?xr) (state-q_1)))
```

Figure 3: STRIPS action schema that models the rule $a, q_0 \rightarrow x, r, q_1$ of the Turing Machine defined in Figure 2.

Learning CSGs with Classical Planning

Here we show that the existing classical planning compilation for learning STRIPS action schemes (Aineto, Jiménez, and Onaindia 2018) from plans can be adapted to address the learning task defined in this paper.

Note that in this case the set of preconditions and delete effects is already known for each action $a \in A$. So the learning task reduces to learning the positive effects of these actions.

Parsing and Production of CSGs with classical planning

The task of parsing can be implemented with the planning model introduced in the previous section by defining a classical planning instance whose fluents and actions encode the transition of the corresponding Turing machine, the initial state encodes the tape with the string to recognize and the goal conditions require that the Turing machine ends in on its acceptor states.

The task of production requires to include actions that only write once a single symbol from the *tape alphabet* at the tape location indicated by the header.

Evaluation

Related work

The learning of CFGs can also be understood in terms of activity recognition, such that the library of activities is formalized as a CFG, the library is initially unknown, and the input strings encode observations of the activities to recognize. *Activity recognition* is traditionally considered independent of the research done on automated planning, using hand-crafted libraries of activities and specific algorithms (Ravi et al. 2005). An exception is the work by Ramírez and Geffner [2009; 2010] where goal recognition is formulated and solved with planning. As far as we know our work is the first that tightly integrates the tasks of (1) grammar learning, (2) recognition and (3) production using a common planning model and an off-the-shelf classical planner.

Hierarchical Task Networks (HTNs) is a powerful formalism for representing libraries of plans (Nau et al. 2003). HTNs are also defined at several levels such that the tasks at one level are decomposed into other tasks at lower levels with HTN decomposition methods sharing similarities with production rules in CFGs. There is previous work in generating HTNs (Hogg, Munoz-Avila, and Kuter 2008; Lotinac and Jonsson 2016) and an interesting research direction is to extend our approach for computing HTNs from flat sequences of actions. This aim is related to Inductive Logic Programming (ILP) (Muggleton 1999) that learns logic programs from examples. Unlike logic programs (or HTNs) the CFGs that we generate are propositional and do not include variables. Techniques for learning high level state features that include variables are promising for learning lifted grammars (Lotinac et al. 2016).

Conclusions

There is exhaustive previous work on learning CFGs given a corpus of correctly parsed input strings (Sakakibara 1992; Langley and Stromsten 2000) or using positive and negative examples (De la Higuera 2010; Muggleton et al. 2014). This work addresses generating CFGs using only a small set of positive examples (in some cases even one single string that belongs to the language). Furthermore we follow a compilation approach that benefits straightforwardly from research advances in classical planning and that is also suitable for *production* and *recognition* tasks with arbitrary CFGs.

Our compilation bounds the number of rules m , the length of these rules n , the size of the stack ℓ and the length of the input strings z . If these bounds are too small, the classical planner used to solve the output planning task will not be able to find a solution. Larger values for these bounds do not formally affect to our approach, but in practice, the performance of classical planners is sensitive to the size of the input. Interestingly our approach can also follow an incremental strategy where we generate the CFG for a given sub-language and then encode this *sub-grammar* as an auxiliary procedure for generating more challenging CFGs (Segovia-Aguas, Jiménez, and Jonsson 2016).

The size of the compilation output also depends on the number of examples. Empirical results show that our approach is able to generate non-trivial CFGs from very small data sets. Another interesting extension would be to add negative input strings, which would require a mechanism for validating that a given CFG does *not* generate a given string, or to accept incomplete input strings that would require combining the generation and production mechanisms.

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