Tree Parsing with Synchronous Tree-Adjoining Grammars

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Abstract

Restricting the input or the output of a grammar-induced translation to a given set of trees plays an important role in statistical machine translation. The problem for practical systems is to find a compact (and in particular, finite) representation of said restriction. For the class of synchronous tree-adjoining grammars, partial solutions to this problem have been described, some being restricted to the unweighted case, some to the monolingual case. We introduce a formulation of this class of grammars which is effectively closed under input and output restrictions to regular tree languages, i.e., the restricted translations can again be represented by grammars. Moreover, we present an algorithm that constructs these grammars for input and output restriction, which is inspired by Earley’s algorithm.

1 Introduction

Many recent systems for statistical machine translation (SMT) (Lopez, 2008) use some grammar at their core. Chiang (2007), e. g., uses synchronous context-free grammars (SCFG) that derive pairs of translationally equivalent sentences. Huang et al. (2006) use tree-to-string transducers (called xRLNS) that describe pairs of the form (phrase-structure tree, string). Other systems, such as (Eisner, 2003; Zhang et al., 2008; Nesson et al., 2006; DeNeefe and Knight, 2009), use variants of synchronous tree-adjoining grammars (STAGs) (Abeille et al., 1990; Joshi and Schabes, 1997) that derive pairs of dependency or phrase-structure trees. Common variants of STAGs are synchronous tree-substitution grammars (STSGs) and synchronous tree-insertion grammars (STIGs).

For grammar-based systems, a variety of tasks can be described using the general concepts of input product and output product (Maletti, 2010b). Roughly speaking, these products restrict the translation described by the grammar to a given tree or string language on the input or output side. For practical purposes, the derivations of the restricted translation are represented in a compact way, e.g., using a weighted regular tree grammar (WRTG) (Alexandrakis and Bozapalidis, 1987).

The process of obtaining this representation is called tree parsing or string parsing, depending on the type of restriction. We illustrate the importance of input and output product by considering its role in three essential tasks of SMT.

Grammar Estimation. After the rules of the grammar have been obtained from a sample of translation pairs (rule extraction), the probabilities of the rules need to be determined. To this end, two approaches have been employed.

Some systems such as those by Chiang (2007) and DeNeefe and Knight (2009) hypothesize a canonical derivation for each translation pair, and apply relative-frequency estimation to the resulting derivations to obtain rule probabilities. While this procedure is computationally inexpensive, it only maximizes the likelihood of the training data under the assumption that the canonical derivations are the true ones.

Other systems such as those by Eisner (2003), Nesson et al. (2006), and Graehl et al. (2008) use a variant of the EM algorithm (Dempster et al., 1977) called Inside-Outside. This algorithm requires that the set of derivations for a given translation pair be representable by a WRTG. In most cases, this can be computed by restricting the grammar at hand to the given translation pair, that is, by applying input and output product. Note that the pair can contain strings or trees or even some combination thereof.

Feature Weight Estimation. In the systems mentioned at the beginning of this section, a probability distribution of the form \( p(e, d | f) \) is chosen from a log-linear model (Berger et al., 1996; Och and Ney, 2002), where \( e, d, \) and \( f \) are an English
sentence, a derivation, and a foreign sentence, respectively. Such a distribution combines information from different sources, called features, such as the grammar or a probability distribution over English sentences. The features are represented by real-valued functions \( h_i(e, d, f) \). For said combination, each feature gets a weight \( \lambda_i \).

The feature weights are usually estimated using minimum-error-rate training (Och, 2003). For this it is necessary to compute, for a given \( f \), the set \( D_f \) of \( n \) highest ranking derivations generating \( f \) on the foreign side. Roughly speaking, this set can be computed by applying the input product with \( f \), and then applying the \( n \)-best algorithm (Huang and Chiang, 2005; Büchse et al., 2010). We note that, while \( f \) is usually a string, it can in some circumstances be a phrase-structure tree, as in (Huang et al., 2006).

**Decoding.** The actual translation, or decoding, problem amounts to finding, for a given \( f \),

\[
\hat{e} = \text{argmax}_e \sum_d \prod_i h_i(e, d, f)^{\lambda_i}
\]

Even for the simplest grammars, this problem is NP hard (Casacuberta and de la Higuera, 2000). As a result, SMT systems use approximations such as crunching or variational decoding (Li et al., 2009). Here we focus on the former, which amounts to restricting the sum in the equation to the set \( D_f \). Since this set is finite, the sum is then zero for almost all \( e \), which makes the computation of \( \hat{e} \) feasible. As mentioned before, the input product can be used to compute \( D_f \).

As we have seen in these tasks, tree parsing is employed in recent SMT systems. Table 1 lists five relevant contributions in this area. These contributions can be classified according to a number of characteristics indicated by the column headings. One of these characteristics is the abstraction level (AL), which we categorize as follows:

1. language-theoretic result,
2. construction,
3. algorithm,
4. implementation.

The first three entries of Tab. 1 deal with contributions that are restricted to tree substitution. Huang et al. (2006) show an algorithm for computing the best derivation of the input product of an xRLN with a single tree. Graehl et al. (2008) present an algorithm for computing the derivation WRTG for the input and output product of a tree-to-tree transducer (called xRLN) with a single pair of trees. Eisner (2003) describes an algorithm for computing the set of derivations for the input and output product of an STSG with a single pair of trees.

We note that the grammar classes covered so far are strictly less powerful than STAGs. This is due to the fact that STAGs additionally permit an operation called adjoining. As Nesson et al. (2006) and DeNeefe and Knight (2009) point out, the adjoining operation has a well-founded linguistic motivation, and permitting it improves translation quality.

There are two papers approaching the problem of tree parsing for STAGs, given in the fourth and fifth entries of the table. These papers establish closure properties, that is, their constructions yield a grammar of the same type as the original grammar. Since the resulting grammars are compact representations of the derivations of the input product or output product, respectively, these constructions constitute tree parsing.

Nederhof (2009) shows that weighted linear index grammars (WLIGs) are closed under weighted intersection with tree languages generated by WRTGs. WLIGs derive phrase-structure trees, and they are equivalent to tree-adjoining grammars (TAGs). His construction can be extended to some kind of synchronous WLIG without problems. However, synchronization interacts with the height restriction present for WLIG rules in a way that makes synchronous WLIGs less powerful than STAGs.

Maletti (2010a) uses an alternative representation of STAG, namely as extended tree transducers (XTT) with explicit substitution. In this framework, adjoining is encoded into the phrase-structure trees by introducing special symbols, to be evaluated in a separate step. He indicates that his representation of STAG is closed under input and output product with regular tree languages by providing a corresponding construction. However, in his setting, both the translations and the languages are unweighted.

The advantage of closure properties of the above kind is that they allow cascades of input and output products to be constructed in a uniform way, as well as applying further operations on the grammars, such as projection. Ultimately, SMT tasks may be described in this framework, as witnessed by toolboxes that exist for WFSTs (Mohri, 2009) and XTTs (May and Knight, 2006).
In this paper, we propose a weighted formulation of STAGs which is closed under input and output product with WRTGs, and we present a corresponding tree-parsing algorithm. This paper is organized as follows.

In Sec. 2, we introduce our formulation of STAGs, which is called weighted synchronous tree-adjoining grammar (WSTAG). The major difference with respect to the classical STAGs is two-fold: (i) we use states and (ii) we encode substitution and adjoining sites as variables in the tree. The states make intersection with regular properties possible (without the need for relabeling as in (Shieber, 2004) and (Maletti, 2010a)). In addition, they permit implementing all features of conventional STAG/STIG, such as potential adjoining and left/right adjoining. The variables are used for synchronization of the input and output sides.

In Sec. 3, we show that WSTAGs are closed under input and output product with tree languages generated by WRTGs (cf. Theorem 1). We do this by means of a direct construction (cf. Sec. 4). Our construction is based on the standard technique for composing two top-down tree transducers (cf. page 195 of (Baker, 1979)). This technique has been extended in Theorem 4.12 of (Engelfriet and Vogler, 1985) to the composition of a macro tree transducer and a top-down tree transducer (also cf. (Rounds, 1970)); in fact, our direct construction is very similar to the latter one.

Section 5 contains Algorithm 1, which computes our construction (modulo reduction). It is inspired by a variant of Earley’s algorithm (Earley, 1970; Graham et al., 1980). In this way we avoid computation of a certain portion of useless rules, and we ensure that the complexity is linear in the size of the input WSTAG. The algorithm is presented in the framework of deductive parsing (Goodman, 1999; Nederhof, 2003).

In Sections 6 and 7, we discuss the correctness of our algorithm and its complexity, respectively.

2 Formalisms

We denote the set of all unranked, ordered, labeled trees over some alphabet $\Sigma$ by $U_\Sigma$. We represent trees as well-formed expressions, e.g., $S(Adv(yesterday), *)$; a graphical representation of this tree occurs at the very bottom of Fig. 1(a). Sometimes we assign a rank (or: arity) $k \in \mathbb{N}$ to a symbol $\sigma \in \Sigma$ and then require that every $\sigma$-labeled position of a tree has exactly $k$ successors. We denote the set of all positions of a tree $t \in U_\Sigma$ by $\text{pos}(t)$. A position is represented as a finite sequence of natural numbers (Gorn notation). If $w \in \text{pos}(t)$, then $t(w)$ denotes the label of $t$ at $w$, and $\text{rk}_t(w)$ denotes the number of successors of $w$.

2.1 Weighted Regular Tree Grammars

A weighted regular tree grammar (for short: WRTG) is a tuple $H = (P, \Sigma, r_0, R, p)$ where $P$ is a finite set of states, $\Sigma$ is an alphabet, $r_0 \in P$ is the initial state, and $R$ is a finite set of rules; every rule $\rho$ has the form $r \rightarrow \sigma(r_1, \ldots, r_k)$ where $k \in \mathbb{N}$, $r, r_1, \ldots, r_k \in P$, and $\sigma \in \Sigma$ (note that $\sigma(r_1, \ldots, r_k)$ is a tree over $\Sigma \cup P$); finally, $p : R \rightarrow \mathbb{R}_{\geq 0}$ is the weight assignment, where $\mathbb{R}_{\geq 0}$ is the set of all non-negative real numbers.

A run (of $H$) is a tree $\kappa \in U_P$. Let $t \in U_\Sigma$ and let $\kappa$ be a run. We say that $\kappa$ is a run on $t$ if $\text{pos}(\kappa) = \text{pos}(t)$ and for every position $w \in \text{pos}(t)$ the rule $\rho(\kappa, t, w)$ is in $R$, where $\rho(\kappa, t, w)$ is defined as

$$\kappa(w) \rightarrow t(w) \left( \kappa(w_1), \ldots, \kappa(w \text{rk}_t(w)) \right).$$

The weight of a run $\kappa$ on $t$ is the value $\text{wt}(\kappa, t) \in \mathbb{R}_{\geq 0}$ defined by

$$\text{wt}(\kappa, t) = \prod_{w \in \text{pos}(t)} p(\rho(\kappa, t, w)).$$

The weighted tree language generated by WRTG $H$ is the mapping $L(H) : U_\Sigma \rightarrow \mathbb{R}_{\geq 0}$.
defined by
\[ L(H)(t) = \sum_{\kappa \text{ run on } t, \kappa(\varepsilon) = r_0} \omega(t, \kappa). \]
The support \( \text{supp}(L(H)) \) of \( L(H) \) is the set of all \( t \in U_\Sigma \) such that \( L(H)(t) \neq 0 \).

2.2 Weighted Tree-Adjoining Grammars

In our formulation of STAGs we use states (cf. Fülöp et al. (2010) for the use of states in STSGs). The states make intersection with devices of finite-state power possible. More specifically, they allow for a product construction as is common in automata theory (cf. Sec. 4). Moreover, they permit implementing all features of conventional STAG/STIG, such as potential adjoining and left/right adjoining. In contrast to the traditional setting, substitution sites and adjoining sites are formalized as explicit positions in the right-hand sides of rules; these positions are labeled by variables. For this, we assume that \( x_1, x_2, \ldots \) and \( z_1, z_2, \ldots \) are two fixed infinite and disjoint sequences of pairwise distinct variables. We assume that every \( x_j \) has rank 0 and every \( z_j \) has rank 1. We use \( x_1, x_2, \ldots \) to denote substitution sites and \( z_1, z_2, \ldots \) to denote adjoining sites. The foot node is labeled by an additional nullary symbol \( * \). The input and output components are synchronized via these sites and the corresponding states.

A weighted synchronous tree-adjoining grammar with states (for short: WSTAG) is a tuple \( G = (Q, F, \Sigma, q_0, R, p) \) where
- \( Q \) and \( F \) are disjoint finite sets of (nullary and unary states, respectively), each denoted by variants of \( q \) and \( f \), respectively,
- \( \Sigma \) is an alphabet (terminal alphabet),
- \( q_0 \) is a nullary state (initial state),
- \( R \) is a finite set of rules of either of the following forms:
  \[ q \rightarrow \langle \zeta, q_1 \ldots q_m, f_1 \ldots f_l \rangle \]  \hspace{0.5cm} (\alpha)
  \[ f(*) \rightarrow \langle \zeta, q_1 \ldots q_m, f_1 \ldots f_l \rangle \]  \hspace{0.5cm} (\beta)
where \( \zeta \) and \( \zeta' \) are trees over \( \Sigma \cup V \) and
\[ V = \{ x_1, \ldots, x_m, z_1, \ldots \} \]  \hspace{0.5cm} (\alpha)
\[ V = \{ x_1, \ldots, x_m, z_1, \ldots, z_l, * \} \]  \hspace{0.5cm} (\beta)
and every element of \( V \) occurs exactly once in each of \( \zeta \) and \( \zeta' \), and
- \( p : R \rightarrow \mathbb{R}_{\geq 0} \) is the weight assignment.

Rules of the forms (\( \alpha \)) and (\( \beta \)) are called \((m, l)\)-rules; \( \zeta \) and \( \zeta' \) are called the input tree and the output tree of the rule, respectively. For fixed \( q \) and \( f \), the sets of all rules of the form (\( \alpha \)) and (\( \beta \)) are denoted by \( R_q \) and \( R_f \), resp. Figure 1(a) shows an example of a WSTAG. In the following, let \( G = (Q, F, \Sigma, q_0, R, p) \) be a WSTAG.

We define the semantics in terms of bimorphisms (Shieber, 2006). For this we define a WRTG \( H_G \) that generates the weighted tree language of derivation trees of \( G \), and two tree homomorphisms \( h_1 \) and \( h_2 \) that retrieve from a derivation tree the derived input tree and output tree, respectively.

The derivation tree WRTG of \( G \) is the WRTG \( H_G = (Q \cup F, R, q_0, R', p') \) where
- we assign the rank \( m + l \) to every \((m, l)\)-rule,
- \( R' \) is the set of all rules \( D(\rho) \) with \( \rho \in R \) and
  - if \( \rho \) is of the form (\( \alpha \)), then
    \[ D(\rho) = q \rightarrow \rho(q_1, \ldots, q_m, f_1, \ldots, f_l) \],
  - if \( \rho \) is of the form (\( \beta \)), then
    \[ D(\rho) = f \rightarrow \rho(q_1, \ldots, q_m, f_1, \ldots, f_l) \],
- \( p'(D(\rho)) = p(\rho) \).

Recall that \( L(H_G) \) is the weighted tree language generated by \( H_G \). We call the trees in \( \text{supp}(L(H_G)) \) derivation trees. For instance, with the WSTAG of Fig. 1(a), the tree \( d_{ex} = \rho_1(\rho_2, \rho_3(\rho_4), \rho_5) \) is a derivation tree of the derived trees shown in Fig. 1(b) and Fig. 1(c).

Formally, the derived trees are obtained by the tree homomorphisms \( h_1 \) and \( h_2 \), each of type \( \text{supp}(L(H_G)) \rightarrow U_\Sigma \), which we define inductively as follows:

\[ h_1(\rho(d_1, \ldots, d_m, d'_1, \ldots, d'_l)) = \zeta[\vec{z}/h_1(\bar{d})[\vec{z}/h_1(\bar{d}')] \]

where \([\vec{z}/h_1(\bar{d})]\) abbreviates the \( m \) first-order substitutions \([x_1/h_1(d_1)] \ldots [x_m/h_1(d_m)]\), and \([\vec{z}/h_1(\bar{d}')]\) abbreviates the \( l \) second-order substitutions \([z_1/h_1(d'_1)] \ldots [z_l/h_1(d'_l)]\). The first-order substitution \([x/s]\) replaces every occurrence of \( x \) by \( s \), and the second-order substitution \([z/s]\) is defined inductively in Fig. 2. The tree homomorphism \( h_2 \) is defined in the same way as \( h_1 \), but with \( \zeta' \) instead of \( \zeta \). We call \( d \) a derivation tree of the pair \((h_1(\bar{d}), h_2(\bar{d}))\).

In continuation of our running example, we calculate \( h_1(d_{ex}) \), where we use \([1]\), \([2]\), and \([3]\) as abbreviations for the substitutions \([x_1/h_1(\rho_2)]\),
Figure 1: (a) Example of a WSTAG (following Joshi and Schabes, 1997), (b) input tree, and (c) output tree.

$$\sigma(\zeta_1, \ldots, \zeta_k)[z/s] = \sigma(\zeta_1[z/s], \ldots, \zeta_k[z/s])$$

$$x_j[z/s] = x_j$$

$$*[z/s] = *$$

$$z_j(\zeta)[z/s] = \begin{cases} 
  s' & \text{if } z = z_j \text{ and } s' \text{ is obtained from } s \text{ by replacing the } * \text{ by } \zeta \\
  z_j(\zeta[z/s]) & \text{otherwise.} 
\end{cases}$$

Figure 2: Second-order substitution $[z/s]$, where $\sigma \in \Sigma$, $x_j$ is a nullary variable, and $z_j$ is a unary variable.
\[ [x_2/h_1(\rho_3(\rho_4))], \text{ and } [z_1/h_1(\rho_5)], \text{ respectively:} \]
\[ h_1(d_{ex}) = z_1(S(x_1, VP(V(saw), x_2))) [1][2][3] \]
\[ = z_1(S(h_1(\rho_2), VP(V(saw), x_2))) [2][3] \]
\[ = z_1(S(h_1(\rho_2), VP(V(saw), h_1(\rho_3(\rho_4)))) [3] \]
\[ = S(Adv(yesterday), \xi) , \]
which evaluates to the tree of Fig. 1(b).

The weighted tree transformation specified by WSTAG is \( T(G) : U_\Sigma \times U_\Sigma \rightarrow \mathbb{R}_{\geq 0} \) defined by
\[ T(G)(s, t) = \sum_d \{ L(H_G)(d) \} \]
where \( \sum_d \) is the sum over all derivation trees of \( (s, t) \).

We note that for every derivation tree \( d \) there is a unique run \( \kappa_d \) of \( H_G \) on \( d \): \( \kappa_d(w) \) is the state occurring in the left-hand side of the rule \( d(w) \), for every \( w \in \text{pos}(d) \).

As an example, we reconsider \( d_{ex} \), which is a derivation tree of the translation pair \((s, t)\), given by Fig. 1(b) and Fig. 1(c). Then we have \( L(H_G)(d_{ex}) = \) \( wt(\kappa_{d_{ex}}, d_{ex}) = \prod_{i=1}^5 p(\rho_i) = 0.24 \). Since \( d_{ex} \) is the only derivation tree of \((s, t)\), we have that \( T(G)(s, t) = 0.24 \).

STSGs as defined in Fülöp et al. (2010) are WSTAGs which only have nullary states. Also classical STAGs (Abeille et al., 1990; Shieber and Schabes, 1990) and STIGs (Nesson et al., 2005; Nesson et al., 2006; DeNeefe and Knight, 2009) can be viewed as particular WSTAGs. In particular, potential adjoining as it occurs in classical STAGs can be simulated, as the following excerpt of a WSTAG shall illustrate:
\[ q \rightarrow (z_1(A(x_1))) \xi', q', f) \]
\[ f(\ast) \rightarrow (\ast, \ast, \ast) \]
\[ f(\ast) \rightarrow (z_1(\ast), z_1(\ast), \ast, f') \]

Moreover, the left-right adjoining restriction of STIGs can be handled by keeping appropriate finite information in the states.

3 Closure Result

First we define the input product and output product of a weighted tree transformation \( T \): \( U_\Sigma \times U_\Sigma \rightarrow \mathbb{R}_{\geq 0} \) and a weighted tree language \( L \): \( U_\Sigma \rightarrow \mathbb{R}_{\geq 0} \). Formally, the input product of \( T \) and \( L \) is the weighted tree transformation \( L \triangleleft T \): \( U_\Sigma \times U_\Sigma \rightarrow \mathbb{R}_{\geq 0} \) such that
\[ (L \triangleleft T)(s, t) = L(s) \cdot T(s, t) \]

Similarly, we define the output product of \( T \) and \( L \) as \( T \triangleright L \): \( U_\Sigma \times U_\Sigma \rightarrow \mathbb{R}_{\geq 0} \) such that
\[ (T \triangleright L)(s, t) = T(s, t) \cdot L(t) \]

We note that the input product and output product can be considered as a kind of composition of weighted relations by viewing \( L \) as mapping \( L' : U_\Sigma \times U_\Sigma \rightarrow \mathbb{R}_{\geq 0} \) with \( L'(s, t) = L(s) \) if \( s = t \) and \( L'(s, t) = 0 \) otherwise.

Here we prove that WSTAGs are closed under input product (and output product) with WRTGs.

**Theorem 1** For every WSTAG \( G \) and WRTG \( H \) there are WSTAGs \( H < G \) and \( G \triangleright H \) such that
\[ T(H < G) = L(H) < T(G) \] and
\[ T(G \triangleright H) = T(G) \triangleright L(H) \]

We will only prove the closure under input product, because the proof for the output product is similar.

For the unweighted case, the closure result follows from classical results. The unweighted case is obtained if we replace the algebra in Sec. 2 by another one: \( \mathbb{R}_{\geq 0} \) is replaced by the set \( \mathbb{B} = \{ \text{true, false} \} \) and the operations + and · are replaced by disjunction and conjunction, respectively. In other words, we replace the inside semiring \( (\mathbb{R}_{\geq 0}, +, \cdot, 0, 1) \) by the Boolean semiring \( (\mathbb{B}, \lor, \land, \text{false, true}) \). Then \( L(H) \) and \( T(G) \) become sets \( L(H) \subseteq U_\Sigma \) and \( T(G) \subseteq U_\Sigma \times U_\Sigma \). In this setting and using \( h : \text{supp}(L(H_G)) \rightarrow U_\Sigma \times U_\Sigma \) defined by \( h(d) = (h_1(d), h_2(d)) \), we have that
\[ L(H) < T(G) = h(h_1^{-1}(L(H))) \]

Note that \( h_1^{-1}(L(H)) \subseteq \text{supp}(L(H_G)) \). Now we observe that \( h_1 \) can be computed by a particular macro tree transducer (Engelfriet, 1980; Courcelle and Franchi-Zanettacci, 1982); we note that in (Shieber, 2006) such macro tree transducers were called embedded tree transducers.

Engelfriet and Vogler (1985) proved in Theorem 7.4 that the class of regular tree languages is closed under the inverse of macro tree transducers. Thus, since \( L(H) \) is a regular tree language, also \( h_1^{-1}(L(H)) \) is a regular tree language. Thus \( L(H) < T(G) = h(L(\bar{H})) \) for some regular tree grammar \( \bar{H} \). Now it is easy to construct (using \( h_1 \) and \( h_2 \)) a STAG \( H < G \) from \( \bar{H} \) such that \( T(H < G) = h(L(\bar{H})) \).

For the weighted case, we give a direct construction in the next section.
4 Direct Construction

We now provide our construction of the WSTAG $H \lhd G$ in Theorem 1 where $G = (Q, F, \Sigma, q_0, R, p)$ is a WSTAG and $H = (P, \Sigma, r_0, R_H, p_H)$ is a WRTG.

First we define an enrichment of $H$ that can generate trees like $\zeta$ as they occur in rules of $G$, that is, including variables $x_j$, $z_j$, and possibly $\ast$. To this end, let $\rho \in R$. A (state) assignment for $\rho$ is a mapping $\theta$ that maps each nullary variable in $\rho$ to a state of $H$ and each unary variable in $\rho$ to a pair of such states. Likewise, if $\ast$ occurs in $\zeta$, then $\theta$ maps it to a state of $H$. For every $r \in P$ and assignment $\theta$, we define the WRTG $H(r, \theta)$, which is obtained from $H$ by using $r$ as initial state and adding the following rules with weight $1$ for every $r, r' \in P$:

\[
\begin{align*}
    r &\rightarrow x_j & \text{if } \theta(x_j) = r, \\
    r &\rightarrow z_j(r') & \text{if } \theta(z_j) = (r, r'), \text{ and} \\
    r &\rightarrow \ast & \text{if } \theta(\ast) = r .
\end{align*}
\]

Roughly speaking, for every rule $\rho \in R$, we let $H(r, \theta)$ “run” on the input tree $\zeta$ of $\rho$. Formally, we define the product WSTAG of $H$ and $G$ as the WSTAG $H \lhd G = (Q \times P, F \times (P \times P), \Sigma, (q_0, r_0), R', p')$ as follows. Let $\rho \in R$, $r \in P$, and $\theta$ an assignment for $\rho$. Then, depending on whether $\rho$ has the form $(\alpha)$ or $(\beta)$, the rule

\[
(\alpha) \quad (q, r) \rightarrow (\zeta', u, v) \\
(\beta) \quad (f, (r, \theta(\ast))) \rightarrow (\zeta', u, v)
\]

is in $R'$ where

- $u = (q_1, \theta(x_1)) \cdots (q_m, \theta(x_m))$ and
- $v = (f_1, \theta(z_1)) \cdots (f_m, \theta(z_l))$.

We denote this rule by $(\rho, r, \theta)$. Its weight is $p'(\rho, r, \theta) = p(\rho) \cdot L(H(r, \theta))$. There are no further elements in $R'$.

We omit a proof for $T(H \lhd G) = L(H) \lhd T(G)$.

We have that $|R'| \in O(|R| \cdot |P| C)$ where $C = \max\{m + 2 \cdot l + y | \exists \rho: \rho$ is an $(m, l)$-rule, $y = 1$ in case $(\alpha), y = 2$ in case $(\beta)\}$.

5 Algorithm

Now we present Algorithm 1, which performs the construction of $H \lhd G$. It uses a strategy similar to that of Earley’s algorithm to construct at least all useful rules of $H \lhd G$ while avoiding construction of a certain portion of useless rules. A rule is useful if it occurs in some derivation tree; otherwise it is useless.

Algorithm 1: Product construction algorithm

Require: $G = (Q, F, \Sigma, q_0, R, p)$ a WSTAG and $H = (P, \Sigma, r_0, R_H, p_H)$ a WRTG,
Ensure: $R_u$ contains at least the useful rules of $H \lhd G$,
$p_u$ coincides with the weight assignment of $H \lhd G$ on $R_u$

\[1: \mathcal{I} \leftarrow \emptyset\]
\[2: \text{repeat}\]
\[3: \text{add items to } \mathcal{I} \text{ by applying the rules in Fig. 3}\]
\[4: \text{until convergence}\]
\[5: R_u \leftarrow \emptyset\]
\[6: \text{for } [\rho, \varepsilon, r, \theta] \in \mathcal{I} \text{ do}\]
\[7: R_u \leftarrow R_u \cup \{[\rho, r, \theta]\} \text{ as in Sec. 4}\]
\[8: \text{perform reachability analysis to remove useless rules from } R_u\]
\[9: \text{for } [\rho, r, \theta] \in R_u \text{ do}\]
\[10: p_u(\rho, r, \theta) \leftarrow p(\rho) \cdot W([\rho, \varepsilon, r, \theta])\]
\[\text{defined in Fig. 4}\]

Conceptually, the algorithm proceeds in four steps. Note that, in practice, some of these steps may be implemented interleaved in order to reduce constants in the runtime complexity.

The first step is based on a deductive system, or deductive parsing schema, which is given in Fig. 3. Its central notion is that of an item, which is a syntactic representation of a proposition. We say that an item holds if the corresponding proposition is true. In Sec. 6 we will explain the meaning of the items in detail. Roughly speaking, the items drive a depth-first left-to-right simulation of $H$ on the trees on the input side of rules of $G$. Items with round brackets are responsible for top-down traversal and items with square brackets for horizontal and bottom-up traversal. The deductive system contains inference rules which are, as usual, syntactic representations of conditional implications (Goodman, 1999; Nederhof, 2003).

The first step of the algorithm computes the least set $\mathcal{I}$ of items that is closed under application of the inference rules. This is done in the usual iterative way, starting with the empty set and applying rules until convergence. Since there are only finitely many items, this process will terminate. Note that, given the soundness of the infer-
Figure 4: Computing the weights of rules in the product grammar $H \triangleleft G$.

If $\zeta(w) \in \Sigma$, with $k = \text{rk}_\zeta(w)$, and $\theta_j$ is the restriction of $\theta$ to variables below node $w_j$ in $\rho$, then:

$$\mathcal{W}(\rho, w, r, \theta) = \sum_{r_1, \ldots, r_k : \rho \in R_q} p_H(r \rightarrow \zeta(w)(r_1, \ldots, r_k)) \cdot \prod_j \mathcal{W}(\rho, w_j, r_j, \theta_j)$$

If $\zeta(w) \in \{*, x_1, \ldots, x_m\}$, then $\mathcal{W}(\rho, w, r, \theta) = 1$.

If $\zeta(w) = \{z_j\}$, with $\theta(z_j) = (r, r')$, then $\mathcal{W}(\rho, w, r, \theta) = \mathcal{W}(\rho, w_1, r', \theta \setminus \{z_j \mapsto (r, r')\})$.

Note: whenever $\rho$ is mentioned, we implicitly assume that

$$\rho = q \rightarrow \langle \zeta', q_1 \cdots q_m, f_1 \cdots f_l \rangle \text{ or } \rho = f(y) \rightarrow \langle \zeta', q_1 \cdots q_m, f_1 \cdots f_l \rangle.$$
ence rules (cf. Sec. 6), all items in $I$ hold.

In the second step, for each $[\rho, \varepsilon, r, \theta]$ in $I$ we construct one rule of $H < G$ as in (a) or as in (b) in Sec. 4, depending on whether $\rho \in R_q$ or $\rho \in R_f$.

The third step is a reachability analysis to remove useless rules. This step is optional—it depends on the application whether the runtime spent here is amortized by subsequent savings.

In the fourth step, we determine the weight of each of the rules we have. For a rule $([\rho, \varepsilon, r, \theta])$ this is $p(\rho) \cdot W((\rho, \varepsilon, r, \theta))$, where $W$ is defined in Fig. 4. The computation can be sped up by storing “back pointers” for each item, i.e., the items which were used for its generation. Alternatively, it is possible to compute the weights on-the-fly during the first step, thus alleviating the need for a separate recursive computation.

To this end, items should be prioritized to make sure that they are generated in the right order for the computation. To be more precise, one has to ensure that all items referred to on the right-hand sides of the equations in Fig. 4 are generated before the items on the left-hand sides.

### 6 Meaning of Items

The meaning of the items can best be illustrated by the concepts of enriched derivation tree and partial enriched derivation tree.

An enriched derivation tree is a modified derivation tree in which the labels have the form ($\rho, c$) for some rule $\rho$ and some decoration mapping $c$; $c$ maps every position of the input tree $\zeta$ of $\rho$ to a state of the WRTG $H$. Moreover, $c$ must be consistent with the rules of $H$, and positions that coincide in the derived tree must be decorated with the same state (cf. Fig. 5, dashed lines). A partial enriched derivation tree (for short: pdet) is an enriched derivation tree in which subtrees can still be missing (represented by ⊥) or the decoration with states from $H$ is not yet complete (i.e., some positions are mapped to ?).

Figure 5 shows an example pdet $d$, where we represent the decoration at each position of $d$ by annotating the corresponding input tree. This pdet can be viewed as representing application of the following rules:

(1), (2$q$), (8$z$), (2$f$), (4), (5), (4), (5), (4), (7), . . .

Now we make our description of pdets more precise. Let $n$ be a position of $d$, $\rho$ be the rule occurring in the label $d(n)$, and $\zeta$ be the input tree of $\rho$. Then there is a position $w$ of $\zeta$ such that (1) every position $u$ which is lexicographically smaller than $w$ is decorated by a state and, if $\zeta(u)$ is a variable $x_j$ or $z_j$, then the subtree of $n$ which corresponds to the variable does not contain ⊥ or ?, (2) every position $v$ which is lexicographically greater than $w$ is decorated by $\gamma$ and, if $\zeta(v)$ is a variable $x_j$ or $z_j$, then the child of $n$ which corresponds to the variable is ⊥. For instance, if we consider the root $n = \varepsilon$ of the pdet in Fig. 5, then $w = 11$ (i.e., the position with label $x_1$).

Finally we can describe the meaning of the items by referring to properties of pdets.

$q, r$ (and $f, r$): There are a pdet $d$, a position $n$ of $d$, a rule $\rho$, and a decoration $c$ such that $d(n) = (\rho, c)$, $\rho \in R_q$ (resp., $\rho \in R_f$), and $c(\varepsilon) = r$.

$q, r$: There are a pdet $d$, a position $n$ of $d$, a rule $\rho$, and a decoration $c$ such that $d(n) = (\rho, c)$, $\rho \in R_q$, $c(\varepsilon) = r$, and $c$ is a complete decoration.

$f, r, r'$: There are a pdet $d$, a position $n$ of $d$, a rule $\rho$, and a decoration $c$ such that $d(n) = (\rho, c)$, $\rho \in R_f$, $c(\varepsilon) = r$, $c$ is a complete decoration, and $c$ maps the $*$-labeled position of the input tree of $\rho$ to $r'$.

$\rho, w, r$: There are a pdet $d$, a position $n$ of $d$, and a decoration $c$ such that $d(n) = (\rho, c)$ and $c(w) = r$.

$\rho, w, r, \theta$: There are a pdet $d$, a position $n$ of $d$, and a decoration $c$ such that $d(n) = (\rho, c)$,
c(w) = r and, if a position u below w of the input tree ζ of ρ is labeled by xj, then c(u) = θ(xj), and if it is labeled by zj, then (c(u), c(u1)) = θ(zj), and if it is labeled by *, then c(u) = θ(*).

[ρ, w, j, r, r1 · · · rk, θ]: There are a pedt d, a position n of d, and a decoration c such that d(n) = (ρ, c), c(w) = r, and, if a position u of the input tree ζ of ρ is labeled by some variable y and u is lexicographically smaller than wj, c and θ agree in the same way as in the preceding item.

Given this semantics of items, it is not difficult to see that the inference rules of the deduction system are sound. The completeness of the system can be derived by means of a small proof by contradiction.

7 Complexity Analysis

In this section, we analyse the worst-case space and time complexity of step 1 of Algorithm 1.

The space complexity is

\[ O(|{G}_w| \cdot |R_H| \cdot |P|^C) \, , \]

which is determined by the number of possible items of the form [ρ, w, j, r, r1 · · · rk, θ]. The first factor, |{G}_w|, denotes the input size of G, defined by \[ \sum_{\rho \in R} |\text{pos}(\zeta(\rho))| \], where \( \zeta(\rho) \) is the input tree of ρ. It captures the components ρ, w, and j in said items, which together identify exactly one node of an input tree of G. The factor |R_H| captures the components r and r1 · · · rk. The final factor, |P|^C, captures the θ, where C is given at the end of Sec. 4.

Following McAllester (2002) we determine the time complexity by the number of instantiations of the inference rules. In our case the time complexity coincides with the space complexity.

8 Conclusion

We have introduced a formulation of STAGs that is closed under input product and output product with regular weighted tree languages. By the result of Maletti and Satta (2009), this implies closure under input product and output product with regular weighted string languages. We have provided a direct construction of the STAG that generates said input product (and, mutatis mutandis, the output product). No such construction has been published before that deals with both weights and synchronization. Moreover, we have presented a novel algorithm for computing our construction. This algorithm is inspired by Earley’s algorithm to the effect that computation of a certain portion of useless rules is avoided.

The next step towards an implementation would be to consider pruning. This amounts to partitioning the set I of items and imposing a bound on the size of each partition. Such a technique has already been presented by Chiang (2007) for his cube-pruning algorithm.

Another possible future contribution could be an algorithm specifically tailored to the input product with a regular weighted string language. For this scenario, several contributions exist, requiring additional restrictions however. For instance, Nesson et al. (2006) show a CYK-like algorithm for intersecting a STIG with a pair of strings. Their algorithm requires that the trees of the grammar be binarized. As DeNeefe and Knight (2009) point out, this makes the grammar strictly less powerful. They in turn propose a construction which converts the STIG into an equivalent tree-to-string transducer, and they use corresponding algorithms for parsing, such as the one by DeNero et al. (2009). However, their construction relies on the fact that tree-insertion grammars are weakly equivalent to context-free grammars. Thus, it is not applicable to the more general STAGs.

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