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Please Mind the Root: Decoding Arborescences for Dependency Parsing

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Abstract

The connection between dependency trees and spanning trees is exploited by the NLP community to train and to decode graph-based dependency parsers. However, the NLP literature has missed an important difference between the two structures: only one edge may emanate from the root in a dependency tree. We analyzed the output of state-of-the-art parsers on many languages from the Universal Dependency Treebank: although these parsers are often able to learn that trees which violate the constraint should be assigned lower probabilities, their ability to do so unsurprisingly degrades as the size of the training set decreases. In fact, the worst constraint-violation rate we observe is 24%. Prior work has proposed an inefficient algorithm to enforce the constraint, which adds a factor of $n$ to the decoding runtime. We adapt an algorithm due to Gabow and Tarjan (1984) to dependency parsing, which satisfies the constraint without compromising the original runtime.

1 Introduction

Developing probabilistic models of dependency trees requires efficient exploration over a set of possible dependency trees, which grows exponentially with the length of the input sentence $n$.

Under an edge-factored model (McDonald et al., 2005; Ma and Hovy, 2017; Dozat and Manning, 2017), finding the maximum-a-posteriori dependency tree is equivalent to finding the maximum weight spanning tree in a weighted directed graph. More precisely, spanning trees in directed graphs are known as arborescences. The maximum-weight arborescence can be found in $O(n^2)$ (Tarjan, 1977; Camerini et al., 1979).\footnote{Our Python library is available at https://github.com/rycolab/spanningtrees.}

However, an oversight in the relationship between dependency trees and arborescences has gone largely unnoticed in the dependency parsing literature. Most dependency annotation standards enforce a root constraint: Exactly one edge may emanate from the root node.\footnote{A notable exception is the Prague Dependency Treebank (Bejček et al., 2013), which allows for multi-rooted trees.} For example, the Universal Dependency Treebank (UD; Nivre et al. (2018)), a large-scale multilingual syntactic annotation effort, states in their documentation (UD Contributors):

There should be just one node with the root dependency relation in every tree.

This oversight implies that parsers may return malformed dependency trees. Indeed, we examined the output of a state-of-the-art parser (Qi et al., 2020) for 63 UD treebanks. We saw that decoding without a root constraint resulted in 1.80% (on average) of the decoded dependency trees being malformed. This increased to 6.21% on languages that contain less than one thousand training instances with the worst case of 24% on Kurmanji.

The NLP literature has proposed two solutions to enforce the root constraint: (1) Allow invalid dependency trees—hoping that the model can learn to assign them low probabilities and decode singly rooted trees, or (2) return the best of $n$ runs of the CLE each with a fixed edge emanating from the root (Dozat et al., 2017).\footnote{In practice, if constraint violations are infrequent, this strategy should be used as a fallback for when the unconstrained solution fails. However, this will not necessarily be the case, and is rarely the case during model training.} The first solution is clearly problematic as it may allow parsers to predict malformed dependency trees. This issue is further swept under the rug with “forgiving” evaluation metrics, such as attachment scores, which give less than one thousand training instances with the worst case of 24% on Kurmanji.

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Figure 1: A malformed dependency tree from our experiment. Shown are the incorrect (highlighted) and correct (highlighted) dependency relations for token 8. Partial credit for malformed output.\(^5\) The second solution, while correct, adds an unnecessary factor of \(n\) to the runtime of root-constrained decoding.

In this paper, we identify a much more efficient solution than (2). We do so by unearthing an \(O(n^2)\) algorithm due to Gabow and Tarjan (1984) from the theoretical computer science literature. This algorithm appears to have gone unnoticed in NLP literature;\(^6\) we adapt the algorithm to correctly and efficiently handle the root constraint during decoding in edge-factored non-projective dependency parsing.\(^7\)

2 Approach

In this section, the marker \(\textcolor{red}{\text{Red}}\) indicates that a recently introduced concept is illustrated the worked example in Fig. 2. Let \(G = (\rho, V, E)\) be a rooted weighted directed graph where \(V\) is a set of nodes, \(E\) is a set of weighted edges, \(E \subseteq \{(i \to j) \mid i, j \in V, w \in \mathbb{R}\}\), and \(\rho \in V\) is a designated root node with no incoming edges. In terms of dependency parsing, each non-\(\rho\) node corresponds to a token in the sentence, and \(\rho\) represents the special root token that is not a token in the sentence. Edges represent possible dependency relations between tokens. The edge weights are scores from a model (e.g., linear (McDonald et al., 2005), or neural network (Dozat et al., 2017)). Fig. 1 shows an example. We allow \(G\) to be a multi-graph, i.e., we allow multiple edges between pairs of nodes. Multi-graphs are a natural encoding of labeled dependency relations where possible labels between words are captured by multiple edges between nodes in the graph. Multi-graphs pose no difficulty as only the highest-weight edge between two nodes may be selected in the returned tree.

An arborescence of \(G\) is a subgraph \(A = (\rho, V, E')\) where \(E' \subseteq E\) such that:

(C1) Each non-root node has exactly one incoming edge (thus, \(|E'| = |V| - 1\);

(C2) \(A\) has no cycles.

A dependency tree of \(G\) is an arborescence that additionally satisfies

\[ \left| \{ (\rho \to j) \in E' \} \right| = 1 \]

In words, (C3) says \(A\) contains exactly one out-edge from \(\rho\). Let \(A(G)\) and \(A^\dagger(G)\) denote the sets of arborescences and dependency trees, respectively.

The weight of a graph or subgraph is defined as

\[ \bar{w}(G) \overset{\text{def}}{=} \sum_{(i \to j) \in G} w \quad (1) \]

In §2.1, we describe an efficient algorithm for finding the best (highest-weight) arborescence

\[ G^* = \arg \max_{A \in A(G)} \bar{w}(A) \quad (2) \]

and, in §2.2, the best dependency tree.\(^9\)

\[ G^\dagger = \arg \max_{A \in A^\dagger(G)} \bar{w}(A) \quad (3) \]

2.1 Finding the best arborescence

A first stab at finding \(G^*\) would be to select the best (non-self-loop) incoming edge for each node. Although, this satisfies (C1), it does not (necessarily) satisfy (C2). We call this subgraph the greedy graph, denoted \(\tilde{G}\). Clearly, \(\bar{w}(\tilde{G}) \geq \bar{w}(G^*)\) since it is subject to fewer restrictions. Furthermore, if \(\tilde{G}\) happens to be acyclic, it is clearly equal to \(G^*\). What are we to do in the event of a cycle? That answer has two parts.

Part I: We call any cycle \(C\) in \(\tilde{G}\) a critical cycle.\(\textcolor{red}{\text{Red}}\) Naturally, (C2) implies that critical cycles can never be part of an arborescence. However, they help us identify optimal arborescences for certain subproblems. Specifically, if we were to “break” the cycle at any node \(j \in C\) by removing its (unique) incoming edge, we would have an opti-

\(^5\)We note exact match metrics, which consider the entire arborescence, do penalize root constraint violations

\(^6\)There is one exception: Corro et al. (2016) mention Gabow and Tarjan (1984)’s algorithm in a footnote.

\(^7\)Much like this paper, efficient root-constrained marginal inference is also possible without picking up an extra factor of \(n\), but it requires some attention to detail (Koo et al., 2007; Zmigrod et al., 2020).

\(^8\)When there is no ambiguity, we may abuse notation using \(G\) to refer to either its node or edge set, e.g., we may write \((i \to j) \in G\) to mean \((i \to j) \in E\), and \(i \in G\) to mean \(i \in V\).
Figure 2: Worked example of finding the best dependency tree. Let $G$ be the graph in the left-most figure, the greedy graph $\mathcal{G}$ (highlighted) contains a critical cycle $C$ (highlighted). Step (a) shows the contraction $G/C$ where $C$ is replaced by $\mathcal{G}$, and edges are cast as enter, exit, external, or dead edges in $G/C$. We see the bookkeeping function $\pi$ (as $\cdots \longrightarrow$), e.g., $\pi(c \rightarrow 1) = (4 \rightarrow 1)$ and $\pi(\rho \rightarrow 170) = (\rho \rightarrow 2)$. Step (b) takes the greedy (sub)graph of $G/C$ and since it contains no cycles, it is $(G/C)^*$ as (highlighted). Note that if we did not require a dependency tree, we could now use Theorem 1 to break $C$ at $\mathcal{G}$. Step (c) takes $(G/C)^*$, which has two root edges, $(\rho \rightarrow 1)$ and $(\rho \rightarrow 170)$, and removes the edge with minimal consequence: removing $(\rho \rightarrow 1)$ leads to $\overline{\omega} = 190$, while removing $(\rho \rightarrow 170)$ leads to $\overline{\omega} = 210$. We pick the latter. As deleting $(\rho \rightarrow 170)$ does not lead to a critical cycle (optimization case), we remove it from the graph (shown as $\cdots$) and so we get $(G/C)^*$ (highlighted). Step (d) stitches $(G/C)^* \rightarrow C^{(3)}$ yielding $G^1$ (highlighted).

Additionally, we define a bookkeeping function, $\pi$, which maps the nodes and edges of $G/C$ to their counterparts in $G$. We overload $\pi(G)$ to apply point-wise to the constituent nodes and edges.

By (C1), we have that for any $A_C \in \mathcal{A}(G/C)$, there exists exactly one incoming edge $(i \rightarrow c)$ to the cycle node $c$. We can use $\pi$ to infer where the cycle was broken with $\pi(i \rightarrow c) = (i \rightarrow j)$. We call $j$ the entrance site of $A_C$. Consequently, we can stitch together an arborescence as $\pi(A_C) \cup C^{(j)}$. We use the shorthand $A_C \bowtie C^{(j)}$ for this operation due to its visual similarity to unraveling a cycle.

$G/C$ may also have a critical cycle, so we have to apply this reasoning recursively. This is captured by Karp (1971)’s Theorem 1.

**Theorem 1.** For any graph $G$, either $G^* = \mathcal{G}$ or $G$ contains a critical cycle $C$ and $G^* = (G/C)^* \bowtie C^{(j)}$ where $j$ is the entrance site of $(G/C)^*$. Furthermore, $\overline{\pi}(G/C)^* = \overline{\omega}(G^*)$.

Theorem 1 suggests a recursive strategy for finding $G^*$, which is the basis of many efficient algorithms (Tarjan, 1977; Camerini et al., 1979; Georgiadis, 2003; Chu and Liu, 1965; Bock, 1971; Edmonds, 1967). We detail one such algorithm in Alg 1. Alg 1 can be made to run in $O(n^2)$ time for dense with the appropriate implementation choices, such as Union-Find (Hopcroft and Ullman, 1973) to maintain membership of nodes to contracted nodes, as well as radix sort (Knuth, 1973) to sort incoming edges to contracted nodes; using a regular sort would add a factor of $\log n$ to the runtime.

\[10\] We have lightly modified the original theorem. For completeness, App. A provides a proof in our notation.
2.2 Finding the best dependency tree

Gabow and Tarjan (1984) propose an algorithm that does additional recursion at the base case of \( \text{opt}(G) \) (the additional if-statement at Line 5) to recover \( G^\dagger \) instead of \( G^* \).

Suppose that the set of edges emanating from the root in \( \overrightarrow{G} \) is given by \( \sigma \) and \( |\sigma| > 1 \). We consider removing each edge in \( (\rho \rightarrow j) \in \sigma \) from \( G \). Since \( G \) may have multiple edges from \( \rho \) to \( j \), we write \( G_{\backslash e} \) to mean deleting all edges with the same edge points as \( e \). Let \( G' \) be the graph \( G_{\backslash e'} \) where \( e' \in \sigma \) is chosen greedily to maximize \( \pi(G') \). Consider the two possible cases:

*Optimization case.* If \( G' \) has no critical cycles, then \( \overrightarrow{G'} \) must be the best arborescence with one fewer edges emanating from the root than \( \overrightarrow{G} \) by our greedy choice of \( e' \).

*Reduction case.* If \( G' \) has a critical cycle \( C \), then all edges in \( C \) that do not point to \( j \) are in \( \overrightarrow{C} \). If \( e' \notin G^\dagger \), then \( C \) is critical cycle in the context of constrained problem and so we can apply Theorem 1 to recover \( G^\dagger \). Otherwise, \( e \in G^\dagger \) and we can break \( C \) from \( j \) to get \( C(j) \), which is comprised of edges in \( \overrightarrow{G} \). Therefore, we can find \( (G|j)^\dagger \) to retrieve \( G^\dagger \). This notion is formalized in the following theorem.\(^{11}\)

**Theorem 2.** For any graph \( G \) with \( G^* = \overrightarrow{G} \), let \( \sigma \) be the set of outgoing edges from \( \rho \) in \( G^* \). If \( |\sigma| = 1 \), then \( G^\dagger = G^* \). Otherwise, let \( G' = G'_{\backslash e'} \) for \( e' \in \sigma \) that maximizes \( \pi(G') \), then either \( G^\dagger = G^\dagger \) or there exists a critical cycle \( C \) in \( G' \) such that

\(^{11}\)For completeness, App. B provides a proof of Theorem 2.
Table 1: Average malformed rate, relative UAS change, and relative exact match score change for different data settings. The 63 languages are split by their training set size $|\text{train}|$ into high ($|\text{train}| \geq 10,000$), medium ($1,000 \leq |\text{train}| < 10,000$), and low ($|\text{train}| < 1,000$).

| Setting | # Languages | Malformed rate | Rel. $\triangle$ UAS | Rel. $\triangle$ Exact Match |
|---------|-------------|----------------|-----------------------|----------------------------|
| High    | 20          | 0.63%          | 0.0041%               | 0.15%                      |
| Medium  | 32          | 1.02%          | 0.0012%               | 0.22%                      |
| Low     | 11          | 6.21%          | 0.0368%               | 2.91%                      |

Figure 4: Relative change in UAS and exact match score when using the unconstrained and constrained algorithms for languages with varying training set sizes.

when using the constrained algorithm as opposed to the unconstrained algorithm.

Nevertheless, given less data, it is harder to learn to exploit the surface correlates; thus, we see an increasing average rate of violation, 6.21%, when examining languages with training set sizes of less than 1,000 sentences. Similarly, the relative change in UAS and exact match score increases to 0.0368% and 2.91% respectively. Indeed, the worst violation rate was 24% was seen for Kurmanji which only contains 20 sentences in the training set. Kurmanji consequently had the largest relative changes to both UAS and exact match scores of 0.41% and 22.22%. We break down the malformed rate and accuracy changes by training size in Tab. 1. Furthermore, the correlation between training size and malformed tree rate can be seen in Fig. 3 while the correlation between training size and relative accuracy change can be seen in Fig. 4. We provide a full table of the results in App. C.

4 Conclusion

In this paper, we have bridged the gap between the graph-theory and dependency parsing literature. We presented an efficient $O(n^2)$ for finding the maximum arborescence of a graph. Furthermore, we highlighted an important distinction between dependency trees and arborescences, namely that dependency trees are arborescences subject to a root constraint. Previous work uses inefficient algorithms to enforce this constraint. We provide a solution which runs in $O(n^2)$. Our hope is that this paper will remind future research in dependency parsing to please mind the root.

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A Proof of Theorem 1

To prove Theorem 1, we note a correspondence between graphs and contracted graphs.

**Proposition 1.** Given a rooted graph $G$ and a (not necessarily critical) cycle $C$ in $G$. For any $A \in \mathcal{A}(G)$ that has a single edge $e = (i \rightarrow j) \in A$ such that $i \notin C$ and $j \in C$, there exists $A_C \in \mathcal{A}(G_{|C})$ and $A' \in \mathcal{A}(G_{|C}^{(j)})$ such that $A = A_C \leftrightarrow A'$. Furthermore,

$$\overline{w}(A) = \overline{w}(A_C) - \overline{w}(C^{(j)}) + \overline{w}(A')$$

(4)

**Proof.** Since $e$ is the only edge in $A$ from a non-cycle node to a cycle node (enter), every edge $e' \in G_{|C}$ such that $\pi(e') \in A$ forms an arborescence $A_C \in \mathcal{A}(G_{|C})$. Note that the set of edges in $A$ for which there is no corresponding edge in $G_{|C}$ are dead edges. In fact, as $A$ satisfies (C1), these edges form an arborescence $A' \in \mathcal{A}(G_{|C}^{(j)})$. Therefore, $A = A_C \leftrightarrow A'$.

Furthermore, consider the weight of $A$:

$$\overline{w}(A) = \sum_{(i \rightarrow j') \in \pi(A_C)} w' + \overline{w}(A')$$

(5)

$$= \sum_{(i \rightarrow j') \in \pi(A_C \setminus \{e\})} w' + w + \overline{w}(A')$$

(6)

$$= \sum_{(i \rightarrow j') \in \pi(A_C \setminus \{e\})} w' + w + \overline{w}(A')$$

(7)

$$= \sum_{(i \rightarrow j') \in A_C} w' - \overline{w}(C^{(j)}) + \overline{w}(A')$$

(8)

$$= \overline{w}(A_C) - \overline{w}(C^{(j)}) + \overline{w}(A')$$

(9)

Note that (7) follows because $e$ is the only edge in $A$ from a non-cycle node to a cycle node, and (8) follows by the construction of enter edges in $G_{|C}$.

As a corollary, we also have that every arborescence in the contracted graph $G_{|C}$ can be expanded into an arborescence in $G$.

**Corollary 1** (Expansion lemma). Given a rooted graph $G$ with a cycle $C$, every arborescence $A_C \in \mathcal{A}(G_{|C})$ is related to an arborescence $A \in \mathcal{A}(G)$ by $A = A_C \leftrightarrow C^{(j)}$ where $j$ is the entrance site of $A_C$. Furthermore, $\overline{w}(A) = \overline{w}(A_C)$.

**Proof.** Let $j$ be the entrance site of $A_C$ into $C$. As $A_C \in \mathcal{A}(G_{|C})$ and $C^{(j)} \in \mathcal{A}(G_{|C}^{(j)})$, Proposition 1 constructs $A \in \mathcal{A}(G)$ as desired. Furthermore, $\overline{w}(A) = \overline{w}(A_C) - \overline{w}(C^{(j)}) + \overline{w}(C^{(j)}) = \overline{w}(A_C)$.

Note that Proposition 1 does not account for all arborescences in $\mathcal{A}(G)$. We next show that such arborescences which cannot be constructed using Proposition 1 will never be $G^*$.

**Lemma 1.** Given a rooted graph $G$ with a critical cycle $C$. We have that for all $j \in C$

$$G_C^{(j)^*} = C^{(j)}$$

(10)

**Proof.** Since $G_C^{(j)}$ is a subgraph of $G$ it must be that $\overline{G}_C^{(j)}$ is also a subgraph of $\overline{G}_C$. Since $C$ is a critical cycle, $C^{(j)}$ does not have cycles and equals $\overline{G}_C^{(j)}$. Therefore $C^{(j)} = G_C^{(j)^*}$.

**Lemma 2.** Given a rooted graph $G$ with a critical cycle $C$ and $A \in \mathcal{A}(G)$. If $e = (i \rightarrow j) \in A$ and $e' = (i' \rightarrow j')$ such that $i, i' \notin C$ and $j, j' \in C$, then there exists a $A' \in \mathcal{A}(G)$ with $e \in A'$ and $e' \notin A'$ such that $\overline{w}(A) \leq \overline{w}(A')$. 
Proof. Construct $A'$ such that for every edge $e'' = (i'' \rightarrow j'') \in G_{C}$, if $j'' \neq c$ and $\pi(e'') \in A$, then $\pi(e'') \in A'$. Additionally, let $e$ be in $A'$ as well as the edges in $C^{(j)}$. Then $A'$ has no cycles and each non-root node contains a single incoming edge, so $A' \in \mathcal{A}(G)$. Since $A$ and $A'$ contain identical edges except for those pointing to nodes in $C \setminus \{j\}$, by Lemma 1, $\overline{w}(A) \leq \overline{w}(A')$.

Theorem 1. For any graph $G$, either $G^* = \overrightarrow{G}$ or $G$ contains a critical cycle $C$ and $G^* = (G_{C})^* \leftarrow C^{(j)}$ where $j$ is the entrance site of $(G_{C})^*$. Furthermore, $\overline{w}(G_{C}^*) = \overline{w}(G^*)$.

Proof. There are two cases to consider.

Case 1: $G$ does not contain a critical cycle. Trivially, $G^* = \overrightarrow{G}$.

Case 2: $G$ contains a critical cycle $C$. By Corollary 1, we can construct an arborescence $A = (G_{C})^* \leftarrow C^{(j)} \in \mathcal{A}(G)$, we now prove that no other $A' \in \mathcal{A}(G)$ can have a higher weight. Firstly, by Lemma 2, we only need to consider $A'$ that satisfy Proposition 1. Therefore, $A'$ must be decomposable into an arborescence $A_C \in \mathcal{A}(G_{C})$ and an arborescence in $\mathcal{A}(G_{C}^{(j)})$ where $j'$ is the entrance site of $A_C$. Then since $(G_{C})^*$ is optimal, we have that $A_C = (G_{C})^*$ and $j' = j$. As $C^{(j)}$ is optimal (by Lemma 1), $A$ must also be optimal and so $G^* = (G_{C})^* \leftarrow C^{(j)}$. \qed
B Proof of Theorem 2

We prove Theorem 2 by showing that both the optimization and reduction cases described in the main text lead to progress towards finding $G^\dagger$.

**Lemma 3.** For any graph $G$ with $G^* = \vec{G}$, let $\sigma$ be the set of outgoing edges from $\rho$ in $\vec{G}$. If $|\sigma| > 1$, let $G' = G_\setminus e'$ for $e' \in \sigma$ that maximizes $\overline{\pi}(G')$. If there exists a critical cycle $C$ in $G'$, then $G^\dagger = (G_{j/C})^\dagger \ni C^{(j)}$ where $j$ is the entrance site of $(G_{j/C})^\dagger$.

**Proof.** Let $e' = (\rho \rightarrow i)$ and $e \in G_{j/C}$ such that $\pi(e) = e'$. We know that $e$ always exists as $e'$ emanates from the root. By Corollary 1, we know that $A = (G_{j/C})^\dagger \ni C^{(j)} \in A(G)$ where $j$ is the entrance site of $(G_{j/C})^\dagger$. Furthermore, As $C$ has no edges emanating from the root, $A \in A^1(G)$. There are two cases to consider:

Case 1 ($e \in (G_{j/C})^\dagger$): As $C^{(j)}$ is a subgraph of $\vec{G}$, $A$ must have the highest weight in $A^1(G)$, so $G^\dagger = A$.

Case 2 ($e \notin (G_{j/C})^\dagger$): Then $e'$ cannot be in $G^\dagger$, and the edge pointing to $i$ in $C$ is the next best possible edge incoming to $j$. Therefore, whichever way we break $C$ in $A$, we will get a set of edges with maximal weight and so $G^\dagger = A$.

**Lemma 4.** For any graph $G$ with $G^* = \vec{G}$, let $\sigma$ be the set of outgoing edges from $\rho$ in $\vec{G}$. If $|\sigma| > 1$, let $G' = G_\setminus e'$ for $e' \in \sigma$ that maximizes $\overline{\pi}(G')$. Either $G^\dagger = G'^\dagger$ or there exists a critical cycle $C$ in $G'$ such that $G^\dagger = (G_{j/C})^\dagger \ni C^{(j)}$ where $j$ is the entrance site of $(G_{j/C})^\dagger$.

**Proof.** Let $j$ be the entrance site of $(G_{j/C})^\dagger$. Proof by induction on $r = |\sigma|$.

Base case ($r = 2$): If $G'$ does not contain a critical cycle, then clearly $G'^\dagger = G'^*$ since we choose $e'$ to maximize $\overline{\pi}(G')$ and $G'$ is a subgraph of $G$, $G'^\dagger = G'^\dagger$. Otherwise, $G'$ has a critical cycle $C$. Then by Lemma 3, $G^\dagger = (G_{j/C})^\dagger \ni C^{(j)}$.

Inductive case ($r > 2$): Let $e'$ be the set of outgoing edge from $\rho$ in $\vec{G}$. Then clearly $|\sigma'| = r - 1 > 1$. If $G'$ does not contain a critical cycle, then $G'^* = G$ and we satisfy the induction hypothesis. Otherwise, $G'$ has a critical cycle $C$. Then by Lemma 3, $G^\dagger = (G_{j/C})^\dagger \ni C^{(j)}$.

**Theorem 2.** For any graph $G$ with $G^* = \vec{G}$, let $\sigma$ be the set of outgoing edges from $\rho$ in $G^*$. If $|\sigma| = 1$, then $G^\dagger = G^*$, otherwise if $G' = G_\setminus e'$ for $e' \in \sigma$ that maximizes $\overline{\pi}(G')$, then either $G^\dagger = G'^\dagger$ or there exists a critical cycle $C$ in $G'$ such that $G^\dagger = (G_{j/C})^\dagger \ni C^{(j)}$ where $j$ is the entrance site of $(G_{j/C})^\dagger$.

**Proof.** There are two cases to consider.

Case 1 ($|\sigma| = 1$): Then $G^*$ has one edge emanating from the root so clearly $G^\dagger = G^*$.

Case 2 ($|\sigma| > 1$). This is immediate from Lemma 4.
### Decoding UD Treebanks

| Language       | | | Malformed Rate | Rel. ∆ UAS | Rel. ∆ Exact Match |
|----------------| | | | | |
| Czech          | 68495 | 10148 | 0.45% | 0.000% | 0.052% |
| Russian        | 48814 | 6491  | 0.49% | 0.000% | 0.027% |
| Estonian       | 24633 | 3214  | 0.93% | 0.000% | 0.448% |
| Korean         | 23010 | 2287  | 0.96% | 0.008% | 0.366% |
| Latin          | 16809 | 2101  | 0.52% | 0.018% | 0.151% |
| Norwegian      | 15696 | 1939  | 0.52% | -0.014% | 0.000% |
| Ancient Greek  | 15014 | 1047  | 0.57% | 0.026% | 0.186% |
| French         | 14450 | 416   | 1.68% | -0.021% | 0.546% |
| Spanish        | 14305 | 1721  | 0.17% | 0.002% | 0.000% |
| Old French     | 13909 | 1927  | 0.52% | 0.031% | 0.145% |
| German         | 13814 | 977   | 1.54% | 0.040% | 0.495% |
| Polish         | 13774 | 1727  | 0.00% | 0.000% | 0.000% |
| Hindi          | 13304 | 1684  | 0.18% | -0.009% | 0.000% |
| Catalan        | 13123 | 1846  | 0.54% | 0.002% | 0.000% |
| Italian        | 13121 | 482   | 0.21% | -0.010% | 0.000% |
| English        | 12543 | 2077  | 0.48% | 0.004% | 0.217% |
| Dutch          | 12264 | 596   | 0.67% | 0.039% | 0.000% |
| Finnish        | 12217 | 1555  | 0.39% | -0.010% | 0.000% |
| Classical Chinese | 11004 | 2073  | 0.96% | -0.010% | 0.304% |
| Latvian        | 10156 | 1823  | 0.88% | -0.012% | 0.000% |
| Bulgarian      | 8907  | 1116  | 0.27% | 0.000% | 0.000% |
| Slovak         | 8483  | 1061  | 0.38% | 0.008% | 0.000% |
| Portuguese     | 8328  | 477   | 0.42% | 0.000% | 0.000% |
| Romanian       | 8043  | 729   | 0.41% | 0.000% | 0.000% |
| Japanese       | 7125  | 550   | 0.00% | 0.000% | 0.000% |
| Croatian       | 6914  | 1136  | 0.88% | 0.027% | 0.000% |
| Slovenian      | 6478  | 788   | 0.38% | -0.022% | 0.000% |
| Arabic         | 6075  | 680   | 0.29% | 0.004% | 0.000% |
| Ukrainian      | 5496  | 892   | 0.90% | 0.032% | 0.000% |
| Basque         | 5396  | 1799  | 0.67% | 0.018% | 0.000% |
| Hebrew         | 5241  | 491   | 1.02% | 0.009% | 0.556% |
| Persian        | 4798  | 600   | 0.67% | -0.007% | 0.000% |
| Indonesian     | 4477  | 557   | 1.26% | -0.029% | 0.000% |
| Danish         | 4383  | 565   | 0.53% | -0.011% | 0.000% |
| Swedish        | 4303  | 1219  | 1.23% | 0.021% | 0.988% |
| Old Church Slavonic | 4124 | 1141  | 1.05% | 0.000% | 0.128% |
| Urdu           | 4043  | 535   | 1.12% | -0.029% | 0.000% |
| Chinese        | 3997  | 500   | 1.80% | -0.020% | 0.000% |
| Turkish        | 3664  | 983   | 2.54% | 0.080% | 0.513% |
| Gothic         | 3387  | 1029  | 0.78% | 0.011% | 0.000% |
| Serbian        | 3328  | 520   | 0.19% | 0.009% | 0.446% |
| Galician       | 2272  | 861   | 1.16% | 0.011% | 1.282% |
| North Sami     | 2257  | 865   | 1.27% | 0.000% | 0.230% |
| Armenian       | 1975  | 278   | 0.00% | 0.000% | 0.000% |
| Greek          | 1662  | 456   | 0.44% | 0.020% | 0.565% |
| Uyghur         | 1656  | 900   | 0.56% | 0.024% | 0.309% |
| Vietnamese     | 1400  | 800   | 3.38% | -0.076% | 0.000% |
| Afrikaans      | 1315  | 425   | 6.35% | 0.011% | 1.460% |
| Wolof          | 1188  | 470   | 1.49% | -0.021% | 0.625% |
| Maltese        | 1123  | 518   | 0.58% | -0.010% | 0.000% |
| Telugu         | 1051  | 146   | 0.00% | 0.000% | 0.000% |
| Scottish Gaelic| 1015  | 536   | 0.75% | -0.024% | 0.000% |
| Hungarian      | 910   | 449   | 4.23% | 0.022% | 0.000% |
| Irish          | 858   | 454   | 2.42% | 0.000% | 0.000% |
| Tamil          | 400   | 120   | 0.00% | 0.000% | 0.000% |
| Marathi        | 373   | 47    | 2.13% | 0.000% | 0.000% |
| Belarusian     | 319   | 253   | 0.79% | 0.024% | 0.000% |
| Lithuanian     | 153   | 55    | 7.27% | -0.317% | 0.000% |
| Kazakh         | 31    | 1047  | 2.58% | -0.016% | 3.226% |
| Upper Sorbian  | 23    | 623   | 6.42% | 0.178% | 2.439% |
| Kurmanji       | 20    | 734   | 23.57% | 0.405% | 22.222% |
| Buryat         | 19    | 908   | 6.61% | 0.107% | 4.082% |
| Livvi          | 19    | 106   | 12.26% | 0.000% | 0.000% |

Table 2: Accompanying table for §3