Abstract

We propose a transition-based approach that, by training a single model, can efficiently parse any input sentence with both constituent and dependency trees, supporting both continuous/projective and discontinuous/non-projective syntactic structures. To that end, we develop a Pointer Network architecture with two separate task-specific decoders and a common encoder, and follow a multitask learning strategy to jointly train them. The resulting quadratic system, not only becomes the first parser that can jointly produce both unrestricted constituent and dependency trees from a single model, but also proves that both syntactic formalisms can benefit from each other during training, achieving state-of-the-art accuracies in several widely-used benchmarks such as the continuous English and Chinese Penn Treebanks, as well as the discontinuous German NEGRA and TIGER datasets.

1 Introduction

Two widely-known formalisms are commonly used to represent the syntactic structure of sentences in human languages: constituent and dependency representations.

Constituent trees, which are commonly used in tasks where span information is crucial, describe the syntax of a sentence in terms of constituents and their hierarchical order. We can find two kinds of constituent trees: continuous and discontinuous (described in Figure 1(a) and (d), respectively). The latter extend the former by allowing crossing branches and constituents with gaps in the middle. These are necessary for describing some wh-movement, long-distance extractions, dislocations, cross-serial dependencies and other linguistic phenomena common in free word order languages such as German (Müller, 2004).

On the other hand, a dependency tree straightforwardly connects each word of a sentence as a dependent of another, which is considered its head word. This structure composed of binary syntactic dependencies is known for representing information closer to semantic relations and can be classified as projective or non-projective (depicted in Figure 1(c) and (f), respectively). Non-projective dependency trees allow crossing dependencies, and can model the same linguistic phenomena described by discontinuous constituent trees.

Since the information described in a constituent tree cannot be fully represented in a dependency tree and vice versa (Kahane and Mazziotta, 2015), typically parsers are exclusively trained to produce either dependency or constituent structures and, in some cases, restricted to the less complex continuous/projective representations.

There are a few exceptions, i.e., approaches trained to generate both constituents and dependencies. For instance, the chart parser of Zhou and Zhao (2019) generates continuous and projective structures with a single $O(n^5)$ model, and the sequence labeling parser of Strzyz et al. (2019a) combines continuous constituents with non-projective dependency structures. In both cases, which are discussed in more detail in Section 5, representations are shown to benefit each other in terms of accuracy.

However, to our knowledge, no such joint training approaches have been defined that support both non-projective dependency trees and discontinuous constituents; and the most accurate and least computationally complex models for these formalisms are single-representation approaches: graph-based (Dozat and Manning, 2017) and transition-based (Ma et al., 2018; Fernández-González and Gómez-Rodríguez, 2019) models for non-projective dependencies, and transition-based parsers (Coavoux et al., 2019; Coavoux and Cohen, 2019; Fernández-González and Gómez-Rodríguez, 2020) for discontinuous phrase-structure trees.
In order to fill this gap, we propose a novel multitask transition-based parser that can efficiently generate unrestricted constituent and dependency structures (i.e., discontinuous constituents and non-projective dependencies, although it can also be restricted to continuous/projective structures if desired) from a single trained model. We design an encoder-decoder neural architecture that is jointly trained across the syntactic information represented in the two formalisms by following a multitask learning strategy (Caruana, 1997). Inspired by (Fernández-González and Gómez-Rodríguez, 2020), we model constituent trees as augmented dependency structures (Fernández-González and Martins, 2015) and use two separate task-specific decoders to produce both augmented and augmented dependency trees. Each decoder relies on Pointer Networks (Vinyals et al., 2015) and a biaffine classifier (Dozat and Manning, 2017) to incrementally generate labelled dependencies from left to right, as proposed by Fernández-González and Gómez-Rodríguez (2019). Finally, the decoding runtime (\(O(n^2)\)) and the required memory space of our multi-representational approach remains the same as the single-task dependency parser by Fernández-González and Gómez-Rodríguez (2019), since a single model is trained and the multitask learning strategy has no impact on decoding time, allowing both decoders to be run in parallel.

We test our multi-representational neural model\(^1\) on the continuous English and Chinese Penn Treebanks (Marcus et al., 1993; Xue et al., 2005) and on the discontinuous NEGRA (Skut et al., 1997) and TIGER (Brants et al., 2002) datasets. In all benchmarks, our approach outperforms single-task parsers (Fernández-González and Gómez-Rodríguez, 2019; Fernández-González and Gómez-Rodríguez, 2020), which proves that learning across regular dependency trees and constituent information (encoded in dependency structures) leads to gains in accuracy in both tasks, obtaining competitive results in all cases and surpassing the current state of the art in several datasets.

2 Constituent trees as dependency structures

Since our multitask approach is based on the dependency parser by Fernández-González and Gómez-Rodríguez (2019), constituent trees must be represented as dependencies in order to be processed. This was recently explored for neural discontinuous constituent parsing (Fernández-González and Gómez-Rodríguez, 2020) by using the encoding by Fernández-González and Martins (2015). In this work, we extend it to continuous phrase-structure datasets, where the non-negligible frequency of unary nodes requires additional processing.

Let \(w_1, w_2, \ldots, w_n\) be a sentence (where \(w_i\) denotes the word at position \(i\)). A constituent tree is composed of these \(n\) words as leaf nodes plus phrases (or constituents) as internal nodes. Each constituent can be represented as a tuple \((X, C, w_h)\), where \(X\) is a non-terminal symbol, \(C\) is the set of words \(w_i\) included in its span, and \(w_h\) is the word in \(C\) that acts as head, which can be selected by using a language-specific handwritten set of rules. For instance, the head word of constituents S and VP in Figure 1(a) is the word is. Furthermore, we say that a constituent tree is continuous if the set \(C\) of each of its constituents is a continuous substring of the sentence. Otherwise, the tree is classified as discontinuous, and then there is at least one constituent with a span that is interrupted by one or more gaps between its words. For instance, the span of constituent (NP, \{Es, nicht, Interessantes\}, Interessantes) in Figure 1(d) is interrupted by the word kam from a different constituent, generating crossing branches. Finally, constituents with exactly one child are known as unary constituents (for instance, ROOT, NP, ADVP and ADJP in Figure 1(a)).

On the other hand, a dependency tree is a directed tree whose nodes are the words \(w_i\) of the sentence. Each dependency arc is represented as \((w_h, w_d, l)\), where \(w_h\) is the head word of the dependent word \(w_d\) \((h, d \in [1, n])\) and \(l\) a dependency label. Additionally, an artificial ROOT node is used to attach the actual root word. If, for every dependency arc \((w_h, w_d, l)\), there is a directed path from \(w_h\) to all words \(w_i\) between words \(w_h\) and \(w_d\), the dependency tree is projective. If not, it is considered a non-projective dependency tree, as the one with crossing arcs depicted in Figure 1(f).

Fernández-González and Martins (2015) designed an encoding technique to represent a unariless constituent tree with \(m\) words as a set of \(m-1\) labelled dependency arcs with enriched information (plus an arc from root), where discontinuous phrase structures are encoded as non-projective dependency trees and continuous structures as projective.

\(^1\)Source code available at https://github.com/danifg/MultiPointer.
She is still cautious.

Figure 1: Constituent, augmented and regular dependency representations of continuous English and discontinuous German sentences. Head words of constituent trees are marked in bold.

jective trees, as shown in Figure 1(b) and (e) for constituent trees in Figure 1(a) and (d), respectively. To that end, for each constituent \((X, C, w_h)\), each non-head child node (which can be a word \(w_d\) or a constituent \((Y, G, w_d)\) with \(w_d \neq w_h\)) is encoded into the unlabelled dependency arc \((w_h, w_d)\). Additionally, these dependencies are augmented with an arc label that includes the non-terminal symbol \(X\) plus an index \(k\) that indicates the hierarchical order in which nodes are built, resulting in labelled dependency arcs with the form \((w_h, w_i, X \#k)\). Index \(k\) is necessary for those cases where more than one constituent share the same head word, but they are at a different level in the tree. For instance, constituent \((NP, \{nichts, Interessantes\}, Interessantes)\) in Figure 1(d) is encoded as the augmented dependency arc \((Interessantes, nichts, NP\#1)\) in Figure 1(e); and constituent \((NP, \{Es, nichts, Interessantes\}, Interessantes)\) is represented with \((Interessantes, Es, NP\#2)\). Both constituents share the same head word \(Interessantes\), but they are attached in a different level.

Finally, unary constituents are not directly supported by this encoding strategy. While Fernández-González and Martins (2015) proposed to remove all unary nodes and recover them in a post-processing step, we decided to incorporate unary constituents into the resulting augmented dependency tree by collapsing non-leaf unary chains (for instance, ROOT from Figure 1(a) into ROOT+S) and saving leaf unary nodes lost after the encoding by assigning them to words (as can be seen in Figure 1(b) for NP, ADVP and ADJP).

Original constituent trees can be easily decoded from augmented dependencies by, starting from the root word and continuing through outgoing dependencies, building constituents according to the hierarchical order dictated by index \(k\). It is worth noting that, while Penn Treebanks present a significant amount of unary constituents, they are very uncommon in discontinuous datasets: NEGRA has no unaries at all and TIGER has less than 1%.

Therefore, we only perform unary recovery in Penn Treebanks, by uncollapsing unary chains from arc labels and assigning leaf unary nodes with a neural sequence tagger (Yang and Zhang, 2018) in a post-processing step.²

Although both the constituent-based and regular dependency structures are directed trees of \(n\) nodes, each provides exclusive information: span phrase information is included in arc labels of the augmented variants, and regular dependency labels provide additional semantic information not described in phrase-structure trees. Furthermore, regular dependency trees differ from augmented ones, not only in the label set, but also in the conversion process. Although dependency trees are often generated from constituent trees, different head-rule sets and transformations can be applied

²The tagger assigns to each word a possible leaf unary node seen in the training dataset or the tag NONE if there is no unary node above that word.
in that process. This is the reason why dependency structures in Figure 1(b) and (c) are different: in our constituent-to-dependency encoding we use the head-rule set by Collins (1999), while regular dependency trees were obtained following the Stanford Dependencies conversion (de Marneffe and Manning, 2008). This will train the parser across a broader variety of syntactic representations and notations.

Figure 2: Simplified sketch of our multitask neural architecture and decoding steps to parse the sentence in Figure 1(a). Decoder 0 and Decoder 1 perform constituent-based and regular dependency parsing, respectively.

3 Multitask Neural Architecture

To develop a neural network capable of producing state-of-the-art, unrestricted constituent and dependency parses, we join two transition-based parsers recently presented under the same architecture: (Fernández-González and Gómez-Rodríguez, 2019) for non-projective dependency parsing, and (Fernández-González and Gómez-Rodríguez, 2020), an extension of the former that can produce discontinuous constituent trees. As explained before, we additionally extend the latter to also deal with continuous phrase structures and unary constituents.

(Fernández-González and Gómez-Rodríguez, 2019) relies on Pointer Networks (Vinyals et al., 2015) to perform unlabelled dependency parsing. After learning the conditional probability of an output sequence of discrete numbers that correspond to positions from an input sequence, these encoder-decoder neural networks use a mechanism of attention (Bahdanau et al., 2014) to select positions from the input, without requiring a fixed size of the output dictionary. Thanks to them and starting at the first word of a sentence of length \( n \), the transition-based approach by Fernández-González and Gómez-Rodríguez (2019) sequentially attaches, from left to right, the current focus word to the pointed head word, incrementally building a well-formed dependency tree in just \( n \) steps. From a transition-based perspective, this can be seen as a sequence of \( n \) SHIFT-ATTACH-\( p \) transitions, each of which connects the current focus word to the head word in the pointed position \( p \), and then moves the focus to the next word. In addition, a biaffine classifier (Dozat and Manning, 2017) jointly trained is used for predicting dependency labels.

Inspired by (Fernández-González and Gómez-Rodríguez, 2019), we introduce a novel neural architecture with two task-specific decoders: each word of the input sentence is attached to its regular head by the first decoder, and to its augmented dependency head by the second decoder. Additionally, each decoder provides a biaffine classifier trained on its task-specific label set. Since both decoders are aligned, the resulting system requires just \( n \) steps to dependency and constituent parse a sentence of length \( n \), easily allowing joint training.

More specifically, our neural architecture is composed of:

**Shared Encoder** Each input sentence \( w_1, \ldots, w_n \) is encoded by a BiLSTM-CNN architecture (Ma and Hovy, 2016), word by

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\(^3\)Constituent trees are obtained after decoding resulting augmented dependency trees.
word, into a sequence of encoder hidden states \( h_1, \ldots, h_n \). A CNN is used for extracting character-level representations of words (\( e_i^c \)) and this is concatenated with word embeddings (\( e_i^w \)) to represent each input word \( w_i \). Additionally, POS tag embeddings (\( e_i^p \)) are used when gold POS tags are available:4

\[
\mathbf{x}_i = e_i^c \oplus e_i^w \oplus e_i^p
\]

Then, the word representation \( \mathbf{x}_i \) is fed one-by-one into a BiLSTM that captures context information in both directions and generates a vector representation \( \mathbf{h}_i \):

\[
\mathbf{h}_i = \mathbf{h}_{t_i} \oplus \mathbf{h}_{r_i} = \text{BiLSTM}(\mathbf{x}_i)
\]

Finally, a special vector representation \( \mathbf{h}_0 \), denoting the ROOT node, is prepended at the beginning of the sequence of the encoder hidden states.

**Task-specific Decoders** Each decoder \( d \) is implemented by a separate LSTM that, at each time step \( t \), receives as input the encoder hidden state \( \mathbf{h}_i \) of the current focus word \( w_i \) and generates a decoder hidden state \( \mathbf{s}^{d_t} \):

\[
\mathbf{s}^{d_t} = \text{LSTM}_d(\mathbf{h}_i)
\]

Additionally, a pointer layer is implemented for each decoder by an attention vector \( \mathbf{a}^{d_t} \) to perform unlabelled parsing. This vector is generated by computing scores for all possible head-dependent pairs between the current focus word (represented by \( \mathbf{s}_t^d \)) and each word from the input (represented by encoder hidden representations \( \mathbf{h}_j \) with \( j \in [0, n] \)). To that end, a scoring function based on the biaffine attention mechanism by (Dozat and Manning, 2017) is used and, then, a probability distribution over the input words is computed:

\[
\mathbf{v}^{d}_{lj} = \text{score}(\mathbf{s}^{d_t}_t, \mathbf{h}_j) = f_1(s^{d_t}_t)^T W f_2(h_j)
+ U^T f_1(s^{d_t}_t) + V^T f_2(h_j) + \mathbf{b};
\]

\[
\mathbf{a}^{d_t} = \text{softmax}(\mathbf{v}^{d}_{lj})
\]

where parameter \( W \) is the weight matrix of the bilinear term, \( U \) and \( V \) are the weight tensors of the linear terms, \( \mathbf{b} \) is the bias vector and \( f_1(\cdot) \) and \( f_2(\cdot) \) are two single-layer multilayer perceptrons (MLP) with ELU activation (Dozat and Manning, 2017).

Each attention vector \( \mathbf{a}^{d_t} \) will serve as a pointer to the highest-scoring position \( p \) from the input, leading the parsing algorithm to create a dependency arc from the head word \( (w_p) \) to the current focus word \( (w_i) \). In case this dependency arc is forbidden due to the acyclicity constraint, the next highest-scoring position in \( \mathbf{a}^{d_t} \) will be considered as output instead. Furthermore, the projectivity constraint is also enforced when processing continuous treebanks, discarding arcs that produce crossing dependencies.

Finally, each decoder trains a labeler layer (implemented as a multi-class classifier) to predict arc labels and produce a labelled dependency tree. In particular, after the pointer layer attaches the pointed head word \( (w_p) \) to the current focus word \( (w_i) \), this layer uses the same scoring function as the pointer to compute the score of each possible label for that arc and assign the highest-scoring one:

\[
\mathbf{u}^{dp}_{tp} = \text{score}(\mathbf{a}^{d_t}, \mathbf{h}_p, l) = g_1(s^{d_t}_t)^T W g_2(h_p)
+ U^T g_1(s^{d_t}_t) + V^T g_2(h_p) + \mathbf{b}_l
\]

where a distinct weight matrix \( W_l \), weight tensors \( U_l \) and \( V_l \) and bias \( \mathbf{b}_l \) are used for each label \( l \), where \( l \in \{1, 2, \ldots, L\} \) and \( L \) is the number of labels. In addition, \( g_1(\cdot) \) and \( g_2(\cdot) \) are two single-layer MLPs with ELU activation.

Figure 2 depicts the multitask neural architecture and the decoding procedure for parsing the sentence in Figure 1(a). The described transition-based algorithm can process unrestricted non-projective sentences in \( O(n^2) \) time complexity, since each decoder \( d \) requires \( n \) attachments to successfully parse a sentence with \( n \) words, and at each step the attention vector \( \mathbf{a}^{d_t} \) is computed over the whole input.

**Multitask Training** We follow a multitask learning strategy (Caruana, 1997), where a single neural architecture is jointly trained for more than one task by optimizing the sum of their objectives and sharing a common encoder representation.

As both tasks use a dependency representation, the training objective of the pointer of each decoder is to learn the probability \( P_O(y|x) \), where \( y \) is the correct unlabelled dependency tree for a given sentence \( x \): \( P_O(y|x) \). This probability can

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4As noticed by Ma et al. (2018); Fernández-González and Gómez-Rodríguez (2020), the usage of predicted POS tags does not lead to gains in accuracy. Therefore, we only use POS tags in experimental settings where they are gold.

5Unlike (Fernández-González and Gómez-Rodríguez, 2019), we do not use other encoder hidden states as extra feature information for the decoder, since we noticed that practically the same accuracy can be achieved with this simple framework.
be factorized to a set of head-dependent pairs as follows:

\[ P_\theta(y|x) = \prod_{i=1}^{n} P_\theta(a_i|a_{<i}, x) \]

\[ = \prod_{i=1}^{n} P_\theta(w_i|w_h, a_{<i}, x) \]

where \( a_i \) denotes each arc of the dependency tree \( y \) that connects each word \( w_i \) to the head word \( w_h \) following a left-to-right order, and \( a_{<k} \) represents previous predicted arcs. We minimize the negative log of this probability implemented as cross-entropy loss:

\[ \mathcal{L}_\text{pointer}^d = -\log P_\theta(w_h|w_i, a_{<i}, x) \]

Additionally, the labeler of each decoder is trained with softmax cross-entropy to minimize the negative log likelihood of assigning the correct label \( l \), given a dependency arc with head word \( w_h \) and dependent word \( w_i \):

\[ \mathcal{L}_\text{labeler}^d = -\log P_\theta(l|w_h, w_i) \]

Then, the whole neural model is jointly trained by summing the pointer and labeler losses of each decoder:

\[ \mathcal{L} = \mathcal{L}_\text{pointer}^\text{const} + \mathcal{L}_\text{labeler}^\text{const} + \mathcal{L}_\text{pointer}^\text{dep} + \mathcal{L}_\text{labeler}^\text{dep} \]

Finally, since both are considered main tasks and our goal is to train exclusively a single model, we neither use weights nor perform auxiliary-task training.

4 Experiments

4.1 Data

To test our approach, we focus on parallel data, where both constituent and dependency representations are available. In particular, we conduct experiments on well-known continuous datasets: the English Penn Treebank (PTB) (Marcus et al., 1993) and its Stanford Dependencies (de Marneffe and Manning, 2008) conversion (using the Stanford parser v3.3.0)\(^6\) with standard splits; and the Chinese Penn Treebank 5.1 (Xue et al., 2005) and its converted dependency variant (Zhang and Clark, 2008) with gold POS tags and two different splits: ZCTB (Zhang and Clark, 2008), for dependency parsing, and LCTB (Liu and Zhang, 2017b), commonly used for constituent parsing. In addition, we test our approach on two widely-used discontinuous German treebanks and their available non-projective dependency representations: NEGRA (Skut et al., 1997) with standard splits (Dubey and Keller, 2003) and TIGER (Brants et al., 2002) with the split provided in the SPMRL14 shared task (Seddah et al., 2013; Crabbé, 2014). For both datasets, we report results with and without gold POS tags.

For the constituent-to-dependency encoding, we apply the head-rule sets by (Rehbein, 2009) to identify head words in German constituent structures and (Collins, 1999) and (Zhang and Clark, 2008) for English and Chinese, respectively. The resulting augmented dependencies match regular variants by around 70% in all languages, except for Chinese where the unlabelled augmented and regular dependency trees are exactly the same.

Following standard practice, we discard punctuation for evaluating on both Penn Treebanks, using the EVALB script to report constituent accuracy. Furthermore, while we use disco-dop\(^7\) (van Cranenburgh et al., 2016) and ignore punctuation and root symbols for evaluating on discontinuous constituent treebanks, all tokens are considered when reporting dependency performance on German datasets.

4.2 Settings

Word vectors are initialized with pre-trained structured-skipgram embeddings (Ling et al., 2015) for all languages and character and POS tag embeddings are randomly initialized. All of them are fine-tuned during training. POS tag embeddings are only enabled when gold information is used.

Additionally, we report accuracy gains by augmenting our model with deep contextualized word embeddings from the pre-trained language model BERT (Devlin et al., 2019). We avoid fine-tuning the whole BERT model for our specific tasks and follow a greener and less resource-consuming approach: we feed fixed weights directly extracted from BERT as input of the shared encoder. In Appendix A.1, we describe how these weights are obtained.

In each training epoch, we use the same number of examples from each task and choose the mult-
Table 1: Accuracy comparison of single-task baseline parsers to the proposed multi-representational approach in both constituent and dependency parsing. We report Labeled Attachment Scores (LAS) and Unlabeled Attachment Scores (UAS) for dependency parsing and, for constituent parsing, the LAS on the augmented dependency trees and F-score on the post-decoding constituent structure.

| Treebank       | Single-Dep.  | Single-Const.     | Multi-Representational |
|---------------|--------------|------------------|------------------------|
|                | UAS | LAS | F1 (LAS) | UAS | LAS | F1 (LAS) |
| PTB            | 96.06 | 94.50 | 93.29 (93.57) | 96.25 | 94.64 | 93.67 (93.93) |
| LCTB           | 93.26 | 92.67 | 88.28 (88.49) | 93.40 | 92.88 | 88.65 (88.61) |
| ZCTB           | 90.61 | 89.51 | 86.01 (84.38) | 90.79 | 89.69 | 86.09 (84.43) |
| NEGRA          | 94.71 | 93.87 | 86.42 (92.22) | 94.80 | 94.05 | 87.30 (92.68) |
| NEGRA          | 94.20 | 93.19 | 85.65 (91.36) | 94.33 | 93.33 | 86.78 (91.85) |
| TIGER          | 94.24 | 92.86 | 86.74 (91.81) | 94.31 | 92.90 | 87.25 (92.22) |
| TIGER          | 93.73 | 92.27 | 85.96 (90.89) | 93.85 | 92.35 | 86.61 (91.36) |

4.3 Results and Discussion

In Table 1, we compare our own implementation of the single-task dependency and constituent parsers by Fernández-González and Gómez-Rodríguez (2019); Fernández-González and Gómez-Rodríguez (2020) to the proposed multitask approach. In all datasets tested, training a single model of the multi-representational parser across both syntactic representations leads to accuracy gains on both tasks. This proves that, not only the encoding strategy by Fernández-González and Martins (2015) adequately translates constituent information into a common dependency representation, but also training a parser across both regular and augmented dependencies is beneficial for each individual task. We hypothesize that the information exclusively encoded by each formalism (span phrase information in constituent trees and semantic relations in dependency structures) may complete each other and, therefore, be the reason why the multi-representational approach is obtaining such improvements.

In order to further put our approach into context, we provide a comparison against current state-of-the-art models. In Table 2, we show how our approach outperforms the best dependency parsers to date on the PTB and ZCTB with regular pre-trained word embeddings. Moreover, although some of the included parsers are augmented with several parameter-heavy layers of BERT and additionally perform a task-specific adaptation via expensive fine-tuning, our approach achieves similar performance on PTB and improves over all models on ZCTB.

Furthermore, Table 3 shows that our novel transition-based parser obtains competitive accuracies on constituent PTB and LCTB with non-contextualized word embeddings (best F-score to date on the latter), while being more efficient than $O(n^3)$ and $O(n^5)$ approaches such as (Kitaev and Klein, 2018; Zhou and Zhao, 2019).

Regarding discontinuous parsing, in Table 4 we can see that our novel neural architecture outperforms all existing single-task parsers on the NEGRA and TIGER datasets with regular word embeddings, providing a notable performance on discontinuous constituents (probably thanks to the joint training with regular non-projective dependency structures).

It can be noticed that our multitask neural network achieves better accuracies on discontinuous constituent datasets than continuous phrase-structure benchmarks. This can be mainly explained by the fact that the encoding technique cannot directly handle unary nodes (that are collapsed, increasing the label set size, or, in case of leaf unary nodes, assigned with a regular sequence tagger), losing some accuracy in continuous treebanks where the amount of this kind of structures is significant. Despite that, our approach obtains the best accuracy to date among all existing transition-based parsers in both continuous and discontinuous constituent structures.

Finally, it is worth mentioning that even on Chi-
Table 2: Accuracy comparison of state-of-the-art dependency parsers on PTB and ZCTB. Models that fine-tune BERT are marked with *.

| Parser                      | PTB UAS | ZCTB UAS |
|-----------------------------|---------|----------|
| Andor et al. (2016)         | 94.61   | 92.79    |
| Wang and Chang (2016)       | 94.08   | 91.82    |
| Cheng et al. (2016)         | 94.10   | 91.49    |
| Kuncoro et al. (2016)       | 94.26   | 90.06    |
| Zhang et al. (2016)         | 93.42   | 91.29    |
| Zhang et al. (2016)         | 94.10   | 91.90    |
| Ma and Hovy (2017)          | 94.88   | 92.96    |
| Dozat and Manning (2017)    | 95.74   | 94.08    |
| Li et al. (2018)            | 94.11   | 92.08    |
| Ma et al. (2018)            | 95.87   | 94.19    |
| Fdez-G & Gómez-R (2019)    | 96.04   | 94.43    |
| Li et al. (2020)            | 95.83   | 94.54    |
| Zhou and Zhao (2019)        | 96.09   | 94.68    |
| This work                   | 96.25   | 94.64    |
| Li et al. (2020)+BERT       | 96.34   | 94.63    |
| Li et al. (2020)+BERT*      | 96.57   | 95.05    |
| Zhou and Zhao (2019)+B.      | 97.00   | 95.43    |
| This work + BERT            | 96.97   | 95.46    |

Table 3: F-score comparison of state-of-the-art constituent parsers on PTB and LCTB. Models that fine-tune BERT are marked with *.

| Parser                      | PTB     | LCTB    |
|-----------------------------|---------|---------|
| Dyer et al. (2016)          | 91.2    | 84.6    |
| Cross and Huang (2016)      | 91.3    | -       |
| Liu and Zhang (2017b)       | 91.7    | 85.5    |
| Liu and Zhang (2017a)       | 91.8    | 86.1    |
| Fernández-G & Gómez-R (2018)| 92.0    | 86.6    |
| Stern et al. (2017a)        | 91.8    | -       |
| Stern et al. (2017b)        | 92.56   | -       |
| Shen et al. (2018)          | -       | 86.5    |
| Fried and Klein (2018)      | 92.2    | 87.0    |
| Gaddy et al. (2018)         | 92.07   | -       |
| Teng and Zhang (2018)       | 92.4    | 87.3    |
| Kitaev and Klein (2018)     | 95.57   | -       |
| Zhou and Zhao (2019)        | 93.78   | -       |
| This work                   | 93.67   | 88.65   |
| Kitaev et al. (2019)+BERT   | 95.39   | 91.75   |
| Zhou and Zhao (2019)+BERT*  | 95.84   | 92.18   |
| This work + BERT            | 95.23   | 90.20   |

Table 2: Accuracy comparison of state-of-the-art dependency parsers on PTB and ZCTB. Models that fine-tune BERT are marked with *.

nese datasets (where augmented and regular dependencies are the same) our approach benefits from learning across both structures, meaning that both constituent-based and regular dependency label sets provide useful syntactic information.

5 Related work

It is known that parsers based on lexicalized grammar are trained using both constituent and unla belled dependency information. This includes classic chart parsers (Collins, 2003) as well as lexicalized parsers that build dependencies with reduce transitions, such as (Crabbé, 2015), which can generate both structures. These are restricted to dependencies that are directly inferred from the lexicalized constituent trees. In this sense, the multitask approach is more flexible, as it does not have that limitation and one can use dependencies and constituents from different sources.

In the deep learning era, there have been a few recent attempts to jointly train a neural model across constituent and dependency trees, producing, during decoding, both syntactic representations from a single model.

In particular, Strzyz et al. (2019a) propose a multitask sequence labelling architecture that, by representing constituent and dependency trees as linearizations (Gómez-Rodríguez and Vilares, 2018; Strzyz et al., 2019b), can learn and perform parsing in both formalisms as joint tasks. While being a linear and fast parser, the parsing accuracy provided by this approach is notably behind the state of the art (even training separate models by performing an auxiliary-task learning for each formalism) and the linearization strategy used for constituent parsing is restricted to continuous structures.

Zhou and Zhao (2019) also explore the benefits of training a model across syntactic representations. They propose to integrate dependency and constituent information into a simplified variant of the Head-Driven Phrase Structure Grammar formalism (HPSG). Then, to implement a HPSG parser, they modify the constituent chart-based parser by Kitaev and Klein, 2018 that employs an $O(n^5)$ CKY-style algorithm (Stern et al., 2017b) for decoding. Although their approach can produce both syntactic structures at the same time and achieve state-of-the-art accuracies on PTB and CTB treebanks, their parser is bounded to produce continuous and projective structures with a high runtime complexity.

Our approach can handle any kind of constituent and dependency structures and provides an efficient runtime complexity, crucial for some downstream applications.

6 Conclusions and Future Work

We propose a novel encoder-decoder neural architecture based on Pointer Networks that, after being jointly trained on regular and constituent-based dependency trees, can syntactically parse a sentence to both constituent and dependency trees. Apart from just requiring to train a single model, our...
| Parser                        | NEGRA F1 | TIGER F1 | NEGRA DF1 | TIGER DF1 |
|------------------------------|----------|----------|-----------|-----------|
| Predicted/Without POS tags   |          |          |           |           |
| Fernández-G and Martins (2015) | 77.0     | -        | 77.3      | -         |
| Versley (2016)               | -        | -        | 79.5      | -         |
| Stanojević and G. Alhama (2017) | -        | -        | 77.0      | -         |
| Coavoux and Crabbé (2017)    | -        | -        | 79.3      | -         |
| Coavoux et al. (2019)        | 83.2     | 54.6     | 82.7      | 55.9      |
| Coavoux and Cohen (2019)     | 83.2     | 56.3     | 82.5      | 55.9      |
| Fernández-G and Gómez-R (2020) | 85.7     | 58.6     | 85.7      | 60.4      |
| Corro (2020)                 | 86.3     | 56.1     | 85.2      | 51.2      |
| This work                   | 86.8     | 69.5     | 86.6      | 62.6      |
| Corro (2020) + BERT          | 91.6     | 66.1     | 90.0      | 62.1      |
| This work + BERT             | 91.0     | 76.6     | 89.8      | 71.0      |
| Gold POS tags                |          |          |           |           |
| Maier (2015)                 | 77.0     | 19.8     | 74.7      | 18.8      |
| Fernández-G and Martins (2015) | 80.5     | -        | 80.6      | -         |
| Maier and Lichte (2016)      | -        | -        | 76.5      | -         |
| Corro et al. (2017)          | -        | -        | 81.6      | -         |
| Stanojević and G. Alhama (2017) | 82.9     | -        | 81.6      | -         |
| Coavoux and Crabbé (2017)    | 82.2     | 50.0     | 81.6      | 49.2      |
| Gebhardt (2018)              | -        | -        | 75.1      | -         |
| Fernández-G and Gómez-R (2020) | 86.1     | 59.9     | 86.3      | 60.7      |
| This work                   | 87.3     | 71.0     | 87.3      | 64.2      |

Table 4: F-score and Discontinuous F-score (DF1) comparison of state-of-the-art discontinuous constituent parsers on NEGRA and TIGER. Models that fine-tune BERT are marked with *.

approach can produce not only the simplest continuous/projective trees, but also discontinuous/non-projective structures in just $O(n^2)$ runtime. We test our parser on the main dependency and constituent benchmarks, obtaining competitive results in all cases and reporting state-of-the-art accuracies in several datasets.

As future work, we plan to perform auxiliary-task learning and train a separate model for each task, testing different weights for the loss computation. This will lose the advantage of training a single model to undertake both tasks, but will certainly lead to further improvements in accuracy.

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A Appendices

A.1 Deep Contextualized Word Embeddings Augmentation

In the literature, we can find different approaches to initialize deep contextualized word embeddings from the pre-trained language model BERT. Typically, weights of one or several layers are considered for each token as a word-level representation. In addition, since BERT is trained on subwords, we take the vector of each subword of an input token \( w_i \) and use the average embedding as the final representation \( e_i^{BERT} \). Then, this is directly concatenated to the resulting basic word representation \( x_i \) before feeding the BiLSTM-based encoder:

\[
x'_i = x_i \oplus e_i^{BERT}; \quad h_i = \text{BiLSTM}(x'_i)
\]

In our experiments, we use the pre-trained cased German and Chinese BERT\_BASE models with 12 768-dimensional hidden vectors; and uncased BERT\_LARGE with 24 1024-dimensional layers for English. Depending on the specific task, some layers proved to be more beneficial than others, which is especially crucial when the resulting embeddings are not fine-tuned during training.

In order to check which layers are more suitable for our tasks, we test on development sets the combination of different layers. In Table 5, we compare, for the English pre-trained model BERT\_LARGE, the accuracy obtained by averaging several groups of four consecutive layers (from last layer 24 to layer 13) and by just using weights from the second-to-last hidden layer (the simplest and commonly-used strategy, since it is less biased than the last layer to the target objectives used to train BERT). As can be seen, the combination of layers from 17 to 20 achieves the highest accuracy on both tasks and, therefore, this setup is used in our experiments on the PTB.

| Layer   | Regular UAS | Regular LAS | Augmented UAS | Augmented LAS |
|---------|-------------|-------------|---------------|---------------|
| Layers 11 | 96.41       | 95.56       | 95.04         | 94.48         |
| Layers 9-12 | 96.40       | 95.57       | 95.02         | 94.50         |
| Layers 5-8 | 96.31       | 95.50       | 94.89         | 94.40         |

Table 5: Accuracy comparison on regular and augmented dependency trees of the NEGRA development set by using weights from different BERT layers.

Regarding the pre-trained models BERT\_BASE for German and Chinese, we noticed that comparable accuracies can be obtained by just using weights from the second-to-last layer instead of combining the four last layers as can be seen, for instance, in Table 6 for the NEGRA dataset. Therefore, we decided to follow the simplest configuration and use the second-to-last layer in all experiments on German and Chinese languages.

| Layer   | Regular UAS | Regular LAS | Augmented UAS | Augmented LAS |
|---------|-------------|-------------|---------------|---------------|
| Layer 11 | 96.41       | 95.56       | 95.04         | 94.48         |
| Layers 9-12 | 96.40       | 95.57       | 95.02         | 94.50         |
| Layers 5-8 | 96.31       | 95.50       | 94.89         | 94.40         |

Table 6: Accuracy comparison on regular and augmented dependency trees of the PTB development set by using weights from different BERT layers.

We discarded other combinations such as the concatenation of several layers in order to not increase the dimension of the resulting BERT embeddings.

Finally, by adapting BERT-based embeddings to our specific tasks, our approach would certainly obtain some gains in accuracy; however, we consider that the amount of resources necessary to that end will not justify the expensive fine-tuning of parameter-heavy BERT layers.

A.2 Hyperparameters

| Architecture hyper-parameters |
|-------------------------------|
| CNN window size               | 3                            |
| CNN number of filters         | 50                           |
| BiLSTM encoder layers         | 3                            |
| BiLSTM encoder size           | 512                          |
| LSTM decoder layers           | 1                            |
| LSTM decoder size             | 512                          |
| LSTM layers dropout           | 0.33                         |
| English BERT embedding dimension | 100                         |
| German BERT embedding dimension | 1024                        |
| Chinese BERT embedding dimension | 768                          |
| Embeddings dropout            | 0.33                         |
| MLP layers                    | 1                            |
| MLP activation function       | ELU                          |
| Arc MLP size                  | 512                          |
| Label MLP size                | 128                          |
| UNK replacement probability   | 0.5                          |
| Beam size                     | 10                           |

| Adam optimizer hyper-parameters |
|---------------------------------|
| Initial learning rate           | 0.001                        |
| \( \beta_1, \beta_2 \)          | 0.9                          |
| Batch size                     | 32                           |
| Decay rate                     | 0.75                         |
| Gradient clipping              | 5.0                          |

Table 7: Model hyper-parameters.
Table 8: Labelled Attachment Scores (LAS) of single-task baseline parsers and the proposed multi-representational approach on both regular and augmented dependency trees on development sets.

A.3 Accuracy on Validation Sets