Something Old, Something New —
Grammar Based CCG Parsing with Transformer Models

by Steven Clark
Abstract

This report describes the parsing problem for Combinatory Categorial Grammar (CCG), showing how a combination of Transformer-based neural models and a symbolic CCG grammar can lead to substantial gains over existing approaches. The report also documents a 20-year research program, showing how NLP methods have evolved over this time. The staggering accuracy improvements provided by neural models for CCG parsing can be seen as a reflection of the improvements seen in NLP more generally. The report provides a minimal introduction to CCG and CCG parsing, with many pointers to the relevant literature. It then describes the CCG supertagging problem, and some recent work from Tian et al. (2020) which applies Transformer-based models to supertagging with great effect. I use this existing model to develop a CCG multitagger, which can serve as a front-end to an existing CCG parser. Simply using this new multitagger provides substantial gains in parsing accuracy. I then show how a Transformer-based model from the parsing literature can be combined with the grammar-based CCG parser, setting a new state-of-the-art for the CCGbank parsing task of almost 93% F-score for labelled dependencies, with complete sentence accuracies of over 50%.
1 Introduction

Combinatory Categorial Grammar (CCG) is a lexicalized grammar formalism in the type-driven tradition, building on historical work by Ajdukiewicz (1935) and Bar-Hillel (1953). The original formalism, often referred to as classical categorial grammar, uses the rules of forward and backward application to combine the categorial types. CCG, developed over many years by Mark Steedman (Steedman, 2000), uses a number of additional combinatory rules to deal with “movement” phenomena in natural languages – syntactic environments in which phrases are moved from their canonical argument positions, often creating an unbounded dependency between the argument and predicate. Examples in English include questions and relative clause extraction (Rimell et al., 2009). This movement phenomena is what motivated Chomsky to develop transformational grammar (Chomsky, 1965). Unlike transformational grammar, however, CCG is a “monostratal” theory in which the apparent movement of syntactic units is handled by a single level of representation. Other approaches to categorial grammar include the type-logical approach (Moortgat, 1997), in which linguistic types are the formulas of a logic and derivations are proofs, and the algebraic approach of the later work of Lambek (Lambek, 2008), in which linguistic types are the partially-ordered objects of an algebra (specifically a pregroup), and derivations are given by the partial order.

Figure 1 gives an example CCG derivation using only the basic rules of forward (>) and backward (<) application. The categorial types that are assigned to words at the leaves of the derivation are referred to as lexical categories. The internal structure of categories is built recursively from atomic categories and slashes (’\’, '/') which indicate the directions of arguments. In a typical CCG grammar there are only a small number of atomic categories, such as $S$ for sentence, $N$ for noun, $NP$ for noun phrase, and $PP$ for prepositional phrase. However, the recursive combination of categories and slashes can lead to a large number of categories; for example, the grammar used in the parsing experiments below has around 1,300 lexical categories. CCG is referred to as lexicalised because most of the grammatical information—which is language-dependent and encoded in the lexical categories—resides in the lexicon, with the remainder of the grammar being provided by a small number of combinatory rules.

One way to think of the application of these rules, or rule schema (since they apply to an unbounded set of category pairs), is that the matching parts of the combining categories effectively cancel, leading to the rules being called cancellation laws in some of the earlier work on categorial grammar. For example, when the lexical categories for Exchange and Commission in Figure 1 are combined, the argument $N$ required by Exchange in $N$/N cancels with the lexical category $N$ for Commission. We can also think of $N$/N as a function that is applied to its argument $N$. The forward in forward application refers to the fact that the argument is to the right. Backward (<) application—for when

\footnotetext{1}{Figure 1 follows the typical presentation for a CCG derivation with the leaves at the top.}
\footnotetext{2}{The square brackets on some $S$ nodes in the example denote grammatical features such as [dcl] for declarative sentence (Hockenmaier and Steedman, 2007).}
the argument is to the left—is used in the example when combining the subject NP Investors with the derived verb phrase S[decl]/NP.

Figure 2 shows the derivation for a noun phrase containing a relative clause, where the object has been extracted out of its canonical position to the right of the transitive verb. The bracketing structure of the lexical category of the transitive verb ((S[decl]/NP)/NP) means that the verb is expecting to combine with its object to the right before its subject to the left. However, in this example the object has been moved away from the verb so that is not possible. The solution provided by CCG is to use two new combinatory rules. First, the unary rule of type-raising (>T) turns an atomic NP category into a complex category S/(S\NP). A useful way to think about this new category is that it’s a sentence missing a verb phrase (S\NP) to the right, which is a natural way to conceive of a subject NP as a function. Second, the rule of forward composition (>B) enables the combination of the type-raised noun phrase (S/(S\NP)) and the transitive verb (S[decl]/NP)/NP, again with the idea that the verb-phrase categories “in the middle” effectively cancel. This results in the slightly unusual constituent S[decl]/NP, which reflects the fact that the linguistic unit the fund reached is a sentence missing an NP to its right. Note that the lexical category for the relative pronoun in this example (NP\NP)/(S[decl]/NP) is expecting such a constituent to its right, so the relative pronoun can combine with the derived category using forward application.

There are additional combinatory rules in CCG which are designed to deal with other linguistic phenomena, including some rules in which the main slashes of the combining categories point in different directions – the so-called “non-harmonic” or crossing rules, such as backward crossed composition. These are all based on the operators of combinatory logic [Curry and Feys 1958; hence the term combinatory in Combinatory Categorial Grammar. Steedman 1996, Steedman 2000 and Baldrige 2002 contain many linguistic examples which motivate the particular set of rules in the theory.

There is much work on the formal properties of CCG, including the seminal papers of Vijay-Shanker, Weir and Joshi in which it was proven that CCG is strictly more powerful than context-free grammars, but substantially less pow-

Figure 1: Example derivation using forward and backward application.
Figure 2: Example derivation using type-raising and forward composition.

erful than context-sensitive grammars – hence the term mildly context-sensitive (Weir, 1992). Joshi et al. (1991) prove that CCG is weakly equivalent—i.e. generating the same string sets—to Tree Adjoining Grammar, Head Grammar, and Linear Indexed Grammar. This was a remarkable result given the apparent differences between these formalisms. Tree Adjoining Grammar (Joshi, 1987), like CCG, has become a standard grammar formalism in Computational Linguistics and has formed the basis for much experimental work in developing parsers and NLP systems (Kasai et al., 2018). Kuhlmann et al. (2015) build on the earlier formal work and show that there are versions of CCG that are more powerful than CFGs, but strictly less powerful than TAG. Despite the additional power of CCG (and TAG), there are still efficient parsing algorithms for CCG (and TAG) which are polynomial in the length of the input sentence (Vijay-Shanker and Weir, 1993, Kuhlmann et al., 2018).

The mildly context-sensitive nature of CCG is much trumpeted, and rightly so given that it enables analyses of the crossing dependencies in Dutch and Swiss German (Shieber, 1985). However, it is perhaps worth pointing out that, for practical CCG parsing of English at least, the successful parsers have either used a CCG grammar which is context free by construction, being built entirely from rules instances observed in a finite CCG treebank (Hockenmaier and Steedman, 2002, Fowler and Penn, 2010), or a grammar which is context free in practice by limiting the applicability of the combinatory rules to the rule instances in the treebank (Clark and Curran, 2007b). Hence the parsing algorithms used by practical CCG parsers tend not to exploit the (somewhat complicated) structure-sharing schemes which define the more general polynomial-time parsing algorithms referenced above.

The remainder of this report starts out with the CCG supertagging task (Section 2), showing the 20-year evolution of CCG supertagging from feature-based models in which the features are defined by hand, to neural models in which the features are induced automatically by a neural network. Section 3 then demonstrates the gains that can be obtained by simply using a neural CCG supertagger as a front-end to an existing CCG parser, as well as additional improvements from using a neural classifier for the parsing model itself. Note that much of this report is a survey of existing work carried out by other researchers—or at least existing work replicated by the author—with the new
material appearing in Section 3.2 which reports new state-of-the-art accuracy figures for the CCGbank parsing task. It also acts as something of a survey of the 20-year wide-coverage CCG parsing project that began in Edinburgh. For a more detailed exposition of the linguistic theory of CCG, the reader is referred to Steedman (1996), Steedman (2000) and Baldridge (2002). For an introduction to wide-coverage CCG parsing, the reader is referred to Clark and Curran (2007b) and Hockenmaier and Steedman (2007).

2 CCG Supertagging

CCG supertagging is the task of assigning a single lexical category (or “supertag”) to each word in an input sentence. The term supertag originates from the seminal work of Bangalore and Joshi (1999) for lexicalised tree-adjoining grammar (LTAG), and reflects the fact that CCG lexical categories (and elementary trees in LTAG) contain so much information. As an indication of how much information, note that the CCG grammar used in this report contains around 1,300 lexical categories, compared with the 50 or so part-of-speech tags in the original Penn Treebank (Marcus et al., 1993).

Figure 3 shows a sentence from Wikipedia with the correct lexical category assigned to each word (Clark et al., 2009). The words highlighted in blue demonstrate why CCG supertagging is a difficult task. The lexical category assigned to by takes two arguments: an NP to the right and a verb phrase (S\NP) to the left. The lexical category assigned to in is similar, but takes an NP to the left. In the Penn Treebank, both of these prepositions would be assigned the part-of-speech tag IN. The point of the example is that, in order to assign the correct lexical category to these prepositions (or at least the second one), the supertagger has to decide whether the preposition attaches to a noun or a verb; i.e. it effectively has to resolve a prepositional phrase attachment ambiguity, which is one of the more difficult, classical parsing ambiguities (Collins and Brooks, 1995). This led Bangalore and Joshi (1999) to describe supertagging as almost parsing.

3https://groups.inf.ed.ac.uk/ccg/index.html
The data most used for training and testing CCG supertaggers is from CCG-bank (Hockenmaier and Steedman, 2007), which is a CCG version of the original Penn Treebank (Marcus et al., 1993), a corpus of newswire sentences manually annotated with syntactic parse trees. A standard split is to take Sections 2-21 (39,604 sentences) as training data, Section 00 (1,913 sentences) as development data, and Section 23 (2,407 sentences) as test data. Extracting a grammar from Sections 2-21 results in 1,286 distinct lexical category types, with 439 of those types occurring only once in the training data.

The original CCG supertagger (Clark, 2002) was a maximum entropy (“maxent”) tagger (Ratnaparkhi, 1996), which was state-of-the-art for sequence labelling tasks at the time. The main difference with today’s neural taggers is that the features were defined by hand, in terms of feature templates, based on linguistic intuition. For example, the NLP researcher may have decided that a good feature for deciding the correct tag for a word is the previous word in the sentence, which would then become a feature template which gets filled in for each particular word being tagged. Both types of tagger use iterative algorithms for training, typically maximising the likelihood of the (supervised) training data, with the neural models benefiting from specialised GPU hardware. Another difference is that the Transformer-based model described in Section 2.1 builds on a pre-trained model which has already been trained on large amounts of data to perform a fairly generic language modelling task. It turns out that this pre-training stage—which has become available since the maxent taggers because of developments in neural networks, hardware, and the availability of data—is crucial for the resulting performance of the supertagger, which is fine-tuned for the supertagging task.

The per-word accuracy for the maxent supertagger was around 92% (see Table 1), compared with over 96% for the Penn Treebank pos-tagging task (Ratnaparkhi, 1996; Curran and Clark, 2003). An accuracy of 92% may sound reasonable, given the difficulty of the task, but with an average sentence length in the treebank of around 20-25 words, this would result in approximately two errors every sentence. Given the amount of information in the lexical categories, it is crucial for the subsequent parsing stage that the supertagging is correct. Hence Clark and Curran (2004a) developed a “multitagging” approach in which the supertagger is allowed to dynamically assign more than one lexical category to a word, based on how certain the supertagger is of the category for that word. Allowing more than one lexical category increases the accuracy to almost 98% with only a small increase in the average per-word lexical category ambiguity (see the end of Section 2.1 below).

Development of the maxent supertagger from 2007 mainly consisted of adapting it to other domains (Rimell and Clark, 2008) and using it to increase the speed of CCG parsers (Kummerfeld et al., 2010). The first paper to use neural methods for CCG supertagging was Xu et al. (2015), which applies a vanilla RNN to the sequence labelling task. This resulted in substantial accuracy improvements (Table 1), and also produced a more robust supertagger that performed better on sentences from domains other than newswire (see the paper for details). Another improvement was that the maxent supertagger relied heav-
Table 1: Supertagger accuracy evolution on Section 00 of CCGbank.

<table>
<thead>
<tr>
<th>Supertagger</th>
<th>Model</th>
<th>Per-word acc</th>
</tr>
</thead>
<tbody>
<tr>
<td>Clark and Curran (2007b)</td>
<td>Maxent</td>
<td>91.5</td>
</tr>
<tr>
<td>Clark and Curran (2007b) (w/gold pos)</td>
<td>Maxent</td>
<td>92.6</td>
</tr>
<tr>
<td>Xu et al. (2015)</td>
<td>RNN</td>
<td>93.1</td>
</tr>
<tr>
<td>Lewis et al. (2016)</td>
<td>BiLSTM</td>
<td>94.1</td>
</tr>
<tr>
<td>Lewis et al. (2016) (+tri-training)</td>
<td>BiLSTM</td>
<td>94.9</td>
</tr>
<tr>
<td>Tian et al. (2020)</td>
<td>Transformer</td>
<td>96.2</td>
</tr>
</tbody>
</table>

illy on part-of-speech (POS) tags to define effective feature templates, and the accuracy degraded significantly when using automatically assigned, as opposed to gold-standard, POS tags (see the first two rows in Table 1). The RNN supertagger was able to surpass the accuracy of the maxent supertagger relying on gold POS, but without using POS tags as input at all.

Lewis et al. (2016) improved on the performance of the vanilla RNN by using a bi-directional LSTM, and obtained additional gains by training on large amounts of automatically parsed data. More specifically, the tri-training method (row 5 in the table) uses the lexical category sequences from parsed sentences as additional training data, but only those supertagged sentences on which two different CCG parsers agree. Finally, the last row of Table 1 shows the staggering improvements that can be had—over 50% reduction in error rate compared to the original maxent model—when using a pre-trained neural language model that is fine-tuned for the supertagging task. This model is described in the next section.

Other recent neural approaches to CCG supertagging include Clark et al. (2018) and Bhargava and Penn (2020). Bhargava and Penn (2020) is noteworthy because it uses neural sequence models to model the internal structure of lexical categories, which allows the supertagger to meaningfully assign non-zero probability mass to previously unseen lexical categories, as well as model rare categories, which is important given the long tail in the lexical category distribution.

2.1 CCG Supertagging with a Transformer-based Model

The field of NLP has experienced a period of rapid change in the last few years, due to the success of applying large-scale neural language models to a range of NLP tasks. The new paradigm relies on taking a pre-trained neural language model, which has been trained to carry out a fairly generic language modelling task such as predicting a missing word in a sentence, and fine-tuning it through additional supervised training for the task at hand (Brown et al., 2020). Despite the generic nature of the original language modelling task, the neural model is able to acquire large amounts of linguistic (and world) knowledge which can then be exploited for the downstream task.
Another innovation which has been particularly influential is the development of the Transformer neural architecture, which consists of many self-attention layers, where every pair of words in a sentence is connected via a number of attention “heads” (Vaswani et al., 2017, Devlin et al., 2019). Each attention head calculates a similarity score between transformed representations of the respective word embeddings, where one word acts as a “query” and the other as a “key”. These scores are then used by each word to derive a probabilistic mixture of all the other words in the sentence, where the mixture elements (“values”) are again transformed representations of the word embeddings. This mixture acts as a powerful word-in-context representation, and stacking the attention layers a number of times, combined with some non-linear, fully-connected layers, results in a highly non-linear contextualised representation of each word in the sentence.

Tian et al. (2020) apply this method to the CCG supertagging task, with great success. Figure 4, which is an embellished version of Figure 1 from the paper, shows the neural architecture. The first component is the BERT encoder (Devlin et al., 2019), which has already been pre-trained on large amounts of text using a masked language modelling objective. The output of BERT is a word embedding for each word in the input sentence. Then, an additional neural network takes the output of BERT, and also produces an embedding for each word. This additional network has not been pre-trained, and so requires supervised training data for its weights to be learned. In Tian et al. (2020)
the additional network is a novel graph convolutional neural network (GCNN). Finally, there is an additional set of parameters which, for each output word embedding, define a softmax over the set of lexical categories. The output of the supertagger, for each input word, is the most probable lexical category according to the softmax distribution.

Training proceeds in a standard fashion, using the lexical category sequences from Sections 2-21 of CCGbank as supervised training data. The loss function is the cross-entropy loss, the minimisation of which is equivalent to putting as much probability mass as possible on each correct lexical category, relative to the incorrect lexical categories for each word (i.e. maximising the probability of the training data). A form of batch-based stochastic gradient descent is used to minimise the loss function, and dropout is used to prevent overfitting (Goodfellow et al., 2016). All of these techniques have now become standard in neural NLP. The implementation uses the neural network library PyTorch.

One feature of the neural supertagger, compared with the maxent supertagger, is that it does not model the lexical category sequence at all. One of the challenges in developing taggers using sequence modelling methods, such as HMMs (Brants, 2000), CRFs (Lafferty et al., 2001), and maxent models, is that the number of possible tag sequences grows exponentially with sentence length, so modelling them explicitly requires either heuristic methods such as beam search, or dynamic programming techniques such as Viterbi. In contrast, the probabilistic decision made by the neural supertagger of what lexical category to assign to each word is made independently of the decisions for the other words. The reason it performs so well is because of the highly contextualised nature of the output word embeddings, which already contain substantial amounts of information about the other words in the sentence.

There are a number of possibilities for the additional neural network in Figure 4. In fact, one possibility is not to add any additional layers at all, and simply fine-tune BERT, which works almost as well as the GCNN (Table 5 in Tian et al. (2020)). It is likely that adding in some additional attention layers, and training those with the supervised data, would work just as well.

In order to replicate the results in Tian et al. (2020), and to use the supertagger as a front-end to an existing CCG parser, I downloaded and ran the code from the github repository\footnote{https://github.com/cuhksz-nlp/NeST-CCG} retraining the supertagger on Sections 2-21 of CCGbank. One difference compared to Tian et al. (2020) is that I used the full lexical category set of 1,286 categories, rather than the 425 which result from applying a frequency cutoff. I also downloaded the 2019_05_30 BERT-Large Uncased model from the BERT repository\footnote{https://github.com/google-research/bert} to serve as the BERT encoder.

If the NeST-CCG supertagger is to act as an effective front-end to a CCG parser, it would be useful for it to sometimes output more than one category for a word. In fact, NeST-CCG already has a hyperparameter—clipping_threshold—which retains lexical categories based on their log-probabilities. Tuning this hyperparameter—let’s call it $\gamma$—turns out to be highly effective for producing
a multitagger. There is a trade-off between using a low $\gamma$ value, which increases the chance of assigning the correct category, and a high $\gamma$ which reduces the average number of categories per word. One of the motivations for supertagging is that, if the average number of categories per word can be kept low, then this greatly increases the efficiency of the parser [Clark and Curran 2007b].

The optimal $\gamma$ value depends on how “sharp” the lexical category distributions are, and this is affected by the number of training epochs for the NeST-CCG supertagger. NeST-CCG also has an additional hyperparameter—call it $\alpha$—which sets a maximum number of lexical categories that can be assigned to a single word. I experimented with various combinations of $\gamma$, $\alpha$, and number of training epochs, and found a happy medium with $\gamma = 0.0005$, $\alpha = 10$, and 10 epochs, which resulted in a multitagging accuracy of 99.3% on the development data with 1.7 lexical categories per word on average. This compares very favourably with 97.6% at 1.7 categories per word from Clark and Curran [2007b]. Hence the expectation is that this greatly improved multitagger will lead to improved parsing performance, which we turn to next.

3 CCG Parsing

The job of a CCG parser is to take the output of a CCG supertagger as input, combine the categories together using the CCG combinatory rules, and return the best analysis as the output. This process requires a parsing algorithm, which determines the order in which the categories are put together; a parsing model, which scores each possible analysis; and a search algorithm, which efficiently finds the highest-scoring analysis. In addition, there are various options for what kind of analysis the parser returns as output.

The most popular form of parsing algorithms for CCG have been bottom-up, in which the lexical categories are combined first, followed by combinations of categories with increasing spans, eventually resulting in a root category spanning the whole sentence [Steedman 2000]. The first parsing algorithms to be successfully applied to wide-coverage CCG parsing were chart-based [Hockenmaier and Steedman 2002, Clark and Curran 2004b], followed by shift-reduce parsers [Zhang and Clark 2011, Xu et al. 2014, Ambati et al. 2016]. In this report we will be using a chart-based parser (described in Section 3.1).

The original CCG parsing models were based on lexicalised PCFGs and used relative frequency counts to estimate the model parameters, with backoff techniques to deal with data sparsity [Hockenmaier and Steedman 2002, Collins 1997]. These were superseded by discriminative, feature-based models, essentially applying the maxent models that had worked so well for tagging to the parsing problem [Clark and Curran 2004b, Riezler et al. 2002].

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6 In order for a set of lexical categories assigned to a word to be “correct”, the set needs to contain the one correct category. Hence multitagging “accuracy” increases monotonically with smaller $\gamma$ values, as does the per-word ambiguity, reflecting the trade-off described above.

7 For a number of citation lists in this section, the first citations give the relevant CCG papers, followed by the (non-CCG) work on which they were based.
Alternative estimation methods based on the structured perceptron framework—which provides a particularly simple estimation technique—were also applied successfully to CCG (Clark and Curran, 2007a; Collins and Roark, 2004). The more recent neural parsing models that have been applied to CCG are mentioned in Section 3.2.

In terms of search, the choice is between optimal dynamic programming, heuristic beam search, or optimal A* search (Lee et al., 2016). The early CCG parsing work focused on dynamic programming algorithms (Hockenmaier and Steedman, 2002; Clark and Curran, 2004b), whereas the shift-reduce CCG parsers tended to use beam search, performing surprisingly well even with relatively small beam widths (Zhang and Clark, 2011). The CCG parser described below also uses beam search, but applied to a chart.

Finally, the main output formats have been either the CCG derivation itself, a dependency graph where the dependency types are defined in terms of the CCG lexical categories (Clark et al., 2002; Hockenmaier and Steedman, 2002), or a dependency graph using a fairly formalism-independent representation (Clark and Curran, 2007b). It has been argued that dependency types are especially useful for parser evaluation (Carroll et al., 1998), in particular for CCG (Clark and Hockenmaier, 2002), as well as for downstream NLP tasks and applications. In this report the parser output will be CCG dependencies (used for evaluation), with a novel application of the derivations suggested in the Conclusion. There is also a large body of work on interpreting CCG derivations to produce semantic representations as logical forms, in particular for Discourse Representation Theory (Bos et al., 2004, 2017; Liu et al., 2021), Abstract Meaning Representation (Artzi et al., 2015), as well as for more general semantic parsing tasks (Zettlemoyer and Collins, 2005; Artzi et al., 2014).

3.1 CCG Parsing with a Neural Supertagger Front End

This section describes the accuracy gains that can be obtained by simply using the neural supertagger described in Section 2.1 as a front-end to an existing CCG parser. These experiments further demonstrate the importance of supertagging for CCG (Clark and Curran, 2004a), and further realise the original vision of Bangalore and Joshi (1999) for supertagging as almost parsing.

The CCG parser that we will use is the Java C&C parser described in Clark et al. (2015). This is essentially a Java reimplementation of the C&C parser, which was highly optimised C++ code designed for efficiency (Clark and Curran, 2007b; Curran et al., 2007); one of the aims of the reimplementation was to make the code more readable and easier to modify. There were also some improvements made to the grammar, by extending the lexical category set that can be handled by the parser from the 425 lexical categories in C&C to the full set of 1,286 derived from Sections 2-21 of CCGbank[8]. Also, Java C&C uses a new chart-based beam-search decoder, which removes any restrictions imposed

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[8] Extending the grammar in this way required an extension of the so-called *markedup* file, which encodes how CCG dependencies are generated from the lexical categories.
Table 2: Parser accuracy of (Java) C&C on Sec. 00 with different supertaggers.

<table>
<thead>
<tr>
<th>Parser</th>
<th>S-tagger</th>
<th>P</th>
<th>R</th>
<th>F</th>
<th>Cat</th>
<th>Cov.</th>
</tr>
</thead>
<tbody>
<tr>
<td>C&amp;C</td>
<td>Maxent</td>
<td>–</td>
<td>–</td>
<td>85.3</td>
<td>–</td>
<td>99.1</td>
</tr>
<tr>
<td>C&amp;C (w/gold pos)</td>
<td>Maxent</td>
<td>88.1</td>
<td>86.4</td>
<td>87.2</td>
<td>94.2</td>
<td>99.1</td>
</tr>
<tr>
<td>Java C&amp;C (w/gold pos)</td>
<td>Maxent</td>
<td>88.0</td>
<td>87.3</td>
<td>87.7</td>
<td>94.3</td>
<td>100.0</td>
</tr>
<tr>
<td>Java C&amp;C</td>
<td>Transformer</td>
<td>91.9</td>
<td>91.5</td>
<td>91.7</td>
<td>96.3</td>
<td>100.0</td>
</tr>
</tbody>
</table>

by dynamic programming algorithms on the locality of the model features (at the cost of optimality), together with the max-violation framework of [Huang et al. (2012)] for training the linear model. And finally, Java C&C has a new “skimmer” mode which enables the parser to return a dependency analysis even when there is no full spanning derivation of the input sentence in the chart.

Table 2 shows the accuracy on the development data of the original C&C parser and the Java C&C parser, the latter with both the maxent supertagger and the neural supertagger. The parser accuracy scores are the standard measures of labelled precision and recall over CCG dependencies, F-score (harmonic mean of precision and recall), and lexical category accuracy. The coverage figure is the percentage of sentences in Section 00 used for the evaluation. The figures for the C&C parser are taken from [Clark and Curran (2007b)]

Moving from row 1 to 2 in the table, we again see the reliance on POS tags as features, for both the maxent supertagger and the original C&C parsing model. Using automatically-assigned POS tags reduces the overall F-score by almost 2%. Row 3 shows the improvements that are obtained with Java C&C, both in terms of accuracy, but also in terms of coverage, since the parser now returns an analysis for all the sentences in the development data (using the “skimmer” mode mentioned above). Finally, row 4 shows the staggering improvements that can be obtained by simply replacing the maxent supertagger with the neural supertagger. The coverage is again 100% through use of the skimmer. These figures were obtained using a beam size of 32 in the parser, and the default parser model that ships with the Java C&C codebase (and using automatically-assigned POS tags as features in the model). The settings on the supertagger were $\gamma = 0.0005$, $\alpha = 10$, and the supertagger model had been trained for 10 epochs, as described in Section 2.1.

### 3.2 CCG Parsing with a Transformer-based Model

The parser model used in Section 3.1 is a linear model based on discrete feature templates defined by hand, which raises the obvious question of whether addi-
tional gains can be obtained by using a neural model in the parser, as well as the supertagger. Some neural models for CCG parsing have already appeared in the literature (Xu et al., 2016; Xu, 2016; Lee et al., 2016; Ambati et al., 2016; Stanojević and Steedman, 2019), but none of these use the pre-trained plus fine-tuning Transformer-based paradigm that was so successful for the supertagger.

The difficulty with applying a similar technique to a parse chart is that scores need to be defined for each cell in the chart (corresponding to each span in the sentence), whereas the neural architecture only produces output embeddings for each word. Figure 5 gives the general idea (adapted from Figure 4 for the supertagger). How can the output embeddings for each word be used to produce an embedding for each span? In fact, this problem has already been solved for dependency parsing by Wang and Chang (2016), and successfully applied to the Penn Treebank constituency parsing task by Stern et al. (2017) and Kitaev and Klein (2018), in the latter case using a fine-tuned BERT encoder. The idea is to produce an embedding for a span by subtracting the embedding for the word at the beginning of the span from the embedding of the word at the end. This is highly intuitive for the left-to-right LSTM used by Wang and Chang (2016) (and in the bidirectional setting, the subtraction would be performed in the opposite order for the right-to-left LSTM); however, it is less intuitive for the Transformer, which has no encoding direction. Even so, Stern et al. (2017) were able to successfully adapt this method for the Transformer.
Now that we have a method of producing an embedding for each cell, an extra set of parameters can be used to define a softmax over all possible constituent labels in the chart. This softmax can then be applied to each cell, producing a list of label-score pairs, with the score for a derivation defined as the sum of the scores (log-probabilities) for each node in the derivation. Kitaev and Klein (2018) used these scores to define a Viterbi-style dynamic programming algorithm for finding the highest-scoring derivation. Note that, as for the supertagger case, the scores for each cell are calculated independently of all the other cells (i.e. there is no explicit statistical modelling of the tree structure). The reason the model is so effective, despite this very strong independence assumption, is because of the highly contextualised nature of the word embeddings used to derive the cell embeddings. However, for the CCG case (and unlike the Penn Treebank parsing problem), there is a twist: any categories that are selected by a parsing algorithm to form a derivation must conform to the combinatory rules of CCG, and the independence assumption means that the highest-scoring tree may not satisfy this constraint.

Kato and Matsubara (2021) solve this problem by defining a new representation for a CCG constituent so that the items being scored conform to the CCG grammar. Here I adopt a much simpler method: only apply the score function to derivations that are produced by the grammar. That way, even if a category receives a high score for a span, it will only appear in the output if it forms part of a high-scoring, legal CCG derivation. Moreover, adapting the chart-based beam-search algorithm to use the new scores is particularly straightforward: simply replace the scores for a sub-derivation previously calculated according to the feature-based model with the scores from the neural model (where the score for a sub-derivation is the sum of the scores of the category labels on each node).

I downloaded the codebase for Kitaev and Klein (2018) and Kitaev et al. (2019) from the github repository and trained a CCG parsing model by running the training code on the derivations in Sections 2-21 of CCGbank. Following Kitaev and Klein (2018), unary chains in the CCG derivations—which arise as a result of type-raising and the unary type-changing rules in CCGbank (Hockenmaier and Steedman, 2007)—were represented as a single label. As explained above, it is not possible to simply run the corresponding parser code at test time, since this may not produce legal CCG derivations, which makes it difficult to produce dependency structures for evaluation. Hence I modified the test-time parsing code to output the scores for each possible category in each cell and modified the Java C&C code so that it is able to accept these charts as input, which now provide the scores for the beam-search decoder. As before, the parser model also uses the log-probabilities from the supertagger as additional scores, but this time weighted equally with the span-based scores (so

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1. A useful side-effect of the new representation is the possibility of modelling unseen categories, a feature shared with Bhargava and Penn (2020).
3. The category set derived from Sections 2-21 contains 964 categories (including the unary chains, and excluding lexical categories).
Table 3: Parser accuracy of Java C&C on Sec. 23 with neural models for both supertagger and parser, compared to other supertagger-parser combinations.

<table>
<thead>
<tr>
<th>Parser</th>
<th>S-tagger/Parser Model</th>
<th>P</th>
<th>R</th>
<th>F</th>
<th>Cat</th>
<th>Cov.</th>
</tr>
</thead>
<tbody>
<tr>
<td>C&amp;C</td>
<td>Maxent/Maxent</td>
<td>86.2</td>
<td>84.7</td>
<td>85.5</td>
<td>93.0</td>
<td>99.6</td>
</tr>
<tr>
<td>C&amp;C (w/gold pos)</td>
<td>Maxent/Maxent</td>
<td>88.3</td>
<td>87.0</td>
<td>87.6</td>
<td>94.3</td>
<td>99.6</td>
</tr>
<tr>
<td>Java C&amp;C</td>
<td>T-former/Linear</td>
<td>92.0</td>
<td>91.8</td>
<td>91.9</td>
<td>96.4</td>
<td>100.0</td>
</tr>
<tr>
<td>Java C&amp;C</td>
<td>T-former/T-former</td>
<td>92.8</td>
<td>93.0</td>
<td>92.9</td>
<td>96.5</td>
<td>100.0</td>
</tr>
</tbody>
</table>

Table 4: Parser accuracy of Java C&C on Sec. 23 with neural models for both supertagger and parser, compared to some recent CCG parsers in the literature.

<table>
<thead>
<tr>
<th>Paper</th>
<th>S-tagger/Parser Model</th>
<th>F</th>
<th>Cat</th>
</tr>
</thead>
<tbody>
<tr>
<td>Xu (2016)</td>
<td>LSTM/Shift-Reduce(LSTM)</td>
<td>87.8</td>
<td>94.6</td>
</tr>
<tr>
<td>Lewis et al., (2016)</td>
<td>LSTM/A*</td>
<td>88.1</td>
<td>–</td>
</tr>
<tr>
<td>Vaswani et al., (2016)</td>
<td>LSTM/Java C&amp;C</td>
<td>88.3</td>
<td>–</td>
</tr>
<tr>
<td>Lee et al., (2016)</td>
<td>LSTM/A*(Tree-LSTM)</td>
<td>88.7</td>
<td>–</td>
</tr>
<tr>
<td>Yoshikawa et al., (2017)</td>
<td>LSTM/A*(LSTM)</td>
<td>88.8</td>
<td>–</td>
</tr>
<tr>
<td>Stanojevic and Steedman (2020)</td>
<td>LSTM/Shift-Reduce(LSTM)</td>
<td>90.6</td>
<td>95.6</td>
</tr>
<tr>
<td>Tian et al., (2020)</td>
<td>T-former/EasyCCG</td>
<td>90.7</td>
<td>96.4</td>
</tr>
<tr>
<td>This report</td>
<td>T-former/Java C&amp;C (w/T-former)</td>
<td>92.9</td>
<td>96.5</td>
</tr>
</tbody>
</table>

The score for a derivation is the sum of the scores on each node, including the lexical categories at the leaves.

Table 3 shows the performance of the new parser on the Section 23 test set, compared with the other C&C parsers, which use various combinations of supertagger and parser models. Replacing the linear parsing model based on hand-defined feature templates with the span-based neural model resulted in an absolute improvement of 1.0 F-score, and the improvement over the original C&C model represents a reduction in error rate of more than 50%. Moreover, the percentage of sentences that are completely correct is now 54.1 (not shown in the table), compared with 32.9% for the original C&C parser.

Table 4 shows the performance of the Java C&C parser with neural models compared with recent CCG parsing results from the literature, where all the accuracy figures are taken from the respective papers. The final F-score of 92.9 on the test set represents a new state-of-the-art for the CCGbank parsing task.

Table 5 shows the accuracy of the parser by dependency relation, with the table copied from Clark and Curran (2007b); the new figures for this report are in the final F column, and the #deps column gives the number of dependencies of the corresponding type in Section 00 (recalculated to reflect the 100% coverage with Java C&C). Substantial improvements over the original C&C parser can be seen across the board. Of particular note are the improvements for
The speeds themselves are eclipsed by the need for search—has been seen already for parsing, especially for shift-reduce parsing where even fully-greedy parsers can be highly accurate (Chen and Manning, 2014; Xu et al., 2016). The speeds themselves are eclipsed by the

<table>
<thead>
<tr>
<th>Lexical category</th>
<th>Arg Slot</th>
<th>#deps</th>
<th>F(C&amp;C)</th>
<th>F</th>
</tr>
</thead>
<tbody>
<tr>
<td>N/N</td>
<td>1</td>
<td>nominal modifier</td>
<td>7 433</td>
<td>95.5</td>
</tr>
<tr>
<td>NP/N</td>
<td>1</td>
<td>determiner</td>
<td>4 153</td>
<td>96.3</td>
</tr>
<tr>
<td>(NP\NP_)/NP</td>
<td>2</td>
<td>np modifying prep</td>
<td>2 390</td>
<td>85.4</td>
</tr>
<tr>
<td>(NP\NP_)/NP</td>
<td>1</td>
<td>np modifying prep</td>
<td>2 193</td>
<td>83.6</td>
</tr>
<tr>
<td>((S/NP)/(S/NP))/NP</td>
<td>2</td>
<td>vp modifying prep</td>
<td>1 177</td>
<td>72.6</td>
</tr>
<tr>
<td>((S/NP)/(S/NP))/NP</td>
<td>1</td>
<td>vp modifying prep</td>
<td>1 068</td>
<td>71.4</td>
</tr>
<tr>
<td>(S[cl]/NP)/NP</td>
<td>1</td>
<td>transitive verb</td>
<td>877</td>
<td>83.5</td>
</tr>
<tr>
<td>(S[cl]/NP)/NP</td>
<td>2</td>
<td>transitive verb</td>
<td>923</td>
<td>83.9</td>
</tr>
<tr>
<td>(S\NP)/(S\NP)</td>
<td>1</td>
<td>adverbial modifier</td>
<td>750</td>
<td>86.8</td>
</tr>
<tr>
<td>PP/NP</td>
<td>1</td>
<td>prep complement</td>
<td>885</td>
<td>72.5</td>
</tr>
<tr>
<td>(S[b]/NP)/NP</td>
<td>2</td>
<td>inf transitive verb</td>
<td>648</td>
<td>85.5</td>
</tr>
<tr>
<td>(S[cl]/NP)/(S[b]/NP)</td>
<td>2</td>
<td>auxiliary</td>
<td>480</td>
<td>97.8</td>
</tr>
<tr>
<td>(S[cl]/NP)/(S[b]/NP)</td>
<td>1</td>
<td>auxiliary</td>
<td>488</td>
<td>93.6</td>
</tr>
<tr>
<td>(S[b]/NP)/NP</td>
<td>1</td>
<td>inf transitive verb</td>
<td>529</td>
<td>75.8</td>
</tr>
<tr>
<td>(NP/N)/NP</td>
<td>1</td>
<td>s genitive</td>
<td>385</td>
<td>96.1</td>
</tr>
<tr>
<td>(NP/N)/NP</td>
<td>2</td>
<td>s genitive</td>
<td>374</td>
<td>98.0</td>
</tr>
<tr>
<td>(S[cl]/NP)/S[cl]</td>
<td>1</td>
<td>sentential comp verb</td>
<td>387</td>
<td>92.9</td>
</tr>
<tr>
<td>(NP/N)/S[cl]/NP</td>
<td>1</td>
<td>subject rel pronoun</td>
<td>277</td>
<td>83.5</td>
</tr>
<tr>
<td>(NP/N)/S[cl]/NP</td>
<td>2</td>
<td>subject rel pronoun</td>
<td>279</td>
<td>97.3</td>
</tr>
<tr>
<td>(NP/N)/S[cl]/NP</td>
<td>1</td>
<td>object rel pronoun</td>
<td>26</td>
<td>75.0</td>
</tr>
<tr>
<td>(NP/N)/S[cl]/NP</td>
<td>2</td>
<td>object rel pronoun</td>
<td>23</td>
<td>84.4</td>
</tr>
<tr>
<td>NP/(S[cl]/NP)</td>
<td>1</td>
<td>headless obj rel pron</td>
<td>17</td>
<td>100.0</td>
</tr>
</tbody>
</table>

Table 5: Parser accuracy on Section 00 by dependency relation.

np modifying prep and vp modifying prep, which are dependencies potentially resulting from PP-attachment ambiguities, and the 100% accuracy scores for object rel pronoun, which are long-range dependencies resulting from extraction out of a relative clause and particularly difficult for parsers to recover correctly (Rimell et al., 2009).

Finally, Table 6 shows how the parser accuracy and parser speed varies with beam width. Accuracies are reported for Section 00, and the approximate speeds are calculated using the first 1,000 sentences of Section 00, running on a linux server.\footnote{Model Intel Xeon W-2265 CPU @ 3.50GHz.} The %-skimmed column gives the percentage of sentences that are analysed using the skimmer mode of the parser.\footnote{This percentage goes up and down with beam width because there are two parameters which affect it: the beam width itself, since a smaller beam reduces the chances of the chart containing a spanning derivation; and the maximum chart size allowed by the parser, which will get hit more often—hence triggering the skimmer—with a larger beam.} The parser is remarkably resilient to a decreasing beam width, with accuracy and coverage only being substantially affected with beam widths as low as 4. The ability of neural models to effectively utilise a large context when making decisions—thereby reducing the need for search—has been seen already for parsing, especially for shift-reduce parsing where even fully-greedy parsers can be highly accurate (Chen and Manning, 2014; Xu et al., 2016). The speeds themselves are eclipsed by the
parser of Lewis et al. (2016), which can parse over 2,000 sentences a second by exploiting the efficiency of the A* parsing algorithm and running the supertagger in parallel on a GPU. However, the speeds reported in Table 6 are reasonable considering that the implementation is in Java and has not been optimised, and the parser was run on the CPU; these speeds of around 100 sentences per second are still high enough to be used for large-scale textual data analysis.

<table>
<thead>
<tr>
<th>Beam-width</th>
<th>F (Sec. 00)</th>
<th>Sents/sec</th>
<th>%-skimmed</th>
</tr>
</thead>
<tbody>
<tr>
<td>64</td>
<td>93.0</td>
<td>8</td>
<td>0.9</td>
</tr>
<tr>
<td>32</td>
<td>93.0</td>
<td>23</td>
<td>0.7</td>
</tr>
<tr>
<td>16</td>
<td>93.0</td>
<td>51</td>
<td>0.5</td>
</tr>
<tr>
<td>8</td>
<td>92.9</td>
<td>105</td>
<td>0.4</td>
</tr>
<tr>
<td>4</td>
<td>91.7</td>
<td>167</td>
<td>2.2</td>
</tr>
</tbody>
</table>

Table 6: The speed/accuracy trade-off with different beam sizes.

4 Conclusion

This report has shown how a combination of Transformer-based neural models and a symbolic CCG grammar can lead to substantial gains over existing approaches to CCG parsing. The staggering improvements compared to the original C&C parser (Clark and Curran, 2004b), with overall dependency accuracies of almost 93% and complete sentence accuracies of 54%, are representative of how NLP has evolved over this time. In terms of how useful such parsers are for downstream tasks and applications, the success of large-scale language models (Brown et al., 2020) has, for now at least, largely replaced the old NLP pipeline in which parsers played a prominent role. Whether this trend will continue, and what this trend means for the nature of linguistic representation and learning, remain open questions (Lappin, 2021). However, even if this trend does continue, there may still be unforeseen roles for structural analysis in NLP; for example at Cambridge Quantum we are investigating how parsers can be used to build quantum circuits, exploiting the similarities between the compositional structures in categorial grammar and those in vector spaces, the latter of which lie at the heart of quantum computation (Coecke et al., 2010, Yeung and Kartsaklis, 2021, Lorenz et al., 2021).

Acknowledgments

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