University of Warsaw
Faculty of Philosophy

Magdalena Borysiak
Record book number: 446267

Dependency structure of English coordination: a surface-syntactic approach

Bachelor's thesis
in the field of Cognitive Science

The thesis was written under the supervision of
prof. dr hab. Adam Przepiórkowski
Faculty of Philosophy, University of Warsaw
Institute of Computer Science, Polish Academy of Sciences

Warsaw 2024

Summary

Key words

Streszczenie

Słowa kluczowe

Contents

Chapter 1

Introduction

The aim of this work is to expand on already existing research on the coordinate structures in the English language. An example of a coordination from the Corpus of Contemporary American English (Davies, 2023) (COCA, henceforth) is given in (1) – the word *and* serves as the conjunction, *this* and *so many things* as the conjuncts.

(1) We're opposites *in* [[this] and [so many things]].

This coordination is consistent with the observation that in English often the conjuncts on the left of a coordination are shorter than the ones on the right. According to Przepiórkowski and Woźniak (2023) however, the placement of the coordination's governor (the head of the whole structure, the word *in* in the example above) might have an influence on the way the coordination is structured: if the governor is on the left (as in (1)) or absent from the coordination altogether (as in (2)), then the left conjunct will be shorter. That is not necessarily the case if the governor is on the right (as in (3)).

(2) [[She was right], but [he didn't want to say so]].

(3) [[Cuban flags unfurled from windows] and [women wept]], Perez *says*.

The Dependency Length Minimization effect is proposed as an explanation for this, which paired with the results of the research provides an argument for symmetric theories of coordination and against asymmetric ones. There were however some limitations to the research that needed to be addressed. The study was based on the Penn Treebank, a corpus already annotated with constituency structures. The presence of a manually approved syntactic annotation is a huge advantage for research like this, but unfortunately the corpus describes only a narrow fragment of the English language – it is made up exclusively of the material from the Wall Street Journal and consists of 1.25M tokens, among which there were only 21,825 coordinations to analyse.

A replication of those results using a different resource has already been attempted and described in an unpublished manuscript by Przepiórkowski et al. (2024). The results were similar, but more precise – they supported not symmetric approaches to coordination in general, but specifically the multi-headed one. The corpus used there was COCA, which consists of over one billion words found in eight different genres ranging from academic to spoken. Unfortunately, it does not have any syntactic annotation that would immediately allow for data extraction and analysis similar to those in the study described above – it had to be annotated automatically. Because of that, the quality of the data was significantly lower – only 50.1% of the coordinations included in the evaluation of data were parsed and extracted correctly.

Issues with the data could possibly appear either at the parsing stage or at the extraction stage, and using Surface Syntactic Universal Dependencies (SUD) could help with both of those. According to Tuora et al. (2021), for some parsers (particularly the graph-based ones) the SUD annotation scheme might be easier to learn than Universal Dependencies – the annotation scheme used in the replication study mentioned above. As for the issues at the extraction stage, the SUD scheme has some structural benefits, that can be used to create more accurate heuristics.

Work reported in this thesis is based on COCA annotated automatically using Stanza (Qi et al., 2020), a graph-based dependency parser, in accordance with the SUD annotation scheme. The structure of this thesis is the following: Chapter 2 describes in more detail some of the theoretical aspects mentioned in the current chapter – this includes previous findings on coordinations in English, the Dependency Length Minimization effect and how it corresponds to different annotation schemes used in dependency treebanks, relevant differences between the UD and SUD annotation schemes and why the syntactic scheme seems to be more appropriate here. Chapter 3 describes how the corpus data was prepared for analysis – from training the parser to extracting the information about coordinate structures. Chapter 4 presents the analysis of the data, which is discussed in Chapter 5. Finally Chapter 6 covers the limitations of this research.

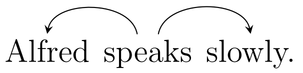
Chapter 2

Theoretical background

2.1 Dependency grammars

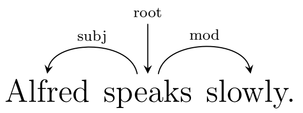
The first full-fledged dependency grammar was proposed by Tesnière (2015). One of the key ideas included in his work, was that a sentence is not comprised solely of its words, but also of the connections between them – dependencies. The connections he proposed were directed, therefore one of the words is always a governor (head) and the other is a dependent. Another crucial element of Tesnière's approach was verb centrality – the verb is the root of every sentence structure in dependency grammar.

(4)



Tesnière as an example used the sentence *Alfred speaks slowly*, for which a dependency tree is shown in (4). It visualises the rules described above – all of the words in a sentence are connected, those connections are directed and the verb is central the whole structure.

Dependency grammars have changed significantly since Tesnière's ideas were published. One example of such changes is the widespread usage of dependency labels, which describe the grammatical function that a word serves – Tesnière differentiated only between actants and circumstants, which can be understood as obligatory dependencies of a verb, that complete its meaning, and optional dependencies, that are not necessary to complete the meaning of the verb. Different corpora have their own ideas for sets of dependency labels, for instance full annotation for (4) could look similarly to (5), with the label `root` marking the central element of the sentence, `subj` marking the subject of the sentence and `mod` marking a modifier of the verb.

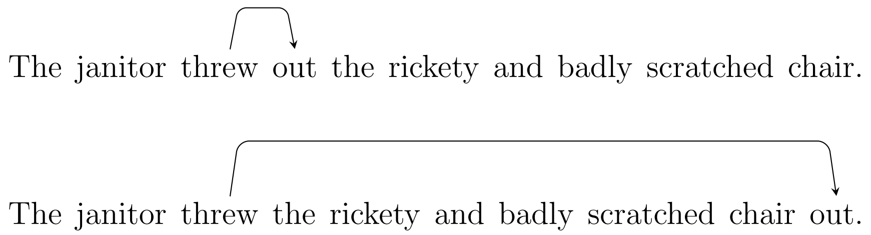


(5)

Section 2.2 describes some specific phenomena that can be explained using dependency grammars. In Section 2.3 there are described some of the ideas for dependency annotation of coordinate structures that have been used in different corpora and in Section 2.4 the studies, that this one is based on, are described. The last two sections of this chapter delve into more detail about two projects concerned with creating consistent dependency annotation schemes – Universal Dependencies in Section 2.5 and Surface-syntactic Universal Dependencies in 2.6.

2.2 Dependency length minimization

Familiarity with dependency grammars helps understand the principle of Dependency Length Minimization (henceforth DLM). It states that natural languages prefer shorter dependencies in their sentences. An example from Hunter and Prideaux (1983), shown in (6) illustrates this.



(6) a. The janitor threw out the rickety and badly scratched chair.

b. The janitor threw the rickety and badly scratched chair out.

The study has shown that speakers deem sentences similar to (6a) more acceptable than the ones similar to (6b)[1]. Proposed explanations for this preference are based on language-processing constraints, which are usually said to be caused by working memory limitations. With longer dependencies, while reading or hearing a sentence, a person has to keep certain words in their working memory for a longer time. The longer the dependency, the harder the retrieval of the needed word from the working memory. Similar effects have been found in other studies, both psycholinguistic ones (Gibson, 1998; King and Just, 1991) and the ones based on corpus research (Dyer, 2023; Gildea and Temperley, 2007, 2010).

The DLM effect has been observed both at the level of usage and at the level of grammar. The former has been explained already – when speakers have a few grammatically correct ways of phrasing a sentence, they are most likely to choose phrasing that will minimize the distance between connected words. As for DLM in grammar, an example is provided by Futrell et al. (2020). They first compared aggregate dependency lengths within natural language sentences to those in sentences created by randomising the word order while keeping the structure of the tree the same. Random-order sentences turned out to have longer overall dependencies than the natural language sentences, which was proof that, assuming grammar allows for multiple structures of a sentence, people choose the ones with shorter dependencies, therefore DLM works at the level of usage. The next step was to see if it works also at the level of grammar – to this end they checked whether the possible grammatical

[1] In the study it is actually found that its not the distance between the verb and the particle that affects the acceptability of sentences like those, but the syntactic complexity of the phrases within that distance. It was shown however, syntactic complexity as a measure of dependency length correlates with many others proposed, intervening words included (Wasow, 2002).

sentences (not necessarily chosen by speakers) minimised dependency lengths compared to sentences generated by the less constrained grammars. This way they found DLM to be influencing the grammar as well.

One of the earlier formulations of rules similar to DLM was made by Behaghel (1930). He proposed two laws of word order:

1. That which belongs together mentally is placed close together.
2. Of two sentence components, the shorter goes before the longer, when possible.

The first of these could be understood as DLM, while the other is a consequence of DLM in head-initial languages. Looking at how syntactic trees are usually shaped in a language allows for a judgement on the headedness or directionality of said language – it can be head-initial if most dependencies are directed to right, or head-final if they are mostly directed to the left. English is an example of a head-initial language, therefore the second law proposed by Behaghel holds for English sentences.

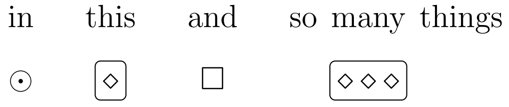
2.3 Possible dependency structures of a coordination

Different corpora choose different approaches to annotating the dependency structure of a coordination. Popel et al. (2013) proposed a taxonomy of those, which consists of three families of annotation styles: Prague, Stanford and Moscow. Przepiórkowski and Woźniak (2023) add to those three a London family. All four of those families are described in more detail in the following subsections. Diagrams are used to better illustrate them, where:

- ⊙ is the governor of the coordination;
- each ◇ symbolises a token, grouped together with a few others in a rectangle, forming a conjunct;
- □ is the conjunction of the coordination.

Therefore a coordination presented in (1) using this set of symbols would look like in (7).

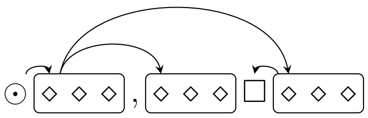
(7)



2.3.1 Bouquet/Stanford

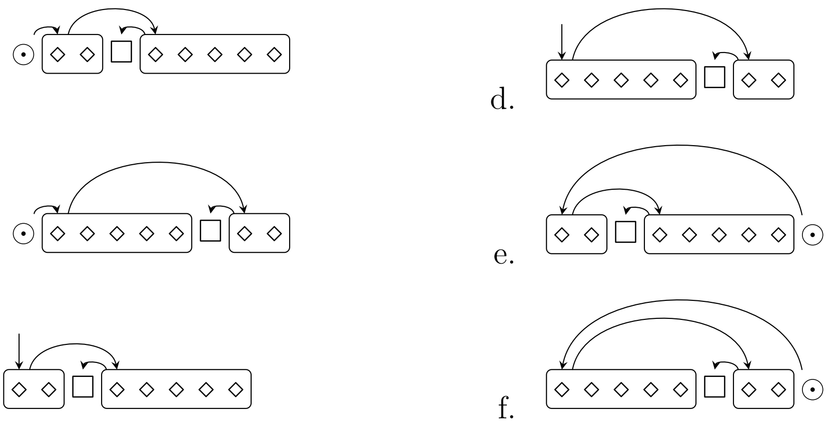
The bouquet structure comes from the Stanford parser (de Marneffe et al., 2006). Below is a simplified illustration of such a structure[2].

[2] It should be mentioned that in all of the diagrams in Section 2.3 it is assumed that the head of the conjunct is its first word. Such an assumption is justified, because the work presented here is based solely on the English language, which is mostly head-initial, therefore those structures are more likely to be shaped in the way presented here, than in any other.



There is a dependency connecting the governor of the coordination to the first conjunct, which is then connected to the heads of each conjunct, thus forming a bouquet. The conjunction is simply attached to the last conjunct in the structure. This style of annotating is one of the asymmetrical ones, since it does not treat all conjuncts of the coordination equally – it places emphasis on the first conjunct of a coordination by making it the head of every other conjunct.

(8)



a.

b.

c.

d.

e.

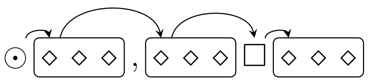
f.

The diagrams in (8) show how the annotation looks depending on different governor positions as well as conjunct lengths. In this particular case, the dependencies are always the shortest when the shorter conjunct is the one on the left, regardless of the position of the governor. This would suggest that, according to the DLM principle, coordinations with shorter conjuncts placed on the left would always be preferred.

As the Universal Dependencies annotation scheme (described in Section 2.5) was based on the annotations produced by the Stanford Parser, the scheme now uses the Bouquet style to annotate coordinations.

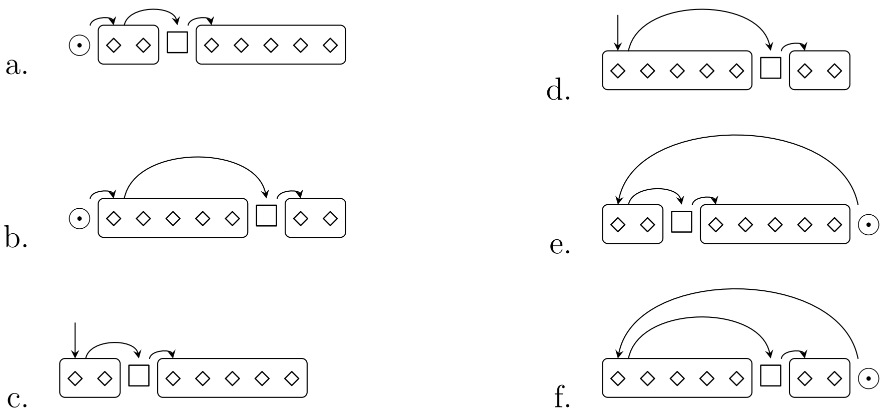
2.3.2 Chain/Moscow

Another asymmetrical approach is the chain, or Moscow one. It is utilised in the Meaning-Text Theory proposed by Mel'čuk (1988).



The structure is created by connecting the governor to the first conjunct of the coordination, then every other element of the coordination (including the conjunction) to the next one. As the dependency between the governor and the coordination is specifically between the governor and the first conjunct, the chain approach is another example of an asymmetrical annotation style.

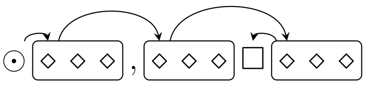
(9)



The diagrams in (9) show that in this case, similarly to the bouquet approach, the placement of the shorter conjunct on the left would be preferred, assuming the DLM principle. The placement of the governor again does not seem to have an effect on the ordering.

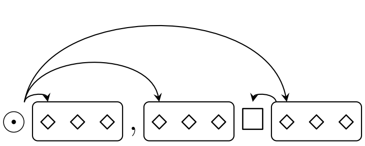
A variation of this annotation style is now used in the Surface-syntactic Universal Dependencies scheme (described in Section 2.6), which is based on the Universal Dependencies. The authors chose the Chain style instead of the Bouquet, as it minimizes the dependency lengths, which the authors wanted to be reflected in the syntactic structure. The difference between their style and the one shown in (9) is that the conjunction is not attached to the preceding conjunct, but to the next one. This annotation is illustrated in (10).

(10)



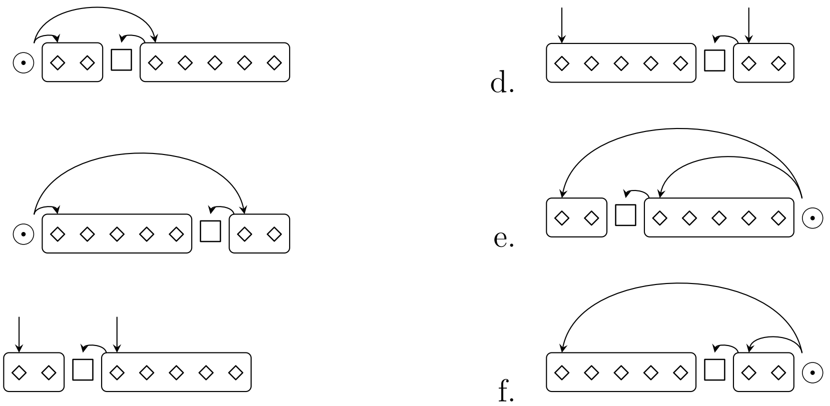
2.3.3 Multi-headed/London

The symmetrical approaches, as the name suggests, treat every conjunct in the coordination the same way. One of them is the multi-headed, or London approach, for which Przepiórkowski and Woźniak (2023) propose the name based on its appearance in Word Grammar developed by Hudson Richard (2010) at University College London.



The symmetry of the approach comes from the fact that no conjunct is highlighted by being the only direct dependent of coordinations governor. Instead, all of the conjuncts have dependencies connecting them to the governor, and the conjunction is dependent on the last conjunct, similarly to the bouquet approach.

(11)

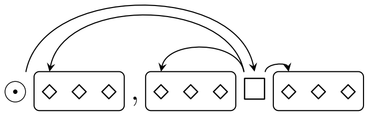


a. b. c. d. e. f.

Here, the predictions for the preferred ordering of conjuncts are different to those in asymmetrical approaches. This annotation suggests that the placement of the governor influences the conjunct ordering, specifically that the shorter conjunct will always be placed near the governor – with the governor on the left, as in (11a-b), the dependencies are shorter with the shorter conjunct placed on the left, and with the governor on the right (11e-f) the shorter conjunct should be placed on the right. In case of no word governing the coordination, there seems to be no preference for any ordering.

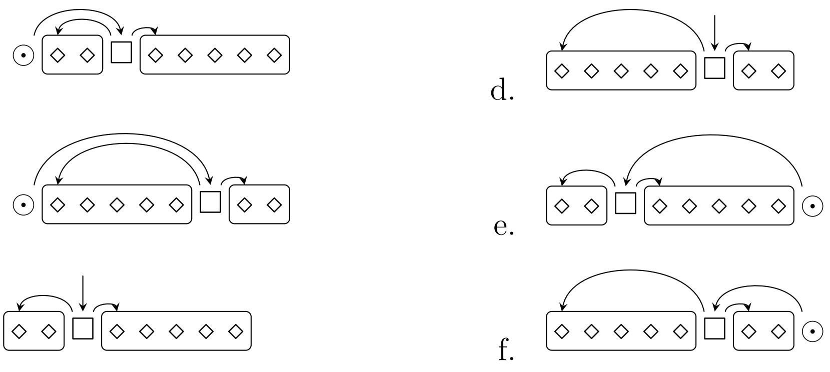
2.3.4 Conjunction-headed/Prague

The last approach discussed here is the one associated with the Prague Dependency Treebank, called the Prague approach by Popel et al. (2013) or the conjunction-headed by Przepiórkowski and Woźniak (2023).



This is another example of the symmetrical styles, as here again the governor treats all of the conjuncts the same way – in this case, does not connect to any of them. Instead, there is a dependency connecting the governor and the conjunction, which then has the conjuncts of the coordination as its dependents. In case of a coordination without a conjunction, the governor would connect to a punctuation mark.

(12)



a. b. c. d. e. f.

This annotation style again generates new predictions about the preferred ordering of conjuncts. With the governor placed on the left and without any governor present, this approach should prefer to have the shorter conjunct on the left side of the coordination. With the governor on the right, this approach predicts that ordering does not matter – in both cases presented here the sum of dependency lengths is the same.

2.4 Previous studies

The current study is a replication of Przepiórkowski and Woźniak (2023), who researched coordinate structures to find out whether ordering of conjuncts in English is as simple as placing shorter conjuncts on the left or the placement of the governor of the coordination has some influence on the ordering. They used the Penn Treebank, which is an annotated corpus of texts from the Wall Street Journal. This relatively small, but high quality dataset allowed them to make an argument for the symmetric styles of annotating coordination – they found that the proportion of shorter left conjuncts rose with increasing length differences between conjuncts, but only in coordinations with the governor on the left or without a governor. If the governor was on the right of the coordination, chances for the shorter conjuncts appearing on either side were equal. This is compatible with what the Prague approach would predict, assuming DLM working at the level of usage. The London approach could also explain those results, but only if DLM at the level of grammar was assumed. Since English is a head-initial language, DLM still suggests that shorter dependencies will be placed first, according to the second word of law order proposed by Behaghel (1930). This means that there is a grammaticalised pressure to place shorter conjuncts on the left, and since in case where there is no governor there are no immediate pressures to order the conjuncts in a certain way, the general, grammaticalised pressure may be visible.

Przepiórkowski et al. (2024) have already conducted a replication study of this research. The aims were to see whether the conclusions drawn in the original study hold up when the data come from a bigger and more diverse corpus, but annotated automatically using the Stanza parser. The results were slightly different, but sharpened the conclusions from the original study. In the bigger dataset they found the coordinations with the governor on the left and without a governor to behave the same – with growing length differences between conjuncts the proportion of shorter left conjuncts was higher. Only this time, when the governor was on the right, proportion of shorter left conjuncts was lower with bigger length differences, meaning that the shorter conjunct was drawn to the governor. The Prague annotation predicts that with governor on the right there should be no pressures to order the conjuncts in any way, therefore it turned out to be less compatible than the London approach. Assuming this annotation style, the coordinations with the governor on the right should in fact have shorter conjuncts on the right and the rising proportion of the shorter left conjuncts when there is no governor could be again explained by the grammaticalised pressures of DLM.

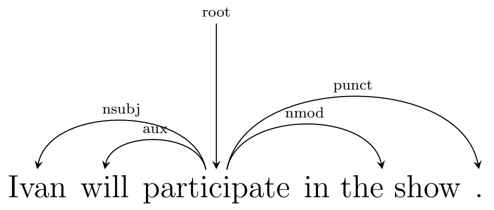
The main issue with this replication study was the low evaluation score of the extracted data. Only 50.1% coordinations in the evaluation sample turned out to have correct information for analysis. Reasons for such a low outcome, as well as potential solutions are discussed in Section 2.6.

2.5 Universal Dependencies

As seen in Section 2.3, there have been many ideas on how to create dependency annotation. Universal Dependencies (UD, henceforth) is a project focused on formulating guidelines for creating dependency annotation, that would suit as many languages as possible, while maintaining the possibility to represent phenomena specific to any given language. The guidelines outline how one should deal with word segmentation, part-of-speech tagging, assigning morphological features and creating an appropriate dependency structure for a sentence.

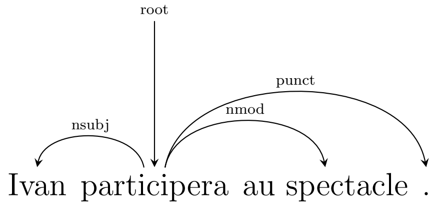
Rules for creating a dependency structure are the most relevant part here. In the first version of UD (Nivre et al., 2016) three of them are specified: dependency relations appear between content words, function words are attached to the content words, which they describe, and punctuation marks are attached to the head of the phrase or clause in which it appears. Content words chosen here for dependency heads can otherwise be called ”lexical” or ”semantic” centers, whereas function words serve mostly a syntactic purpose in a sentence. In the sentence (13) among the words *will* and *participate*, the latter is the one that carries the meaning, thus it is the content word, head of the dependency and, in this case, root of the whole sentence.

(13)



The reasoning behind setting those criteria is that it increases the chance of finding similar tree structures in different languages, for example when comparing sentences between English and French, which is morphologically richer. In (14) there is a tree for the French translation of the sentence in (13). Even though the French sentence does not have an auxiliary word to mark the future tense, the structures of those sentences are almost identical, which would not be possible if UD chose to create dependencies between functional words, rather than content words.

(14)



For an annotation project on such a significant scale, a unified format for the data was needed, therefore the CoNLL-X format was adapted to the UD needs. This version of the format is used in the current work.

2.6 Surface-syntactic Universal Dependencies

Surface-syntactic Universal Dependencies (SUD, henceforth) is another example of an attempt at creating a set of universal guidelines for dependency annotation. Gerdes et al. (2018) describe it as ”near-isomorphic to UD” and offer a set of conversion rules between the schemes. Most of the SUD annotation guidelines are the same as in UD, the most prominent difference is the change in choosing dependency heads, from content words to function words. This section covers the relevant differences between the schemes and how those are beneficial for research described in this work.

2.6.1 Criteria for choosing heads of dependencies

Instead of favoring content words, SUD uses the distributional criteria for choosing dependency heads, which means that ”the surface syntactic head determines the distribution of the unit” (Gerdes et al., 2018). It can be tested by checking which of the words within a dependency behaves in sentences similarly to the way the whole unit does, so which of the words can be replaced by the unit and *vice versa*. The example sentence the authors use to explain their criteria is *The little boy talked to Mary*. There is a dependency between words *little* and *boy*, and sentences in (15) and (16) show why the head of this dependency is the word *boy*. In (15a) the word *boy* can be replaced by the unit *little boy*, as shown in (15b), and the sentence is still grammatical.

(15) a. I saw a **boy**.
b. I saw a **little boy**.

The same is not the case for the word *little*. Trying to replace that word with the whole unit in (16a) results in an ungrammatical sentence in (16b). Sentences (16c-d) shows that replacement in the other way is not possible either, therefore the word *little* cannot be the head of this dependency.

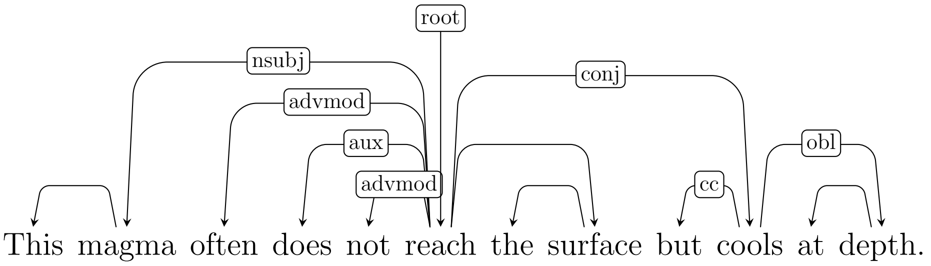
(16) a. The boy was **little**.
b. * The boy was **little boy**.
c. I found the **little boy**.
d. * I found the **little**.

It is not always possible to test both of the words within a dependency, but in such cases showing that one of the words does not commute with the whole unit is enough to decide it is not the head, therefore the other one must be. As shown in Gerdes et al. (2018), that is exactly the case with the words *to Mary* – it is impossible to see how the word *to* behaves on its own, as it needs a noun or a verb, but the sentences in (17) show that *Mary* does not have the same distribution as those two words together.

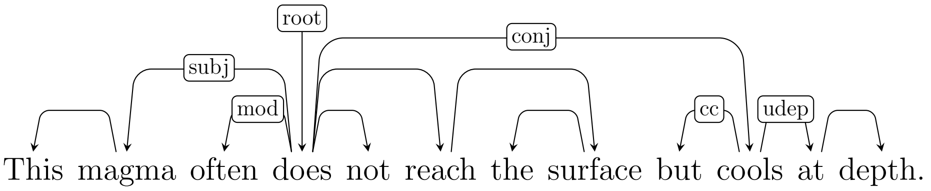
(17) a. I saw **Mary**.
b. * I saw **to Mary**.
c. I talked **to Mary**.
d. * I talked **Mary**.

This key difference between UD and SUD has crucial consequences for extracting the exact length of conjuncts in a coordinate structure, which is an integral part of this work. As Przepiórkowski and Woźniak (2023) mention, the UD scheme is not ideal for coordination analysis, as it is not clear which dependencies are shared by the conjuncts and which are private. This is clearly illustrated by the example sentence *Never drink and drive*, where a human parser knows that the word *never* applies to both conjuncts of a coordination, but this would not be obvious to an algorithm. As shown in Przepiórkowski et al. (2024), some heuristics can be employed to find the extents of conjuncts, but they can fail in some cases. It might however be easier to construct accurate heuristics when working with a more syntax-focused annotation scheme than UD, such as SUD.

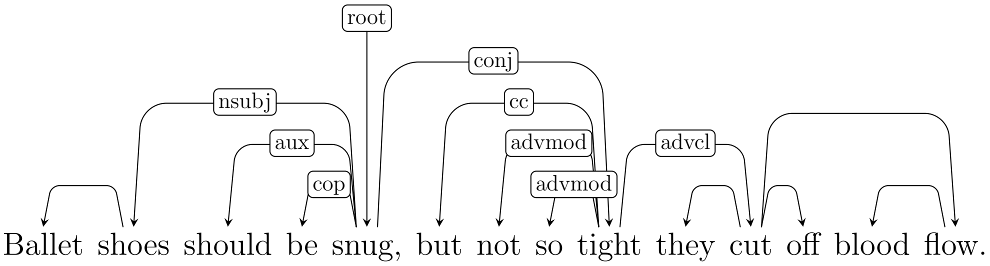
(18)


root
nsubj
advmod
aux
advmod
conj
cc
obl
This magma often does not reach the surface but cools at depth.

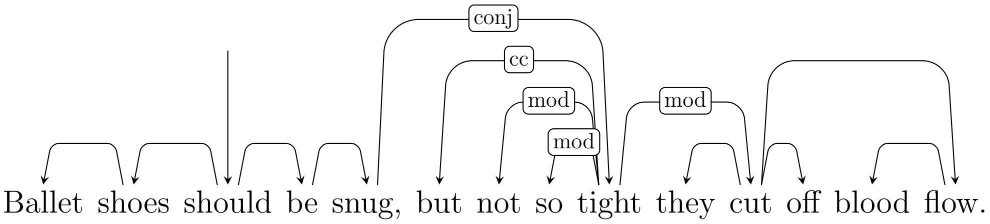
(19)


root
conj
subj
mod
cc
udep
This magma often does not reach the surface but cools at depth.

(20)


root
conj
nsubj
cc
aux
advmod
cop
advmod
advcl
Ballet shoes should be snug, but not so tight they cut off blood flow.

(21)


conj
cc
mod
mod
mod
Ballet shoes should be snug, but not so tight they cut off blood flow.

Based on heuristics used by Przepiórkowski et al. (2024), the tree in (18) would give a coordination with conjuncts *go near my father* and *kept my hand in my pocket*. That would be, because the head of the left conjunct, *go*, has on its left side a dependency labeled `aux` and the head of the right conjunct, *kept* does not have a dependency like this one, therefore `aux` has to be shared by both conjuncts. The correct parse of this sentence gives a coordination with conjuncts *did not go near my father* and *kept my hand in my pocket*, so the dependencies *did not* should not be shared, but private to the first conjunct.

Modifying the heuristics, so that they fit this example, for instance by saying that aux dependencies should always be included in the left conjunct, would on the other hand mean that sentences such as in (20) would have incorrect extracted coordinations. In this example the correct coordinate structure has conjuncts *snug* and *not so tight they cut off blood flow*, but was the algorithm to include the aux dependency in the first conjunct (as would be required in (18)), the result would be conjuncts *should be snug* and *not so tight they cut off blood flow*.

This however is not an issue when using the SUD scheme. There, the words *did not* cannot be dependencies of the coordination, because it is the coordination that is dependent on the word *did*. This way it is ensured that words *did not* will not be a part of the first conjnuct and this results in the correct extraction of the coordinate structure. Changing the annotation scheme to SUD does not affect the sentence in (20) – the word *snug* has to be the whole left conjunct, because it also does not have any dependencies in this annotation scheme.

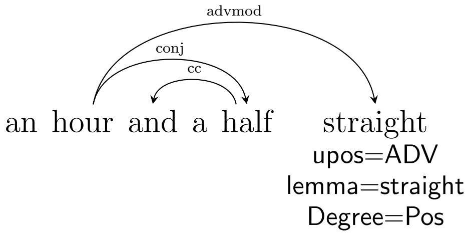
2.6.2 Explicit information about shared dependencies

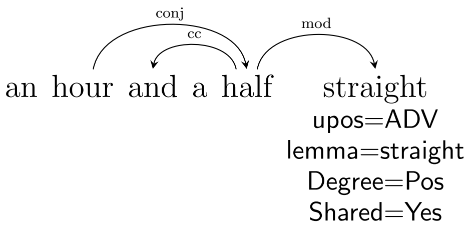
Besides the structural advantages that SUD has over UD when it comes to analysing coordination, there is one additional feature that is added in SUD treebanks that helps find the extent of conjuncts.

While UD corpora are often created specifically for the purpose of participating in the UD project or converted with manual corrections from different dependency annotations, the SUD corpora are mostly converted automatically from UD. There are a few French treebanks, as well as for Beja, Zaar, Chinese and Naija, that are natively made for SUD, but all others are converted from UD using rule-based graph transformation grammars, which are described in more detail in Chapter 3.

As was mentioned in Section 2.3, UD uses the Bouquet approach to annotating coordination, while SUD uses the Chain one. This means that in the conversion process, some information about the privacy status of a dependency of the coordination can be lost. This is visible in the coordination presented in the sentence *I just sat in there for like an hour and a half straight and studied* (GUM_vlog_studying-27 from the GUM corpus). As annotation in UD in (22) shows, the word *straight* is shared by the whole structure. This is not structurally visible in the SUD version in (23), where the mod dependency for the word *straight* is attached to the last conjunct.

(22)





(23)

So as not to lose this information while converting the annotation scheme, feature Shared=Yes is added. Similarly, in coordinations where a dependent is attached to the right conjunct in the UD scheme (therefore private to the right conjuct), during the conversion to SUD the feature Shared=No is added.

While the work described here is not based on the conversion code itself, this information still might prove itself useful. The parser was trained on SUD corpora, therefore it might be able to provide additional clues as to which dependents are shared and which are private.

2.6.3 Learnability of dependency schemes

The current study is another replication of Przepiórkowski and Woźniak (2023). As was pointed out in Chapter 1, Przepiórkowski et al. (2024) have conducted identical analysis on the COCA corpus annotated automatically in the UD scheme. After evaluating the automatically annotated data they found only 50.1% of the coordinations in the evaluation sample to be correctly extracted from the corpus. Reason for such an outcome can be twofold: the issues lie either within the parsing accuracy or the script for extracting coordinations from dependency trees.

The latter has been addressed to some extent in Section 2.6.1 – heuristics for finding conjunct extents are easier to develop within a function-word focused annotation scheme. As for the former, there are studies showing that the UD scheme is harder to parse. Rehbein et al. (2017) show that choosing content words rather than function words for dependency heads increases arc direction entropy (measure describing how consistent are dependency directions in a given treebank), which then lowers parsing accuracy. In another study, Kohita et al. (2017) converted UD trees into ones with function heads, rather than content heads. They then used the converted trees for training parsers and parsed 19 treebanks using both UD and converted models. After parsing, the results from the converted model were converted back to UD and for most of the languages (11 out of 19) those results had better scores.

Criterion for choosing dependency heads may not be the only structural advantage that SUD has over UD in terms of parsing. As Gerdes et al. (2018) demonstrate in their article, the Chain approach to annotating coordination, that is used in SUD, minimises the dependency lengths compared to the Bouquet approach used in UD. This may be beneficial for parsing accuracy, as parsers tend to perform better when working with shorter dependencies (Nilsson et al., 2006; Eisner and Smith, 2005).

In the studies cited above the comparison was between UD and a scheme that differed from UD only in some particular aspect, not a new, comprehensive scheme. Tuora et al. (2021) however compared UD to SUD, which matters because, as they say, ”any realistic annotation schema which employs a more ‘syntactic’ approach to headedness than UD will also differ from UD in the repertoire and distribution of dependency labels, and will also take into account the intrinsic linguistic interaction between various constructions”. They trained five parsers, two of which were transition-based and three graph-based, using 21 corpora representing 18 languages. While transition-based parser seemed to perform similarly on both annotation schemes, the graph-based ones preferred SUD. As for attachment scores for the English corpus tested in this experiment (GUM), all of the parsers scored higher with the SUD annotation. The parser utilised in the current study, Stanza, is graph-based and the language of the texts it annotates is English, therefore SUD might be the better choice for the annotation scheme for this data.

Chapter 3

Data processing

The data used in this work is based on the Corpus of Contemporary American English. The corpus consists of raw texts collected in a span of 30 years (1990 – 2019) representing 8 styles: academic, fiction, newspapers, magazines, TV/movies, websites, blogs and spoken data. For the analysis of coordinations to be possible, first the texts have to be annotated syntactically – here the Stanza parser was chosen for this task. The default parsing model provided for English annotates in the Universal Dependencies scheme, but as was explained earlier, the Surface-syntactic Universal Dependencies scheme is preferred here. The parser therefore had to be trained to annotate in the SUD scheme.

The current chapter has two sections: the first one describes the process of training the parsing models that created the syntactic annotation. The second one describes the procedure of finding coordinate structures in parsed sentences and creating a table with data ready for analysis.

3.1 Parser training

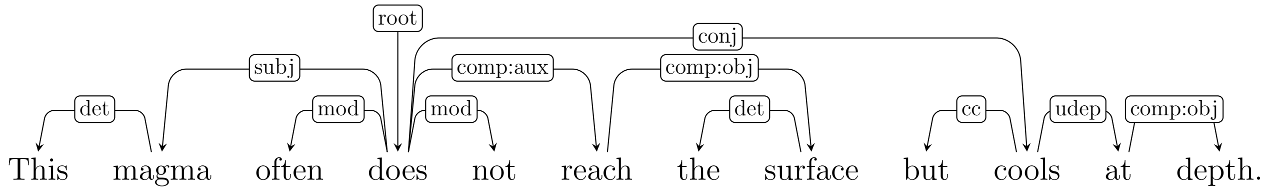
Training was conducted using scritps made available on github by the Stanza developers.[1] For the parser to learn annotation, there needs to be already annotated data. The Surface-syntactic Universal Dependencies is a much smaller project than Universal Dependencies, therefore there are not many corpora annotated natively in this scheme. Because of that, a set of graph conversion rules was developed.[2] Using this conversion code, almost all of the UD corpora have been translated to SUD.

Dependency trees as shown in previous chapters, though possibly comprehensible for people, are not written in a way that is easily understandable by computer programs, including parsers. Hence Buchholz and Marsi (2006) created the CoNLL-X format. The exact purpose was to compare parser outputs in a dependency parsing shared task. Today it is widely used for representing dependency trees in a plain-text form. The UD project adapted the format to their needs by replacing some of the information included in CoNLL-X and thus creating the CoNLL-U format. In (24) there is an example of a SUD dependency tree presented as a tree and in the CoNLL-U format.

[1] https://github.com/stanfordnlp/stanza-train

[2] https://github.com/surfacesyntacticud/tools/blob/v2.12/converter/grs/UD_to_SUD.grs

(24)


root
conj
subj
comp:aux
comp:obj
det
mod
mod
det
cc
udep
comp:obj
This magma often does not reach the surface but cools at depth.

```
# text = This magma often does not reach the surface but cools at depth.
  1     This      this     DET     DT    Number=Sing|PronType=Dem                              2     det        _   start_char=0|end_char=4
  2     magma     magma    NOUN    NN    Number=Sing|Shared=No                                 4     subj       _   start_char=5|end_char=10
  3     often     often    ADV     RB    _                                                     4     mod        _   start_char=11|end_char=16
  4     does      do       AUX     VBZ   Mood=Ind|Number=Sing|Person=3|Tense=Pres|VerbForm=Fin  0     root       _   start_char=17|end_char=21
  5     not       not      PART    RB    _                                                     4     mod        _   start_char=22|end_char=25
  6     reach     reach    VERB    VB    VerbForm=Inf                                          4     comp:aux   _   start_char=26|end_char=31
  7     the       the      DET     DT    Definite=Def|PronType=Art                             8     det        _   start_char=32|end_char=35
  8     surface   surface  NOUN    NN    Number=Sing                                           6     comp:obj   _   start_char=36|end_char=43
  9     but       but      CCONJ   CC    _                                                     10    cc         _   start_char=44|end_char=47
  10    cools     cool     VERB    VBZ   Mood=Ind|Number=Sing|Person=3|Tense=Pres|VerbForm=Fin  4     conj       _   start_char=48|end_char=53
  11    at        at       ADP     IN    Shared=No                                             10    udep       _   start_char=54|end_char=56
  12    depth     depth    NOUN    NN    Number=Sing                                           11    comp:obj   _   start_char=57|end_char=62
  13    .         .        PUNCT   .     _                                                     4     punct      _   start_char=62|end_char=63
```

Corpora in the CoNLL-U format were downloaded from the SUD website. If a corpus is large enough, it is split into three parts: training, development and testing. The training set is used to expose the parser to the correct dependency trees and based on that a prediction model is created. The model is tuned using the development set – the model tries to predict what is the correct dependency tree for a sentence and the prediction is then confronted with the data in the set. Adjustments are made until there is no gain in the scores acheived by the parser for a certain number of learning steps (in the scripts used here this is 3000 steps).

Training a model requires word vector data (which is provided with the default model for English) and a prepared treebank – this means that all of the possible annotations from a treebank have to be listed for the prediction model to choose from. After all the needed files were provided, the training script was run. The batch size was set to 5000 and the dropout rate was 0.33. This means that the whole training dataset was split into batches, each with 5000 elements – the bigger the batch the more precise the gradient function and thus the predictions. Dropout rate is the proportion of nodes in the neural network that are dropped during training. Without any dropout, a model might become overfitted for the training data. This means that it will be very good at predicting annotations for the sentences it has already seen, but not so much with any other data. The dropout rate chosen for training here was recommended in the training documentation.

All of the corpora used in this experiment were ready for training, besides one – the GUMReddit corpus, as it is not fully available online. All of the dependencies and morphological features and so on are included in the CoNLL-U files, but the words themselves and the lemmas are missing. As the textual data is required for training, the appropriate script from the GUM corpus repository was utilised.[3]

The following subsections describe the models that were trained as a part of this study.

[3] https://github.com/amir-zeldes/gum/blob/master/get_text.py

3.1.1 Combined model

The most crucial of the models was the combined one. It was used to annotate most of the data analysed in this study. The corpora used for training were SUD_English-EWT, SUD_English-GUM, SUD_English-ParTUT.

The first of these is based on the English Web Treebank. It has 5 primary sources of data: weblogs, newsgroups, emails, reviews and question-answers. The first two – weblogs and newsgroups – were collected in the years 2003–2006. Email messages are from the Enronsent Corpus, which contains emails sent by the employees of Enron Corporation in the years 1999–2002, that were made public domain during the investigation of Enron. The emails in the corpus were processed to have as little non-human input as possible. The reviews of businesses and services included in the corpus were taken from various Google websites in 2011, but no specific dates were provided. The case was similar with question-answer data, which was collected in 2011 from the Yahoo! Answers website. In total, the corpus contains 254,820 words. The original constituency annotation was automatically converted into Stanford Dependencies and then manually corrected to UD. Using the code mentioned earlier in this chapter it was then converted to SUD. The corpus was chosen for training this model, as it is the biggest available annotated corpus for English.

The second corpus used for this model was SUD_English-GUM, which is a SUD-converted version of the Georgetown University Multilayer corpus. While the early versions of GUM were annotated in Stanford Dependencies scheme, they were later manually converted into UD and the later versions have been created natively in UD. The corpus comprises a variety of styles, for instance academic, interviews, travel guides, letters, how-to guides and forum discussions. The last of these requires special attention, since it is sometimes considered seperately from the rest of the GUM corpus. The source for this data are Reddit forum discussions, which means that the text within this part of the corpus is protected by the Reddit terms and conditions and thus not freely available. In this data, words are substituted by underscores in the form and lemma fields in CoNLL-U files. Using it for training requires first running a script that completed the corpus, as was mentioned eariler. Including the Reddit data, there are 228,399 tokens in the corpus, which makes it the second largest corpus among the ones available for English and an obvious choice for training a parser.

The third corpus used for training the combined model was one based on the English part of ParTUT, the multilingual parallel treebank from the University of Turin. It consists of legal texts, Wikipedia articles and transcriptions of TED Talks. It was originally annotated in a style specific to the treebanks developed at the University of Turin, then converted to UD and from that to SUD. The corpus has 49,602 tokens, which is a lot less compared to the corpora described earlier, but is still a significant contribution to the model, especially considering the style difference between this corpus and the other ones.

One additional reason for choosing the corpora listed above is consistency of annotation. Some corpora, despite the style diversity they could provide for the parsing model, had to be excluded from training, because some information was missing or inconsistent with the other corpora used here.

For English, the Stanza parser by default also uses a model trained on multiple corpora: EWT, GUM, PUD and Pronouns. The two last ones were not used to train the model here, as they were too small to have been split into the training, development and testing sets.

3.1.2 Spoken model

Spoken and written language differ significantly, which can lead to poor automatic parsing performance. To avoid that, this experiment involves training a model specialising in spoken data. The corpora used to this end were SUD_English-Atis and parts of the SUD_English-GUM corpus.

Parts of the GUM corpus utilised here were those with interviews, conversations and vlogs. The relevant sentences were extracted from the original CoNLL-U files by looking for documents labelled `id = GUM_interview`, `id = GUM_vlog` or `id = GUM_conversation`.

As for the other corpus, Atis comprises sentences from the Airline Travel Informations dataset. Those are transcriptions of people asking automated inquiry systems for flight information. The corpus has 61,879 tokens and was natively annotated in UD.

3.1.3 Comparison models

The main purpose of the combined model is to create annotation for analysis, though one of the intentions of this study was also to compare the learnability of the two dependency annotation schemes: the "semantic" UD and the "syntactic" SUD. However a direct comparison between the two combined models is not be possible for a lack of information about the UD combined model. The datasets included in the training are described in the Stanza documentation,[4] however there is no information on how the datasets were split into training and testing sets. The splits are known for big corpora, such as GUM and EWT, but the PUD and Pronouns are too small to be split into smaller sets. Another issue is that the evaluation for the UD combined model was not made available and running an evaluation script on this model is not possible without the training, development and testing splits.

Considering this, the learnability of the annotation schemes described here is compared based on the models that are trained on one corpus each. All of those models have been trained on corpora big enough to have official splits into training, development and testing sets. Evaluation of those models trained on UD is reported in the Stanza documentation and was conducted on the testing sets. The comparison SUD models were trained using the official splits for every corpus. Results of the evaluation of this training along with the evaluation results for the corresponding UD models are shown in Section (there will be a ref here).

[4] https://stanfordnlp.github.io/stanza/combined_models.html

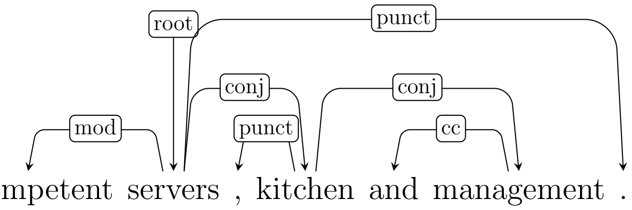
3.2 Data extraction

The input data from the COCA corpus was in the form of text files. Those were split into sentences using another parser, Trankit (Nguyen et al., 2021), as the sentence segmentation outputs from Trankit and Stanza suggested that this would provide better quality data for further analysis. Split texts were then put into .tsv files, so that along with the sentence text, also the information about text identifier and the index of the sentence in a document could be included. Those sentences were then put into batches, but separated with `\n\n`. This way the parsing process was faster than it would be when parsing sentence by sentence, but the sentences were clearly already split. The next step was parsing the texts, which was done using a parsing pipeline. Creating a parsing pipeline requires specifying the input language and the processors that make up the pipeline – in this case those were the tokeniser, part-of-speech-tagger, lemmatiser and dependency parser. Here the tokeniser and lemmatiser were those of the default English model, as those two processes are the same in UD and SUD. The other two processors, POS-tagger and dependency parser were trained on SUD and used in the pipeline. Additionally, it was specified that the text was already split into sentences by setting the `tokenize_no_split` parameter to `True`. The pipeline configuration is shown in (25).

(25)
```
config = {
    'processors': 'tokenize,pos,lemma,depparse',
    'lang': 'en',
    'use_gpu': True,
    'pos_model_path':
'./saved_models/en_combined-sud_charlm_tagger.pt',
    'depparse_model_path':
'./saved_models/en_combined-sud_charlm_parser.pt',
    'tokenize_pretokenized': False,
    'tokenize_no_ssplit': True,
    'download_method': stanza.DownloadMethod.REUSE_RESOURCES
    }
nlp = stanza.Pipeline(**config)
```

The process of extracting coordinations will be illustrated by the sentence shown in (26) with a SUD tree.[5]

(26)



The text is then given to the `nlp` pipeline and parsed. In the output there is a list of Sentence objects, which have a list of dependencies as one of their attributes.

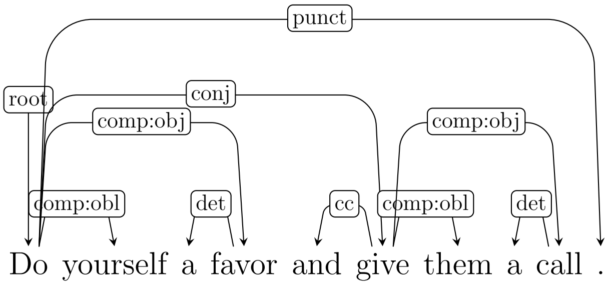
Coordinations are found by looking for `conj` dependencies within a sentence. The SUD approach assumes the chain representation of a coordination,

[5] Sentence `reviews-357217-0002` from the EWT corpus (Silveira et al., 2014).

therefore once there a `conj` dependency is found, the script looks for more links in the chain. In the sentence (26) first the `conj` dependency will be found between the words *servers* and *kitchen*. Indices of those two words are saved in a list and the script looks through the dependencies attached to the word *kitchen*: there is `punct` and `conj`. The `conj` one is attached to the word *management*, therefore the same is then done for that word: its index is saved to the list and the script checks whether it has a `conj` dependency. Since it does not have such a dependency, the whole coordination has been found – it has three conjuncts: *servers*, *kitchen* and *management*.

Once all lists of indices representing coordinations in a given sentence are ready, for each one of them a dictionary is created. An example of such a dictionary will be presented for the coordination in the sentence in (27)[6].

(27)



The first and last indices are popped from the list and added to the dictionary as the left and right conjunct heads respectively with the keys `'L'` and `'R'`. The rest of the conjuncts are added with the key `'other_conjuncts'` – for the coordination in sentence (27) that list is empty, as there are only two conjuncts. This coordination does not have a governor, therefore the key `'gov'` is not added to the dictionary. The next step is looking for the conjunction of the coordination. If there is one, it is always attached to the right conjunct and it is labelled `cc`. Once it is found, the whole word is added to the dictionary with the `'conj'` key.

Finally, the information about the conjunct lengths has to be extracted. All of the dependencies appearing between the left and right conjunct heads are considered private to the conjuncts they are attached to. This means that in sentence (27) the case of the left conjunct is simple – both of the dependencies of the word *Do* (`comp:obj` and `comp:obl`) are directed to the right and are therefore part of the left conjunct. As for the head of the right conjunct, the word *give*, its dependencies could be shared by the whole coordination. A heuristic applied here is that if any of the other conjuncts have a dependency with the same label as some external dependency of the leftmost or rightmost conjunct, that external dependency is private to this conjunct. Here, the word *give* has a dependency `comp:obj` directed to the right. The head of the other conjunct, *Do*, also has a dependency with this label, therefore this dependency is private to and part of the right conjunct. If the word *Do* did not have such a dependency, the word *call* would have to be excluded from the right conjunct and shared by the whole coordination.

[6] Sentence `answers-20111024111513AAAQhAO_ans-0006` from the EWT corpus (Silveira et al., 2014).

With conjunct texts found, they can be measured. This is done in characters by taking the length of the conjunct text, in words and tokens by counting how many of those parser found in the conjunct and in syllables using the `cmudict` from the `nltk` package. In (28) there are contents of the dictionary corresponding to the coordination found in sentence (27).

(28)

```
’L’: {"id": 1,
    "text": "Do",
    "lemma": "do",
    "upos": "VERB",
    "xpos": "VB",
    "feats": "Mood=Imp|VerbForm=Fin",
    "head": 0,
    "deprel": "root"}
’Lconj’: ’Do yourself a favor’
’Lwords’: 4
’Ltokens’: 4
’Lsyl’: 6

’conj’: {"id": 5,
    "text": "and",
    "lemma": "and",
    "upos": "CCONJ",
    "xpos": "CC",
    "head": 6,
    "deprel": "cc"}

’R’: {"id": 6,
    "text": "give",
    "lemma": "give",
    "upos": "VERB",
    "xpos": "VB",
    "feats": "Mood=Imp|VerbForm=Fin",
    "head": 1,
    "deprel": "conj"}
’Rconj’: ’give them a call’
’Rwords’: 4
’Rtokens’: 4
’Rsyl’: 4

’other_conjuncts’: []
’conj_lengths’: [(4, 19), (4, 16)]
’sentence’: ’Do yourself a favor and
give them a call.’
’sent_id’:
’answers-20111024111513AAAQhAO_ans-0006’
```

A list of dictionaries like the one in (28) is created for every processed corpus file. Then every dictionary becomes an observation in an output .csv table.

Bibliography

Behaghel, O. (1930). Zur wortstellung des deutschen. *Language*, 6(4):29–33.

Buchholz, S. and Marsi, E. (2006). CoNLL-X shared task on multilingual dependency parsing. In Màrquez, L. and Klein, D., editors, *Proceedings of the Tenth Conference on Computational Natural Language Learning (CoNLL-X)*, pages 149–164, New York City. Association for Computational Linguistics.

Davies, M. (2008–2023). The Corpus of Contemporary American English (COCA). https://www.english-corpora.org/coca/.

de Marneffe, M.-C., MacCartney, B., and Manning, C. D. (2006). Generating typed dependency parses from phrase structure parses. In Calzolari, N., Choukri, K., Gangemi, A., Maegaard, B., Mariani, J., Odijk, J., and Tapias, D., editors, *Proceedings of the Fifth International Conference on Language Resources and Evaluation (LREC'06)*, Genoa, Italy. European Language Resources Association (ELRA).

Dyer, A. (2023). Revisiting dependency length and intervener complexity minimisation on a parallel corpus in 35 languages. In *Proceedings of the 5th Workshop on Research in Computational Linguistic Typology and Multilingual NLP*, pages 110–119.

Eisner, J. and Smith, N. A. (2005). Parsing with soft and hard constraints on dependency length. In Bunt, H. and Malouf, R., editors, *Proceedings of the Ninth International Workshop on Parsing Technology*, pages 30–41, Vancouver, British Columbia. Association for Computational Linguistics.

Futrell, R., Levy, R., and Gibson, E. (2020). Dependency locality as an explanatory principle for word order. *Language*, 96:371–412.

Gerdes, K., Guillaume, B., Kahane, S., and Perrier, G. (2018). SUD or surface-syntactic Universal Dependencies: An annotation scheme near-isomorphic to UD. In de Marneffe, M.-C., Lynn, T., and Schuster, S., editors, *Proceedings of the Second Workshop on Universal Dependencies (UDW 2018)*, pages 66–74, Brussels, Belgium. Association for Computational Linguistics.

Gibson, E. (1998). Linguistic complexity: locality of syntactic dependencies. *Cognition*, 68(1):1–76.

Gildea, D. and Temperley, D. (2007). Optimizing grammars for minimum dependency length. In Zaenen, A. and van den Bosch, A., editors, *Proceedings* *of the 45th Annual Meeting of the Association of Computational Linguistics*, pages 184–191, Prague, Czech Republic. Association for Computational Linguistics.

Gildea, D. and Temperley, D. (2010). Do grammars minimize dependency length? *Cognitive Science*, 34(2):286–310.

Hunter, P. J. and Prideaux, G. D. (1983). Empirical constraints on the verb-particle construction in English. *Journal of the Atlantic Provinces Linguistic Association*.

King, J. and Just, M. A. (1991). Individual differences in syntactic processing: The role of working memory. *Journal of Memory and Language*, 30(5):580–602.

Kohita, R., Noji, H., and Matsumoto, Y. (2017). Multilingual back-and-forth conversion between content and function head for easy dependency parsing. In Lapata, M., Blunsom, P., and Koller, A., editors, *Proceedings of the 15th Conference of the European Chapter of the Association for Computational Linguistics: Volume 2, Short Papers*, pages 1–7, Valencia, Spain. Association for Computational Linguistics.

Mel'čuk, I. (1988). *Dependency Syntax: Theory and Practice.* The SUNY Press, Albany, NY.

Nguyen, M. V., Lai, V., Veyseh, A. P. B., and Nguyen, T. H. (2021). Trankit: A light-weight transformer-based toolkit for multilingual natural language processing. In *Proceedings of the 16th Conference of the European Chapter of the Association for Computational Linguistics: System Demonstrations*.

Nilsson, J., Nivre, J., and Hall, J. (2006). Graph transformations in data-driven dependency parsing. In Calzolari, N., Cardie, C., and Isabelle, P., editors, *Proceedings of the 21st International Conference on Computational Linguistics and 44th Annual Meeting of the Association for Computational Linguistics*, pages 257–264, Sydney, Australia. Association for Computational Linguistics.

Nivre, J., de Marneffe, M.-C., Ginter, F., Goldberg, Y., Hajič, J., Manning, C. D., McDonald, R., Petrov, S., Pyysalo, S., Silveira, N., Tsarfaty, R., and Zeman, D. (2016). Universal Dependencies v1: A multilingual treebank collection. In Calzolari, N., Choukri, K., Declerck, T., Goggi, S., Grobelnik, M., Maegaard, B., Mariani, J., Mazo, H., Moreno, A., Odijk, J., and Piperidis, S., editors, *Proceedings of the Tenth International Conference on Language Resources and Evaluation (LREC'16)*, pages 1659–1666, Portorož, Slovenia. European Language Resources Association (ELRA).

Popel, M., Mareček, D., Štěpánek, J., Zeman, D., and Žabokrtský, Z. (2013). Coordination structures in dependency treebanks. In *Proceedings of the 51st Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)*, pages 517–527.

Przepiórkowski, A., Borysiak, M., and Głowacki, A. (2024). An argument for symmetric coordination from Dependency Length Minimization: A replication study. To appear in the proceedings of *LREC-COLING 2024*.

Przepiórkowski, A. and Woźniak, M. (2023). Conjunct lengths in English, Dependency Length Minimization, and dependency structure of coordination. In Rogers, A., Boyd-Graber, J., and Okazaki, N., editors, *Proceedings of the 61st Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)*, pages 15494–15512, Toronto, Canada. Association for Computational Linguistics.

Qi, P., Zhang, Y., Zhang, Y., Bolton, J., and Manning, C. D. (2020). Stanza: A Python natural language processing toolkit for many human languages. In *Proceedings of the 58th Annual Meeting of the Association for Computational Linguistics: System Demonstrations*.

Rehbein, I., Steen, J., Do, B.-N., and Frank, A. (2017). Universal Dependencies are hard to parse – or are they? In Montemagni, S. and Nivre, J., editors, *Proceedings of the Fourth International Conference on Dependency Linguistics (Depling 2017)*, pages 218–228, Pisa, Italy. Linköping University Electronic Press.

Richard, H. (2010). *An Introduction to Word Grammar*. Cambridge Textbooks in Linguistics. Cambridge University Press.

Silveira, N., Dozat, T., de Marneffe, M.-C., Bowman, S., Connor, M., Bauer, J., and Manning, C. D. (2014). A gold standard dependency corpus for English. In *Proceedings of the Ninth International Conference on Language Resources and Evaluation (LREC-2014)*.

Tesnière, L. (2015). *Elements of Structural Syntax*. John Benjamins.

Tuora, R., Przepiórkowski, A., and Leczkowski, A. (2021). Comparing learnability of two dependency schemes: 'semantic' (UD) and 'syntactic' (SUD). In *Findings of the Association for Computational Linguistics: EMNLP 2021*. Association for Computational Linguistics.

Wasow, T. (2002). *Postverbal Behavior*. CSLI Stanford.