What can we learn from natural and artificial dependency trees

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Abstract

This paper is centered around two main contributions : the first one consists in introducing several procedures for generating random dependency trees with constraints, we later use these artificial treebanks to compare the properties of these random trees with natural trees (i.e trees extracted from treebanks) and analyze the relationships between these properties in both cases in order to better understand which relationships are formally constrained and which relationships are linguistically motivated. We take into consideration five metrics: tree length, height, maximum arity, mean dependency distance and mean flux weight, and also look into the distribution of configurations for pairs and triples of nodes. This analysis is based on UD treebanks (version 2.3, Nivre et al. 2018) for four languages: Chinese, English, French and Japanese.

1 Introduction

We are interested in understanding the linguistic constraints on syntactic dependency trees to understand what makes certain structures plausible while others are not so plausible. To effectively do this kind of work, we need to observe natural trees (syntactic trees that are the results of linguistic analysis) to see what this population looks like. But if we only look at natural trees we are limited because we cannot cleanly separate every constraint from the others to see its effect, we only get the structures that are the result of all the constraints and their interactions. On the other hand, if we start from a blank canvas, randomly generated trees, and incrementally add constraints on these trees, we might closer and closer to natural trees, and we can use those trees to determine which constraints are formally motivated (they are a result of the mathematical structure of the tree) and which constraints are linguistically and cognitively motivated. These constraints help to explain why we only find a small subset of all potential trees in syntactic analyses on real data.

Our objective is therefore twofold: first we want to see how different properties of syntactic dependency trees correlate, in particular properties that are related to syntactic complexity such as height, mean dependency distance and mean flux weight, then we want to find out if these properties can allow us to distinguish between artificial dependency trees (trees that have been manipulated using random components and constraints), and dependency trees from real data.

2 Looking into the properties of syntactic dependency trees

2.1 Features

In this work we use the five following metrics to analyze the properties of dependency trees:

Feature name	Description
Length	Number of nodes in the tree
Height	Number of edges between the root and its deepest leaf
Maximum arity	Maximum number of dependents of a node
Mean Dependency Distance (MDD)	Two nodes in a dependency relation are at distance 1 if they are neighbours, distance 2 if there is a node between them etc. For every tree, we look at the mean of those dependency distances. See (Liu 2008) for more information about this property.
Mean flux weight	Mean of the number of concomitant disjoint dependencies (Kahane et al. 2017; see comments below)

Table 1: Tree-based metrics

We chose these properties because we believe that they all interfere in linearization strategies, that is how words are ordered in sentences, and the effects of those linearization strategies. Recently, there have been many quantitative works (Futrell et al., 2015; Liu 2008) that have focussed on dependency length and its minimization across many natural languages. In complement to these linear properties we also use "flux weight", a metrics proposed by Kahane et al. (2017) which captures the level of nestedness of a syntactic construction (the more nested the construction is, the higher its weight in terms of dependency flux). In their paper, they claim the existence of a universal upper bound for flux weight, as they have found it to be to 5 for 70 treebanks in 50 languages.

In addition to these tree-based metrics, we are also interested in studying local configurations using the linearised dependency trees. To look at these configurations, we extract and compare the proportion of all potential configurations of bigrams (two successive nodes) and trigrams (three successive nodes). For bigrams, we have three possible configurations: a -> b which indicates that a and b are linked with a relation on the right, a <- b which indicates that a and b are linked with a relation on the left, and a ◊ b, which indicates that a and b are not linked by a dependency. For trigram configurations (a, b, c), the possibility is much wider, we have 25 possible configurations. There are projective configurations like: a -> b -> c, (a -> b) & (a -> c), (a -> c) and (b <- c), but also non-projective cases like: a <- c and b -> c.

2.2 Hypotheses

In this section, we describe some of our hypotheses concerning the relationship between our selected properties. First, we expect to find that tree length is positively correlated with other properties. As the number of nodes increases, the number of possible trees increases including more complex trees with longer dependencies (which would increase MDD) and more nestedness (which would result in a higher mean flux weight). The relationship with maximum arity is less clear, as there could be an upper limit, which would make the relation between both of these properties non-linear. We're also particularly interested in the relationship between mean dependency distance and mean flux weight. An increase in nestedness is likely to result in more descendents being placed between a governor and its direct dependents, which would mean an overall increase in mean dependency distance.

For local configurations, we know that in natural trees, most of the dependencies occur between neighbours. It will be interesting to see how much that is still the case in the different random tree-banks, depending on the added constraints.

For trigrams of nodes we are interested in particular in the distribution of four groups of configurations that represent four different strategies of linearization : "chained" subtrees that introduce more depth in the dependency tree in one direction, "balanced" subtrees that alternate dependents on both sides of the governor, "zigzag" subtrees which are similar to chains but with the second dependent going in the opposite direction as the first one, and "bouquet" subtrees where the two dependents are linked to the same governor (see example in Figure A1 in the Annex). If one group of configurations is preferred, it could indicate that this linearisation strategy is more economical. We're also interested in the hypothesis advanced by [Temperley 2008] who proposes that languages that strongly favor head-initial or head-final dependencies will still tend to have some short phrases depending on the opposite direction, which could constitute a way of limiting dependency distances.

3 Random tree generation with constraints

In this section we will look at random dependency tree generation with constraints. We distinguish two different steps in the dependency tree generation process : the generation of the unordered structure, and the generation of the linearisation of the nodes. In order to compare the properties of natural and random trees we used 3 different tree generating algorithm, to which we assign the following names : original random (1), original optimal (2) and random random (3).

The first algorithm "original random" samples an unordered dependency structure from a treebank (i.e the original structure), and generates a random linearisation for it. We imposed a projectivity constraint on this linearisation and proposed the following algorithm to generate it:

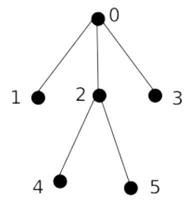

Figure 1: unordered tree

1. We start the linearisation at the root.
2. Then, we select its dependent nodes [1,2,3] and randomly order them, which gives us [2,1,3].
3. We select their direction at random, which gives us ["left", "left", "right"], and the linearisation steps [0], [20], [120], [1203].
4. We repeat steps 1 through 2 until every node has been linearized, which gives us for example [124503].

The second algorithm "original optimal" also sample an unordered dependency structure from a treebank, but instead of generating a simple projective linearisation, we add a second constraint to minimize dependency distances inside the linearised dependency tree. The idea is inspired from [Temperley 2008]: to minimize dependency distances in a projective setting dependents of a governor should be linearized alternatively on opposing sides of the governor, with the smallest dependent nodes (i.e those that have the smallest number of direct and indirect descendants) linearized first. Using the same structure unordered tree as in fig. 1 we described the procedure below:

1. We start the linearisation at the root.

2. Then, we select its dependent node [1,2,3] and order them in order of their decreasing number of descendant nodes, which gives us [1,3,2].
3. We select a first direction at random, for example “left”, and order these nodes alternating between left and right, which gives us these linearisation steps [0], [10], [103], [2103].
4. We repeat steps 1 through 2 until every node has been linearized, which gives us for example [425103].

The third algorithm “random random” is the only one to implement two random steps : first generate a completely random structure, then linearize it following the same procedure as in algorithm 1). The unordered structure generation step is described in fig 2.

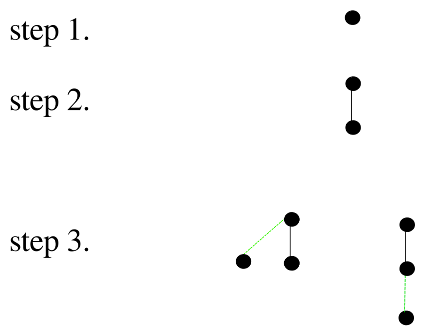

Figure 2: Random tree generation

1. We start the generation process with a single node
2. We introduce a new node and randomly draws its governor. For now since there is only one potential governor, the edge has a probability of 1.
3. We introduce a new node and randomly draws its governor. There are two potential governors which gives us a probability 0.5 of drawing the node 0 and the same probability for the node 1. These potential edges are drawn in green on the graph.
4. We repeat this last step until all nodes have been drawn and attached to their governor.[1].

These tree generation algorithms give us tools to analyze how different generation strategies will affect the properties of the generated trees as we incorporate more and more constraints into the two generation steps. For example during the linearisation process in 1) we could introduce a probability of creating a head-final edge, to produce trees that resemble more the trees of a head-final language like Japanese. For the unordered structure generation, we could introduce a constraint to limit length, arity or height. We need to distinguish constraints that happen during the unordered structure generation step and constraints that have to do with linearisation, like constraints on dependency distances and on flux weights.

One question that still remains concerns the ordering of the two steps : unordered structure generation and linearisation generation. So far we have only implemented the full generation starting with the generation of the unordered structure and then moving on to the linearisation, which is a synthesis approach as described in Meaning-Text-Theory [Mel'čuk 1998], but it would be interesting to go in the analysis direction, starting with a sequence of nodes, and then randomly producing a structure for it. This could allow us to see how the distribution of trees is impacted, especially as more constraints are added on the generation. We could then see if one type of random generation (synthesis vs analysis) produces structures that resemble natural dependency structures more.

[1] Note that this algorithm gives us a uniform probability on derivations, but that some derived trees are more probable than others, for example if the length of the tree is 4 we only have 1 derivation to obtain a tree of height 4, and 2 derivations to obtain a tree with 2 dependent on the root and 1 on one of these dependents.

4 Results and discussion

4.1 A continuum of constraints

When we look at the relationship between different properties of the trees, we can see how the trees and their configurations are affected by the generation process. One such example can be found in the fig. 3:

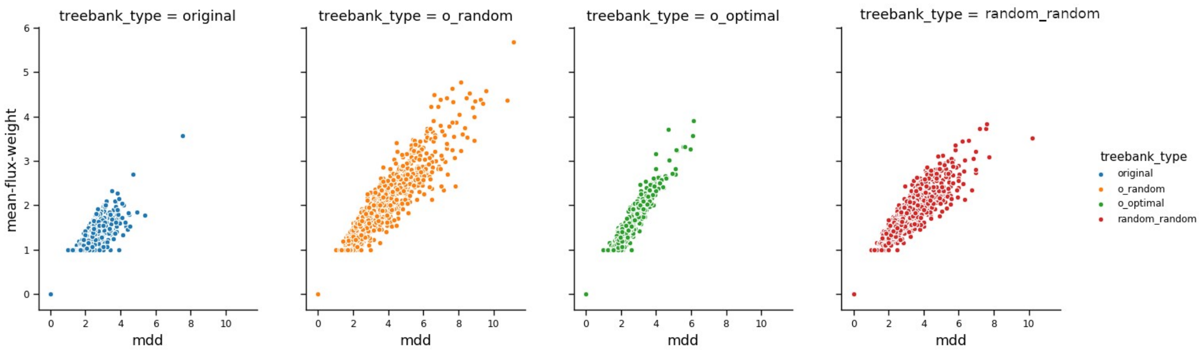

Figure 3: relation between MDD and MFW in french_partut

This diagram presents the relation between the mean dependency distance and the mean flux weight for every tree in the UD_French-ParTUT treebank. Each subplot illustrates a different kind of manipulation on the trees. From the overall shape of the scatterplots, we can tell that the "original optimal" treebank has been generated with more constraints : it contains less variation in terms of configurations, which means that there is less dispersion and the relationship between the two properties is more apparent. The next treebank showing the most constraints is the original one, it has lost the "optimality" constraint, but is still more constrained than the two random treebanks as it has preserved the linguistic constraints of French. The two random treebanks show more variation, with the "original random" still a bit less dispersed than its "random random" counterpart, as it still preserves the integrity of the unordered structure.

4.2 Correlation between properties

For each pair of properties, we measured the pearson correlation coefficient to find out how much the two variables are in a linear relationship. We looked into these results for the different natural treebanks and the artificial ones ("original random", "random random" and "original optimal"). The full results are presented in tables 1-4 in annex.

Based on these results, we notice that mean dependency distance and mean flux weight are overall the most correlated properties with values ranging from 0.70 (jp_pud, "original") to 0.95 (fr_partut, "original optimal"). The correlation is strongest in the artificial treebanks, especially in the "original optimal" version. On the other hand, the correlation between length and height is a bit stronger (0.78 correlation) in the original structures than in the random ones (0.71 correlation in "random random", which is the only format in which the height is affected by the manipulation). We also find quite strong correlations between mean dependency distance and height in the artificial treebanks (0.76, 0.79, 0.72 respectively for "original random", "original optima" and "random random") while this correlation is less important for the natural treebanks (0.46). It is also important to note that we find a lot of variation between different treebanks of the same language, which is why we also looked at the ranking of these correlations.

4.3 Distribution of configurations

For configurations, we are mainly interested in the distribution of the four different groups presented in section 2.2, and how they are impacted by language and the type of treebank (natural and artificial). We will discuss here a few points, and the full results are present in annex. In fig 4, we can see the distribution of these groups (in terms of percentage of all possible configurations, some of which are not in these four main groups) for French, depending on the type of treebank considered. In the original treebanks of French, the two main types of configurations are chains and "zigzag" with 34% and 33% of all trigram configurations. The balanced strategy is far less used, as it represents only 7% of all occurences, which is interesting as this strategy is more frequent in the artificial treebanks, especially in those that optimize for dependency distances, where they reach 18%. The proportion of "bouquet" configuration is stable across the treebanks, with the exception of the completely random ones that use this strategy less. The two types of treebanks that include random components seem to favour chain and zigzag configurations.

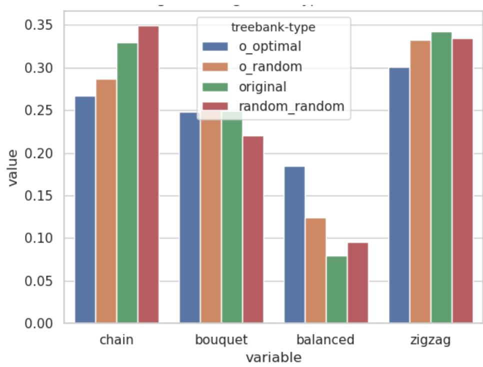

Figure 4: Trigram configuration types in French

Across the four languages, the zigzag configurations seem to take the lead, especially in Japanese where they are far more frequent than in the artificial treebanks. This type of configuration is used in the Japanese treebanks to annotate various types of particles which are very frequent, such as the case markers に, が, の or the topic marker は, which explains why these configurations are much more frequent than in the artificial ones.

5 Conclusion

In this paper we introduced several ways to generate artificial syntactic dependency trees and proposed to use those trees as a way of looking into the structural and linguistic constraints on syntactic structures for 4 different languages. We propose to incrementally add constraints on these artificial trees to observe the effects these constraints produce and how they interact with each other. We limited ourselves to generating projective trees, which we now realize was a very strong constraint that strongly restricts the types of structures available, and therefore the variations of the different observed properties, and it would be interesting to also look at the result if we allow for non-projective edges.

To expand on this work we would also like to see how the observed properties and the relations between them are affected by the annotation scheme, in particular contrasting schemas where content words are governors (as is the case in UD) and schemas where function words are governors (for example using the SUD schema proposed by [Gerdes et al. 2018]), as it will have an impact on height, dependency distances, and the types of configurations that can be extracted from the treebanks. We also plan on digging deeper into the analysis of the present data, through the use of predicting models, that could help us clarify the relationship (whether they be linear or not) between the different features and to build a more solid basis to verify our hypotheses.

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Annex

original treebanks

	height_length	arity_length	arity_height	mdd_length	mdd_height	mdd_arity	mfw_length	mfw_height	mfw_arity	mfw_mdd
en_lines	0.77 (1)	0.62 (6)	0.37 (10)	0.68 (4)	0.44 (8)	0.72 (3)	0.65 (5)	0.49 (7)	0.42 (9)	0.77 (2)
en_gum	0.8 (2)	0.68 (4)	0.5 (10)	0.68 (5)	0.53 (9)	0.79 (3)	0.64 (6)	0.57 (7)	0.56 (8)	0.83 (1)
en_esl	0.71 (2)	0.57 (6)	0.2 (10)	0.62 (5)	0.23 (9)	0.65 (3)	0.62 (4)	0.33 (7)	0.32 (8)	0.72 (1)
en_partut	0.76 (2)	0.55 (6)	0.3 (10)	0.57 (5)	0.31 (9)	0.6 (3)	0.58 (4)	0.37 (7)	0.33 (8)	0.78 (1)
en_ewt	0.82 (3)	0.72 (4)	0.61 (10)	0.7 (5)	0.64 (9)	0.85 (2)	0.65 (8)	0.66 (7)	0.68 (6)	0.87 (1)
en_pud	0.65 (2)	0.44 (6)	0.09 (9)	0.49 (3)	0.08 (10)	0.48 (5)	0.48 (4)	0.19 (7)	0.13 (8)	0.72 (1)
fr_gsd	0.73 (2)	0.52 (6)	0.22 (10)	0.61 (5)	0.28 (9)	0.65 (3)	0.63 (4)	0.37 (7)	0.32 (8)	0.74 (1)
fr_sequoia	0.81 (3)	0.69 (4)	0.56 (9)	0.68 (5)	0.54 (10)	0.82 (2)	0.67 (6)	0.59 (8)	0.63 (7)	0.83 (1)
fr_spoken	0.84 (1)	0.59 (6)	0.42 (10)	0.61 (5)	0.44 (9)	0.78 (2)	0.67 (4)	0.56 (7)	0.46 (8)	0.71 (3)
fr_partut	0.79 (1)	0.54 (6)	0.35 (10)	0.61 (5)	0.37 (8)	0.67 (3)	0.65 (4)	0.47 (7)	0.37 (9)	0.77 (2)
fr_pud	0.64 (2)	0.47 (6)	0.1 (10)	0.58 (3)	0.17 (9)	0.54 (5)	0.56 (4)	0.29 (7)	0.21 (8)	0.77 (1)
zh_cfl	0.76 (2)	0.61 (5)	0.37 (10)	0.58 (7)	0.52 (8)	0.63 (4)	0.6 (6)	0.66 (3)	0.42 (9)	0.78 (1)
zh_gsd	0.58 (6)	0.56 (7)	0.14 (10)	0.61 (4)	0.39 (8)	0.65 (2)	0.63 (3)	0.6 (5)	0.27 (9)	0.74 (1)
zh_pud	0.57 (3)	0.53 (6)	0.07 (10)	0.56 (5)	0.41 (8)	0.52 (7)	0.56 (4)	0.59 (2)	0.19 (9)	0.77 (1)
zh_hk	0.83 (2)	0.73 (6)	0.56 (10)	0.79 (4)	0.72 (7)	0.79 (3)	0.69 (8)	0.74 (5)	0.61 (9)	0.86 (1)
jp_pud	0.58 (4)	0.47 (6)	0.0 (10)	0.59 (3)	0.13 (9)	0.59 (2)	0.54 (5)	0.36 (7)	0.17 (8)	0.7 (1)
jp_gsd	0.74 (2)	0.61 (6)	0.31 (10)	0.69 (4)	0.37 (9)	0.7 (3)	0.66 (5)	0.48 (7)	0.4 (8)	0.8 (1)
jp_modern	0.85 (1)	0.62 (4)	0.46 (9)	0.58 (6)	0.44 (10)	0.72 (3)	0.61 (5)	0.58 (7)	0.5 (8)	0.81 (2)

original_optimal

	height_length	arity_length	arity_height	mdd_length	mdd_height	mdd_arity	mfw_length	mfw_height	mfw_arity	mfw_mdd
jp_gsd	0.74 (4)	0.61 (7)	0.31 (9)	0.76 (3)	0.74 (5)	0.57 (8)	0.68 (6)	0.79 (2)	0.26 (10)	0.89 (1)
jp_pud	0.58 (5)	0.47 (7)	0.01 (10)	0.64 (3)	0.59 (4)	0.36 (8)	0.57 (6)	0.71 (2)	0.05 (9)	0.88 (1)
jp_modern	0.85 (4)	0.62 (7)	0.46 (9)	0.81 (5)	0.86 (3)	0.6 (8)	0.79 (6)	0.88 (2)	0.41 (10)	0.94 (1)
en_esl	0.71 (4)	0.57 (7)	0.2 (9)	0.73 (3)	0.7 (5)	0.48 (8)	0.63 (6)	0.75 (2)	0.16 (10)	0.89 (1)
en_ewt	0.82 (4)	0.72 (7)	0.61 (10)	0.8 (6)	0.84 (2)	0.8 (5)	0.69 (8)	0.82 (3)	0.63 (9)	0.93 (1)
en_partut	0.76 (4)	0.55 (7)	0.3 (9)	0.76 (5)	0.77 (3)	0.47 (8)	0.71 (6)	0.8 (2)	0.27 (10)	0.94 (1)
en_lines	0.77 (4)	0.62 (8)	0.37 (9)	0.79 (3)	0.77 (5)	0.63 (7)	0.72 (6)	0.8 (2)	0.35 (10)	0.9 (1)
en_gum	0.8 (4)	0.68 (8)	0.5 (9)	0.79 (5)	0.81 (3)	0.7 (7)	0.7 (6)	0.81 (2)	0.49 (10)	0.92 (1)
en_pud	0.65 (4)	0.44 (7)	0.08 (9)	0.68 (3)	0.62 (5)	0.35 (8)	0.61 (6)	0.69 (2)	0.07 (10)	0.89 (1)
zh_gsd	0.58 (5)	0.56 (6)	0.13 (10)	0.72 (2)	0.55 (7)	0.53 (8)	0.65 (4)	0.65 (3)	0.21 (9)	0.86 (1)
zh_cfl	0.76 (2)	0.61 (8)	0.38 (10)	0.75 (4)	0.69 (6)	0.68 (7)	0.7 (5)	0.75 (3)	0.39 (9)	0.87 (1)
zh_hk	0.83 (2)	0.73 (6)	0.57 (9)	0.81 (4)	0.79 (5)	0.81 (3)	0.62 (8)	0.73 (7)	0.55 (10)	0.87 (1)
zh_pud	0.58 (5)	0.53 (7)	0.08 (9)	0.65 (3)	0.6 (4)	0.39 (8)	0.54 (6)	0.68 (2)	0.07 (10)	0.86 (1)
fr_sequoia	0.81 (4)	0.69 (8)	0.56 (10)	0.8 (5)	0.83 (2)	0.72 (7)	0.73 (6)	0.83 (3)	0.56 (9)	0.94 (1)
fr_gsd	0.73 (4)	0.52 (7)	0.22 (10)	0.74 (3)	0.73 (5)	0.44 (8)	0.69 (6)	0.78 (2)	0.22 (9)	0.92 (1)
fr_partut	0.78 (4)	0.54 (7)	0.35 (9)	0.75 (5)	0.81 (3)	0.47 (8)	0.71 (6)	0.82 (2)	0.31 (10)	0.95 (1)
fr_spoken	0.84 (3)	0.59 (8)	0.42 (9)	0.82 (4)	0.81 (5)	0.67 (7)	0.77 (6)	0.84 (2)	0.32 (10)	0.88 (1)
fr_pud	0.64 (5)	0.47 (7)	0.1 (10)	0.68 (3)	0.65 (4)	0.36 (8)	0.63 (6)	0.72 (2)	0.14 (9)	0.92 (1)

original_random

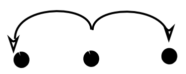
	height_length	arity_length	arity_height	mdd_length	mdd_height	mdd_arity	mfw_length	mfw_height	mfw_arity	mfw_mdd
fr_pud	0.64 (3)	0.47 (7)	0.1 (10)	0.63 (4)	0.62 (5)	0.37 (8)	0.61 (6)	0.71 (2)	0.2 (9)	0.85 (1)
fr_spoken	0.84 (3)	0.59 (8)	0.42 (9)	0.82 (4)	0.8 (6)	0.6 (7)	0.81 (5)	0.86 (2)	0.4 (10)	0.9 (1)
fr_partut	0.79 (4)	0.54 (8)	0.36 (10)	0.78 (5)	0.79 (3)	0.55 (7)	0.76 (6)	0.85 (2)	0.41 (9)	0.92 (1)
fr_gsd	0.73 (3)	0.52 (7)	0.22 (10)	0.71 (4)	0.69 (6)	0.45 (8)	0.7 (5)	0.78 (2)	0.26 (9)	0.88 (1)
fr_sequoia	0.81 (4)	0.69 (8)	0.56 (10)	0.81 (5)	0.82 (3)	0.69 (7)	0.78 (6)	0.86 (2)	0.59 (9)	0.93 (1)
jp_gsd	0.74 (4)	0.61 (7)	0.31 (10)	0.75 (3)	0.71 (6)	0.57 (8)	0.73 (5)	0.8 (2)	0.37 (9)	0.87 (1)
jp_modern	0.85 (4)	0.62 (7)	0.46 (10)	0.85 (3)	0.83 (6)	0.6 (8)	0.84 (5)	0.87 (2)	0.47 (9)	0.93 (1)
jp_pud	0.58 (4)	0.47 (7)	0.0 (10)	0.6 (3)	0.54 (6)	0.39 (8)	0.57 (5)	0.71 (2)	0.07 (9)	0.78 (1)
en_esl	0.71 (3)	0.57 (7)	0.2 (10)	0.69 (4)	0.64 (6)	0.44 (8)	0.65 (5)	0.74 (2)	0.23 (9)	0.85 (1)
en_pud	0.65 (3)	0.44 (7)	0.08 (10)	0.6 (5)	0.62 (4)	0.33 (8)	0.6 (6)	0.71 (2)	0.13 (9)	0.85 (1)
en_partut	0.76 (3)	0.55 (7)	0.3 (10)	0.73 (6)	0.74 (4)	0.48 (8)	0.73 (5)	0.81 (2)	0.33 (9)	0.9 (1)
en_gum	0.8 (3)	0.68 (7)	0.5 (10)	0.79 (4)	0.77 (5)	0.67 (8)	0.76 (6)	0.82 (2)	0.55 (9)	0.9 (1)
en_ewt	0.82 (4)	0.72 (8)	0.61 (10)	0.81 (5)	0.82 (3)	0.76 (7)	0.77 (6)	0.86 (2)	0.67 (9)	0.92 (1)
en_lines	0.77 (4)	0.62 (7)	0.37 (10)	0.77 (3)	0.74 (6)	0.58 (8)	0.75 (5)	0.8 (2)	0.42 (9)	0.9 (1)
zh_gsd	0.58 (5)	0.56 (6)	0.13 (10)	0.66 (2)	0.48 (8)	0.52 (7)	0.64 (3)	0.63 (4)	0.23 (9)	0.8 (1)
zh_hk	0.83 (2)	0.73 (8)	0.56 (10)	0.82 (3)	0.79 (5)	0.75 (6)	0.74 (7)	0.8 (4)	0.6 (9)	0.89 (1)
zh_cfl	0.76 (3)	0.61 (8)	0.37 (10)	0.75 (4)	0.67 (6)	0.63 (7)	0.71 (5)	0.76 (2)	0.42 (9)	0.85 (1)
zh_pud	0.57 (5)	0.53 (6)	0.07 (10)	0.63 (2)	0.47 (7)	0.45 (8)	0.59 (4)	0.62 (3)	0.18 (9)	0.81 (1)

random_random

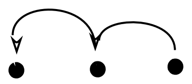
	height_length	arity_length	arity_height	mdd_length	mdd_height	mdd_arity	mfw_length	mfw_height	mfw_arity	mfw_mdd
zh_gsd	0.61 (5)	0.53 (7)	0.14 (10)	0.65 (3)	0.55 (6)	0.42 (8)	0.64 (4)	0.65 (2)	0.23 (9)	0.85 (1)
zh_hk	0.8 (3)	0.75 (7)	0.58 (10)	0.8 (4)	0.79 (5)	0.73 (8)	0.75 (6)	0.81 (2)	0.63 (9)	0.91 (1)
zh_pud	0.57 (5)	0.54 (6)	0.14 (10)	0.62 (3)	0.54 (7)	0.44 (8)	0.61 (4)	0.62 (2)	0.25 (9)	0.85 (1)
zh_cfl	0.72 (5)	0.6 (8)	0.37 (10)	0.77 (2)	0.68 (6)	0.64 (7)	0.75 (4)	0.76 (3)	0.47 (9)	0.88 (1)
fr_pud	0.57 (4)	0.51 (7)	0.11 (10)	0.59 (3)	0.52 (6)	0.41 (8)	0.57 (5)	0.61 (2)	0.19 (9)	0.83 (1)
fr_partut	0.68 (6)	0.65 (7)	0.42 (10)	0.72 (3)	0.68 (5)	0.61 (8)	0.7 (4)	0.75 (2)	0.48 (9)	0.89 (1)
fr_spoken	0.75 (5)	0.68 (7)	0.49 (10)	0.76 (3)	0.74 (6)	0.66 (8)	0.76 (4)	0.79 (2)	0.52 (9)	0.9 (1)
fr_sequoia	0.75 (5)	0.71 (8)	0.6 (10)	0.77 (4)	0.79 (3)	0.73 (7)	0.75 (6)	0.83 (2)	0.63 (9)	0.92 (1)
fr_gsd	0.63 (5)	0.58 (7)	0.23 (10)	0.68 (3)	0.59 (6)	0.5 (8)	0.66 (4)	0.68 (2)	0.31 (9)	0.86 (1)
en_lines	0.71 (5)	0.65 (7)	0.4 (10)	0.74 (3)	0.68 (6)	0.6 (8)	0.72 (4)	0.75 (2)	0.45 (9)	0.89 (1)
en_pud	0.58 (5)	0.52 (6)	0.08 (10)	0.61 (3)	0.51 (7)	0.4 (8)	0.6 (4)	0.64 (2)	0.18 (9)	0.82 (1)
en_partut	0.65 (5)	0.59 (7)	0.28 (10)	0.66 (3)	0.61 (6)	0.52 (8)	0.66 (4)	0.72 (2)	0.36 (9)	0.86 (1)
en_ewt	0.77 (6)	0.75 (7)	0.66 (10)	0.79 (4)	0.82 (3)	0.77 (5)	0.74 (8)	0.85 (2)	0.7 (9)	0.93 (1)
en_esl	0.63 (5)	0.57 (6)	0.17 (10)	0.67 (2)	0.57 (7)	0.47 (8)	0.65 (4)	0.66 (3)	0.27 (9)	0.85 (1)
en_gum	0.73 (6)	0.71 (7)	0.53 (10)	0.77 (3)	0.75 (4)	0.69 (8)	0.74 (5)	0.8 (2)	0.59 (9)	0.91 (1)
jp_gsd	0.69 (5)	0.64 (7)	0.37 (10)	0.73 (3)	0.66 (6)	0.59 (8)	0.72 (4)	0.74 (2)	0.44 (9)	0.89 (1)
jp_pud	0.52 (5)	0.5 (6)	0.06 (10)	0.56 (3)	0.48 (7)	0.36 (8)	0.53 (4)	0.6 (2)	0.13 (9)	0.82 (1)
jp_modern	0.7 (5)	0.69 (7)	0.46 (10)	0.72 (3)	0.69 (6)	0.67 (8)	0.7 (4)	0.78 (2)	0.54 (9)	0.9 (1)

Examples of 4 types of trigram configurations

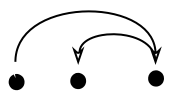
1. Balanced



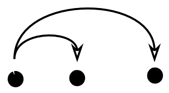
2. Chain



3. Zigzag

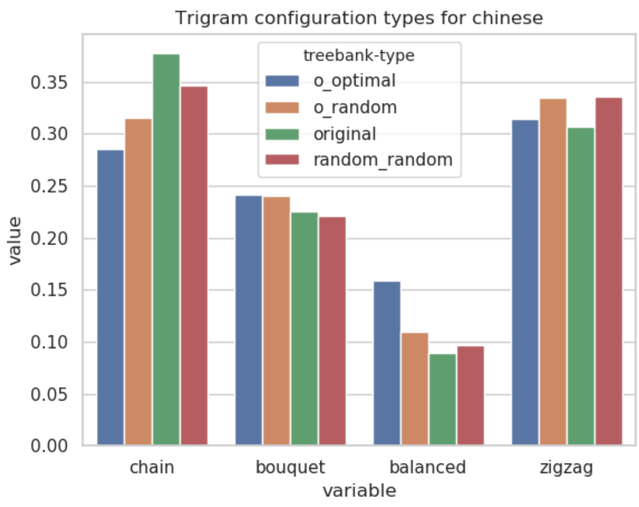


4. Bouquet

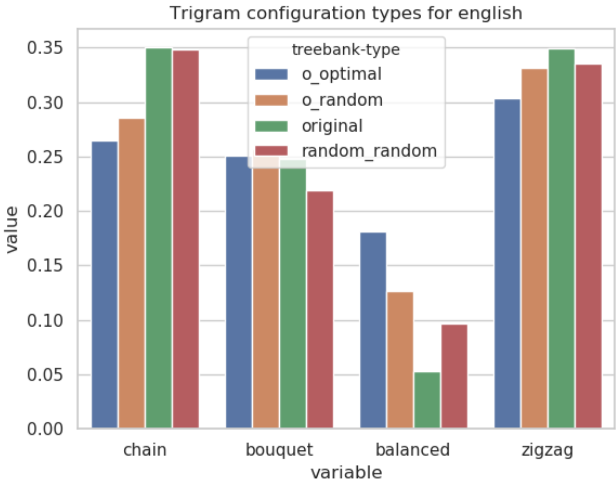


Trigrams configurations by type

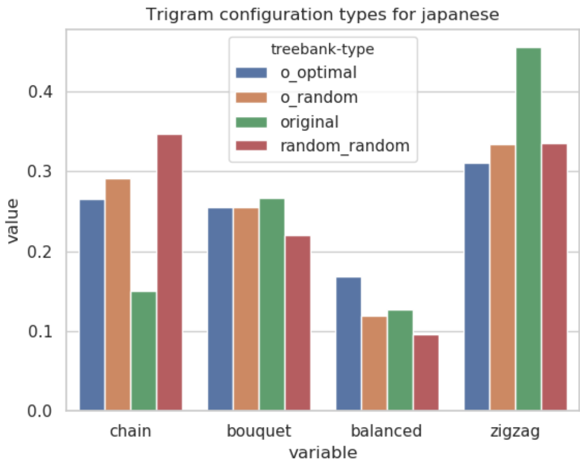
Chinese



English


Trigram configuration types for english
treebank-type
o_optimal
o_random
original
random_random
value
0.35
0.30
0.25
0.20
0.15
0.10
0.05
0.00
chain
bouquet
balanced
zigzag
variable

Japanese


Trigram configuration types for japanese
treebank-type
o_optimal
o_random
original
random_random
value
0.4
0.3
0.2
0.1
0.0
chain
bouquet
balanced
zigzag
variable