An Empirical Study on the Effect of Morphological and Lexical Features in Persian Dependency Parsing

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Abstract

This paper investigates the impact of different morphological and lexical information on data-driven dependency parsing of Persian, a morphologically rich language. We explore two state-of-the-art parsers, namely MSTParser and MaltParser, on the recently released Persian dependency treebank and establish some baselines for dependency parsing performance. Three sets of issues are addressed in our experiments: effects of using gold and automatically derived features, finding the best features for the parser, and a suitable way to alleviate the data sparsity problem. The final accuracy is 87.91% and 88.37% labeled attachment scores for MaltParser and MSTParser, respectively.

1 Introduction

Researchers have paid a lot of attention to data-driven dependency parsing in recent years (Bohnet and Kuhn, 2012; Bohnet and Nivre, 2012; Balleseros and Nivre, 2013). This approach is language-independent and is solely dependent on the availability of annotated corpora. Using data-driven parsers for some languages requires careful selection of features and tuning of the parameters to reach maximum performance. Difficulty of dependency parsing in each language depends on having either free word order or morphological information. Languages with free word order have a high degree of freedom in arranging the words of a sentence. Consequently, they usually have a high percentage of non-projective structures. Morphology is determined by large inventory of word forms (Tsarfaty et al., 2010).

According to the results from CoNLL shared task 2007, languages are classified to three classes, namely low, medium and high accuracy languages. Among them, low-accuracy languages have high degree of free word order along with inflection (Nivre et al., 2007a). Languages which are more challenging in parsing are called morphologically rich languages (MRLs). In MRLs, multiple levels of information, concerning syntactic units and relations, are expressed at the word-level (Tsarfaty et al., 2010).

Free word order can be handled by non-projective parsing algorithms via either post-processing the output of a strictly projective parser (Nivre and Nilsson, 2005), combining adjacent (Nivre, 2009) or non-adjacent sub-structures (McDonald et al., 2005). Nevertheless, there is no general solution for resolving rich morphology issue and hence many researcher focus on features of a specific language. Most data-driven dependency parsers do not use any information that is specific to the language being parsed, but it is shown that using language specific features has a crucial role in improving the overall parsing accuracy (Ambati et al., 2010a).

Persian is an Indo-European language that is written in Perso-Arabic script (written from right to left). The canonical word order of Persian is SOV.
(subject-object-verb), but there are a lot of frequent exceptions in word order that turn this language into a free word order language (Shamsfard, 2011). This language has a high degree of free word order and complex inflections. As an example of rich morphology, there are more than 100 conjugates and 2800 declensions for some lemmas in Persian (Rasooli et al., 2011).

Dependency treebank for Persian (Rasooli et al., 2013) language has newly become available. Due to the lack of deep research on dependency parsing in Persian, we establish some baselines for dependency parsing performance. We also conduct a set of experiments in order to estimate the effect of errors in morphological disambiguation on the parsers. We show that with two simple changes to the input data, performance of the two parsers can be improved for both gold (manually annotated) and predicted data.

The remainder of the paper is organized as follows. Section 2 presents a brief overview of recent studies on parsing morphologically rich languages. In section 3, we introduce available morphological features annotated in our experiments. Section 4 describes the experimental setup, including corpus and parsers we use, and presents our experiments. Experimental evaluation and analysis of parsing errors are demonstrated in Section 5. Finally, we draw conclusions and suggest future work in Section 6.

2 Related work

Many studies have been done on using morphological features for parsing morphologically rich languages, (e.g. Bengoetxea and Gojenola (2010), Seeker and Kuhn (2013), etc.). Koo et al. (2008) introduce cluster-based features that incorporate word clusters derived from a large corpus of plain text, to improve statistical dependency parsing for English and Czech. Agirre et al. (2011) use lexical semantic information derived from WordNet.

Marton et al. (2011) augment the baseline model for Arabic with nine morphological features. They show that using predicted features causes a substantial drop in accuracy while it greatly improves performance in the gold settings. They show that using noisy morphological information is worse than using nothing at all. Same phenomenon is reported for Hebrew (Goldberg and Elhadad, 2010), except that using morphological-agreement feature improves the accuracy of both gold and predicted morphological information.

Another interesting research direction is to find the most beneficial features for dependency parsing for each language. Ambati et al. (2010b) explored the pool of features for Hindi through a series of experiments. In their setting, features are incrementally selected to create the best parser feature set. In Korean, Choi and Palmer (2011b) focus on feature extraction and suggest a rule-based way of selecting important morphemes to use only these as features to build dependency parsing models.

For the Persian language, Seraji et al. (2012b) investigated state-of-the-art dependency parsing algorithms on UPDT\(^1\) (Seraji et al., 2012a). They test three feature settings, namely gold POS tags for both the training and the test sets (GG), gold POS tags for the training set and auto-generated POS tags for the test set (GA), and auto-generated POS tags for both the training and the test sets (AA). The best result is obtained in GG setting with 68.68% and 63.60% LAS, for MaltParser (Nivre et al., 2007b) and MSTParser (McDonald et al., 2005) respectively. Using AA and GA settings show worse results than GG, namely 2.29% and 3.66% drop in accuracy for MaltParser, and 1.8% and 3.23% drop for MSTParser. They only explore the effect of gold and non-gold POS tags with a small treebank with about 1,300 sentences. We apply GG and AA settings in our experiments on a larger treebank that contains richer morphological information. We define pool of 10 morphological and lexical semantic features in order to create the best feature set for the parser.

3 Features of Persian

In this section, among possible morphological and semantic features that exist in Persian, we briefly review a subset of them that is either annotated in Persian dependency treebank (Rasooli et al., 2013) or is available from other studies.

3.1 Features from Treebank

Table 1 represents the features available in the Persian dependency treebank, along with possible values for each feature.

\(^1\)Uppsala Persian Dependency Treebank
Table 1: Description of features in Treebank

| Feature  | Values                                      |
|----------|---------------------------------------------|
| Attachment | \{NXT, PRV, ISO\}                         |
| Animacy  | \{animate, inanimate\}                     |
| Number   | \{singular, plural\}                       |
| Person   | \{1, 2, 3\}                                |
| Comparison | \{positive, comparative, superlative\}       |
| TMA      | see Table 2                                 |

Table 2: Tense/Mood/Aspect types in Persian verbs. Imp., Ind., Sub., Fut., and Pres. stand for imperative, indicative, subjunctive, future and present, respectively.

| TMA         | Meaning                              | Mood  | Tense |
|-------------|--------------------------------------|-------|-------|
| HA          | Imperative                           | Imp.  | Pres. |
| AY          | Indicative Future                    | Ind.  | Fut.  |
| GNES        | Indicative Imperfective Perfect      | Ind.  | Past  |
| GBES        | Indicative Imperfective Pluperfect   | Ind.  | Past  |
| GES         | Indicative Imperfective Preterit     | Ind.  | Past  |
| GN          | Indicative Perfect                   | Ind.  | Past  |
| GB          | Indicative Pluperfect                | Ind.  | Past  |
| H           | Indicative Present                   | Ind.  | Pres. |
| GS          | Indicative Preterit                  | Ind.  | Past  |
| GBES        | Subjunctive Imperfective Pluperfect  | Sub.  | Past  |
| GESEL       | Subjunctive Imperfective Preterit    | Sub.  | Past  |
| GBEL        | Subjunctive Pluperfect               | Sub.  | Past  |
| HEL         | Subjunctive Present                  | Sub.  | Pres. |
| GEL         | Subjunctive Preterit                 | Sub.  | Past  |

3.2 Automatic Semantic Features

Word Clusters [WC]: We use all the words of the treebank as inputs to the modified version of Brown clustering algorithm (Liang, 2005). In order to tune the parameters for the two parsers, we tweak the cluster count from 50 to 300 with steps of 50, and bit strings from 4 to 14. Finally, we choose 300 clusters and 6-bit strings for MaltParser and 150 clusters and 10-bit strings for MSTParser

Semantic Verb Clustering [VC]: Semantic verb cluster is a generalization over verbs according to their semantic properties that capture large amounts of verb meaning without defining details for each verb. Aminian et al. (2013) clustered 1082 Persian verbs into 43 (fine-grained) semantic classes using spectral clustering. For each verb in the treebank, we included the corresponding cluster ID if the verb exists in the list of clustered verbs.

Synset Identifier [SID]: FarsNet (Shamsfard et al., 2010) is a lexical ontology for the Persian language that contains approximately 10000 synsets. For each word in the treebank, we look up for possible synsets in FarsNet. If any synset is found, we add the ID of the first synset to our feature set. About 59% of words in the treebank were supplied with a synset.

Semantic File [SF]: In English WordNet, each synset belongs to a unique semantic file. There is a total of 45 semantic files (1 for adverbs, 3 for adjectives, 15 for verbs, and 26 for nouns), based on syntactic and semantic categories (Agirre et al., 2011). FarsNet has a mapping to those of WordNet synsets. We use both synsetId and semantic files as instances of fine-grained and coarse-grained semantic representations, respectively. Thus, we can

https://github.com/mojtaba-khallash/verb-spectral-cluster
learn what level of granularity in semantic features can help improve performance of the parser.

4 Experiments

Corpus Persian dependency treebank version 1.0 (Rasooli et al., 2013) is a freely-available resource with about 30,000 sentences, and half a million tokens, annotated with syntactic roles in addition to morpho-syntactic features. The annotation employs 17 coarse-grained and 30 fine-grained POS tags, 22 morphological feature values and 43 dependency labels. 21.93% of the sentences and 2.47% of the edges are non-projective.

Table 3 provides statistical properties of Persian dependency treebank, compared to UPDT. In Persian dependency treebank, syntactic and/or morphological features are represented as key-value pairs separated by vertical bars (‘|’), while in UPDT, they are represented as a single atomic feature.

| Treebank | Persian DT | UPDT |
|-----------|------------|------|
| Tok       | 498081     | 151671 |
| Sen       | 29982      | 6000  |
| AvgSL     | 16.61      | 25.28 |
| Lem       | yes        | no    |
| CPoS      | 17         | 15    |
| PoS       | 30         | 30    |
| MSF       | 22         | 30    |
| Dep       | 43         | 48    |
| NPT       | 2.47%      | 0.17% |
| NPS       | 21.93%     | 2.73% |

Table 3: Comparison of UPDT (Seraji et al., 2012a) and Persian dependency treebank (Rasooli et al., 2013). Tok = number of tokens; Sen = number of sentences; AvgSL = Average sentence length; Lem = lemmatization present; CPoS = number of coarse-grained part-of-speech tags; PoS = number of (fine-grained) part-of-speech tags; MSF = number of morphosyntactic features (split into atoms); Dep = number of dependency types; NPT = proportion of non-projective dependencies/tokens (%); NPS = proportion of non-projective dependency graphs/sentences (%)

The data is split into standard train, development and test sets by the ratio of 80-10-10 percent in the CoNLL dependency format. Furthermore, the treebank is released in two representations with little changes in their annotations. A sample comparison between the two annotations is shown in Figure 1. In the first representation, which is manually annotated, the accusative case marker \( \text{را} \) is supposed to be the head of the object plus \( \text{رو} \). In the second representation, which is an automatic conversion of the first one obtained by reverse ordering the manual annotation, \( \text{رو} \) is not the head of the object word. Instead, \( \text{رو} \) is regarded as the accusative case marker for the direct object.

Evaluation metric The most commonly used metrics for dependency parsing are unlabeled attachment score (UAS), labeled attachment score (LAS) and label accuracy (LA). UAS is the proportion of words that are assigned the correct head, LAS is the proportion of words that are assigned the correct head and dependency type, and LA is the proportion of words that are assigned the correct dependency graphs/sentences.

Figure 1: Two representation of object-verb relation for “I read the book that you mentioned.” (Rasooli et al., 2013).

https://github.com/mojtaba-khallash/semantic-tagger
http://www.dadegan.ir/en
Freely available at http://stp.lingfil.uu.se/~mojgan/UPDT.html
W e use LAS as our evaluation metric and take punctuation into account as for evaluating our parsing results. We use McNemars statistical significance test as implemented by (Nilsson and Nivre, 2008), and denote \( p < 0.05 \) and \( p < 0.01 \) with \( + \) and ++, respectively.

**Parsers** We use two off-the-shelf data-driven parsers, namely MaltParser (Nivre et al., 2007b) and MSTParser (McDonald et al., 2005), which are the two state-of-the-art dependency parsers that represent dominant approaches in data-driven dependency parsing.

MaltParser\(^7\) is based on a transition-based approach to dependency parsing. Transition-based approach is based on transition systems for deriving dependency trees, that greedily searches for highest scoring transitions and uses features extracted from parse history to predict the next transition (Choi and Palmer, 2011a). We use MaltParser 1.7.1 along with nine different parsing algorithms. In order to select the best algorithm and tune the parameters of MaltParser, we use MaltOptimizer (Ballesteros and Nivre, 2012) on the whole of training data. MaltOptimizer analyzes data in three-phase optimization process: data analysis, parsing algorithm selection, and feature selection.

MSTParser\(^8\) is based on a graph-based approach to dependency parsing. The algorithm searches globally in a complete graph to extract a spanning tree during derivations using dynamic programming. We use MSTParser 0.5 which has two implementations of maximum spanning tree (MST) algorithm with projective and non-projective models\(^9\).

**Baseline Experiments** We run three phases of MaltOptimizer on the training set in order to find the best parsing algorithm in MaltParser. The first phase validates the data and gains 84.02% LAS with the default settings. In the second phase, using non-projective version of the Covington algorithm, which has the best accuracy, and after parameter tuning, 85.86% LAS was obtained. In the third phase, the feature model was optimized and by tuning the regularization parameter of the multiclass SVM; it led to 87.43% LAS. Finally, we trained the best algorithm with optimized settings on training set and parsed on development set, thereby we reached 87.70% LAS as the baseline of MaltParser.

We tested four parsing algorithms that exist in MSTParser and as a result, non-projective algorithm with a second-order feature decoder gave 88.04% LAS, which shows the highest improvement. Therefore, we selected that as our baseline for MSTParser.

The baselines are obtained on the first representation of the treebank. We found baselines for the second representation of the treebank on the development set. Results are compared in Table 4.

The first representation performs better than the second one. This was expected before, since \( r_{A} \) is a constant word that is annotated as the object of a sentence in the first representation. This helps parsers to find the object in a sentence. Moreover, as shown in Figure 1, \( r_{A} \) is closer to the verb than the direct object, hence it has more chance to select.

**Table 4: Comparison of two representations of Persian treebank**

| Representation | Malt | MST |
|----------------|------|-----|
| First          | 87.70| 88.04|
| Second         | 87.22(-0.48)| 87.03(-1.01) |

**Results** In our experiments, we use the first representation of treebank with algorithms and new configurations presented in previous paragraph. For all experiments in this section, we use training and development sets of the treebank. In order to study the effects of morphology in dependency parsing of Persian, we organize experiments into three types of challenges which are presented by Tsarfaty et al. (2010): architecture and setup, representation and modeling, and estimation and smoothing.

**Architecture and Setup** When using dependency parsing on real-world tasks, we usually face with sentences that must be tokenized, lemmatized, and tagged with part of speech and morphological information to offer those information as input features to the parsing algorithms. Bijankhan corpus (Bijankhan, 2004) is the first manually tagged Persian
corpus that consists of morpho-syntactic and minimal semantic annotation of words. It is commonly used to train POS tagger, but its POS tagset is different from tagset of the treebank that we use. Sarabi et al. (2013) introduce PLP Toolkit which is a comprehensive Persian Language Processing (PLP) toolkit that contains fundamental NLP tools such as tokenizer, POS tagger, lemmatizer and dependency parser. They merged the POS tagset of 10 million words from bijankhan corpus with Persian dependency treebank in order to create a bigger corpus with the same tagset. They choose the tagset of Persian dependency treebank as the base setting and convert Bijankhan tagset to them. They have 11 coarse-grained and 45 fine-grained POS tags. PLP POS tagger can automatically recognize three morphological features, namely number, person, and TMA. TMA values of the PLP tool are not the same as Persian dependency treebank. Despite 14 possible TMA values in dependency treebank (Table 2), only four out of the 14 values exist in PLP (AY, GS, H, and HA), because there is no other value in Bijankhan tagset for verbs. The accuracy of PLP POS tagger on the fine grained tagset is about 98.5%. We use this tagger and apply it on our training, development, and test data. Results from these experiments are presented in Table 5.

| POS tags type | Malt         | MST         |
|---------------|--------------|-------------|
| Gold          | 87.70        | 88.04       |
| Predicted     | 86.98 (-0.72)| 86.81 (-1.23)|

Table 5: Effect of gold vs. predicted POS tags and morphological information in dependency parsers for Persian.

Representation and Modeling In our experiment, we use ten features of morphological and semantic information. Using a forward selection procedure, the best feature set for each parser can be found. Beside morphological features which exist in the treebank (Attachment [A], Person [P], Number [N], TMA), we add Tense [T] and Mood [M] with a simple conversion table, shown in Table 2, based on the value of TMA.

Table 6 shows the effect of each feature for MaltParser and MSTParser parser. For the former, mood with slight differences achieves the best result and for the latter, TMA has the highest accuracy than other features. TMA and two derivate features, namely T and M, stands at the top of this ranking, and four semantic features are placed in the middle. This means that our newly added features can help to improve performance of each parser.

In the next steps, we incrementally add one feature to the best result from previous step. As shown in Table 7, combination of M and SF obtains the best result for MaltParser (87.81%), while for MSTParser, combination of TMA and WC is the best (88.25%). In the second step, adding one semantic feature gets the best result. By trying to continue this approach, we do not see any improvement in the accuracy for both parser.

Table 6: Effect of each feature on two parsers

| Feature    | Malt       | Feature     | MST    |
|------------|------------|-------------|--------|
| M          | 87.77      | TMA         | 88.21+ |
| TMA        | 87.77      | M           | 88.17  |
| T          | 87.73      | P           | 88.09  |
| SF         | 87.70      | T           | 88.04  |
| WC         | 87.69      | N           | 88.04  |
| VC         | 87.68      | SID         | 88.03  |
| SID        | 87.67      | SF          | 88.03  |
| A          | 87.67      | WC          | 88.02  |
| P          | 87.66      | VC          | 87.98  |
| N          | 87.65      | A           | 87.93  |

Table 7: Combinations of two features

10 https://github.com/mojtaba-khallash/treebank-transform
**Estimation and Smoothing** Using a few training data, especially for languages with rich morphology, lexical features may infrequently appear during training. In MRLs like Persian, due to many feature combination by the inflectional system, we face a high rate of out-of-vocabulary. There are some ways to cope with this problem:

- **Replacing word forms by lemma**: Lemma of a word has less data sparsity than word form.

- **Number Normalization**: This is the default approach in MSTParser, in which each number is replaced by a constant. We apply this approach for numbers written either in English or Persian scripts.

- **Word Clustering and Semantic File**: The cluster ID of a word or its semantic file can be used instead of the original word form. These are two ways to categorize words into a group bigger than their lemma.

Table 8 illustrates the effect of each smoothing method on the accuracy for parsing MaltParser and MSTParser. For MaltParser, number normalization is the only technique that improves the accuracy. For MSTParser, replacing word forms by lemma and number normalization improves the accuracy. In the case of MSTParser, we apply each method separately and simultaneously on the development set, but replacing word forms by lemma gets the best improvement, and hence we use it in our final configuration.

| Smoothing                          | Malt | MST |
|-----------------------------------|------|-----|
| Baseline                          | 87.70| 88.04|
| Replacing word forms by lemma     | 87.38| **88.10**|
| Number Normalization              | **87.71**| 88.09|
| Word Clustering                   | 86.98| 87.47|
| Semantic File                     | 87.31| 85.25|

Table 8: Accuracy obtained after applying different sparsity-reduction tricks.

5 **Error Analysis**

We use the best configurations from the previous section on the training and test data, for gold annotation and an automatically derived one. Table 9 shows the final test results of the two parsers for Persian. In addition to LAS, we also include UAS and LA to facilitate comparisons in the future. Baseline results are included in the table. In the case of MaltParser, after applying new configurations on data, we repeat the third phase of MaltOptimizer in order to find the best feature template for the new training data. It seems that the graph-based parser performs better than transitions-based parsers in general. Despite a high overall parsing accuracy, only 1017 and 922 (33.91% and 30.74%) of sentences in the test set (with 2999 sentences) are parsed without errors by MaltParser and MSTParser, respectively. MaltParser has lower overall accuracy compared to MSTParser, but the number of completely correct parsed sentences for MaltParser is more than MSTParser.

In the case of predicted setting, as mentioned in section 4, there are four values for TMA. This means that we cannot create tense and mood from TMA. For this reason, we force to use TMA in the final configuration of both parsers in the predicted setting.

In order to evaluate parsing errors, we use the same approach as (McDonald and Nivre, 2011) to shows a set of linguistic and structural properties of the baseline and our best setting for each parser. In our analysis, we use MaltEval (Nilsson and Nivre, 2008). The area under the curve of final MaltParser

11 Number of arcs in the reverse path from the modifier of the arc to the root.

12 Number of arcs in the reverse path from the modifier of the arc to the root.
Table 9: Baseline and final results of gold (predicted) test data for MaltParser

| Parser | Method   | LAS       | UAS       | LA       |
|--------|----------|-----------|-----------|----------|
| Malt   | Baseline | 87.68 (87.04) | 90.41 (89.92) | 90.03 (89.49) |
|        | Final    | 87.91++ (87.16)+ | 90.58+ (90.05)++ | 90.22+ (89.60)+ |
|        | Diff.    | +0.23 (+0.12) | +0.17 (+0.13) | +0.19 (+0.11) |
| MST    | Baseline | 87.98 (86.82) | 91.30 (90.27) | 90.53 (89.90) |
|        | Final    | 88.37++ (86.97)++ | 91.55++ (90.36)++ | 90.86++ (90.05)++ |
|        | Diff.    | +0.39 (+0.15) | +0.25 (+0.09) | +0.33 (+0.15) |

Figure 2: Accuracy relative to sentence length. Both parsers perform better than their baselines.

is less than baseline, but it is over baseline for MSTParser. F-score of MSTParser for shorter distance is much better than the baseline and by increasing the distance to root, F-score degrades to be less than the baseline.

Linguistic Factors MaltParser and MSTParser can find 90.22% and 90.86% of all labels correctly. Figure 4 shows the F-score of some important dependency labels in the test data. MaltParser only improves subject and object categories, while MSTParser improves object, ROOT, and adverb categories. If we only consider the final results, MaltParser performs better for predicting subject and object, while MSTParser performs better for predicting ROOT and ezafe dependent (MOZ)\(^\text{13}\), and both have the same accuracy for adverb.

Table 10 gives the accuracy of arcs for each dependent part-of-speech. Final MSTParser performs

\(^{13}\text{Ezafe construction is referred to nouns or pronouns that imply a possessed-possessor relation (like first name-last name). The relation between the possessed and possessor is called mozaf (MOZ) that its sign is a vowel /e/ that pronounced right after the head noun (Dadegan Research Group, 2012).}\)
better than its baseline for all categories, except pronouns and better than MaltParser for all categories, except preposition. Final MaltParser, performs better than its baseline in all categories, except preposition.

### 6 Conclusion

In this paper, we have investigated a number of issues in data-driven dependency parsing of Persian. Because there is no previous study on parsing the Persian dependency treebank (Rasooli et al., 2013), we first have drawn the baseline for each parser, by selecting best performing algorithm and tuning its parameters. For MaltParser (Nivre et al., 2007b) different between best algorithm (non-projective version of Covington) with default settings and after optimizing feature template by the third phase of MaltOptimizer (Ballesteros and Nivre, 2012) is about 1.5 percent. This shows that the definition of feature template is a crucial aspect of transition-based parsing.

Our first experiment shows the effect of using automatic annotation of POS tags and morphological information. Our new configuration improves two parsers in both gold and predicted setting, but the improvement for MSTParser is higher than for MaltParser. MSTParser has higher accuracy in the gold setting, while MaltParser has better performance in predicted setting. It might mean that MaltParser is more robust against noisy information.

In the second experiment, we have explored the best combination of morphological and lexical semantic features for dependency parsing of Persian. We find that the combination of one morphological feature and one lexical semantic feature gets the best combination for each parser. Our lexical semantic features can be automatically produced for any word and thus we need to predict one morphological feature for real-world settings.

Finally we have proposed two simple methods for reducing data sparsity of each parser. After applying our solutions to three types of challenges, we reached 87.91% and 88.37% LAS on the test set (0.23% and 0.39% improvement over our baseline) for MaltParser and MSTParser, respectively.

Note that all of the experiments we reported in this paper use existing parsers as black boxes. We only changed the input data to obtain the best possible performance given our data sets. We plan to explore modifications of the underlying parsing algorithms to better make use of morphological information.

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