

# Leveraging Newswire Treebanks for Parsing Conversational Data with Argument Scrambling

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## Abstract

We investigate the problem of parsing conversational data of morphologically-rich languages such as Hindi where argument scrambling occurs frequently. We evaluate a state-of-the-art non-linear transition-based parsing system on a new dataset containing 506 dependency trees for sentences from Bollywood (Hindi) movie scripts and Twitter posts of Hindi monolingual speakers. We show that a dependency parser trained on a newswire treebank is strongly biased towards the canonical structures and degrades when applied to conversational data. Inspired by Transformational Generative Grammar (Chomsky, 1965), we mitigate the sampling bias by generating all theoretically possible alternative word orders of a clause from the existing (kernel) structures in the treebank. Training our parser on canonical and transformed structures improves performance on conversational data by around 9% LAS over the baseline newswire parser.

## 1 Introduction

In linguistics, every language is assumed to have a basic constituent order in a clause (Comrie, 1981). In some languages, constituent order is fixed to define the grammatical structure of a clause and the grammatical relations therein, while in others, that convey grammatical information through inflection or word morphology, constituent order assumes discourse function and defines the information structure of a sentence (Kiss, 1995). Despite word order freedom, most of the morphologically-rich languages exhibit a preferred word order in formal registers such as newswire. Word order alternations are more commonplace in informal lan-

guage use such as day-to-day conversations and social media content. For statistical parsing, word order alternations (argument scrambling) are a major bottleneck. Given appropriate pragmatic conditions a transitive sentence in a morphologically-rich language allows  $n$  factorial ( $n!$ ) permutations, where  $n$  is the number of verb arguments and/or adjuncts. Argument scrambling often leads to structural discontinuities. Moreover, these scramblings worsen the data sparsity problem since data-driven parsers are usually trained on a limited size treebank where most of the valid structures may never show up. More importantly, most of the available treebanks are built on newswire text which is more formal (Plank, 2016). The chances of any deviation from the canonical word order are smaller, thereby creating sampling bias.

A common solution to address the sampling bias is to alter the distribution of classes in the training data by using sampling techniques (Van Hulse et al., 2007). However, simple sampling techniques such as minority oversampling may not be a feasible solution for parsing argument scramblings which are almost non-existent in the newswire treebanks (see Table 1). Newswire data usually represent only a sample of possible syntactic structures and, therefore, suffer from non-representation of certain classes that encode valid arc directionalities. In the Hindi dependency treebank (HTB) (Bhat et al., 2015), for example, dependency relations such as source, time and place are never extraposed. Therefore, we instead generate training examples for varied arc directionalities by transforming the gold syntactic trees in the training data. We experiment with the Hindi dependency treebank and show that such transformations are indeed helpful when we deal with data with diverse word-orders such as movie dialogues. Our work is in conformity with earlier attempts where modifying source syntactic trees to match

target distributions benefited parsing of noisy, conversational data (Van der Plas et al., 2009; Foster, 2010).

S.No.	Order	Percentage
1	S O V	91.83
2	O S V	7.80
3	O V S	0.19
4	S V O	0.19
5	V O S	0.0
6	V S O	0.0

Table 1: The table shows theoretically possible orders of Subject (S), Object (O) and Verb (V) in transitive sentences in the HTB training data with their percentages of occurrence.

## 2 Sampling Argument Scrambling via Syntactic Transformations

In (Chomsky, 1965), Noam Chomsky famously described syntactic transformations which abstract away from divergent surface realizations of related sentences by manipulating the underlying grammatical structure of simple sentences called kernels. For example, a typical transformation is the operation of subject-auxiliary inversion which generates yes-no questions from the corresponding declarative sentences by swapping the subject and auxiliary positions. These transformations are essentially a tool to explain word-order variations (Mahajan, 1990; Taylan, 1984; King, 1995).

We apply this idea of transformations to canonical structures in newswire treebanks for generating trees that represent all of the theoretically viable word-orders in a morphologically-rich language. For example, we create a dependency tree where an indirect object is extraposed by inverting its position with the head verb, as shown in Figure 1.

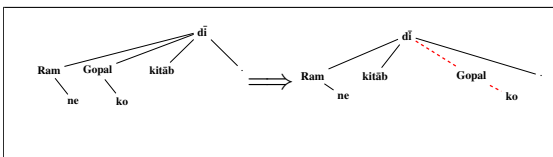


Figure 1: The figure depicts one possible permutation for the sentence *Ram ne Gopal ko kitāb dī*. ‘Ram ERG Gopal DAT book give.’ (Ram gave Gopal a book.). The indirect object *Gopal ko* (red, dashed arcs) is postposed by swapping its position with the ditransitive verb *dī* ‘give’.

Recently, a related approach was proposed by Wang and Eisner (2016), who employed the concept of creolization to synthesize artificial treebanks from Universal Dependency (UD) treebanks. They transform nominal and verbal projections in each tree of a UD language as per the word-order parameters of other UD language(s) by using their supervised word-order models. In single-source transfer parsing, the authors showed

that a parser trained on a target language chosen from a large pool of synthetic treebanks can significantly outperform the same parser when it is limited to selecting from a smaller pool of natural language treebanks.

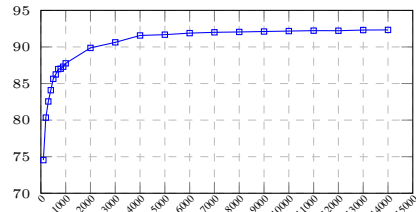


Figure 2: Learning curves plotted against data size on the X axis and LAS score on the Y axis.

Unlike Wang and Eisner (2016), we do not choose one word-order for a verbal projection based on a target distribution, but instead generate all of its theoretically possible orders. For each dependency tree, we alter the linear precedence relations between arguments of a verbal projection in ‘ $n!$ ’ ways, while keeping their dominance relations intact. However, simply permuting all the nodes of verbal projections can lead to an overwhelming number of trees. For example, a data set of ‘ $t$ ’ syntactic trees each containing an average of 10 nodes would allow around  $t \times 10!$  i.e., 3 million possible permutations for our training data size, making training infeasible. Moreover, we may only need a subset of the permutations to have a uniform distribution over the possible word orders. We therefore apply a number of filters to restrict the permutations. First, we only permute a subset of the training data which is representative of the newswire domain. It is often the case that domain specific constructions are covered by a limited number of sentences. This can be seen from the learning curves in Figure 2; the learning curves flatten out after 4,000 training instances. Second, for each sentence, we only take the  $k$  permutations with the lowest perplexity assigned by a language model where  $k$  is set to the number of nodes permuted for each verbal projection. The language model is trained on a large and diverse data set (newswire, entertainment, social media, stories, etc.) Finally, we make sure that the distribution of the possible word-orders is roughly uniform or at least less skewed in the augmented training data.

## 3 Evaluation Data

For an intrinsic evaluation of the parsing models on conversational data, we manually annotated de-

pendency trees for sentences that represent natural conversation with at least one structural variation from the canonical structures of Hindi.<sup>1</sup> We used Bollywood movie scripts as our primary source of conversational data. Although, dialogues in a movie are technically artificial, they mimic an actual conversation. We also mined Twitter posts of Hindi monolingual speakers. Tweets can often be categorized as conversational. The data set was sampled from old and new Bollywood movies and a large set of tweets of Indian language users that we crawled from Twitter using Tweepy<sup>2</sup>. For Twitter data, we used an off-the-shelf language identification system<sup>3</sup> to select Hindi only tweets. From this data, we only want those dialogues/tweets that contain a minimum of one argument scrambling. For this purpose we trained an off-the-shelf convolutional neural network classifier for identifying sentences with argument scrambling (Kim, 2014).<sup>4</sup> We trained the model using the canonical and transformed treebank data and achieved around  $\sim 97\%$  accuracy on canonical and transformed versions of HTB test data.<sup>5</sup> After automatic identification, we manually selected 506 sentences from the true positives for annotation. For POS tagging and dependency annotation, we used the AnnCorra guidelines defined for treebanking of Indian languages (Bharati et al., 2009). The data was annotated by an expert linguist with expertise in Indian language treebanking. The annotations were automatically converted to Universal Dependencies (UD) following UD v1 guidelines for multilingual experimentation (De Marneffe et al., 2014). Table 2 shows the distribution of theoretically possible word orders in transitive sentences in the evaluation set. Unlike their distribution in the HTB training data, the word orders in the evaluation set are relatively less skewed.

S.No.	Order	Percentage
1	S O V	33.07
2	O S V	23.62
3	O V S	17.32
4	S V O	14.17
5	V O S	9.45
6	V S O	2.36

Table 2: The table shows theoretically possible orders of Subject, Object and Verb in transitive sentences in the Evaluation set with their percentages of occurrence.

<sup>1</sup>HTB’s conversation section has around  $\sim 16,00$  sentences taken from fiction which, however, strictly obey Hindi’s preferred SOV word-order. Therefore, we needed a new dataset with word-order variations.

<sup>2</sup><http://www.tweepy.org/>

<sup>3</sup><https://github.com/irshadbhat/litcm>

<sup>4</sup>[https://github.com/yoonkim/CNN\\_sentence](https://github.com/yoonkim/CNN_sentence)

<sup>5</sup>The system often misclassified noisy sentences from movie scripts and tweets as scrambled.

Most of the movie scripts available online and the tweets are written in Roman script instead of the standard Devanagari script, requiring back-transliteration of the sentences in the evaluation set before running experiments. We also need normalization of non-standard word forms prevalent in tweets. We followed the procedure adapted by Bhat et al. (2017a) to learn a single back-transliteration and normalization system. We also performed sentence-level decoding to resolve homograph ambiguity in Romanized Hindi vocabulary.

## 4 Experimental Setup

The parsing experiments reported in this paper are conducted using a non-linear neural network-based transition system which is similar to (Kiperwasser and Goldberg, 2016). The monolingual models are trained on training files of HTB which uses the Pāṇinian Grammar framework (PG) (Bharati et al., 1995), while the multilingual models are trained on Universal Dependency Treebanks of Hindi and English released under version 1.4 of Universal Dependencies (Nivre et al., 2016).

**Parsing Models** Our underlying parsing method is based on the arc-eager transition system (Nivre, 2003). The arc-eager system defines a set of configurations for a sentence  $w_1, \dots, w_n$ , where each configuration  $C = (S, B, A)$  consists of a stack  $S$ , a buffer  $B$ , and a set of dependency arcs  $A$ . For each sentence, the parser starts with an initial configuration where  $S = [\text{ROOT}]$ ,  $B = [w_1, \dots, w_n]$  and  $A = \emptyset$  and terminates with a configuration  $C$  if the buffer is empty and the stack contains the  $\text{ROOT}$ . The parse trees derived from transition sequences are given by  $A$ . To derive the parse tree, the arc-eager system defines four types of transitions ( $t$ ): Shift, Left-Arc, Right-Arc, and Reduce.

We use a non-linear neural network to predict the transitions for the parser configurations. The neural network model is the standard feed-forward neural network with a single layer of hidden units. We use 128 hidden units and the  $\text{ReLU}$  activation function. The output layer uses a softmax function for probabilistic multi-class classification. The model is trained by minimizing negative log-likelihood loss with  $l_2$ -regularization over

<sup>6</sup>We also experimented with minority oversampling and instance weighting, however improvements over newswire were minimal (see §1 for possible reasons).

Data-set	Newswire <sup>PG/UD</sup>				Newswire <sup>PG/UD</sup> +Transformed Newswire <sup>PG/UD</sup>				Newswire <sup>UD</sup> +English <sup>UD</sup>			
	Gold POS		Auto POS		Gold POS		Auto POS		Gold POS		Auto POS	
	UAS	LAS	UAS	LAS	UAS	LAS	UAS	LAS	UAS	LAS	UAS	LAS
Newswire <sup>PG</sup>	96.41	92.08	94.55	89.51	96.07 <sup>-0.34</sup>	91.75 <sup>-0.33</sup>	94.29 <sup>-0.26</sup>	89.28 <sup>-0.23</sup>	-	-	-	-
Conversation <sup>PG</sup>	74.03	64.30	69.52	58.91	84.68 <sup>+10.65</sup>	73.94 <sup>+9.64</sup>	79.07 <sup>+9.55</sup>	67.41 <sup>+8.5</sup>	-	-	-	-
Newswire <sup>UD</sup>	95.04	92.65	93.85	90.59	94.59 <sup>-0.45</sup>	92.03 <sup>-0.62</sup>	93.32 <sup>-0.53</sup>	89.98 <sup>-0.61</sup>	94.56 <sup>-0.48</sup>	91.87 <sup>-0.78</sup>	93.22 <sup>-0.63</sup>	89.72 <sup>-0.87</sup>
Conversation <sup>UD</sup>	73.23	64.77	68.81	59.43	83.97 <sup>+10.74</sup>	74.61 <sup>+9.84</sup>	78.38 <sup>+9.57</sup>	67.98 <sup>+8.55</sup>	77.73 <sup>+4.5</sup>	68.12 <sup>+3.35</sup>	71.29 <sup>+2.48</sup>	62.46 <sup>+3.03</sup>

Table 3: Accuracy of our different parsing models on conversational data as well as newswire evaluation sets. Improvements in superscript are over the newswire baseline. <sup>6</sup>

the entire training data. We use Momentum SGD for optimization (Duchi et al., 2011) and apply dropout (Hinton et al., 2012).

From each parser configuration, we extract features related to the top three nodes in the stack, the top node in the buffer and the leftmost and rightmost children of the top three nodes in the stack and the leftmost child of the top node in the buffer. Similarly to Kiperwasser and Goldberg (2016), we use two stacked Bidirectional LSTMs with 128 hidden nodes for learning the feature representations over conjoined word-tag sequences for each training sentence. We use an additional Bidirectional LSTM (64 nodes) for learning separate representations of words over their character sequences for capturing out-of-vocabulary (OOV) words at testing time. We use word dropout with a dropout probability of 0.1 which enables character embeddings to drive the learning process around 10% of the time instead of full word representations. This is important for evaluation on noisy data where OOV words are quite frequent. The monolingual models are initialized using pre-trained 64 dimensional word embeddings of Hindi, while multilingual models use Hindi-English bilingual embeddings from Bhat et al. (2017a)<sup>7</sup>, while POS embeddings are randomly initialized within a range of  $-0.25$  to  $+0.25$  with 32 dimensions.

Moreover, we use pseudo-projective transformations of Nivre and Nilsson (2005) to handle a higher percentage of non-projective arcs in the evaluation data (6% as opposed to 2% in the training data). We use the most informative scheme of `head+path` to store the transformation information. Inverse transformations based on breadth-first search are applied to recover the non-projective arcs in a post-processing step.

## 5 Experiments and Results

We ran two experiments to evaluate the effectiveness of the tree transformations on the parsing

<sup>7</sup><https://bitbucket.org/irshadbhat/indic-word2vec-embeddings>

of conversational data. In the first, we leverage the monolingual annotations by applying syntactic transformations; in the second we use a cross-lingual treebank with diverse word-orders. For each experiment type, we report results using both predicted and gold POS tags. The POS taggers are trained using an architecture similar to the parser’s with a single layer MLP which takes its input from Bi-LSTM representation of the focus word (see Appendix for the results). We used the newswire parsing models as the baseline for evaluating the impact of tree transformations and multilingual annotations. The augmented models are trained on the union of the original newswire training data and the transformed trees. We generated 9K trees from 4K representative sentences (Figure 2) which were projectivized before applying syntactic transformations to preserve non-projective arcs. Our results are reported in Table 3.

As the table shows, our newswire models suffer heavily when applied to conversational data. The parser indeed seems biased towards canonical structures of Hindi. It could not correctly parse extraposed arguments, and could not even identify direct objects if they were not adjacent to the verb. However, in both gold and predicted settings, our augmented parsing models produce results that are approximately 9% LAS points better than the state-of-the-art baseline newswire parsers (Bhat et al., 2017b). Our augmented models even provided better results with UD dependencies. Probably due to the increased structural ambiguity, augmenting transformed trees with the original training data led to a slight decrease in the results on the original Hindi test sets in both UD and PG dependencies. Interestingly, our cross-lingual model also captured certain levels of scrambling which could be because the English treebank would at least provide training instances for SVO word order.

## 6 Conclusion

In this paper, we showed that leveraging formal newswire treebanks can effectively handle

argument scrambling in informal registers of morphologically-rich languages such as Hindi. Inspired by Chomskyan syntactic tradition, we demonstrated that sampling bias can be mitigated by using syntactic transformations to generate non-canonical structures as additional training instances from canonical structures in newswire. We also showed that multilingual resources can be helpful in mitigating sampling bias.

The code of the parsing models is available at the GitHub repository <https://github.com/riyazbhat/conversation-parser>, while the data can be found under the Universal Dependencies of Hindi at [https://github.com/UniversalDependencies/UD\\_Hindi](https://github.com/UniversalDependencies/UD_Hindi).

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Freitas, Katarína Gajdošová, Daniel Galbraith, Marcos Garcia, Moa Gärdenfors, Sebastian Garza, Filip Ginter, Iakes Goenaga, Koldo Gojenola, Memduh Gökrmak, Yoav Goldberg, Xavier Gómez Guinovart, Berta González Saavedra, Matias Grioni, Normunds Grūzītis, Bruno Guillaume, Jan Hajič, Linh Hà M, Dag Haug, Barbora Hladká, Radu Ion, Elena Irimia, Anders Johannsen, Fredrik Jørgensen, Hüner Kaşkara, Hiroshi Kanayama, Jenna Kanerva, Boris Katz, Jessica Kenney, Natalia Kotsyba, Simon Krek, Veronika Laippala, Lucia Lam, Phng Lê Hng, Alessandro Lenci, Nikola Ljubešić, Olga Lyashevskaya, Teresa Lynn, Aibek Makazhanov, Christopher Manning, Cătălina Mărănduc, David Mareček, Héctor Martínez Alonso, André Martins, Jan Mašek, Yuji Matsumoto, Ryan McDonald, Anna Missilä, Verginica Mititelu, Yusuke Miyao, Simonetta Montemagni, Keiko Sophie Mori, Shunsuke Mori, Bohdan Moskalevskyi, Kadri Muischnek, Nina Mustafina, Kaili Müürisep, Lng Nguyn Th, Huyn Nguyn Th Minh, Vitaly Nikolaev, Hanna Nurmi, Petya Osenova, Robert Östling, Lilja Øvrelid, Valeria Paiva, Elena Pascual, Marco Passarotti, Cene-Augusto Perez, Slav Petrov, Jussi Piitulainen, Barbara Plank, Martin Popel, Lauma Pretkalnia, Prokopis Prokopidis, Tiina Puolakainen, Sampo Pyysalo, Alexandre Rademaker, Loganathan Ramasamy, Livy Real, Laura Rituma, Rudolf Rosa, Shadi Saleh, Baiba Saulīte, Sebastian Schuster, Wolfgang Seeker, Mojgan Seraji, Lena Shakurova, Mo Shen, Natalia Silveira, Maria Simi, Radu Simionescu, Katalin Simkó, Mária Šimková, Kiril Simov, Aaron Smith, Carolyn Spadine, Alane Suhr, Umut Sulubacak, Zolt Szántó, Takaaki Tanaka, Reut Tsarfaty, Francis Tyers, Sumire Uematsu, Larraitz Uria, Gertjan van Noord, Viktor Varga, Veronika Vincze, Lars Wallin, Jing Xian Wang, Jonathan North Washington, Mats Wirén, Zdeněk Žabokrtský, Amir Zeldes, Daniel Zeman, and Hanzhi Zhu. 2016. [Universal dependencies 1.4](#). LINDAT/CLARIN digital library at the Institute of Formal and Applied Linguistics, Charles University in Prague. <http://hdl.handle.net/11234/1-1827>.

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## A Supplementary Material

$(Score_{LeftArc}, Score_{RightArc}, Score_{Shift}, Score_{Reduce})$

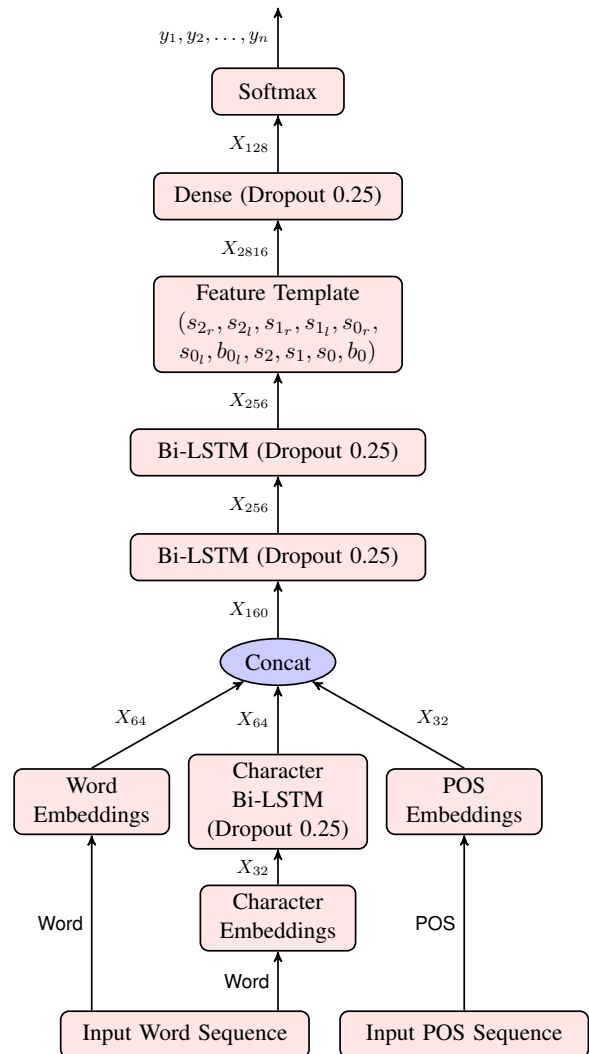


Figure 3: Parsing Architecture

S.No.	Data-set	Recall
1.	Newswire <sup>PG</sup>	96.98
2.	Conversation <sup>PG</sup>	91.33
3.	Newswire <sup>UD</sup>	97.59
4.	Conversation <sup>UD</sup>	89.40

Table 4: POS tagging accuracies on PG and UD evaluation (newswire and conversation) data.