Learning Hierarchical Discourse-level Structure for Fake News Detection

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Abstract
On the one hand, nowadays, fake news articles are easily propagated through various online media platforms and have become a grand threat to the trustworthiness of information. On the other hand, our understanding of the language of fake news is still minimal. Incorporating hierarchical discourse-level structure of fake and real news articles is one crucial step toward better understanding of how these articles are structured. Nevertheless, this has rarely been investigated in the fake news detection domain and faces tremendous challenges– existing methods for capturing discourse-level structure rely on annotated corpora which are not available for fake news datasets as well as how and what insightful information can be extracted from such discovered structures. To address these challenges, we propose Discourse-level Hierarchical Structure for Fake news detection. DHSF constructs discourse-level structures of fake/real news articles in an automated manner. Moreover, we identify insightful structure-related properties, which can explain the discovered structures and boost our understating of fake news. Extensive experiments show the effectiveness of the proposed approach. Further structural analysis suggests that real and fake news present substantial differences in the hierarchical discourse-level structure.

1 Introduction
In this work, we focus on detecting fake news articles (hereafter referred to as documents) based on their contents. Many existing linguistic approaches for fake news detection (Feng et al., 2012; Pennebaker et al., 2015; Ott et al., 2011) overlook a crucial linguistic aspect of fake/real news documents, i.e., hierarchical discourse-level structure. Usually, in a document, discourse units (e.g., sentences) are organized in a hierarchical structure, e.g., a tree. The importance of considering the hierarchical discourse-level structure for fake news detection is three-fold. First, previous studies (Bachenko et al., 2008; Rubin and Lukoianova, 2015) explored discourse structure in fake news detection and discovered that the way two discourse units of a document are connected could be quite revealing and insightful about the truthfulness of a document. For instance, Rubin and Lukoianova (Rubin and Lukoianova, 2015) applied Rhetorical Structure Theory (RST) (Mann and Thompson, 1988) and noted that fake stories lack “evidence” as a discourse-level rhetorical relation. Second, fake news is typically produced by connecting disjoint pieces and unlike well-established journalism (e.g., New York Times) lack a meticulous editorial board. Therefore, by incorporating the hierarchical discourse-level structure, we can investigate the coherence of fake/real news documents (we will show this later). Third, a substantial number of studies have shown that using hierarchical structures yields a better document representation in various downstream tasks whose predictions depend on the entire text (Bhatia et al., 2015; Morey et al., 2018; Li et al., 2014b). Since typically fake news detection is considered as a classification problem based on the entire text, applying discourse analysis has the potential to advance fake news detection.

On the other hand, incorporating the hierarchical structure at the discourse level for fake news detection faces tremendous challenges. First, many existing methods incorporating structural discourse (Li et al., 2014a; Bhatia et al., 2015) rely on annotated cor-
A sample document from our corpus

Figure 1: An illustration of the discourse-level hierarchical representation of a document using dependency tree parsing

Figure 2: The proposed framework Discourse-level Hierarchical Structure for Fake news detection (DHSF)

2 Problem Statement

Following the previous work (Allcott and Gentzkow, 2017; Shu et al., 2017), we define the fake news as follows.

Definition. We define a news document fake if its content is verified to be false and real otherwise.

Let’s briefly introduce some notation. Let a document $d$ from corpus $D$ contain $k$ sentences $s_1, s_2, \ldots, s_k$. Suppose sentence $s_j$ ($1 \leq j \leq k$) includes words $W_j = \{w_1, w_2, \ldots, w_{T_j}\}$ where $T_j$ denotes the number of words in sentence $s_j$. Additionally, binary labels $Y$ (i.e., fake or real labels) hold ground-truth labels of documents.

Given a corpus $D$ of fake/real news documents, we aim to learn model $\mathcal{M}$ that can automatically construct hierarchical and structurally rich representations for documents in $D$. Meanwhile, given binary labels $Y$, the model $\mathcal{M}$ uses hierarchical representations to automatically predict the labels for unseen news documents.

3 The Proposed Framework

For taking into account a hierarchical structure at the discourse level for fake news detection, we need to extract the struc-
ture without relying on an annotated corpus. To achieve this, we propose the framework DHSF illustrated in Figure 2. It provides three components: Discourse-level Hierarchical Structure Learning component automatically learns a proper structure for a given document, Document-level Structural Representation yields a representation for the entire document, which is used by Fake News Classification component to identify the label of the document.

3.1 Discourse-level Hierarchical Structure Learning

In this component, we aim to construct a hierarchical structure between discourse units, i.e., sentences. For doing so, we consider the hierarchical discourse-level structures based on dependency parsing (Liu and Lapata, 2017; Li et al., 2014a; Kim et al., 2017), i.e., the structure is a dependency tree (see Figure 1 as an example). Utilizing a dependency parsing approach has two main advantages. First, in dependency parsing, we mainly need to identify if a discourse unit semantically depends on another one. If so, a parent-child link in the dependency tree can be established. Therefore, unlike syntactic-based approaches such as RST, we do not need to define a set of rules for interior nodes, which is a challenging task (Li et al., 2014a). Second, discourse-level dependency parsing can be performed along with a downstream task (in this work fake news detection) in such a way that straightforward and meaningful parent-child links are optimized for that particular downstream task in an automated manner and without any discourse-related annotated corpus.

Next, we describe a method to discover the underlying connections between sentences, which is essential for the construction of a dependency tree presented in Section 3.1.2.

3.1.1 Identifying Inter-sentential Relations

Since discourse units are defined as sentences, we first need to get a fixed representation for each sentence. To this end, we utilize Bi-directional Long Short-Term Memory (BLSTM) network (Schuster and Paliwal, 1997). We represent each word in $W_j$ by a fixed-size word embedding, and further the BLSTM network at each time step $t \in [1, T_j]$ executes the following functions:

$$\overrightarrow{h_t} = \mathcal{F}(\overrightarrow{h}_{t-1}; w_{t-1})$$
$$\overleftarrow{h_t} = \mathcal{F}(\overleftarrow{h}_{t-1}; w_{T_j-t+1})$$

(1)

where $\mathcal{F}$ is the LSTM function (Hochreiter and Schmidhuber, 1997), and $\overrightarrow{h_t}$ and $\overleftarrow{h_t}$ are outputs of the forward and backward LSTM networks at time step $t$, respectively. Then, a fixed representation for a sentence $s_j$, denoted as $f_j$, is defined as the average of last output of forward and backward LSTM networks:

$$f_j = \frac{[\overrightarrow{h}_{T_j} + \overleftarrow{h}_{T_j}]}{2}$$

(2)

Similarly, we apply the BLSTM network to all sentences of a document (see Figure 2) and obtain a sequence of sentential representations denoted as $S = \{f_1, f_2, \ldots, f_k\}$.

As mentioned before, in dependency parsing, we need to identify how two discourse units are connected. To do this, we construct an inter-sentential attention matrix $A \in \mathbb{R}^{k \times k}$, which is obtained from the individual sentential representations. Entry $(m, n)$ of $A$ holds the probability of sentence $s_m$ being the parent of sentence $s_n$ where $1 \leq m, n \leq k$ and $m \neq n$. In other words, $A$ contains parent-child probabilities and is computed as follows.

$$u_m = \mathcal{G}(W \times f_m + b)$$
$$u_n = \mathcal{G}(W \times f_n + b)$$

$$A[m, n] = \frac{e^{\sum_{i=1}^{k} u_i \odot u_{i+1}}}{\sum_{i=1}^{k} e^{\sum_{i=1}^{k} u_i \odot u_{i+1}}}$$

(3)

where $\mathcal{G}$ is a non-linear activation function, $W$ is some weight matrix, $b$ is a bias vector, and $\odot$ denotes the dot product operator. Further, since we need a root node in a dependency tree, we compute the probability of a sentence being the root node:

$$u_j = \mathcal{G}(W \times f_j + b)$$
$$r_j = \frac{e^{\sum_{y} u_j[y]}}{\sum_{i=1}^{k} e^{\sum_{y} u_i[y]}}$$

(4)

where $r_j$ denotes the probability of sentence $s_j$ being the root node, and $u_j[y]$ is the $y$-th element of vector $u_j$.\footnote{Note that the backward LSTM (i.e., the lower part of Eq. 1) takes a sequence of words in a reverse order.}
3.1.2 Discourse Dependency Tree Construction

We use the learned matrix of inter-sentential parent-child probabilities (i.e., $A$) as well as the array of root probabilities (i.e., $r = \{r_1, r_2, \ldots, r_k\}$) and propose a greedy algorithm to construct the discourse dependency tree of a document. The algorithm is illustrated in Algorithm 1. A sentence with the maximum value in $r$ is considered as the root node and is inserted into the tree (line 5). Then, at each iteration, the algorithm finds the maximum entry in a block of the matrix $A$ whose rows correspond to the current nodes in the tree (i.e., $V$) and its columns correspond to the rest of nodes, i.e., $N \setminus V$ (see line 7). Note that, the columns corresponding to the current nodes are excluded because their parents have already been identified and also each node should have exactly one parent (except the root which has no parent). Assume the search results in the entry $(p, c)$ ($1 \leq p, c \leq k$) of $A$. Then, sentence $s_t$ is added as the child node of sentence $s_p$ (line 8). Algorithm 1 continues until all sentences of a document are added to the tree $T$.

Algorithm 1: The proposed algorithm for discourse dependency tree construction

\begin{verbatim}
Input: A: r
Output: Discourse dependency tree T
1 T = empty
2 N = \{s_1, s_2, \ldots, s_k\} // All nodes
3 V = \{\} ; // Set of current nodes
4 Add $N[\text{argmax}(r)]$ to $V$ // Determining the root node
5 $T$.root = $N[\text{argmax}(r)]$
6 while $|V| \neq k$
7     $p, c = \text{argmax}(A[V, N\setminus V])$ // Search block
8     $T$.addNode($N[c], N[p]$)
9     Add $N[c]$ to $V$
10 end
11 return $T$
\end{verbatim}

To fix the idea of Algorithm 1, we present a step-by-step execution of the algorithm, which is demonstrated in Figure 3. First of all, the algorithm identifies the root of the tree as shown in Step 0 of Figure 3. As mentioned before, the root is a sentence (a discourse unit) corresponding to the maximum value in the array of the root probabilities, i.e., $r$, which in our example is the sentence $s_1$. Next in Step 1, the algorithm searches for the maximum probability in the row $s_1$ while the column $s_1$ is excluded. Note the highlighted search block in the matrix $A$. The maximum value is 0.4 and corresponds to entry $(s_1, s_2)$. Therefore, the sentence $s_2$ is added as the child node of the sentence $s_1$ (note the letter 'p' for the parent and 'c' for the child in Figure 3). In Step 2, the search block includes rows $s_1$ and $s_2$ (i.e., the current nodes) while columns $s_1$ and $s_2$ are excluded. The maximum probability in this block is 0.45 and corresponds to entry $(s_2, s_4)$. Therefore, the sentence $s_4$ is added as the child node of the sentence $s_2$. The algorithm continues until all 6 sentences are added to the tree.

3.2 Document-level Structural Representation

We adopt a similar method in (Liu and Lapata, 2017) to extract a structurally rich representation for the entire document. First, for each sentence (i.e., a discourse unit), we obtain a structurally-aware representation. To achieve this, we take into account the parent-child probabilities as well as the root probabilities:

$$p_j = \sum_{z=1}^{k} A[z, j] \times f_z + r_j \times e_{\text{root}}$$

$$c_j = \sum_{z=1}^{k} A[j, z] \times f_j$$

$$g_j = \hat{g}(W[p_j]|c_j||f_j| + b)$$

where $p_j$ and $c_j$ are context vectors taking into account possible parents and children of sentence $s_j$, respectively, $e_{\text{root}}$ is a particular root embedding, $||$ is vector concatenation operator, and $g_j$ is a structurally-aware representation for sentence $s_j$. Finally, to extract a structurally rich representation for the entire document, we average all $g_j$ vectors:

$$x = \frac{1}{k} \sum_{j=1}^{k} g_j$$

where $x$ denotes the document-level structurally rich representation for a document.
3.3 Fake News Classification

We hypothesize that the document-level structurally rich representations offer a discriminatory power to detect fake news documents. Therefore, as shown in Figure 2, we employ a binary classification for fake news detection formulated as follows:

\[
L(\theta) = \sum_{d \in D} c_i = - (y_i \log(p_i^f) + (1 - y_i) \log(p_i^r))
\]

where \(y_i\) is the ground-truth label of the document \(d_i \in D\), \(c_i\) is the cross-entropy loss value, \(p_i^f\) and \(p_i^r\) are probabilities of the document \(d_i\) being fake or real, respectively, which are obtained from representation \(x\) for the document \(d_i\) using a fully connected layer followed by softmax function. In Eq. 7, \(\theta\) denotes the framework’s parameters, and \(L\) is the overall loss function to be optimized. Since the entire framework is fully differentiable, we utilize backpropagation to calculate the gradients followed by stochastic gradient descent to update and optimize the parameters.

4 Structural Property Definitions and Analysis

Structurally-aware representations achieved via incorporating discourse-level structure offer a discriminatory power distinguishing fake and real documents apart, which will be verified in Section 5.3. We expect more than this discriminatory power. We expect to identify insightful and interpretable information from extracted structures which can delineate intrinsic differences between fake and real news documents. To meet this expectation, we define three fundamental properties of constructed discourse dependency trees. Note that we leave the definitions of more advanced properties as one future work. We seek to fulfill two goals by defining these properties. First, we intend to highlight the way fake and real news documents are different. Secondly, we intend to leverage these properties to shed light on an essential topic in text linguistics, i.e., coherence. Coherence is concerned with how constituents of a document (e.g., discourse units) are linked together in a way that the entire text creates a clear mental picture to the readers (Storrer, 2002) and it has been the subject of many studies (Barzilay and Lapata, 2008; Lin et al., 2011; Guinaudeau and Strube, 2013; Li and Hovy, 2014). Notwithstanding its importance, coherence has not been investigated in the fake news domain in a large-scale and systematic fashion. Aiming at filling this gap, we naturally connect the defined de-
dependency tree properties with the coherence of fake/real news documents.

Property 1 (Number of Leaf Nodes)
This property, denoted as $P_1$, defines the normalized number of leaf nodes in a discourse dependency tree:

$$P_1 = \frac{l}{\log(k)}$$

where $l$ is the number of leaf nodes (sentences) in the discourse tree of a document. Recall that $k$ is the total number of sentences in a document.

The intuition behind defining Property 1 is as follows. According to the description of the dependency tree in Section 3.1, leaf nodes are isolated discourse units while no other discourse units depend on them. Thus, the more the number of leaf nodes is, the less interlinked are the discourse units will be, and vice versa. Therefore, Property 1 is likely to indicate the coherence of a document – the higher $P_1$ is, the more isolated sentences in $d_i$, the less coherent the document. Also, for a document with $k$ sentences $P_1 \in \left[\frac{1}{\log(k)}, \frac{k-1}{\log(k)}\right]$.

Property 2 (Preorder Difference) This property, denoted as $P_t$, defines the normalized positional difference between preorder traversal of a document’s discourse dependency tree and its original sentential sequential order:

$$P_t = \frac{\sum_{j=1}^{k} |s_j^{position} - j|}{\log(k)}$$

where $s_j^{position}$ denotes the position of sentence $s_j$ in the preorder traversal of dependency tree of a document and its position in the original sequential order is simply $j$. As an example, consider the sample dependency tree presented in Figure 1. Preorder traversal results in the sequence $\{s_1, s_2, s_4, s_3, s_5\}$ (e.g., $s_3^{position} = 4$) and the original sentential sequential is $\{s_1, s_2, s_3, s_4, s_5\}$. Therefore, according to the definition of Property 2:

$$P_t = \frac{1+2+2+2+2}{\log(5)} \approx 2.86.$$ 

Preorder traversal2 takes into consideration the organization of a document according to dependencies between sentences reflected in a document’s discourse dependency tree. Then, the purpose of Property 2 is to measure how much the organization of a document, captured from preorder traversal, deviates from its sentential sequential order. Sentence order is highly related to the coherence of a document where the displaced order of sentences in a document makes it less coherent (Li and Hovy, 2014). Thus, intuitively, the less the value of Property 2 for a document is, the more coherent that document should be. Also, for a document with $k$ sentences $P_t \in \left[\frac{k-1}{\log(k)}, \frac{k^2-1}{2\log(k)}\right]$ if $k$ is odd and $P_t \in \left[\frac{k-1}{\log(k)}, \frac{k^2}{2\log(k)}\right]$ if $k$ is even.

Property 3 (Parent-Child Distance)
This property, denoted as $P_c$, defines the normalized sum of positional distances between child nodes and their parents when they are considered in the original sequential order:

$$P_c = \sum_{c,p \in T} \frac{|c^{position} - p^{position}|}{\log(k)}$$

where $c^{position}$ and $p^{position}$ denote the positions of a child node $c$ and a parent node $p$, respectively, in the original sentential sequential order. For instance, in our running example, the parent node $p = s_3$ has $p^{position} = 3$ (i.e., it is the third sentence) and its child node $c = s_5$ has $c^{position} = 5$. So, their parent-child distance is $|5 - 3| = 2$. Following a similar calculation for other parent-child pairs for the tree in Figure 1 we have $P_c = \frac{4+2+2+2}{\log(5)} \approx 10$. Similar to Property 2, Property 3 pertains to the organization of a document and takes into consideration the deviation from sentential sequential order. Intuitively speaking: usually, we expect that a child node and its parent to be close to each other in the original sequential order. Consequently, the less value of this property is, the more coherent a document is likely to be. The range of Property 3 in a document containing $k$ sentences is $P_c \in \left[\frac{k-1}{\log(k)}, \frac{k(k-1)}{2\log(k)}\right]$.

5 Experiments
To verify the performance of the proposed framework DHSF, we conduct a set of experiments. We seek to answer the following research questions:
1. How does the proposed framework perform on fake news detection?

2. How do the defined structure-related properties describe the fake and real news documents?

In this section, we first describe the datasets followed by presenting the experimental settings. Afterward, we evaluate the performance of DHSF compared to several representative baselines. Finally, we present a structural analysis of fake/real news documents.

5.1 Datasets
We utilize five available fake news datasets in this study. The first two datasets are collected by (Shu et al., 2017) and include online articles whose veracities have been identified by experts in BuzzFeed and PolitiFact, respectively. For the next two datasets, we utilize two available online fake news datasets provided by kaggle.com. Finally, we include the dataset constructed and shared by McIntire.

Since the proposed framework DHSF is a general-purpose framework investigating discourse-level structures of fake/real news documents based on their textual contents, we do not restrict DHSF to a particular source of data and therefore combine all datasets. Similar to previous work (Shu et al., 2017), we balance the dataset to avoid a trivial solution as well as ensuring a fair performance comparison. In total, we have 3360 fake and 3360 real documents.

5.2 Experimental Settings
First, we pre-process the documents by removing numbers, non-English characters, stopwords (e.g., ‘with’), and converting all characters to lower case. We randomly select 134 documents as a development set, (67 from each class) and 134 documents (67 from each class) as a test set. The remaining 6452 documents are used for training. The development set is used for tuning the hyper-parameters as well as saving the best model during the training. We initialize the word embeddings from Google news pre-trained word2vec embeddings (Mikolov et al., 2013). LeakyReLU (Xu et al., 2015) is used as the non-linear activation function and the number of hidden units in the BLSTM network is set to 100. Each simulation is run for 200 steps with a random mini-batch size of 40 documents. The learning rate starts at 0.01 with the decay rate of 0.9 after every 50 steps. We use ADAM optimizer (Kingma and Ba, 2014) to optimize the parameters. The Pytorch package is utilized for the implementation and the code and data are publicly available in https://github.com/hamidkarimi/DHSF.

5.3 Comparison Results
Research question (1) is concerned with the performance of the proposed framework for fake news detection. To answer this question, we compare the performance of DHSF with the following representative baselines:

- **N-grams.** In this baseline method, we extract and combine unigrams, bigrams, and trigrams features and use SVM (Support Vector Machines) as the classifier.
- **LIWC.** LIWC (Linguistic Inquiry and Word Count) offers various psycholinguistic features from a written document. We extract 94 features for each document and use SVM as the classifier.
- **RST.** We extract RST relations of documents using the implementation of the method proposed by (Ji and Eisenstein, 2014). Then, we vectorize the relations and employ SVM for classification. This baseline takes into account the hierarchical structure of documents via RST.
- **BiGRNN-CNN.** A CNN (Convolutional Neural Network) is applied at the sentence-level on word embeddings, and a BiGRNN (Bi-Directional Gated Recurrent Neural Network) extracts features from a sequence of extracted sentential features. This baseline takes into consideration a two-level sequential structure for a document.
- **LSTM[w+s].** In this baseline, we apply an LSTM network on a sequence of word embed-
dings belonging to a sentence and then apply another LSTM on a sequence of extracted sentential features. LSTM[w+s] also considers a two-level sequential structure for a document. LSTM[s]. This method is similar to LSTM[w+s] except that the mean of word embeddings in a sentence is used instead of applying an LSTM network. LSTM[s] considers a single sequential structure for a document.

We use accuracy as the metric of performance evaluation given that the dataset is fully balanced. Table 1 shows the comparison results on the test set. Based on this table, we make the following observations:

1. N-grams achieve a better performance than LIWC. In line with the previous study (Ott et al., 2011), this shows that for fake news detection, taking into account the context of a document as n-grams do, is more effective than employing the existing pre-defined dictionaries as LIWC does.

2. Most of the time, methods wherein a document’s structure is somehow taken into account outperform n-grams and LIWC. This observation shows that for fake news detection, the content’s structure plays an important role.

3. The poor performance of RST is because of the following reasons. a) Using RST without an annotated corpus is not very efficient, and b) RST relations are extracted using auxiliary tools optimized for other corpora which cannot be applied effectively to the fake news corpus in hand.

4. The proposed framework DHSF significantly outperforms all other methods. This observation shows that hierarchical discourse-level representations extracted for documents are effectively rich for fake news detection.

5.4 DHSF Inspection

To further verify the working of DHSF framework, we investigate how does the model act during the training process regarding optimizing the deep model as well as its performance on the fake news prediction task. According to the inspection demonstration in Figure 4, as training proceeds, the model’s training error is decreasing (Figure 4a) and the accuracy of the model is improving (Figure 4b). Hence, we can ensure the framework learns how to classify fake news documents.

5.5 Structural Analysis for Fake/Real Documents

In Section 4, we defined three properties for describing constructed discourse-level dependency trees for fake/real news documents. In this section, we compute the average values of these properties for fake/real news documents of the test set. Figure 5 shows the results. We make the two key observations based on this figure:

1. There is a significant difference in all three properties for fake news documents vs. real news documents. This observation shows the fact that structures of fake news documents at the discourse-level are substantially different from those of real ones.

2. Noticeably, in all three properties, real news documents show less value than fake documents. As described in Section 4, all three properties are closely connected to the coherence of a document. Therefore,
real news documents indicate more degree of coherence.

6 Related Work

Content-based fake news detection has been the subject of many linguistic research endeavors. DePaulo et al. (DePaulo et al., 2003) investigated fake stories from the physiological perspective and introduced insightful cues in fake stories as well as highlighted ‘unusual’ language in such stories. N-grams and Part-of-Speech (POS) tags are fundamental features of a text which have been utilized for fake news detection (Ahmed et al., 2017; Ott et al., 2013). Also, LIWC (Pennebaker et al., 2015) has been employed to investigate the role of individual words in a document for deception detection (Ott et al., 2011).

Syntax-based approaches have been employed to take into account the hierarchical structure of textual documents for fake news detection (Feng et al., 2012; Pérez-Rosas and Mihalcea, 2015). These approaches utilize Probabilistic Context-Free Grammars (PCFG) to encode sentences into a set of generative rules. One caveat of syntax-based approaches is their reliance on auxiliary parsing tools which might propagate error in later part of a developed model. Moreover, generating the production (generative) rules in an automated manner is a complicated process.

Another way of incorporating structure is discourse-level parsing (Mann and Thompson, 1988; Li et al., 2014a; Ren and Zhang, 2016) which has seldom been explored for fake news detection. The noticeable exception is the approach developed by Rubin and Lukoianova (Rubin and Lukoianova, 2015). They extracted a set of RST relations in fake and real documents and vectorized them using the Vector Space Model (VSM) method. In this work, we proposed an automated and data-driven discourse-level parsing approach which used neither any annotated corpus nor any external tool.

7 Conclusion and Future Work

In this work, we looked into fake news detection from a new perspective. We hypothesized that hierarchical discourse-level structure of news documents offers a discriminatory power for fake news detection. To investigate this hypothesis, we proposed a new framework DHSF, which can automatically extract discourse-level structures of real/fake news documents represented by dependency trees while does not rely on an annotated corpus. Moreover, we defined a set of insightful properties describing tree structures. Extensive experiments confirmed the power of our approach where it outperformed representative baselines. More importantly, we managed to highlight noticeable differences between structures of fake and real news documents. These differences also indicated less coherency in the fake news documents.

The new perspective pursued in this paper can be continued in several directions. First, we would like to define more advanced properties from the discourse dependency trees. Second, investigating the hierarchical structure at the word-level will be an exciting research inquiry. Finally, unsupervised discourse-level structure extraction of fake/real news documents is a worthwhile research topic.
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