Text Generation from Discourse Representation Structures

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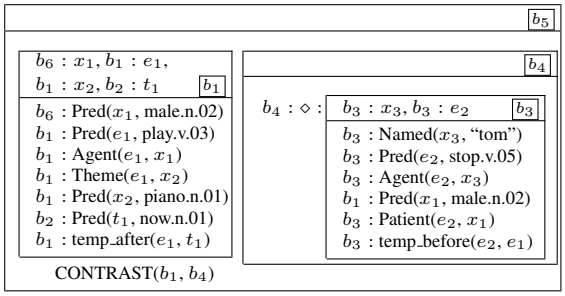
Abstract

We propose neural models to generate text from formal meaning representations based on Discourse Representation Structures (DRSs). DRSs are *document-level* representations which encode rich semantic detail pertaining to rhetorical relations, presupposition, and co-reference *within* and *across* sentences. We formalize the task of neural DRS-to-text generation and provide modeling solutions for the problems of condition ordering and variable naming which render generation from DRSs non-trivial. Our generator relies on a novel sibling treeLSTM model which is able to accurately represent DRS structures and is more generally suited to trees with wide branches. We achieve competitive performance (59.48 BLEU) on the GMB benchmark against several strong baselines.

1 Introduction

It is not uncommon for text generation systems to produce natural language output from intermediate semantic representations (Yao et al., 2012; Takase et al., 2016). The literature presents several examples of generating text from logical forms underlying various grammar formalisms (Wang, 1980; Shieber et al., 1990; Carroll and Oepen, 2005; White et al., 2007), typed lambda calculus (Lu and Ng, 2011), Abstract Meaning Representations (AMR; Flanigan et al. 2016; Konstas et al. 2017; Song et al. 2018; Beck et al. 2018; Damonte and Cohen 2019; Ribeiro et al. 2019; Zhu et al. 2019; Cai and Lam 2020; Wang et al. 2020), Discourse Representation Theory (DRT; Basile and Bos 2011; Basile 2015), and Minimal Recursion Semantics (MRS; Horvat et al. 2015; Hajdik et al. 2019).

In this work, we propose neural models to generate high-quality text from semantic representations based on Discourse Representation Structures (DRSs). DRSs are the basic meaning-carrying units in Discourse Representation Theory (DRT; Kamp 1981; Kamp and Reyle 1993; Asher and Lascarides 2003), a formal semantic theory designed to handle a variety of linguistic phenomena, including anaphora, presuppositions (Van der Sandt, 1992; Venhuizen et al., 2018), and temporal expressions within and across sentences. DRSs are scoped meaning representations, they capture the semantics of negation, modals, and quantification.



The man is going to play the piano. Tom may stop him.

Figure 1: DRS representing two-sentence discourse.

Figure 1 displays in box format the meaning representation for a discourse consisting of two sentences. The outermost box is a *segmented* DRS expressing the rhetorical relation CONTRAST between box b_1 representing the first sentence and box b_4 representing the second sentence. Boxes b_1 and b_2 are DRSs, the top layers contain variables (e.g., x_1, x_2) indicating discourse referents and the bottom layers contain conditions (e.g., Named(x_3, "tom")) representing information about discourse referents. Variables and conditions have pointers (denoted by b in the figure) pointing to the boxes where they should be interpreted.[1] Predicates are disambiguated to their Wordnet (Fellbaum, 1998) senses (e.g., male.n.02 and play.v.03).

Although there has been considerable activity recently in developing models which analyze text in the style of DRT (van Noord et al., 2018, 2019; Liu et al., 2019a, 2018; Fancellu et al., 2019), attempts

[1] In Figure 1, b_6 is a presuppositional box for the interpretation of *the man* in the context of the two-sentence discourse.

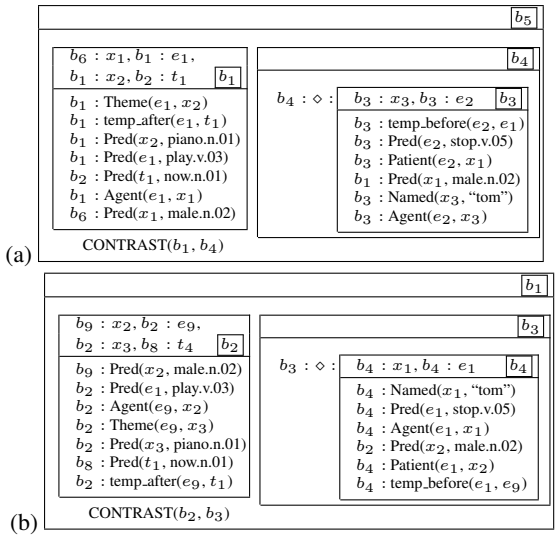


Figure 2: DRS from Figure 1 with (a) shuffled conditions and (b) different variable names.

to *generate* text from DRSs have been few and far between (however see Basile 2015 and Narayan and Gardent 2014 for notable exceptions). This is primarily due to two properties of DRS-based semantic representations which render generation from them challenging. Firstly, DRS conditions are *unordered* representing a *set* (rather than a list).[2] A hypothetical generator would have to produce the same output text for any DRSs which convey the same meaning but appear different due to their conditions having a different order (see Figures 1 and 2a which are otherwise identical but the order of conditions in boxes b_1 and b_4 varies). The second challenge concerns *variables* and their prominent status in DRSs. Variables identify objects in discourse (such as entities and predicates), and are commonly used to model semantic phenomena including coreference, control constructions, and scope. In Figure 1, variables x, e, s, t, p, and b denote entities, events, states, time, propositions and boxes, respectively. Variable names themselves are arbitrary and meaningless posing a challenge for learning. Our generator must verbalize different variable names to the same surface form. The meaning representations in Figures 1 and 2b are identical and both correspond to the same discourse except that the variables have been given different names (b_5 in Figure 1 has been named b_1 in Figure 2b, b_1 is now b_2, x_1 is x_2, e_1 is e_9, and so on).

[2] An exception are conditions in segmented DRSs whose order can be retrieved deterministically based on the arguments of rhetorical relations. For example, given the relation BECAUSE(b_1, b_3), we can assume that box b_1 precedes b_3.

These two problems are further compounded by the way DRSs are displayed, in a box-like format which is intuitive and easy to read but not convenient for modeling purposes. As a result, DRSs are often post-processed in a format that can be handled more easily by modern neural network models. For example, DRS variables and conditions are converted to clauses (van Noord et al., 2018) or DRSs are modified to trees where each box is a subtree and conditions within the box correspond to children of the subtree (Liu et al., 2019a, 2018).

In this paper we propose novel solutions to condition ordering and variable naming. We argue that even though DRS conditions appear unordered, they have a *latent* order due to biases in the way the training data is created. To give a concrete example, the Groningen Meaning Bank (GMB; Bos et al. 2017) provides the largest collection to date of English texts annotated with DRSs. These annotations were generated with the aid of a CCG parser (Clark and Curran, 2007); atomic DRS conditions were associated with CCG supertags and then semantically combined following the syntactic CCG derivations. Even annotators creating DRSs manually would be prone to follow a canonical order (e.g., listing named entities first, then verbal predicates and their thematic roles, and finally temporal conditions). We propose a graph-based model which learns to recover the latent order of conditions without explicitly enumerating all possible orders which can be prohibitive. We also handle variable names with a method which rewrites arbitrary indices to *relative* ones which are in turn determined by the order of conditions.

Following previous work, we convert DRSs to a more amenable format. Specifically, we consider Discourse Representation Tree Structures (DRTSs; Liu et al. 2019b) as the semantic representation input to our document generation task, and generate a sequence of words autoregressively. We adopt an encoder-decoder framework with a treeLSTM (Tai et al., 2015) encoder and a standard LSTM (Hochreiter and Schmidhuber, 1997) decoder. Problematically, DRS trees are wide and the number of children for a given node can be as many as 180. It therefore becomes memory-consuming and sparse to assign a forget gate for each child as in the case of conventional (N-ary) treeLSTM (Tai et al., 2015). We propose a variant which we call *Sibling* treeLSTM that replaces N forget gates with a *parent* gate and a *sibling* gate. As a result, it reduces

memory usage from $O(N)$ to $O(2)$, and is more suitable for modeling wide and flat trees.

Our contributions can be summarized as follows: (1) we formalize the task of neural DRS-to-text generation; (2) we provide solutions for the problems of condition ordering and variable naming, which render generation from DRS-based meaning representations non-trivial; and (3) propose a novel sibling treeLSTM model that can be also generally used to model wide tree structures. We make our code and datasets publicly available.[3]

2 Problem Formulation

Let S denote a DRS-based meaning representation. The aim of DRS-to-text generation is to produce text T that verbalizes input meaning S:

$$T^* = \arg\max_{T \in \mathbb{T}} P(T|S, \Theta),$$

where $\mathbb{T}$ is the set of all possible texts, S has an arbitrary order of conditions and indexing of variables, and Θ is the set of model parameters.

Our generation model is based on the encoder-decoder framework (Bahdanau et al., 2015) and operates over tree structures. Moreover, prior to training, variable names are rewritten so that their (arbitrary) indices denote relative order of appearance. We propose a novel sibling TreeLSTM for encoding tree structures. The decoder is a sequential LSTM equipped with an attention mechanism generating word sequence $T = [t_0, t_1, ..., t_{m-1}]$, where m is the length of the text. At test time, DRS conditions are normalized, i.e., they are reordered following a canonical order learned from data, and used as input to our generation model.

We first describe our DRS-to-tree conversion and variable renaming procedures (Sections 2.1 and 2.2). We next present our tree-to-sequence generation model (Section 2.3), and explain how DRS conditions are ordered (Section 2.4).

2.1 DRS-to-Tree Conversion

The algorithm of Liu et al. (2018) renders DRSs in a tree-style format. It constructs trees based on DRS conditions in the bottom box layers, without considering variables in the top layer. This results in oversimplified semantic representations and information loss (e.g., presuppositions cannot be handled). We improve upon their approach by

[3] https://github.com/LeonCrashCode/Discourse-Representation-Tree-Structure/tree/main/gmb/DRS-to-text

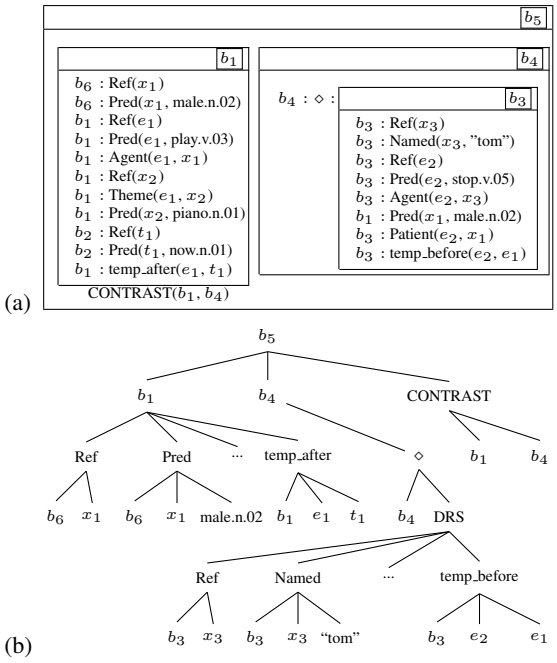


Figure 3: (a) Box-style DRSs; (b) Tree-style DRSs.

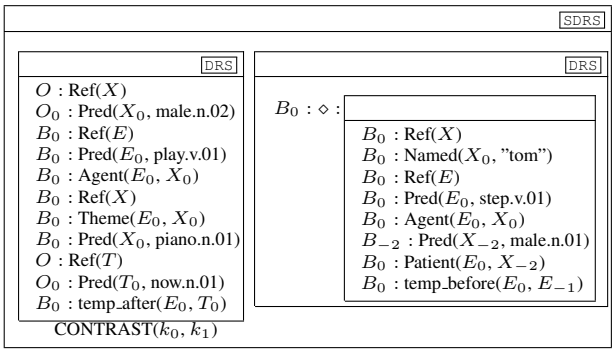


Figure 4: DRSs with relative variables.

merging variables in the top layer with variables in the bottom layer via introducing *special* conditions.

We collect variables in top layers of DRS boxes to construct a dictionary $d = \{v : b\}$, where v denotes a variable and b is a presupposition box label (e.g., $x_1 : b_1$). We then move variables from the top to the bottom layer by expressing them as special conditions b : Ref(v) and placing them before conditions on variable v. For example, $b_6 : x_1$ in Figure 1 becomes special condition b_6 : Ref(x_1) and is placed before condition b_6 : Pred(x_1, male.n.02) in Figure 3(a).

Once top variables have been rewritten as special conditions, the resulting DRSs are converted into trees as shown in Figure3(b). Box variables (e.g., b_1, b_5) become parent nodes, while conditions, which are also subtrees, become children.

2.2 Relative Variables

We rename variables with regard to their relative position in a given DRS following a predefined traversal order.

We obtain the sequence of *box variables* by traversing DRSs in an outer-to-inner and left-to-right manner, e.g., $[b_5, b_1, b_4, b_3]$ in Figure 1. For SDRSs, we replace variables in discourse relations with k_i, where i denotes th ith box from left to right. For example "CONTRAST(b_1, b_4)" in Figure 1 is rewritten to "CONTRAST(k_0, k_1). Variables and conditions within presupposition boxes are rewritten to B_i, where $i \in \mathbb{Z}$ denotes the distance of the current box to the presupposition box. For example, b_1 : Agent(e_1, x_1) is rewritten to B_0 : Agent(e_1, x_1) because it is in the current box b_1, while b_1 : Pred(x_1, "male.n.02") is rewritten to B_{-2} : Pred(x_1, "male.n.02") because it is in box b_3 and two hops away from presupposition box b_1. We use special label O for presupposition boxes pertaining to semantic content outwith the current DRS. For example, b_6 : Ref(x_1) is rewritten to O : Ref(x_1) because it introduces a new presupposition box, and b_6 : Pred(x_1, male.n.02) is rewritten to O_0 : Pred(x_1, male.n.02) because the condition can only be interpreted in this new presupposition box (now O_0 and previoulsy b_6).

We obtain a sequence of *general variables* by traversing conditions as they appear in the DRS. Variables introduced for the first time are denoted by their type (going from left-to-right), while subsequent mentions of the same variables are rewritten with relative indices denoting their distance from the position where they were first introduced. Take Figure 3(a) as an example. The sequence of general variables is [x_1, x_1, e_1, e_1, e_1, x_1, x_2, e_1, x_2, x_2, t_1, t_1, e_1, t_1, x_3, x_3, e_2, e_2, e_2, x_3, x_1, e_2, x_1, e_2, e_1], and is rewritten to [X, X_0, E, E_0, E_0, X_0, X, E_0, X_0, X_0, T, T_0, E_0, T_0, X, X_0, E, E_0, E_0, X_0, X_{-2}, E_0, X_{-2}, E_0, E_{-1}]. The DRS from Figure 3(a) is shown in Figure 4 with relative variables.

2.3 Generation Model

Our generation model is based on the encoder-decoder framework, where an encoder is used to encode input DRS trees and a decoder outputs a sequence of words. A limitation of sequential encoders is that they only allow sequential information propagation without considering the structure of the input (Tai et al., 2015; Wang et al., 2019). In our case, DRS tree structures are additionally wide (the longer a document, the wider the tree) and relatively flat (see Figure 3(b)). To better model these aspects, we propose a treeLSTM encoder which takes *sibling* information into account.

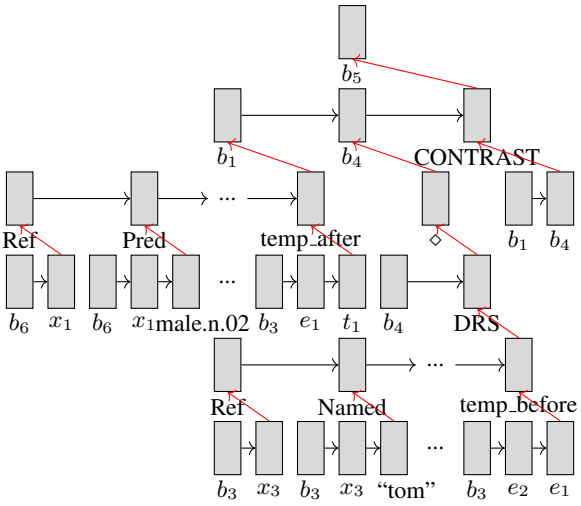


Figure 5: The sibling treeLSTM; grey boxes are hidden representations of nodes, black/red arrows represent sibling/parent information flow.

As shown in Figure 5, the hidden representations of the sibling TreeLSTM cells are updated from preceding sibling and child nodes. More formally, the hidden representation for node j is given by:

$$u_j = \tanh(g^u([x_j; h_{js}; h_{jp}])) \quad (1)$$

$$i_j, o_j = \sigma(g^{io}([x_j; h_{js}; h_{jp}])) \quad (2)$$

$$f_{js} = \sigma(g^f_s([x_j; h_{js}])) \quad (3)$$

$$f_{jp} = \sigma(g^f_p([x_j; h_{jp}])) \quad (4)$$

$$c_j = i_j \cdot u_j + f_{js} \cdot c_{js} + f_{jp} \cdot c_{jp} \quad (5)$$

$$h_j = o_j \cdot \tanh(c_j), \quad (6)$$

where x_j is the token input representation, h_{js} is the hidden representation of the sibling node preceding j, h_{jp} is the hidden representation of the last child of node j (Equation (1)), g^* are linear functions, and σ is a sigmoid function (Equations (2)–(4)). For each node j, we obtain its cell input representation u_j (Equation (1)), its input gate i_j and output gate o_j (Equation (2)), and two forget gates f_{js} (Equation (3)) and f_{jp} (Equation (4)) for its neighbor cell and the last child cell, respectively. The memory of the current cell c_j (Equation (5)) is updated by the gated sum of its cell input representation and the memories of its neighbor and child cells. The hidden representation of current node h_j is computed with its output gate o_j (Equation (6)).

Finally, a DRS tree is represented by the hidden representations of its nodes $[h_0, h_1, ..., h_{n'-1}]$ as computed by the sibling treeLSTM (n' denotes the number of nodes). The decoder is a standard LSTM with global attention (Bahdanau et al., 2015).

2.4 Condition Ordering

As discussed previously, DRSs at test time may exhibit an arbitrary order of conditions, which our model should be able to handle. Our solution is to to reorder conditions prior to generation by learning a latent canonical order from training data (e.g., to recover boxes b_1 and b_3 in Figure 1 from boxes b_1 and b_3 in Figure 2). More formally, given a set of conditions R_{set}, we obtain an optimal ordering $R = [r_0, r_1, ..., r_{n-1}]$ such that:

$$R^* = \arg\max_{R \in \pi(R_{set})} \textsc{Score}_{\mathbb{K}}(R|R_{set}), \qquad (7)$$

where $\pi(R_{set})$ are all permutations of R_{set}, and R^* is the order with the highest likelihood according to $\textsc{Score}_{\mathbb{K}}$. Here, $\mathbb{K}$ parametrizes $\textsc{Score}$ as "knowledge" we collect from our training data by observing canonical orders of conditions. Unfortunately, the time complexity of calculating Equation (7) is $O(n!)$, we must enumerate all possible permutations for a set of conditions with n as large as 180. Since this is prohibitive, we resort to *graph ordering* which allows us to recover the order of the conditions without enumeration.

Graph Construction We construct a graph from the set of DRS conditions which we break down into graph nodes and edges. Conditions in DRSs can be *simple* or *complex* according to their type of arguments. A simple condition might have a relation name with two arguments (e.g., Named(x_3, "tom") and Agent(e_1, x_3)), while a complex condition has a scoped name (e.g., possibility $\diamond$) and takes one or more DRSs as arguments. Simple conditions are denoted by a 3-tuple (l_s, a_0, a_1), where l_s is the condition name (e.g., Named and Agent) and a_0 and a_1 are its first and the second argument, respectively, which could be a variable or constant (e.g., e_1, x_3 and "piano.n.01"). Complex conditions are a 2-tuple (l_c, V_r), where l_c is the scope name, and V_r the set of arguments scoped by the condition. For example, the set of arguments for the possibility scope ($\diamond$) in Figure 1 is {e_1, e_2, x_1, x_3, "tom", "stop.v.05", "male.n."}.

Condition names become nodes in our graph. Simple conditions are further divided into constant and thematic nodes. Constant nodes are

(a)

Conditions	Nodes	Edges
Pred(x_1, "male.n.02")	Pred "male.n.02"	$a_0 = x_1$
Pred(e_1, "play.v.03")	Pred "play.v.03"	$a_0 = e_1$
Agent(e_1, x_1)	Agent	$a_0 = e_1, a_1 = x_1$
Theme(e_1, x_2)	Theme	$a_0 = e_1, a_1 = x_2$
Pred(x_2, "piano.n.01")	Pred "piano.n.01"	$a_0 = x_2$
Pred(t_1, "now.n.01")	Pred "now.n.01"	$a_0 = t_1$
temp_after(e_1, t_1)	temp_after	$a_0 = e_1, a_1 = t_1$

(b)

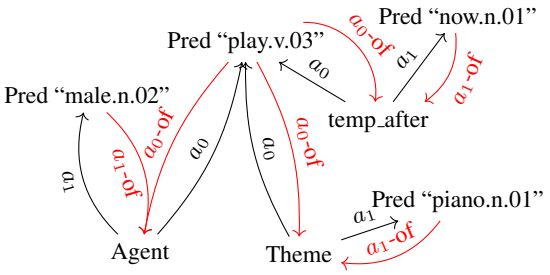


Figure 6: (a) Conditions and their corresponding graph nodes (b) graph with inverse edges (shown in red).

constructed by concatenating the relation name in the condition with the constant argument (e.g., condition Pred(x_1, "male.n.02") becomes node Pred "male.n.02"). Thematic nodes correspond to the relation name of the thematic condition (e.g., Agent(e_1, x_1) becomes the node "Agent"). Complex nodes correspond to the name of complex conditions (e.g., possibility $\diamond$).

We insert edges between graph nodes if these share arguments. For example, in Figure 6(b), there is an edge connecting node Pred "male.n.02" with Agent as they share argument x_1. We label this edge with a_1 to denote the fact that it is the second argument of Agent. Another edge is drawn between Pred "play.v.03" and Agent (as they share argument e_1) with label a_0 denoting that this is the first argument of Agent. Edges between nodes are bidirectional, with inverse edges bearing the suffix "-of". Edges drawn between constant and complex nodes bear the label "Related", while edges between two constant nodes (with the same variables) bear the label "Equal" (we provide a more formal description in the Appendix).

Ordering Model Given graph $G = (R_{set}, E)$, where $R_{set} = \{r_0, r_1, ..., r_{n-1}\}$ is the set of nodes and E is the set of edges in G, our model outputs R^* as the optimal order of R_{set}.

As shown Figure 6(a), each node is a sequence of words. A BiLSTM is applied to obtain representation x_i of each node $r_i = [w_0^i, ..., w_{m-1}^i]$:

$$x_i = \text{BiLSTM}([w_0^i, ..., w_{m-1}^i]). \qquad (8)$$

We encode the graph with a Graph Convolutional Recurrent network (GCRN; Seo et al. 2018). For

each node r_i, we collect information from neighbor hidden representations with a gate controling the information flow from neighbors to current nodes:

$$h_i'^k = \sum_j g_j^k \cdot h_j^{k-1}; \quad (9)$$

$$g_j^k = \sigma(f([e_{ji}, h_i^{k-1}, h_j^{k-1}])), \quad (10)$$

where e_{ji} is the embedding of edges from node r_j to r_i, and k is the recurrent step in the GRU. The node hidden representations are updated as:

$$h_i^k = \text{GRUCell}([x_i; g_G^{k-1}], h_i^{k-1}) \quad (11)$$

$$g_G^k = \text{GRUCell}(\frac{1}{n}\sum_i h_i^k, g_G^{k-1}) \quad (12)$$

where g_G represents the hidden representation of the graph as the average of (hidden) node representations, and GRUCell denotes the gated recurrent cell function. We obtain the hidden representations of nodes in the final recurrent step (K) as $H^K = \{h_0^K, h_1^K, ..., h_{n-1}^K\}$.

Our *decoder* obtains the orders with the highest probability. We avoid enumerating all possible permutations for a set of nodes by generating their order autoregressively with an LSTM-based Pointer Network (PN; Vinyals et al. 2015):

$$\text{SCORE}_{\mathbb{K}}(R|R_{set}) = \text{PN}(R|R_{set}, H^K, \theta) \quad (13)$$

$$\text{PN}(R|R_{set}, H^K, \theta) = \prod_i P(r_i|r_{<i}, H^K) \quad (14)$$

$$P(r_i|r_{<i}, H^K) = \text{softmax}(v^{\mathrm{T}} \tanh(W[h_i^d; H^K])) \quad (15)$$

where θ are the parameters of the Pointer Network, h_i^d is the ith step hidden representation of the Pointer Network, and v, and W are parameters. Hidden representation h_i^d is updated by the input representation of the $(i-1)$th ordered node: $h_i^d = \text{LSTMCell}(x_{r_{i-1}}, h_{i-1}^d)$. All parameters are optimized with standard back-propagation.

3 Experiments

Our experiments were carried out on the Groningen Meaning Bank (GMB; Bos et al. 2017) which provides a large collection of English documents annotated with DRSs. We used the standard training, development, and test splits that come with the distribution of the corpus. All DRSs in the GMB were preprocessed into the tree-based format discussed in Section 2.1. We also extracted from the training data conditions and their order for training our graph ordering model. Dataset statistics are shown in Table 1.

Task	train	dev	test
Generation	7,970	992	1,038
Condition Ordering	133,332	16,493	17,624

Table 1: GMB dataset statistics; number of documents (generation) and number of different sequences of conditions (ordering).

3.1 Condition Ordering

Models and Settings Before evaluating our generator per se, we assess the effectiveness of the proposed condition ordering model (see Section 2.4). Specifically we compare four kinds of graphs: **NoEdges**, is a graph without edges; **FullEdges**, is a complete graph where each pair of nodes has edges; **SiGraph**, is the proposed graph without bidirectional edges; and **BiGraph**, is the proposed graph with bidirectional edges (see Figure 6). We also consider **Counting**, a baseline model which greedily orders pairs of conditions according to their frequency of appearance in the training data (see the Appendix for details).

For all neural models the embedding dimension was 50 and the hidden dimension 300. The bidirectional LSTM used for representing the graph nodes has a single layer, and the recurrent step in the GCRN is 2 ($K = 2$). We applied the Adam optimizer (Kingma and Ba, 2014). We use accuracy to measure the percentage of absolute orders which are predicted correctly and Kendall's τ coefficient to measure the relationship between two lists of ordered items; τ ranges from -1 to 1, where -1 means perfect inversion and 1 means perfect agreement.

Results Table 2 summarizes our results. SiGraph performs better than NoEdges (+14.83% accuracy), showing that edge information is helpful for the representation of nodes which are used to order conditions. FullEdges performs worse than SiGraph (-13.68% accuracy), underlying the fact that graph structure matters (i.e., edges are helpful when connecting certain pairs of nodes). BiGraph achieves the best ordering performance by a large margin compared to SiGraph (+9.63 % accuracy). One possible reason is that bidirectionality ensures all nodes have incoming edges, which can be used to update the node representations.

Models	Acc (%)	τ	Parameters
Counting	14.38	0.57	—
NoEdges	44.64	0.75	6.1M
FullEdges	45.79	0.75	6.1M
SiGraph	59.47	0.85	6.1M
BiGraph	69.10	0.89	6.1M

Table 2: Results for condition ordering (dev set).

Models	BLEU	Parameters
Seq	71.79	47.4M
ChildSum	72.98 (+1.19)	47.1M
Nary	73.24 (+1.45)	49.2M
Sibling	**74.22 (+2.43)**	49.2M

Table 3: Ideal-world generation (dev set); improvements compared to Seq shown in parentheses.

3.2 Ideal-World Generation

Models and Settings We first examine generation performance in an ideal setting where (gold standard) condition orders are given and the indices of variables are fixed.

We compared the proposed treeLSTM against **Seq**, a baseline sequence-to-sequence model which adopts a bidirectional LSTM as its encoder.[4] Trees were linearized in a top-down and left-to-right fashion, $X = [x_0, x_1, ...x_{n-1}]$, where n is the tree length. We obtained hidden representations $H = [h_0, h_1, ..., h_{n-1}]$ of the input with:

$$[h_0, h_1, ..., h_{n-1}] = \text{BiLSTM}([x_0, x_1, ..., x_n])$$

In addition, we included various models with tree-based encoders: **ChildSum**, is the bidirectional childsum-treeLSTM encoder of Tai et al. (2015); it operates over right-branch binarized trees; **Nary**, is the bidirectional Nary-TreeLSTM of Tai et al. (2015), again over right-branch binarized trees;[5] and **Sibling** is our bidirectional sibling-TreeLSTM. All models were equipped with the same LSTM decoder, global attention (Bahdanau et al., 2015), and the copy strategy of See et al. (2017).

The embedding dimension was 300 and the hidden dimension 512. All encoders and decoders have 2 layers. The detailed settings are shown in the Appendix. We measure generation quality with case-insensitive BLEU (Papineni et al., 2002).

[4]The length of the input tokens can be around 4,000.

[5]We experimented with n-ary ($n > 2$) trees, but found that binary trees perform best. Right-branch binary trees are also empirically better than left-branch ones.

Models	BLEU
Seq+Naive	4.61
Seq+Random	24.34 (16.77)
Seq+Counting	45.17
Seq+GraphOrder	55.57
Sibling+Naive	6.98
Sibling+Random	43.43 (0.26)
Sibling+Counting	49.54
Sibling+GraphOrder	**58.73**

Table 4: Real-world generation (dev set). For Random, we report average results after shuffling 5 times (variance shown in parentheses).

Models	BLEU	Parameters
Graph	45.72	30.1M
Seq+GraphOrder	55.28	32.4M + 6.1M
Sibling+GraphOrder	59.26	34.5M + 6.1M

Table 5: Real-world generation (test set).

Results Table 3 shows our results on the development dataset. Overall, treeLSTM models performs better (average +1.69 BLEU) than sequence models. Nary performs better (+0.26 BLEU) than ChildSum because the latter cannot model the order of children. Sibling performs best (74.22 BLEU), because it it not only encodes the tree structure but also keeps track of sequential information.

3.3 Real-World Generation

Models and Settings We finally, present our results in a more realistic setting where both problems of condition ordering and variable naming must be addressed. We recover condition order using four approaches: a **Naive** method which has no special-purpose ordering mechanism; the order of conditions is random in the development/test sets and fixed in the training set; **Random**, the order of conditions is random in the training, development, and test sets; **Counting**, the order of conditions is recovered by the Counting method; **GraphOrder** recovers the order of conditions with **BiGraph**. All comparison systems employ variable renaming as introduced in Section 2.2. We report experiments with a sequence-to-sequence generator and our sibling-TreeLSTM.

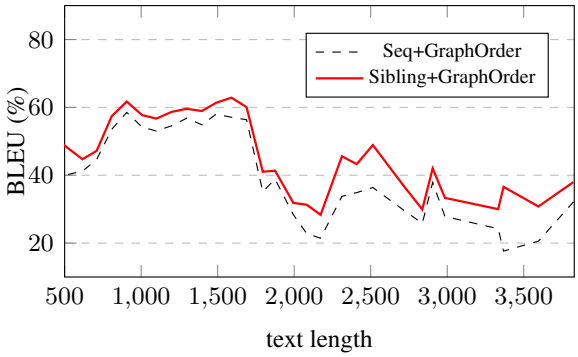


Figure 7: BLEU score against DRS size (test set).

Results Table 4 summarizes our results on the development set. Naive performs poorly, indicating that both Seq and Sibling models are sensitive to the order of conditions. Random, has higher variance with Seq (+16.51) compared to Sibling. Hidden representations for each timestep in Seq are heavily influenced by all previous steps, which are sequentially encoded; subtrees are encoded as a unit in Sibling, which is a more global representation for capturing patterns. Overall, we observe that the order of conditions plays a key role in the generation: both Seq and Sibling models improve when ordering of conditions is explicitly incorporated (either with Counting or GraphOrder). We observe that the combination of Sibling with GraphOrder achieves the best results (58.73 BLEU).

Table 5 presents our results on the test set. We compare our Sibling encoder against a sequential one. Both models are interfaced with GraphOrder. We also compare to a previous graph-to-text model (Song et al., 2018; Damonte and Cohen, 2019) which has been used for generating from AMRs. We converted DRSs to graphs following the method of Liu et al. (2020); graphs were encoded with a GCRN (Seo et al., 2018) and decoded with an LSTM. As can be seen, Sibling+GraphOrder outperforms all comparison systems achieving a BLEU of 59.26. However, compared to ideal-world generation (see Table 3) there is still considerable room for improvement.

3.4 Analysis

Figure 7 shows model performance on test set against DRS size (i.e., the number of nodes in a DRS tree). Perhaps unsurprisingly, we see that generation quality deteriorates with bigger DRSs (i.e., with >1,600 nodes).

While BLEU is frequently adopted as an automatic evaluation metric for genration tasks, it is somewhat problematic in our case as it merely calculates word overlap between generated and gold-standard text without assessing whether model output is faithful to the semantics of the input (i.e., the DRS meaning representations). To this effect, we present examples of text generated by our model, demonstrating how the DRS input constrains and affects the output text.

Figure 8 shows examples of text generation from the test set. In the first example, the model generates the word *because* from the rhetorical relation, BECAUSE(b_{10}, b_{12}). Temporal information (highlighted in blue in the figure) is also accurately reflected in the generated text (*sell* is inflected to its present tense form). In addition, the model tends to over-generate (e.g., the word *dollar* is mentioned twice) and sometimes misses out on important determiners (e.g., *some*). In the second example, the model generates the word *themselves* referring to the entities mentioned before, e.g., x_{29} equals to x_{27} which refers to *inmates*, resolving the coreference. In the third example, the model generates the modal verb *must* in accordance with the scope operator NEC (a shorthand for Necessity, $\Box$). Also, the model generates *all* for *food* and *goods* corresponding to the Implication (IMP) condition (i.e., $\forall x(P(x) \rightarrow Q(x))$).

4 Related Work

Much previous work has focused on text generation from formal representations of meaning focusing exclusively on isolated sentences or queries. The literature offers a collection of approaches to generating from AMRs most of which employ neural models and structured encoders (Song et al., 2018; Beck et al., 2018; Damonte and Cohen, 2019; Ribeiro et al., 2019; Zhu et al., 2019; Cai and Lam, 2020; Wang et al., 2020). Other work generates text from structured query language (SQL) adopting either sequence-to-sequence (Iyer et al., 2016) or graph-to-sequence models (Xu et al., 2018).

Basile (2015) was the first to attempt generation from DRT-based meaning representations. He proposes a pipeline system which operates over graphs and consists of three components: an alignment module learns the correspondence between surface text and DRS structure, an ordering module determines the relative position of words and phrases in the surface form and a realizer generates the final text. Narayan and Gardent (2014) simplify complex sentences with a two-stage model which

DRS	... DRS(b_{10} Pred(b_{10} x_{24} "speculator.n.01") Pred(b_{10} x_{25} "dollar.n.01") Pred(b_{10} e_8 "sell.v.01") Agent(b_{10} e_8 x_{24}) Theme(b_{10} e_8 x_{25}) Pred(b_4 t_1 "now.r.01") Equ(b_{10} x_{26} t_1) temp_includes(b_{10} t_5 x_{26}) temp_overlap(b_{10} e_8 t_5)) SDRS(b_{12} DRS(b_{11} Pred(b_3 x_5 "thing.n.12") Pred(b_{11} e_9 "expect.v.01") Agent(b_{11} e_9 x_5) ... BECAUSE(b_{10} b_{12})))
Gold	... **some** speculators are selling dollars because they expect ...
Ours	... , the dollar . speculators are selling dollars because they expect ...
DRS	... Pred(b_{16} e_{11} "be.v.00") Agent(b_{16} e_{11} x_{26}) Ref(b_{16} x_{27}) Card(b_{16} x_{27} 7) Ref(b_{16} x_{28}) Pred(b_{16} x_{27} "inmate n.01") Ref(b_{16} x_{29}) Equ(b_{16} x_{27} x_{29}) Ref(b_{17} x_{30}) Pred(b_{17} x_{30} "group.n.01") Ref(b_{16} e_{12}) Pred(b_{16} e_{12} "disguise.v.01") Theme(b_{16} e_{12} x_{29}) ...
Gold	... were among seven inmates who disguised themselves ...
Ours	... were among seven inmates disguised themselves ...
DRS	.... DRS(b_4 NEC(b_4 DRS(b_5 IMP(b_5 DRS(b_6 Ref(b_6 x_{11}) Ref(b_6 x_{10}) subset_of(b_6 x_{11} x_{10}) Ref(b_6 x_{12}) subset_of(b_6 x_{12} x_{10}) Ref(b_6 x_{13}) Pred(b_6 x_{13} "food.n.01") In(b_6 x_{11} x_{13}) Pred(b_6 x_{11} "goods.n.01") Ref(b_6 s_2) Topic(b_6 s_2 x_{12}) Pred(b_6 s_2 "manufactured.a.01") Pred(b_6 x_{12} goods n.01)) DRS(b_7 Ref(b_7 e_4) Pred(b_7 e_4 "import.v.01") Theme(b_7 e_4 x_{10}) Pred(b_3 t_1 "now.r.01") Ref(b_7 t_3) temp_included(b_7 e_4 t_3) temp_before(b_7 t_1 t_3)))$_{\text{IMP}}$)$_{\text{NEC}}$) ...
Gold	... all food and manufactured goods must be imported ...
Ours	... all food and manufactured goods must be imported ...

Figure 8: DRS example from test set with gold and automatically generated text by ours (Sibling+GraphOrder). Temporal information marked in blue, rhetorical relations marked in red, co-reference marked as green, and scope marked in brown.

first performs sentence splitting and deletion operations over DRSs and then uses a phrase-based machine translation model for surface realization.

Our work is closest to Basile (2015); we share the same goal of generating from DRSs, however, our model is trained end-to-end and can perform long-form generation for documents and sentences alike. We also adopt an ordering component, but we order DRS conditions rather than lexical items, and propose a model capable of inferring a global order. There has been long-standing interest in information ordering within NLP (Lapata, 2003; Abend et al., 2015; Chen et al., 2016; Gong et al., 2016; Logeswaran et al., 2018; Cui et al., 2018; Yin et al., 2019; Honovich et al., 2020). Our innovation lies in conceptualizing ordering as a graph scoring task which can be further realized with graph neural network models (Wu et al., 2020).

5 Conclusions

In this paper, we have focused on *document-level* generation from formal meaning representations. We have adopted DRT as our formalism of choice and highlighted various challenges associated with the generation task. We have introduced a novel sibling treeLSTM for encoding DRSs rendered as trees and shown it is particularly suited to trees with wide branches. We have experimentally demonstrated that our encoder coupled with a graph-based condition ordering model outperforms strong comparison systems. In the future, we would like to embed our generator in practical applications such as summarization and question answering.

Acknowledgments

We thank the anonymous reviewers for their feedback. We gratefully acknowledge the support of the European Research Council (Lapata, Liu; award number 681760), the EU H2020 project SUMMA (Cohen, Liu; grant agreement 688139) and Bloomberg (Cohen, Liu).

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A Counting Method

We count how frequently condition r_i appears before r_j with type t. Type t is identified according to the overlap between the arguments of the two conditions[6]. For example, r_i = (Named, x_3, "tom") and r_j = (Agent, e_1, x_3) has the type "$a_0 \rightarrow a_1$", showing that the first argument in r_i equals to the second argument in r_j. We score the order of two conditions using the following function:

$$\begin{aligned}\textsc{Score}_{\mathbb{K}}(R|R_{set}) = &\textstyle\sum_i(\sum_{i<j}\textsc{Count}_{\mathbb{K}}(r_i, r_j)) \\ &- \textstyle\sum_{j<i}\textsc{Count}_{\mathbb{K}}(r_i, r_j)\end{aligned} \quad (16)$$

where COUNT returns the frequency of a pair of conditions subject to a dataset or corpus $\mathbb{K}$; the score increases with r_j following r_i more frequently than preceding it.

A.1 Types

We define different types of relations between two conditions based on argument overlap (i.e., two simple conditions, a simple and a complex condition, and two complex conditions).

Simple and Simple Given two simple conditions, $r_i = (l_i, a_{0i}, a_{1i})$ and $r_j = (l_j, a_{0j}, a_{1j})$ (with different arguments), we define their types as:

- $t = a_0 \rightarrow a_0$ if $a_{0i} = a_{0j}$ and $a_{1i} \neq a_{1j}$.
- $t = a_1 \rightarrow a_1$ if $a_{0i} \neq a_{0j}$ and $a_{1i} = a_{1j}$.
- $t = a_0 \rightarrow a_0, a_1 \rightarrow a_1$ if $a_{0i} = a_{0j}$ and $a_{1i} = a_{1j}$.
- $t = a_0 \rightarrow a_1$ if $a_{0i} = a_{1j}$ and $a_{1i} \neq a_{0j}$.
- $t = a_1 \rightarrow a_0$ if $a_{1i} = a_{0j}$ and $a_{0i} \neq a_{1j}$.
- $t = a_0 \rightarrow a_1, a_1 \rightarrow a_0$ if $a_{1i} = a_{0j}$ and $a_{0i} = a_{1j}$.
- $t =$ *None* if others

Simple and Complex Given a simple conditions $r_i = (l_i, a_{0i}, a_{1i})$ and a complex condition $r_j = (l_j, V_j)$, the types are defined as:

- $t = 1$ if $a_{0i} \in V_j$ and $a_{1i} \notin V_j$.
- $t = 1$ if $a_{0i} \notin V_j$ and $a_{1i} \in V_j$.
- $t = 2$ if $a_{0i} \in V_j$ and $a_{1i} \in V_j$.
- $t =$ *None* if others

[6]We only consider (and count) conditions with overlapping rguments, i.e., their type t is not None.

Algorithm 1 Greedy Ordering Algorithm

Input: R_{set}, set of conditions
Output: R^*, list of ordered conditions

```
R* = []
while R_set is not empty do
    r* = arg max_{r∈R_set} PARTIAL(r)
    R_set removes r*
    R* appends r*
end while
```

Complex and Complex Given two complex conditions, $r_i = (l_i, V_i)$ and $r_j = (l_j, V_j)$, the types are defined as:

- $t =$ *intersection* if $V_i \cap V_j \neq \emptyset$.
- $t =$ *None* otherwise

A.2 Greedy Algorithm

We generate an ordering of conditions following greedy Algorithm 1 which identifies the highest scoring pair in R_{set}, appends it to partial ordering R^*, and keeps going until R_{set} is empty. The score is given by the function:

$$\begin{aligned}\textsc{Partial}_{\mathbb{K}}(r) = &\sum_{r' \in R_{set}} \textsc{Count}(r, r')_{\mathbb{K}} \\ &- \sum_{r'' \in R} \textsc{Count}(r, r'')_{\mathbb{K}},\end{aligned} \quad (17)$$

B Edge Construction Algorithm

Algorithm 2 shows how edges are created for graph ordering.

C Model Settings

In the following, we report the best experimental settings for our condition ordering and text generation models.

C.1 Condition Ordering Models

Model hyperparameters are shown in Table 6. The size of the token embeddings (in the graph nodes) and edge embeddings is 100. The node hidden dimension is the same as the hidden dimension of the BILSTM which is used to encode a sequence of input words for each node and the hidden dimension of PointerNet. The BILSTM and PointerNet have one layer. Training hyperparameters are shown in Table 7.

Algorithm 2 Edges Construction

Input: N_t thematic nodes; N_c, complex nodes; N_e, constant nodes
Output: E, set of edges

$E = []$
for n_t, n_e in N_t, N_e **do**
  if $n_t.a_0$ is $n_e.a_0$ **then**
    $E = E \cup \{n_t \xrightarrow{a_0} n_e\}$
    $E = E \cup \{n_e \xrightarrow{a_0\_of} n_t\}$
  end if
  if $n_t.a_1$ is $n_e.a_0$ **then**
    $E = E \cup \{n_t \xrightarrow{a_1} n_e\}$
    $E = E \cup \{n_e \xrightarrow{a_1\_of} n_t\}$
  end if
end for
for n_c, n_e in N_c, N_e **do**
  if $n_e.a_0$ in $n_c.V$ **then**
    $E = E \cup \{n_c \xrightarrow{\text{Related}} n_e\}$
    $E = E \cup \{n_e \xrightarrow{\text{Related\_of}} n_c\}$
  end if
end for
for n_e, n'_e in N_e, N_e **do**
  if $n_e.a_0$ is $n'_e.a_0$ and n_e not is n'_e **then**
    $E = E \cup \{n_e \xrightarrow{\text{Equal}} n'_e\}$
  end if
end for

hyperparameters	value
embedding dim	50
hidden dim	300
LSTM layer	1
graph step	2
beam size	64

Table 6: Hyperparameters of condition ordering model.

C.2 Text Generation Models

Model hyperparameters are shown in Table 8. The size of the input embeddings in the encoder and the decoder is 300. The hidden dimensions of the encoder and decoder are 512. Both the encoder and decoder have two layers. The hyperparameters of the training are shown in Table 9.

D Hyperparameter Tuning

We show below model performance with various hyperparameters. Best hyperparameters were manually chosen after monitoring model accuracy on the development set.

We take **BiGraph** as our final condition ordering model (see Table 10) and **Sibling** with **BiGraph** as the DRS-to-text generation model (see Table 11).

hyperparameters	value
optimizer	adam
learning rate	0.001
β	(0.9, 0.999)
dropout rate	0.5
batch size	32
max gradient norm	5
training steps	400,000
learning rate decay	0.3
start decay steps	200,000
decay steps	20,000
warmup steps	40,000

Table 7: Training hyperparameters for the condition ordering models.

hyperparameters	value
embedding dim	300
hidden dim	512
layer	2
attention	general
beam size	5

Table 8: Hyperparameters of text generation model.

hyperparameters	value
optimizer	adam
learning rate	0.001
β	(0.9, 0.999)
dropout rate	0.5
batch size	30000
batch type	tokens
max gradient norm	5
training steps	30,000
learning rate decay	0.5
start decay steps	8,000
decay steps	1,000
warmup steps	4,000

Table 9: Training hyperparameters for text generation model.

embedding	hidden	step	dropout	beam	Acc
50	300	2	0.5	64	69.10
100	—	—	—	—	68.61
150	—	—	—	—	67.76
—	100	—	—	—	67.33
—	200	—	—	—	68.77
—	—	1	—	—	55.71
—	—	3	—	—	69.12
—	—	—	0.2	—	68.02
—	—	—	0.4	—	68.52
—	—	—	0.6	—	67.83
—	—	—	—	16	69.03
—	—	—	—	32	69.07
—	—	—	—	96	69.10

Table 10: Performance of condition ordering model (development set; various hyperparameters). Increasing model size leads to out-of-memory problems when training on a single GPU.

E Examples

We provide example output of our final model (**Sibling+GraphOrder**) on the GMB test dataset. The DRS in tree format with condition ordering given by **GraphOrder** is shown in Figures 9–11. Figure 10 expands nonterminal b_{33} in Figure 9, and Figure 11 expands nonterminal b_{28} in Figure 10. The corresponding document generated by **Sibling** is:

> *the u.s. dollar hit a record low against the euro tuesday . it took a dollar , but 48 cents to buy one euro , and a series of problems including the key of the u.s. housing sector in which has been battered by the slowing n.01 , including continuing the u.s. economy , the dollar . speculator are selling dollars because they expect that the u.s. central bank will try to stimulate the economy by cutting interest rates soon . u.s. lower interest rates can cut the return on investments . the falling dollar is prompting oil-rich nations around the persian gulf to consider ending the practice of linking the value of its currency to those of the dollar and instead supplement the u.s. currency . such a move would reduce demand for dollars and weaken the u.s. currency .*

embedding	hidden	layer	dropout	beam	BLEU
300	512	2	0.5	5	58.97
100	—	—	—	—	58.19
200	—	—	—	—	58.81
—	128	—	—	—	43.36
—	256	—	—	—	55.06
—	—	1	—	—	52.58
—	—	3	—	—	58.94
—	—	—	0.1	—	47.43
—	—	—	0.2	—	58.24
—	—	—	0.3	—	58.97
—	—	—	0.4	—	58.96
—	—	—	0.6	—	58.22
—	—	—	—	1	58.73
—	—	—	—	3	58.91
—	—	—	—	10	58.97

Table 11: Performance of text generation model (development set; various hyperparameters). Increasing model size leads to out-of-memory problems when training on a single GPU.

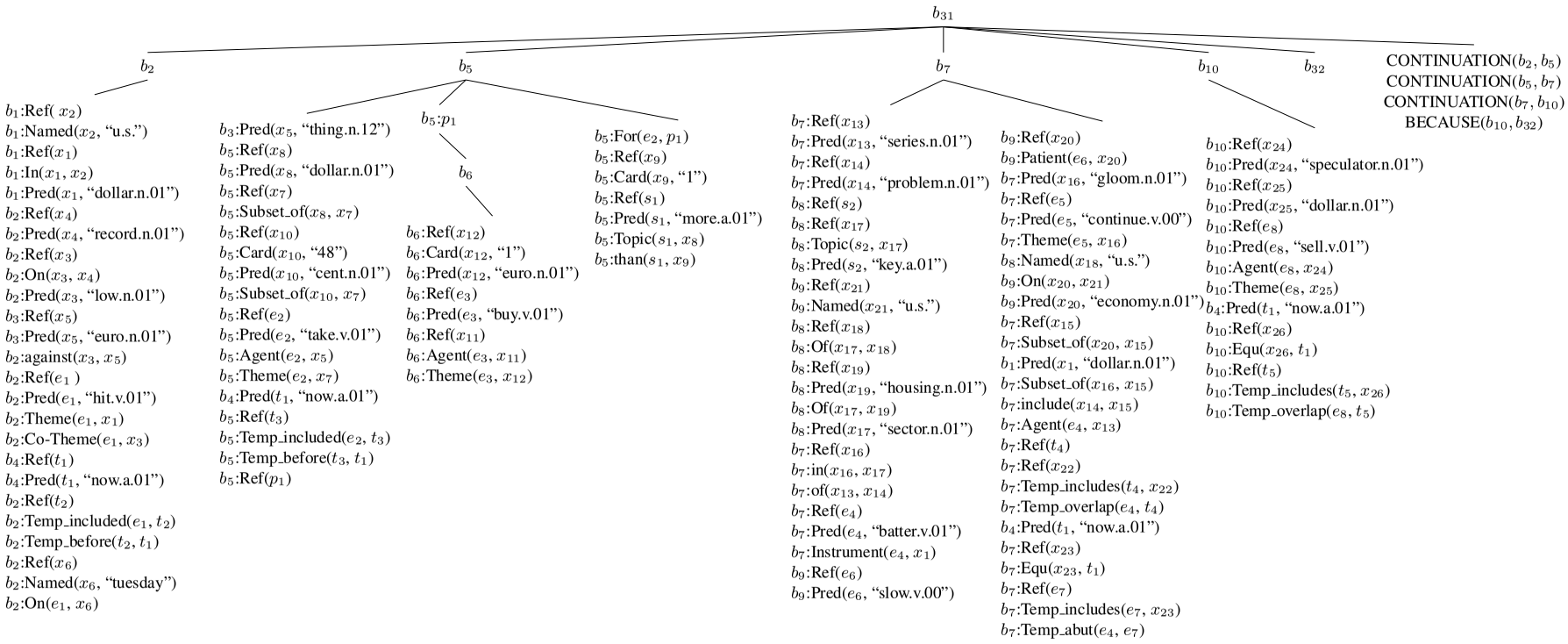

Figure 9: A partial DRS in tree format with condition ordering recovered by **GraphOrder**.

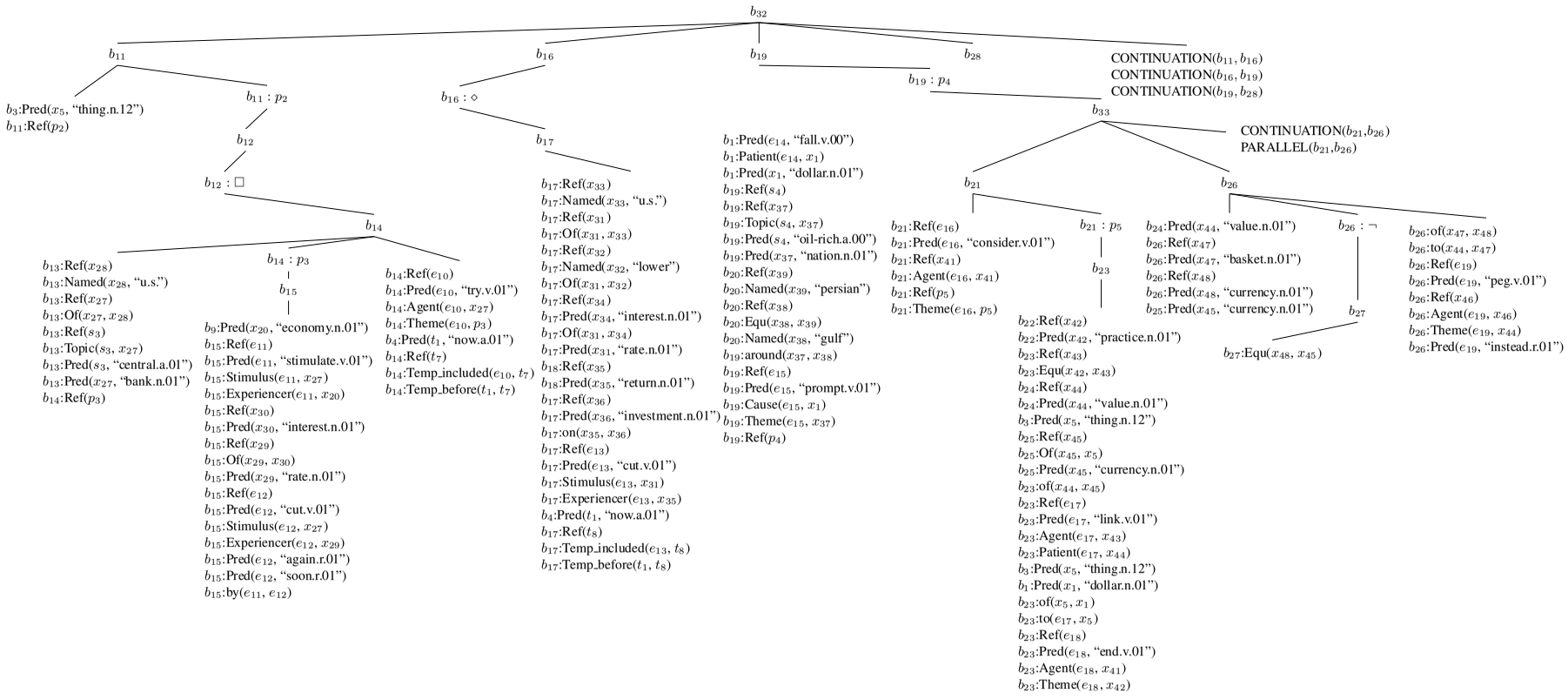

Figure 10: A partial DRS in tree format with condition ordering recovered by **GraphOrder**.

Figure 11: A partial DRS in tree format with condition ordering recovered by **GraphOrder**.