Minimal Dependency Length in Realization Ranking

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Abstract

Comprehension and corpus studies have found that the tendency to minimize dependency length has a strong influence on constituent ordering choices. In this paper, we investigate dependency length minimization in the context of discriminative realization ranking, focusing on its potential to eliminate egregious ordering errors as well as better match the distributional characteristics of sentence orderings in news text. We find that with a state-of-the-art, comprehensive realization ranking model, dependency length minimization yields statistically significant improvements in BLEU scores and significantly reduces the number of heavy/light ordering errors. Through distributional analyses, we also show that with simpler ranking models, dependency length minimization can go overboard, too often sacrificing canonical word order to shorten dependencies, while richer models manage to better counterbalance the dependency length minimization preference against (sometimes) competing canonical word order preferences.

1 Introduction

In this paper, we show that for the constituent ordering problem in surface realization, incorporating insights from the minimal dependency length theory of language production (Temperley, 2007) into a discriminative realization ranking model yields significant improvements upon a state-of-the-art baseline. We demonstrate empirically using OpenCCG, our CCG-based (Steedman, 2000) surface realization system, the utility of a global feature encoding the total dependency length of a given derivation. Although other works in the realization literature have used phrase length or head-dependent distances in their models (Filippova and Strube, 2009; Velldal and Oepen, 2005; White and Rajkumar, 2009, i.a.), to the best of our knowledge, this paper is the first to use insights from the minimal dependency length theory directly and study their effects, both qualitatively and quantitatively.

The impetus for this paper was the discovery that despite incorporating a sophisticated syntactic model borrowed from the parsing literature—including features with head-dependent distances at various scales—White & Rajkumar’s (2009) realization ranking model still often performed poorly on weight-related decisions such as when to employ heavy-NP shift. Table 1 illustrates this point. In wsj_0034.9, the full model (incorporating numerous syntactic features) succeeds in reproducing the reference sentence, which is clearly preferable to the rather awkward variant selected by the baseline model (using various n-gram models). However, in wsj_0013.16, the full model fails to shift the temporal modifier for now next to the phrasal verb turned down, leaving it at the end of its very long verb phrase where it is highly ambiguous (with multiple intervening attachment sites). Conversely, in wsj_0044.3, the full model shifts before next to the verb, despite the NP cheating being very light, yielding a very confusing ordering given that before is meant to be intransitive.

The syntactic features in White & Rajkumar’s (2009) realization ranking model are taken from Clark & Curran’s (2007) normal form model
Table 1: Examples of OpenCCG output with White & Rajkumar’s (2009) models—the first represents a successful case, the latter two egregious ordering errors

| wsj_0034.9 | they fell into oblivion after the 1929 crash. |
| wsj_0013.16 | separately, the Federal Energy Regulatory Commission \([VP \text{ turned down for now [NP a request by Northeast [VP seeking approval of [NP its possible purchase of PS of New Hampshire]]]}]\). |
| wsj_0044.3 | she had seen cheating before, but these notes were uncanny. |

In this model, head-dependency distances are considered in conjunction with lexicalized and unlexicalized CCG derivation steps, thereby appearing in numerous features. As such, the model takes into account the interaction of dependency length with derivation steps, but in essence does not consider the main effect of dependency length itself. In this light, our investigation of dependency length minimization can be viewed as examining the question of whether realization ranking models can be made more accurate—and in particular, avoid egregious ordering errors—by incorporating a feature to account for the main effect of dependency length.

It is important to observe at this point that dependency length minimization is more of a preference than an optimization objective, which must be balanced against other order preferences at times. A closer reading of Temperley’s (2007) study reveals that dependency length can sometimes run counter to many canonical word order choices. A case in point is the class of examples involving pre-modifying adjunct sequences that precede both the subject and the verb. Assuming that their parent head is the main verb of the sentence, a long-short sequence would minimize overall dependency length. However, in 613 examples found in the Penn Treebank, the average length of the first adjunct was 3.15 words while the second adjunct was 3.48 words long, thus reflecting a short-long pattern, as illustrated in the Temperley p.c. example in Table 2. Apart from these, Hawkins (2001) shows that arguments are generally located closer to the verb than adjuncts. Gildea and Temperley (2007) also suggest that adverb placement might involve cases which go against dependency length minimization. An examination of 295 legitimate long-short post-verbal constituent orders (counter to dependency length) from Section 00 of the Penn Treebank revealed that temporal adverb phrases are often involved in long-short orders, as shown in wsj_0075.13 in Table 2. In our setup, the preference to minimize dependency length can be balanced by features capturing preferences for alternate choices (e.g. the argument-adjunct distinction in our dependency ordering model, Table 4). Via distributional analyses, we show that while simpler realization ranking models can go overboard in minimizing dependency length, richer models largely succeed in overcoming this issue, while still taking advantage of dependency length minimization to avoid egregious ordering errors.

2 Background

2.1 Minimal Dependency Length

Comprehension and corpus studies (Gibson, 1998; Gibson, 2000; Temperley, 2007) point to the tendency of production and comprehension systems to adhere to principles of dependency length minimization. The idea of dependency length minimization is based on Gibson’s (1998) Dependency Locality Theory (DLT) of comprehension, which predicts that longer dependencies are more difficult to process. DLT predictions have been further validated using comprehension studies involving eye-tracking corpora (Demberg and Keller, 2008). DLT metrics also correlate reasonably well with activation decay over time expressed in computational models of
comprehension (Lewis et al., 2006; Lewis and Vasishth, 2005).

Extending these ideas from comprehension, Temperley (2007) poses the question: Does language production reflect a preference for shorter dependencies as well as to facilitate comprehension? By means of a study of a Penn Treebank data, Temperley shows that English sentences do display a tendency to minimize the sum of all their head-dependent distances as illustrated by a variety of constructions. Further, Gildea and Temperley (2007) report that random linearizations have higher dependency lengths compared to actual English, while an “optimal” algorithm (from the perspective of dependency length minimization), which places dependents on either sides of a head in order of increasing length, is closer to actual English. Tily (2010) also applies insights from the above cited papers to show that dependency length constitutes a significant pressure towards language change. For head-final languages (e.g., Japanese), dependency length minimization results in the “long-short” constituent ordering in language production (Yamashita and Chang, 2001). More generally, Hawkins’s (1994; 2000) processing domains, dependency length minimization and end-weight effects in constituent ordering (Wasow and Arnold, 2003) are all very closely related. The dependency length hypothesis goes beyond the predictions made by Hawkins’ Minimize Domains principle in the case of English clauses with three post-verbal adjuncts: Gibson’s DLT correctly predicts that the first constituent tends to be shorter than the second, while Hawkins’ approach does not make predictions about the relative orders of the first two constituents.

However, it would be very reductive to consider dependency length minimization as the sole factor in language production. In fact, a large body of prior work discusses a variety of other factors involved in language production. These other preferences are either correlated with dependency length or can override the minimal dependency length preference. Complexity (Wasow, 2002; Wasow and Arnold, 2003), animacy (Snider and Zaenen, 2006; Branigan et al., 2008), information status considerations (Wasow and Arnold, 2003; Arnold et al., 2000), the argument-adjunct distinction (Hawkins, 2001) and lexical bias (Wasow and Arnold, 2003; Bresnan et al., 2007) are a few prominent factors. More recently, Anttila et al. (2010) argued that the principle of end weight can be revised by calculating weight in prosodic terms to provide more explanatory power. As Temperley (2007) suggests, a satisfactory model should combine insights from multiple approaches, a theme which we investigate in this work by means of a rich feature set adapted from the parsing and realization literature. Our feature design has been inspired by the conclusions of the above-cited works pertaining to the role of dependency length minimization in syntactic choice in conjunction with other factors influencing constituent order. However, going beyond Temperley’s corpus study, we confirm the utility of incorporating a feature for minimizing dependency length into machine-learned models with hundreds of thousands of features found to be useful in previous parsing and realization work, and investigate the extent to which these features can counterbalance a dependency length minimization preference in cases where canonical word order considerations should prevail.

2.2 Surface Realization with Combinatory Categorial Grammar (CCG)

We provide here a brief overview of CCG and the OpenCCG realizer; for further details, see the works cited below.

CCG (Steedman, 2000) is a unification-based categorial grammar formalism defined almost entirely in terms of lexical entries that encode sub-
### Feature Type Example

| Feature Type     | Example                                      |
|------------------|----------------------------------------------|
| LexCat + Word    | s/s/np + before                              |
| LexCat + POS     | s/s/np + IN                                  |
| Rule             | \(s_{dcl} \rightarrow np \ s_{dcl} \backslash np\) |
| Rule + Word      | \(s_{dcl} \rightarrow np \ s_{dcl} \backslash np + bought\) |
| Rule + POS       | \(s_{dcl} \rightarrow np \ s_{dcl} \backslash np + VBD\) |
| Word-Word        | \(\langle\text{company}, s_{dcl} \rightarrow np \ s_{dcl} \backslash np, \text{bought}\rangle\) |
| Word-POS         | \(\langle\text{company}, s_{dcl} \rightarrow np \ s_{dcl} \backslash np, \text{VBD}\rangle\) |
| POS-Word         | \(\langle\text{NN}, s_{dcl} \rightarrow np \ s_{dcl} \backslash np, \text{bought}\rangle\) |
| POS + \(\Delta_w\) | \(\langle\text{VBD}, s_{dcl} \rightarrow np \ s_{dcl} \backslash np + d_w\rangle\) |
| Word + \(\Delta_w\) | \(\langle\text{bought}, s_{dcl} \rightarrow np \ s_{dcl} \backslash np + d_w\rangle\) |
| POS + \(\Delta_p\) | \(\langle\text{VBD}, s_{dcl} \rightarrow np \ s_{dcl} \backslash np + d_p\rangle\) |
| Word + \(\Delta_v\) | \(\langle\text{bought}, s_{dcl} \rightarrow np \ s_{dcl} \backslash np + d_v\rangle\) |
| POS + \(\Delta_v\) | \(\langle\text{VBD}, s_{dcl} \rightarrow np \ s_{dcl} \backslash np + d_v\rangle\) |

Table 3: Basic and dependency features from Clark & Curran’s (2007) normal forms model: distances are in intervening words, punctuation marks and verbs, and are capped at 3, 3 and 2, respectively.

Categorization as well as syntactic features (e.g., number and agreement). OpenCCG is a parsing/generation library which includes a hybrid symbolic-statistical chart realizer (White, 2006; White and Rajkumar, 2009). The input to the OpenCCG realizer is a semantic graph, where each node has a lexical predication and a set of semantic features; nodes are connected via dependency relations. Internally, such graphs are represented using Hybrid Logic Dependency Semantics (HLDS), a dependency-based approach to representing linguistic meaning (Baldrige and Kruijff, 2002). Alternative realizations are ranked using integrated n-gram or averaged perceptron scoring models. In the experiments reported below, the inputs are derived from the gold standard derivations in the CCGbank (Hockenmaier and Steedman, 2007), and the outputs are the highest-scoring realizations found during the realizer’s chart-based search.\(^1\)

### 3 Feature Design

In the realm of paraphrasing using tree linearization, Kempen and Harbusch (2004) explore features which have later been appropriated into classification approaches for surface realization (Filippova and Strube, 2007). Prominent features include information status, animacy and phrase length. In the case of ranking models for surface realization, by far the most comprehensive experiments involving linguistically motivated features are reported in work of Cahill for German realization ranking (Cahill et al., 2007; Cahill and Riester, 2009). Apart from language model and Lexical Functional Grammar (LFG) e-structure and f-structure based features, Cahill also designed and incorporated features modeling information status considerations.

The feature sets explored in this paper extend those in previous work on realization ranking with OpenCCG using averaged perceptron models (White and Rajkumar, 2009; Rajkumar et al., 2009; Rajkumar and White, 2010) to include more comprehensive ordering features. The feature classes are listed below, where DEPLEN, HOCKENMAIER and DEPORD are novel, and the rest are as earlier OpenCCG models. The inclusion of the DEPORD features is intended to yield a model with a similarly rich set of ordering features as Cahill and Forster’s (2009) realization ranking model for German. Except where otherwise indicated, features are integer-valued, representing counts of occurrences in a derivation.

**DEPLEN** The total of the length between all semantic heads and dependents for a realization, where length is in intervening words\(^2\) excluding punctuation. For length purposes, collapsed named entities were counted as a single word in the experiments reported here.

**NGRAMS** The log probabilities of the word sequence scored using three different n-gram models: a trigram word model, a trigram word model with named entity classes replacing words, and a trigram model over POS tags and supertags.

**HOCKENMAIER** As an extra component of the generative baseline, the log probability of the derivation according to (a reimplementation

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\(^1\)The realizer can also be run using inputs derived from OpenCCG’s parser, though informal experiments suggest that parse errors tend to decrease generation quality.

\(^2\)We also experimented with two other definitions of dependency length described in the literature, namely (1) counting only nouns and verbs to approximate counting by discourse referents (Gibson, 1998) and (2) omitting function words to approximate prosodic weight (Anttila et al., 2010); however, realization ranking accuracy was slightly worse than counting all non-punctuation words.
Table 4: Basic head-dependent and sibling dependent ordering features

| Feature Type                                                                 | Example                                      |
|-----------------------------------------------------------------------------|----------------------------------------------|
| HeadBroadPos + Rel + Precedes + HeadWord + DepWord                          | ⟨VB, Arg0, dep, wants, he⟩                  |
| ... + HeadWord + DepPOS                                                     | ⟨VB, Arg0, dep, wants, PRP⟩                 |
| ... + HeadPOS + DepWord                                                     | ⟨VB, Arg0, dep, VBZ, he⟩                    |
| ... + HeadWord + DepPOS                                                     | ⟨VB, Arg0, dep, VBZ, PRP⟩                   |
| HeadBroadPos + Side + DepWord1 + DepWord2                                  | ⟨NN, left, an, important⟩                  |
| ... + DepWord1 + DepPOS2                                                   | ⟨NN, left, an, JJ⟩                         |
| ... + DepPOS1 + DepWord2                                                   | ⟨NN, left, DT, important⟩                 |
| ... + Rel1 + Rel2                                                           | ⟨NN, left, Det, Mod⟩                      |

Table 6: Model sizes—number of features in alphabet for each model (satisfying count cutoff of 5) along with number active in model after 5 training epochs

| Model     | # Alph Feats | # Model Feats |
|-----------|--------------|---------------|
| GLOBAL    | 4            | 4             |
| DEPLEN-GLOBAL | 5         | 5             |
| DEPORD-NONF       | 790,887     | 269,249       |
| DEPORD-NODIST     | 1,035,915   | 365,287       |
| DEPORD-NF         | 1,173,815   | 431,226       |
| DEPLEN            | 1,173,816   | 428,775       |

4 Evaluation

4.1 Experimental Conditions

We followed the averaged perceptron training procedure of White and Rajkumar (2009) with a couple of updates. First, as noted earlier, we used a reimplementation of Hockenmaier’s (2003) generative syntactic model as an extra component of our generative baseline; and second, only five epochs of training were used, which was found to work as well as using additional epochs on the development set. As in the earlier work, the models were trained on the standard training sections (02–21) of an enhanced version of the CCGbank, using a lexico-grammar extracted from these sections.

The models tested in the experiments reported below are summarized in Table 5. The three groups of models are designed to test the impact of the dependency length feature when added to feature sets of increasing complexity. In more detail, the GLOBAL and DEPLEN-GLOBAL models contain dense features on entire derivations; their values are the log probabilities of the three n-gram mod-
els used in the earlier work along with the Hockenmaier model (and the dependency length feature, in DEPLEN-GLOBAL). The second group is centered on DEPORD-NODIST, which contains all features except the dependency length feature and the distance features in Clark & Curran’s normal form model, which may indirectly capture some dependency length minimization preferences. In addition to DEPORD-NODIST—where the dependency length feature is added—this group also contains DEPORD-NONF, which is designed to test (as a side comparison) whether the Clark & Curran normal form base features are still useful even when used in conjunction with the new dependency ordering features. In the final group, DEPORD-NF contains all the features examined in this paper except the dependency length feature, while DEPLEN contains all the features including the dependency length feature. Note that the learned weight of the total dependency length feature was negative in each case, as expected.

Table 6 shows the sizes of the various models. For each model, the alphabet—whose size increases to over a million features—is the set of applicable features found to have discriminative value in at least 5 training examples; from these, a subset are made active (i.e., take on a non-zero weight) through perceptron updates when the feature value differs between the model-best and oracle-best realization.

| Model          | Dep Len | Ngram Mods | Hockenmaier | Discr Ngrams | Agreement | C&C NF Base | C&C NF Dist | Dep Ord |
|----------------|---------|------------|-------------|--------------|-----------|-------------|-------------|---------|
| GLOBAL         | N       | Y          | Y           | N            | N         | N           | N           | N       |
| DEPLEN-GLOBAL  | Y       | Y          | Y           | N            | N         | N           | N           | N       |
| DEPORD-NONF    | N       | Y          | Y           | Y            | Y         | N           | N           | Y       |
| DEPORD-NODIST  | N       | Y          | Y           | Y            | Y         | Y           | Y           | Y       |
| DEPLEN-NODIST  | Y       | Y          | Y           | Y            | Y         | Y           | Y           | Y       |
| DEPORD-NF      | N       | Y          | Y           | Y            | Y         | Y           | Y           | Y       |
| DEPLEN         | Y       | Y          | Y           | Y            | Y         | Y           | Y           | Y       |

Table 5: Legend for experimental conditions

4.2 BLEU Results

Following the usual practice in the realization ranking, we first evaluate our results quantitatively using exact matches and BLEU (Papineni et al., 2002), a corpus similarity metric developed for MT evaluation. Realization results for the development and test sections appear in Table 7. For all three model groups, the dependency length feature yields significant increases in BLEU scores, even in comparison to the model (DEPORD-NF) containing Clark & Curran’s distance features in addition to the new dependency ordering features (as well as all other features but total dependency length). The second group additionally shows that the Clark & Curran normal form base features do indeed have a significant impact on BLEU scores even when used with...
the new dependency ordering model, as DEPORD-NONF is significantly worse than DEPORD-NODIST (the impact of the distance features is evident in the increases from the second group to the third group). As with the dev set, the dependency length feature yielded a significant increase in BLEU scores for each comparison on the test set also.

For each group, the statistical significance of the difference in BLEU scores between a model and the unmarked model (-) is determined by bootstrap re-sampling (Koehn, 2004). Note that although the differences in BLEU scores are small, they end up being statistically significant because the models frequently yield the same top scoring realization, and reliably deliver improvements in the cases where they differ. In particular, note that DEPLN and DEPORD-NF agree on the best realization 81% of the time, while DEPORD-NODIST and DEPORD-NODIST have 78.1% agreement, and DEPORD-GLOBAL and GLOBAL show 77.4% agreement; by comparison, DEPORD-NODIST and GLOBAL only agree on the best realization 51.1% of the time.

4.3 Detailed Analyses

The effect of the dependency length feature on the distribution of dependency lengths is illustrated in Table 8. The table shows the mean of the total dependency length of each realized derivation compared to the corresponding gold standard derivation, as well as the number of derivations with greater and lower dependency length. According to paired t-tests, the mean dependency lengths for the DEPLEN-NODIST and DEPLEN models do not differ significantly from the gold standard. In contrast, the mean dependency length of all the models that do not include the dependency length feature does differ significantly ($p < 0.001$) from the gold standard. Additionally, all these models have more realizations with dependency length greater than the gold standard, in comparison to the dependency length minimizing models; this shows the efficacy of the dependency length feature in approximating the gold standard. Interestingly, the DEPLEN-GLOBAL model significantly undershoots the gold standard on mean dependency length, and has the most skewed distribution of sentences with greater vs. lesser dependency length than the gold standard.

Apart from studying dependency length directly, we also looked at one of the attested effects of dependency length minimization, viz. the tendency to prefer short-long post-verbal constituents in production (Temperley, 2007). The relative lengths of adjacent post-verbal constituents were computed and their distribution is shown in Table 9. While calculating length, punctuation marks were excluded. Four kinds of constituents were found in the post-verbal domain. For every verb, apart from single constituents and equal length constituents, short-long and long-short sequences were also observed. Table 9 demonstrates that for both the gold standard corpus as well as the realizer models, short-long constituents were more frequent than long-short or equal length constituents. This follows the trend re-

| Model         | % Short | % Long | % Eq   | % Single |
|---------------|--------|-------|-------|---------|
| DEPLEN        | 25.25  | 4.87  | 4.08  | 65.79   |
| DEPORD-NF     | 23.74  | 5.92  | 3.96  | 66.40   |
| DEPLN         | 24.36  | 5.36  | 4.07  | 66.21   |

Table 9: Distribution of various kinds of post-verbal constituents in the development set (Section 00); 4692 gold cases considered

\[\text{Kudos to Kevin Gimpel for making his resampling scripts available from http://www.ark.cs.cmu.edu/MT/paired_bootrap_v13a.tar.gz.}\]
Table 10: Distribution of heavy unequal constituents (length difference > 5) in Section 00; 4692 gold cases considered and significance tested against the gold standard using a \(\chi^2\)-square test

| Model             | % Light / Heavy | % Heavy / Light | Signif |
|-------------------|-----------------|-----------------|--------|
| GOLD              | 8.60 / 0.36     | -              |        |
| GLOBAL            | 7.73 / 2.02     | ***             |        |
| DEPLEN-GLOBAL     | 8.35 / 0.75     | **              |        |
| DEPORD-NONF       | 7.98 / 1.15     | ***             |        |
| DEPORD-NODIST     | 8.04 / 1.12     | ***             |        |
| DEPLEN-NODIST     | 8.23 / 0.45     | n.s.            |        |
| DEPORD-NF         | 8.26 / 0.71     | **              |        |
| DEPLEN            | 8.36 / 0.51     | n.s.            |        |

The experiments show a consistent positive effect of the dependency length feature in improving BLEU scores and achieving a better match with the corpus distributions of dependency length and short/long constituent orders. The results in Table 10 are particularly encouraging, as they show that minimizing dependency length reduces the number of realizations in which a heavy constituent precedes a light one down to essentially the level of the corpus, thereby eliminating many realizations that can be expected to have egregious errors like those shown in Table 11.

4.5 Interim Discussion

The experiments show a consistent positive effect of the dependency length feature in improving BLEU scores and achieving a better match with the corpus distributions of dependency length and short/long constituent orders. The results in Table 10 are particularly encouraging, as they show that minimizing dependency length reduces the number of realizations in which a heavy constituent precedes a light one down to essentially the level of the corpus, thereby eliminating many realizations that can be expected to have egregious errors like those shown in Table 11.

Intriguingly, there is some evidence that a negatively weighted total dependency length feature can go too far in minimizing dependency length, in the absence of other informative features to counterbalance it. In particular, the DEPORD model mistakenly leaves before at the end of the sentence where it is again apt to be interpreted as modifying the preceding verb. In wsj_0075.13, both models put the temporal modifier on Thursday in its canonical VP-final position, despite this order running counter to dependency length minimization. Finally, wsj_0014.2 shows a case where DEPORD is nearly an exact match (except for a missing comma), but the dependency length model fronts the PP on the 12-member board, where it is grammatical but rather marked (and not motivated in the discourse context).
the exact amount of the refund will be determined next year based on actual collections made until Dec. 31 of this year.

DEPLEN [same]

DEPORD the exact amount of the refund will be determined based on actual collections made until Dec. 31 of this year next year.

DEPLEN the U.S. claiming some success in its trade diplomacy , removed South Korea , Taiwan and Saudi Arabia from a list of countries it is closely watching for allegedly failing to honor U.S. patents , copyrights and other intellectual-property rights.

DEPORD the U.S. removed from a list of countries it is watching closely for allegedly failing to honor U.S. patents , copyrights and other intellectual-property rights , claiming some success in its trade diplomacy , South Korea , Taiwan and Saudi Arabia .

DEPLEN the U.S. , claiming some success in its trade diplomacy , removed South Korea , Taiwan and Saudi Arabia from a list of countries it is closely watching for allegedly failing to honor U.S. patents , copyrights and other intellectual-property rights.

DEPORD the U.S. removed from a list of countries it is watching closely for allegedly failing to honor U.S. patents , copyrights and other intellectual-property rights , claiming some success in its trade diplomacy , South Korea , Taiwan and Saudi Arabia .

but he has not said before that the country wants half the debt forgiven .

DEPLEN but he not has said before the country wants half the debt forgiven .

DEPORD but he not has said before the country wants half the debt forgiven before .

The Treasury also said it plans to sell [$ 10 billion] [in 36-day cash management bills] [on Thursday].

DEPLEN [same]

DEPORD [same]

they succeed Daniel M. Rexinger , retired Circuit City executive vice president , and Robert R. Glauber , U.S. Treasury undersecretary , on the 12-member board .

DEPORD they succeeded Daniel M. Rexinger , retired Circuit City executive vice president , and Robert R. Glauber , U.S. Treasury undersecretary on the 12-member board .

DEPLEN on the 12-member board they succeed Daniel M. Rexinger , retired Circuit City executive vice president , and Robert R. Glauber , U.S. Treasury undersecretary .

Table 11: Examples of realized output for full models with and without the dependency length feature

4.6 Targeted Human Evaluation

To determine whether heavy-light ordering differences often represent ordering errors (including egregious ones), rather than simply representing acceptable variation, we conducted a targeted human evaluation on examples of this kind. Specifically, for each of the DEPLEN* models and their corresponding models without the dependency length feature, we chose the 25 sentences from the development section whose realizations exhibited the greatest difference in dependency length between sibling constituents appearing in opposite orders, and asked two judges (not the authors) to choose which of the two realizations best expressed the meaning of the reference sentence in a grammatical and fluent way, with the choice forced (2AFC). Table 12 shows the results. Agreement between the judges was high,

Table 12: Targeted human evaluation—percentage of realizations preferred by two human judges in a 2AFC test among the 25 development set sentences with the greatest differences in dependency length, with a binomial test for significance

| Model           | % Preferred | % Agr | Signif |
|-----------------|-------------|-------|--------|
| GLOBAL          | 22          | -     | -      |
| DEPLEN-GLOBAL   | 78          | 84    | ***    |
| DEPORD-NODIST   | 24          | -     | -      |
| DEPLEN-NODIST   | 76          | 92    | ***    |
| DEPORD-NF       | 26          | -     | -      |
| DEPLEN          | 74          | 96    | ***    |

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with only one disagreement on the realizations from the DEPLEN and DEPORD-NF models (involving an acceptable paraphrase in our judgment), and only four disagreements on the DEPLEN-GLOBAL and GLOBAL realizations. Pooling the judgments, the preference for the DEPLEN* models was well above the chance level of 50% according to a binomial test ($p < 0.001$ in each case). Inspecting the data ourselves, we found that many of the items did indeed involve egregious ordering errors that the DEPLEN* models managed to avoid.

5 Related Work

As noted in the introduction, to the best of our knowledge this paper is the first to examine the impact of dependency length minimization on realization ranking. While there have been quite a few papers to date reporting results on Penn Treebank data, since the various systems make different assumptions regarding the specificity of their inputs, all but the most broad-brushed comparisons remain impossible at present, and thus detailed studies such as the present one can only be made within the context of different models for the same system. Some progress on this issue has been made in the context of the Generation Challenges Surface Realization Shared Task (Belz et al., 2011), but it remains to be seen to what extent fair cross-system comparisons using common inputs can be achieved.

For (very) rough comparison purposes, Table 13 lists our results in the context of those reported for various other systems on PTB Section 23. As the table shows, the OpenCCG scores are quite competitive, exceeded only by Callaway’s (2005) extensively hand-crafted system as well as Bohnet et al.’s (2011) system on shared task shallow inputs (-S), which performs much better than their system on deep inputs (-D) that more closely resemble OpenCCG’s.

| System                | Coverage | BLEU  | % Exact |
|-----------------------|----------|-------|---------|
| Callaway (05)         | 98.5%    | 0.9321| 57.5    |
| Bohnet et al.-S (11)  | 100%     | 0.8911| -       |
| **OpenCCG (12)**     | 97.1%    | 0.8596| 42.1    |
| OpenCCG (09)         | 97.1%    | 0.8506| 40.5    |
| Ringger et al. (04)  | 100%     | 0.836 | 35.7    |
| Bohnet et al.-D (11) | 100%     | 0.7943| -       |
| Langkilde-Geary (02) | 83%      | 0.757 | 28.2    |
| Guo et al. (08)      | 100%     | 0.7440| 19.8    |
| Hogan et al. (07)    | ≈100%    | 0.6882| -       |
| OpenCCG (08)         | 96.0%    | 0.6701| 16.0    |
| Nakanishi et al. (05)| 90.8%    | 0.7733| -       |

Table 13: PTB Section 23 BLEU scores and exact match percentages in the NLG literature (Nakanishi et al.’s results are for sentences of length 20 or less)

In this paper, we have investigated dependency length minimization in the context of realization ranking, focusing on its potential to eliminate egregious ordering errors as well as better match the distributional characteristics of sentence orderings in news text. When added to a state-of-the-art, comprehensive realization ranking model, we showed that including a dense, global feature for minimizing total dependency length yields statistically significant improvements in BLEU scores and significantly reduces the number of heavy-light ordering errors. Going beyond the BLEU metric, we also conducted a targeted human evaluation to confirm the utility of the dependency length feature in models of varying richness. Interestingly, even with the richest model, in some cases we found that the dependency length feature still appears to go too far in minimizing dependency length, suggesting that further counter-balancing features—especially ones for the sentence-initial position (Filippova and Strube, 2009)—warrant investigation in future work.

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