Dependency Graph-to-String Statistical Machine Translation

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We present graph-based translation models which translate source graphs into target strings. Source graphs are constructed from dependency trees with extra links so that non-syntactic phrases are connected. Inspired by phrase-based models, we first introduce a translation model which segments a graph into a sequence of disjoint subgraphs and generates a translation by combining subgraph translations left-to-right using beam search. However, similar to phrase-based models, this model is weak at phrase reordering. Therefore, we further introduce a model based on a synchronous node replacement grammar which learns recursive translation rules. We provide two implementations of the model with different restrictions so that source graphs can be parsed efficiently. Experiments on Chinese–English and German–English show that our graph-based models are significantly better than corresponding sequence- and tree-based baselines.

1. Introduction

Statistical Machine Translation (SMT) starts from sequence-based models where the basic translation units are words or phrases. IBM made the first breakthrough on SMT by statistically modeling the translation process at the word-level (Brown et al. 1990, 1993). The well-known phrase-based translation model (Koehn, Och, and Marcu 2003) significantly improved upon word-based models by extending translation units from single words to phrases which allow local phenomena, such as word order, word deletion, and word insertion, to be captured. However, conventional phrase-based models are known to be weak at reordering phrases and learning generalizations. For example, assume the following Chinese sentence and its English translation:

Chinese: 2010年 FIFA 世界杯 在 南非 成功 举行
Pinyin: 2010nian FIFA shijiebei zai Nanfei chenggong juxing
Alignment: 2010 FIFA World Cup in South Africa successfully held

English: 2010 FIFA World Cup was held successfully in South Africa

From this example, the phrase-based model learns phrase pairs such as \(\langle chenggong juxing, was held successfully \rangle\) and \(\langle shijiebei, World Cup \rangle\). Word reordering inside these phrase pairs is fully captured. However, how to reorder them on the target side to

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generate a translation is not specified in the model. In addition, generalizations such as ⟨shijiebei ... chenggong juxing, World Cup was held successfully⟩ are ignored in the phrase-based model because it only uses continuous phrases.

Therefore, tree-based (or syntax-based) translation models have been proposed to learn translation rules from tree structures over sentences. For example, given the dependency tree in Figure 1, a dependency treelet-based model (Menezes and Quirk 2005; Quirk, Menezes, and Cherry 2005; Xiong, Liu, and Lin 2007), where a treelet is defined as an arbitrarily connected subgraph, can extract the following rule from the aforementioned example:

\[
\text{shijiebei chenggong juxing} \rightarrow \text{World Cup was held successfully}
\] (1)

where the source side is a tree structure which covers a discontinuous phrase shijiebei ... chenggong juxing. When a tree-based model is formalized by a synchronous grammar, it will be able to reorder phrases. For example, a dependency tree-to-string model (Xie, Mi, and Liu 2011) can learn the following translation rule:

\[
\text{NR}_{[1]} \ P_{[2]} \ chenggong juxing \rightarrow X_{[1]} \text{was held successfully} \ X_{[2]}
\] (2)

where \( NR \) and \( P \) are source non-terminals representing gaps, \( X \) is a general target non-terminal, and indexes indicate mappings between source and target non-terminals and specify how target phrases are reordered when they are inserted into gaps.

However, despite its effectiveness in introducing linguistic knowledge into translation models, syntactic tree structures confine models focusing on linguistically motivated phrases (i.e., syntactic phrases). For example, the dependency treelet-based model only covers phrases which are connected in the tree, while the dependency tree-to-string model only uses phrases which are fully covered by a subtree. Therefore, phrases like 2010nian FIFA will not be considered in both models. Although linguistically motivated phrases are more reliable in quality and have linguistic meanings, discarding other phrases is a harsh decision which usually does not work well in practice, as these phrases can be quite useful to improve rule coverage and system performance (Koehn, Och, and Marcu 2003; Hanneman and Lavie 2009).

An obvious observation is that those phrases which are not encouraged in trees actually are connected in terms of sequential structures (i.e., continuous phrases), such as the phrase 2010nian FIFA. Since both trees and sequences are special cases of graphs, a
possible way of integrating these phrases is using graphs. Therefore, different from previous work which usually incorporates these phrases into tree-based models by using extended labels (Marcu et al. 2006; Almaghout, Jiang, and Way 2011, 2012; Meng et al. 2013; Xie, Xu, and Liu 2014), we make a step forward to graph-based models where connected subgraphs are the basic translations units. Figure 2 shows an example graph which is obtained by adding an edge (from FIFA to 2010nian) to the dependency tree in Figure 1 so that the phrase 2010nian FIFA will be available in graph-based models.

In this paper, we explore ways of constructing graphs and design models to translate graphs into strings. Graphs in this paper are constructed by adding edges to dependency trees and thus called dependency graphs. Dependency trees are used because (i) they directly model syntactic and/or semantic relations between words; (ii) they have the best inter-lingual phrasal cohesion property, i.e., phrases in one language tend to stay together during translation (Fox 2002); and (iii) we can easily build a large parallel graph–string corpus using dependency parsers. To translate dependency graphs, inspired by phrase-based and tree-based models, we present graph-based models based on graph segmentation and a synchronous grammar. Experiments on Chinese–English (ZH–EN) and German–English (DE–EN) show that our graph-based models are significantly better than their corresponding sequence- and tree-based baselines.

This paper is based on previous work, including Li, Way, and Liu (2016) and the PhD thesis of Li (2017), by the same authors but with significant differences and contributions. 1) This paper provides formal definitions and more details on graphs and graph-based translation models. 2) This paper introduces a general graph-based model which is based on a synchronous grammar and allows hypotheses covering discontinuous source phrases. Accordingly, a general rule extraction algorithm, a deductive system for decoding and two new features which penalize large distortion and gaps are presented. 3) Because of the exponential complexity when handling graphs during decoding, we present two decoders with different constraints on subgraphs: one is a traditional chart decoder (Chiang 2007) which only considers subgraphs covering continuous source phrases; the other one is a novel beam search decoder which allows subgraphs covering discontinuous source phrases. The beam search-based decoder is our first step towards a general graph-based decoding algorithm. 4) We conducted more experiments and analyze the time complexity of decoding in each experimental system.

In the rest of this paper, we first introduce related work in Section 2. Then, we present formal definitions on graphs and introduce two types of dependency graphs (Section 3). After that, we describe a segmentation-based model which segments a graph into a sequence of disjoint subgraphs and generates translations by combining subgraph translations (Section 4). In Section 5, we further introduce a model based on a synchronous graph grammar which enables our model to learn recursive translation rules.
Our experimental results are demonstrated in Section 6. Finally, Section 7 summarizes our work and discusses possible avenues for future research.

2. Related Work

According to the fundamental structures used, we divide different translation models into three categories: sequence-based models, tree-based models and graph-based models.

2.1 Sequence-Based Models

Since the breakthrough made by IBM on word-based models in the 1990s (Brown et al. 1990, 1993), SMT has developed rapidly. The phrase-based model (Koehn, Och, and Marcu 2003) advanced the state-of-the-art by translating multi-word units, which makes it better able to capture local phenomena within phrases. However, it cannot reorder the phrases themselves. Even though reordering models (Koehn, Och, and Marcu 2003; Koehn et al. 2005; Xiong, Liu, and Lin 2006; Galley and Manning 2008; Cherry 2013) can be used to guide the phrase reordering, it is still known to be weak at long-distance reordering. Another disadvantage is that only continuous phrases are considered, and thus the learned translation pairs cannot be generalized even though sometimes an apparent pattern can be recognized. Galley and Manning (2010) extended the phrase-based model by allowing phrases with gaps (i.e., discontinuous phrases). However, without using linguistic knowledge, the model can learn plenty of unreliable translation rules.

2.2 Tree-Based Models

Tree-based models are proposed to alleviate problems in sequence-based models by learning translation rules which allow phrase reordering and generalization.

2.2.1 Hierarchical Phrase-Based Models. A hierarchical phrase is an extension of a phrase by allowing gaps where other hierarchical phrases are embedded (Chiang 2005, 2007). The hierarchical phrase-based (HPB) model (Chiang 2005, 2007) is formulated by a synchronous context-free grammar (SCFG) with only one general non-terminal \( X \). Even though it provides the model with more flexibility, the only non-terminal \( X \) often makes it hard for the model to select the most appropriate rules. Therefore, some work refines this non-terminal using linguistic information, such as syntactic categories from constituent structures (Zollmann and Venugopal 2006), POS tags or word classes (Zollmann and Vogel 2011), supertags based on combinatory categorical grammars (CCGs) (Almaghout, Jiang, and Way 2011, 2012), and head information from dependency structures (Li et al. 2012).

2.2.2 Constituent Tree-Based Models. A constituent (or phrasal) structure displays the functional components of a sentence. Typically, models based on constituent trees are formulated in a synchronous tree-substitution grammar (STSG) (Eisner 2003). Galley et al. (2004, 2006) proposed a well-known string-to-tree model based on STSG which translates source sentences into target trees. Given word-aligned string-tree pairs, this model automatically extracts transfer rules which map source phrases into target tree fragments. Similarly but differently, tree-to-string models (Huang, Knight, and Joshi 2006a,b; Liu, Liu, and Lin 2006) use parse trees on the source
side. Compared with string-to-tree models, tree-to-string models can decode a sentence in linear time in practice with respect to the sentence length (Huang and Mi 2010). Tree-to-tree models (Zhang et al. 2007; Nesson, Shieber, and Rush 2006) use trees on both sides. Despite benefits brought by linguistic trees, constituent tree-based models have severe problems on integrating non-syntactic phrases which are not linguistically well-formed but can be important to translation performance of systems (Koehn, Och, and Marcu 2003; Hanneman and Lavie 2009; Huck, Hoang, and Koehn 2014). To make use of such phrases, additional non-terminal symbols (Marcu et al. 2006; Zollmann and Venugopal 2006; Almaghout, Jiang, and Way 2011, 2012) or binarization of syntax trees (Zhang et al. 2006; Wang, Knight, and Marcu 2007) may be needed. However, such kinds of relaxation of syntactic constraints can result in less grammatical translations (Kaljahi et al. 2012).

### 2.2.3 Dependency Tree-Based Models

Dependency structures directly model relations between words in a sentence, each of which indicates the syntactic and/or semantic function of one word in relation to another word. A dependency tree can be segmented into a set of elementary units, such as edges, paths, or treelets which can be used in SMT. Lin (2004) proposed a dependency path-based model which translates a source dependency tree by combining translations of each path. The treelet approach (Menezes and Quirk 2005; Quirk, Menezes, and Cherry 2005) translates a dependency tree by bottom-up combining translations of disjoint treelets. Xiong, Liu, and Lin (2007) extended the treelet approach to allow gaps. Chen et al. (2014) proposed an edge-based model where the basic translation units are dependency edges. However, in these models, translation rules do not encode enough reordering information. By contrast, models based on synchronous grammars have proven to be better capable of handling phrase reordering. Shen, Xu, and Weischedel (2010) presented a model which is based on the HPB model with an extension using target dependency trees. Because the model only considers structures which cover continuous spans, it is easier to integrate a dependency-based language model which can significantly improve the system. Different from string-to-dependency models, Xie, Mi, and Liu (2011) presented a dependency tree-to-string model with an extended SCFG by including dependency links. However, the model only considers syntactic phrases. Since dependency trees are flatter than constituent trees, this model has a severe data-sparsity problem (Meng et al. 2013; Xie, Xu, and Liu 2014). To incorporate non-syntactic phrases, Meng et al. (2013) proposed to simultaneously use dependency trees and constituent trees so that phrases which are non-syntactic in dependency trees but syntactic in constituent trees can be covered. Xie, Xu, and Liu (2014) incorporated fixed and floating structures into the dependency tree-to-string model by creating special labels at run-time. Li et al. (2014) extended this model by decomposing dependency structures so that the translation of a syntactic phrase can be generated by combining translations of subphrases inside it.

### 2.3 Graph-Based Models

Graphs are more general and powerful representations than trees and thus believed to be better able to capture sentence meanings. In recent year, abstract meaning representation (AMR) (Banarescu et al. 2013) has been widely investigated which uses hypergraphs to represent semantic meanings of sentences. Jones et al. (2012) presented a semantics-based translation model, where a source sentence is firstly parsed into a hypergraph using a *synchronous hyperedge replacement grammar* (SHERG) and then the hypergraph is transformed into a target string using a target SHERG. However, the recognition
algorithm for SHERG is in polynomial time but potentially of a high degree (Lautemann 1990; Chiang et al. 2013). Furthermore, large parallel corpora annotated with hypergraphs are not readily available.

Compared to tree-based models which are usually based on a binary SCFG such as the HPB model and allow only phrasal discontinuities, graph-based models use subgraphs as basic translation units which may cover discontinuous phrases and thus have more powerful expressiveness than tree-based models (Galley and Manning 2010).

3. Dependency Graphs

Graphs used in this paper are called dependency graphs which are node-labeled, directed and connected. We do not consider edge labels as they did not improve translation performance in our experiments (Section 6) and will complicate our explanation. Before introducing how dependency graphs are constructed, we first provide a formal definition:

**Definition 1**
A node-labeled and directed dependency graph (or graph for short) is a tuple \( \langle V, E, \phi \rangle \), where \( V \) is a finite set of nodes, \( E \subseteq V^2 \) is a finite set of edges, and \( \phi : V \rightarrow C \) is a function which assigns a label from \( C \) to each node.

For simplicity, from now on we use the terms graph and dependency graph interchangeably. Note that although in Definition 1 nodes are unordered, we will assume that nodes are ordered according to word order as this is an important source of information for SMT. Figure 3 shows two example graphs which have different node order and thus are different. The basic translation units in our graph-based models are node-induced subgraphs, which are connected and defined as follows.

**Definition 2**
A node-induced subgraph of a graph \( \langle V, E, \phi \rangle \) is a graph \( \langle V', E', \phi' \rangle \), where \( V' \subseteq V \), \( E' \subseteq E \), \( \forall u \in V' : \phi'(u) = \phi(u) \), and \( \forall u, v \in V' : (u, v) \in E \iff (u, v) \in E' \).

According to Definition 2, a node-induced subgraph is a subset of nodes of a graph together with all edges whose endpoints are both in this subset. Figure 4 provides examples of two subgraphs of Figure 3a with one of them node-induced. Since in this paper we only deal with node-induced subgraphs, from now on, we will assume that all subgraphs are node-induced subgraphs and use the two terms without distinction.

Figure 3: Two example graphs. The two graphs are different because two nodes B and C are in different order: while (a) covers a sequence ABCD, (b) covers ACBD.
3.1 Dependency-Bigram Graphs

The first kind of graph used in this paper directly combines a sequence and a dependency tree by using bigram links and dependency links. The graph is therefore called a dependency-bigram graph (DBG). Figure 5 shows an example DBG. Each edge in the DBG denotes either a bigram relation or a dependency relation. Bigram relations are implied in sequences and provide local and sequential information on pairs of continuous words. Phrases connected by bigram relations, i.e., continuous phrases, are known to be useful for improving phrase coverage (Hanneman and Lavie 2009). By contrast, dependency relations come from dependency structures which model syntactic and/or semantic relations between words. Phrases connected by dependency relations are covered by treelets and thus more linguistically motivated and reliable (Quirk, Menezes, and Cherry 2005). By combining the two kinds of relations together, we can make use of both continuous and linguistically-informed discontinuous phrases without distinction as long as they are covered by subgraphs.

For instance, given the graph in Figure 5, we can use subgraphs which are connected by different combinations of links as in Figure 6. These subgraphs cover three kinds of phrases:

1. Phrases as in Figures 6a–6c which are connected in terms of bigram links. These phrases are continuous and also used in phrase-based models.
2. Phrases as in Figures 6b–6d which are connected in terms of dependency links. These phrases can also be used in dependency treelet-based models.
3. Phrases as in Figure 6e which are only connected when both types of links are considered. These phrases cannot be covered by both phrase-based systems and dependency treelet-based systems.
In experiments, we found \( \sim 70\% \) of rules are extracted from continuous phrases on both ZH–EN and DE–EN in our segmentation-based model (Section 4). This also means that source sides of most rules are connected by bigram links. Around 42\%–48\% of rules are connected by dependency links. We also observed that \( >30\% \) of rules are connected by not only bigram links but also dependency links. About 15\%–17\% of rules falls into the third category which slightly improve our model resulting in the best translation performance.

### 3.2 Dependency-Sibling Graphs

Another kind of graph used in this paper is called a dependency-sibling graph (DSG) which is constructed by adding sibling links to a dependency tree. Figure 7 shows an example DSG. Compared with bigram relations used in DBGs, phrases connected by sibling relations are usually fewer in number but more linguistically motivated. Given the graph in Figure 7, we can also use subgraphs covering three kinds of phrases: (i) phrases which are connected by sibling links and thus may be discontinuous as in Figure 8a; (ii) phrases as in Figure 8b which are connected by dependency links; (iii) phrases as in Figure 8c which are not connected by a single type of link.

By comparing Figure 6 and Figure 8, we can see that some phrases covered by subgraphs are shared by the DBG and DSG (e.g., Figure 6d and Figure 8b). However, there are also some phrases which are only available in either a DBG (e.g., Nanfei

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**Figure 6**: Example subgraphs of Figure 5. Dotted lines are bigram relations. Solid lines are dependency relations. Dashed lines are shared by bigram and dependency relations. (a) is only connected by bigram links; (b) is connected by not only bigram links but also dependency links; (c) is connected by a link shared by bigram relations and dependency relations; (d) is only connected by dependency links; and (e) is connected when both bigram links and dependency links are used.

**Figure 7**: An example dependency-sibling graph by directly adding edges between siblings to a dependency tree. Dotted lines are sibling relations. Solid lines are dependency relations.

Nanfei chengggong

(a) zai Nanfei

(b) FIFA shijiebei

(c)

shijiebei juxing

(d) 2010nian shijiebei zai Nanfei

(e)
Figure 8: Example subgraphs of Figure 7. Dotted lines are sibling relations. Solid lines are dependency relations. (a) is connected by sibling links; (b) is connected by dependency links; and (c) is connected when both types of links are considered.

4. Graph Segmentation-Based Translation

In this section, we present a segmentational graph-based translation model (called SegGBMT). Inspired by phrase-based models, our model segments an input graph into a sequence of disjoint subgraphs and generates a complete translation by combining translations of each subgraph left-to-right using beam search. In the following subsections, we firstly introduce notation and some definitions (Section 4.1) which will also be used in Section 5. Then, we present a training algorithm (Section 4.2), features (Section 4.3) and a decoding process (Section 4.4).

4.1 Notation and Definitions

Let \( \langle G(s), t, a \rangle \) be a parallel graph–string pair, where \( G \) is a graph covering a source sentence \( s \), \( t \) is a target sentence, and \( a \) is a set of mappings between positions of \( s \) and positions of \( t \). We use \( s_i \) and \( t_j \) to denote individual words at a source position \( i \) and a target position \( j \), respectively. We denote a source discontinuous phrase as \( \tilde{s} = \bar{s}_1 \bar{s}_2 \cdots \bar{s}_K \) which contains \( K \) continuous phrases \( \bar{s}_1 \cdots \bar{s}_K \) and thus \( K - 1 \) gaps. When \( K = 1 \), \( \tilde{s} \) is a continuous phrase. A subraph covering \( \tilde{s} \) is denoted as \( G(\tilde{s}) \) if it exists.

Our SegGBMT model can be seen as an extension of the phrase-based model by taking subgraphs as the basic translation units, as in Equation (3):

\[
p(G(\tilde{s}_1^I) \mid \tilde{t}_1^I) = \prod_{i=1}^{I} p(G(\tilde{s}_a_i) \mid \tilde{t}_i) d(G(\tilde{s}_a_i), G(\tilde{s}_{a_{i-1}}))
\]

\[
\approx \prod_{i=1}^{I} p(G(\tilde{s}_a_i) \mid \tilde{t}_i) d(\tilde{s}_a_i, \tilde{s}_{a_{i-1}})
\]

where \( d(\cdot) \) is a distortion function as in the phrase-based model which will be defined in Section 4.3. According to Equation (3), a target sentence is segmented into a sequence of
Figure 9: A source DBG is segmented into three subgraphs, each of which corresponds to a target phrase. Dashed lines denote alignments between source subgraphs and target phrases. Edges in dotted lines are ignored during segmentation of the graph.

Figure 10: An example subgraph–phrase pair extracted from the example in Section 1 using the DBG in Figure 5.

I phrases in SegGBMT. Each $\vec{t}_i$ is a translation of a source subgraph $G(\vec{s}_a)$. Accordingly, the sequence of subgraphs $\{G(\vec{s}_a), \cdots, G(\vec{s}_a)\}$ is called a graph segmentation, where subgraphs are disjoint with each other, as in Definition 3.

**Definition 3**

A segmentation of a graph $\langle V, E, \phi \rangle$ is a sequence of disjoint subgraphs $\{(V_1, E_1, \phi_1), \cdots, (V_I, E_I, \phi_I)\}$, where $V_1 \cup \cdots \cup V_I = V$.

Note that during segmentation of a graph, nodes are divided into subgraphs and edges between subgraphs are ignored. Therefore, subgraphs in a graph segmentation cover all nodes rather than edges. This also means that when subgraphs in a graph segmentation are combined to form a graph, their nodes remain disjoint and new edges are formed between them. Figure 9 shows a graph–string pair where the graph is segmented into three subgraphs, each of which corresponds to a target phrase.

**4.2 Rule Extraction**

Different from phrase-based models, the basic translation units in our SegGBMT model are subgraphs. Accordingly, given a parallel graph–string pair $\langle G(s), t, a \rangle$, we extract subgraph–phrase pairs $\langle G(\vec{s}), \vec{t} \rangle$ as translation rules, which are consistent with the word alignment $a$ (Och and Ney 2004). An example subgraph–phrase pair extracted from the running example using the DBG in Figure 5 is shown in Figure 10. It translates a source subgraph into a target phrase 2010 FIFA World Cup. We now provide a formal definition of a subgraph–phrase pair.

**Definition 4**

Given a graph–string pair $\langle G(s), t, a \rangle$, let $\vec{t}$ be a phrase of $t$ and $G(\vec{s})$ be a subgraph of $G(s)$ covering a source subsequence $\vec{s}$, $\langle G(\vec{s}), \vec{t} \rangle$ is a subgraph–phrase pair of $\langle G(s), t, a \rangle$, iff $\langle \vec{s}, \vec{t} \rangle$ is consistent with $a$, i.e.
Figure 11: Examples pairs which are not subgraph-phrase pairs because: (a) is not consistent with the word alignment as *shijiebei* should be aligned to *World Cup*, and the source side of (b) is not a subgraph of the DBG in Figure 5.

1. \( \exists s_i \in \tilde{s}, t_j \in \tilde{t}: (i, j) \in a \).
2. \( \forall s_i \in \tilde{s}; (i, j) \in a \Rightarrow t_j \in \tilde{t} \).
3. \( \forall t_j \in \tilde{t}; (i, j) \in a \Rightarrow s_i \in \tilde{s} \).

Note that the source side of a subgraph-phrase pair in SegGBMT is a subgraph which is connected and does not contain any non-terminals. The subgraph can be used to cover either a continuous phrase or a discontinuous phrase. The target side of the pair is always a phrase. Figure 11 shows two pairs which are not considered as subgraph-phrase pairs: in Figure 11a the pair is not consistent with the word alignment, and in Figure 11b the source side is not a subgraph of the DBG in Figure 5.

The procedure of extracting subgraph-phrase pairs is as follows:

**Step 1:** Find a new target phrase \( \tilde{t} : |\tilde{t}| \leq L \);

**Step 2:** Find all source subsequences \( Q = \{ \tilde{s} : \forall t_j \in \tilde{t}; (i, j) \in a \Rightarrow s_i \in \tilde{s} \text{ and } |\tilde{s}| \leq L \} \);

**Step 3:** Pop an element \( \tilde{s} \) from \( Q \);

**Step 4:** If \( \langle \tilde{s}, \tilde{t} \rangle \) is consistent with \( a \) and \( G(\tilde{s}) \) exists, \( \langle G(\tilde{s}), \tilde{t} \rangle \) is a subgraph-phrase pair;

**Step 5:** Go back to Step 3 until \( Q \) is empty;

**Step 6:** Go back to Step 1 until all target phrases have been visited.

This procedure traverses each pair \( \langle \tilde{s}, \tilde{t} \rangle \), which is within a length limit \( L \) (\( L = 7 \) in our experiments) and consistent with the word alignment \( a \), and outputs \( \langle G(\tilde{s}), \tilde{t} \rangle \) if \( \tilde{s} \) is covered by a subgraph \( G(\tilde{s}) \). A source subsequence can be extended with unaligned source words which are adjacent to it on boundaries so that all phrases which are consistently aligned to the same target phrase can be accessed.

### 4.3 Model and Features

We define our model in the log-linear framework (Och and Ney 2002) over a derivation \( d = r_1 r_2 \cdots r_N \), as in Equation (4):

\[
p(d) \propto \prod_{i} \phi_i(d)^{\lambda_i}
\]  

(4)

where \( r_i \) are translation rules, \( \phi_i \) are features defined on derivations, and \( \lambda_i \) are feature weights. In our experiments, we use the following standard features:
Two translation probabilities $p(G(s)|t)$ and $p(t|G(s))$ based on frequency;

Two lexical translation probabilities $p_{\text{lex}}(s|t)$ and $p_{\text{lex}}(t|s)$ based on word alignment (Och, Tillmann, and Ney 1999);

A language model $p(t)$ to score a translation $t$;

A rule penalty $\exp(-N)$;

A word penalty $\exp(-|t|)$;

A distortion penalty $\exp(-d(\cdot))$ for distance-based reordering.

The calculation of the distortion function $d(\cdot)$ in our model is different from the one in conventional phrase-based models, because we need to take discontinuity into consideration. In our model, we use a distortion function as in Equation (5) to penalize discontinuous phrases that have relatively long gaps (Galley and Manning 2010):

$$d(\tilde{s}_a, \tilde{s}_{a-1}) = |\tilde{s}^b_a - \tilde{s}^e_{a-1} - 1| + \sum_{k=2}^{K} |\tilde{s}^b_{a,k} - \tilde{s}^e_{a,k-1} - 1|$$

where superscripts $b$ and $e$ denote the beginning and end positions of a subsequence, respectively. $\tilde{s}_a = \tilde{s}_{a,1} \cdots \tilde{s}_{a,K}$ is a subsequence which has $K - 1$ gaps and thus consists of $K$ phrases $\tilde{s}_{a,k}$. Figure 12 shows an example of calculating distortion values. According to Equation (5), the value of the distortion function $d$ is a summation (denoted by $+$) of two values. While the first value measures the distance between the current and a previous subsequence, the second value calculates the length of gaps in the current subsequence. In practice, instead of adding them together as a single distortion value, we treat the two values as two distinct features (Galley and Manning 2010) so in experiments there are in total 9 features in our SegGBMT model.

### 4.4 Decoding

During decoding, the SegGBMT model searches for the best derivation $\hat{d}$ whose source yield $f(\hat{d})$ corresponds to a segmentation of $G(s)$ denoted by a $\sim$ relation and target yield $e(\hat{d})$ is a target sentence $\hat{t}$, as in Equation (6):

$$\hat{t} = e \left( \arg \max_{d \in D: f(d) \sim G(s)} p(d) \right)$$
2010nian FIFA shijiebei zai Nanfei chenggong juxing

$\mathbf{r_1}$: 2010nian FIFA $\rightarrow$ 2010 FIFA

$\therefore \mathbf{h_1}$: 2010 FIFA

shijiebei zai Nanfei chenggong juxing

$\mathbf{r_2}$: shijiebei juxing $\rightarrow$ World Cup was held

$\therefore \mathbf{h_2}$: 2010 FIFA World Cup was held

zai Nanfei chenggong

$\mathbf{r_3}$: zai Nanfei chenggong $\rightarrow$ successfully in South Africa

$\therefore \mathbf{h_3}$: 2010 FIFA World Cup was held successfully in South Africa

The decoder in SegGBMT is similar to the phrase-based decoder, which generates hypotheses (partial translations) from left to right using beam search. Each hypothesis maintains a coverage vector and can be extended by translating an uncovered subgraph. Positions covered by the subgraph are then marked as translated. The translation process ends when no untranslated words remain. Hypotheses in the same stack can be recombined and pruned according to their partial translation cost and an estimated future cost (Koehn, Och, and Marcu 2003; Galley and Manning 2010). Figure 13 shows a derivation of translating an input DBG in Chinese to an English string.

The decoding procedure for SegGBMT is shown in Algorithm 1. The algorithm maintains $|s| + 1$ stacks $B_0, B_1, \cdots, B_{|s|}$. Each $B_i$ contains a set of hypotheses covering exactly $i$ source words. The algorithm starts from an empty hypothesis $h_0$ which does not cover any words (Line 1). Then, it traverses each stack $B_i$ and each hypothesis $h_c$ in $B_i$ (Lines 2–3) where the coverage vector $c$ maintains the set of positions already covered by the hypothesis. To extend $h_c$, the algorithm considers all translation rules...
Algorithm 1 Beam-search decoder for SegGBMT

1: add $h_∅$ to $B_0$
2: for $i = 0$ to $|s|$ do
3:   for all $h_c \in B_i$ do
4:     $j = \min\{k \mid k \notin c\}$ $\triangleright$ the first uncovered position
5:     for all $r \in \{\langle G(\tilde{s}), \tilde{t} \rangle \mid \tilde{s}^k \leq j + d_{\text{max}} \text{ and } \forall k \in c \Rightarrow s_k \notin \tilde{s}\}$ do
6:       $h_c' := \text{Create}(h_c, r)$ where $\tilde{c}' = c \cup \{k \mid s_k \in \tilde{s}\}$
7:     add $h_c'$ to $B_{i+|\tilde{s}|}$
8: recombine and prune if applicable

which are within a distortion limit of $d_{\text{max}}$ (6 in our experiments) in terms of the first uncovered position and do not overlap with already covered source words (Lines 4–5). Given an applicable rule $r = \langle G(\tilde{s}), \tilde{t} \rangle$, the function $\text{Create}$ extends $h_c$ to generate a new hypothesis $h_{c'}$ by appending $\tilde{t}$ to the right and updating the coverage vector and weights (Line 6). Then new hypothesis is then added to a stack according to the number of words covered (Line 7). When all stacks have been visited, the decoder returns the best hypothesis in stack $B_{|s|}$ as the final translation.

5. Synchronous Grammar-Based Translation

In Section 4, we presented a graph-based translation model which only uses non-recursive rules and generates a translation by segmenting a graph and combining subgraph translations. Although the model naturally takes both continuous phrases and discontinuous phrases into consideration, it is difficult to reorder target phrases. Therefore, in this section, we introduce a new model (called GramGBMT) which uses a synchronous graph grammar to parse input graphs and simultaneously generate target strings. Translation rules in GramGBMT may contain non-terminals which are used to specify how target phrases are reordered.

In the following sections, we firstly introduce the grammar (Section 5.1). Then, we present an algorithm to extract translation rules (Section 5.2), features (Section 5.3) and a deductive proof system (Shieber, Schabes, and Pereira 1995; Goodman 1999) for decoding with two different implementations (Section 5.4).

5.1 Grammar

Similar to tree grammars which are used to generate trees, graph grammars are rewriting formalisms for generating graphs. In this section, we present a synchronous node replacement grammar (SNRG) which generates graph pairs by replacing nodes with other graphs. It will be used in this paper to translate graphs. In an SNRG, the elementary units are graph fragments, which are also the right-hand sides of production rules in the grammar. Its definition is as follows:

**Definition 5**

A graph fragment is a tuple $\langle V, E, \phi, \eta \rangle$, where $\langle V, E, \phi \rangle$ is a graph and $\eta$ is an embedding mechanism which consists of a set of connection instructions to indicate how to add edges when integrating a graph into another graph.
Figure 14 shows an example graph fragment which consists of a graph (on the left) and an embedding mechanism (on the right). According to the embedding mechanism, when we integrate the graph into another one, if *juxing* and *zai* are neighbours of the graph, two edges (*juxing* → *shijiebei* and *zai* → *shijiebei*) will be added. Based on graph fragments, we define an SNRG as in Definition 6.

**Definition 6**

A synchronous node replacement grammar (SNRG) is a tuple \( \langle N, T, T', P, S \rangle \), where \( N \) is a finite set of non-terminal symbols, \( T \) and \( T' \) are finite sets of terminal symbols, and \( S \in N \) is the start symbol. \( P \) is a finite set of productions of the form \( (A \rightarrow (R, R', \sim)) \), where \( A \in N \), \( R \) is a graph fragment over \( N \cup T \) and \( R' \) is a graph fragment over \( N \cup T' \). \( \sim \) is a one-to-one mapping between non-terminal symbols in \( R \) and \( R' \).

Note that the embedding mechanism is important during the generation of graphs, but can be ignored when parsing graphs (Kukluk 2007). This is because generation requires adding connections between two graphs to form a new graph, whereas parsing graphs has no such requirements. Therefore, instead of using an SNRG exactly following Definition 6, we use a simplified version, which excludes embedding mechanisms, to build a translation model which parses source graphs and generates target strings. Informally, rules in our SNRG-based model are in the form of (7):

\[
X \rightarrow \langle \gamma, \alpha, \sim \rangle
\]  

(7)

where \( X \) is the general non-terminal, \( \gamma \) is a graph where nodes are labeled by source terminals and non-terminals, \( \alpha \) is a string over target terminals and non-terminals, and \( \sim \) is a one-to-one mapping between source and target non-terminals. Figure 15 shows an example translation rule.

**5.2 Rule Extraction**

In addition to rules which only contain terminals as in SegGBMT, GramGBMT also includes translation rules which contain non-terminals as in Figure 15. Non-terminals

Figure 15: An example translation rule in our SNRG-based model. \( X \) is a general non-terminal. Indexes indicate mappings between source and target non-terminals.
are obtained by replacing subgraphs with single nodes and also can be replaced by subgraphs. Such a replacement requires representing a subgraph by joining other subgraphs. Because we only need to handle graphs on the source side, given a source subsequence \( \tilde{s} \), the subgraph \( G(\tilde{s}) \) covering \( \tilde{s} \) is already known and unique. Therefore, this subgraph-joining problem is simplified as a join of two subsequences, as defined in Definition 7.

**Definition 7**

Given a sequence \( s \), the join of its two disjoint subsequences \( \tilde{s}_1 \) of length \( m \) and \( \tilde{s}_2 \) of length \( n \) is a subsequence \( \hat{s} \) of length \( m + n \) such that \( \forall s_i : s_i \in \tilde{s} \Leftrightarrow s_i \in \tilde{s}_1 \) or \( \tilde{s}_2 \). In this paper, the join is denoted as a commutative operation \( \oplus \), i.e., \( \hat{s} = \tilde{s}_1 \oplus \tilde{s}_2 = \tilde{s}_2 \oplus \tilde{s}_1 \).

According to Definition 7, word order is preserved during the joining of two subsequences. For example, the join of \( shijiebei juxing \) and \( zai Nanfei juxing \) is a subsequence \( shijiebei zai Nanfei juxing \). It is trivial to keep word order for terminals. However, the existence of non-terminals brings another question: what is the position of a non-terminal \( X \) covering a subsequence \( \hat{s} \) when it is joined with another subsequence \( \tilde{s}_2 \)? It is straightforward to join \( X \) with \( \tilde{s}_2 \) when spans of \( \tilde{s}_1 \) and \( \tilde{s}_2 \) do not overlap: if \( s_1^i > s_2^b \), \( X \oplus \tilde{s}_1 = X \tilde{s}_1 \); otherwise, if \( s_1^i < s_2^b \), \( X \oplus \tilde{s}_2 = X \tilde{s}_2 \). We now provide a definition of how to join \( X \) with \( \tilde{s}_2 \) when the two spans overlap:

**Definition 8**

The position of a non-terminal which covers a subsequence \( \hat{s} \) is the start position of \( \tilde{s} \).

For example, assuming \( X \) covers \( shijiebei juxing \), the join of \( X \) with \( zai Nanfei \) would result in \( X zai nanfei \) as the start position of \( X \), i.e. the position of \( shijiebei \), is prior to the position of \( zai \). This definition is useful when we extract rules and decode source graphs where we need to represent a subgraph with the non-terminal \( X \).

Based on Definition 7 and Definition 8, the set of rules is obtained in two steps by a similar extraction algorithm as in the HPB model, except that the source sides of rules in our model are graphs rather than strings. The rule set is defined over subgraph-phrase pairs (Definition 4). Given a word-aligned graph–string pair \( P = (G(s), t, a) \), the set of rules from \( P \) satisfies the following:

1. If \( (G(\tilde{s}), \tilde{t}) \) is a subgraph–phrase pair, then

   \[ X \rightarrow (G(\tilde{s}), \tilde{t}) \]

   is a rule of \( P \).

2. If \( X \rightarrow (\gamma, \alpha) \) is a rule of \( P \) and \( (G(\tilde{s}_1), \tilde{t}_1) \) is a subgraph–phrase pair such that \( \gamma = G(\tilde{s}_1 \oplus \tilde{s}_2) \) and \( \alpha = r_1 \tilde{t}_2 \), then

   \[ X \rightarrow (G(\tilde{s}_2 \oplus X_{[k]}), r_1 X_{[k]} r_2) \]

   is a rule of \( P \), where \( k \) is a unique index for a pair of non-terminal symbols.

All GramGBMT rules can be automatically learned from word-aligned graph–string pairs. A rule extractor firstly extracts rules without non-terminals which will be subsequently used to produce recursive rules by replacing subgraph-phrase pairs inside them with non-terminals. The extraction algorithm is similar to the one in the HPB model, except that we handle source subgraphs which have structures and may
2010 FIFA World Cup was held successfully in South Africa

Extracted rule: $X \rightarrow (X_{[1]} \text{ zai Nanfei } X_{[2]} , X_{[3]} X_{[4]} \text{ in South Africa})$

Figure 16: Illustrating the extraction of a translation rule in GramGBMT by replacing subsequences in grey with non-terminals. Indexes on non-terminals indicate mappings. Solid lines are phrase alignment while dashed lines are word alignment.

cover discontinuous phrases. Figure 16 illustrates how to extract a rule containing non-terminals. As in the HPB model, restrictions are added to the rule extractor to avoid generating a large volume of rules, namely:

1. The length of subgraph-phrase pairs on both sides is limited to 10 at maximum.
2. The number of symbols on the source side of a rule is limited to 5.
3. Rules can have at most two non-terminals.
4. There is at least one pair of aligned words in a rule.

In addition to the translation rules above, two glue rules (Chiang 2005, 2007) are used for robustness:

$$S \rightarrow (S_{[1]} X_{[2]} , S_{[1]} X_{[2]} )$$  \hspace{1cm} (8)
$$S \rightarrow (X_{[1]} , X_{[1]} )$$ \hspace{1cm} (9)

Glue rules segment a graph into a sequence of subgraphs which will be translated separately, and then their translations are combined without reordering. They work similarly to glue rules in the HPB model. With the help of glue rules, we can make sure to obtain at least one translation of any input graph.

5.3 Model and Features

We define our model in the log-linear framework over a derivation $d = r_1 r_2 \cdots r_N$, as in Equation (4). In our experiments, we use the standard 8 features in the HPB model:

- Two translation probabilities $p(G(s)|t)$ and $p(t|G(s))$;
- Two lexical translation probabilities $p_{\text{lex}}(s|t)$ and $p_{\text{lex}}(t|s)$;
• A language model $p(t)$ over a translation $t$;
• A rule penalty $\exp(-n)$ where $n$ is the number of non-glue rules;
• A word penalty $\exp(-|t|)$;
• A glue rule penalty $\exp(-m)$ where $m$ is the number of glue rules;

In addition, we add two new features:

• A distortion penalty $\exp(-d(\cdot))$ as defined in Equation (5) when glue rules are used;
• A gap penalty $\exp(-g(d))$ where $g(d)$ is the total number of gaps introduced by non-glue rules in the derivation $d$.

Assuming a rule $r = (\gamma, \alpha)$ translates a subsequence $\hat{s}$ by replacing non-terminals with translations of smaller subsequences $\hat{s}_1, \cdots, \hat{s}_k$, the number of gaps introduced by the rule can be calculated by Equation (10).

$$g(r) = (\hat{s}^e - \hat{s}^b + 1) - |\{s_i | s_i \in \gamma \text{ or } \exists j : i \in [\hat{s}_j^b, \hat{s}_j^e]\}|$$  \hspace{1cm} (10)

Equation (10) is a subtraction of two values. The first value is the span length of $\hat{s}$ while the second value is the number of words which are considered by the current rule or by the gap penalty from previous rules. For example, given a rule which covers $\hat{s} = s_1s_2s_3s_5s_8$ and has two non-terminals covering $\hat{s}_1 = s_1s_3$ and $\hat{s}_2 = s_2s_5$, respectively:

$s = s_1s_2s_3s_4s_5s_6s_7s_8$
$\hat{s} = s_1s_2s_3s_5s_8$
$\hat{s}_1 = s_1s_3$
$\hat{s}_2 = s_2s_5$

According to Equation (10), the span length of $\hat{s}$ is $8 - 1 + 1 = 8$, while the number of words covered is $|\{s_1s_2s_3s_4s_5s_8\}| = 6$. Therefore, the number of gaps introduced by the rules is $8 - 6 = 2$.

5.4 Decoding

Similar to the SegGBMT, during decoding, the GramGBMT model searches for the best derivation $\hat{d}$ whose source yield $f(\hat{d})$ corresponds to $G(s)$ and target yield $e(\hat{d})$ is a target sentence $\hat{t}$. Figure 17 shows a derivation which parses a Chinese DBG and simultaneously generates an English string. When a rule is applied, a subgraph in the source graph is replaced by a non-terminal node, and a new hypothesis is generated. Non-terminals in the target string of the rule are replaced by previous hypotheses.

In this section, following Chiang (2007), we present the decoding procedure for GramGBMT as a deductive proof system (Shieber, Schabes, and Pereira 1995; Goodman 1999) which consists of (i) a set of weighted items $I : w$ containing axioms and goals, and (ii) a set of inference rules of the form:

$$\frac{I_1 : w_1 \cdots I_k : w_k}{I : w} \Phi$$
where items $I_i$ are antecedents with weights $w_i$, the item $I$ is a consequence with a weight $w$, and $\Phi$ is a side condition. The inference rule means that given all proven items $I_i : w_i$ and the side condition $\Phi$, we can derive $I : w$. Axioms are consequences without antecedents while goals are items which will cause the inference process to stop once proven.

Similar to the HPB model, items in our deductive system can take one of two forms:

- $[X, \hat{s}]$ denoting that a subgraph or a sequence of subgraphs with a non-terminal $X$ and covering $\hat{s}$ have already been recognized;
- $X \rightarrow \gamma$ if $(X \rightarrow \langle\gamma, \alpha\rangle)$ belongs to the SNRG (Goodman 1999; Chiang 2007).
Note that we simply use the covered subsequence \( \tilde{s} \) to represent a subgraph \( G(\tilde{s}) \) or a sequence of subgraphs \( G(\tilde{s}_1) \cdots G(\tilde{s}_n) \) where \( \tilde{s} = \tilde{s}_1 \oplus \cdots \oplus \tilde{s}_n \). The sequence of subgraphs exists because glue rules combine subgraphs which may be disconnected. For simplicity, we use \( G(\tilde{s}) \) to denote a sequence of subgraphs covering \( \tilde{s} \). Clearly, \( G(\tilde{s}) = G(\tilde{s}) \) when \( G(\tilde{s}) \) exists.

The inference process in the deductive system starts from axioms in the form of (11):

\[
X \rightarrow \gamma : w \quad (X \xrightarrow{w} (\gamma, \alpha)) \in \text{SNRG} \tag{11}
\]

Each rule in GramGBMT with a weight \( w \), including glue rules, is an axiom. The goal item in the system is \([S, \tilde{s}]\) which means that we have already recognized the source graph covering \( \tilde{s} \). Given the axioms, our decoder can derive new weighted items in three ways:

- If a rule consists of only terminals, we can use the following inference rule

\[
\frac{X \rightarrow G(\tilde{s}) : w}{[X, \tilde{s}] : w} \tag{12}
\]

to generate a new item \([X, \tilde{s}]\) with a weight \( w \).

- Given a rule containing only one non-terminal \( X \), if the deductive system has recognized a subsequence \( \tilde{s}_3 \) covered by the non-terminal, then we use the following rule to create a new weighted item:

\[
\frac{Z \rightarrow G(\tilde{s}_1 \oplus X \oplus \tilde{s}_2) : w_1}{[Z, \tilde{s}_1 \oplus \tilde{s}_2 \oplus \tilde{s}_3] : w_1 w_2} \tag{13}
\]

- Finally, if we have a rule which contains two non-terminals, each of which has been recognized, we can use the following rule to derive a new weighted item.

\[
\frac{Z \rightarrow G(\tilde{s}_1 \oplus X \oplus \tilde{s}_2 \oplus Y \oplus \tilde{s}_3) : w_1}{[Z, \tilde{s}_1 \oplus \tilde{s}_2 \oplus \tilde{s}_4 \oplus \tilde{s}_5 \oplus \tilde{s}_3] : w_1 w_2 w_3} \tag{14}
\]

Note that different from rule (13), rule (14) uses the notion of \( G(\tilde{s}) \). This is because disconnectivity may appear only when glue rules are used to combine two subgraphs each of which has been recognized.

Inspired by the conventional chart decoder for SCFGs, ideally, proven items should be organized into a chart (Chiang 2007) where each cell \( \text{chart}[X, \tilde{s}] \) consists of a set of items which have the same non-terminals and cover the same subsequences. However, because the number of subsequences in a sentences \( s \) is exponential to the sentence length \( |s| \), the chart would contain \( 2^{|s|} \) cells, which results in exponential time and space complexity so will not work in practice. Since the high complexity is caused by the exponential number of subsequences, to efficiently decode source graphs, we will add some restrictions so that the number of allowed subsequences can be reduced to be polynomial or even linear to sentence length.
Algorithm 2 Beam-search decoder for GramGBMT

1: for all rules $X \rightarrow \langle \gamma, \alpha \rangle$ do
2:   add $(X \rightarrow \gamma)$ to Axiom
3: for $l = 1$ to $|s|$ do
4:   if $l \leq L_{\text{max}}$ then
5:     for all items $[X, \bar{s}]$ : w s.t. $|\bar{s}| = l$ inferable from Axiom and chart do
6:       add $[X, \bar{s}]$ to $B[X, l]$
7:       recombine and prune if applicable
8:   for all items $[S, \bar{s}]$ : w s.t. $|\bar{s}| = l$ inferable from Axiom and chart do
9:     add $[S, \bar{s}]$ to $B[S, l]$
10:    recombine and prune if applicable
11:   for all items $[x, \bar{s}] \in B[x, l]$ s.t. $x \in \{X, S\}$ do
12:     add $[x, \bar{s}]$ to chart

5.4.1 Beam-Search Decoder. The first decoder we build is based on beam search inspired by the decoder in Section 4.4. This means that hypotheses which cover the same number of source words and have the same non-terminals are organized into the same stack. The difference is that the decoder in GramGBMT generates translations in a bottom-up manner rather than left-to-right. In addition, hypotheses are grouped into different stacks according to their corresponding non-terminals. This is because glue rules (using non-terminals $S$) combine two subgraphs and their translations by ignoring the connectivity of the two subgraphs.

A decoding procedure based on beam search for GramGBMT is shown in Algorithm 2. In the algorithm, proven items are organized into stacks $B[\cdot, \cdot]$, according to the number of covered source words and their non-terminals (Line 6 and Line 9), so that these items can be recomposed and pruned according to their partial translation cost and an estimated future cost (Koehn, Och, and Marcu 2003; Galley and Manning 2010). When the decoder has recognized all subsequences with length $l$, items which are in the same stack are grouped into chart for inferences in the next iteration (Lines 11–12). The translation ends when items which cover the whole sentence are proven. For efficiency and effectiveness, the maximum size of subgraphs is limited to a certain value $L_{\text{max}}$ (20 in our experiments) (Line 4), and the maximum span of a subsequence covered by a subgraph is limited to 20 as well. Therefore, the total number of stacks in this algorithm is $L_{\text{max}} + |s|$. The maximum number of subsequences allowed is reduced from exponential to $(L_{\text{max}} + |s|)b$, where $b$ is the beam width.

5.4.2 Chart Decoder. Although the beam search decoder efficiently reduces the time and space complexity by organizing hypotheses which cover the same number of source words and have the same non-terminals into the same stack, it is known to suffer from search errors (Koehn 2010). Therefore, in this section, we present a chart decoder.

It is easy to see that the large number of subsequences is caused by the free combination of words. Therefore, in our chart decoder, we try to use another restriction: only subgraphs which cover continuous spans are allowed. Items $[X, \bar{s}]$ in the deductive system can then be represented in the form of $[X, i, j]$ where $i$ and $j$ are the start and end positions of $\bar{s}$, respectively. Therefore, items which cover the same phrases will be organized into the same cell. Algorithm 3 shows a decoding procedure where the continuity restriction reduces the complexity of decoding from exponential time to cubic
Algorithm 3 Chart decoder (Chiang 2007) for GramGBMT.

1: for all rules $X \rightarrow \langle \gamma, \alpha \rangle$ do
2: add $(X \rightarrow \gamma)$ to Axiom
3: for $l = 1$ to $|s|$ do
4: for all $i, j : j - i = l$ do
5: if $l \leq g_{\text{max}}$ then
6: for all items $[X, i, j] : w$ inferable from Axiom and chart do
7: add $[X, i, j]$ to chart
8: if $i = 0$ then
9: for all items $[S, i, j] : w$ inferable from Axiom and chart do
10: add $[S, i, j]$ to chart

As in tree-based models. Note that although Algorithm 3 looks the same as the decoding algorithm in HPB (Chiang 2007), the source side $\gamma$ of a rule is a subgraph rather than a sequence. In addition, instead of accessing all continuous spans as in the HPB model, our decoder only accesses spans which are covered by subgraphs.

The continuity restriction also has a significant impact on the rule-extraction algorithm and feature functions. As described in Section 5.2, while recursive rules are being extracted, we need to check whether a subsequence is nested in another subsequence. Time complexity of the checking is linear to the size of subsequences. However, if the continuity restriction is adopted, the checking would be in constant time as we only need to compare their start and end positions. In addition, values of the distortion penalty and gap penalty will always be 0 when the restriction is applied, resulting in 8 active features as in the HPB model.

5.4.3 Language Model Integration and Pruning. Given that the target sides of translation rules are hierarchical phrases, we use the same policy as that in the HPB model (Chiang 2007) to integrate a language model. $k$-best lists are generated using the algorithm in Chiang (2007). To speed up the decoding process, cube pruning (Chiang 2007) is used when the decoder derives new items from proved items.

6. Experiments

In this paper, we conduct large-scale experiments on two language pairs, ZH–EN and DE–EN. The two language pairs have syntactically different word order, and thus recursive rules ought to be more helpful for phrase reordering. We experimented with 9 systems implemented in Moses (Koehn et al. 2007) using the same default configurations:

- **PBMT** and **HPBMT** are phrase-based and HPB models, respectively.
- **SDTU** extends the phrase-based model by allowing source discontinuous phrases (Galley and Manning 2010).
- **TBMT** extends the phrase-based model by using treelets as the basic translation units. Different from (Quirk, Menezes, and Cherry 2005), translations in TBMT are generated from left to right using beam search.
Table 1: ZH–EN and DE–EN corpora. Word counts are averaged across all references.

|        | #Sentences | #Words (ZH) | #Words (EN) |
|--------|------------|-------------|-------------|
| **ZH–EN** |            |             |             |
| Train  | 1.5M+      | 38M+        | ~45M        |
| MT02   | 878        | 22,655      | 26,905      |
| MT04   | 1,597      | 43,719      | 52,705      |
| MT05   | 1,082      | 29,880      | 35,326      |
| **DE–EN** |            |             |             |
| Train  | 2M+        | 52M+        | 55M+        |
| WMT11  | 3,003      | 72,661      | 74,753      |
| WMT12  | 3,003      | 72,603      | 72,988      |
| WMT13  | 3,000      | 63,412      | 64,810      |

- **SegGBMT** is our graph-based model which translates graphs using graph segmentation. When inputs are trees, it is similar to TBMT except that during training TBMT takes all unaligned words on the source side into consideration while SegGBMT only uses unaligned words on boundaries.

- **Dep2Str** is an improved dependency tree-to-string model (Xie, Mi, and Liu 2011) which handles non-syntactic phrases by decomposing dependency structures (Li et al. 2014).

- **GramGBMT_b** is our SNRG-based model with a beam-search decoder.

- **GramGBMT_c** is our SNRG-based model with a chart decoder.

- **SERG** is a SERG-based model which translates an edge-labeled dependency structure (**DEG** for short) into a target string (Li, Way, and Liu 2015). The system SERG is similar to GramGBMT_chart when DSGs are used as inputs except that SERG uses edge-labeled graphs. By default, we only use the general non-terminal $X$ on both source and target sides.

While PBMT, TBMT, SDTU and SegGBMT are segmentation-based models$^1$, HPBMT, Dep2Str, SERG and GramGBMT$_c$ use synchronous grammars. All of these systems are implemented in Moses with the same settings to enable fair comparisons. The number of hypotheses in a stack, i.e. beam width, is always limited to 200 in all systems.

### 6.1 Data Sets and Experimental Setup

Table 1 provides a summary of our corpora. The ZH–EN training corpus is from the LDC data, including LDC2002E18, LDC2003E07, LDC2003E14, LDC2004T07, the Hansards portion of LDC2004T08, and LDC2005T06. NIST 2002 (MT02) is taken as a development set to tune weights while NIST 2004 (MT04) and NIST 2005 (MT05) are used as test sets to evaluate systems. The Stanford Chinese word segmenter

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$^1$ It is well known that lexical reordering models (LRMs) can significantly improve phrase-based systems. However, according to Galley and Manning (2010), the overall improvement brought by an LRM on both phrase-based and DTU systems is similar. The results in Table 4.7 in the PhD thesis of Li (2017) also show similar improvement by incorporating an LRM into SegGBMT. Therefore, we presume the observation also applies to this article and did not conduct experiments on LRMs.
Table 2: BLEU scores of all systems on all test sets. * means a system is significantly better than PBMT at \( p \leq 0.01 \). + means a system is significantly better than HPBMT at \( p \leq 0.01 \).

| System       | Graph | #Rules     | ZH–EN MT04 | ZH–EN MT05 | DE–EN WMT12 | DE–EN WMT13 |
|--------------|-------|------------|-----------|-----------|-------------|-------------|
| PBMT         |       | 69M/107M   | 33.2      | 31.8      | 19.5        | 21.9        |
| TBMT         |       | 122M/151M  | 33.8*     | 31.4      | 19.6        | 22.2*       |
| SDTU         | Tree  | 224M/352M  | 34.7*     | 32.6*     | 19.7*       | 22.4*       |
| SegGBMT      | DSG   | 42M/73M    | 32.1      | 30.9      | 18.1        | 20.4        |
|              | DBG   | 122M/151M  | 33.8*     | 31.4*     | 19.6*       | 22.2*       |
| SegGBMT      | Tree  | 224M/352M  | 34.7*     | 32.6*     | 19.7*       | 22.4*       |
| SegGBMT      | DSG   | 42M/73M    | 32.1      | 30.9      | 18.1        | 20.4        |
| SegGBMT      | DBG   | 122M/151M  | 33.8*     | 31.4*     | 19.6*       | 22.2*       |

(Chang, Galley, and Manning 2008) is used to segment Chinese sentences into words. The Stanford dependency parser (Chang et al. 2009) parses a Chinese sentence into a projective dependency tree.

The DE–EN training corpus is from WMT 2014, including Europarl V7 (Koehn 2005) and News Commentary. News-Test 2011 (WMT11) is taken as a development set while News-Test 2012 (WMT12) and News-Test 2013 (WMT13) are our test sets. We tokenize German sentences with scripts in Moses and use mate-tools to perform morphological analysis and parse the sentences (Bohnet 2010). Then, MaltParser converts the parse results into projective dependency trees (Nivre and Nilsson 2005).

Word alignment is performed by GIZA++ (Och and Ney 2003) with the heuristic function \texttt{grow-diag-final-and} (Koehn et al. 2005). We use SRILM (Stolcke 2002) to train a 5-gram language model on the Xinhua portion of the English Gigaword corpus 5th edition with modified Kneser-Ney discounting (Chen and Goodman 1996). Batch MIRA (Cherry and Foster 2012) is used to tune weights with a maximum iteration of 25. We report BLEU scores (Papineni et al. 2002) and significance averaged over three MIRA runs (Clark et al. 2011).

6.2 Evaluation of Translation Quality

Table 2 shows BLEU scores of all systems on all test sets. We found that while on average TBMT is comparable with PBMT, SDTU is significantly better than PBMT (+1.2
Li et al. Dependency Graph-to-String Translation

Ref: The American government said that it has nothing to do with the American delegation to visit North Korea

PBMT: The government has said that the United States and North Korea delegation has visited the United States

SegGBMT: The United States has indicated that it has nothing to do with the US delegation visited North Korea

Figure 18: Examples of translations from SegGBMT and PBMT. SegGBMT successfully translated a Chinese collocation (underlined) into a target phrase. PBMT failed to capture this generalization because it only uses continuous phrases.

Figure 18 shows examples of translations where SegGBMT successfully translated a Chinese collocation Yu...WuGuan into has nothing to do with. By contrast, PBMT failed to catch the generalization since it only considers continuous phrases. Figure 19 shows examples of translations where TBMT translated a discontinuous phrase Dui...Zuofa only to one word on and therefore an important target word practice was dropped. By contrast, bigram relations allowed our system SegGBMT to translate a more proper phrase De Zuofa to practice of.

Compared with PBMT, HPBMT is significantly better (+2.9 BLEU on ZH–EN and +1.1 on DE–EN on average) because of its capability of phrase reordering by using synchronous grammars. Both Dep2Str and SERG are significantly better than HPBMT...
The us government has expressed their resentment against practice of brazil on many occasions

Ref: The us government has repeatedly expressed dissatisfaction with the practice of brazil

Treelet: The us government on many occasions brazil expressed dissatisfaction

SegGBMT: The us government has expressed their resentment against practice of brazil on many occasions

Figure 19: Examples of translations from SegGBMT and TBMT. By using bigram links, SegGBMT successfully translated the underlined continuous phrase which is not connected in the dependency tree.

on ZH–EN (+0.4 BLEU on average in terms of SERG) but worse on DE–EN (-0.3 BLEU on average in terms of SERG). We found that on DE–EN the number of rules in the two systems is dramatically reduced from 684M to around 95M, whereas the reduction on ZH–EN is less significant (from 388M to 84M/131M). This means that the two systems use more strict restriction on dependency trees when extracting rules on DE–EN. However, the fact that the two systems uses significantly fewer rules than HPBMT also suggests that linguistic structures are helpful in reducing model size.

Although GramGBMT_b is better than SegGBMT (+0.4 BLEU on ZH–EN and +0.4 on DE–EN on average when DSG is used), it is significantly worse than HPBMT (-1.6 BLEU on ZH–EN and -0.2 on DE–EN on average when DSG is used). We presume that this is mainly because GramGBMT_b uses beam search to reduce its search space where better hypotheses could be wrongly pruned. However, GramGBMT_b is a meaningful trial towards a more general graph-based translation system as it allows hypotheses covering discontinuous source phrases when decoding using synchronous grammars.

Profoundly, GramGBMT_c outperforms HPBMT when graphs are used (+0.3 BLEU on ZH–EN and +0.3 on DE–EN on average when DSG is used). GramGBMT_c with tree inputs is comparable with HPBMT on both language pairs. This suggests that dependency trees effectively reduces model size without degrading translation quality when non-terminal rules are allowed. Compared with tree inputs, DSGs and DBGs bring consistently improvement as they introduce many more rules. We also found that in both GramGBMT_b and GramGBMT_c, while DBGs achieves the best performance on ZH–EN, DSGs are better on DE–EN. This may be caused by the fact that Chinese sentences have a larger mean dependency distance than German sentences (Eppler 2013) resulting sibling links less effective than bigram links on ZH–EN.

When structure information is added to rules, one concern is about the data sparsity issue, i.e., a single rule is refined into multiple rules with different structures. However, by comparing the number of rules extracted by HPBMT and GramGBMT_c (with DBGs as inputs), we found the increase in the number of rules brought by graph structures is very small (specifically 6.96% on ZH–EN and 8.19% on DE–EN). In terms of SegGBMT with DBGs as inputs, after excluding rules with discontinuous phrases (around
30%), the number of rules approximates to that in PBMT. This means our methods do not cause severe issues of data sparsity.

6.3 Time Complexity of Decoding

Decoding procedures implemented in segmentation-based models follow the beam search algorithm used in the phrase-based model. The decoder goes over each beam stack which stores hypotheses covering a specific number of source words. Each hypothesis in the beam stack is extended by applying a set of rules matching the input sentence which are usually called translation options and collected before decoding using efficient data structures and algorithms (Koehn 2010; Galley and Manning 2010). Apparently, the time complexity of such a decoding procedure is \( O(|s| \times |B| \times |R_s|) \), where \( |s| \) is the length of an input sentence \( s \), \( |B| \) is the beam width and \( R_s \) is the number of translation options at a given step. In PBMT, the number of translation options is linear to the sentence length as only continuous phrases with a bounded length are allowed. Therefore, the decoding complexity of PBMT can be rewrite as \( O(|s|^2 \times |B|) \). By considering a maximum distortion limit \( d_{\text{max}} \) the complexity can be further reduced to \( O(|s| \times |B| \times d_{\text{max}}) \) because only a limited number of translation options is available at a given step. However, because the number of discontinuous phrases of an input sentence is exponential to the input length, the complexity of SDTU would be \( O(|s| \times |B| \times |s|^{L_{\text{max}}}) \) where \( L_{\text{max}} \) is the maximum phrase length. The complexity can be further reduced to \( O(|s| \times |B| \times C) \), where the constant \( C \propto g_{\text{max}}^{L_{\text{max}}} \times d_{\text{max}} \), by using a maximum span \( g_{\text{max}} \) and the distortion limit. Similar to SDTU, both TBMT and SegGBMT have a time complexity of \( O(|s| \times |B| \times C) \), however, with a smaller constant value than SDTU. This is because the connectivity constraint on tree and graph structures greatly reduces the number of discontinuous phrases (See the number of rules in Table 2).

Synchronous grammar-based models, such as HPBMT, Dep2Str, SERG and GramGBMTc, in our experiments use the chart decoder as in Algorithm 3. The algorithm maintains a beam stack for each continuous span of a source sentence, and translations of large spans are constructed by combining translations of smaller spans by applying rules with (at most 2 in experiments) non-terminals. The time complexity of the chart decoder is \( O(|s|^2 \times |R_s| \times |B|^2) \). However, because tree structures used by Dep2Str and SERG greatly reduce the number of available spans, the two systems run faster in practice than HPBMT. Compared to HPBMT, GramGBMTc needs additional time spent on matching graph edges, However, the time is a small constant as the number of edges in a subgraph is bounded in our experiments. When trees and DSGs are used as inputs, GramGBMTc runs faster. When DBGs are used as inputs, GramGBMTc takes more time to decode than HPBMT. GramGBMTc uses a beam search decoder described in Algorithm 2 which takes discontinuous source spans into consideration. The algorithm goes over each beam stack and apply rules over each subgraphs with a specific size and span (Section 5.4.1). Therefore, the complexity of decoding is reduced from being exponential to \( O(|s|^2 \times g_{\text{max}}^{L_{\text{max}}} \times |R_s| \times |B|^2) \).

6.4 Influence of Edge Labels

Our graphs combine dependency relations with sequential relations, including bigram relations and sibling relations, to enable non-syntactic phrases. By default, the two kinds of relations are used without distinction. However, it would be interesting to see how edge types impact on translation performance. Therefore, we conducted further exper-
Table 3: Evaluation results when edges are labeled by their relation types: either dependency or sequential. * means a system is significantly better than its counterpart at $p \leq 0.01$.

| System       | Graph | #Rules       | ZH–EN | DE–EN |
|--------------|-------|--------------|-------|-------|
|              |       |              | MT04  | MT05  | WMT12 | WMT13 |
| SegGBMT      | DBG   | 99.2M/153.4M | 34.7  | 32.4  | 20.1  | 22.9  |
| +EdgeLabel   |       | 99.7M/153.8M | 34.7  | 32.7* | 20.1  | 22.9  |
| GramGBMT$_c$ | DSG   | 157M/241M    | 36.9  | 34.5  | 20.7  | 23.4  |
| +EdgeLabel   |       | 160M/243M    | 36.7  | 34.7  | 20.6  | 23.3  |

Table 4: Evaluation results when linguistic non-terminals are used (denoted as +POS). * means a system is significantly better than its counterpart with or without POS tags at $p \leq 0.01$. MGS means minimum size of gaps which can be represented by non-terminals during training.

| System       | Graph | #Rules       | ZH–EN | DE–EN |
|--------------|-------|--------------|-------|-------|
|              |       |              | MT04  | MT05  | WMT12 | WMT13 |
| SERG         | DEG   | 131M/98M     | 36.7  | 34.8  | 20.2  | 22.8  |
| +POS         |       | 153M/180M    | 36.8  | 34.8  | 20.6* | 23.3* |
| GramGBMT$_c$ | DSG   | 157M/241M    | 36.9  | 34.5  | 20.7  | 23.4  |
| +POS         |       | 185M/276M    | 36.8  | 34.6  | 20.7  | 23.4  |

Impacts where graph edges are labeled by link types: either dependency or sequential. Table 3 shows BLEU scores of SegGBMT with DBG inputs and GramGBMT$_c$ with DSG inputs when edge types are taken into consideration (+EdgeLabel). The two systems are chosen because they achieve the best performance among the segmentation-based models and synchronous grammar-based models, respectively.

Results show that edge types do not improve our systems on the two language pairs overall. This is reasonable since we found adding edge labels to rules did not significantly increase the number of rules in our systems, as shown in Table 3. This suggests that when a rule is matched with a subgraph, in most cases edge types are matched as well.

6.5 Influence of Linguistic Non-terminals

Similar to HPBMT, by default in our synchronous grammar-based models, we only use a general non-terminal symbol $X$ on both source and target sides. In this section, we
conducted experiments to examine the impact of non-terminals on our models. The source non-terminal \( X \) is replaced by non-terminals based on POS tags, which can be easily obtained as a by-product of dependency parsing.

The definition of a linguistic non-terminal for a subgraph follows Li et al. (2012) and Li, Way, and Liu (2015). When a subgraph is connected by dependency relations, there must be one and only one node whose dependency head is not in the subgraph. We then denote the node as a head of the subgraph and simply use its POS tag as a non-terminal to represent the subgraph. For example, the head of Figure 6b is \( zai \) whose POS tag is \( P \), so the non-terminal for Figure 6b is \( P \). When a subgraph is disconnected and thus has two or more heads, we use a joint POS tag of these heads as a non-terminal. For example, because the heads of Figure 6e are \( shijiebei \) and \( zai \), the non-terminal for the subgraph is \( NT_P \), where \( NT \) and \( P \) are POS tags of the two heads, respectively.

By default, during training each non-terminal covers at least two source words, i.e., the minimum size of gaps is 2 (denoted as MGS=2). This setting significantly reduces the number of non-terminals which are POS tags of single words and may influence translation performance. Therefore, we conducted two groups of experiments with MGS=2 and MGS=1, respectively.

Table 4 shows BLEU scores of systems when linguistic non-terminals are used. We found that when MGS=2, linguistic non-terminals have no significant impact on translation performance of systems except SERG on DE–EN. When MGS=1, we first found that both SERG and GramGBMTc are improved compared to their counterpart with MGS=2 (e.g., +0.3 BLEU on ZH–EN and +0.1 on DE–EN on average in terms of GramGBMTc). This may be caused by that more rules are extracted when MGS=1. In addition, when MGS=1, POS tags have more significant influence, especially on ZH–EN (+0.8 BLEU on average on both systems). Because MGS=1 means more rules with single POS tags as non-terminals are included, this suggests that these non-terminals are more useful on ZH–EN.

7. Conclusion

In this paper, we present novel graph-based translation models which translate source graphs into target strings. Graphs are built on top of dependency trees with extra links added to make non-syntactic phrases connected. The first model we introduce is based on graph segmentation which segments a graph into a sequence of subgraphs and generates translations by combining subgraph translations. Because the model is weak at phrase reordering, we further present a model based on a synchronous node replacement grammar to learn recursive translation rules. Experiments on Chinese–English and German–English show that our graph-based models significantly outperformed sequence- and tree-based baselines. We also found that edge labels have no significant impact on translation performance.

In future work, we would like to consider using other kinds of graphs, such as graphs representing feature structures which have proven to be a powerful tool for modeling morpho-syntactic aspects of natural languages (Graham 2011; Williams 2014) and investigate the impact of parsers’ accuracy on translation quality when graphs are used. Recent progress on neural networks shows a promising way to perform MT with less feature engineering effort (Cho et al. 2014; Bahdanau, Cho, and Bengio 2015). However, how to use graphs in neural MT models is still an open problem. Therefore, we did not compare our models with neural models in this paper as we mainly focus on examining the effectiveness of graphs in MT. In future, it would be interesting to explore how these kinds of graphs can be used in neural MT and how they impact on
its translation performance. It would also be interesting to try our methods on more experimental settings, such as low resource translation which is more challenging for neural MT than SMT (Koehn and Knowles 2017) and would strength our methods.

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