Massive-scale Decoding for Text Generation using Lattices

Jiacheng Xu and Greg Durrett
Department of Computer Science
The University of Texas at Austin
{jcxu, gdurrett}@cs.utexas.edu

Abstract

Neural text generation models like those used for summarization and translation generate high-quality outputs, but often concentrate around a mode when what we really want is a diverse set of options. We present a search algorithm to construct lattices encoding a massive number of generation options. First, we restructure decoding as a best-first search, which explores the space differently than beam search and improves efficiency by avoiding pruning paths. Second, we revisit the idea of hypothesis recombination: we can identify pairs of similar generation candidates during search and merge them as an approximation. On both document summarization and machine translation, we show that our algorithm encodes hundreds to thousands of diverse options that remain grammatical and high-quality into one linear-sized lattice. This algorithm provides a foundation for building downstream generation applications on top of massive-scale diverse outputs.

1 Introduction

Although pre-trained text generation models (Lewis et al., 2020; Raffel et al., 2020) have achieved impressive results across a range of tasks, these models do not always deliver what system developers want. Machine generated text may be non-factual (Kryscinski et al., 2020; Maynez et al., 2020; Goyal and Durrett, 2021) or toxic (Gehman et al., 2020). We might patch these problems by applying discriminators over the output (Holtzman et al., 2018; Yang and Klein, 2021) to enforce these properties post-hoc; we could, for instance, apply a secondary model as a reranker over a small collection of outputs. However, if the generator returns a homogeneous set of outputs, we may fail to find any usable generation output.

What if generation models could return massive numbers of candidates rather than a few outputs with optimal score? With a large set of candidates, our secondary model could more easily find an acceptable one without having to take more extreme steps like re-training the initial generation model. Output diversity has separately been established as a useful goal for applications such as dialogue and story generation (Li et al., 2016; Fan et al., 2019; Cao and Wang, 2021).

Standard approaches including beam search (BS) and sampling methods fall short of our goal. Beam search uses significant computational resources to explore similar hypotheses, and much of the computation in the search process is invested into paths that could be acceptable generation outputs, but are ultimately pruned; we explore these issues in Section 3. Sampling approaches like nucleus sampling (Holtzman et al., 2020), although achieving better diversity than beam search, often re-discover seen hypotheses and can be harder to control for quality. A central problem with both methods is that they do not handle very similar hypotheses efficiently.

In this paper, we present a decoding framework with two key components. First, we argue that a modified best-first search (BFS) is the right way to explore the search space. We augment standard
best-first search with an ad-hoc path completion strategy: we eagerly expand each node until we reach an EOS token, thereby guaranteeing that each node is part of some completed path returned to the user. This generation strategy avoids exploring large numbers of states which end up being pruned. BFs is also more flexible than static beam search and can prioritize exploration in more uncertain parts of the generation.

Second, our algorithm returns a massive number of generation options encoded in a lattice, with different hypotheses recombined in an approximate fashion. Recombination is a technique where similar decoder hypotheses are merged in the search. In Figure 1, we show an illustration of the lattice structure this recombination can form for document summarization. “A Cardiff recycling company has gone into” and “A Cardiff waste management company has gone into” are preserved as different states in beam search, but actually have very similar distributions of following words under the model. If we can heuristically identify such states, we can merge them (Figure 2) and assume that any high-scoring continuation of one hypothesis can continue the other. We broaden a recombination method used previously in beam search for machine translation (Och et al., 2001; Zhang et al., 2018), enabling us to compactly encode large number of generation candidates (Buckman and Neubig, 2018) and achieve dense lattices as shown in Figure 1.

We show results for both document summarization and machine translation in three language pairs. For each setting, we show that our lattice encodes a large number of high-quality candidates, including good matches with annotated reference generations. We further show that a variant of our method can still achieve strong results with a lower number of nodes expanded than the baselines, suggesting that this can be a path towards saving computational resources. We believe that computing thousands of high-quality generation candidates within a single compact data structure can provide a powerful starting point for various downstream purposes: diversity, factuality, customizability, and more.

2 Problem & Setup

We define our algorithm in the context of conditional text generation (Sutskever et al., 2014; Bahdanau et al., 2014). Conditional text generation is formulated as sequence transformation from a source input \( x \) to target output \( y = (y_1, \ldots, y_n) \) via a neural text generation model \( \theta \). Each \( y_i \) is a symbol in a vocabulary \( \mathcal{V} \). The probability of a decoded sequence is \( p(y \mid x; \theta) = \prod_{t=1}^{n} p(y_t \mid y_{<t}, x; \theta) \). Decoding text from a model can be framed as a search problem, where the search objective is to find the output sequence that maximizes the conditional probability under the model:

\[
\arg \max_{\hat{y}} p(\hat{y} \mid x; \theta). 
\]

Because \( p(\hat{y}_t \mid \hat{y}_{<t}, x; \theta) \) depends on the entire generated sequence, this decoding problem is intractable to solve exactly.

While typically the goal of decoding is to find the hypothesis with the highest possible model score, we instead focus on finding a large set of “good enough” hypotheses. That is, finding a set \( \mathcal{Y} \):

\[
\arg \max_{\mathcal{Y}} \quad \text{s.t. } p(y \mid x; \theta) > \epsilon \quad \text{for all } y \in \mathcal{Y} \quad (1)
\]

for some threshold \( \epsilon \). \( \epsilon \) emerges naturally by adjusting search hyperparameters to control the number of returned hypotheses. Our goal in this paper is to design an algorithm that can efficiently find \( \mathcal{Y} \).

2.1 Notation

We encode predicted generation candidates \( \hat{y} \) in a lattice. A lattice \( L = (N, E) \) is a directed graph where each node represent a word token and paths defined by directed edges encode candidates. A path \( \pi \) in \( L \) from \( n_{\text{sos}} \) to any node \( n \) represents a (partially) decoded string, consisting of the words in that path. All completed paths start with a single start-of-sequence node \( n_{\text{sos}} \) and end at (potentially different) end-of-sequence nodes \( n_{\text{eos}} \). In beam search or sampling, \( L \) is strictly a tree, where each node has exactly one parent. However, our
constructed lattices are no longer trees due to the recombination mechanism, which we will discuss in Sec. 5.

**Search Graph** $L$ is constructed iteratively through a search procedure. We maintain the closed graph $C$ with explored nodes and edges as well as a search frontier $O$, a set consisting of successors to nodes currently in the graph. For each node, there are $|V|$ possible successors.

We define the **search budget** as the number of nodes expanded from the search frontier. Our experiments will seek to compare different methods using the same search budget. We will define this more precisely in Sec. 7.

### 2.2 Baselines

We consider two categories of decoding methods as the baselines: beam search based and sampling based. Beam search is widely used to find near optimal solutions in NLP (Tillmann and Ney, 2003; Meister et al., 2020a). We consider two variants, original beam search (BS) and diverse beam search (DBS), an improved version targeting diverse text generation (Vijayakumar et al., 2016). Some implementation details of beam search are described in Appendix A. Sampling-based decoding methods involve randomness and construct candidates by sampling from the next-token distribution rather than maximizing. Methods like temperature annealing (TEMP) (Ficler and Goldberg, 2017), top-$k$ sampling (Fan et al., 2018) and nucleus sampling (NCLS) (Holtzman et al., 2020) are also widely used to find high-quality text from models. We compare with BS, DBS, NCLS, and TEMP in our experiments.

### 3 Inadequacies of Beam Search

As we have alluded to, beam search is inadequate for our goal for several reasons.

**Better Model Score ≠ Better Hypothesis** The most critical issue is that beam search is designed to efficiently approximate $\arg \max \hat{y} = p(\hat{y} \mid x; \theta)$, but the optimal model score is neither our goal nor a guarantee of a good hypothesis. In Figure 3, we compare the correlation of model score and ROUGE under beam search for text summarization. The Pearson correlation between these two variables is very weak. Beyond ROUGE score, the example in Fig. 1 shows that the main differences between these summaries may be minor differences in surface realization that have little effect on our qualitative judgments of summary quality. **Finding the best model score does not substantially improve the quality over a near-optimal model score.** Allocating resources to eke out slight improvements over the greedy hypothesis, as beam search does, is a poor use of resources for most applications.

**Lack of Diversity in (Diverse) Beam Search** Are the model outputs from BS and DBS diverse? We use Self-BLEU (sBL) (Zhu et al., 2018) to measure the BLEU score for randomly sampled pairs from each algorithm’s output. The lower the self-BLEU, the more dissimilar the pairs are. On decoding summaries on XSum, the sBL for BS/DBS are 87/79 while a nucleus sampling method can achieve 57/50 depending on configuration. Although DBS slightly improves the diversity compared to the original variant, the overlap of outputs from beam search based method is
Table 1: Pruning ratio of BS and DBS on different tasks and datasets with beam size \( k \). We report the average percentage of explored nodes getting pruned and not appearing in a finished hypothesis.

| \( D \) | k | XSum | zh-en | fr-en | en-fr |
|-------|----|------|------|------|------|
| BS    | 16 | 71.3%| 63.3%| 54.0%| 59.2%|
| DBS   | 71.2%| 56.1%| 50.4%| 55.7%|

still very high, and the diversity remains a challenge.

Poor Scaling Behavior  In spite of these shortcomings, perhaps beam search could still be viable with larger beam sizes if more computational resources are available. We experiment with beam sizes of \( 2^{4,5,6,7} \) and see how diversity scales with beam size. In Figure 4, we found that the exponential increase of beam size does not scale with the increase of number of novel bigram in beam search. In DBS, the diversity does ramp up, but the quality of the generated text is getting very bad very soon. For BS and DBS, increasing beam size is not an effective solution for better diversity. We also show that increasing beam size does not scale well in terms of finding better hypotheses, which is shown in Appendix B.

Poor Efficiency from Pruning  One final issue with beam search is that most of its computation is not even useful in producing finished hypotheses; that is, the set \( \mathcal{V} \) of answers produced does not contain most of the nodes expanded in the typical course of operation. We conduct an empirical pruning study on a summarization dataset and three translation datasets and show the results in Table 1. For all studied cases, beam search and diverse beam search prunes over half of the expanded nodes. Many pruned hypotheses are not truly ungrammatical or low quality, but are merely slightly less likely than other nodes. How we can preserve more of the explored lattice and do so efficiently is addressed in the next section by our use of best-first search.

4 Best-first Search

As established in the previous section, beam search prunes many paths that would potentially yield high-quality summaries and wastes computational resources expanding nodes that aren’t included in a final search graph. We tackle this issue by changing from beam search to best-first search (BFS) (Hart et al., 1968; Pearl, 1984). BFS prioritizes searching over nodes according to a scoring function, giving us more flexibility in how we explore the space. Our chief modification of the base algorithm is a heuristic called ad-hoc completion.

Ad-Hoc Path Completion  Neural text generation is a search problem with large branching factor (\( \mathcal{V} \)) and deep search depth (sequence length). As a result, applying BFS with the scoring function being the model score of a state often leads to a broad search that rarely returns a valid path. One solution to this problem is to incorporate a heuristic based on length. Model score is monotonically decreasing as a sequence grows in length, so prior work (Wu et al., 2016; Zhang et al., 2018; Meister et al., 2020b) has used a length reward term to alleviate this issue.\(^2\) We found that, even with a length heuristic, BFS will still have “dangling” nodes that are not part of any path to an EOS (goal) token, and in some cases it will return few or no valid hypotheses.

Recognizing our objective from Equation 1, we can take a simple step to ensure that every node ends up on some completed path: eagerly do a greedy “rollout” from each node until we reach \( n_{eos} \). In Algorithm 1, we implement this by modifying the priority of the highest scored token with \( \infty \) (line 12), so it will be explored immediately after the current time step. In Figure 5, we show an illustrative example of ad-hoc completion.

Search Algorithm  We describe BFS with ad-hoc completion in Algorithm 1. The algorithm is a slightly modified best-first search algorithm applied to text generation. \( s(\cdot) \) is a function to evaluate the value of a path. Typically it is defined as

\[
s(\cdot) = \sum \log p(y_t \mid y_{<t}).
\]

\( b \) is the budget for total model calls to neural text generation model. Note that \( isRecomb \) and \( doRecomb \) do not invoke neural generation model so they do not count towards the computation budget we defined here. In practice, we only consider top 5 expansions rather than the whole vocabulary \( \mathcal{V} \) for line 10.

5 Path Recombination

Path recombination, also known as hypothesis recombination or state merging, was originally pro-
The idea of path recombination is to combine similar paths if what the model predicts for them in the future is the same, reflecting a similar dynamic programming principle as the Viterbi algorithm. We focus on finding hypotheses which approximately exhibit this property, and show that merging them can yield high-quality outputs. Figure 2 shows an example of recombination. The two hypotheses being merged here roughly convey the same intent; a neural model could prefer one path over the other, but because neural model scoring does not factor over n-grams, no pair of hypotheses will have this property.

5.1 Prerequisites of Recombination

In the strictest form, recombining two hypotheses assumes the following equivalence between them:

**Definition 5.1 (Strong equivalence).** Let \( a \) and \( b \) be two prefix strings starting with \( n_{sos} \). \( a \) and \( b \) are strongly equivalent if \( P(y \mid a) = P(y \mid b) \) holds for all \( y \).

This criterion we can actually check empirically. However, it is still not practical to check during search itself, as it requires expanding a number of nodes. We will define even weaker criteria and show that these can be good proxies for identifying weakly equivalent nodes.

5.2 Canonical Paths

After recombination, a single node may represent multiple different possible sentence prefixes. We define the notion of a canonical path, which represents the single path used to score candidate expansions.

**Type of Edge & Path** If the edge is created due to the extension of search graph via model’s prediction, we call it a GEN edge. Otherwise, the edge is created due to path recombination, and we call it a MKG edge. In Fig 6, the edges in orange are MKG edges.

**Definition 5.3 (Canonical Path).** Let \( n \) be a node. The canonical path to \( n \) is defined as the unique path from \( n_{sos} \) to \( n \) consisting only of GEN edges.
A Cardiff waste company has gone into bankruptcy.

Figure 6: Illustration of two path recombination strategies. We show the input and the recombination output from RCB and ZIP. Orange lines are the merging edges (MERG) built by recombination. Dotted lines and circles are removed components after recombination. The key difference of RCB and ZIP is how much does the recombination propagate, 1 step or n step.

**Theorem 5.1.** For any node \( n \) in the graph except \( n_{\text{sos}} \), there exists exactly one canonical path.

We present the proof in Appendix. C

In the rest of the paper, unless specified, the path of a node \( n \), \( \pi(n) \) returns the sequence of words corresponding to the canonical path of that node. Expanding \( n \) computes \( P(y \mid \pi(n)) \) under the neural model.

### 5.3 Merging Criteria

Strong and weak equivalence are too expensive to establish during inference. We instead rely on even simpler functions to approximate this further. We define a similarity function \( \text{merge}(h, \hat{h}) \) to determine if an expanded node \( \hat{h} \) should be merged with an existing expanded node \( h \). Note that to tractably implement the \( iSRecomb \) step of Algorithm 1, we need this check to be very efficient, as it needs to check a node against the entire lattice thus far.

A similar recombination idea was explored in Zhang et al. (2018). Following their work, we explore a family of rule-based heuristics for merging. There are two rules: (1) two strings share a common \( n \)-gram suffix, (2) the length difference of two strings is less than \( \alpha \). Assume that the canonical paths for \( h \) and \( \hat{h} \) are lengths \( l \) and \( \hat{l} \). Then

\[
\text{merge}(h, \hat{h}) = 1 \left[ \pi(h)_{l-n+1, \ldots, l} = \pi(\hat{h})_{\hat{l}-n+1, \ldots, \hat{l}} \right] \\
\wedge |l - \hat{l}| < \alpha \tag{2}
\]

where \( \alpha \) and \( n \) are hyper-parameters.\(^5\) For a large enough value of \( n \), note that the shared suffixes

\(^5\)In Zhang et al. (2018), there is one extra constraint requiring \( P(h \mid x) < P(\hat{h} \mid x) \) for Eq. 2, which requires that the path getting recombined has lower model score than the existing path. However, we found that model score is not always a good indicator for merging, as suggested in Fig. 3, encourage hypotheses like this in Figure 6 that share large parts of the structure already.

### 6 Implementing Recombination

In this work, we present two path recombination strategies, RCB and ZIP. RCB is a natural generalization of ZBEAM and ZIP is a more aggressive recombination strategy which produces a denser lattice at the cost of potentially introducing more noise. We present an illustration of them in Figure 6.

**RCB: Generalization of ZBEAM** ZBEAM has a major limitation: a limited set of merging candidates. The potential merge candidates in ZBEAM are only nodes in the current beam hypotheses and their previous steps, so the method cannot merge with nodes from earlier timesteps. For example, “A waste plant has gone into” cannot be merged with the hypothesis with ending in node 4 shown in Figure 6. The proposed generalization, RCB, addresses this limitation. We index all of the nodes in the lattice across all timesteps by their \( n \)-grams using a hash table, making it \( O(1) \) time to look up an \( n \)-gram pattern and retrieve potential merge candidates if they exist.

**ZIP: Recombining More** If we take a closer look at RCB in Figure 6, we see that even in the merged structure, nodes 3 and 7 and nodes 2 and 6 are preserved as separate. They do not pass the recombination criterion themselves, but these nodes are part of the suffix matched strings, still correspond to the same words, and have the same directly generated next word. There is reason to partially because it is challenging to calibrate scores across different sequence lengths, so we disregard this constraint.
believe that these might be equivalent as well.

Hence, we explore a variant called ZIP that propagates the merge backwards through the lattice. This change relaxes the merging criterion and potentially up to \( n \) pairs of nodes are combined when a merge is identified, leading to a more compact lattice. We describe some of the implementation detail in the Appendix D.

**Methods with Path Recombination** We implement path recombination on two of our baseline methods: beam search and nucleus sampling. For beam search, we implement BSZBEAM following Zhang et al. (2018). Due to the flaws of beam search as discussed earlier and the inherent complexity, we do not integrate RCB and ZIP with beam search. We integrate RCB with nucleus sampling, and they are denoted as NCLS\(_{0.8}\)RCB and NCLS\(_{0.9}\)RCB. Finally, we use both merging variants in best-first search, yielding BFSRCB and BFSZIP, respectively.

### 7 Evaluation

To evaluate the proposed methods, we conduct experiments on two conditional text generation tasks: abstractive text summarization and machine translation. Our evaluation focuses on two questions: (1) how large and diverse are our lattices; (2) are the candidates encoded in the lattices high quality and grammatical?

#### 7.1 Datasets & Base Models

We obtain all the models and certain baseline decoding methods from the Transformers library (Wolf et al., 2020). Since our methods are inference techniques with rule based heuristics, we do not re-train any models.

**Summarization** We use XSum (Narayan et al., 2018), a popular English news summarization dataset. We sample 100 examples from the validation set. The base model we use is BART-large-XSum (Lewis et al., 2020). We set the max length to 35 tokens according to the reference summaries.

**Machine Translation** We study our models on the English-French (en-fr) pairs from WMT 2014 (Bojar et al., 2014) and Chinese-to-English (zh-en) pair from WMT 2019 (Barrault et al., 2019). We use mBART (Liu et al., 2020), a state-of-the-art neural machine translation model. We set the max decoding length to be twice the input length, so it varies per example.

#### 7.2 Evaluation Details

##### Search Budget

We want to compare our different methods under a similar search budget, or number of nodes expanded. Each node expansion requires running the neural generation model to get a probability distribution over the vocabulary, which is the dominant factor in runtime; we incur negligible overhead from rule-based matching in the merging step, as well as the computational costs of computing diversity term in DBS and modifying sampling distributions in sampling methods.

We define the number of nodes expanded in terms of a quantity we call equivalent beam size. Recall that \( T \) denotes the maximum length of decoded hypotheses for beam search. Let the total computation budget be \( kT \). For beam search based methods, \( k \) is the original beam size and the total budget covers running beam search once with beam size \( k \) and maximum decoding length \( T \). For sampling based methods, \( k \) is the number of independent samples we draw from the model. Each sample is a completed path starting with \( n_{\text{sos}} \) and ending with \( n_{\text{eos}} \). After obtaining \( k \) paths, we merge them into one graph (i.e., a trie) to compactly represent duplicate prefix strings. For best-first search methods, \( kT \) is the total number of nodes explored by the algorithm.

**Enforcing a uniform search budget** Since hypotheses may terminate before they reach EOS, empirically there is a gap between effective length (the average generated hypothesis length) and max length for both beam search and sampling. Beam search can exit out before reaching the maximum hypothesis length if a sufficient number of finished paths are found, but this amounts to dynamically changing the budget for each instance. Running our method with a budget derived from beam search is artificial and not realistic in practice.

Instead, we apply a corpus-level correction factor so that the different methods are expanding the same number of nodes. We increase the beam size \( k \) by 50% for translation and 25% for summarization for our baseline methods: \( k \) to BS, DBS, NCLS, TEMP, and BSZBEAM. This correction balances the number of nodes expanded between our method and the baselines.
7.3 Search Algorithms

**Greedy** is the deterministic greedy decoding method that always selects the highest probability token as prediction. The equivalent beam size for this approach is 1 since we only run one pass.

**BS & DBS** stand for beam search and its variant diverse beam search (Vijayakumar et al., 2016). In our configuration, we use Hamming distance as the diversity function and set the diversity strength to 1.5, following Vijayakumar et al. (2016).

**NCLS** is the nucleus sampling method proposed in Holtzman et al. (2020), which encourages quality by truncating the distribution over the vocabulary with a parameter $p$ before sampling. We experimented it with $p = 0.9$ and $p = 0.8$.

**Temp** changes the temperature of softmax function to reshape the prediction distribution (Ficler and Goldberg, 2017). We set the temperature parameter $\tau = 1.5$ so the prediction picks more low-scored tokens than $\tau = 1$.

**BFS** is the standard best-first search method without path recomposition. We use our ad-hoc path completion technique to ensure that finished hypotheses are produced. Our preliminary study shows a regular best-first search method can not always yield at least one valid hypothesis, even with a length-aware model score function.

Our Methods with Path Recomposition

**BSZBeam** is our implementation of Zhang et al. (2018). We integrate RCB with nucleus sampling and best-first search as NCLSRCB and BFSRCB. We also test BFS with the ZIP strategy. \( \mathcal{E} \)BfsZIP is a resource-efficient version of BFSZIP where only 25% of search budget is used, exploring what this method can achieve with a lower budget given its more aggressive merges.

7.4 Evaluation Metrics

We describe our metrics to evaluate both quality and diversity. Several of our methods build on ROUGE\(^6\) (Lin, 2004) and BLEU (Papineni et al., 2002; Post, 2018) for evaluating the generated text compared to reference summaries or translations.

**Diversity-oriented Metrics** We evaluate the diversity of generated texts with the following metrics. (1) \([\text{path}]\) is the average number of unique paths in the produced lattice.\(^7\) (2) Number of unique $n$-grams encoded in the lattice; this captures a different type of diversity than the number of paths, since there could be many paths reusing the same words. N1 and N2 are average number of novel unigrams and bigrams in the graph. (3) sBl is the average self-BLEU among $m$ samples (Zhu et al., 2018). The samples are drawn from a uniform random walk from $n_{sos}$. The range of sBl is [0, 100]. (4) ED is the average edit-distance among $m$ samples. We set $m = 5$ in our experiment.

**Quality: Grammaticality** One concern about our method is that by recombining different hypotheses, we could introduce grammatical errors, e.g., if two hypotheses have different parses despite a shared $n$-gram suffix. Following past work (Xu and Durrett, 2019; Xu et al., 2020b), we opt for an automated approach to evaluating grammaticality. We adopt GECToR\(^8\), a state-of-the-art neural grammatical error correction model (Omelianchuk et al., 2020) to automatically assess the grammaticality of generated texts. We use the RoBERTa version of the model, which achieves an $F_{0.5}$ of 71.8 on the test set of BEA-2019 (Bryant et al., 2019). We report GRMERR(%), the average number of grammar errors per token, for all English-output experiments.

**Quality: Oracle Reference Match** Given the reference summary or translation, we find the path with highest ROUGE or BLEU over all found paths. Oracle ROUGE is defined as $\text{OR}(\gamma, y^*) = \max_{y \in \gamma} \text{ROUGE}(y(y, y^*))$. For ROUGE metrics, we maximize over $R2$ and present $R1$, $R2$, and $RL$. This metric captures both quality and diversity: the algorithm needs to find something close to the reference, but a diverse lattice will have a higher chance of exhibiting a good candidate all else being equal. We denote this metric as OR.

**Quality: Average Reference Match** Although our method focuses on deriving diverse text summaries or translations, we aim to guarantee that the generated text is highly relevant to the generation target and is of high quality in general. We sample 1,000 paths from the lattice with replacement and

\(^6\)https://github.com/google-research/google-research/tree/master/rouge

\(^7\)Due to the exponentially growing number of paths in some of our models, we cap the number of incoming paths each node could hold to a constant $C = 10^4$. Incoming paths are the paths starting with $n_{sos}$ and ending with the current node.

\(^8\)https://github.com/grammarly/gector
evaluate the average ROUGE or BLEU compared to the reference. We denote this metric as Sp.

8 Results

8.1 Text Summarization

We present the experimental results on the dev set of XSum in Table 2. Full results are kept in Table 5 for reference. The top half of the table shows the results of non-recombination methods. Among non-recombination methods, BS and DBS are the least diverse methods compared to other methods. Sampling based methods including Temp are generally more diverse, but the oracle ROUGE is lower than that of BFS. Given the sacrificed text quality (lower sample ROUGE and more grammar errors) of sampling based methods, we argue that best-first search is an ideal decoding strategy itself even without path recombination. It achieves a good balance of diversity and quality, and is more likely to find a candidate close to the reference under the same amount of computation resources.

The bottom half shows all methods with path recombination techniques. Recombination significantly improves the diversity of generated outputs, with a much higher number of paths. The self-BLEU of the recombination variants are lower than their non-recombination counterparts.

In terms of search quality, the proposed BFSRCB and BFSZIP methods obtain significantly higher oracle ROUGE compared to all other methods. We show these results later in Figure 9: our approach can find much better oracle solutions, even compared with beam search method with quadruple the amount of computation resources. The design of the oracle ROUGE metric is also motivated by a real use case: if you want a specific summary (e.g., a summary covering a specific entity or topic), does it exist in the search graph? Higher oracle ROUGE indicates a closer match, meaning a strategy using some kind of reranking model could help find the user’s preferred summary.

NCLSRCB generates more novel tokens than other methods, but the number of paths is very limited, indicating that these are largely disjoint paths that cannot be recombined. Moreover, the oracle and sample ROUGE are low, showing the lower quality of these outputs.

Comparison: RCB & ZIP The ZIP method yields even more diverse output at the cost of text quality. There are a few reasons for this: 1) recombination of more nodes makes the lattice denser, increasing the number of paths but also potential errors; 2) elimination of unexplored children from merged branch reduces the waste of exploration which means ZIP can explore more varied hypothesis than RCB. With the same amount of computational resources, ZIP explores a larger search space while RCB explores a smaller collection more reliably.

ZIP exploits the efficiency of ZIP to achieve high diversity, and by searching through fewer states, it manages to achieve higher quality as well.

---

Table 2: Main results for all methods decoding text summaries on XSum. Diversity metrics are rounded to integer due to space limit. We use ↑, ↓ and ≥ to denote the desired trend, the higher the better, the lower the better, or good if it passes some threshold. Among the methods with path recombination excluding BFSZIP, we denote the best, second and third best, and the worst one in color.
Table 3: Results on WMT14 Fr-En and WMT19 Zh-En. Columns are the same as for summarization, although BLEU is used instead of ROUGE. Trends in the system performance are roughly similar, with BfsRCB providing high diversity at good quality and BfsZIP offering a strong tradeoff between computational resources and diversity.

Table 4: Results on machine translation WMT14 English to French. BfsRCB and BfsZIP are strong in both diversity and quality.

8.2 Machine Translation

We show the result on machine translation in Table 3 and 4. As im summarization, results on translation tasks shows the consistent gains of diversity from path recombination models. In Table 3, we show two translation task where the target language is English. BfsRCB works better than BfsZIP because it disables some aggressive and bad merges which explores bad hypotheses. Compared to summarization, we found the search space in MT to be more constrained, so there was less room for aggressive merging and exploration to improve over RCB.

Our lower-resource method, BfsZIP approach, actually performs quite well on most metrics with only 25% of search budget. It has better diversity performance than any non-recombination methods, and comes with quality better than most of the recombination methods. The usage of BFS and path recombination methods like BfsRCB and BfsZIP is promising for being able to find a better cost-diversity tradeoff in MT.

8.3 Validating the Merging Criterion

Our merging criterion is fundamentally an approximation of the equivalence criteria described in
Section 5. As described before, no pairs of generation candidates really follow the strong equivalence assumption, but we can explicitly check the weak equivalence assumption. Our question is: what fraction of nodes merged by our merging criterion satisfy the weak equivalence assumption? We conduct an experiment to verify this. We consider all merges on BFSRCB on XSum. For each pair, we compute the greedy completion for $L$ timesteps and check whether the continuation of the base candidates would be the same.

In Figure 7, we show the fraction of merged pairs for which the generations match exactly under three values of the recombination criterion ($n = 2$, $n = 4$ and $n = 6$). For BFSRCB, when using $n = 4$ the greedy continuation over 4 timesteps is the same 71.2% of the time. For BFSZIP, when using $n = 4$ the greedy continuation over 4 timesteps is the same 62.5% of the time. Following the weak equivalence criterion is a strong indication that these hypotheses can admit many of the same continuations. RCB is more reliable than ZIP on recombination assumption, but both methods show moderate adherence to the equivalence criterion.

8.4 Error Analysis & Visualization

In Figure 8, we present two examples on XSum by BFSZIP. The upper example has more word level recombination and paraphrasing during generation while the bottom one has more ways of ending and more diverse content coverage (e.g., Albania, 5 June, Leicester City, 1982, etc.). We show more examples on both summarization and translation in Appendix. E.

We manually examine the output and found a few common types of errors introduced by our algorithm. (1) Factual errors at high entropy nodes. Our approach assumes that high-scoring candidates under the model are good quality, but this assumption is violated in certain cases, like when the model attempts to hallucinate information. For example, given the prefix “The company, founded in 1989” will cause the model to guess answers like “1989” or “1999”. Encoding all of these in the lattice is incorrect. This can still happen in BS but is less likely due to pruning. We did not see significant factual errors introduced by merging specifically. (2) Aggressive bad merges. In the upper example in Figure 8, the cluster of “GPS”, “nurses”, “paramedics” is an example case. The lattice encodes paths like “GPS, nurses and nurses should ...”. This could be fixed by heuristics or rules, but we leave it for future work.

9 Related Work

The techniques used in this work partially reflect an outgrowth of a few lines of literature: understanding the behavior of text generation models (Xu et al., 2020a; Xu and Durrett, 2021; Zhong et al., 2021), investigations into beam search (Stahlberg and Byrne, 2019; Meister et al., 2020a), and studies of diversity in generation.

Search Strategies in Neural Text Generation

Best-first beam search (Meister et al., 2020b) is a method integrating best-first search with beam search. Some other variants of search have also been studied in previous work (Meister et al., 2021b,a). Beam search has been critically examined in some recent work (Huang et al., 2017; Stahlberg and Byrne, 2019), but largely of focused on machine translation and specific challenges in MT.

Diversity Neural text degeneration has been observed and discussed in Radford et al. (2019); Holtzman et al. (2020); Welleck et al. (2020), which led to an interest in diverse generation models. Diverse text generation has been studied in previous work (Yu et al., 2017), including in dialogue (Li et al., 2016), story generation (Fan et al., 2019),
and particularly paraphrasing (Iyyer et al., 2018; Goyal and Durrett, 2020). Many of the diverse options we observe in summarization correspond to text compressions (Xu and Durrett, 2019; Desai et al., 2020), but our method can also diversify content coverage (Gehrmann et al., 2018) and word choice (Cao and Wang, 2021).

10 Discussion & Conclusion

We presented an algorithm for decoding in text generation with two main components: best-first search to more efficiently structure exploration of the space and hypothesis recombination to encode summaries in a lattice structure. We showed that across summarization and machine translation, these lattices successfully encode large numbers of high-quality generation options.

There are a few limitations of our method. First, we currently benchmark these techniques using number of nodes expanded, not wall clock time. There are strategies for parallelizing the BFS expansion (Shu and Nakayama, 2018), but it remains to be seen how this parallelism compares to the parallelism achieved by beam search. Regardless, the dramatically larger number of hypotheses we return outweighs efficiency differences for now. Second, we focus on auto-regressive methods in this paper. However, we believe our framework could also be applied and adopted to non auto-regressive generation models (Song et al., 2021).

Acknowledgments

We would like to thank Sid J Reddy, Zhisong Zhang, Eunsol Choi, Yasumasa Onoe, Shuyang Cao, and Jonathan Kummerfeld for input and feedback on this work. This work was partially supported by a gift from Amazon, NSF Grant IIS-1814522, and a gift from Salesforce Inc.

References

Dzmitry Bahdanau, Kyunghyun Cho, and Yoshua Bengio. 2014. Neural machine translation by jointly learning to align and translate. arXiv preprint arXiv:1409.0473.

Loïc Barrault, Ondřej Bojar, Marta R. Costa-jussà, Christian Federmann, Mark Fishel, Yvette Graham, Barry Haddow, Matthias Huck, Philipp Koehn, Shervin Malmasi, Christof Monz, Mathias Müller, Santanu Pal, Matt Post, and Marcos Zampieri. 2019. Findings of the 2019 conference on machine translation (WMT19). In Proceedings of the Fourth Conference on Machine Translation (Volume 2: Shared Task Papers, Day 1), pages 1–61, Florence, Italy. Association for Computational Linguistics.

Ondřej Bojar, Christian Buck, Christian Federmann, Barry Haddow, Philipp Koehn, Johannes Leveling, Christof Monz, Pavel Pecina, Matt Post, Herve Saint-Amand, Radu Soricut, Lucia Specia, and Aleš Tamchyna. 2014. Findings of the 2014 workshop on statistical machine translation. In Proceedings of the Ninth Workshop on Statistical Machine Translation, pages 12–58, Baltimore, Maryland, USA. Association for Computational Linguistics.

Christopher Bryant, Mariano Felice, Øistein E. Andersen, and Ted Briscoe. 2019. The BEA-2019 shared task on grammatical error correction. In Proceedings of the Fourteenth Workshop on Innovative Use of NLP for Building Educational Applications, pages 52–75, Florence, Italy. Association for Computational Linguistics.

Jacob Buckman and Graham Neubig. 2018. Neural lattice language models. Transactions of the Association for Computational Linguistics, 6:529–541.

Shuyang Cao and Lu Wang. 2021. Inference time style control for summarization. In Proceedings of the 2021 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, pages 5942–5953, Online. Association for Computational Linguistics.

Shrey Desai, Jiacheng Xu, and Greg Durrett. 2020. Compressive summarization with plausibility and salience modeling. In Proceedings of the 2020 Conference on Empirical Methods in Natural Language Processing (EMNLP), pages 6259–6274, Online. Association for Computational Linguistics.

Angela Fan, Mike Lewis, and Yann Dauphin. 2018. Hierarchical neural story generation. In Proceedings of the 56th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers), pages 889–898, Melbourne, Australia. Association for Computational Linguistics.

Angela Fan, Mike Lewis, and Yann Dauphin. 2019. Strategies for structuring story generation. In Proceedings of the 57th Annual Meeting of the Association for Computational Linguistics, pages 2650–2660, Florence, Italy. Association for Computational Linguistics.

Jessica Ficler and Yoav Goldberg. 2017. Controlling linguistic style aspects in neural language generation. In Proceedings of the Workshop on Stylistic Variation, pages 94–104, Copenhagen, Denmark. Association for Computational Linguistics.

Samuel Gehman, Suchin Gururangan, Maarten Sap, Yejin Choi, and Noah A. Smith. 2020. RealToxicityPrompts: Evaluating neural toxic degeneration in language models. In Findings of the Association for Computational Linguistics: EMNLP 2020, pages 3356–3369, Online. Association for Computational Linguistics.
Sebastian Gehrmann, Yuntian Deng, and Alexander Rush. 2018. Bottom-up abstractive summarization. In Proceedings of the 2018 Conference on Empirical Methods in Natural Language Processing, pages 4098–4109, Brussels, Belgium. Association for Computational Linguistics.

Tanya Goyal and Greg Durrett. 2020. Neural syntactic preordering for controlled paraphrase generation. In Proceedings of the 58th Annual Meeting of the Association for Computational Linguistics, pages 238–252, Online. Association for Computational Linguistics.

Tanya Goyal and Greg Durrett. 2021. Annotating and modeling fine-grained factuality in summarization. In Proceedings of the 2021 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, pages 1449–1462, Online. Association for Computational Linguistics.

Peter E Hart, Nils J Nilsson, and Bertram Raphael. 1968. A formal basis for the heuristic determination of minimum cost paths. IEEE transactions on Systems Science and Cybernetics, 4(2):100–107.

Ari Holtzman, Jan Buys, Li Du, Maxwell Forbes, and Yejin Choi. 2020. The curious case of neural text degeneration. In International Conference on Learning Representations.

Ari Holtzman, Jan Buys, Maxwell Forbes, Antoine Bosselut, David Golub, and Yejin Choi. 2018. Learning to write with cooperative discriminators. In Proceedings of the 56th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers), pages 1638–1649, Melbourne, Australia. Association for Computational Linguistics.

Liang Huang, Kai Zhao, and Mingbo Ma. 2017. When to finish? optimal beam search for neural text generation (modulo beam size). In Proceedings of the 2017 Conference on Empirical Methods in Natural Language Processing, pages 2134–2139, Copenhagen, Denmark. Association for Computational Linguistics.

Mohit Iyyer, John Wieting, Kevin Gimpel, and Luke Zettlemoyer. 2018. Adversarial example generation with syntactically controlled paraphrase networks. In Proceedings of the 2018 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, Volume 1 (Long Papers), pages 1875–1885, New Orleans, Louisiana. Association for Computational Linguistics.

Philipp Koehn, Franz J. Och, and Daniel Marcu. 2003. Statistical phrase-based translation. In Proceedings of the 2003 Human Language Technology Conference of the North American Chapter of the Association for Computational Linguistics, pages 127–133.

Wojciech Kryscinski, Bryan McCann, Caiming Xiong, and Richard Socher. 2020. Evaluating the factual consistency of abstractive text summarization. In Proceedings of the 2020 Conference on Empirical Methods in Natural Language Processing (EMNLP), pages 9332–9346, Online. Association for Computational Linguistics.

Mike Lewis, Yinhan Liu, Naman Goyal, Marjan Ghazvininejad, Abdelrahman Mohamed, Omer Levy, Veselin Stoyanov, and Luke Zettlemoyer. 2020. BART: Denoising sequence-to-sequence pre-training for natural language generation, translation, and comprehension. In Proceedings of the 58th Annual Meeting of the Association for Computational Linguistics, pages 7871–7880, Online. Association for Computational Linguistics.

Jiwei Li, Michel Galley, Chris Brockett, Jianfeng Gao, and Bill Dolan. 2016. A diversity-promoting objective function for neural conversation models. In Proceedings of the 2016 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, pages 110–119, San Diego, California. Association for Computational Linguistics.

Chin-Yew Lin. 2004. ROUGE: A package for automatic evaluation of summaries. In Text Summarization Branches Out, pages 74–81, Barcelona, Spain. Association for Computational Linguistics.

Yinhan Liu, Jiatao Gu, Naman Goyal, Xian Li, Sergey Edunov, Marjan Ghazvininejad, Mike Lewis, and Luke Zettlemoyer. 2020. Multilingual denoising pre-training for neural machine translation. Transactions of the Association for Computational Linguistics, 8:726–742.

Joshua Maynez, Shashi Narayan, Bernd Bohnet, and Ryan McDonald. 2020. On faithfulness and factuality in abstractive summarization. In Proceedings of the 58th Annual Meeting of the Association for Computational Linguistics, pages 1906–1919, Online. Association for Computational Linguistics.

Clara Meister, Afra Amini, Tim Vieira, and Ryan Cotterell. 2021a. Conditional Poisson stochastic beams. In Proceedings of the 2021 Conference on Empirical Methods in Natural Language Processing, pages 664–681, Online and Punta Cana, Dominican Republic. Association for Computational Linguistics.

Clara Meister, Ryan Cotterell, and Tim Vieira. 2020a. If beam search is the answer, what was the question? In Proceedings of the 2020 Conference on Empirical Methods in Natural Language Processing (EMNLP), pages 2173–2185, Online. Association for Computational Linguistics.

Clara Meister, Martina Forster, and Ryan Cotterell. 2021b. Determinantal beam search. In Proceedings of the 59th Annual Meeting of the Association
abstractive summarization with syntactic compression. In Proceedings of the 2019 Conference on Empirical Methods in Natural Language Processing and the 9th International Joint Conference on Natural Language Processing (EMNLP-IJCNLP), pages 3292–3303, Hong Kong, China. Association for Computational Linguistics.

Jiacheng Xu and Greg Durrett. 2021. Dissecting generation modes for abstractive summarization models via ablation and attribution. In Proceedings of the 59th Annual Meeting of the Association for Computational Linguistics and the 11th International Joint Conference on Natural Language Processing (Volume 1: Long Papers), pages 6925–6940, Online. Association for Computational Linguistics.

Jiacheng Xu, Zhe Gan, Yu Cheng, and Jingjing Liu. 2020b. Discourse-aware neural extractive text summarization. In Proceedings of the 58th Annual Meeting of the Association for Computational Linguistics, pages 5021–5031, Online. Association for Computational Linguistics.

Kevin Yang and Dan Klein. 2021. FUDGE: Controlled text generation with future discriminators. In Proceedings of the 2021 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, pages 3511–3535, Online. Association for Computational Linguistics.

Lantao Yu, Weinan Zhang, Jun Wang, and Yong Yu. 2017. Seqgan: Sequence generative adversarial nets for efficient decoding of neural machine translation. In Proceedings of the 2018 Conference on Empirical Methods in Natural Language Processing, pages 4785–4790, Brussels, Belgium. Association for Computational Linguistics.

Zhisong Zhang, Rui Wang, Masao Utiyama, Eiichiro Sumita, and Hai Zhao. 2018. Exploring recombination for exploring unfinished hypotheses. Naturally, finished hypotheses \( F \) in the end can be of variable length. After reaching the max generation step \( T \), we sort all hypotheses in \( F \) according to the model score. Following common practice in libraries such as Transformers (Wolf et al., 2020), we return a number of completed hypotheses equal to the beam size.

\[
\text{Oracle R2} = \frac{\text{Number of completed hypotheses}}{\text{Number of completed hypotheses} + \text{Number of unfinished hypotheses}}
\]

Figure 9: Oracle R2 of BS/DBS with larger beam size \( k \). Blue star represents BFSRCB with equivalent \( k = 16 \).

\section*{B Pool Scaling Behavior: Optimality}

As a search algorithm, how do BS and DBS with larger beam size perform at finding solutions close to the reference? We compare the oracle R2 of BS/DBS with larger beam size in Figure 9. The oracle R2 increases slowly as the \( k \) doubles, but our model BFSRCB with \( k = 16 \) achieves 35.8, much higher than all BS/DBS cases.

\section*{C Proof of Theorem 5.1}

Proof by induction. Base case: we begin with just \( n \text{sos} \) in the lattice, which has exactly one canonical path consisting of itself.

\section*{A Implementation Details: Beam Search}

In our beam search implementation, the size of the search frontier \( \mathcal{O} \) is up to the beam size \( k \). When a path is completed, we move it from the search frontier \( \mathcal{O} \) to a completed set \( \mathcal{F} \) to free up the beam for exploring unfinished hypotheses. Naturally, finished hypotheses \( \mathcal{F} \) in the end can be of variable length. After reaching the max generation step \( T \), we sort all hypotheses in \( \mathcal{F} \) according to the model score. Following common practice in libraries such as Transformers (Wolf et al., 2020), we return a number of completed hypotheses equal to the beam size.

\[
\text{Oracle R2} = \frac{\text{Number of completed hypotheses}}{\text{Number of completed hypotheses} + \text{Number of unfinished hypotheses}}
\]

Figure 10: An illustration of removing unexplored hypotheses from search frontier in ZIP.
Table 5: Full results for all methods decoding text summaries on XSum.

| Method   | BSZBEAM | NCLS0.8RCB | NCLS0.0RCB | BFSRCB | BfsZIP | BFSZIP |
|----------|---------|------------|------------|--------|--------|--------|
| BS       | 1,701   | 36         | 7,758      | 95,744 | 297    |
| RCB      | 4,701   | 36         | 7,758      | 95,744 | 297    |
| ZIP      | 4,701   | 36         | 7,758      | 95,744 | 297    |

Table 6: Key differences in path recombination methods. rBS is the recombination method used in Zhang et al. (2018). ALGOS shows which searching or decoding methods this method is used with. CAND is where the merge candidates come from in the lattice. LEN reflects how many nodes are recombined per operation. DEDUP denotes whether duplicates on the merged branch will be removed from heap.

Inductive case: assume every node in the lattice has exactly one canonical path. We have to consider two cases when expanding a node in the lattice:

1. Expanding the node as normal. In this case, the node is on the search frontier due to its parent node $n'$ being expanded, which establishes a GEN edge from $n'$ to $n$. Since $n'$ has exactly one canonical path, $n$ then has exactly one canonical path consistent of the canonical path to $n'$ extended to $n$.

2. Applying recombination. This operation only adds MRG edges and deletes nodes, neither of which have any impact on the canonical paths.

D Implementation Details: ZIP

We summarize the key differences of ZBEAM, RCB and ZIP in Table 6. In ZIP, nodes that are already expanded might be removed from the lattice due to recombination. For example, in Figure 6, node 6 and 7 are removed in this fashion. In general, we handle this by re-mapping the eliminated node to its surviving counterpart. Any reference to node 7 is routed to node 3, or whatever node 3 is mapped to. This procedure is defined and implemented as a union-find data structure.

Deduplication of Unexplored Successors

After the ZIP procedure, we also remove the unexplored successors of the merged nodes, like node 6, 7, and 8 in Fig. 6. We show a more detailed example in Figure 10. In ZIP, we will merge node 3 and node 6. If we take a closer look at the successors of these two nodes, the distributions could be similar and in fact are expected to be if the equivalence criteria hold. We remove the unexplored direct successors of the merged node as part of the merging process, and the surviving node (node 3) captures these with similar probabilities regardless.

E Examples

We show three examples with visualization in Figure 11, 12 and 13. We use PyVis as the visualization tool. More examples are available at https://github.com/jiacheng-xu/lattice-generation.
Figure 11: Visualization of one example output for beam search on XSum. $n_{\text{sos}}$ is labeled. Each color represents one unique ending.
Figure 12: Visualization of one example output for BFSRCB on XSum.
Figure 13: Visualization of one example output for BFSZIP on XSum.