Tree-constrained Pointer Generator with Graph Neural Network Encodings for Contextual Speech Recognition

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Abstract

Incorporating biasing words obtained as contextual knowledge is critical for many automatic speech recognition (ASR) applications. This paper proposes the use of graph neural network (GNN) encodings in a tree-constrained pointer generator (TCPGen) component for end-to-end contextual ASR. By encoding the biasing words in the prefix-tree with a tree-based GNN, lookahead for future wordpieces in end-to-end ASR decoding is achieved at each tree node by incorporating information about all wordpieces on the tree branches rooted from it, which allows a more accurate prediction of the generation probability of the biasing words. Systems were evaluated on the Librispeech corpus using simulated biasing tasks, and on the AMI corpus by proposing a novel visual-grounded contextual ASR pipeline that extracts biasing words from slides alongside each meeting. Results showed that TCPGen with GNN encodings achieved about a further 15% relative WER reduction on the biasing words compared to the original TCPGen, with a negligible increase in the computation cost for decoding.

Index Terms: graph neural networks, end-to-end ASR, contextual speech recognition, pointer generator, audio-visual

1. Introduction

Contextual speech recognition aims at addressing the long-tail word problem in end-to-end ASR systems by incorporating contextual knowledge, and has become increasingly important in many applications [1–16]. Informative contextual knowledge can be extracted from text-based resources such as a users’ contact book, playlist and the ontology in a dialogue system, or from other modalities such as presentation slides or objects in a scene. Such contextual knowledge is often integrated via contextual biasing which represents contextual knowledge as a biasing list of words (referred to as biasing words) that are likely to appear in a given context. Despite the relatively small impact of biasing words on the overall word error rate (WER), biasing words are often highly valuable content words, as they are nouns or proper nouns and are indispensable to downstream understanding tasks. Meanwhile, these words are more likely to be correctly recognised if they are included in the biasing list. Therefore, contextual biasing is crucial to the correct recognition of these words in an end-to-end ASR system.

Incorporating dynamic contextual knowledge into end-to-end ASR systems is a challenging problem. Dedicated contextual biasing approaches have been developed, such as shallow fusion (SF) with a special weighted finite-state transducer (WFST), a language model (LM) adapted for contextual knowledge [1–3, 14–16]; attention-based deep context approaches [4–8], and also deep biasing (DB) with a prefix-tree for improved efficiency when dealing with large biasing lists [9, 10].

More recently, model components that use neural shortcuts to directly modify ASR output distributions were proposed for contextual biasing [20–22].

Further exploiting the prefix-tree structure in the tree-constrained pointer generator component (TCPGen) [20] for contextual biasing, this paper proposes the use of graph neural network (GNN) encodings in TCPGen to obtain more powerful node representations for the prefix-tree. Specifically, a tree recursive neural network (tree-RNN) [24, 25], which is an instance of a GNN, is used to obtain a lookahead functionality for prefix-tree search in end-to-end ASR decoding. Each node representation, encoded with a tree-RNN, encapsulates information about not only its corresponding wordpiece but also all wordpieces on its branches. The use of such node representations in TCPGen improves the prediction of the generation probability for the biasing words to better determine how much contextual biasing is needed by incorporating information about future wordpieces for lookahead at each ASR decoding step.

TCPGen with GNN encodings is integrated into both the attention-based encoder-decoder (AED) model and the recurrent neural network transducer (RNN-T) model in this paper. Experiments were first performed on the Librispeech audio-data using simulated contextual knowledge, where biasing lists were organised for each utterance following [10, 20], as it was shown to be a valid simulation. To further demonstrate the effectiveness of TCPGen and GNN encodings in real-life scenarios, a visual-grounded contextual ASR pipeline is also proposed for the augmented multi-party interaction (AMI) meeting data, which obtains the possible biasing words from the presentation slides alongside each meeting with an optical character recognition (OCR) tool. Consistent improvements in WER were achieved in both AED and RNN-T using GNN encodings in TCPGen compared to the original TCPGen system, with a significant WER reduction on the biasing words in particular.

The rest of this paper is organised as follows: Sec. 2 reviews related studies. Sec. 3 introduces TCPGen, followed by Sec. 4 which gives details about GNN encodings. Sec. 5 describes the experimental setup, and Sec. 6 discusses the results. Finally, conclusions are provided in Sec. 7.

2. Related work

2.1. End-to-end contextual speech recognition

Previous research on end-to-end contextual speech recognition has explored both SF-based score-level interpolation and deep neural representation approaches. For SF-based methods [1–3, 14–16], biasing lists are represented as extra WFSTs incorporated into a class-based LM, which usually relies on special context prefixes like “call” or “play.” Meanwhile, neural network-based deep context approaches [4–8] address the dependency issue on fixed syntactic prefixes, but becomes more memory intensive and less effective for large biasing lists. Work
in [9, 10] jointly used deep context and SF in an RNN-T, along
with a prefix-tree search for improved efficiency. It also pro-
posed a simulation of biasing tasks using a public dataset that
was adopted in [20, 23]. More recently, neural shortcuts to
the final output distribution via a pointer generator [20, 21] or
neural-FST [22] have been proposed which can be optimised in
an end-to-end fashion. The TCPGen [20] approach further im-
proved the efficiency by combining the neural shortcut with the
symbolic prefix-tree search to handle large biasing lists.

2.2. Tree-RNN
The tree-RNN [24, 25] has been widely applied to various types
of tree-structured data. In language technologies, sentences can
be arranged into tree structures according to their syntax, to be
encoded by the tree-RNN or its variants. Such an encoding has
been applied for semantic or sentiment classification [26–28],
named-entity recognition [29], and has also been used in neural
machine translation [32, 33]. Moreover, encoding of subword-
unit-based tree structures using tree-RNN [30, 31] has also been
studied for better word representations.

3. Tree-constrained pointer generator
TCPGen is a neural network-based component combining the
symbolic prefix-tree search with a neural pointer generator [17]
for contextual biasing, which enables end-to-end optimisation
with ASR systems including AED [18] and RNN-T [19]. At
each output step, TCPGen calculates a distribution over all valid
wordpieces constrained by a word-piece-level prefix tree built
from the biasing list (referred to as the TCPGen distribution).
TCPGen also predicts a generation probability indicating how
much contextual biasing is needed at a specific output step. The
final output distribution is thus the interpolation between the
TCPGen distribution and the original AED or RNN-T output
distribution, weighted by the generation probability.

Specifically, a set of valid wordpieces, \( \mathcal{Y}^\text{tree} \), is obtained
by searching the prefix-tree with a given history output sequence.
Then, denoting \( x_{i, 1: T} \) and \( y_i \) as input acoustic features and output
wordpieces, \( q_i \) as the query vector carrying the history and
acoustic information, and \( K = \{ k_1, k_2, \ldots \} \) as the key vectors, a
scaled dot-product attention is performed between \( q_i \) and \( K \) to
compute the TCPGen distribution \( P^\text{tlp} \) and an output vector \( h^\text{tree} \)
as shown in Eqns. (1) and (2).

\[
P^\text{tlp}(y_i | y_{i-1}, x_{i:1:T}) = \text{Softmax}(\text{Mask}(q_i K^T / \sqrt{d})),
\]
\[
h^\text{tree} = \sum_k P^\text{tlp}(y_i | j, y_{i-1}, x_{i:1:T}) v^T_j,
\]

where \( d \) is the size of \( q_i \) (see [34]), \( \text{Mask}(\cdot) \) sets the probabili-
ty of wordpieces that are not in \( \mathcal{Y}^\text{tree} \) to zero, and \( v_j \) is the value
vector relevant to \( j \). In AED, the query combines the context
vector and the previously decoded token embedding, while the
keys and values are computed from the decoder wordpiece
embedding, with a shared projection matrix. The generation
probability in AED, which takes a value between 0 and
1, is calculated using the decoder hidden state and the TCP-
Gen output vector \( h^\text{tp} \). In RNN-T, the TCPGen distribution
is calculated for each combination of the encoder and the pre-
dictor step, and the query is computed from the corresponding
encoder and predictor hidden states. Keys and values in RNN-
T are computed from the predictor wordpiece embeddings.
The generation probability for RNN-T is computed using the joint
network output and the TCPGen output vector \( h^\text{tree} \). To ensure
that the probability of the null symbol in RNN-T is unchanged,
\( P^\text{ml} (\emptyset | x_{1:T}, y_{i-1}) \) is set to 0 and the generation probability is

\[
P(y_i) = (1 - P^\text{ml}(\emptyset | x_{1:T}, y_{i-1})) + P^\text{ml}(\emptyset | y_{i-1}),
\]

where conditions, \( y_{i-1}, x_{1:T} \), are omitted for clarity. \( P^\text{ml}(\emptyset) \)
represents the output distribution from the standard end-to-end
model, and \( P^\text{tree} \) is the generation probability.

4. GNN encodings in TCPGen
This paper exploits a specific type of GNN, the tree-RNN struc-
ture for prefix-tree encoding in TCPGen. Specifically, at node
\( n_j \) which contains child nodes \( n_1, \ldots, n_k, \ldots, n_{nx} \), the vector
representation of \( n_j \) can be written as Eqn. (4).

\[
h^\text{tree}_{nj} = f(W_1 y_j + \sum_{k=1:N} W_2 h^\text{tree}_{nk}),
\]

where \( h^\text{tree}_{nk} \) is the vector representation of node \( n_k \), \( f(\cdot) \) is an
activation function which was ReLU in this paper, and \( y_j \) is the
embedding vector of the wordpiece of node \( n_j \). \( W_1 \) and
\( W_2 \) are parameter matrices jointly optimised with the ASR
system by allowing gradient back-propagation through \( h^\text{tree}_{nj} \).
In this way, each node recursively encodes information from its
child nodes, such that the information of the entire branch rooted
from it can be incorporated in the node encoding \( h^\text{tree}_{nj} \).

The keys and values used to calculate the TCPGen distribution
come from the encoding of nodes in the set of valid wordpieces,
in place of wordpiece embeddings as shown in Eqn. (5).

\[
k_j = W^K h^\text{tree}_{nj}, \quad v_j = W^V h^\text{tree}_{nj},
\]

where \( W^V \) and \( W^K \) are parameter matrices. Fig. 1 shows an
element of tree-RNN computation over the prefix-tree
representing the biasing list of 3 biasing words. A word end
unit is denoted by \( \omega \).
early as in the encoding of Tur. Such lookahead functionality in the prefix-tree search allows a more accurate generation probability to determine when contextual biasing is needed.

The high efficiency of TCPGen in handling large biasing list is also retained when the tree-RNN is used. In training, with a large biasing list of 1000 words, TCPGen with a tree-RNN was three times slower than the standard AED or RNN-T model, with a negligible increase in space complexity. However, since the GNN encodings can be generated offline before the start of decoding once the biasing list is available, making the time and space complexity during inference close to the standard AED or RNN-T for biasing lists of thousands of words.

5. Experimental setup

5.1. Data
Experiments were performed using the Librispeech audiobook data and the AMI meeting corpus with individual headset microphone (IHM) recordings. The Librispeech corpus [35] contains 960 hours of read English from audiobooks. The dev sets were held out for validation, and test-clean and test-other used for evaluation. The AMI meeting corpus [38] contains 100 hours of meeting recordings with 4-5 people, and was split into train, dev and eval sets. To show the effectiveness of applying contextual biasing to data in another domain with limited training resources, 10% of the utterances from the AMI train set corresponding to 8 hours of audio were used to finetune the models trained on the Librispeech 960-hour data. There were 14 meetings in the dev set and 8 meetings in the eval set with slides. They were put together to form the slides test set for AMI experiments. Model input used 80-dimensional (-d) log-Mel filter bank features at a 10 ms frame rate concatenated with 3-d pitch features. SpecAugment [36] with the setting \((W, F, m_F, T, p, m_T) = (40, 27, 2, 40, 1.0, 2)\) was used without any other data augmentation or speaker adaptation.

5.2. Biasing list extraction
Biasing lists for Librispeech experiments were arranged following [10]: the full rare word list containing 200k distinct words was obtained by removing the most common 5k words in the Librispeech LM training corpus. Rare words were defined as words belonging to this list. Biasing lists were then organised by finding words that belong to the full rare word list from the reference of each utterance and adding 1000 distractors.

The visual-grounded contextual ASR pipeline for AMI using OCR output for slides is shown in Fig. 2. First, slides for each meeting series (e.g. ES2011 for ES2011[a-d]) were collected and passed through the Tesseract 4 OCR engine with long-short term memory (LSTM) models\(^1\). Distinct word tokens were then extracted from the OCR output text files, and those in the full rare word list that also appeared fewer than 100 times in the AMI train set were included in the biasing list for that specific meeting series. These meeting-specific biasing lists were then used for the recognition of all utterances in that meeting series. The size of the biasing lists ranged from 175 to 576 and the total number of word tokens covered by these biasing lists was 1,751 out of 112,110 word tokens (1.5%), and hence had a small impact on the overall WER. However, as shown in the example in Fig. 2, these words were mostly highly valuable content words, and correct recognition was critical to understanding the utterance. Details of the meetings with slides and the extraction pipeline can be found in [43].

5.3. Model and evaluation metrics
Systems were built using the ESPnet toolkit [40]. Conformer-based [39] AED and RNN-T were used in the experiments. The encoder structure which comprised of 16 conformer blocks with 512-d hidden state and 4-head attention was the same for both AED and RNN-T. AED used a 1024-d single-head location-sensitive attention and a 1024-d single-layer unidirectional LSTM decoder. RNN-T used a 640-d single-layer unidirectional LSTM predictor and a 640-d fully-connected layer joint network. The encoding size of each node in the prefix tree was 1024-d. SF with a target domain LM was also performed. For AMI experiments, the density-ratio LM SF approach following [37] was performed. The LM for the target domain was a 2-layer 2048-d unidirectional LSTM-LM trained on the joint AMI and Fisher text corpus. The source domain LM was a single-layer 1024-d unidirectional LSTM-LM trained on the same 10% AMI train set used for ASR model training.

Systems were evaluated using WER and rare word error rate (R-WER) following [10, 20]. R-WER is the total number of error word tokens that belong to the biasing list divided by the total number of word tokens in the test set that belong to the biasing list. In contrast to [21], insertion errors were counted in R-WER if the inserted word belonged to the biasing list. The slides rare word error rate (R-W) reported for the AMI experiments was the same way as R-WER, but for the rare words in slides. Insertions of slides biasing words were included in R-WER. Furthermore, a speaker-by-speaker sign test for TCPGen with or without GNN encodings was performed to show the significance of improvements.

6. Results

6.1. Librispeech experiments
First, experiments were performed on the Librispeech data using the AED as shown in Table 1. Compared to the baseline, WER, and in particular, R-WER reductions were achieved using TCPGen. Compared to the original TCPGen, using GNN encodings achieved a further R-WER reduction, enlarging the relative R-WER improvements from 37% to 50% on the test-clean set and from 32% to 45% on the test-other set.
But in this vignette copied from Turner you have the two principles brought out perfectly

TCPGen
TCPGen + GNN encodings
But in this vignette copied from Turner you have the two principles brought out perfectly

Test-clean(%) Test-other(%)

| System          | Test-clean | Test-other |
|-----------------|------------|------------|
| WER  | R-WER | WER  | R-WER |
| Baseline        | 3.8       | 13.4      | 9.6   | 30.5 |
| TCPGen          | 3.3       | 8.4       | 8.3   | 20.7 |
| + GNN enc.      | 3.1       | 6.7       | 7.9   | 17.8 |

**Table 1: WER and R-WER using AED on Librispeech test-clean and test-other sets. Baseline refers to the standard AED model.**

TCPGen
TCPGen + GNN encodings
But in this vignette copied from Turner you have the two principles brought out perfectly

Figure 3: Heat map of the generation probability for each wordpiece in a recognised utterance illustrating the effect of lookahead using GNN encodings. Biasing words are *Vignette, copied* and *Turner.*

To better illustrate how the lookahead functionality benefits the prediction of the generation probability in TCPGen, a heat map of $P_i^n$ for each wordpiece in an example utterance is plotted in Fig. 3. The generation probabilities for the first several wordpieces of the biasing word were much higher with GNN encodings. This corroborates the claim in Sec. 4 that since the tree-RNN allows information about wordpieces on the branches to be accessed at much earlier nodes, better generation probabilities were predicted than with the original TCPGen.

| System         | Test-clean | Test-other |
|----------------|------------|------------|
| WER  | R-WER | WER  | R-WER |
| Baseline        | 4.0       | 14.1      | 10.1  | 33.1 |
| TCPGen          | 3.4       | 8.9       | 8.8   | 22.2 |
| + GNN enc.      | 3.1       | 7.6       | 8.2   | 18.8 |

**Table 2: WER and R-WER on Librispeech test-clean and test-other sets using RNN-T. Baseline refers to the standard RNN-T.**

The effectiveness of GNN encodings was then verified for RNN-T on Librispeech data as shown in Table 2. Using GNN encodings further improved the relative R-WER reduction compared to the baseline standard RNN-T from 37% to 46% on the test-clean set and from 33% to 43% on the test-other set. TCPGen also achieved zero-shot learning of words that did not occur in training (referred to as OOV words) if incorporated in the biasing list, which was further improved with GNN encodings. There were 439 OOV word tokens in the combined test-clean and test-other set covered by biasing lists. For AED, the OOV WER, measured in the same way as R-WER but for OOV words, decreased from 73% to 40% using TCPGen, and then to 33% using GNN encodings. A similar reduction in OOV WER was found with RNN-T.

6.2. AMI experiments
Experiments were performed on AMI for AED and RNN-T following the visual-grounded contextual biasing pipeline in Fig. 2, with results in Table 3. The baseline and TCPGen systems were all initialised from the corresponding models trained on the Librispeech 960-hour data from Sec. 6.1, and finetuned on 10% of the AMI train set. Additionally, the AMI baseline was included, which used the same AED or RNN-T structure with the same set of wordpieces and trained on the full AMI train set. Compared to the AMI baseline, both finetuned standard models achieved a better WER with only 10% of the full AMI train set.

| System          | AED (%) | RNN-T (%) |
|-----------------|---------|-----------|
| WER  | R-WER | WER  | R-WER |
| Baseline        | 23.6    | 56.3     | 26.5  | 58.0 |
| TCPGen          | 22.0    | 40.5     | 25.5  | 44.7 |
| + GNN enc.      | 21.9    | 36.7     | 25.4  | 40.7 |
| Baseline + SF   | 21.1    | 45.5     | 24.3  | 46.5 |
| TCPGen + SF     | 20.9    | 34.2     | 24.1  | 37.7 |
| + GNN enc. + SF | 20.8    | 31.0     | 23.8  | 33.9 |

**Table 3: %WER and %R-WER on the AMI slides test set using AED and RNN-T finetuned on the 10% of AMI train set. AMI baseline refers to the same AED or RNN-T system trained on full AMI train set only. SF denotes using shallow fusion.**

The best WER and R-WER results without SF were obtained by GNN encodings in TCPGen for both AED and RNN-T on the 22 meetings of the AMI slides test set. Compared to the baseline, TCPGen achieved a 21% relative R-WER reduction for AED, and 15% relative R-WER reduction for RNN-T. These improvements increased to 28% and 23% for AED and RNN-T respectively using GNN encodings. The speaker-level sign test showed that R-WER reductions using GNN encodings compared to the original TCPGen were significant at $p < 0.05$. WER reductions were not significant for TCPGen but were significant for TCPGen with GNN encodings compared to the baseline at $p < 0.05$.

As the biasing lists were relatively small compared to the 1000 entries used in Librispeech, and hence the TCPGen distribution was sharp, insertions of biasing words occupied a non-negligible portion of the R-WER. To mitigate this issue, the density-ratio SF approach was used which also mitigated the domain mismatch between the training and test data. The SF factor for the target LM was 0.3 and the discounting factor for the source LM was 0.2 for all systems in Table 3. As a result, the relative R-WER reduction increased from 28% to 32% for AED, and from 23% to 27% for RNN-T when GNN encodings were used. The speaker-level sign test showed that R-WER reductions from using GNN encodings compared to the original TCPGen were all significant at $p < 0.05$ with SF. Similar improvements were also found using SF for TCPGen with GNN encodings on Librispeech data.

7. Conclusions
This paper proposed GNN encodings using tree-RNN in TCPGen for contextual speech recognition. Tree-RNN enables lookahead in prefix-tree search by encoding information about wordpieces on all branches rooted from each node. Experiments were performed on both Librispeech and AMI using both Conformer AED and RNN-T, with an audio-visual contextual ASR pipeline for AMI proposed as a realistic multi-modal evaluation setup. Consistent WER reductions were obtained using TCPGen with GNN encodings, with a significant reduction in R-WER and R-WER for biasing words compared to baselines. As a future direction, other effective GNN structures will be explored in TCPGen, such as the graph convolutional network (GCNs) [41] and graph attention networks (GATs) [42].
8. References

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