Graph Masking Pre-training for Graph-to-Text Generation

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Abstract

Large-scale pre-trained language models (PLMs) have advanced Graph-to-Text (G2T) generation by processing the linearised version of a graph. However, the linearisation is known to ignore the structural information. Additionally, PLMs are typically pre-trained on free text which introduces domain mismatch between pre-training and downstream G2T generation tasks. To address these shortcomings, we propose efficient graph masking pre-training strategies that neither require supervision signals nor adjust the architecture of the underlying pre-trained encoder-decoder model. When used with a pre-trained T5, our approach achieves new state-of-the-art results on WebNLG+2020 and EventNarrative G2T generation datasets. Our method also shows to be very effective in the low-resource setting. Our code is available at `https://github.com/Jiuzhouh/Graph-Masking-Pre-training`.

1 Introduction

Graph-to-Text (G2T) generation (Gatt and Krahmer, 2018) is the task of generating natural language from graph-structured data. While there are several tasks that could leverage a G2T component Zhou et al. (2018); Ji et al. (2020); Chen et al. (2021) the direct generation of text description from knowledge graphs (KGs) have attracted a lot of attention due to its potential in providing a more accessible presentation of knowledge to non-experts Schmitt et al. (2020).

In parallel, Transformer-based (Vaswani et al., 2017) PLMs such as T5 (Raffel et al., 2019) and BART (Lewis et al., 2019) have facilitated state-of-the-art (SotA) results on several tasks (Ribeiro et al., 2020; Kale and Rastogi, 2020; Mager et al., 2020). It has been argued that their success, in part, is due to factual memorisation that guides the generation Ribeiro et al. (2020). Although PLMs benefit the G2T generation, the linearisation step required to use these models ignores the structural information of the graph (Wang et al., 2021), while explicitly modelling structured data could also lead to catastrophic forgetting of distributional knowledge (Ribeiro et al., 2021).

To address this, Wang et al. (2021) proposed adding extra positional embedding layers to capture the inter-dependency structures of input graphs. Ribeiro et al. (2021) proposed using a structure-aware adapter in PLMs to supplement the input with its graph structure. For table data, Xing and Wan (2021) considered the structure of the table input by predicting the surrounding cells for a cell in a table. However, these methods either change the design of the PLMs (limiting their use for other task settings) or require labelled training data to capture the graph structure information.

In this work, we propose self-supervised graph masking pre-training strategies to enhance the structure awareness of PLMs. To achieve this, we formulate several graph masking strategies to inject local and global awareness of the input structure into the PLM. Our method has two key advantages: (i) it does not require to introduce extra layers or change of architecture in the underlying PLM, and (ii) it pre-trains the PLMs in a self-supervised setting on graphs, without requiring labelled training data. After our pre-training, the fine-tuning on downstream tasks is done as per usual.

We conduct extensive experiments on three G2T generation datasets of diverse graphs. Our empirical findings highlight that our self-supervised strategies significantly outperform a strong underlying T5 baseline and achieve two new SotA results on two of the datasets WebNLG+2020 (Zhou and

Pre-training Task	Input (Triples format: [S|head$_1$, P|relation$_1$, O|tail$_1$, l_1])	Target Output
Triple Prediction	[<X>, 1], [S | New York City, P | country, O | United States, 2], [S | New York City, P | is Part Of, O | Manhattan, 2], [S | Manhattan, P | leader Name, O | Cyrus Vance Jr., 3], [S | Manhattan, P | is Part Of, O | New York, 3]	<X> [S | Asser Levy Public Baths, P | location, O | New York City] <Z>
Relation Prediction	[S | Asser Levy Public Baths, P | location, O | New York City, 1], [S | New York City, <Y>, O | United States, 2], [S | New York City, P | is Part Of, O | Manhattan, 2], [S | Manhattan, P | leader Name, O | Cyrus Vance Jr., 3], [S | Manhattan, P | is Part Of, O | New York, 3]	<Y> P | country <Z>
Triple Prediction + Relation Prediction	[<X>, 1], [S | New York City, P | country, O | United States, 2], [S | New York City, P | is Part Of, O | Manhattan, 2], [S | Manhattan, <Y>, O | Cyrus Vance Jr., 3], [S | Manhattan, P | is Part Of, O | New York, 3]	<X> [S | Asser Levy Public Baths, P | location, O | New York City] <Y> P | leader Name <Z>

Table 1: The input-output format for our graph masking strategies.

Lampouras, 2020) and EventNarrative (Colas et al., 2021). Additionally, we show our pre-training strategies are very efficient in utilising data and have a great potential for low-resource setting.

2 Self-Supervised Graph Masking

Our desiderata is to infuse structural knowledge into widely used pre-trained encoder-decoder Transformer models, without modifying the model architecture or relying on supervision signal. To achieve this, we propose three self-supervised learning tasks to further pre-train a `T5-LARGE` (Raffel et al., 2020) model prior to fine-tuning on G2T generation downstream tasks. In this section we first describe our graph linearisation step which prepares the data in the right format for T5 encoder while injecting some weak structural information into the input (§2.1), then we introduce our three graph masking pre-training tasks (§2.2).

2.1 Linearising a Graph

We linearise a graph into a set of triples in the format of [subject, predicate, object], representing [head entity, relation, tail entity] for every edge in a graph. Following Wang et al. (2021), we prepend S|, P|, O| tokens to further specialise each entity or relation with its role in a triple. Additionally, to provide a weak structural signal from the graph, we also augment every triple by a level marker l, indicating the distance of its object entity from the root (the node that does not have a parent in the graph). This is similar to (Wang et al., 2021), noting the key difference in that they embed the tree level using an extra layer together with other positional embeddings, but we simply augment the linearised input without adding any extra layers. The final augmented triple has the following format: [S|`head entity`, P|`relation`, O|`tail entity`, l]. For a visual example of this, see *Appendix* A.

2.2 Graph Masking Pre-training Strategies

Triple Prediction (`Triple`). For a linearised graph, on each level we randomly mask one full triple and replace it with a mask token <X>, which is then used as the target for prediction. The masked triple can be seen as a sub-graph of the original graph. This is to encourage the model to automatically identify the most relevant parts of a full graph related to each of its sub-graph.

Relation Prediction (`Relation`). In this strategy, we focus on the relations within triples. We randomly mask one relation on each level with a mask token <Y>, and the model is tasked to predict the masked relation as the target. This task requires the model to leverage very local information (i.e., between a head and a tail) to predict the masked relation. Local cohesiveness is expected to translate into better translation of triples into text fragments.

Triple + Relation Prediction (`Triple+Relation`). This ultimate strategy combines both Triple and Relation Prediction tasks to leverage the benefits of both worlds. In this setting, the Triple Prediction task follows the same protocol as stated above, but for Relation Prediction, we only consider the relation in triples that are not connected with the masked triple. We randomly mask one triple with the mask token <X>. For the triples that do not have common subject or object with the masked triple, we also randomly mask one relation with the mask token <Y>. The model jointly learns to predict both the masked sub-graphs and relations at the same time.

In all pre-training tasks we also add a token <Z> as the end token in the target output. Table 1 summarises these three pre-training tasks via an example of each kind of graph masking strategy.

Data	Metric	T5 LARGE	SotA	Triple	Relation	Triple+ Relation
WebNLG	BLEU	53.60	55.41	**57.64**	56.93	57.49
	METEOR	39.52	41.90	**42.24**	41.94	42.19
	TER	41.48	39.20	**38.86**	39.42	39.08
	BERTScore	95.02	-	**95.36**	95.23	95.28
EventNar	BLEU	34.31	35.08	38.27	**38.36**	38.08
	METEOR	26.84	27.50	**31.01**	30.80	30.99
	TER	58.26	-	**55.19**	56.11	55.32
	BERTScore	93.02	93.38	**95.24**	95.07	95.21
DART	BLEU	50.66	**51.95**	50.85	50.71	50.83
	METEOR	40	**41.07**	40.31	40.23	40.37
	TER	43	**42.75**	43.23	43.68	43.51
	BERTScore	95	95	95.11	95.04	95.16

Table 2: G2T generation results on 3 datasets.

Tr.Size	Model Setting	BLEU	METEOR	TER	BERTScore
5%	w/o pre-training	48.52	37.44	43.97	94.66
	same 5% for pre-training	**52.79**	**40.41**	**42.02**	**94.94**
	remaining 95% for pre-training	50.69	39.06	42.97	94.72
10%	w/o pre-training	48.64	37.24	43.33	94.65
	same 10% data for pre-training	**53.56**	**40.45**	**41.19**	**95.03**
	remaining 90% data for pre-training	52.57	39.75	42.17	94.75
25%	w/o pre-training	50.35	37.87	43.82	94.66
	same 25% data for pre-training	**56.04**	**41.57**	**39.38**	**95.24**
	remaining 75% data for pre-training	55.93	41.46	39.78	95.20

Table 3: Results of each model in the low-resource setting on WebNLG+2020 dataset. Tr.Size denotes the amount of data used for downstream task fine-tuning.

3 Experiments

3.1 Experimental Setups

Tasks and Datasets. We evaluate on three G2T generation datasets: WebNLG+2020 (Zhou and Lampouras, 2020), DART (Nan et al., 2021), EventNarrative (Colas et al., 2021). WebNLG+2020 contains a set of triples extracted from DBpedia (Auer et al., 2007) and text description for 16 distinct DBpedia categories. DART is an open-domain heterogeneous structured dataset collected from different sources which cover a broad range of topics. EventNarrative is a large-scale, event-centric dataset extracted and paired from existing large-scale data repositories, including Wikidata, Wikipedia, and EventKG (Gottschalk and Demidova, 2018). See *Appendix* B for full data statistics.

Pre-training Datasets. For each pre-training strategy, we create the pre-training datasets on the graph side of the task training data with the right format.

Evaluation Metrics. We report the automatic evaluation using BLEU (Papineni et al., 2002), METEOR (Banerjee and Lavie, 2005), TER (Snover et al., 2006) which are used in the official WebNLG challenge (Gardent et al., 2017) and BERTScore (Zhang et al., 2020) which considers the semantic meanings of words or phrases.

Baseline, SotA, Our Models. We use the T5-LARGE model as our baseline for fine-tuning. T5-large results are based on the published results Ribeiro et al. (2020). All our models further pre-train the vanilla T5-LARGE model and are further fine-tuned for G2T generation tasks as usual. We denote our configurations as Triple, Relation, Triple+Relation. SotA results for WebNLG and DART are from Clive et al. (2021), and for EventNarrative are based on Colas et al. (2022). Our implementation is based on the Huggingface Library (Wolf et al., 2019). Optimisation was done using Adam (Kingma and Ba, 2015) with a learning rate of 3e-5 and a batch size of 3 both in the pre-training and fine-tuning stages. We used a V100 16GB GPU for all experiments.

Data	Time	BLEU	METEOR	TER	BERTScore
100%	10h	57.64	42.24	38.86	95.36
75%	7.5h	56.92	41.98	39.07	95.29
50%	5h	56.78	41.96	39.90	95.18
25%	2.5h	56.73	41.85	40.13	95.21
5%	0.5h	56.40	41.28	40.24	95.12

Table 4: Results of using different amounts of pre-training data. Time denotes pre-training duration.

3.2 Graph-to-text Generation Results

Table 2 reports the results of fine-tuning the baseline, SotA and our models on three G2T generation tasks. For WebNLG and EventNarrative, all of our strategies outperform both the baseline and SotA results. The performance difference among our three variants is statistically insignificant. For DART, the improvement over the baseline is not as significant as for the other two datasets, while our method matches SotA on BERTScore but falls behind on the other metrics. We speculate this to be reflective of the heterogeneous nature of DART, which has a large proportion of data with very limited relations (e.g., roughly 52% of DART contains only 7 types of relations). In this setting, the pre-training tasks cannot capture much useful structure information on this sparse data.

3.3 Low-resource Setting

We investigated the performance of our methods in low-resource scenario. For this we used `Triple` as the pre-training strategy and k% (k=5, 10, 25) of WebNLG+2020 training data for downstream task fine-tuning. We tried two configurations to see if pre-training (still without using the labels) with the same training data would be better than pre-training on the non-overlapping training data: (1) used the same k% between pre-training and fine-tuning, (2) used 100-k% for pre-training and k% for fine-tuning. We compared the results of these two settings with the `T5 LARGE` which was only task fine-tuned (without additional pre-training). The results are shown in Table 3.

The models using pre-training significantly outperform the models without pre-training. For instance in 5% training scenario, the pre-trained model with `Triple` which used the same amount of data for both pre-training and fine-tuning outperforms `T5 LARGE` by a margin of 4 BLEU scores. This indicates that our graph masking pre-training strategies can effectively improve the performance of the underlying PLM in the low-resource scenario. With the increment of training data, the improvement effect of pre-training method is greater. Moreover, pre-training with the same training data leads to better results compared with using non-overlapping data. We speculate this happens since the model in this configuration is exposed to learn specific structural knowledge that will be used in the seen training data for fine-tuning downstream tasks. This also suggests a potential for our approach in multi-task learning, which we leave to future work. As the increase of training data, the gap of the performance of pre-training using different parts of data also decreases.

3.4 Analysis on Effect of Pre-training Data Size

To explore how the size of the used pre-training data affects the performance of our strategies in downstream tasks, we experimented on WebNLG+2020 dataset using our `Triple` strategy. We used 5%, 10%, 25%, 50%, and 100% of the graph side of training data for pre-training, and the whole training data to fine-tune the models. We recorded the performance, and training duration in Table 4. As the amount of pre-training data decreased, the performance of the model also decreased slightly. However, even with using 5% of pre-training data and less than 30 minutes spent on pre-training, our method outperforms both the SotA and `T5 LARGE` models (Table 2) by a significant margin.

4 Conclusion and Future Work

We proposed various self-supervised pre-training strategies to improve the structural awareness of PLMs without refining the architecture or relying on labelled data. Our graph masking strategies outperformed the strong PLM baseline and achieve new SotA results on WebNLG+2020 and EventNarrative datasets. We demonstrated that our approach is very efficient in utilising even a small pre-training or fine-tuning datasets. For future work, we will explore different graph masking strategies to adapt for different domains of graph.

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Checklist

1. For all authors...
   (a) Do the main claims made in the abstract and introduction accurately reflect the paper's contributions and scope? [Yes]
   (b) Did you describe the limitations of your work? [Yes] See Section 3.2
   (c) Did you discuss any potential negative societal impacts of your work? [Yes] See Section 1
   (d) Have you read the ethics review guidelines and ensured that your paper conforms to them? [Yes]
2. If you are including theoretical results...
   (a) Did you state the full set of assumptions of all theoretical results? [N/A]
   (b) Did you include complete proofs of all theoretical results? [N/A]
3. If you ran experiments...
   (a) Did you include the code, data, and instructions needed to reproduce the main experimental results (either in the supplemental material or as a URL)? [Yes]
   (b) Did you specify all the training details (e.g., data splits, hyperparameters, how they were chosen)? [Yes]
   (c) Did you report error bars (e.g., with respect to the random seed after running experiments multiple times)? [Yes]
   (d) Did you include the total amount of compute and the type of resources used (e.g., type of GPUs, internal cluster, or cloud provider)? [Yes]
4. If you are using existing assets (e.g., code, data, models) or curating/releasing new assets...
   (a) If your work uses existing assets, did you cite the creators? [Yes]
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   (d) Did you discuss whether and how consent was obtained from people whose data you're using/curating? [N/A]
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5. If you used crowdsourcing or conducted research with human subjects...
   (a) Did you include the full text of instructions given to participants and screenshots, if applicable? [N/A]
   (b) Did you describe any potential participant risks, with links to Institutional Review Board (IRB) approvals, if applicable? [N/A]
   (c) Did you include the estimated hourly wage paid to participants and the total amount spent on participant compensation? [N/A]

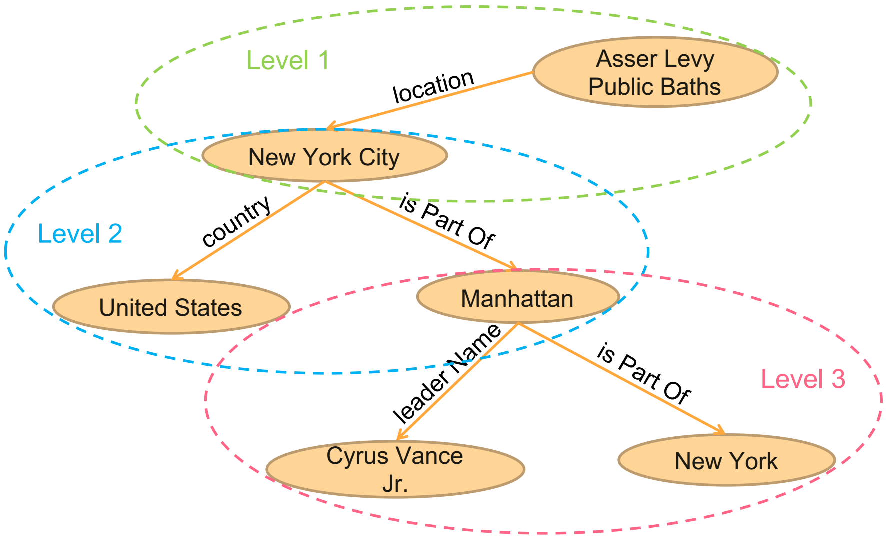


Figure 1: An example of graph with level markers. The structure-aware input of this graph is: [Asser Levy Public Baths, location, New York City, 1], [S | New York City, P | country, O | United States, 2], [S | New York City, P | is Part Of, O | Manhattan, 2], [S | Manhattan, P | leader Name, O | Cyrus Vance Jr., 3], [S | Manhattan, P | is Part Of, O | New York, 3].

Pre-training Tasks	BLEU	METEOR	TER	BERTScore
Triple	57.64	42.24	38.86	95.36
-w/o level marker	56.48	41.77	39.94	95.17
Triple+Relation	57.49	42.19	39.08	95.28
-w/o level marker	56.28	41.70	39.72	95.24
No pre-training	54.86	40.62	40.58	95.09
-w/o level marker	53.60	39.52	41.48	95.02

Table 5: Ablation results on WebNLG+2020 dataset.

Appendix

A Level Marker Augmentation

A graph and linearised version of a level-augmented input is provided in Figure 1.

Ablation Study. To show the contribution of input augmentation with level markers (§2.1), we experimented with Triple and Triple+Relation strategies on WebNLG+2020. We also report the results of using input augmentation with level marker during fine-tuning T5 LARGE. The results are shown in Table 5. We observe that the input augmentation with level markers brings improvement across all settings, even when it is only used during fine-tuning (last two rows of Table 5). We speculate this to be an indication that some useful positional information is augmented to the the linearised input through adding level markers.

B Data Statistics

The data statistics for tasks used in the paper are summarized in Table 6.

C Generated Samples

We demonstrate two qualitative examples of generated texts on WebNLG+2020 and EventNarrative test sets in Table 7 and Table 8.

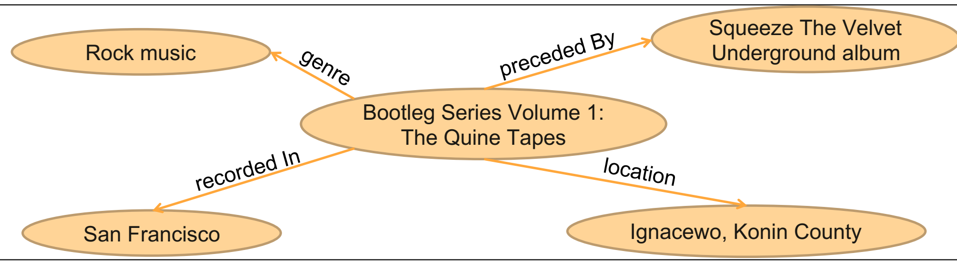
Dataset	Domain	Examples	Train/Dev/Test
WebNLG+2020	16 DBpedia Categories	38,872	35,426/1,667/1,779
EventNarrative	Events	224,428	179,544/22,442/22,442
DART	Wikipedia	11,998	62,659/6,980/12,552
	15 DBpedia Categories	27,731	
	Restaurant and Hotel Descriptions	42,462	

Table 6: Statistics of WebNLG+2020, EventNarrative and DART.

For the WebNLG, in the first example, while `T5 LARGE` generates fluent texts but misses to cover the "recorded in" relation. Previous SotA model generates all information from the graph, but it breaks the order of arguments for "preceded By". While our model can not only produce the sentences with correct information. In the second example, `T5 LARGE` misses to cover the "manufacturer" and "body Style" information. Although previous SotA and our model both can generate correct sentences, the output of our model shows a more complex syntactic structure.

For the EventNarrative, in the first example, the "Russian" information in the reference does not exist in the graph, which should be inferred by the PLM. For `T5 LARGE` and previous SotA, neither can generate such information, while our model can generate this additional information without missing any information from the graph. In the second example, the sentences generated from `T5 LARGE` have a big difference with the reference sentences and do not cover all information from the graph. Previous SotA model misses to cover the "office contested" information, while the output from our model covers all information.

WebNLG+2020

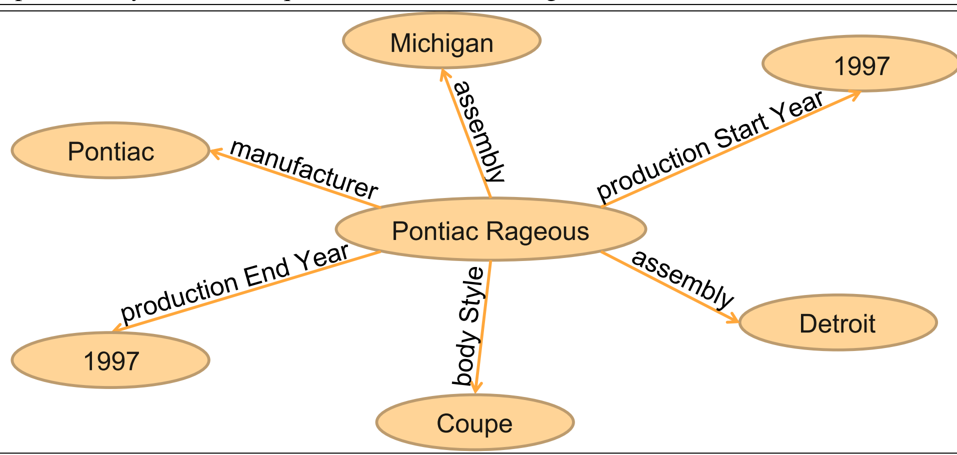


Reference: The Velvet Underground Squeeze album was succeeded by the rock album Bootleg Series Volume 1: The Quine Tapes, recorded under record label Polydor Records in San Francisco.

T5-Large: The genre of Bootleg Series Volume 1: The Quine Tapes is rock music and was preceded by the album Squeeze The Velvet Underground. The album was released by Polydor Records.

Previous SotA: Squeeze The Velvet Underground was preceded by Bootleg Series Volume 1: The Quine Tapes, which was recorded in San Francisco and released by Polydor Records. The genre of the album is rock music.

Graph Masking Pre-training+T5-Large: Bootleg Series Volume 1: The Quine Tapes, whose genre is rock music, were recorded in San Francisco and are signed to Polydor Records. They were preceded by the album Squeeze The Velvet Underground.



Reference: The Pontiac Rageous was a car with a coupe body style manufactured by Pontiac. Assembled in both Michigan and Detroit, it went into production in 1997, ending in the same year.

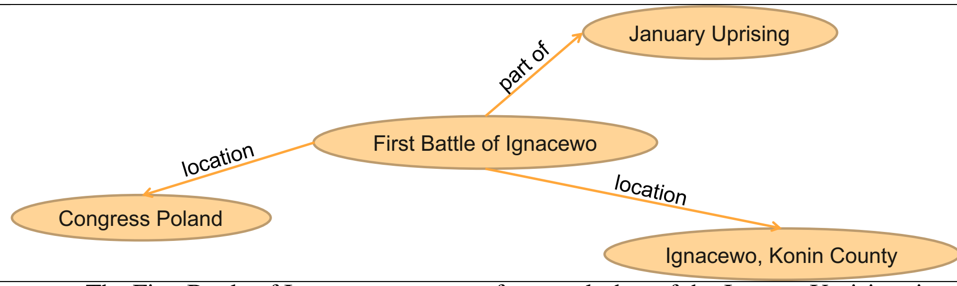
T5-Large: The Pontiac Rageous is assembled in Detroit, Michigan. Its production began in 1997 and ended in 1997. The Pontiac Rageous is a 4 door, 5 passenger vehicle.

Previous SotA: The Pontiac Rageous is manufactured by Pontiac in Detroit, Michigan. Its production began in 1997 and ended in 1997. The Pontiac Rageous has a coupe body style.

Graph Masking Pre-training+T5-Large: Pontiac is the manufacturer of the Pontiac Rageous which has a coupe body style. The Pontiac Rageous is assembled in Detroit, Michigan and began production in 1997.

Table 7: Examples of output texts on WebNLG+2020 test sets.

EventNarrative

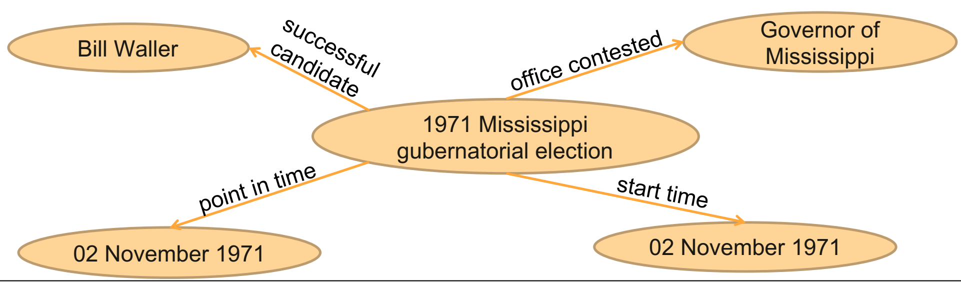


Reference: The First Battle of Ignacewo was one of many clashes of the January Uprising. it took place on may 8, 1863, near the village of Ignacewo, Konin County, which at that time belonged to Russian empire's Congress Poland.

T5-Large: The First Battle of Ignacewo was fought in Ignacewo, Konin County, Congress Poland, during the January Uprising.

Previous SotA: The First Battle of Ignacewo was one of the first battles of the January Uprising. It took place on January 6, 1863, near the village of Konin, in Congress Poland.

Graph Masking Pre-training+T5-Large: The First Battle of Ignacewo was one of battles of the January Uprising. It took place on January 11, 1863, near the village of Ignacewo, Konin County, Russian-controlled Congress Poland.



Reference: The 1971 Mississippi gubernatorial election took place on 02 November 1971 for the post of Governor of Mississippi. Democrat Bill Waller was elected into office and served as Governor of Mississippi from 1972 to 1976.

T5-Large: The 1971 Mississippi gubernatorial election took place on 02 November 1971. Incumbent Governor of Mississippi Bill Waller ran for re-election.

Previous SotA: The 1971 Mississippi gubernatorial election was held on 02 November 1971. Incumbent Governor Bill Waller won re-election to a second term, defeating the democratic nominee, former speaker of the chamber of deputies Thomas H. Williams, by a wide margin.

Graph Masking Pre-training+T5-Large: The 1971 Mississippi gubernatorial election took place on 02 November 1971, in order to elect the Governor of Mississippi. Incumbent Governor Bill Waller, who was first elected Governor in 1964, ran for re-election.

Table 8: Examples of output texts on EventNarrative test sets.