Plan-then-Seam: Towards Efficient Table-to-Text Generation

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Abstract

Table-to-text generation aims at automatically generating text to help people conveniently obtain salient information in tables. Recent works explicitly decompose the generation process into content planning and surface generation stages, employing two autoregressive networks for them respectively. However, they are computationally expensive due to the nonparallelizable nature of autoregressive decoding and the redundant parameters of two networks. In this paper, we propose the first totally non-autoregressive table-to-text model (Planthen-Seam, PTS) that produces its outputs in parallel with one single network. PTS firstly writes and calibrates one plan of the content to be generated with a novel *rethinking* pointer predictor, and then takes the plan as the context for seaming to decode the description. These two steps share parameters and perform iteratively to capture token inter-dependency while keeping parallel decoding. Experiments on two public benchmarks show that PTS achieves $3.0 \sim 5.6$ times speedup for inference time, reducing 50% parameters, while maintaining as least comparable performance against strong two-stage table-to-text competitors ¹.

1 Introduction

Table-to-text generation (Lebret et al., 2016a; Wiseman et al., 2017) is a long-standing problem that aims to generate natural language descriptions of structured table data. A good table-to-text system can help end users better identify the informative elements and their relations from a table. Therefore, developing table-to-text systems is of tremendous value in a wide range of applications, such as biography generation (Lebret et al., 2016a), basketball news generation (Wiseman et al., 2017), advertising text generation (Shao et al., 2019), and table-based question answering (Yu et al., 2019).



Figure 1: (a): example of table-to-text generation from WikiBio. Tokens from the content planning are colored in red. (b): two-stage model, which disentangles table-to-text generation into two stages: content planning and surface generation.

Recently, neural network-based approaches have made significant progress in this field. The modern neural models for table-to-text generation can be roughly categorized into one-stage models and twostage models. One-stage models generate natural language descriptions directly from the table by simply relying on representation learning to generate well-organized fluent descriptions. Along this line, some studies propose to modify the model architectures to effectively learn from structured table (Liu et al., 2018; Gong et al., 2019), while some other works introduce auxiliary tasks to help the encoder capture a more accurate semantic representation (Liu et al., 2019; Li et al., 2021). The major drawback of one-stage models is the lack of interpretability and controllability, making the models prone to suffer from unfaithful hallucinations (Wiseman et al., 2017).

To alleviate the aforementioned shortcoming of one-stage models, some researchers propose a twostage paradigm for table-to-text generation (Puduppully et al., 2019; Su et al., 2021), which explicitly

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¹https://github.com/liang8qi/Plan-then-Seam

decomposes the whole generation process into two separate stages: content planning and surface generation (illustrated in Figure 1). The content planning model generates an intermediate sequence that specifies the tokens to be verbalized. The generated plan provides some interpretability and controllability, thus can potentially reduce the risk of hallucinations (Puduppully et al., 2019). The surface generation model then completes the description based on the intermediate plan.

Although two-stage models have some superiority over one-stage models, they are often computationally intensive. The cause of the high computational cost is two-fold. Firstly, most twostage models use autoregressive (AR) decoders, which is quite time-consuming due to their nonparallelizable nature, especially for long sequences (Gu et al., 2018). Secondly, the two-stage systems often consist of two different models, which usually double the parameter scale (see Section 4.4). The increased parameter scale may introduce more computation overhead and thus slow down the inference speed. These disadvantages limit the deployment of current neural table-to-text systems in practical applications. Recently, non-autoregressive (NAR) generation has attracted much attention because it can significantly accelerate inference speed for text generation (Gu et al., 2018; Stern et al., 2019; Qian et al., 2021a). However, as demonstrated in our preliminary experiments (see also Section 4.4), applying the NAR models directly to table-to-text generation may suffer from lower generation quality because NAR models do not explicitly model the content planning procedure, which can provide good initial input for NAR decoder.

In this work, we propose to reduce the computational cost of two-stage models through a unified NAR framework, which is called Plan-then-Seam (PTS). PTS is a iterative NAR table-to-text model. Specifically, PTS first generates the content plan in the first iteration. Then it fills in the other surface tokens in subsequent multiple iterations to seam the intermediate plan tokens. Note that PTS conducts the content planning and surface generation tasks in a single model, thus the model size is smaller than previous two-stage models. Moreover, since PTS is a NAR model, it is more efficient than the AR counterparts. Given that fully NAR content planning may ignore the dependency between planned tokens, we introduce a rethinking pointer predictor, which can better calibrate the planning conditioned

on the generated ones. Our contributions can be summarized as follows:

- We are the first work concerning the computational cost (parameter and inference efficiency) problem in table-to-text. Contrastly, previous works only focus on how to improve the model performance. We hope this can raise more attention to the computational cost problem in table-to-text.
- Regarding methodology, we present the first totally NAR ² framework for table-to-text generation, achieving a desired quality–efficiency trade-off. Further, we introduce a rethinking mechanism to improve the NAR planning capability of the model. We demonstrate that initializing the decoder with a good content plan is the key to improving the NAR model.
- Experiments show that, compared with previous strong two-stage competitors, our method can achieve a 3.0 ~ 5.6× speedup with only 50% model parameters without degrading the generation quality.

2 Related Work

Table-to-text generation has long aroused interest in the Natural Language Generation (NLG) community (Kukich, 1983; Reiter and Dale, 1997). Recently, neural models have been the mainstream for this task and made impressive progress. Models for this task can be mainly categorized into two types: one-stage models and two-stage models. One-stage models generate text directly from structured data through a neural encoder-decoder architecture (Sutskever et al., 2014). They simply rely on representation learning to improve the generation. Liu et al. (2018) propose a structure-aware seq2seq architecture, which incorporates the filed information as the additional inputs to the table encoder. Some works design hierarchical table encoder which model table's representation from the row and column levels (Gong et al., 2019). Liu et al. (2019); Li et al. (2021) introduce auxiliary supervision tasks to help the encoder capture a more accurate semantic representation of the tables. However, one-stage methods are prone to produce unfaithful hallucinations and uncontrollable generation (Wiseman et al., 2017).

As the improvement, neural two-stage models (Ma et al., 2019; Puduppully et al., 2019;

²This means both content planning and surface generation are non-autoregressive.

Moryossef et al., 2019; Puduppully and Lapata, 2021; Su et al., 2021) decompose the table-to-text generation into content planning and surface generation stages. In general, content planning is implemented by Pointer Networks (Vinyals et al., 2015). The explicit content planning mechanism not only decomposes the complex table-to-text generation into two easier tasks but also makes the generation process more interpretable and controllable by generating an intermediate representation. However, the hallucination problem persists in the surface generation stage as it is autoregressive (AR). To address this issue, SANA (Wang et al., 2021) proposes an edit-based non-autoregressive (NAR) surface generation model that generates texts through iterative insertion and deletion operations while maintaining an AR planning stage. Existing twostage methods solely pay attention to improving the generation quality while ignoring its efficiency. Compared with one-stage models, two-stage methods double the number of parameters. Additionally, the AR generation is slow at inference time. These problems hinder the practical deployment of current neural table-to-text models.

3 Methodology

Given a region of a table as input, table-to-text generation is to produce a natural language description $Y = \{y_1, ..., y_n\}$ to describe the selected table region. This paper proposes the first totally nonautoregressive table-to-text model, Plan-then-Seam (PTS). As depicted in Figure 2, PTS consists of three major components, a table encoder, a nonautoregressive content planning decoder (NAR-P), and a non-autoregressive seaming decoder (NAR-S), which collaborate to generate a description for a source table in an iterative manner. At the first iteration, NAR-P generates content planning sequence in a fully non-autoregressive manner by conditioning on the source table. At the subsequent iterations, NAR-S seams the content planning tokens by inserting connective tokens between them to generate a fluent description. Next, we will describe the proposed PTS in detail.

3.1 Table Encoder

As shown on the left of Figure 2, the source table is a collection of key-value pairs in which each value may contain several tokens. Following Lebret et al. (2016a), we first linearize the source table by flattening all its values to a record sequence $T = \{r_1, r_2, ..., r_K\}$. Each record r_i is represented as a 4-tuple (w_i, k_i, p_i^+, p_i^-) , where w_i is the value token, k_i is its key name. p_i^+ and p_i^- are the relative positions of w_i , where p_i^+ counts from the beginning and p_i^- counts from the end of the sentence. For example, the key-value pair <Name, Thaila Ayala> is represented as two records: (Thaila, Name, 1, 2) and (Ayala, Name, 2, 1). We adopt four trainable embedding matrices to convert each record represented by (w_i, k_i, p_i^+, p_i^-) into dense vectors $e_{w_i}, e_{k_i}, e_{p_i^+}$, and $e_{p_i^-}$. We concatenate these embeddings and use a linear projection to map the four vectors into \mathbf{e}_i , which serves as the initial representation of the corresponding record r_i :

$$\mathbf{e}_{i} = \text{ReLU}(\mathbf{W}_{e}[e_{w_{i}}; e_{k_{i}}; e_{p^{+}}; e_{p^{-}}] + \mathbf{b}_{e}), \quad (1)$$

where \mathbf{W}_e and \mathbf{b}_e are trainable parameters. $[\cdot; \cdot]$ denotes the vector concatenation operation. Finally, we transform $\{\mathbf{e}_1, \mathbf{e}_2, ..., \mathbf{e}_K\}$ into contextual sequence representation $\mathbf{H}^e = \{\mathbf{h}_1^e, \mathbf{h}_2^e, ..., \mathbf{h}_K^e\}$ with the Transformer encoder (Vaswani et al., 2017).

3.2 Non-autoregressive Content Planning Decoder

We utilize the Transformer decoder layer (Vaswani et al., 2017) as the basic building block of the content planning component. We also remove the causal mask in self-attention modules to realize parallel generation. As shown in Figure 2, given the initial decoder input $y^0 = [BOS][EOS]$, nonautoregressive planning decoder (NAR-P) aims to generate the planned sequence (e.g., y^p = Thaila Ayalia actress model). y^p specifies the records that are to be verbalized (what to say) in the description and the order in which they are described. To this end, NAR-P consists of three major components: a placeholder predictor π^l , a pointer predictor π^p , and a token deleter π^d . These components work in a serial fashion. First, the placeholder predictor π^l determines the number of plan tokens to be inserted:

$$\pi^l(l|y^0, T) = \operatorname{Softmax}(\mathbf{W}_l[\mathbf{h}_0^{d_1}; \mathbf{h}_1^{d_1}]), \quad (2)$$

where $\mathbf{h}_0^{d_1}$ and $\mathbf{h}_1^{d_1}$ are respectively the decoder states of two symbol tokens in y^0 , $\mathbf{W}_l \in \mathbb{R}^{L \times 2d}$ is the projection matrix and L is the pre-defined maximal placeholder number. $\pi^l(l) \in \mathbb{R}^L$ denotes the the probability distribution of possible placeholder numbers, and we choose the one l with the



Figure 2: An overview of our Plan-then-Seam non-autoregressive table-to-text model. The modules with the same color share the parameters. The left part contains an example of how to linearize a table, where Spou, Occup, and YearsA denote Spouse(s), Occupation, and Years active, respectively.

highest probability. We insert l placeholders [PLH] between [BOS] and [EOS] to obtain the placeholder sequence y^l .

Then, we need to replace each [PLH] in y^l with an actual token. y^l is firstly passed into the Transformer decoder layer to generate the decoder state $\mathbf{h}_i^{d_2}$ of each placeholder. As all plan tokens are from the source table, we then introduce a pointer predictor π^p that selects tokens from T to reduce hallucinations. Specifically, for the *i*-th placeholder, we calculate the confidence scores α_j^i of copying the *j*-th record in T as a plan token by:

$$\pi^p(\alpha_j^i|y^l, T) = \text{Softmax}(\mathbf{W}_p[\mathbf{h}_i^{d_2}; \mathbf{h}_j^e]). \quad (3)$$

Then we replace each placeholder with the most possible record to get y^r .

Last, considering the predictor π^p may copy incorrect or repetitive tokens, we build a token deleter π^d to remove these false plan tokens. For the *i*-th token in y^r , π^d is employed to decide whether it is required to be deleted or not:

$$\pi^{d}(d_{i}|y^{r},T) = \operatorname{Softmax}(\mathbf{W}_{d}\mathbf{h}_{i}^{d_{3}}), \quad (4)$$

where $\mathbf{h}_i^{d_3}$ is the representation generated by transformer decoder. $\pi^d(d_i) \in [0, 1]$ is the predicted probability of the deletion operation. The token with $\pi^d(d_i = 1) > 0.5$ is deleted, which yields the final content plan y^p .

Rethinking Pointer Predictor Although nonautoregressive models can accelerate the generation process, they are based on the assumption



Figure 3: Architecture of the proposed rethinking pointer predictor. Our basic idea is to augment the non-autoregressive predictor with inter-token dependencies.

that the generated tokens are conditionally independent with each other (Gu et al., 2018). As a result, the pointer predictor may suffer from incoherence or repetition (Qian et al., 2021a). We believe that the pointer predictor would produce a better plan by partially observing generated plan tokens. Motivated by this intuition, we adapt the naive pointer predictor and propose its variant re*thinking* pointer predictor. As illustrated in Figure 3, the rethinking pointer predictor first employs a navie pointer predictor to generate a primary record plan $y_{1st}^r = \{r_1, r_2, r_6, r_6\}$, then calibrate it with another pointer predictor. Particularly, for each record r_i in y_{1st}^r , we concatenate its embedding e_i with the transformer hidden state h_i and further process it by a linear layer $\hat{h}_i = W_f[h_i; e_i]$. \hat{h}_i is fed into a transformer decoder block (removing

causal attention) to rebuild representation for the token at *i*-th position in y_{1st}^r by conditioning on the source table T and the generated plan y_{1st}^r . By looking at the tokens in other positions, the 2-nd pointer predictor can determine if the token at the *i*-th position is incorrect or repeated with others. The *rethinking* process helps the model adjust the incorrect tokens in y_{1st}^r to generate a precise plan. Moreover, to improve the confidence of y_{1st}^r , both pointer predictors are supervised by the ground truth plan when training.

3.3 Non-autoregressive Content Seaming Decoder

After obtaining the content plan y^p , at the seaming stage, the non-autoregressive seaming decoder (NAR-S) constructs a fluent description y by iteratively inserting the connective tokens into y^p . Specifically, we employ y^p as the initial input of NAR-S. In each iteration, similar to NAR-P, NAR-S also firstly predicts the number of placeholders should be inserted into at every consecutive position pairs in the generated sentence of the previous iteration, then replace placeholders with actual tokens, and finally delete abundant tokens. NAR-S share parameters in placeholder predictor π^l and token deleter π^d with NAR-P. The difference is that NAR-S replaces the pointer predictor π^p with a token predictor π^t that replaces the placeholders with actual tokens from the predefined vocabulary rather than copies from the table. For example, as shown on the right of Figure 2, given the content plan Thaila Ayalia actress model, NAR-S inserts two tokens, is and an, between Ayalia and actress in the first iteration.

3.4 Training

We joint train the content planning and seaming tasks and the final learning objective is:

$$\mathcal{L} = \lambda \mathcal{L}_{plan} + \mathcal{L}_{seam},\tag{5}$$

where λ is the hyper parameter. Next, we describe them in detail.

The content planning learning objective consists of three sub-goals: $\mathcal{L}_{plan} = \mathcal{L}_l^p + \mathcal{L}_p^p + \mathcal{L}_d^p$. Given the source table *T*, the ground truth content plan y^{p^*} as well as its pointers $y^{idx} = \{y_i^{idx}\}_{i=1}^{|y^{p^*}|}$ with each entry pointing to an input record in *T*, the placeholder predictor learning objective \mathcal{L}_l^p is computed as follows:

$$\mathcal{L}_{l}^{p} = -\log \pi^{l}(l_{0}^{*}|y^{0}, T), \qquad (6)$$

where l_0^* is the length of ground truth plan y^{p^*} . And then, we replace all the tokens in y^{p^*} with [PLH] to get y^l , which is utilized to train the pointer predictor:

$$\mathcal{L}_{p}^{p} = -\sum_{i=1}^{|y^{p^{*}}|} \log \pi^{p}(\alpha_{y_{i}^{idx}}^{i}|y^{l}, T).$$
(7)

To train the deletion predictor, we apply the pointer predictor π^p to y^l to yild y^r . The loss for deletion predictor is calculated as:

$$\mathcal{L}_{d}^{p} = -\sum_{i=1}^{|y^{r}|} \log \pi^{d}(d_{i}|y^{r}, T),$$
(8)

where d_i is the golden deletion operation at the *i*-th position, and is set as 1 if y_i^r is same with $y_i^{p^*}$, otherwise 0.

The seaming loss also consists of three parts: $\mathcal{L}_{seam} = \mathcal{L}_l^s + \mathcal{L}_p^s + \mathcal{L}_d^s$. Its training process is very similar to content planning task. The biggest difference between them is the initial input. Given a source table, a plan and a reference (T, y^{p^*}, y^*) , we follow previous works (Gu et al., 2019; Wang et al., 2021) to construct an intermediate sequence y^m as the initial input to NAR-S. Specially, we first calculate the longest common subsequence \hat{y} between y^{p^*} and y^* . And then we apply random deletion on y^* except the part of \hat{y} to obtain y^m . Last, the three subgoals are calculated as following:

$$\mathcal{L}_{l}^{s} = -\sum_{i=1}^{|y^{m}|} \log \pi^{l}(l_{i}^{*}|y^{m}, T), \qquad (9)$$

$$\mathcal{L}_{p}^{s} = -\sum_{i=1}^{|y^{*}|} \log \pi^{t}(y_{i}^{*}|y^{l},T), \qquad (10)$$

$$\mathcal{L}_{d}^{s} = -\sum_{i=1}^{|y^{*}|} \log \pi^{d}(d_{i}|y^{t}, T), \qquad (11)$$

where l_i^* is the number of placeholder that should be inserted between y_i^m and y_{i+1}^m . l_i^* is obtained by calculating the Levenshtein distance (Levenshtein et al., 1966) between y^m and y^* . y^t is yielded by applying π^t on y^l .

3.5 Inference

As mentioned above, PTS is an iterative NAR model. Different from the previous iterative NAR model, at the first iteration, PTS first utilizes NAR-P to generate the content plan in a fully NAR manner, where NAR-P alternately performs placeholder prediction, pointer prediction, and deletion operation. In the subsequent iterations, it uses the generated plan as the initial decoder input for NAR-S, which iteratively fills in the other surface tokens between the content planning tokens. We stop the seaming process when the current text does not change or the predefined maximum iteration has been reached.

4 Experiment

4.1 Datasets and Evaluation Metrics

Following Wang et al., we conduct experiments on two datasets, WikiBio (Lebret et al., 2016b) and WikiPerson (Wang et al., 2018). Both datasets are designed to generate descriptions from a Wikipedia table. Specifically, WikiBio aims to generate the first sentence of a biograph. The average length of the description is 26.1 tokens. Different from Wikibio, the reference of WikiPerson contains multiple sentences to cover as many factors in the source table as possible. The average length of the description in WikiPerson is 70.6. We use the official training, development, and test splits for both datasets, which are 582,657/72,831/72,831 in WikiBio and 250,186/30,487/29,982 in WikiPerson. We use these two datasets for two considerations. First, this paper focuses on the inference speed and generation quality of models with similar frameworks. The similar input structures allow us to use the same encoder architecture and prevent us from designing an additional one. Second, the different output length distributions of the two datasets facilitate us to compare the models' performance and efficiency.

We use BLEU (Papineni et al., 2002) and ROUGE-L to evaluate the fluency, and PARENT (Dhingra et al., 2019) to examine the faithfulness. We also employ inference latency to evaluate the inference speed of the involved approaches. Specifically, Latency is the average time to run an epoch on the test dataset while the batch size is set to 32 with one NVIDIA Tesla V100 GPU.

4.2 Baselines

To rule out the effect of model architecture on the inference speed, we only compare our method to some representative baselines built on the Transformer (Vaswani et al., 2017) model:

• TABLETRANSFORMER is a transformerbased model that replaces the naive transformer encoder with the table encoder.

- LEVT (Gu et al., 2019) is an iterative NAR model. In the first iteration, the decoder input is initialized by "[BOS][EOS]".
- CONTENT-PLAN (Puduppully et al., 2019) is a representative two-stage method that firstly uses a pointer network to generate the content plan and then uses a pointer generator to complete the remaining text. To make a fair comparison, we reimplement it using Transformer. See Appendix B.2 for more details.
- SANA (Wang et al., 2021) is also a twostage method. The major difference between SANA and CONTENT-PLAN lies in that SANA uses a LEVT for surface token generation. Additionally, SANA integrates hard constraints by forbidding the LEVT from deleting planned tokens.

4.3 Implementation Details

Our method is implemented by fairseq (Ott et al., 2019). For fair comparison, all the involved systems use a similar configuration. Specifically, the vocabulary sizes on WikiBio and WikiPerson are 30K and 50K, respectively. The dimensions of token embedding, key embedding and position embedding are set to 420, 80, and 50, respectively. All Transformer components used in our methods adopt the base Transformer setting with $d_{model} = 512, d_{hidden} = 2048, \text{ and } n_{head} = 8.$ The depth is 6 for both the encoder and the decoder. Please refer to Appendix B.1 for more details about training setting. During inferance, the maximum iterations of the NAR model is 10 and 40 in WikiBio and WikiPerson, respectively. We conduct experiments over 4 different random seeds and report the average scores.

4.4 Main Results

Table 1 shows the performance of our method and the baselines. For WikiBio, the NAR LEVT model are approximately $3 \times$ faster than the AR TABLE-TRANSFORMER model. However, the description quality of LEVT is much lower than TABLETRANS-FORMER, regarding both fluency (-1.27 BLEU) and faithfulness (-4.62 PARENT-F1). Moreover, we observe that two-stage approaches can outperform the one-stage ones (e.g., SANA vs. LEVT), indicating the superiority of explicitly content planning. However, they double the parameters scale and increase the inference latency. Surprisingly, our proposed method can combine the advantages

Models	BLEU	ROUGE-L	PARENT (P / R / F1)	#Param	Latency↓	$\mathbf{I_{DEC}}\downarrow$
One-Stage Systems						
TABLETRANSFORMER	$44.32_{\pm 0.32}$	$66.75_{\pm 0.36}$	74.09 $_{\pm 0.32}$ / 42.41 $_{\pm 0.18}$ / 51.76 $_{\pm 0.31}$	76	680	22.10
LEVT	$43.05 _{\pm 0.21}$	$65.61_{\pm 0.31}$	72.22 $_{\pm 0.16}$ / 37.62 $_{\pm 0.14}$ / 47.14 $_{\pm 0.11}$	74	223	2.48
			Two-Stage Systems			
CONTENT-PLAN	$43.44_{\pm 0.00}$	$66.21_{\pm 0.31}$	74.55 $_{\pm 0.29}$ / 43.45 $_{\pm 0.30}$ / 52.38 $_{\pm 0.11}$	150	1,381	30.47
SANA †	45.78	-	76.93 / 46.01 / 55.42	-	-	-
w/o hard constraints †	45.31	-	76.32 / 45.26 / 54.64	-	-	-
SANA	$45.50_{\pm 0.13}$	$67.98_{\pm 0.15}$	77.01 $_{\pm 0.25}$ / 45.52 $_{\pm 0.08}$ / 55.16 $_{\pm 0.10}$	148	756	11.02
w/o hard constraints	$44.94_{\pm 0.16}$	$67.72_{\pm 0.16}$	76.89 $_{\pm 0.26}$ / 44.70 $_{\pm 0.26}$ / 54.68 $_{\pm 0.59}$	148	761	11.03
OURS	$45.65_{\pm 0.13}$	$68.30_{\pm 0.38}$	$77.29_{\pm 0.24}$ / $45.80_{\pm 0.10}$ / $55.41_{\pm 0.24}$	80	245	3.49
w/o rethinking	$45.21_{\pm 0.07}$	$67.99_{\pm 0.16}$	76.88 $_{\pm 0.39}$ / 45.29 $_{\pm 0.10}$ / 55.07 $_{\pm 0.17}$	75	290	3.63
		(a)	Results on WikiBio			
(a) Results off WIRIBIO						
Models	BLEU	ROUGE-L	PARENT (P / R / F1)	#Param	Latency↓	$I_{DEC}\downarrow$
Models	BLEU	ROUGE-L	PARENT (P / R / F1) One-Stage Systems	#Param	Latency↓	$I_{DEC}\downarrow$
Models TABLETRANSFORMER	BLEU 25.11±0.63	ROUGE-L 44.06±0.56	PARENT (P / R / F1) One-Stage Systems 61.13 _{±0.89} / 52.08 _{±0.90} / 54.45 _{±0.41}	#Param 92	Latency ↓ 2,092	I _{DEC} ↓ 62.42
Models TableTransformer LevT	BLEU 25.11±0.63 22.10±0.36	ROUGE-L 44.06 ±0.56 43.60±0.57	PARENT (P / R / F1) One-Stage Systems 61.13±0.89 / 52.08±0.90 / 54.45±0.41 61.43±0.44 / 49.58±0.00 / 53.65±0.16	#Param 92 91	Latency↓ 2,092 449	I _{DEC} ↓ 62.42 3.60
Models TableTransformer LevT	BLEU 25.11±0.63 22.10±0.36	ROUGE-L 44.06 ±0.56 43.60±0.57	PARENT (P / R / F1) One-Stage Systems 61.13 _{±0.89} / 52.08 _{±0.90} / 54.45 _{±0.41} 61.43 _{±0.44} / 49.58 _{±0.00} / 53.65 _{±0.16} Two-Stage Systems	#Param 92 91	Latency↓ 2,092 449	I _{DEC} ↓ 62.42 3.60
Models TableTransformer LevT Content-Plan	BLEU 25.11±0.63 22.10±0.36 25.17±0.78	ROUGE-L 44.06±0.56 43.60±0.57 44.47±0.03	PARENT (P / R / F1) One-Stage Systems 61.13±0.89 / 52.08±0.90 / 54.45±0.41 61.43±0.44 / 49.58±0.00 / 53.65±0.16 Two-Stage Systems 62.09±0.55 / 53.63±0.44 / 56.68±0.29	#Param 92 91 187	Latency↓ 2,092 449 2,708	I _{DEC} ↓ 62.42 3.60 82.61
Models TABLETRANSFORMER LEVT CONTENT-PLAN SANA †	BLEU 25.11±0.63 22.10±0.36 25.17±0.78 25.23	ROUGE-L 44.06±0.56 43.60±0.57 44.47±0.03	PARENT (P / R / F1) One-Stage Systems $61.13_{\pm 0.89}$ / $52.08_{\pm 0.90}$ / $54.45_{\pm 0.41}$ $61.43_{\pm 0.44}$ / $49.58_{\pm 0.00}$ / $53.65_{\pm 0.16}$ Two-Stage Systems $62.09_{\pm 0.55}$ / $53.63_{\pm 0.44}$ / $56.68_{\pm 0.29}$ 65.69 / 56.88 / 59.96	#Param 92 91 187 183	Latency↓ 2,092 449 2,708	I DEC↓ 62.42 3.60 82.61
Models TABLETRANSFORMER LEVT CONTENT-PLAN SANA † w/o hard constraints †	BLEU 25.11±0.63 22.10±0.36 25.17±0.78 25.23 24.97	ROUGE-L 44.06±0.56 43.60±0.57 44.47±0.03	PARENT (P / R / F1) One-Stage Systems $61.13_{\pm 0.89}$ / $52.08_{\pm 0.90}$ / $54.45_{\pm 0.41}$ 61.43_{\pm 0.44} / $49.58_{\pm 0.00}$ / $53.65_{\pm 0.16}$ Two-Stage Systems 62.09_{\pm 0.55} / $53.63_{\pm 0.44}$ / $56.68_{\pm 0.29}$ 65.69 / 56.88 / 59.96 64.72 / 56.42 / 59.29	#Param 92 91 187 183 183	Latency↓ 2,092 449 2,708	I _{DEC} ↓ 62.42 3.60 82.61
Models TABLETRANSFORMER LEVT CONTENT-PLAN SANA † w/o hard constraints † SANA	BLEU 25.11 \pm 0.63 22.10 \pm 0.36 25.17 \pm 0.78 25.23 24.97 24.95 \pm 0.31	ROUGE-L 44.06 ± 0.56 43.60 ± 0.57 44.47 ± 0.03 - 45.35 ± 0.13	PARENT (P / R / F1) One-Stage Systems $61.13_{\pm 0.89}$ / $52.08_{\pm 0.90}$ / $54.45_{\pm 0.41}$ $61.43_{\pm 0.44}$ / $49.58_{\pm 0.00}$ / $53.65_{\pm 0.16}$ Two-Stage Systems $62.09_{\pm 0.55}$ / $53.63_{\pm 0.44}$ / $56.68_{\pm 0.29}$ 65.69 / 56.88 / 59.96 64.72 / 56.42 / 59.29 $69.26_{\pm 0.83}$ / $58.16_{\pm 0.06}$ / $62.39_{\pm 0.15}$	#Param 92 91 187 183 183 183	Latency↓ 2,092 449 2,708 - 1,370	I _{DEC} ↓ 62.42 3.60 82.61 - 29.20
Models TABLETRANSFORMER LEVT CONTENT-PLAN SANA † w/o hard constraints † SANA w/o hard constraints	BLEU 25.11 \pm 0.63 22.10 \pm 0.36 25.17 \pm 0.78 25.23 24.97 24.95 \pm 0.31 22.37 \pm 0.38	ROUGE-L 44.06 \pm 0.56 43.60 \pm 0.57 44.47 \pm 0.03 - 45.05 \pm 0.13 45.08 \pm 0.15	PARENT (P / R / F1) One-Stage Systems $61.13_{\pm 0.89}$ / $52.08_{\pm 0.90}$ / $54.45_{\pm 0.41}$ $61.43_{\pm 0.44}$ / $49.58_{\pm 0.00}$ / $53.65_{\pm 0.16}$ Two-Stage Systems $62.09_{\pm 0.55}$ / $53.63_{\pm 0.44}$ / $56.68_{\pm 0.29}$ 65.69 / 56.88 / 59.96 64.72 / 56.42 / 59.29 $69.26_{\pm 0.83}$ / $58.16_{\pm 0.06}$ / $62.39_{\pm 0.15}$ $69.10_{\pm 0.49}$ / $56.62_{\pm 0.38}$ / $61.38_{\pm 0.28}$	#Param 92 91 187 183 183 183 183 183	Latency↓ 2,092 449 2,708 - 1,370 1,217	I DEC ↓ 62.42 3.60 82.61 - 29.20 28.92
Models TABLETRANSFORMER LEVT CONTENT-PLAN SANA † w/o hard constraints † SANA w/o hard constraints OURS	$\begin{array}{c} \textbf{BLEU} \\ \hline \textbf{25.11}_{\pm 0.63} \\ 22.10_{\pm 0.36} \\ \hline \textbf{25.23} \\ 24.97 \\ 24.95_{\pm 0.31} \\ \underline{22.37}_{\pm 0.38} \\ \underline{25.11}_{\pm 0.35} \\ \end{array}$	$\begin{array}{c} \textbf{ROUGE-L} \\ \textbf{44.06}_{\pm 0.56} \\ \textbf{43.60}_{\pm 0.57} \\ \textbf{44.47}_{\pm 0.03} \\ \textbf{-} \\ \textbf{44.47}_{\pm 0.03} \\ \textbf{-} \\ \textbf{45.08}_{\pm 0.13} \\ \textbf{45.08}_{\pm 0.15} \\ \textbf{-} \\ \textbf{45.23}_{\pm 0.31} \\ \textbf{-} \end{array}$	PARENT (P / R / F1) One-Stage Systems $61.13_{\pm 0.89}$ / $52.08_{\pm 0.90}$ / $54.45_{\pm 0.41}$ $61.43_{\pm 0.44}$ / $49.58_{\pm 0.00}$ / $53.65_{\pm 0.16}$ Two-Stage Systems $62.09_{\pm 0.55}$ / $53.63_{\pm 0.44}$ / $56.68_{\pm 0.29}$ 65.69 / 56.88 / 59.96 64.72 / 56.42 / 59.29 $69.26_{\pm 0.83}$ / $58.16_{\pm 0.06}$ / $62.39_{\pm 0.15}$ $69.10_{\pm 0.49}$ / $56.62_{\pm 0.38}$ / $61.38_{\pm 0.28}$ $69.72_{\pm 0.63}$ / $58.12_{\pm 0.49}$ / $62.58_{\pm 0.36}$	#Param 92 91 187 183 183 183 183 183 183 97	Latency↓ 2,092 449 2,708 - 1,370 - 1,217 - 547	$I_{DEC} ↓$ 62.42 3.60 82.61 - 29.20 - 28.92 - 4.83
Models TABLETRANSFORMER LEVT CONTENT-PLAN SANA † w/o hard constraints † SANA w/o hard constraints OURS w/o rethinking	$\begin{array}{c} \textbf{BLEU} \\ \hline \textbf{25.11}_{\pm 0.63} \\ 22.10_{\pm 0.36} \\ \hline \textbf{25.17}_{\pm 0.78} \\ \textbf{25.23} \\ 24.97 \\ 24.95_{\pm 0.31} \\ 22.37_{\pm 0.38} \\ \hline \textbf{25.11}_{\pm 0.35} \\ 24.45_{\pm 0.28} \\ \end{array}$	ROUGE-L 44.06 ± 0.56 43.60 ± 0.57 44.47 ± 0.03 - 45.35 ± 0.13 45.08 ± 0.15 $\overline{45.23} \pm 0.31$ 44.87 ± 0.21	PARENT (P / R / F1) One-Stage Systems $61.13_{\pm 0.89}$ / $52.08_{\pm 0.90}$ / $54.45_{\pm 0.41}$ $61.43_{\pm 0.44}$ / $49.58_{\pm 0.00}$ / $53.65_{\pm 0.16}$ Two-Stage Systems $62.09_{\pm 0.55}$ / $53.63_{\pm 0.44}$ / $56.68_{\pm 0.29}$ 65.69 / 56.88 / 59.96 64.72 / 56.42 / 59.29 $69.26_{\pm 0.83}$ / $58.16_{\pm 0.06}$ / $62.39_{\pm 0.15}$ $69.10_{\pm 0.49}$ / $56.62_{\pm 0.38}$ / $61.38_{\pm 0.28}$ $69.72_{\pm 0.63}$ / $58.12_{\pm 0.49}$ / $62.58_{\pm 0.36}$ $68.17_{\pm 0.74}$ / $57.45_{\pm 0.52}$ / $61.55_{\pm 0.43}$	#Param 92 91 187 183 183 183 183 97 97 92	Latency↓ 2,092 449 2,708 - 1,370 1,217 - 547 572	I DEC ↓ 62.42 3.60 82.61 - 29.20 28.92 - 4.83 4.95

(b) Results on WikiPerson

Table 1: Results on WikiBio and WikiPerson test sets. Results marked with "†" are copied from previous studies while the other results are implemented in this work. Latency and I_{DEC} denote the average inference time and the average number of decoder iterations, respectively. Mean (±s.d.) over 4 seeds.

of both the two kinds of baselines. On both WikiBio and WikiPerson, our approach can achieve comparable description quality with the strong twostage baseline (i.e., SANA), while maintaining the model size and the inference speed. Compared with SANA, our model does not require external constraints to guarantee the appearance of planned tokens in the final output. The results also demonstrate the effectiveness of the newly proposed rethinking mechanism, confirming that the inter-dependency between different positions is essential for NAR-P, which can provide a better starting point for NAR-S. Additionally, we notice that the latency increase without rethinking. We believe this is because removing this module reduces the content planning capability of the model, which in turn lowers the quality of the initial input to NAR-S, making the model require more iterations to satisfy the termination condition. The results on WikiPerson show a similar trend to WikiBio. An obvious difference is that the inference speed is much slower for all models, since the average description length is longer than WikiBio (70.6 vs. 26.1). When generating longer sentences, the speedup of our method over the AR baseline is much higher. On both datasets, our method can achieve high description quality and inference efficiency at the same time.

4.5 Analysis and Discussion

Due to the page limit, we have placed more experimental results and analyses in Appendix A.

Content Planning As mentioned above, explicit content planning is important for table-to-text generation. We thus further investigate the content planning performance in Table 2. We compare our method with two baselines: POINTERNETWORK and NAR-P. POINTERNETWORK is a widely used planning method for two-stage models (Puduppully et al., 2019; Wang et al., 2021). The results indicate that our proposed PTS model performs comparable with POINTERNETWORK. NAR-P has a same architecture with PTS, the difference is that NAR-P is totally trained with the content planning task, while PTS is trained to perform both content planning and seaming. The results show that training the model with both content planning and seaming does not significantly affect the planning perfor-

Models	BLEU	#Param	Latency
	WikiBio		
POINTERNETWORK	64.97	76	261
w/o beam search	62.03	76	259
NĀR-P	64.78	80	54 -
w/o rethinking	64.36	75	59
PTS-PLAN	64.75	80	64-
w/o rethinking	64.43	75	59
	WikiPerson	ı	
POINTERNETWORK	52.42	91	851
w/o beam search	43.48	91	926
NĀR-P	52.51	97	61
w/o rethinking	52.14	92	63
PTS-PLAN	52.27		60-
w/o rethinking	51.67	92	58

Table 2: Performance of different content planning models. "NAR-P" is solely trained using the content planning objective, while "PTS-PLAN" is to use the final PTS model to perform content planning.



Figure 4: Quality-Speed trade-off on the WikiBio test set. Quality is estimated by BLEU. For clarity, the inference speed is measured by the relative speedup with respect to TABLETRANSFORMER with beam size = $5. N \in [1, 10]$ denotes the maximum iteration number.

mance, which implies that learning the two tasks with a unified model does not decrease the model's planning ability.

Quality-Speed Trade-off Since PTS is an iterative NAR model, it is easy to balance the description quality and the inference speed by changing the number of the iterations. As shown in Figure 4, PTS achieves comparable performance with substantially higher speed up than the other involved models. For PTS, increasing the iteration number can improve the description quality while reduce the inference speed. In practice, we can change the iteration number to meet different requirements under various application cases.

Tokens Generated at the Seaming Stage To build a deeper understanding of the proposed PTS model, we investigate the problem of which tokens

Token	Percentage (%)
,	8.01%
	7.69%
-lrb-	7.28%
-rrb-	7.26%
а	5.21%
is	5.07%
born	4.51%
the	3.12%
an	2.74%
was	2.27%
and	2.41%
in	2.26%
-	2.13%
of	2.12%
who	1.64%
Total	64.18%

Table 3: Top 15 tokens generated by our proposed PTS at the seaming stage on WikiBio test set. -lrb- and -rrb- represent (and), respectively.

are most likely to be generated by PTS at the seaming stage on the WikiBio test set. Specifically, we first remove the words generated at the planning stage from the descriptions generated by PTS to obtain a word set. Then, we count the token frequency for the word in the set. We present the top 15 frequent tokens in Table 3. As we can see, at the seaming stage, PTS is more likely to generate connective tokens, e.g., punctuation, and copulas, than the specific tokens existing in the input table, such as name, time, etc. And the connective tokens are mainly used to link planning words (seaming). The observation is consistent with our motivation and design that PTS first copies content from the input table to construct a plan sequence and then inserts tokens from a pre-defined vocabulary between plan tokens to generate a fluent description. We believe this make our approach more interpretable and controllable.

5 Human Evaluation

To verify whether the system performance is consistent with what the automatic metrics show, we further conduct a human evaluation on the WikiBio test set. We randomly sample 50 instances from each model's generated outputs. Then, we invite three graduate students, whose English level is very high to understand the text, to score each generated text from 1 to 5 in terms of two criteria: Fluency (is

Models	Fluency	Faithfulness
TABLETRANSFORMER	$3.24_{\pm 0.77}$	$2.89_{\pm 0.86}$
LevT	$2.75_{\pm 0.89}$	$2.57_{\pm 0.78}$
CONTENT-PLAN	$3.18_{\pm 0.32}$	$3.01_{\pm 0.72}$
SANA	$3.31_{\pm0.74}$	$3.26_{\pm 0.69}$
OURS	$3.42_{\pm 0.58}$	$3.42_{\pm 0.59}$

Table 4: Human evaluation results on WikiBio test set.

the sentence fluency?) and Faithfulness (is the sentence related to the input table?). For each criterion, we average the scores from all annotators as the final score. When evaluating, each annotator is provided the input tables as the references and does not know which model the generated text comes from. The results are summarized in Table 4. As we can see, the overall trend of the human evaluation is similar to the automatic metrics in Table 1. First, the two-stage systems have an advantage over the one-stage ones in generating result fidelity. Second, our method is competitive to these table-to-text baselines regarding generation fluency and faithfulness. Meanwhile, our approach performs better than the LEVT transferred from machine translation. These results indicate that introducing the content planning process in the NAR process and using its results as the initial decoder input can significantly improve the NAR model.

6 Conclusion

We propose a unified non-autoregressive framework, Plan-then-Seam (PTS), for table-to-text generation. Given a source table, PTS first generates the content plan in a fully NAR manner. Then we iteratively fill in the other surface tokens. Experimental results demonstrate that PTS achieves a $3.0 \sim 5.6$ speedup with only 50% model parameters compared with previous two-stage table-to-text models, without degrading the description quality. Further analysis reveals that the success of PTS comes from the proposed NAR-P with a rethinking mechanism, whose content planning performance is comparable with AR models. By changeing the iteration number, PTS can balance the generation quality and inference efficiency for various practical application requirements.

Limitations

As described in the paper, the content planning ability is important for table-to-text models. However, the planning performance of all the involved methods is still far from satisfactory. We will explore more advanced methods to improve the content planning performance. Moreover, we train all the models on WikiBio and WikiPerson from scratch, and the training cost is rather expensive: 2.5 days using 4 NVIDIA V100 32G GPUs. Lastly, this paper does not compare the pre-trained language models (PLMs) (Devlin et al., 2019; Raffel et al., 2020), though our approach may also benefit from some pre-trained table encoders, such as TAPAS (Müller et al., 2021). The main reasons why we do not consider PLMs are that PLMs will bring an unfair comparison and bring more variables and may make our work lose focus. See Appendix B.2 for detailed justification. In the future, we will explore how pre-trained models, e.g., pre-trained table encoder TAPAS, can be used to improve our model's performance and accelerate the training process.

Ethics Statement

We consider our work can make more researchers in table-to-text pay attention to the computational cost problem, which may benefit from saving the cost of the online table-to-text model. We experimented on the public datasets with no discriminatory or insulting sentences.

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Models	Token Repetitions (%)	Dist-1	Dist-2
Gold	12.58	5.6	22.83
TableTransformer	9.29	1.5	10.87
LevT	14.59	2.1	13.97
Content-Plan	9.81	4.7	15.11
SANA	9.93	5.0	19.32
Ours	8.22	4.9	18.15

Table 5: The token repetitions and diversity on WikiBio test dataset. Dist-1 and Dist-2 denote Distinct-1 and Distinct-2, respectively.

Models	BLEU	PARENT(P/R/F1)
CONTENT-PLAN	43.72	76.55 / 38.79 / 49.02
+ Golden Plan	51.16	76.32 / 47.33 / 56.45
SĀNĀ	45.68	76.79/45.64/55.12
+ Golden Plan	54.30	80.03 / 51.02 / 61.01
OURS	45.75	77.34/45.91/55.48
+ Golden Plan	55.50	79.59 / 51.92 / 61.14

The second contract of conden plan on two blace methods	Table 6:	Effect of	golden	plan on	two-stage	methods
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A More Experimental Results

A.1 Token Repetitions and Diversity

Previous works manifest NAR model tends to predict the same token with high confidence, but at different positions, which is caused by the multimodality problem. Therefore, we doubt whether the NAR table-to-text generation has any preference towards token repetitions and diversity. We measure the percentage of repetitive tokens in the generated sent as a proxy metric for the multimodality problem (Gu et al., 2018). Additionally, we utilize Distinct-1 and Distinct-2 (Li et al., 2016) to evaluate the diversity of the output text. All results are summarized in Table 5. We observe that the AR model TABLETRANSFORMER significantly reduces the lexical diversity. Therefore, to better train the non-autoregressive model, AR model is usually used as a teacher model to reduce the complexity of the training corpus (Knowledge Distillation) (Gu et al., 2018). And then, LEVT tends to generate repetitive tokens. We can see that, when explicitly modelling the content planning, two-stage methods can increase the tokens diversity. Especially, the content planning can substantially reduce the tokens repetitions for NAR models (e.g., LEVT vs. SANA and OURS).

A.2 Performance Bottleneck of Two-stage Model

We provide the ground-truth content plan to the models at the second stage, and the results are summarized in Table 6. When fed with the golden plan, all the two-stage models achieves better fluency and faithfulness. The results indicate that the quality of content planning is a important bottleneck for two-stage table-to-text approaches.

A.3 Case Study

Table 7 shows the descriptions generate by PTS from the test set of WikiBio. First, we observe that when the number of tokens in the generated plan is relatively small, the 1-st pointer predictor can generate a precise content plan. However, when the number of planning tokens increases, it tends to produce repetitive and incorrect ones. We consider this is because the fully NAR generation cannot accurately model the dependencies between planning tokens. After introducing the *rethinking* mechanism, the 2-nd pointer predictor can determine if the token is incorrect or repeated with others and calibrate it by looking at the tokens in other positions. Therefore, the model can generate a more precise plan.

B More Implementation Details

B.1 Training and Hyper-parameter Settings

All models are optimized by Adam (Kingma and Ba, 2015). We use the same learning rate schedule as presented in Vaswani et al. (2017). The maximum value of the learning rate is 5e-4 and the warmup step is set to 10K. The maximum training step is set to 300K. We use the validation BLEU for early stopping and explore $\lambda = [0.05, 0.08]$. During inferance, we use beam search with a beam size 5 for the autoregressive models and the maxinum decoding lengths are set to 80 and 160 in WikiBio and Wikiperson. For non-autoregressive models, we set the maximum iterations as 10 and 40 in WikiBio and WikiPerson, respectively.

B.2 Experimental Setting Details

To rule out the effect of model architecture on the inference speed and make a fair comparison, we only compare our method to some table-totext models built on the Transformer model. For the one-stage models, we chose the autoregressive TableTrasnforme and non-autoregressive LevT. For the two-stage methods, we compare with Content-Plan and SANA. Both planning generation and tableau generation of the former are autoregressive, while the second stage of the latter is a nonautoregressive process. All these baselines employ the same table encoder as ours. Additionally, the original Content-Plan is implemented by LSTM. To make a fair comparison, we re-implemented Content-Plan by replacing its LSTM-based encoder and decoder with Transformer-based ones. And the transformer setting is the same as our model.

We do not consider the pre-trained models (PLMs) in this paper, though our model's performance may be significantly improved by initializing our table encoder with the pre-trained one, such as TAPAS (Herzig et al., 2020). The reasons why we do not consider PLMs are as follows:

- We consider PLMs will bring an unfair comparison. Because most PLMs (e.g., TAPAS, T5 (Raffel et al., 2020)) are pre-trained on Wikipedia data, and WikiBio and WikiPerson are built from Wikipedia. It may lead to data leakage. Moreover, to our best knowledge, most of the works in the NAR machine translation (please refer to Appendix C) do not compare with PLMs.
- This paper focuses on comparing inference speed and quality under a similar model architecture rather than improving the model performance. And our experimental setting is fair, and all the baselines employ a similar setting as our model. Additionally, in related domains such as neural machine translation, previous work (Zhu et al., 2020) indicates that simply initializing the encoders of sequence-to-sequence models with the pretrained BERT (Devlin et al., 2019) will actually hurt the performance. And directly finetuning NAR sequence-to-sequence models initialized by BERT is very unstable and sensitive to the learning rate (Guo et al., 2020). Therefore, though pre-trained checkpoint may benefit our model, it will bring more variables and may make our work lose focus. We leave this for feature work.

B.3 Content Plan Annotation

We follow previous work (Wang et al., 2021) to employ the heuristic method to obtain the content plan annotation for WikiBio and WikiPerson. Specifically, we start by counting the tokens that appear both in the table and in the corresponding description. Then we remove the stop tokens in the tokens collection and sort the rest of the tokens by the their positions in the description in ascending order. The sorted sequence is regard the content planning sequence. We refer the readers to Wang et al. (2021)'s paper for more details.

C Non-autoregressive Neural Machine Translation

Recently, autoregressive (AR) models have achieved outstanding performances in natural language generation tasks (Raffel et al., 2020). However, AR is quite time-consuming when generating target sentences, especially for long sentences. To overcome this problem and accelerate decoding, Gu et al. (2018) first propose the nonautoregressive generation (NAR) for machine translation, which generates all the target tokens in parallel and hugely increases the inference speed. Therefore, much attention has been attracted to NAR with impressive progress (Stern et al., 2019; Qian et al., 2021a; Song et al., 2021; Qian et al., 2021b). However, compared with AR models, the generation quality is sacrificed because NAR breaks the conditional dependence assumption that prevents a model from properly capturing the highly multimodal distribution of target translations, which is called the "multi-modality" problem Gu et al. (2018). To mitigate the problem, some studies (Lee et al., 2018; Stern et al., 2019; Ghazvininejad et al., 2019; Gu et al., 2019; Saharia et al., 2020) propose the iterative NAR models which need N iterations for inference and keep the non-autoregressive property in every iteration step. More specifically, the generated results of the previous iteration will be fed into the decoder again for refinements. In this way, partial target information is provided in each iteration step.

First Example				
Source Table	<name: macias="" sean="">, <birth california="" place:="">, <known for:="" litigation="">,</known></birth></name:>			
Source Table	Coccupation: lawyer>, Chationality: american>, Carticle Title: sean macias>.			
	(Name, sean,	1, 2), (Name , macias,	2, 1), (Birth Place, california, 1, 1),	
Flatten Table	(Known For , american, 1, 1	litigation, 1, 1), (Occu), (Article Title , sean, 1	<pre>pation, lawyer, 1, 1), (Nationality, , 2), (Article Title, macias, 2, 1).</pre>	
Rerence	sean ernesto r litigation lawy	nacias -lrb- born 31 oct er known for handling h	tober 1972 -rrb- is a pasadena-based nigh-profile cases .	
	1st iteration	1st pointer predictor 2nd pointer predictor	sean macias american litigation lawyer sean macias american litigation lawyer	
PTS	2nd Iteration	sean macias is an ame	rican litigation lawyer.	
	1	Second Examp	le	
	<name: dave<="" th=""><th>green>, <poisition< b="">: p</poisition<></th><th>unter placekicker >, <number< b="">: 4>,</number<></th></name:>	green>, <poisition< b="">: p</poisition<>	unter placekicker >, <number< b="">: 4>,</number<>	
	<birth 2<="" date:="" th=""><th>21 september 1949>, <d< b=""></d<></th><th>ebutyear: 1973>, <finalyear: 1978="">,</finalyear:></th></birth>	21 september 1949>, <d< b=""></d<>	ebutyear: 1973>, <finalyear: 1978="">,</finalyear:>	
Source Table	Chaityear: 1	9/2>, <draitround: 1="" <br="">Statlabel: punts punting</draitround:>	>, $<$ Draitpick: 418>, $<$ College: onto	
	< Nfl : re16228	32>, <brith b="" place<="">: mas</brith>	son city iowa> ,< Article Title : dave	
	green -lrb- am	erican football -rrb->.		
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	nlacekicker	(1, 2), (1) (Number 4 1)	1) (Birth Date 21 1 3) (Birth	
	Date, septem	ber, 2, 2), (Birth Date	, 1949, 3, 1), (Debutyear , 1973, 1,	
Flatten Table	1), (Finalyear, 1978, 1, 1), (Draftyear, 1972, 1, 1),, (Birth Place, mason,			
	1, 3), (Birth P)	lace, city, 2, 2), (Birth F Title groon $2, 5$) (Art	Place , 10wa, 3, 1), (Article Title , dave, ticle Title , 1rb, 3, 4), (Article Title	
	1, 6), (Article Title, green, 2, 5), (Article Title, -lrb-, 3, 4), (Article Title, american, 4, 3), (Article Title, football, 5, 2), (Article Title, -rrb-, 6, 1).			
	dave green -lrb- horn september 21 1949 in mason city jowa -rrb- is a			
Rerence	dave green -Irb- born september 21, 1949 in mason city, iowa -rrb- is a former punter and placekicker in the national football league.			
		1st pointer predictor	dave dave september 21 1949 american	
	1st iteration	Tst pointer predictor	kicker football	
			dave green september 21 1949 mason	
PTS		2nd pointer predictor	city iowa american football punter place- kicker football	
		dava alan graan Irb	horn contamber 21 1040 in meson	
	2nd Iteration	city, iowa -rrb- is a former american football punter and		
		placekicker in the national football league .		
		dave green -lrb- born se	eptember 21, 1949 in mason city, iowa	
	3rd Iteration	-rrb- is a former american football punter and placekicker in		
		the national football le	ague.	

Table 7: Two examples from the WikiBio test set that illustrates how PTS generates a description for a source table by planning and then seaming. The incorrect and repetitive planning tokens are in red.