

Few-Shot Data-to-Text Generation via Unified Representation and Multi-Source Learning

Alexander Hanbo Li, Mingyue Shang, Evangelia Spiliopoulou, Jie Ma
Patrick Ng, Zhiguo Wang, Bonan Min, William Wang
Kathleen McKeown, Vittorio Castelli, Dan Roth, Bing Xiang

AWS AI Labs

{hanboli, myshang, spilieva, jieman, patricng, zhiguow, bonanmin, wyw}@amazon.com
{mckeownk, vittorca, drot, bxiang}@amazon.com

Abstract

We present a novel approach for structured data-to-text generation that addresses the limitations of existing methods that primarily focus on specific types of structured data. Our proposed method aims to improve performance in multi-task training, zero-shot and few-shot scenarios by providing a unified representation that can handle various forms of structured data such as tables, knowledge graph triples, and meaning representations. We demonstrate that our proposed approach can effectively adapt to new structured forms, and can improve performance in comparison to current methods. For example, our method resulted in a 66% improvement in zero-shot BLEU scores when transferring models trained on table inputs to a knowledge graph dataset. Our proposed method is an important step towards a more general data-to-text generation framework.¹

1 Introduction

Data-to-text generation is the task of converting structured data into natural language text that can be easily understood by humans. Previous methods for data-to-text generation have been limited to specific structured forms. For example, graph neural networks (GNNs) have been used to encode knowledge graph input (Rik Koncel-Kedziorski and Hajishirzi, 2019; Ribeiro et al., 2020; Guo et al., 2020; Li et al., 2021), while table-specific encoders have been proposed for tables (Liu et al., 2017; Bao et al., 2018; Nema et al., 2018; Jain et al., 2018; Wang et al., 2022). However, these methods are not easily transferable to other structured forms, creating a barrier for scientific development and preventing models from learning across tasks. Recent work has attempted to address the problem of limited structured form applicability by using pretrained language models (PLMs) as a single text-to-text framework for all data structures, by

linearizing the data as text sequences. As shown by Kale and Rastogi (2020); Xie et al. (2022), these methods achieve state-of-the-art performance on a wide range of data-to-text tasks.

Despite the advancements made in the field, there are still unresolved questions regarding the relationship between various structured forms, particularly in the context of zero-shot or few-shot settings, where models are required to rapidly adapt to new structured forms. This is particularly pertinent in cases of data scarcity, when structured forms vary across different domains and there is a limited amount of data available for a specific structured form, but a single model is needed to operate on all of them. Such an example is to adapt a knowledge-graph-to-text model to a new domain with data in table format. Even when there is an abundance of data, developing a universal model that can handle all structured forms remains a challenging task. As seen in Xie et al. (2022), a multi-task trained model may perform worse than a single-task model on table inputs. One important reason for such performance drop is because previous research has not fully examined the impact of various linearization methods on these tasks and their effect on cross-task generalization. Despite the use of text-to-text transformers, linearization methods for various structured forms remain diverse, and even within one structured form, linearization can vary across studies. For example, the linearization of KG triples differs in Nan et al. (2021) and Xie et al. (2022), highlighting the need for further research on the relationship between data formats and data-to-text tasks.

In this paper, we address the unresolved questions surrounding the relationship between various structured forms by introducing a *unified representation* for knowledge graphs, tables, and meaning representations. We demonstrate that our method allows for the conversion of knowledge graph triples and meaning representations into virtual ta-

¹Our code will be open-sourced at [anonymous-link](#).

bles, which can then be linearized in a consistent manner. Through evaluating our approach on five representative data-to-text tasks across the aforementioned formats, we show that our method not only achieves competitive performance compared to other data-specific linearizations for individual tasks, but also leads to significant improvements in transfer learning scenarios across structured forms, particularly in zero-shot or few-shot settings. For example, using the unified representation improves the zero-shot BLEU score by relatively 66% when transferring from ToTTo (Parikh et al., 2020) to DART (Nan et al., 2021). Additionally, our approach results in improved performance when used in multi-task settings compared to models trained with varied linearizations. These results provide a clear indication of the effectiveness of our proposed unified representation in enhancing cross-task generalization.

2 Related Work

Data-Type Specific Knowledge Encoding Research has been conducted to encode structured knowledge using various models and approaches, including Graph Neural Networks (GNNs) (Rik Koncel-Kedziorski and Hajishirzi, 2019; Ribeiro et al., 2020; Guo et al., 2020; Li et al., 2021; Song et al., 2018; Ribeiro et al., 2019; Cai and Lam, 2020; Zhang et al., 2020; Ribeiro et al., 2021b; Schmitt et al., 2021) and neural encoder-decoder models based on Gated Recurrent Units (GRUs) and Transformers (Gehrmann et al., 2018; Ferreira et al., 2019). These models have been used to assist in encoding knowledge graph inputs and meaning representations. Additionally, several models have been proposed for table-to-text generation, including approaches that combine content selection or entity memory in a Long Short-Term Memory (LSTM) model (Puduppully et al., 2018, 2019), and others that focus on table-specific encoders (Liu et al., 2017; Bao et al., 2018; Nema et al., 2018; Jain et al., 2018). More recent studies have utilized the capabilities of pre-trained language models in their designs, but have also incorporated specialized encoder structures or attention mechanisms specifically for table inputs. These include encoder-only models (Arik and Pfister, 2019; Yin et al., 2020; Herzig et al., 2020; Huang et al., 2020; Wang et al., 2021; Iida et al., 2021; Eisenschlos et al., 2021; Yang et al., 2022), as well as encoder-decoder models (Cao, 2020; Andrejczuk et al., 2022; Wang et al.,

2022). However, it should be noted that the encoder structures of these works are specifically tailored for table input and cannot be directly applied to other types of data.

Structured Data Linearization Recent developments in pretrained language models (Devlin et al., 2019; Radford et al., 2019; Lewis et al., 2020; Raffel et al., 2020) have made it possible to use a single text-to-text framework for various types of data by linearizing them as text sequences. Studies have been conducted on finetuning PLMs on table input (Parikh et al., 2020) and knowledge graph input (Kasner and Dušek, 2020; Ribeiro et al., 2021a), single-task and multi-task training on a collection of structured data grounding tasks (Xie et al., 2022), and the effectiveness of pretraining and fine-tuning strategies for data-to-text tasks (Kale and Rastogi, 2020) and table-based question answering tasks (Shi et al., 2022). These studies have consistently found that linearizing structured data as a sequence of tokens without modifying the model structure, is a simple yet effective strategy that outperforms pipelined neural architectures specifically tailored to particular data types.

Zero/Few-Shot Data-to-Text Generation The studies such as Chen et al. (2020b) and Ke et al. (2021) have evaluated the zero and few-shot performance of PLMs on knowledge graph input, highlighting the benefits of a joint pretraining strategy on knowledge graphs and texts for learning better KG representations. Keymanesh et al. (2022) studied the prompt-tuning method for KG-to-text generation and found it to be effective in a few-shot setting. Chen et al. (2020d) combines PLM with a table content selector using a switch policy. Other researchers have also explored methods such as data augmentation (Chang et al., 2021) and retrieval-based input augmentation (Su et al., 2021) to aid in few-shot data-to-text generation. Kasner and Dusek (2022) proposes a pipeline approach involving a sequence of operations, such as ordering and aggregation, and only finetunes the PLMs of these modules to make the pipeline more domain-independent.

3 Unified Representation

In this section, we demonstrate that structured data, such as tables, highlighted cells, knowledge graph triples, and meaning representations, can be linearized in a consistent manner. We begin by show-

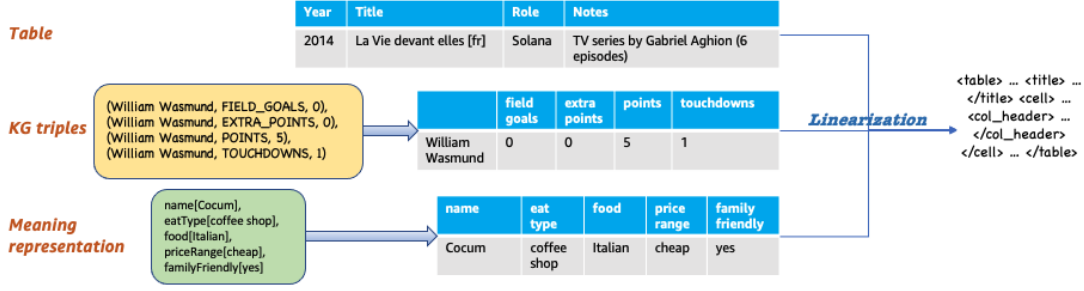


Figure 1: unified representation of three data types: table, KG triples, and meaning representations. The latter two are first converted to virtual tables, and then linearized using the same method as table input.

ing in Section 3.1 how knowledge graph triples and meaning representations can be mapped to a virtual table and subsequently linearized in the same way as tables. Next, in Section 3.2, we demonstrate the process of linearizing a table or highlighted cells. The entire method is illustrated in Figure 1.

3.1 Virtual Table

KG Triple The method for converting triples from a connected sub-graph into a virtual table involves using the tail node of each triple as a cell value and the relation as the column header. Nodes that do not appear as tail nodes are not assigned a column header. An example is provided in Figure 1. "William Wasmund" does not have a column header assigned since it never appears as a tail node. If a set of knowledge graph triples contains multiple connected components, each component is converted into a separate table.

Meaning Representation We focus on textual MRs that appear as a list of comma-separated attribute-value pairs (Dušek et al., 2020). These MRs can be treated as virtual tables by associating each Attribute[Value] with a cell value, represented by the "Value", and the "Attribute" as its corresponding column header. An example of this can be seen in Figure 1.

3.2 Linearization of Tables

After converting both KGs and MRs into virtual tables, we end up with only table inputs that need to be linearized. In this section, we discuss one choice of such a linearization method, motivated by ToTTo linearization (Parikh et al., 2020). Additionally, we will provide a specific example of how to linearize Table 1 in the following sections.

Basic Units The basic units for linearization are presented in Table 2. Each unit is defined by a start

Table Title: Alma Jodorowsky
Section Title: Filmography

Year	Title	Role
2014	La Vie devant elles [fr]	Solana
2016	Kids in Love	Evelyn
2017	The Starry Sky Above Me	Justyna

Table 1: An example table to showcase our linearization.

symbol, <xx>, and an end symbol, </xx>.

Start Symbol	Meaning
<table>	contents in a table
<column>	contents in a column
<row>	contents in a row
<cell>	content in a cell
<col_header>	column header name
<row_header>	row header name
<title>	main title /domain / topic of the input
<sub_title>	sub-title /domain /topic of the input

Table 2: Basic units of our linearization.

Linearization of Highlighted Cells To linearize the highlighted cells, we proceed in a left-to-right, top-to-bottom order. For instance, in Table 1, the linearization of the highlighted cells (in yellow background) appears as follows:²

```

1 <title> Alma Jodorowsky </title>
2 <sub_title> Filmography </sub_title>
3 <table>
4   <cell> 2016
5     <col_header> Year </col_header>
6   </cell>
7   <cell> Kids in Love
8     <col_header> Title </col_header>
9   </cell>
10  <cell> Evelyn
11    <col_header> Role </col_header>
12  </cell>
13 </table>

```

²Indentation is used for clarity in this example, but it is not present in the actual input.

Linearization of (Sub)Table A row-wise linearization of the entire Table 1 is:

```

1 <title> Alma Jodorowsky </title>
2 <sub\_title> Filmography </sub\_title>
3 <table>
4   <row>
5     <cell> 2014
6     <col\_header> Year </col\_header>
7   </cell>
8   <cell> La Vie devant elles [fr]
9     <col\_header> Title </col\_header>
10  </cell>
11  <cell> Solana
12    <col\_header> Role </col\_header>
13  </cell>
14 </row>
15 ... (other rows) ...
16 </table>

```

Such a linearization method can also be applied to column-wise. An example is provided in the Appendix B.

4 Experiments

Datasets We test our method on five data-to-text datasets: The **ToTTo** dataset (Parikh et al., 2020) poses the challenge of generating a one-sentence description, given highlighted cells from a Wikipedia table. Our models are evaluated on the validation set, as the annotations for the test set are not publicly available. The **DART** corpus (Nan et al., 2021) is an open-domain structured data-to-text resource, consisting of entity-relation triples. The **LogicNLG** dataset (Chen et al., 2020a) investigates the ability to generate logical inferences from table contents to implicit insights, as the target sentences. The **WebNLG** dataset (Gardent et al., 2017) includes triples from 15 DBpedia categories, which are mapped to their verbalization. Results are reported on the Seen (S), Unseen (U), and All (A) subsets of the data. The **E2E clean** dataset (Dušek et al., 2019) consists of meaning representations (MRs) from the restaurant domain. The task is to generate a sentence that verbalizes the *useful* information from the MR. Dataset statistics are summarized in Table 7 in the appendix.

Evaluation Metrics We evaluate the quality of generated texts using several widely accepted metrics. *BLEU* (Papineni et al., 2002) measures the similarity between generated text and references in terms of n-gram overlap. *METEOR* (Banerjee and Lavie, 2005) assesses the quality of generated text by comparing unigram matches between the text and references, including exact, stem, synonym, and paraphrase matches. *TER* (Snover et al., 2006)

is a measure of the number of edits required to change the generated text into one of the references. *PARENT* (Dhingra et al., 2019) takes into account the table input when evaluating generated text. *NIST* (Doddington, 2002) is similar to BLEU, but also considers the informativeness of each n-gram. *CIDEr* (Vedantam et al., 2015) uses TF-IDF to lower the weights of common n-grams that appear in all references when calculating uni-gram to 4-gram overlaps between generated and reference sentences. We also use the *NLI score* (Chen et al., 2020a) on the LogicNLG dataset to evaluate the logical fidelity, which is a model-based evaluation using the BERT model trained on the TabFact (Chen et al., 2020c) dataset.

Comparing Linearizations We compare our proposed *unified representation* to other linearization methods from previous papers. Specifically, on DART, WebNLG, and E2E datasets, we compare our method to the linearization used in Unified-SKG (Xie et al., 2022).³ On ToTTo and LogicNLG datasets, we use the linearization from their original papers (Parikh et al., 2020; Chen et al., 2020a) for comparison. Examples of their linearization methods can be found in the appendix.

4.1 Zero and Few-Shot Experiments

Our hypothesis is that a model trained on one structured form will transfer better to other forms under zero or few-shot settings when using our unified method of representation. We test this by focusing on transferring from ToTTo data (table input) to other types and from WebNLG (KGs) to ToTTo in this section. Results for other transfers can be found in the appendix.

Setting	Src representation	Tgt representation
<i>Only on tgt</i>	-	Others
<i>Src to tgt, unified</i>	Unified	Unified
<i>Src to tgt, varied</i>	Others	Others

Table 3: Comparison of source and target task representations. "Unified" uses our proposed unified representation, "Others" uses linearizations from other papers for each task.

As shown in Table 3, for each experiment, we compare **three settings**: (i) *Only on tgt* – In few-shot experiments, we only train the model on the target task using the linearization from other papers.

³The E2E dataset is not studied in the paper, but the linearization is included in their [official repository](#).

In zero-shot experiments, we use the foundational model without any training. (ii) *Src to tgt, unified* – First, train the model on the source task and then fine-tune it on k -shot⁴ target-task data, using our unified representation for both. (iii) *Src to tgt, varied* – Similar to (ii), but we use the linearization from other papers for each task, as described in 4. We refer to this as the varied setting because the source and target-task linearizations are different.

During inference, we apply the same linearization method utilized during training to each target task. More implementation details are presented in the appendix.

4.1.1 Zero-Shot Performance

The zero-shot results are summarized in Table 4. We compare our results to recent works GPT2-XL (Keymanesh et al., 2022), KGPT (Chen et al., 2020b), JointGT (Ke et al., 2021) and HTML (Aghajanyan et al., 2022). Both KGPT and JointGT models are pretrained on large amounts of aligned knowledge graph and text data. HTML is a hyper-text language model pre-trained on a large-scale web crawl. It allows for structured prompting in the HTML format.

From the results, we make several observations. (1) The *Only on tgt* performance is very low as expected, as the T5-base model has not been trained on any data. However, surprisingly the NLI score on LogicNLG is the highest under this setting. We observe that this NLI score is very unstable and might not be a good metric for judging the entailment of generated text. (2) The performance of *Src to tgt, unified* consistently and significantly surpasses that of *Src to tgt, varied*, even though both models are trained using the same source-task data, but with different representations. This demonstrates that representing source and target tasks in the same format is crucial for successful zero-shot transfer, as a common representation facilitates the transfer of knowledge learned on the source data to other structured forms and tasks. (3) The zero-shot performance of the "unified" model is even better than few-shot results of the baseline models. On DART, the "unified" model's BLEU score is 43% higher than that of HTML. The improvement on WebNLG is particularly noteworthy for unseen categories. Utilizing a unified representation results in a zero-shot BLEU score of 39.82, surpassing the few-shot results of 37.18 by Ke et al. (2021) and

18.5 by Aghajanyan et al. (2022).

4.1.2 Few-Shot Results

Figure 2 shows the few-shot results for sample sizes 8, 16, 32, 64, and 128. We repeat the experiments 5 times for each sample size and report the mean and 95% confidence intervals.

Table → **KG Triples** From Figure 2a, 2b and 2c, we have identified three key observations: (1) Both the models *Src to tgt, unified* and *Src to tgt, varied*, which were initially trained on ToTTo, perform significantly better than the model *Only on tgt*, which was only trained on target tasks. This indicates that these two structured forms share common knowledge and that training the model on tabular input can greatly enhance its understanding of KG triples. (2) Furthermore, *Src to tgt, unified* (represented by the red curve) outperforms *Src to tgt, varied* (represented by the blue curve) by a substantial margin. This observation aligns with our previous findings in the zero-shot setting (as seen in Table 4) and highlights the importance of our unified representation approach in transferring knowledge learned from tables to KG triples. (3) Additionally, on the task of WebNLG, the improvement on unseen categories is particularly notable, further reinforcing our zero-shot findings.

Table → **Meaning Representations** Based on Figure 2d, similar observations can be made for the E2E dataset. The improvement in terms of CIDEr is particularly significant when using fewer than 64 samples, indicating that the unified model generates more informative text compared to the varied and vanilla models.

Table Description → **Table Insights** The LogicNLG task is distinct from the ToTTo task in that it requires the model to generate insights by analyzing the contents of a table, rather than generating surface-form descriptions based on highlighted cells. As shown in Figure 2e, when using only 8 samples, the *Src to tgt, varied* model performs better than the *Src to tgt, unified* model. This may be due to the fact that both tasks involve generating text from tables, and that the unified model is more proficient at transferring knowledge learned on the source task to the target task, which may lead to the generation of table descriptions rather than insights when provided with a limited number of samples. However, as the number of samples increases, the performance of the unified model improves, and it

⁴ $k = 0$ means no training on target task at all.

Setting	DART (KG)			WebNLG (KG)			E2E clean (MR)			LogicNLG (Table)	
	BLEU	MET	TER ↓	S	U	A	BLEU	NIST	CIDEr	BLEU-3	NLI
GPT2-XL	13.3	0.24	0.65	-	-	-	-	-	-	-	-
KGPT	-	-	-	-	-	13.9	-	-	-	-	-
JointGT (0.5%) ^a	-	-	-	-	37.2	-	-	-	-	-	-
HTLM (1-shot) ^a	22.1	0.12	0.91	28.1	18.5	22.8	-	-	-	-	-
Only on tgt ^b	0.3	0.01	2.82	0.36	0.08	0.23	0.0	0.0	0.0	0.2	85.1
Src to tgt, varied	18.9	0.21	1.00	34.1	28.5	31.3	12.1	2.8	0.3	7.8	70.9
Src to tgt, unified	31.5	0.32	0.56	35.9	39.8	37.7	22.6	4.4	0.9	8.9	81.3

^a We compare our results to their few-shot performance, as zero-shot results are not reported in their papers.

^b Under zero-shot, this means directly testing T5-base model on target test set without any training.

Table 4: Zero-shot results. Our foundational model is T5-base (220M). MET stands for METEOR, and lower scores on TER indicate better performance. On WebNLG, BLEU scores are reported for seen (S), unseen (U), and all (A) categories. The NLI-accuracy is calculated using the NLI model provided in LogicNLG official codebase. On papers without zero-shot results, we report their few-shot performance.

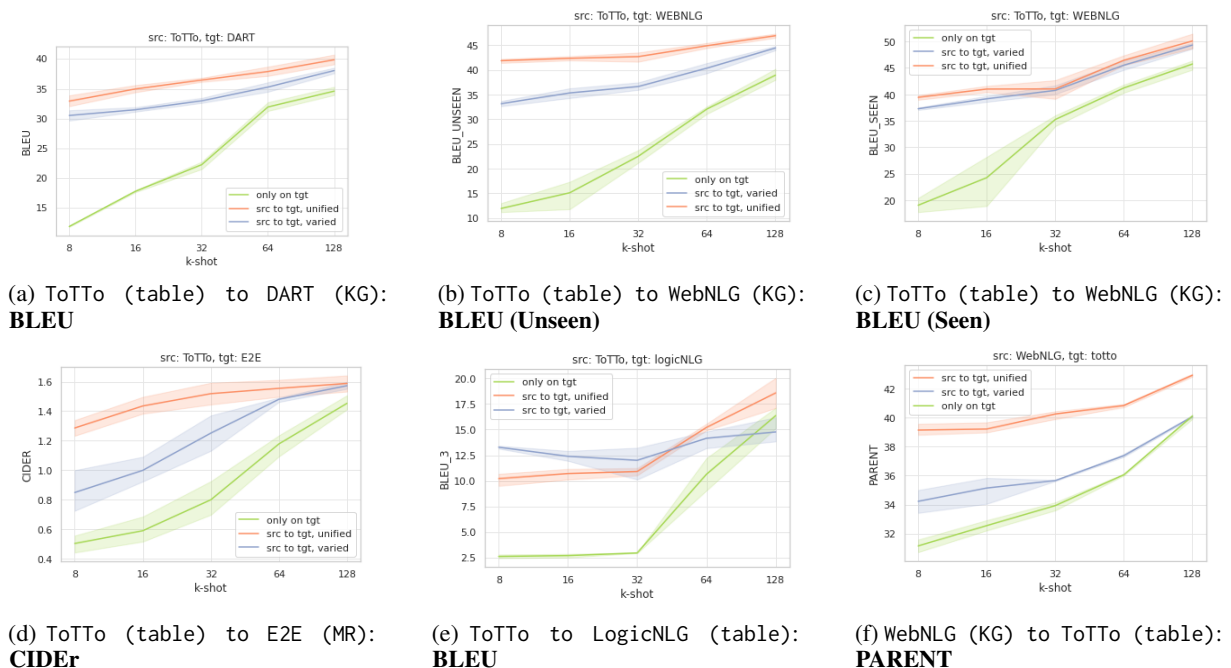


Figure 2: Results of few-shot experiments transferring models between two structured forms. Each figure shows three curves, the green curve "only on tgt" is the performance of the T5-base model fine-tuned directly on the target task, the red curve "src to tgt, unified" is the performance of the model fine-tuned on both tasks using our proposed unified representation, and the blue curve "src to tgt, varied" is the performance of the model fine-tuned on both tasks using linearization from other papers, resulting in varied linearization for source and target tasks. The LogicNLG task differs from ToTTo by requiring the model to generate insights from analyzing a table rather than generating descriptions from highlighted cells.

surpasses the varied model when k=128. A concrete example is provided in the case study section 4.3 to further illustrate our observation.

KG Triples → **Table** The benefits of utilizing unified representation are particularly substantial when transferring models that have been trained on knowledge graphs to table inputs. In Figure 2f, the PARENT gap between unified and varied models is consistently greater than 2 points. In fact, the performance of "varied" and "only on tgt"

models converge when utilizing 128 samples, and is only slightly superior to that of the "unified" model when provided with only 8 samples. This suggests that the use of unified representation is highly efficient in terms of sample utilization.

4.2 Full-Set Finetuning Results

In this section, we train the models on full training sets, in either single-task or multi-task settings. Additional experimental results are presented in the appendix.

Model	Linear	ToTTo		DART	WebNLG			LogicNLG	E2E	
		BLEU	PARENT	BLEU	S	U	A	BLEU-3	BLEU	CIDEr
<i>Single-Task Training</i>										
<i>LATTICE</i> (Wang et al., 2022)	Tab	48.6	-	-	-	-	-	20.1	-	-
<i>UnifiedSKG (base)</i>	O	48.3	-	46.2	-	-	-	-	-	-
<i>UnifiedSKG (3B)</i>	O	49.0	-	46.7	-	-	-	-	-	-
<i>DCVED</i> (Chen et al., 2021)	O	-	-	-	-	-	-	15.3	-	-
<i>HTLM</i> (Aghajanyan et al., 2022)	O	-	-	47.2	65.4	48.4	55.6	-	-	-
T5-base	Uni	49.3	58.9	48.6	65.4	50.1	58.5	24.7	41.8	1.90
	O	49.2	58.9	49.0	65.9	49.5	58.2	25.2	42.1	1.91
T5-3B	Uni	49.4	58.9	49.6	65.1	52.7	59.5	25.1	42.8	1.92
	O	49.6	59.0	49.3	65.3	53.5	60.0	25.3	42.5	1.94
<i>Multi-Task Training</i>										
<i>UnifiedSKG (base)</i>	O	45.3	-	-	-	-	-	-	-	-
<i>C-P (large)</i> (Clive et al., 2021)	O	-	-	52.0	67.0	55.6	61.8	-	44.2	-
T5-base	Uni	49.7	59.2	49.8	64.9	50.3	58.3	25.2	42.9	1.94
	O	48.5	58.7	48.1	64.1	50.2	57.9	24.7	41.7	1.89
T5-3B	Uni	50.8	60.4	50.2	65.4	53.4	60.0	25.4	43.2	1.99
	O	50.2	59.5	49.8	65.3	51.9	59.4	25.3	41.8	1.89

Table 5: Single-task and multi-task training results using full training sets. In the "Linear" column, "Uni" represents using unified representation, "O" means using other linearizations from previous papers, and "Tab" mean we use table-specific encoder.

Single-Task Training From the "single-task training" results in Table 5, a key finding is that the proposed unified representation method results in performance comparable to other linearization techniques studied in previous research. This is particularly evident on the DART, WebNLG, and E2E tasks, where the data was first converted into virtual tables, and the results from both methods are similar, indicating that this conversion does not result in a significant loss of information.

Multi-Task Training The performance of multi-task models is summarized in Table 5 under the "multi-task training" section, revealing several key findings: (1) *Overall, multi-task training using different linearizations for each dataset results in a worse performance compared to single-task training.* BLEU scores for T5-base models decrease from 49.2 to 48.5 on ToTTo, from 49.0 to 48.1 on DART, and from 65.9 to 64.1 on seen categories of WebNLG. This confirms the findings of UnifiedSKG (Xie et al., 2022), which found that single-task model performance was higher than multi-task performance on ToTTo dataset. However, it is unclear if this drop in performance was due to task differences, as their study included other tasks. Our results provide further insight into data-to-text tasks alone and show that multi-task performance can still be inferior if input formats are not unified. (2) *In contrast, multi-task trained "unified" models consistently outperform single-task models,*

with the only exception of the base model on the WebNLG dataset. This demonstrates that utilizing a unified representation approach helps models learn common knowledge across various tasks without negatively impacting performance. (3) *The "unified" models consistently demonstrate superior performance compared to "varied" models in multi-task training, with a larger margin of improvement observed in base-sized models.*

4.3 Qualitative Study

We conduct a qualitative case study to compare the texts generated by the *Src to tgt, unified* and *Src to tgt, varied* models. The results are illustrated in Table 6, which displays the model's generations for different sample sizes.

For the WebNLG example, the input contains 5 KG triples. When $k = 8$, the "varied" model only covers one KG triple fact, while the "unified" model includes many more nodes and relations from the input. As the sample size increases to 128, the "unified" model's generation covers all facts accurately, while the "varied" model's generation still misses the "funk and disco" origin of pop music.

In the E2E example, the "unified" model output is consistent and accurate with both 8 and 128 samples. In contrast, the "varied" model produces "Sorrento" twice. This serves as additional evidence that using a unified representation enhances the transfer of the generation style learned on table input to meaning representations.

k-shot =	Src to tgt, unified	Src to tgt, varied																																				
<i>ToTTo (table) → WebNLG (KG) example</i>																																						
8	Hip hop music is influenced by Disco by Allen Forrest (born in Fort Campbell) and Funk with drum and bass.	Allen Forrest was born in Fort Campbell.																																				
128	Allen Forrest, born in Fort Campbell, is known for his roots in hip hop music. Disco and Funk are stylistic origins, while drum and bass are derivatives.	Allen Forrest was born in Fort Campbell and is known for hip hop music. Hip hop music is a derivative of drum and bass.																																				
Groundtruth	Allen Forrest was born in Fort Campbell and is a hip hop musician. Hip hop originates from funk and disco and was derived into drum and bass music.																																					
KG triples	(Hip hop music, stylistic origin, Disco) (Allen Forrest, birth place, Fort Campbell) (Allen Forrest, genre, Hip hop music) (Hip hop music, stylistic origin, Funk) (Hip hop music, derivative, Drum and bass)																																					
<i>ToTTo (table) → E2E (MR) example</i>																																						
8	Zizzi is a pub near The Sorrento.	Zizzi is a gastropub in Sorrento, near The Sorrento.																																				
128	Zizzi is a pub near The Sorrento.	Zizzi is a pub near The Sorrento.																																				
Groundtruth	There is a pub called Zizzi located near The Sorrento.																																					
MRs	name[Zizzi], eatType[pub], near[The Sorrento]																																					
<i>ToTTo (table) → LogicNLG (table) example</i>																																						
8	In the world golf championships, the United States has 12 individual winners, Australia has 3 individual winners, England has 3 individual winners, South Africa has 1 individual winner, Canada has 1 individual winner, Fiji has 1 individual winner, Italy has 1 individual winner, Japan has 0 individual winner, and Wales has no individual winner.	The United States has the highest number of individual winners of any country in the world.																																				
128	The United States is the only nation to have won 12 World Golf Championship.	The United States has the highest number of individual winners.																																				
Input table	<table border="1"> <thead> <tr> <th>Nation</th> <th>United States</th> <th>Australia</th> <th>England</th> <th>South Africa</th> <th>Northern Ireland</th> <th>Germany</th> <th>Canada</th> <th>Fiji</th> <th>Sweden</th> <th>Italy</th> <th>Japan</th> <th>Wales</th> </tr> </thead> <tbody> <tr> <td>Individual winner</td> <td>12</td> <td>3</td> <td>3</td> <td>1</td> <td>1</td> <td>1</td> <td>1</td> <td>1</td> <td>1</td> <td>1</td> <td>0</td> <td>0</td> </tr> </tbody> </table>												Nation	United States	Australia	England	South Africa	Northern Ireland	Germany	Canada	Fiji	Sweden	Italy	Japan	Wales	Individual winner	12	3	3	1	1	1	1	1	1	1	0	0
Nation	United States	Australia	England	South Africa	Northern Ireland	Germany	Canada	Fiji	Sweden	Italy	Japan	Wales																										
Individual winner	12	3	3	1	1	1	1	1	1	1	0	0																										

Table 6: Case study: few-shot prediction examples on WebNLG and E2E.

The results of the LogicNLG input generation offer validation for our hypothesis that the "unified" model performs less effectively than the "varied" model when the sample size is small, due to its persistent focus on generating descriptions of the table input, as it has been trained to do on the ToTTo data. Indeed, the descriptions generated by the "unified" model when sample size is 8, are accurate reflections of the table's content. When the sample size is increased to 128, both models generate sentences that are more akin to insights. It is noteworthy that the "unified" model generates "world golf championship" even though it is not present in the table, which pertains to the golf championship. We posit that this information is carried over from the ToTTo data, and the "unified" model is able to retain this information while the "varied" model does not.

5 Conclusion and Future Work

We have introduced a unified representation approach for data-to-text tasks, which effectively converts table contents, knowledge graph triples, and

meaning representations into a single representation. Our experiments demonstrate that this unified representation significantly improves generalization across different structured forms, especially in zero-shot or few-shot settings. Our method is particularly beneficial in situations where data is scarce. Additionally, by using the unified representation, our multi-task-trained models consistently outperform single-task models, which is in contrast to previous findings that mixing different data types can negatively impact overall performance.

One future direction is to apply our method to other tasks that involve heterogeneous inputs, such as question answering over knowledge bases, where knowledge can be stored in both tables and knowledge graphs. It would also be interesting to investigate whether a model pre-trained on large knowledge graphs can more effectively transfer learned commonsense knowledge to table QA tasks, when using our unified representation approach.

Limitations

It is important to note that the unified representation proposed in our study is just one option among many. Other linearization methods may potentially yield better results. For example, research by Yin et al. (2022) and Aghajanyan et al. (2022) has explored using code generation with Jupyter notebooks and a hyper-text language model with structured prompting, respectively. Further research in these areas, such as converting all structured forms to markdown language or hyper-texts, may yield alternative unified representations.

Ethics Statement

We acknowledge the importance of the ACL Ethics Policy and agree with it. This study addresses the problem of data-to-text generation and explores whether a unified representation can enhance cross-task performance on various structured forms. Since our input comes from knowledge bases, a potential concern is that biases or fairness issues may be present in the KB, which could also be reflected in the generated text. Therefore, it is crucial to use the model with caution in practice. We believe this work can contribute to the field of data-to-text generation, particularly in situations where data is scarce.

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A Data Statistics

We summarize the input type and number of examples in each dataset.

Dataset	Input	# Examples		
		Train	Validation	Test
ToTTo	Table	120,761	7,700	7,700
DART	KG	30,526	2,768	6,959
LogicNLG	Table	28,450	4,260	4,305
WebNLG	KG	18,102	872	1,862
E2E clean	MR	33,525	1,484	1,847

Table 7: Data statistics.

B Column-wise Linearization of (Sub)Table

A column-wise linearization of Table 1 is:

```
1 <title> Alma Jodorowsky </title>
2 <sub_title> Filmography </sub_title>
3 <table>
4   <column>
5     <col_header> Year </col_header>
6     <cell> 2014 </cell>
7     <cell> 2016 </cell>
8     <cell> 2017 </cell>
9   </column>
10  ... other columns ...
11 </table>
```

C Other Linearizations Used in Previous Papers

Table highlights : Our unified representation is motivated by ToTTo linearization, and hence they are very similar. The only difference is ToTTo uses `<page_title>` instead of `<title>` and `<section_title>` instead of `<sub_title>`.

KG triples : Given a set of triples $\{(William\ Wasmund, FIELD_GOALS, 0), (William\ Wasmund, EXTRA_POINTS, 0)\}$, an alternative linearization used in UnifiedSKG (Xie et al., 2022) is William Wasmund : field goals : 0 | William Wasmund : extra points : 0

Entire table : The alternative linearization used in LogicNLG (Chen et al., 2020a) for Table 1 is: Given the table title of Alma Jodorowsky, Filmograph. In row 1 , the Year is 2014 , the Title is La ... , the Role is Solana, the Notes is TV ... In row 2 , ...

Meaning representation : The alternative linearization we use for the example in Figure 1 is simply concatenating all the MRs: name[Cocum], eatType[coffee shop], food[Italian],

priceRange[cheap], familyFriendly[yes].

D Implementation Details

In the zero- and few-shot experiments, we employ the T5-base model as the base model and train it for 30 epochs for both the source and target tasks. For the source task, we use a learning rate of 5e-5 and a batch size of 32, and for the target task, we use a learning rate of 2e-5 and a batch size of 8.

E More Multi-Task Results

We present more detailed multi-task results on each of the dataset in this section. The results are summarized in Table 8, 9, 10 and 11.

F More Few-shot Results

We present other few-shot results using more metrics in Figure 3, 4 and 5.

G Human Evaluation

We conducted a human evaluation on the few-shot ToTTo to WebNLG transferring experiment. Specifically, we randomly selected 50 WebNLG test data from the unseen schema and compared the performance of the 8-shot *src to tgt, unified* and *src to tgt, varied* models.

For each of the 50 samples, we generated texts using both models and asked three annotators to choose the better option based on factuality, coverage of the triples, and fluency. We received only two annotations for two of the samples as one of the annotators did not respond. For the remaining 48 samples, all three annotators reached a consensus on 21 of them (43.75%). Out of these 21 samples, the "unified" model received unanimous preference from the annotators in 15 cases (71.43%). If we consider the majority vote among the three annotators, then 75% of the results favored the "unified" model. The Fleiss Kappa value, which measures agreement among the three annotators, is around 0.23 (fair agreement).

H More Qualitative Study

We present additional few-shot predictions for models transferred from ToTTo to WebNLG and LogicNLG in Tables 12 and 13, respectively. We also provide error analysis under each example.

Model	Task	Linearization	METEOR	ROUGE-L	CIDEr	NIST	BLEU
CONTROL PREFIX (large)	MT	Alt	39.2	-	-	-	44.2
T5-base	ST	Unified	38.3	56.6	1.90	6.20	41.8
	ST	Alt	38.3	56.4	1.91	6.23	42.1
	MT	Unified	38.6	57.0	1.94	6.31	42.9
	MT	Varied	38.3	56.6	1.89	6.20	41.7
T5-3B	ST	Unified	38.5	56.7	1.92	6.30	42.8
	ST	Alt	38.5	56.5	1.94	6.31	42.5
	MT	Unified	38.7	57.4	1.99	6.34	43.2
	MT	Varied	38.3	56.8	1.89	6.21	41.8

Table 8: Test set performance on E2E clean.

Model	Task	Linearization	Overall		Overlap		Non-overlap	
			BLEU	PARENT	BLEU	PARENT	BLEU	PARENT
<i>LATTICE (T5-base)</i>	ST	Table-specific	48.6	-	56.6	-	40.8	-
<i>UnifiedSKG (base)</i>	ST	Alt	48.3	-	-	-	-	-
<i>UnifiedSKG (base)</i>	MT	Varied	45.3	-	-	-	-	-
<i>UnifiedSKG (3B)</i>	ST	Alt	49.0	-	-	-	-	-
<i>Text2Text (3B)</i>	ST	Alt	48.4	57.8	-	-	40.4	53.3
T5-base	ST	Unified	49.3	58.9	57.1	62.7	41.9	55.3
	MT	Unified	49.7	59.2	57.7	63.2	41.9	55.2
	MT	Varied	48.5	58.7	56.2	62.5	41.1	55.0
T5-3B	ST	Unified	49.4	58.9	57.1	62.7	42.0	55.3
	MT	Unified	50.8	60.4	58.5	64.4	43.4	56.5
	MT	Varied	50.2	59.5	57.5	63.2	43.2	55.9

Table 9: Development set performance on ToTTo.

Model	Task	Linearization	DART			WebNLG		
			BLEU (\uparrow)	METERO (\uparrow)	TER (\downarrow)	Seen	Unseen	All
UnifiedSKG (base)	ST	Alt	46.2	-	-	-	-	-
UnifiedSKG (3B)	ST	Alt	46.7	-	-	-	-	-
CONTROL PREFIX (large)	MT	Alt	52.0	0.41	0.43	67.0	55.6	61.8
T5-base	ST	Unified	48.6	0.40	0.45	65.4	50.1	58.5
	ST	Alt	49.0	0.40	0.45	65.9	49.5	58.2
	MT	Unified	49.8	0.40	0.44	64.9	50.3	58.3
	MT	Varied	48.1	0.39	0.45	64.1	50.2	57.9
T5-3B	ST	Unified	49.6	0.40	0.45	65.1	52.7	59.5
	ST	Alt	49.3	0.40	0.45	65.3	53.5	60.0
	MT	Unified	50.2	0.40	0.44	65.4	53.4	60.0
	MT	Varied	49.8	0.40	0.44	65.3	51.9	59.4

Table 10: Test set performance on DART and WebNLG.

Model	Task	Linearization	Orientation	Surface-Level Fidelity			Logical Fidelity	
				BLEU-1	BLEU-2	BLEU-3	NLI-acc	SP-acc
GPT-TabGen	ST	Alt	row	48.8	27.1	12.6	68.7	42.1
DCVED	ST	Alt	row	49.5	28.6	15.3	76.9	43.9
T5-base	ST	Unified	column	52.8	34.9	24.3	79.6	45.2
	ST	Unified	row	53.3	35.4	24.7	84.7	45.8
	ST	Alt	row	54.6	36.1	25.2	85.5	45.9
	MT	Unified	column	53.8	35.8	25.1	78.7	47.2
	MT	Unified	row	54.4	36.1	25.2	80.4	46.3
	MT	Varied	row	53.9	35.5	24.7	84.2	46.3
T5-3B	ST	Unified	column	54.9	36.4	25.4	88.4	49.8
	ST	Unified	row	54.1	35.9	25.1	87.1	47.9
	ST	Alt	row	54.4	36.1	25.3	81.1	47.3
	MT	Unified	column	54.8	36.3	25.4	87.0	49.4
	MT	Unified	row	55.1	36.4	25.4	82.9	49.1
	MT	Varied	row	54.4	36.0	25.3	80.7	47.4

Table 11: Test set performance on LogicNLG.

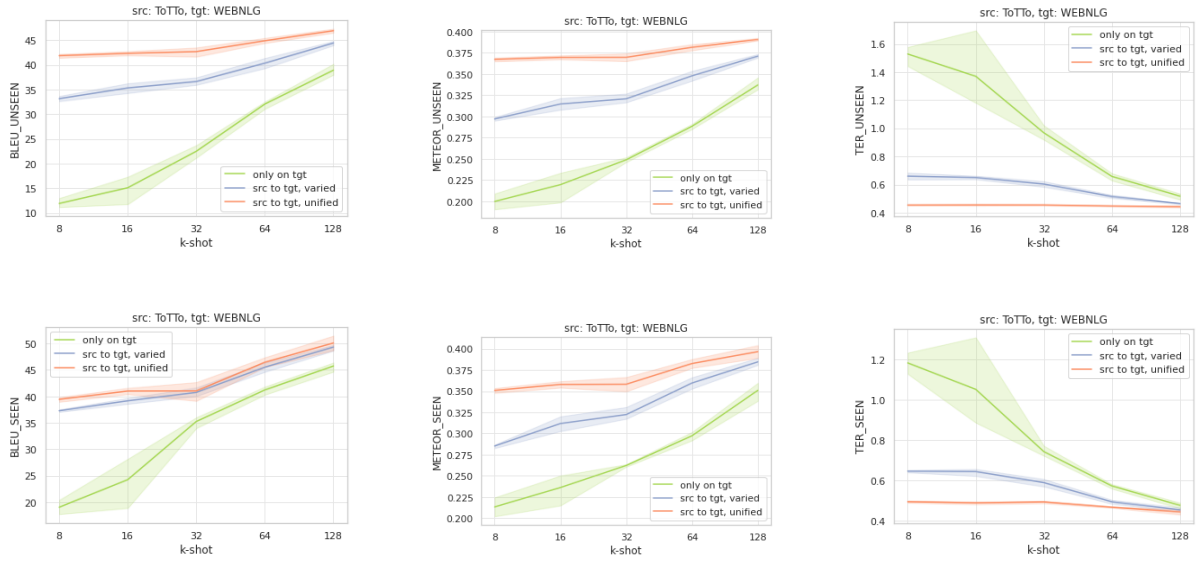
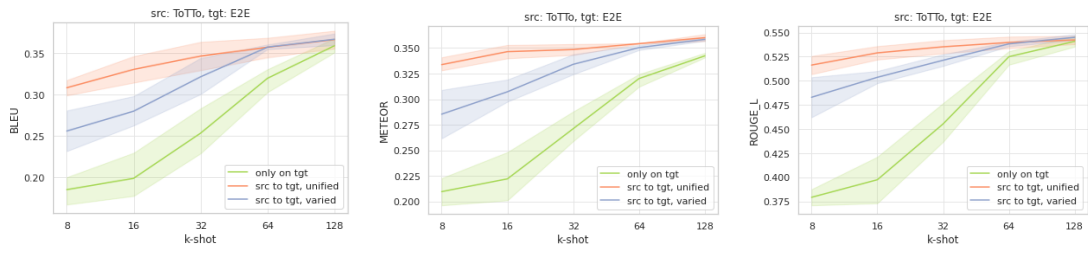


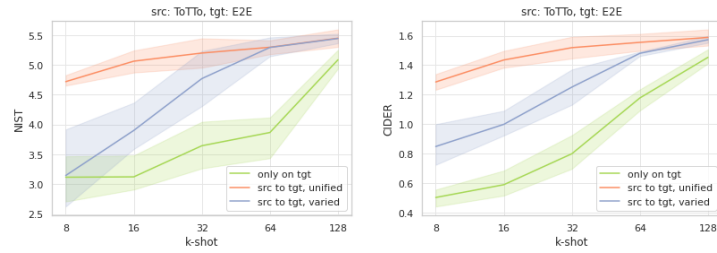
Figure 3: Few-shot experiments of format transferring from ToTTo (table) to WebNLG (KG triples).



(a) BLEU

(b) METEOR

(c) ROUGE-L



(d) NIST

(e) CIDEr

Figure 4: Few-shot experiment results of task transferring from ToTTo (table) to E2E (meaning representation).

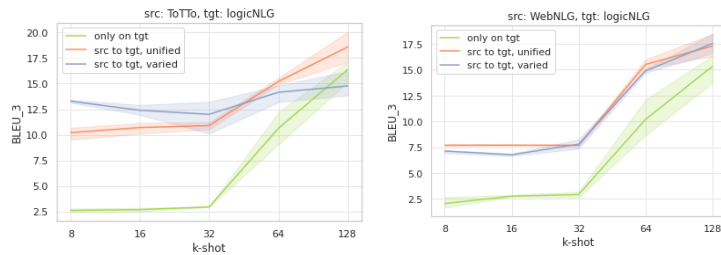


Figure 5: Few-shot experiment results of task transferring from ToTTo (table highlights description) or WebNLG (KG triples) to LogicNLG (logical inference on table).

k-shot =	Src to tgt, unified	Src to tgt, varied
<i>ToTTo (table) → WebNLG (KG) example</i>		
8	Uruguay is led by Ral Fernando Sendic Rodriguez, who died in Montevideo, and by Daniel Martnez, a Spanish politician.	Ral Fernando Sendic Rodriguez died in Montevideo.
128	The leader of Uruguay is Ral Fernando Sendic Rodriguez who died in Montevideo, where Alfredo Zitarrosa died. The leader is Daniel Martnez who speaks Spanish.	Ral Fernando Sendic Rodriguez was the leader of Uruguay and Alfredo Zitarrosa died in Montevideo. Daniel Martnez was a politician who led the country in Spanish.
Groundtruth	Alfredo Zitarrosa died in Montevideo, Uruguay. Daniel Martinez is a political leader in Montevideo, and Raul Fernando Sendic Rodriguez is a leader in Uruguay, where Spanish is spoken.	
KG triples	(Uruguay : leader name : Ral Fernando Sendic Rodriguez Alfredo Zitarrosa : death place : Montevideo Montevideo : country : Uruguay Montevideo : leader name : Daniel Martnez (politician) Uruguay : language : Spanish language	
Error analysis	When sample size is 8, the "unified" model generation contains almost all nodes except Alfredo Zitarrosa, but the "varied" model output only contains one triple.	
8	Twilight (band) is a black metal band with Aaron Turner, and Old Man Gloom is a death metal band with electric guitar.	Twilight is a black metal music fusion genre.
128	Twilight (band) is associated with black metal, and Old Man Gloom is associated with death metal, where Aaron Turner played electric guitar.	Twilight is a genre of black metal music and Aaron Turner plays the electric guitar in Old Man Gloom. Death metal is a genre of black metal music.
Groundtruth	Aaron Turner is an electric guitar player who has played with the black metal band Twilight and with Old Man Gloom. Death metal is a musical fusion of black metal.	
KG triples	(Twilight (band) : genre : Black metal Aaron Turner : associated band/associated musical artist : Twilight (band) Aaron Turner : associated band/associated musical artist : Old Man Gloom Aaron Turner : instrument : Electric guitar Black metal : music fusion genre : Death metal	
Error analysis	In "unified" model output, the Twilight is always recognized correctly as a band, but in varied model output, it is wrongly predicted as a genre.	
8	Al Anderson (NRBQ band) played guitar in rock music, country music and blues music, while Bhangra (music) is a genre of music fusion.	Al Anderson is a guitarist with the NRBQ band.
128	Bhangra is a genre of music fusion, where Al Anderson plays guitar, Country music and Blues.	Al Anderson is an Indian country musician who plays guitar and plays Bhangra (music). Country music is a music fusion genre which is influenced by blues and rock music.
Groundtruth	Al Anderson plays the guitar for rock band NRBQ. Rock comes from country music which originates from blues. Bhangra music is a musical fusion of rock music.	
KG triples	(Rock music : music fusion genre : Bhangra (music) Al Anderson (NRBQ band) : instrument : Guitar Al Anderson (NRBQ band) : genre : Rock music Rock music : stylistic origin : Country music Country music : stylistic origin : Blues	
Error analysis	This is an negative example for "unified" model. When sample size is 8, the unified model generation covers more nodes compared to "varied" model generation. However, when sample size is 128, the "unified" model wrongly generates Anderson to play guitar, country music and Blue. This is a wrong fact. But "varied" model generation is able to be more aligned with the input triples.	

Table 12: Case study: few-shot prediction examples on WebNLG.

k-shot =	Src to tgt, unified	Src to tgt, varied																																	
<i>ToTTo (highlighted cells) \rightarrow LogicNLG (table) example</i>																																			
8	Eric Turner, Ed King, James Jones, Pio Sagapolutele, Michael Jackson, Raymond Irvin, Shawn Wiggins, Brian Greenfield, Todd Jones, Todd Jones, and Elijah Austin played in the 1991 cleveland browns season.	In the 1991 cleveland browns season, Eric Turner, Ed King, Pio Sagapolutele and Raymond Irvin were the Defensive Tackle.																																	
128	Raymond Irvin was the Defensive Back in the 1991 Cleveland Browns season.	Brian Greenfield, Todd Jones and Elijah Austin were the Defensive Tackle in the 1991 Cleveland Browns season.																																	
8	Eric Turner, Ed King, James Jones, Pio Sagapolutele, Michael Jackson, Raymond Irvin, Shawn Wiggins, Brian Greenfield, Todd Jones, Todd Jones, and Elijah Austin played in the 1991 cleveland browns season.	In the 1991 cleveland browns season, Eric Turner, Ed King, Pio Sagapolutele and Raymond Irvin were the Defensive Tackle.																																	
128	Raymond Irvin was the Defensive Back in the 1991 Cleveland Browns season.	Brian Greenfield, Todd Jones and Elijah Austin were the Defensive Tackle in the 1991 Cleveland Browns season.																																	
8	Eric Turner, Ed King, James Jones, Pio Sagapolutele, Michael Jackson, Raymond Irvin, Shawn Wiggins, Brian Greenfield, Todd Jones, Todd Jones, and Elijah Austin played in the 1991 cleveland browns season.	In the 1991 cleveland browns season, Eric Turner, Ed King, Pio Sagapolutele and Raymond Irvin were the Defensive Tackle.																																	
128	Raymond Irvin was the Defensive Back in the 1991 Cleveland Browns season.	Brian Greenfield, Todd Jones and Elijah Austin were the Defensive Tackle in the 1991 Cleveland Browns season.																																	
Groundtruths	"Raymond Irvin is the second Defensive Back to get drafted", "Frank Conover is the third Defensive Tackle to get drafted", "Elijah Austin is the last Defensive Tackle to get drafted", "Frank Conover has an Overall that is 56 higher than Michael Jackson", "Shawn Wiggins is the second Wide Receiver to get drafted"																																		
Input table	<table border="1"> <thead> <tr> <th>player</th> <td>Eric Turner</td> <td>Ed King</td> <td>James Jones</td> <td>Pio Sagapolutele</td> <td>Michael Jackson</td> <td>Frank Conover</td> <td>Raymond Irvin</td> <td>Shawn Wiggins</td> <td>Brian Greenfield</td> <td>Todd Jones</td> <td>Elijah Austin</td> </tr> <tr> <th>position</th> <td>Defensive Back</td> <td>Guard</td> <td>Defensive Tackle</td> <td>Defensive Tackle</td> <td>Wide Receiver</td> <td>Defensive Tackle</td> <td>Defensive Back</td> <td>Wide Receiver</td> <td>Punter</td> <td>Offensive Tackle</td> <td>Defensive Tackle</td> </tr> </thead> </table>											player	Eric Turner	Ed King	James Jones	Pio Sagapolutele	Michael Jackson	Frank Conover	Raymond Irvin	Shawn Wiggins	Brian Greenfield	Todd Jones	Elijah Austin	position	Defensive Back	Guard	Defensive Tackle	Defensive Tackle	Wide Receiver	Defensive Tackle	Defensive Back	Wide Receiver	Punter	Offensive Tackle	Defensive Tackle
player	Eric Turner	Ed King	James Jones	Pio Sagapolutele	Michael Jackson	Frank Conover	Raymond Irvin	Shawn Wiggins	Brian Greenfield	Todd Jones	Elijah Austin																								
position	Defensive Back	Guard	Defensive Tackle	Defensive Tackle	Wide Receiver	Defensive Tackle	Defensive Back	Wide Receiver	Punter	Offensive Tackle	Defensive Tackle																								
Error analysis	Similar to our analysis in Section 4.3, the "unified" model generation is more like description when sample size is 8. Again this is because the source task is ToTTo, which is a task to generate surface-level description of table contents. The "unified" model transfers this learned knowledge better, and hence generates sentences that are more like descriptions. When sample size is 128, both models generate similar contents.																																		

Table 13: Case study: few-shot prediction examples on LogicNLG.