Text-to-Table: A New Way of Information Extraction

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Abstract

We study a new problem setting of information extraction (IE), referred to as text-to-table. In text-to-table, given a text, one creates a table or several tables expressing the main content of the text, while the model is learned from text-table pair data. The problem setting differs from those of the existing methods for IE. First, the extraction can be carried out from long texts to large tables with complex structures. Second, the extraction is entirely data-driven, and there is no need to explicitly define the schemas. As far as we know, there has been no previous work that studies the problem. In this work, we formalize text-to-table as a sequence-to-sequence (seq2seq) problem. We first employ a seq2seq model fine-tuned from a pre-trained language model to perform the task. We also develop a new method within the seq2seq approach, exploiting two additional techniques in table generation: table constraint and table relation embeddings. We consider text-to-table as an inverse problem of the well-studied table-to-text, and make use of four existing table-to-text datasets in our experiments on text-to-table. Experimental results show that the vanilla seq2seq model can outperform the baseline methods of using relation extraction and named entity extraction. The results also show that our method can further boost the performances of the vanilla seq2seq model. We further discuss the main challenges of the proposed task. The code and data will be made publicly available.

1 Introduction

Information extraction (IE) is a task that aims to extract information of interest from text data and represent the extracted information in a structured form. Traditional IE tasks include named entity recognition which recognizes entities and their types (Huang et al., 2015; Ma and Hovy, 2016; Lample et al., 2016; Devlin et al., 2019), relation extraction which identifies the relationships between entities (Zheng et al., 2017; Zeng et al., 2018; Luan et al., 2019; Zhong and Chen, 2020), etc. Since the results of IE are structured, they can be easily used by computer systems in different applications such as text mining.

The Celtics saw great team play in their Christmas Day win, and it translated to the box score. Boston had 25 assists to just 11 for New York, and the team committed just six turnovers on the night. All-Star Isaiah Thomas once again led Boston with 27 points, while star center Al Horford scored 15 points and stuffed the stat sheet with seven rebounds, five assists, three steals, and two blocks. Third-year point guard Marcus Smart impressed off the bench, dishing seven assists and scoring 15 points including the game - winning three - pointer. New York, meanwhile, saw solid play from its stars. Sophomore big man Kristaps Porzingis had 22 points and 12 rebounds as well as four blocks. All-Star Carmelo Anthony had 29 points, 22 of which came in the second half. Point guard Derrick Rose also had 25 points in one of his highest - scoring outings of the season.

Team:

	Number of team assists
Knicks	11
Celtics	25

Player:

	Assists	Points	Total rebounds	Steals
Al Horford	5	15	7	3
Isaiah Thomas		27		
Marcus Smart	7	15		
Carmelo Anthony		29		
Kristaps Porzingis		22	12	
Derrick Rose		25		

Figure 1: An example of text-to-table from the Rotowire dataset. The text is a report of a basketball game, and the tables are the scores of the teams and players.

In this work, we study IE in a new setting, referred to as text-to-table. First, the system receives a training dataset containing text-table pairs. Each text-table pair contains a text and a table (or tables) representing information extracted from the text. The system learns a model for information extraction. Next, the system employs the learned model to conduct information extraction from a new text and outputs the result in a table (or tables). Figure 1 gives an example of text-to-table, where the input (above) is a report of a basketball game, and the output (below) is two tables summarizing the scores of the teams and players from the input.

Text-to-table is unique compared to the traditional IE approaches. First, it is mainly designed to extract structured data in a complex form from a long text. As in the example in Figure 1, extraction of information is performed from the entire document. The extracted information contains multiple types of scores of teams and players in a basketball game structured in table format. Second, the schemas for extraction are implicitly included in the training data, and there is no need to explicitly define the schemas. This reduces the need for manual efforts for schema design and annotations.

Our work is inspired by research on the so-called table-to-text (or data-to-text) problem, which is the task of generating a description for a given table. Table-to-text is useful in applications where the content of a table needs to be described in natural language. Thus, text-to-table can be regarded as an inverse problem of table-to-text. However, there are also differences. Most notably, their applications are different. Text-to-table can be applied to document summarization, text mining, etc.

In this work, we formalize text-to-table as a sequence-to-sequence (seq2seq) task. More specifically, we translate the text into a sequence representation of a table (or tables), where the schema of the table is implicitly contained in the representation. We also build the seq2seq model on top of a pre-trained language model, which is the state-of-the-art approach for seq2seq tasks (Lewis et al., 2019; Raffel et al., 2020). Although the approach is a natural application of existing technologies, as far as we know, there has been no previous study to investigate to what extent the approach works. We also develop a new method for text-to-table within the seq2seq approach with two additional techniques, table constraint and table relation embeddings. Table constraint controls the creation of rows in a table and table relation embeddings affect the alignments between cells and their row headers and column headers. Both are to make the generated table well-formulated.

The approach to IE based on seq2seq has already been proposed. Methods for conducting individual tasks of relation extraction (Zeng et al., 2018; Nayak and Ng, 2020), named entity recognition (Chen and Moschitti, 2018; Yan et al., 2021), and event extraction (Lu et al., 2021) have been developed. Methods for jointly performing multiple tasks of named entity recognition, relation extraction, and event extraction have also been devised (Paolini et al., 2021). Most of the methods exploit suitable pre-trained models such as BERT. However, all the existing methods rely on pre-defined schemas for extraction. Moreover, their models are designed to extract information from short texts, rather than long texts, and extract information with simple structures (such as an entity and its type), rather than information with complicated structures (such as a table).

We conduct extensive experiments on four datasets. Results show that the vanilla seq2seq model fine-tuned from BART (Lewis et al., 2019) can outperform the state-of-the-art IE models fine-tuned from BERT (Devlin et al., 2019; Zhong and Chen, 2020). Furthermore, results show that our proposed approach to text-to-table with the two techniques can further improve the extraction accuracies. We also summarize the challenging issues with the seq2seq approach to text-to-table for future research.

Our contributions are summarized as follows:

1. We propose the new task of text-to-table for IE. We derive four new datasets for the task from existing datasets.
2. We formalize the task as a seq2seq problem and propose a new method within the seq2seq approach using the techniques of table constraint and table relation embeddings.
3. We conduct extensive experiments to verify the effectiveness of the proposed approach.

2 Related Work

Information Extraction (IE) is a task of extracting information (structured data) from a text (unstructured data). For example, named entity recognition (NER) recognizes entities appearing in a text. Relation extraction (RE) identifies the relationships between entities. Event extraction (EE) discovers events occurring in a text.

Traditionally, researchers formalize the task as a language understanding problem. The state-of-the-art methods for NER perform the task on the basis of the pre-trained language model BERT (Devlin et al., 2019). The pipeline approach to RE divides the problem into NER and relation classification, and conducts the two sub-tasks in a sequential manner (Zhong and Chen, 2020), while the end-to-end approach jointly carries out the two sub-tasks (Zheng et al., 2017; Zeng et al., 2018; Luan et al., 2019). The state-of-the-art methods for EE also employ BERT and usually jointly train the models with other tasks such as NER and RE (Wadden et al., 2019; Zhang et al., 2019; Lin et al., 2020). All the methods assume the use of pre-defined schemas (e.g., entity types for NER, entity and relation types for RE, and event templates for EE). Besides, most methods are designed for extraction from short texts. Therefore, existing methods for IE cannot be directly applied to text-to-table.

Another series of related work is open information extraction (OpenIE), which aims to extract information from texts without relying on explicitly defined schemas (Banko et al., 2007; Wu and Weld, 2010; Mausam et al., 2012; Stanovsky et al., 2018; Zhan and Zhao, 2020). However, OpenIE aims to extract information with simple structures (i.e., relation tuples) from short texts, and the methods in OpenIE cannot be directly applied to text-to-table.

IE is also conducted at document level, referred to as doc-level IE. For example, some NER methods directly perform NER on a long document (Strubell et al., 2017; Luo et al., 2018), and others encode each sentence in a document, use attention to fuse document-level information, and perform NER on each sentence (Hu et al., 2020; Xu et al., 2018). There are also RE methods that predict the relationships between entities in a document (Yao et al., 2019; Nan et al., 2020a). However, existing doc-level IE approaches usually do not consider extraction of complex relations between many items.

Sequence-to-sequence (seq2seq) is the general problem of transforming one text into another text (Sutskever et al., 2014; Bahdanau et al., 2014), which includes machine translation, text summarization, etc. The use of the pre-trained language models of BART (Lewis et al., 2019) and T5 (Raffel et al., 2020) can significantly boost the performances of seq2seq, such as machine translation (Lewis et al., 2019; Raffel et al., 2020; Liu et al., 2020) and text summarization (Lewis et al., 2019; Raffel et al., 2020; Huang et al., 2020).

Recently, some researchers also formalize the IE problems as seq2seq, that is, transforming the input text into an internal representation. One advantage is that one can employ a single model to extract multiple types of information. Results show that this approach works better than or equally well as the traditional approach of language understanding, in RE (Zeng et al., 2018; Nayak and Ng, 2020), NER (Chen and Moschitti, 2018; Yan et al., 2021) and EE (Lu et al., 2021). Methods for jointly performing multiple tasks including NER, RE and EE have also been devised (Paolini et al., 2021).

Data-to-text aims to generate natural language descriptions from the input structured data such as sport commentaries (Wiseman et al., 2017). The structured data is usually represented as tables (Wiseman et al., 2017; Thomson et al., 2020; Chen et al., 2020), sets of table cells (Parikh et al., 2020; Bao et al., 2018), semantic representations (Novikova et al., 2017), or sets of relation triples (Gardent et al., 2017; Nan et al., 2020b). The task requires the model to select the salient information from the data, organize it in a logical order, and generate an accurate and fluent natural language description (Wiseman et al., 2017). Data-to-text models usually adopt the encoder-decoder architecture. The encoders are specifically designed to model the input data, such as multi-layer perceptron (Puduppully et al., 2019a,b), recurrent neural network (Juraska et al., 2018; Liu et al., 2018; Shen et al., 2020), graph neural network (Marcheggiani and Perez-Beltrachini, 2018; Koncel-Kedziorski et al., 2019), or Transformer (Gong et al., 2019).

3 Problem Formulation

As shown in Figure 1, Text-to-table takes a text as input and produces a table or several tables to summarize the content of the text.

Formally, the input is a text denoted as $\mathbf{x} = x_1, x_2, \cdots, x_{|\mathbf{x}|}$. The output is one table or multiple tables. For simplicity suppose that there is only one table denoted as T. Further suppose that T has n_r rows and n_c columns. Thus, T contain $n_r \times n_c$ cells, where the cell of row i and column j is a sequence of words $\mathbf{t}_{i,j} = t_{i,j,1}, t_{i,j,2}, ..., t_{i,j,|\mathbf{t}_{i,j}|}$.

There are three types of table: one that has both column headers and row headers, one that has only column headers, and one that only has row headers. For example, the player table in Figure 1 has both column headers ("Assists", "Points", etc) and row headers ("Al Horford", "Isaish Thomas", etc). We let $\mathbf{t}_{1,j},\ j = 2, 3, \cdots, n_c$ to denote the column headers, let $\mathbf{t}_{i,1},\ i = 2, 3, \cdots, n_r$ to denote the row headers, and let $\mathbf{t}_{1,j},\ i = 2, 3, \cdots, n_r, j = 2, 3, \cdots, n_c$ to denote the non-header cells of the table. For example, in the player table in Figure 1, $\mathbf{t}_{1,2} =$ Assists, $\mathbf{t}_{2,1} =$ Al Horford, and $\mathbf{t}_{2,2} = 5$.

The information extracted via text-to-table can be leveraged in many different applications such as document summarization and text mining. For example, in Figure 1, one can quickly obtain the key information of the text by simply looking at the tables summarized from the text.

There are differences between text-to-table and

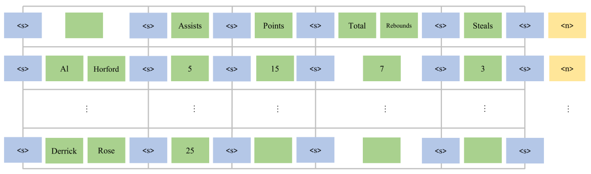

Figure 2: The sequence representation of the player table in Figure 1. The blue items are separation tokens ⟨s⟩ and the yellow items are new-line tokens ⟨n⟩.

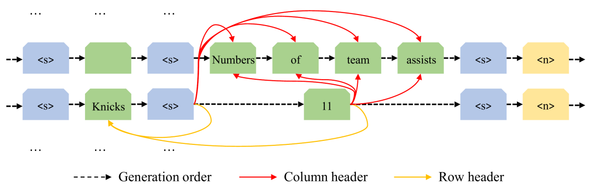

Figure 3: Construction of relation vectors. Red and yellow arrows represent alignments with column headers and row headers respectively. The relation vectors regarding tokens "11" and one ⟨s⟩ are illustrated.

traditional IE settings. As can be seen from the example in Figure 1, extraction of information is performed from the entire document. The extracted information (structured data) is in a complex form, specifically multiple types of scores of teams and players in a basketball game. Furthermore, the data-driven approach is taken, and the schemas of the tables do not need to be explicitly defined.

4 Our Method

We develop a method for text-to-table using the seq2seq approach and the two techniques of table constraint and table relation embeddings.

4.1 Vanilla Seq2Seq

We formalize text-to-table as a sequence-to-sequence (seq2seq) problem (Sutskever et al., 2014; Bahdanau et al., 2014). Specifically, given an input text, we generate a sequence representing the output table (or tables). We introduce two special tokens, a separation token denoted as "⟨s⟩" and a new-line token denoted as "⟨n⟩". For a table $\mathbf{t}$, we represent each row $\mathbf{t}_i$ with a sequence of cells delimited by separation tokens:

$$\mathbf{t}_i = \langle \mathrm{s} \rangle, \mathbf{t}_{i,1}, \langle \mathrm{s} \rangle, \cdots, \langle \mathrm{s} \rangle, \mathbf{t}_{i,n_c}, \langle \mathrm{s} \rangle. \quad (1)$$

We represent the entire table with a sequence of rows delimited by new-line tokens:

$$\begin{aligned} \mathbf{t} = \quad & \langle \mathrm{s} \rangle, \mathbf{t}_{1,1}, \langle \mathrm{s} \rangle, \cdots, \langle \mathrm{s} \rangle, \mathbf{t}_{1,n_c}, \langle \mathrm{s} \rangle, \langle \mathrm{n} \rangle, \quad (2) \\ & \langle \mathrm{s} \rangle, \mathbf{t}_{2,1}, \langle \mathrm{s} \rangle, \cdots, \langle \mathrm{s} \rangle, \mathbf{t}_{2,n_c}, \langle \mathrm{s} \rangle, \langle \mathrm{n} \rangle, \\ & \qquad \cdots\cdots \\ & \langle \mathrm{s} \rangle, \mathbf{t}_{n_r,1}, \langle \mathrm{s} \rangle, \cdots, \langle \mathrm{s} \rangle, \mathbf{t}_{n_r,n_c}, \langle \mathrm{s} \rangle \end{aligned}$$

Figure 2 shows the sequence of the player table in Figure 1. When there are multiple tables, we create a sequence of tables using the captions of the tables as delimiters.

Let $\mathbf{x} = x_1, \cdots, x_{|\mathbf{x}|}$ and $\mathbf{y} = y_1, \cdots, y_{|\mathbf{y}|}$ denote the input and output sequences respectively. In inference, the model generates the output sequence based on the input sequence. The model conducts generation in an auto-regressive way, which generates one token at each step based on the tokens it has generated so far. In training, we learn the model based on the text-table pairs $\{(\mathbf{x}_1, \mathbf{y}_1), (\mathbf{x}_2, \mathbf{y}_2), \cdots, (\mathbf{x}_n, \mathbf{y}_n)\}$. The objective of learning is to minimize the cross-entropy loss.

We refer to the method described above as "vanilla seq2seq". There is no guarantee, however, that the output sequence of vanilla seq2seq represents a well-formulated table. We add a post-processing step to ensure that the output sequence is a table. The post-processing method takes the first row generated as well-defined, deletes extra cells at the end of the other rows and inserts empty cells at the end of the other rows.

4.2 Techniques

We develop two techniques to improve table generation, called table constraint and table relation embeddings. We use "our method" to denote the seq2seq approach with these two techniques.[1]

Table Constraint

Our method exploits a constraint in the decoding process to ensure that the output sequence represents a well-formulated table. Specifically, our method calculates the number of cells in the first row it generates, and then forces the following rows to contain the same number of cells.

Table Relation Embeddings

Our method also incorporates table relation embeddings including row relation embeddings and column relation embeddings into the self-attention of the Transformer decoder. Given a token in a non-header cell, the row relation embeddings τ_r^K and τ_r^V indicate which row header the token is aligned to, and the column relation embeddings τ_c^K and τ_c^V indicate which column header the token is aligned to.

[1]Our methods is able to generate the output containing multiple tables. This is discussed in Appendix C.

Let us consider the self-attention function in one block of Transformer decoder: at each position, self-attention only attends to the previous positions. For simplicity, let us only consider one head in the self-attention. At the t-th position, the input of self-attention is the sequence of representations $z = (z_1, \cdots, z_t)$ and the output is the sequence of representations $h = (h_1, \cdots, h_t)$, where $z_i \in \mathbb{R}^d$ and $h_i \in \mathbb{R}^d$ are the representations at the i-th position ($i = 1, \cdots, t$).

In a conventional Transformer decoder, self-attention is defined as follows,

$$h_i = \left(\sum_{j=1}^{i} \alpha_{ij} (z_j W^V) \right) W^O, \tag{3}$$

$$\alpha_{ij} = \frac{e^{e_{ij}}}{\sum_{j=1}^{i} e^{e_{ij}}}, e_{ij} = \frac{(z_i W^Q)(z_j W^K)^{\mathrm{T}}}{\sqrt{d_k}}, \tag{4}$$

$$i = 1, \cdots, t, \; j = 1, \cdots, i$$

where $W^Q, W^K, W^V \in \mathbb{R}^{d \times d_k}$ are the query, key, and value weight matrices respectively, and $W^O \in \mathbb{R}^{d_k \times d}$ is the output weight matrix.

In our method, self-attention is defined as:

$$h_i = \left(\sum_{j=1}^{i} \alpha_{ij} (z_j W^V + r_{ij}^V) \right) W^O, \tag{5}$$

$$\alpha_{ij} = \frac{e^{e_{ij}}}{\sum_{j=1}^{i} e^{e_{ij}}}, e_{ij} = \frac{(z_i W^Q)(z_j W^K + r_{ij}^K)^{\mathrm{T}}}{\sqrt{d_k}}, \tag{6}$$

$$i = 1, \cdots, t, \; j = 1, \cdots, i$$

where r_{ij}^K and r_{ij}^V are relation vectors representing the relationship between the i-th position and the j-th position.

The relation vectors r_{ij}^K and r_{ij}^V are defined as follows. For the token at the i-th position, if the token at the j-th position is a part of its row header, then r_{ij}^K and r_{ij}^V are set to the row relation embeddings τ_r^K and τ_r^V. Similarly, for the token at the i-th position, if the token at the j-th position is a part of its column header, then r_{ij}^K and r_{ij}^V are set to the column relation embeddings τ_c^K and τ_c^V. Otherwise, r_{ij}^K and r_{ij}^V are set to 0. In inference, to identify the row header or the column header of a token, we parse the sequence generated so far to create a partial table using the new-line tokens and separation tokens in the sequence. Figure 3 illustrates how relation vectors are constructed.

5 Experiments

5.1 Datasets

We make use of four existing datasets which are traditionally utilized for data-to-text: Rotowire (Wiseman et al., 2017), E2E (Novikova et al., 2017), WikiTableText (Bao et al., 2018), and WikiBio (Lebret et al., 2016). In each dataset, we filter out the content in the tables that does not appear in the texts. We plan to make the processed datasets publicly available for future research. Table 2 gives the statistics of the Rotowire dataset and Table 1 gives the statistics of the other three datasets.

Rotowire is from the sports domain. Each instance is composed of a text and two tables, where the text is a report of a basketball game and the two tables represent the scores of teams and players respectively (cf., Figure 1). Each table has column headers describing the types of scores, and row headers describing the names of teams or players. The texts are long and may contain irrelevant information such as the performance of players in other games. Therefore, this is a challenging dataset.

E2E is from the restaurant domain. Each instance is a pair of short text and automatically constructed table, where the text is a description of a restaurant, and the table has two columns with column headers summarizing the characteristics of the restaurant. The tables are automatically constructed, where the texts in the tables are from a limited set and thus are lack of diversity.

WikiTableText is an open-domain dataset. Each instance includes a text and a table, where the text is a description and the table has a row and two columns with column headers, collected from a Wikipedia infobox. The texts are short and contain information similar to that in the tables.

WikiBio is extracted from the Wikipedia biography pages. Each instance consists of a text and a table, where the text is the introduction of Wikipedia page[2] and the table is from the infobox of Wikipedia page and has two columns with column headers. The input texts are usually long and contain more information than the tables.

5.2 Procedure

Methods: We conduct experiments with vanilla seq2seq and our method, as well as baselines.

We know of no existing method that can be directly employed in text-to-table. For each dataset,

[2]The original dataset only uses the first sentence of the introduction. We use the entire introduction.

Dataset	Train	Valid	Test	# of tokens	# of rows	# of columns
E2E	42.1k	4.7k	4.7k	24.90	4.58	2.00
WikiTableText	10.0k	1.3k	2.0k	19.59	4.26	2.00
WikiBio	582.7k	72.8k	72.8k	122.30	4.20	2.00

Table 1: Statistics of E2E, WikiTableText, and WikiBio datasets, including number of instances in training, validation, and test sets, number of BPE tokens per instance and number of rows per instance.

Train	Valid	Test	# of tokens
3.4k	727	728	351.05

	# of rows	# of columns	# of cells
Team	2.71	4.84	6.56 (85.40%)
Player	7.26	8.75	22.63 (43.93%)

Table 2: Statistics of Rotowire dataset. The first table shows sizes of training, validation, and test sets, number of BPE tokens per instance. The second table shows number of rows, number of columns, and number and ratio of non-empty cells.

we first define the schemas based on the training data, then use an existing method of relation extraction (RE) or named entity extraction (NER) to extract information, and finally create tables based on the schemas and extracted information. We take it as the baseline for the dataset. No baseline can be applied to all four datasets. For RE, we use PURE, a state-of-the-art method (Zhong and Chen, 2020). For NER, we use BERT (Devlin et al., 2019).

Training: For vanilla seq2seq and our method, we adopt Transformer (Vaswani et al., 2017) as the model and fine-tune the models from BART-base. We also experiment with BART-large. For RE and NER, we fine-tune the models from BERT-base-uncased. All models are trained with Adam optimizer until convergence. Hyper-parameters are shown in Appendix A. For the small datasets of Rotowire and WikiTableText, we run experiments five times with different random seeds and take average of results to reduce variance.

Evaluation: We evaluate the performance of a method based on the number of correct non-header cells in the tables. To judge whether a cell is correctly generated in the table, we use not only its content but also its row header and column header to ensure that the cell is on the right row and right column. Exact match is used to compare the content of the generated cell and the ground truth. We adopt precision, recall, and F1 score as evaluation measures. We calculate the measures on each generated table and then take the average on all tables. This evaluation assumes that the ordering of rows and columns is not important. We find that this assumption is applicable to the four datasets and many real-world scenarios. We also evaluate the percentage of output sequences that cannot represent well-formulated tables, referred to as error rate.

5.3 Results on Rotowire

Table 3 shows the results on the Rotowire dataset. One can see that in terms of F1 score, our method performs the best followed by vanilla seq2seq, and both outperform the baselines of doc-level RE and sent-level RE. The RE baselines perform quite well, but they heavily rely on rules and cannot beat the seq2seq approach. Among them the doc-level RE performs better than sent-level RE, because some information in Rotowire can only be extracted when cross-sentence context is provided.

We implement two baselines of RE, namely doc-level RE and sent-level RE. We take team names, player names, and numbers of scores as entities and take types of scores as relations. Sent-level RE predicts the relations between entities within each sentence. Doc-level RE predicts the relations between entities within a window (the window size is 12 entities) and uses the approximation model proposed by Zhong and Chen (2020) to speed up inference.

5.4 Results on E2E, WikiTableText and WikiBio

Table 4 shows the results of our method, vanilla seq2seq, and the baseline of NER on E2E, WikiTableText, and WikiBio. Again, the seq2seq approach outperforms the baseline. The NER baseline has slightly higher precision, but the seq2seq approach has significantly higher recall and F1. Our method and vanilla seq2seq are comparable, because the table structures in the three datasets are very simple (there are only two columns in the tables), and the use of the two techniques does not further improve the performances. The NER baseline has high precision but low recall, mainly because NER can only make the right decision when it is clear.

	Team				Player			
	Pre.	Rec.	F1	Err.	Pre.	Rec.	F1	Err.
Sent-level RE	81.05	75.29	77.17	0.00	86.10	76.00	79.59	0.00
Doc-level RE	78.57	74.74	75.66	0.00	**86.19**	77.88	80.76	0.00
Vanilla seq2seq	84.05	83.59	82.97	0.49	84.56	81.32	81.96	7.40
lOur method	**84.40**	**84.01**	**83.36**	0.00	84.77	**82.20**	**82.53**	0.00

Table 3: Results of our method, vanilla seq2seq, and the baselines of doc-level RE and sent-level RE, on Rotowire.

	E2E				WikiTableText				WikiBio			
	Pre.	Rec.	F1	Err.	Pre.	Rec.	F1	Err.	Pre.	Rec.	F1	Err.
NER	**99.39**	84.99	90.80	0.00	**60.63**	47.02	52.23	0.00	**73.64**	49.87	56.51	0.00
Vanilla seq2seq	97.95	**97.87**	**97.87**	0.00	59.84	**59.30**	**59.26**	0.41	70.78	**70.44**	68.98	0.00
Our method	97.97	**97.89**	**97.88**	0.00	59.74	59.17	59.14	0.00	70.93	70.38	**69.02**	0.00

Table 4: Results of our method, vanilla seq2seq, and the baseline of NER, on E2E, WikiTableText and WikiBio.

Pre	TC	TRE	Rotowire/Team	Rotowire/Player	E2E	WikiTableText	WikiBio
✗	✗	✗	28.05	7.75	94.45	46.37	67.51
✗	✓	✓	30.61	10.67	95.53	47.13	67.43
✓	✗	✗	82.97	81.96	97.87	59.26	68.98
✓	✓	✗	83.09‡	82.24‡	**97.88**	**59.29**†	68.98
✓	✗	✓	83.30†	82.50‡	97.87	59.12	**69.02**
✓	✓	✓	**83.36**†	**82.53**‡	**97.88**	59.14	**69.02**

Table 5: Results of ablation study on our method by excluding pre-trained language model (Pre), table constraint (TC) and table relation embeddings (TRE). We conduct a significance test to check whether the performance is significantly better than vanilla seq2seq with pretrained language models (i.e., with Pre but without TC or TRE). † and ‡ represent $p < 0.05$ and $p < 0.01$ respectively.

We implement the baseline of NER in the following way. We view the non-head cells in the tables as entities and their row headers as entity types. In training, we match the non-head cells into the texts and take them as "entities" in the texts. Only a proportion of the non-header cells can be matched into the texts (85% for E2E, 74% for WikiTableText, and 69% for WikiBio).

5.5 Additional Study

We carry out ablation study on our method. Specifically, we exclude pre-trained language model, table constraint (TC) and table relation embeddings (TRE) from our method. Note that our method without TC and TRE is equivalent to vanilla seq2seq. Table 5 gives the results on the four datasets.

It can be seen that the use of both TC and TRE can significantly improve the performance on Rotowire, which indicates that our method is particularly effective when the tables are large with many rows and columns. There are not significant improvements on E2E, WikiTableText, and WikiTableText, apparently because formulation of tables is easy for the three datasets. Therefore, we conclude that the two techniques of TC and TRE are helpful when the task is difficult.

The use of pre-trained language model can boost the performance on all datasets, especially on Rotowire and WikiTableText. This indicates that pre-trained language model is particularly helpful when the task is difficult and the size of training data is small.

We observe that vanilla seq2seq makes more formatting errors than our method, especially on player tables in Rotowire that have a large number of columns. It indicates that for vanilla seq2seq, it is difficult to keep track of the columns in each row and make alignments with the column headers. In contrast, the two techniques of our method can help effectively cope with the problem. Figure 4 shows a bad case of vanilla seq2seq, where the model correctly infers the column of "assists" but fails to infer the columns of "personal fouls", "points", and "total rebounds" for the row of "Rajon Rondo". In contrast, our method can successfully handle the case, because TC can eliminate the incorrectly formatted output, and TRE can make correct align-

Method	Rotowire/Team	Rotowire/Player	E2E	WikiTableText	WikiBio
Vanilla seq2seq (BART base)	82.97	81.96	97.87	59.26	68.98
Our method (BART base)	83.36	82.53	97.88	59.14	69.02
Vanilla seq2seq (BART large)	**86.31**	86.59	**97.94**	**62.71**	69.66
Our method (BART large)	**86.31**	**86.83**	97.90	62.41	**69.71**

Table 6: Results of our method and vanilla seq2seq with base and large BART models on all four datasets.

```
. . .
|             | Assists | · · · | Personal fouls | Points | Total rebounds | Steals | Turnovers | \n
| Rajon Rondo |   18    | · · · |       7        |   8    |                |        |           | \n
. . .
```

Figure 4: A bad case generated by vanilla seq2seq. The assists, points and total rebounds of Rajon Rondo should be 18, 7 and 8 respectively. The model generates one less column between "Assists" and "Personal fouls".

ments with the column headers.

We also investigate the effect of the scale of pre-trained language model BART. We use both BART-base and BART-large and conduct fine-tuning on top of them for vanilla seq2seq and our method. Table 6 gives the results on the four datasets. The results show that the use of BART-large can further boost the performances on all four datasets, indicating that it is better to use larger pre-trained models when computation cost is not an issue.

5.6 Discussions

We analyze the experimental results on the four datasets and identify five challenging issues.

(1) Text Diversity: Extraction of the same content from different expressions is one challenge. For example, the use of synonyms is very common in Rotowire. The team of "Knicks" is often referred to as "New York", its home city. Identification of the same entities from different expressions is needed in the task.

(2) Text Redundancy: There are cases such as those in WikiBio, in which the texts contain much redundant information. This poses a challenge to the text-to-table model to have a strong ability in summarization. It seems that the seq2seq approach works well to some extent but further improvement is undoubtedly necessary.

(3) Large Table: The tables in Rotowire have large numbers of columns, and the extraction from them is challenging even for our method of using TC and TRE.

(4) Background Knowledge: WikiTableText and WikiBio are from open domain. Thus, performing text-to-table on such kind of datasets require the use of much background knowledge. A possible way to address this challenge is to use more powerful pre-trained language models or external knowledge bases.

(5) Reasoning: Sometimes the information is not explicitly presented in the text, and reasoning is required to conduct correct extraction. For example, an article in Rotowire reports a game between the two teams "Nets" and "Wizards". From the sentence: "The Nets seized control of this game from the very start, opening up a 31 - 14 lead after the first quarter", humans can infer that the point of "Wizards" is 14, which is still difficult for machines.

6 Conclusion

We propose employing text-to-table as a new way of information extraction (IE), which extracts information of interest from the input text and summarizes the extracted information in tables. The advantage of the approach is that one can easily conduct information extraction from either short texts or long texts to create simple tables or complex tables without explicitly defining the schemas. Text-to-table can be viewed as an inverse problem of table-to-text. We formalize text-to-table as a sequence-to-sequence problem on top of a pre-trained model. We further propose an improved method using a seq2seq model and table constraint and table relation embeddings techniques. We conduct experiments on four datasets derived from existing table-to-text datasets. The results demonstrate that our proposed approach outperforms existing methods using conventional IE techniques. We further analyze the challenges of text-to-table for future study. The issues include diversity of text, redundancy of text, large-table, background knowledge, and reasoning.

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A Hyper-parameters

We list the hyper-parameters of the pre-trained models in Table 7. The training hyper-parameters for BART-base model in vanilla seq2seq and our method are listed in Table 8.

B Table Constraint Algorithm

The pseudo-codes for table constraint are in Algorithm 1.

C Our Method with Multiple Tables

Our method is able to generate the output containing multiple tables. For example, in Rotowire dataset, the output data contains two tables representing the scores of teams and players respectively. In this section, we illustrate how our method works for Rotowire dataset as a special case.

To represent the tables with a sequence, we use captions as delimiters. For Rotowire, as shown in Figure 1, the first table is the team table, and its caption is "Team:". The second table is the player table, and its caption is "Player:". Let $\mathbf{t}^{\text{team}}$ and $\mathbf{t}^{\text{player}}$ denote the table and player tables respectively. Therefore, the sequence representation is "Team: $\langle\text{n}\rangle$ $\mathbf{t}^{\text{team}}$ $\langle\text{n}\rangle$ Player: $\langle\text{n}\rangle$ $\mathbf{t}^{\text{player}}$".

For table constraint (TC), we only use TC when the seq2seq model is generating a table. When generating a caption, we do not pose any constraints to the decoding process. Since the captions do not start with the separation token $\langle\text{s}\rangle$, if the current line starts with the separation token $\langle\text{s}\rangle$, then the model is generating a table. Otherwise, it is generating a caption.

For table relation embeddings (TRE), we calculate the relation vectors separately for each table. However, the parameters including the row relation embeddings (i.e., τ_r^K and τ_r^V) and the column

Pre-trained model	Methods	layers	hidden dim.	heads	parameters
BART-base	Vanilla seq2seq and ours	12	768	16	139M
BART-large	Vanilla seq2seq and ours	24	1024	16	406M
BERT-base-uncased	NER and RE	12	768	12	110M

Table 7: The hyper-parameters of the pre-trained models in our experiments. We list the number of layers, hidden dimensions (hidden dim.), heads, and parameters. BART-base and BART-large are used for vanilla seq2seq and our method, while BERT-base-uncased is used for the baselines of RE and NER.

	warmup	total upd.	lr	bsz
Rotowire	400	8000	3e-05	4096
E2E	400	8000	1e-05	4096
WikiTableText	2000	8000	1e-04	4096
WikiBio	4000	40000	1e-04	4096

Table 8: The training hyper-parameters for BART-base model on all four datasets. We list the warmup updates (warmup), total updates (total upd.), learning rate (lr), and batch size (bsz, in terms of how many tokens per batch).

relation embeddings (i.e., τ_c^K and τ_c^V) are shared among the tables.

D Evaluation Details

To evaluate a text-to-table system, we adopt precision, recall, and F1 score as evaluation measures. We calculate the measures on each generated table and then take the average on all tables.

Specifically, we represent each non-header cell as a tuple containing the row header, column header, and cell content. Then, we take the collection of cell tuples in the ground truth table as reference, and calculate the precision, recall, and f1 score of the predicted cell tuples. We use exact match to check whether a predicted non-header cell is correct. A predicted non-header cell will be considered as a true positive only when it is exactly the same as the ground truth, that is, when they have the same row header, cell header, and content. In other words, we use not only its content but also its row header and column header to ensure that the cell is on the right row and right column. A limitation of exact match is that it will fail to consider the cases where the prediction is a synonym of the reference. However, we observe that the row/column names and cell contents in datasets are quite consistent, so such mistakes are uncommon. Therefore, we use exact match for simplicity.

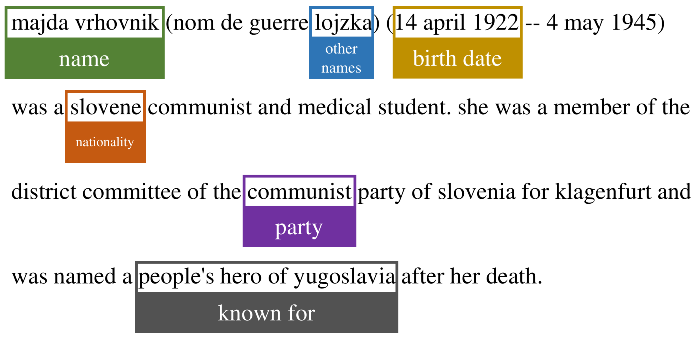
As shown in Figure 1, the tables in the dataset contain some empty cells, that is, cells with word sequences of zero length. These cells do not contain actual information and are only used as placeholders. Therefore, for both the golden reference and the prediction, we ignore the empty cells and

Algorithm 1: Decoding using table constraint. ⟨eos⟩, ⟨s⟩, and ⟨n⟩ denote the end of sentence, separation token, and new-line token respectively. Seq2seq denotes the seq2seq model. Decode denotes the decoding algorithm such as beam search and greedy search.

```
Input: $\mathbf{x} = [x_1, x_2, \cdots, x_{|\mathbf{x}|}]$
Output: $\mathbf{y} = [y_1, y_2, \cdots, y_{|\mathbf{y}|}]$
$\mathbf{y} \leftarrow []$

repeat
    /* generates the first row: only allows generation
       of ⟨n⟩ or ⟨eos⟩ after ⟨s⟩                          */
    $p(\cdot) \leftarrow$ seq2seq(x, y)
    if $\mathbf{y}_{|\mathbf{y}|} \neq \langle s \rangle$ then
        $p(\langle n \rangle) \leftarrow 0,\ p(\langle eos \rangle) \leftarrow 0$
    y.append(decode $(p)$)
until $\mathbf{y}_{|\mathbf{y}|} = \langle n \rangle$ or $\mathbf{y}_{|\mathbf{y}|} = \langle eos \rangle$
if $\mathbf{y}_{|\mathbf{y}|} = \langle eos \rangle$ then
    return y
$n_c \leftarrow$ number of cells of the first row

repeat
    /* generates the next rows: each row contains
       exactly $n_c$ cells                                */
    repeat
        /* generates a row                                */
        $p(\cdot) \leftarrow$ seq2seq(x, y)
        if current row has $n_c$ columns then
            $p(t) \leftarrow 0,\ \forall t \neq \langle eos \rangle$ and $t \neq$
            ⟨n⟩
        else
            $p(\langle n \rangle) \leftarrow 0,\ p(\langle eos \rangle) \leftarrow 0$
        y.append(decode $(p)$)
    until $\mathbf{y}_{|\mathbf{y}|} = \langle n \rangle$ or $\mathbf{y}_{|\mathbf{y}|} = \langle eos \rangle$
    if $\mathbf{y}_{|\mathbf{y}|} = \langle eos \rangle$ then
        return y
```


majda vrhovnik (nom de guerre lojzka) (14 april 1922 -- 4 may 1945)
name
other names
birth date
was a slovene communist and medical student. she was a member of the
nationality
district committee of the communist party of slovenia for klagenfurt and
party
was named a people's hero of yugoslavia after her death.
known for

known for	people's hero of yugoslavia
other names	lojzka
party	communist
name	majda vrhovnik
nationality	slovene
birth date	14 april 1922

Figure 5: An example of NER data on WikiBio dataset. Each row header is an entity type, and each non-header cell is an entity.

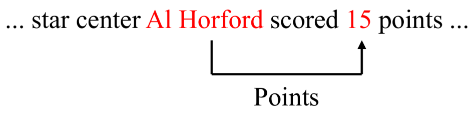


Figure 6: An example of RE data from Rotowire dataset. "Al Horford" and "15" are entities, and "Points" is the relation type.

only take the non-empty cells to calculate the metrics.

E Information Extraction Baselines

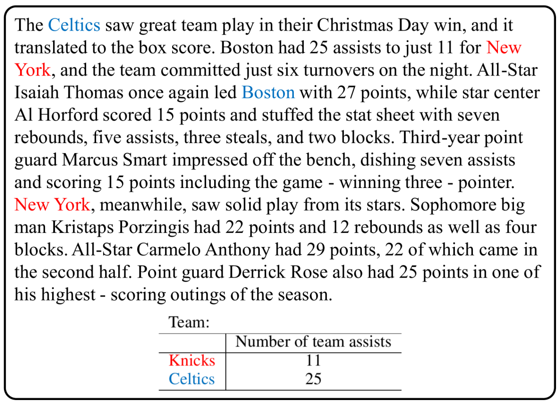
E.1 Relation Extraction

To use relation extraction (RE) as our baseline for Rotowire dataset, we take team names, player names, and numbers of scores as entities and take types of scores as relations. An example relation is shown in Figure 6, which can be represented as a relation tuple (Al Horford, Points, 15). "Al Horford" is the subject entity, "15" is the object entity, and "Points" is one of the pre-defined relation types. There are 38 relations in total.

To create synthetic training data, we match the player names, team names and score numbres to the texts. We adapt the rules provided by Wiseman et al. (2017) which is able to conduct fuzzy match.

E.2 Named Entity Recognition

We use named entity recognition (NER) as our baseline for E2E, WikiTableText, and WikiBio datasets. Specifically, since each table is a two-column table with a header column, we consider the row header as entity type and the non-header cells as entity mentions. An example is shown in Figure 5. For the row with a header "name" and a non-header cell "majda vrhnovnik", we take "majda vrhnovnik" as an entity with the type "name". Here, "name" is one of the pre-defined entity types. We collect



The Celtics saw great team play in their Christmas Day win, and it translated to the box score. Boston had 25 assists to just 11 for New York, and the team committed just six turnovers on the night. All-Star Isaiah Thomas once again led Boston with 27 points, while star center Al Horford scored 15 points and stuffed the stat sheet with seven rebounds, five assists, three steals, and two blocks. Third-year point guard Marcus Smart impressed off the bench, dishing seven assists and scoring 15 points including the game - winning three - pointer. New York, meanwhile, saw solid play from its stars. Sophomore big man Kristaps Porzingis had 22 points and 12 rebounds as well as four blocks. All-Star Carmelo Anthony had 29 points, 22 of which came in the second half. Point guard Derrick Rose also had 25 points in one of his highest - scoring outings of the season.

Team:

	Number of team assists
Knicks	11
Celtics	25

Figure 7: Illustration of the use of synonyms for the example in Figure 1. The red color denotes the team of "Knicks", which is often referred to as "New York", its home city. The blue color denotes the team of "Celtics", which is often referred to as "Boston", its home city.

all headers in the training set to collect the entity types. We have 7 entity types for E2E, 2262 entity types for WikiTableText, and 2272 entity types for WikiBio.

To create synthetic training data, we match the contents of non-header cells to the texts. However, the data is usually paraphrased or even abstracted from the text, so not all non-header cells can be matched to the text. We match 85% non-header cells for E2E, 74% for WikiTable, and 69% for WikiBio.

F Detailed Cases for Challenges

In this section, we provide cases for the challenges discussed in Section 5.6.

(1) Text Diversity: Extraction of the same content from different expressions is one challenge. For example, the use of synonyms is very common in Rotowire. Figure 7 illustrates the use of synonyms for the example in Figure 1. The team of

philippe adnot (born 25 august 1945 in rhèges) is a member of the senate of france. he was first elected in 1989, and represents the aube department. a farmer by profession, he serves as an independent, and also serves as the head of the general council of aube, to which he was elected to represent the canton of méry-sur-seine in 1980. in 1998 and 2008, he was re-elected to the senate in the first round, avoiding the need for a run-off vote. having contributed to the creation of the university of technology of troyes, in 1998 he was made the first vice president of the university board, of which he is currently the president. he is a member of the senate's committee on the laws relating to the freedoms and responsibilities of universities. as of 2009, he serves as the delegate from the administrative meeting for senators not on the list of another group he is decorated as a chevalier of the ordre national de mérite agricole.

name	philippe adnot
birth place	france
occupation	farmer
residence	france
birth date	25 august 1945
constituency	aube canton de méry-sur-seine

Figure 8: An example from WikiBio dataset to illustrate the challenges of text redundancy and background knowledge. Only the highlighted information is captured in the output table. Other information such as the experience of Philippe Adnot is redundant. Moreover, the system should have background knowledge about the French political system to extract information about the constituency of Philippe Adnot.

The Denver Nuggets defeated the Milwaukee Bucks, 121 - 117, at Pepsi Center on Friday. It was n't the ideal win for Denver considering they nearly blew a monster lead, but they were able to hold on for a much needed victory. In fact, the Nuggets led by 22 in the third quarter, before allowing the Bucks to get it within two points late in the fourth. Denver were able to hold on though, despite missing their last four free - throws. Rebounding was the biggest factor in the game, with Denver winning that battle, 48 - 38. The Nuggets also dominated the assist - to - turnover ratio, recording five more assists and committing four less turnovers. The Bucks (21 - 28) put in a valiant effort to pull out a comeback win, but fell just shy to mark their 10th loss in 11 games. Jabari Parker was Milwaukee's best player, as he accrued 27 points, 11 rebounds, four assists and two steals. Giannis Antetokounmpo was n't far behind, collecting 23 points, eight rebounds, five assists, two steals and two blocks. John Henson was the only other Buck in double figures, as he amassed 16 points, five rebounds and four blocks. The Nuggets (22 - 27) have now won eight of their last 12 games, as they could n't be happier to see Nikola Jokic back and healthy. Jokic recorded his first career triple - double in the win. as he accumulated 21 points, 13 rebounds and 11 assists. Wilson Chandler started for Danilo Gallinari (groin) and tallied 23 points, eight rebounds, three assists, two steals and four blocks. Kenneth Faried recorded a double - double, totaling 19 points and 11 rebounds. Jamal Murray was the leading scorer off the bench, dropping 18 points on 5 - of - 9 from the field.

Team:

	Losses	Total points	Points in 2nd quarter	Wins
Nuggets	27	121		22
Bucks	28	117	22	21

Player:

	Assists	Blocks	Field goals attempted	Field goals made	Points	Total rebounds	Steals
Giannis Antetokounmpo	5	2			23	8	2
Jabari Parker	4				27	11	2
John Henson		4			16	5	
Wilson Chandler	3	4			23	8	2
Kenneth Faried					19	11	
Nikola Jokic	11			8		12	
Jamal Murray			9	5	18		

Figure 9: The team table has 3 rows and 4 columns, and the player table has 8 rows and 8 columns.

"Knicks" is often referred to as "New York", its home city. Similarly, "Celtics" is often referred to as "Boston", its home city. Identification of the same entities from different expressions is needed in the task.

(2) Text Redundancy: There are cases such as those in WikiBio, in which the texts contain much redundant information. An example is shown in Figure 8, where only the highlighted information is captured in the output table. Other information such as the experience of Philippe Adnot is redundant. This poses a challenge to the text-to-table model to have a strong ability in summarization. It seems that the seq2seq approach works well to some extent but further improvement is undoubtedly necessary.

(3) Large Table: The tables in Rotowire have large numbers of columns, so extraction from them is challenging even for our method of using TC and TRE. As presented in Table 2, team tables have 2.71 rows and 4.84 columns on average, and player tables have 7.26 rows and 8.75 columns on average. An example is shown in Figure 9, where the team table has 3 rows and 4 columns, and the player table has 8 rows and 8 columns.

(4) Background Knowledge: WikiTableText and WikiBio are from open domain. Thus, performing text-to-table on such kind of datasets require

the use of much background knowledge. Also in Figure 8, the extraction system should have background knowledge about the French political system in order to extract information about the constituency of Philippe Adnot. A possible way to address this challenge is to use more powerful pretrained language models or external knowledge bases.

(5) Reasoning: Sometimes the information is not explicitly presented in the text, and reasoning is required to conduct correct extraction. For example, as shown in Figure 10, an article in Rotowire reports a game between the two teams “Nets” and “Wizards”. From the sentence: “The Nets seized control of this game from the very start, opening up a 31 - 14 lead after the first quarter”, humans can infer that the point of “Wizards” is 14, which is still difficult for machines.

The Brooklyn Nets (37 - 42) defeated the Washington Wizards (45 - 34) 117 - 80 on Friday in Brooklyn. The Nets seized control of this game from the very start, opening up a 31 - 14 lead after the first quarter. …

Team:

	Points in 1st quarter
Nets	31
Wizards	14

Figure 10: An example from Rotowire which requires reasoning to perform information extraction. The article in Rotowire reports a game between the two teams “Nets” and “Wizards”. From the sentence: “The Nets seized control of this game from the very start, opening up a 31 - 14 lead after the first quarter”, humans can infer that the point of “Wizards” is 14, which is still difficult for machines.