Learning Better Representation for Tables by Self-Supervised tasks

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Abstract
Table-to-text generation aims at automatically generating natural text to help people to conveniently obtain the important information in tables. Although neural models for table-to-text have achieved remarkable progress, some problems still overlooked. The first is that the values recorded in many tables are mostly numbers in practice. The existing approaches do not do special treatment for these, and still regard these as words in natural language text. Secondly, the target texts in training dataset may contain redundant information or facts do not exist in the input tables. These may give wrong supervision signals to some methods based on content selection and planning and auxiliary supervision. To solve these problems, we propose two self-supervised tasks, Number Ordering and Significance Ordering, to help to learn better table representation. The former works on the column dimension to help to incorporate the size property of numbers into table representation. The latter acts on row dimension and help to learn a significance-aware table representation. We test our methods on the widely used dataset ROTOWIRE which consists of NBA game statistic and related news. The experimental results demonstrate that the model trained together with these two self-supervised tasks can generate text that contains more salient and well-organized facts, even without modeling context selection and planning. And we achieve the state-of-the-art performance on automatic metrics.

1 Introduction
Table-to-text generation is an important task for text generation from structured data. It aims at automatically producing descriptive natural language text that covers the salient information in table to help people to get the salient information of the tables. Practical applications can be found in domains such as weather forecasts [Mei, Bansal, and Walter 2015], biography generation [Lebret, Grangier, and Auli 2016], NBA news generation [Wiseman, Shieber, and Rush 2017], etc.

Over the pass several years, neural text generation methods have made significant progress on this task. Lebret, Grangier, and Auli; Wiseman, Shieber, and Rush; Bao et al. model it as a machine translation task and view the input table a record sequence. To generate text that contains more salient and well-organized facts, Sha et al.; Pudupully, Dong, and Lapata; Moryossef, Goldberg, and Dagan explicitly model content selection and planning. To learning better representation for tables, Liu et al.; Bao et al.; Nema et al.; Jain et al.; Gong et al. explicitly model the structure of table from multiple levels or different dimensions. In addition, Liu et al. propose three auxiliary supervision tasks to capture accurate semantic representation of the table.

However, some issues have been overlooked. First, many tables (Figure 1(a)) contain a large number of numerical records. For instance, 86.82% of records and almost 86.49% of column types are numeric in ROTOWIRE (Wiseman, Shieber, and Rush 2017), a benchmark of NBA basketball games. Current methods treat these records as words in natural language text and ignore the characteristics of the number itself which play an important role in table representation, such as size attribute. In addition, there are noises in human-written summaries in dataset. These noises include redundant information and records that do not exist in the input tables (Figure 1(b)). These noises may cause incorrect alignments between input tables and target text or wrong supervision signals. And they can affect the performance of models based on content selection and planning or auxiliary supervision.

To solve above problems, we explore the use of the information contained in the tables and introduce two self-
supervised tasks to learn better representation for tables. We argue that the better representation of tables can help the model to capture and organize the important facts, even without explicitly modeling content selection and planning. Specially, we improve Gong et al.’s method and employ a hierarchical table encoder to model the table structure from record level and row level. The record-level encoder utilizes two cascaded self-attention models to encode the table from column and row dimension, respectively. And then, we introduce a row-level fusion gate to obtain the row-level representation for each row. To learn a number-aware record representation, we introduce a Number Ordering (NO) task. This task utilizes a pointer network to generate a descending record sequence for each column in table, according to their content. Figure 1(c) shows a number ordering example for column PTS. To the best of our knowledge, this is the first work on neural table-to-text generation via focusing on learning representation for number in table. Another self-supervised task, Significance Ordering (SO), is further proposed to learn a significance-aware representation for the record. The significance denotes the relative relation between records in same row. This is inspired by the intuition that when humans describe the performance of a player, they tend to focus on his more salient records. For example, in Figure 1(a), K. Thompson’s scores 43 is more likely to be described than his other’s records. The SO task executes a descending sort operation on each row according to the significance scores of records. We use the position index of record to measure its importance and the smaller the significance score, the more important the record is. The position index of record is obtained by the results of Number Ordering. For example, in Figure 1(d), K. Thompson scores 43 points which are the largest in PTS, so the significance score of this record is 1. The proposed two tasks are trained together with the table2text generation model and they share the same encoder parameters. Obviously, the two proposed tasks are self-supervised and the training labels are easily obtained from the input tables. Therefore, the errors caused by noises in training set are avoided.

We conducted experiments on ROTOWIRE to verify the effectiveness of the proposed approach. The experimental results demonstrate that, even without explicitly modeling content selection or introducing extra knowledge, our method can help to generate text that contains more salient and well-organized facts. And we achieve the state-of-the-art performance on automatic metrics.

2 Related Work

Recently, neural models have been the mainstream for table-to-text generation and obtained impressive results. Early works on table-to-text generation regard it as a distinct machine translation task and view a structured table as a sequence of records (Lebret, Grangier, and Auli 2016; Wiseman, Shieber, and Rush 2017; Bao et al. 2018). Most recent works inspired by the traditional methods for data-to-text generation and introduce explicit content selection and planning to improve the results (Sha et al. 2018; Puduppully, Dong, and Lapata 2019b; Moryossef, Goldberg, and Dagan 2019; Trisedya, Qi, and Zhang 2020; Bai et al. 2020), and they obtain training labels by aligning the input tables with related summaries. However, this alignment may introduce additional errors. Some works attempt to use additional knowledge to improve the quality of generated text. Nie et al. utilize pre-executed symbolic operations on input table in a sequence-to-sequence model to improve the fidelity of neural table-to-text generation. Chen et al. introduce the background knowledge of entity in table to improve results.

In addition to introducing external knowledge, some works learn better representation for table by explicitly modeling the structure of table. Liu et al. propose a structure-aware learning which incorporates the filed information as the additional inputs to the table encoder. Some works (Bao et al. 2018; Nema et al. 2018; Jain et al. 2018) model the representation of table from row level and column level and utilize the dual attention decoder to generate. Gong et al. introduce the historical data for each table and utilize a self-attention based hierarchical encoder on three dimensions (row, column and time) to enrich table’s representation. Furthermore, Liu et al. propose three auxiliary supervision tasks (sequence labeling, text auto-encoding, and multi-label classification) to capture accurate semantic representation of the tables and the supervised signals of text auto-encoding task are from summary which there may be noises in.

3 Approach

3.1 Preliminaries

Each input instance consists of three different tables $S^1, S^2, S^3$, containing records about players’ performance in home team, players’ performance in visiting team and team’s overall performance respectively. We regard each cell in the table as a record. Each record $r$ consists of four types of information including entity $r.e$ (the name of team or player, such as Kobe), type $r.t$ (the types of team or player, e.g., pointer, a) and value $r.v$ as well as feature $r.f$ (e.g., home or visiting) which indicates whether a player or a team compete in home court or not. In practice, each player or team takes one row in the corresponding table and each column contains a type of record such as points, assists, etc. Following previous works (Wiseman, Shieber, and Rush 2017), we utilize to 1-layer MLP to encode the embeddings of each record’s four types of information into a dense vector $r_{emb}^{i,j}$, $r_{emb}^{i,j} = \text{Relu}(W^e[r_{i,j}.e; r_{i,j}.t; r_{i,j}.v; r_{i,j}.f] + b^e)$, where $i,j$ denote a record in the table of $i$-th row and $j$-th column, $[; ]$ denotes the vector concatenation, $W^e$ and $b^e$ are trainable parameters. Giving these tables, the model is expected to generate a natural language text $y = y_1, ..., y_T$ describing these tables. $T$ denotes the length of the text.

3.2 Hierarchical Self-Attention Encoder

Inspired by Gong et al., we use a hierarchical self-attention encoder to encode a table from record level and row level. It consists of a record encoder, a record fusion gate and a row-level encoder. In the following, we explain how the structure-aware table representations are obtained.

Record Encoder Intuitively, in addition to its own value, each record in the table should contain two other types of information. The first one is its context information on column
Figure 2: An overview of Hierarchical Self-Attention Encoder with Number Ordering (NO) and Significance Ordering (SO). REL and RFG denote Record Embedding Layer and Record Fusion Gate, respectively.

dimension and the another one is its context on row dimension. Inspired by [Gong et al.], we obtain these two types of context information through the self-attention network. First, we use a self-attention network to model record in the context of other records in the same column and obtain the column dimension representation vector \( r_{i,j}^{\text{col}} \) as:

\[
\alpha_{i,j,i',i}^{\text{col}} \propto \exp(W_2^{\text{col}} \tanh(W_1^{\text{col}} [r_{i,j}^{\text{emb}}, r_{i',j}^{\text{emb}}]))
\]

\[
r_{i,j}^{\text{col}} = \sum_{i'=1, i' \neq i}^{R} \alpha_{i,j,i'i}^{\text{col}} r_{i',j}^{\text{emb}}
\]

where \( W_1^{\text{col}} \) and \( W_2^{\text{col}} \) are trainable parameters, \( R \) represents the number of rows in the table. The representations will be also used by downstream Number Ordering task.

Next, based on the column dimension record representation \( r_{i,j}^{\text{col}} \), we use another same self-attention network on row dimension to obtain the row dimension representation for records. The motivation is that not only some records in same row will be mentioned in the generated describing but also the column representations of records may supply the information that which records are more important in their corresponding columns. We obtain the row dimension record representation \( r_{i,j}^{\text{row}} \) as:

\[
\alpha_{i,j,i',j}^{\text{row}} \propto \exp(W_2^{\text{row}} \tanh(W_1^{\text{row}} [r_{i,j}^{\text{col}}, r_{i',j}^{\text{col}}]))
\]

\[
r_{i,j}^{\text{row}} = \sum_{j'=1, j' \neq j}^{C} \alpha_{i,j,i'j}^{\text{row}} r_{i,j}^{\text{col}}
\]

where \( W_1^{\text{row}} \) and \( W_2^{\text{row}} \) are trainable parameter, \( C \) denotes the number of columns. The row dimension representation will be also utilized by the downstream Significance Ordering task.

Record Fusion Gate After obtaining the two dimension representations of a record, we utilize a fusion gate [Puduppully, Dong, and Lapata 2019b] to obtain the final representation for it. First, we concatenate the two dimension representations of a record, and utilize a MLP to obtain a general representation for it as \( r_{i,j}^{\text{gen}} \). Then, we compare each dimension representation with \( r_{i,j}^{\text{gen}} \) to obtain their important scores. Finally we obtain the final record representation \( r_{i,j}^{f} \) by weighted sum and a residual connection [He et al. 2016]:

\[
r_{i,j}^{f} = W_f [r_{i,j}^{\text{col}}, r_{i,j}^{\text{row}}]
\]

\[
s_{i,j}^{\text{col}} \propto \exp(W_2^{\text{col}} \tanh(W_1^{\text{col}} [r_{i,j}^{\text{gen}}, r_{i,j}^{\text{col}}]))
\]

\[
s_{i,j}^{\text{row}} \propto \exp(W_2^{\text{row}} \tanh(W_1^{\text{row}} [r_{i,j}^{\text{gen}}, r_{i,j}^{\text{row}}]))
\]

\[
r_{i,j}^{f} = s_{i,j}^{\text{col}} r_{i,j}^{\text{col}} + s_{i,j}^{\text{row}} r_{i,j}^{\text{row}} + r_{i,j}^{\text{emb}}
\]
where $W_f$, $W_f^j$ and $W_f^j$ are trainable parameters. The residual network is used to retain information about the value of the record itself. The final record representations $\{r_i^{f,j}\}_{i=1,j=1}^{R,C}$ will be used as the input of text decoder.

**Row-level Encoder** Considering that different records in the same row may not contribute the same, therefore, we employ an attention-based gate to combine its records dynamically. We first compute a general representation vector $\text{row}_i^{gen}$ for $i$-th row, which is given by mean-pooling over the sequence of the row. Then we compare each record in one row with its general representation and obtain its weight in the final row representation. In the end, we obtain the row-level representation $\text{row}_i$:

$$\text{row}_i^{gen} = \text{MeanPooling}(r_{i,1}^f, r_{i,2}^f, ..., r_{i,C}^f)$$  \hspace{1cm} (9)

$$\alpha_{i,j}^r \propto \exp(W_2^f \tanh(W_1^f \text{row}_i^{gen}; r_{i,j}^f))$$  \hspace{1cm} (10)

$$\text{row}_i = \sum_{j=1}^{C} \alpha_{i,j}^r r_{i,j}^f$$  \hspace{1cm} (11)

**Decoder with Dual Attention** To make fair comparison with previous, we chose a recurrent neural network with LSTM units as text decoder. The decoder is initialized with the average of row-level representations $\text{row}_i^{avg} = \sum_{i=1}^{R} \text{row}_i$. In order to make use of record-level and row-level semantics information, we use a dual attention. Specifically, at decoding step $t$, the input of the LSTM unit is the embedding of the previously predicted word $y_{t-1}$. And given the decoder state $d_t$, we first calculate the row-level attention $\beta_{t,i}$, which is based on similarity between decoder state $d_t$ and row representations of table $\{\text{row}_i\}_{i=1}^R$. Then we compute the record-level attention $\alpha_{t,i}$ over all the record representations $\{r_{i,j}^f\}_{i,j=1}^{R,C}$ which are normalized among records in same row. Finally, we fuse these two level attention and obtain the context representation as:

$$\alpha_{t,i,j}^r \propto \alpha_{t,i}^d \beta_{t,i}^s$$  \hspace{1cm} (12)

$$c_t^d = \sum_{i=1}^{R} \sum_{j=1}^{C} \alpha_{t,i,j}^r r_{i,j}^f$$  \hspace{1cm} (13)

Given a reference output $\{y_t\}_{t=1}^T$, we use cross-entropy loss as the objective function of table-to-text generation:

$$L_{lm} = - \sum_{i=1}^{T} p(y_i | y_{1:t-1}; c_t^d)$$  \hspace{1cm} (14)

### 3.3 Self-Supervised Record Ordering

To avoid the errors caused by the noises in the target texts in the training set and learn better table representation, we proposed two self-supervised tasks, Number Ordering (NO) and Significance Ordering (SO), which are trained together with table-to-text model.

**Number Ordering** In practice, many tables are mainly composed of number records. For example, almost 86.82% records of ROTOWIRE dataset [Wiseman, Shieber, and Rush 2017] are numerical contents. Different from text-type content, the numerical content contains less semantic information but size attribute. The size attribute means the value of a record is larger or smaller than others and it plays an important role in records selection. For example, human always tend to describe the highest scores in a game. Therefore, it is necessary to endow the model the number-aware ability. To make the column dimension representation of a record contains the size information, we propose a self-supervised Number Ordering (NO) task. Next, we take a list of records in column PTS (Figure 2 left) as an example to illustrate how number ordering works. Specifically, we regard the PTS column of the table as an out-of-order set of $C$ records $r_1, r_2, ..., r_C$, the goal is to generate a sequence of record pointers in descending order according to their content’s size. We utilize the Pointer Networks [Vinyals, Fortunato, and Jaitly 2015] to solve this problem and the output of column dimension encoder $r_{i,t}$ (we omitted the indices on the column dimension) as its input. Let $z = z_1, ..., z_R$ denote the sequence of indices of ordered records. Each $z_k$ points to an input record and is between 1 and $R$. As shown in Figure 2, we use an LSTM as the decoder. The MeanPooling$(r_{i,t})_R$ is used as the initialization of the first hidden state of the decoder. At each decoding step $t$, we calculate a distribute over the input records:

$$h_t = \text{LSTM}(h_{t-1}; r_{z_{i,t-1}})$$  \hspace{1cm} (15)

$$p_{t,i}^n \propto \exp(W[h_t; r_{i}^{col}])$$  \hspace{1cm} (16)

where $W$ is a trainable parameter, and $p_{t,i}^n$ denotes the probability that the output points to the record $r_{i}$ at step $t$.

The column dimension record ordering task is trained jointly with the table-to-text learning. We use cross entropy loss for this task:

$$L_{no} = - \sum_{j=1}^{R} \log p_{t,i}^n$$  \hspace{1cm} (17)

Please note that for column whose value type is not numeric (e.g., Name), the model outputs in the order of input.

**Significance Ordering** When humans describe a player’s performance in a game, they are likely to focus on his or her records that stand out, such as high scores, high assists, etc. Inspired by this, we propose to utilize significance to model this relative relationship between records in same row. However, the content of the record itself can not be used directly to measure its significance. To solve this, we use the position index of a record obtained by Number Ordering to measure its significance. For example, in Figure 2 for player K. Thompson, the significance score of his scores is 1, because that rank first in the PTS column. In a similar way, the significance score of his rebounds (REB) is 4. Therefore, his scoring record is more prominent than his rebounding record. To learn a significance-aware representation for record, we propose the Significance Ordering task (SO) which works on each row. Obviously, this task is also self-supervised because its training labels can be easily obtained from the input tables. The input of this task is a sequence records in same row, and the output is a sequence of records in descending
order of significance scores. Please note that the lower significance score means the record is more significant. We employ a pointer network similar to the one used in Number Ordering task to model this task. Take the fourth row of table in Figure 2 as an example, the input of the decoder is the output of row dimension encoder \((r_{row}^j)_{j=1}^{C}\). Similarly, we employ the MeanPooling \((\text{MeanPooling}((r_{row}^j)_{j=1}^{C}))\) to initial the first hidden state of decoder. Let \(p_{t,j}^s\) denotes the probability of pointing to record \(r_j\) at decoding step \(t\), then the negative log-likelihood as the loss function for this task:

\[
L_{so} = - \sum_{t=1}^{R} \sum_{j=1}^{C} \log p_{t,j}^s \quad (18)
\]

**Loss Function and Training** These two tasks are trained together with the table-to-text task, and the overall objective function consists of three parts:

\[
L = L_{lm} + \lambda_1 L_{so} + \lambda_2 L_{no} \quad (19)
\]

where \(\lambda_1\) and \(\lambda_2\) are hyper parameters. Please note that when we train model with Significance Ordering task, Number Ordering is also executed by default. In other words, when \(\lambda_2 > 0\), there must be \(\lambda_1 > 0\).

4 Experiment

4.1 Dataset and Evaluation Metrics

We conducted experiments on the ROTOWIRE dataset (Wiseman, Shieber, and Rush 2017), a dataset contains NBA basketball game summaries paired with corresponding box-and line-score tables. We used the official training, development, and test splits of 3,398/727/728 instances.

Following previous works, we used BLEU and three extractive evaluation metrics Relation Generation (RG), Content Selection (CS) and Content Ordering (CO) (Wiseman, Shieber, and Rush 2017) to evaluate the table-to-text results. The extractive metrics use an Information Extraction (IE) model to extract records mentioned in the generated texts. And then compare them with tables or records extracted from reference to evaluate the model. Specifically, RG measures the content fidelity of generated text, CS measures how well the generated text matches the reference in terms of selecting which records to generate, and CO measures the ability on context planning. We refer the readers to Wiseman, Shieber, and Rush’s paper for more detailed information on these extractive metrics.

We used Accuracy (Acc) and normalized Damerau-Levenshtein Distance (DLD%) to evaluate the self-supervised tasks. Accuracy measures the percentage of sentences for which their absolute position was correctly predicted (Logeswaran, Lee, and Radev 2016).

4.2 Implementation Details

To make a fair comparison, we followed configurations in Puduppully, Dong, and Lapata 2019a (Gong et al. 2019). For basic table-to-text model, we set word embedding and LSTM decoder hidden size as 600. We employed two-layer LSTMs decoder with Input feeding during text generation. We applied dropout at a rate 0.3. For text decoding, we used BPTT and set the truncate size to 100. We set the beam size to 5 during inference. For two self-supervised tasks, we employed two one-layer LSTM as decoder and set the LSTM decoder hidden size as 600, respectively. We did not adjust \(\lambda_1\), just set it to 1.0, and turned \(\lambda_2\) between 0.2-1.0 and finally set it to 0.35. For inferring, we used greedy search. All experiments were conducted on a single Tesla P100. We will open source code of our methods.

4.3 Baselines

We compared our methods with several strong baselines, including:

- TEMP (Wiseman, Shieber, and Rush 2017) is a template based method. We refer the readers to this paper for more detailed information on templates.
- CC (Wiseman, Shieber, and Rush 2017) is a standard encoder-decoder system with conditional copy mechanism.
- NCP+CC (Puduppully, Dong, and Lapata 2019a) is a Conditional Copy model with explicit content planning.
- ENT (Puduppully, Dong, and Lapata 2019b) is a method which creates entity-specific representations and generates text using hierarchical attention over the input table and entity memory.
- 3-Dims (Gong et al. 2019) is a method modeling table from three different dimensions (Row, Column and Time).

4.4 Main Results

**Automatic Evaluation** Our results on the development set are summarized in Table 1. As can be seen, compared with basic model, the two tasks obtain a great improvement on Relation Generation Precision, all Content Selection metrics, Content Ordering and BLEU. It demonstrates that it is necessary to establish special representations for the numeric contents in the tables, rather than just treat them as words in natural language text. And the significance information also is helpful for the record representations. Compared with previous, our method achieves the state-of-the-art.

| Model      | RG # | RG P% | CS P% | CS R% | CS F1% | CO DLD% | BLEU |
|------------|------|-------|-------|-------|--------|---------|------|
| Gold       | 23.34| 94.79 | 100   | 100   | 100    | 14.42   | 100  |
| TEMP       | 54.29| 99.92 | 26.61 | 59.16 | 36.69  | 8.51    | 100  |
| CC         | 23.95| 75.10 | 28.11 | 35.86 | 31.52  | 15.33   | 14.57|
| NCP+CC     | 33.88| 87.51 | 33.52 | 51.21 | 40.52  | 18.57   | 16.19|
| ENT        | 30.39| 91.98 | 36.62 | 48.18 | 41.62  | 19.66   | 15.97|
| 3-Dims     | 32.11| 91.84 | 35.39 | 48.98 | 41.09  | 20.70   | 16.24|
| Ours       | 30.21| 91.31 | 40.10 | 50.97 | 44.88  | 23.53   | 18.05|
| -w/o SO    | 30.19| 90.01 | 37.10 | 49.30 | 42.34  | 22.69   | 17.28|
| -w/o NO    | 32.02| 90.50 | 34.41 | 48.75 | 40.34  | 20.00   | 16.55|

Table 1: Automatic evaluation on RotoWire development set using relation generation (RG) count (#) and precision (P%), content selection (CS) precision (P%) and recall (R%), content ordering (CO) in normalized Damerau-Levenshtein distance (DLD%), and BLEU.
on Content Selection (precision and F-1), Content Ordering and BLEU. It is a remarkable fact that even without explicitly modeling content selection, our method still obtains the best results on Content Ordering metric.

The test set results in Table 2 follow a pattern similar to the development set. The self-supervised tasks improve the model on metrics including relation generation (RG), content selection (CS), content ordering, and BLEU. These results give credence to our hypothesis that the better table representation can help to generate summaries that contain more salient and well-organized facts, even without explicitly modeling content selection and planning.

Table 3 shows the performance of two self-supervised tasks on development set. As can be seen, even without using beam search at testing, the proposed two self-supervised tasks achieve good results on dev set and test set. These results show that our proposed methods can work on the two development sets. NO_Ptr and SO_Ptr denote the pointer networks for Number Ordering task and Significance Ordering task, respectively.

Impact of Self-Supervised Tasks Figure 3 is the BLEU results curve of our basic model and two self-supervised tasks on dev set. It shows that these two self-supervised tasks achieve substantially improvement on text generation. In Tables 1 and Table 2, it is noticed that the self-supervised tasks help to improve the results on content selection, ordering and BLEU, but obtains a lower score on relation generation. We believe this is because the two tasks make the model pay more attention on the salient information in the table, when generating summaries. Because the Gold also has lower CS count(#).

We also explored the impact of different settings of number ordering and significance ordering on the results. As shown in Table 3 we find that setting the same sorting directions for the two tasks seems to be a better choice. Further, compared with the basic model, almost all the settings have been improved to a certain extent on RR, Content Selection (CS), Content Ordering (CO) and BLEU. And the reduced repetition rate shows that they also help to reduce excessive attention to some records. In general, the Number Ordering and Significance ordering tasks are beneficial to table-to-text generation.
Gold The Spurs saw a solid set of stat lines en route to a win over the Clippers on Friday. Star forward Kawhi Leonard led the team with 21 points on 7-of-16 shooting. Veteran Pau Gasol returned from injury with a double-double off the bench, netting 17 points and 11 rebounds. Point guard Tony Parker also had 17 points. The Spurs shot under 43 percent, but held a 11-30 advantage in the rebounding column. San Antonio hit nine three-pointers. All-Star forward Blake Griffin led the team with 29 points on 9-of-17 shooting. He also had nine rebounds and five assists. Bench point guard Austin Rivers had a solid 23 points. Star point guard Chris Paul returned from injury and posted a line of 17 points, six rebounds, and five assists. The Clippers only shot 44 percent and had just seven three-pointers.

Basic The San Antonio Spurs defeated the Los Angeles Clippers, 105-97, at Staples Center on Monday. Kawhi Leonard led the way with 21 points, six assists, three rebounds and one steal, in 31 minutes, while Austin Rivers followed up with 23 points on 8-of-14 shooting, including 2-of-6 from long range, to go along with three assists and three steals, in 27 minutes. LaMarcus Aldridge followed up with 15 points, 11 rebounds, in 34 minutes, while Patty Mills chipped in 14 points on 5-of-10 shooting, in 21 minutes off the bench, while Patty Mills chipped in 14 points on 5-of-10 shooting, in 21 minutes off the bench. The Spurs shot 43 percent from the field and 35 percent from long range, while holding the Clippers to 24 percent from the field and 30 percent from long range. Blake Griffin led the way for the Spurs, with 29 points, to go along with nine rebounds, five assists and one steal, in 38 minutes. LaMarcus Aldridge followed up with 15 points and 11 rebounds, in 34 minutes.

+NO The San Antonio Spurs defeated the Los Angeles Clippers, 105-97, at Staples Center on Wednesday evening. Kawhi Leonard led the way for San Antonio with 21 points, six assists, three rebounds and one steal... LaMarcus Aldridge followed up with 15 points, 11 rebounds, an assist, a steal and a block. Tony Parker contributed 17 points, three assists, two rebounds and two steals. Patty Mills paced the bench with 14 points, one rebound and one assist. Pau Gasol led the way for Los Angeles with 17 points, six rebounds, five assists and two steals. Chris Paul turned in a 17-point, six-rebound, five-assist effort that also included two steals and two blocks. Blake Griffin led the second unit with 29 points, nine rebounds, five assists and one steal. Austin Rivers was right behind him with 23 points, three assists and three rebounds. DeAndre Jordan posted a 14-point, eight-rebound that also included two steals and two blocks. Patty Mills paced the second unit with 14 points, a rebound and an assist.

+SO The San Antonio Spurs defeated the host Los Angeles Clippers, 105-97, at Staples Center on Saturday. The assist-to-turnover ratio was the decisive statistic, with San Antonio recording 23 assists to 13 turnovers, while Los Angeles Clippers committed 12 turnovers to just 18 assists. Kawhi Leonard led San Antonio in scoring, as he tallied 21 points, three rebounds and six assists on 7-of-16 shooting. LaMarcus Aldridge finished second on the team, totaling 15 points and 11 rebounds. Pau Gasol was the only other Spur in double figures, as he totalled 17 points and 12 rebounds off the bench... The Clippers (35-23)... Blake Griffin did all he could for Los Angeles, as he led the team with 29 points, nine rebounds and five assists. Austin Rivers was second on the team, as he provided 23 points and three assists off the bench. Chris Paul finished with 17 points, six rebounds and five assists. DeAndre Jordan totalled 14 points and eight rebounds.

Figure 4: Examples of model output from Gold and our methods. The salient entity names and records that exist in Gold output are highlighted in red and those that do not appear in are in orange. And the repetitive or erroneous descriptions are in blue.

Human Evaluation To examine whether improvements in automatic evaluation metrics are indeed corroborated by human judgments, we conducted human evaluation. Three graduate students with basketball background knowledge and good English reading ability were invited to conduct evaluation. We compared our best performing model (NO+SO) against Gold, NCP+CC, ENT, and 3-Dims. Specifically, we randomly selected 30 games from the test set and each game is rated by three workers. For each game, we arranged every 5-tuple of summaries into 10 pairs. Given each pair, the participants were asked to choose which one is better according to five criteria: Supporting (does the summary contain more supported facts?), Contradicting (does the summary contain more contradicting facts?), Grammaticality (is the summary fluent and grammatical?), Coherence (do the sentences in summary follow a coherent discourse?) and Conciseness (does the summary contain less redundant information and repetitions?). Following previous work [Puduppully, Dong, and Lapata 2019a], we calculated the score of a model for each criterion as the difference between percentage of times when the model is chosen as the best and percentage of times when the model is chosen as the worst. The results are summarized in Table 5. As can be seen, the gold texts have great advantages in terms of grammaticality, coherence and conciseness. Compared with other methods, our method receives the highest scores in terms of Coherence and it obtains competitive results in terms of Contradicting, Grammaticality and Coherence. These show that our proposed two self-supervised tasks can help the model generate texts that contain more salient and well-organized facts. More importantly, our methods do not conflict with other methods and can be easily introduced into other methods. We leave this for future work.

Case Study As shown in Figure 2, we provide an example to illustrate the improvement of our model more intuitively. As can be seen, when Number Ordering (NO) task is introduced, the basic model can better capture the salient information (e.g., Pau Gasol, Tony Parker, Chris Paul and DeAndre Jordan). When the basic model is further trained together with Significance Ordering (SO), we find the model not only captures salient records, but also significantly reduces the focus on less important contents (e.g., descriptions about Patty Mills). More importantly, the description order of the records is well organized. Also, we notice that some problems that not only exist in our methods, but also in others. First, most methods generate error game time. We think this is because most methods removed the game time information when preprocess the data. And then, we find players and teams are sometimes incorrectly linked in some outputs, which may be caused by the lack of exchange of information between the player tables and team table. We will attempt to solve these problems in the future.

5 Conclusion

In the existing table-to-text datasets, there are noises in the target texts which may cause incorrect alignments between table and related text or wrong supervision signals. These errors may influence the performance of methods based on content selection and auxiliary supervision. Also, the representation of numbers in table are also overlooked. To solve these issues, we propose two self-supervised tasks: Number Ordering and Significance Ordering. Because the training labels of these two tasks are obtained from the inputs tables, the errors caused by noises in training dataset are avoided. And, they also help to learn number-aware and significance-aware representation for tables. Experimental results conducted on ROTOWIRE dataset demonstrate that these two self-supervised tasks can help encoder to learn better representation for tables. And the better table representation can help the model to capture and organize the salient facts in table even without explicitly modeling content selection.
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