Diversity Enhanced Table-to-Text Generation via Type Control

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Abstract
Generating natural language statements to convey information from tabular data (i.e., Table-to-text) is a process with one input and a variety of valid outputs. This characteristic underscores the abilities to control the generation and produce a diverse set of outputs as two key assets. Thus, we propose a diversity enhancing scheme that builds upon an inherent property of the statements, namely, their logictypes, by using a type-controlled Table-to-text generation model. Employing automatic and manual tests, we prove its twofold advantage: users can effectively tune the generated statement type, and, by sampling different types, can obtain a diverse set of statements for a given table.

1 Introduction
Table-to-text (T2T) generation is the task of generating natural language statements to convey information appearing in tabular data. This task is relevant in real-world scenarios including generation of weather forecasts (Goldberg et al., 1994), sport results (Wiseman et al., 2017), and more.

A statement generated from tabular data can be inferred based on different levels of information. These range from a value of a specific cell to the result of logical or numerical operations across multiple cells, such as the average value of a column, or a comparison between rows. The task of statement generation that captures complex logical and numerical operations from tables, Logical NLG, was introduced by Chen et al. (2020a). It was accompanied by a dataset, LOGICNLG, that contains a set of (table, statement) pairs, and several baselines for statement generation.

Generally in NLG, generating a diverse set of hypotheses given a single input is favorable as it offers different perspectives on the data, provides the user with multiple options to choose from, and facilitates further improvement of output quality via all sorts of post-generation re-ranking algorithms (Gimpel et al., 2013). Controllability is often another key feature in T2T generation, since the plethora of different valid statements, that could vary greatly, may prompt the user to require a subset or a specific distribution of statement types. Nevertheless, current T2T methods have typically overlooked the importance of these key features.

In T2T generation and specifically in Logical NLG, diversity naturally emerges from the different logical inferences of the statements extracted from the table. Chen et al. (2020b) proposes 7 logictypes in this context, $c = \{\text{count, comparative, superlative, unique, ordinal, aggregation, majority}\}$, some of which are exemplified in Figure 1(a).

Logic-types were used by Liu et al. (2021) as input to a generation module in a data augmentation framework. Here, we propose to realize a generation model controlled by logic-type, to support better diversification and controllability in T2T generation. By producing a diverse set of statements, each generated controlled by a different logic-type, our model enables Diversity enhancement via Type Control, hence named DEVTC. Controllability is plainly facilitated by DEVTC as it enables users to guide the model to generate statements of specific type(s), out of the many different valid statements that may correspond to the input table.
Diversification obtained by employing common decoding techniques have been shown to suffer from a trade-off between diversity and quality measures such as fluency and adequacy (Ippolito et al., 2019). By this trade-off, high quality hinders diversity, as exemplified in Figure 1(b). In contrast, DEVTC readily generates a diverse set of high quality statements, tuned each by a different logic-type, without suffering any degradation in quality. Through extensive experimentation, we show that DEVTC surpasses SOTA methods on the trade-off between diversity and quality, measured here in factuality which is a paramount quantity in T2T. We also show that DEVTC generates statements according to a user required logic-type, and performs on par with current SOTA on measured quality metrics even in the absence of input logic-type.

2 Related Work

Along with the LOGICNLG dataset, Chen et al. (2020a) presented two methods based on GPT2 (Radford et al., 2019). Both models receive the same input: a table in conjunction with a title, denoted as a natural language sequence, T, but differ in their generation scheme. GPT-TABGEN learns to generate a statement Y directly: \( p_θ(Y|T) \); whereas GPT-C2F generates a statement-template, \( \tilde{Y} \), and conditions on it to create the final statement, effectively learning \( p_θ([\tilde{Y}; \{SEP\}; Y]|T) \).

In a subsequent work, Chen et al. (2021) proposed DCVED, a scheme based on a conditional variational auto-encoder architecture. Their scheme can generate multiple statements for a single input, but these only undergo a re-ranking, and their diversity or quality aspects are not discussed. LOGIC2TEXT (Chen et al., 2020b) is a small dataset similar to LogicNLG. In its accompanying task, a model receives an additional logical-form input, specifying its full logical description. Liu et al. (2021) aims to circumvent the problem of data scarcity of LOGIC2TEXT with an approach combining data-augmentation, data-weighting and semi-supervised learning using type-controlled generation module. In contrast to their work, we pair the type-controlled model with a diversity enhancing scheme and investigate its generation diversity and factuality. Additionally, our novel training scheme also allows our type-controlled generation to perform well in scenarios where type is unavailable such as the case for Logical NLG.

3 Method

3.1 Type controlled T2T Generation Model

We propose to re-purpose GPT-TABGEN as a type controlled generation model, learning \( p_θ(Y|T, c) \). At training, we predict the logic-type from the gold statement using a dedicated classifier and concatenate it to the table and title (see Fig 2(a)). The model is then trained to minimize the autoregressive cross entropy loss between the generated and reference tokens. To add robustness for scenarios where logic-type is unavailable, we mask the logic-type with probability \( p_{mask} \) during training.

3.2 Statement Logic-Type Classifier

To enable – weakly – supervised learning for our model with LOGICNLG, we had to augment the dataset with type information. Thus, we automatically annotated LOGICNLG with statement logictypes \( c = \{ \text{count, comparative, . . .} \} \), by employing a BERT (Devlin et al., 2018) based classifier \( p_φ(c|Y) \) that was fine-tuned on 8.5K (statement, logic-type) pairs from the LOGIC2TEXT train set. This classifier achieved 97% macro F1 on the corresponding test set. The classifier further achieved 90% macro F1 on 200 randomly sampled statements from LOGICNLG annotated by the authors.

3.3 Diversity Enhancement via Type Control

The above \( p_θ(Y|T, c) \) model enables our Diversity Enhancement via Type Control (DEVTC) scheme. Specifically, given a table, we generate multiple statements, each conditioned on a different logic-type, ending up with a diverse output (see Fig 2(b)).

4 Experiments

4.1 Datasets

Datasets used in our experiments are LOGICNLG (Chen et al., 2020a) and LOGIC2TEXT (Chen et al., 2020b) (Table 1). Each data-point in LOGICNLG consists of a parent-table crawled from Wikipedia from which 5 tables are derived, each containing a subset of the parent-table columns and an associated statement generated by crowd-workers. LOGIC2TEXT is similar but further provides statement logical-form (its full logical description).

| Dataset      | Parent tables | Statements | Train / Dev / Test |
|--------------|---------------|------------|--------------------|
| LOGICNLG     | 7,392         | 37,015     | 28,450 / 4,260 / 4,305 |
| LOGIC2TEXT   | 5,554         | 10,753     | 8,566 / 1,095 / 1,092  |

Table 1: Datasets statistics.

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1 Models and code will be made public upon acceptance.
Figure 2: DevTC architecture; (a) DevTC is trained to generate a reference statement given the statement logictype as it is predicted by our type classifier; (b) at inference time, DevTC can receive a table and multiple logictypes, enabling the generation of a diverse set of statements for a single table.

| Agg. | Comp. | Count | Maj. | Ord. | Super. | Unique |
|------|-------|-------|------|------|--------|--------|
| 0.77 | 0.91  | 0.87  | 0.78 | 0.26 | 0.91   | 0.88   |

Table 2: Control-generation type consistency.

4.2 Hyper-parameters & Compared Models

We use the same configurations and settings as in Chen et al. (2020a), apart from the learning rate (LR) for which we tried 6 values between $1e^{-6}$ to $5e^{-5}$ and chose the best LR per method according to our model selection scheme, that uses the dev. set BLEU3 score. Of the baselines, only GPT-TABGEN benefited from the sweep, and we marked the improved version as GPT-TABGEN*. Further details can be found in Appendix A.1.

As for models, we compare DevTC with the GPT-C2F and GPT-TABGEN* across both small / medium GPT2 model versions. DCVED is considered medium since it uses two GPT2-small and two Fully-connected networks, adding up to a larger parameter count than GPT2-medium.

4.3 Metrics

To evaluate the quality of a generated text, we use BLEU to measure consistency with the reference text as (Chen et al., 2020a); and the SP-Acc and NLI-Acc metrics to estimate its factuality, using semantic parsing and a pretrained NLI model, respectively. Specifically, we focus on NLI-Acc that was found to better agree with human preference for factuality evaluation (Honovich et al., 2022). For measuring the diversity of the generated statements we use (1) Ent-\(n\) (Zhang et al., 2018), the average entropy for each \(n\)-gram relative to the other generated statements; (2) Dist-\(n\) (Li et al., 2016), the total number of distinct \(n\)-grams divided by the total number of produced tokens; and (3) Self-BLEU\(n\) (Zhu et al., 2018): average \(n\)-gram BLEU score between the statements in the generated set.

5 Results

5.1 Type Consistency - Controlled generation

To measure the effectiveness of type-control in directing the generated statement type, we paired a set of 5 control types with each table in the LOGIC-NLG test-set, selecting each at uniform probability from the possible 7 types. Using our most consistent type-controlled model (\(p_{mask}=0\)), we generated a statement for every (table, control type) pair, then predicted its type using our statement type classifier (see Section 3.2), and matched the prediction with the control. Table 2 shows high type-consistency for all types but ordinal, which is characterized with relatively high lexical variance, and for which we had relatively scarce training data (see Appendix A.2).

5.2 Robustness for Missing Logic-Types

To demonstrate DevTC performance in a conventional setup when type is unavailable as input at test time, we compared our type-controlled model using a masked token as control, with SOTA methods, on the LOGIC-NLG and LOGIC2TEXT test-sets, using the standard evaluation protocol. For both datasets, across all metrics and model sizes, our model with trained \(p_{mask}=0.5\) is leading the benchmark along with GPT-TABGEN*. For detailed results, see Table 3 in Appendix A.3.

5.3 Factuality-Diversity Trade-off

While DevTC uses type-control to generate a diverse set of statements, baseline methods rely on stochastic decoding. As an exemplar decoding strategy, we use the nucleus sampling (Holtzman et al., 2019) technique due to its effectiveness, wide acceptability and reported advantages (Zhang et al., 2020). To compare the small versions of DevTC trained with \(p_{mask}=0.5\) versus the strongest baseline, GPT-TABGEN*, on the factuality-diversity
plane, for each method we generated a set of 5 statements per table in the LogicNLG test-set. To evaluate, we measured the diversity within each set, along with the average NLI-Acc. For DevTC we used greedy decoding and generated the set by conditioning on 5 types sampled uniformly from the 7 types. For the baseline, 5 statements were generated using nucleus sampling; following Ippolito et al. (2019) we varied the top \( p \) decoding parameter to explore the factuality-diversity trade-off. Figure 3 shows that DevTC is better positioned on the factuality-diversity plane, surpassing GPT-TabGen*. Similar results with the other diversity measures can be found in Appendix A.4.

Since testing with different choices of type distributions for DevTC sampling result in different accuracy and diversity, we further evaluate DevTC when types are sampled from the baseline’s output type distribution (see Appendix A.2). In this scenario, DevTC achieves 75.6 and 4.6 for NLI-Acc and Ent4, respectively. The diversity drop in this scenario is due to the type distribution that makes repeated types more probable. For factuality, we attribute our remaining advantage to the controlled generation training scheme, where data selection (choosing a logic) is delegated to a different module, allowing for further generation specialisations.

5.4 Masking Ratio Effect

To analyze how the different type masking ratios used in training fare in test time, we trained 11 type-controlled models with \( p_{\text{mask}} \) varying from 0.0 (no masking) to 1.0 (always masked) with a 0.1 interval. In Figure 4 we compare these models using the same evaluation protocol as in Section 5.3. As expected, both factuality and diversity obtained by DevTC gain significantly from strengthening the control. That is, a lower masking ratio means a more stable training process with better type correspondence, which in turn results with higher diversity and better factuality on the test set.

5.5 Human Evaluation

We complement the automatic evaluation results with human evaluation. We sampled 100 tables from the set used in Section 5.3 and distribute them independently to human experts. Each table was presented along with two 5-statement sets – one generated by DevTC, and the other by GPT-TabGen* with the \( p_{\text{top}} = 0.5 \). The experts were asked which of the two sets is more factual, i.e., properly describes the data in the table (ties are also allowed), and which is more diverse – on Likert scale, from \(-2 \) (set-1 is much better) to \(+2 \) (set-2 is much better). In 50\% of the samples, DevTC reported to be more factual vs. 31\% for GPT-TabGen*. 19\% of the samples were reported as a tie. DevTC advantage is statistically significant \((P_{\text{value}} < 0.05)\) using two-sided t-test. For diversity, the average score was 0.14, implying no significant difference, in line with Figure 3.

6 Conclusions and Future Work

Our DevTC facilitates the generation of a statement of a desired type, and the option to generate a diverse set of high quality statements. Both features are unlocked by adding a control of the statement type to the input. Results show the merit of our approach compared to existing baselines. In future work we plan to study how to further improve factuality, i.e., the faithfulness, of the statements generated by our approach, to bring it to practical use.
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A Appendix

A.1 Implementation Details

All models are trained with batch size of 32 on 1 NVIDIA A100 GPUs for 12 epochs. We use Adam optimizer (Kingma and Ba, 2014) and an autoregressive cross entropy loss to optimize the models. During test time, we use a greedy search to generate text and calculate the BLEU-1,2,3 scores with the 5 references from all 5 sub-tables as suggested by (Chen et al., 2020a). We base our implementation on Huggingface’s Transformers (Wolf et al., 2019) version 4.16.2 in the (Paszke et al., 2019) flavour and use the pre-trained version of GPT-2 (Radford et al., 2019) small/medium with subword unit vocabulary of 30K. All Model selection is based on the bleu-3 score on dev set. All our models and models marked with a * were found to have the best performance with learning rate set to 1e-5.

A.2 Logic-type Distributions

Figure 5 shows two different types distributions: (left) the LOGICNLG training set and (right) GPT-TABGEN* generation over the LogicNLG test-set.

A.3 Automatic Evaluations

Table 3 demonstrates DeVTCs performance in the conventional setup. In the table, our type-controlled models (marked as DeVTC) are using a mask token as control, the oracle version (marked as DeVTC (oracle)) are receiving the type as classified by the logic-type generator while the baselines are not receiving types. Evaluation was done on the LOGICNLG and LOGIC2TEXT test-sets. As in (Chen et al., 2021), when evaluating on LOGIC2TEXT we follow the Logical NLG task formulation and do not use the logical-form annotations. We further note that, we report the original variant of DCVED without an additional generate-and-select scheme also reported by them, since multiple generation and re-ranking is complementary and could potentially be applied to all compared methods.

We see that for both datasets, across all metrics and model sizes, our model with $p_{mask}=0.5$ is leading the benchmark along with GPT-TABGEN*. Also, we note that the oracle methods enjoys the types perform the best by a great margin in four of the five metrics. We attribute the decline in SP-ACC to the different type distribution the model generates when in oracle mode that impacts the SP-ACC since different types are more likely to be labeled as accurate by SP-ACC.

Table 3: Quality results on the test split of LOGICNLG and Logic2Text. Baseline models trained with our learning rate are marked with a *, all DeVTC and starred results are the average over 5 different seeds, SEMs of our models are in Table 4.

Table 4 is complementary to the automatic evaluation and includes the standard error of the mean for our models.

### A.4 Factuality-Diversity Trade-off: Other diversity measures

Figure 7 displays the factuality-diversity trade-off discussed in Section 5.3 for the other two diversity metrics, SelfBLEU4 and Dist2.

### A.5 Examples of generated statements and their types

Table 5 shows some examples of statements generated with our $p_{mask}=0.5$ model.
Figure 5: Type distribution as classified by the type classifier of: (left) the LOGICNLG training set and (right) GPT-TABGEN* generation over the LogicNLG test-set.

Figure 6: An illustration of the quality-diversity trade-off evaluation. NLI-Acc is a fact checking model proposed by Chen et al. (2020a) that labels the statement as true or false given the table.

Figure 7: Factuality-Diversity trade-off for Dist-2 and Self-BLEU4: each dot in the orange line represents an average over 5 seeds (error bars are SEMs) of the baseline model (GPT-TABGEN*) with a different nucleus sampling decoding parameters (shown in the figure). The blue star is our method that surpasses the trade-off line created by the baseline and the decoding strategy.

Utilizing the same setting, Figure 8 shows an example of DEVTC generated statements (and their logic-types) along with the input table.
Table 5: Examples of DEVTC generated statements and their types.

| Table id        | Type        | Statement                                                                 |
|-----------------|-------------|---------------------------------------------------------------------------|
| 2-11630008-8    | comparative | Kim Field Directed more Episode than Chip                                   |
| 1-26250145-1    | superlative | Didi benami’s highest Song Choice was played by Angel                       |
| 2-171666-1      | aggregation | the average National Share (%) of all Administrative Division in the country is 2.13 |
| 2-15220147-3    | count       | Germany won 4 medal in the 1995 European Judo Championship                  |
| 2-11965402-8    | ordinal     | the second lowest Attendance figure for a game was 17388                   |
| 2-15250161-2    | majority    | the majority of the racer in the top 10 have a Class of 50cc                |
| 2-15100419-13   | comparative | Justin Durant was picked before Uche Nwaneri                                 |
| 2-12406580-1    | superlative | Vladimir Uhlírová’s highest number of Grand Slam Tournament was in 2006    |
| 2-12261872-2    | superlative | Tony Rominger won the most Point Classification of any Stage                |
| 2-11036258-13   | superlative | the most Silver medal were won by the same Nation                           |
| 1-28051859-3    | aggregation | the average number of game played by the team in Summit County is 3.5      |
| 2-11772462-4    | aggregation | Washington scored a total of 7 point in their win against Atlanta           |
| 1-2602958-4     | count       | there were 2 Director who wrote more than 5 Episode                         |
| 1-29920800-1    | count       | there were 2 episode that had more than 2 million Viewer                    |
| 2-17503198-4    | majority    | the most game were won by team with a score of 0                            |
| 2-13286158-7    | aggregation | the Blazer scored a total of 7 point in game 35 and 36                     |
| 2-11218948-6    | count       | there are 3 Municipality In Quebec that have a Type V1                     |
| 2-10746808-4    | superlative | the game with the highest Crowd was on 22 May 1926                         |
| 2-13312898-52   | superlative | the Colt had the most Pick in the first 3 Round                            |
| 2-12423174-1    | majority    | all of the team listed are from the same country                            |
| 2-1064216-1     | unique      | only 1 of the university has a Total of more than 100                      |
| 2-15100419-13   | unique      | Justin Durant was the only player drafted by the Jacksonville Jaguar in the first round |
| 2-13312898-52   | comparative | the Colt had 2 more Pick in the first Round than they did in the second Round |
| 2-11960196-3    | unique      | Dalembert had the High Point in only 1 game                                |
| 2-15387537-1    | count       | 2 team Played 17 game                                                       |
| 1-28132970-5    | majority    | all of the Vessel were Built in 2010                                       |
| 2-14655820-2    | superlative | the most point scored by the Packer in a game was 38                       |
| 2-17744976-11   | majority    | Kevin Martin scored the most Point in every game                           |
| 2-14195712-1    | comparative | the Soviet Union had 7 more game than the Czechoslovakia team               |
| 2-13219504-10   | count       | there were 3 match held in Johannesburg                                     |
| 2-15250161-2    | ordinal     | the first and last place finisher of the race were both in the 125cc Class |

Figure 8: 5 statements generated using DEVTC along with the table that was used for their generation, sentences marked in red display false type correspondence.