

Appendix for Enhancing Content Selection and Planning for Table-to-Text Generation with Data Understanding and Verification

A Implementation Details

A.1 Data Statistics

We conduct experiments on ROTOWIRE (Wiseman et al., 2017) and MLB (Puduppully et al., 2019b) datasets. The statistics are listed in Table 1. For ROTOWIRE, we use the official dataset with official splits. For MLB, as the contents are not released, we retrieve the dataset via official scripts¹. Since the script misses some important types of records that appears in reference (extracted by IE model), we add “team runs” and “bf”, “out”, “bs” for pitchers into the input. Corresponding statistics is in Table 1. For preprocessing on those two datasets, we follow the one used by Puduppully et al. (2019a) and Puduppully et al. (2019b)’s released code for the corresponding dataset.

A.2 Hyper-Parameters

We follow the training configurations of Puduppully et al. (2019a) and Puduppully et al. (2019b) in the base model for ROTOWIRE and MLB respectively (Table 2).

As for pre-trained task for contextual numerical value representations, we set transformer layers as 2 from {1, 2, 3}, feed-forward hidden size as 1024 from {512, 1024}, numbers of heads as 3 from {2, 3, 4}, and the ranking margin as 0.3 from {0.1, 0.2, 0.3, 0.4, 0.5}. The pre-trained task is optimized with Adam with warm-up steps 1000 and learning rate schedule as the one in Vaswani et al. (2017). We also explore fixing or finetuning parameters from the pre-trained task jointly with parameters of the table-to-text generation model. Results show that treating pre-trained model fixed yields better performance and predicting which numerical value’s contextual representation has higher value with 99.99% accuracy on held-out data.

For content planning verification module, we discuss weights for $\lambda_1 - \lambda_5$ from {(0.2, 0.2, 0.2, 0.2, 0.2), (0.15, 0.15, 0.15, 0.15, 0.3), (0.15, 0.25, 0.1, 0.2, 0.3)}. The first gives equal importance for all, the second gives equal importance for precision, recall and content ordering and the last is based on model’s performance from following aspects: Entity Importance (EI), Record Importance (RI), Entity Recall (ER), Record Recall (RR) and Record Ordering (RO). The poorer the performance, the higher the weight. We find that the last setting of $\lambda_1 - \lambda_5$ performs the best. We also choose λ_6 as 0.3 from {0.1, 0.2, 0.3, 0.4, 0.5} and β as 0.2 from {0.1, 0.2, 0.3, 0.4, 0.5}. Hyper-parameters of DUV, discussed in this section, are chosen based on performance on development set.

	ROTOWIRE	MLB
Vocab Size	11.3K	42.8K
# Tokens	1.5M	15.7M
# Instances	4.9K	26.3K
Avg Length	337	595
# Record Types	39	108
Avg Records	628	591

Table 1: Statistics of ROTOWIRE and MLB. MLB is re-collected via official script because the contents are not released.

A.3 Training Statistics

We train our models on a NVIDIA GeForce RTX 2080 Ti with 11GB memory for ROTOWIRE. As for MLB, we train the models on a NVIDIA Tesla V100-SXM3-32GB. Please note that models for MLB can still fit into the GPU used for ROTOWIRE and the difference is merely due to the availability of GPUs at that moment.

On ROTOWIRE, DUV costs 1 minutes to train with MLE and 4 minutes for finetuning with pol-

¹<https://github.com/ratishsp/mlb-data-scripts>

	ROTOWIRE	MLB
Word Embeddings	600	300
Hidden state hize	600	600
LSTM Layers	2	1
Input Feeding	Yes	Yes
Dropout	0.3	0.3
Optimizer	Adagrad	Adagrad
Initial learning rate	0.15	0.15
Learning rate decay	0.97	0.97
Epochs	25	25
BPTT size	100	100
Batch size	5	12
Inference beam size	5	5

Table 2: Hyper-parameters of base model (Module 2).

icy gradient a epoch for Stage 1 (12.42M parameters). For Stage 2 (32.35M parameters) it costs 20 minutes a epoch (these two stages can be run in parallel). NCP (33.94M parameters) takes 21 minutes for a epoch (including Stage 1 and 2). On MLB, DUV costs 5 minutes to train with MLE and 14 minutes for finetuing with policy gradient for a epoch in Stage 1 (11.23M parameters). For Stage 2 (35.24M parameters), it costs 51 minutes for a epoch. NCP (42.57M parameters) takes 65 minutes a epoch, while ENT (34.27M parameters) takes 176 minutes.

B Validation Performance

We presents the comparing methods’ (Sec.4.2) performance on development set in Table 3. They shows the same pattern as results on test set in the paper.

C Qualitative Example

Due to page limit, we present the qualitative example on ROTOWIRE in the paper, and the example on MLB here. Compared to base model NCP, DUV generate a more concise and meaningful text report describing both important MLB statistical and event data. Compared to ENT, DUV can include more important and correct statistical data with less redundant ones, while perform less satisfying with repect to event data.

References

Ratish Puduppully, Li Dong, and Mirella Lapata. 2019a. Data-to-text generation with content selec-

tion and planning. *Proceedings of AAAI Conference on Artificial Intelligence*.

Ratish Puduppully, Li Dong, and Mirella Lapata. 2019b. Data-to-text generation with entity modeling. In *Proceedings of the 57th Annual Meeting of the Association for Computational Linguistics*.

Ashish Vaswani, Noam Shazeer, Niki Parmar, Jakob Uszkoreit, Llion Jones, Aidan N. Gomez, Lukasz Kaiser, and Illia Polosukhin. 2017. Attention is all you need. In *Advances in Neural Information Processing Systems*, pages 5998–6008.

Sam Wiseman, Stuart M. Shieber, and Alexander M. Rush. 2017. Challenges in data-to-document generation. In *Proceedings of the Conference on Empirical Methods in Natural Language Processing*.

ROTOWIRE (RW)	RG		CS			CO	BLEU
	P%	#	P%	R%	F1%	DLD%	
TEMP	99.92	54.23	26.60	59.13	36.69	14.39	8.62
ED+CC	75.10	23.95	28.11	35.86	31.52	15.33	14.57
NCP+CC (NCP)	87.51	33.88	33.52	51.21	40.52	18.57	16.19
ENT	91.97	31.84	36.65	48.18	41.63	19.68	15.97
HETD	91.84	32.11	35.39	48.98	41.09	20.70	16.24
NCP(R)	85.60	26.60	36.29	44.68	40.05	19.68	15.16
S-NCP	84.07	26.78	35.38	45.16	39.68	19.36	15.32
S-NCP+V (S-N+V)	84.70	25.40	37.17	44.68	40.58	19.47	14.60
DU	87.23	28.81	39.03	51.64	44.46	22.97	16.64
DUV	87.35	26.11	42.00	50.63	45.91	24.86	16.29

MLB	RG		CS			CO	BLEU
	P%	#	P%	R%	F1%	DLD%	
TEMP	98.02	57.46	23.15	66.49	34.34	10.54	2.77
ED+CC	91.67	17.35	63.08	48.50	54.84	25.97	9.64
NCP+CC (NCP)	88.38	15.99	63.40	52.12	57.21	27.51	8.24
ENT	85.41	22.12	55.18	61.53	58.18	24.07	12.84
S-NCP	88.08	16.74	62.22	54.43	58.07	27.75	9.47
S-NCP+V (S-N+V)	88.32	16.72	62.57	54.70	58.37	28.21	9.53
DU	88.41	16.88	62.41	54.91	58.42	27.92	9.58
DUV	88.72	16.63	62.95	54.50	58.42	28.34	9.45

Table 3: Automatic evaluation results on development set. We use the same Information Extraction (IE) models as described in the automatic evaluation results on test set in the paper.

