Recent work in NLP with tabular data

彭凯龙

目录

- 前言
- 近期论文
- 总结

前言

- 表格数据的意义

  半结构化数据

- 处理表格的特殊之处

  关键字

  “上下文”

Model	Development						
	RG		CS			CO	BLEU
	P%	#	P%	R%	F1%	DLD%	
Gold	94.79	23.31	100.00	100.00	100.00	100.00	100.00
Template	**99.92**	**54.23**	26.60	**59.13**	36.69	14.39	8.62
CC (Wiseman et al., 2017)	75.10	23.95	28.11	35.86	31.52	15.33	14.57
NCP+CC (Puduppully et al., 2019)	87.51	33.88	33.52	51.21	40.52	18.57	16.19
Hierarchical LSTM Encoder	91.59	32.56	31.62	44.22	36.87	17.49	15.21
Hierarchical CNN Encoder	90.86	30.59	30.32	40.28	34.60	15.75	14.08
Hierarchical SA Encoder	90.46	29.82	34.39	45.43	39.15	19.81	15.62
Hierarchical MHSA Encoder	92.87	28.42	34.87	42.41	38.27	18.28	15.12
CC (Our implementation)	76.50	22.48	29.18	34.22	31.50	15.43	13.65
Our Model	91.84	32.11	**35.39**	48.98	**41.09**	**20.70**	**16.24**
-row-level encoder	90.19	27.90	34.70	42.53	38.22	20.02	15.32
-row	91.08	30.95	35.03	47.09	40.17	20.03	15.50
-column	91.66	28.63	34.83	43.62	38.73	19.59	15.99
-time	90.94	31.43	34.62	47.74	40.13	19.81	16.10
-position embedding	89.97	28.37	34.72	43.69	38.69	19.54	16.05
-record fusion gate	89.34	32.22	32.28	46.68	38.17	18.49	14.97

前言

- 表格处理方向热度

ACL2021

- Towards Table-to-Text Generation wi...
- De-Confounded Variational Encoder-...
- Improving Encoder by Auxiliary Supe...
- Joint Verification and Reranking for ...
- TAT-QA: A Question Answering Benc...
- Dual Reader-Parser on Hybrid Textua...

NAACL2021

- Open Domain Question Answering o...
- Capturing Row and Column Semanti...
- Incorporating External Knowledge to...
- TABBIE: Pretrained Representations o...

EMNLP2021

- MATE: Multi-view Attention for Table...
- Logic-level Evidence Retrieval and Gr...
- Topic Transferable Table Question An...
- Table-based Fact Verification with Sal...
- Few-Shot Table-to-Text Generation ...
- Exploring Decomposition for Table-b...

论文介绍

- Towards Table-to-Text Generation with Numerical Reasoning. ACL/IJCNLP (1) 2021: 1451-1465
- Incorporating External Knowledge to Enhance Tabular Reasoning. NAACL-HLT 2021: 2799-2809
- MATE: Multi-view Attention for Table Transformer Efficiency. CoRR abs/2109.04312 (2021)
- Improving Encoder by Auxiliary Supervision Tasks for Table-to-Text Generation. ACL/IJCNLP (1) 2021: 5979-5989
- TABBIE: Pretrained Representations of Tabular Data. NAACL-HLT 2021: 3446-3456
- Joint Verification and Reranking for Open Fact Checking Over Tables. ACL/IJCNLP (1) 2021: 6787-6799

Towards Table-to-Text Generation with Numerical Reasoning (ACL-IJCNLP2021)

- 动机：

  源于论文的table-to-text数值推理任务

  强化数值推理能力的table-to-text生成框架

- 表格数据预处理

Table 2: The overall mention detection results on the test set of OntoNotes.

Model	Precision	Recall	F1
Our full model	89.6	82.2	85.7
Lee et al. (2018)	86.2	83.7	84.9

Target Header
Our full model
Description
Table 2 shows the mention detection results on the test set. Similar to coreference linking results, **our model achieves higher precision and F1 score**, which indicates that our model can significantly reduce false positive mentions while it can still find a reasonable number of mentions.

table 2: the overall mention detection results on the test set of ontonotes.

		preci sion	recall	f1
model	our full model	89.6	82.2	85.7
model	lee et al.(2018)	86.2	83.7	84.9

target header: our full model
metric-type: precision, recall, f1

Data Table (T_D)

header name		**val**	**metric (m)**	**tar get**
h	**th**			
our full model	model	89.6	precision	1
our full model	model	82.2	recall	1
our full model	model	85.7	f1	1
lee et al. (2018)	model	86.2	precision	0
lee et al. (2018)	model	83.7	recall	0
lee et al. (2018)	model	84.9	f1	0

Pre-executed Operation Table (T_{OP})

op name	**op arguments**		**metric**	**result**	
	h	**th**		**h**	**val**
max	our full model, lee et al. (2018)	model	precision	our full model	89.6
max	our full model, lee et al. (2018)	model	f1	our full model	85.7
max	our full model, lee et al. (2018)	model	recall	lee et al. (2018)	83.7
min	our full model, lee et al. (2018)	model	recall	our full model	82.2
min	our full model, lee et al. (2018)	model	precision	lee et al. (2018)	86.2
min	our full model, lee et al. (2018)	model	f1	lee et al. (2018)	84.9
diff	our full model, lee et al. (2018)	model	precision		3.4
diff	our full model, lee et al. (2018)	model	recall		-1.5
diff	our full model, lee et al. (2018)	model	f1		0.8

Towards Table-to-Text Generation with Numerical Reasoning (ACL-IJCNLP2021)

- 使用模板转换表格
  - 简单模板
  - 数据模板
  - 推理模板
  - 数据、推理结合模板

caption: <table_id> <caption>. row name: <rh$_1$> ... <rh$_{nr}$>. column name: <ch$_1$> ... <ch$_{nc}$>. metric:<m$_1$>, ..., <m$_{nr/nc}$>. value: <val$_{1.1}$> ... <val$_{nr.nc}$> .

<table_id> shows <caption>. <m$_{1.1}$> of <h$_{1.1}$> is <val$_{1.1}$> ... <m$_{nr.nc}$> of <h$_{nr.nc}$> is <val$_{nr.nc}$>.

<table_id> shows <caption>. <h$_{max}$> has the largest <m$_{max}$> (<val$_{max}$>) of <th$_{max}$>. <h$_{min}$> has the smallest <m$_{min}$> (<val$_{max}$>) of <th$_{min}$>. <m$_{diff}$> of <h$_{diff1}$> is larger/smaller than <h$_{diff2}$> .

Towards Table-to-Text Generation with Numerical Reasoning (ACL-IJCNLP2021)

- 使用模板训练模型

  将模板“翻译”为描述

- Copy mechanism

  Fine-tune：用占位符替换描述中的实体，生成Y_{temp}

  Inference：利用原表内容给生成的$\hat{Y}_{temp}$填空

  Placeholder memory

- 效果

Model	Generated Text
Reference	table 2 shows the mention detection results on the test set. similar to coreference linking results, our model achieves higher precision and f1 score, which indicates that our model can significantly reduce false positive mentions while it can still find a reasonable number of mentions.
Template-based	table 2 shows the overall mention detection results on the test set of ontonotes. we can see that our full outperforms other model with **85.7** f1.
Pointer-generator	the table 2 shows the results of the results of the results of the results of the the art of the art of...
Fine-tuned GPT2 ($T_D + T_{OP}$ temp)	the table shows the recall performance with our full model. the result of our full model is **88.7**, which is comparable with the **89.3** performance of our full model but still better than the **89.9** and **89.2** performance in both the f1, prec and full models. we also find that our full model does not perform very well when compared against a full one, with **89.4%** and **89.4%** recall and **89.2%** recall respectively. we can also find that our full model is slightly inferior in terms of recall.
Fine-tuned GPT2 ($T_D + T_{OP}$ temp) + Copy	table 2 : (the - d model : a) the : aa . the: the, the: and, the: the: the,the and, theand: the and, theand: theand: theand, theand: ... (<table_id>: table 2; <cat_header>: model)
Fine-tuned T5 ($T_D + T_{OP}$ temp)	table 2 presents the overall mention detection results on ontonotes. our full model outperforms all the state-of-the-art systems in terms of recall and f1 score.
Fine-tuned T5 ($T_D + T_{OP}$ temp) + Copy	table 2 shows the overall mention detection results on the test set of ontonotes. our full model outperforms the previous state-of-the-art models by a large margin, which confirms the effectiveness of our proposed approach. (<table_id>: table 2; <header_max>: our full model)

Incorporating External Knowledge to Enhance Tabular Reasoning (NAACL-HLT 2021)

- 动机：

  使用额外知识帮助模型推理

- 方法：

  Paragraph Representation:

  Money/Date/Cardinal/Bool

  Implicit/ Explicit Knowledge Addition:

  MultiNLI 文本蕴含关系数据集

  WordNet/Wikipedia 概念补充关键词

  Distracting Row Removal

  计算每一行与问题的相关度，取top K

- 效果

Orignal Premise Sentence *"The Died of Jesse Ramsden are November 1800 (1800-11-05) (aged 65) Brighton, Sussex."*

BPR Sentence *"Jesse Ramsden Died on 5 November 1800 (1800-11-05) (aged 65) Brighton, Sussex."*

Premise	Dev	α_1	α_2	α_3
Human	**79.78**	**84.04**	**83.88**	**79.33**
Para	75.55	74.88	65.55	64.94
BPR	76.42	75.29	66.50	64.26
+KG implicit	**79.57**	78.27	71.87	66.77
+DRR	78.77	78.13	70.90	68.98
+KG explicit	79.44	**78.42**	**71.97**	**70.03**

Train	Dev	k = 2	k = 3	k = 4	k = 5	k = 6
BPR	DRR	71.72	74.83	77.50	78.50	79.00

Table Fact Verification with Structure-Aware Transformer (EMNLP 2020)

- 动机：

  单纯对表格做linearization会丢失结构信息

- 方法：

  将表格结构信息注入self-attention layer的mask中

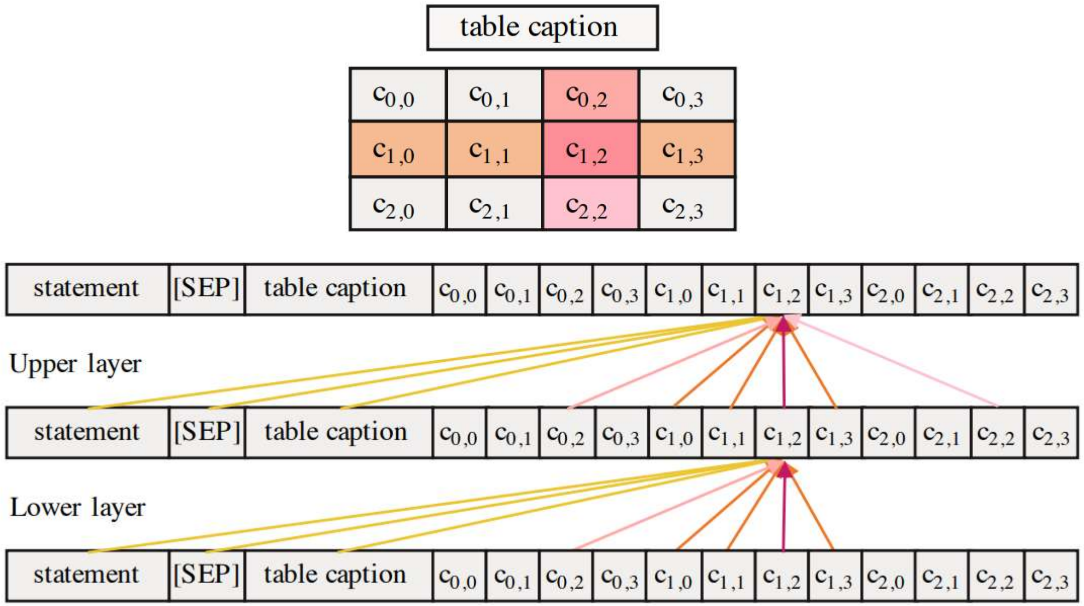
$$M_{i,j} = \begin{cases} 0 & w_i \sim w_j \\ -\infty & w_i \nsim w_j \end{cases}$$

$$\boldsymbol{Q}^l, \boldsymbol{K}^l, \boldsymbol{V}^l = \boldsymbol{H}^l \boldsymbol{W}_q, \boldsymbol{H}^l \boldsymbol{W}_k, \boldsymbol{H}^l \boldsymbol{W}_v$$

$$\boldsymbol{A}^l = \mathrm{softmax}(\frac{\boldsymbol{Q}^l \boldsymbol{K}^{lT} + \boldsymbol{M}}{\sqrt{d_k}})$$

$$\boldsymbol{H}^{l+1} = \boldsymbol{A}^l \boldsymbol{V}^l$$

  将符号推理问题转化为匹配问题（summary row）



TAPAS: Weakly Supervised Table Parsing via Pre-training (ACL 2020)

- 动机:

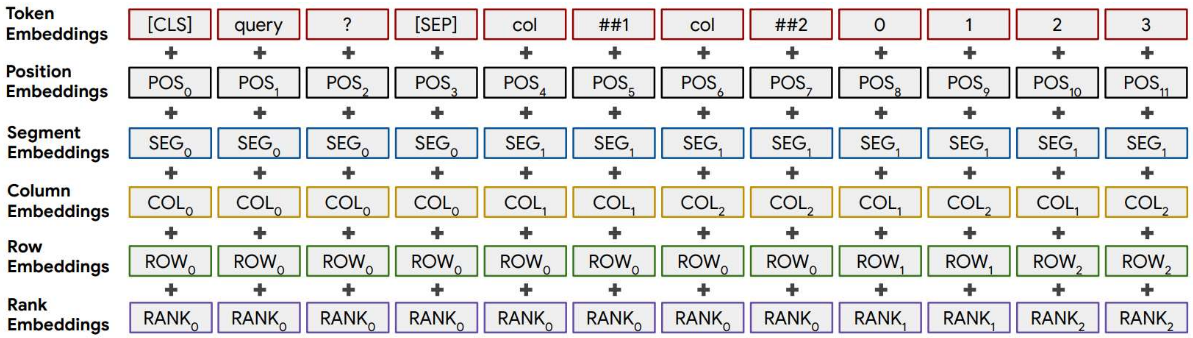
  补充位置信息

- 方法:

  Additional embeddings

Table

col1	col2
0	1
2	3



MATE: Multi-view Attention for Table Transformer Efficiency (EMNLP2021)

- 动机

  处理大型表格的sparse-attention Transformer

- 模型-MATE

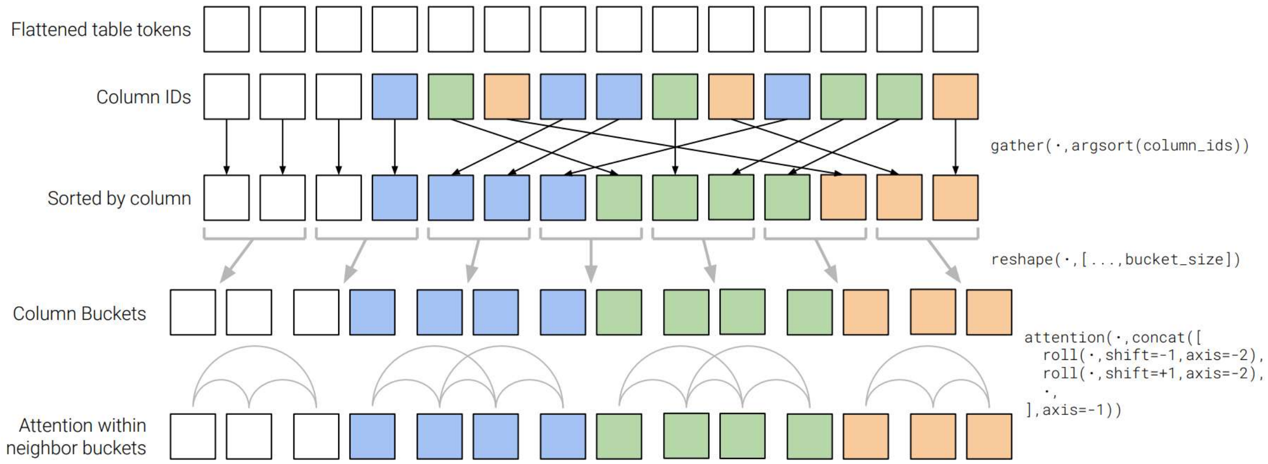
  继续使用row, column, rank embedding

  限制attention范围：row/ col headers

$$\mathrm{Head}_k^i(\mathbf{X}) = \mathbf{W}_V^i \mathbf{X}_{\mathcal{A}_k^i} \sigma \left[\left(\mathbf{W}_K^i \mathbf{X}_{\mathcal{A}_k^i} \right)^{\intercal} \mathbf{W}_Q^i \mathbf{X}_k \right]$$

$$\mathcal{A}_k^i = \begin{cases} \{1, \cdots, n\} & \text{if } k \in Q \text{, else} \\ Q \cup \{j : r_j = r_k\} & \text{if } 1 \leq i \leq h_r \\ Q \cup \{j : c_j = c_k\} & \text{otherwise.} \end{cases}$$

  提升计算效率：将输入划分为全局、局部部分



MATE: Multi-view Attention for Table Transformer Efficiency (EMNLP2021)

- 模型-POINTER

Cell selection：

$$S(t) = \texttt{MLP}(\texttt{MATE}(q, e)[t])$$

$$S(c) = \texttt{avg}_{t \in c} S(t)$$

$$P(c) = \frac{\texttt{exp}(S(c))}{\sum_{c' \in e} \texttt{exp}(S(c'))}$$

$$q(z) = p_\Theta(z|x, z \in \mathcal{C})$$

$$\mathcal{L}(\Theta, x, \mathcal{C}) = \sum_{z \in \mathcal{C}} -q(z) \log p_\Theta(z|x)$$

Passage reading：

$$h_{start} = \text{BERT}_r(q, c)[\texttt{START}(s)]$$

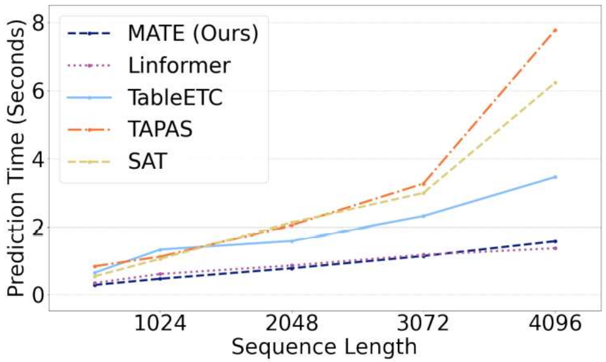
$$h_{end} = \text{BERT}_r(q, c)[\texttt{END}(s)]$$

$$\text{S}_{\text{read}}(q, c) = \texttt{MLP}([h_{start}, h_{end}])$$

MATE: Multi-view Attention for Table Transformer Efficiency (EMNLP2021)

- 效果

Model	Dev In-Table EM	Dev In-Table F1	Dev In-Passage EM	Dev In-Passage F1	Dev Total EM	Dev Total F1	Test In-Table EM	Test In-Table F1	Test In-Passage EM	Test In-Passage F1	Test Total EM	Test Total F1
Table-Only	14.7	19.1	2.4	4.5	8.4	12.1	14.2	18.8	2.6	4.7	8.3	11.7
Passage-Only	9.2	13.5	26.1	32.4	19.5	25.1	8.9	13.8	25.5	32.0	19.1	25.0
HYBRIDER (τ=0.8)	54.3	61.4	39.1	45.7	44.0	50.7	56.2	63.3	37.5	44.4	43.8	50.6
POINTR + SAT	66.5 ±0.33	71.8 ±0.28	60.3 ±0.11	69.2 ±0.04	61.2 ±0.29	68.7 ±0.31	64.6	70.1	59.6	68.5	60.1	67.4
POINTR + TAPAS	68.1 ±0.33	73.9 ±0.37	62.9 ±0.25	72.0 ±0.21	**63.3** ±0.25	**70.8** ±0.12	67.8	73.2	62.0	70.9	62.7	70.0
POINTR +TABLEETC	36.0 ±1.26	42.4 ±1.13	37.8 ±1.19	45.3 ±1.53	36.1 ±1.30	42.9 ±1.36	35.8	40.7	38.8	45.7	36.6	42.6
POINTR + LINFORMER	65.5 ±0.78	71.1 ±0.55	59.4 ±0.59	69.0 ±0.68	60.8 ±0.68	68.4 ±0.63	66.1	71.7	58.9	67.8	60.2	67.6
POINTR + MATE	68.6 ±0.37	74.2 ±0.26	62.8 ±0.25	71.9 ±0.20	**63.4 ±0.16**	**71.0 ±0.17**	66.9	72.3	62.8	71.9	**62.8**	**70.2**
Human											88.2	93.5



Improving Encoder by Auxiliary Supervision Tasks for Table-to-Text Generation (ACL-IJCNLP 2021)

- 动机

  以单元格为单位进行编码，依靠GAT推理

  辅助任务提升编码能力

- 模型

  Record Embedding：单元格初始化

$$r_{i,j}^{emb} = Relu(W^e[r_{i,j}.e; r_{i,j}.t; r_{i,j}.v; r_{i,j}.f] + b^e)$$

  Column-Row Encoder：

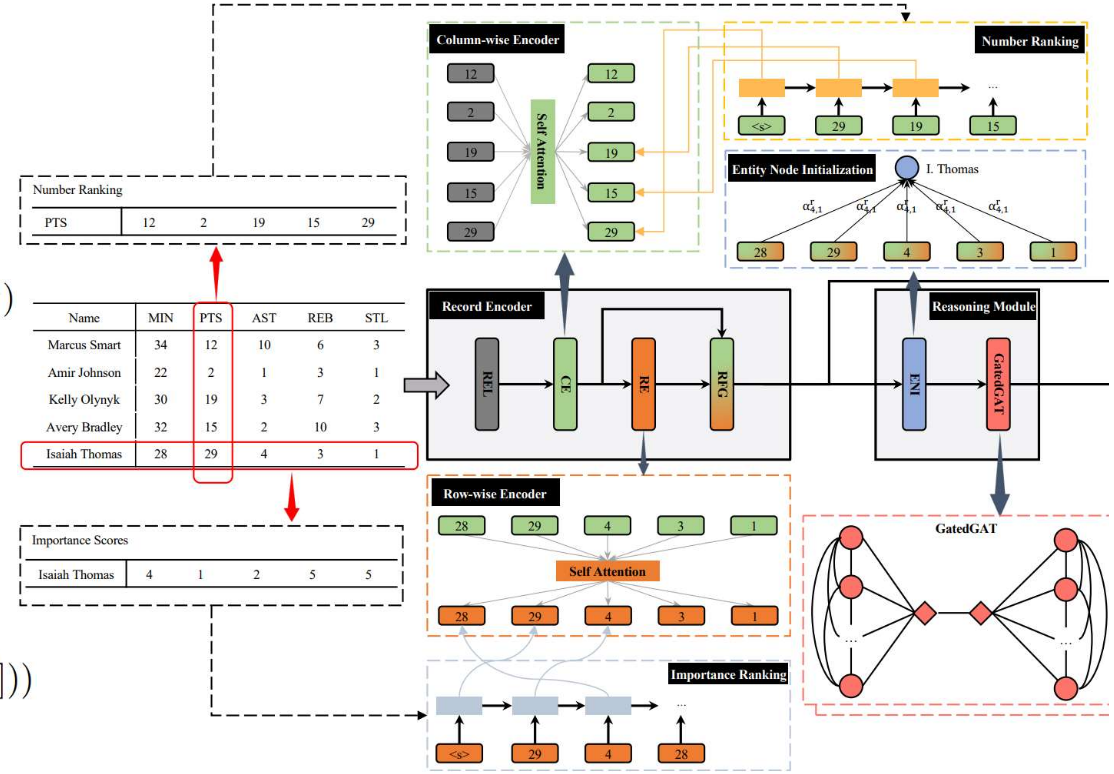
$$\alpha_{i,j,i'}^{col} \propto \exp(W_2^{col} \tanh(W_1^{col}[r_{i,j}^{emb}; r_{i',j}^{emb}])$$

$$\tilde{r}_{i,j}^{col} = \sum_{i'=1, i' \neq i}^{R} \alpha_{i,j,i'}^{col} r_{i',j}^{emb}$$

$$r_{i,j}^{col} = W_3^{col}[\tilde{r}_{i,j}^{col}; r_{i,j}^{emb}]$$

  Record Fusion： $s_{i,j}^{col} \propto \exp(W_2^f \tanh(W_1^f[r_i^{gen}; r_{i,j}^{col}]))$

$$r_{i,j}^{f} = s_{i,j}^{col} r_{i,j}^{col} + s_{i,j}^{row} r_{i,j}^{row}$$



Improving Encoder by Auxiliary Supervision Tasks for Table-to-Text Generation (ACL-IJCNLP 2021)

- 模型

Reasoning Module

Entity Initialization：

$$\alpha^r_{i,j} \propto \exp(W^r_2 \tanh(W^r_1[e^{gen}_i; r^f_{i,j}]))$$

$$e^0_i = \sum_{j=1}^{j=C} \alpha^r_{i,j} r^f_{i,j}$$

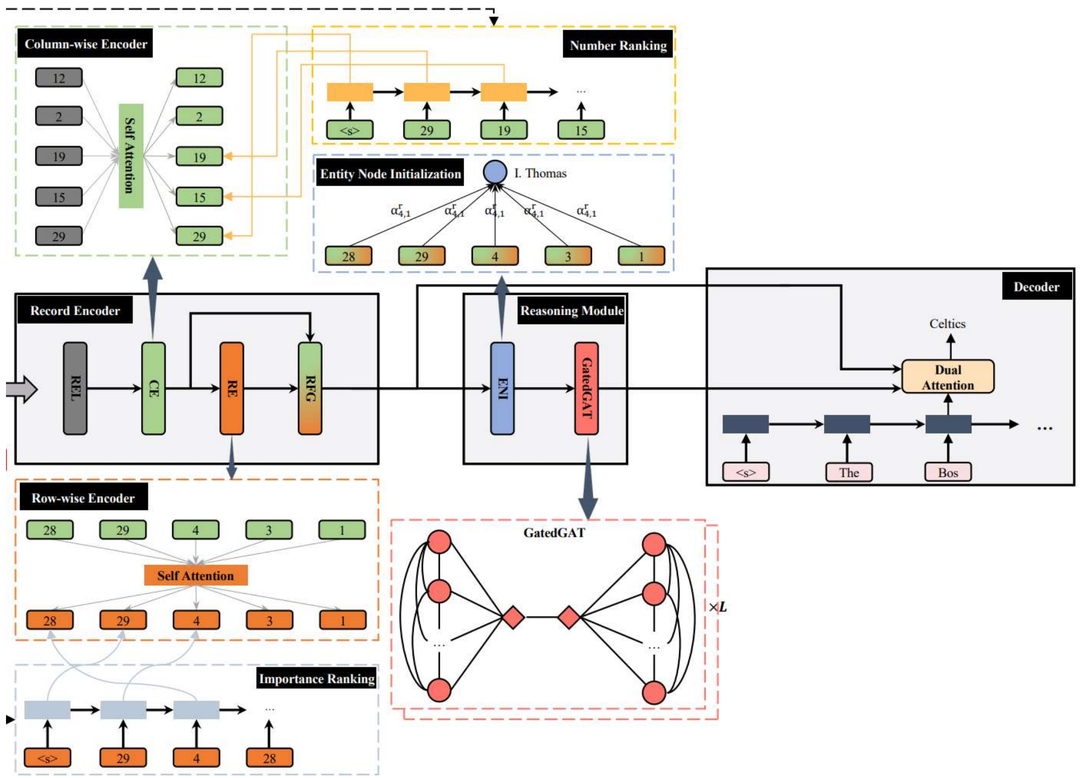
GatedGAT：

$$\alpha^l_{i,j} = MultiHeadAttention(e^{l-1}_i, e^{l-1}_j)$$

$$\tilde{e}^l_i = ELU(\sum_{j \in N_i} \alpha^l_{i,j} e^{l-1}_j)$$

$$gate^l_i = sigmoid(W^l[e^{l-1}_i; \tilde{e}^l_i])$$

$$e^l_i = gate^l_i * e^{l-1}_i + (1 - gate^l_i) * \tilde{e}^l_i$$



Improving Encoder by Auxiliary Supervision Tasks for Table-to-Text Generation (ACL-IJCNLP 2021)

- 模型

Dual-attention Decoder

$$\alpha'_{t,i,j} = \alpha_{t,i}\beta_{t,i,j}$$

$$c_t^d = \sum_{i=1}^{R}\sum_{j=1}^{C}\alpha'_{t,i,j} r_{i,j}$$

$$L_{lm} = -\sum_{i=1}^{T} p_\theta(y_t|y_{1:t-1}; c_t^d)$$

Auxiliary Supervision Task

Number ranking

$$h_t = LSTM(h_{t-1}, r^{col}_{z_{t-1}})$$

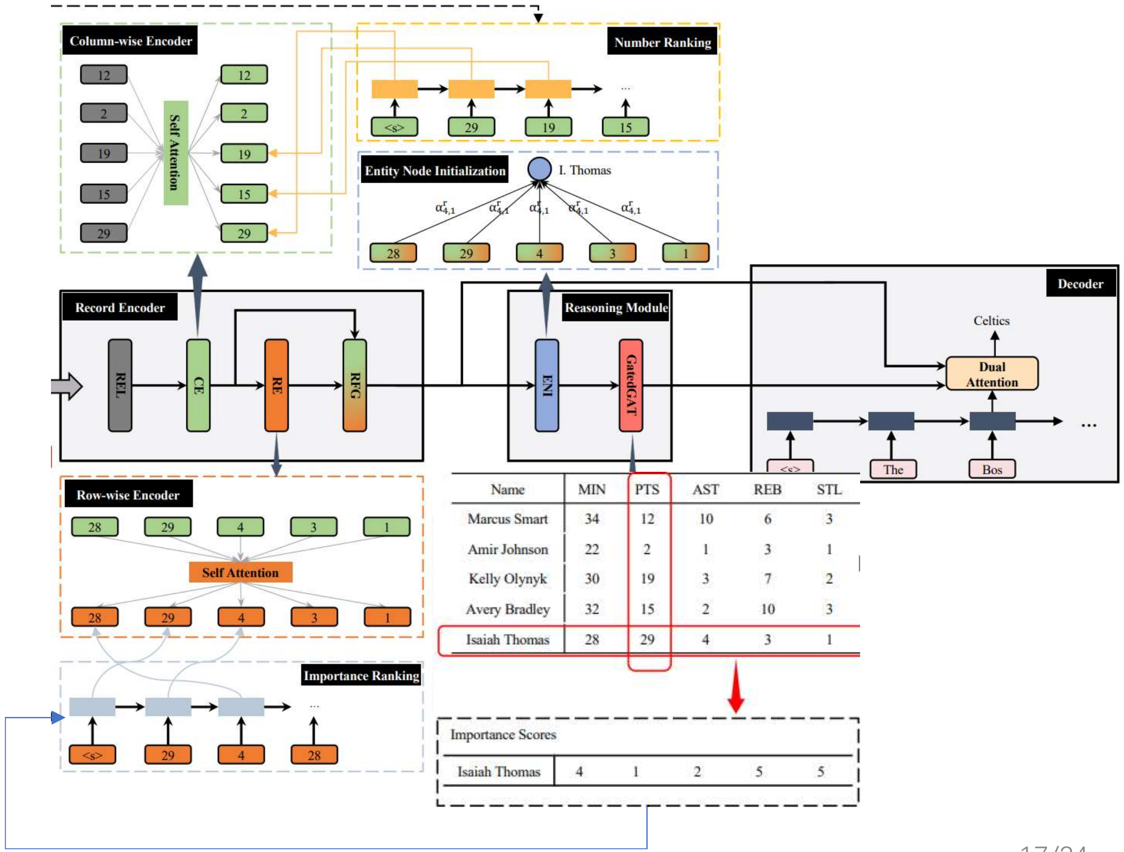
$$p^n_{t,i} \propto exp(W_{nr}[h_t; r^{col}_i])$$

$$L_{nr} = -\sum_{j=1}^{C}\sum_{i=1}^{R}\log p^n_{i,z_i}$$

Importance ranking

$$L_{ir} = -\sum_{i=1}^{R}\sum_{j=1}^{C}\log p^s_{j,z_j}$$

$$L = L_{lm} + \lambda_1 L_{nr} + \lambda_2 L_{ir}$$



Improving Encoder by Auxiliary Supervision Tasks for Table-to-Text Generation (ACL-IJCNLP 2021)

- 效果

Model	RG #	RG P%	CS P%	CS R%	CS F1%	CO DLD%	BLEU
	ROTOWIRE						
Gold	23.31	94.79	100	100	100	100	100
TEMP	**54.23**	**99.94**	26.99	**58.16**	-	14.92	8.46
CC (Wiseman et al., 2017)	23.72	74.80	29.49	36.18	31.52	15.42	14.19
NCP (Puduppully et al., 2019a)	**34.28**	87.47	34.18	51.22	40.99	18.58	16.50
NCP (Our implementation)	31.95	86.96	33.13	47.59	39.06	17.47	15.26
ENT (Puduppully et al., 2019b)	30.11	92.96	38.67	48.51	43.09	20.17	16.12
HETD (Gong et al., 2019)	31.47	91.46	36.09	48.01	41.21	20.86	16.85
DU (Gong et al., 2020)	29.42	88.05	38.19	49.66	43.18	22.14	16.12
DUV (Gong et al., 2020)	26.94	87.45	40.73	48.78	44.39	23.32	15.92
Ours	32.73	**93.14**	**40.80**	**55.88**	**47.16**	**25.30**	**17.96**

Model	RG #	RG P%	CS F1%	CO DLD%	BLEU
Our Model	34.37	90.03	44.34	23.64	17.31
- *Series*	32.74	91.56	41.42	21.52	17.19
- *RM*	33.91	89.58	43.71	23.04	16.98
+ *NE*	**38.41**	92.28	44.22	23.16	16.23
+ *NE & IE*	32.85	92.68	45.33	24.49	16.81
+ *NR*	32.47	**93.76**	45.93	24.29	**18.56**
+ *IR*	35.30	92.65	43.34	22.04	17.47
+ *NR & IR*	33.93	92.40	**46.13**	**25.28**	17.68

TABBIE: Pretrained Representations of Tabular Data (NAACL-HLT 2021)

- 动机

  单元格、行、列向量

  辅助任务

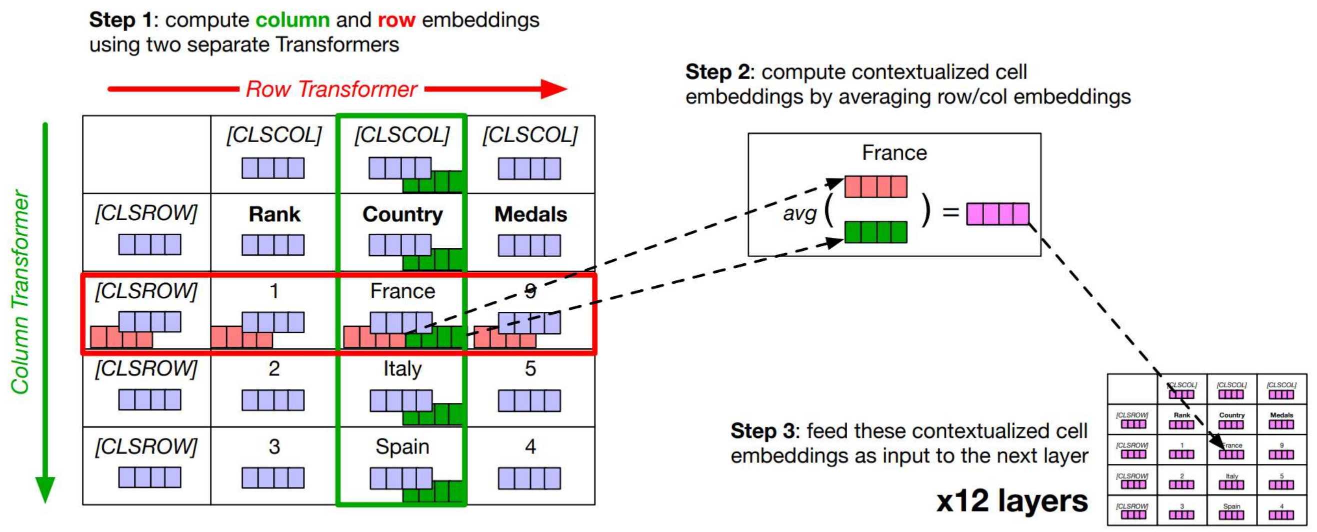
- 模型

  初始化：BERT + positional embedding

  Contextualizing：Row/Col Transformers

$$x_{i,j}^{L+1} = \frac{r_{i,j}^{L} + c_{i,j}^{L}}{2}$$

  Row/Col Representation



TABBIE: Pretrained Representations of Tabular Data (NAACL-HLT 2021)

- 辅助任务

  Cell Corruption Detection

$$P_{\text{corrupt}}(\text{cell}_{i,j}) = \sigma(\boldsymbol{w}^{\intercal}\boldsymbol{x}^{L}_{i,j})$$

(a) original table

Rank	Country	Gold
1	France	9
2	Italy	5
3	Spain	4

(b) sample cells from other tables

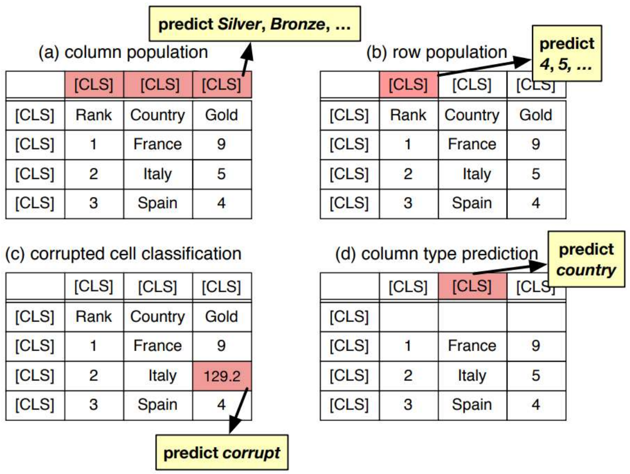
Rank	Size	Gold
1	France	3.6
2	Italy	5
3	Spain	4

(c) swap cells on the same row

Rank	Country	Gold
1	France	9
2	5	Italy
3	Spain	4

(d) swap cells on the same column

Rank	Country	Gold
1	France	9
3	Italy	5
2	Spain	4



TABBIE: Pretrained Representations of Tabular Data (NAACL-HLT 2021)

- 效果

N	Method	MAP	MRR	Ndcg-10	Ndcg-20
1	GPM	25.1	37.5	-	-
	GPM+TH	25.5	0.38.0	27.1	31.5
	TaBERT	33.1	41.3	35.1	38.1
	TABBIE (FREQ)	**37.9**	**49.1**	**41.2**	**43.8**
	TABBIE (MIX)	37.1	48.7	40.4	43.1
2	GPM	28.5	40.4	-	-
	GPM+TH	33.2	44.0	36.1	41.3
	TaBERT	51.1	60.1	54.7	56.6
	TABBIE (FREQ)	**52.0**	**62.8**	**55.8**	**57.6**
	TABBIE (MIX)	51.7	62.3	55.6	57.2
3	GPM	28.5	35.5	-	-
	GPM+TH	40.0	50.8	45.2	48.5
	TaBERT	53.3	60.9	56.9	57.9
	TABBIE (FREQ)	**54.5**	**63.3**	**57.9**	**58.9**
	TABBIE (MIX)	54.1	62.3	57.4	58.7

Method	n=1000	n=10000	n=all
Sherlock	-	-	86.7
SATO	-	-	90.8
TaBERT	**84.7**	93.5	**97.2**
TABBIE (FREQ)	**84.7**	**94.2**	96.9
TABBIE (MIX)	84.1	93.8	96.7

N	Method	MAP	MRR	Ndcg-10	Ndcg-20
1	Entitables	36.8	45.2	-	-
	TaBERT	**43.2**	**55.7**	**45.6**	**47.7**
	TABBIE (FREQ)	42.8	54.2	44.8	46.9
	TABBIE (MIX)	42.6	54.7	45.1	46.8
2	Entitables	37.2	45.1	-	-
	TaBERT	43.8	56.0	46.4	48.8
	TABBIE (FREQ)	**44.4**	**57.2**	**47.1**	**49.5**
	TABBIE (MIX)	43.7	55.7	46.2	48.6
3	Entitables	37.1	44.6	-	-
	TaBERT	42.9	55.1	45.6	48.5
	TABBIE (FREQ)	**43.4**	**56.5**	**46.6**	**49.0**
	TABBIE (MIX)	42.9	55.5	45.9	48.3

Corruption	Method	Prec.	Rec.	F1
Intra-row swap	TaBERT	85.5	83.0	84.2
	TABBIE (FREQ)	99.0	81.4	89.4
	TABBIE (MIX)	99.6	95.8	**97.7**
Intra-column swap	TaBERT	31.2	19.0	23.7
	TABBIE (FREQ)	90.9	22.3	35.8
	TABBIE (MIX)	91.5	55.0	**68.8**
Intra-table swap	TaBERT	81.2	69.5	74.9
	TABBIE (FREQ)	98.2	73.3	84.0
	TABBIE (MIX)	98.4	86.2	**91.9**
Random FREQ cell	TaBERT	86.7	87.0	86.8
	TABBIE (FREQ)	99.3	98.2	**98.8**
	TABBIE (MIX)	99.1	98.1	98.6
All	TaBERT	75.6	65.2	70.0
	TABBIE (FREQ)	98.2	69.5	81.4
	TABBIE (MIX)	97.8	84.1	**90.5**

Joint Verification and Reranking for Open Fact Checking Over Tables (ACL-IJCNLP 2021)

- 动机

  开放世界设定下的表格事实验证

- 模型

  Entity-based retrieval

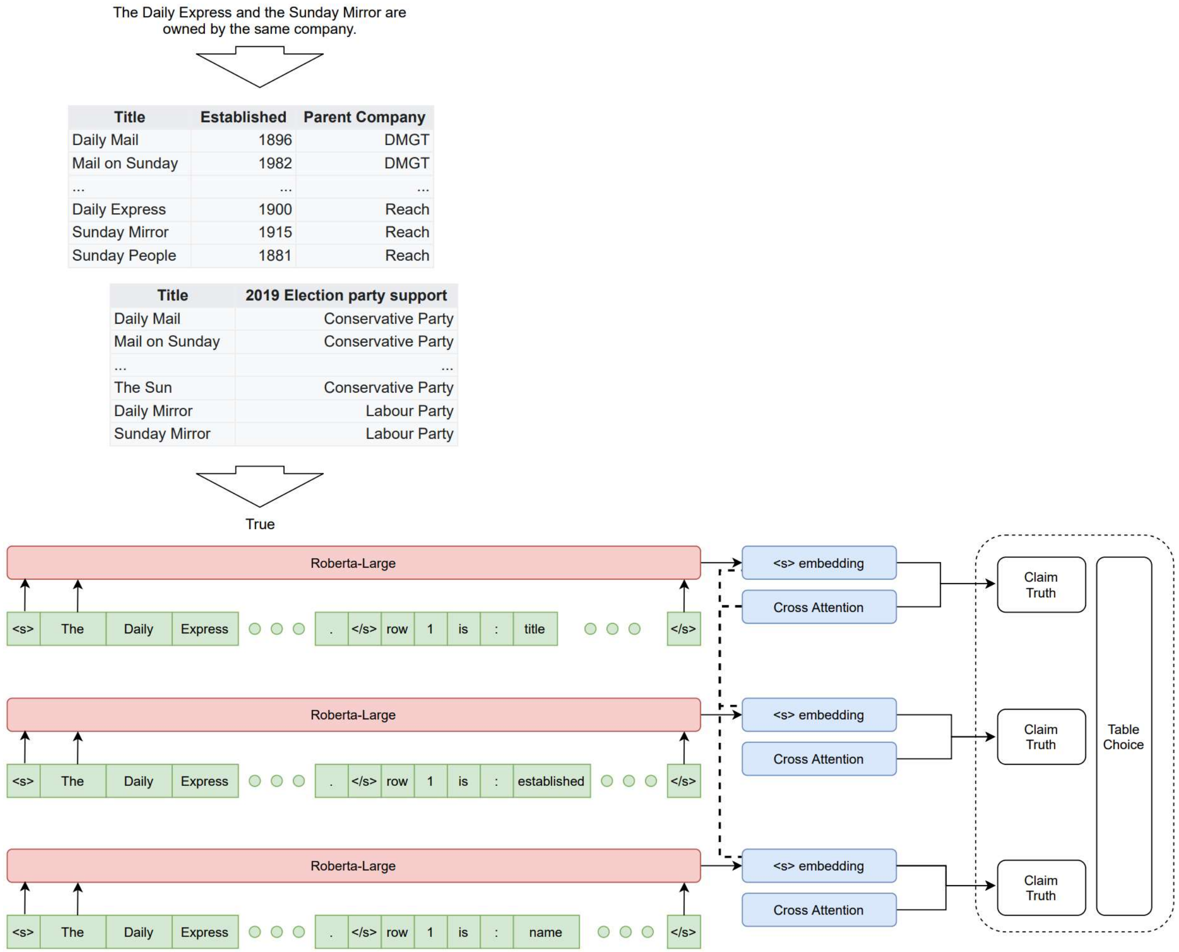
$$score(q,t) = \sum_{i=1}^{n} \max_{j=1}^{m} z(e_q^i)^\intercal \cdot z(c_t^j)$$

  Verification

$$\alpha_{ij}^h = \sigma\left(\frac{W_Q^h f(d_q^i)(W_K^h f(d_q^j))^T}{\sqrt{dim(K)}}\right)$$

$$A_i^h = \sum_{j \in D_q} \alpha_{ij} W_V^h f(d_q^j)$$

$$f^*(d_q^k) = [f(d_q^k), A_i^1, ..., A_i^h]$$



Title	Established	Parent Company
Daily Mail	1896	DMGT
Mail on Sunday	1982	DMGT
...	...	...
Daily Express	1900	Reach
Sunday Mirror	1915	Reach
Sunday People	1881	Reach

Title	2019 Election party support
Daily Mail	Conservative Party
Mail on Sunday	Conservative Party
...	...
The Sun	Conservative Party
Daily Mirror	Labour Party
Sunday Mirror	Labour Party

Joint Verification and Reranking for Open Fact Checking Over Tables (ACL-IJCNLP 2021)

- 模型

Joint Reranking and Verification

$$p(s, v|q, D_q) = \sigma(W(F^*(D_q)_s)_v)$$

$$p_v(v|q, D_q) = \sum_{t \in D_q} p(v, s = t|q, D_q)$$

$$p_s(s|q, D_q) = \sum_{v_q \in \{true, false\}} p(s, v = v_q|q, D_q)$$

Ternary Verification

$$p(i|q, t, D_q) = \sigma(W'(F^*(D_q)_t)_i)$$

$$\sum_{t \in D_q} p(i = true|q, t) > \sum_{t \in D_q} p(i = false|q, t)$$

- 效果

Model	Dev	Test	Simple Test	Complex Test	Small Test
Table-BERT (Chen et al., 2020b)	66.1	65.1	79.1	58.2	68.1
LogicalFactChecker (Zhong et al., 2020)	71.8	71.7	85.4	65.1	74.3
ProgVGAT (Yang et al., 2020)	74.9	74.4	88.3	67.6	76.2
TAPAS (Eisenschlos et al., 2020)*	81.0	81.0	92.3	75.6	83.9
Ours (Oracle retrieval)	78.2	77.6	88.9	72.1	79.4
Ours (1 retrieved table)	74.1	73.2	86.7	67.8	76.6
Ours (Ternary loss, 3 tables)	73.8	73.5	86.9	68.1	76.9
Ours (Ternary loss, 5 tables)	74.1	73.7	87.1	67.9	76.5
Ours (Ternary loss, 10 tables)	73.9	73.1	86.5	67.9	77.3
Ours (Joint loss, 3 tables)	74.6	73.8	87.0	68.3	78.1
Ours (Joint loss, 5 tables)	**75.9**	**75.1**	**87.8**	**69.5**	**77.8**
Ours (Joint loss, 10 tables)	73.9	73.8	86.9	68.1	76.9

总结

- **编码**
  不使用预训练模型：融合关键词、位置信息
  使用预训练模型：文本线性化、修改模型
- **推理**
  视下游任务而定
- **新问题**
  开放世界表格处理
  数据筛选
- **未来方向**
  异构数据编码 ✓
  跨表编码/多表任务 ？
  单元格为单位过滤 ？