Numerical Tuple Extraction from Tables with Pre-training

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Background

- A tremendous amount of important data is stored in tables from the Web or vertical domains.
- However, these data are difficult to understand and apply to downstream tasks.
 - Reason: tables project high-dimensional data to twodimensional layouts by leveraging visual grammar, which brings substantial flexibility to the table layouts.
- Most tools or models for tables only handle relational tables.
 - Converting arbitrary tables into relational data requires a massive investment in table layouts and specific scripts.

	A	В	С
1			2019
2		Assets	Changes from the Previous Year (%)
3	Current	21,614	12.4
4	Inventories	16,883	18.1
5	Cash and cash equivalents	4,731	-4.2
6	Non-current	2,341	5.0
7	Trade and other receivables	921	17.9
8	Inventories	1,420	1.2
9	Total	23,955	11.8



Background

- A critical step to understanding data in tables is extracting numerical data.
 - Numerical tuple consists a value and several descriptions
- A table can be parsed into a set of numerical tuples with a relational format.
- For example, the meaning of cell C4: "Compared from the previous year, the change of inventory in current assets for 2019 is 18.1%."

• TASK: Numerical Tuple Extraction (NTE) from Tables.

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Numerical Tuples:



Background



The process of NTE can be imaged as an inverse process of table making.







• The relationships between cell

- Hierarchy
- Juxtaposition

		A	В	С	
	1			2019	
Left hierarchy				Changes from	
tree	2		Assets	the Previous	(B2) (C2)
				Year (%)	\cup \cup
A3	3	Current	21,614	12.4	Top hierarchy
A4)	4	Inventories	16,883	18.1	lice
A5	5	Cash and cash equivalents	4,731	-4.2	
(A6)	6	Non-current	2,341	5.0	
A7	7	Trade and other receivables	921	17.9	
A8	8	Inventories	1,420	1.2	
A9	9	Total	23,955	11.8	

(a) Top and Left Hierarchy Trees

		Juxtaposition Continuity	B1	C1	→D1	E1	→ F1	
Ι		А	В	С	D	E	F	
	1		Accounts Receivable	In Credit Period	Rate	Outside Credit Period	Rate	
Î	2	2015/12/31	9,549.48	8,063.10	84.43	1,393.38	14.59	
	3	2016/12/31	9,348.04	8,602.26	92.02	621.96	6.65	
	4	2016/12/31	13,332.10	11,485.92	86.15	1,823.05	13.67	
	5	2018/06/30	9,515.41	7,442.60	78.21	2,072.81	21.78	
	14.59 (2015/12/31) Accounts Receivable Outside Credit Period Rate							

(b) Juxtaposition of Cells



- Previous methods for NTE:
 - First inferring the hierarchical tree of table headers and then constructing a numerical tuple from that tree [1, 2].
 - Transforming spreadsheet data using some examples provided by users [3, 4].
- There are three limitations:
 - Do not consider the *juxtaposition* between cells.
 - Require algorithm-human interaction or rule sets made by domain experts
 - Only evaluate their systems on small corpora that have up to 200 tables.

^[1] Automatic web spreadsheet data extraction. International Workshop on Semantic Search over the Web. 2013.

^[2] Rule-based spreadsheet data transformation from arbitrary to relational tables. 2017.

^[3] FlashRelate: extracting relational data from semi-structured spreadsheets using examples. ACM SIGPLAN Notices. 2015.

^[4] Foofah: Transforming Data By Example. SIGMOD. 2017.



- We propose a new framework and evaluate it on a large test set.
 - Convert NTE task into a binary relation extraction task.
 - Encode each cell into a hidden vector by a table representation model.
 - Aggregate vectors in each candidate pair to obtain their predicting result.

- The crucial question is how to represent a cell.
 - TableLM, a BERT-based pre-trained language model.
 - Multi-modal.
 - Work on arbitrary types of tables.
 - Remove numerical values.
 - Pre-trained with contrastive learning.





- Numerical cell set T_{v}
- Non-numerical cell set T_s
- Numerical Tuple

$$r = (v, D)$$
$$v \in T_v, D = \{d_i | 1 \le i \le K, d_i \in T_s\}$$



- Problem Conversion
 - A tuple are converted into several pairs.
 - The task is converted into a problem of relation extraction between cells.







Overview







• Embeddings



Visual representation of cells





• Transformer with Tabular Masked Attention

attention(Q, K, V) = softmax(
$$\frac{QK^T}{\sqrt{d}}M$$
)V

- *M* is the tabular visibility matrix
 - $M_{i,j} = 1$, if token_i and token_j are in the same row or column.
- Cell Representations
 - Non-numerical cells

$$H_{i,j} = \text{LayerNorm}([\text{SEP}]_{i,j} + V_{i,j})$$

- Numerical cells
 - Numerical Attention





- Loss functions:
 - Masked Language Model Loss
 - Cell Contrastive Loss
 - Mask whole cell randomly and get their own semantic representation.





- Dataset
 - FinTab-Tuples,
 - 19,264 tables from Chinese financial documents crawled from CNINFO [5]
 - Tables in finance are data-intensive.
 - FinTab-Tuples-CT (Complex Table)
 - Complex tuple: contains a description that is not in the same row or column as the value of the tuple.
 - Complex Table: contains at least one complex tuple.
 - Dataset for pre-training
 - FinFormulas [6]
 - 190,179 tables from 4,746 Chinese financial documents.

Table 1: Statistic of FinTab-Tuples

# tables	19,264
# complex tables	8,906
# labeled tuples	604,111
# labeled complex tuples	191,344
Avg. % numerical cells per table	63.29%
Avg. % tuples in cells per table	58.19%
Avg. % complex tuples in tuples per table	27.22%
Avg. % tuples in cells per complex table	60.01%
Avg. % complex tuples in tuples per complex table	58.90%
Avg. # rows per table	9.32
Avg. # columns per table	5.88



- Metric
 - F1-score at pair level.
 - F1-score at tuple level.
 - Table Level Accuracy.
- Baseline
 - TAFOR [6]
 - Encodes a table and produces hidden representations of its cells.



• Performance

Table 2: Results (%) of methods on two test sets. Here, Acc. is an abbreviation for accuracy, F1-P is the F1-score at pair level, F1-T is the F1-score at tuple level.

	FinTab-Tuples-T			FinTab-Tuples-CT		
	Acc.	F1-P	F1-T	Acc.	F1-P	F1-T
TAFOR	63.06	95.53	80.43	56.47	94.91	74.28
TableLM	71.44	96.99	85.63	63.58	96.20	79.44

Table 3: Ablation Results (%) on two test sets. Here Acc., F1-P, F1-T are the same as Table 2.

	Fin	FinTab-Tuples-T			FinTab-Tuples-CT		
	Acc.	F1-P	F1-T	Acc.	F1-P	F1-T	
TableLM	71.44	96.99	85.63	63.58	96.20	79.44	
w/o vision	n 54.34	95.25	77.17	55.53	94.30	71.52	
w/o CCL	66.49	96.51	83.54	64.58	95.66	78.34	
from scrat	ch 63.47	96.58	83.66	58.66	94.84	74.98	

