Bridging Between Tables and Human Languages
From Tables to Knowledge: Recent Advances in Table Understanding (Part IV)

Muhao Chen
Department of Computer Science / Information Sciences Institute
University of Southern California
How Do Table Understanding Interface with Natural Language Understanding?
Table Understanding and NLU Are Related

Searching for an entity at Google.

Attributes in a compact table

Experimental result table(s)

Result discussions

Reading about experiments in a scientific paper.

Tables and text: two views of information, complementary sources of knowledge

From Tables to Knowledge (KDD21): Pujara, Szekely, Sun, Chen
Natural Language Interfaces to Tabular Content

Connecting tables and NL lead to a flexible and user-friendly way of accessing tabular content.

The best-selling video game?

A wii game by Nintendo.

Semantic retrieval of tables

Retrieving cell content

Generating summarizations for tables

Table showing the growing revenue of Zoom.
The best-selling video game of all time is **Minecraft.**

The best-selling video game of all time is **Tetris.**

**Tables as evidence for natural language claim verification**

**Tables as reference for answering questions**

<table>
<thead>
<tr>
<th>Year</th>
<th>City</th>
<th>Country</th>
<th>Nations</th>
</tr>
</thead>
<tbody>
<tr>
<td>1896</td>
<td>Athens</td>
<td>Greece</td>
<td>14</td>
</tr>
<tr>
<td>1900</td>
<td>Paris</td>
<td>France</td>
<td>24</td>
</tr>
<tr>
<td>1904</td>
<td>St. Louis</td>
<td>USA</td>
<td>12</td>
</tr>
<tr>
<td>2004</td>
<td>Athens</td>
<td>Greece</td>
<td>201</td>
</tr>
<tr>
<td>2008</td>
<td>Beijing</td>
<td>China</td>
<td>204</td>
</tr>
<tr>
<td>2012</td>
<td>London</td>
<td>UK</td>
<td>204</td>
</tr>
</tbody>
</table>

$x_1$: “Greece held its last Summer Olympics in which year?”
$y_1$: {2004}

$x_2$: “In which city’s the first time with at least 20 nations?”
$y_2$: {Paris}

$x_3$: “Which years have the most participating countries?”
$y_3$: {2008, 2012}

$x_4$: “How many events were in Athens, Greece?”
$y_4$: {2}

$x_5$: “How many more participants were there in 1900 than in the first year?”
$y_5$: {10}
Common Challenges for Connecting Tables and Natural Language

Handling heterogeneous structures

- Weak connections between tables and text
  - Precise alignment rarely exists

- Capturing multi-granular content
  - Changes of earnings and taxes?
  - Dependent children tax allowances?

Gameloft

Gameloft is a French video game publisher based in Paris, founded in December 1999 by Ubisoft co-founder Michel Guillemot. The company operates 19 development studios worldwide, and publishes games with a special focus on the mobile games market.

From Wikipedia, the free encyclopedia

Gameloft is a French video game publisher based in Paris, founded in December 1999 by Ubisoft co-founder Michel Guillemot. The company operates 19 development studios worldwide, and publishes games with a special focus on the mobile games market. Previously a public company traded at the Paris Bourse, Gameloft was acquired by media conglomerate Vivendi in 2016.

Table 1: Data from Gameloft

<table>
<thead>
<tr>
<th>Country</th>
<th>United States</th>
</tr>
</thead>
<tbody>
<tr>
<td>State</td>
<td>California</td>
</tr>
<tr>
<td>County</td>
<td>Los Angeles</td>
</tr>
<tr>
<td>Region</td>
<td>South California</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Right-handed</th>
<th>Left-handed</th>
</tr>
</thead>
<tbody>
<tr>
<td>Males</td>
<td>43</td>
</tr>
<tr>
<td>Females</td>
<td>44</td>
</tr>
<tr>
<td>Totals</td>
<td>87</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Lake</th>
<th>Area</th>
</tr>
</thead>
<tbody>
<tr>
<td>Windermere</td>
<td>5.69 sq mi</td>
</tr>
<tr>
<td>Ullswater</td>
<td>3.86 sq mi</td>
</tr>
<tr>
<td>Derwent Water</td>
<td>2.06 sq mi</td>
</tr>
</tbody>
</table>

From Tables to Knowledge (KDD21): Pujara, Szekely, Sun, Chen
Minecraft is the best-selling game. (✓/✗)

Singapore Cup

<table>
<thead>
<tr>
<th>Year</th>
<th>Champions</th>
<th>Runners-up</th>
</tr>
</thead>
<tbody>
<tr>
<td>1996</td>
<td>Geylang United</td>
<td>Singapore Armed Forces</td>
</tr>
<tr>
<td>1997</td>
<td>Singapore Armed Forces</td>
<td>Woodlands Wellington</td>
</tr>
<tr>
<td>1998</td>
<td>Tanjong Pagar United</td>
<td>Sembawang Rangers</td>
</tr>
</tbody>
</table>

Singapore Armed forces was the champion of Singapore Cup in 1997.
Agenda

1. Representation Learning for Tables + Language

2. Natural Language Interface for Tabular Content

<table>
<thead>
<tr>
<th>Attribute</th>
<th>Year</th>
<th>Champions</th>
<th>Runners-up</th>
</tr>
</thead>
<tbody>
<tr>
<td>Cell</td>
<td>1996</td>
<td>Geylang United</td>
<td>Singapore Armed Forces</td>
</tr>
<tr>
<td></td>
<td>1997</td>
<td>Singapore Armed Forces</td>
<td>Woodlands Wellington</td>
</tr>
<tr>
<td></td>
<td>1998</td>
<td>Tanjong Pagar United</td>
<td>Sembawang Rangers</td>
</tr>
</tbody>
</table>

3. Table-assisted Natural Language Understanding

Minecraft is the best-selling game. (√/✗)

4. Open Research Directions
The backbone of NL interfaces to tables and table-assisted NLU

Goal

Relevance between NL and tabular content

Joint (latent) representation

Challenges

- Precise table-text alignment rarely exists.
- Tabular content is presented in different granularities (cells, rows, cols, etc.)
- Linear text vs. structured tables
TaBERT: Joint Language Modeling for Tables and Text

1. Coarse-grained table-text association

- \(\times 2.6\text{M from Wikipedia and WDC Web Tables}\)
- surrounding text

- Coarse-grained association

\[
\begin{array}{|c|c|c|c|}
\hline
\text{Year} & \text{Venue} & \text{Position} & \text{Event} \\
\hline
R_1 & 2003 & Tampere & 3rd & EU Junior Championship \\
R_2 & 2005 & Erfurt & 1st & EU U23 Championship \\
R_3 & 2005 & Izmir & 1st & Universiade \\
R_4 & 2006 & Bangkok & 1st & Universiade \\
R_5 & 2007 & Moscow & 2nd & World Indoor Championship \\
\hline
\end{array}
\]

- Top K rows based on n-gram overlapping with the text utterance (\(n \leq 3\))

2. BERT-based encoding with three pre-training tasks

- pre-training objectives
  - Masked Language Modeling (MLM) objective
  - Masked Column Prediction: recovering column names and data types
  - Cell Value Recovery

- Transformer (BERT)

\[
R_2 \ [CLS] \ \text{In which city did Piotr's...} \ [SEP] \ \text{Year} \ | \ \text{real} \ | \ 2005 \ [SEP] \ \text{Venue} \ | \ \text{text} \ | \ \text{Erfurt} \ [SEP] \ \text{Position} \ | \ \text{text} \ | \ 1st \ [SEP] \ ...
\]

- Row linearization: a sequence of (column name, data type, value) tuples

Yin, et al. TaBERT: Pretraining for Joint Understanding of Textual and Tabular Data. ACL-20

https://github.com/facebookresearch/TaBERT

From Tables to Knowledge (KDD21): Pujara, Szekely, Sun, Chen
TaPas: Weakly-supervised Table Question Answering

1. Pretraining

- **6.2M Tables**: 3.3M infoboxes and 2.9M WikiTables
- Table captions, article titles, article descriptions, segment titles and surround segment text

2. Fine-tuning

WIKITQ (Pasupat+ ACL-15)
SQA (Iyyer+ ACL-17)
WikiSQL (Zhong+ 2017)

MLM Pretraining on BERT

Text
Flattened table

TaPas offers SOTA performance as the backbone model of table-based NLI tasks.

Herzig, et al. TaPas: Weakly Supervised Table Parsing via Pre-training. ACL-20
Eisenschlos, et al. Understanding tables with intermediate pre-training. Findings of EMNLP-20
https://github.com/google-research/tapas
From Tables to Knowledge (KDD21): Pujara, Szekely, Sun, Chen

Graph Representation Learning for Complex Tables

What if tables have complex structures?

Complex tables

Cell adjacency graph

Graph representation learning (e.g. Graph Transformer)

Graph-text matching

Comparing to language models

Pros:
- Can handle arbitrary table layout structures
- Can easily summarize multi-granular contents (with global nodes)

Con:
- Weaker table-text association (semantic shifts between feature spaces of the LM and the graph encoder)

Zhang, et al. A Graph Representation of Semi-structured Data for Web Question Answering. COLING-20
Wang, et al. Retrieving Complex Tables with Multi-Granular Graph Representation Learning. SIGIR-21
Agenda

1. Representation Learning for Tables + Language

2. Natural Language Interface for Tabular Content

<table>
<thead>
<tr>
<th>Attribute</th>
<th>Year</th>
<th>Champions</th>
<th>Runners-up</th>
</tr>
</thead>
<tbody>
<tr>
<td>Cell</td>
<td>1996</td>
<td>Geylang United</td>
<td>Singapore Armed Forces</td>
</tr>
<tr>
<td>Cell</td>
<td>1997</td>
<td>Singapore Armed Forces</td>
<td>Woodlands Wellington</td>
</tr>
<tr>
<td>Cell</td>
<td>1998</td>
<td>Tanjong Pagar United</td>
<td>Sembawang Rangers</td>
</tr>
</tbody>
</table>

Text: Singapore Armed forces was the champion of Singapore Cup in 1997.

3. Table-assisted Natural Language Understanding

Minecraft is the best-selling game. (√/X)

4. Open Research Directions
1. Using natural language to retrieve the tabular content

The best-selling video game?

<table>
<thead>
<tr>
<th>Rank</th>
<th>Title</th>
<th>Sales</th>
<th>Platform</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Advance</td>
<td>290,000,000</td>
<td>Multi-platform</td>
</tr>
<tr>
<td>2</td>
<td>Grand Theft Auto V</td>
<td>185,000,000</td>
<td>Multi-platform</td>
</tr>
<tr>
<td>3</td>
<td>Tekken (PS4)</td>
<td>120,000,000</td>
<td>PS4</td>
</tr>
<tr>
<td>4</td>
<td>We Spoke</td>
<td>92,900,000</td>
<td>Vita</td>
</tr>
<tr>
<td>5</td>
<td>PlayerUnknown's Battlegrounds</td>
<td>76,000,000</td>
<td>Multi-platform</td>
</tr>
<tr>
<td>6</td>
<td>Super Mario Bros.</td>
<td>48,340,000</td>
<td>Wii</td>
</tr>
<tr>
<td>7</td>
<td>Pokemon Red/Green/Sword/Shield</td>
<td>47,320,000</td>
<td>Multi-platform</td>
</tr>
</tbody>
</table>

2. Describing tabular content with natural language

Caption: Singapore Cup

<table>
<thead>
<tr>
<th>Attribute</th>
<th>Year</th>
<th>Champions</th>
<th>Runners-up</th>
</tr>
</thead>
<tbody>
<tr>
<td>Cell</td>
<td>1996</td>
<td>Geylang United</td>
<td>Singapore Armed Forces</td>
</tr>
<tr>
<td></td>
<td>1997</td>
<td>Singapore Armed Forces</td>
<td>Woodlands Wellington</td>
</tr>
<tr>
<td></td>
<td>1998</td>
<td>Tanjong Pagar United</td>
<td>Sembawang Rangers</td>
</tr>
</tbody>
</table>

Text: Singapore Armed forces was the champion of Singapore Cup in 1997.
Semantic Table Retrieval

Input:
○ A natural language query
○ A set of tables, where each table consists of:
  ■ table body (headers, data cells, etc.)
  ■ context (captions, footnotes, etc.)

Output:
○ A ranked list of semantically relevant tables

Changes of taxes in U.S.?

Taxing wages in the United States

<table>
<thead>
<tr>
<th>Indicator</th>
<th>2000</th>
<th>2001</th>
</tr>
</thead>
<tbody>
<tr>
<td>Standard tax allowances</td>
<td>7200</td>
<td>7200</td>
</tr>
<tr>
<td>Basic</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Dependent children</td>
<td>0</td>
<td>0</td>
</tr>
</tbody>
</table>

Olympic Games Host Cities

<table>
<thead>
<tr>
<th>City</th>
<th>Country</th>
<th>Year</th>
<th>Continent</th>
</tr>
</thead>
<tbody>
<tr>
<td>Los Angeles</td>
<td>U.S.</td>
<td>2028</td>
<td>North America</td>
</tr>
<tr>
<td>Milan–Cortina d'Ampezzo</td>
<td>Italy</td>
<td>2026</td>
<td>Europe</td>
</tr>
<tr>
<td>Paris</td>
<td>France</td>
<td>2024</td>
<td></td>
</tr>
<tr>
<td>Beijing</td>
<td>China</td>
<td>2022</td>
<td>Asia</td>
</tr>
</tbody>
</table>
Semantic Table Retrieval

Earlier methods

Lexical matching
- **Multi-field doc ranking**: Pimplikar and Sarawagi. 2012. Answering table queries on the web using column keywords. PVLDB-12
- **Lexical Table Retrieval**: Zhang and Balog: Ad hoc table retrieval using semantic similarity. WWW-18

Feature engineering / statistical machine learning
- **Linear regression**: Cafarella et al. Data integration for the relational web. PVLDB-09
- **Tab-Lasso**: Bhagavatula, et al. Methods for exploring and mining tables on wikipedia. KDD-13

Recent language models offer more precise and generalizable retrieval

**BERT4TR**
- Using BERT to match between queries and linearized tables
- Chen, et al. Table Search Using a Deep Contextualized Language Model. SIGIR-20

**TaBERT** offers even better performance
Semantic Table Retrieval

More challenges: Complex tables and diverse query intents

Various layout structures

(a) Relational table

(b) Entity table

(c) Matrix table

(d) Nested table

Diverse query intents

From Tables to Knowledge (KDD21): Pujara, Szekely, Sun, Chen

Wang, et al. Retrieving Complex Tables with Multi-Granular Graph Representation Learning. SIGIR, 2021
Semantic Table Retrieval

Arbitrary table layouts
- Changes of earnings and taxes?
- Dependent children tax allowances?

Multi-granular tabular graph
- Cell node adjacency
- Row-/Col- node summarization

Model Architecture

Wang, et al. Retrieving Complex Tables with Multi-Granular Graph Representation Learning. SIGIR, 2021
Semantic Table Retrieval

Pre-trained Graph Transformer (GTR)

Results on WikiTables

<table>
<thead>
<tr>
<th>Method</th>
<th>NDCG@5</th>
<th>NDCG@10</th>
<th>NDCG@15</th>
<th>NDCG@20</th>
<th>MAP</th>
</tr>
</thead>
<tbody>
<tr>
<td>BM25</td>
<td>0.3196</td>
<td>0.3377</td>
<td>0.3732</td>
<td>0.4045</td>
<td>0.4260</td>
</tr>
<tr>
<td>WebTable</td>
<td>0.2980</td>
<td>0.3150</td>
<td>0.3486</td>
<td>0.3922</td>
<td>-</td>
</tr>
<tr>
<td>SDR</td>
<td>0.4573</td>
<td>0.4841</td>
<td>0.5195</td>
<td>0.5534</td>
<td>-</td>
</tr>
<tr>
<td>MDR</td>
<td>0.5021</td>
<td>0.5116</td>
<td>0.5451</td>
<td>0.5761</td>
<td>-</td>
</tr>
<tr>
<td>Tab-Lasso</td>
<td>0.5161</td>
<td>0.5018</td>
<td>0.5330</td>
<td>0.5481</td>
<td>-</td>
</tr>
<tr>
<td>LTR</td>
<td>0.5910</td>
<td>0.5712</td>
<td>0.5858</td>
<td>0.6041</td>
<td>0.5615</td>
</tr>
<tr>
<td>TaBERT</td>
<td>0.5926</td>
<td>0.6108</td>
<td>0.6451</td>
<td>0.6668</td>
<td>0.6326</td>
</tr>
<tr>
<td>BERT4TR</td>
<td>0.6052</td>
<td>0.6171</td>
<td>0.6386</td>
<td>0.6689</td>
<td>0.6191</td>
</tr>
<tr>
<td>GTR (w/o pre-training)</td>
<td>0.6554</td>
<td>0.6747</td>
<td>0.6978</td>
<td>0.7211</td>
<td>0.6665</td>
</tr>
<tr>
<td>GTR</td>
<td>0.6671</td>
<td>0.6856</td>
<td>0.7065</td>
<td>0.7272</td>
<td>0.6859</td>
</tr>
</tbody>
</table>

Graph Transformer vs. Linear Language Models

- >8% relative improvement on all metrics
- better than BERT-based methods even w/o pre-training

Wang, et al. Retrieving Complex Tables with Multi-Granular Graph Representation Learning. SIGIR, 2021
Table-to-text Generation

Generating NL descriptions to summarize tabular content
- WIKIBIO dataset [Lebret+ EMNLP-16]: surface-level NLG.
- Logical NLG dataset [Chen+ ACL-20]

The emerging challenge: describing logical comparison

<table>
<thead>
<tr>
<th>Nation</th>
<th>Gold Medal</th>
<th>Silver Medal</th>
<th>Bronze Medal</th>
<th>Sports</th>
</tr>
</thead>
<tbody>
<tr>
<td>Canada</td>
<td>3</td>
<td>1</td>
<td>2</td>
<td>Ice Hockey</td>
</tr>
<tr>
<td>Mexico</td>
<td>2</td>
<td>3</td>
<td>1</td>
<td>Baseball</td>
</tr>
<tr>
<td>Colombia</td>
<td>1</td>
<td>3</td>
<td>0</td>
<td>Roller Skating</td>
</tr>
</tbody>
</table>

Surface-level Generation
- Sentence: Canada has got 3 gold medals in the tournament.
- Sentence: Mexico got 3 silver medals and 1 bronze medal.

Logical Natural Language Generation
- Sentence: Canada obtained 1 more gold medal than Mexico.
- Sentence: Canada obtained the most gold medals in the game.
Table-to-text Generation

**GPT-TabGen [Chen+ ACL-20]**
1. Generating a per-row (intermediate) description based on a <col name, value> template.
2. Summarize the intermediate description: fulfilling a summary template with GPT-2

Existing models can only achieve 20% logical correctness (according to Chen+ ACL-20)!

Lebret, et al. Neural Text Generation from Structured Data with Application to the Biography Domain. EMNLP-16
Chen et al. Logical Natural Language Generation from Open-Domain Tables. ACL-20
Controlled Table-to-text Generation

Summarizing facts only based on several highlighted cells

- The ToTTo dataset: 121,000 training examples; 7,500 examples each for development and test.

**The challenge:** overgeneration (missing descriptions) and under generation (unexpected descriptions).

- **BART(sub-table):** Bill Dooley served as the head coach at North Carolina from 1967 to 1974 and at Virginia Tech from 1974 to 1992.
- **BART(full-table):** Bill Dooley served as the head coach at North Carolina from 1967 to 1989 and at Virginia Tech from 1990 to 2005, compiling a career coaching record of 201–151–10.

An open question: graph representation learning as prior?

Parikh,, et al. ToTTo: A Controlled Table-To-Text Generation Dataset. EMNLP-20
From Tables to Knowledge (KDD21): Pujara, Szekely, Sun, Chen

Agenda

1. Representation Learning for Tables + Language

2. Natural Language Interface for Tabular Content

<table>
<thead>
<tr>
<th>Attribute</th>
<th>Year</th>
<th>Champions</th>
<th>Runners-up</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>1996</td>
<td>Geylang United</td>
<td>Singapore Armed Forces</td>
</tr>
<tr>
<td></td>
<td>1997</td>
<td>Singapore Armed Forces</td>
<td>Woodlands Wellington</td>
</tr>
<tr>
<td></td>
<td>1998</td>
<td>Tanjong Pagar United</td>
<td>Sembawang Rangers</td>
</tr>
</tbody>
</table>

3. Table-assisted Natural Language Understanding

4. Open Research Directions

Minecraft is the best-selling game. (✓/✗)
**Table-assisted Natural Language Understanding**

1. Web tables as trustworthy evidence for verifying claims
   - The best-selling video game of all time is **Minecraft**. ✅
   - The best-selling video game of all time is **Tetris**. ❌

2. Web tables as clean references for answering questions
   - x = Greece held its last Summer Olympics in which year? **2004**.

---

**From Tables to Knowledge (KDD21): Pujara, Szekely, Sun, Chen**
The TabFact dataset: 16k Wikipedia tables as evidence for verifying 118k human annotated statements

United States House of Representatives Elections, 1972

<table>
<thead>
<tr>
<th>District</th>
<th>Incumbent</th>
<th>Party</th>
<th>Result</th>
<th>Candidates</th>
</tr>
</thead>
<tbody>
<tr>
<td>California 3</td>
<td>John E. Moss</td>
<td>democratic</td>
<td>re-elected</td>
<td>John E. Moss (d) 69.9% John Rakus (r) 30.1%</td>
</tr>
<tr>
<td>California 5</td>
<td>Phillip Burton</td>
<td>democratic</td>
<td>re-elected</td>
<td>Phillip Burton (d) 81.8% Edlo E. Powell (r) 18.2%</td>
</tr>
<tr>
<td>California 8</td>
<td>George Paul Miller</td>
<td>democratic</td>
<td>lost renomination democratic hold</td>
<td>Pete Stark (d) 52.9% Lew M. Warden , Jr. (r) 47.1%</td>
</tr>
<tr>
<td>California 14</td>
<td>Jerome R. Waldie</td>
<td>republican</td>
<td>re-elected</td>
<td>Jerome R. Waldie (d) 77.6% Floyd E. Sims (r) 22.4%</td>
</tr>
<tr>
<td>California 15</td>
<td>John J. Mcfall</td>
<td>republican</td>
<td>re-elected</td>
<td>John J. Mcfall (d) unopposed</td>
</tr>
</tbody>
</table>

Entailed Statement
1. John E. Moss and Phillip Burton are both re-elected in the house of representative election.
2. John J. Mcfall is unopposed during the re-election.
3. There are three different incumbents from democratic.

Refuted Statement
1. John E. Moss and George Paul Miller are both re-elected in the house of representative election.
2. John J. Mcfall failed to be re-elected though being unopposed.
3. There are five candidates in total, two of them are democrats and three of them are republicans.

1. Table retrieval: finding evidence table(s)
2. NLI: textual entailment using the table as premise and the statement as hypothesis
Table-based Fact Verification

**Logical program based approach:** learn to parse NL statements into logical programs, and execute the program on tables

<table>
<thead>
<tr>
<th>Year</th>
<th>Tournaments Played</th>
<th>Avg. Score</th>
<th>Scoring Rank</th>
</tr>
</thead>
<tbody>
<tr>
<td>2007</td>
<td>22</td>
<td>72.46</td>
<td>81</td>
</tr>
<tr>
<td>2008</td>
<td>29</td>
<td>71.65</td>
<td>22</td>
</tr>
<tr>
<td>2009</td>
<td>25</td>
<td>71.90</td>
<td>34</td>
</tr>
<tr>
<td>2010</td>
<td>18</td>
<td>73.42</td>
<td>92</td>
</tr>
<tr>
<td>2011</td>
<td>11</td>
<td>74.42</td>
<td>125</td>
</tr>
</tbody>
</table>

Zhong et al. LogicalFactChecker: Leveraging Logical Operations for Fact Checking with Graph Module Network. ACL-20

Yang et al. Program Enhanced Fact Verification with Verbalization and Graph Attention Network. EMNLP-20

Jointly learning for table retrieval and textual entailment.
Textual entailment seems to be the right direction. Table-assisted language modeling (TaPas) provides a strong solution.

Herzig, et al. TaPas: Weakly Supervised Table Parsing via Pre-training. ACL-20
**Table QA**

**Searching for table cells that answer natural language questions**

- **TabMCQ** [Jauhar+, ACL-16] and **WikiTableQuestions** [Pasupat and Liang, EMNLP-15]

**Chain representations**

- **TabMCQ**
- **WikiTableQuestions**

**Given:**

What languages do people in France speak?

<table>
<thead>
<tr>
<th>Country</th>
<th>Capital</th>
<th>Location</th>
<th>Main Language</th>
<th>Currency</th>
</tr>
</thead>
<tbody>
<tr>
<td>Algeria</td>
<td>Algiers</td>
<td>Africa</td>
<td>Arabic, French</td>
<td>Dinar</td>
</tr>
<tr>
<td>France</td>
<td>Paris</td>
<td>Europe</td>
<td>French</td>
<td>Euro</td>
</tr>
<tr>
<td>Hungary</td>
<td>Budapest</td>
<td>Europe</td>
<td>Hungarian</td>
<td>Forint</td>
</tr>
<tr>
<td>Singapore</td>
<td>Singapore</td>
<td>Asia</td>
<td>Malay, Chinese, Tamil</td>
<td>Dollar</td>
</tr>
</tbody>
</table>

**Goal:** to find a table cell containing answers.

**Answer**

French

**Evidence**

<table>
<thead>
<tr>
<th>Country</th>
<th>Main Language</th>
</tr>
</thead>
<tbody>
<tr>
<td>France</td>
<td>French</td>
</tr>
</tbody>
</table>

Source: http://hasibul.info/gk/countries.php

**Chain matching**

**Candidate Chain Collection**

1. Country --> Table
2. Country --> MainLanguage
3. ...

**Top-K Chains**

1. Country --> MainLanguage
2. Mainly spoken in -- language
3. ...

**Pruned Chain Collection**

1. Country --> Table
2. Country --> MainLanguage
3. ...

Sun, et al. Table Cell Search for Question Answering. WWW-16
Table QA

1. Coarse-grained table-text association

- **TaBERT [ACL-20]** + Weakly-supervised Semantic Parser (MAPO [Liang+ NIPS-18])
- Top K rows based on n-gram overlapping with the text utterance ($n \leq 3$)

2. TaBERT as encoder for parsing questions into symbolic forms

```
Table.contains(column=Position, value=1st)
.argmax(order_by=Year)
.hop(column=Venue)
```

# Get rows whose 'Position' field contains '1st'
# Get the row which has the largest 'Year' field
# Select the value of 'Venue' in the result row

51.8 testing accuracy on WIKITQ, one of the SOTA's
Answering questions based on complementary information in tables and documents:
- 13K Wiki Tables
- Hyperlinked paragraphs

Need to combine both TableQA and Doc QA

**Agenda**

1. Representation Learning for Tables + Language

2. Natural Language Interface for Tabular Content

3. Table-assisted Natural Language Understanding

4. Open Research Directions

---

From Tables to Knowledge (KDD21): Pujara, Szekely, Sun, Chen
Grounding text spans (in scientific literature) to corresponding tabular content

4.3 Ablation Study

We report an ablation study of EVA in Tab. 4 using DBP15k (FR→EN). As shown, IL brings ca. 8% absolute improvement. This gap is smaller than what has been reported previously (Sun et al. 2018). This is because the extra visual supervision in our method already allows the model to capture fairly good alignment in the first 500 epochs, leaving smaller room for further improvement from IL. CSLS gives little but consistent improvement to all metrics during inference.

### Automated Table Cleaning and Expansion

How to automatically query Web corpora, verify what are in the table and add what are not there?

**1. Answer-agnostic question generation**

- How many sales does Minecraft have?
- What are popular Nintendo Switch games?

<table>
<thead>
<tr>
<th>Rank</th>
<th>Title</th>
<th>Sales</th>
<th>Platform(s)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Minecraft</td>
<td>200,000,000</td>
<td>Multi-platform</td>
</tr>
<tr>
<td>2</td>
<td>Grand Theft Auto V</td>
<td>135,000,000</td>
<td>Multi-platform</td>
</tr>
<tr>
<td>3</td>
<td>Tetris (EA)</td>
<td>100,000,000</td>
<td>Mobile</td>
</tr>
<tr>
<td>4</td>
<td>Wii Sports</td>
<td>82,900,000</td>
<td>Wii</td>
</tr>
<tr>
<td>5</td>
<td>Player/Unknown's Battlegrounds</td>
<td>70,000,000</td>
<td>Multi-platform</td>
</tr>
<tr>
<td>6</td>
<td>Super Mario Bros</td>
<td>48,240,000</td>
<td>Multi-platform</td>
</tr>
<tr>
<td>7</td>
<td>Pokémon Red / Green / Blue / Yellow</td>
<td>47,520,000</td>
<td>Multi-platform</td>
</tr>
</tbody>
</table>

**2. Cleaning:** Open-domain QA + Claim verification

**3. Expansion:** Open-domain QA + Answer consolidation

From Tables to Knowledge (KDD21): Pujara, Szekely, Sun, Chen
From Tables to Knowledge (KDD21): Pujara, Szekely, Sun, Chen

**Table-assisted Dialogue Agent**

I want to reserve a table in Beverly Hills.

What type of food?

A popular steakhouse. But not too expensive.

How about Lawry’s the Prime Rib?

**Conversational Spreadsheet Editing**

- delete 6 rows from the beginning
- delete the left most two rows
- merge the cells from C1 to C3
- create line charts using data from B2 through D20
References

Yin, et al. TaBERT: Pretraining for Joint Understanding of Textual and Tabular Data. ACL-20
Herzig, et al. TaPas: Weakly Supervised Table Parsing via Pre-training. ACL-20
Eisenschlos, et al. Understanding tables with intermediate pre-training. Findings of EMNLP-20
Zhang, et al. A Graph Representation of Semi-structured Data for Web Question Answering. COLING-20
Wang, et al. Retrieving Complex Tables with Multi-Granular Graph Representation Learning. SIGIR-21
Chen, et al. Table Search Using a Deep Contextualized Language Model. SIGIR-20
Lebret, et al. Neural Text Generation from Structured Data with Application to the Biography Domain. EMNLP-16
Chen et al. Logical Natural Language Generation from Open-Domain Tables. ACL-20
Parikh,, et al. ToTTo: A Controlled Table-To-Text Generation Dataset. EMNLP-20
Chen et al. TabFact : A Large-scale Dataset for Table-based Fact Verification. ICLR-20
Schlichtkrull, et al. Joint Verification and Reranking for Open Fact Checking Over Tables. 2020
Zhong et al. LogicalFactChecker: Leveraging Logical Operations for Fact Checking with Graph Module Network. ACL-20
Yang et al. Program Enhanced Fact Verification with Verbalization and Graph Attention Network. EMNLP-20
Sun, et al. Table Cell Search for Question Answering. WWW-16
Iyyer, et al. Search-based neural structured learning for sequential question answering. ACL-17
Thank You