RECA: Related Tables Enhanced Column Semantic Type Annotation Framework

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Outline

- Background and Motivation
- Definitions
- Methodology
- Experiments
- Summary

- Accurate column semantic type annotation is important for various applications:
	- schema matching, data cleaning, data integration, etc.

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- Two challenges exist:
	- The proper handle of wide tables
	- The utilization of inter-table context

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	- The proper handle of wide tables
	- The utilization of inter-table context

• Tables with the same/similar named entity schemata tend to be from the same/similar data source and thus tend to have the same/similar column semantic types.

• W: Work of art; P: Person; D: Date; O: Organization

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2. Definitions - Concepts

- Named Entity Schema: Named Entity Schema is the table schema generated based on the most frequent named entity type extracted from each column.
- Related Tables: The tables that share the same named entity schema and are similar in content (Jaccard Similarity $> \delta$) with the original table.
- Sub-related Tables: The tables that share a similar named entity schema (the edit distance between their named entity schemata is less than a threshold) and are similar in content (Jaccard Similarity $> \delta$) with the original table.

2. Definitions - Problem

• (Column semantic type annotation): Given a web table T (without table headers) from the dataset *D,* denote the target column as \mathcal{C}_t in $T.$ The column semantic type annotation model *W* annotates C_t with a semantic type $\overline{y}_t = W$ (C_t, T, D) , such that \bar{y}_t best fits the semantics of C_t .

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3. Methodology - Named Entity Tagging

- Given a table T with M columns and N rows, we use the spaCy tagging tool to identify the named entities in each column and tag them.
- We further classify the DATE and PERSON types based on the data format.
	- E.g. DD-MM-YYYY; YYYY; January 16th 2022; 2023
	- E.g. J. K. Rowling; Anna
- We include an additional EMPTY type.
- The most frequent named entity type in each column forms the named entity schema.

3. Methodology - Table Filtering

• To filter out tables that are irrelevant in content, we compute the Jaccard similarity between the set of words for each table pair.

$$
\text{Jaccard}(A_i, A_j) = \frac{|A_i \cap A_j|}{|A_i \cup A_j|}
$$

• If Jaccard $(A_i, A_j) > \delta$, include T_j as a candidate table of T_i .

3. Methodology - Table Finding and Alignment

- Related tables: candidate tables T_j that share the same named entity schema as T_i .
- Sub-related tables: we consider the following two requirements:
	- Schema similarity: the named entity schemata should not be very different (edit distance less than a threshold).
	- Column location alignment: The named entity type of the target column matches with that of the column at the identical location in the sub-related table.

3. Methodology - Column Encoding

- The target column is encoded with BERT solely.
- The aligned columns in related tables and sub-related tables are encoded separately with BERT.
- The tokens are allocated fairly to each related table (or sub-related table).

3. Methodology - Classification

- The embeddings of the target column, related tables, and sub-related tables are passed to three corresponding classification modules.
- Each classification module contains two layers: dropout and linear layers.
- The generated output embeddings are combined with learnable weights:

$$
a_i^t = \alpha * \hat{v}_i^t + \beta * \hat{r}_i^t + \gamma * \hat{x}_i^t
$$

• We use the cross-entropy loss as the loss function.

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4. Experiments – Datasets and Metrics

• Datasets:

- Metrics:
	- Support-weighted F1: weighted support of per type F1 scores
	- Macro average F1: average of per type F1 scores (emphasize on long-tail types)

4. Experiments – Main Results

• RECA outperforms all the state-of-the-arts in terms of the F1 scores.

4. Experiments – Ablation Study

- We conducted ablation study on RECA:
	- RECA target only: only encode the target column
	- RECA w/o re: encode both target column and aligned columns in sub-related tables
	- RECA w/o sub: encode both target column and aligned columns in related tables
- Performance drops on macro average F1 scores are greater than that on support-weighted F1 scores – incorporating inter-table context can improve the annotation quality on less-populated semantic types.

4. Experiments - Learning and Input Data Utilization

• RECA is efficient in utilizing the learning data and the input data.

| Datasets | $\lceil \% \rceil$ | Support-weighted F1 | Macro average F1 |
|------------|--------------------|---------------------|-------------------|
| Semtab2019 | 25 | 0.697 ± 0.041 | 0.442 ± 0.074 |
| Semtab2019 | 50 | 0.792 ± 0.020 | 0.566 ± 0.045 |
| Semtab2019 | 75 | 0.820 ± 0.021 | 0.631 ± 0.047 |
| Semtab2019 | 100 | 0.853 ± 0.005 | 0.674 ± 0.007 |
| WebTables | 25 | 0.909 ± 0.002 | 0.680 ± 0.008 |
| WebTables | 50 | 0.924 ± 0.004 | 0.738 ± 0.019 |
| WebTables | 75 | 0.930 ± 0.002 | 0.772 ± 0.013 |
| WebTables | 100 | 0.937 ± 0.002 | 0.783 ± 0.014 |

Learning data utilization **Input data utilization** Input data utilization

| Datasets | Max | Support-weighted F1 | Macro average F1 |
|-----------------|-----|---------------------|-------------------|
| Semtab2019 | 8 | 0.540 ± 0.009 | 0.319 ± 0.010 |
| Semtab2019 | 16 | 0.654 ± 0.013 | 0.436 ± 0.006 |
| Semtab2019 | 32 | 0.728 ± 0.010 | 0.507 ± 0.020 |
| Semtab2019 | 128 | 0.816 ± 0.017 | 0.620 ± 0.033 |
| Semtab2019 | 256 | 0.851 ± 0.011 | 0.662 ± 0.024 |
| Semtab2019 | 512 | 0.853 ± 0.005 | 0.674 ± 0.007 |
| WebTables | 8 | 0.907 ± 0.004 | 0.737 ± 0.011 |
| WebTables | 16 | 0.923 ± 0.002 | 0.762 ± 0.011 |
| WebTables | 32 | 0.931 ± 0.002 | 0.780 ± 0.010 |
| WebTables | 128 | 0.937 ± 0.002 | 0.783 ± 0.014 |
| WebTables | 256 | 0.936 ± 0.003 | 0.783 ± 0.020 |
| WebTables | 512 | 0.936 ± 0.001 | 0.780 ± 0.011 |

4. Experiments – Parameter Sensitivity

• RECA achieves stable performance when the Jaccard threshold is in the range of [0, 0.3].

• S-SW and S-MA stand for the support-weighted and macro average F1 scores on the Semtab2019 dataset; W-SW and W-MA stand for the support-weighted and macro average F1 scores on the WebTables dataset.

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5. Summary

- We propose RECA for column semantic type annotation. RECA extracts and leverages inter-table context to enhance the annotation quality of the target column, thus resolving the wide table issue.
- We define a novel named entity schema for RECA to efficiently align related and sub-related tables, which resolves the difficulty of incorporating inter-table context.
- We conduct extensive experiments on two real-world web table datasets to show that RECA outperforms all the state-of-the-art methods. The result demonstrates the effectiveness of utilizing the inter-table context to annotate column semantic types accurately.
- We show that RECA is data efficient and learning efficient, since it requires shorter input token sequences and fewer training data to achieve high performance.