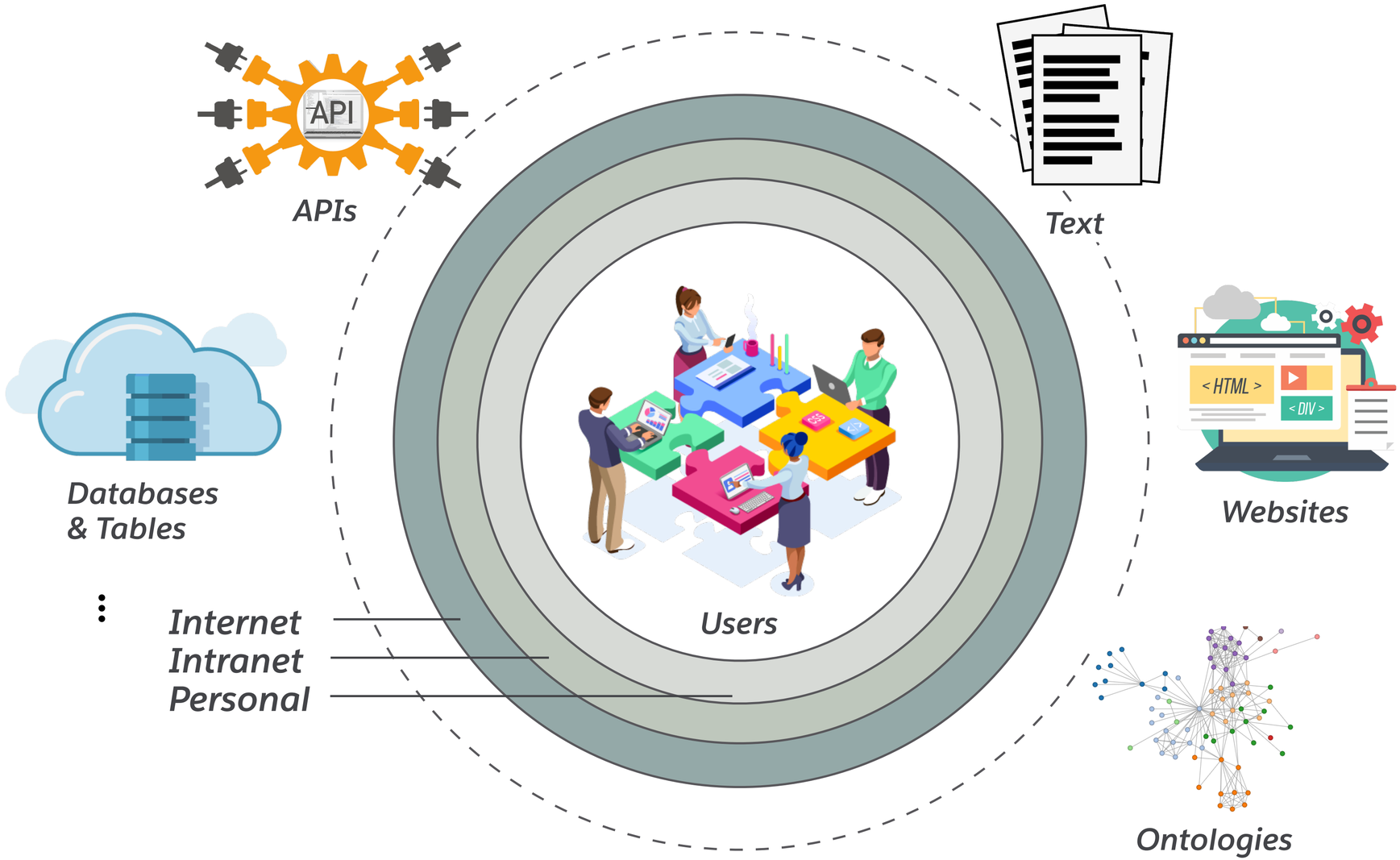
Bridging Textual and Tabular Data: Is Attention All We Need?

Invited Talk - KR2ML Workshop @NeurIPS'20

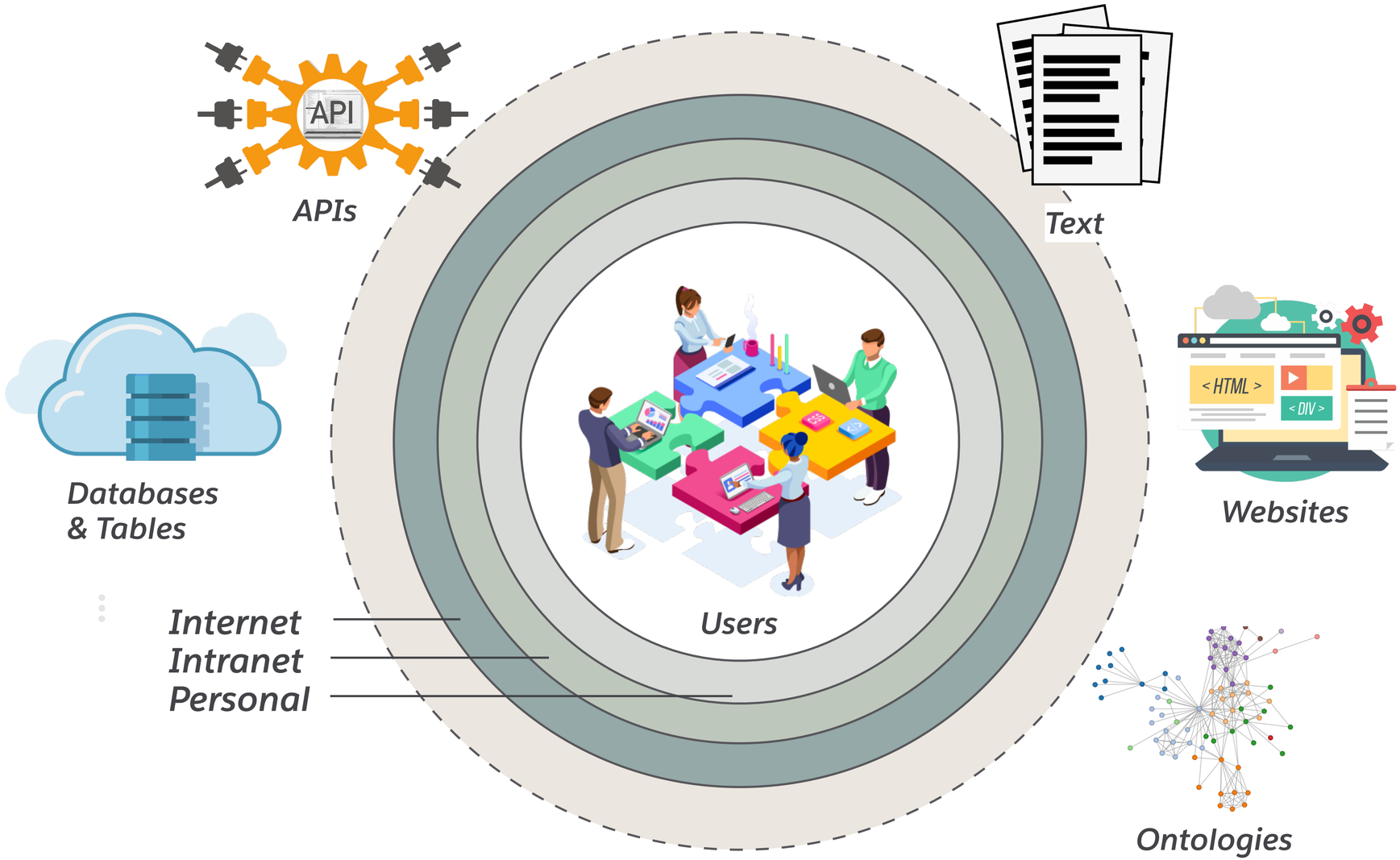
Victoria Lin

Salesforce AI Research

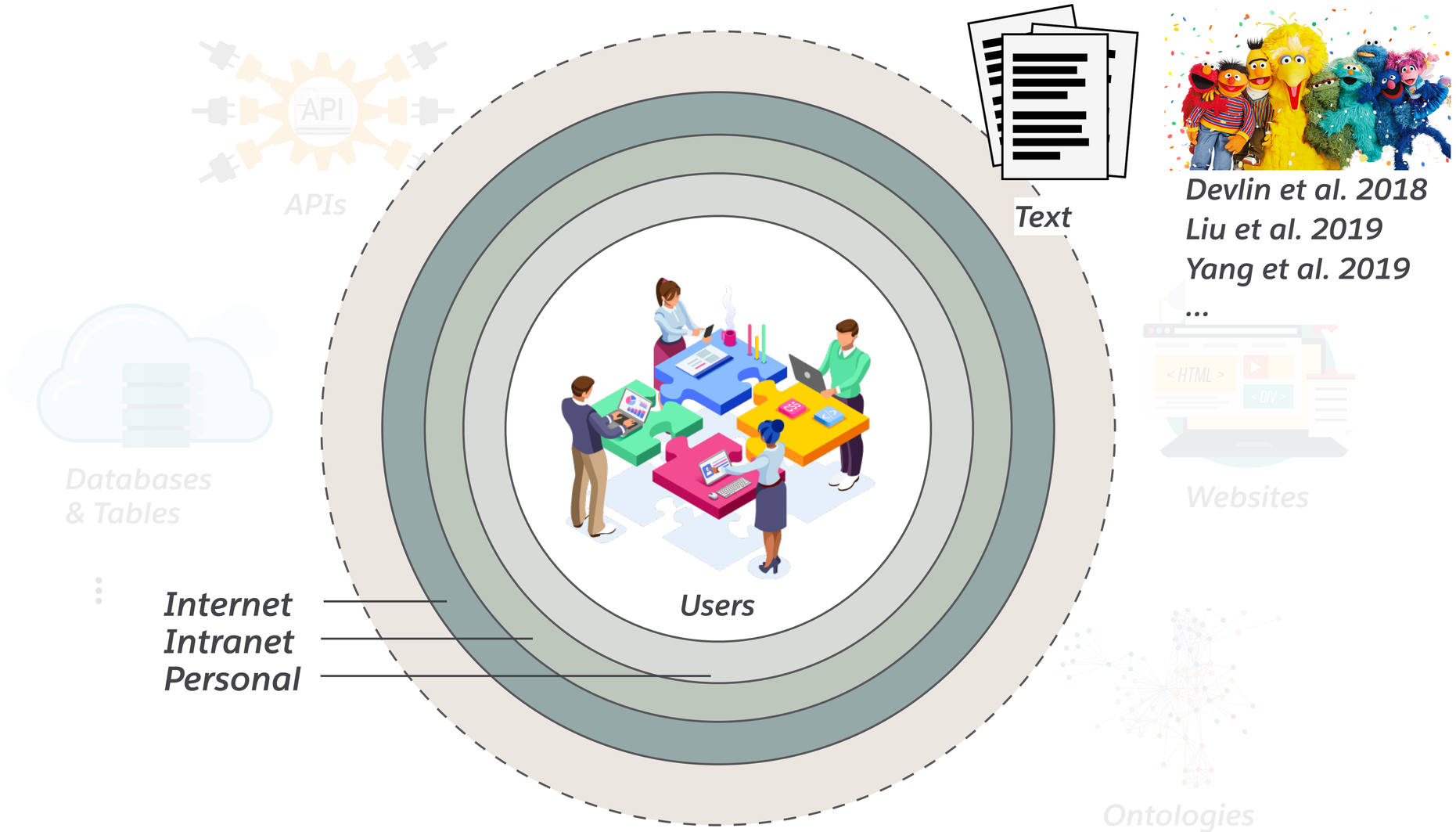
Reasoning over Heterogeneous Data



Representing Heterogeneous Data



Deep Representations



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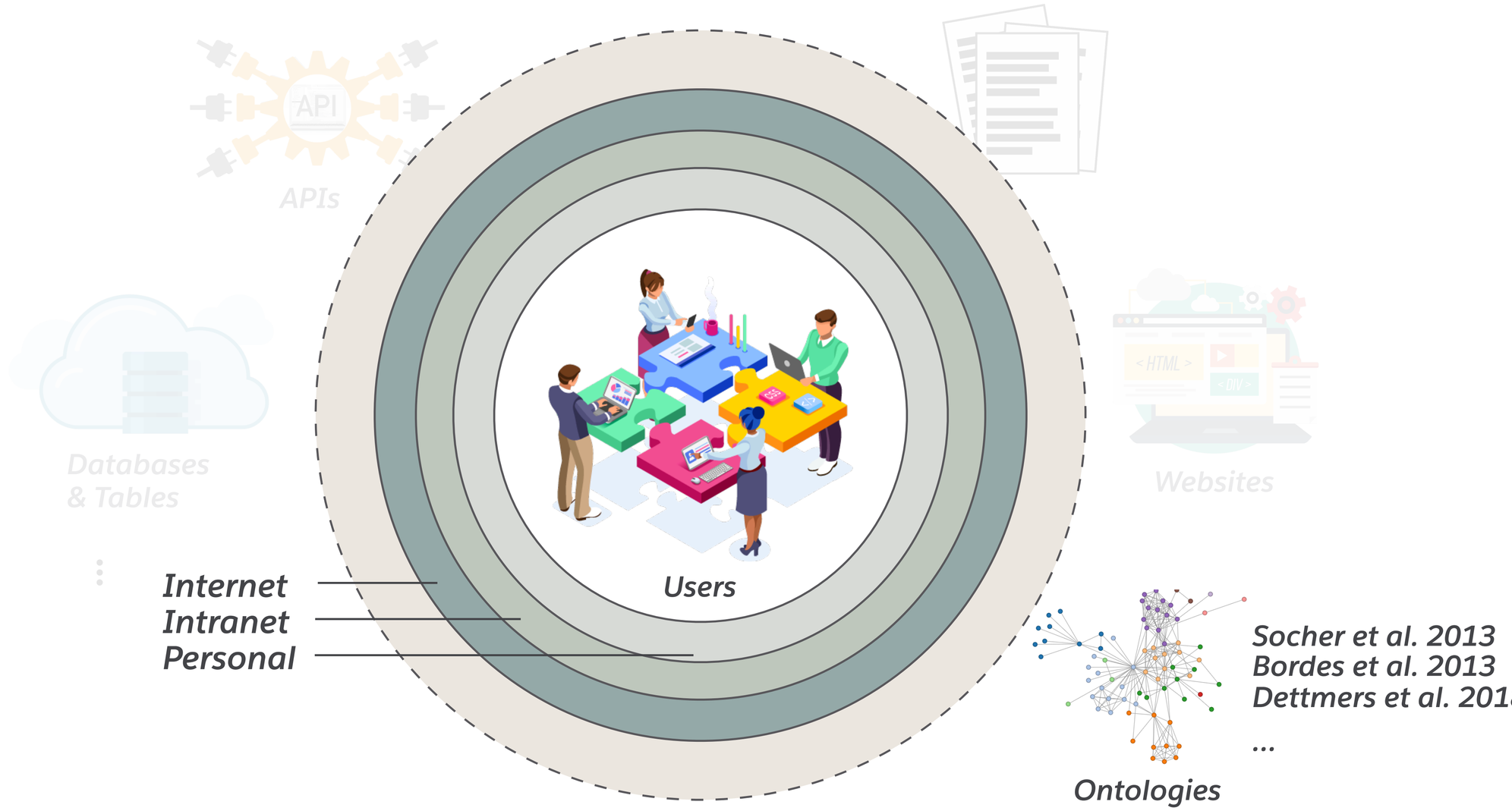

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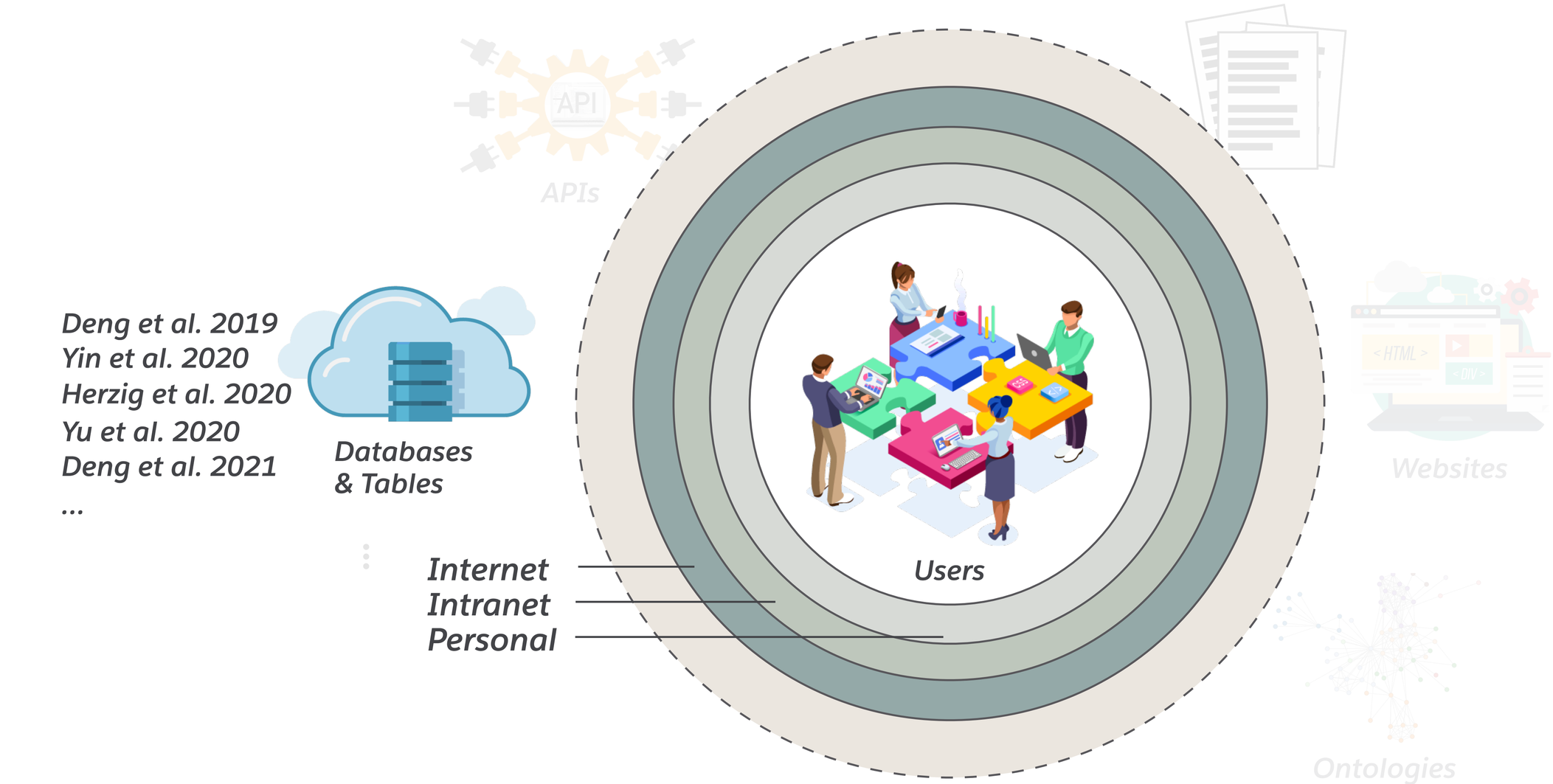
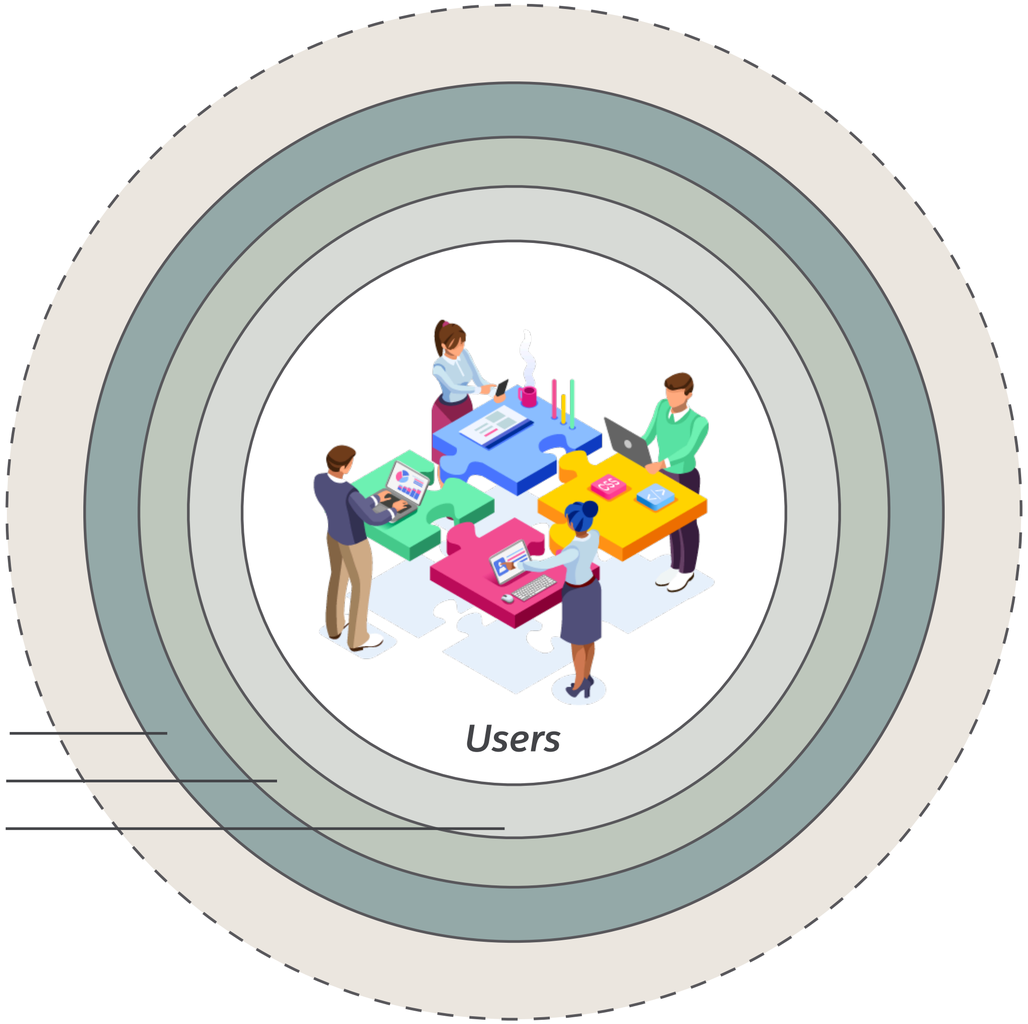


Deep Representations



Deng et al. 2019
Yin et al. 2020
Herzig et al. 2020
Yu et al. 2020
Deng et al. 2021
...

Databases & Tables

Benefits of learning continuous representation for structured data

Deep Representations

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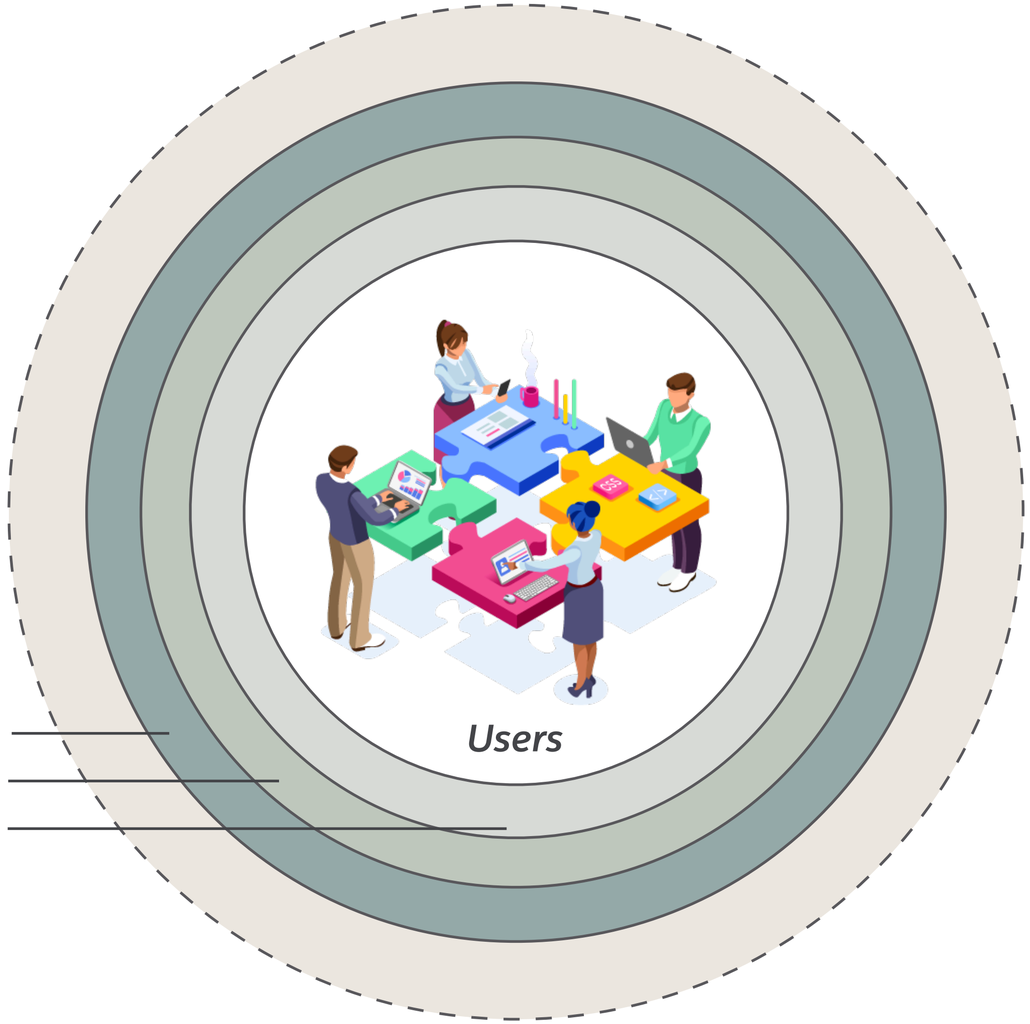
Databases & Tables



Benefits of learning continuous representation for structured data

- Continuous representations typically outperform sparse, discrete representations in data-driven prediction tasks

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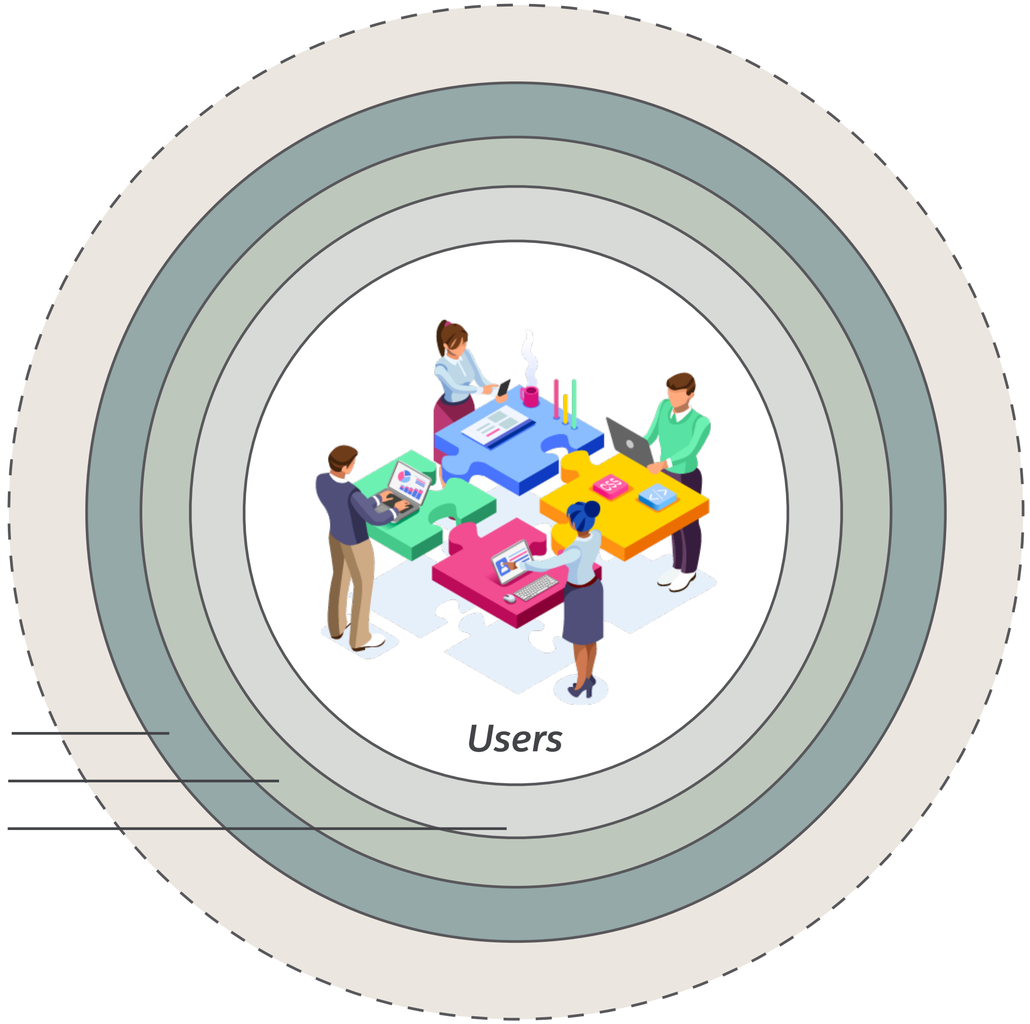
Databases & Tables



Benefits of learning continuous representation for structured data

- Continuous representations typically outperform sparse, discrete representations in data-driven prediction tasks

- Most structured data have lexical sub-components (e.g. entity names/relation labels in ontologies, table headers/cells)

- Many structured data are heterogeneous on their own (e.g. databases may contain both text and image cells)

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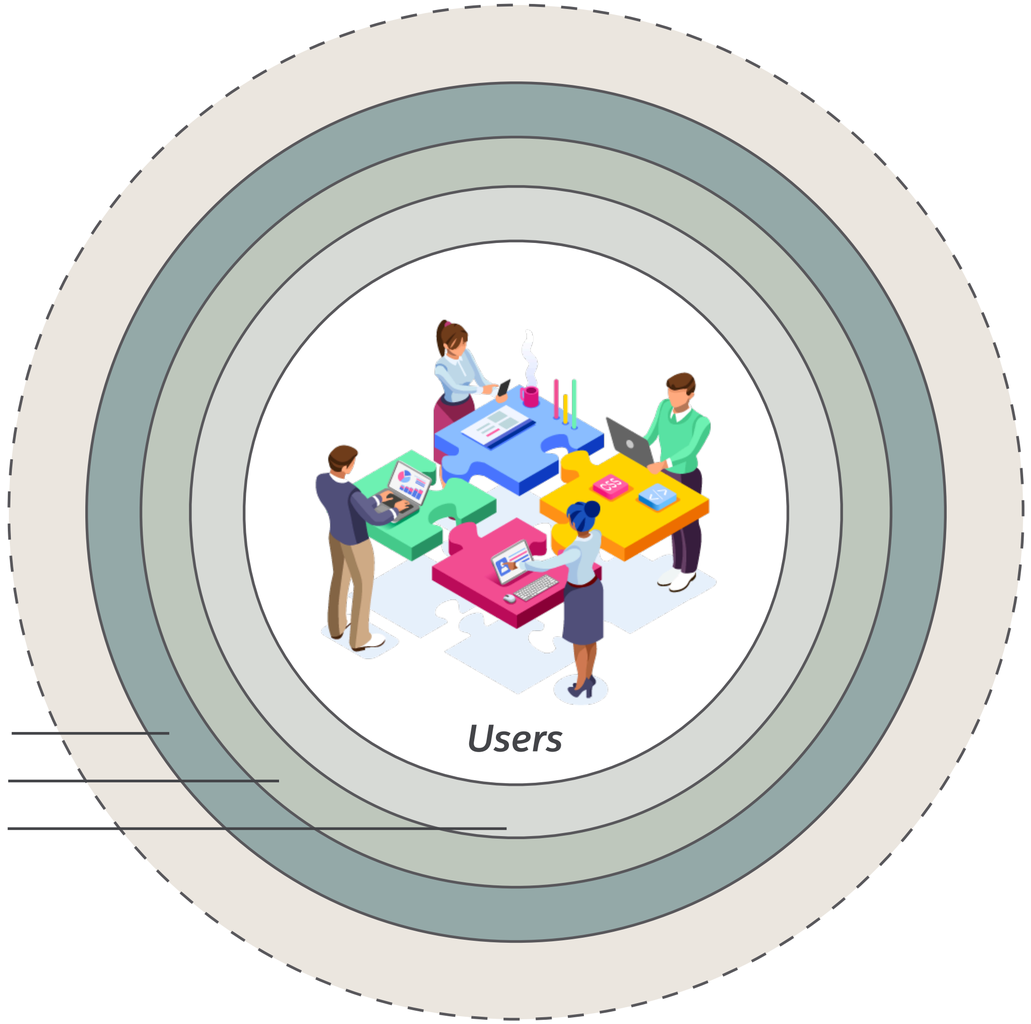
Databases & Tables



Benefits of learning continuous representation for structured data

- Continuous representations typically outperform sparse, discrete representations in data-driven prediction tasks

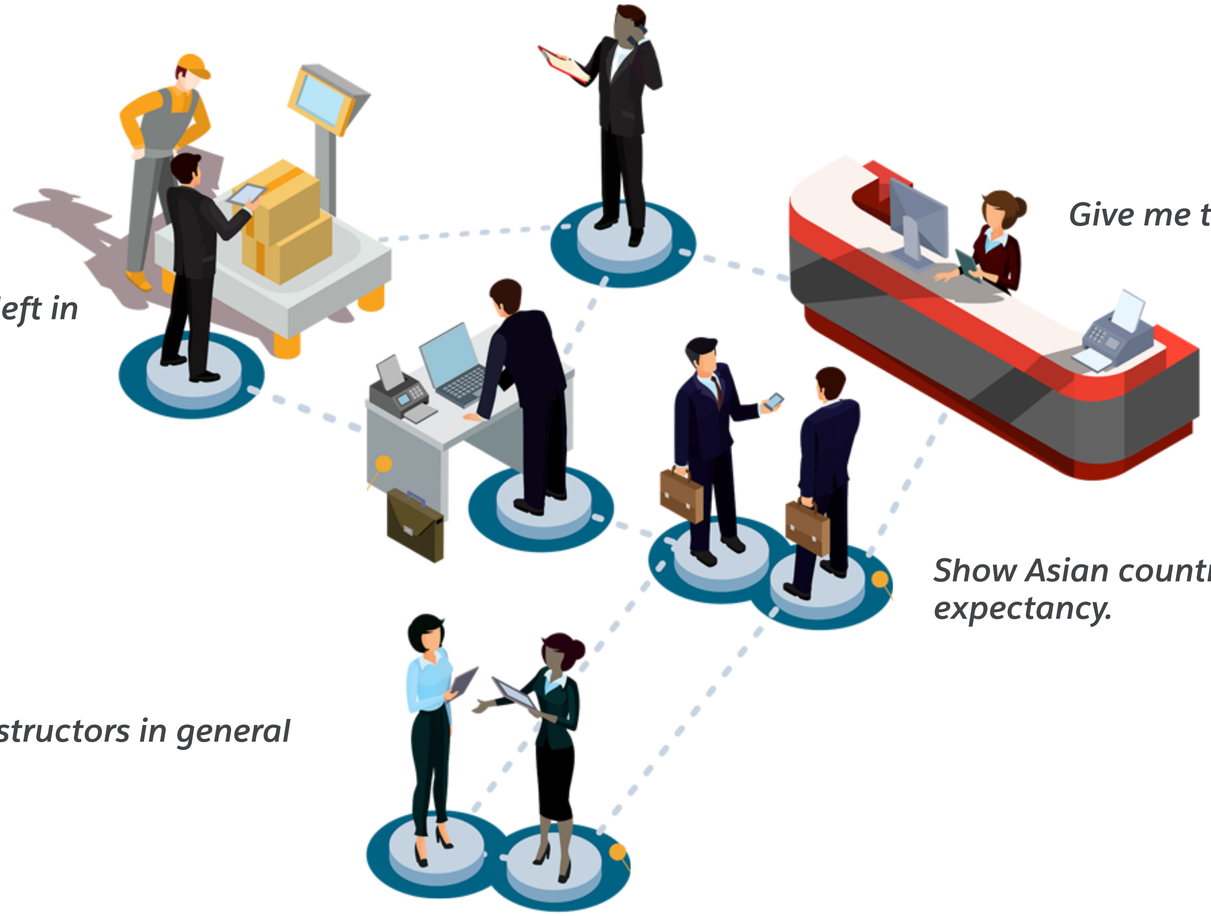
- Most structured data have lexical sub-components (e.g. entity names/relation labels in ontologies, table headers/cells)

- Many structured data are heterogeneous on their own (e.g. databases may contain both text and image cells)

- Inducing “uniform” joint representation for both structured and unstructured data (e.g. text)

Representation Learning for Databases

Our goal is to learn **representations** for **tables and databases** in the **vector space** to power downstream AI applications, in particular, **voice interfaces.**



How many “Hoverboard x10” are left in stock?

Give me the arriving time of “CZ327”.

Show Asian countries ordered by life expectancy.

Which departments have instructors in general rated above average?

Relational Database

User Profile

UserID	Name	Nationality	PartitionID	# Followers	...
103041	Smith, John	Canada	P10	3	…
103042	Hanks, Tom	United States	P11	16.6M	…
103043	Obama, Barack	United States	P11	127M	…
…	…	…	…	…	…

Relational Database

User Profile ← Table Name

UserID	Name	Nationality	PartitionID	# Followers	...
103041	Smith, John	Canada	P10	3	…
103042	Hanks, Tom	United States	P11	16.6M	…
103043	Obama, Barack	United States	P11	127M	…
…	…	…	…	…	…

A table typically represents a type of entities (or events).

Relational Database

User Profile

Table Header

UserID	Name	Nationality	PartitionID	# Followers	...
103041	Smith, John	Canada	P10	3	…
103042	Hanks, Tom	United States	P11	16.6M	…
103043	Obama, Barack	United States	P11	127M	…
…	…	…	…	…	…

Relational Database

User Profile

Name of user

Nationality of user

Partition ID of user

followers of user

UserID	Name	Nationality	PartitionID	# Followers	…
103041	Smith, John	Canada	P10	3	…
103042	Hanks, Tom	United States	P11	16.6M	…
103043	Obama, Barack	United States	P11	127M	…
…	…	…	…	…	…

A column name defines the semantic relationship between columns and between a column and the entity/event type represented by the table.

Relational Database

User Profile

ROW

UserID	Name	Nationality	PartitionID	# Followers	…
103041	Smith, John	Canada	P10	3	…
103042	Hanks, Tom	United States	P11	16.6M	…
103043	Obama, Barack	United States	P11	127M	…
…	…	…	…	…	…

A row is typically an instantiation of the entity/event.

Relational Database

User Profile

Column/field

UserID	Name	Nationality	PartitionID	# Followers	...
103041	Smith, John	Canada	P10	3	…
103042	Hanks, Tom	United States	P11	16.6M	…
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…	…	…	…	…	…

Relational Database

User Profile

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…	…	…	…	…	…

Integer

Relational Database

User Profile

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103043	Obama, Barack	United States	P11	127M	…
…	…	…	…	…	…

String

Relational Database

User Profile

UserID	Name	Nationality	PartitionID	# Followers	...
103041	Smith, John	Canada	P10	3	…
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…	…	…	…	…	…

Integer

Relational Database

User Profile

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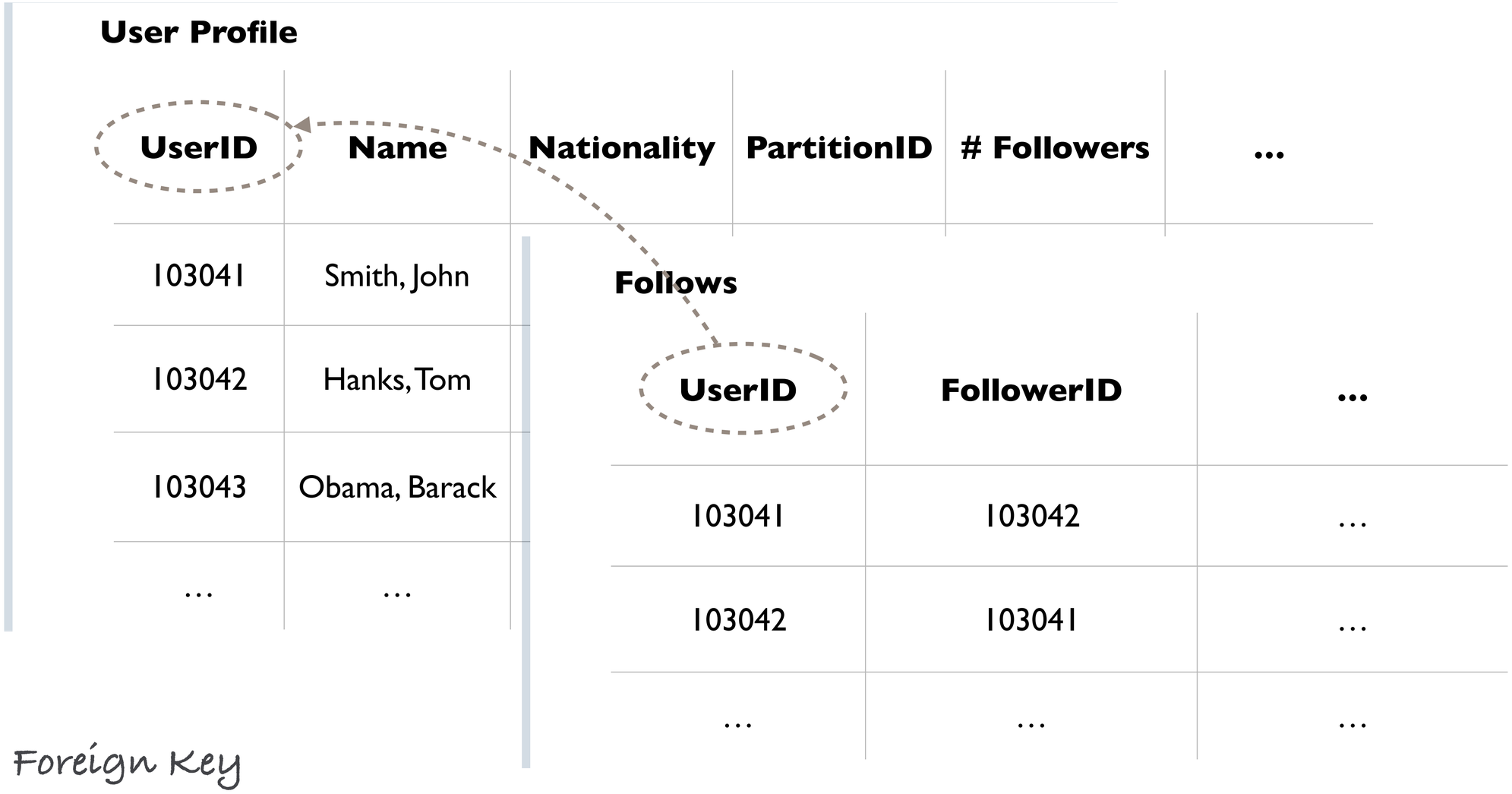
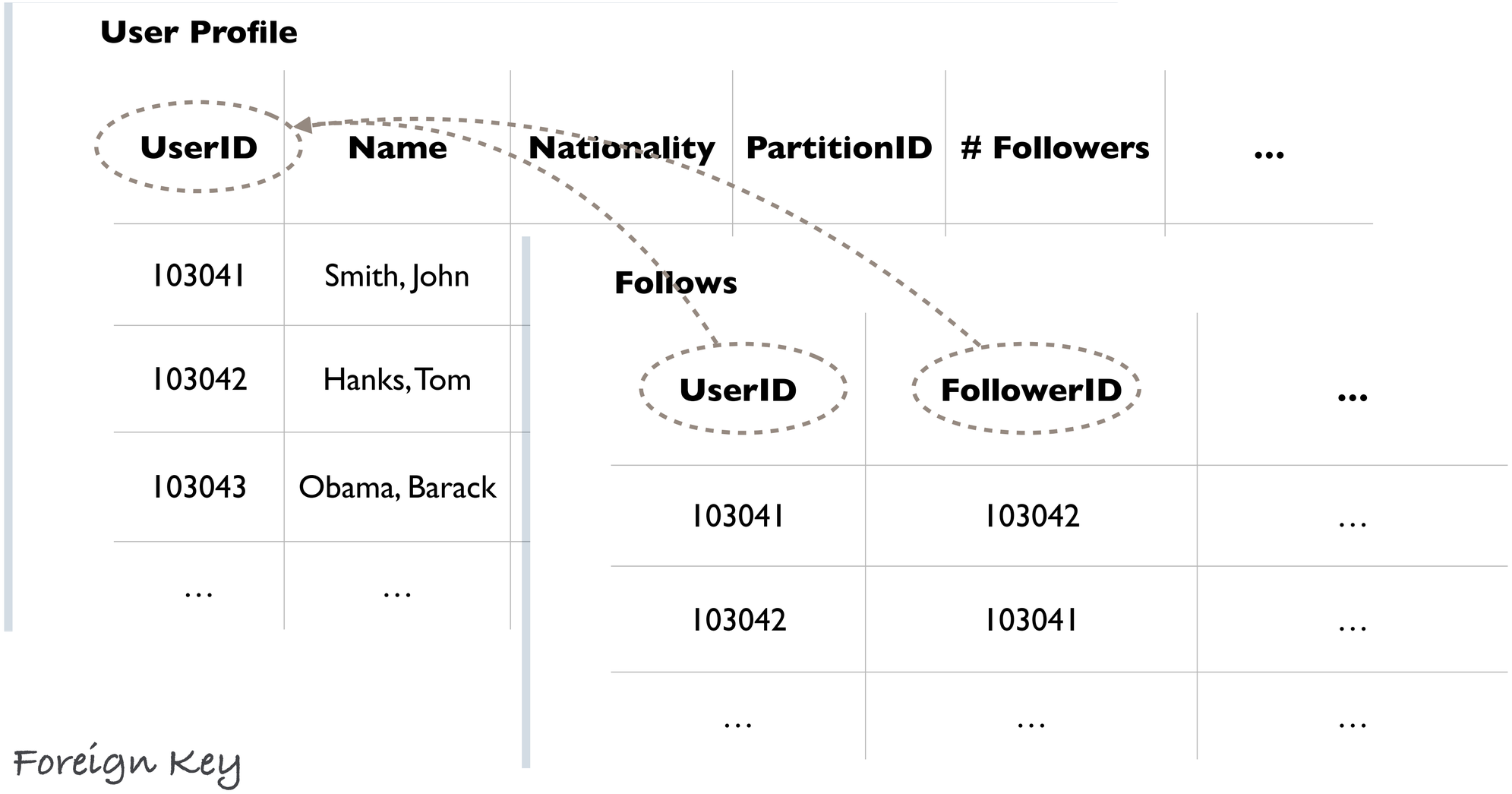
…	…	…	…	…	…

Primary Key

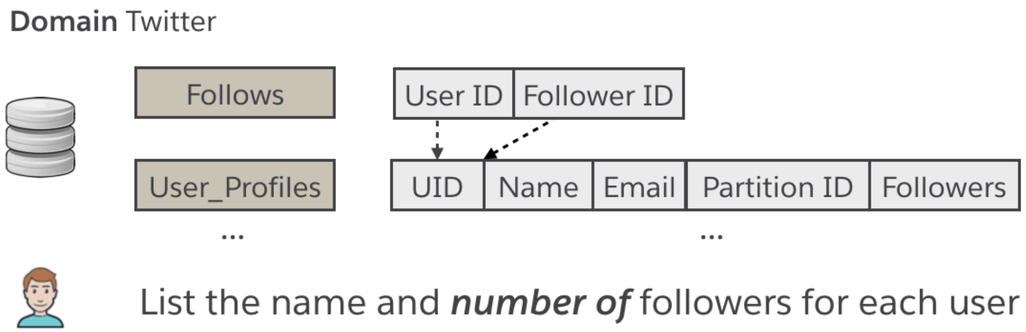
Relational Database



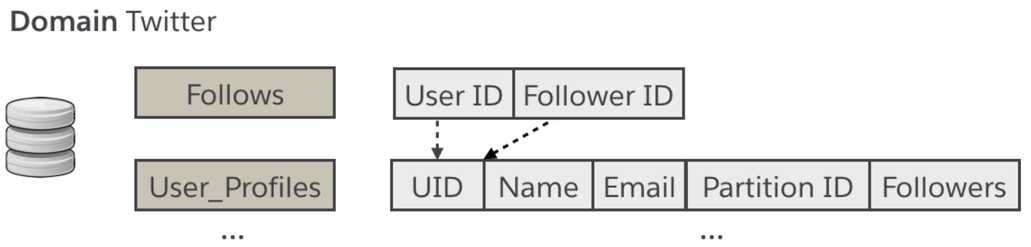
Relational Database



Question Answering over Databases



Structured Query Language

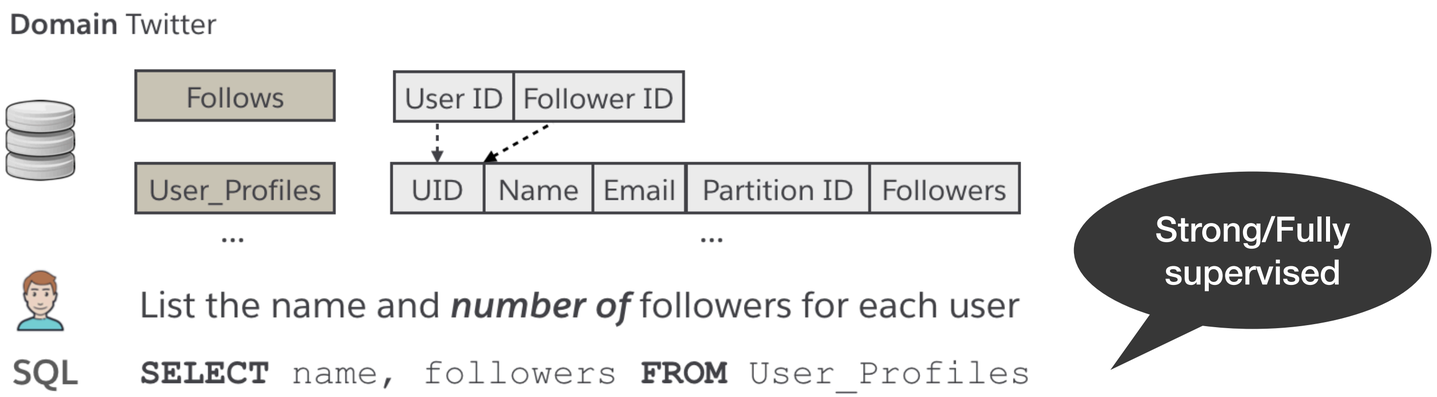


List the name and ***number of*** followers for each user

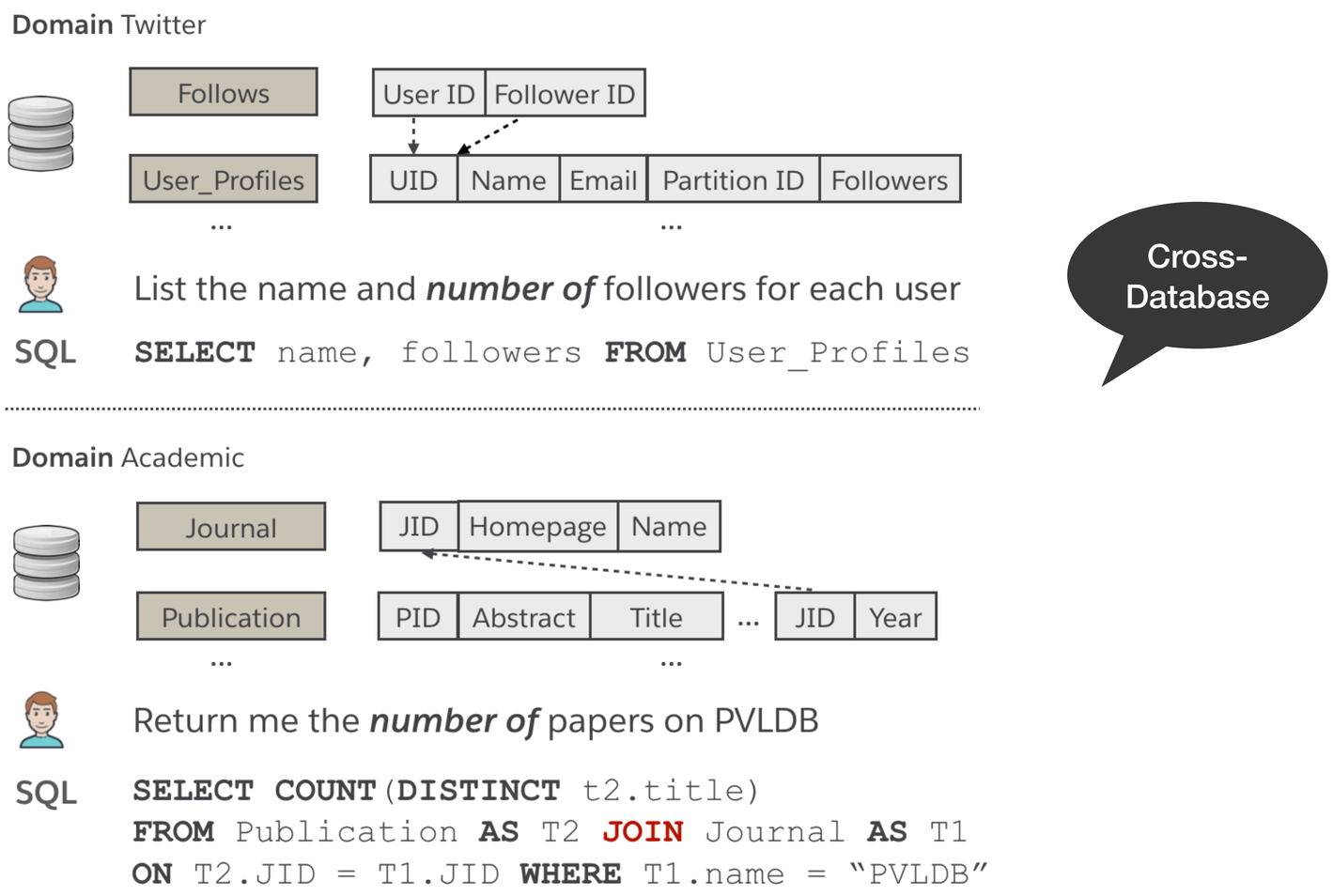
SQL

```
SELECT name, followers FROM User_Profiles
```

Text-to-SQL Semantic Parsing



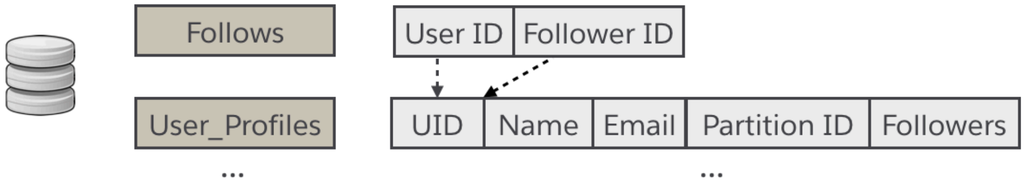
Text-to-SQL Semantic Parsing



Challenges and Observations

Challenge 1: Questions with similar intent may map to very different SQL logical forms when issued to different DBs.

Domain Twitter



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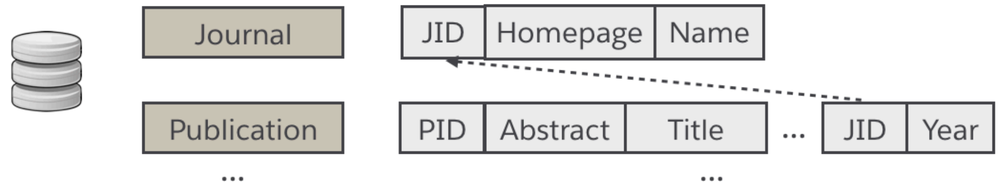
Cross-Database

Domain Academic



Return me the ***number of*** papers on PVLDB

SQL

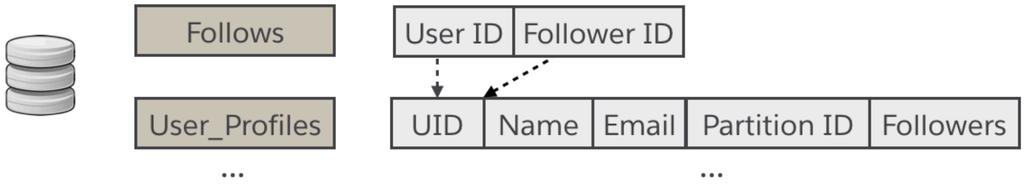
```
SELECT COUNT(DISTINCT t2.title)
FROM Publication AS T2 JOIN Journal AS T1
ON T2.JID = T1.JID WHERE T1.name = "PVLDB"
```

Challenges and Observations

Challenge 1: Questions with similar intent may map to very different SQL logical forms when issued to different DBs.

Observation 1: The meaning of a column is critical for predicting the output SQL query, and it is captured in both the column name and the corresponding cell values.

Domain Twitter



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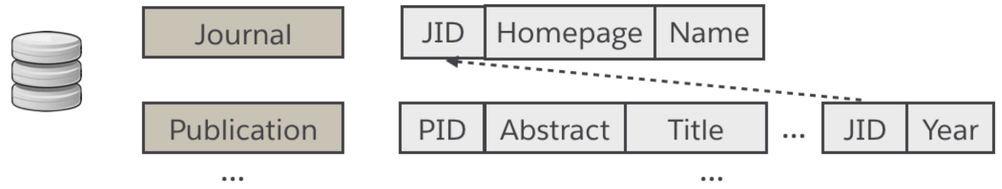

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Challenges and Observations

Challenge 2: Quite often we encounter long-tail, domain-specific entities.

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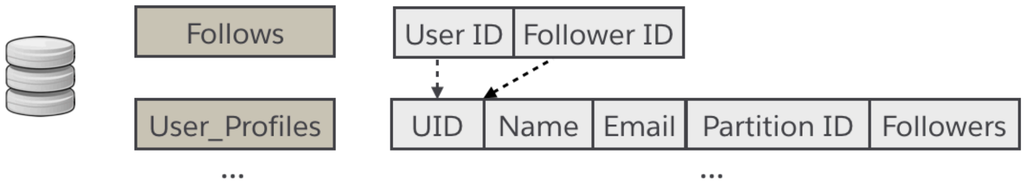

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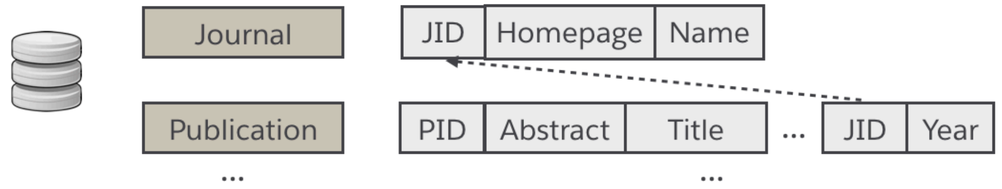

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```

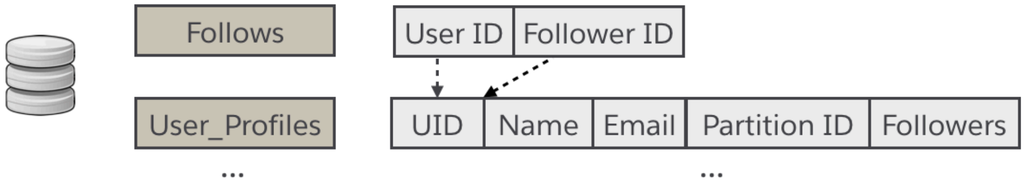
Domain Diversity

Challenges and Observations

Challenge 2: Quite often the question contains rare domain-specific entities.

Observation 2: The meaning of such entities can often be determined by grounding them to the database.

Domain Twitter



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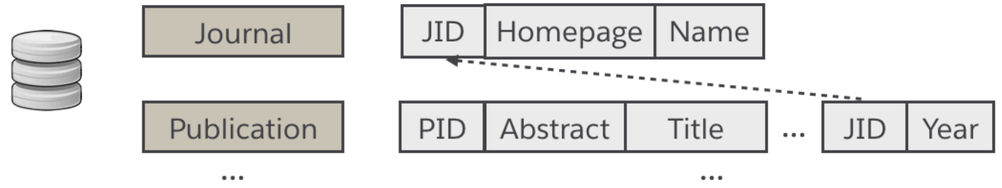

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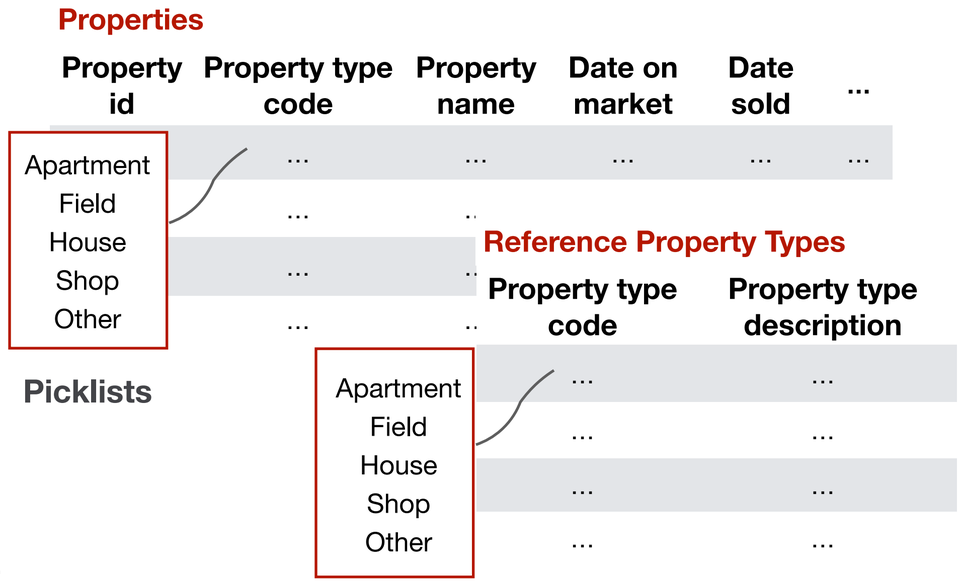
Domain Diversity

Model

Question | Database Schema

Show names of properties that are either houses or apartments



Bridging Textual and Tabular Data for Cross-Domain Text-to-SQL Semantic Parsing. Lin et. al. 2020.

Model

Research Question:

Can we build a model which seeks information from structured relational databases in a similar way to seeking information from textual paragraphs?

Question | Database Schema

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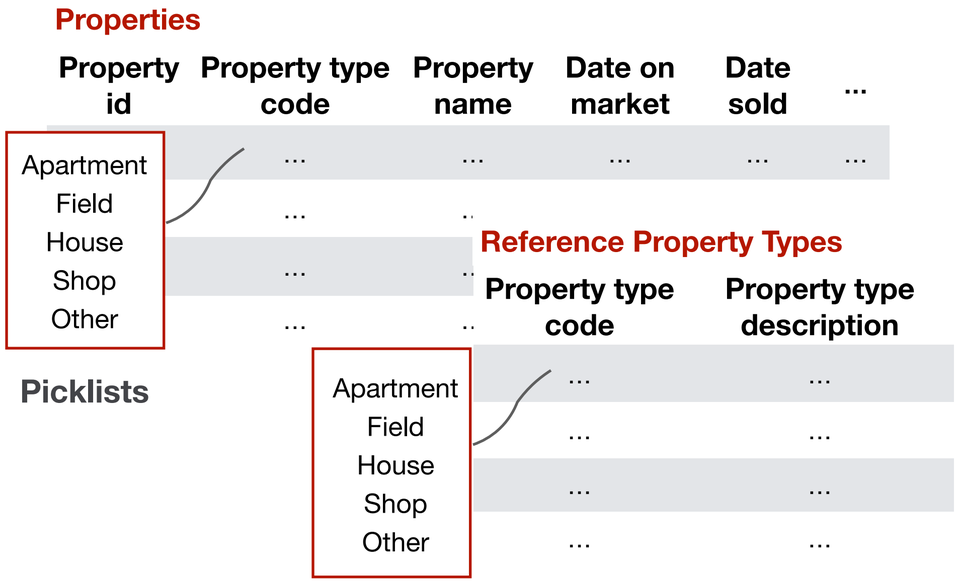

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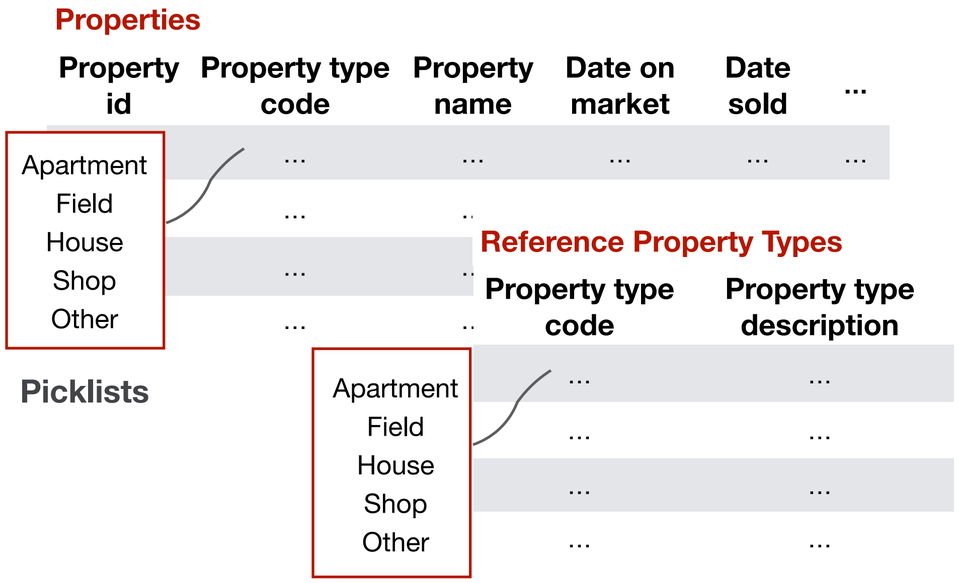
Model

Research Question:

More specifically, can pre-trained transformer language models effectively encode the question, the semantics of a relational DB model and their joint contextualization?

Question | Database Schema

Show names of properties that are either houses or apartments



Textual-Tabular Data Encoding

Serialize Table Header/DB Schema

Show names of properties that are either houses or apartments

Properties

Property id	Property type code	Property name	Date on market	Date sold	...
Apartment	...	...	...	...	...
Field	...	..			
House	...	..			
Shop	...	..			
Other					

Reference Property Types

Property type code	Property type description
...	...
...	...
...	...
...	...

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Textual-Tabular Data Encoding

Serialize Table Header/DB Schema

Show names...	T	Properties	...	C	Property Type Code	C	...	T	Reference Property Types	...	C	Property Type Code	C	...

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	...	..			
	...	..			
	...	..			

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House
Shop
Other

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Property type code	Property type description
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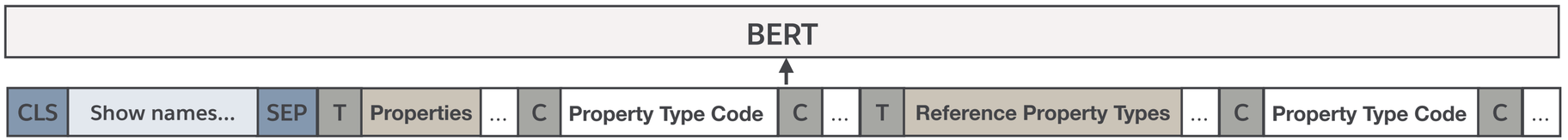

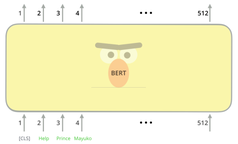

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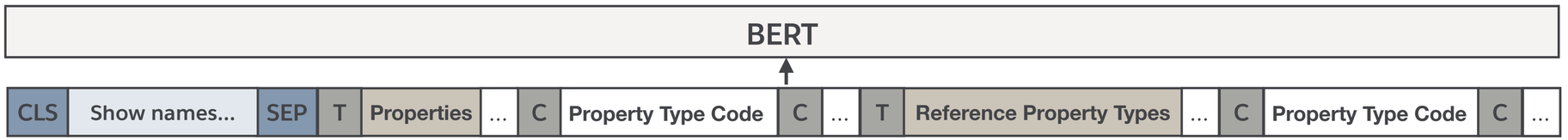
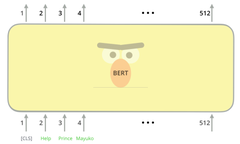
Textual-Tabular Data Encoding

Serialize Table Header/DB Schema

Lexical Information





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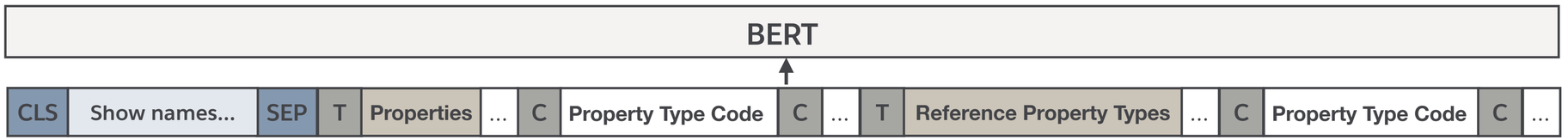
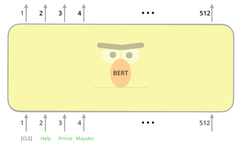
Textual-Tabular Data Encoding

Serialize Table Header/DB Schema

Structural Dependencies

Lexical Information





Show names of properties that are either houses or apartments

Properties

Property id	Property type code	Property name	Date on market	Date sold	...
	...	...	...	...	...
	...	..			
	...	..			
	...	..			

Apartment
Field
House
Shop
Other

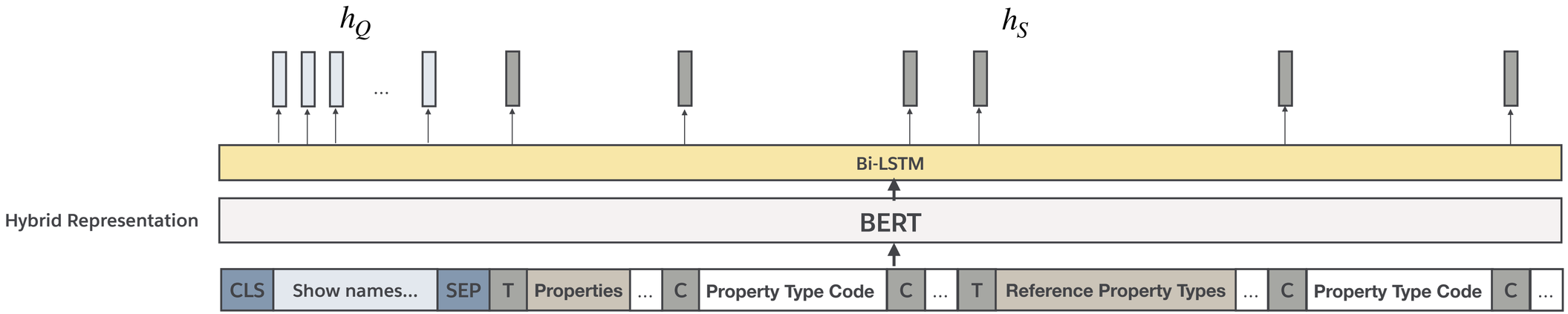
Reference Property Types

Property type code	Property type description
...	...
...	...
...	...
...	...

Apartment
Field
House
Shop
Other

Bridging Textual and Tabular Data for Cross-Domain Text-to-SQL Semantic Parsing. Lin et. al. 2020.

Textual-Tabular Data Encoding



Show names of properties that are either houses or apartments

Properties

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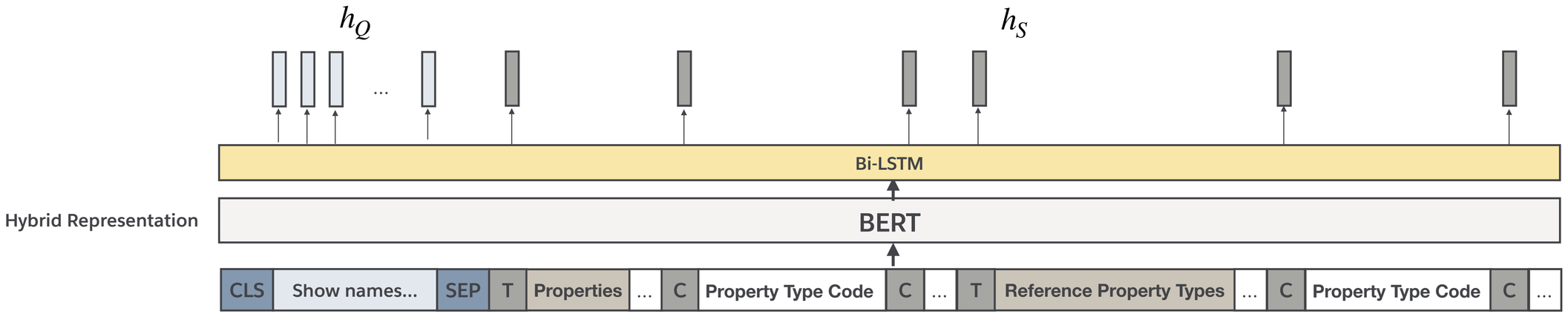
Bridging Textual and Tabular Data for Cross-Domain Text-to-SQL Semantic Parsing. Lin et. al. 2020.

Bridging



Show names of properties that are either houses or apartments

Fuzzy String Match

Properties

Property id	Property type code	Property name	Date on market	Date sold	...
	...	...	...	...	...
	...	..			
	...	..			
	...	..			

Apartment
Field
House
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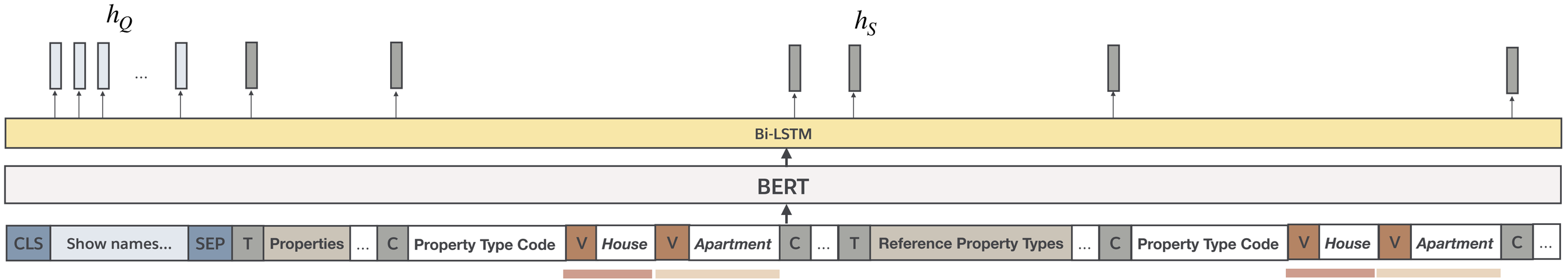
Bridging



Show names of properties that are either houses or apartments

Fuzzy String Match

Properties

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	...	...	...	...	...
	...	...			
	...	...			
	...	...			

Apartment
Field
House
Shop
Other

Reference Property Types

Property type code	Property type description
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...	...
...	...

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Field
House
Shop
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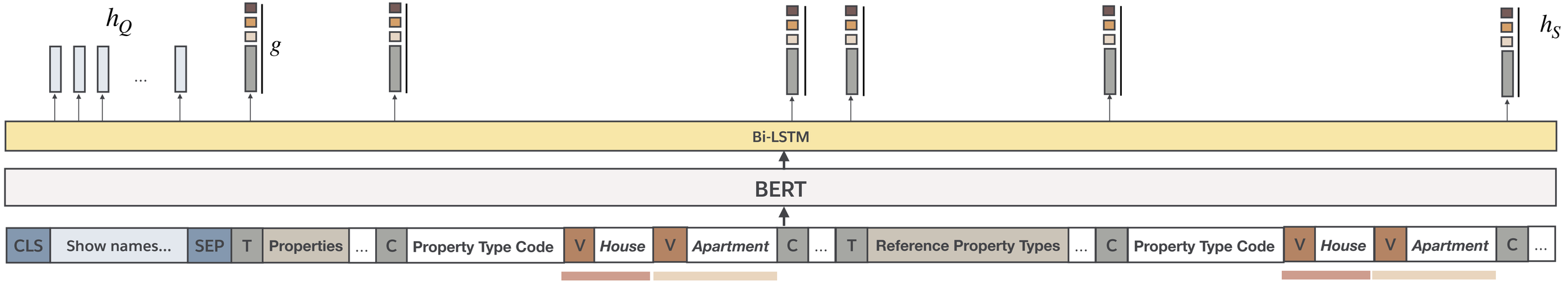
Bridging Textual and Tabular Data for Cross-Domain Text-to-SQL Semantic Parsing. Lin et. al. 2020.

Meta-Data Encoding



Show names of properties that are either houses or apartments

Fuzzy String Match

Properties

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	...	...			
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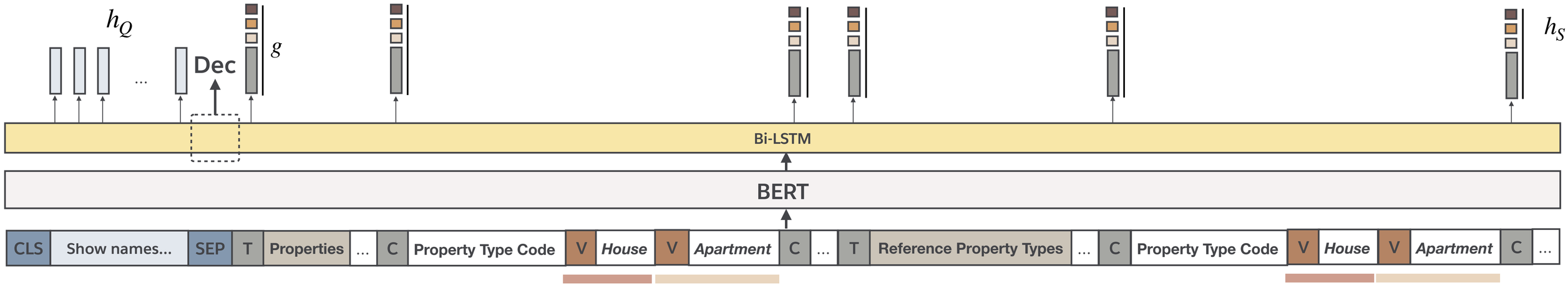
Decoder



Show names of properties that are either houses or apartments

LSTM-based pointer-generator (See et al. 2017)

p^t_{out}

- SQL Keywords and digits
- Question words
- Tables and columns

Properties

Property id	Property type code	Property name	Date on mark...	D...
	...	...		
	...			

Apartment
Field
House
Shop
...

Cross-Entropy Loss

...perty Types

...ty type code	Property type description
...	...
...	...
...	...
...	...

Apartment
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Bridging Textual and Tabular Data for Cross-Domain Text-to-SQL Semantic Parsing. Lin et. al. 2020.

Main Dataset

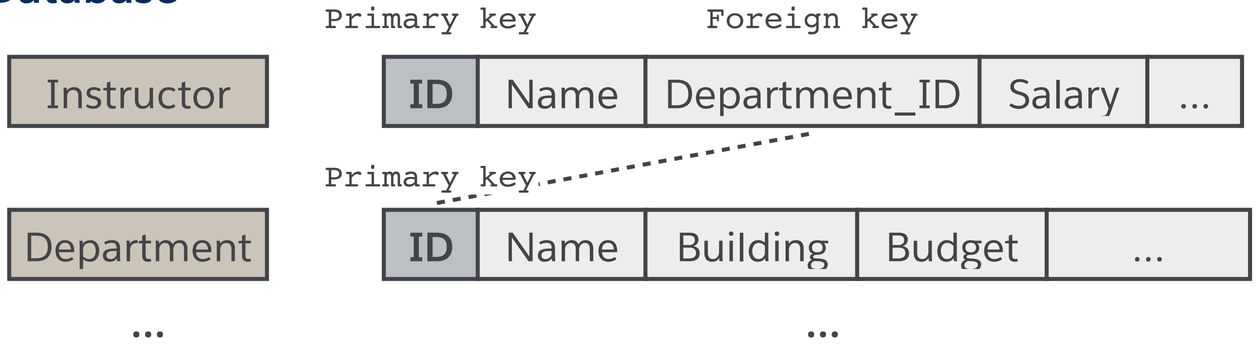
Spider (Yu et al. 2018)

Expert-annotated, **cross-domain**, **complex** text-to-SQL dataset

No overlap between Train/Dev/Test databases, enabling the development of text-to-SQL models which generalize to unseen DBs

	Train	Dev	Hidden Test
# DBs	146	20	40
# Examples	8,659	1,034	2,147

Database



Question What are the name and budget of the departments with average instructor salary above the overall average?

SQL

```
SELECT T2.name, T2.budget
FROM Instructor AS T1 JOIN Department AS T2 ON
T1.Department_ID = T2.ID
GROUP BY T1.Department_ID
HAVING AVG(T1.salary) >
     (SELECT AVG(Salary) FROM Instructor)
```

Experiments

Pre-processing

- Compute fuzzy string match between the input question and the picklists of each DB field to identify value mentions
- For each DB field, keep top-K matches and use them to augment the DB schema representation

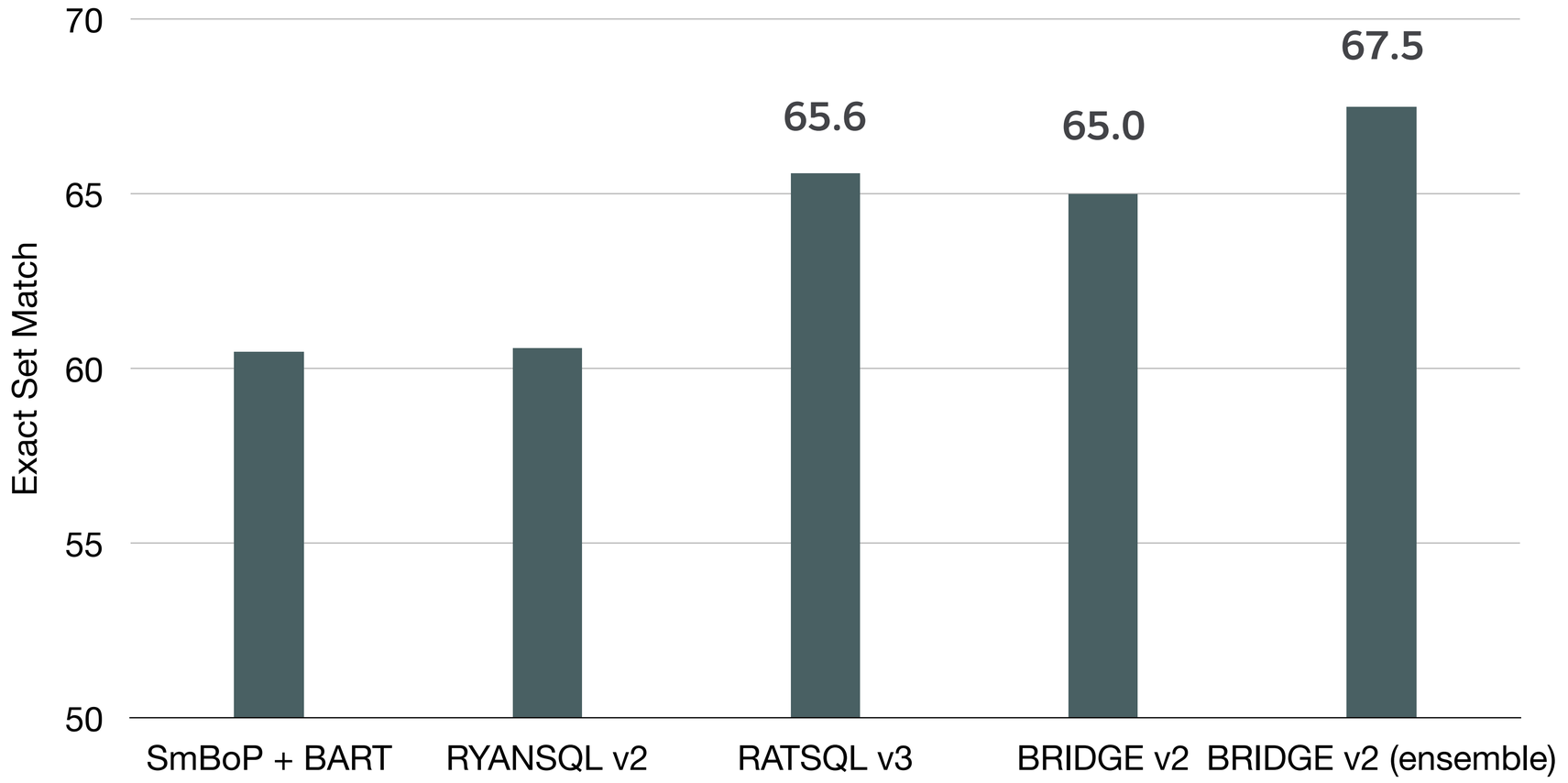
Evaluation

- Exact set match
  - Logical form match ignoring values and SQL component order invariance
- Execution accuracy
  - Check if the execution results of the predicted SQL query matches the executions results of the ground-truth SQL query

Better evaluation for text-to-SQL is still an open research problem

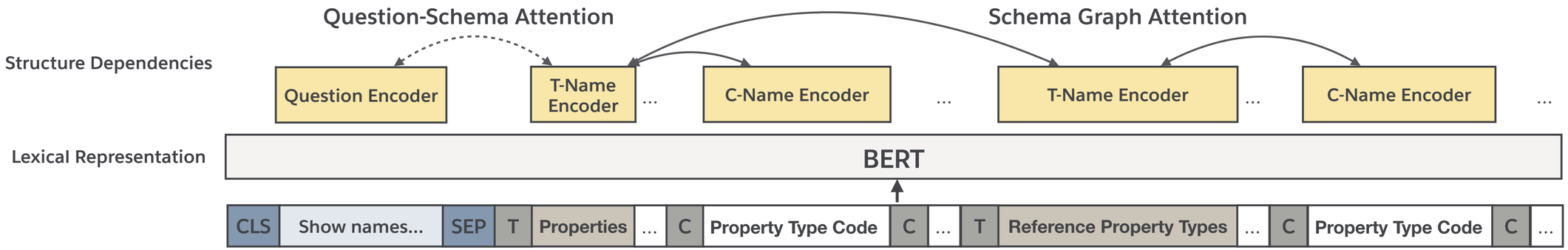
Semantic Evaluation for Text-to-SQL with Distilled Test Suites. Zhong et al. 2020.

Performance on Spider Leaderboard



Comparison to other top-performing text-to-SQL models on the Spider leaderboard as of Dec 01, 2020,

RAT-SQL Encoder



Show names of properties that are either houses or apartments

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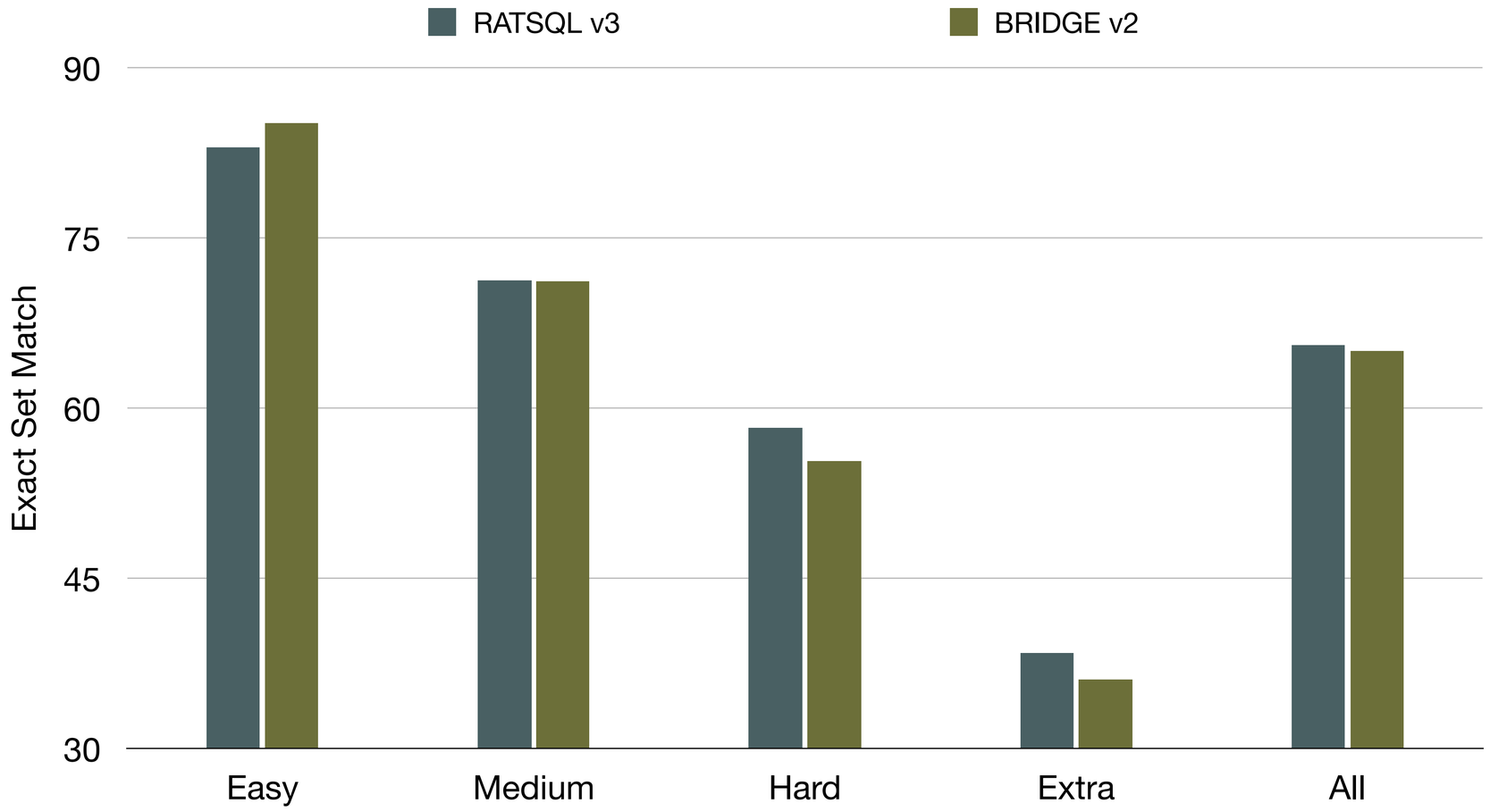
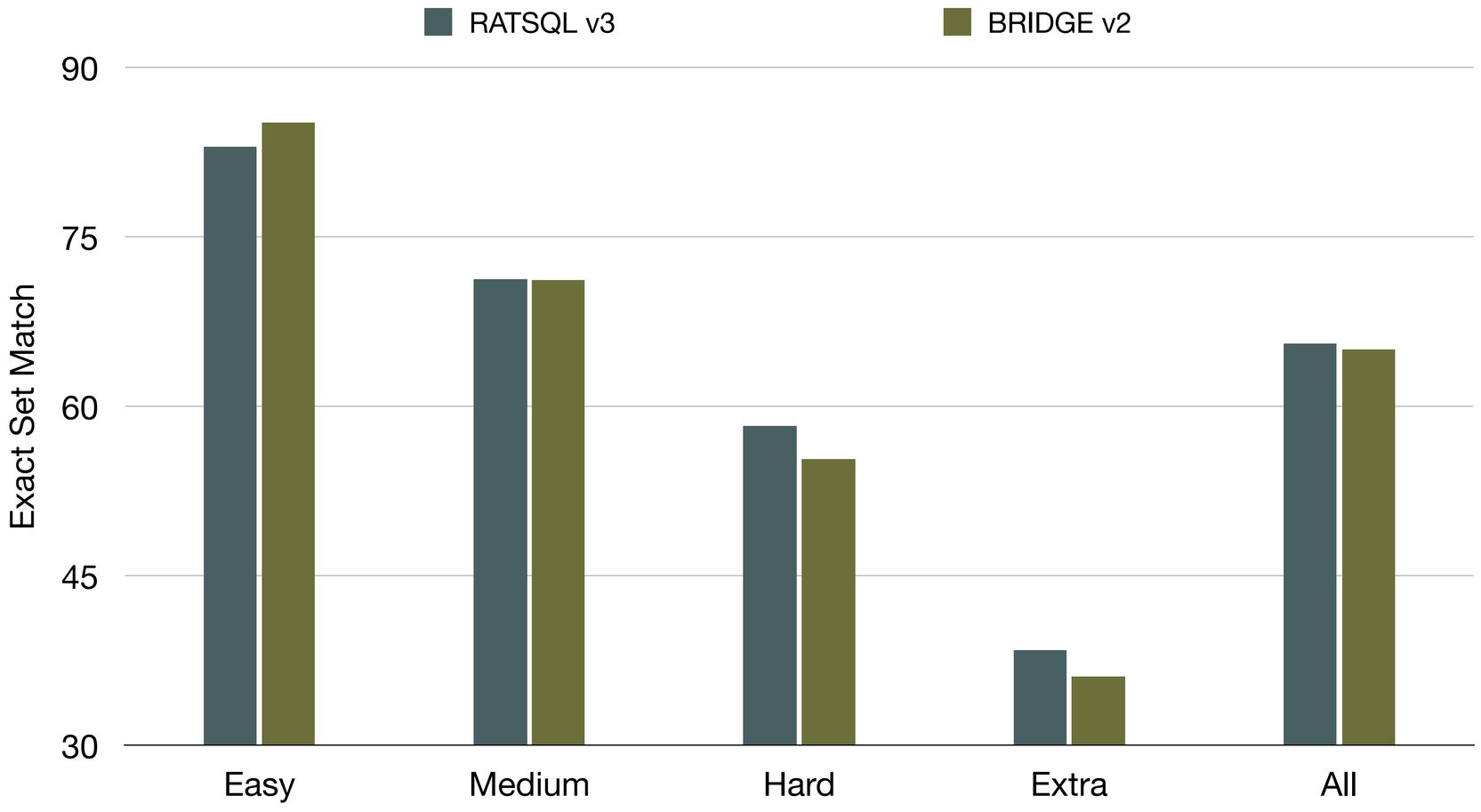
RAT-SQL: Relation-Aware Schema Encoding and Linking for Text-to-SQL Parsers. Wang et al. 2020.

Performance by Difficulty Level



Performance of BRIDGE v2 compared to RATSQL v3 on the Spider Test set.

Performance by Difficulty Level



Performance of BRIDGE v2 compared to RATSQL v3 on the Spider Test set.

The comparison is not entirely informative as the two models adopted different pre- and post-processing steps.

For a more thorough ablation study over RAT-SQL, check out Scholak et al. 2020 “DuoRAT: Towards Simpler Text-to-SQL Models”

Ablation Study

Model	Exact Set Match (%)	
	Mean	Max
BRIDGE ($k = 2$)	65.8 ± 0.8	66.9
- SC-guided decoding	65.4 ± 0.7	66.3 **(-0.6)**
- static SQL check	64.8 ± 0.9	65.9 **(-1.0)**
- execution order	64.2 ± 0.1	64.3 **(-2.6)**
- table shuffle & drop	63.9 ± 0.3	64.3 **(-2.6)**
- anchor text	63.3 ± 0.6	63.9 **(-3.0)**
- BERT	17.7 ± 0.7	18.3 **(-48.6)**

Ablation study of BRIDGE model (w/ BERT-base-uncased) on the Spider Dev set.

Performance on WikiSQL Leaderboard

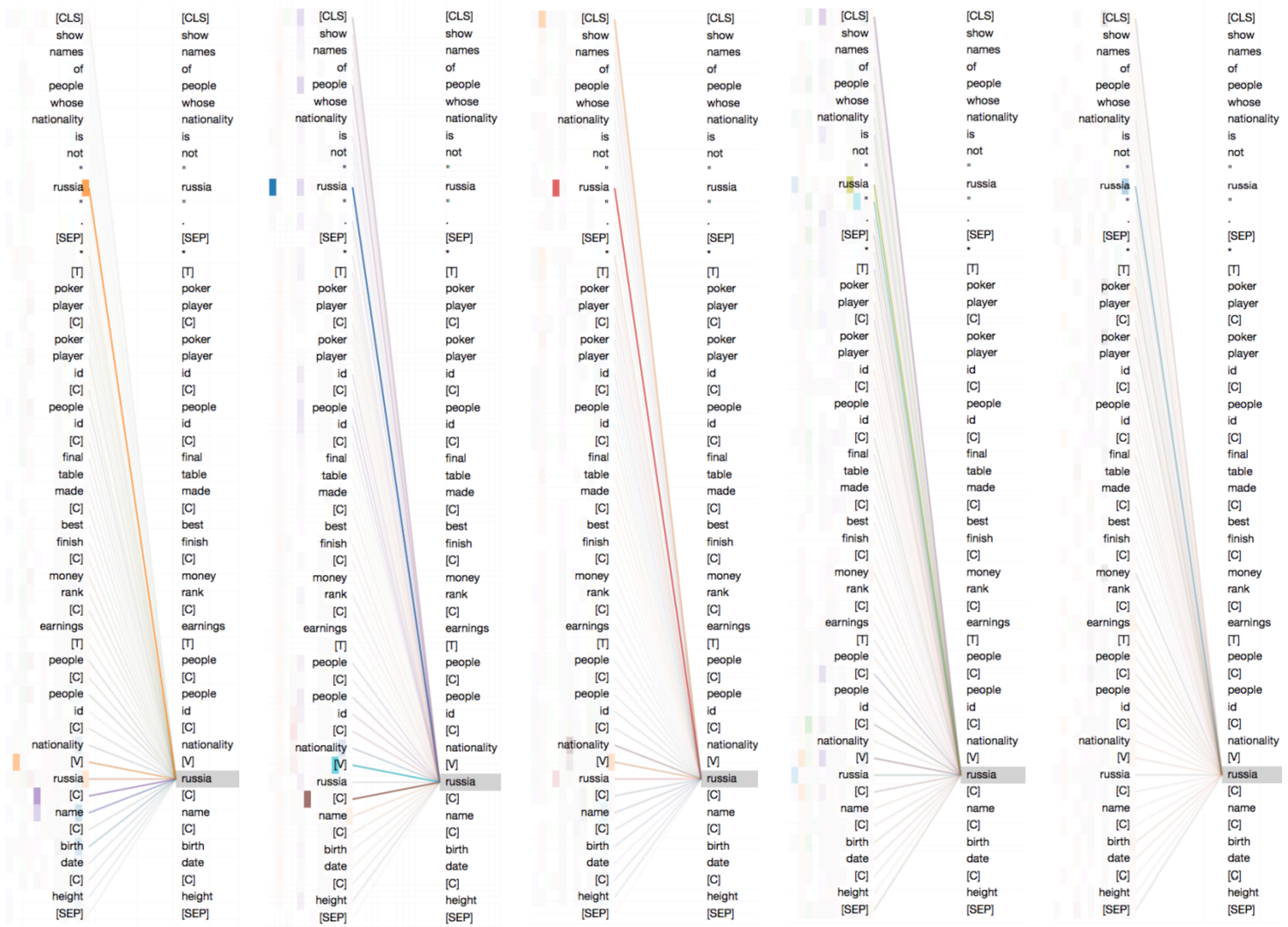
Model	Dev		Test	
	EM	EX	EM	EX
SQLova (Hwang et al., 2019)	81.6	87.2	80.7	86.2
X-SQL (He et al., 2019b)	83.8	89.5	83.3	88.7
HydraNet (Lyu et al., 2020)	83.6	89.1	83.8	89.2
BRIDGE +B_L ($k = 2$) ♠	**85.1**	**91.1**	**84.8**	**90.4**
SQLova+EG (Hwang et al., 2019)	84.2	90.2	83.6	89.6
BRIDGE +B_L ($k = 2$)+EG ♠	86.1	**92.5**	85.8	91.7
X-SQL+EG (He et al., 2019b)	86.2	92.3	86.0	91.8
HydraNet+EG (Lyu et al., 2020)	**86.6**	92.4	**86.5**	**92.2**

Comparison between BRIDGE and other top-performing models on the WikiSQL (Zhong et al. 2017) leaderboard as of August 20, 2020. +EG denotes approaches using execution guided decoding.

Attention Visualization after Fine-tuning

BertViz (Vig 2019)

Bridging

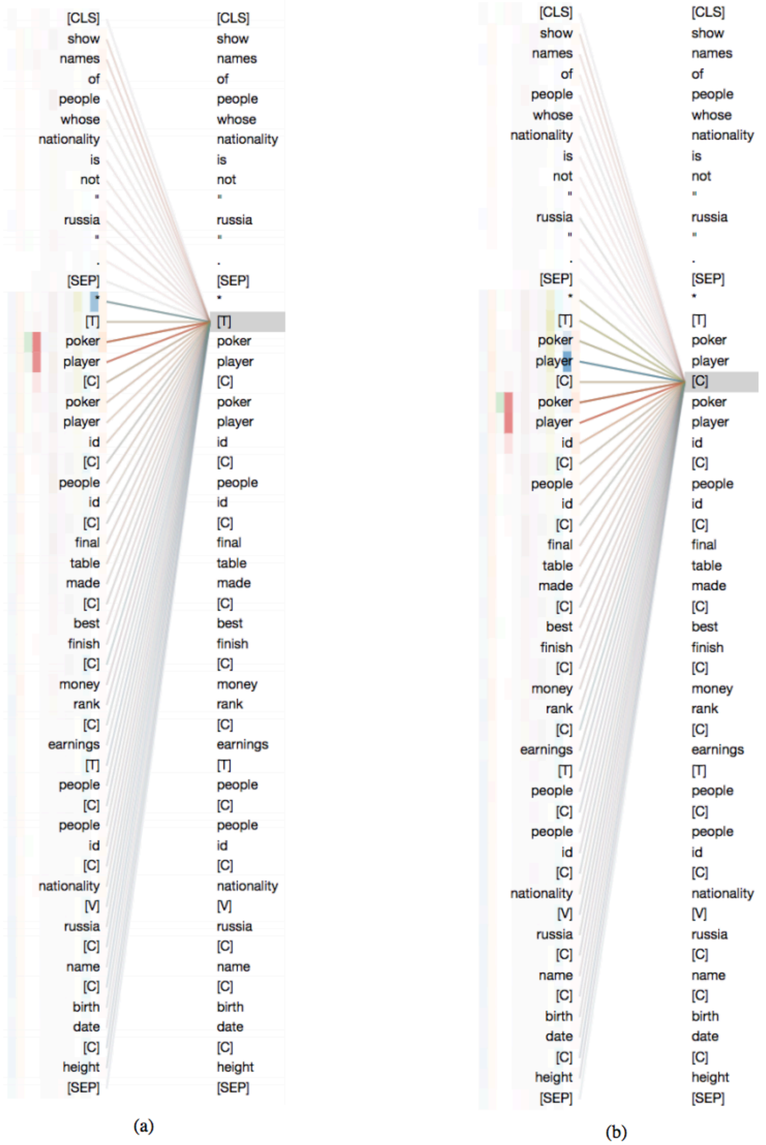


(a) Layer = 2 (b) Layer = 4 (c) Layer = 5 (a) Layer = 10 (b) Layer = 11

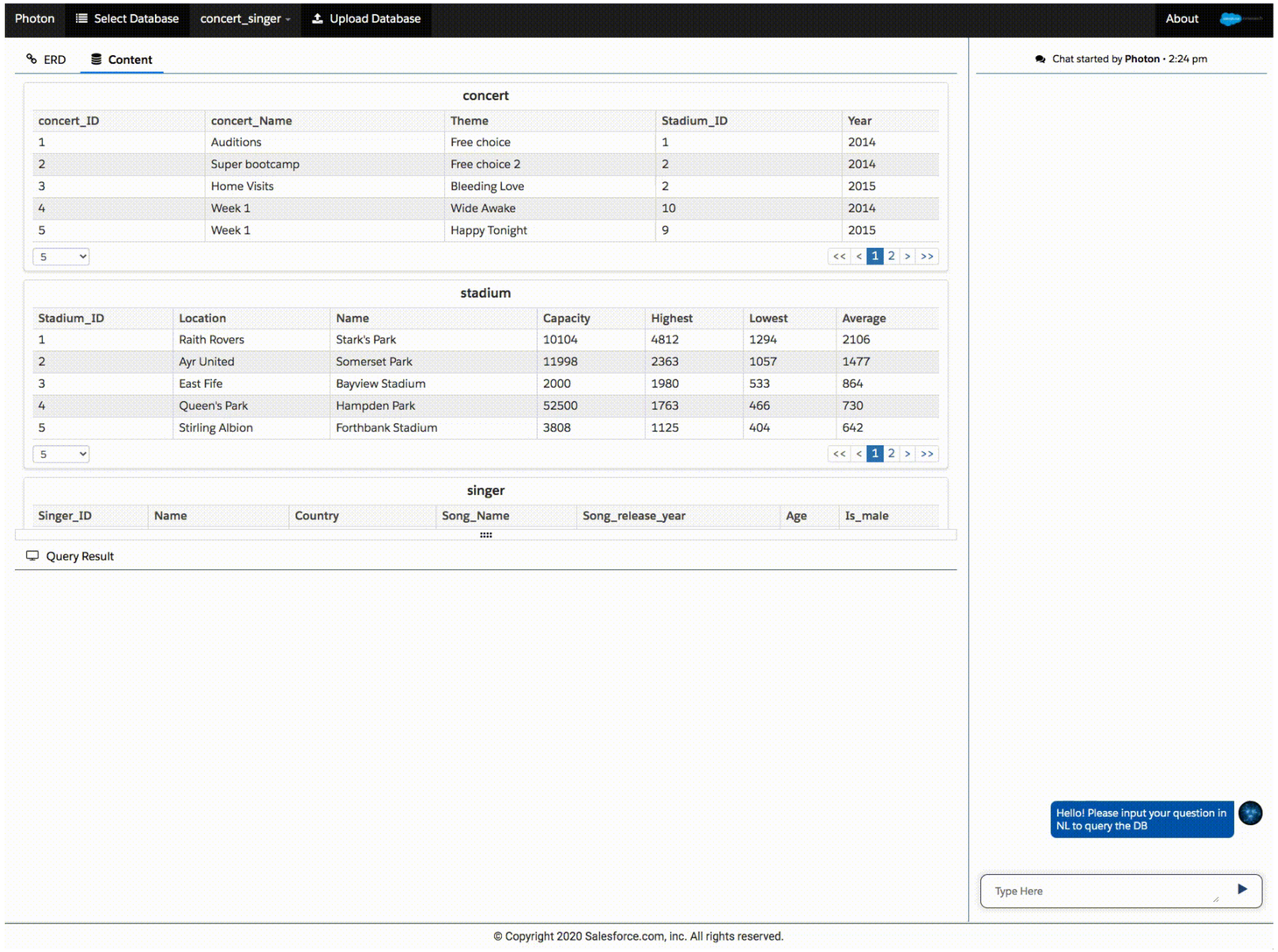
Attention Visualization after Fine-tuning

BertViz (Vig 2019)

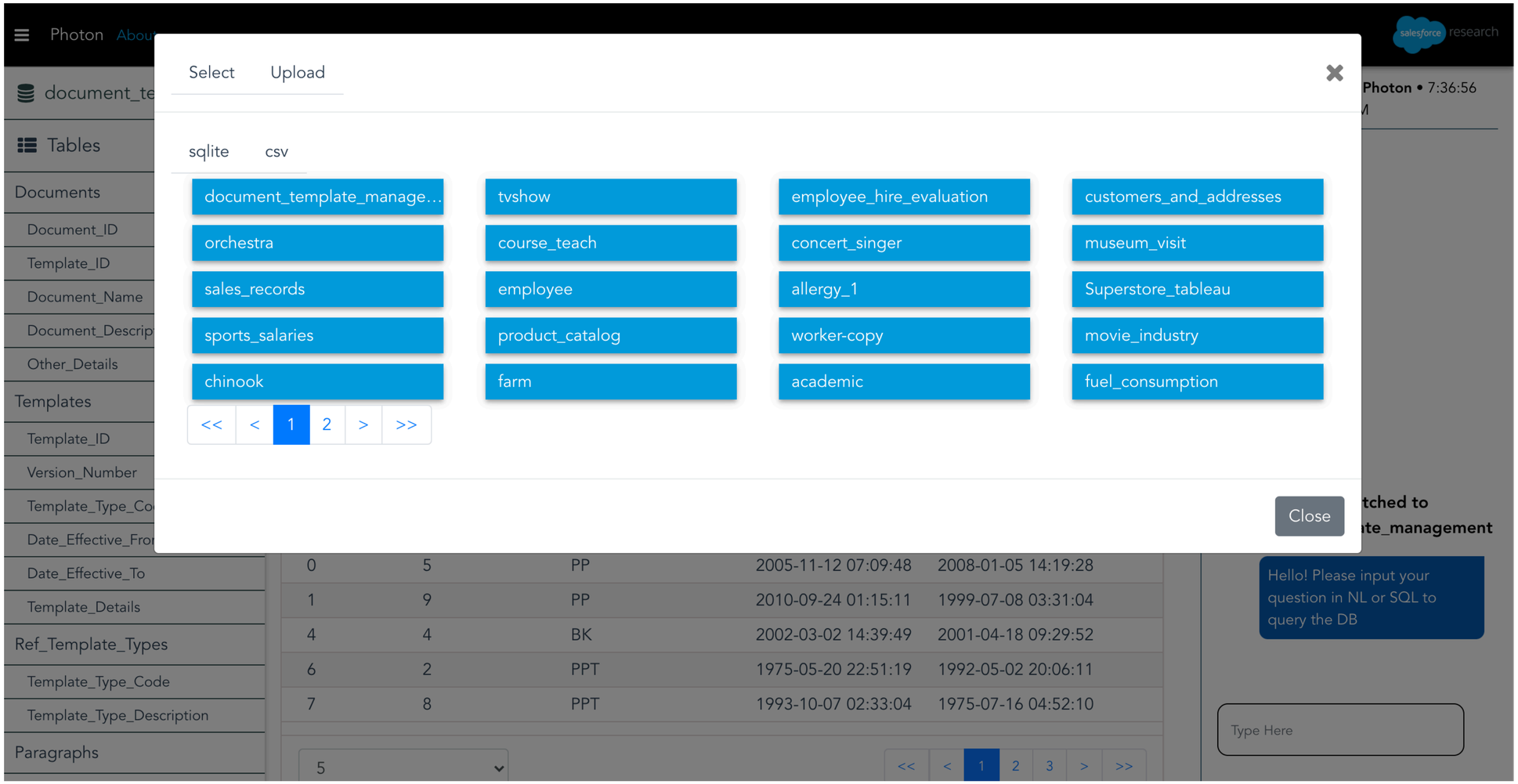
- Pooling effect in special tokens [T] and [C], layer 1



Photon Live Demo https://naturalsql.com



Photon Live Demo V2.0 Is Coming!



Recap

Research Question:

Can we build a model which seeks information from structured relational databases in a similar way to seeking information from textual paragraphs?

Bridging Textual and Tabular Data for Cross-Domain Text-to-SQL Semantic Parsing. Lin et. al. 2020.

Recap

Research Question:

Can we build a model which seeks information from structured relational databases in a similar way to seeking information from textual paragraphs?

1. The BRDIGE model has significantly more parameters in the encoder than the decoder. Learning good column representations is critical.
2. Transformer language models (e.g. BERT) are strong pattern learners.
3. The cross-database setup adopted by the standard Spider dataset does not systematically separate generalization over compositionally vs. natural language variations. The models need to be benchmarked in more systematic ways following recent works by Suhr et al. 2020 and Shaw et al. 2020.

Bridging Textual and Tabular Data for Cross-Domain Text-to-SQL Semantic Parsing. Lin et. al. 2020.

Recap

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Can we build a model which seeks information from structured relational databases in a similar way to seeking information from textual paragraphs?

Despite competitive performance on the standard benchmark datasets, we saw several issues with the current approach:

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Despite competitive performance on the standard benchmark datasets, we saw several issues with the current approach:

1. **Robustness**

Model performance is sensitive to random seeds. We plan to benchmark the model on more datasets using more evaluation metrics. (Suhr et al. 2020; Scholak et al. 2020; Shaw et al. 2020)

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1. **Robustness**

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2. **Interpretability and Control**

   Model lacks interpretability and control to the output. Introducing the relation-aware attention layers (RAT-SQL, Wang et al. 2020) improves interpretability to some degree.

Related Work

To our knowledge, the following works have also demonstrated the effectiveness of pre-trained transformer LMs on the text-to-SQL problem:

1. A Comprehensive Exploration on WikiSQL with Table-Aware Word Contextualization. Hwang et al. 2019
2. Exploring Unexplored Generalization Challenges for Cross-Database Semantic Parsing. Suhr et al. 2020
3. Compositional Generalization and Natural Language Variation: Can a Semantic Parsing Approach Handle Both? Shaw et al. 2020
4. Compositional Generalization in Semantic Parsing: Pre-training vs. Specialized Architectures. Furrer et al. 2020

Related Work

Pre-training textual-tabular representations leveraging unlabeled tables, to name a few:

1. GraPPa: Grammar-Augmented Pre-training for Table Semantic Parsing. Yu et al. 2020
2. TaBERT: A New Model for Understanding Queries over Tabular Data. Yin et al. 2020
3. TAPAs: Weakly Supervised Table Parsing via Pre-training. Herzig et al. 2020
4. Structure-Grounded Pre-training for Text-to-SQL. Deng et al. 2020
5. TURL: Table Understanding through Representation Learning. Deng et al. 2021

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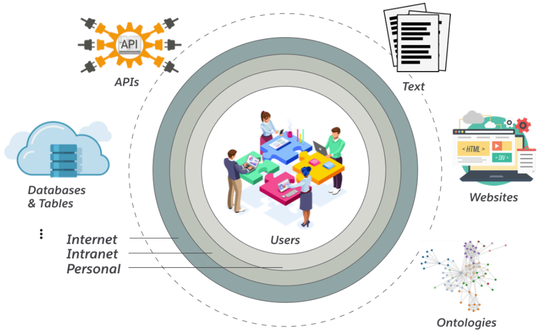
Future Work:

Can we learn table representations that universally benefit tasks s.a. semantic parsing, summarization, data completion, etc.?

Can we learn table representations that can be "plugged" into the representations of other data modality?



https://einstein.ai/research/publications

Tao Yu
Yale University

Chien-Sheng Wu
Salesforce AI Research

Bailin Wang
University of Edinburgh

Jichuan Zeng
Chinese University of Hong Kong

Karthik Radhakrishnan
CMU

Heather Lent
University of Copenhagen

Arvind Srikantan
Salesforce Inc.

Dragomir Radev
Yale University

Richard Socher
You.com

Steven Hoi
Salesforce Research Asia

Yingbo Zhou
Salesforce AI Research

Caiming Xiong
Salesforce AI Research


thank you
BLAZE YOUR TRAIL
salesforce

Error Analysis

Qualitative observations

What are the names and release years for all the songs of the youngest singer? **concert_singer**

✗ `SELECT Song_Name, Age FROM singer ORDER BY Age LIMIT 1`

✓ `SELECT song_name, song_release_year FROM singer ORDER BY age LIMIT 1`

What are the full names of all left handed players, in order of birth date? **WTA_1**

✗ `SELECT first_name, last_name FROM players ORDER BY birth_date`

✓ `SELECT first_name, last_name FROM players WHERE hand = 'L' ORDER BY birth_date`

What are the names of students who have 2 or more likes? **network_1**

✗
```
SELECT Likes.student_id FROM Likes JOIN Friend ON Likes.student_id = Friend.student_id
GROUP BY Likes.student_id HAVING COUNT(*) >= 2
```

✓
```
SELECT Highschooler.name FROM Likes JOIN Highschooler ON Likes.student_id =
Highschooler.id GROUP BY Likes.student_id HAVING count(*) >= 2
```

Robustness issue

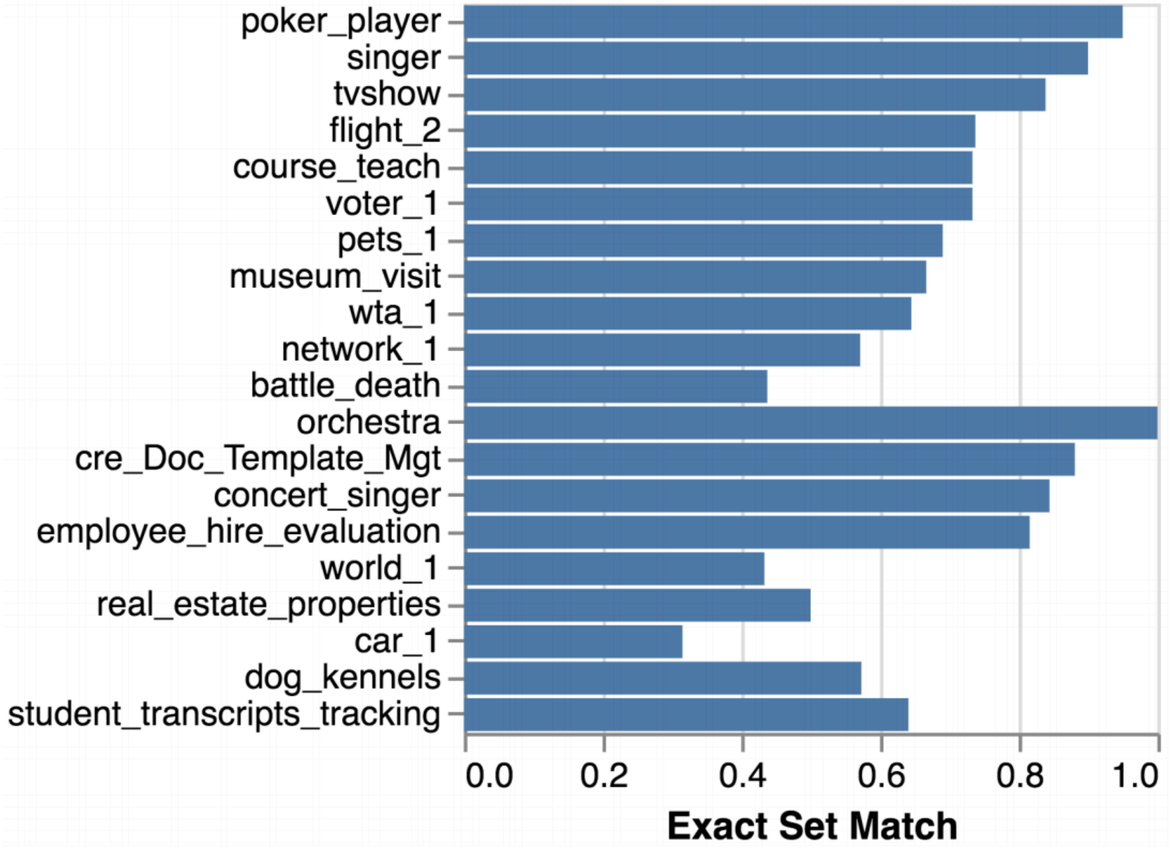
Rare relation & value surface form

Commonsense

"Friend" table stores students who has a friend, not all students

Performance by DB

Exact match accuracy on each DB in the Spider dev set. The DBs are sorted by size (smallest -> largest) from top to bottom.



Better characterization of “similar” examples could help transfer learning