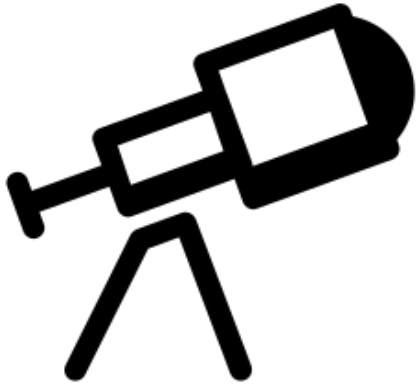
TypeSQL: From Natural Text to SQL Queries

DataBase Systems 2020
Apostolos Papatheodorou

Slides Structure

- ***TypeSQL introduction***
- ***Implementation***
- ***Evaluation & Plan***



Presentation: Instead of Introduction 1/2

Question for a relation

Corresponding Sql query

TypeSQL

a) ***Slot filling approach***
b) ***Knowledge based & Type aware***

i.e. Assign each query word a type(Column, Number, KB entity)

c) ***Search DB rows for better accuracy*** **(+9% improvement)**

Presenatation: Basic idea (2/2)

What are Slots ???

SELECT $AGGR $SEL_COL
WHERE $COND_COL $OP $COND_VAL
(AND $COND_COL $OP $COND_VAL)*

Query:

Was J. Biden v. president of US in 2019 ?

(none) (person) (column) (country) (year)

Three steps Formula

1) *Preprocessing: type recognition*

2) *Bi-directional LSTM for*
   a) *Type-word encoding*
   b) *Column's name encoding*

3) *Slot Prediction (more Bi-LSTMs)*

Implementation: Encoding (1/3)

Two Bi-LSTMs for

a) Quest: word-type → *Output H-QT*

b) Column schema → *Output H-COL*

Slot Predictions

SELECT $AGGR $SEL_COL
WHERE $COND_COL $OP $COND_VAL
*(AND $COND_COL $OP $COND_VAL)**

Implementation of

Three LSTMs for prediction

- *$AGG*
- *$OP, $COND_VAL,*
- *$SEL_COL, $COND_COL, $COND#*

(5 LSMTs all together)

$$\alpha_{\mathrm{QT/COL}} = \mathbf{softmax}(\mathbf{H}_{\mathrm{COL}} \mathbf{W}_{ct} \mathbf{H}_{\mathrm{QT}}^{\top})$$

$$\mathbf{H}_{\mathrm{QT/COL}} = \alpha_{\mathrm{QT/COL}} \mathbf{H}_{\mathrm{QT}}$$

Implementation: Encoding (1/3)

Two Bi-LSTMs for

a) Quest: word-type → *H-QT*

b) Column schema → *H-COL*

Output

Slot Predictions

SELECT $AGGR $SEL_COL
WHERE $COND_COL $OP $COND_VAL
*(AND $COND_COL $OP $COND_VAL)**

Implementation of

Three LSTMs for prediction

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Implementation: Preprocessing (2/3)

Query:

Was J. Biden v. president of US in 2019 ?

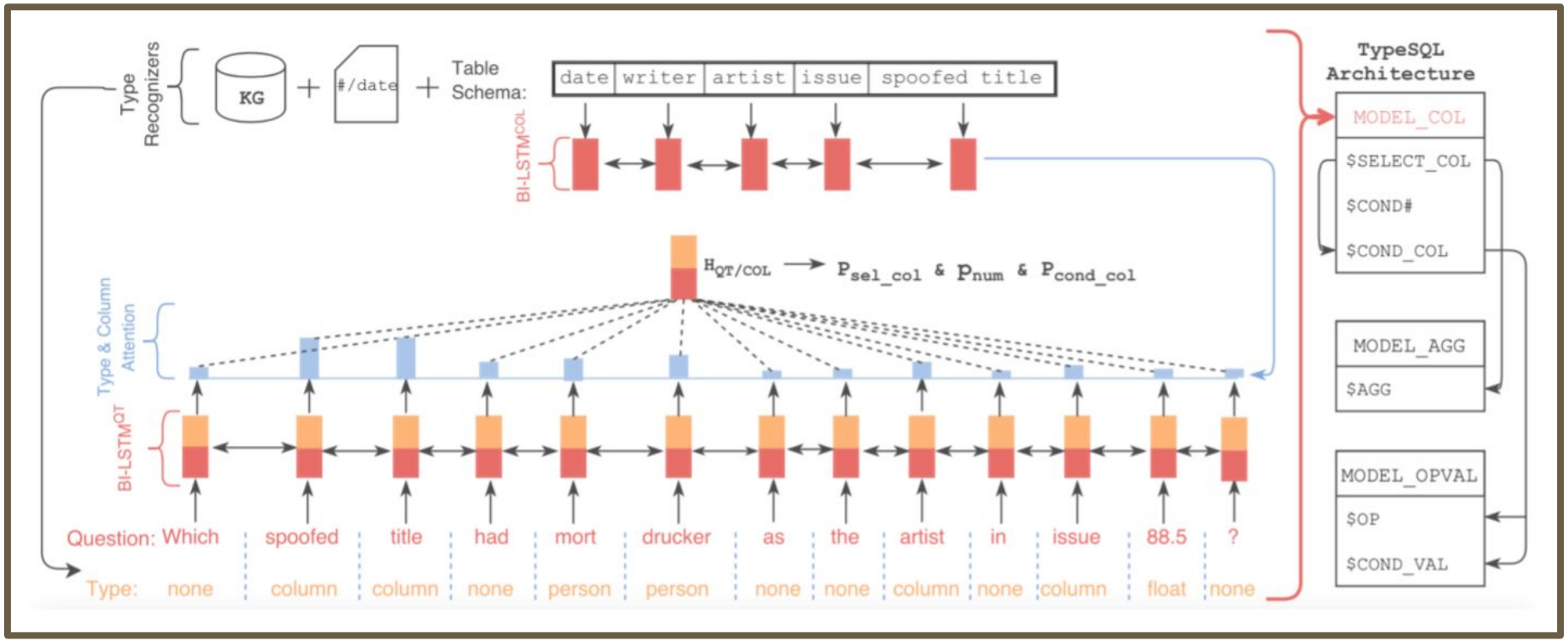
(none) (person) (column) (country) (year)

1) **Tokenization k-grams, k=[2-6] => type assignment.**

- ***Based on k-grams: Search***
  - *a) numbers, dates, years*
  - *b) Columns from schema*
  - *c) Entities in Freebase KB*

- ***If Table's rows are available: use them!***
  - *a) Content sensitive model*
  - *b) Match tokes with both table schema and entries.*

Paper's paradigm



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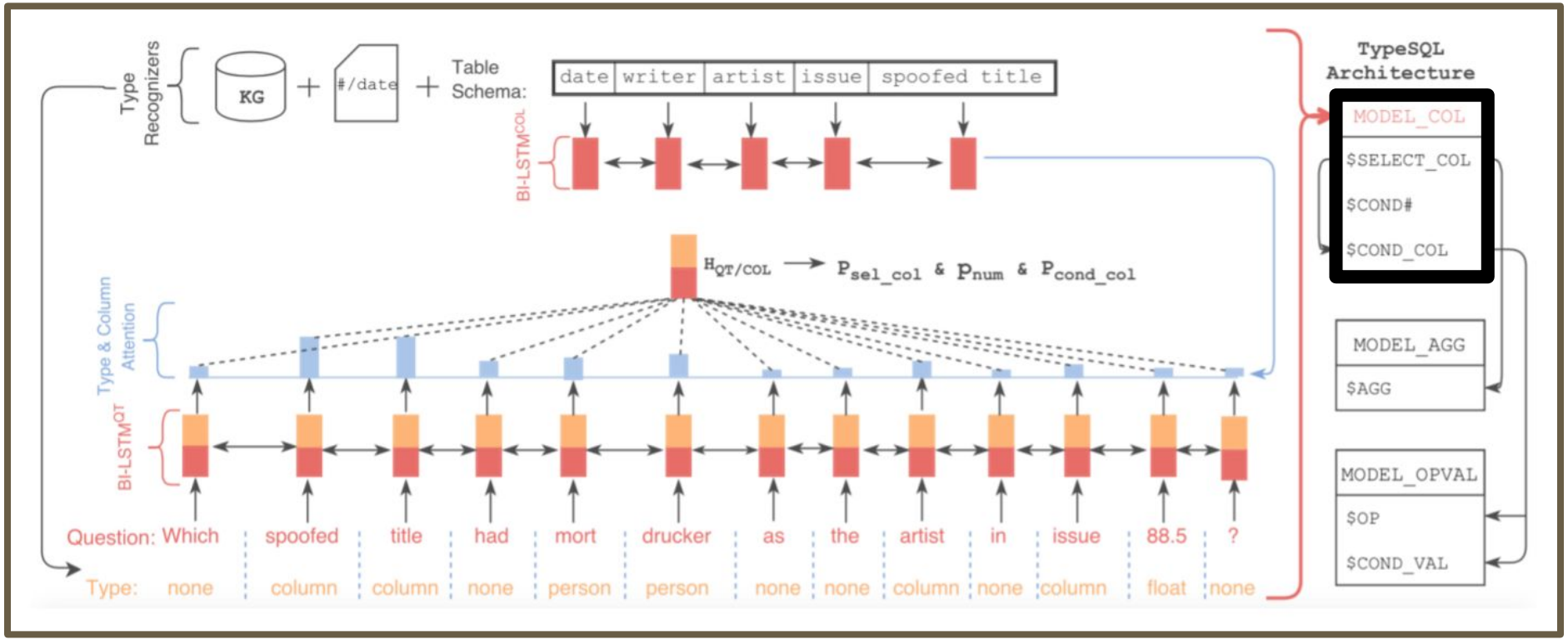

Implementation: Final Models(3/3)

MODEL_COL: (3 Slots)

$SELECT_COL
$COND#
$COND_Col

MODEL_COL- $SELECT_COL

$$s = \mathbf{V}^{sel}\tanh(\mathbf{W}_c^{sel}\mathbf{H}_{\text{COL}}^{\top} + \mathbf{W}_{qt}^{sel}\mathbf{H}_{\text{QT/COL}}^{\top})$$
$$P_{sel\_col} = \mathbf{softmax}(s)$$

MODEL_COL- $SELECT_COND#

$$c = \mathbf{V}^{col}\tanh(\mathbf{W}_c^{col}\mathbf{H}_{\text{COL}}^{\top} + \mathbf{W}_{qt}^{col}\mathbf{H}_{\text{QT/COL}}^{\top} + \mathbf{W}_{qt}^{scol}\mathbf{H}_{\text{QT/SCOL}}^{\top})$$
$$P_{cond\_col} = \mathbf{softmax}(c)$$

Evaluation & Plan

	Dev			Test		
	Acc_{agg}	Acc_{sel}	Acc_{where}	Acc_{agg}	Acc_{sel}	Acc_{where}
Seq2SQL (Zhong et al., 2017)	90.0%	89.6%	62.1%	90.1%	88.9%	60.2%
SQLNet (Xu et al., 2017)	90.1%	91.5%	74.1%	90.3%	90.9%	71.9%
TypeSQL (ours)	90.3%	**93.1%**	**78.5%**	90.5%	**92.2%**	**77.8%**
TypeSQL+TC (ours)	90.3%	**93.5%**	**92.8%**	90.5%	**92.1%**	**87.9%**

Recap & Action Plan

Accomplishing the ultimate goal: **NLP text** to **SQL query**

Three LSTMs for prediction

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+2 LSMTs During preprocessing

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Two Basic Competitors:
Seq2SQL & SQLNet

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Implementation details

- WikiSQL Dataset & **Adam** optimizer
- Tuning: **dimens**, **dropout rate**, etc.
- Embed: **Glove** & **paragram_sl 999 czeng**
- ***My experiments on optimizers & tuning***

Thanks for watching