

7 REFERENCES

- [1] V. Zhong, C. Xiong, and R. Socher, ‘Seq2sql: Generating structured queries from natural language using reinforcement learning’, *arXiv preprint arXiv:1709.00103*, 2017.
- [2] C. Finegan-Dollak *et al.*, ‘Improving text-to-sql evaluation methodology’, *arXiv preprint arXiv:1806.09029*, 2018.
- [3] T. Yu *et al.*, ‘Sparc: Cross-domain semantic parsing in context’, *arXiv preprint arXiv:1906.02285*, 2019.
- [4] C. Wang *et al.*, ‘Robust text-to-sql generation with execution-guided decoding’, *arXiv preprint arXiv:1807.03100*, 2018.
- [5] J. Guo *et al.*, ‘Towards complex text-to-sql in cross-domain database with intermediate representation’, *arXiv preprint arXiv:1905.08205*, 2019.
- [6] K. Xu, Y. Wang, Y. Wang, Z. Wen, and Y. Dong, ‘Sead: End-to-end text-to-sql generation with schema-aware denoising’, *arXiv preprint arXiv:2105.07911*, 2021.
- [7] T. Guo and H. Gao, ‘Content enhanced bert-based text-to-sql generation’, *arXiv preprint arXiv:1910.07179*, 2019.
- [8] Y. Cai and X. Wan, ‘IGSQL: Database schema interaction graph based neural model for context-dependent text-to-SQL generation’, *arXiv preprint arXiv:2011.05744*, 2020.
- [9] B. Hui *et al.*, ‘Improving text-to-sql with schema dependency learning’, *arXiv preprint arXiv:2103.04399*, 2021.
- [10] B. Wang, R. Shin, X. Liu, O. Polozov, and M. Richardson, ‘Rat-sql: Relation-aware schema encoding and linking for text-to-sql parsers’, *arXiv preprint arXiv:1911.04942*, 2019.
- [11] Matthew Peters, Mark Neumann, Mohit Iyyer, Matt Gardner, Christopher Clark, Kenton Lee, and Luke Zettlemoyer. 2018a. Deep contextualized word representations. In NAACL.
- [12] W. Hwang, J. Yim, S. Park, and M. Seo, ‘A comprehensive exploration on wikisql with table-aware word contextualization’, *arXiv preprint arXiv:1902.01069*, 2019.
- [13] R. Zhang *et al.*, ‘Editing-based SQL query generation for cross-domain context-dependent questions’, *arXiv preprint arXiv:1909.00786*, 2019.
- [14] K. Balaraman, ‘A Robust Text-to-SQL Parser With Optimized Pretraining Approach’, Dublin, National College of Ireland, 2021.
- [15] Hristidis, V., Gravano, L., Papakonstantinou, Y.: Efficient IR-style keyword search over relational databases. In: VLDB, pp. 850–861 (2003).
- [16] Hristidis, V., Papakonstantinou, Y.: Discover: keyword search in relational databases. In: VLDB, pp. 670–681 (2002).
- [17] Y. Luo, X. Lin, W. Wang, and X. Zhou, ‘Spark: top-k keyword query in relational databases’, in *Proceedings of the 2007 ACM SIGMOD international conference on management of data*, 2007, pp. 115–126.
- [18] Z. Zhong, L. Mong Li, and L. Tok Wang, ‘Answering Keyword Queries

- involving Aggregates and Group-Bys in Relational Databases’, 2015.
- [19] U. Brunner and K. Stockinger, ‘ValueNet: A neural text-to-SQL architecture incorporating values’, *Proc. VLDB Endowment*, pp. 1–14, 2020.
 - [20] J. Pennington, R. Socher, and C. D. Manning, ‘Glove: Global vectors for word representation’, in *Proceedings of the 2014 conference on empirical methods in natural language processing (EMNLP)*, 2014, pp. 1532–1543.
 - [21] J. D. M.-W. C. Kenton and L. K. Toutanova, ‘Bert: Pre-training of deep bidirectional transformers for language understanding’, in *Proceedings of naacL-HLT*, 2019, vol. 1, p. 2.
 - [22] P. Yin, G. Neubig, W.-T. Yih, and S. Riedel, ‘TaBERT: Pretraining for joint understanding of textual and tabular data’, *arXiv preprint arXiv:2005.08314*, 2020.
 - [23] X. Xu, C. Liu, and D. Song, ‘Sqlnet: Generating structured queries from natural language without reinforcement learning’, *arXiv preprint arXiv:1711.04436*, 2017.
 - [24] D. Choi, M. C. Shin, E. Kim, and D. R. Shin, ‘Ryansql: Recursively applying sketch-based slot fillings for complex text-to-sql in cross-domain databases’, *Computational Linguistics*, vol. 47, no. 2, pp. 309–332, 2021.
 - [25] L. Dong and M. Lapata, ‘Coarse-to-fine decoding for neural semantic parsing’, *arXiv preprint arXiv:1805.04793*, 2018.
 - [26] T. Scholak, N. Schucher, and D. Bahdanau, ‘PICARD: Parsing incrementally for constrained auto-regressive decoding from language models’, *arXiv preprint arXiv:2109.05093*, 2021.
 - [27] Liu, Y., Ott, M., Goyal, N., Du, J., Joshi, M., Chen, D., Levy, O., Lewis, M., Zettlemoyer, L., Stoyanov, V.: Roberta: a robustly optimized bert pretraining approach (2019).
 - [28] T. Yu *et al.*, ‘Spider: A large-scale human-labeled dataset for complex and cross-domain semantic parsing and text-to-sql task’, *arXiv preprint arXiv:1809.08887*, 2018.
 - [29] M. Lewis *et al.*, ‘Bart: Denoising sequence-to-sequence pre-training for natural language generation, translation, and comprehension’, *arXiv preprint arXiv:1910.13461*, 2019.
 - [30] R. Cao, L. Chen, Z. Chen, Y. Zhao, S. Zhu, and K. Yu, ‘LGESQL: line graph enhanced text-to-SQL model with mixed local and non-local relations’, *arXiv preprint arXiv:2106.01093*, 2021.
 - [31] T. Yu *et al.*, ‘Grappa: Grammar-augmented pre-training for table semantic parsing’, *arXiv preprint arXiv:2009.13845*, 2020.
 - [32] T.-Y. Lin, P. Goyal, R. Girshick, K. He, and P. Dollar, ‘Focal Loss for dense object detection’, *IEEE Trans. Pattern Anal. Mach. Intell.*, vol. 42, no. 2, pp. 318–327, Feb. 2020.
 - [33] J. Qi *et al.*, ‘RASAT: Integrating relational structures into pretrained Seq2Seq model for text-to-SQL’, *arXiv [cs.CL]*, 14-May-2022.
 - [34] C. Raffel *et al.*, ‘Exploring the limits of transfer learning with a unified text-to-text transformer’, *arXiv [cs.LG]*, 23-Oct-2019.

- [35] Y. Gan *et al.*, ‘Towards robustness of text-to-SQL models against synonym substitution’, *arXiv [cs.CL]*, 02-Jun-2021.
- [36] “Models”, Hugging Face. [Online]. Available: <https://huggingface.co/models>. [Accessed: 09- May- 2023]
- [37] I. Loshchilov and F. Hutter, ‘Decoupled weight decay regularization’, arXiv preprint arXiv:1711.05101, 2017.
- [38] Aadhil Rushdy, "Google Colaboratory", Colab.research.google.com, 2023. [Online]. Available: https://colab.research.google.com/drive/1WLbHPXFWzw_K14fwoXqqKCm3rt3KgVcY?usp=sharing. [Accessed: 22- May- 2023]
- [39] T. Yu *et al.*, ‘CoSQL: A conversational text-to-SQL challenge towards cross-domain natural language interfaces to databases’, arXiv preprint arXiv:1909.05378, 2019.
- [40] D. H. D. Warren and F. C. N. Pereira, ‘An efficient easily adaptable system for interpreting natural language queries’, *American journal of computational linguistics*, vol. 8, no. 3–4, pp. 110–122, 1982.
- [41] I. Androustopoulos, G. D. Ritchie, and P. Thanisch, ‘Natural language interfaces to databases—an introduction’, *Natural language engineering*, vol. 1, no. 1, pp. 29–81, 1995.
- [42] A.-M. Popescu, A. Armanasu, O. Etzioni, D. Ko, and A. Yates, ‘Modern natural language interfaces to databases: Composing statistical parsing with semantic tractability’, in *COLING 2004: Proceedings of the 20th International Conference on Computational Linguistics*, 2004, pp. 141–147.
- [43] H. Bast and E. Hausmann, ‘More accurate question answering on freebase’, in *Proceedings of the 24th ACM international on conference on information and knowledge management*, 2015, pp. 1431–1440.
- [44] L. Blunschi, C. Jossen, D. Kossman, M. Mori, and K. Stockinger, ‘Soda: Generating sql for business users’, arXiv preprint arXiv:1207.0134, 2012.
- [45] A. Simitsis, G. Koutrika, and Y. Ioannidis, ‘Precis: from unstructured ‘keywords as queries to structured databases as answers’, *The VLDB Journal*, vol. 17, pp. 117–149, 2008.
- [46] D. Damjanovic, M. Agatonovic, and H. Cunningham, ‘Natural language interfaces to ontologies: Combining syntactic analysis and ontologybased lookup through the user interaction’, in *The Semantic Web: Research and Applications: 7th Extended Semantic Web Conference, ESWC 2010, Heraklion, Crete, Greece, May 30–June 3, 2010, Proceedings, Part I 7*, 2010, pp. 106–120.
- [47] W. Zheng, H. Cheng, L. Zou, J. X. Yu, and K. Zhao, ‘Natural language question/answering: Let users talk with the knowledge graph’, in *Proceedings of the 2017 ACM on Conference on Information and Knowledge Management*, 2017, pp. 217–226.
- [48] A. Vaswani *et al.*, ‘Attention is all you need’, *Advances in neural information processing systems*, vol. 30, 2017.