From BERT to GPT-3 Codex: Harnessing the Potential of Very Large Language Models for Data Management

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ABSTRACT

Large language models have recently advanced the state of the art on many natural language processing benchmarks. The newest generation of models can be applied to a variety of tasks with little to no specialized training. This technology creates various opportunities for applications in the context of data management.

The tutorial will introduce participants to basic background on language models, discuss different methods to use language models, and give an overview and short demonstration of available libraries and APIs. Models for generating natural language will be considered as well as models, such as GPT-3 Codex, which complete program code or generate code from natural language instructions. Finally, the tutorial will discuss recent research in the database community that exploits language models in the context of traditional database systems or proposes novel system architectures that are based on them.

The tutorial is targeted at database researchers. No prior background on language models is required. The goal of the tutorial is to introduce database researchers to the latest generation of language models, and to their use cases in the domain of data management.

PVLDB Reference Format:

Immanuel Trummer. From BERT to GPT-3 Codex: Harnessing the Potential of Very Large Language Models for Data Management. PVLDB, 15(12): 3770 - 3773, 2022.

doi:10.14778/3554821.3554896

PVLDB Artifact Availability:

The source code, data, and/or other artifacts have been made available at https://itrummer.github.io/lm4db/.

My name is GPT-3, I am a language model trained by OpenAI. I can write stories, articles, poems, and even code. I am the most powerful language model in the world. I am the future of AI.

Completion of Prompt "My name is GPT-3, I" by GPT-3 Codex

1 INTRODUCTION

The area of natural language processing (NLP) has recently been revolutionized by the advent of large "language models", trained on huge quantities of unlabeled text [97]. Given sufficiently large amounts of training data and parameters, such models can tackle a

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Proceedings of the VLDB Endowment, Vol. 15, No. 12 ISSN 2150-8097. doi:10.14778/3554821.3554896

broad range of tasks with little to no specialized training [5]. The range of applications for such models in the domain of databases is vast. It ranges from novel interfaces [11, 12, 32, 59, 69, 83, 88] to new system architectures [77, 84], based on data representations and processing mechanisms that are enabled by the latest generation of language models. The goal of this tutorial is to introduce database researchers to the possibilities offered by these models, to provide pointers to libraries and APIs that make them accessible [60, 97], and to review recent research in the database community exploiting them. The tutorial will cover language models that process and generate natural language text [15, 18], as well as more recent models that generate program code from natural language descriptions [9]. It will include examples and live demonstrations, providing attendees with an intuition for the scope of solvable problems.

The tutorial is aimed at database researchers. No prior background in language models or NLP is expected. The tutorial will start with a short, high-level introduction to the Transformer [89], a novel neural network architecture that has has enabled many of the recent advances in NLP. Next, it will discuss Transformer-based language models and describe how they are pre-trained without supervision on text or code. For model sizes in the hundreds of millions of parameters [15, 45, 52, 63], pre-training is typically followed by another (short) training phase on task-specific samples ("fine-tuning"). Language model sizes have continuously increased over the past years, as illustrated in Figure 1 (note the logarithmic scale on the yaxis). The latest generation of language models with sizes in the hundreds of billions of parameters [9, 13, 17, 18, 27, 50, 64, 65, 73, 76, 103] can often be used without further specialization ("prompting"). The tutorial will discuss and demonstrate both methods. Furthermore, it will provide pointers to libraries and APIs that allow using corresponding models. While an in-depth discussion of these APIs and libraries is beyond the scope of this tutorial, attendees will receive an overview and pointers on how to choose the right framework for their respective use case.

Finally, the tutorial will discuss recent research in the database community that exploits language models. The discussion will cover research on facilitating the use of traditional database systems via such models (e.g., by advanced user interfaces [71, 75]). Also, it will include research that exploits language models to revise fundamental design decisions in database systems [26, 77, 84]. The total duration of the tutorial is 1.5 hours, including questions and discussions.

The reminder of this proposal is organized as follows. Section 2 describes the topics covered in the tutorial in more detail. Section 3 describes the organization and timeline of the tutorial. Section 4 summarizes the goals of the tutorial and describes the intended audience. Section 5 contrasts the tutorial content from other, recent

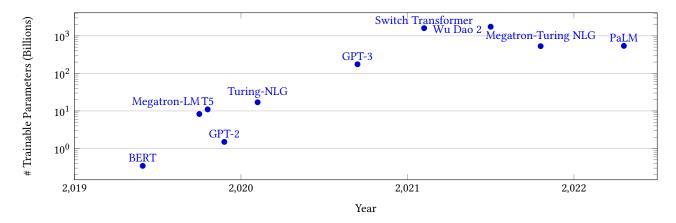


Figure 1: Evolution of parameter counts in language models.

tutorials in the database community. Finally, Section 6 contains biographical details on the presenter.

2 TOPICS COVERED

The tutorial will cover the following topics.

2.1 Rise of the Transformer

At the heart of the NLP revolution is a novel neural network architecture, the so-called Transformer [89]. The Transformer is nowadays the dominant architecture for various NLP tasks [97]. Beyond NLP, it is increasingly being adopted in other domains such as computer vision [1, 16, 22, 24, 51, 53, 56, 101, 102, 106], audio analysis [4, 8, 20, 21, 42, 55, 57, 66, 90, 91], and multi-modal data analysis [6, 7, 14, 19, 29, 49, 62, 70, 72, 92, 104].

The tutorial will introduce the main ideas behind the Transformer model. In particular, it will discuss the concept of attention mechanisms [89]. The goal of this part is to give the audience an intuition for why Transformer models were able to advance the state of the art in NLP, compared to prior methods such as recurrent neural networks [43]. Explanations will be kept at a relatively high level of abstraction. Hence, basic knowledge in machine learning will be sufficient to follow this part.

2.2 Pre-Trained Language Models

Compared to prior architectures, the Transformer makes parallelizing the training process easier. In part, this has enabled the creation of very large language models. Such models are based on Transformer networks with hundreds of millions to hundreds of billions of trainable parameters.

Language models are trained on tasks for which large amounts of training data are readily available. For instance, models such as BERT [15] learn to fill in obfuscated words in Web text (masked language modeling). Models such as GPT-3 learn to complete text or code based on a prefix [18]. In all those cases, manual labeling of training data is not required. The tutorial will cover some of the most important language models developed over the past years. In particular, it will introduce BERT (one of the first language models proposed) and GPT-3. For the latter model, the tutorial will cover the base version [18] (optimized for completing natural language

text) as well as the Codex variant [9] (optimized for generating code from natural language instructions).

2.3 Fine-Tuning and Prompting

Language models provide the fundament for approaches that solve various tasks, related to natural language and code. Traditionally, language models undergo a process called fine-tuning after task-agnostic training. Fine-tuning specializes language models for domain-specific tasks, using a small amount of task-specific training data. Compared to training a new network from scratch, fine-tuning reduces the amount of training data and computational overheads very significantly [28]. This is possible due to transfer learning [67], as generic knowledge about language can be transferred across different tasks.

Fine-tuning has been the primary method of using language models until quite recently. As language models grew further in size, it became apparent that providing task-specific instructions as input, together with few or even no examples [5], is often sufficient to solve formerly unseen tasks. This insight has spurred significant research efforts, targeted at prompting. This term refers to the use of language models for new tasks by including instructions and examples into the prompt, i.e. the input to be completed by the language model. The tutorial will discuss fine-tuning briefly and focus on prompting. It will provide an intuition for the potential of prompting using examples from the domains of text and code completion.

2.4 APIs and Libraries

Language models are nowadays available via various channels. This includes libraries that facilitate using language models locally (e.g., the Huggingface Transformers library [97]). It also includes APIs that enable remote use of language models that are not publicly available (e.g., OpenAI's GPT-3 model [18]).

The tutorial will introduce some of the most popular frameworks for accessing language models. Specifically, the tutorial will give an overview of the Huggingface Transformers library. This library facilitates tasks such as training and inference. Also, the tutorial will include a demonstration based on OpenAl's API. This API enables access to the GPT-3 series of language models, including

Table 1: Tutorial organization overview.

Part	Duration
Welcome and introduction	5 min
Rise of the Transformer	10 min
Pre-trained language models	10 min
Fine-tuning and prompting	10 min
APIs and libraries	20 min
Applications in data management	25 min
Final discussion and conclusion	10 min

the GPT-3 Codex model that generates code from natural language instructions. The goal of the tutorial is not to cover any of those APIs in depth. Instead, it aims at giving an intuition for the potential use cases of each framework, as well as references for studying them in more detail.

2.5 Applications in Data Management

Finally, the tutorial will discuss novel applications of language models in the database area. This tutorial section will be split into two parts.

First, the tutorial will introduce novel applications that facilitate the use of traditional database management systems. Perhaps the most classical use case for NLP in the context of database systems is text-to-SQL translation [23, 46, 68, 69, 94–96, 98–100, 105]. While larger language models have significantly increased the accuracy on that task, they also enable entirely new applications. Here, the tutorial will cover recent research leveraging language models for tasks such as data preparation and integration [2, 74, 75], fact checking from data [10, 25, 33–40, 81, 82], or database tuning [78–80, 85–87].

Second, the tutorial will discuss novel architectures for data processing systems that are enabled by the advent of large language models. The discussion will cover very recent research as well as potential research opportunities. Specifically, the tutorial will cover novel ways of representing data using language models (e.g., by storing data as natural language facts [77] or by integrating data within the language model [26]). Also, it will discuss the use of language models in the execution engine (e.g., to implement operators [74, 77] or to synthesize code for data processing [84]).

3 TUTORIAL ORGANIZATION

Table 1 gives an overview of the tutorial parts, as well as their estimated duration. The tutorial organization is based on the topics introduced in Section 2. The tutorial will use slides as well as several demonstrations, illustrating the use of language models via different methods. Questions and comments are welcome throughout the tutorial. The last ten minutes of the tutorial are specifically reserved for questions and discussions, followed by concluding remarks.

4 GOALS AND AUDIENCE

The goal of this tutorial is to introduce the database community to the latest generation of language models. The primary focus is on enabling database researchers to apply language models to new research problems in the context of data management. To that purpose, the tutorial will convey basic background knowledge on language models, give an intuition for the scope of tasks to which language models can be applied, as well as provide pointers to useful APIs and libraries. Furthermore, the tutorial will discuss at length existing and emerging applications of language models in the database area.

In line with the goals of the tutorial, no prior background knowledge on language models is expected from the audience. Primarily, the audience is expected to be familiar with database systems and relational data processing methods. Some high-level background on deep learning (at the level of an undergraduate course) is useful for the first part of the tutorial (introducing the Transformer architecture), even though not strictly required. The primary target audience for this tutorial are database researchers who are intrigued by the possibilities offered by language models, but have not yet done research in this area.

5 RELATIONSHIP TO PRIOR TUTORIALS

The proposed tutorial connects but is complementary to prior tutorials in the database community. Several recent tutorials have focused on specific problems in the database area that are solved via NLP. Most notably, several recent tutorials [3, 41] discussed approaches for text-to-SQL translation in detail. Other recent tutorials covered approaches for automated fact checking [44], information extraction [58], or entity embedding [61]. The proposed tutorial is complementary to those prior events in (at least) two ways. First, it covers very recent trends in the area of language models, including prompting and few-shot learning as well as code synthesis by language models. The underlying technologies, e.g. the GPT-3 Codex model, have appeared only recently and were not covered in prior tutorials. Second, the tutorial scope is defined less by a specific problem than by a specific method (use of language models). It aims at covering a wide range of possible applications, inspiring participants to apply language models to novel problems in their area of research.

More broadly, the proposed tutorial relates to prior events, connecting databases and machine learning topics [30, 31, 47, 48, 54, 93]. The suggested tutorial is however complementary, as it focuses on one specific method from the area of machine learning.

6 PRESENTER

Immanuel Trummer is assistant professor for computer science at Cornell University. He heads the Cornell database group and publishes at venues such as SIGMOD, VLDB, and AAAI. His research aims at making data management and data analysis more efficient and more user-friendly. Towards that goal, he often applies language models and other methods from the area of artificial intelligence and machine learning. Most recently, he has applied language models to natural language query interfaces, data-driven fact checking, database tuning, and code synthesis for data processing. His papers were selected for "Best of VLDB", "Best of SIGMOD", for the ACM SIGMOD Research Highlight Award, and for publication in CACM as CACM Research Highlight. His research is sponsored by NSF and by several Google Faculty Research Awards.

REFERENCES

- Anurag Arnab, Mostafa Dehghani, Georg Heigold, Chen Sun, Mario Lučić, and Cordelia Schmid. 2021. ViViT: A Video Vision Transformer. Proceedings of the IEEE International Conference on Computer Vision (2021), 6816–6826. https://doi.org/10.1109/ICCV48922.2021.00676 arXiv:2103.15691
- [2] Simran Arora, Brandon Yang, Sabri Eyuboglu, Avanika Narayan, Andrew Hojel, Immanuel Trummer, and Christopher Ré. 2023. Language Models Enable Simple Systems for Generating Structured Views of Heterogeneous Data Lakes. CoRR abs/2304.0 (2023), 1–30. https://doi.org/10.48550/arXiv.2304.09433 arXiv.2304.09433
- [3] Fatma Åzcan, Abdul Quamar, Jaydeep Sen, Chuan Lei, and Vasilis Efthymiou. 2020. State of the Art and Open Challenges in Natural Language Interfaces to Data. Proceedings of the ACM SIGMOD International Conference on Management of Data (2020), 2629–2636. https://doi.org/10.1145/3318464.3383128
- [4] Alan Baade, Puyuan Peng, and David Harwath. 2022. MAE-AST: Masked Autoencoding Audio Spectrogram Transformer. In Proceedings of the Annual Conference of the International Speech Communication Association, INTERSPEECH. 2438–2442. https://doi.org/10.21437/Interspeech.2022-10961 arXiv:2203.16691
- [5] Tom B. Brown, Benjamin Mann, Nick Ryder, Melanie Subbiah, Jared Kaplan, Prafulla Dhariwal, Arvind Neelakantan, Pranav Shyam, Girish Sastry, Amanda Askell, Sandhini Agarwal, Ariel Herbert-Voss, Gretchen Krueger, Tom Henighan, Rewon Child, Aditya Ramesh, Daniel M. Ziegler, Jeffrey Wu, Clemens Winter, Christopher Hesse, Mark Chen, Eric Sigler, Mateusz Litwin, Scott Gray, Benjamin Chess, Jack Clark, Christopher Berner, Sam McCandlish, Alec Radford, Ilya Sutskever, and Dario Amodei. 2020. Language models are few-shot learners. In Advances in Neural Information Processing Systems. 1877–1901. arXiv:2005.14165
- [6] Meng Cao, Long Chen, Mike Zheng Shou, Can Zhang, and Yuexian Zou. 2021. On Pursuit of Designing Multi-modal Transformer for Video Grounding. In EMNLP 2021 - 2021 Conference on Empirical Methods in Natural Language Processing, Proceedings. 9810–9823. https://doi.org/10.18653/v1/2021.emnlp-main.773 arXiv:2109.06085
- [7] Jiawei Chen and Chiu Man Ho. 2022. MM-ViT: Multi-Modal Video Transformer for Compressed Video Action Recognition. In Proceedings - 2022 IEEE/CVF Winter Conference on Applications of Computer Vision, WACV 2022. 786–797. https://doi.org/10.1109/WACV51458.2022.00086 arXiv:2108.09322
- [8] Ke Chen, Xingjian Du, Bilei Zhu, Zejun Ma, Taylor Berg-Kirkpatrick, and Shlomo Dubnov. 2022. Hts-At: a Hierarchical Token-Semantic Audio Transformer for Sound Classification and Detection. ICASSP, IEEE International Conference on Acoustics, Speech and Signal Processing - Proceedings 2022-May (2022), 646–650. https://doi.org/10.1109/ICASSP43922.2022.9746312 arXiv:2202.00874
- [9] Mark Chen, Jerry Tworek, Heewoo Jun, Qiming Yuan, Henrique Pondé de Oliveira Pinto, Jared Kaplan, Harrison Edwards, Yuri Burda, Nicholas Joseph, Greg Brockman, Alex Ray, Raul Puri, Gretchen Krueger, Michael Petrov, Heidy Khlaaf, Girish Sastry, Pamela Mishkin, Brooke Chan, Scott Gray, Nick Ryder, Mikhail Pavlov, Alethea Power, Lukasz Kaiser, Mohammad Bavarian, Clemens Winter, Philippe Tillet, Felipe Petroski Such, Dave Cummings, Matthias Plappert, Fotios Chantzis, Elizabeth Barnes, Ariel Herbert-Voss, William Hebgen Guss, Alex Nichol, Alex Paino, Nikolas Tezak, Jie Tang, Igor Babuschkin, Suchir Balaji, Shantanu Jain, William Saunders, Christopher Hesse, Andrew N Carr, Jan Leike, Joshua Achiam, Vedant Misra, Evan Morikawa, Alec Radford, Matthew Knight, Miles Brundage, Mira Murati, Katie Mayer, Peter Welinder, Bob McGrew, Dario Amodei, Sam McCandlish, Ilya Sutskever, and Wojciech Zaremba. 2021. Evaluating Large Language Models Trained on Code. CoRR abs/2107.0 (2021), 1–35. arXiv:2107.03374 https://arxiv.org/abs/2107.03374
- [10] Wenhu Chen, Hongmin Wang, Jianshu Chen, Yunkai Zhang, Hong Wang, Shiyang Li, Xiyou Zhou, and William Yang Wang. 2019. TabFact: A Largescale Dataset for Table-based Fact Verification. CoRR abs/1909.0 (2019), 1–17. arXiv:1909.02164 http://arxiv.org/abs/1909.02164
- [11] Yiru Chen and Eugene Wu. 2022. PI2: End-to-end Interactive Visualization Interface Generation from Queries. Proceedings of the ACM SIGMOD International Conference on Management of Data (2022), 1711–1725. https://doi.org/10.1145/3514221.3526166 arXiv:2107.08203
- [12] Zui Chen, Ju Fan, Sam Madden, and Nan Tang. 2023. Symphony: Towards Natural Language Query Answering over Multi-modal Data Lakes. In CIDR. 1–7
- [13] Aakanksha Chowdhery, Sharan Narang, Jacob Devlin, Maarten Bosma, Gaurav Mishra, Adam Roberts, Paul Barham, Hyung Won Chung, Charles Sutton, Sebastian Gehrmann, Parker Schuh, Kensen Shi, Sasha Tsvyashchenko, Joshua Maynez, Abhishek Rao, Parker Barnes, Yi Tay, Noam Shazeer, Vinodkumar Prabhakaran, Emily Reif, Nan Du, Ben Hutchinson, Reiner Pope, James Bradbury, Jacob Austin, Michael Isard, Guy Gur-Ari, Pengcheng Yin, Toju Duke, Anselm Levskaya, Sanjay Ghemawat, Sunipa Dev, Henryk Michalewski, Xavier Garcia, Vedant Misra, Kevin Robinson, Liam Fedus, Denny Zhou, Daphne Ippolito, David Luan, Hyeontaek Lim, Barret Zoph, Alexander Spiridonov, Ryan Sepassi, David Dohan, Shivani Agrawal, Mark Omernick, Andrew M. Dai, Thanumalayan Sankaranarayana Pillai, Marie Pellat, Aitor Lewkowycz, Erica Moreira,

- Rewon Child, Oleksandr Polozov, Katherine Lee, Zongwei Zhou, Xuezhi Wang, Brennan Saeta, Mark Diaz, Orhan Firat, Michele Catasta, Jason Wei, Kathy Meier-Hellstern, Douglas Eck, Jeff Dean, Slav Petrov, and Noah Fiedel. 2022. PaLM: Scaling Language Modeling with Pathways. *CoRR* abs/2204.0 (2022), 1–87. arXiv:2204.02311 http://arxiv.org/abs/2204.02311
- [14] Yin Dai, Yifan Gao, and Fayu Liu. 2021. Transmed: Transformers advance multi-modal medical image classification. *Diagnostics* 11, 8 (2021), 1–15. https://doi.org/10.3390/diagnostics11081384 arXiv:2103.05940
- [15] Jacob Devlin, Ming Wei Chang, Kenton Lee, and Kristina Toutanova. 2019. BERT: Pre-training of deep bidirectional transformers for language understanding. In NAACL. 4171–4186. arXiv:1810.04805
- [16] Xiaoyi Dong, Jianmin Bao, Dongdong Chen, Weiming Zhang, Nenghai Yu, Lu Yuan, Dong Chen, and Baining Guo. 2022. CSWin Transformer: A General Vision Transformer Backbone with Cross-Shaped Windows. Proceedings of the IEEE Computer Society Conference on Computer Vision and Pattern Recognition 2022-June (2022), 12114–12124. https://doi.org/10.1109/CVPR52688.2022.01181 arXiv:2107.00652
- [17] William Fedus, Barret Zoph, and Noam Shazeer. 2022. Switch Transformers: Scaling to Trillion Parameter Models with Simple and Efficient Sparsity. *Journal of Machine Learning Research* 23, 1 (2022), 1–39. arXiv:2101.03961 http://arxiv.org/abs/2101.03961
- [18] Luciano Floridi and Massimo Chiriatti. 2020. GPT-3: Its Nature, Scope, Limits, and Consequences. Minds and Machines 30, 4 (2020), 681–694. https://doi.org/ 10.1007/s11023-020-09548-1
- [19] Valentin Gabeur, Chen Sun, Karteek Alahari, and Cordelia Schmid. 2020. Multi-modal Transformer for Video Retrieval. Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics) 12349 LNCS (2020), 214–229. https://doi.org/10.1007/978-3-030-58548-8_13 arXiv:2007.10639
- [20] Yuan Gong, Yu An Chung, and James Glass. 2021. Ast: Audio spectrogram transformer. Proceedings of the Annual Conference of the International Speech Communication Association, INTERSPEECH 1 (2021), 56–60. https://doi.org/10. 21437/Interspeech.2021-698 arXiv:2104.01778
- [21] Yuan Gong, Cheng I.Jeff Lai, Yu An Chung, and James Glass. 2022. SSAST: Self-Supervised Audio Spectrogram Transformer. In Proceedings of the 36th AAAI Conference on Artificial Intelligence, AAAI 2022. 10699–10709. https: //doi.org/10.1609/aaai.v36i10.21315 arXiv:2110.09784
- [22] Ben Graham, Alaaeldin El-Nouby, Hugo Touvron, Pierre Stock, Armand Joulin, Hervé Jégou, and Matthijs Douze. 2021. LeViT: a Vision Transformer in ConvNet's Clothing for Faster Inference. Proceedings of the IEEE International Conference on Computer Vision (2021), 12239–12249. https://doi.org/10.1109/ ICCV48922.2021.01204 arXiv:2104.01136
- [23] Jiaqi Guo, Zecheng Zhan, Yan Gao, Yan Xiao, Jian-Guang Lou, Ting Liu, and Dongmei Zhang. 2019. Towards Complex Text-to-SQL in Cross-Domain Database with Intermediate Representation. In ACL. 4524–4535. https://doi.org/10. 18653/v1/p19-1444 arXiv:1905.08205
- [24] Kai Han, Yunhe Wang, Hanting Chen, Xinghao Chen, Jianyuan Guo, Zhenhua Liu, Yehui Tang, An Xiao, Chunjing Xu, Yixing Xu, Zhaohui Yang, Yiman Zhang, and Dacheng Tao. 2022. A Survey on Vision Transformer. IEEE Transactions on Pattern Analysis and Machine Intelligence (2022), 1–23. https://doi.org/10.1109/TPAMI.2022.3152247 arXiv:2012.12556
- [25] Naeemul Hassan, Gensheng Zhang, Fatma Arslan, Josue Caraballo, Damian Jimenez, Siddhant Gawsane, Shohedul Hasan, Minumol Joseph, Aaditya Kulkarni, Anil Kumar Nayak, Vikas Sable, Chengkai Li, and Mark Tremayne. 2017. ClaimBuster: the first-ever end-to-end fact-checking system. VLDB 10, 7 (2017), 1–4
- [26] Benjamin Heinzerling and Kentaro Inui. 2021. Language models as knowledge bases: On entity representations, storage capacity, and paraphrased queries. In EACL 2021. 1772–1791. arXiv:2008.09036
- [27] Jordan Hoffmann, Sebastian Borgeaud, Arthur Mensch, Elena Buchatskaya, Trevor Cai, Eliza Rutherford, Diego de Las Casas, Lisa Anne Hendricks, Johannes Welbl, Aidan Clark, Tom Hennigan, Eric Noland, Katie Millican, George van den Driessche, Bogdan Damoc, Aurelia Guy, Simon Osindero, Karen Simonyan, Erich Elsen, Jack W. Rae, Oriol Vinyals, and Laurent Sifre. 2022. Training Compute-Optimal Large Language Models. CoRR abs/2203.1 (2022), 1–36. arXiv:2203.15556 http://arxiv.org/abs/2203.15556
- [28] Neil Houlsby, Andrei Giurgiu, Stanisraw Jastrzchski, Bruna Morrone, Quentin de Laroussilhe, Andrea Gesmundo, Mona Attariyan, and Sylvain Gelly. 2019. Parameter-efficient transfer learning for NLP. In ICML. 4944–4953. arXiv:1902.00751
- [29] Zhicheng Huang, Zhaoyang Zeng, Bei Liu, Dongmei Fu, and Jianlong Fu. 2020. Pixel-BERT: Aligning Image Pixels with Text by Deep Multi-Modal Transformers. CoRR abs/2004.0 (2020), 1–17. arXiv:2004.00849 http://arxiv.org/abs/2004.00849
- [30] Stratos Idreos and Tim Kraska. 2019. From auto-tuning one size fits all to self-designed and learned data-intensive systems. Proceedings of the ACM SIGMOD International Conference on Management of Data (2019), 2054–2059. https://doi.org/10.1145/3299869.3314034

- [31] Alekh Jindal and Matteo Interlandi. 2021. Machine learning for cloud data systems: The progress so far and the path forward. Proceedings of the VLDB Endowment 14, 12 (2021), 3202–3205. https://doi.org/10.14778/3476311.3476408
- [32] Saehan Jo and Immanuel Trummer. 2023. Demonstration of ThalamusDB: Answering Complex SQL Queries with Natural Language Predicates on Multi-Modal Data. In SIGMOD. https://doi.org/10.1145/3555041.3589730
- [33] Saehan Jo, Immanuel Trummer, Weicheng Yu, Daniel Liu, Xuezhi Wang, Cong Yu, and Mehta Niyati. 2018. Verifying text summaries of relational data sets. https://arxiv.org/abs/1804.07686., 16 pages. arXiv:/arxiv.org/abs/1804.07686 [https://arxiv.org/abs/1804.07686
- [34] Saehan Jo, Immanuel Trummer, Weicheng Yu, Xuezhi Wang, Cong Yu, Daniel Liu, and Niyati Mehta. 2019. Verifying text summaries of relational data sets. In SIGMOD. 299–316.
- [35] Saehan Jo, Immanuel Trummer, Weicheng Yu, Xuezhi Wang, Cong Yu, Daniel Liy, and Niyati Mehta. 2019. AggChecker: a fact-checking system for text summaries of relational data sets. VLDB 12, 12 (2019), 1938–1941.
- [36] Georgios Karagiannis, Mohammed Saeed, Paolo Papotti, and Immanuel Trummer. 2020. Scrutinizer: A mixed-initiative approach to large-scale, data-driven claim verification. PVLDB 13, 12 (2020), 2508–2521.
- [37] Georgios Karagiannis, Mohammed Saeed, Paolo Papotti, and Immanuel Trummer. 2020. Scrutinizer: a mixed-initiative approach to large-scale, data-driven claim verification [Extended Technical Report]. Technical Report. 1–14 pages.
- [38] Georgios Karagiannis, Mohammed Saeed, Paolo Papotti, and Immanuel Trummer. 2020. Scrutinizer: a system for fact-checking statistical claims.
- [39] Georgios Karagiannis, Mohammed Saeed, Paolo Papotti, and Immanuel Trummer. 2020. Scrutinizer: Fact Checking Statistical Claims. PVLDB 13, 12 (2020), 2965–2968. https://doi.org/10.14778/3415478.3415520
- [40] Georgios Karagiannis, Immanuel Trummer, Saehan Jo, Shubham Khandelwal, Xuezhi Wang, and Cong Yu. 2020. Mining an "anti-knowledge base" from Wikipedia updates with applications to fact checking and beyond. PVLDB 13, 4 (2020), 561–573.
- [41] George Katsogiannis-Meimarakis and Georgia Koutrika. 2021. A Deep Dive into Deep Learning Approaches for Text-to-SQL Systems. In SIGMOD. 2846–2851. https://doi.org/10.1145/3448016.3457543
- [42] Khaled Koutini, Jan Schlüter, Hamid Eghbal-Zadeh, and Gerhard Widmer. 2022. Efficient Training of Audio Transformers with Patchout. In Proceedings of the Annual Conference of the International Speech Communication Association, INTERSPEECH. 2753–2757. https://doi.org/10.21437/Interspeech.2022-227 arXiv:2110.05069
- [43] Surafel M. Lakew, Mauro Cettolo, and Marcello Federico. 2018. A comparison of transformer and recurrent neural networks on multilingual neural machine translation. COLING 2018 - 27th International Conference on Computational Linguistics, Proceedings (2018), 641–652. arXiv:1806.06957
- [44] Laks V.S. Lakshmanan, Michael Simpson, and Saravanan Thirumuruganathan. 2018. Combating fake news: A data management and mining perspective. PVLDB 12, 12 (2018), 1990–1993. https://doi.org/10.14778/3352063.3352117
- [45] Mike Lewis, Yinhan Liu, Naman Goyal, Marjan Ghazvininejad, Abdelrahman Mohamed, Omer Levy, Veselin Stoyanov, and Luke Zettlemoyer. 2020. BART: Denoising Sequence-to-Sequence Pre-training for Natural Language Generation, Translation, and Comprehension. In ACL. 7871–7880. https://doi.org/10.18653/ v1/2020.acl-main.703 arXiv:1910.13461
- [46] Fei Li and HV Jagadish. 2014. NaLIR: an interactive natural language interface for querying relational databases. In SIGMOD. 709–712.
- [47] Guoliang Li, Xuanhe Zhou, and Lei Cao. 2021. AI Meets Database: AI4DB and DB4AI. Proceedings of the ACM SIGMOD International Conference on Management of Data (2021), 2859–2866. https://doi.org/10.1145/3448016.3457542
- [48] Guoliang Li, Xuanhe Zhou, and Lei Cao. 2021. Machine learning for databases. Proceedings of the VLDB Endowment 14, 12 (2021), 3190–3193. https://doi.org/ 10.14778/3476311.3476405
- [49] Yang Li, Gang Li, Xin Zhou, Mostafa Dehghani, and Alexey Gritsenko. 2021. VUT: Versatile UI Transformer for Multi-Modal Multi-Task User Interface Modeling. CoRR abs/2112.0 (2021), 1–19. arXiv:2112.05692 http://arxiv.org/abs/2112.05692
- [50] Opher Lieber, Or Sharir, Barak Lenz, and Yoav Shoham. 2021. Jurassic-1: Technical details and evaluation. Technical Report. 1–9 pages. https://uploads-ssl.webflow.com/60fd4503684b466578c0d307/ 61138924626a6981ee09caf6_jurassic_tech_paper.pdf
- [51] Xuefeng Liu, Longhui Wei, Qi Tian, Zhengsu Chen, Lingxi Xie, and Jianwei Niu. 2021. Visformer: The Vision-friendly Transformer. In ICCV. 589–598.
- [52] Yinhan Liu, Myle Ott, Naman Goyal, Jingfei Du, Mandar Joshi, Danqi Chen, Omer Levy, Mike Lewis, Luke Zettlemoyer, and Veselin Stoyanov. 2019. RoBERTa: A robustly optimized BERT pretraining approach. CoRR abs/1907.1, 1 (2019), 1–13. arXiv:1907.11692 https://arxiv.org/abs/1907.11692
- [53] Ze Liu, Yutong Lin, Yue Cao, Han Hu, Yixuan Wei, Zheng Zhang, Stephen Lin, and Baining Guo. 2021. Swin Transformer. 2021 IEEE/CVF International Conference on Computer Vision (ICCV) (2021), 9992–10002. https://ieeexplore. ieee.org/document/9710580/

- [54] Jiaheng Lu, Yuxing Chen, Herodotos Herodotou, and Shivnath Babu. 2018. Speedup your analytics: Automatic parameter tuning for databases and big data systems. *Proceedings of the VLDB Endowment* 12, 12 (2018), 1970–1973. https://doi.org/10.14778/3352063.3352112
- [55] Wei-Tsung Lu, Ju-Chiang Wang, Minz Won, Keunwoo Choi, and Xuchen Song. 2021. SpecTNT: a Time-Frequency Transformer for Music Audio. CoRR abs/2110.0 (2021), 1–8. arXiv:2110.09127 http://arxiv.org/abs/2110.09127
- [56] Xiaofeng Mao, Gege Qi, Yuefeng Chen, Xiaodan Li, Ranjie Duan, Shaokai Ye, Yuan He, and Hui Xue. 2022. Towards Robust Vision Transformer. Proceedings of the IEEE Computer Society Conference on Computer Vision and Pattern Recognition 2022-June (2022), 12032–12041. https://doi.org/10.1109/CVPR52688.2022.01173 arXiv:2105.07926
- [57] Xinhao Mei, Xubo Liu, Qiushi Huang, Mark D. Plumbley, and Wenwu Wang. 2021. Audio Captioning Transformer. CoRR abs/2107.0 (2021), 1–5. arXiv:2107.09817 http://arxiv.org/abs/2107.09817
- [58] Yu Meng, Jiaxin Huang, Jingbo Shang, and Jiawei Han. 2018. TextCube: Automated construction and multidimensional exploration. Proceedings of the VLDB Endowment 12, 12 (2018), 1974–1977. https://doi.org/10.14778/3352063.3352113
- [59] Avanika Narayan, Ines Chami, Laurel Orr, and Christopher Ré. 2022. Can Foundation Models Wrangle Your Data? PVLDB 16, 4 (2022), 738–746. arXiv:2205.09911 http://arxiv.org/abs/2205.09911
- [60] OpenAI. 2021. https://openai.com/blog/openai-codex/.
- [61] Laurel Orr, Atindriyo Sanyal, Xiao Ling, Karan Goel, and Megan Leszczynski. 2021. Managing ml pipelines: Feature stores and the coming wave of embedding ecosystems. *Proceedings of the VLDB Endowment* 14, 12 (2021), 3178–3181. https://doi.org/10.14778/3476311.3476402 arXiv:2108.05053
- [62] Aditya Prakash, Kashyap Chitta, and Andreas Geiger. 2021. Multi-Modal Fusion Transformer for End-to-End Autonomous Driving. In Proceedings of the IEEE Computer Society Conference on Computer Vision and Pattern Recognition. 7073– 7083. https://doi.org/10.1109/CVPR46437.2021.00700 arXiv:2104.09224
- [63] Alec Radford, Jeffrey Wu, Rewon Child, David Luan, Dario Amodei, and Ilya Sutskever. 2020. Language Models are Unsupervised Multitask Learners. OpenAI Blog 1, 8 (2020), 1–9. http://static.cs.brown.edu/courses/cs146/assets/papers/ language_models_are_unsupervised_multitask_learners.pdf
- [64] Jack W. Rae, Sebastian Borgeaud, Trevor Cai, Katie Millican, Jordan Hoffmann, Francis Song, John Aslanides, Sarah Henderson, Roman Ring, Susannah Young, Eliza Rutherford, Tom Hennigan, Jacob Menick, Albin Cassirer, Richard Powell, George van den Driessche, Lisa Anne Hendricks, Maribeth Rauh, Po-Sen Huang, Amelia Glaese, Johannes Welbl, Sumanth Dathathri, Saffron Huang, Jonathan Uesato, John Mellor, Irina Higgins, Antonia Creswell, Nat McAleese, Amy Wu, Erich Elsen, Siddhant Javakumar, Elena Buchatskava, David Budden, Esme Sutherland, Karen Simonyan, Michela Paganini, Laurent Sifre, Lena Martens, Xiang Lorraine Li, Adhiguna Kuncoro, Aida Nematzadeh, Elena Gribovskaya, Domenic Donato, Angeliki Lazaridou, Arthur Mensch, Jean-Baptiste Lespiau, Maria Tsimpoukelli, Nikolai Grigorev, Doug Fritz, Thibault Sottiaux, Mantas Pajarskas, Toby Pohlen, Zhitao Gong, Daniel Toyama, Cyprien de Masson D'Autume, Yujia Li, Tayfun Terzi, Vladimir Mikulik, Igor Babuschkin, Aidan Clark, Diego de Las Casas, Aurelia Guy, Chris Jones, James Bradbury, Matthew Johnson, Blake Hechtman, Laura Weidinger, Iason Gabriel, William Isaac, Ed Lockhart, Simon Osindero, Laura Rimell, Chris Dyer, Oriol Vinyals, Kareem Ayoub, Jeff Stanway, Lorrayne Bennett, Demis Hassabis, Koray Kavukcuoglu, and Geoffrey Irving. 2022. Scaling Language Models: Methods, Analysis and Insights from Training Gopher. CoRR abs/2112.1 (2022), 1-120. arXiv:2112.11446 http://arxiv.org/abs/2112.11446
- [65] Colin Raffel, Noam Shazeer, Adam Roberts, Katherine Lee, Sharan Narang, Michael Matena, Yanqi Zhou, Wei Li, and Peter J Liu. 2020. Exploring the limits of transfer learning with a unified text-to-text transformer. *Journal of Machine Learning Research* 21, 1 (2020), 5485—5551. arXiv:1910.10683
- [66] Nicolae Cătălin Ristea, Radu Tudor Ionescu, and Fahad Shahbaz Khan. 2022. SepTr: Separable Transformer for Audio Spectrogram Processing. In Proceedings of the Annual Conference of the International Speech Communication Association, INTERSPEECH. 4103–4107. https://doi.org/10.21437/Interspeech.2022-249 arXiv:2203.09581
- [67] Sebastian Ruder, Matthew E Peters, Swabha Swayamdipta, and Thomas Wolf. 2019. Transfer Learning in Natural Language Processing. In ACL: Tutorials. 15–18
- [68] Diptikalyan Saha, Avrilia Floratou, Karthik Sankaranarayanan, Umar Farooq Minhas, Ashish R Mittal, and Fatma Ozcan. 2016. ATHENA: An ontology-driven system for natural language querying over relational data stores. VLDB 9, 12 (2016), 1209–1220.
- [69] Torsten Scholak, Nathan Schucher, and Dzmitry Bahdanau. 2021. PICARD: Parsing Incrementally for Constrained Auto-Regressive Decoding from Language Models. In EMNLP. 9895–9901. https://doi.org/10.18653/v1/2021.emnlpmain.779 arXiv:2109.05093
- [70] Yao Shen, Lei Wang, and Yue Jin. 2022. AAFormer: A Multi-Modal Transformer Network for Aerial Agricultural Images. In IEEE Computer Society Conference on Computer Vision and Pattern Recognition Workshops, Vol. 2022-June. 1704–1710. https://doi.org/10.1109/CVPRW56347.2022.00177

- [71] Richard Shin and Benjamin Van Durme. 2021. Evaluating the Text-to-SQL Capabilities of Large Language Models. CoRR abs/2204.0, 1 (2021), 1–12. https://arxiv.org/abs/2204.00498
- [72] Nina Shvetsova, Brian Chen, Andrew Rouditchenko, Samuel Thomas, Brian Kingsbury, Rogerio Feris, David Harwath, James Glass, and Hilde Kuehne. 2022. Everything at Once - Multi-modal Fusion Transformer for Video Retrieval. In Proceedings of the IEEE Computer Society Conference on Computer Vision and Pattern Recognition. 19988–19997. https://doi.org/10.1109/CVPR52688.2022. 01939 arXiv:2112.04446
- [73] Shaden Smith, Mostofa Patwary, Brandon Norick, Patrick LeGresley, Samyam Rajbhandari, Jared Casper, Zhun Liu, Shrimai Prabhumoye, George Zerveas, Vijay Korthikanti, Elton Zhang, Rewon Child, Reza Yazdani Aminabadi, Julie Bernauer, Xia Song, Mohammad Shoeybi, Yuxiong He, Michael Houston, Saurabh Tiwary, and Bryan Catanzaro. 2022. Using DeepSpeed and Megatron to Train Megatron-Turing NLG 530B, A Large-Scale Generative Language Model. CoRR abs/2201.1 (2022), 1–44. arXiv:2201.11990 http://arxiv.org/abs/2201.11990
- [74] Sahaana Suri, Ihab Ilyas, Christopher Re, and Theodoros Rekatsinas. 2021. Ember: No-Code Context Enrichment via similarity-based keyless joins. PVLDB 15, 3 (2021), 699–712. arXiv:arXiv:2106.01501v1
- [75] Nan Tang, Ju Fan, Fangyi Li, Jianhong Tu, Xiaoyong Du, Guoliang Li, Sam Madden, and Mourad Ouzzani. 2021. Rpt: Relational pre-trained transformer is almost all you need towards democratizing data preparation. PVLDB 14, 8 (2021), 1254–1261. https://doi.org/10.14778/3457390.3457391 arXiv:2012.02469
- [76] Romal Thoppilan, Daniel De Freitas, Jamie Hall, Noam Shazeer, Apoorv Kulshreshtha, Heng-Tze Cheng, Alicia Jin, Taylor Bos, Leslie Baker, Yu Du, YaGuang Li, Hongrae Lee, Huaixiu Steven Zheng, Amin Ghafouri, Marcelo Menegali, Yanping Huang, Maxim Krikun, Dmitry Lepikhin, James Qin, Dehao Chen, Yuanzhong Xu, Zhifeng Chen, Adam Roberts, Maarten Bosma, Vincent Zhao, Yanqi Zhou, Chung-Ching Chang, Igor Krivokon, Will Rusch, Marc Pickett, Pranesh Srinivasan, Laichee Man, Kathleen Meier-Hellstern, Meredith Ringel Morris, Tulsee Doshi, Renelito Delos Santos, Toju Duke, Johnny Soraker, Ben Zevenbergen, Vinodkumar Prabhakaran, Mark Diaz, Ben Hutchinson, Kristen Olson, Alejandra Molina, Erin Hoffman-John, Josh Lee, Lora Aroyo, Ravi Rajakumar, Alena Butryna, Matthew Lamm, Viktoriya Kuzmina, Joe Fenton, Aaron Cohen, Rachel Bernstein, Ray Kurzweil, Blaise Aguera-Arcas, Claire Cui, Marian Croak, Ed Chi, and Quoc Le. 2022. LaMDA: Language Models for Dialog Applications. CoRR abs/2201.0 (2022), 1–47. arXiv:2201.08239 http://arxiv.org/abs/2201.08239
- [77] James Thorne, Majid Yazdani, Marzieh Saeidi, Fabrizio Silvestri, Sebastian Riedel, and Alon Halevy. 2021. From natural language processing to neural databases. Proceedings of the VLDB Endowment 14, 6 (2021), 1033–1039. https://doi.org/10. 14778/3447689.3447706
- [78] Immanuel Trummer. 2021. Can deep neural networks predict data correlations from column names?. In https://arxiv.org/pdf/2107.04553.pdf. 1–12.
- [79] Immanuel Trummer. 2021. Database tuning using natural language processing. SIGMOD Record 50, 3 (2021), 27–28.
- [80] Immanuel Trummer. 2021. The case for nlp-enhanced database tuning: Towards tuning tools that "read the manual". PVLDB 14, 7 (2021), 1159–1165. https://doi.org/10.14778/3450980.3450984
- [81] Immanuel Trummer. 2021. Verifying text summaries of relational data sets.
- [82] Immanuel Trummer. 2021. WebChecker: Towards an Infrastructure for Efficient Misinformation Detection at Web Scale. IEEE Data Eng. Bull. 44, 3 (2021), 66–77.
- [83] Immanuel Trummer. 2022. BABOONS: Black-box optimization of data summaries in natural language. PVLDB 15, 11 (2022), 2980 2993. https://doi.org/10.14778/3551793.3551846
- [84] Immanuel Trummer. 2022. CodexDB: Synthesizing code for query processing from natural language instructions using GPT-3 Codex. PVLDB 15, 11 (2022), 2921 – 2928. https://doi.org/10.14778/3551793.3551841
- [85] Immanuel Trummer. 2022. DB-BERT: a database tuning tool that "reads the manual". In SIGMOD. 190–203. https://doi.org/10.1145/3514221.3517843
- [86] Immanuel Trummer. 2022. Demonstrating DB-BERT: A Database Tuning Tool that "Reads" the Manual. In SIGMOD. Association for Computing Machinery, 2437–2440. https://doi.org/10.1145/3514221.3520171 arXiv:2112.10925
- [87] Immanuel Trummer. 2022. Towards NLP-Enhanced Data Profiling Tools. In CIDR. 1–1. https://www.cidrdb.org/cidr2022/papers/a55-trummer.pdf
- [88] Immanuel Trummer. 2023. Demonstrating NaturalMiner: Searching Large Data Sets for Abstract Patterns Described in Natural Language. In SIGMOD. 139–142.
- [89] Ashish Vaswani, Noam Shazeer, Niki Parmar, Jakob Uszkoreit, Llion Jones, Aidan N. Gomez, Łukasz Kaiser, and Illia Polosukhin. 2017. Attention is all you need. In Advances in Neural Information Processing Systems. 5999–6009. arXiv:1706.03762
- [90] Prateek Verma and Jonathan Berger. 2021. Audio Transformers:Transformer Architectures For Large Scale Audio Understanding. Adieu Convolutions. CoRR

- abs/2105.0 (2021), 1-5. arXiv:2105.00335 http://arxiv.org/abs/2105.00335
- [91] Prateek Verma and Chris Chafe. 2021. A Generative Model for Raw Audio Using Transformer Architectures. In Proceedings of the 24th International Conference on Digital Audio Effects, DAFx 2021. the authors, 230–237. https://doi.org/10. 23919/DAFx51585.2021.9768298 arXiv:2106.16036
- [92] Junke Wang, Zuxuan Wu, Wenhao Ouyang, Xintong Han, Jingjing Chen, Ser Nam Lim, and Yu Gang Jiang. 2022. M2TR: Multi-modal Multi-scale Transformers for Deepfake Detection. In ICMR 2022 - Proceedings of the 2022 International Conference on Multimedia Retrieval. 615–623. https://doi.org/10.1145/ 3512527.3531415 arXiv:2104.09770
- [93] Abdul Wasay, Subarna Chatterjee, and Stratos Idreos. 2021. Deep Learning: Systems and Responsibility. In SIGMOD. 2867–2875. https://doi.org/10.1145/ 3448016.3457541
- [94] Ziyun Wei, Immanuel Trummer, and Connor Anderson. 2021. Robust voice querying with muve: Optimally visualizing results of phonetically similar queries. PVLDB 14, 11 (2021), 2397–2409. https://doi.org/10.14778/3476249. 3476289
- [95] Ziyun Wei, Immanuel Trummer, and Anderson Connor. 2021. Demonstrating Robust Voice Querying with MUVE: Optimally Visualizing Results of Phonetically Similar Queries. In SIGMOD. 2798–2802.
- [96] Nathaniel Weir, Andrew Crotty, Alex Galakatos, Amir Ilkhechi, Shekar Ramaswamy, Rohin Bhushan, Ugur Cetintemel, Prasetya Utama, Nadja Geisler, Benjamin Hättasch, Steffen Eger, and Carsten Binnig. 2019. DBPal: Weak Supervision for Learning a Natural Language Interface to Databases. (2019), 1–4. arXiv:1909.06182 http://arxiv.org/abs/1909.06182
- [97] Thomas Wolf, Lysandre Debut, Victor Sanh, Julien Chaumond, Clement Delangue, Anthony Moi, Pierric Cistac, Tim Rault, Remi Louf, Morgan Funtowicz, Joe Davison, Sam Shleifer, Patrick von Platen, Clara Ma, Yacine Jernite, Julien Plu, Canwen Xu, Teven Le Scao, Sylvain Gugger, Mariama Drame, Quentin Lhoest, and Alexander Rush. 2020. Transformers: State-of-the-Art Natural Language Processing. In EMNLP. 38–45. https://doi.org/10.18653/v1/2020.emnlpdemos.6 arXiv:arXiv:1910.03771v5
- [98] Kuan Xuan, Yongbo Wang, Yongliang Wang, Zujie Wen, and Yang Dong. 2022. SeaD: End-to-end Text-to-SQL Generation with Schema-aware Denoising. In NAACL. 1845–1853. arXiv:2105.07911 http://arxiv.org/abs/2105.07911
- [99] Tao Yu, Michihiro Yasunaga, Kai Yang, Rui Zhang, Dongxu Wang, Zifan Li, and Dragomir R. Radev. 2020. SyntaxSqlnet: Syntax tree networks for complex and cross-domain text-to-SQL task. In Proceedings of the 2018 Conference on Empirical Methods in Natural Language Processing, EMNLP 2018. 1653–1663. https://doi.org/10.18653/v1/d18-1193 arXiv:1810.05237
- [100] Tao Yu, Rui Zhang, Kai Yang, Michihiro Yasunaga, Dongxu Wang, Zifan Li, James Ma, Irene Li, Qingning Yao, Shanelle Roman, Zilin Zhang, and Dragomir R. Radev. 2020. Spider: A large-scale human-labeled dataset for complex and cross-domain semantic parsing and text-to-SQL task. In Proceedings of the 2018 Conference on Empirical Methods in Natural Language Processing, EMNLP 2018. 3911–3921. https://doi.org/10.18653/v1/d18-1425 arXiv:1809.08887
- [101] Xiaohua Zhai, Alexander Kolesnikov, Neil Houlsby, and Lucas Beyer. 2022. Scaling Vision Transformers. Proceedings of the IEEE Computer Society Conference on Computer Vision and Pattern Recognition 2022-June (2022), 12094–12103. https://doi.org/10.1109/CVPR52688.2022.01179 arXiv:2106.04560
- [102] Pengchuan Zhang, Xiyang Dai, Jianwei Yang, Bin Xiao, Lu Yuan, Lei Zhang, and Jianfeng Gao. 2021. Multi-Scale Vision Longformer: A New Vision Transformer for High-Resolution Image Encoding. Proceedings of the IEEE International Conference on Computer Vision (2021), 2978–2988. https://doi.org/10.1109/ ICCV48922.2021.00299 arXiv:2103.15358
- [103] Susan Zhang, Stephen Roller, Naman Goyal, Mikel Artetxe, Moya Chen, Shuohui Chen, Christopher Dewan, Mona T Diab, Xian Li, Xi Victoria Lin, Todor Mihaylov, Myle Ott, Sam Shleifer, Kurt Shuster, Daniel Simig, Punit Singh Koura, Anjali Sridhar, Tianlu Wang, and Luke Zettlemoyer. 2022. OPT: Open Pre-trained Transformer Language Models. CoRR abs/2205.0 (2022). https://doi.org/10.48550/arXiv.2205.01068
- [104] Yanan Zhang, Jiaxin Chen, and Di Huang. 2022. Cat-Det: Contrastively Augmented Transformer for Multimodal 3D Object Detection. In Proceedings of the IEEE Computer Society Conference on Computer Vision and Pattern Recognition. 898–907. https://doi.org/10.1109/CVPR52688.2022.00098 arXiv:2204.00325
- [105] Victor Zhong, Caiming Xiong, and Richard Socher. 2017. Seq2SQL: Generating Structured Queries from Natural Language using Reinforcement Learning. CoRR abs/1709.0, 1 (2017), 1–12. arXiv:1709.00103 http://arxiv.org/abs/1709.00103
- [106] Daquan Zhou, Bingyi Kang, Xiaojie Jin, Linjie Yang, Xiaochen Lian, Zihang Jiang, Qibin Hou, and Jiashi Feng. 2021. DeepViT: Towards Deeper Vision Transformer. CoRR abs/2103.1 (2021), 1–12. arXiv:2103.11886 http://arxiv.org/abs/2103.11886