ID	Referências
E01	lyer, V., Agarwal, A., and Kumar, H. (2020b). Veealign: a supervised deep learning approach to ontology alignment.
E02	lyer, V., Agarwal, A., and Kumar, H. (2021). Veealign: multifaceted context representation using dual attention for ontology alignment.
E03	Srinivas, K., Gale, A., and Dolby, J. (2018). Merging datasets through deep learning. arXiv preprint arXiv:1809.01604.
E04	Sun, J., Takeuchi, S., and Yamasaki, I. (2020). Few-shot ontology alignment model with attribute attentions. IEEE.
E05	Chen, J., Jimenez-Ruiz, E., Horrocks, I., Antonyrajah, D., Hadian, A., and Lee, J. ´ (2021). Augmenting ontology alignment by semantic embedding and distant supervision. Springer
E06	lyer, V., Agarwal, A., and Kumar, H. (2020a). Multifaceted context representation using dual attention for ontology alignment. arXiv preprint arXiv:2010.11721.
E07	Xue, X., Jiang, C., Zhang, J., Zhu, H., and Yang, C. (2021c). Matching sensor ontologies through siamese neural networks without using reference alignment. PeerJ Computer Science, 7:e602.
E08	Bento, A., Zouaq, A., and Gagnon, M. (2020). Ontology matching using convolutional neural networks.
E09	Wang, P., Zou, S., Liu, J., and Ke, W. (2022). Matching biomedical ontologies with gcn-based feature propagation. Math. Biosci. Eng, 19:8479–8504.
E10	Jiang, C. and Xue, X. (2020). Matching biomedical ontologies with long short-term memory networks. IEEE.
E11	Maji, S., Rout, S. S., and Choudhary, S. (2021). Dcom: A deep column mapper for semantic data type detection. arXiv preprint arXiv:2106.12871.
E12	Sun, C. and Shen, D. (2022). Towards deep entity resolution via soft schema matching. Neurocomputing, 471:107–117.
E13	Mohamed, A., Ali, C., Fakhri, Y., Noreddine, G., et al. (2022). Schema matching based on deep learning using lstm model. IEEE.
E14	Chakraborty, J., Bansal, S. K., Virgili, L., Konar, K., and Yaman, B. (2021). Ontoconnect: Unsupervised ontology alignment with recursive neural network.
E15	Shraga, R. and Gal, A. (2022). Powarematch: A quality-aware deep learning approach to improve human schema matching. ACM Journal of Data and Information Quality (JDIQ), 14(3):1–27.
E16	Koutras, C., Fragkoulis, M., Katsifodimos, A., and Lofi, C. (2020). Rema: Graph embeddings-based relational schema matching. In EDBT/ICDT Workshops.
E17	Xue, X., Jiang, C., Yang, C., Zhu, H., and Hu, C. (2021b). Artificial neural network based sensor ontology matching technique.
E18	Khan, R. and Gubanov, M. (2020). Weblens: Towards web-scale data integration, training the models. IEEE.
E19	Shraga, R., Gal, A., and Roitman, H. (2020). Adnev: Cross-domain schema matching using deep similarity matrix adjustment and evaluation. Proceedings of the VLDB Endowment, 13(9):1401–1415.
E20	Hao, J., Lei, C., Efthymiou, V., Quamar, A., Ozcan, F., Sun, Y., and Wang, W. (2021). "Medto: Medical data to ontology matching using hybrid graph neural networks
E21	Jurisch, M. and Igler, B. (2019). Graph-convolution-based classification for ontology alignment change prediction.
E22	Hulsebos, M., Hu, K., Bakker, M., Zgraggen, E., Satyanarayan, A., Kraska, T., Demiralp, C, ., and Hidalgo, C. (2019). Sherlock: A deep learning approach to semantic data type detection
E23	Lima, B., Branco, R., Castanheira, J., Fonseca, G., and Pesquita, C. (2020). Learning reference alignments for ontology matching within and across domains
E24	Bulygin, L. (2018). Combining lexical and semantic similarity measures with machine learning approach for ontology and schema matching problem
E25	Xue, X., Chen, D., and Liu, W. (2021a). Naive bayesian classifier based semi-supervised learning for matching ontologies. IEEE.
E26	Laadhar, A., Ghozzi, F., Megdiche, I., Ravat, F., Teste, O., and Gargouri, F. (2019a). Partitioning and local matching learning of large biomedical ontologies.
E27	Schmidts, O., Kraft, B., Siebigteroth, I., and Zundorf, A. (2019). Schema matching with "frequent changes on semi-structured input files: A machine learning approach on biological product data. In ICEIS (1), pages 208–215.
E28	Berlin, J. and Motro, A. (2002). Database schema matching using machine learning with feature selection. Springer.

E29	Nikovski, D., Esenther, A., Ye, X., Shiba, M., and Takayama, S. (2012). Bayesian networks for matcher composition in automatic schema matching. SCITEPRESS.
E30	Amrouch, S., Mostefai, S., and Fahad, M. (2016). Decision trees in automatic ontology matching. International Journal of Metadata, Semantics and Ontologies, 11(3):180–190.
E31	Nezhadi, A. H., Shadgar, B., and Osareh, A. (2011). Ontology alignment using machine learning techniques. International Journal of Computer Science & Information Technology, 3(2):139.
E32	Rodrigues, D., da Silva, A., Rodrigues, R., and dos Santos, E. (2015). Using active learning techniques for improving database schema matching methods. IEEE.
E33	Bulygin, L. and Stupnikov, S. A. (2019). Applying of machine learning techniques to combine string-based, language-based and structure-based similarity measures for ontology matching.
E34	Nkisi-Orji, I., Wiratunga, N., Massie, S., Hui, KY., and Heaven, R. (2019). Ontology alignment based on word embedding and random forest classification. Springer.
E35	Rodrigues, D. and Silva, A. (2021). A study on machine learning techniques for the schema matching network problem. Journal of the Brazilian Computer Society, 27
E36	Jimenez-Ruiz, E., Agibetov, A., Samwald, M., and Cross, V. (2018b). We divide, you 'conquer: from large-scale ontology alignment to manageable subtasks with a lexical index and neural embeddings. In CEUR Workshop Proceedings, volume 2288, pages 13–24.
E37	Fast and Accurate Framework for Ontology Matching in Web of Things
E38	Schema matching using neural network
E39	He, Y., Chen, J., Antonyrajah, D., and Horrocks, I. (2021). Biomedical ontology alignment with bert
E40	Yorsh, U., Behr, A. S., Kockmann, N., and Holena, M. (2022). Text-to-ontology mapping via natural language processing models.
E41	Neutel, S. and de Boer, M. H. (2021). Towards automatic ontology alignment using bert
E42	Pan, Z., Pan, G., and Monti, A. (2022). Semantic-similarity-based schema matching for management of building energy data. Energies, 15(23):8894.
E43	He, Y., Chen, J., Antonyrajah, D., and Horrocks, I. (2022). Bertmap: a bert-based ontology alignment system
E44	Hertling, S., Portisch, J., and Paulheim, H. (2020). Supervised ontology and instance matching with melt. arXiv preprint arXiv:2009.11102.
E45	Bulygin, L. (2018). Combining lexical and semantic similarity measures with machine learning approach for ontology and schema matching problem.
E46	Teslya, N. and Savosin, S. (2019). Matching ontologies with word2vec-based neural network. Springer
E47	Li, G. (2020a). Deepfca: Matching biomedical ontologies using formal concept analysis embedding techniques.
E48	Nozaki, K., Hochin, T., and Nomiya, H. (2019). Semantic schema matching for string attribute with word vectors. IEEE
E49	Li, G. (2020b). Improving biomedical ontology matching using domain-specific word embeddings.
E50	Chen, J., Jimenez-Ruiz, E., Horrocks, I., Antonyrajah, D., Hadian, A., and Lee, J. ´ (2021). Augmenting ontology alignment by semantic embedding and distant supervision. Springer.
E51	Creating embeddings of heterogeneous relational datasets for data integration tasks
E52	Hattasch, B., Truong-Ngoc, M., Schmidt, A., and Binnig, C. (2022). It's ai match: "A two-step approach for schema matching using embeddings. arXiv preprint arXiv: 2203.04366.
E53	Zhang, Y., Wang, X., Lai, S., He, S., Liu, K., Zhao, J., and Lv, X. (2014). Ontology matching with word embeddings. Springer.
E54	Tounsi Dhouib, M., Faron Zucker, C., and Tettamanzi, A. G. (2019). An ontology alignment approach combining word embedding and the radius measure. Springer International Publishing.
E55	Ayala, D., Hernandez, I., Ruiz, D., and Rahm, E. (2022). Leapme: Learning-based pro- ' perty matching with embeddings. Data & Knowledge Engineering, 137:101943.
E56	Li, W., Duan, X., Wang, M., Zhang, X., and Qi, G. (2019). Multi-view embedding for biomedical ontology matching. OM@ ISWC, 2536:13–24.

E57	Jimenez-Ruiz, E., Agibetov, A., Samwald, M., and Cross, V. (2018a). Breaking-down the ´ontology alignment task with a lexical index and neural embeddings. arXiv preprint arXiv:1805.12402.
E58	Zhang, J., Shin, B., Choi, J. D., and Ho, J. C. (2021). Smat: An attention-based deep learning solution to the automation of schema matching. Springer.
E59	Li, X., Wang, G., Shen, D., Nie, T., and Kou, Y. (2021). Heterogeneous embeddings for relational data integration tasks. Springer.
E60	Laadhar, A., Ghozzi, F., Megdiche, I., Ravat, F., Teste, O., and Gargouri, F. (2019b). Pomap++ results for oaei 2019: fully automated machine learning approach for ontology matching. In 14th International Workshop on Ontology Matching co-located with the International Semantic Web Conference (OM@ ISWC 2019), pages 169–174.
E61	EL AISSAOUI, O. and OUGHDIR, L. (2020). A learning style-based ontology matching to enhance learning resources recommendation. In 2020 1st international conference on innovative research in applied science, engineering and technology (IRASET), pages 1–7. IEEE.
E62	Doan, A., Konda, P., Suganthan GC, P., Govind, Y., Paulsen, D., Chandrasekhar, K., Martinkus, P., and Christie, M. (2020). Magellan: toward building ecosystems of entity matching solutions. Communications of the ACM, 63(8):83–91.
E63	Mukherjee, D., Bandyopadhyay, A., Chowdhury, R., and Bhattacharya, I. (2021). Learning knowledge graph for target-driven schema matching.
E64	Shraga, R. (2022). Humanal: Calibrating human matching beyond a single task.
E65	Lv, Z. (2022). An effective approach for large ontology matching using multi-objective grasshopper algorithm.
E66	Rangel, C., Aguilar, J., Cerrada, M., and Altamiranda, J. (2015). An approach for the emerging ontology alignment based on the bees colonies.
E67	Xue, X., Chen, J., and Ren, A. (2019). Interactive ontology matching based on evolutionary algorithm. In 2019 15th International Conference on Computational Intelligence and Security (CIS), pages 1–5. IEEE.
E68	Przyborowski, M., Pabis, M., Janusz, A., and ´Slezak, D. (2021). Schema matching using ´gaussian mixture models with wasserstein distance. arXiv preprint arXiv: 2111.14244.