really bring the researcher or practitioner close to the physics of the underlying system, can have a strong impact on the solution quality or on the likelihood of finding a good solution but are not yet well understood.

Overall, this work has shown that Quadratic Unconstrained Binary Optimization (QUBO) and Quantum Annealing (QA) are viable options for improving feature selections for both classification and ranking and the above discussion on future perspectives gives an idea of how much room for improvement is already possible to imagine. Therefore, it would be definitely worth if we, as a community, undertake a systematic exploration of these promising research directions, not forgetting that while feature selection is a specific task, for other relevant tasks as well it may be possible to develop a formulation suitable for applying quantum computing approaches. Ranking and classification are central not only to IR but also to several neighbourhood areas, such as natural language processing and recommender systems. Therefore, we could promote some joint effort across these communities, in order to maximize the impact and benefit from cross-fertilization. In this respect, IR has an extremely long tradition in community-wide cooperation on shared research activities, very successfully embodied by large scale evaluation campaigns, as TREC, CLEF, NTCIR and FIRE. It would be extremely valuable if such initiatives take a lead and promote the organization of shared activities for exploring the application of quantum computing to IR, NLP, and RecSys in a comparable and shared way.

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REFERENCES

[1] Steven H. Adachi and Maxwell P. Henderson. 2015. Application of Quantum Annealing to Training of Deep Neural Networks. *CoRR* abs/1510.06356 (2015). arXiv:1510.06356 http://arxiv.org/abs/1510.06356

[2] Tameem Albash and Daniel A Lidar. 2018. Adiabatic quantum computation. *Reviews of Modern Physics* 90, 1 (2018), 015002.

[3] Mohammad H Amin, Evgeny Andriyash, Jason Rolfe, Bohdan Kulchytskyy, and Roger Melko. 2018. Quantum boltzmann machine. *Physical Review X* 8, 2 (2018), 021050.

[4] B Apolloni, N Cesa-Bianchi, and D De Falco. 1988. *A numerical implementation of "quantum annealing"*. Technical Report BIBOS-324. Bielefeld TU. Bielefeld-Bochum-Stochastik, Bielefeld. https://cds.cern.ch/record/192546

[5] Christian Bauckhage, Nico Piatkowski, Rafet Sifa, Dirk Hecker, and Stefan Wrobel. 2019. A QUBO Formulation of the k-Medoids Problem. In *Proceedings of "Lernen, Wissen, Daten, Analysen" (CEUR Workshop Proceedings, Vol. 2454)*. 54–63. http://ceur-ws.org/Vol-2454/paper_39.pdf

[6] Emily M. Bender, Timnit Gebru, Angelina McMillan-Major, and Shmargaret Shmitchell. 2021. On the Dangers of Stochastic Parrots: Can Language Models Be Too Big?. In *FAccT ’21: 2021 ACM Conference on Fairness, Accountability, and Transparency, Virtual Event / Toronto, Canada, March 3-10, 2021*, Madeleine Clare Elish, William Isaac, and Richard S. Zemel (Eds.). ACM, 610–623. https://doi.org/10.1145/3442188.3445922

[7] Trevor J. Bihl, Kenneth W. Bauer Jr., and Michael A. Temple. 2016. Feature Selection for RF Fingerprinting With Multiple Discriminant Analysis and Using ZigBee Device Emissions. *IEEE Trans. Inf. Forensics Secur.* 11, 8 (2016), 1862–1874. https://doi.org/10.1109/TIFS.2016.2561902

[8] Kelly Boothby, Paul Bunyk, Jack Raymond, and Aidan Roy. 2020. Next-generation topology of d-wave quantum processors. *arXiv preprint arXiv:2003.00133* (2020).

[9] Christopher JC Burges. 2010. From ranknet to lambdarank to lambdamart: An overview. *Learning* 11, 23-581 (2010), 81.

[10] Christopher J. C. Burges, Robert Ragno, and Quoc Viet Le. 2006. Learning to Rank with Nonsmooth Cost Functions. In *Advances in Neural Information Processing Systems 19, Proceedings of the Twentieth Annual Conference on Neural Information Processing Systems, Vancouver, British Columbia, Canada, December 4-7, 2006*, Bernhard Schölkopf, John C. Platt, and Thomas Hofmann (Eds.). MIT Press, 193–200. https://proceedings.neurips.cc/paper/2006/hash/af44c4c56f385c43f2529f9b1b018f6a-Abstract.html

[11] Costantino Carugno, Maurizio Ferrari Dacrema, and Paolo Cremonesi. 2022. Evaluating the job shop scheduling problem on a D-wave quantum annealer. *Nature Scientific Reports* 12, 1 (21 Apr 2022), 6539. https://doi.org/10.1038/s41598-022-10169-0

[12] Girish Chandrashekar and Ferat Sahin. 2014. A survey on feature selection methods. *Comput. Electr. Eng.* 40, 1 (2014), 16–28. https://doi.org/10.1016/j.compeleceng.2013.11.024

[13] Vicky Choi. 2008. Minor-embedding in adiabatic quantum computation: I. The parameter setting problem. *Quantum Inf. Process.* 7, 5 (2008), 193–209. https://doi.org/10.1007/s11128-008-0082-9

[14] Maurizio Ferrari Dacrema, Nicolò Felicioni, and Paolo Cremonesi. 2021. Optimizing the Selection of Recommendation Carousels with Quantum Computing. In *RecSys ’21: Fifteenth ACM Conference on Recommender Systems, Amsterdam, The Netherlands, 27 September 2021 - 1 October 2021*, Humberto Jesús Corona Pampín, Martha A. Larson, Martijn C. Willemsen, Joseph A. Konstan, Julian J. McAuley, Jean Garcia-Gathright, Bouke Huurnink, and Even Oldridge (Eds.). ACM, 691–696. https://doi.org/10.1145/3460231.3478853

[15] Vasil S. Denchev, Sergio Boixo, Sergei V. Isakov, Nan Ding, Ryan Babbush, Vadim Smelyanskiy, John Martinis, and Hartmut Neven. 2016. What is the Computational Value of Finite-Range Tunneling? *Phys. Rev. X* 6 (Aug 2016), 031015. Issue 3. https://doi.org/10.1103/PhysRevX.6.031015

[16] R Dhanya, Irene Rose Paul, Sai Sindhu Akula, Madhumathi Sivakumar, and Jyothisha J Nair. 2020. F-test feature selection in Stacking ensemble model for breast cancer prediction. *Procedia Computer Science* 171 (2020), 1561–1570. https://doi.org/10.1016/j.procs.2020.04.167 Third International Conference on Computing and Network Communications (CoCoNet’19).

[17] Maurizio Ferrari Dacrema, Tang-Tang Zhou, Riccardo Nembrini, and Paolo Cremonesi. 2021. Quantum Annealing Linear Regression For Collaborative Filtering Recommendations. *2nd European Quantum Technologies Virtual Conference (EQTC), 29 November, 2021* (2021).

[18] Artur J. Ferreira and Mário A. T. Figueiredo. 2012. Efficient feature selection filters for high-dimensional data. *Pattern Recognit. Lett.* 33, 13 (2012), 1794–1804. https://doi.org/10.1016/j.patrec.2012.05.019

[19] Jerome H. Friedman. 2001. Greedy Function Approximation: A Gradient Boosting Machine. *The Annals of Statistics* 29, 5 (2001), 1189–1232. http://www.jstor.org/stable/2699986

[20] Andrea Gigli, Claudio Lucchese, Franco Maria Nardini, and Raffaele Perego. 2016. Fast Feature Selection for Learning to Rank. In *Proceedings of the 2016 ACM on International Conference on the Theory of Information Retrieval, ICTIR 2016, Newark, DE, USA, September 12- 6, 2016*, Ben Carterette, Hui Fang, Mounia Lalmas, and Jian-Yun Nie (Eds.). ACM, 167–170. https://doi.org/10.1145/2970398.2970433

[21] Fred W. Glover, Gary A. Kochenberger, and Yu Du. 2019. Quantum Bridge Analytics I: a tutorial on formulating and using QUBO models. *4OR* 17, 4 (2019), 335–371. https://doi.org/10.1007/s10288-019-00424-y

[22] John K. Golden and Daniel O’Malley. 2020. Reverse Annealing for Nonnegative/Binary Matrix Factorization. *CoRR* abs/2007.05565 (2020). arXiv:2007.05565 https://arxiv.org/abs/2007.05565

[23] Nathalie Japkowicz and Mohak Shah (Eds.). 2011. *Evaluating Learning Algorithms: A Classification Perspective.* Cambridge University Press.

[24] Alan Jovic, Karla Brkic, and Nikola Bogunovic. 2015. A review of feature selection methods with applications. In *38th International Convention on Information and Communication Technology, Electronics and Microelectronics, MIPRO 2015, Opatija, Croatia, May 25-29, 2015*, Petar Biljanovic, Zeljko Butkovic, Karolj Skala, Branko Mikac, Marina Cicin-Sain, Vlado Sruk, Slobodan Ribaric, Stjepan Gros, Boris Vrdoljak, Mladen Mauher, and Andrej Sokolic (Eds.). IEEE, 1200–1205. https://doi.org/10.1109/MIPRO.2015.7160458

[25] Alexandr Katrutsa and Vadim V. Strijov. 2017. Comprehensive study of feature selection methods to solve multicollinearity problem according to evaluation criteria. *Expert Syst. Appl.* 76 (2017), 1–11. https://doi.org/10.1016/j.eswa.2017.01.048

[26] Scott Kirkpatrick, D. Gelatt Jr., and Mario P. Vecchi. 1983. Optimization by Simmulated Annealing. *Sci.* 220, 4598 (1983), 671–680.

[27] Hanjiang Lai, Yan Pan, Yong Tang, and Rong Yu. 2013. FSMRank: Feature Selection Algorithm for Learning to Rank. *IEEE Trans. Neural Networks Learn. Syst.* 24, 6 (2013), 940–952. https://doi.org/10.1109/TNNLS.2013.2247628

[28] Andrew Lucas. 2014. Ising formulations of many NP problems. *Frontiers in Physics* 2 (2014), 5. https://doi.org/10.3389/fphy.2014.00005

[29] Claudio Lucchese and Franco Maria Nardini. 2017. Efficiency/Effectiveness Trade-offs in Learning to Rank. In *Proceedings of the ACM SIGIR International Conference on Theory of Information Retrieval, ICTIR 2017, Amsterdam, The Netherlands, October 1-4, 2017*, Jaap Kamps, Evangelos Kanoulas, Maarten de Rijke, Hui Fang, and Emine Yilmaz (Eds.). ACM, 329–330. https://doi.org/10.1145/3121050.3121109

[30] Stefano Marchesin, Alberto Purpura, and Gianmaria Silvello. 2020. Focal elements of neural information retrieval models. An outlook through a reproducibility study. *Inf. Process. Manag.* 57, 6 (2020), 102109. https://doi.org/10.1016/j.ipm.2019.102109

[31] Catherine C. McGeoch. 2020. Theory versus practice in annealing-based quantum computing. *Theor. Comput. Sci.* 816 (2020), 169–183. https://doi.org/10.1016/j.tcs.2020.01.024

[32] Massimo Melucci. 2015. *Introduction to Information Retrieval and Quantum Mechanics*. The Information Retrieval Series, Vol. 35. Springer. https://doi.org/10.1007/978-3-662-48313-8

[33] Riccardo Nembrini, Maurizio Ferrari Dacrema, and Paolo Cremonesi. 2021. Feature Selection for Recommender Systems with Quantum Computing. *Entropy* 23, 8 (2021), 970. https://doi.org/10.3390/e23080970

[34] Hartmut Neven, Vasil S. Denchev, Geordie Rose, and William G. Macready. 2012. QBoost: Large Scale Classifier Training with Adiabatic Quantum Optimization. In *Proceedings of the 4th Asian Conference on Machine Learning, ACML 2012, Singapore, Singapore, November 4-6, 2012 (JMLR Proceedings, Vol. 25)*, Steven C. H. Hoi and Wray L. Buntine (Eds.). JMLR.org, 333–348. http://proceedings.mlr.press/v25/neven12.html

[35] Gintaras Palubeckis. 2004. Multistart Tabu Search Strategies for the Unconstrained Binary Quadratic Optimization Problem. *Ann. Oper. Res.* 131, 1-4 (2004), 259–282. https://doi.org/10.1023/B:ANOR.0000039522.58036.68

[36] Hanchuan Peng, Fuhui Long, and Chris H. Q. Ding. 2005. Feature Selection Based on Mutual Information: Criteria of Max-Dependency, Max-Relevance, and Min-Redundancy. *IEEE Trans. Pattern Anal. Mach. Intell.* 27, 8 (2005), 1226–1238. https://doi.org/10.1109/TPAMI.2005.159

[37] Alberto Purpura, Karolina Buchner, Gianmaria Silvello, and Gian Antonio Susto. 2021. Neural Feature Selection for Learning to Rank. In *Advances in Information Retrieval - 43rd European Conference on IR Research, ECIR 2021, Virtual Event, March 28 - April 1, 2021, Proceedings, Part II (Lecture Notes in Computer Science, Vol. 12657)*, Djoerd Hiemstra, Marie-Francine Moens, Josiane Mothe, Raffaele Perego, Martin Potthast, and Fabrizio Sebastiani (Eds.). Springer, 342–349. https://doi.org/10.1007/978-3-030-72240-1_34

[38] Tao Qin, Tie-Yan Liu, Jun Xu, and Hang Li. 2010. LETOR: A benchmark collection for research on learning to rank for information retrieval. *Inf. Retr.* 13, 4 (2010), 346–374. https://doi.org/10.1007/s10791-009-9123-y

[39] Tao Qin and Tie-Yan Liu. 2013. Introducing LETOR 4.0 datasets. *arXiv preprint arXiv:1306.2597* (2013).

[40] Irene Rodríguez-Luján, Ramón Huerta, Charles Elkan, and Carlos Santa Cruz. 2010. Quadratic Programming Feature Selection. *J. Mach. Learn. Res.* 11 (2010), 1491–1516. http://portal.acm.org/citation.cfm?id=1859900

[41] Noelia Sánchez-Maroño, María Caamaño-Fernández, Enrique F. Castillo, and Amparo Alonso-Betanzos. 2006. Functional Networks and Analysis of Variance for Feature Selection. In *Intelligent Data Engineering and Automated Learning - IDEAL 2006, 7th International Conference, Burgos, Spain, September 20-23, 2006, Proceedings (Lecture Notes in Computer Science, Vol. 4224)*, Emilio Corchado, Hujun Yin, Vicente J. Botti, and Colin Fyfe (Eds.). Springer, 1031–1038. https://doi.org/10.1007/11875581_123

[42] Jean Tague-Sutcliffe and James Blustein. 1994. A Statistical Analysis of the TREC-3 Data. In *Proceedings of The Third Text REtrieval Conference, TREC 1994, Gaithersburg, Maryland, USA, November 2-4, 1994 (NIST Special Publication, Vol. 500-225)*, Donna K. Harman (Ed.). National Institute of Standards and Technology (NIST), 385.

[43] Kari Torkkola. 2003. Feature Extraction by Non-Parametric Mutual Information Maximization. *J. Mach. Learn. Res.* 3 (2003), 1415–1438. http://jmlr.org/papers/v3/torkkola03a.html

[44] Sagar Uprety, Dimitris Gkoumas, and Dawei Song. 2020. A Survey of Quantum Theory Inspired Approaches to Information Retrieval. *ACM Comput. Surv.* 53, 5 (2020), 98:1–98:39. https://doi.org/10.1145/3402179

[45] Hayato Ushijima-Mwesigwa, Christian F. A. Negre, and Susan M. Mniszewski. 2017. Graph Partitioning using Quantum Annealing on the D-Wave System. *In Proceedings of the Second International Workshop on Post Moores Era Supercomputing (PMES '17)* abs/1705.03082 (2017). arXiv:1705.03082 http://arxiv.org/abs/1705.03082

[46] Cornelis Joost van Rijsbergen. 2004. *The geometry of information retrieval*. Cambridge University Press.

[47] Joaquin Vanschoren, Jan N. van Rijn, Bernd Bischl, and Luís Torgo. 2013. OpenML: networked science in machine learning. *SIGKDD Explor.* 15, 2 (2013), 49–60. https://doi.org/10.1145/2641190.2641198

[48] Dennis Willsch, Madita Willsch, Hans De Raedt, and Kristel Michielsen. 2020. Support vector machines on the D-Wave quantum annealer. *Comput. Phys. Commun.* 248 (2020), 107006. https://doi.org/10.1016/j.cpc.2019.107006

[49] Zilin Zeng, Hongjun Zhang, Rui Zhang, and Chengxiang Yin. 2015. A novel feature selection method considering feature interaction. *Pattern Recognit.* 48, 8 (2015), 2656–2666. https://doi.org/10.1016/j.patcog.2015.02.025