DAFTAR PUSTAKA

Abdollahpouri, H., Burke, R., & Mobasher, B. (2019). The impact of popularity bias on fairness and accuracy in recommendation. *Proceedings of the 13th ACM Conference on Recommender Systems*, (pp. 205–213).

Adomavicius, G., Bockstedt, J., Curley, S., & Zhang, J. (2019a). Reducing recommender system biases: An investigation of rating display designs. *MIS Quarterly: Management Information Systems*, *43*, 1321–1341.

Adomavicius, G., Bockstedt, J., Curley, S., & Zhang, J. (2019b). Reducing recommender systems biases: An investigation of rating display designs. *MIS Quarterly*, *43*, 19–18.

Agrahari, S., & Singh, A. K. (2022). Concept drift detection in data stream mining : A literature review. *Journal of King Saud University - Computer and Information Sciences*, *34*, 9523–9540.

Albatayneh, N. A., Ghauth, K. I., & Chua, F.-F. (2022). Discriminate2Rec: Negation-based dynamic discriminative interest-based preference learning for semantics-aware content-based recommendation. *Expert Systems with Applications*, *199*, 116988.

Almotairi, B., Alrige, M., & Abdullah, S. (2021). Personalized recommender system for arabic news on twitter. *International Journal of Advanced Computer Science and Applications*, *12*.

Alshbanat, H. I., Benhidour, H., & Kerrache, S. (2025). A survey of latent factor models in recommender systems. *Information Fusion*, *117*, 102905.

Aoumeur, N. E., Li, Z., & Alshari, E. M. (2023). Improving the polarity of text through word2vec embedding for primary classical arabic sentiment analysis. *Neural processing letters*, *55*, 2249–2264.

Bui, H., Nguyen-Hoang, T.-A., Vo, B., Nguyen, H., & Le, T. (2021). A sliding window-based approach for mining frequent weighted patterns over data streams. *IEEE Access*, *9*, 56318–56329.

Carroll, J. D., & Chang, J.-J. (1970). Analysis of individual differences in multidimensional scaling via an N-way generalization of "Eckart-Young" decomposition. *Psychometrika*, *35*, 283–319.

Cattell, R. B. (1944). Parallel proportional profiles and other principles for determining the choice of factors by rotation. *Psychometrika*, *9*, 267–283.

Chan, K. Y., Abu-Salih, B., Qaddoura, R., Al-Zoubi, A. M., Palade, V., Pham, D.-S., Ser, J. D., & Muhammad, K. (2023). Deep neural networks in the cloud: Review, applications, challenges and research directions. *Neurocomputing*, *545*, 126327.

Chen, C., Li, D., Yan, J., & Yang, X. (2022). Modeling dynamic user preference via dictionary learning for sequential recommendation. *IEEE Transactions on Knowledge and Data Engineering*, *34*, 5446–5458.

Chen, J., Dong, H., Wang, X., Feng, F., Wang, M., & He, X. (2023). Bias and debias in recommender system: A survey and future directions. *ACM Transactions on Information Systems*, *41*.

Chen, T., Yin, H., Nguyen, Q. V. H., Peng, W.-C., Li, X., & Zhou, X. (2019). Sequence-aware factorization machines for temporal predictive analytics.

Chen, T., & Zhang, H. (2019). Sentiment-aware neural collaborative filtering for personalized recommendation. *ACM Transactions on Intelligent Systems and Technology*, *10*, 1–24.

Cheng, S., & Wang, W. (2020). Rating prediction algorithm based on user time-sensitivity. *Information*, *11*.

Curtis, F. E., & Shi, R. (2020). A fully stochastic second-order trust region method. *Optimization Methods and Software*, *35*, 885–915.

Dash, A., Chakraborty, A., Ghosh, S., Mukherjee, A., & Gummadi, K. P. (2023). FaiRIR: Mitigating exposure bias from related item recommendations in two-sided platforms. *IEEE Transactions on Computational Social Systems*, *10*, 1301–1313.

Ding, H., Liu, Q., & Hu, G. (2022). Tdtmf: A recommendation model based on user temporal interest drift and latent review topic evolution with regularization factor. *Information Processing Management*, *59*, 103037.

Duan, J., Zhang, P.-F., Qiu, R., & Huang, Z. (2022). Long short-term enhanced memory for sequential recommendation. *World Wide Web*, *26*, 561–583.

Elkahky, A. M., Song, Y., & He, X. (2015). A multi-view deep learning approach for cross domain user modeling in recommendation systems. In *Proceedings of the 24th International Conference on World Wide Web* WWW '15 (p. 278–288). Republic and Canton of Geneva, CHE: International World Wide Web Conferences Steering Committee.

Eslami, G., & Ghaderi, F. (2020). Incremental matrix factorization for recommender systems. In *2020 25th International Computer Conference, Computer Society of Iran (CSICC)* (pp. 1–7).

Ferreira José, E., Enembreck, F., & Paul Barddal, J. (2020). ADADRIFT: An adaptive learning technique for long-history stream-based recommender systems. In *2020 IEEE International Conference on Systems, Man, and Cybernetics (SMC)* (pp. 2593–2600).

Gan, M., & Cui, H. (2021). Exploring user movie interest space: A deep learning based dynamic recommendation model. *Expert Systems with Applications*, *173*, 114695.

Gao, Y., & Zhang, Q. (2021). Context-aware sentiment analysis for improved recommendation systems. *Neurocomputing*, *426*, 189–203.

Gong, S., & Cheng, G. (2008). Mining user interest change for improving collaborative filtering. In *2008 Second International Symposium on Intelligent Information Technology Application* (pp. 24–27). volume 3.

Gouk, H., Frank, E., Pfahringer, B., & Cree, M. J. (2021). Regularisation of neural networks by enforcing lipschitz continuity. *Machine Learning*, *110*, 393–416.

Gultekin, S., & Paisley, J. (2014). A collaborative kalman filter for time-evolving dyadic processes. In *2014 IEEE International Conference on Data Mining* (pp. 140–149).

Hanafi, & Mohd Aboobaider, B. (2021). Word sequential using deep LSTM and matrix factorization to handle rating sparse data for e-commerce recommender system. *Computational intelligence and neuroscience*, *2021*, 8751173.

He, R., & McAuley, J. (2018). Modeling the evolution of user preferences for sentiment-aware recommendation. *Proceedings of the 27th International Conference on the World Wide Web*, (pp. 671–681).

Hong, M., & Jung, J. J. (2021). ClustPTF: Clustering-based parallel tensor factorization for the diverse multi-criteria recommendation. *Electronic Commerce Research and Applications*, *47*, 101041.

Hong, W., Li, L., & Li, T. (2012). Product recommendation with temporal dynamics. *Expert Systems with Applications*, *39*, 12398–12406.

Jain, K., & Jindal, R. (2023). Sampling and noise filtering methods for recommender systems: A literature review. *Engineering Applications of Artificial Intelligence*, *122*, 106129.

Jalali, S., & Hosseini, M. (2022). Collaborative filtering in dynamic networks based on deep auto-encoder. *The Journal of Supercomputing*, *78*, 7410–7427.

Jang, D., Li, Q., Lee, C., & Kim, J. (2024). Attention-based multi attribute matrix factorization for enhanced recommendation performance. *Information Systems*, *121*, 102334.

Jiang, X., Li, Y., Cao, B., Xie, S.-Y., & Liu, H. (2020). A fast deep autoencoder for high-dimensional and sparse matrices in collaborative filtering. *Neurocomputing*, *400*, 271–282.

Jin, Z., Zhang, Y., Mu, W., Wang, W., & Jin, H. (2018). Leveraging the dynamic changes from items to improve recommendation. In J. C. Trujillo, K. C. Davis, X. Du, Z. Li, T. W. Ling, G. Li, & M. L. Lee (Eds.), *Conceptual Modeling* (pp. 507–520). Cham: Springer International Publishing.

Kasabov, N. K. (1996). *Foundations of Neural Networks, Fuzzy Systems, and Knowledge Engineering*. (1st ed.). Cambridge, MA, USA: MIT Press.

Khan, Z., Iltaf, N., Afzal, H., & Abbas, H. (2020). Enriching non-negative matrix factorization with contextual embeddings for recommender systems. *Neurocomputing*, *380*, 246–258.

Kim, H.-N., Alkhaldi, A., El Saddik, A., & Jo, G.-S. (2011). Collaborative user modeling with user-generated tags for social recommender systems. *Expert Systems with Applications*, *38*, 8488–8496.

Kim, M., & Lee, J. (2022). A comprehensive survey on bias mitigation in recommendation systems. *Artificial Intelligence Review*, *55*, 857–883.

Kim, W. (2024). A random focusing method with jensen–shannon divergence for improving deep neural network performance ensuring architecture consistency. *Neural Processing Letters*, *56*, 199.

Koren, Y. (2009). Collaborative filtering with temporal dynamics. In *Proceedings of the 15th ACM SIGKDD International Conference on Knowledge Discovery and Data Mining* KDD '09 (p. 447–456). New York, NY, USA: Association for Computing Machinery.

Koren, Y., Bell, R., & Volinsky, C. (2009). Matrix factorization techniques for recommender systems. *Computer*, *42*, 30–37.

Koren, Y., Rendle, S., & Bell, R. (2021). Advances in collaborative filtering. *Recommender systems handbook*, (pp. 91–142).

Łukasz Korycki, & Krawczyk, B. (2022). Instance exploitation for learning temporary concepts from sparsely labeled drifting data streams. *Pattern Recognition*, *129*, 108749.

Krishnan, S., Patel, J., Franklin, M. J., & Goldberg, K. (2014). A methodology for learning, analyzing, and mitigating social influence bias in recommender systems. In *Proceedings of the 8th ACM Conference on Recommender Systems* RecSys '14 (p. 137–144). New York, NY, USA: Association for Computing Machinery.

Lei, J., Li, Y., Yang, S., Shi, W., & Wu, Y. (2022). Two-stage sequential recommendation for side information fusion and long-term and short-term preferences modeling. *Journal of Intelligent Information Systems*, *59*, 657–677.

Li, J., Wang, Y., & McAuley, J. (2020). Time interval aware self-attention for sequential recommendation. In *Proceedings of the 13th International Conference on Web Search and Data Mining* WSDM '20 (p. 322–330). New York, NY, USA: Association for Computing Machinery.

Li, K., Zhou, X., Lin, F., Zeng, W., & Alterovitz, G. (2019). Deep probabilistic matrix factorization framework for online collaborative filtering. *IEEE Access*, *7*, 56117–56128.

Li, X., Deng, Z., Wu, L., Zhang, Z., & Gao, J. (2023). DistVAE: Distributed variational autoencoder for sequential recommendation. *Neural Networks*, *162*, 489–499.

Liang, S., Ren, Z., Zhao, Y., Ma, J., Yilmaz, E., & Rijke, M. D. (2017). Inferring dynamic user interests in streams of short texts for user clustering. *ACM Transactions on Information Systems*, *36*.

Liang, Y., Niu, C., Yan, P., & Wang, G. (2024). Flipover outperforms dropout in deep learning. *Visual Computing for Industry, Biomedicine, and Art*, *7*, 4.

Liu, D., Li, J., Wu, J., Du, B., Chang, J., & Li, X. (2022). Interest evolution-driven gated neighborhood aggregation representation for dynamic recommendation in e-commerce. *Information Processing & Management*, *59*, 102982.

Liu, H., Jing, L., Yu, J., & Ng, M. K. (2019). Social recommendation with learning personal and social latent factors. *IEEE transactions on knowledge and data engineering*, *33*, 2956–2970.

Liu, N. N., Zhao, M., Xiang, E., & Yang, Q. (2010). Online evolutionary collaborative filtering. In *Proceedings of the Fourth ACM Conference on Recommender Systems* RecSys ’10 (p. 95–102). New York, NY, USA: Association for Computing Machinery.

Liu, Y., Zhu, H., Chen, Y., Tian, F., Ma, D., Zeng, J., & Zheng, Q. (2020). Long- and short-term preference model based on graph embedding for sequential recommendation. In *Database Systems for Advanced Applications. DASFAA 2020 International Workshops: BDMS, SeCoP, BDQM, GDMA, and AIDE, Jeju, South Korea, September 24–27, 2020, Proceedings* (p. 241–257). Berlin, Heidelberg: Springer-Verlag.

Lo, Y.-Y., Liao, W., Chang, C.-S., & Lee, Y.-C. (2018). Temporal matrix factorization for tracking concept drift in individual user preferences. *IEEE Transactions on Computational Social Systems*, *5*, 156–168.

Lu, Z., Agarwal, D., & Dhillon, I. S. (2009). A spatio-temporal approach to collaborative filtering. In *Proceedings of the Third ACM Conference on Recommender Systems* RecSys '09 (p. 13–20). New York, NY, USA: Association for Computing Machinery.

Luo, L., Xie, H., Rao, Y., & Wang, F. L. (2019). Personalized recommendation by matrix co-factorization with tags and time information. *Expert Systems with Applications*, *119*, 311–321.

Luo, M., Zhang, X., Li, J., Duan, P., & Lu, S. (2022). User dynamic preference construction method based on behavior sequence. *Scientific Programming*, *2022*, 6101045.

Maryam Jallouli, S. L., & Amous, I. (2022). When contextual information meets recommender systems: extended SVD++ models. *International Journal of Computers and Applications*, *44*, 349–356.

Matuszyk, P., Vinagre, J., Spiliopoulou, M., Jorge, A. M., & Gama, J. (2018). Forgetting techniques for stream-based matrix factorization in recommender systems. *Knowledge and Information Systems*, *55*, 275–304.

McAuley, J., & Leskovec, J. (2013). Hidden factors and hidden topics: understanding rating dimensions with review text. In *Proceedings of the 7th ACM Conference on Recommender Systems* RecSys '13 (p. 165–172). New York, NY, USA: Association for Computing Machinery.

Meehan, K., Lunney, T., Curran, K., & McCaughey, A. (2013). Context-aware intelligent recommendation system for tourism. In *2013 IEEE International Conference on Pervasive Computing and Communications Workshops (PERCOM Workshops)* (pp. 328–331).

Menéndez, M., Pardo, J., Pardo, L., & Pardo, M. (1997). The jensen-shannon divergence. *Journal of the Franklin Institute*, *334*, 307–318.

Mongia, A., Jhamb, N., Chouzenoux, E., & Majumdar, A. (2020). Deep latent factor model for collaborative filtering. *Signal Processing*, *169*, 107366.

Mukherjee, S., Lamba, H., & Weikum, G. (2015). Experience-aware item recommendation in evolving review communities. In *2015 IEEE International Conference on Data Mining* (pp. 925–930).

Prince, S. J. (2023). *Understanding Deep Learning*. The MIT Press.

Priya, S., & Uthra, R. A. (2023). Deep learning framework for handling concept drift and class imbalanced complex decision-making on streaming data. *Complex & Intelligent Systems*, *9*, 3499–3515.

Qiu, R., Huang, Z., Chen, T., & Yin, H. (2021). Exploiting positional information for session-based recommendation. *ACM Transactions on Information Systems*, *40*.

Rabiu, I., Salim, N., Da'u, A., & Nasser, M. (2022). Modeling sentimental bias and temporal dynamics for adaptive deep recommendation system. *Expert Systems with Applications*, *191*, 116262.

Rabiu, I., Salim, N., Da'u, A., Osman, A., & Nasser, M. (2021). Exploiting dynamic changes from latent features to improve recommendation using temporal matrix factorization. *Egyptian Informatics Journal*, *22*, 285–294.

Rafailidis, D. (2018). A multi-latent transition model for evolving preferences in recommender systems. *Expert Systems with Applications*, *104*, 97–106.

Rafailidis, D., Kefalas, P., & Manolopoulos, Y. (2017). Preference dynamics with multimodal user-item interactions in social media recommendation. *Expert Systems with Applications*, *74*, 11–18.

Rajput, I. A., Saxena, V., Tiwari, R. K., & Tiwari, P. K. (2024). An autoencoder-based deep learning model for solving the sparsity problem in collaborative filtering. *Expert Systems with Applications*, *234*, 121265.

Rendle, S. (2010). Factorization machines. In *2010 IEEE International Conference on Data Mining* (pp. 995–1000).

Sezerer, E., & Tekir, S. (2021). A survey on neural word embeddings. *arXiv preprint arXiv:2110.01804*, .

Shen, R. (2022). A recommender system integrating long short-term memory and latent factor. *Arabian Journal for Science and Engineering*, *47*, 9931–9941.

Su, H., Lin, X., Yan, B., & Zheng, H. (2015). The collaborative filtering algorithm with time weight based on mapreduce. In *Big Data Computing and Communications: First International Conference, BigCom 2015, Taiyuan, China, August 1-3, 2015, Proceedings 1* (pp. 386–395). Springer.

Tahmasbi, H., Jalali, M., & Shakeri, H. (2021). TSCMF: Temporal and social collective matrix factorization model for recommender systems. *Journal of Intelligent Information Systems*, *56*, 169–187.

Taneja, A., & Arora, A. (2019). Modeling user preferences using neural networks and tensor factorization model. *International Journal of Information Management*, *45*, 132–148.

Tong, C., Qi, J., Lian, Y., Niu, J., & Rodrigues, J. J. (2019). TimeTrustSVD: A collaborative filtering model integrating time, trust and rating information. *Future Generation Computer Systems*, *93*, 933–941.

Tucker, L. R. (1966). Some mathematical notes on three-mode factor analysis. *Psychometrika*, *31*, 279–311.

Vinagre, J., Jorge, A. M., & Gama, J. (2015). An overview on the exploitation of time in collaborative filtering. *Wiley interdisciplinary reviews: Data mining and knowledge discovery*, *5*, 195–215.

Wang, D., Zhang, X., Wan, Y., Yu, D., Xu, G., & Deng, S. (2022). Modeling sequential listening behaviors with attentive temporal point process for next and next new music recommendation. *IEEE Transactions on Multimedia*, *24*, 4170–4182.

Wang, L.-Y., Park, C., Yeon, K., & Choi, H. (2017). Tracking concept drift using a constrained penalized regression combiner. *Computational Statistics & Data Analysis*, *108*, 52–69.

Wang, S., Zhou, W., & Jiang, C. (2020). A survey of word embeddings based on deep learning. *Computing*, *102*, 717–740.

Wangwatcharakul, C., & Wongthanavasu, S. (2020). Dynamic collaborative filtering based on user preference drift and topic evolution. *IEEE Access*, *8*, 86433–86447.

Wangwatcharakul, C., & Wongthanavasu, S. (2021). A novel temporal recommender system based on multiple transitions in user preference drift and topic review evolution. *Expert Systems with Applications*, *185*, 115626.

Wu, D., Yuan, Z., Yu, K., & Pan, H. (2012). Temporal social tagging based collaborative filtering recommender for digital library. In *The Outreach of Digital Libraries: A Globalized Resource Network: 14th International Conference on*

Asia-Pacific Digital Libraries, ICADL 2012, Taipei, Taiwan, November 12-15, 2012, Proceedings 14 (pp. 199–208). Springer.

Wu, T., Feng, Y., Sang, J., Qiang, B., & Wang, Y. (2018). A novel recommendation algorithm incorporating temporal dynamics, reviews and item correlation. *IEICE transactions on Information and Systems*, *101*, 2027–2034.

Wu, W., Zhao, J., Zhang, C., Meng, F., Zhang, Z., Zhang, Y., & Sun, Q. (2017). Improving performance of tensor-based context-aware recommenders using bias tensor factorization with context feature auto-encoding. *Knowledge-Based Systems*, *128*, 71–77.

Xia, P., Jiang, W., Wu, J., Xiao, S., & Wang, G. (2021). Exploiting temporal dynamics in product reviews for dynamic sentiment prediction at the aspect level. *ACM Transactions on Knowledge Discovery from Data*, *15*.

Xiong, L., Chen, X., Huang, T.-K., Schneider, J., & Carbonell, J. G. (2010). Temporal collaborative filtering with bayesian probabilistic tensor factorization. In *Proceedings of the 2010 SIAM international conference on data mining* (pp. 211–222). SIAM.

Xu, Y., Yang, Y., Han, J., Wang, E., Zhuang, F., Yang, J., & Xiong, H. (2019). NeuO: Exploiting the sentimental bias between ratings and reviews with neural networks. *Neural Networks*, *111*, 77–88.

Xue, H.-J., Dai, X., Zhang, J., Huang, S., & Chen, J. (2017). Deep matrix factorization models for recommender systems. In *Proceedings of the Twenty-Sixth International Joint Conference on Artificial Intelligence, IJCAI-17* (pp. 3203–3209).

Yi, B., Shen, X., Liu, H., Zhang, Z., Zhang, W., Liu, S., & Xiong, N. (2019). Deep matrix factorization with implicit feedback embedding for recommendation system. *IEEE Transactions on Industrial Informatics*, *15*, 4591–4601.

Yuan, Y.-x. (2000). A review of trust region algorithms for optimization. In *ICIAM99: Proceedings of the Fourth International Congress on Industrial & Applied Mathematics Edinburgh* (p. 271–282). Oxford University Press.

Zafari, F., Moser, I., & Baarslag, T. (2019). Modelling and analysis of temporal preference drifts using a component-based factorised latent approach. *Expert Systems with Applications*, *116*, 186–208.

Zhang, C., Wang, K., Yu, H., Sun, J., & Lim, E.-P. (2014). Latent factor transition for dynamic collaborative filtering. In *Proceedings of the 2014 SIAM international conference on data mining* (pp. 452–460). SIAM.

Zhang, G., Wang, M., & Liu, K. (2021). Deep neural networks for global wildfire susceptibility modelling. *Ecological Indicators*, *127*, 107735.

Zhang, S., Yao, L., Sun, A., & Tay, Y. (2019). Deep learning based recommender system: A survey and new perspectives. *ACM Computing Surveys*, *52*.

Zhang, Y., Zhang, M., Zhang, Y., Lai, G., Liu, Y., Zhang, H., & Ma, S. (2015). Daily-aware personalized recommendation based on feature-level time series analysis. In *Proceedings of the 24th International Conference on World Wide Web* WWW '15 (p. 1373–1383). Republic and Canton of Geneva, CHE: International World Wide Web Conferences Steering Committee.

Zhao, J., Wang, W., Zhang, Z., Sun, Q., Huo, H., Qu, L., & Zheng, S. (2020). TrustTF: A tensor factorization model using user trust and implicit feedback for context-aware recommender systems. *Knowledge-Based Systems*, *209*, 106434.

Zhao, J., Yang, S., Huo, H., Sun, Q., & Geng, X. (2021). TBTF: an effective time-varying bias tensor factorization algorithm for recommender system. *Applied Intelligence*, *51*, 4933–4944.

Zheng, X., Ni, Z., Zhong, X., & Luo, Y. (2024). Kernelized deep learning for matrix factorization recommendation system using explicit and implicit information. *IEEE Transactions on Neural Networks and Learning Systems*, *35*, 1205–1216.

Zhu, Z., Li, D., Liang, J., Liu, G., & Yu, H. (2018). A dynamic personalized news recommendation system based on bap user profiling method. *IEEE Access*, *6*, 41068–41078.