



Figure 5: The variants of PRFM and LambdaFM based on various pairwise loss functions.

to a set of well-known ranking loss functions. Furthermore, we have built a family of PRFM and LambdaFM algorithms, shedding light on how they perform in real tasks. In our evaluation, we have shown that LambdaFM largely outperforms state-of-the-art counterparts in terms of four standard ranking measures, but underperforms PRFM methods in terms of AUC, known as a binary classification measure.

LambdaFM is also applicable to other important ranking tasks based on implicit feedback, e.g., personalized microblog retrieval and learning to personalize query auto-completion. In future work, it would be interesting to investigate its effectiveness in these scenarios.

8. ACKNOWLEDGMENTS

Fajie thanks the CSC funding for supporting the research. This work is also supported by the National Natural Science Foundation of China under Grant No. 61402097.

9. REFERENCES

- [1] Baltrunas. Incarmusic: Context-aware music recommendations in a car. In *EC-Web*, pages 89–100, 2011.
- [2] C. Burges, T. Shaked, E. Renshaw, A. Lazier, M. Deeds, N. Hamilton, and G. Hullender. Learning to rank using gradient descent. In *ICML*, pages 89–96, 2005.
- [3] Z. Cao, T. Qin, T. Liu, M. Tsai, and H. Li. Learning to rank: from pairwise approach to listwise approach. In *ICML*, pages 129–136, 2007.
- [4] T. Chen, W. Zhang, Q. Lu, K. Chen, Z. Zheng, and Y. Yu. Svdfeature: a toolkit for feature-based collaborative filtering. *JMLR*, pages 3619–3622, 2012.
- [5] K. Christakopoulou and A. Banerjee. Collaborative ranking with a push at the top. In *WWW*, pages 205–215, 2015.
- [6] P. Cremonesi, Y. Koren, and R. Turrin. Performance of recommender algorithms on top-n recommendation tasks. In *RecSys*, pages 39–46, 2010.
- [7] Y. Freund, R. Iyer, R. E. Schapire, and Y. Singer. An efficient boosting algorithm for combining preferences. *JMLR*, pages 933–969, 2003.
- [8] H. Gao, J. Tang, X. Hu, and H. Liu. Exploring temporal effects for location recommendation on location-based social networks. In *RecSys*, pages 93–100, 2013.
- [9] R. Herbrich, T. Graepel, and K. Obermayer. Support vector learning for ordinal regression. 1999.
- [10] L. Hong, A. S. Doumith, and B. D. Davison. Co-factorization machines: modeling user interests and predicting individual decisions in twitter. In *WSDM*, pages 557–566, 2013.
- [11] A. Karatzoglou, X. Amatriain, L. Baltrunas, and N. Oliver. Multiverse recommendation: n-dimensional tensor factorization for context-aware collaborative filtering. In *RecSys*, pages 79–86, 2010.
- [12] X. Li, G. Cong, X.-L. Li, T.-A. N. Pham, and S. Krishnaswamy. Rank-geofm: a ranking based geographical factorization method for point of interest recommendation. In *SIGIR*, pages 433–442, 2015.
- [13] Q. Lu, T. Chen, W. Zhang, D. Yang, and Y. Yu. Serendipitous personalized ranking for top-n recommendation. In *WI-IAT*, pages 258–265, 2012.
- [14] B. McFee and G. R. Lanckriet. Metric learning to rank. In *ICML*, pages 775–782, 2010.
- [15] M. Tsai, T. Liu, T. Qin, H. Chen, and W. Ma. Frank: a ranking method with fidelity loss. In *SIGIR*, pages 383–390, 2007.
- [16] W. Pan and L. Chen. GBPR: Group preference based bayesian personalized ranking for one-class collaborative filtering. In *IJCAI*, pages 2691–2697, 2013.
- [17] Y.-J. Park and A. Tuzhilin. The long tail of recommender systems and how to leverage it. In *RecSys*, pages 11–18, 2008.
- [18] R. Qiang, F. Liang, and J. Yang. Exploiting ranking factorization machines for microblog retrieval. In *CIKM*, pages 1783–1788, 2013.
- [19] C. Quoc and V. Le. Learning to rank with nonsmooth cost functions. 19:193–200, 2007.
- [20] S. Rendle. Factorization machines. In *ICDM*, pages 995–1000, 2010.
- [21] S. Rendle. Factorization machines with libFM. *TIST*, pages 57:1–57:22, 2012.
- [22] S. Rendle and C. Freudenthaler. Improving pairwise learning for item recommendation from implicit feedback. In *WSDM*, pages 273–282, 2014.
- [23] S. Rendle, C. Freudenthaler, Z. Gantner, and L. Schmidt-Thieme. BPR: bayesian personalized ranking from implicit feedback. In *UAI*, pages 452–461, 2009.
- [24] Y. Shi, A. Karatzoglou, L. Baltrunas, M. Larson, and A. Hanjalic. Cars2: Learning context-aware representations for context-aware recommendations. In *CIKM*, pages 291–300, 2014.
- [25] Y. Shi, A. Karatzoglou, L. Baltrunas, M. Larson, A. Hanjalic, and N. Oliver. TFMMap: optimizing map for top-n context-aware recommendation. In *SIGIR*, pages 155–164, 2012.
- [26] Y. Shi, A. Karatzoglou, L. Baltrunas, M. Larson, N. Oliver, and A. Hanjalic. CLiMF: learning to maximize reciprocal rank with collaborative less-is-more filtering. In *RecSys*, pages 139–146, 2012.
- [27] N. Usunier, D. Buffoni, and P. Gallinari. Ranking with ordered weighted pairwise classification. In *ICML*, pages 1057–1064, 2009.
- [28] J. Weston, S. Bengio, and N. Usunier. Wsabie: Scaling up to large vocabulary image annotation. In *IJCAI*, pages 2764–2770, 2011.
- [29] F. Yuan, G. Guo, J. Jose, L. Chen, H. Yu, and W. Zhang. Optimizing factorization machines for top-n context-aware recommendations. In *WISE*, 2016.
- [30] T. Zhang. Solving large scale linear prediction problems using stochastic gradient descent algorithms. In *ICML*, page 116, 2004.
- [31] W. Zhang, T. Chen, J. Wang, and Y. Yu. Optimizing top-n collaborative filtering via dynamic negative item sampling. In *SIGIR*, pages 785–788, 2013.