























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.