Supplemental Material for JCGS-18-113 Entitled "A Logistic Factorization Model for Recommender Systems with Multinomial Responses"

Table 1: Comparison of the root mean square error of different methods. RSVD, RBM, RB, SI, GS, TML, and TMLCI stand for the regularized singular value decomposition method [24], the restricted Boltzmann machine [38], the regression-based latent factor model [3], the Soft-Impute method [28], the group-specific recommender system [8], the proposed two-way multinomial logistic model, and the proposed two-way multinomial logistic model with covariate information, respectively. The simulated data are generated in five categories by RSVD with 1500 users and 1500 items with $K = 4$, $\lambda = 6$, and randomly generated latent factors.

Missing rate	RSVD	RBM	RB	SI	GS	**TML**	**TMLCI**
0.7	1.0456	1.0326	1.0734	1.0358	0.9738	**0.9782**	**0.9530**
0.8	1.0570	1.0404	1.0954	1.0570	0.9755	**0.9743**	**0.9587**
0.9	1.0726	1.0652	1.1177	1.0652	0.9800	**0.9831**	**0.9636**
0.95	1.1056	1.1043	1.1290	1.0868	0.9841	**0.9891**	**0.9673**

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