Supplementary Materials

Competitors

We compare our fine-grained model with 8 competitors:

1. **RankSVM** (Joachims, 2009): With the modification of input features in a way that $\boldsymbol{x}_{ij} = \boldsymbol{x}_i - \boldsymbol{x}_j$, RankSVM then casts the learning to rank problem to a standard SVM with input $\{\boldsymbol{x}_{ij}, y_{ij}\}_{(i,j)}$. We record the performance of RankSVM to as a standard learning to rank baseline model.
2. **RankBoost** (Freund et al., 2003): RankBoost develops a boosting method in the context of ranking. Similar with our methods, RankBoost also embraces a forward model selection strategy where the initial model starts from a simple weak learner model and it gradually ensembles more and more weak learners by leveraging bigger weights on the hard examples.
3. **RankNet**: (Burges et al., 2005): RankNet provides a neural network for learning to rank via a three-layer MLP.
4. **gdbt** (Friedman, 2001): Gradient Boosting Decision Tree (gbdt) extends the idea of boosting, which generates a weak learner in each iteration by learning the recursive residual. It has gained surprising improvements in many traditional tasks and competitions. Accordingly, we compare our methods with gbdt to show its strength.
5. **dart** (Vinayak and Gilad-Bachrach, 2015): Recently, the well-known drop-out trick has also been applied to ensemble-based learning, be it the dart method. We also record the performance of dart to show the superiority of our method.
6. **HodgeRank** (Jiang et al., 2011): HodgeRank model directly aggregates crowdsourced pairwise annotations with the Hodge decomposition theory. We compare our method with HodgeRank to see if the preference learning outperforms the census predictions.
7. **URLR** (Fu et al., 2016): URLR is a unified robust learning to rank framework which aims to tackle both the outlier detection and learning to rank jointly.
8. **Lasso** (Tibshirani, 1996): Lasso is a well-known method which leverages parsimonious parameters with an ℓ_1 penalty. We compare our method with Lasso to show the improvement with respect to traditional parsimonious learning methods.

Dining Preference Prediction

Dataset In order to investigate users' preference for restaurants, the Restaurant and consumer data Dataset [3] is adopted in this experiment, which is comprised of 130 Mexican restaurants rated by 138 users. Each restaurant is rated on a scale from 0 to 2, with 2 indicating the best restaurant and 0 indicating the worst one. For each restaurant, we crawled the meta information including restaurant name and cuisine. In particular, the cuisine contains 59 dining types (i.e., Afghan, African, American, Armenian, Asian, Bagels, Bakery, Bar, Bar-Pub-Brewery, Barbecue, Brazilian, Breakfast-Brunch, Burgers, Cafe-Coffee-Shop, Cafeteria, California, Caribbean, Chinese, Contemporary, Continental-European, Deli-Sandwiches, Dessert-Ice-Cream, Diner, Dutch-Belgian, Eastern-European, Ethiopian, Family, Fast-Food, Fine-Dining, French, Game, German, Greek, Hot-Dogs, International, Italian, Japanese, Juice, Korean, Latin-American, Mediterranean, Mexican, Mongolian, Organic-Healthy, Persian, Pizzeria, Polish, Regional, Seafood, Soup, Southern, Southwestern, Spanish, Steaks, Sushi, Thai, Turkish, Vegetarian, Vietnamese). Additionally, for each user, we crawled the meta information including age (i.e., under 25, 25-45, 45+), and occupation (i.e., student, professional, unemployed, working-class).

[3] https://archive.ics.uci.edu/ml/datasets/Restaurant+%26+consumer+data

Individual Preference Dining behavior, similar to movie preference, should certainly be influenced by multiple factors. We then adopt the restaurant cuisine information and concatenate them into a 59-dimensional vector to represent the feature of each restaurant. As experimental design above, we also split the dataset into training set and testing set. All the experiments were repeated 20 times with different training/testing partitions to reduce variance. Similar to the results in simulated data and real-world movie dataset, the proposed fine-grained method could produce better performance than coarse-grained models with smaller mean test error, shown in Tab.4. Moreover, Fig.5 successfully illustrates the linear speedup of SynPar-SplitLBI on this dining preference dataset.

Age and Occupation Preference Next, we would like to see the dining preference differences among different age ranges. As shown in Fig.6, the pink bars present the proportions of restaurant cuisines among top 50 restaurants returned by common ranking scores. It clearly indicates that the top 4 kinds of cuisines users prefer are Mexican, Cafeteria, Burgers, and International, while Mexican occupies the largest proportion. Besides, we can find that Mexican is the most popular dish for customers of all ages. All this is reasonable, after all, this dataset is collected from Mexican restaurants. When customers are young (i.e., under 25), besides Mexican, they also like Bar-Pub-Brewery, Bar, and Barbecue, which is almost consistent with their real life. Especially young guys under highly competitive pressures would like to spend their leisure time in bars/pubs. When they entered middle age, Cafeteria, Seafood, and Contemporary, together with the popular Mexican, become their top 4 favorites. For customers over 45, they exhibit similar dietary habits with the common preference, indicating that the dining ratings are largely contributed by customers older than 45.

For dining preference behavior, another influence factor may be the occupation of consumers. To exhibit the occupation influence of dining preference behavior, users from the same occupation are treated as a group. Fig.7 presents the proportions of restaurant cuisines of these 4 groups. For students, the top 4 cuisines are Mexican, Bar-Pub-Brewery, Bar, and Barbecue, which is consistent with the group preference of customers under 25 in Fig.6. This again demonstrates the effectiveness of our proposed multi-

Table 3: Occupations and age ranges on movie dataset.

(a) Occupation categories

Index	Occupation	Index	Occupation	Index	Occupation
1	academic or educator	8	farmer	15	scientist
2	artist	9	homemaker	16	self-employed
3	clerical or admin	10	K-12 student	17	technician or engineer
4	college or grad student	11	lawyer	18	tradesman or craftsman
5	customer service	12	programmer	19	unemployed
6	doctor or health care	13	retired	20	writer
7	executive or managerial	14	sales or marketing	21	other or not specified

(b) Age ranges

Index	Age Range
1	Under 18
2	18-24
3	25-34
4	35-44
5	45-49
6	50-55
7	56+

M	T(M)(s)	M	T(M)(s)
1	759.40	9	90.28
2	377.85	10	81.20
3	252.26	11	74.50
4	190.16	12	68.32
5	156.39	13	65.67
6	130.52	14	60.32
7	112.57	15	59.66
8	98.67	16	53.11

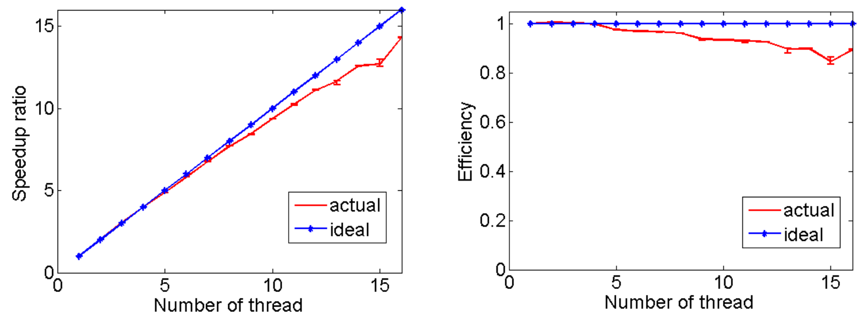

Figure 5: Left: Mean running time (20 times repeat) of SynPar-SplitLBI with thread number changing from 1 to 16 on dining dataset. Middle: The linear speedup of parallel SplitLBI on dining dataset. Right: The efficiency of parallel SplitLBI on dining dataset.

Table 4: Coarse-grained vs. Fine-grained (i.e., Ours) model on dining dataset.

	min	mean	max	std
RankSVM	0.4345	0.4734	0.4963	0.0142
RankBoost	0.4493	0.4734	0.5011	0.0148
RankNet	0.4529	0.4791	0.5127	0.0154
gdbt	0.4256	0.4587	0.4807	0.0141
dart	0.4335	0.4577	0.4827	0.0140
HodgeRank	0.4547	0.4769	0.4951	0.0113
URLR	0.4403	0.4684	0.4839	0.0117
Lasso	0.4374	0.4684	0.4895	0.0130
Ours	0.3450	**0.3708**	0.4069	0.0149

level mixed-effect model. For professionals, besides Mexican, they like Pizzeria, Burgers and Cafeteria. For unemployed and working-class, American magically jumped into the top 4.

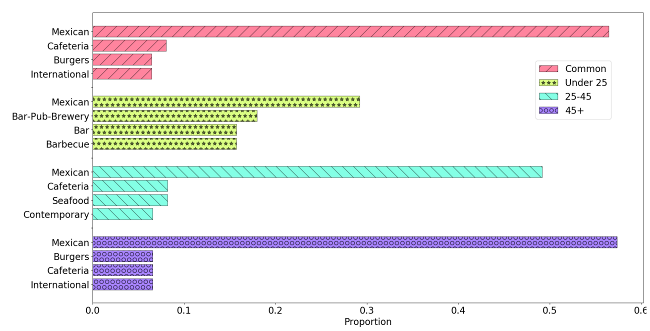

Figure 6: Common preference and 3 groups' preference with different age ranges on dining dataset.

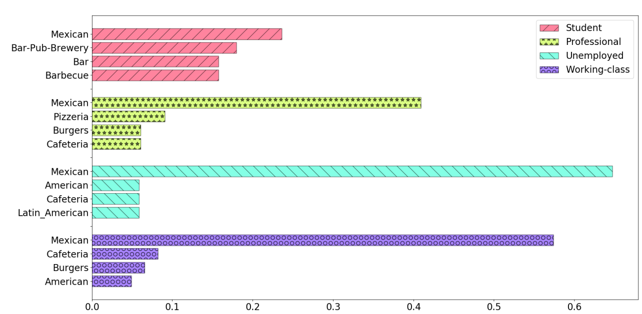

Figure 7: Preference of 4 groups with different occupations on dining dataset.