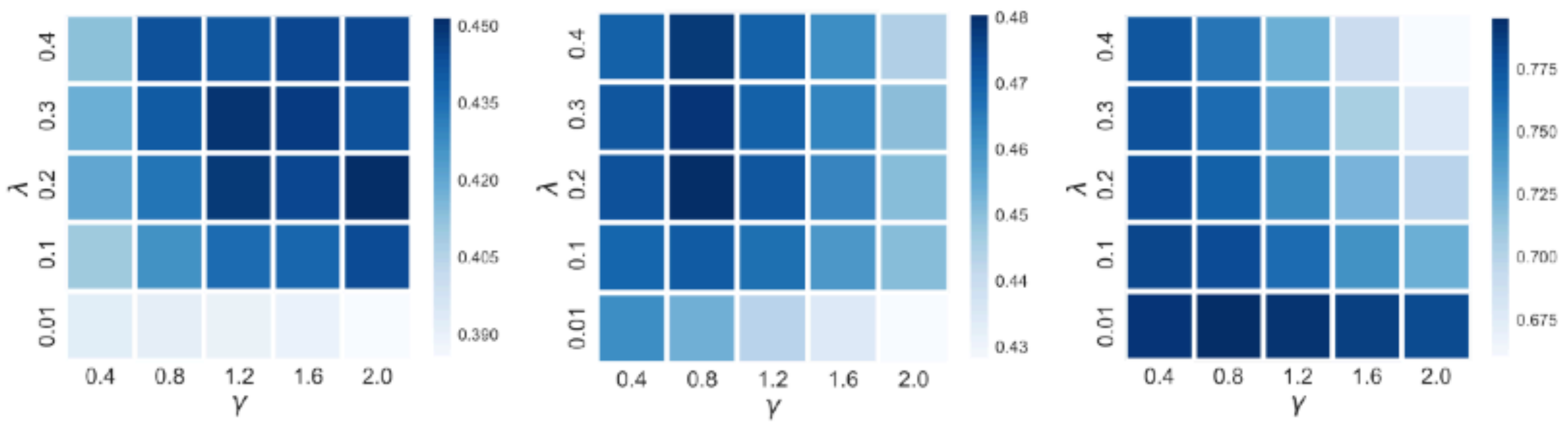
$$L^P(\theta) = \sum_{(u,i^+)\in P} \sum_{(u,i^-)\notin P} L_C^P(u,i^+,i^-) + \lambda L_S^P(u,i^+,i^-)$$

Experiments

$$Score(u,i) = -\{d(\mathsf{C},\mathsf{T}_{u,i}) + \gamma d(\mathsf{S},\mathsf{T}_{u,i})\}$$

Effect of Balancing Coefficients



(a) Toys (b) Health (c) Yelp

- Illustrates the sensitivity of the balance coefficients λ and γ:
  - CRIS achieves the best performance with small λ but large γ, which indicates the importance of the ISSs.
  - Conjecture the inconsistency between training and evaluation time is caused by the noise in the ISSs.
  - While training, CRIS depends less on the L_S^P to avoid overfitting to noisy ISSs.
  - In the evaluation time, CRIS largely depends on the denoised ISSs when determining the recommendation scores.
- CRIS can handle the noise in the ISSs by adjusting the balance coefficients λ and γ
- λ less than 0.5 is the best, reaffirms that ISSs should modeled with L_C^P to learn users' personalized preference.

Experiments

Effect of Periods

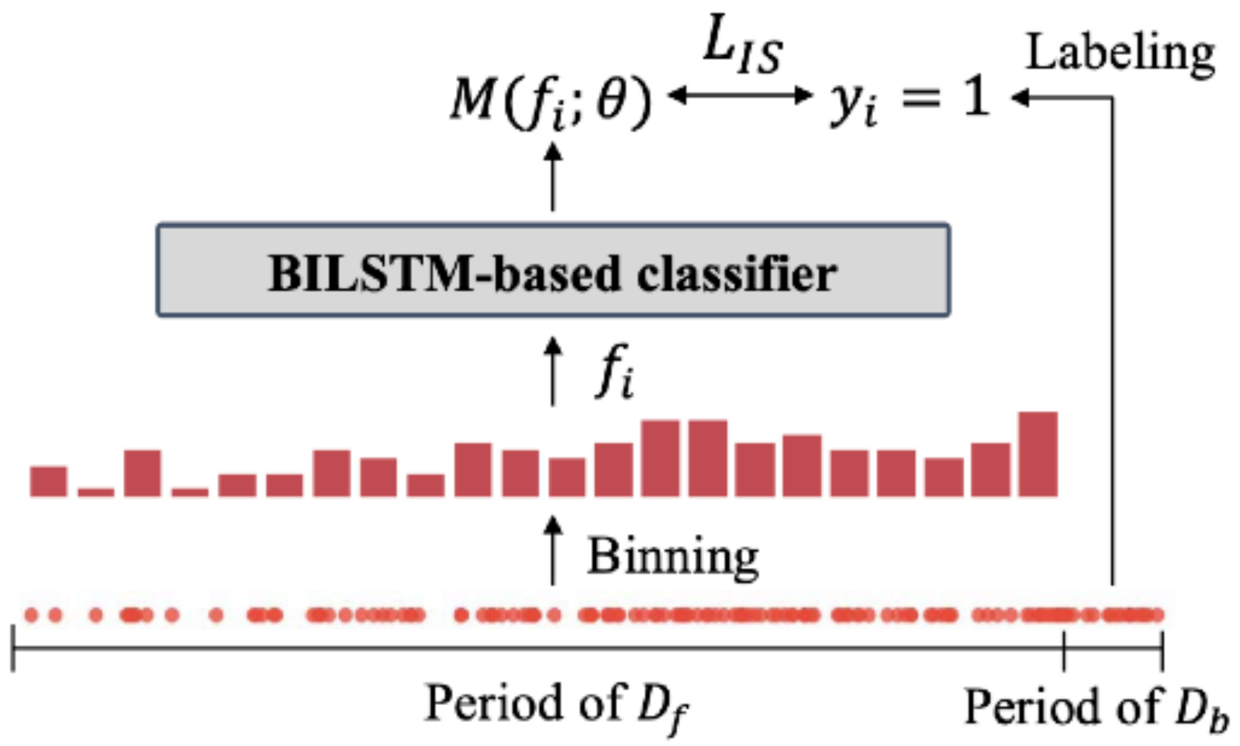
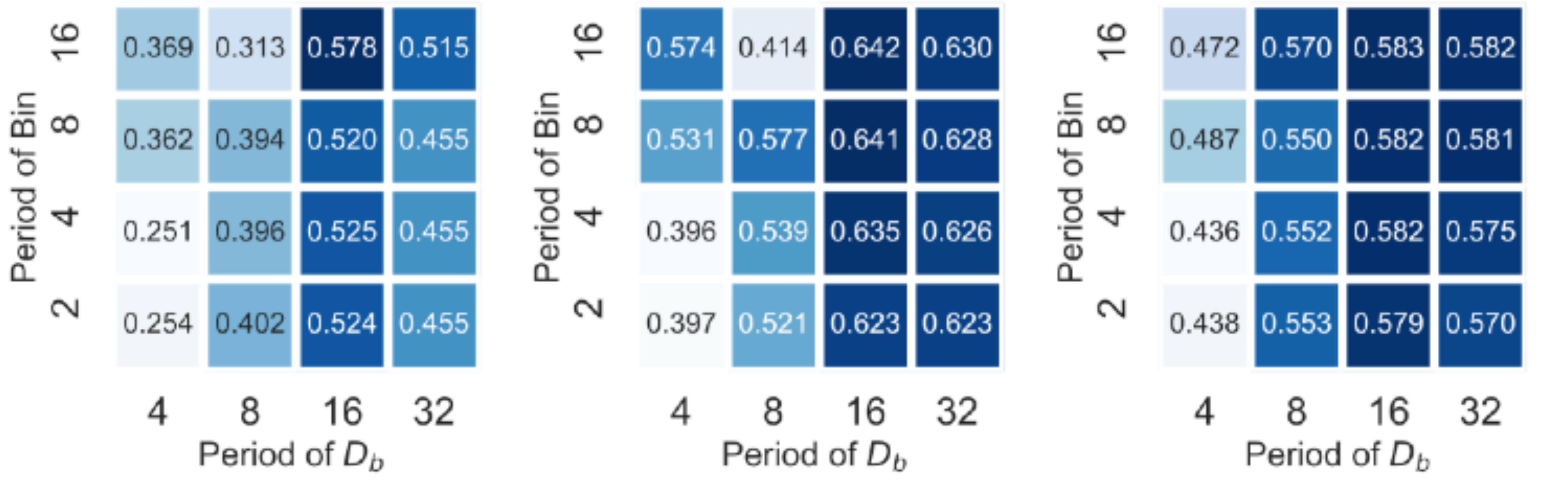


Fig. 2: Training process of a propose classifier on the interest sustainability prediction.



(a) Clothing (b) Kindle (c) GoodReads

Fig. 8: Sensitivity analysis on the periods of data D_b and frequency bins. The numbers in both axes denote the number of weeks.

- Performances are sensitive to the period of D_b, and long periods show the best perf.
- Speculate the period of data D_b should be long enough to reliably determine whether an item will be consumed in the future.
- Second, the long period of the frequency bins generally shows better classification performances. If the period too short, will makes feature of items noisy.
- Therefore, adjusting these two periods is essential to successfully predicting the interest sustainability of items.