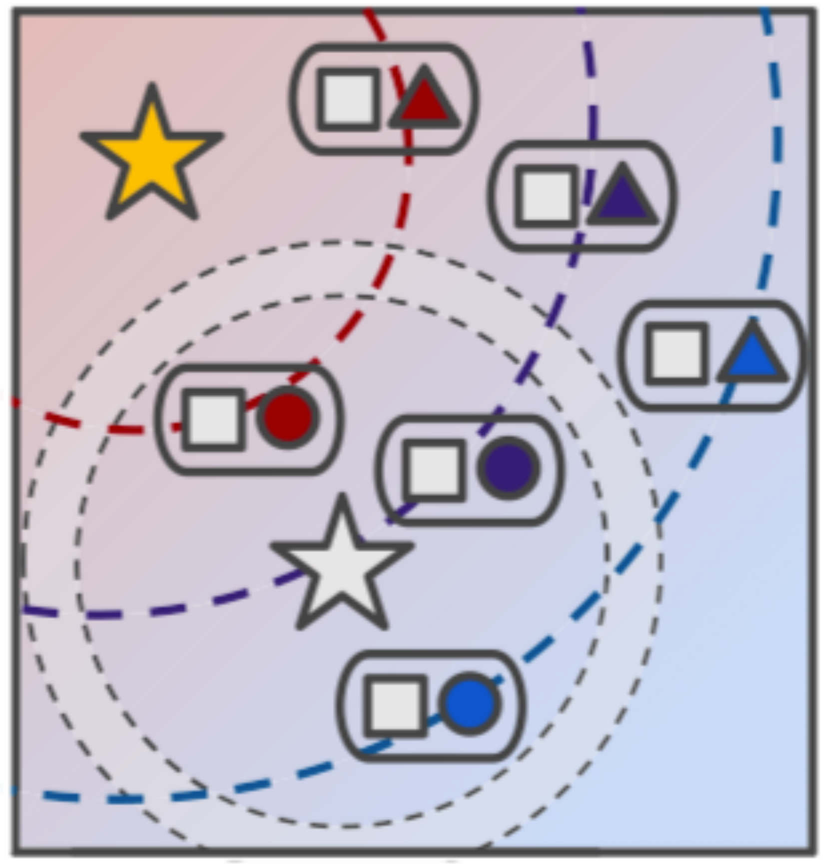
Proposed Method
Prototype Learning

- Given two prototypes, reformulate the objectives of CRIS^{reg} as follows:
  - $L_C^P(u, i^+, i^-) = [m + d(\mathsf{C}, \mathsf{T}_{u,i^+}) - d(\mathsf{C}, \mathsf{T}_{u,i^-})]_+$
  - $L_S^P(u, i^+, i^-) = \{(d(\mathsf{S}, \mathsf{T}_{u,i^+}) - d(\mathsf{S}, \mathsf{T}_{u,i^-})) - (p_{i^-} - p_{i^+})\}^2$
- Based on the prototypes, the consumption loss L_C^P makes the pair of a user and T_{u,i^+} closer to prototype C than the pair of the user and T_{u,i^-}.
- Similarly, L_S^P make the pair of a user and an item with higher ISS closers to prototype S than user and an item with lower ISS.

Proposed Method

Prototype Learning



(c) CRIS

- The recommender system can optimize both objectives with less conflicts between them than the approach of CRIS^{reg}.

- Combine the prototype-based objectives with a balancing coefficient λ:

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

- Train the system by minimizing the loss using SGD with respect to the θ (i.e. $\min_\theta L^P(\theta)$)

- Under the prototype-based learning, a recommendation score of user u on item i is as follow:

  - $Score(u, i) = -\{d(\mathrm{C}, \mathrm{T}_{u,i}) + \gamma d(\mathrm{S}, \mathrm{T}_{u,i})\}$, γ: parameter to control the importance of the ISS