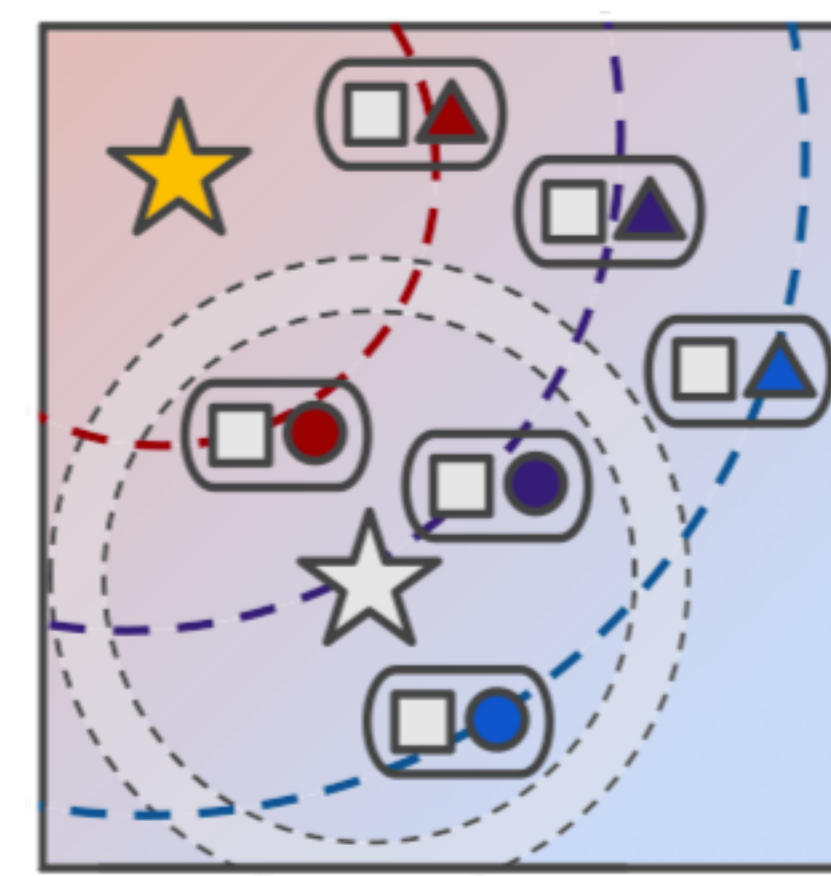


# Proposed Method

## Prototype Learning



- 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  $\lambda$ :
 
$$L^P(\theta) = \sum_{(u, i^+) \in P} \sum_{(u, i^-) \notin P} L_C^P(u, i^+, i^-) + \lambda L_S^P(u, i^+, i^-)$$
- Train the system by minimizing the loss using SGD with respect to the  $\theta$  (i.e.  $\min_{\theta} L^P(\theta)$ )
- Under the prototype-based learning, a recommendation score of user  $u$  on item  $i$  is as follow:
  - $Score(u, i) = - \{d(C, T_{u,i}) + \gamma d(S, T_{u,i})\}$ ,  $\gamma$ : parameter to control the importance of the ISS

# Experiments

## Dataset

- Amazon, Yelp, GoodReads
- Filtered out noisy data from Yelp and GoodReads datasets by maintaining only user who made at least 10 interactions and item that were involved to at least 5 interactions.

TABLE I: Data Statistics. Int. denotes user-item interactions.

Data	# Users	# Items	# Int.(M)	Avg. Int. per user	Period
Tools	16,472	10,177	0.133	7.7	Nov 1999 - Jul 2014
Toys	19,153	11,865	0.165	8.3	Jul 2000 - Jul 2014
Cell Phones	27,372	10,279	0.190	6.5	Feb 2001 - Jul 2014
Clothing	38,651	22,974	0.274	6.6	Mar 2003 - Jul 2014
Sports	34,974	18,294	0.291	7.9	Mar 2002 - Jul 2014
Health	37,842	18,358	0.339	8.4	Dec 2000 - Jul 2014
Kindle	67,193	58,110	0.935	12.7	Mar 2000 - Jul 2014
CDs	74,926	64,342	1.093	14.4	Nov 1997 - Jul 2014
Movies	122,923	49,976	1.688	13.3	Nov 1997 - Jul 2014
Yelp	47,906	78,734	2.304	47.2	Oct 2004 - Nov 2018
GoodReads	58,003	45,330	2.791	47.5	Feb 2001 - Nov 2017