Active Learning for Matching Problems
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Our contributions:
- Matching-aware active learning methods
- Probabilistic matching procedure

(P) Score Prediction
Any score prediction model can be used
-Assume model keeps a distr. over $S^u: \Pr(S^u|S^o, X, \theta)$

(M) Matching Problem
max. $J(Y) = \sum_r \sum_p s_{rp} y_{rp}$
s.t. $y_{rp} \in \{0, 1\}, \quad \forall r, p$
$\sum_r y_{rp} = R_{r\text{arg}}, \quad \forall p$
$\sum_p y_{rp} \geq P_{\min}, \quad \sum_p y_{rp} \leq P_{\max}, \quad \forall r.$

Taking predicted score uncertainty into account:
$\Pr(Y|S^o, X, \theta) = \int Y(S^u \cup S^o) \Pr(S^u|S^o, X, \theta) dS^u$
- Intractable but we use sampling:

(E) Elicitation: Active Learning Methods
Query the scores that will be most helpful for matching:
- Active learning methods should take the matching objective $(J)$ into account
- Computing EVOI is expensive
- We propose methods that operate in matching space

Matching Max-score query
$Y(M) = \arg \max_{(rp) \in S^u} y_{rp} \hat{s}_{rp}$
$\overline{Y}(M) = \arg \max_{(rp) \in S^u} \overline{y}_{rp} \hat{s}_{rp}$

Matching Max-entropy query
$\overline{Y}E = \arg \max_{(rp) \in S^u} \left[ - \sum_{\overline{y}_{rp} \in \{0, 1\}} \overline{y}_{rp} \log \Pr(\overline{y}_{rp}) \right]$

Experimental Setup
- Simulate elicitation procedure
  - Every user starts with a few obs. scores
  - At each round each user is queried (batch)
  - Bayesian PMF is used to predict scores
- Data
  - Jokes (Jester):
    - 300 users, 10 jokes
  - Dating (LibimSeTi.cz):
    - 250 users, 250 items (users)
    - Match 15 to 25 users per item
  - Conference (NIPS'10):
    - 1250 papers, 48 revs
    - Match 20 to 30 papers per rev.

Conclusion: Effective for determining high-quality matches with significantly less elicitation
Current work: EVOI extensions, different types of queries (side-information, higher level)