Max-Utility Based Arm Selection Strategy For Sequential Query Recommendations

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- State-of-the-art methods for query recommendations doesn't make use of real time user feedback.
- We propose MAB algorithms to solve query recommendation problem

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- Pre-selection to handle discovery-exploitation trade-off in CMAB settings
- Standard pre-selection methods like random arm selection or similarity based arm selection fails in practice

Likelihood of arm selection

- Given the currently executing arm a_i and a similarity threshold ε, we define the likelihood that the arm a_j to be played next as $p(a_j|a_i,\varepsilon) = \dfrac{\pi^2_{\star,i}(\varepsilon)s_{j,i}(\varepsilon) + \bar{\pi}^2_{\star,i}s_{j,i}(\varepsilon)}{\pi^2_{\star,i}(\varepsilon) + \bar{\pi}^2_{\star,i}(\varepsilon)}$
  where $\qquad \pi_{\star,i}(\varepsilon) = \dfrac{\sum_j s_{j,i}[\![a_j \in S^i_{\geq}(\varepsilon)]\!]}{\sum_j s_{j,i}}$

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- For log utility function, the pre-selection reduces to the optimization problem

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  where $g(\mathcal{C}, a_i)$ is the joint probability of the arms in $\mathcal{C}$ conditioned on a_i
- log is a concave function, hence the optimization problem is a submodular maximization problem that can be solved using simple greedy heuristic

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- We compared regret of Linear UCB and Linear Thomson Sampling with different pre-selection algorithms

Thank You