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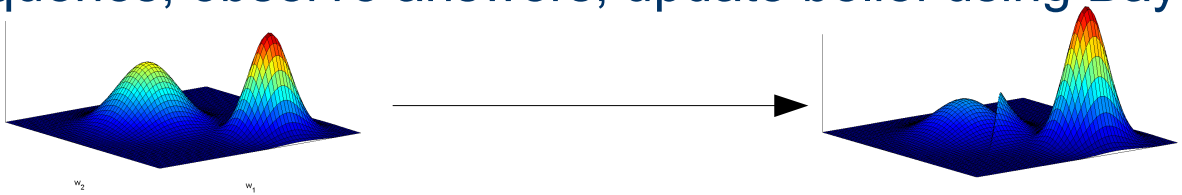
Optimal Bayesian Recommendation Sets and Myopically Optimal Choice Query Sets (W47)

- Bayesian approach to adaptive utility elicitation
  - Underlying decision problem with structured utility (as in MAUT)
  - Uncertain utility
- Probabilistic belief about utility parameters
  - Ask queries, observe answers, update belief using Bayes

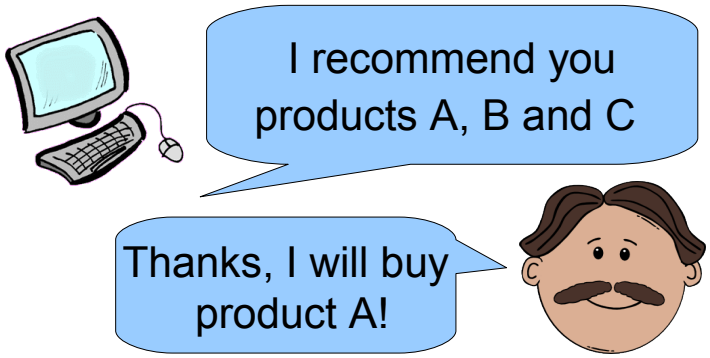


  - Make a recommendation: show product that maximizes *expected utility*
  - Natural criterion for queries: *Expected Value of Information* (EVOI)
  - Because of complexity, most approaches use heuristics to select queries with no theoretical guarantees

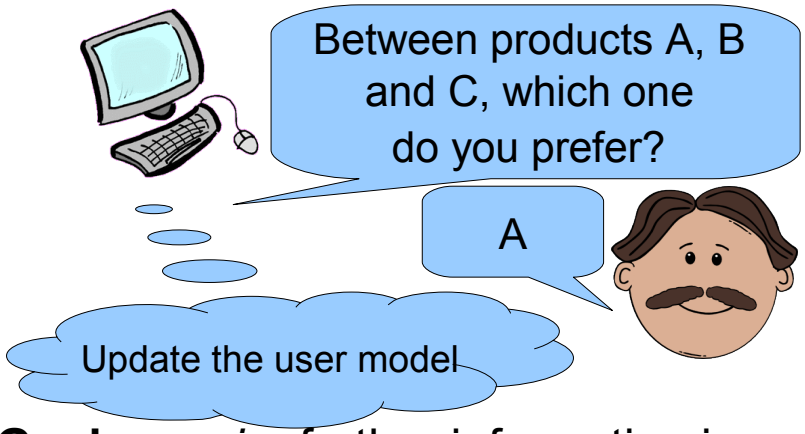
Paper contribution: Bayesian set-based recommendations and how they offer optimal or near-optimal EVOI choice queries

Exploitation vs Exploration ?

- Natural tension between *recommendation* and *elicitation*

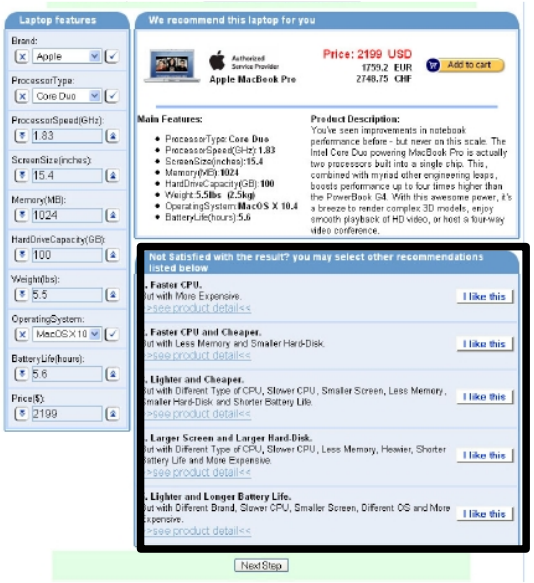


Goal: *exploit* current information
Note: since utility is uncertain, *there can be value in recommending a set*



Goal: *acquire* further information in order to make better recommendation

Online recommender systems: options shown with dual goal of recommendation and elicitation



[Pu et. al.,08]

- Sets can be viewed as **both** recommendation and choice queries
  - *Expected Utility of Selection:* value of a set as recommendation
  - *Expected Value of Information:* value of a set as a choice query
- Different response/selection models: *noiseless*, *constant noise*, *logistic* (aka mixed multinomial logit, Luce-Sheppard)

Theorem:
Optimal recommendation sets are optimal choice queries

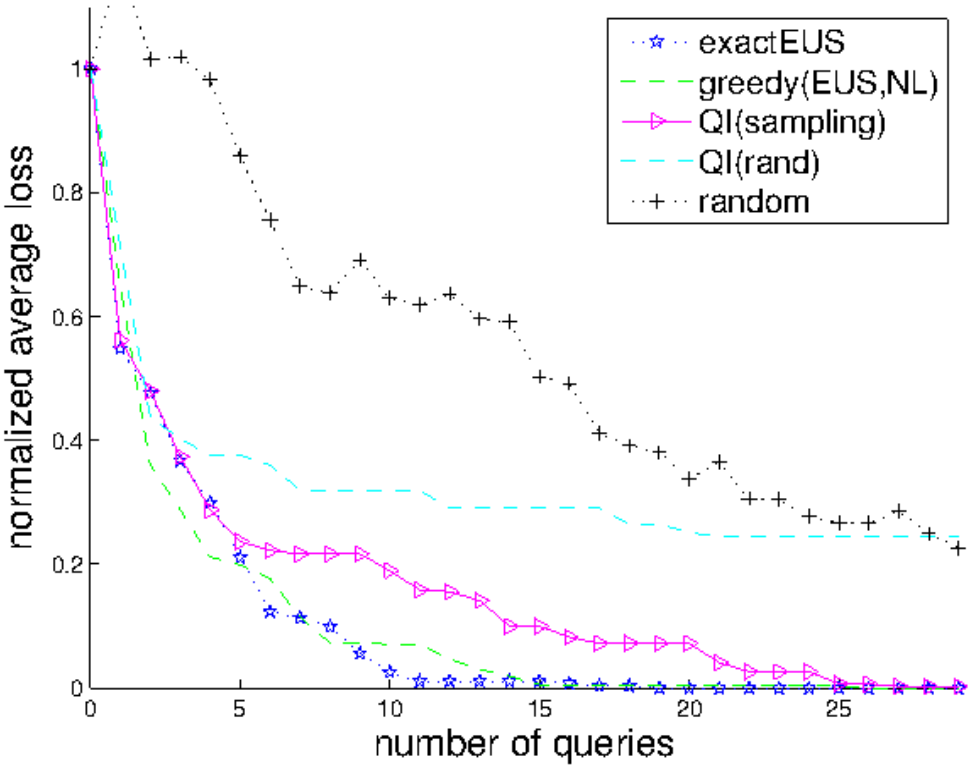
- Assuming noiseless responses or a constant noise model
- No particular assumption about prior distribution, methods of Bayesian inference.

Theorem: ***Optimal recommendation sets are near-optimal queries under the logistic noise model***

- We provide the expression for the worst-case loss Δ_{max} (surprisingly small)
- Also, the optimal query assuming *noiseless* responses is a near-optimal query under logistic *noise*

Algorithms

- Consequences of our theoretical results: efficient algorithms to generate choice queries
  - Optimizing a recommendation set is simpler and *submodular*
  - Approximated strategies with worst-case guarantees
  - *Noiseless* optimization quite effective in *noisy* settings
  - Query Iteration strategy particularly efficient for large datasets



Computation time	Dataset 1 Size=187	Dataset 2 Size=506
Exact EVOI	1815s	~2 weeks
Exact EUS	405s	~2 hours
Greedy with lazy evaluation	1.02s	0.93 s
Query Iteration (local search)	0.15s	0.05 s

Poster W47, Paolo Viappiani and Craig Boutilier