Reward Function Complexity and Goals in Exploration-Exploitation Tasks

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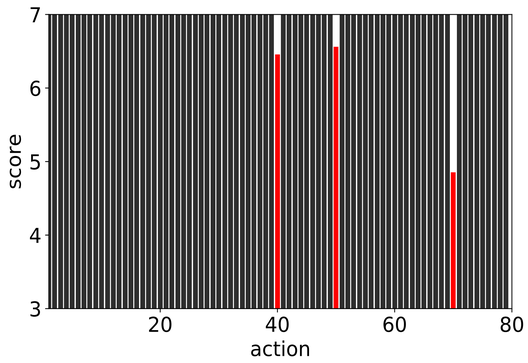
Contextual Multi-Armed Bandits

Choose one of *k* actions (Restaurants)

Each action is associated with a set of features (Menu items, location)

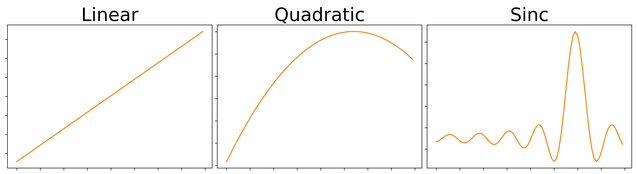
Explore-Exploit Dilemma: Should you choose an action with high expected reward or one that will give you more information about the reward function?

Task: actions are associated with one feature ranging from 1-80, with this feature determining the reward of an action via an unknown reward function. Rewards are initially hidden (grey) and revealed (red) after being selected.

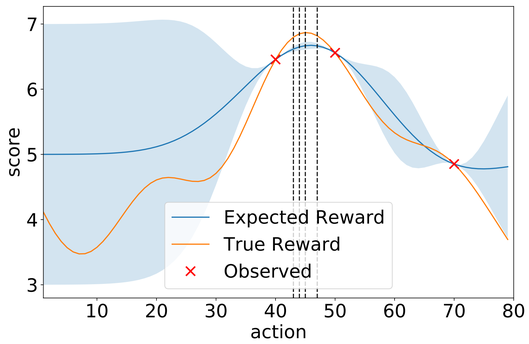


Goal Conditions:
- Maximize cumulative reward over N trials
- Find the maximum reward within N trials

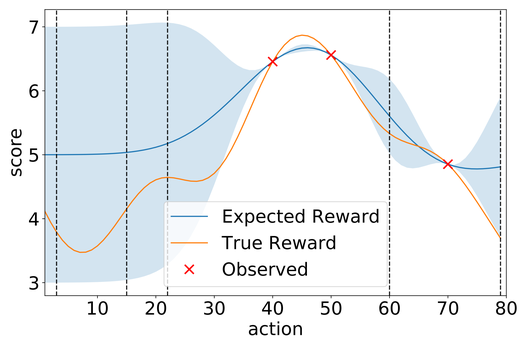
Reward Function Conditions:



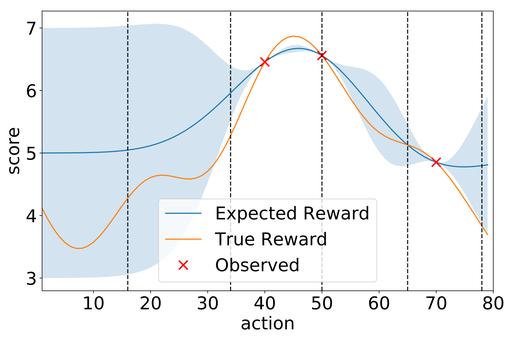
Explore-Exploit Strategies



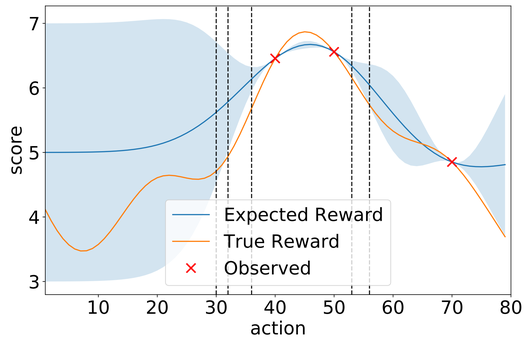
Mean greedy: Only choose actions with high expected reward



Variance greedy: Choose actions with highly uncertain reward



Stochastic: Choose actions at random, without using any information about the reward function



Entropy Search: Choose actions that will reduce uncertainty about some global property of the reward function (e.g. location of the maximum, value of the maximum)

How do people choose a strategy?

Goal?
- Maximize cumulative reward: balance exploration and exploitation on each trial (e.g. Upper confidence bound, expected improvement)
- Find the maximum reward: gain as much information about the value of the maximum as possible on each trial (Max-value entropy search)

Reward Function Complexity?
- Simple reward function: Generalize to new actions
- Complex reward function: Explore randomly

Model

Mixed Strategy:

$$p(a_t = k) \propto \exp[\ \underbrace{m_t(k)}_{\text{expected value}} + \beta\ \underbrace{v_t(k)}_{\text{uncertainty}} + \lambda\ \underbrace{I(\{k, r\}; r^*)}_{\text{mutual information}}\ ]/\tau$$

High β: Exploration directed by local uncertainty
High λ: Exploration directed by global uncertainty
High τ: Undirected (random) exploration

Infinite Mixture of Strategies:

$$p(a_t^i | g_i = z) = p(a_t^i | \beta_z, \lambda_z, \tau_z)$$

Conclusions

Most participants fell into one of four strategies:
Stochastic: Relied primarily on random exploration (High τ, low β and λ)
Mixed: Used a mixture of random, local uncertainty directed, and global uncertainty directed exploration (High β, λ, and τ)
Directed: Used a mixture of local uncertainty directed and global uncertainty directed exploration, with less random exploration (High β and λ, low τ)
Greedy: Didn't explore (low β, λ, and τ)

No strong evidence that strategies depend on goal or function complexity

	β	λ	τ	N Participants
Stochastic	0.29 ± 0.17	6.01 ± 8.87	5.23 ± 3.57	15
Mixed	1.58 ± 1.15	8.56 ± 8.32	1.77 ± 2.43	14
Directed	1.4 ± 1.29	11.19 ± 9.21	0.24 ± 0.22	11
Greedy	0.77 ± 0.44	0.61 ± 0.84	0.14 ± 0.19	8
	0.53 ± 0.27	4.06 ± 5.35	1.3 ± 1.14	7
	1.21 ± 0.55	6.38 ± 9.77	1.32 ± 0.61	6
	0.87 ± 0.33	8.77 ± 9.51	0.22 ± 0.24	4
	3.12 ± 2.33	0.99 ± 0.48	1.82 ± 1.14	2
	1.12 ± 0.39	6.98 ± 6.09	0.89 ± 0.63	2

Mean parameters for each group