

Dynamic decision making with stopping

Daniel Karlík

The Czech Academy of Sciences, Institute of Information Theory and Automation

daniel@karlik.cz

June 23, 2022

- Dynamic decision making (DM)
- Stopping rule
- Fully Probabilistic Design

Stopping rule & secretary problem

- Often called stopping time
- As a stopping rule we understand a method for making a decision whether to continue or stop a process
- Famous stopping rule example: **Secretary problem**
- Also known as **marriage problem** or the **best choice problem**



Source ScottHYoung.com Services Ltd.

Fully probabilistic design I.

- Different approach to the regular Markov decision processes
- Markov decision processes use a loss function to evaluate optimal policy
- Whereas FPD quantifies agent's aims and desires probabilistically, from which derives the optimal policy

Fully probabilistic design II.

- We assume a finite set of possible actions \mathcal{A} and possible states \mathcal{S} ; finite time horizon $|\mathcal{T}|$
- States are denoted as s_t and actions as a_t
- We operate on a closed-loop formed by an agent and its environment
- Probability behaviour of closed-loop:

$$c^\pi(b) = \prod_{t \in \mathcal{T}} m(s_t | a_t, s_{t-1}) r(a_t | s_{t-1})$$

- Ideal probability behaviour of closed-loop:

$$c^j(b) = \prod_{t \in \mathcal{T}} m^j(s_t | a_t, s_{t-1}) r^j(a_t | s_{t-1})$$

Fully probabilistic design III.

- Distance between these probabilities is evaluated using Kullback-Leibler divergence

$$D(c^\pi || c^i) = \int_{b \in \mathcal{B}} c^\pi(b) \ln \left(\frac{c^\pi(b)}{c^i(b)} \right) db$$

- As optimal policy is selected

$$\pi^o \in \arg \min_{\pi \in \Pi} D(c^\pi || c^i)$$

- Optimal decision rules can be numerically evaluated using formula:

$$r^o(a_t | s_{t-1}) = r^i(a_t | s_{t-1}) \frac{\exp[-d(a_t, s_{t-1})]}{h(s_{t-1})}$$

FPD with stopping I.

We extend the action and state spaces in the following way.

Extension of the classical actions

The actions with stopping are defined as $\alpha_t := (a_t, \tilde{a}_t)$, where a_t represents regular action and \tilde{a}_t is defined as follows

$$\tilde{a}_t := \begin{cases} 1 & \text{continue in generating the regular action } a_t, \\ 0 & \text{take the final regular action } a_t \text{ and stop.} \end{cases}$$

Extension of the classical states

With a similar way to actions we extend the states as $\beta_t := (s_t, \tilde{s}_t)$, where s_t is classical state and \tilde{s}_t reflects if the DM process is stopped or not and is defined as

$$\tilde{s}_t := \begin{cases} 1 & \text{DM process continues,} \\ 0 & \text{DM process is stopped.} \end{cases}$$

FPD with stopping II.

- The key is a proper design of ideal pd c^i
- Process is not stopped \Rightarrow KLD increase with continuing of DM
- Process is already stopped \Rightarrow KLD does not increase
- When we stop we pay for the final choice/selection

Advantages of the use of FPD with stopping

- Most of the hard work is transferred to the design of ideal model, which reflects agent's aims
- This approach seems to be more robust, in can handle changing tasks conditions
- Can extend the static (one-shot) stopping to dynamic DM carrying

- Constructing of some numerical examples and usages of the proposed method
- Comparison of the results with those obtained by MDP
- Testing this approach on some real world tasks
- Exploitation of possibility to stop a part of dynamic DM

Thank You for your attention



T. S. Ferguson (1989)

Who solved the secretary problem?

Statistical Science 4(3), pp. 282 – 296.



Kárný, M., T. V. Guy (2006)

Fully probabilistic control design

Systems & Control Letters 55(6), pp. 259–265.



Kárný, M., T. V. Guy (2014)

On the Origins of Imperfection and Apparent Non-Rationality

Studies in Computational Intelligence 538, pp. 57–92.