

Master Thesis

Topic:

Unsupervised learning in decision making

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I Table of Contents

I	Table of Contents	I
II	List of Figures	II
III	List of Tables	III
IV	List of Listings	IV
V	List of mathematical symbols	V
VI	List of abbreviations	VI
1	Introduction and conceptual approach	1
2	Simulation	1
2.1	Data generation	1
2.2	Reinforcement Learning background	1
2.3	Unsupervised Learning	1
2.4	Simulation results	1
3	List of Literature	2
	Appendix	A

II List of Figures

III List of Tables

Tab. 1	Overview Outcome	B
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IV List of Listings

V List of mathematical symbols

Symbol	Meaning
a_t	Action at time t
$Q(a)_t$	Value function at time t
ϵ	Probability of exploration in epsilon greedy
α	Learning rate
τ	Softmax parameter

VI List of abbreviations

Abbreviations	Description
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1 Introduction and conceptual approach

2 Simulation

2.1 Data generation

Challenge: Categorical data with time series attributes. Apply transformation choice probabilities () Define similarity measures on categories

2.2 Reinforcement Learning background

Reinforcement Learning (RIL) is a branch of *Machine Learning* try model how an artificial agents interact with its environment and learns from the process over time.

In particular an agents is confronted with the task of choosing sequently from a set of choices. In comparison to *supervised learning*, where an agent is learning based on set of examples an agent in RIL The objective is to let the agent learn within a certain the optimal action. Since it doesn't have any apriori information about the system it has to explore new possible action and so has to deviate from the optimal action. Furthermore, it has to keep track of value of each action he did so far. So the main task of the agent is to balance exploration and explotation. There are to basic approaches to model this trade-off; An "*Epsilon-Greedy*" selection method and Soft "*Softmax*" selection method.

Considering first epsilon greedy action selection mehtod: Let $Q_t(a)$ be the value function of action. In general select the next action as a as $a_{t+1} = \arg \max Q_t(a)$. However, to model exploration there is a probability to deviate from that greedy strategy. Choose next action Let p_e be the probability of exploration. $p = \epsilon$

$$Q_t(a) = \frac{R_1 + R_2 + \dots + R_{K_\alpha}}{K_\alpha}$$

$$Q_{k+1} = Q_k + \alpha [R_k - Q_k]$$

There are two basic

a. "*Epsilon Greedy*"

Soft Max Selection

$$P(a_t|X) = \frac{e^{\frac{Q_t(a)}{\tau}}}{\sum_i^K e^{\frac{Q_t(i)}{\tau}}}$$

2.3 Unsupervised Learning

2.4 Simulation results

3 List of Literature

Appendix

Specification	μ	σ	CL Size	SD	Decision	α	τ	N	ALG	TRNS	MI	NMI	AMI	CS	HS	VMS
1	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-

Table 1: Overview Outcome