Konya Mühendislik Bilimleri Dergisi., c. 8, s. 2, 258-268, 2020
Konya Journal of Engineering Sciences v. 8, n. 2, 258-268, 2020
ISSN: 2667-8055 (Elektronic)
DOI: 10.36306/konjes.745756

A MARKOV DECISION PROCESS APPROACH FOR MENTAL HEALTH

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(Geliş/Received: 21.02.2019; Kabul/Accepted in Revised Form: 21.10.2019)

ABSTRACT: Mind has various functions such as remembering a certain event, processing information, and providing responses to information it faces. During depression, mind does not work in an efficient way because of wasteful thoughts constantly occupying it. In this paper, we study the problem of how to react during depression, focusing on two decisions: ignoring the effects of wasteful thoughts on mind, and attempting to resolve depression. We model the problem of how to react during depression as a Markov Decision Process and solve it optimally. We also test the performance of two easy-to-use decision rules under diverse scenarios: always ignoring and always attempting to resolve.

Keywords: *Markov Decision Processes, mental health, optimality equations*

Zihinsel Sağlık için Markov Karar Süreci Yaklaşımı

ÖZ: Zihin belirli bir olayı hatırlama, bilgiyi proses etme ve maruz kaldığı bilgiye tepki verme gibi çeşitli fonksiyonlara sahiptir. Depresyon boyunca zihin, kendisini sürekli olarak meşgul eden gereksiz düşüncelerden dolayı verimli bir şekilde çalışmaz. Bu makalede, şu iki karara odaklanarak depresyon boyunca nasıl tepki verilmesi gerektiği problemini çalışmaktayız: gereksiz düşüncelerin zihin üzerindeki etkisini ihmal etme ve depresyonu çözmeye çalışma. Depresyon boyunca nasıl tepki verilmesi gerektiği problemini Markov Karar Süreci ile modellemekteyiz ve problemi optimal olarak çözmekteyiz. Ayrıca çeşitli senaryolar altında şu iki kolay-kullanılabilir karar kurallarının performansını test etmekteyiz: her zaman ihmal etme ve her zaman çözmeye çalışma.

Anahtar Kelimeler: *Markov Karar Süreçleri, zihinsel sağlık, optimallik denklemleri*

INTRODUCTION AND LITERATURE REVIEW

Mind is always in a particular state; it receives what it reads or sees, and begins to process them. During depression, mind is continuously affected by the source of depression, which can be a tragic event such as getting divorced, death of a family member, being bullied, or the image of a perpetrator. As a result, the information mind receives includes memories of a tragic event, which decreases the efficiency of mind since it struggles with thoughts related to such an event when performing a usual activity such as reading a text or performing a daily task at workplace.

An individual facing the abovementioned situation can be thought to choose one of the following decisions: 1) ignoring the effects of wasteful thoughts (depression) on mind, 2) attempting to resolve depression. In the former case, mind is constantly occupied by wasteful thoughts while the individual is working on her task. In the latter case, the individual tries to resolve the issue by having a break from her task and focusing on a relaxing activity for a short period. Certainly, both decisions cause waste of time and decrease in attention level.

To that end, we consider the problem of how to react during depression, focusing on the abovementioned decisions. The problem has the feature that the cause of depression dynamically arrives at mind over time, forcing the individual to either ignore or attempt to resolve. We formulate the problem as a discrete-time finite horizon Markov Decision Process (MDP), a mathematical framework used to model systems that evolve probabilistically over time (Puterman, 1994).

In this paper, the following contributions are made:

- We introduce a depression handling problem in which an individual seeks to find optimal policy with the objective of maximizing her well-being, which we define as attention level minus the amount of time wasted.
- We formulate the problem as an MDP and solve it optimally.
- We test the performance of easy-to-use decision rules under diverse scenarios.
- We derive certain policy insights from our computational results.

There have been numerous studies on mental health (Parker *et al.,* 2016), (Bettis *et al.,* 2017), (Momotani and Yamamoto, 2014), (Fergusson *et al.,* 2015), (Kessler *et al.,* 2015). Examples of topics studied in the literature include adult mental health, long-term effects of being bullied, workplace bullying as an antecedent of mental health problems, and child and adolescent mental health. The related literature is reviewed below.

Lereya *et al.* (2015) studied consequences of peer bullying in childhood. Their analysis revealed that young adults' mental health is adversely affected by being bullied by peers in childhood. Outcalt *et al.* (2015) focused on chronic pain and comorbid mental health conditions. They analyzed baseline data to investigate whether posttraumatic stress disorder and major depression are associated with factors such as psychological status and quality of life. Sigurdson *et al.* (2015) studied the effects of being bullied on health problems in adulthood. Their findings revealed that there is an association between involvement in bullying in adolescence and later mental health problems.

Cuijpers *et al.* (2016) conducted a comprehensive meta-analysis for interpersonal psychotherapy for mental health problems. Their results indicate that interpersonal psychotherapy can be used to treat depression effectively. Einarsen and Nielsen (2015) examined whether there is a relationship between exposure to workplace bullying and mental health. They found that health and well-being of workers are threatened by workplace bullying. Bor *et al.* (2014) conducted a literature review to examine whether "child and adolescent mental health problems are increasing in the 21st century". Their findings revealed that, compared with previous cohorts, internalizing symptoms appear increasingly in recent cohorts of adolescent girls. Bruffaerts *et al.* (2018) studied mental health problems in college freshman. They point out that there is an association between mental health problems in college freshman and lower academic functioning.

Boardman *et al.* (2011) addressed the question of how the stigma of depression is linked to the responses to depression. Their results revealed that stigma is associated with ideas about depressive sypmtoms. Buckaloo *et al.* (2009) performed research on the effects of exercise on prison inmates, and found that exercise is a proper strategy to tackle incarceration. Jorm *et al.* (2006) conducted research on the claim that dealing with depression alone is better than seeking help. They concluded that adults generally embrace the view that personal weakness causes depression.

Patten (2005) developed Markov models that represent incidence, prevalence, and recovery from depression, and used Monte Carlo simulation to constrain model parameters to the respective data. Their study reveals that incidence and episode duration influences the period prevalence of depression. Other methods to deal with depression include longitudinal cohort studies (Boardman *et al.,* 2011), data analysis and statistical methods such as prediction (Buckaloo *et al.,* 2009), and meta-analysis (Corrigan *et al.,* 2014).

Examples of studies focusing on the impact of mental health problems can be summarized as follows. Corrigan *et al.* (2014) studied the elements of mental illness stigma and investigate public policy considerations that tackle this illness. They concluded that it is necessary to resort to policy change in overcoming the structural stigma. Motivated by the impact of working conditions of academic settings on mental health, Levecque *et al.* (2017) evaluated the prevelance of mental health problems in a group of PhD students in Belgium. Their analysis revealed that factors such as job demands, the supervisor's leadership style, and the culture of team decision making are associated with mental health problems. Reiss (2013) surveys the literature on the relationships between a variety of indicators of socioeconomic status and mental health outcomes for children. Their review emphasizes the need for early childhood interventions to improve mental health in children.

MDP has been applied to a variety of health problems. Examples of those problems include "optimal assignment of treatments to health states" (Bala and Mauskopf, 2006), control of patient admissions in hospitals (Nunes *et al.,* 2009), assessment of pharmacoeconimics and health technology (Stahl, 2008), and disease prevention, disease screening and surveillance, and treatment decisions (Denton *et al.,* 2011).

Unlike our work, the mental health literature does not contain any work that models a mental health problem using MDPs.

PROBLEM DESCRIPTION AND MATHEMATICAL FORMULATION

The problem of dealing with depression can be described as follows.

- We consider depression in the sense that persistent thoughts and memories constantly occupy mind, thereby focusing on the negative effects of depression on the way mind works.
- We consider a finite time horizon, considering the effect of depression on mind for certain number of periods. This corresponds to a period in which the individual works on a particular task. Once this period ends, the individual's performance is evaluated.
- The imagination of a person who is the source of depression or the rememberance of a tragic event arrives at mind randomly at each time period, with probability p_d. We assume that at most one arrival occurs at each time period. The probability that depression is resolved at any given period when the individual attempts to resolve it is represented by p_r. We assume that depression may be resolved by having a break from work for a little while and being involved in a relaxing activity.
- If the individual ignores the effect of depression, then her attention level decreases by y_1 units and time lost increases by x_1 units. If the individual attempts and resolves depression, with certain probability p_r, attention level decreases by y_2 unit and time lost increases by x_2 units; with probability $1-p_r$, attention level decreases by y_3 units and time lost increases by x_3 units.
- If depression arises during a given period, at the beginning of the next period, the individual performs the decision of ignoring or attempting to resolve.
- There are weights for attention level and time lost, respectively. These weights represent the effect of attention level and time lost on the individual's well-being, and are denoted by w_{al} and w_{tl} respectively.
- The objective is to handle depression with the objective of maximizing the well-being of the individual.

Markov Decision Process Model

Markov Decision Process (MDP) is a mathematical framework used to model systems that evolve probabilistically over time. An MDP consists of the following components: (Gocgun, 2018)

- Stage: "It consists of time periods through which the system evolves."
- State: "States capture the key features of the system at various time-points."
- Action: At each state, one of the feasible actions is selected.
- Probabilistic state transitions: The process switches to a new state probabilistically after an action is chosen at each state.
- Reward/cost: A reward is obtained or a cost is incurred for each state-action pair.

The objective of an MDP is "to compute an action in each state so as to maximize expected net reward (or minimize expected cost)" (Gocgun, 2018).

State Space

The state space $s \in S$ takes the following form.

$s = (al, tl, c)$,

where al is attention level, tl is time lost, and c is a binary variable indicating whether there is a depression to be dealt with or not.

Action Sets

The decision of the individual at the beginning of each period is to either ignore or attemt to resolve depression, if there is depression. Otherwise there is no decision to be made. A_s denotes the set of available actions in state s. Any action in s is represented by:

$a = (d)$,

where d is *ignore* or *attempt to resolve*. Note that actions are chosen deterministically.

Transition Probabilities

After a decision is made, the state changes as follows.

If there is depression and the decision of the individual is to ignore,

$$s' = \begin{cases} (al - y_1, tl + x_1, 0), & \text{with probability } 1 - p_d \\ (al - y_1, tl + x_1, 1) & \text{with probability } p_d \end{cases} \tag{1}$$

If there is depression and the individual's decision is to attempt to resolve depression,

$$s' = \begin{cases} (al - y_2, tl + x_2, 0), & \text{with probability } (1 - p_d)(p_r) \\ (al - y_2, tl + x_2, 1) & \text{with probability } p_d(p_r) \\ (al - y_3, tl + x_3, 0) & \text{with probability } (1 - p_d)(1 - p_r) \\ (al - y_3, tl + x_3, 1) & \text{with probability } (p_d)(1 - p_r) \end{cases} \tag{2}$$

Rewards

The immediate reward is expressed as

$$r(a) = w_{al}(al) - w_{tl}(tl), \tag{3}$$

and represents the well-being of the individual at current stage.

Optimality Equations

Optimality equations for finding a policy that maximizes the expected well-being of the individual is expressed as follows:

$$v_n(s) = \max_{a \in A_s} \left\{ r(a) + \sum_{s' \in S} P(s' \mid s, a) v_{n+1}(s') \right\}, n = 1\ldots, N, \forall s \in S, \tag{4}$$

where $v_n(s)$ **is the value function and gives us the optimal value of the MDP for state** *s*, $P(s^{'} \mid s, a)$ is the probability that the next state is $s^{'}$ given that action *a* is chosen at state s.

$$v_{N+1}(s) = al(w_{fa}) - tl(w_{ft}), \tag{5}$$

where w_{fa} is the end-of-period weight for attention level, and w_{ft} is end-of-period weight for time lost.

The following calculation is performed at each stage:

$$a*(s) \in \underset{a \in A_S}{\operatorname{argmax}} \left\{ r(a) + \sum_{s^{'} \in S} P(s^{'} \mid s, a) v_{n+1}(s^{'}) \right\}, n = 1\ldots, N-1. \tag{6}$$

At the end of the horizon (which could be a day), the inidividual's performance will be evaluated; these end-of-period weights are used to determine whether attention level or time lost is more important for the individual.

The solution of the above standard recursive equations for all s and $n = 1, \ldots, N$ provides us an optimal policy((Puterman, 1994)). In particular, we solve our finite-horizon MDP by using the backward induction technique (BIT). The BIT solves the optimality equations given in equations (4) and (5) backwards in time and and then obtains the optimal actions given in Equations (6). We define initial conditions through Equation (1) and calculate the value function one stage at a time (Alagoz *et al.*, 2010).

NUMERICAL RESULTS

This section contains computational results obtained by employing optimal policy as well as easy-to-use decision rules. We used R, a free software environment for statistical computing, for employing these decision rules.

Experimental Design

We consider a depression handling problem in which the length of the finite horizon is 48 (the length of each period is 10 minutes; therefore the length of the horizon is 8 hours). Probability that depression occurs at any period (p_d) is assigned two levels: 0.9 and 0.5 (the first level corresponds to high-frequency depression situation and the second one corresponds to medium-frequency depression situation).

Probability that depression is resolved after the individual attemts to resolve has three levels: 0.25, 0.5, and 0.75 (corresponding to low, medium, and high levels). By varying the levels of w_{fa}, w_{ft}, w_{al}, w_{tl} and , we created 15 scenarios, which are described in Table 1. The ratio of any of w_{al} and w_{tl} to any of w_{fa} and w_{ft} is set to at least 1/200 and at most 1/25 as end-of-period weights are expected to be reasonably higher than w_{al} and w_{tl}. In order to create enough trade-offs, the ratio of w_{al} to w_{tl} is set to two levels: 1 and 2.

Table 1. Scenarios used in testing decision rules.

Scenario	w_{al}	w_{tl}	w_{fa}	w_{ft}
1	1	1	50	100
2	1	1	100	50
3	1	1	50	200
4	1	1	200	50
5	1	1	100	200
6	1	1	200	100
7	2	1	50	50
8	2	1	50	100
9	2	1	100	50
10	2	1	50	200
11	2	1	200	50
12	2	1	100	100
13	2	1	100	200
14	2	1	200	100
15	2	1	200	200

Regarding the relationship between x_i's and y_i's, we consider the following two cases.

Case 1: $y_1 = y_3 = 4y_2$, $x_3 = 2x_1 = 2x_2$

Case-2: $y_1 = y_3 = 2y_2$, $x_3 = 2x_1 = 2x_2$

Without loss of generality, we set y_2 to 1 and x_2 to 2. Consider Case-1; if the individual ignores the effect of depression, then her attention level decreases by 4 units and time lost increases by 2 units. This is due to the fact that in this case wasteful thoughts will occupy the mind, which adversely affects attention level and cause waste of time due to decrease in the efficiency of mind. On the other hand, if the individual attempts to resolve depression, with probability p_r , attention level decreases by 1 unit and time lost increases by 2 units; with probability $(1-p_r)$, attention level decreases by 4 units and time lost increases by 4 units. The reason is that when depression is resolved, attention level will decrease slightly and the amount of time lost will be moderate; if it is not resolved, attention level will decrease significantly and the amount of time lost will be high.

We generated 180 problem sets since the number of scenarios is 15, the probability that depression is resolved has three levels, the probability that depression occurs at a given period has two levels, and we have two cases regarding the values of x_i s and y_i s. For each problem set, we ran 1000 independent simulations for the policy retrieval process (i.e., utilizing the optimal action for each state visited). To be more specific, we first find the optimal policy for a given problem set using the BIT, which gives us the optimal action at each state. Then we simulate the system, which transitions to various states because of random arrivals of the source of depression. Since we know the optimal action for each state visited, we are able to calculate the resulting cost for each of 48 stages.

In this work, we tested the performance of the following decision rules.

Always Ignore (IGN): According to this rule, the individual always chooses to ignore in case of depression.

Always Attempt to Resolve (RES): In case of depression, this rule always chooses the option of attempting to resolve.

Results

Our results are presented in tables 2,3,4, and 5. Tables 2 and 3 correspond to Case-1, whereas tables 4 and 5 correspond to Case-2. Each row of the below tables corresponds to a different problem set. The values provided in each table are percentage differences between the optimal policy and the respective decision rule. Further, "Best str" means best strategy, and IGN and RES correspond to "always ignore" and "always attempt to resolve" decision rules.

We begin with the analysis of Table 2 for which $p_d = 0.9$. Our results reveal that, for $p_r = 0.5$ (the probability that depression is resolved after the individual attempts to resolve it), the "always attempt to resolve" decision rule performs better in 10 out of 15 problem sets. Whereas the "always ignore" decision rule performs better in 4 out of 15 problem sets. Additionally, if average percentage difference between the optimal policy and the respective decision rule is considered, the "always attempt to resolve " decision rule performs significantly better than the other rule. When p_r is 0.25, the "always ignore" decision rule outperforms the other rule in 11 out of 15 problem sets, whereas the "always attempt to resolve" decision rule is the best rule in 2 out 15 problem sets. The two decision rules perform nearly the same in the remaining 2 problem sets. Further, the "always attempt to resolve" decision rule performs better in all the problem sets when p_r is 0.75.

When the end-of-period weight for attention level (w_{fa}) is higher than the end-of-period weight for happiness level for time lost (w_{ft}), which corresponds to scenarios 2,4,6,9,11, and 14, the "always attempt to resolve" decision rule always outperforms the other rule for the $p_r = 0.5$ and $p_r = 0.75$ cases.

When depression occurs less frequently, which corresponds to $p_d = 0.5$, the only change with respect to Table 2 is in percentage differences between the optimal policy and the respective decision rule. In this case, the percentage difference values drop significantly. What is more, the "always attept to solve" decision rule performs as well as the optimal policy in almost all the problem sets when p_r is 0.75 (see Table 3).

When the effect of the action of *ignore* is less severe (corresponding to Case-2), the "always ignore" decision rule generally performs better than the other decision rule for the $p_r = 0.25$ and $p_r = 0.5$ cases. On the other hand, for the $p_r = 0.75$ case, the "always attempt to resolve" decision rule generally performs better than the other rule (see tables 4 and 5).

Table 2. Case-1 results for $p_d = 0.9$.

	Resolve prob		0.25	Resolve prob		0.5	Resolve prob		0.75
Scenario	IGN	RES	best str	IGN	RES	best str	IGN	RES	best str
1	247	386	IGN	245	260	IGN	177	91	RES
2	1025	1095	IGN	2804	1763	RES	1425	240	RES
3	165	306	IGN	147	201	IGN	100	81	RES
4	396	362	RES	1366	677	RES	2047	151	RES
5	230	361	IGN	223	244	IGN	155	88	RES
6	997	1035	IGN	2513	1568	RES	1167	211	RES
7	3836	4533	IGN	864	536	RES	2496	233	RES
8	426	617	IGN	181	161	RES	191	44	RES
9	3223	3226	BOTH	13688	6963	RES	1862	98	RES
10	206	362	IGN	78	105	IGN	69	34	RES
11	1316	1124	RES	1020	435	RES	697	27	RES
12	784	955	IGN	355	244	RES	375	52	RES
13	291	438	IGN	126	127	BOTH	114	36	RES
14	97	97	BOTH	1345	716	RES	1453	94	RES
15	517	640	IGN	252	186	RES	229	40	RES

Table 3. Case-1 results for $p_d = 0.5$

	Resolve prob		0.25	Resolve prob		0.5	Resolve prob		0.75
Scenario	IGN	RES	best str	IGN	RES	best str	IGN	RES	best str
1	48	169	IGN	47	61	IGN	93	0	RES
2	631	832	IGN	187	12	RES	128	0	RES
3	26	123	IGN	24	64	IGN	32	13	RES
4	155	90	RES	121	3	RES	111	0	RES
5	38	131	IGN	34	50	IGN	61	0	RES
6	501	582	IGN	311	19	RES	151	0	RES
7	53	101	IGN	65	5	RES	82	0	RES
8	507	1566	IGN	2657	1747	RES	254	0	RES
9	62	62	BOTH	78	2	RES	88	0	RES
10	40	177	IGN	33	73	IGN	65	0	RES
11	74	36	RES	85	2	RES	91	0	RES
12	453	899	IGN	210	35	RES	132	0	RES
13	62	199	IGN	70	72	BOTH	142	0	RES
14	179	180	BOTH	127	2	RES	112	0	RES
15	137	278	IGN	312	86	RES	275	0	RES

Table 4. Case-2 results for $p_d = 0.9$

	Resolve prob		0.25	Resolve prob		0.5	Resolve prob		0.75
Scenario	IGN	RES	best str	IGN	RES	best str	IGN	RES	best str
1	143,22	284,37	IGN	143,22	217,63	IGN	143,18	149,65	IGN
2	286,77	423,09	IGN	286,77	310,10	IGN	299,32	204,61	RES
3	119,42	260,90	IGN	119,42	203,61	IGN	117,94	143,73	IGN
4	586,57	710,43	IGN	586,57	509,69	RES	655,17	346,03	RES
5	145,62	285,95	IGN	145,62	221,21	IGN	145,18	154,97	IGN
6	321,95	455,45	IGN	321,95	337,27	IGN	337,05	228,49	RES
7	278,88	460,78	IGN	272,43	326,56	IGN	208,52	148,38	RES
8	181,32	342,25	IGN	171,79	245,17	IGN	128,93	120,79	RES
9	444,25	626,86	IGN	444,44	448,34	IGN	339,53	197,32	RES
10	135,91	287,08	IGN	127,67	210,06	IGN	91,92	107,97	IGN
11	1024,54	1209,61	RES	1131,13	944,68	RES	782,64	362,86	RES
12	246,62	406,32	IGN	238,15	292,40	IGN	181,02	140,40	RES
13	165,09	315,34	IGN	157,14	231,64	IGN	115,28	116,79	IGN
14	410,86	567,47	IGN	409,52	413,59	IGN	310,37	189,10	RES
15	229,93	378,15	IGN	222,62	276,95	IGN	166,89	136,30	RES

Table 5. Case-2 results for $p_d = 0.5$

	Resolve prob		0.25	Resolve prob		0.5	Resolve prob		0.75
Scenario	IGN	RES	best str	IGN	RES	best str	IGN	RES	best str
1	22	121	IGN	22	75	IGN	22	27	IGN
2	58	181	IGN	58	81	IGN	76	0	RES
3	18	108	IGN	18	72	IGN	17	33	IGN
4	162	313	IGN	203	103	RES	545	0	RES
5	22	112	IGN	22	71	IGN	21	28	IGN
6	57	160	IGN	57	71	IGN	73	0	RES
7	89	368	IGN	89	175	IGN	116	0	RES
8	32	165	IGN	32	96	IGN	34	25	RES
9	228	664	IGN	215	226	IGN	1289	0	RES
10	21	123	IGN	21	80	IGN	20	34	IGN
11	602	1090	IGN	417	137	IGN	158	0	RES
12	48	186	IGN	48	97	IGN	55	7	RES
13	26	129	IGN	26	79	IGN	26	28	IGN
14	94	251	IGN	91	96	IGN	146	0	RES
15	38	143	IGN	38	78	IGN	41	14	RES

In light of the abovementioned results, we have the following insights for the depression handling problem.

- Probability that depression is resolved is one of the determinants for the best decision rule.
- If probability that depression is resolved has moderate values, the “always attempt to resolve” decision rule generally performs better than the “always ignore” decision rule when the effect of ignoring is severe (corresponding to Case-1). Whereas the “always ignore” rule generally performs better than the other decision rule when the effect of ignoring is not severe.
- If probability that depression is resolved has small values, the individual should generally follow the “always ignore” decision rule.
- If probability that depression is resolved is considerably high, the individual should generally follow the “always attempt to resolve” decision rule.

CONCLUSIONS

We studied the problem of how to deal with depression, focusing on two decisions: : ignoring the effects of wasteful thoughts on mind, and attempting to resolve depression. We modeled the problem as an MDP, solved it optimally and assessed the performance of two easy-to-use decision rules under diverse scenarios. Our computational results revealed that the best decision rule to implement depends on the probabiltiy that depression is resolved.

Our work reveals that easy-to-use decision rules provide somewhat good solutions for the depression handling problem we introduced. Future research could consider similar problems that lead to more realistic models. In particular, different types of arrivals of events that cause depression can be considered, and models in which state space is more complex can be studied. It would also be interesting to use inifinite-horizon MDPs for modeling such problems. In that case, because of the computational intractability, an approximate solution rather than an optimal solution can be obtained through approximate dynamic programming techniques.

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