

# DISCRETE RANDOM PROCESSES WITH MEMORY: MODELS AND APPLICATIONS

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*Abstract.* The contribution focuses on Bernoulli-like random walks where the past events affect significantly the walk's future development. The main concern of the paper is therefore the formulation of models describing the dependence of transition probabilities on the process history. Such an impact can be incorporated explicitly and transition probabilities modulated using a few parameters reflecting the current state of the walk as well as the information about the past path. The behavior of proposed random walks, as well as the task of their parameters estimation, are studied both theoretically and with the aid of simulations.

*Keywords:* Random walk, history dependent transition probabilities, non-Markov process, success punishing/rewarding walk

*MSC 2010:* 60G50, 62F10

## 1. INTRODUCTION

One of the most common types of a discrete random process is a random walk, first introduced by K. Pearson in 1905 [6]. There exist many variations of a random walk with various applications to real life problems [9, 8]. Yet there are still new possibilities and options how to alter and improve the classical random walk and present yet another model representing different real life events. One of such modifications is the random walk with varying step size introduced in 2010 by Turban [9] which together with the idea of *self-exciting point processes* [2] and the perspective of model applications in reliability analysis and also in sports statistics, served as an inspiration to the random walk with varying transition probabilities introduced by

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Kouřim [3, 4]. In the present paper, the theoretical properties of the model are described and further examined, numerical procedures of model parameters estimation are specified and the results are tested on generated data.

The rest of the paper is organized as follows. Sections 2 and 3 describe the properties of different versions of the model, section 4 provides results from simulated model testing and finally section 5 concludes the work.

## 2. RANDOM WALK WITH VARYING PROBABILITIES

The random walk with varying probabilities is based on a standard Bernoulli random walk [1] with some starting transition probability  $p_0$ . This probability is then altered after each step of the walk using a coefficient  $\lambda$  so that the repetition of the same step becomes less probable. Formally, it can be defined as

**Definition 1.** Let  $\{X_n\}_{n=1}^{\infty}$  and  $\{P_n\}_{n=1}^{\infty}$  be sequences of discrete random variables, and  $p_0 \in [0, 1]$  and  $\lambda \in (0, 1)$  constant parameters, such that the first random variable  $X_1$  is given by

$$P(X_1 = 1) = p_0, \quad P(X_1 = -1) = 1 - p_0.$$

Further

$$(2.1) \quad P_1 = \lambda p_0 + \frac{1}{2}(1 - \lambda)(1 - X_1)$$

and for  $i \geq 2$

$$P(X_i = 1 | P_{i-1} = p_{i-1}) = p_{i-1}, \quad P(X_i = -1 | P_{i-1} = p_{i-1}) = 1 - p_{i-1},$$

$$(2.2) \quad P_i = \lambda P_{i-1} + \frac{1}{2}(1 - \lambda)(1 - X_i).$$

The sequence  $\{S_n\}_{n=0}^{\infty}$ ,  $S_N = S_0 + \sum_{i=1}^N X_i$  for  $n \in \mathbb{N}$ , with  $S_0 \in \mathbb{R}$  some given starting position, is called a *random walk with varying probabilities*, with  $\{X_n\}_{n=1}^{\infty}$  being the steps of the walker and  $\{P_n\}_{n=1}^{\infty}$  transition probabilities.

From [4], it can be further derived that at each step  $t + k$ ,  $t, k > 0$  the value of a transition probability  $P_{t+k}$  can be computed from the knowledge of transition probability  $P_t$  and the realization of the walk  $X_{t+1}, \dots, X_{t+k}$  using formula

$$P_{t+k} = P_t \lambda^{t+k} + \frac{1}{2}(1 - \lambda) \sum_{i=t+1}^{t+k} \lambda^{t+k-i} (1 - X_i).$$

**2.1. Properties.** Basic properties of the random walk with varying probabilities are described in [4], namely that

$$(2.3) \quad EP_t = (2\lambda - 1)^t p_0 + \frac{1 - (2\lambda - 1)^t}{2}$$

and

$$(2.4) \quad ES_t = S_0 + (2p_0 - 1) \frac{1 - (2\lambda - 1)^t}{2(1 - \lambda)}$$

for all  $t \geq 1$ . This further yields  $EP_t \rightarrow \frac{1}{2}$  and  $ES_t \rightarrow S_0 + \frac{2p_0 - 1}{2(1 - \lambda)}$  for  $t \rightarrow +\infty$ .

Now to describe the variance of the transition probability, let us prove the following proposition.

**Proposition 2.1.** For all  $t \geq 1$ , it holds that

$$(2.5) \quad Var(P_t) = (3\lambda^2 - 2\lambda)^t p_0^2 + \sum_{i=1}^t K(i-1)(3\lambda^2 - 2\lambda)^{t-i} - k(t)^2,$$

where

$$k(t) = EP_t = (2\lambda - 1)^t p_0 + \frac{1 - (2\lambda - 1)^t}{2}$$

and

$$K(t) = k(t) \cdot (-3\lambda^2 + 4\lambda - 1) + (1 - \lambda)^2.$$

*Proof.* To prove the proposition several support formulas has to be derived first. From the definition of variance it follows

$$(2.6) \quad Var(P_t) = E(P_t^2) - E(P_t)^2.$$

$E(P_t)$  is given by (2.3), therefore in order to prove the proposition it is sufficient to prove the following statement

$$(2.7) \quad E(P_t^2) = (3\lambda^2 - 2\lambda)^t p_0^2 + \sum_{i=1}^t K(i-1)(3\lambda^2 - 2\lambda)^{t-i}.$$

To do so, let us first express the relation between  $E(P_t^2)$  and  $E(P_{t-1}^2)$  and  $E(P_{t-1})$ . From the definition of the expected value and the definition of the walk (2.2) it follows

$$(2.8) \quad \begin{aligned} E(P_t^2) &= E[E(P_t^2 | P_{t-1}^2)] = E[E(P_t^2 | P_{t-1})] = \\ &= E[E(\lambda P_{t-1} + \frac{1}{2}(1 - \lambda)(1 - X_t))^2 | P_{t-1}]. \end{aligned}$$

Using that  $E(X_t|P_{t-1}) = 2P_{t-1} - 1$ ,  $E(X_t^2) = 1$  and further that

$$E[(1 - X_t)^2|P_{t-1}] = E[(1 - 2X_t + X_t^2)|P_{t-1}] = E[(2 - 2X_t)|P_{t-1}] = 4(1 - P_{t-1}).$$

Equation (2.8) further yields

$$\begin{aligned} E(P_t^2) &= E[\lambda^2 P_{t-1}^2 + \lambda P_{t-1}(1 - \lambda)E(1 - X_t|P_{t-1}) + \frac{1}{4}(1 - \lambda)^2 E((1 - X_t)^2|P_{t-1})] = \\ &= E[\lambda^2 P_{t-1}^2 + 2\lambda P_{t-1}(1 - \lambda)(1 - P_{t-1}) + (1 - \lambda)^2(1 - P_{t-1})] \end{aligned}$$

and finally

$$(2.9) \quad E(P_t^2) = E(P_{t-1}^2)(3\lambda^2 - 2\lambda) + EP_{t-1}(-3\lambda^2 + 4\lambda - 1) + (1 - \lambda)^2.$$

Statement (2.7) can be proved using induction. Based on the trivial fact that  $Ep_0 = p_0$  and  $E(p_0)^2 = p_0^2$ , for  $t = 1$  we get

$$\begin{aligned} E(P_1^2) &= (3\lambda^2 - 2\lambda)^1 p_0^2 + \sum_{i=1}^1 K(i-1)(3\lambda^2 - 2\lambda)^{1-i} = (3\lambda^2 - 2\lambda)p_0^2 + K(0) = \\ &= (3\lambda^2 - 2\lambda)p_0^2 + ((2\lambda - 1)^0 p_0 + \frac{1 - (2\lambda - 1)^0}{2}) \cdot (-3\lambda^2 + 4\lambda - 1) + (1 - \lambda)^2 = \\ &= (3\lambda^2 - 2\lambda)p_0^2 + p_0(-3\lambda^2 + 4\lambda - 1) + (1 - \lambda)^2, \end{aligned}$$

and from (2.9) it follows that the induction assumption holds. Now for the induction step  $t \rightarrow t + 1$  we get by substituting (2.7) into (2.9)

$$\begin{aligned} E(P_{t+1}^2) &= E(P_t^2)(3\lambda^2 - 2\lambda) + EP_t(-3\lambda^2 + 4\lambda - 1) + (1 - \lambda)^2 = \\ &= ((3\lambda^2 - 2\lambda)^t p_0^2 + \sum_{i=1}^t K(i-1)(3\lambda^2 - 2\lambda)^{t-i}) \cdot (3\lambda^2 - 2\lambda) + K(t) = \\ &= (3\lambda^2 - 2\lambda)^{t+1} p_0^2 + \sum_{i=1}^t K(i-1)(3\lambda^2 - 2\lambda)^{t+1-i} + K(t) = \\ &= (3\lambda^2 - 2\lambda)^{t+1} p_0^2 + \sum_{i=1}^{t+1} K(i-1)(3\lambda^2 - 2\lambda)^{t+1-i} \end{aligned}$$

and the formula thus holds. Now substituting (2.3) and (2.7) into (2.6) yields (2.5) and proves the Proposition.  $\square$

From Proposition 2.1 the limit behavior of  $Var(P_t)$  can be derived easily:

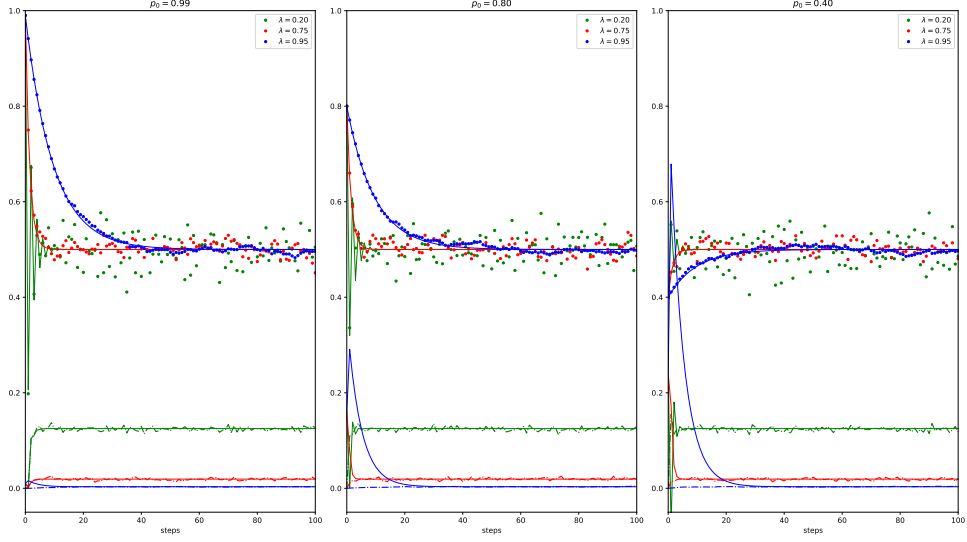


FIGURE 1. The development of the observed average transition probability (dotted, upper part of the figure) of a *success punished* version of the random walk and its observed variance (dot-dashed lines, lower part of the figure) compared to the theoretical values computed using from (2.3) and Proposition 2.1 (same colors, solid lines). The values were aggregated from 100 simulated realizations of each parameter combination.

**Corollary 1.** For  $t \rightarrow +\infty$ ,

$$(2.10) \quad \lim_{t \rightarrow +\infty} Var(P_t) = \frac{\frac{1}{2}(1 - \lambda^2)}{1 - 3\lambda^2 + 2\lambda} - \frac{1}{4}.$$

Figure 1 shows the comparison of computed theoretical values of transition probability variance and its expected value and the actual observed values of average transition probability and variance for different starting probabilities  $p_0$  and memory coefficients  $\lambda$ .

### 3. RANDOM WALK WITH VARYING TRANSITION PROBABILITY - ALTERNATIVES

**3.1. Success rewarded model.** The basic definition of the random walk (Definition 2) presents a *success punished* model, meaning the probability of an event is decreased every time that event occurs. Opposite situation can be considered, where

the probability of an event is increased every time that event occurs. Formally, such a random walk is defined in a following manner [4]:

**Definition 2.** Let  $\{X_n\}_{n=1}^\infty$ ,  $p_0$  and  $\lambda$  be as in Definition 1. Further let  $\{P_n\}_{n=1}^\infty$  be a sequence of discrete random variables given by

$$(3.1) \quad P_1 = \lambda p_0 + \frac{1}{2}(1 - \lambda)(1 + X_1),$$

$$(3.2) \quad P_i = \lambda P_{i-1} + \frac{1}{2}(1 - \lambda)(1 + X_i) \quad \forall i \geq 2.$$

The sequence  $\{S_n\}_{n=0}^\infty$ ,  $S_N = S_0 + \sum_{i=1}^N X_i$  for  $n \in \mathbb{N}$ , with  $S_0 \in \mathbb{R}$  some given starting position, is a random walk with varying probabilities - *success rewarded*.

In this section, all variables are considered to be related to the *success rewarded* model, whereas the variables with the same notations ( $P$ ,  $X$ ,  $S$ ) from previous Section 2 are considered to be related to the model from Definition 1.

The *success rewarded* version of the model behaves differently than the *success punished* version, which can be observed with the help of the following propositions.

**Proposition 3.1.** For all  $t \geq 2$ ,

$$(3.3) \quad P_t = p_0 \lambda^t + \frac{1}{2}(1 - \lambda) \sum_{i=1}^t \lambda^{t-i}(1 + X_i).$$

*Proof.* The proposition is proved using induction. For  $t = 2$  using (3.1) and (3.2) it holds that

$$\begin{aligned} P_2 &= \lambda P_1 + \frac{1}{2}(1 - \lambda)(1 + X_2) = \lambda(\lambda p_0 + \frac{1}{2}(1 - \lambda)(1 + X_1)) + \frac{1}{2}(1 - \lambda)(1 + X_2) = \\ &= p_0 \lambda^2 + \frac{1}{2}(1 - \lambda) \sum_{i=1}^2 \lambda^{2-i}(1 + X_i), \end{aligned}$$

which is in accordance with (3.3). Now for the induction step  $t \rightarrow t + 1$  we obtain from (3.2) and the induction assumption

$$\begin{aligned} P_{t+1} &= \lambda P_t + \frac{1}{2}(1 - \lambda)(1 + X_{t+1}) = \\ &= \lambda(p_0 \lambda^t + \frac{1}{2}(1 - \lambda) \sum_{i=1}^t \lambda^{t-i}(1 + X_i)) + \frac{1}{2}(1 - \lambda)(1 + X_{t+1}) = \end{aligned}$$

$$\begin{aligned}
&= p_0 \lambda^{t+1} + \frac{1}{2}(1-\lambda) \sum_{i=1}^t \lambda^{t-i+1}(1+X_i) + \frac{1}{2}(1-\lambda)(1+X_{t+1}) = \\
&= p_0 \lambda^{t+1} + \frac{1}{2}(1-\lambda) \sum_{i=1}^{t+1} \lambda^{t+1-i}(1+X_i).
\end{aligned}$$

□

**Proposition 3.2.** For all  $t \geq 1$ ,  $E(P_t) = p_0$ .

*Proof.* Using  $E(X_t|P_{t-1}) = 2P_{t-1} - 1$  and (3.2) we obtain

$$\begin{aligned}
EP_t &= E[E(P_t|P_{t-1})] = E[E(\lambda P_{t-1} + \frac{1}{2}(1-\lambda)(1+X_t)|P_{t-1})] = \\
&= E[\lambda P_{t-1} + \frac{1}{2}(1-\lambda)(1+2P_{t-1}-1)] = E[\lambda P_{t-1} + (1-\lambda)P_{t-1}] = E(P_{t-1}).
\end{aligned}$$

Recursively we get

$$(3.4) \quad E(P_t) = E(p_0) = p_0.$$

□

Now to calculate the expected position of the walker at a given step  $t \geq 1$ , it is easy to see that  $E(S_t) = S_{t-1} + 2P_{t-1} - 1$ . From this, we can prove the following statement about the expected position of the walker after step  $t$  just from the knowledge of the input parameters.

**Proposition 3.3.** For all  $t \geq 1$ ,

$$E(S_t) = S_0 + t(2p_0 - 1).$$

*Proof.* Using the result of Proposition 3.2 we get

$$E(S_{t+1}) = E[E(S_{t+1}|S_t)] = E[S_t + (2P_{t-1} - 1)] = ES_t + (2p_0 - 1)$$

which then recursively proves the statement. □

**Corollary 2.** For  $t \rightarrow +\infty$ ,

$$\lim_{t \rightarrow +\infty} E(S_t) = \begin{cases} +\infty & p_0 > \frac{1}{2} \\ 0 & p_0 = \frac{1}{2} \\ -\infty & p_0 < \frac{1}{2} \end{cases}.$$

**Proposition 3.4.** For all  $t \geq 1$ ,

$$(3.5) \quad \text{Var}(P_t) = (2\lambda - \lambda^2)^t p_0^2 + p_0(1 - \lambda)^2 \sum_{i=1}^t (2\lambda - \lambda^2)^{t-i} - p_0^2.$$

*Proof.* The proof will be done in several steps similar as in Proposition 2.1. It is based on the definition of variance

$$(3.6) \quad \text{Var}(P_t) = E(P_t^2) - E(P_t)^2.$$

From Proposition 3.2 it follows  $E(P_t) = p_0$  and it is thus sufficient to prove that

$$(3.7) \quad E(P_t^2) = (2\lambda - \lambda^2)^t p_0^2 + p_0(1 - \lambda)^2 \sum_{i=1}^t (2\lambda - \lambda^2)^{t-i}.$$

The proof will be done using induction again. First observe that

$$\begin{aligned} E(P_t^2) &= E[E(P_t^2 | P_{t-1})] = E[E(P_t | P_{t-1})] = \\ &= E[E(\lambda P_{t-1} + \frac{1}{2}(1 - \lambda)(1 + X_t))^2 | P_{t-1}] = \\ (3.8) \quad &= EP_{t-1}^2(2\lambda - \lambda^2) + p_0(1 - \lambda)^2, \end{aligned}$$

where the facts that  $E[(1 + X_t)^2 | P_{t-1}] = 4P_{t-1}$ ,  $E[(1 + X_t) | P_{t-1}] = 2P_{t-1}$  and Proposition 3.2 were used. Now for  $t = 1$  we get

$$EP_1 = p_0^2(2\lambda - \lambda^2) + p_0(1 - \lambda)^2 = (2\lambda - \lambda^2)^1 p_0^2 + p_0(1 - \lambda)^2 \sum_{i=1}^1 (2\lambda - \lambda^2)^{1-i}$$

and the induction assumption holds. For the induction step  $t \rightarrow t + 1$  we get from the induction assumption and (3.8)

$$\begin{aligned} E(P_{t+1}^2) &= EP_t^2(2\lambda - \lambda^2) + p_0(1 - \lambda)^2 = \\ &= ((2\lambda - \lambda^2)^t p_0^2 + p_0(1 - \lambda)^2 \sum_{i=1}^t (2\lambda - \lambda^2)^{t-i}) \cdot (2\lambda - \lambda^2) + p_0(1 - \lambda)^2 = \\ &= (2\lambda - \lambda^2)^{t+1} p_0^2 + p_0(1 - \lambda)^2 \sum_{i=1}^t (2\lambda - \lambda^2)^{t-i+1} + p_0(1 - \lambda)^2 = \\ &= (2\lambda - \lambda^2)^{t+1} p_0^2 + p_0(1 - \lambda)^2 \sum_{i=1}^{t+1} (2\lambda - \lambda^2)^{t+1-i}. \end{aligned}$$

The Proposition statement is then obtained by substituting (3.4) and (3.7) into (3.6).  $\square$



Notice that the last sum in (3.5), after re-indexing by  $j = t - i$ , yields  $\sum_{j=0}^{t-1} (2\lambda - \lambda^2)^j = \frac{1-(2\lambda-\lambda^2)^t}{1-2\lambda+\lambda^2}$ . Hence the limit follows immediately:

**Corollary 3.** For  $t \rightarrow +\infty$ ,

$$\lim_{t \rightarrow +\infty} \text{Var}(P_t) = p_0(1 - p_0).$$

**3.2. Model with two  $\lambda$  parameters.** Another level of complexity can be added by using separate  $\lambda$  parameters for each direction of the walk. Again, two ways of handling success are available. The *success punished* version is defined as follows.

**Definition 3.** Let  $\{X_n\}_{n=1}^\infty$  and  $p_0$  be as in Definition 1. Further let  $\lambda_0, \lambda_1 \in (0, 1)$  be constant coefficients and  $\{P_n\}_{n=1}^\infty$  be a sequence of discrete random variables given by

$$(3.9) \quad P_1 = \frac{1}{2}[(1 + X_1)\lambda_0 p_0 + (1 - X_1)(1 - \lambda_1(1 - p_0))]$$

$$(3.10) \quad P_i = \frac{1}{2}[(1 + X_i)\lambda_0 P_{i-1} + (1 - X_i)(1 - \lambda_1(1 - P_{i-1}))] \quad \forall i \geq 2.$$

The sequence  $\{S_n\}_{n=0}^\infty$ ,  $S_N = S_0 + \sum_{i=1}^N X_i$  for  $n \in \mathbb{N}$ , with  $S_0 \in \mathbb{R}$  some given starting position, is a random walk with varying probabilities - *success punished two*  $\lambda$ . The *success rewarded* version of the model can be defined similarly.

**Definition 4.** Let  $\{X_n\}_{n=1}^\infty$  and  $p_0$  be as in Definition 1. Further let  $\lambda_0, \lambda_1 \in (0, 1)$  be constant coefficients and  $\{P_n\}_{n=1}^\infty$  be a sequence of discrete random variables given by

$$P_1 = \frac{1}{2}[(1 - X_1)\lambda_0 p_0 + (1 + X_1)(1 - \lambda_1(1 - p_0))]$$

$$P_i = \frac{1}{2}[(1 - X_i)\lambda_0 P_{i-1} + (1 + X_i)(1 - \lambda_1(1 - P_{i-1}))] \quad \forall i \geq 2.$$

The sequence  $\{S_n\}_{n=0}^\infty$ ,  $S_N = S_0 + \sum_{i=1}^N X_i$  for  $n \in \mathbb{N}$ , with  $S_0 \in \mathbb{R}$  some given starting position, is a random walk with varying probabilities - *success rewarded two*  $\lambda$ .

Derivation of model properties is not so straightforward. The development of transition probability and its variance for different starting probabilities  $p_0$  and memory coefficients pairs  $\bar{\lambda}$  for the *success punished two*  $\lambda$  version of the model is shown on Figure 2. Similarly as in the single  $\lambda$  version of the model, the variance seems to depend on the  $\bar{\lambda}$  pair only. The expected transition probability seems to converge to a constant value independently on both the starting probability  $p_0$  and memory coefficients  $\bar{\lambda}$ . This interesting property of the walk will be subject to further study.

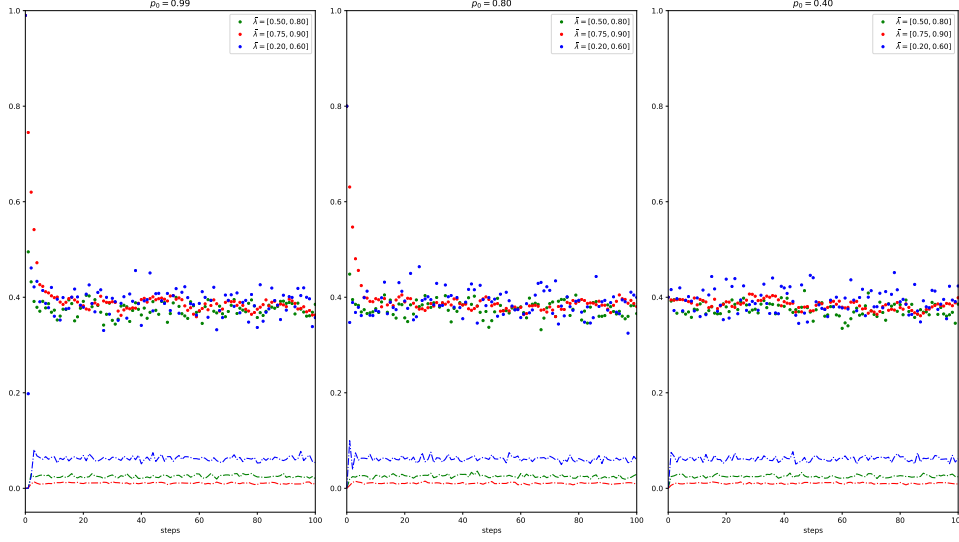


FIGURE 2. The development of the observed average transition probability (dotted, upper part of the figure) of a *success punished* two  $\lambda$  version of the random walk and its observed variance (dot-dashed lines, lower part of the figure). The values were aggregated from 100 simulated realizations of each parameter combination.

**3.3. Other alternatives.** The presented model of a random walk can be further developed and more versions can be derived and described. These variants include but are not limited to multidimensional walk (with either one or multiple  $\lambda$  parameters, again with *success rewarded* or *success punished*), a walk with the transition probability explicitly dependent on more than the last step, i.e.  $P_t(k) \sim P_t(X_t, X_{t-1}, \dots, X_{t-(k-1)})$ , or the walk with  $\lambda$  parameter not constant, but a function of the time  $t$ , i.e.  $P_t(\lambda(t))$ . Detailed properties of such walks together with their possible applications on real life problems will be subject of a further study.

#### 4. SIMULATIONS

Testing dataset was generated in order to validate the quality of the model and its ability to be fitted on a real life problem. The data generation was performed using the Python programming language and its package NumPy. Following values of input parameters were chosen. The memory coefficient values varied in  $\lambda \in \{0.5, 0.8, 0.9, 0.99\}$  and similarly the pair of memory coefficients  $[\lambda_0, \lambda_1] \in$

TABLE 1. Fitting results. *SP* stands for *success punished*, *SR* for *success rewarded*.  $1\lambda$  vs.  $2\lambda$  distinguish between the basic model with a single  $\lambda$  parameter and the more advanced model with two  $\lambda$  parameters.

	SP - $1\lambda$	SR - $1\lambda$	SP - $2\lambda$	SR - $2\lambda$
Find $\vec{\lambda}$	96.9 %	34.4 %	80.2 %	77.1 %
Find $p_o$	92.2 %	82.8 %	89.6 %	93.8 %
Find $\vec{\lambda}, p_o$	91.4 %	84.4 %	83.3 %	79.9 %
Find model type	1.6 %	1.6 %	87.5 %	89.6 %

TABLE 2. Finding the optimal model type using the AIC.

	SP - $1\lambda$	SR - $1\lambda$	SP - $2\lambda$	SR - $2\lambda$
Find model type	79.7	79.7%	83.3%	83.3%

$\{[0.5, 0.8], [0.5, 0.99], [0.99, 0.9]\}$ . The starting transition probability  $p_0$  was chosen from the set  $P_0 = \{0.5, 0.8, 0.9, 0.99\}$  and the length of the walk was  $n \in \{5, 10, 50, 100\}$ . For each permutation of the parameters 100 walks were generated.

Four different fitting tasks were performed on the generated dataset. Using the maximum likelihood estimate (MLE) [7] and Python language with SciPy package the fitting tasks were

- Find  $\vec{\lambda}$  with known  $p_0$  and model type
- Find  $p_0$  with known  $\vec{\lambda}$  and model type
- Find  $p_0, \vec{\lambda}$  with known model type
- Find model type without any prior knowledge

Table 1 shows the results of the model and parameter fitting algorithms using the MLE method. The data shows the model can be fitted with high accuracy. The only exception is finding the correct model type when the original model was based on a single  $\lambda$  parameter. The maximum-likelihood estimate almost always prefers the model with two  $\lambda$  parameters. To improve the results the Akaike Information Criterion  $AIC = 2k - 2\ln(\hat{L})$ , which helps to correctly identify models with smaller number of parameters, was used. Here  $k$  is the number of model parameters and  $\hat{L}$  is the maximal likelihood. This approach shows much better results. The performance can be observed in Table 2.

## 5. CONCLUSION

This work follows up on the recent results on random walks with varying probabilities. It describes and proves certain properties of such a walk, other properties have

been studied with the help of numerical methods. The study also shows the results of the maximum likelihood and *AIC* based estimations of model parameters and types using optimization procedures. The method has been tested successfully on a set of randomly generated data. The presented model has also many possible uses in real life application. Such a type of random walk describes especially well processes where either a single or just a small number of events can significantly affect the future development of the process. Such processes can be found in reliability analysis, medical as well as econometric studies, and very often in sports modeling. The authors recently published a study where the success rewarded model was applied to predict the *in-play* development of a Grand Slam tennis matches with compelling results when used for live betting against a bookmaker [5].

The source code containing all functionality mentioned in this article is freely available as open source at GitHub (<https://github.com/tomaskourim/amistat2019>).

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