DISCRETE RANDOM PROCESSES WITH MEMORY: MODELS AND APPLICATIONS

Tomáš Kouřim, Petr Volf, Prague

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 [7]. There exist many variations of a random walk with various applications to real life problems [10, 9]. 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 [10] which together with the idea of *self-exciting point processes* [3] 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 Kouřim [4, 5].

NEW:

The research was supported by the grant No. 18-02739S of the Grant Agency of the Czech Republic.

Naturally, there exists also a number of recent papers dealing with discrete random walks and time series. Thus, the paper of Davis and Liu (2016) [1] contains a rather broad definition of such a process dynamics. Formally, our definition is covered as well, however, other assumptions, e.g. the condition of contraction, are not fulfilled.

——

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 [2] with some starting transition probability p_0. This probability is then altered after each step of the walk using a coefficient λ so that the repetition of the same step becomes less probable. Formally, it can be defined as

Definition 2.1. 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

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

Further

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

and for $i \geq 2$

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

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

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 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.

2.1. **Properties.** The random walk with varying probabilities was first introduced in [4] and further elaborated in [5]. Basic properties of the walk were also described in the previous work. Namely, the value of a transition probability P_{t+k} at each step $t+k,\ t,\ k>0$ 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

$$P_{t+k} = P_t \lambda^k + \frac{1}{2}(1-\lambda) \sum_{i=t+1}^{t+k} \lambda^{t+k-i}(1-X_i) \tag{2.3}$$

and further formulas to compute the expected value of transition probability and position of the walker

$$EP_t = (2\lambda-1)^t p_0 + \frac{1-(2\lambda-1)^t}{2} \tag{2.4}$$

and

$$ES_t = S_0 + (2p_0-1)\frac{1-(2\lambda-1)^t}{2(1-\lambda)} \tag{2.5}$$

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

Now to describe the walk in more detail, let us prove the following propositions about the expected step of the walk and variance of the transition probability.

Proposition 2.2. *For all $t \geq 1$, it holds that*

$$E(X_t) = (2\lambda-1)^{t-1}(2p_0-1). \tag{2.6}$$

Proof. Using that $E(X_t) = 2P_{t-1} - 1$ the proposition can be proved directly using (2.4) as

$$\begin{aligned} E(X_t) = E(E(X_t)|X_{t-1}) = E(2P_{t-1}-1) = 2E(P_{t-1}) - 1 = \\ = 2((2\lambda-1)^{t-1}p_0 + \frac{1-(2\lambda-1)^{t-1}}{2}) - 1 = \\ = (2\lambda-1)^{t-1}(2p_0-1). \end{aligned}$$

□

NEW:

Corollary 2.3. *The limit distribution of X_t is the Bernoulli distribution with $p=\frac{1}{2}$. It is also the stationary distribution of the chain X_t.*

Proof. As X_t are Bernoulli(1,-1), they are fully characterized by their expectations, and it holds that $EX_t = 2 \cdot EP_{t-1} - 1$. Then the limit distribution follows from Proposition 2.2 or also from the fact that EP_t tends to $\frac{1}{2}$.

Let $EP_{t-1} = \frac{1}{2}$ be the characteristics of X_t, i.e. $EX_t = 0$. As then $EP_t = EP_{t-1}\lambda + (1-\lambda)/2(1 - EX_t) = \frac{1}{2}$, therefore $EX_{t+1} = 0$ again.

$\square$

Proposition 2.4. *For all $t \geq 1$, it holds that*

$$Var(P_t) = (3\lambda^2 - 2\lambda)^t p_0^2 + \sum_{i=1}^{t} K(i-1)(3\lambda^2 - 2\lambda)^{t-i} - k(t)^2, \tag{2.7}$$

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

$$Var(P_t) = E(P_t^2) - E(P_t)^2. \tag{2.8}$$

$E(P_t)$ is given by (2.4), therefore in order to prove the proposition it is sufficient to prove the following statement

$$E(P_t^2) = (3\lambda^2 - 2\lambda)^t p_0^2 + \sum_{i=1}^{t} K(i-1)(3\lambda^2 - 2\lambda)^{t-i}. \tag{2.9}$$

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

$$E(P_t^2) = E[E(P_t^2|P_{t-1})] =$$

$$= E[E(\lambda P_{t-1} + \frac{1}{2}(1-\lambda)(1 - X_t))^2 | P_{t-1}]. \tag{2.10}$$

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 (2.10) further yields

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

$$= E[\lambda^2 P_{t-1}^2 + 2\lambda P_{t-1}(1-\lambda)(1-P_{t-1}) + (1-\lambda)^2(1-P_{t-1})]$$

and finally

$$E(P_t^2) = E(P_{t-1}^2)(3\lambda^2 - 2\lambda) + EP_{t-1}(-3\lambda^2 + 4\lambda - 1) + (1-\lambda)^2. \tag{2.11}$$

Statement (2.9) can be proved using mathematical induction. Based on the trivial fact that $Ep_0 = p_0$ and $E(p_0)^2 = p_0^2$, for $t = 1$ we get

$$E(P_1^2) = (3\lambda^2 - 2\lambda)^1 p_0^2 + \sum_{i=1}^{1} K(i-1)(3\lambda^2 - 2\lambda)^{1-i} = (3\lambda^2 - 2\lambda)p_0^2 + K(0) =$$

$$= (3\lambda^2 - 2\lambda)p_0^2 + ((2\lambda - 1)^0 p_0 + \frac{1 - (2\lambda - 1)^0}{2}) \cdot (-3\lambda^2 + 4\lambda - 1) + (1-\lambda)^2 =$$
$$= (3\lambda^2 - 2\lambda)p_0^2 + p_0(-3\lambda^2 + 4\lambda - 1) + (1-\lambda)^2,$$

and from (2.11) it follows that (2.9) holds for $t = 1$. Now for the induction step $t \to t+1$ we get by substituting (2.9) into (2.11)

$$E(P_{t+1}^2) = E(P_t^2)(3\lambda^2 - 2\lambda) + EP_t(-3\lambda^2 + 4\lambda - 1) + (1-\lambda)^2 =$$

$$= ((3\lambda^2 - 2\lambda)^t p_0^2 + \sum_{i=1}^{t} K(i-1)(3\lambda^2 - 2\lambda)^{t-i}) \cdot (3\lambda^2 - 2\lambda) + K(t) =$$
$$= (3\lambda^2 - 2\lambda)^{t+1} p_0^2 + \sum_{i=1}^{t} K(i-1)(3\lambda^2 - 2\lambda)^{t+1-i} + K(t) =$$
$$= (3\lambda^2 - 2\lambda)^{t+1} p_0^2 + \sum_{i=1}^{t+1} K(i-1)(3\lambda^2 - 2\lambda)^{t+1-i}$$

and the formula thus holds. Now substituting (2.4) and (2.9) into (2.8) yields (2.7) and proves the Proposition. □

From Proposition 2.4 the limit behavior of $Var(P_t)$ can be derived easily:

Corollary 2.5. *For $t \to +\infty$,*

$$\lim_{t \to +\infty} Var(P_t) = \frac{\frac{1}{2}(1-\lambda^2)}{1 - 3\lambda^2 + 2\lambda} - \frac{1}{4}. \tag{2.12}$$

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 λ.

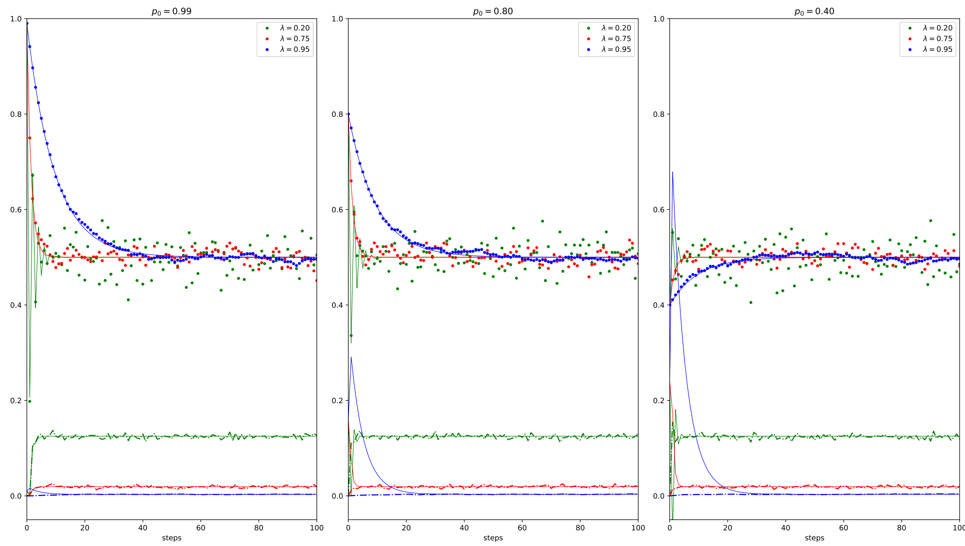

FIGURE 1. The development of the observed average transition probability (dotted, upper part of the figure) of a *success punished* version of the random walk and its observed variance (dot-dashed lines, lower part of the figure) compared to the theoretical values computed using (2.4) and Proposition 2.4 (same colors, solid lines). The values were computed from 100 simulated realizations of each parameter combination.

3. Random walk with varying transition probability - alternatives

3.1. **Success rewarded model.** The basic definition of the random walk (Definition 2.1) 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 [5]:

Definition 3.1. Let $\{X_n\}_{n=1}^{\infty}$, p_0 and λ be as in Definition 2.1. Further let $\{P_n\}_{n=1}^{\infty}$ be a sequence of discrete random variables given by

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

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

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 2.1.

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 3.2. *For all $t \geq 2$,*

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

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

$$P_2 = \lambda P_1 + \frac{1}{2}(1-\lambda)(1+X_2) = \lambda(\lambda p_0 + \frac{1}{2}(1-\lambda)(1+X_1)) + \frac{1}{2}(1-\lambda)(1+X_2) =$$

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

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

$$P_{t+1} = \lambda P_t + \frac{1}{2}(1-\lambda)(1+X_{t+1}) =$$

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

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

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

□

Proposition 3.3. *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

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

$$= E[\lambda P_{t-1} + \frac{1}{2}(1-\lambda)(1+2P_{t-1}-1)] = E[\lambda P_{t-1} + (1-\lambda)P_{t-1}) = E(P_{t-1}).$$

Recursively we get

$$E(P_t) = E(p_0) = p_0. \tag{3.4}$$

□

NEW STRONGER FORMULATION!!:

Proposition 3.4. *The sequence X_t is a stationary sequence of Bernoulli random variables with values 1,-1 and $P(X_t = 1) = p_0$.*

Proof. As the distribution of X_t is fully given by $E(P_{t-1})$, the statement follows directly from Proposition 3.3. □

NEW: ale neni nutno

Further, simulation studies revealed that the distribution of probabilities P_t tends to Bernoulli (0,1) distribution with parameter (probability of 1) p_0. Moreover, the following holds:

Proposition 3.5. *This Bernoulli distribution is then the stationary distribution of the process P_t.*

Proof. Let P_{t-1} be either 1 with probability p_0, then $X_t = 1$, or $P_{t-1} = 0$ with $1-p_0$, then $X_t = -1$. As $P_t = \lambda P_{t-1} + (1-\lambda)(1+X_t)/2$, it follows that with probability p_0 $P_t = \lambda \cdot 1 + (1-\lambda)\cdot 2/2 = 1$, while with probability $1-p_0$ $P_t = \lambda \cdot 0 + (1-\lambda)\cdot 0/2 = 0$. It means that P_t has the same Bernoulli distribution as P_{t-1}. □

——

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 3.6. *For all $t \geq 1$,*

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

Proof. Using the result of Proposition 3.3 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 3.7. *For* $t \to +\infty$,

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

Proposition 3.8. *For all* $t \geq 1$,

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

Proof. The proof will be done in several steps similar as in Proposition 2.4. It is based on the definition of variance

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

From Proposition 3.3 it follows $E(P_t) = p_0$ and it is thus sufficient to prove that

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

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

$$E(P_t^2) = E[E(P_t^2|P_{t-1})] =$$

$$= E[E(\lambda P_{t-1} + \frac{1}{2}(1-\lambda)(1+X_t))^2 | P_{t-1}] =$$

$$= EP_{t-1}^2(2\lambda - \lambda^2) + p_0(1-\lambda)^2, \tag{3.8}$$

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 3.3 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 thus (3.7) holds for $t = 1$. For the induction step $t \to t+1$ we get from the induction assumption and (3.8)

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

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

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

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

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

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 3.9. *For $t \to +\infty$,*

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

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

Definition 3.10. Let $\{X_n\}_{n=1}^{\infty}$ and p_0 be as in Definition 2.1. 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

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

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

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* λ.

The *success rewarded* version of the model can be defined similarly.

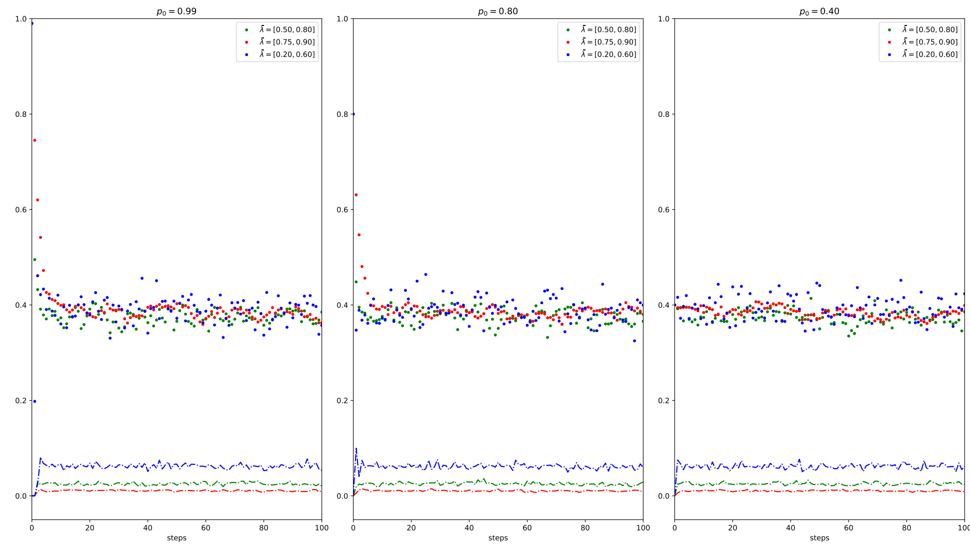

FIGURE 2. The development of the observed average transition probability (dotted, upper part of the figure) of a *success punished two* λ version of the random walk and its observed variance (dot-dashed lines, lower part of the figure). The values were computed from 100 simulated realizations of each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

Definition 3.11. Let $\{X_n\}_{n=1}^{\infty}$ and p_0 be as in Definition 2.1. 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

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

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

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* λ.

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* λ version of the model is shown on Figure 2. Similarly as in the single λ 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.

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 λ parameters, again with *success rewarded* or *success punished*), a walk with the transition probability explicitly dependent on more than the last step, i.e. $P_t(k) \sim P_t(X_t, X_{t-1}, \ldots, X_{t-(k-1)})$, or the walk with λ 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 by 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 $[\lambda_0, \lambda_1] \in \{[0.5, 0.8], [0.1, 0.5], [0.5, 0.99], [0.99, 0.9]\}$. 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 $steps \in \{5, 10, 50, 100\}$. All four described models of the random walk were tested. For each permutation of the parameters and the model type 100 walks were generated and considered as 1 "observation". Further, 100 such "observations" of each set of walks were generated, which then formed a dataset consisting of $100 \cdot 100 \cdot 4^4 = 2\,560\,000$ random walks.

Four different fitting tasks were performed on each of the 100 "observations", generating 100 different estimates for each walk configuration. The tasks were:

- find λ or $[\lambda_0, \lambda_1]$ with known p_0 and model type,
- find p_0 with known λ or $[\lambda_0, \lambda_1]$ and model type,
- find p_0 and λ or $[\lambda_0, \lambda_1]$ with known model type,
- find model type without any prior knowledge.

The first three tasks consist of estimation of parameters and were based on the maximum likelihood estimate (MLE) [8]. The evaluation of the likelihood function for given parameters is easy, however the computation of the log-likelihood derivatives is hardly tractable. The ML estimates were therefore obtained using numerical methods with the help of the Python programming language and it's scientific package SciPy. The Akaike Information Criterion $AIC = 2k - 2ln(\hat{L})$, where k is the number of model parameters and $\hat{L}$ is the maximal likelihood, was then used for the last task.

To evaluate the quality of the parameter fitting results four different testing criteria were tested. First, the standard $(100-\alpha)\%$ two-sided confidence interval around the mean was constructed and the test was positive if the true parameter value was in

TABLE 1. $p_0 = 0.8$ fitting results. *SP* stands for *success punished*, *SR* for *success rewarded*. The table shows the mean and median values of the 100 "observations" of the specific walk configuration together with the corresponding "confidence", "percentile" and "proximity" intervals.

Type	$\overrightarrow{\lambda}$	steps	mean	median	CI	percentile	proximity
SP	0.5	5	0.802	0.802	$[0.796, 0.808]$	$[0.74, 0.85]$	$[0.76, 0.84]$
SR	0.9	50	0.798	0.797	$[0.796, 0.801]$	$[0.77, 0.82]$	$[0.76, 0.84]$
SP	$[0.5, 0.99]$	10	0.795	0.795	$[0.79, 0.8002]$	$[0.74, 0.84]$	$[0.76, 0.84]$
SR	$[0.99, 0.9]$	5	0.8	0.799	$[0.797, 0.803]$	$[0.77, 0.84]$	$[0.76, 0.84]$

that interval. Second, the $\frac{\alpha}{2} - th$ and $(100 - \frac{\alpha}{2}) - th$ percentile were chosen as a lower and upper bounds of a "percentile" interval and again the test was positive if the true parameter value fell within the interval. Finally, a "proximity" interval was constructed based on the true parameter value ω as $[\omega - \frac{\alpha/100}{2}\omega,\, \omega + \frac{\alpha/100}{2}\omega]$ and it was tested whether the mean fitted parameter value and median fitted parameter value fell into that interval. To evaluate the quality of model estimation simply the proportion of correctly predicted models for each task, over all walk configurations was computed.

Together there were 1024 different fitting setups. The overall performance of the fitting is rather satisfying with average success rate of the tests at about 80% (for $\alpha = 10$). As expected, the less parameters there were to estimate the better the results. Longer walks show better results when finding the coefficients λ or $[\lambda_0, \lambda_1]$ while the performance in finding correct p_0 seems independent on the walk's length. This is not surprising as the parameter p_0 affects mostly the first few steps of the walk, while λ or $[\lambda_0, \lambda_1]$ play their role thorough the entire course of the walk. An example of the results can be seen in Table 1.

The previous statement, however, does not hold for the *success rewarded* version of the model. In this case the optimization algorithm often provided a very bad estimate or did not converge at all. The reason for such behavior can be explained be the difference between the theoretical model (where $0 < p_t < 1, \forall t$) and its representation in computer simulation, where the limited precision handles values very close to 1 or 0 as equal to them. This is especially true for walks with more steps. An example of such results can be seen in Table XXX. Handling of such unwanted behavior will be subject of further research.

Full results of all testing setups as well as several values of parameter α can be seen in the GitHub repository (see the last paragraph of the paper).

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

	SP - 1λ	SR - 1λ	SP - 2λ	SR - 2λ
Find model type	79.7	79.7%	83.3%	83.3%

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 [6].

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

References

[1] Richard A Davis and Heng Liu. Theory and inference for a class of observation-driven models with application to time series of counts. *arXiv preprint arXiv:1204.3915*, 2012.

[2] William Feller. An introduction to probability theory and its applications. *1957*.

[3] Alan G Hawkes. Spectra of some self-exciting and mutually exciting point processes. *Biometrika*, 58(1):83–90, 1971.

[4] Tomáš Kouřim. Random walks with varying transition probabilities. *Doktorandské dny FJFI*, 2017. Available at http://kmwww.fjfi.cvut.cz/ddny/historie/17-sbornik.pdf.

[5] Tomáš Kouřim. Statistical analysis, modeling and applications of random processes with memory. *PhD Thesis Study, ČVUT FJFI*, 2019.

[6] Tomáš Kouřim and Petr Volf. Tennis match as random walk with memory: Application to grand slam matches modelling. *Submitted to IMA Journal of Management Mathematics*, 2019.

[7] Karl Pearson. The problem of the random walk. *Nature*, 72(1865):294, 1905.

[8] Richard J Rossi. *Mathematical Statistics: An Introduction to Likelihood Based Inference*. John Wiley & Sons, 2018.

[9] Gunter M Schütz and Steffen Trimper. Elephants can always remember: Exact long-range memory effects in a non-markovian random walk. *Physical Review E*, 70(4):045101, 2004.

[10] Loïc Turban. On a random walk with memory and its relation with markovian processes. *Journal of Physics A: Mathematical and Theoretical*, 43(28):285006, 2010.

Authors' addresses: *Tomáš Kouřim*, Faculty of Nuclear Sciences and Physical Engineering, Czech Technical University in Prague, Czech Republic e-mail: `kourim@outlook.com`.

Petr Volf, Institute of Information Theory and Automation, Academy of Sciences of the Czech Republic, Prague e-mail: `volf@utia.cas.cz`.