A model of random walk with varying transition probabilities

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Outline

1. Motivation
2. Model description
3. Model application

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Random walk

Definition

A man starts from a point O and walks l yards in a straight line; he then turns through any angle whatever and walks another l yards in a second straight line. He repeats this process n times. I require the probability that after these n stretches he is at a distance between r and $r + \delta r$ from his starting point, O.

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Where is the *drunken sailor*?

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- Failure of a machine
  - repair after failure
  - preventive maintenance
- Occurrence of a disease
  - cure of the disease
  - prevention (i.e. lifestyle change)
- Development of sports match
  - goal scored, point achieved
  - period won

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Random walk with varying probabilities

- Random walk with memory
- Memory coefficient $\lambda \in (0, 1)$ affecting the transition probabilities
- First step of the walk X_1 depends on an initial transition probability p_0
- Further steps depend on a transition probability p_t evolving as

$$X_{t-1} = 1 \rightarrow p_t = \lambda p_{t-1} \quad X_{t-1} = -1 \rightarrow p_t = 1 - \lambda(1 - p_{t-1})$$

–> "Success punished"

$$X_{t-1} = 1 \rightarrow p_t = 1 - \lambda(1 - p_{t-1}) \quad X_{t-1} = -1 \rightarrow p_t = \lambda p_{t-1}$$

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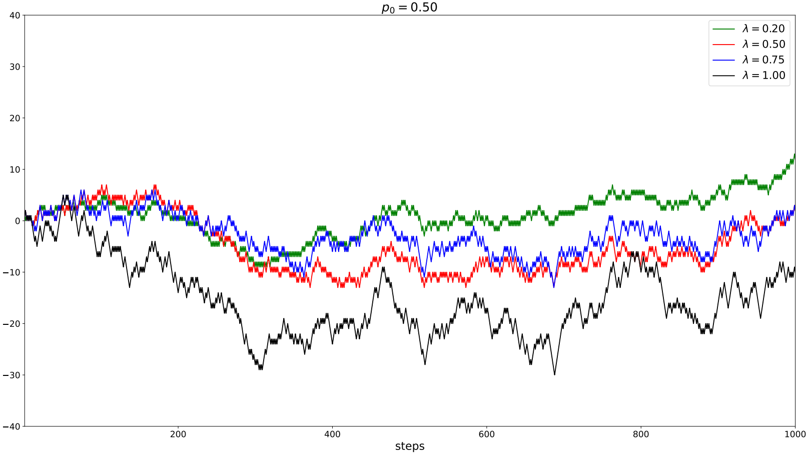
Example - RW development



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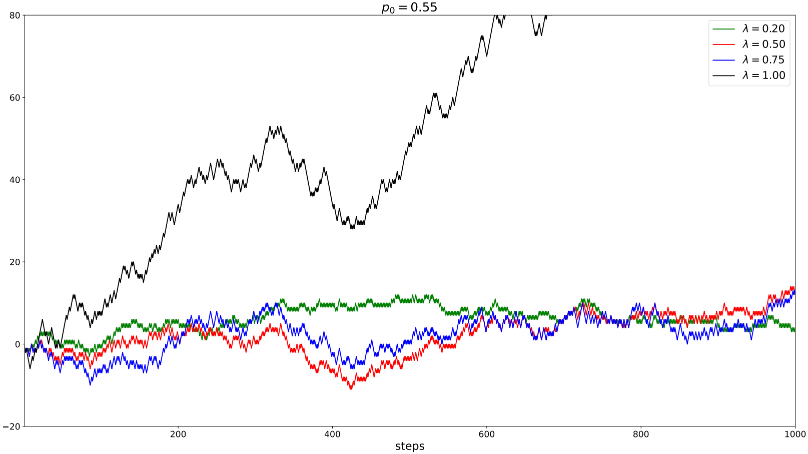

Walk steps properties

$$EX_t = (2\lambda - 1)^{t-1}(2p_0 - 1)$$

$$\lim_{t \to +\infty} EX_t = 0$$

$$Var\, X_t = 1 - (2\lambda - 1)^{2(t-1)}(2p_0 - 1)^2$$

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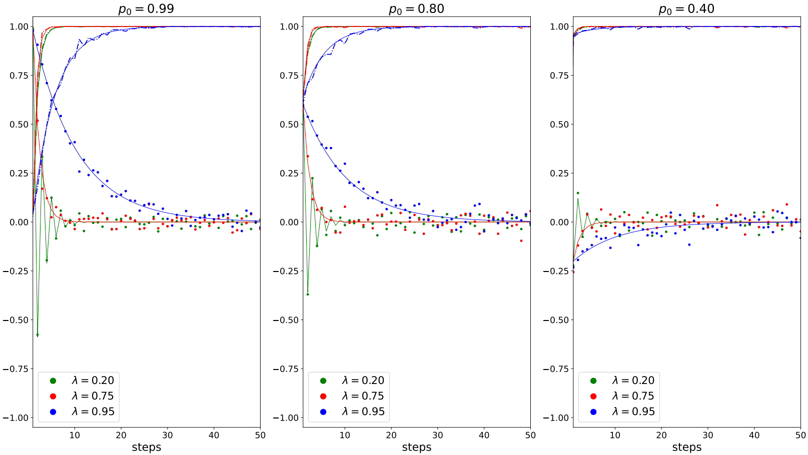

Walk probabilities properties

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

$$\lim_{t \to +\infty} EP_t = \frac{1}{2}$$

$$Var\ P_t = (3\lambda^2 - 2\lambda)^t p_0^2 + \sum_{i=0}^{t-1} K(i; p_0, \lambda)(3\lambda^2 - 2\lambda)^{t-1-i} - k(t; p_o, \lambda)^2$$

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

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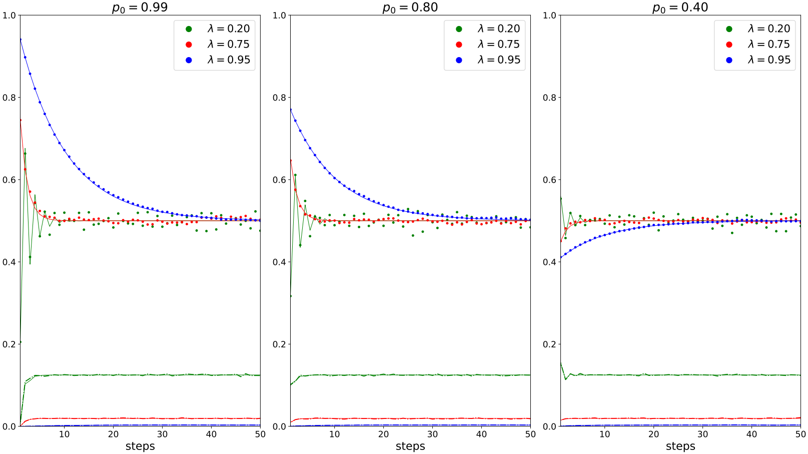

Walk position properties

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

$$\lim_{t\to+\infty} ES_t = S_0 + \frac{(2p_0 - 1)}{2(1-\lambda)}$$

$$Var\, S_t = t + 4\sum_{i=0}^{t-1} \sigma(i; p_0, 0, \lambda) - a(t; p_0, \lambda)$$

$$\lim_{t\to+\infty} Var\, S_t = c_1(p_0, \lambda)t + c_2(p_0, \lambda)$$

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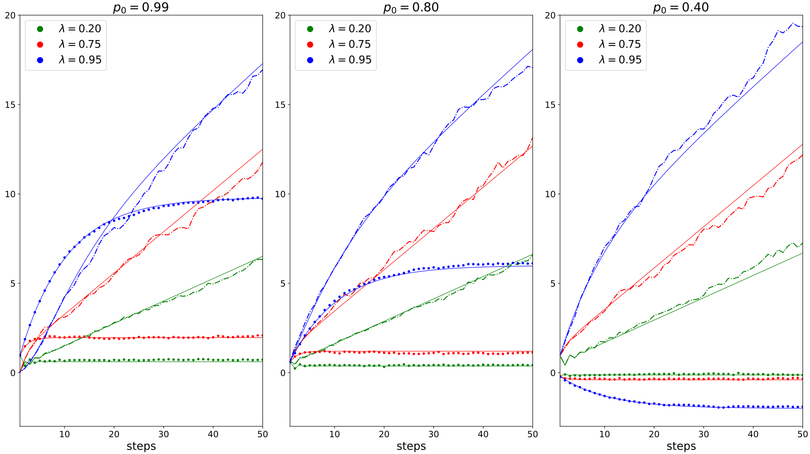

Success rewarding model

$$EX_t = 2p_0 - 1$$

$$Var\, X_t = 4p_0(1 - p_0)$$

$$EP_t = p_0$$

$$Var\, P_t = (2\lambda - \lambda^2)^t p_0^2 + p_0(1 - \lambda)^2 \sum_{i=0}^{t-1} (2\lambda - \lambda^2)^i - p_0^2$$

$$ES_t = S_0 + t(2p_0 - 1)$$

$$Var\, S_t = 4p_0(1 - p_0)t^2 + a(p_0, \lambda)t - a(p_0, \lambda)\frac{1 - (2\lambda - \lambda^2)^t}{(1 - \lambda)^2}$$

Two-parameter model

- Two λ parameters each affecting one direction of the walk
- Again two variants – success punishing and success rewarding

$$X_{t-1} = 1 \rightarrow p_t = \lambda_0 p_{t-1} \quad X_{t-1} = -1 \rightarrow p_t = 1 - \lambda_1(1 - p_{t-1})$$

–> "Two-parameter success punishing model"

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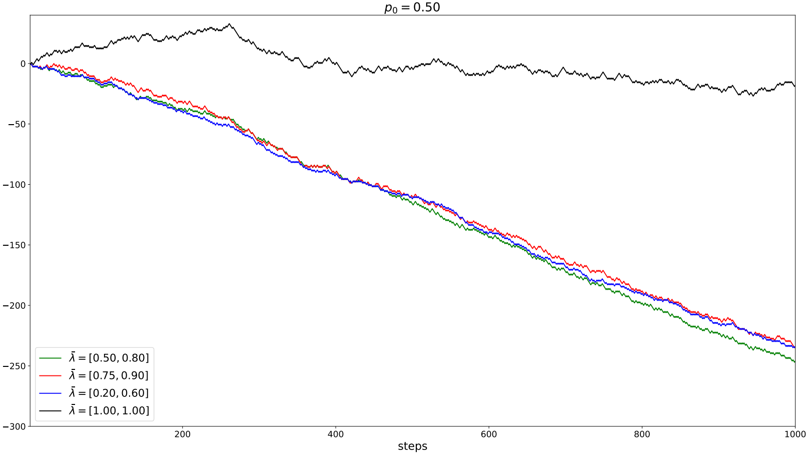
Example - two-parameter success punishing model



Model fitting

1. Find $\overrightarrow{\lambda}$ with known p_0, model type
2. Find p_0 with known $\overrightarrow{\lambda}$, model type
3. Find p_0, $\overrightarrow{\lambda}$ with known model type
4. Find model type without any prior knowledge

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4. Find model type without any prior knowledge
   - Using Akaike information criterion & numerical optimization

Real life application

- Success rewarding model well suited for modelling tennis matches
- Model trained on 2009–2018 men Grand Slam tournaments
- Model applied on 2019 US Open
    - Live betting against bookmaker
    - 0.52 units total necessary bankroll
    - 2.24 units total profit $\rightarrow$ 430% ROI
    - Only 128 bets placed

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Summary

- A specific model of a random walk with memory
- Model properties derived
- Application shows big future potential of the model
- Possible applications in a set of real life scenarios

Thank you.

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