

# Foundations of Data science

Foundations of data science, summer 2020  
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## 4. Exercise sheet

Hand in solutions until Thursday, 14 May 2020, 12:00

**Exercise 4.1** (Random point in a ball). (8+3 points)

Write a Python routine (eg. in a jupyter notebook) to choose a uniformly random point in a unit ball of dimension  $d$ . 5

Use your routine with  $d = 2$  to pick 1 000 points and plot them, so that we can visually check the correctness of the algorithm. 3

Can you also plot a sample with  $d = 3$ ? +3

**Exercise 4.2** (Random exit). (10 points)

Consider an experiment for which some general indicator variable  $X$  has  $\text{prob}(X = 1) = p \neq 0$ .

We create new random variables as following: Repeat the experiment to obtain  $X_i$  for all  $i \in \mathbb{N}$ . That is, ... (fill in!)

Then we set the exit time

$$T = \min \{i \mid X_i = 1\}.$$

We simply may assume that this minimum always exists.

(i) Prove that 2

$$T = i \iff X_i = 1 \wedge X_{i-1} = 0 \wedge \dots \wedge X_1 = 0.$$

(ii) Compute(!)  $\text{prob}(T = 1)$ ,  $\text{prob}(T = 2)$ ,  $\text{prob}(T = 3)$ . 1

(iii) Prove a formula for  $\text{prob}(T = i)$ . 2

(iv) Express  $E(T)$  as an infinite sum. 1

(v) Use the geometric series to derive a formula for  $\sum_{i=1}^{\infty} ix^{i-1}$ . 1

(vi) Compute the expected exit time  $E(T)$ . 1

(vii) Consider the method 0 algorithm from class. What is its expected runtime? 2

i) Given:  $T=i \Rightarrow X_i=1 \wedge X_{i-1}=0 \wedge \dots \wedge X_1=0$

since we know by definition of indicator variable:  
 $X \leftarrow \{0, 1\}$ ,  $P(1)$  is the probability of the indicated event.  $A = \{X=1\}$ .

$$\begin{aligned} \text{ii) } T_i &= X_i = 1 \wedge X_{i-1} = 0 \wedge \dots \wedge X_1 = 0 \\ \text{prob}(T_i) &= \text{prob}(X_i = 1 \wedge X_{i-1} = 0 \wedge \dots \wedge X_1 = 0) \\ &= \text{prob}(X_i = 1) \cdot \text{prob}(X_{i-1} = 0) \cdot \dots \cdot \text{prob}(X_1 = 0) \\ &= P(1-P) \cdot \dots \cdot (1-P) \end{aligned}$$

$$\begin{aligned} \text{ii) } T(1) &= P, \quad T(2) = \text{prob}(X_2=1) \cdot \text{prob}(X_1=0) \\ &= P(1-P) \\ T(3) &= \text{prob}(X_3=1) \cdot \text{prob}(X_2=0) \cdot \text{prob}(X_1=0) \\ &= P \cdot (1-P)(1-P) = P(1-P)^2 \end{aligned}$$

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iv) By the definition we know

$$E(D) = \sum_{x \in D} x \cdot \text{prob}(D=x)$$

$$\begin{aligned} \text{Here, } E(T) &= \sum_{x=1}^{\infty} x \cdot (\text{prob } T=x) \\ &= \sum_{i=1}^{\infty} x \cdot (p \cdot (1-p)^{x-1}) \end{aligned}$$