Probability Theory and Statistics Lecture 5

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Remainder Random Variables

Definition

A (one-dimensional) random variable is a function $X : \Omega \to \mathbb{R}$ that assigns to each outcome $\omega \in \Omega$ a real number $X(\omega) \in \mathbb{R}$.

Binomial distribution

Definition

A random variable X has the binomial distribution with parameters $n \in$ and $p \in [0,1]$ if

$$p_X(k) = \mathbb{P}(X=k) = \binom{n}{k} p^k (1-p)^{n-k}, \quad \forall k \in \{0,1,\ldots,n\}.$$

Notation: $X \sim B(n; p)$.

Geometric distribution

Definition

A random variable X has the geometric distribution with parameter $p \in (0,1)$ if

$$p_X(k) = \mathbb{P}(X = k) = (1 - p)^{k-1}p, \quad \forall k \in \{1, 2, \ldots\}.$$
 (1)

Notation: $X \sim \text{Geo}(p)$.

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Poisson Distribution

The binomial distribution models precisely the situation where we know how many trials we perform and the success probability in each.

There are situations where a certain random quantity X can also be viewed as the number of successes in many repeated and independent trials, but:

- the number of trials is large,
- the success probability in each trial is small,
- and neither the number of trials nor the success probability is necessarily known exactly.

Examples:

- the number of people older than 100 living in Budapest,
- the number of phone calls in Hungary between 4 and 5 pm today,
- the number of shooting stars observed in an hour on an August evening,
- ullet further (more or less good) examples o in the exercise class.

In such cases X is approximately Poisson distributed,

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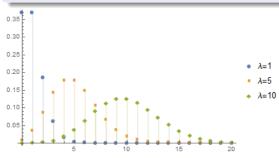
Poisson Distribution

Definition

A random variable X has the Poisson distribution with parameter $\lambda>0$ if

$$p_X(k) = \mathbb{P}(X = k) = \frac{\lambda^k}{k!} e^{-\lambda}, \quad \forall k \in \{0, 1, 2, \ldots\}.$$

Notation: $X \sim \text{Pois}(\lambda)$.



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Property of Poisson

Theorem

The Poisson distribution is indeed a pmf.

(Proof)

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Intuition (see previous slide): the Poisson distribution is like a binomial distribution with "large n and small p".

This is not just a heuristic; it can be made mathematically precise (including how to choose p as a function of n), for which it helps to already know the notion of expectation. We will return to this soon.

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Poisson Approximation to the Binomial Distribution

Recall: for many independent trials with identical success probability, if there are n trials and each succeeds with probability p, then the number of successes $\sim B(n; p)$.

Questions:

- For large n and a suitably small, n-dependent $p = p_n$, can the distribution $B(n; p_n)$ indeed be approximated by some $Pois(\lambda)$? This would greatly simplify calculations, since we would not need to evaluate huge binomial coefficients (even when n is known exactly).
- If yes: how should we choose p_n ; how should p_n tend to 0 as $n \to \infty$?
- What will the value of λ be (as a function of the p_n 's)?

We have seen: if $X_n \sim \mathrm{B}(n; p_n)$, then $\mathbb{E}(X_n) = np_n$. If $X \sim \mathrm{Pois}(\lambda)$, then $\mathbb{E}(X) = \lambda$.

Intuition: choosing $p_n = \lambda/n$ should work (this keeps the expectation unchanged).

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Poisson Approximation to the Binomial Distribution

Theorem

Let n be a positive integer, $\lambda \in (0, \infty)$, and set $p_n = \lambda/n$. Then

$$\lim_{n\to\infty} \binom{n}{k} p_n^k (1-p_n)^{n-k} \; = \; \frac{\lambda^k}{k!} \, \mathrm{e}^{-\lambda}, \qquad k\in\{0,1,2,\ldots\}.$$

(Proof)

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(Proof)

The same proof works when p_n is not exactly λ/n but satisfies $np_n \to \lambda$. For example, the statement also holds for $p_n = \frac{\lambda}{n-42}$ or $p_n = \frac{\lambda}{n+\ln n}$. We may add to or subtract from n any quantity whose ratio to n tends to 0 as $n \to \infty$.

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The expected value of a simple random variable is

$$\mathbb{E}(X) \stackrel{\text{def}}{=} \sum_{k \in \text{Ran}(X)} k \mathbb{P}(X = k) = \sum_{k \in \text{Ran}(X)} k p_X(k). \tag{2}$$

Question: does the same formula work for an *arbitrary* discrete random variable X?

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Question: does the same formula work for an *arbitrary* discrete random variable *X*? Answer: yes, provided the expected value exists! **Example:**

Roll a fair die and let $X := \{\text{rolled number}\}.$

$$\mathbb{E}(X)=3.5$$

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Definition

Let X be a discrete random variable such that

$$\sum_{k\in \mathrm{Ran}(X)} |k| \, p_X(k) < \infty.$$

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In most cases $Ran(X) \subseteq \mathbb{N}$, hence the absolute value does not matter.

Expected Value — Geometric and Poisson Distributions

Theorem

Let $X \sim \text{Bin}(n; p)$ with $p \in (0, 1)$. Then $\mathbb{E}(X) = np$.

(Proof)

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Let $X \sim \text{Geo}(p)$ with $p \in (0,1)$. Then $\mathbb{E}(X) = \frac{1}{p}$

(Proof)

Theorem

Let $X \sim \text{Pois}(\lambda)$ with $\lambda > 0$. Then $\mathbb{E}(X) = \lambda$.

(Proof)

Further Properties of the Expected Value

Theorem

The linearity of expectation $(\mathbb{E}(X+Y)=\mathbb{E}(X)+\mathbb{E}(Y), \mathbb{E}(cX)=c\,\mathbb{E}(X),$ cf. Claim 3.2.3) holds for arbitrary (not necessarily discrete) random variables X,Y whose expected values exist.

(Proof)

For continuous random variables \rightarrow the method of computing expectation will differ from the discrete case (see later), but linearity still holds.

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(Proof)

For continuous random variables \rightarrow the method of computing expectation will differ from the discrete case (see later), but linearity still holds.

Other easy properties: for a (not necessarily discrete) random variable X and real numbers $-\infty < a < b < \infty$,

- if $\mathbb{P}(a \leq X \leq b) = 1$, then $a \leq \mathbb{E}(X) \leq b$,
- if $\mathbb{P}(X \ge a) = 1$, then $\mathbb{E}(X)$ is definable (in the worst case with value $+\infty$) and $\mathbb{E}(X) \ge a$.

Special case: if X is nonnegative, then $\mathbb{E}(X) \in [0, \infty]$,

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