CS 107, Probability, Spring 2020 Lecture 24

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AUA

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Content

- Some important Discrete rv.s
 - Poisson Distribution;
 - Negative Binomial Distribution;
 - Hypergeometric Distribution

Poisson Distribution

Poisson Distribution

Distribution Name: Pois, Poisson;

Parameters: λ ($\lambda > 0$)

Poisson Distribution

We say that the r.v. X has a Poisson Distribution with the parameter (rate per unit of measure) λ ($\lambda > 0$), and we will write $X \sim Pois(\lambda)$, if the PMF of X is given by

$$\mathbb{P}(X = k) = e^{-\lambda} \cdot \frac{\lambda^k}{k!}, \qquad k = 0, 1, 2, ...$$

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that is,

Values of
$$X \mid 0 \mid 1 \mid 2 \mid \dots \mid k \mid \dots$$

$$\mathbb{P}(X = x) \quad e^{-\lambda} \mid e^{-\lambda} \cdot \frac{\lambda^1}{1!} \mid e^{-\lambda} \cdot \frac{\lambda^2}{2!} \mid \dots \mid e^{-\lambda} \cdot \frac{\lambda^k}{k!} \mid \dots$$

Exercise: Use $Calc2 \cup RA$ to prove that $\sum_{k=0}^{\infty} \mathbb{P}(X = k) = 1$.

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- Do not read Poisson as **Poison**! $\ddot{-}$

For example, we can model the following events by using the Poisson distribution:

• The number of emails received in a day

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- The number of goals in a football game;
- etc.



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 There is a fixed interval of time or space during or in which we are considering our events (say, every minute, every day, every month, every day from 10:30AM till 11:20AM, every square cm etc.)

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- The occurrence of one event does not affect the probability that a second event will occur. That is, events occur independently.
- The rate at which events occur is constant. The rate cannot be higher in some intervals and lower in other intervals.
- Two events cannot occur at exactly the same instant.



Example 24.1: Which of the following r.v.s can be modeled as a Poisson r.v.?

- a. X = number of cars passing by my window in an hour;
- b. Y = number of cars passing by my window between 10AM and 11AM;
- c. Z = no of calls at taxi center per hour;
- d. T = no of call at some emergency center per hour;
- E. U = daily number of absent students from Probability class.

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- c. Find $\mathbb{P}(3 \le X < 5.5)$;
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- e. Sketch the graph of the CDF *F*.

Example 24.3: Assume that the average number of traffic jams during a day at the Arshakunyats ave. is approximately 2.3. Assuming that for the number of traffic jams the Poisson model is appropriate, let X be the number of traffic jams today.

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- d. Calculate the probability that exactly 2 traffic jams will be today at the Arshakunyats ave.;
- e. Calculate the probability that the number of traffic jams there will be more than 5.

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Idea: OTB



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Remark, 18+: In fact, for the error of the approximation, the following is known¹: if $X \sim Binom(n, p)$ and $Y \sim Pois(np)$, then for any set $A \subset \{0, 1, 2, 3, ...\}$,

$$|\mathbb{P}(X \in A) - \mathbb{P}(Y \in A)| \le \min(p, np^2).$$

Example 24.4: Assume that the probability of having a broken egg in an egg-box is 0.5%. Tomorrow, one of the supermarkets will receive 1000 egg-boxes. What is the probability that exactly 6 out of that 1000 egg-boxes will contain broken eggs?

Solution:

- a. Using the Binomial Model:
- b. Using the Poisson Approximation:

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So why is it more appropriate to use Poisson Distribution in many cases? Let me explain by giving examples.

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We will give two models: the first one is Binomial, and the second one is Poisson, and make comparison.

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- independence in making misprints in characters in different positions. Say, the event of having a misprint in the 3rd character in a page is independent of having misprinted the 10th character etc.

Now, having all this, we can model this situation (the number of misprints in a page), using the Binomial Distribution:



We are making an independent repeated trials model:

• Trial = considering if a character is misprinted or not;

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$$= \binom{3000}{k} \cdot \frac{1}{50000^k} \cdot \left(1 - \frac{1}{50000}\right)^{3000 - k}$$



For example, some values (rounded) are:

Values of X	0	1	2	3	 3000
$\mathbb{P}(X=x)$	0.942	0.056	0.002	$3.4 \cdot 10^{-5}$	 0

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Now, the point is that this will work for a page with n=3000 characters. If we will have, say a page with 3200 characters, we need to recalculate everything.

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Well, in fact, people are not usually doing this way: usually people are using Statistics - in this case, we fix some books, we calculate the number of pages, we calculate the number of misprints in that pages, and divide the second one to the first one, to obtain the average number of misprints in a page.

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Now, under the Poisson Model, the Probability that we will have exactly k misprints will be:

$$\mathbb{P}(X = k) = e^{-\lambda} \cdot \frac{\lambda^k}{k!} = e^{-0.06} \cdot \frac{0.06^k}{k!}.$$

For example, some values (again rounded) are:

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You can check that the (rounded) probabilities coincide for Binomial model and Poisson one: the exact values do not coincide, but are very close to each other:

Here I am giving these probabilities side by side:

Values of X	Binomial Prob	Poisson Prob
0	0.9417640	0.9417645
1	0.05650697	0.05650587
2	0.001694678	0.001695176
3	3.387164e - 05	3.390352e - 05
:	:	i:
3000	0	0
3001		0
3002		0
:		0

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Note: Important difference in Binomial and Poisson Models: for the Poisson model, we forget/do not talk about the number of characters in a page! The only important thing is the average number of misprints.

Another example:

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- If we will do it in a little bit wise way, we can calculate the probability that in a day customers will buy more than, say, k packages. Let X be the number of customers that will buy that cheese tomorrow. We will calculate $\mathbb{P}(X>k)$ for different values of k, and choose the minimum value of k such that $\mathbb{P}(X>k)<0.05$ so we will leave a small, 5%, chance (risk) that not all our clients will be satisfied, but that's OK for us.

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- Meth 2: We can calculate the average daily number of customers that buy that cheese, λ (Statistics!!!), and assume $X \sim Pois(\lambda)$. Then calculate the above probabilities.

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The second approach is usually what people are using.

Poisson Distribution: Examples

Example 24.5: Assume that the probability of having no misprinted character in a book page is 96% for some publisher.

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a. Calculate the probability that we will find exactly 1 misprints in one page of that publisher's book;

Poisson Distribution: Examples

Example 24.5: Assume that the probability of having no misprinted character in a book page is 96% for some publisher.

- a. Calculate the probability that we will find exactly 1 misprints in one page of that publisher's book;
- b. Calculate the probability that we will find more than 3 misprints in one page of that publisher's book.

Example 24.6:

- a. Generate Poisson random numbers in R;
- b. Plot in **R** and compare the PMFs of Poisson r.v. with different rates;
- c. Plot the CDF of some Poisson r.v. in R.

The Poisson Distribution has the following nice property: assume X is a r.v. counting the number of occurrences of some event during one unit of measure, say during 1 hour.

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- $\mathbb{P}(X=0)$ = the probability of having 0 event in 1 hour;
- $\mathbb{P}(X=1)$ = the probability of having 1 event in 1 hour;
- ullet $\mathbb{P}(X=2)=$ the probability of having 2 events in 1 hour,

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Now, assume we want to model the number of events in 3 hours, *Y*.

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Now, assume we want to model the number of events in 3 hours, Y. Then, since λ is the hourly average number of events, we will have that the average number of events in 3 hours is 3λ .

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- $\mathbb{P}(X=2)=$ the probability of having 2 events in 1 hour, ...

Now, assume we want to model the number of events in 3 hours, Y. Then, since λ is the hourly average number of events, we will have that the average number of events in 3 hours is 3λ . So we will have

$$Y \sim Pois(3 \cdot \lambda)$$
.



Example 24.7: Let X be the annual number of Atlantic hurricanes. Assume we can model X by the Poisson r.v.,

$$X \sim Pois(5.44)$$
.

- a. What is the annual average number of Atlantic hurricanes?
- b. What is the probability of having more than 10 Atlantic hurricanes in a year?
- c. Let Y be the number of Atlantic hurricanes in 5 years. Give a model for Y;
- d. What is the probability of having more that 30 hurricanes in 5 years?



Example 24.8: Assume X is the hourly number of my LinkedIn profile views. Say, my profile has 2 views in 10 hours in average.

- a. Write an appropriate Probabilistic model for X;
- b. What is the probability that I will have 1 view in the next hour?
- c. What is the probability that I will have 3 views in the next 5 hours?
- d. Are the following events equiprobable:
 - A = I will have 1 views in the next 1 hour;
 - B = I will have 3 views in the next 3 hours?

Example 24.9: Assume that *X* is the number of pizza orders at Pandok Yerevan between 1PM and 3PM; let *X* be a Poisson r.v. with rate 2. Find the distribution of the number of pizza orders at Pandok Yerevan between 1PM and 3PM for days, when there was at least one order.

Examples of data fitting using the Poisson distribution

Poisson Distribution: Bortkiewicz data

Example 24.10 This is a classical example of fitting data by the Poisson distribution. The data set is given by Ladislaus von Bortkiewicz, in 1898^2 .

 $^{^2} https://archive.org/download/dasgesetzderklei00bortrich/dasgesetzderkl$

Poisson Distribution: Bortkiewicz data

Example 24.10 This is a classical example of fitting data by the Poisson distribution. The data set is given by Ladislaus von Bortkiewicz, in 1898². It shows the annual number of Prussian cavalryman in 10 corps killed by the kick of a horse, for 20 years. Here is the data:

Fit the Poisson Distribution to this data.

 $^{{\}it 2https://archive.org/download/dasgesetzderklei00bortrich/dasgesetzderklei0000bortrich/dasgesetzderklei0000bortrich/dasgesetzderklei0000bortrich/dasgesetzderklei00000$

Poisson Distribution: R's Discoveries data

Example 24.11: There is a native dataset in **R**, called *Discoveries*. It shows the yearly number of important scientific discoveries in each year from 1860 to 1959.

Fit the Poisson Distribution to this data.

Poisson Distribution: Flying Bomb data

Example 24.12: This is another classic example. During the WWII, Germany army used unmanned aircraft, called V1 Flying Bombs, to attack London. They hit the ground at more or less random points. The area of London was divided into 576 sectors of about 1/4 km each, and the number of hits for each sector was later calculated, for 537 Flying Bombs. The number of hits was

No of Hits	0	1			l	≥ 5
No of Sectors	229	211	93	35	7	1

Fit the Poisson Distribution to this data (take ≥ 5 as 5).

Poisson Distribution: Raisins Problem

Example 24.13: Assume we have a 2D cookie in the form of a square, and raisins are randomly (and uniformly!) spread out around the cookie dough. Do the simulation in \mathbf{R} , divide the cookie area into small squares by a square grid, calculate the number of raisins in each square, and fit the Poisson Distribution to the data for the number of raisins per small square.

Of course, this is the simulation of the previous, Flying Bombs, problem.

Poisson Distribution: Raisins Problem

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Exercise: State and do 1D and 3D case problems and simulations.

Poisson Distribution: Hurricane data

Example 24.14: At http://www.stormfax.com/huryear. htm you can find the Atlantic Hurricane Numbers By Year for 1851-2017.

Fit the Poisson Distribution to the data for the number of Atlantic Hurricanes.

Poisson Distribution: Hurricane data

Example 24.15: You can find data for the distribution of word lengths in various languages at http://www.ravi.io/language-word-lengths.

Fit the Poisson Distribution to the data for the number of characters for German words.

Poisson Distribution: Goals data

Example 24.16: You can find the UK Premiere League matches results for 2019/2020 at https://www.football-data.co.uk/englandm.php.

Fit the Poisson Distribution to the data for the number of goals.

Negative Binomial Distribution