

## Lecture 4

Last time

- ▷ Weak convergence
- ▷ Levy's convergence Theorem.

Wed Jan 1/2024

Today

- ▷ Poisson Distribution
- ▷ Law of rare events

## ▷ Poisson Distribution

Imagine we have a Bernoulli dist.

$S_n = \sum_{k=1}^n X_k$  where  $X_i$  are iid r.v.

with

$$P(X_1 = 1) = p_n = 1 - P(X_1 = 0).$$

Question: What happens to  $S_n$  as  $n \rightarrow \infty$ ?

We can think of two regimes

- ▷ Fix probability:  $p_n = p$ . Then the CLT in HW 1 gives

$$\frac{S_n - np}{\sqrt{np(1-p)}} \xrightarrow{\omega} N(0, 1).$$

- ▷ Fix the mean:  $np_n = \lambda$ .  
In this case the asymptotic dist

This models rare events!

is Poisson!

Theorem: Suppose  $S_n \sim \text{Binomial}(n, p_n)$ , and  $n p_n \rightarrow e^{(0, \infty)}$  as  $n \rightarrow \infty$ . Then

$$P(S_n = k) \rightarrow e^\lambda \frac{\lambda^k}{k!}.$$

+

We will use the place holder Poisson( $\lambda$ ) to denote this distribution.

We will prove a more general version of this result today. But first let's cover some properties of the Poisson dist:

Proposition The Poisson( $\lambda$ ) satisfies the following.

- 1) It's Moment generating func is  $e^{\lambda(e^t - 1)}$
- 2) It's characteristic func is  $e^{\lambda e^{it} - 1}$
- 3) It's mean is  $\lambda$ .
- 4) It's variance is  $\lambda$ .

Consequence  
sum of Poisson( $\lambda_1$ )  
and Poisson( $\lambda_2$ )  
is Poisson( $\lambda_1 + \lambda_2$ ).

Proof:

1) By def

$$\begin{aligned}
 M(t) &= \mathbb{E}(e^{tx}) = \sum_{k=0}^{\infty} e^{tk} \frac{e^{-\lambda} \lambda^k}{k!} \\
 &= e^{-\lambda} \sum_{k=0}^{\infty} \frac{(\lambda e^t)^k}{k!} \\
 &= e^{-\lambda} e^{\lambda e^t} = e^{\lambda(e^t - 1)}
 \end{aligned}$$

2) Follows from  $\varphi(t) = M(it)$ . pth der.

3) Recall that  $\mathbb{E}(x^p) = M^{(p)}(0)$ .

$$M'(0) = \lambda e^t e^{\lambda(e^t - 1)}|_0 = \lambda.$$

3) Similar to the above

$$M''(0) - (M'(0)) = \lambda.$$

Exercise

□

Demo.

## Law of rare events

The following is a more general version of the Theorem regarding Binomials.

Theorem For each  $n$ , let  $X_{n,m}$  [mean] be ind. r.v.'s such that

$$X_{n,m} = \begin{cases} 1 & \text{with prob } p_{n,m} \\ 0 & \text{with prob } 1 - p_{n,m}. \end{cases}$$

Generalizes

$d_1, \dots, d_n$

Moreover, suppose that

1)  $\sum_{m=1}^n p_{n,m} \rightarrow \lambda \in (0, \infty),$

2)  $\max_{m \in [n]} p_{n,m} \rightarrow 0 \text{ as } n \rightarrow \infty.$

Let  $S_n = \sum_{k=1}^n X_{n,k}$ , then,

$S_n \xrightarrow{\omega} Z \text{ with } Z \sim \text{Poisson}(\lambda).$  †

To prove this result we will introduce a new notion of distance. For two measures  $\mu$  and  $\nu$  supported on a countable set  $S$ , we let the total variation distance be

$$\|\mu - \nu\|_{TV} = \frac{1}{2} \sum_z |\mu(z) - \nu(z)| = \sup_{A \subset S} |\mu(A) - \nu(A)|$$

Will omit for simplicity

Exercise.

We will require a couple of lemmas.

Lemma: The total variation distance defines a metric on prob. measures on  $\mathbb{Z}$ . Moreover, given a seq.  $(\mu_n) \subseteq \mathcal{P}(\mathbb{Z})$  and  $\mu \in \mathcal{P}(\mathbb{Z})$ ,

$$\mu_n \xrightarrow{\omega} \mu \iff \|\mu_n - \mu\| \rightarrow 0$$
 †

Left as exercise.

Lemma If  $\mu \times v \in P(\mathbb{Z} \times \mathbb{Z})$  given by  $(\mu \times v)(x, y) = \mu(x)v(y)$ . Then

$$\|\mu_1 \times v_1 - \mu_2 \times v_2\| \leq \|\mu_1 - \mu_2\| + \|v_1 - v_2\|$$

Proof: By def

$$\begin{aligned} 2\|\mu_1 \times v_1 - \mu_2 \times v_2\| &= \sum_{x,y} |\mu_1(x)v_1(y) - \mu_2(x)v_2(y)| \\ &\leq \sum_{x,y} |\mu_1(x)v_1(y) - \mu_2(x)v_1(y)| \\ &\quad + \sum_{x,y} |\mu_2(x)v_1(y) - \mu_2(x)v_2(y)| \\ &= \sum_y v_1(y) \sum_x |\mu_1(x) - \mu_2(x)| \\ &\quad + \sum_x \mu_2(x) \sum_y |v_1(y) - v_2(y)| \\ &\leq 2(\|\mu_1 - \mu_2\| + \|v_1 - v_2\|). \end{aligned}$$

□

Lemma If  $\mu * v$  denotes the convolution

$$\mu * v(x) = \sum_y \mu(x-y)v(y).$$

Then,  $\|\mu_1 * v_1 - \mu_2 * v_2\| \leq \|\mu_1 \times v_1 - \mu_2 \times v_2\|$ .

Proof:

$$2\|\mu_1 * v_1 - \mu_2 * v_2\| = \sum_x \left| \sum_y \mu_1(x-y)v_1(y) - \mu_2(x-y)v_2(y) \right|$$

$$\leq \sum_x \sum_y |\mu_1(x-y) v_1(y) - \mu_2(x-y) v_2(y)|$$

$$= 2 \|\mu_1 \times v_1 - \mu_2 \times v_2\|. \quad \text{The sums are shifted, but } x-y = y-x \quad \square$$

Lemma: Let  $\mu$  be such that  $\mu(1)=p$  and  $\mu(0)=1-p$ . Then,

$$\|\mu - \text{Poisson}(p)\| \leq p^2.$$

Proof:  $2 \|\mu - \nu\| = |\mu(0) - \nu(0)| + |\mu(1) - \nu(1)| + \sum_{k \geq 2} \nu(k)$

$$(0) = |1-p - e^{-p}| + |p - pe^{-p}| + 1 - e^{-p}(1+p).$$

Note that  $1-x \leq \exp(-x) \leq 1 \quad \forall x \geq 0$

$$(0) = e^{-p} - 1 + p + p - pe^{-p} + 1 - e^{-p}(1+p)$$

$$= 2p(1 - e^{-p})$$

$$\leq 2p^2.$$

Proof of Theorem (x-x):

Let  $\mu_{n,m}$  be the dist of  $X_{n,m}$  on  $\mu_n$  the dist of  $S_n$ . Let

$$Y_{nm} = \text{Poisson}(p_{nm}), \quad Y_n = \text{Poisson}\left(\sum_{m=1}^n p_{nm}\right)$$

and  $\nu = \text{Poisson}(\lambda)$ .

Since  $\mu_n = \mu_{n,1} * \dots * \mu_{n,n}$  and  $\nu_n = \nu_{n,1} * \dots * \nu_{n,n}$ ,  
the Lemmas above imply

$$\|\mu_n - \nu_n\| \leq \sum_{m=1}^n \|\mu_{nm} - \nu_{nm}\| \leq \sum_{m=1}^n p_{n,m}^2 \xrightarrow{\substack{\uparrow \\ \max_{m \in \mathbb{N}} p_{n,m} \sum_{m \in \mathbb{N}} p_{n,m}}} \rightarrow 0 \quad \text{as } n \rightarrow \infty.$$

This even give us a rate  
of convergence.

Moreover, by construction  $\nu_n \xrightarrow{w} \nu$ .

Using triangle ineq.

$$\lim_{n \rightarrow \infty} \|\mu_n - \nu\| \leq \lim_{n \rightarrow \infty} \|\mu_n - \nu_n\| + \|\nu_n - \nu\| \\ = 0.$$

Thus, by the first Lemma,  $\mu_n \xrightarrow{w} \nu$ . 4

We can easily generalize this result

Theorem 2.0 For each  $n$ , let  $X_{n,m} \in \mathbb{N} \cup \{0\}$   
be ind. r.v.'s such that

$$X_{n,m} = \begin{cases} 1 & \text{with prob } p_{n,m} \\ 0 & \text{with prob } 1 - p_{n,m} - \epsilon_{n,m} \\ \geq 2 & \text{with prob } \epsilon_{n,m} \end{cases}$$

Moreover, suppose that

- 1)  $\sum_{m=1}^n p_{n,m} \rightarrow \lambda \in (0, \infty),$
- 2)  $\max_{m \in [n]} p_{n,m} \rightarrow 0 \text{ as } n \rightarrow \infty.$
- 3)  $\sum_{m=1}^n \epsilon_{n,m} \rightarrow 0 \text{ as } n \rightarrow \infty.$

Let  $S_n = \sum_{k=1}^n X_{nk}$ , then,

$$S_n \xrightarrow{\omega} Z \text{ with } Z \sim \text{Poisson}(\lambda).$$

Proof: Define  $X'_{nm} = 1$  if  $X_{nm}$ , and 0 otherwise. Theorem ( $\underline{x}$ ) gives that  $S'_n = \sum_{m=1}^n X'_{nm}$  converges weakly to  $Z$ . Moreover

$$\begin{aligned}\|\mu_{S_n} - \mu_{S'_n}\| &= \sum \| \mu_{X_{nm}} - \mu_{X'_{nm}} \| \\ &\leq \sum (1 - p_{nm} - (1 - p_{nm} - \epsilon_{nm})) + \epsilon_{nm} \\ &= 2 \sum \epsilon_{nm} \\ &\rightarrow 0.\end{aligned}$$

□