CS70 Geometric and Poisson Distributions

Kelvin Lee

UC Berkeley

June 22, 2021

Kelvin Lee (UC Berkeley)

Discrete Math and Probability Theory

э June 22, 2021 1/8

B b

→ Ξ →

Overview





3 Poisson Distribution

4 Sum of Independent Poisson Random Variables

< ⊒ >

Kelvin Lee (UC Berkeley)

イロト イヨト イヨト イヨト

• X ~ Geo (p).

- *X* ~ Geo (*p*).
- PMF:

A D N A B N A B N A B N

- X ~ Geo (p).
- PMF:

$$P(X = k) = (1 - p)^{k-1}p$$
, for $i = 1, 2, 3, ...$

A D N A B N A B N A B N

- X ~ Geo (p).
- PMF:

$$P(X = k) = (1 - p)^{k-1}p$$
, for $i = 1, 2, 3, ...$

• Expectation:

- X ~ Geo (p).
- PMF:

$$P(X = k) = (1 - p)^{k-1}p$$
, for $i = 1, 2, 3, ...$

• Expectation:

$$\mathbb{E}[X] = \frac{1}{p}.$$

- X ~ Geo (p).
- PMF:

$$P(X = k) = (1 - p)^{k-1}p$$
, for $i = 1, 2, 3, ...$

• Expectation:

$$\mathbb{E}[X] = \frac{1}{p}.$$

• Variance:

- *X* ~ Geo (*p*).
- PMF:

$$P(X = k) = (1 - p)^{k-1}p$$
, for $i = 1, 2, 3, ...$

• Expectation:

$$\mathbb{E}[X] = \frac{1}{p}.$$

$$Var(X) = \frac{1-p}{p^2}.$$

Kelvin Lee (UC Berkeley)

Discrete Math and Probability Theory

▶ < ≣ ▶ ≣ ∽ < @ June 22, 2021 3/8

Kelvin Lee (UC Berkeley)

Discrete Math and Probability Theory

э June 22, 2021 4/8

∃ →

(日)

(Memoryless Property).

Kelvin Lee (UC Berkeley)

(Memoryless Property). For $X \sim \text{Geo}(p)$,

(Memoryless Property). For $X \sim \text{Geo}(p)$,

$$\mathbb{P}(X > n + m \mid X > n) = \mathbb{P}(X > m).$$

(Memoryless Property). For $X \sim \text{Geo}(p)$,

$$\mathbb{P}(X > n + m \mid X > n) = \mathbb{P}(X > m).$$

Proof:

(Memoryless Property). For $X \sim \text{Geo}(p)$,

$$\mathbb{P}(X > n + m \mid X > n) = \mathbb{P}(X > m).$$

Proof:

$$\mathbb{P}(X > n + m \mid X > n) = \frac{\mathbb{P}(X > n + m \text{ and } X > n)}{\mathbb{P}(X > n)}$$

(Memoryless Property). For $X \sim \text{Geo}(p)$,

$$\mathbb{P}(X > n + m \mid X > n) = \mathbb{P}(X > m).$$

Proof:

$$\mathbb{P}(X > n + m \mid X > n) = \frac{\mathbb{P}(X > n + m \text{ and } X > n)}{\mathbb{P}(X > n)}$$
$$= \frac{\mathbb{P}(X > n + m)}{\mathbb{P}(X > n)}$$

(Memoryless Property). For $X \sim \text{Geo}(p)$,

$$\mathbb{P}(X > n + m \mid X > n) = \mathbb{P}(X > m).$$

Proof:

$$\mathbb{P}(X > n + m \mid X > n) = \frac{\mathbb{P}(X > n + m \text{ and } X > n)}{\mathbb{P}(X > n)}$$
$$= \frac{\mathbb{P}(X > n + m)}{\mathbb{P}(X > n)}$$
$$= \frac{(1 - p)^{n + m}}{(1 - p)^n}$$

(Memoryless Property). For $X \sim \text{Geo}(p)$,

$$\mathbb{P}(X > n + m \mid X > n) = \mathbb{P}(X > m).$$

Proof:

$$\mathbb{P}(X > n + m \mid X > n) = \frac{\mathbb{P}(X > n + m \text{ and } X > n)}{\mathbb{P}(X > n)}$$
$$= \frac{\mathbb{P}(X > n + m)}{\mathbb{P}(X > n)}$$
$$= \frac{(1 - p)^{n + m}}{(1 - p)^n}$$
$$= (1 - p)^m.$$

Kelvin Lee (UC Berkeley)

(Memoryless Property). For $X \sim \text{Geo}(p)$,

$$\mathbb{P}(X > n + m \mid X > n) = \mathbb{P}(X > m).$$

Proof:

$$\mathbb{P}(X > n + m \mid X > n) = \frac{\mathbb{P}(X > n + m \text{ and } X > n)}{\mathbb{P}(X > n)}$$
$$= \frac{\mathbb{P}(X > n + m)}{\mathbb{P}(X > n)}$$
$$= \frac{(1 - p)^{n + m}}{(1 - p)^n}$$
$$= (1 - p)^m.$$

Kelvin Lee (UC Berkeley)

< □ > < □ > < □ > < □ > < □ >

• $X \sim \text{Poisson}(\lambda)$.

Kelvin Lee (UC Berkeley)

A D N A B N A B N A B N

- $X \sim \text{Poisson}(\lambda)$.
- Models rare events, such as number of arrivals of a bus in an hour.

→ ∃ →

- $X \sim \text{Poisson}(\lambda)$.
- Models rare events, such as number of arrivals of a bus in an hour.
- Defined in terms of a rate λ, which specifies the average number of times an event occurs in a time interval.

- $X \sim \text{Poisson}(\lambda)$.
- Models rare events, such as number of arrivals of a bus in an hour.
- Defined in terms of a rate λ, which specifies the average number of times an event occurs in a time interval.
- PMF:

- $X \sim \text{Poisson}(\lambda)$.
- Models rare events, such as number of arrivals of a bus in an hour.
- Defined in terms of a rate λ, which specifies the average number of times an event occurs in a time interval.

• PMF:
$$P(X=k) = \frac{\lambda^k e^{-\lambda}}{k!}, \quad \text{for } i = 0, 1, 2, \dots.$$

- $X \sim \text{Poisson}(\lambda)$.
- Models rare events, such as number of arrivals of a bus in an hour.
- Defined in terms of a rate λ, which specifies the average number of times an event occurs in a time interval.

• PMF:

$$P(X = k) = \frac{\lambda^k e^{-\lambda}}{k!}, \text{ for } i = 0, 1, 2,$$

۲

$$\sum_{i=0}^{\infty} P(X=i) = \sum_{i=0}^{\infty} \frac{\lambda^k e^{-\lambda}}{k!} = e^{-\lambda} \sum_{i=0}^{\infty} \frac{\lambda^k}{k!} = e^{-\lambda} \cdot e^{\lambda} = 1.$$

- $X \sim \text{Poisson}(\lambda)$.
- Models rare events, such as number of arrivals of a bus in an hour.
- Defined in terms of a rate λ, which specifies the average number of times an event occurs in a time interval.

• PMF:
$$P(X = k) = \frac{\lambda^k e^{-\lambda}}{k!}, \text{ for } i = 0, 1, 2,$$

۲

 $\sum_{k=1}^{\infty} P(X=i) = \sum_{k=0}^{\infty} \frac{\lambda^k e^{-\lambda}}{k!} = e^{-\lambda} \sum_{k=0}^{\infty} \frac{\lambda^k}{k!} = e^{-\lambda} \cdot e^{\lambda} = 1.$

Recall the Taylor series expansion from calculus:

- $X \sim \text{Poisson}(\lambda)$.
- Models rare events, such as number of arrivals of a bus in an hour.
- Defined in terms of a rate λ, which specifies the average number of times an event occurs in a time interval.

• PMF:
$$P(X = k) = \frac{\lambda^k e^{-\lambda}}{k!}, \text{ for } i = 0, 1, 2,$$

۲

$$\sum_{i=0}^{\infty} P(X=i) = \sum_{i=0}^{\infty} \frac{\lambda^k e^{-\lambda}}{k!} = e^{-\lambda} \sum_{i=0}^{\infty} \frac{\lambda^k}{k!} = e^{-\lambda} \cdot e^{\lambda} = 1.$$

Recall the Taylor series expansion from calculus:

$$e^{x} = \sum_{i=1}^{\infty} \frac{x^{i}}{i!}.$$

Kelvin Lee (UC Berkeley)

< □ > < □ > < □ > < □ > < □ >

• Expectation:

A D N A B N A B N A B N

• Expectation:

$$\mathbb{E}[X] = \sum_{i=0}^{\infty} i \cdot P(X=i)$$

A D N A B N A B N A B N

• Expectation:

$$\mathbb{E}[X] = \sum_{i=0}^{\infty} i \cdot P(X = i)$$
$$= \sum_{i=1}^{\infty} \frac{\lambda^{i} e^{-\lambda}}{i!}$$

• Expectation:

$$\mathbb{E}[X] = \sum_{i=0}^{\infty} i \cdot P(X = i)$$
$$= \sum_{i=1}^{\infty} \frac{\lambda^{i} e^{-\lambda}}{i!}$$
$$= \lambda e^{-\lambda} \sum_{i=1}^{\infty} \frac{\lambda^{i-1}}{(i-1)!}$$

A D N A B N A B N A B N

• Expectation:

$$\mathbb{E}[X] = \sum_{i=0}^{\infty} i \cdot P(X = i)$$

= $\sum_{i=1}^{\infty} \frac{\lambda^{i} e^{-\lambda}}{i!}$
= $\lambda e^{-\lambda} \sum_{i=1}^{\infty} \frac{\lambda^{i-1}}{(i-1)!}$
= $\lambda e^{-\lambda} e^{\lambda}$ $(e^{\lambda} = \sum_{j=1}^{\infty} \frac{\lambda^{j}}{j!} \text{ with } j = i-1)$

Kelvin Lee (UC Berkeley)

A D N A B N A B N A B N

• Expectation:

$$\mathbb{E}[X] = \sum_{i=0}^{\infty} i \cdot P(X = i)$$

= $\sum_{i=1}^{\infty} \frac{\lambda^i e^{-\lambda}}{i!}$
= $\lambda e^{-\lambda} \sum_{i=1}^{\infty} \frac{\lambda^{i-1}}{(i-1)!}$
= $\lambda e^{-\lambda} e^{\lambda}$ $(e^{\lambda} = \sum_{j=1}^{\infty} \frac{\lambda^j}{j!} \text{ with } j = i-1)$
= λ .

イロト イポト イヨト イヨト

• Expectation:

$$\mathbb{E}[X] = \sum_{i=0}^{\infty} i \cdot P(X = i)$$

= $\sum_{i=1}^{\infty} \frac{\lambda^i e^{-\lambda}}{i!}$
= $\lambda e^{-\lambda} \sum_{i=1}^{\infty} \frac{\lambda^{i-1}}{(i-1)!}$
= $\lambda e^{-\lambda} e^{\lambda}$ $(e^{\lambda} = \sum_{j=1}^{\infty} \frac{\lambda^j}{j!} \text{ with } j = i - 1)$
= λ .

• Variance:

A D N A B N A B N A B N

• Expectation:

$$\mathbb{E}[X] = \sum_{i=0}^{\infty} i \cdot P(X = i)$$

= $\sum_{i=1}^{\infty} \frac{\lambda^i e^{-\lambda}}{i!}$
= $\lambda e^{-\lambda} \sum_{i=1}^{\infty} \frac{\lambda^{i-1}}{(i-1)!}$
= $\lambda e^{-\lambda} e^{\lambda}$ $(e^{\lambda} = \sum_{j=1}^{\infty} \frac{\lambda^j}{j!} \text{ with } j = i - 1)$
= λ .

• Variance:

 $Var(X) = \lambda.$

Discrete Math and Probability Theory

< □ > < □ > < □ > < □ > < □ >

Kelvin Lee (UC Berkeley)

Discrete Math and Probability Theory

▶ < ≣ ▶ ≣ ∽ Q @ June 22, 2021 7/8

Image: A match a ma

∃ →

(日)

Theorem. Let $X \sim \text{Poisson}(\lambda)$ and $Y \sim \text{Poisson}(\mu)$ be independent Poisson random variables. Then, $X + Y \sim \text{Poisson}(\lambda + \mu)$.

▲ □ ▶ ▲ □ ▶ ▲ □ ▶

Theorem. Let $X \sim \text{Poisson}(\lambda)$ and $Y \sim \text{Poisson}(\mu)$ be independent Poisson random variables. Then, $X + Y \sim \text{Poisson}(\lambda + \mu)$. *Proof:*

・ 何 ト ・ ヨ ト ・ ヨ ト

Theorem. Let $X \sim \text{Poisson}(\lambda)$ and $Y \sim \text{Poisson}(\mu)$ be independent Poisson random variables. Then, $X + Y \sim \text{Poisson}(\lambda + \mu)$.

Proof:

$$\mathbb{P}(X+Y=k) = \sum_{j=0}^{k} \mathbb{P}(X=j, Y=k-j)$$

▲ □ ▶ ▲ □ ▶ ▲ □ ▶

Theorem. Let $X \sim \text{Poisson}(\lambda)$ and $Y \sim \text{Poisson}(\mu)$ be independent Poisson random variables. Then, $X + Y \sim \text{Poisson}(\lambda + \mu)$.

Proof:

$$\mathbb{P}(X+Y=k) = \sum_{j=0}^{k} \mathbb{P}(X=j, Y=k-j)$$

$$= \sum_{j=0}^{k} \mathbb{P}(X=j)\mathbb{P}(Y=k-j)$$

・ 何 ト ・ ヨ ト ・ ヨ ト

Theorem. Let $X \sim \text{Poisson}(\lambda)$ and $Y \sim \text{Poisson}(\mu)$ be independent Poisson random variables. Then, $X + Y \sim \text{Poisson}(\lambda + \mu)$.

Proof:

$$\mathbb{P}(X+Y=k) = \sum_{j=0}^{k} \mathbb{P}(X=j, Y=k-j)$$

$$= \sum_{j=0}^{k} \mathbb{P}(X=j)\mathbb{P}(Y=k-j)$$

$$= \sum_{j=0}^{k} \frac{\lambda^{j}}{j!} e^{-\lambda} \frac{\mu^{k-j}}{(k-j)!} e^{-\mu}$$

< (回) < (三) < (三) < (三) < (二) < (二) < (二) < (-) < (-) < (-) < (-) < (-) < (-) < (-) < (-) < (-) < (-) < (-) < (-) < (-) < (-) < (-) < (-) < (-) < (-) < (-) < (-) < (-) < (-) < (-) < (-) < (-) < (-) < (-) < (-) < (-) < (-) < (-) < (-) < (-) < (-) < (-) < (-) < (-) < (-) < (-) < (-) < (-) < (-) < (-) < (-) < (-) < (-) < (-) < (-) < (-) < (-) < (-) < (-) < (-) < (-) < (-) < (-) < (-) < (-) < (-) < (-) < (-) < (-) < (-) < (-) < (-) < (-) < (-) < (-) < (-) < (-) < (-) < (-) < (-) < (-) < (-) < (-) < (-) < (-) < (-) < (-) < (-) < (-) < (-) < (-) < (-) < (-) < (-) < (-) < (-) < (-) < (-) < (-) < (-) < (-) < (-) < (-) < (-) < (-) < (-) < (-) < (-) < (-) < (-) < (-) < (-) < (-) < (-) < (-) < (-) < (-) < (-) < (-) < (-) < (-) < (-) < (-) < (-) < (-) < (-) < (-) < (-) < (-) < (-) < (-) < (-) < (-) < (-) < (-) < (-) < (-) < (-) < (-) < (-) < (-) < (-) < (-) < (-) < (-) < (-) < (-) < (-) < (-) < (-) < (-) < (-) < (-) < (-) < (-) < (-) < (-) < (-) < (-) < (-) < (-) < (-) < (-) < (-) < (-) < (-) < (-) < (-) < (-) < (-) < (-) < (-) < (-) < (-) < (-) < (-) < (-) < (-) < (-) < (-) < (-) < (-) < (-) < (-) < (-) < (-) < (-) < (-) < (-) < (-) < (-) < (-) < (-) < (-) < (-) < (-) < (-) < (-) < (-) < (-) < (-) < (-) < (-) < (-) < (-) < (-) < (-) < (-) < (-) < (-) < (-) < (-) < (-) < (-) < (-) < (-) < (-) < (-) < (-) < (-) < (-) < (-) < (-) < (-) < (-) < (-) < (-) < (-) < (-) < (-) < (-) < (-) < (-) < (-) < (-) < (-) < (-) < (-) < (-) < (-) < (-) < (-) < (-) < (-) < (-) < (-) < (-) < (-) < (-) < (-) < (-) < (-) < (-) < (-) < (-) < (-) < (-) < (-) < (-) < (-) < (-) < (-) < (-) < (-) < (-) < (-) < (-) < (-) < (-) < (-) < (-) < (-) < (-) < (-) < (-) < (-) < (-) < (-) < (-) < (-) < (-) < (-) < (-) < (-) < (-) < (-) < (-) < (-) < (-) < (-) < (-) < (-) < (-) < (-) < (-) < (-) < (-) < (-) < (-) < (-) < (-) < (-) < (-) < (-) < (-) < (-) < (-) < (-) < (-) < (-) < (-) < (-) < (-) < (-) < (-) < (-) < (-) < (-) < (-) < (-) < (-) < (-) < (-) < (-) < (-) < (-) < (-) < (-) < (-) < (-) < (-) < (-) < (-) < (-) < (-) < (-) < (-) < (-) < (-) < (-) < (-)

Theorem. Let $X \sim \text{Poisson}(\lambda)$ and $Y \sim \text{Poisson}(\mu)$ be independent Poisson random variables. Then, $X + Y \sim \text{Poisson}(\lambda + \mu)$.

Proof:

$$\mathbb{P}(X+Y=k) = \sum_{j=0}^{k} \mathbb{P}(X=j, Y=k-j)$$

$$= \sum_{j=0}^{k} \mathbb{P}(X=j)\mathbb{P}(Y=k-j)$$

$$= \sum_{j=0}^{k} \frac{\lambda^{j}}{j!} e^{-\lambda} \frac{\mu^{k-j}}{(k-j)!} e^{-\mu}$$

$$= e^{-(\lambda+\mu)} \frac{1}{k!} \sum_{j=0}^{k} \frac{k!}{j!(k-j)!} \lambda^{j} \mu^{k-j}$$

< (日) × < 三 × <

Theorem. Let $X \sim \text{Poisson}(\lambda)$ and $Y \sim \text{Poisson}(\mu)$ be independent Poisson random variables. Then, $X + Y \sim \text{Poisson}(\lambda + \mu)$.

Proof:

$$\mathbb{P}(X+Y=k) = \sum_{j=0}^{k} \mathbb{P}(X=j, Y=k-j)$$

$$= \sum_{j=0}^{k} \mathbb{P}(X=j)\mathbb{P}(Y=k-j)$$

$$= \sum_{j=0}^{k} \frac{\lambda^{j}}{j!} e^{-\lambda} \frac{\mu^{k-j}}{(k-j)!} e^{-\mu}$$

$$= e^{-(\lambda+\mu)} \frac{1}{k!} \sum_{j=0}^{k} \frac{k!}{j!(k-j)!} \lambda^{j} \mu^{k-j}$$

$$= e^{-(\lambda+\mu)} \frac{(\lambda+\mu)^{k}}{k!}.$$

・ 同 ト ・ ヨ ト ・ ヨ ト

Problem Time!

Kelvin Lee (UC Berkeley)

Discrete Math and Probability Theory

▶ < ≣ ▶ ≣ ∽ < @ June 22, 2021 8/8

A D N A B N A B N A B N