CS70: Jean Walrand: Lecture 37.

Gaussian RVs and CLT

- 1. Review: Continuous Probability
- 2. Normal Distribution
- 3. Central Limit Theorem
- 4. Confidence Intervals
- 5. Bayes' Rule with Continuous RVs

Continuous Probability

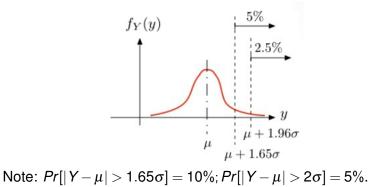
- 1. pdf: $Pr[X \in (x, x + \delta]] = f_X(x)\delta$.
- 2. CDF: $Pr[X \le x] = F_X(x) = \int_{-\infty}^x f_X(y) dy$.
- 3. U[a,b], $Expo(\lambda)$, target.
- 4. Expectation: $E[X] = \int_{-\infty}^{\infty} x f_X(x) dx$.
- 5. Expectation of function: $E[h(X)] = \int_{-\infty}^{\infty} h(x) f_X(x) dx$.
- 6. Variance: $var[X] = E[(X E[X])^2] = E[X^2] E[X]^2$.
- 7. Variance of Sum of Independent RVs: If X_n are pairwise independent, $var[X_1 + \dots + X_n] = var[X_1] + \dots + var[X_n]$

Normal (Gaussian) Distribution.

For any μ and σ , a **normal** (aka **Gaussian**) random variable *Y*, which we write as $Y = \mathcal{N}(\mu, \sigma^2)$, has pdf

$$f_Y(y) = rac{1}{\sqrt{2\pi\sigma^2}} e^{-(y-\mu)^2/2\sigma^2}$$

Standard normal has $\mu = 0$ and $\sigma = 1$.



Scaling and Shifting

Theorem Let $X = \mathcal{N}(0, 1)$ and $Y = \mu + \sigma X$. Then

$$Y = \mathscr{N}(\mu, \sigma^2).$$

Proof:
$$f_X(x) = \frac{1}{\sqrt{2\pi}} \exp\{-\frac{x^2}{2}\}$$
. Now,
 $f_Y(y) = \frac{1}{\sigma} f_X(\frac{y-\mu}{\sigma})$
 $= \frac{1}{\sqrt{2\pi\sigma^2}} \exp\{-\frac{(y-\mu)^2}{2\sigma^2}\}$.

Expectation, Variance.

Theorem If
$$Y = \mathcal{N}(\mu, \sigma^2)$$
, then

$$E[Y] = \mu$$
 and $var[Y] = \sigma^2$.

Proof: It suffices to show the result for $X = \mathcal{N}(0, 1)$ since $Y = \mu + \sigma X$,....

Thus,
$$f_X(x) = \frac{1}{\sqrt{2\pi}} \exp\{-\frac{x^2}{2}\}.$$

First note that E[X] = 0, by symmetry.

$$var[X] = E[X^{2}] = \int x^{2} \frac{1}{\sqrt{2\pi}} \exp\{-\frac{x^{2}}{2}\} dx$$

= $-\frac{1}{\sqrt{2\pi}} \int x d \exp\{-\frac{x^{2}}{2}\} = \frac{1}{\sqrt{2\pi}} \int \exp\{-\frac{x^{2}}{2}\} dx$ by IBP¹
= $\int f_{X}(x) dx = 1$. \Box

¹Integration by Parts: $\int_{a}^{b} f dg = [fg]_{a}^{b} - \int_{a}^{b} g df$.

Review: Law of Large Numbers.

Theorem: For any set of independent identically distributed random variables, X_i , $A_n = \frac{1}{n} \sum X_i$ "tends to the mean."

Say X_i have expectation $\mu = E(X_i)$ and variance σ^2 .

Mean of A_n is μ , and variance is σ^2/n .

Thus,

$$\Pr[|A_n - \mu| > \varepsilon] \leq rac{var[A_n]}{\varepsilon^2} = rac{\sigma^2}{n\varepsilon} o 0.$$

Central Limit Theorem

Central Limit Theorem

Let $X_1, X_2, ...$ be i.i.d. with $E[X_1] = \mu$ and $var(X_1) = \sigma^2$. Define $S_n := \frac{A_n - \mu}{\sigma/\sqrt{n}} = \frac{X_1 + \dots + X_n - n\mu}{\sigma\sqrt{n}}.$

Then,

$$S_n \to \mathcal{N}(0,1), \text{as } n \to \infty.$$

That is,

$$Pr[S_n \leq \alpha] \rightarrow \frac{1}{\sqrt{2\pi}} \int_{-\infty}^{\alpha} e^{-x^2/2} dx.$$

Proof: See EE126.

Note:

$$E(S_n) = \frac{1}{\sigma/\sqrt{n}}(E(A_n) - \mu) = 0$$
$$Var(S_n) = \frac{1}{\sigma^2/n} Var(A_n) = 1.$$

CI for Mean

Let X_1, X_2, \ldots be i.i.d. with mean μ and variance σ^2 . Let

$$A_n=\frac{X_1+\cdots+X_n}{n}.$$

The CLT states that

$$\frac{A_n - \mu}{\sigma/\sqrt{n}} = \frac{X_1 + \dots + X_n - n\mu}{\sigma\sqrt{n}} \to \mathscr{N}(0, 1) \text{ as } n \to \infty.$$

Thus, for $n \gg 1$, one has

$$Pr[-2 \leq |rac{A_n-\mu}{\sigma/\sqrt{n}}| \leq 2] \approx 95\%.$$

Equivalently,

$$Pr[\mu \in [A_n - 2\frac{\sigma}{\sqrt{n}}, A_n + 2\frac{\sigma}{\sqrt{n}}]] \approx 95\%.$$

That is,

$$[A_n - 2\frac{\sigma}{\sqrt{n}}, A_n + 2\frac{\sigma}{\sqrt{n}}]$$
 is a 95% – CI for μ .

CI for Mean

Let X_1, X_2, \ldots be i.i.d. with mean μ and variance σ^2 . Let

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The CLT states that

$$\frac{X_1 + \dots + X_n - n\mu}{\sigma\sqrt{n}} \to \mathscr{N}(0,1) \text{ as } n \to \infty.$$

Also,

$$[A_n - 2\frac{\sigma}{\sqrt{n}}, A_n + 2\frac{\sigma}{\sqrt{n}}]$$
 is a 95% – CI for μ .

Recall: Using Chebyshev, we found that

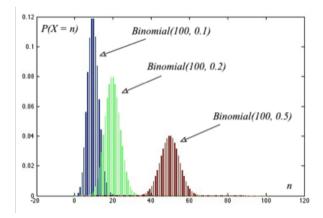
$$[A_n - 4.5 \frac{\sigma}{\sqrt{n}}, A_n + 4.5 \frac{\sigma}{\sqrt{n}}]$$
 is a 95% – CI for μ .

Thus, the CLT provides a smaller confidence interval.

Coins and normal.

Let $X_1, X_2, ...$ be i.i.d. B(p). Thus, $X_1 + \cdots + X_n = B(n, p)$. Here, $\mu = p$ and $\sigma = \sqrt{p(1-p)}$. CLT states that

$$\frac{X_1 + \dots + X_n - np}{\sqrt{p(1-p)n}} \to \mathscr{N}(0,1).$$



Coins and normal.

Let
$$X_1, X_2, ...$$
 be i.i.d. $B(p)$. Thus, $X_1 + \dots + X_n = B(n, p)$.
Here, $\mu = p$ and $\sigma = \sqrt{p(1-p)}$. CLT states that
$$\frac{X_1 + \dots + X_n - np}{\sqrt{p(1-p)n}} \to \mathcal{N}(0, 1)$$

and

$$[A_n - 2\frac{\sigma}{\sqrt{n}}, A_n + 2\frac{\sigma}{\sqrt{n}}]$$
 is a 95% – CI for μ

with $A_n = (X_1 + \cdots + X_n)/n$. Hence,

$$[A_n - 2\frac{\sigma}{\sqrt{n}}, A_n + 2\frac{\sigma}{\sqrt{n}}]$$
 is a 95% – CI for *p*.

Since $\sigma \leq$ 0.5,

$$[A_n - 2\frac{0.5}{\sqrt{n}}, A_n + 2\frac{0.5}{\sqrt{n}}]$$
 is a 95% – CI for *p*.

Thus,

$$[A_n - \frac{1}{\sqrt{n}}, A_n + \frac{1}{\sqrt{n}}]$$
 is a 95% – Cl for *p*.

Application: Polling.

How many people should one poll to estimate the fraction of votes that will go for Trump?

Say we want to estimate that fraction within 3% (margin of error), with 95% confidence.

This means that if the fraction is p, we want an estimate \hat{p} such that

 $Pr[\hat{p} - 0.03$

We choose $\hat{p} = \frac{X_1 + \dots + X_n}{n}$ where $X_m = 1$ if person *m* says she will vote for Trump, 0 otherwise.

We assume X_m are i.i.d. B(p).

Thus, $\hat{p} \pm \frac{1}{\sqrt{n}}$ is a 95%-confidence interval for *p*. We need

$$\frac{1}{\sqrt{n}} = 0.03$$
, i.e., $n = 1112$.

Application: Testing Lightbulbs.

Assume that lightbulbs have i.i.d. $Expo(\lambda)$ lifetimes. We want to make sure that $\lambda^{-1} > 1$. Say that we measure the average lifetime A_n of n = 100 bulbs and we find that it is equal to 1.2.

What is the confidence that we have that $\lambda^{-1} > 1$? We have,

$$\frac{A_n-\lambda^{-1}}{\lambda^{-1}/\sqrt{n}}=\sqrt{n}(\lambda A_n-1)\approx \mathscr{N}(0,1).$$

Thus,

$$\Pr[\sqrt{n}(\lambda A_n - 1) > \sqrt{n}(\lambda 1.2 - 1)] \approx \Pr[\mathcal{N}(0, 1) > \sqrt{n}(\lambda 1.2 - 1)].$$

If $\lambda^{-1} < 1$, this probability is at most $Pr[\mathscr{N}(0,1) > \sqrt{n}(1.2-1)] = Pr[\mathscr{N}(0,1) > 2] = 2.5\%.$

Thus, we conclude that $Pr[\lambda^{-1} > 1] \ge 97.5\%$.

Continuous RV and Bayes' Rule Example 1:

W.p. 1/2, X, Y are i.i.d. Expo(1) and w.p. 1/2, they are i.i.d. Expo(3). Calculate E[Y|X = x].

Let *B* be the event that $X \in [x, x + \delta]$ where $0 < \delta \ll 1$.

Let *A* be the event that X, Y are Expo(1).

Then,

$$Pr[A|B] = \frac{(1/2)Pr[B|A]}{(1/2)Pr[B|A] + (1/2)Pr[B|\overline{A}]} = \frac{\exp\{-x\}\delta}{\exp\{-x\}\delta + 3\exp\{-3x\}\delta}$$
$$= \frac{\exp\{-x\}}{\exp\{-x\} + 3\exp\{-3x\}} = \frac{e^{2x}}{3 + e^{2x}}.$$

Now,

$$E[Y|X = x] = E[Y|A]Pr[A|X = x] + E[Y|\overline{A}]Pr[\overline{A}|X = x]$$

= $1 \times Pr[A|X = x] + (1/3)Pr[\overline{A}|X = x]... = \frac{1 + e^{2x}}{3 + e^{2x}}.$

We used $Pr[Z \in [x, x + \delta]] \approx f_Z(x)\delta$ and given A one has $f_X(x) = \exp\{-x\}$ whereas given A one has $f_X(x) = 3\exp\{-3x\}$.

Continuous RV and Bayes' Rule

Example 2:

W.p. 1/2, Bob is a good dart player and shoots uniformly in a circle with radius 1. Otherwise, Bob is a very good dart player and shoots uniformly in a circle with radius 1/2.

The first dart of Bob is at distance 0.3 from the center of the target.

(a) What is the probability that he is a very good dart player?

(b) What is the expected distance of his second dart to the center of the target?

Note: If uniform in radius r, then $Pr[X \le x] = (\pi x^2)/(\pi r^2)$, so that $f_X(x) = 2x/(r^2)$. (a) We use Bayes' Rule:

$$Pr[VG|0.3] = \frac{Pr[VG]Pr[\approx 0.3|VG]}{Pr[VG]Pr[\approx 0.3|VG] + Pr[G]Pr[\approx 0.3|G]}$$

= $\frac{0.5 \times 2(0.3^2)\varepsilon/(0.5^2)}{0.5 \times 2(0.3^2)\varepsilon/(0.5^2) + 0.5 \times 2\varepsilon(0.3^2)} = 0.8.$

(b) $E[X] = 0.8 \times 0.5 \times \frac{2}{3} + 0.2 \times \frac{2}{3} = 0.4.$

Summary

Gaussian and CLT

1. Gaussian: $\mathcal{N}(\mu, \sigma^2)$: $f_X(x) = ...$ "bell curve" 2. CLT: X_n i.i.d. $\implies \frac{A_n - \mu}{\sigma/\sqrt{n}} \rightarrow \mathcal{N}(0, 1)$ 3. Cl: $[A_n - 2\frac{\sigma}{\sqrt{n}}, A_n + 2\frac{\sigma}{\sqrt{n}}] = 95\%$ -Cl for μ . 4. Bayes' Rule: Replace $\{X = x\}$ by $\{X \in (x, x + \varepsilon)\}$.