

Cont: x can be any value in range, uncountably infinite. If diff of neighbour vals similar, consider cont.

Need to consider intervals of x for a probability.

$P(-\infty < X < \infty) = 1$, < same as <=, > same as >=

Mode(X) = $\arg\max_x f_X(x)$

$$H(X) = - \int_x f_X(x) \log[f_X(x)] dx.$$

Entropy:

Entropy can be negative for cont.

Mean:

$$E(X) = \int_x x f_X(x) dx.$$

Variance:

$$\text{Var}(X) = E[(X - \mu_X)^2] = \int_x (x - \mu_X)^2 f_X(x) dx.$$

Median: AuC = 0.5, its empirically-based definition is the "middle value" after sorting the outcomes from the smallest to the largest value. Probably best for single decision for random outcome.

Quantile: Q(p) where $P(X \leq Q(p)) = p$

Prediction interval: lower = $Q((1-p)/2)$, upper = $Q((1+p)/2)$

$$\text{Skewness}(X) = E\left[\left(\frac{X - \mu_X}{\sigma_X}\right)^3\right] = \int_x \left(\frac{x - \mu_X}{\sigma_X}\right)^3 \cdot f_X(x) dx.$$

Skewness:

	Left (negative skew)	Symmetric (0 skew)	Right (positive skew)
Typical dist:	mean < med < mode	All same	Mode < med < mean

$$F_X(x) = \int_{-\infty}^x f_X(t) dt.$$

PDF: $f_X(x)$, CDF: $F_X(x) = P(X \leq x)$

CDF has no units, PDF has units 1 / units of x

CDF strictly increasing, must be between 0 & 1, $x \rightarrow -\infty$, CDF $\rightarrow 0$, vice-versa

Survival: $S_X(x) = P(X > x) = 1 - F_X(x)$, prob of surviving after x. CDF upside down

Quantile: $Q(p) = F^{-1}(p)$ for $0 \leq p \leq 1$. Inverse of CDF.

$X \sim \text{Unif}(a, b)$, PDF = $1 / (b - a)$, mean = $(a + b) / 2$, var = $(b - a)^2 / 12$ $a \leq x \leq b$

$$f_X(x | \mu, \sigma^2) = \frac{1}{\sqrt{2\pi\sigma^2}} \exp\left[-\frac{(x - \mu)^2}{2\sigma^2}\right]$$

$X \sim \text{Norm}(\mu, \text{var})$, PDF =

Mean = μ , Var = var $-\infty < x < \infty$

$X \sim \text{Log-Norm}(\mu, \text{var})$, pdf same but $\log(x)$, $\mu = e^{\mu + \text{var}/2}$ $x \geq 0$

$$\text{Var} = \exp[2(\mu + \sigma^2)] - \exp(2\mu + \sigma^2).$$

$X \sim \text{Exp}(\lambda)$, PDF = $\lambda \cdot e^{-\lambda x}$ $x \geq 0$, wait time for event, memoryless meaning regardless of how much time has passed, same dist
mean = $1/\lambda$, var = $1/\lambda^2$ NOTE: $\lambda = 1 / \text{beta}$ (rate vs. wait time)

$X \sim \text{Beta}(\alpha, \beta)$, PDF = $\text{dbeta}(x, \alpha, \beta)$ - support between 0 and 1.

$$\text{Var}(X) = \frac{\alpha\beta}{(\alpha + \beta)^2(\alpha + \beta + 1)}.$$

Mean = $\alpha / (\alpha + \beta)$, Var =

$$f_X(x | \lambda, k) = \frac{k}{\lambda} \left(\frac{x}{\lambda}\right)^{k-1} \exp^{-(x/\lambda)^k}$$

$X \sim \text{Weibull}(\lambda, k)$, PDF = $x \geq 0$

Event more likely the longer you wait, time until event.

$$E(X) = \lambda \Gamma\left(1 + \frac{1}{k}\right).$$

Mean =

$$\text{Var}(X) = \lambda^2 \left[\Gamma\left(1 + \frac{2}{k}\right) - \Gamma^2\left(1 + \frac{1}{k}\right) \right].$$

, Var =

$$f_X(x | k, \theta) = \frac{1}{\Gamma(k)\theta^k} x^{k-1} \exp(-x/\theta)$$

$X \sim \text{Gamma}(k, \theta)$, PDF = $x \geq 0$

Mean = $k \cdot \theta$, Var = $k \cdot \theta^2$

Bivariate case: $f_{X,Y}(x, y)$ compute volume under density surface

Identify surface area, determine probability for event

For conditional, $P(A) = 0$ then use density instead of probability.

$f_{X|X \geq 2500}(x) = 0$ for $x < 2500$

When $P(B) = 0$, can use general formula

$f_{Y|X}(y) = (f_{Y,X}(y, x)) / (f_X(x))$

If x and y indep, multiply indivi. Marginal probs.

RS: collection of RV's/outcomes, iid

MLE: estimate pop. parameters, relies on n obs from pop.

Given data and some family, finds values of params that fit data the best.

Since iid, multiply each indiv. Pdf which is also likelihood since equiv.

Use $d^*(\cdot)$ to compute values of potential dist.

We take log since the likelihood can be extremely small. Empirical solution

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Ex: exp_values <- tibble(
  possible_betas = seq(5, 50, 0.5),
  likelihood = map_dbl(1 / possible_betas, ~ prod(dexp(sample_n30$values, .))),
  log_likelihood = map_dbl(1 / possible_betas, ~
    log(prod(dexp(sample_n30$values, .))))))
```

Deterministic: certain outcome, stochastic is opposite

$\text{set.seed}(\#)$, $\text{np.random.seed}(\#)$

$\text{sample}(\text{outcomes}, \text{size} = n, \text{replace} = \text{TRUE}, \text{prob} = \text{probs})$

$\text{np.random.choice}(a = \text{outcomes}, \text{size} = n, p = \text{probs})$

$r^*(\cdot)$ vs $\text{scipy.stats.dist.rvs}()$

Sample mean = $\text{sum}(\text{obs}) / n$, Sample var = $\text{sum}(\text{obs} - \text{mean}) / (n - 1)$

For PMF, use $\text{table}()$ or $\text{tapply}()$

Theoretical: use formula, Empirical: use built-in functions (mean, sd, var etc...)

LLN: as n go up, empirical mean approaches true mean we estimating.

iid if 1. Each pair of observations are independent, and

2. each observation comes from the same distribution.

Assuming no additional sampling assumptions.