STATS 100A: RANDOM VARIABLES

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Some pictures are taken from the internet.
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Connection to events:
Randomly sample a person ω from a population Ω.
$X(\omega)$: gender of ω, $\Omega \to \{0, 1\}$.
$Y(\omega)$: height of ω, $\Omega \to \mathbb{R}^+$.
$A = \{\omega : X(\omega) = 1\}$. $P(A) = P(X = 1)$. Discrete.
$B = \{\omega : Y(\omega) > 6\}$. $P(B) = P(Y > 6)$. Continuous.
We shall study random variables more systematically.

Discrete random variables

Roll a die

x	1	2	3	4	5	6
p(x)	$\frac{1}{6}$	$\frac{1}{6}$	$\frac{1}{6}$	$\frac{1}{6}$	$\frac{1}{6}$	$\frac{1}{6}$

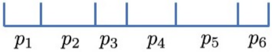
$$p(x) = P(X = x).$$

Capital letter: random variable
Lower case: particular value, running variable

$$X \sim p(x).$$

Probability distribution

Biased die:
Randomly throw a point into [0, 1], which bin (1, 2, ..., 6) it falls into?
Throw 1 million points, what is the proportion of points in each bin? Or how often the points fall into each bin?



Probability distribution

Biased die:

x	1	2	3	4	5	6
p(x)	0.1	0.2	0.1	0.2	0.1	0.3
	10%	*20%*	*10%*	*20%*	*10%*	*30%*

$$p(x) = P(X = x).$$

$p(x)$: how often $X = x$.
$p(x)$: probability mass function, probability distribution, law
$\sum_x p(x) = 1$.
$P(X \in \{5, 6\}) = p(5) + p(6)$.
$P(X \in [a, b]) = \sum_{x \in [a,b]} p(x)$.

Expectation

Biased die

x	1	2	3	4	5	6
p(x)	0.1	0.1	0.2	0.2	0.1	0.3

x	1	2	3	4	5	6
#	0.1m	0.1m	0.2m	0.2m	0.1m	0.3m
%	*10%*	*10%*	*20%*	*20%*	*10%*	*30%*

$$average = \frac{(1\times 0.1m + 2\times 0.1m + 3\times 0.2m + 4\times 0.2m + 5\times 0.1m + 6\times 0.3m)}{1m}$$

$$\mathbb{E}(X) = \sum_x x p(x).$$

Expectation

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Discrete

Continuous

Movie

Biased die

x	1	2	3	4	5	6
p(x)	0.1	0.1	0.2	0.2	0.1	0.3

x	1	2	3	4	5	6
#	0.1m	0.1m	0.2m	0.2m	0.1m	0.3m
%	*10%*	*10%*	*20%*	*20%*	*10%*	*30%*

$$average = \frac{(1\times 0.1m + 2\times 0.1m + 3\times 0.2m + 4\times 0.2m + 5\times 0.1m + 6\times 0.3m)}{1m}$$

x	1	2	3	4	5	6	x
payoff	-\$30	-\$20	\$0	\$20	\$30	\$100	h(x)
	h(1)	*h(2)*	*h(3)*	*h(4)*	*h(5)*	*h(6)*	

longrun average = (-\$30)×0.1 + (-\$20) ×0.1 + (\$0)×0.2 + (\$20)×0.2 + (\$30)×0.1 + (\$100)×0.3

$$\mathbb{E}(h(X)) = \sum_x h(x)p(x).$$

Utility, reward, value

$$\mathbb{E}(h(X)) = \sum_x h(x)p(x).$$

Offer 1	
x	\$100
p(x)	1

$E(X) = (\$100)\times 1 = \$100$

Offer 2		
x	\$0	\$200
p(x)	1/2	1/2

$E(X) = (\$0)\times\frac{1}{2} + (\$200)\times\frac{1}{2} = \$100$

x: face value	\$0	\$100	\$200
h(x): perceived value	\$0	\$100	\$150

Offer 1: $E(h(X)) = (\$100)\times 1 = \$100$ ← Risk Averse

Offer 2: $E(h(X)) = (\$0)\times\frac{1}{2} + (\$150)\times\frac{1}{2} = \$75$ ← Risk Taking

Variance

$$\mathbb{E}(X) = \sum_x xp(x) = \mu (= \$0 \times 1/2 + \$200 \times 1/2 = \$100)$$

$$\begin{aligned}\text{Var}(X) = \mathbb{E}[(X-\mu)^2] = \sum_x (x-\mu)^2 p(x) = \sigma^2 \\ = (\$0 - \$100)^2 \times 1/2 + (\$200 - \$100)^2 \times 1/2 \\ = \$^2 10,000.\end{aligned}$$

Long run average of squared deviation from the mean.

$$SD(X) = \sqrt{\text{Var}(X)} = \sigma (= \$100).$$

Extent of variation from the mean.

Variance

x	1	2	3	4	5	6	*x*
payoff	-\$30	-\$20	\$0	\$20	\$30	\$100	h(*x*)
	h(1)	*h(2)*	*h(3)*	*h(4)*	*h(5)*	*h(6)*	

longrun average = (-\$30)×0.1 + (-\$20) ×0.1 + (\$0)×0.2 + (\$20)×0.2 + (\$30)×0.1 + (\$100)×0.3

$$\mathbb{E}(h(X)) = \sum_x h(x)p(x).$$

$$\text{Var}[h(X)] = \mathbb{E}[(h(X) - \mathbb{E}(h(X)))^2].$$

Variance

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Discrete

Continuous

Movie

$$\mathbb{E}(X) = \sum_x x p(x) = \mu.$$

$$\text{Var}(X) = \mathbb{E}[(X-\mu)^2] = \sum_x (x-\mu)^2 p(x) = \sigma^2.$$

Long run average of squared deviation from the mean.
Sampling $p(x) \to x_1, ..., x_i, ..., x_n$
(e.g., rolling a die $\to$ 2, 1, 6, 5, 3, 2, 5, 4, 3, ...)

$$\bar{x} = \frac{1}{n}\sum_{i=1}^{n} x_i \to \mathbb{E}(X) = \mu.$$

$$s^2 = \frac{1}{n}\sum_{i=1}^{n} (x_i - \bar{x})^2 \to \text{Var}(X) = \sigma^2$$

Linear transformation

$$\mathbb{E}(h(X)) = \sum_x h(x)p(x).$$

$$Y = aX + b.$$

$$\begin{aligned}
\mathbb{E}(Y) &= \mathbb{E}(aX + b) \\
&= \sum_x (ax + b)p(x) \\
&= \sum_x axp(x) + \sum_x bp(x) \\
&= a\sum_x xp(x) + b\sum_x p(x) \\
&= a\mathbb{E}(X) + b.
\end{aligned}$$

Linear transformation

Sampling $p(x) \to x_1, ..., x_i, ..., x_n$
(e.g., rolling a die $\to$ 2, 1, 6, 5, 3, 2, 5, 4, 3, ...)

$$y_i = a x_i + b.$$

$$\bar{x} = \frac{1}{n} \sum_{i=1}^{n} x_i \to \mathbb{E}(X) = \mu.$$

$$\bar{y} = \frac{1}{n} \sum_{i=1}^{n} y_i = \frac{1}{n} \sum_{i=1}^{n} (a x_i + b) = a \frac{1}{n} \sum_{i=1}^{n} x_i + b = a\bar{x} + b.$$

Linear transformation

$$\mathrm{Var}(h(X)) = \mathbb{E}[(h(X) - \mathbb{E}(h(X)))^2].$$

$$\mathrm{Var}(Y) = \mathbb{E}[(Y - \mathbb{E}(Y))^2].$$

$$\mathbb{E}(Y) = a\mathbb{E}(X) + b.$$

$$\begin{aligned}
\mathrm{Var}(aX + b) &= \mathbb{E}[((aX + b) - \mathbb{E}(aX + b))^2] \\
&= \mathbb{E}[(aX + b - (a\mathbb{E}(X) + b))^2] \\
&= \mathbb{E}[(a(X - \mathbb{E}(X)))^2] \\
&= a^2\mathbb{E}[(X - \mathbb{E}(X))^2] = a^2\mathrm{Var}(X).
\end{aligned}$$

Linear transformation

Sampling $p(x) \to x_1, ..., x_i, ..., x_n$
(e.g., rolling a die → 2, 1, 6, 5, 3, 2, 5, 4, 3, ...)

$$\bar{x} = \frac{1}{n}\sum_{i=1}^{n} x_i \to \mathbb{E}(X) = \mu.$$

$$y_i = ax_i + b.$$

$$\bar{y} = \frac{1}{n}\sum_{i=1}^{n}(ax_i + b) = a\frac{1}{n}\sum_{i=1}^{n} x_i + b = a\bar{x} + b.$$

$$\frac{1}{n}\sum_{i=1}^{n}(y_i - \bar{y})^2 = \frac{1}{n}\sum_{i=1}^{n}(ax_i + b - (a\bar{x} + b))^2 = \frac{1}{n}\sum_{i=1}^{n} a^2(x_i - \bar{x})^2.$$

Variance

$$\mu = \mathbb{E}(X).$$

$$\begin{aligned}
\mathrm{Var}(X) &= \mathbb{E}[(X-\mu)^2] \\
&= \mathbb{E}[X^2 - 2\mu X + \mu^2] \\
&= \mathbb{E}(X^2) - 2\mu\mathbb{E}(X) + \mu^2 \\
&= \mathbb{E}(X^2) - \mu^2 = \mathbb{E}(X^2) - [\mathbb{E}(X)]^2.
\end{aligned}$$

$$\begin{aligned}
\mathbb{E}[h(X)+g(X)] &= \sum_x [h(x)+g(x)]p(x) \\
&= \sum_x h(x)p(x) + \sum_x g(x)p(x) \\
&= \mathbb{E}[h(X)] + \mathbb{E}[g(X)].
\end{aligned}$$

Transformation

$$h(x) = ax + b.$$

$$\mathbb{E}[h(X)] = \mathbb{E}(aX + b) = a\mathbb{E}(X) + b = h(\mathbb{E}(X)).$$

$$\mathrm{Var}(X) = \mathbb{E}(X^2) - [\mathbb{E}(X)]^2.$$

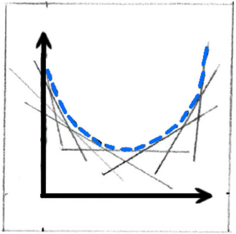
$$h(x) = x^2.$$

$$\mathbb{E}[h(X)] = \mathbb{E}(X^2);$$

$$h(\mathbb{E}(X)) = [\mathbb{E}(X)]^2.$$

Convex function

Upper envelop and supporting lines

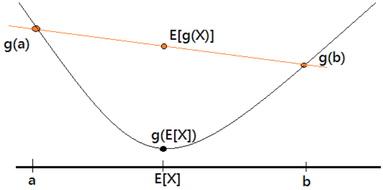


$$g(x) \geq a_0 x + b_0;\ g(x_0) = a_0 x_0 + b_0.$$

Supporting line at x_0 touches $g(x)$ at x_0, but below $g(x)$ at other places.

Jensen inequality

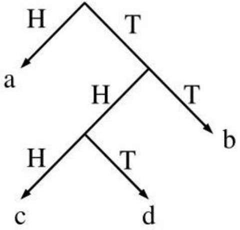
$P(X = a) = P(X = b) = 1/2.$
$\mathbb{E}(X) = (a + b)/2,\ g(\mathbb{E}(X)) = g((a + b/2).$
$\mathbb{E}(g(X)) = (g(a) + g(b))/2.$
$\mathbb{E}(g(X)) \geq g(\mathbb{E}(X)).$



$x_0 = \mathbb{E}(X).$
$g(x_0) = a_0x_0 + b_0$ (supporting line at x_0)
$g(x) \geq a_0x + b_0.$
$\mathbb{E}(g(X)) \geq \mathbb{E}(a_0X+b_0) = a_0\mathbb{E}(X)+b_0 = a_0x_0+b_0 = g(\mathbb{E}(X)).$

Entropy

	a	b	c	d
Pr	1/2	1/4	1/8	1/8
flips	*H*	*TT*	*THH*	*THT*



Coin flippings

Ω	a	b	c	d
Pr	1/2	1/4	1/8	1/8
$-\log p$	1	2	3	3

$$H(X) = \frac{1}{2}\times 1 + \frac{1}{4}\times 2 + \frac{1}{8}\times 3 + \frac{1}{8}\times 3 = \frac{7}{4}\,\mathbf{flips}$$

	a	b	c	d
Pr	1/2	1/4	1/8	1/8
flips	H	TT	THH	THT

Prefix code

	a	b	c	d
Pr	1/2	1/4	1/8	1/8
code	1	00	011	010

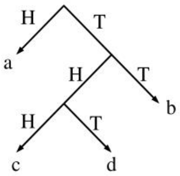
100101100010→abacbd

$$\mathbf{E}[l(X)] = \sum_x l(x)p(x) = 1\times\frac{1}{2} + 2\times\frac{1}{4} + 3\times\frac{1}{8} + 3\times\frac{1}{8} = \frac{7}{4}\,\textbf{bits}$$

Coding

Optimal code

	a	b	c	d
Pr	1/2	1/4	1/8	1/8
code	1	00	011	010



100101100010→abacbd

Sequence of coin flipping
A completely random sequence
Cannot be further compressed

$$l(x) = -\log p(x)$$

$$\mathbf{E}[l(X)] = H(p)$$

e.g., two words I, probability

Bernoulli

Flip a coin (probability of head is p)
$Z \sim \text{Bernoulli}(p)$
$Z \in \{0, 1\}$, $P(Z = 1) = p$ and $P(Z = 0) = 1 - p$.

$$\mathbb{E}(Z) = 0 \times (1 - p) + 1 \times p = p.$$

$$\begin{aligned} \text{Var}(Z) &= (0 - p)^2 \times (1 - p) + (1 - p)^2 \times p \\ &= p(1 - p)[p + (1 - p)] = p(1 - p). \end{aligned}$$

$$\mathbb{E}(Z^2) = p.$$

$$\text{Var}(Z) = \mathbb{E}(Z^2) - \mathbb{E}(Z)^2 = p - p^2 = p(1 - p).$$

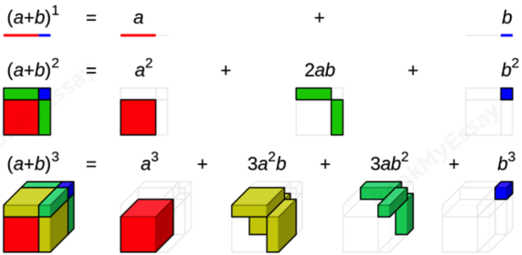
Binomial

Flip a coin (probability of head is p) n times independently.
X = number of heads.
$X \sim \text{Binomial}(n, p)$

$$P(X = k) = \binom{n}{k} p^k (1-p)^{n-k}.$$

$\binom{n}{k}$ is the number of sequences with exactly k heads.
$p^k(1-p)^{n-k}$ is the probability of each sequence with exactly k heads.
e.g., $n = 3$,
$P(X = 2) = P(HHT) + P(HTH) + P(THH) = 3p^2(1-p)$.
$p = 1/2$, we have $P(X = k) = \binom{n}{k}/2^n$.

Binomial



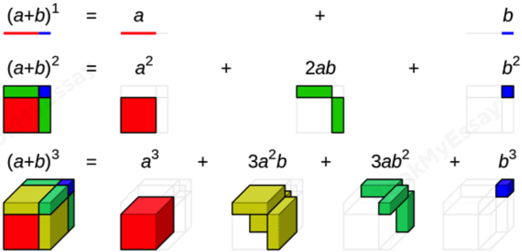
$$(p+q)^n = \sum_{k=0}^{n} \binom{n}{k} p^k q^{n-k}.$$

Let $a = p$, $b = q = 1 - p$. Randomly throw a point into unit cube.

Each rectangular piece corresponds to a particular sequence.

Each color corresponds to a particular number of heads.

Binomial



Let $a = p$, $b = q = 1 - p$.
$n = 2$, $P(X = 2) = P(HH) = p^2$.
$P(X = 0) = P(TT) = (1 - p)^2$.
$P(X = 1) = P(HT) + P(TH) = 2p(1 - p)$.
$n = 3$, $P(X = 3) = P(HHH) = p^3$.
$P(X = 2) = P(HHT) + P(HTH) + P(THH) = 3p^2(1 - p)$.

Binomial

$$X = Z_1 + Z_2 + ... + Z_n,$$

where $Z_i \sim \text{Bernoulli}(p)$ independently.

$$\mathbb{E}(X) = \sum_{i=1}^{n} \mathbb{E}(Z_i) = np.$$

Due to independence of Z_i, $i = 1, ..., n$,

$$\text{Var}(X) = \sum_{i=1}^{n} \text{Var}(Z_i) = np(1-p).$$

Binomial

X/n is the frequency of heads.

$$\mathbb{E}(X/n) = \mathbb{E}(X)/n = p.$$

$$\mathrm{Var}(X/n) = \mathrm{Var}(X)/n^2 = p(1-p)/n.$$

$\mathrm{Var}(X/n) \to 0$ as $n \to \infty$.

$$X/n \to p, \text{ in probability}$$

Law of large number
Probability = long run frequency

Law of large number

Probability = long run frequency
Flip a fair coin independently $\to 2^n$ sequences, Ω.

$$A_\epsilon = \{\omega : X(\omega)/n \in (1/2 - \epsilon, 1/2 + \epsilon)\},$$

the set of sequences whose frequencies of heads are close to 1/2.

$$P(X/n \in (1/2 - \epsilon, 1/2 + \epsilon)) = \frac{|A_\epsilon|}{|\Omega|} \to 1.$$

Almost all the sequences have frequencies of heads close to 1/2.
e.g., $n = 1$ million. Almost all the $2^{1 \text{ million}}$ sequences have frequencies of heads to be within [.49, .51].

Law of large number

e.g., $n = 1$ million. Almost all the $2^{\text{1 million}}$ sequences have frequencies of heads to be within [.49, .51].

$$P(X/1m \in [.49, .51]) = P(X \in [.49m, .51m]) = \sum_{k=.49m}^{.51m} \binom{1m}{k} / 2^{1m}.$$

Binomial

$$\mathbb{E}(X) = \sum_{k=0}^{n} kP(X = k)$$
$$= \sum_{k=0}^{n} k \frac{n!}{k!(n-k)!} p^k (1-p)^{n-k}$$
$$= \sum_{k=1}^{n} np \frac{(n-1)!}{(k-1)!(n-k)!} p^{k-1} (1-p)^{n-k}$$
$$= \sum_{k'=0}^{n'} np \binom{n'}{k'} p^{k'} (1-p)^{n'-k'} = np.$$

$$k' = k - 1; \; n' = n - 1.$$

Binomial

$$
\begin{aligned}
\mathbb{E}(X(X-1)) &= \sum_{k=0}^{n} k(k-1)P(X=k) \\
&= \sum_{k=0}^{n} k(k-1)\frac{n!}{k!(n-k)!}p^k(1-p)^{n-k} \\
&= \sum_{k=2}^{n} n(n-1)p^2\frac{(n-2)!}{(k-2)!(n-k)!}p^{k-2}(1-p)^{n-k} \\
&= \sum_{k'=0}^{n'} n(n-1)p^2\binom{n'}{k'}p^{k'}(1-p)^{n'-k'} \\
&= n(n-1)p^2.
\end{aligned}
$$

$$k' = k-2;\ n' = n-2.$$

Binomial

$$\mathbb{E}(X) = np.$$

$$\mathbb{E}(X(X-1)) = \mathbb{E}(X^2) - \mathbb{E}(X) = n(n-1)p^2.$$

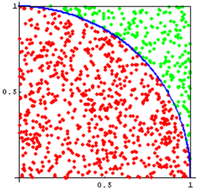
$$\begin{aligned}\mathrm{Var}(X) &= \mathbb{E}(X^2) - \mathbb{E}(X)^2 \\ &= n(n-1)p^2 + np - (np)^2 \\ &= np - np^2 = np(1-p).\end{aligned}$$

Binomial

A box with R red balls and B blue balls. $N = R + B$ balls in total.
Randomly pick a ball. $P(red) = R/N = p$.
Randomly pick n balls sequentially (with replacement, put the picked ball back). Let $X =$ number of red balls.
The distribution of X:
$X \sim \text{Binomial}(n, p = R/N)$.

Binomial

Randomly throw n points into the unit square. Let m be the number of points falling below the curve.



The distribution of m is:
$m \sim \mathrm{Binomial}(n, p = \pi/4)$.

Geometric

$T \sim \text{Geometric}(p)$
T is the number of flips to get the first head, if we flip a coin independently and the probability of getting a head in each flip is p.

$$P(T = k) = (1-p)^{k-1}p.$$

e.g., $T = 1$, H
$T = 2$, TH.
$T = 3$, TTH.
$T = 4$, $TTTH$.
Waiting time.

Geometric

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Discrete

Continuous

Movie

$T \sim \text{Geometric}(p)$

$$
\begin{aligned}
\mathbb{E}(T) &= \sum_{k=1}^{\infty} kP(T=k) \\
&= \sum_{k=1}^{\infty} kq^{k-1}p = p\sum_{k=1}^{\infty} \frac{d}{dq}q^k \\
&= p\frac{d}{dq}\sum_{k=1}^{\infty} q^k = p\frac{d}{dq}\left(\frac{1}{1-q} - 1\right) \\
&= p\frac{1}{(1-q)^2} = \frac{1}{p}.
\end{aligned}
$$

Geometric

$$\begin{aligned}(1-a)(1+a+...+a^m) &= 1+a+...+a_m \\ &\quad -(a+a^2+...+a^m+a^{m+1}) \\ &= 1-a^{m+1}.\end{aligned}$$

$$1+a+...+a^m = \frac{1-a^{m+1}}{1-a}.$$

If $|a|<1$,

$$a^{m+1} \to 0, \ as \ m \to \infty.$$

Continuous random variable

Recall discrete (e.g., gender)

$$P(X = x) = p(x).$$

Continuous (e.g., height)

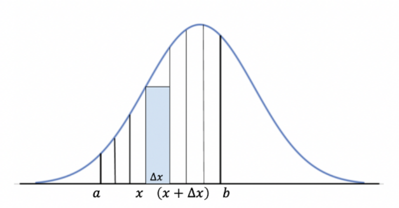
$$P(X \in (x, x + \Delta x)) \doteq f(x)\Delta x,$$

e.g., (6 ft, 6 ft 1 inch).

$$f(x) = \lim_{\Delta x \to 0} \frac{P(X \in (x, x + \Delta x))}{\Delta x}.$$

$f(x)$: probability density function
$X \sim f(x)$.

Probability density function



$$\int_{-\infty}^{\infty} f(x)dx = 1$$

$$P\big(X\epsilon(a,b)\big) = \sum_{X\epsilon(a,b)} f(x)\Delta x \xrightarrow{\Delta x=0} \int_a^b f(x)dx$$

Probability density function

Recall discrete

$$P(X = x) = p(x).$$

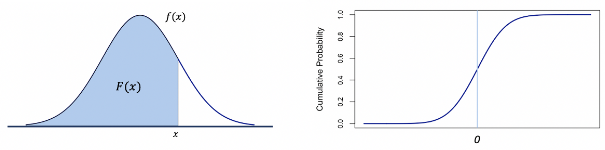
$$P(X \in [a,b]) = \sum_{x \in [a,b]} p(x).$$

Continuous

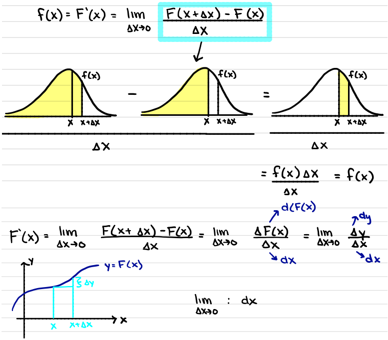
$$P(X \in (x, x+\Delta x)) \doteq f(x)\Delta x,$$

$$\begin{aligned} P(X \in [a,b]) &= \sum_{x \in [a,b]} P(X \in (x, x+\Delta x)) \\ &\doteq \sum_{a}^{b} f(x)\Delta x \doteq \int_a^b f(x)dx. \end{aligned}$$

Cumulative density function



Area and slope

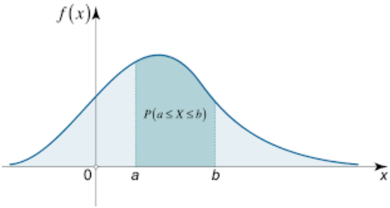


$$F(x) = \int_{-\infty}^{x} f(x)dx.$$

$$F'(x) = \frac{dF(x)}{dx} = \frac{d}{dx}F(x) = f(x).$$

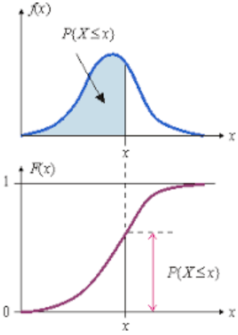
$$dF(x) = F'(x)dx = f(x)dx$$

Integral



$$\int_a^b f(x)dx = F(b) - F(a).$$

cdf vs pdf



Expectation

100A

Ying Nian Wu

Discrete

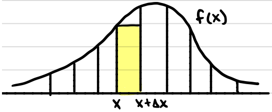
Continuous

Movie

Recall discrete:

how often $X = x$

$$E(X) = \sum_x x\, p(X = x) = \sum_x x\, p(x)$$



Continuous:

how often $X \in (x, x+\Delta x)$

$$E(X) = \boxed{\sum_x x\, p(X \in (x, x+\Delta x))} = \underset{\text{(sum over bins)}}{\sum_x} x\, f(x)\, \Delta x \xrightarrow[0]{\Delta x} \int x f(x)\, dx$$

$$E(X) = \int x f(x) dx$$

$$E(h(X)) = \underset{\text{(bins)}}{\sum_x} h(x)\, P(X \in (x, x+\Delta x))$$

$$\mathrm{Var}(X) = E((X - \boxed{E(X)}^{\,\mu})^2) = \int \overbrace{(x-\mu)^2}^{h(x)} f(x)\, dx = E(X^2) - E(X)^2$$

Expectation

100A

Ying Nian Wu

Discrete

Continuous

Movie

$$
\begin{aligned}
\mathbb{E}(X) &= \sum_x x P(X \in (x, x+\Delta x)) \\
&\doteq \sum_x x f(x) \Delta x \doteq \int x f(x) dx.
\end{aligned}
$$

$$\mathbb{E}(h(X)) = \sum_x h(x) f(x) \Delta x \doteq \int h(x) f(x) dx.$$

Let $X_i \sim f(x)$ independently for $i = 1, ..., n$. Then

$$\frac{1}{n} \sum_{i=1}^{n} X_i \to \mathbb{E}(X).$$

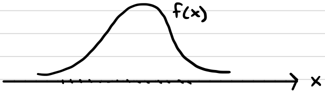
Population or large sample

Continuous R.V.

$X \sim f(x)$ prob. density fxn

A large population $X(\omega)$ $\omega \in \Omega$

A large sample $X_1, X_2 \cdots X_n$ large n



1 million points

$$f(x) = \frac{\text{\# of points in millions in } (x, x+\Delta x)}{\Delta x}$$

$$= \frac{P(X \in (x, x+\Delta x))}{\Delta x}$$

e.g., population density at LA = f(LA) = proportion of people in LA/area of LA.

Population or large sample

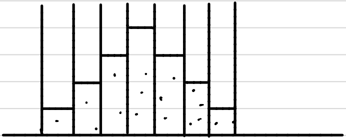
100A

Ying Nian Wu

Discrete

Continuous

Movie

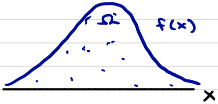


Continuous : $P(X \in (x, x+\Delta x)) = f(x)\Delta x$

vs. Discrete: $P(X = x) = p(x)$

Area under curve

Thought Experiment:



Randomly take x-coordinate point into Ω

Continuous : $P(X \in (x, x+\Delta x)) = f(x)\,\Delta x$

vs. Discrete: $P(X = x) = p(x)$

Population or large sample

Count Large Population:

$\{X(\omega),\ \omega \in \Omega\}$ or large sample $X_1, X_2, \ldots, X_n \sim f(x)$

Scatter Plot:

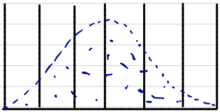
Density

$$\boxed{f(x) = \frac{\#\text{ of points (in millions)}}{\Delta x}}$$

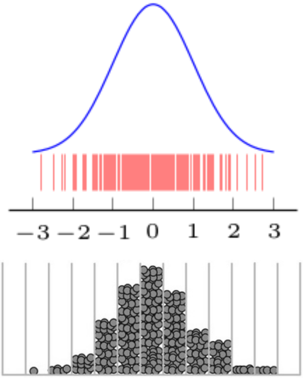
$$\frac{1}{n}\sum_{i=1}^{n} X_i = \sum_{\substack{x \\ \text{(bins)}}} x \cdot \underbrace{\text{number of points in } \frac{(x,\, x+\Delta x)}{n}}_{f(x)\cdot\Delta x}$$

$$= \int x f(x)\,dx$$

$$= E(x)$$

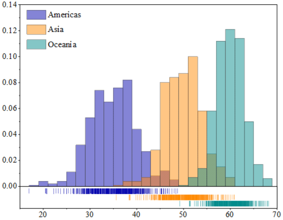


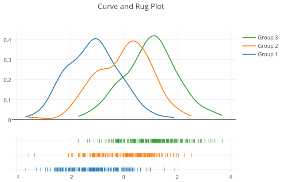
Population or large sample



$$P(X \in (x, x + \Delta x)) = f(x)\Delta x.$$
$$f(x) = P(X \in (x, x + \Delta x))/\Delta x.$$

Population or large sample





$$P(X \in (x, x+\Delta x)) = f(x)\Delta x.$$
$$f(x) = P(X \in (x, x+\Delta x))/\Delta x.$$

Population or large sample

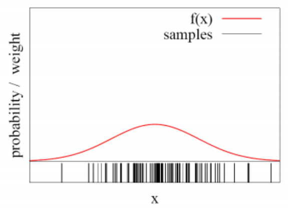
100A

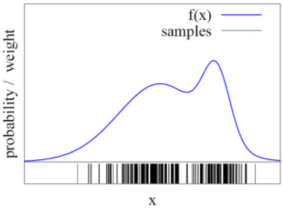
Ying Nian Wu

Discrete

Continuous

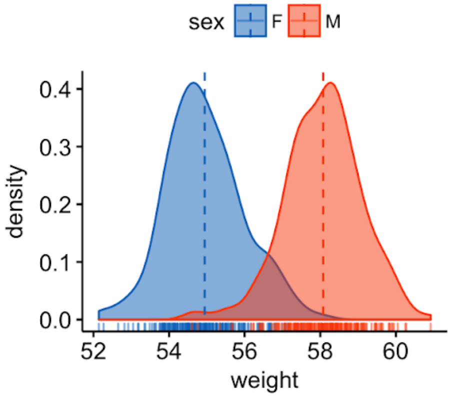
Movie





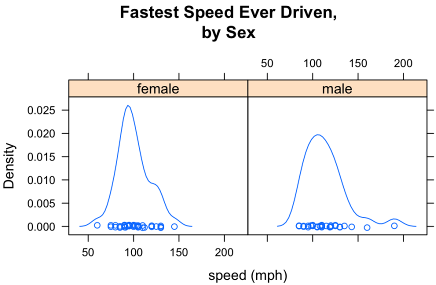
$$P(X \in (x, x + \Delta x)) = f(x)\Delta x.$$
$$f(x) = P(X \in (x, x + \Delta x))/\Delta x.$$

Population or large sample



$$P(X \in (x, x + \Delta x)) = f(x)\Delta x.$$
$$f(x) = P(X \in (x, x + \Delta x))/\Delta x.$$

Population or large sample

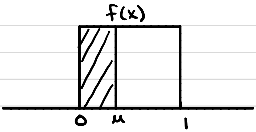


$$P(X \in (x, x + \Delta x)) = f(x)\Delta x.$$
$$f(x) = P(X \in (x, x + \Delta x))/\Delta x.$$

Uniform

$$U \sim \underset{\text{uniform}}{\text{Unif}}\,[0,1]$$

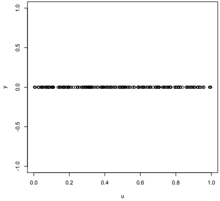
$$f(u) = \begin{cases} 1 & u \in [0,1] \\ 0 & u \notin [0,1] \end{cases}$$



$$F(u) = \begin{cases} 0 & u < 0 \\ u & u \in [0,1] \\ 1 & u > 1 \end{cases} \longrightarrow \boxed{P(U \le u) = u}$$

Uniform

$U \sim \text{Uniform}[0, 1]$, i.e., the density of U is
$f(u) = 1$ for $u \in [0, 1]$,
$f(u) = 0$ otherwise.



$P(U \in (u, u + \Delta u)) = f(u)\Delta u = \Delta u.$
Imagine 1 million points distributed uniformly in [0, 1].
Number of points in $(u, u + \Delta u)$ is Δu million.
e.g., Number of points in $(.3, .31)$ is $.01$ million.

Uniform

$$F(u) = P(U \leq u) = \begin{cases} 0 & 0 < u \\ u & 0 \leq u \leq 1 \\ 1 & u > 1 \end{cases}$$

$F(u)$: proportion of points below u.

$$\mathbb{E}(U) = \int_0^1 u f(u) du = \frac{1}{2}.$$

$$\mathbb{E}(U^2) = \int_0^1 u^2 f(u) du = \frac{1}{3}.$$

$$\mathrm{Var}(U) = \mathbb{E}(U^2) - (\mathbb{E}(U))^2 = \frac{1}{3} - \frac{1}{4} = \frac{1}{12}.$$

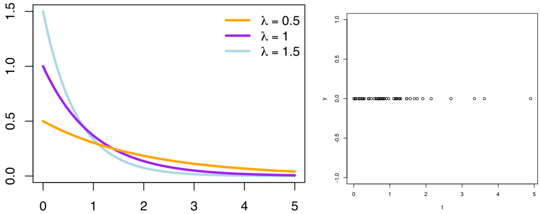
Pseudo-random number generator

Start from an integer X_0, and iterate

$$X_{t+1} = aX_t + b \bmod M.$$

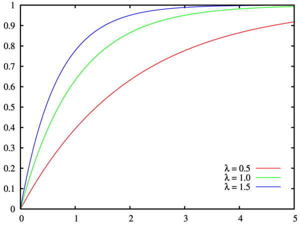
Output $U_t = X_t/M$. e.g., $a = 7^5$, $b = 0$, and $M = 2^{31} - 1$.
mod: divide and take the remainder, e.g., 7 = 2 mod 5.
e.g., $a = 7$, $b = 1$, $M = 5$, $X_0 = 1$, then
$X_1 = 1 \times 7 + 1$ mod 5 $= 3$.
$X_2 = 3 \times 7 + 1$ mod 5 $= 2$.

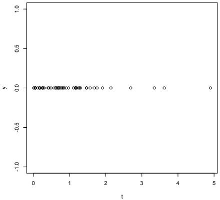
Exponential



$T \sim \text{Exponential}(\lambda)$,
$f(t) = \lambda e^{-\lambda t}$ for $t \geq 0$,
$f(t) = 0$ for $t < 0$.
$P(T \in (t, t + \Delta t)) = \lambda e^{-\lambda t} \Delta t$.
Imagine 1 million particles, mark the times when they decay.
1 million points on real line. Their distribution is exponential.
Number of points in $(t, t + \Delta t)$ is $\lambda e^{-\lambda t} \Delta t$ million.

Exponential





$$F(t) = \int_0^t f(t)dt = \int_0^t \lambda e^{-\lambda t} dt$$
$$= -e^{-\lambda t}\Big|_0^t = 1 - e^{-\lambda t}.$$

$F(t)$: proportion of points below t

Half-life: $F(t_{\text{half}}) = P(T \le t_{\text{half}}) = 1/2$.

1 million particles, by half life, half million will have decayed.

Exponential

100A

Ying Nian Wu

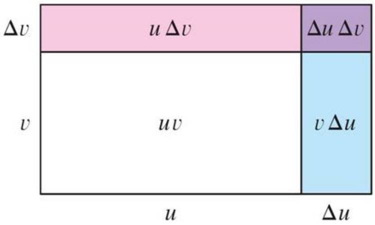
Discrete

Continuous

Movie

$$
\begin{aligned}
\mathbb{E}(T) &= \int_0^\infty t\lambda e^{-\lambda t} dt \\
&= -\int_0^\infty t de^{-\lambda t} \\
&= -(te^{-\lambda t}|_0^\infty - \int_0^\infty e^{-\lambda t} dt) \\
&= -(0 - 0 + \frac{1}{\lambda} e^{-\lambda t}|_0^\infty) = \frac{1}{\lambda}.
\end{aligned}
$$

Integral by parts



$$\frac{d}{dx}u(x)v(x) = u'(x)v(x) + u(x)v'(x).$$

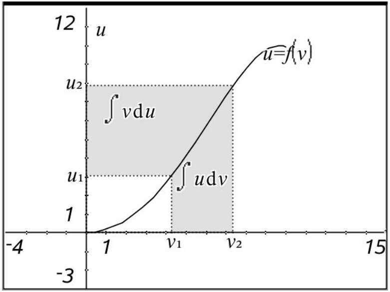
$$duv = udv + vdu.$$

$$\int [u'(x)v(x) + u(x)v'(x)]dx = u(x)v(x).$$

$$\int u(x)v'(x)dx = u(x)v(x) - \int v(x)u'(x)dx.$$

$$\int udv = uv - \int vdu.$$

Integral by parts



$$\int u dv = uv - \int v du.$$

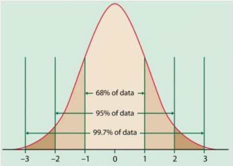
$$\int u(x)v'(x)dx = u(x)v(x) - \int v(x)u'(x)dx.$$

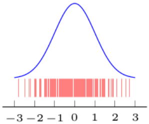
$$\frac{du(x)}{dx} = \frac{d}{dx}u(x) = u'(x);\ du(x) = u'(x)dx.$$

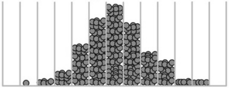
Normal or Gaussian

Let $Z \sim \mathrm{N}(0, 1)$, i.e., the density of Z is

$$f(z) = \frac{1}{\sqrt{2\pi}} e^{-z^2/2}.$$







$$\int_{-2}^{2} f(z) dz = 95\%.$$

Normal or Gaussian

Let $Z \sim \mathrm{N}(0, 1)$, i.e., the density of Z is

$$f(z) = \frac{1}{\sqrt{2\pi}} e^{-z^2/2}.$$

$$\begin{aligned}
\mathbb{E}(Z) &= \int_{-\infty}^{\infty} z \frac{1}{\sqrt{2\pi}} e^{-\frac{z^2}{2}} dz \\
&= -\frac{1}{\sqrt{2\pi}} e^{-\frac{z^2}{2}} |_{-\infty}^{\infty} \\
&= 0.
\end{aligned}$$

The density is symmetric around 0.

Normal or Gaussian

Let $Z \sim \mathrm{N}(0,1)$, i.e., the density of Z is

$$f(z) = \frac{1}{\sqrt{2\pi}} e^{-z^2/2}.$$

$$\begin{aligned}
\mathbb{E}(Z^2) &= \int_{-\infty}^{\infty} z^2 \frac{1}{\sqrt{2\pi}} e^{-\frac{z^2}{2}} dz \\
&= \frac{1}{\sqrt{2\pi}} \int_{-\infty}^{\infty} (-z) d e^{-\frac{z^2}{2}} \\
&= \frac{1}{\sqrt{2\pi}} (-z e^{-\frac{z^2}{2}} |_{-\infty}^{\infty} - \int_{-\infty}^{\infty} e^{-\frac{z^2}{2}} d(-z)) \\
&= \int_{-\infty}^{\infty} \frac{1}{\sqrt{2\pi}} e^{-\frac{z^2}{2}} dz = 1.
\end{aligned}$$

$$\mathrm{Var}(Z) = \mathbb{E}(Z^2) - (\mathbb{E}(Z))^2 = 1.$$

Variance

For $X \sim f(x)$, let $\mu = \mathbb{E}(X)$.

$$\begin{aligned}
\mathrm{Var}(X) &= \mathbb{E}[(X-\mu)^2] \\
&= \mathbb{E}[X^2 - 2\mu X + \mu^2] \\
&= \mathbb{E}(X^2) - 2\mu\mathbb{E}(X) + \mu^2 \\
&= \mathbb{E}(X^2) - (\mathbb{E}(X))^2.
\end{aligned}$$

$$\begin{aligned}
\mathbb{E}[r(X)+s(X)] &= \int [r(x)+s(x)]f(x)dx \\
&= \int r(x)f(x)dx + \int s(x)f(x)dx \\
&= \mathbb{E}[r(X)] + \mathbb{E}[s(X)].
\end{aligned}$$

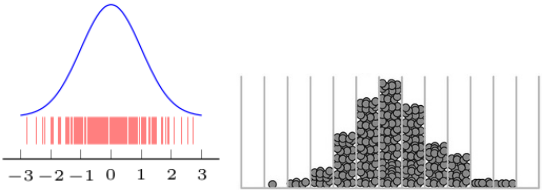
Linear transformation

For $X \sim f(x)$. Let $Y = aX + b$.

$$\begin{aligned}\mathbb{E}(Y) = \mathbb{E}(aX+b) &= \int (ax+b)f(x)dx \\ &= a\int xf(x)dx + b\int f(x)dx \\ &= a\mathbb{E}(X) + b.\end{aligned}$$

$$\begin{aligned}\mathrm{Var}(Y) = \mathrm{Var}(aX+b) &= \mathbb{E}[((aX+b) - \mathbb{E}(aX+b))^2] \\ &= \mathbb{E}[(aX+b-(a\mathbb{E}(X)+b))^2] \\ &= \mathbb{E}[a^2(X-\mathbb{E}(X))^2] \\ &= a^2\mathbb{E}[(X-\mathbb{E}(X))^2] = a^2\mathrm{Var}(X).\end{aligned}$$

Large sample



Sampling $f(x) \rightarrow x_1, ..., x_i, ..., x_n$
(e.g., random number generator $\rightarrow$ .22, .31, .92, .45, ...)

$$\bar{x} = \frac{1}{n}\sum_{i=1}^{n} x_i \rightarrow \mathbb{E}(X) = \mu.$$

$$s^2 = \frac{1}{n}\sum_{i=1}^{n}(x_i - \bar{x})^2 \rightarrow \mathrm{Var}(X) = \sigma^2$$

Linear transformation

Sampling $f(x) \to x_1, ..., x_i, ..., x_n$
(e.g., random number generator $\to$ .22, .31, .92, .45, ...)

$$y_i = ax_i + b.$$

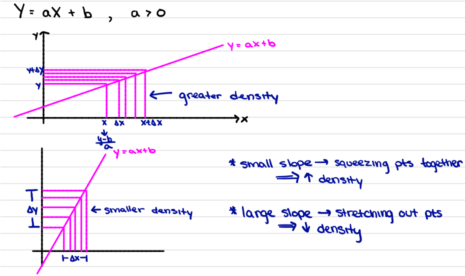
$$\bar{x} = \frac{1}{n}\sum_{i=1}^{n} x_i \to \mathbb{E}(X) = \mu.$$

$$\bar{y} = \frac{1}{n}\sum_{i=1}^{n} y_i = \frac{1}{n}\sum_{i=1}^{n}(ax_i + b) = a\frac{1}{n}\sum_{i=1}^{n} x_i + b = a\bar{x} + b.$$

$$\frac{1}{n}\sum_{i=1}^{n}(y_i - \bar{y})^2 = \frac{1}{n}\sum_{i=1}^{n}(ax_i + b - (a\bar{x} + b))^2 = \frac{1}{n}\sum_{i=1}^{n} a^2(x_i - \bar{x})^2.$$

Linear transformation

$$X \sim f(x),\ Y = aX + b\ (a > 0).\ Y \sim g(y).$$



$$y = ax + b,\ x = (y - b)/a.$$

$$P(X \in (x, x + \Delta x)) = P(Y \in (y, y + \Delta y)).$$

$$f(x)\Delta x = g(y)\Delta y.$$

$$g(y) = f(x)\frac{\Delta x}{\Delta y} = f((y - b)/a))/a.$$

Normal or Gaussian

Let $Z \sim \mathrm{N}(0,1)$, i.e., the density of Z is

$$f(z) = \frac{1}{\sqrt{2\pi}} e^{-z^2/2}.$$

Let $X = \mu + \sigma Z$. $Z = (X - \mu)/\sigma$. Then

$$\mathbb{E}(X) = \mathbb{E}(\mu + \sigma Z) = \mu + \sigma \mathbb{E}(Z) = \mu.$$

$$\mathrm{Var}(X) = \mathrm{Var}(\mu + \sigma Z) = \sigma^2 \mathrm{Var}(Z) = \sigma^2.$$

$$f(z)\Delta z = g(x)\Delta x.$$

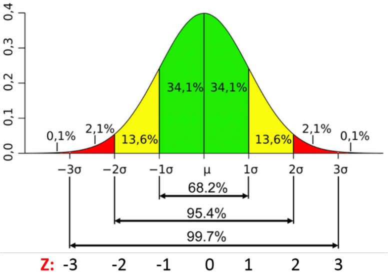
$$\begin{aligned} g(x) &= f(z)\frac{\Delta z}{\Delta x} \\ &= f((x-\mu)/\sigma)/\sigma \\ &= \frac{1}{\sqrt{2\pi\sigma^2}} \exp\left[-\frac{(x-\mu)^2}{2\sigma^2}\right]. \end{aligned}$$

Normal or Gaussian

Let $Z \sim \mathrm{N}(0,1)$. Let $X = \mu + \sigma Z$. $Z = (X - \mu)/\sigma$.
$X \sim \mathrm{N}(\mu, \sigma^2)$,

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

(we now use $f(x)$ to denote the density of X.)



$P(\mu - 2\sigma \leq X \leq \mu + 2\sigma) = P(-2 \leq Z \leq 2) = 95\%.$

Uniform and Exponential

Let $U \sim \text{Unif}(0,1)$. Let $X = a + (b-a)U \in [a,b] \sim \text{Unif}[a,b]$. $U = (X-a)/(b-a)$.

$$f(u)\Delta u = g(x)\Delta x.$$

$$\Delta u = g(x)\Delta x,$$

$$g(x) = \Delta u/\Delta x = 1/(b-a), \; x \in [a,b].$$

Let $T \sim \text{Exp}(1)$. Let $X = T/\lambda$. $T = \lambda X$.

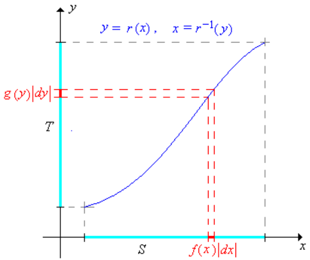
$$f(t)\Delta t = g(x)\Delta x.$$

$$\exp(-t)\Delta t = g(x)\Delta x.$$

$$g(x) = \lambda \exp(-\lambda x), \; x \geq 0.$$

Non-linear transformation

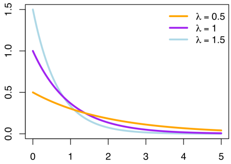
$X \sim f(x)$, $Y = r(X)$. $Y \sim g(y)$.

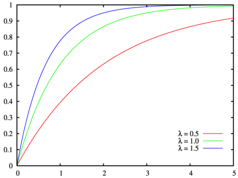


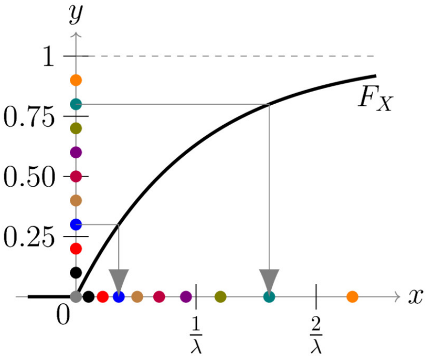
$$y = r(x),\ x = r^{-1}(y).$$
$$P(X \in (x, x + \Delta x)) = P(Y \in (y, y + \Delta y)).$$
$$f(x)\Delta x = g(y)\Delta y.$$
$$\Delta y / \Delta x = r'(x).$$

Locally linear.

Inversion method







Inversion method

$F(x)$ is a cdf. $x = F^{-1}(u)$ means that x is the solution to the equation $F(x) = u$.
$U \sim \mathrm{Unif}[0, 1]$. $X = F^{-1}(U)$. Then $F(x)$ is the cdf of X.

$$P(U \in (u, u + \Delta u)) = P(X \in (x, x + \Delta x)).$$

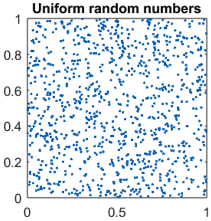
$$\Delta u = f(x)\Delta x.$$

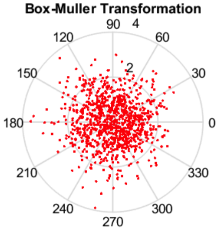
$$f(x) = \frac{\Delta u}{\Delta x} = F'(x).$$

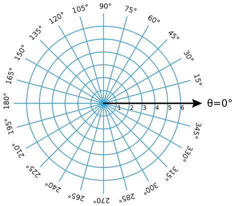
Inversion method

Suppose we want to generate $X \sim \text{Exponential}(1)$.
$F(x) = 1 - e^{-x}$.
$F(x) = u$, i.e., $1 - e^{-x} = u$, $e^{-x} = 1 - u$. $x = -\log(1-u)$.
Generate $U \sim \text{Unif}[0,1]$. Return $X = -\log(1-U)$.

Polar method







Polar method

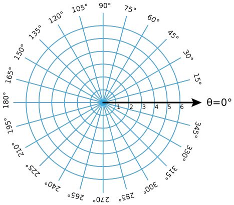
$X \sim \mathrm{N}(0,1)$, $f(x) = \frac{1}{\sqrt{2\pi}} \exp\left(-\frac{x^2}{2}\right)$.
$Y \sim \mathrm{N}(0,1)$, $f(y) = \frac{1}{\sqrt{2\pi}} \exp\left(-\frac{y^2}{2}\right)$.
X and Y are independent.

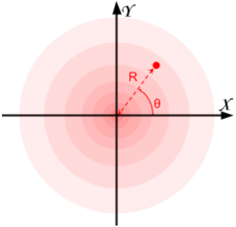
$$\begin{aligned} & P(X \in (x, x+\Delta x), Y \in (y, y+\Delta y)) \\ = \; & P(X \in (x, x+\Delta x)) \times P(Y \in (y, y+\Delta y)). \end{aligned}$$

$$f(x,y)\Delta x \Delta y = f(x)\Delta x \times f(y)\Delta y.$$

$$f(x,y) = \frac{1}{2\pi} \exp\left(-\frac{x^2+y^2}{2}\right).$$

Polar method





$x = r\cos\theta$, $y = r\sin\theta$.

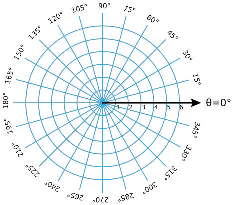
Area of ring $R \in (r, r + \Delta r)) = 2\pi r \Delta r$.

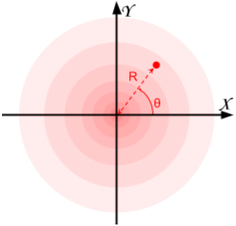
Count proportion of points in the ring = density $\times$ area.

$$P(R \in (r, r+\Delta r)) = \frac{1}{2\pi}\exp\left(-\frac{r^2}{2}\right) 2\pi r \Delta r$$

$$= \exp\left(-\frac{r^2}{2}\right) r\Delta r = \exp\left(-\frac{r^2}{2}\right) d\frac{r^2}{2}.$$

Polar method





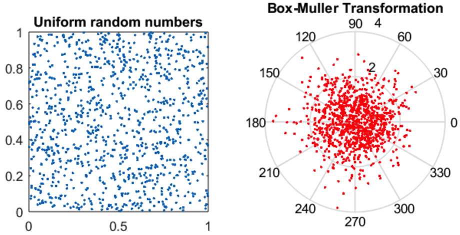
$x = r\cos\theta$, $y = r\sin\theta$.
Let $t = r^2/2$. $\Delta t = r\Delta t$.

$$P(T \in (t, t+\Delta t)) = P(R \in (r, r+\Delta r)).$$

$$f(t)\Delta t = \exp\left(-\frac{r^2}{2}\right) r\Delta r = \exp(-t)\Delta t.$$

$$T \sim \text{Exponential}(1).$$

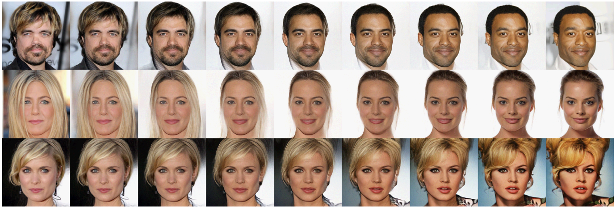
Polar method



$$T = -\log(1 - U_1).$$
$$R = \sqrt{2T}.$$
$$\theta = 2\pi U_2.$$
$$X = R\cos\theta,\ Y = R\sin\theta.$$
$$(U_1, U_2) \to (X, Y).$$

Non-linear transformation

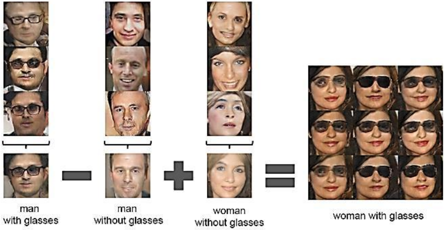
$X \sim f(x)$, $Y = r(X)$. $Y \sim g(y)$.
X consists of iid Gaussian $\mathrm{N}(0, 1)$ noises.
r is learned from training examples by neural network (deep learning).



Interpolation in x space.

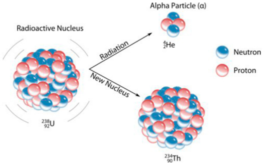
Non-linear transformation

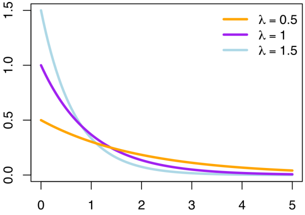
$X \sim f(x)$, $Y = r(X)$. $Y \sim g(y)$.
X consists of iid Gaussian $\mathrm{N}(0,1)$ noises.
r is learned from training examples by neural network (deep learning).



arithmetics in x space.

Particle decay





T: time until decay.
$T \sim \text{Exponential}(\lambda)$.
$P(T \in (t, t + \Delta t)) = f(t)\Delta t = \lambda e^{-\lambda t}\Delta t$.

Continuous time process

Making a movie

Divide the time into small intervals of length Δt (e.g., 1/24 second, or 1/100 second).

Show a picture at 0, Δt, $2\Delta t$, ...

Give an illusion of continuous time process as $\Delta t \to 0$.

Bank account

Divide $[0, t]$ into n small intervals, $\Delta t = t/n$.
Interest rate $= r$.
Time 0: $\$1$.
Time Δt: $\$(1 + r\Delta t)$.
Time $2\Delta t$: $\$(1 + r\Delta t)^2$.
Time $3\Delta t$: $\$(1 + r\Delta t)^3$.
...
Time $t = n\Delta t$: $\$(1 + r\Delta t)^n$.

$$\left(1 + r\frac{t}{n}\right)^n \to e^{rt},$$

as $n \to \infty$ or $\Delta t \to 0$.

Continuous time process

Bank account

Divide $[0, t]$ into n small intervals, $\Delta t = t/n$.
Interest rate $= r$.

$$\left(1 + \frac{1}{n}\right)^n \to e.$$

$$1 + \frac{1}{n} \doteq e^{1/n}.$$

$$1 + \Delta x \doteq e^{\Delta x}.$$

$$\left(1 + r\frac{t}{n}\right)^n \to e^{rt}.$$

$$(1 + r\Delta t)^{t/\Delta t} \doteq \left(e^{r\Delta t}\right)^{t/\Delta t} = e^{rt}.$$

Poisson process

Flip a coin within each interval.
$p = \lambda \Delta t$ (e.g., $\Delta t = 1$ hour. $\lambda =$ once every 10 year.
$\lambda \Delta t = 1/3650 \times 1/24$).
Geometric waiting time

$$
\begin{aligned}
P(T \in (t, t+\Delta t)) &= (1-\lambda\Delta t)^{t/\Delta t}\lambda\Delta t \\
&\doteq \left(e^{-\lambda\Delta t}\right)^{t/\Delta t}\lambda\Delta t = e^{-\lambda t}\lambda\Delta t.
\end{aligned}
$$

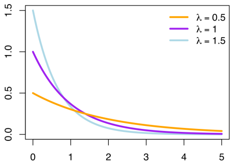
Exponential distribution

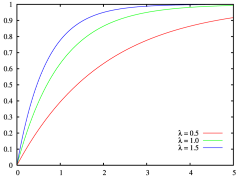
Flip a coin within each interval.
$p = \lambda \Delta t$ (e.g., $\Delta t = .001$ second. $\lambda =$ once every minute. $\lambda \Delta t = 1/60 \times .001$).

Exponential waiting time

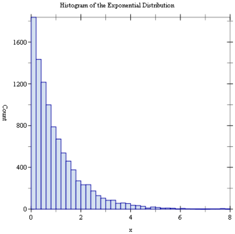
$$\frac{P(T \in (t, t + \Delta t))}{\Delta t} = \lambda e^{-\lambda t}.$$

$$P(T > t) = (1 - \lambda \Delta t)^{t/\Delta t} \doteq (e^{-\lambda \Delta t})^{t/\Delta t} = e^{-\lambda t}.$$





Exponential = geometric



1 million particles decay in different period. Each small period is a bin.

Geometric waiting time

We can write $T = \tilde{T}\Delta t$, where $\tilde{T} \sim \text{Geometric}(p = \lambda\Delta t)$. Then

$$\mathbb{E}(T) = \mathbb{E}(\tilde{T})\Delta t = \frac{1}{p}\Delta t = \frac{1}{\lambda\Delta t}\Delta t = 1/\lambda.$$

Poisson distribution

Flip a coin within each interval.
Let X be the number of heads within $[0, t]$, then
$X \sim \text{Binomial}(n = t/\Delta t, p = \lambda \Delta t)$.

$$P(X = k) = \binom{n}{k} p^k (1-p)^{n-k} \to \frac{(\lambda t)^k}{k!} e^{-\lambda t}.$$

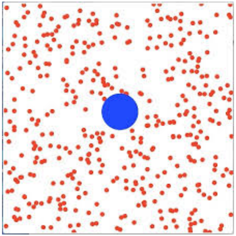
$\mathbb{E}(X) = np = (t/\Delta t)(\lambda \Delta t) = \lambda t$.
$\lambda = \mathbb{E}(X)/t$, rate or intensity.

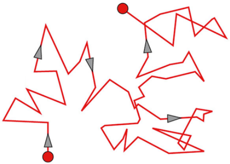
Poisson distribution

$$
\begin{aligned}
P(X = k) &= \frac{n(n-1)...(n-k+1)}{k!} p^k (1-p)^{n-k} \\
&= \frac{t/\Delta t(t/\Delta t - 1)...(t/\Delta t - k + 1)}{k!} \\
&\times (\lambda \Delta t)^k (1 - \lambda \Delta t)^{t/\Delta t - k} \\
&= \frac{t(t-\Delta t)(t - 2\Delta t)...(t-(k-1)\Delta t)}{k!} \\
&\times \lambda^k (1 - \lambda \Delta t)^{t/\Delta t} (1 - \lambda \Delta t)^{-k} \\
&\to \frac{t^k}{k!} \lambda^k (e^{-\lambda \Delta t})^{t/\Delta t} = \frac{(\lambda t)^k}{k!} e^{-\lambda t}.
\end{aligned}
$$

Diffusion or Brownian motion

Dust particle in water





Diffusion or Brownian motion

Divide $[0, t]$ into n intervals, $\Delta t = t/n$.
Within each small interval, move forward or backward by Δx.
$P(Z_i = 1) = P(Z_i = -1) = 1/2$. Z_i are independent.

$$X = \sum_{i=1}^{n} Z_i \Delta x,$$

$$\mathbb{E}(X) = \sum_{i=1}^{n} \mathbb{E}(Z_i)\Delta x = 0.$$

Diffusion or Brownian motion

Divide $[0, t]$ into n intervals, $\Delta t = t/n$.
Within each small interval, move forward or backward by Δx.
$P(Z_i = 1) = P(Z_i = -1) = 1/2$. Z_i are independent.

$$X = \sum_{i=1}^{n} Z_i \Delta x,$$

$$\mathrm{Var}(X) = \sum_{i=1}^{n} \mathrm{Var}(Z_i)\Delta x^2 = n\Delta x^2 = \sigma^2 t.$$

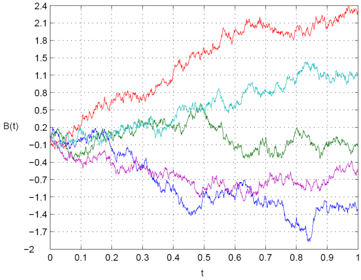
$$\Delta x^2 = \sigma^2 t/n = \sigma^2 \Delta t.$$

$$\Delta x = \sigma\sqrt{\Delta t}.$$

$$v = \Delta x/\Delta t = \sigma/\sqrt{\Delta t} \to \infty.$$

Einstein, σ related to the size of molecules.

Diffusion or Brownian motion



$X = B(t)$.
Nowhere differentiable.
σ: volatility of stock price, basis for option pricing.

Normal approximation

100A

Ying Nian Wu

Discrete

Continuous

Movie

Central limit theorem
$P(Z_i = 1) = P(Z_i = -1) = 1/2$. Z_i are independent.

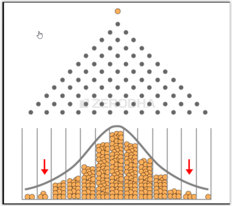
$$X = \sum_{i=1}^{n} Z_i \Delta x \sim \mathrm{N}(0, \sigma^2 t),$$

as $n \to 0$.
Sum of independent random variables $\sim$ Normal distribution.
A drop of milk (millions of particles) diffuses in coffee.

Normal approximation

$P(Z_i = 1) = P(Z_i = -1) = 1/2$. Z_i are independent.

$$X = \sum_{i=1}^{n} Z_i \Delta x \sim \mathrm{N}(0, \sigma^2 t).$$



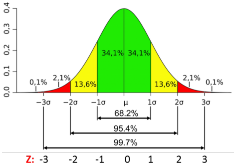
Let $Y \sim \text{Binomial}(n, 1/2)$, $\Delta x = \sigma\sqrt{\Delta t} = \sigma\sqrt{t/n}$.

$$X = Y\Delta x - (n - Y)\Delta x = \sigma\sqrt{t}(Y - n/2)/(\sqrt{n}/2).$$

$$\mathbb{E}(Y) = n/2, \mathrm{Var}(Y) = n/4, SD(Y) = \sqrt{n}/2.$$

Normal approximation

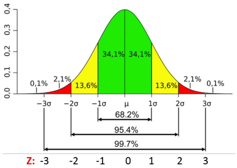
Let $X \sim \text{Binomial}(n, p)$, sum of independent Bernoulli.
$\mathbb{E}(X) = np$, $\text{Var}(X) = np(1-p)$.
$\mathbb{E}(X/n) = p$, $\text{Var}(X/n) = p(1-p)/n$.
Approximately,
$X \sim \text{N}(np, np(1-p))$.
$X/n \sim \text{N}(p, p(1-p)/n)$.
e.g., $n = 100$, $p = 1/2$. $X \sim \text{N}(50, 25)$.
$P(X \in [50 - 2 \times 5, 50 + 2 \times 5]) = P(X \in [40, 60]) = 95\%$.



Recall $\sum_{k=40}^{60} \binom{100}{k} / 2^{100} \to$ integral.

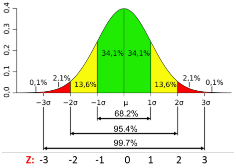
Normal approximation

Let $X \sim \text{Binomial}(n, p)$, sum of independent Bernoulli.
$\mathbb{E}(X) = np$, $\text{Var}(X) = np(1-p)$.
$\mathbb{E}(X/n) = p$, $\text{Var}(X/n) = p(1-p)/n$.
Approximately,
$X \sim \text{N}(np, np(1-p))$.
$X/n \sim \text{N}(p, p(1-p)/n)$.
e.g., Polling $n = 100$, $p = .2$. $X/n \sim \text{N}(.2, .04^2)$.
$P(X/n \in [.2 - 2 \times .04, .2 + 2 \times .04]) = P(X/n \in [.12, .28]) = 95\%$.



Normal approximation

Let $X \sim \text{Binomial}(n, p)$, sum of independent Bernoulli.
$\mathbb{E}(X) = np$, $\text{Var}(X) = np(1-p)$.
$\mathbb{E}(X/n) = p$, $\text{Var}(X/n) = p(1-p)/n$.
Approximately,
$X \sim \text{N}(np, np(1-p))$.
$X/n \sim \text{N}(p, p(1-p)/n)$.
e.g., Monte Carlo $n = 10000$, $p = \pi/4$.
$4m/n \sim \text{N}(\pi, \pi(4-\pi)/10000)$.



Normal approximation

$X \sim \text{Binomial}(n, 1/2)$. $\mu = \mathbb{E}(X) = n/2$,
$\sigma^2 = \text{Var}(X) = n/4$, $\sigma = SD(X) = \sqrt{n}/2$.
Let $Z = (X - \mu)/\sigma$, then $\mathbb{E}(Z) = 0$, $\text{Var}(Z) = 1$, no matter what n is.
$X = \mu + Z\sigma = n/2 + Z\sqrt{n}/2$.

$$P(X = k) = \frac{\binom{n}{k}}{2^n} = \frac{n!}{k!(n-k)!2^n},$$

Normal approximation

For big n,

$$n! \sim \sqrt{2\pi n} n^n e^{-n},$$

$$\begin{aligned} P(X = n/2) &\sim \frac{n!}{(n/2)!^2 2^n} \\ &\sim \frac{\sqrt{2\pi n} n^n e^{-n}}{(\sqrt{2\pi (n/2)}(n/2)^{n/2})^2 2^n} \\ &\sim \frac{1}{\sqrt{2\pi}} \frac{2}{\sqrt{n}}. \end{aligned}$$

Normal approximation

Let $k = \mu + z\sigma = n/2 + z\sqrt{n}/2 = n/2 + d$.

$$\frac{P(X = n/2 + d)}{P(X = n/2)} = \frac{\binom{n}{n/2+d}}{\binom{n}{n/2}}$$

$$= \frac{n!/[(n/2+d)!(n/2-d)!]}{n!/[(n/2)!(n/2)!]}$$

$$= \frac{(n/2)!(n/2)!}{(n/2+d)!(n/2-d)!}$$

$$= \frac{(n/2)(n/2-1)...(n/2-(d-1))}{(n/2+1)(n/2+2)...(n/2+d)}$$

$$= \frac{1(1-2/n)(1-2\times 2/n)...(1-(d-1)\times 2/n)}{(1+2/n)(1+2\times 2/n)...(1+d\times 2/n)}$$

$$= \frac{(1-\delta)(1-2\delta)...(1-(d-1)\delta)}{(1+\delta)(1+2\delta)...(1+d\delta)}$$

Normal approximation

$$
\begin{aligned}
&\to \quad \frac{e^{-\delta}e^{-2\delta}\ldots e^{-(d-1)\delta}}{e^{\delta}e^{2\delta}\ldots e^{d\delta}} \\
&= \quad \frac{e^{-(1+2+\ldots+(d-1))\delta}}{e^{(1+2+\ldots+d)\delta}} \\
&= \quad \frac{e^{-d(d-1)\delta/2}}{e^{d(d+1)\delta/2}} \\
&= \quad e^{-[d(d-1)/2+d(d+1)/2]\delta} = e^{-d^2\delta} \\
&= \quad e^{-(z\sqrt{n}/2)^2(2/n)} = e^{-\frac{z^2}{2}},
\end{aligned}
$$

where $\delta = 2/n$, and $d = z\sqrt{n}/2$.

Normal approximation

$$
\begin{aligned}
P(X = n/2 + z\sqrt{n}/2) &= P(X = \mu + z\sigma) \\
&\sim \frac{1}{\sqrt{2\pi}} e^{-\frac{z^2}{2}} \frac{2}{\sqrt{n}} = f(z)\Delta z,
\end{aligned}
$$

where $f(z) = \frac{1}{\sqrt{2\pi}} e^{-\frac{z^2}{2}}$ and $\Delta z = \frac{2}{\sqrt{n}}$. Thus with $\mu = n/2$, $\sigma = \sqrt{n}/2$, and $Z = (X - \mu)/\sigma$, we have

$$
\begin{aligned}
P(X \in [\mu + a\sigma, \mu + b\sigma]) &= P(Z \in [a, b]) \\
&= \sum_{z \in [a,b]} f(z)\Delta z \to \int_a^b f(z)dz,
\end{aligned}
$$

where the space between two consecutive values of $z = (k - \mu)/\sigma$ is $1/\sigma = 2/\sqrt{n} = \Delta z$.