Markov chain

P(X_n = i_n | X_{n-1} = i_{n-1}) = P(X_n = i_n | X_0 = i_0, X_1 = i_1, ..., X_{n-1} = i_{n-1}).

recurrent if you can go back; else transient

transient states' prob converge to 0

classes are no communication set of states

markov chain converge if

- 1 recurrent class
- this class is not periodic

periodic states

move from one group to the other with p = 1

[frequency](#) [Birth-death](#)

MISC

Median

Middle number in sorted. If discrete distro, check up to where we have $p < 0.5$ and then $p > 0.5$, the number we have to add to cross threshold is median (see [here](#))

Mode

Most likely value/appears most often.

derivative of norm squared

$\left(\| h(x) \|^2\right)\prime = 2h(x)h\prime(x)$

COUNTING

n choose k

nb of combinations (any order)

$\binom{n}{k} = \frac{n!}{k!(n-k)!}$

permutations

nb of ways of ordering n elements (order matters)

$n!$

subsets of n elements

2^n

partitions

n objects into r groups

$\frac{n!}{n_1! n_2! \ldots n_r!}$

PROB BASICS

Properties

$P(A \cup B) = P(A) + P(B) - P(A \cap B)$

$P(A \cup B) \leq P(A) + P(B)$

Conditional

$P(A \mid B) = \frac{P(A \cap B)}{P(B)}$

$P(A \cap B) = P(B)P(A \mid B)$

⚠ **Total Prob Theorem** ⚠

$P(B) = P(A_1 \cap B) + \ldots + P(A_n \cap B)$

$= P(A_1)P(B \mid A_1) + \ldots$

Bayes

$P(A \mid B) = \frac{P(A)P(B \mid A)}{P(B)}$

Independence

$P(A \mid B) = P(A)$

$P(A \cap B) = P(A)P(B)$

CONT. DISTROS

$P(a \leq x \leq b) = \int_a^b f_X(x)dx$

Disjoint

$P(1 \leq x \leq 3 \text{ or } 4 \leq x \leq 5)$

$= P(1 \leq x \leq 3) + P(4 \leq x \leq 5)$

Properties

$f(x) \geq 0$ and $\int_{-\infty}^{\infty} f_X(x)dx = 1$

CDF Properties

$\cdot \to_{x \to \infty} 1$ and $\to_{x \to -\infty} 0$

·increasing/monotonic

·right-continuous ___*---

Uniform CONT

$f_X(x) = \frac{1}{b-a}$ $\qquad \hat{b}^{\text{MLE}} = \max(X_i)$

$F_X(x) = \frac{x-a}{b-a}$

$E[X] = \frac{a+b}{2}$

$Var(X) = \frac{(b-a)^2}{12}$

Exponential

time to wait for something

$f_X(x) = \lambda e^{-\lambda x}$

$P(X \geq a) = \int_a^{\infty} \lambda e^{-\lambda x}dx = e^{-\lambda a}$

$F_X(x) = 1 - e^{-\lambda x}$

$E[X] = \frac{1}{\lambda}$

$E\left[X^2\right] = \frac{2}{\lambda^2}$

$Var(X) = \frac{1}{\lambda^2}$ $\qquad I = \frac{1}{\lambda^2}$

Beta

$f(x) = \frac{1}{k}x^{a-1}(1-x)^{b-1}\mathbf{1}\{x \in [0,1]\}$

$k = \int_0^1 t^{a-1}(1-t)^{b-1}dt$

$E[X] = \frac{a}{a+b}$

DISCRETE DISTROS

Bernouilli

$P(X=1) = p$ $\qquad I = \frac{1}{p(1-p)}$

$E[X] = p$ $\qquad \hat{p}^{\text{MLE}} = \overline{X_n}$

$Var(X) = p(1-p)$

Uniform DISCRETE

$p_X(x) = \frac{1}{b-a+1}$

$F_X(k) = \frac{\lfloor k \rfloor - a + 1}{n}$

$E[X] = \frac{a+b}{2}$

$Var(X) = \frac{(b-a+1)^2 - 1}{12}$

Binomial

k successes in n trials

$p_X(k) = \binom{n}{k}p^k(1-p)^{n-k}$

$E[X] = np$

$Var(X) = np(1-p)$

Geometric

number of trials until success

$p_X(k) = (1-p)^{k-1}p$

$F_X(k) = 1 - (1-p)^k$

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

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

Poisson

how many occurrences k in τ given rate λ

$P(k, \tau) = \frac{(\lambda\tau)^k e^{-\lambda\tau}}{k!}$

$E[N_\tau] = \lambda\tau$

$Var(N_\tau) = \lambda\tau$

$I = \frac{1}{\lambda}$

$\lambda \in R_{>0}$

NORMALS

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

$E[X] = \mu$ $\qquad I(\mu, \sigma^2) = \begin{pmatrix} 1/\sigma^2 & 0 \\ 0 & 1/(2\sigma^4) \end{pmatrix}$

$Var(X) = \sigma^2$ $\quad Var\left(X^2\right) = 2\sigma^4$

Linear Functions

$Y = aX + b$ with $X \sim N\left(\mu, \sigma^2\right)$ $\qquad \hat{\mu}^{\text{MLE}} = \overline{X_n}$

$Y = N\left(a\mu + b, a^2\sigma^2\right)$ $\qquad \widehat{\sigma^2}^{\text{MLE}} = S_n$ (sample var)

Indie Sum

$Z \sim N\left(\mu_X + \mu_Y, \sigma_X^2 + \sigma_Y^2\right)$

nb: $Z \sim N\left(\mu_X - \mu_Y, \sigma_X^2 + \sigma_Y^2\right)$ if $Z = N_1 - N_2$

Tables

$\Phi(-2) = P(Y \leq -2) = 1 - P(Y \leq 2) = 1 - \Phi(2)$

Standardising

$X \sim N\left(\mu, \sigma^2\right)$ and $Y \sim N(0,1)$

$Y = \frac{X - \mu}{\sigma}$ $\quad X = \mu + \sigma Y$

Goal: Estimate model parameters when data is incomplete or has latent variables.
Process:
E-step (Expectation): Estimate the distribution of the latent variables using the current parameters.
M-step (Maximization): Optimize parameters to maximize the likelihood given the estimated distribution of the latent variables.
Repeat: Alternate between E-step and M-step until convergence.

CONDITIONAL VARS

same for PDF

$p_{X|Y}(x \mid y) = \frac{p_{X,Y}(x,y)}{p_Y(y)}$

Multiplication Rule

$p_{X,Y}(x,y) = p_Y(y)p_{X|Y}(x \mid y)$

$p_{X,Y,Z}(x,y,z) = p_X(x)p_{Y|X}(y \mid x)p_{Z|X,Y}(z \mid x,y)$

$p_{X,Y|Z}(x,y \mid z) = \frac{p_{X,Y,Z}(x,y,z)}{p_Z(z)}$

MULTIPLE VARS

$\sum_x \sum_y p_{X,Y}(x,y) = 1$

$P((X,Y) \in B) = \int\int_{(x,y) \in B} f_{X,Y}(x,y)dxdy$

Marginals / Total Probability

$p_X(x) = \sum_y p_{X,Y}(x,y) = \sum_y p_Y(y)p_{X|Y}(x \mid y)$

$f_X(x) = \int f_Y(y)f_{X|Y}(x \mid y)dy$

⚠ ranges: what values can Y take when X = x?

$= \int f_{X,Y}(x,y)dy$

Expected Value Rule

$E[g(X,Y)] = \sum_x \sum_y g(x,y)p_{X,Y}(x,y)$

$E[g(X,Y)] = \int E[g(x,y) \mid Y = y]f_Y(y)dy$

$E[g(X,Y) \mid Y = y] = \int g(x,y)f_{X|Y}(x \mid y)dy$

CDF

$F_{X,Y}(x,y) = P(X \leq x, Y \leq y)$

$= \int_{-\infty}^{y}\int_{-\infty}^{x} f_{X,Y}(s,t)dsdt$

EXPECTATIONS

Expected Value

$E[g(x)] = \sum_x g(x)p_X(x)$

$E[g(x)] = \int_{-\infty}^{\infty} g(x)f_X(x)dx$

Linearity of Expectations

$E[aX + b] = aE[X] + b$

$E[X + Y] = E[X] + E[Y]$

Total Expectation Th.

$E[X] = \sum_y p_Y(y)E[X \mid Y = y]$

$E[X] = \int_{-\infty}^{\infty} f_Y(y)E[X \mid Y = y]dy$

$E[X] = \sum_i P(A_i)E[X \mid A_i]$

Cond. Expectation

$E[g(x) \mid Y = y] = \sum_x g(x)p_{X|Y}(x \mid y)$

Iterated Expectation

$E[E[X \mid Y]] = E[X]$ ([ex.](#))

INDEPENDENCE

If Indie

$E[XY] = E[X]E[Y]$

$Var(X + Y) = Var(X) + Var(Y)$

$p_{X,Y|Z}(x,y \mid z) = p_{X|Z}(x \mid z)p_{Y|Z}(y \mid z)$

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

$f_{X|Y}(x \mid y) = f_X(x)$

$Cov(X,Y) = 0$

MIXED RV

$X = Y$ (discrete) w.p p

$\quad Z$ (continuous) w.p (1-p)

$F_X(x) = pF_Y(x) + (1-p)F_Z(x)$

$E[X] = pE[Y] + (1-p)E[Z]$

$f_X(x)$ take CDF and derive for x

VARIANCE

$Var(X) = E\left[(X - \mu)^2\right]$ and $\sigma = \sqrt{Var(X)}$

Properties

$Var(aX + b) = a^2 Var(X)$

$Var(X) = E\left[X^2\right] - (E[X])^2$

Dependent Sum

$Var(X_1 + \ldots + X_n) = \sum_{i=1}^{n} Var(X_i) + \sum_{\{i,j\}: i \neq j} Cov(X_i, X_j)$

Independent Sum

$Var(X + Y) = Var(X - Y) = Var(X) + Var(Y)$

Law of Total Var

$Var(X) = E[Var(X \mid Y)] + Var(E[X \mid Y])$

Sample Variance

$S_n = \frac{1}{n}\sum^{n}\left(X_i - \overline{X_n}\right)^2$

$E[S_n] = \frac{n-1}{n}\sigma^2$

Unbiased Sample Variance

$\widetilde{S_n} = \frac{n}{n-1}S_n$

$E\left[\widetilde{S_n}\right] = \sigma^2$

STATISTICAL MODEL

$(E, (P_\theta)_{\theta \in \Theta})$

E: sample space $(X_1 \ldots)$

P: family of prob measures on E

Θ: Param set

well specified if $\theta^\star \in \Theta$

⚠ sample space must not depend on parameter

⚠ sample space must be the support for the distribution. i.e. $\left([0, \infty), \left\{N\left(\mu, \sigma^2\right)\right\}\right)$ is not valid because the sample space for a N is all R

RANDOM NB OF RANDOM VARIABLES

N: nb of stores visited

X_i: money spent in store i

$Y = \sum^{N} X_i$

$E[Y] = E[N]E[X]$

$Var(Y) = E[N]var(X) + (E[X])^2 var(N)$

DERIVED DISTROS

PMF function of discrete RV

$p_Y(y)=P(g(x)=y)=\sum_{x:g(x)=y} p_X(x)$

Linear Functions

$Y=aX+b$

$p_Y(y)=p_X\left(\frac{y-b}{a}\right)$

$f_Y(y)=\frac{1}{|a|}f_X\left(\frac{y-b}{a}\right)$

g is monotonic

$f_Y(y)=f_X(h(y))\left|\frac{dh}{fy}(y)\right|$ where h is inverse of g

general case

1) find CDF: $F_Y(y)=P(g(x)\le y)$
2) derive CDF for y to find PDF

CONVOLUTIONS

$Z=X+Y$

$p_Z(z)=\sum_x p_X(x)p_Y(z-x)$

$f_Z(z)=\int_{-\infty}^{\infty} f_X(x)f_Y(z-x)dx$

COVARIANCE

$Cov(X,Y)=E[(X-E[X])(Y-E[Y])]$

If Indie

$Cov(X,Y)=0$

⚠ inverse not usually true but true for Gaussians:
$Cov(X,Y)=0$ → X,Y ~ N indie

Properties

$Cov(X,X)=Var(X)$
$Cov(X,Y)=E[XY]-E[X]E[Y]$
$Cov(aX+b,Y)=aCov(X,Y)$
$Cov(X,Y+Z)=Cov(X,Y)+Cov(Y,Z)$

⚠ don't use the above for multiplications!

CORRELATION COEF.

$\rho(X,Y)=\frac{Cov(X,Y)}{\sigma_X\sigma_Y}$ measures linear rel

FRESH START/MEMORYLESSNESS

Exponential

$f_{X|X>t}(x \mid x>t)=f_X(x)$

Bernouilli/Poisson

$P(A \mid B)=P(A)$

i.e. prob of two arrivals (A) after 1 arrival (B) = prob of 2 arrivals (A)

MISC

$\sum_{k=0}^{\infty}\frac{\lambda^k}{k!}=\exp(\lambda)$

e limits

$\lim_{n\to\infty}\left(1-\frac{t}{n}\right)^n=e^{-t}$

$\lim_{n\to\infty}\left(1+\frac{t}{n}\right)^n=e^{t}$

BERNOUILLI PROCESS

requires indie, time homogen.

Properties

$S=X_1+...+X_n$

$P(S=K)=\binom{n}{k}p^k(1-p)^{n-k}$

$E[S]=np$

$Var(S)=np(1-p)$

Time until 1st success

$T_1=\min\{i:X_i=1\}$

$P(T_1=k)=(1-p)^{k-1}p$

Time of kth arrival

$p_{Y_k}(t)=\binom{t-1}{k-1}p^k(1-p)^{t-k}$

$E[Y_k]=\frac{k}{p}$ ⚠ memoryless (ex.)

$Var(Y_k)=\frac{k(1-p)}{p^2}$

Merging

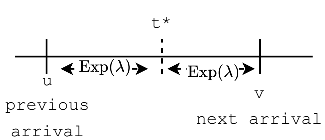
$Z_t=g(X_t,Y_t)\ \sim\ Ber(p+q-pq)$

⇒ prob either or both have arrival at time t

Splitting

flip a coin with prob q
$A\sim Ber(qp)$
$B\sim Ber((1-q)p)$
⚠ these streams are not indie

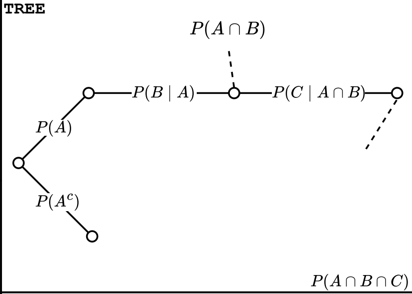
INTER-ARRIVAL TIMES / R.INCIDENCE (ex.)



we arrive at t*
u,v are each $Exp(\lambda)$ away from t*

⇒ $E[V-U]$ is twice the expectation of $Exp(\lambda)$

TREE



MIN/MAX

$P(\max> x)=1-P(\max< x)=1-[P(X_i<x)]^n$
$P(\min> x)=[P(X_i>x)]^n=[1-P(X_i<x)]^n$
$P(\min< x)=1-P(\min> x)$

POISSON PROCESS ⚠ use Wiki page

indie, time homogen. seq of exp
λ: arrival rate

$P(k,\tau)=\frac{(\lambda\tau)^k e^{-\lambda\tau}}{k!}$ $\quad I=\frac{1}{\lambda}$

$E[N_\tau]=\lambda\tau$
$Var(N_\tau)=\lambda\tau$
$\lambda=\frac{E[N_\tau]}{\tau}$

Time of kth arrival / Erlang

$f_{Y_k}=\frac{\lambda^k y^{k-1}e^{-\lambda y}}{(k-1)!}=Erlang(k)=Erlang\left(\frac{k}{2}\right)+Erlang\left(\frac{k}{2}\right)$

Sum

⚠ must be indie
M: $Poisson(\mu)$ N: $Poisson(v)$
M+N: $Poisson(\mu+v)$

Merging

A: λ_A B: λ_B
$\lambda=\lambda_A+\lambda_B$

$P\left(k^{th}\text{arrival is A}\right)=\frac{\lambda_A}{\lambda_A+\lambda_B}$

$P(\text{k arrivals are A})$ is $\text{Binomial}\left(\frac{\lambda_A}{\lambda_A+\lambda_B}\right)$

Splitting

flip a coin with prob q
⚠ these streams are indie
A: $\lambda_A=\lambda q$
B: $\lambda_B=\lambda(1-q)$

Multiple Engine Example

3 engines with death rate λ_e
rate until 1st dies is $\lambda=3\lambda_e$
then rate until 2nd dies $\lambda=2\lambda_e$

Min

$P(\min\{X,Y,Z\}\ge t)$
$=P(X\ge t,Y\ge t,Z\ge t)$
$=e^{-3\lambda t}$

⇒ have 3 merged Poissons and want to know first arrival
⇒ $\min\{X,Y,Z\}$ is $\text{Exp}(3\lambda)$

$E[\min\{X,Y,Z\}]=\frac{1}{3\lambda}$

Max

$P(\max(T_1,T_2,T_3)\le t)$
$=P(T_1\le t)P(T_2\le t)P(T_3\le t)$
$=\left(1-e^{-\lambda t}\right)^3$

then derive this to get PDF

LLN

req. iid and $E[|X_i|]<-\infty$

$\overline{X_n}=\frac{1}{n}\sum^n X_i=E[X]$

$E\left[\overline{X_n}^2\right]=Var\left(\overline{X_n}\right)+\left(E\left[\overline{X_n}\right]\right)^2$

⚠ because $\overline{X_n}$ is a RV like any other

ASYM VAR.

considers estimator multiplied by $\sqrt{n}$

CONT MAPPING TH.

$T_n\to T$ then $f(T_n)\to f(T)$

COVARIANCE MATRIX AND MV STUFF

$\Sigma=\begin{pmatrix}Cov(X,X) & Cov(X,Y)\\ Cov(Y,X) & Cov(Y,Y)\end{pmatrix}$

$=E\left[(X-E[X])(Y-E[Y])^T\right]$

$Var(\mathbf{X})=Cov(\mathbf{X})$
$Cov(\mathbf{AX}+\mathbf{B})=Cov(\mathbf{AX})=\mathbf{A}Cov(\mathbf{X})\mathbf{A}^T=\mathbf{A}\Sigma\mathbf{A}^T$

Gaussian vector

defined by $\boldsymbol{\mu}$ and Σ, $x\in R^d$

$f_X(x)=\frac{1}{\sqrt{(2\pi)^d\det\Sigma}}\exp\left(-\frac{1}{2}(\mathbf{x}-\boldsymbol{\mu})^T\Sigma^{-1}(\mathbf{x}-\boldsymbol{\mu})\right)$

MV CLT

$X_i\ \sim\ R^d\quad E[\mathbf{X}_i]=\boldsymbol{\mu}\quad Cov(\mathbf{X}_i)=\Sigma$

MV Delta

$\sqrt{n}(g(T_n)-g(\theta))\to\ N\left(0,\nabla g(\theta)^T\Sigma\nabla g(\theta)\right)$

CLT

req. iid, $E[X_i]<\infty$ and $Var(X_i)<\infty$

$\sqrt{n}\frac{\overline{X_n}-\mu}{\sigma}\to N(0,1)$ $\quad$ alt $\quad \frac{\left(\sum X_i\right)-n\mu}{\sqrt{n}\sigma}\to N(0,1)$

$\sqrt{n}\left(\overline{X_n}-\mu\right)\to N\left(0,\sigma^2\right)$

QUANTILES

$P(X\le q_\alpha)=1-\alpha$
$\alpha=.1\to q_\alpha$ is 90th percentile
$P(|Z|>1.96)=0.05$

α	2.5%	5%	7.5%	10%
q_α	1.96	1.65	1.44	1.28

SLUTSKY TH.

$T_n\to T$ and $U_n\to u$
T is r.v. and u is real

$T_n+U_n\to T+u$
$T_nU_n\to Tu$
$\frac{T_n}{U_n}\to\frac{T}{u}$

LIKELIHOODS

Bernouilli $p^{\sum^n X_i}(1-p)^{n-\sum^n X_i}$

Poisson $\frac{\lambda^{\sum X_i}}{x_1!...x_n!}\exp(-n\lambda)$

Gaussian $\frac{1}{(2\pi\sigma^2)^{\frac{n}{2}}}\exp\left(-\frac{1}{2\sigma^2}\sum(x_i-\mu)^2\right)$

Exponential $\lambda^n\exp\left(-\lambda\sum X_i\right)$

Uniform $\frac{1}{b^n}\mathbf{1}\{\max X_i\le b\}$

⚠ a=0 here

IDENTIFIABILITY

θ identifiable iff mapping $\theta\in\Theta\to P_\theta$ is injective
(injective: $\theta\neq\theta\prime\Rightarrow P_\theta\neq P_{\theta\prime}$)

ESTIMATORS

Asym. normal if

$\sqrt{n}\left(\widehat{\theta_n}-\theta\right)\to N\left(0,\sigma^2\right)$

Consistency

$\widehat{\theta_n}\to\theta$ as $n\to\infty$

Bias

$bias\left(\widehat{\theta_n}\right)=E\left[\widehat{\theta_n}\right]-\theta$

Quadratic Risk

$R\left(\widehat{\theta_n}\right)=E\left[\left|\widehat{\theta_n}-\theta\right|^2\right]$

Confidence Interval level $1-\alpha$

conf.int. can't depend on unknown

$P\left(\overline{X_n}-q_{\frac{\alpha}{2}}\frac{\sigma}{\sqrt{n}}\le\mu\le\overline{X_n}+q_{\frac{\alpha}{2}}\frac{\sigma}{\sqrt{n}}\right)=1-\alpha$

UNBIASED ESTIMATOR

we want $bias\left[\widehat{\theta_n\prime}\right]=0$

find $\widehat{\theta_n}$ and use linear property of expectations to create a new estimator such that

$E\left[\widehat{\theta_n\prime}\right]=cE\left[\widehat{\theta_n}\right]=\theta$

1D DELTA METHOD

g: cont. differentiable

$\sqrt{n}(Z_n-\theta)\to N\left(0,\sigma^2\right)$

$\sqrt{n}(g(Z_n)-g(\theta))\to N\left(0,(g\prime(\theta))^2\cdot\sigma^2\right)$

P-VALUE

⚠ is a level α

what is the probability of observing a result more extreme than this one under H_0?

⚠ low p-value is bad → H_0 is unlikely

i.e. $P\left(|\hat{a}|\ge\hat{a}_{\text{obs}}\right)$

KL DIVERGENCE

$KL(P_\theta,P_{\theta\prime})=\sum_{x\in E}p_\theta(x)\log\left(\frac{p_\theta(x)}{p_{\theta\prime}(x)}\right)$

$KL(P_\theta,P_{\theta\prime})=\int_E f_\theta(x)\log\left(\frac{f_\theta(x)}{f_{\theta\prime}(x)}\right)dx$

Properties

not symmetric
not negative
definite
triangle ineq

TESTS

⚠ failing to reject H_0 does not mean accepting H_0

Errors

test / reality	H_0	H_1
H_0	✓	type 1 error (reject when shouldn't)
H_1	type 2 error (fail to reject when should)	✓

level α
max type 1 error rate
higher $\alpha \to$ more likely to reject H_0

power β
$\pi_\psi = \inf_{\theta \in \Theta_n}(1-\beta_\psi(\theta))$

example 2 sided
coin $H_0 : p = \frac{1}{2}$ and $H_1 : p \neq \frac{1}{2}$

$$\psi = 1\left\{\sqrt{n}\frac{|\overline{X_n} - \frac{1}{2}|}{\sqrt{\frac{1}{2}\left(1-\frac{1}{2}\right)}} > q_{\frac{\alpha}{2}}\right\}$$

stats diff between X and Y? (ex.)
$\overline{X_n} \sim N\left(\mu_1, \sigma_1^2\right)$ and $\overline{Y_n} \sim N\left(\mu_2, \sigma_2^2\right)$
$H_0 : \mu_1 = \mu_2$ and $H_1 : \mu_1 \neq \mu_2$
$\sqrt{n}\frac{\overline{X_n} - \overline{Y_n}}{\sqrt{\sigma_1^2 + \sigma_2^2}} \sim N(0,1)$

single-sided
⚠ evaluate H_0 at boundary (see part c here)
$H_0 \mu \geq \sigma$ and $H_1 \mu < \sigma$
boundary is $\mu = \sigma$ for $g(\theta)$ or θ

TOTAL VARIATION DISTANCE

max dist between two distros
⚠ E is joint set of values of RVs

$$TV(P_\theta, P_{\theta'}) = \frac{1}{2}\sum_{x \in E}|p_\theta(x) - p_{\theta'}(x)|$$
$$TV(P_\theta, P_{\theta'}) = \frac{1}{2}\int_{-\infty}^{\infty}|f_\theta(x) - f_{\theta'}(x)|dx$$

Properties
symmetric: $TV(P_\theta, P_{\theta'}) = TV(P_{\theta'}, P_\theta)$
positive: $0 \leq TV \leq 1$
definite: if $TV(P_\theta, P_{\theta'}) = 0$ then $P_\theta = P_{\theta'}$
triangle ineq:
$TV(P_\theta, P_{\theta'}) \leq TV(P_\theta, P_{\theta''}) + TV(P_{\theta''}, P_{\theta'})$
if disjoint: $TV = 1$
if same: $TV = 0$

MAXIMIZATION

global extremes on range
test critical points and end points

min/max
$h''(x) \leq 0 \to$ concave, maximum, h' decr.
$h''(x) < 0 \to$ concave, global max, h' decr
$h''(x) \geq 0 \to$ convexe, minimum, h' incr.

MV min/max
$X^T H h(\theta) X \leq 0$ concave, max
+1 top diag: convexe, minimum $\begin{pmatrix} +1 & ? \\ ? & ? \end{pmatrix}$

MLE

minimizes KL divergence
$\hat{\theta}_n^{MLE} = arg\max_{\theta \in \Theta} \log(L)$
⚠ MLE can be Biased
⚠ function must be cont. diff. to use derivative to find extremums. use a plot and think if not

Consistency and Asym. Norm.
if
- param is identifiable
- support of P_θ does not depend on θ
- $\theta^\star$ is not at boundary
- $I(\theta)$ is invertible
- more stuff

then
consistent: $\hat{\theta}_n^{MLE} \to \theta^\star$
A.normal: $\sqrt{n}\left(\hat{\theta}_n^{MLE} - \theta^\star\right) \to N\left(0, I(\theta^\star)^{-1}\right)$

Process to find extremum
- get l_n
- find crits with $l_n'(\theta) = 0$
- check if crits are local min/max
- check values at endpoints

METHOD OF MOMENTS

$\widehat{m}_k = \overline{X_n^k} = \frac{1}{n}\sum X_i^k$
LLN $\widehat{m}_k \to m_k(\theta) = E_\theta\left[X_1^k\right]$
ASYM NORM $\sqrt{n}\left(\hat{\theta} - \theta\right) \to N(0, \Gamma(\theta))$

$$\Gamma(\theta) = \left[\frac{\delta M^{-1}}{\delta\theta}\right]^T \Sigma(\theta)\left[\frac{\delta M^{-1}}{\delta\theta}\right]$$

finding $\hat{\theta}$
write θ as function $E[X]$, $E\left[X^2\right]$...
then sub for $\overline{X_n}$, $\overline{X_n^2}$

M-ESTIMATION

Lecture 12, tab 2

FISHER INFORMATION

⚠ use ONE observation
not well defined if support depends on unknown (shifted exp)
⚠ $l''(\theta)$ must exist
$I(\theta) = Var(l'(\theta)) = -E[l''(\theta)]$
⚠ the E[] is of the observation X and not the unknown! $E[\theta X] = \theta E[X]$

χ^2 DISTRO

distro of sum of $Z_i \sim N(0,1)$
$E[V] = d$
$Var(V) = 2d$

COCHRAN'S TH.

$\frac{nS_n}{\sigma^2} \sim \chi_{n-1}^2$ or $nS_n \sim \frac{\sigma^2}{n}\chi_{n-1}^2$

t DISTRO

for small nb of Gaussian samples w/
$Z \sim N(0,1)$ and $V \sim \chi_d^2$ and
$\text{SampleVar} = \frac{V}{d}$
$\frac{Z}{\sqrt{\frac{V}{d}}}$ ⚠ Z and V must be indie

t TEST

- requires Gaussian samples
- is pivotal (q in tables)
- test is non-asymptotic

one sample two-sided
$H_0 : \mu = \mu_0$ vs $H_1 : \mu \neq \mu_0$

$$T_n = \frac{\sqrt{n}\overline{X_n}}{\sqrt{\widetilde{S_n}}} = \frac{\sqrt{n}\frac{\overline{X_n} - \mu_0}{\sigma}}{\sqrt{\frac{\widetilde{S_n}}{\sigma^2}}} \sim t_{n-1}$$

$\psi_\alpha = \mathbf{1}\left\{|T_n| > q_{\frac{\alpha}{2}}\right\}$

one sample one-sided
$H_0 : \mu \leq \mu_0$ vs $H_1 : \mu > \mu_0$

$$T_n = \frac{\sqrt{n}\left(\overline{X_n} - \mu_0\right)}{\sqrt{\widetilde{S_n}}} \sim t_{n-1}$$

$\psi_\alpha = \mathbf{1}\{T_n > q_\alpha\}$

two sample
$\overline{X_n} \sim N\left(\Delta_d, \frac{\sigma_d^2}{n}\right)$ and $\overline{Y_m} \sim N\left(\Delta_c, \frac{\sigma_c^2}{m}\right)$

$$\frac{\overline{X_n} - \overline{Y_m} - (\Delta_d - \Delta_c)}{\sqrt{\frac{\hat{\sigma}_d^2}{n} + \frac{\hat{\sigma}_c^2}{m}}} \sim t_N$$

where N according to Welch-Satter:

$$N = \frac{\left(\frac{\hat{\sigma}_d^2}{n} + \frac{\hat{\sigma}_c^2}{m}\right)^2}{\frac{\hat{\sigma}_d^4}{n^2(n-1)} + \frac{\hat{\sigma}_c^4}{m^2(m-1)}} \geq \min(n, m)$$

WALD'S TEST

- test is asymptotic
- not invariant to change in rep of H_0
- only req est of unrestricted model, lower computation

⚠ MLE conditions must be satisfied
$H_0 : \theta = \theta_0$ vs $H_1 : \theta \neq \theta_0$ for $\theta \in \mathbb{R}^d$

$$n\left(\hat{\theta}^{\text{MLE}} - \theta_0\right)^T I\left(\hat{\theta}^{\text{MLE}}\right)\left(\hat{\theta}^{\text{MLE}} - \theta_0\right) \to \chi_d^2$$

equivalently

$$T_n = \|\sqrt{n}I(\theta_0)^{\frac{1}{2}}\left(\hat{\theta}^{\text{MLE}} - \theta_0\right)\|^2 \to \chi_d^2$$

which gives test $\psi_\alpha = \mathbf{1}\{T_n > q_\alpha\}$
where q_α is the $(1-\alpha)$-quantile of χ_d^2

LIKELIHOOD RATIO TEST (ex. @ 21:00)

X_i iid $\Theta \in \mathbb{R}^d$
$H_0 : (\theta_{r+1}, \ldots, \theta_d) = \left(\theta_{r+1}^{(0)}, \ldots, \theta_d^{(0)}\right)$

$$T_n = 2\left(l_n\left(\hat{\theta}_n^{\text{MLE}}\right) - l_n\left(\hat{\theta}_n^{0}\right)\right) = -2\ln\left(\frac{L_{H_0}}{L_{H_1}}\right)$$

⚠ same n for both likelihoods
Wilk Th. (dim. ex. @ 16:00)
assuming H_0 is true and MLE conditions. is asymptotic
$T_n \to \chi_{d-r}^2$
$\psi_\alpha = \mathbf{1}\{T_n > q_\alpha\}$

CATEGORICAL LIKELIHOOD

i.e. are Zodiac signs uniformly distributed? $p_0 = \left(\frac{1}{12}, \frac{1}{12}\ldots\right)$
$L_n = p_1^{N\_1} \ldots p_k^{N\_k}$
$N_j = \#\{X_i = a_j\}$
$\vec{p}^{\text{MLE}} : \hat{p}_j = \frac{N_j}{n}$ prob of obs. outcome j
$p_j = P(X = a_j) = \prod p_i^{\mathbf{1}(a_i = a_j)}$

χ^2 TEST

$H_0 : \vec{p} = \vec{p}^0$ vs. $H1 : \vec{p} \neq \vec{p}^0$

$$T_n = n\sum^k\left[\frac{\left(\hat{p}_j - p_j^0\right)^2}{p_j^0}\right] \to \chi_{k-1}^2$$

where k is nb of categories

χ^2 TEST FOR FAMILY OF DIST

$H_0 : p \in \{\text{Bin}(k, \theta)\}_{\theta \in \Theta}$ vs $H_1 : p \notin \{\text{Bin}(k, \theta)\}_{\theta \in \Theta}$

$$T_n = n\sum_{j=0}^{k}\frac{\left(\frac{N_j}{n} - f_{\hat{\theta}}(j)\right)^2}{f_{\hat{\theta}}(j)} \to \chi_{(k+1)-d-1}^2$$

⚠ $k - d - 1$ if we start at j=1
$\Theta \in \mathbb{R}^d$
f_θ is PMF of $\text{Bin}(k, \theta)$
$\hat{\theta}$ is MLE here

EMPIRICAL CDF

$F_n(t) = \frac{1}{n}\sum \mathbf{1}\{X_i \leq t\}$
it is discontinuous
$\sqrt{n}(F_n(t) - F(t)) \to N(0, F(t)(1 - F(t)))$

DONSKER'S TH.

if F cont:
$\sqrt{n}\max_{t \in \mathbb{R}}|F_n(t) - F(t)| \to \max_{0 \leq t \leq 1}|B(t)|$
where B is Brownian bridge

KS TEST (example)

X_i: real RV with unk CDF
$H_0 : F = F^0$ vs $H1 : F \neq F^0$
$\delta_\alpha^{\text{KS}} = \mathbf{1}\{T_n > q_\alpha\}$
$= \mathbf{1}\left\{\max_{t \in \mathbb{R}}\sqrt{n}|F_n(t) - F(t)| > q_\alpha\right\}$
p-value $P(Z > T_n \mid T_n)$
computation

$$\frac{T_n}{\sqrt{n}} = \max_{1 \leq i \leq n}\left[\max\left(\left|F^0(x_i) - \frac{i}{n}\right|, \left|F^0(x_i) - \frac{i-1}{n}\right|\right)\right]$$

needs tables (pivotal statistic)

CDF OF SAMPLE IS UNIFORM

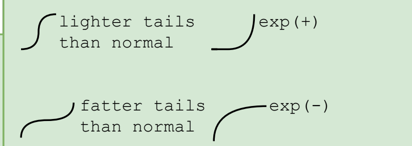
$Y = F_X(x)$
$F_Y \sim Un$ if $(0, 1)$

KL TEST (example)

is my data Gaussian?
more likely to reject than KS test
$\max_{t \in \mathbb{R}}\left|F_n(t) - \Phi_{\hat{\mu}, \hat{\sigma}^2}(t)\right|$

QQ PLOT (example 1, 2)

$F_n^{-1}\left(\frac{i}{n}\right) = X_i$ (F_n is sample CDF, F is th.)
points are $\left(F^{-1}\left(\frac{1}{n}\right), x_1\right), \left(F^{-1}\left(\frac{2}{n}\right), x_2\right)\ldots$
to find inverse F^{-1}: "what input value to F gives output value t. we are looking for input value to F that gives $\frac{1}{n}$"



MARKOV INEQUALITY

$X \geq 0$ and $a > 0$
$P(X \geq a) \leq \frac{E[X]}{a}$

CHEBYSHEV INEQUALITY (link)

probability of estimate of mean deviating from true mean by more than C
$P(|X - \mu| \geq c) \leq \frac{\sigma^2}{c^2}$

CONVERGENCE IN PROBABILITY

a seq. converges to a in probability if:
$\lim_{n \to \infty} P(|X_n - \mu| \geq \varepsilon) = 0$
another way to show convergence in prob is to determine expectation and variance. if $Var \to 0$ then convergence

properties
- if g is continuous then $g(X_n) \to g(a)$
- $X_n + Y_n \to a + b$
- but $E[X_n]$ doesn't need to converge to a

ESTIMATE BINOMIAL WITH NORMAL

PMF of # success in n trials w/p p approximates $N(np, np(1-p))$ with
$'P(X = 19)' = P(18.5 \leq X \leq 19.5)$

MOIVRE LAPLACE CORRECTION

when estimating an integer R.V. with the CLT, can do the "1/2 correction":
$P(S_n \leq 21) \to P(S_n \leq 21.5)$

is estimator consistent?
check lim as $n \to \infty$ against estimator
is estimator asym. normal?
start with CLT definition, then put in the estimator. also get aVar like this.
see examples.

BAYESIAN STATS

$\pi(\theta \mid X_1 ... X_n) = \frac{\pi(\theta) L_n(X_1...X_n \mid \theta)}{\int_\Theta \pi(\theta) L_n(X_1...X_n \mid \theta)}$

$\propto \pi(\theta) L_n(X_1...X_n \mid \theta)$

conjugate prior if post. distro. same as prior distro.

improper prior i.e. uniform $\pi(\theta) = 1$, not a valid distro

Jeffrey's prior

non-informative prior, not always improper. reflects no prior belief, only stats model

$\pi_J(\theta) \propto \sqrt{\det I(\theta)}$

reparam. invariance

we have Jeff prior for θ, want $\eta = \Phi(\theta)$

· replace θ with $\Phi^{-1}(\eta)$

· multiply by $\frac{d\theta}{d\eta} = \frac{1}{\Phi\prime(\theta)}$

confidence region

$P(\theta \in \mathbb{R} \mid X_1...X_n) = 1 - \alpha$

BAYESIAN STATS - NORMALS

$f_X(x) = c \exp\left(-\left(\alpha x^2 + \beta x + \gamma\right)\right)$

$\mu = -\frac{\beta}{2\alpha}$ and $\sigma^2 = \frac{1}{2\alpha}$

the peak is min. of exponent:

· derive exponent and set to 0

$\widehat{\Theta}_{\text{MAP}} = \widehat{\Theta}_{\text{LMS}} = E[\Theta \mid X = x]$

(in general this is true if posterior is unimodal and symmetric)

MAP

$\hat{\theta}^{\text{MAP}} = arg \max_\theta \pi(\theta \mid X_1...X_n)$

$= arg \max_\theta L_n(X_1...X_n \mid \theta)\pi(\theta)$

⚠ look at posterior PDF/PMF and ask "which actual possible values of θ make this result most likely, i.e. the mode

i.e. is $\left|\theta_1 - \hat{\theta}^{\text{Bayes}}\right| > \left|\theta_2 - \hat{\theta}^{\text{Bayes}}\right|$

⚠ if discrete, MAP is in set of possible values

find MAP continuous

take derivative, find critical points, maximum

LINEAR REGRESSION (STATS)

this describes the practical model. LLMS in Prob describes theory.

⚠ nb: stats and prob flip the a, b like theoretical model but assume some Gaussian noise

$Y_i = a^\star + b^\star X_i + \varepsilon_i$

use least squares to find estimators

$\min \sum (Y_i - a - bX_i)^2$

$\hat{a} = \overline{Y} - \hat{b}\overline{X}$

$\hat{b} = \frac{\overline{XY} - \overline{X}\,\overline{Y}}{\overline{X^2} - \left(\overline{X}\right)^2}$

BAYES ESTIMATOR

mean of posterior

also known as **LMS** "conditional expectation" $E[\Theta \mid X = x]$

⚠ MUST USE ACTUAL POSTERIOR, not the prop. one if we calculate it like below, else we may also use mean of the distribution if i.e. Beta without having to calculate denominator

$\hat{\theta}^\pi = \int_\Theta \theta \pi(\theta \mid X_1...X_n) d\theta$

aVar $= I^{-1}(\theta)$ of distro sampled

properties of LMS estimation error

let $\widehat{\Theta} = E[\Theta \mid X]$ and error $\widetilde{\Theta} = \widehat{\Theta} - \theta^\star$

· $E\left[\widetilde{\Theta} \mid X = x\right] = 0$

· $cov\left(\widetilde{\Theta}, \widehat{\Theta}\right) = 0$

· $Var(\Theta) = Var\left(\widehat{\Theta}\right) + Var\left(\widetilde{\Theta}\right)$

conditional MSE of LMS estimator

$E\left[\left(\Theta - \widehat{\Theta}\right)^2 \mid X = x\right] = Var(\Theta \mid X = x)$

LLMS / LINEAR REGRESSION

unknown Θ, observation X

$\widehat{\Theta} = aX + b$

minimises $E\left[(\Theta - aX - b)^2\right]$

$a = \frac{Cov(\Theta, X)}{Var(X)}$

$b = E[\Theta] - aE[X]$

⚠ if all vars normals then LMS=LLMS

MSE

$MSE\left(\hat{\theta}\right) = E\left[\left(\hat{\theta} - \theta\right)^2\right] = Var\left(\hat{\theta}\right) + \left(Bias\left(\hat{\theta}\right)\right)^2$

Gaussian

$MSE\left(\overline{X_n}\right) = E\left[\left(\overline{X_n} - \mu\right)^2\right] = \left(\frac{\sigma}{\sqrt{n}}\right)^2$

$MSE\left(\widetilde{S_n}\right) = \frac{2}{n-1}\sigma^4$

$MSE(S_n) = \frac{2n-1}{n^2}\sigma^4$

LINEAR REGRESSION FUNCTION

$E[Y \mid X = x] = \mu(x) = \int y h(y \mid x) dy = X^T \beta$

SIGNIFICANCE TESTS

is j^{th} explanatory variable significant

$H_0 : \beta_j = 0 \quad H_1 : \beta_j \neq 0$ (ex. for $\beta_1 = \beta_2$)

assume γ_j is j$^{\text{th}}$ diagonal coefficient of $\left(\mathbb{X}^T\mathbb{X}\right)^{-1}$ $(\gamma_j > 0)$

$\Rightarrow T_n = \frac{\widehat{\beta}_j - \beta_j}{\sqrt{\widehat{\sigma}^2 \gamma_j}} \sim t_{n-p}$

$\Rightarrow R_{j,\alpha} = \left\{\left|T_n^{(j)}\right| > q_{\frac{\alpha}{2}}(t_{n-p})\right\}$

MV LINEAR REGRESSION (STATS)

$\vec{Y} = \mathbb{X}\vec{\beta}^\star + \vec{\varepsilon}$

$\vec{\beta} \in \mathbb{R}^p$, $\vec{Y} \in \mathbb{R}^n$, $\mathbb{X} \in \mathbb{R}^{n \times p}$

LSE (same as Bayes estimator)

$\widehat{\vec{\beta}} = arg \min_{\beta \in \mathbb{R}^p} \left|\left|\vec{Y} - \mathbb{X}\vec{\beta}\right|\right|^2$

$\widehat{\vec{\beta}} = \left(\mathbb{X}^T\mathbb{X}\right)^{-1}\mathbb{X}^T Y$

$Rank(\mathbb{X}) = p$ and need $n \geq p$ for this to work

assumptions

· $\mathbb{X}$ is deterministic, rank=p

· ε_i are iid

· $\vec{\varepsilon} \sim N\left(0, \sigma^2 I_n\right)$

$\Rightarrow Y \sim N_n\left(\mathbb{X}\beta^\star, \sigma^2 I_n\right)$

$\Rightarrow I(\beta) = \frac{1}{\sigma^2}\mathbb{X}^T\mathbb{X}$

properties of LSE

· LSE is MLE in homoscedatic Gaussian case

· $\widehat{\beta} \sim N_p\left(\beta^\star, \sigma^2\left(\mathbb{X}^T\mathbb{X}\right)^{-1}\right)$ ⚠ asym

· quadratic risk: $E\left[\left|\left|\widehat{\beta} - \beta\right|\right|^2\right] = \sigma^2 trace\left(\left(\mathbb{X}^T\mathbb{X}\right)^{-1}\right)$

· prediction error: $E\left[\left|\left|Y - \mathbb{X}\widehat{\beta}\right|\right|^2\right] = \sigma^2(n-p)$

· unbiased estimator: $\sigma^2 = \frac{\left|\left|Y - \mathbb{X}\widehat{\beta}\right|\right|^2}{n-p} = \frac{1}{n-p}\sum \hat{\varepsilon}^2$

theorems

· $(n-p)\frac{\widehat{\sigma^2}}{\sigma^2} \sim \chi^2_{n-p}$

· $\widehat{B}$ and $\widehat{\sigma^2}$ are orthogonal and indie

BONFERRONI'S TEST (ex.)

test whether group of explanatory vars is significant FWER $\leq \alpha$

⚠ non asymptotic test

$H_0 : \beta_j = 0 \ \forall j \in S$ where $S \subseteq \{1, ..., p\}$

$H_1 : \exists j \in S$ where $\beta_j \neq 0$

$R_{S,\alpha} = \bigcup_{j \in S} R_{j,\frac{\alpha}{k}}$ (OR statement!)

where k is # in S, and $\frac{\alpha}{k}$ usually passed to a 2 sided test so that final quantile may be $q_{\frac{\alpha}{2k}}$

$\psi = \mathbf{1}\left\{\frac{\max\left(\left|\widehat{\beta}_1\right|, \left|\widehat{\beta}_2\right|, ...\right)}{\sqrt{Var\left(\widehat{\beta}_j\right)}} > q_{\frac{\alpha}{2k}}\right\}$

WOLFRAM

Probability x>4.03, Chi Squared Distribution degrees of freedom 1

CDF[NormalDistribution[2, 1], 0.65] ⚠ CDF uses <u>STANDARD DEVIATION</u>

Quantile[ChiSquareDistribution[1], 0.95]

Round[5.15517, 0.001] plot 1/(x^2-x) from x=1 to 10

1 PARAM CANON EXP FAMILY (ex)

$f_\theta(y) = \exp\left(\frac{y\theta - b(\theta)}{\phi} + c(y, \theta)\right)$

θ is canon. param

ϕ (dispersion), b and c known

$b(\theta)$ is log partition

$E[Y] = b\prime(\theta)$

$Var(Y) = b\prime\prime(\theta)\phi$

linear transformations of these are also canon.

⚠ we can do a substitution i.e $\theta = \frac{1}{\lambda}$ to express. then substitute again to express as λ

· $N(\mu, 1)$

· $Poisson(\lambda)$

· $Ber(p)$

· $\text{Binomial}(1000, p)$

· $Exp(\lambda)$

canon link

links $\mu(x)$ to canon param θ:

$g(\mu(x)) = \theta = (b\prime)^{-1}(\mu(x))$

if $\phi > 0$ canon link is strictly increasing

GLM MODEL

$\vec{Y} = (Y_1, ..., Y_n)$ and $\mathbb{X} = (X_1, ..., _X - n)$

$\mu_i = E[Y_i \mid X_i]$ is related to canonical param θ_i via $\mu_i = b\prime(\theta_i)$

μ_i depends linearly on the coavariates through link function g:

$g(\mu_i) = X_i^T \beta$

using predictor

use mean function in table below once we have $\widehat{\beta}$

asymptotic normality

$\widehat{\beta}$ is asym normal

finding β

MLE/Gradient Descent

Link function Linear predictor

$\ln \lambda_i = b_0 + b_1 x_i$

$y_i \sim \text{Poisson}(\lambda_i)$

Probability distribution

CANON PARAMETER

$\theta = a + bX = \mathbb{X}\beta = g(\mu)$

here μ is the param of our distro, and θ is the canon param

$\mu = g^{-1}(\theta)$

MULTIPLE HYPOTHESIS TESTING (see @ 9:24)

family-wise error rate

FWER = P(at least one false significant result) $\leq \alpha$ use Bonferroni's test

$= 1 - P(V = 0) = 1 - 0.95^{100} \approx 0.99$

very restrictive

reject when $m \cdot p - value \leq \alpha$

false discovery rate

FDR = expected fraction of false significant results among all significant results $\leq \alpha$

Holm-Bonferroni correction

Bonferroni-Hochberg correction

Distribution	Support of distribution	Typical uses	Link name	Canon Link function, $\mathbf{X}\boldsymbol{\beta} = g(\mu)$	Mean function
Normal	real: $(-\infty, +\infty)$	Linear-response data	Identity	$\mathbf{X}\boldsymbol{\beta} = \mu$	$\mu = \mathbf{X}\boldsymbol{\beta}$
Exponential Gamma	real: $(0, +\infty)$	Exponential-response data, scale parameters	Negative inverse	$\mathbf{X}\boldsymbol{\beta} = -\mu^{-1}$	$\mu = -(\mathbf{X}\boldsymbol{\beta})^{-1}$
Inverse Gaussian	real: $(0, +\infty)$		Inverse squared	$\mathbf{X}\boldsymbol{\beta} = \mu^{-2}$	$\mu = (\mathbf{X}\boldsymbol{\beta})^{-1/2}$
Poisson	integer: $0, 1, 2, \ldots$	count of occurrences in fixed amount of time/space	Log	$\mathbf{X}\boldsymbol{\beta} = \ln(\mu)$	$\mu = \exp(\mathbf{X}\boldsymbol{\beta})$
Bernoulli	integer: $\{0, 1\}$	outcome of single yes/no occurrence	Logit	$\mathbf{X}\boldsymbol{\beta} = \ln\left(\frac{\mu}{1-\mu}\right)$	$\mu = \frac{\exp(\mathbf{X}\boldsymbol{\beta})}{1 + \exp(\mathbf{X}\boldsymbol{\beta})} = \frac{1}{1 + \exp(-\mathbf{X}\boldsymbol{\beta})}$
Binomial	integer: $0, 1, \ldots, N$	count of # of "yes" occurrences out of N yes/no occurrences	Logit	$\mathbf{X}\boldsymbol{\beta} = \ln\left(\frac{\mu}{n-\mu}\right)$	$\mu = \frac{\exp(\mathbf{X}\boldsymbol{\beta})}{1 + \exp(\mathbf{X}\boldsymbol{\beta})} = \frac{1}{1 + \exp(-\mathbf{X}\boldsymbol{\beta})}$