MAS-1
Study Review

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- Probability Review
- Stochastic Processes
- Life Contingencies
- Simulation
- Statistics
- Extended Linear Model
- Time Series

Lesson 1 : Probability Review

- **Bernouilli Shortcut :** If a random variable can only assume two values a and b with probabilility q and $1-q$, then is variance is $q(1-q)(b-a)^2$

Lesson 2 : Parametric Distributions

- **Transformations :**
  - Transformed : $\tau > 0$
  - Inverse : $\tau = -1$
  - Inverse-Transformed : $\tau < 0, \tau \neq 1$

Lesson 4 : Markov Chains

- **Chapman-Kolmogorov :**
$$P_{ij}^{(n+m)} = \sum_{k=0}^{\infty} P_{ik}^{(n)} P_{kj}^{(m)}$$
- **Gambler's ruin :** Let N the target and j the actual status.
$$p_j = \begin{cases} \frac{j}{N} & , r = 1 \\ \frac{r^j - 1}{r^N - 1} & , r \neq 1 \end{cases}$$
où $r = \dfrac{q}{p}$, p : winning prob.
- **Algorithmic efficency :** with N_j = number of steps from j^{th} solution to best solution.
$$\mathrm{E}[N_j] = \sum_{i=1}^{j-1} \frac{1}{i}$$
$$\mathrm{Var}(N_j) = \sum_{i=1}^{j-1} \left(\frac{1}{i}\right)\left(1 - \frac{1}{i}\right)$$
As $j \to \infty$, $\mathrm{E}[N_j] \to \ln j$, $\mathrm{Var}(N_j) \to \ln j$

Lesson 5 : Markov Chain Classification

- An **absorbing** state is one that cannot be exited.
- State j is **accessible**$(i \to j)$ from state i if $p_{ij}^n > 0$,
$\forall n \geq 0$.
- Two states **communicate** if $i \leftrightarrow j$.
- A **class** of states is a maximal set of state that communicate with each other.
- A Markov chain is **irreductible** if it has only one class.
- A state (class) is **recurrent** if the probability of reentering the state is 1. $\sum_{n=1}^{\infty} p_{ii}^{(n)} = \infty$
- A state (class) si **transcient** if it is not recurrent.
$\sum_{n=1}^{\infty} p_{ii}^{(n)} < \infty$
- A finite Markov Chain must have at least one recurrent class. If it is irreductible, then it is recurrent.

Lesson 6 : Markov Chains Limiting Probability

- A chain is **positive recurrent** is the expected number of transitions until the state occur is finite, **null recurrent** otherwise. Null recurrent mean that the long-term proportion of time in each state is 0.
- A chain is **periodic** when states occur every n periods for $n > 1$.
- A chain is **aperiodic** when the period is 1. In other world, $P_{ii}^{(1)} > 0, \forall i$
- A chain is **ergodic** when the chain is aperiodic and positive irreductible recurrent.
- **Stationary probability :**
$$\pi_j = \sum_{i=1}^{n} P_{ij} \pi_i \qquad \sum_{i=1}^{n} \pi_i = 1$$
- **Limiting probabilities :** if the chain is ergodic, then
$$\mathbf{P}^{(\infty)} = \begin{pmatrix} \pi_1 & \pi_2 & \pi_3 \\ \pi_1 & \pi_2 & \pi_3 \\ \pi_1 & \pi_2 & \pi_3 \end{pmatrix}$$

Lesson 7 : Time in Transient States

- Tips : **??**
- $\mathbf{S} = (\mathbf{I} - \mathbf{P}_{\text{transcient}})^{-1}$, where s_{ij} is the time in state j given that the current state is i.
- $f_{ij} = \frac{s_{ij} - \delta_{i,j}}{s_{jj}} = \sum_{n=1}^{\infty} f_{ij}^{(n)}$, where f_{ij} is the probability that state i ever transitions to state j.

Lesson 8 : Branching Processes

- A branching process is a special type of Markov chain representing the growth or extinction of a population.
- $\mathrm{E}[X_n] = \mathrm{E}[Z]^n$, where $\mathrm{E}[Z]$ is the expected number of people born in a generation.
- $\mathrm{Var}(X_n) = \mathrm{Var}(Z) \cdot \mathrm{E}[Z]^{n-1} \sum_{k=1}^{n} \mathrm{E}[Z]^{k-1}$
- If $X_0 \neq 1$ mean and variance of X_n need to be multiplicated by X_0.
- **Probability of extinction :**
$$\pi_0 = \sum_{j=1}^{\infty} p_j \pi_0^j$$
  - $\mu \leq 1 \Rightarrow \pi_0 \geq 1$,if $X_0 = 1$.
  - $\mu > 1 \Rightarrow \pi_0 < 1$,if $X_0 = 1$.

For cubic equation, it guaranteed to factor $(\pi_0 - 1)$. Tips : **??**

Lesson 9 : Time Reversible

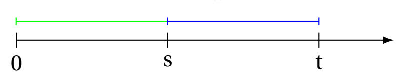
- If $\mathbf{Q}$ is the reverse-time Markov chain for ergodic $\mathbf{P}$, then
$$\pi_i Q_{ij} = \pi_j P_{ji}$$
with $P_{ii} = Q_{ii}$ and if $p_{ij} = 0 \Leftrightarrow Q_{ji} = 0$
- If $\mathbf{Q} = \mathbf{P}$, then $\mathbf{P}$ is said to be **time-reversible**.

Lesson 10 : Exponential Distribution

- **Lack of memory :**
$$\Pr(X > k + x | X > k) = \Pr(X > x)$$
- **Minimum :** if $X_i \sim \mathrm{Exp}(\lambda_i)$, then
$$\min(X_1, X_2, ..., X_n) \sim \mathrm{Exp}\left(\sum_{i=1}^{n} \lambda_i\right)$$
- The sum of 2 Exponentials randoms variables is the sum of the maximum and the minimum, since one must be the min and the other the max.
$$X_1 + X_2 = \min(X_1, X_2) + \max(X_1, X_2)$$

Lesson 11 : Poisson Process

- $X(t) \sim \mathrm{Poisson}[m(t)]$,where $m(t)$ is **mean value function** representing the mean of the number events before time t.
- Poisson process can't decrease over time. $N(t) \geq N(s) \quad \text{for } t \geq s$
- $N(0) = 0$
- Increament are **independent** :



$$\Pr[N(t) - N(s) = n | N(s) = k] = \Pr[N(t) - N(s) = n]$$
- **Non-homogeneous Poisson process :**
$$m(t) = \int_0^t \lambda(u)\,\mathrm{d}u$$
where $\lambda(t)$ is the **intensity function**
- **Homogeneous Poisson process :** The Poisson process is said to be homogeneous when the intensity function is a constant.
$$m(t) = \int_0^t \lambda\,\mathrm{d}u = \lambda t$$
We then say that the process have **stationary increments**.
$$\Pr[N(s-t)] = \Pr[N(t) - N(s)]$$

Lesson 12 : Poisson Process Time To Next Events

- T_n is the time between the n[th] event and the (n-1)[th] event.
- $S_n = \sum_{i=1}^{n} T_i$, is the time for the n[e] event.
- $F_{T_1}(t) = 1 - e^{-\int_0^t \lambda(u)\,\mathrm{d}u}$
- For homogeneous process :
$$T_n \sim \mathrm{Exp}(\lambda)$$
$$S_n \sim \mathrm{Gamma}(n, \lambda)$$

Lesson 13 : Poisson Process Counting Special Type

- If event of type 1 occur with probability $\alpha_1(t)$, then the event follow a Poisson process with intensity $\lambda(t) \cdot \alpha_1(t)$.
$$m(t) = \int_0^t \lambda(u)\alpha_1(u)\,\mathrm{d}u$$

Lesson 14 : Poisson Process Other Characteristics

- Only for homogeneous Poisson processes.
- The probability of k event from process 1 is given by :
$$k \sim \text{Binomial}\left(k+l-1, \frac{\lambda_1}{\lambda_1+\lambda_2}\right)$$
Then the probability that k event from process 1 occur before l from process 2 is :
$$\sum_{i=k}^{k+l-1} \binom{k+l-1}{i} \left(\frac{\lambda_1}{\lambda_1+\lambda_2}\right)^i \left(\frac{\lambda_2}{\lambda_1+\lambda_2}\right)^{k+l-1-i}$$
- Given that exactly $N(t) = k$ Poisson events occured before time t, the joint distribution of event time is the joint distribution of k independent uniform random variables on $(0, t)$.
$$F_{S_1,\ldots,S_n|n(t)}(s_1,\ldots s_n|k) = \frac{k!}{t^k}$$
- For k independent uniform random variable on $(0, t)$, the expected value of the j^{th} order statistics is : $E[T^{[j]}] = \frac{jt}{(k+1)}$.
- Tips : **??**

Lesson 15 : Poisson Process Sums and Mixtures

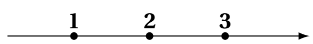
- A **Sums** of independent Poisson random variables is a Poisson random with intensify function $\lambda(t) = \sum \lambda_i(t)$. Warning : Substraction don't give a Poisson random variable.
- A **Mixture** of Poisson processes is not a Poisson processes.
  - **Discrete** mixture :
  $$F_{X(t)}(t) = \sum_i w_i F_{X_i(t)}(t)$$
  where $w_i > 0, \sum w_i = 1$
  - **Continuous** mixture :
  $$F_{X(t)}(t) = \int F_{\{X_u(t)\}}(t) f(u)\,\mathrm{d}u$$
  - If $N(t)|\lambda$ is a Poisson random variable and $\lambda \sim \text{Gamma}(\alpha, \theta)$, then $N(t) \sim \text{NegBin}(r = \alpha, \beta = \theta t)$.

Lesson 16 : Compound Poisson Processes

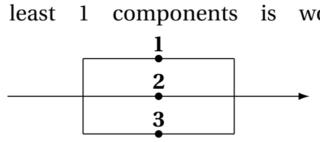
- A **compound** random variable S is define by $S = \sum_{i=1}^N X_i$ where N is the **primary** distribution and X the **secondary** distribution.
- If $N(t)$ is a Poisson process, then $S(t)$ is a compound Poisson process with :
  - $\mathrm{E}[S(t)] = \lambda t \mathrm{E}[X]$
  - $\mathrm{Var}(S(t)) = \lambda t \mathrm{E}\left[X^2\right]$
- If X_i is discrete, we can separate the process into a sum of subprocess view in **??**.
- **Sums of compound** homogeneous Poisson process is also a Poisson process with :
  - $N(t) \sim \text{Pois}(\sum \lambda_i)$
  - $F_X(x) = \sum_i w_i F_{X_i(t)}(t), \quad w_i = \frac{\lambda_i}{\sum \lambda_i}$

Lesson 17 : Reliability Structure Functions

- $\phi(\mathbf{x})$ is the **structure** function for a systeme. It equal 1 if the systeme work, 0 otherwise.
- A **series** system is define as a **minimal path set**. The system is working if all components are working.



The serie structure function is define as
$$\phi(\mathbf{x}) = \prod_{i=1}^n x_i$$
- A **parallel** system is define as a **minimal cut set**. The systeme is working if at least 1 components is working.



The parallel structure function is define as
$$\phi(\mathbf{x}) = 1 - \prod_{i=1}^n (1 - x_i)$$
- Tips : Minimal path set is all way for the system to work, and the minimal cut set is all the way for the system to not work.
- Tips : If set is $\{1,2,3\}$ and $\{1,2\}$, the *minimal* mean we only take $\{1,2\}$.
- Tips : *Minimal cut* is a serie of parallel structure and *minimal path* is a parallel of serie structure.

Lesson 18 : Reliability Probabilities

- $r(\mathbf{p})$ is the same polynomial as $\phi(\mathbf{x})$.
- Inclusion/exclusion bounds using minimal path :
$$r(\mathbf{p}) \le \sum A_i$$
$$r(\mathbf{p}) \ge \sum A_i - \sum A_i \cup A_j$$
$$r(\mathbf{p}) \le \sum A_i - \sum A_i \cup A_j + \sum A_i \cup A_j \cup A_k$$
where $A_i = \sum p_i$ is the probability of the i$^{\text{e}}$ minimal path set work.
- Inclusion/exclusion bounds using minimal cut :
$$1 - r(\mathbf{p}) \le \sum A_i$$
$$1 - r(\mathbf{p}) \ge \sum A_i - \sum A_i \cup A_j$$
$$1 - r(\mathbf{p}) \le \sum A_i - \sum A_i \cup A_j + \sum A_i \cup A_j \cup A_k$$
where $A_i = \sum(1 - p_i)$ is the probability of the i^{e} minimal cut set work.
- Bounds using intersections :
$$\prod \phi(\mathbf{X})^{\textbf{min. cut}} \le r(\mathbf{p}) \le \prod \phi(\mathbf{X})^{\textbf{min. path}}$$
- **Random graph** :
$$1 - P_n = \sum_{k=1}^{n-1} \binom{n-1}{k-1} q^{k(n-k)} P_k$$
$$1 - P_n \le (n+1)q^{n-1}$$
$$P_1 = 1$$

Lesson 19 : Reliability Time to Failure

- Expected amound of time to failure :
$$\mathrm{E}\left[\textbf{system life}\right] = \int_0^\infty r(\bar{\mathbf{F}}(\mathbf{t}))\,\mathrm{d}t$$
where,
  - For serie system :
  $$r(\bar{\mathbf{F}}(\mathbf{t})) = \prod_{i=1}^n \bar{F}_i(t)$$
  - For parallel system :
  $$r(\bar{\mathbf{F}}(\mathbf{t})) = 1 - \prod_{i=1}^n F_i(t)$$
- *Shortcut* : k out of n system with exponentials(θ) : $\mathrm{E}[T] = \theta \sum_{i=k}^n \frac{1}{i}$
- **Hazard rate function** (*failure rate function*) :
$$h(t) = \frac{f(t)}{\bar{F}(t)}$$
and we say that the distribution
  - is an increasing failure rate if $h(t)$ is non-deacreasing function of t.
  - is an deacreasing failure rate if $h(t)$ is non-increasing function of t.
- **Cumulatice hazard function** :
$$H(t) = \int_0^t h(u)\,\mathrm{d}u = -\ln \bar{F}(t)$$
with $\frac{H(t)}{t}$ the average of the hazard rate.

Lesson 20 : Survival Models

- ${}_tp_x = \frac{\ell_{x+t}}{\ell_x}, \quad {}_tq_x = \frac{\ell_x - \ell_{x+t}}{\ell_x}$
- ${}_{t|u}q_x = \frac{\ell_{x+t} - \ell_{x+t+u}}{\ell_x}$
- ${}_{t+u}p_x = {}_up_x \cdot {}_tp_{x+u}$
- ${}_{t|u}q_x = {}_{t+u}q_x - {}_tq_x = {}_tp_x \cdot {}_uq_{x+t}$
- Let be N_x the number of life surviving to age x, then
$$(N_{x+t}|N_x = n) \sim \text{Bin}(n, {}_tp_x)$$
- **Force of mortality** :
$$\mu_{x+t} = \frac{f_{T_x}(t)}{{}_tp_x} = -\frac{\mathrm{d}}{\mathrm{d}t} \ln {}_tp_x$$

- **Linear interpolation(D.U.D) :**
$$\ell_{x+t} = (1-t)\ell_x + t\ell_{x+1}$$
Shortcut : $\forall t \in (0,1), \forall x \in \mathbb{N}, x < x+t < x+1$:
  - ➟ ${}_tq_x = t \cdot q_x$
  - ➟ $\mu_{x+t} = \frac{q_x}{1-t\cdot q_x}$
- **Expected life time :** Let $k_x = \lfloor T_x \rfloor$, the *full years* until death. Then e_x is the **curtate life expectancy** and $\mathring{e}_x$ the **complete life expectancy**. ω is the age where $\ell_\omega = 0$ and $\omega = \infty$ by convention is nothing is said.
$$e_x = \mathrm{E}[K_x] = \sum_{k=1}^{\omega-x-1} {}_kp_x$$
$$\mathring{e}_x = \mathrm{E}[T_x] = \int_0^{\omega-x} {}_tp_x \,\mathrm{d}t \overset{\text{D.U.D}}{=} e_x + 0.5$$

Lesson 21 : Contingent Payments

The contract here are define with K_x to pay at the end of death year. All same contract can be define with T_x to pay at the moment of death. Then we use integral instead of sum and use
$$\Pr(K=k) = {}_kp_x q_{x+k} \Rightarrow f_{T_x}(t) = {}_tp_x \mu_{x+t}$$

- **Life Insurance :**
  - Whole Life insurance :
$$A_x = \sum_{k=0}^{\infty} v^{k+1} {}_kp_x q_{x+k}$$
  - Term Life insurance :
$$A^1_{x:\overline{n}|} = \sum_{k=0}^{n} v^{k+1} {}_kp_x q_{x+k}$$
  - Deferred insurance :
$${}_{m|}A_x = \sum_{k=m}^{\infty} v^{k+1} {}_kp_x q_{x+k}$$
  - Endowment insurance :
$$A_{x:\overline{n}|} = A^1_{x:\overline{n}|} + {}_nE_x$$
  - Pure Endowment :
$${}_nE_x = v^n {}_np_x$$
- **Life Annuities :**
  - Whole Life annuity
$$\ddot{a}_x = \sum_{k=0}^{\infty} v^k {}_kp_x$$
  - Temporary Life annuity
$$\ddot{a}_{x:\overline{n}|} = \sum_{k=0}^{n} v^k {}_kp_x$$
  - Deferred annuity
$${}_{m|}\ddot{a}_x = \sum_{k=m}^{\infty} v^k {}_kp_x$$
  - Certain and life annuity
$$\ddot{a}_{\overline{\overline{x:n}|}} = \ddot{a}_{\overline{n}|} + {}_{m|}\ddot{a}_x$$
- **Illustrative Life Table :**
  - $A_x = v q_x + v p_x A_{x+1}$
  - $\ddot{a}_x = 1 + v p_x \ddot{a}_{x+1}$
  - $A^1_{x:\overline{n}|} = A_x - {}_nE_x A_{x+n}$
  - $\ddot{a}_{x:\overline{n}|} = \ddot{a}_x - {}_nE_x \ddot{a}_{x+n}$
  - ${}_{m|}A_x = {}_mE_x A_{x+m}$
  - ${}_{m|}\ddot{a}_x = {}_mE_x \ddot{a}_{x+m}$
  - $\ddot{a}_x = 1 + a_x$
  - $A_x = 1 - d\ddot{a}_x$
- **Joint life annuity**($\ddot{a}_{xy}$) make payments until the earliest death pf two lives.
- **Last survivor annuity**($\ddot{a}_{\overline{xy}}$) make payments until the last death of two lives.
$$\ddot{a}_x + \ddot{a}_y = \ddot{a}_{xy} + \ddot{a}_{\overline{xy}}$$
- **Premiums :**
$$M \cdot A_x = P\ddot{a}_x$$
$$P = \frac{M\cdot A_x}{\ddot{a}_x} = \frac{M}{\ddot{a}_x} - M\cdot d$$

Lesson 22 : Simulation Inverse Method

- **Linear congruential generators :**
$$x_k = (ax_{k-1} + c) \bmod m$$
$$x_k = b - \left\lfloor \frac{b}{m} \right\rfloor m$$
where $b = (ax_{i-k} + c)$ and $x_0 \equiv$ seed
- **Inverse transformation method :**
$\Pr\left(F^{-1}(u) \le x\right) = \Pr(u \le F(x)) = F(x)$
then $x = F^{-1}(u)$ where $U \sim \mathrm{Unif}(0,1)$
  - Normal Case : $x = \mu + \sigma z$
  - Log-Normal Case : $x = e^{\mu+\sigma z}$

  where $z = \Phi^{-1}(u)$, with linear interpolation.
- Tips : **??**
- Tips : if $\Uparrow U \equiv \Downarrow X$ then $(1-u_i) \Rightarrow u_i$

Lesson 23 : Simulation Application

- $\Pr(X \le x) \simeq \frac{1}{m}\sum_{j=1}^{m} \mathbb{1}_{\{x^{(j)} \le x\}}$
- $\mathrm{E}[X^k] \simeq \frac{1}{m}\sum_{j=1}^{m} [x^{(j)}]^k$
- $\mathrm{VaR}_k(X) \simeq X^{[j_0]}$
- $$\mathrm{TVaR}_k(X) \simeq \frac{1}{m(1-k)} \sum_{j=j_0+1}^{m} X^{(j)} \mathbb{1}_{\{X^{(j)} > X^{[j_0]}\}} \simeq \frac{1}{m-j_0} \sum_{j=j_0+1}^{m} X^{[j]}$$
  where
  - $j_0 = \lfloor m\cdot k \rfloor$
  - m is the number of simulations.
  - $X^{(j)}$ is the jth simulations.
  - $X^{[j]}$ is the jth simulations in order statistics.

Lesson 24 : Simulation Rejection Method

- **General method :** Let $f(x)$ be the density function of variable to simulate, and let $g(x)$ be the **base distribution**, a random density function that is easy-to-simulate with nonzero wherever $f(x) \neq 0$.
$$c = \max \frac{f(x)}{g(x)}$$
Generate two uniform number u_1, u_2. Let $x_1 = G^{-1}(u_1)$. Accept x_1 only if
$$u_2 \le \frac{f(x_1)}{c\cdot g(x_1)}$$
- **Simulating gamma distribution :** Use $\mathrm{Exp}(\alpha\cdot\theta)$ as the base distribution and $x = \alpha\cdot\theta$ that maximize c.
- **Simulating standard normal distribution :** Generate 3 uniform u_1, u_2, u_3. Let $y_1 = -\ln u_2$ and $y_2 = -\ln u_2$. Accept y_1 if
$$y_2 \ge \frac{(y_1-1)^2}{2}$$
and add $(-)$ if $u_3 \ge 0.5$
- The **Number of iteration** is a Ross-geometric distribution with mean c. Let be β the mean of a geometric distribution given in the exam appendix :
$$\mathrm{E}[N] = 1 + \beta = c$$
$$\mathrm{Var}(N) = \beta(1+\beta)$$

Lesson 25 : Estimator Quality

- **Bias :** This quality measures if, on average, the estimator is on the expected value of the parameter.
$$\mathrm{E}[\hat{\theta}] = \theta + \mathrm{bias}_{\hat{\theta}}(\theta)$$
  - If $\mathrm{bias}_{\hat{\theta}}(\theta) = 0$, then $\hat{\theta}$ is **unbiased**.
  - If $\lim_{n\to\infty} \mathrm{bias}_{\hat{\theta}}(\theta) = 0$, then $\hat{\theta}$ is **asymptotically unbiased**.
  - If $\mathrm{bias}_{\hat{\theta}}(\theta) \neq 0$, then $\hat{\theta}$ is **biased**.
- **Consistency :** This quality measures if the probability that the estimator is different from the parameter by more than ε goes to 0 as n goes to infinity.
$$\lim_{n\to\infty} \Pr\left(|\hat{\theta} - \theta| > \varepsilon\right) \to 0,\ \forall\varepsilon > 0$$
In other word, as $n \to \infty$, $\mathrm{E}[\hat{\theta}] \to \theta$, $\mathrm{Var}(\hat{\theta}) \to 0$
- **Efficiency :** This quality measures the variance of the estimator. Lower the variance is, more efficient is the estimator.
$$\text{Efficiency of } \hat{\theta} = \frac{\mathrm{Var}(\hat{\theta})^{\text{rao}}}{\mathrm{Var}(\hat{\theta})}$$
$$\text{Relative efficiency of } \hat{\theta}_1 \text{ to } \hat{\theta}_2 = \frac{\mathrm{Var}(\hat{\theta}_2)}{\mathrm{Var}(\hat{\theta}_1)}$$
See the rao-cramer lower bound.
- **Mean Square Error :** This quality measures the expected value of the square difference between the estimator and the parameter.
$$\mathrm{MSE}_{\hat{\theta}}(\theta) = \mathrm{E}\left[(\hat{\theta}-\theta)^2\right] = \left(\mathrm{bias}_{\hat{\theta}}(\theta)\right)^2 + \mathrm{Var}(\hat{\theta})$$
- An estimator is called a **uniformly minimum variance unbiased estimator(UMVUE)** if it's unbiased and if there is no other unbiased estimator with a smaller variance for any true value θ.
- Some estimator :
  - $\bar{x} = \frac{1}{n}\sum x_i$ is a unbiased estimator of the mean μ. $\mathrm{Var}(\bar{x}) = \frac{1}{n}\mathrm{Var}(x)$

- $s^2 = \sum \frac{(x_i-\bar{x})^2}{n-1}$ is a unbiased estimator of the variance σ^2.
- $\hat{\sigma}^2 = \sum \frac{(x_i-\bar{x})^2}{n}$ is an asymptotically unbiased of the variance σ^2.
- $\hat{\mu}'_k = \frac{1}{n}\sum x_i^k$, where $\hat{\mu}'_1 = \bar{x}$ and $\hat{\mu}_k = \frac{1}{n}\sum(x_i-\bar{x})^k$, where $\hat{\mu}_1 = 0$ and $\hat{\mu}_2 = \hat{\sigma}^2$.

Lesson 26 : Kernel Density Estimation

- **Empirical distribution :** All data is assigning a probability of $\frac{1}{n}$. This is the same method used for simulation, see **??**.

$$F_e(x) = \frac{1}{n}\sum_{i=1}^{n} \mathbb{1}_{\{x_i \le x\}}$$
$$f_e(x) = \frac{1}{n}\sum_{i=1}^{n} \mathbb{1}_{\{x_i = x\}} = F_e(x) - F_e(x_{i-1})$$

- **Kernel Density** is a empirical distribution smoothed with a base fonction. Let define the scaling factor b called **bandwith**.
  - The kernel-density estimate of the density function is : $\hat{f}(x) = \frac{1}{n}\sum k\left(\frac{x-x_i}{b}\right)$ $\Leftrightarrow \sum f_e(x) k\left(\frac{x-x_i}{b}\right)$
  - The kernel-density estimate of the distribution is : $\hat{F}(x) = \frac{1}{n}\sum K\left(\frac{x-x_i}{b}\right)$
- **Rectangular(uniform, box) kermel :**

$$k(x) = \begin{cases} \frac{1}{2b}, & -1 \le x \le 1 \\ 0, & \text{otherwise} \end{cases}$$
$$K(x) = \begin{cases} 0, & x < -1 \\ 0.5(x+1), & -1 \le x \le 1 \\ 1, & x > 1 \end{cases}$$
$$\hat{f}(x) = \frac{F_e(x+b) - F_e(x-b^-)}{2b}$$

- **Triangular kernel :**

$$k(x) = \begin{cases} \frac{1-|x|}{b}, & -1 \le x \le 1 \\ 0, & \text{otherwise} \end{cases}$$
$$K(x) = \begin{cases} 0, & x < -1 \\ \frac{(1+x)^2}{2}, & -1 \le x \le 0 \\ 1 - \frac{(1-x)^2}{2}, & 0 \le x \le 1 \\ 1, & x > 1 \end{cases}$$

- **Gaussian kernel :** The distribution become normal with $\mu = x_i$ and $\sigma = b$.

$$k(x) = \frac{e^{-x^2/2}}{b\sqrt{2\pi}}$$
$$K(x) = \Phi(x)$$

- Other kernel : $k(x) = \beta(x)$ and $k(x) = B(x)$
- **kernel moments :** Let X be the kernel density estimate and x_i the empirical estimate. We then condition on x_i.

$$\mathrm{E}[X] = \mathrm{E}\big[\mathrm{E}[X|x_i]\big] = \mathrm{E}[x_i]$$
$$\mathrm{Var}(X_R) = \mathrm{Var}(x_i) + \frac{b^2}{3}$$
$$\mathrm{Var}(X_T) = \mathrm{Var}(x_i) + \frac{b^2}{6}$$
$$\mathrm{Var}(X_G) = \mathrm{Var}(x_i) + b^2$$

- Tips : For rectangular kernel, $\mathrm{E}[x|x_i]$ is a uniform$(x_i - b, x_i + b)$.

Lesson 27 : Method of Moments

- **Types of data :**
  - Complete data : Data is complete if we are given the exact value of each observation.
  - Grouped data : Set of interval and we know how many observation are in each.
  - Censored data : Value that are in a interval, but we don't know the exact value. Like limits ($\min(X,u)$).
  - Truncated data : We have data only when it in certain range, otherwise we don't know. Like deductible ($X|X>d$).
- **Method of Moments :** We match $\hat{\mu}'_k = \mathrm{E}\left[X^k\right]$ and find the parameters. If data is Censored or Truncated, we need to match the censored or truncated moment : $\hat{\mu}'_k = \mathrm{E}\left[\min(X,u)^k\right]$ or $\hat{\mu}'_k = \mathrm{E}\left[X^k|X>d\right]$.
- For pareto distribution, if $\hat{\mu}'_2 = \hat{\sigma}^2 + \bar{x}^2 \le 2\bar{x}^2$, the method of moment is unstable and can't be used.

Lesson 28 : Percentile Matching

- **Percentile Matching :** We match $F_e(\hat{\pi}_p) = p$ and find the parameters.
  - For censored data, we need select percentiles within the range of the uncensored portion of the data.
  - For truncated data, we need to match the percentiles of the conditional distribution :
    $F(x|X>d) = \frac{\Pr(d<X\le x)}{\Pr(X>d)} = \frac{F(x)-F(d)}{1-F(d)}$
    $S(x|X>d) = \frac{S(x)}{S(d)}$
- **Smoothed empirical percentile :**

$$\hat{\pi}_p = (1-h)X^{[j]} + hX^{[j+1]}$$

where
  - $j = \lfloor (n+1)p \rfloor$
  - $h = (n+1)p - j$
  - $X^{[j]}$ is the j^th order statistics.

Lesson 29 : Maximum Likehood Estimators

- **Maximum Likehood Estimators :** We maximize the probability of observing the data.

$$L(\theta) = \prod g(x_i;\theta)$$
$$l(\theta) = \sum \ln g(x_i;\theta)$$

  - Individual data : $g(x_i;\theta) = f(x_i)$
  - Grouped data : $g(x_i;\theta) = F(x_i) - F(x_{i-1})$
  - Censored data : $g(x_i;\theta) = S(x_i)$
  - Truncated data : $g(x_i;\theta) = \frac{f(x)}{s(x)}$

Lesson 30 : MLE Special Techniques

- Case MLE equals MME
  - For Exponential, $\hat{\theta}^{\text{MLE}} = \bar{x}$
  - For Gamma with fixed α, $\hat{\theta}^{\text{MLE}} = \hat{\theta}^{\text{MME}}$
  - For Normal, $\hat{\mu}^{\text{MLE}} = \bar{x}$ and $(\hat{\sigma}^2)^{\text{MLE}} = \frac{1}{n}\sum(x_i - \hat{\mu})^2$
  - For Binomial, $mq = \bar{x}$ then given m, $\hat{q}^{\text{MLE}} = \frac{\bar{x}}{m}$
  - For Poisson, $\hat{\lambda}^{\text{MLE}} = \hat{\lambda}^{\text{MME}}$
  - For Binomial Negative, given r or β, $(r\beta)^{\text{MLE}} = \bar{x}$
- Parametrization and Shifting :
  - Parametrization : MLE's are independent of parametrization
    $\lambda = \frac{1}{\theta} \Leftrightarrow \hat{\lambda}^{\text{MLE}} = \frac{1}{\hat{\theta}^{\text{MLE}}}$
  - Shifting the distribution is equivalent of shifting the data.
- Transformations : MLE's are invariant under one-to-one transformation. Then if we have a transformed variable, we can untransform the data and find the parameter of the untransform distribution.
  Tips : **??**
- Weibull distribution : If the data is censored(u) or truncated(d), then

$$\left(\hat{\theta}^{\text{MLE}}\right)^{\tau} = \frac{\sum x_i^{\tau} - \sum d_i^{\tau}}{\sum \mathbb{1}_{\{x_i \le u\}}}$$

if $\tau = 1$, then the distribution is Exponential.
- Pareto distribution with fixed θ : $\hat{\alpha} = -\frac{n}{K}$

$$K = \sum_{i=1}^{n+c} \ln(\theta + d_i) - \sum_{i=1}^{n+c} \ln(\theta + x_i)$$

where $n \equiv$ number of non-censored(c) data.
- Single-parameter Pareto : $\hat{\alpha} = -\frac{n}{K}$

$$K = \sum_{i=1}^{n+c} \ln \max(\theta, d_i) - \sum_{i=1}^{n+c} \ln x_i$$

where $n \equiv$ number of non-censored(c) data.
- Uniform$(0,\theta)$: We take the smalest θ possible, $\hat{\theta}^{\text{MLE}} = \max(x_1, \ldots, x_n)$
  - Censored(u) : $\hat{\theta}^{\text{MLE}} = \frac{nd}{\sum \mathbb{1}_{\{x_i < d\}}}$

- Grouped : We take the heighest interval(L, U). $\hat{\theta}^{\text{MLE}} = \min(U, \hat{\theta}^{\text{MLE}}_{\text{Censored(L)}})$

- Bernouilli : Let have a random variable that can take 2 values, n and m. Then
$$\hat{p} = \frac{n}{n+m}$$
- Tips : If $L(\theta)$ look like a density distribution, $\hat{\theta}^{\text{MLE}} \equiv$ mode of this distribution.
- **Ground-up loss** is define as (x|x>d).

Lesson 31 : Variance of MLE

- **Fisher information matrix** :
$$I(\theta) = n\text{E}\left[\left(\frac{\text{d}\ln f(x;\theta)}{\text{d}\theta}\right)^2\right] = -n\text{E}\left[\frac{\text{d}^2\ln f(x;\theta)}{\text{d}\theta^2}\right]$$
using the loglikehood function
$$I(\theta) = \text{E}\left[\left(\frac{\text{d}l(x_1,\ldots,x_n;\theta)}{\text{d}\theta}\right)^2\right] = -\text{E}\left[\frac{\text{d}^2 l(x_1,\ldots,x_n;\theta)}{\text{d}\theta^2}\right]$$
- **Rao-Cramer lower bound** is the lowest possible variance for a unbiased estimator $\hat{\theta}$ of θ. Then $\hat{\theta} \sim \text{Normal}(0, \text{Var}(\hat{\theta})^{\text{rao}})$
$$\text{Var}(\hat{\theta})^{\text{rao}} \geq \frac{1}{I(\theta)}$$
under certains regularity conditions
  - The seconde derivative of the loglikehood exist.
  - The support of the density function is not function of θ.

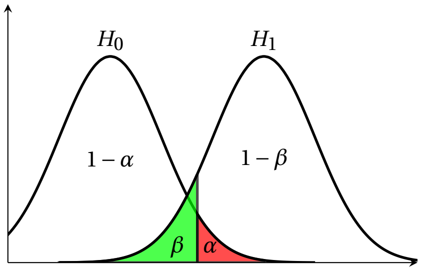
Lesson 32 : Sufficient Statistics

- A **sufficient statistics** are statistics that capture all the information about the parameter we are estimating that the sample as to offer.
- A statistics is sufficient when the distribution of a sample given a statistics does not depend on the parameter. Y is a sufficient statistics for a parameter θ if and only if
$$L(x_1,\ldots,x_n;\theta|Y) = h(x_1,\ldots,x_n)$$
$$L(x_1,\ldots,x_n;\theta) = g(y)h(x_1,\ldots,x_n)$$
where $h(x_1,\ldots,x_n)$ is a function that does not involve θ.
- **Rao-Blackwell** Theorem : For any unbiased estimator $\hat{\theta}$ and sufficient statistic Y, the estimator $\text{E}[\hat{\theta}|Y]$ is unbiased and has variance less than or equal to $\text{Var}(\hat{\theta})$.
- The maximum likehood estimator is a function of a sufficient statistic.

Lesson 33 : Hypothesis Testing

- Let be H_0 the **null hypothesis** and H_1 the **alternative hypothesis**.

	Accept H_0	Reject H_0
H_0 True	$1-\alpha$	α
H_1 True	β	$1-\beta$



- The α value is usuly name :
  - Probability of Type I error
  - Size of critical region
  - signifiance level

  The β value is usuly name :
  - Probability of Type II error

  The $(1-\beta)$ value is usuly name :
  - The power of test.
- We will reject H_0 in favor of H_1 if a certain condition occured $(X > \gamma)$, named the **critical region**. Then the probability of rejecting H_0 is giving by
$$\Pr(X > \gamma | H_0 \equiv \text{true}) = \alpha$$
- Lowering the probability of type I error came at the cost of raising the probability of type II error. One way to lower both is to increase sample size.
- The **p-value** is the probability of being greater or equal to the observation if H_0 is true. H_0 is rejected if and only if the p-value is less then the signifiance level.
$$P_{\text{value}} < \alpha$$

Lesson 34 : Confidence Interval and Sample Size

- Let be c the **confidence coefficient**. Then we can say the we're $100c\%$ confident that the parameter is between (a,b), called the **confidence interval**. $\alpha = 1-c$
$$\theta \in \hat{\theta} \pm z_{\frac{1+c}{2}}\sqrt{\text{Var}(\hat{\theta})}$$
- We can found the probability that the half-width of the interval is less then k.
$$\Pr(|\hat{\theta}-\theta| \leq k) \geq \frac{1+c}{2}$$
$$\Phi\left(\frac{k}{\sqrt{\sigma^2/n}}\right) \geq \frac{1+c}{2}$$
- To find the sample size needed to have a certain (α) and $(1-\beta)$, we resolve
$$\Pr(\bar{x} > k | H_0) = 1 - \Phi\left(\frac{k-\mu_0}{\sqrt{\sigma^2/n}}\right) = \alpha$$
$$\Pr(\bar{x} > k | H_1) = 1 - \Phi\left(\frac{k-\mu_1}{\sqrt{\sigma^2/n}}\right) = 1-\beta$$

Lesson 35 : Confidence Intervals for Means

- The **chi-square** is a one-parameter family distribution. In definition, it a gamma with $\alpha = \frac{n}{2}$ and $\theta = 2$. The only parameter n is called **degree of freedom**.
  - Let $X_i, i = i,\ldots,n$ be normal random variable with mean μ and varianve σ^2.
$$Y = \sum_{i=1}^{n}\frac{(X_i-\mu)^2}{\sigma^2} \sim \chi^2_{(n)}$$
  - Let $x_i, i = i,\ldots,n, n \geq 2$ be random sample from normal distribution with variance σ^2.
$$W = \sum_{i=1}^{n}\frac{(x_i-\bar{x})^2}{\sigma^2} \sim \chi^2_{(n-1)}$$
  - Tips : $\chi^2_{(2)} \sim \text{Exp}(\theta = 2)$
- The **strudent** is a one-parameter family distribution. We define it as
$$T_{(n)} = \frac{Z}{\sqrt{W/n}}$$
where $Z \sim \text{N}(0,1)$ and $W \sim \chi^2_{(n)}$.
Note that as $n \to \infty$, $T_{(n)} \to N(0,1)$
- When the variance is unknow, we need to estimate it with the unbiased estimator S^2.
$$T_{(n-1)} = \frac{\bar{x}-\mu}{\sqrt{S^2/n}}$$
- Testing the difference of means from two population.
$$x_1,\ldots,x_n \sim N(\mu_x, \sigma^2_x)$$
$$y_1,\ldots,y_m \sim N(\mu_y, \sigma^2_y)$$
$$T_{(n+m-2)} = \frac{(\bar{x}+\bar{y})-(\mu_x-\mu_y)}{S\sqrt{\frac{1}{n}+\frac{1}{m}}}$$
where $S^2 = \frac{(n-1)S^2_x+(m-1)S^2_y}{m+n-2}$.
- Testing for mean of bernouilli population. Let p_0 the probability on H_0.
$$Z = \frac{\hat{p}-p_0}{\sqrt{\frac{p_0(1-p_0)}{n}}}$$

Lesson 36 : Kolmogorov-Smirnov Tests

- The **Kolmogorov-Smirnov test** is one methode for determining how well a parametric model fits its data. This test is only appropriate for continuous distribution.
$$D = \max|F_e(x) - F^*(x;\hat{\theta})|$$

where $d \leq x \leq u$ and $F^*(x) = \frac{F(x)-F(u)}{S(d)}$.

x_i	$F^*(x_i)$	$F_e(x_i^-)$	$F_e(x_i)$	max
x_1	0.5	0.2	0.6	0.3
⋮	⋮	⋮	⋮	⋮

Lesson 37 : Chi Square Test

- The **Chi Square** look for equality of means between k group. Let O_i be the observation and $E_i = np_i$ the expected on each group.
$$H_0 : \mu_1 = \ldots = \mu_k$$
$$Q = \sum_{i=1}^{k} \frac{(O_i - E_i)^2}{E_i} = \sum_{i=1}^{k} \left(\frac{O_i^2}{E_i}\right) - n \sim \chi^2_{(k-1-\theta')}$$
Note : This test can be use to test the fit of as parametric model. θ' is the number of parameter fited with the same data as the test.
- **Two-dimensional chi-square :**
$$Q = \sum_{i=1}^{k} \sum_{j=1}^{c} \frac{(O_{ij} - E_{ij})^2}{E_{ij}} \sim \chi^2_{(k-1)(c-1)}$$

Lesson 38 : Confience Interval for Variances

- To find a confidence interval for the variance, we need the following statistic.
$$W = \frac{(n-1)S^2}{\sigma^2} \sim \chi^2_{(n-1)}$$
- Warning : W is on the denominator, so for upper one-sided interval, we take the lower percentile α and $1-\alpha$ for lower one-sided interval.
  1. $\left(0, \frac{(n-1)S^2}{w_\alpha}\right)$
  2. $\left(\frac{(n-1)S^2}{w_{1-\alpha}}, \infty\right)$
  3. $\left(\frac{(n-1)S^2}{w_{1-\frac{\alpha}{2}}}, \frac{(n-1)S^2}{w_{\frac{\alpha}{2}}}\right)$
- The **Fisher** distribution is define as
$$F_{(r_1,r_2)} = \frac{W_1/r_1}{W_2/r_2}$$
where r_1 and r_2 are the degree of freedom.
- If $T \sim$ Strudent, then $T^2 \sim$ Fisher.
- To find a confidence interval for variance ratio, we need the following statistic.
$$F_{(n_x-1, n_y-1)} = \frac{S_x^2/\sigma_x^2}{S_y^2/\sigma_y^2}$$

Lesson 39 : Uniformly Most Powerful critical Regions

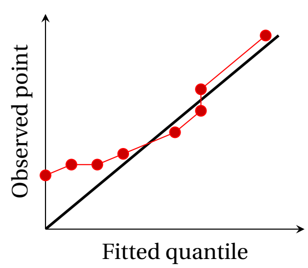
- The **Neyman-Pearson lemma** states that for tests of one *simple* hypothesis against another, the best critical region for any (α) is to select all that minimize the likehood ratio.
$$h(x) = \frac{L(x_1,\ldots,x_n;\theta|H_0)}{L(x_1,\ldots,x_n;\theta|H_1)} < c$$
  - If $h(x)$ is increasing, $F(k|H_0) < \alpha$.
  - If $h(x)$ is deacreasing, $S(k|H_0) < \alpha$.
- If the alternative hypothesis is *composite*, then we can find the **uniformly most powerful critical region** with the same likehood ratio. This region only exist for one-sided test.

Lesson 40 : Likehood Ratio Tests

- This test is usefull when there is no uniformly most powerful critical region.
$$h(x) = \frac{g(x_1,\ldots,x_n;\theta|H_0)}{g(x_1,\ldots,x_n;\theta|H_1)}$$
where $g(x_1,\ldots,x_n;\theta)$ is the maximum likehood.
- For large sample, we can use the asymptotic distribution of the likehood.
$$-2[l(\theta|H_0) - l(\theta|H_1)] \sim \chi^2_{(k-l)}$$
where k is the number of parameters specifies by H_0 and l is the combinaison of numbers of parameters specifies by H_0 and H_1.
- The last test can also be use to dicide if it worth to add parameter to a distribution fit.

Lesson 41 : q-q Plots

- This plot compare quantile of two distribution. It consiste of a plot of coordinate pairs : $(\mathbf{x_i}, \mathbf{F^{-1}(p_i)})$ where p_i is the empirical percentile of x_i. Then the fit is good if the point are close to a 45° line.



Lesson 42 : Introduction to Extended Linear Models

There are two purposes in building a extended linear model.

1. **Prediction :** We want to predic the valu of the *response* variable given specific values of the *explanatory* variables.
2. **Inference :** We want to understand which *explanatory* variables explain the *response* variable and how much their explain it.

To evaluate the accuracy of a model, we estimate it mean square error.
$$\text{MSE} = \frac{1}{n} \sum_{i=1}^{n} (y_i - \hat{y}_i)$$

Lesson 43 : How a Generalized Linear Model Works

- **Linear Model :**
$$Y = \eta + \varepsilon = \beta_0 + \beta_1 x_1 + \ldots + \beta_p x_p + \varepsilon$$
where
$$\varepsilon \sim N(0, \sigma^2)$$
$$Y \sim N(\eta, \sigma^2)$$
Hypothesis :
$$(\mathbf{H_1}) \quad \mathrm{E}[\varepsilon] = 0 \quad \text{(Linearity)}$$
$$(\mathbf{H_2}) \quad \mathrm{Var}(\varepsilon) = \sigma^2 \quad \text{(Homoscedasticity)}$$
$$(\mathbf{H_3}) \quad \mathrm{Cov}\left(\varepsilon_i, \varepsilon_j\right) = 0 \quad \text{(Independence)}$$
- The **Box-Cox transformation** is a general set of transformation. When the variance of the error terms is not constant(H_2), we need to transform Y.
$$Y^* = \begin{cases} \frac{Y^\lambda - 1}{\lambda} & \lambda \neq 0 \\ \ln Y & \lambda = 0 \end{cases}$$
where λ is chossen to best stabilize the variance of the error terms.
- The *feature* must be linearly independent. That mean their can't be a function of another. Ex : $X_3 = 1 - X_2$.
- We need to encode categorials variables with k levels into $(k-1)$ indicators variables(called *dummy* variables) to avoid *feature* to be dependent. For interaction with 2 categorials variables, $(k-1)(l-1)$ dummy variables are needed.
- **GLM :**
$$g(\mathrm{E}[Y]) = \beta_0 + \sum_{i=1}^{n} \beta_i x_i$$
where g(·) is the link function.
- **Exponential Family :**
$$f(y;\theta) = \exp\{a(y)b(\theta) + c(\theta) + d(y)\}$$
with
$$\mathrm{E}\left[a(y)\right] = -\frac{c'(\theta)}{b'(\theta)}$$
$$\mathrm{Var}\left(a(y)\right) = \frac{b''(\theta)c'(\theta) - c''(\theta)b'(\theta)}{[b'(\theta)]^3}$$
- **Tweedie** distribution :
$$\mathrm{Var}(Y) = a\mathrm{E}\left[y\right]^p$$
- **link function :** The GLM estimate is unbiased when the canonical link is used.

Distribution	Canonical link
Normal	$g(y) = y$
Binomial	$g(y) = \ln \frac{y}{1-y}$
Poisson	$g(y) = \ln y$
Gamma	$g(y) = \frac{1}{y}$

- **Offset :** We add $\ln n_i$ for cell with n_i exposure.
- **Rate ratio :**
$$RR = \frac{\mathrm{E}\left[Y_i | x_j = 1\right]}{\mathrm{E}\left[Y_i | x_j = 0\right]}$$

Lesson 44 : Categorial Response

Binomial Response

- Let $\pi_i \in (0,1)$ be the response variable. We than need to have link that map η into $(0,1)$.
  - **logit :** $\ln\left(\frac{\pi}{1-\pi}\right) = \eta$
  - **Probit :** $\Phi^{-1}(\pi) = \eta$
  - **Log-log :** $\ln(-\ln(1-\pi)) = \eta$
- **Odds Ratio :** $o = \frac{\pi}{1-\pi}$

Nominal Response

- Suppose the response can be J values. Then we create a model of relative odds.
$$\ln \frac{\pi_j}{\pi_1} = \eta_j \Leftrightarrow \pi_j = \pi_1 e^{\eta_j}$$
  - $\pi_i = \frac{1}{1+\sum_{j=2}^{J} e^{\eta_j}}$
  - $\pi_j = \frac{e^{\eta_j}}{1+\sum_{j=2}^{J} e^{\eta_j}}$
- If x_i is a binary feature, then the odds ratio of this **variable** in the category j to the base categorie is $e^{\beta_{ij}}$.

Ordinal Response

Ordinal response variables have several categories in logical order.

- **Cumulative logit and proportional odds models :**
$$\ln o_j = \ln \frac{\sum_{k=1}^{j} \pi_k}{1-\sum_{k=1}^{j} \pi_k} = \eta_j$$
Tips : The model is cumulative, so to find π_2, we need to find π_1 and $\pi_1 + \pi_2$.
This model is proportional so if we **fix** the categorie but consider two set of feature x_{i1} and x_{i2}, the relative odds are
$$\frac{(o_j | x_i = x_{i1})}{(o_j | x_i = x_{i2})} = e^{\sum \beta_i (x_{i1} - x_{i2})}$$
- **Adjacent categorie logit model :**
$$\ln \frac{\pi_j}{\pi_{j+1}} = \eta_j$$
$$\sum_{j=1}^{J} \pi_j = 1$$
- **Continuation ratio logit model :**
$$\ln \frac{\pi_j}{\sum_{k=j+1}^{J} \pi_k} = \ln \frac{\pi_j}{1-\sum_{k=1}^{j} \pi_k} = \eta_j$$
Tips : Resolve for π_1 then for π_2 and so on ...

Lesson 45 : Estimating Parameters

- Let **X** be the **design matrix**, the p x n features matrix.
- **Linear Regression :**
$$\hat{\beta}_1 = \frac{\sum x_i y_i - n\bar{x}\bar{y}}{\sum x_i^2 - n\bar{x}^2}$$
$$\hat{\beta}_0 = \bar{y} - \hat{\beta}_1 \bar{x}$$
$$\mathbf{b} = (\mathbf{X}^\top \mathbf{X})^{-1} \mathbf{X}^\top \mathbf{y}$$
- The **score** function is define as the derivative of the loglikehood
$$\mathbf{U}(\beta) = \ell'(\beta)$$
- **Newton-Raphson** algorithm :
$$\beta^{(k+1)} = \beta^{(k)} - \frac{\mathbf{U}(\beta^{(k)})}{\mathbf{U}'(\beta^{(k)})}$$
- **Fisher Scoring** algorithm :
$$\beta^{(k+1)} = \beta^{(k)} - \frac{\mathbf{U}(\beta^{(k)})}{\mathrm{E}[\mathbf{U}'(\beta^{(k)})]}$$
- The score vector has components
$$U_j = \sum_{i=1}^{n} \frac{y_i - \mu_i}{\mathrm{Var}(y_i)} x_{ij} \left(\frac{\mathrm{d}g(\mu_i)}{\mathrm{d}\mu_i}\right)$$
- The information matrix : $I(\theta) = \mathbf{X}^\top \mathbf{W} \mathbf{X}$
- Let **W** be the diagonal matrix with entries
$$w_{ii} = \left(\left(\frac{\mathrm{d}g(\mu_i)}{\mathrm{d}\mu_i}\right)^2 \mathrm{Var}(y_i)\right)^{-1}$$
- Let **G** be the diagonal matrix with entries
$$G_{ii} = \frac{g(\mu_i)}{\mu_i}$$
- The regression variable for one iteration
$$\mathbf{z}^{(k-1)} = \mathbf{X}\mathbf{b}^{(k-1)} + \mathbf{G}^{(k-1)}(\mathbf{y} - \mu^{(k-1)})$$
- The **Weighted Least Square** :
$$\mathbf{b}^{(k)} = (\mathbf{X}^\top \mathbf{W}^{(k-1)} \mathbf{X})^{-1} \mathbf{X}^\top \mathbf{W}^{(k-1)} \mathbf{z}^{(k-1)}$$

Lesson 46 : Measures of Fit

- The **satured** model is when we have as much feature as parameters($p = n$). $g^{-1}(\mathbf{X}^\top \mathbf{b}) = \mathbf{y}$
- The **deviance** statistic test compare a model to the satured model.
$$D = 2[\ell(\mathbf{b}_{max}) - \ell(\mathbf{b})] \approx n - p'$$
where $p' = p + 1$ and p the number of feature.
  - Binomial :
  $D = 2\sum_{i=1}^{n} \left(y_i \ln \frac{y_i}{\hat{y}_i} + (n_i - y_i) \ln \frac{n_i - y_i}{n_i - \hat{y}_i}\right)$
  - Normal (*scaled deviance*) :
  $\sigma^2 D = \sum_{i=1}^{n} (y_i - \hat{y}_i)^2$
  - Poisson :
  $D = 2\sum_{i=1}^{n} \left(y_i \ln \frac{y_i}{\hat{y}_i} - (y_i - \hat{y}_i)\right)$
  - Gamma :
  $D = 2\alpha \sum_{i=1}^{n} \left(-\ln \frac{y_i}{\hat{y}_i} + \frac{y_i - \hat{y}_i}{\hat{y}_i}\right)$

Signifiance of Feature

- **Loglikehood ratio test :** These tests compare a **unconstrained** modele with $p+q$ parameters versus another **constrained** model with p parameters.
$$2(\tilde{\ell}_{p+q} - \hat{\ell}_p) \sim \chi^2_{(q)}$$
$$\hat{D} - \tilde{D} \sim \chi^2_{(1)}$$
- **Wald test :** To test wheter a single parameter $\beta_j = r$.
$$W = \frac{(\hat{\beta}_j - r)^2}{\mathrm{Var}(\hat{\beta}_j)} \sim \chi^2_{(1)}$$
$\sqrt{W} \sim N(0,1)$, is usefull for confidence interval.
$I(\theta)^{-1} = (\mathbf{X}^\top \mathbf{W} \mathbf{X})^{-1}$ is the covariance matrix.
- **Score text :** $\mathbf{U}^\top I(\theta)^{-1} \mathbf{U} \sim \chi^2_{(q)}$
If $q = 1$, $\frac{U}{\sqrt{I(\theta)}} \sim N(0,1)$.
- We want the lowest AIC and BIC.

Lesson 47 : Standard Error, R^2, and Strudent Statistic

$$SST = SSE + SSR$$

- **Total sum of square :** $SST = \sum_{i=1}^{n} (y_i - \bar{y})^2$
- **Error sum of square :** $SSE = \sum_{i=1}^{n} (y_i - \hat{y}_i)^2$
$$SSE = \varepsilon^\top \varepsilon = \mathbf{y}^\top \mathbf{y} - \mathbf{b}^\top \mathbf{x}^\top \mathbf{y}$$
- **Regression sum of square :** $SSR = \sum_{i=1}^{n} (\hat{y}_i - \bar{y})^2$

ANOVA			
SS	df	MS	F
SSR	p	MSR = SSR/df	$\frac{MSR}{MSE}$
SSE	n-p'	MSE = SSE/df	
SST	n-1	MST = SST/df	

- The standort error of the regression is
$$s = \sqrt{MSE}$$
- The **coefficient of determination** is the proportion explain by the regression.
$$R^2 = \frac{SSR}{SST} = 1 - \frac{SSE}{SST}$$
- **Strudent test :** To test $\beta_i = \beta^*$
$$t_{n-p'} = \frac{\beta_i - \beta^*}{s_{\beta_i}}$$
Matrice variance-covariance : $\sigma^2 (\mathbf{X}^\top \mathbf{X})^{-1}$
- Simple linear regression :
  - $\mathrm{Var}(\hat{\beta}_0) = \sigma^2 \left(\frac{1}{n} + \frac{\bar{x}^2}{S_{xx}}\right)$
  - $\mathrm{Var}(\hat{\beta}_1) = \frac{\sigma^2}{S_{xx}}$
  - $\mathrm{Cov}(\hat{\beta}_0, \hat{\beta}_1) = -\frac{\bar{x}\sigma^2}{S_{xx}}$

Lesson 48 : Fisher Statistic and VIF

- The **Fisher** statistic test the significance od the entire regression, in other word if all $\beta_i = 0$. For simple linear regression $F = T^2$. Tips : Divide numerator and denominator of F by SST to find R^2.
- For simple linear regression, since $p = 1$, then $T_{(n)} = \sqrt{F_{1,n}}$.
- **Partial Fisher test :** To test is q added variables have significance.
$$F_{\Delta_{df},n-p'} = \frac{SSE^{(0)} - SSE^{(1)}/\Delta_{df}}{SSE^{(1)}/(n-p')}$$
- The **Variance Inflation Factor** test the collinearity of the features. To mesure it, we take the x_j feature and take it as the response. Let $R^2_{(j)}$ be the R^2 of this regression.
$$\text{VIF} = \frac{1}{1-r^2_{(j)}}$$
We want the lowest VIF.
- **Coeficient of correlation :**
$$r = \frac{\text{Cov}(X,Y)}{\sigma_x \sigma_y} = \frac{\sum(x_i-\bar{x})(y_i-\bar{y})}{\sqrt{\sum(x_i-\bar{x})^2 \sum(y_i-\bar{y})^2}}$$
- For two-feature model $R^2_{(y)} = r^2$.

Lesson 49 : Validation

- The **Hat matrix** put a hat on y since $\hat{\mathbf{y}} = \mathbf{Hy}$.
$$\mathbf{H} = \mathbf{X}(\mathbf{X}^\intercal\mathbf{X})^{-1}\mathbf{x}^\intercal$$
- It follow that $\text{Var}(\hat{\varepsilon}) = (\mathbf{I} - \mathbf{H})\sigma^2$
- For simple linear regression :
$$h_{ii} = \frac{1}{n} + \frac{(x_i - \bar{x})^2}{S_{xx}}$$
- The **studentized residuals** are define as
$$r_i = \frac{\hat{\varepsilon}_i}{\sqrt{S^2(1-h_{ii})}}$$
where h_{ii} is the **leverage**. Average leverage should be at $\frac{p'}{n}$. $\sum h_{ii} = p'$
- A **influence point** is a observatio that influence a lot y. A **outliers** is a observation that have $|r_i| > 3$.
- Two mesure for influence point.
  - $\text{DFITS}_i = r_i\sqrt{\frac{h_{ii}}{1-h_{ii}}}$
  - **Cook :** $D_i = \frac{\sum(\hat{y}_j - y_{j(i)})^2}{p' S^2} = r_i^2 \frac{h_{ii}}{p'(1-h_{ii})}$

    $D_i > 1$ is too high.

Lesson 50 : Prediction

- A **confidence interval** for predicted values.
$$y^* \in \hat{y}^* \pm t_{(n-2)}\sqrt{S^2\left(\frac{1}{n} + \frac{(x^*-\bar{x})^2}{S_{xx}}\right)}$$
- A **prediction interval** for predicted values.
$$y^* \in \hat{y}^* \pm t_{(n-2)}\sqrt{S^2\left(1 + \frac{1}{n} + \frac{(x^*-\bar{x})^2}{S_{xx}}\right)}$$

Lesson 51 : ANOVA

One-factor ANOVA

$$\text{SST} = \text{SSE} + \text{SSTR}$$

Model	Sum of square	Deviance
$Y = \mu + \varepsilon_{ij}$	SST	D_M
$Y = \mu_i + \varepsilon_{ij}$	SSE	D_A

- **Within sum of square**
$$\text{SSE} = \sum_{i=1}^{k}\sum_{j=1}^{n_i}(y_{ij} - \bar{y}_{i\Sigma})^2$$
- **Between sum of square**
$$\text{SSTR} = \sum_{i=1}^{k} n_i(\bar{y}_{i\Sigma} - \bar{y}_{\Sigma\Sigma})^2 = \sum_{i=1}^{k}\left(\frac{y^2_{i\Sigma}}{n_i}\right) - n\bar{y}^2_{\Sigma\Sigma}$$
- **Total sum of square**
$$\text{SST} = \sum_{i=1}^{k}\sum_{j=1}^{n_i}(y_{ij} - \bar{y}_{\Sigma\Sigma})^2 = \sum_{j=1}^{n_i}(y^2_{ij}) - n\bar{y}^2_{\Sigma\Sigma}$$
- **Fishier test**
$$F_{(k-1,n-k)} = \frac{\text{SSTR}/(k-1)}{\text{SSE}/(n-k)} = \frac{(D_M - D_A)/(k-1)}{D_A/(n-k)}$$
where D_M is the *scale deviance* of the minimal model.

Two-factor ANOVA without replication

$$\text{SST} = \text{SSE} + \text{SSTR} + \text{SSB}$$

Model	Sum of square (DF)
$Y = \mu + \varepsilon_{ij}$	SST$(bk-1)$
$Y = \mu + \alpha_i + \varepsilon_{ij}$	SSTR $(k-1)$
$Y = \mu + \beta_j + \varepsilon_{ij}$	SSB$(b-1)$
$Y = \mu + \alpha_i + \beta_j + \varepsilon_{ij}$	SSE$(k-1)(b-1)$

- The formula are the same but n_i is k for SSTR and b for SSB.

Two-factor ANOVA with replication

- To test interaction :
$$F_{(I-1)(J-1),IJ(K-1)} = \frac{(D_I - D_s)/(I-1)(J-1)}{D_s/IJ(k-1)}$$
- To test factor A :
$$F_{(I-1),IJ(K-1)} = \frac{(D_B - D_I)/(I-1)}{D_s/IJ(k-1)}$$
- To test factor B :
$$F_{(J-1),IJ(K-1)} = \frac{(D_M - D_B)/(J-1)}{D_s/IJ(k-1)}$$
where D_s is the satured model, I for additive model.
- ANCOVA

Lesson 52 : Measures of Fit II

For **contingencies table** with binomial or poisson distribution.

- Pearson : $\chi^2 = \sum\frac{(O_i - E_i)^2}{E_i} \sim \chi^2_{(n-p')}$
- Likelihood ratio chi-square :
$$C = 2[\ell - \ell_{\textbf{min}}] \sim \chi^2_{(p'-1)}$$
- **Pseudo**R^2 : pseudo$R^2 = \frac{\ell_{\textbf{min}} - \ell}{\ell_{\textbf{min}}}$

Residus

- Pearson residual : $X_k = \frac{y_i - \hat{\mu}_i}{\sqrt{\text{Var}(\hat{\mu}_i)}}$
- Deviance residual : $d_k = s_k\sqrt{\text{deviance}}$
where s_k is the signe of $y_k - \hat{y}_i$
- To standartize them, divide by $\sqrt{1-h_{ii}}$

Lesson 53 : Resampling Methods

- **Cross-Validation :**
$$\text{CV}_{(K)} = \frac{1}{k}\sum_{i=1}^{k} MSE_i$$
As $k \to n$ bias $\Downarrow$ Var$(CV_k) \Uparrow$
If $k = n$ then is the LOOCV statistic.
- LOOCV for least-square regression :
$$\text{CV}_{(K)} = \frac{1}{n}\sum_{i=1}^{n}\left(\frac{\varepsilon_i}{1-h_{ii}}\right)^2$$
- **Bootstap :**
$$\text{SE}_B(\alpha) = \sqrt{\frac{1}{1-B}\sum_{i=1}^{B}(\hat{\alpha} - \bar{\alpha})^2}$$

Lesson 54 : Subset Selection

Using a lot of feature will result of lower standard error on training data, but poor prediction. We need to keep only the feature that truly impact the response.

- **Subset selection** For k possible feature, 2^k different model are possible.
  - For 2 model with same number of feature, we take the one with lowest SSE.
  - Otherwise, we compare with : Mallow's C_p, AIC, BIC and adjusted R^2.
- **Foward stepwise selection** consist of starting with the null, then fit k models with one variable and select the best base on SSE, then fit $k-1$ variables and so on. We obtain $k+1$ model, the best for each number of predictor, and select the final one with cross-validation or the 4 statistics. For categorial variables, each categorie is added independently.
- **Total fitted model :**
  - Foward : $1 + \sum_{i=0}^{\min(p,n)}(\min(p,n) - i)$
  - Backward : $1 + \sum_{i=1}^{\min(p,n)} i$

Choosing the best model

- **Cross-validation** is the more accurate.
- **Mallow's $\mathbf{C_p}$:** $C_p = \frac{1}{n}(SSE + 2p\hat{\sigma}^2)$
IF $\hat{\sigma}^2$ is unbiased then C_p is unbiased.
- **Adjested $\mathbf{R^2}$:** $R^2_a = 1 - \frac{MSE}{MST}$
- We want the lowest Mallow's C_p, AIC, BIC and the heighest R^2_a.

Lesson 55 : Shrinkage and Dimension Reduction

- **Ridge Regression :** Minimize $\left(\sum_{i=1}^{n} y_i - \beta_0 - \sum_{j=1}^{p'-1} \beta_j x_{ij}\right) + \lambda \sum_{j=1}^{p'-1} \beta_j^2$
- **Lasso Regression :** Minimize $\left(\sum_{i=1}^{n} y_i - \beta_0 - \sum_{j=1}^{p'-1} \beta_j x_{ij}\right) + \lambda \sum_{j=1}^{p'-1} |\beta_j|$
- **Standart Predictors** $\tilde{x} = \frac{x_{ij}}{\sqrt{\frac{1}{n}\sum(x_{ij}-\bar{x})^2}}$

$$\lambda \to \infty \Leftrightarrow \beta_j \to 0$$
$$\lambda \to 0 \Leftrightarrow \beta_j \to \hat{\beta}_j^{\text{normal}}$$

PCA	Partial Least Square
unsupervised	supervised
variables are linear combianaire of the original	
Higher bias	Lower bias
Lower variance	Higher variance

Lesson 56 :Extension to the Linear Model

- **Extention :** These type can be treate as same as GLM. $y_i = \beta_0 + \beta_1 b_1(x_i) + \beta_2 b_2(x_i) + \ldots + \varepsilon_i$
  For **polynomial regression**, $b_j(x) = x^j$.
  For **piecewise constant regression** $b_j(x) = \mathbb{1}_{\{a \le x < b\}}(x)$
- **Generalized Additive Model :**
  $$y_i = \beta_0 + \sum_{j=1}^{p} f_i(x_{ij}) + \varepsilon_i$$
  - Allows nonlinear fits for each explanatory variable.
  - Effet on each explanatory is separate, so easily identifiable.
  - Does not allow foe effect of interaction among variable.

Lesson 57 : Trend and Seasonality

- **Trend** measures the amount by which the serie increase from period to period.
- **Seasonal** variation measure cycle within a year.
- **Decomposition models**
  - Additive Model : $x_t = m_t + s_t + z_t$
  - Multiplicative Seasonality : $x_t s_t + z_t$
  - Multiplicative Model : $x_t = m_t s_t z_t$
- **Centered moving average :** $\hat{m}_t = \frac{0.5m_{t-k} + m_{t-k+1} + \ldots + m_t + \ldots + m_{t+k-1} + 0.5m_{t+k}}{2k}$
- **Seasonal variation factor :**
  - Additive Seasonality : $\hat{s}_t = x_t - \hat{m}_t$
    Ajusted so that $\sum(s_t + c) = 0$.
  - Multiplicative Seasonality $\hat{s}_t = \frac{x_t}{\hat{m}_t}$
    Ajusted so that $\sum \frac{\hat{s}_t \cdot c}{n} = 1$.

Lesson 58 : correlation

- if $\mu(t)$ and $\sigma^2(t)$ does not vary with t then the time serie is **second order stationnary**
- **Variance :** $\sigma^2(t) = \mathrm{E}\left[(x_t - \mu(t))^2\right]$

Stationnary Time serie

- **sample variance** $s^2 = \frac{1}{n-1}\sum_{i=1}^{n}(x_t - \bar{x})^2$
- **Covariance** at lag k :
  $\mathrm{Cov}(x_t, x_{t+k}) = \gamma_k = \mathrm{E}\left[(x_t - \mu)(x_{t+k} - \mu)\right]$ (**acvf**)
  $c_k = \frac{1}{n}\sum_{i=1}^{n-k}(x_t - \bar{x})(x_{t+k} - \bar{x})$ (**sample acvf**)
- **Auto-correration**
  $\rho_k = \frac{\mathrm{Cov}(x_t, x_{t+k})}{\sigma^2}$ (**acf**)
  $r_k = \frac{c_k}{c_0}$ (**sample acf**)

Relationships of different time serie

- A **leading variable** is one that impact another.
- **Cross-covariance**
  $\gamma_k(x,y) = \mathrm{E}\left[(x_{t+k} - \mu_x)(y_t - \mu_y)\right]$ (**ccvf**)
  $c_k = \frac{1}{n}\sum_{i=1}^{n-k}(x_{t+k} - \bar{x})(y_t - \bar{y})$ (**sample ccvf**)
- **Cross-correration**
  $\rho_k(x,y) = \frac{\gamma_k(x,y)}{\sigma_x \sigma_y}$ (**ccf**)
  $r_k = \frac{c_k(x,y)}{\sqrt{c_0(x,x)c_0(y,y)}}$ (**sample ccf**)
- Notice
  $$\gamma_k(x,y) = \gamma_{-k}(x,y)$$
  $$\rho_k(x,y) = \rho_{-k}(x,y)$$
  $$c_0(x,x) = c_0$$

Lesson 59 : White Noise and Random Walks

- **White noise** each term are independant and variance σ^2. The correlogram has autocorrelations all close to 0 except for r_0.
  $$w \sim N(0, \sigma^2)$$
- A **Random Walks** is a nonstationary time series which is the accumulation of white noise. The correlogram will decrease slowly from 1 to 0.
  $$x_1 = w_1$$
  $$x_t = x_{t-1} + w_t$$
  with
  $$\mu(t) = 0$$
  $$\sigma^2(t) = t\sigma_w^2$$
  $$\gamma_k(t) = t\sigma_w^2$$
  $$\rho_k(t) = \frac{1}{\sqrt{1 + \frac{k}{t}}}$$
- A **Walk with drift** drift the mean $\mu(t) = t\delta$ by don't affect variance and autocorrelations.
  $$x_t = x_{t-1} + \delta + w_t$$

Lesson 60 : Autoregressive Models

- An **autoregressive** model of order (p), or AR(p) is a time series where term may be expressed in term of previous terms plus white noise.
  $$x_t - \mu = \alpha_1(x_{t-1} - \mu) + \alpha_2(x_{t-2} - \mu) + \ldots + \alpha_p(x_{t-p} - \mu) + w_t$$
- An AR(1) process is stationary if $|a| < 1$. correlogram is deacreasing exponentially. For a stationary AR(1) process
  $$\mu_k = 0$$
  $$\gamma_k = \frac{\alpha^k \sigma_w^2}{1 - \alpha^2}$$
  $$\rho = \alpha^k$$
- Notation : $\mathbf{B}^k x_t = x_{t-k}$
  $$\begin{aligned} w_t &= x_t - \alpha_1 x_{t-1} - \alpha_2 x_{t-2} \\ &= (\alpha_2 \mathbf{B}^2 - \alpha_1 \mathbf{B} + 1)x_t \\ &= \theta_p(\mathbf{B})x_t \end{aligned}$$
  where $\theta_p(\mathbf{B})$ is the **characterictic equation**.
- Testing stationarity : Root < 1

(given) $x_t = \alpha_1 x_{t-1} + \alpha_2 x_{t-2} + w_t$

(solve) $\theta_p(\mathbf{B}) = 0$

(answer) If $|\mathbf{B}| > 1$, the process is stationary.

- tips : For 2 param :
  $$\alpha_2 - \alpha_1 < 1$$
  $$\alpha_2 + \alpha_1 < 1$$
  $$|\alpha_2| < 1$$
- Forecast $\hat{x}_{n+1|n}$ is the same equation omitting w_t.

Lesson 61 : Regression

- Variance of sample mean with correlation is given by
  $$\mathrm{Var}(\bar{x}) = \frac{\sigma^2}{n}\left(1 + 2\sum_{k=1}^{n-1}\left(1 - \frac{k}{n}\right)\rho_k\right)$$
- **Harmonic Seasonal model**
  $$x_t = m_t + \sum_{i=1}^{[S/2]} s_i \sin(2\pi i t/s) + c_i \cos(2\pi i t/s) + z_t$$
- Forecast correction
  - Lognormal : $e^{\sigma^2/2}$
  - Empirical : $\frac{\sum e^{z_t}}{n}$

Lesson 62 : Moving Average Models

- A **moving average** time serie (MA(q)) is alway stationary. It define as
$$x_t = \mu + w_t + \beta_1 w_{t-1} + ... + \beta_q w_{t-q}$$
$$= \mu + \phi(\mathbf{B}) w_t$$
with
$$\mu(t) = 0$$
$$\gamma_k = \sigma_w^2 \sum_{i=0}^{q-k} \beta_i \beta_{i+k} \quad \beta_0 = 1$$
and $\gamma_k = 0$ for $k > q$ so MA(q) may be good fit is we observe $\gamma_q = 0$ in correlogram.
- q beta $+ \mu + \sigma_w^2 = q + 2$ parameters fit.
- A MA(q) is **Inversible** if all the root of $\phi(\mathbf{B})$ are $|\mathbf{B}| > 1$
- Express MA(q) in form of AR(∞). If $\phi(\mathbf{B})$ is reversible :
$\frac{1}{1+x} = 1 - x + x^2 - x^3 + x^4 + ..$
$\frac{1}{1-x} = 1 + x + x^2 + x^2 + x^4 + ...$
- ARIMA with $p = d = 0$ is a MA(q) model.
- conditional sum of squared residuals : $\sum w_t^2$

Lesson 63 : ARMA Models

- The ARMA(p,q) models :
$x_t = \alpha_1 x_{t-1} + ... + \alpha_p x_{t-p} + \beta_1 + w_{t-1} + ... + \beta_q w_{t-q} + w_t$
$\theta_p(\mathbf{B}) x_t = \phi_q(\mathbf{B}) w_t$
- The process is stationary if all roots of $\theta(x) > 1$ and the process is inversible if all roots of $\phi(x) > 1$
$$\gamma_0 = \sigma_w^2 \left(\frac{1 + 2\alpha\beta + \beta^2}{1 - \alpha^2} \right)$$
$$\gamma_k = \sigma_w^2 (\alpha + \beta) \alpha^{k-1} \left(\frac{1 + \alpha\beta}{1 - \alpha^2} \right)$$
$\rho_k = \alpha \rho_{k-1}$ for $k \geq 2$.
- If the process is stationary, $\mathrm{E}[x_t] = \mathrm{E}[x_{t-1}]$.

Lesson 64 : ARIMA and SARIMA models

- $\nabla x_t + x_t - x_{t-1} = (1 - \mathbf{B}) x_t$
- An **ARIMA** model is a nonstationary process. If x_t is an ARIMA model, then $y_t = \nabla^d x_t$ is an ARMA(p,q). Then the ARIMA(p,d,q) is
$$\theta(\mathbf{B})(1 - \mathbf{B})^d x_t = \phi(\mathbf{B}) w_t$$
  - With no MA(q), this is ARI(p,d)
  - With no AR(p), this is IMA(d,q)
- An **SARIMA** model is a ARIMA with seasonal effect.
- To forecast, we take the difference and then forecast ARMA(p,q) model.

Appendix

Inverting a matrix

$$\begin{pmatrix} a & b \\ c & d \end{pmatrix}^{-1} = \frac{1}{ad - bc} \begin{pmatrix} d & -b \\ -c & a \end{pmatrix}$$

Ajouter pour une matrice 3x3

Synthetic Division

Exemple : Factorize $x^3 - 12x^2 - 81$

	1	-12	0	-81
3		3	-27	-81
	1	-9	-27	0

then, $x^3 - 12x^2 - 81 = (x - 3)(x^2 - 9x - 27)$

Deductible and Limite

$$X = \min(X; d) + \max(0; X - d)$$
$$\mathrm{E}[X] = \mathrm{E}[\min(X; d)] + \mathrm{E}[\max(0; X - d)]$$
$$= \mathrm{E}[(X \wedge d)] + \mathrm{E}[(x - d)_+]$$
$$= \mathrm{E}[(X \wedge d)] + e_x(d) \cdot S_x(d)$$

Statistic Order

- $Y_1 = \min(X_1, ..., X_n)$
$$f_{Y_1}(y) = n f(y) [S(y)]^{n-1}$$
$$S_{Y_1}(y) = \prod_{i=1}^{n} \Pr(X_i > x)$$
- $Y_n = \max(X_1, ..., X_n)$
$$f_{Y_n}(y) = n f(y) [F(y)]^{n-1}$$
$$F_{Y_n}(y) = \prod_{i=1}^{n} \Pr(X_i \leq x)$$
- $Y_k \in (Y_1, ..., Y_k, ..., Y_n)$
$$f_{Y_k}(y) = \frac{n! \cdot f(y) [F(y)]^{k-1} [S(y)]^{n-k}}{(k-1)!(n-k)!}$$
$$F_{Y_k}(y) = \Pr(\text{at least k of n } X_i \text{ are} \leq \text{y})$$
$$= \sum_{i=k}^{n} \binom{n}{i} [F(y)]^i [S(y)]^{n-j}$$
- $x + y = \min(x, y) + \max(x, y)$, since one is for sure the max and the other the min.

Mode : Most likely probability

- $g(x) = f(x)$ or some time $g(x) = \ln f(x)$
- **Mode** is the x that respects : $g'(x) = 0$

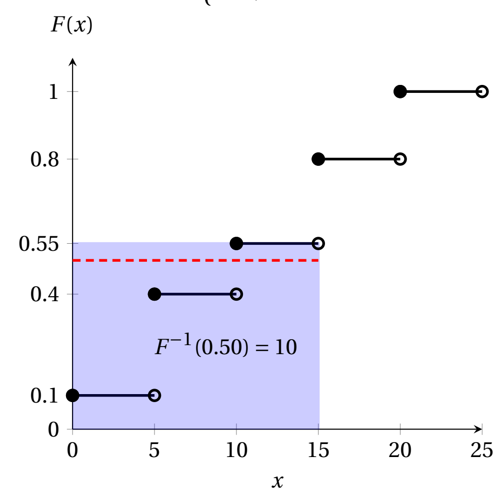
Normal Approximation

- $F_X(x) = \Phi\left(\frac{X - \mathrm{E}[X]}{\sqrt{\mathrm{Var}(X)}} \right)$
- **Continuity correction** is necessary when X is discrete. $F_X(x) = \Phi\left(\frac{(X \pm k) - \mathrm{E}[X]}{\sqrt{\mathrm{Var}(X)}} \right)$ where k is the mid-point of the discrete value.

Discrete Cumulative Function

$$\Pr(X = x) = \begin{cases} 0.10, & x = 0 \\ 0.30, & x = 5 \\ 0.15, & x = 10 \\ 0.25, & x = 15 \\ 0.20, & x = 20 \end{cases}$$

$$\Pr(X \leq x) = \begin{cases} 0.10, & 0 \leq x < 5 \\ 0.40, & 5 \leq x < 10 \\ 0.55, & 10 \leq x < 15 \\ 0.80, & 15 \leq x < 20 \\ 1, & x \geq 20 \end{cases}$$



Contract

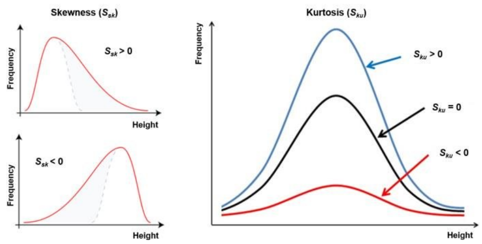
- **Deductible(d)**
- **Maximum(u)**
- **Inflation(r)**
- **Coinsurance(α)**

$$Y = \begin{cases} 0 & x \leq \frac{d}{1+r} \\ \alpha[(1+r)x - d] & \frac{d}{1+r} < x < \frac{u}{1+r} \\ \alpha[u - d] & x \geq \frac{u}{1+r} \end{cases}$$

Warning : The maximal don't include the deductible.

Moments

- k^e moment about the origin. $\mu_k' = \mathrm{E}\left[X^k\right]$
- k^e moment about the mean. $\mu_k = \mathrm{E}\left[(X-\mu)^k\right]$
- The **Skewness** moment give infomation about the asymmetry of the distribution. If $S_{sk} = 0$, the distribution is normal.
$$S_{sk} = \mathrm{E}\left[\left(\frac{X-\mu}{\sigma^2}\right)^3\right]$$



- The **kurtosis** moment give infomation about the flattening of the distribution. If $S_{ku} = 0$, the distribution is normal.
$$S_{ku} = \mathrm{E}\left[\left(\frac{X-\mu}{\sigma^2}\right)^4\right]$$
- The **coefficient of variation** give information about the dispersion of the distribution.
$$\mathrm{CV} = \frac{\sigma}{\mathrm{E}[X]}$$

Transformations of distribution

- Lognormal : $Y = e^X$, where
$$Y \sim \mathrm{Lognormal}(\mu, \sigma)$$
$$X \sim \mathrm{Normal}(\mu, \sigma)$$
- Inverse Exponential : $Y = \frac{1}{X}$, where
$$Y \sim \mathrm{Inverse\,Exponential}(1/\theta)$$
$$X \sim \mathrm{Exponential}(\theta)$$
- Weibull : $Y = X^{1/\tau}$, where
$$Y \sim \mathrm{Weibull}(\sqrt[\tau]{\theta})$$
$$X \sim \mathrm{Exponential}(\theta)$$

Parameter interpretation

- **Scale parameter (θ, β, σ) :** Affect the spread of the distribution.
- **Rate parameter (λ) :** Affect the rate of data at mean. (1/scale)
- **Shape parameter (α, τ, γ) :** Affect the shape rather then simply shift the distribution.

Produit de convolution

The convolution of 2 random variable is difine as the sum of the two.

$$f_{X_1+X_2}(x) = \int_{-\infty}^{\infty} f_{X_1}(x-s) f_{X_2}(s)\,\mathrm{d}s$$
$$F_{X_1+X_2}(x) = \int_{-\infty}^{x} F_{X_1}(x-s) f_{X_2}(s)\,\mathrm{d}s$$

Shifting Exponential

$$f(x;\theta;d) = \frac{1}{\theta} e^{-(x-d)/\theta}$$
$$\mathrm{E}[x] = \theta + d$$
$$\mathrm{Var}(x) = \theta^2$$

Norme d'un vecteur

$$\ell_1 = x_1 + x_2 + \ldots + x_n$$
$$\ell_2 = \sqrt{x_1^2 + x_2^2 + \ldots + x_n^2}$$

Greedy algorithm

A group of n peoples is to be assigned to k job, one to each job. The cost of job j is c_{ij} if person i is assigned. Select the assignement to have the minimal cost. We fixe the job or the people such as the $\min(n,k)$ and take the **minimum** cost for this personne(job).

$$c_{ij} \sim \mathrm{Exp}(\theta)$$
$$\mathrm{E}[\textbf{Total cost}] = \sum_{i=1}^{\min(n,k)} \frac{\theta}{\max(n,k)}$$

Potential outliers

Let Q_1 and Q_2 be the 25^e and the 75^75 quantile. Then $h = 1.5(Q_3 - Q_1)$. Observation are potential outliers if their are not in
$$(Q_1 - h, Q_3 + h)$$

Test III

Type III tests are tests on variable or set of variable that assume that all other variables are present in the model. The **Wald** test is type III.

Overdispersion

If the variance of the observation is **higher** than indicated by the binomial or poisson model. **Hight diviance** may indicate Overdispersion. We can solve it with **quasi-likehood** : $\phi\mathrm{Var}(y)$. This don't affect the fit but many statistic like Pearson. For Poison, we can use a Binomial Negative model.

Tail Value at Risk

$$\begin{aligned}\mathrm{TvaR}_k(x) &= \mathrm{VaR}_k(x) + \frac{\mathrm{E}\left[(x-\mathrm{VaR}_k)_+\right]}{S_x(\mathrm{VaR}_k)} \\ &= \mathrm{VaR}_k(x) + \frac{\mathrm{E}[x] - \mathrm{E}\left[x \wedge \mathrm{VaR}_k\right]}{S_x(\mathrm{VaR}_k)}\end{aligned}$$