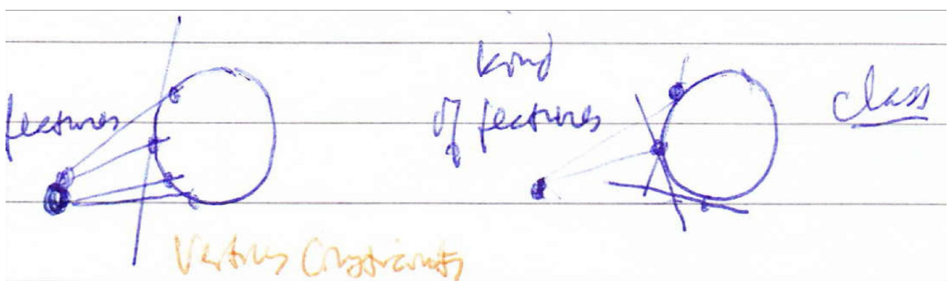
Duality and Work
Dotation en Mobilité et Post Learning.

Nature of the Problem: determinating parameter ϑ in the probability distribution function $f(x \mid \vartheta)$ as unknown. Belonging to an Interval Ω in $\mathbb{R}$. (observed values in sample). We estimate ϑ. Comparative Estimator and relation to this document. An objective is for me is to proceed. Introduce the department.

The Duality Principle: problem expressed in terms of vectors in Space (features) and Problem expressed in terms of hyperplanes in the Space. The Linear Program Relation: the shorter (min) distance form point P, to Convex Set (Feasible) as Max on candidate distances from point P to π_i Hypreplanes (that separate P from Convex Set (feasible)): see Vertices and Constraints as Post Learning Problem. The Original minimization (on vectors) is converted to maximation over the Hyperplanes. (separing) The Space consisting containing continuous linear functionals on Original Space constructed as planes. The linear functionals are as $\{$thinking,building,improving.producing$\}$ (Equity and extreme investment): $\{$Art,Business,Communcations,Care,Hospitality,IT,Law,Sales Transport,Education$\}$ (at Partition of Work Invertibility). As Partition we have: Minimization as development of Projection Theorem and Maximization separating Convex Space as by Hyperplanes: Chernokova as existence of the Riesz Frechét (Dual of all Hilbert Spces) and we know that dual of $C[a;b]$ as an incresing function incresing as $\ln(x)$. The Invertibility and Minimum Norms relate to NATO (distance form P to Convex Set).



Invertibility and Minimum Norms: to NATO (distance form P to Convex Set).

Main Statement as Minimum Norm Duality: $x_1 \in X, \exists d > 0$ such that $d =$distance from Convex Set K to set support functional h:

$$d = \inf_{x \in K} |x - x_i| = \max_{\|x^*\|=1} (\langle x, x^* \rangle - h(x^*))$$

Transform acheived by some $x_0^* \in X^*$ Adjunct Work and Kind of Work:

$\exists x_0 \in K$ and $-x_0^*$ aligned with $x_0 - x_1$. (Feature Like as Transform in a Linear Program).

Affine Transformation as presence of $(a_{ij}) = b_i$ as **inversion** from bounded $(a_{ij}) \leq b_i$, and lets A^{-1} exist.

Occurrence and Relaxation.

The Delay is defined as a difference inbetween the application of external stress to the response of the system. The means are iterations to solve $Ax = b$. (the method of Jacobi). From $A = D - (E + F)$ we introduce the linear iteration $x^{i+1} = D^{-1}(E+F)x^i + D^{-1}b = Jx^i + b'$. From x^0 we have the suite $x^1, x^2 \ldots$. The matrix

$D = (a_{ii})$ is a diagonal matrix made from diagonal of A. The E matrix is made from the lower sub-part of A, namely $E = \begin{bmatrix} 0 & 0 & 0 \\ a_{21} & 0 & 0 \\ a_{n1} & a_{n,n-1} & 0 \end{bmatrix}$, and $F = \begin{bmatrix} 0 & a_{12} & a_{1n} \\ 0 & 0 & a_{n-1,n} \\ 0 & 0 & 0 \end{bmatrix}$.

Clearly the space is $Ax \lesseqgtr 0$ and the comeback from equilibrium is $Ax = b$ after excitation.

Occurrence of $y = 0$, is clear at $x = 1$ for $y = 2x = \vartheta x$. The Big Data is known as $(r,\vartheta) = (\vartheta, 2\vartheta)$ as (x,y) cartesian. (This is called a polar description of relationship of $(x,y).$). This is an Angular Occurrence. (angle as a parameter)

The Inversion Topic: $(a_{ij} \mid b_i)\begin{bmatrix} x \\ x_{n+1} \end{bmatrix} = 0$. If $x_{n+1} = 1$ then the Dual theorem may be stated. It is:

Duality Theorem.

Personal Event in front of News. Editorial (⊗Media) Opinion ↔Life and Arts.

Domain specifying: **Claims**: **Identification Assumptions**: selling point of Data Alignement- find quality of purchase, manage pain and benefits by credit card. Lower drug prices and claims. (essential particular properties of phenomena: identified). (Phenomena picked out by the indentification assumptions: Grouping Asumptions). Claims as Sytstem: 1. identification, 2. properties associated, 3. grouping in Variable. (Suivi Segment: complete HalfLine: dependent independent forms:

Definition of **Market Like No Man's**: $g(t) \to A, h(t) \to B$, $\frac{g(t)}{h(t)} \mid_{x\to a} = \frac{g'(t)}{h'(t)} \mid_{x\to a}$ with $\left\| \begin{matrix} \frac{A}{B} \text{ if } B \neq 0 \\ \infty \text{ if } B = 0, A > 0 \\ 0 \text{ if } A = B = 0 \text{ indeterminate form} \end{matrix} \right\|$ for well chosen $g(t)$ and $h(t)$ in I_n as $F'(x)$. This is the Quotient Limit Law. Here $g(t)$ and $h(t)$ exist (see f and g_i).

$\lim_{x\to 1} \frac{1-x}{\ln x} = \lim_{x\to 1} \frac{-1}{\frac{1}{x}} = -1$ indeterminate at $x = 1$ (lack of representation).

$\lim_{x\to 0} \frac{1-\cos x}{x^2} = \lim_{x\to 0} \frac{\sin x}{2x} = \lim_{x\to 0} \frac{\cos x}{2} = \frac{1}{2}$. $\lim_{x\to 1} \frac{x^2-1}{x^2+1} = \lim_{x\to 1} \frac{2x}{2x} = 1$,

$\lim_{x\to 0}(1+x)^{\frac{1}{x}} \to e \Rightarrow B = 0$ indeterminate.

$\lim_{x\to 0} \ln(1+x)^{\frac{1}{x}} = \lim_{x\to 0} \frac{\ln(1+x)}{x} = \lim_{x\to 0} \frac{\frac{1}{1+x}}{1} = 1 = \ln e$ installement.

$\lim_{x\to\infty} \frac{\ln(1+\frac{1}{x})}{\ln(1-\frac{1}{x})} = \lim_{x\to\infty} \frac{-\frac{1}{x^2}(\frac{1}{1+\frac{1}{x}})}{\frac{1}{x^2}(\frac{1}{1-\frac{1}{x}})} = \lim_{x\to\infty} -\frac{x-1}{x+1} = -1$. The Quotient Limit Law : the Mean Value Principle, $\exists X$ such that $\frac{g(t)}{h(t)} = \frac{g'(X)}{h'(X)} \to \frac{g'(t)}{h'(t)} \mid_{t=X} \to L = \lim_{t\to X} \frac{g(t)}{h(t)}$.

$\lim_{x\to\infty} \frac{\ln x}{x} = \lim_{x\to\infty} \frac{\frac{1}{x}}{1} = \frac{0}{1} = 0$. $\lim_{x\to 0} x\ln x = \lim_{x\to 0} \frac{\ln x}{\frac{1}{x}} = \lim_{x\to 0} \frac{\frac{1}{x}}{\frac{-1}{x^2}} = \lim_{x\to 0} -x = 0$.

$\lim_{x\to\infty} \frac{x^2}{e^x} = \lim_{x\to\infty} \frac{2x}{e^x} = \lim_{x\to\infty} \frac{2}{e^x} = 0$.

Definition of **Talboden**: by the Factor $(x - r_{n+1})$ in $(x - r_{n+1})\prod_{i=1}^{n}(x - r_i)$ where $\prod_{i=1}^{n}(x - r_i)$ is a **Fat Tail**. *Condition initiales* as boundary values. See $(g(t), h(t))$ and Path Length as $\frac{ArcLength}{chord} \to 1$. **El Passeo is a First Order Separable** equation from $x_i \to y_i$, as $\frac{\partial y}{\partial x} = \frac{g(x)}{h(x)}$ negative on I_n. The **Inventory Getaway** as **Factor** and **Fat Tail** at lieu as

Codomain (sector of Perimeter) by Machine Learning at Marlborough from Reikyavik in Policy with Investing Sum at the Sheraton at Hérmès Thot by $(x,y,z) \in \mathbb{R}^3$ where z is a third dimension in the Fat Tail. (Access): **Epimorphism** Help (Forward House Maison les Étapes). : Plancher : trésors de Moscou. Domain: Gap: $x_i \to y_i, \to i$, an Occurrence. Here x_i is a pricing and y_i is a reserve. (a Model for Insurance). Panel: Null Space and Rules: inequalities, family and Range: convergence Produits durables tel supervision. Continuous in a Year as Mathematics: determining Segment. (Safeguard).

Positivie definite Work: Differentials Equations and Integral Equations: Dynamical Systems and Linear Algebra (Marinela). The **basic Equations**: $x'(t) = ax(t) \to x(t) = ake^{at}$ as $\int x' = a\int x$.

$$f(t) = ke^{at}, \qquad f'(t) = ake^{at}.$$

The **Study** of: $u(t)e^{-at}$, e^{-at} at assympthotic to 0.

$$\frac{\partial}{\partial t}(u(t)e^{-at}) = u'(t)e^{-at} + u(t)(-ae^{-at}) = au(t)e^{-at} = au(t)e^{-at} = 0$$

defined as **Positive definite**. Here $a(x(t))$ is a linear Operator. $Ae_k = \mathrm{col}\,um(A)_k \to \forall Matrices\ A_k \to Linear(\mathbb{R}^n), Te_k = Ae_k$ as any Operator. TS composition of Operators as $A_T \cdot A_S$. $T + S \to A_T + A_S$. As $\exists T \in \mathbb{R}^n \to \mathbb{R}^n$: $\lambda_i(Tx) = (\lambda T)x = Px$. **For Subspaces** $S_1..S_n$ of $E = \mathbb{R}^n \to A$ projected on S_i, $x' = Ax$ & $x(0) = x_0$. **Eigenvalues of Positive definite** as $\lambda_i \in \mathbb{R}^+, \frac{1}{\lambda} \in [0,1] \subset \mathbb{R}^+$. How to change each Dimension. $(x'(t)) = \begin{bmatrix} 1 & 0 & 0 \\ 1 & 2 & 0 \\ 1 & 0 & -1 \end{bmatrix} x_i . \lambda_i = \{1,2,-1\},\ x(0) = (1,0,0)$.
$x(t) = (e^t, -e^t + e^{2t}, \frac{1}{2}e^t - \frac{1}{2}e^{2t})$. $A^{Adj} \approx A^{-1}$. The transition Matrix A: traverse (Transverse traverse téléverser iCould on Google Drive.). **Opportunity at Algiers**: 1st Sign In of each Dimension Dual Space as StartUp Grind (Media). $\delta x = a_{ij}x \to \delta y$ of $f = y(x) \to \delta y(\delta x)$ called Summability, $ABx = Ax$.

Rebordering is defined as: **Commands in Optimal Time are close to Google Drive**.

$[x^i(t)]$ are Phase coordinates. $[u^i(t)]$ command coordinates. See $[x^i(t)] \in X$ the Phase Space, and the admissible Command $[u^i(t)]$ may lead to $[u^i] \in \mathbb{R}^r$, with the closed domain of Command Space $U \subset \mathbb{R}^r$.

Yet if constraints $j \in \{1;2;3..\}$ and $i \in \mathbb{N} - \{1;2;3..\}$ then we have constraints $A_jx \leq b_j$ and $A_ix \leq b_i$. This may be changed in

$$\max c^{\perp}x + \lambda^{\perp}(b_i - Ax) \quad \text{on} \quad A_jx \leq b_j, \Rightarrow c^{\perp} \cup \lambda^{\perp}$$

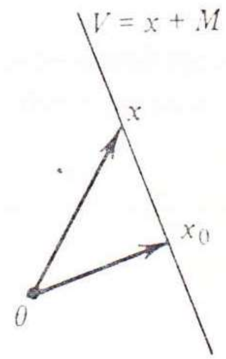
(also called *Lagrangian Relaxation*). At this point we relax the first worry or concern, namely the constraint i. Here $\lambda = \begin{bmatrix} \lambda_1 & \lambda_2 & ..\lambda_n \end{bmatrix}^{\perp}$ is called the dual parameter. The codomain relaxation problem is stated as:

$$\min P(\lambda) \ \text{ such that } \ \lambda \geq 0, \ \text{ and } \ P(\lambda) = \max c^{\perp}x + \lambda^{\perp}(b_i - A_ix) \ \text{ on } \ A_jx \leq b_j \Rightarrow \lambda$$

The penalty of the chosen constraint, alters the polytope as from the algorithm of Chernikova. A direction method is written as $\min_{x,y} f(x) + g(y)$ on $x = y$. The direction is given by the space $y \in \mathbb{R}^n$. There is no b_j upper bound. For parallelism belief, we have for each constraint $a_{j}^{\perp}.x \leq b_j$ known as $\frac{\lambda^j e^{-\lambda}}{j!}$ from the Poisson Process. There is ordering in the domain i and j.

The Minimum Norm Problem in as much as The Projection Theorem.

The Projection: $X \rightarrow$ Part of X finite dimensional by Normal Equations. We are given $M \subset H$ a Hilbert Space. $x \in H$ and the variety is known as $x + M = V \rightarrow \exists x_0$ unique in $x + M$ of minimum norn and $x_0 \perp M$.



Minimum norm to a linear variety

Definintion of Variety (an n dimensional variety) $x + \sum_{i=1}^{n} a_i x_i$ with $x_i \otimes x_{i+1} \approx M \subset H, x \in H$ with the following Theorem.

Theorem of Approximation.

$\exists x \in H, \exists y_i$ such that $y_i \otimes y_{i+1} \approx M$ and $\langle x, y_i \rangle = c_i$, then if $c_i = 0$ then $x \in M^{\perp}$ We want a minimum norm problem of seeking the closest vector. $\begin{bmatrix} \langle y_1 y_1 \rangle & \langle y_1 y_2 \rangle & .. & \langle y_1 y_n \rangle \\ \langle y_2 y_1 \rangle & & .. & \\ & & .. & \\ \langle y_n y_1 \rangle & & .. & \langle y_n y_n \rangle \end{bmatrix} \begin{bmatrix} \beta_1 \\ \beta_2 \\ .. \\ \beta_n \end{bmatrix} = \begin{bmatrix} c_1 \\ c_2 \\ .. \\ c_n \end{bmatrix}$ with $x_0 \perp M^{\perp}, x_0 \in M, x_0 \in M^{\perp\perp}$ and $x_0 = \beta_1 y_1 + \ldots + \beta_n y_n$. We know about translation of the $M^{\perp}$ subspace. We know $y_i \otimes y_{i+1} \approx M$ and $\exists_j$ with $c_j = 0$ then the linear Variety $V = x + M$ is the $M^{\perp}$ subspace. If $c_j \neq 0$ then $x + M = z + M^{\perp}$.

Existence and Uniqueness Result in a Quadratic Loss Control Problem.

$$\min J = \int_0^T [x^2(t) - u^2(t)]dt \;\text{ with }\; x'(t) = u(t) \;\text{ and }\; x(0) = K$$

The statement of the Problem is: reduce $x(t)$ quickly by controlling $\dot{u}(t)$ (ControlEnergy). You want small $x(t)$.

$$x(t) = x(0) + \int_0^t u(\tau)d\tau$$

Define $H : L_2[0;T] \otimes L_2[0;T],\ (x,u) \in H$, and define the *Inner Product*:

$$\langle (x_1y_1), (x_2y_2) \rangle = \int_0^T (x_1x_2 - u_1u_2)dt$$

with $\|(x,u)\| = \int_0^T [x^2(t) - u^2(t)]$. We have $(x,u) \in H$ and $x(t) = x(0) + \int_0^t u(\tau)d\tau$ with $x(t) \in V = x + M \subset H$

The solution is: find $(x,u) \in V$ such that $\|(x,u)\| \to \min$

The existence et uniqueness of $\|(x,u)\| \to \min$, $\exists x_n$ with $\{(x_nu_n)\} \to (x,u) \in V = x + M$.

We let $y(t) = x(0) + \int_0^t u(\tau)d\tau$ and want to show $x(t) = y(t)$ for $x(0) + \int_0^t u(\tau)d\tau$ with

$$|y(t) - x(t)|^2 \leq t\int_0^t |u(\tau) - u_n(\tau)|^2 d\tau \leq T\|u - u_n\|^2$$

$\|y - x_n\| \leq T\|u - u_n\|$ and

$$\|y - x\| \leq \|y - x_n\| + \|x_n - x\| \leq T\|u - u_n\|T\|u - u_n\| + \|x_n - x\|$$

and as $\|u - u_n\| \to 0$ and $\|x_n - x\| \to 0$ we have $x(t) = y(t)$.

Introducing Duality.

The shaft angular velocity w, counter of $u(t)$ a current source. $w'(t) + w(t) = u(t)$. The angular position ϑ is a time integral of w. $\vartheta(0) = w(0) = 0$ initially at rest. Find $u(t)$ for minimum energy that rotates the shaft to a new rest position $\vartheta = 1$.

$$\int_0^1 w(t)dt \text{ at } \vartheta(1)$$

$\vartheta(1) = K\int_0^1 u(t)dt$ is called the Cost Criterium on control function $u(t)$.

$w(1) = \int_0^1 e^{(t-1)}u(t)dt$ and from $w'(t) + w(t) = u(t)$.

$\vartheta(1) = \int_0^1 u(t)dt - w(1)$

$\vartheta(1) = \int_0^1 [1 - e^{(t-1)}]u(t)dt - w(1),\ u(t) \in H = L_2[0;1]$ with

$$w(1) = \langle u, y_1 \rangle \text{ and } \vartheta(1) = \langle u, y_2 \rangle$$

$\exists u \in L_2[0;T]$ with $0 = \langle u, y_1 \rangle$ and $1 = \langle u, y_2 \rangle$
and from the Theorem of Approximation, the optimal solution is in subspace $y_i \otimes y_2$
with $u(t) = \alpha_1 + \alpha_2 e^t = \frac{1}{3-e}[1 + e - 2e^t]$ from $\begin{bmatrix} \langle y_1, y_1 \rangle & \langle y_1, y_2 \rangle \\ \langle y_2, y_1 \rangle & \langle y_2, y_2 \rangle \end{bmatrix} \begin{bmatrix} \alpha_1 \\ \alpha_2 \end{bmatrix} = \begin{bmatrix} 0 \\ 1 \end{bmatrix}$

There are two basic forms of minimum norm in H that reduces to a solution of a finite number of simoultaneous linear equations. Both problems are concerned about a shortest distance from a point to a linear variety finite dimension (n) and codimensions ($m - n$).

The linear variety dimension and finite codimension

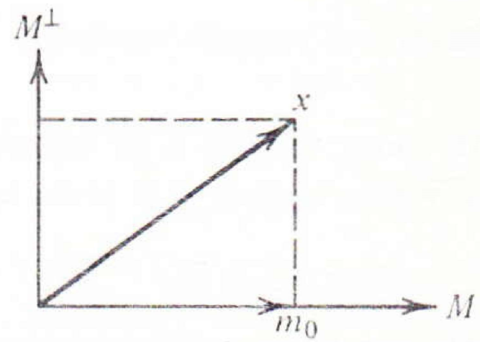


Figure 3.5 Dual projection problems

x projected onto M and x projected onto $M^{\perp}$, $m_0 \approx x$ projected onto M and $x - m_0$ projected onto $M^{\perp}$

Point of Restauration. **Naturalization Plugins and Segment**.

Media and Virtual Reality at the Point of Sale as Existence of w_k Slack and Framing Human Machine Interface Intervention.

Design on How the Guide sees the Tourist Probe.

The generalization of the mean value principle we be presented.

We assume we have the path: $(x, y) \to (g(t), h(t))$ from (x_0, y_0) and (x_1, y_1)

We have the secant line through these two points must be parallel to the tangent line at some in-between point. If the line is not vertical, then the slope is: $\frac{y_1 - y_0}{x_1 - x_0}$. h and g are continuos on $[a, b]$, then $\frac{h(b) - h(a)}{g(b) - g(a)} = \frac{h'(T)}{g'(T)}$ where $T \in (a, b)$.

Parametrization is free of theory.

If we assume that $x \to y(x)$, we let $h(x)$ be the error $E(x)$ in the tangent line approximation, namely $E(x) = y(x) - y(a) - y'(a)(x - a)$, where $E(a)$ and $E'(a)$ are both zero, and $E''(x) = y''(x)$, and $g(x) = (x - a)^2$, then $g(a)$ and $g'(a)$ are both zero, then

$$\frac{E(x)}{(x-a)^2} = \frac{E'(y)}{2(y-a)} = \frac{E''(T)}{2} = \frac{y''(T)}{2} \text{ where } y \in (a, x) \text{ and } T \in (a, y)$$

If y is twice differentiable on I, containing the point a, $\forall x \in I$,

$E = y(x) - [y(a) - y'(a)(x-a)]$, and

$E = \frac{y''(T)}{2}(x-a)^2$ where $T \in (a,x)$

The Hôpital Rule is: $y(x) \to 0$, $g(x) \to 0$ as $x \to a$, and $\frac{y'(x)}{g'(x)} \to L \leq \infty$, as $x \to a$, then $\frac{y(x)}{g(x)} \to L \leq \infty$ as $x \to a$

Introduction in a process where we have data we may learn from. (**Erschli**βen)

In mathematical proofs we know the contrapositive argument. The contrapositive argument is relating from a sentence in front and presence of the second, that is contrapositioned.

$$\neg q \to \neg p$$

$$p \to q.$$

A known example is the proof that **if** x^2 **is even then** x **is even**. : 1.x is not even. 2. x is odd. 3.The product of two odds is odd. 4. Hence x^2 is odd. 5. x^2 is not even. 6. if x^2 is even then (1.) is false, namely x has to be even.

1. **The prescription from data**.

The training examples are $\{(x^{(1)},y^{(1)}),(x^{(2)},y^{(2)})\ldots(x^{(n)},y^{(n)})\}$. It is also known that $y^{(i)} = y \in [0;1]$, and $x^{(i)} \to y^{(i)}$. The specialization is in Beijing. The well estimated probability is $\Pr(y = 1 \in [0;1] \mid x;\vartheta)$, and we say it is parametrized by ϑ, knowing the cost function for the training set is $0 \leq h_\vartheta \leq 1$ a specialization in Beijing. We know

$$h_\vartheta = \frac{1}{(1+e^{\vartheta^\perp x})} \text{ a logistic regression.}$$

2. **Boundaries on the plane**. There are linear and non-linear boundaries. $\exists y = 1$ as $\vartheta^\perp x \geq 0$. We relate as $\vartheta_0 + \vartheta_1 x^{(1)} + \vartheta_2 x^{(2)} .. \vartheta_n x^{(n)}$ or $\vartheta_0 + \vartheta_1 x^{(1)} + \vartheta_2 x^{(2)2} .. \vartheta_n x^{(n)n}$.

3. **The cost function**

$$J(\vartheta) = \begin{bmatrix} -\log(h_\vartheta(x)) \text{ if } y = 1 \\ -\log(1 - h_\vartheta(x)) \text{ if } y = 0 \end{bmatrix}$$

has the simplified version

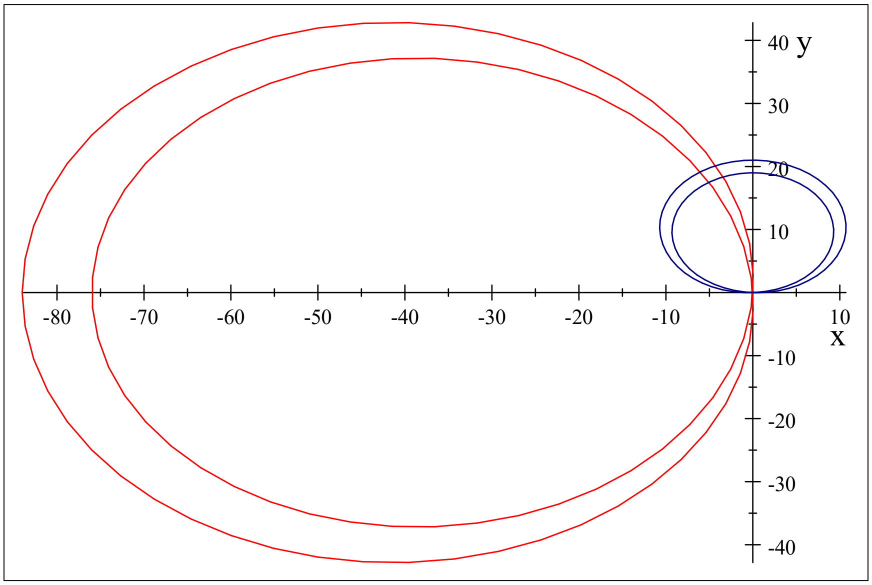
$$J(\vartheta) = \sum_{i=1}^{n} y^{(i)} \log(h_\vartheta(x^{(i)})) + (1-y^{(i)}) \log(1 - h_\vartheta(x^{(i)}))$$

The programme is $\min_\vartheta J(\vartheta)$ as $\vartheta_j := \vartheta_j - \alpha \sum_{i=1}^{m} h_\vartheta(x^{(i)}) - y^{(i)} x_j^{(i)}$., and update all ϑ_i.

The learning algorithm indicates ϑ_i.

The Conséquence or Result in front of Work.

$a(1 - n\cos\vartheta)$ has been seen as Late Quality Work where n is the time. Here $a = 20$. The interior loop represents the Conséquence (big ray). This is a Cardioid. We met $1 + a\sin\vartheta$ as a **Growth from Prospect** called a, -the Limaçon (small ray), here $a = 20$.



Use of Germanity.

$(h(t), g(t)) \to m = \frac{h'(t)}{g'(t)} = \frac{h'(T)}{g'(T)}$, $T \in [a;b] \Rightarrow f$ twice differentiable on $[a;b]$; an f as Interest on a, with Error

$$E = f(x) - [f(a) + f'(a)(x-a)] = \frac{f''(X)}{2}(x-a)^2,\ X \in [a;x]$$

(also called Parametric Mean Value Theorem)

Evaluation of Limits in Discourse.

$f(x) \to A,\ \ g(x) \to B,\ \ x \to a,\ \ \lim_{x\to a} \frac{f(x)}{g(x)} = \frac{A}{B},\ A, B = 0$

$$\text{The Hôpital's Rule}\ \ \frac{f'(x)}{g'(x)} \to L,\ \ \frac{f(x)}{g(x)} \to L$$

$\lim_{x\to 1} \frac{1-x}{\ln x} = \lim_{x\to 1} \frac{-1}{\frac{1}{x}} = -1$: Actualité of PharmAsia

$\lim_{x\to 0} \frac{1-\cos x}{x^2} = \lim_{x\to 0} \frac{\sin x}{2x} = \lim_{x\to 0} \frac{\cos x}{2} = \frac{1}{2}$

$lim_{x\to 1} \frac{x^2-1}{x^2+1} = \frac{0}{2} = 0$

$\lim_{x\to\infty} (1+x)^{\frac{1}{x}} = e$

$\lim_{x\to\infty} \frac{\ln(1+\frac{1}{x})}{\ln(1-\frac{1}{x})} = \lim_{x\to\infty} \frac{(-\frac{1}{x^2})\frac{1}{(1+\frac{1}{x})}}{(\frac{1}{x^2})\frac{1}{(1-\frac{1}{x})}} = \lim_{x\to\infty} -\frac{(x-1)}{(x+1)} = -1$: Quality of $\frac{1}{x}$ as $x \to \infty$, a selectionable parameter.

Indeterminate Forms by Lack.

$|f(x)| \to \infty\ \ |g(x)| \to \infty\ \ a \to \infty$ with $\frac{f'(x)}{g'(x)} \to L,\ \ \frac{f(x)}{g(x)} \to L$

$\lim_{x\to\infty} \frac{\ln x}{x} = \lim_{x\to\infty} \frac{\frac{1}{x}}{1} = \frac{0}{1} = 0$: necessity of Talk with PharmAsia

$\lim_{x\to 0+} x \ln x = \lim_{x\to 0} \frac{\ln x}{\frac{1}{x}} = \lim_{x\to 0+} \frac{\frac{1}{x}}{-\frac{1}{x^2}} = \lim_{x\to 0+} -x = 0$:Function Parameter $x \in [1;\infty)$ with Cost $\ln x$.

$\lim_{x\to\infty} \frac{x^2}{e^x} = \lim_{x\to\infty} \frac{2x}{e^x} = \lim_{x\to\infty} \frac{2}{e^x} = 0$:Determination of Distance by Lack.

(Money, Function, Distance, Determination)

Beijing and an Unitary Transformation.

If rows or columns $\{A_{\cdot i}\}$ or $\{A_{i\cdot}\}$ are Orthonormal (definition of Unitary), and $\exists u \cdot v$, $\exists \|u\|_2 < L$ and $\exists \|v\|_2 < L$ then if $\cos\vartheta = \frac{u \cdot v}{\|u\|+\|v\|}$ we have $proj(u,v) = \frac{u \cdot v}{\|u\|+\|v\|}$. The **Model is Volatile** if there exists z_i such that $z_i \ggg y_i$.

It is Spatial as being known from Short Term Risk.

We see w_i first and then z_i. In general we may have $[\epsilon_{\cdot 1}\epsilon_{\cdot 2}\epsilon_{\cdot 3}\ldots\epsilon_{\cdot n}] \in \mathbb{R}^{n\times n}$. $[\epsilon_{\cdot k}] = w_{\cdot i}$ and $[\epsilon_{\cdot l}] = z_{\cdot i}$. These columns (namely k and l stand close to x_i and y_i).The conditioning number should be as close to 1. The matrix is ill conditioned if the number is big, and the matrix in this case is not invertible.

An example for Beijing, where data comes at: dimensions $\begin{bmatrix} 1 & 2 & 3 & 4 \end{bmatrix}^{\perp}$ and effort $\begin{bmatrix} 2 & 4 & 3 & 1 \end{bmatrix}^{\perp}$. We may advise a Human condition as $\begin{bmatrix} 0.4 & 0.2 & 0.2 & 0.2 \end{bmatrix}^{\perp}$ and say Money $\begin{bmatrix} 0.1 & 0.3 & 0.3 & 0.3 \end{bmatrix}^{\perp}$. The augmented matrix is: $\begin{bmatrix} 0.4 & 2 & 0.1 & 1 \\ 0.2 & 4 & 0.3 & 2 \\ 0.2 & 3 & 0.3 & 3 \\ 0.2 & 1 & 0.3 & 4 \end{bmatrix}$, its inverse: $\begin{bmatrix} 3 & 3. & -7 & 3 \\ 0 & -1. & 2 & -1 \\ -2 & 28 & -42 & 18 \\ 0 & -2 & 3 & -1 \end{bmatrix}$, and the condition number: 397. 8. This is not ill conditioning. Clearly there is need of a correct Decision. $\exists f : choice \to conséquence$. Clearly the condition number is sensitive to a pick on row 2 at column on Money, or 3, or 1. We expect *f*, as a decision tree with lines of control and chance. Backward induction from right to left, is one way to take advantage from Control. This is also called *Posterior Analysis*, is contrary to Risk, and unites Control and Sample Evidence of Chance. (for a total of 4). The Backward exercise is $a_{x3} \to \begin{bmatrix} a_{14} & a_{24} & a_{34} & a_{44} \end{bmatrix}$ and so on to make the tree backward. We saw $a_{\cdot 3}$ as before last, and in the case of *x* big and main first qualifying for a node. The Forward Process is made clearly on Control, called *Prior Analysis*, and runs like $a_{11} \to \begin{bmatrix} a_{12} & a_{22} & a_{32} & a_{42} \end{bmatrix}$. We saw a_{11} as before last, and in this case big and main, qualifying for a first node. In this scheme there is no loss of opportunity. All dimensions should be screened well. The prescription for choosing columns is: The calculation is in the order:

$$\Pr(E_1),\to \quad E_2 \cap E_2,\to \quad \Pr(E_2 \cap E_2),\to \quad \Pr(E_2 \mid E_1)$$

	$Pr(E_1)$	$Pr(E_2)$	$Pr(E_3)$	$Pr(E_4)$	
$Pr(E_1)$	..	$Pr(E_2 \mid E_1)$	..	..	
$Pr(E_2)$	..	..	..	..	If $\epsilon_{\cdot 1} \leq \epsilon_{\cdot 2} \leq \epsilon_{\cdot 3} \leq \ldots \leq \epsilon$ then
$Pr(E_3)$	..	..	..	..	
$Pr(E_4)$	..	..	..	..	

$0 \leq [\epsilon_{\cdot 1}\epsilon_{\cdot 2}\epsilon_{\cdot 3}\ldots\epsilon_{\cdot n}][\vec{x}]$, is a cone. Here we have a polytope of vertices (Control) and Cone Rays (Sample Evidence of Chance). The Chernikova's Algorithm is to be used to find these. A quality approach is: $O(n)$ of vertices, and link acquisition of Rays lead to SEO. (in Yelp, Yellow Pages or Event Sites). A presentation of the Mean and Median for the Distribution is as follows: The Mean is the convex combinations of Vertices, and the Median is the middle value when Rays are arranged in order of magnitude. This is also known as a range from a Deal to Expansion, studied by Locution, resuming from Complements.

The gain is merily as from an endomorphism: no **Professionnalization and presence of** *Référenceurs*.

The Observation is through **Press** and **Pioneers**.

If $\begin{bmatrix} x \\ x_{n+1} \end{bmatrix} \in Cone$ and $[A \mid b]\begin{bmatrix} x \\ x_{n+1} \end{bmatrix} = 0$ then it may be $Ax \leq b$ that has relational $a_j.x_i \leq b_i$ as work functionals with additive angles from traditional to non traditional Tourism.

The Embassy and Journey.

The following generalities are explicit as dual programs:

$\min EX + FY - d$ subject to
$AX + BY = G,$
$CX + DY \geq H, X \geq 0$

$\max G^T U + H^T V - d$ subject to
$V \geq 0$
$A^T U + C^T V \leq E^T$
$B^T U + D^T V = F^T$

We know them from:
$\min CX - d$ subject to $AX = B, X \geq 0$ and
$\max B^T U - d$ subject to $A^T U \leq C^T$

These hold as $B^T U = U^T B = U^T AX \leq CX$

The Duality Theorem says that for dual pairs of programs:
1: d is unique to both programs
2: a solution optimal to one is optimal to both
3: $B^T U = U^T B = U^T AX \leq CX$ The values of each feasible solutions of the min program bounds above the solution of the max program.

Venue is by Augmented Reality: $x_{\cdot i}$ in $AX = B$ is a solution to $\min CX - d$ subject to $AX + B, X \geq 0$. We call $x_{\cdot i}$ a feature of Venue.

Work is the dual of the Augmented Reality: $\max B^T U - d$ subject to $A^T U \leq C^T$, where $u_{\bullet i}$ is a feature of Work.