International Journal of Engineering Sciences Paradigms and Researches, Vol. 02, Issue 01, December 2012
ISSN (Online): 2319-6564
www.ijesonline.com

Analysis of Brain Cancer and Nervous Cancer Population with Age and Brain Cancer Type In North America

Akash K Singh, PhD
IBM Corporation, Sacramento, USA
akashs@us.ibm.com

Abstract

This paper discuss about statistical representation of Brain Cancer in America. Brain cancer morbidity is high and treatment plans like chemotherapy, surgical resection of Tumor, Hyperthermia and Radio Surgery is key elements for the treatment of patients suffering from Brain Cancer. Who and Disease control prevention dataset is used to perform analysis. Incidence Rate, Death Rate, Incidence Count and Death count in male and female are rising; Classification of Data is based on Brain Tumor and other Nervous. Brain Tumor is a leading cause of death and once its diagnosed base on the stage of cancer life expectancy is about 5 Years or so. Incidence rate of Brain Cancer in age group and gender difference is analyzed based on States. Spatially Analytic data is used for the geo-visualization of Cancer. Sources of data are from Cancer registries, World Health Organization, Health Information Database and remote sensing data.

Keywords: *Brain Cancer, Spatial Analysis, Autocorrelation, Fuzzy Logic.*

I. INTRODUCTION

This research is focus on giving tools and techniques to the field of epidemiology to study and provide treatment to Brain Cancer patient. This would help to control the disease and create the disease model and act on the trends of Brain Cancer. Large and highly complex data structure are analysed on grid computing environment. Purpose of this research is to provide the growth of Brain Cancer in America and find out the similarity and differences in the regions of Brain Cancer depending upon spatial information. Geo Spatial information helps in predicting the spread of disease. Mathematical model helps in analysing the Brain cancer Characteristics. Cancer Etiology is also represented in spatial form and pattern on Treatment [1]. Spatial data refer to data with locational attributes. Most commonly, locations are given in Cartesian coordinates referenced to the earth's surface. These coordinates may describe points, lines, areas or volumes. This need not be the only spatial framework; "relative spaces" may be defined in which distance is defined in terms of some other attribute, such as socio-demographic similarly or connectedness along transportation networks [2][3]. There are over 600,000 people in the US living with a primary brain tumor and over 28,000 of these cases are among children under the age of 20.1

Metastatic brain tumors (cancer that spreads from other parts of the body to the brain) occur at some point in 20 to 40% of persons with cancer and are the most common type of brain tumor.

Over 7% of all reported primary brain tumors in the United States are among children under the age of 20.

Each year approximately 210,000 people in the United States are diagnosed with a primary or metastatic brain tumor. That's over 575 people a day:

- An estimated 62,930 of these cases are primary malignant and non-malignant tumors.
- The remaining cases are brain metastases (cancer that spreads from other parts of the body to the brain).
- Among children under age 20, brain tumors are:
  - the most common form of solid tumor
  - the second leading cause of cancer-related deaths, following leukemia
  - the second leading cause of cancer-related deaths among females
- Among adults, brain tumors are:
  - the second leading cause of cancer-related deaths among males up to age 39
  - the fifth leading cause of cancer-related deaths among women ages 20-39

There are over 120 different types of brain tumors, making effective treatment very complicated. Because brain tumors are located at the control center for thought, emotion and movement, their effects on an individual's physical and cognitive abilities can be devastating. At present, brain tumors are treated by surgery, radiation therapy, and chemotherapy, used either individually or in combination. No two brain tumors are alike. Prognosis, or expected outcome, is dependent on several factors including the type of tumor, location, response to treatment, an individual's age, and overall health status.

An estimated 35% of adults living with a primary malignant brain or CNS tumor will live five years or longer.

Brain tumors in children are different from those in adults and are often treated differently. Although over 72% percent of children with brain tumors will survive, they are often left with long-term side effects [4].

II. METHODOLOGY

Study of spatial autocorrelation analysis supports the hypotheses to predict the geo location and volume of epidemiological insights. Information pertained from first order autocorrelation (Brain Cancer & Nervous) gives the pattern of mortality in spatial space.Applied spatial autocorrelation to define correlation of a cancer dataset in variable array with itself through Fuzzy Topological space. Measured the characteristics at one state example California are similar or dissimilar to nearby states example Nevada. Measure the most probable occurrence of event at one location with nearby inter-connected locations.Applied the measurement using Joint Count Statistics, Moran's I , Geary's ratio, General G, Local Index of Spatial Autocorrelation and Global Index of Spatial Autocorrelation.Spatial Autocorrelation produced positive results with similar values Fuzzy Cluster on the map and Negative dissimilar values Fuzzy Cluster on the map. Fuzzy connectedness technique is used to measure brain tumor volume; this is also applied on brain lesion volume estimation. Multiple Fuzzy spaces are defined to layout the computational framework. Fuzzy compactness and connectedness are distinct absolute property that is used for fuzzy topology. Absolute topology is where all subspaces Z $\subseteq$ Y $\subseteq$ X of a space X, Z fulfills P (property) a subspace of Y iff Z fulfills P as a subspace of X. We consider the following anycast field equations defined over an open bounded piece of network and /or feature space $\Omega \subset R^d$. They describe the dynamics of the mean anycast of each of p node populations.

$$\begin{cases} (\frac{d}{dt}+l_i)V_i(t,r) = \sum_{j=1}^{p}\int_{\Omega} J_{ij}(r,\bar{r})S[(V_j(t-\tau_{ij}(r,\bar{r}),\bar{r})-h_{|j})]d\bar{r} \\ \qquad + I_i^{ext}(r,t), \qquad t \geq 0, 1 \leq i \leq p, \\ V_i(t,r) = \phi_i(t,r) \qquad t \in [-T,0] \end{cases} \tag{1}$$

We give an interpretation of the various parameters and functions that appear in (1), Ω is finite piece of nodes and/or feature space and is represented as an open bounded set of R^d . The vector r and $\bar{r}$ represent points in Ω . The function $S : R \to (0,1)$ is the normalized sigmoid function:

$$S(z) = \frac{1}{1+e^{-z}} \tag{2}$$

It describes the relation between the input rate v_i of population i as a function of the packets potential, for example, $V_i = v_i = S[\sigma_i(V_i - h_i)].$ We note V the $p-$ dimensional vector $(V_1,...,V_p).$ The p function $\phi_i, i = 1,..., p,$ represent the initial conditions, see below. We note ϕ the $p-$ dimensional vector $(\phi_1,...,\phi_p).$ The p function $I_i^{ext}, i = 1,..., p,$ represent external factors from other network areas. We note I^{ext} the $p-$ dimensional vector $(I_1^{ext},..., I_p^{ext}).$ The $p \times p$ matrix of functions $J = \{J_{ij}\}_{i,j=1,...,p}$ represents the connectivity between populations i and $j,$ see below. The p real values $h_i, i = 1,..., p,$ determine the threshold of activity for each population, that is, the value of the nodes potential corresponding to 50% of the maximal activity. The p real positive values $\sigma_i, i = 1,..., p,$ determine the slopes of the sigmoids at the origin. Finally the p real positive values $l_i, i = 1,..., p,$ determine the speed at which each anycast node potential decreases exponentially toward its real value. We also introduce the function $S : R^p \to R^p,$ defined by $S(x) = [S(\sigma_1(x_1 - h_1)),..., S(\sigma_p - h_p))],$ and the diagonal $p \times p$ matrix $L_0 = diag(l_1,...,l_p).$ Is the intrinsic dynamics of the population given by the linear response of data transfer. $(\frac{d}{dt}+l_i)$ is replaced by $(\frac{d}{dt}+l_i)^2$ to use the alpha function response. We use $(\frac{d}{dt}+l_i)$ for simplicity although our analysis applies to more general intrinsic dynamics. For the sake, of generality, the propagation delays are not assumed to be identical for all populations, hence they are described by a matrix $\tau(r,\bar{r})$ whose element $\tau_{ij}(r,\bar{r})$ is the propagation delay between population j at $\bar{r}$ and population i at $r.$ The reason for this assumption is that it is still unclear from anycast if propagation delays are independent of the populations. We assume for technical reasons that τ is continuous, that is $\tau \in C^0(\bar{\Omega}^2, R_+^{p\times p}).$

Moreover packet data indicate that τ is not a symmetric function i.e., $\tau_{ij}(r,\bar{r}) \neq \tau_{ij}(\bar{r},r),$ thus no assumption is made about this symmetry unless otherwise stated. In order to compute the righthand side of (1), we need to know the node potential factor V on interval $[-T,0].$ The value of T is obtained by considering the maximal delay:

$$\tau_m = \max_{i,j(r,\bar{r}\in\Omega\times\Omega)} \tau_{i,j}(r,\bar{r}) \qquad (3)$$

Hence we choose $T = \tau_m$

III. Mathematical Framework

A convenient functional setting for the non-delayed packet field equations is to use the space $F = L^2(\Omega, R^p)$ which is a Hilbert space endowed with the usual inner product:

$$\langle V,U \rangle_F = \sum_{i=1}^{p} \int_\Omega V_i(r) U_i(r) dr \qquad (1)$$

To give a meaning to (1), we defined the history space $C = C^0([-\tau_m, 0], F)$ with $\|\phi\| = \sup_{t\in[-\tau_m,0]} \|\phi(t)\| F,$ which is the Banach phase space associated with equation (3). Using the notation $V_t(\theta) = V(t+\theta), \theta \in [-\tau_m, 0],$ we write (1) as

$$\begin{cases} \dot{V}(t) = -L_0 V(t) + L_1 S(V_t) + I^{ext}(t), \\ \qquad V_0 = \phi \in C, \end{cases} \qquad (2)$$

Where

$$\begin{cases} L_1 : C \to F, \\ \phi \to \int_\Omega J(.,\bar{r}) \phi(\bar{r}, -\tau(.,\bar{r})) d\bar{r} \end{cases}$$

Is the linear continuous operator satisfying $\|L_1\| \leq \|J\|_{L^2(\Omega^2, R^{p\times p})}.$ Notice that most of the papers on this subject assume Ω infinite, hence requiring $\tau_m = \infty.$

Proposition 1.0 If the following assumptions are satisfied.

1. $J \in L^2(\Omega^2, R^{p\times p}),$
2. The external current $I^{ext} \in C^0(R, F),$
3. $\tau \in C^0(\overline{\Omega^2}, R_+^{p\times p}), \sup_{\overline{\Omega^2}} \tau \leq \tau_m.$

Then for any $\phi \in C,$ there exists a unique solution $V \in C^1([0,\infty), F) \cap C^0([-\tau_m, \infty, F)$ to (3)

Notice that this result gives existence on $R_+,$ finite-time explosion is impossible for this delayed differential equation. Nevertheless, a particular solution could grow indefinitely, we now prove that this cannot happen.

Boundedness of Solutions

A valid model of neural networks should only feature bounded packet node potentials.

Theorem 1.0 All the trajectories are ultimately bounded by the same constant R if $I \equiv \max_{t\in R^+} \|I^{ext}(t)\|_F < \infty.$

Proof :Let us defined $f : R \times C \to R^+$ as

$$f(t,V_t) \stackrel{def}{=} \langle -L_0 V_t(0) + L_1 S(V_t) + I^{ext}(t), V(t) \rangle_F = \frac{1}{2} \frac{d\|V\|_F^2}{dt}$$

We note $l = \min_{i=1,\dots p} l_i$

$$f(t,V_t) \leq -l\|V(t)\|_F^2 + (\sqrt{p|\Omega|}\,\|J\|_F + I)\|V(t)\|_F$$

Thus, if

$$\|V(t)\|_F \geq 2\frac{\sqrt{p|\Omega|}.\|J\|_F + I}{l} \stackrel{def}{=} R, f(t,V_t) \leq -\frac{lR^2}{2} \stackrel{def}{=} -\delta < 0$$

Let us show that the open route of F of center 0 and radius $R, B_R,$ is stable under the dynamics of equation. We know that $V(t)$ is defined for all $t \geq 0s$ and that $f < 0$ on $\partial B_R,$ the boundary of B_R. We consider three cases for the initial condition $V_0.$ If $\|V_0\|_C < R$ and set $T = \sup\{t \mid \forall s \in [0,t], V(s) \in \overline{B_R}\}.$ Suppose that $T \in R,$ then $V(T)$ is defined and belongs to $\overline{B_R},$ the closure of $B_R,$ because $\overline{B_R}$ is closed, in effect to $\partial B_R,$ we also have $\frac{d}{dt}\|V\|_F^2 |_{t=T} = f(T, V_T) \leq -\delta < 0$ because $V(T) \in \partial B_R.$ Thus we deduce that for $\varepsilon > 0$ and small enough, $V(T+\varepsilon) \in \overline{B_R}$ which contradicts the definition of T. Thus $T \notin R$ and $\overline{B_R}$ is stable. Because f<0 on $\partial B_R, V(0) \in \partial B_R$ implies that $\forall t > 0, V(t) \in B_R$. Finally we consider the case $V(0) \in C\overline{B_R}$. Suppose that $\forall t > 0, V(t) \notin \overline{B_R},$ then

$\forall t > 0, \frac{d}{dt}\|V\|_F^2 \le -2\delta,$ thus $\|V(t)\|_F$ is monotonically decreasing and reaches the value of R in finite time when $V(t)$ reaches ∂B_R. This contradicts our assumption. Thus $\exists T > 0 \,|\, V(T) \in B_R.$

Proposition 1.1 : Let s and t be measured simple functions on X. for $E\varepsilon M$, define

$$\phi(E) = \int_E s\, d\mu \qquad (1)$$

Then ϕ is a measure on M .

$$\int_X (s+t) d\mu = \int_X s\, d\mu + \int_X t d\mu \qquad (2)$$

Proof : If s and if $E_1, E_2, \ldots$ are disjoint members of M whose union is $E,$ the countable additivity of μ shows that

$$\phi(E) = \sum_{i=1}^{n} \alpha_i \mu(A_i \cap E) = \sum_{i=1}^{n} \alpha_i \sum_{r=1}^{\infty} \mu(A_i \cap E_r)$$

$$= \sum_{r=1}^{\infty} \sum_{i=1}^{n} \alpha_i \mu(A_i \cap E_r) = \sum_{r=1}^{\infty} \phi(E_r)$$

Also, $\varphi(\phi) = 0,$ so that φ is not identically ∞ .

Next, let s be as before, let $\beta_1, \ldots, \beta_m$ be the distinct values of t,and let $B_j = \{x : t(x) = \beta_j\}$ If $E_{ij} = A_i \cap B_j,$ the

$$\int_{E_{ij}} (s+t) d\mu = (\alpha_i + \beta_j)\mu(E_{ij})$$

and $\int_{E_{ij}} s d\mu + \int_{E_{ij}} t d\mu = \alpha_i \mu(E_{ij}) + \beta_j \mu(E_{ij})$ Thus (2) holds with E_{ij} in place of X . Since X is the disjoint union of the sets E_{ij} $(1 \le i \le n, 1 \le j \le m),$ the first half of our proposition implies that (2) holds.

Theorem 1.1: If K is a compact set in the plane whose complement is connected, if f is a continuous complex function on K which is holomorphic in the interior of , and if $\varepsilon > 0,$ then there exists a polynomial P such that $|f(z) = P(z)| < \varepsilon$ for all $z\varepsilon K$. If the interior of K is empty, then part of the hypothesis is vacuously satisfied, and the conclusion holds for every $f \varepsilon C(K)$. Note that K need to be connected.

Proof: By Tietze's theorem, f can be extended to a continuous function in the plane, with compact support. We fix one such extension and denote it again by f . For any $\delta > 0,$ let $\omega(\delta)$ be the supremum of the numbers $|f(z_2) - f(z_1)|$ Where z_1 and z_2 are subject to the condition $|z_2 - z_1| \le \delta$. Since f is uniformly continous, we have $\lim_{\delta \to 0} \omega(\delta) = 0$ (1) From now on, δ will be fixed. We shall prove that there is a polynomial P such that

$$|f(z) - P(z)| < 10{,}000\ \omega(\delta) \quad (z\varepsilon K) \qquad (2)$$

By (1), this proves the theorem. Our first objective is the construction of a function $\Phi\varepsilon C_c^{'}(R^2),$ such that for all z

$$|f(z) - \Phi(z)| \le \omega(\delta), \qquad (3)$$

$$|(\partial\Phi)(z)| < \frac{2\omega(\delta)}{\delta}, \qquad (4)$$

And

$$\Phi(z) = -\frac{1}{\pi}\iint_X \frac{(\partial\Phi)(\zeta)}{\zeta - z} d\zeta d\eta \qquad (\zeta = \xi + i\eta), \qquad (5)$$

Where X is the set of all points in the support of Φ whose distance from the complement of K does not δ. (Thus X contains no point which is "far within" K.) We construct Φ as the convolution of f with a smoothing function A. Put $a(r) = 0$ if $r > \delta,$ put

$$a(r) = \frac{3}{\pi\delta^2}(1 - \frac{r^2}{\delta^2})^2 \qquad (0 \le r \le \delta), \qquad (6)$$

And define

$$A(z) = a(|z|) \qquad (7)$$

For all complex z. It is clear that $A\varepsilon C_c^{'}(R^2)$. We claim that

$$\iint_{R^s} A = 1, \qquad (8)$$

$$\iint_{R^2} \partial A = 0, \qquad (9)$$

$$\iint_{R^3} |\partial A| = \frac{24}{15\delta} < \frac{2}{\delta}, \qquad (10)$$

The constants are so adjusted in (6) that (8) holds. (Compute the integral in polar coordinates), (9) holds simply because A

has compact support. To compute (10), express ∂A in polar coordinates, and note that $\partial A/\partial\theta = 0,$

$$\partial A/\partial r = -a',$$

Now define

$$\Phi(z) = \iint_{R^2} f(z-\zeta) A\, d\xi\, d\eta = \iint_{R^2} A(z-\zeta) f(\zeta)\, d\xi\, d\eta \qquad (11)$$

Since f and A have compact support, so does Φ. Since

$$\Phi(z) - f(z) = \iint_{R^2} [f(z-\zeta) - f(z)] A(\xi)\, d\xi\, d\eta \quad (12)$$

And $A(\zeta) = 0$ if $|\zeta| > \delta,$ (3) follows from (8). The difference quotients of A converge boundedly to the corresponding partial derivatives, since $A \varepsilon C_c'(R^2)$. Hence the last expression in (11) may be differentiated under the integral sign, and we obtain

$$(\partial\Phi)(z) = \iint_{R^2} (\overline{\partial A})(z-\zeta) f(\zeta)\, d\xi\, d\eta$$

$$= \iint_{R^2} f(z-\zeta)(\partial A)(\zeta)\, d\xi\, d\eta$$

$$= \iint_{R^2} [f(z-\zeta) - f(z)](\partial A)(\zeta)\, d\xi\, d\eta \qquad (13)$$

The last equality depends on (9). Now (10) and (13) give (4). If we write (13) with Φ_x and Φ_y in place of $\partial\Phi,$ we see that Φ has continuous partial derivatives, if we can show that $\partial\Phi = 0$ in $G,$ where G is the set of all $z\varepsilon K$ whose distance from the complement of K exceeds $\delta.$ We shall do this by showing that

$$\Phi(z) = f(z) \qquad (z\varepsilon G); \qquad (14)$$

Note that $\partial f = 0$ in G, since f is holomorphic there. Now if $z\varepsilon G,$ then $z-\zeta$ is in the interior of K for all ζ with $|\zeta| < \delta.$ The mean value property for harmonic functions therefore gives, by the first equation in (11),

$$\Phi(z) = \int_0^{\delta} a(r) r dr \int_0^{2\pi} f(z - re^{i\theta})\, d\theta$$

$$= 2\pi f(z) \int_0^{\delta} a(r) r dr = f(z) \iint_{R^2} A = f(z) \qquad (15)$$

For all $z \ \varepsilon\ G$, we have now proved (3), (4), and (5) The definition of X shows that X is compact and that X can be covered by finitely many open discs $D_1, \ldots, D_n,$ of radius $2\delta,$ whose centers are not in $K.$ Since $S^2 - K$ is connected, the center of each D_j can be joined to ∞ by a polygonal path in $S^2 - K$. It follows that each D_j contains a compact connected set $E_j,$ of diameter at least $2\delta,$ so that $S^2 - E_j$ is connected and so that $K \cap E_j = \phi.$ with $r = 2\delta$. There are functions $g_j \varepsilon H(S^2 - E_j)$ and constants b_j so that the inequalities.

$$|Q_j(\zeta, z)| < \frac{50}{\delta}, \qquad (16)$$

$$\left| Q_j(\zeta, z) - \frac{1}{z-\zeta} \right| < \frac{4{,}000\delta^2}{|z-\zeta|^2} \qquad (17)$$

Hold for $z \notin E_j$ and $\zeta \in D_j,$ if

$$Q_j(\zeta, z) = g_j(z) + (\zeta - b_j) g_j^2(z) \qquad (18)$$

Let Ω be the complement of $E_1 \cup \ldots \cup E_n.$ Then Ω is an open set which contains $K.$ Put $X_1 = X \cap D_1$ and $X_j = (X \cap D_j) - (X_1 \cup \ldots \cup X_{j-1}),$ for $2 \le j \le n,$

Define

$$R(\zeta, z) = Q_j(\zeta, z) \qquad (\zeta \varepsilon X_j, z\, \varepsilon\, \Omega) \qquad (19)$$

And

$$F(z) = \frac{1}{\pi} \iint_X (\partial\Phi)(\zeta) R(\zeta, z)\, d\zeta\, d\eta \qquad (20)$$

$$(z\ \varepsilon\ \Omega)$$

Since,

$$F(z) = \sum_{j=1} \frac{1}{\pi} \iint_{X_i} (\partial\Phi)(\zeta) Q_j(\zeta, z)\, d\xi\, d\eta, \qquad (21)$$

(18) shows that F is a finite linear combination of the functions g_j and g_j^2. Hence $F\varepsilon H(\Omega).$ By (20), (4), and (5) we have

$$|F(z) - \Phi(z)| < \frac{2\omega(\delta)}{\pi\delta} \iint_X | R(\zeta, z) - \frac{1}{z-\zeta} |\, d\xi\, d\eta \quad (z\ \varepsilon\ \Omega) \quad (22)$$

Observe that the inequalities (16) and (17) are valid with R in place of Q_j if $\zeta \ \varepsilon \ X$ and $z \ \varepsilon \ \Omega.$ Now fix $z \ \varepsilon \ \Omega.$, put $\zeta = z + \rho e^{i\theta},$ and estimate the integrand in (22) by (16) if $\rho < 4\delta,$ by (17) if $4\delta \le \rho.$ The integral in (22) is then seen to be less than the sum of

$$2\pi\int_0^{4\delta}\left(\frac{50}{\delta}+\frac{1}{\rho}\right)\rho d\rho = 808\pi\delta \qquad (23)$$

And

$$2\pi\int_{4\delta}^{\infty}\frac{4,000\delta^2}{\rho^2}\rho d\rho = 2,000\pi\delta. \qquad (24)$$

Hence (22) yields

$$\left|F(z)-\Phi(z)\right| < 6,000\omega(\delta) \qquad (z \ \varepsilon \ \Omega) \qquad (25)$$

Since $F \ \varepsilon \ H(\Omega),\ K \subset \Omega,$ and $S^2 - K$ is connected, Runge's theorem shows that F can be uniformly approximated on K by polynomials. Hence (3) and (25) show that (2) can be satisfied. This completes the proof.

Lemma 1.0 : Suppose $f \varepsilon C_c^{'}(R^2),$ the space of all continuously differentiable functions in the plane, with compact support. Put

$$\partial = \frac{1}{2}\left(\frac{\partial}{\partial x}+i\frac{\partial}{\partial y}\right) \qquad (1)$$

Then the following "Cauchy formula" holds:

$$f(z) = -\frac{1}{\pi}\iint_{R^2}\frac{(\partial f)(\zeta)}{\zeta - z}d\xi d\eta$$

$$(\zeta = \xi + i\eta) \qquad (2)$$

Proof: This may be deduced from Green's theorem. However, here is a simple direct proof:

Put $\varphi(r,\theta) = f(z+re^{i\theta}),\ r>0,\ \theta$ real

If $\zeta = z + re^{i\theta},$ the chain rule gives

$$(\partial f)(\zeta) = \frac{1}{2}e^{i\theta}\left[\frac{\partial}{\partial r}+\frac{i}{r}\frac{\partial}{\partial\theta}\right]\varphi(r,\theta) \qquad (3)$$

The right side of (2) is therefore equal to the limit, as $\varepsilon \to 0,$ of

$$-\frac{1}{2}\int_{\varepsilon}^{\infty}\int_0^{2\pi}\left(\frac{\partial\varphi}{\partial r}+\frac{i}{r}\frac{\partial\varphi}{\partial\theta}\right)d\theta dr \qquad (4)$$

For each $r>0, \varphi$ is periodic in $\theta,$ with period 2π. The integral of $\partial\varphi/\partial\theta$ is therefore 0, and (4) becomes

$$-\frac{1}{2\pi}\int_0^{2\pi}d\theta\int_{\varepsilon}^{\infty}\frac{\partial\varphi}{\partial r}dr = \frac{1}{2\pi}\int_0^{2\pi}\varphi(\varepsilon,\theta)d\theta \qquad (5)$$

As $\varepsilon \to 0,\ \varphi(\varepsilon,\theta) \to f(z)$ uniformly. This gives (2)

If $X^{\alpha} \in a$ and $X^{\beta} \in k\left[X_1,\ldots X_n\right]$, then $X^{\alpha}X^{\beta} = X^{\alpha+\beta} \in a$, and so A satisfies the condition $(*)$. Conversely,

$$\left(\sum_{\alpha\in A}c_\alpha X^\alpha\right)\left(\sum_{\beta\in\mathbb{N}^n}d_\beta X^\beta\right) = \sum_{\alpha,\beta}c_\alpha d_\beta X^{\alpha+\beta} \qquad (\textit{finite sums}),$$

and so if A satisfies $(*)$, then the subspace generated by the monomials $X^{\alpha}, \alpha \in a$, is an ideal. The proposition gives a classification of the monomial ideals in $k\left[X_1,\ldots X_n\right]$: they are in one to one correspondence with the subsets A of $\mathbb{N}^n$ satisfying $(*)$. For example, the monomial ideals in $k\left[X\right]$ are exactly the ideals $(X^n),\ n \ge 1$, and the zero ideal (corresponding to the empty set A). We write $\left\langle X^{\alpha} \mid \alpha \in A\right\rangle$ for the ideal corresponding to A (subspace generated by the $X^{\alpha}, \alpha \in a$).

LEMMA 1.1. Let S be a subset of $\mathbb{N}^n$. The the ideal a generated by $X^{\alpha}, \alpha \in S$ is the monomial ideal corresponding to

$$A \overset{df}{=} \left\{\beta \in \mathbb{N}^n \mid \beta - \alpha \in \mathbb{N}^n, \quad some\ \alpha \in S\right\}$$

Thus, a monomial is in a if and only if it is divisible by one of the $X^{\alpha}, \alpha \in\mid S$

PROOF. Clearly A satisfies $(*)$, and $a \subset \left\langle X^{\beta} \mid \beta \in A\right\rangle$. Conversely, if $\beta \in A$, then $\beta - \alpha \in \mathbb{N}^n$ for some $\alpha \in S$, and $X^{\beta} = X^{\alpha}X^{\beta-\alpha} \in a$. The last statement follows from the fact that $X^{\alpha} \mid X^{\beta} \Leftrightarrow \beta - \alpha \in \mathbb{N}^n$. Let $A \subset \mathbb{N}^n$ satisfy $(*)$. From the geometry of A, it is clear that there is a finite set of elements $S = \left\{\alpha_1,\ldots\alpha_s\right\}$ of A such that $A = \left\{\beta \in \mathbb{N}^n \mid \beta - \alpha_i \in \mathbb{N}^2,\ some\ \alpha_i \in S\right\}$ (The α_i's are the corners of A) Moreover, $a \overset{df}{=} \langle X^{\alpha} \mid \alpha \in A \rangle$ is generated by the monomials $X^{\alpha_i}, \alpha_i \in S$.

DEFINITION 1.0. For a nonzero ideal a in $k[X_1,...,X_n]$, we let $(LT(a))$ be the ideal generated by $\{LT(f) \mid f \in a\}$

LEMMA 1.2 Let a be a nonzero ideal in $k[X_1,...,X_n]$; then $(LT(a))$ is a monomial ideal, and it equals $(LT(g_1),...,LT(g_n))$ for some $g_1,...,g_n \in a$.

PROOF. Since $(LT(a))$ can also be described as the ideal generated by the leading monomials (rather than the leading terms) of elements of a.

THEOREM 1.2. Every ideal a in $k[X_1,...,X_n]$ is finitely generated; more precisely, $a=(g_1,...,g_s)$ where $g_1,...,g_s$ are any elements of a whose leading terms generate $LT(a)$

PROOF. Let $f \in a$. On applying the division algorithm, we find

$$f = a_1g_1 + ... + a_sg_s + r, \qquad a_i, r \in k[X_1,...,X_n],$$

where either $r=0$ or no monomial occurring in it is divisible by any $LT(g_i)$. But $r = f - \sum a_i g_i \in a$, and therefore $LT(r) \in LT(a) = (LT(g_1),...,LT(g_s))$, implies that every monomial occurring in r is divisible by one in $LT(g_i)$. Thus $r=0$, and $g \in (g_1,...,g_s)$.

DEFINITION 1.1. A finite subset $S=\{g_1,|...,g_s\}$ of an ideal a is a standard ($Gr\ddot{o}bner$) bases for a if $(LT(g_1),...,LT(g_s)) = LT(a)$. In other words, S is a standard basis if the leading term of every element of a is divisible by at least one of the leading terms of the g_i.

THEOREM 1.3 The ring $k[X_1,...,X_n]$ is Noetherian i.e., every ideal is finitely generated.

PROOF. For $n=1$, $k[X]$ is a principal ideal domain, which means that every ideal is generated by single element. We shall prove the theorem by induction on n. Note that the obvious map $k[X_1,...X_{n-1}][X_n] \to k[X_1,...X_n]$ is an isomorphism – this simply says that every polynomial f in n variables $X_1,...X_n$ can be expressed uniquely as a polynomial in X_n with coefficients in $k[X_1,...,X_n]$:

$$f(X_1,...X_n) = a_0(X_1,...X_{n-1})X_n^r + ... + a_r(X_1,...X_{n-1})$$

Thus the next lemma will complete the proof

LEMMA 1.3. If A is Noetherian, then so also is $A[X]$

PROOF. For a polynomial

$$f(X) = a_0X^r + a_1X^{r-1} + ... + a_r, \quad a_i \in A, \quad a_0 \neq 0,$$

r is called the degree of f, and a_0 is its leading coefficient. We call 0 the leading coefficient of the polynomial 0.

Let a be an ideal in $A[X]$. The leading coefficients of the polynomials in a form an ideal a' in A, and since A is Noetherian, a' will be finitely generated. Let $g_1,...,g_m$ be elements of a whose leading coefficients generate a', and let r be the maximum degree of g_i. Now let $f \in a,$ and suppose f has degree $s>r$, say, $f = aX^s + ...$ Then $a \in a'$, and so we can write

$$a = \sum b_i a_i, \qquad b_i \in A,$$

$$a_i = \textit{leading coefficient of } g_i$$

Now

$$f - \sum b_i g_i X^{s-r_i}, \quad r_i = \deg(g_i),$$ has degree $< \deg(f)$.

By continuing in this way, we find that $f \equiv f_t \quad \mod(g_1,...g_m)$ With f_t a polynomial of degree $t<r$. For each $d<r$, let a_d be the subset of A consisting of 0 and the leading coefficients of all polynomials in a of degree $d;$ it is again an ideal in A. Let $g_{d,1},...,g_{d,m_d}$ be polynomials of degree d whose leading coefficients generate a_d. Then the same argument as above shows that any polynomial f_d in a of degree d can be written $f_d \equiv f_{d-1} \quad \mod(g_{d,1},...g_{d,m_d})$ With f_{d-1} of

degree $\leq d-1$. On applying this remark repeatedly we find that $f_t \in (g_{r-1,1}, \dots g_{r-1,m_{r-1}}, \dots g_{0,1}, \dots g_{0,m_0})$ Hence

$$f_t \in (g_1, \dots g_m g_{r-1,1}, \dots g_{r-1,m_{r-1}}, \dots, g_{0,1}, \dots, g_{0,m_0})$$

and so the polynomials $g_1, \dots, g_{0,m_0}$ generate a

One of the great successes of category theory in computer science has been the development of a "unified theory" of the constructions underlying denotational semantics. In the untyped λ-calculus, any term may appear in the function position of an application. This means that a model D of the λ-calculus must have the property that given a term t whose interpretation is $d \in D,$ Also, the interpretation of a functional abstraction like λx . x is most conveniently defined as a function from $D \, to \, D$, which must then be regarded as an element of D. Let $\psi : [D \to D] \to D$ be the function that picks out elements of D to represent elements of $[D \to D]$ and $\phi : D \to [D \to D]$ be the function that maps elements of D to functions of D. Since $\psi(f)$ is intended to represent the function f as an element of D, it makes sense to require that $\phi(\psi(f)) = f,$ that is, $\psi \, o \, \psi = id_{[D \to D]}$ Furthermore, we often want to view every element of D as representing some function from D to D and require that elements representing the same function be equal – that is

$$\psi(\varphi(d)) = d$$

$$or$$

$$\psi \, o \, \phi = id_D$$

The latter condition is called extensionality. These conditions together imply that $\phi \, and \, \psi$ are inverses--- that is, D is isomorphic to the space of functions from D to D that can be the interpretations of functional abstractions: $D \cong [D \to D]$ .Let us suppose we are working with the untyped $\lambda - calculus$, we need a solution ot the equation $D \cong A + [D \to D],$ where A is some predetermined domain containing interpretations for elements of C. Each element of D corresponds to either an element of A or an element of $[D \to D],$ with a tag. This equation can be solved by finding least fixed points of the function $F(X) = A + [X \to X]$ from domains to domains --- that is, finding domains X such that $X \cong A + [X \to X],$ and such that for any domain Y also satisfying this equation, there is an embedding of X to Y --- a pair of maps

$$X \underset{f^R}{\overset{f}{\rightleftarrows}} Y$$

Such that

$$f^R \, o \, f = id_X$$

$$f \, o \, f^R \subseteq id_Y$$

Where $f \subseteq g$ means that $f \, approximates \, g$ in some ordering representing their information content. The key shift of perspective from the domain-theoretic to the more general category-theoretic approach lies in considering F not as a function on domains, but as a functor on a category of domains. Instead of a least fixed point of the function, F.

Definition 1.3: Let K be a category and $F : K \to K$ as a functor. A fixed point of F is a pair (A,a), where A is a K-object and $a : F(A) \to A$ is an isomorphism. A prefixed point of F is a pair (A,a), where A is a K-object and a is any arrow from F(A) to A

Definition 1.4 : An $\omega - chain$ in a category K is a diagram of the following form:

$$\Delta = D_o \xrightarrow{f_o} D_1 \xrightarrow{f_1} D_2 \xrightarrow{f_2} \dots\dots$$

Recall that a cocone μ of an $\omega - chain \ \Delta$ is a K-object X and a collection of K –arrows $\{\mu_i : D_i \to X \mid i \geq 0\}$ such that $\mu_i = \mu_{i+1} o \, f_i$ for all $i \geq 0$. We sometimes write $\mu : \Delta \to X$ as a reminder of the arrangement of μ's components Similarly, a colimit $\mu : \Delta \to X$ is a cocone with the property that if $v : \Delta \to X'$ is also a cocone then there exists a unique mediating arrow $k : X \to X'$ such that for all $i \geq 0,, \ v_i = k \, o \, \mu_i$. Colimits of $\omega - chains$ are sometimes referred to as $\omega - co\lim its$. Dually, an $\omega^{op} - chain$ in K is a diagram of the following form:

$$\Delta = D_o \xleftarrow{f_o} D_1 \xleftarrow{f_1} D_2 \xleftarrow{f_2} \dots\dots$$

A cone $\mu : X \to \Delta$ of an $\omega^{op} - chain \ \Delta$ is a K-object X and a collection of K-arrows $\{\mu_i : D_i \mid i \geq 0\}$ such that for all $i \geq 0, \ \mu_i = f_i \, o \, \mu_{i+1}$. An ω^{op} -limit of an $\omega^{op} - chain \ \ \Delta$ is a cone $\mu : X \to \Delta$

with the property that if $\nu : X' \to \Delta$ is also a cone, then there exists a unique mediating arrow $k : X' \to X$ such that for all $i \geq 0, \mu_i o k = \nu_i$. We write $\perp_k$ (or just $\perp$) for the distinguish initial object of K, when it has one, and $\perp \to A$ for the unique arrow from $\perp$ to each K-object A. It is also convenient to write $\Delta^- = D_1 \xrightarrow{f_1} D_2 \xrightarrow{f_2} \ldots$ to denote all of Δ except D_o and f_0. By analogy, μ^- is $\{\mu_i \mid i \geq 1\}$. For the images of Δ and μ under F we write

$$F(\Delta) = F(D_o) \xrightarrow{F(f_o)} F(D_1) \xrightarrow{F(f_1)} F(D_2) \xrightarrow{F(f_2)} \ldots$$

and $F(\mu) = \{F(\mu_i) \mid i \geq 0\}$

We write F^i for the i-fold iterated composition of F – that is, $F^o(f) = f, F^1(f) = F(f), F^2(f) = F(F(f))$,etc. With these definitions we can state that every monitonic function on a complete lattice has a least fixed point:

Lemma 1.4. Let K be a category with initial object $\perp$ and let $F : K \to K$ be a functor. Define the $\omega-chain\,\Delta$ by

$$\Delta = \perp \xrightarrow{!\perp \to F(\perp)} F(\perp) \xrightarrow{F(!\perp \to F(\perp))} F^2(\perp) \xrightarrow{F^2(!\perp \to F(\perp))} \ldots\ldots\ldots$$

If both $\mu : \Delta \to D$ and $F(\mu) : F(\Delta) \to F(D)$ are colimits, then (D,d) is an intial F-algebra, where $d : F(D) \to D$ is the mediating arrow from $F(\mu)$ to the cocone μ^-

Theorem 1.4 Let a DAG G given in which each node is a random variable, and let a discrete conditional probability distribution of each node given values of its parents in G be specified. Then the product of these conditional distributions yields a joint probability distribution P of the variables, and (G,P) satisfies the Markov condition.

Proof. Order the nodes according to an ancestral ordering. Let $X_1, X_2, \ldots\ldots\ldots X_n$ be the resultant ordering. Next define.

$$P(x_1, x_2, \ldots. x_n) = P(x_n \mid pa_n) P(x_{n-1} \mid Pa_{n-1}) \ldots$$
$$\ldots P(x_2 \mid pa_2) P(x_1 \mid pa_1),$$

Where PA_i is the set of parents of X_i of in G and $P(x_i \mid pa_i)$ is the specified conditional probability distribution. First we show this does indeed yield a joint probability distribution. Clearly, $0 \leq P(x_1, x_2, \ldots x_n) \leq 1$ for all values of the variables. Therefore, to show we have a joint distribution, as the variables range through all their possible values, is equal to one. To that end, Specified conditional distributions are the conditional distributions they notationally represent in the joint distribution. Finally, we show the Markov condition is satisfied. To do this, we need show for $1 \leq k \leq n$ that

$$P(pa_k) \neq 0, if\ P(nd_k \mid pa_k) \neq 0$$
$$and\ \ P(x_k \mid pa_k) \neq 0$$

whenever $then\ P(x_k \mid nd_k, pa_k) = P(x_k \mid pa_k),$

Where ND_k is the set of nondescendents of X_k of in G. Since $PA_k \subseteq ND_k$, we need only show $P(x_k \mid nd_k) = P(x_k \mid pa_k)$. First for a given k, order the nodes so that all and only nondescendents of X_k precede X_k in the ordering. Note that this ordering depends on k, whereas the ordering in the first part of the proof does not. Clearly then

$$ND_k = \{X_1, X_2, \ldots. X_{k-1}\}$$
$$Let$$
$$D_k = \{X_{k+1}, X_{k+2}, \ldots. X_n\}$$

follows $\sum_{d_k}$

We define the m^{th} cyclotomic field to be the field $Q[x]/(\Phi_m(x))$ Where $\Phi_m(x)$ is the m^{th} cyclotomic polynomial. $Q[x]/(\Phi_m(x))$ $\Phi_m(x)$ has degree $\varphi(m)$ over Q since $\Phi_m(x)$ has degree $\varphi(m)$. The roots of $\Phi_m(x)$ are just the primitive m^{th} roots of unity, so the complex embeddings of $Q[x]/(\Phi_m(x))$ are simply the $\varphi(m)$ maps

$$\sigma_k : Q[x]/(\Phi_m(x)) \mapsto C,$$
$$1 \leq k \prec m, (k,m) = 1, \quad where$$
$$\sigma_k(x) = \xi_m^k,$$

ξ_m being our fixed choice of primitive m^{th} root of unity. Note that $\xi_m^k \in Q(\xi_m)$ for every k; it follows that $Q(\xi_m) = Q(\xi_m^k)$ for all k relatively prime to m. In particular, the images of the σ_i coincide, so $Q[x]/(\Phi_m(x))$ is Galois over Q. This means that we can write $Q(\xi_m)$ for $Q[x]/(\Phi_m(x))$ without much fear of ambiguity; we will do so from now on, the identification being $\xi_m \mapsto x$. One advantage of this is that one can easily talk about cyclotomic fields being extensions of one another,or intersections or compositums; all of these things take place considering them as subfield of C. We now investigate some basic properties of cyclotomic fields. The first issue is whether or not they are all distinct; to determine this, we need to know which roots of unity lie in $Q(\xi_m)$.Note, for example, that if m is odd, then $-\xi_m$ is a $2m^{th}$ root of unity. We will show that this is the only way in which one can obtain any non-m^{th} roots of unity.

LEMMA 1.5 If m divides n, then $Q(\xi_m)$ is contained in $Q(\xi_n)$

PROOF. Since $\xi^{n/m} = \xi_m$, we have $\xi_m \in Q(\xi_n)$, so the result is clear

LEMMA 1.6 If m and n are relatively prime, then

$$Q(\xi_m, \xi_n) = Q(\xi_{nm})$$

and

$$Q(\xi_m) \cap Q(\xi_n) = Q$$

(Recall the $Q(\xi_m, \xi_n)$ is the compositum of $Q(\xi_m)$ *and* $Q(\xi_n)$)

PROOF. One checks easily that $\xi_m\xi_n$ is a primitive mn^{th} root of unity, so that

$$Q(\xi_{mn}) \subseteq Q(\xi_m, \xi_n)$$

$$[Q(\xi_m, \xi_n) : Q] \le [Q(\xi_m) : Q][Q(\xi_n : Q]$$

$$= \varphi(m)\varphi(n) = \varphi(mn);$$

Since $[Q(\xi_{mn}) : Q] = \varphi(mn);$ this implies that $Q(\xi_m, \xi_n) = Q(\xi_{nm})$ We know that $Q(\xi_m, \xi_n)$ has degree $\varphi(mn)$ over Q, so we must have

$$[Q(\xi_m, \xi_n) : Q(\xi_m)] = \varphi(n)$$

and

$$[Q(\xi_m, \xi_n) : Q(\xi_m)] = \varphi(m)$$

$$[Q(\xi_m) : Q(\xi_m) \cap Q(\xi_n)] \ge \varphi(m)$$

And thus that $Q(\xi_m) \cap Q(\xi_n) = Q$

PROPOSITION 1.2 For any m and n

$$Q(\xi_m, \xi_n) = Q(\xi_{[m,n]})$$

And

$$Q(\xi_m) \cap Q(\xi_n) = Q(\xi_{(m,n)});$$

here $[m,n]$ and (m,n) denote the least common multiple and the greatest common divisor of m and n, respectively.

PROOF. Write $m = p_1^{e_1}......p_k^{e_k}$ *and* $p_1^{f_1}....p_k^{f_k}$ where the p_i are distinct primes. (We allow e_i *or* f_i to be zero)

$$Q(\xi_m) = Q(\xi_{p_1^{e_1}})Q(\xi_{p_2^{e_2}})...Q(\xi_{p_k^{e_k}})$$

and

$$Q(\xi_n) = Q(\xi_{p_1^{f_1}})Q(\xi_{p_2^{f_2}})...Q(\xi_{p_k^{f_k}})$$

Thus

$$\begin{aligned} Q(\xi_m, \xi_n) &= Q(\xi_{p_1^{e_1}})........Q(\xi_{p_2^{e_k}})Q(\xi_{p_1^{f_1}})...Q(\xi_{p_k^{f_k}}) \\ &= Q(\xi_{p_1^{e_1}})Q(\xi_{p_1^{f_1}})...Q(\xi_{p_k^{e_k}})Q(\xi_{p_k^{f_k}}) \\ &= Q(\xi_{p_1^{\max(e_1,f_1)}}).......Q(\xi_{p_1^{\max(e_k,f_k)}}) \\ &= Q(\xi_{p_1^{\max(e_1,f_1)}........p_1^{\max(e_k,f_k)}}) \\ &= Q(\xi_{[m,n]}); \end{aligned}$$

An entirely similar computation shows that $Q(\xi_m) \cap Q(\xi_n) = Q(\xi_{(m,n)})$

Mutual information measures the information transferred when x_i is sent and y_i is received, and is defined as

$$I(x_i, y_i) = \log_2 \frac{P(x_i / y_i)}{P(x_i)} \; bits \qquad (1)$$

In a noise-free channel, each y_i is uniquely connected to the corresponding x_i , and so they constitute an input –output pair (x_i, y_i) for which $P(x_i / y_j) = 1$ *and* $I(x_i, y_j) = \log_2 \frac{1}{P(x_i)}$ bits; that is, the transferred information is equal to the self-information that corresponds to the input x_i In a very noisy channel, the output y_i and input x_i would be completely uncorrelated, and so $P(x_i / y_j) = P(x_i)$ and also $I(x_i, y_j) = 0;$ that is, there is no transference of information. In general, a given channel will operate between these two extremes. The mutual information is defined between the input and the output of a given channel. An average of the calculation of the mutual information for all input-output pairs of a given channel is the average mutual information:

$$I(X,Y) = \sum_{i.j} P(x_i, y_j) I(x_i, y_j) = \sum_{i.j} P(x_i, y_j) \log_2 \left[\frac{P(x_i / y_j)}{P(x_i)} \right]$$

bits per symbol . This calculation is done over the input and output alphabets. The average mutual information. The following expressions are useful for modifying the mutual information expression:

$$P(x_i, y_j) = P(x_i / y_j) P(y_j) = P(y_j / x_i) P(x_i)$$

$$P(y_j) = \sum_i P(y_j / x_i) P(x_i)$$

$$P(x_i) = \sum_i P(x_i / y_j) P(y_j)$$

Then

$$I(X,Y) = \sum_{i.j} P(x_i, y_j)$$

$$= \sum_{i.j} P(x_i, y_j) \log_2 \left[\frac{1}{P(x_i)} \right]$$

$$- \sum_{i.j} P(x_i, y_j) \log_2 \left[\frac{1}{P(x_i / y_j)} \right]$$

$$\sum_{i.j} P(x_i, y_j) \log_2 \left[\frac{1}{P(x_i)} \right]$$

$$= \sum_i \left[P(x_i / y_j) P(y_j) \right] \log_2 \frac{1}{P(x_i)}$$

$$\sum_i P(x_i) \log_2 \frac{1}{P(x_i)} = H(X)$$

$$I(X,Y) = H(X) - H(X/Y)$$

$$H(X/Y) = \sum_{i,j} P(x_i, y_j) \log_2 \frac{1}{P(x_i / y_j)}$$

Where is usually called the equivocation. In a sense, the equivocation can be seen as the information lost in the noisy channel, and is a function of the backward conditional probability. The observation of an output symbol y_j provides $H(X) - H(X/Y)$ bits of information. This difference is the mutual information of the channel. Mutual Information: Properties Since

$$P(x_i / y_j) P(y_j) = P(y_j / x_i) P(x_i)$$

The mutual information fits the condition

$$I(X,Y) = I(Y,X)$$

And by interchanging input and output it is also true that

$$I(X,Y) = H(Y) - H(Y/X)$$

Where

$$H(Y) = \sum_j P(y_j) \log_2 \frac{1}{P(y_j)}$$

This last entropy is usually called the noise entropy. Thus, the information transferred through the channel is the difference between the output entropy and the noise entropy. Alternatively, it can be said that the channel mutual information is the difference between the number of bits needed for determining a given input symbol before knowing the corresponding output symbol, and the number of bits needed for determining a given input symbol after knowing the corresponding output symbol

$$I(X,Y)=H(X)-H(X/Y)$$

As the channel mutual information expression is a difference between two quantities, it seems that this parameter can adopt negative values. However, and is spite of the fact that for some $y_j, H(X/y_j)$ can be larger than $H(X)$, this is not possible for the average value calculated over all the outputs:

$$\sum_{i,j} P(x_i,y_j)\log_2 \frac{P(x_i/y_j)}{P(x_i)} = \sum_{i,j} P(x_i,y_j)\log_2 \frac{P(x_i,y_j)}{P(x_i)P(y_j)}$$

Then

$$-I(X,Y)=\sum_{i,j} P(x_i,y_j)\frac{P(x_i)P(y_j)}{P(x_i,y_j)} \le 0$$

Because this expression is of the form

$$\sum_{i=1}^{M} P_i \log_2 \left(\frac{Q_i}{P_i}\right) \le 0$$

The above expression can be applied due to the factor $P(x_i)P(y_j)$, which is the product of two probabilities, so that it behaves as the quantity Q_i, which in this expression is a dummy variable that fits the condition $\sum_i Q_i \le 1$. It can be concluded that the average mutual information is a non-negative number. It can also be equal to zero, when the input and the output are independent of each other. A related entropy called the joint entropy is defined as

$$\begin{aligned} H(X,Y) &= \sum_{i,j} P(x_i,y_j)\log_2 \frac{1}{P(x_i,y_j)} \\ &= \sum_{i,j} P(x_i,y_j)\log_2 \frac{P(x_i)P(y_j)}{P(x_i,y_j)} \\ &+ \sum_{i,j} P(x_i,y_j)\log_2 \frac{1}{P(x_i)P(y_j)} \end{aligned}$$

Theorem 1.5: Entropies of the binary erasure channel (BEC) The BEC is defined with an alphabet of two inputs and three outputs, with symbol probabilities.

$P(x_1)=\alpha \ \ and \ \ P(x_2)=1-\alpha,$ and transition probabilities

$$P(y_3/x_2)=1-p \ \ and \ \ P(y_2/x_1)=0,$$
$$and \ \ P(y_3/x_1)=0$$
$$and \ \ P(y_1/x_2)=p$$
$$and \ \ P(y_3/x_2)=1-p$$

Lemma 1.7. Given an arbitrary restricted time-discrete, amplitude-continuous channel whose restrictions are determined by sets F_n and whose density functions exhibit no dependence on the state s, let n be a fixed positive integer, and $p(x)$ an arbitrary probability density function on Euclidean n-space. $p(y|x)$ for the density $p_n(y_1,...,y_n|x_1,...x_n)$ and $F \ for \ F_n$. For any real number a, let

$$A=\left\{(x,y):\log\frac{p(y|x)}{p(y)}>a\right\} \qquad (1)$$

Then for each positive integer u, there is a code (u,n,λ) such that

$$\lambda \le ue^{-a}+P\{(X,Y)\notin A\}+P\{X\notin F\} \qquad (2)$$

Where

$$P\{(X,Y)\in A\}=\int_A ...\int p(x,y)dxdy, \qquad p(x,y)=p(x)p(y|x)$$

and

$$P\{X\in F\}=\int_F ...\int p(x)dx$$

Proof: A sequence $x^{(1)}\in F$ such that

$$P\left\{Y\in A_{x^1} \mid X=x^{(1)}\right\}\ge 1-\varepsilon$$
$$where \ A_x=\{y:(x,y)\varepsilon A\};$$

Choose the decoding set B_1 to be $A_{x^{(1)}}$. Having chosen $x^{(1)},........,x^{(k-1)}$ and $B_1,...,B_{k-1}$, select $x^k\in F$ such that

$$P\left\{Y\in A_{x^{(k)}}-\bigcup_{i=1}^{k-1}B_i \mid X=x^{(k)}\right\}\ge 1-\varepsilon;$$

Set $B_k=A_{x^{(k)}}-\bigcup_{i=1}^{k-1}B_i$, If the process does not terminate in a finite number of steps, then the sequences $x^{(i)}$ and decoding sets $B_i,\ i=1,2,...,u,$ form the desired code. Thus assume that the process terminates after t steps. (Conceivably $t=0$). We will show $t\ge u$ by showing that $\varepsilon \le te^{-a}+P\{(X,Y)\notin A\}+P\{X\notin F\}$. We proceed as follows.

$B=\bigcup_{j=1}^{t} B_j. \quad (If \ \ t=0, \ take \ \ B=\phi). \ \ Then$

$$P\{(X,Y)\in A\}=\int\limits_{(x,y)\in A} p(x,y)dx\,dy$$

$$=\int\limits_{x} p(x)\int\limits_{y\in A_x} p(y\,|\,x)dy\,dx$$

Let $$=\int\limits_{x} p(x)\int\limits_{y\in B\cap A_x} p(y\,|\,x)dy\,dx+\int\limits_{x} p(x)$$

Algorithms

Let A be a ring. Recall that an ideal a in A is a subset such that a is subgroup of A regarded as a group under addition;

$a\in a, r\in A \Rightarrow ra\in A$

The ideal generated by a subset S of A is the intersection of all ideals A containing a ----- it is easy to verify that this is in fact an ideal, and that it consist of all finite sums of the form $\sum r_i s_i$ with $r_i\in A, s_i\in S$. When $S=\{s_1,.....,s_m\}$, we shall write $(s_1,.....,s_m)$ for the ideal it generates.

Let a and b be ideals in A. The set $\{a+b\,|\,a\in a, b\in b\}$ is an ideal, denoted by $a+b$. The ideal generated by $\{ab\,|\,a\in a, b\in b\}$ is denoted by ab. Note that $ab\subset a\cap b$. Clearly ab consists of all finite sums $\sum a_i b_i$ with $a_i\in a$ and $b_i\in b$, and if $a=(a_1,...,a_m)$ and $b=(b_1,...,b_n)$, then $ab=(a_1b_1,...,a_ib_j,...,a_mb_n)$.Let a be an ideal of A. The set of cosets of a in A forms a ring A/a, and $a\mapsto a+a$ is a homomorphism $\phi: A\mapsto A/a$. The map $b\mapsto \phi^{-1}(b)$ is a one to one correspondence between the ideals of A/a and the ideals of A containing a

An ideal p if prime if $p\neq A$ and $ab\in p\Rightarrow a\in p$ or $b\in p$. Thus p is prime if and only if A/p is nonzero and has the property that $ab=0, \quad b\neq 0\Rightarrow a=0,$ i.e., A/p is an integral domain. An ideal m is maximal if $m\neq| A$ and there does not exist an ideal n contained strictly between m and A. Thus m is maximal if and only if A/m has no proper nonzero ideals, and so is a field. Note that m maximal $\Rightarrow$ m prime. The ideals of $A\times B$ are all of the form $a\times b$, with a and b ideals in A and B. To see this, note that if c is an ideal in $A\times B$ and $(a,b)\in c$, then $(a,0)=(a,b)(1,0)\in c$ and $(0,b)=(a,b)(0,1)\in c$. This shows that $c=a\times b$ with

$a=\{a\,|\,(a,b)\in c \ \ some \ \ b\in b\}$

and

$b=\{b\,|\,(a,b)\in c \ \ some \ \ a\in a\}$

Let A be a ring. An A-algebra is a ring B together with a homomorphism $i_B: A\to B$. A homomorphism of A-algebra $B\to C$ is a homomorphism of rings $\varphi: B\to C$ such that $\varphi(i_B(a))=i_C(a)$ for all $a\in A$. An A-algebra B is said to be finitely generated (or of finite-type over A) if there exist elements $x_1,...,x_n\in B$ such that every element of B can be expressed as a polynomial in the x_i with coefficients in $i(A)$, i.e., such that the homomorphism $A[X_1,...,X_n]\to B$ sending X_i to x_i is surjective. A ring homomorphism $A\to B$ is finite, and B is finitely generated as an A-module. Let k be a field, and let A be a k-algebra. If $1\neq 0$ in A, then the map $k\to A$ is injective, we can identify k with its image, i.e., we can regard k as a subring of A. If 1=0 in a ring R, the R is the zero ring, i.e., $R=\{0\}$. Polynomial rings. Let k be a field. A monomial in $X_1,...,X_n$ is an expression of the form $X_1^{a_1}...X_n^{a_n}, \quad a_j\in N$. The total degree of the monomial is $\sum a_i$. We sometimes abbreviate it by $X^{\alpha}, \ \alpha=(a_1,...,a_n)\in \mathbb{N}^n$. The elements of the polynomial ring $k[X_1,...,X_n]$ are finite sums $\sum c_{a_1....a_n} X_1^{a_1}...X_n^{a_n}, \quad c_{a_1....a_n}\in k, \quad a_j\in \mathbb{N}$

With the obvious notions of equality, addition and multiplication. Thus the monomials from basis for $k[X_1,...,X_n]$ as a k-vector space. The ring $k[X_1,...,X_n]$ is an integral domain, and the only units in it are the nonzero constant polynomials. A polynomial $f(X_1,...,X_n)$ is irreducible if it is nonconstant and has only the obvious factorizations, i.e., $f=gh\Rightarrow g$ or h is constant. Division in $k[X]$. The division algorithm allows us to divide a nonzero polynomial into another: let f and g be polynomials in $k[X]$ with $g \neq 0;$ then there exist unique polynomials $q, r \in k[X]$ such that $f = qg + r$ with either $r = 0$ or deg r < deg g. Moreover, there is an algorithm for deciding whether $f \in (g)$, namely, find r and check whether it is zero. Moreover, the Euclidean algorithm allows to pass from finite set of generators for an ideal in $k[X]$ to a single generator by successively replacing each pair of generators with their greatest common divisor.

(Pure) lexicographic ordering (lex). Here monomials are ordered by lexicographic(dictionary) order. More precisely, let $\alpha = (a_1, \ldots a_n)$ and $\beta = (b_1, \ldots b_n)$ be two elements of $\square^n$; then $\alpha > \beta$ and $X^\alpha > X^\beta$ (lexicographic ordering) if, in the vector difference $\alpha - \beta \in \square$, the left most nonzero entry is positive. For example,

$XY^2 > Y^3Z^4; \quad X^3Y^2Z^4 > X^3Y^2Z$. Note that this isn't quite how the dictionary would order them: it would put $XXXYYZZZZ$ after $XXXYYZ$. Graded reverse lexicographic order (grevlex). Here monomials are ordered by total degree, with ties broken by reverse lexicographic ordering. Thus, $\alpha > \beta$ if $\sum a_i > \sum b_i$, or $\sum a_i = \sum b_i$ and in $\alpha - \beta$ the right most nonzero entry is negative. For example:

$X^4Y^4Z^7 > X^5Y^5Z^4$ (total degree greater)

$XY^5Z^2 > X^4YZ^3, \quad X^5YZ > X^4YZ^2$.

Orderings on $k[X_1, \ldots X_n]$. Fix an ordering on the monomials in $k[X_1, \ldots X_n]$. Then we can write an element f of $k[X_1, \ldots X_n]$ in a canonical fashion, by re-ordering its elements in decreasing order. For example, we would write

$$f = 4XY^2Z + 4Z^2 - 5X^3 + 7X^2Z^2$$

as

$$f = -5X^3 + 7X^2Z^2 + 4XY^2Z + 4Z^2 \quad (lex)$$

or

$$f = 4XY^2Z + 7X^2Z^2 - 5X^3 + 4Z^2 \quad (grevlex)$$

Let $\sum a_\alpha X^\alpha \in k[X_1, \ldots, X_n]$, in decreasing order:

$$f = a_{\alpha_0} X^{\alpha_0} +_{\alpha_1} X^{\alpha_1} + \ldots, \qquad \alpha_0 > \alpha_1 > \ldots, \quad \alpha_0 \neq 0$$

Then we define.

- The multidegree of f to be multdeg(f)= α_0;
- The leading coefficient of f to be LC(f)= a_{α_0};
- The leading monomial of f to be LM(f) = X^{α_0};
- The leading term of f to be LT(f) = $a_{\alpha_0} X^{\alpha_0}$

For the polynomial $f = 4XY^2Z + \ldots,$ the multidegree is (1,2,1), the leading coefficient is 4, the leading monomial is XY^2Z, and the leading term is $4XY^2Z$. The division algorithm in $k[X_1, \ldots X_n]$. Fix a monomial ordering in $\square^2$. Suppose given a polynomial f and an ordered set $(g_1, \ldots g_s)$ of polynomials; the division algorithm then constructs polynomials $a_1, \ldots a_s$ and r such that $f = a_1g_1 + \ldots + a_sg_s + r$ Where either $r = 0$ or no monomial in r is divisible by any of $LT(g_1), \ldots, LT(g_s)$

Step 1: If $LT(g_1) \mid LT(f)$, divide g_1 into f to get

$$f = a_1g_1 + h, \qquad a_1 = \frac{LT(f)}{LT(g_1)} \in k[X_1, \ldots, X_n]$$

If $LT(g_1) \mid LT(h)$, repeat the process until $f = a_1g_1 + f_1$ (different a_1) with $LT(f_1)$ not divisible by $LT(g_1)$. Now divide g_2 into f_1, and so on, until $f = a_1g_1 + \ldots + a_sg_s + r_1$ With $LT(r_1)$ not divisible by any $LT(g_1), \ldots LT(g_s)$ Step 2: Rewrite $r_1 = LT(r_1) + r_2$, and repeat Step 1 with r_2 for f: $f = a_1g_1 + \ldots + a_sg_s + LT(r_1) + r_3$ (different a_i's) Monomial ideals. In general, an ideal a will contain a polynomial without containing the individual terms of the polynomial; for example, the ideal $a = (Y^2 - X^3)$ contains $Y^2 - X^3$ but not Y^2 or X^3.

DEFINITION 1.5. An ideal a is monomial if $\sum c_\alpha X^\alpha \in a \Rightarrow X^\alpha \in a$ all α with $c_\alpha \neq 0$.

PROPOSITION 1.3. Let a be a monomial ideal, and let $A=\{\alpha \mid X^{\alpha}\in a\}$. Then A satisfies the condition $\alpha\in A,\ \beta\in \square^{n} \Rightarrow \alpha+\beta\in$ $(*)$ And a is the k-subspace of $k[X_1,...,X_n]$ generated by the $X^{\alpha},\alpha\in A$. Conversely, of A is a subset of $\square^{n}$ satisfying $(*)$, then the k-subspace a of $k[X_1,...,X_n]$ generated by $\{X^{\alpha}\mid\alpha\in A\}$ is a monomial ideal.

PROOF. It is clear from its definition that a monomial ideal a is the k-subspace of $k[X_1,...,X_n]$ generated by the set of monomials it contains. If $X^{\alpha}\in a$ and $X^{\beta}\in k[X_1,...,X_n]$.

If a permutation is chosen uniformly and at random from the $n!$ possible permutations in S_n, then the counts $C_j^{(n)}$ of cycles of length j are dependent random variables. The joint distribution of $C^{(n)}=(C_1^{(n)},...,C_n^{(n)})$ follows from Cauchy's formula, and is given by

$$P[C^{(n)}=c]=\frac{1}{n!}N(n,c)=1\left\{\sum_{j=1}^{n} jc_j=n\right\}\prod_{j=1}^{n}\left(\frac{1}{j}\right)^{c_j}\frac{1}{c_j!}, \qquad (1.1)$$

for $c\in\square_{+}^{n}$.

Lemma1.7 For nonnegative integers $m_{1,...,}m_n$,

$$E\left(\prod_{j=1}^{n}(C_j^{(n)})^{[m_j]}\right)=\left(\prod_{j=1}^{n}\left(\frac{1}{j}\right)^{m_j}\right)1\left\{\sum_{j=1}^{n} jm_j\le n\right\} \qquad (1.4)$$

Proof. This can be established directly by exploiting cancellation of the form $c_j^{[m_j]}/c_j^{!}=1/(c_j-m_j)!$ when $c_j\ge m_j$, which occurs between the ingredients in Cauchy's formula and the falling factorials in the moments. Write $m=\sum jm_j$. Then, with the first sum indexed by $c=(c_1,...c_n)\in\square_{+}^{n}$ and the last sum indexed by $d=(d_1,...,d_n)\in\square_{+}^{n}$ via the correspondence $d_j=c_j-m_j$, we have

$$E\left(\prod_{j=1}^{n}(C_j^{(n)})^{[m_j]}\right)=\sum_{c}P[C^{(n)}=c]\prod_{j=1}^{n}(c_j)^{[m_j]}$$

$$=\sum_{c:c_j\ge m_j\ for\ all\ j}1\left\{\sum_{j=1}^{n} jc_j=n\right\}\prod_{j=1}^{n}\frac{(c_j)^{[m_j]}}{j^{c_j}c_j!}$$

$$=\prod_{j=1}^{n}\frac{1}{j^{m_j}}\sum_{d}1\left\{\sum_{j=1}^{n} jd_j=n-m\right\}\prod_{j=1}^{n}\frac{1}{j^{d_j}(d_j)!}$$

This last sum simplifies to the indicator $1(m\le n)$, corresponding to the fact that if $n-m\ge 0$, then $d_j=0$ for $j>n-m$, and a random permutation in S_{n-m} must have some cycle structure $(d_1,...,d_{n-m})$. The moments of $C_j^{(n)}$ follow immediately as

$$E(C_j^{(n)})^{[r]}=j^{-r}1\{jr\le n\} \qquad (1.2)$$

We note for future reference that (1.4) can also be written in the form

$$E\left(\prod_{j=1}^{n}(C_j^{(n)})^{[m_j]}\right)=E\left(\prod_{j=1}^{n}Z_j^{[m_j]}\right)1\left\{\sum_{j=1}^{n} jm_j\le n\right\}, \qquad (1.3)$$

Where the Z_j are independent Poisson-distribution random variables that satisfy $E(Z_j)=1/j$

The marginal distribution of cycle counts provides a formula for the joint distribution of the cycle counts C_j^n, we find the distribution of C_j^n using a combinatorial approach combined with the inclusion-exclusion formula.

Lemma 1.8. For $1\le j\le n$,

$$P[C_j^{(n)}=k]=\frac{j^{-k}}{k!}\sum_{l=0}^{[n/j]-k}(-1)^l\frac{j^{-l}}{l!} \qquad (1.1)$$

Proof. Consider the set I of all possible cycles of length j, formed with elements chosen from $\{1,2,...n\}$, so that $|I|=n^{[j]/j}$. For each $\alpha\in I$, consider the "property" G_{α} of having α; that is, G_{α} is the set of permutations $\pi\in S_n$ such that α is one of the cycles of π. We then have $|G_{\alpha}|=(n-j)!$, since the elements of $\{1,2,...,n\}$ not in α must be permuted among themselves. To use the inclusion-exclusion formula we need to calculate the term S_r, which is the sum of the probabilities of the r-fold intersection of properties, summing over all sets of r distinct properties. There are two cases to consider. If the r properties are indexed by r cycles having no elements in common, then the intersection specifies how rj elements are moved by the permutation, and there are $(n-rj)!1(rj \le n)$ permutations in the intersection. There are $n^{[rj]}/(j^r r!)$ such intersections. For the other case, some two distinct properties name some element in common, so no permutation can have both these properties, and the r -fold intersection is empty. Thus

$$S_r = (n-rj)!1(rj \le n)$$

$$\times \frac{n^{[rj]}}{j^r r!} \frac{1}{n!} = 1(rj \le n) \frac{1}{j^r r!}$$

Finally, the inclusion-exclusion series for the number of permutations having exactly k properties is

$$\sum_{l \ge 0} (-1)^l \binom{k+l}{l} S_{k+l,}$$

Which simplifies to (1.1) Returning to the original hat-check problem, we substitute j=1 in (1.1) to obtain the distribution of the number of fixed points of a random permutation. For $k = 0,1,...,n,$

$$P[C_1^{(n)} = k] = \frac{1}{k!} \sum_{l=0}^{n-k} (-1)^l \frac{1}{l!}, \qquad (1.2)$$

and the moments of $C_1^{(n)}$ follow from (1.2) with $j = 1.$ In particular, for $n \ge 2,$ the mean and variance of $C_1^{(n)}$ are both equal to 1. The joint distribution of $(C_1^{(n)},...,C_b^{(n)})$ for any $1 \le b \le n$ has an expression similar to (1.7); this too can be derived by inclusion-exclusion. For any $c = (c_1,...,c_b) \in \mathbb{Z}_+^b$ with $m = \sum ic_i,$

$$P[(C_1^{(n)},...,C_b^{(n)}) = c]$$

$$= \left\{ \prod_{i=1}^{b} \left(\frac{1}{i}\right)^{c_i} \frac{1}{c_i!} \right\} \sum_{\substack{l \ge 0 \text{ with} \\ \sum il_i \le n-m}} (-1)^{l_1+...+l_b} \prod_{i=1}^{b} \left(\frac{1}{i}\right)^{l_i} \frac{1}{l_i!} \qquad (1.3)$$

The joint moments of the first b counts $C_1^{(n)},...,C_b^{(n)}$ can be obtained directly from (1.2) and (1.3) by setting $m_{b+1} = ... = m_n = 0$

The limit distribution of cycle counts

It follows immediately from Lemma 1.2 that for each fixed $j,$ as $n \to \infty,$

$$P[C_j^{(n)} = k] \to \frac{j^{-k}}{k!} e^{-1/j}, \quad k = 0,1,2,...,$$

So that $C_j^{(n)}$ converges in distribution to a random variable Z_j having a Poisson distribution with mean $1/j;$ we use the notation $C_j^{(n)} \to_d Z_j$ where $Z_j \sim P_o(1/j)$ to describe this. Infact, the limit random variables are independent.

Theorem 1.6 The process of cycle counts converges in distribution to a Poisson process of $\mathbb{N}$ with intensity j^{-1}. That is, as $n \to \infty,$

$$(C_1^{(n)}, C_2^{(n)},...) \to_d (Z_1, Z_2,...) \qquad (1.1)$$

Where the $Z_j, j = 1,2,...,$ are independent Poisson-distributed random variables with $E(Z_j) = \frac{1}{j}$

Proof. To establish the converges in distribution one shows that for each fixed $b \ge 1,$ as $n \to \infty,$

$$P[(C_1^{(n)},...,C_b^{(n)}) = c] \to P[(Z_1,...,Z_b) = c]$$

Error rates

The proof of Theorem says nothing about the rate of convergence. Elementary analysis can be used to estimate this rate when $b = 1$. Using properties of alternating series with decreasing terms, for $k = 0,1,...,n,$

$$\frac{1}{k!}\left(\frac{1}{(n-k+1)!} - \frac{1}{(n-k+2)!}\right) \le \left| P[C_1^{(n)} = k] - P[Z_1 = k] \right|$$

$$\le \frac{1}{k!(n-k+1)!}$$

It follows that

$$\frac{2^{n+1}}{(n+1)!} \frac{n}{n+2} \le \sum_{k=0}^{n} \left| P[C_1^{(n)} = k] - P[Z_1 = k] \right| \le \frac{2^{n+1}-1}{(n+1)!} \qquad (1.11)$$

Since

$$P[Z_1 > n] = \frac{e^{-1}}{(n+1)!}\left(1 + \frac{1}{n+2} + \frac{1}{(n+2)(n+3)} + ...\right) < \frac{1}{(n+1)!},$$

We see from (1.11) that the total variation distance between the distribution $L(C_1^{(n)})$ of $C_1^{(n)}$ and the distribution $L(Z_1)$ of Z_1

Establish the asymptotics of $\mathrm{P}\left[A_n(C^{(n)})\right]$ under conditions (A_0) and $(B_{01}),$ where

$$A_n(C^{(n)}) = \bigcap_{1 \le i \le n} \bigcap_{r_i' + 1 \le j \le r_i} \left\{ C_{ij}^{(n)} = 0 \right\},$$

and $\zeta_i = (r_i^{'} / r_{id}) - 1 = O(i^{-g^{'}})$ as $i \to \infty,$ for some $g^{'} > 0.$ We start with the expression

$$P[A_n(C^{(n)})] = \frac{P[T_{0m}(Z^{'}) = n]}{P[T_{0m}(Z) = n]}$$

$$\prod_{\substack{1 \le i \le n \\ r_i^{'}+1 \le j \le r_i}} \left\{1 - \frac{\theta}{ir_i}(1 + E_{i0})\right\} \qquad (1.1)$$

$$P[T_{0n}(Z^{'}) = n]$$
$$= \frac{\theta d}{n} \exp\left\{\sum_{i \ge 1} [\log(1 + i^{-1}\theta d) - i^{-1}\theta d]\right\}$$
$$\left\{1 + O(n^{-1}\varphi^{'}_{\{1,2,7\}}(n))\right\} \qquad (1.2)$$

and

$$P[T_{0n}(Z^{'}) = n]$$
$$= \frac{\theta d}{n} \exp\left\{\sum_{i \ge 1} [\log(1 + i^{-1}\theta d) - i^{-1}\theta d]\right\}$$
$$\left\{1 + O(n^{-1}\varphi_{\{1,2,7\}}(n))\right\} \qquad (1.3)$$

Where $\varphi^{'}_{\{1,2,7\}}(n)$ refers to the quantity derived from $Z^{'}$. It thus follows that $P[A_n(C^{(n)})] \square Kn^{-\theta(1-d)}$ for a constant K, depending on Z and the $r_i^{'}$ and computable explicitly from (1.1) – (1.3), if Conditions (A_0) and (B_{01}) are satisfied and if $\zeta_i^* = O(i^{-g^{'}})$ from some $g^{'} > 0,$ since, under these circumstances, both $n^{-1}\varphi^{'}_{\{1,2,7\}}(n)$ and $n^{-1}\varphi_{\{1,2,7\}}(n)$ tend to zero as $n \to \infty.$ In particular, for polynomials and square free polynomials, the relative error in this asymptotic approximation is of order n^{-1} if $g^{'} > 1.$

For $0 \le b \le n/8$ and $n \ge n_0,$ with n_0

$$d_{TV}(L(C[1,b]), L(Z[1,b]))$$
$$\le d_{TV}(L(\tilde{C}[1,b]), L(\tilde{Z}[1,b]))$$
$$\le \varepsilon_{\{7,7\}}(n,b),$$

Where $\varepsilon_{\{7,7\}}(n,b) = O(b/n)$ under Conditions $(A_0), (D_1)$ and (B_{11}) Since, by the Conditioning Relation,

$$L(\tilde{C}[1,b] \mid T_{0b}(C) = l) = L(\tilde{Z}[1,b] \mid T_{0b}(Z) = l),$$

It follows by direct calculation that

$$d_{TV}(L(\tilde{C}[1,b]), L(\tilde{Z}[1,b]))$$
$$= d_{TV}(L(T_{0b}(C)), L(T_{0b}(Z)))$$
$$= \max_A \sum_{r \in A} P[T_{0b}(Z) = r]$$
$$\left\{1 - \frac{P[T_{bn}(Z) = n - r]}{P[T_{0n}(Z) = n]}\right\} \qquad (1.4)$$

Suppressing the argument Z from now on, we thus obtain

$$d_{TV}(L(\tilde{C}[1,b]), L(\tilde{Z}[1,b]))$$
$$= \sum_{r \ge 0} P[T_{0b} = r]\left\{1 - \frac{P[T_{bn} = n - r]}{P[T_{0n} = n]}\right\}_+$$
$$\le \sum_{r > n/2} P[T_{0b} = r] + \sum_{r=0}^{[n/2]} \frac{P[T_{0b} = r]}{P[T_{0b} = n]}$$
$$\times \left\{\sum_{s=0}^{n} P[T_{0b} = s](P[T_{bn} = n - s] - P[T_{bn} = n - r]\right\}_+$$
$$\le \sum_{r > n/2} P[T_{0b} = r] + \sum_{r=0}^{[n/2]} P[T_{0b} = r]$$
$$\times \sum_{s=0}^{[n/2]} P[T_{0b} = s] \frac{\{P[T_{bn} = n - s] - P[T_{bn} = n - r]\}}{P[T_{0n} = n]}$$
$$+ \sum_{s=0}^{[n/2]} P[T_{0b} = r] \sum_{s=[n/2]+1}^{n} P[T = s] P[T_{bn} = n - s] / P[T_{0n} = n]$$

The first sum is at most $2n^{-1}ET_{0b};$ the third is bound by

$$(\max_{n/2 < s \le n} P[T_{0b} = s]) / P[T_{0n} = n]$$
$$\le \frac{2\varepsilon_{\{10.5(1)\}}(n/2, b)}{n} \frac{3n}{\theta P_\theta[0,1]},$$
$$\frac{3n}{\theta P_\theta[0,1]} 4n^{-2}\phi^*_{\{10.8\}}(n) \sum_{r=0}^{[n/2]} P[T_{0b} = r] \sum_{s=0}^{[n/2]} P[T_{0b} = s] \frac{1}{2}|r - s|$$
$$\le \frac{12\phi^*_{\{10.8\}}(n)}{\theta P_\theta[0,1]} \frac{ET_{0b}}{n}$$

Hence we may take

$$\varepsilon_{\{7,7\}}(n,b) = 2n^{-1}ET_{0b}(Z)\left\{1+\frac{6\phi^{*}_{\{10.8\}}(n)}{\theta P_{\theta}[0,1]}\right\}P$$

$$+\frac{6}{\theta P_{\theta}[0,1]}\varepsilon_{\{10.5(1)\}}(n/2,b) \qquad (1.5)$$

Required order under Conditions $(A_0),(D_1)$ and $(B_{11}),$ if $S(\infty)<\infty.$ If not, $\phi^{*}_{\{10.8\}}(n)$ can be replaced by $\phi^{*}_{\{10.11\}}(n)$ in the above, which has the required order, without the restriction on the r_i implied by $S(\infty)<\infty$. Examining the Conditions $(A_0),(D_1)$ and $(B_{11}),$ it is perhaps surprising to find that (B_{11}) is required instead of just $(B_{01});$ that is, that we should need $\sum_{l\geq 2} l\varepsilon_{il} = O(i^{-a_1})$ to hold for some $a_1>1$. A first observation is that a similar problem arises with the rate of decay of ε_{i1} as well. For this reason, n_1 is replaced by $\tilde{n}_1$. This makes it possible to replace condition (A_1) by the weaker pair of conditions (A_0) and (D_1) in the eventual assumptions needed for $\varepsilon_{\{7,7\}}(n,b)$ to be of order $O(b/n);$ the decay rate requirement of order $i^{-1-\gamma}$ is shifted from ε_{i1} itself to its first difference. This is needed to obtain the right approximation error for the random mappings example. However, since all the classical applications make far more stringent assumptions about the $\varepsilon_{i1}, l\geq 2,$ than are made in (B_{11}). The critical point of the proof is seen where the initial estimate of the difference $P[T^{(m)}_{bn}=s]-P[T^{(m)}_{bn}=s+1]$. The factor $\varepsilon_{\{10.10\}}(n),$ which should be small, contains a far tail element from $\tilde{n}_1$ of the form $\phi^{\theta}_1(n)+u^{*}_1(n),$ which is only small if $a_1>1,$ being otherwise of order $O(n^{1-a_1+\delta})$ for any $\delta>0,$ since $a_2>1$ is in any case assumed. For $s\geq n/2,$ this gives rise to a contribution of order $O(n^{-1-a_1+\delta})$ in the estimate of the difference $P[T_{bn}=s]-P[T_{bn}=s+1],$ which, in the remainder of the proof, is translated into a contribution of order $O(tn^{-1-a_1+\delta})$ for differences of the form $P[T_{bn}=s]-P[T_{bn}=s+1],$ finally leading to a contribution of order $bn^{-a_1+\delta}$ for any $\delta>0$ in $\varepsilon_{\{7.7\}}(n,b).$ Some improvement would seem to be possible, defining the function g by $g(w)=1_{\{w=s\}}-1_{\{w=s+t\}},$ differences that are of the form $P[T_{bn}=s]-P[T_{bn}=s+t]$ can be directly estimated, at a cost of only a single contribution of the form $\phi^{\theta}_1(n)+u^{*}_1(n).$ Then, iterating the cycle, in which one estimate of a difference in point probabilities is improved to an estimate of smaller order, a bound of the form
$\left|P[T_{bn}=s]-P[T_{bn}=s+t]\right| = O(n^{-2}t+n^{-1-a_1+\delta})$ for any $\delta>0$ could perhaps be attained, leading to a final error estimate in order $O(bn^{-1}+n^{-a_1+\delta})$ for any $\delta>0$, to replace $\varepsilon_{\{7.7\}}(n,b).$ This would be of the ideal order $O(b/n)$ for large enough $b,$ but would still be coarser for small $b.$

With b and n as in the previous section, we wish to show that

$$\left|d_{TV}(L(C[1,b]),L(Z[1,b]))-\frac{1}{2}(n+1)^{-1}\left|1-\theta\right|E\left|T_{0b}-ET_{0b}\right|\right|$$
$$\leq \varepsilon_{\{7,8\}}(n,b),$$

Where $\varepsilon_{\{7.8\}}(n,b)=O(n^{-1}b[n^{-1}b+n^{-\beta_{12}+\delta}])$ for any $\delta>0$ under Conditions $(A_0),(D_1)$ and $(B_{12}),$ with β_{12}. The proof uses sharper estimates. As before, we begin with the formula

$$d_{TV}(L(\tilde{C}[1,b]),L(\tilde{Z}[1,b]))$$
$$=\sum_{r\geq 0}P[T_{0b}=r]\left\{1-\frac{P[T_{bn}=n-r]}{P[T_{0n}=n]}\right\}_{+}$$

Now we observe that

$$\left|\sum_{r\geq 0} P[T_{0b}=r]\left\{1-\frac{P[T_{bn}=n-r]}{P[T_{0n}=n]}\right\}_{+} - \sum_{r=0}^{[n/2]}\frac{P[T_{0b}=r]}{P[T_{0n}=n]}\right|$$
$$\times\left|\sum_{s=[n/2]+1}^{n} P[T_{0b}=s](P[T_{bn}=n-s]-P[T_{bn}=n-r])\right|$$
$$\leq 4n^{-2}ET_{0b}^2+(\max_{n/2<s\leq n} P[T_{0b}=s])/P[T_{0n}=n]$$
$$+P[T_{0b}>n/2]$$
$$\leq 8n^{-2}ET_{0b}^2+\frac{3\varepsilon_{\{10.5(2)\}}(n/2,b)}{\theta P_\theta[0,1]}, \qquad (1.1)$$

We have

$$\left|\sum_{r=0}^{[n/2]}\frac{P[T_{0b}=r]}{P[T_{0n}=n]}\right.$$
$$\times\left(\left\{\sum_{s=0}^{[n/2]} P[T_{0b}=s](P[T_{bn}=n-s]-P[T_{bn}=n-r]\right\}_{+}\right.$$
$$\left.\left.-\left\{\sum_{s=0}^{[n/2]} P[T_{0b}=s]\frac{(s-r)(1-\theta)}{n+1}P[T_{0n}=n]\right\}_{+}\right)\right|$$

$$\leq \frac{1}{n^2P[T_{0n}=n]}\sum_{r\geq 0}P[T_{0b}=r]\sum_{s\geq 0}P[T_{0b}=s]|s-r|$$
$$\times\left\{\varepsilon_{\{10.14\}}(n,b)+2(r\vee s)|1-\theta|n^{-1}\left\{K_0\theta+4\phi^*_{\{10.8\}}(n)\right\}\right\}$$
$$\leq \frac{6}{\theta nP_\theta[0,1]}ET_{0b}\varepsilon_{\{10.14\}}(n,b)$$
$$+4|1-\theta|n^{-2}ET_{0b}^2\left\{K_0\theta+4\phi^*_{\{10.8\}}(n)\right\}$$
$$\left(\frac{3}{\theta nP_\theta[0,1]}\right)\ \}, \qquad (1.2)$$

The approximation in (1.2) is further simplified by noting that

$$\sum_{r=0}^{[n/2]} P[T_{0b}=r]\left|\left\{\sum_{s=0}^{[n/2]} P[T_{0b}=s]\frac{(s-r)(1-\theta)}{n+1}\right\}_{+}\right.$$
$$\left.-\left\{\sum_{s=0} P[T_{0b}=s]\frac{(s-r)(1-\theta)}{n+1}\right\}_{+}\right|$$
$$\leq \sum_{r=0}^{[n/2]} P[T_{0b}=r]\sum_{s>[n/2]} P[T_{0b}=s]\frac{(s-r)|1-\theta|}{n+1}$$
$$\leq |1-\theta|n^{-1}E(T_{0b}1\{T_{0b}>n/2\})\leq 2|1-\theta|n^{-2}ET_{0b}^2, \qquad (1.3)$$

and then by observing that

$$\sum_{r>[n/2]} P[T_{0b}=r]\left\{\sum_{s\geq 0} P[T_{0b}=s]\frac{(s-r)(1-\theta)}{n+1}\right\}$$
$$\leq n^{-1}|1-\theta|(ET_{0b}P[T_{0b}>n/2]+E(T_{0b}1\{T_{0b}>n/2\}))$$
$$\leq 4|1-\theta|n^{-2}ET_{0b}^2 \qquad (1.4)$$

Combining the contributions of (1.2) –(1.3), we thus find tha

$$\left| d_{TV}(L(\tilde{C}[1,b]),L(\tilde{Z}[1,b]))\right.$$
$$\left.-(n+1)^{-1}\sum_{r\geq 0}P[T_{0b}=r]\left\{\sum_{s\geq 0}P[T_{0b}=s](s-r)(1-\theta)\right\}_{+}\right|$$
$$\leq \varepsilon_{\{7.8\}}(n,b)$$
$$=\frac{3}{\theta P_\theta[0,1]}\left\{\varepsilon_{\{10.5(2)\}}(n/2,b)+2n^{-1}ET_{0b}\varepsilon_{\{10.14\}}(n,b)\right\}$$
$$+2n^{-2}ET_{0b}^2\left\{4+3|1-\theta|+\frac{24|1-\theta|\phi^*_{\{10.8\}}(n)}{\theta P_\theta[0,1]}\right\} \qquad (1.5)$$

The quantity $\varepsilon_{\{7.8\}}(n,b)$ is seen to be of the order claimed under Conditions $(A_0),(D_1)$ and (B_{12}), provided that $S(\infty)<\infty;$ this supplementary condition can be removed if $\phi^*_{\{10.8\}}(n)$ is replaced by $\phi^*_{\{10.11\}}(n)$ in the definition of $\varepsilon_{\{7.8\}}(n,b)$, has the required order without the restriction on the r_i implied by assuming that $S(\infty)<\infty.$ Finally, a direct calculation now shows that

$$\sum_{r\geq 0}P[T_{0b}=r]\left\{\sum_{s\geq 0}P[T_{0b}=s](s-r)(1-\theta)\right\}_{+}$$
$$=\frac{1}{2}|1-\theta|E|T_{0b}-ET_{0b}|$$

Example 1.0. Consider the point $O=(0,...,0)\in \mathbb{R}^n$. For an arbitrary vector r, the coordinates of the point $x=O+r$ are equal to the respective coordinates of the vector $r: x=(x^1,...x^n)$ and $r=(x^1,...,x^n)$. The vector r such as in the example is called the position vector or the radius vector of the point x. (Or, in greater detail: r is the radius-vector of x w.r.t an origin O). Points are frequently specified by their radius-vectors. This presupposes the choice of O as the “standard origin”. Let us summarize. We have considered $\mathbb{R}^n$ and interpreted its elements in two ways: as points and as vectors. Hence we may say that we leading with the two copies of $\mathbb{R}^n$: $\mathbb{R}^n$ = {points}, $\mathbb{R}^n$ = {vectors}

Operations with vectors: multiplication by a number, addition. Operations with points and vectors: adding a vector to a point (giving a point), subtracting two points (giving a vector). $\mathbb{R}^n$ treated in this way is called an n-dimensional affine space. (An "abstract" affine space is a pair of sets , the set of points and the set of vectors so that the operations as above are defined axiomatically). Notice that vectors in an affine space are also known as "free vectors". Intuitively, they are not fixed at points and "float freely" in space. From $\mathbb{R}^n$ considered as an affine space we can precede in two opposite directions: $\mathbb{R}^n$ as an Euclidean space $\Leftarrow$ $\mathbb{R}^n$ as an affine space $\Rightarrow$ $\mathbb{R}^n$ as a manifold.Going to the left means introducing some extra structure which will make the geometry richer. Going to the right means forgetting about part of the affine structure; going further in this direction will lead us to the so-called "smooth (or differentiable) manifolds". The theory of differential forms does not require any extra geometry. So our natural direction is to the right. The Euclidean structure, however, is useful for examples and applications. So let us say a few words about it:

Remark 1.0. Euclidean geometry. In $\mathbb{R}^n$ considered as an affine space we can already do a good deal of geometry. For example, we can consider lines and planes, and quadric surfaces like an ellipsoid. However, we cannot discuss such things as "lengths", "angles" or "areas" and "volumes". To be able to do so, we have to introduce some more definitions, making $\mathbb{R}^n$ a Euclidean space. Namely, we define the length of a vector $a=(a^1,...,a^n)$ to be

$$|a|:=\sqrt{(a^1)^2+...+(a^n)^2} \qquad (1)$$

After that we can also define distances between points as follows:

$$d(A,B):=|\overrightarrow{AB}| \qquad (2)$$

One can check that the distance so defined possesses natural properties that we expect: is it always non-negative and equals zero only for coinciding points; the distance from A to B is the same as that from B to A (symmetry); also, for three points, A, B and C, we have $d(A,B)\le d(A,C)+d(C,B)$ (the "triangle inequality"). To define angles, we first introduce the scalar product of two vectors

$$(a,b):=a^1b^1+...+a^nb^n \qquad (3)$$

Thus $|a|=\sqrt{(a,a)}$. The scalar product is also denote by dot: $a.b=(a,b)$, and hence is often referred to as the "dot product" . Now, for nonzero vectors, we define the angle between them by the equality

$$\cos\alpha:=\frac{(a,b)}{|a||b|} \qquad (4)$$

The angle itself is defined up to an integral multiple of 2π . For this definition to be consistent we have to ensure that the r.h.s. of (4) does not exceed 1 by the absolute value. This follows from the inequality

$$(a,b)^2\le|a|^2|b|^2 \qquad (5)$$

known as the Cauchy–Bunyakovsky–Schwarz inequality (various combinations of these three names are applied in different books). One of the ways of proving (5) is to consider the scalar square of the linear combination $a+tb,$ where $t\in R$. As $(a+tb,a+tb)\ge 0$ is a quadratic polynomial in t which is never negative, its discriminant must be less or equal zero. Writing this explicitly yields (5). The triangle inequality for distances also follows from the inequality (5).

Example 1.1. Consider the function $f(x)=x^i$ (the i-th coordinate). The linear function dx^i (the differential of x^i) applied to an arbitrary vector h is simply h^i .From these examples follows that we can rewrite df as

$$df=\frac{\partial f}{\partial x^1}dx^1+...+\frac{\partial f}{\partial x^n}dx^n, \qquad (1)$$

which is the standard form. Once again: the partial derivatives in (1) are just the coefficients (depending on x); $dx^1,dx^2,...$ are linear functions giving on an arbitrary vector h its coordinates $h^1,h^2,...,$ respectively. Hence

$$df(x)(h)=\partial_{hf(x)}=\frac{\partial f}{\partial x^1}h^1+ ...+\frac{\partial f}{\partial x^n}h^n, \qquad (2)$$

Theorem 1.7. Suppose we have a parametrized curve $t\mapsto x(t)$ passing through $x_0\in\mathbb{R}^n$ at $t=t_0$ and with the velocity vector $x(t_0)=\upsilon$ Then

$$\frac{df(x(t))}{dt}(t_0)=\partial_\upsilon f(x_0)=df(x_0)(\upsilon) \qquad (1)$$

Proof. Indeed, consider a small increment of the parameter $t:t_0\mapsto t_0+\Delta t$, Where $\Delta t\mapsto 0$. On the other hand, we have $f(x_0+h)-f(x_0)=df(x_0)(h)+\beta(h)|h|$ for an arbitrary vector h, where $\beta(h) \to 0$ when $h \to 0$. Combining it together, for the increment of $f(x(t))$ we obtain

$$f(x(t_0+\Delta t)-f(x_0)$$
$$=df(x_0)(\upsilon.\Delta t+\alpha(\Delta t)\Delta t)$$
$$+\beta(\upsilon.\Delta t+\alpha(\Delta t)\Delta t).|\upsilon\Delta t+\alpha(\Delta t)\Delta t|$$
$$=df(x_0)(\upsilon).\Delta t+\gamma(\Delta t)\Delta t$$

For a certain $\gamma(\Delta t)$ such that $\gamma(\Delta t) \to 0$ when $\Delta t \to 0$ (we used the linearity of $df(x_0)$). By the definition, this means that the derivative of $f(x(t))$ at $t=t_0$ is exactly $df(x_0)(\upsilon)$. The statement of the theorem can be expressed by a simple formula:

$$\frac{df(x(t))}{dt}=\frac{\partial f}{\partial x^1}x^1+...+\frac{\partial f}{\partial x^n}x^n \qquad (2)$$

To calculate the value Of df at a point x_0 on a given vector υ one can take an arbitrary curve passing Through x_0 at t_0 with υ as the velocity vector at t_0 and calculate the usual derivative of $f(x(t))$ at $t=t_0$.

Theorem 1.8. For functions $f,g:U \to \mathbb{R}$, $U \subset \mathbb{R}^n$,

$$d(f+g)=df+dg \qquad (1)$$
$$d(fg)=df.g+f.dg \qquad (2)$$

Proof. Consider an arbitrary point x_0 and an arbitrary vector υ stretching from it. Let a curve $x(t)$ be such that $x(t_0)=x_0$ and $x(t_0)=\upsilon$.

Hence

$$d(f+g)(x_0)(\upsilon)=\frac{d}{dt}(f(x(t))+g(x(t)))$$

at $t=t_0$ and

$$d(fg)(x_0)(\upsilon)=\frac{d}{dt}(f(x(t))g(x(t)))$$

at $t=t_0$ Formulae (1) and (2) then immediately follow from the corresponding formulae for the usual derivative Now, almost without change the theory generalizes to functions taking values in $\mathbb{R}^m$ instead of $\mathbb{R}$. The only difference is that now the differential of a map $F:U \to \mathbb{R}^m$ at a point x will be a linear function taking vectors in $\mathbb{R}^n$ to vectors in $\mathbb{R}^m$ (instead of $\mathbb{R}$). For an arbitrary vector $h \in \mathbb{R}^n$,

$$F(x+h)=F(x)+dF(x)(h)$$
$$+\beta(h)|h| \qquad (3)$$

Where $\beta(h) \to 0$ when $h \to 0$. We have $dF=(dF^1,...,dF^m)$ and

$$dF=\frac{\partial F}{\partial x^1}dx^1+...+\frac{\partial F}{\partial x^n}dx^n$$
$$=\begin{pmatrix}\frac{\partial F^1}{\partial x^1}\cdots\frac{\partial F^1}{\partial x^n}\\ \cdots\ \cdots\ \cdots\\ \frac{\partial F^m}{\partial x^1}\cdots\frac{\partial F^m}{\partial x^n}\end{pmatrix}\begin{pmatrix}dx^1\\ \cdots\\ dx^n\end{pmatrix} \qquad (4)$$

In this matrix notation we have to write vectors as vector-columns.

Theorem 1.9. For an arbitrary parametrized curve $x(t)$ in $\mathbb{R}^n$, the differential of a map $F:U \to \mathbb{R}^m$ (where $U \subset \mathbb{R}^n$) maps the velocity vector $x(t)$ to the velocity vector of the curve $F(x(t))$ in $\mathbb{R}^m$:

$$\frac{dF(x(t))}{dt}=dF(x(t))(\dot{x}(t)) \qquad (1)$$

Proof. By the definition of the velocity vector,

$$x(t+\Delta t)=x(t)+\dot{x}(t).\Delta t+\alpha(\Delta t)\Delta t \qquad (2)$$

Where $\alpha(\Delta t) \to 0$ when $\Delta t \to 0$. By the definition of the differential,

$$F(x+h)=F(x)+dF(x)(h)+\beta(h)|h \qquad (3)|$$

Where $\beta(h) \to 0$ when $h \to 0$. we obtain

$$F(x(t+\Delta t)) = F(x + \underbrace{\dot{x}(t).\Delta t + \alpha(\Delta t)\Delta t}_{h})$$

$$= F(x) + dF(x)(\dot{x}(t)\Delta t + \alpha(\Delta t)\Delta t) +$$

$$\beta(\dot{x}(t)\Delta t + \alpha(\Delta t)\Delta t).\left|\dot{x}(t)\Delta t + \dot{\alpha}(\Delta t)\Delta t\right|$$

$$= F(x) + dF(x)(\dot{x}(t)\Delta t + \gamma(\Delta t)\Delta t$$

For some $\gamma(\Delta t) \to 0$ when $\Delta t \to 0$. This precisely means that $dF(x)\,\dot{x}(t)$ is the velocity vector of $F(x)$. As every vector attached to a point can be viewed as the velocity vector of some curve passing through this point, this theorem gives a clear geometric picture of dF as a linear map on vectors.

Theorem 1.10 Suppose we have two maps $F: U \to V$ and $G: V \to W$, where $U \subset \mathbb{R}^n, V \subset \mathbb{R}^m, W \subset \mathbb{R}^p$ (open domains). Let $F: x \mapsto y = F(x)$. Then the differential of the composite map $GoF: U \to W$ is the composition of the differentials of F and G:

$$d(GoF)(x) = dG(y)odF(x) \qquad (4)$$

Proof. We can use the description of the differential .Consider a curve $x(t)$ in $\mathbb{R}^n$ with the velocity vector $\dot{x}$. Basically, we need to know to which vector in $\mathbb{R}^p$ it is taken by $d(GoF)$. the curve $(GoF)(x(t) = G(F(x(t))$. By the same theorem, it equals the image under dG of the Anycast Flow vector to the curve $F(x(t))$ in $\mathbb{R}^m$. Applying the theorem once again, we see that the velocity vector to the curve $F(x(t))$ is the image under dF of the vector $\dot{x}(t)$. Hence $d(GoF)(\dot{x}) = dG(dF(\dot{x}))$ for an arbitrary vector $\dot{x}$.

Corollary 1.0. If we denote coordinates in $\mathbb{R}^n$ by $(x^1,...,x^n)$ and in $\mathbb{R}^m$ by $(y^1,...,y^m)$, and write

$$dF = \frac{\partial F}{\partial x^1}dx^1 + ... + \frac{\partial F}{\partial x^n}dx^n \qquad (1)$$

$$dG = \frac{\partial G}{\partial y^1}dy^1 + ... + \frac{\partial G}{\partial y^n}dy^n, \qquad (2)$$

Then the chain rule can be expressed as follows:

$$d(GoF) = \frac{\partial G}{\partial y^1}dF^1 + ... + \frac{\partial G}{\partial y^m}dF^m, \qquad (3)$$

Where dF^i are taken from (1). In other words, to get $d(GoF)$ we have to substitute into (2) the expression for $dy^i = dF^i$ from (3). This can also be expressed by the following matrix formula:

$$d(GoF) = \begin{pmatrix} \frac{\partial G^1}{\partial y^1} \cdots \frac{\partial G^1}{\partial y^m} \\ \cdots \quad \cdots \quad \cdots \\ \frac{\partial G^p}{\partial y^1} \cdots \frac{\partial G^p}{\partial y^m} \end{pmatrix} \begin{pmatrix} \frac{\partial F^1}{\partial x^1} \cdots \frac{\partial F^1}{\partial x^n} \\ \cdots \quad \cdots \quad \cdots \\ \frac{\partial F^m}{\partial x^1} \cdots \frac{\partial F^m}{\partial x^n} \end{pmatrix} \begin{pmatrix} dx^1 \\ \cdots \\ dx^n \end{pmatrix} \qquad (4)$$

i.e., if dG and dF are expressed by matrices of partial derivatives, then $d(GoF)$ is expressed by the product of these matrices. This is often written as

$$\begin{pmatrix} \frac{\partial z^1}{\partial x^1} \cdots \frac{\partial z^1}{\partial x^n} \\ \cdots \quad \cdots \quad \cdots \\ \frac{\partial z^p}{\partial x^1} \cdots \frac{\partial z^p}{\partial x^n} \end{pmatrix} = \begin{pmatrix} \frac{\partial z^1}{\partial y^1} \cdots \frac{\partial z^1}{\partial y^m} \\ \cdots \quad \cdots \quad \cdots \\ \frac{\partial z^p}{\partial y^1} \cdots \frac{\partial z^p}{\partial y^m} \end{pmatrix} \begin{pmatrix} \frac{\partial y^1}{\partial x^1} \cdots \frac{\partial y^1}{\partial x^n} \\ \cdots \quad \cdots \quad \cdots \\ \frac{\partial y^m}{\partial x^1} \cdots \frac{\partial y^m}{\partial x^n} \end{pmatrix}, \qquad (5)$$

Or

$$\frac{\partial z^\mu}{\partial x^a} = \sum_{i=1}^{m} \frac{\partial z^\mu}{\partial y^i}\frac{\partial y^i}{\partial x^a}, \qquad (6)$$

Where it is assumed that the dependence of $y \in \mathbb{R}^m$ on $x \in \mathbb{R}^n$ is given by the map F, the dependence of $z \in \mathbb{R}^p$ on $y \in \mathbb{R}^m$ is given by the map $G,$ and the dependence of $z \in \mathbb{R}^p$ on $x \in \mathbb{R}^n$ is given by the composition GoF.

Definition 1.6. Consider an open domain $U \subset \mathbb{R}^n$. Consider also another copy of $\mathbb{R}^n$, denoted for distinction $\mathbb{R}^n_y$, with the standard coordinates $(y^1 ... y^n)$. A system of coordinates in the open domain U is given by a map $F : V \to U$, where $V \subset \mathbb{R}^n_y$ is an open domain of $\mathbb{R}^n_y$, such that the following three conditions are satisfied :

(1) F is smooth;

(2) F is invertible;

(3) $F^{-1} : U \to V$ is also smooth

The coordinates of a point $x \in U$ in this system are the standard coordinates of $F^{-1}(x) \in \mathbb{R}^n_y$

In other words,

$$F : (y^1 ..., y^n) \mapsto x = x(y^1 ..., y^n) \qquad (1)$$

Here the variables $(y^1 ..., y^n)$ are the "new" coordinates of the point x

Example 1.2. Consider a curve in $\mathbb{R}^2$ specified in polar coordinates as

$$x(t) : r = r(t), \varphi = \varphi(t) \qquad (1)$$

We can simply use the chain rule. The map $t \mapsto x(t)$ can be considered as the composition of the maps $t \mapsto (r(t), \varphi(t)), (r, \varphi) \mapsto x(r, \varphi)$. Then, by the chain rule, we have

$$\dot{x} = \frac{dx}{dt} = \frac{\partial x}{\partial r}\frac{dr}{dt} + \frac{\partial x}{\partial \varphi}\frac{d\varphi}{dt} = \frac{\partial x}{\partial r}\dot{r} + \frac{\partial x}{\partial \varphi}\dot{\varphi} \qquad (2)$$

Here $\dot{r}$ and $\dot{\varphi}$ are scalar coefficients depending on t, whence the partial derivatives $\partial x/\partial r, \partial x/\partial \varphi$ are vectors depending on point in $\mathbb{R}^2$. We can compare this with the formula in the "standard" coordinates: $\dot{x} = e_1 \dot{x} + e_2 \dot{y}$.

Consider the vectors $\partial x/\partial r, \partial x/\partial \varphi$. Explicitly we have

$$\frac{\partial x}{\partial r} = (\cos\varphi, \sin\varphi) \qquad (3)$$

$$\frac{\partial x}{\partial \varphi} = (-r\sin\varphi, r\cos\varphi) \qquad (4)$$

From where it follows that these vectors make a basis at all points except for the origin (where $r = 0$). It is instructive to sketch a picture, drawing vectors corresponding to a point as starting from that point. Notice that $\partial x/\partial r, \partial x/\partial \varphi$ are, respectively, the velocity vectors for the curves $r \mapsto x(r, \varphi)$ $(\varphi = \varphi_0 \ fixed)$ and $\varphi \mapsto x(r, \varphi)$ $(r = r_0 \ fixed)$. We can conclude that for an arbitrary curve given in polar coordinates the velocity vector will have components $(\dot{r}, \dot{\varphi})$ if as a basis we take $e_r := \partial x/\partial r, e_\varphi := \partial x/\partial \varphi$:

$$\dot{x} = e_r \dot{r} + e_\varphi \dot{\varphi} \qquad (5)$$

A characteristic feature of the basis e_r, e_φ is that it is not "constant" but depends on point. Vectors "stuck to points" when we consider curvilinear coordinates.

Proposition 1.3. The velocity vector has the same appearance in all coordinate systems.

Proof. Follows directly from the chain rule and the transformation law for the basis e_i. In particular, the elements of the basis $e_i = \partial x/\partial x^i$ (originally, a formal notation) can be understood directly as the velocity vectors of the coordinate lines $x^i \mapsto x(x^1, ..., x^n)$ (all coordinates but x^i are fixed). Since we now know how to handle velocities in arbitrary coordinates, the best way to treat the differential of a map $F : \mathbb{R}^n \to \mathbb{R}^m$ is by its action on the velocity vectors. By definition, we set

$$dF(x_0) : \frac{dx(t)}{dt}(t_0) \mapsto \frac{dF(x(t))}{dt}(t_0) \qquad (1)$$

Now $dF(x_0)$ is a linear map that takes vectors attached to a point $x_0 \in \mathbb{R}^n$ to vectors attached to the point $F(x) \in \mathbb{R}^m$

$$dF = \frac{\partial F}{\partial x^1}dx^1 + ... + \frac{\partial F}{\partial x^n}dx^n$$

$$(e_1, ..., e_m)\begin{pmatrix} \frac{\partial F^1}{\partial x^1} ... \frac{\partial F^1}{\partial x^n} \\ ... \ ... \ ... \\ \frac{\partial F^m}{\partial x^1} ... \frac{\partial F^m}{\partial x^n} \end{pmatrix}\begin{pmatrix} dx^1 \\ ... \\ dx^n \end{pmatrix}, \qquad (2)$$

In particular, for the differential of a function we always have

$$df = \frac{\partial f}{\partial x^1} dx^1 + ... + \frac{\partial f}{\partial x^n} dx^n, \qquad (3)$$

Where x^i are arbitrary coordinates. The form of the differential does not change when we perform a change of coordinates.

Example 1.3 Consider a 1-form in $\mathbb{R}^2$ given in the standard coordinates:

$A = -ydx + xdy$ In the polar coordinates we will have $x = r\cos\varphi, y = r\sin\varphi$, hence

$$dx = \cos\varphi dr - r\sin\varphi d\varphi$$

$$dy = \sin\varphi dr + r\cos\varphi d\varphi$$

Substituting into A, we get

$$A = -r\sin\varphi(\cos\varphi dr - r\sin\varphi d\varphi)$$

$$+ r\cos\varphi(\sin\varphi dr + r\cos\varphi d\varphi)$$

$$= r^2(\sin^2\varphi + \cos^2\varphi)d\varphi = r^2 d\varphi$$

Hence $A = r^2 d\varphi$ is the formula for A in the polar coordinates. In particular, we see that this is again a 1-form, a linear combination of the differentials of coordinates with functions as coefficients. Secondly, in a more conceptual way, we can define a 1-form in a domain U as a linear function on vectors at every point of U:

$$\omega(\upsilon) = \omega_1 \upsilon^1 + ... + \omega_n \upsilon^n, \qquad (1)$$

If $\upsilon = \sum e_i \upsilon^i$, where $e_i = \partial x / \partial x^i$. Recall that the differentials of functions were defined as linear functions on vectors (at every point), and

$$dx^i(e_j) = dx^i\left(\frac{\partial x}{\partial x^j}\right) = \delta^i_j \qquad (2)$$

at every point x.

Theorem 1.9. For arbitrary 1-form ω and path γ, the integral $\int_\gamma \omega$ does not change if we change parametrization of γ provide the orientation remains the same.

Proof: Consider $\left\langle \omega(x(t)), \frac{dx}{dt'} \right\rangle$ and $\left\langle \omega(x(t(t'))), \frac{dx}{dt'} \right\rangle$ As

$$\left\langle \omega(x(t(t'))), \frac{dx}{dt'} \right\rangle = \left| \left\langle \omega(x(t(t'))), \frac{dx}{dt'} \right\rangle . \frac{dt}{dt'} \right.,$$

Let p be a rational prime and let $K = \mathbb{Q}(\zeta_p)$. We write ζ for ζ_p or this section. Recall that K has degree $\varphi(p) = p-1$ over $\mathbb{Q}$. We wish to show that $O_K = \mathbb{Z}[\zeta]$. Note that ζ is a root of $x^p - 1$, and thus is an algebraic integer; since O_K is a ring we have that $\mathbb{Z}[\zeta] \subseteq O_K$. We give a proof without assuming unique factorization of ideals. We begin with some norm and trace computations. Let j be an integer. If j is not divisible by p, then ζ^j is a primitive p^{th} root of unity, and thus its conjugates are $\zeta, \zeta^2, ..., \zeta^{p-1}$. Therefore

$$Tr_{K/\mathbb{Q}}(\zeta^j) = \zeta + \zeta^2 + ... + \zeta^{p-1} = \Phi_p(\zeta) - 1 = -1$$

If p does divide j, then $\zeta^j = 1$, so it has only the one conjugate 1, and $Tr_{K/\mathbb{Q}}(\zeta^j) = p-1$ By linearity of the trace, we find that

$$Tr_{K/\mathbb{Q}}(1-\zeta) = Tr_{K/\mathbb{Q}}(1-\zeta^2) = ...$$

$$= Tr_{K/\mathbb{Q}}(1-\zeta^{p-1}) = p$$

We also need to compute the norm of $1-\zeta$. For this, we use the factorization

$$x^{p-1} + x^{p-2} + ... + 1 = \Phi_p(x)$$

$$= (x-\zeta)(x-\zeta^2)...(x-\zeta^{p-1});$$

Plugging in $x = 1$ shows that

$$p = (1-\zeta)(1-\zeta^2)...(1-\zeta^{p-1})$$

Since the $(1-\zeta^j)$ are the conjugates of $(1-\zeta)$, this shows that $N_{K/\mathbb{Q}}(1-\zeta) = p$ The key result for determining the ring of integers O_K is the following.

LEMMA 1.9

$$(1-\zeta)O_K \cap \mathbb{Z} = p\mathbb{Z}$$

Proof. We saw above that p is a multiple of $(1-\zeta)$ in O_K, so the inclusion $(1-\zeta)O_K \cap \mathbb{Z} \supseteq p\mathbb{Z}$ is immediate. Suppose now that the inclusion is strict. Since $(1-\zeta)O_K \cap \mathbb{Z}$ is an ideal of $\mathbb{Z}$ containing $p\mathbb{Z}$ and $p\mathbb{Z}$ is

a maximal ideal of $\mathbb{Z}$, we must have $(1-\zeta)O_K \cap \mathbb{Z} = \mathbb{Z}$ Thus we can write $1=\alpha(1-\zeta)$
For some $\alpha \in O_K$. That is, $1-\zeta$ is a unit in O_K.

COROLLARY 1.1 For any $\alpha \in O_K$, $Tr_{K/\mathbb{Q}}((1-\zeta)\alpha) \in p.\mathbb{Z}$

PROOF. We have

$$\begin{aligned} Tr_{K/\mathbb{Q}}((1-\zeta)\alpha) &= \sigma_1((1-\zeta)\alpha) + ... + \sigma_{p-1}((1-\zeta)\alpha) \\ &= \sigma_1(1-\zeta)\sigma_1(\alpha) + ... + \sigma_{p-1}(1-\zeta)\sigma_{p-1}(\alpha) \\ &= (1-\zeta)\sigma_1(\alpha) + ... + (1-\zeta^{p-1})\sigma_{p-1}(\alpha) \end{aligned}$$

Where the σ_i are the complex embeddings of K (which we are really viewing as automorphisms of K) with the usual ordering. Furthermore, $1-\zeta^j$ is a multiple of $1-\zeta$ in O_K for every $j \neq 0$. Thus $Tr_{K/\mathbb{Q}}(\alpha(1-\zeta)) \in (1-\zeta)O_K$ Since the trace is also a rational integer.

PROPOSITION 1.4 Let p be a prime number and let $K = \mathbb{Q}(\zeta_p)$ be the p^{th} cyclotomic field. Then $O_K = \mathbb{Z}[\zeta_p] \cong \mathbb{Z}[x]/(\Phi_p(x));$ Thus $1, \zeta_p, ..., \zeta_p^{p-2}$ is an integral basis for O_K.

PROOF. Let $\alpha \in O_K$ and write $\alpha = a_0 + a_1\zeta + ... + a_{p-2}\zeta^{p-2}$ With $a_i \in \mathbb{Q}$. Then

$$\alpha(1-\zeta) = a_0(1-\zeta) + a_1(\zeta - \zeta^2) + ... + a_{p-2}(\zeta^{p-2} - \zeta^{p-1})$$

By the linearity of the trace and our above calculations we find that $Tr_{K/\mathbb{Q}}(\alpha(1-\zeta)) = pa_0$ We also have $Tr_{K/\mathbb{Q}}(\alpha(1-\zeta)) \in p\mathbb{Z}$, so $a_0 \in \mathbb{Z}$ Next consider the algebraic integer $(\alpha - a_0)\zeta^{-1} = a_1 + a_2\zeta + ... + a_{p-2}\zeta^{p-3};$ This is an algebraic integer since $\zeta^{-1} = \zeta^{p-1}$ is. The same argument as above shows that $a_1 \in \mathbb{Z}$, and continuing in this way we find that all of the a_i are in $\mathbb{Z}$. This completes the proof.

Example 1.4 Let $K = \mathbb{Q}$, then the local ring $\mathbb{Z}_{(p)}$ is simply the subring of $\mathbb{Q}$ of rational numbers with denominator relatively prime to p. Note that this ring $\mathbb{Z}_{(p)}$ is not the ring $\mathbb{Z}_p$ of p-adic integers; to get $\mathbb{Z}_p$ one must complete $\mathbb{Z}_{(p)}$. The usefulness of $O_{K,p}$ comes from the fact that it has a particularly simple ideal structure. Let a be any proper ideal of $O_{K,p}$ and consider the ideal $a \cap O_K$ of O_K. We claim that $a = (a \cap O_K)O_{K,p};$ That is, that a is generated by the elements of a in $a \cap O_K$. It is clear from the definition of an ideal that $a \supseteq (a \cap O_K)O_{K,p}$. To prove the other inclusion, let α be any element of a. Then we can write $\alpha = \beta/\gamma$ where $\beta \in O_K$ and $\gamma \notin p$. In particular, $\beta \in a$ (since $\beta/\gamma \in a$ and a is an ideal), so $\beta \in O_K$ and $\gamma \notin p$. so $\beta \in a \cap O_K$. Since $1/\gamma \in O_{K,p}$, this implies that $\alpha = \beta/\gamma \in (a \cap O_K)O_{K,p}$, as claimed.We can use this fact to determine all of the ideals of $O_{K,p}$. Let a be any ideal of $O_{K,p}$ and consider the ideal factorization of $a \cap O_K$ in O_K. write it as $a \cap O_K = p^n b$ For some n and some ideal b, relatively prime to p. we claim first that $bO_{K,p} = O_{K,p}$. We now find that $a = (a \cap O_K)O_{K,p} = p^n bO_{K,p} = p^n O_{K,p}$ Since $bO_{K,p}$. Thus every ideal of $O_{K,p}$ has the form $p^n O_{K,p}$ for some n; it follows immediately that $O_{K,p}$ is noetherian. It is also now clear that $p^n O_{K,p}$ is the unique non-zero prime ideal in $O_{K,p}$. Furthermore, the inclusion $O_K \mapsto O_{K,p}/pO_{K,p}$ Since $pO_{K,p} \cap O_K = p$, this map is also surjection, since the residue class of $\alpha/\beta \in O_{K,p}$ (with $\alpha \in O_K$ and $\beta \notin p$) is the image of $\alpha\beta^{-1}$ in $O_{K/p}$, which makes sense since β is invertible in $O_{K/p}$. Thus the map is an isomorphism. In particular, it is now abundantly clear that every non-zero prime ideal of $O_{K,p}$ is maximal. To show that $O_{K,p}$ is a Dedekind domain, it remains to show that it is integrally closed in K. So let $\gamma \in K$ be a root of a polynomial with coefficients in $O_{K,p}$; write this polynomial as $x^m + \frac{\alpha_{m-1}}{\beta_{m-1}} x^{m-1} + \ldots + \frac{\alpha_0}{\beta_0}$ With $\alpha_i \in O_K$ and $\beta_i \in O_{K-p}$. Set $\beta = \beta_0 \beta_1 \ldots \beta_{m-1}$. Multiplying by β^m we find that $\beta\gamma$ is the root of a monic polynomial with coefficients in O_K. Thus $\beta\gamma \in O_K$; since $\beta \notin p$, we have $\beta\gamma / \beta = \gamma \in O_{K,p}$. Thus $O_{K,p}$ is integrally close in K.

COROLLARY 1.2. Let K be a number field of degree n and let α be in O_K then $N'_{K/\square}(\alpha O_K) = \left| N_{K/\square}(\alpha) \right|$

PROOF. We assume a bit more Galois theory than usual for this proof. Assume first that $K/\square$ is Galois. Let σ be an element of $Gal(K/\square)$. It is clear that $\sigma(O_K)/\sigma(\alpha) \cong O_{K/\alpha}$; since $\sigma(O_K) = O_K$, this shows that $N'_{K/\square}(\sigma(\alpha)O_K) = N'_{K/\square}(\alpha O_K)$. Taking the product over all $\sigma \in Gal(K/\square)$, we have $N'_{K/\square}(N_{K/\square}(\alpha)O_K) = N'_{K/\square}(\alpha O_K)^n$ Since $N_{K/\square}(\alpha)$ is a rational integer and O_K is a free $\square$ -module of rank n, $O_K / N_{K/\square}(\alpha)O_K$ Will have order $N_{K/\square}(\alpha)^n$; therefore

$$N'_{K/\square}(N_{K/\square}(\alpha)O_K) = N_{K/\square}(\alpha O_K)^n$$

This completes the proof. In the general case, let L be the Galois closure of K and set $[L:K] = m$.

A. Spatial Analysis

Spatial Analysis of people suffering from Cancer in North America and the trend in Geo Location. Spatial Analysis is to measure properties and relationship with spatial localization and the events like Brain Cancer in America. The model processes define the distribution of spread of cancer in space.

Taxonomy used are Events, Point Patterns to express occurrences of Cancer patient as points in space listed as Point Processes and give the localization coordinates. This study developed the modelling process for exploratory analysis to provide graphs, maps and spatial patterns.

In Point Pattern Analysis the object of interest is the spatial location of cancer events as the type of cancer and the numbers associated with Mortality. Objective is to study the spatial distribution and develop testing hypothesis about the observed and forecast pattern.

The model uses the geostatistics techniques to define homogeneous bahavior on the spatial correlation data structure in geolocation.

Spatial Autocorrelation is the spatial dependency based on computation framework, this is to measure relationship between two random variables, but are applying the concept on multiple variable the distinguish Brain Tumor Types, Nervous Cancer Types, Location and Influence Factors. Verifying spatial dependency varies based on comparative analysis of population sample and nearest points.

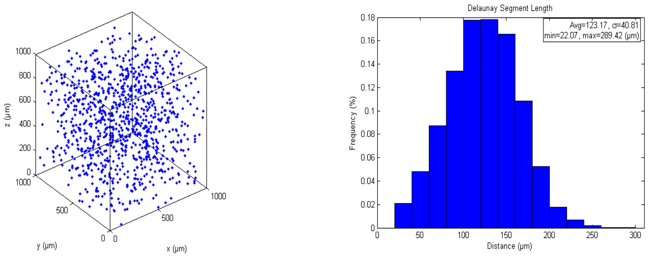

Fig 1 : Delaunay Tetrahedra Volume

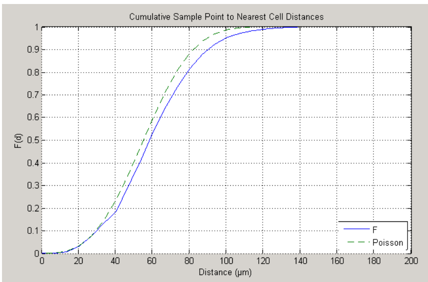

Fig. 2: F Function (Cumulative Sample Point to Nearest Cell Distances)

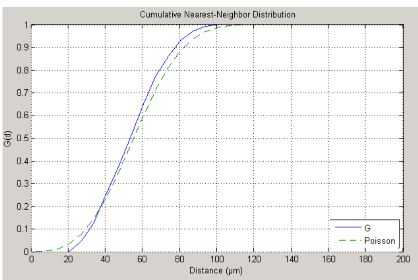

Fig 3: G Function (Cumulative Nearest Neighbor Distribution)

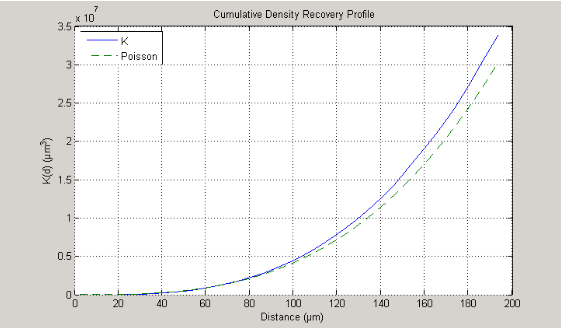

Fig 4: K Function (Cumulative Density)

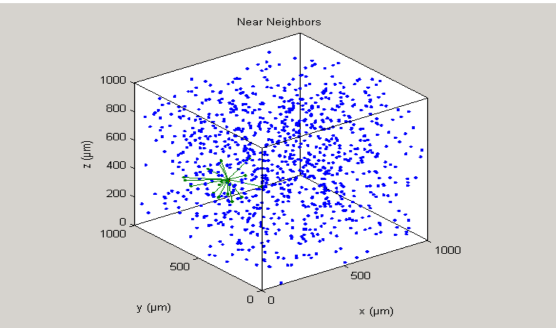

Fig 5 : Near Neighbors

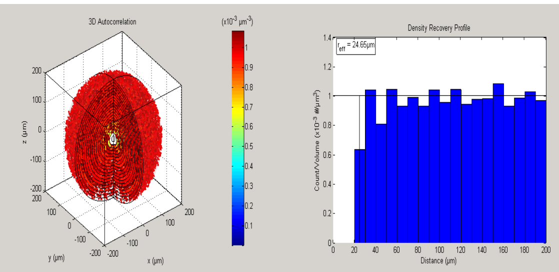

Fig 6 : Three Dimension Autocorrelation and Histogram

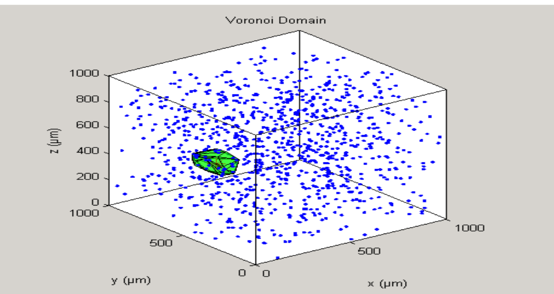

Fig 7 : Voronio Domain

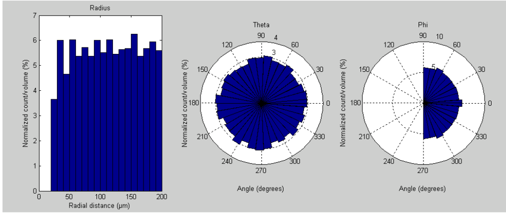

Fig 8 : Autocorrelation Histogram

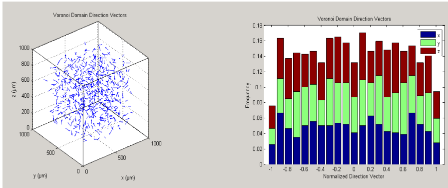

Fig 9 : Voronio Domain Director Vector and Histogram

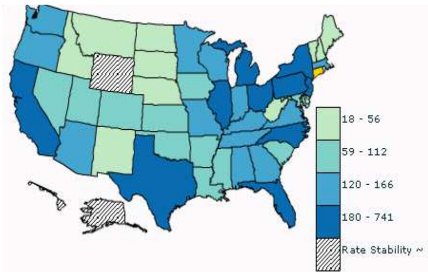

Fig 10 : North America Cancer patient distribution

Cancer Types	0-19		20+	
	Benign/Borderline	**Malignant**	**Benign/Borderline**	**Malignant**
Total	1.6 (1.5-1.8)	3.4 (3.3-3.6)	12.1 (11.9-12.3)	10 (9.8-10.2)
Tumors of Neuroepthelial Tissue	.6 (0.5-0.6)	3.1 (2.9-3.3)	.4 (0.4-0.5)	8.5 (8.3-8.7)
Pilocytic astrocytoma		.8 (0.7-0.9)		.1 (0.1-0.2)
Diffuse astrocytoma		.1 (0.0-0.1)		.2 (0.1-0.2)
Anaplastic astrocytoma		.1 (0.1-0.2)		.6 (0.6-0.6)
Unique astrocytoma variants	.1 (0.0-0.1)	.1 (0.0-0.1)	.1 (0.1-0.1)	0. (0.0-0.0)

Astrocytoma, NOS		.2 (0.2-0.3)		.6 (0.5-0.6)
Glioblastoma		.2 (0.1-0.2)		5.3 (5.2-5.5)
Oligodendroglioma		.1 (0.0-0.1)		.4 (0.3-0.4)
Anaplastic oligodendroglioma				.2 (0.1-0.2)
Ependymoma/anaplastic ependymoma		.3 (0.2-0.3)		.2 (0.2-0.3)
Ependymoma variants	0. (0.0-0.1)		.1 (0.1-0.1)	
Mixed glioma				.3 (0.3-0.3)
Glioma malignant, NOS		.5 (0.5-0.6)		.4 (0.4-0.5)
Choroid plexus	.1 (0.1-0.1)	~	0. (0.0-0.0)	~
Neuroepithelial				0. (0.0-0.0)
Neuronal/glial, neuronal	.4 (0.3-0.4)	.1 (0.0-0.1)	.2 (0.1-0.2)	0. (0.0-0.0)
Pineal parenchymal		0. (0.0-0.1)		
Embryonal/primitive/medulloblastoma		.7 (0.6-0.8)		.1 (0.1-0.1)
Tumors of Cranial and Spinal Nerves	.3 (0.2-0.3)		2.1 (2.1-2.2)	0. (0.0-0.0)
Nerve sheath, benign and malignant	.3 (0.2-0.3)		2.1 (2.1-2.2)	0. (0.0-0.0)

Tumors of the Meninges	.2 (0.1-0.2)		5.3 (5.1-5.4)	.2 (0.2-0.2)
Meningioma	.1 (0.1-0.1)		5 (4.8-5.1)	.2 (0.1-0.2)
Other mesenchymal			.1 (0.1-0.1)	0. (0.0-0.0)
Hemangioblastoma	0. (0.0-0.1)		.2 (0.2-0.3)	
Lymphomas and Hematopoietic Neoplasms				.7 (0.6-0.7)
Germ Cell Tumors		.2 (0.2-0.3)	0. (0.0-0.0)	.1 (0.1-0.1)
	0-19		**20+**	
Cancer Types	**Benign/Borderline**	**Malignant**	**Benign/Borderline**	**Malignant**
Tumors of Sellar Region	.4 (0.3-0.5)		3.5 (3.4-3.6)	0. (0.0-0.0)
Pituitary	.2 (0.2-0.3)		3.3 (3.2-3.4)	0. (0.0-0.0)
Craniopharyngioma	.2 (0.1-0.2)		.2 (0.1-0.2)	
Local Extensions from Regional Tumors				0. (0.0-0.0)
Unclassified Tumors	.2 (0.2-0.3)	.1 (0.0-0.1)	.7 (0.7-0.8)	.5 (0.5-0.6)
Hemangioma	.1 (0.1-0.1)		.2 (0.2-0.2)	
Neoplasm, unspecified	.1 (0.1-0.2)	.1 (0.0-0.1)	.5 (0.5-0.6)	.5 (0.5-0.6)
All other				

Fig11: Crude Incidence Rate [4]

Classification of Brain Cancer

Glimos- Lowest grade tumors	Pilocytic astrocytoma	Subependymoma	Subependymal giant cell astrocytoma	Ganglioglioma	Xanthomatous astrocytoma	Protoplasmic astrocytoma	Subependymoma
Gliomas - Lower grade malignancies	Fibrillary (gemistocytic, protoplasmic) astrocytoma	Ependymoma	Oligodendroglioma	Mixed oligo-astrocytoma	Optic nerve glioma		
Gliomas - Higher-grade malignancies	Anaplastic astrocytoma	Anaplastic oligodendroglioma	Anaplastic mixed glioma				
Gliomas - Highest-grade malignancies	Glioblastoma multiforme	Gliosarcoma	Gliomatosis cerebri				
Meningioma	Benign	Atypical	Malignant				
Primitive neuroectodermal tumors (PNET)	Medulloblastoma	Ependymoblastoma	Pineoblastoma				
Pituitary tumors	Pituitary adenoma	Pituitary carcinoma	Craniopharyngioma	Rathke's cleft cyst			
Pineal Tumors	Pineal cyst	Pineocytoma	Pineoblastoma	Germinoma	Mixed germ cell tumor	Pineal gliomas	Pineal teratoma
Choroid plexus tumors	Choroid plexus papilloma	Choroid plexus carcinoma					
benign primary tumors	Neurocytoma	Dysembroplastic neuroepithelial tumor (DNT)	Lipoma	Hemangioblastoma	Hamartoma	Teratoma	
Tumors of nerves and/or nerve sheaths	Neuroma	Schwannoma	Neurofibroma				
Cysts	Colloid cyst	Arachnoid cysts	Dermoid	Epidermoid	Rathke's cleft cyst	Pineal cyst	
primary tumors, including skull base	Chondroma	Chordoma	Sarcomas	Gliosarcoma	Chondrosarcoma	Rhabdomyosarcoma	
others	Primary Central Nervous System Lymphoma (PCNSL)	Metastatic brain tumors and carcinomatous meningitis					

Fig. 12 Classification of Brain Cancer

IV. CONCLUSIONS

Cancer patients in America is reducing and especially Brain Cancer percentage is in control and not increase as compared to Lung Cancer. Next work is to layout the framework for epidemic models

REFERENCES

[1] Francis P Boscoe, Mary H Ward and Peggy Reynolds,Current practices in spatial analysis of cancer data: data characteristics and data sources for geographic studies of cancer,International Journal of Health Geographics 2004, 3:28

[2] Burkitt DP: Geography of a disease: purpose and possibilities from geographical medicine. In Biocultural aspects of disease Edited by: Rothschild HR. New York, Academic Press; 1981.

[3] Gould P, Wallace R: Spatial structures and scientific paradoxes in the AIDS pandemic. Geografiska Annaler B 1994, 76:105-116.

[4] http://www.braintumor.org/news/press-kit/brain-tumor-facts.html Central Brain Tumor Registry of the United States statistics report