

**Multidimensional version of Kolmogorov's Theorem.**

Let us do  $d = 2$ .  $d > 2$  is not all that different. We need to interpolate a function from the four corners of a square to its interior. Pretending the square to be  $[0, 1]^2$ , the function will be of the form

$$f(x_1, x_2) = a + bx_1 + cx_2 + dx_1x_2$$

It is linear in each variable. The values on the edge of a square are obtained by linear interpolation from the corners. This guarantees that the function defined on each one for the sub-squares separately matches at the common edges and defines a continuous function on the big square. The comparison between the interpolated functions  $u_n, u_{n+1}$  at  $n$ -th stage and the  $n + 1$ -th stage involves differences at  $2^{2n}$  possible nodes. [This will be  $2^{nd}$  in  $d$ -dimensions]. As before

$$\sup_x |u_n(x) - u_{n+1}(x)| \leq \max_{1 \leq i \leq c_d 2^{2n}} |u(x_i) - u(y_i)|$$

with  $\sup_i |x_i - y_i| \leq 2^{-n}$ .  $x_i$  is the mid point of an edge at the  $n$ -th stage and  $y_i$  is either end point of that edge. At the  $n$ -th stage the number of such comparisons can be bounded by  $c_d 2^{2n}$  where  $c_d$  is a simple constant that depends on the dimension. Now Tchebechev inequality will do the trick provided we have for some  $\alpha > 0$ ,

$$E[|u(x) - u(y)|^\beta] \leq |x - y|^{2+\alpha}$$

**Converse Estimate.** We now prove the reverse estimate

**Theorem.**

$$\|f\|_{L_p(P)} \leq C_p \|\Delta f\|_{1,p}$$

**Proof:** This is done by duality. We note that

$$\langle -\mathcal{L}f, g \rangle_{L_2(P)} = \int_X \langle Df, Dg \rangle_{\mathcal{H}}(x) P(dx)$$

provided  $f$  and  $g$  are in  $\cup_n \mathcal{K}_n$  i.e. are polynomials. Therefore

$$\langle f|g \rangle = \int_X [\langle Df(x), Dg(x) \rangle_{\mathcal{H}} + f(x)g(x)] P(dx)$$

defines an inner product on polynomials.

$$\begin{aligned} E^P[f g] &= E^P[(\Lambda^2 f)((I - \mathcal{L})g)] = \langle \Lambda f | \Lambda g \rangle \\ &= \int_X [\langle (D\Lambda f)(x), (D\Lambda g)(x) \rangle_{\mathcal{H}} + (\Lambda f)(x)(\Lambda g)(x)] P(dx) \end{aligned}$$

If we now take sup over  $g \in L_q(P)$ , and use the inequalities in the other direction we get the theorem.

### Comments on Higher Derivatives.

Suppose  $f(\omega)$  is a function on  $X$  then the higher derivatives  $D^r f$  are symmetric  $r$ -linear functional on  $\mathcal{H}$  and can be viewed as a symmetric element of the tensor product  $\otimes_r \mathcal{H}$  and derives its norm. For instance, for  $r = 2$ , it would be the Hilbert-Schmidt norm, where an element in  $\mathcal{H} \otimes \mathcal{H}$  is viewed as a symmetric operator. Now Leibnitz rule applies and

$$D^k(fg) = \sum_{r+s=k} c_{r,s} D^r f \otimes D^s g$$

for some coefficients  $c_{r,s}$ . In particular if  $f, g \in \mathcal{S}$ , where

$$\mathcal{S} = \cap_{p,r} \{f \in L_p(P), \|D^r f\|_{\otimes_r \mathcal{H}} \in L_p(P)\}$$

then  $fg \in \mathcal{S}$ .

For each  $k$ , the norm

$$\|f\|_{k,p} = \sum_{0 \leq r \leq k} \|D^r f\|_{L_p}$$

can be shown to be equivalent to the norm  $\|\Lambda^{-k} f\|_{L_p}$  i.e

$$D^k \Gamma^k$$

is bounded from  $L_p \rightarrow L_p$ .

We cannot use directly the estimates for maps into a Hilbert space because our goal is to estimate  $D^n \Lambda^n f$  with values in  $\otimes_{j=1}^n \mathcal{H}$  in terms of the scalar function  $f$ . The idea is to study some intertwining operators and reduce the problem to the boundedness of  $D\Lambda$ .

The norms for higher derivatives can be defied inductively, in fact for functions with values in some  $\mathcal{V}$ .

$$\|f\|_{r,p} = \|f\|_{r-1,p} + \|Df\|_{L_p(P, \mathcal{H}^{\otimes(r-1)} \otimes \mathcal{V})}$$

**Theorem.** There exists a constant  $c = c(r, p)$  such that

$$c^{-1} \|f\|_{L_p(P)} \leq \|\Lambda^r f\|_{r,p} \leq c \|f\|_{L_p(P)}$$

**Proof:** Consider the map  $\Gamma : \mathcal{D}_{1,p}(X; \mathcal{V}) \rightarrow L_p(P; \mathcal{V} \oplus (\mathcal{H} \otimes \mathcal{V}))$  defined by

$$\Gamma f = (f, Df)$$

Basically by induction

$$c_r^{-1} \|f\|_{p,r} \leq \|\Gamma^r f\|_{L_p(P)} \leq c_r \|f\|_{p,r}$$

We construct a map  $A_k : L_p(P; \mathcal{V}) \oplus L_p(P; \mathcal{H} \otimes \mathcal{V}) \rightarrow L_p(P; \mathcal{V}) \oplus L_p(P; \mathcal{H} \otimes \mathcal{V})$  so that

$$A_k \Gamma = \Lambda^{-k} \Gamma \Lambda^k$$

We see that in the chaos decomposition  $D$  lowers the degree by 1, so that  $\Gamma$  leaves the first component alone while lowering the degree by one in the second component. Therefore  $A_k$  can be taken as  $I$  in the first component and as multiplication by  $\left(\frac{n+1}{n+2}\right)^{\frac{k}{2}}$  on terms of degree  $n$ . We see that

$$\begin{aligned} \Gamma^n \Lambda^n &= \Gamma^{n-1} \Gamma \Lambda^{n-1} \Lambda \\ &= \Gamma^{n-1} \Lambda^{n-1} A_{n-1} \Gamma \Lambda \\ &= (\Gamma \Lambda) A_1 (\Gamma \Lambda) A_2 \cdots (\Gamma \Lambda) A_{n-1} (\Gamma \Lambda) \end{aligned}$$

Since at each step  $A_j$  and  $\Gamma \Lambda$  are bounded operators in every  $L_p$  we are done.

**Divergence Operator:** Given a map  $u \in L_p(P; \mathcal{H} \otimes \mathcal{V})$  the divergence  $v = D^* u$  is defined as the map  $X \rightarrow \mathcal{V}$  defined by

$$\int_X \langle f(x), v(x) \rangle_{\mathcal{V}} = \int_X \langle (Df)(x), u(x) \rangle_{\mathcal{H} \otimes \mathcal{V}} P(dx)$$

for all smooth functions  $f$  with values in  $\mathcal{V}$ .

**Theorem.** For  $u \in \mathcal{D}_{1,p}$ ,  $v = D^* u$  exists in  $L_p(P; \mathcal{V})$ . More precisely there is a constant  $c_p$  such that

$$\|D^* u\|_{L_p(P; \mathcal{V})} \leq c_p \|u\|_{1,p}$$

**Proof:**

**Commutation relations.**

$$\begin{aligned} DP_t &= e^{-t} P_t D \\ D\Lambda^{-1} &= M\Lambda^{-1}D \end{aligned}$$

where

$$Mf = \sqrt{\frac{n+1}{n+2}} f$$

on  $\mathcal{K}_n$ .

**Riesz Transform.** If we define  $R = D\Lambda : L_p(P) \rightarrow L_p(P; \mathcal{H})$ , then

$$\|Rf\|_{L_p(P; \mathcal{H})} \leq c_p \|f\|_{L_p(P)}$$

We also have

$$D = R\Lambda^{-1} \quad \text{and} \quad D = \Lambda^{-1}MR$$

Finally,

$$\begin{aligned} \int_X \langle (Df)(x), u(x) \rangle_{\mathcal{H}} P(dx) &= \int_X \langle (\Lambda^{-1}MR) f(x), u(x) \rangle_{\mathcal{H}} P(dx) \\ &= \int_X f(x) (R^*M\Lambda^{-1})u(x) P(dx) \end{aligned}$$

Therefore

$$D^*u = R^*M\Lambda^{-1}u$$

and satisfies the bound

$$\|D^*u\|_{L_p(P)} \leq c_p \|u\|_{1,p}.$$

We can think of a map  $A : X \rightarrow H$  as a vector field and its divergence

$$\delta A = D^*A$$

satisfies

$$\|\delta A\|_{L_p(P)} \leq c_p \|A\|_{1,p}.$$

**Malliavin Covariance Matrix.** Suppose  $g(x) : X \rightarrow R^d$  is a map with  $\|g\|_{1,p} < \infty$ .

Then

$$(Dg)(x) \in \mathcal{H} \otimes R^d \quad \text{a.e. } P$$

or representing  $g = \{g_i\}$  we have for each  $i = 1, \dots, d$

$$(Dg_i)(x) \in \mathcal{H} \quad \text{a.e. } P$$

The Malliavin Covariance Matrix is the symmetric positive semi-definite matrix

$$\sigma(x) = \sigma_{i,j}(x) = \langle (Dg_i)(x), (Dg_j)(x) \rangle_{\mathcal{H}}$$

exists and is in  $L_{\frac{p}{2}}(P)$  provided  $p \geq 2$ . The map  $g$  is called *non degenerate* if

$$[\det \sigma(x)]^{-1} \in L_p(P)$$

for every  $1 \leq p < \infty$ . It is called *weakly non degenerate* if

$$\det \sigma(x) > 0 \quad \text{a.e. } P$$

The map  $g : X \rightarrow R^d$  defines a gradient  $(Dg)(x)$  which is a linear map  $g'(x)$  from the tangent space  $\mathcal{H}$  of  $X$  at  $x$  to the tangent space  $R^d$  of  $R^d$  at  $g(x)$ . Then  $\sigma(x) = g'(x)g'^*(x)$ . Given a map  $g$  and a vector field  $z = z(y)$  on  $R^d$  i.e. a map  $R^d \rightarrow R^d$ , we can look for a vector field  $\tilde{Z}$  on  $X$  a *lift* of  $z$  such that

$$g'(x)\tilde{Z}(x) = z(g(x))$$

In the nondegenerate case this is possible, at least for almost all  $x$ . A canonical choice which, for each  $x$ , minimizes  $\|\tilde{Z}(x)\|_{\mathcal{H}}$  is given by

$$Z(x) = g'^*(x)[\sigma(x)]^{-1} z(g(x))$$

In particular we can lift  $\frac{\partial}{\partial y_k}$  to

$$Z_k(x) = \sum_j \gamma_{k,j}(x) g'_j(x)$$

where  $\gamma(x)$  is the inverse of  $\sigma(x)$ .

**Smoothness of distributions.** Let  $g(x)$  be a map into  $R^d$  that is nondegenerate and smooth in the sense that  $\|g\|_{r,p} < \infty$  for all  $r$  and  $p$ . If  $f(y)$  is a smooth function on  $R^d$ , and  $\rho(dy)$  is the distribution  $\rho = Pg^{-1} = g_*P$  we have

$$\begin{aligned} \int_{R^d} \frac{\partial f}{\partial y_k}(y) \rho(dy) &= \int_X \langle Df, Z_k \rangle(x) dP \\ &= \int_X \tilde{f}(x) (\delta Z_k)(x) dP \\ &= \int_{R^d} f(y) v_k(y) \rho(dy) \end{aligned}$$

where  $\tilde{f} = f(g(x))$  is the lifted function  $f$  and  $v_k(y) = E^P[\delta Z_k | g(\cdot)]$  is the conditional expectation. If we can get estimates on  $\|\delta Z_k\|_{L_p(P)}$  that will be fine because

$$\int_{R^d} \left| \frac{\partial r}{\partial y_k}(y) \right|^p r(y) dy = \int_{R^d} |v_k(y)|^p \rho(dy) \leq \int_X |\delta Z_k(x)|^p P(dx)$$

where  $\rho(dy) = r(y)dy$ .

**Calculation of  $\delta Z_k$ .** From the definition

$$Z_k = \sum_j \gamma_{k,j}(x) g'_j(x)$$

we can compute

$$(\delta Z_k)(x) = \sum_j \langle [D \gamma_{k,j}](x), (Dg_j)(x) \rangle + \sum_j \gamma_{k,j}(x) (\delta Dg_j)(x)$$

and using the relations

$$\delta D = -\mathcal{L} \quad \text{and} \quad D\gamma = D\sigma^{-1} = \sigma^{-1}(Da)\sigma^{-1} = \gamma(Da)\gamma$$

we can write

$$\begin{aligned} (\delta Z_k)(x) &= - \sum_j \gamma_{k,j}(x) (\mathcal{L}g_j)(x) + \sum_{s,j,i} \gamma_{k,s}(x) \gamma_{j,i}(x) \langle (D\sigma_{s,j})(x), (Dg_i)(x) \rangle \\ &= - \sum_j \gamma_{k,j}(x) (\mathcal{L}g_j)(x) \\ &\quad + \sum_{s,j,i} \gamma_{k,s}(x) \gamma_{j,i}(x) \langle (D \langle (Dg_s)(\cdot), (Dg_j)(\cdot) \rangle)(x), (Dg_i)(x) \rangle \\ &= - \sum_j \gamma_{k,j}(x) (\mathcal{L}g_j)(x) + \sum_{s,j,i} \gamma_{k,s}(x) \gamma_{j,i}(x) \left[ (D^2g_s)(x) [(Dg_j)(x), (Dg_i)(x)] \right] \\ &\quad + \sum_{s,j,i} \gamma_{k,s}(x) \gamma_{j,i}(x) \left[ (D^2g_j)(x) [(Dg_s)(x), (Dg_i)(x)] \right] \\ &= - \sum_j \gamma_{k,j}(x) (\mathcal{L}g_j)(x) + \sum_{s,i} \gamma_{k,s}(x) [(D^2g_s)(Z_i, Dg_i)](x) \\ &\quad + \sum_j [(D^2g_j)(Z_k, Z_j)](x) \end{aligned}$$

Since terms of the form

$$[(D^2g)(u, v)](x)$$

can be estimated by

$$\|(D^2g)(x)\|_{\mathcal{H} \otimes \mathcal{H}} \times \|u(x)\|_{\mathcal{H}} \times \|v(x)\|_{\mathcal{H}}$$

we can control  $\|\delta Z_k\|_{L_p(P)}$  by  $\|\gamma\|_{L_{p'}(P)}$  and  $\|g\|_{2,p'}$  with large enough  $p'$ .