

# High-Dimensional Measures and Geometry

## Lecture Notes from Feb 4, 2010

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We apply the martingale method to the boolean cube.

**4.1.1 Theorem.** Let  $f : I_n \rightarrow \mathbb{R}$  be 1-Lipshitz,  $a_f = \int_{I_n} f d\mu_n$ . Then for all  $t \geq 0$ ,

$$\mu_n(\{x \in I_n : f(x) \geq a_f + t\}) \leq e^{-\frac{2t^2}{n}}$$

and

$$\mu_n(\{x \in I_n : f(x) \leq a_f - t\}) \leq e^{-\frac{2t^2}{n}}$$

*Proof.* Take  $\mathcal{F}_0 = \{\emptyset, I_n\}$ ,  $\mathcal{F}_n$  be the maximal  $\sigma$ -algebra and  $\mathcal{F}_1 = \{\emptyset, I_n^1, I_n^0, I_n\}$  and proceed by subdividing  $I_n^1, I_n^0 \cong I_{n-1}$ .

A function  $f$  is measurable with respect to  $\mathcal{F}_k$  if it depends on the last  $k$  coordinates only.

Estimate  $|f_n - f_{n-1}|$ :

We see that,

$$f_{n-1}(x'_1, x_2, \dots, x_n) = \frac{1}{2} (f_n(0, x_2, \dots, x_n) + f_n(1, x_2, \dots, x_n))$$

By Lipshitz continuity  $|f_n(0, x_2, \dots, x_n) - f_n(1, x_2, \dots, x_n)| \leq 1$ . So we have,

$$|f_{n-1}(x) - f_n(x)| \leq \frac{1}{2} = d_n$$

Proceeding iteratively, we get

$$\|f_i - f_{i-1}\|_\infty \leq \frac{1}{2} = d_i$$

Now the theorem gives desired estimate. Rescaling  $t = \epsilon\sqrt{n}$  gives,

$$\mu_n(\{x \in I_n : |f(x) - a_f| \geq \epsilon\sqrt{n}\}) \leq 2e^{-2\epsilon^2}$$

□

## 5 Concentration in Product Spaces

### 5.1 The martingale method on product spaces

Let  $X = X_1 \times X_2 \dots X_n$  and each  $X_i$  be equipped with a probability measure  $\mu_i$ . Then  $X$  can be equipped with a product measure with measurable sets in a  $\sigma$ -algebra generated by,  $A = A_1 \times A_2 \dots A_n$ , where each  $A_i$  is measurable in  $X_i$  and  $\mu(A) = \prod_{i=1}^n \mu_i(A_i)$ . Also let  $d(x, y) = |\{i : x_i \neq y_i\}|$  denote the Hamming distance between  $x = (x_1, x_2, \dots, x_n)$  and  $y = (y_1, y_2, \dots, y_n)$ .

**5.1.1 Theorem.** Let  $f : X \rightarrow \mathbb{R}$  be integrable and  $d_1, d_2, \dots, d_n$  be such that  $|f(x) - f(y)| \leq d_i$  if  $x$  and  $y$  have  $x_j = y_j$  for all  $j$  except  $j = i$ . Let  $a = \int_X f d\mu$ ,  $D = \sum_{j=1}^n d_j^2$ . Then for  $t \geq 0$ ,

$$\begin{aligned} \mu(\{x : f(x) \geq a + t\}) &\leq e^{-\frac{t^2}{2D}} \\ \mu(\{x : f(x) \leq a - t\}) &\leq e^{-\frac{t^2}{2D}}. \end{aligned}$$

*Proof.* Uses Martingale method.

Let  $f_0 : X \rightarrow \mathbb{R}$ ,  $f_n = f$  and,

$$f_i(x_1, x_2, \dots, x_i, x'_{i+1}, x'_{i+2} \dots x'_n) = \int_{X_{i+1} \times \dots \times X_n} f(x_1, x_2, \dots, x_n) d\mu_{i+1} \dots d\mu_n.$$

This means for  $f_i$  we have averaged over  $n - i + 1$  dimensions. This is a conditional expectation with respect to  $\mathcal{F}_i$  generated by  $A_1 \times A_2 \dots A_i \times X_{i+1} \times \dots X_n$  with  $A_j \subseteq X_j$  measurable.

If  $g(x) = f_i(x) - f_{i-1}(x)$  then, this difference comes from averaging over the  $i$ th coordinate and thus,

$$|g_i(x)| = \left| f_i(x'_1, x'_2, \dots, x'_i, \dots, x'_n) - \int f_i(x'_1, \dots, x'_{i-1}, x_i, x'_{i+1}, \dots, x'_n) d\mu_i(x_i) \right| \leq d_i$$

for each  $1 \leq i \leq n$ . Moreover,

$$\begin{aligned} E[g_i | \mathcal{F}_{i-1}] &= E[f_i - f_{i-1} | \mathcal{F}_{i-1}] \\ &= E[f_i | \mathcal{F}_{i-1}] - f_{i-1} \\ &= f_{i-1} - f_{i-1} = 0 \end{aligned}$$

So the Martingale method applies verbatim, as before. □

### 5.2 Law of large Numbers

Suppose  $h : Y \rightarrow \mathbb{R}$  is integrable and  $a = E[h] = \int_Y h d\nu$ . If we "sample"  $n$  copies of  $h$  independently and average then how far would

$$f(y) = \frac{h(y_1) + \dots + h(y_n)}{n}$$

typically be from  $a$ ?

Let  $X_i = Y$  and  $\mu_i = \nu$  and let  $x = (x_1, x_2, \dots, x_n)$ , then consider

$$f(x) = \frac{h(x_1) + \dots + h(x_n)}{n}$$

Assume  $0 \leq h(x_1) \leq d$  for all  $x_1 \in X_1$ , then changing one coordinate of  $(x_1, x_2, \dots, x_n)$  changes  $f(x)$  by at most  $\frac{d}{n}$ . Thus we can apply the preceding theorem with,

$$D = \sum_{i=1}^n \left(\frac{d}{n}\right)^n = \frac{d^2}{n}$$

We conclude that,

$$\mu_n(\{x : f(x) \geq a + t\}) \leq e^{-\frac{nt^2}{2d^2}}$$

and  $\mu_n(\{x : f(x) \leq a - t\}) \leq e^{-\frac{nt^2}{2d^2}}$

Choosing  $t = \frac{\epsilon d}{\sqrt{n}}$  gives,

$$\mu_n\left(\{x : |f(x) - a| \geq \frac{\epsilon d}{\sqrt{n}}\}\right) \leq 2e^{-\frac{\epsilon^2}{2}}$$

### 5.3 Vector Valued Functions

If we have  $h_1, h_2, \dots, h_N$  instead of just one function  $h$ , with corresponding averages  $a_1, a_2, \dots, a_N$  and we sample,

$$f_i(x) = \frac{h_i(x_1) + \dots + h_i(x_n)}{n}$$

then which  $n$  should we choose to guarantee that each average  $f_i$  is close to  $a_i$  on a set of large measure?

Using union bound,

$$\mu_n(\{x : |f_i(x) - a_i| \leq t \forall i\}) \geq 1 - 2Ne^{-\frac{nt^2}{2d^2}}$$

Choosing  $t = \epsilon d$  gives  $1 - 2Ne^{-\frac{n\epsilon^2}{2}}$  on RHS.