STAT 206A: Polynomials of Random Variables

Lecture 4

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1 The Hermite Polynomial and Fourier Coefficients

Let γ be the 1-dimensional gaussian measure and $f : \mathbf{R} \to \mathbf{R}$ a function in $L^2(\gamma)$ such that the set of points $x \in \mathbf{R}$ where $f(X)$ is discontinuous has measure 0. Consider the probability measure $\{-1,1\}^n_\theta$ on n variables, where each variable equals -1 independently with probability $(1-\theta)/2$ and equals +1 independently with probability $(1+\theta)/2$. Let $f_n : \{-1,1\}^n \to \mathbf{R}$ be a function such that $f_n(x_1,...,x_n) = f(\sum_{i=1}^n (x_i - \theta)/\sqrt{n(1-\theta^2)}\,)$, and consider the basis of all symmetric[1] functions $W^n_k(x_1,...,x_n) = (1-\theta^2)^{-k/2}\binom{n}{k}^{-1/2}(\sum_{S\subseteq[n]:|S|=k}\prod_{i\in S}(x_i-\theta))$. From the previous lecture, we know that $f_n(x_1,...,x_n) = \sum_{k=0}^n \hat{f}_n(k)W^n_k(x_1,...,x_n)$ and $f(X) = \sum_{k=0}^n \hat{f}(k)h_k(X)$, where $\hat{f}_n(k) = \langle f_n, W^n_k\rangle_\theta$, $\hat{f}(k) = \langle f, h_k\rangle_\gamma$, and h_k is the normalized kth Hermite polynomial. (See previous lecture for full definitions). We now prove the following theorem:

Theorem 1 *$\forall\ k \in \mathbf{N}$, $\lim_{n\to\infty} \hat{f}_n(k) = \hat{f}(k)$.*

Proof: For notation it will be useful to define the random variable, $X_n = \sum_{i=1}^n (x_i - \theta)/\sqrt{n(1-\theta^2)}$. To prove our theorem, we will prove $\lim_{n\to\infty}\langle W^k_n(x_1,...,x_n), f_n(x_1,...,x_n)\rangle_\theta = \lim_{n\to\infty}\langle h_k(X_n), f_n(x_1,...,x_n)\rangle_\theta = \lim_{n\to\infty}\langle h_k(X_n), f(X_n)\rangle_\theta = \langle h_k(X), f(X)\rangle_\gamma$.

The second equality follows by definition as $f_n(x_1,...,x_n) = f(X_n)$. The third equality follows by the central limit theorem, which implies that for a fixed k, $\lim_{n\to\infty}\langle h_k(X_n), f(X_n)\rangle_\theta = \langle h_k(X), f(X)\rangle_\gamma$. Therefore, we just need to prove $\lim_{n\to\infty}\langle W^k_n(x_1,...,x_n), f_n(x_1,...,x_n)\rangle_\theta = \lim_{n\to\infty}\langle h_k(X_n), f_n(x_1,...,x_n)\rangle_\theta$. To complete the proof, we prove the following statement by induction on k, which implies the statement above.

$$\lim_{n\to\infty} \mathbf{E}_\theta[|(W^n_0(x_1,...,x_n),...,W^n_k(x_1,...,x_n)) - (h_0(X_n),...,h_k(X_n))|_2] = 0$$

The base case is trivial, as $W^n_0(x_1,...,x_n) = h_0(X_n) = 1$. The inductive step can be proved by noting:

[1] By symmetric, we mean a function f_n such that $f_n(x_1,...,x_n) = f_n(x_{\sigma(1)},...,x_{\sigma(n)})$ for any permutation σ.

1. By the central limit theorem, $\lim_{n\to\infty}\langle h_i(X_n), h_j(X_n)\rangle_\theta = \delta_{i,j}$
2. $W_i^n(x_1, ..., x_n)$ is a symmetric polynomial of degree i. (See Footnote 1 for definition of symmetric).
3. $h_i(X_n)$ and $W_i^n(x_1, ..., x_n)$ have positive coefficient for all monomials of highest degree.

We leave the formal proof of the inductive step to the reader.

$\square$

Example: To illustrate the use of this theorem, consider the majority function $f_n(x_1, ..., x_n) = \mathrm{Maj}(x_1, ..., x_n)$ and the uniform measure $\{-1, 1\}_0^n$. Note that if we define $f(X) = \mathrm{sgn}(X)$, where

$$\mathrm{sgn}(X) = \begin{cases} -1 & \text{if } X < 0 \\ 0 & \text{if } X = 0 \\ +1 & \text{if } X > 0 \end{cases}$$

then $f_n(x_1, ..., x_n) = f((\sum_{i=1}^n x_i)/\sqrt{n})$ and we can apply Theorem 1. Although computing $\hat{f}_n(k)$ is difficult, Theorem 1 implies that if we can compute $\hat{f}(k)$, then it will be a good estimate of $\hat{f}_n(k)$ for large n.

To compute $\hat{f}(k) = \langle f, h_k\rangle_\gamma$, first note that f is an odd function and h_k is an even function when k is even. Therefore, $\hat{f}(k) = 0$ for even k, and we only need to compute $\hat{f}(k)$ for odd k. For odd k:

$$
\begin{aligned}
\hat{f}(k) &= \langle f, h_k\rangle_\gamma = (2/\sqrt{k!})\int_0^\infty H_k(x)d\gamma(x) \\
&= (-2/\sqrt{2\pi k!})\int_0^\infty \frac{d^k}{dx^k}(e^{-x^2/2})dx \\
&= (-2/\sqrt{2\pi k!})\cdot(\frac{d^{k-1}}{dx^{k-1}}(e^{-x^2/2})|_0^\infty) \\
&= \sqrt{2/(\pi k!)}\cdot H_{k-1}(0) \\
&= \sqrt{2/(\pi k!)}\cdot(k-1)!/(2^{(k-1)/2}\cdot((k-1)/2)!) \\
&= \sqrt{2/(\pi k)}\cdot\sqrt{(k-1)!/(2^{k-1}\cdot(((k-1)/2)!)^2)} \\
&= \sqrt{2/(\pi k)}\cdot\sqrt{\binom{k-1}{(k-1)/2}/2^{k-1}} \\
&\approx \sqrt{2/(\pi k)}\cdot\sqrt{(2^{k-1}/\sqrt{\pi(k-1)/2}\ )/2^{k-1}} \\
&\approx \sqrt{2/(\pi k)}\cdot\sqrt{1/\sqrt{\pi(k-1)/2}} \\
&= \Theta(k^{-3/4})
\end{aligned}
$$

In the third to last step, we use the approximation $\binom{m}{m/2} \approx 2^m/\sqrt{\pi m/2}$.

With this estimate of $\hat{f}(k)$, it follows that $\sum_{r:r>k}\hat{f}^2(r) = \theta(k^{-1/2})$. Then since $\sum_{k=0}^\infty \hat{f}^2(r) = |f|_2^2 = 1$, we can conclude $\sum_{r:r\leq k}\hat{f}^2(r) = 1-\theta(k^{-1/2})$ for large n. This observation implies that the fourier coefficients of the majority function are largely concentrated on the coefficients of low degree polynomials.

2 Influence

2.1 Definition and Examples

Definition 2 *Let $f \in L^2(\prod_{i=1}^n \mu_i)$. The influence of the ith variable is defined as follows:*

$$I_i(f) = \mathbf{E}_{\prod_{j:j\neq i}\mu_j}[\mathbf{Var}_{\mu_i}[f]]$$

Example: Let $f : \{-1,1\}^n \to \{-1,1\}$ be a function, and let $\{-1,1\}_0^n$ be our measure (i.e. $\mu_i = \{-1,1\}_0$ for all $i \in [n]$). For $x \in \{-1,1\}^n$, we define $x^{\oplus i}$ to be the operation that flips the ith coordinate of x (i.e. $x^{\oplus i}$ returns $x' \in \{-1,1\}^n$, such that $x'_i = -x_i$ and $x'_j = x_j$ for all $j \neq i$). It is not difficult to show the following lemma:

Lemma 3 $I_i(f) = \mathbf{P}_{\prod_{j:j\neq i}\mu_j}[f(x) \neq f(x^{\oplus i})]$.

Proof: Consider all the variables of $x \in \{-1,1\}^n$ as fixed except the ith coordinate. Then

$$\mathbf{Var}_{\mu_i}[f(x)] = \begin{cases} 1 & \text{if } f(x) \neq f(x^{\oplus i}) \\ 0 & \text{if } f(x) = f(x^{\oplus i}) \end{cases}$$

When we no longer assume x_j is fixed for $j \neq i$, then $\mathbf{Var}_{\mu_i}[f(x)]$ can be thought of as an indicator random variable M_f that is 1 if $f(x) \neq f(x^{\oplus i})$ and 0 otherwise. Then the proof is trivial as:

$$\begin{aligned} I_i(f) &= \mathbf{E}_{\prod_{j:j\neq i}\mu_j}[\mathbf{Var}_{\mu_i}[f]] \\ &= \mathbf{E}_{\prod_{j:j\neq i}\mu_j}[M_f] \\ &= \mathbf{P}_{\prod_{j:j\neq i}\mu_j}[f(x) \neq f(x^{\oplus i})] \end{aligned}$$

$\square$

Exercise 4 (1 point) *Suppose f only attains values a and b, and our measure is $\{-1,1\}^n_\theta$. Write $I_i(f)$ in terms of a, b, θ, and Pr[$f(x) \neq f(x^{\oplus i})$].*

Included below are some examples of influence. Unless otherwise stated, assume $x_1, ..., x_n$ are drawn from measure $\prod_{i=1}^n \mu_i$.

Example: Let $f(x_1, ..., x_n) = g(x_1)$. Then applying the definition of influence, we have:

$$I_i(f) = \begin{cases} \mathbf{Var}_{\mu_1}[g] & \text{if } i = 1 \\ 0 & \text{if } i > 1 \end{cases}$$

Example: Let $f(x_1, ..., x_n) = g_1(x_1) \cdot g_2(x_2) \cdot ... \cdot g_n(x_n)$. Then applying the definition of influence and simplifying, we have:

$$I_i(f) = \mathbf{Var}_{\mu_i}[g_i] \cdot \prod_{j:j\neq i} \mathbf{E}_{\mu_j}[g_j^2]$$

Example: Assuming measure $\{-1,1\}^n_0$ and $f(x_1, ..., x_n) = \mathrm{Maj}(x_1, ..., x_n)$, then applying the definition of influence and using Lemma 3, we have:

$$
\begin{aligned}
I_i(f) &= \mathbf{P}_{\prod_{j:j\neq i}\mu_j}[(\sum_{j:j\neq i} x_j) = 0] \\
&\approx \sqrt{2/(\pi n)} \cdot (1 + o(1))
\end{aligned}
$$

2.2 Influences and Expansions

Next, we prove a general theorem about influence. Consider a function $f \in L^2(\prod_{i=1}^n \mu_i)$, where $f(x_1, ..., x_n) = \sum_{S:S\subseteq[n]} f_S(x_1, ..., x_n) = \sum_J \hat{f}(J) U_J(x_1, ..., x_n)$. Although not explicitly stated, J is a multi-index of size n, $U_J \in U^1 \otimes U^2 \otimes ... \otimes U^n$, and U^l is assumed to be a standard basis of μ_l for all $l \in [n]$. (See previous lectures for more details).

Theorem 5 $I_i(f) = \sum_{S\subseteq[n]:i\in S} |f_S|_2^2 = \sum_{J:J_i\neq 0} \hat{f}^2(J)$

Proof: To prove the theorem, we first show $\sum_{S\subseteq[n]:i\in S} |f_S|_2^2 = \sum_{J:J_i\neq 0} \hat{f}^2(J)$. Note that by definition $f_S = \sum_{J:J\in J_S} \hat{f}(J) \cdot U_J$, where J_S is the set of multi-indices J such that $J_k \neq 0$ for all $k \in S$ and $J_k = 0$ for all $k \notin S$. Then $|f_S|_2^2 = \sum_{J:J\in J_S} \hat{f}(J)^2$, and $\sum_{S\subseteq[n]:i\in S} |f_S|_2^2 = \sum_{S\subseteq[n]:i\in S} \sum_{J:J\in J_S} \hat{f}^2(J) = \sum_{J:J_i\neq 0} \hat{f}^2(J)$.

Now we only need to prove $I_i(f) = \sum_{J:J_i\neq 0} \hat{f}^2(J)$. To prove this consider all variables other than x_i as fixed, and let us compute $\mathbf{Var}_{\mu_i}[f]$:

$$
\begin{aligned}
\mathbf{Var}_{\mu_i}[f] &= \mathbf{Var}_{\mu_i}[\sum_{J:J_i=0} \hat{f}(J) U_J(x_1, ..., x_n) + \sum_{J:J_i\neq 0} \hat{f}(J) U_J(x_1, ..., x_n)] \\
&= \mathbf{E}_{\mu_i}[(\sum_{J:J_i\neq 0} \hat{f}(J) U_J(x_1, ..., x_n))^2] \\
&= \sum_{J,K:J_i\neq 0,K_i\neq 0} \hat{f}(J)\hat{f}(K) \cdot \mathbf{E}_{\mu_i}[U_J \cdot U_K]
\end{aligned}
$$

To get from the first equation to the second, we note that $\sum_{J:J_i=0} \hat{f}(J) U_J(x_1, ..., x_n)$ is constant when all variables except x_i are fixed and $\mathbf{E}_{\mu_i}[\sum_{J:J_i\neq 0} \hat{f}(J) U_J(x_1, ..., x_n)] = 0$ because we started with a standard basis. To get from the second line to the third, note that the fourier coefficients $\hat{f}(J)$ are constant.

Finally, note that by orthogonality $\mathbf{E}_{\prod_{j\in[n]}\mu_j}[U_J \cdot U_K] = 1$ if $K = J$ and $\mathbf{E}_{\prod_{j\in[n]}\mu_j}[U_J \cdot U_K] = 0$ otherwise. Now plugging in definitions, the theorem is easy to see:

$I_i(f) = \mathbf{E}_{\prod_{j:j\neq i}\mu_j}[\mathbf{Var}_{\mu_i}[f]] = \mathbf{E}_{\prod_{j:j\neq i}\mu_j}[\sum_{J,K:J_i\neq 0,K_i\neq 0}\hat{f}(J)\hat{f}(K) \cdot \mathbf{E}_{\mu_i}[U_J \cdot U_K]] = \sum_{J,K:J_i\neq 0,K_i\neq 0}\hat{f}(J)\hat{f}(K) \cdot \mathbf{E}_{\prod_{j\in[n]}\mu_j}[U_J \cdot U_K] = \sum_{J:J_i\neq 0}\hat{f}(J)^2$. $\square$