

Johns Hopkins Engineering

625.464 Computational Statistics

Orthogonal Polynomials

Module 10 Lecture 10D



JOHNS HOPKINS
WHITING SCHOOL
of ENGINEERING

Orthogonal Polynomials

Can be developed from $1, x, x^2, x^3, \dots$
by applying b-S w/ approp. weight + normalize

$$\sqrt{\langle g_i, g_i \rangle}$$

Ex/ Legendre Poly Range $[-1, 1]$ $w(x) = 1$

$$\tilde{g}_0 = g_0 = 1$$

$$\langle g_i, g_j \rangle = \int_{-1}^1 g_i(x) g_j(x) dx$$

$$\tilde{g}_1 = x - \frac{\langle 1, x \rangle}{\langle 1, 1 \rangle}$$
$$= x$$

$$\langle 1, x \rangle = \int_{-1}^1 x dx = \left. \frac{x^2}{2} \right|_{-1}^1 = 0$$

$$\langle 1, 1 \rangle = \int_{-1}^1 1 dx = x \Big|_{-1}^1 = 2$$

$$\tilde{g}_2 = x^2 - \frac{\langle 1, x^2 \rangle}{\langle 1, 1 \rangle} - \frac{\langle x, x^2 \rangle}{\langle x, x \rangle} x$$
$$= x^2 - \frac{1}{3}$$

$$\langle 1, x^2 \rangle = \langle x, x \rangle = \int_{-1}^1 x^2 dx = \frac{2}{3}$$

$$\langle x, x^2 \rangle = \int_{-1}^1 x^3 dx = 0$$

orthogonal

Orthogonal Polynomial Recurrences

For the k th polynomial in an orthog set
 \exists an a_k (not dep on x) st.

$q_k(x) - a_k x q_{k-1}(x)$ is a poly of degree $k-1$

$$\therefore q_k(x) - a_k x q_{k-1}(x) = \sum_{i=0}^{k-1} c_i q_i(x) \text{ for some } c_i$$

$$q_k(x) = (a_k x + c_{k-1}) q_{k-1}(x) + c_{k-2} q_{k-2}(x) + \dots$$

$$c_0 = c_1 = \dots = c_{k-3} = 0$$

for some a_k, b_k, c_k

$$\therefore q_k(x) = (a_k x + b_k) q_{k-1}(x) - c_k q_{k-2}(x)$$

Polynomial Recurrence Example

~~Ex~~ Legendre Polynomials

$$p_k(x) = \frac{2k-1}{k} x p_{k-1}(x) - \frac{k-1}{k} p_{k-2}(x)$$

Using Orthogonal Polynomial for Statistics

Q: How to apply O.P. to a data set $\mathcal{X} = \{x_1, x_2, \dots, x_n\}$ from an unknown density p ?

A: Let's suppose $f(x) = g(x)p(x)$ where $p(x)$ is a prob. density function. Then for any orthonormal set $\{q_i(x)\}$ we can approx f

$$f(x) = \sum_{k=0}^{\infty} a_k q_k(x) \quad \{a_k\}?$$

Finding c_k from \mathbf{X}

$$f(x) = \sum_{k=0}^{\infty} c_k q_k(x)$$

$$\begin{aligned} c_k = \langle f, q_k \rangle &= \int_{\mathcal{D}} q_k(x) f(x) p(x) dx \\ &= E[q_k(X) f(X)] \end{aligned}$$

where $X \sim p$

$\therefore X_1, \dots, X_n$ then we can unbiasedly est c_k
by

$$\hat{c}_k = \frac{1}{n} \sum_{i=1}^n q_k(x_i) f(x_i)$$

Our Function Estimator... Finally

$$\hat{f}(x) = \frac{1}{n} \sum_{k=0}^v \sum_{i=1}^n g_k(x_i) g(x_i) g_k(x)$$

$$f(x) = g(x)p(x)$$

iid x_1, \dots, x_n
 $\sim f$

if $f(x)$ is a density

$$C_k = E[g_k(x)]$$

$$\begin{aligned} \hat{f}(x) &= \sum_{k=0}^v E[g_k(x)] g_k(x) \\ &= \frac{1}{n} \sum_{k=0}^v \left[\sum_{i=1}^n g_k(x_i) \right] g_k(x) \end{aligned}$$