

Polynomial Approximation

in L_2

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So far we talked about interpolation as a way to approximate a non polynomial function $f(x)$ on some interval $[a, b]$. The advantages are:

- 1) All we needed were values of the function at the $(n+1)$ interpolation nodes, we didn't even need to know the function $f(x)$ [^{"black box"} mode]

①

2) Easy to evaluate interpolant using barycentric interpolation.

The main disadvantages are:

1) The choice of nodes really matters and equi-spaced is bad

2) Even if $P_n(x_k) = f(x_k)$ at the nodes, this does not guarantee anything about $|f(x) - p(x)|$ for x in-between the nodes (recall Runge function)

We improved on these issues

by using piecewise polynomial interpolation like splines, but that was not very accurate

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so to get 16 digits in $f(x)$
we would need thousands of
nodes/points.

Is there another way to
approximate $f(x)$ by $P_n(x)$
on $[a, b]$?

Yes!

$$P_n^* = \arg \min_{P_n \in \mathcal{P}^n} \|f - P_n\|_2$$

"Least squares" polynomial approx,

This is just like doing least
squares fitting to data, but
now we use the function
 L_2 norm not vector one.

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E.g. Approximate $f(x) = -2x^2$
with a constant function ($n=0!$)

on $[-1, 1]$:

$$\|f - p_0\|_2^2 = \int_{-1}^1 (-2x^2 - a_0)^2 dx$$

$$\boxed{P_0(x) = a_0} = 2a_0^2 + \frac{8a_0}{3} + \frac{8}{5}$$

$$a_0^* = \arg \min_{a_0} \left(2a_0^2 + \frac{8a_0}{3} + \frac{8}{5} \right)$$

$$\left. \frac{d}{da_0} \left(2a_0^2 + \frac{8a_0}{3} + \frac{8}{5} \right) \right|_{a_0=a^*} = 0 \Rightarrow$$

$$a_0^* = -\frac{2}{3} = p_0^*(x)$$

Better & more instructive
is to do this for a general
 $f(x)$ [OFTEN SIMPLER!!!] ④

$$a_0^* = \arg \min \int (f(x) - a_0)^2 dx$$

$$= \arg \min \int f(x)^2 dx - 2a_0 \int f(x) dx$$

↗ + $\int a_0^2 dx$

Differentiate w.r.t a_0 :

$$2 a_0^* \int dx - 2 \int f(x) dx = 0$$

$$\Rightarrow a_0^* = \frac{\int f(x) dx}{\int dx} = \frac{\int f(x) dx}{b-a}$$

which is simply the mean

(average) of $f(x)$ over $[a, b]$.

$$\text{If } f(x) = -2x^2, \text{ mean} = \frac{-2 \int_{-1}^1 x^2 dx}{2} = -\frac{2}{3} \quad (5)$$

Let's now repeat this for an arbitrary degree polynomial.

First, choose a basis for \mathcal{P}_n :

$$\text{basis} = \{p_0(x), p_1(x), p_2(x), \dots, p_n(x)\}$$

$$p_n^*(x) = \sum_{j=0}^n a_j p_j(x) = \begin{matrix} \text{best } L_2 \\ \text{approximation} \end{matrix}$$

How do we find the $(n+1)$ coefficients \vec{a} ? (drop *)

Standard approach in textbooks:

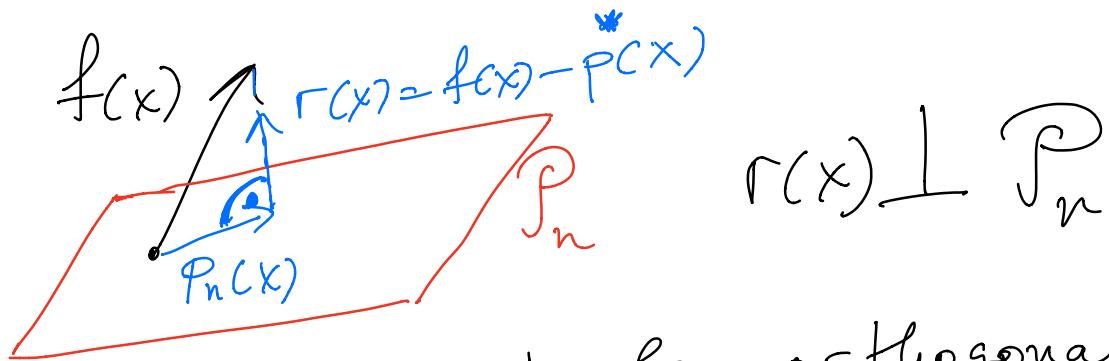
$$F(\vec{a}) = \int_a^b \left(f(x) - \sum c_j p_j(x) \right)^2 dx$$

$$\frac{\partial F}{\partial a_k} = 0, \quad k=0, \dots, n+1$$

$\nwarrow_{(n+1) \text{ equations}}$

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Easy to do by expanding the square. But let's instead follow a more linear algebra "geometric" approach:



$$r(x) \perp P_n$$

Residual must be orthogonal to all polynomials of degree n , i.e., it must be orthogonal to $P_k(x)$, $k=0, \dots, n$.

$$(r, P_k) = 0 \quad \forall k$$

$$(f - P_n^*, P_k) = 0 \quad \forall k$$

\Rightarrow

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$$(f - p_n^*, \varphi_k) = 0 \quad \forall k$$

$$(f - \sum_{j=0}^n a_j \varphi_j, \varphi_k) = 0$$

$$\left(\sum_{j=0}^n a_j \varphi_j, \varphi_k \right) = (f, \varphi_k)$$

 (properties of inner product)

$$\sum_{j=0}^n a_j (\varphi_j, \varphi_k) = (f, \varphi_k)$$

$k = 0, \dots, n+1$

 n+1 equations for n+1 unknowns

⑧

In matrix form

$$\begin{matrix} \leftarrow \\ V \end{matrix} \vec{a} = \vec{f}$$

$$V_{ij} = (P_i, P_j) = \int_a^b P_i(x) P_j(x) dx$$

(A "Vandermonde" matrix)

$$\vec{f}_k = (f, P_k) = \int_a^b f(x) P_k(x) dx$$

Here we assumed a real-valued function.

Once again, like for interpolation, it boils down to solving a linear system!

Expensive? Ill-conditioned?

⑨

Let's take monomials as

basis :

$$P_k(x) = x^k \text{ on } [0, 1]$$

$$V_{ij} = \int_0^1 x^i x^j dx = \frac{x^{i+j+1}}{i+j+1} \Big|_0^1$$

$$V_{ij} = \frac{1}{i+j+1} \leftarrow \begin{matrix} \text{Hilbert} \\ \text{matrix} \end{matrix}$$

You learned in worksheets that the Hilbert matrix is very ill conditioned, just like the Vandermonde matrix.

So using a monomial basis is not a good idea.

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Instead, we need something akin to Lagrange polynomials for interpolation but for L_2 approximation.

What this means is that we want to choose basis such that $V_{ij} = \delta_{ij}$, i.e.,

\vec{V} is the identity matrix, because then we have

$$a_k = (f, p_k) = \int f(x) p_k(x) dx$$

if $V_{ij} = \int p_i(x) p_j(x) dx = \delta_{ij}$

$$\Rightarrow \int p_i(x) p_j(x) dx = 0$$

(11) if $i \neq j$ or 1 if $i=j$

This means that we want to use as basis a set of $(n+1)$ orthogonal polynomials.

How do we find an orthonormal basis for P_n ?

I.E. how do we find an orthonormal basis for the space spanned by $\{x^0, x^1, \dots, x^n\}$?

In the case of vectors, we did this using QR factorization, which was really simply doing the Gram-Schmidt orthogonalization process.

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