# Sparse Grids

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Main job: Investigating sparse grid methods.

### Intepolation 1

The sparse grid method is a method used for interpolation or integration. It selects a subset of the full tensor product collocation points to construct the interpolation. It is an approximation of the full tensor product method, which is a linear combination of tensor product formulas. It sacrifices the accuracy of logarithmic loss and obtains a large computational reduction, which effectively alleviates the curse of dimensionality in the case of high dimensions.

#### 1.1 1D Interpolation

Let  $f:[0,1]\to\mathbb{R}$  be a function in 1D, We can approximate it with the following interpolation formula:

$$U^{k}(f) = \sum_{j=1}^{m_{k}} f(\xi_{j}^{k}) l_{j}^{k}(\xi) , k \ge 1 , U^{0} = 0$$

U is the interpolation operator with the set of support nodes  $\mathcal{X}^k = \{\xi_i^k \mid \xi_i^k \in$  $[0,1], j=1,2...,m_k$  and interpolation basis functions  $l^k=\{l_i^k\mid l_i^k\in\mathcal{C}[0,1],j=1\}$  $1, 2..., m_k$ , the interpolation basis functions satisfy  $l_j^k(\xi_i^k) = \delta_{ij}$ . Here k and  $m_k$  refer to the depth of interpolation and the total number of support nodes at depth k, respectively. The chioce of support nodes and interpolation basis functions can be as follows[1],

(1) Equidistant nodes with piecewise linear basis functions

$$m_k = \begin{cases} 1 & \text{if } k = 1 \\ 2^{k-1} + 1 & \text{if } k > 1 \end{cases}$$
 
$$\xi_j^k = \begin{cases} 0.5 & \text{for } j = 1 \text{ if } m_k = 1 \\ \frac{j-1}{m_k-1} & \text{for } j = 1, ..., m_k \text{ if } m_k > 1 \end{cases}$$
 
$$l_j^k(\xi) = 1, k = 1$$
 
$$l_j^k(\xi) = \begin{cases} 1 - (m_k - 1) \mid \xi - \xi_j^k \mid, & \text{if } \mid \xi - \xi_j^k \mid < \frac{1}{m_k - 1} \\ 0, & \text{otherwise}, \end{cases}$$

(2) Chebyshev Gauss–Lobatto nodes (CGL) with Lagrange polynomial basis functions

$$m_k = \begin{cases} 1 & \text{if } k = 1 \\ 2^{k-1} + 1 & \text{if } k > 1 \end{cases}$$

$$\xi_j^k = \begin{cases} 0.5 & \text{for } j = 1 \text{ if } m_k = 1 \\ (1 - \cos(\frac{(j-1)\pi}{m_k - 1}))/2 & \text{for } j = 1, ..., m_k \text{ if } m_k > 1 \end{cases}$$

$$l_j^k(\xi) = \begin{cases} 1, & k = 1 \\ \prod_{i=1, i \neq j}^{m_k} \frac{\xi - \xi_i^k}{\xi_j^k - \xi_i^k}, & k > 1, j = 1, ..., m_k \end{cases}$$
is easy to see that the points are perted, that is  $\mathcal{X}_j^k \subset \mathcal{X}_j^{k+1}$ .

It is easy to see that the points are nested, that is  $\mathcal{X}^k \subset \mathcal{X}^{k+1}$ 

#### 1.2Hierarchical interpolation

Due to the property of nested points the interpolation can be written as a hierarchical form[2]. We first define the incremental interpolant  $\Delta^k = U^k$  $U^{k-1}$ ,  $\forall k \ge 1$ . Thus,

$$\begin{split} U^{k-1}, & \forall k \geq 1. \text{ Thus,} \\ & \Delta^k(f) = U^k(f) - U^{k-1}(f) \\ & \text{and we have } U^{k-1}(f) = U^k(U^{k-1}(f)). \text{ Using this, we obtain} \\ & \Delta^k(f) = \sum_{\xi_j^k \in \mathcal{X}^k} f(\xi_j^k) l_j^k - \sum_{\xi_j^k \in \mathcal{X}^k} U^{k-1}(f) (\xi_j^k) l_j^k \\ & = \sum_{\xi_j^k \in \mathcal{X}^k} (f(\xi_j^k) - U^{k-1}(f) (\xi_j^k)) l_j^k \\ & \text{due to } f(\xi_j^k) - U^{k-1}(f) (\xi_j^k) = 0 \; \forall \; \xi_j^k \in \mathcal{X}^{k-1} \;, \text{ we have} \\ & \Delta^k(f) = \sum_{\xi_j^k \in \mathcal{X}_\Delta^k} (f(\xi_j^k) - U^{k-1}(f) (\xi_j^k)) l_j^k \end{split}$$

where  $\mathcal{X}_{\Delta}^{k}$  denotes the nodes added by interpolation from depth k-1 to depth kdue to the property of nested nodes, we can easy to see it have  $m_k^{\Delta} = m_k - m_{k-1}$ nodes. Thus we can rewrite above formula as,

$$\Delta^{k}(f) = \sum_{j=1}^{m_{k}^{\Delta}} \underbrace{(f(\xi_{j}^{k}) - U^{k-1}(f)(\xi_{j}^{k}))}_{w_{j}^{k}} l_{j}^{k}$$

We define  $w_i^k$  as the 1D hierarchical surpluses, which is the difference between the actual function value and the value obtained using the interpolant at the  $\mathcal{X}_{\Delta}^{k}$ . The  $l_{i}^{k}$  we call it hierarchical basis functions. By shifting the terms we can

$$U^{k}(f) = U^{k-1}(f) + \Delta^{k}(f) = \sum_{i=1}^{k} \Delta^{i}(f)$$

the set of support nodes can be rewritten as  $\mathcal{X}^k = \bigcup_{i=1}^k \mathcal{X}^i_{\Delta}$ .

#### 1.3 Multi-variate interpolation

The multi-variate interpolation formula could simply use tensor product of univariate interpolation formula to construct, given as

$$U^{k_1} \otimes \cdots \otimes U^{k_d}(f) = \sum_{\substack{\xi_{j_1}^{k_1} \in \mathcal{X}^{k_1} \\ j_d \in \mathcal{X}^{k_d}}} \cdots \sum_{\substack{\xi_{j_d}^{k_d} \in \mathcal{X}^{k_d} \\ j_d \in \mathcal{X}^{k_d}}} f(\xi_{j_1}^{k_1}, \dots, \xi_{j_d}^{k_d}) \cdot (l_{j_1}^{k_1} \otimes \cdots \otimes l_{j_d}^{k_d})$$

where  $\mathbf{k} = [k_1, \dots, k_d]$  represents the depth of interpolation used in each dimension. The hierarchical form can be rewritten as,

$$U^{k_1} \otimes \cdots \otimes U^{k_d}(f) = \sum_{i_1=1}^{k_1} \cdots \sum_{i_d=1}^{k_d} (\Delta^{i_1} \otimes \cdots \otimes \Delta^{i_d})(f)$$

### Sparse Grids $\mathbf{2}$

Sparse grid interpolation is a linear combination of tensor products of onedimensional interpolation. In the high-dimensional case, it obtains a large reduction in computational effort by sacrificing some interpolation accuracy. It is an approximation of the full tensor product method and also known as Smolyak

algorithm[3], the algorithm give the formula as,
$$A(q,d)(f) = \sum_{|\mathbf{k}| \leq d+q} (\Delta^{k_1} \otimes \cdots \otimes \Delta^{k_d})(f) = A(q-1,d)(f) + \Delta A(q,d)(f)$$

with A(-1,d)=0, and  $|\mathbf{k}|=k_1+\ldots k_d$ . The d-dimensional incremental sparse

with 
$$A(-1,d) = 0$$
, and  $|\mathbf{k}| = k_1 + \dots k_d$ . The d-dimensional incremental sparse interpolant  $\Delta A(q,d)(f)$ , can be written as,
$$\Delta A(q,d)(f) = \sum_{|\mathbf{k}| = d+q} (\Delta^{k_1} \otimes \dots \otimes \Delta^{k_d})(f)$$

$$= \sum_{|\mathbf{k}| = d+q} \sum_{\mathbf{j}} \underbrace{(l_{j_1}^{k_1} \otimes \dots \otimes l_{j_d}^{k_d})}_{l_{\mathbf{j}}^{\mathbf{k}}} \cdot \underbrace{(f(\xi_{j_1}^{k_1}, \dots, \xi_{j_d}^{k_d}) - A(q-1,d)(f)(\xi_{j_1}^{k_1}, \dots, \xi_{j_d}^{k_d}))}_{w_{\mathbf{j}}^{\mathbf{k}}}$$

where  $\mathbf{j}=(j_1,\ldots,j_d)$  denotes the multi-index. As for the 1D case, the coefficients  $w_{\mathbf{i}}^{\mathbf{k}}$  are defined as hierarchical surpluses. Most of the time people use its explicit form,

$$A(q,d) = \sum_{q-d+1 \le |\mathbf{k}| \le q} (-1)^{q-|\mathbf{k}|} \binom{d-1}{q-|\mathbf{k}|} \cdot (U^{k_1} \otimes \cdots \otimes U^{k_d})(f)$$

### References

- [1] N. Agarwal and N. R. Aluru, "A domain adaptive stochastic collocation approach for analysis of mems under uncertainties," Journal of Computational Physics, vol. 228, no. 20, pp. 7662-7688, 2009.
- [2] A. Klimke, "Piecewise multilinear sparse grid interpolation in matlab," 2003.
- [3] S. A. Smolyak, "Quadrature and interpolation formulas for tensor products of certain classes of functions," in Doklady Akademii Nauk, vol. 148, no. 5. Russian Academy of Sciences, 1963, pp. 1042–1045.