

# Ramansh Sharma Written Qualifying Exam

Read the questions carefully. Follow the indicated page lengths. Feel free to cite references. You have one week.

1. Let  $0 < m < d_1, d_2 < \infty$  be integers. Let  $(X_1, Y_1), \dots, (X_N, Y_N)$  be data points in  $\mathbb{R}^{d_1} \times \mathbb{R}^{d_2}$ .

We want to derive a kernelized autoencoder. Given a kernel  $K$  on  $\mathbb{R}^{d_1}$  with RKHS  $\mathcal{H}_K$  and a kernel  $\Gamma$  on  $\mathbb{R}^{d_2}$  with RKHS  $\mathcal{H}_\Gamma$ , we seek

$$g = (g_1, \dots, g_m), \quad g_i \in \mathcal{H}_K, \quad f = (f_1, \dots, f_{d_2}), \quad f_j \in \mathcal{H}_\Gamma,$$

that minimize

$$\min_{g_1, \dots, g_m \in \mathcal{H}_K, f_1, \dots, f_{d_2} \in \mathcal{H}_\Gamma} \sum_{i=1}^m \|g_i\|_K^2 + \sum_{j=1}^{d_2} \|f_j\|_\Gamma^2 + \lambda \|f \circ g(X) - Y\|_2^2, \quad (1)$$

where  $X = (X_1, \dots, X_N)$ ,  $Y = (Y_1, \dots, Y_N)$ , and  $f \circ g(X)$  denotes the vector  $(f(g(X_1)), \dots, f(g(X_N)))$ . Reduce (1) to a finite-dimensional optimization problem.

**Recommended answer length: less than a page. AI/LLM not allowed. Answer:**

In order to reduce (1) to a finite-dimensional problem, we have to rewrite the functions  $(g_1, \dots, g_m)$  and  $(f_1, \dots, f_{d_2})$  in terms of their respective reproducing kernels. We assume kernels  $K$  and  $\Gamma$  are real valued kernels. By definition [Fasshauer and McCourt, 2015, Chapter 2.3], the real valued functions from the RKHS  $\mathcal{H}_K$  and  $\mathcal{H}_\Gamma$  can respectively be written as,

$$g_i(\cdot) = \sum_{p=1}^N c_p^i K(\cdot, \mathbf{x}_p), \quad (2)$$

$$f_j(\cdot) = \sum_{k=1}^m d_k^j \Gamma(\cdot, \mathbf{y}_k), \quad (3)$$

where  $i$  and  $j$  denote the indices of the functions from the respective RKHS and  $\mathbf{x} \in \mathbb{R}^{d_1}, \mathbf{y} \in \mathbb{R}^{d_2}$  are arbitrary points in the respective domains of the kernels. Using the properties of symmetry and positive definiteness of reproducing kernels [Fasshauer and

McCourt, 2015, Chapter 2.3], and the forms of functions that belong to RKHS described above, we have the following Hilbert space norms,

$$\|g_i\|_K^2 = \langle g_i, g_i \rangle_K = \left\langle \sum_{p=1}^N c_p^i K(\cdot, \mathbf{x}_p), \sum_{b=1}^N c_b^i K(\cdot, \mathbf{x}_b) \right\rangle = (\mathbf{c}^i)^\top \mathbf{K} \mathbf{c}^i, \quad (4)$$

$$\|f_j\|_\Gamma^2 = \langle f_j, f_j \rangle_\Gamma = \left\langle \sum_{k=1}^m d_k^j \Gamma(\cdot, \mathbf{y}_k), \sum_{t=1}^m d_t^j \Gamma(\cdot, \mathbf{y}_t) \right\rangle = (\mathbf{d}^j)^\top \mathbf{\Gamma} \mathbf{d}^j, \quad (5)$$

where,  $\mathbf{K}$  and  $\mathbf{\Gamma}$  are the full  $(N \times N)$  and  $(m \times m)$  kernel matrices respectively. The goal now is to rewrite (1) as an optimization problem in terms of the expansion coefficients  $\mathbf{c}$  and  $\mathbf{d}$ . We reformulate (1) below,

$$\min_{\mathbf{c}^1, \dots, \mathbf{c}^m, \mathbf{d}^1, \dots, \mathbf{d}^{d_2}} \sum_{i=1}^m (\mathbf{c}^i)^\top \mathbf{K} \mathbf{c}^i + \sum_{j=1}^{d_2} (\mathbf{d}^j)^\top \mathbf{\Gamma} \mathbf{d}^j + \lambda \sum_{n=1}^N \left( \begin{bmatrix} f_1(g(X_n)) \\ f_2(g(X_n)) \\ \vdots \\ f_{d_2}(g(X_n)) \end{bmatrix} - Y_n \right)^2, \quad (6)$$

$$\min_{\mathbf{c}^1, \dots, \mathbf{c}^m, \mathbf{d}^1, \dots, \mathbf{d}^{d_2}} \sum_{i=1}^m (\mathbf{c}^i)^\top \mathbf{K} \mathbf{c}^i + \sum_{j=1}^{d_2} (\mathbf{d}^j)^\top \mathbf{\Gamma} \mathbf{d}^j + \lambda \sum_{n=1}^N \sum_{j=1}^{d_2} (f_j(g(X_n)) - Y_n^j)^2, \quad (7)$$

where  $X_n$  and  $Y_n$  are the  $n^{\text{th}}$  data points respectively. For brevity, we use  $\mathbf{g}_n$  to denote  $g(X_n) = (\mathbf{K}(X_n, X) \mathbf{c}^1, \dots, \mathbf{K}(X_n, X) \mathbf{c}^m)$ , where  $\mathbf{K}(X_n, X)$  is a column vector. Further, let  $\mathbf{g} = (\mathbf{g}_1, \mathbf{g}_2, \dots, \mathbf{g}_N)$ . Then, (7) can be written as,

$$\min_{\mathbf{c}^1, \dots, \mathbf{c}^m, \mathbf{d}^1, \dots, \mathbf{d}^{d_2}} \sum_{i=1}^m (\mathbf{c}^i)^\top \mathbf{K} \mathbf{c}^i + \sum_{j=1}^{d_2} (\mathbf{d}^j)^\top \mathbf{\Gamma} \mathbf{d}^j + \lambda \sum_{n=1}^N \sum_{j=1}^{d_2} (\mathbf{\Gamma}(\mathbf{g}_n, \mathbf{g}) \mathbf{d}_j - Y_n^j)^2. \quad (8)$$

In the final form shown in (8), the optimization problem is with respect to the finite-dimensional expansion coefficients  $(\mathbf{c}^1, \dots, \mathbf{c}^m)$  and  $(\mathbf{d}^1, \dots, \mathbf{d}^{d_2})$ .

2. Consider the setting of operator learning, with an oracle/exact operator  $G$ :

$$A \ni a \overset{G}{\mapsto} u \in U, \quad G \in B(A; U), \quad A = A(D_a; \mathbb{R}^a), \quad U = U(D_u; \mathbb{R}^u),$$

where  $A$  and  $U$  are function spaces (i.e., appropriate measure spaces, such as Hilbert or Banach spaces), with  $a, u \in \mathcal{N}$ . E.g.,  $A$  is a space of functions mapping some domain  $D_a$  to  $\mathbb{R}^a$ , where  $D_a$  is a subset of a Euclidean space. We likewise assume  $B$  is some measurable space of mappings (operators) that map elements in  $A$  to elements in  $U$ . We consider the *supervised* learning setting, where  $G$  is approximated through (possibly noisy) input-output pairs.

Informally, a *neural operator* is a model class mapping class  $A$  to  $U$  that is constructed through iterative applications of affine global operators with componentwise/local non-linear (“activation”) operators. Neural operator model classes with finite encodings are of particular interest, as they represent a feasible space of computable maps. The concept of *universal approximation* is popular to investigate in neural operators, with the goal to establish that, e.g., given an arbitrary  $G$  and tolerance  $\epsilon$ , there is a finite-encoding neural operator that is  $\epsilon$ -close to  $G$ .

Summarize the current state of universal approximation results/theorems in the literature, paying particular attention to pros and cons of these results (either individually or collectively). In particular, describe how (or if) one can use these universal approximation statements to guide computational construction of architectures. Propose a strategy to use some tools from existing methods for approximating functions over finite-dimensional spaces that might be used to provide more constructive and quantitatively rigorous methods for constructing neural operators.

In your response, consider the following aspects:

1. Provide a reasonable high-level survey of current universal approximation results. Theoretical precision is appreciated, but the main goal is to summarize overall strengths and weaknesses of approximability statements. It’s not important to cite every single result on universal approximation for neural operators, but provide enough breadth of narrative to cover “much” of the literature.
2. Identify the practical utility of universal approximation results in the computational construction of neural operators. I.e., how would you use these results to actually construct computational architectures? (Are these results useful for that purpose?)
3. Describe or propose how one might leverage existing quantitative results on approximation of functions to augment the current neural operator approximation theory. (Here, “quantitative” refers to actual, fairly precise rates of approximability or convergence for finite-dimensional approximation of functions.) In particular, how might one attempt to port quantitative results from function approximation to operators? What challenges require new investigations to address? It’s perhaps most useful to narrow this discussion to leveraging a particular class/type of function

approximation results, rather than attempting to broadly consider existing results on function approximation.

**Recommended answer length: 3-5 pages. AI/LLM not allowed.**

3. I will ask two questions both related to your work. Answer one in detail ( 1 page) and one in short ( 1/2 page) (your choice).

- (a) One of the challenges as I understand in SciML applications is that your error requirements are much more stringent than those in ML applications. For certain kinds of ML models, there are so-called "scaling laws" (e.g., <https://arxiv.org/pdf/2001.08361>). Go over the paper above, summarizing the main results. Would you expect analogous results for SciML applications (e.g., learning very simple PDEs' solutions), and if so, do you expect to drive the error to an arbitrarily small quantity? This is an open ended question, so please include references to existing work.
- (b) Study one of the early papers on "in context" learning, specifically: <https://arxiv.org/pdf/2208.01066>. While SciML papers do not think about what they do as ICL, expecting a model to learn a solution to a "new" PDE is quite similar in spirit. Go over the paper above and summarize the main results. There have been many follow up works to the paper above claiming that the distributions are important, etc., but one interesting paper is: <https://arxiv.org/pdf/2306.09927>. *Skim* the main results, but especially look at Section 4.2. Are you aware of analogous results in the SciML area? Does the distribution over boundary conditions, etc. matter for learnability?

**Answer:**

**Part a:** [Kaplan et al., 2020] is a study on neural scaling laws that investigates the effect of variables such as the model architecture, the model size (the network's width and depth for example), the computing power used to train, and the amount of training dataset on the overall performance. While related work exists that explore such trends in models such as random forests [Biau, 2012] and image models [Tan and Le, 2019], this study focuses on language models. The authors in [Kaplan et al., 2020] investigate and report power-law relationships between the performance (in terms of the loss on the test set) of the classical Transformer model [Vaswani et al., 2017] on the WebText2 dataset [Radford et al., 2019] and three main variables of interest; the number of model parameters  $N$ , the dataset size  $D$ , and the amount of compute required  $C$ . Across the variety of the experiments conducted, the following trends are reported in the paper:

- 1. **Power laws:** When not bottlenecked by the other two, the performance has a power-law relationship with each of the three factors  $N, D, C$ .
- 2. **Overfitting:** If suboptimal values of  $N$  or  $D$  are used, the performance incurs a penalty as the scaling variable is increased.
- 3. **Model size:** Large models tend to perform better overall; they need fewer optimization steps and a smaller dataset to achieve the same accuracy as smaller models. In fact, according to the authors the optimal performance is reached by training very large models and stopping significantly short of the convergence criteria.

4. **Transfer learning:** Interestingly, the model’s performance on a dataset from a different distribution than the training one is strongly correlated to the performance on the training set but with a constant offset.

Since these scaling laws do not assume any special properties about the functions they are approximating, it is reasonable to expect these trends to carry over to SciML applications. While it is hard to find such studies done for physics-informed neural networks (architectures that can learn a given PDE solution function), a number of scaling studies are done in the field of operator learning, where many operators of interest are solution operators of PDEs. For example, the original DeepONet (deep operator network) paper [Lu et al., 2019] showed various error convergence rates as a function of the amount of the network width, the amount of training data (number of functions), and the number of “sensor locations” (locations where the input functions are sampled). [de Hoop et al., 2022] reports power-law relationship between in- and out-of-distribution performance and the size of the training dataset for DeepONet, FNO, PCA-Net, and PARA-Net. [Lanthaler et al., 2022] studied the effect of the DeepONet network size on its approximation and generalization errors for specific operators. Finally, [Liu et al., 2024a] presents neural scaling laws (observed to be power laws) for DeepONets’ approximation and generalization errors for general Lipschitz operators with respect to model and dataset sizes. While according to the scaling laws for operator learning methods the error can be driven down arbitrarily, the empirical results from [Lu et al., 2019] show that this is not true. For example, Figure 6 in the paper shows that the relationship between training and test mean squared error with respect to the number of sensor locations initially follows a power law but plateaus after the number exceeds  $10^1$ . We see similar trends with the network width in Figure 2. This is consistent with the insights put forth by [Kaplan et al., 2020], that most scaling power laws plateau.

**Part b:** [Garg et al., 2022] aims to study in-context learning of function classes with transformers. In-context learning is the ability of a model to, for a *previously unseen* function  $f$ , accurately predict  $f(x_{i+1})$  at query point  $x_{i+1}$  when given a prompt of  $i$  “in context” sampling locations and samples of  $f$ ,  $(x_1, f(x_1), x_2, f(x_2), \dots, x_i, f(x_i))$ . For the class of linear functions, the transformer model can in-context learn well enough to be on par with several baselines; least squares estimator (known to be optimal),  $n$ -nearest neighbors, and averaging. In-context learning is also robust, it performs well even when the in-context outputs  $(f(x_1), f(x_2), \dots, f(x_i))$  are noisy at inference time and when the distribution of the in-context examples and the query differ. The transformer model is also shown to in-context learn other function classes, mainly sparse linear functions, decision trees, and shallow neural networks. [Zhang et al., 2024] go a step further and show how in-context learning is “learning a learning algorithm from data” and study different distribution shifts under which the standard approach fails. Section 4.2 revisits three such shifts; task ( $\mathcal{D}_f^{\text{train}} \neq \mathcal{D}_f^{\text{test}}$ ), query ( $\mathcal{D}_{\text{query}}^{\text{test}} \neq \mathcal{D}_x^{\text{test}}$ ), and covariate ( $\mathcal{D}_x^{\text{train}} \neq \mathcal{D}_x^{\text{test}}$ ). Transformers handle well the task and query shifts (the latter as long as  $\mathcal{D}_x^{\text{train}} = \mathcal{D}_x^{\text{test}}$ ) but not covariate shifts. Interestingly, the same covariate shift

phenomenon has been observed in SciML!

The original DeepONet paper [Lu et al., 2019] states clearly that in order for the architecture to work, the sensor locations must be constant across all instances, essentially requiring  $\mathcal{D}_x^{\text{train}} = \mathcal{D}_x^{\text{test}}$ . This is generally true for most operator learning methods, though there is some work exploring ways to mitigate this by learning function encoders [Ingebrand et al., 2025, Zhang et al., 2023]. Most operator learning architectures also suffer from task shifts but none from query shifts (either at training or test time). When learning solution operators of PDEs, often the input functions are different initial and/or boundary conditions. As such, in order to avoid suffering from task shifts, the instances of input functions across training and test sets need to come from the same underlying distribution.

4. (a) Please introduce and summarize existing operator learning methods. Please give some categories, and summarize pros and cons for each category.

**Recommendation: no less than 2 pages.**

- (b) What do you think about the future of operator learning? You can explain whatever thoughts you have, positive, negative, and future development direction, etc.

**Recommendation: no less than 1 page.**

**Answer:**

**Part a:** Scientific machine learning methods can be categorized into three areas [Boullé and Townsend, 2024]; (i) PDE solvers [Raissi et al., 2019], (ii) PDE discovery [Brunton et al., 2016], and operator learning. Operator learning methods *approximate* a “function-to-function” map between two separable infinite-dimensional function spaces. In the most general setting, consider two such Banach function spaces,  $\mathcal{U}(\Omega_u; \|\cdot\|_{\mathbb{R}^{d_u}})$  and  $\mathcal{V}(\Omega_v, \|\cdot\|_{\mathbb{R}^{d_v}})$  where  $\Omega_u \subset \mathbb{R}^{d_u}$  and  $\Omega_v \subset \mathbb{R}^{d_v}$ . Then, given a finite number of function pairs  $\{(u_1, v_1), (u_2, v_2), \dots, (u_N, v_N)\}$  where,  $u_i \in \mathcal{U}$  (input functions) and  $v_i \in \mathcal{V}$  (output functions), one aims to approximate the true operator  $\mathcal{G} : \mathcal{U} \rightarrow \mathcal{V}$  with some approximation  $\tilde{\mathcal{G}}$  such that  $\|\tilde{\mathcal{G}} - \mathcal{G}\|$  is minimized.

In recent years, with the advent of machine learning being used for SciML applications, many neural network architectures have emerged for operator learning. We enumerate and explain below the popular methods, neural network and otherwise.

- **DeepONet:** First introduced in [Lu et al., 2019], the DeepONet architecture consists of two networks, a branch network  $\beta : \mathbb{R}^{N_x} \rightarrow \mathbb{R}^p$  that takes an input function  $u$  sampled at  $N_x$  locations, and a trunk network  $\tau : \mathbb{R}^{d_v} \rightarrow \mathbb{R}^p$  that takes as input a  $d_v$  dimensional location to evaluate the output function at. The DeepONet output then is the  $p$ -dimensional inner product between the branch output (can be thought of as coefficients) multiplying the trunk output (a set of spatial basis functions for the output function space)  $\tilde{\mathcal{G}}(u)(y) = \langle \tau(y), \beta(u) \rangle$ , where  $y$  is a location where the output function is evaluated and  $u$  is sampled at some points  $\{x_i\}_{i=1}^{N_x} \in \Omega_u$ . The two networks are trained by minimizing the loss function  $\|\tilde{\mathcal{G}}(u_i)(y) - v_i(y)\|_2^2$  to some tolerance for all input-output function pairs (the output functions are sampled at  $N_y$  points  $\{y_k\}_{k=1}^{N_y} \in \Omega_v$ ). In fact, the same loss function is used by all neural operator architectures albeit with different parametrizations of  $\tilde{\mathcal{G}}$ .

The DeepONet is a simple but effective architecture. It’s architecture presents its output as a linear expansion of basis functions which allows problem-dependent basis functions to be picked (POD-DeepONet in [Lu et al., 2022], ensemble and partition-of-unity (PoU) DeepONets in [Sharma and Shankar, 2024]). However, while DeepONets are architecturally elegant and modifiable, they are generally outperformed by other neural operators.

- **FNO:** [Li et al., 2020a] introduced one of the most popular neural operator architectures. The FNO parametrizes the integral kernel in the Fourier space. Their architecture consists of a lifting operator for the input functions to multiple “channels”,



followed by multiple Fourier layers with kernel integral operators that parametrize the kernel with neural networks directly in the Fourier space by using the fast Fourier transform (FFT), and finally a projection layer that undoes the lifting operation. Let  $L$  and  $P$  be the lift and projection operators respectively and  $f_i$  denote the  $i^{th}$  of  $T$  intermediate Fourier layer. Then the FNO can simply be written as  $\mathcal{G}(u)(y) = P(\sigma(f_T(\sigma(\dots f_2(\sigma(f_1(L(u(y))))))\dots)))$ , where  $\sigma$  is a chosen nonlinear activation function. A given Fourier layer, say the  $(t+1)^{th}$  one, can be written as

$$f_{t+1}(y) = \sigma(\mathcal{F}^{-1}(\mathcal{F}(f_t)(x))(y) + Wf_t(y)), \quad (9)$$

where  $\mathcal{F}$  and  $\mathcal{F}^{-1}$  are the kernel integral operators defined in Fourier space using FFT and IFFT respectively, and  $W$  is a pointwise convolution operator. This architecture requires the functions to be sampled on points on equispaced grids, which has tremendous benefits as well as limitations. FNOs are naturally resolution-invariant and can do zero-shot super resolution (evaluate on a different resolution at inference time than the one it is trained on) accurately that other architectures such as CNNs cannot ([Li et al., 2020a, Section 4]). Various FNO architectures have emerged over the years that mitigate two primary issues in the original method, (i) the requirement for the functions to be on regular grids (as need by the FFT algorithm), and (ii) output functions being evaluated on a different set of points than the input functions. [Lu et al., 2022] came up with the gFNO and dFNO architectures that mitigate both these issues. [Li et al., 2023] came up with the geometry-aware FNO architecture that can work with arbitrary domain geometries. [Cao et al., 2024] came up with the Laplace Neural Operator (LNO) which uses the pole-residue relationship between the input and output function spaces and outperforms FNO. Finally, [Guo and Li, 2024] introduced the multi-grid FNO architecture that uses a three-level hierarchy; three different networks, for coarse scale, intermediate scale, fine scale are trained simultaneously to achieve high-resolution accuracy.

- **Deep green networks:** This class of neural operators learn the kernel of the kernel integral operator directly in the physical space [Gin et al., 2021, Boullé et al., 2022]. It parametrizes  $\tilde{\mathcal{G}}$  as

$$\tilde{\mathcal{G}}(u)(y) = \int_{\Omega} G(x, y)u(x)dx, \quad x \in \Omega, \quad (10)$$

where  $\Omega$  is the domain of the PDE whose solution operator is being learned and  $G : \Omega \times \Omega$  is the Green's kernel learned from the data parametrized as a neural network [Boullé et al., 2022]. A key advantage here is that the Green's kernel can be visualized. To discretize the integral operator a valid quadrature rule needs to be found which scales quadratically with the number of points where the function is evaluated [Boullé and Townsend, 2024].

- **Graph Neural Operator:** [Li et al., 2020b] came up with the graph neural operator (GNO) architecture which is similar to the deep green network (DGN) in that it aims to learn the Green’s kernel. However, instead of learning the kernel globally like in DGN, GNO performs the integral operation locally on a ball of radius  $r$ ,  $B(x, r)$  around each point  $x$ . This leads to the choice of discretizing  $\Omega$  with a graph whose nodes are the spatial points. GNO therefore instead approximates the local kernel  $G_r$ . [Li et al., 2020b] go over errors bounds for  $\|G - G_r\|_{L^2(\Omega \times \Omega)}$  and show that the limited kernel  $G_r$  well approximates  $G$  especially in higher dimensions. [Li et al., 2020c] build up on this idea with the **Multipole graph neural operator** (MGNO) that learns both short- and long-range interactions in  $G$  by decomposing the kernel into a sum of low rank kernels,  $G = K_1 + K_2 + \dots + K_L$ . This approach has the added advantage of evaluating the integral operation in linear complexity. Interestingly, MGNO is similar to DeepONets in that they both are low rank neural operators (because of the limitation of  $p$  basis functions in DeepONets), but the MGNO architecture is more flexible since the kernel it is approximation,  $G$ , itself is not low-rank [Boullé and Townsend, 2024]!
- **Kernels:** Finally, [Batlle et al., 2024] show that kernel methods are indeed competitive for operator learning! Using the theory of reproducible Kernel Hilbert spaces (RKHS) and Gaussian Processes (GP), the authors come up with an operator learning framework well supported by convergence proofs and error bounds. In many examples this method outperforms popular neural operator architectures. Given a chosen kernel  $K$  (for example the rational quadratic, Gaussian, or the class of Matérn kernels), the method approximates output functions as

$$\mathcal{G}(u) = K(u, U)K(U, U)^{-1}V, \quad (11)$$

where  $U$  and  $V$  are all the input and output functions “stacked” together as block vectors respectively. Since,  $K(U, U)^{-1}V$  can be computed once and stored, the inference time of this method is significantly smaller compared to neural operators! The method also has mesh invariance (see Section 2.4). Another huge advantage of GPs in this method is that uncertainty quantification is possible.

**Part b:** The field of operator learning is growing fast! The methods outlined above are already being used in real world scientific applications. To list some, weather and climate modeling [Bora et al., 2023, Pathak et al., 2022, Jiang et al., 2023, Yang et al., 2024], earthquake modeling [Haghighat et al., 2024], carbon sequestration [Lee et al., 2024], ocean modeling [Choi et al., 2024], hydrology [Sun et al., 2024], and material science [Gupta and Brandstetter, 2022, Oommen et al., 2024].

There are several directions of growth that the field is seeing. The first is a fundamental exploration of new neural operator architectures apart from the common ones listed above. [Kurz et al., 2024] uses shallow radial basis function neural networks to come up with the first neural operator to learn entirely in both time and frequency domains, and achieve small error in both in-distribution and out-of-distribution tests. [Ingebrand

et al., 2025] came up with a novel methodology to learn the underlying basis functions for both the input and output function spaces to be able to evaluate them at arbitrary locations at inference time. [Bhattacharya et al., 2021] introduced the PCA-Net architecture that reduces the dimensionality of input and output functions to a lower dimensional latent space where it learns the operator map. While this is not an exhaustive list, the salient trend to highlight here is the emergence of innovative architectures that borrow inspiration from a variety of traditional machine learning methods to bring to operator learning.

To further that note, [Hao et al., 2023] and Liu et al. [2025] are examples of the operator learning community moving to towards amalgamation with transformer style architectures. [Hao et al., 2023] designed a framework that allows for multiple input functions and irregular meshes. They also introduce a gating mechanism that can be viewed to help with multi-scale problems. [Liu et al., 2025] can make predictions on arbitrary geometries with surface point clouds that are unordered and have non-uniform point density on 2D and 3D problems, a remarkable feat compared to traditional neural operators. Other novel transformer based operator learning architectures include [Cao, 2021, Liu et al., 2024b, Li et al., 2022]. This is a very promising direction to scale operator learning methods on scientific applications to extremely large datasets using the expressivity of transformers and the efficient parallelized computational methods they’ve been developed with since their advent.

Finally, a crucial step forward necessary for operator learning methods for scientific computing applications is trustworthiness. Physical constraints such as conservation laws are hard to accurately build in as hard constraints into neural network architectures. Physical-informed hard constraints result in increased computational cost which requires specialized methods to make them feasible [Chalapathi et al., 2024]. A specific property of interest is the incompressibility constraint of velocity fields in fluid dynamics, commonly written as the divergence-free constraint. While there is attempt on building this constraint exactly into an FNO [Khorrami et al., 2024], problems still remain. My current work revolves around a novel kernel based operator learning method that can analytically encode not just the incompressibility constraint but other desirable properties while maintaining state-of-the-art accuracy on fluid dynamics problems. This leads into the most promising future direction for operator learning; trustworthy and expressive neural operator architectures for scientific computing applications.

5. Consider partition of unity (PoU) kernel methods in the context of divergence-free approximation. These methods allow one to scale global interpolation to very large numbers of points without a loss of computational efficiency. However, there are some specific challenges to applying PoU methods to divergence-free approximations. **Note that we are not talking about operator learning, but just function approximation/interpolation.**

**No AI/LLM allowed.**

- (a) It is quite straightforward to use a global divergence-free kernel for interpolation. However, in the PoU context, this is not straightforward at all. *Show why* mathematically.

**Recommendation: No more than 1/2 a page.**

- (b) Drake, Fuselier, and Wright present an approach in <https://arxiv.org/abs/2010.15898> that works for 2D approximations. Summarize their approach. What is the *primary mathematical* difficulty in applying their technique to 3D problems? Hint: It relates to the nature of the div-free potentials in 3D, Eq 2.10.

**Recommendation: No more than 1 page.**

- (c) How would you use machine learning (ML) to overcome these difficulties? Derive a new ML-based PoU technique to do so that is also divergence-free by construction; describe the ML architecture, point out how it overcomes the issue with the Drake-Fuselier-Wright method, discuss training procedures and difficulties. Briefly connect it to your answer in part 1. Assume you already have a div-free approximant/interpolant on each patch.

**Recommendation: 1-2 pages.**

## References

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