

Neural Operator

Problem Setting

Problem Setting

Our goal is to learn a map between two infinite dimensional spaces.

Problem Setting

Our goal is to learn a map between two infinite dimensional spaces.

$$\mathcal{G}_\theta : \mathcal{A} \rightarrow \mathcal{U}, \theta \in \mathbb{R}^p$$

Problem Setting

Our goal is to learn a map between two infinite dimensional spaces.

$$\mathcal{G}_\theta : \mathcal{A} \rightarrow \mathcal{U}, \theta \in \mathbb{R}^p$$

Here \mathcal{A} and \mathcal{U} are two function space.

Problem Setting

Our goal is to learn a map between two infinite dimensional spaces.

$$\mathcal{G}_\theta : \mathcal{A} \rightarrow \mathcal{U}, \theta \in \mathbb{R}^p$$

Here \mathcal{A} and \mathcal{U} are two function space.

For Equation $\mathcal{L}u = f \quad u = 0$ on $\partial\Omega$, we want to find $\mathcal{G} = \mathcal{L}^{-1}$ such that $u = \mathcal{G}[f]$, which directly solve the PDE.

Problem Setting

Our goal is to learn a map between two infinite dimensional spaces.

$$\mathcal{G}_\theta : \mathcal{A} \rightarrow \mathcal{U}, \theta \in \mathbb{R}^p$$

Here \mathcal{A} and \mathcal{U} are two function space.

For Equation $\mathcal{L}u = f \quad u = 0$ on $\partial\Omega$, we want to find $\mathcal{G} = \mathcal{L}^{-1}$ such that $u = \mathcal{G}[f]$, which directly solve the PDE.

Problem Setting

Example

Problem Setting

Example

Consider an ODE first:

Problem Setting

Example

Consider an ODE first:

$$\frac{du}{dt} = f(t), \quad u(0) = u_0$$

Problem Setting

Example

Consider an ODE first:

$$\frac{du}{dt} = f(t), \quad u(0) = u_0$$

Given $\{f_j, u_j\}_{j=1}^N$ pairs of functions, we want to learn the inverse operator.

Problem Setting

Example

Consider an ODE first:

$$\frac{du}{dt} = f(t), \quad u(0) = u_0$$

Given $\{f_j, u_j\}_{j=1}^N$ pairs of functions, we want to learn the inverse operator.

the inverse operator $u(t) = \mathcal{G}[f](t) = u_0 + \int_0^t f(\tau) d\tau$

Problem Setting

Example

Consider an ODE first:

$$\frac{du}{dt} = f(t), \quad u(0) = u_0$$

Given $\{f_j, u_j\}_{j=1}^N$ pairs of functions, we want to learn the inverse operator.

the inverse operator $u(t) = \mathcal{G}[f](t) = u_0 + \int_0^t f(\tau) d\tau$

Problem Setting

Example

Problem Setting

Example

Consider a second order elliptic equation:

Problem Setting

Example

Consider a second order elliptic equation:

$$-\nabla(a(x)\nabla u(x)) = f(x) \quad x \in \Omega$$

$$u(x) = 0 \quad x \in \partial\Omega$$

Problem Setting

Example

Consider a second order elliptic equation:

$$-\nabla(a(x)\nabla u(x)) = f(x) \quad x \in \Omega$$

$$u(x) = 0 \quad x \in \partial\Omega$$

Given $\{a_j, u_j\}$ pairs of functions, want to learn the inverse operator.

Problem Setting

Example

Consider a second order elliptic equation:

$$\begin{aligned} -\nabla(a(x)\nabla u(x)) &= f(x) & x \in \Omega \\ u(x) &= 0 & x \in \partial\Omega \end{aligned}$$

Given $\{a_j, u_j\}$ pairs of functions, want to learn the inverse operator.

the inverse operator $u(x) = \mathcal{G}[a](x) = \int_{\Omega} G_a(x, y)f(y)dy$, where G_a is the green's function

Problem Setting

Example

Consider a second order elliptic equation:

$$\begin{aligned} -\nabla(a(x)\nabla u(x)) &= f(x) & x \in \Omega \\ u(x) &= 0 & x \in \partial\Omega \end{aligned}$$

Given $\{a_j, u_j\}$ pairs of functions, want to learn the inverse operator.

the inverse operator $u(x) = \mathcal{G}[a](x) = \int_{\Omega} G_a(x, y)f(y)dy$, where G_a is the green's function

Deep ONet

Network Structure

Deep ONet

Network Structure

$$\mathcal{G}[a](y) = \sum_{k=1}^p \sum_{i=1}^n c_i^k \sigma \left(\sum_{j=1}^m w_{ij}^k u(x_j) + b_i^k \right) \sigma(\omega_k y + \beta)$$

Deep ONet

Network Structure

$$\mathcal{G}[a](y) = \sum_{k=1}^p \sum_{i=1}^n c_i^k \sigma \left(\sum_{j=1}^m w_{ij}^k u(x_j) + b_i^k \right) \sigma(\omega_k y + \beta)$$

where $j = 0, \dots, m$, and x_j are the uniform mesh points on the space, for example $x_j = \frac{j}{m} \in [0,1]$ in one dimensional case.

Deep ONet

Network Structure

$$\mathcal{G}[a](y) = \sum_{k=1}^p \sum_{i=1}^n c_i^k \sigma \left(\sum_{j=1}^m w_{ij}^k u(x_j) + b_i^k \right) \sigma(\omega_k y + \beta)$$

where $j = 0, \dots, m$, and x_j are the uniform mesh points on the space, for example $x_j = \frac{j}{m} \in [0,1]$ in one dimensional case.

Banch block: $b_k(u(x_1), \dots, u(x_m)) = \sum_{i=1}^n c_i^k \sigma \left(\sum_{j=1}^m w_{ij}^k u(x_j) + b_i^k \right)$

Deep ONet

Network Structure

$$\mathcal{G}[a](y) = \sum_{k=1}^p \sum_{i=1}^n c_i^k \sigma \left(\sum_{j=1}^m w_{ij}^k u(x_j) + b_i^k \right) \sigma(\omega_k y + \beta)$$

where $j = 0, \dots, m$, and x_j are the uniform mesh points on the space, for example $x_j = \frac{j}{m} \in [0,1]$ in one dimensional case.

Banch block: $b_k(u(x_1), \dots, u(x_m)) = \sum_{i=1}^n c_i^k \sigma \left(\sum_{j=1}^m w_{ij}^k u(x_j) + b_i^k \right)$

Trunk block: $t_k(y) = \sigma(\omega_k y + \beta_k)$

Deep ONet

Network Structure

$$\mathcal{G}[a](y) = \sum_{k=1}^p \sum_{i=1}^n c_i^k \sigma \left(\sum_{j=1}^m w_{ij}^k u(x_j) + b_i^k \right) \sigma(\omega_k y + \beta)$$

where $j = 0, \dots, m$, and x_j are the uniform mesh points on the space, for example $x_j = \frac{j}{m} \in [0,1]$ in one dimensional case.

Banch block: $b_k(u(x_1), \dots, u(x_m)) = \sum_{i=1}^n c_i^k \sigma \left(\sum_{j=1}^m w_{ij}^k u(x_j) + b_i^k \right)$

Trunk block: $t_k(y) = \sigma(\omega_k y + \beta_k)$

The full network is done as $\mathcal{G}[u](y) = \sum_{k=1}^p b_k t_k(y)$

Neural Operators

Network Structure

Neural Operators

Network Structure

Lifting \mathcal{P} : Using a pointwise function $\mathbb{R}^{d_a} \rightarrow \mathbb{R}^{d_{v_0}}$, map the input function

Neural Operators

Network Structure

Lifting \mathcal{P} : Using a pointwise function $\mathbb{R}^{d_a} \rightarrow \mathbb{R}^{d_{v_0}}$, map the input function

$$\{a(x) : \Omega \rightarrow \mathbb{R}^a\} \rightarrow \{v_0(x) : \Omega \rightarrow \mathbb{R}^{d_{v_0}}\}. (d_{v_0} > d_a)$$

Neural Operators

Network Structure

Lifting \mathcal{P} : Using a pointwise function $\mathbb{R}^{d_a} \rightarrow \mathbb{R}^{d_{v_0}}$, map the input function

$$\{a(x) : \Omega \rightarrow \mathbb{R}^a\} \rightarrow \{v_0(x) : \Omega \rightarrow \mathbb{R}^{d_{v_0}}\}. (d_{v_0} > d_a)$$

Iterative Kernel Integration: for $l = 0, \dots, L - 1$, map each hidden representation to next

Neural Operators

Network Structure

Lifting \mathcal{P} : Using a pointwise function $\mathbb{R}^{d_a} \rightarrow \mathbb{R}^{d_{v_0}}$, map the input function

$$\{a(x) : \Omega \rightarrow \mathbb{R}^a\} \rightarrow \{v_0(x) : \Omega \rightarrow \mathbb{R}^{d_{v_0}}\}. (d_{v_0} > d_a)$$

Iterative Kernel Integration: for $l = 0, \dots, L - 1$, map each hidden representation to next

$$\{v_l(x) : \Omega \rightarrow \mathbb{R}^{d_{v_l}}\} \rightarrow \{v_{l+1}(x) : \Omega \rightarrow \mathbb{R}^{d_{v_{l+1}}}\}$$

Neural Operators

Network Structure

Lifting \mathcal{P} : Using a pointwise function $\mathbb{R}^{d_a} \rightarrow \mathbb{R}^{d_{v_0}}$, map the input function

$$\{a(x) : \Omega \rightarrow \mathbb{R}^a\} \rightarrow \{v_0(x) : \Omega \rightarrow \mathbb{R}^{d_{v_0}}\}. (d_{v_0} > d_a)$$

Iterative Kernel Integration: for $l = 0, \dots, L - 1$, map each hidden representation to next

$$\{v_l(x) : \Omega \rightarrow \mathbb{R}^{d_{v_l}}\} \rightarrow \{v_{l+1}(x) : \Omega \rightarrow \mathbb{R}^{d_{v_{l+1}}}\}$$

Projection: using a pointwise function $\mathcal{Q} : \mathbb{R}^{d_{v_T}} \rightarrow \mathbb{R}^{d_u}$

Neural Operators

Network Structure

Lifting \mathcal{P} : Using a pointwise function $\mathbb{R}^{d_a} \rightarrow \mathbb{R}^{d_{v_0}}$, map the input function

$$\{a(x) : \Omega \rightarrow \mathbb{R}^a\} \rightarrow \{v_0(x) : \Omega \rightarrow \mathbb{R}^{d_{v_0}}\}. (d_{v_0} > d_a)$$

Iterative Kernel Integration: for $l = 0, \dots, L - 1$, map each hidden representation to next

$$\{v_l(x) : \Omega \rightarrow \mathbb{R}^{d_{v_l}}\} \rightarrow \{v_{l+1}(x) : \Omega \rightarrow \mathbb{R}^{d_{v_{l+1}}}\}$$

Projection: using a pointwise function $\mathcal{Q} : \mathbb{R}^{d_{v_T}} \rightarrow \mathbb{R}^{d_u}$

$$\{v_L(x) : \Omega \rightarrow \mathbb{R}^{d_{v_L}}\} \rightarrow \{u(x) : \Omega \rightarrow \mathbb{R}^{d_u}\}$$

Neural Operators

Integral Kernel Operators

Neural Operators

Integral Kernel Operators

V1:

Neural Operators

Integral Kernel Operators

V1:

$$(\mathcal{K}_l[v_l])(x) = \int_{\Omega} \kappa^{(l)}(x, y) v_l(y) \, dy \quad \forall x \in \Omega.$$

Neural Operators

Integral Kernel Operators

V1:

$$(\mathcal{K}_l[v_l])(x) = \int_{\Omega} \kappa^{(l)}(x, y) v_l(y) \, dy \quad \forall x \in \Omega.$$

where $\kappa^{(l)} : \Omega \times \Omega \rightarrow \mathcal{R}^{d_{v_{l+1}} \times d_{v_l}}$.

Neural Operators

Integral Kernel Operators

V1:

$$(\mathcal{K}_l[v_l])(x) = \int_{\Omega} \kappa^{(l)}(x, y) v_l(y) \, dy \quad \forall x \in \Omega.$$

where $\kappa^{(l)} : \Omega \times \Omega \rightarrow \mathcal{R}^{d_{v_{l+1}} \times d_{v_l}}$.

V2:

Neural Operators

Integral Kernel Operators

V1:

$$(\mathcal{K}_l[v_l])(x) = \int_{\Omega} \kappa^{(l)}(x, y) v_l(y) \, dy \quad \forall x \in \Omega.$$

where $\kappa^{(l)} : \Omega \times \Omega \rightarrow \mathcal{R}^{d_{v_{l+1}} \times d_{v_l}}$.

V2:

$$(\mathcal{K}_l[v_l])(x) = \int_{\Omega} \kappa^{(l)}(x, y, a(x), a(y)) v_l(y) \, dy$$

Neural Operators

Integral Kernel Operators

V1:

$$(\mathcal{K}_l[v_l])(x) = \int_{\Omega} \kappa^{(l)}(x, y) v_l(y) \, dy \quad \forall x \in \Omega.$$

where $\kappa^{(l)} : \Omega \times \Omega \rightarrow \mathcal{R}^{d_{v_{l+1}} \times d_{v_l}}$.

V2:

$$(\mathcal{K}_l[v_l])(x) = \int_{\Omega} \kappa^{(l)}(x, y, a(x), a(y)) v_l(y) \, dy$$

where $\kappa^{(l)} : \Omega \times \Omega \times \mathbb{R}^{d_a} \times \mathbb{R}^{d_a} \rightarrow \mathcal{R}^{d_{v_{l+1}} \times d_{v_l}}$.

Neural Operators

Integral Kernel Operators

V1:

$$(\mathcal{K}_l[v_l])(x) = \int_{\Omega} \kappa^{(l)}(x, y) v_l(y) \, dy \quad \forall x \in \Omega.$$

where $\kappa^{(l)} : \Omega \times \Omega \rightarrow \mathcal{R}^{d_{v_{l+1}} \times d_{v_l}}$.

V2:

$$(\mathcal{K}_l[v_l])(x) = \int_{\Omega} \kappa^{(l)}(x, y, a(x), a(y)) v_l(y) \, dy$$

where $\kappa^{(l)} : \Omega \times \Omega \times \mathbb{R}^{d_a} \times \mathbb{R}^{d_a} \rightarrow \mathcal{R}^{d_{v_{l+1}} \times d_{v_l}}$.

V3:

Neural Operators

Integral Kernel Operators

V1:

$$(\mathcal{K}_l[v_l])(x) = \int_{\Omega} \kappa^{(l)}(x, y) v_l(y) \, dy \quad \forall x \in \Omega.$$

where $\kappa^{(l)} : \Omega \times \Omega \rightarrow \mathcal{R}^{d_{v_{l+1}} \times d_{v_l}}$.

V2:

$$(\mathcal{K}_l[v_l])(x) = \int_{\Omega} \kappa^{(l)}(x, y, a(x), a(y)) v_l(y) \, dy$$

where $\kappa^{(l)} : \Omega \times \Omega \times \mathbb{R}^{d_a} \times \mathbb{R}^{d_a} \rightarrow \mathcal{R}^{d_{v_{l+1}} \times d_{v_l}}$.

V3:

$$(\mathcal{K}_l[v_l])(x) = \int_{\Omega} \kappa^{(l)}(x, y, v_l(x), v_l(y)) v_l(y) \, dy$$

Neural Operators

Integral Kernel Operators

V1:

$$(\mathcal{K}_l[v_l])(x) = \int_{\Omega} \kappa^{(l)}(x, y) v_l(y) \, dy \quad \forall x \in \Omega.$$

where $k^{(l)} : \Omega \times \Omega \rightarrow \mathcal{R}^{d_{v_{l+1}} \times d_{v_l}}$.

V2:

$$(\mathcal{K}_l[v_l])(x) = \int_{\Omega} \kappa^{(l)}(x, y, a(x), a(y)) v_l(y) \, dy$$

where $k^{(l)} : \Omega \times \Omega \times \mathbb{R}^{d_a} \times \mathbb{R}^{d_a} \rightarrow \mathcal{R}^{d_{v_{l+1}} \times d_{v_l}}$.

V3:

$$(\mathcal{K}_l[v_l])(x) = \int_{\Omega} \kappa^{(l)}(x, y, v_l(x), v_l(y)) v_l(y) \, dy$$

where $k^{(l)} : \Omega \times \Omega \times \mathbb{R}^{d_l} \times \mathbb{R}^{d_l} \rightarrow \mathcal{R}^{d_{v_{l+1}} \times d_{v_l}}$.

Neural Operators

Integral Kernel Operators

V1:

$$(\mathcal{K}_l[v_l])(x) = \int_{\Omega} \kappa^{(l)}(x, y) v_l(y) \, dy \quad \forall x \in \Omega.$$

where $k^{(l)} : \Omega \times \Omega \rightarrow \mathcal{R}^{d_{v_{l+1}} \times d_{v_l}}$.

V2:

$$(\mathcal{K}_l[v_l])(x) = \int_{\Omega} \kappa^{(l)}(x, y, a(x), a(y)) v_l(y) \, dy$$

where $k^{(l)} : \Omega \times \Omega \times \mathbb{R}^{d_a} \times \mathbb{R}^{d_a} \rightarrow \mathcal{R}^{d_{v_{l+1}} \times d_{v_l}}$.

V3:

$$(\mathcal{K}_l[v_l])(x) = \int_{\Omega} \kappa^{(l)}(x, y, v_l(x), v_l(y)) v_l(y) \, dy$$

where $k^{(l)} : \Omega \times \Omega \times \mathbb{R}^{d_l} \times \mathbb{R}^{d_l} \rightarrow \mathcal{R}^{d_{v_{l+1}} \times d_{v_l}}$.

$$v_{l+1}(x) = \sigma(W_l v_l(x) + \mathcal{K}_l([v_l])(x) + b_l(x))$$

Neural Operators

Integral Kernel Operators

V1:

$$(\mathcal{K}_l[v_l])(x) = \int_{\Omega} \kappa^{(l)}(x, y) v_l(y) \, dy \quad \forall x \in \Omega.$$

where $k^{(l)} : \Omega \times \Omega \rightarrow \mathcal{R}^{d_{v_{l+1}} \times d_{v_l}}$.

V2:

$$(\mathcal{K}_l[v_l])(x) = \int_{\Omega} \kappa^{(l)}(x, y, a(x), a(y)) v_l(y) \, dy$$

where $k^{(l)} : \Omega \times \Omega \times \mathbb{R}^{d_a} \times \mathbb{R}^{d_a} \rightarrow \mathcal{R}^{d_{v_{l+1}} \times d_{v_l}}$.

V3:

$$(\mathcal{K}_l[v_l])(x) = \int_{\Omega} \kappa^{(l)}(x, y, v_l(x), v_l(y)) v_l(y) \, dy$$

where $k^{(l)} : \Omega \times \Omega \times \mathbb{R}^{d_l} \times \mathbb{R}^{d_l} \rightarrow \mathcal{R}^{d_{v_{l+1}} \times d_{v_l}}$.

$$v_{l+1}(x) = \sigma(W_l v_l(x) + \mathcal{K}_l([v_l])(x) + b_l(x))$$

Fourier Neural Operator

Motivation

Fourier Neural Operator

Motivation

Define for f :

Fourier Neural Operator

Motivation

Define for f :

$$(\mathcal{F}f)(k) = \int f(x) \exp(-2\pi i \langle x, k \rangle)$$

$$(\mathcal{F}^{-1}f)(x) = \int f(k) \exp(2\pi i \langle x, k \rangle)$$

Fourier Neural Operator

Motivation

Define for f :

$$(\mathcal{F}f)(k) = \int f(x) \exp(-2\pi i \langle x, k \rangle)$$

$$(\mathcal{F}^{-1}f)(x) = \int f(k) \exp(2\pi i \langle x, k \rangle)$$

Fourier integral operator \mathcal{K} :

Fourier Neural Operator

Motivation

Define for f :

$$(\mathcal{F}f)(k) = \int f(x) \exp(-2\pi i \langle x, k \rangle)$$

$$(\mathcal{F}^{-1}f)(x) = \int f(k) \exp(2\pi i \langle x, k \rangle)$$

Fourier integral operator \mathcal{K} :

$$(\mathcal{K}(\phi)v_l)(x) = \mathcal{F}^{-1}(R_\theta \cdot \mathcal{F}(v_l))(x)$$

Fourier Neural Operator

Motivation

Define for f :

$$(\mathcal{F}f)(k) = \int f(x) \exp(-2\pi i \langle x, k \rangle)$$

$$(\mathcal{F}^{-1}f)(x) = \int f(k) \exp(2\pi i \langle x, k \rangle)$$

Fourier integral operator \mathcal{K} :

$$(\mathcal{K}(\phi)v_l)(x) = \mathcal{F}^{-1}(R_\theta \cdot \mathcal{F}(v_l))(x)$$

For frequency mode $k \in \mathbb{Z}^d$ and $v_l : \Omega \subset \mathbb{R}^d \rightarrow \mathbb{R}^{d_{v_l}}$, we have $(\mathcal{F}v_l)(k) \in \mathbb{C}^{d_{v_l}}$ and $R_\theta(k) \in \mathbb{C}^{d_{v_l} \times d_{v_{l+1}}}$

Fourier Neural Operator

Choice for \mathbf{R}

Fourier Neural Operator

Choice for \mathbf{R}

Direct: Define the parameters $\theta_k \in \mathbb{C}^{d_{v_l} \times d_{v_{l+1}}}$ for each wave number k :

Fourier Neural Operator

Choice for \mathbf{R}

Direct: Define the parameters $\theta_k \in \mathbb{C}^{d_{v_l} \times d_{v_{l+1}}}$ for each wave number k :

$$R_{\theta}(k, \mathcal{F} v_l(k)) := \theta_k$$

Fourier Neural Operator

Choice for \mathbf{R}

Direct: Define the parameters $\theta_k \in \mathbb{C}^{d_{v_l} \times d_{v_{l+1}}}$ for each wave number k :

$$R_{\theta}(k, \mathcal{F} v_l(k)) := \theta_k$$

Linear: Define the parameters $\theta_{1,k} \in \mathbb{C}^{d_{v_{l+1}} \times d_{v_l} \times d_a}$ and $\theta_{2,k} \in \mathbb{C}^{d_{v_{l+1}} \times d_{v_l}}$ for each wave number k :

Fourier Neural Operator

Choice for \mathbf{R}

Direct: Define the parameters $\theta_k \in \mathbb{C}^{d_{v_l} \times d_{v_{l+1}}}$ for each wave number k :

$$R_{\theta}(k, \mathcal{F} v_l(k)) := \theta_k$$

Linear: Define the parameters $\theta_{1,k} \in \mathbb{C}^{d_{v_{l+1}} \times d_{v_l} \times d_a}$ and $\theta_{2,k} \in \mathbb{C}^{d_{v_{l+1}} \times d_{v_l}}$ for each wave number k :

$$R_{\theta}(k, \mathcal{F} v_l(k)) := \theta_{1,k}(\mathcal{F} a)(k) + \theta_{2,k}$$

Fourier Neural Operator

Choice for \mathbf{R}

Direct: Define the parameters $\theta_k \in \mathbb{C}^{d_{v_l} \times d_{v_{l+1}}}$ for each wave number k :

$$R_\theta(k, \mathcal{F}v_l(k)) := \theta_k$$

Linear: Define the parameters $\theta_{1,k} \in \mathbb{C}^{d_{v_{l+1}} \times d_{v_l} \times d_a}$ and $\theta_{2,k} \in \mathbb{C}^{d_{v_{l+1}} \times d_{v_l}}$ for each wave number k :

$$R_\theta(k, \mathcal{F}v_l(k)) := \theta_{1,k}(\mathcal{F}a)(k) + \theta_{2,k}$$

Neural Network: Let $\Phi_\theta : \mathbb{Z}^d \times \mathbb{C}^{d_a} \rightarrow \mathbb{C}^{d_{v_l} \times d_{v_{l+1}}}$ then:

Fourier Neural Operator

Choice for \mathbf{R}

Direct: Define the parameters $\theta_k \in \mathbb{C}^{d_{v_l} \times d_{v_{l+1}}}$ for each wave number k :

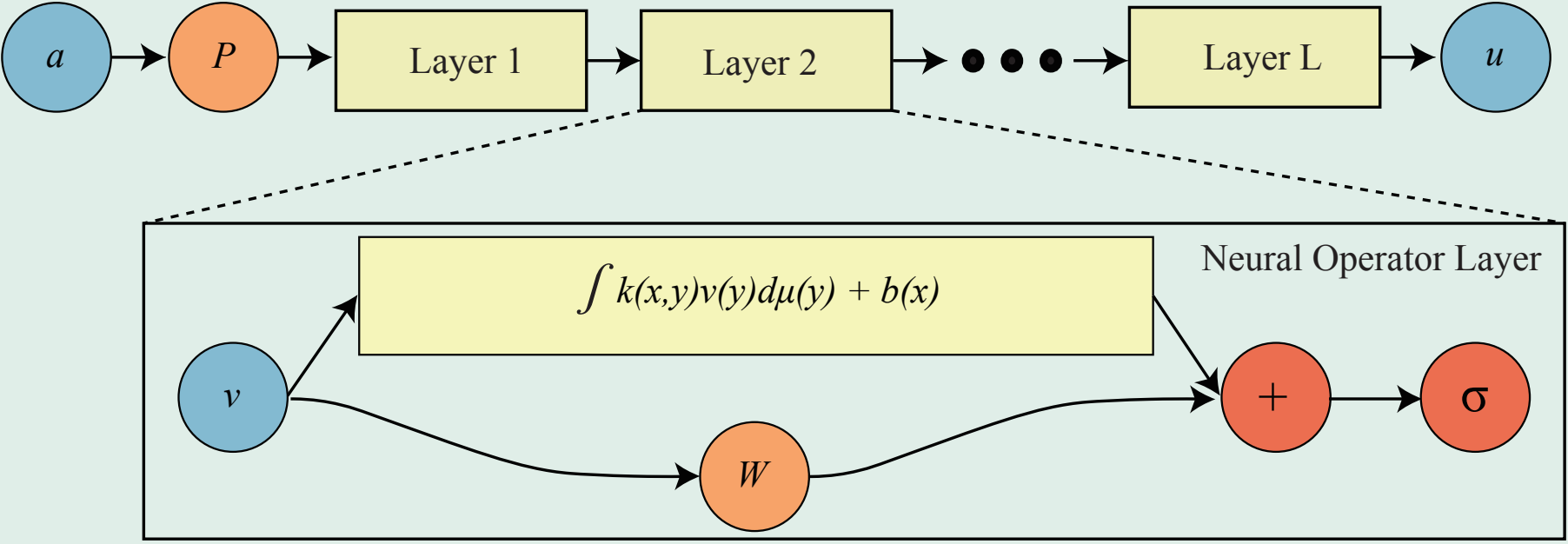
$$R_\theta(k, \mathcal{F}v_l(k)) := \theta_k$$

Linear: Define the parameters $\theta_{1,k} \in \mathbb{C}^{d_{v_{l+1}} \times d_{v_l} \times d_a}$ and $\theta_{2,k} \in \mathbb{C}^{d_{v_{l+1}} \times d_{v_l}}$ for each wave number k :

$$R_\theta(k, \mathcal{F}v_l(k)) := \theta_{1,k}(\mathcal{F}a)(k) + \theta_{2,k}$$

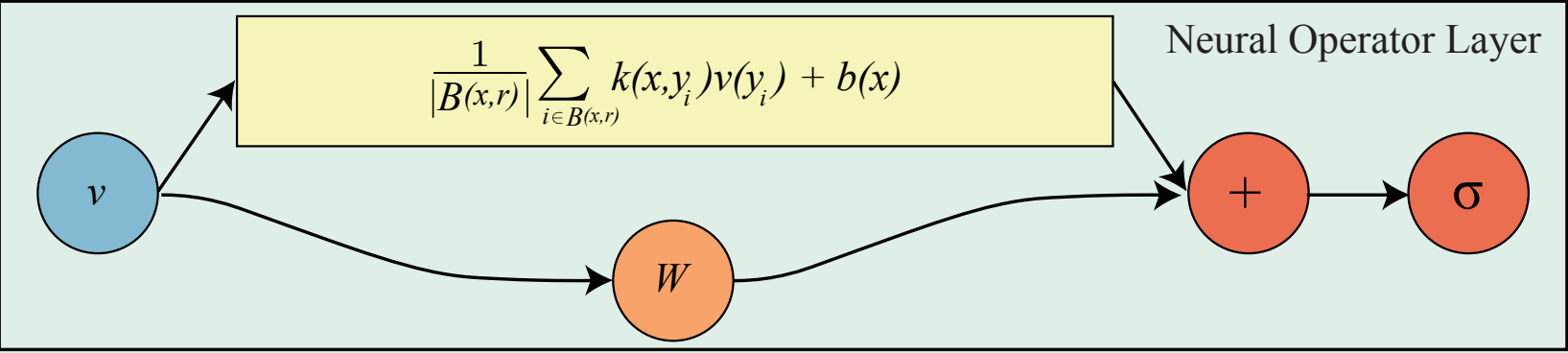
Neural Network: Let $\Phi_\theta : \mathbb{Z}^d \times \mathbb{C}^{d_a} \rightarrow \mathbb{C}^{d_{v_l} \times d_{v_{l+1}}}$ then:

$$R_\theta(k, \mathcal{F}v_l(k)) := \Phi_\theta(k, (\mathcal{F}a)(k))$$

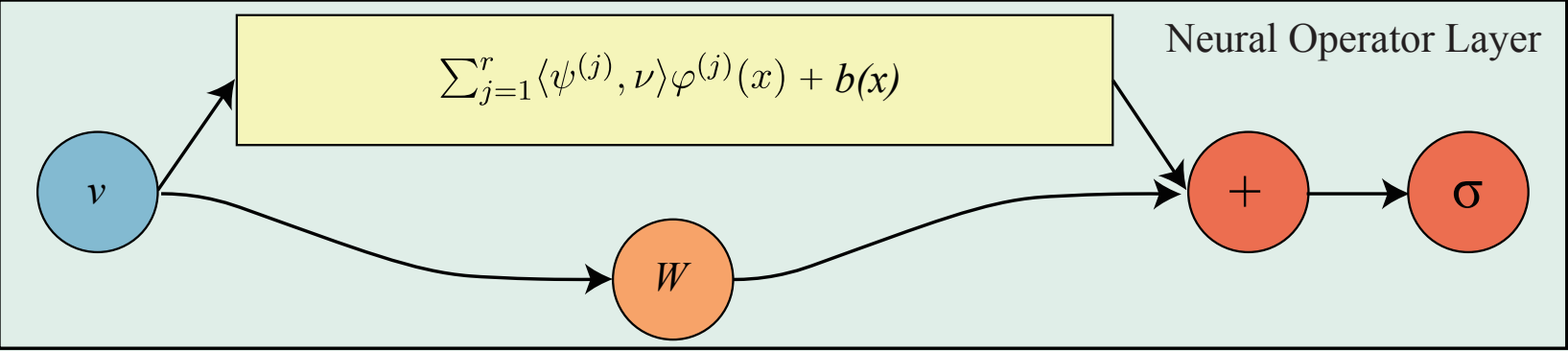


Instantiations of neural operator layer

GNO layer



LNO layer



FNO layer

