Message Passing Neural PDE Solvers

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Partial Differential Equations (PDEs) of the form

$$
\partial_t \mathbf{u} = F(t, \mathbf{x}, \mathbf{u}, \partial_{\mathbf{x}} \mathbf{u}, \partial_{\mathbf{x}} \mathbf{x}, \dots) \tag{1}
$$

are abundant, yet numerical PDE solving is a **splitter field**:

User requirements, structural requirements, implementation requirements

Goal is to design a **fully numerical PDE solver** which offers flexibility to satisfy as many requirements as possible.

Common way to solve PDEs is to approximate **spatial derivatives** and solve for **temporal derivatives**.

Message passing neural network to update $\mathbf{u}(\mathbf{x},t) \rightarrow \mathbf{u}'(\mathbf{x},t')$:

 \mathbf{u}^t_i *i* is a node in the graph with coordinates **x***i* .

$$
\blacksquare \,\, \mathsf{Message}_{\mathsf{edge} \, j \to i} : \,\, \mathbf{m}_{ij}^m = \phi\left(\mathbf{f}_i^m, \mathbf{f}_j^m, \mathbf{u}_i^t - \mathbf{u}_j^t, \mathbf{x}_i - \mathbf{x}_j, \theta_{\mathsf{PDE}}\right).
$$

- Generalizes **estimation of spatial derivatives**.
- Finite difference, finite volume and WENO scheme are representationally contained (if one, two, or three message passing layers are used).

Decoder is a shallow 1D convolutional network with shared weights across spatial locations.

- Smoothes signal over time.
- Reminiscent of linear multistep methods (**temporal update**).

Solving PDEs iteratively gives strong physical interpretability, however:

- Hard to train since errors at test time accumulate.
- \blacksquare How to enforce stability? How to simulate error input distribution in training?

Temporal bundling and pushforward trick

- **Pushforward trick**: mimics distribution shift via adversarial perturbation.
- **Temporal bundling:** synchronous prediction of multiple future timesteps.

One-step training Gradients flow back one time step only

Unrolled training Gradients flow back through all time steps

Pushforward training Gradients flow only through last time step

Generalization across different equations, different resolutions

Generalization across boundary conditions, irregular grids, applicability to higher dimensional problems

POSTER: 7134 PAPER: MESSAGE PASSING NEURAL PDE Solvers *arXiv:2202.03376* **Code**: *https://github.com/brandstetterjohannes/MP-Neural-PDE-Solvers*