

# Message Passing Neural PDE Solvers

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## Generalizing neural PDE solver

Partial Differential Equations (PDEs) of the form

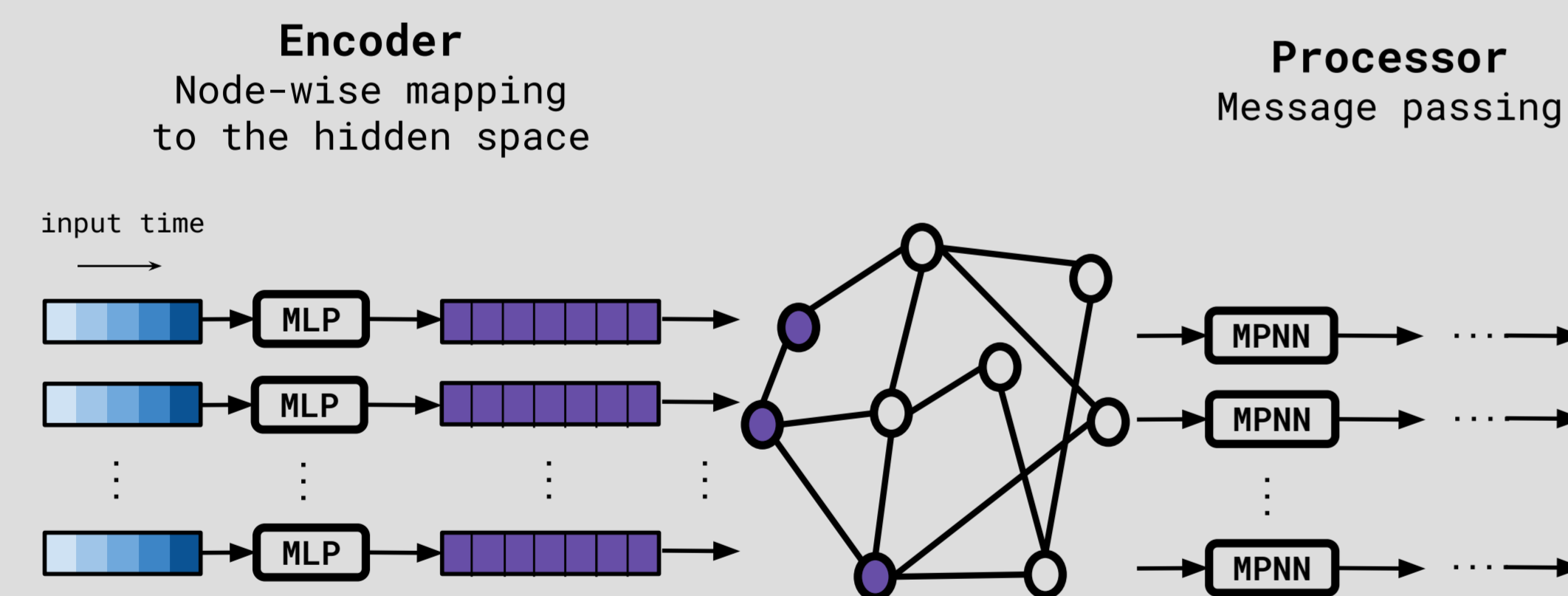
$$\partial_t \mathbf{u} = F(t, \mathbf{x}, \mathbf{u}, \partial_x \mathbf{u}, \partial_{xx} \mathbf{u}, \dots)$$

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

- 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  $\mathbf{u}(\mathbf{x}, t) \rightarrow \mathbf{u}'(\mathbf{x}, t')$

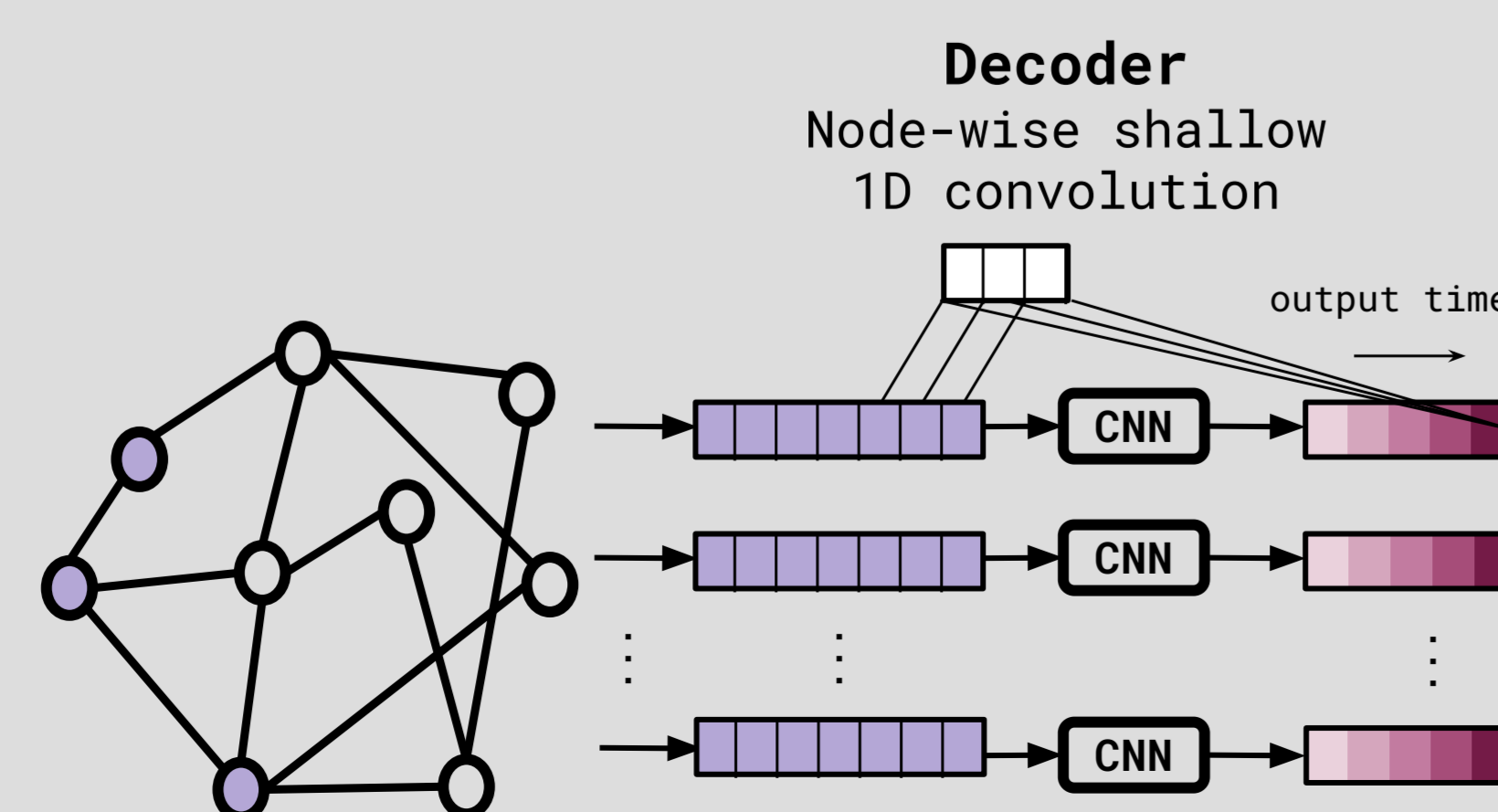
## Representational containment of spatial solvers

- Message<sub>edge  $j \rightarrow i$</sub> :  $\mathbf{m}_{ij}^m = \phi(\mathbf{f}_i^m, \mathbf{f}_j^m, \mathbf{u}_i^t - \mathbf{u}_j^t, \mathbf{x}_i - \mathbf{x}_j, \theta_{\text{PDE}})$ .
- 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).



## Representational containment of temporal solvers

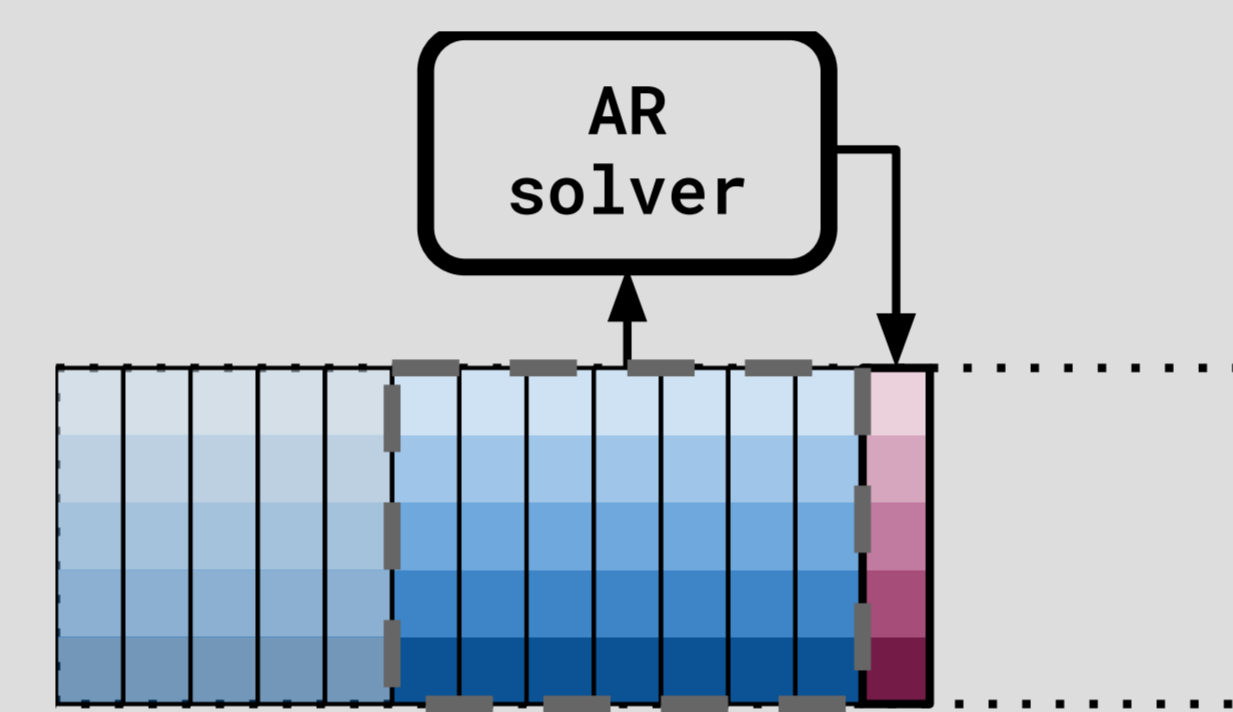
Decoder as 1D convolutional network with shared weights across spatial locations (reminiscent of **linear multistep methods**).



## Challenges for autoregressive solvers

Solving PDEs iteratively gives strong physical interpretability, however:

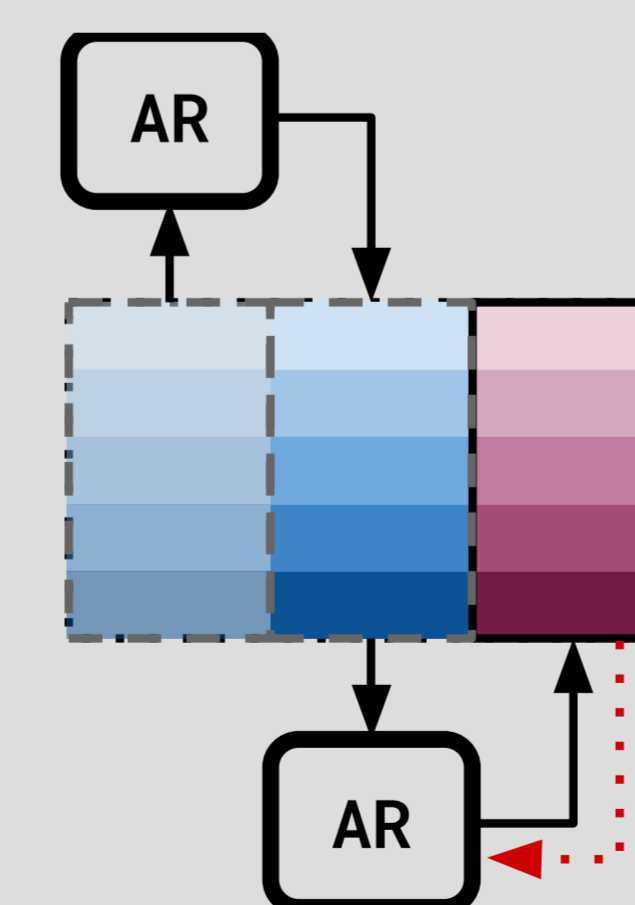
- Hard to train since errors at test time accumulate.
- How to enforce stability? How to simulate error input distribution in training?



**Autoregressive model**  
Mapping between temporally consecutive time steps

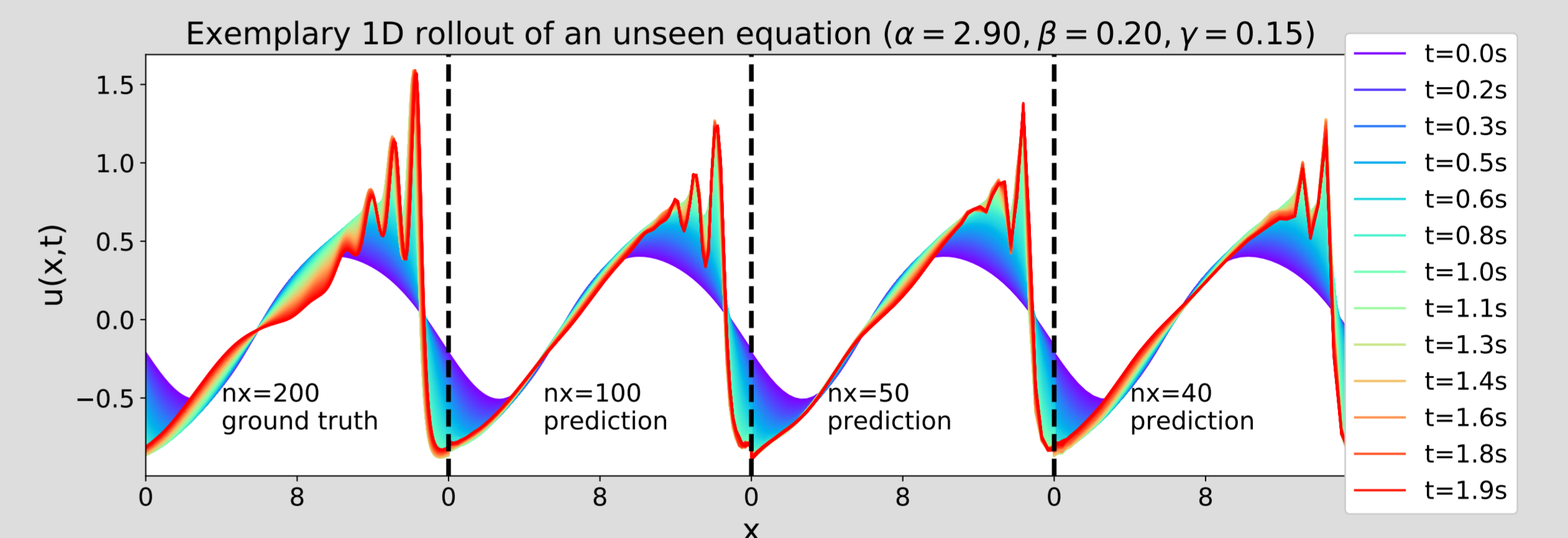
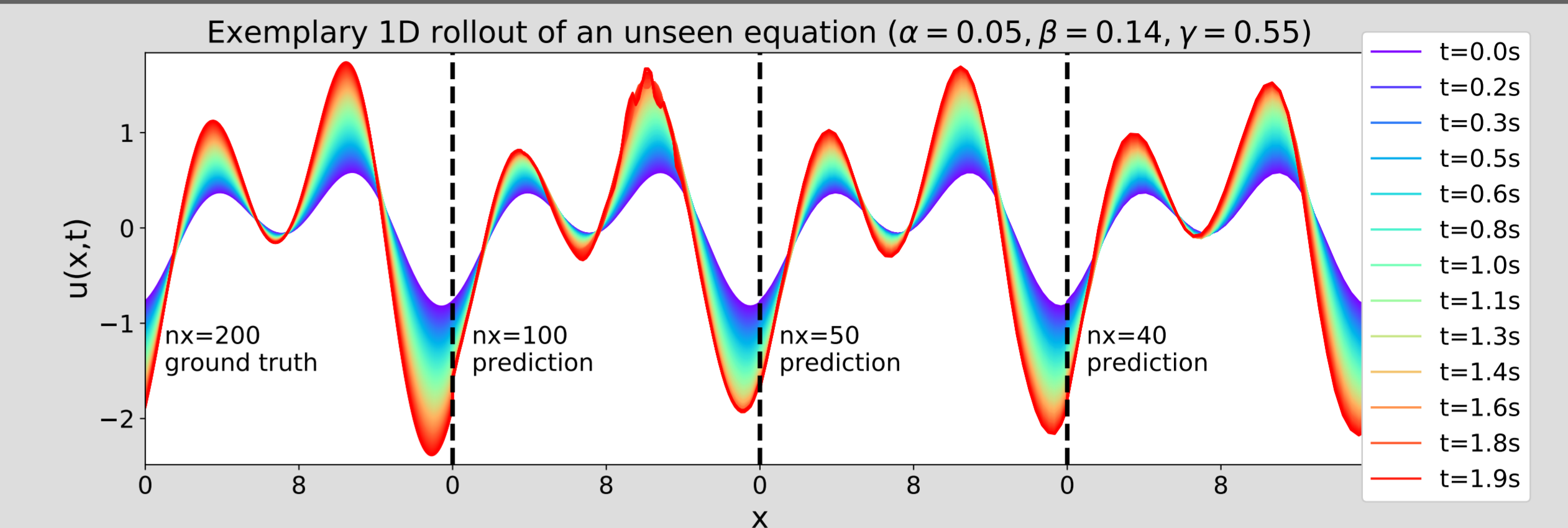
## Temporal bundling, pushforward trick

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

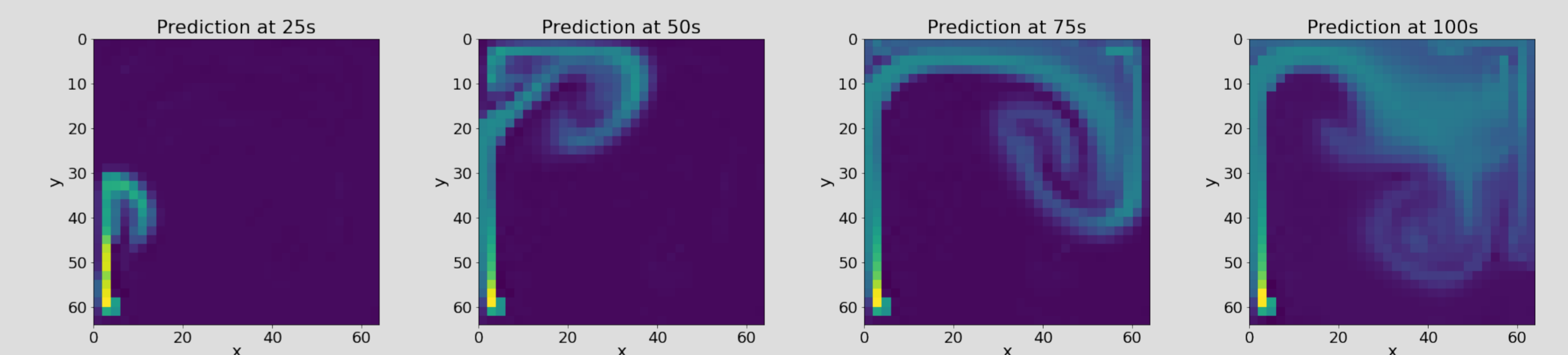
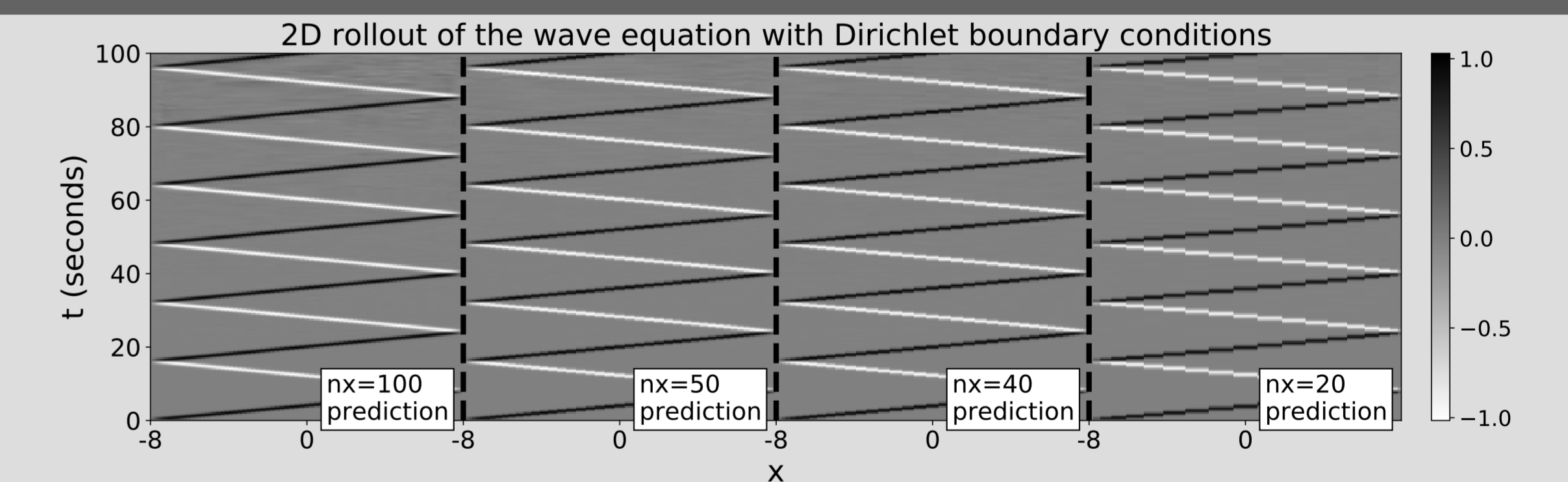


**Pushforward training**  
Gradients flow only through last time step

## Generalization across different equations, different resolutions



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



## References

- Paper: <https://arxiv.org/abs/2202.03376>
- Code: <https://github.com/brandstetter-johannes/MP-Neural-PDE-Solvers>