

Sobolev Cubatures Strengthen the Approximation Power of Physics Informed Neural Nets

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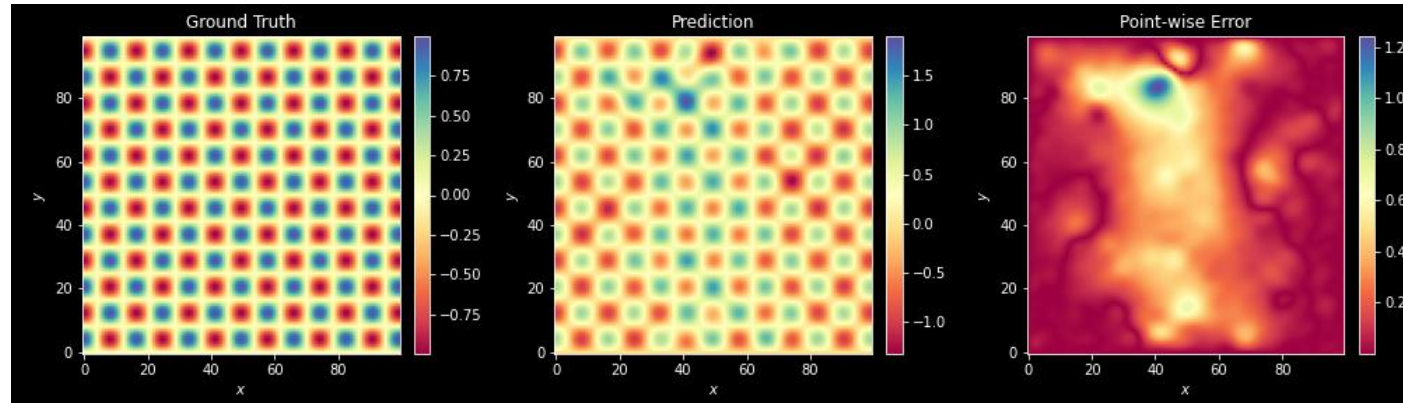
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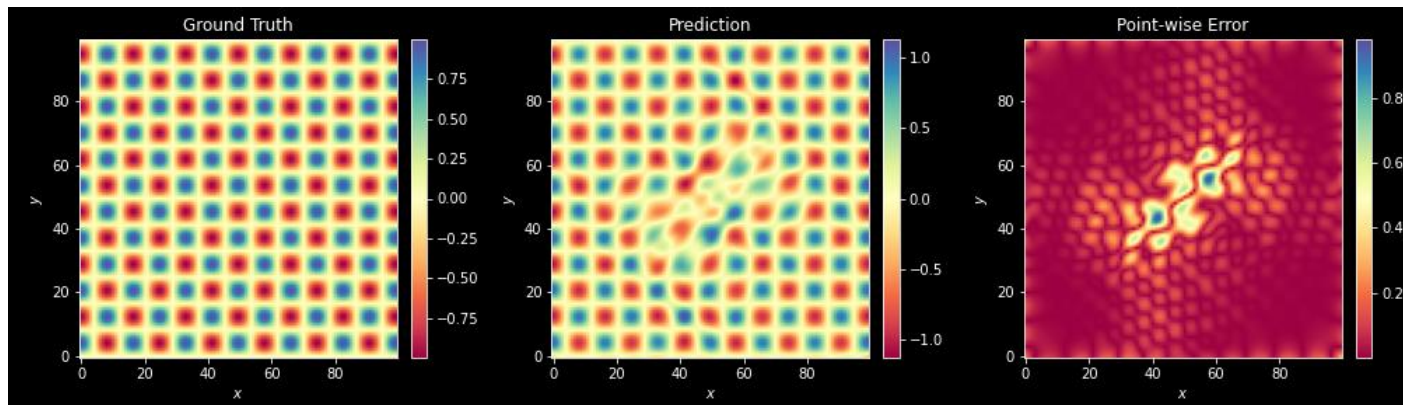
What are PINNs and why not use classic PDE solvers ?

- Neural Networks with physics encoded by a PDE Loss
- Forward problem learning  surrogate models
- Inverse problem / Inferring parameters and governing equations
 Costly for classic solvers
- Accuracy of PINNs  Challenge we want to tackle

- **2-D Poisson equation forward problem**, $N_{points} = 961$, $\omega = 6\pi$
- MSE Loss with Inverse Dirichlet [2] and A.D., $\epsilon_{L^\infty} = 1.24$, $t_{cpu} \approx 400$



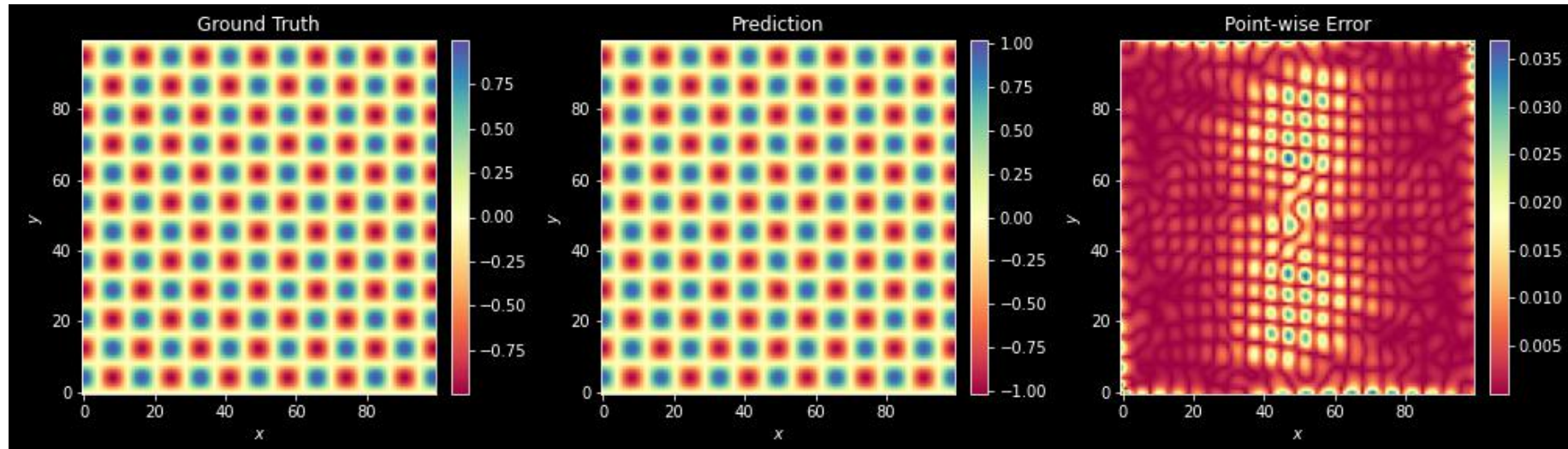
- Sobolev Loss ($\mathcal{L}_r = d_{L^2}$, $\mathcal{L}_b = d_{H^2}$) with A.D., $\epsilon_{L^\infty} = 9.78 \cdot 10^{-1}$, $t_{cpu} \approx 321$



[2] Suryanarayana Maddu et al 2021 Mach. Learn.: Sci. Technol. in press <https://doi.org/10.1088/2632-2153/ac3712>

2-D Poisson equation forward problem, $N_{points} = 961$

- Sobolev Loss ($\mathcal{L}_r = d_{L^2}, \mathcal{L}_b = d_{H^2}$) **without** A.D., $\epsilon_{L^\infty} = 3.6 \cdot 10^{-2}$, $t_{cpu} \approx 190$



- Automatic differentiation is replaced by a discrete differential operator on a polynomial space.

Sobolev Spaces H^k

- $H^0 = L^2$ –Lebesgue space, $\Omega := (-1, 1)^m \subset \mathbb{R}^m$
- The k -th Sobolev space $H^k(\Omega; \mathbb{R})$ is defined as:

$$H^k(\Omega; \mathbb{R}) := \{f \in L^2(\Omega; \mathbb{R}) \mid \forall |\alpha| \leq k, D^\alpha f \in L^2(\Omega; \mathbb{R})\}$$

- H^k is a Hilbert space with the norm:

$$\|u - v\|_{H^k}^2 := \|u - v\|_{L^2}^2 + \sum_{|\alpha| \leq k} \|D^\alpha u - D^\alpha v\|_{L^2}^2$$

- Sobolev Embedding Theorem: For $k > \frac{m}{2}$, $H^k(\Omega; \mathbb{R}) \subseteq C^0(\Omega; \mathbb{R})$
If $\|u - v\|_{H^k} = 0 \longrightarrow u(x) = v(x)$, for all $x \in \Omega$

Variational Formulations (Example)

- Poisson equation with Dirichlet boundary conditions:

$$\begin{cases} -\Delta u - f = 0 & \text{for } x \in \Omega \\ u = g & \text{for } x \in \partial\Omega \end{cases}$$

- We denote by **strong variational formulation**:

$$\int_{\Omega} (-\Delta u - f)\phi \, dx = 0, \quad \text{for } x \in \Omega, \forall \phi \in C^{\infty}(\Omega; \mathbb{R})$$

- We denote by **weak variational formulation**:

$$\int_{\Omega} (\nabla u \cdot \nabla \phi - f\phi) \, dx + \int_{\partial\Omega} (\phi \nabla u) \cdot \mathbf{n} \, dx = 0, \quad \text{for } x \in \Omega, \forall \phi \in C^{\infty}(\Omega; \mathbb{R})$$

- In practice we solve over a Polynomial space $\Pi_A \subset C^{\infty}(\Omega; \mathbb{R})$, spanned by the Lagrange basis $\{L_{\alpha}\}_{\alpha \in A}$

Computing Losses

- MSE Loss \longrightarrow Approximation of the L^2 -integral

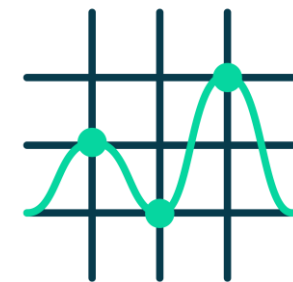
$$\int_{\Omega} (u - v)^2 dx \approx \frac{1}{N} \sum_{n \leq N} (u(x_n) - v(x_n))^2$$

- Gauss-Legendre cubature rules \longrightarrow Integrating polynomials exactly

$$\int_{\Omega} (u - v)^2 dx \approx \sum_{\alpha \in A} (u(P_{\alpha}) - v(P_{\alpha}))^2 \omega_{\alpha}$$

- Generalize the Gauss-Legendere rule to Sobolev-Cubatures, *minterpy* [1]

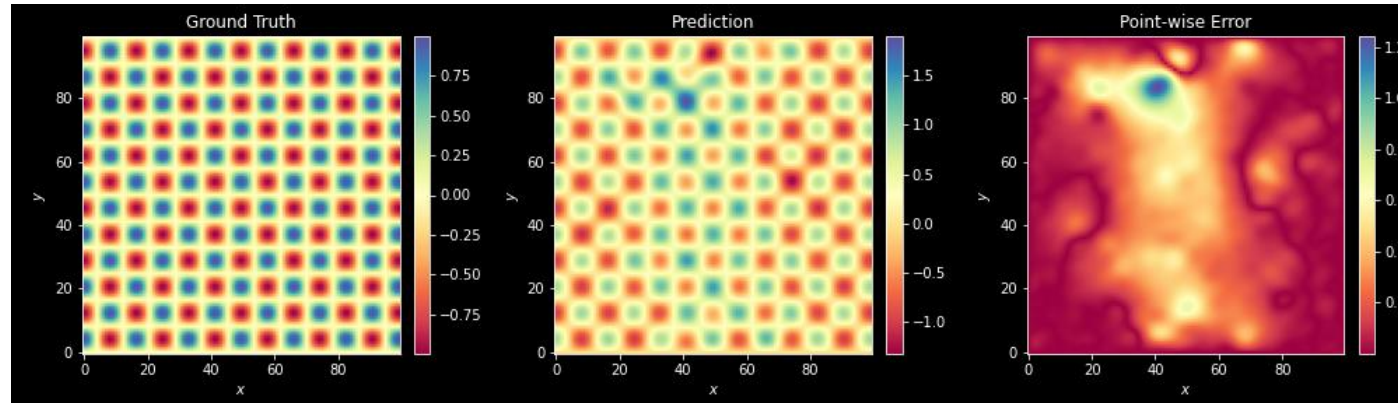
$$\int_{\Omega} (D^{\alpha} u - D^{\alpha} v)^2 dx \approx \sum_{\alpha \in A} (u(P_{\alpha}) - v(P_{\alpha}))^2 s_{\alpha}$$



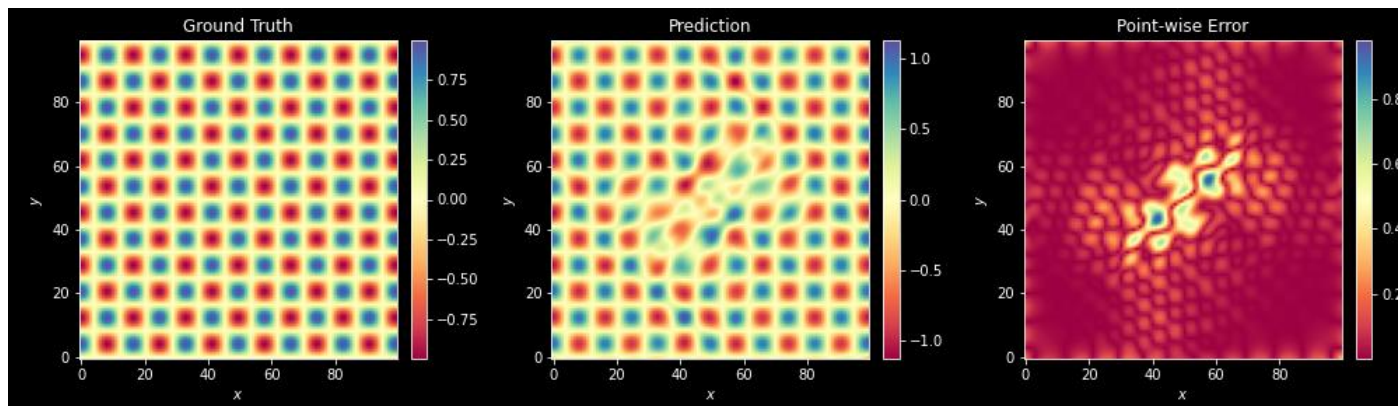
MINTERPY

[1] *minterpy* Multi dimensional interpolation python 2021 <https://github.com/casus/minterpy/releases>

- **2-D Poisson equation forward problem, $N_{points} = 961$**
- **MSE Loss with Inverse Dirichlet [2] and A.D., $\epsilon_{L^\infty} = 1.24, t_{cpu} \approx 400$**



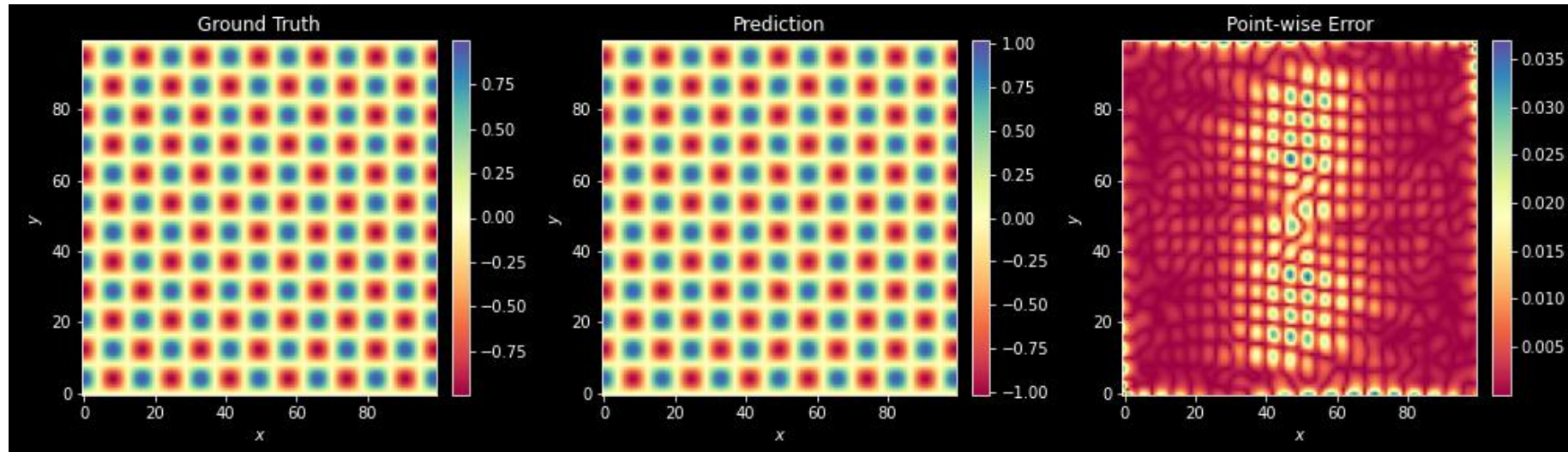
- **Strong Sobolev Loss ($\mathcal{L}_r = d_{L^2}, \mathcal{L}_b = d_{H^2}$) with A.D., $\epsilon_{L^\infty} = 9.78 \cdot 10^{-1}, t_{cpu} \approx 321$**



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2-D Poisson equation forward problem, $N_{points} = 961$

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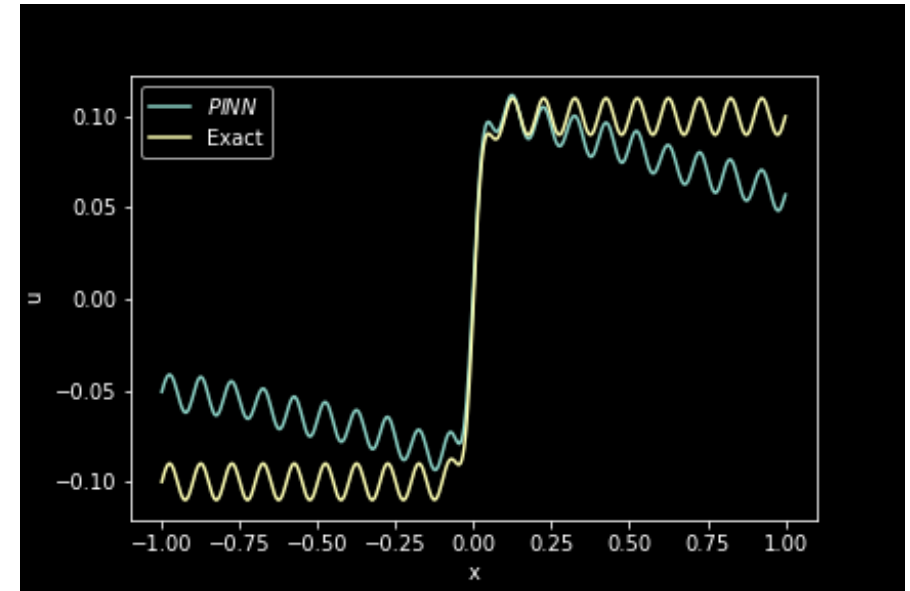


- Automatic differentiation is replaced by a discrete differential operator on a polynomial space.

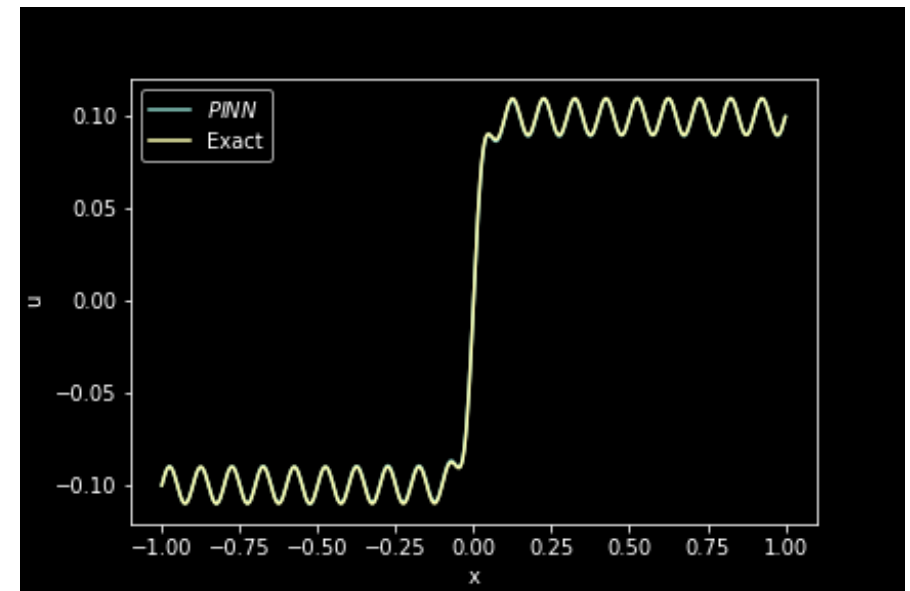
Other Numerical Results

- **1-D Poisson equation forward problem, $\omega = 15\pi$, $N_{points} = 100$**

- Strong Sobolev Loss, $\epsilon_{L^\infty} = 0.049$



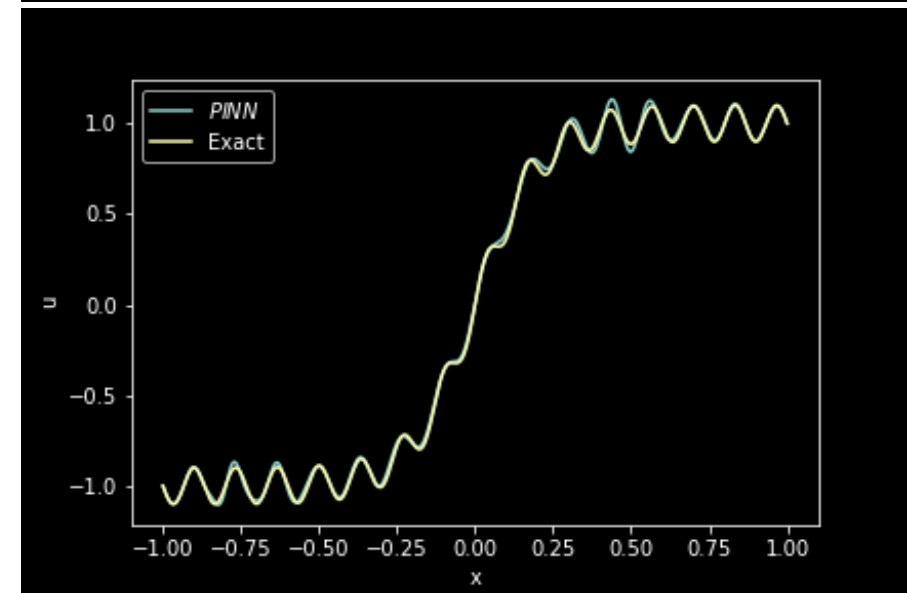
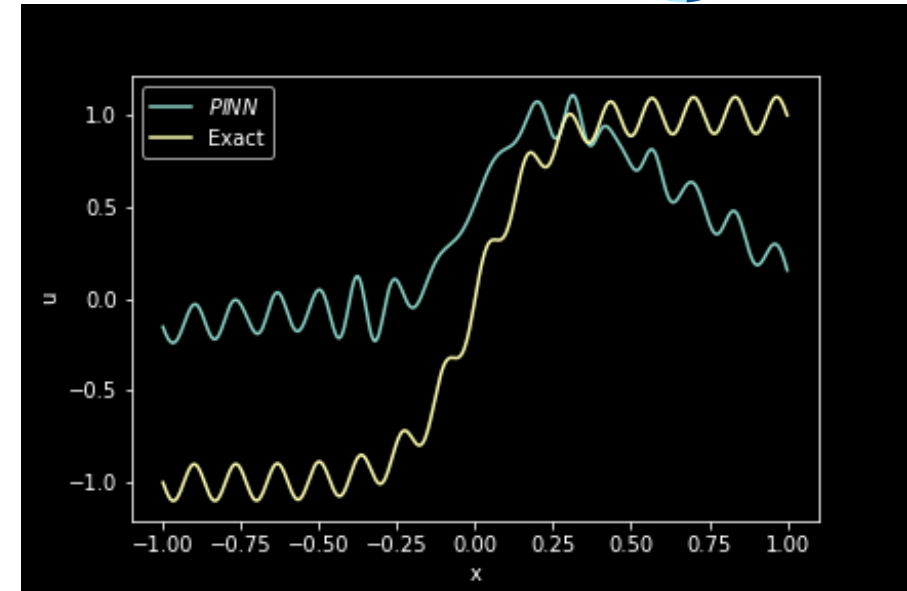
- Strong Variational Loss, $\epsilon_{L^\infty} = 0.002$



- **1-D Poisson equation forward problem, $\omega = 15$, $N_{points} = 50$**

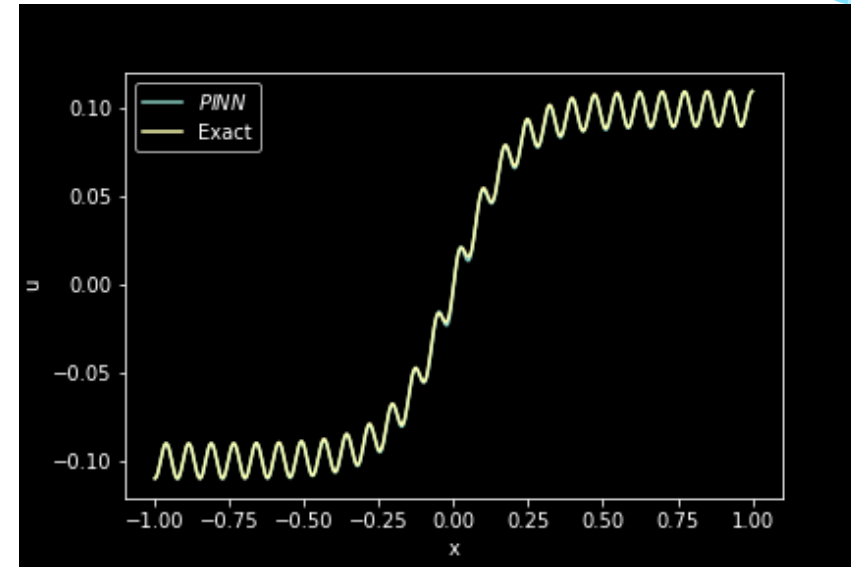
- Strong Sobolev Loss, $\epsilon_{L^\infty} = 1.002$

- Variational Loss, $\epsilon_{L^\infty} = 0.063$

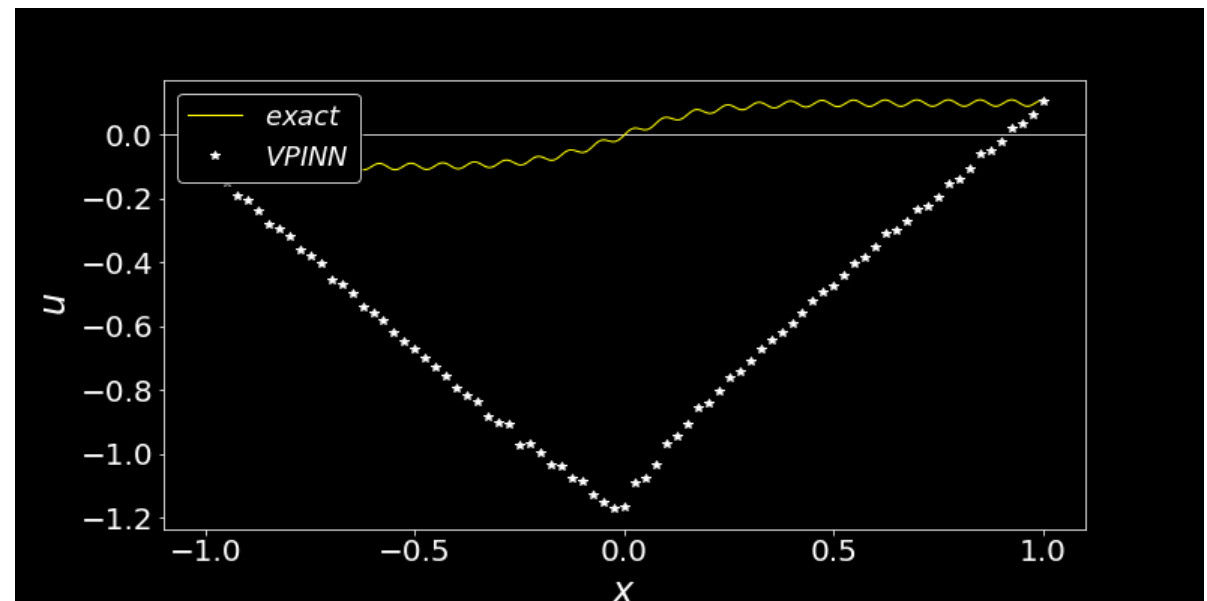


1-D scaled Poisson equation forward problem, $\omega = 26.5\pi$, $N_{points} = 100$

- Variational Loss, $\epsilon_{L^\infty} = 0.003$, $t_{cpu} \approx 130$



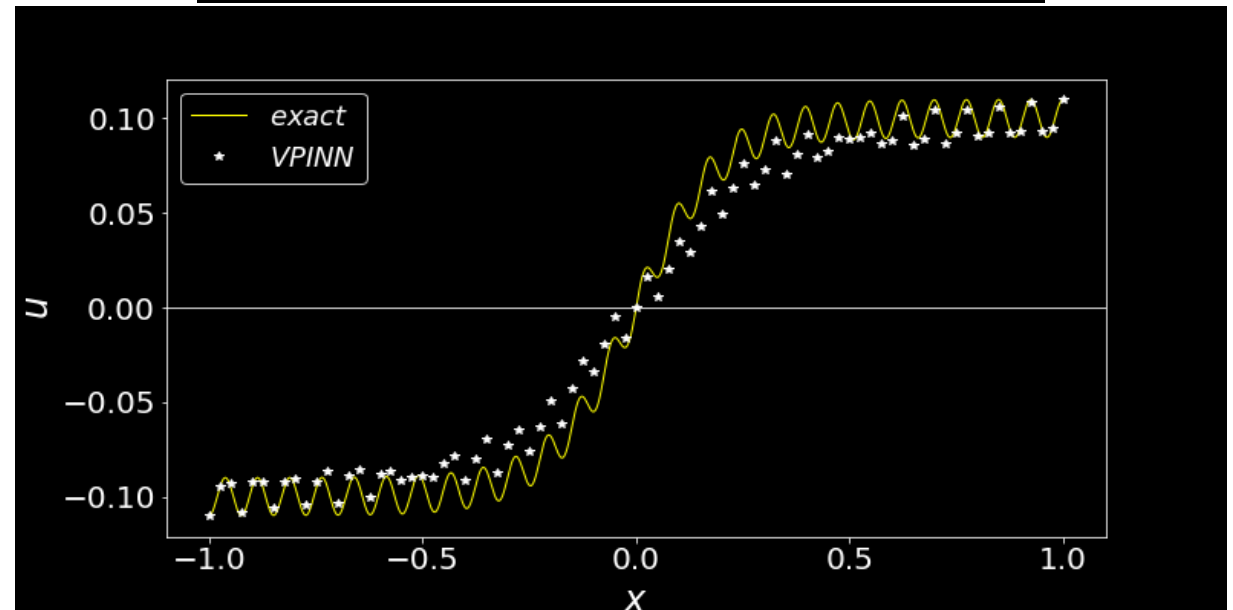
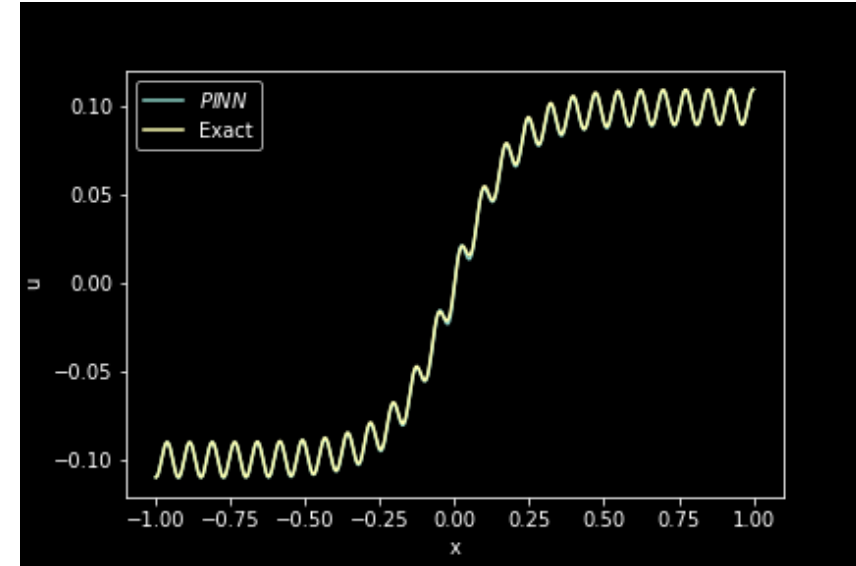
- VPINN [3], $\epsilon_{L^\infty} = 1.17$, $t_{cpu} \approx 144$



[3] Kharazmi E. et al 2021,
Computer Methods in Applied Mechanics and Engineering in press
<https://doi.org/10.1016/j.cma.2020.113547>

1-D scaled Poisson equation forward problem, $\omega = 26.5$, $N_{points} = 100$

- Variational Loss, $\epsilon_{L^\infty} = 0.003$,
 $t_{cpu} \approx 130$
- VPINN [3], wit domain decomposition, $N_{dom} = 3$,
 $\epsilon_{L^\infty} = 0.02$, $t_{cpu} \approx 360$
- MSE with I.D. [2] becomes unstable



- This are preliminary results ———> we are working to scale it up, e.g. higher dimensions
- Sobolev Cubatures are expected to be included as feature on the Beta release of *mintropy*
- We want to extend the approach to complex geometries (Biological Systems)
- We want to apply the method to real problems in cooperation with:
 - Ivo Sbalzarini, MOSAIC group CSBD
 - Attila Cangi, Matter Under Extreme Conditions CASUS
 - Nico Hoffman, ML group HZDR
- Contact us if you are interested ! j.suarez-cardona@hzdr.de

Thank you !

References

- [1] *minterpy* Multi dimensional interpolation python 2021
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