



Towards Universal Mesh Movement Networks

NeurIPS 2024 (Spotlight)

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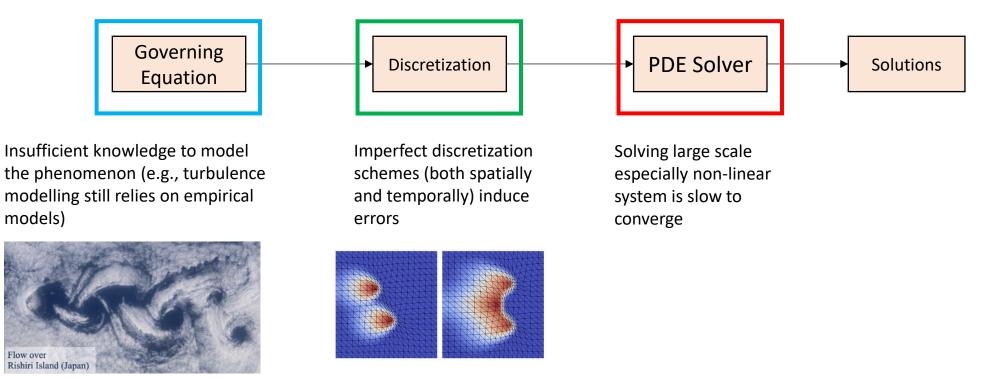
Numerical Simulation

Numerical Physical Simulation

Physical knowledge (e.g., Governing Equation) -> Solutions

Pros: Physical plausible, generalizable

Cons: Computational expensive, discretization errors, undiscovered physics



photograph from NASA, 2001; STS-100

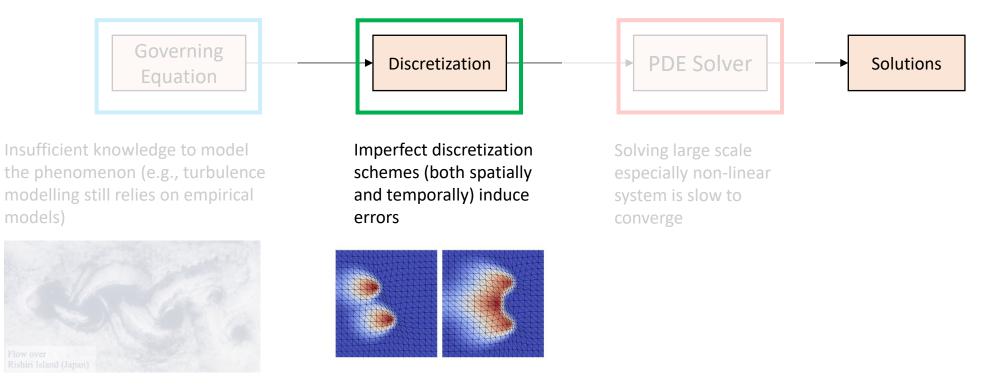
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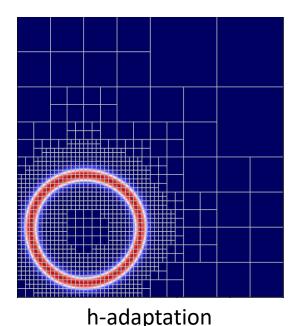
Cons: <u>Computational expensive</u>, <u>discretization errors</u>, <u>undiscovered physics</u>

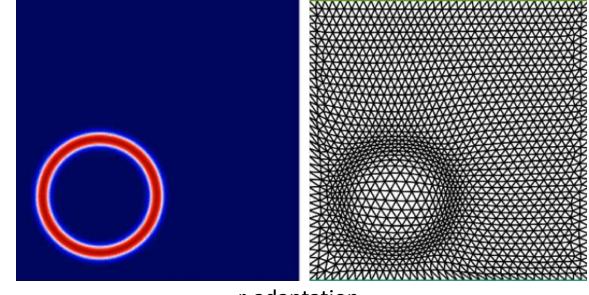


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Mesh Adaptation

 Mesh adaptation are techniques for distributing mesh according to the requirements of numerical accuracy. Two main categories of mesh adaptation techniques can be identified: h-adaptation and radaptation.





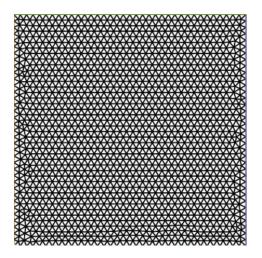
r-adaptation

Corbin Foucart, Aaron Charous, and Pierre F.J. Lermusiaux. Deep reinforcement learning for adaptive mesh refinement. Journal of Computational Physics, 491:112381, 2023.

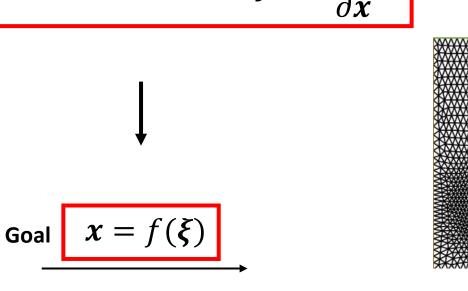
Mesh Movement

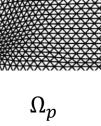
• A monitor function *m* over the spatial domain is used to specify the desired mesh density. Finding a mapping so that *m* is equidistributed over the adapted (i.e., physical) mesh.

$$m(\mathbf{x}) \det(\mathbf{J}) = const.$$
 $\mathbf{J} = \frac{\partial f(\boldsymbol{\xi})}{\partial \mathbf{x}}$



 Ω_c

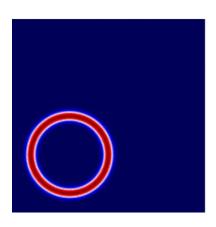




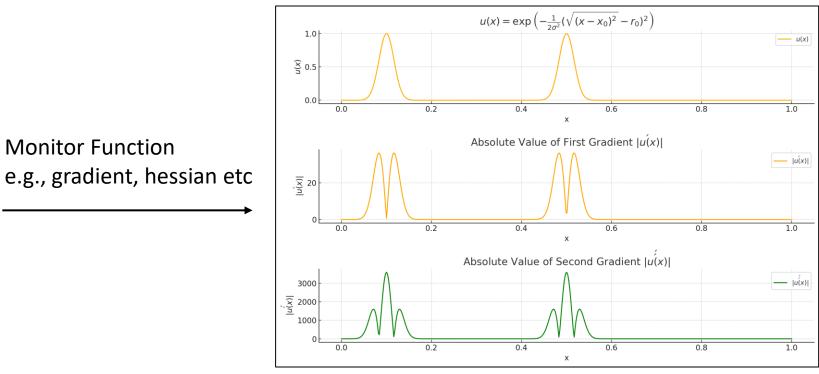
Monitors

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Monitor Function



Solution

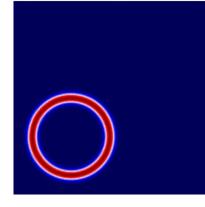


Monitors

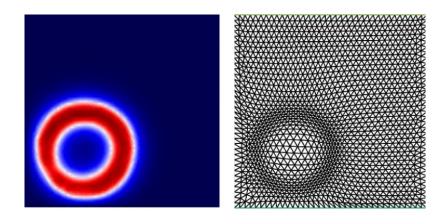
Monitors

• A monitor function *m* over the spatial domain is used to specify the desired mesh density. Finding a mapping so that *m* is equidistributed over the adapted (i.e., physical) mesh.

$$m(\mathbf{x}) = 1 + \max\left(\alpha \frac{\|H(u)\|}{\max\|H(u)\|}, \beta \frac{\|G(u)\|}{\max\|G(u)\|}\right)$$



e.g., Combined gradient and hessian with smoothing



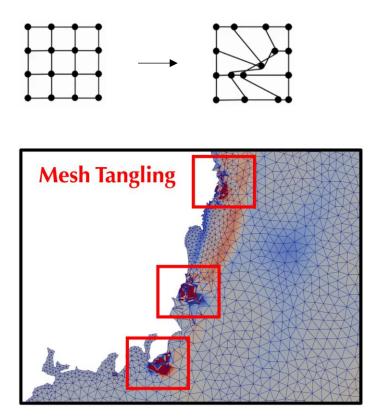
Monitors

Adapted mesh

Solution

Mesh tangling

• Mesh tangling occurs when elements of a computational mesh overlap or intersect, i.e., negative Jacobians or inverted elements.



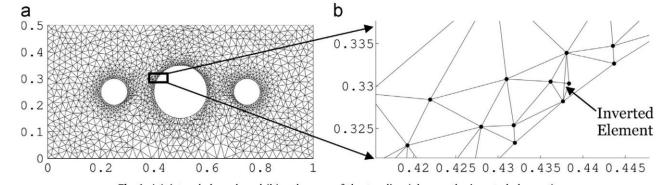


Fig. 1. (a) A tangled mesh and (b) a close-up of the tangling (observe the inverted element).

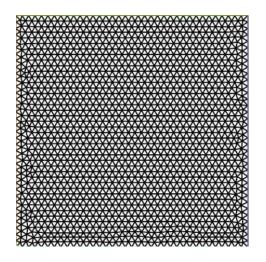
Mesh tangling leads divergence in simulations!

Josh Danczyk, Krishnan Suresh, Finite element analysis over tangled simplicial meshes: Theory and implementation, Finite Elements in Analysis and Design, Volumes 70–71,2013

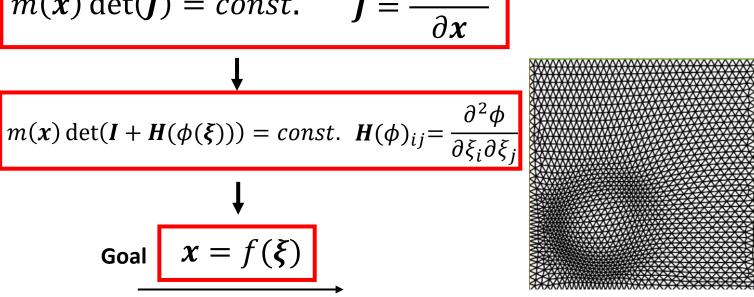
Monge-Ampère Mesh Movement

• By using concepts from **optimal transport theory**, the problem can be constrained to have a unique solution, with the deformation of the map expressed as the gradient of a scalar potential ϕ , i.e., $x(\xi) = \xi + \nabla_{\xi}\phi(\xi)$:

$$m(\mathbf{x}) \det(\mathbf{J}) = const.$$
 $\mathbf{J} = \frac{\partial f(\boldsymbol{\xi})}{\partial \mathbf{x}}$



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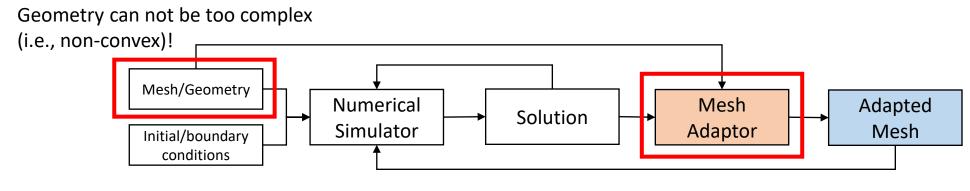
Monge-Ampère Mesh Movement

• Pros

• Output a non-tangled adapted mesh which satisfies equal-distributed theory

• Cons

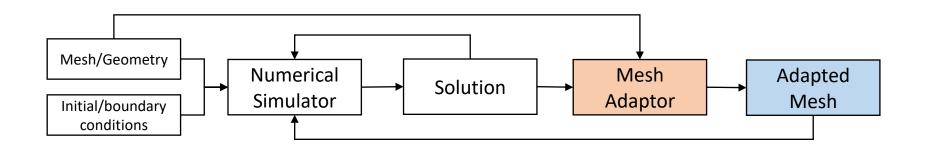
- Computational expensive: we need to solve an additional non-linear PDE!
- Complex geometry: Monge-Ampère fails on scenarios with complex geometries.



MA PDE solver is too expensive!

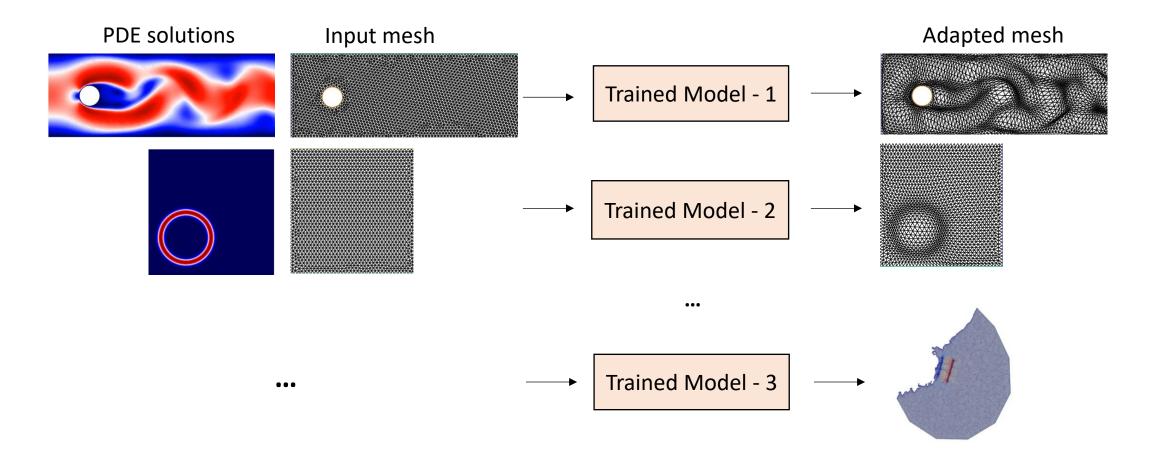
Learning based mesh adaptation

- Goals:
 - Mesh adaptor is efficient
 - Adapted mesh is non-tangled
 - Geometry can be complex (e.g., non-convex)



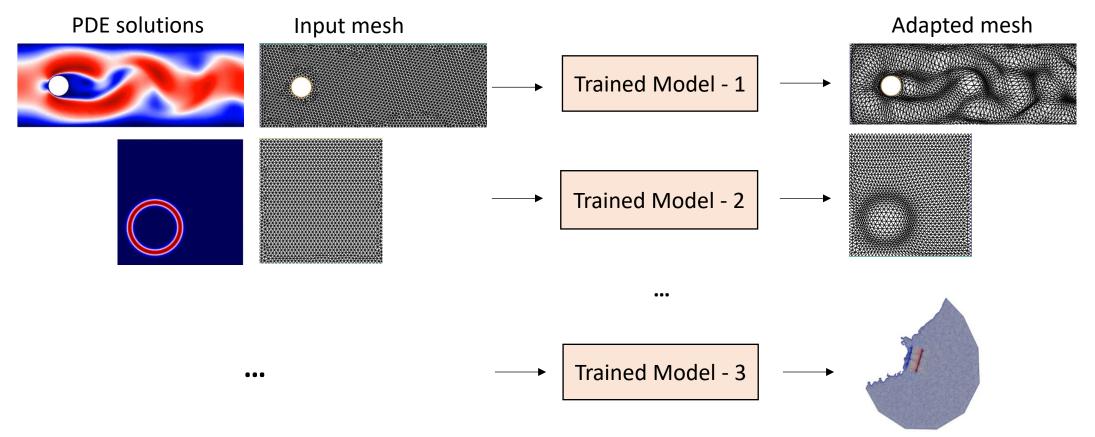
Limitation of Existing Work

• Require to re-train the model from scratch given a new problem or scenario



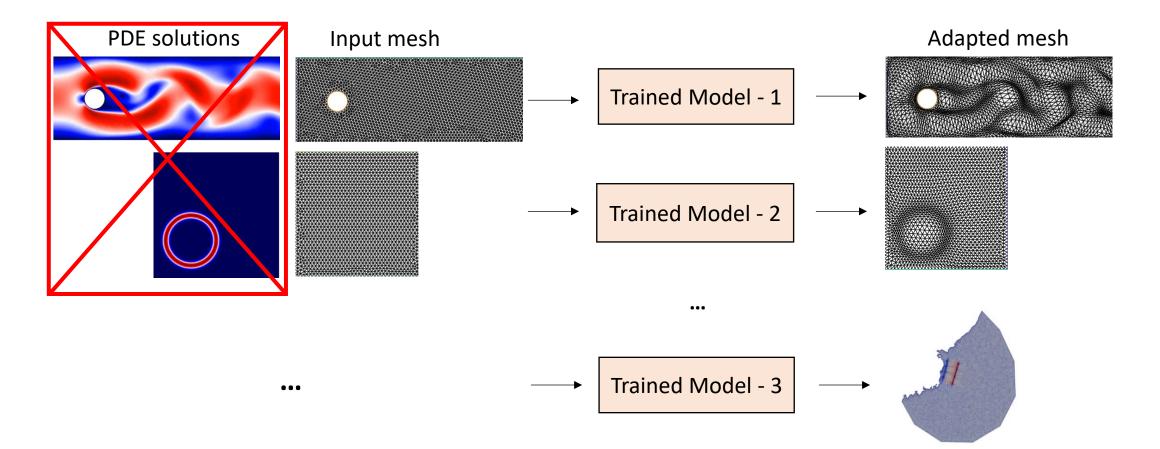
Limitation of Existing Work

• Can we train once and and zero-shot apply the trained model to other problems or scenarios?



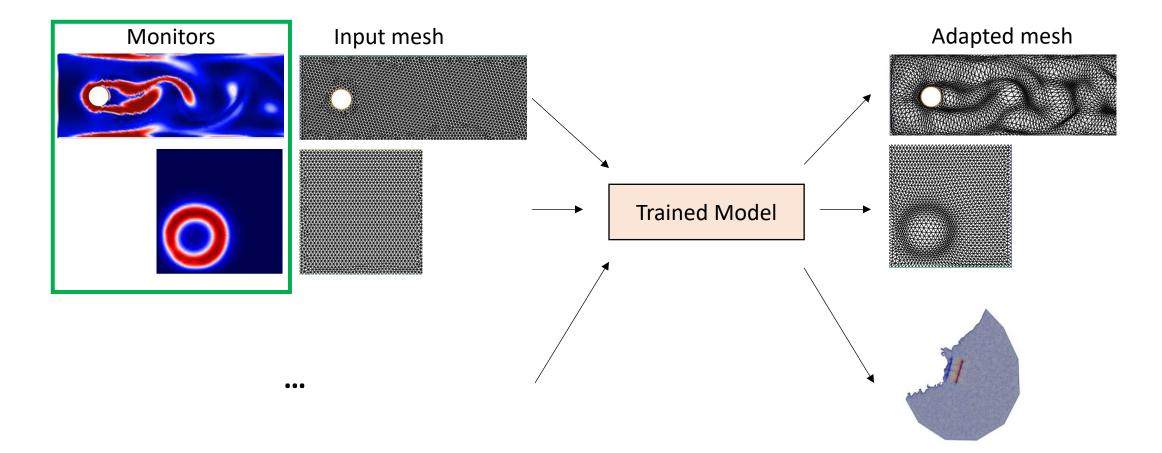
Key Intuition

• Decouple the inputs from the PDEs, use monitors instead of PDE solutions



Key Intuition

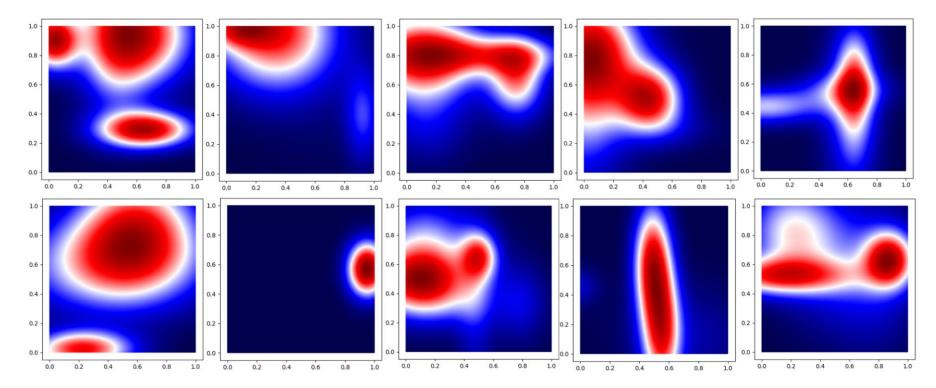
• Decouple the inputs from the PDEs, use monitors instead of PDE solutions



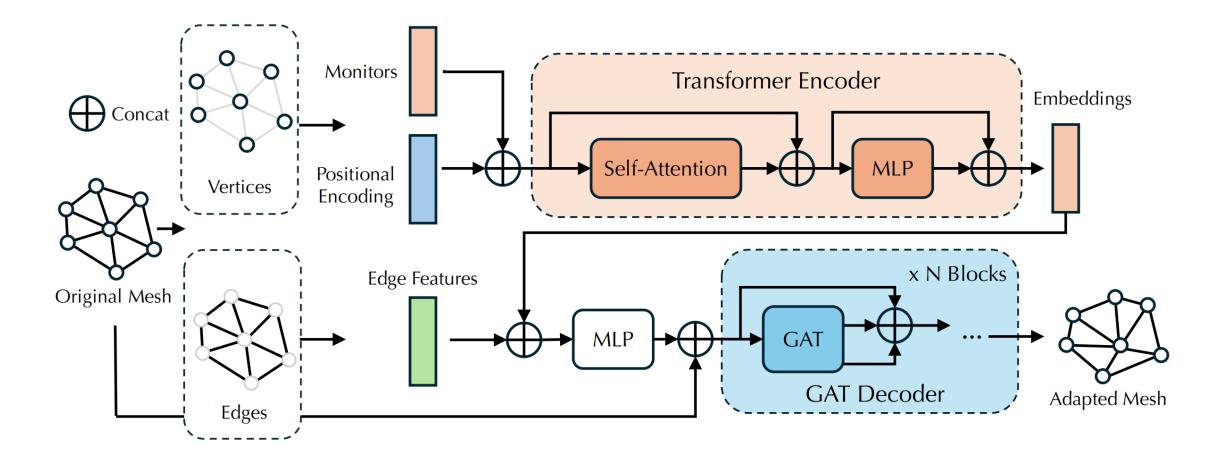
PDE-independent training

• Randomly generating generic fields as monitors for PDE-independent training

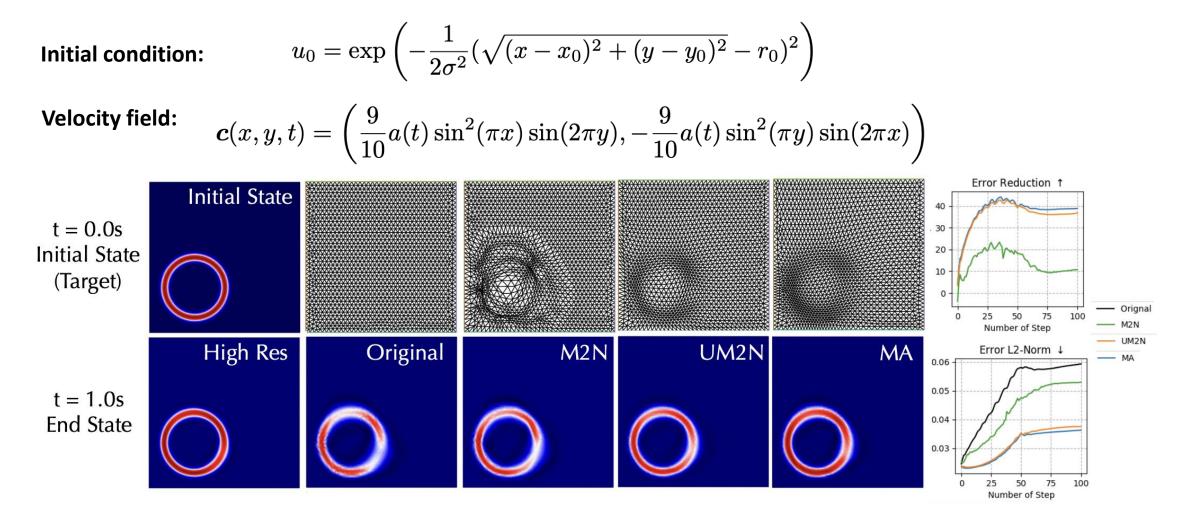
$$u = \sum_{k=1}^{N} \exp\left(\frac{(x - \mu_x)^2}{{\sigma_x}^2} + \frac{(y - \mu_y)^2}{{\sigma_y}^2}\right)$$



Networks



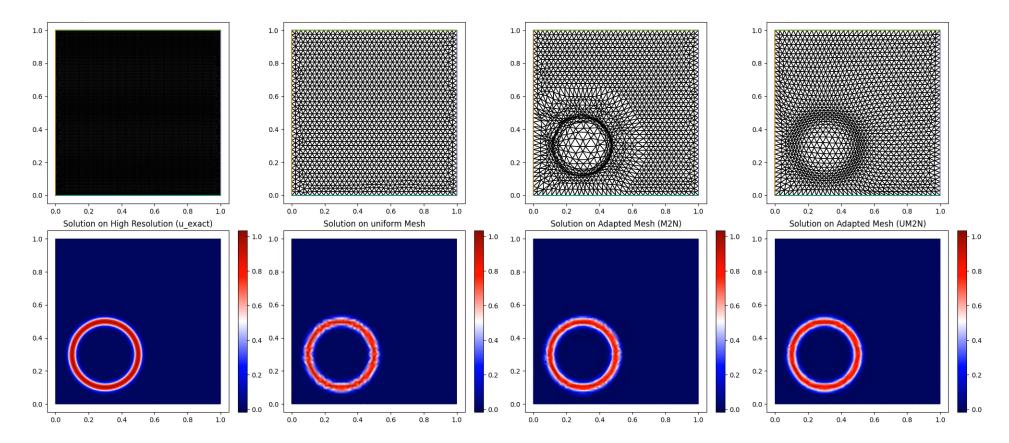
Results on Swirl



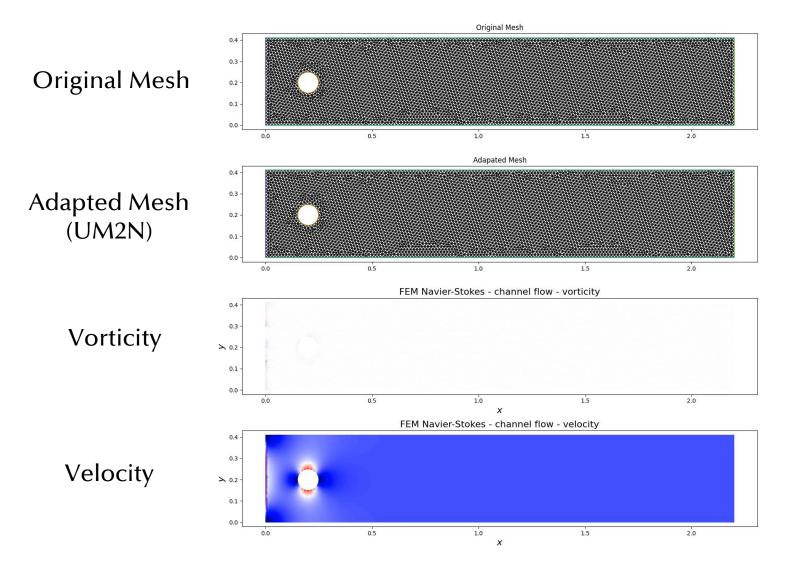
Results on Swirl

Adapted Mesh Adapted Mesh (M2N)

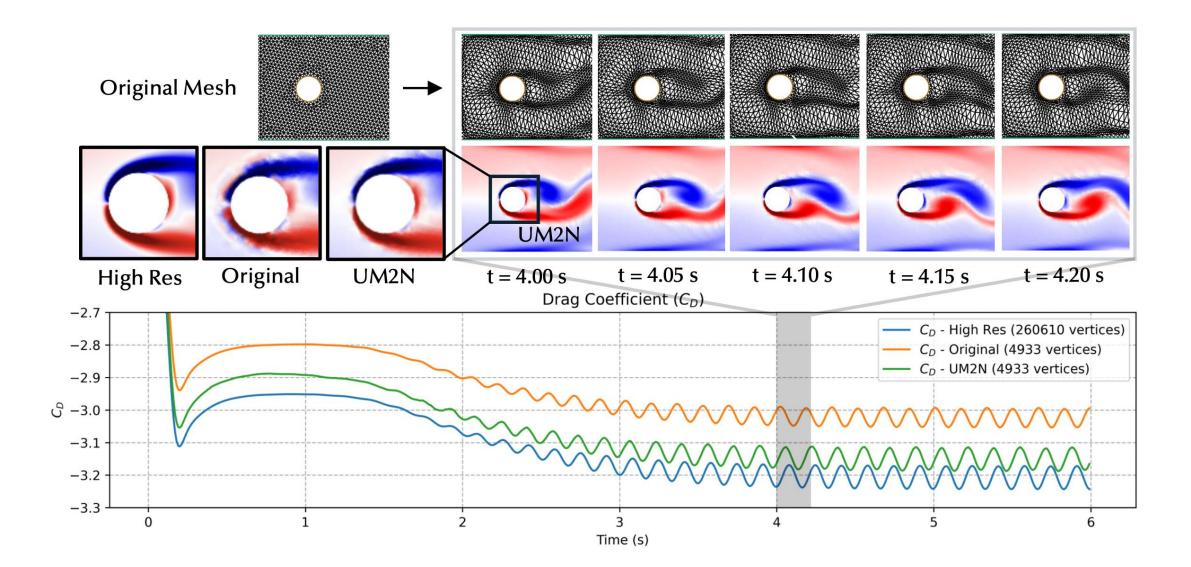
. (UM2N)



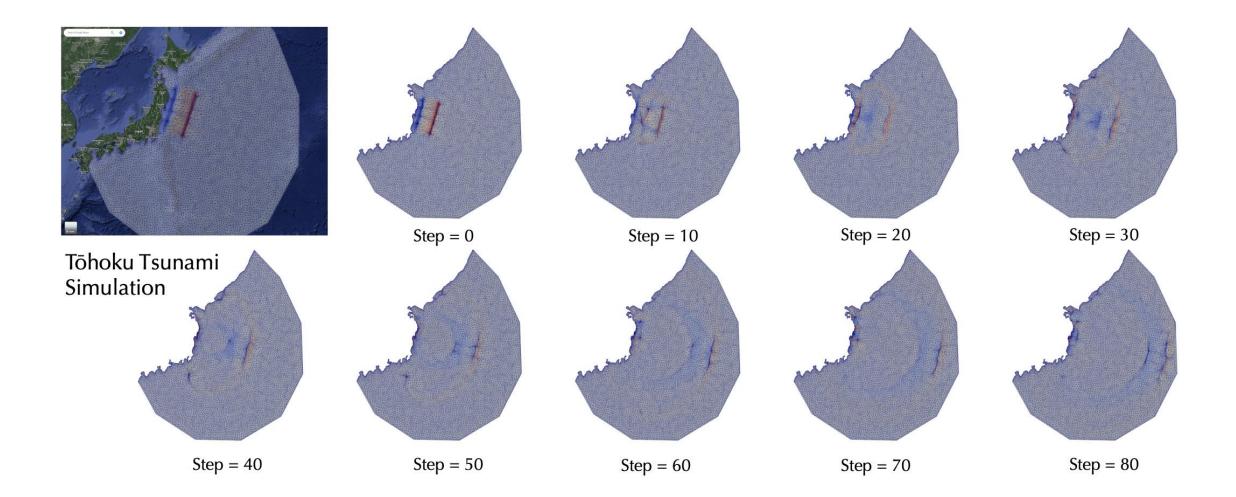
Flow Past a Cylinder



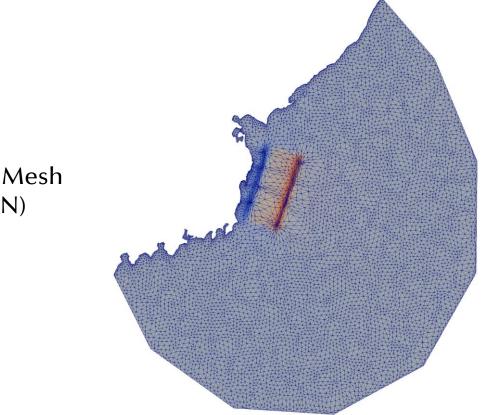
Results on Flow Past Cylinder



Results on Tsunami Simulation

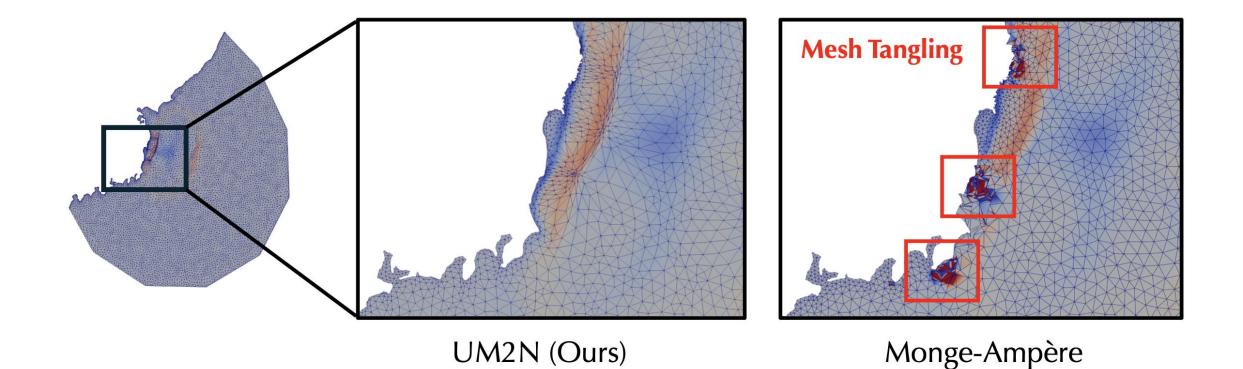


Tohoku Tsunami Simulation

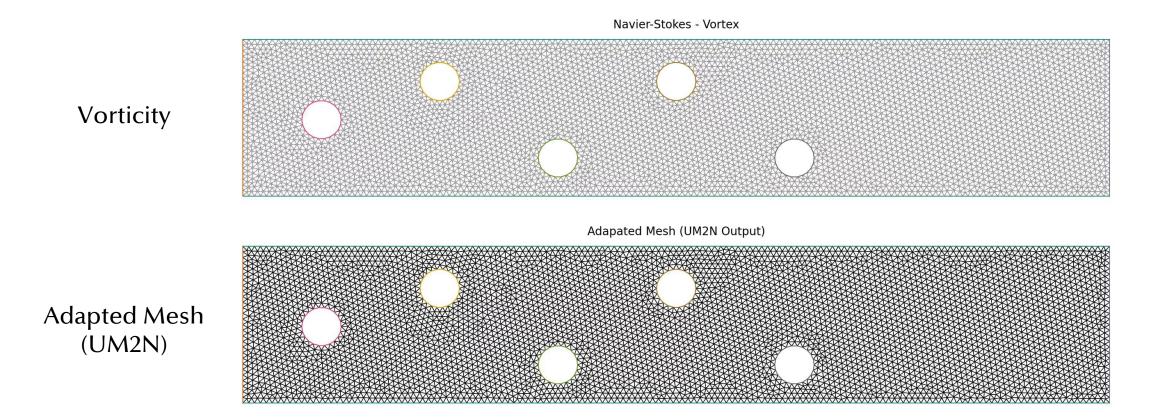


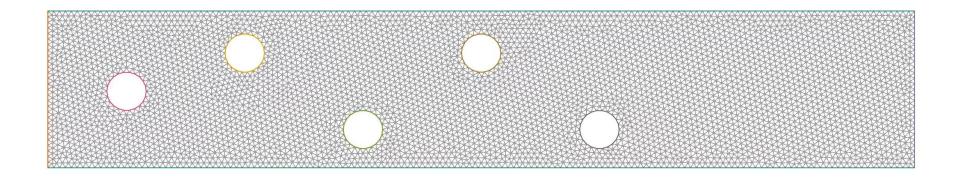
Adapted Mesh (UM2N)

Results on Tsunami Simulation



More Results





Thanks!



https://erizmr.github.io/UM2N/