



Motivation

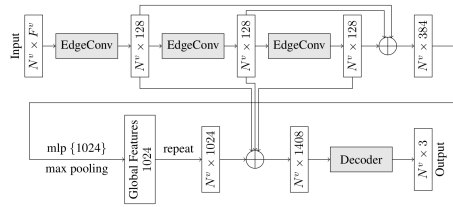
- Target:**
- Modelling fluid dynamical quantities, i.e. velocities \mathbf{w}_i and pressure p_i
 - Graph neural network to learn direct predictions of the final steady-state velocity and pressure fields
- Given:**
- Meshed domain as a bidirectional graph $G = (V, E)$, with Nodes V and Edges E
 - Node feature vector $\mathbf{v}_i = [\mathbf{u}_i, \mathbf{n}_i]$
 - Mesh-space coordinates \mathbf{u}_i
 - Quantities \mathbf{n}_i describing the domain, e.g. angle of attack, Mach number, node type

Dataset

- Three data sets with fluid dynamical simulations to evaluate our method
- AIRFOIL**
- NACA0012 airfoil for varying angle of attacks α and Mach numbers m
 - CFD: Steady-state, compressible, inviscid Euler equation
- AIRFOILROT**
- Rotation of whole simulation domain of AIRFOIL by angle α
- CHANNEL**
- Channel flow with varying number of generic objects randomly placed inside the channel
 - CFD: Steady-state, incompressible, inviscid Navier-Stokes equation

Results

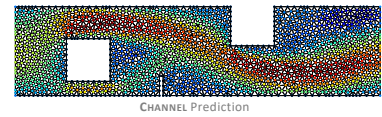
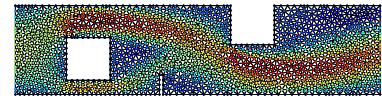
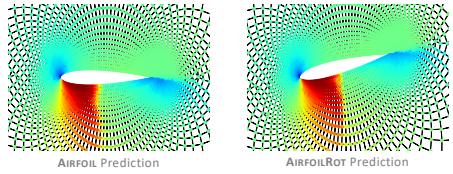
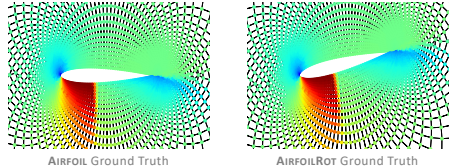
- Comparing with models from literature: Base GCN and MESHGRAPHNETS with two extensions (Abs..Absolute values, POOL.Global Max Pooling)
- AIRFOIL**
- Same geometry for all samples, solution only depending on α and m
 - Low RMSE with all methods
- AIRFOILROT**
- Sensitive understanding of geometric structure required
 - Global information by absolute values \mathbf{v}_i and relative displacement $(\mathbf{v}_j - \mathbf{v}_i)$ necessary
 - MESHGRAPHNETS with only relative displacement fails
- CHANNEL**
- Strong understanding of complex geometric structure required
 - Absolute values \mathbf{v}_i and relative displacement $(\mathbf{v}_j - \mathbf{v}_i)$ together with local and global feature descriptors necessary
 - Our methods achieves lowest RMSE
 - Generalizes well to new unseen geometric setups of the channel flow



Model

- Edge Function**
- Local and global feature extraction with EDGECONV as edge function:
- $$\mathbf{e}_{ij} = \text{ReLU}(\theta \cdot (\mathbf{v}_j - \mathbf{v}_i) + \phi \cdot \mathbf{v}_i)$$
- $$\mathbf{v}_{ij} = \max \mathbf{e}_{ij}$$
- with θ and ϕ as a shared MLP and max as aggregation operation
- Local neighborhood information by relative displacement $(\mathbf{v}_j - \mathbf{v}_i)$
 - Global shape structure by absolute values \mathbf{v}_i

- Architecture**
- EdgeConv layers as local feature descriptors
 - ⊕ Concatenation to include multi-scale features
 - Global max pooling for global feature vector
 - Decoder transforming the latent features to output \mathbf{p}_i



Test root mean square error RMSE $\times 10^{-2}$			
Method	AIRFOIL	AIRFOILROT	CHANNEL
GCN	1.40	-	-
MESHGRAPHNETS	0.95	7.34	13.30
MESHGRAPHNETS (Abs)	0.73	1.28	13.04
MESHGRAPHNETS (Abs+POOL)	1.25	0.99	6.58
Ours	1.40	0.87	5.81

