



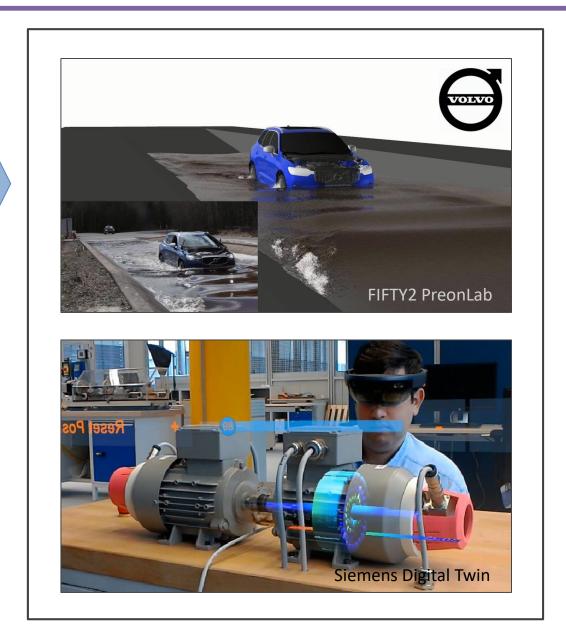
Data driven Fluid Simulation EG22 STAR

Barbara Solenthaler



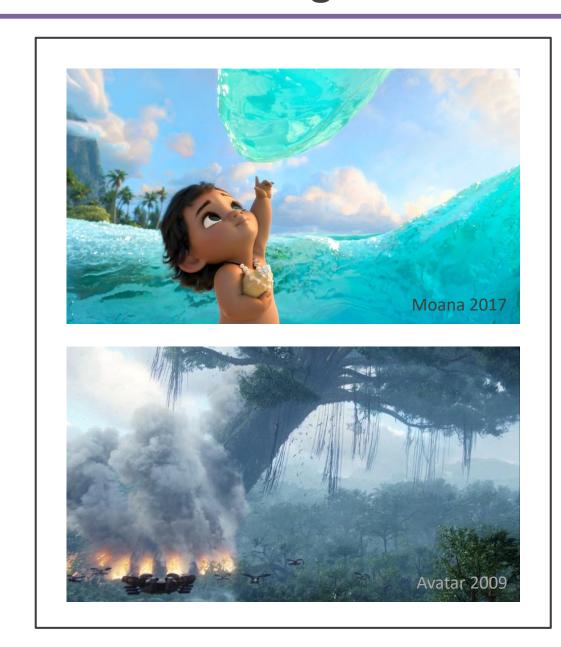
Persistent Challenges of Fluid Simulations

Fluid Simulation





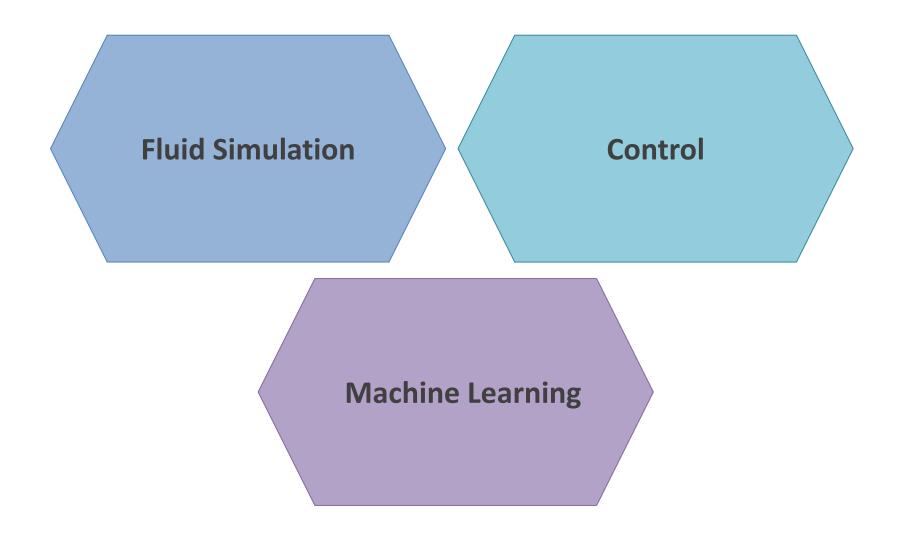
Persistent Challenges of Fluid Simulations



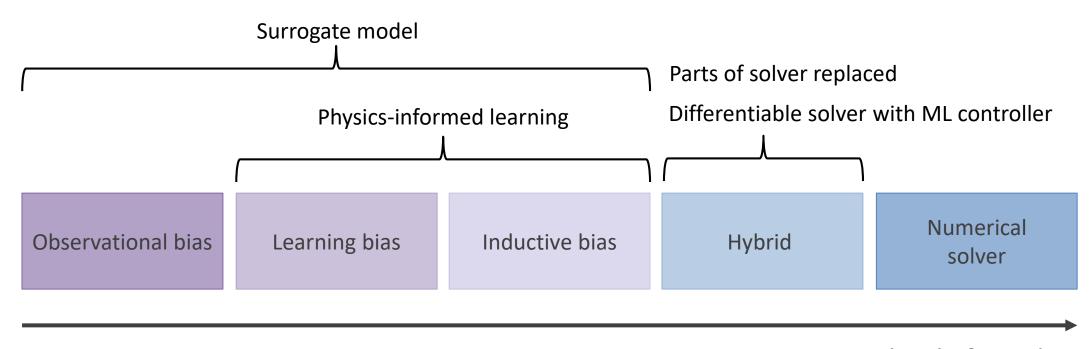




The Rise of Data-driven Modeling and Simulation



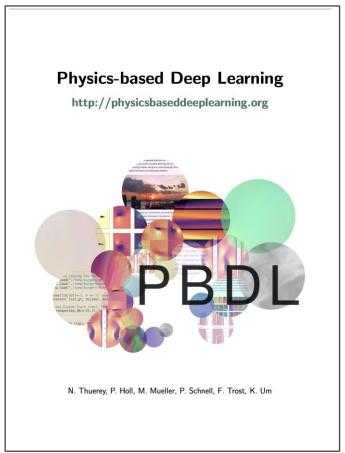
Shifting from First Principles to Data-driven Approaches

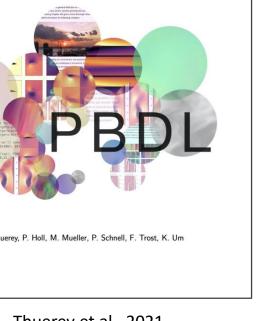






Digital Book and Review Articles





REVIEWS Check for updates Physics-informed machine learning George Em Karniadakis 01.2 , Ioannis G. Kevrekidis 4, Lu Lu 05, Paris Perdikaris 6 Sifan Wang⁷ and Liu Yang¹⁰ $Abstract \,|\, Despite \,great \,progress \,in \,simulating \,multiphysics \,problems \,using \,the \,numerical$ discretization of partial differential equations (PDEs), one still cannot seamlessly incorporate noisy data into existing algorithms, mesh generation remains complex, and high-dimensional problems governed by parameterized PDEs cannot be tackled. Moreover, solving inverse problems with hidden physics is often prohibitively expensive and requires different formulations and elaborate computer codes. Machine learning has emerged as a promising alternative, but training deep neural networks requires big data, not always available for scientific problems. Instead, such networks can be trained from additional information obtained by enforcing the physical laws (for example, at random points in the continuous space-time domain). Such physics-informed learning integrates (noisy) data and mathematical models, and implements them through neural networks or other kernel-based regression networks. Moreover, it may be possible to design specialized network architectures that automatically satisfy some of the physical invariants for better accuracy, faster training and improved generalization. Here, we review some of the prevailing trends in embedding physics into machine learning, present some of the current capabilities and limitations and discuss diverse applications of physics-informed learning both for forward and inverse problems, including discovering hidden physics and tackling high-dimensional problems. Modelling and forecasting the dynamics of multiphysics in the next decade, including airborne, seaborne and and multiscale systems remains an open scientific prob-satellite remote sensing, a wealth of multi-fidelity obserlem. Take for instance the Earth system, a uniquely com-²School of Engineering, Brown plex system whose dynamics are intricately governed by ods. However, despite the volume, velocity and variety of the interaction of physical, chemical and biological pro-available (collected or generated) data streams, in many Department of Chemical and cesses taking place on spatiotemporal scales that span 17 orders of magnitude. In the past 50 years, there has been rate such multi-fidelity data into existing physical models tremendous progress in understanding multiscale physics Mathematical (and practical) data-assimilation efforts Department of Applied
Mathematics and Statistics, in diverse applications, from geophysics to biophysics, by have been blossoming; yet the wealth and the spatiotem numerically solving partial differential equations (PDEs) poral heterogeneity of available data, along with the lack using finite differences, finite elements, spectral and even of universally acceptable models, underscores the need meshless methods. Despite relentless progress, model- for a transformative approach. This is where machine Department of Mather ling and predicting the evolution of nonlinear multiscale learning (ML) has come into play. It can explore massive systems with inhomogeneous cascades-of-scales by design spaces, identify multi-dimensional correlations using classical analytical or computational tools inevi-tably faces severe challenges and introduces prohibitive cost and multiple sources of uncertainty. Moreover, solvdynamic variables such as precipitation or vegetation ing inverse problems (for inferring material properties in functional materials or discovering missing physics in naturally provide tools for automatically extracting feareactive transport, for example) is often prohibitively expensive and requires complex formulations, new turns from massive amounts of multi-fidelity observational data that are currently available and characterized algorithms and elaborate computer codes. Most impor- by unprecedented spatial and temporal coverage⁴. They tantly, solving real-life physical problems with missing, can also help to link these features with existing approxigappy or noisy boundary conditions through traditional mate models and exploit them in building new predictive proaches is currently impossible. tools. Even for biophysical and biomedical modelling, this This is where and why observational data play a cru-synergistic integration between ML tools and multiscale cial role. With the prospect of more than a trillion sensors and multiphysics models has been recently advocated. 422 | JUNE 2021 | VOLUME



Thuerey et al., 2021

Karniadikis et al., 2021

Brunton and Koumoutsakos, 2020



SPH with Regression Forests

Lagrangian Fluids with Convolutional Neural Networks

Graph Network-based Simulations

Differentiable Solvers and Neural Networks

Particles and Learning

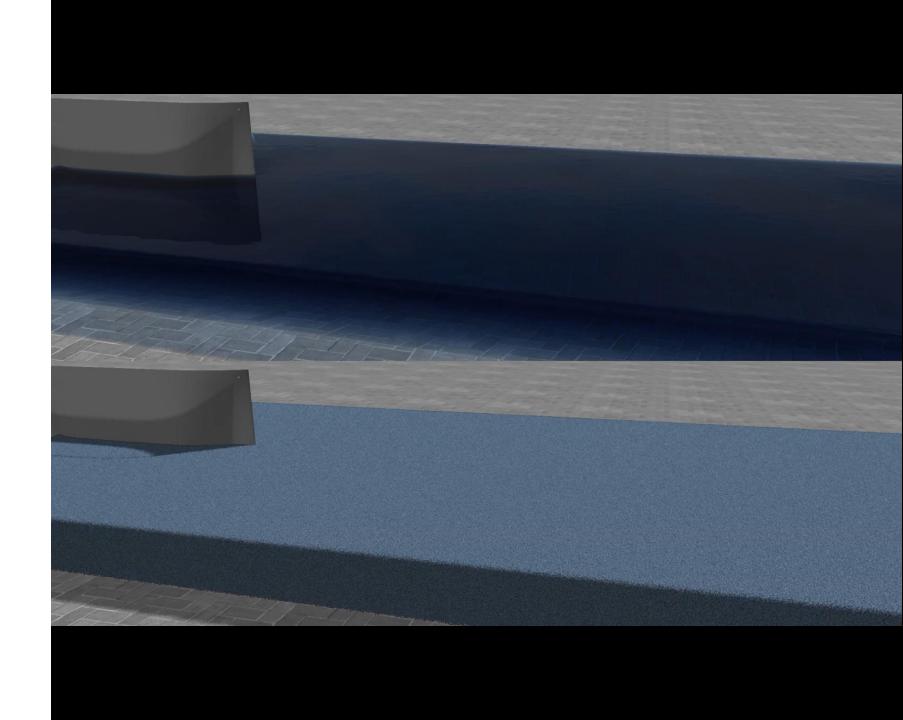
SPH with Regression Forests

Lagrangian Fluids with Convolutional Neural Networks

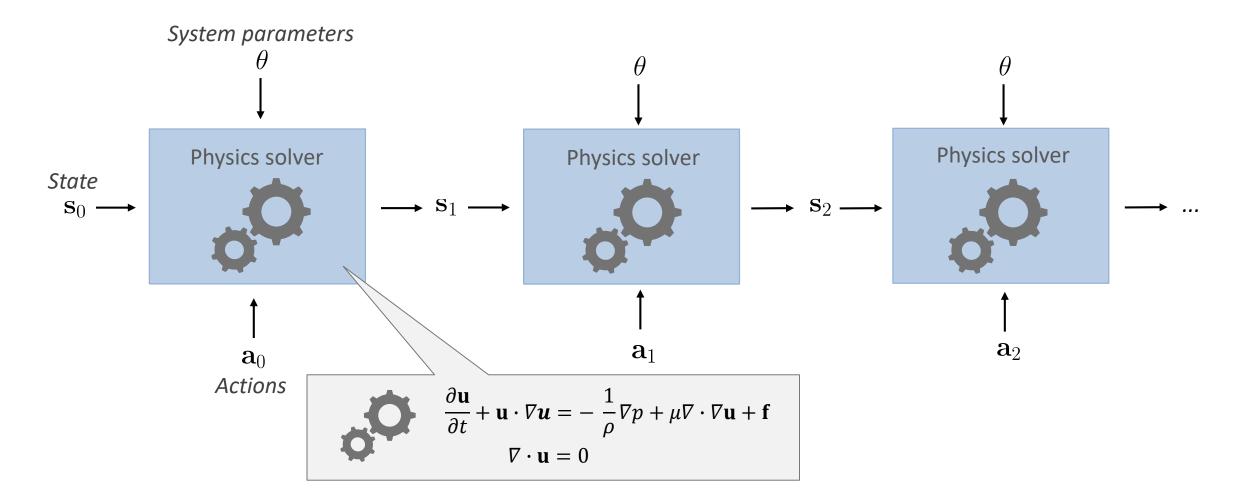
Graph Network-based Simulations

Differentiable Solvers and Neural Networks

Decision Tree Driven Model

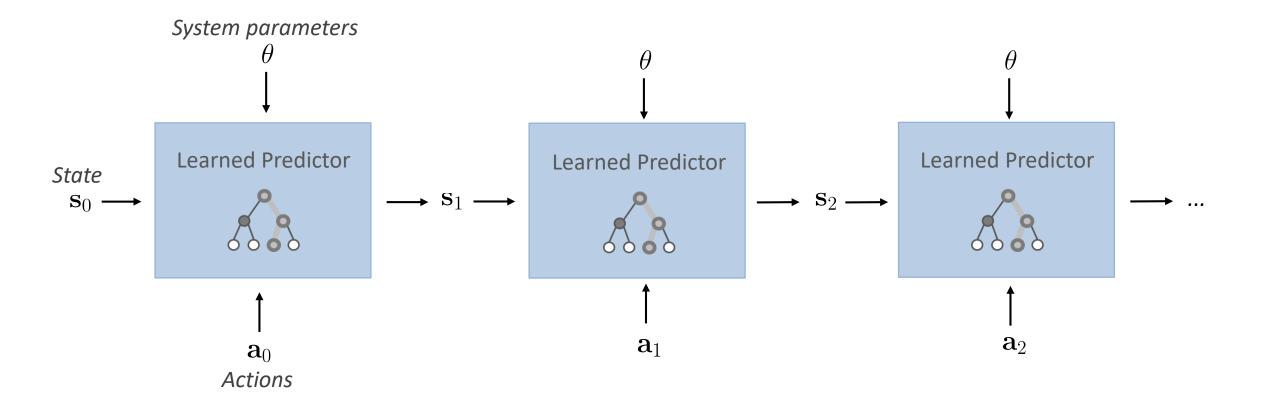


Forward Simulation



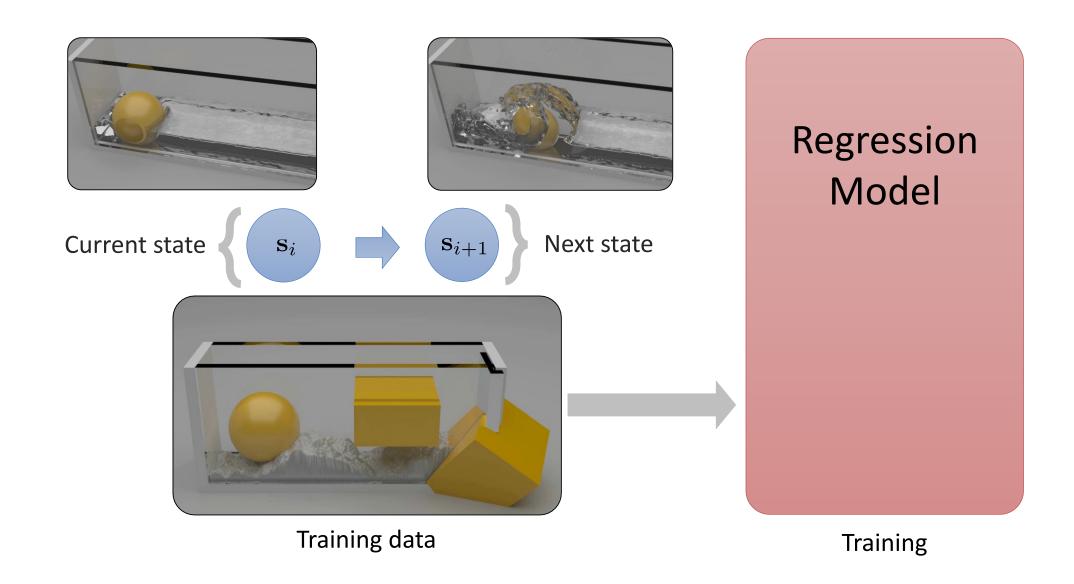


Surrogate Model for Particle Fluids

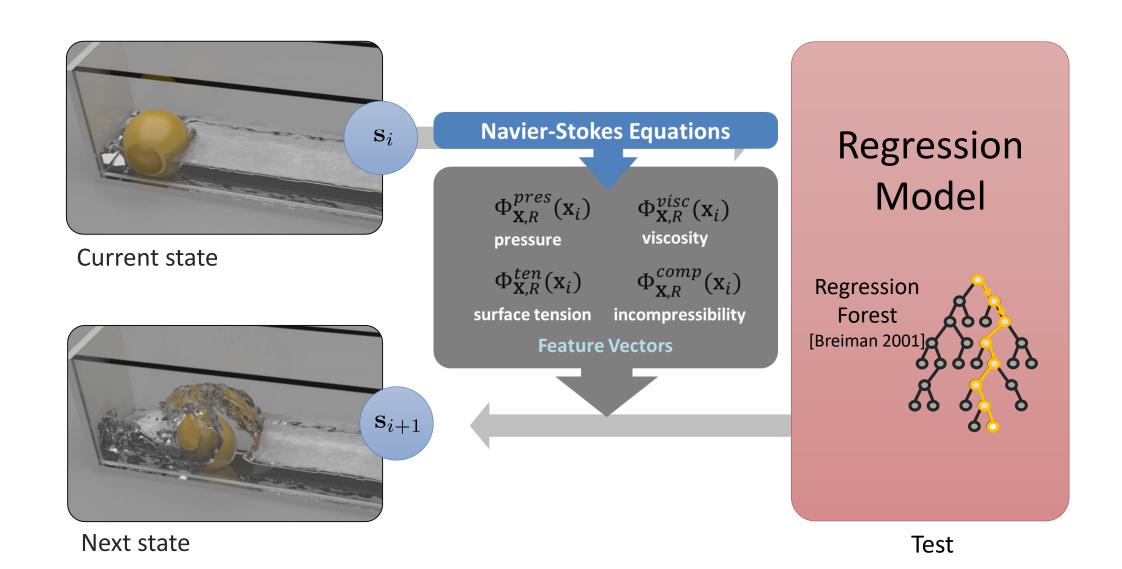




SPH with Regression Forests



SPH with Regression Forests

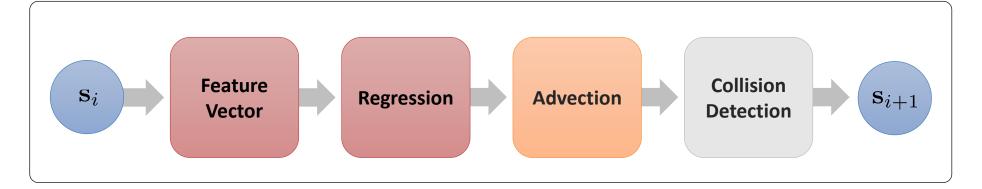




Learning Strategies

Standard Regression Pipeline

Naïve approach



Learn accelerations

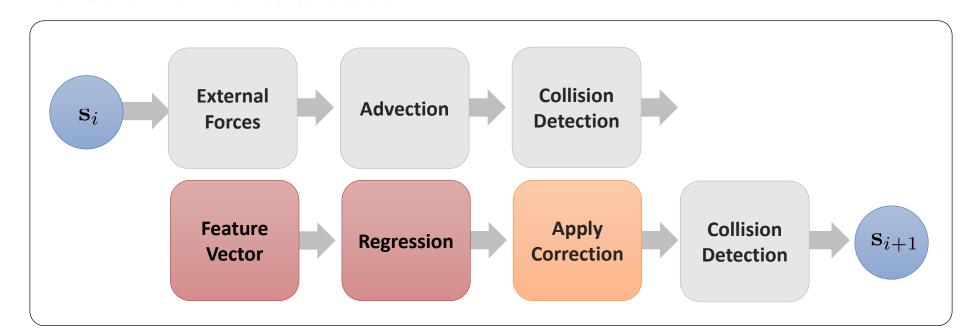
-> mimics standard SPH (no incompressibility)



Learning Strategies

Correction from Advected States

Correction approach



Learn acceleration corrections

-> mimics incompressible SPH methods

Learn velocity corrections

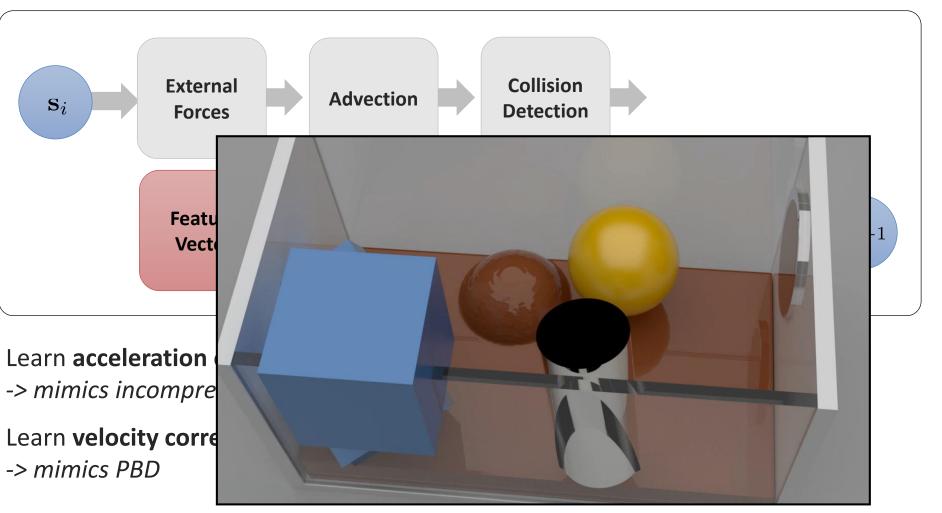
-> mimics PBD



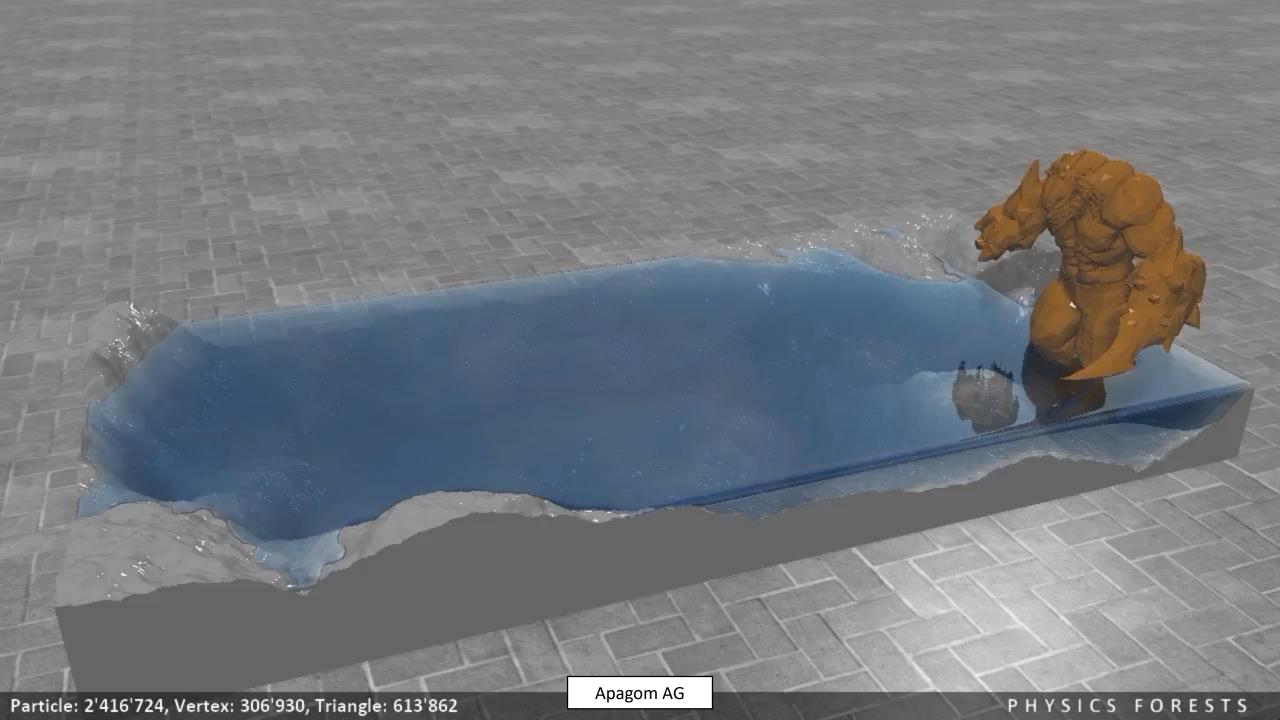
Changing Parameters at Test Time

Correction from Advected States

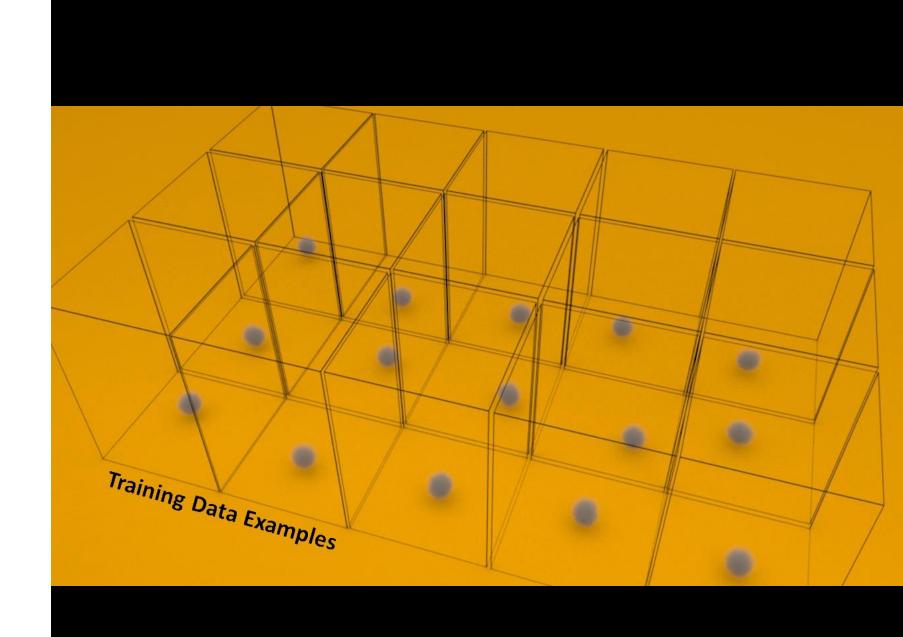
Correction approach



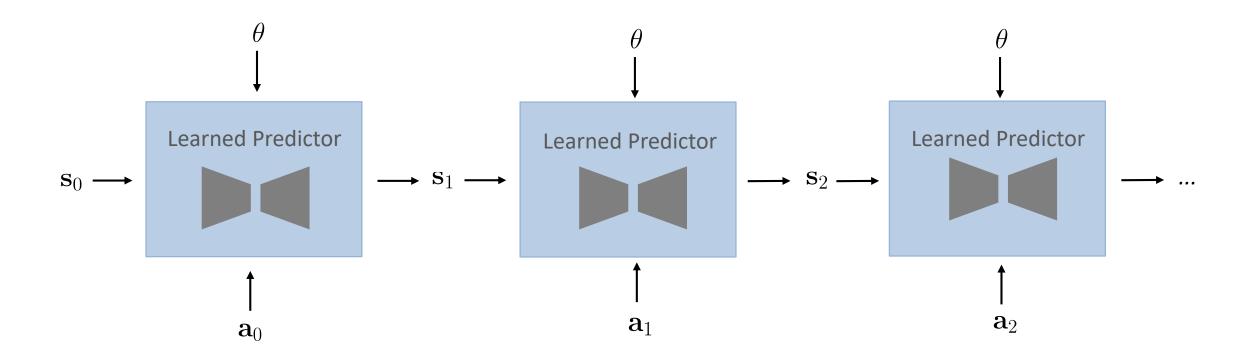




Neural Simulations

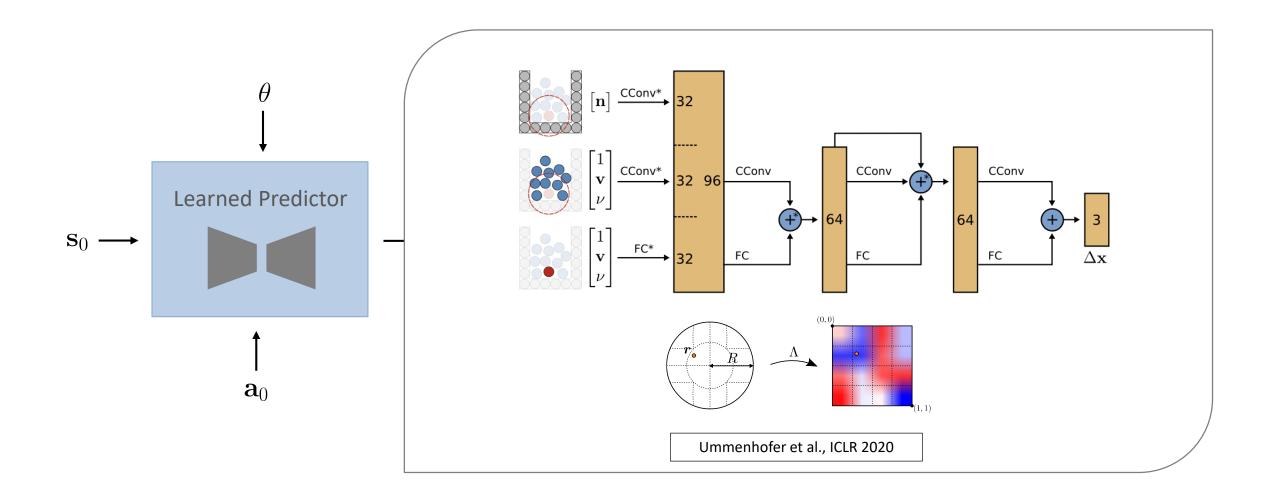


Surrogate Model for Particle Fluids



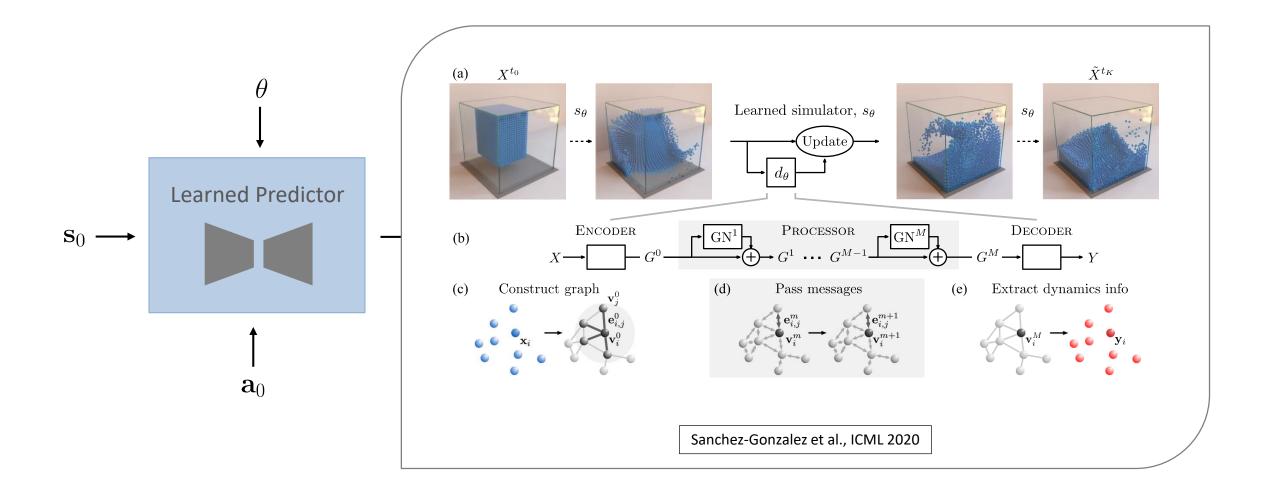


Lagrangian Fluid Simulation with Continuous Convolutions



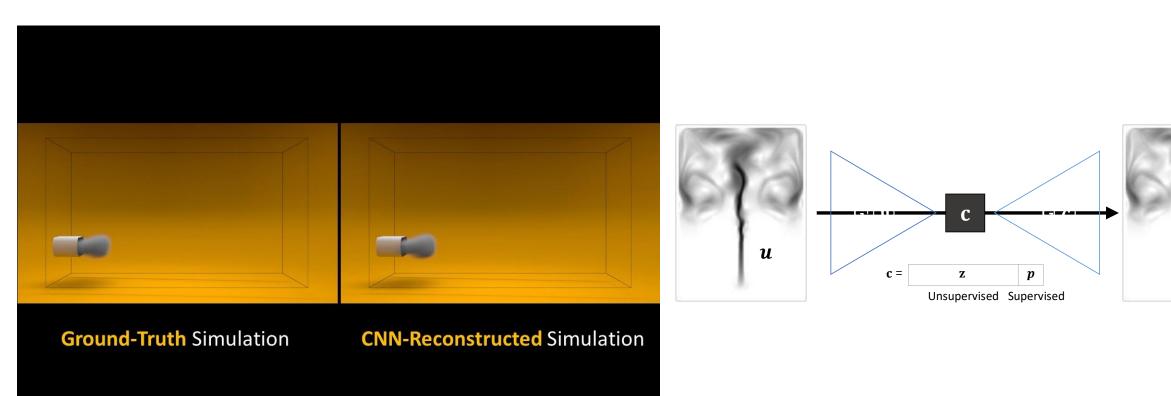


Learning to Simulate Complex Physics with Graph Networks





Digression: Neural Eulerian Simulations

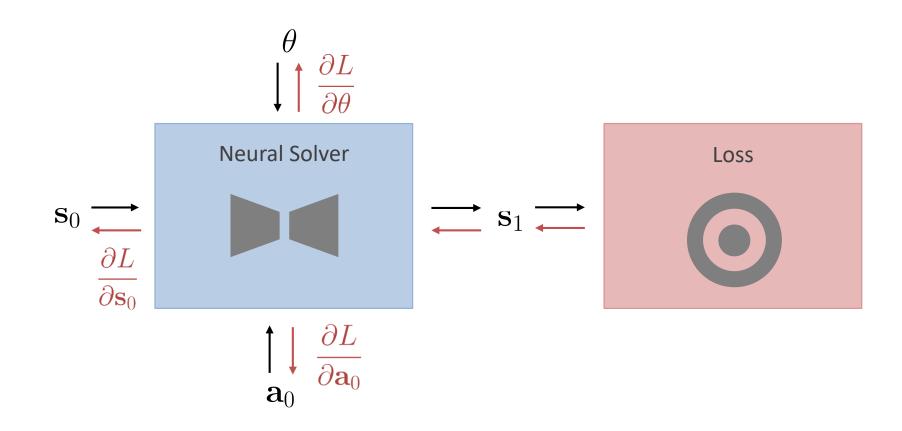




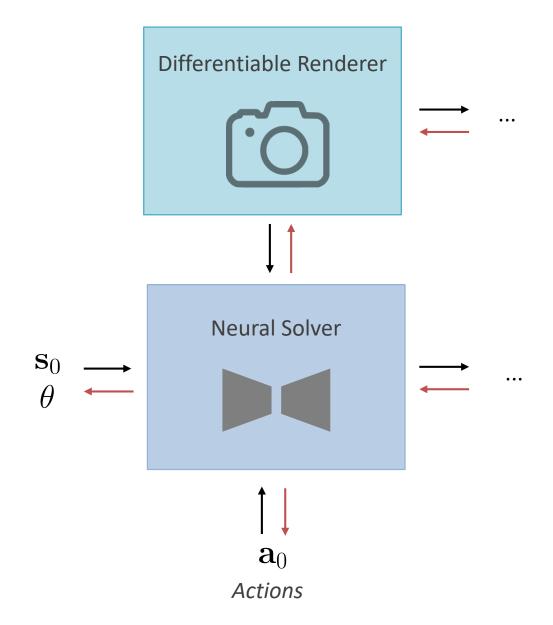
Differentiable
Physics for
Fluid Control



The Key Player for Control: Differentiable Simulation

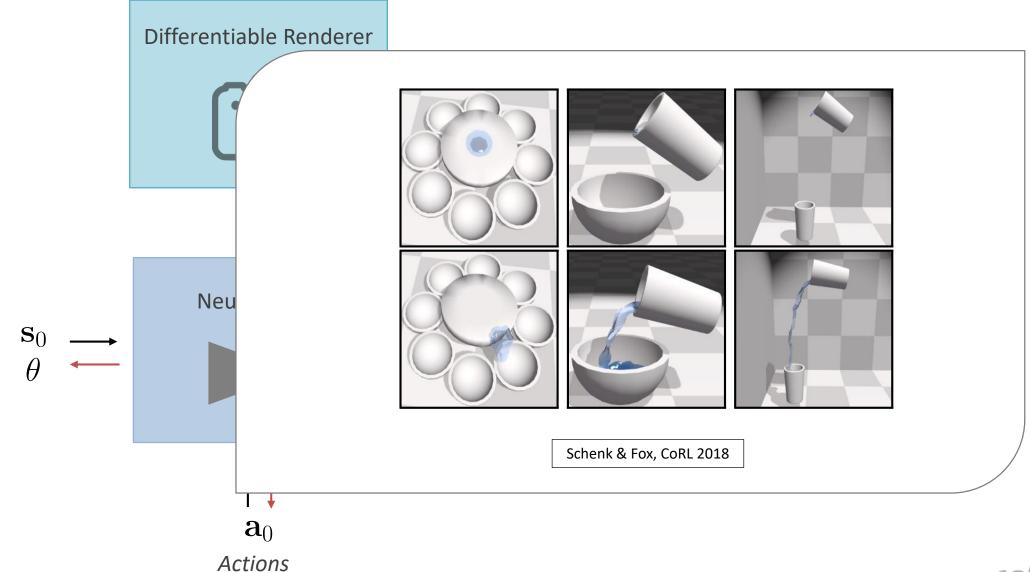


The Key Player for Control: Differentiable Simulation



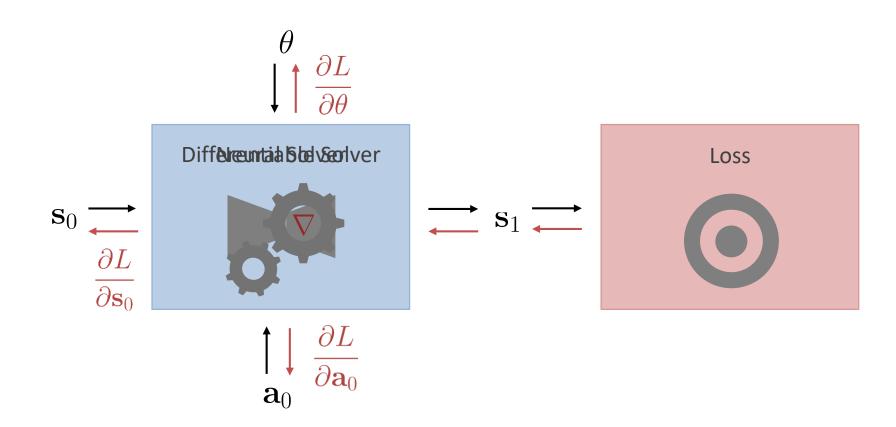


SPNets: Differentiable Fluid Dynamics for Deep Neural Networks





The Key Player for Control: Differentiable Simulation



Lagrangian Neural Style Transfer for Fluids

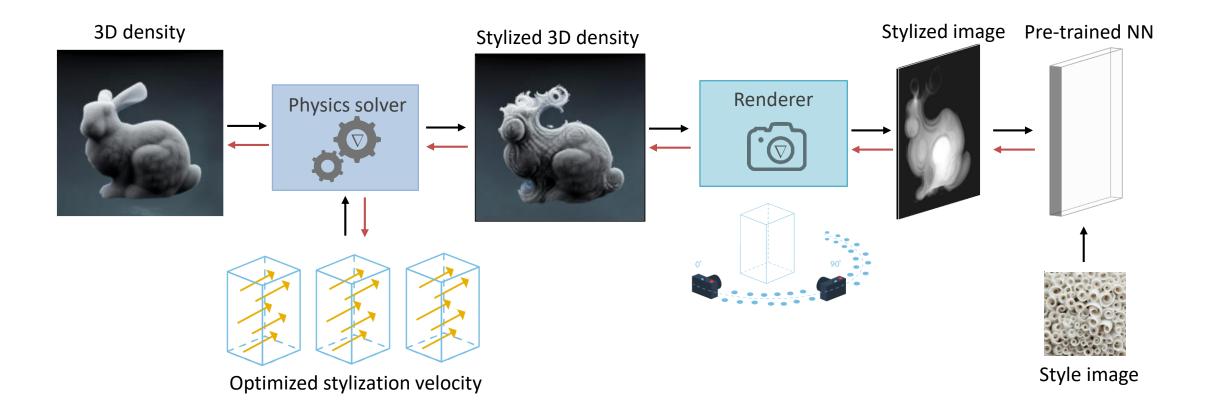


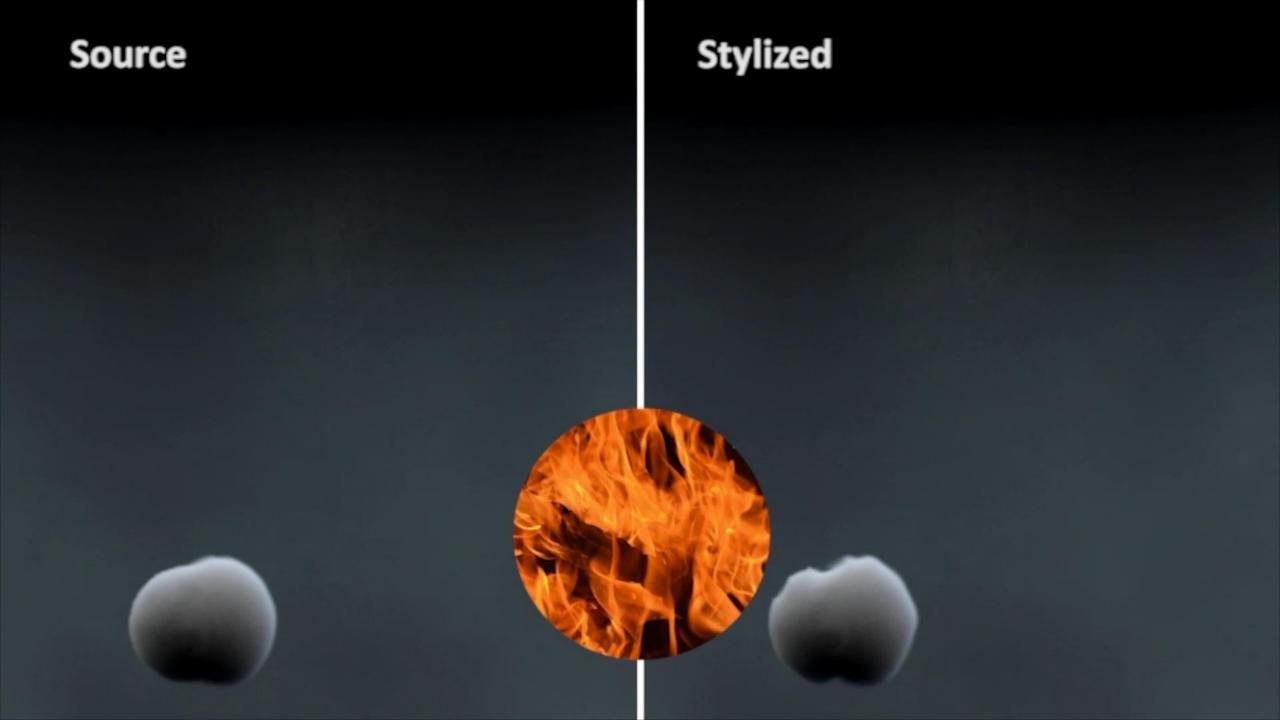




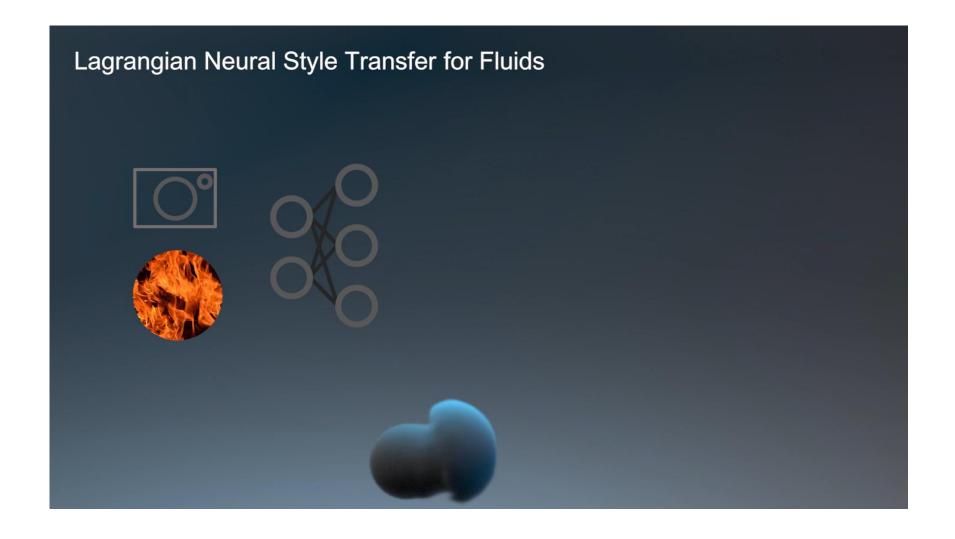


Transport-based Stylization (Eulerian)

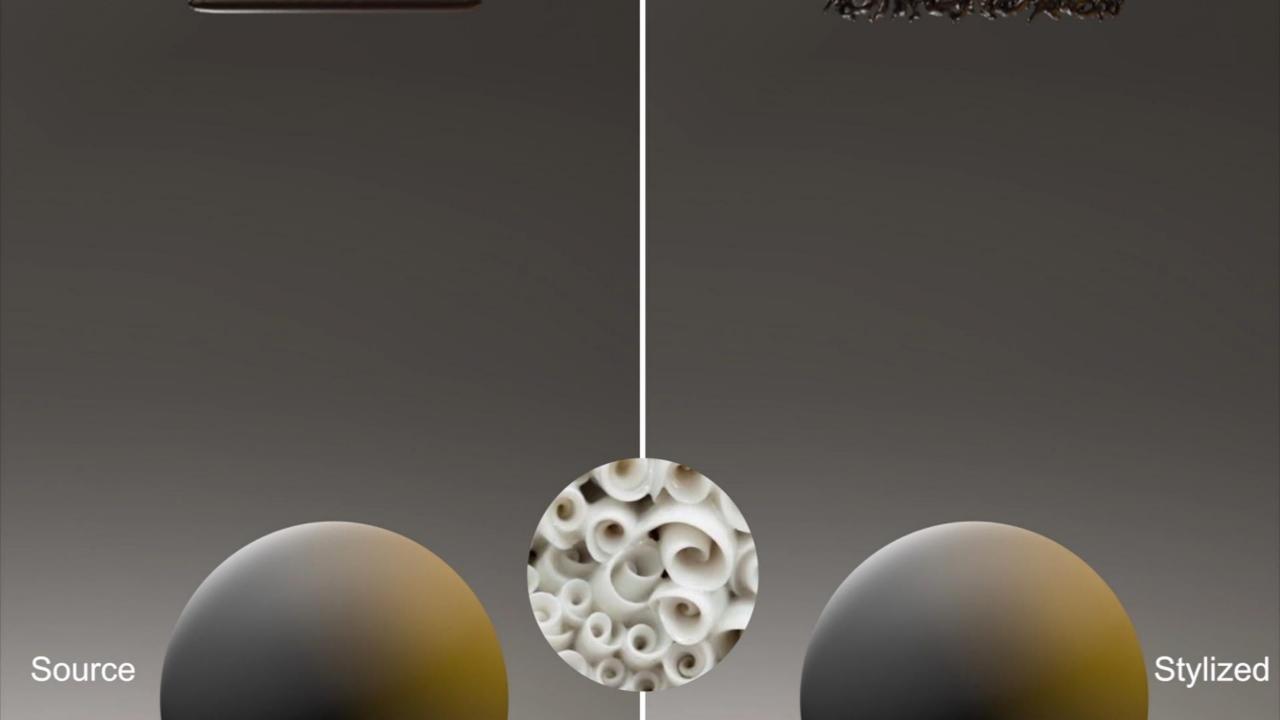




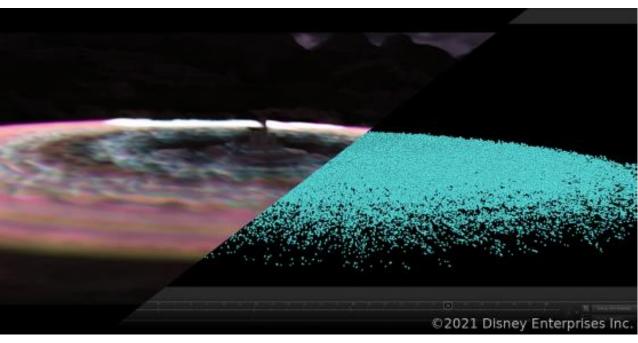
Particles to the Rescue!







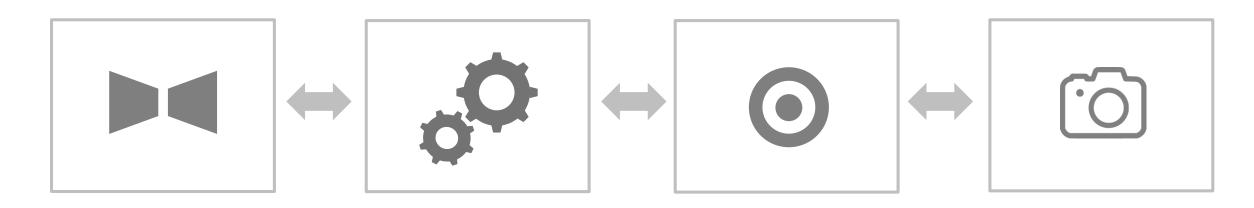
Lagrangian Flow Stylization used in Practice

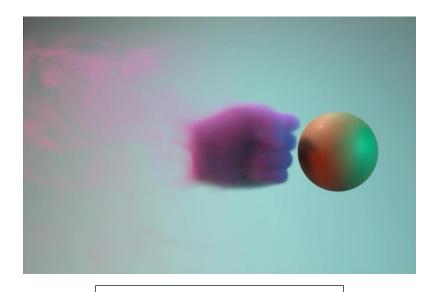






Al Revolution for Fluid Simulation and Animation?

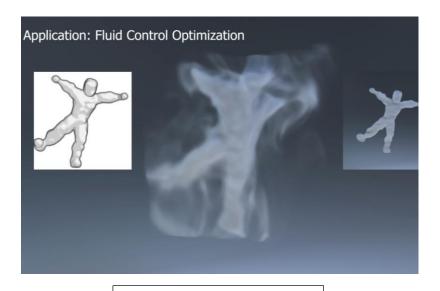








Franz et al., CVPR 2021



Kim et al., Eurographics 2022

