Outline

<u>Block 1</u> (9:00 - 10:30)

- Foundations of SPH
- Governing equations
- Time integration
- <u>Example</u>: Our first SPH solver
- Neighborhood Search

Coffee break (30min)

<u>Block 2</u> (11:00 - 12:30)

- Enforcing incompressibility
  - State equation solvers
  - Implicit pressure solvers
- Boundary Handling
  - Particle-based methods
  - Implicit approaches

Lunch break (60min)

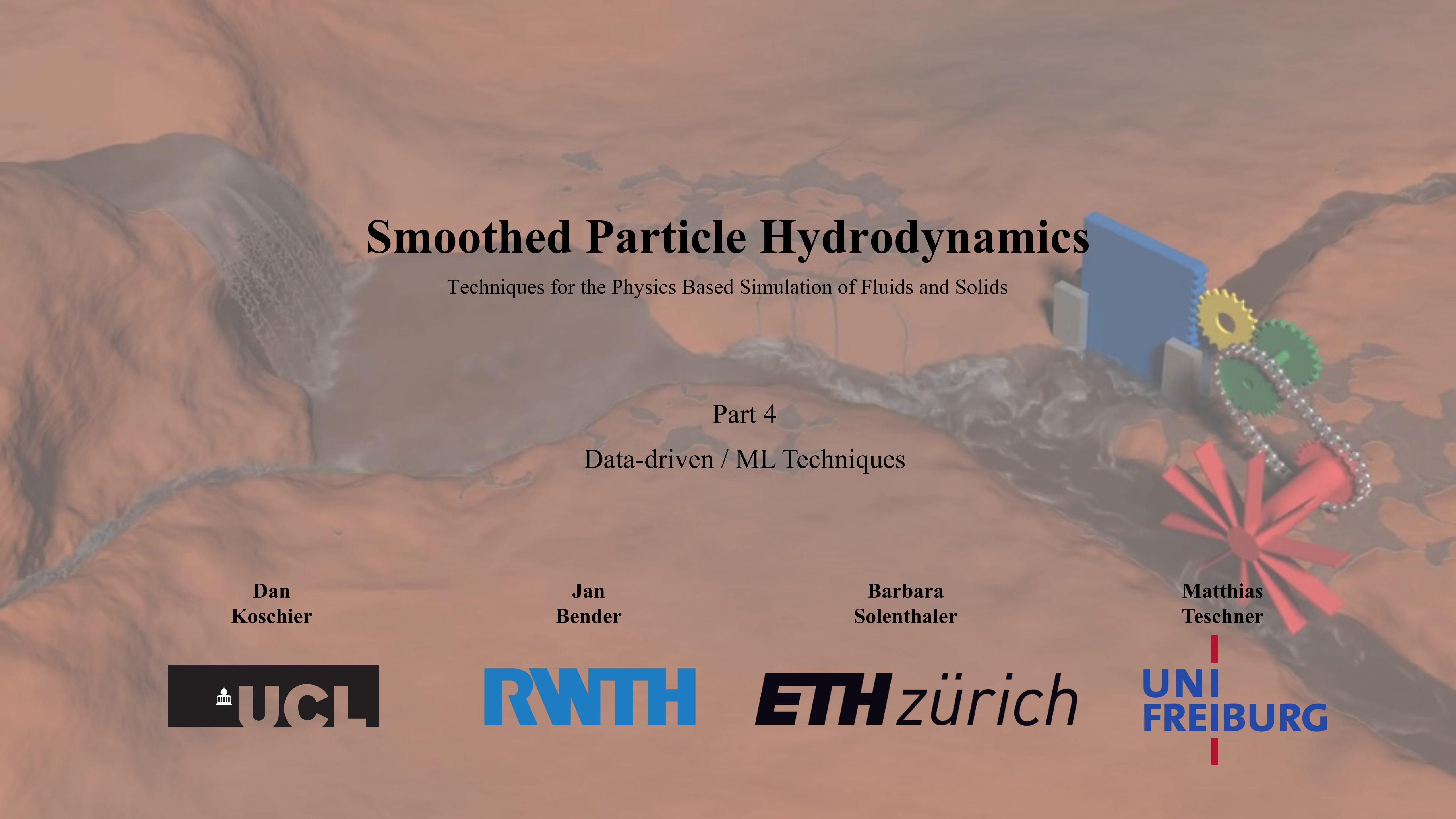
<u>Block 3</u> (13:30 - 15:00)

- Multiphase fluids
- Highly-viscous fluids
- Vorticity and turbulent fluids
- <u>Demo</u>:

Coffee break (30min)

<u>Block 4</u> (15:30 - 17:00)

- Deformable solids
- Rigid body simulation
  - Dynamics and coupling
- Data-driven/ML techniques
- Summary and conclusion



Smoothed Particle Hydrodynamics

Techniques for the Physics Based Simulation of Fluids and Solids

Part 4

Data-driven / ML Techniques

Dan Koschier

Jan Bender

Barbara Solenthaler

Matthias Teschner

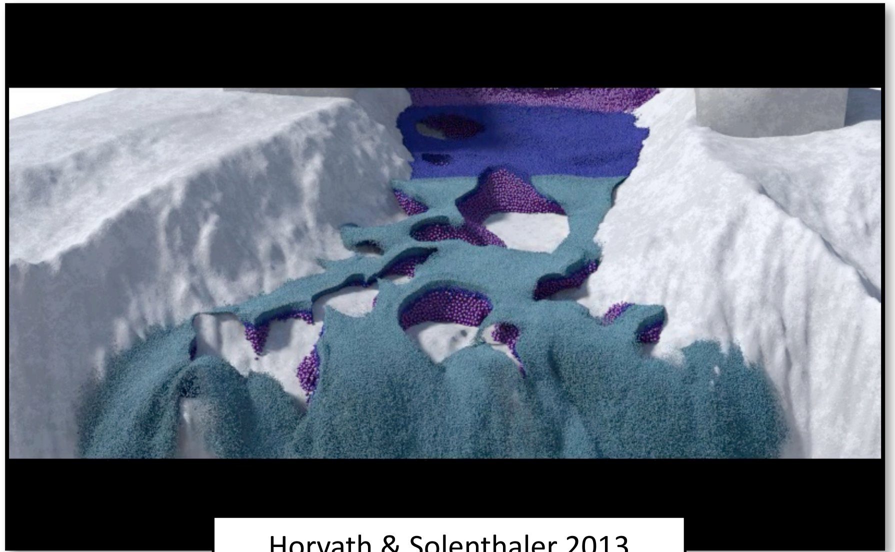
Motivation

- Substantial improvements in speed, robustness, versatility…

Incompressibility

Ihmsen et al. 2013

Multi-scale simulations



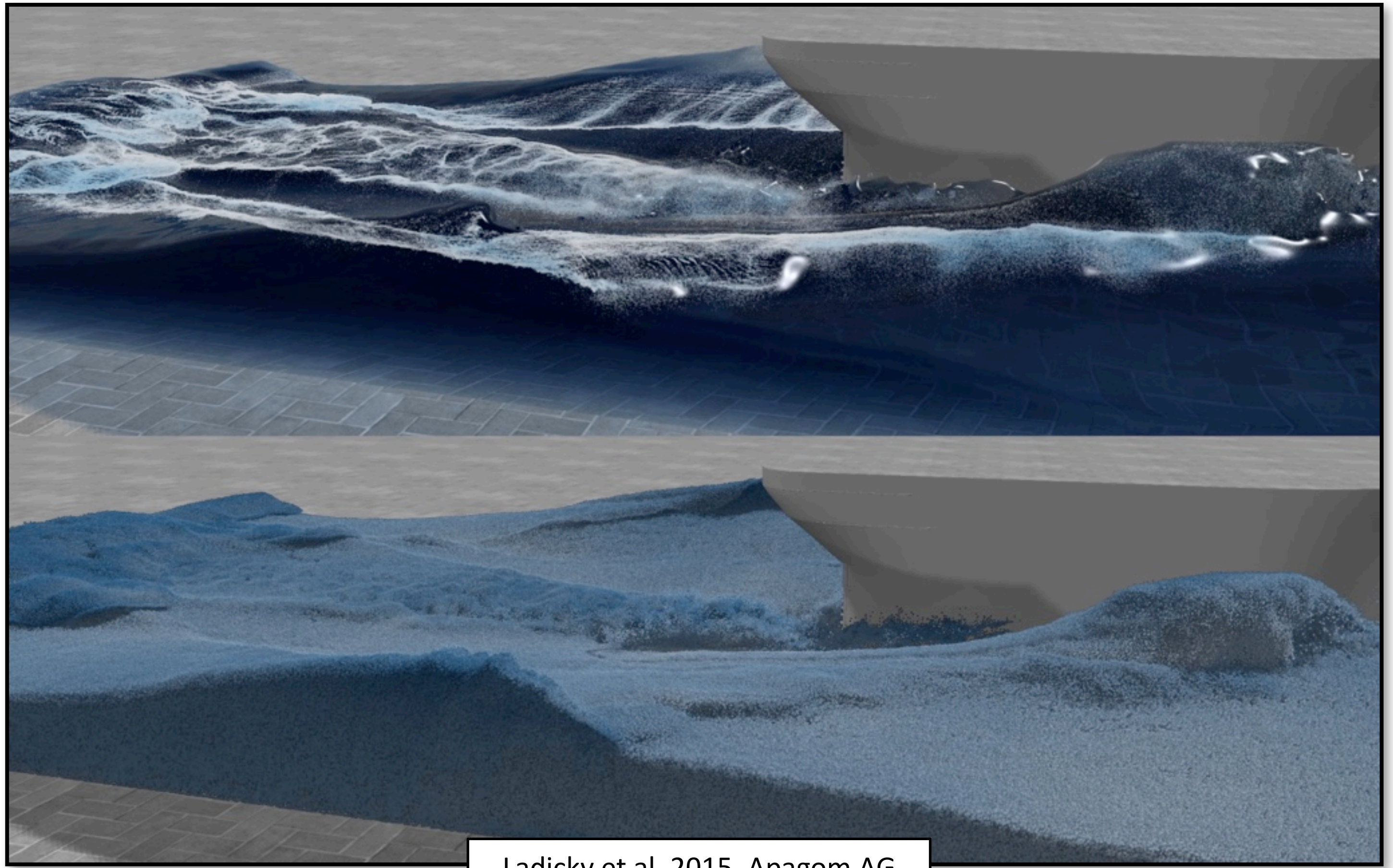
Horvath & Solenthaler 2013

- Potential of data-driven approaches?
  - PhysicsForest: Real-time SPH simulations
  - Deep Learning & Fluids: Related work and Outlook

- Computation time
- Trial & error, parameters
- Data reuse
- Edit & control simulations
- …

Machine Learning based Simulations

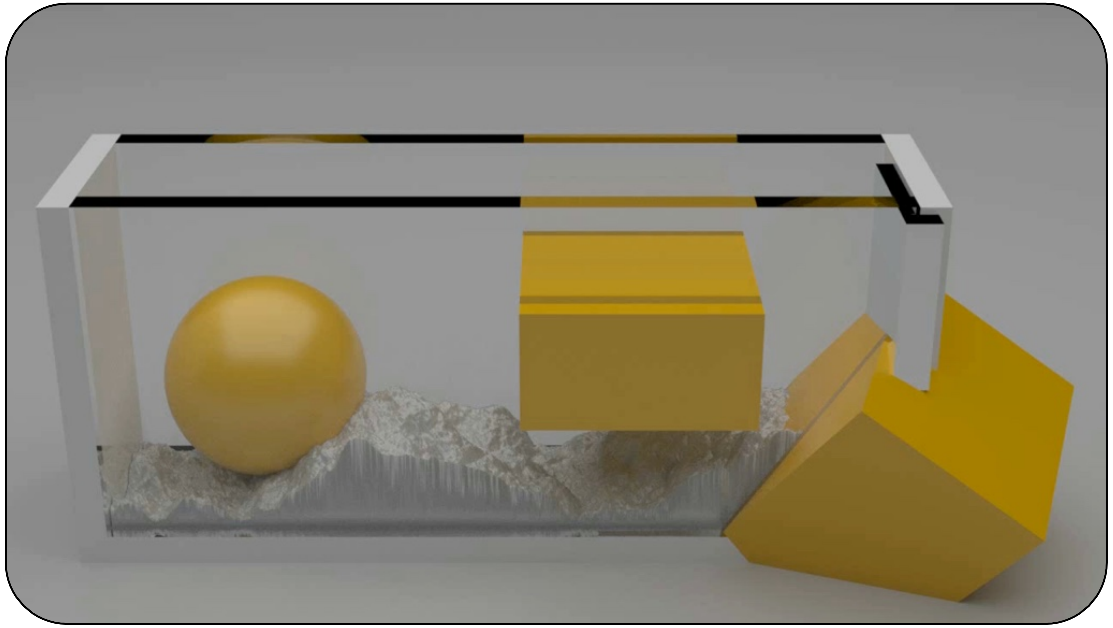
Real-time prediction of fluids with Regression Forests



Ladicky et al. 2015, Apagom AG

Physics Forest

Current State S^n → S^{n+1} *Next State*



Simulation training data

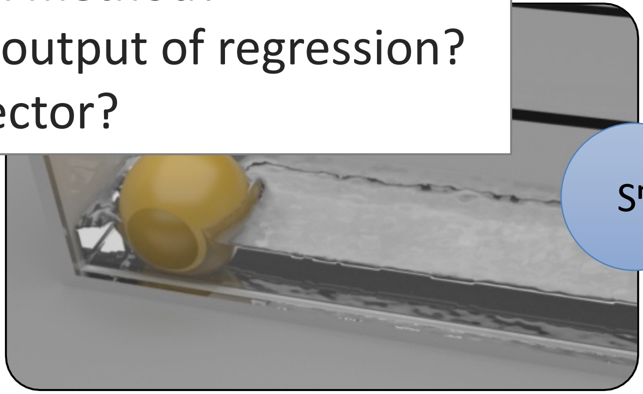
Regression Model

Data size:
165 scenes x 6s x 30fps x 1-6M particles

Training

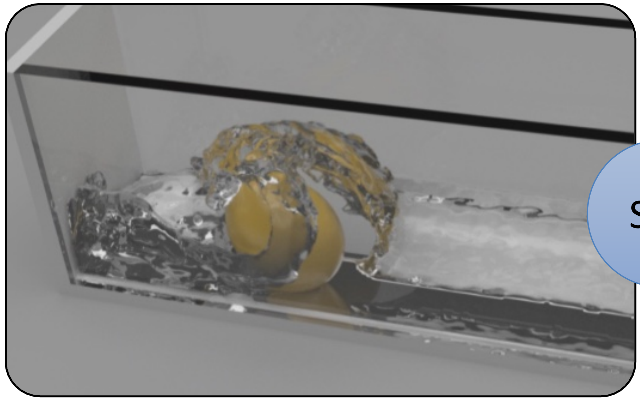
Physics Forest

1) Regression method?
2) Input and output of regression?
3) Feature vector?



S^n

Current State



S^{n+1}

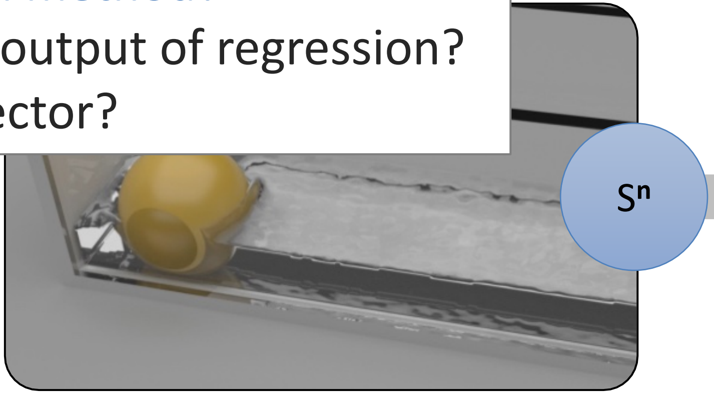
Next State

Regression Model

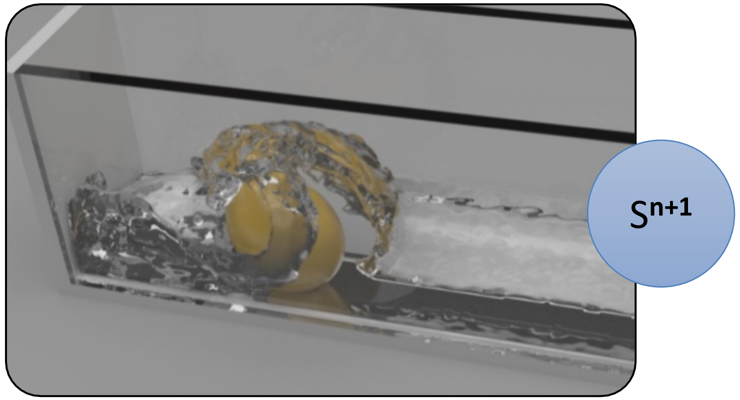
Test

Physics Forest

1) Regression method?
2) Input and output of regression?
3) Feature vector?



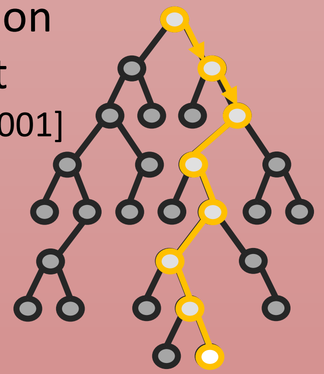
Current State



Next State

Regression Model

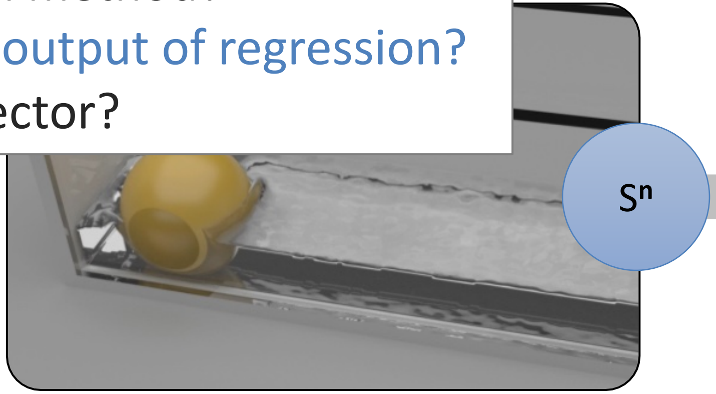
Regression Forest [Breiman 2001]



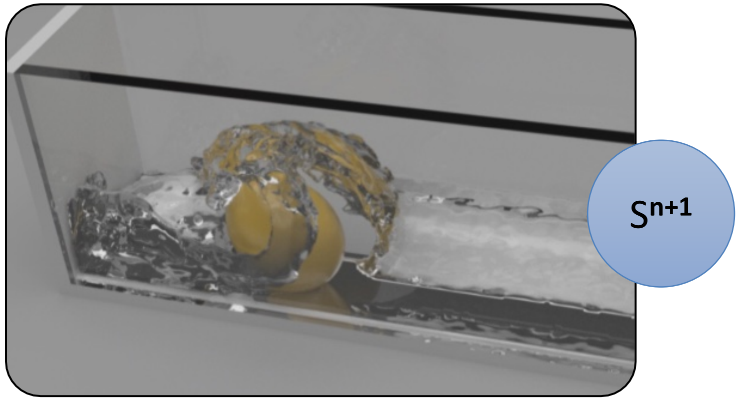
Test

Physics Forest

1) Regression method?
2) Input and output of regression?
3) Feature vector?



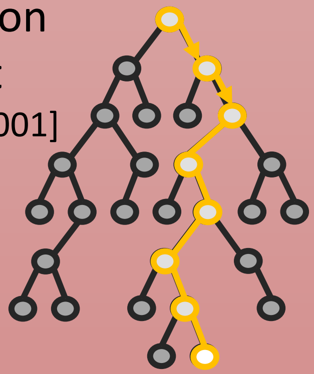
Current State



Next State

Regression Model

Regression Forest [Breiman 2001]

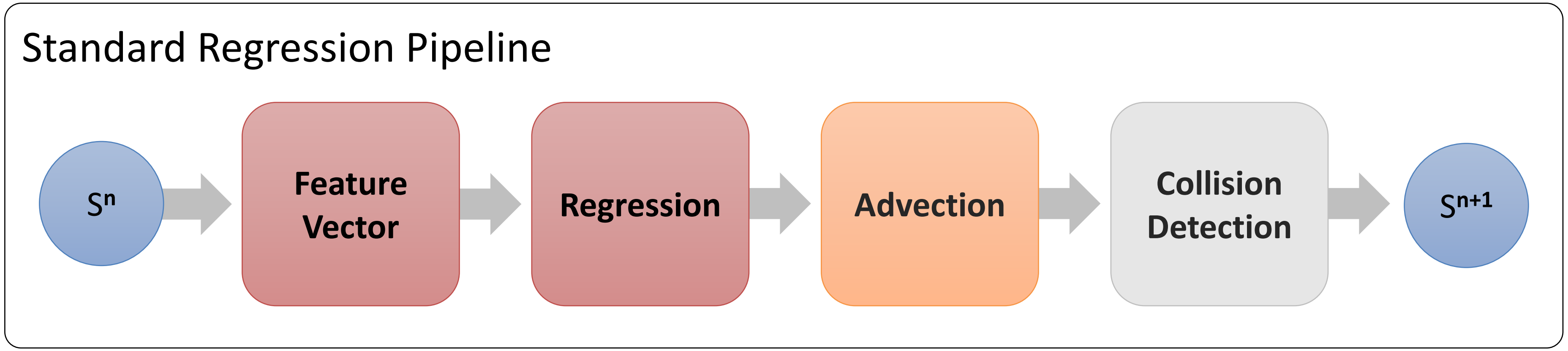


Test

Learning Strategies

Learn velocity or acceleration?
Problem: no self-correction possible

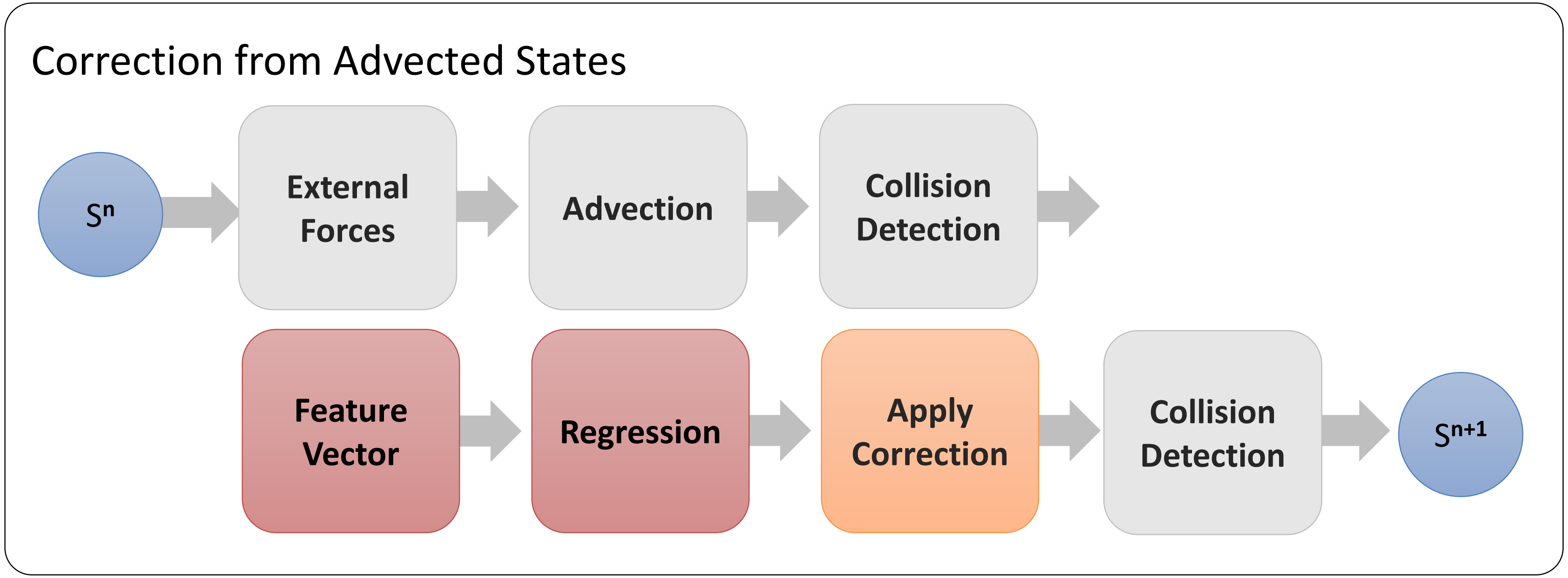
Naïve approach



Learn accelerations
-> mimics standard SPH (no incompressibility)

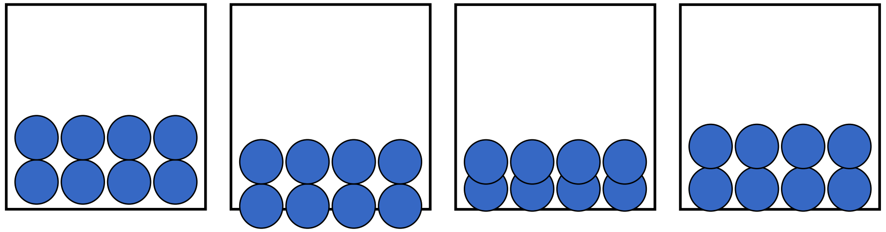
Learning Strategies

Correction approach



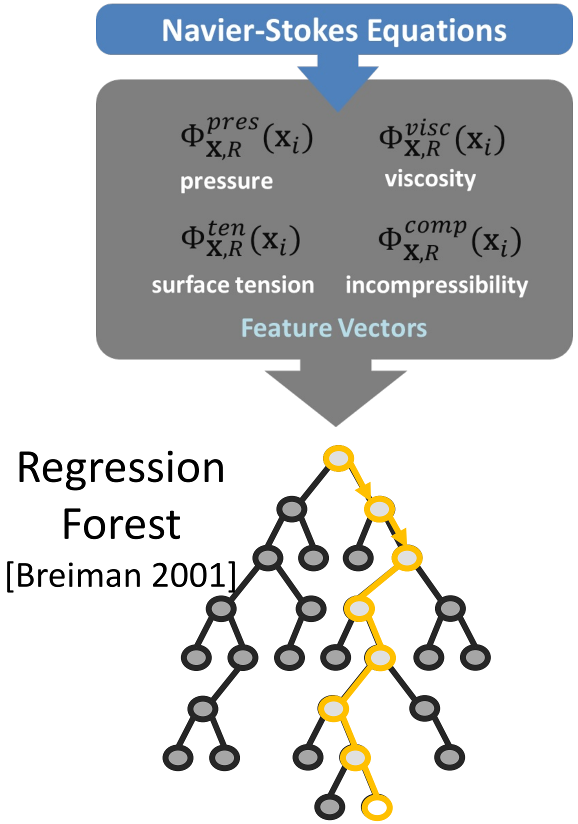
Learn acceleration corrections
-> mimics PCISPH (incompressibility)

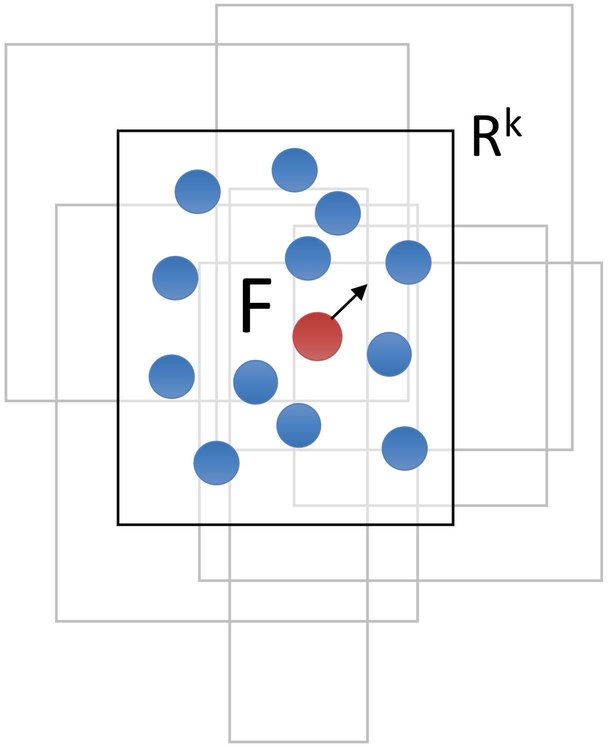
Learn **velocity corrections**
-> mimics PBD (incompressibility)



Feature Vector

1) Regression method?
2) Input and output of regression?
3) Feature vector?





$\Phi_i = \{ F_{R0}\ F_{R1}\ F_{R2} \cdots F_{Rk} \}$

Integral features:

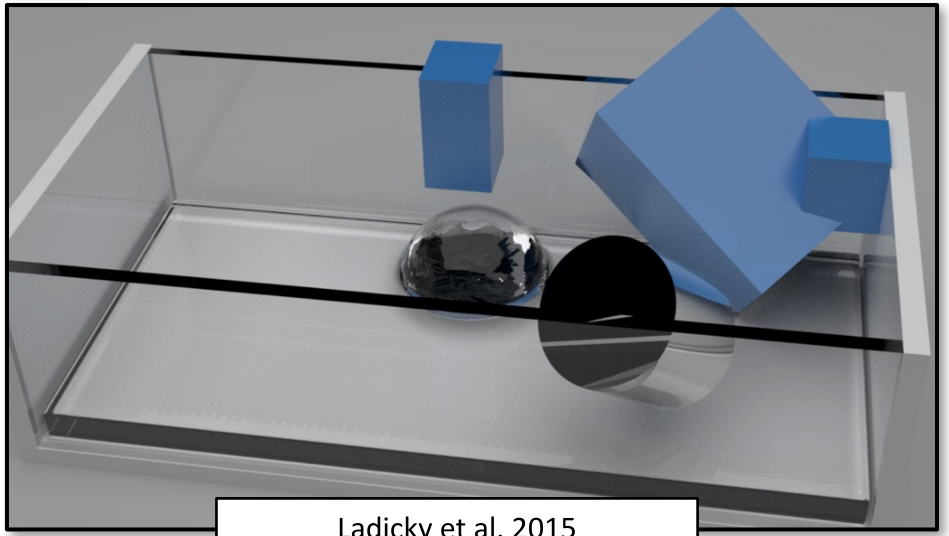
Flat-kernel sums of rectangular regions around particle

- Regional forces and constraints over the set of boxes
- Fast evaluation
- Robust to small input deviations
- Evaluation in constant time (linear in number of particles)

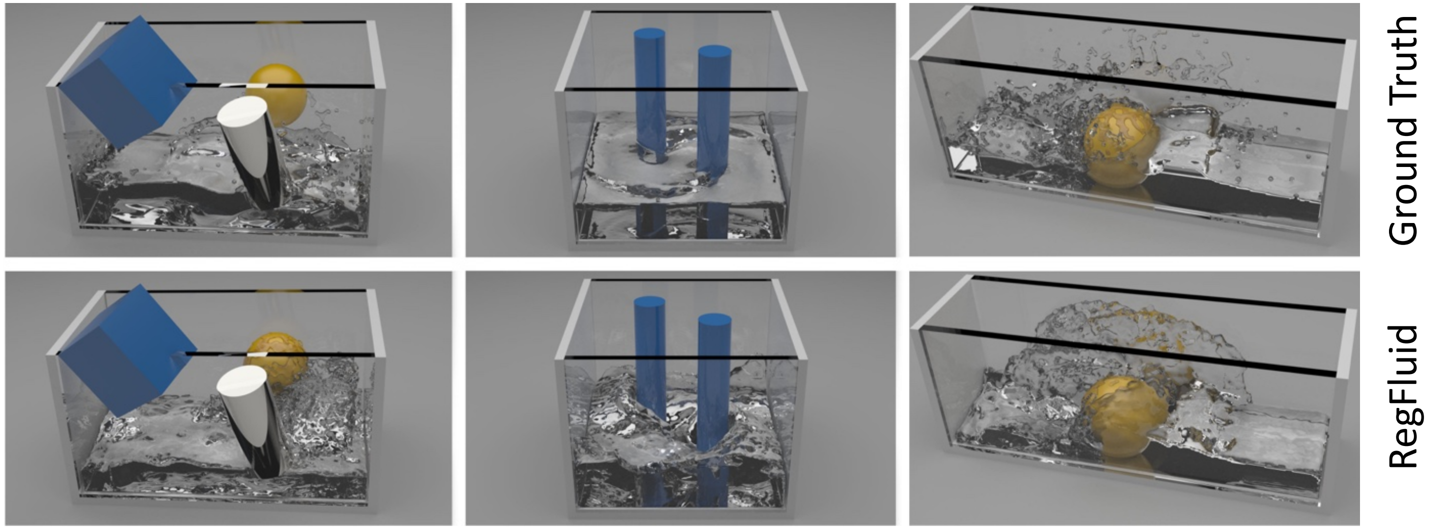
Training Data and Performance

- Data size: 165 scenes x 6s x 30fps x 1-6M particles
- Training: 4 days on 12 CPUs
- Size of trained model: 40MB
- Only use most discriminative features (pressure, compressibility)

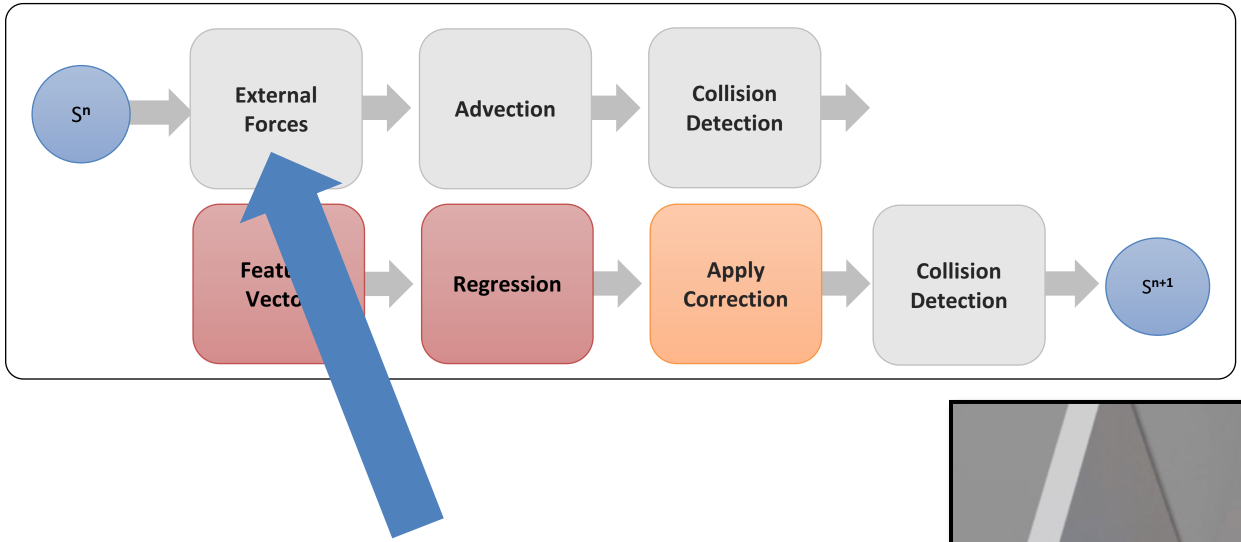
1-1.5M particles in real-time



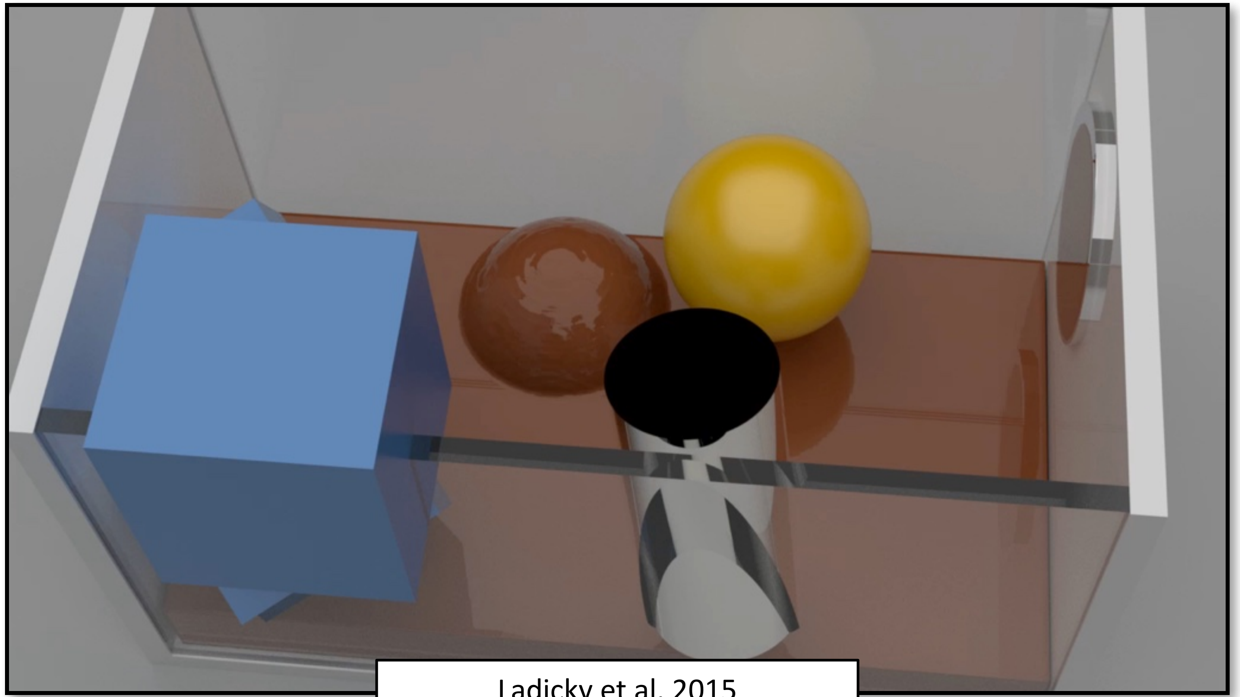
Ladicky et al. 2015



Varying Material Properties



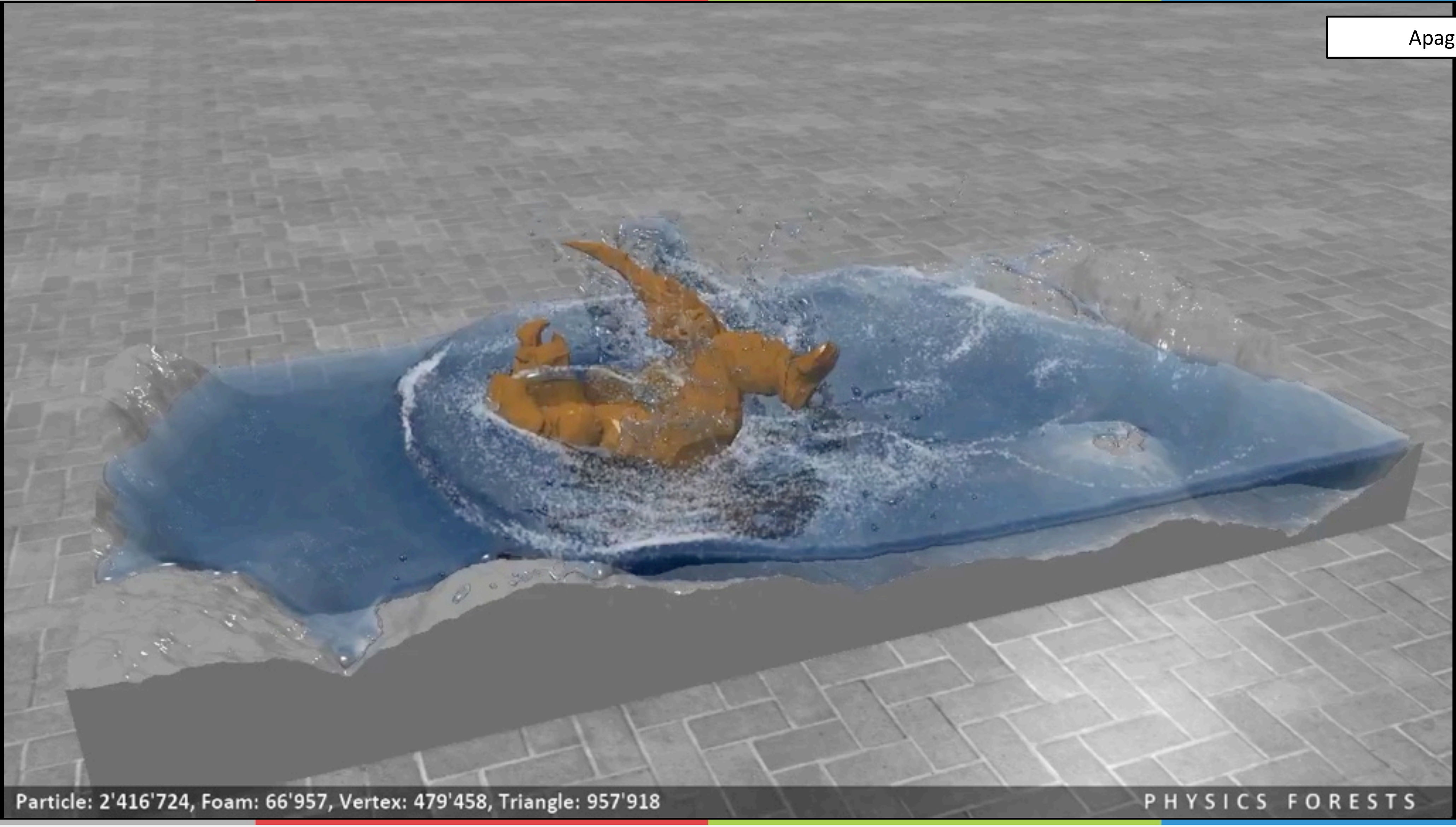
- Viscosity
- Surface Tension
- Static Friction
- Adhesion
- Drag
- Vorticity Confinement



Ladicky et al. 2015

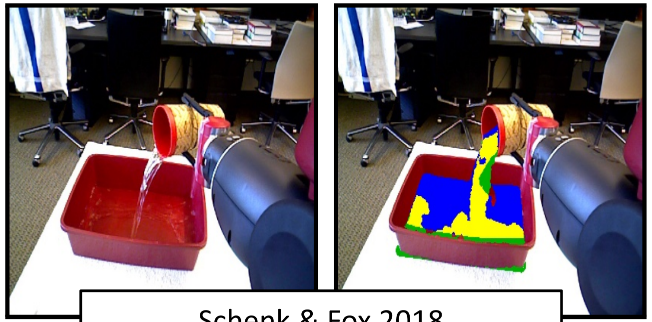
Real-time Simulations with PhysicsForests

Apagom AG



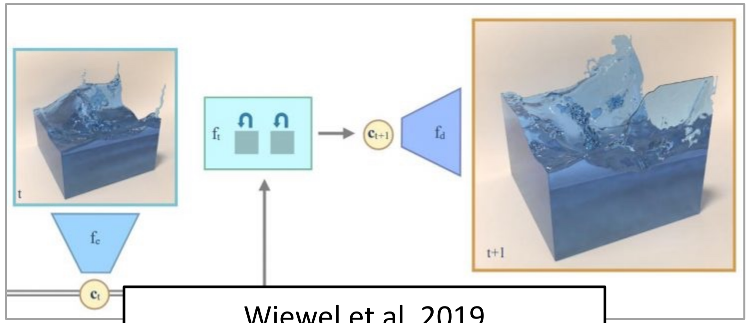
Related Work

- RegressionFluid: fast, but hand-crafted features
  -> Deep Learning (DL)
- Using DL for fluids (physics) is largely unexplored!



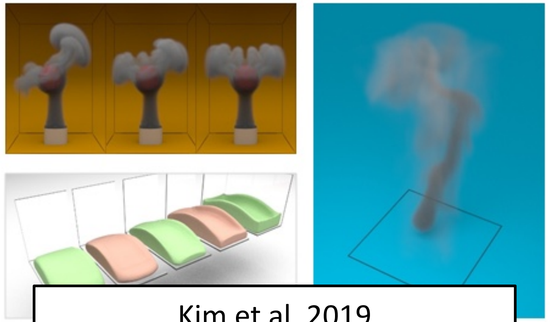
Schenk & Fox 2018

Talk tomorrow 10:00

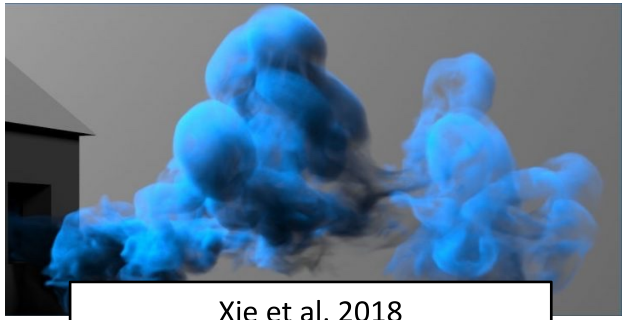


Wiewel et al. 2019

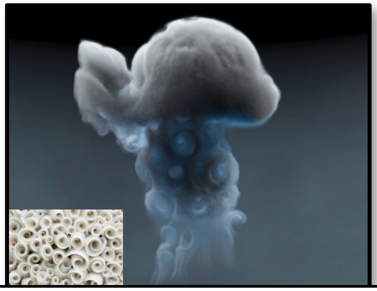
Talk tomorrow 9:30



Kim et al. 2019



Xie et al. 2018

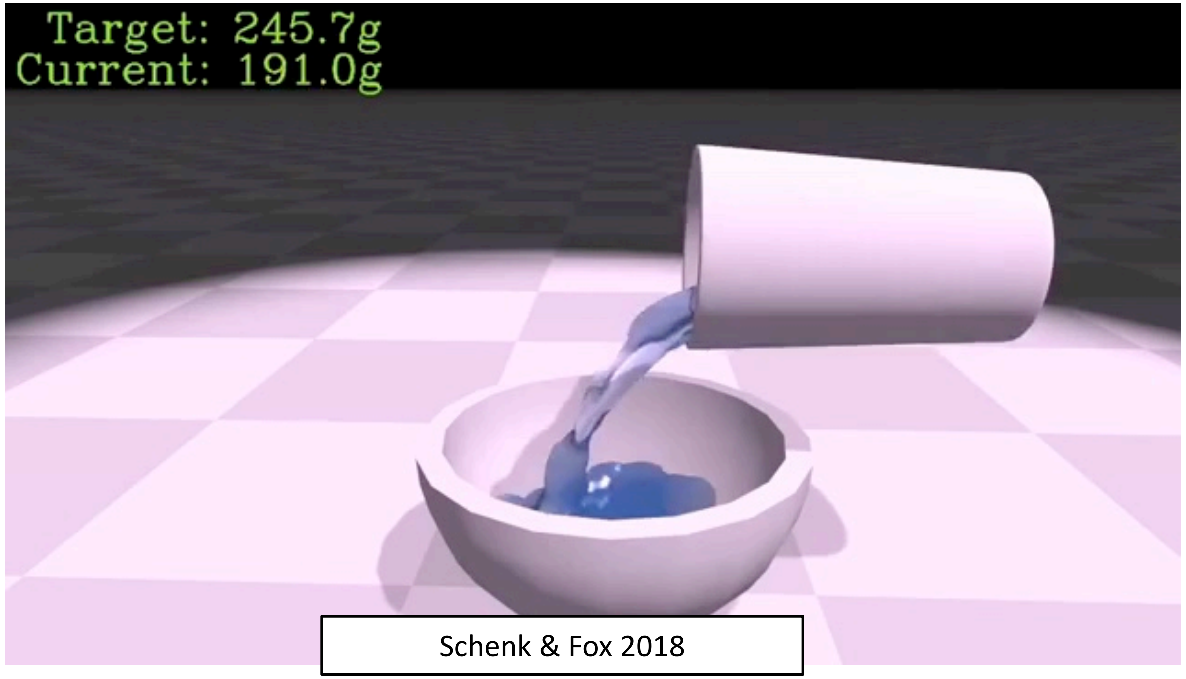


Kim et al. 2019

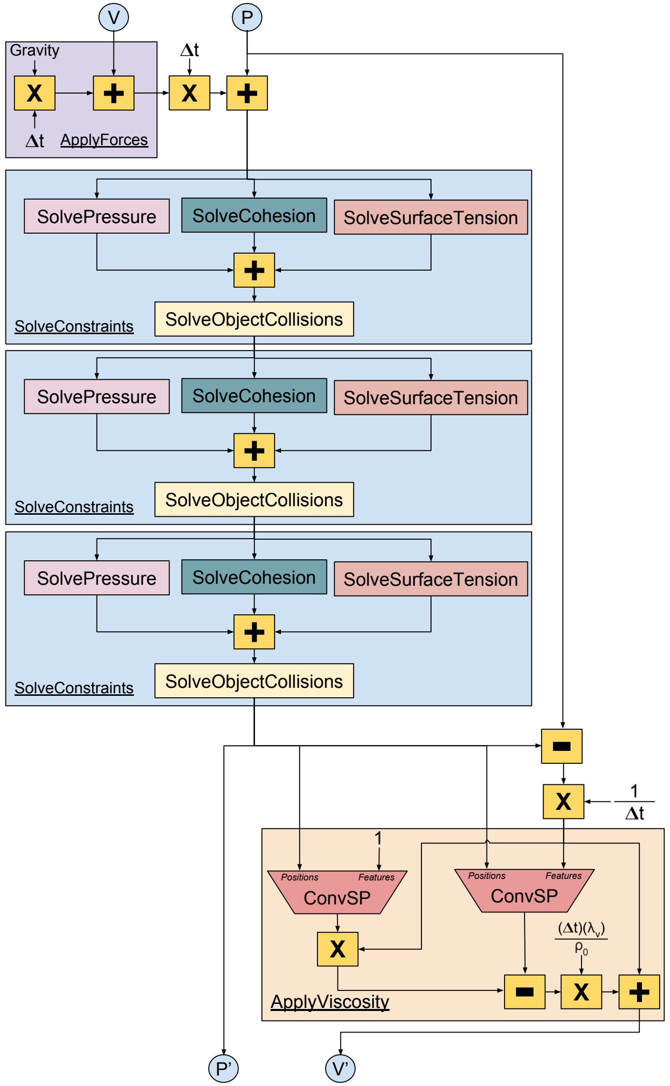
Panel discussion CreativeAI tomorrow 9:30

SPNets - Smoothed Particle Network for PBF

- PBF with a deep neural network
  -> can compute full analytical gradients (differentiable solver)
- Two new layers: ConvSP for particle-particle interactions
  ConvSDF for particle-object interaction
- Robots interacting with liquids (learning parameters, control)



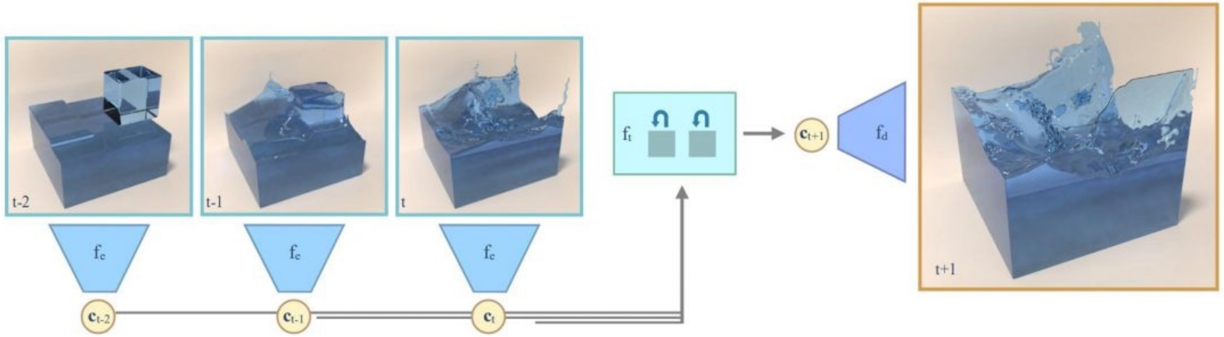
Schenk & Fox 2018



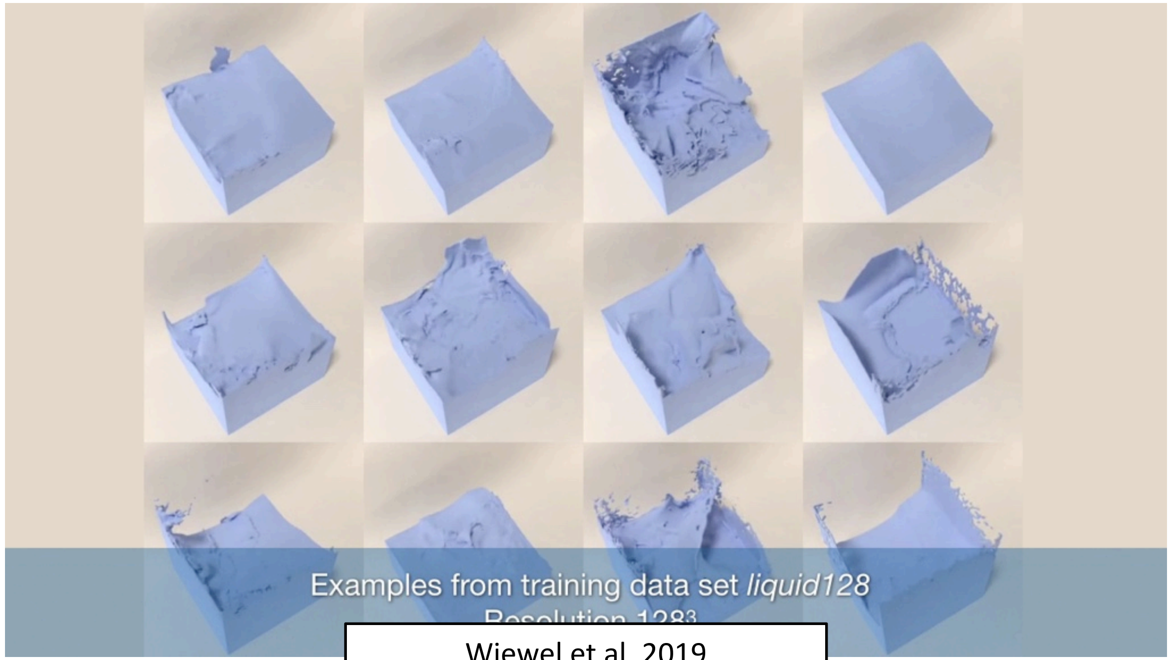
cgl SA

Latent Space Physics – Learning Temporal Evolution

- LSTM network to predict changes of pressure field over time (3D + time) within the latent space
- Uses a history of 6 steps to infer next [1…x] steps, followed by a regular sim step
- 155x speed-up



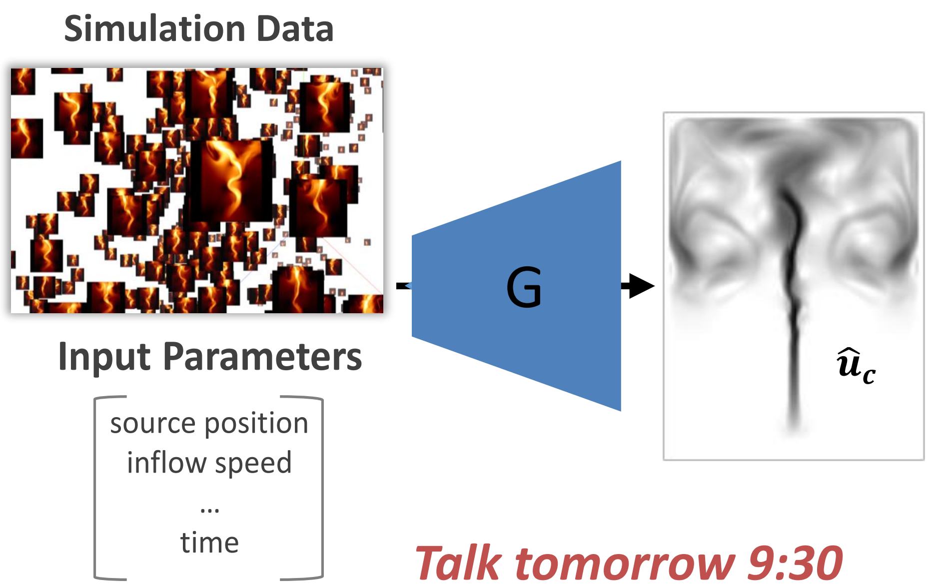
Talk tomorrow 10:00



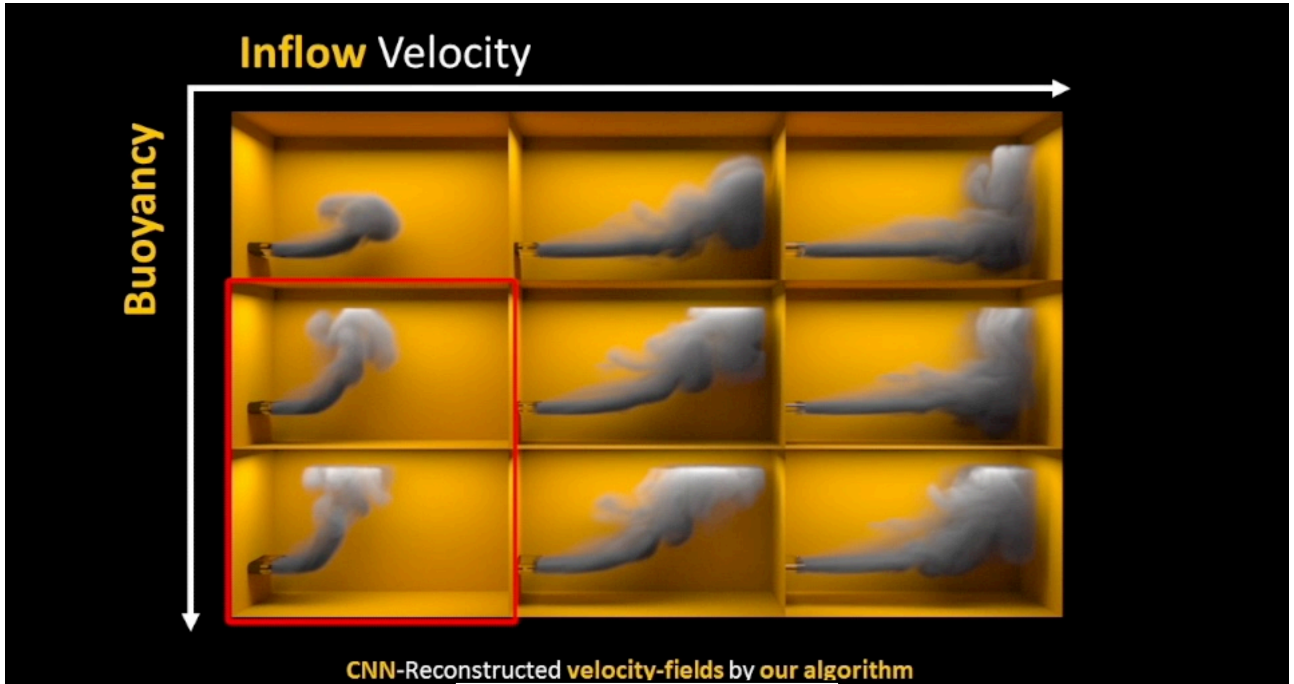
Wiewel et al. 2019

DeepFluids: Generative Net for Parameterized Simulation

- Input parameterizable data set
- Generative network with supervised training
- Latent space time integration network
- >1300x compression, >700x speed-up, trained model 30MB



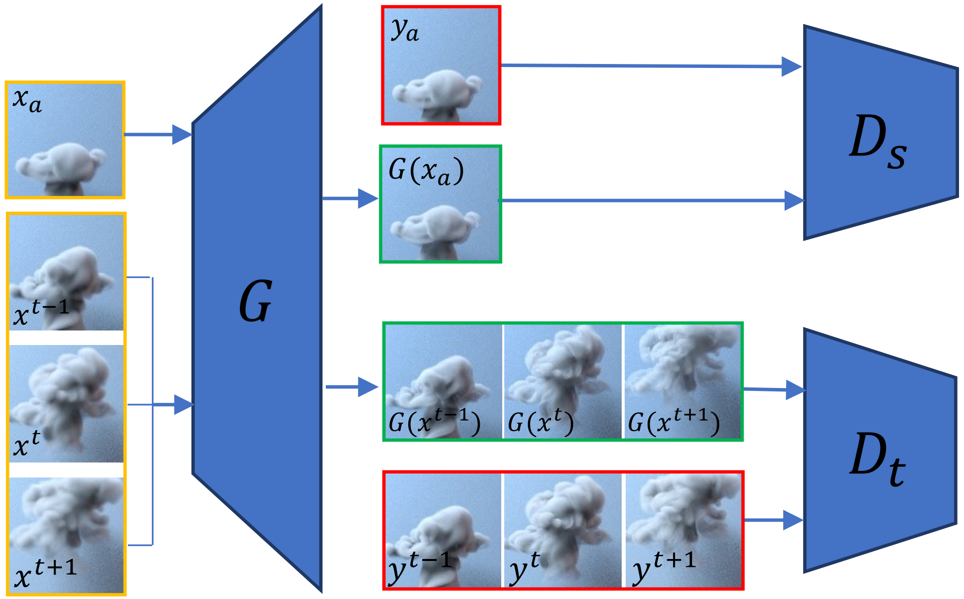
Talk tomorrow 9:30

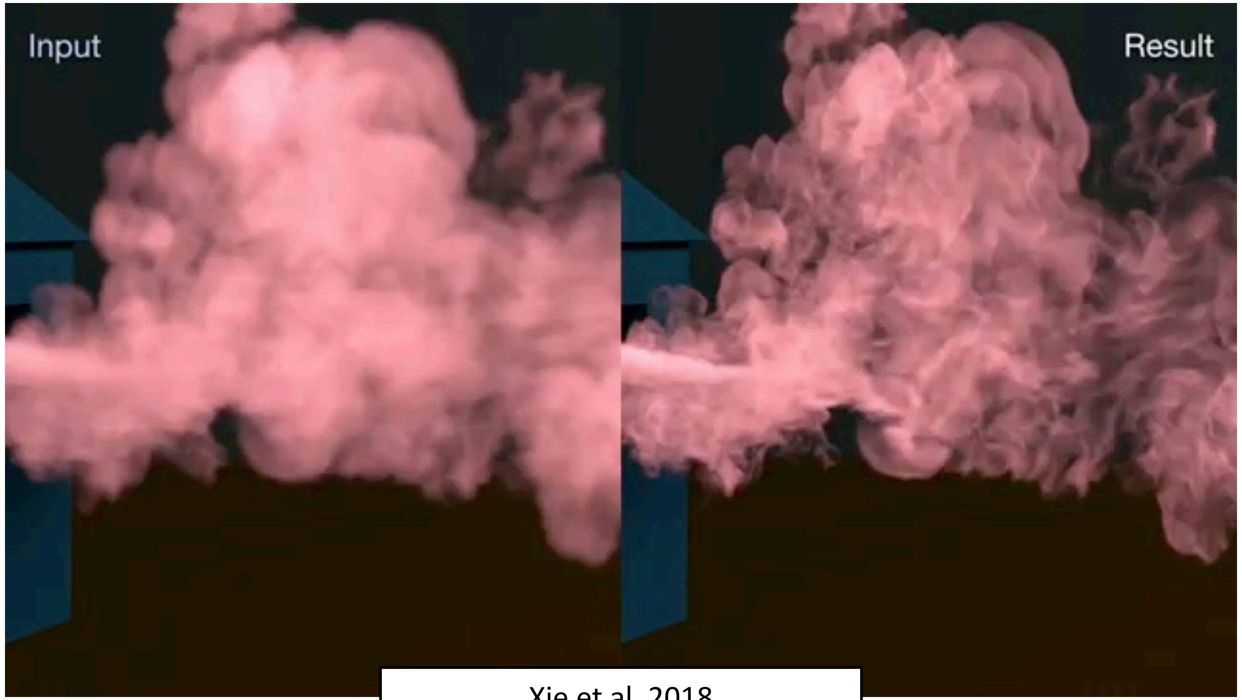


Kim 2019

TempoGAN - Superresolution Fluids

- Infer high-resolution details
- Generator, guided during training by two discriminator networks (space and time)
- Training data: low- and high-res density pairs (density, velocity, vorticity)

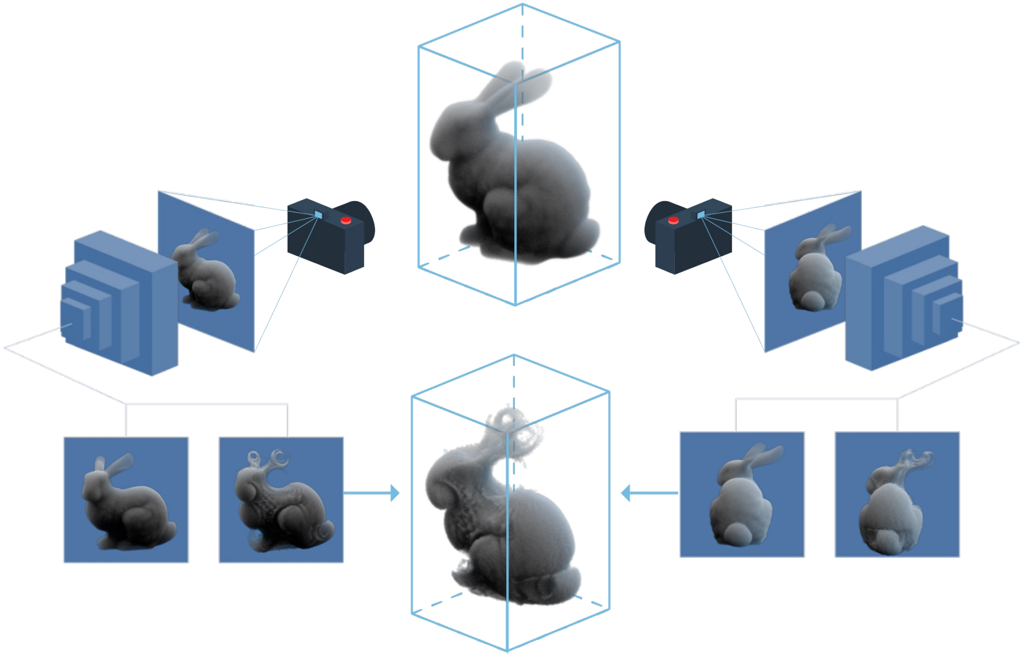


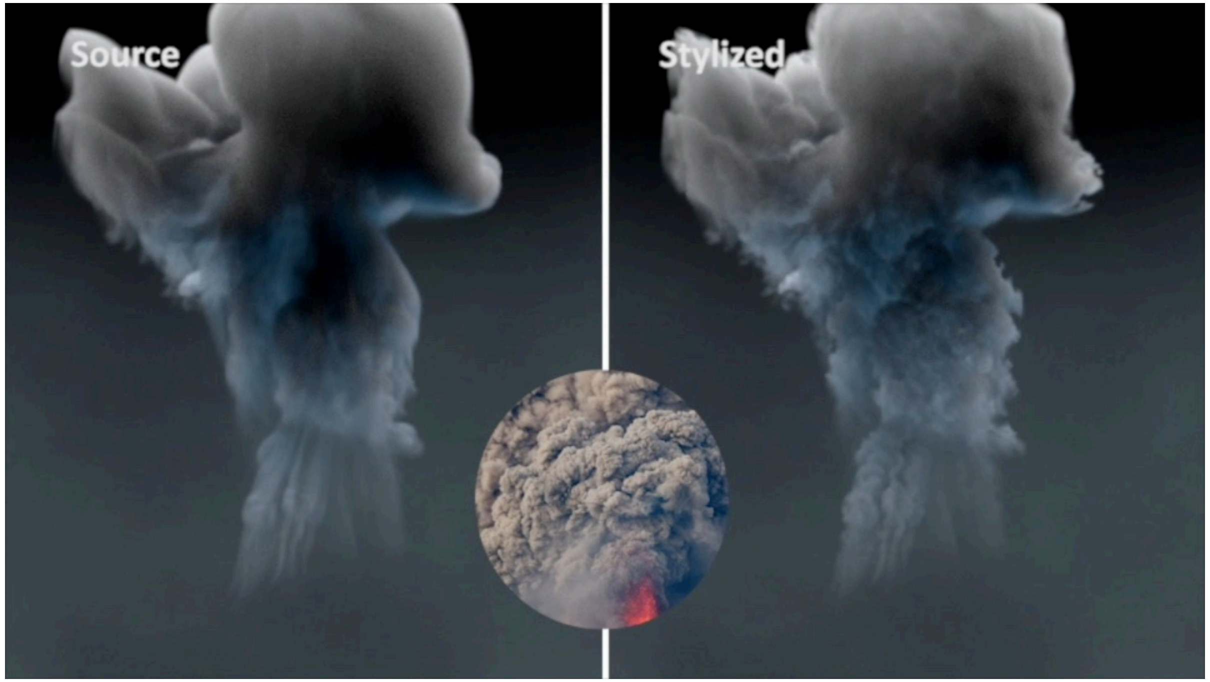


Xie et al. 2018

FlowStyle – Neural Stylization of Flows

- Transfer low- and high-level style features from images to 4D fluid data
- Structurally and temporally coherent
- Pre-trained networks on images, 3d reconstruction





Potential and Challenges of Data-driven Fluids

Unexplored area

Exciting research, triggers research and collaborations across disciplines

What is the potential of data-driven simulations?

Computational speed, data compression, novel applications: quick simulation previews, interpolation of simulations, image-based modeling and control...

Use DL as a black box?

No; synergistic combination of mathematical models and data

What are the challenges?

Loads of data (expensive, lack of data sets), training time / re-training, visual quality (memory limitations), 4D data, network architecture and parameters