Liquid Splash Modeling with Neural Networks

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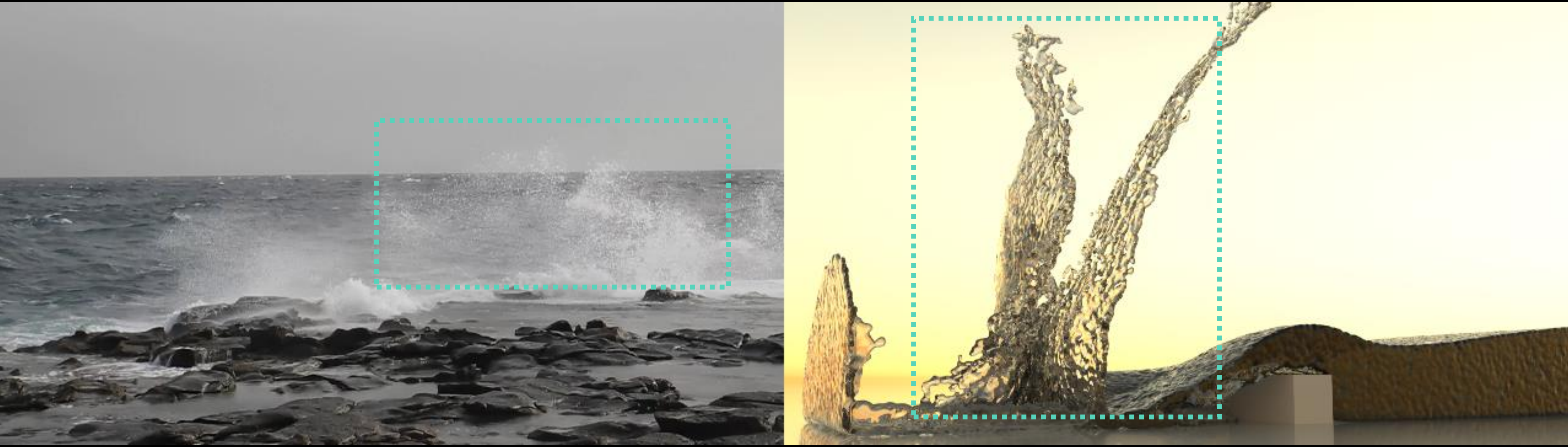
Initiate a Question

What are the missing features in the simulation?

Motivation

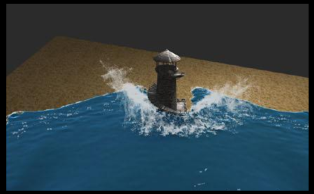


Where are such interesting complex small droplet details in the simulation?

Previous Work

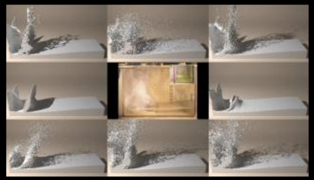
Lossaso et al.,
“Two-way coupled SPH and particle level set fluid simulation”,
TVCG 2008

Ihmsen et al.,
“Unified spray, foam and air bubbles for particle-based fluids”,
TVC 2012



Gerszewski and Bargteil,
“Physics-based animation of large-scale splashing liquids”,
TOG 2013

Um et al.,
“Perceptual evaluation of liquid simulation methods”,
TOG 2017



Idea

Fluid implicit particle (FLIP)

- Governing flow
- *De facto* standard in visual effects (VFX)
- Efficient hybrid particle-grid method

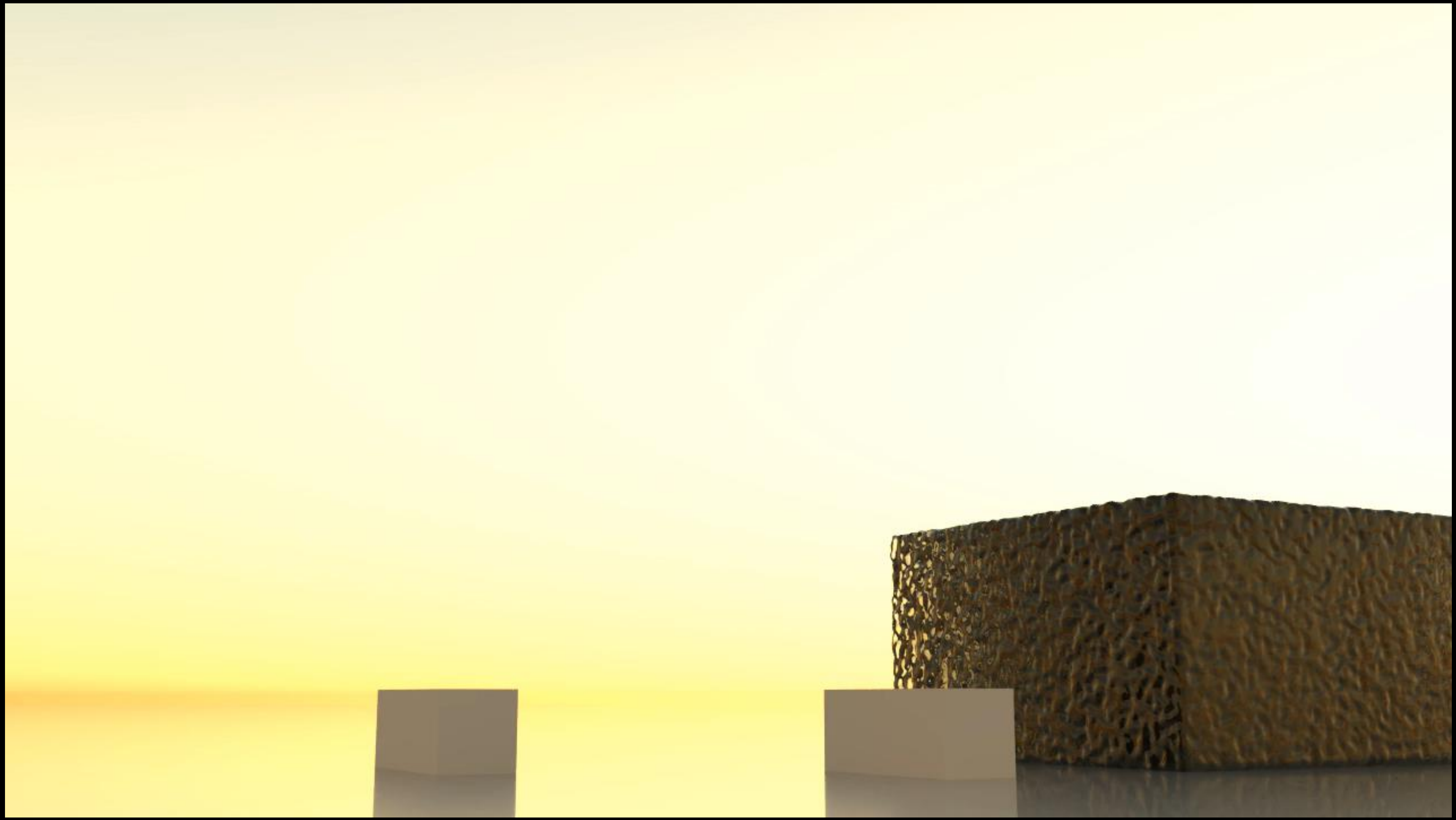
~~Heuristic Method?~~

Learn Physics!

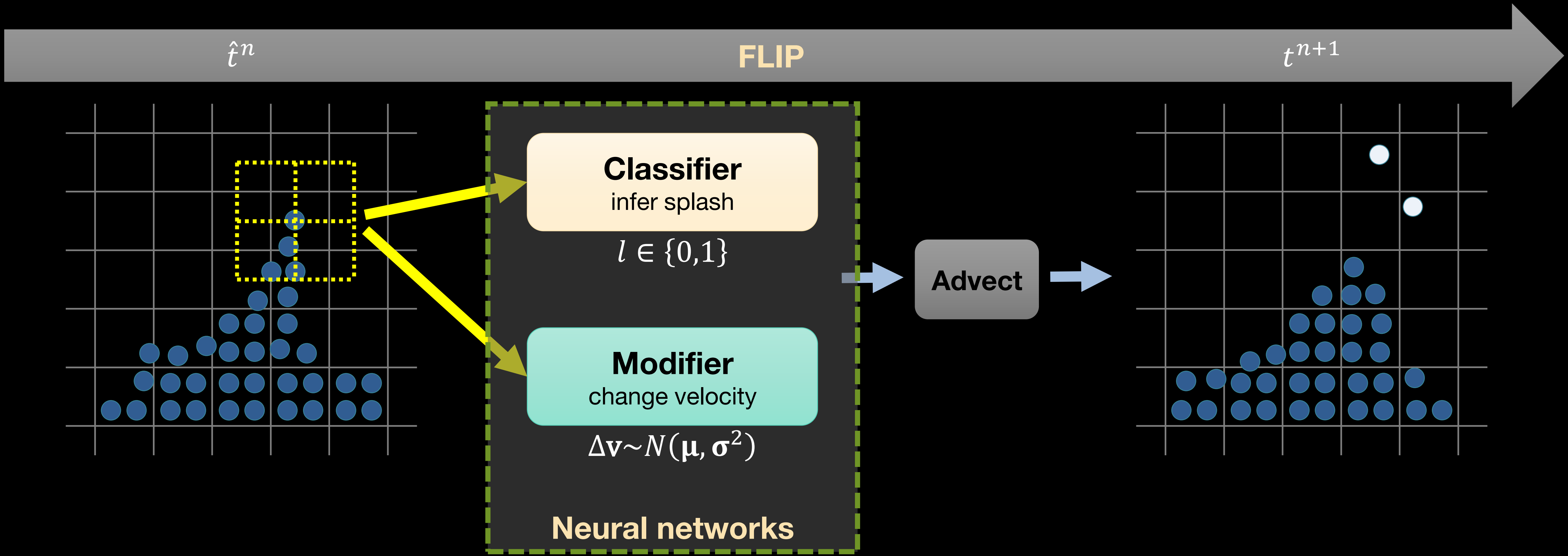
Machine learning (i.e., neural networks)

- Unresolved complex small scale details such as splashes
- Effective and efficient
- *MLFLIP*

Preview

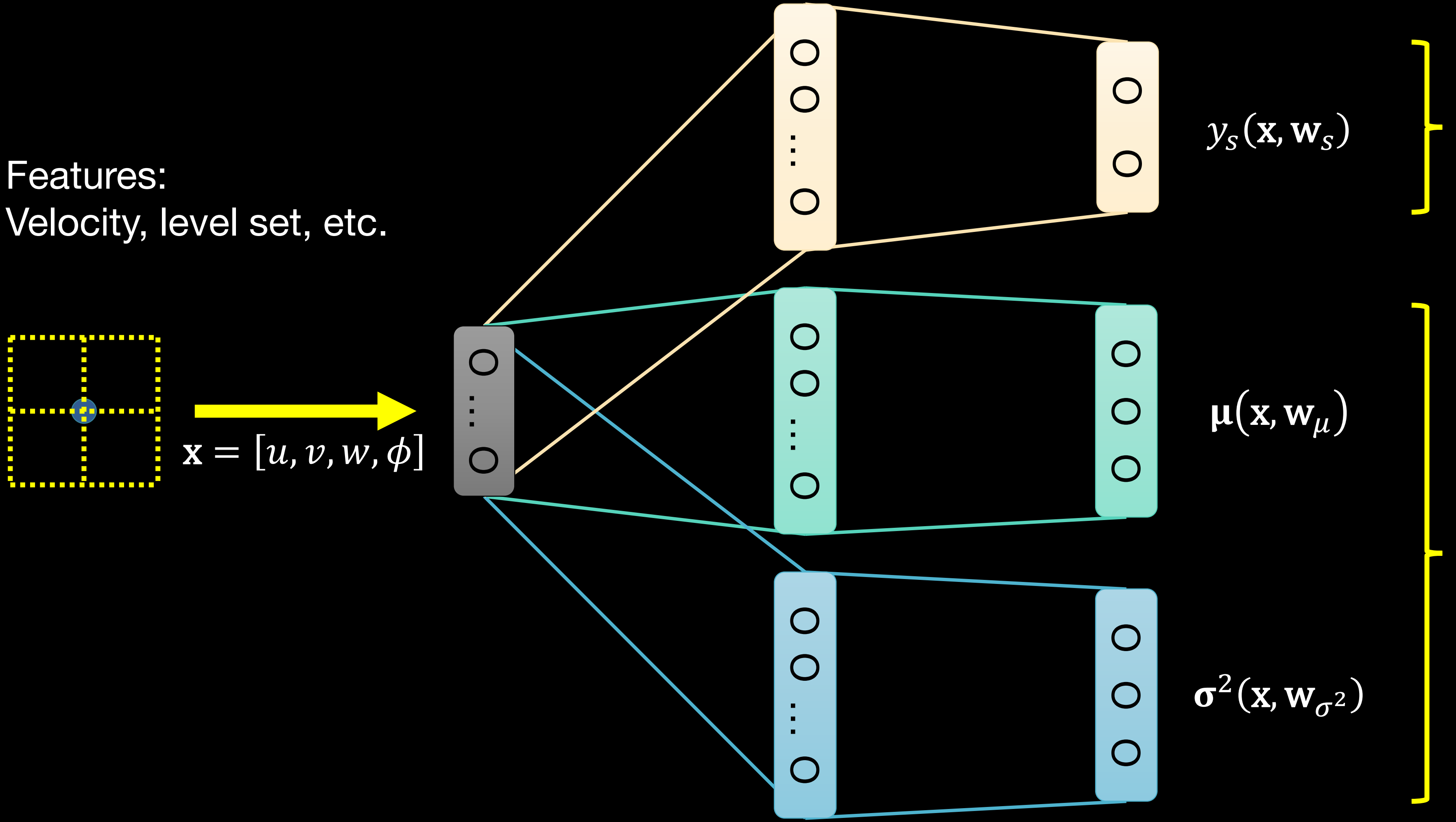


Overview



$\hat{t}^n$
FLIP
t^{n+1}
Classifier
infer splash
$l \in \{0,1\}$
Modifier
change velocity
$\Delta\mathbf{v} \sim N(\boldsymbol{\mu}, \boldsymbol{\sigma}^2)$
Neural networks
Advect

Neural Networks



Classification
$l \in \{0, 1\}$

Modification
$\Delta\mathbf{v} \sim N(\boldsymbol{\mu}, \boldsymbol{\sigma}^2)$

Neural Networks: Classification

A data set

Feature vectors $\mathbf{X} = \{\mathbf{x}_1, \mathbf{x}_2, \cdots, \mathbf{x}_N\}$ and splash labels $\mathbf{L} = \{l_1, l_2, \cdots, l_N\}$

The probability that a feature vector $\mathbf{x}_i$ is in the class l_i

$$P_s(l_i|\mathbf{x}_i) \sim P\big(l_i|y_s(\mathbf{x}_i, \mathbf{w}_s)\big)$$

The likelihood function

$$L_d(\mathbf{L}|\mathbf{X}) = \prod_{i=1}^{N} P\big(l_i|y_s(\mathbf{x}_i, \mathbf{w}_s)\big)$$

Maximize the likelihood function: softmax (well-established for classification)

Neural Networks: Modification

A data set

Feature vectors $\mathbf{X} = \{\mathbf{x}_1, \mathbf{x}_2, \cdots, \mathbf{x}_N\}$ and velocity modifications $\Delta\mathbf{V} = \{\Delta\mathbf{v}_1, \Delta\mathbf{v}_2, \cdots, \Delta\mathbf{v}_N\}$

The modification function

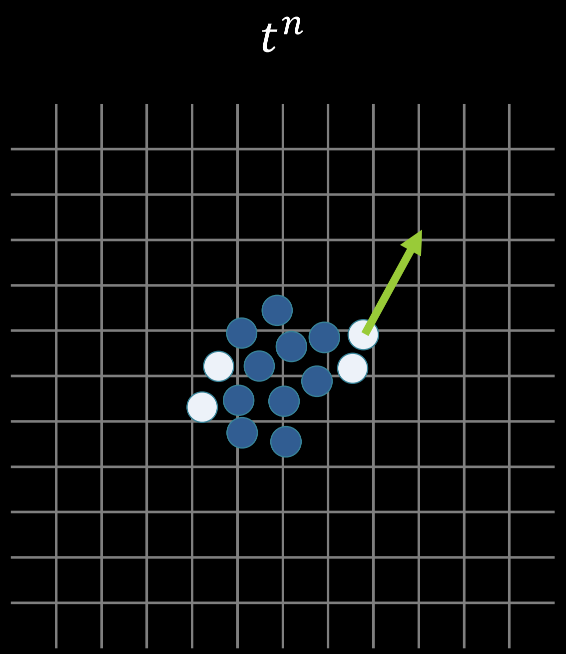
$$f_m(\Delta\mathbf{v}_i|\mathbf{x}_i) \sim N\left(\Delta\mathbf{v}_i|\boldsymbol{\mu}(\mathbf{x}_i, \mathbf{w}_\mu), \boldsymbol{\sigma}^2(\mathbf{x}_i, \mathbf{w}_{\sigma^2})\right) \sim \frac{1}{\sqrt{2\pi\sigma_i^2}} e^{\left(\frac{-(\Delta\mathbf{v}_i - \mu_i)^2}{2\sigma_i^2}\right)}$$

The (negative log) likelihood function (a.k.a. loss function)

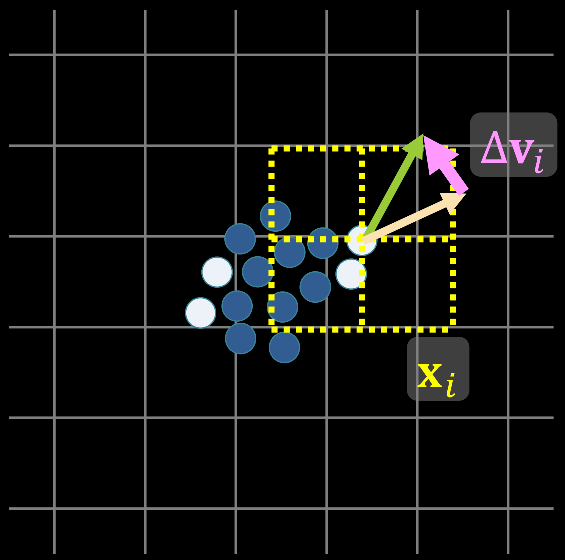
$$L_m(\Delta\mathbf{V}|\mathbf{X}) = \frac{\mathbf{1}}{\mathbf{2}} \sum_{i=1}^{N} \sum_{j=1}^{d} \left[\frac{\left(\Delta\mathbf{v}_{i,j} - \mu_{i,j}\right)^2}{\sigma_{i,j}^2} + \ln\boldsymbol{\sigma}_{i,j}^2\right]$$

Minimize the loss function: a mean variance estimation (MVE) problem

Training Data



High-resolution
or
ground truth

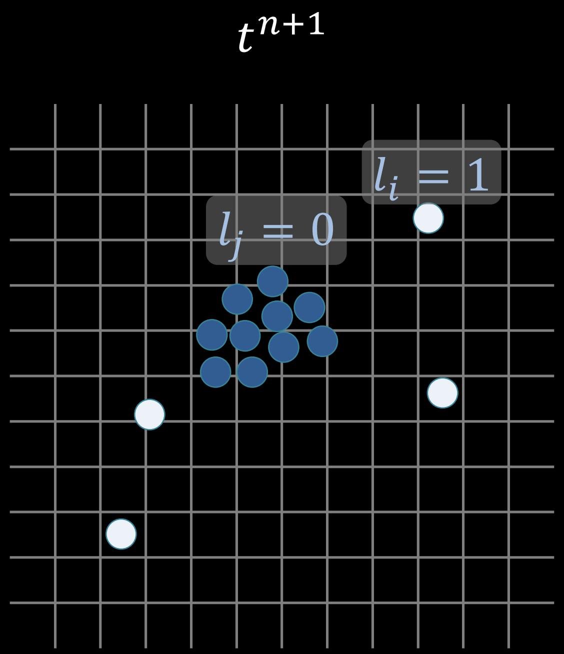


Target resolution

$\mathbf{X} = \{\mathbf{x}_1, \mathbf{x}_2, \cdots, \mathbf{x}_N\}$

$\mathbf{L} = \{l_1, l_2, \cdots, l_N\}$

$\Delta\mathbf{V} = \{\Delta\mathbf{v}_1, \Delta\mathbf{v}_2, \cdots, \Delta\mathbf{v}_N\}$



High-resolution
or
ground truth

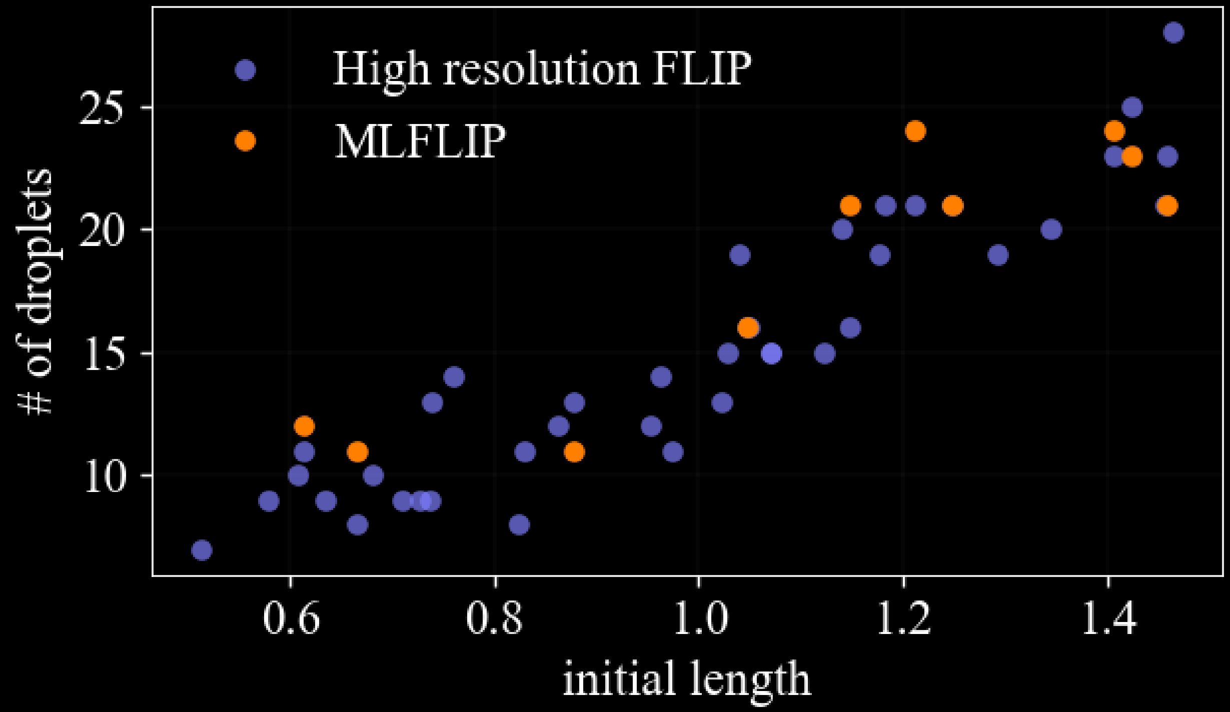
Plateau-Rayleigh Instability Test

High resolution
40 different initial lengths
1000x100

Recovery of Surface Tension Effects

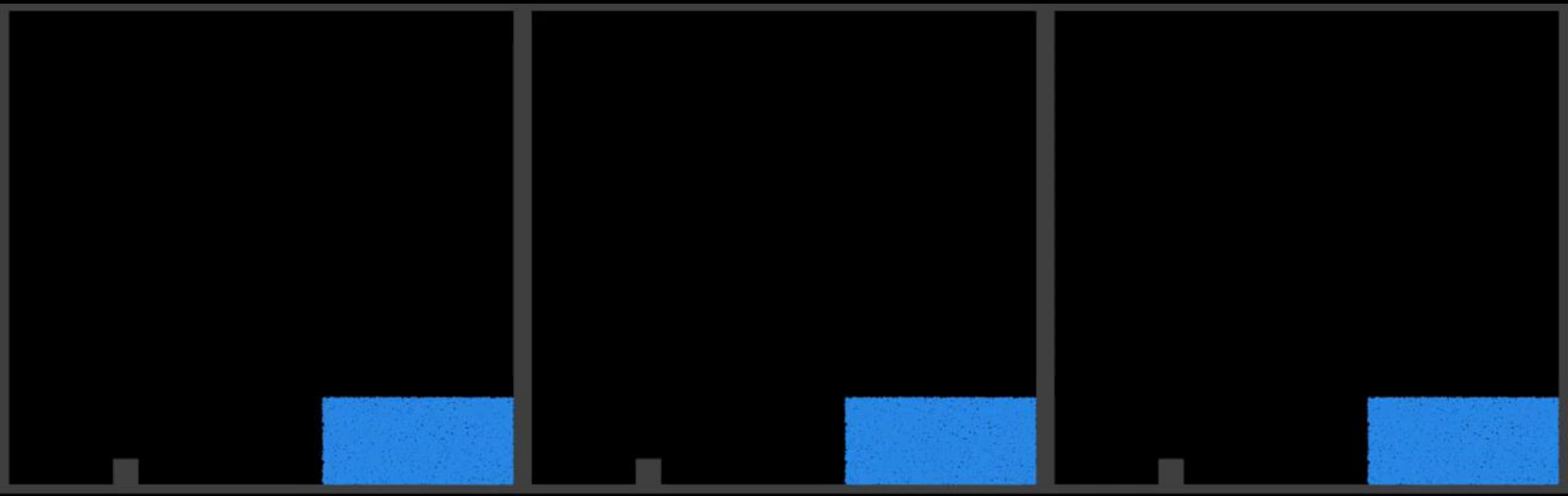
Low resolution
10 different initial lengths
250x25 (i.e., **0.25x**)

Statistics



Our model (**orange**) accurately captures reference physics (**blue**).

Different Methods for Training

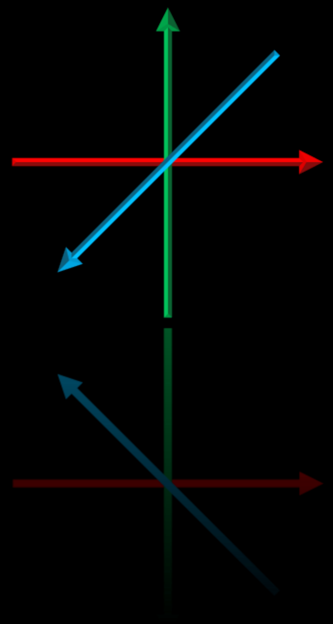


MLFLIP
(trained using **FLIP**)

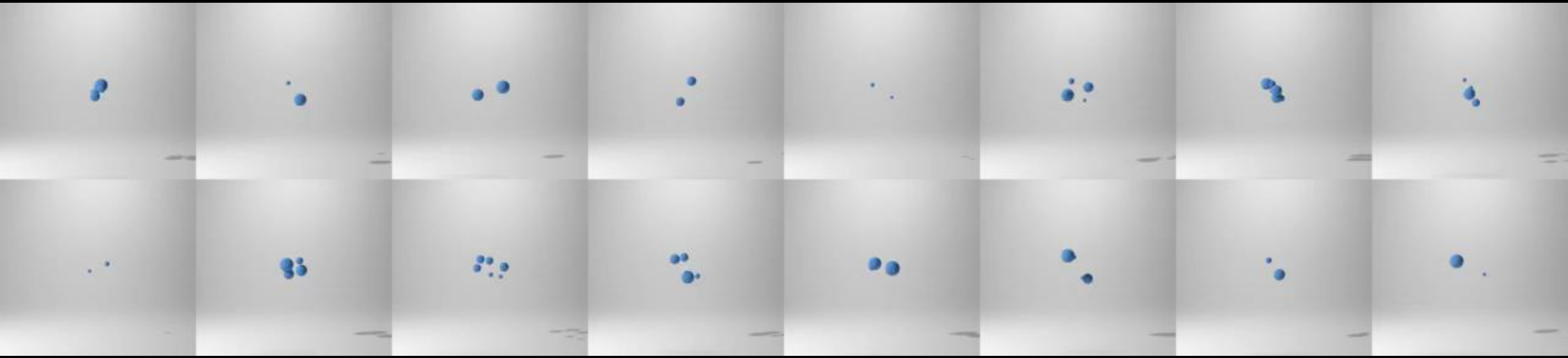
MLFLIP
(trained using **SPH**)

FLIP

Results

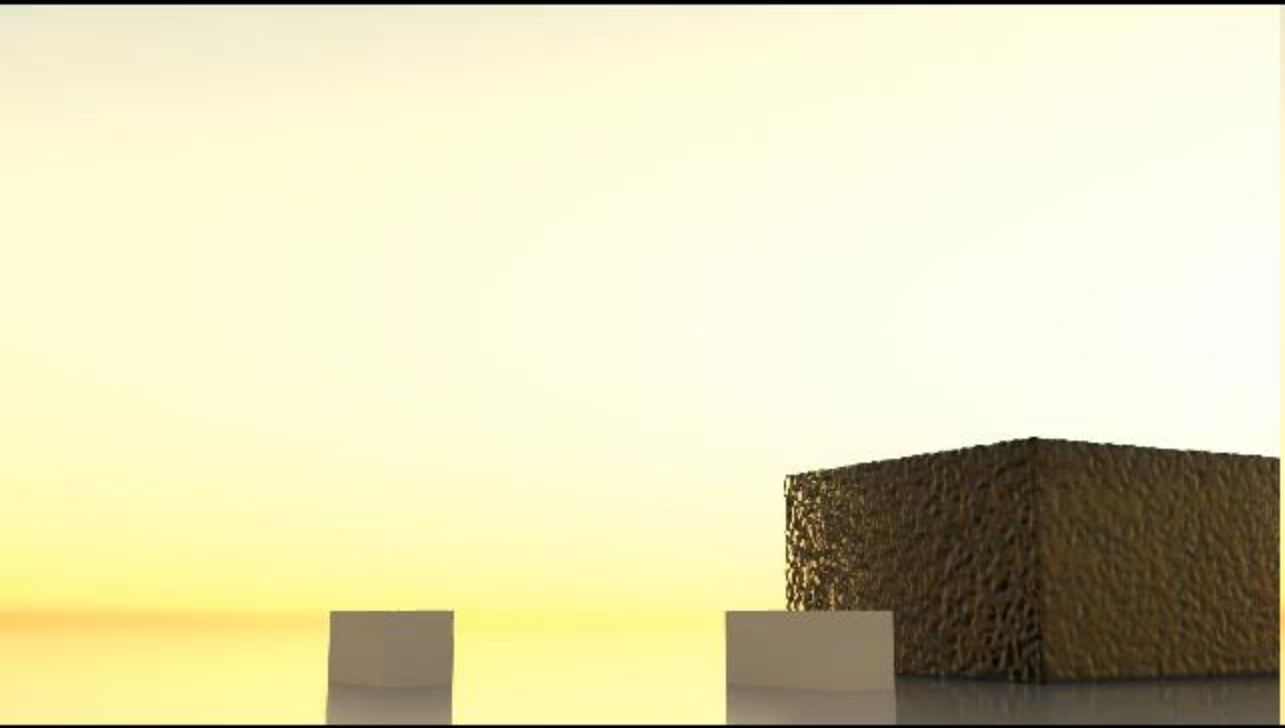


Training Simulations: 5mm

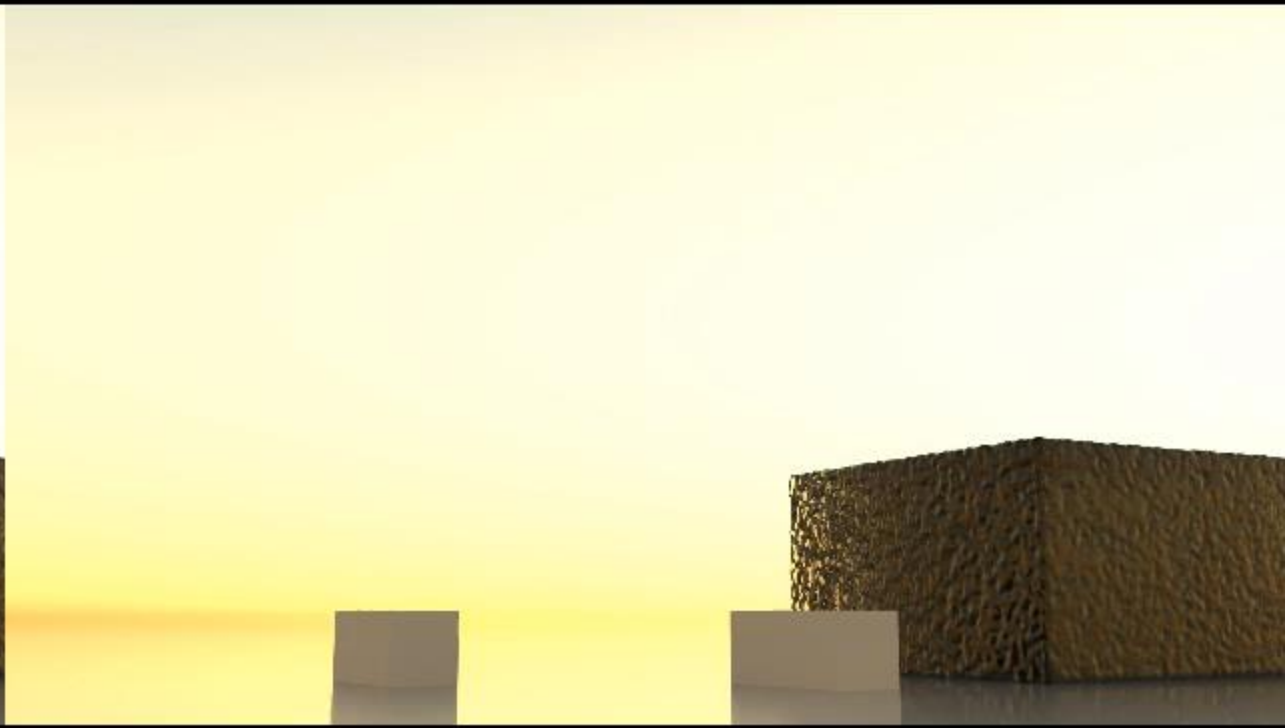


~1.3M samples
200x200x200

Improved Splashes in Dam



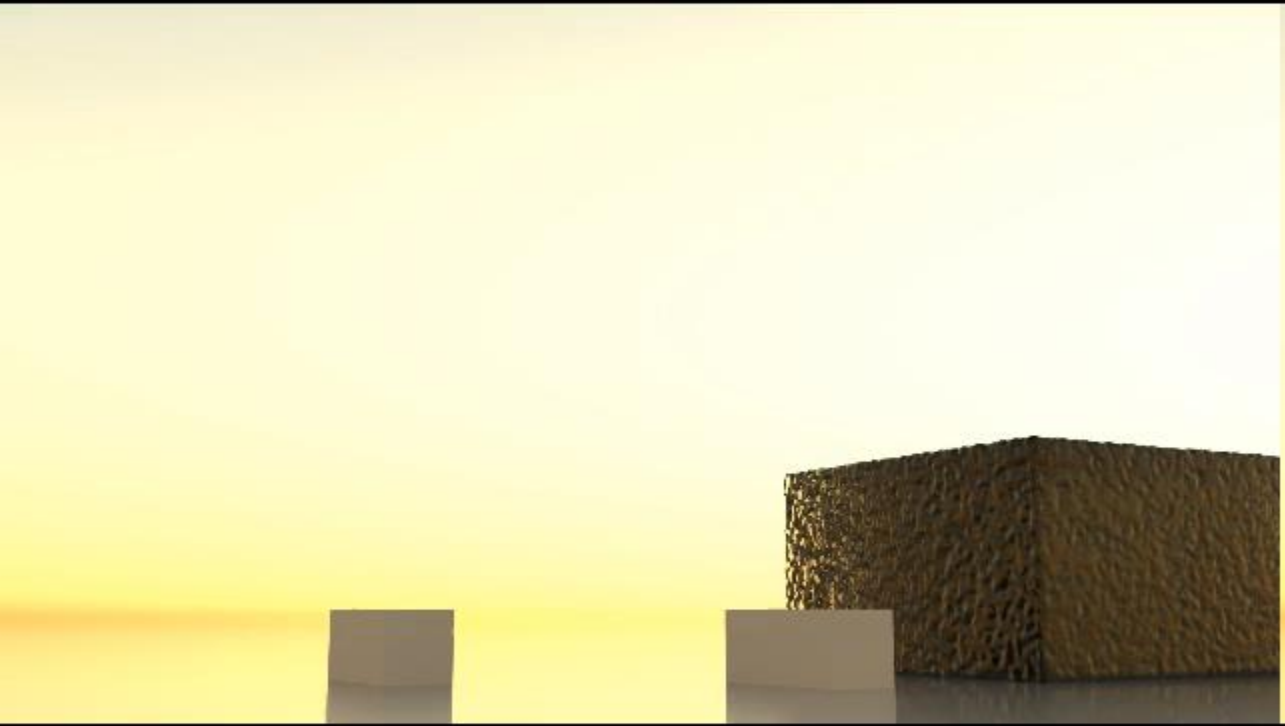
MLFLIP



FLIP

Additional cost: **~13%**

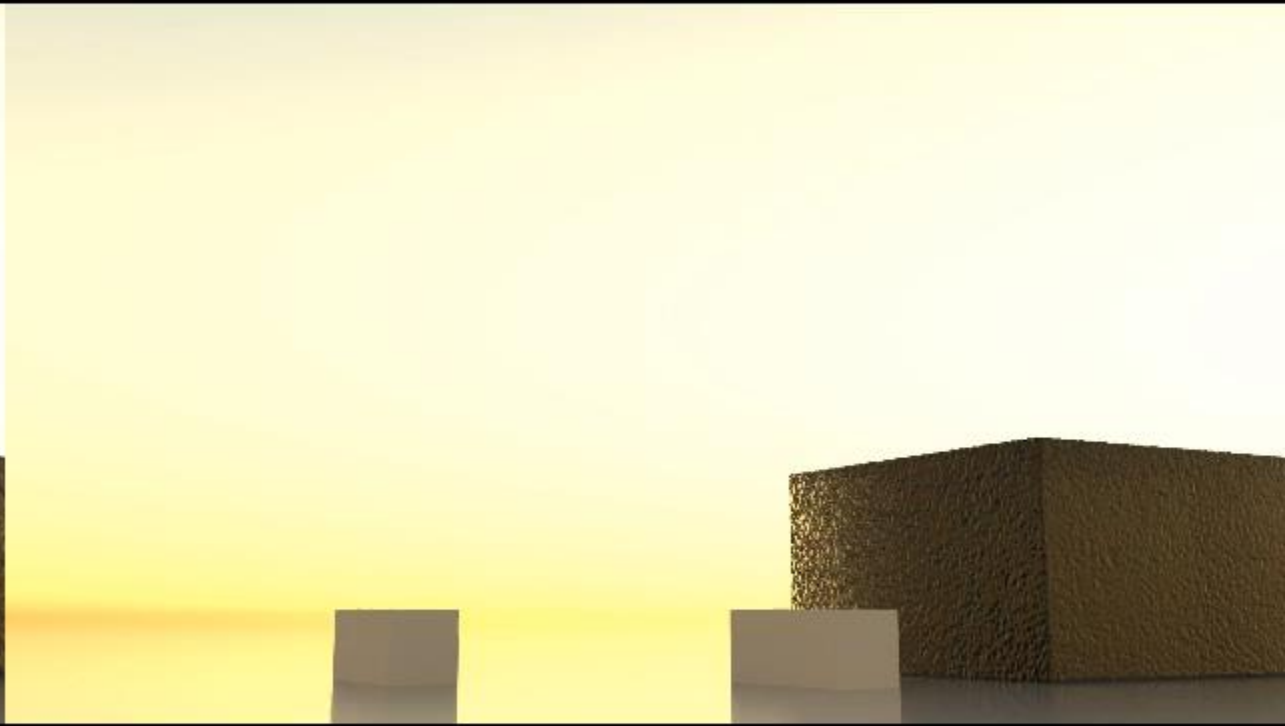
MLFLIP vs. High-res FLIP



MLFLIP

160x150x50

0.60 sec./step

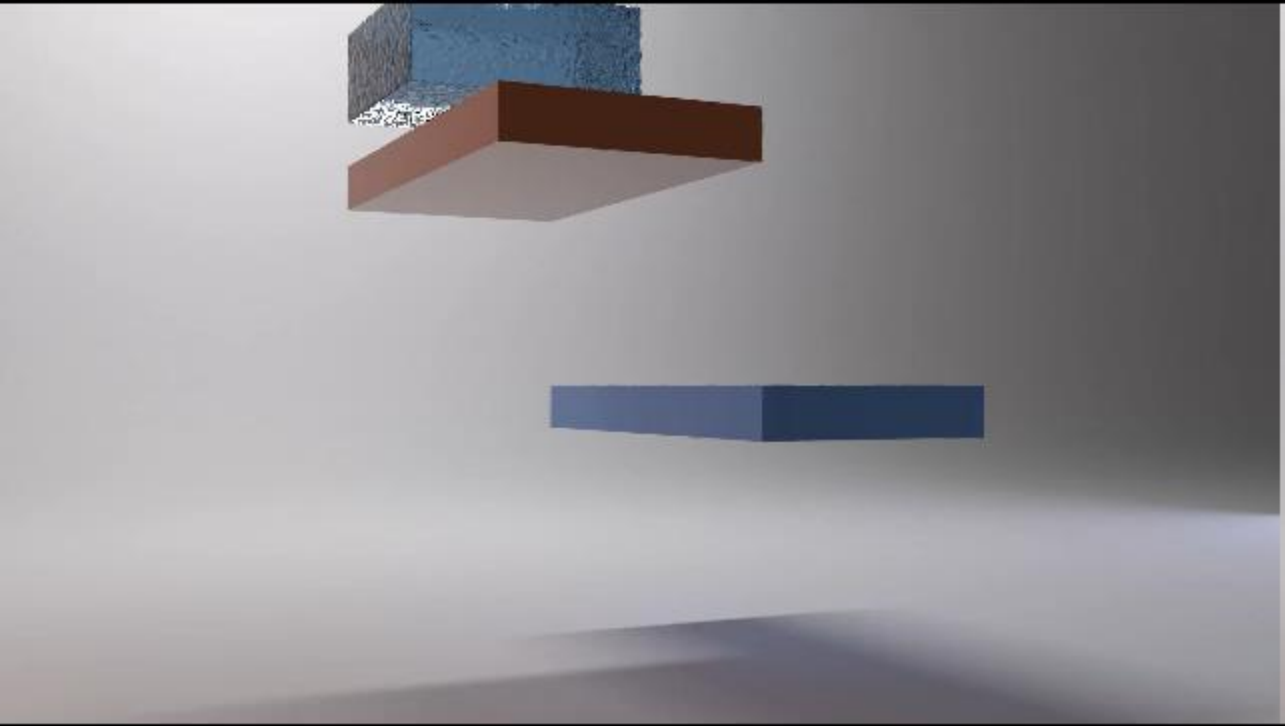


High resolution FLIP

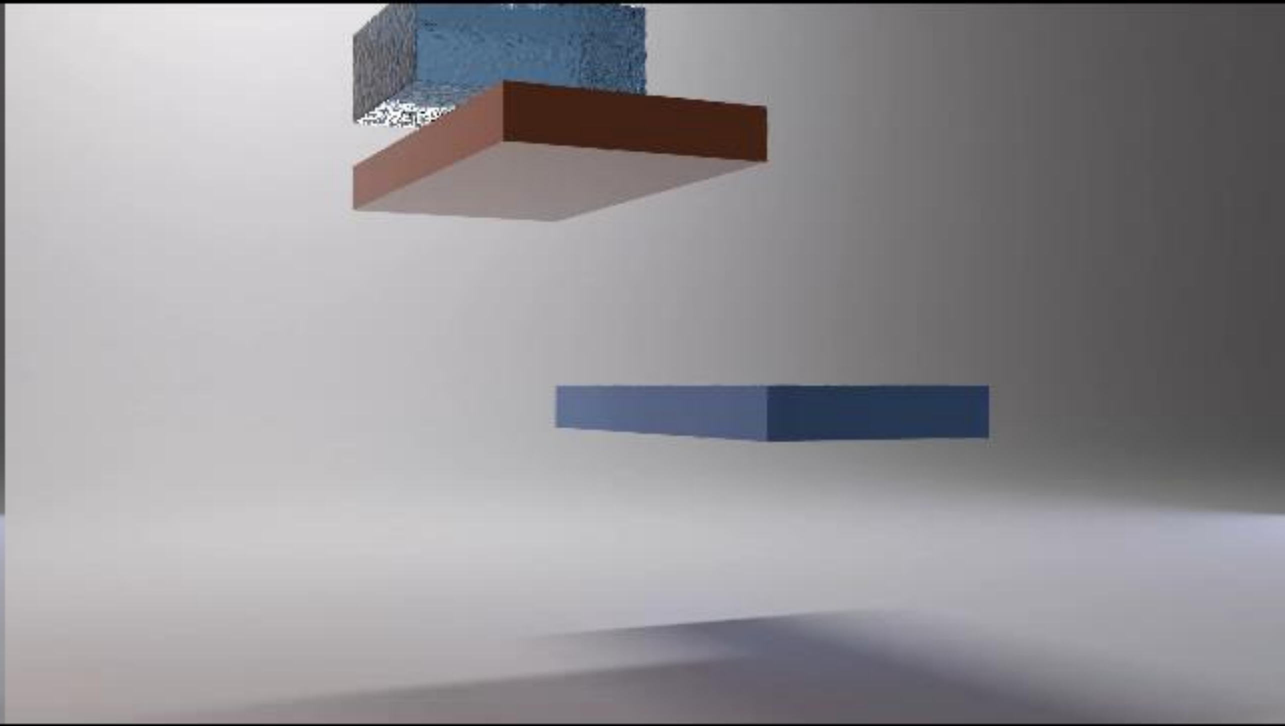
320x300x100

5.43 sec./step (~**9x** slower)

Improved Splashes in Stairs

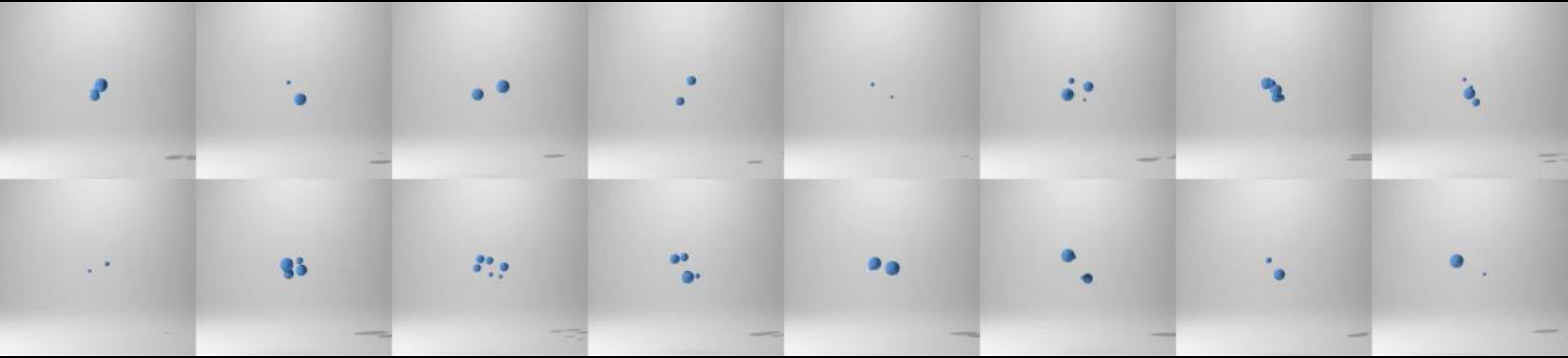


MLFLIP



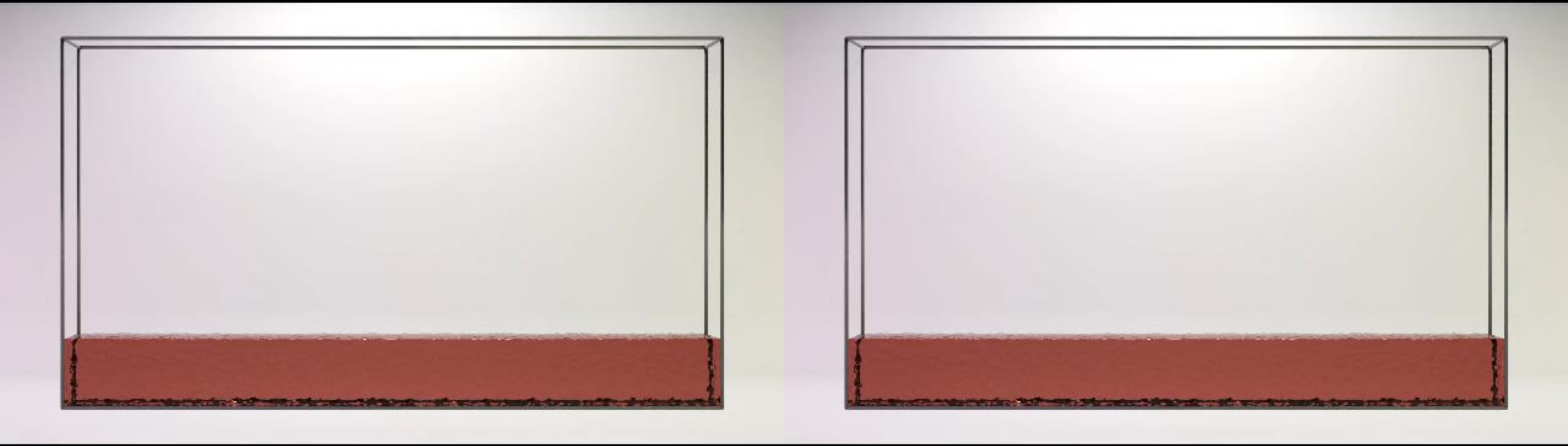
FLIP

Training Simulations: 1.5mm



~441K samples
200x200x200

Improved Splashes in Wave Tank



MLFLIP FLIP

Conclusion and Future Work

New data-driven splash generation model via neural networks

- Effective and efficient
- Easy to integrate into FLIP (or variants)
- Trainable from the data you can collect (e.g., via FLIP, SPH, or so.)
- Extendable to the secondary particle model

Interaction among droplets

Bubbles, capillary waves, and foam