Deep learning on fluid simulation

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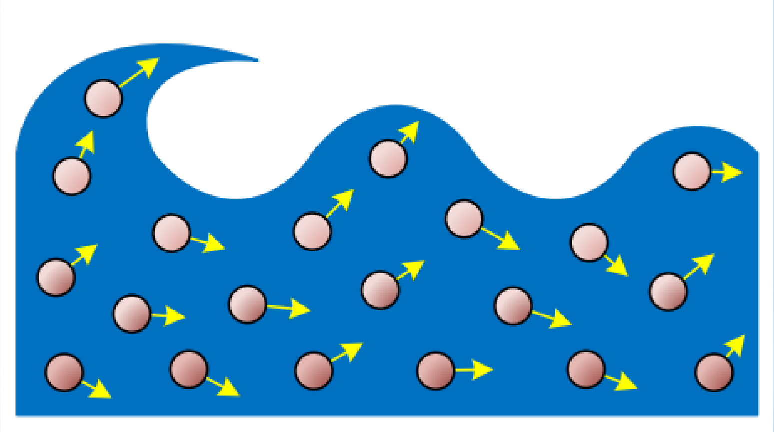
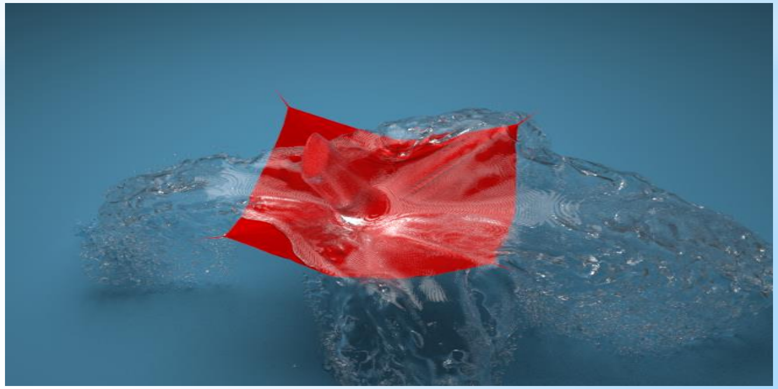
Introduction - Background

* As people have higher and higher requirements on the visual effects of movies and games, the **realistic fluid animation** is getting more and more demanding
* Simulating turbulent liquids with **breaking waves** and **splashes** is among the most desired features in fluid animation.
* Lagrangian methods such as **SPH** are a promising way to capture such properties





Introduction - Background

Limitations in Traditional Simulation Methods

* **Requirement for Expensive Computing & Memory Resources:**

  Traditional fluid simulation is time consuming and requires large computational resources.

* **Difficulty on Scenario Reuse:**

  For similar scenarios, it still needs to re-simulate once even the initial state has only a slight change.

* **Exponential Time Complexity on the Scale of Scenarios:**

  For large-scale liquid simulations, it is impossible to obtain highly realistic simulation in real-time.

Introduction - Motivation

Could we find a model which is:

faster,

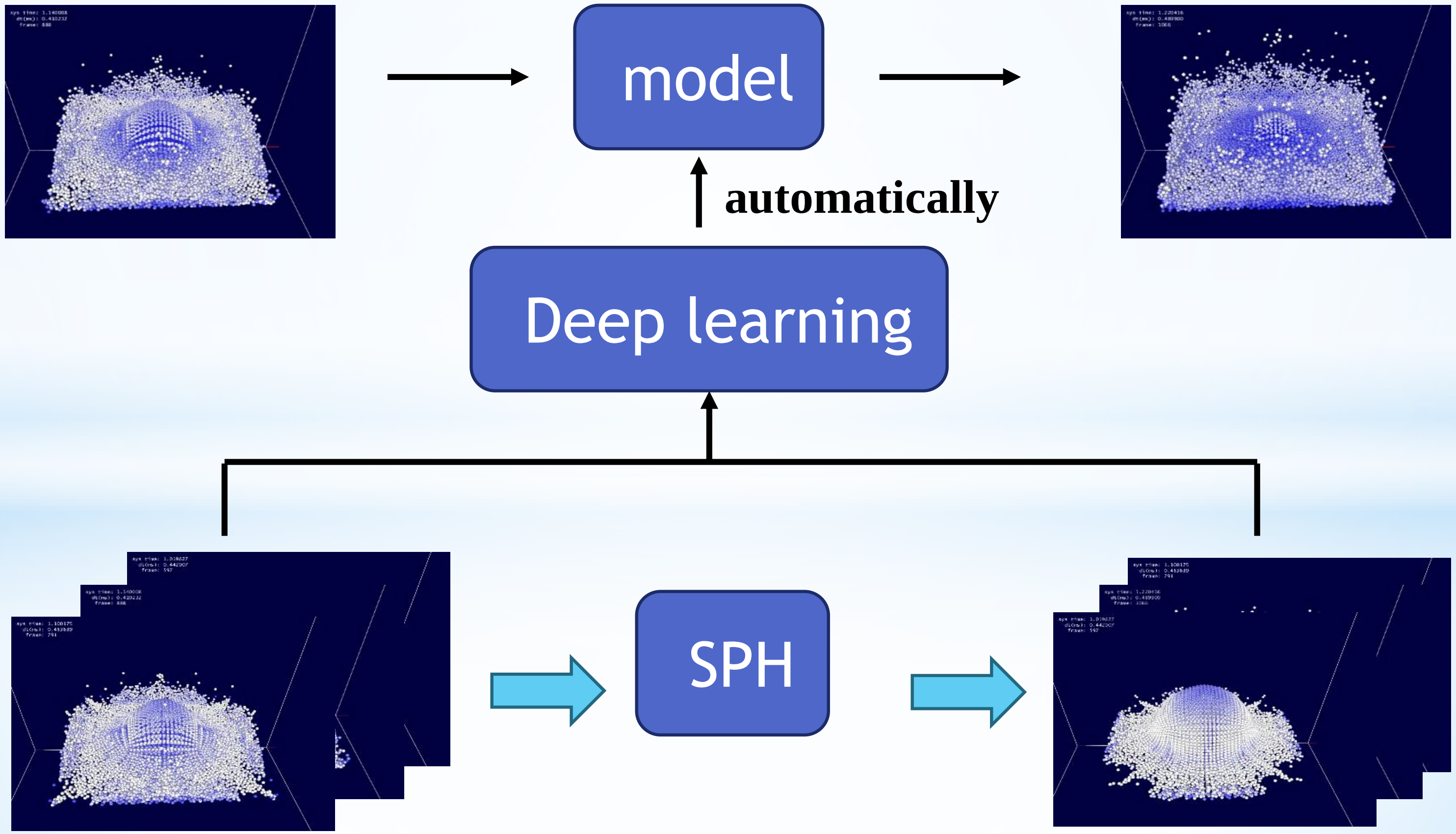
low resources demand &

keep accuracy,

that takes place of SPH to complete fluid simulation?

Introduction - Goal

Utilize Machine Learning (ML) to automatically find a model to generate fluid animation



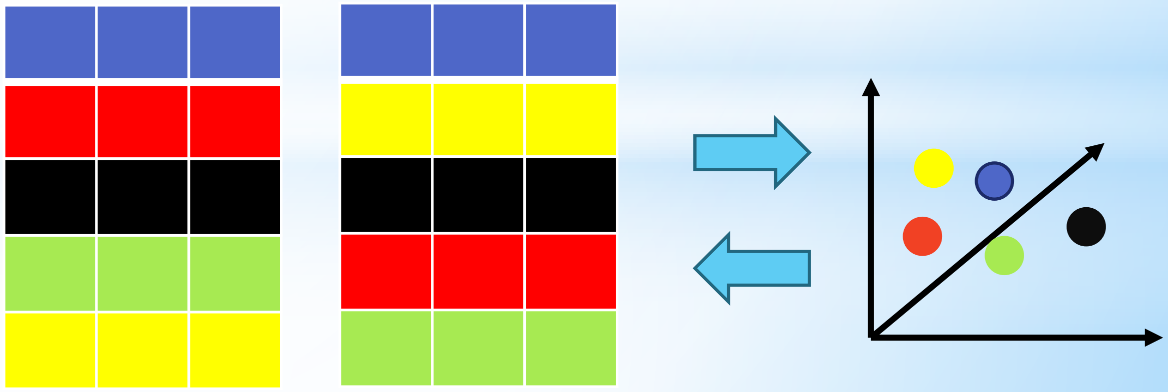
Introduction - Challenge #1

* **Non-ordered Spatial Data:**

SPH simulation data is a set of 3D points without specific order.

However, ML usually requires Independent & Identical Distributions (I.I.D.) data (e.g., Fully Connected Networks), grid-spatial data (e.g., Convolutional Networks), or sequential data (e.g., Recurrent Networks).

How to make model invariant to permutated inputs?



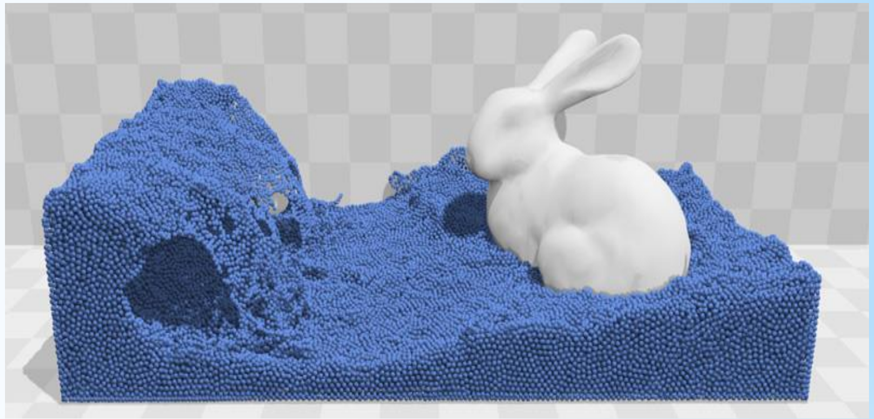
permutated inputs

Same scene

Introduction – Challenge #2

* **Global Information Extraction:**

Fluid particles are not isolated. The model needs to be able to capture both local information from nearby particles and global information from the scene.



How to make model understand the current state of a fluid particle in the entire scene?

Introduction – Challenge #3

* **Obedience of Physics Laws (Bias and Variance Tradeoff)**

The model is expected to simulate fluid for not only the training scenarios. It is important to make sure that the model learns the universal physics laws rather than some bias from particular inputs.

How to make model simulate fluid with limited amount of data?

Related Work

Lagrange method

Regression Forests

Euler method

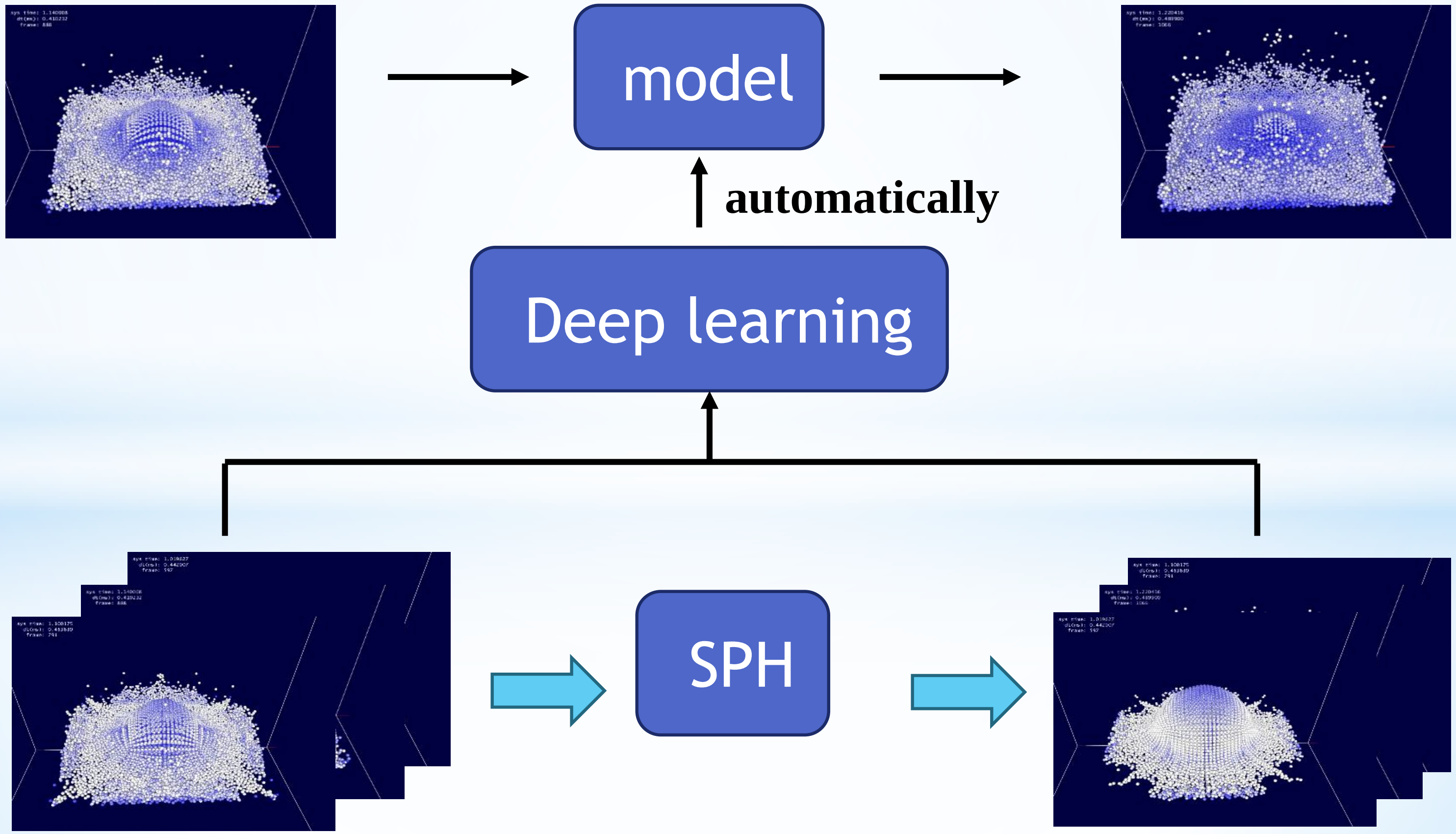
CNN LSTM GAN

Limitations
Resources demand

Limitations
Different data formats

Goal

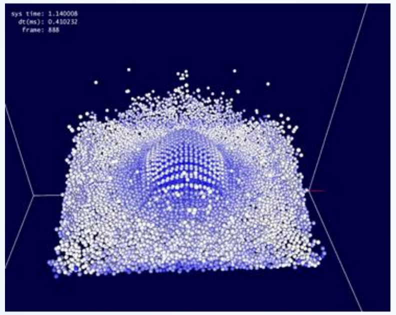
Utilize Machine Learning (ML) to automatically find a model to generate fluid animation

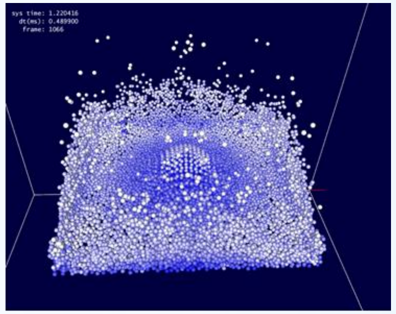


Approach

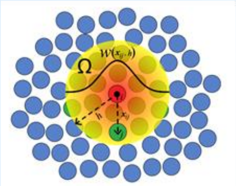
Symmetry function for unorder input → Pooling layers and triplet loss for global information → CNN for **Physics Laws**

Implementation

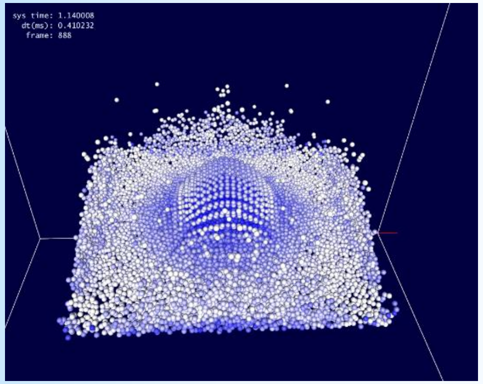


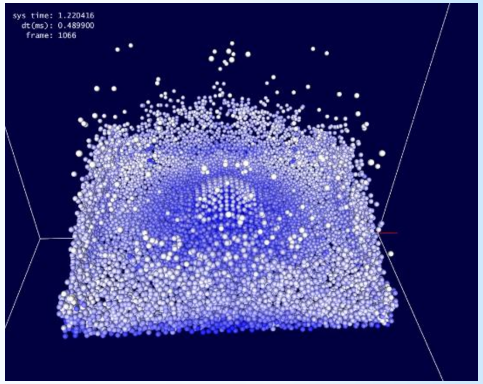


Search Neirhborhood → Forces → v^* x^* → ρ^* → Pressure



Implementation





n*8

Global information

Fluid simulation

n*3

acceleration

Technical Details

* **Challenge 1: Sequence non-related.** How to make model invariant to input permutation?
* **Solution:**

Three strategies exist:

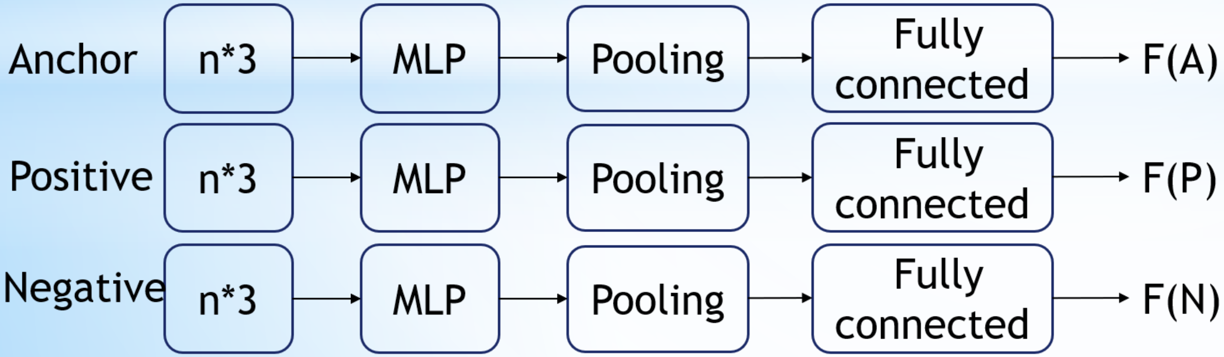
1) Sort input into a canonical order;

2) Treat the input as a sequence to train an RNN, but augment the training data by all kinds of permutations;

3) Use a simple symmetric function to aggregate information from each point

Technical Details

- **Challenge 2: Global information.** How to make model understand the current state of input fluid data?
- **Solution:**
  - Using MLP & pooling layers, get the global signature of the input set.
  - Using triplet loss to train this part.

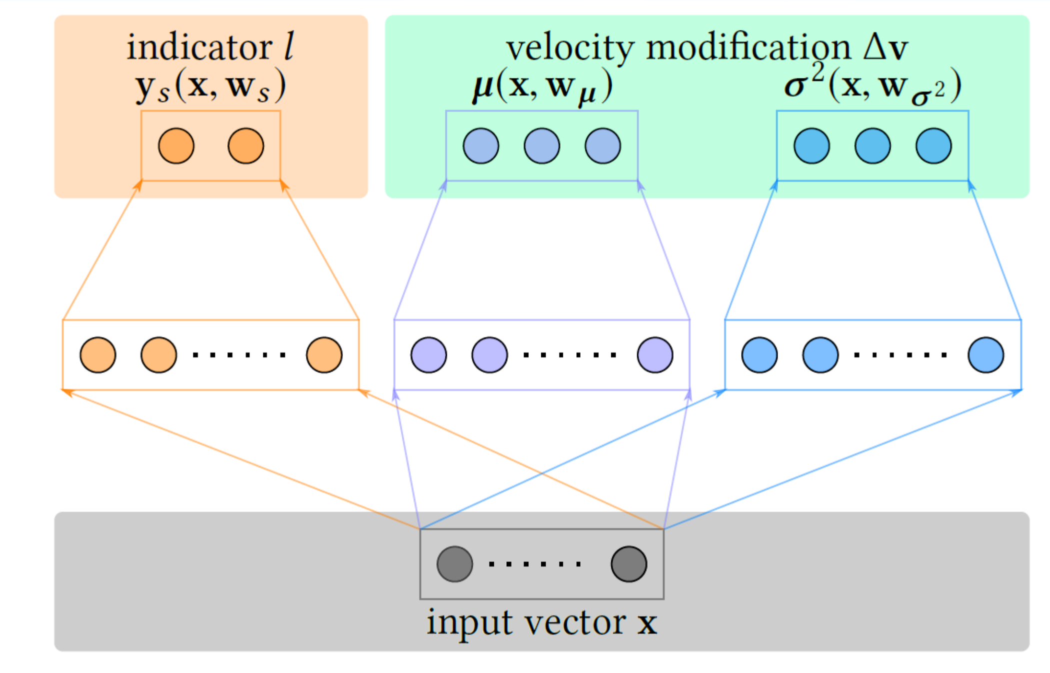


$\mathrm{L}(A, P, N)$

$$J = \sum_{i=1}^{m} L(A^i, P^i, N^i)$$

Technical Details

- Challenge 3: Infer physical functions. Is that possible to make model simulate fluid?



Um K, Hu X, Thuerey N. Liquid Splash Modeling with Neural Networks[J]. arXiv preprint arXiv:1704.04456, 2017.

Experiment

Input (n*8)

3 dimensions of position,
3 dimensions of velocity,
2 marked features

Output (n*3)

3 dimensions of acceleration

Cost function：

Input data preprocessing & Global information: Triplet loss

Fluid simulation: Mean squared error

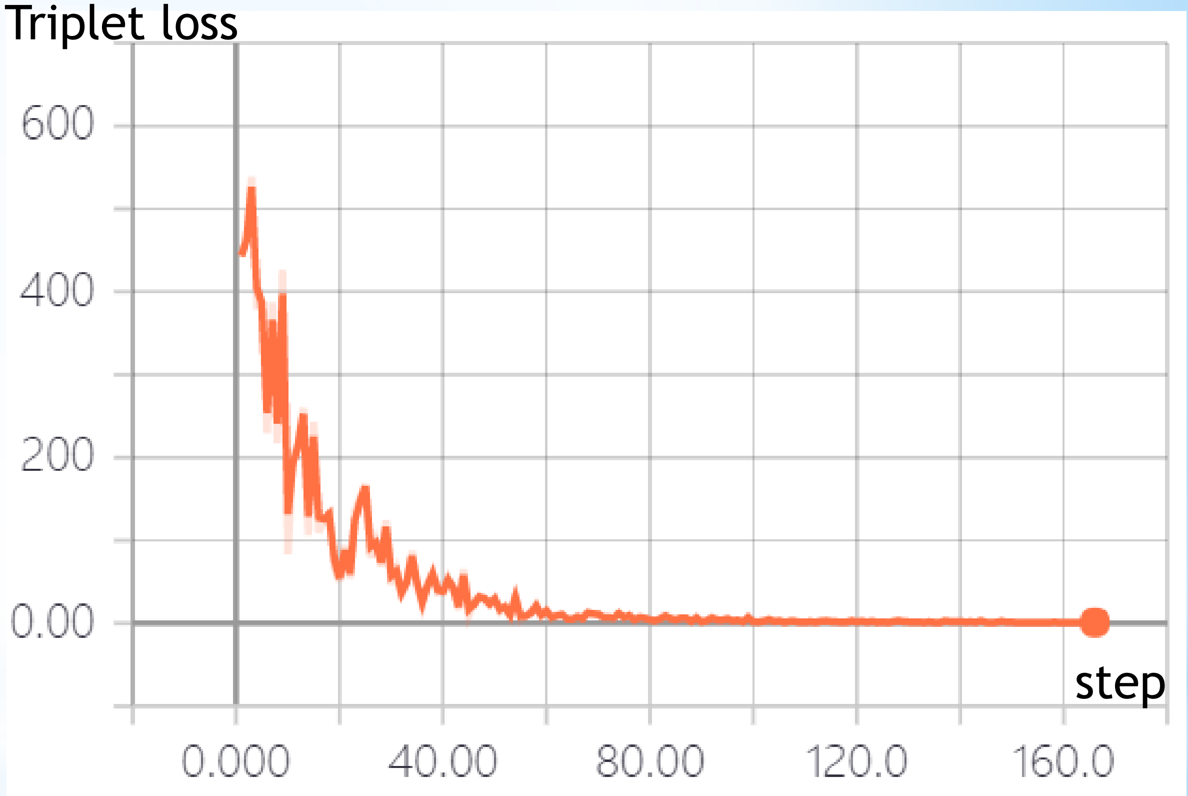
Optimizer：

Adaptive Movement Estimation

Preliminary Results

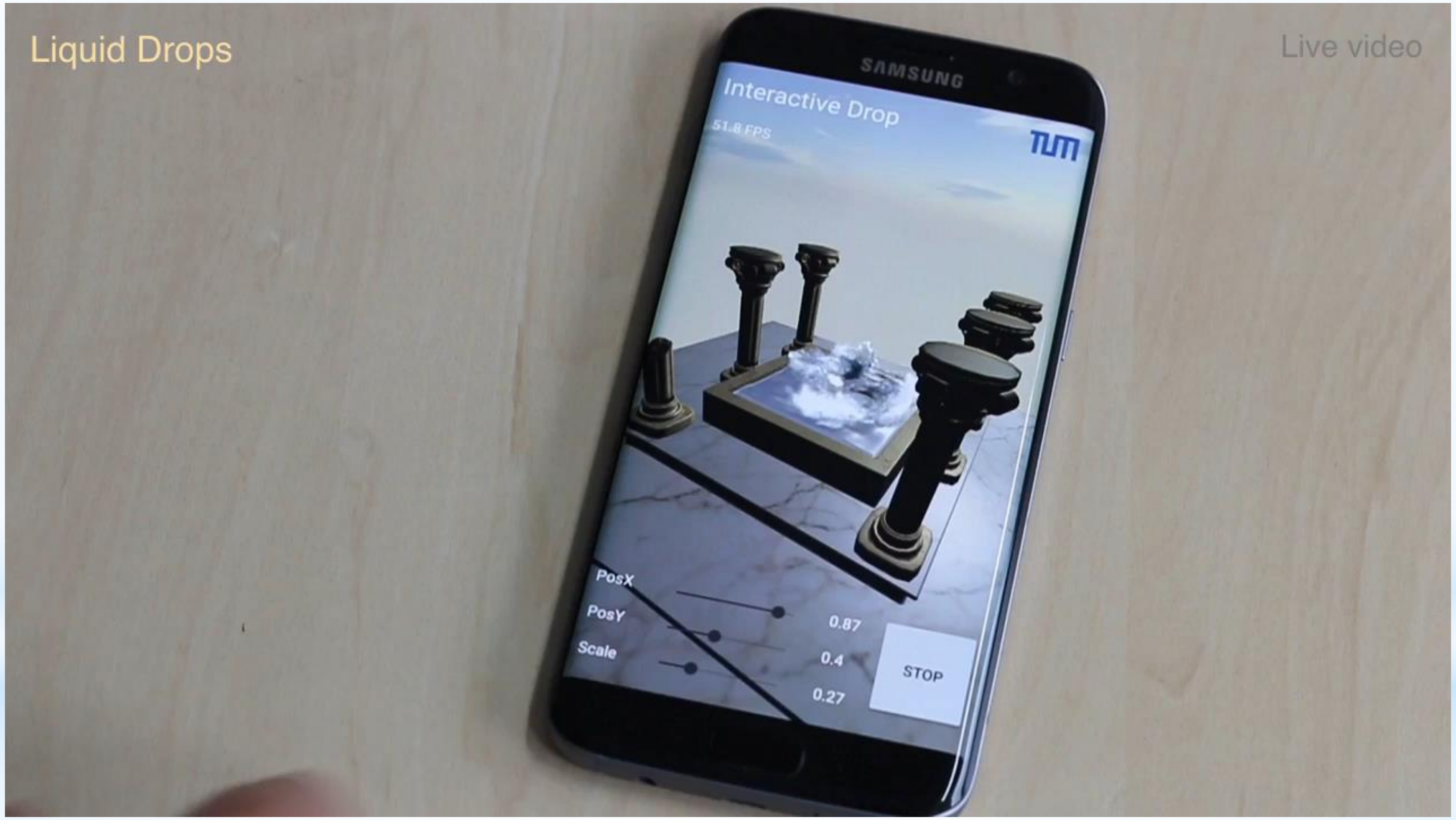
Input Unordered & Global information

- The scene after panning and rotation is the same scene as the original scene
- Every 5 frames contain the same global information
- For any two scenarios, the model is able to tell if they are same.



Loss for global information part

Expected outcome



Conclusion

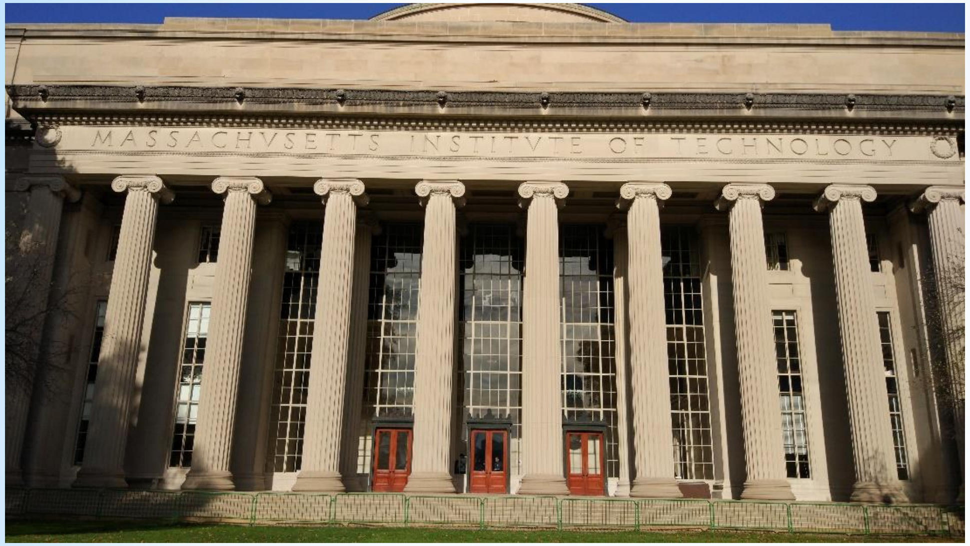
* **Use symmetric function** to make model invariant to input permutation
* Use **MLP with pooling layers** to make model learn to simulate fluid
* Maybe model could learn to simulate fluid

Future Work

1. Maintain spatial relationships of input data
2. Learn fluid simulation
3. Learn the temporal evolution of fluid simulation

Tips

1. 发够论文
2. 找个华裔教授
3. 常催老外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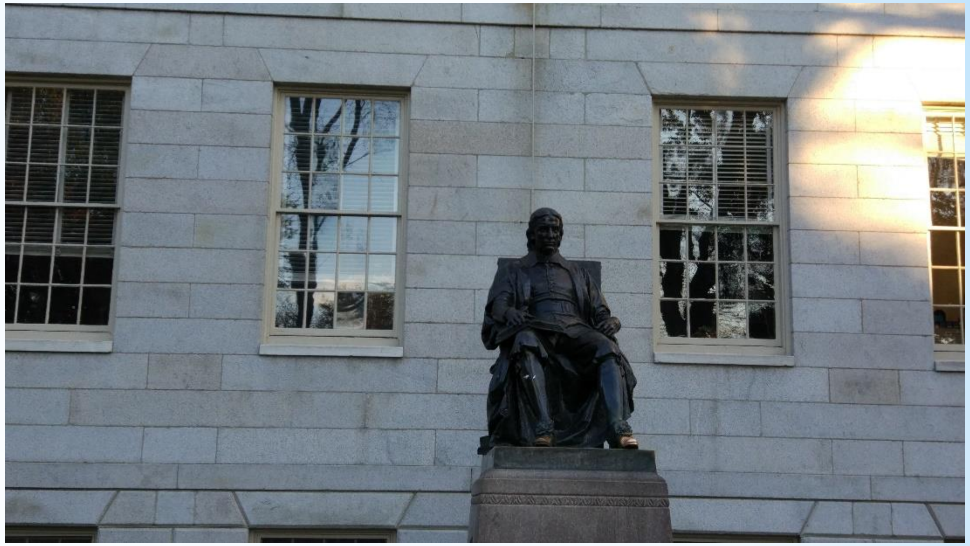

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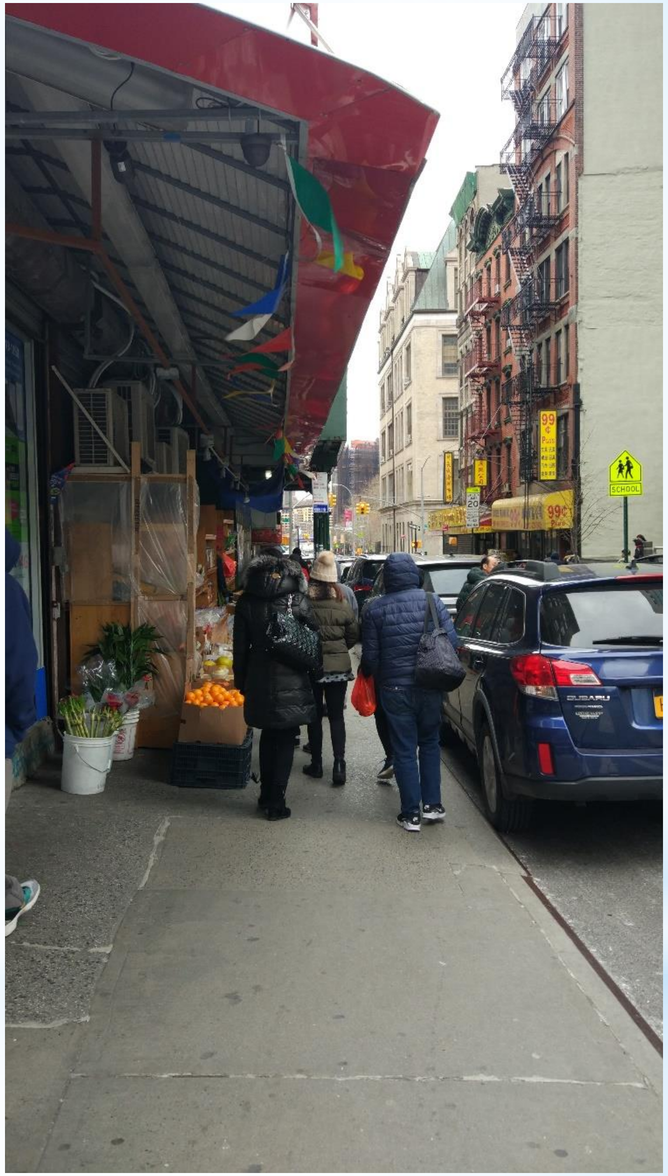

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