SIML.AI PRODUCT OVERVIEW

The vast majority of technologies in the world come to life through months or years of extensive simulation during their development. High-performance computing, parallel processing, and GPUs helped push the computation time from months to weeks. With the help of applied machine learning, we are seeing a reduction from weeks to days. We think that this technology is only scratching the surface. At DimensionLab, we are building tools for engineers and researchers to tame the physics of their projects in hours, some even in minutes. In addition, we're also focusing on makers and creators, who are not trained physicists or mathematicians and want to leverage the extreme effectiveness of AI for physics without dealing with its complexities. Collectively, they make up a cohesive platform we call **Siml.ai**.

As Nils Thuerey put it:

> *"Understanding our environment, and predicting how it will evolve is one of the key challenges of humankind. A key tool for achieving these goals are simulations, and next-gen simulations could strongly profit from integrating deep learning components to make even more accurate predictions about our world."*

Siml.ai is a software platform for AI Engineering. It provides powerful tools for building high-performance AI-based physics simulators and easy-to-use interface to use them in their projects. There's a paradigm shift happening in the world of physics simulation. Deep learning methods are outperforming even the most optimized classical numerical solvers[1]. The key component of these methods are **physics-informed neural networks (PINNs)**.

These AI-based simulators have a massive advantage because they are orders of magnitude faster, more efficient, and with the right approaches, more accurate. However, this paradigm shift is not happening fast enough due to a lack of focus on streamlining the process of rapid experimentation, training, and optimizing PINNs and no easy-to-use tools that leverage AI-based simulators for solving engineering problems.

At DimensionLab, we saw an opportunity to bridge great user experience with state-of-the-art AI methods to create a product that significantly increases the effectiveness of working with AI-based physics simulators.

Under the hood, Siml.ai consists of two parts - **Model Engineer** and **Simulation Studio**.

AI in physics simulation

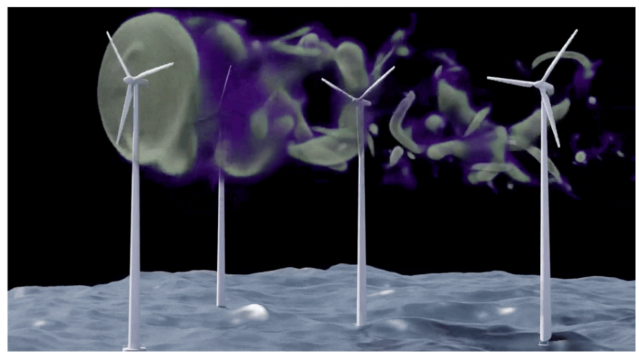
So far, it has taken people a very long time to design the optimal shape and layout of wind turbines, the aerodynamics of cars and flying vehicles, optimize electronics cooling and power consumption, develop efficient methods of converting hydrogen into fuel and its storage, understand the properties of alternative energy sources, etc.. Everywhere it is necessary to first prepare a description of what is probably going on "under the hood" using mathematical equations (mathematical modeling, mostly still done by humans) and then validate or refute the theory by analysis using numerical simulations.

Currently, both human modeling and numerical simulation calculations are reaching their limits. But artificial intelligence is beginning to show us a new path in physics. Based on an incomplete description of a problem, AI can create a very accurate mathematical model that humans have no chance of understanding yet - the task of humans is now just to validate it, or "test it from every angle" to make sure it is correct. At the same time, there is a great advantage in terms of using such a model in analysis by numerical simulations in the **several thousand times faster** speed of its computation. The result of such an analysis is, for example, the visualization of physical phenomena and their understanding for problem-solving, optimization, fault prediction, or technological development. By speeding up this process, we will reduce research and development time while being able to explore many more possibilities in the same amount of time as before.

Use cases

Wind farm energy optimization

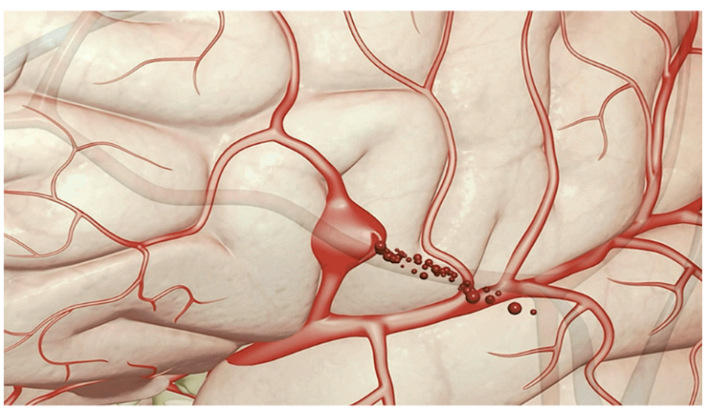
Siemens Gamesa leveraged PINNs to optimize energy generation from wind farms by automatic AI-assisted positioning of the turbines. Before PINNs, doing this was highly infeasible: **simulation of 1 wind turbine takes 30-40 days with traditional simulation software** with LES turbulence modeling. Thanks to AI-based physics simulator trained **using PINNs, tens of wind turbines can be simulated in under 5 minutes**, unlocking inverse physics simulation like extremely fast optimization of energy output.

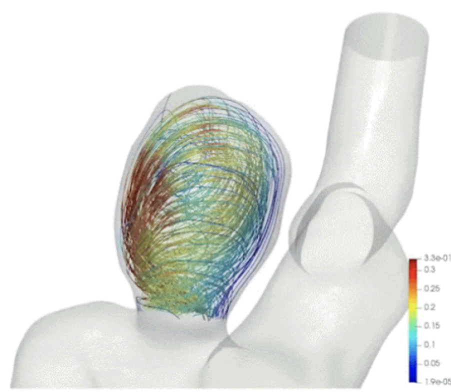


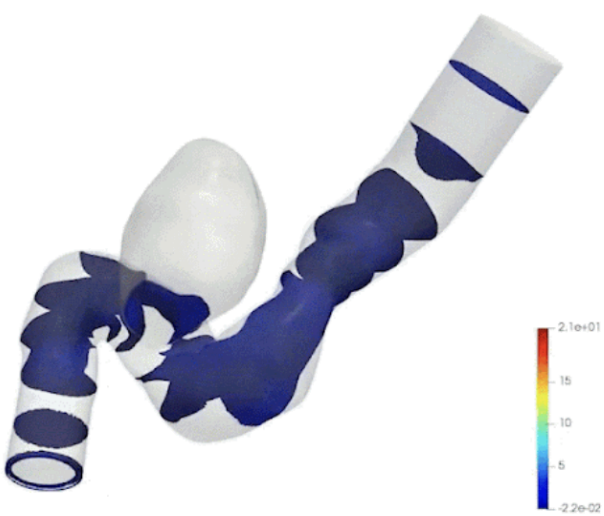
Blood flow simulation in intracranial aneurysm

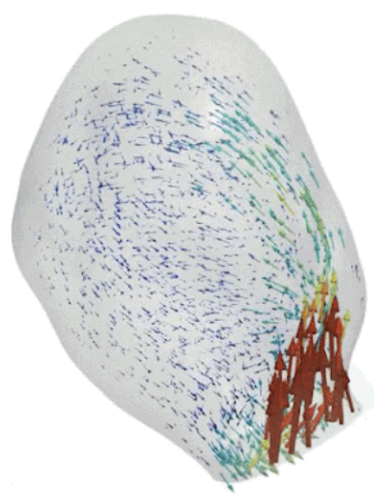
Simulation is highly beneficial for understanding blood flows in the body, mainly in life-threatening anomalies like aneurysms. It’s possible to generate a 3D geometry of these anomalies from MRI and CT scans, which vary from patient to patient. Simulating the physics of blood flow and pressure for such a vast space of different shapes for every patient takes too much time with traditional simulation software. The time it takes to understand the situation at hand and decide on the correct treatment will impact the life of each patient, possibly preventing death if acting fast.

With AI-based physics simulators of blood flows leveraging PINNs, doctors would be able to analyze each anomaly in detail in a few hours instead of days or weeks. They would be able to visualize the impact of treatment and interactively test tens of “what if” scenarios in a day. Surgeons will be presented with a detailed report of predicted physiological variables, which will help them prevent catastrophic medical events.









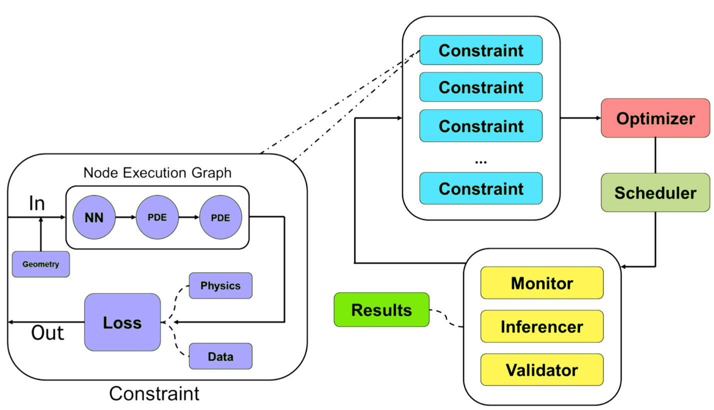
Technical overview

In complex physics simulations, it's important to precisely quantify the underlying physical mechanisms in order to analyze them. High-dimensional scientific simulations are computationally very expensive to run, and solvers and parameters must often be tuned individually to each system studied.

Machine learning approaches tend to considerably decrease the load on computational resources by reducing the dimensionality of the studied problem[2] and by factoring in the fact that **AI-based simulators need to be <u>trained only once</u>** while the actual numerical simulation is computed during the inference of the model. This, compared to computing physics every time a simulation is re-run, brings large efficiency benefits together with shortened time for the actual computations as trained models.

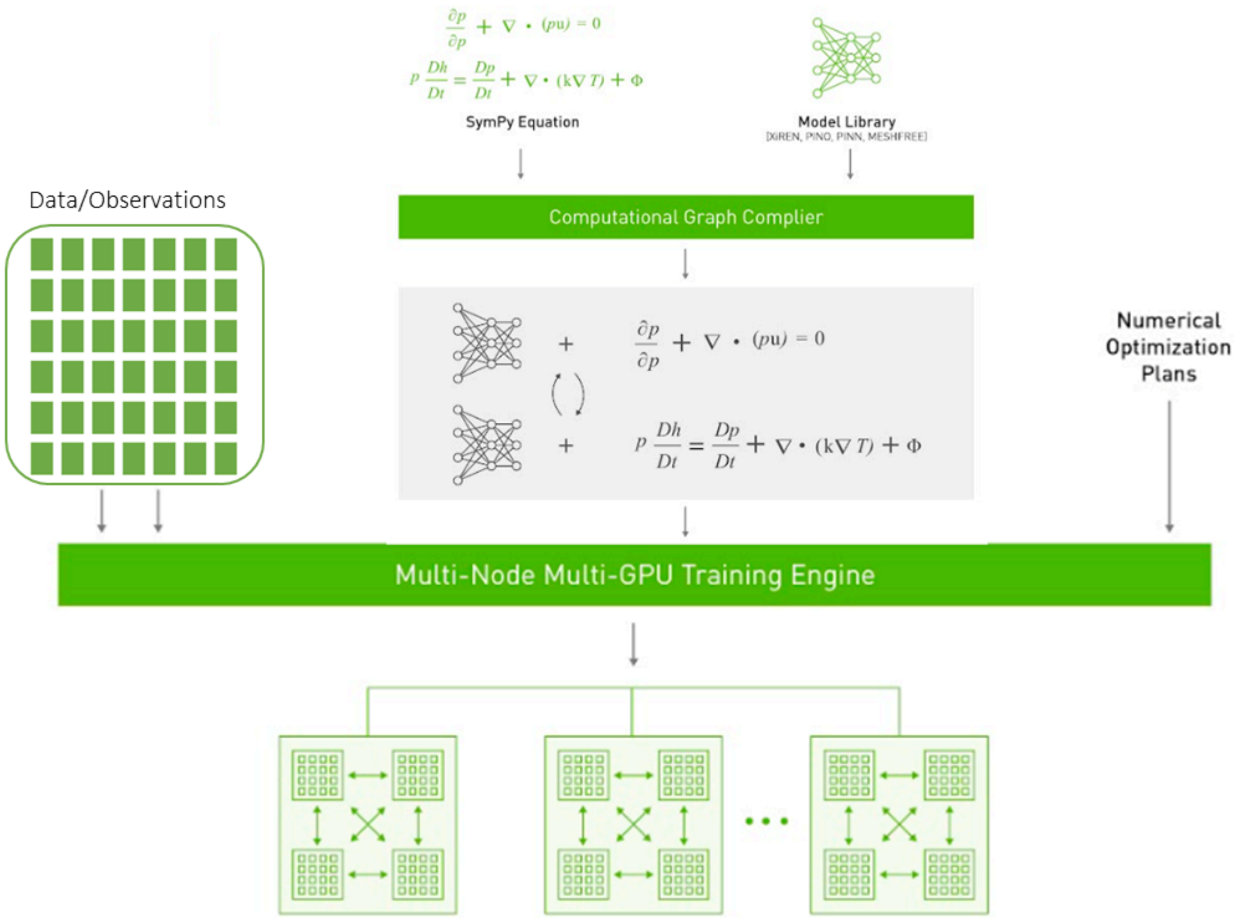
Siml.ai platform provides a set of tools to easily create, train, and deploy powerful physics-informed neural network models with complex physics and custom partial differential equations. We provide a cloud-based environment called Simulator Inference Training Environment (SITE) available through the Siml.ai Model Engineer application. SITE is optimized for NVIDIA GPUs and offers everything needed for creating AI-based physics simulators:

- NVIDIA Modulus framework for creating and training PINNs
- Training and inference pipelines tuned and optimized by DimensionLab's team of engineers for allowing to use Siml.ai generally for many multiphysics applications
- High-performance rendering
- Real-time hardware usage monitoring (GPU utilization and memory)



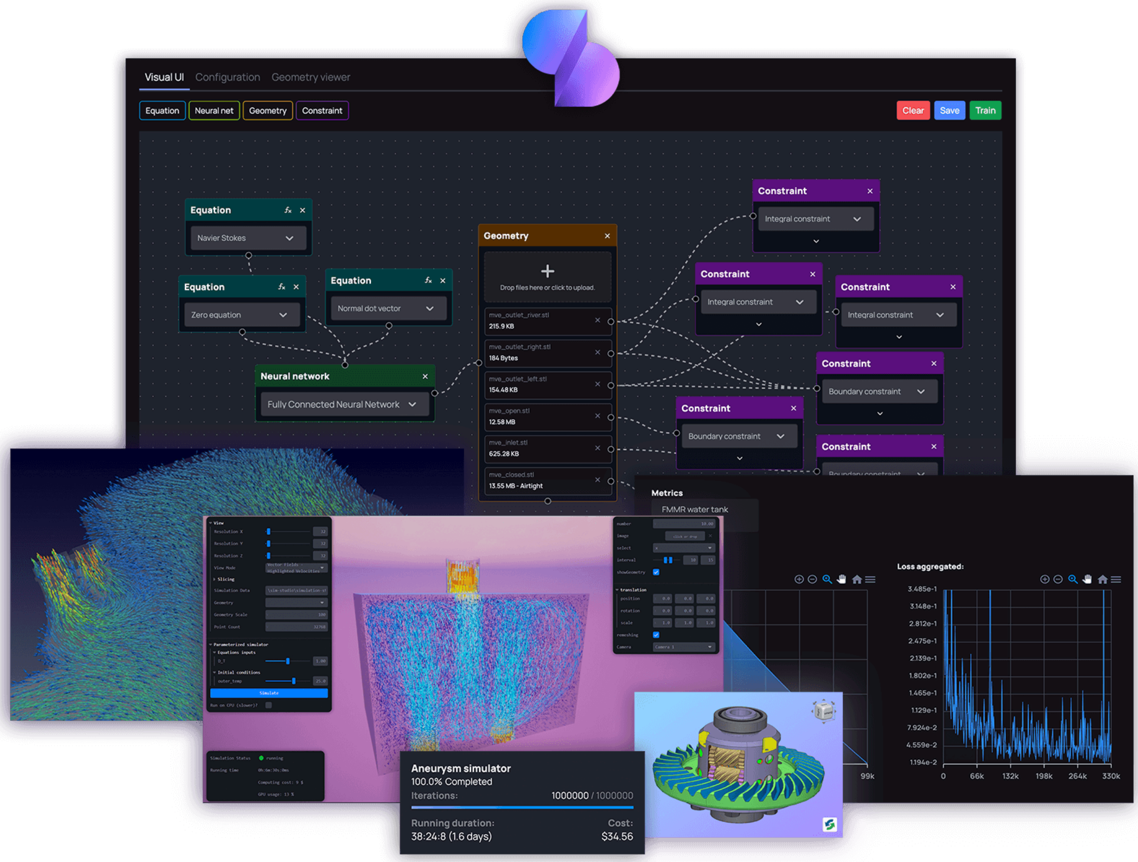
We use state-of-the-art neural network architectures (PINNs, FNOs, DeepONets) that can be trained to approximate physics, fit experimental data from physical processes (e.g. from sensors), or group them together to build hybrid physics+data surrogate models.

[NVIDIA Modulus](#) is a framework we use in Siml.ai for training and inference that blends the power of physics in the form of governing partial differential equations (PDEs) with data to build high-fidelity, parameterized surrogate models with near-real-time latency.



For the training and optimization workflow of AI-based simulation models, we are building the Model Engineer application. It removes the pain of managing complex cloud infrastructure and instead helps users to stay focused on creating extremely high-performance AI-based physics simulators. We are putting emphasis on building a powerful, automated optimization workflow into Model Engineer to optimize the speed and efficiency of these simulators.

Model Engineer



Model Engineer is a web application for training and optimizing general-purpose learnable simulators (e.g. for simulating fluid flows, multiphase flows, mechanical deformation, solid-fluid interaction and so on) using deep learning techniques. Our aim is to make the process of training and optimizing such simulators simple, visual and understandable.

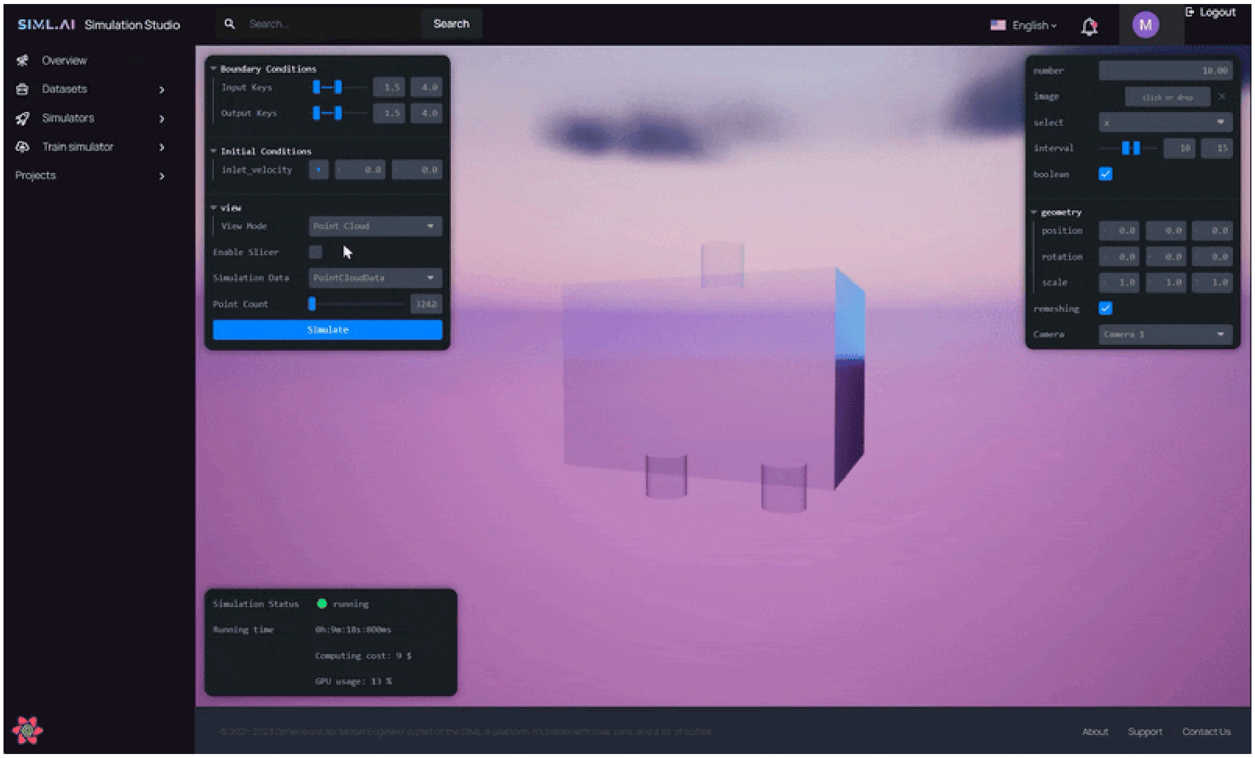
Complexity of the PINN model varies based on the physics simulator capabilities, e.g. how complex the underlying physics is, how many hyperparameters to track and how big is the dataset to train on. Currently, there doesn't yet exist a powerful and easy-to-use software tool for the task of building AI-based physics simulators with state-of-the-art architectures.

In cloud platforms like AWS, users need to set volume, Elastic Compute instance, big data processing pipeline through EMR, etc., before actually using the GPU server. Also, when deploying and maintaining the model, machines with the latest hardware (e.g., GPU) may fail to install the original package versions, which causes issues in reproducing the model training and inference performance and accuracy.

Our goal with Model Engineer is to simplify and streamline the whole process, from constructing large datasets from classical simulation exports or physical sensors that collect precise measurements from real-world experiments, to quickly constructing the correct model architecture for the simulators' desired capabilities and constraints, to training and aggressively optimizing the learnable simulators in high-performance, GPU-powered cloud or HPC centers without the need to deal with the complexities of managing the cloud infrastructure.

Within the Siml.ai platform, Model Engineer has a powerful position of being a funnel through which we plan to build a large database of trained models by individual engineers, researchers or companies. This will allow us to create a new market for ready-to-use, "packaged" AI simulators – essentially a marketplace in which these entities can earn money from simulators trained by them by allowing other users to use them in their projects through Simulation Studio.

Simulation Studio

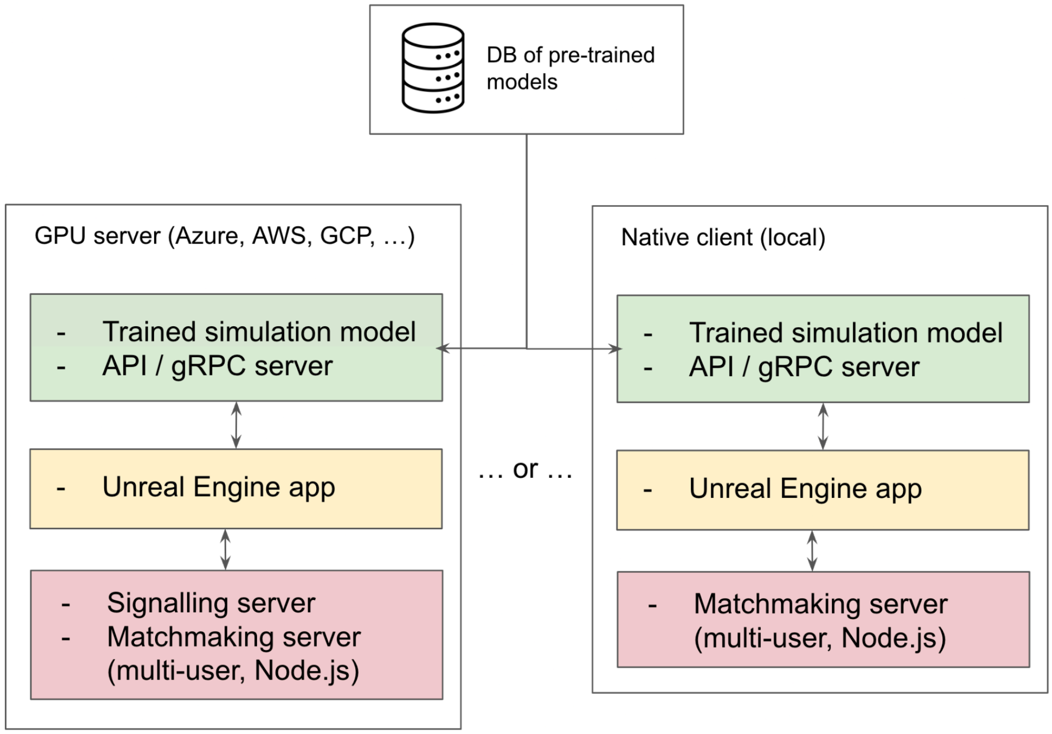


Simulation Studio is a hybrid between web-based and native application for solving engineering and scientific problems leveraging pre-trained and optimized models of AI-based physics simulators. Since the simulations are computed by inferring these models, the time it takes to compute one timestep even of highly irregular simulation domain is in low tens of milliseconds, resulting in near-real-time simulation and visualization of physical phenomena. High-fidelity visualization rendering is achieved by leveraging the powerful Unreal Engine under the hood.

Simulation Studio provides a 3D interface for high-fidelity, interactive in-situ visualizations of running numerical simulations.

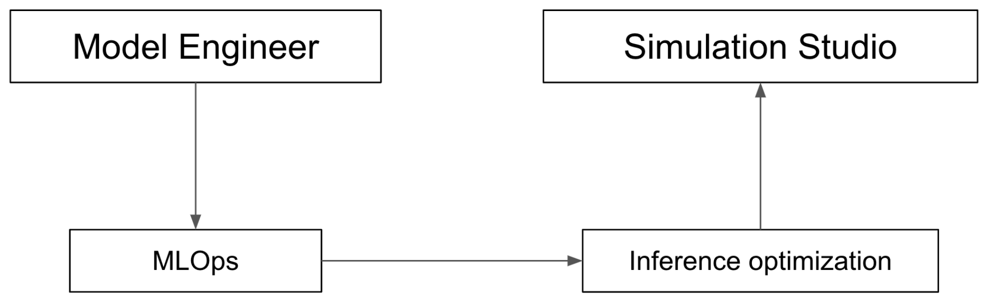
There will be three ways of using Simulation Studio (currently in Siml.ai beta, we provide only the first option):

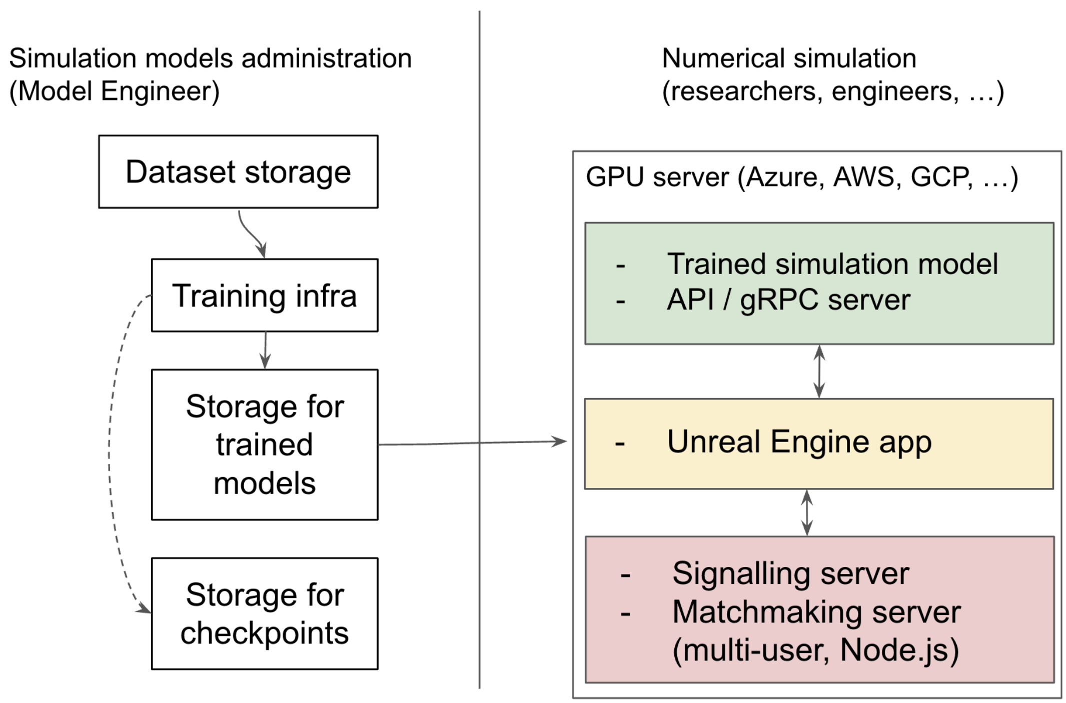
1. Web application running completely in cloud, streamed to the browser,
2. Native application with rendering in cloud,
3. Native application with rendering on-premises.



By using Simulation Studio on your local hardware, you can also opt-in to run simulations completely offline (requires 1 or more NVIDIA GPU installed).

Siml.ai high-level architecture overview





References:

1. Hennigh et al., "NVIDIA SimNet: an AI-accelerated multi-physics simulation framework." [url]
2. Brunton et al, "Machine Learning for Fluid Mechanics."
3. Pathak et. al., "FourCastNet: A Global Data-Driven High-Resolution Weather Model Using Adaptive Fourier Neural Operators." [url]

QR code to this document: