# Is data science killing numerical mathematics?

**4TU.AMI symposium Big Data**

Mark Roest


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CONTENT
PROCESSING
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CONSUMER DEMAND MARKETS
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WEB MARKETING
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SOCIAL NETWORKS
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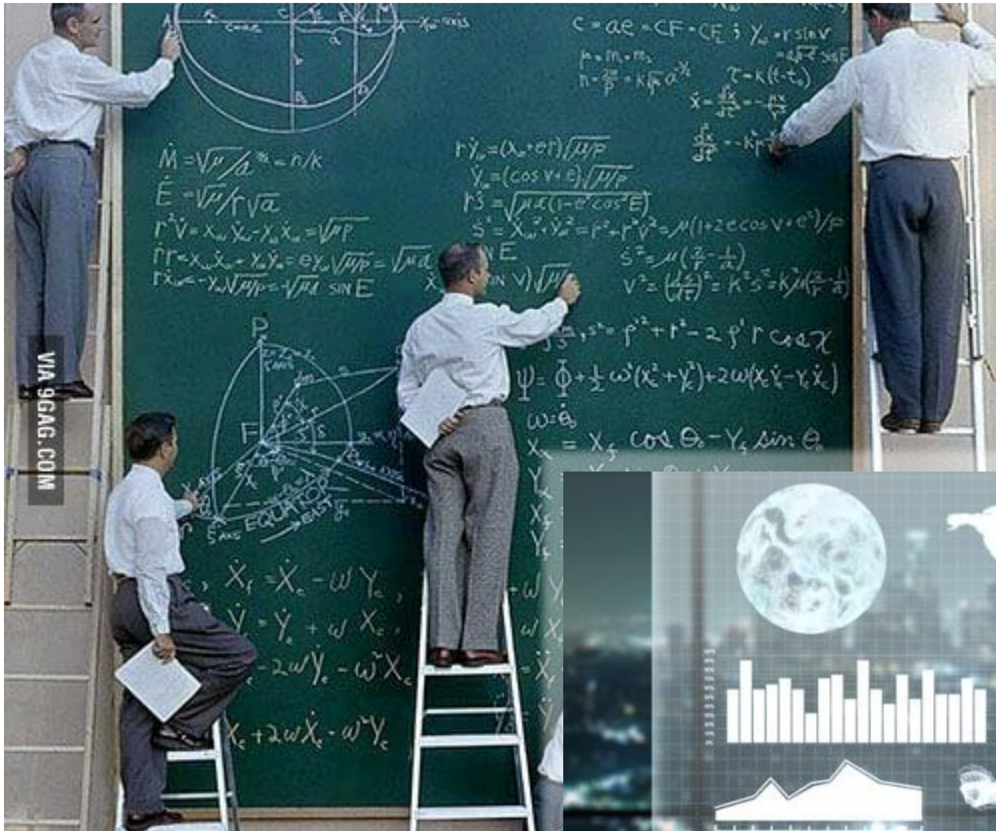
VIA 9GAG.COM

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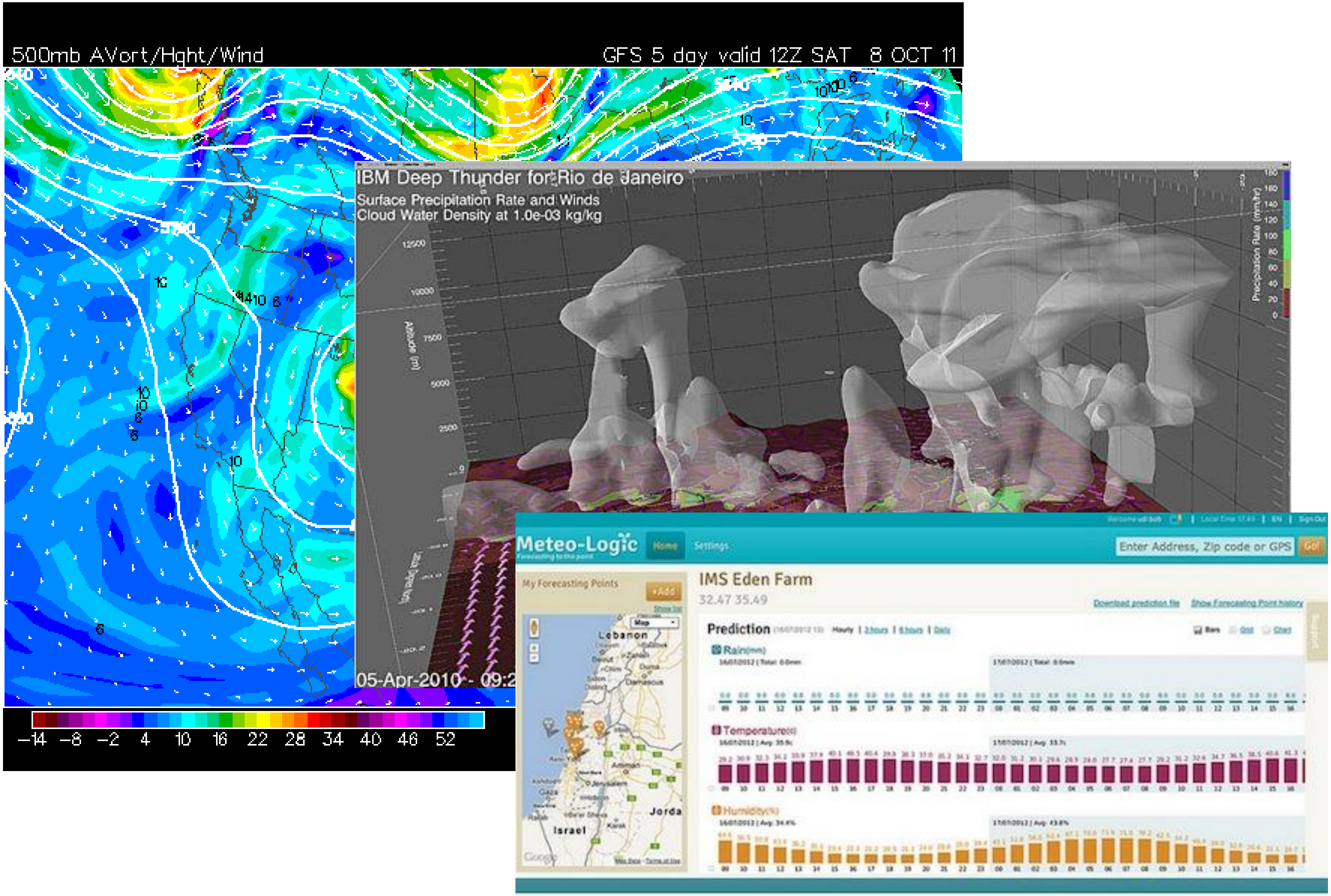

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IBM Deep Thunder for Rio de Janeiro
Surface Precipitation Rate and Winds
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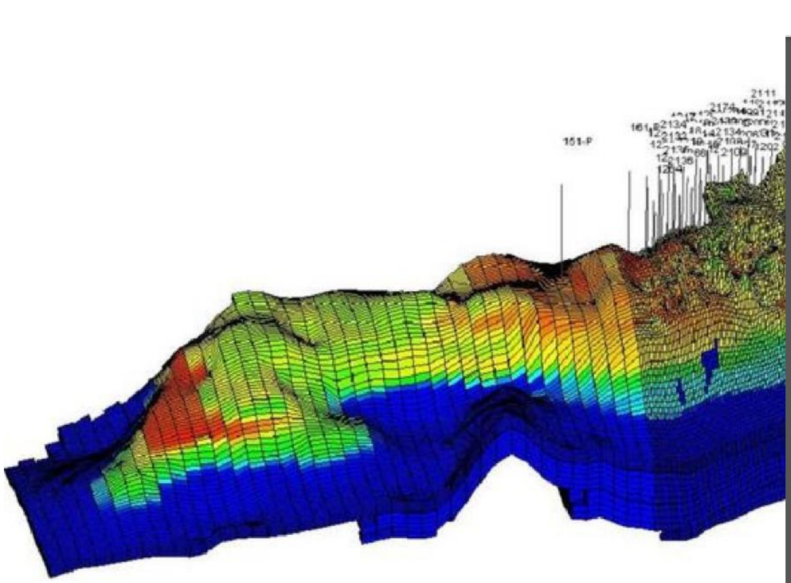

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# AI-BASED RESERVOIR MANAGEMENT

## ANALTERNATIVE TO TRADITIONAL RESERVOIR MODELING

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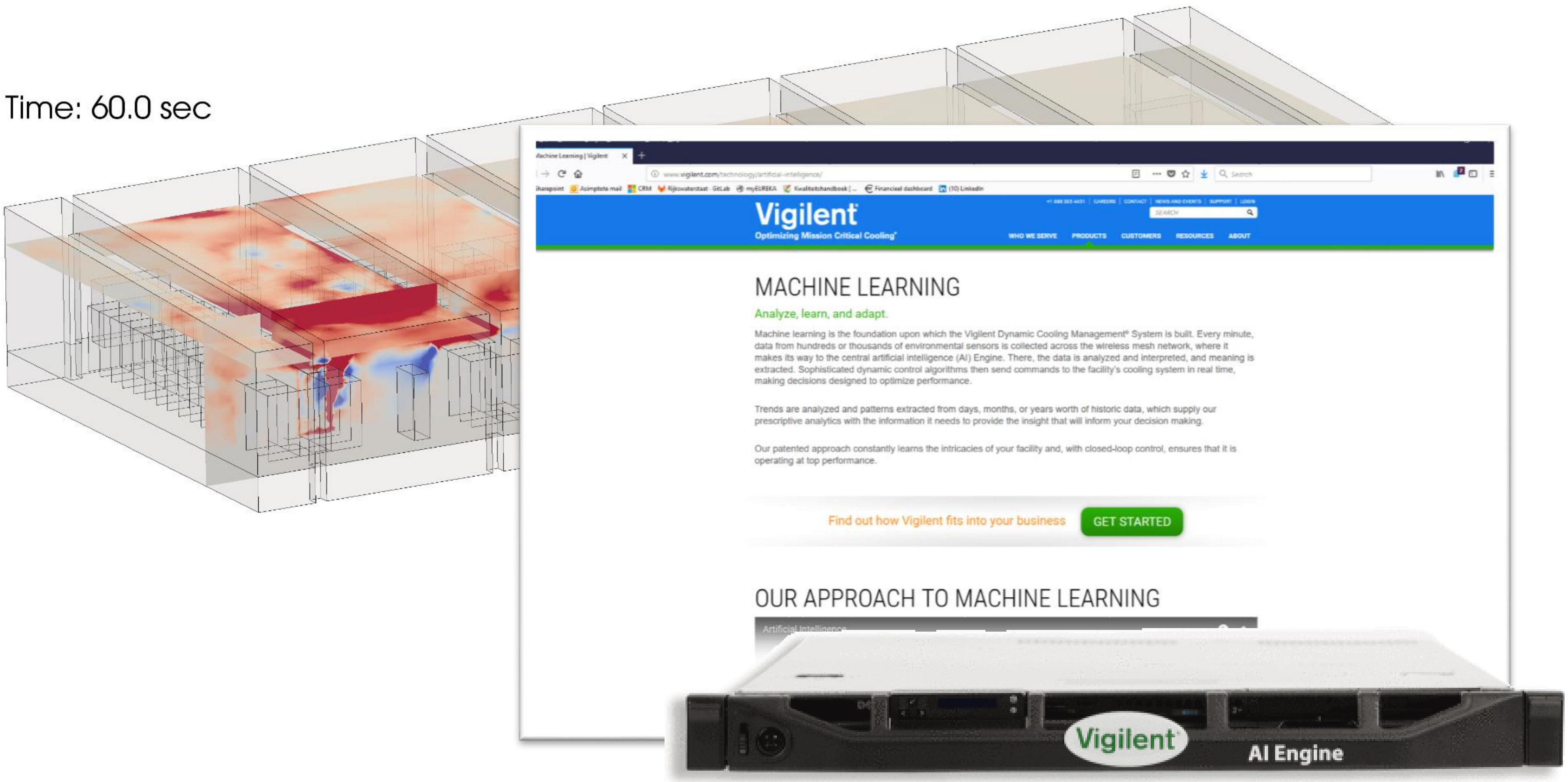
Time: 60.0 sec
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Find out how Vigilent fits into your business
GET STARTED
OUR APPROACH TO MACHINE LEARNING
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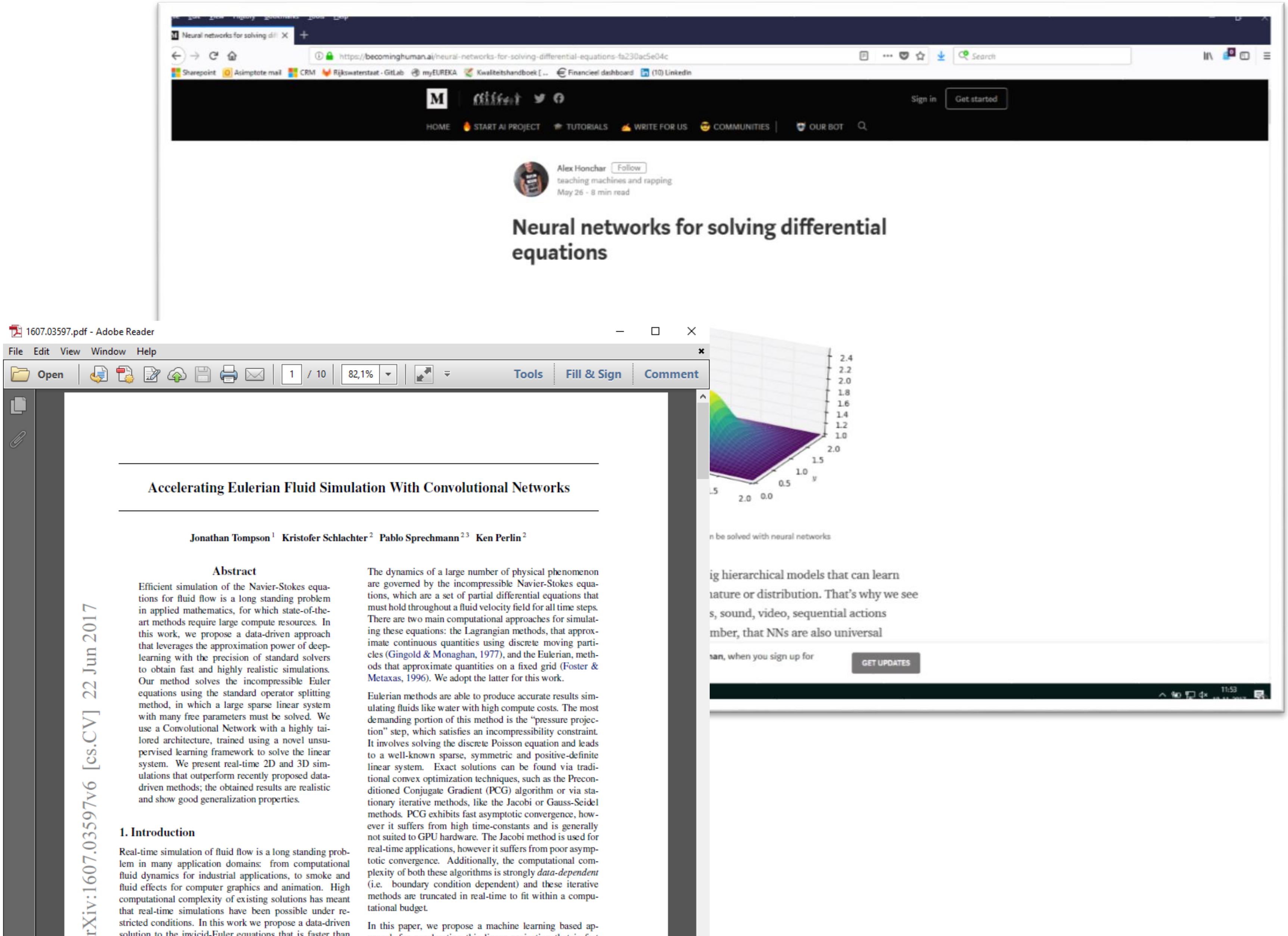


arXiv:1607.03597v6 [cs.CV] 22 Jun 2017

# Accelerating Eulerian Fluid Simulation With Convolutional Networks

Jonathan Tompson[1] Kristofer Schlachter[2] Pablo Sprechmann[2 3] Ken Perlin[2]


## Abstract

Efficient simulation of the Navier-Stokes equations for fluid flow is a long standing problem in applied mathematics, for which state-of-the-art methods require large compute resources. In this work, we propose a data-driven approach that leverages the approximation power of deep-learning with the precision of standard solvers to obtain fast and highly realistic simulations. Our method solves the incompressible Euler equations using the standard operator splitting method, in which a large sparse linear system with many free parameters must be solved. We use a Convolutional Network with a highly tailored architecture, trained using a novel unsupervised learning framework to solve the linear system. We present real-time 2D and 3D simulations that outperform recently proposed data-driven methods; the obtained results are realistic and show good generalization properties.


## 1. Introduction

Real-time simulation of fluid flow is a long standing problem in many application domains: from computational fluid dynamics for industrial applications, to smoke and fluid effects for computer graphics and animation. High computational complexity of existing solutions has meant that real-time simulations have been possible under restricted conditions. In this work we propose a data-driven solution to the invicid-Euler equations that is faster than

The dynamics of a large number of physical phenomenon are governed by the incompressible Navier-Stokes equations, which are a set of partial differential equations that must hold throughout a fluid velocity field for all time steps. There are two main computational approaches for simulating these equations: the Lagrangian methods, that approximate continuous quantities using discrete moving particles (Gingold & Monaghan, 1977), and the Eulerian, methods that approximate quantities on a fixed grid (Foster & Metaxas, 1996). We adopt the latter for this work.

Eulerian methods are able to produce accurate results simulating fluids like water with high compute costs. The most demanding portion of this method is the "pressure projection" step, which satisfies an incompressibility constraint. It involves solving the discrete Poisson equation and leads to a well-known sparse, symmetric and positive-definite linear system. Exact solutions can be found via traditional convex optimization techniques, such as the Preconditioned Conjugate Gradient (PCG) algorithm or via stationary iterative methods, like the Jacobi or Gauss-Seidel methods. PCG exhibits fast asymptotic convergence, however it suffers from high time-constants and is generally not suited to GPU hardware. The Jacobi method is used for real-time applications, however it suffers from poor asymptotic convergence. Additionally, the computational complexity of both these algorithms is strongly *data-dependent* (i.e. boundary condition dependent) and these iterative methods are truncated in real-time to fit within a computational budget.

In this paper, we propose a machine learning based approach for accelerating this linear projection that is fast

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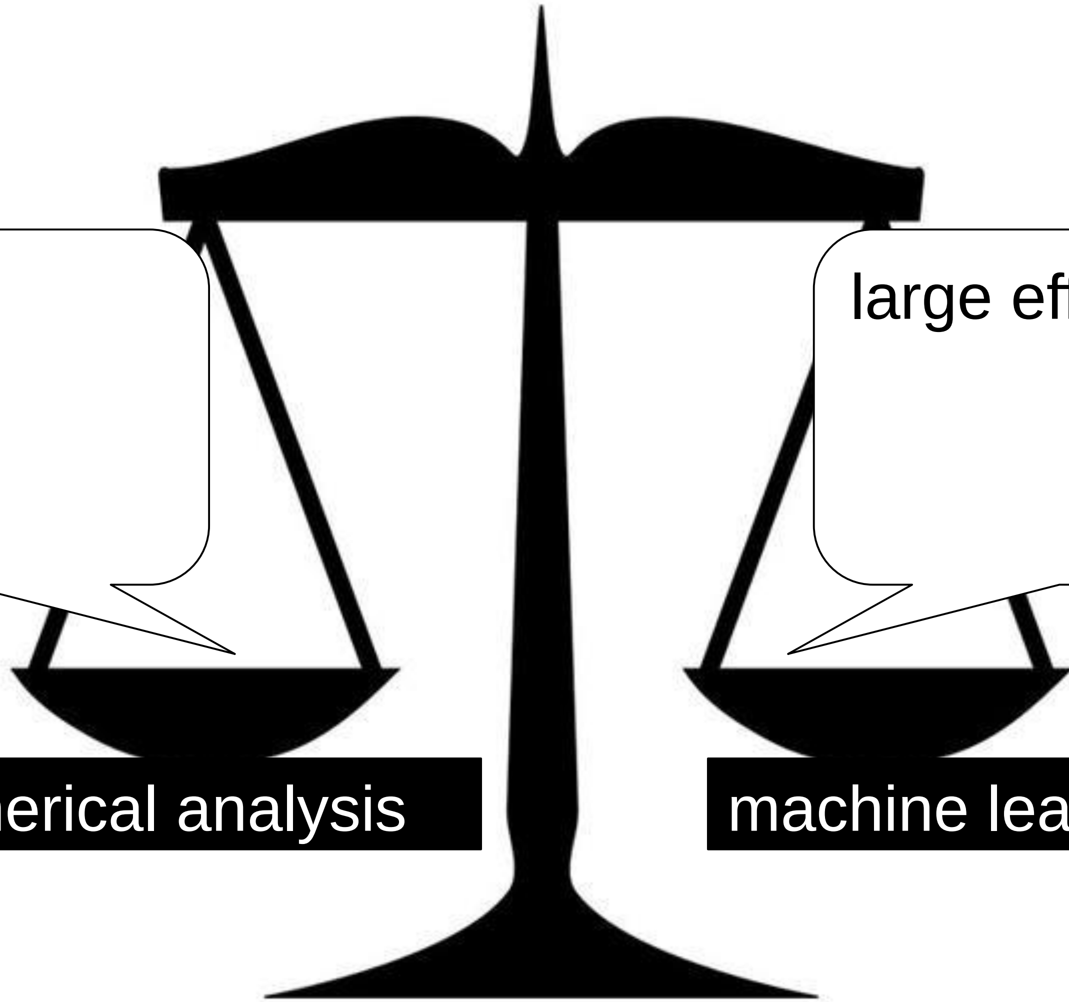
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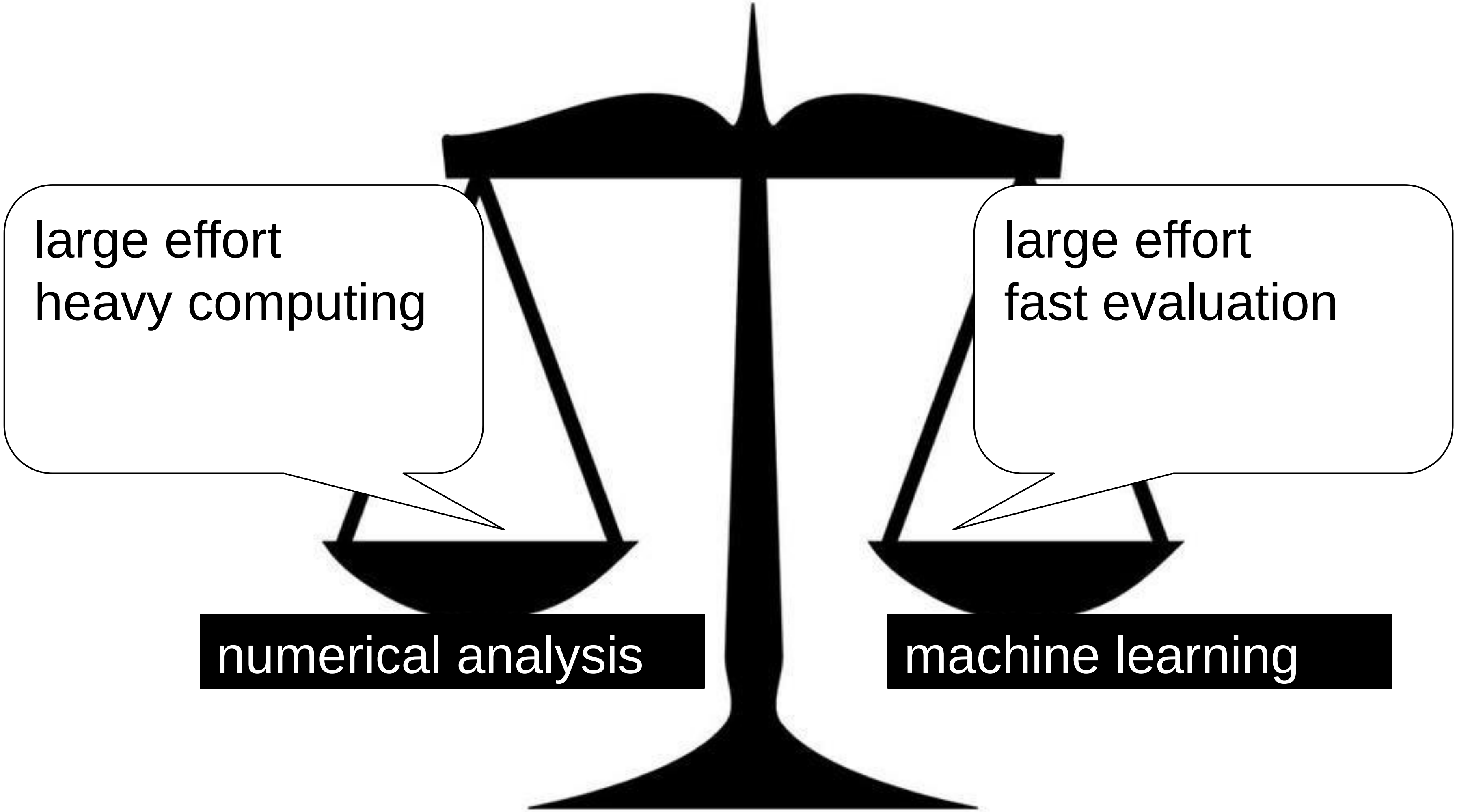
large effort
numerical analysis
machine learning


large effort
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fast evaluation
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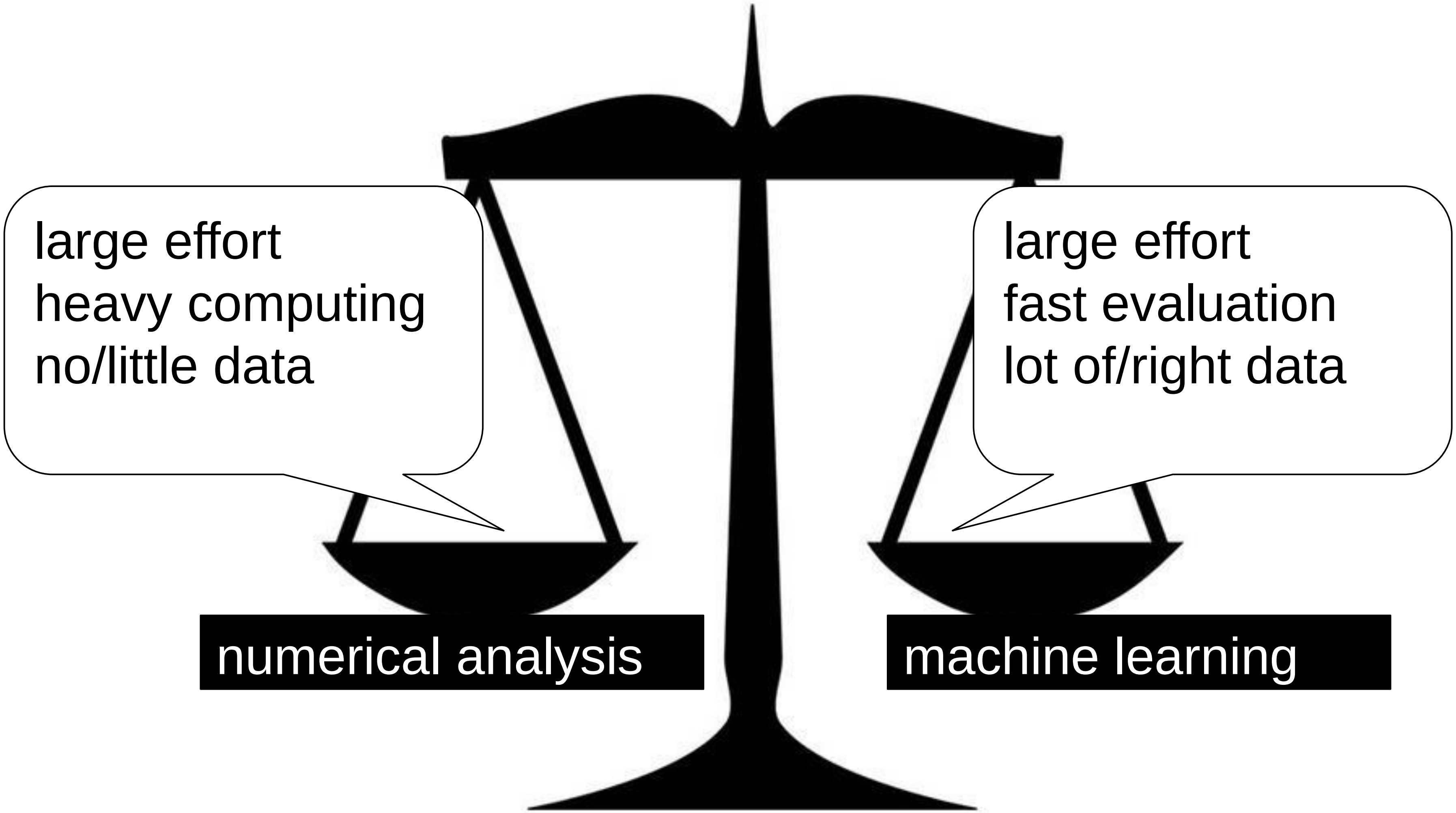
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fast evaluation
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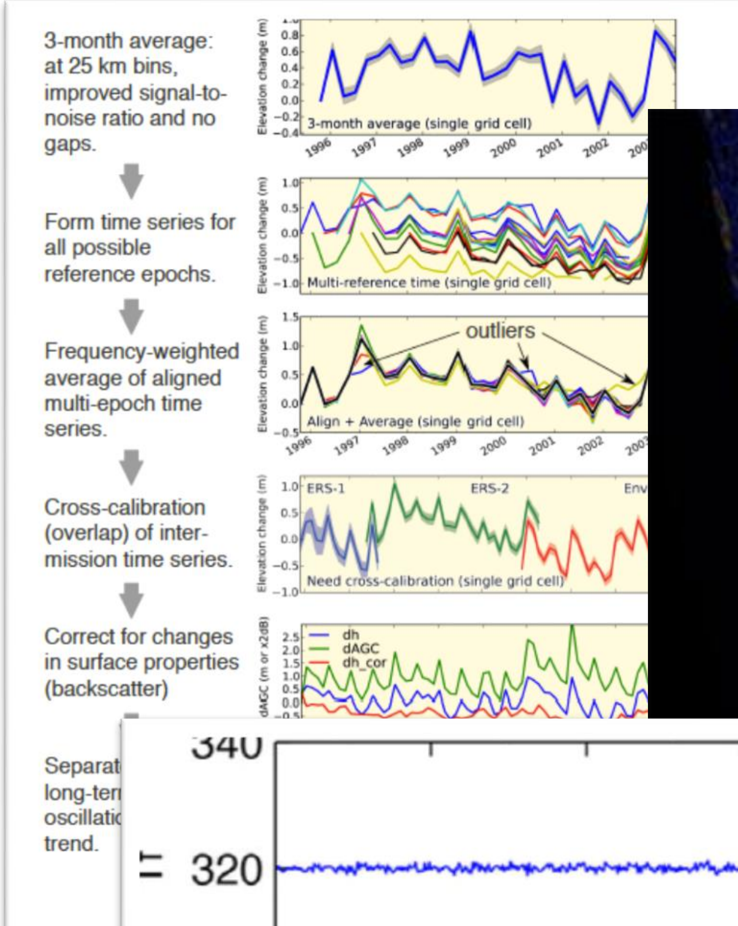
numerical analysis
machine learning


3-month average: at 25 km bins, improved signal-to-noise ratio and no gaps.
3-month average (single grid cell)
Form time series for all possible reference epochs.
Multi-reference time (single grid cell)
Frequency-weighted average of aligned multi-epoch time series.
outliers
Align + Average (single grid cell)
Cross-calibration (overlap) of inter-mission time series.
ERS-1
ERS-2
Need cross-calibration (single grid cell)
Correct for changes in surface properties (backscatter)
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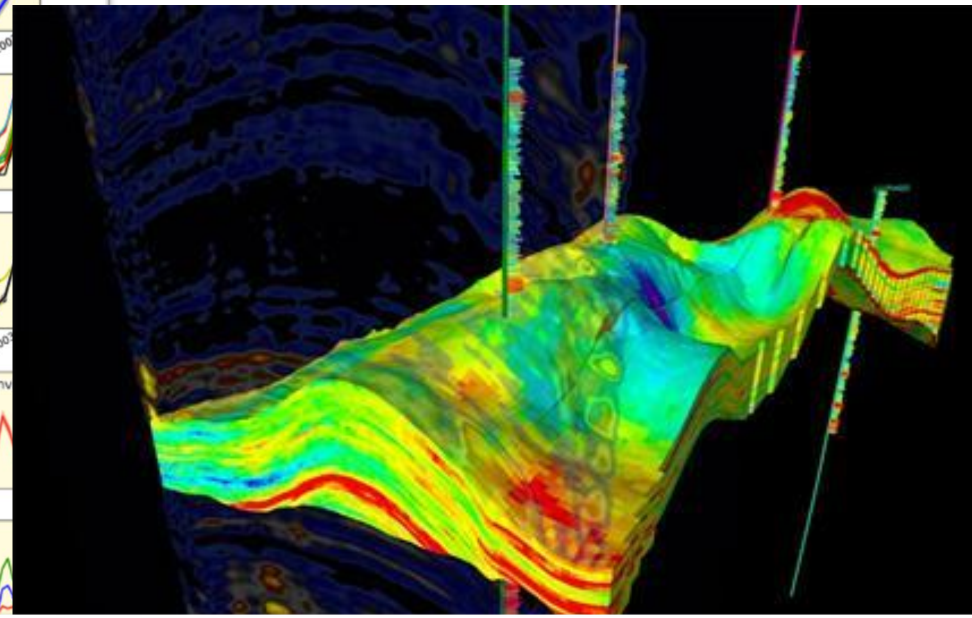

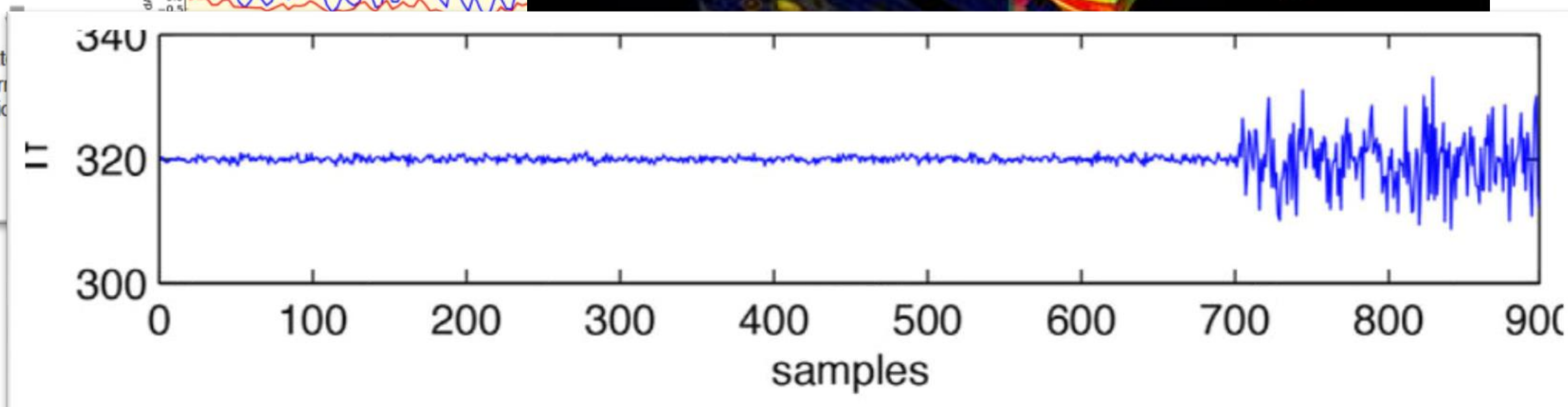
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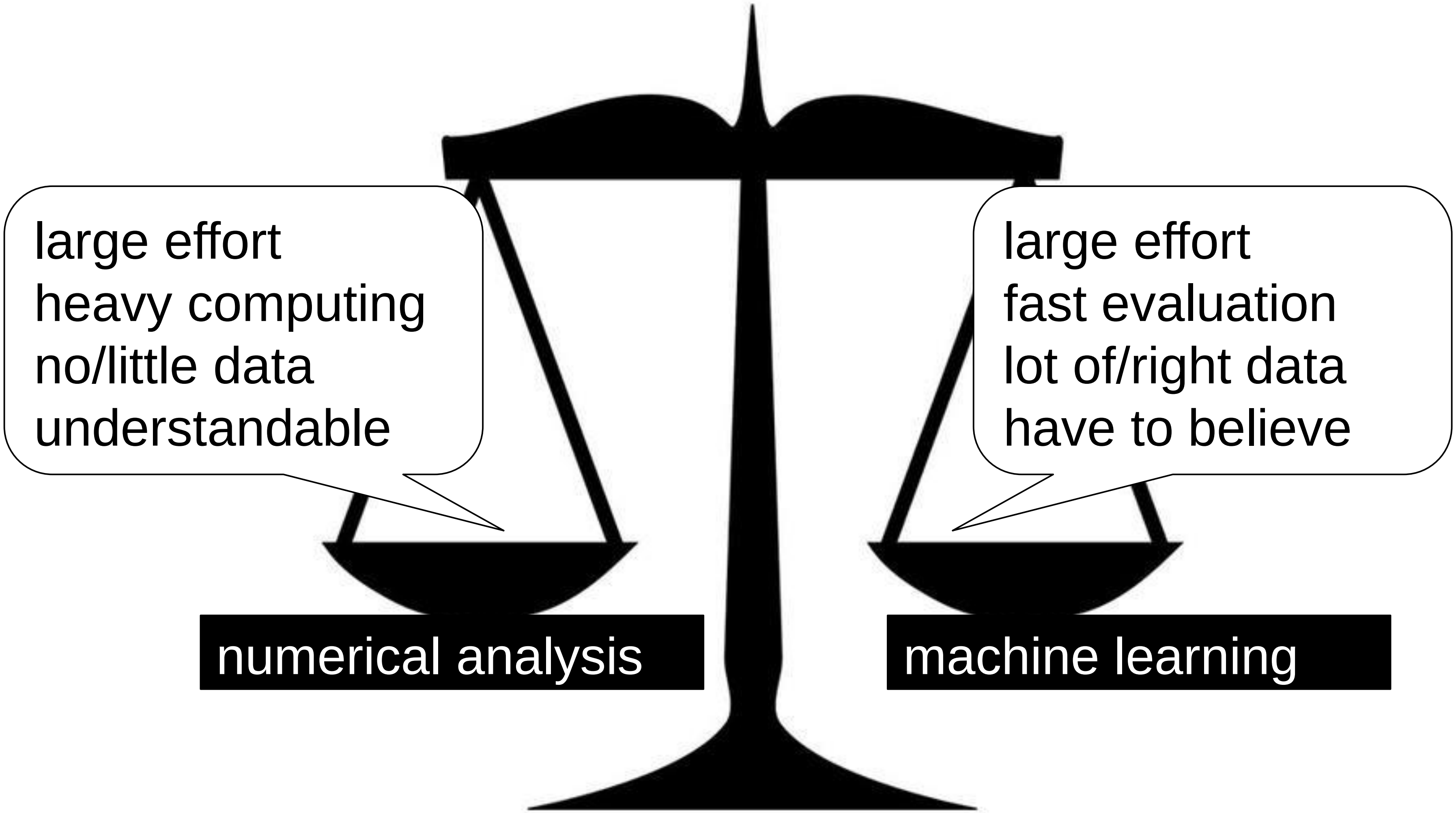
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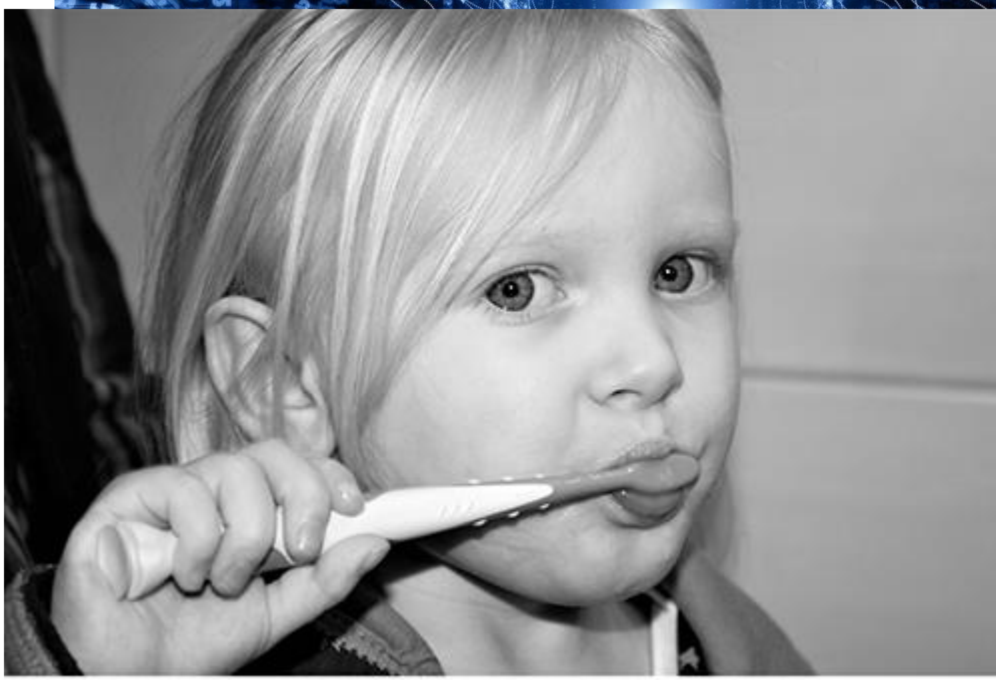
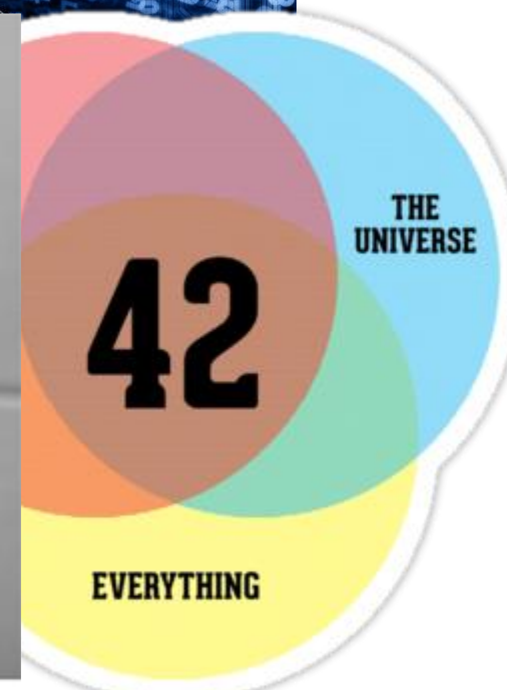
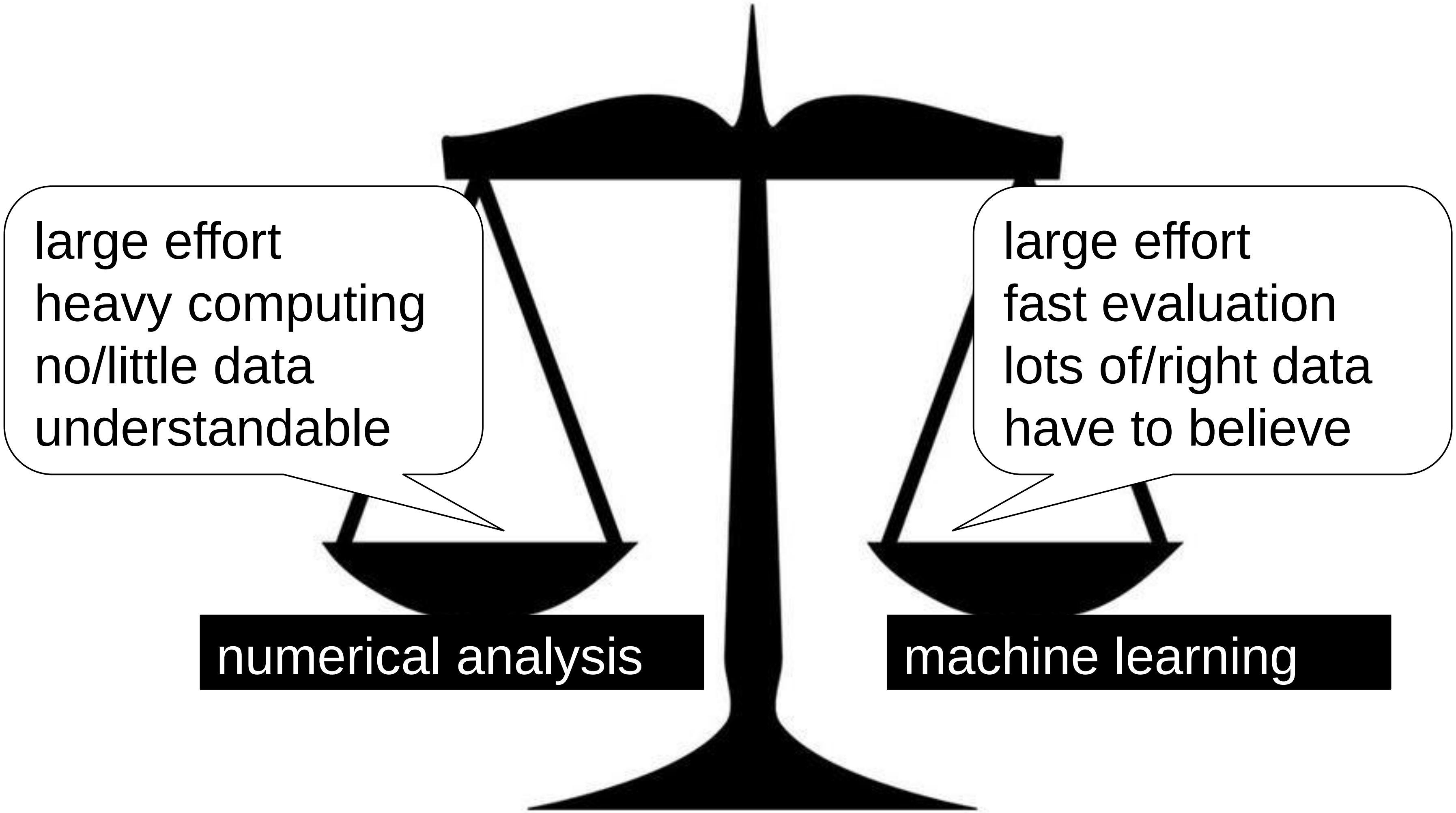


The boy is holding a baseball bat.

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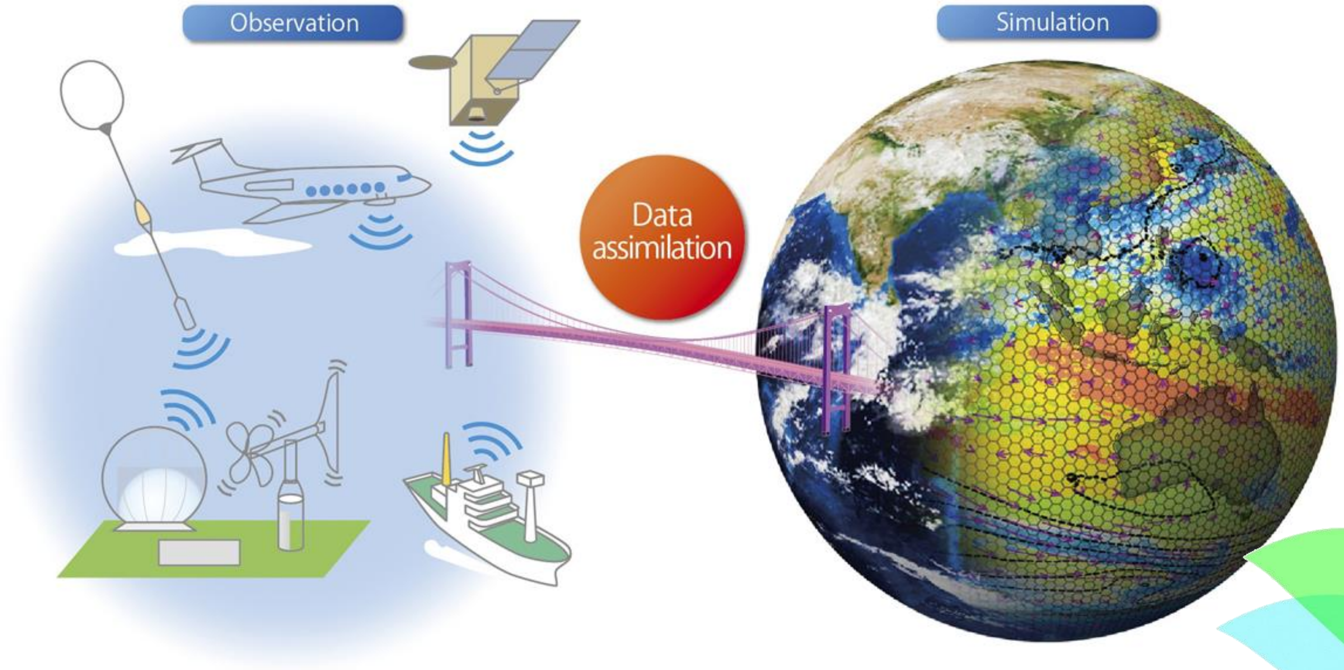


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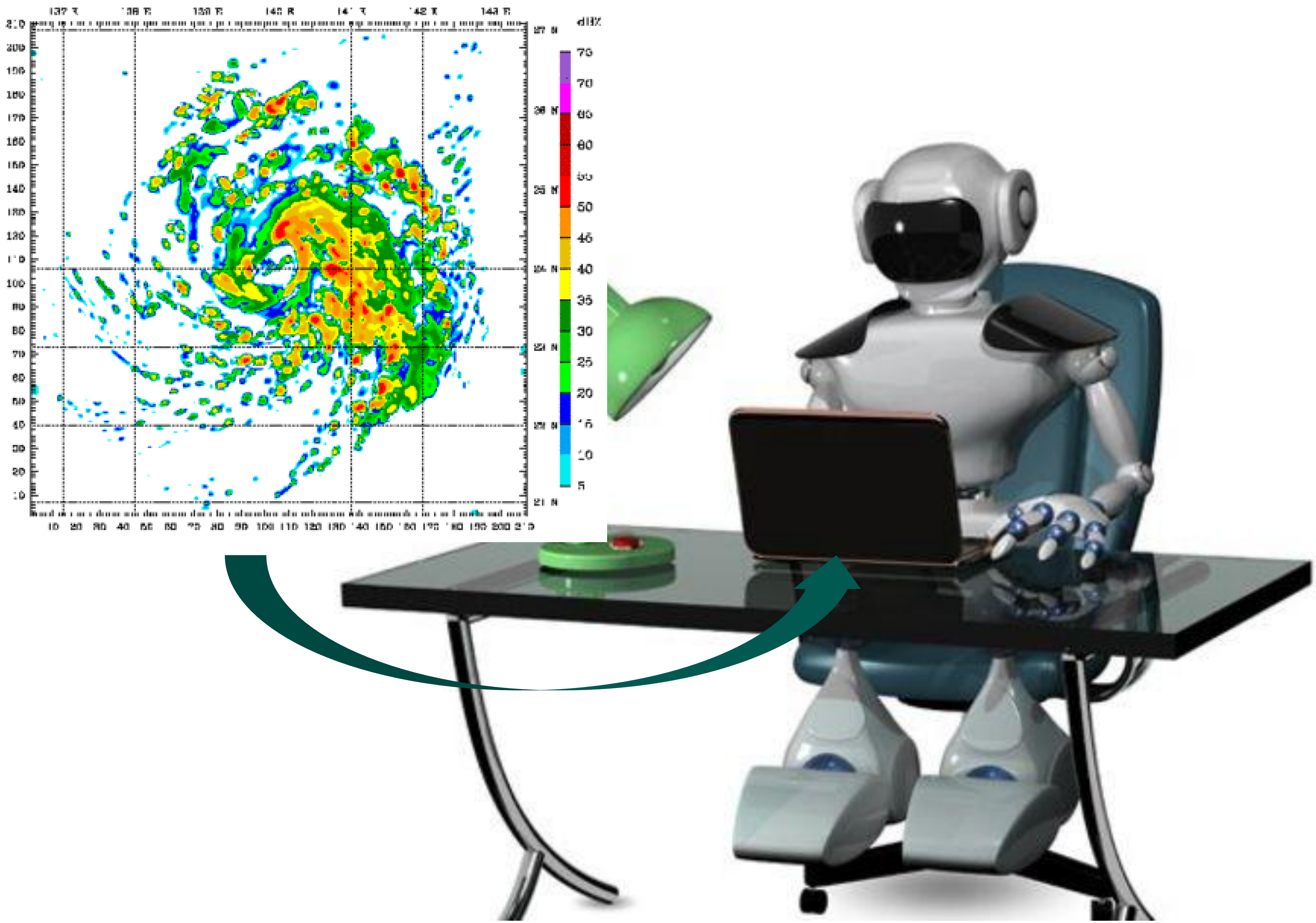

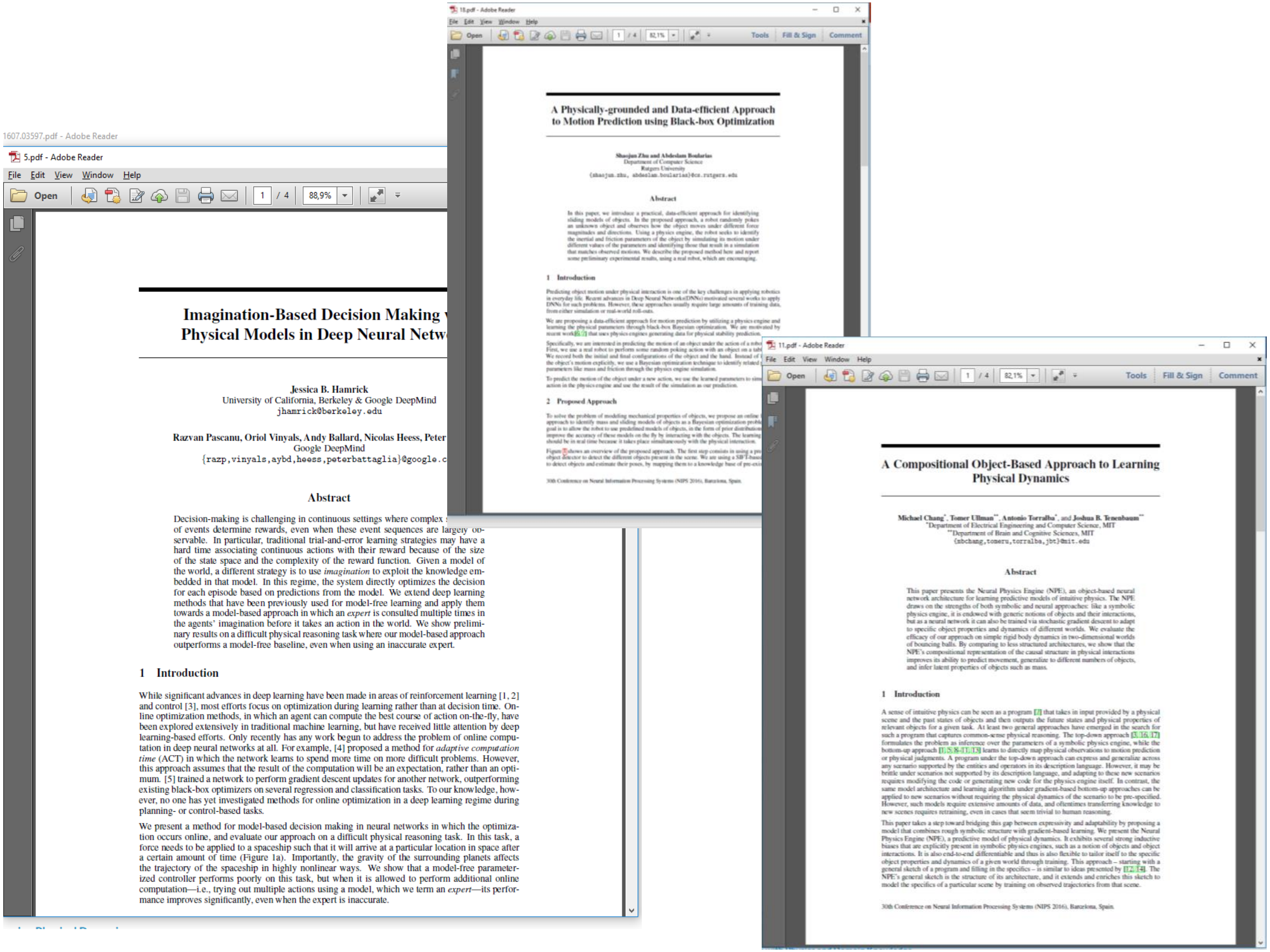

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# Imagination-Based Decision Making w
# Physical Models in Deep Neural Netw

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**Razvan Pascanu, Oriol Vinyals, Andy Ballard, Nicolas Heess, Peter**
Google DeepMind
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**Abstract**

Decision-making is challenging in continuous settings where complex s of events determine rewards, even when these event sequences are largely observable. In particular, traditional trial-and-error learning strategies may have a hard time associating continuous actions with their reward because of the size of the state space and the complexity of the reward function. Given a model of the world, a different strategy is to use *imagination* to exploit the knowledge embedded in that model. In this regime, the system directly optimizes the decision for each episode based on predictions from the model. We extend deep learning methods that have been previously used for model-free learning and apply them towards a model-based approach in which an *expert* is consulted multiple times in the agents' imagination before it takes an action in the world. We show preliminary results on a difficult physical reasoning task where our model-based approach outperforms a model-free baseline, even when using an inaccurate expert.

## 1 Introduction

While significant advances in deep learning have been made in areas of reinforcement learning [1, 2] and control [3], most efforts focus on optimization during learning rather than at decision time. Online optimization methods, in which an agent can compute the best course of action on-the-fly, have been explored extensively in traditional machine learning, but have received little attention by deep learning-based efforts. Only recently has any work begun to address the problem of online computation in deep neural networks at all. For example, [4] proposed a method for *adaptive computation time* (ACT) in which the network learns to spend more time on more difficult problems. However, this approach assumes that the result of the computation will be an expectation, rather than an optimum. [5] trained a network to perform gradient descent updates for another network, outperforming existing black-box optimizers on several regression and classification tasks. To our knowledge, however, no one has yet investigated methods for online optimization in a deep learning regime during planning- or control-based tasks.

We present a method for model-based decision making in neural networks in which the optimization occurs online, and evaluate our approach on a difficult physical reasoning task. In this task, a force needs to be applied to a spaceship such that it will arrive at a particular location in space after a certain amount of time (Figure 1a). Importantly, the gravity of the surrounding planets affects the trajectory of the spaceship in highly nonlinear ways. We show that a model-free parameterized controller performs poorly on this task, but when it is allowed to perform additional online computation—i.e., trying out multiple actions using a model, which we term an *expert*—its performance improves significantly, even when the expert is inaccurate.

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# A Physically-grounded and Data-efficient Approach to Motion Prediction using Black-box Optimization

**Shaojun Zhu and Abdeslam Boularias**
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Rutgers University
{shaojun.zhu, abdeslam.boularias}@cs.rutgers.edu

**Abstract**

In this paper, we introduce a practical, data-efficient approach for identifying sliding models of objects. In the proposed approach, a robot randomly pokes an unknown object and observes how the object moves under different force magnitudes and directions. Using a physics engine, the robot seeks to identify the inertial and friction parameters of the object by simulating its motion under different values of the parameters and identifying those that result in a simulation that matches observed motions. We describe the proposed method here and report some preliminary experimental results, using a real robot, which are encouraging.

## 1 Introduction

Predicting object motion under physical interaction is one of the key challenges in applying robotics in everyday life. Recent advances in Deep Neural Networks(DNNs) motivated several works to apply DNNs for such problems. However, these approaches usually require large amounts of training data, from either simulation or real-world roll-outs.

## 2 Proposed Approach

30th Conference on Neural Information Processing Systems (NIPS 2016), Barcelona, Spain.

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# A Compositional Object-Based Approach to Learning Physical Dynamics

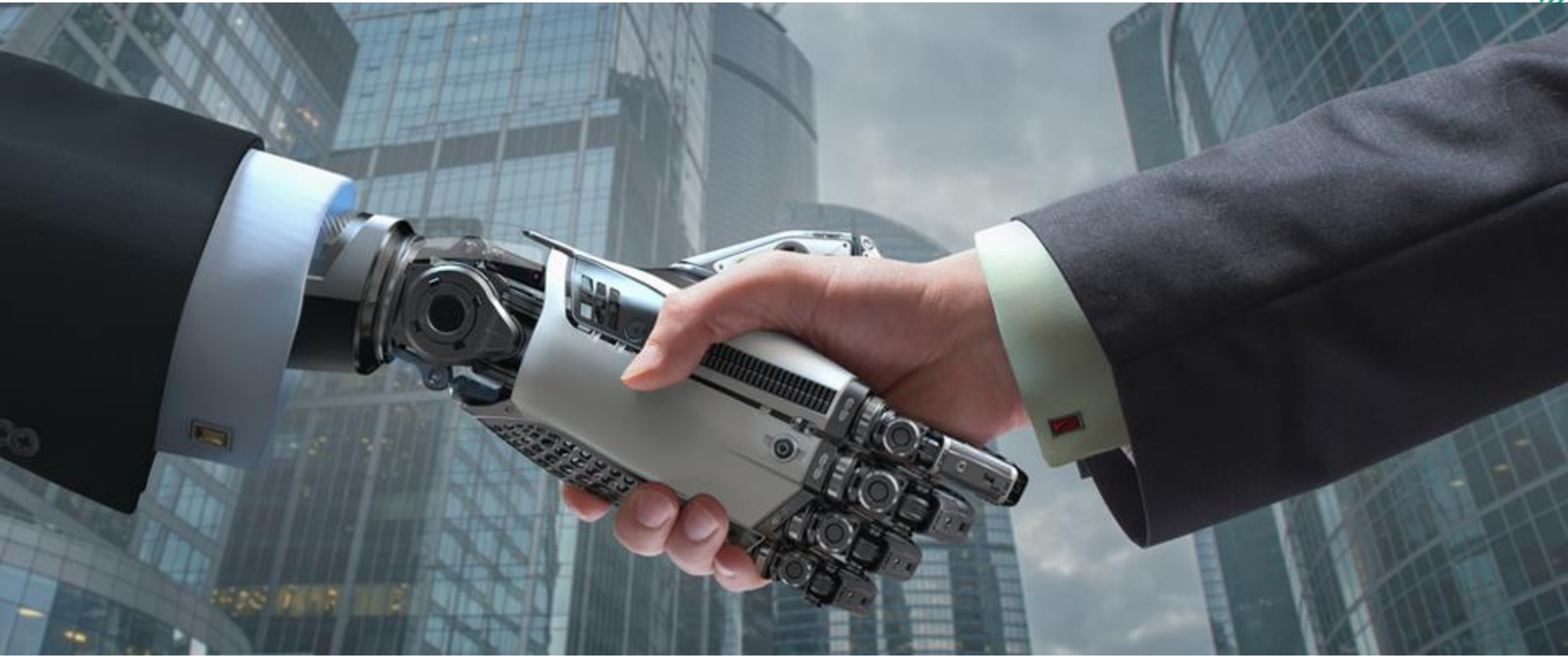
**Michael Chang**[*], **Tomer Ullman**[**], **Antonio Torralba**[*], and **Joshua B. Tenenbaum**[**]
[*]Department of Electrical Engineering and Computer Science, MIT
[**]Department of Brain and Cognitive Sciences, MIT
{mbchang,tomeru,torralba,jbt}@mit.edu

**Abstract**

This paper presents the Neural Physics Engine (NPE), an object-based neural network architecture for learning predictive models of intuitive physics. The NPE draws on the strengths of both symbolic and neural approaches: like a symbolic physics engine, it is endowed with generic notions of objects and their interactions, but as a neural network it can also be trained via stochastic gradient descent to adapt to specific object properties and dynamics of different worlds. We evaluate the efficacy of our approach on simple rigid body dynamics in two-dimensional worlds of bouncing balls. By comparing to less structured architectures, we show that the NPE's compositional representation of the causal structure in physical interactions improves its ability to predict movement, generalize to different numbers of objects, and infer latent properties of objects such as mass.

## 1 Introduction

30th Conference on Neural Information Processing Systems (NIPS 2016), Barcelona, Spain.



# Constructive comments are welcome

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