

Deep Learning for Graphics

Niloy J. Mitra¹ Tobias Ritschel¹ Iasonas Kokkinos¹ Paul Guerrero¹ Vladimir Kim² Konstantinos Rematas³ Ersin Yumer²

¹University College London ²Adobe Research ³University of Washington

Abstract

In computer graphics, many traditional problems are now better handled by deep-learning based data-driven methods. In applications that operate on regular 2D domains, like image processing and computational photography, deep networks are state-of-the-art, beating dedicated hand-crafted methods by significant margins. More recently, other domains such as geometry processing, animation, video processing, and physical simulations have benefited from deep learning methods as well. The massive volume of research that has emerged in just a few years is often difficult to grasp for researchers new to this area. This tutorial gives an organized overview of core theory, practice, and graphics-related applications of deep learning.

CCS Concepts

• **Computing methodologies** → Neural networks; Computer graphics;

1. Outline and Motivation

In the last few years, advances in computational power assisted by easy-to-use GPU resources have resulted in an amazing resurrection in research centered around machine learning, particularly neural networks (including CNNs, RNNs, LSTMs, etc.). Given suitable training data, neural networks provide a surprisingly unified setup for learning non-linear functions. Considering the many scenarios in graphics where we have easy access to (synthetic) training data (e.g., from rendering, simulation, scanning, etc.), neural networks (NNs), particularly deep neural networks (DNNs), provide the perfect tools for many challenging graphics applications, both in research and industry. Therefore, we believe, NNs are now essential tools in any graphics researcher's toolbox. Hence, it is in our collective best interest to understand the basic theory and common practices related to such data-driven frameworks.

In computer graphics, the NN-based success examples are too many to list. For example, in image processing and computational photography, many classical problems, such as denoising, edge-preserving filtering, upsampling, super-resolution, tone mapping, etc., have been shown to be particularly suitable for such NN-based processing and the corresponding methods are state-of-the-art, beating dedicated hand-crafted methods. The situation is similar in geometry processing, animation, video processing, and physical simulations. While almost all the subareas in graphics have seen a significant rise of interest in DNNs, the massive volume of research that has emerged in just a few years is often difficult to grasp for researchers new to this area. This tutorial was created as a platform to organize the relevant corpus and go over the core the-

ory, practice (implementation tricks and tips), and graphics-related applications.

The tutorial brings together a team of machine learning (ML) and graphics researchers, who have been working on different fronts of deep learning, with a good background to teach and explain the basics of neural networks and discuss in detail the science behind system design decisions and architecture choices for various applications that have been explored in computer graphics research.

The goal of this tutorial is to provide the basics of deep learning to researchers so that they can join the research effort to drive the field forward. Course notes/slides and example code is available via the course website.

2. Audience Background

We expect members of the audience to have a background in computer graphics and have been researching on one of its subareas. Familiarity with basic linear algebra notations (vectors, tensors, etc.) and experience with standard single- and multi-variable optimization will be advantageous. No prior experience in neural networks will be assumed. We would assume the participants to have a good programming background.

3. Structure

1 Introduction

- a) Motivation and the Rise of Data-driven Graphics
- b) Brief History of Machine Learning

- c) Simulation vs. Data-driven Graphics
- d) Examples from Graphics
- 2 Background Theory**
 - a) Regression
 - b) Optimization
 - c) Hyper-parameters and Parameters
 - d) Loss
 - e) Data
- 3 Neural Networks - Basics**
 - a) Perceptrons
 - b) Nonlinearities
 - c) Backpropagation
 - d) Training / Optimization
 - e) Deep Networks
 - f) Convolutional Neural Networks
- 4 Neural Networks - Applications**
 - a) Autoencoders
 - b) Variational Autoencoders
 - c) Generative Adversarial Networks
 - d) Deep Learning Frameworks
- 5 Data**
 - a) Popular Datasets
 - b) Data Augmentation
 - c) Collecting Data
 - d) Synthetic Data
- 6 Beyond 2D: 3D, Time, Unstructured Data and More**
 - a) Recursive Neural Networks
 - b) 3D Data (Mesh, Pointclouds)
 - c) Visualizing Features
 - d) Using Features
 - e) Feature Inversion
 - f) Physical Simulation
- 7 Outlook**

4. Presenter Backgrounds

Niloy J. Mitra leads the Smart Geometry Processing group in the Department of Computer Science at University College London. He received his PhD degree from Stanford University. His research interests include shape analysis, geometry processing, and computational design and fabrication. Niloy received the ACM Siggraph Significant New Researcher Award in 2013 and the BCS Roger

Needham award in 2015. His work has twice been selected and featured as research highlights in the Communication of ACM, received best paper award at ACM Symposium on Geometry Processing 2014, best software SGP 2017, and Honourable Mention at Eurographics 2014.

Tobias Ritschel is a Senior Lecturer at University College London. Previously he was a junior research group leader at the Max Planck Center for Visual Computing and Communication at Max Planck Institut Informatik. His interests include interactive and non-photorealistic rendering, human perception, and data-driven graphics. Ritschel received a PhD in computer graphics from Max Planck Institut Informatik. In 2011, he received the Eurographics PhD dissertation award and the Eurographics Young Researcher Award in 2014.

Iasonas Kokkinos obtained the Diploma of Engineering in 2001 and the Ph.D. Degree in 2006 from the School of Electrical and Computer Engineering of the National Technical University of Athens in Greece, and the Habilitation Degree in 2013 from Université Paris-Est. He is currently a faculty at the University College London and Facebook AI Research (FAIR). His research activity is currently focused on deep learning for computer vision, focusing in particular on structured prediction for deep learning and multi-task learning architectures. He has been awarded a young researcher grant by the French National Research Agency, has served as associate editor for the Image and Vision Computing journal and the Computer Vision and Image Understanding journal, and serves regularly as a reviewer and area chair for all major computer vision conferences and journals.

Paul Guerrero received his PhD degree in computer science from Vienna University of Technology. His main research focus is on methods for shape modeling, shape analysis, and image editing, combining methods from machine learning, optimization, and computational geometry. Paul has published several research papers in high-quality journals, including five papers in Transactions on Graphics, is a regular reviewer for conferences and journals, and a conference IPC member.

Vladimir Kim works as a Research Scientist at Adobe Systems Incorporated since August 2015. Prior to that, he was a postdoctoral scholar at Stanford University (2013-2015), and received PhD from Princeton University in 2013. His research focuses on geometry processing with a heavy use of machine learning techniques.

Konstantinos Rematas is a postdoctoral researcher in the GRAIL lab of University of Washington, working with Steve Seitz, Brian Curless and Ira Kemelmacher-Shlizerman. His current research interests are in the area of virtual and augmented reality. In particular I am looking into ways of capturing and visualizing real-life content in VR/AR headsets. His PhD thesis focused on generating novel views of 2D objects with the guidance of 3D models.

Ersin Yumer is a research scientist at Adobe. Prior to joining Adobe research, Ersin earned his PhD degree from Carnegie Mellon University, where his thesis focused on intelligent 3D modeling systems, and geometry analysis with machine learning. His current

research interests lie at the intersection of machine learning, 3D computer vision, and graphics. He develops end-to-end learning systems and holistic machine learning applications that bring signals of the visual world together: images, depth scans, video, 3D shapes and points clouds. More specifically, he is actively working on deep structured 3D inference from the limited view of the world obtained by a learning agent, under realistic assumptions of limited data and experience.