An Introduction to Deep Learning on Meshes

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Here goes an abstract.

1 COURSE DESCRIPTION

Deep learning has demonstrated phenomenal progress on images [Karras et al. 2019], videos and text [Brown et al. 2020]. Much of their success relies on their structured representation, which facilitates ease of use with standard neural network architectures. This success has sparked a rising interest in computer graphics, and geometry in particular, to use neural networks to address difficult problems in geometry processing. Despite incredible progress in deep learning on regular structures, applying deep networks on irregular structures, particularly shapes and geometry, remains challenging. One popular representation of shapes is the mesh representation, but this structure is irregular and unordered, making fundamental neural network operations ill-defined.

This survey aims to cover the fundamentals of deep learning on meshes. It provides the necessary background knowledge of deep learning from a *geometry-centric point-of-view*. Starting with foundations of machine learning, and then going through both fundamental (*e.g.,* back-propagation) as well as modern deep learning concepts. The challenges of learning on irregular, non-Euclidean meshes will be clearly illustrated, and demonstrate that standard neural network operators are not well defined for meshes. It presents several recent advances in the literature which propose techniques for neural network operators (*e.g.,* convolution, pooling) on directly on meshes. Common loss functions will be described, as well as their strengths and weaknesses. Finally, end-to-end applications for mesh analysis and synthesis tasks will be presented.

Through a combination of theory and hands-on exercises, the reader is expected to garner sufficient tools to incorporate deep learning tools in their geometry processing research. **RANA:** this probably sounds really cheesy.

Part 1 — Introduction

The course starts with a high-level overview of the topics covered, starting with the basics of machine learning, moving through neural shape representations, and finally taking a deep dive into neural mesh operators, geometric loss functions and a discussion and examples of practical applications.

Part 2 — Machine Learning Background

We begin by introducing the basic concepts of machine learning from both a *supervised* and an *unsupervised* perspective.

We aim at equipping readers with minimum amount of background in machine learning in order to understand the main content of this course.

Part 3 — Deep Learning on Meshes

2 SCHEDULE

Part 1 — Introduction *(10 minutes)*

1º Course outline and motivation (10 minutes: Speaker A) TODO: fix this weird enumeration punctuation

Part 2 — Machine Learning Background *(20 minutes)*

1º Classic Machine Learning (X minutes: Speaker A)
2º Deep Learning (X minutes: Speaker A)

additional bullet points to consider

1º Warming up with linear regression
2º Perceiving machine learning models (e.g., MLP) as a "multi-layer" linear regression with non-linear activation functions in between layers
3º How to *train* a model? This will cover some technical terms, including loss function, training (gradient descent), back propagation
4º (copy your suggestion here) ReLU/batch norm
5º What is a convolutional neural network for image classification?
6º (not sure whether this is needed) CNNs for other applications that are not classification. Since we may cover other applications later on.

Part 3 — Deep Learning on Meshes *(120 minutes)*

do you think it would be better if we change it to something like "CNN on Meshes"?

1º how to generalize CNNs to 3D?
  - Overview of alternative 3D representations (X minutes: Speaker A)
  - Overview of alternative 3D representations for doing 3D convolution (e.g., voxel, parameterization, spectral, diffusion, etc.)
  - Why not points or graphs? Ans: we could do better (e.g., orientation invariant) if we utilize the discrete mesh structure.

2º Operators on Meshes (X minutes: Speaker A)
  - Convolution on Meshes **RANA:** we may also want to talk about the mesh as a general graph...?we can talk about this when talking about other representations. Point clouds are basically meshes without connectivity, and graphs are basically meshes without the triangle structure. Although we can directly use point/graph CNNs on meshes, we should be able to do better if we take the mesh structure into consideration.
  - Pooling on Meshes

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- **RANA:** should we also discuss ReLU/batch-norm and stuff like this?Could we move this to the ML background section?
- could we list the papers/techniques that we are going to cover (e.g., spiral conv, random walker, edge conv, half edge conv, face conv)?

3° Loss Functions (X minutes: Speaker A) I wonder how many papers use the Earth mover and Hausdorff distance?

- $\ell 1/\ell 2$ distance
- Chamfer distance
- Earth mover's distance
- Hausdorff distance
- mesh quality regularization. I found that A TON of vision papers use a lot of regularization to avoid bad mesh quality (e.g., loss function on surface normals, smoothness of the deformation vector, preserve the Laplacian of the mesh, etc.. Should we cover this as part of the loss function?)

Part 4 — Applications and Conclusions *(60 minutes)*

1° Supervised Shape Classification and Segmentation
2° Shape Regression
3° perhaps we can also cover other applications: texture synthesis, subdivision, deformation (neural cage), shape matching, shape descriptors, etc.?
4° The future

Part 5 — Hands-on Coding Exercise *(? minutes)*

1° a simple example of mesh classification in PyTorch

3 TARGET AUDIENCE AND BACKGROUND

Intended Audience. The target audience of this tutorial includes graduate students and researchers in geometry processing that are drawn to the advancements of deep learning, but lack the necessary tools to incorporate deep learning in their research problems. Our goals are to (i) provide a valuable resource that equips geometry processing researchers with the tools of deep learning; (ii) introduce hands-on exercises of practical applications of deep learning on meshes; (iii)

Prerequisites. Basic knowledge about geometry processing on meshes is assumed.

Difficulty. Advanced Course. **RANA:** alec?

4 COURSE RATIONALE

5 LECTURERS BIOGRAPHIES

REFERENCES

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Tero Karras, Samuli Laine, and Timo Aila. 2019. A style-based generator architecture for generative adversarial networks. In *Proceedings of the IEEE conference on computer vision and pattern recognition*. 4401–4410.