Learning Topological Priors on Shapes given by Point Clouds  
(Master internship project)

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Location: LIRIS, Lyon.

Duration: 6 months

Context:

While Deep Learning methods have shown tremendous progress in recent years for structured data such as audio signals or images, handling non euclidean data is to this day still an open problem. In this context the study of surfaces (2-manifolds) embedded in some Euclidean space is of particular interest. In most cases, the raw format for surface data is a point set, i.e. a list of 3D coordinates of points sampled on the surface (e.g. by time-of-flight laser scanners). This format is sadly not so handy for deep learning methods since it is completely unstructured. To alleviate this problem, several methods tackle the problem by embedding the data in some structured space, such as a graph, a surface mesh, voxel grids or multiview rendering, at the risk of introducing some bias, by enforcing connectivity based on non-learned criteria (surface meshes or graph) or losing accuracy (voxel grids and multiview rendering). In 2017 a new type of neural nets dedicated to the processing of point clouds was introduced (PointNet [1]) using so-called 1x1 convolutions and max or sum pooling to be independent of the ordering. Since then it has been extended to handle local information (PointNet++ [2]) and used for various purposes such as normal or curvature estimation.

Method:

In this internship, we propose to study the use of deep neural networks for the estimation of topological properties of non-Euclidean data (point clouds), eg. the genus. Starting from known models for the classification and segmentation of this kind of data, e.g. PointNet[1] and PointNet++[2], we will explore the inductive biases for neural models to represent and learn topological properties, taking into account the non-smooth nature of the underlying decision space. We will target point clouds acquired on real-world objects (as opposed to complete scenes) and estimate the genus of the underlying continuous shape. This first part of the internship requires to set up a new dataset of point sets and devise a new neural net dedicated to topology learning.

In a second step, these differentiable neural estimators will be used for a generative model to generate 3D surfaces with desired topological properties and geometrical variety. While shape generation has been tackled using tree structures and local voxel grids [5] or based on
auto-encoders using the pointnet architecture [3], the level of details remain low. Recently, a mesh-based generation algorithm disentangles geometry from structure to synthesize high resolution shapes [5] directly as meshes. However, working directly with point clouds has several advantages: the generator can be seen as a shape sampler, able to sample an infinite number of points on each shape. It also raises several issues such as ensuring some manifoldness of the generated results (i.e. the points should follow a surface distribution and not a volumetric distribution), and being able to account for local properties, something methods such as pointnet++ only achieve via an explicit partition of local overlapping regions.

Références :


