CS395T Numerical Optimization: Manifold Inspired 3D Convolutions

Lihang Liu, Angela Lin

1 Motivation

Deep neural networks have made transformative impacts on various fields including Computer Vision, Natural Language Processing, and Audio Processing. A common theme among these fields is that the data being used is regular, like 1d audio, 2d images, and so on. However, in contrast to regular data, developing neural networks on irregular data becomes far more challenging, such as 3d shapes, trajectories in motion planning, etc.

We are interested in developing efficient neural networks for low-dimensional manifolds embedded in high-dimensional spaces. More specifically, we focus on 3D models, which are locally 2-dimensional. This work aims to improve 3D shape understanding while reducing the number of parameters in the neural network.

- **Manifold kernel.** To enforce the 2D parameter space, we take a 2D kernel H as the hidden states of a 3D kernel W. More concretely, given a 2D kernel H in the 3D space, we can rotate it by θ and then map to the 3D kernel along the normal of H. This approach enforces the 3D kernel to have a 2D parameter space and enforces smoothness at the same time.

- **Domain Adaptation from 2D CNN**. One advantage of the above manifold kernel is that it can naturally link the 2D CNN kernels trained on large scale image datasets to the 3D kernel in 3D CNN. We can formulate the relationship as:

$$\min_{\omega^{2D},\omega^{3D}} L_{2D}(\omega^{2D}) + L_{3D}(\omega^{3D}) + \lambda|\omega^{2D} - \omega^{3D}| \tag{1}$$

  where L_{2D} and L_{3D} are the loss function of 2D CNN and 3D CNN respectively. ω stands for the network weights.