URSA: A Neural Network for Unordered Point Clouds Using Constellations

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Abstract

This paper describes a neural network layer, named URSA, that uses a constellation of points to learn classification information from point cloud data. Similar to new methods such as PointNet [4], this architecture works directly on D-dimensional points rather than first converting the points to a D-dimensional volume. URSA is invariant to permutations of the input data. We use an URSA layer, followed by a series of dense layers, to classify 2D and 3D objects from point cloud. Experiments on ModelNet40 and MNIST data show classification results comparable with current methods, while requiring half or fewer trained parameters.

1 Introduction

A large bulk of the recent computer vision research has focused on applying artificial neural networks to 2D images. More recently, a growing research area focuses on applying neural networks to 3D physical scenes. Point clouds or point sets are a common format to represent 3D data since some sensors, including laser-based systems, collect scene data directly to point clouds. Voxelization is a straightforward way of applying powerful deep convolutional neural network techniques to point clouds, as is done in VoxNet [3] and 3DShapeNets [12]. Voxelization, however, is not always desirable because point clouds can, in many cases, represent structural information more compactly and more accurately than their voxel alternatives.

In contrast to voxelization methods, PointNet [4] and others have developed architectures that operate directly on point clouds, including ECC [9], Kd-Net [11], DGCNN [11], and KCNet [8]. This research adds to the growing body of knowledge about deep learning on point sets.

This paper describes a constellation neural network layer (URSA layer) that takes advantage of the compact nature of point cloud data and efficiently learns to convert these sets of points into a feature vector that can be used to classify objects. The trainable weights within the layer can be described as a set (constellation) of points (stars) of the same dimension as the input point cloud data. The constellation stars shift around during the training process using gradient descent learning. The URSA layer is invariant to the ordering of the input points. The URSA layer is not inherently invariant to shift, scale, or rotation; rather, it relies on demonstrations of those types of variations (possibly through data augmentation) in the input data during training to learn these variations. The output of the URSA layer is a global shape descriptor that is fed to a multi-layer perceptron (MLP) classifier to obtain the final classification.

Experiments on this architecture show the classification accuracy falls within the range of current point cloud-based classifiers, but with a significantly smaller model size. We have tested the URSA architecture with various distance measures and various numbers of constellation stars using MNIST (2D) data and ModelNet40 (3D) data. Experimentally, the best distance measure was dependent on
the data set. We found that for both data sets, too few or too many stars degrades performance. We found the optimal number of stars for both data sets was approximately between 265 and 512 stars in the constellation.

2 Selected Related Works

The work presented herein relies on the PointNet [4] research and architecture. In [4], Qi, et al., introduce the concept of symmetric functions for unordered points. A symmetric function aggregates the information from each point and outputs a new vector that is invariant to the input order. Example symmetric operators are summation, multiplication, maximum, and minimum. Alternatives to a symmetric function for point order invariance would be to sort the input into a canonical order or augment the training data with all kinds of permutations. PointNet uses a 5-layer MLP to convert the inputs points to a higher-dimensional space, then uses max pooling as the symmetric function to generate a single global feature, which is then fed through 3-layer MLP for classification. The architecture we experimented on in this paper replaces PointNet’s first 5 MLP layers and max pooling layer with a single URSA layer. The URSA layer generates a global feature and, as in PointNet, uses a 3-layer MLP for classification. As with PointNet, the URSA layer’s output is invariant to the order of the input data.

This work is also closely related to the KCNet architecture [8]. KCNet uses a concept similar to our URSA constellation layer, which they call kernel correlation. Kernel correlation has been used for point set registration, including by [10]. Whereas [10] attempts to find a transformation between two sets of points to align them, URSA and KCNet allow each point in the constellation (or kernel) to freely move and adjust during training. The KCNet architecture maintains all the layers of PointNet, and augments them by concatenating kernel correlation information to the intermediate vectors within the 5 layers of MLP. In a forward pass in PointNet, each input point is treated independently of all other points until the global max pooling layer, but that is not the case for KCNet. KCNet uses a set of kernels that operate on local subsets of the input points using a K-nearest neighbor approach. The kernels are trained to learn local feature structures important for classification and segmentation. Thus, KCNet improves on PointNet by adding additional local geometric structure and feature information prior to global max pooling.

There are several difference between the KCNet and the URSA-based architecture used for this paper. The KCNet kernel correlation produces a scalar value while the URSA layer produces a vector. KCNet uses several kernels at the local level to augment the PointNet architecture. Our architecture uses a single star constellation at the global level to replace the first several layers of PointNet.

Other deep learning methods that operate on point clouds include Dynamic Graph Convolutional Neural Networks (DGCNNs) [11], Edge-Conditioned Convolution (ECC) [9], kd-Networks [1], and OctNet [7]. These methods organize the data into graphs. In the cases of [11] and [9], the graphs are based on a vertex for each point and edges that define a relationship between the vertex and near neighbors, and weighted sum operations that operate on vertices and edges of the graph. The DGCNN architecture in [11] is quite similar to the PointNet structure, but where the multi-layer perceptron layers are replaced with Edge Convolution Layers. Both [11] and [7] use non-uniform spatial structure to partition the input space, and they also used weighted sum operations. In contrast to these methods, the learning in the URSA layer is not stored in the weights of a weighted sum operation. Instead the learning is stored in the locations of a set of constellation stars as will be described in the next section.

3 Our Method

We now describe the URSA layer and a neural network architecture that uses a URSA layer to classify objects. The overall classification architecture is shown in Fig. [1]. It is an URSA layer followed by a three-layer fully connected (dense) multi-layer perceptron classifier. The three-layer MLP portion mirrors the PointNet architecture and others [4], [6], [11], and [8]. Maintaining an end structure similar to other methods aids in comparison.

During training we also make use of data augmentation at the input and data dropout just prior to the final MLP layer. Because the final layers are straightforward, the remainder of this section will focus on the only the URSA layer. Parameters used during implementation are discussed in Section [4].
To define the URSA layer, let us consider a set of $N$ $D$-dimensional input points in $\mathbb{R}^D$ that make up a point cloud $P = \{p_1, ..., p_N\} \subset \mathbb{R}^D$. $P$ makes up the input to the URSA layer. Within the layer is a constellation of $M$ stars, with the same dimensionality as the input points, $Q = \{q_1, ..., q_M\} \subset \mathbb{R}^D$. The output of the layer is an $M \times 1$ vector $V = \{v_1, ..., v_M\} \subset \mathbb{R}$. The URSA layer converts a set of $N$ points into an $M$-dimensional feature vector.

The relationship between $P$, $Q$, and $V$ is a minimum distance measure

$$v_m = \min_{1 \leq n \leq N} \|p_n - q_m\|$$

(1)

where $\| \cdot \|$ is the L2 norm. So, the output feature vector is made up of the Euclidean distances from each constellation star to its closest input point. The minimization provides the symmetry that makes the output of the layer invariant to the ordering of the input points.

We also experimented with an exponential distance measure and a radial basis function (RBF) distance measure shown in Eqs. 2 and 3, respectively.

$$v_m = \sum_{n=1}^{N} \exp\left(-\frac{\|p_n - q_m\|^2}{2\sigma^2}\right)$$

(2)

$$v_m = \sum_{n=1}^{N} \exp\left(-\lambda \|p_n - q_m\|\right)$$

(3)

With these latter two measures, the symmetry is provided by the summation. The relative effectiveness of all three measures is shown in Section 4.

The URSA layer is followed by a three-layer MLP. The non-linearity for each layer is the ReLU function, except for the final layer, which uses softmax. Each ReLU is followed by a batch normalization. Technically, the URSA layer does not require a ReLU function afterward because the $v_m$ in Eqs. 1, 2, and 3 are always always positive. Additionally, the URSA distance measures defined by these equations are not matrix multiplies, which require a separate non-linearity afterward to keep the layer from collapsing into another layer; the L2 norm within the computations provides an inherent nonlinear component to the layer. All three distance measures are differentiable and are trained as part of the overall back-propagation of the entire network.

4 Experiments

We evaluate the described URSA network architecture for classification of 2D and 3D objects. For 3D data, we used the ModelNet40 shape database [12]. For 2D data, we used the MNIST handwritten character recognition database [2] converted to 2D point clouds.

For the ModelNet40 data, we used 2048 points per object evenly sampled on mesh faces and normalized into the unit sphere as provided by [6]. During training, we augmented the data by scaling.
The shape to between 0.8 and 1.25 of the original size with a random uniform distribution; shifting shape in every dimension between -0.1 and 0.1 away from its original position with a random uniform distribution; and adding jitter between -0.05 and 0.05 to each point according to a random normal distribution (clipped) with standard deviation 0.01. Also during training we added a dropout layer with a dropout rate of 0.3 just before the last dense layer.

To convert an MNIST image to a 2D point cloud, we used the coordinates of all pixels with values larger than 128. We used 312 points per character, which was the maximum number of pixels greater than 128 for any MNIST image. For those images with less than 312 points, we randomly repeated enough points from the set to reach 312 points. We used the same data augmentation parameters and dropout rate for the MNIST data experiments as we used with the ModelNet40 data.

We conducted experiments with the three distance measures in Eqs. 1, 2, and 3 and for several values of $M$ the length of the URSA layer feature vector output. In our experiments we evaluated classification performance for $M = 32, 64, 128, 256, 512, \text{ and } 1024$. We ran 10 independent tests with each of the distance measures at each value of $M$ and plotted the average accuracy in Figs. 2 and 3. All experiments were trained for 1,000 epochs. On the ModelNet40 data, the minimum distance measure slightly outperforms the other two methods. Constellations with 256 stars worked best for all distance measures. On the MNIST data, the RBF distance measure slightly outperforms the other two methods. Constellations with 512 stars worked best when using the Minimum distance measure, but 512 stars was better for the other two distance measures.

Table 1 shows how the baseline URSA network compares to other classification methods on the same data sets. URSA achieved impressive results, especially considering the Baseline URSA model uses far fewer parameters than any other method we compared. While some more sophisticated methods outperformed URSA, this paper demonstrates the viability and effectiveness of the URSA layer and the constellation approach to pattern learning.

We chose $\sigma$ in Eq. 2 to be 0.1 and $\lambda$ in Eq. 3 to be 10. Additional tuning of these parameters may improve performance.

The 2D data was used to demonstrate the evolution of the URSA constellation stars over time during training. We did this using both the minimum distance measure of Eq. 1 and the radial basis function distance measure of Eq. 2, as shown in Figs. 4 and 5, respectively. These figures show...
Figure 3: The performance of the URSA architecture on MNIST for each of the distance measures with respect to the number of constellations stars. The radial basis function distance measure slightly outperforms the other two methods. Constellations with 512 stars outperformed all other values of $M$ evaluated for all distance measures.

Table 1: Classification results and model size comparisons for various methods. Accuracy results for the URSA method are an average of 10 independent runs for each data set. Accuracy results for the other methods are adapted from [8] and [11].

| Method          | ModelNet40 Accuracy (in percent) | MNIST Accuracy (in percent) | Model Size (in MB) |
|-----------------|----------------------------------|----------------------------|--------------------|
| LeNet5 [2]      | –                                | 99.2                       | –                  |
| 3DShapeNets [12]| 84.7                             | –                          | –                  |
| VoxNet [3]      | 85.9                             | –                          | –                  |
| Subvolume [5]   | 89.2                             | –                          | –                  |
| ECC [12]        | 87.4                             | 99.4                       | –                  |
| PointNet (Baseline) [4] | 87.2                       | 98.7                       | 0.8                |
| PointNet [4]    | 89.2                             | 99.2                       | 3.5                |
| PointNet++ [6]  | 90.7                             | 99.5                       | 1.0                |
| KCNet [8]       | 90.0                             | 99.3                       | 0.9                |
| Kd-Net [1]      | 91.8                             | 99.1                       | 2.0                |
| DGCNN [11]      | 92.2                             | –                          | 1.8                |
| URSA w/256 stars (Ours) | 88.3                       | 99.0                       | 0.3                |
Figure 4: Depiction of the URSA constellation stars and their evolution during training for m=128 and using the minimum distance measure. Sub-figures show (a) random initialization, (b) after 10 training epochs, (c) after 100 epochs, (d) after 200 epochs, (e) after 300 epochs, and (f) after 500 epochs.

Figure 5: Depiction of the URSA constellation stars and their evolution during training for m=128 and using the RBF distance measure. Sub-figures show (a) random initialization, (b) after 10 training epochs, (c) after 100 epochs, (d) after 200 epochs, (e) after 300 epochs, and (f) after 500 epochs.

the constellation stars adjusting over time to span the space. The constellation resulting from the minimization distance measure appears more compact in the center and the stars are more spread out toward the outside. On the other hand, the RBF distance measure constellation is more uniformly distributed throughout the space. Also, the resulting range is larger for the minimization measure than for the RBF measure.

5 Conclusion

This paper has presented an URSA neural network layer and demonstrated its effectiveness and viability for classification of point cloud data. The URSA layer stores information in the form of constellation points, rather than a set of multiplicative weights in a matrix. While other more
sophisticated methods achieved higher classification rates on the data sets we tested, all other methods we compared used at least twice the model parameters of the baseline URSA network.

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