Optimization Beyond the Convolution: Generalizing Spatial Relations with End-to-End Metric Learning

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Abstract—To operate intelligently in domestic environments, robots require the ability to understand arbitrary spatial relations between objects and to generalize them to objects of varying sizes and shapes. In this work, we present a novel end-to-end approach to generalize spatial relations based on distance metric learning. We train a neural network to transform 3D point clouds of objects to a metric space that captures the similarity of the depicted spatial relations, using only geometric models of the objects. Our approach employs gradient-based optimization to compute object poses in order to imitate an arbitrary target relation by reducing the distance to it under the learned metric. Our results based on simulated and real-world experiments show that the proposed method is able to generalize to unknown objects over a continuous spectrum of spatial relations.

I. INTRODUCTION

Understanding and leveraging spatial relations between objects is a desirable capability of service robots to function in human-centered environments. However, our environments are rich with everyday objects of various shapes and sizes, making it infeasible to pre-program a robot with sufficient knowledge to handle all arbitrary relations and objects it might encounter in the real world. Instead, we should equip robots with the ability to learn arbitrary relations in a lifelong manner and to generalize them to new objects, see Fig. 1. For example, having learned how to place a book inside a drawer, a robot should be able to generalize this spatial relation to place a toy inside a basket.

In this work, we propose a novel, neural-network-based approach to generalize spatial relations from the perspective of distance metric learning. Rather than considering a pre-specified set of relations and learning an individual model for each, our approach considers a continuous spectrum of pairwise relations and learns a metric that captures the similarities between scenes with respect to the relations they embody. Accordingly, we use this metric to generalize a relation to two new objects by minimizing the distance between the corresponding scenes in the learned metric as shown in Fig. 2.

Following the metric-learning approach by Chopra et al. [1], we use a variation of the siamese architecture [2], [3] to train a convolutional neural network as a function that maps an input point cloud of a scene consisting of two objects to the metric space such that the Euclidean distance between points in that space captures the similarity between the spatial relations in the corresponding scenes. Our deep metric learning approach allows the robot to learn rich representations of spatial relations directly from point cloud input and without the need for manual feature design.

Furthermore, to generalize spatial relations in an end-to-end manner, we introduce a novel, gradient-descent based approach that leverages the learned distance metric to optimize the 3D poses of two objects in a scene in order to imitate an arbitrary relation between two other objects in a reference scene, see Fig. 2. For this, we backpropagate beyond the first convolution layer to optimize the translation and rotation of the object point clouds. Our gradient-based optimization enables the robot to imitate spatial relations based on visual demonstrations in an online and intuitive manner. In summary, we make the following contributions in this work: (1) an end-to-end approach to learning a metric for spatial relations from point clouds, (2) a differentiable projection layer to reduce the input dimensionality of point clouds by projecting them to depth images, (3) a network architecture that models a differentiable metric function using a gradient approximation that allows for optimization beyond the first convolution layer, and (4) a demonstration that this technique enables gradient-based optimization in the learned feature space to optimize 3D translations and rotations of two new objects in order to generalize a demonstrated spatial relation.

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II. RELATED WORK

Learning spatial relations provides a robot with the necessary capability to carry out tasks that require understanding object interactions, such as object manipulation [4], human-robot interaction [5], [6] and active object search in complex environments [7]. In the context of robotics, learning spatial relations between objects has previously been phrased as a supervised classification problem based on handcrafted features such as contact points and relative poses [8], [9], [10]. Spatial relations can also be learned from human-robot interaction using active learning, where the robot queries a teacher in order to refine a spatial model [11]. However, the above techniques require learning an individual model for each relation and are thus limited in the number of relations they can handle. In contrast to these works, our metric learning approach allows us to reason about a continuous spectrum of relations. Learning of object interactions from contact distributions has been addressed in the context of object grasping [12] and object placing [13]. While those approaches perform classification, our metric learning approach enables generation of spatial relations between objects solely based on visual information and without explicit modeling of contacts or physical object interaction.

In our previous work we introduced a novel method that leverages large margin nearest neighbor metric learning in order to generalize spatial relations to new objects [14]. For this, we relied on hand-crafted 3D features to describe a scene. In contrast to this, we learn representations in an end-to-end fashion based on 2D image projections of scenes. Additionally, the previous work employed a grid search-based optimization with one object kept fixed whereas our approach optimizes on the full continuous spectrum of possible poses for both objects.

Our approach is related to deep learning techniques that learn similarity metrics directly from images, such as siamese [15] and triplet networks [16]. In comparison, our network takes point clouds as input and processes them using our differentiable point cloud to depth image projection layer for input dimensionality reduction. In addition, we leverage the gradient of the metric to optimize the translation and rotation of objects in the point cloud space. This strategy is in spirit similar to previous works that manipulate input images by backpropagating with respect to the input to visualize representations [17], transfer artistic styles [18], and trick neural networks into making wrong classifications [19]. We explore and analyze the utility of the metric’s gradient for optimization of 3D translation and rotation in Section V.B.

III. PROBLEM FORMULATION

We aim to learn a continuous representation for spatial relations between everyday objects in the form of a metric function, i.e., a representation that is not restricted to a finite set of relations, and to use this metric to enable a robot to imitate these spatial relations with new objects. Our goal is to learn this representation directly from geometric information in the form of raw point clouds, without requiring any semantics and without relying on handcrafted features. For this, we consider pairwise spatial relations between objects. We denote these objects by \( o_m \) and \( o_n \) and we represent them as point clouds \( P_m \) and \( P_n \). Together with the respective translation vectors \( t_m, t_n \) expressed relative to a global world frame and rotation quaternions \( q_m, q_n \), we define a scene \( s_i \) as the tuple \( s_i = (o_m, o_n, t_m, t_n, q_m, q_n) \).

As a reference frame, we assume that the gravity vector \( g \) is known and oriented in the opposite direction of the global z-axis.

To learn the metric, we require a set of training scenes \( S = \{s_0, ..., s_n\} \) accompanied by labels in the form of a similarity
matrix $\mathbf{Y}$ where the entry $\mathbf{Y}_{ij}$ denotes the similarity of the spatial relation between scenes $s_i \in S$ and $s_j \in S$. That is $\mathbf{Y}_{ij}$ should be small for similar relations and large for dissimilar relations. Note that we do not require all possible scene combinations to be labeled, i.e. $\mathbf{Y}$ does not need to be fully specified. To ease labeling, we allow the entries of $\mathbf{Y}$ to be binary such that $\mathbf{Y}_{ij} \in \{0, 1\}$, where 0 means similar and 1 dissimilar.

Our goal is to learn a metric function $f(s_i, s_j) = d$ that maps two scenes to a distance $d$ such that the following properties hold: (1) $d$ captures the similarity of the spatial relations depicted in scenes $s_i$ and $s_j$, that is $d$ is small for similar relations and large for dissimilar relations, and (2) $f$ is differentiable. The latter ensures that we can employ gradient based optimization on the metric function. Instead of directly learning the metric function $f$, we learn a mapping function $\Gamma$ that maps each input scene into a low-dimensional space such that the Euclidean distance captures the similarity of spatial relations. Concretely, we define our metric function $f$ as

$$f(s_i, s_j) = ||\Gamma(s_i) - \Gamma(s_j)||_2. \quad (1)$$

As a smaller distance denotes higher similarity, we formulate the problem of generalizing a spatial relation in a reference scene $s_r$ to a test scene $s_t$ as finding the translations and rotations of both objects in $s_r$ which minimize the distance between the two scenes under the learned metric, i.e. we seek to solve the following problem:

$$\min_{t_m, t_r, q_m, q_r, q_n, t_n} f(s_r, s_t). \quad (2)$$

In this work, we focus on computing the poses of both objects to imitate the semantics of a reference relation, and do not consider the physical feasibility of the resulting scene, e.g., collision checks.

### IV. Approach

Our method consists of two phases. In the first, we learn a distance metric function to capture the semantics of spatial relations. In the second, we leverage the gradient of this function to imitate spatial relations in a continuous manner via optimization of the object poses. The key challenges are to learn a rich representation from high dimensional input and to backpropagate the gradient information into the raw point cloud.

#### A. Distance Metric Learning: General Architecture and Training

The goal of learning the distance metric is to express the similarity between spatial relations. As input we use high-dimensional 3D point cloud data. Therefore we seek a mapping function $\Gamma$ that reduces the dimensionality from the point cloud space to a low-dimensional metric space. We implement $\Gamma$ as a composition of three functions, which we will now outline briefly and then describe two of the functions more detailed. First, $\psi$ transforms the scene by applying the corresponding transformation $t, q$ to each object point cloud. Second, we project the point clouds to three orthogonal planes to create three depth images. We denote this projection function by $\rho$. Third, we apply a mapping function $G_W$ parameterized by $W$, which maps the three projections to the metric space, see Fig.3 for an overview. More formally, we compose the mapping $\Gamma$ as

$$\Gamma := G_W \circ \rho \circ \psi. \quad (3)$$

We tackle the dimensionality of the input data using a function $\rho$ that projects the point clouds to three depth images. This serves as a non-parameterized reduction of the input dimensionality in comparison to 3D representations such as octrees or voxels. Concretely, we scale the scene to fit in a unit cube, see Fig.3. We then project each point to three orthogonal image planes of size $100 \times 100$ pixels fit to the top, front, and side faces of the cube such that the image plane normals are either parallel or orthogonal to the gravity vector $g$. We place the projection of each object in a separate channel. In this work, we will refer to a single orthogonal projection of one object as projection image. To learn the parameters $W$ of the mapping function $G_W$ we use a variation of the siamese convolutional network. We found that using three inputs instead of two inputs, similar to a triplet network [16], leads to improved performance. Therefore, we construct our network of three identical, weight-sharing networks $G_W$ and train it on input triplets of projections $(\langle \rho \circ \psi \rangle(s_i), \langle \rho \circ \psi \rangle(s_j^+), \langle \rho \circ \psi \rangle(s_k^-))$ where $s_i \in S$ is a reference scene and $s_j^+, s_k^- \in S$ are similar and dissimilar to $s_i$, respectively, that is, for the case of binary...
tuned independently of a specific set of learned parameters. This upper bound ensures that the learning approach by Chopra et al. in contrast to an actual triplet network we do not employ connected layer, see Fig. 4 for network architecture details. The sibling network of a subnet receives the top view, the second the front view, and the third the side view. The convolution layers of each subnetwork share the weights. All three subnets are connected with a fully connected layer. The sibling network $G_W$ is then cloned three times into a triplet network when training the distance metric and cloned two times into a siamese network when generalizing a relation at test time.

![Fig. 4: The hyperparameters of the subnet of a sibling $G_W$. Each subnet receives one projection of one side, i.e. the first subnet receives the top view, the second the front view, and the third the side view. The convolution layers of each subnetwork share the weights. All three subnets are connected with a fully connected layer.](Image 317x666 to 362x711)

labels, $Y_{ij} = 0$ and $Y_{ik} = 1$. We run each projection through its own sub-network with the sub-networks also sharing the weights and we combine them with a fully connected layer, see Fig. 4 for network architecture details. In contrast to an actual triplet network we do not employ a ranking loss but adapt the hinge loss function as in the approach by Chopra et al. to enforce an upper bound on the distance $[1]$. This upper bound ensures that the learning rate used for optimizing the poses of a test scene can be tuned independently of a specific set of learned parameters $W$. Concretely, we compute the loss function

$$C(\Gamma(s), \Gamma(s^+), \Gamma(s^-)) = \frac{1}{2}(d_+)^2 + \frac{1}{2}(\max(0, 1 - d_-))^2,$$

where $\Gamma(s)$ denotes the embedding of the scene s, i.e. $\Gamma(s) = G_W(\rho \circ \psi)(s)$, and $d_+$, $d_-$ denote the Euclidean distance of $\Gamma(s^+)$ and $\Gamma(s^-)$ to the embedding $\Gamma(s)$ of the reference scene, respectively.

B. Generalizing Spatial Relations Using the Backward Pass

Having learned the neural network mapping function $G_W$, we can now leverage the backpropagation algorithm to imitate a relation by optimizing the parameters of the 3D transformations applied to the point clouds. As stated in [2], we formulate the generalization of a spatial relation as a minimization problem with respect to the rotations and translations in the scene. Note that this differs from the representation learning process in that we keep the parameters $W$ fixed.

To employ gradient based optimization, the transformation $\Gamma$ must be differentiable. While the functions $G_W$ and $\psi$ are differentiable, backpropagating the error to the projection $\rho$ needs a more thorough consideration. When backpropagating through the input layer of the first convolutional operation of $G_W$, we need to consider that an input pixel not only contains depth information, but also discrete spatial information. Projecting a point onto the image plane discretizes two dimensions, which makes gradient-based optimization on these two axes impractical. Although projecting a scene to three sides sustains one continuous gradient for each axis, in our application the important information is contained in the location of the pixel, i.e. in the discretized dimensions. To ease notation we will refer to the image axes as $y, x$ in the following section.

As an example, consider an above-view projection image $U$ of a ‘box on top of a cube’, that is the pixel values correspond to the $z$-values of the points in the world frame. With only the depth information one cannot conclude if the top box is residing on the cube or if it is hovering above it, as no height measure is available for the cube. The side view however captures this information on the $y$-axis of the image which also corresponds to the $z$-axis in the world coordinate frame.

The crux here is that the function $G_W$, expressed as a convolutional neural network, only computes partial derivatives with respect to the input $\frac{\partial C}{\partial u_{y,x}}$, i.e. the partial derivative only depends on the magnitude $u_{y,x}$ but not on the position of a pixel. However, the hierarchical structure of $G_W$ retains the spatial context of the error, which we will use to propagate the error of a projection image back to all three coordinates of the 3D points.

Therefore, we convolve the matrix containing the error with respect to the input image of $G_W$ with a Sobel-derived kernel. This procedure approximates the rate of change of the
error of the input image with respect to $x$ and with respect to $y$. That is, we approximate the change of the error with respect to shifting a pixel on the $x$ and $y$ axis and use this as the error of the respective pixels spatial coordinate. This error can then be backpropagated to the 3D point it resulted from via applying the inverse orthogonal projection.

More formally, for a projection image $U$, i.e. one input channel of the function $G_{\mathbf{W}}$, the backpropagation can be formulated as follows. Let $U'$ be the error matrix of this projection image where the entry $u'_{y,x} = \frac{\delta C}{\delta u_{y,x}}$ denotes the error with respect to the input pixel at position $(x, y)$. We compute the matrices of derivatives with respect to the $y$ and $x$ position $U'_y$ and $U'_x$ as $U'_y = S_y \ast U'$ and $U'_x = S_x \ast U'$ with $S_y, S_x$ being the Sobel kernels

$$S_y = \begin{bmatrix} 1 & 0 & 0 \\ 0 & -1 & 0 \\ 0 & -2 & 1 \end{bmatrix} \quad \text{and} \quad S_x = \begin{bmatrix} 1 & 2 & 1 \\ 0 & 0 & 0 \\ -1 & -2 & -1 \end{bmatrix}.$$ 

Once we have computed an error on the pixel $u_{y,x}$ with respect to $x$ and $y$ we assign this error value to all points whose projection would result in the pixel $y, x$. Fig. 5 depicts an example for a projection image, the respective error matrix and the resulting gradient images after applying the Sobel kernels.

As an additional remark, we empirically found that using a larger Sobel-derived kernel to approximate the derivatives achieves better results. We also note that for computing efficiency reasons, we only consider three projections instead of projections to all six sides of the cube. Hereby, we make the assumption, that the gradient for all parallel projection planes is the same and we propagate the error of a pixel to all points mapped to this pixel, with the error divided by the number of points mapped to this pixel.

V. EXPERIMENTAL RESULTS

In this section we conduct several quantitative and qualitative experiments to benchmark the performance of our overall approach. Hereby, we demonstrate the following: 1) our learned feature representation is able to generalize over a rich set of different spatial relations and yields improved performance for a spatial nearest neighbor retrieval task with respect to a state-of-the-art method, 2) using our novel gradient-based optimization method we are able to generalize spatial relations to new objects and to capture the intention of the reference scenes being imitated without prior semantic knowledge about the relation they embody.

A. Nearest Neighbor Retrieval

We train the distance metric function on the Freiburg Spatial Relations dataset [14], which features 546 scenes each containing two out of 25 household objects. To reduce training time, we pre-compute the depth projections. As stated before we train the metric using a triplet network. The network weights $\mathbf{W}$ are randomly initialized and optimized for 30,000 iterations with batch size 100. Further, we apply data augmentation including rotation (augmentation factor 16) and translation of objects (augmentation factor 20), but take into account that the augmentation does not change the underlying ground truth spatial relation. Additionally, we

| Method                     | 3-out-of-5 acc.  | 5-out-of-5 acc. |
|----------------------------|------------------|-----------------|
| LMNN [14]                  | $86.32\% \pm 1.98$ | N/A             |
| GBLMNN [14]                | $87.6\% \pm 1.94$ | N/A             |
| Our NN-based metric        | $91.21\% \pm 2.78\%$ | $76.25\% \pm 7.21\%$ |

**TABLE I:** Nearest neighbor performance on the Freiburg Spatial Relations dataset. We report results for correctly retrieving 3-out-of-5 and 5-out-of-5 target neighbors of a query scene.
balance the distribution of spatial relations during training. For this, we make use of the provided spatial relation class annotations in the dataset. We apply dropout with a probability of 50%, use the Adam solver with $\beta_1 = 0.9$, $\beta_2 = 0.999$, $\epsilon = 10^{-8}$ and set the learning rate $\eta = 10^{-2}$.

We evaluate the nearest neighbor performance of our learned metric on the fifteen train/test splits of the Freiburg Spatial Relations Dataset provided with the dataset. As performance measure, we compute the mean 3-out-of-5 and 5-out-of-5 accuracy for nearest neighbor retrieval. Table I shows that our method yields an accuracy of 91.21% ± 2.78%, which is a relative improvement of 3.6% compared to the GBLMNN approach by Mees et al. [14]. Our results show that the learned metric allows us to retrieve similar scenes from a continuous spectrum of relations in the learned space with high accuracy. Further, they suggest that the learned feature representation of the metric, captured in the last fully connected layer of the network siblings (see Fig. 4), is rich enough to be leveraged for gradient-based optimization in the next experiments.

### B. Generalizing Relations to Known Objects

Next, we quantitatively evaluate the capability of our approach to imitate spatial relations. For testing we randomly selected 13 scenes including 15 different objects such that every scene was similar to at most one other scene. We then considered all 156 combinations of these 13 scenes excluding 31 scenes that cannot be transformed into each other, e.g., a plate and a cup cannot be generalized to an inside relation. From the remaining 125 combinations, we used one scene as a reference to generalize the other scene, as qualitatively depicted in Fig. 6. Overall, 70 of the imitations successfully generalized the reference scene. 41 of these imitated scenes were physically infeasible scenes, e.g., containing objects placed on their edges. However, we do not account for scene stability or feasibility in this work and therefore consider them successful. 55 of the generalizations converged to a non-optimal solution. Fig. 6 qualitatively depicts exemplary results for each. Among successful generalizations the figure shows a bowl that is correctly optimized into a tray and several inclined object relations. Note that both object transformations are optimized in a continuous manner, without specifying any semantic knowledge, see Fig. 7. Despite the fact that we do not provide knowledge about physical concepts such as collisions during the training process and despite the fact that we approximate the 3D world using our 2D projection technique, our approach is able to leverage the learned metric to generalize relations in the 3D domain.

In addition, we conducted a real-world experiment with a Kinect2 camera, where we demonstrated reference scenes containing common spatial relations, see Fig. 1. To retrieve the point clouds and the poses of the reference objects we used the Simtrack framework [20]. In this experiment we demonstrate the capability of our method to successfully generalize spatial relations in real-time. A video of this experiment is available at [http://spatialrelations.cs.uni-freiburg.de].

### C. Generalizing Relations to Unknown Objects

To evaluate how well our approach handles previously unseen objects, we chose five common 3D models such as the Utah tea pot and the Stanford bunny, as shown in Fig. 8. We emphasize that the shapes of these objects differ notably from the objects of the Freiburg Spatial Relations dataset used during training. As reference scenes we used a subset of the 13 previously used scenes. As test scenes we used all two-permutations without replacement of the five new objects, sampled next to each other. We then considered all 160 transformable combinations of training and test scenes, excluding the test object combinations that cannot form an inside relation. Our approach was able to successfully generalize 68 scenes and failed on 92 scenes. As expected, this is a more challenging task compared to the previous experiment since none of the test object shapes were used in training. Additionally, the dataset used for training covers only a small subset of the space of possible object arrangements, posing a challenge on dealing with intermediate relations the approach encounters during optimization. Nonetheless, our approach is able to imitate the semantics of a given spatial relation with considerably different objects and generalize them without the need for prior knowledge.

### VI. CONCLUSIONS

In this paper we presented a novel approach to learning the similarity between pairwise spatial relations in 3D space and to imitate arbitrary relations between objects. Our approach learns a metric that allows reasoning over a continuous spectrum of such relations. In this way, our work goes...
Fig. 8: Examples of four successfully and one unsuccessfully generalized relations to objects unseen during training. The new objects are colored green and yellow. In each row, the leftmost scene depicts the reference scene, the middle scene depicts the test scene before optimizing, and the rightmost scene depicts the generalized result. Despite the complex, unknown shapes, the optimized scenes capture the semantic of the relation. The last example is counted as unsuccessful because the opening of the cube should point upwards when trying to imitate an inside relation.

beyond the state of the art in that we do not require learning a model for each new spatial relation. Furthermore, our work enables learning the metric and using it to generalize relations in an end-to-end manner and without requiring pre-defined expert features. For this, we introduced a novel approach for backpropagating the gradient of the metric to optimize the 3D transformation parameters of two objects in a scene in order to imitate an arbitrary spatial relation between two other objects in a reference scene. We evaluated our approach extensively using both simulated and real-world data. Our results demonstrate the ability of our method to capture the similarities between relations and to generalize them to objects of arbitrary shapes and sizes, which is a crucial requirement for intelligent service robots to solve tasks in everyday environments. As we did not consider physical constraints such as collisions between objects in this work, it would be interesting to extend our work in the future to incorporate intuitive physics into our network module, for example through a differentiable gravity simulation [21].

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