POCO: Point Convolution for Surface Reconstruction

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Abstract

Implicit neural networks have been successfully used for surface reconstruction from point clouds. However, many of them face scalability issues as they encode the isosurface function of a whole object or scene into a single latent vector. To overcome this limitation, a few approaches infer latent vectors on a coarse regular 3D grid or on 3D patches, and interpolate them to answer occupancy queries. In doing so, they loose the direct connection with the input points sampled on the surface of objects, and they attach information uniformly in space rather than where it matters the most, i.e., near the surface. Besides, relying on fixed patch sizes may require discretization tuning. To address these issues, we propose to use point cloud convolutions and compute latent vectors at each input point. We then perform a learning-based interpolation on nearest neighbors using inferred weights. Experiments on both object and scene datasets show that our approach significantly outperforms other methods on most classical metrics, producing finer details and better reconstructing thinner volumes. The code is available at https://github.com/valeoai/POCO.

1. Introduction

Constructing a surface or volume representation from 3D points sampled at the surface of an object or scene has numerous applications, from digital twins processing to augmented and virtual reality. Cheaper sensors directly producing 3D points (depth cameras, low-cost lidars) and mature multi-view stereo techniques [95, 96] operating on images offer increasing opportunities for such reconstructions.

Traditional 3D reconstruction approaches [6] generally express the target surface as the solution to an optimization problem under some prior constraints. Possibly leveraging visibility or normal information, they are generally scalable to large scenes and offer a substantial robustness to noise and outliers [56, 77, 111, 51, 131, 102, 118, 88]. Although some try to cope with density variation [46, 47, 10], a common limitation of these approaches is their inability to properly complete parts of the scene that are less densely sampled or that are missing (typically due to occlusions). A variety of hand-crafted priors try to address this completeness issue: local or global smoothness [64], decomposition into geometric primitives [94] (in particular for piecewise-planar man-made environments [15, 30, 8, 78, 5]) and structural regularities [85, 58]. Data-driven priors have also been explored, based on shape retrieval [32], possibly with defor-
Figure 2: Overview of our method (inference). Given 3D points sampled on a surface, we construct latent vectors at each input point. Then, to estimate the occupancy of an arbitrary query point in space, we interpolate with inferred weights the relative occupancy scores in a neighborhood. Last, a mesh is reconstructed based on a number of occupancy queries, using a form of Marching Cubes.

Our approach, based on point convolution, overcomes these issues. It is illustrated on Fig. 2. Our contributions are:

- We attach features representing the implicit function to input points. Not only does it preserve point positions until later processing stages, rather than abstract them away too soon, but it concentrates the information where it matters the most: close to the surface.
- We compute features using point convolution, which yields a natural coverage and scalability to scenes of arbitrary size. (Rather than tailor yet another specific network architecture, we rely on a general point convolution backbone, which offers prospects for improvement when better point convolutions are designed.)
- Rather than relying on hand-designed forms of averaging, we extend prior learning to interpolation, which we apply to occupancy logits rather than latent vectors, as our experiments show it leads to better results.
- We propose an efficient test-time augmentation to treat inputs of high density or large size.
- While simple, our approach outperforms other methods both on object and scene datasets, yielding finer details. It is robust to domain shift (training on objects, testing on scenes) and faster than methods that overfit to a scene or infer from scratch for each query.

2. Related work

2.1. 3D representations

Voxels have been a natural choice for learning to represent 3D volumes [121, 74, 21, 119, 122, 123]. However, they come with a cubic complexity in space, leading to coarse discretizations due to memory constraints. Multi-scale refinement [24, 43] and sparsity-based octrees...
Points clouds are also produced as a sparse 3D representation, with various density and sampling distribution [31, 1, 71, 128, 60, 127, 116]. Point processing and generation do not suffer from the complexity and discretization induced by 3D grids; yet, the range of applications is limited regarding representing actual surfaces and volumes.

Meshes are a preferred representation for many uses, such as visualizations and simulations, but they are harder to directly produce from a neural network (vertex regression and face construction) [80]. Most existing approaches thus prefer to operate by deforming geometric primitives [38, 112, 61, 115], voxelized approximations [59, 36] or learned templates [39, 50]. Rather than actually inferring vertices, a mesh can also be extracted from labels inferred on a Delaunay tetrahedralization [70].

Implicit representations rely on a neural network to model a function expressing the occupancy of a given 3D point [16, 75] or its distance to the surface, whether it is signed [76, 83, 37] or unsigned [2, 19]. The signed or unsigned distance field (SDF, UDF) is often truncated (TSDF, TUDF) and estimated via a multi-layer perceptron (MLP). The isosurface can then be extracted from this occupancy or distance field with various methods such as the Marching Cubes [69]. Whereas voxels, points and mesh vertices are intrinsically discrete representations, implicit representations offer a virtually infinite resolution. Moreover, while mesh-based approaches struggle to enforce watertightness, to limit self-intersections and to address complex topologies (non genus-0), meshes reconstructed from implicit representations are guaranteed to be watertight and have no self-intersections. Besides, they can easily model arbitrary complex topologies. These advantages may explain the recent success of this representation, including to model 3D shapes from images without 3D supervision [66, 99, 81], with texturing [82] or specific rendering [67]. Departing from occupancy or distance fields, ShapeGF [11] models a shape by learning the gradient field of its log-density, then samples points on high likelihood regions of the shape and meshes them. Other work also study the decomposition of shapes and implicit surfaces into parts [35, 34, 84, 28, 48, 109], possibly overfitting networks to generate or render a single object or scene [117, 101, 65, 129, 103, 73, 126].

Scalability, however, is an issue for all these methods. While they can encode reasonably well one object or a class of objects, they cannot cope with the variability and size of an arbitrary scene involving several objects. Even considering a single object and assuming a powerful decoder, the encoding of a single or a few latent vectors hardly can develop into detailed shape information. Using periodic activation functions [101, 104] or adding a 2D convolutional component on input images [93, 124] helps, but is not enough.

A solution is to split the input points on a regular 3D grid and to optimize one latent vector per voxel [12] (DeepLS), possibly from overlapping input patches. Patch splitting can also be irregular and optimization-driven to favor self-similarities, with a global post-optimization to flip inconsistent local signs [129] (SAIL-S3). But whether these methods optimize only the latent vectors or a whole network as well, for patch decoding, they make surface reconstruction significantly slower, leading to reduced test sets.

Besides, these methods rely on fully-connected architectures whereas, we believe, convolutions, and in particular point convolutions [44, 113, 125, 57, 68, 120, 72, 108, 7, 9], are the key to scalability and increased details.

2.2. Convolutions for implicit representations

LIG [49] divides the input point cloud along a regular 3D grid to create 3D patches and capture local geometric shapes shared by several objects at a medium scale. For each of these patches, a 3D CNN then computes a local feature vector, which goes through a reduced IM-NET [17] for SDF decoding. However, later on, only the learned decoder is exploited; no local embedding is inferred. Given an input point cloud, latent vectors on the grid are optimized from scratch to minimize an objective function similar to the loss used for training. LIG additionally requires to be provided with oriented normals to make use of points known to be inside or outside the shape. This, however, may introduce artificial back-faces, which can partly be addressed in a postprocessing stage. In contrast, we can work without...
normals, we directly operate with convolutions on surface points rather than on a regular grid, and we directly use inferred embeddings without any heavy optimization.

IF-Net [18] introduces a multi-scale pyramid of 3D convolutional encoders aligned on a discrete voxel grid and trained on voxels at different scales. The occupancy of a query point is decided by a decoder taking as input the interpolated features extracted at this point for each pyramid level. In contrast, we do not discretize into voxels; we use point cloud convolution. Also, we learn how to interpolate the latent vectors rather than use a basic trilinear interpolation. Last, we provide results on scenes, not just on objects.

NDF [19] uses the same multi-scale encoding as IF-Net but relies on a UDF rather than occupancy for decoding. It allows the generation of very dense point clouds that can directly be meshed into possibly open surfaces.

SG-NN [25] uses a sparse 3D convolution [20] to learn a TSDF in a self-supervised setting, training for completion from partial scans. In contrast, we use point convolution and infer occupancy rather than SDF, which is easier to learn.

ConvONet [87] also uses a grid-based convolution, training an autoencoder that predicts occupancy. (It generalizes ONet [75], which only uses a single encoding and full connection.) For input point clouds, the encoder is a shallow PointNet [89] operating on points rather than on a voxelized discretization, and the decoder is a 3D U-Net [22]. The occupancy of a 3D point is inferred from a trilinear interpolation of grid features. Besides 3D convolution, variants based on a combination of 2D convolutions in a few spatial directions are proposed. DP-ConvONet [62] is a variant that considers a dynamic family of such directions. SA-ConvONet [105] overfits a pre-trained ConvONet model on the input using a sign-agnostic optimization of the implicit field. It improves accuracy at the cost of computation time.

As inference applies to grids, whose vertices or centers may be far from input points, the above methods loose the direct connection with the input surface samples. They are also suboptimal in that the latent vectors holding the information are uniformly distributed in space rather than concentrated where it matters the most, i.e., near the surface. To address these issues, we use point convolution and compute latent vectors at each input point. We then interpolate occu-
pency decisions of nearest neighbors using learned weights.

AdaConv [110] uses point convolution like us but aggregates multi-scale information on an adaptive voxel grid, while we attach features to points, closer to the surface. Besides, it requires oriented normals, contrary to us.

RetrievalFuse [98] splits a scene along a regular grid and encodes each 3D chunk as a latent vector via convolutional layers. But rather than using them for decoding, it retrieves similar chunks from the training set and combines their distance field to create a surface, enhancing the completion capability. In contrast, we are fully convolutional and the implicit function is directly obtained by interpolating inferred features, without the need to maintain the dataset samples used for training and with more generalization capacity.

Points2Surf [29] collects, for each query point, both a patch of neighbors (which gives a convolution flavor) and globally-sampled input points to help to provide a sign to the local distance field. The local patch and the global subsampling go through an MLP to create latent vectors that are concatenated and decoded into a signed distance. In contrast, we directly get non-local information as our receptive field is much larger. Besides, we are faster as we only compute a limited number of latent vectors (one per input point) that we later use for interpolation given a query point, while Points2Surf samples local+global points and goes through the whole encoder for each query point, i.e., a large number of times, that grows with the Marching Cubes resolution.

To infer occupancy or distance of a query point, methods that compute several latent vectors for a single object or scene either select the most appropriate latent vector to decode, typically in a multi-scale grid [110], or interpolate the latent vectors of query neighbors [18, 49, 87, 19, 62, 105]. We perform interpolation too, based on features computed on input points. However, given a query point, we do not interpolate the features themselves but the occupancy logits, as our experiments shows it leads to better results. Besides, we use a learned interpolation rather than the usual tri-linear interpolation [18, 49, 87, 19, 62, 105] or the inverse-distance interpolation backbone, only changing the last layer to yield a vector of some chosen dimension \( n \) as the size of vectors \( z_p \). (In our experiments, the convolution backbone is FKACConv [9] and \( n = 32 \).) To also use normals (optionally), the input points are just augmented with the 3 normal coordinates. Although different in nature, learning has also been used in [98] to blend retrieved chunks.

3. Our method

Goal. Given as input a set of 3D points \( \mathcal{P} \) sampled on a surface, possibly with noise, our goal is to construct a continuous function \( \omega : \mathbb{R}^3 \rightarrow [0, 1] \) indicating the probability of occupancy \( o_q = \omega(q) \) at any given query point \( q \in \mathbb{R}^3 \). We learn this function with a neural network using data consisting of point clouds sampled in the whole space and labeled with 0 (in empty space) or 1 (within the shape). The surface of the shape can then be extracted as the isosurface of the implicit function \( \omega \) with occupancy level 0.5.

Overview. Our method consist of the following steps:

1. We encode input points \( p \in \mathcal{P} \) into latent vectors \( z_p \).
2. Given a query point \( q \), we consider a interpolation neighborhood \( \mathcal{N}_q \) of input points in \( \mathcal{P} \).
3. For each neighbor \( p \in \mathcal{N}_q \), we construct a relative latent vector \( z_{p,q} \) from \( z_p \) and local coordinates \( q - p \).
4. We decode each relative latent vector \( z_{p,q} \) into relative occupancy scores \( o_{p,q} \), which are pairs of logit values.
5. In parallel, we extract significance weights \( s_{p,q} \) for each relative latent vector \( z_{p,q} \).
6. The occupancy scores of \( q \) are the weighted sum of the relative occupancy scores: \( o_q = \sum_{p \in \mathcal{N}_q} s_{p,q} o_{p,q} \).
7. The final probability of occupancy \( o_q \) is obtained as the softmax of scores \( o_q \).

These steps are further detailed in the following.

Absolute encoding. A point convolution first produces a latent vector \( z_p = E(p) \) for each input point \( p \in \mathcal{P} \). The encoder \( E \) can be implemented by any point cloud segmentation backbone, only changing the last layer to yield a vector of some chosen dimension \( n \) as the size of vectors \( z_p \).

Query neighborhood. Given an arbitrary query point \( q \) (when training or to predict occupancy at test time), we construct a set of neighbors \( \mathcal{N}_q \) from input points \( \mathcal{P} \). (In our experiments, \( \mathcal{N}_q \) is the \( k \) nearest neighbors of \( q \), with \( k = 64 \).)

Relative encoding. We augment the latent vector \( z_p \) of each neighbor \( p \in \mathcal{N}_q \) with the local coordinates \( q - p \) of query point \( q \) relatively to \( p \). These augmented latent vectors are then processed by an MLP \( R \) to produce relative latent vectors \( z_{p,q} = R(z_p \parallel q - p) \), where \( \parallel \) is the concatenation. (In our experiments, \( z_p \) and \( z_{p,q} \) have size \( n = 32 \).)

Raw decoding. A linear layer \( D \) decodes relative latent vectors \( z_{p,q} \) into relative occupancy scores \( o_{p,q} = D(z_{p,q}) \).
that are two-logit vectors classifying the position \( q \) as occupied or not, from \( p \)’s point of view. The relative encoder and the decoder (steps 3-7) are illustrated on Figure 5.

**Attention weighting.** As PRNet [114], we observe that the norm of embeddings \( z_{p,q} \) tends to correlate with their significance: it tends to indicate how much an input point \( p \), given its own neighbors and the relative position of query point \( q \), matters for deciding the occupancy at \( q \). We use this observation to infer significance weights for combining the relative occupancy scores \( o_{p,q} \). Concretely, we use an attention mechanism (blue frame in Figure 5): The relative embeddings \( z_{p,q} \) go through a linear layer parameterized by a weight vector \( w \), also of size \( n \), producing relative weights \( w_{p,q} = w \cdot z_{p,q} \), that are then normalized by softmax over \( N_q \) into positive interpolation weights \( s_{p,q} \) that sum to 1.

We actually use a multi-head strategy to obtain a form of ensembling. We learn \( h \) independent linear layers, parameterized by \( h \) corresponding weight vectors \( (w_i)_{i=1...h} \), producing \( h \) relative weights \( w_{p,q,i} = w_i \cdot z_{p,q} \), that are softmaxed as \( s_{p,q,i} \) and finally averaged as \( s_{p,q} = \frac{1}{h} \sum_i s_{p,q,i} \). (In our experiment, we use \( h = 64 \).)

**Interpolation.** Occupancy score vector \( o_q \) is interpolated from relative score vectors \( o_{p,q} \) of neighbors \( p \) as the weighted sum \( o_q = \sum_{p \in N_q} s_{p,q} o_{p,q} \), which yields an estimated probability of occupancy of \( q \) as \( o_q = \text{softmax}(o_q) \).

**Loss function.** To train the network, we use a binary cross-entropy loss that penalizes wrong occupancy predictions, like in IF-Net [18] or ConvONet [87].

### 4. Refinements

**Adapting to high density.** We train our network with a fixed number \( N_{\text{train}} \) of input points for easy mini-batching. (In our experiments, \( N_{\text{train}} = 3k \) or 10k.) At test time, if the surface is more densely sampled, the receptive field of the backbone may lack enough global context to decide which side of the surface is full or empty, unless oriented normals are also provided with points. A way to broaden enough the receptive field is to downsample the input point cloud, but it then naturally leads to a loss of details.

To reduce this effect, we rely on test-time augmentation (TTA) [55], which can be seen as a form of ensembling: we average several runs on different subsamples. However, aggregating final results, as often done in TTA [97], would be very time consuming in our case as we would have to do it to answer the occupancy of each query, basically multiplying the inference running time by the number of subsamples.

Instead, we perform TTA at latent vector level, thus running several times only the first step of our approach (absolute encoding), before query decoding. It depends on the number of input points (to attach a latent vector on), rather than on the number of query points, which is much larger. Concretely, we randomly create enough subsamples so that each point \( p \in P \) is seen at least \( N_{\text{view}} \) times, and average each \( z_p \) over all samples. (In experiments, \( N_{\text{view}} = 10 \).) The subsamples are randomly generated by sequentially picking a point \( p \in P \) with a priority that is the opposite of the number of times \( p \) appears in previous subsamples.

**Adapting to large size.** As our method is convolutional, it naturally adapts to input point clouds \( P \) of arbitrary size. Yet, while \( P \) may contain millions of points, GPU memory limits in practice the number of points \( N_{\text{test}} \) that can be treated together by the backbone. (We use \( N_{\text{test}} = 100k \).)

As with semantic segmentation [9], we can use a sliding-window with overlapping chunks of \( P \) of maximum size \( N_{\text{test}} \). Alternatively, as above, we can make subsamples of \( P \) by iteratively picking a low-priority point \( p \in P \) and its \( N_{\text{test}} - 1 \) nearest neighbors. (In our experiments, \( N_{\text{view}} = 3 \).)

**Scene scaling.** At inference time, the scale of the input point cloud may differ from the scales in the training set. As point-based backbones can be sensitive to variations of scale and density, we rescale the input such that the average distance between a point and its nearest neighbor is the same both in the training set and in the test point cloud.

### 5. Experiments

We experiment both on objects and scenes, in different point density regimes, with or without normal information depending on the baseline methods we compare with.

Because existing methods often perform well in some setting but not in others, most published papers tend to evaluate on different datasets or in specific configurations: number of train/test points, added noise, normals, generalization, etc. Some methods are also too slow to be evaluated...
on full datasets and report results only on dataset fractions. To be fair with these methods, we evaluate in their setting (when enough information is provided to do so) rather than impose them specific settings. It also illustrates the ability of our method to adapt to various configurations.

### 5.1. Datasets, baselines and metrics

**ShapeNet** [14], as pre-processed by [21], contains watertight meshes of shapes in 13 classes, with train/val splits and 8500 objects for testing. As [87], we sample 3000 points from each mesh (at each epoch) and apply a Gaussian noise with zero mean and standard deviation 0.05.

**Synthetic Rooms** [87] has 5000 synthetic scenes with random walls and populated with ShapeNet objects. We use [87]’s protocol for sampling 10k pts on the meshes to create train/val/test data, with noise as for ShapeNet. Shapes are scenes in terms of complexity, objects in terms of size.

**ABC** [53] is a set of CAD models, mainly mechanical parts. We use splits and point preprocessing from [29]: 4950 shapes for training, 100 for validation and 100 for testing.

**Famous** [29] contains 22 shapes of various origins, e.g., from the Stanford 3D Scanning Repository [54].

**Thingi10k** [130], as prepared by [29], has 100 shapes.

**SceneNet** [40, 41] is a synthetic dataset of indoor scenes. Data prepared in the same way as [45] yield 34 scenes.

**MatterPort3D** [13] has indoor scenes too. We use the same 2 scenes as prepared and used by [105]: with 65k pts.

**Baselines** are drawn among the state-of-the-art methods presented in Section 2.2. We also compare to SPR [51], a popular, non-learning-based reconstruction method that requires oriented normals (which is a strong hypothesis) and, possibly, a trimming parameter tuning (factor 6 in Tab. 4).

**Our method**, unless otherwise stated, uses the FKAConv backbone [9], feature size \( n = 32 \) as in ConvONet [87] or LIG [49], \( k = 64 \) neighbors, \( h = 64 \) interpolation heads, and does not use normals nor TTA.

**Mesh Generation**, for implicit functions, is done with the Marching Cubes [69] with resolution \( 256^3 \) for objects, 1 cm for SceneNet, 2 cm for MatterPort3D.

**Metrics.** We use the following common metrics: volumetric IoU, symmetric Chamfer L1-Distance \( \times 10^{-3} \) (CD), normal consistency (NC), i.e., mean absolute cosine of normals in one mesh and normals at nearest neighbors in the other mesh, and F-Score [107] with threshold value 1% (FS).

### 5.2. Alternative and ablation studies

To justify our algorithmic choices, we experiment on ShapeNet in generalization mode, training on chairs but evaluating on all the classes. We use the same train/test split as [75, 87], evaluating on 130 shapes (10 per class).

As can be seen in Table 1(a), the convolutional backbone FKAConv [9] is more efficient by a large margin than the PointNet-based segmentation network with residual connections [89, 75], which looses small scale information [90]. \( k = 64 \) interpolation neighbors offer the best performance (cf. Tab. 1(b)) and so does the interpolation with multi-head attention using \( h = 64 \) (cf. Tab. 1(c)). Also note that interpolating logits works better than interpolating features.

Last, Tab. 2 and Fig. 3 show the benefits of the TTA strategy with models trained with 3k and 10k points on ABC.

### 5.3. Reconstruction

**Reconstruction without normals.** Because of long running times, only a few published methods evaluate on the whole ShapeNet dataset. We outperform them on all metrics with a significant margin (Table 3). We reconstruct finer details (Figure 6) and we do not have the same tendency as ConvONet to fill volumes; we can instead generate more easily thin surfaces, which explain our superior IoU. We outperform other methods as well on Synthetic Rooms (Table 4), where also we capture much finer details.

**Generalization.** LIG is specifically designed for scalability and generality. It learns to reconstruct small shape patches from a given dataset, and then applies it to any new object or scene. Points2Surf is a patch-learning method too, although its requirement for a global view of the input and its running time make it less suited for scene reconstruction.

We compare to LIG, training both methods on ShapeNet objects (with normals as LIG requires them) and testing on SceneNet. We generalize better (Tab. 5) at all densities, capturing finer details and not erasing thin objects (Fig. 4).

We compare to Points2Surf, training on ABC in the same

| (a) Backbone         | IoU ↑ | CD ↓ | NC ↑ |
|----------------------|-------|------|------|
| Residual PointNet    | 0.661 | 10.583 | 0.817 |
| FKAConv              | 0.882 | 4.069 | 0.929 |

| (b) No. interp. neighbors | IoU ↑ | CD ↓ | NC ↑ |
|---------------------------|-------|------|------|
| 1                         | 0.799 | 6.951 | 0.867 |
| 8                         | 0.819 | 6.723 | 0.912 |
| 64                        | 0.882 | 4.069 | 0.929 |
| 128 (⇒ reduced batch size)| 0.827 | 6.550 | 0.925 |

| (c) Interpolation        | IoU ↑ | CD ↓ | NC ↑ |
|--------------------------|-------|------|------|
| Max                      | logits| 0.882 | 4.069 | 0.929 |
| Mean                     | logits| 0.883 | 3.703 | 0.933 |
| Inverse distance         | logits| 0.877 | 3.947 | 0.935 |
| Inverse distance         | features| 0.851 | 4.724 | 0.912 |
| Single-head attention    | logits| 0.879 | 3.686 | 0.934 |
| Multi-head attention     | logits| 0.895 | 3.702 | 0.938 |

Table 1: Alternative study. We train on ShapeNet chairs, without normals, 3k input points, with noise, and unless otherwise stated, FKAConv backbone, \( k = 64 \) neighbors, and max-logit interpolation. We test on 10 models from each of the 13 ShapeNet classes.
setting. We outperform Points2Surf on most of their settings (Tab. 2), both on ABC and when generalizing to Famous and Thingi10k. Points2Surf outperforms POCO only on very noisy or dense inputs, and only with a small margin.

**Scene reconstruction without normals.** We compare to SA-ConvONet on MatterPort3D scenes (Fig. 1) in their same actual setting (downsampling to 65536 pts). Our reconstruction is less smooth than SA-ConvONet but has finer details. As SA-ConvONet overfits many networks at inference time on top of ConvONet, it is notably slower too.

**5.4. Discussion and limitations.**

Our approach is suited both for single-object and whole-scene reconstruction. However, although it can cope with a substantial variation of point density, it cannot complete shapes when large parts are missing. Apart from a few methods like [26, 27, 25, 98], only object-targeted methods can presently do it, for classes known at training time, but they cannot reconstruct scenes at all.

Inferring surface orientation, when normals are not provided, requires wide context information. But a high density may reduce the receptive field, yielding orientation failures and artifacts. Our TTA only partly addresses the issue; handling it directly at backbone level would be better.

Nevertheless, POCO reaches the state of the art for both object and scene reconstruction, with or without oriented normals. It shows good generalization capabilities to shapes and scenes that are very different from the training set.
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Figure 7: Receptive field of the FKAConv backbone on a point cloud from SceneNet with density 100 pts/m$^2$. The receptive field of the marked point (green) is colored in red.

To evaluate the actual (maximum) receptive field of a given point, we apply the following procedure:
1. We use a variant of the network without RELU activations and where the convolutions are replaced with averaging.
2. We apply the loss on a single output location.
3. We back-propagate the loss signal.
4. We identify the input points that receive a non-zero gradient.

On a SceneNet living-room scene, with density 100 pts/m$^2$, we obtain an average receptive field of 29k points when looking at non-zero gradient. If we only look at points for which the back-propagated gradient has a norm greater than $10^{-7}$ (i.e., a significant gradient), then the receptive field encompasses 16k points.

Training settings. We train with Adam optimizer [52] with learning rate $10^{-3}$. The batch size is 16 for training with 3k input points and 8 for training with 10k input points.

Metrics evaluation. We use exactly the same metrics as Peng et al. [87], as specified formally in their supplementary material.

Meshing for occupancy. Mesh generation, for implicit functions, is often done using the Marching Cubes variant in [75], that locally refines the resolution depending on a heuristics. To ensure we have little chances of missing refinements, in particular for locally complex surfaces or thin volumes, we use a different strategy. We consider from the outset a fine-grained resolution but, to prevent a large amount of useless queries in large empty or full regions, we adopt a region growing approach. The seeds are the input points, for which we compute the occupancy. We then compute the occupancy for query points that are both in the close neighborhood of both a location in the empty volume and a location in the full volume, i.e., close to the surface, and we iterate.
Besides, with the Marching Cubes algorithm, a vertex is placed on a cube’s edge by linearly interpolating the two scalar values at the edge’s endpoints. But contrary to distance fields, occupancy fields may have sharp transitions. Consequently, opposite-side endpoints frequently have values close to 0 and 1, and vertices tend to be placed in the middle of segments, creating discretization effects. To prevent it, we perform a dichotomic search to better locate the occupancy transition on edges.

Running times. Some running times are given in Figures 1 and 4 in the paper, as well as here in Table 6. Although in this case, because of the high point cloud density (50k pts), we apply the test-time augmentation (TTA) strategy and run the latent vector inference on many different point cloud subsamples (such that each point is seen at least $N_{view} = 10$ times), our method is significantly faster than Points2Surf. The time for the backbone to extract features is negligible (< 1%). The bottleneck is the decoding, as we have to respond to many occupancy queries depending on the resolution of the Marching Cubes (MC). And to answer an MC query, the bottleneck is the computation of nearest neighbors at low MC resolution to reduce the GPU-CPU communication overhead.

In contrast, grid-based methods such as those based on ConvONet [87, 62, 105] do not need such an optimization as they do not depend on nearest neighbors. However, while our approach requires extracting one feature per point for encoding (typically a few thousands points for an object), these methods extract one feature per grid cell, typically $64^3 \approx 262k$. Besides, as we show in the paper, loosing the “connection” with input points induces a loss of details.

**B. Experiments**

**B.1. Choices**

**Datasets.** For lack of time, we did not evaluate on ScanNet [23] nor all scenes of MatterPort3D [13]. As the CVPR policy forbids us to include results on additional datasets in the supplementary material, we are not doing it here. We will include such results in a later version of the paper.

**Methods.** Following the success of methods such AtlasNet [38] and DeepSDF [83], a dozen of new learning-based reconstruction methods have been published per year in the last 2 or 3 years.

As said in the submitted paper, existing methods often perform well in some setting but not in others. Consequently, most published papers tend to evaluate on different datasets (see Table 7) or in specific configurations: low or high density of train/test points, with or without added noise and outliers, with or without oriented normals, training specifically for a class of shapes or generalizing to any shape, addressing single object or whole scene reconstruction, etc. Some methods are also too slow to be evaluated on full datasets and report results only on dataset fractions. Last, although most methods make code available, some do not offer pre-trained models, or scripts, or parameters. All this makes comparisons particularly difficult. The fact is we cannot compare to all existing methods on all available datasets. We chose to compare to some of the most cited or most recent methods. To be fair with these methods, we evaluate in their setting (when enough information is provided to do so) rather than impose them other specific settings. It also illustrates the ability of our method to adapt to various configurations.

Here are some methods we would have liked to compare to but could not:

- **AdaConv**[^1]: The repository provides raw code but no pre-trained model nor instructions or scripts to train or test, which may lead to misuse and wrong comparison.
- **NDF**[^2]: The repository provides code but only a pre-trained model for ShapeNet cars. For scene reconstruction, it does not offer preprocessed data or any data preprocessing procedure to retrain a model, nor instructions to run NDF using a sliding window scheme, as alluded to in the supplementary material.

As indicated in Table 7, some authors also have not made their code or their model available to allow comparisons.

[^1]: https://github.com/isl-org/adaptive-surface-reconstruction
[^2]: https://github.com/jchibane/ndf

**Code release.** We will make freely available the code of POCO for the community to use, compare and build upon our approach. It will be released under open source license.
| Method          | Normals Required | Code Available | Pre-Training Available | Objects | Scenes | Synthetic Rooms | Tanks and Temples |
|-----------------|------------------|----------------|------------------------|---------|--------|-----------------|-------------------|
| AdaConv         | ✓                | ✓              |                        | ABC     |        |                 |                   |
| ConvONet        | [87]             |                |                        |         |        |                 |                   |
| DeepLS          | [12]             | ✓              | ✓                      | D-Faist |        |                 |                   |
| DeepSDF         | [83]             | ✓              |                        |         |        |                 |                   |
| DefTet          | [33]             | ✓              | ✓                      |         |        |                 |                   |
| DP-ConvONet     | [62]             |                |                        |         |        |                 |                   |
| IF-NET          | [18]             |                |                        |         |        |                 |                   |
| IGR             | [37]             |                |                        |         |        |                 |                   |
| IM-NET          | [17]             |                |                        |         |        |                 |                   |
| LDIF            | [34]             | ✓              |                        |         |        |                 |                   |
| LIG             | [49]             | ✓              |                        |         |        |                 |                   |
| MetaSDF         | [100]            | ✓              |                        |         |        |                 |                   |
| NDF             | [19]             |                |                        |         |        |                 |                   |
| Neural-Pull     | [4]              |                |                        |         |        |                 |                   |
| Neural Splines  | [118]            | ✓              |                        |         |        |                 |                   |
| ONet            | [75]             |                |                        |         |        |                 |                   |
| Points2Surf     | [29]             |                |                        |         |        |                 |                   |
| RetrievalFuse   | [98]             | ✓              |                        |         |        |                 |                   |
| SA-ConvONet     | [105]            |                |                        |         |        |                 |                   |
| SAIL-S3         | [129]            | ✓              | ✓                      |         |        |                 |                   |
| SAL             | [2]              |                |                        |         |        |                 |                   |
| SALD            | [3]              | ✓              | ✓                      |         |        |                 |                   |
| SAP             | [86]             |                |                        |         |        |                 |                   |
| ScanComplete    | [27]             |                |                        |         |        |                 |                   |
| SG-NN           | [25]             |                |                        |         |        |                 |                   |
| SPR             | [51]             | ✓              |                        |         |        |                 |                   |
| POCO (ours)     |                  |                |                        |         |        |                 |                   |

Table 7: Datasets used for the evaluation of 3D reconstruction methods from point clouds in their published paper, if freely available and > 10 shapes are used, and availability of code or pre-trained models suited for testing on the datasets (at the time of writing).

- ■: test on all/many shapes of the dataset (> 1000), □: test on a few shapes (≤ 100 or a single category), ⊥: test with ground-truth normals as input, *: actual scans rather than uniformly sampled points.

Tests on a given dataset may however be done in different settings (number of sampled points, amount of added noise or outliers, use many shapes but excluded classes or objects, etc.). For instance, many different numbers can be found in various publications for the performance of ONet on the ShapeNet dataset.
B.2. More visualizations

We provide on Figure 8 more visualizations of ShapeNet reconstructions, comparing LIG to POCO. LIG reconstructions were done using the best parameter setting for the method, i.e., with part size 0.20 for 512 and 2048 points, and part size 0.10 for 8192 points.

C. Use of existing assets

C.1. Pre-existing code

The implementation of our approach has several dependencies, that are all free to use for research purposes. The main dependencies of our code are as follows:

- FKACOnv\(^3\) [9], under Apache License v2.0.
- PyTorch\(^4\), under the Apache CLA.
- PyTorch-Geometric\(^5\), under the MIT License.

Our code itself will be made freely available upon publication, under Apache License v2.0.

C.2. Datasets

For the experiments, we used several datasets that are freely available for research purposes:

- ABC\(^6\) is under the Onshape Terms of Use\(^7\). We used the subset preprocessed and made available by the authors of Points2Surf\(^8\) [29].
- Famous is a set of shapes of various origins, among which the Stanford 3D Scanning Repository\(^8\) [54]. This set of shapes is described, preprocessed and made available by the authors of Points2Surf\(^9\) [29].
- MatterPort3D\(^10\) [13] is under a user license agreement for academic use. We used scenes preprocessed by the authors of SA-ConvONet\(^11\) [105].
- Real-World point clouds used in the paper are described, preprocessed and made available by the authors of Points2Surf\(^12\) [29].
- SceneNet\(^13\) [40, 42, 41] is under the CC BY-NC 4.0, for research purposes only. We made meshes watertight using Watertight Manifold\(^11\) [45], that enables code use under mild conditions.
- ShapeNet\(^14\) [14] has a licence for non commercial research or educational purposes. We used the version of ShapeNet as preprocessed by the authors of ONet\(^15\) [75], which itself reuses the preprocessing of the authors of 3D-R2N2\(^16\) [21].

- Synthetic Rooms\(^16\) is a dataset created by the authors of ConvONet [87] based on ShapeNet models.
- Thingi10K\(^17\) [130] is a freely available collection of shapes under various licences. We used the subset preprocessed and made available by the authors of Points2Surf\(^18\) [29].

C.3. Compared methods

We compared to a number of reconstruction methods, reusing the code made available by their authors:

- ConvONet\(^16\) [87] under the MIT License.
- LIG\(^17\) [49] probably under Apache License v2,
- Neural Splines\(^18\) [118] under the MIT License,
- Points2Surf\(^19\) [29] under the MIT License,
- SA-ConvONet\(^20\) [105] under the MIT License,
- SPR\(^21\) [51] under the MIT License.

We also compared to AtlasNet [38], DeepSDF [83], DPConvONet [63], ONet [75], but only reusing the numbers mentioned in [87, 63].

D. Societal impact

We believe our 3D reconstruction approach has very little potential for malicious uses (including disinformation, surveillance, invasion of privacy, endangering security), not more, e.g., than image enhancement methods in the 2D data case, and not more than hundreds of previously published 3D reconstruction methods. Besides, we are not bound nor promoting any dataset that would lead to unfairness in any sense. The use of our method has a modest environmental impact as the training time (a few days on a single GPU for a large dataset) and the inference times (minutes, or hours for very large point clouds) are somewhat moderate, and favorably compare to many learning-based approaches.

On the contrary, applications of our method can be found in various domains, with positive societal impacts:

\(^3\)https://github.com/valeoai/FKAConv
\(^4\)https://pytorch.org/
\(^5\)https://deep-geometry.github.io/pytorch-geometric.readthedocs.io/
\(^6\)https://deep-geometry.github.io/abc-dataset/
\(^7\)https://www.onshape.com/en/legal/terms-of-use
\(^8\)http://graphics.stanford.edu/data/3Dscanrep/
\(^9\)https://niessner.github.io/Matterport/
\(^10\)https://robotvault.bitbucket.io/
\(^11\)https://github.com/hjwdzh/Manifold
\(^12\)https://shapenet.org/
\(^13\)https://github.com/autonomousvision/occupancy_networks
\(^14\)https://github.com/chrischoy/3D-R2N2
\(^15\)https://ten-thousand-models.appspot.com
\(^16\)https://github.com/autonomousvision/convolutional_occupancy_networks
\(^17\)https://github.com/tensorflow/graphics/tree/master/tensorflow_graphics/projects/local_implicit_grid
\(^18\)https://github.com/fwilliams/neural-splines
\(^19\)https://github.com/ErlerPhilipp/points2surf
\(^20\)https://github.com/tangjiapeng/SA-ConvONet
\(^21\)https://github.com/mkazhdan/PoissonRecon
| Input | 512 pts | POCO | Input | 2048 pts | POCO | Input | 8192 pts | POCO |
|-------|---------|------|-------|----------|------|-------|----------|------|
| ![Input LIG POCO](image1) | ![LIG](image2) | ![POCO](image3) | ![Input LIG POCO](image4) | ![LIG](image5) | ![POCO](image6) | ![Input LIG POCO](image7) | ![LIG](image8) | ![POCO](image9) |

**Figure 8:** ShapeNet reconstructions (input with normals), LIG (part size 0.20 for 512 and 2048 pts, 0.10 for 8192 pts) and POCO (ours).
Heritage preservation. Digitizing cultural objects and monuments allows a form of heritage preservation and enables virtual museums to make works of art and culture more widely accessible.

Infrastructure and building maintenance. Reconstructing models of existing infrastructures and buildings is of high interest for the construction industry. These models are particularly useful to plan and organize maintenance. This is particularly useful in a context of aging infrastructures and building renovation for energy-saving insulation.

Augmented and virtual reality. Surface and volume reconstruction are useful assets for augmented and virtual
reality, whether it is for professional use (e.g., on-site maintenance of equipment) or entertainment (video games, special effects for the film industry), which is however to be consumed in moderation.