Supplementary Material
3DPoseLite: A Compact 3D Pose Estimation Using Node Embeddings

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1. Graphs Details

As discussed in the main article, we have voxelised and generated skeletons [2, 3] for each CAD model. These were used to identify and prune the nodes required for shape representation for each graph. Being invariant to euclidean transforms and computationally efficient, they form a suitable choice for 3D shape representation [4, 6]. These aid in reduction in training and inference time of neural networks. For better clarity, we present the details about graphs generated using Pascal3D Dataset [7]. As shown in Figure 2, the number of nodes in each graph per category (including all 12 classes) have been defined. It depends on the complexity of the CAD model and the skeleton obtained.

1.1. Pix3D Dataset

Pix3D [5] is a recent dataset containing 5,711 non-occluded and non-truncated images of 395 CAD shapes among 9 categories including tool, wardrobe, desk, bed, chair, etc. It mainly features furniture, with a strong bias towards chairs. Figure 1 represents the skeleton and corresponding graphs obtained for a few categories. The objects are less complex as compared to Pascal3D [7].
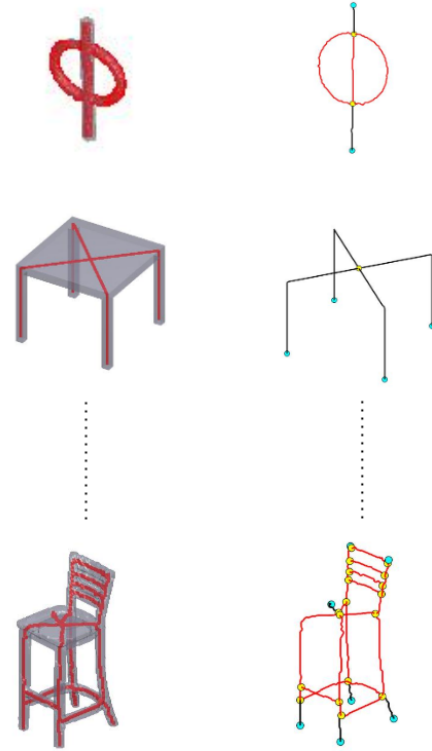

Figure 1. Illustration of skeletons generated from CAD models in Pix3D dataset [5] (in grey) using prairie-fire analogy [1] and their respective graphs on the right. The blue nodes represent the leaf nodes, yellow denote the non-leaf nodes and edges are represented in red color. (best viewed in color)

References

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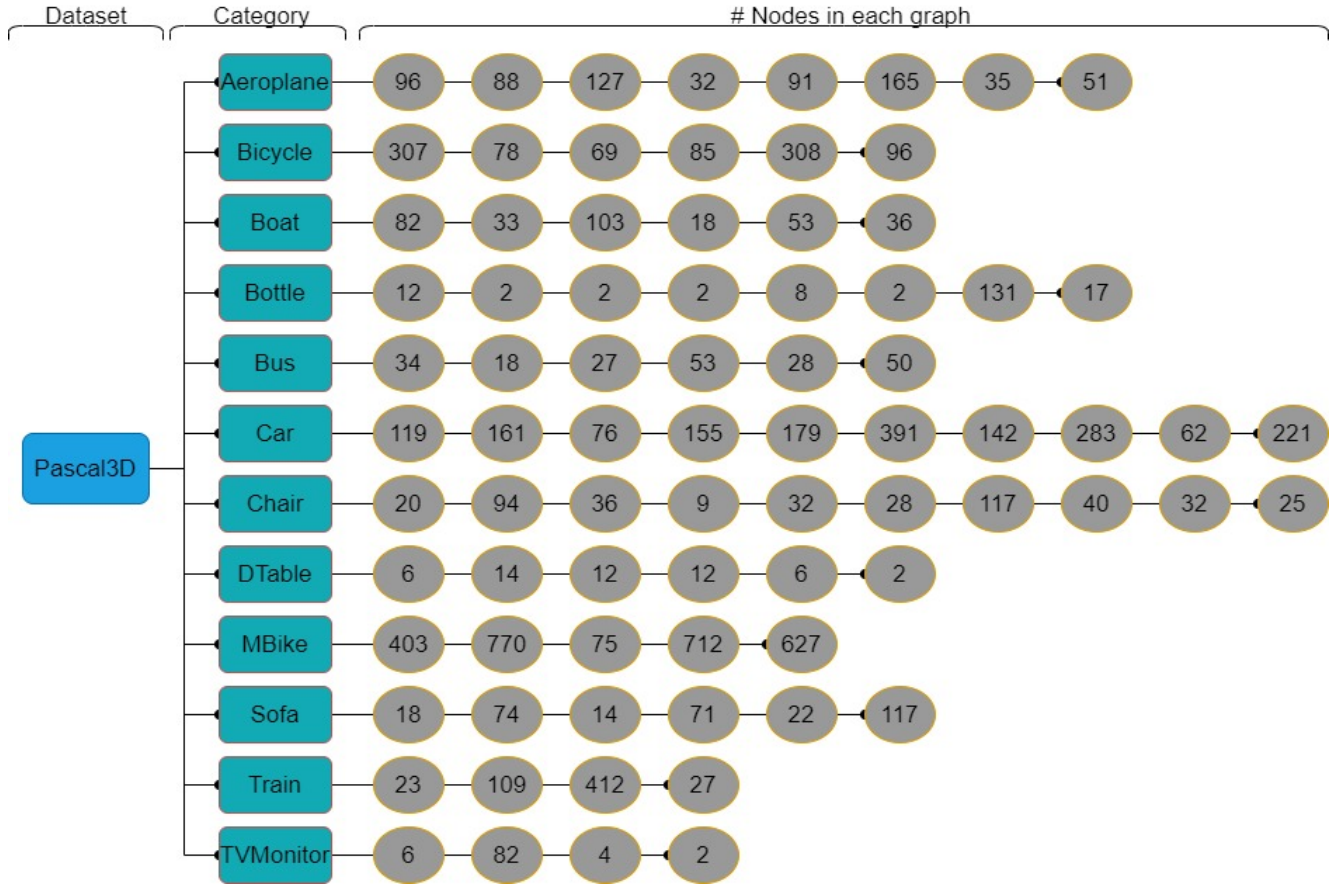
Figure 2. Hierarchical representation of Number of Nodes(in gray) in graphs of each category (in green) for Pascal3D dataset.

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