Reaction Report 4 – Deep Marching Cubes

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What I like about this paper: In this paper, the authors have proposed an end-to-end trainable model that directly produces an explicit surface representation and optimizes geometric loss functions. The previous 3D representation approaches involving voxel and point-based methods required a post-processing step to retrieve the actual 3D surface mesh. In the Deep MC, algorithm authors have added an additional layer to the existing Marching cube algorithm called *Differentiable Marching Cubes Layer (DMCL)* to make it fully differentiable and backpropagate the losses. Specifically, in contrast to predicting signed distance values, the authors predict the probability of occupancy for each voxel in addition to the vertex location of each cell. The idea of introducing different losses like mesh loss, occupancy loss, smoothness loss, and curvature loss to enhance different aspects of the surface reconstruction is impressive. This adds a strong prior to the models leveraging the real-world experience. I also liked the evaluation of each component of the loss. The model also evaluates well for partial uniformly sampled point clouds. Deep MC method infers occupancy using only unstructured points as supervision while both baselines require this knowledge explicitly.

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What I didn't like about this paper: This method predicts the probability for all the points in the grid for which the computational complexity increases by N^3 * 3. Thus, for a higher resolution, this method Deep Marching cubes might be heavy to use. This might lead to serious issues while using this method on real-world datasets. Moreover, most of the predicted vertices are not eventually used to construct a 3D surface only the edges having a change in occupancy sign are used. Also, this method is not effective for intricate surfaces since max-polling operation may lead to loss of information. The robustness of the model could be more evident if other datasets apart from Shape Net would have been used. Also, we can see that the approach failed for thin surfaces and disconnected parts. Additionally, for sparse datasets, the authors have not mentioned how the model will perform for non-uniform sampling.

Future work: The fact that most of the vertices of the grid are not used in surface reconstruction may be used to explore the possibility of using only the edges containing the surfaces. Thus, if in the network architecture instead of branching, if we first learn the occupancy and identify the edges containing the surfaces and then use this information to selectively predict vertex displacements. This might significantly decrease the computational expense. Deep Marching Cubes could be very effective in higher resolutions and it would be interesting to integrate OCNN with it. It would also be interesting to see the implementation of this method on 3D volumetric information or 2D images.