POINTCAPS: RAW POINT CLOUD RECONSTRUCTION AND CLASSIFICATION USING CAPSULE NETWORKS WITH ERROR ROUTING - SUPPLEMENTARY RESULTS

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1. ROBUSTNESS TO NOISE

To evaluate the robustness of our architecture to noise, we train noise-free version of ModelNet10 [1] dataset using two augmentation techniques; 1) point perturbation and 2) adding outliers, and evaluate the reconstruction loss and the accuracy matrix. In the perturbation test, Gaussian noise $\mathcal{N}(0, \sigma)$ is added to the points where $\sigma \in [0, 0.2]$. As shown in Fig. 1.(1), even though the network shows a considerable accuracy drop when $\sigma >= 0.15$, the network still achieves a minimum of 89.1% accuracy. Our outlier test replaces various numbers of points in both training and testing sets. Fig. 1.(2,3) depicts this behaviour. In Fig. 1.(2, 3) the $X-$axis denotes the number of outlier points in the test set. The three colours represent different number of outliers in the training set. As shown in Fig. 1.(2, 3), PointCaps delivers more than 90% accuracy up to 400 outliers in the test set. We also observe that the accuracy increases when we add outliers during the training phase. Hence, we conclude that the Pointcaps is significantly more robust to Gaussian noise and to anomalies and provides good reconstruction.

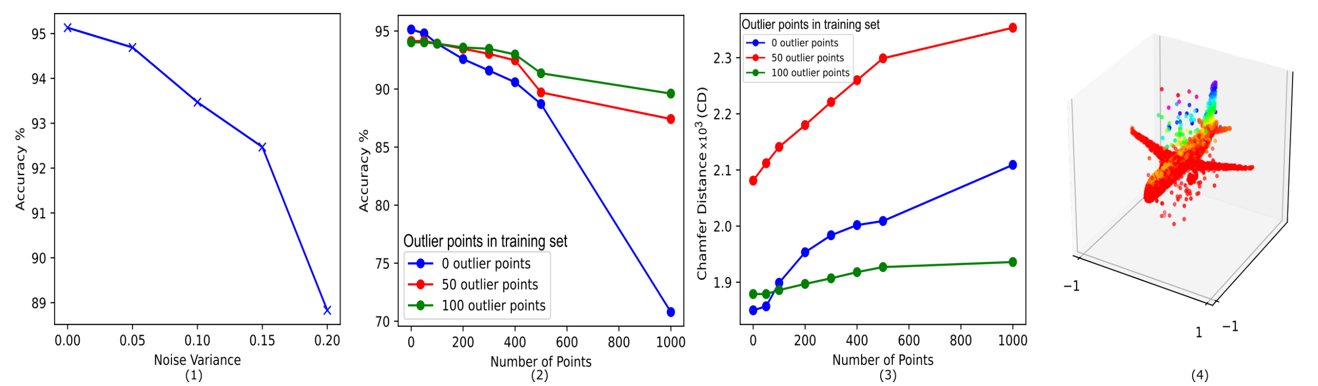

Fig. 1. Noise analysis on ModelNet10 dataset. (1) The network is trained without any perturbation and tested with Gaussian noise, with variance in the range $0 - 0.2$. (2-3) The network is subjected to different number of anomaly points (in the X axis we increase the number of outlier points in the test set) and the performance (accuracy and reconstruction) is analyzed on ModelNet10 dataset. The network is trained with various number of outliers with Gaussian noise $\mathcal{N}(0, 0.2)$. (4) An example of 100 Points replaced with Gaussian noise $\mathcal{N}(0, 0.2)$.

2. POINTS TO PART CAPSULE

Here, we analyse the capability of pointCapA at representing point-part relationship with error routing. We compare the ability to represent point to part relationships of PointCaps (error routing based) with 3D-PointCapsNet (dynamic routing based). In 3D-PointCapsNet, the output of the capsule is assigned to the relevant parent capsule through cosine similarity. However, the PointCapA agreement is simply euclidean distance. Fig. 2 illustrates the local part representation of capsules. As indicated in the Sec. 3.2 of the paper, each parent capsule has a coupling coefficient which increases for the possible parent during routing. This represents the contribution of lower level capsules to the higher level capsule. We use this coupling coefficient to identify the relevant part labels for each point. As shown in Fig. 2, the parts are better visually understood in PointCaps (error routing based) compared to 3D-PointCapsNet (dynamic routing based), which validates our argument.

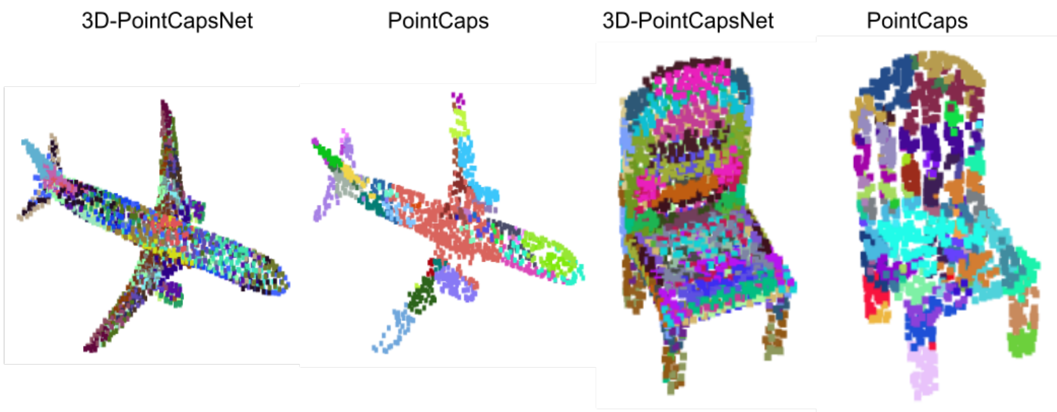

Fig. 2. Part representation with dynamic routing in 3D-pointCapsNet[2] and with error routing in PointCaps. 3D-pointCapsNet interprets 32 parts, each having 64 points, whereas PointCaps has 64 parts with different number of points.

3. REFERENCES

[1] Zhirong Wu, Shuran Song, Aditya Khosla, Fisher Yu, Linguang Zhang, Xiaoou Tang, and Jianxiong Xiao, "3D shapenets: A deep representation for volumetric shapes," in *CVPR*, 2015, pp. 1912–1920.

[2] Yongheng Zhao, Tolga Birdal, Haowen Deng, and Federico Tombari, "3D point capsule networks," in *CVPR*, 2019, pp. 1009–1018.