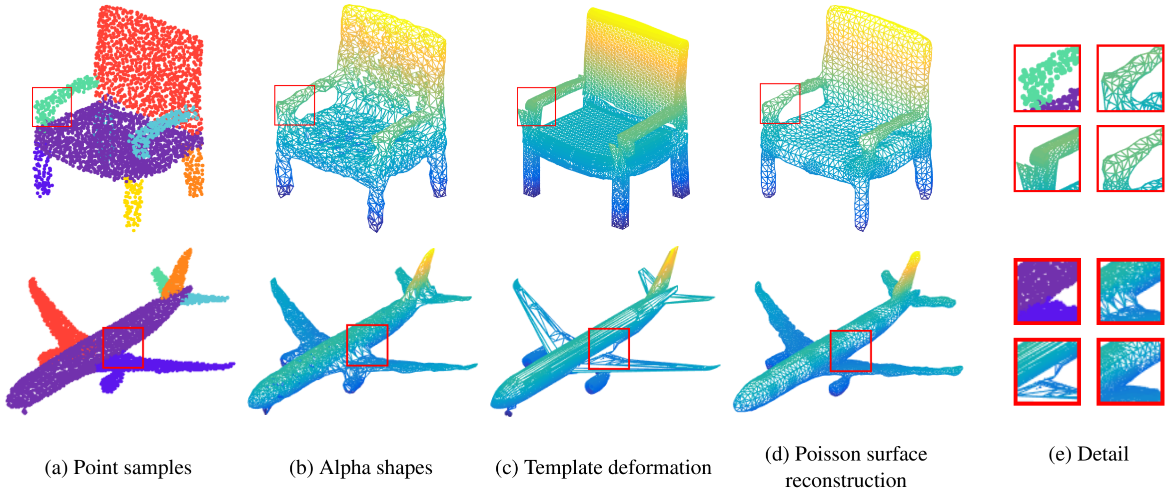

Figure 12: ***Mesh reconstruction***. *(a) A sampled 3D point cloud with surface normals. Surface reconstruction using (b) alpha shapes, (c) template deformation, and (d) Poisson surface reconstruction. (e) Surface reconstruction detail for (top left) point samples, (top right) alpha shapes, (bottom left) template deformation and (bottom right) Poisson surface reconstruction.*

significant issue is is that the notion of one-to-one point correspondences for objects in diverse datasets such as chairs is ill-founded. The result is that the input data for our method can feature poor correspondences, which has a knock-on effect on sample quality. We believe that a promising avenue for future research is to represent objects using unordered point sets, which would enable the use of large datasets without pre-processing, and correspondence quality issues. Some work has already taken place in this area, with deep learning methods applied to 3D point sets for the purpose of object classification, semantic scene parsing and part segmentation [QSMG16]. We believe there is potential to modify these methods for generative modelling, which would enable the synthesis of arbitrary point clouds.

Although the ShapeVAE's samples display a good range of variability, they are somewhat lacking in fine detail in comparison with the input point sets. This is an issue that has been documented in the machine learning literature, in which VAE-based generative models of images demonstrate blurriness and a lack of detail [DB16]. This effect has been attributed to the use of unimodal generative distributions such as Gaussians. One solution to this issue that has emerged in generative models is the use of generative adversarial networks (GANs), which demonstrate mode-seeking behaviour, and thus produce samples closer to the true data manifold than alternative approaches. As such, a potential future direction is to make use of GAN with a similar architecture to the ShapeVAE decoder to generate objects.

7. Acknowledgements

The work of CW is supported in part by EPSRC grant EP/N510129/1. CN is supported by the Centre for Doctoral Training in Data Science, funded by EPSRC grant EP/L016427/1. We thank Haibin Huang, Vangelis Kalogerakis and Ben Marlin for sharing their data and providing information about their methods, and Niloy Mitra for his valuable comments on an early draft.

References

[AKZM14] Averkiou M., Kim V. G., Zheng Y., Mitra N. J.: Shapesynth: Parameterizing model collections for coupled shape exploration and synthesis. *Comput. Graph. Forum 33*, 2 (2014), 125–134. 2

[BGS15] Burda Y., Grosse R. B., Salakhutdinov R.: Importance weighted autoencoders. *CoRR abs/1509.00519* (2015). 7

[BGS16] Burda Y., Grosse R., Salakhutdinov R.: Importance weighted autoencoders. 9

[BLRW16] Brock A., Lim T., Ritchie J. M., Weston N.: Generative and discriminative voxel modeling with convolutional neural networks. *CoRR abs/1608.04236* (2016). 3

[CSCS15] Choy C. B., Stark M., Corbett-Davies S., Savarese S.: Enriching object detection with 2D-3D registration and continuous viewpoint estimation. In *CVPR* (2015), IEEE Computer Society, pp. 2512–2520. 2

[CTCG95] Cootes T. F., Taylor C. J., Cooper D. H., Graham J.: Active shape models-their training and application. *Computer Vision and Image Understanding 61*, 1 (1995), 38–59. 2

[DB16] Dosovitskiy A., Brox T.: Generating images with perceptual similarity metrics based on deep networks. In *NIPS* (2016), pp. 658–666. 10

[DCSF15] Denton E. L., Chintala S., Szlam A., Fergus R.: Deep generative image models using a laplacian pyramid of adversarial networks. In *NIPS* (2015), pp. 1486–1494. 3

[Doe16] Doersch C.: Tutorial on variational autoencoders. *arXiv preprint arXiv:1606.05908* (2016). 5

[EHWW14] Eslami S. M. A., Heess N., Williams C. K. I., Winn J. M.: The shape boltzmann machine: A strong model of object shape. *International Journal of Computer Vision 107*, 2 (2014), 155–176. 3

[EKS83] Edelsbrunner H., Kirkpatrick D. G., Seidel R.: On the shape of a set of points in the plane. *IEEE Trans. Information Theory 29*, 4 (1983), 551–558. 9

[FAvK*14] Fish N., Averkiou M., van Kaick O., Sorkine-Hornung O., Cohen-Or D., Mitra N. J.: Meta-representation of shape families. *ACM Trans. Graph. 33*, 4 (2014), 34:1–34:11. 2

[FSG16] Fan H., Su H., Guibas L.: A point set generation network for 3d object reconstruction from a single image. *arXiv preprint arXiv:1612.00603* (2016). 3