Generative design for Social Manufacturing

Carlos González-Val[1] and Santiago Muiños-Landin[1]

[1]Technological Centre AIMEN, C/ Relva, 27 A. Torneiros - 36410 Porriño - Pontevedra, Spain

Abstract— **Social Manufacturing is a novel approach where different members of a community can interact within a cyber-physical social space in order to achieve specific and personalized solution for manufacturing processes. In such digital scenario, interactions, driven by information flows, can be divided in different branches depending on the actors involved in the whole process. One particularly critic branch for such collective production, is the one that captures the information related with product design, due to its direct link with creativity. Here we show how active tools based on Artificial Intelligence triggers artificial creativity that can be used for the user capabilities augmentation. We show how the use of deep generative models, based on Variational Autoenconders, offers solutions for a particular social manufacturing platform for furniture design combined with additive manufacturing to drive the transition from a digital framework to a real context.**

I. INTRODUCTION

The co-creation of fully customized products can be achieved though the exchange of data and processes between members of a community [1], [2], [3], [4]. This is the essence of social manufacturing (SM), a novel approach where such data is shared within a cyber-physical social space (CPSS) [5], [6], triggering massive decentralized co-creation processes. As a collective phenomena, interactions define behavior and emergent dynamics of the individuals and the group [7], [8]. Such interactions can take place with the environment but also among individuals of the community, meaning an individual or cognitive component and a social one of the information hold by the whole system. While in a biological framework such information driven by physical interactions is enconded in complex biochemical networks [9], [10], [11], the way artificial agents interact is usually sensed, digitalized and processed by hardware and software, and through the use artificial intelligence algorithms these interactions derives in artificial collective behavior. Considering the digital social space defined within a SM framework, the information that quantifies such interactions comes from very different sources related with the different actors involved in a manufacturing process. Even in some cases, this information is embedded in the actions taken by the members of the community, coming from experiences out form the CPSS. Which results in a high difficulty to extract information hidden in a space different from that where cyber-physical interactions take place, and that could be used by intelligent algorithms to drive production strategies. With this in mind, one can visualize the cyber-physical social space as a multidimensional one, with multiple channels holding information flows in terms of services (see 1), technology or design each of them with different degree of explicitness regarding agent (community member) knowledge. One key element within the SM landscape is the so called *prosumer*, a consumer that participates actively in social manufacturing assuming also the role of a producer. The more involved the prosumers (agents) get into the product manufacturing, the more reach the final product results through self-organizing and social-enabled mechanism. However, contrary to what would be an ideal SM context, where all the members of a community are pure prosumers, the current approaches to SM shows the presence of customers and also services providers in an independent way. In such scenario, the symmetry conditions of the assumed roles distribution, or the fact that all the actors might be not equally active, results in a potential weakness of the whole SM workflow for the emergence of a collective production.

In order to achieve such customization of products based on collective behavior, one particularly critic channel that captures the interactions within the CPSS is the one composed by the information related with product design. Such criticality comes not just from the above mentioned risks regarding the possible absence of agents providing such knowledge to the CPSS. But also from the intrinsic difficulty to define variables that hold the essence of a design, to represent it as information to be stored, shared and customized. To overcome such issue Artificial Intelligence provides different approaches. Specifically Deep Generative Design tools such as Generative Adversarial Networks [12] (GANs) and Variational Autoencoders [13] (VAE) have been shown as powerful frameworks to provide solutions in a wide range of complexity dimensional reduction problems and generation [14], [15]. And more interestingly for the scope of this work, they have also been reported as active tools for 3D shapes generation [16] of specific products. In this context. these kind of methods by training through existing large 3D datasets such as *Shapenet* [17], manage to encode, in terms of distributions, the values of the most representative variables of certain family of shapes into what is called a latent space. And introducing variational methods they trigger the generation of new models based on the information stored in the latent space. We propose the use of this information captured in such latent space to overcome the sparsity within the CPSS channel that holds information in terms of product design.

In this work we present an active tool based on generative modelling for augmented design to be developed within the

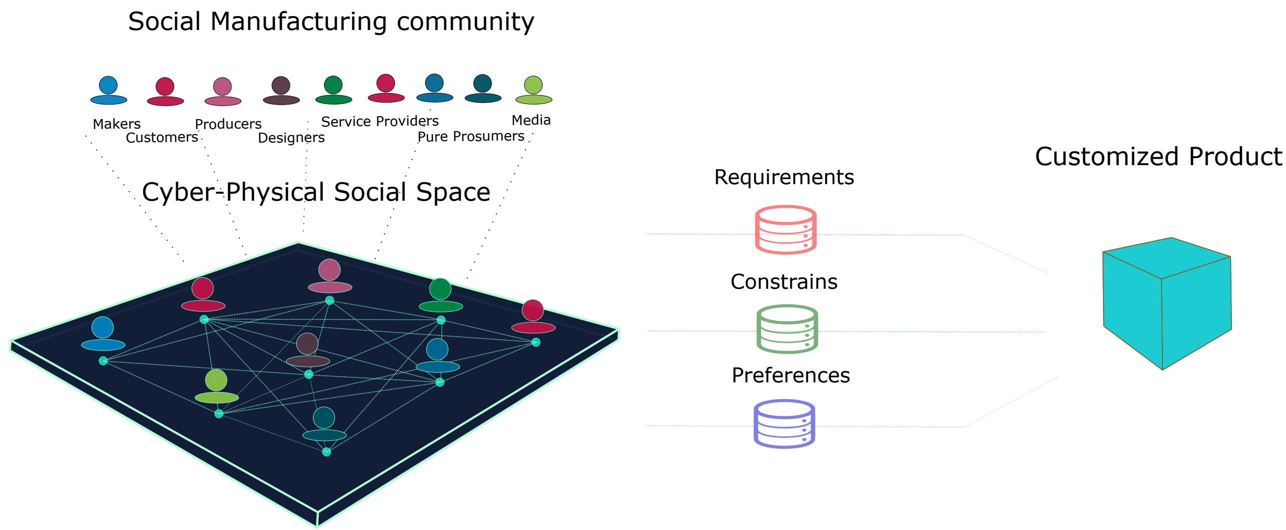

Fig. 1: Cyber-physical social space for Social Manufacturing Different roles within Social Manufacturing Frameworks are projected into an interation space (CPSS). In real frameworks most of the actors are not pure prosumers so that many different roles appears and interact. From the interactions different information channels can be separated and summarized in three main branches (requirements, constrains and preferences) to drive a model for a final customized product.

european project INEDIT [18]. The main goal of this project is to build a Do it Together ecosystem to demonstrate the potential of real SM approaches within Circular Economy [19]. For that the INEDIT platform brings together a very wide spectrum of stakeholders around the furniture manufacturing providing four cross use cases: sustainable wood panels manufacturing and 3D-printing of wood as a disruptive approach [20], 3D printing of recycled plastic and 'smartification'. Keeping the as a central principle the idea of designing globally and producing locally. The part of our contribution to this project that we present in this paper covers the augmentation of the design capabilities of a potential user of the INEDIT platform. For that we developed a VAE following the β-VAE approach [21], [22] developed for a progressive processing of the information during the training process of the network. We will show how our VAE works and provide results for the creation of digital models of furniture. Furthermore we provide real examples of such outcomes obtained through additive manufacturing[23].

II. Results and Discussion

For the development of the generative model, we used a Variational Auto Encoder structure, adapted for 3D convolutions, as shown in Figure 2. In the encoder section, each stage comprises a 3D convolutional layer, a batch normalization [24] and a Leaky ReLU activation [25]. The convolutional layer uses a kernel of (4 x 4 x 4) with a stride of two, therefore, decreasing the spatial dimensions while increasing the number of filters. The final vector of features is then reshaped into a tensor of size [n] and connected with fully connected layers to the "mean" and "std" layers. These two layers are used to conform a set of n Gaussian distributions with mean and standard deviation given by the output of the layers. These distributions are then randomly sampled to conform the latent vector of the given input. In the decoder, the reverse process is applied, using 3D Transposed Convolutions with kernel size (4 x 4 x 4) and stride of two to increase the spatial dimensions along the decoder, resulting in a tensor of the same dimensions than the input tensor.

This architecture was trained in pytorch [26] using 3d models of chairs, taken from the dataset Shapenet [17] under the category "chair", and converted to a voxelized representation of shape [32 x 32 x 32] via the library Kaolin [27]. A total of 4 samples were used.

The loss function to minimize is a compound function between Binary Cross-Entropy and Kullback-Leibler divergence [28], adjusted with a gain proportional to the epoch number, as shown in 1, with i being the epoch number, y_v the input value of each voxel and $\hat{y_v}$ the predicted value of each voxel. With this loss, we look that, at the beginning of the training, the focal point of the optimization is the reconstruction, meaning, the weights in the convolutional layers. However, as the training advances, the loss gives more weight to the disentanglement of the latent variables, therefore optimizing the latent representation.

$$\begin{aligned} Loss = & -\sum_{v \in V} (y_v \log \hat{y_v} + (1 - y_i v) \log(1 - \hat{y}_v)) \\ & + i\beta \sum_{j=0}^{n} \sigma_j^2 + \mu_j^2 - \log(\sigma_j) - 1 \end{aligned} \tag{1}$$

This training procedure was performed for a different

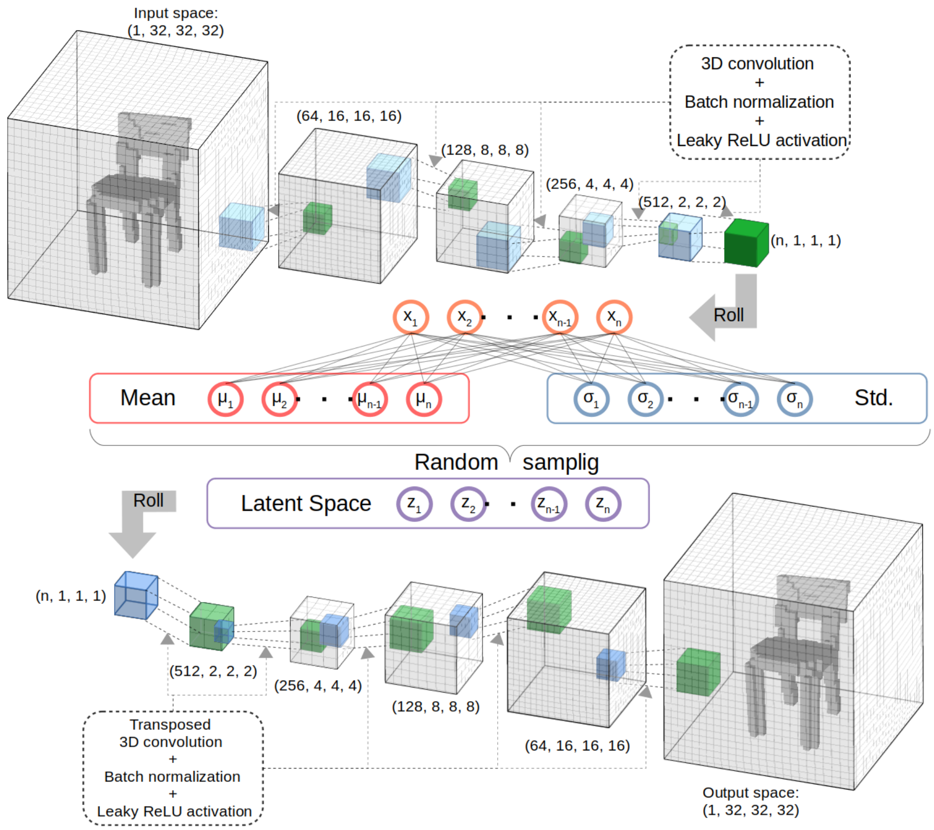

Fig. 2: Network architecture The network architecture. In blue: the input kernels and in green: the output kernels The figure is so wide in order to hold also the printed models to compare with the outcome of the digital platform.

number of dimensions for the latent space and for different number of epochs. We find that the optimal point that minimizes both KL-divergence and reconstruction is $n = 50$ and $Epochs = 100$.

After the training, the samples were obtained by random sampling the latent space with samples from a $N(0, 1)$ distribution. The voxelized representations were transformed to a 3D mesh using the marching cubes algorithm [29], and the artifacts of this transformation were removed using a Laplacian smoothing operation [30] and a re-mesh filter.

Finally, the samples were 3D printed at 1:10 scale using a consumer 3D printer with a wood-filled filament [1]. The results, while not being comparable to the fabrication of a real-scale chair, demonstrate the possibility of manufacturing complex shapes with a wood-like appearance, texture, touch and smell.

III. Conclusions

We have developed a augmented design tool based on Variational Autoencoders for its integration in a Social Manufacturing platform. Specifically we have presented a contextualization of our tool within the INEDIT project framework as a co-creation landscape for furniture manufacturing based on the Do it Together concept. The presented approach, adapted from β-VAE model, will provide a powerful tool for designers but also a help tool for users without any previous experience or expertise in design. The results have shown how Variational Autoenconders provide a robust method for creativity augmentation, which might be a fundamental active tool to increase the knowledge encoded in the CPSS. This works shows how Artificial Intelligence might enhance the capabilities hidden in Social Manufacturing frameworks.

[1]FormFutura Filaments: https://www.formfutura.com/

References

[1] K. Ding, P. Jiang, and X. Zhang, "A framework for implementing social manufacturing system based on customized community space configuration and organization," *Advanced Materials Research, vol. 2450, no. 712, pp. 3191-3194*, 2013.

[2] R. Duray, "Mass customization origins: mass or custom manufacturing?," *International Journal of Operations Production Management, Vol., pp. 314-328*, 2002.

[3] B. D. . F. F. S. Da Silveira, G., "Mass customization: Literature review and research directions," *International Journal of Production Economics, 72(1), 1-13*, 2001.

[4] B. Mohajeri, "Paradigm shift from current manufacturing to social manufacturing," *Aalto University*, 2015.

[5] F. Wang, "From social computing to social manufacturing: The coming industrial revolution and new frontier in cyber-physical-social space," *Bulletin of Chinese Academy of Sciences, vol. 6, no. 1,pp.658-669*, 2012.

[6] P. Jiang, K. Ding, and J. Leng, "Towards a cyber-physical-socialconnected and service-oriented manufacturing paradigm: Social manufacturing," *Manufacturing Letters, vol. 7 pp. 15-21*, 2016.

[7] J. Parrish and W. Hamner, "Animal groups in three dimensions: How species aggregate," *Cambridge University Press*, 1997.

Fig. 3: Results Main results of the VAE at different stages. **A.)** First outcome of the network expressed in voxels with a 32 x 32 x 32 resolution. The figure shows the values of two different outputs from the same class (chairs). **B.)** Shows the results shown in A after smoothing. **C.)** Shows the outcome of our VAE in real scenario. The results obtained from the algorithm are now obtained through additive manufacturing.

[8] T. S. P. F. M. . A. G. Camerlink, I., "The influence of experience on contest assessment strategies," *Sci Rep 7, 14492*, 2017.

[9] J. C. Pomerol, "Artificial intelligence and human decision making," *Eur J Oper Res 99, 3–25*, 1997.

[10] K. R. W. D. M. . S. M. N. Resulaj, A., "Changes of mind in decision-making," *Nature 461, 263–266*, 2009.

[11] Y. Dayan, P. Niv, "Choice values," *Nat Neurosci 9, 987–988*, 2006.

[12] I. Goodfellow, J. Pouget-Abadie, B. Xu, M. Mirza, D. Warde-Farley, S. Ozair, A. Courville, and Y. Bengio, "Generative adversarial nets," *NIPS,2, 5, 6, 8*, 2015.

[13] D. Kingma and W. M., "An introduction to variational autoencoders," *Foundations and Trends R in Machine Learning: Vol. xx, No. xx, pp 1–18. DOI: 10.1561/XXXXXXXXX*, 2019.

[14] W. Wang, Z. Gan, H. Xu, R. Zhang, G. Wang, D. Shen, C. Chen, and L. Carin, "Topic-guided variational auto-encoder for text generation," pp. 166–177, 01 2019.

[15] X. Zhang, Y. Yang, S. Yuan, D. Shen, and L. Carin, "Syntax-infused variational autoencoder for text generation," in *Proceedings of the 57th Annual Meeting of the Association for Computational Linguistics*, (Florence, Italy), pp. 2069–2078, Association for Computational Linguistics, July 2019.

[16] C. Nash and C. Williams, "The shape variational autoencoder: A deep generative model of part-segmented 3d objects," *Computer Graphics Forum*, vol. 36, pp. 1–12, 08 2017.

[17] A. A. Chang, T. Funkhouser, L. Guibas, P. Hanrahan, Q. Huang, Z. Li, S. Savarese, A. Savva, S. Song, H. Su, J. Xiao, L. Yi, and Y. Yu, "Shapenet: An information-rich 3d model repository," *arxiv:1512.03012*, 2015.

[18] "Eu publications office. "cordis site for inedit project". last viewed: 13th dec. 2019. url: https://cordis.europa.eu/project/rcn/224848,"

[19] Y. Kalmykova, M. Sadagopan, and L. Rosado, "Circular economy e from review of theories and practices to development of implementation tools," *Resou. Conserv. Recyc. 135, 190201*, 2018.

[20] J. Kietzmann, L. Pitt, and P. Berthon, "Disruptions, decisions, and destinations: enter the age of 3-d printing and additive manufacturing," *Business Horizons 58, 209–215*, 2015.

[21] C. Burgess, I. Higgins, A. Pal, L. Matthey, N. Watters, G. Desjardins, and A. Lerchner, "Understanding disentangling in β-vae," 04 2018.

[22] I. Higgins, L. Matthey, A. Pal, C. Burgess, X. Glorot, M. M. Botvinick, S. Mohamed, and A. Lerchner, "beta-vae: Learning basic visual concepts with a constrained variational framework," in *ICLR*, 2017.

[23] B. Berman, "3-d printing: The new industrial revolution," *Business Horizons, 55 (2), pp. 155-162*, 2012.

[24] S. Ioffe and C. Szegedy, "Batch normalization: Accelerating deep network training by reducing internal covariate shift," *arXiv preprint arXiv:1502.03167*, 2015.

[25] K. He, X. Zhang, S. Ren, and J. Sun, "Delving deep into rectifiers: Surpassing human-level performance on imagenet classification," 2015.

[26] A. Paszke, S. Gross, S. Chintala, G. Chanan, E. Yang, Z. DeVito, Z. Lin, A. Desmaison, L. Antiga, and A. Lerer, "Automatic differentiation in pytorch," in *NIPS-W*, 2017.

[27] K. J., E. Smith, J.-F. Lafleche, C. Fuji Tsang, A. Rozantsev, W. Chen, T. Xiang, R. Lebaredian, and S. Fidler, "Kaolin: A pytorch library for accelerating 3d deep learning research," *arXiv:1911.05063*, 2019.

[28] V. Prokhorov, E. Shareghi, Y. Li, M. T. Pilehvar, and N. Collier, "On the importance of the kullback-leibler divergence term in variational autoencoders for text generation," 2019.

[29] W. E. Lorensen and H. E. Cline, "Marching cubes: A high resolution 3d surface construction algorithm," *SIGGRAPH Comput. Graph.*, vol. 21, p. 163–169, Aug. 1987.

[30] H. Badri, M. El Hassouni, and D. Aboutajdine, "Kernel-based laplacian smoothing method for 3d mesh denoising," vol. 7340, pp. 77–84, 06 2012.

IV. Acknowledgements

This research has received funding from the European Union's Horizon 2020 research and innovation programme under the project INEDIT with Grant Agreement 869952.

The authors want to thank the comments and fruitful discussions with all the members of the Artificial Intelligence Group at the Robotics and Control Department of AIMEN.