Enhancing Deep Generative Models for Distinguishing Sampling Zeros and Structural Zeros in Population Synthesis

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EXTENDED ABSTRACT

The recent advancements in the field of natural language processing have ushered in the era of ChatGPT. Building on prior deep generative models, these developments leverage the transformer architecture to enhance the model's understanding of the relationships between words and generate coherent responses. A similar innovative approach has been observed in the transportation research field, particularly in the application of activity-based models. One area of focus is population synthesis using deep generative models. Conventionally, household travel surveys have been used to gather data for traffic demand modeling, enabling the study of travel patterns and behaviors. Similarly, to natural language processing tasks, individual trip patterns coupled with socio-demographic information reflect contextual relationships between attributes. To capture this knowledge, we aim to leverage embedding layers extracted by sophisticatedly designed language models. In addition to standard fully connected layers (Dense), our adopted models include LSTM, Multi-head Attention, Seq2Seq, and Transformer models. Furthermore, we incorporate two loss terms into the generative model to ensure that the generated distribution remains within the boundaries of the total population distribution(Kim & Bansal, 2023). This approach helps the model differentiate between sampling zeros and structural zeros, relying on a representative embedding space to measure the minimum distance. Sampling zeros represent attribute combinations that are present in the population but missing from the household travel survey samples, whereas structural zeros refer to infeasible or invalid attribute combinations. The challenge lies in generating sampling zeros to enhance diversity while avoiding the generation of structural zeros. During training, there is a risk of unintentionally distorting the embedding space, which can lead to the generation of structural zeros, as illustrated in the Figure 1.

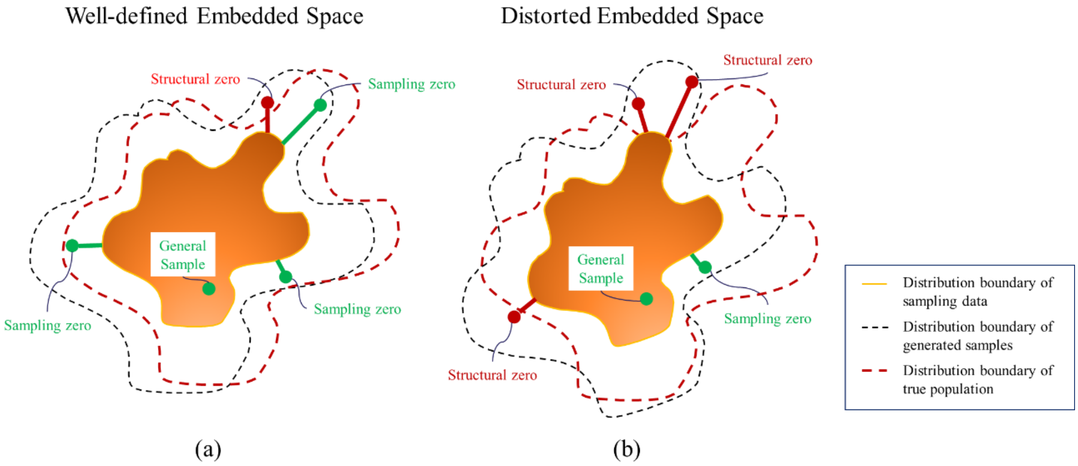

Figure 1 Generation of sampling zeros and structural zeros based on the embedding space. (a) Desirable Embedded Space. (b) Distorted Embedded Space

In the population synthesis task, Wasserstein Generative Adversarial Networks (WGANs) have been employed to predict rare feature combinations while taking into account sampling zeros and structural zeros(Gulrajani et al., 2017). The accuracy of predicting target attribute results is assessed for each masking combination, and the test loss from the best models is reported. To facilitate multi-class classification tasks, we utilized the commonly used sparse categorical entropy loss function. The performance of the WGAN model is evaluated using precision and recall, which collectively measure the feasibility and diversity of the generated samples, as summarized in Table 1 and Table 2.

Table 1 Evaluation Metrics for Masked Attribute Combinations Performance

	Dense	**LSTM**	**Seq2Seq**	**Multi-head Attention**	**Transformers**
Masking 1	0.818	0.844	0.834	0.843	0.846
Masking 2	0.809	0.846	0.834	0.842	0.849
Masking 3	0.806	0.847	0.834	0.843	0.850
Masking 4	0.767	0.849	0.833	0.842	0.849
Masking 5	0.729	0.848	0.832	0.842	0.850
Test Loss	2.563	1.691	1.863	1.778	1.669

Table 2 Performance measurement of the WGAN model

	Dense	**LSTM**	**Seq2Seq**	**Multi-head Attention**	**Transformers**
Precision	0.764	0.779	0.786	0.793	0.824
Recall	0.520	0.549	0.459	0.560	0.576
F1	0.618	0.644	0.579	0.656	0.678

Obtaining an accurate population is a critical concern that impacts the entire process. It forms the basis for defining activity generation and scheduling, and even a minor error in population synthesis can accumulate and result in undesirable outcomes(Garrido et al., 2020). Hence, it is essential to effectively extract the embedding space from the sample data to achieve desirable results using the DGM methodology. Our findings suggest that a well-trained model capable of capturing contextual relationships can greatly enhance the performance of DGM.

Keywords: Synthetic population, Activity-based model, Deep generative model, Pre-trained language model

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