This inequality does not exist: Repurposing generative AI to study urban deprivation in the UK

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I. A GAN trained on the streets of London

This inequality does not exist is a generative model and an interactive interface that describe visual features associated with urban deprivation and privilege in London. The project attempts to "*think with AI*", i.e. develop models to clarify conceptual implications otherwise unseen. Though the model has limitations, it probes what type of knowledge generative models can produce from large visual datasets and how synthetic images can be read as research material.

Figure 1: Examples of actual (non-synthetic) Streetview photographs from London

For the project, a StyleGAN2 model was trained on 14,564 photographs of housing in London, sourced from Google Streetview. StyleGAN2 is a canonical Generative Adversarial Network (GAN).

II. Photographs into vectors

GANs work by identifying a continuous shape (called a *manifold*) close to which most data points (Streetview photographs) in the training set lie. They then map data points from a Gaussian distribution from a so-called latent space onto the manifold. Distinct features of the generated images can be controlled or modified independently by moving along specific directions in the latent space.

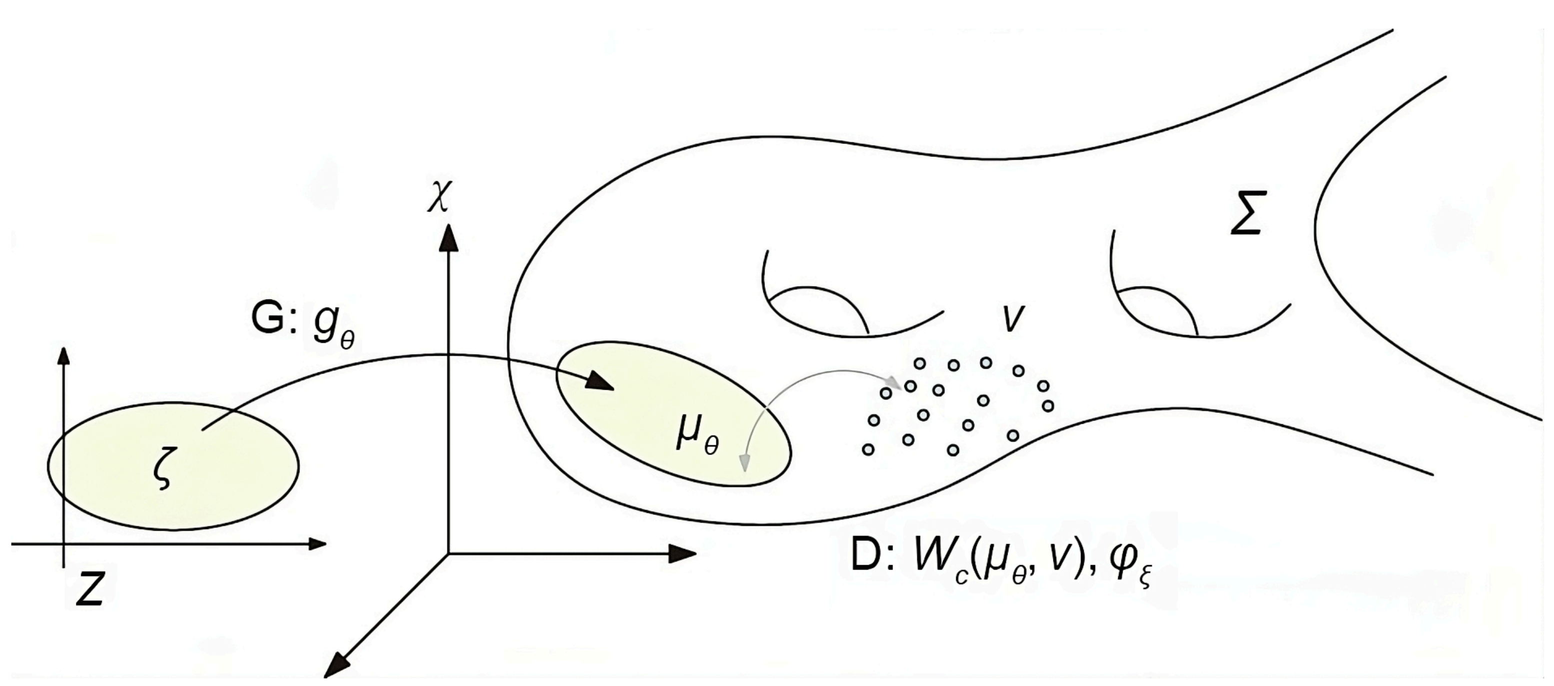

Figure 2: GAN models learn a generator G that maps latent space Z to the manifold V

After training the GAN, the next step is to find points in the latent space that correspond as closely as possible to the Streetview photographs. We compare results from three methods (Encoder4Editing, ReStyle and the StyleGAN2-ADA optimiser). The inversion process loses many visual features from the Streetview photographs.

III. Finding the visual features of inequality

Each Streetview photograph is connected with a point in the latent space and with socioeconomic data about the level of income, health and education related to the area where the photograph was taken. The statistics are from the Indices of Multiple Deprivation (IMD), published by the UK government.

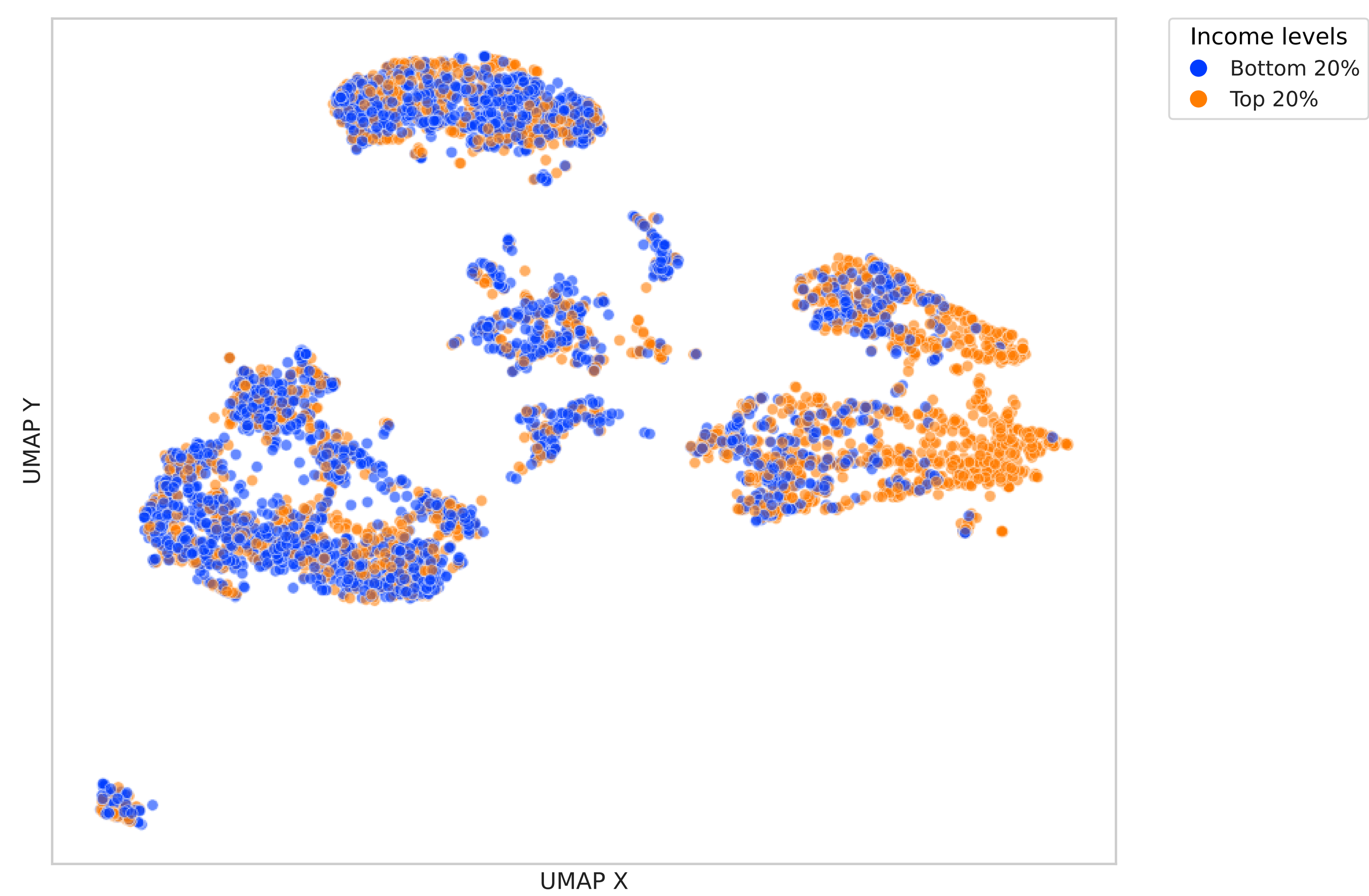

Figure 3: A two-dimensional projection of Streetview photographs in high-dimensional latent space from high- and low-income locations

Another model is then used to map which regions of the model's latent space correspond to the socioeconomic features of London. A support vector machine (SVM) finds a separation boundary in the latent space between data points from the low and high end of the scale in health, income and education. The high accuracy of the SVM (see Table 1) suggests the latent space contains relevant features for distinguishing between deprived and privileged areas.

Dimension	Inversion Method	Precision	Recall	F1 score
Income	E4E	0.794	0.721	0.756
Education	E4E	0.769	0.781	0.775
Health	E4E	0.899	0.754	0.820
Income	Restyle	0.788	0.772	0.780
Education	Restyle	0.773	0.763	0.768
Health	Restyle	0.836	0.788	0.811
Income	SG2-ADA	0.716	0.738	0.727
Education	SG2-ADA	0.735	0.700	0.717
Health	SG2-ADA	0.747	0.738	0.742

Table 1. Precision, recall and F1 scores for SVM classification in three distinct dimensions and with three inversion methods

IV. Walking in the latent space

A random location in the latent space corresponds to some synthetic image. If one takes the separation boundary found by the SVM and moves to a direction perpendicular to this boundary in latent space, the image will change according to the visual features typical for deprived or privileged areas. There are distinct boundaries for health, income and education.

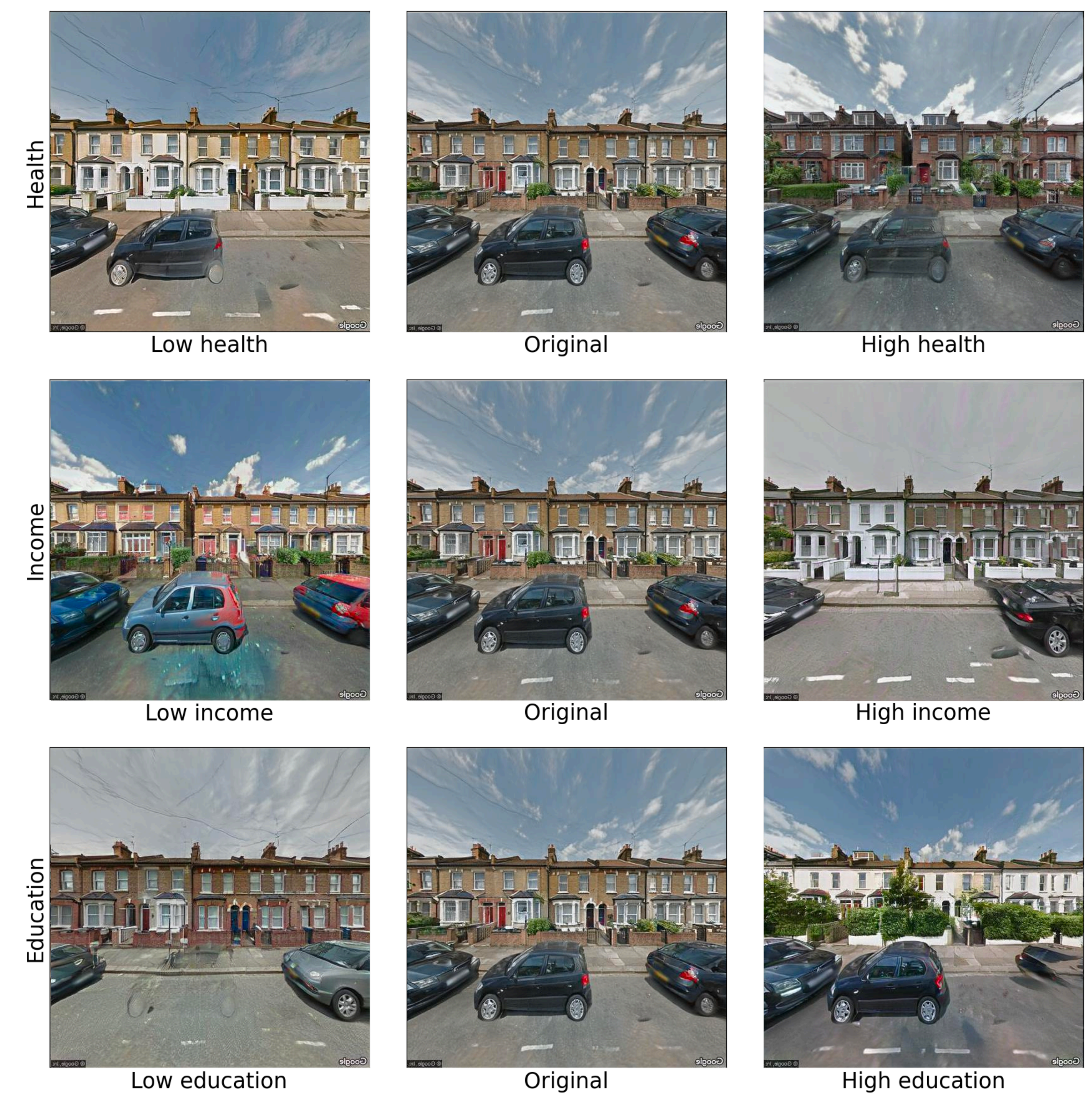

Figure 4: A matrix displaying a single synthetic image manipulated in 3 different dimensions (health, income and education)

Since the visual features corresponding with socioeconomic variables are unknown, comparing images generated through a walk in the model's latent space reveals something new. One way to organise such comparisons is by displaying images in a table. Figure 4 is a table that shows changes to a single generated image according to health, income and education. It is also possible to move in the latent space continuously and to combine the dimensions of health, income and education. An interactive interface for this is published on the web and is displayed next to this poster.

The interactive interface to the model, a technical paper and a blog post with further details are available at https://knuutila.net/thisinequality.