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USING DEEP LEARNING TO QUANTIFY THE BEAUTY OF OUTDOOR PLACES

This briefing has been prepared by the Data Science Lab, Warwick Business School, University of Warwick.

Context

Beautiful outdoor locations are often protected by governments. In a previous study, we provided evidence that scenic urban, suburban and rural environments are associated with better health. But what makes an outdoor space beautiful? Does a beautiful outdoor location differ from an outdoor location that is simply natural?

Here, we explore whether ratings of over 200,000 images of Great Britain from the online game *Scenic-Or-Not*, combined with hundreds of image features extracted using a 'deep learning' algorithm, might help us understand what beautiful outdoor spaces are composed of.

Key findings

We used the *MIT Places Convolutional Neural Network* – a 'deep learning' model – to analyse the images from *Scenic-Or-Not*, which were rated over 1.5 million times, and find which visual attributes, such as 'trees', 'mountain', 'hospital' and 'highway', corresponded to high and low scenic ratings.

Key takeaways

- We have previously found that people who live in areas rated as more scenic report their health to be better, even when data on greenspace and indicators of deprivation are taken into account. This relationship holds in urban areas, suburban areas and rural areas alike.
- Here, we investigate what makes an outdoor space beautiful. In urban areas, we find that canals and rivers are related to greater city beauty, as well as tree-lined paths and formal gardens.
- However, we find that beautiful places are not only composed of natural elements; man-made features such as bridge-like structures and characterful buildings can also increase the beauty of a scene.
- Large areas of grass are associated with lower scenic ratings. It might be that such areas result in an uninteresting scene.

Deep learning models are a particular kind of 'neural network' – simulated networks of neurons, like those in the human brain – and have driven recent dramatic advances in artificial intelligence tasks, such as facial recognition and speech recognition.

Across Great Britain as a whole, we find results that accord with intuition. Features such as 'valley', 'coast' and 'mountain' are most associated with higher scenic ratings, whereas features such as 'construction site', 'industrial area', 'hospital', and 'parking lot' are most associated with lower scenic ratings.

Interestingly however, we also see associations that contradict the simple "what is natural is beautiful" explanation. In urban areas, we find that 'canal natural', 'forest path' and 'river' are associated with higher scenic ratings, but also buildings with character, such as 'church', 'castle', 'tower' and 'cottage', as well as bridge-like structures such as 'viaduct' and 'aqueduct'.

Similarly, in urban areas and across Great Britain as a whole, we find that features reflecting large areas of grass, such as 'grass' and 'athletic field', lead to lower rather than higher scenic ratings. It might be that areas that contain the most grass lack other features, such as trees, resulting in an uninteresting scene.

We also provide evidence that we can train a deep learning model to rate photographs for scenic beauty itself. When identifying the top 5% scenic views in London, the model again chooses images not only of natural areas such as Hampstead Heath, but also built locations such as Big Ben and the Tower of London.

Scenic environments and health

In a previous study, we compared the crowdsourced scenic ratings from *Scenic-Or-Not* to data on self-reported health from the Census for England and Wales. We found that people who live in areas rated as more scenic reported their health to be better. This relationship holds across urban, suburban and rural areas, even when taking data on socioeconomic indicators of deprivation into account. Crucially, while previous studies have provided evidence of a link between greenspace and health, we found that traditional measurements of greenspace from aerial photography are not sufficient to explain the relationship between scenic locations and health.

Our new findings from our deep learning analysis help explain why the measurements of greenspace and the measurements of environmental aesthetics differ. We suggest that the distinction between greenspace and environmental aesthetics has relevance for planning decisions which aim to improve the wellbeing of local inhabitants.

The new deep learning model we train also opens up the possibility of generating quantitative data on outdoor beauty at great scale, without the need for crowdsourcing human ratings. Such measurements may be of use in valuing both natural and urban environments.

Further information

This briefing is based on:

Seresinhe, C. I., Preis, T., & Moat, H. S. (2017). Using deep learning to quantify the beauty of outdoor places. *Royal Society Open Science, 4,* 170170.
rsos.royalsocietypublishing.org/content/4/7/170170

Seresinhe, C. I., Preis, T., & Moat, H. S. (2015). Quantifying the impact of scenic environments on health. *Scientific Reports, 5,* 16899.
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