







Using deep learning to get computers to recognize beautiful places

July 19 2017, by Bob Yirka



(a)

most scenic images						
Places365 categories	0.293 valley 0.203 lake natural 0.128 mountain	0.686 lake natural 0.129 river 0.080 valley	0.857 forest broadleaf 0.114 forest path 0.018 field wild	0.514 castle 0.152 ruin 0.047 kasbah	0.594 mountain path 0.337 tundra 0.026 valley	0.245 mountain snowy 0.203 ski slope 0.130 desert sand
SUN scene attributes	0.856 natural light 0.081 open area 0.058 sailing/boating	0.686 natural light 0.129 still water 0.080 natural	0.953 natural light 0.046 no horizon	0.954 man made 0.045 open area 0.001 natural light	0.997 natural light 0.002 open area 0.001 hiking	0.832 open area 0.127 natural light 0.017 far away horizon

(b)

most unscenic images						
Places365 categories	0.947 industrial area 0.026 water tower 0.011 construction site	0.986 highway 0.003 raceway 0.003 forest road	0.505 construction site 0.363 parking garage 0.044 industrial area	0.279 industrial area 0.157 campus 0.119 office building	0.406 res. neighbourhood 0.187 industrial area 0.065 motel	0.251 farm 0.175 field cultivated 0.112 vineyard
SUN scene attributes	0.565 man made 0.405 open area 0.021 natural light	1.000 man made	0.557 man made 0.44 natural light 0.002 open area	1.000 man made	0.867 grass 0.061 open area 0.037 man made	0.672 open area 0.200 natural light 0.066 vegetation

(c)

most scenic urban built-up images						
Places365 categories	0.786 canal natural 0.107 moat water 0.025 river	0.787 forest road 0.064 driveway 0.040 forest path	0.611 formal garden 0.093 topiary garden 0.056 oast house	0.948 cottage 0.033 oast house 0.016 house	0.987 viaduct 0.007 arch 0.003 aqueduct	0.588 church outdoor 0.181 tower 0.058 ruin
SUN scene attributes	0.982 natural light 0.013 trees 0.003 open area	0.999 trees	0.652 grass 0.127 foliage 0.074 open area	0.991 man made 0.008 shingles 0.001 natural light	0.989 open area 0.010 man made	0.518 vertical components 0.288 touring 0.107 natural light

Top three place categories and top three scene attributes of sample scenic and unscenic images across Great Britain. To help us understand what elements comprise scenic and unscenic images, for each Scenic-Or-Not image, we extract the probability of 102 scene attributes (e.g. ‘natural’, ‘man made’ and ‘open area’) and 365 place categories (e.g. ‘mountain’, ‘lake natural’, ‘residential neighbourhood’) using the Places CNN. Note that only those categories and

features given a probability of 0.001 or higher have been included in the figure.
Credit: *Royal Society Open Science* (2017). DOI: 10.1098/rsos.170170

(TechXplore)—A trio of researchers with the University of Warwick in the U.K. has used a deep learning algorithm to help a computer system better understand what constitutes a beautiful place. In their paper published in the journal *Royal Society Open Science*, the group describes how they trained their system, how well it worked and possible applications.

Beauty, as the saying goes, is in the eye of the beholder. That being said, humans are remarkably consistent when appraising the beauty of a person, place or thing. Show slides of places around the globe to a group of individuals, and they will most likely agree on which are beautiful places and which are eyesores. In this new effort, the researchers sought to use a deep learning algorithm to give a computer the same sort of ability.

To teach the computer system, the researchers fed it 20,000 pictures posted on the website Scenic-or-Not, which, as its name implies, allows visitors to rate photos of British locations on how beautiful or ugly they are. The researchers also fed the ratings into the [computer](#). The deep learning system analyzed the images, noting similarities and differences between them looking for features identified with beauty. It then used what it had learned to create a ratings system for itself that could be used as a means to judge whether a given image was beautiful or ugly.

In testing the system, the researchers found it to be quite accurate—it found pictures of South Wheal Frances, Embley Wood and Loch Scavaig to be quite beautiful, for example, as would most people. And it found places like the A42, the old Brancepeth Works and a view of Rake

Lane in Cheshire to be quite ugly, as many have noted on social media.

Notably, the researchers found that the system identified beauty in both the natural and man-made world, just as humans do, though notably, it also panned some scenes that people might argue are quite beautiful—like stretches of flat green grass.

More information: Chanuki Illushka Seresinhe et al. Using deep learning to quantify the beauty of outdoor places, *Royal Society Open Science* (2017). [DOI: 10.1098/rsos.170170](https://doi.org/10.1098/rsos.170170)

Abstract

Beautiful outdoor locations are protected by governments and have recently been shown to be 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 the Places Convolutional Neural Network, might help us understand what beautiful outdoor spaces are composed of. We discover that, as well as natural features such as 'Coast', 'Mountain' and 'Canal Natural', man-made structures such as 'Tower', 'Castle' and 'Viaduct' lead to places being considered more scenic. Importantly, while scenes containing 'Trees' tend to rate highly, places containing more bland natural green features such as 'Grass' and 'Athletic Fields' are considered less scenic. We also find that a neural network can be trained to automatically identify scenic places, and that this network highlights both natural and built locations. Our findings demonstrate how online data combined with neural networks can provide a deeper understanding of what environments we might find beautiful and offer quantitative insights for policymakers charged with design and protection of our built and natural environments.

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