Satellite Image Spoofing: Creating Remote Sensing Dataset with Generative Adversarial Networks

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Abstract

The rise of Artificial Intelligence (AI) has brought up both opportunities and challenges for today's evolving GIScience. Its ability in image classification, object detection and feature extraction has been frequently praised. However, it may also apply for falsifying geospatial data. To demonstrate the thrilling power of AI, this research explored the potentials of deep learning algorithms in capturing geographic features and creating fake satellite images according to the learned 'sense'. Specifically, Generative Adversarial Networks (GANs) is used to capture geographic features of a certain place from a group of web maps and satellite images, and transfer the features to another place. Corvallis is selected as the study area, and fake datasets with 'learned' style from three big cities (i.e. New York City, Seattle and Beijing) are generated through CycleGAN. The empirical results show that GANs can 'remember' a certain 'sense of place' and further apply that 'sense' to another place. With this paper, we would like to raise both public and GIScientists' awareness in the potential occurrence of fake satellite images, and its impacts on various geospatial applications, such as environmental monitoring, urban planning, and land use development.

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1 Introduction

Deep learning and Artificial intelligence (AI) techniques are attracting more and more attentions from geographers and spatial scientists. Big data with geospatial information like satellite images and crowdsourcing data are perfect input for computer-based learning algorithms, especially considering the huge success of machine learning and deep learning methods in computer vision problems, such as image classification, object detection and feature extraction[1]. Deep neural networks are developed so powerful that they are applied to enable geospatial system to capture underlying features and patterns at a near-human perception level[6]. For example, recent studies indicate that convolutional neural networks (CNNs) are highly effective in perceiving features in large-scale image recognition and semantic segmentation[5, 7]. Deep learning algorithm can facilitate the research in the domain of geoscience and remote sensing, and it is encouraged to be used with expertise from

Figure 1 Input Datasets:(a) Google satellite images; (b) CartoDB basemap.

geospatial and remote-sensing scientists as an implicit general model to tackle large-scale and unprecedented challenges like climate change and urbanization[8].

But can AI be trusted to take care of our location information? How can we deal with fake information if deep learning and AI act as a 'bad' agency? 'Fake' is a big concern because of the popularity of fake news and post-truth politics. In geography, the falsification and spoofing of geospatial data have become a heated topics[9]. And 'fake' has also been a highly popular word in AI since 2014, when Generative Adversarial Networks (GANs) were introduced by Ian Goodfellow as a kind of artificial intelligence algorithm with huge potential to mimic various data distribution[2]. GANs have been used in hyperspectral image classification as a semi-supervised learning algorithm[3]. It provides us insight into how the machine can 'remember' what it saw in the past, and then generate fake data in any fields like image, speech or music. Instead of being used as a potential tool to deal with pragmatic mapping issue in cartography, will it be meaningful and operable to create fake satellite images with a certain kind of patterns or features?

To answer this question, this study aims to explore the potentials of GANs in capturing geographic features and whether the machine can generate a 'sense of place' like humans. Previous studies have indicated that it is possible to generate satellite images from street map through a mapping from image to image (or from pixel to pixel)[4, 10].In this study, Corvallis is used as the place of study, and fake satellite images with a certain style will be generated through GANs to discuss this problem.

2 Data and method

2.1 Data

Satellite images from Google Earth and positron (no label) basemap from CartoDB are used as input datasets in this study. Positron basemaps from CartoDB are developed based on data from OpenStreetMap. The basemap is designed with latest data and has limited color schemes, which gives users freedom to customize according to their visualization use. Satellite images and maps are collected as multi-level raster tiles through a script based on Google maps API and Qtile in QGIS. The image tile is 512*512.

2.2 Method

Cycle-Consistent Adversarial Networks (CycleGAN)[10]were implemented in this study to train the model from training set and generate fake satellite images. CycleGAN is a kind of image-to-image translation algorithm that can work without paired examples

Figure 2 Satellite images and basemaps of three cities (i.e. New York City, Seattle and Beijing) were used as input dataset for CycleGAN to extract city styles. Corvallis in Oregon is used as a sample for fake satellite images generation.

of transformation from source to target domain. Compared to previous image-to-image translation algorithm Pix2Pix, CycleGAN can learn the transformation without one to one mapping. Adversarial losses and cycle consistency losses are applied to mapping functions as follows[10]:

$$\mathcal{L}_{cyc}(G,F) = \mathbb{E}_{x\sim p_{data}(x)}[\|F(G(x)) - x\|_1] + \mathbb{E}_{y\sim p_{data}(y)}[\|G(F(y)) - y\|_1]. \tag{1}$$

$$\mathcal{L}_{GAN} = \mathbb{E}_{y\sim p_{data}(y)}[\log D_Y(y)] + \mathbb{E}_{x\sim p_{data}(x)}[\log(1 - D_Y(G(x)))]. \tag{2}$$

In this study, CycleGAN was used to reconstruct the satellite imagery from its basemap tiles for three typical cities in the world: New York City, Seattle and Beijing. It is assumed in this study that these three cities have different urban styles. As the center of the New York metropolitan area, New York City is the most populous urban agglomerations with a modern style, while buildings in Seattle have relatively low heights even in the urban center. Beijing is a hybrid of historical and modern style, with most urban area has been covered with tall buildings and new architectures. The geographic features are shown on the satellite images with different textures, such as shade, color scheme or spectral signatures, which are significant information for image interpretation and supervised classification. Despite of the spatial heterogeneity in internal urban area, these three cities in general give people different sense of place, which is a little bit obscure and elusive. Although hard to describe and quantify, we can still differentiate cities with their features from satellite images.

To examine whether it is possible for CycleGAN to extract city styles and transfer the potentially learned style to another place, Corvallis, where Oregon State University locates, was then used as a sample for generating satellite images. For the training dataset, there are 1066, 1196 and 1122 pairs of images for New York City, Seattle and Beijing respectively, and there are 360 map tiles covering Corvallis.

3 Result

3.1 Training process

Taking the training process with input data from Seattle as an example, CycleGAN training process was set with 200 epochs. Figure 3 shows some results during training process. After the first epoch, the training model can learn and generate some geometric features. More

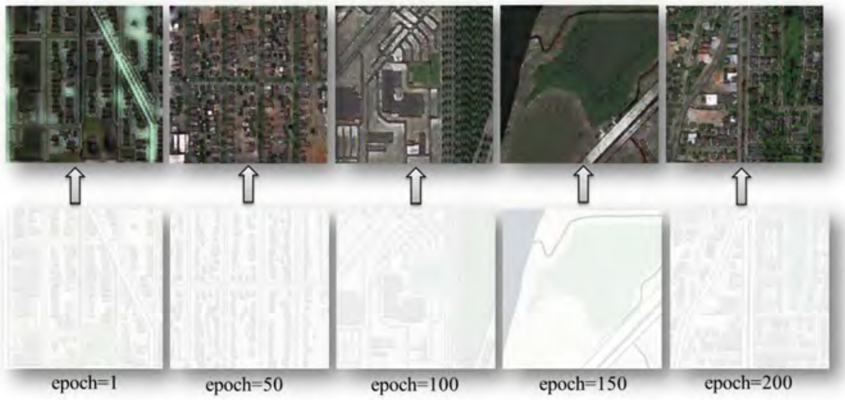

Figure 3 Some results during training process using training dataset of Seattle.

details can be captured and created as the number of epoch increases. As the basemap has limited color schemes, CycleGAN seems very sensitive in capturing green land.

3.2 Fake image generated for a single tile

It is difficult to quantify geographic features with a certain character or pattern, especially taking spatial variability and heterogeneity into account. Landscape exhibits various patterns and processes in different scales. However, it seems that CycleGAN is able to extract some general features from spatial distribution of city structures.

Take a specific location in northwest of Corvallis as an illustration. In general, three models are performing well in generating green land in the park area. But the details differ.

Although the fake satellite image with New York's style failed to generate details in some community block, some structures like tall building are created in the left corner of the image. And the one with Seattle's style has more detailed information, including low houses and buildings created around the park. What's more, the fake image with Beijing's style has most detailed information of tall buildings and shadow around them.

3.3 Fake images generated in a large scale

To examine the stability of the training model, fake satellite images are generated in a relatively large-scale area north to Oregon State University. Nine tiles covering this area are put together using mosaic method.

As New York model was not well-trained and failed to generate detailed information, fake satellite images with Seattle and Beijing are generated to examine the stability of the model in a large scale. Due to the blank in the northeast area of the basemap, less details are generated there compared to other areas in the fake satellite images with Seattle's style. Generally speaking, the images created from the model have similar pattern and style with Corvallis in terms of geographic characteristics.

But we can easily differentiate the fake images with transferred style from Beijing with that of Seattle. As is shown in figure 5, almost all building created with Beijing's style are tall with shadows. The fake city is really crowded considering the small block. As the real satellite images from Beijing have various temporal resolutions, the shadows looks unreasonable as the sunshine looks from various directions. However, the style of the imaginary city looks pretty unify across the whole area. In terms of the mosaic, no obvious edge could be observed

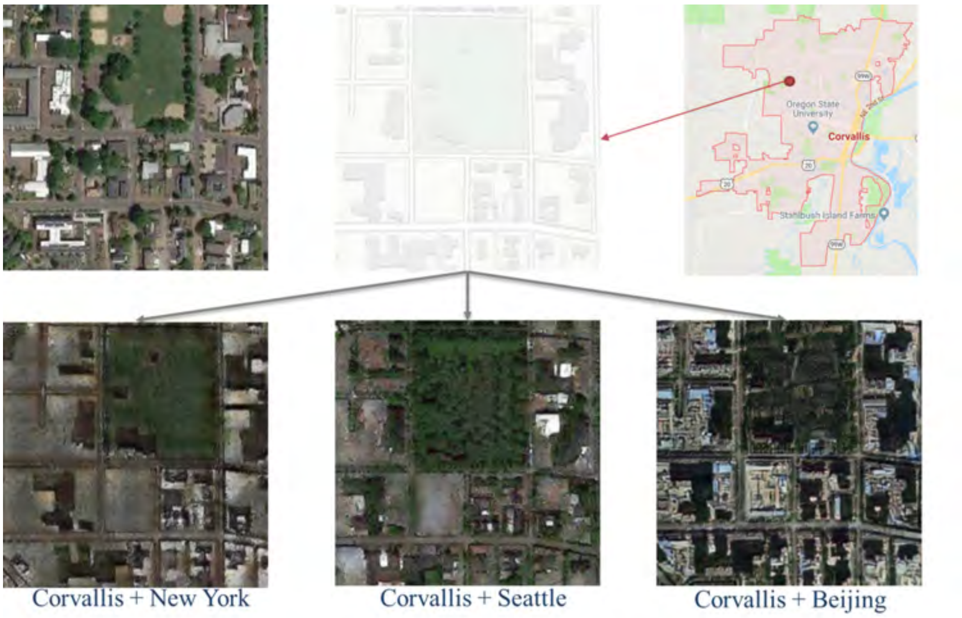

Figure 4 Fake satellite image with transferred style from different cities for a single tile.

Figure 5 (a) CartoDB basemap of large-scale study area in Corvallis;(b) Fake satellite image with transferred style from Seattle; (c)Fake satellite image with transferred style from Beijing.

from the image edges, which suggests that the model performs well and generates stable results for this area in Corvallis.

4 Conclusion and discussion

CycleGAN and Pix2Pix networks have the ability to generate non-exist but realistic images. This study explored whether it can capture complicated geographic features and patterns from a large dataset of a certain city, and transfer the style to another place in a large scale. The results show that CycleGAN can learn general styles from input dataset. And it seems that the more specific features the dataset share, the better CycleGAN model performs. There are big potentials to use CycleGAN or Pix2Pix mapping to transfer city styles and geographic features from one place to another, which provides us insight into its future use in urban planning or visualization.

To some extent, Geographic feature is a very elusive concept to perceive. We tend to develop sense of place based on our impression and experience subconsciously. However, it is very difficult to quantify our feelings. CycleGAN may provide a new perspective on how we think of a certain place with a vivid way.

There are many potential directions worth further exploration. Firstly, CartoDB Positron basemap has limited color schemes and symbols. Although this can give GANs a great deal of latitude to generate fake images, it also 'confuses' the machine. Therefore other map style may improve the performance of the model efficiently. Second, GANs are often regarded as an unsupervised learning algorithm, but more expertise from geographers or spatial scientists is necessary to develop the training set and the network architectures. Moreover, instead of taking the whole city as the input, using certain type of landscape or building as training set may generate much better images.

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