Machine Learning Final Project: Detecting Volcanoes on Venus

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Abstract

One of the most time-consuming aspects of studying planetary geology is having to painstakingly comb through hundreds to thousands of satellite images and radar data to identify various topographic features. Automating this process could greatly ease the workload on planetary scientists, and their research assistants. Using a relatively simple multilayer perceptron trained on volcanic features found on the surface of Venus, I am able to identify other volcanoes with an accuracy up to around 93%. Similar algorithms hold promise in potentially being able to automate the mapping of relatively large-scale topographic features on other planets.

Introduction

One of the primary challenges in studying rocky planets within our solar system is that nearly all of our data comes from satellite imagery. Such large datasets can be incredibly difficult and time consuming to go through by hand and identify features of importance, geologic or otherwise.

Notably, volcanism plays an important role in the formation of rocky planets, and its spatial distribution across a planet, as well the differing morphologies of volcanoes can lend significant insight on the geology of a planet, its formation, and the presence or lack of active or historical plate tectonics, further informing us of the underlying processes that drive plate tectonics and how they likely occurred on Earth. However, in order to investigate this, we need to be well informed on the spatial distribution, size, and varying morphology of volcanic features.

On Earth, we have well supported evidence of plate tectonics (Burke, 2011; Wilson, 1965). As far as volcanism in concerned, this evidence consists of three patterns of volcanoes: Arc-volcanism, hot spot volcanism, and spreading centers or rifts. While each of these have different and discernable characteristics, the first two are similar in that they generally consist of linear strings of volcanoes. While arc-volcanism generally produces multiple volcanoes at the same time, hot spots generally yield strings of volcanoes that grow younger in age mirroring the movement of the overriding crust.

Despite finer differences in geology and morphology, the volcanoes formed by these two processes are largely circular mountains, and as such provide a suitable task for a relatively simple neural network, in this case a multilayer perceptron. While volcanoes on Earth can be broadly classified into four different categories based largely on morphology alone (shield, strato, cinder come, and rhyolite dome), we make no attempt to classify them here as ground truth itself is difficult to confirm (M. C. Burl et al., 1994). Many landforms including craters, mountains, and geologic structures can produce similar patterns as volcanoes on a region's topography (Baioni & Wezel, 2010; Dietz et al., 1969), thus trying to ascertain certain geologic properties would almost certainly be pushing the limits of what the data allows.

Data

In May of 1989, the Magellan probe was launched and sent to orbit Venus, with the goal of using Synthetic Aperture Radar (SAR) to map the surface topography of the planet. The probe was able to acquire topographic data of over 80% of the surface of Venus over its 5 year lifetime (Michael C Burl et al., 1998; Meyer & Sandwell, 2012; Saunders, 1992). The dataset used was compiled by the University of California, Irvine Machine Learning and downloaded from Kaggle. It contains 9734 different images of resolution 110 x 110. All images only contain one channel derived from the synthetic aperture radar, representing line of site distance between the ground and the satellite, scaled to be from 0 to 255, effectively representing a scaled topography of the planet. The dataset was also pre-split into a training set of 7000 individual images and a test set of 2734 individual images.

Methods

In developing a multilayer perceptron to identify volcanoes, multiple configurations were attempted. First, I started with a simple network with one hidden layer of 8 nodes, using a sigmoid activation function. Parameters and methods that were edited include number of nodes, number of layers, various combinations of activation functions, stochastic and batch gradient descent, learning rate, and number of epochs.

Building off of the initial run, subsequent iterations of the model used up to three layers with the largest including 128 different nodes, with the number of nodes decreasing in subsequent layers. The final configuration of hidden layers I settled on included two separate layers, with the first layer consisting of 16 nodes and the second layer consisting of 8 nodes. It is notable to mention that versions of the model with fewer nodes didn't necessarily preform worse, they required more epochs and a smaller learning rate.

In total, I tried using six different activation functions within the neural network (sigmoid, sin, tan, sinh, cosh, and ReLu). Most of the functions resulted in different levels of accuracy in the training and test sets though certain functions yielded far lower accuracies than others, notably, the worst came from using tangent, while sigmoid, and hyperbolic sine and cosine resulted in similar mid-range accuracies. The final configuration that yielded the highest accuracy for the test set used both cosine and rectified linear units for the activation functions, faring slightly better than using only ReLu, and closely followed by sine and cosine.

Additionally, I did test modifications to batch size, learning rate, and number of epochs, the changes did not significantly increase test set accuracy without significantly increasing required computation time. Furthermore, when the number of epochs was significantly increased, the algorithm began to memorize the training set at the expense of test set accuracy, indicating that some data augmentation might help improve the model though this was not attempted as the accuracy, even with such a simple neural network, was high enough yield good results and predictive capability.

Results

Of all the different neural network configurations attempted, the maximum test set accuracy approached 93-94% with a training set accuracy closer to 96%. This was achieved using two hidden layers, the first with 16 nodes and the second with 8 nodes. Additionally two different activation functions were used, first cosine, then rectified linear units. Using different activation functions tended to yield a test set accuracy of around 85%, except for tangent which was closer to 60%. Using fewer nodes than 8 in any hidden layer also decreased the test set accuracy to less than 90%, while using a single hidden layer with less than 8 nodes had test set accuracies ranging from around 30% to 82% depending on the activation function used, unsurprisingly indicating that the activation functions play a more important role than the number of nodes or hidden layers.

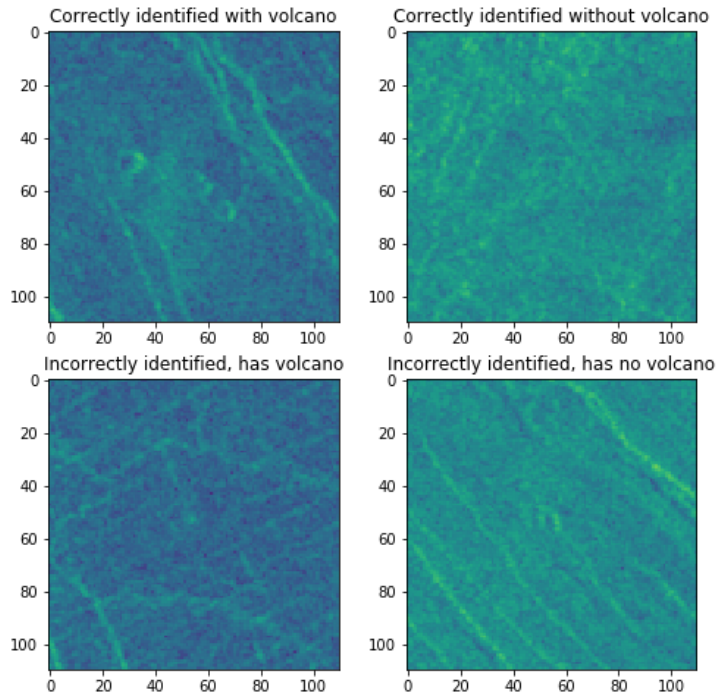

Figure 1: Example of different correctly and incorrectly classified images.

Looking through some examples of correctly and incorrectly classified images (Figure 1), it seems clear that while the size of the volcano does not seem to matter as long at it is large enough to appear at the resolution of these images. The algorithm appears likely to get confused on images where there are lineations in addition to the round forms of volcanoes. Additionally, images where there is significant noise tend to also result in misclassifications. Lastly, there are a few misclassified images (not pictured), that show no apparent round volcanic forms, but instead have wide linear features which have been identified as volcanic rifts, which suggests that the algorithm is largely looking for points or round forms to identify as volcanic features.

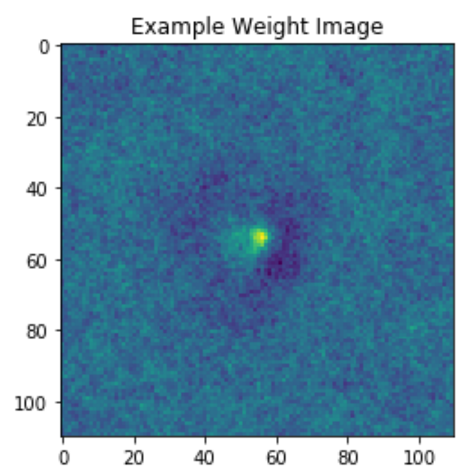

Figure 2: Example weight image

Discussion and Conclusion

One of the largest problems that this algorithm seems to have is in identifying volcanoes when there are larger topographic features that stand out prominently in the images, in addition to correctly classifying features as volcanic when they are not of the standard volcano morphology (ie round, and raised portions of the ground).

For instance, it is easy to understand why such a simple algorithm may not recognize a rift, being a linear feature, as volcanic when there have been several volcanic rifts identified on the Venusian surface (Campbell et al., 1984). Looking at the images made by the algorithm in training, nearly all of them look incredibly similar to the example in figure 2, thus the algorithm is effectively searching for dots at different elevations than the surrounding ground, potentially surrounded by concentric rings of somewhat uniform elevation. In addition to the problems in identifying more linear volcanic features, images with multiple volcanoes may also be misclassified more often. With these pitfalls, it is possible to speculate on how we can improve the accuracy of the algorithm. Obviously, more data in the training set would likely improve the predictive capability, but data augmentation also seems like a good idea moving forward.

While this model was trained on data from the Venusian surface, its simplicity and relatively high accuracy suggests that it may be useful to try and identify similar features using synthetic aperture radar data from other planets. While using it on earth would likely prove to be ineffective due to the vastly different speeds of erosion on each planet, one without running water, like mars, may yield more promising results. Additionally, it is easy to envision a similar algorithm being trained on different or more geometrically complex topographic features, for instance mountains ranges, valleys, faults, and landslide scarps to see if it can also effectively identify those features on Venus, as well as other planets.

Sources

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