Futuristic LANDSAT View

Literature Review

Before specific works are discussed below, it is important to note that most papers working with satellite images and using them to make predictions in many different ways. Satellite images are available of various kinds. We use data from the Landstat 7 collection. Whereas most other works focus on specific classification or regression goals, using heatmaps, satellite data distributions etc., our goal is generative. Here is the literature we found on various procedures employed to fulfill our objective within and outside of our field of satellite images.

Learning Continuous Face Age Progression: A Pyramid of GANs

The first paper reviewed is Hongyu Yang et al.'s Continuous Face Age Progression paper which catches one's attention when thinking of capturing and recreating transformations through time. Staying with our goal of generating an image based on land image progression, this paper employs a special architecture of GANs to synthesize an image to show how a person would look as they grow older.

A single generator is trained and multiple parallel discriminators (or single pyramidal adversarial discriminator) is trained to estimate high-level age-related features at multiple scales, resulting in smooth continuous face aging sequences. Whereas, the generator is CNN based to capture different age distributions. This is an idea that is quite important because for our goal, we realize that different locations in the world will not have a similar rate of change that their lands undergo. For example, Dubai and its coast have been transformed radically over the last 20 years as observed through satellite images – to the point where they created artificial islands alongside their coast. The rate of change observed in the images of the coast of Karachi are not the same over the same time-period. Hence, this idea of capturing different age distributions gives us an idea about setting a few constraints and parameters for the model we will design regarding these different rates of change.

The metrics used to test how successful the generated faces are requirements of age progression models: aging accuracy and identity preservation. Both of which, may be hints to our evaluation criterion that we can tweak to suit our needs.

Prediction of a typhoon track using a generative adversarial network and satellite images

This is a paper with around the same aspirations we are striving towards. The input is a time sequence of satellite images of water movement and cloud cover, representing typhoon tracks. The final goal of this work by Mario Rüttgers et al. was to produce a 6-hour track of a typhoon so the target land could be identified and alerted beforehand. Along with identification of location, their model also identifies deformed cloud structures.

We know that satellite images in their original form when usually received, are not simply RGB images. An RGB image must be extracted from the various channels of data that a GeoTIFF metadata file is composed of. For this paper, they had look into further channels and information from this data to include velocity fields to predict sudden changes of typhoon tracks that were otherwise difficult to do with just RGB satellite images. Perhaps once the model for our research is finalized, we could look into what further elements we can add to the input to get a better result as has been done here.

As for their GAN framework, they use a CNN based generator and then its output is forwarded to a fully connected network of the discriminator. The model was tested in chronological sequences of ordered images. Their prediction of the typhoon center was a one hot pixel image, and the prediction of deformed cloud shape generated through the GAN was a little blurry. This blurriness, for their purposes was not a hindrance. Whereas, for our purposes, valuable information about smaller emerging settlements on land will be lost if our image accuracy is not better.

Satellite Image Prediction Relying on GAN and LSTM Neural Networks.

This paper by Zhan Xu et al. also deals with cloud satellite images. Motivated by the need to have more accurate visible proof of weather forecasts by predicting next frames using current cloud image. Essentially, just like the problem presented before, and the problem we have posed before ourselves of predicting land transformation, it is a spatiotemporal sequence problem. Nonetheless, the novelty in this paper lies in their solution. Using a hybrid approach, the paper combines the generative ability of GANs with the forecasting ability of LSTM to achieve its desired result.

Since here too, they deal with non-uniformity in its input distribution - weather and cloud arrangement over time domain, a sequence model is a mind-blowing approach. It would not be incorrect to say that the latent space to the GAN generator input is in a way provided by the LSTM, which has extracted evolutionary information from the satellite images beforehand. These evolutionary features are called implicit features. After the generator is trained to produce satellite images, it is cut off from the GAN and attached to the LSTM. After which, the generator tries to unfold the implicit features provided to it by the LSTM.

Comparing this to Hongyu Yang et al.'s Continuous Face Age Progression paper, here our timestep bounds are controlled in a different way than the pyramid discriminator. However, they concluded that their generated images though may not have been accurate, the trend they displayed was correct. This loss to accuracy may have been due to the steps where they get rid of 'redundant' information during the GAN training, but it is not a luxury our land transformation goal will be able to endure. Our main outcome is based upon visuals and details so it will be a challenge to achieve visual accuracy for us.

The Sen1-2 Dataset for Deep Learning in Sar-Optical Data Fusion:

The paper The Sen1-2 Dataset for Deep Learning in Sar-Optical Data Fusion, by M. Schmitt, provides a detailed overview of how to prepare the satellite image for deep learning techniques to be applied on them. The paper initially discusses the Sentinel 1-2 dataset and then talks about several applications of the dataset.

Google Engine has been used to create a random region of interest sampling. While creating Random ROI, an artificial bias was added by including more urban points and points which were located close by were removed. Google Engine tools were used on data to filter it into four seasons and then these images were exported as GeoTIFFs. To remove images that could have created problem for deep learning model two rounds of manual inspection was done, one before generating patch-pairs of the dataset and one after it. This information on how to prepare the satellite dataset before applying deep learning techniques is important to us as it gives us an insight on what steps can we follow to prepare our dataset as an input to a deep learning model.

Unpaired Image-to-Image Translation using Cycle-Consistent Adversarial Networks

In this paper, the problem of learning a mapping from one input image to an output image without a set paired input-output training set is addressed. To do so, the translation used is called ‘cycle consistent’ that is if a translator G translates X to Y then the translator F which maps Y to X is an inverse of G. Both the translation G and F are trained simultaneously and a cycle consistency loss is introduced which let $F(G(X)) \approx X$ and vice versa.

The property of CycleGANs that allows the mapping of an input image to an output image without using a training set of aligned image pairs will be very useful for us to map an input image of a landscape to an image that shows how the landscape will look x years later where x is the specified number of years. Since, we do not have paired input-output training set, i.e. images of landscape x years earlier paired with images of landscape x years later, CycleGANs can help us get an output image without the need of paired input-output training set.

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

In this paper, the power of Artificial Intelligence is highlighted by discussing GANs that have the ability to ‘remember a certain sense of a place and apply that sense to another place. In this paper, CycleGANs are used to extract city styles of few cities from the satellite images. As discussed in the previous paper, since CycleGANs do not require one-to-one mapping, they are used to reconstruct city style from the satellite images. Using the Google Engine’s mosaic methods have been used to put together multiple tiles which are patch-pairs of the dataset.It wasnoticed that images generated on a large-scale area, made by putting together many tiles, made more sense than generated when generated on a smaller area.

The idea of using CycleGANs on satellite images discussed in this paper is significant to us as it shows us how CycleGANs can learn general styles from the input dataset and can transfer them to a different place. The process of mapping city styles satellite images and vice versa by using CycleGANs provides us an insight into how CycleGANs can be used to map satellite images from x years earlier to satellite images of x years later.

Conclusion:

All these papers go over various techniques and methodologies we can employ to achieve our goal. These papers were chosen because of their relevance in different aspects of the situation. From the pyramid GAN structure, to a GAN-LSTM combination, to image to image translation method of Cycle GANs, these methods give us insight to how we can approach this spatiotemporal problem in image generation. Besides which, since we also rely on the LANDSTAT 7 collection that we can extract through Google Earth Engine as in a paper mentioned above, it provides information about the different ways we can go through to extract, prepare and process our data.

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