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Amaury Gutiérrez Acosta

FECHA

FIRMA

A la ε-cercanía.

- A Lety por plantar la semilla de lo que soy.
- A Ricardo por regar esa semilla, no sería nada sin ti.
- A Dolores, Dafne y Jorge por la adopción y el cariño.
- A Victor y Meli por embarcarse en esta empresa conmigo, por depositar la confianza.
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- A José Manuel Orozco Garibay por la retórica, por compartir la belleza de la palabra.
- Al lector casual, en caso de que existas, este trabajo fué pensado para ti, para compartir mi experiencia descubriendo este mundo, si le das una oportunidad y lo disfrutas, todo habrá valido la pena. Recuerda...

Don't Panic

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Chapter 1

Intruduction

> Good work is not done by 'humble' men. (...) A man's first duty, a young man's at any rate, is to be ambitious.
>
> A Mathematician's Apology
> G. H. Hardy

This is the introduction of this work, here we will give a short summary of the other chapters.

Chapter 2

Nothing new under the sun

> Archimides will be remembered
> when Aeschylus is forgotten, because
> languages die and mathematical
> ideas do not.
>
> A Mathematician's Apology
> G. H. Hardy

In this chapter we talk about the state of the art in computer vision and how it has been used for remote sensing problems. We also give a brief account of natural disaster assesment, and how are these machine techniques applied in this sense. We use Sandy Huricane as a study case because of the data that was publicly made available by the NOAA.

2.1 Computer vision

Le Cun *et al.* [1] propose to use an architecture of a multi-layer neural network that was able to learn directly from the data with no prior feature extraction. In contrast to the usual path that was used in the context of pattern classification, they created an architecture that was able to automatically extract the features directly from the date without prior manipulation. Instead of using a fully connected network, they proposed a locally connected net. It was capable of extracting local features and passed them down to the subsequent layers in what they called a *feature map*. Each unit took the information of a 5×5 neighborhood of the pixel in the previous layer. The last layer of the architecture consisted of ten units that represented each of the possible digits. This architecture was trained using backpropagation are now known as Convolutional Neural Networks (CNNs). The big leap forward of their result was that their architecture needed very little information about the task it was performing, they where able to extend the use of their method to other symbols, however, they state that the method was not able to be applied to very complex objects.

With the tremendous advances that computer power has suffer in the late years, this has been proven to be incorrect. In 2009 a big image database was gather and published [2]. Ever since this database became the defacto dataset to test classification methods. A few years later, in 2012 Krizhevsky *et al.* [3] proposed the use of CNNs in this daunting task.

2.2 Remote sensing

In late years groundbreaking advances in computer vision have had a tremendous impact in other science fields. In particular, we are interested in landcover classification.

The use of CNNs in the context of landcover classification was explored by Kussul *et al.* [4]. The use an ensamble of CNNs to obtain state of the art results in the classification of different types of crops using multitemporal and multisensor satellite data. They explore 2 aproaches, first they use a 1-D CNN to perform the convolutions in the spectral domain by stacking the different bands from the Sentinel-1 A and La ndsat-8 scenes. This process outputs a pixelwise classification, then they perform a traditional 2-D CNN on the scenes. In order not to lose resolution with the 2-D CNN, they use a sliding window approach assigning the class to the center pixel of the sliding window. Finally, they ensamble both opinions and filter the result to improve the quality of the map.

The usual approach with landcover classification is the use of classical classification methods such as support vector machines (SVM) and random forests (RF). In order to improve the performance, features must be handcrafted from the original bands. In [5], Grant *et al.* explore the use of Transfer Learning and Data Augmentation in the context of remote sensing images. By exploring well-known high-resolution datasets, they obtain state of the art results.

Transfer Learning (TF) is the process of using an already trained CNN, to

2.3 Damage Assessment

Chapter 3

Reinventing the wheel

> We may say, roughly, that a mathematical idea is 'significant' if it can be connectted, in a natural and illuminating way, with a large complex of other mathematical ideas.
>
> ---
>
> A Mathematician's Apology
> G. H. Hardy

In this chapter we will talk about the implementation of our experiment. The details of the pipeline architecture, and the techniques used to obtain and curate data. Details on the data munging and preprocessing are also given.

3.1 Ingestion

We built a system to ingest the images from the NOAA service. It lazily downloads the images by checking first if the file is already present in the temporary folder. If the file does not exists it downloads it, then the system tries to add it to the database and persistent file system. To maintain a coherent one to one mapping between the database and the file system, the process of adding a new scene must be successful both in the database and in the filesystem, otherwise the file is erased from both, and the state of the system remains as it was before the ingestion atempt.

3.2 Training data

Aerial tagged data is scarce. In particular, for the purpose of our experiment, we don't have any useful metadata on the images. We propose a method to tag samples of the scenes using crowd sourcing. We built a service that crops samples from the images and exposes them to a online application that lets any user with access to tag an image. We have three categories: the image has water in it, the image does not have water in it, and it is not possible to tell. When a possitive answer is obtained, the sistem persist de image in the data base with the information of from which scene was it extracted.

3.3 Data augmentation

Given the nature of our task, it is hard to adquire the tagged images. To increment the size of our training data set even more, we use a technique known as data augmentation. It relies on the fact that affine transformations do not change the content of the scenes, however a transformed scene appears as a completely new one to the classifier.

The images where rotated by 10 degrees, and reflected by the x-axis and the y-axis this gives us a $x144$ factor, this means that for each tagged image, the training corpus is incremented by 144 images. The problem with this aproach is that when a square image is rotated, some information on the corners is lost so we have to adjust the original image so that we can still crop a complete square from the desired size from it. For our experiment, the input size for the neural network is 227×227 pixels, so the original images must be at least $\sqrt{2}$ times 227 on each side. This way no matter how we rotate the original image, we can still crop a 227×227 from the center of the rotation without losing any data.

Chapter 4

Some catchy name

A mathematical proof should resemble a simple and clear-cut constellation, not a scattered cluster in the Milky Way.

A Mathematician's Apology
G. H. Hardy

chapter 4

Chapter 5

Some catchy name

A mathematican, like a painter or a poet, is a maker of patterns. The mathematician's patterns, like painter's or the poet's, must be *beautiful*; the ideas, like the colours or the words, must fit together in a harmonious way.

A Mathematician's Apology
G. H. Hardy

chapter 5

Chapter 6

Some catchy name

> If intellectual curiosity, professional pride, and ambition are the dominant incentives to research, then assuderedly no one has a fairer chance of gratifying them than a mathematician.
>
> A Mathematician's Apology
> G. H. Hardy

chapter 6

Chapter 7

Some catchy name

(...) it is obvious that irrationals are uninteresting to an engineer, since he is concerned only with aproximations, and all approximations are rational.

A Mathematician's Apology
G. H. Hardy

chapter 7

Chapter 8

Some catchy name

> I believe that mathematical reality lies outside us, that our function is to discover or *observe* it, and that the theorems which we prove, and which we describe grandiloquently as our 'creations', are simply our notes of our observations.
>
> ---
>
> A Mathematician's Apology
> G. H. Hardy

chapter 7

Appendix A

chapter a

Appendix B

chapter a

Appendix C

chapter a

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