Categorizing Solar Flares with Machine Learning

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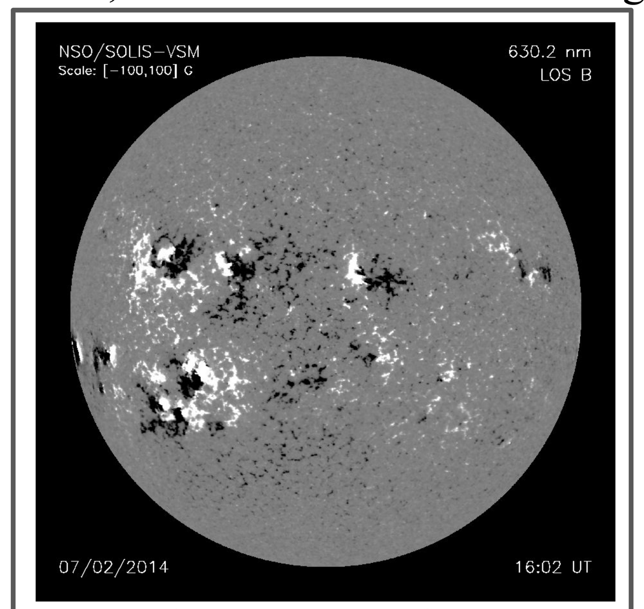
Abstract

The Sun, a giant fusion reactor ~1.5x10^8 km from Earth, is a naturally chaotic system. Periodically, explosive releases of magnetic energy from the sun's surface, events known as solar flares, propagate out into space. On Earth, solar flares pose a looming threat to an increasingly technology-dependant humanity, and pose a poignant question: are there reliable ways of detecting these events? This poster addressed if Neural Nets can be trained to detect solar flares with magnetograms from non-events? We find that this process is well founded in "Deep flare net (Defn) model for solar flare prediction"[4] as their system produces successful detections ranging from 82-96% depending on Solar Flare size. After collecting 100+Gb of magnetograms from the JSOC, and constructing a Neural Net, we had detection accuracy of 50% using B-class solar flares.

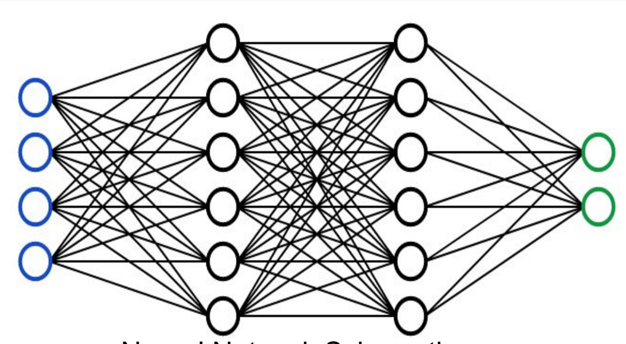
Background

The Sun's plasma (charged gas) is constantly in motion, producing magnetic fields. Sunspots, or convection currents breaking the sun's surface, are associated with strong magnetic field eruptions; if the magnetic fields "break" because of torsion, radiation and plasma are released, causing solar flares and coronal mass ejections. These solar flares can disrupt our radio systems and coronal mass ejections are able to elicit widespread power outages. Although it may be too chaotic a system to manually predict solar flares from magnetic field behavior, machine learning presents the opportunity to make such predictions.



Full-Disk Magnetogram: Sunspots

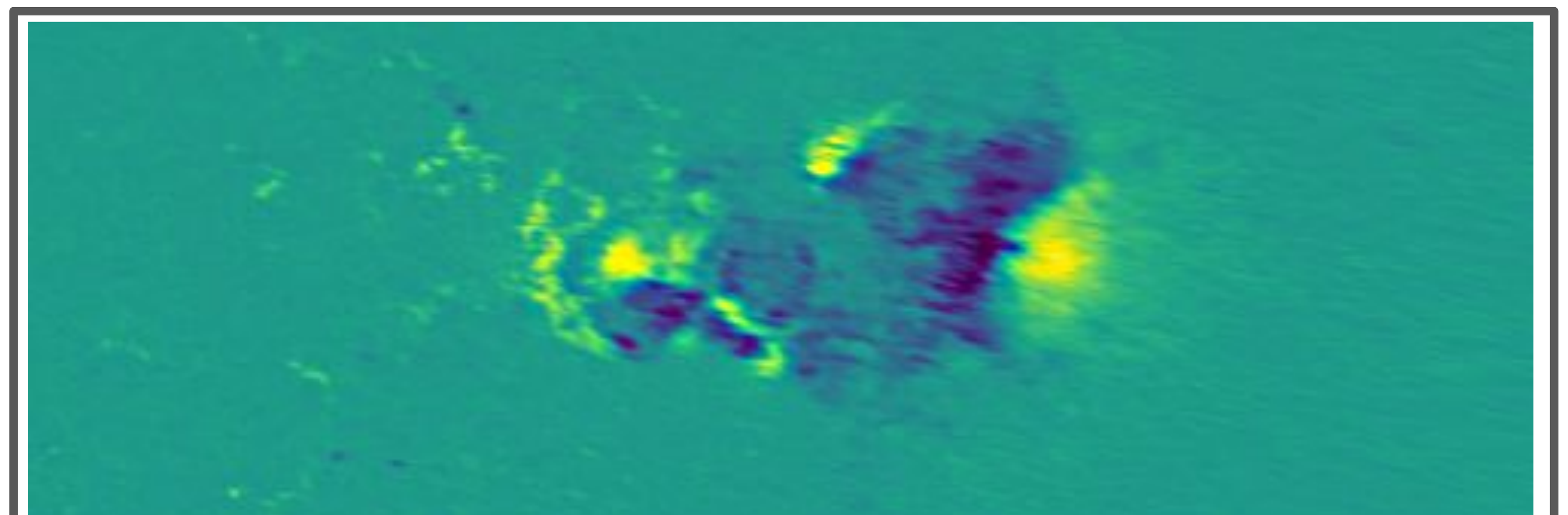
Neural networks are a way to map an input to an output. By creating many layers of connections between input and output variables, users have a set of parameters (connections) that can be adjusted to correctly map an input to its output. By training the network with many inputs that have known outputs, the system adjusts itself to become optimized, developing a network that can be applied to new inputs.


Neural Network Schematic: Densely Connected Layers

Methodology (Data Aquisition)

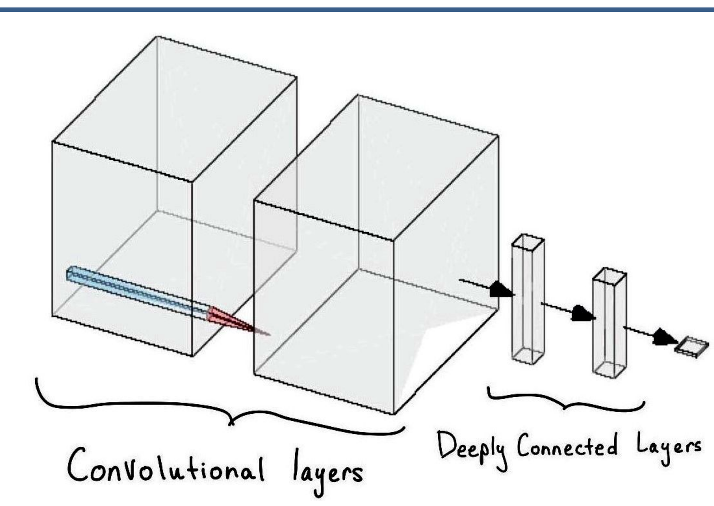
We used the JSOC as our source for acquiring magnetograms. In order to pull thousands of magnetograms, we developed a script that can pull and download many magnetograms of desired specification from the JSOC. With the script, we are able to indicate which active region and helicity from which to pull for our positive data. For our negative data, we pulled random magnetograms from random active region sites. In order to confirm that our negative data that we pulled was indeed negative, we checked the data against our Solar Flare.csv file and disregarded every match we found. After confirming, we checked the dimensions of both positive and negative magnetograms and found that they differed vastly, which will cause issues for our Neural Network. Thus, we padded each image in order to make each image the same size. There were some images that were too large for processing; those images were left out. After parsing and padding through all the data, we feed our data into the Neural Network.

Data


Magnetogram of a Active Region on the Sun

We conducted two main experiments in our analysis: the first involved a negative data set which contained image from one NOAA region exclusively, and the second contained a broader array of images taken from several NOAA regions. The first analysis produced consistent results, our training accuracy hovered at about 89% each epoch with a batch size of 10, and our test results were 99% accurate. On first glance, this would appear to mean that Neural Nets are an excellent way of detecting solar flares - but, this is directly challenged by our second data set. In the second set, our training accuracy was as high as 60%, but testing accuracy struggled to reach 50% constantly.

What this ultimately means is that our neural net detected that images in the first set which were negative all looked very similar (as they were all of the same region of the Sun), and thus, weeding out these images mathematically proved rather trivial. The more complex case, despite its lower accuracy, is actually more promising. Given that we are significantly RAM/data limited, it stands to reason that with more data we can achieve more accurate results.



Binary Detection Neural Network Schematic

Methodology (Neural Network)

Having successfully queried and collected the data from the JSOC, a proper analysis of our collection of images can begin. Referencing DeepBlue's[2] list of magnetograms, we can parse through the negative data to double check its integrity before we formally create training and test sets fit for Keras's image processing methods: this is done by matching the date of the image to the 12k confirmed solar flares we know took place. Due to the limited amount of Ram allotted to us through Google Colab Notebooks, of our total data set we consider a subset of our collected data set consisting of 200 images, split into 100 flare images and 100 'blank' images at a time. With preprocessing done, all that is left is to construct and run the Neural Network. Using the Keras framework within Tensorflow, our network is a standard boolean classifier meant to separate solar flares from regular solar activity. The structure of our Neural Net can be seen above. Due to the nature of Neural Networks, we don't have exact knowledge on how the linear algebra going on under the hood directly translates to picking a solar flare out of a collection of images - but the justification for its functioning is well established mathematically.

```
Model: "sequential"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
conv2d (Conv2D)              (None, 398, 598, 32)      320
_________________________________________________________________
conv2d_1 (Conv2D)            (None, 396, 596, 32)      9248
_________________________________________________________________
global_max_pooling2d (Global (None, 32)                0
_________________________________________________________________
dense (Dense)                (None, 50)                1650
_________________________________________________________________
dropout (Dropout)            (None, 50)                0
_________________________________________________________________
dense_1 (Dense)              (None, 25)                1275
_________________________________________________________________
dropout_1 (Dropout)          (None, 25)                0
_________________________________________________________________
dense_2 (Dense)              (None, 1)                 26
=================================================================
Total params: 12,519
Trainable params: 12,519
Non-trainable params: 0
_________________________________________________________________
```

Conclusion

We constructed a convolutional neural network, and implemented limited data consisting of magnetograms both associated with flare event times and regions, and unrelated to solar events. In the second regime, which consisted of a mixture of Active Solar regions, we produced testing accuracies of 50% consistently, giving no indication that our data-limited network can predict solar events. Our development of a network and the success of similar projects in literature suggest that with more work and more comprehensive data, a reliable detection system is possible. This project stands as a proof of concept for utilizing Neural Networks and image processing to examine Astronomical data for event detection.

Future Work

- Build a Neural Network to be able to predict whether a solar flare will occur within 24 hours of when the input magnetogram was captured
- Explore Long Short-Term Memory and Generative Adversarial Network architectures to facilitate predictive analysis
- Refine our understanding of available solar data products, as well as how to query this data in an automotive process, to ensure the validity and effectiveness of our positive and negative data
- Experiment with more preprocessing techniques such as Low-Rank Approximation for our input image data

References

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