Implementing a convolutional neural network in the DESGW pipeline

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Background

Many gravitational wave (GW) sources are expected to emit an electromagnetic counterpart. The detection of both kinds of signals helps us understand more about these sources and gives us a measurement of the rate of expansion of the universe[1]. The Dark Energy Survey Gravitational Waves (DESGW) group at Fermilab uses observations from the Dark Energy Camera (DECam), mounted on a telescope at the Cerro Tololo Inter-American Observatory, to detect such electromagnetic follow-ups and to analyze them using a data processing pipeline[2].

The DESGW pipeline

To identify electromagnetic signals that are likely candidates to belong to the GW source, DECam takes observations from a region of the sky in which the source has been detected. These observations are calibrated and corrected for aberrations by the DEGSW pipeline in the "Processing" stage[3,4].

They then enter "Post-Processing", in which all candidates are matched to potential host galaxies. The data from each candidate and host is written in data files and in web pages for further inspection.

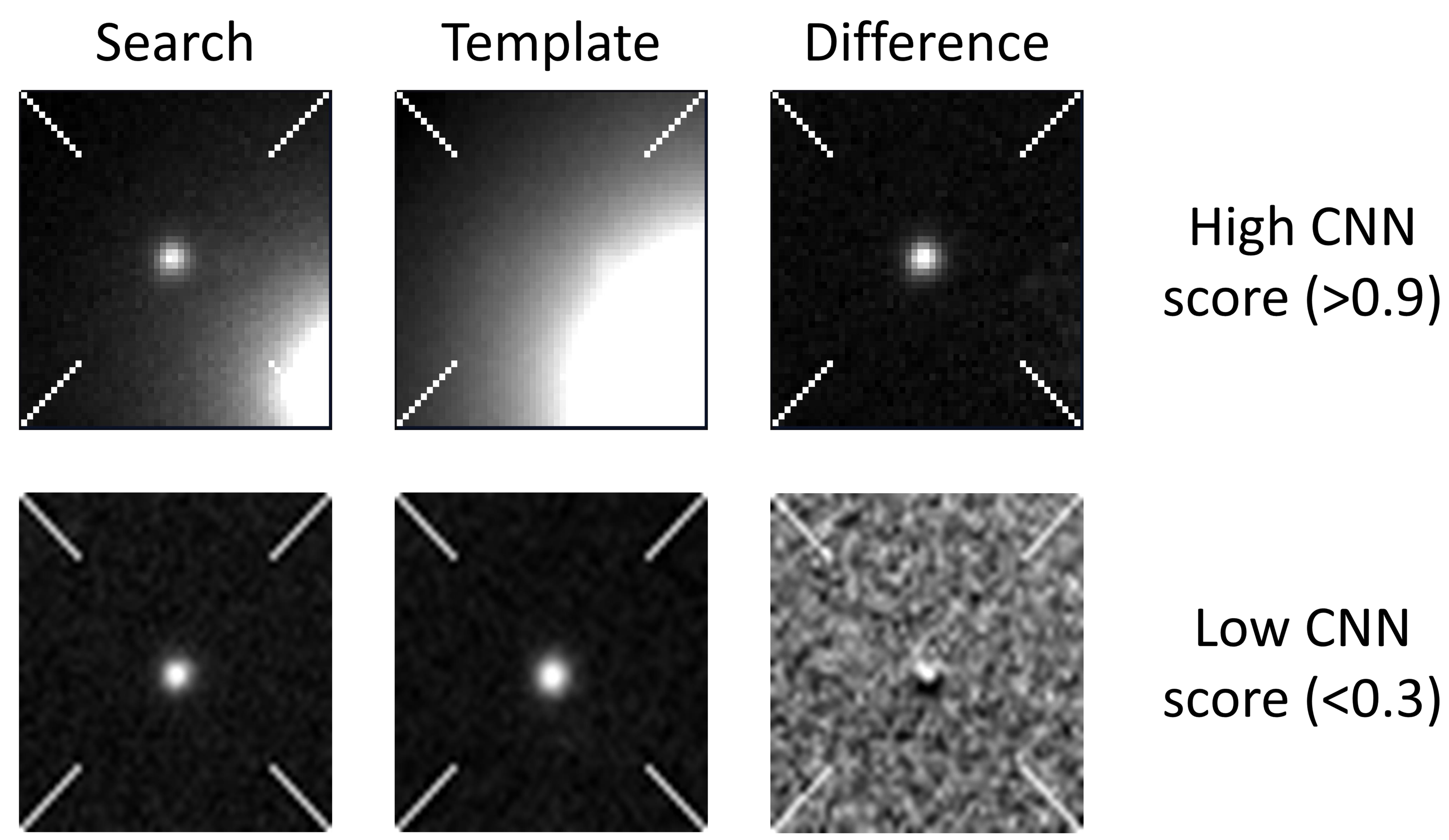
A significant limitation of this pipeline is that the final list of candidates still needs to be visually examined to reject artifacts and moving objects.[4] Common artifacts are "bad subtractions", which are misalignments between the observations (search images) and images of the same region taken before the detection (template images).[5]

Objectives

In this project, I incorporate a convolutional neural network (CNN) to the DESGW pipeline to decrease the amount of human inspection needed in the analysis of the candidates. I also update a section of the pipeline to a state in which it is prepared to take data from DECam upon detection.

Convolutional Neural Network

The convolutional neural network, developed through machine learning by Shandonay et al.[5], takes cutouts, or "stamps", from the search and template images from a given candidate, as well as the difference between the two. It then evaluates their quality in terms of the presence of a bad subtraction and assigns a score from 0 to 1, where a higher score indicates a higher-quality observation. Observations with scores lower than 0.7 are rejected.[5] Given that the CNN evaluates a set of stamps in under one second, it provides for a faster examination of candidates compared to visual inspection.

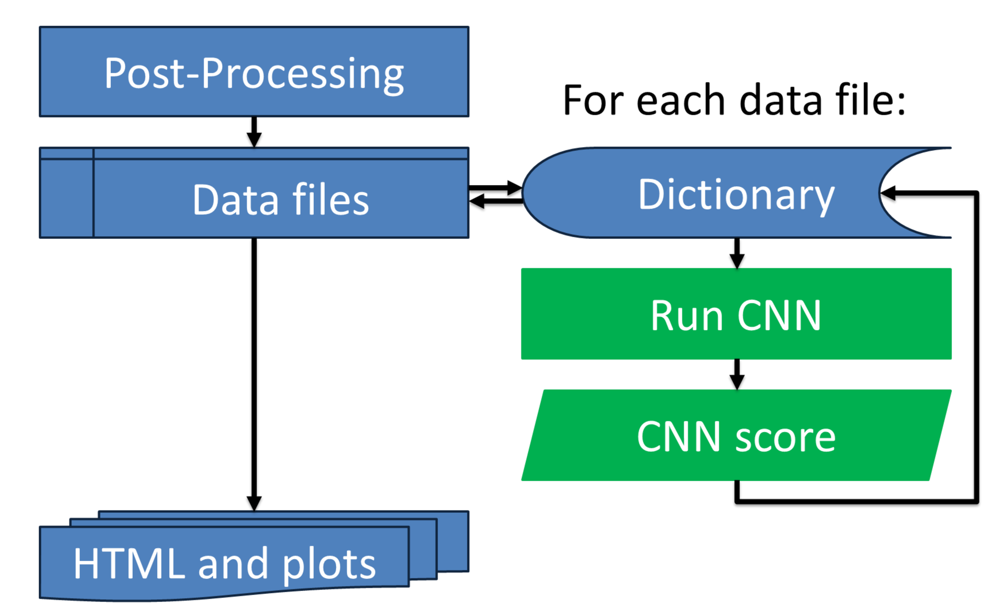


Two sets of stamps from GW170817. The top panel shows a transient object and its host, with a clear difference image. The lower panel shows a bad subtraction, in which the difference image has a dipole like-structure (white and black dots).

Implementing the CNN

In order to incorporate the CNN into Post-Processing, I updated it from Python 2 to Python 3. Most of the modifications consisted in altering syntax and in checking for incompatible or deprecated commands. I tested the pipeline on different sets of observation exposures to ensure its functioning.

I then added the CNN code into one of the functions called by Post-Processing. Here, data about the observation is read from a data file and written into a Python dictionary. The CNN function takes this data to yield the score, which is added to the dictionary and appended to the data file.



Flowchart of relevant processes in Post-Processing. The blue symbols represent the original functioning of the pipeline, while the green symbols are the additions incorporated to the CNN.

Results

- Updating Post-Processing to Python 3 ensures its compatibility with applications developed in this newer version.
- I tested the pipeline with data from GW170817 to compare the results of host galaxy matching with a known source. Despite issues with the output, the pipeline replicated the matching of the signal with elliptical galaxy NGC 4993.[2]
- Ongoing testing on data from GW signal S190814 shows that taking the stamps of a final list of candidates and running the CNN takes about ten seconds per candidate, resulting in a run time of only over one hour.

References

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