Detection of slow-moving solar system objects in LSST using 3D convolutional neural networks

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Objectives and research question

We want to find potential target for the ESA F mission Comet Interceptor in *LSST* data. The *LSST* built-in pipeline will detect moving objects, but not the ones at large heliocentric distances r_h > 200 AU. We are working on building a Convolutional Neural Networks *(CNN)* to detect such slow-moving objects in *LSST* images.

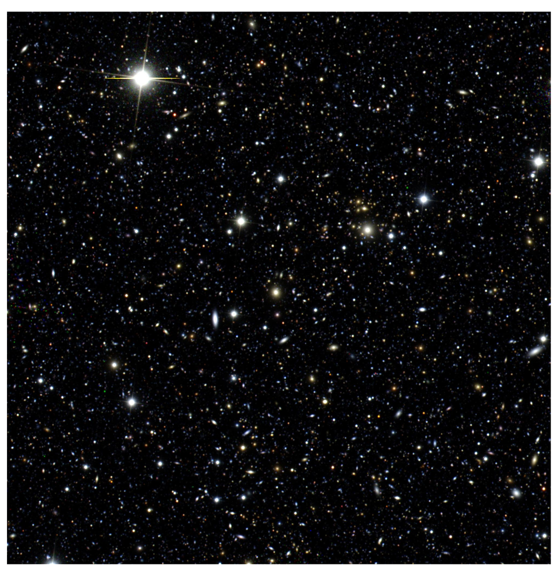

Fig N. 1: This color image, a composite of three individual frames with different filters, corresponds to only 2.6 parts per million of LSST's ultimate sky coverage of 20,000 square degrees.

Background

In order to build our training and test samples, we inject slow-moving objects (SMO) in the simulated *LSST* images from DP0. We randomly select sky coordinates and collect all the images centered at that position, extract small cut-outs from each and order them by observation time. The simulated slow-moving object is obtained by painting a *PSF* of an object whose motion is produced by computing ephemerides of a real trans-Neptunian object listed in the *JPL* data-base but shifted to larger distances.

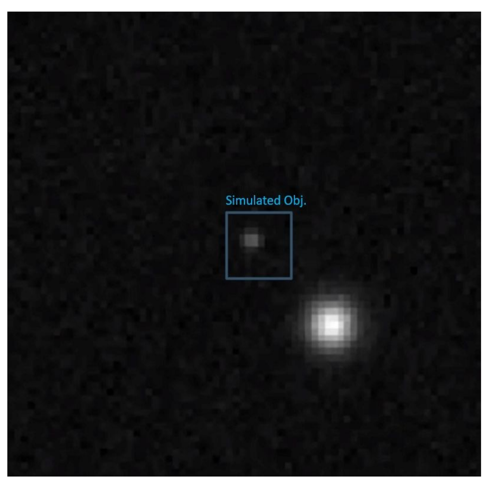

Fig N. 2: A 75x75 pixels cut-out with an injected obj.

Fig N. 3: 15X15 pixels cut-out in time.

We did not inject the small-moving object in all the animations, in this way we made:

- Positive samples -> sky with presence of *SMO.*
- Negative samples -> regular observed sky.

We can also have false positive samples if non-static sources, such as faint variable stars, fall in the selected region.

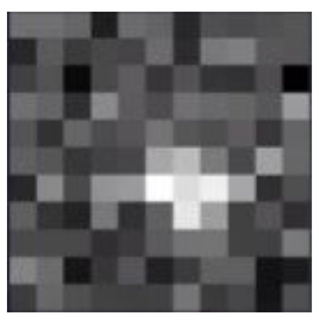

Fig N. 4: Positive sample. 15x15 pixels cut-out with an injected obj.

Fig N. 5: Negative sample. 15x15 pixels cut-out.

Methods

In order to train a Neural Network able to perform this detection, we need a great number of labeled samples. We select an architecture capable of taking as input multidimensional arrays. *CNN*s are the state of the art in the audio/video domain, so a *3D-CNN* model has been used. The first two dimensions of the convolution work on the images, while the third works on the changes in the series of images over time. After a certain number of epochs empirically determined, the network converges and we test it on new samples in order to determine its accuracy.

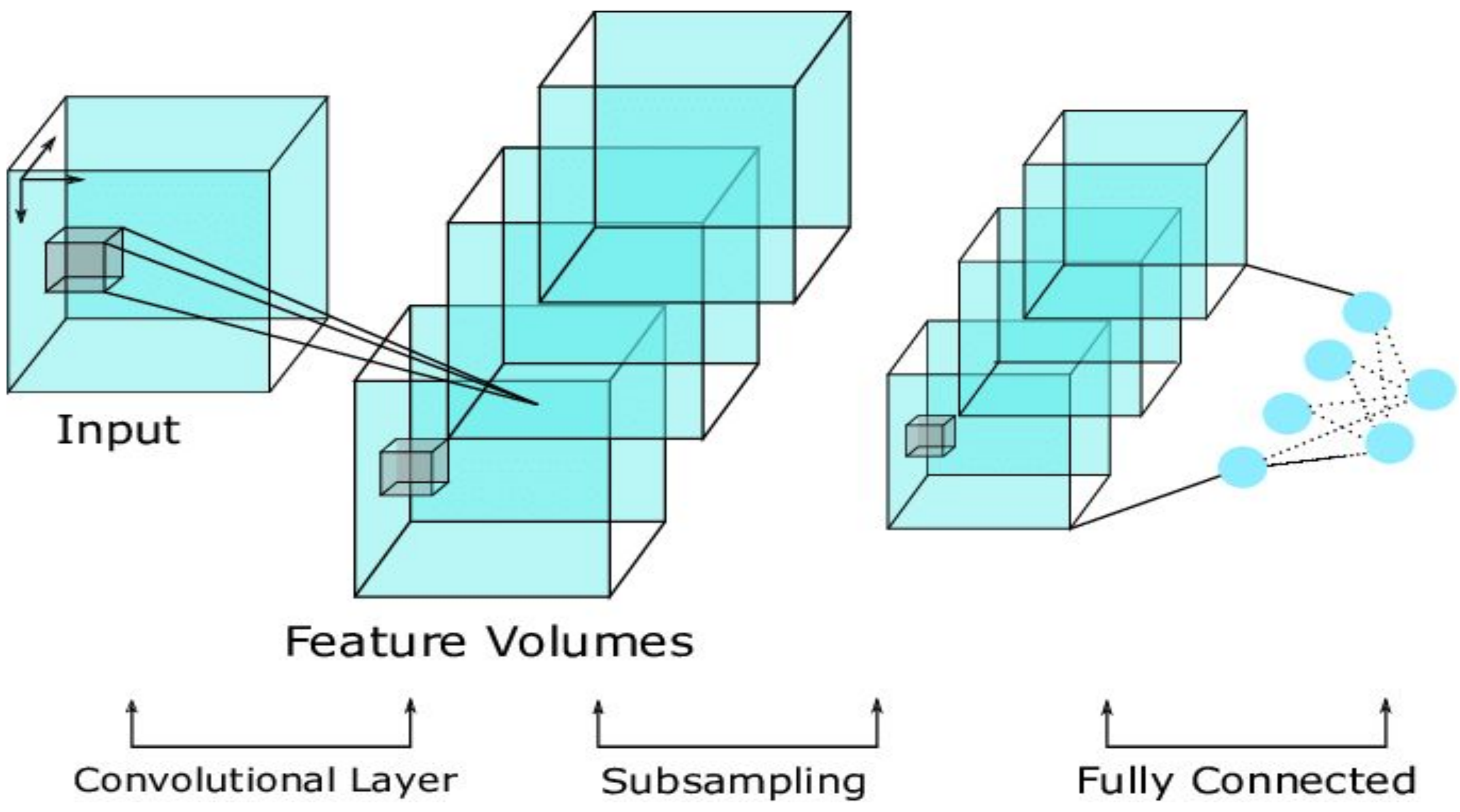

Fig N. 6 *3D-CNN* Architecture. Dropout and Batch normalization have been omitted from the figure for the sake of simplicity.

Preliminary Results

We are still working on assembling a dataset with >1,000 samples. Preliminary results obtained by using a small subsample shows that the Neural Networks performs well, with an accuracy rate around 85%. The miss-classification is partly due to objects that are entering and leaving the cut-out in different frames. We plan to improve on this in the next steps of our analysis.

Discussion

Our preliminary results show that it is possible to entirely automate the process of detection of such slow-moving objects using Machine Learning. We are currently use the Rubin Science Platform together with high-performance computing machines at MIT in order to build the pipeline, which we plan to merge into the LSST data-flow.

What next:

In order to get ready to test the Neural Network on real LSST images different experiments will be done. Firstly, we will build a greater and exhaustive dataset to accomplish more accurate results by using DP0.2 data together with the Solar System Survey simulator (SurveySimPP), built within the Solar System Science Collaboration. Furthermore, we will test new and different models as RNN or LSTM, changing approach of a One class kind or Transformers.

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