Vera C. Rubin Observatory
Data Management

Deep Learning Approach to Real-Bogus Classification for LSST Alert Production

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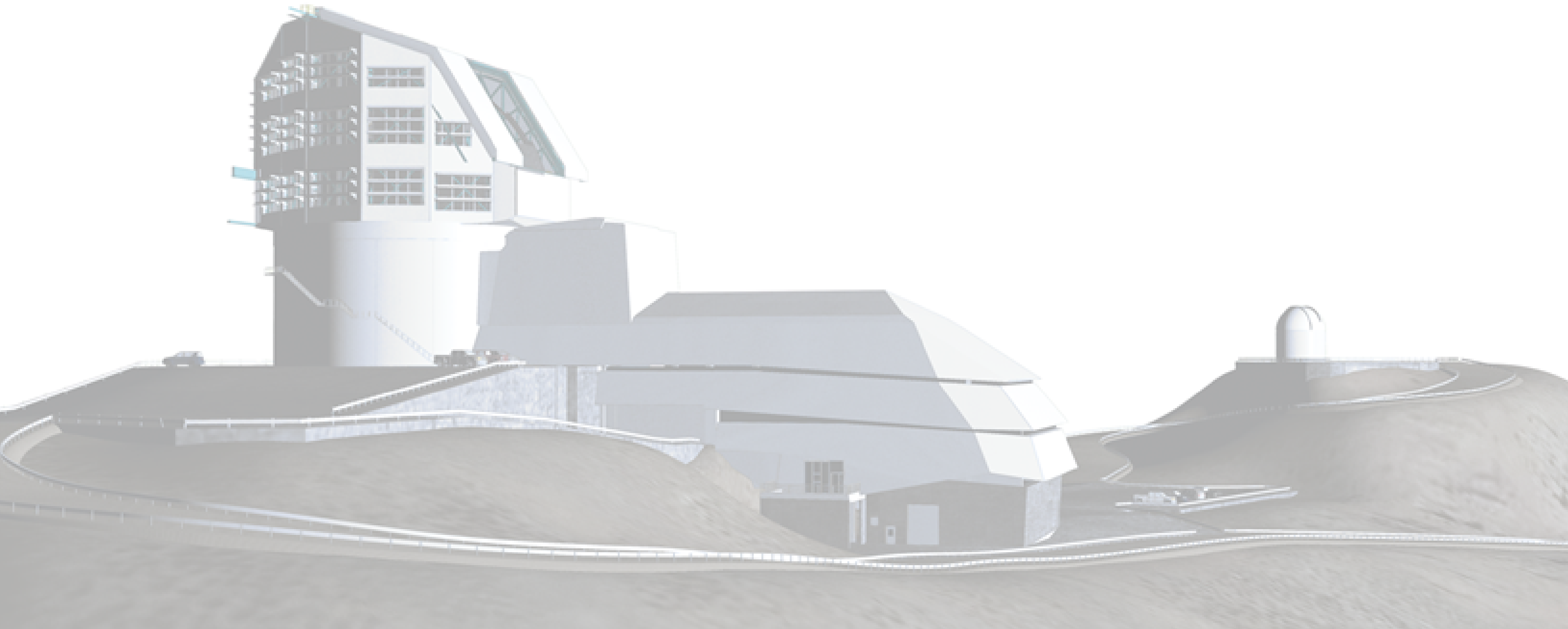

Abstract

This document provides precise definition(s) for the deep learning-based approach to the real-bogus classification task for LSST.

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1 Problem Definition – Big Picture

Loosely speaking, the high-level objective in transient-detection is to locate intrinsically-varying objects in each recent image of the sky. More formally and in the concept of this project, this objective can be defined as finding the mapping

$$(I_t, I_s) \longrightarrow S_t \tag{1}$$

where I_s is the recently captured image, namely the *science image*. I_t is the *template* or *reference* image, and S_t is the set of *true transients* to be detected [1].

However, this problem has traditionally been broken down into two broad sub-problems (Alard & Lupton, 1998; Zackay & Ofek, 2017), namely, *image differencing*[2] and *thresholding*; the latter being the process of finding a threshold above which all the pixels in the diff image, I_d, will be seen as candidate transient sources:

$$(I_t, I_s) \xrightarrow{diff} I_d \xrightarrow{threshold} S_t \tag{2}$$

The *thresholding* step has traditionally been implemented as a simple 5σ-thresholding (Bailey et al., 2007), but other auxiliary approaches, such as pre-convolution with the PSF, may wrap around this stage to make it partially aware of spatial information content – see Bosch (DMTN-015), figure 1

2 Learning-based Approaches

The above process is prone to false positives (contamination) and false negatives (misses). Learning-based approaches come into play to mitigate this...

[1] The term 'detection' in the field of computer vision can be translated to localization+classification in the astrophysics' terminology

[2] or interchangeably, *difference imaging*

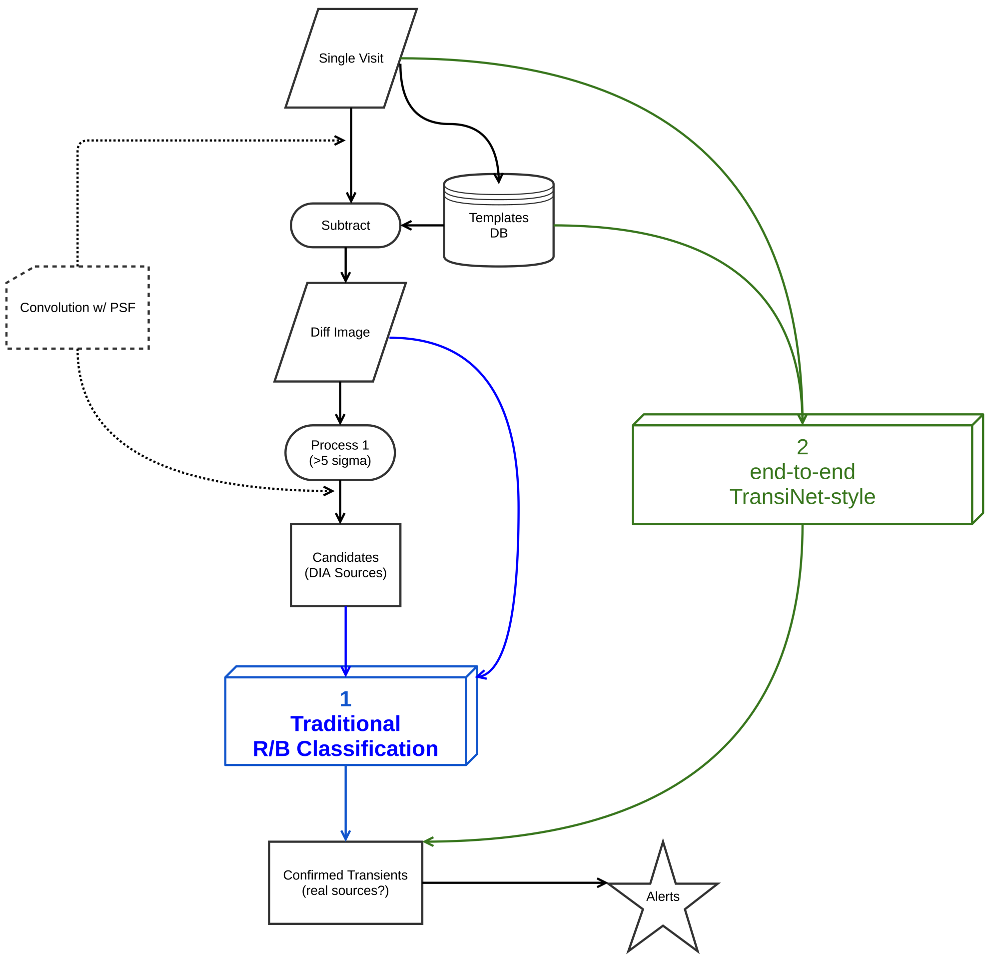

FIGURE 1: Coarse illustration of information flow through the Alert Production (AP) pipeline. Paths in blue and green illustrate the "traditional" and "modern" approaches respectively.

In the context built in the previous section, a learning based approach can be implemented in two broad ways:

- starting off I_d – a.k.a traditional real/bogus classification (Bailey et al., 2007).
- starting off (I_t, I_s) – a.k.a end-to-end, TransiNet-style (Sedaghat & Mahabal, 2018).

Each of the approaches has its own cons and pros, and methods based on both will be implemented for LSST. In this tech-note we focus on details of the former, the real/bogus classifier, and the end-to-end TransiNet will be covered in a future note.

3 Basic Real/Bogus Classifier

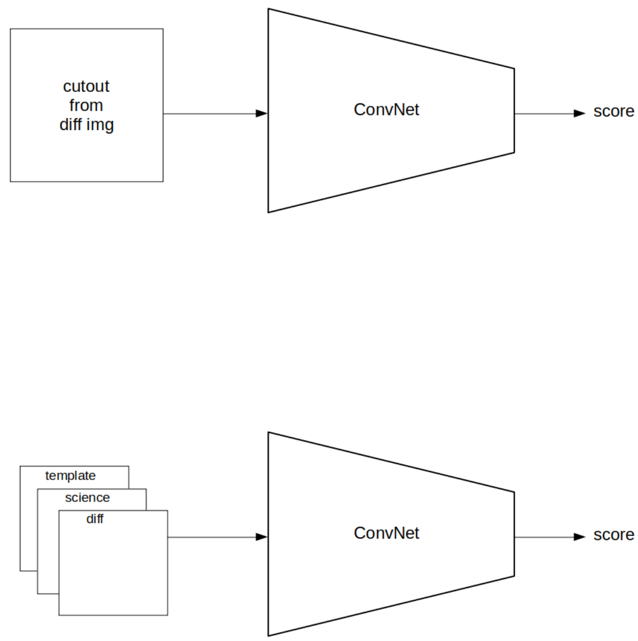

FIGURE 2: Classical Real/bogus classifier (top, section 3) and the modified 3D classifier (bottom, section 4)

Input-output definition of the problem:

- input: cutouts from diff image (I_d) with the potential transient at the center
- output: reliability score for the potential transient

Regardless of how the score is calculated, the placement of the module in the pipeline makes it a score conditioned on the results of the upstream modules:

$$S_t = Score(real|det) \tag{3}$$

where *det* is a flag representing whether a source is detected by the upstream modules or not, and is usually implemented as a 5σ thresholding of the output of the image differencing module – see fig. 1. Note that since typical neural networks do not estimate probability distributions, we do not use a probabilistic notation in eq. (3).

3.1 The score

As the task definition embraces a recognition according to spatial *and* temporal [3] features simultaneously, the score needs to be defined carefully to capture both aspects. More specifically, we need to define the term "real" more precisely: a non-astrophysical detection, such as an artifact, is obviously not "real". But how about a non-varying astrophysical source?

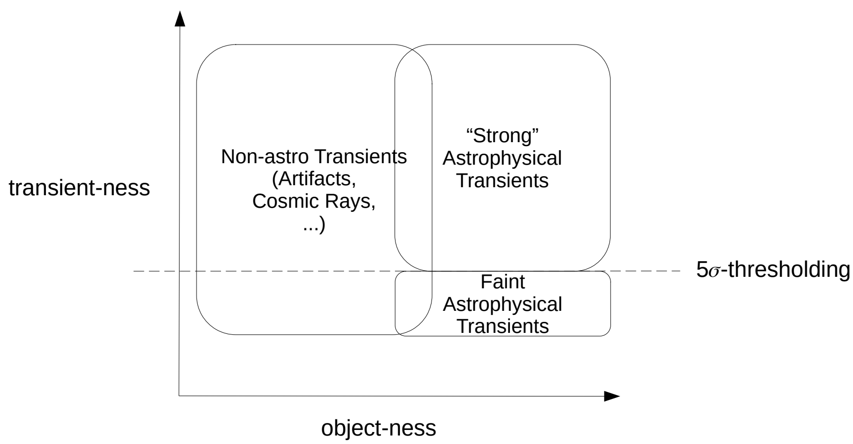

FIGURE 3: The 2-dimensional realness space

As illustrated in figure 3, the real-ness space is composed of (at least) two dimensions, which we name "transient-ness" and "object-ness".

As a data-driven approach, which is being implemented as a supervised task at its core, we do not excert the definition of the problem into the method itself, but the "truth labels" used for training the classifier.

[3] throughout this document the term "temporal" is used to represent the transition from a template/reference image to a science image. It has to do, but should not be confused with the "real" time axis!

We label any suggested candidate as a *positive*, if and only if it matches one of the astrophysical transients in the truth catalog, *spatially* and with a high enough precision. Any other candidate is labeled as a *negative*.

This way, in the training phase we inject our prior knowledge about the "real-ness" of each object into the learning process, regardless of the difficulty of the detection of each object and without adding artificial Aleatoric uncertainty to the system. Later during the test phase (i.e. normal working mode of the pipeline), we use the pseudo-probabilities appearing before thresholding at the final layer of the network as a proxy of the score, which capture the Epistemic uncertainty of the model too.

3.2 Drawbacks

- Any "miss" (false negative) in the upstream modules is inherited and irrecoverable.
- Can only handle single object per cutout – when there are multiple true transients, it *has to* ignore the others.

The former is a result of having separated the temporal processing (i.e. image differencing) from the final classification, whereas the latter has to do with how the problem and solution are defined based on cutouts.

3.3 Benefits

Although as discussed this is just a sub-optimal learning-based approach to this problem, it still has the advantage of *interpretability*; the generated output might be too contaminated with false alarms and (at the same time) missed true transients, but the process is fully transparent to the downstream users of the alerts and they have the possibility to develop their own post-processing blocks per need.

3.4 What will be learned?

Since the temporal behavior of the candidates fed to this module is assumed, it is foreseeable that the neural network will eventually learn a concept close to "PSF-ness", true to its title;

real/bogus classification.

4 Modified 3D Real/Bogus Classifier

In this implementation, we try to feed the network with a glimpse of the temporal behaviour of the candidate, by passing the template and science image pairs along with the diff image – see Duev et al. (2019) for a similar implementation. This allows the network to make use of the temporal behavior of the source too. Note however that still the difference image plays a key role in the process, as the images are cropped around the sources detected in the difference image. This means that the modification only aims for cleanliness of the detections, by passing more information about the existing candidates (diaSources), but cannot affect the completeness of detections, by definition.

5 Future Work

5.1 End-to-End Simultaneous Localization and Classification (TransiNet)

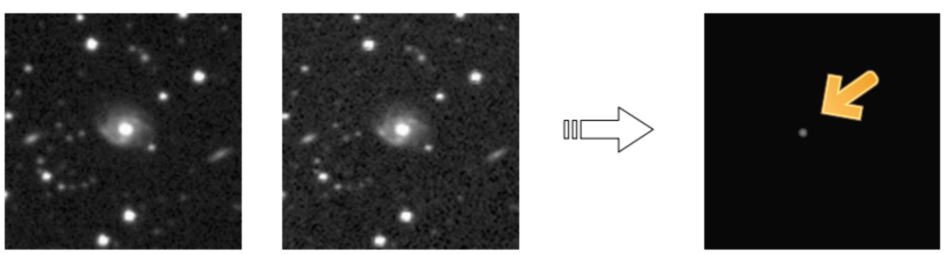

FIGURE 4: End-to-end image differencing, localization and classification. The output has to be clean and complete *by definition*

- input: a pair of science,template images: (I_t, I_s)
- output: S_t, set of true transients
- intermediate output: a "score image" where scores are assigned per-pixel

Based on TransiNet (Sedaghat & Mahabal, 2018). Does full detection (localization + classification) simultaneously – along with any necessary implicit steps. Since the temporal and spatial behaviors are considered at the same time, the definition of the task of this module would be to find all the time-variable real astronomical sources – corresponding to the high-level definition of the problem in 1.

A References

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B Acronyms

Acronym	Description
3D	Three-dimensional
AP	Alert Production
DM	Data Management
DMTN	DM Technical Note
LSST	Legacy Survey of Space and Time (formerly Large Synoptic Survey Telescope)
PSF	Point Spread Function