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Recognition of Temporal Phenomena from LSST Alert Streams

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Abstract. LSST will uncover a few million time-domain alerts per night with a latency of a minute. This will provide a huge discovery space, where previously undiscovered rare phenomena may be revealed. The early detection of such previously unknown events from a minimal set of measurements is critical for discovery and follow-up. Analysis methods to recognise such events are being investigated and developed. A discussion of those approaches was presented.

Keywords. Surveys, catalogues, methods: data analysis

1. The Problem

The Large Synoptic Survey Telescope (LSST) is projected to image approximately half the sky every three or four nights for ten years in one or other of six passbands (u, g, r, i, z, Y). By comparing every exposure to a past template image of the same sky region, it will find objects that change, either in brightness or in position (but we concern ourselves here only with the former). The LSST data system will generate 'alerts' whenever it finds a change, with a remarkable latency of only minutes. Each night we expect of order 10^7 genuine alerts. Many of those will simply be from known objects in the sky, but many will be transients that are interesting for follow-up studies (e.g. supernovæ, gamma-ray bursts, etc.). Brokers such as ANTARES (Saha *et al.* 2014, 2016); (Soraisam, p. 155) are being developed to identify those interesting objects from the LSST alerts. In addition, with its single visit depth of $r \sim 24$ mag, wide sky coverage, and revisits of only a few days, the LSST alert stream will also open up an unprecedented 'discovery space' for rare and unknown phenomena. Many are likely to be transitory, requiring early identification to enable follow-up observations whilst a phenomenon is still active. The challenge is to identify and find such phenomena that behave differently from all others that we know, and to pick them out reliably from the alert deluge that LSST will generate. This paper presented some ideas of how the early identification of such rare and peculiar phenomena might be made possible, given the kind of data that LSST will supply.

2. Boundary Conditions

A phenomenon can be assessed as rare or peculiar only in relation to those that are known to be relatively commonplace. This requires the existence of a dictionary of known variable phenomena (acknowledging that such a dictionary will grow dynamically, especially in the LSST era). We use the term 'feature' to describe some characteristic property of a variable phenomenon, e.g., its light-curve (a sequence of brightness measures in one or more passbands from which we may derive time-scales, amplitudes, shape characteristics, etc.), the location of the object (Galactic coordinates, angular proximity to an external galaxy), plus contextual information such as whether it is a known X-ray emitter or a known radio source. Collating and analysing all of the 'features' gathered for a given source arms us with ways to compare against our dictionary of known variable sources.

Notionally we can construct a hyperspace of our features; we expect the known variables to distribute themselves in a limited volume of that hyperspace. If we have features that discriminate well between the different classes, we expect that the known objects will distribute in this hyperspace into well defined clumps. If the features for a new unknown object make it fall within a particular clump, it may be inferred to be a member of the class corresponding to that clump. In reality, some classes will not be separable from others, and other ambiguities are likely to prevail, but a rare class of phenomenon will have features that place its hyperspace location far from those of any known class of variable. However, we must be mindful of several limitations concerning the observed or derived features:

(a) not all features are known for all known variables or all alerts
(b) some features are better at categorising variable phenomena than others
(c) features are not necessarily independent

These considerations motivate us to focus on those features that are always present and are most efficacious.

The features that are always present (from here on referred to as 'persistent features') are those that are furnished directly by the LSST data. For a given target displaying variability, we always have its position on the sky, angular proximity to other known objects, and the observations over time (in the past), comprised of measurements of brightness in up to 6 bands.

3. Learning from Persistent Features

Learning to use persistent features for maximal benefit is an ongoing process. Here are some simple starting examples. One must of course eventually employ machine-learning methods, but these examples begin with cases that can easily be visualised.

3.1. *Frequency distributions in the brightness/colour – time-interval planes*

Consider a sequence of brightness measurements m for an object at times t. We can take any pair of epochs and obtain Δt and Δm for that pair of observations. We can plot a two-dimensional histogram of Δm vs Δt (in practice we use $\log \Delta t$ rather than Δt). If the sequence of observations samples all Δt bins evenly, such a histogram represents an empirical probability distribution in the sense that it gives the probability distribution for Δm for two observations separated by a given Δt for that object. If we superpose a representative distribution (reflecting the distribution of periods/time-scales and amplitudes within that class) of individual objects from a certain class of variable phenomena, then the superposed distribution will represent the corresponding probability distribution for that class in the Δt vs Δm plane. The top left panel of Fig. 1 shows 'grayscale' representations of such 2-D frequency distributions (using g-band light-curves) for a sample of Long Period Variables (LPVs), from de-reddened photometry (with DECam) of a field in the Galactic bulge; the top right shows the corresponding distribution for Type-Ia supernovæ (SNeIa) from the SDSS supernova survey (Sako *et al.* 2018). Given a set of observations in m and t for an unknown object, we can compute the likelihood (or other measures such as Kullback–Leibler divergence) that the Δm vs Δt from those observations has been drawn from either of these two frequency distributions. We need not of course restrict ourselves to light-curves in one passband; the difference in magnitudes across two different passbands measured at different times, e.g., the distribution of $\Delta(g-r)$, where g is measured at epoch t_1 and r is measured at epoch t_2, can be collated against $\Delta t = t_2 - t_1$. Such distributions for the same two samples of LPVs

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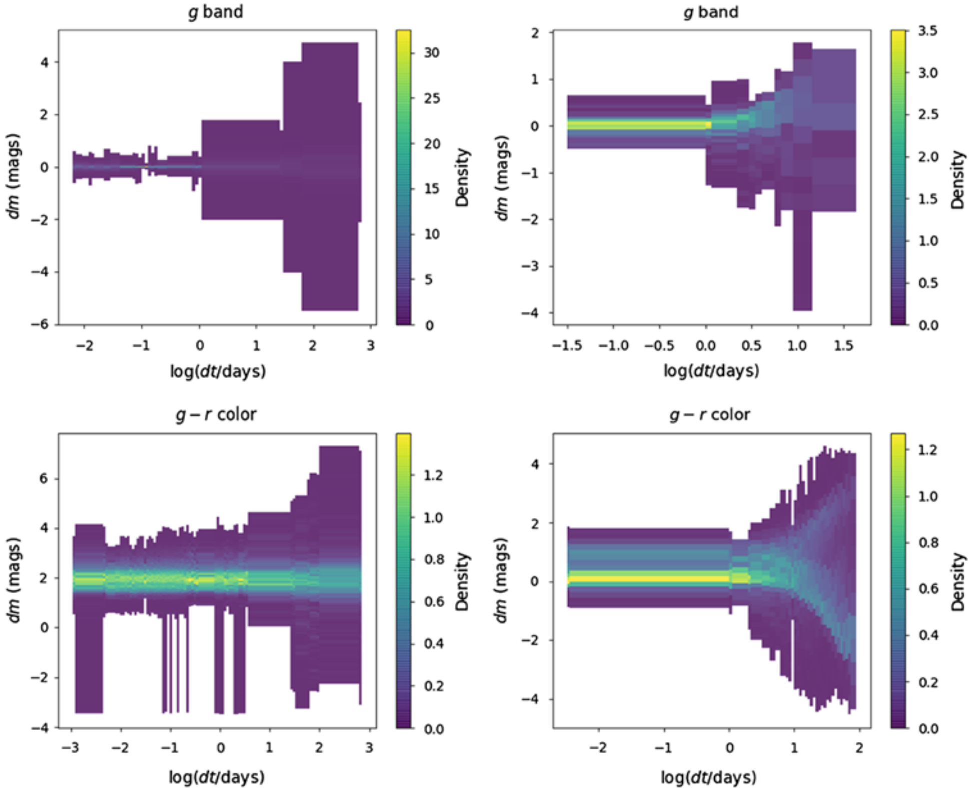

Figure 1. The top panels show the Δm (g-band) vs Δt frequency distributions described in Sect. 3.1 for LPVs (*left*) and SNeIa (*right*). The lower panel shows the frequency distributions for the pseudo-colour (defined in Sect. 3.1) $\Delta(g-r)$ vs Δt, for LPVs (*left*), and SNeIa *right*. (*Courtesy: M. Soraisam, private communication*).

and SNeIa are shown in the lower left and right panels of Fig. 1, respectively. With only g-band measurements, disambiguating between the two classes is not too easy, since the top two panels are not very different. However, the $\Delta(g-r)$ distributions for these two classes are very different (the distributions peak at very different values of the ordinate), and disambiguation between those two specific classes will be easy.

The actual implementation of this method presents several challenges, principally the need to have data samples at all time-scales. In addition, with the very many classes of object present, distinguishing between different classes will require several observations to be at hand. This will not be efficient at early identification of unusual phenomena. Note also that there are inherent correlations that have been ignored; for a given light-curve, there are correlations among the frequencies in the Δm - Δt plane that are being ignored, but a full discussion is beyond the scope of this article.

3.2. Δm *for consecutive* Δt *pairs*

In an effort to account for the correlations, it is useful to look at observed triads, i.e. m_a, m_b and m_c measured at 3 epochs t_a, t_b and t_c. Let $\Delta m_1 = m_b - m_a$ and $\Delta m_2 = m_c - m_b$, corresponding to $\Delta t_1 = t_b - t_a$ and $\Delta t_2 = t_c - t_b$. Consider a sine-wave light-curve with half-amplitude unity and period 0.5 days, for which we have such a triad of observations. We know from our measurements what Δt_1 and Δt_2 are – let us choose an example where they are 0.25 and 0.12 days, respectively. Given the light-curve, we can

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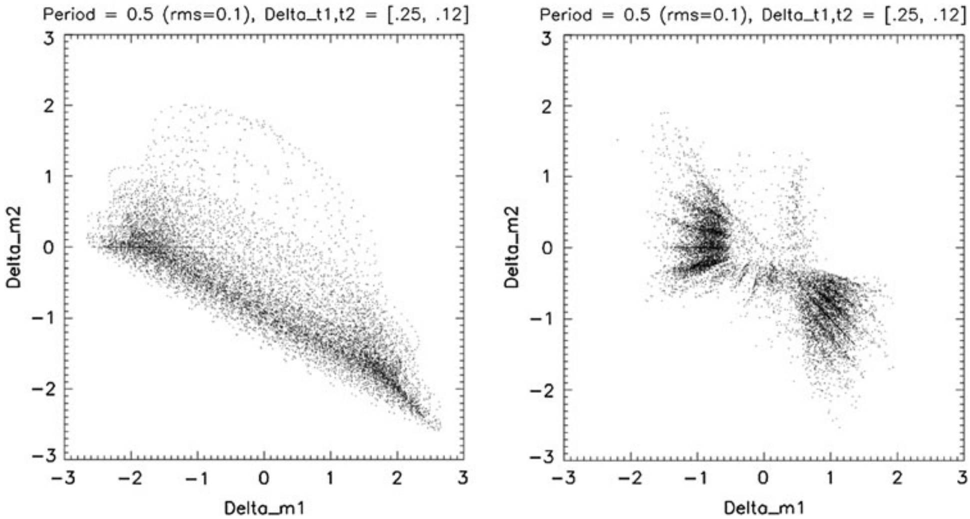

Figure 2. The frequency distribution of magnitude differences for 2 measurements of a sine-wave light-curve (*left*) and a sawtooth one (*right*) with a period of 0.5 days, when sampled at three epochs separated successively by 0.25 and then 0.12 days. See Sect. 3.2 for a full description.

sample Δm_1 and Δm_2 for all possible phases at t_a, and for good measure add a random noise drawn from a normal distribution with $\sigma = 0.1$. The frequency distribution in the $\Delta m_1 - \Delta m_2$ plane for such a uniform sampling of this light-curve for this specific Δt_1 and Δt_2 is shown in the left panel of Fig. 2. The right panel shows the distribution sampled identically for a light-curve with the same period and semi-amplitude, but with a saw-tooth shape. It is striking how different the two frequency distributions are. It should take only a few measured triads to tell whether the unknown is drawn from the left or from the right panel (or from neither) using the likelihood or entropy analysis discussed above for the simple Δm vs Δt case. This method of analysis marginalises over the correlations in Δt and corresponding Δm for any given object that are imposed by the light-curve itself, and provides a way to tell between different light-curve shapes on the basis of just a few observations.

As for the earlier case of 'independent' Δt and corresponding Δm, we can construct frequency distributions for the Δm measured across passbands, which will enhance the discrimination. We can also proceed to higher dimensions, e.g., from 3 to 4 observations, where there are 3 of Δt and 3 of Δm, with the frequency distribution mapped in a 3-D space of 3 Δm, and so on. However, practical considerations of constructing *and storing* frequency distributions for n-dimensional Δt distributions will limit how high one can go. Nevertheless, the example shown here may well hold the key to how a few early observations may characterise a newly discovered transient well enough to decide if it is unlike anything we know. Only continued work will tell.

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