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Alert Production with the Vera C. Rubin Observatory

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ABSTRACT

Describes the LSST Alert Production pipelines, data products, execution environment, and early performance.

Todo list

1. INTRODUCTION

Repeated observations of the night sky enable discovery of transient, variable, and moving objects, and time-domain measurements are one of the foundational techniques of astronomical science. The cadence of the observations, the intrinsic timescales of the phenomena, and the spatial volume probed by the observations set the rate of discovery

Eric: cite me; see also Tonry, Ofek

. In recent years, scientists have conducted dedicated optical time-domain surveys with large CCD mosaic cameras (e.g., PanSTARRS, DECam, ZTF, HSC, Gaia, Kepler, TESS) as well as distributed telescope networks (e.g., ASAS-SN, ATLAS,

Eric: more

). These have yielded large new samples of supernovae, variable stars, active galactic nuclei, and solar system objects. Additionally, they have uncovered the first exemplars of rare new classes of objects

Eric: add some examples: FBOTS, ISOs, asteroids interior to venus, ...

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Frequently, time-critical followup observations are necessary to classify and characterize objects discovered in time-domain surveys. Historically, human-composed circulars or telegrams were used to dissemenate discoveries to the wider community. The increasing rate of transient candidates as well as the desire for rapid automated followup motivated machine-readable alternatives

Eric: VOEvent, GCN, SciMMA/HopSkotch, TNS

. These trends culminated in the public "alert stream" paradigm employed by ZTF

Eric: cite Patterson

, in which hundreds of thousands of unfiltered difference image sources are shipped along with historical lightcurves and image cutouts to third-party alert brokers

Eric: cites

for classification, filtering, and followup. This approach has enabled fully automated identification and reporting of supernova candidates.

The Legacy Survey of Space and Time (LSST) to be conducted by the Vera C. Rubin Observatory promises an order of magnitude

Eric: confirm or cite

increase in transient discovery. Rubin's large collecting area, wide field of view, and fast readout and slew will deliver nearly a thousand

Eric: confirm

exposures across a wide swath of the Southern Hemisphere sky to unprecedented depths. This capability motivated the development of a rapid data processing pipeline to identify and publicize time-variable phenomena in LSST images: the Rubin Alert Production System (AP). Along with the annual Data Release Processing (DRP), these productions make use of the Rubin Science Pipelines software as well as the larger systems and infrastructure of Rubin Data Management (DM).

Eric: cites throughout

In this paper, we describe the design, implementation, and initial performance of the Rubin Alert Production system.

Eric: outline

2. PIPELINE

consider a (simplified?) pipeline graph

2.1. *Template Generation*

Pre-DR1 this may require description independent of DRP.

High-level discussion of DCR correction could go here.

2.2. *Preload*

2.3. *Single Frame Processing*

Construction of calibration products assumed described in Rykoff (2019).

ISR, PSF and Background fitting, photometric and astrometric calibration. Likely major commonalities with DRP.

2.4. *Image Differencing*

2.5. *Source Detection and Measurement*

Including discussion of point source, dipole, and streak detection on difference images.

Algorithmic basics could be discussed elsewhere

2.6. *Initial Filtering*

`FilterDiaSourceCatalogTask` in `lsst.ap.association`

2.7. *Reliability scoring*

Image-differencing searches for transients typically contend with high rates of false positives. Among the raw detections, artifacts may dominate real astrophysical sources by an order of magnitude. These may be due to imperfectly-corrected instrument signatures, astrometric mismatches between the template and the science image, cosmic rays, or algorithmic failures in the differencing. Modern surveys employ machine-learned classifiers to winnow these candidates (e.g., Bailey et al. 2007; Bloom et al. 2012; Brink et al. 2013; Wright et al. 2015; Goldstein et al. 2015; Duev et al. 2019). These have steadily improved in performance and sophistication as the classifiers transitioned from Random Forest models trained on manually-constructed feature sets to deep neural networks trained directly on image pixels. Some approaches have combined both detection and scoring without using the difference image (Sedaghat & Mahabal 2017; Acero-Cuellar et al. 2022).

overview of the algorithm, training, and performance of the ML spuriousness score; detailed discussion likely deferred to separate paper

2.8. *Catalog Transformation*

`TransformDiaSourceCatalogTask` in `lsst.ap.association`

2.9. *Source Association*

Due to AP's real-time nature, it is not possible to perform *post-facto* source association as in the annual data releases. Instead, spatial association is performed on-the-fly by the `DiaPipelineTask` within the `lsst.ap.association` package. A dedicated Alert Production Database (APDB; §4.2) holds the current state of the system.

During the preload step (§??), DIAObjects and SSObjects overlapping the expected field of view of the image are stored in the local prompt processing worker butler repository. The new DIASources are first spatially associated with the existing DIAObjects by finding the closest match within a maximum distance of one arcsecond. Pairs with the closest spatial separations are joined first to minimize misassociations. When a match is found, the DIASource is added to the DIAObject's list of measurements. Unassociated DIASources are then spatially associated with the predicted positions of the SSObjects at the time of the exposure. For DIASources with no matching DIAObject or SSObject, a new DIAObject is created and the DIASource is added to it.

2.10. *Alert Generation*

Formats & contents

2.11. *Alert Distribution*

Mechanisms, connections to community brokers

2.12. *Alert Filtering Service*

2.13. *Forced Photometry*

2.14. *Source Injection*

2.15. *Metrics*

3. PROMPT DATA PRODUCTS

Summary of relevant aspects of the DPDD (Jurić et al. 2023), including latency considerations and user access.

- Images
- Prompt Catalogs and the PPDB
- Alerts

4. PROCESSING ENVIRONMENT

4.1. *Prompt Processing Framework*

4.2. *Databases*

4.3. *Alert Archive*

4.4. *Metrics and Dashboards*

4.5. *Catchup Processing*

5. INITIAL PERFORMANCE

5.1. *Alert Purity*

Raw and after ML scoring

5.2. *Alert Completeness*

5.3. *Alert Latency*

5.4. *Photometric Precision*

5.5. *Astrometric Precision*

5.6. *Association Accuracy*

6. DISCUSSION

7. CONCLUSION

figure out how to make LSST technotes have appropriate information. lsst.bib has them as misc, should be okay?

REFERENCES

Acero-Cuellar, T., Bianco, F., Dobler, G., Sako, M., & Qu, H. 2022, arXiv e-prints, arXiv:2203.07390

Bailey, S., Aragon, C., Romano, R., et al. 2007, ApJ, 665, 1246

Bloom, J. S., Richards, J. W., Nugent, P. E., et al. 2012, PASP, 124, 1175

Brink, H., Richards, J. W., Poznanski, D., et al. 2013, MNRAS, 435, 1047

Duev, D. A., Mahabal, A., Masci, F. J., et al. 2019, MNRAS, 489, 3582

Goldstein, D. A., D'Andrea, C. B., Fischer, J. A., et al. 2015, AJ, 150, 82

Jurić, M., Axelrod, T., Becker, A., et al. 2023, Data Products Definition Document, Vera C. Rubin Observatory. https://lse-163.lsst.io/

Rykoff, E. S. 2019, LSST Calibration Strategy and Pipelines, Vera C. Rubin Observatory. https://pstn-026.lsst.io/

Sedaghat, N., & Mahabal, A. 2017, ArXiv e-prints

Wright, D. E., Smartt, S. J., Smith, K. W., et al. 2015, MNRAS, 449, 451