Transient-optimised source classification with Bayesian convolutional neural networks

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University of Warwick

GOTO

GRAVITATIONAL-WAVE OPTICAL TRANSIENT OBSERVER

Presented at NAM 2021 AstroML session

Time-domain astronomy: the real-bogus problem

How can we efficiently sift the deluge of data from current/upcoming transient surveys to maximise science yield?

~TBs / night

Image subtraction

~100,000s / night

Real-bogus filtering

~1,000s / night

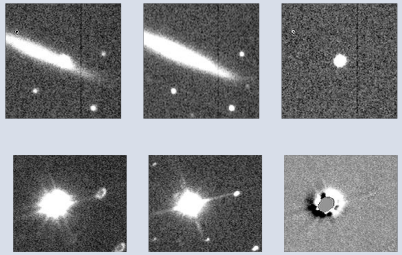
Human inspection

~10s / night

Real-bogus classification

Use ML/DL to automatically identify artifacts in difference images based on extracted properties.

Maximise completeness whilst simultaneously minimising false positives - avoid overwhelming human vetters!



SN2021hiz (real, score 1)

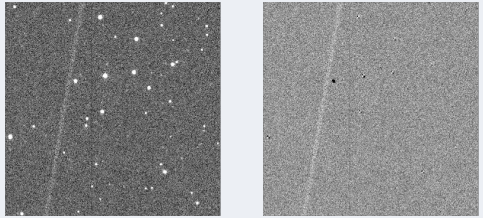
Bad subtraction (bogus, score 0)

see e.g. Bloom+12, Gieseke+17, Duev+19

The Gravitational-wave Optical Transient Observer

Each telescope/node:
8x40cm astrographs, combined FoV of **40 square degrees** - reaches **L ~ 20.5 in 180s** enabling rapid and deep surveys of GW localisation regions in real-time.

Difference imaging



More info: talks in Transients Diversity by Kendall Ackley and Ben Gompertz tomorrow!

Rapidly fading (~hours) GW counterparts necessitates **real-time, accurate** source classification **-** only possible with high-performance ML/DL.

The significant data volume generated by GOTO (and other surveys) provides an ideal **data-rich proving ground** for novel ML/DL algorithms applied to a diverse range of data modalities.

Training set generation

Automated training set

Real:
Minor planets - yield PSF-like detections

Bogus:
Randomly-sampled difference image detections, filtered for purity.

Human labelling optional, can be useful for artifacts

Transient augmentation

Randomly select minor planets in each image

Identify a galaxy near to the MP and extract an offset stamp

Sum galaxy stamp and minor planet to get a synthetic transient

Realistic PSFs, fast, and configurable injection.

Bayesian CNN

Scores are given as posterior distributions
Classifier uncertainty!

99.1% accuracy
0.5% FNR at 1% FPR

Highly configurable, image-level parallelism allows generating a **400k example dataset in under 24h!**

For full implementation details: **Killestein et al., (2021)** [arXiv: 2102.09892, in MNRAS]
All project code is open source via GitHub - *GOTO-OBS/gotorb*

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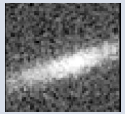

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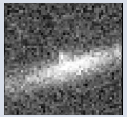

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Model architecture

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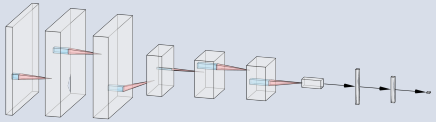

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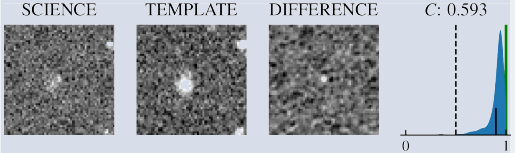

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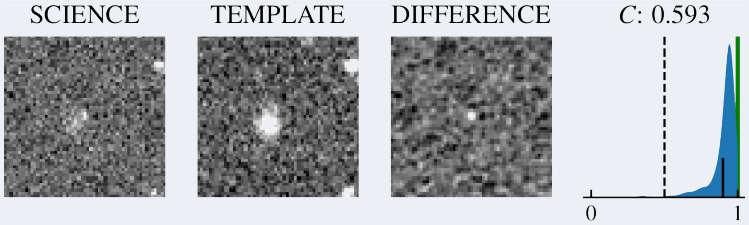
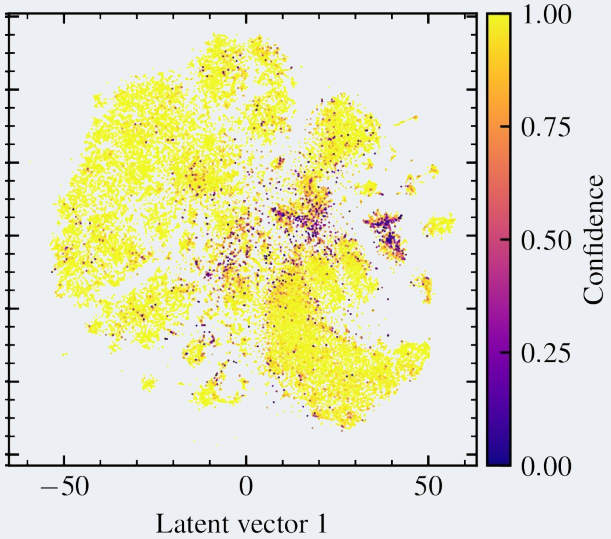
Bayesian neural networks: uncertainty-aware predictions

Dropout: at each train step, **disconnect** some fraction of neurons randomly for regularisation and generalisation.

Monte Carlo Dropout: sampling different realisations of dropped-out models is ~equivalent to sampling from the model output posterior (via an underlying Gaussian process). This allows quantification of **epistemic uncertainty** arising from our choice of model weights, and marginalisation.





t-SNE gives idea of coverage of training space, underrepresented classes, intrinsically difficult source types.

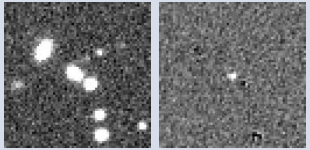
For in-depth theoretical discussion, see **Gal and Ghahramani (2014a,b and 2016)**

Dataset-induced biases and alignment

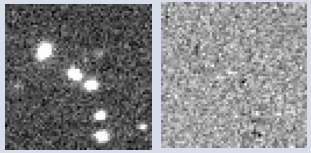
Think carefully about the inductive biases your dataset imposes!

Dataset-induced biases

Although introducing synthetic transients *alone* markedly improves the recovery of supernovae, this introduces an unintended side-effect: because every single one of our synthetic transients has an underlying galaxy, the network learns that all stamps containing a galaxy are **real detections...**



Confirmed SN (real)



Residual (false pos.)

Fix: add galaxies into the negative class as balance

Neural networks only care about **minimising the loss!** It's up to you to make sure your loss function and dataset reflect what you want it to learn.

Combining labelled datasets

Human labelling is a valuable tool for augmenting the performance of a classifier trained on synthetic data - but need to be aware of (hidden) differences in labelling conventions between them.

Minor planets graded bogus by humans (contaminant in GW searches) [FN]

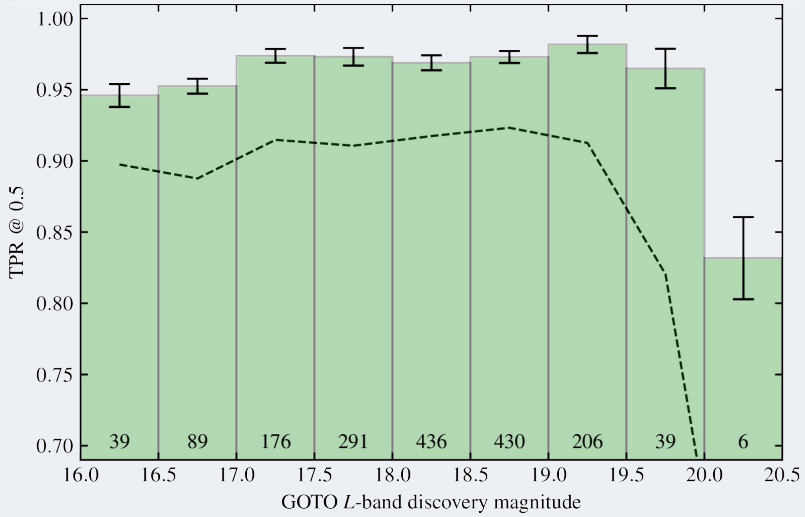
Low-amplitude stellar variability (ambiguous so graded bogus) [FN]

Genuine human errors (misclicks, vetting gets boring!) [FP]

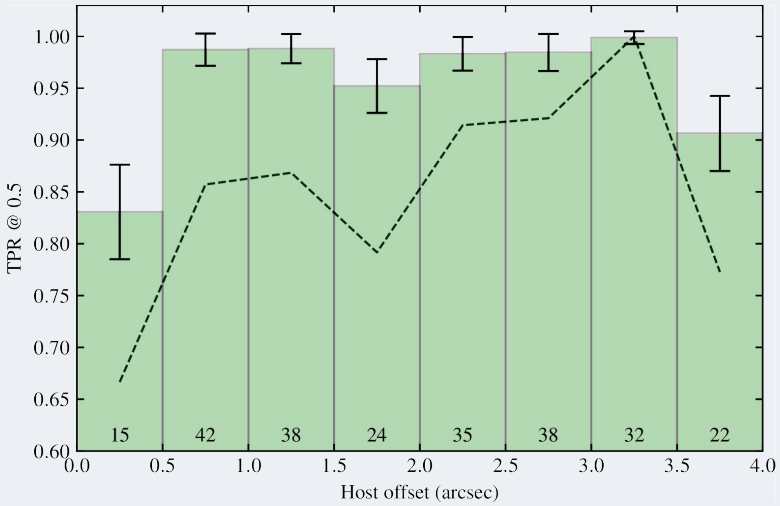
Can exploit the scarcity of mislabelled examples + BNN posterior confidences to semi-automatically filter these out - see Killestein+21 for more details

Transient optimisation: marked performance improvements

Test the classifier on >900 spectroscopically-confirmed transients recovered in the GOTO prototype phase — performance likely to be even better with in-progress instrumentation and pipeline upgrades.



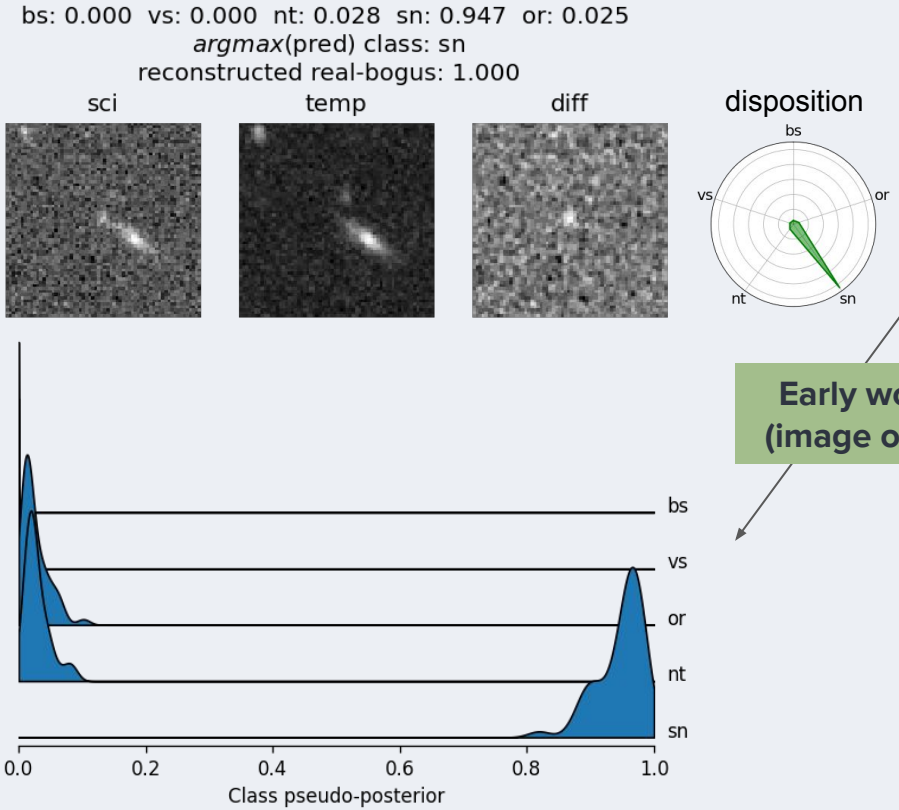
Significant increase in recovery of faint transients - excellent prospects for kilonova recoveries in local Universe.



Uniform coverage of host-offset space leads to **boosted recovery of nuclear transients**

Next steps: context-aware, granular classification

Image-level data can only go so far: need to fold in complex multi-modal data to give the full picture.



Early work (image only)

Use methods developed to build a prompt stamp classifier (similar to ALeRCe, Carrasco-Davis+ 2019) -- principled, Bayesian, high-performance **multi-label classification** for low-latency alerts of interesting candidates

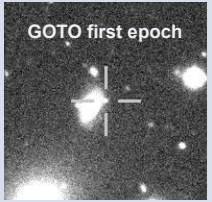
Maximise available information
If a human uses it in their vetting the classifier should too!

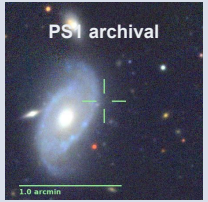
+ contextual awareness
+ hierarchical meta-classification
+ adaptive stream learning

Fusing image-level data and contextual catalogs

Overarching aim: make available all human-interpretable information to any ML/DL classifier

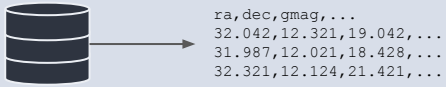
Image-only:





+ Always available (discovery image)
- Limited by image quality/resolution
- Apparent type != actual type

Catalog-only:



Salient information already extracted

+ Far deeper than survey images
- Incomplete (galaxy catalogs)
- Incorrect (misclassifications)
- Inhomogeneous (variable coverage)

Image-level information can compensate for catalog issues!

Ensemble catalogs into VS/AGN/GLX sources, and compute basic nearest-neighbour distances - combine this with image-only CNN scores in a random forest

Train on censored data - randomly exclude contextual information to **simulate incompleteness** and enable **robust classifications** with all information available.

work in progress

96% recovery of supernovae
98% test set accuracy

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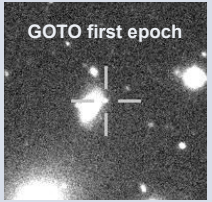

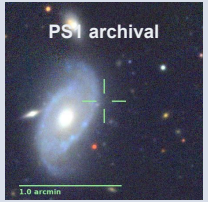

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Catalog-only:

```
ra,dec,gmag,...
32.042,12.321,19.042,...
31.987,12.021,18.428,...
32.321,12.124,21.421,...
```

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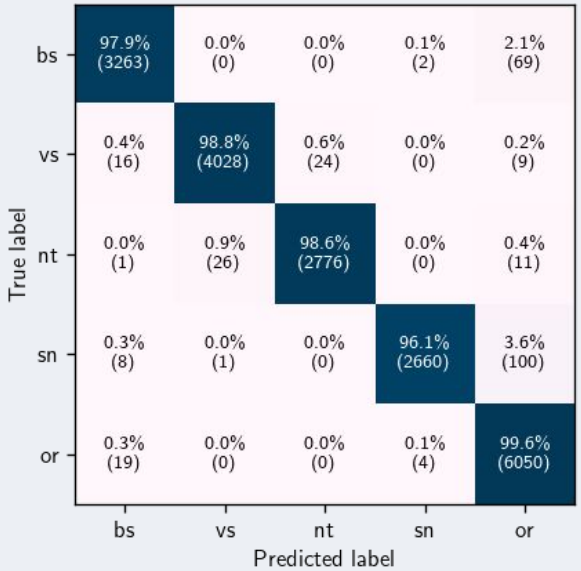

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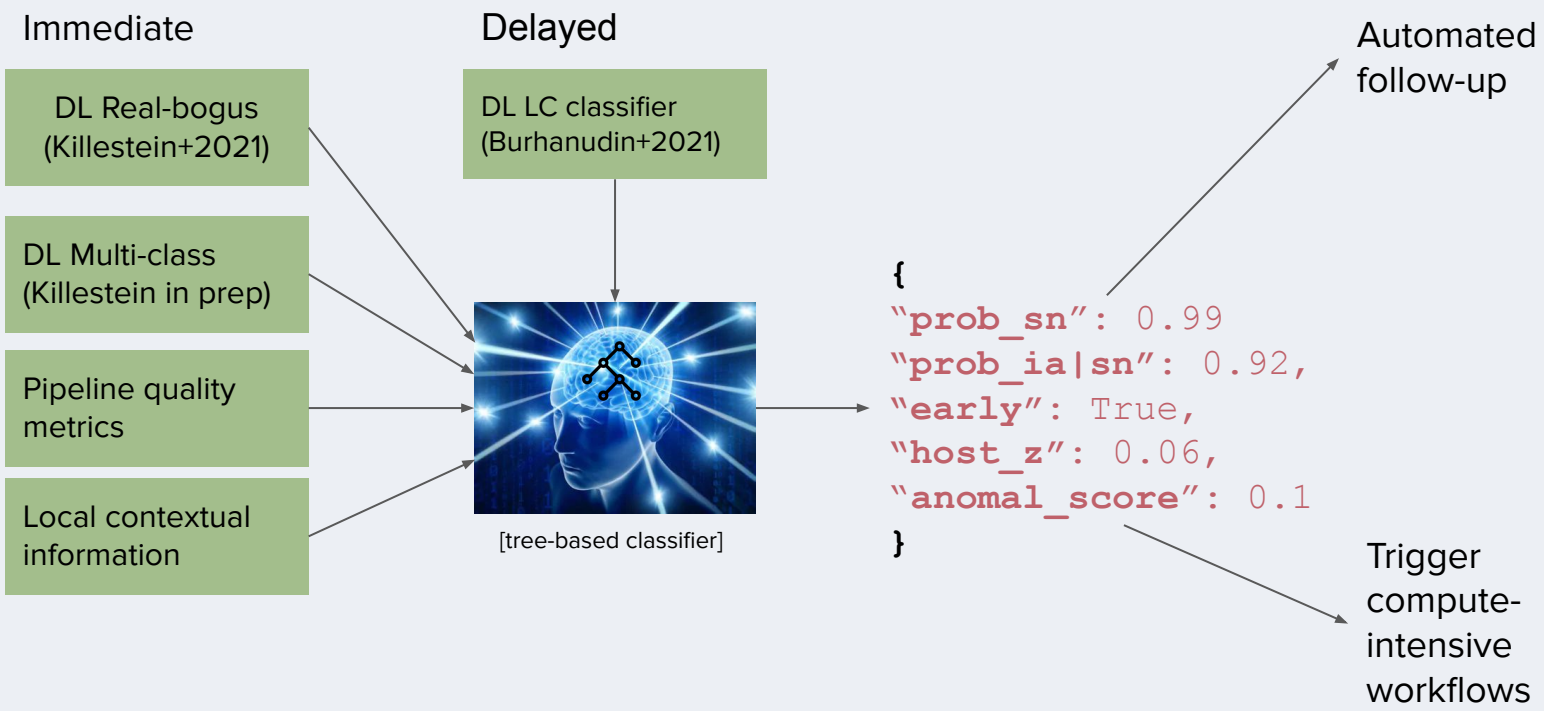
End goal: hierarchical meta-classification

Strong tree-based **ensembles of expert classifiers** - interpretable, efficient, and performant.
Hierarchical approaches **mimic human approaches** to transient classification.



We combine **Bayesian convolutional neural networks** with a **novel training set generation and augmentation procedure** to achieve state of the art results on real-bogus classification with **minimal human labelling**.

In active development: **context-aware deep learning ensembles** to bridge the gap between image-level classification and catalog-based contextual classification in a principled, robust manner for even better source filtering!

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