The Simulated Catalogue of Optical Transients and Correlated Hosts (SCOTCH)

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ABSTRACT

As we observe a rapidly growing number of astrophysical transients, we learn more about the diverse host galaxy environments in which they occur. Host galaxy information can be used to purify samples of cosmological Type Ia supernovae, uncover the progenitor systems of individual classes, and facilitate low-latency follow-up of rare and peculiar explosions. In this work, we develop a novel data-driven methodology to simulate the time-domain sky that includes detailed modeling of the probability density function for multiple transient classes conditioned on host galaxy magnitudes, colours, star formation rates, and masses.

We have designed these simulations to optimize photometric classification and analysis in upcoming large synoptic surveys. We integrate host galaxy information into the Simulated Catalogue of Optical Transients and Correlated Hosts (SCOTCH), a publicly-available catalogue of 5 million idealized transient light curves in LSST passbands and their host galaxy properties over the redshift range $0 < z < 3$. This catalogue includes supernovae, tidal disruption events, kilonovae, and active galactic nuclei. Each light curve consists of true top-of-the-galaxy magnitudes sampled with high ($\leq$2 day) cadence. In conjunction with SCOTCH, we also release an associated set of tutorials and transient-specific libraries to enable simulations of arbitrary space- and ground-based surveys. Our methodology is being used to test critical science infrastructure in advance of surveys by the Vera C. Rubin Observatory and the Nancy G. Roman Space Telescope.

Key words: transients: supernovae – software: simulations – catalogues

1 INTRODUCTION

An era of rapid and large-scale astronomical data collection is underway. Surveys are now detecting transient events across large swaths of the sky, e.g. the Zwicky Transient Facility (ZTF: Bellm et al. 2019), ASAS-SN (Shappee et al. 2014), Gaia (Gaia Collaboration et al. 2016), and MeerKAT (Jonas 2009). Entirely novel classes of events, including those at higher redshifts, will soon be revealed as telescopes such as the Vera C. Rubin Observatory (Ivezić et al. 2019), the Nancy Grace Roman Space Telescope (Spergel et al. 2015), and the James Webb Space Telescope (Gardner et al. 2006) begin collecting data. Notable among these, the Rubin Observatory (set to begin science operations in Chile in 2024) will undertake the Legacy Survey of Space and Time (LSST), expected to observe millions of transients out to and beyond $z \sim 1$ as it repeatedly scans 18,000 square degrees of the sky over ten years.

The scientific goals of these large-scale transient surveys are manifold, but include measuring the expansion history of the universe, improving our understanding of progenitor physics, and discovering faster and fainter transients that have eluded prior searches. Accurate classification will be paramount for each of these goals. In the majority of cases, transients discovered in upcoming surveys must be classified without spectroscopic information. Algorithms that classify transients based on photometry alone have proliferated in recent
years, some based on traditional template-matching methods and others employing novel machine learning algorithms (e.g., Villar et al. 2020; Möller & de Boissière 2020; Qu et al. 2021; Alves et al. 2022).

Multiple studies have demonstrated correlations between the class of a transient and the properties of the galaxy where it occurs (deemed its “host galaxy”). Where light curve sampling is sparse, host galaxy data can be used to more easily distinguish transients of different classes. The occurrence rate of Type Ia supernovae (SNe Ia) is directly proportional to both the stellar mass and the star formation rate of its host galaxy, although a non-negligible subset has also been discovered in passive galaxies (Sullivan et al. 2006). As the end-states of short-lived (~50 Myr) massive stars, Core-Collapse SNe (CCSNe) are most likely to occur in spiral galaxies undergoing periods of significant star formation (Svensson et al. 2010). Variations also arise in the host populations of stripped-envelope SNe, events characterized by a dearth of hydrogen (SNe Ib) and helium (SNe Ic) in spectral observations. Broad-lined SNe Ic (SNe Ic–BL), the only supernovae to be unambiguously associated with long-duration Gamma Ray Bursts (LGRBs; Japelj et al. 2016), have host galaxies with lower average metallicity than their lower-energy counterparts (SNe Ic; Modjaz et al. 2020). This suggests a potential relationship between progenitor metallicity and the formation of jets in the tumult of stellar death (Graham & Fruchter 2013). Further, SED fits to multi-band photometry of Type-I (Hydrogen-poor) Super-Luminous SN (SLSN-I) hosts have revealed that these events occur almost exclusively in metal-poor, low-mass, star-forming host galaxies (Leloudas et al. 2015; Perley et al. 2016; Angus et al. 2016). In the pursuit of optimally-standardized light curves for cosmology, subtler correlations have also been identified between SN Ia photometry and both host galaxy mass and star formation rate (Lampeitl et al. 2010; Sullivan et al. 2010; Barkhudaryan et al. 2019; Rose et al. 2019; Brout & Scolnic 2021).

At low redshifts, spatially resolved studies enabled by multi-wavelength photometry and Integral Field Unit spectroscopy have revealed local-scale correlations. From a sample of 519 host galaxies selected in the Sloan Digital Sky Survey (SDSS; Blanton et al. 2017), Kelly & Kirshner (2012) found that SNe Ic-BL and SNe Ib occurred in extremely blue locations. Local correlations are weak for SNe Ia (Anderson et al. 2015): due to the advanced ages of their white-dwarf progenitors (~Gyrs), these systems can mitigate substantially from formation to explosion. Nevertheless, the environment may alter the evolution of an event for the same progenitor: the observational properties of SNe Ia are correlated with local dust extinction, although this is itself linked to the global properties of the host galaxy (Holwerda et al. 2015; Popovic et al. 2021). Spatially-resolved host galaxy information can also be used to distinguish between SN explosion models in the absence of direct detections of a progenitor (Raskin et al. 2008; Fruchter et al. 2006).

Preliminary correlations have been identified in recent years for rare classes of events, including a preference of Rapidly-Evolving Transients (RETs; Drout et al. 2014; Pursiainen et al. 2018) for hosts of intermediate mass between high-mass SN Ia hosts and low-mass SLSN hosts (Wiseman et al. 2020). For observationally rare events (e.g., kilonovae (KNe); Smartt et al. 2017), correlations remain as yet unconstrained, but may play a decisive role in maximizing the yield of future targeted searches. Upcoming surveys are well-poised to further extend our understanding of these class-specific correlations toward higher redshifts and rare subtypes. However, only a few transient classifiers to date (Foley & Mandel 2013; Gagliano et al. 2021; Kisley et al. 2023) have incorporated host galaxy information. Efforts are stymied by the limited observational data available for training these algorithms; perhaps worse, extant samples are frequently biased toward low-redshift, bright host galaxies, uncharacteristic of the galaxies anticipated from upcoming surveys.

In this transitional period when observed transient samples are limited to the local universe, simulations are vital for developing and testing classification algorithms that incorporate host galaxy information. Such algorithms will need to perform reasonably well on new faint and high-redshift data in the early days of LSST, until they can be iteratively tested and updated using the incoming data and the corresponding advancements in time-domain theory. This interim period requires high-redshift simulations that extrapolate bright, low-redshift existing measurements (such as transient rates and host correlations) to fainter magnitudes and into the universe’s past. High-redshift simulations necessarily require assuming untested theoretical models for evolution, or assuming that trends at low redshift extend to high redshift.

We follow the latter assumption, and present the first large-scale simulation of optical transients and their host galaxies that extrapolates existing data to high redshifts (z ~ 3). This work extends the simulations generated for the Photometric LSST Astronomical Time-Series Classification Challenge (PLAsTiCC; Kessler et al. 2019a). PLAsTiCC data were generated by simulation code in the SuperNova Analyis package (Kessler et al. 2009, SNANA), and the challenge represented the first large-scale effort to realistically simulate a broad diversity of transient phenomena. Simulated host-galaxy information, however, was limited: the dataset only includes the photometric redshifts of host galaxies assigned near the redshift of the transient. This work extends the PLAsTiCC framework with the inclusion of empirical and theoretical host-galaxy correlations for both common and rare transient classes. We embed these correlations using a series of host galaxy libraries (called HOSTLIBs within SNANA) and weight maps (WGTMAPs) that describe the likelihood of a given galaxy to host a transient of a certain class within the simulation.

Our work is enabled by multiple previous efforts to consolidate the properties of transient host galaxy populations. The Gamma Ray Burst (GRB) Host Studies catalogue (GHOSTS; Savaglio et al. 2006a) consolidates derived host galaxy information (including star formation rate, stellar mass, and redshift) for ~100 GRBs, finding that these bursts occur preferentially in star-forming, low-mass galaxies. Gagliano et al. (2021) constructed the Galaxies Hosting Supernovae and other Transients (GHOST) Catalogue, which contains the optical photometric properties of ~16,500 galaxies that have hosted observed SNe of all classes. At the time of writing, Qin et al. (2022) has released the Transient Host Exchange (THEX), a catalogue containing >36,000 host galaxies of many transient types and the photometric properties of their hosts spanning infrared to ultraviolet wavelengths.

There is precedent to the use of host galaxy libraries in supernova simulations. In SNANA, HOSTLIBs were first used to model Poisson noise in simulated bias corrections for SN Ia distances for the Joint Lightcurve Analysis (Kessler et al. 2013; Betoule et al. 2014). HOSTLIBs were similarly used to forecast constraints for the Nancy Grace Roman Space Telescope (Hounsell et al. 2018). The Pantheon (Scolnic et al. 2018) and DES 3-year (Abbott et al. 2019; Brout et al. 2019) SN Ia-cosmology analyses further extended the scope of these files to account for correlations between SN properties and host galaxy stellar mass. An alternative machine learning-based simulation, EmpiricSN (Holoien et al. 2017), employed a library of photometric host galaxy data in SDSS to generate synthetic light curves of SNe Ia.

1 http://www.grbhosts.org/
As part of the recent Dark Energy Survey (DES) cosmology analysis using photometrically-identified SNe Ia, Vincenzi et al. (2021) expanded the SNANA-specific HOSTLIB framework to realistically simulate SN host galaxies by class using a set of physically-motivated WGTMAP files. To account for contamination from non-Ia classes, their simulation includes CCSNe (including SNe II and Ib/c) and considers the dependence on host galaxy mass and star formation rate for each SN type. The resulting SN IA+CC SN simulation of host properties and SN-host correlations shows excellent agreement with DES data, and this simulation is now in use as a training set for photometric classifiers (Möller et al. 2023, in prep.).

In this work, we extend the results of Vincenzi et al. (2021) by simulating additional classes of supernovae and other non-SN transients, incorporating correlations across a wider range of host galaxy properties, and separately validating hosts of different classes across these properties. We extrapolate information from archival events, mostly at low-redshift, to a high-redshift simulated sample across galaxies via associations in intrinsic — rather than observed — properties. In doing so, we encode correlations for each transient class to significantly higher redshifts (z ~ 3) than the ranges spanned by current observations. Due to a lack of high-z evidence, the most practical option is to assume no redshift evolution of the observed transient-host relationships in the local universe and smoothly extrapolate transient rate models measured at low redshifts. Therefore, the simulation is likely to become increasingly inaccurate at higher redshifts, and SCOTCH\(^2\) by itself should not be used for precision cosmological forecasts or high-redshift transient analyses. However, the catalogue can be used to test classifier algorithms and alert broker systems, examine the effects of contamination on cosmological constraints, and model selection biases in current and upcoming transient/host galaxy surveys.

Our paper is organized as follows. We outline the overall methodology in §2. We introduce the archival catalogues used to construct our host galaxy sample in §3. We describe the SNANA simulation code that we use to generate our transient events and summarize the models underlying each event in §4. We present our methods in §5 for combining observed and simulated catalogues into a library containing millions of host galaxies. We then describe our process for incorporating additional class-specific transient correlations using WGTMAPs in §6. We comment briefly on the inclusion of class-specific radial offsets in §7. We validate our results in §8 and present the schema of our final catalogue in §9. We then conclude with a discussion of the limitations of our sample and areas for future research in §10.

2 METHODOLOGY OVERVIEW

Because the methods we use to simulate the transients themselves are nearly identical to those described in Kessler et al. (2019a), this paper focuses on our methodology for constructing a set of HOSTLIBs and WGTMAPs for the SNANA simulation code. This allows us to realistically associate a simulated host galaxy with each transient, given its class. We provide a flowchart of this pipeline in Fig. 1. The initial input is the CosmoDC2 synthetic galaxy catalogue (Korytov et al. 2019, described in §3.1) with slight modifications made via the PZFFlow algorithm (Crenshaw et al. 2021, described in §5.2). First, we create four large galaxy libraries: for SNe, by selecting synthetic galaxies matching the rest-frame colour and absolute magnitude distributions of three broad categories of transient hosts in observational data; and for non-SNe, by generating a generic catalogue of galaxies which will be tailored to match observations at a later stage. For SNe, we utilize the observational data in GHOST (Gagliano et al. 2021), a catalogue of supernova host galaxy properties described in additional detail in §3.2. Our process for selecting synthetic galaxies matching the statistical properties of the observational data, including the use of the ANNOY\(^3\) algorithm, is described in detail in §5.3. The resulting three galaxy libraries include: Type Ia hosts (I); Type II, IIn, IPh hosts (II); and Type Ib, Ic, IIb hosts (III). We construct a fourth library of randomly-selected CosmoDC2 galaxies to serve as the hosts of transients from classes that have little observational data, and for which the correlation between explosion and environment is unconstrained by GHOST. Next, for nine different transient classes including SN and non-SN, we encode the probability that an event of that class will occur in a host galaxy given its mass and star formation rate. These probabilities are motivated by observations and are described in §6. Finally, the SNANA simulation (§4) is used to generate transient light curves and place each in a realistically-associated host galaxy, with host galaxies selected from one of the four libraries depending on the transient class and the probability of selection given by the class-specific functions described in §6.

3 GALAXY DATA

3.1 The DC2 Simulations

Our work aims to simulate transient-host associations to higher redshifts and fainter magnitudes than have been previously observed. We also wish to produce a catalogue containing valuable derived properties of transient hosts, including morphology, star formation rates and stellar masses. Observed galaxy catalogues are limited in these respects, so we use make use of synthetic galaxy data from the LSST Dark Energy Science Collaboration (DESC).

DESC is in the midst of a series of data challenges in preparation for the Rubin Observatory. The goal of the data challenges is to produce realistic end-to-end simulations of LSST survey operations, data reduction, and analysis. For data challenge 2 (DC2), DESC produced a suite of simulated LSST-like datasets, including an extragalactic source catalogue and co-added images (LSST Dark Energy Science Collaboration et al. 2021). We make use of the extragalactic catalogue, named the CosmoDC2 Synthetic Sky catalogue (Korytov et al. 2019), and its associated DC2 image data.

The CosmoDC2 catalogue was constructed from a dark matter only N-body simulation in a 4.225 Gpc\(^3\) volume. This volume is insufficient to probe to z \~ 3 as needed for LSST, so to create lightcones, the volume was replicated once per axis. After the lightcone generation, realistic galaxies with Sersic profiles and SEDs were associated with dark matter halos. The resultant galaxy catalogue, which is delivered in HEALPix\(^4\) (Hierarchical Equal Area iso-Latitude Pixelization) format (Górski et al. 2005), spans 440 deg\(^2\) of the sky and cosmological distances (z \~ 3). The CosmoDC2 data has also undergone rigorous validation to ensure that it matches observed galaxy properties (Kovacs et al. 2021). However, due to necessary compromises made to accommodate the needs of the diverse DESC working groups, the CosmoDC2 distributions of galaxy colours are far from perfect, particularly at higher redshifts (z > 0.5). We discuss how these colour limitations affect the final SCOTCH catalogue in §8.

\(^2\) https://zenodo.org/record/7563623#.Y8_2my9h2yA

\(^3\) https://github.com/spotify/annoy

\(^4\) http://healpix.sourceforge.net
We use the GCRCatalogs\(^5\) analysis tool (Mao et al. 2018) to select CosmoDC2 galaxies within 31 neighbouring HEALPixels from an \(N_{\text{side}} = 32\) pixelisation, corresponding to 104 square degrees of total area. The selected HEALPixels are chosen to completely overlap with the DC2 image catalogues (LSST Dark Energy Science Collaboration (LSST DESC) et al. 2021), which contain image properties for CosmoDC2 galaxies as LSST would observe them over 5 years, corresponding to a co-add depth of \(r = 28\) (where \(r\) is the apparent AB magnitude in the LSST filter). The overlap in coverage between these HEALPixels and the image catalogue is shown in Fig. 2. To ensure the generality of our final catalogue, the sky coverage displayed in the figure is not maintained in SCOTCH (we discuss this in additional detail in §4.1).

Within these HEALPixels, we select CosmoDC2 galaxies with \(r < 28\), which removes the majority of galaxies that were not detected within the DC2 5-year image co-add catalogues. We further refine this sample by removing objects with unreported image properties. After this cut, \(\sim 98\%\) of galaxies have an average \(r\)-band surface brightness within the half-light radius of less than 26 mag/arcsec\(^2\). This selection yields a sample of \(\sim 40\) million galaxies, which represent a realistic magnitude-limited galaxy sample. In Section 5.3, we describe the process of selecting galaxies that match observed properties of transient hosts; this further reduces the sample to \(\sim 10\) million galaxies.

### 3.2 The GHOST Catalogue of Transient-Host Galaxies

The GHOST catalogue (Gagliano et al. 2021) consists of \(\sim 16,500\) archival SNe consolidated from the Transient Name Server (TNS) and the Open SN Catalogue (OSC), as well as the observed properties of their host-galaxies from the first data release of Pan-STARRS (PS1; Chambers et al. 2016). Host galaxies within the catalogue were identified and validated through a combination of the established Directional-Light Radius method (DLR; Gupta et al. 2016) and the Gradient Ascent method (Gagliano et al. 2021). Although this GHOST sample contains realistic statistical correlations between transients and their host galaxies, it does not contain a representative sample of events anticipated from upcoming surveys. First, the catalogue comprises a small number of low-redshift (\(z < 0.2\)) explosions. LSST will dramatically enhance our current discovery rate for luminous SNe, motivating the need to scale the sample sizes in the GHOST catalogue for every class. Further, GHOST does not include non-SN transients such as Tidal Disruption Events (TDEs) and Active Galactic Nuclei (AGN), classes whose discovery and characterization are key science drivers for LSST. Finally, because the catalogue contains only the photometric properties of SN host

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\(^5\) [https://github.com/LSSTDESC/gcr-catalogs](https://github.com/LSSTDESC/gcr-catalogs)
galaxies, it lacks an explicit correlation between a transient and the stellar-mass and star formation rate of its host galaxy.

The CosmoDC2 catalogue provides photometry in LSST (ugrizY) and SDSS (grizY) filters, while GHOST galaxy photometry is provided only in the PS1 (grizY) filter system. To accurately match galaxy photometry between these catalogues, we convert the GHOST photometry from the PS1 to the SDSS system. We use the approximate quadratic conversions defined in Tony et al. (2012) and k-correct the apparent magnitude in each band using the analytic approximations described in Chilingarian et al. (2010) and Chilingarian & Zolotukhin (2012), which were computed according to the SEDs of simple stellar populations ranging from 25 Myr to 16.5 Gyr and $-2.5 < [Fe/H] < +1.0$ dex fit to 170,533 galaxies within SDSS Data Release 7. This transformation allows us to accurately match GHOST galaxies to those in CosmoDC2. Next, we use the spectroscopic redshift of each galaxy’s associated transient (or the spectroscopic redshift of the host, if the former was unreported on TNS) to calculate the absolute rest-frame brightness of each galaxy in SDSS pass-bands. We use these to compute rest-frame g, r, i, and z colours. To ensure that only galaxies with high-SNR photometry are considered, we apply stringent quality cuts to the galaxies in the GHOST sample based on the values of the PS1 primaryDetection and objInfoFlag1, objInfoFlag2, and InfoFlag3 values in each band. This while this may limit our observed sample to only low-redshift events, it ensures that the photometric correlations we encode from this regime are accurate. Our final sample after these cuts consists of 8,800 SN host galaxies.

4 GENERATING TRANSIENTS WITH THE SNANA SIMULATION

4.1 The SNANA Framework for Generating Transients

Our methodology is shaped by the existing framework of the SNANA simulation code (Kessler et al. 2009). Therefore, although the use of SNANA constitutes the final stage of our pipeline as displayed in Fig. 1, we first describe the SNANA simulation and introduce the simulation-specific terminology before detailing our methods for host galaxy association. This simulation reads user-defined transient model SEDs (rest-frame), redshift-dependent rates, and realistic observing conditions, and outputs transient events with realistic light curves and spatial distributions as a function of redshift. The SNANA simulation was used to generate nine distinct classes of extragalactic transients for PLAsTiCC; Figure 1 from Kessler et al. (2019a) shows example output light curves in ugrizY bands from each model. In this paper, we distinguish SNe Ib from SNe Ic and SNe IIn from SNe II to simulate 11 classes: AGN, KN, TDE, SLSN-I, SN Ib, SN Ic, SN II, SN IIn, SN Iax, SN Ia-91bg, and SN Ia, with the addition of SN Ib and SN Ic-BL and with some updates to the PLAsTiCC models as described in §4.2. We implement a cosmology of $\Omega_M = 0.3$, $\Omega_{\Lambda} = 0.7$, $w_0 = -1$, and $H_0 = 70$ km s$^{-1}$Mpc$^{-1}$. We note that, while these values are slightly different from the Planck (Planck Collaboration et al. 2020) parameters used in the Outer Rim simulation to generate the CosmoDC2 catalogue, the small inconsistencies that this difference introduces are far sub-dominant to the shifts that we apply to galaxy redshifts in §5.2. The transient models differ in the distributions of emission across bands, the shape of the light curves, and the peak brightness. For example, most of the SN Ib/c model flux is emitted at redder wavelengths; the KN model exhibits a characteristic timescale shorter than most other transients in our sample; and simulated SLSNe-I emit significantly higher flux than the other models.

The SNANA simulation includes the option of associating each simulated transient to a host galaxy from a user-input catalogue (the host library or ‘HOSTLIB’) that includes redshift and other galaxy properties (§5). After each transient is simulated, the algorithm selects a HOSTLIB galaxy that lies within $\delta z$ of the transient. We set $\delta z$ to correspond approximately to 100 comoving Mpc, which ranges from $0.02$ at $z = 0$ to $0.1$ at $z = 3$ given the 2018 cosmological parameters from the Planck satellite (Planck Collaboration et al. 2020). Host galaxy selection is further influenced by a user-input weight map (WGTMAP) that defines the probability of selecting a galaxy as a function of its properties (§6). The WGTMAP framework is flexible, such that the probability can depend on different galaxy properties for different classes—in other words, the parameter space over which the WGTMAP probabilities are defined is not fixed but rather user-defined.

Following Fig. 1, the simulation begins by generating a transient SED and drawing a redshift according to the class-specific rate model. The rate models are detailed in §4.2 and are entirely responsible for the redshift distributions of events in the final catalogue. This may be counterintuitive, as one might expect that the features of the synthetic host galaxy population should determine the transient event rates; however, myriad uncertainties in the transient-host connections make such an approach far more challenging to match observed event rates at low redshifts.

Next, the transient is matched to a host galaxy. The surface brightness profile of each galaxy in cosmoDC2 is a weighted combination of two Sersic profiles: that of an exponential disk ($n_0$), and that of a deVaucouleurs bulge ($n_1$). For each galaxy associated with a supernova, one of these profiles is selected using their relative weights. Next, a radius and azimuthal angle are selected (where the radius selection is weighted by the Sersic profile), and this determines the position of the transient with respect to the host centre. We further encode simple models for the radial offsets of TDEs, AGN, and KNe as described in §7.

After the transient offset is computed, the host galaxy redshift is set to the redshift of the transient and the host’s apparent magnitudes are

| HOSTLIB | WGTMAP | Class | Cadence (Days) |
|---------|---------|-------|----------------|
| SN Ia Hosts | $P_{\text{SN Ia}}$ | SN Ia | 2.0 |
| SN II Hosts | $P_{\text{SN II}}$ | SN II/Ib/In/IIP/IIL | 2.0 |
| H-Poor SN Hosts | $P_{\text{SN Ib}}$ | SN Ib | 2.0 |
| $R_{\text{SN Ic-BL}}$ | SN Ic-BL | 2.0 |
| $P_{\text{SLSN I}}$ | SLSN-I | 2.0 |
| $P_{\text{SN Ib}}$ | SN Ib | 2.0 |
| $P_{\text{AGN}}$ | AGN | 0.1–2.0 |
| $R_{\text{KN}}$ | KN | 0.1–2.0 |
| $P_{\text{TDE}}$ | TDE | 0.1–2.0 |

Table 1. Summary of the HOSTLIB, WGTMAP, and cadence used for each transient class in our simulation. The first three HOSTLIBs contain CosmoDC2 galaxies that extrapolate distributions of observed hosts in GHOST; the fourth is a representative sample from CosmoDC2. $P_{\text{class}}$ refers to the probability of each transient class occurring given the properties of a galaxy; these functions are defined in §6 and implemented via the WGTMAPs. The cadence refers to the time interval between light curve samples in the simulation.

http://kcor.sai.msu.ru/getthecode/#python

A full list of the imposed quality cuts can be found at the GitHub repository for this work.
updated to reflect the small change in distance (100 comoving Mpc or less). With this framework, one host galaxy from the HOSTLIB can be used multiple times, which is often necessary given the desired number of transients (5M) that we aim to simulate, the similar size of the HOSTLIBs, and the different redshift distributions for the transient model and the HOSTLIBs. In such a case, the single input galaxy is mapped to multiple host galaxies with slightly different redshifts and apparent magnitudes in the final catalogue. Due to this duplication, it is necessary to remove on-sky position information from the galaxies such that duplicated galaxies do not appear at the same sky location. Unfortunately, this loses the initial positioning within realistic large-scale structure from CosmoDC2. We leave an accurate embedding of transients within the cosmic web to future work. In our simulation, the host centres are arbitrarily set to be simulated at (RA,Dec) = (0,0) and positions are not reported in the final catalogue.

The transient SED is modified for cosmic expansion, weak lensing magnification, redshift, and host galaxy extinction. The weak lensing model aims to statistically match the average magnification effects as a function of redshift; Kessler et al. (2019b) describes the model in further detail. We do not explicitly model host extinction from each galaxy’s morphology; rather, we follow the statistical treatment in PLAsTiCC (Kessler et al. 2019a). For the theoretical models (MOSFIT and KNe), extinction is parameterized by $A_V$. For most models, this parameter is drawn from a Galactic Line-of-Sight distribution with a Gaussian core of $\sigma = 0.1$ and an exponential tail parameterized by $\tau = 0.4$ (Sako et al. 2008; Bernstein et al. 2012). Dimming is then computed assuming the Milky Way color law from Fitzpatrick (1999). For TDEs, only the exponential is included in order to simulate significantly higher extinction near the host galaxy centres where these transients occur. For KNe experiencing less host extinction at large offsets (see § 7), the exponential tail is reduced by a factor of two. The other transient models have been constructed from observed photometry, which implicitly includes the effects of host-galaxy extinction. This formalism assumes no evolution in dust properties with redshift.

The final SED corresponds to what an observation would look like from a vantage point just outside the Milky Way, without Galactic extinction, because we have not simulated transient locations on the sky. This leaves flexibility for the user to place events within the sky footprint of a preferred survey and apply the corresponding line-of-sight extinction and noise models. Next, the SED is converted to an apparent magnitude in the LSST photometric system ($ugrizY$). We configure SNANA to report all light curves in true LSST magnitudes without applying any threshold for detection. Therefore, very faint magnitudes are included in the transient light curves. Because hosts are restricted to $r < 28$, catalogue users are encouraged to apply a limiting magnitude equal to or brighter than $r = 28$ to the full catalogue to create consistency before use.

We sample most of our simulated light curves from 100 days preceding peak light to 100 days after peak. Due to the rapid rise and decline of KN photometry, we sample the light curve for only 10 days pre-peak and 60 days after-peak. For each transient class, we implement one of three cadence strategies. For SNe Ia, CCSNe (II, IIn, IIP, and II), and H-poor SNe (Ibc, Ic, IBL, Ib, SLSN-I), we adopt a sampling of $\delta t = 2.0$ days (so that each light curve has 100 observations each in $ugrizY$). Because of the rarity of high-cadence KN and TDE observations, we aim to preserve as much physical information about these light curves as possible while keeping file sizes manageable. For these events, we adopt a logarithmic sampling scheme, with $\delta t = 0.1d$ at peak and increasing toward $\delta t = 2.0d$ in either temporal direction. Because the rise of many transient light curves occurs on significantly shorter timescales than a decline powered by emission from radioactive decay, our cadence increases more slowly from peak light to late times than from peak light to pre-explosion epochs (Fig. 3). This sampling scheme generates ~ 260 observations per pass-band. The rapidly-evolving stochasticity of AGN light curves cannot be accurately characterized by either of these cadences. For the AGN in our catalogue, we provide light curves at cadences of both $\delta t = 0.1d$ (250 events) and $\delta t = 2.0d$ (2,250 events). The choice in light curve can be made by the user, depending on their science goals. We show the cumulative number of observations for our three light curve cadences, along with sample light curves, in Fig. 3.

In summary, the key features of the catalogue are as follows: top-of-the-galaxy observing conditions, near-perfect transient observing efficiency, host galaxies as faint as $r = 28$ associated in a class-dependent manner, and physically-motivated transient-host separations. We provide an overview of the classes of transients generated in this work, the HOSTLIBs and WGTMAPs used to associate them with hosts, and the sampling method for each class, in Table 1.

For completeness, we also summarize here the list of major assumptions and approximations used to construct the SCOTCH catalogue:

- **Representative correlations from observed samples**: Limited observational data exists for many of the transient classes we simulate. Nevertheless, we assume that each data set presents a representative sample of that class’s host population. With small sample sizes, this may cause host-transient correlations to be over-confidently inferred.

- **sGRBs and KNe occur in the same host galaxies**: Given the extremely low number of KNe detected to date, and the intense interest from the community in detecting additional events, we choose to include KNe in our simulation framework with host-galaxy properties determined by a sample of well-localized sGRBs (§ 6.6).

- **Galaxy populations have been shifted in redshift space**: We introduce redshift adjustments to host galaxies in several stages of the pipeline: when smoothing over unphysical tracks in colour-redshift space in CosmoDC2 (see § 5.2) and when adjusting the host redshift to the transient redshift in SNANA. Thus, while the final host galaxy properties depend on redshift in a broadly similar way as in CosmoDC2, any realistic tight redshift dependencies that were encoded into the original simulation may be lost in SCOTCH.

- **No on-sky positions**: The hosts and their transients are not placed realistically on the sky, and thus the catalogue lacks realistic large-scale structure.

- **Similar host-galaxy extinction parameters across cosmic time**: Dust parameters were determined from transient studies at low-$z$ (primarily SNe Ia), and this work extends these properties to $z < 3$. Deep host-galaxy studies will further clarify the dust properties of host galaxies at higher redshifts, which can be used to simulate an evolution in dust properties in future work.

- **k-corrections linked to Simple Stellar Populations**: The k-correction equations used to calculate the rest-frame properties of host galaxies in GHOST (Gagliano et al. 2021) were computed bySED fits to SDSS galaxies assuming simple stellar populations. This is done to obviate the need for detailed SED fitting, which would be a valuable independent study but is outside the scope of this work.

- **No evolution in host-galaxy correlations**: We did not attempt to model any evolution of host-transient correlations with redshift, and therefore host populations at high-$z$ in the catalogue have similar distributions in intrinsic properties to hosts at low-$z$. Upcoming high-$z$ surveys will shed more light on any potential evolution in host galaxy populations.

- **Malmquist-like bias**: The necessary $r < 28$ cut on synthetic...
galaxies causes the hosts at higher redshift to be drawn from an intrinsically brighter population.

4.2 Transient Models

We simulate each transient class with a similar setup as that of the PLAsTiCC challenge (see Kessler et al. 2019a, hereafter K19, and references therein). Unless otherwise noted, the event rate of each class follows the same redshift dependency as in PLAsTiCC. As detailed in K19, the redshift-dependent rates have been measured from existing observations, and thus become increasingly uncertain with redshift. We extrapolate the rates to $z = 3$ for SCOTCH, but caution that the rate functions are unlikely to be trustworthy at high redshifts. We are unable to simulate realistic volumetric rates with the framework described, as our ideal ‘observing’ conditions and wide redshift range would generate a prohibitively large catalogue. Instead, we choose to simulate 5 million events and divide the sample by class based on anticipated interest to users. Table 2 displays the number of light curves and model used per class. The sky density of events at any given redshift, and the relative rates of different classes, are therefore inaccurate. Nevertheless, the volumetric rates predicted for each class by the respective rate model in K19 can be calculated using information in the supplementary material, Appendix B, and the corresponding functions provided in the GitHub repository for this work. This information can also be used to over- or under-sample the catalogue as needed to generate realistic mock observations.

We simulate normal and peculiar SNe Ia using the same models used in K19. Additionally, the core-collapse SN models suffixed with HMF, Templates, and MOSFIT in Table 2 are identical to those detailed in K19. However, several features of our simulation are different from PLAsTiCC. We do not include the parametric SN Ibc MOSFIT model, which was part of PLAsTiCC, because its parameters were drawn from unrealistic flat distributions and the models produce unphysical light curves. We also add the recent core-collapse spectrophotometric templates from Vincenzi et al. (2019), which are suffixed by HostXT_V19 in Table 2. The V19 models add realistic diversity to our core-collapse sample. The V19 models include templates for SNe Ib and SNe Ic-BL, which are both new since PLAsTiCC. SNe Ic-BL are energetic Ic events observed with broad lines in their spectra, indicating enhanced absorption velocities of $\sim 15,000-30,000$ km s$^{-1}$ (Modjaz et al. 2016). Thus, the Ic-BL templates are distinguishable from the typical Ic model primarily through spectroscopy. As we only simulate photometric light curves for SCOTCH, the only relevant difference from SNe Ic is that SN Ic-BL light curves are brighter.

The SLSN I, TDE, and AGN models are similar to those in K19, the only difference being that we impose an upper redshift limit of $z = 3$ to match the limit of CosmoDC2 galaxies within the HOSTL1Bs. PLAsTiCC included a set of kilonova SED models from Kasen et al. (2017). In this work, we incorporate the Kasen model as well as an SED model by Bulla (2019). Both approaches parametrize the rapidly decompressing ejecta from the merger of two neutron stars that are heated by radioactivity from r-process nucleosynthesis. The Bulla (2019) model is parameterized by the mass of the ejecta, the half-opening angle of its lanthanide-rich component, and the angle between the line of sight and the plane of merger. The Kasen et al. (2017) models consider the SED parameterized by the ejecta mass, the lanthanide fraction, and the ejecta velocity, without an observing angle dependence. In general, larger values of the ejecta mass lead to brighter events, while increasing the lanthanide fraction leads to redder, longer-lived kilonovae. Both models are grid-based, i.e., an SED given on a grid of discrete model parameters. Recently, Chatterjee et al. (2021) incorporated the Bulla model into SNANA, and used both these kilonova models to create a classifier to filter kilonovae from other astrophysical transients using photometric and contextual information available from gravitational wave data products. The SED data for both the models are publicly available as part of the SNANA package.

We present the distribution of light curves for a representative sample of each simulated transient class in Fig. 4. We further present the volumetric rate evolution of transients within the catalogue, re-scaled to the match the model predictions using the values in Table B1, in Fig. 5. The re-scaling is necessary because the total event numbers in SCOTCH (Table 2) are arbitrary. For comparison, we...
Figure 4. Light curves for the transient classes simulated in this work. Gray curves show a representative sample of events, and coloured curves show one example event for each class. Due to the rapid rise of the kilonova model, few KN light curves feature emission at epochs prior to peak light.
Table 2. Simulated transients in the SCOTCH catalogue organized by class and model name. $N$, the number of transients simulated per class, sums to 5 million.

| Class | Model name | $N$ |
|-------|------------|-----|
| Ia (2.2M total) | SALT2-Ia | 2M |
| | Iax | 100,000 |
| | 91bg-like | 100,000 |
| H-Rich Core-Collapse (1,999,000 total) | SNII-Templates | 633,000 |
| | SNII-NMF | 633,000 |
| | SNII+HostXT_V19 | 633,000 |
| SN Ia (100,000 total) | SNII+MOSFiT | 50,000 |
| | SNII+HostXT_V19 | 50,000 |
| Stripped Envelope / H-Poor Core-Collapse (500,000 total) | SN Ib/c Templates | 50,000 |
| | SN Ib/c+HostXT_V19 | 50,000 |
| Ib (100,000 total) | SN Ib/c+HostXT_V19 | 50,000 |
| Ic (100,000 total) | SN Ic-Templates | 50,000 |
| | SN Ic+HostXT_V19 | 50,000 |
| IcBL | SN IcBL+HostXT_V19 | 100,000 |
| IIb | SN Ia-Templates | 50,000 |
| | SN Ia+HostXT_V19 | 100,000 |
| SLSN-I | SLSN-I-MOSFiT | 100,000 |
| Non-SN Transients (301,000 total) | Kasen 2017 | 50,000 |
| | Bulka 2019 | 50,000 |
| TDE | TDE-MOSFiT | 101,000 |
| AGN | AGN-LSST | 100,000 |

show the observed volumetric rates for SNe Ia from Rodney et al. (2014) and CCSNe from Strolger et al. (2015). We find agreement with the observed volumetric rates, with the deviations dominated by the theoretical fits to the data and not limitations in the simulation pipeline.

5 HOST LIBRARY CREATION (HOSTLIB)

5.1 Overview

Our first step to realistically associate transients with hosts is to create HOSTLIBs from CosmoDC2 galaxies. In previous work, including Vincenz et al. (2021), HOSTLIBs were constructed of representative field galaxies and correlations with transient class were implemented solely via the WGTMAP schema. However, WGTMAPs that depend on more than a few host properties $N$ are prohibitively memory-intensive and computationally slow, as the SNANA code requires weights to be defined over an evenly-spaced grid across the full $N$-dimensional parameter space. To incorporate additional galaxy properties in our transient-host association, we generate tailored HOSTLIBs for different transient categories containing correlations in host galaxy colour and magnitude.

5.2 Accounting for CosmoDC2 Artifacts with PZFlow

The distribution of CosmoDC2 galaxies in colour-redshift space contains non-physical structure that worsens at higher redshifts. The problem is caused by a mismatch between the colour ranges in different components of the hybrid catalogue production pipeline for CosmoDC2 (Korytov et al. 2019), and manifests as discrete ‘tracks’ in colour-redshift space across the full redshift range (upper panel of Fig. 6). These artifacts limit our ability to test upcoming machine-learning based photometric redshift estimators. Along each track, the dispersion about the colour-redshift relation is unrealistically low. Photometric redshift and classification algorithms trained using these data are likely to achieve unrealistically accurate results. As photo-$z$ estimation is an important component of upcoming large-sky transient and galaxy surveys, we mitigate this effect by smearing the streaky colour-redshift relationship for selected CosmoDC2 galaxies.

We use the code PZFlow\(^{10}\) (Crenshaw et al. 2021) to realistically shift galaxy redshifts and smear the colour-redshift tracks. PZFlow uses normalizing flows (Jimenez Rezende & Mohamed 2015) to efficiently model a multi-dimensional probability density function (PDF). The normalizing flow learns a bijection, a function which maps the PDF to a tractable latent distribution (such as a uniform distribution) in which we can easily sample points and calculate densities. We train a normalizing flow to model the conditional PDF $p(z|m, M_*, SFR)$, where $m$ is a vector of LSST $ugriz$ apparent magnitudes. The latent distribution for the flow is uniform over the range $[−5, 5]$. The bijector consists of two layers: the first layer shifts the redshift range $[0, 3]$ into the range of the latent uniform distribution, $[−5, 5]$; the second layer is a Rational-Quadratic Neural Spline Coupling layer (RQ-NSC; Durkan et al. 2019), which transforms

\(^{10}\) https://github.com/jfcrenshaw/pzflow
the redshift distribution into a uniform distribution. The RQ-NSC performs this transformation using splines parameterized by a set of knots. The number of spline knots, \( K \), can be chosen to increase or decrease the resolution of information captured by the flow. We choose a low value of \( K = 2 \) so that the flow does not learn the discrete tracks in the CosmoDC2 colour-redshift space, and instead smooths over them.

We train the normalizing flow on the 40M \( \rho < 28 \) CosmoDC2 galaxies for 30 epochs using maximum likelihood estimation. Then, for each galaxy, we sample a new redshift \( z_{\text{PZFlow}} \) from the normalizing flow. These new redshifts are consistent with the galaxies' photometry, stellar masses, and star formation rates, but are slightly perturbed from their original values (see left and middle panels of Fig. 7). For 92% of the galaxies, the change in redshift is \( \delta z < 0.1 \). While 8% of redshifts have more substantial perturbations, we stress that each perturbed redshift is consistent with that galaxy's observed and derived properties. It should not be surprising that, for some galaxies, a substantially different redshift remains consistent with its other properties (Salvato et al. 2019), particularly if the original distribution contained discrete artifacts.

We next adjust each galaxy's absolute magnitude to retain the same apparent magnitude given its shifted luminosity distance. The right panel of Fig. 7 shows the size of these adjustments. For 93% of galaxies, the absolute magnitude change is \( \delta M < 0.2 \). We expect the small magnitude perturbations to lie within the realistic scatter of galaxy properties.

We have perturbed the galaxy redshifts with the goal of removing the discrete tracks in colour-redshift space that would lead to overly-optimistic photo-z estimates. We present the original and re-sampled redshift distributions in the upper and lower panels of Fig. 6, respectively, in which only a fraction of the tracks remain (and these are primarily at very high redshift).

After applying PZFlow, we perform an additional cut to clean the CosmoDC2 rest-frame colour distribution. We limit our sample to galaxies with \( -0.18 < i - z < 0.5 \), which maintains the vast majority of the CosmoDC2 colour distribution but removes two unrealistic clumps that were visible on the red and blue extremes after re-sampling.

5.3 Selecting a CosmoDC2 subsample

Ideally, we would sample directly from the CosmoDC2 galaxies, with our selection informed by real data, to populate a catalogue of synthetic host galaxies for each transient class. Although the GHOST dataset includes many SN classes, for most classes (e.g., SNe IIn, Ic-BL, and Ib) the sample size is too small to contain representative information. To combat this issue, before matching we group the hosts of archival GHOST SNe into three broader categories:

(i) 6,284 hosts of Type Ia SNe.
(ii) 1,973 hosts of core-collapse SNe with hydrogen lines in their spectra, including those classified as Type II, IIn, and IIP.
(iii) 443 hosts of hydrogen-poor SNe, including stripped-envelope core-collapse SNe and hydrogen-poor superluminous SNe (SLSNe-I).

For each group, we select a many-times larger sample of synthetic CosmoDC2 galaxies that approximates the distribution in GHOST galaxy properties while extending to higher redshifts. We construct a HOSTLIB for each of these 3 broad categories.

With insufficient high-z data to model any cosmic evolution of transient-host correlations, a reasonable approach to high-redshift HOSTLIB sampling is to find high-z CosmoDC2 galaxies with similar intrinsic properties as low-z galaxies; e.g., rest-frame absolute magnitudes, rest-frame colours, and morphology. This approach ignores the possible evolution of transient-host correlations over cosmic time.

We employ a nearest-neighbour (NN) technique, illustrated in Fig. 8, to achieve this matching. NN algorithms deteriorate in high-dimensional space due to decreased data density (the so-called ‘curse of dimensionality’), so we select a small number of galaxy properties that most strongly correlate with transient properties. We train our NN matching on absolute rest-frame \( r \) - and \( i \)-band magnitudes, rest-frame \( g - r \) and \( i - z \) colours, and the PZFlow-shifted redshifts. This combination of properties incorporates information from all \( gri \) bands (\( u \) and \( y \) being unavailable after converting GHOST data to SDSS filters) without redundancy. Although a similar matching could be achieved by simply using the \( gri \) magnitudes and allowing colour to be implicitly included, doing so would down-weight the importance of colour. We choose to explicitly make two of the four dimensions colours, with an even weighting as the magnitudes, because colour correlates strongly with a galaxy’s star-formation rate, and consequently the rate of core-collapse SNe; while brightness...
The Simulated Catalogue of Optical Transients and Correlated Hosts (SCOTCH)

Figure 7. Left: Difference between PZFlow-sampled redshift and original CosmoDC2 redshift as a function of CosmoDC2 redshift for each galaxy in the sample. Shifts are minimal, and the discrete paths at top left and bottom right reflect the bounds of [0, 3] imposed in generating PZFlow samples. Middle: Histogram of fractional differences in galaxy redshift before and after the PZFlow-oversampling stage. Right: Histogram of fractional differences in absolute magnitude propagated from the PZFlow-shifted redshifts.

Figure 8. Illustration of CosmoDC2 sampling for HOSTLIB generation. Left: We identify GHOST galaxies which hosted transients belonging to a particular category (the three categories are defined in the text). The GHOST sample is observationally biased toward low-redshift, but we assume the rest-frame properties (like color, shown on the y axis) are representative of the true full sample of hosts. Right: For every GHOST galaxy, we select k synthetic galaxies from CosmoDC2 nearby in rest-frame color, brightness, and redshift (with small $d_{\text{ANNOY}}$ values; see Appendix A from the supplementary materials for details) but extending to $z = 3$. For simplicity, the diagram shows $k = 2$ and a 2-dimensional parameter space; in practice, however, $k = 800–18,000$ and 5 parameters are used for matching.

correlates strongly with stellar mass, and consequently the rate of SNe Ia and SNe II (see §6). We manually down-weight redshift with respect to the colours and magnitudes to allow for neighbour matching across a wide range of redshifts. We considered also matching on morphological information such as galaxy radius and ellipticity, but found the difference between observational and simulated estimates to be prohibitive given the necessary corrections to systematics in the GHOST data (e.g., deconvolving the PSF from ellipticity and radius measurements) and the strong redshift-dependent observational bias towards intrinsically large and face-on galaxies in targeted surveys.

Although exact NN algorithms (e.g., scikit-learn’s KNeighbors) are sufficient for samples of $N \sim 10^5$, they become increasingly slow when scaling up to $\sim 10^7$ galaxies. Instead, we make use of a rapid approximate NN method called ANNOY, which leverages Locality-Sensitive Hashing (LSH; Datar et al. 2004), to rapidly cross-match datasets in parallel. We provide additional information on our use of this method in Appendix A in the supplementary materials accompanying this paper, available online. We select $k$ neighbours in CosmoDC2 with low Euclidean distance ($d_{\text{ANNOY}}$) to each GHOST galaxy. Rather than impose a limit on $d_{\text{ANNOY}}$, we set $k$ to a value that produces several million matched CosmoDC2 galaxies. We then remove synthetic galaxies that were matched to
multiple GHOST galaxies, creating HOSTLIBs with ~ 3 million objects each. This requires \( k \) to range from 800–18,000 across the three host categories.

Using this pipeline, we generate HOSTLIBs of CosmoDC2 galaxies matching the host-galaxy distributions in GHOST for the three groups of transient classes described above. We show the distribution of observed GHOST galaxies, a random subset of CosmoDC2 galaxies, and the final matched sample for the Hydrogen-poor host group in Fig 9. In addition to the three HOSTLIBs described above, we create a HOSTLIB consisting of galaxies randomly sampled from CosmoDC2 for transient classes not in the GHOST catalogue. The host correlations for events using this unmatched HOSTLIB originate entirely from the transient-specific WGTMAP.

The CosmoDC2 simulation contains many ultra-faint galaxies that were injected into the simulation to account for its finite mass resolution (Korytov et al. 2019). These galaxies were not assigned properties as rigorously as the normal galaxies in the simulation; as a result, we exclude them from our HOSTLIBs. Our initial \( r < 28 \) cut on CosmoDC2, as well as the matching to GHOST galaxies (which are generally bright), remove many of these galaxies from our sample. We identify any remaining ultra-faint galaxies by their negative halo_id after HOSTLIB creation and cut them from the samples.

### 6 TRANSIENT-HOST GALAXY CORRELATIONS (WGTMAP)

The GHOST database contains only basic photometric properties for SN host galaxies. Additional properties like masses and star formation rates, which can be estimated from galaxy imaging and/or spectra, are not reported in GHOST due to the lack of availability. Thus, the HOSTLIBs of CosmoDC2 galaxies matched to GHOST are realistically distributed in colour and brightness, but only contain an implicit dependence on derived properties. There is motivation to fold in explicit dependence on mass and star formation rate; many studies have empirically verified this dependence for multiple transient classes (using smaller samples than GHOST) and found statistically significant differences between classes. To more precisely simulate these correlations, we construct a series of WGTMAPs that explicitly encode the class-specific dependence of host-transient association on a galaxy’s derived properties. These WGTMAPs enable us to fine-tune the host populations of the three matched HOSTLIBs and add in class-specific correlations for events whose hosts will be drawn from the unmatched, randomly-sampled HOSTLIB.

Each WGTMAP consists of a multidimensional grid of host properties, where values in the grid correspond to the probability of a galaxy with those properties being selected to host a given transient event in SNANA. The weightmap values can be scaled arbitrarily, so long as the relative weights between galaxies of different properties are preserved. When the SNANA simulation generates a transient at \( z \), a sample of host candidate galaxies within \( \delta z \) are retrieved from the HOSTLIB. SNANA then assigns a corresponding weight to each potential host using the WGTMAP. The simulation creates a cumulative distribution function (CDF) for all galaxies, where the horizontal axis orders the galaxies arbitrarily, and the function is augmented by each galaxy’s weight. The CDF is normalized to have a maximum value of one. The simulation selects a random number for the CDF vertical axis, and picks the corresponding galaxy along the horizontal axis, such that highly weighted galaxies have a higher CDF slope and are therefore more likely to be selected. Because the normalization is computed internally within SNANA, only the proportionality linking the probability \( P \) to the host galaxy parameters must be defined for the WGTMAPs.

We emphasize that the transient rate models, described in § 4.2 and extensively detailed in K19, are entered into the SNANA simulation independently of host properties. In other words, the final transient event rate in the simulation is not affected by the associated host galaxies. Transients are generated according to the rate function and the total number desired (Table 2), and only then assigned a host. The WGTMAP plays a role only in determining the relative likelihood of one host being selected over another.

The following subsections review the observations that motivate the WGTMAPs of each class. We caution that for several classes (TDEs, KNe, SNe Ic-BL, and SLSNe-I), the data statistics remain limited, and thus the resulting simulations may not capture the full diversity of host galaxies. Fig. 10 provides some intuition for the probability equations that follow by showing the SFR-mass distribution of hosts selected by SNANA from these equations for six classes.

#### 6.1 SNe Ia

SN Ia explosions are thought to occur when a white dwarf accretes material from a companion star (which may also be degenerate) in a binary system, approaches the Chandrasekhar mass, and ignites in a runaway chain reaction of carbon fusion. SNe Ia occur more frequently in high-mass and highly star-forming galaxies (Sullivan et al. 2006; Smith et al. 2012; Wiseman et al. 2021). Their light curves are parameterized in the SNANA simulation using the Spectral Adaptive Lightcurve Template (SALT2/SALT3) frameworks (Guy et al. 2007a; Kenworthy et al. 2021).

The probability of SNe Ia as a function of galaxy properties can be written as the product of two components:

\[
P_{\text{Ia}}(M_*, \text{SFR}, x_1) = P_{\text{KDE}}^{\text{Ia}}(M_*, \text{SFR}) \times P_{\text{host}}^{\text{Ia}}(x_1, M_*)
\]

where \( M_* \) is the host galaxy stellar mass, SFR is its star formation rate, and \( x_1 \) is the SALT2 stretch parameter of the SN light curve (Guy et al. 2007b).

The first component of the probability, \( P_{\text{KDE}}^{\text{Ia}} \), encodes a dependence on galaxy stellar mass and star formation rate. It has been constructed to replicate the distribution of 200 SN Ia host galaxies from the Dark Energy Survey Supernovae Program (Smith et al. 2020). Using the statsmodel Python package, we perform kernel density estimation on the DES \( \log(M_*) \) and log(SFR) values to estimate a smooth probability density function in \( \log(M_*) \) vs. \( \log(\text{SFR}) \) space. We use a Gaussian kernel for both parameters and determine the best-fit bandwidths from the KDE fit, finding 0.49 and 0.47 for \( \log(M_*) \) and log(SFR), respectively. Because \( P_{\text{KDE}}^{\text{Ia}} \) is non-parametric, this estimate for the probability density of observed events, it has no closed form.

The second component represents the anti-correlation between \( M_* \) and \( x_1 \) as shown in Fig. 4 of Smith et al. (2020). Based on the fact that few events have been observed with \( M_* < 10^{10} \) and negative \( x_1 \), we implement the following model from Vincenzi et al. (2021):

\[
P_{\text{host}}^{\text{Ia}}(x_1, M_*) = \begin{cases} 
\frac{1}{\sqrt{2\pi}} \exp\left(-\frac{x_1^2}{2}\right), & \text{for } x_1 < 0 \text{ and } M_* < 10^{10} \\
1, & \text{for } x_1 > 0 \text{ and } M_* < 10^{10} \\
1, & \text{for } x_1 > 0 \text{ and } M_* > 10^{10} 
\end{cases}
\]

#### 6.2 Peculiar SNe Ia

In addition to ‘normal’ SNe Ia, our simulated sample includes two classes of peculiar transients: SN2002cx-like SNe (SNe Iax; Foley...
which are underluminous and red at peak light relative to their Branch-normal counterparts; and SN1991bg-like SNe Ia, which are more rapidly evolving (Filippenko et al. 1992). Although observed samples are small, there are indications that SNe Iax occur almost exclusively in late-type, star forming galaxies (Jha 2017; Takaro et al. 2020) and SNe 91bg-like preferentially occur in early-type, passive galaxies (van den Bergh et al. 2005; Hakobyan et al. 2020). Accordingly, Vincenzi et al. (2021) set the SN Iax probability to the SN Ia probability in active hosts and 0 in passive hosts; conversely, they define the SN 91bg-like probability as equal to the SN Ia probability in passive hosts and 0 in active hosts. We adopt a similar approach, and assume that the peculiar SNe Ia originate from similar progenitors as normal SNe Ia, but that their hosts represent opposite ends of a continuum in galaxy age and morphology. However, we exponentially taper the probability of SNe Iax in passive galaxies and 91bg-like events in star-forming galaxies. This is done in order to avoid encoding an unrealistically discrete boundary in our catalogue, and to account for the possibility that a sub-population of these events does occur in hosts distinct from those previously discovered.

As in Sullivan et al. (2006) and Vincenzi et al. (2021), we define a threshold between active and passive galaxies at specific star formation rate (sSFR) values of $\log_{10}(\text{sSFR}/\text{Gyr}^{-1}) = -11.5$; active galaxies lie above this threshold and passive galaxies lie below it. For SNe Iax, our combined probability function adopts the normal SN Ia probability (without $x_1$ dependence) for active galaxies and tapers the probability below the passive/active threshold as follows:

$$P_{\text{Ia}}(M_*; \text{sSFR}) = \begin{cases} P_{\text{Ia}}(M_*; \text{sSFR}), & \text{for } x_s \geq -11.5 \\ P_{\text{Ia}}(M_*; \text{sSFR}) \times e^{(x_s+11.5)}, & \text{otherwise} \end{cases}$$

where $x_s = \log_{10}(\text{sSFR}/\text{Gyr}^{-1})$. The SN 91bg-like probability does the opposite, tapering the probability symmetrically above the passive/active threshold:

$$P_{\text{91bg}}(M_*; \text{sSFR}) = \begin{cases} P_{\text{Ia}}(M_*; \text{sSFR}), & \text{for } x_s < -11.5 \\ P_{\text{Ia}}(M_*; \text{sSFR}) \times e^{-(x_s+11.5)}, & \text{otherwise} \end{cases}$$

Because $P_{\text{Ia}}$ is not symmetric about $x_s$ (it increases with galaxy mass and star formation), we note that this formalism results in a higher probability for 91bg-like events to occur in star-forming host galaxies than SNe Iax to occur in passive host galaxies. SCOTCH contains $\sim0.1\%$ of SNe Iax in passive hosts and $>25\%$ of SNe 91bg-like in active hosts. This implementation is motivated by previous work (e.g., Hakobyan et al. 2020) showing a larger tail of 91bg-like hosts toward spiral-type morphologies than of SNe Iax toward elliptical galaxies.

### 6.3 Types II, Ib, and Ic Supernovae (SNe II, SNe Ib/c)

Type II, Type Ib, and Type Ic are three subclasses of core-collapse SNe. Type II events are characterized by strong Hydrogen emission lines, indicating that an outer Hydrogen shell was present in the progenitor star. Types Ib and Ic lack Hydrogen features, indicating that their outer shell was stripped from the progenitor star prior to explosion. Type Ic also lacks Helium features, indicating that the Helium envelope was also lost. Although SNe IIb are typically grouped with these ‘stripped-envelope’ events, they exhibit weak hydrogen features at early times. As the explosion progresses, the Hydrogen emission quickly fades and the light curves begin to resemble those of SNe Ia. Because of their short-lived progenitor systems (typically $<50$ Myr), core-collapse explosions are predominantly observed in galaxies that
are actively forming massive stars. The probability of these events occurring in passive galaxies, in contrast, is suppressed. Active and passive galaxies can be distinguished by their sSFR, defined as the star formation rate of the galaxy per unit of stellar mass.

The probability of these classes of core-collapse supernovae are set to (Vincenzi et al. 2021):

\[
P_{\text{II}}(M_*, \text{sSFR}) \propto \begin{cases} 
(M_*/M_\odot)^{0.16}, & \text{for } x_s \geq -11.5 \\
0, & \text{otherwise}
\end{cases}
\]

(5)

Additionally, we distinguish the hosts of SNe Ic-BL events from the lower-energy class of SNe Ic explosions through the properties of their host galaxies. To do so, we embed a further correlation with host galaxy metallicity. Additional details concerning this correlation are described in Sec. 6.4.

6.4 Type Ic-BL Supernovae (SNe Ic-BL)

It is hypothesized that long-duration gamma ray bursts (IGRBs, lasting longer than ~2 seconds) are produced by relativistic jets originating in an SN explosion and interacting with surrounding circumstellar material (Roy 2021). Broad-Lined SNe Ic (SNe Ic-BL) are the only SNe that have been unambiguously associated with IGRBs, and these explosions have been observed to occur in galaxies of lower average metallicity than the less energetic SNe Ic (Modjaz et al. 2020). A thorough understanding of the host-galaxy correlations of SNe Ic-BL could permit a reconstruction of the physical conditions that give rise to relativistic jets in SNe. To simulate a distinction between SNe Ic and SNe Ic-BL host galaxies, the WGTMAP probabilities for both SNe Ic and SNe Ic-BL are constructed as the product of two terms. The first term embeds the preference for core-collapse events to occur in active galaxies, which is parameterized by equation 6. For the second term, we consider the metallicity of each galaxy and model the distribution of SNe Ic and SNe Ic-BL host galaxy metallicities as a set of logistic distributions:

\[
P_{\text{BL/c}}(M_*, \text{sSFR}) \propto \begin{cases} 
(M_*/M_\odot)^{0.36}, & \text{for } x_s \geq -11.5 \\
0, & \text{otherwise}
\end{cases}
\]

(6)

6.5 Type I Superluminous Supernovae (SLSNe-I)

Superluminous SNe (SLSNe) are unusually bright explosions potentially powered by exotic engines (e.g., pair instability or magnetar spin-down; Kozyreva & Blinnikov 2015; Nicholl et al. 2017). Type-I SLSNe are hydrogen-poor and have been found to occur predominantly in low-mass, metal-poor, and highly star-forming galaxies (Lunnan et al. 2014; Perley et al. 2016; Schulze et al. 2018). We model their rate based on the observations of ~50 SLSN-I hosts from Lunnan et al. (2014); Perley et al. (2016); Schulze et al. (2018). All studies report SLSN-I hosts with specific star formation rates greater than $10^{-10}$ yr$^{-1}$; thus, we model the SLSN-I probability to be exponentially suppressed below this threshold.

Based on the observed distribution of host galaxy masses and star formation rates, we further suppress the probability of events in galaxies that are both massive and highly star-forming:

\[
P_{\text{SLSN-I}} \propto \begin{cases} 
e^{-\left(\frac{5}{2}(x_s-5)\right)} & \text{for } x_s < -10, x_M < 10 \text{ and } x_f < -0.5 \\
1 & \text{otherwise}
\end{cases}
\]

(9)

where $x_M = \log_{10}(M_*/M_\odot)$, $x_s = \log_{10}(\text{sSFR/Gyr}^{-1})$, and $x_f = \log_{10}(\text{SFR/Gyr}^{-1})$. We normalize these probabilities by eye such that hosts in the ’otherwise’ category all have an equal probability of being selected, hosts beyond the defined boundaries are increasingly less likely to be selected, and the discontinuity at the boundaries is minimized.

6.6 Using short-duration gamma-ray bursts as a proxy for kilonova correlations

The discovery of gravitational-wave event GW170817 by the LIGO and Virgo collaborations, followed by short-duration (≤2 sec) Gamma-Ray Burst (sGRB) GRB170817A a few seconds later and the optical kilonova (KN) AT2017gfo several hours later, confirmed the association of these signals during a likely neutron star - neutron star merger (Abbott et al. 2017a; Goldstein et al. 2017). The multi-band photometry of AT2017gfo, an event which took place in the nearby (z = 0.00972) galaxy NGC 4993, provided direct evidence for compact mergers as a site where r-process elements are forged (Drout et al. 2017). Nevertheless, many questions remain. Although the colour of the emission reveals information on the fraction of lanthanides and actinides produced from the neutron-rich ejecta, many questions remain about the relationship between an event’s emission and its precise nucleosynthetic yield. Further, the differences between KNs generated from the merging of a neutron star-black hole system and those originating in a neutron star-neutron star collision remain unknown. Though there have been no observations of KNs from a neutron star-black hole system yet, numerical simulations show differences between these types of KNs (Kawaguchi et al. 2016; Tanaka et al. 2014; Shibata & Hotokezaka 2019; Bulla et al. 2021). The strength of the subsequent electromagnetic signal also encodes information regarding the neutron-star equation of state (Bauswein et al. 2017; Li et al. 2021; Raaijmakers et al. 2021). Because our knowledge of these systems starts and ends at this prototype event, owing to the large sky localization area of gravitational wave observations – especially when events are observed only in some of the existing detectors – and the low intrinsic event rate, additional KN discoveries in upcoming surveys would vastly improve our understanding of these systems.

Because our aim is to improve the ability to accurately identify a diversity of KN events in upcoming survey streams, we do not want to limit our KN host-galaxy model solely to galaxies matching the properties of NGC 4993 (the host of AT2017gfo). Indeed, whereas NGC 4993 is a quiescent galaxy (Levan et al. 2017), sGRBs have been discovered in a variety of both star-forming and quiescent sys-
tems (Prochaska et al. 2006; Berger 2009). Based on recent evidence that these signatures share a common astrophysical site (Abbott et al. 2017a), for this work, we assume that sGRBs and KNe inhabit host galaxies with similar properties. This assumption has the added benefit that GRBs are regularly observed across the full sky (D’Avanzo 2015), and as a result we have amassed hundreds of GRB detections to date.

We begin constructing the KN WGTMAP by retrieving the positions of reasonably well-localized sGRBs (uncertainty radius $r_\star < 0.01\,\text{°}$ and $t_{90} \leq 2\,\text{s}$) from the NASA Fermi GBM Burst catalogue (von Kienlin et al. 2020; Gruber et al. 2014; von Kienlin et al. 2014; Narayana Bhat et al. 2016) and from the GRB Host Studies catalogue (Savaglio et al. 2006b). Next, we use the astro_ghost software to identify the most-likely host galaxy associated with these events and retrieve photometric data from these galaxies. Whereas the original implementation of the package considered only northern-hemisphere galaxies within the Pan-STARRs source catalogue (Flewelling et al. 2020), for this work we have extended the code to query the SkyMapper catalogue (Onken et al. 2019) for southern-hemisphere sources as well. After visually verifying each association, we arrive at a sample of 11 sGRB-hosts, one of which is NGC 4993. Apparent $gri$-band magnitudes are reported for all hosts except two, which lack high-SNR brightness estimates in the sample of 11 sGRB-hosts, one of which is NGC 4993.

As was done for SNe Ia, we model the joint probability distribution $P_{\text{AGN}}(M_\ast, SFR)$ by performing kernel density estimation on the observed sample, using a Gaussian kernel for both parameters and the best-fit bandwidth of 0.18 for both parameters.

### 6.8 Tidal Disruption Events

In a Tidal Disruption Event (TDE), material from a star is stripped during close passage to a supermassive black hole (SMBH; Ayl et al. 2000; Strubbe & Quataert 2009). The stripped material circularizes into a debris disk around the SMBH and accretes onto it, resulting in a luminous flare spanning the electromagnetic spectrum. This occurs when the separation between the star and the SMBH falls within the tidal disruption radius of the star and, in some cases, the star is completely destroyed. Early detection and characterization of these events facilitates photometric and spectroscopic follow-up that illuminates the dynamic accretion physics of SMBHs across a range of mass scales (particularly for quiescent black holes; Evans & Kochanek 1989). To date, however, only a few these events have been observed in detail. TDEs are found predominantly in post-starburst galaxies (French et al. 2017, 2020), and these correlations can be incorporated into targeted searches in upcoming surveys (Zabludoff et al. 2021). We encode these correlations into a TDE WGTMAP by constructing the following functional approximation, which roughly reproduces the distribution of events as a function of host galaxy SFR and $M_\ast$, as shown in Fig. 3 of French et al. (2020).

$$P(M_\ast, SFR) \propto \begin{cases} e^{-s_f M_\ast}, & \text{if SFR} \geq 10^{-9} M_\odot \text{yr}^{-1} \\ e^{-s_M M_\ast}, & \text{if SFR} < 10^{-9} M_\odot \text{yr}^{-1} \\ e^{-(s_f + s_M) M_\ast}, & \text{otherwise} \end{cases}$$ \hspace{1cm} (10)

We use the HOSTLIB of randomly-selected cosmoDC2 galaxies for this class.

### 7 OFFSETS FROM THE HOST CENTRE

#### 7.1 Transient offset model and validation

Within the SNIa simulation, we select the position of a transient relative to its host galaxy centre by randomly sampling from a probability distribution defined by the galaxy’s surface brightness profile. This is motivated by prior studies that, averaging over class, SN surface density profiles roughly trace the surface brightness distribution of the spiral disks that host them (Hakobyan et al. 2009). Nevertheless, differences exist between the observed distributions of radial offsets for multiple transient classes. While we have aimed primarily...
Figure 10. Distribution of derived host-galaxy properties for six simulated classes of transients. Galaxies are coloured by redshift (with red points for high-redshift galaxies). Marginal distributions are given at the top and right of each sub-plot. NGC 4993, the host of GW170817, is shown as the green diamond.

at reproducing global transient-host galaxy correlations in this work, we also integrate a basic local model for three classes of transients: AGN, KNe, and TDEs. When post-processing SCOTCH to place events within a survey footprint, care should be taken to preserve the listed offsets.

Because AGN are nuclear transients by definition, we place them closer to their host centres than any other class. AGN are placed within a radius that encompasses 10% of the total galaxy flux; within this radius, their distribution traces the surface brightness profile. We caution that AGN have been detected that are more offset relative to their galaxy centres, but these are rare (<5%; Comerford & Greene 2014) and may be traced back to specific merger events, which is challenging to model with our existing framework.

TDEs, typically discovered as the optical signal from the tidal interaction between a star and a central supermassive black hole, are placed at small offsets in our simulations. However, the recent discovery of a TDE from a candidate intermediate-mass black hole (IMBH) in the nucleus of a dwarf galaxy (Angus et al. 2022) suggests that future observations may reveal TDEs from IMBHs offset from the nucleus of massive hosts (see Bellovary et al. 2019, for a discussion of wandering IMBHs). To allow for this possibility, we model the TDE offsets slightly more broadly than AGN, with probability profiles truncated beyond the radius that encompasses 30% of the host galaxy flux.

Conversely to TDE and AGN, we place KNe at broad offsets: their positions are sampled from distributions in which the innermost 20% of a host galaxy is truncated. This is done to encode the prediction that natal kicks prior to explosion eject KNe from the inner regions of their host galaxies (Gompertz et al. 2020).

We present the offsets for AGN, KNe, TDEs, and SNe Ia in our catalogue in Fig. 11, and compare the SNe Ia and TDE offsets to observed SNe from the Young Supernova Experiment (YSE) Data Release 1 (Aleo et al. 2022) and the KN offsets to Swift satellite sGRB data (Gehrels et al. 2004) that was previously collected and analyzed in Fong et al. (2013a); Pan et al. (2017). The qualitative differences in our simulation clearly follow our model prescription: AGN lie closest to their host nucleus, TDE are slightly more offset, KN are evacuated from the central region of the host, and SNe Ia (representative of the treatment for all SN classes) appear throughout the host galaxy with most within the inner few kpc. The observational data shows reasonable agreement to the simulations, despite the fact that our approach for offset prescriptions was approximate, and we
did not explicitly aim to replicate observations. We leave a more
detailed prescription for individual SN classes to future work.

7.2 Hostless events

Some transient events are reported without a host in SCOTCH. This
occurs when the distance of the transient from its host exceeds a
particular threshold. After generating the position as described above,
SNANA calculates the $d_{DLR}$, the angular separation from the transient
and nucleus (in arcseconds) normalized by the DLR, which is a
measure of the galaxy radius in the direction of the transient. If
$d_{DLR} > 4$, the host is rejected to simulate the fact that a realistic
survey would be unlikely to match that transient with its host (specifically,
the rate of mismatch within $d_{DLR} < 4$ is expected to be small, ~4%
according to Gupta et al. 2016). Hostless events due to $d_{DLR}$ rejection
do not occur for TDE or AGN due to their inner-galaxy placement;
for all other classes, the rate of hostless events is at the few-percent
level (~3 – 8%).

In SCOTCH, these transients appear without host association in
the final catalogue. A more realistic treatment would be to provide
an incorrect host when another galaxy lies closer to the transient
than the true host. However, because SCOTCH removes all on-sky
position information for hosts, including galaxy neighbors as false
hosts in this manner is infeasible.

8 VALIDATION OF HOST GALAXY CORRELATIONS

To validate the SCOTCH catalogue, we first confirm that the correlations
described in §6 appear in the final sample as expected. Fig. 10
displays the SFR vs. $M_*$ relationships for a representative sample of
hosts associated with six transient classes. Each matches qualitative
trends in host types: SN Ia hosts are massive and highly star-forming,
SLSNe-I occur mainly in galaxies with high specific star formation
rates (and trace the cosmic star formation rate), and SNe 91bg-like occur
in passive, massive galaxies. The generated samples, which
used $\text{WGTMAP}$ probabilities from Vincenzi et al. (2021), match the
correlations therein, but extend to lower masses and star formation
rates due to our use of CosmoDC2 versus their use of observed DES
galaxies. To more directly compare the host-galaxy derived properties
for each class, we plot the CDFs for $M_*$ and SFR in Fig. 12.

The CDFs show that, of all transients simulated in SCOTCH, TDEs
are simulated in the lowest-mass host galaxies, followed by SLSNe-I.
Simulated KNe are hosted by the highest-mass galaxies, followed by
the host galaxies of stripped-envelope systems (particularly SNe Ic).
The star formation rate CDFs indicate an overabundance of TDEs in
galaxies of low star formation rate, which is consistent with observa-
tions of them in post-starburst galaxies. SNe 91bg-like events in
our simulation occur on average in the galaxies with the lowest star
formation rates, a feature of our exponential suppression in active
galaxies for this class. Simulated SNe Ix and KNe occur in galaxies
with the highest average star formation rate. For SNe Ix, this reflects
the exponential suppression of these events in passive hosts.

Consistent with the fact that we simulated nearly all core-
collapse supernovae (besides SNe Ic-BL) with the same $\text{WGTMAP}$
and HOSTLIB, the CDFs do not show any clear differences between
the host galaxy SFR of different core-collapse subclasses. The exception
is the Ic-BL class, which appears more often in the simulation
in galaxies of low mean SFR due to the different implemented $\text{WGTMAP}$.

We note that, in our models, we can distinguish between statistical
samples of SNe Ic and SNe Ic-BL by the mass of their host galaxy,
as SNe Ic-BL occur in lower-metallicity host galaxies (Modjaz et al.
and therefore in lower-mass hosts on average. A detailed analysis of the typical observational uncertainties associated with these derived properties and how they might obfuscate these differences in observed data is beyond the scope of this work.

Fig. 13 shows the distributions of host colours within each class. Redder galaxies appear to the upper-right and bluer to the lower-left. We did not directly encode colour correlations into the WGTMAPs for any of these classes; therefore, the differences between distributions stem from the initial GHOST matching in conjunction with the WGTMAPs in which transient probabilities are dependent on galaxy mass and star formation rate. We caution that we have not converted galaxy colours to the rest-frame for Fig. 13, and so the redshift-dependent rates for each class affect this comparison.

Qualitatively, the observed color plots display many of the intended comparative attributes. Simulated SLSN-I host galaxies are bluer than other SN hosts, reproducing observations that show that these events occur in highly star-forming galaxies (Schulze et al. 2018). SN 91bg-like host galaxies are redder than normal SN Ia, as intended. The KN hosts are surprisingly blue; given the broad redshift distribution of simulated events (Fig. 13), this may reflect the preference of observed SGRBs for late-type hosts (Fong et al. 2013b). As GW170817 (diamond in Fig. 13) occurred in a lenticular galaxy, its host galaxy is redder than the majority of the simulated sample. The simulated $g-r$ distribution for TDE host galaxies is broader than all others, which is consistent with observations (French et al. 2020); however, the $i-z$ span may be unrealistically restricted.

Next, we quantitatively compare the colours of SNe Ia (including peculiar) hosts with the observed distributions reported in Hakobyan et al. (2020, H20). H20 examined $u-r$ colours (SDSS photometry) for a low-redshift sample and found statistically significant differences between the $<u-r>$ of ‘normal’ SNe Ia, 91bg-type, and Iax-type host galaxies. The authors reported that galaxies hosting SNe Iax are bluer than normal, while SNe 91bg are redder than normal, with $\Delta <u-r> \approx -0.4$ in each case. To investigate this trend in our own data, we calculate the average $u-r$ SDSS rest-frame colour among 10,000 random members of the SCOTCH host sample for the same three classes. Although H20 examined hosts with $z<0.04$, for the comparison we draw the SCOTCH host sample from the entire $z<3$ redshift range because our simulation methodology treats high-z host selection equivalently to low-z. The results are shown in Table 3. Our average mean simulated host colours are significantly bluer than those of the H20 sample for two of the three classes. Our mean SN Iax host colour is also bluer, but consistent within $2\sigma$ with the H20 observations. The blue trend may be a consequence of unrealistic galaxy colours in CosmoDC2, as demonstrated in Fig. 3 of Kovacs et al. (2021): the CosmoDC2 $u-g$ distribution is significantly bluer than observational data while $g-r$ is consistent with observations, suggesting that $u-r$ tends to be nonphysically blue. The colour differences between the Ia classes in SCOTCH are in the same direction as the observed differences and are statistically significant. The magnitudes of the differences are somewhat mismatched from observations. Although qualitatively imperfect, the fact that SCOTCH reproduces the general trend in colour differences between the SN Ia subtypes should enable catalogue users to test algorithms which include host information for classification.

We also aim to reproduce observed colour correlations between the photometric light curves of SNe Ia and their host galaxies. These have been extensively studied in the literature due to the use of these events as cosmological distance indicators. We present the SALT2 (Guy et al. 2007b) fitted parameters $x_1$ and $c$ (describing the stretch and colour of an SN Ia light curve, respectively) as a function of the intrinsic properties of our associated hosts in Fig. 14. We find similar distributions to those presented in Childress et al. (2013), including a mass-step at $10^{10} M_\odot$ (this has been explicitly encoded in our simulations, so its presence is not surprising), and weak anti-correlations between $x_1$ and both host galaxy $M_*$ and sSFR. We observe a few SALT2 $c$ values above $c=0.2$, and multiple are identified in Childress et al. (2013); although these are anomalous, our model their presence indicates that our correlation model is able to reproduce the central distribution and the tails of the observed data.

We present SDSS-$griz$ histograms of the absolute magnitudes of host galaxies associated with each transient in Fig. 15. GHOST data with $z<0.05$ are shown for several classes with black histograms; the cut is motivated by the fact that SCOTCH has very few events below this redshift. The data reasonably fit the simulation. The impact of our encoded correlations is readily apparent by the variation in median and skew between distributions. However, we caution that the host magnitude differences between classes are not only due to encoded correlations, but also due to two important redshift-dependent effects within SCOTCH: the intrinsic rate of different transients across cosmological distances and the $r<28$ magnitude cut imposed prior to matching in order to cross-match with the 5-yr DC2 image catalogue. The confluence of these effects results in a Malmquist-like bias in the sample, with the distribution of host galaxies for a given class tending toward intrinsically brighter galaxies with increasing redshift (fainter hosts being unavailable to draw from the HOSTLIB at those redshifts). For events occurring in galaxies ranging in brightness and observed only at low and intermediate redshifts (e.g., TDEs), we observe a realistic skew toward fainter galaxies that dominate the HOSTLIBs at these redshifts. For bright classes (e.g., SLSNe-I) and common ones spanning the full simulated redshift range (SNe II), the majority of events will be simulated at high-redshift where this bias is strongest. As a result, the histograms in Fig. 15 reveal a distribution for SNe Ia, SNe II, and SLSNe-I skewed toward bright hosts. This effect is especially visible when examining absolute magnitude as a function of redshift for both GHOST data and SCOTCH results (not shown): the distributions match well across the overlapping redshift range, but both the simulated and observed hosts taper rapidly from including a broad range of magnitudes at low-$z$ to a tighter, brighter range of hosts as $z$ increases.

We next compare the distributions of various properties of our final sample to GHOST to examine the combined effects of our two-step host selection process. Fig. 16 shows the galaxy colour distribution for the hydrogen-poor event HOSTLIB (consisting of SN Ib, Ic, Ibb, and SLSN host matches to GHOST) and the distribution of hosts selected by SNANA after WGTMAPs are applied. The WGTMAPs cause the overall $g-r$ distribution to become slightly bluer and more peaked than the GHOST data. Examining the colours for individual host classes reveals how the different WGTMAPs cause the distributions to stratify. The final SLSN-I host sample is bluer than the others, as encoded via SFR. The Ic hosts separate from the Ic-BL hosts in colour space due to the implemented metallicity dependence. Overall, the final combined host grouping remains similar to observed data, but the individual host classes within that group are subtly different, demonstrating the combined power of the HOSTLIB + WGTMAP formalism.

To further demonstrate the utility of including both a HOSTLIB and WGTMAP in our simulation, we compare our final results for SN Ia host galaxies with (1) a sample simulated only using the GHOST-matched HOSTLIB and no WGTMAP, and (2) a sample simulated using a randomly-selected (unmatched) CosmoDC2 HOSTLIB and the SN Ia WGTMAP. Figure 17 demonstrates how the implementation of either a HOSTLIB or a WGTMAP results in reasonable distributions for some, but not other, host properties. Implementing both the HOSTLIB and
Figure 12. CDFs in host galaxy stellar mass (left), star formation rate (middle), and specific star formation rate (right) for a representative sample of transient classes in the catalogue. Differences between transient classes reflect a combination of WGTMAP and HOSTLIB effects.

| H20 | This work |
|-----|-----------|
| \( <u - r> \) | \( \Delta \text{-norm} \) | \( <u - r> \) | \( \Delta \text{-norm} \) |
| SN Ia (normal) | 1.86 ± 0.03 | 1.372 ± 0.005 |
| SN Iax | 1.47 ± 0.10 | 0.39 ± 0.10 | 1.255 ± 0.006 | 0.117 ± 0.008 |
| SN Ia-91bg | 2.23 ± 0.05 | 0.37 ± 0.06 | 1.908 ± 0.003 | 0.536 ± 0.007 |

Table 3. A comparison of the mean rest-frame \( u - r \) colour of observed SN Ia host galaxies (all \( z < 0.04 \)) in Hakobyan et al. 2020 (H20) with the simulated catalogue (spanning all redshifts) presented in this work. Each reported uncertainty is the standard error of the mean. \( \Delta \text{-norm} \) is the difference between \( <u - r> \) of the peculiar SN Ia sample and the normal sample. All simulated hosts are bluer than the observed hosts; SN Ia and SN Ia-91bg-like hosts are significantly bluer, while SN Iax are consistent within 2\( \sigma \). The qualitative relationship between the classes (SN Iax hosts are bluer, SN 91bg-like hosts are redder) is similar.

Table 4. The properties of the transient and host catalogue are listed in Tables 4 and 5, respectively. Each row lists the properties of the transient (column 1), the properties of the host (column 2), and finally the match probability (column 3).

9 CATALOGUE ACCESS AND INTENDED USE

The SCOTCH catalogues are presented in HDF5 format and can be accessed on Zenodo at https://zenodo.org/record/7563623#.Y8_2my9h2yA. There are two separate catalogues, one for transients and one for hosts, which can be cross-matched to access the complete associated host-transient information. The properties of the transient and host catalogue are listed in Tables 4 and 5, respectively. Each transient in the catalogue is assigned a unique transient ID (TID) and each host a unique galaxy ID (GID), which are reported in bothcatalogues to enable cross-matching. If an event is considered hostless using our pipeline, we include an associated entry in the host catalogue with a unique GID, but populate the host properties with filler values (999).

We additionally provide dc2ID, the original ID of each galaxy within the CosmoDC2 catalogue, so that users can query the CosmoDC2 image simulations\(^\text{14}\) for additional properties. For example, although SCOTCH erases the realistic position information of host galaxies due to the necessary repeat use of HOSTLIB galaxies (see §4), if a user is interested in the original position and large-scale environment of a galaxy, e.g. to check whether the galaxy was a cluster member, they may retrieve the relevant information from CosmoDC2. A user in need of host galaxy SED information may access the original CosmoDC2 SED, find the amount that the galaxy’s redshift has changed from CosmoDC2 to SCOTCH, and red- or blue-shift the SED accordingly. However, we warn that for kilonova hosts in particular, the magnitude and colours of SCOTCH hosts are not directly traceable to the CosmoDC2 native values, as the kilonova host galaxy magnitudes in SCOTCH have been shifted (§6.6). In the case of hostless events, the dc2ID of the galaxy which was rejected by the \( d_{DLR} \) threshold is included in order to enable fetching information about the rejected host.

With top-of-the-galaxy observing conditions, users aiming to simulate optical surveys with similar passbands to LSST have a straightforward path to forecasting survey data. The path would include converting the magnitudes accordingly, subselecting events according to expected survey densities, updating transient and host positions to span the survey footprint, and implementing Galactic extinction and atmospheric noise. The ideally-sampled light curves can be degraded by adding noise and by sub-sampling as needed. We provide a series of basic tutorials for querying the catalogue and post-processing the data in Appendix B, available in the online supplementary materials.

Due to the increased volumes at higher redshifts in the universe and the fact that we simulate a fixed number of transient events per class, the full \( z < 3 \) catalogue is sparsely populated at very low redshifts. Users wishing to access a larger amount of low-\( z \) data may alternatively make use of an additional \( z \)-limited catalog that we release. In this catalog, we restrict the maximum \( z \) to 0.8 for each transient class so that the same number of events \( N \) as the full catalogue, as given in Table 2, are generated at lower redshifts. The \( z < 3 \) catalogue is named SCOTCH_Z3 and the additional catalogue is named SCOTCH_ZLIM.

For users wishing to simulate significantly different surveys, we also provide the HOSTLIBs and WGTMAPs in the Zenodo release for re-running the SNANA simulation code.

\(^\text{14}\) CosmoDC2_v1.1.4_image at https://data.lsstdesc.org/doc/cosmodc2.
Figure 13. Density distribution of observed colours for simulated transient classes (combining WGTMAP and HOSTLIB contributions). Marginal histograms are shown at top and at right of each sub-panel. The green diamond indicates NGC 4993, the host of the single kilonova observed. Overdensities near $g-r=0$ reflect remaining discrete tracks in CosmoDC2 galaxy distribution.

| Variable | Summary |
|----------|---------|
| TID      | Transient ID |
| $z$      | True Redshift (of host and transient) |
| GID      | Host-galaxy ID |
| MJD      | Array of Modified Julian Dates of light curve observations (only spacing is meaningful) |
| $m_{\text{band}}$ | Apparent brightness in LSST $ugrizY$ bands (AB magnitudes) |
| Class    | Transient class |
| Model    | Simulation model from Table 2 |
| Cadence  | Time-spacing of light curve samples [days] |
| RAoff    | Transient offset from host nucleus in R.A. ["] |
| δoff     | Transient offset from host nucleus in Dec. ["] |
| Sep      | Total great-circle distance between transient and host nucleus ["] |

Table 4. Summary of the transient information in the SCOTCH catalogue.

10 CONCLUSIONS AND DISCUSSION

We have presented our methodology for constructing the SCOTCH catalogue, a dataset consisting of multiple classes of simulated transients and their host galaxies. The final catalogue includes 5 million light curves for 10 distinct classes of supernovae and 3 additional transient classes, as well as the observed and derived properties of their host galaxies and physically-motivated offsets between the galaxy and transient positions. The cadence of these simulated light curves is class-specific in order to resolve rapidly-evolving features while limiting total data volumes. This catalogue significantly advances the framework for simulating the time-domain sky initially constructed for PLAsTiCC, which included minimal host-galaxy information.

This catalogue can be used for a broad range of scientific studies. First, teams developing transient classification algorithms for upcoming surveys can test the value of large samples of realistic host information. This added contextual information may help classify transients earlier in their light curves, facilitating rapid follow-up of interesting objects. Host information can also increase the precision of classifications, of particular value for collecting large uncon-
transient rates extrapolated to observational limitations of any particular survey. With empirically-derived transient rates, the catalogue is not tailored to fit cosmological applications – using upcomming survey data. Besides population-level studies of transients – e.g., for progenitor studies – an anomaly detection should be able to flag a totally unknown class of event in an upcoming survey, and this will be an important aspect of upcoming surveys.

Table 5. Summary of the host galaxy information in the SCOTCH catalogue. We note that the original CosmoDC2 catalog contains inaccurate ellipticities due to a bug; in SCOTCH, we report the corrected ellipticity and minor axis values following the corrections from https://github.com/LSSTDESC/gcr-catalogs/blob/ellipticity_bug_fix/GCRCatalogs/cosmodc2.py.

| Variable       | Summary                                                                 |
|----------------|-------------------------------------------------------------------------|
| GID            | Host-galaxy ID |
| TID            | Transient ID |
| dc2ID          | ID of corresponding CosmoDC2 galaxy |
| $m_{<\text{band}^>}$ | Apparent AB magnitudes in LSST $ugrizY$ bands |
| $\sigma_{m_{<\text{band}^>}}$ | 10-year estimated apparent AB magnitude errors for LSST |
| $e$            | Shear ellipticity $(1-q)/(1+q)$, where $q$ is the axis ratio |
| $R_d$          | Disk half-light radius in physical kpc |
| $R_s$          | Spheroid half-light radius in physical kpc |
| log ($M_*$)    | Log stellar mass [$M_\odot$] |
| log (SFR)      | Log star formation rate [$M_\odot$/yr] |
| $n_i$          | Sersic index for $i=0, 1$; $n_0=1$ (exponential disk) and $n_1=4$ (deVaucouleurs bulge) |
| $w_i$          | Weight of $i=0, 1$ Sersic components (bulge and disk) |
| $a_i$          | Major-axis half-light size ["] for $i=0, 1$ Sersic components |
| $b_i$          | Minor-axis half-light size ["] for $i=0, 1$ Sersic components |
| $\epsilon_i$  | Ellipticity of $i=0, 1$ Sersic components |
| $\epsilon_{tot}$ | Luminosity-weighted sum of bulge and disk ellipticities |
| $\alpha_{rot}$ | Rotation angle of major axis with respect to the +RA coordinate [°] |

Figure 14. SALT2 (Guy et al. 2007b) fitted parameters $x_1$ and $c$ as a function of host galaxy $M_*$ and sSFR. Our simulations reproduce the distribution of events observed in Childress et al. (2013).

contaminated samples of Type Ia supernovae for precision dark energy measurements. However, users should take caution when training classifiers on this catalogue, as overconfidence in the correlations represented therein could limit classifiers from finding transients in hosts not described by extant samples. We have not attempted to include any anomalies in the catalogue to mitigate this problem. Additionally, this catalogue is missing some known transient classes, and does not include any mock new classes of transients. Classifier trained for anomaly detection should be able to flag a totally unknown class of event in an upcoming survey, and this will be an important aspect of upcoming surveys.

Beyond classification, this catalogue can be used to forecast future population-level studies of transients – e.g., for progenitor studies or cosmological applications – using upcoming survey data. Besides the LSST-specific passbands, the catalogue is not tailored to fit the observational limitations of any particular survey. With empirically-derived transient rates extrapolated to $z=3$ and host galaxy magnitudes as faint as $r=28$, users can post-process the catalogue to reflect the expected footprint, depth, and observational biases of planned surveys. The catalogue can then be used to generate a proof-of-concept for science ideas, forecast results, estimate expected biases, and test new methods to mitigate them.

Although not the focus of this work, the validated correlations between simulated SNe Ia and their host galaxies are encouraging. Because we have linked the properties of observed SN Ia host galaxies to synthetic galaxies in CosmoDC2, myriad intrinsic host properties are available. The authors encourage future catalogue users to evaluate the use of synthetic SNe Ia for cosmological analyses, and explore additional correlations between Hubble Residuals and the CosmoDC2 properties of host galaxies.

The realism of this simulated catalogue is limited by approximations made during the simulation pipeline and the limitations of pre-existing transient-host galaxy catalogues. Here we re-emphasize several points and discuss opportunities for future improvements.

Generally, we allow the catalogue to reflect the trends seen in the existing data, so that developers of classification algorithms can better incorporate host galaxy information where available. The classes with the sparsest currently available data will have the least accurate host property distributions. Thus the transient-host correlations learned by a classifier trained on SCOTCH may be revealed to be too strong, or even fully inaccurate, with future data influxes.

Future updates to the catalog should seek to augment the small samples with recent data. For example, the Transient Host Exchange (Qin et al. 2022) could be ingested into our simulation framework to incorporate additional data into the existing SCOTCH classes as well as expand to more classes. During the writing of this work, the first long-duration GRB (IGRB) was discovered with evidence for coincident kilonova emission (Rastinejad et al. 2022). This result underscores our limited understanding of these events. Should additional future events be discovered with joint IGRB-KN emission, upcoming iterations of host galaxy simulations should include the properties of IGRB host galaxies as possible KN sites. The authors will consider incorporating this in future SCOTCH releases given sufficient demand. Finally, while preparing this manuscript, O’Connor et al. (2022) also investigated a series of high-redshift ($z<2$) sGRB host
Figure 15. Distribution of host-galaxy absolute magnitudes for a representative sample of SCOTCH transients using both HOSTLIBs and WGTMAPs. Host galaxy photometry from the GHOST catalogue for classes with statistical samples is shown as a black outline. Photometry is presented in the SDSS filter system.
Figure 16. Histogram of $g - r$ colour for synthetic Hydrogen-poor SN hosts before and after running the SNANA simulation. **Left:** The HOSTLIB of all H-poor (Ib/c, SLSN, IIb) hosts (gray), which was tailored to match the GHOST data (dashed line). The hosts selected after running the SNANA simulation for all H-poor classes with their respective WGTMAPs are shown in yellow. **Right:** SNANA-selected hosts of SLSN, Ic, and Ic-BL events. SLSN hosts are bluest, and Ic-BL hosts are bluer than the rest of the Ic class due to SFR and metallicity correlations. GHOST data are shown with a dashed outline, and we avoid plotting SNe Ic-BL hosts in GHOST due to the small sample size.

galaxies and found a potential increase in the number of hostless events with redshift. Given the small number of observed sGRBs considered in this study, additional work should be devoted to identifying and integrating correlations among high-z samples.

In addition, a major approximation in SCOTCH is that the hosts and transients are not distributed in a realistic large-scale-structure. Although the relative offsets between transients and their host galaxies are physically motivated, we have avoided placing these systems on the sky so that the catalogue may be of general use for generating synthetic transient catalogues for both northern and southern hemisphere surveys by the user. Therefore, the SCOTCH catalogue cannot be used to forecast cosmological applications of surveys that rely on realistic positions or velocities within the large-scale structure. Previous studies have found SNe to be highly clustered within the large-scale structure of the universe (Tsaprazi et al. 2022), so at the very least, retaining the locations of the synthetic SNe hosts within their simulated cosmic web environment would be a major improvement in realism. To retain large-scale structure information while matching empirically-determined transient rates, it is necessary to have very large HOSTLIBs. The current computational time required to read the large files into memory many times during the simulation is a bottleneck. In addition, retaining realistic position information would limit the sky area to the 440 sq. deg. currently simulated in CosmoDC2, which is less helpful for creating survey mocks. The future release of 5,000 sq. deg. of CosmoDC2 will present an opportunity for expansion, while other larger-volume synthetic galaxy catalogues could also be explored (e.g., Buzzard, DeRose et al. 2019).

Another possible extension of this work is to implement correlations between a transient and its location within a galaxy, as multiple studies have revealed local transient correlations (for example, with the amount of host-galaxy extinction for SNe Ia; see Holwerda 2008; Holwerda et al. 2015; Popovic et al. 2021). For some classes (e.g., TDEs), this local information may be more valuable in early classification than global host galaxy information (Gomez et al. 2022).

In addition to these catalogue-level corrections, our methods could be expanded to produce simulated images. This is a non-trivial issue because the transient image must be overlaid on the host galaxy image as well as surrounded by a realistic background which accurately reflects the galaxy density at the location in the simulation (which would require the preservation of large-scale structure information). Machine learning-based algorithms such as Generative Adversarial Networks (GAN) have shown significant promise in generating galaxy images that are both survey-specific and realistic (Fussell & Moews 2019; Dia et al. 2020; Buncher et al. 2021, among others), and conditional networks allow for the encoding of model-specific parameters in generated images (Ravanbakhsh et al. 2016).
Marginal kernel density estimates are shown at top and at right in each panel. In the upper left panel, the HOSTLIB-only simulation (blue) decently reproduces the colour-magnitude spread of SN Ia hosts in GHOST (grey), although it is worse in \( g-r \) than in \( M_r \) due to the CosmoDC2 colour limitations. The blue points, however, are a poor match to DES data from Smith et al. (2020) (black) in SFR-stellar mass (SFR-\( M_* \)) space (lower left), especially in the SFR distribution. A random sampling of CosmoDC2 galaxies which is associated with SNANA transients via a realistic WGTMAP (yellow) yields more realistic SFR-\( M_* \) results but does worse in colour-magnitude space. Notably, the yellow distribution in \( g-r \) is in strong disagreement with GHOST. Simulations using both HOSTLIB and WGTMAP (green at right) result in decent matches to both data sets in both parameter spaces. In all plots, the redshift range is limited to \( z < 0.85 \) to enable fairer comparison with observational data. In the lower plots the simulations are further limited to \( r < 23.8 \), the 10-\( \sigma \) magnitude limit for the DES3yr sample, for optimal comparison.

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Author contributions are listed below.

M. Lokken: Data curation, SCOTCH simulations and validation, writing - editing, tutorial creation

A. Gagliano: Data curation, SCOTCH simulations and validation, writing - editing, tutorial creation

R. Hložek: supervision, PLAsTiCC data curation and validation, project administration for PLAsTiCC, writing - editing

G. Narayan: supervision, ELAsTiCC data curation and validation, project administration for ELAsTiCC, writing - editing

R. Kessler: supervision, updating code for SNANA simulations, setting up SNANA simulations, writing - editing

J. F. Crenshaw: Supervising use of PZFlow, writing - editing

L. Salo: Data curation of kilonova hosts, writing - editing

C. Alves: SNANA simulation setup, writing - editing

D. Chatterjee: Updating kilonova light curve model, writing - editing

M. Vincenzi: consulting on WGTMAP and HOSTLIB setup, updating core collapse SN light curve model, writing - editing

A.I. Malz: Discussions and infrastructure for follow-up work

DATA AVAILABILITY

The simulated data are available at https://zenodo.org/record/7563623#.Y8_2my9h2yA (Lokken et al. 2022). Any updates after the publication of this manuscript will be given a unique Zenodo identifier and link, and accompanied by text describing the changes. The most up-to-date version can always be accessed using https://doi.org/10.5281/zenodo.6601210. All code used for this project is publicly visible at https://github.com/LSSTDESC/transient-host-sims. Users are encouraged to report any catalog problems or bugs in the code via GitHub Issues or by e-mail to the authors. The supplementary materials to this paper, available online, include a description of the nearest-neighbors matching from Sec. 5.3 (Appendix A) and a description of the catalogue walk-through tutorials (Appendix B).

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APPENDIX A: APPROXIMATE NEAREST-NEIGHBOURS MATCHING OF GHOST AND COSMODC2 GALAXIES WITH ANNOY

In LSH methods, a hashing function \( h \) is constructed that maps a high-dimensional observation to a scalar such that, for any three observations \( a, b, \) and \( c \) for which some distance metric \( s \) is defined in the original space, the following criterion is met:

\[
(d(a, b) < d(b, c) \Rightarrow h(a, b) < h(b, c))
\]

(A1)

In this example, the two observations \( a \) and \( b \) with a small relative distance will retain a small relative distance (high relative similarity) after being mapped to a scalar value. Because \( d \neq h \), the nearest neighbours returned by LSH methods may vary from those returned by a brute-force distance calculation between all observations; but the ‘approximate’ solution is achieved in significantly less time.

A multitude of methods exist both for constructing the hashing function \( h \) and the distance measure \( d \) (see Wang et al. 2014, for additional details). In the random projection method employed by ANNOY, a catalogue of observations is provided and two are selected at random. A maximum-margin hyperplane is then constructed that separates the two observations (Charikar 2002). This process is repeated and a decision tree is constructed with each node in the tree corresponding to a hyperplane. The hashing function encodes the sides of each separating hyperplane on which the observations fall. Similar to random forest algorithms, multiple decision trees are constructed in ANNOY. The nearest-neighbours returned by an observation query to the space are the indexed observations that fall on the same side of all separating hyperplanes in a combination of decision trees.

In contrast with previous implementations of LSH methods, ANNOY decouples the construction of the indexed space and the querying of the space for individual vectors. Because the indexed space can be saved as a static file and then loaded into shared memory, matching can be achieved in parallel to dramatically reduce matching time.

We construct our indexed space from the following properties of 30M galaxies in CosmoDC2: absolute rest-frame \( r \)- and \( i \)-band magnitudes, \( g - r \) and \( i - z \) colours, and redshift. We normalize all properties by the StandardScaler algorithm, after which the distribution for each parameter has a mean of 0 and a variance of 1. Finally, we weight the redshift by 5%, enabling a wider distribution of redshifts in the matched sample than the low-\( z \) GHOST data. We select the same parameters from observed galaxies within the CosmoDC2 catalogue, normalize them, and query the indexed space for \( k \) approximate nearest-neighbours in CosmoDC2. For a transient class \( i \), we set \( k = 2 \times 10^6 / N_i \), where \( N_i \) is the number of galaxies of class \( i \) in the GHOST catalogue. This allows our matched sample to contain \( \sim 2 \)M galaxies for each class.

APPENDIX B: USING THE SCOTCH CATALOGUE

We have released the SCOTCH catalogue as an HDF5 file consisting of a transient table and a host galaxy table. We present an overview of the SCOTCH catalogue hierarchy in Fig. B1, and provide Python code for retrieving basic information about transients and host galaxies below. Full tutorials can be found in the repository associated with this release.15

15 https://github.com/LSSTDESC/transient-host-sims/blob/main/notebooks/SCOTCH_walkthroughs.ipynb

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**B1 Properties of Transient Host Galaxies**

To load in the SCOTCH catalogue, we use the Python package h5py\(^{16}\):

```python
>> scotch = h5py.File("./scotch.hdf5", "r")
>> print(scotch.keys())
<KeysViewHDF5 ['HostTable', 'TransientTable']>
```

The host galaxy table is further broken down by transient class:

```python
>> scotch_hosts = scotch['HostTable']
>> print(scotch_hosts.keys())
<KeysViewHDF5 ['AGN', 'KN', 'SLSN-I', 'SNII', 'SNIIb', 'SNIa', 'SNIIb', 'SNIIc', 'TDE']>
```

The parameters linked to each host galaxy are given by retrieving the hosts of a given class:

```python
>> print(scotch_hosts['AGN'].keys())
<KeysViewHDF5 ['GID', 'T', 'TID', 'a0', 'al', 'a_rot', 'b0', 'b1', 'dc2ID', 'ellipticity', 'logMstar', 'logSFR', 'mag_Y', 'mag_g', 'mag_i', 'mag_r', 'mag_u', 'mag_z', 'magerr_Y', 'magerr_g', 'magerr_i', 'magerr_r', 'magerr_u', 'magerr_z', 'n0', 'n1', 'w0', 'w1', 'z']>
```

Values for each parameter can then be retrieved for each event:

```python
>> print(scotch_hosts['AGN']['logSFR'][0])
-0.4994781
```

**B2 Recovering Transient Light Curves**

We now consider the table of transient properties in SCOTCH, and focus on SNe II in the catalogue.

```python
>> scotch_transients = scotch['TransientTable']
>> SNII = scotch_transients['SNII']
```

Each transient table is further broken down by transient model.

```python
>> print(SNII.keys())
<KeysViewHDF5 ['SNII+HostXT_V19', 'SNII-NMF', 'SNII-Templates', 'SNIIn+HostXT_V19', 'SNIIIn+Rosenberg']>
```

The details for these models are provided in §4.2 of the main text as well as Kessler et al. (2019a).

Below, we retrieve these models and plot the light curves of a single event for each model:

```python
>> SNII_models = list(SNII.keys())
>> bands = 'ugrizY'
>> cols_sns = sns.color_palette("colorblind", 10)
>> cols = [cols_sns[4], cols_sns[9], cols_sns[2], cols_sns[1], 'tab:red', cols_sns[5]]
>> fig, axs = plt.subplots(nrows=3, ncols=2, figsize=(10, 10),)
```

---

\(^{16}\) [https://www.h5py.org/](https://www.h5py.org/)
The Simulated Catalogue of Optical Transients and Correlated Hosts (SCOTCH)

Figure B2. Sample light curves from the SCOTCH catalogue for each SN II model used.

```python
>>> sharex=True, sharey=True)
>>> axs[2, 1].set_axis_off()
>>> plt.subplots_adjust(hspace=0.25, wspace=0.2)
>>> for i in np.arange(len(SNII_models)):
    >> model = SNII_models[i]
    >> SNII_oneModel = SNII[model]
    >> ax = axs.ravel()[i]
    >> for j in np.arange(len(bands)):
        >> ax.plot(SNII_oneModel['MJD'][0],
                   SNII_oneModel['mag_%s' % bands[j]][0],
                   c=cols[j], label=bands[j])
    >> if i==0:
        >> ax.legend(bbox_to_anchor=(2.05, -1.7),
                     borderaxespad=0, ncol=2)
    >> ax.set_ylim((35, 23))
    >> ax.set_xlim((53120, 53300))
    >> ax.set_ylabel("mag$_{LSST}$")
    >> ax.set_title(model)
    >> axs.ravel()[4].set_xlabel("MJD")
```

This code produces Fig. B2.

B3 Survey-Specific Analyses

SCOTCH is intended as a truth catalog, but for many purposes the goal is to simulate observations taken by real surveys with specific footprints and limited efficiency. In the associated tutorials for this work, we provide a basic example of how to emulate observations matching the depths and sky footprint of the LSST Deep Drilling Fields (DDFs), using PLAsTiCC data\(^{17}\) as a comparison.

We plot the results of our magnitude limit cuts in Fig. B3, where we have also placed SCOTCH SNe realistically on the sky. The redshift distributions for SNe Ia and SLSN-I now show reasonable agreement to those from the test set of the PLAsTiCC challenge. The remaining discrepancy reflects Milky Way extinction, which is considered in PLAsTiCC and not in SCOTCH; and the difference in observational limits are incorporated into the SNANA simulated framework (as an efficiency versus SNR curve, and not as an explicit SNR cut as we have imposed here).

Because SCOTCH does not simulate Milky Way extinction or instrument systematics, some additional work is required to more accurately reflect the observed distribution of transients from a survey. We can roughly estimate these observational effects for an observational catalogue such as the Zwicky Transient Facility Bright Transient Sample (ZTF BTS; Fremling et al. 2020). We download the ZTF BTS, model the distribution of Galactic $A_V$ values across the sample, and draw new values for SCOTCH transients. After mapping the given trigger criterion to LSST-$gr$ bands, we arrive at the distribu-

\(^{17}\)https://zenodo.org/record/2539456#.YmHSu5LMKNF
Figure B4. Distribution for SCOTCH SNe post-processed to match the detection criteria of the ZTF BTS. Observed samples are shown as solid lines.

We find reasonable agreement, despite the facts that the photometric systems used are different and that the precise observing strategy of the survey is unknown.

The number of objects per class in SCOTCH do not represent realistic volumetric rates. However, SANA provides calculations of the expected number of events per solid angle per survey time given the input volumetric rate models. These are shared in Table B1 to enable re-sampling the simulation to create realistic volumetric populations.

We provide additional tutorials for comparing the properties of transient light curves and their host galaxies in the associated repository.

This paper has been typeset from a TeX/LaTeX file prepared by the author.

| Class | Model name | $n$ [yr$^{-1}$] |
|-------|------------|----------------|
| Ia    | SALT2-Ia   | 21,773,710     |
|       | Iax        | 15,933,345     |
|       | 91bg-like  | 5,035,905      |
| SN II | SNII-Templates | 15,652,660   |
|       | SNII-NMF   | 15,652,660     |
|       | SNII+HostXT_V19 | 31,402,045 |
| SN IIn| SNIIn-MOSFiT | 2,270,665     |
|       | SNIIn+HostXT_V19 | 2,270,665 |
| Stripped Envelope / H-Poor Core-Collapse |
| Ib    | SNIb-Templates | 5,217,675     |
|       | SNIb+HostXT_V19 | 5,217,675 |
| Ic    | SNIc-emplates | 3,623,355     |
|       | SNIc+HostXT_V19 | 3,623,355    |
| IcBL  | SNIcBL+HostXT_V19 | 1,062,880  |
| IIb   | SNIIb+HostXT_V19 | 10,531,710   |
| SLSN-I| SLSN-I-MOSFiT | 53,290       |
| KN    | Kasen 2017  | 122,640        |
|       | Bulla 2019 | 122,640        |
| TDE   | TDE_MOSFiT | 38,690         |

Table B1. Number of transients per year, $n$, predicted by each model for the entire sky and for $z < 3$. The relative amounts of core collapse SNe follow the relative rates measured by Shivvers et al. (2017).