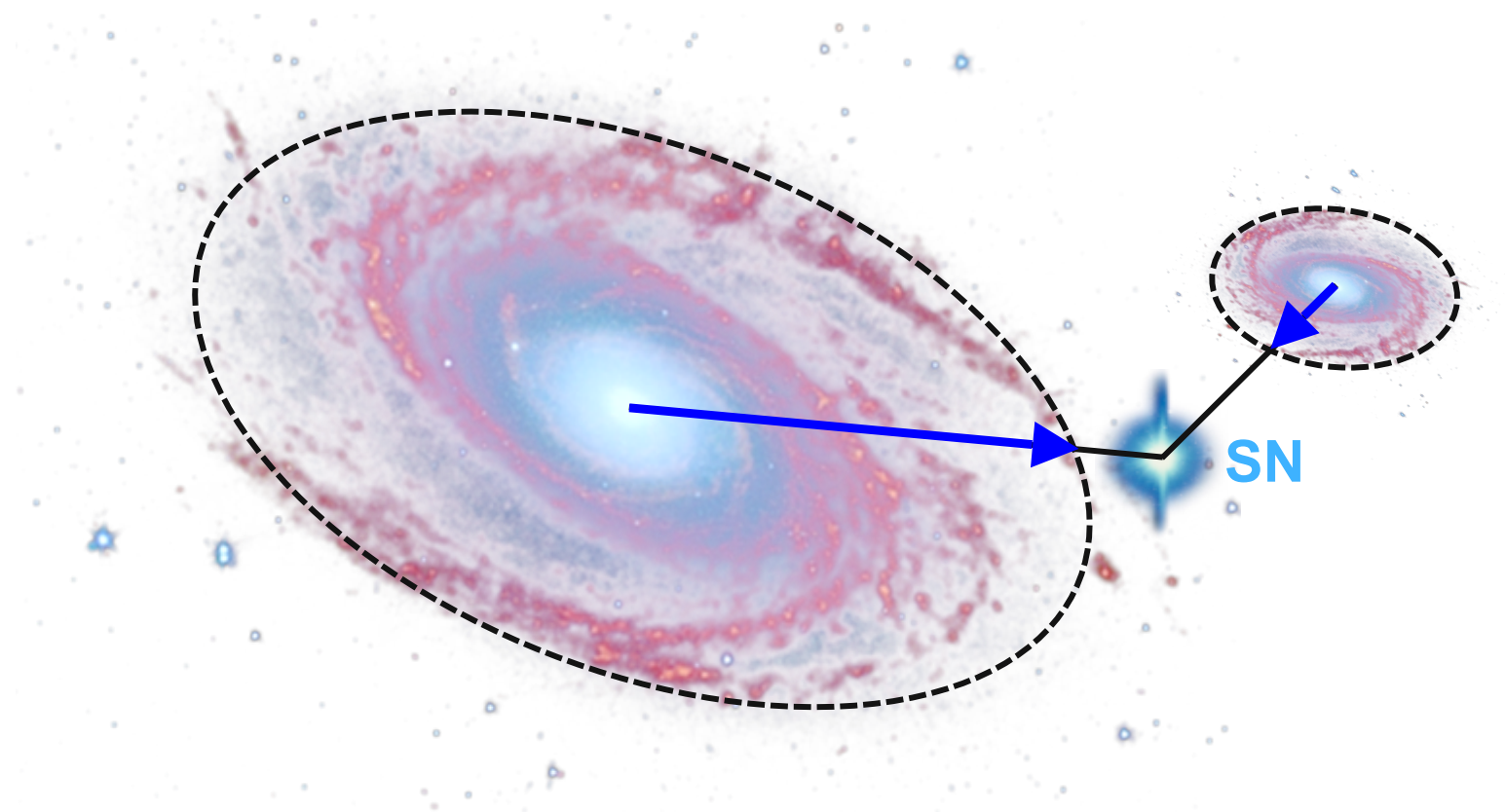


# Host Galaxy Identification for Supernova Surveys



**Ravi Gupta (Bldg 360, Room L-173)**

Steve Kuhlmann, Eve Kovacs, Hal Spinka, Camille Liotine, Kasia Pomian + DES

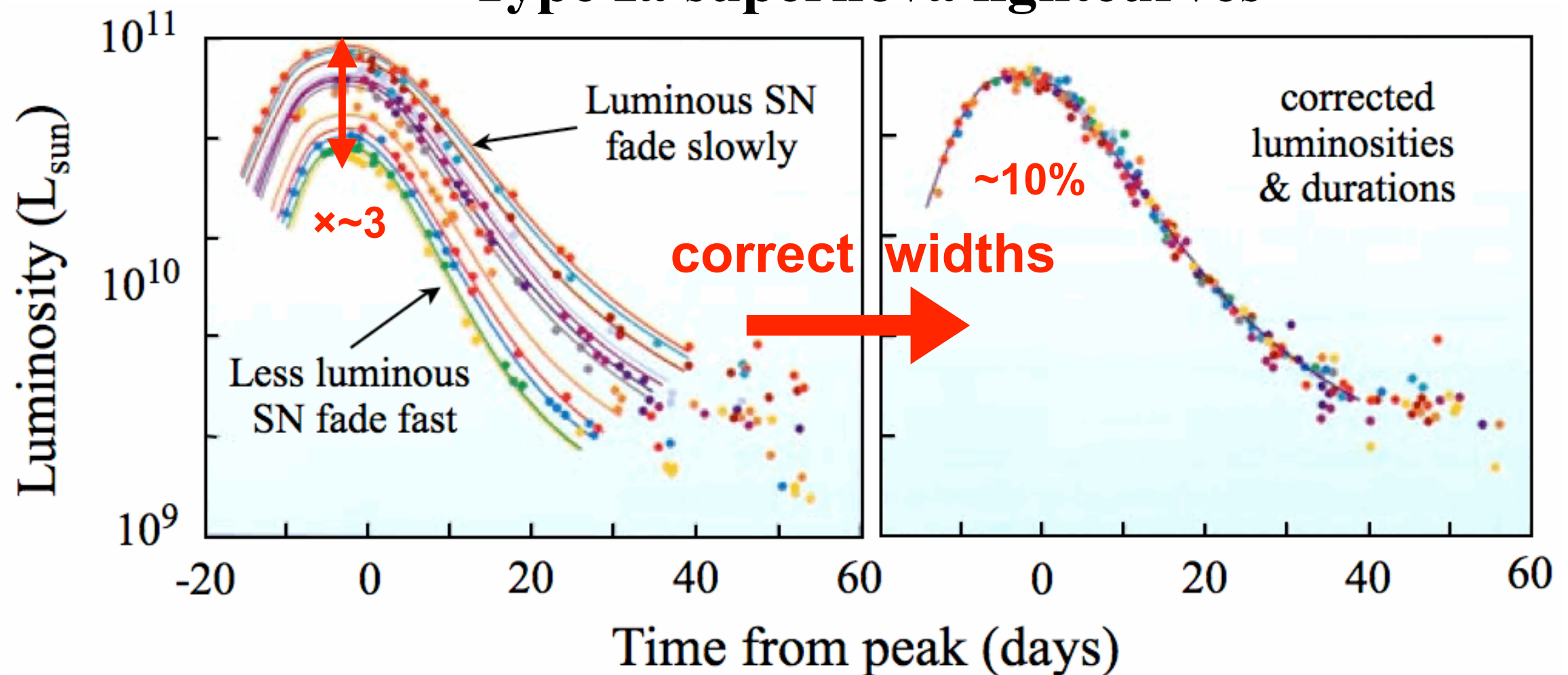
HEP Division Young Scientist Symposium Series

16 February 2016

# Type Ia Supernovae (SNe Ia): Standardizable Candles

- ▶ SNe Ia are thermonuclear explosions of carbon-oxygen white dwarfs
- ▶ Peak luminosity is related to both lightcurve width and color
- ▶ Calibrating the luminosity based on these empirical relations allows us to use SNe Ia as distance indicators and probe cosmology via the distance-redshift relation

## Type Ia supernova lightcurves

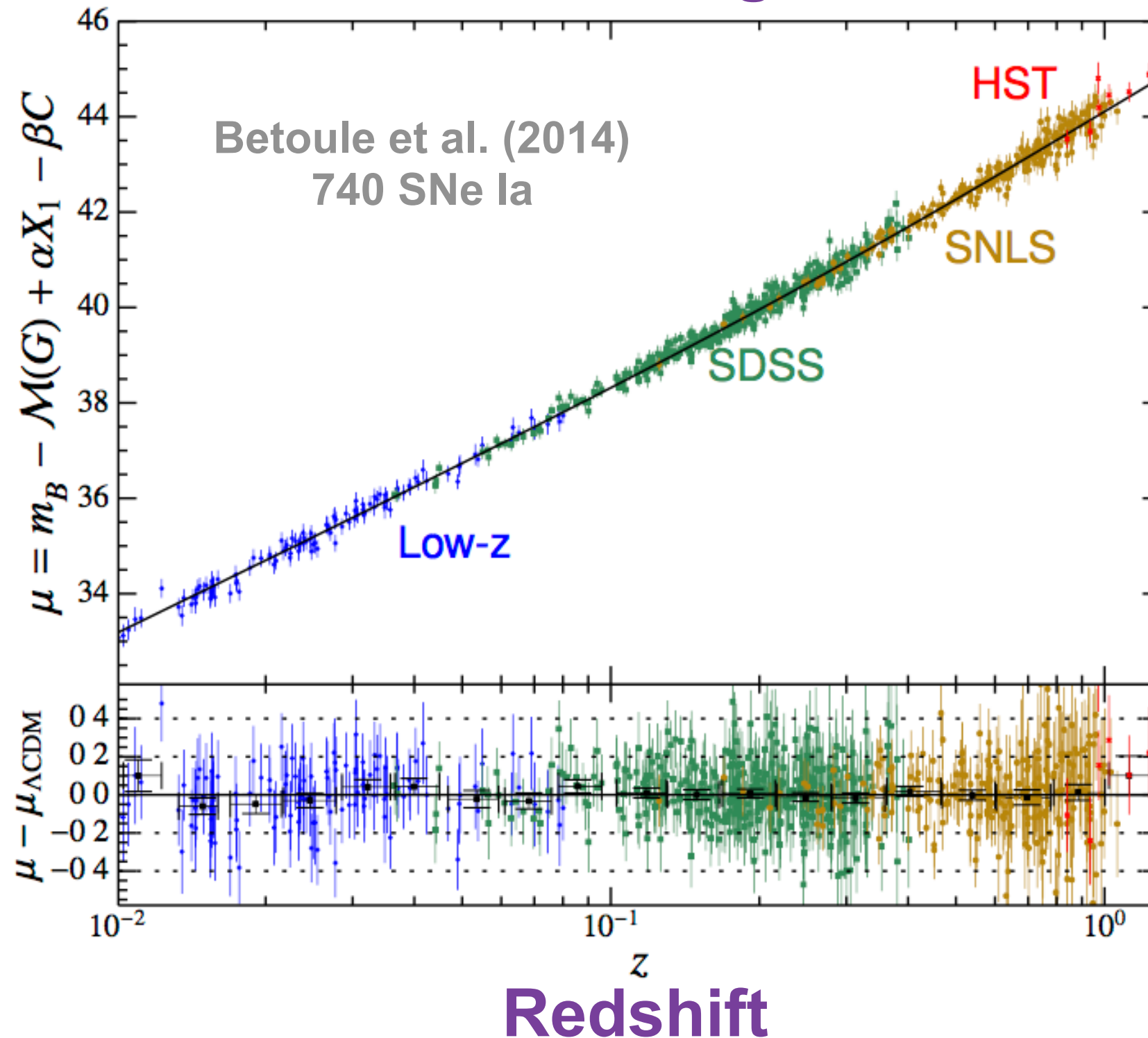


# Type Ia Supernovae (SNe Ia): Cosmological Probes

## Hubble Diagram

Distance

Hubble Residuals



- ▶ Past surveys discovered tens to hundreds of SNe Ia
- ▶ Current and future surveys will find thousands and even hundreds of thousands more
- ▶ SN cosmology is becoming limited by systematic uncertainties rather than statistics:
  1. Photometric calibration
  2. Host galaxy correlations



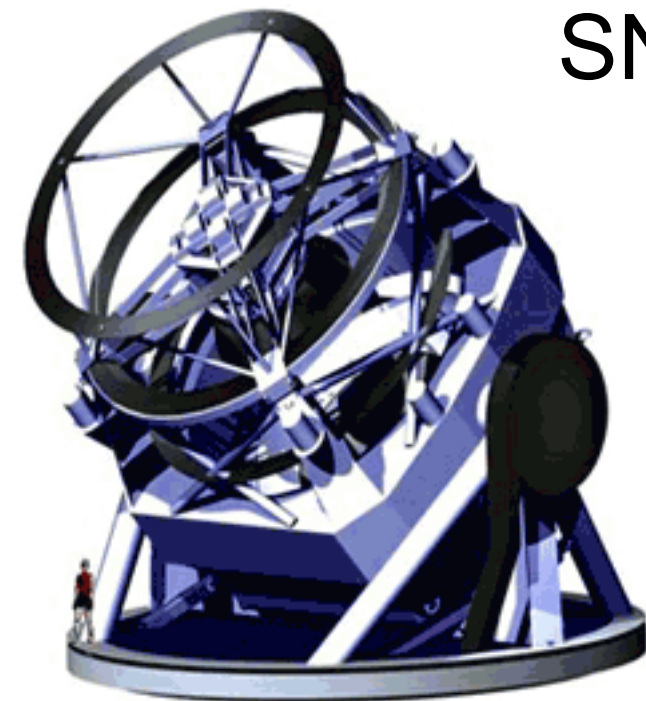
# The Importance of Host Galaxy Identification

- ▶ *Host galaxy identification* (“host matching”) is a crucial step for modern SN surveys
- ▶ The Dark Energy Survey (DES) is on track to discover ~3500 SNe Ia
- ▶ The upcoming Large Synoptic Survey Telescope (LSST) will discover  $\gg 10\text{K}$  SNe Ia
- ▶ In the absence of SN spectroscopy to determine SN types, we **rely mainly on host galaxy spectra** to obtain redshifts which are used to photometrically type SNe

**DES: ~3500  
SNe Ia**



**LSST:  $\gg 10\text{K}$   
SNe Ia**



LSST Corp.

# The Importance of Host Galaxy Identification: Photometric SN Classification

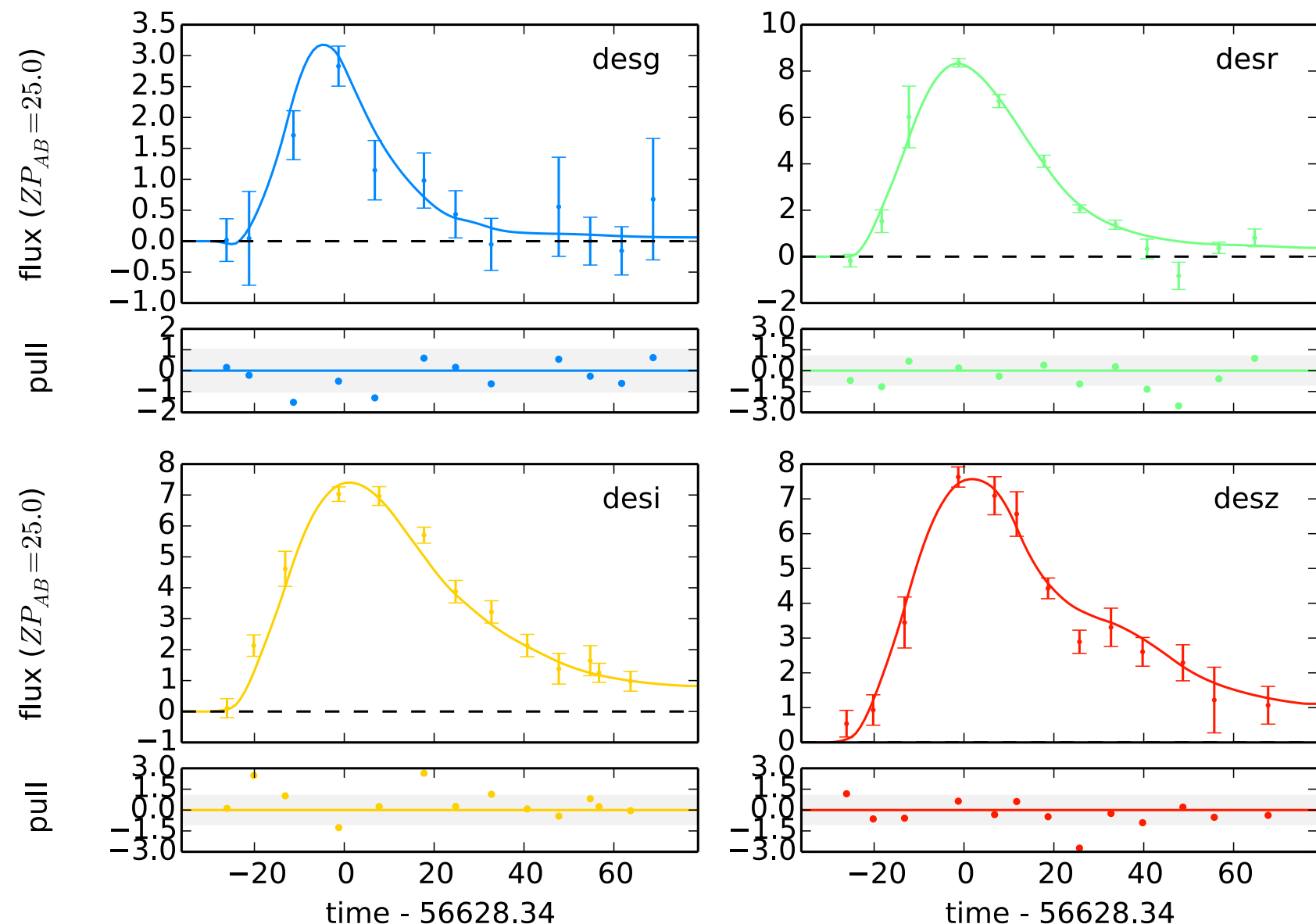
- ▶ By fitting the shape of the lightcurve, we can determine if the SN was Type Ia or other type
- ▶ Redshift of host galaxy (from spectrum of the host) greatly improves fit
- ▶ Only ~10% of our final sample of SNe Ia will be spectroscopically confirmed
- ▶ The majority rely on this method of photometric classification

## DES Year 1 SN Ia candidate fit using host galaxy redshift prior

DES13X3tvl  
 $\chi^2 / \text{dof} = 0.92786035$

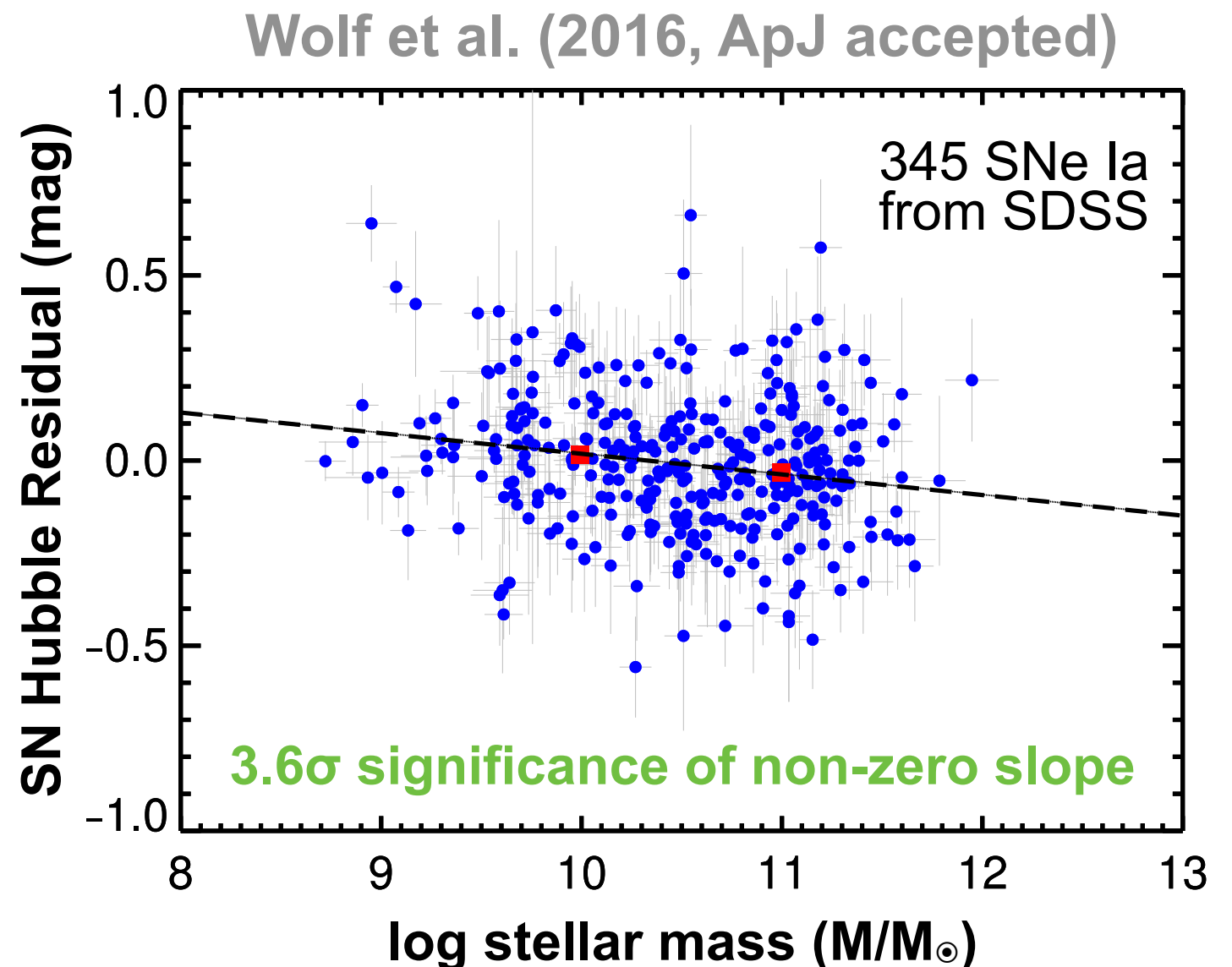
$z = 0.5191 \pm 0.0025$   
 $t_0 = 56628.34 \pm 0.37$   
 $x_0 = (9.64 \pm 0.28) \times 10^{-6}$

$x_1 = -0.03 \pm 0.25$   
 $c = -0.041 \pm 0.028$   
mw  $E(B-V) = 0.040928748$



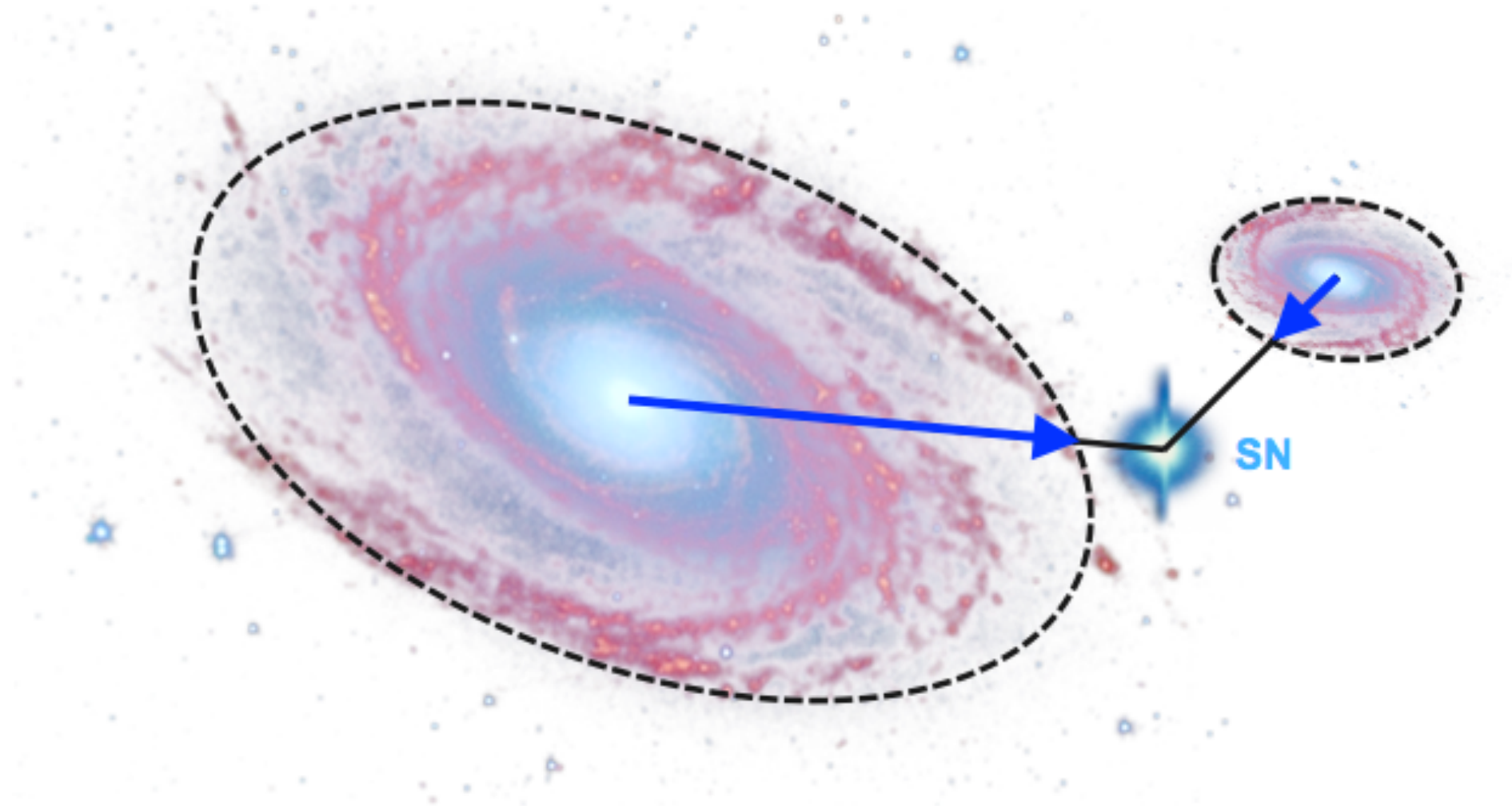
# The Importance of Host Galaxy Identification: Host Galaxy Correlations

- ▶ In addition, SN luminosities are known to correlate with host galaxy properties
- ▶ The origin of this correlation is not yet understood, but cosmology analyses already use host galaxy properties to correct for SN luminosities
- ▶ **Reliable identification of host galaxies is essential for cosmology and SN science**



# Method: Directional Light Radius (DLR)

DLR = radius of a galaxy in the direction of the SN

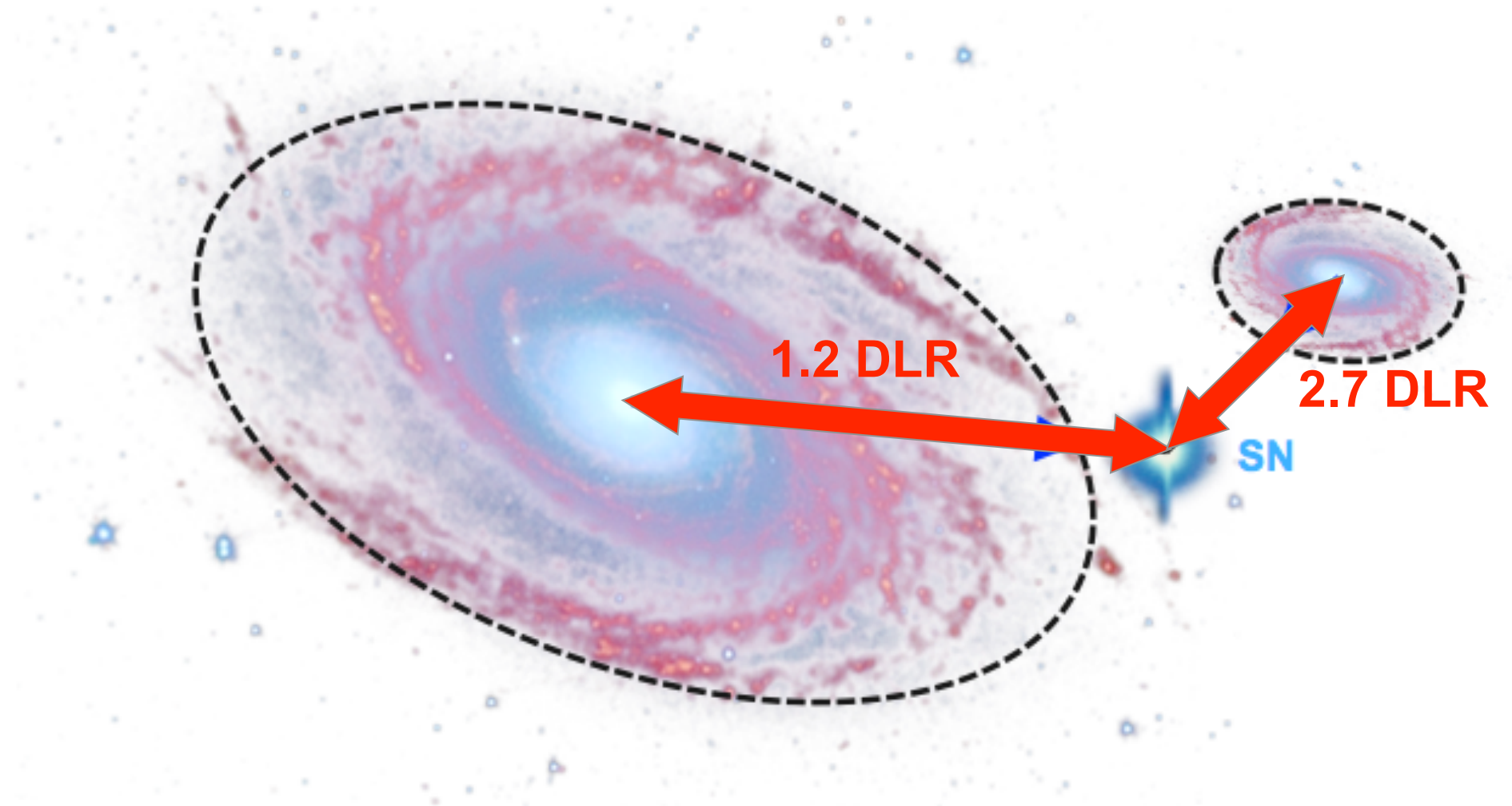




# Method: Directional Light Radius (DLR)

DLR = radius of a galaxy in the direction of the SN

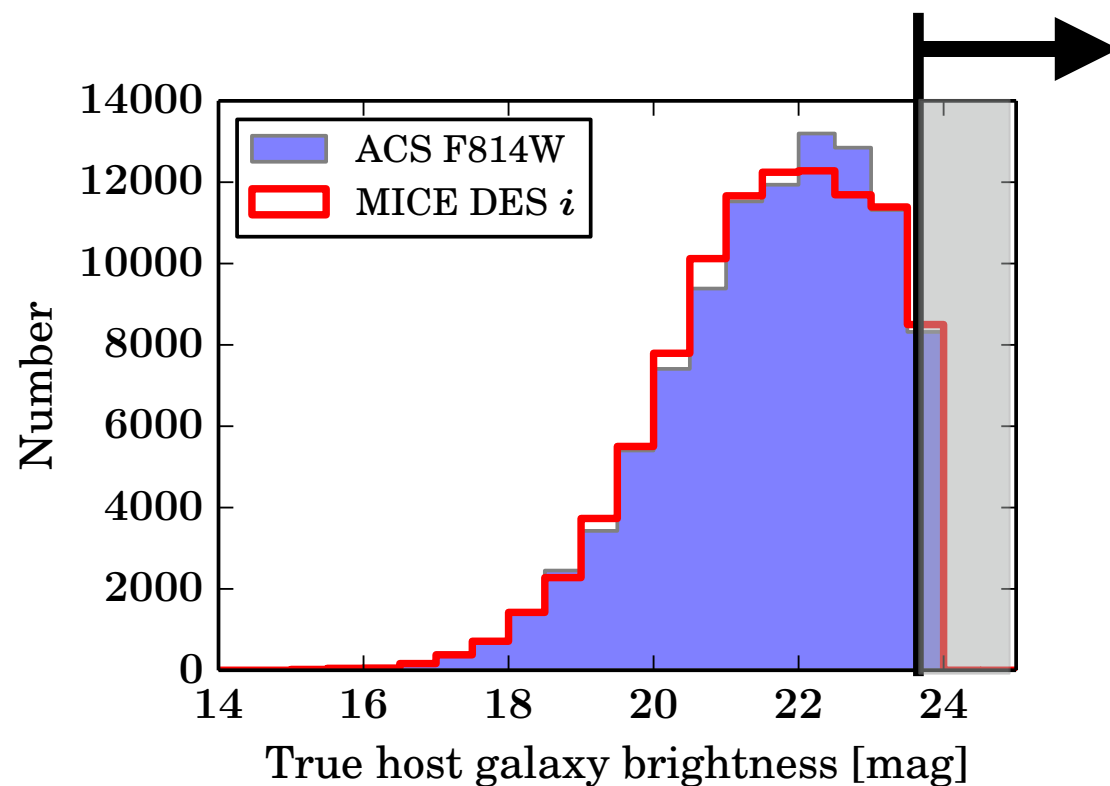
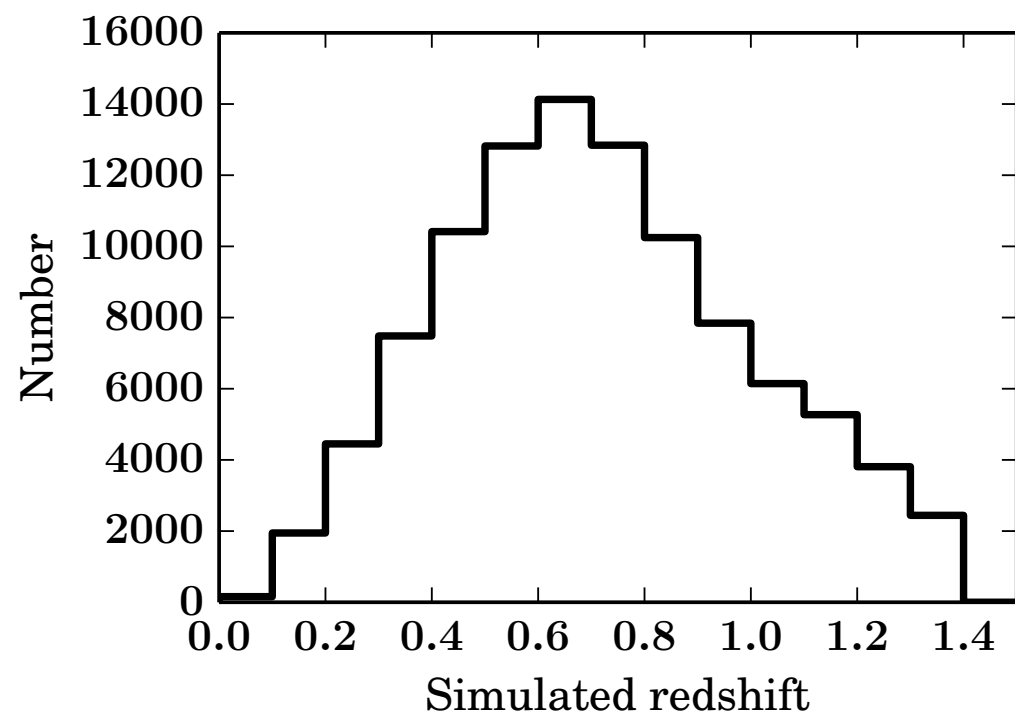
- ▶ Search for galaxies within a  $30''$  radius of SN position
- ▶ Match SN to the galaxy that is nearest in units of galaxy radius (DLR)
- ▶ In this way, the separation distance is normalized by the apparent size of the galaxy





# Testing Host Matching with Simulations

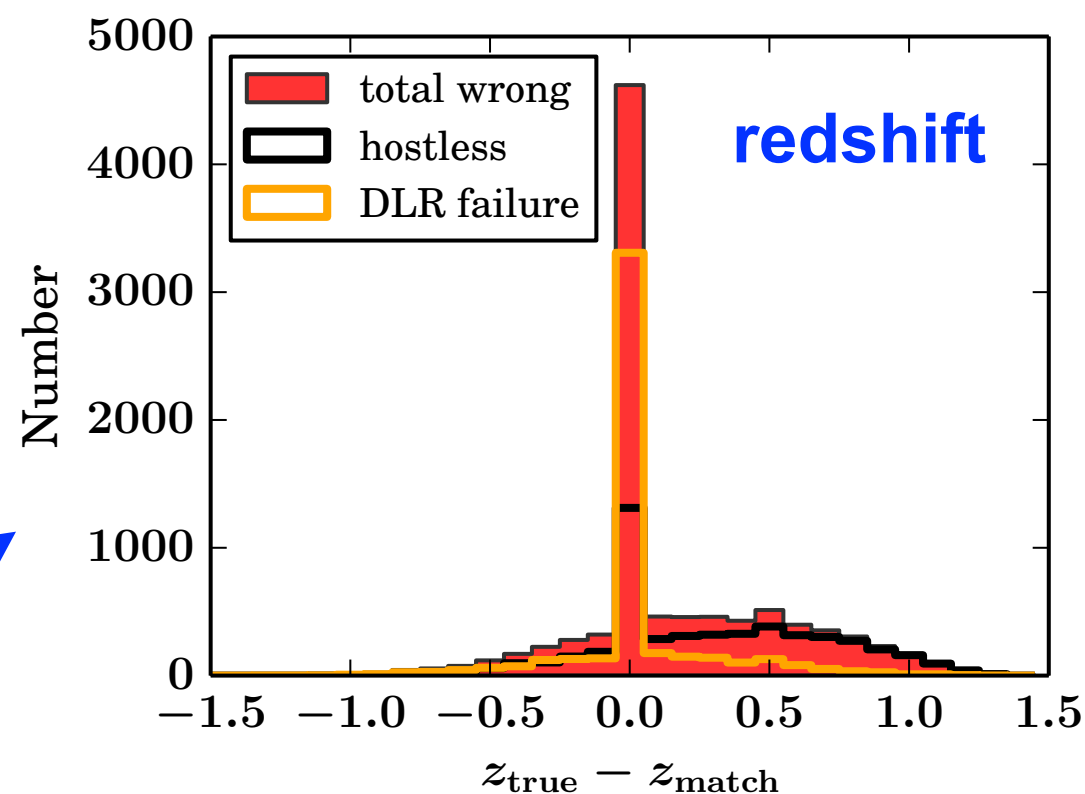
- ▶ Using galaxy catalogs we can place simulated SN locations onto galaxies
  - Mock catalog: MICECATv2.0 (Carretero et al. 2015)
  - Real catalog: *HST* ACS General Catalog (Griffith et al. 2012)
- ▶ SN redshifts simulated to reproduce DES-like SN Ia redshift distribution
- ▶ SN positions placed such that they follow the light distribution of their host galaxies (Sérsic profiles)
- ▶ When matching, assume fiducial hostless SN rate of 5% to simulate magnitude-limited survey



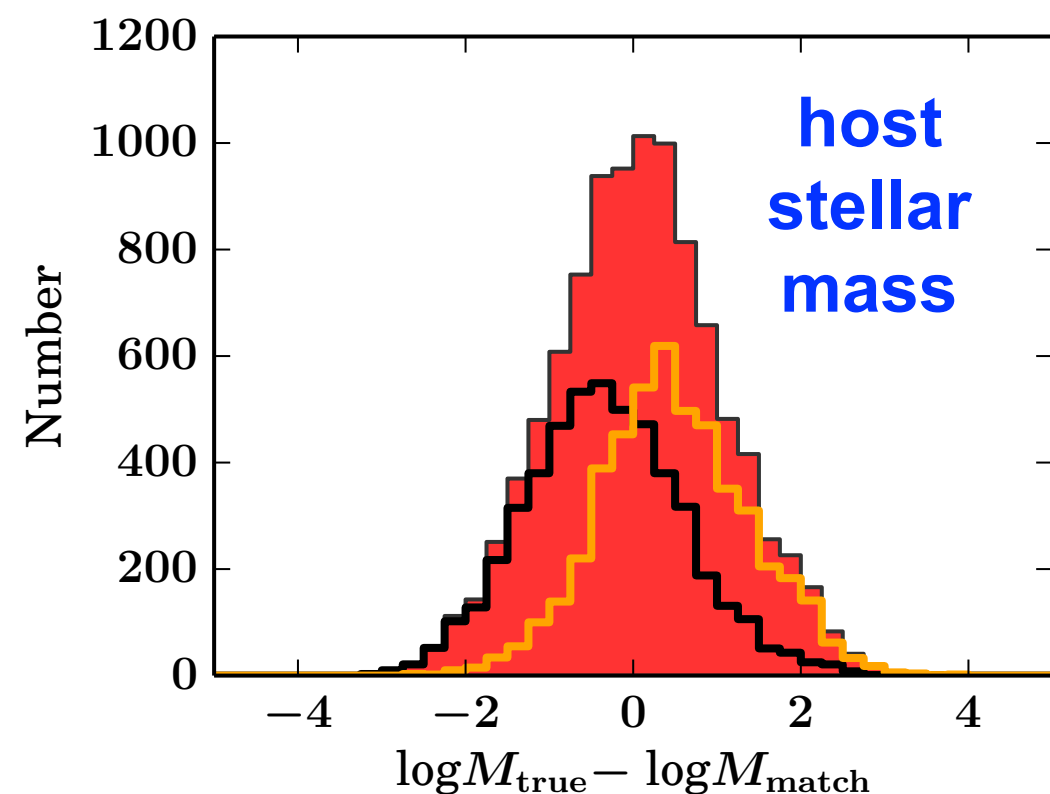
**HOSTLESS:**  
After simulating SNe, perform a magnitude cut on catalog such that the faintest 5% of hosts are removed

# Testing Host Matching with Simulations: Results

- ▶ DLR distance to nearby galaxies is computed from the galaxy coordinates, sizes, shapes, and orientations given in the catalog
- ▶ Nearest galaxy in DLR-space is designated as the host
- ▶ Since the true host is known, we can test the matching accuracy
- ▶ **The DLR method performs with ~91% accuracy** (we know the 5% hostless will be mismatched to galaxies brighter than the true host)



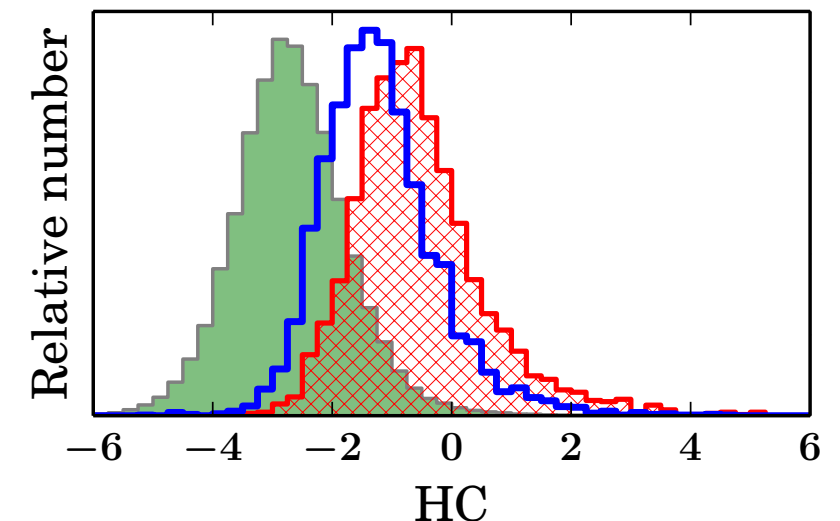
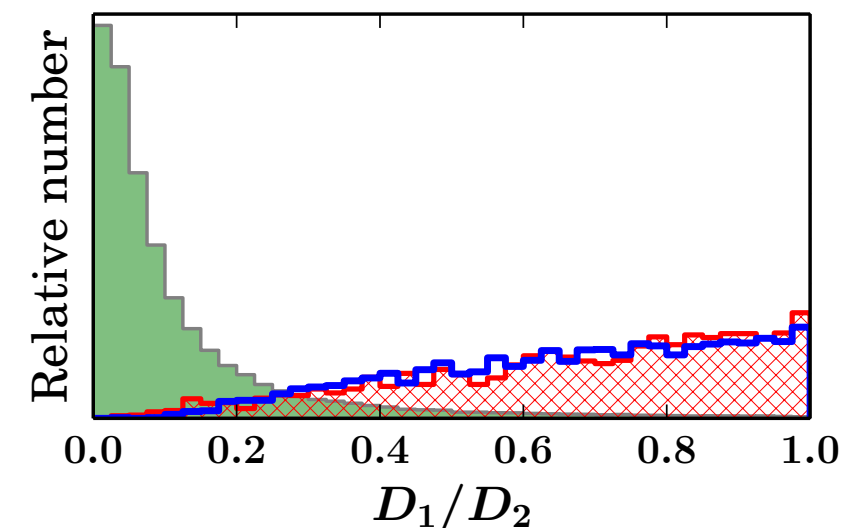
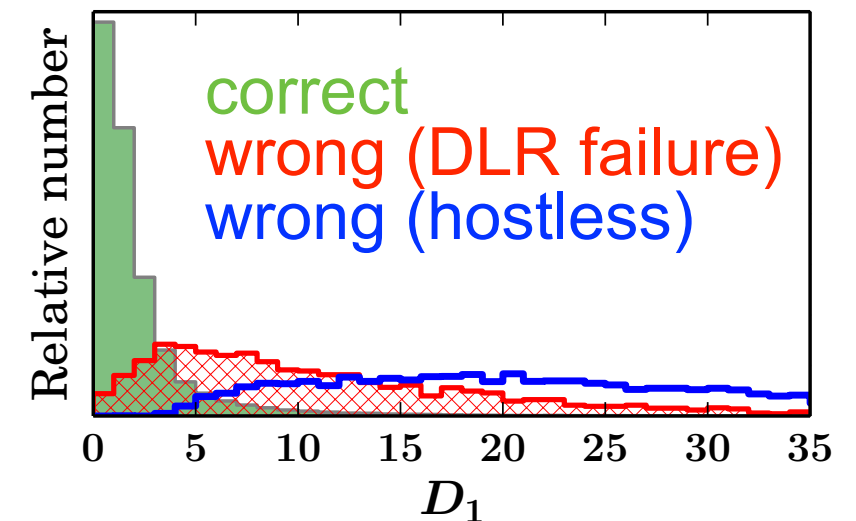
Even if the incorrectly-matched host happens to have a similar redshift,...



... this is still a problem given what we know about SN-host correlations

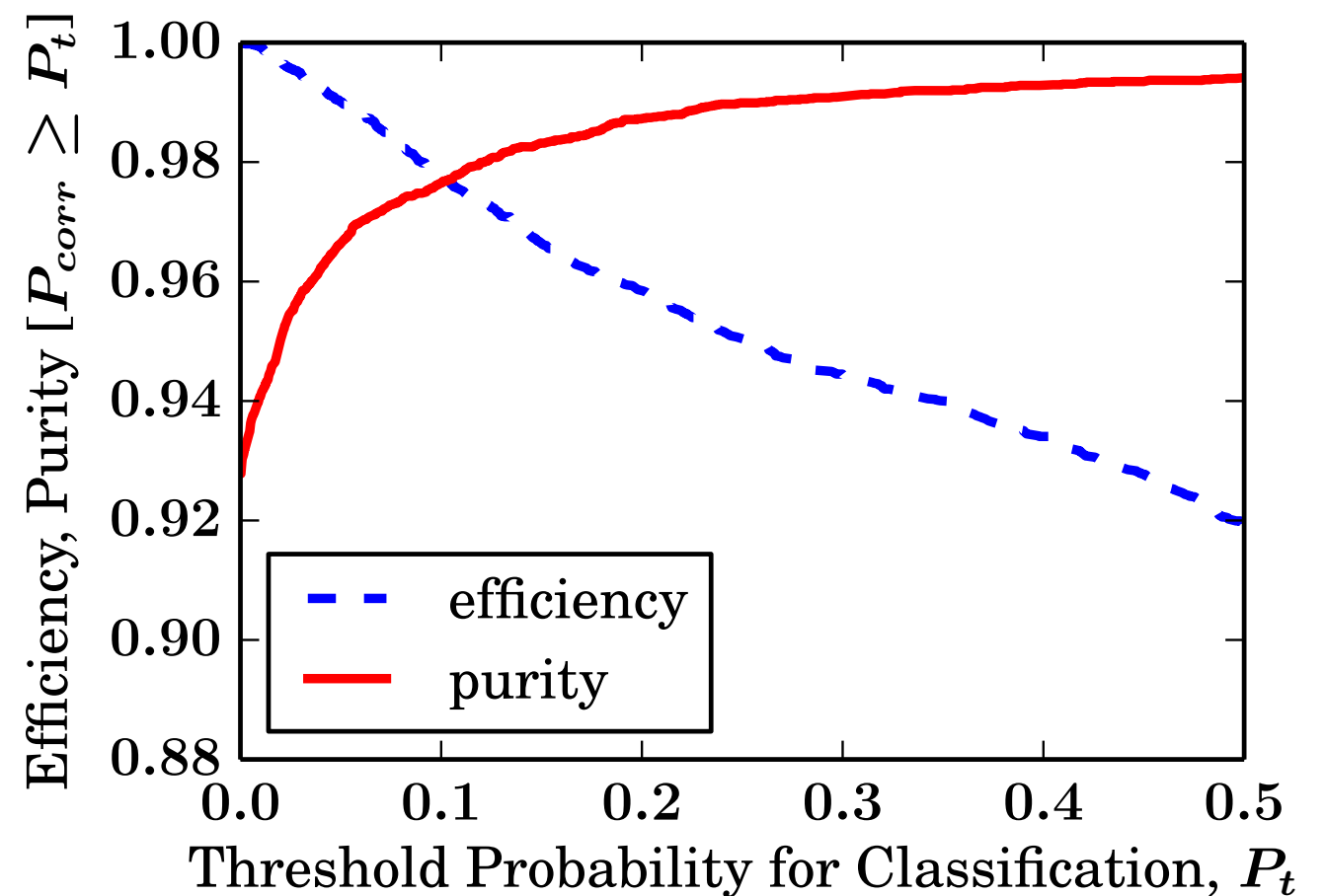
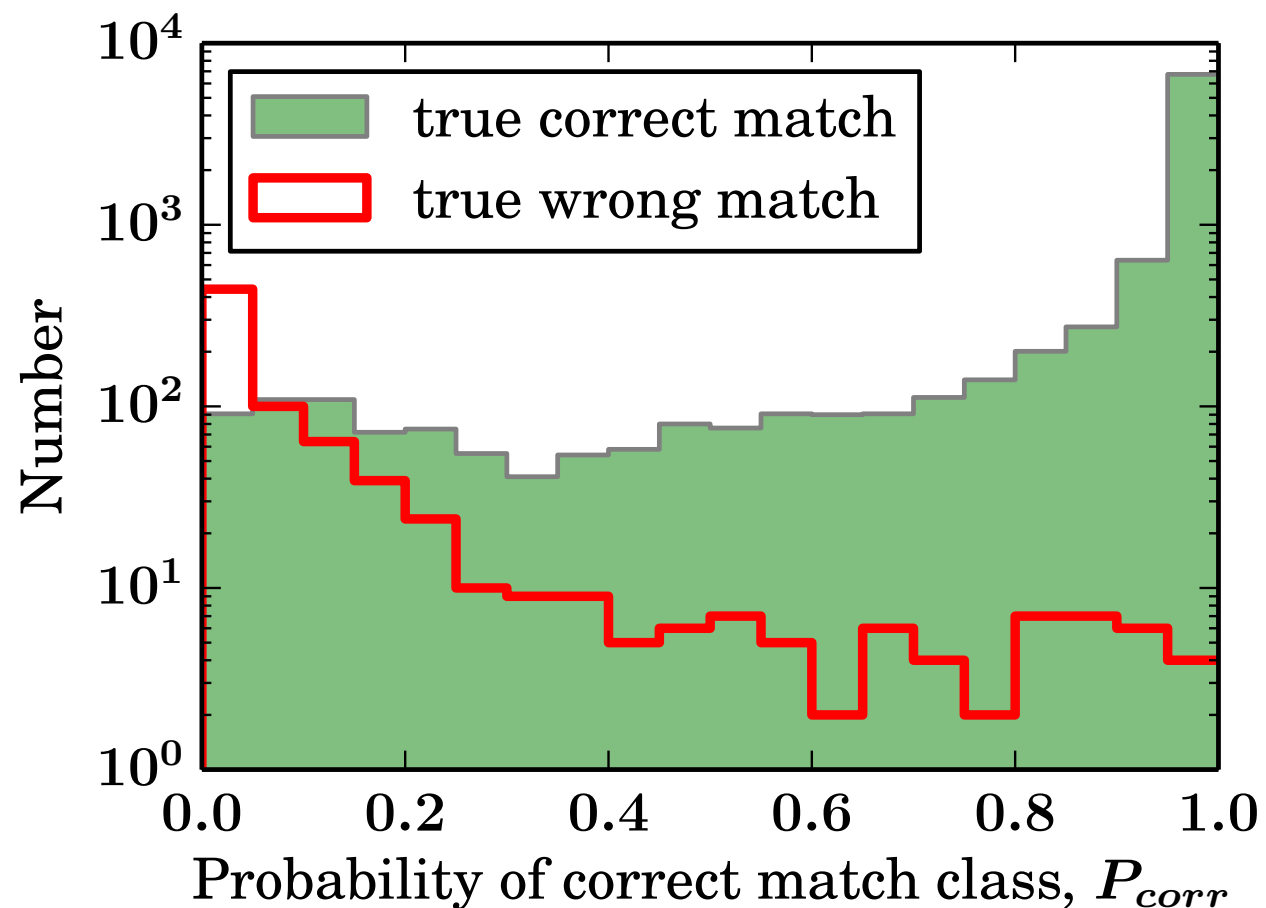
# Improvements with Machine Learning

- ▶ We would like some way of quantifying the probability of a correct match for each SN, while also improving the matching accuracy, if possible
- ▶ After initial DLR matching algorithm, implement Random Forests for binary classification into {correct match, wrong match}
- ▶ Features of the SN-matched host pairs are used to train the classifier



# Improvements with Machine Learning: Results

- ▶ Applying the trained ML classifier to a validation set, we can obtain (for each SN-host match) the probability of a correct match
- ▶ Fixing the efficiency at 98%, we find that **ML boosts the matching accuracy (purity) up to ~97%**





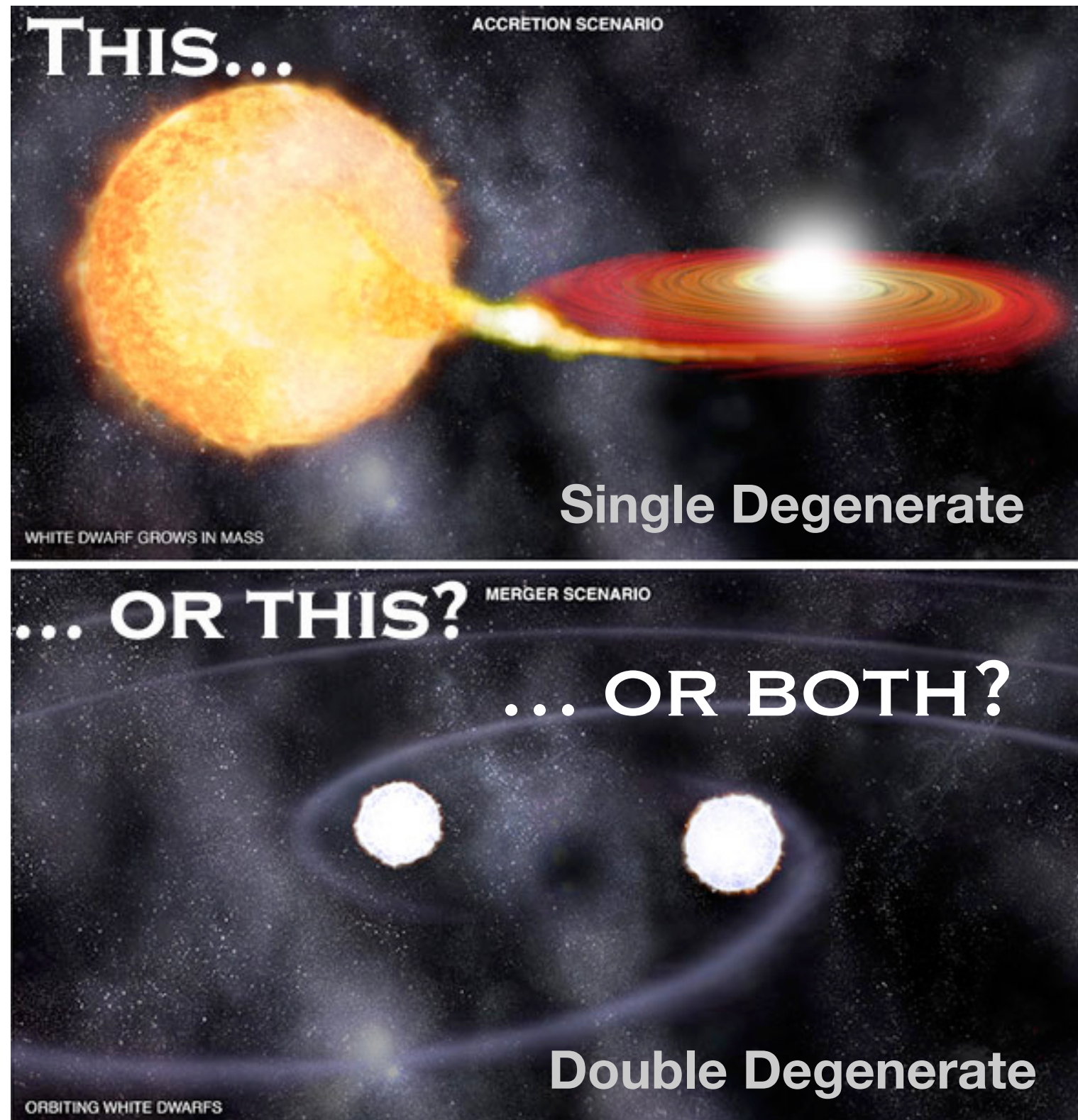
# Next Steps

- ▶ This paper is headed for DES collaboration-wide review in a couple weeks
- ▶ A follow-up paper will focus specifically on SNe Ia and DES, including propagating the effects of host galaxy mismatches to photometric SN classification and biases on cosmological parameters
- ▶ Train the ML classifier on real DES galaxy catalogs so we can begin assigning ML probabilities to actual DES SNe

# EXTRA SLIDES

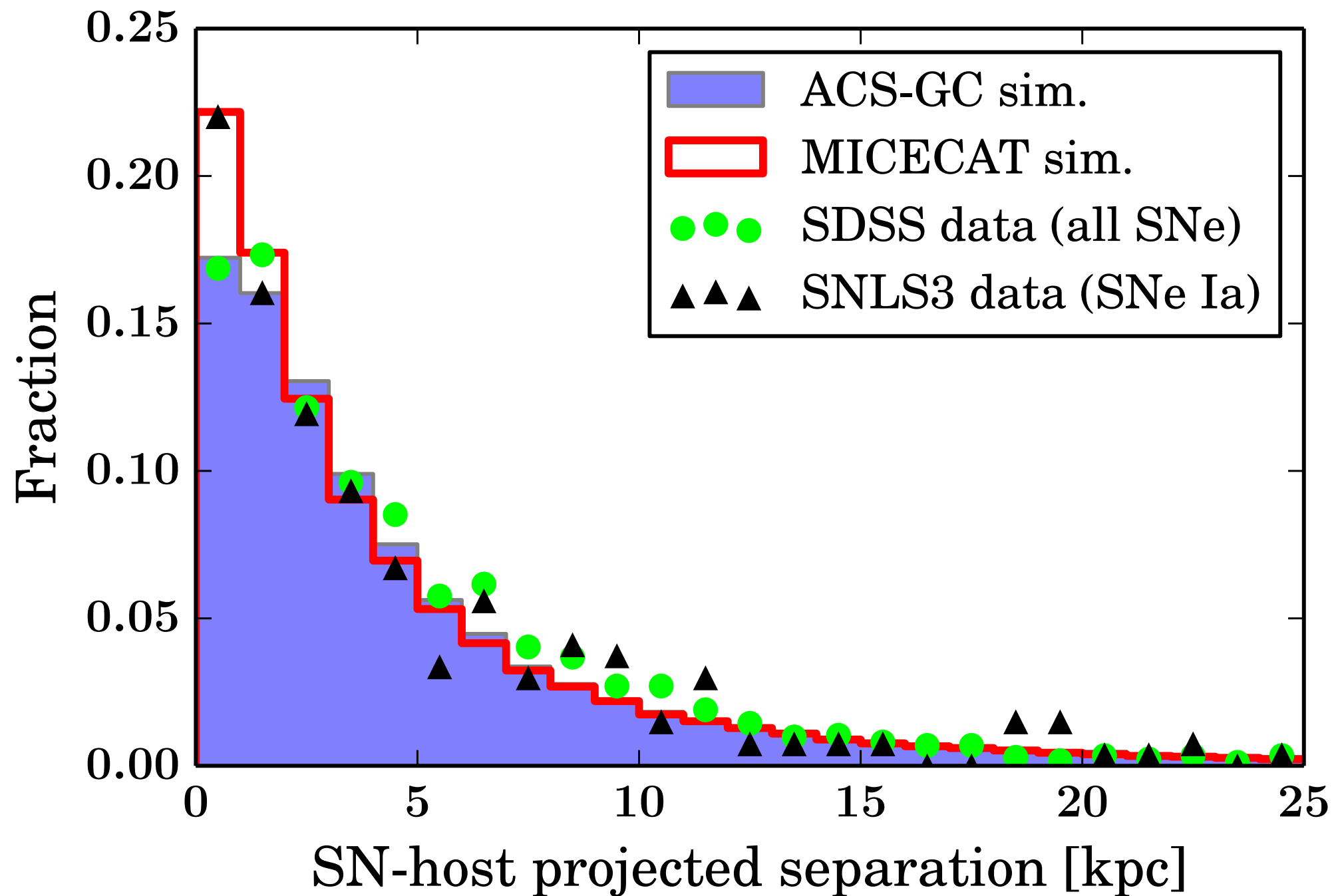


# Type Ia Supernova Progenitors



NASA/CXC/M.Weiss/Bad Astronomer

# Comparing SN Simulations with Data





# Machine Learning: Definitions

		TRUE CLASS	
		Correct Match	Wrong Match
PREDICTED CLASS	Correct Match	True Positives $T_P$	False Positives $F_P$
	Wrong Match	False Negatives $F_N$	True Negatives $T_N$

- ▶ Efficiency = fraction of true correct matches recovered by the classifier
  - $T_P / (T_P + F_N)$
- ▶ Purity = the accuracy with which objects are classified as correct matches
  - $T_P / (T_P + F_P)$