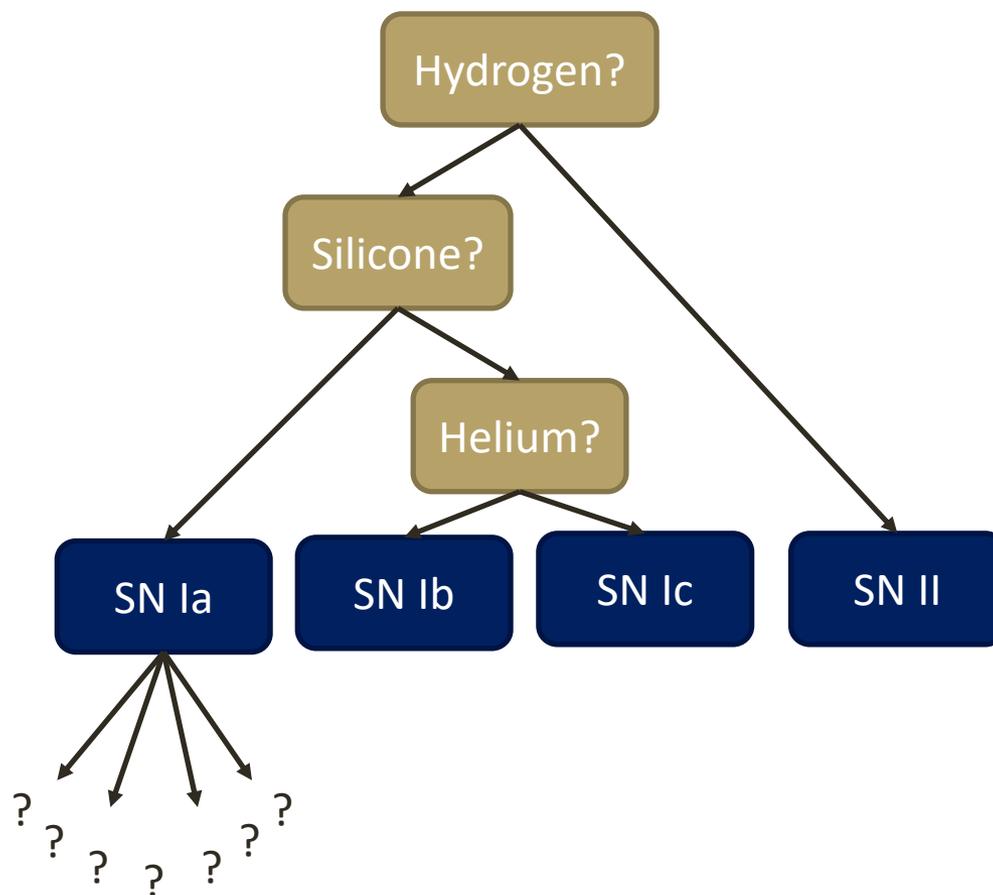


# Supernova Classification: How to Find What You're Looking For



Daniel Perrefort  
<https://djperrefort.github.io>

University of Pittsburgh  
April 3 2021

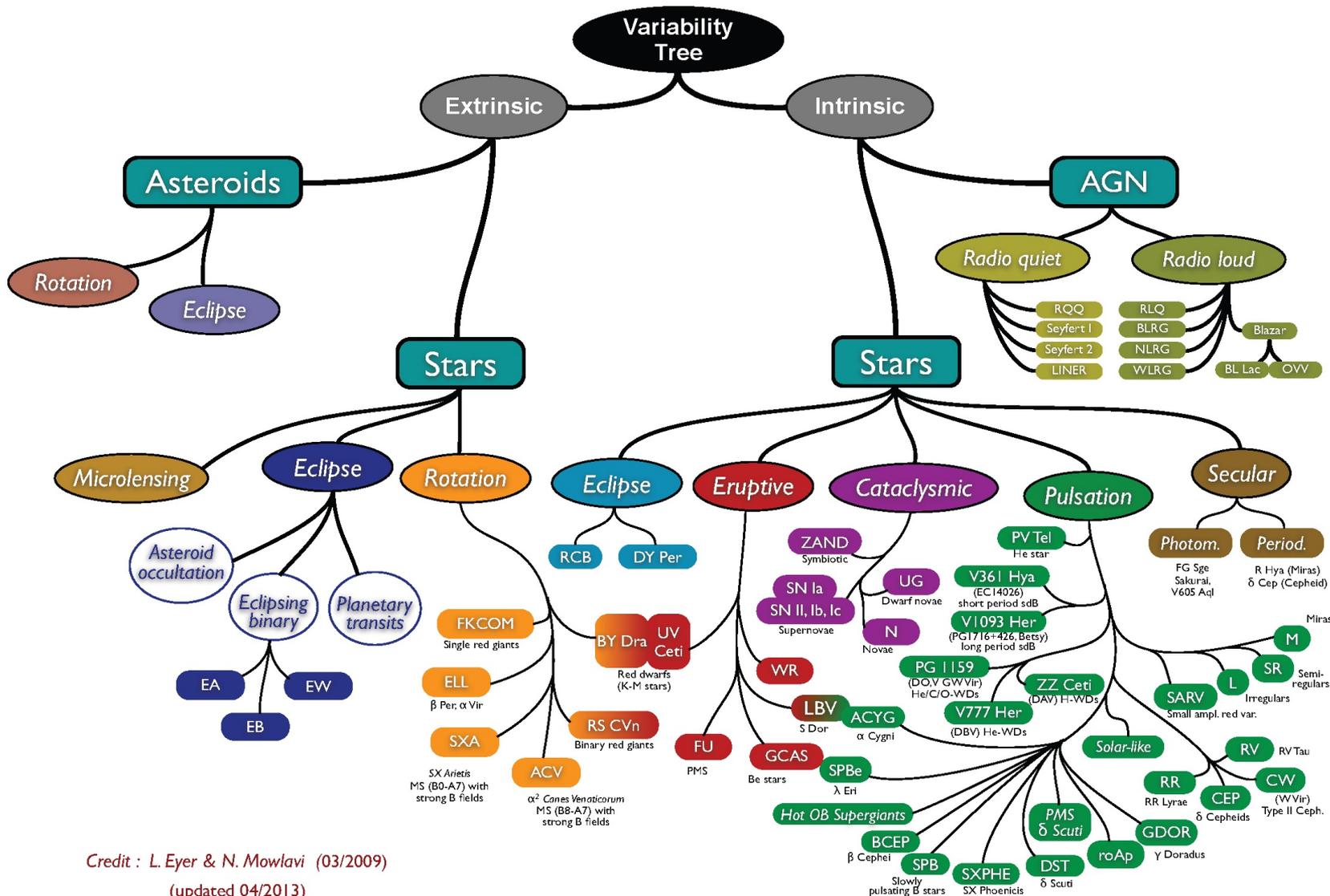
# Let's talk about...

1. How Do You Classify SNe?
2. Classifying SNe Ia in the LSST Era
3. Properties of 91bg-like SNe in SDSS

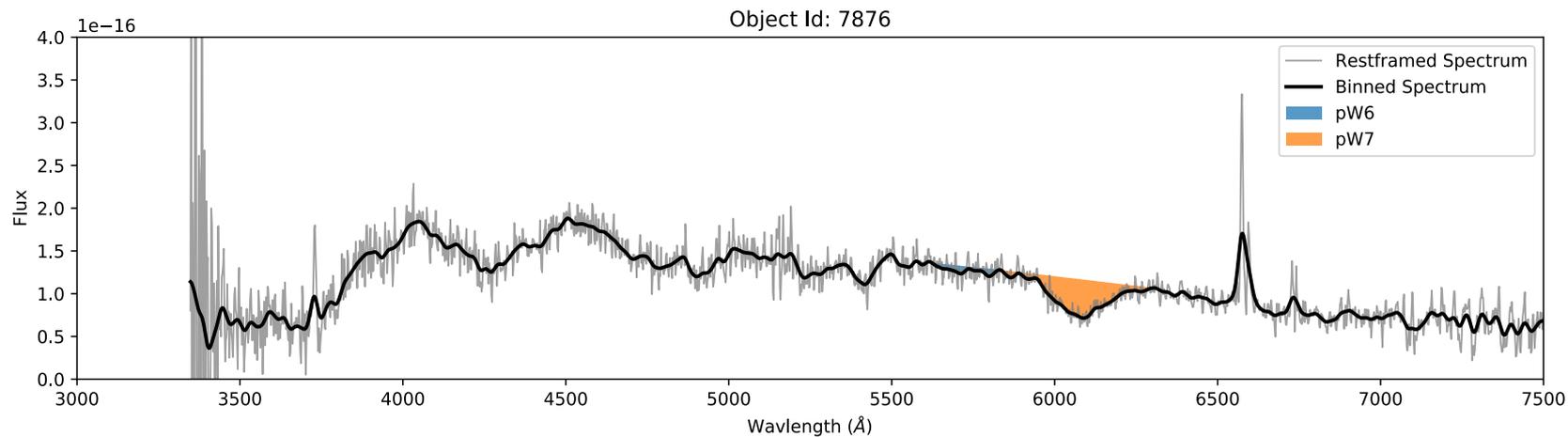
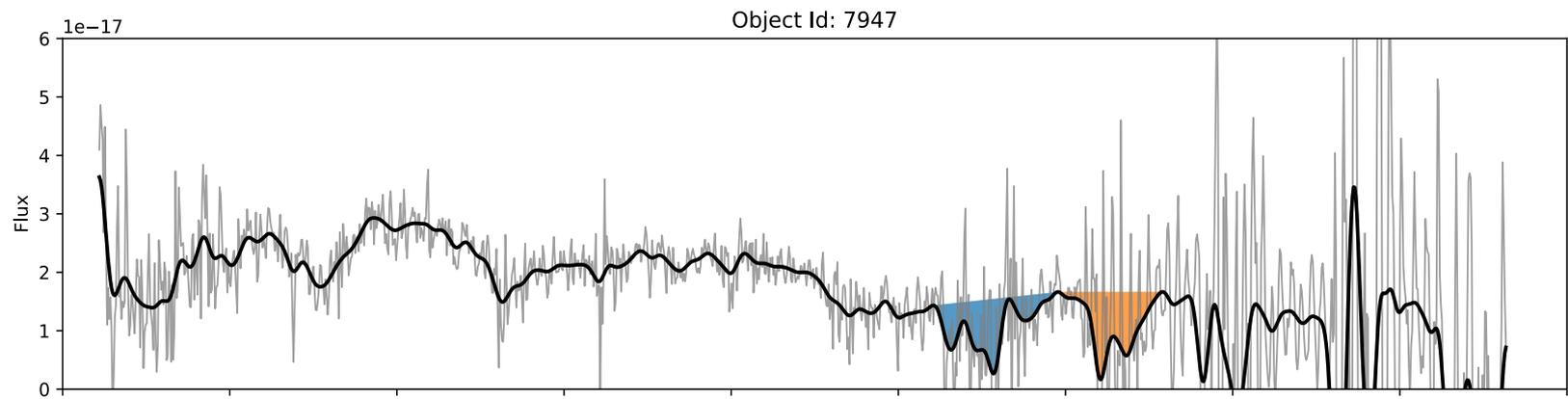
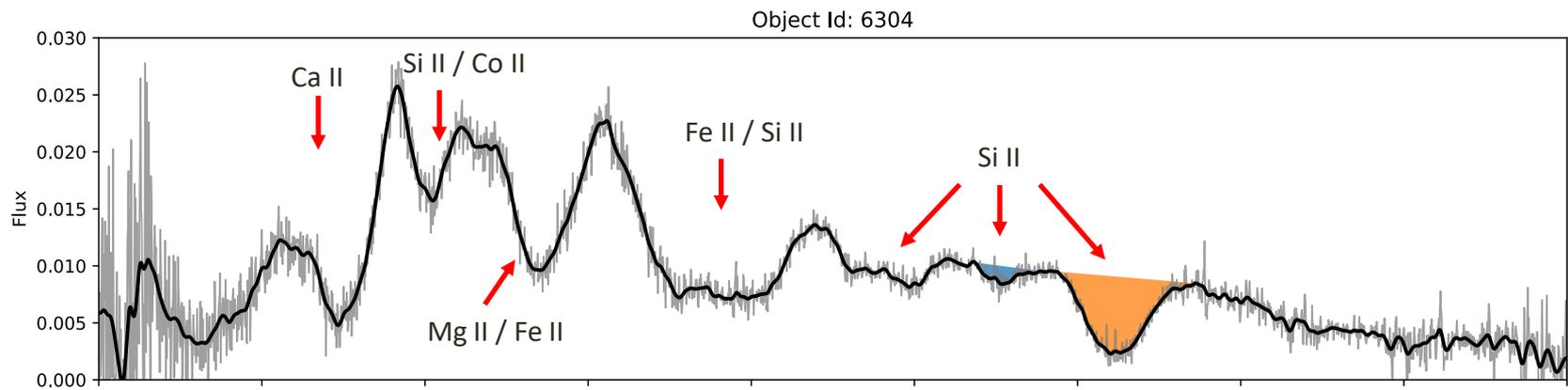
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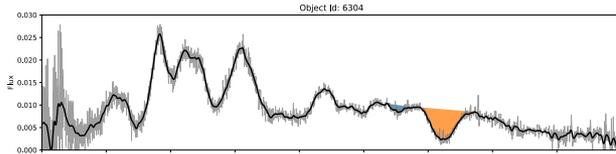
# The Variability Landscape



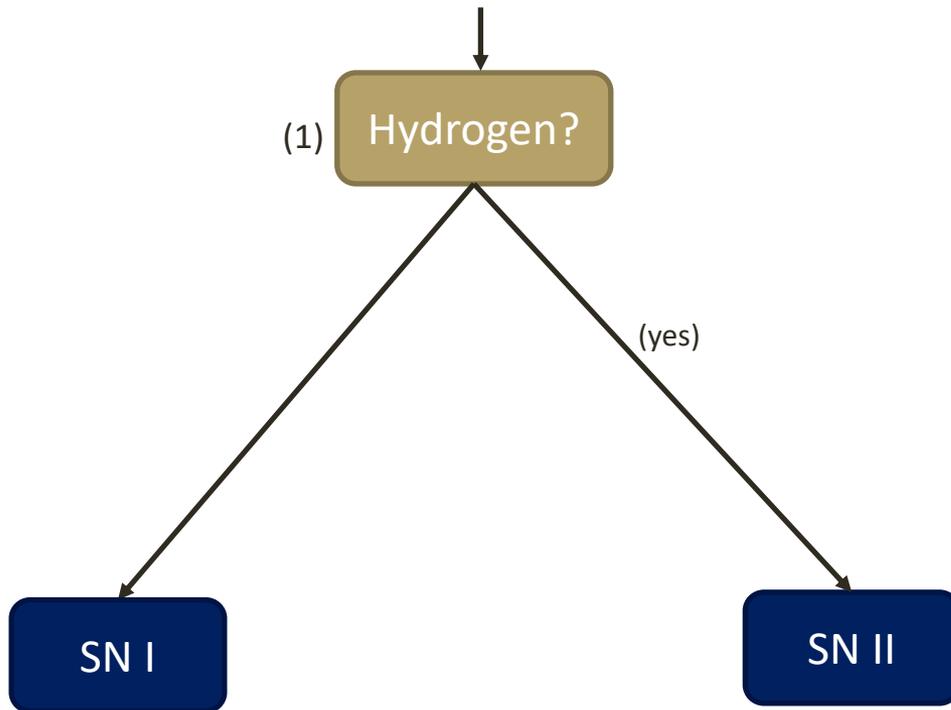
Credit : L. Eyer & N. Mowlavi (03/2009)  
(updated 04/2013)



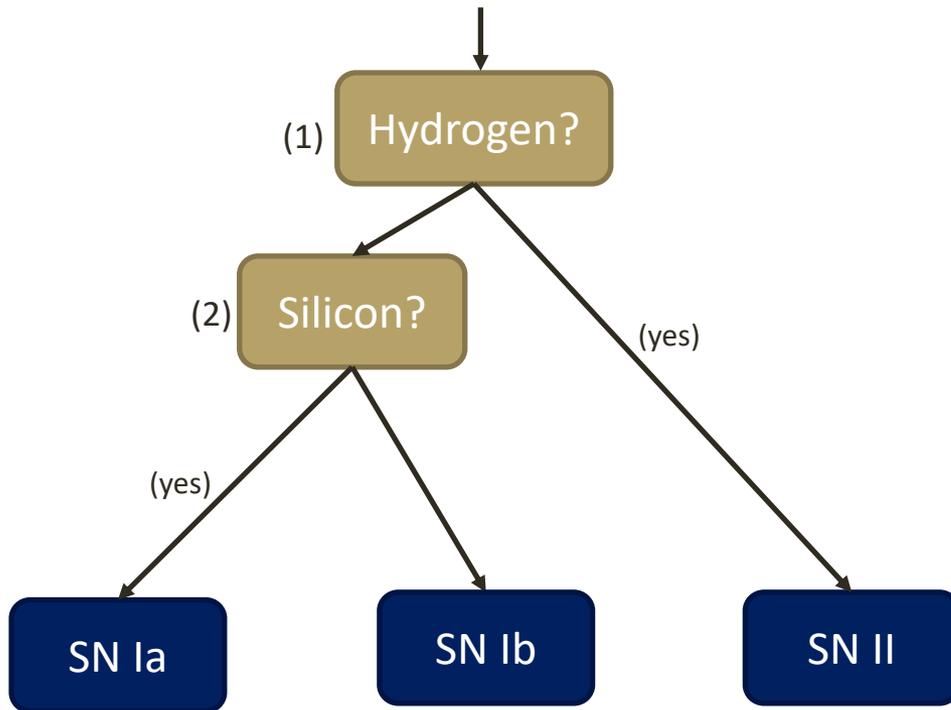
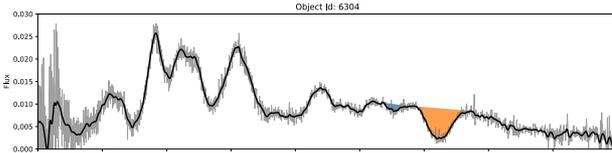
# Evolution of SN Classification



1. Minkowski (1941):  
Introduces type I/II

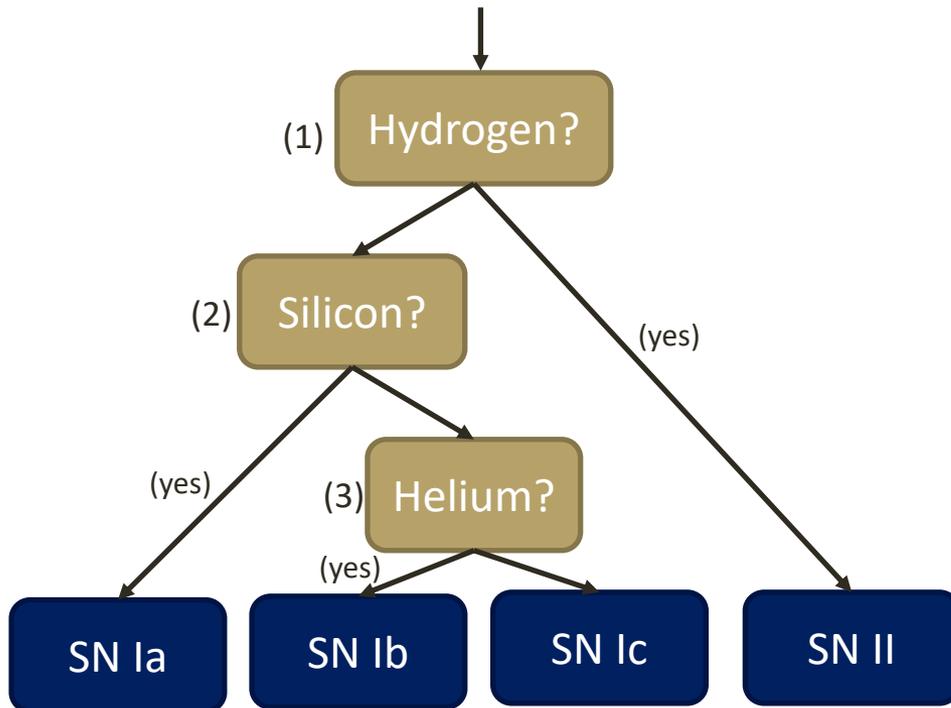
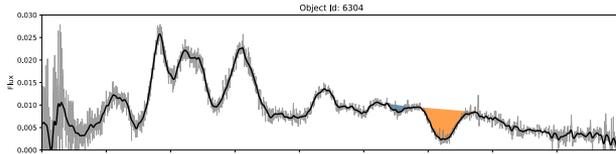


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# Evolution of SN Classification



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and Elias+ (1985):  
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3. Wheeler Harkness (1990):  
Introduces type Ic



# Defining Peculiar SNe

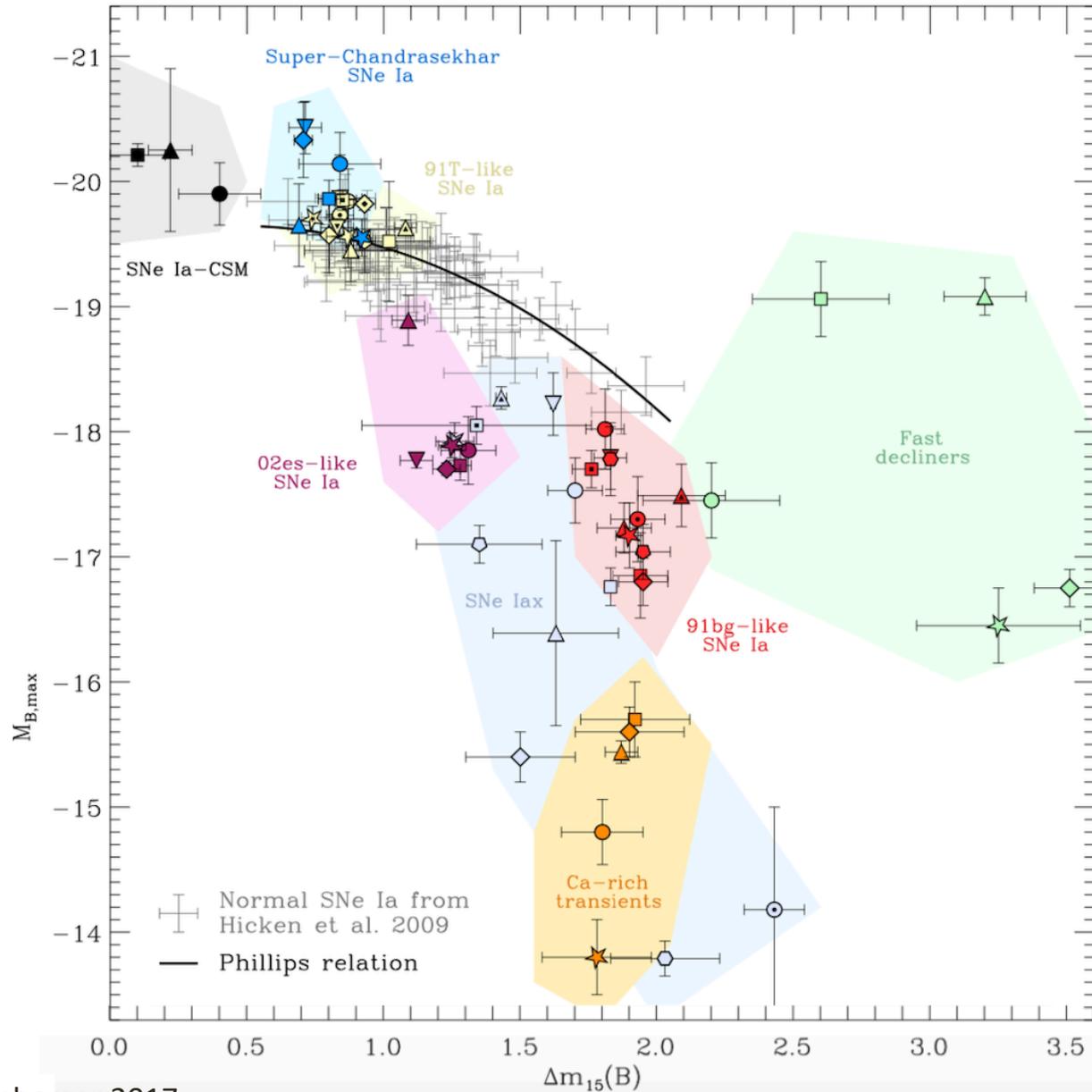


Figure: Taubenberger 2017

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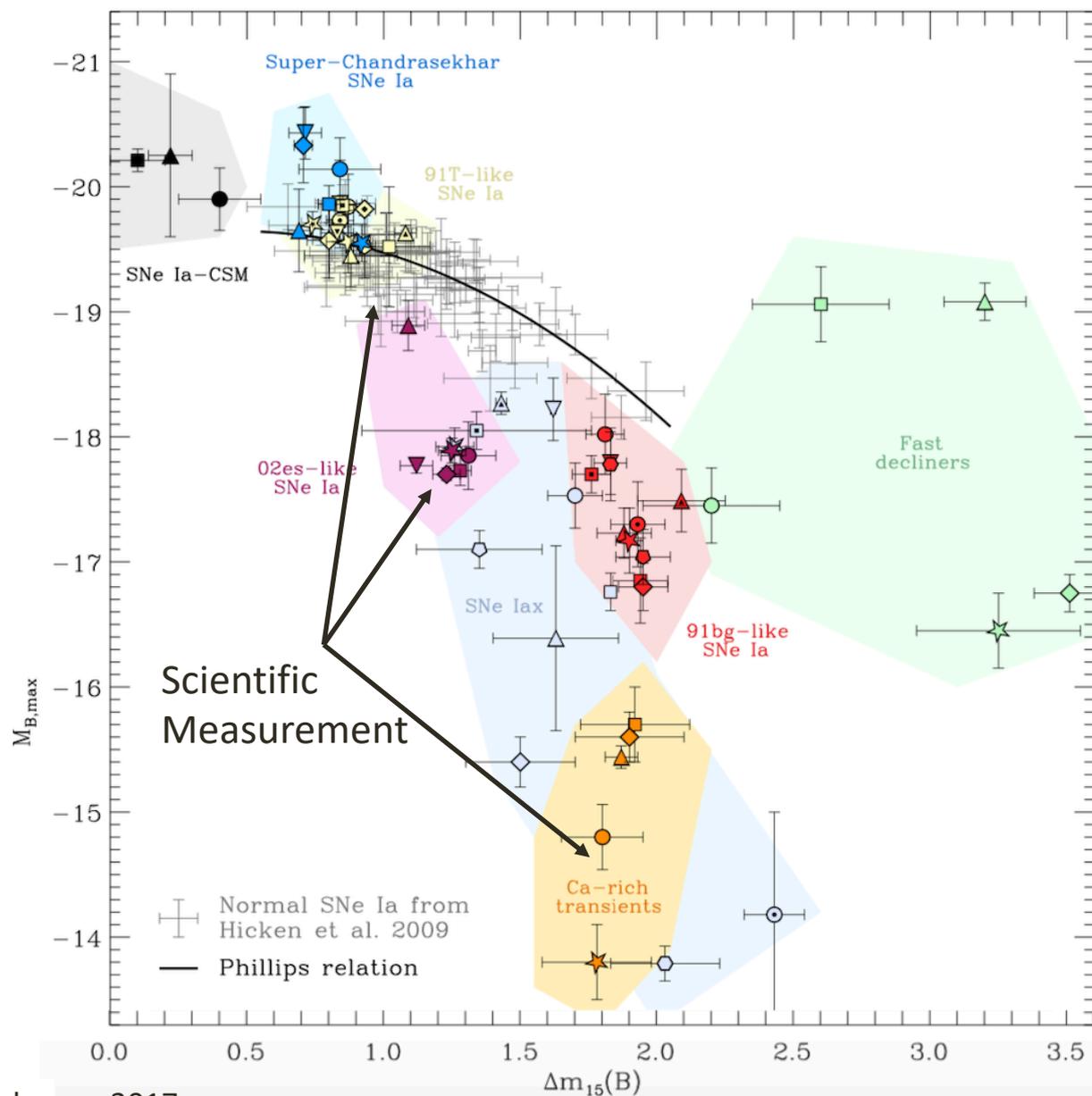


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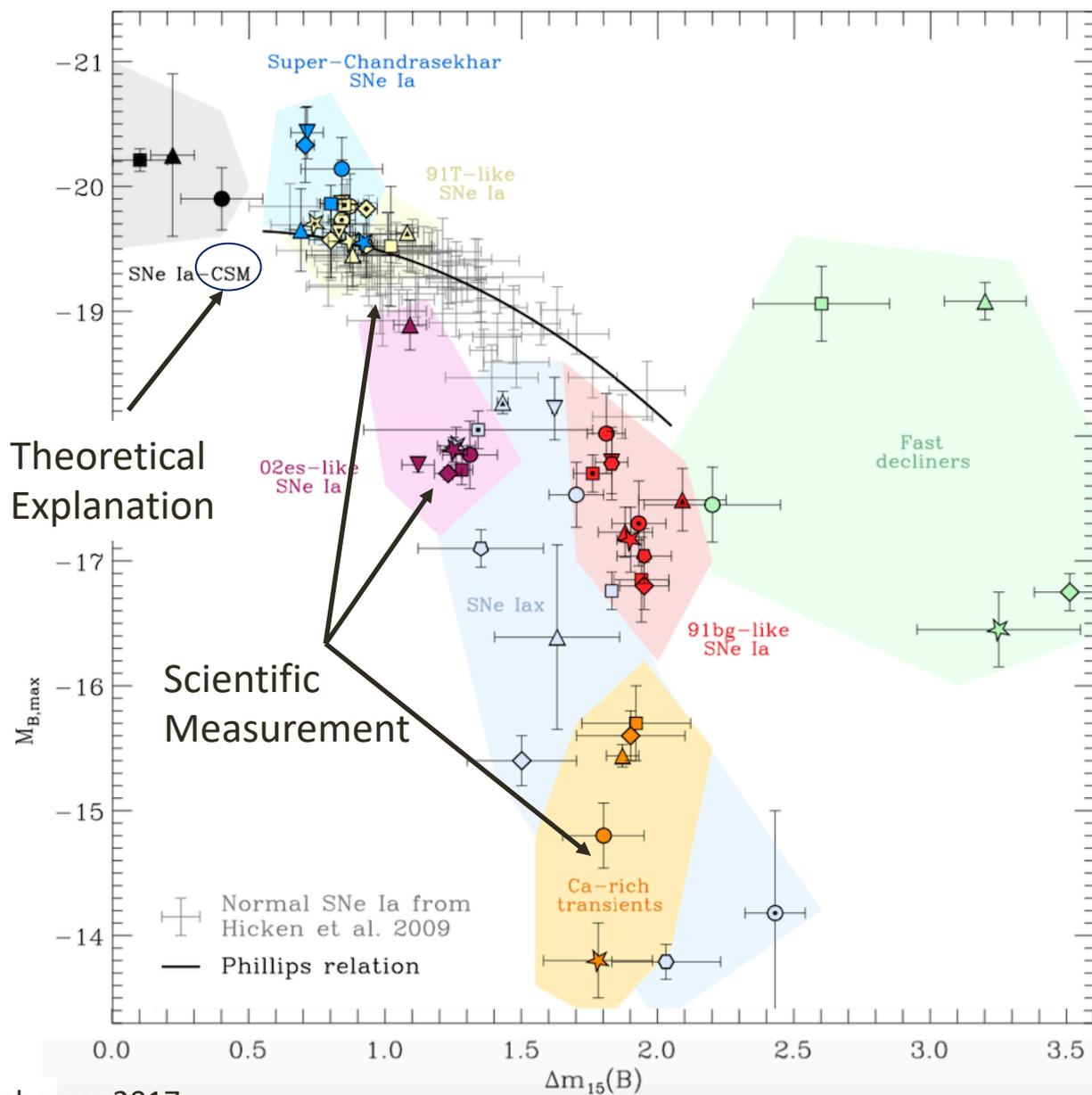


Figure: Taubenberger 2017

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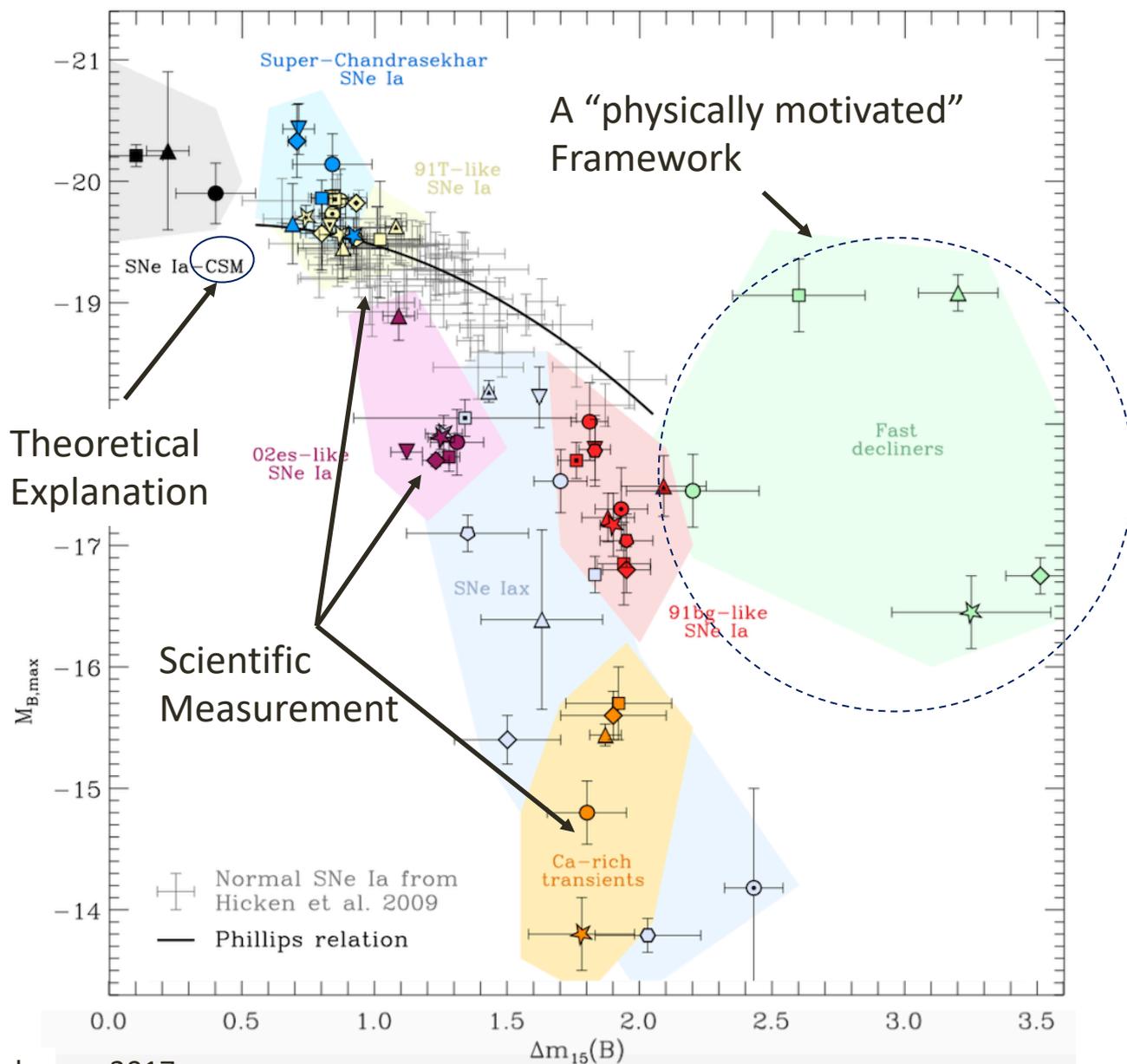
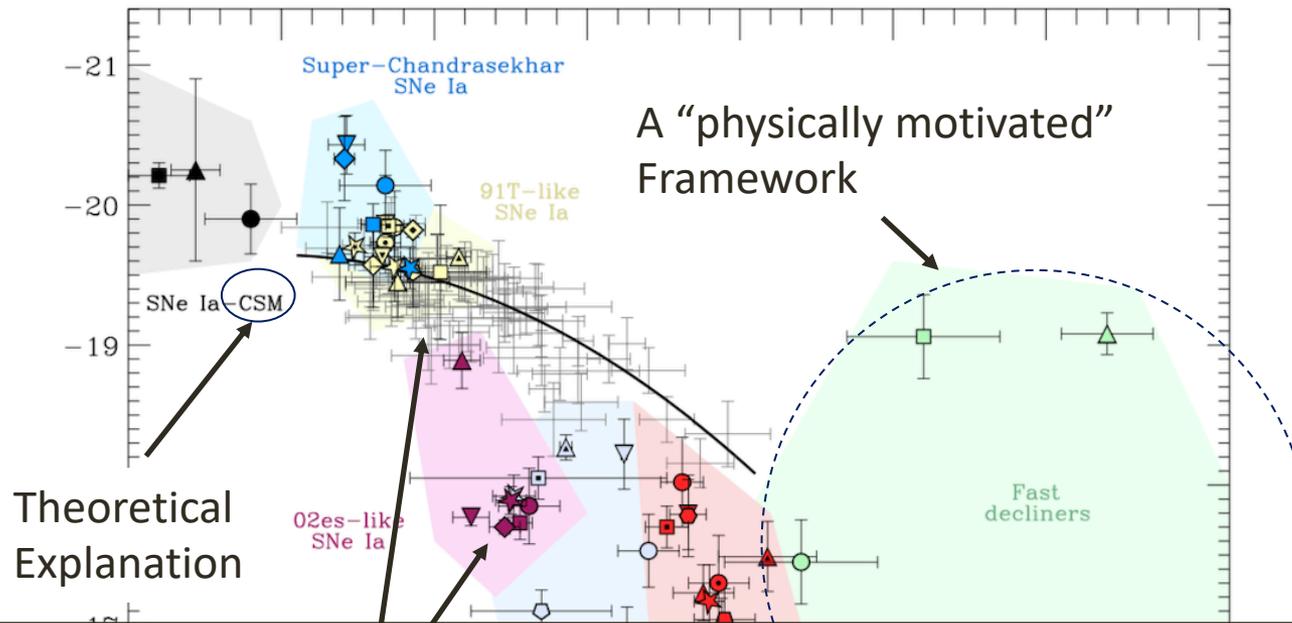


Figure: Taubenberger 2017

# Defining Peculiar SNe



## Problem 1

*“... [supernova] class names are not systematically defined according to a set of underlying principles, some of the class names are quite opaque to non-experts and form a barrier for general astrophysicists in following the SN literature, and some class names mix observational properties with physical interpretation that may be debated...” - Gal-Yam (2016)*

## SN Ia Sub-types Vary in their:

- Rates
- Chemical yields
- Ejecta velocities / energy yield
- Host galaxy biases
  - Mass
  - Star formation
  - Distances

## Key Questions:

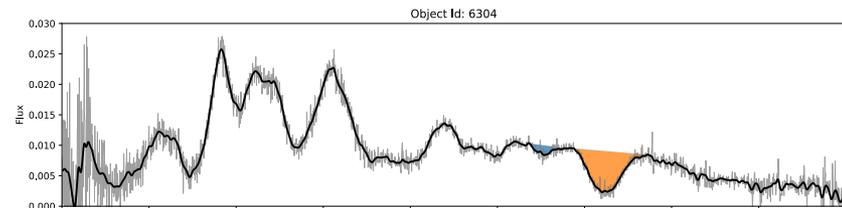
- What causes this variety?
- Are there multiple physical mechanisms?
- Are there continuous or discrete subtypes?

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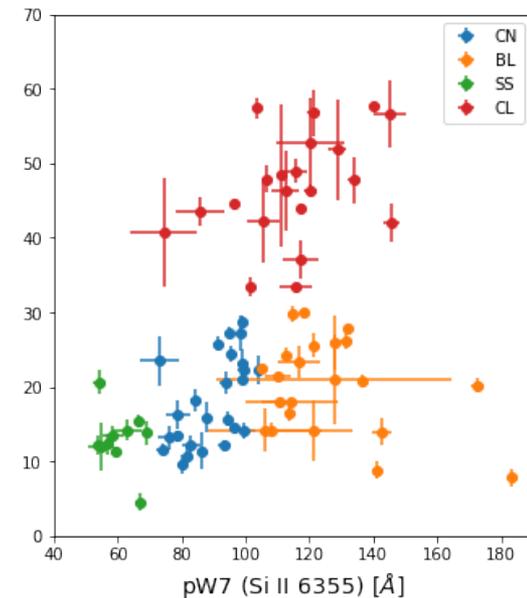
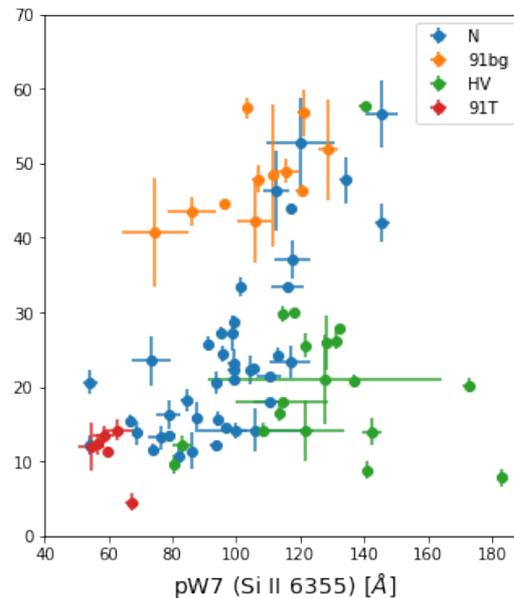
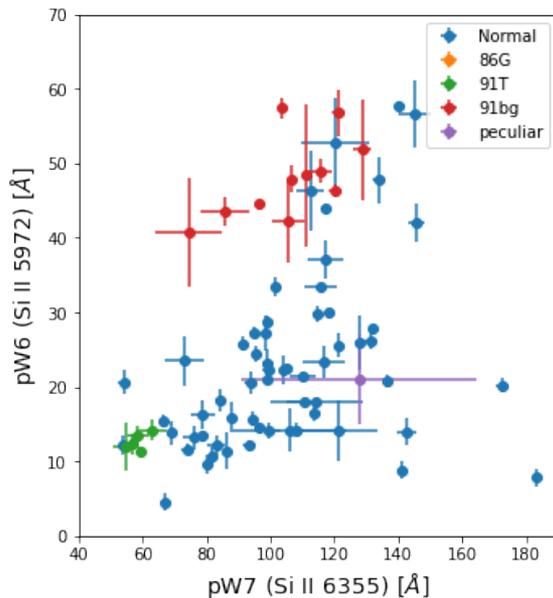
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## Discrete groups?

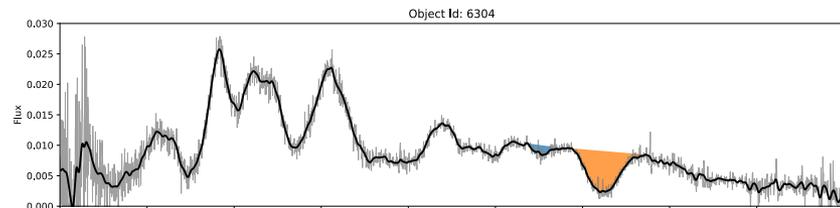


## SN Ia Sub-types Vary in their:

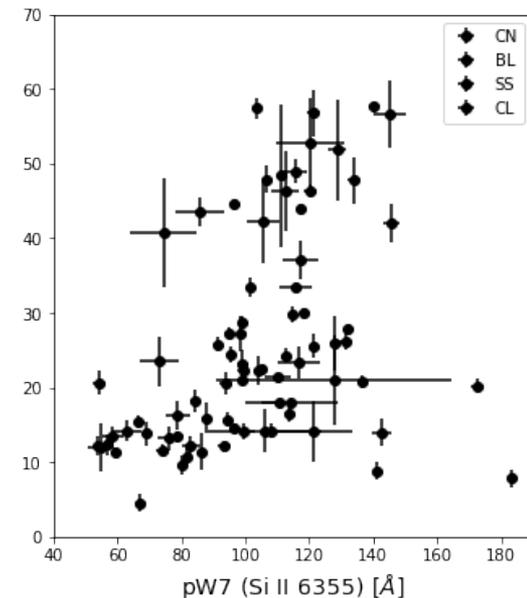
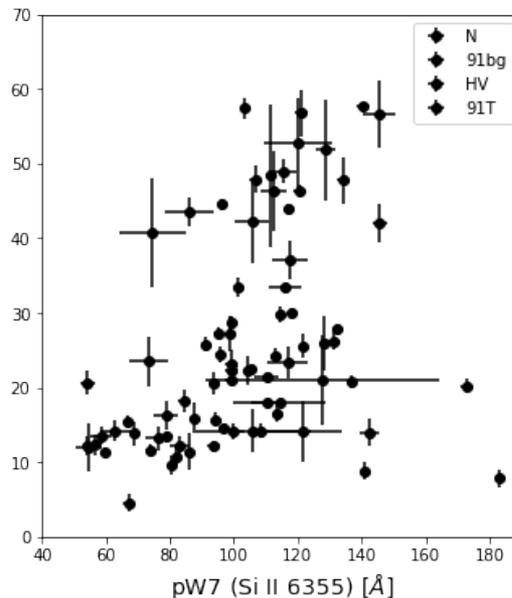
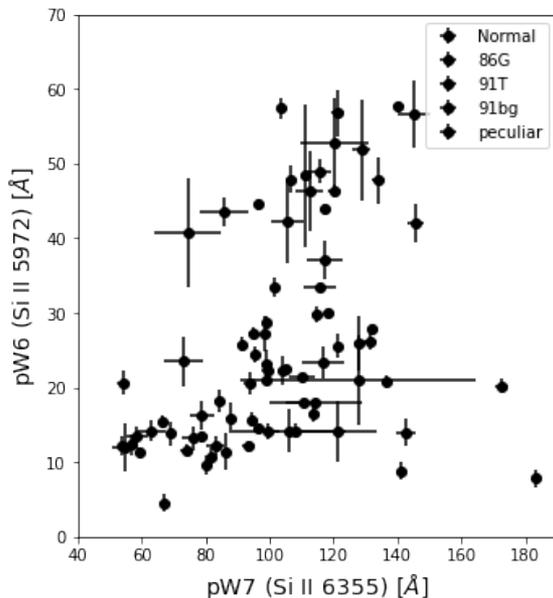
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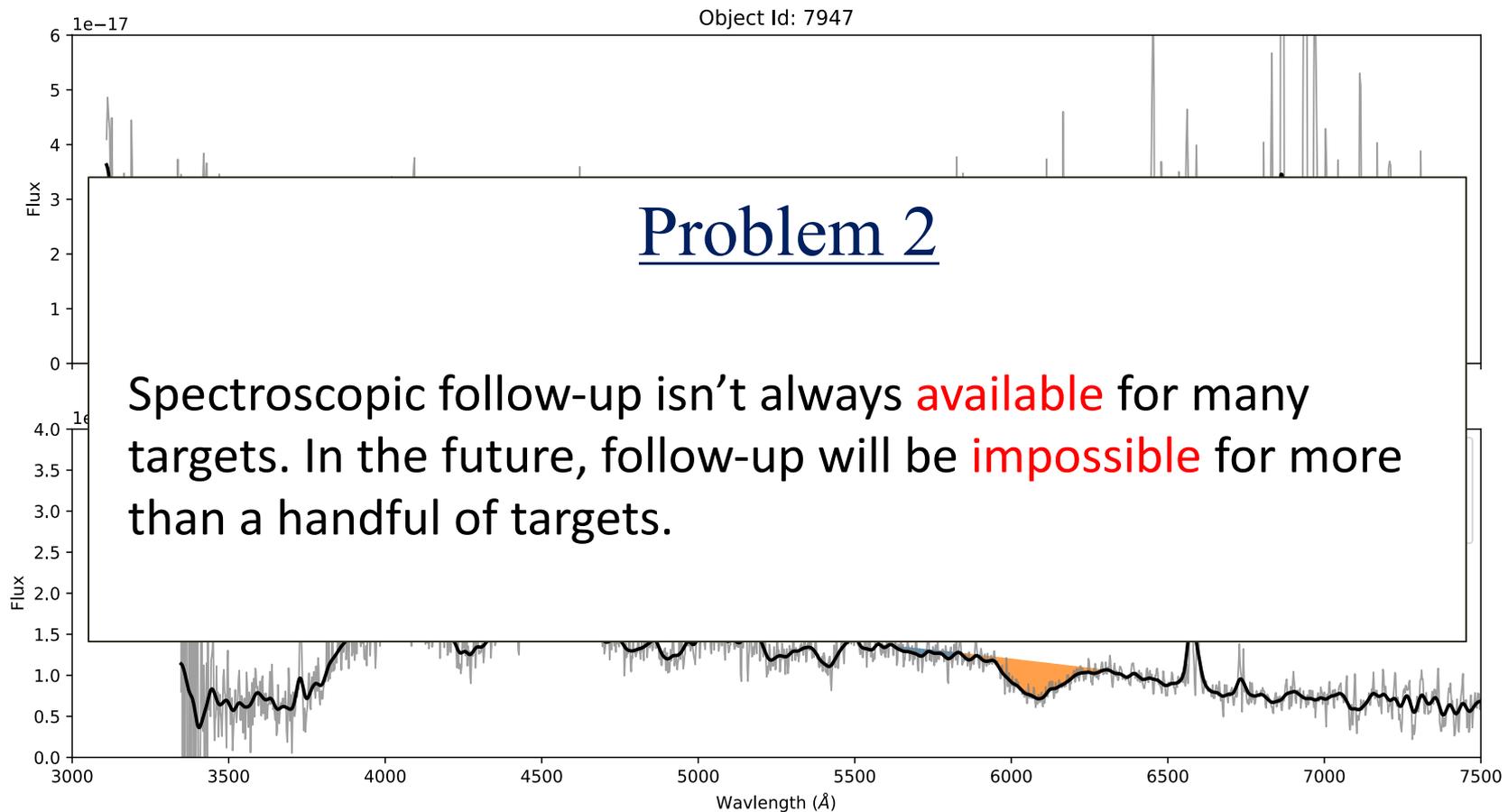
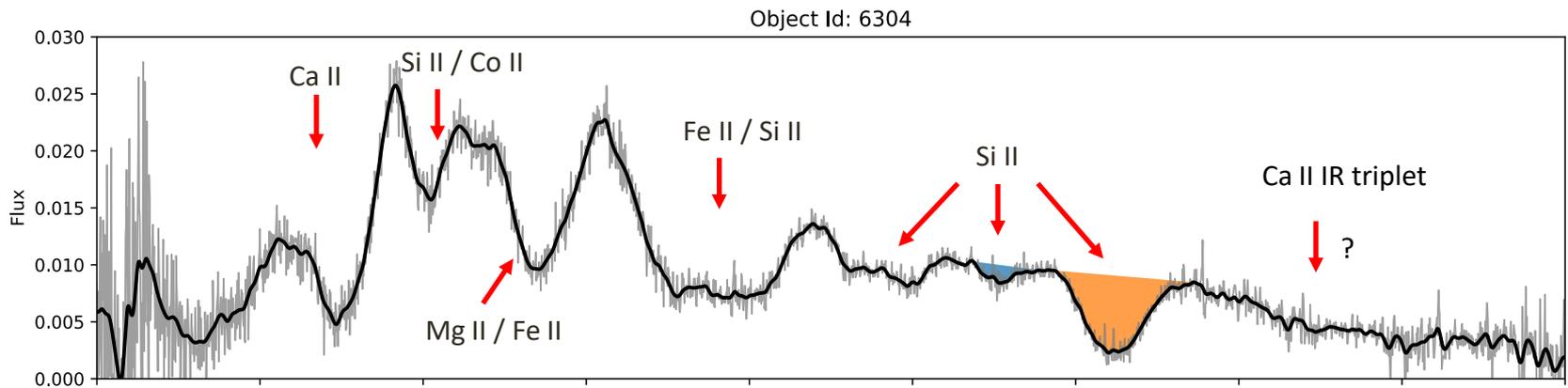
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## Discrete groups? Or continuous Distribution?



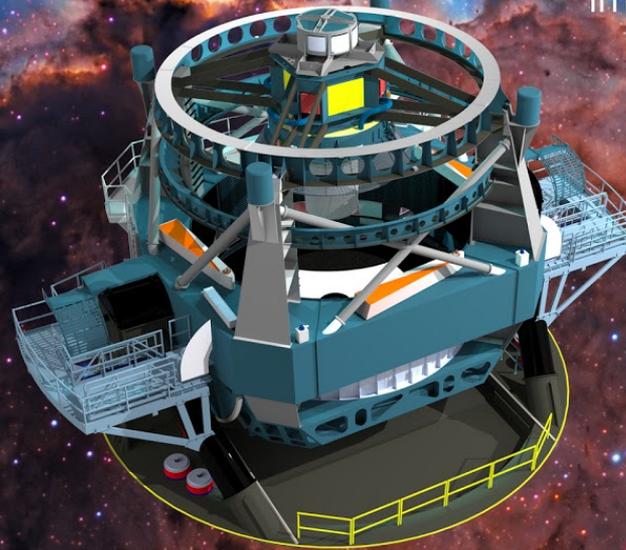


**8,4 meters**  
Primary mirror diameter

**3 200 Megapixels**  
Resolution of the Telescope Camera

**3 Nights**  
Time needed for an all-sky imaging

**1.23 F/D**  
Telescope aperture



**15 seconds**  
Exposure time needed to capture an image

**800 times**  
Number of times a same object will be captured



**37 Billion**  
Number of celestial objects detected after 10 years

**15 TB**  
Amount of data collected every night



AstroSpace

# Let's talk about...

1. How Do You Classify SNe?
2. Classifying SNe Ia in the LSST Era
3. Properties of 91bg-like SNe in SDSS



# Approaches to Phot. Classification

## **Classify Everything**

- Lends well to ML (Scalable)
- Useful for data filtering and performance metrics
- Tackles multiple science cases



(Dai et al. 2018; Muthukrishna et al. 2019;  
Pasquet, Johanna et al. 2019)

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## Identify a Single Class

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- Interpret in terms of physical parameters
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(González-Gaitán 2014; Blondin 2007 Perrefort 2020 - submitted)

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- Can leverage existing models / techniques
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- Often includes analysis steps we need to perform anyways

### Cons:

- Targeted at specific science cases
- Very model dependent



(González-Gaitán 2014; Blondin 2007 Perrefort 2020 - submitted)

# Characterizing a 91bg

- Cooler due to stronger Ti lines
- Sub-luminous ( $\sim 1.1$  mag)
- Redder / faster declining light curves
- No secondary maximum in redder bands
- Reach reddest point faster (+15d) than normal (+30 d)
- Older, more massive host environments
- Normal Ejecta velocities

(Note that many of these distinctions can be observed photometrically)

These things

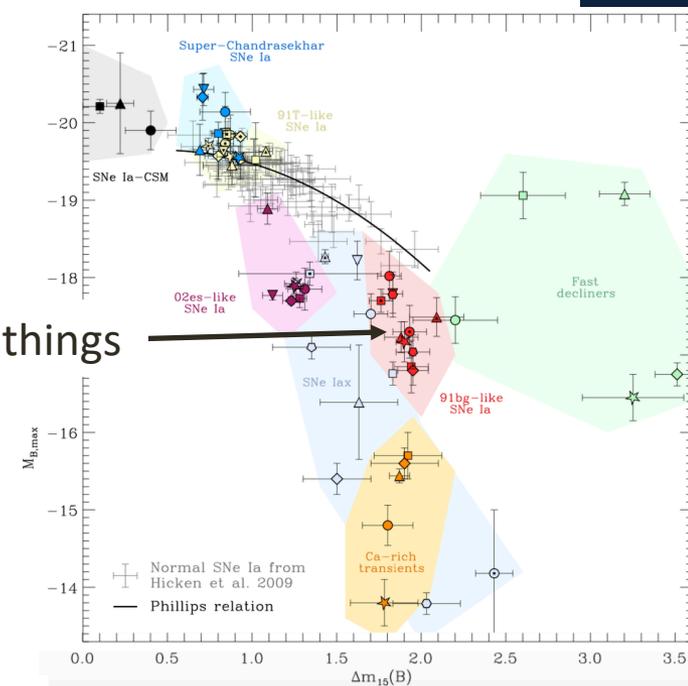
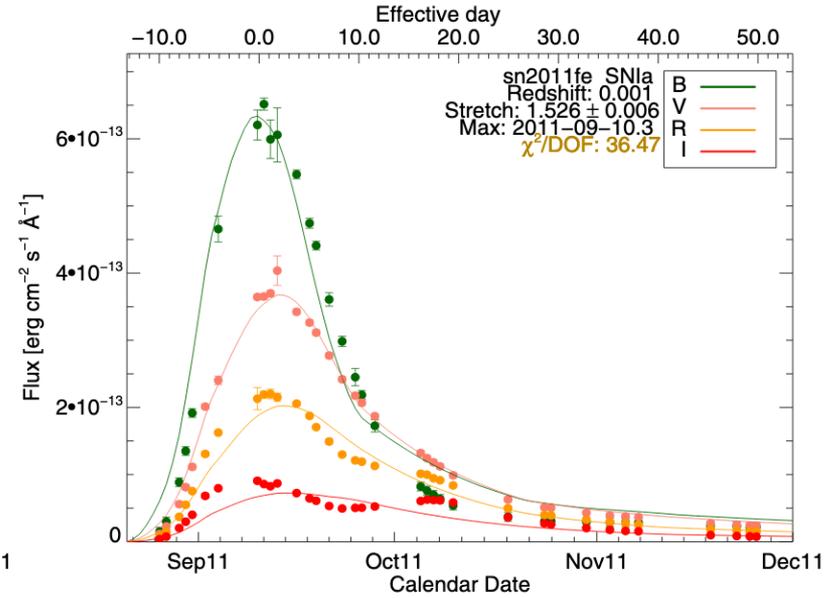
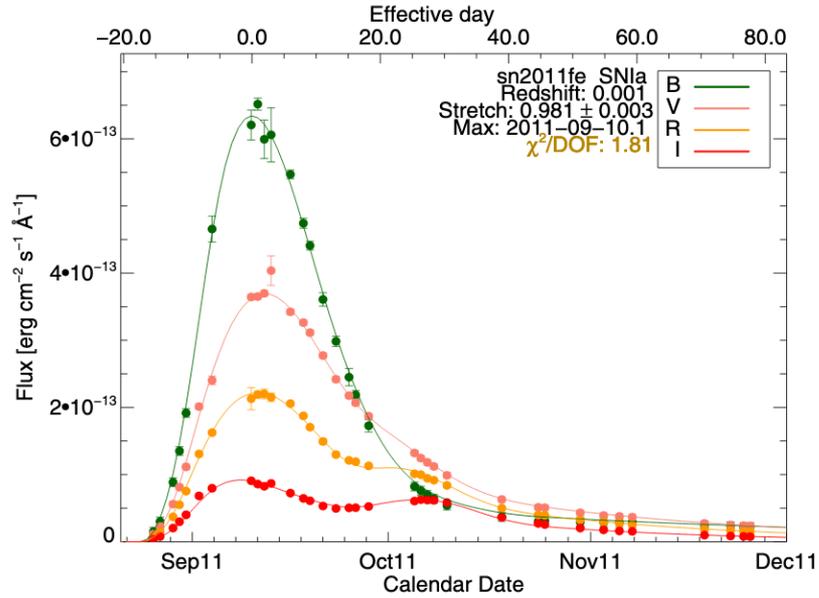
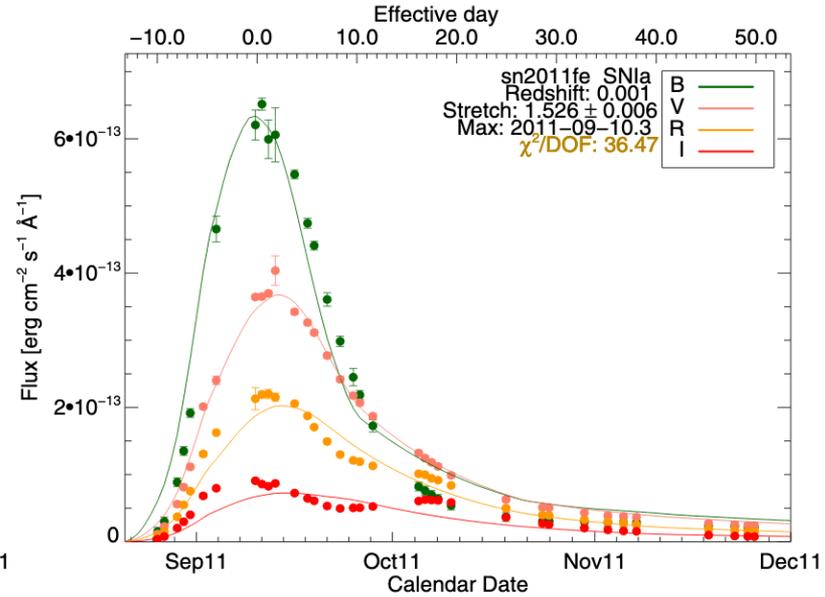
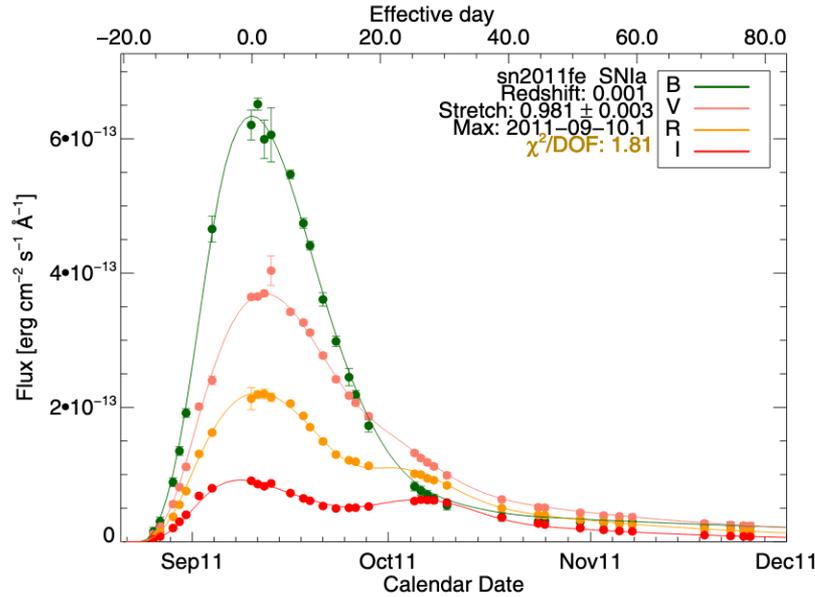


Figure: Taubenberger 2017

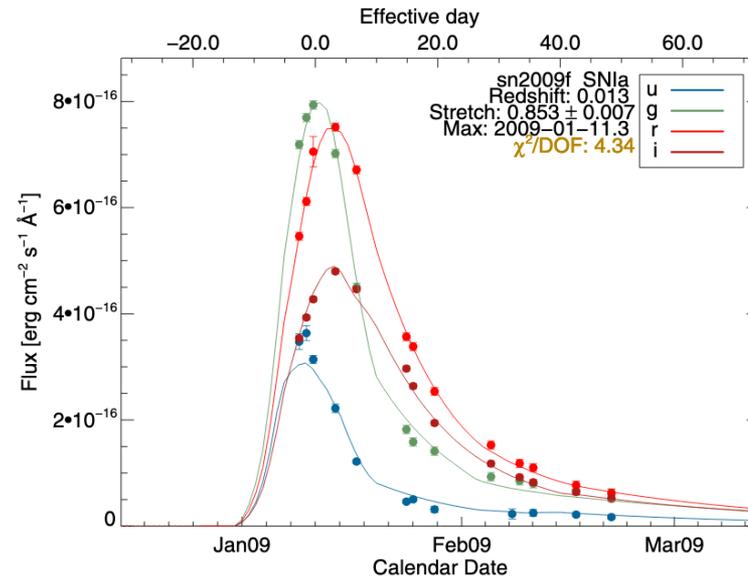
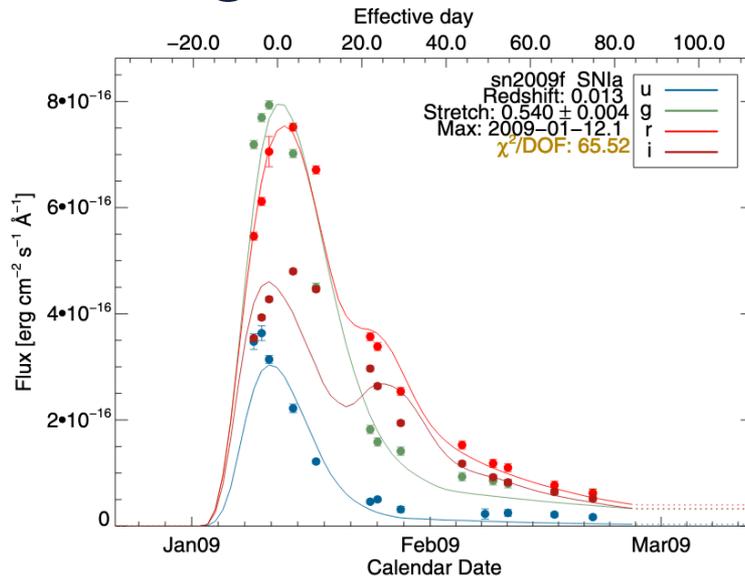
# Normal SN



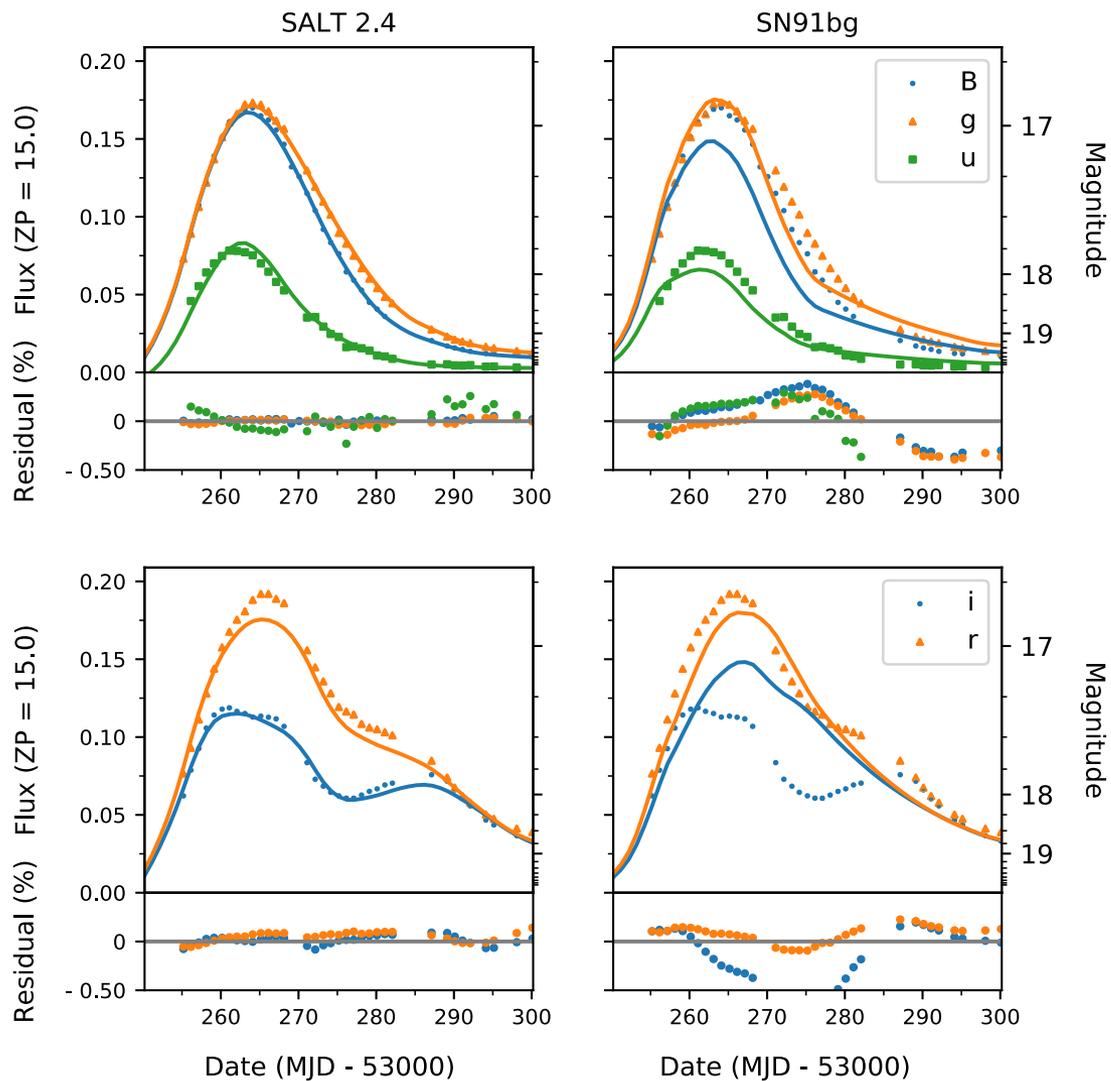
# Normal SN



# SN 1991bg-like SN



# Running Multiple Fits



# Empirical Classification

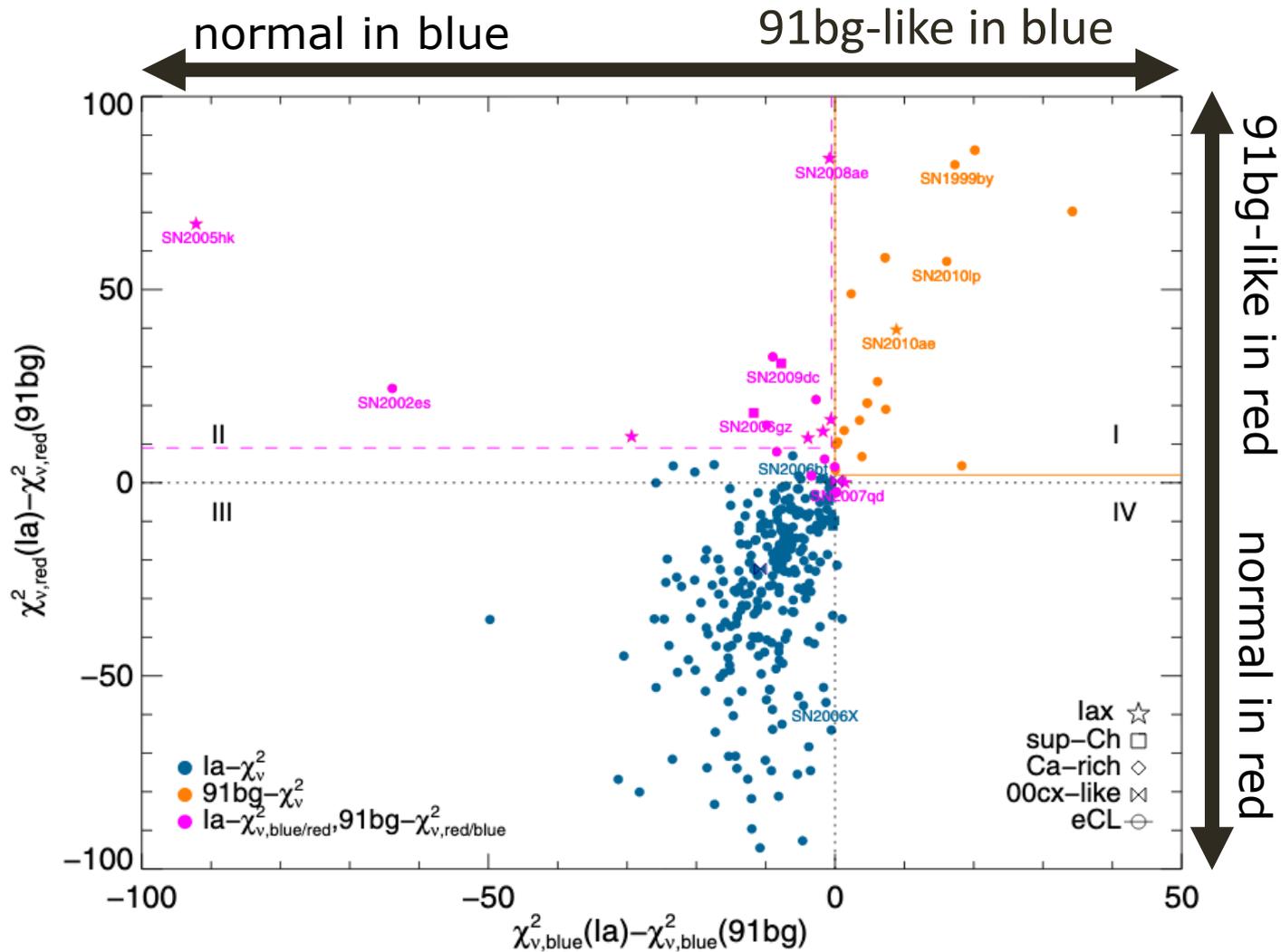


Figure: (González-Gaitán 2014)

# Empirical Classification

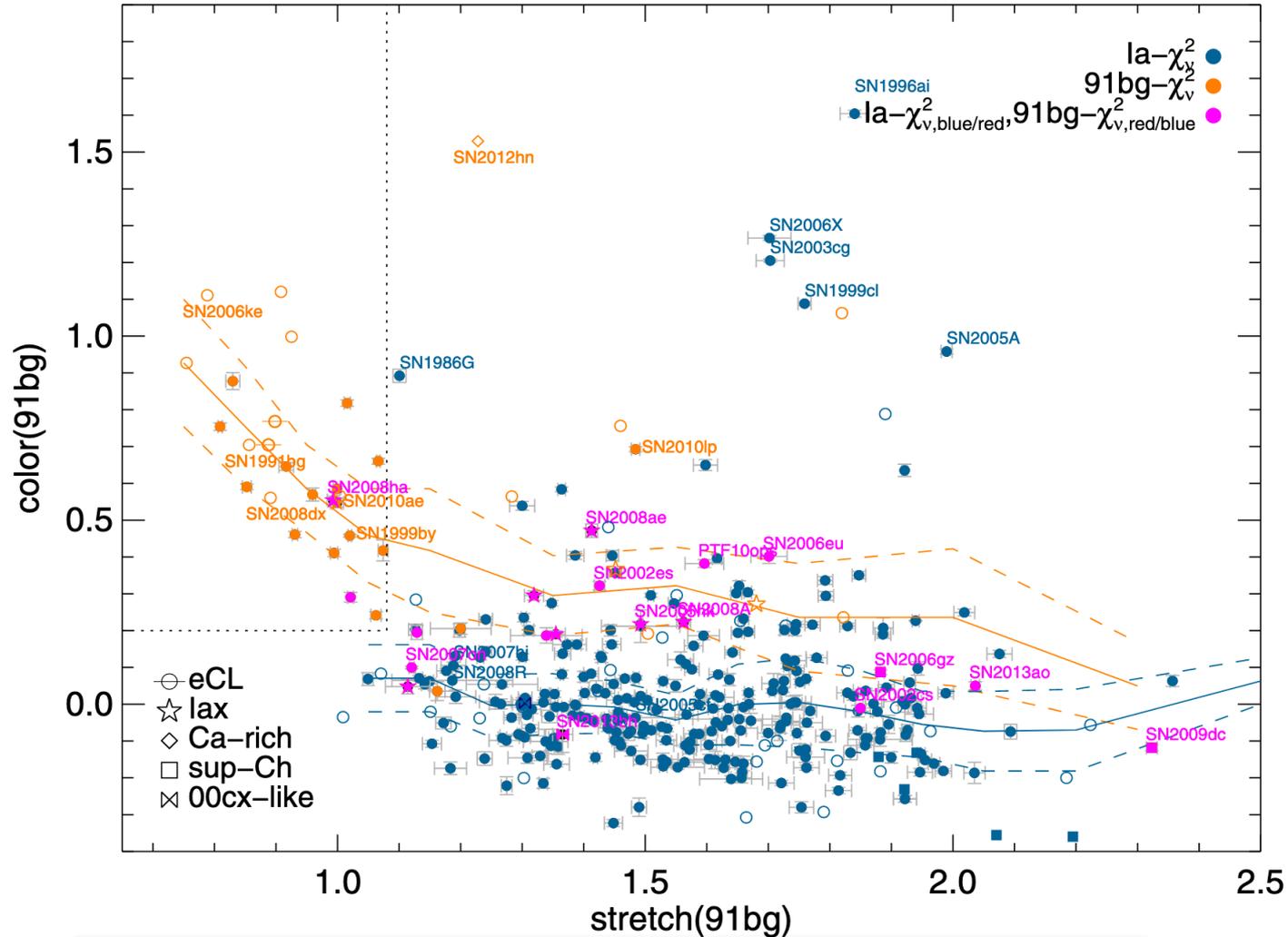
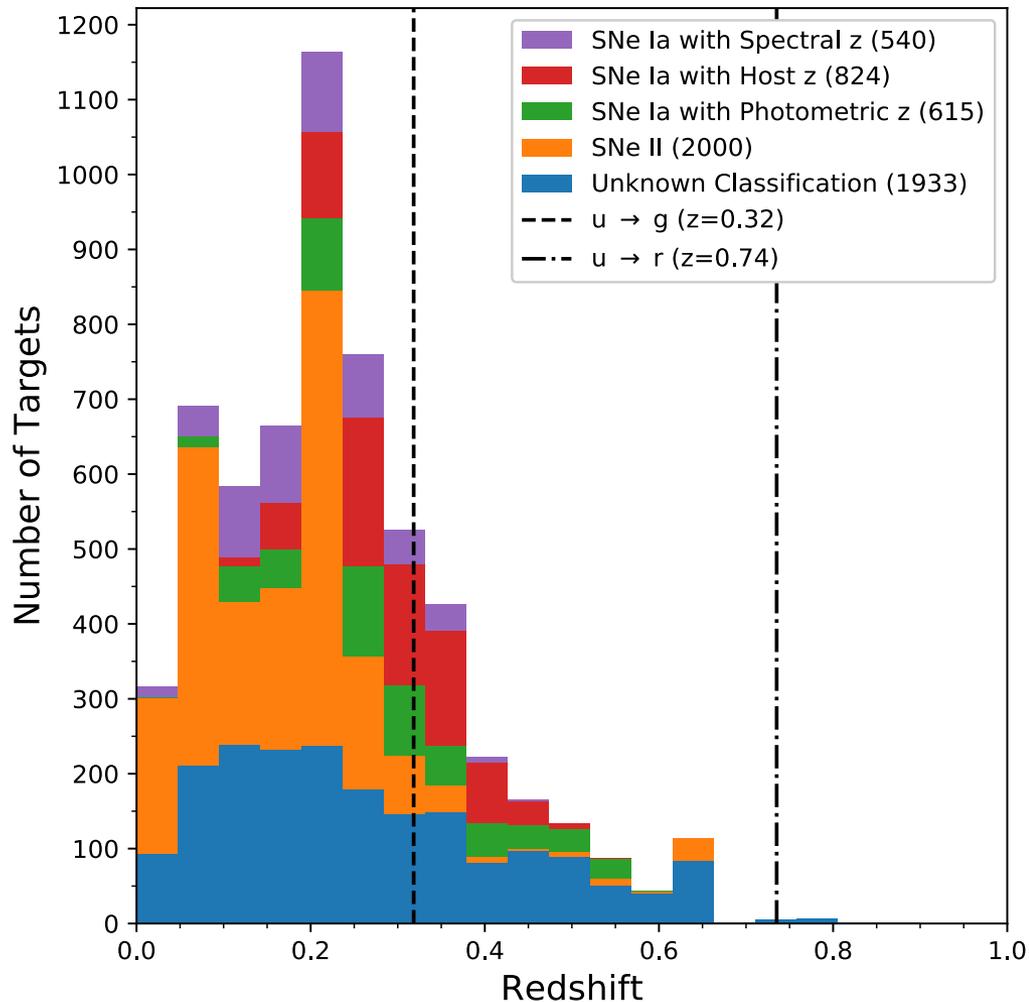


Figure: (González-Gaitán 2014)

# Let's talk about...

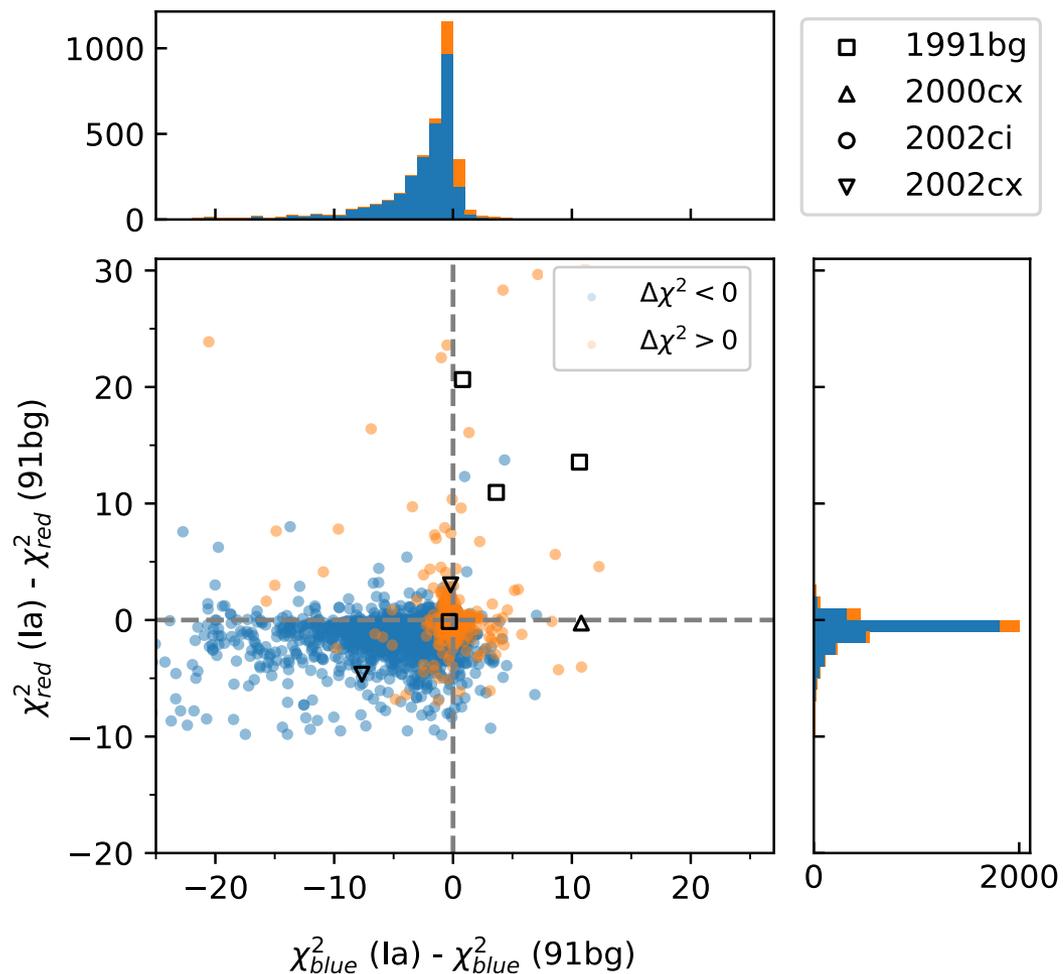
1. How Do You Classify SNe?
2. Classifying SNe Ia in the LSST Era
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# SDSS SN Sample

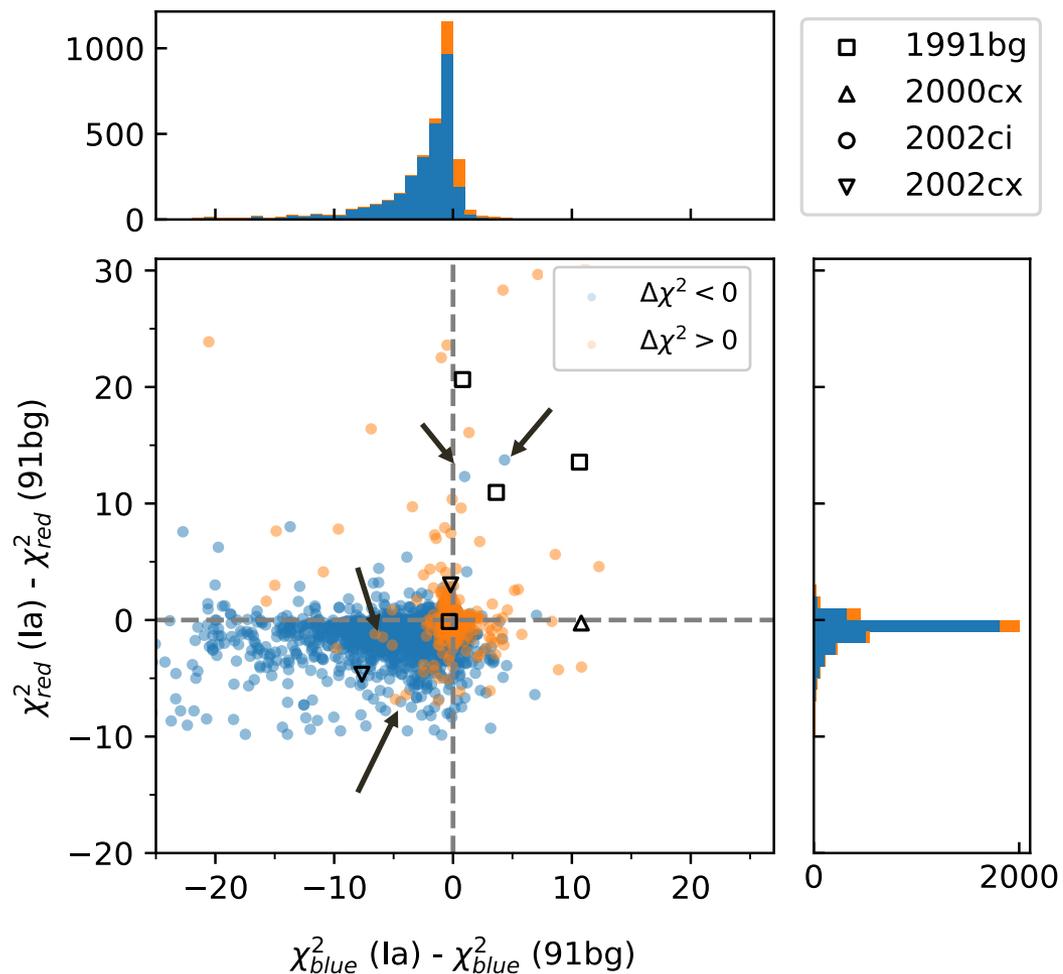


- 10,258 variable and transient sources
- Limited spectroscopic follow up (540 SNe Ia)
- Existing classifications with PSNID (Sako+ 2008)
- No Subtypes... but 4 *potential* 91bg SNe

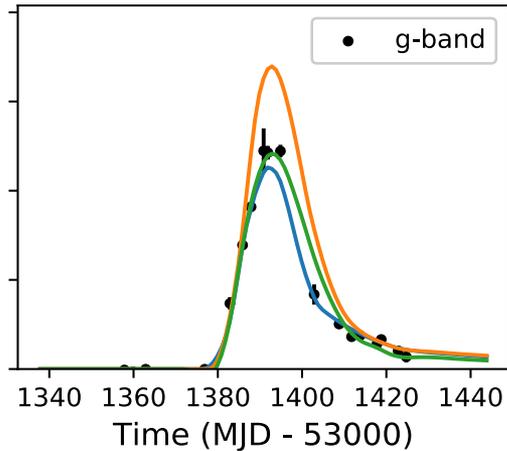
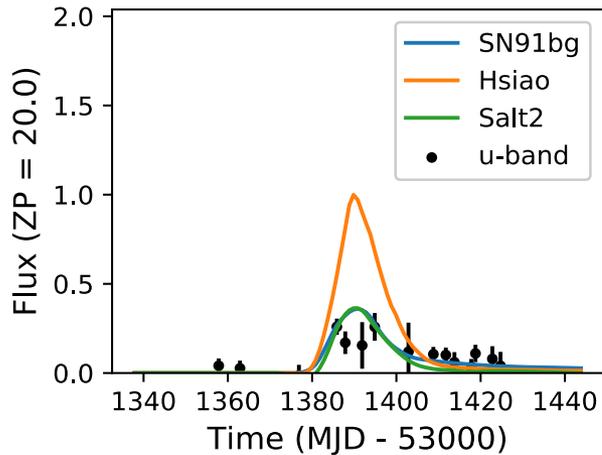
# Target Classifications for SDSS



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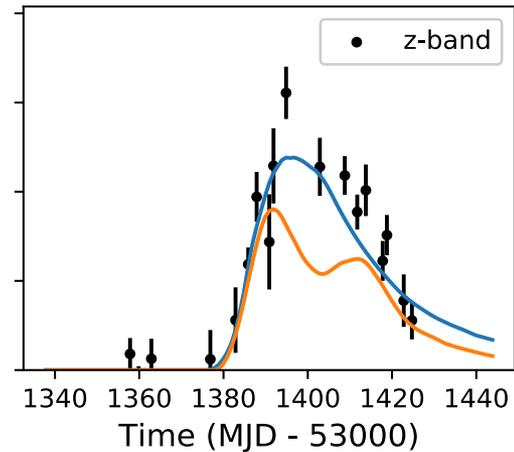
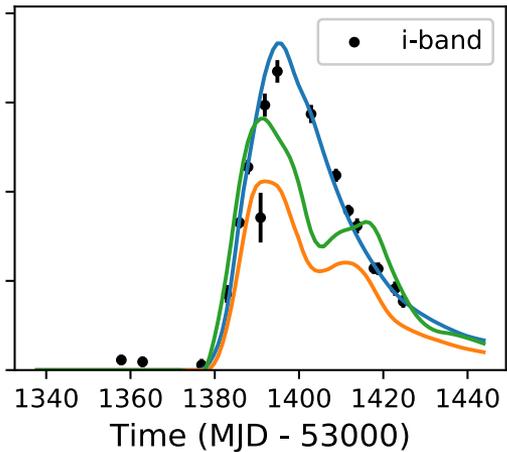
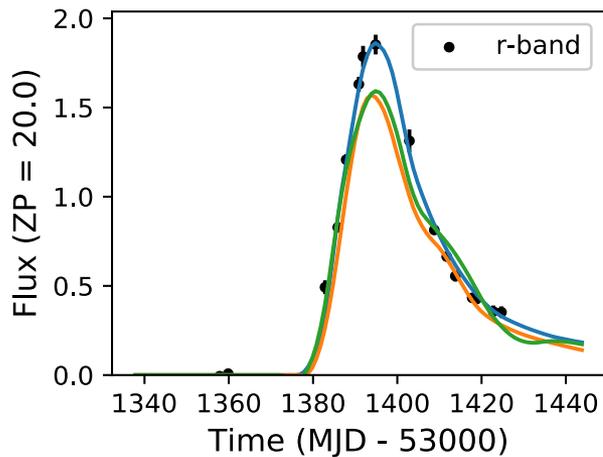


# Example 91bg Object

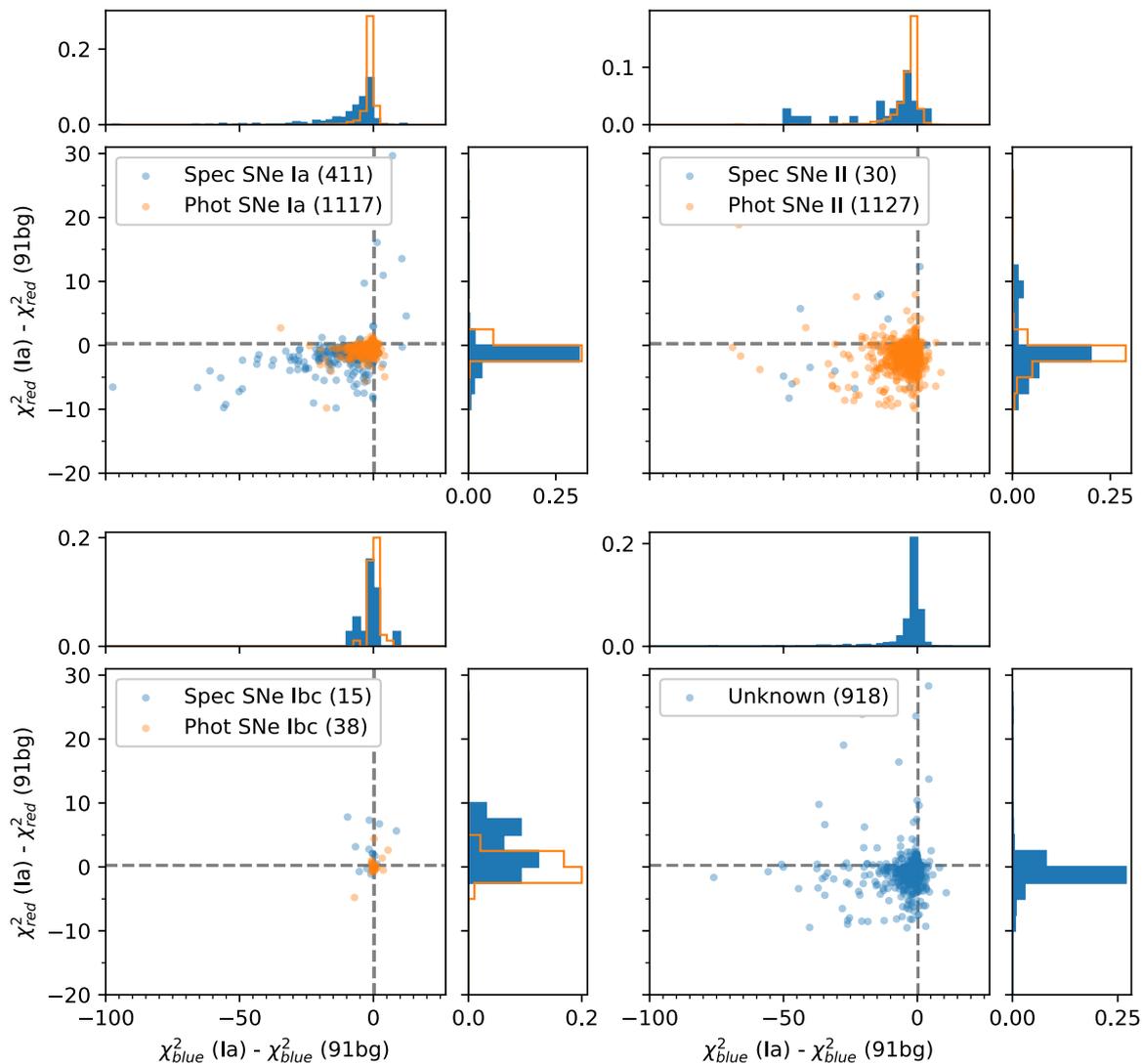


Object CID 18890

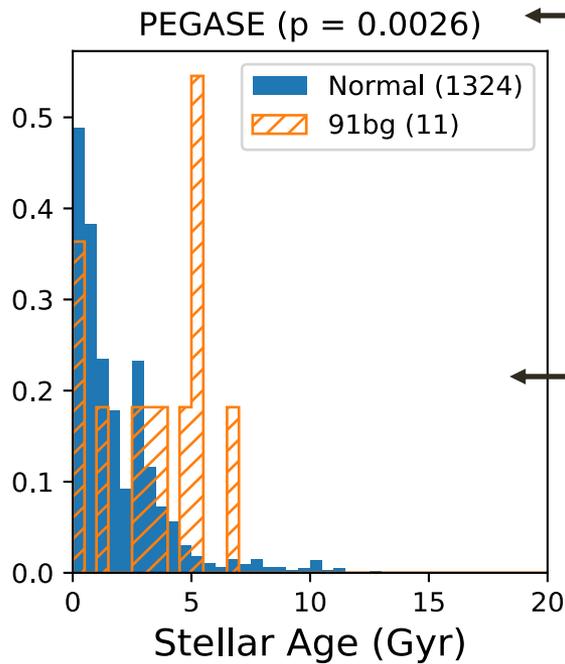
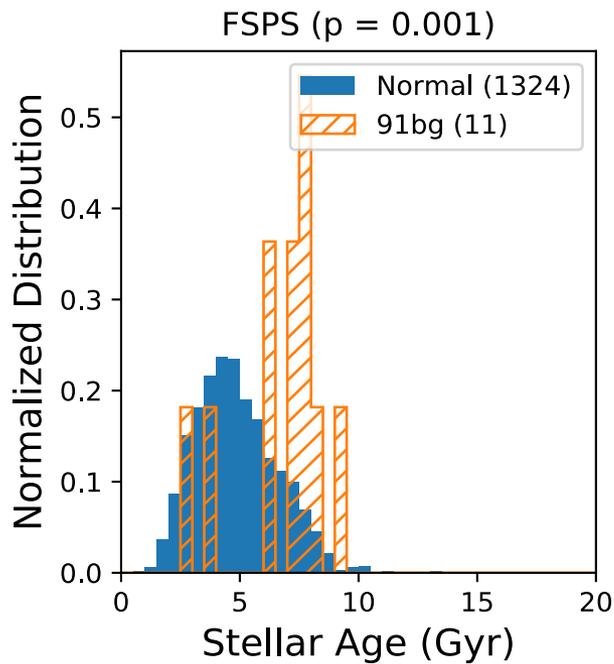
- $z_{bg} = 0.065$
- $x = 3.64$
- $y = 10.95$



# Classification Comparison

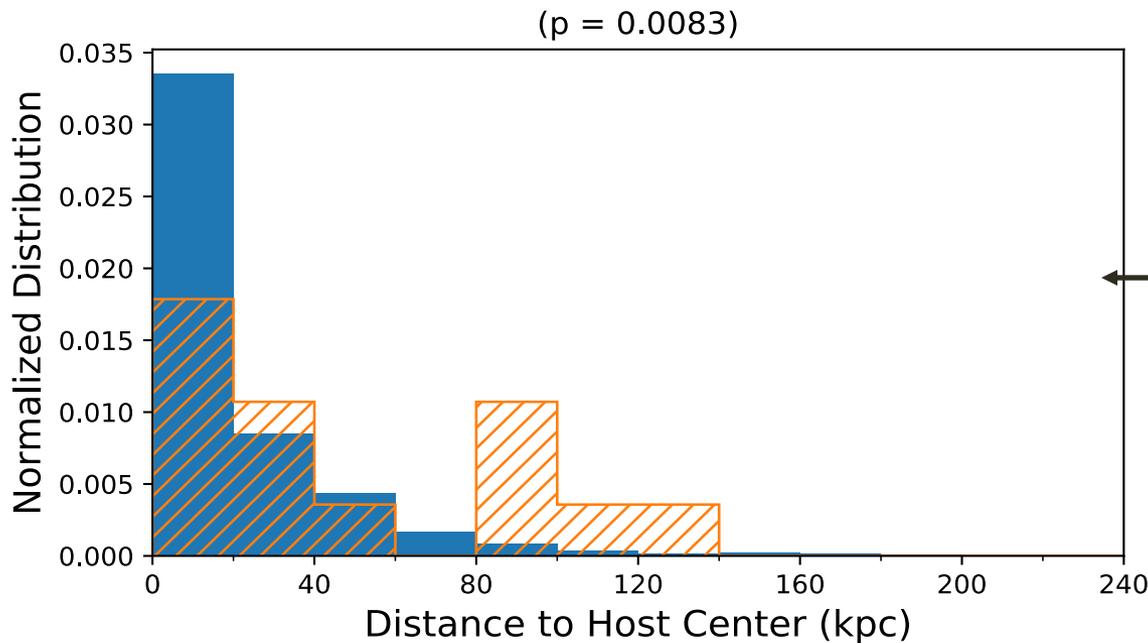


- Clustering of CC events
- No spectroscopic or photometric SNe II in 91bg quadrant
- Lack of 91bg classifications for CC SNe is surprising given redder peak colors

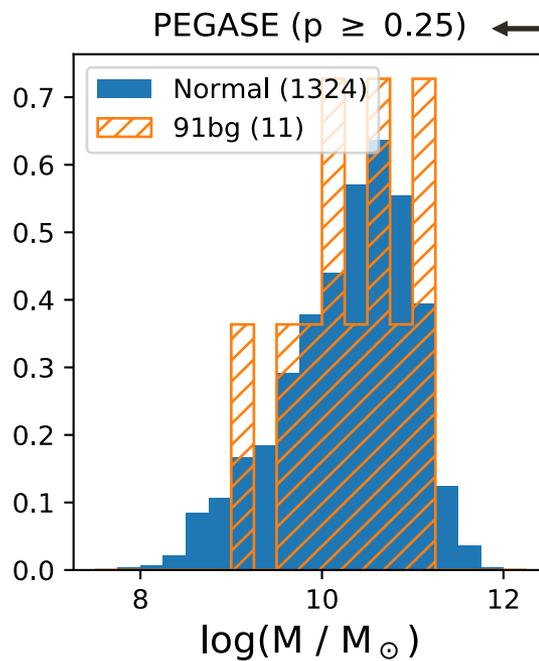
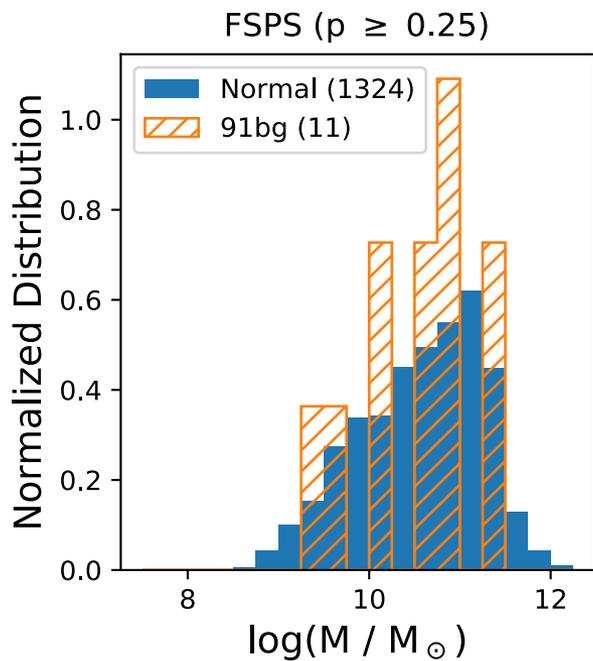
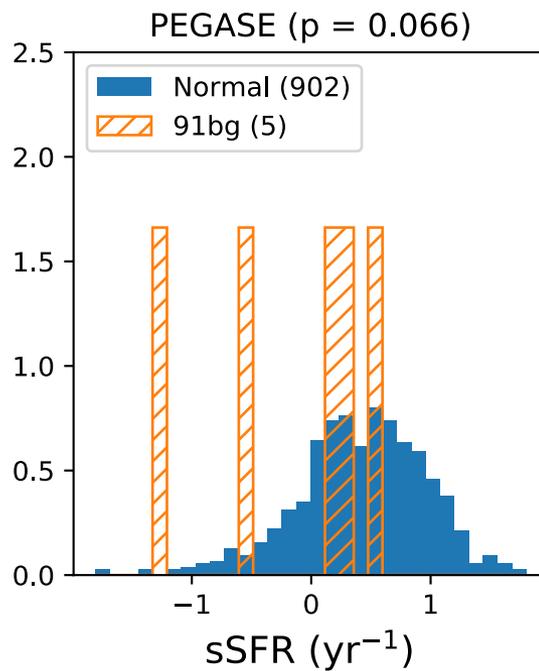
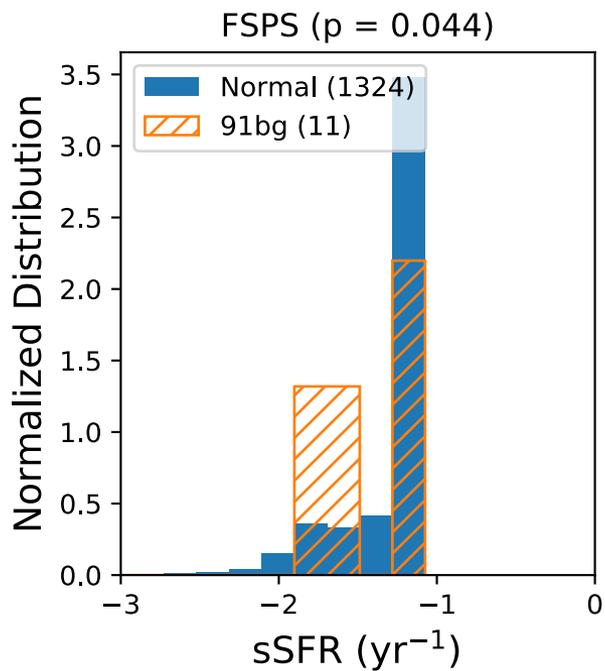


Anderson Darling  
test (Anderson+ 2014)

Preference for older  
hosts

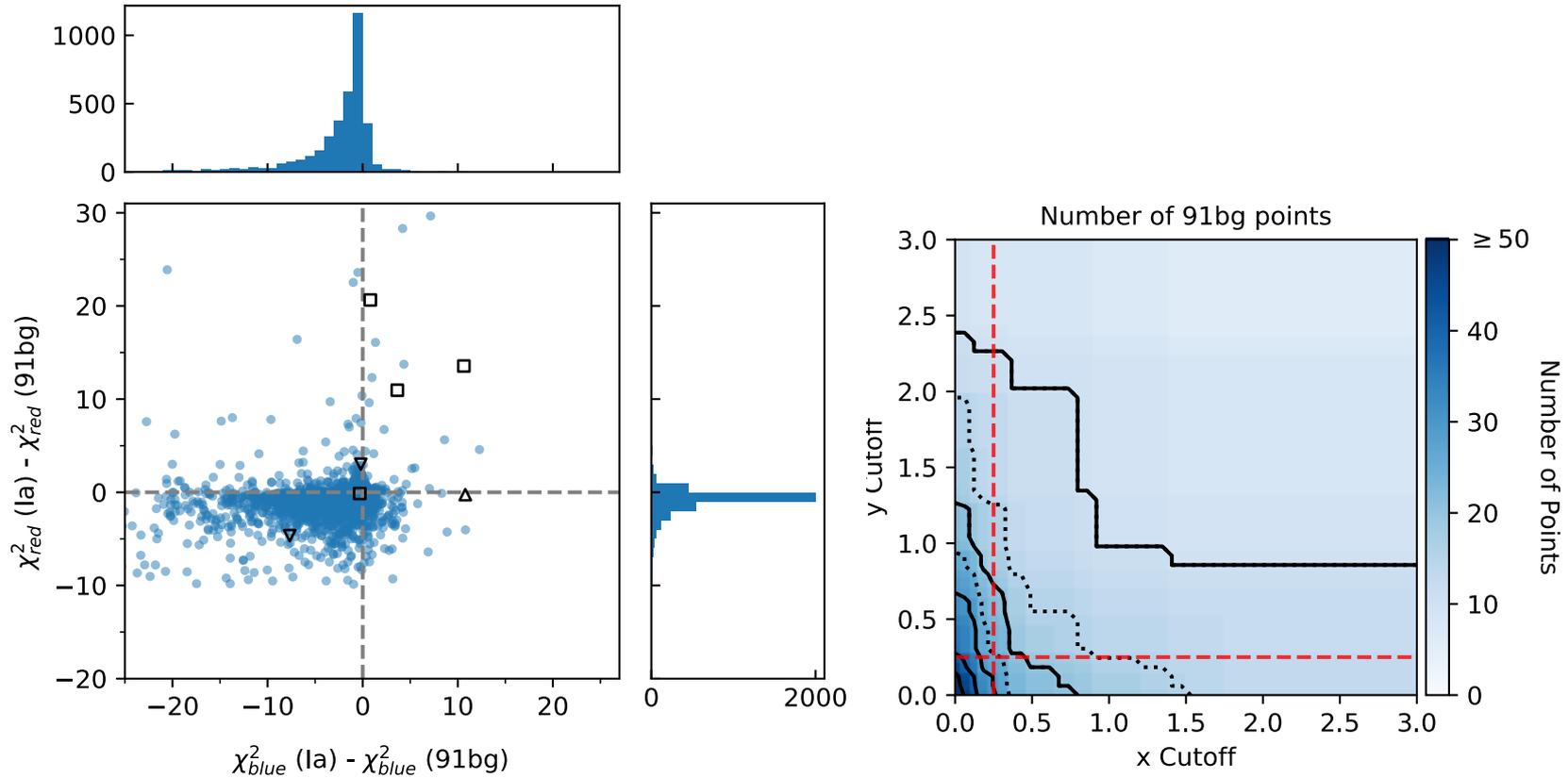


Preference for further  
distances

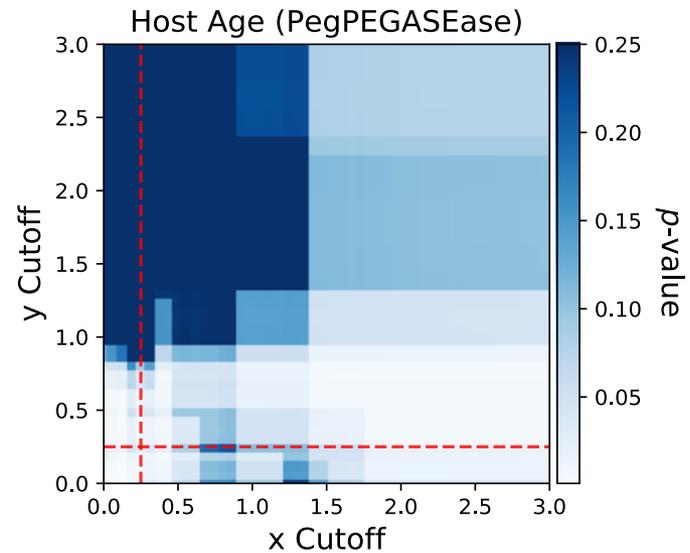
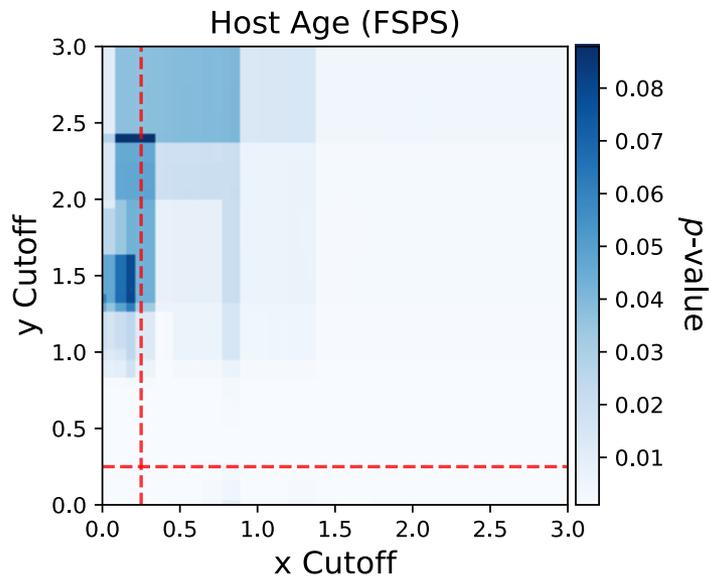
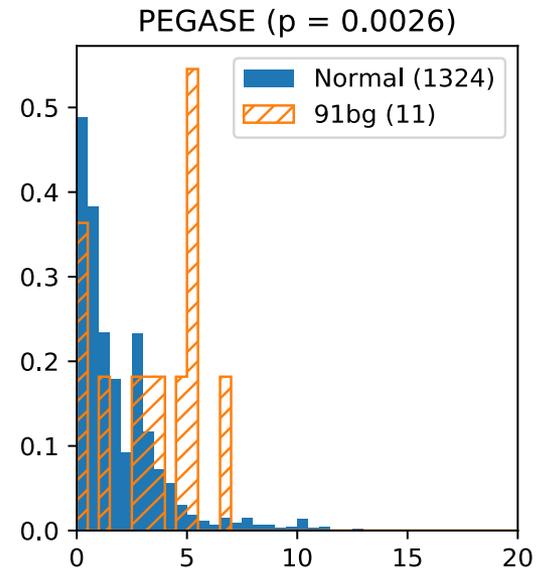
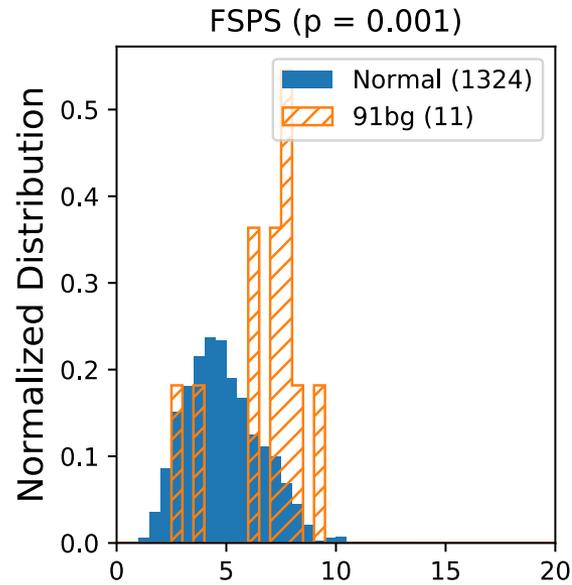


$P$ -values depend on quadrant boundaries

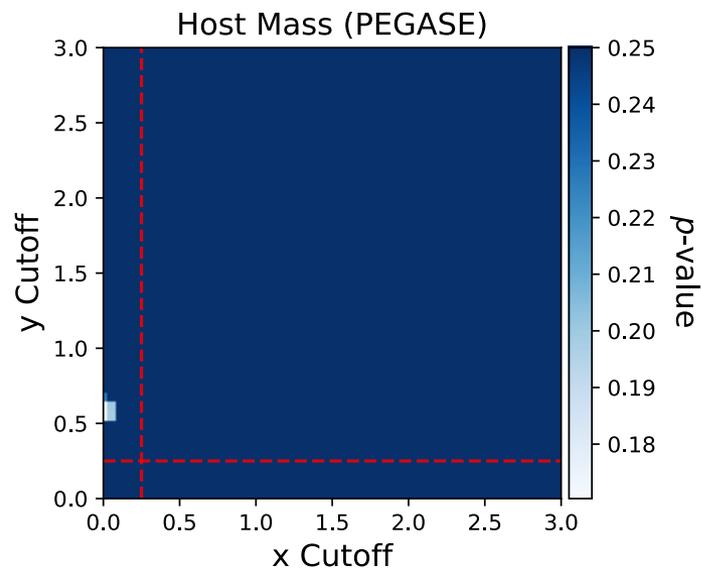
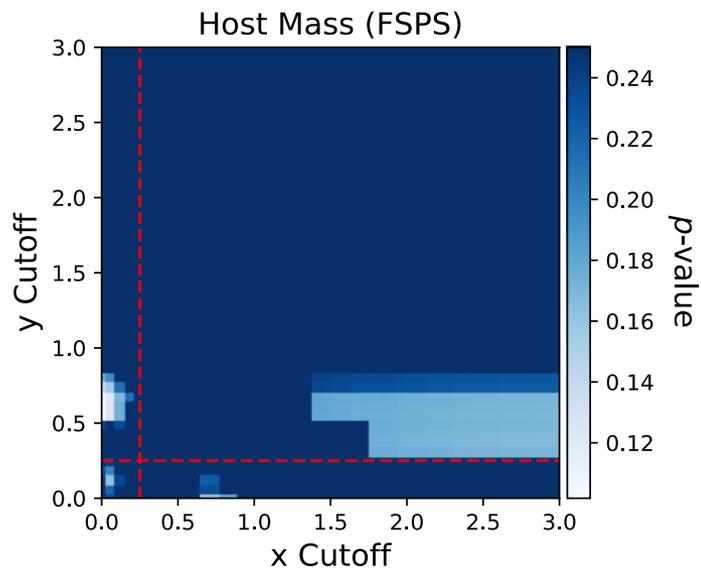
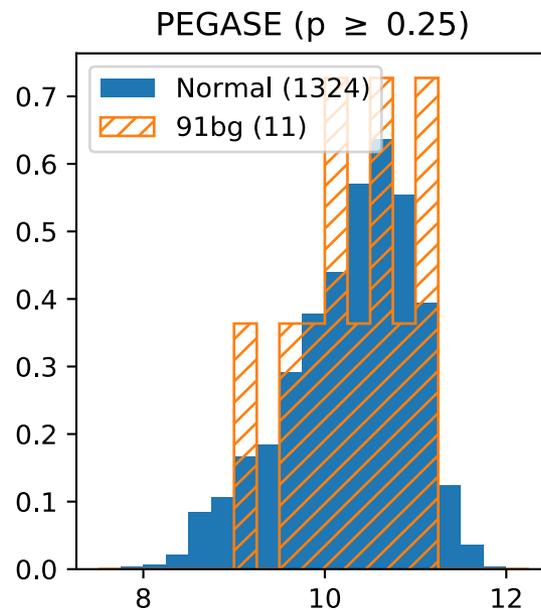
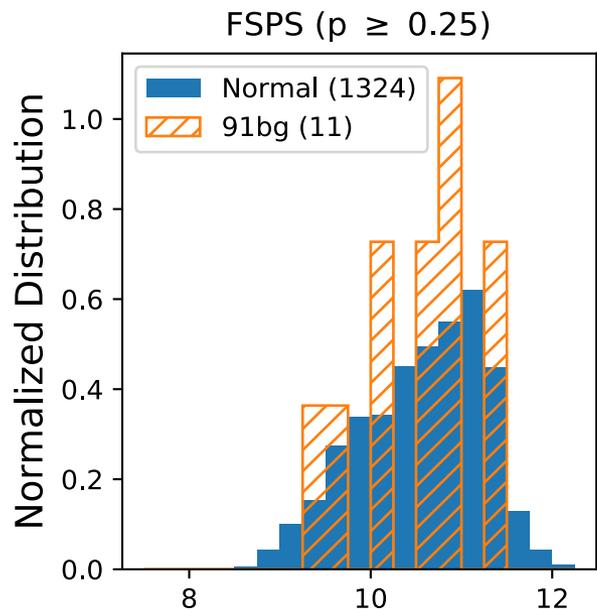
# Boundary Choices



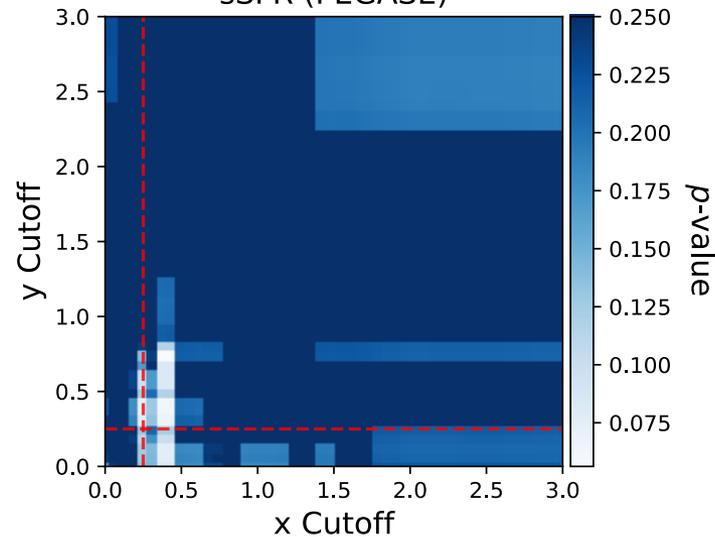
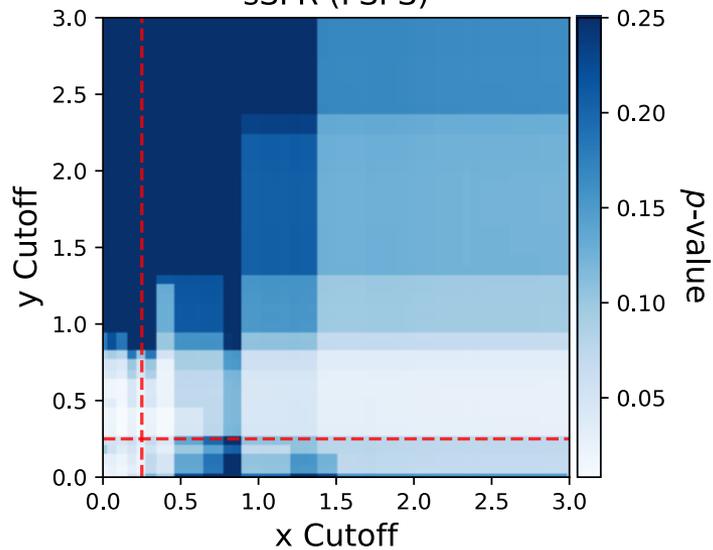
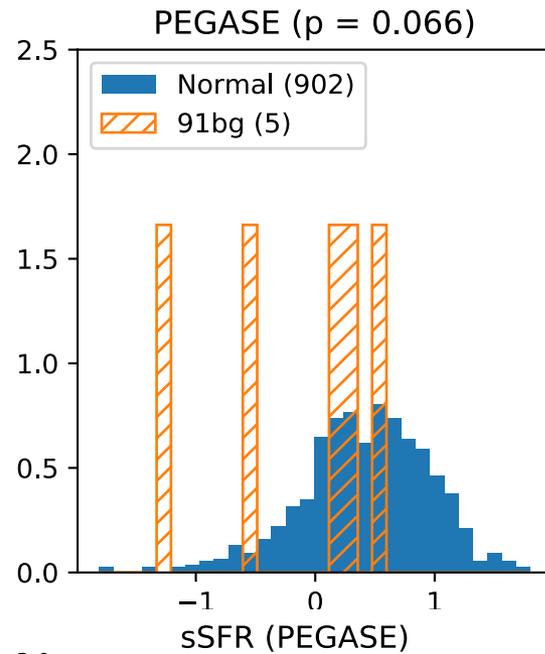
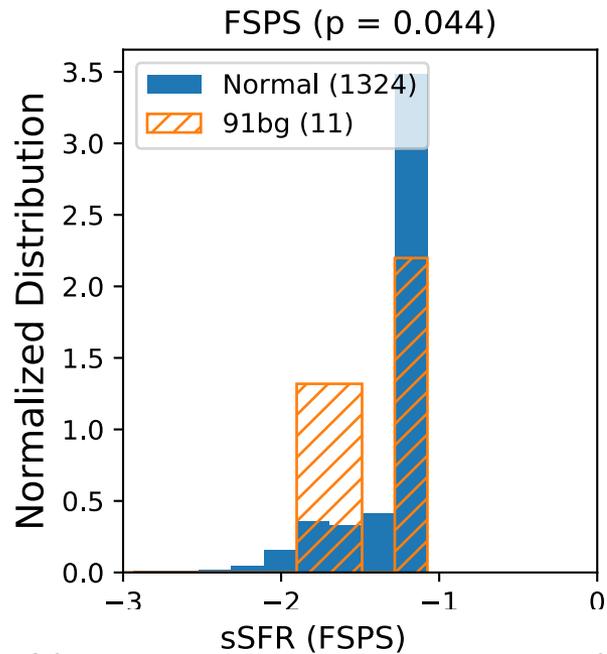
# Host Stellar Age



# Host Mass



# Star Formation Rate



# Applying Phot. Classifications

- Classifications are built to represent underlying physics
  - Photometric classifications need to recover this.
  - Thankfully light-curve morphology is driven by the underlying SED (although in a non-trivial way)
- If we estimate 10% (6% – 15%) SNe are 91bg-like, we expect on order 1000 targets with LSST
  - Improved demographic constraints
  - Targeted temporal and spectroscopic follow-up to constrain models
  - Fill in observed parameter space to determine potential for multiple physical channels
- More generally, the most diverse SNe are the rarest and are still under-represented

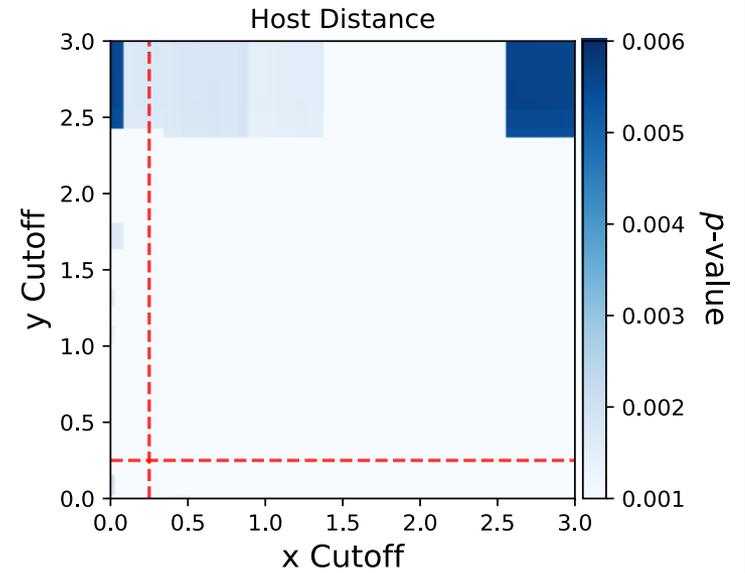
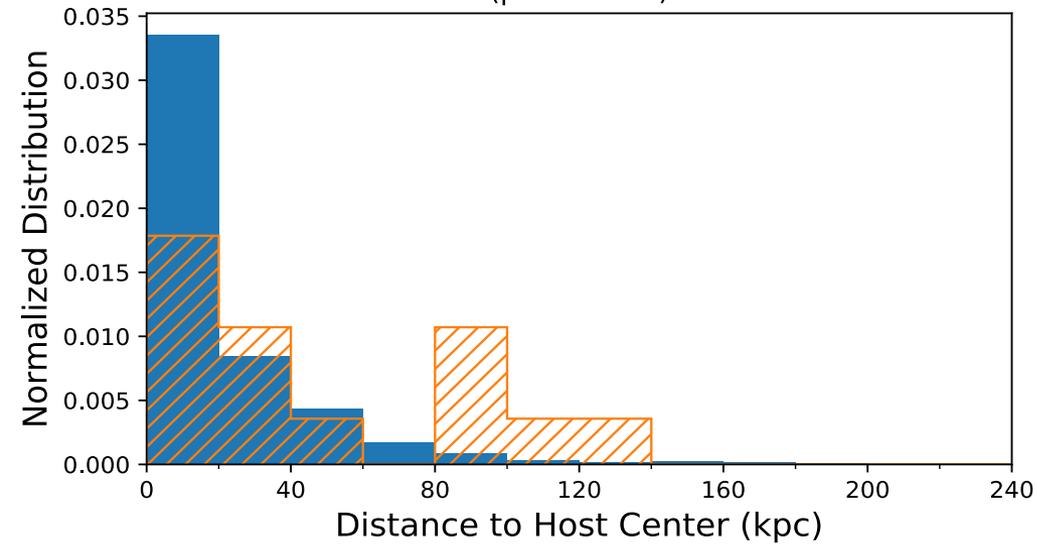
# Conclusions

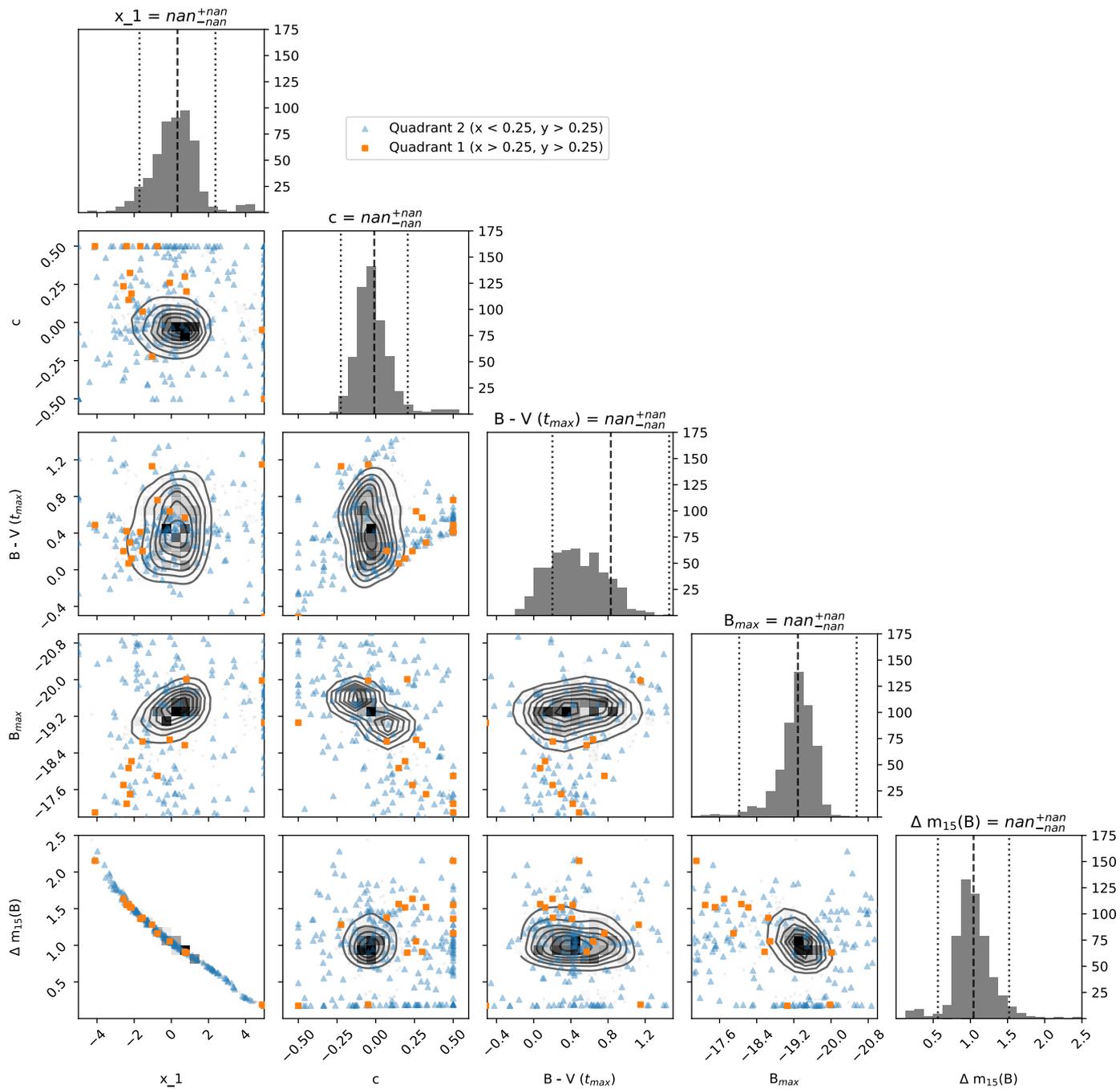
- SN (Ia) classifications are a mix of theory, observations, and physics
  - Diversity hints at physics we don't yet understand
- To understand the underlying physics, we need classifications to determine how diverse the SN Ia population really is
- Once we have well sampled populations in hand (LSST!), we can understand how different (or similar) SN subtypes really are in terms of physical properties.

Questions?

# Distance to Host

( $p = 0.0083$ )





# Empirical Classification

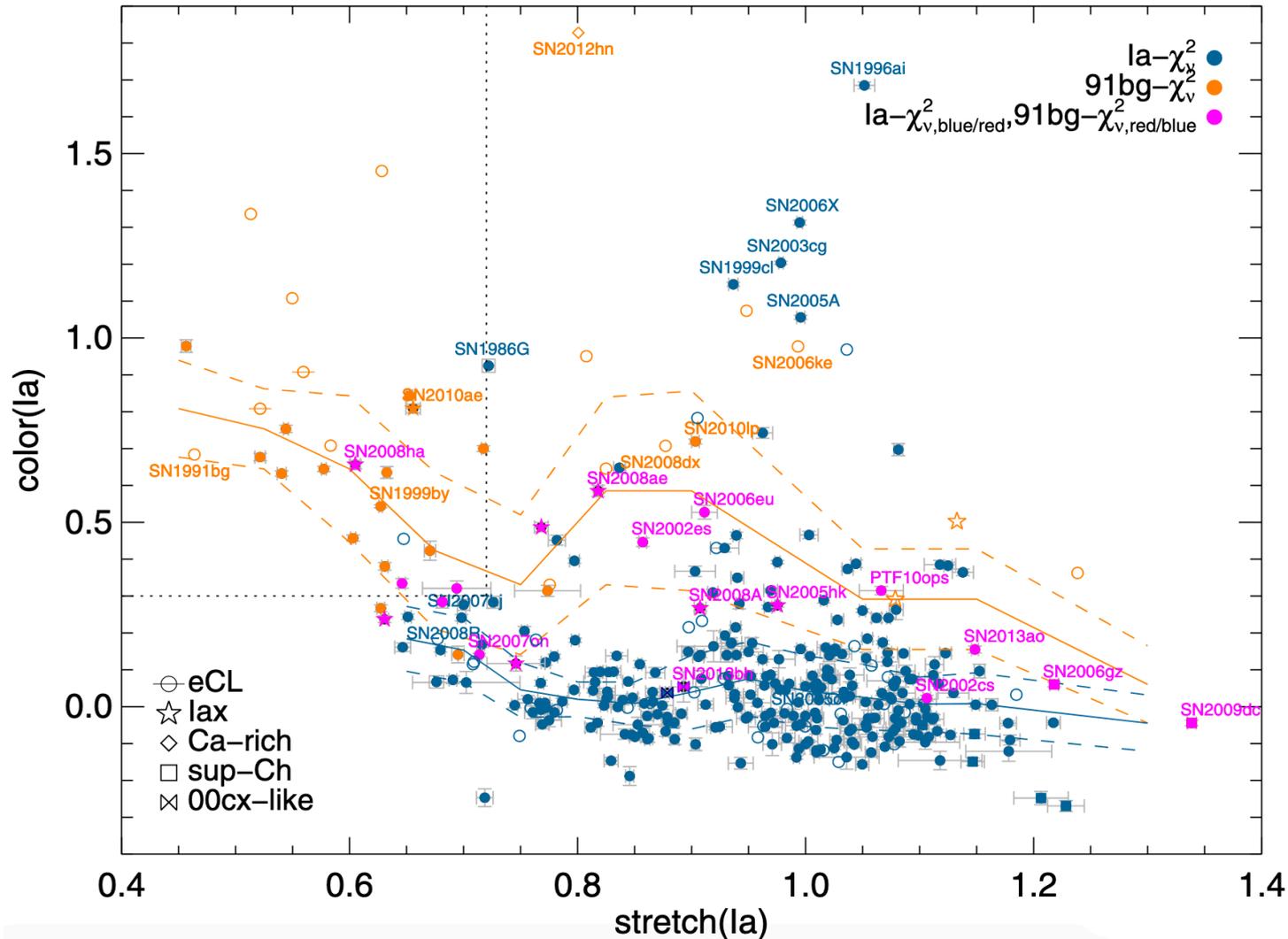


Figure: (González-Gaitán 2014)