

# **ML in Astronomy:** classification of cosmic explosions

**Maria Vincenzi**

2<sup>nd</sup> PhD student,

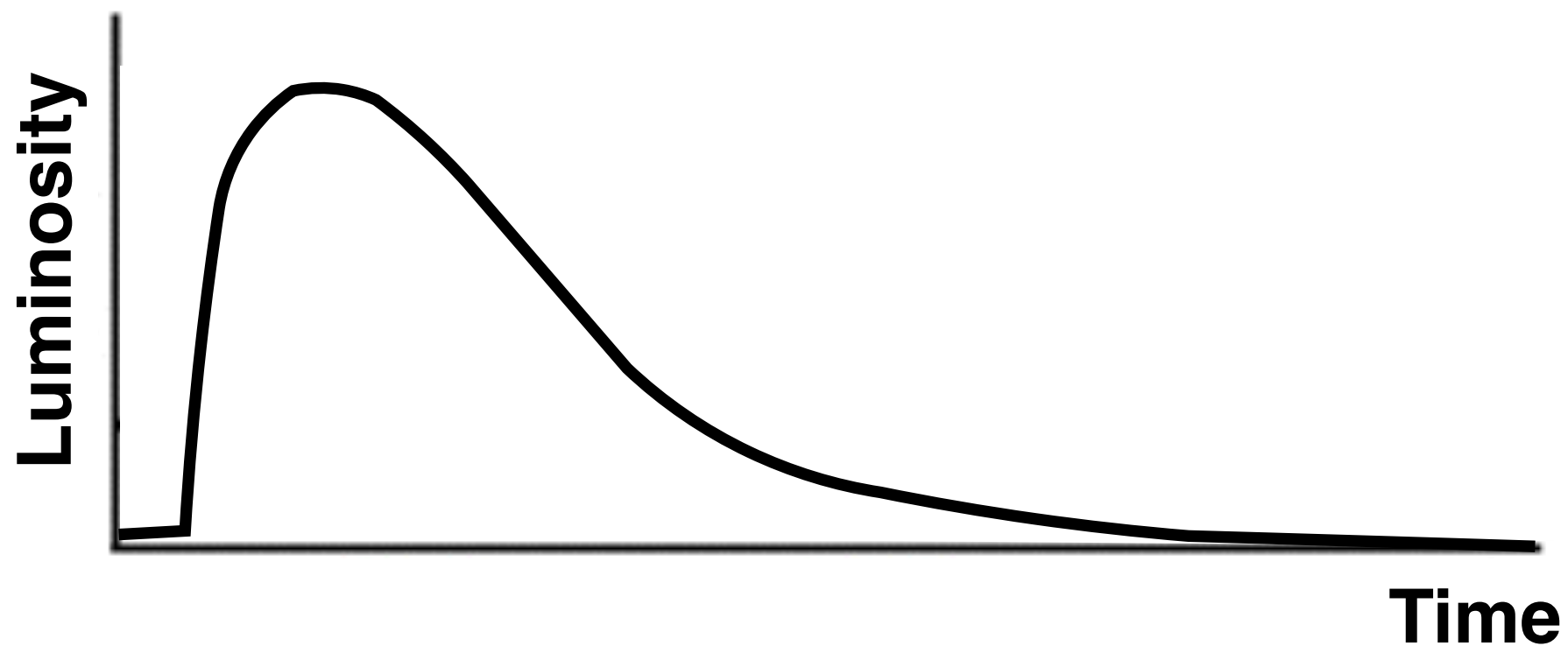
*Institute of Cosmology and Gravitation*

Supervisors: Mark Sullivan, Bob Nichol

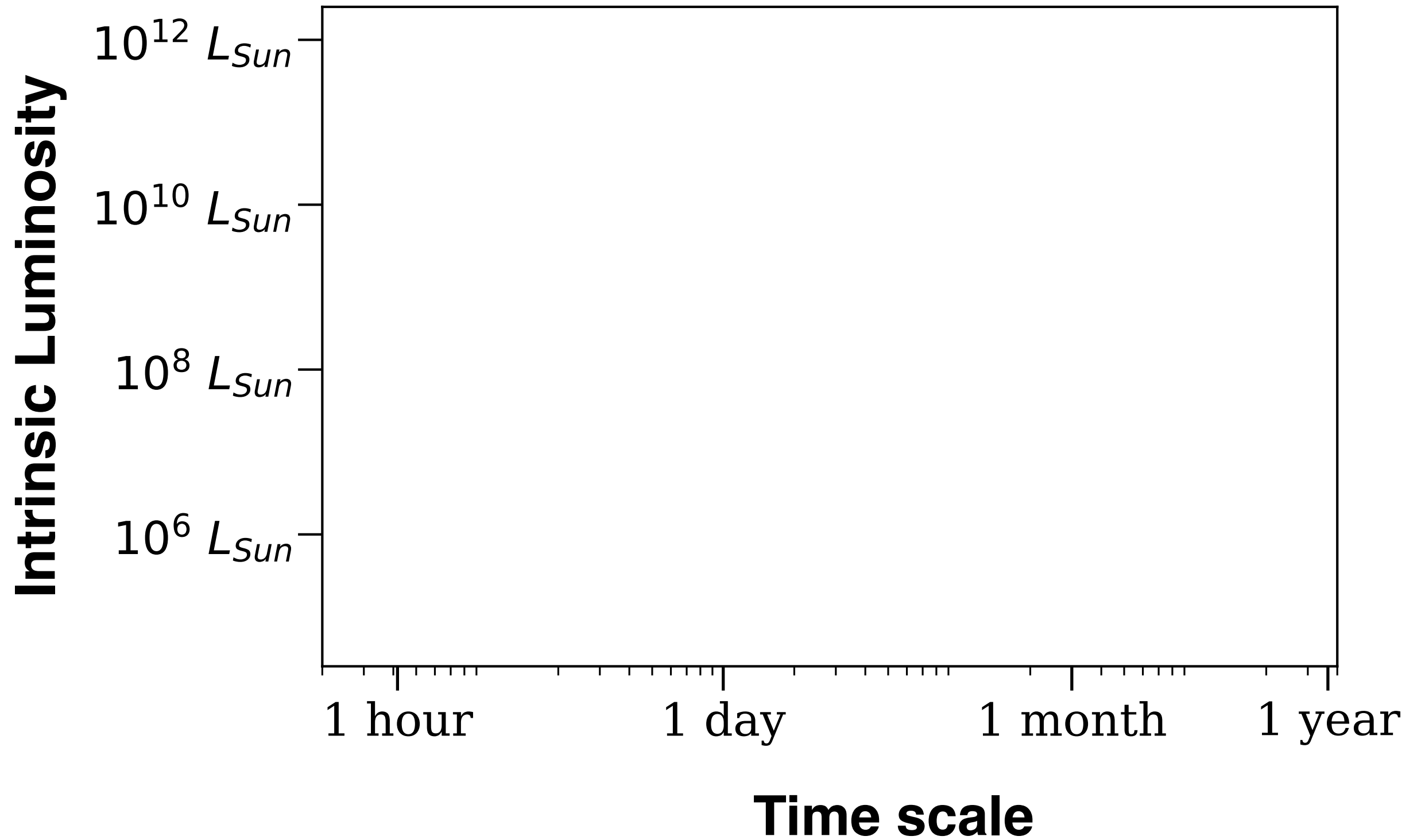
# Outline

- What are **cosmic explosions** and why we study them?
- How we **detect** them,
- How we **classify** them,
- What people have done on this classification problem,
- What I have done for this classification problem.

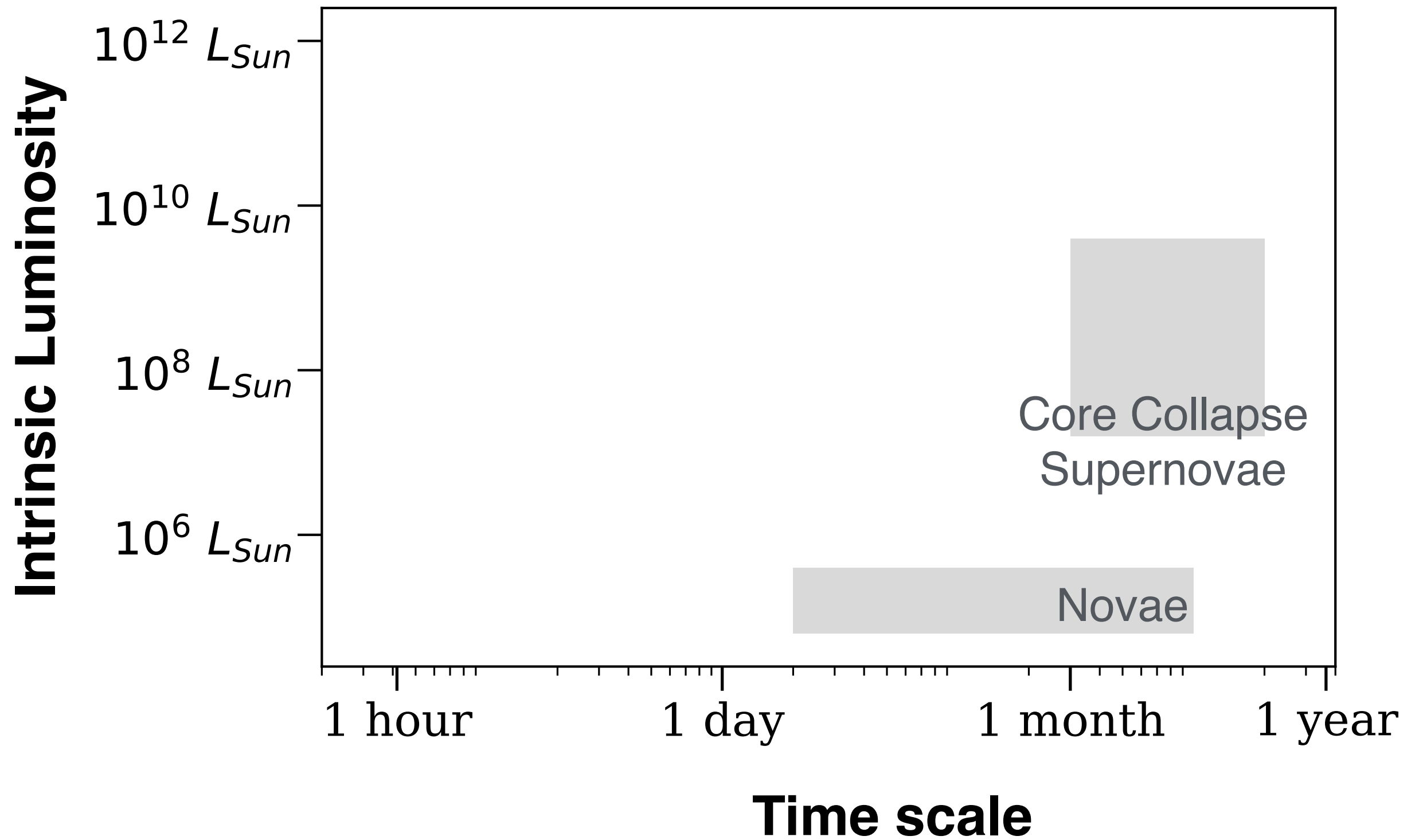
# What are cosmic explosions and why we study them?



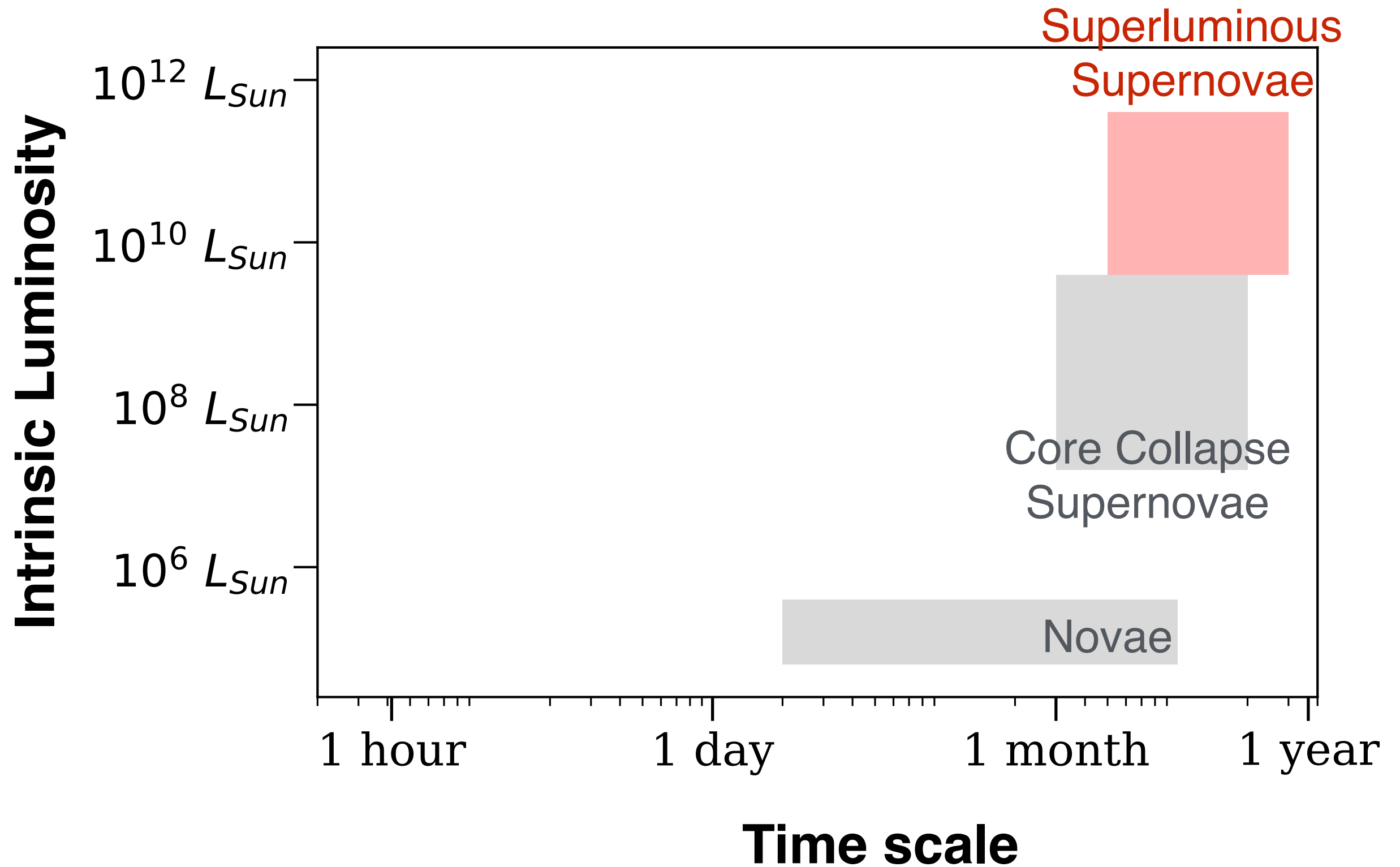
# The cosmic explosion ZOO



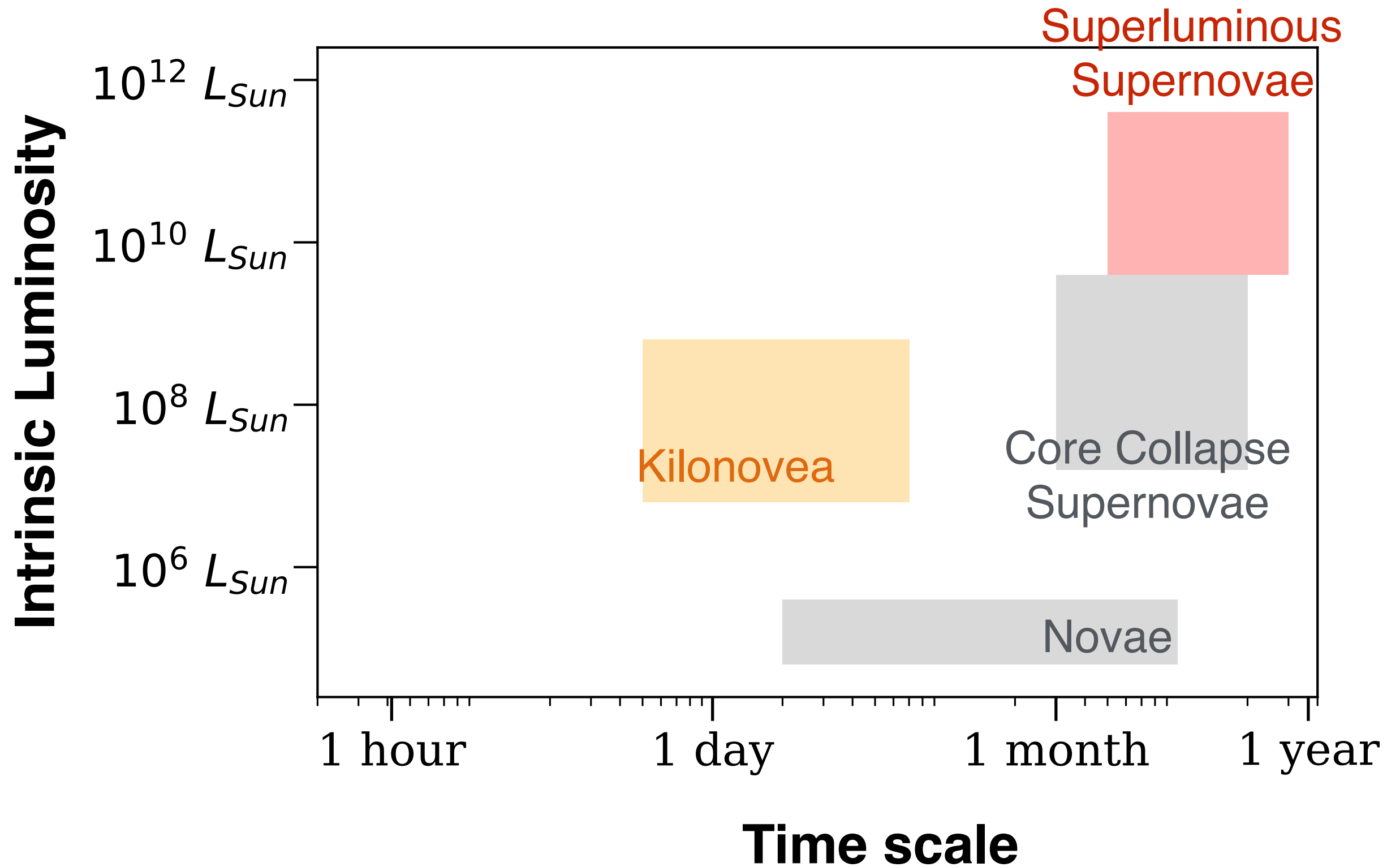
# The cosmic explosion ZOO



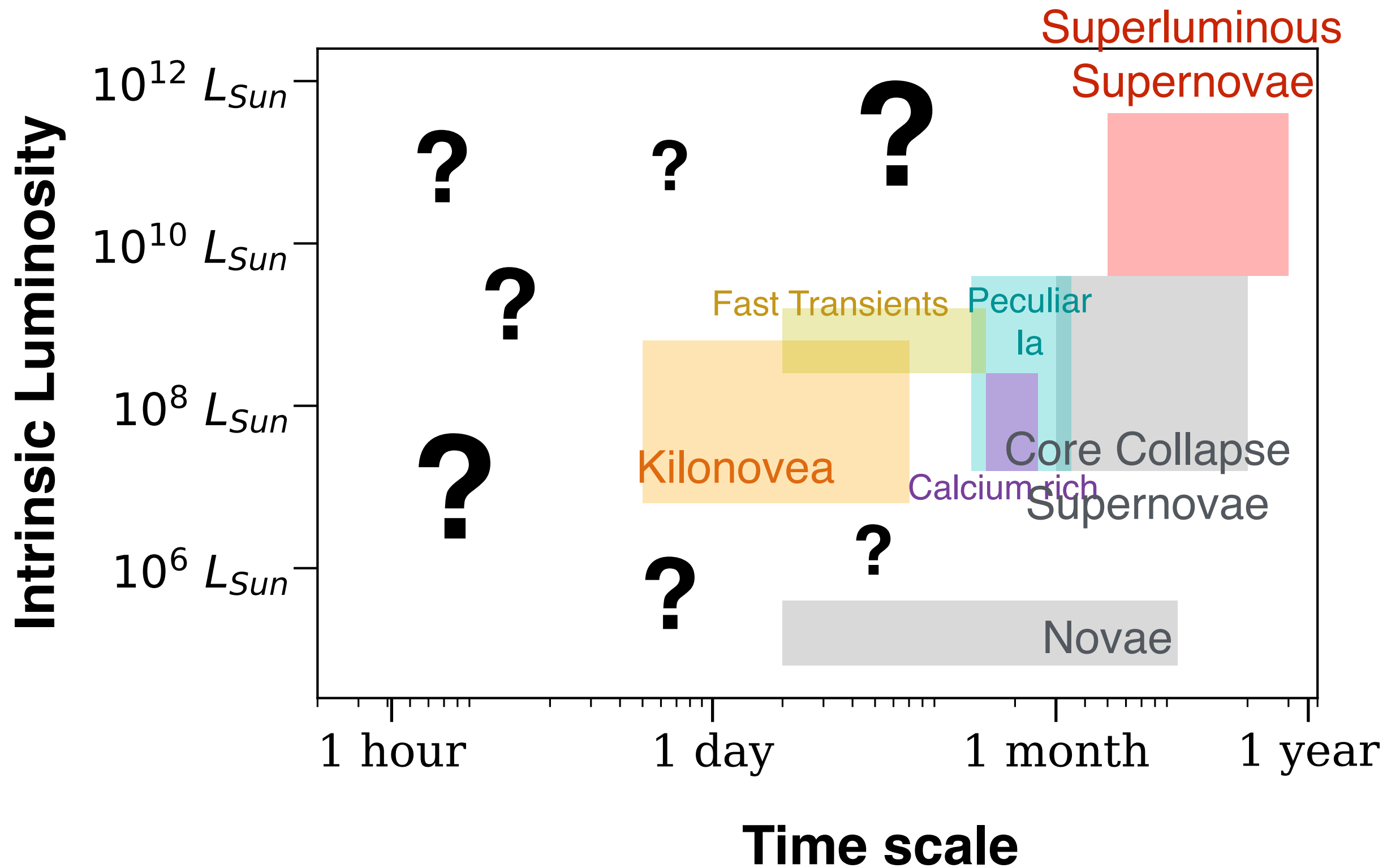
# The cosmic explosion ZOO



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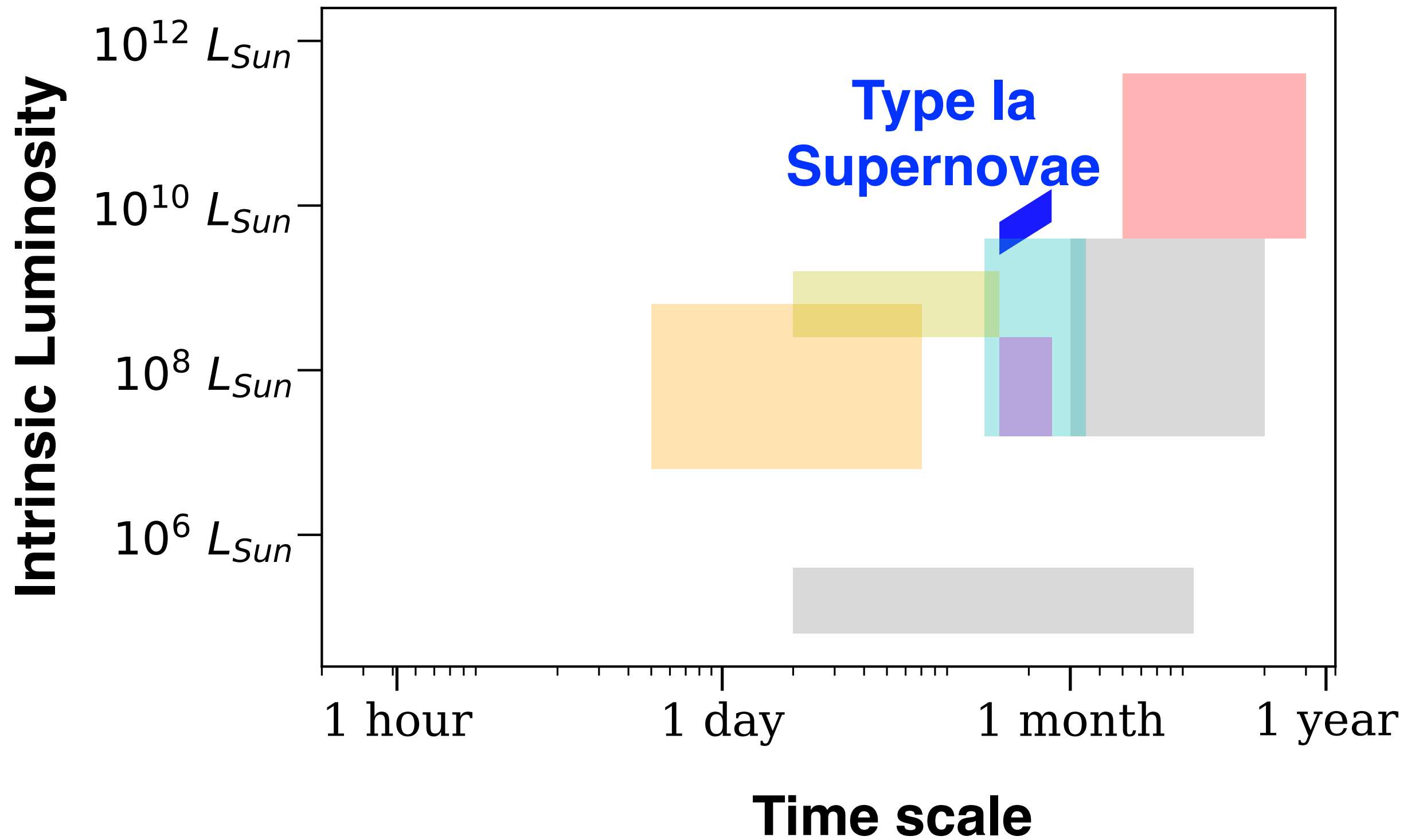


# The cosmic explosion ZOO





# The cosmic explosion ZOO



# Type Ia Supernovae



Thermonuclear explosions of  
dwarf stars made of Carbon  
and Oxygen

Critical Mass =  $1.4 M_{\text{Sun}}$

**Standard evolution and  
brightness!**

# Type Ia Supernovae



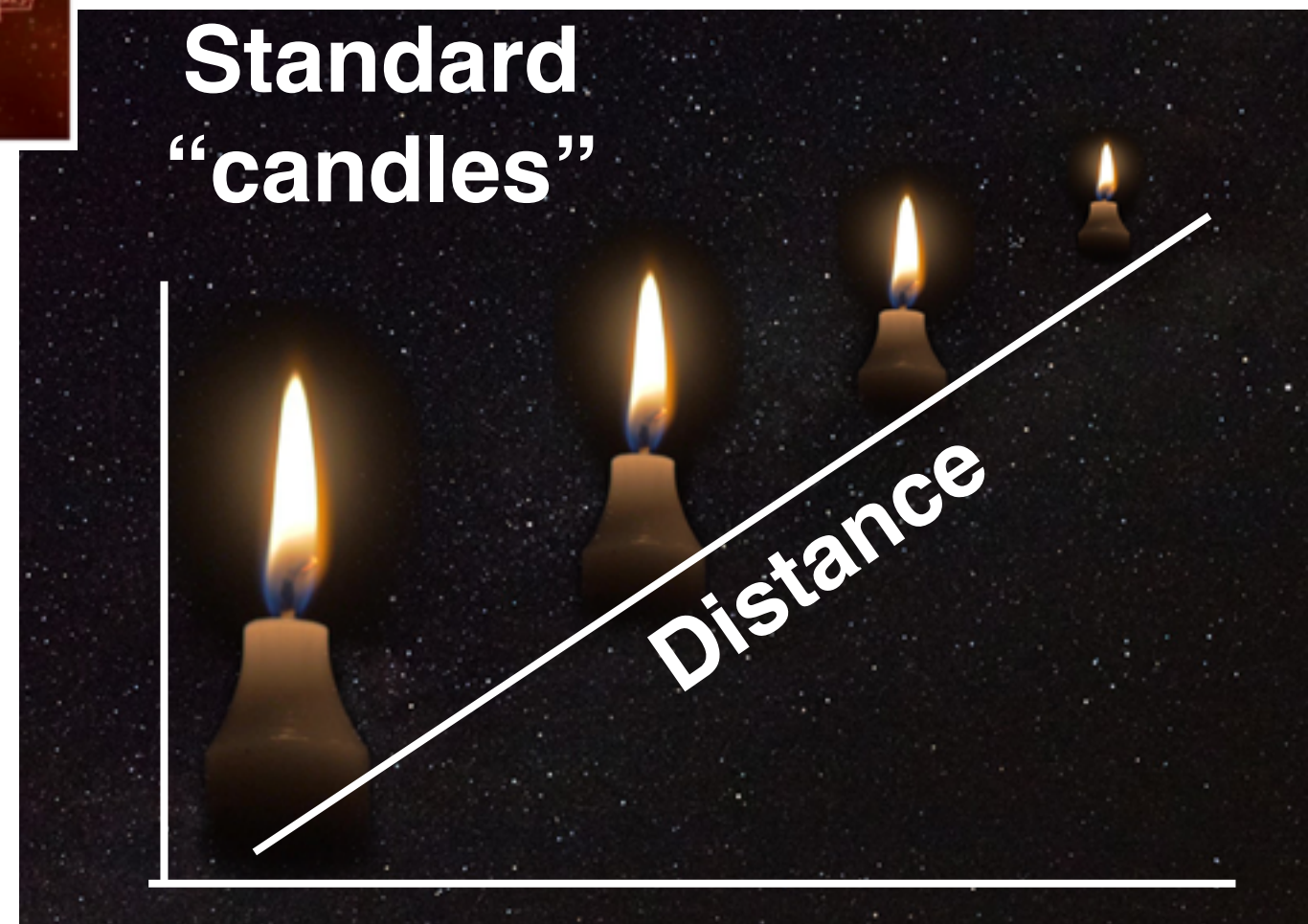
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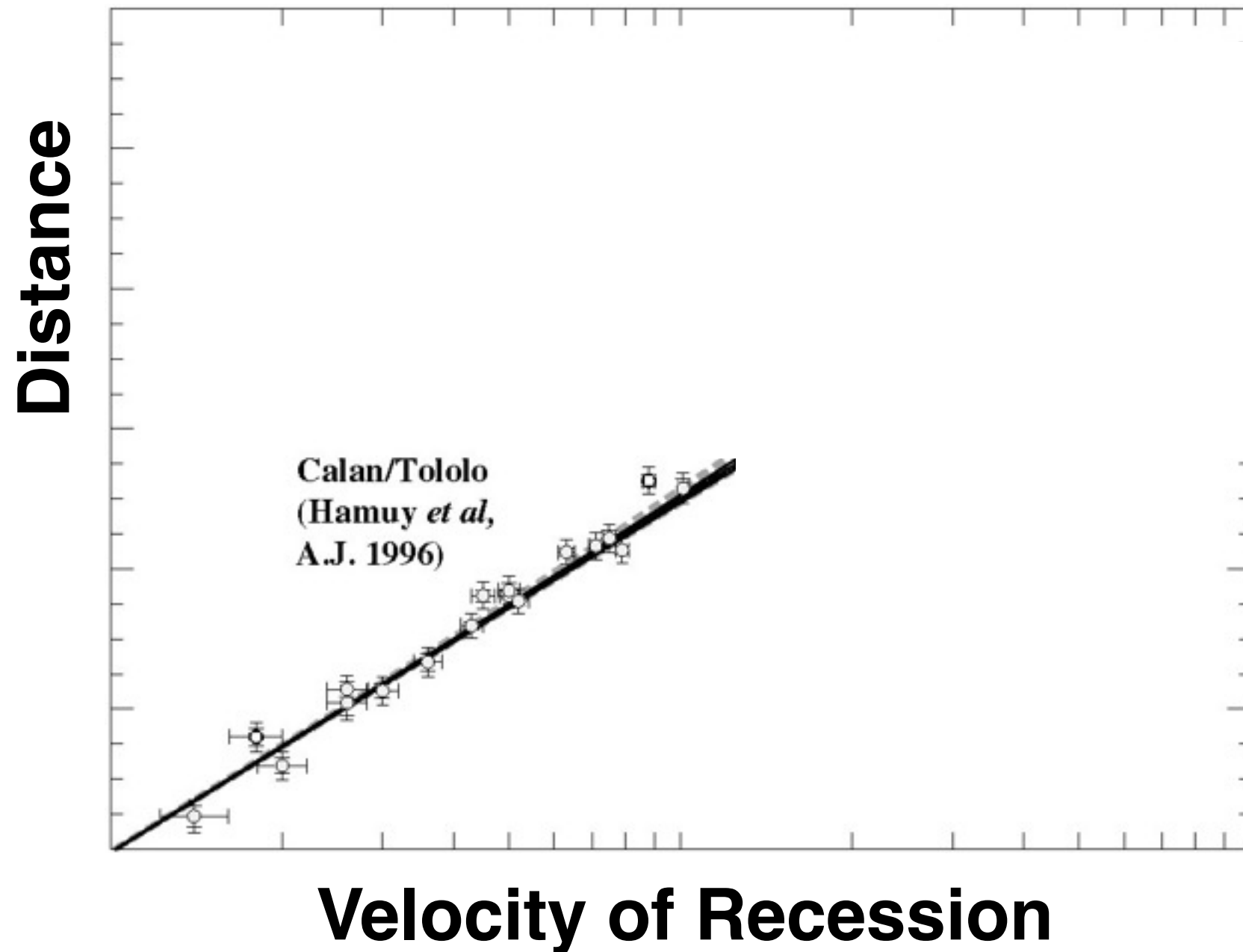
**Excellent objects to  
measure distances!  
( $< 5\%$  accuracy)**

**Standard  
“candles”**



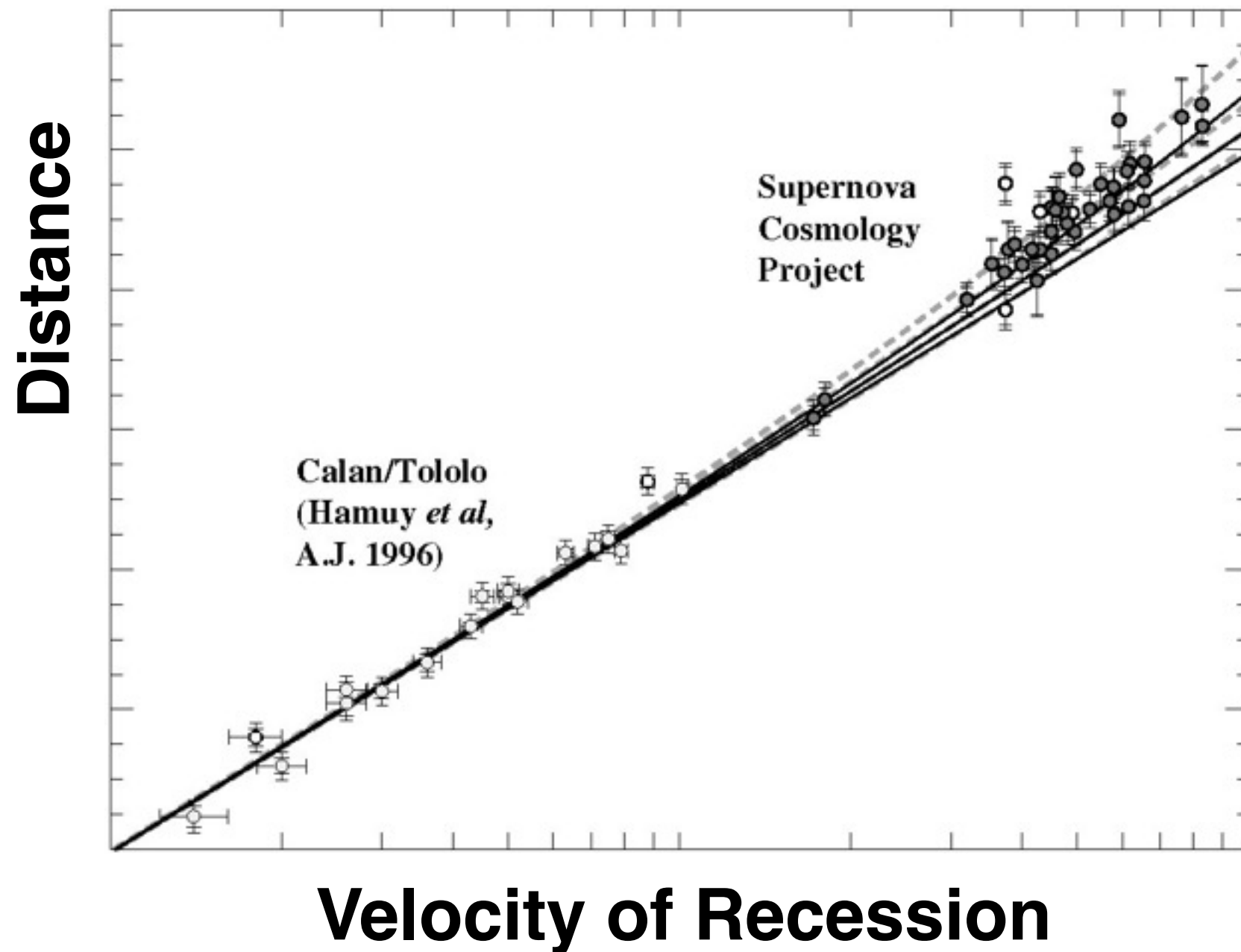
# Type Ia Supernovae

The expansion of the Universe is.....



# Type Ia Supernovae

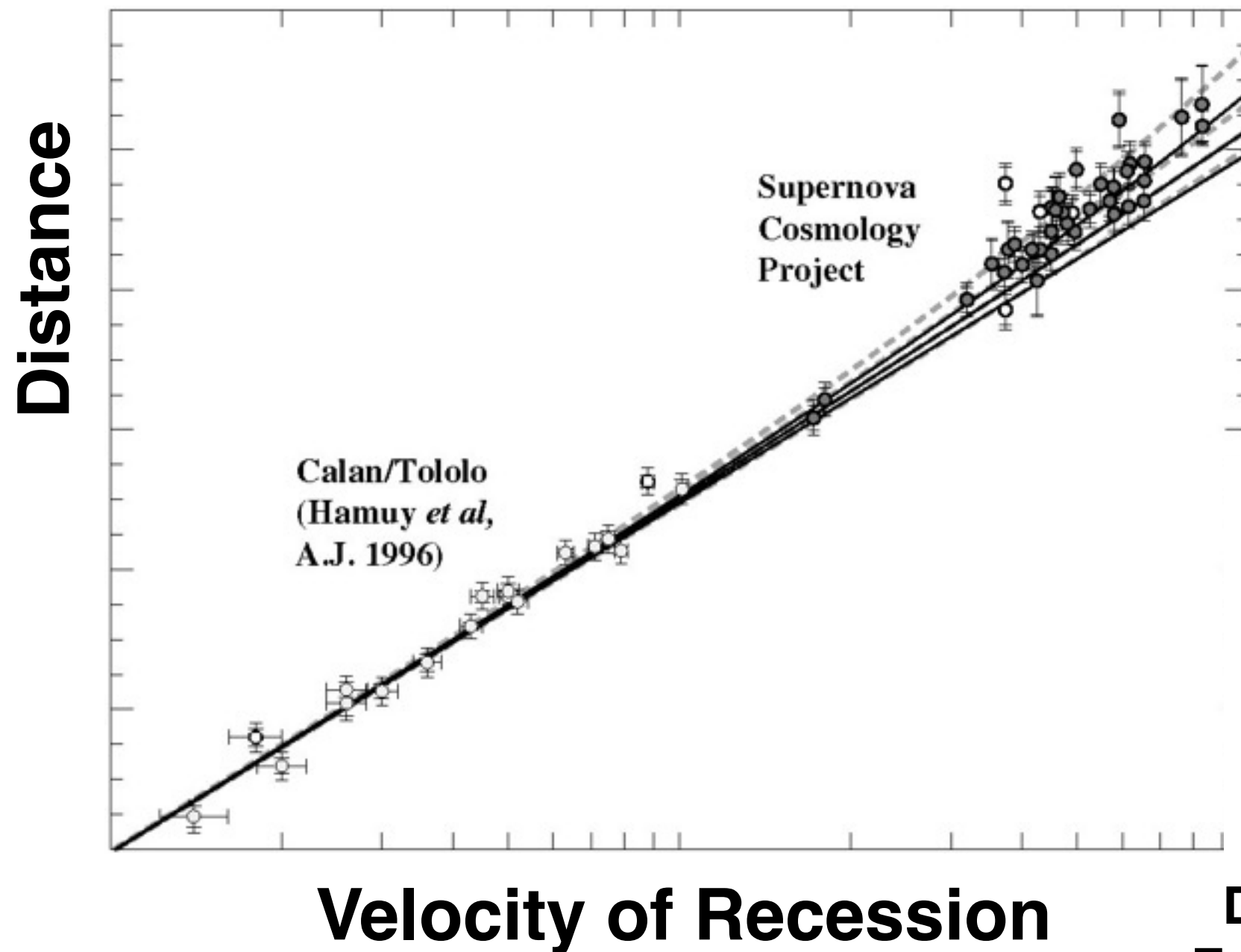
The expansion of the Universe is **ACCELERATING !!**



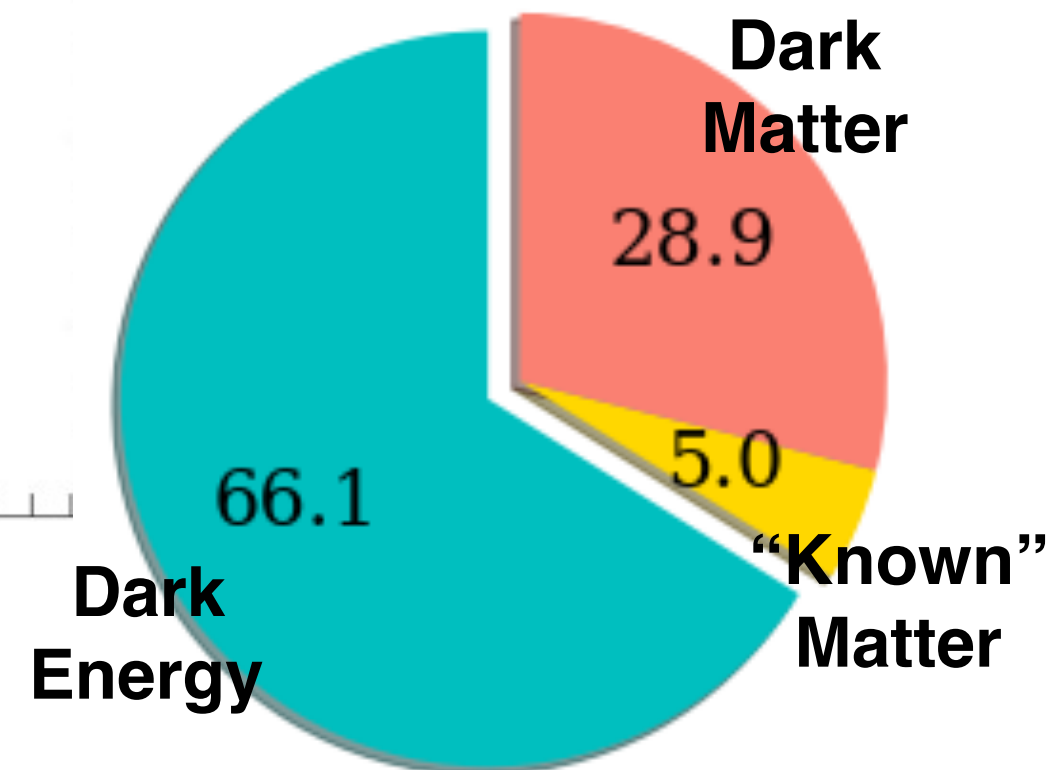


# Type Ia Supernovae

The expansion of the Universe is **ACCELERATING !!**

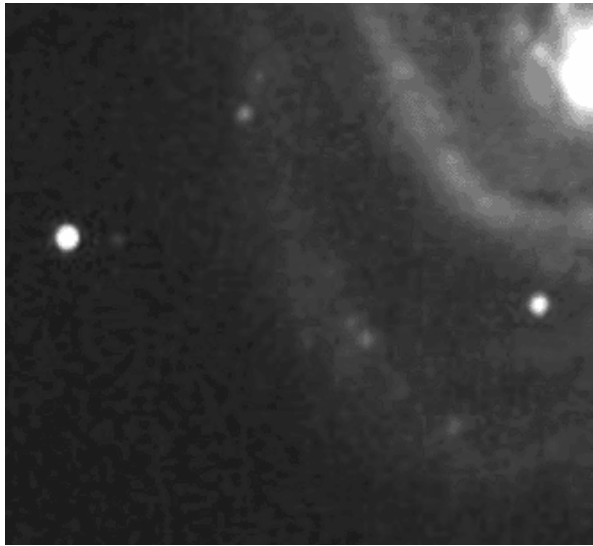


Dark Energy?  
“Wrong” gravity theory?

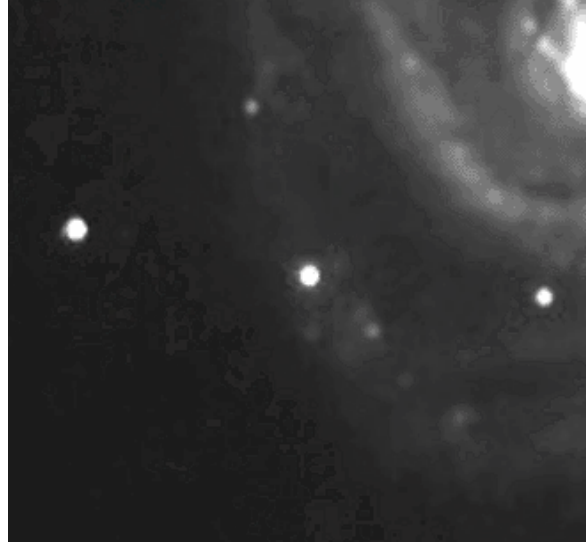


# Detection

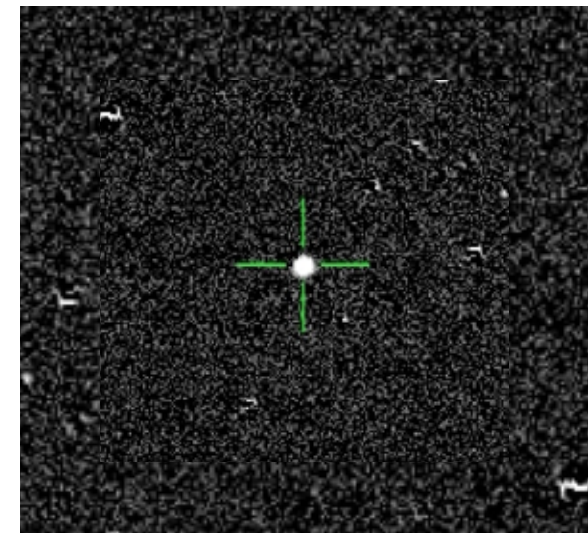
# Detection



Reference  
Image



**New  
Image**

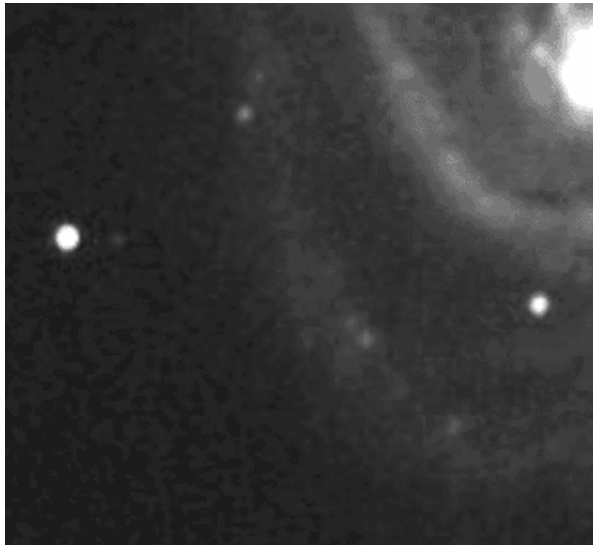


Difference  
Image

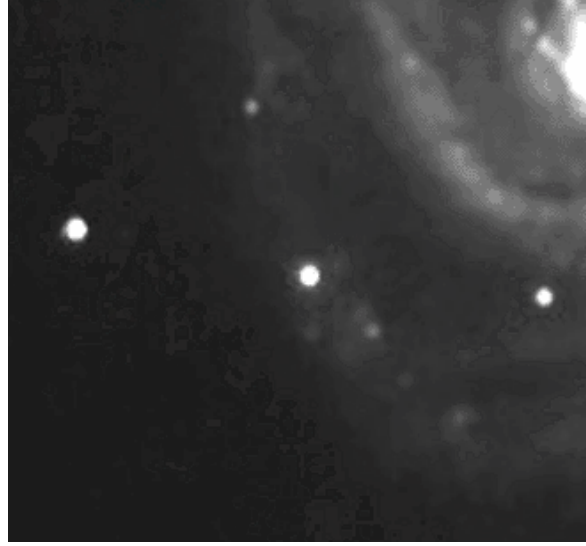
**New detection!**



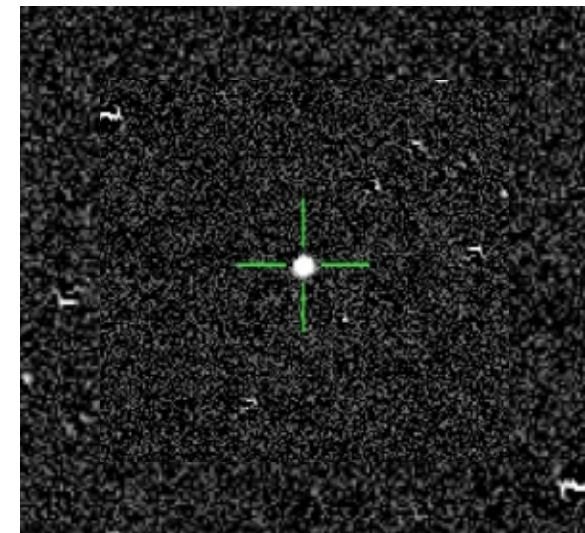
# Detection



Reference  
Image



**New  
Image**



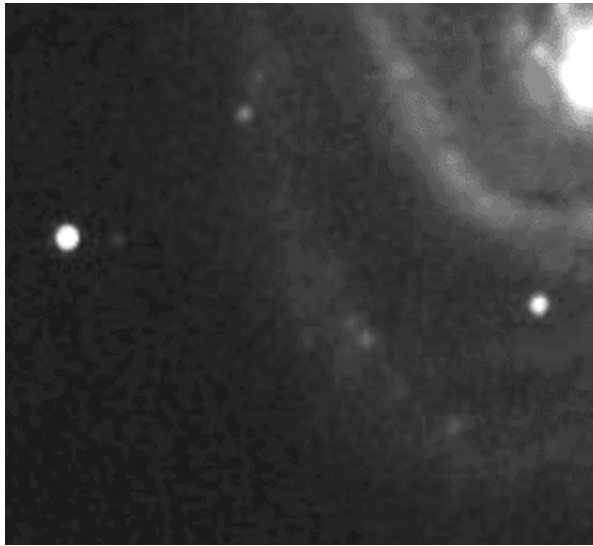
Difference  
Image

**Luminosity**

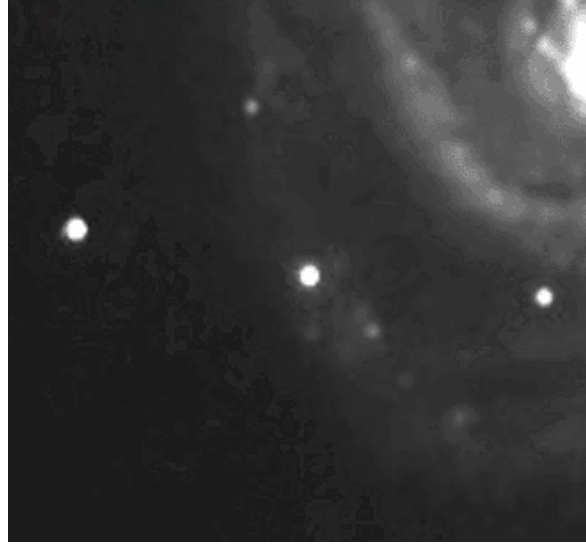


**Time**

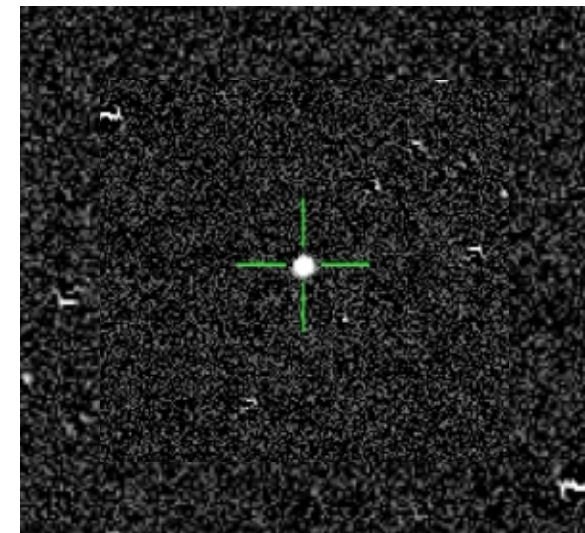
# Detection



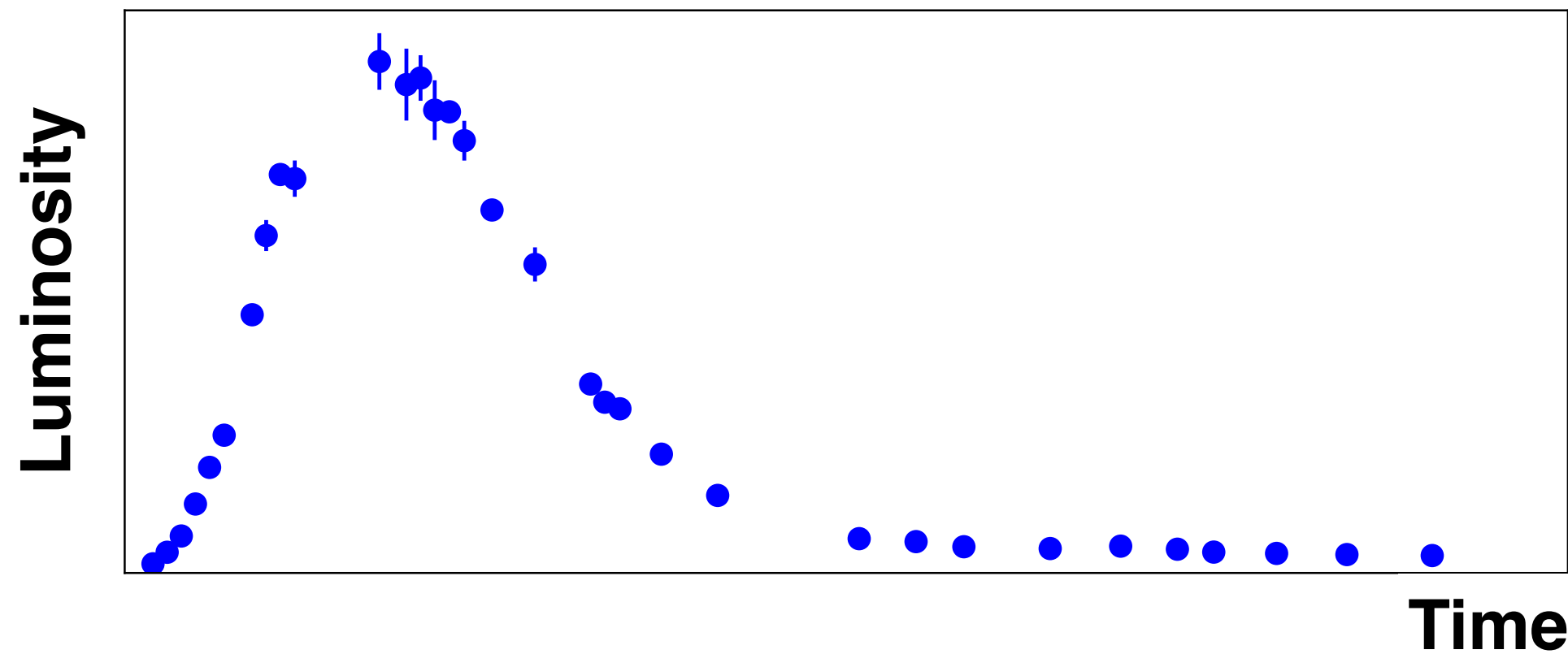
Reference  
Image



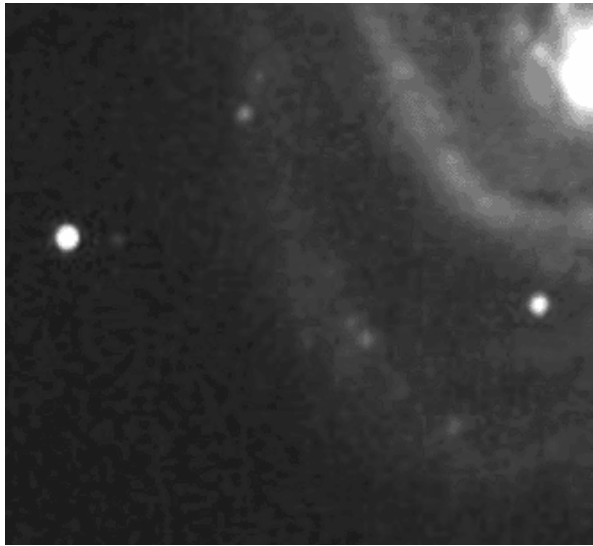
**New  
Image**



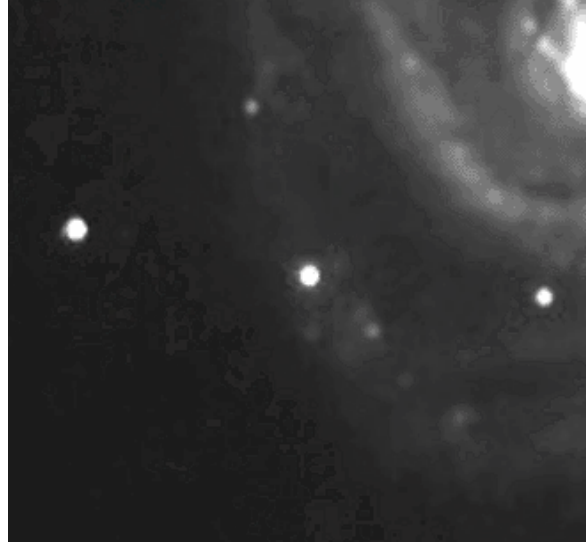
Difference  
Image



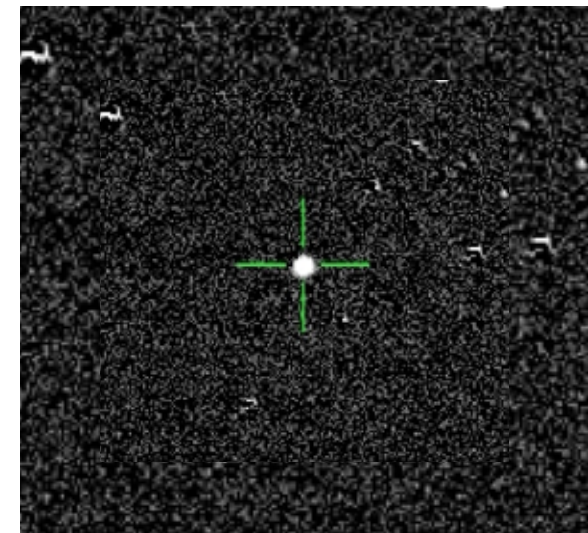
# Detection



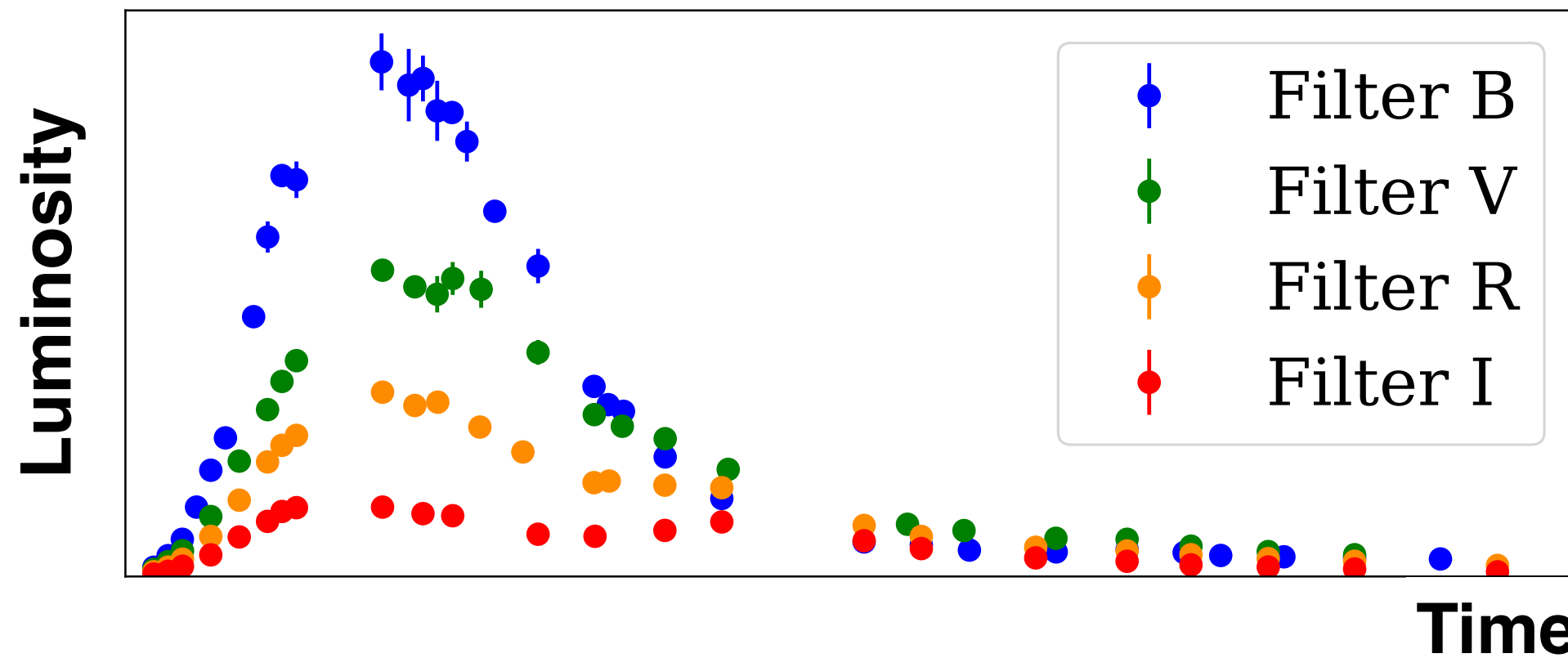
Reference  
Image

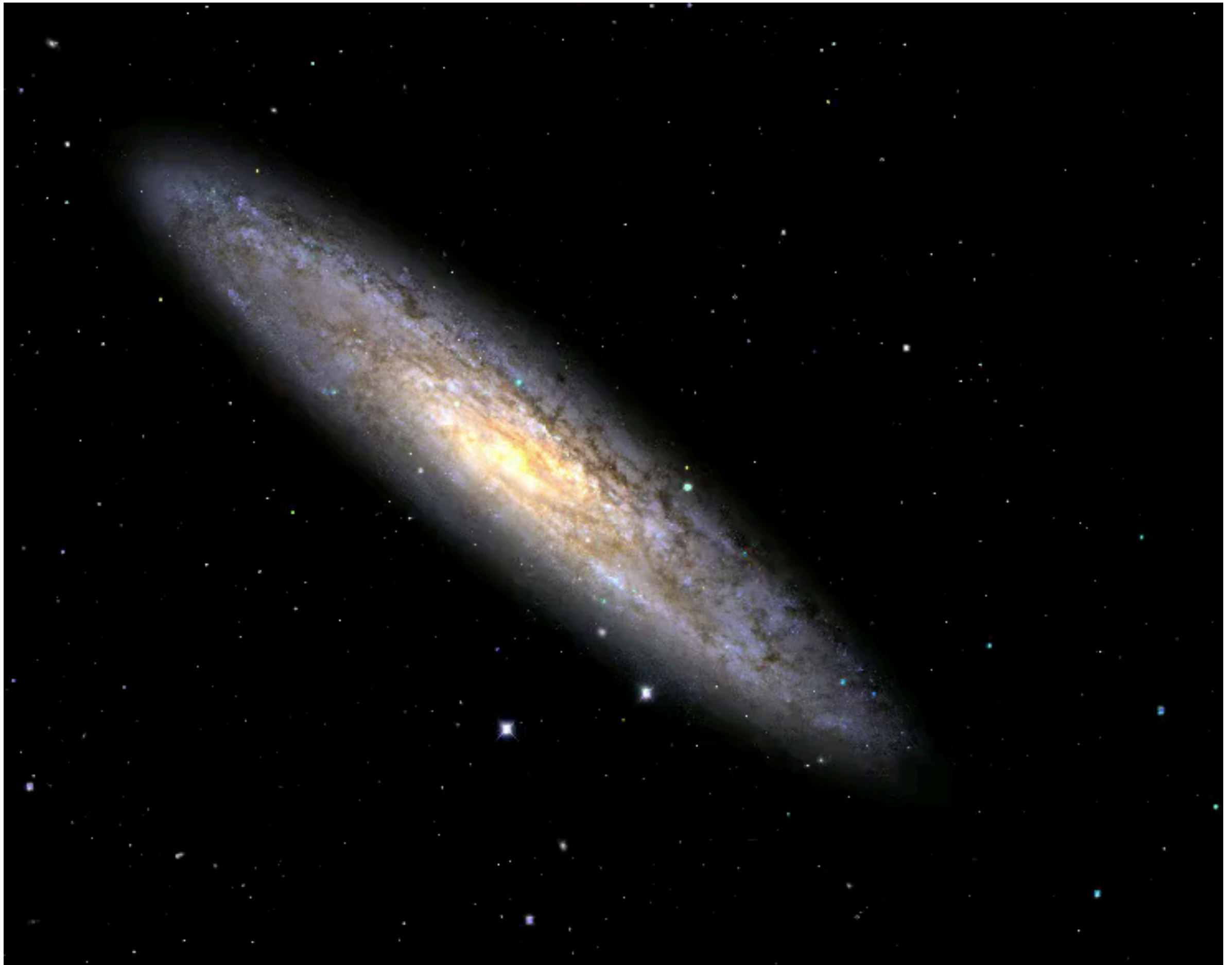


**New  
Image**



Difference  
Image





# Surveys

**Dark Energy Survey  
(DES)**

2013-2018

**Large Synoptic Survey  
Telescope (LSST)**

2020-2030



# Surveys

## Dark Energy Survey (DES)

2013-2018

- 27 deg<sup>2</sup> of the sky
- 4 filters



## Large Synoptic Survey Telescope (LSST)

2020-2030

>0.1 TB of data per night

30.000 transients in 5 years

# Surveys

## Dark Energy Survey (DES)

2013-2018

- 27 deg<sup>2</sup> of the sky
- 4 filters

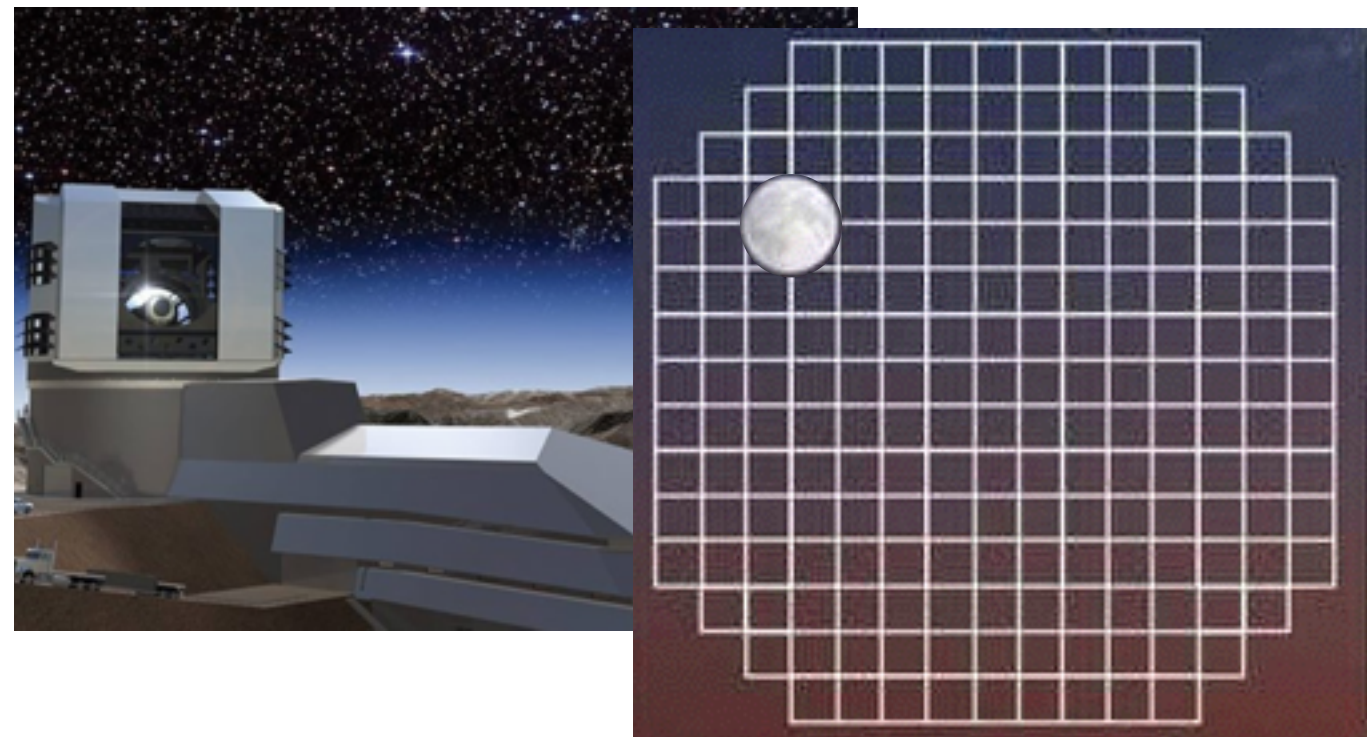


>0.1 TB of data per night  
30.000 transients in 5 years

## Large Synoptic Survey Telescope (LSST)

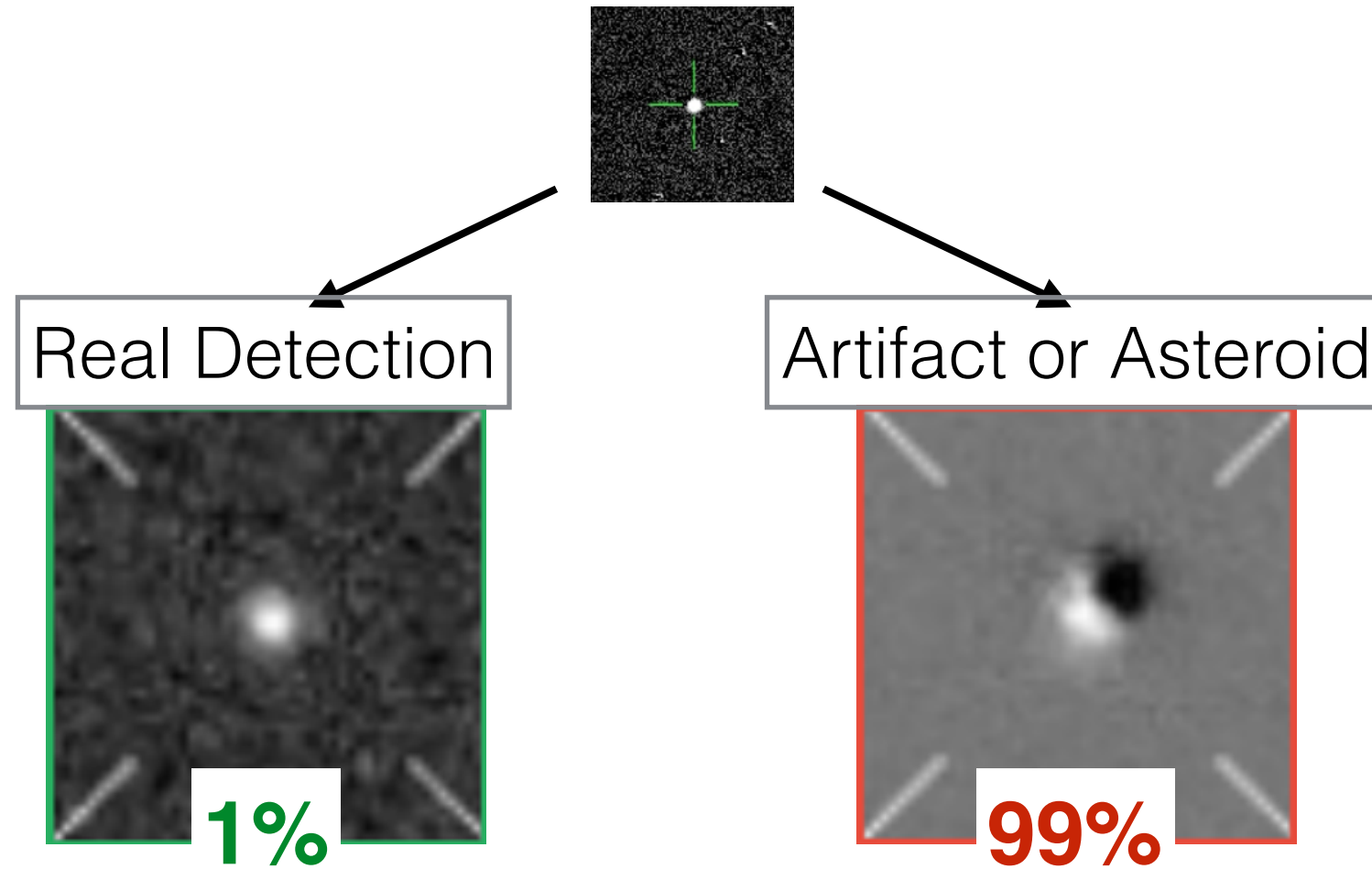
2020-2030

- 1500 deg<sup>2</sup> of the sky
- 6 filters



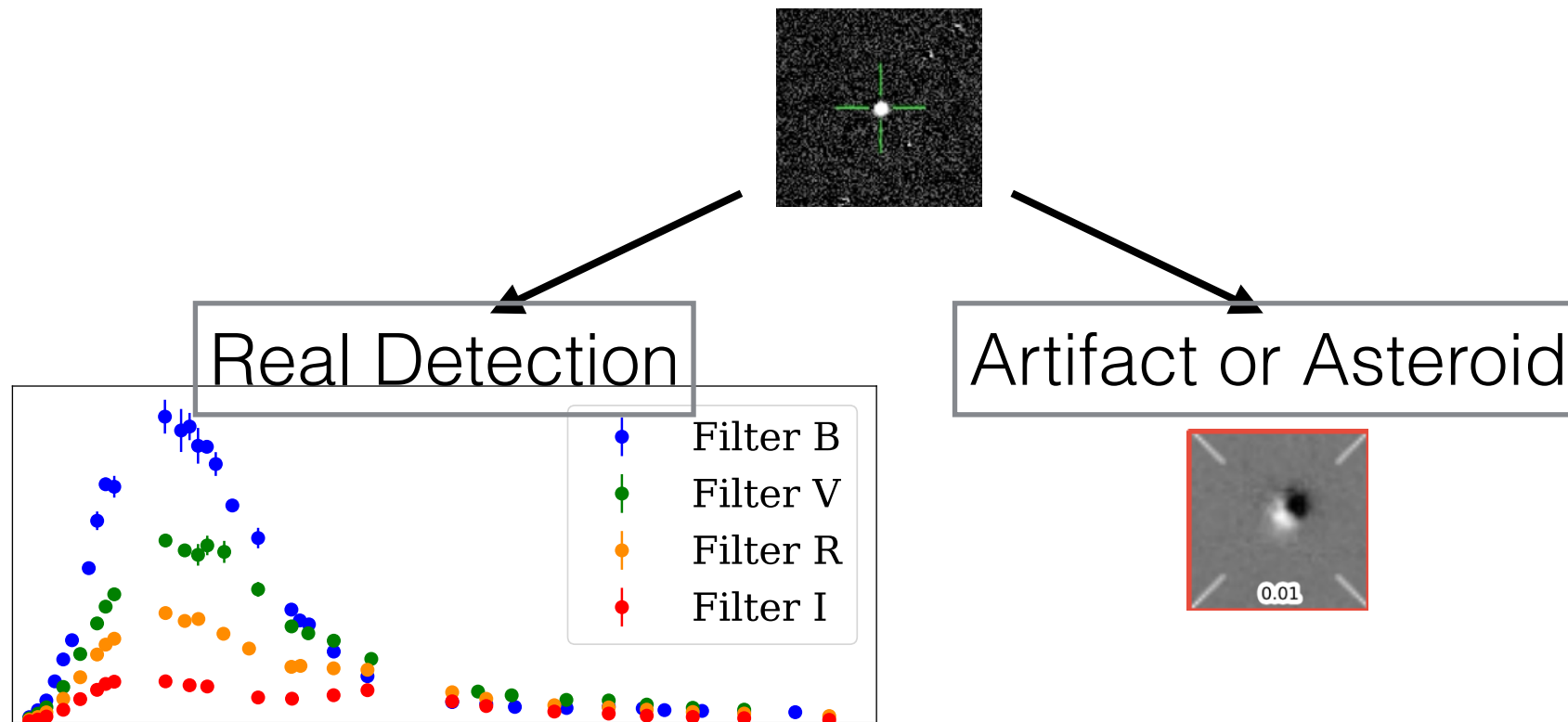
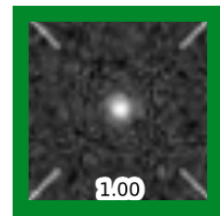
20 TB of data to process **per night**  
10<sup>6</sup> transients alerts **per night**  
Billions of transients in 10 years

# How this works in practice

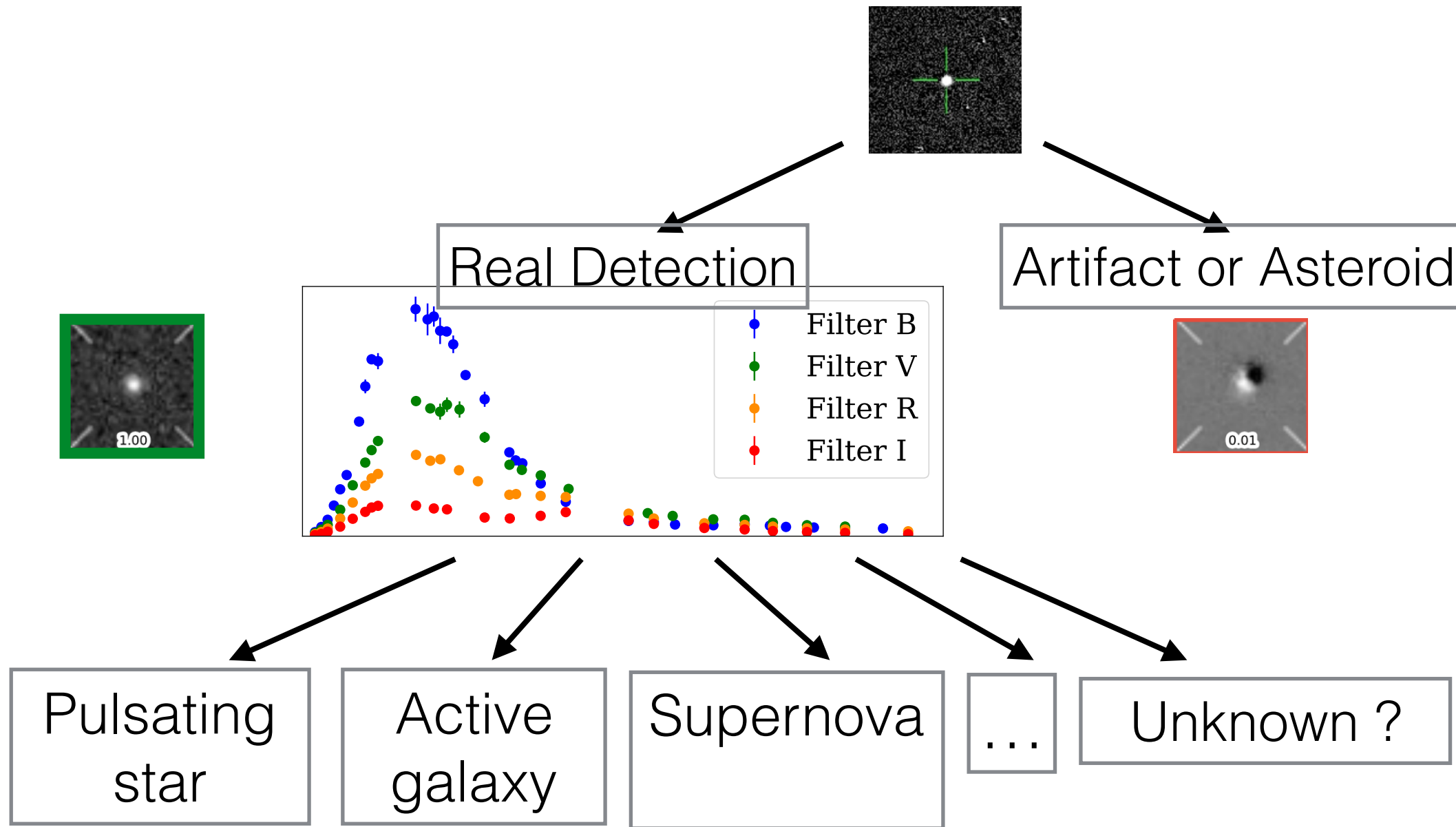




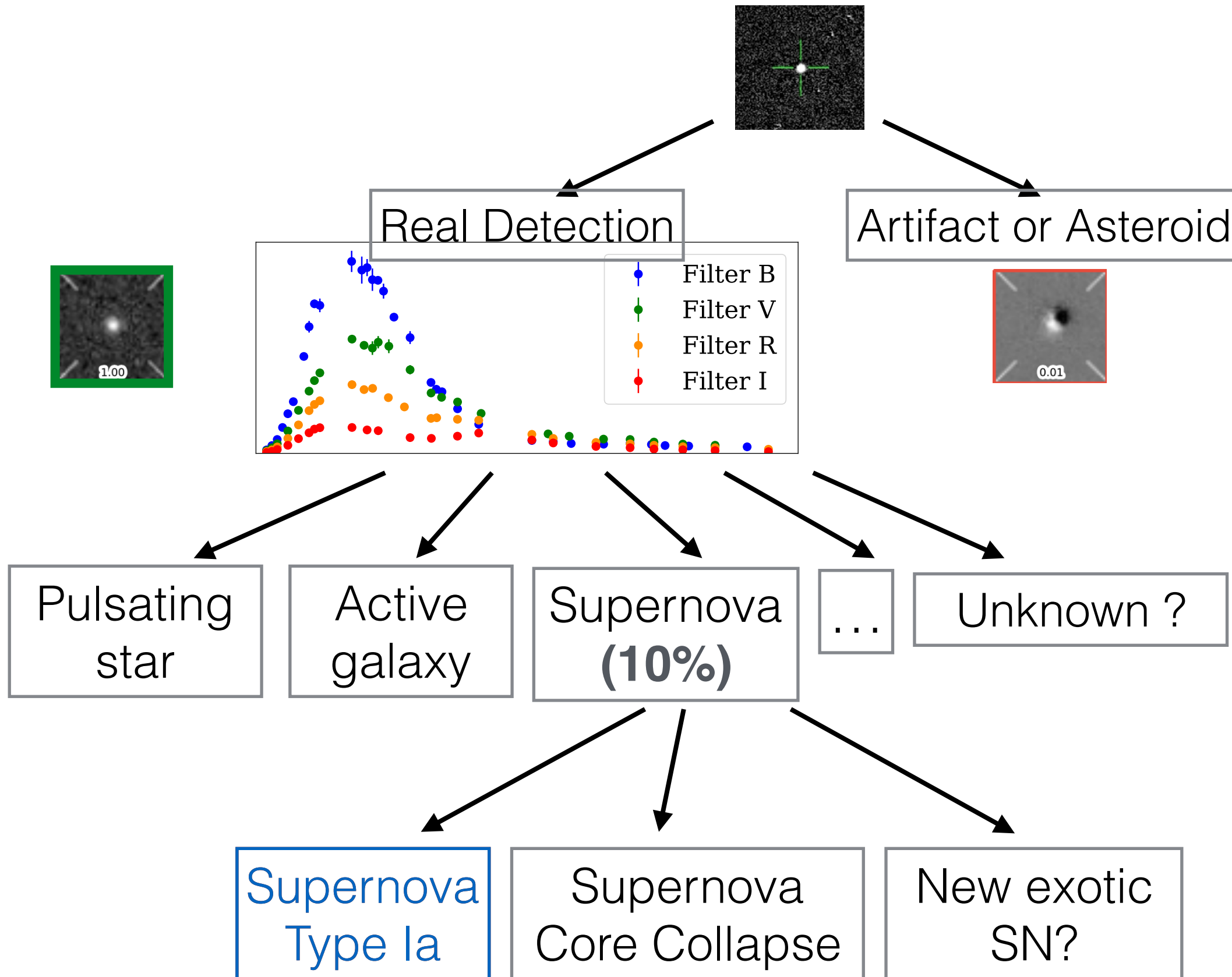
# How this works in practice



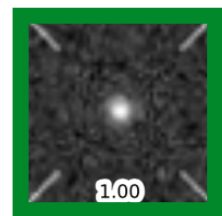
# How this works in practice



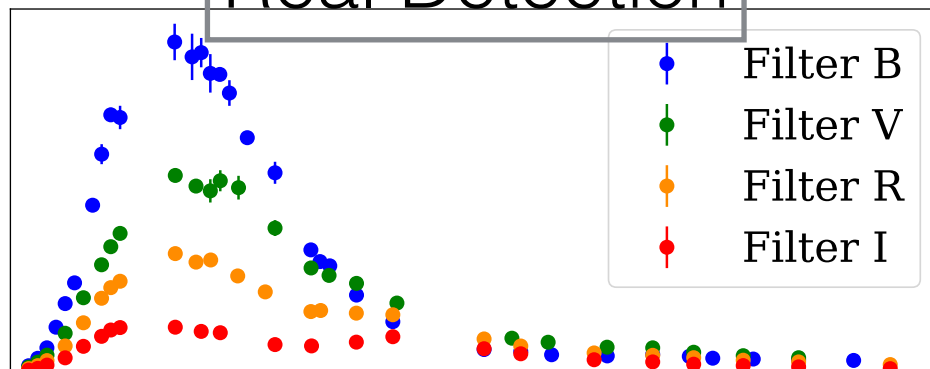
# How this works in practice



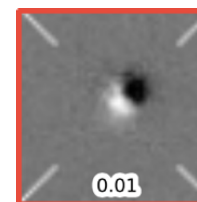
# How this works in practice



Real Detection



Artifact or Asteroid



*OK!*

Goldstein et al. 2016

Pulsating  
star

Active  
galaxy

Supernova  
(10%)

...

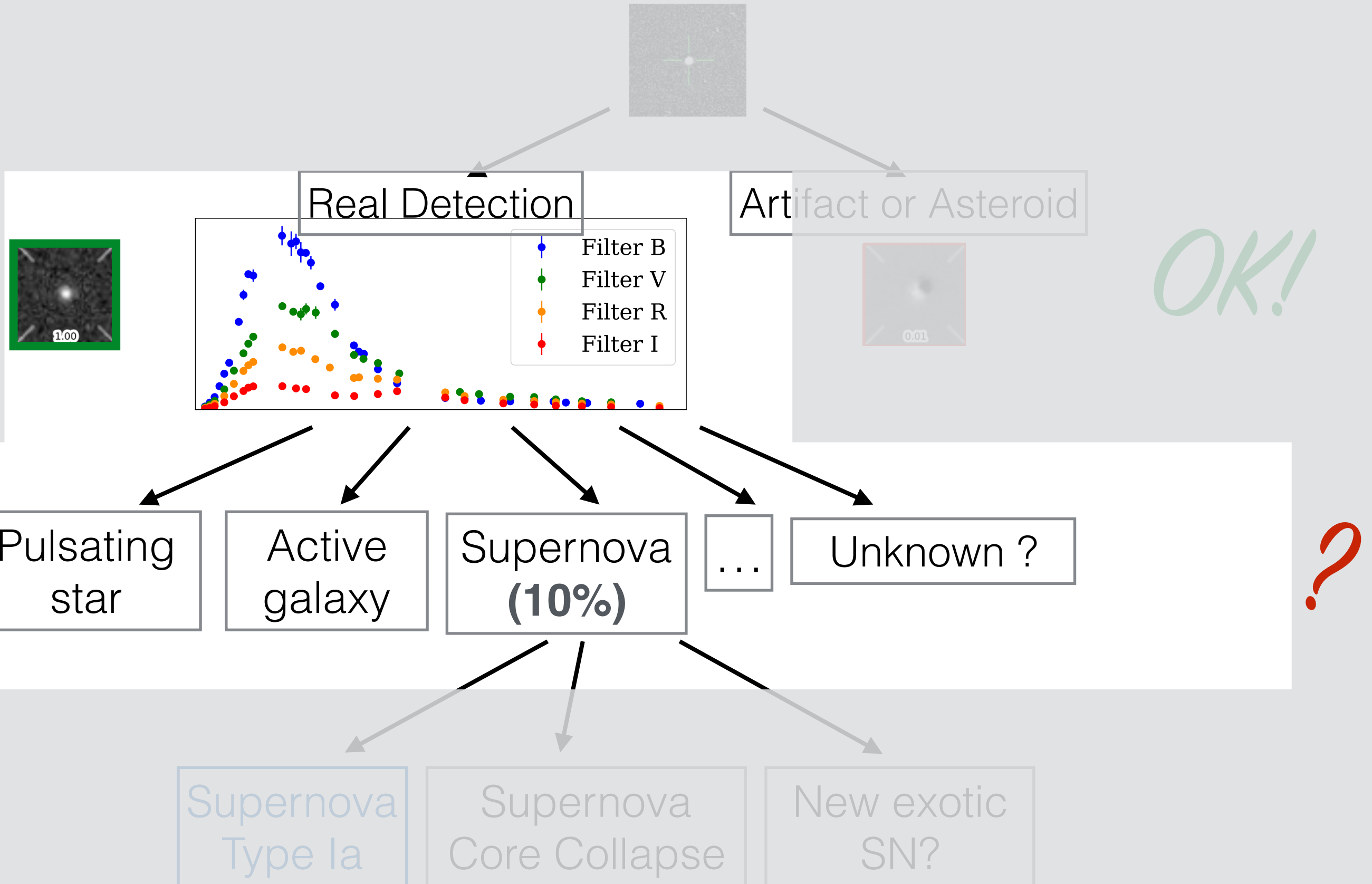
Unknown ?

Supernova  
Type Ia

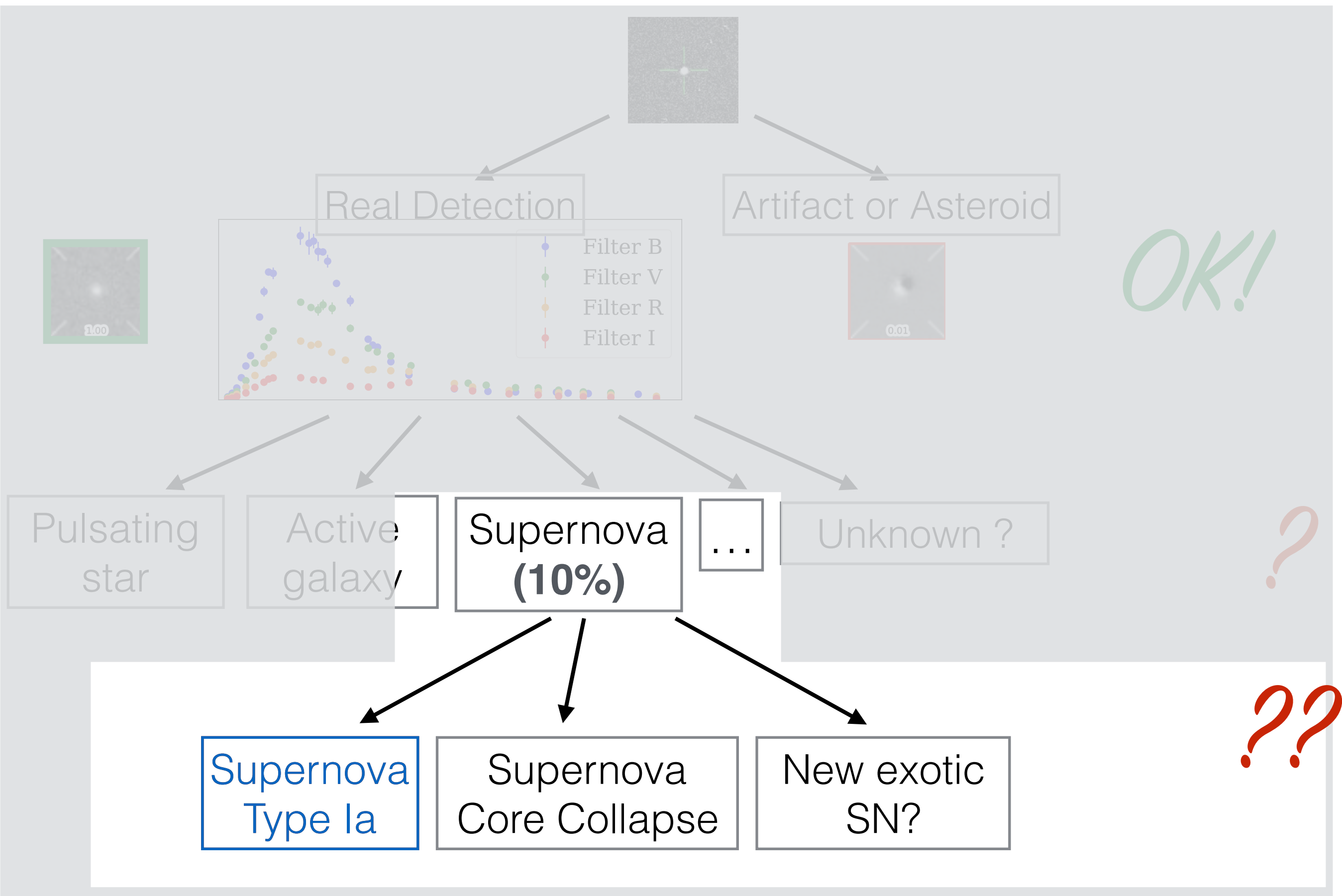
Supernova  
Core Collapse

New exotic  
SN?

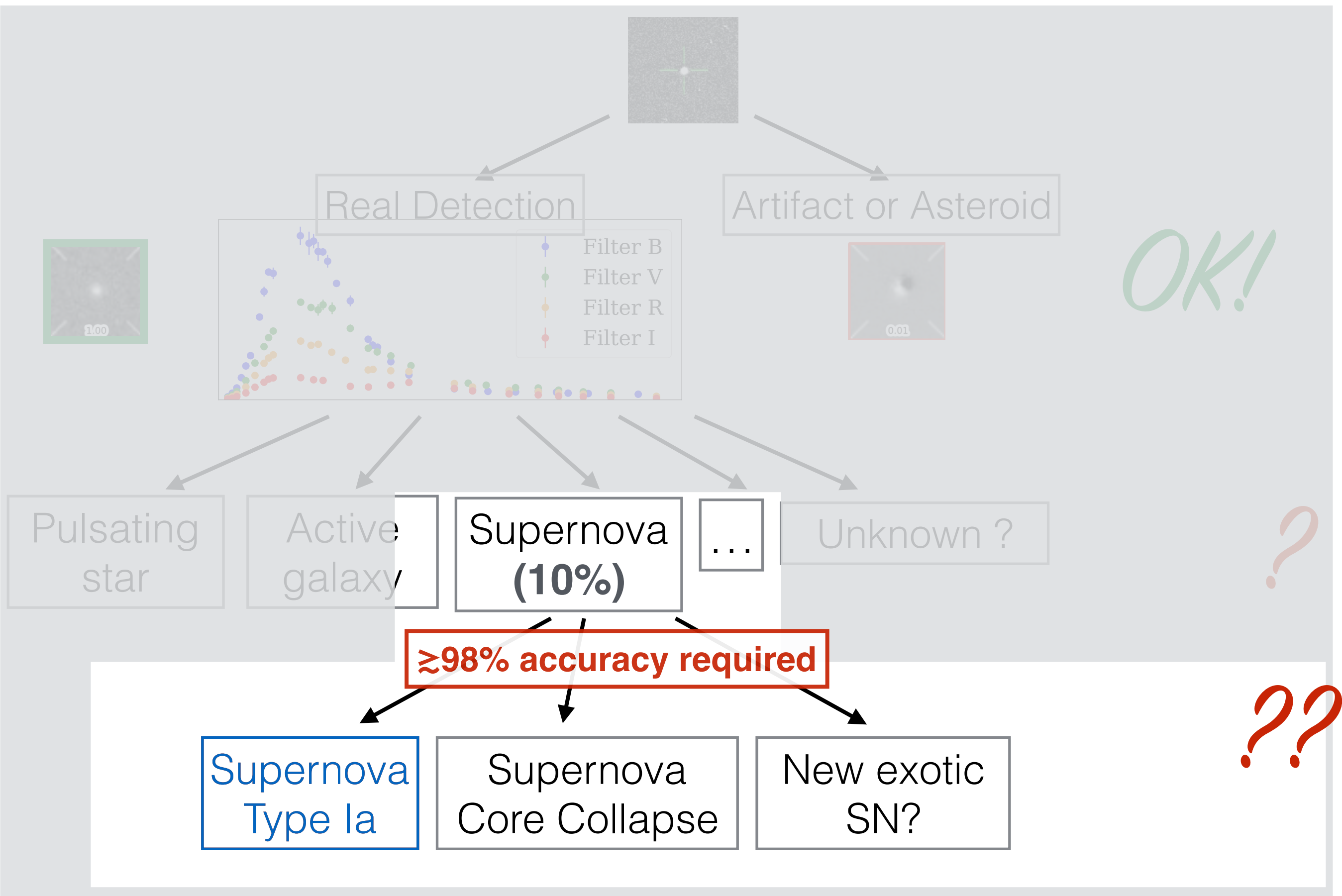
# How this works in practice



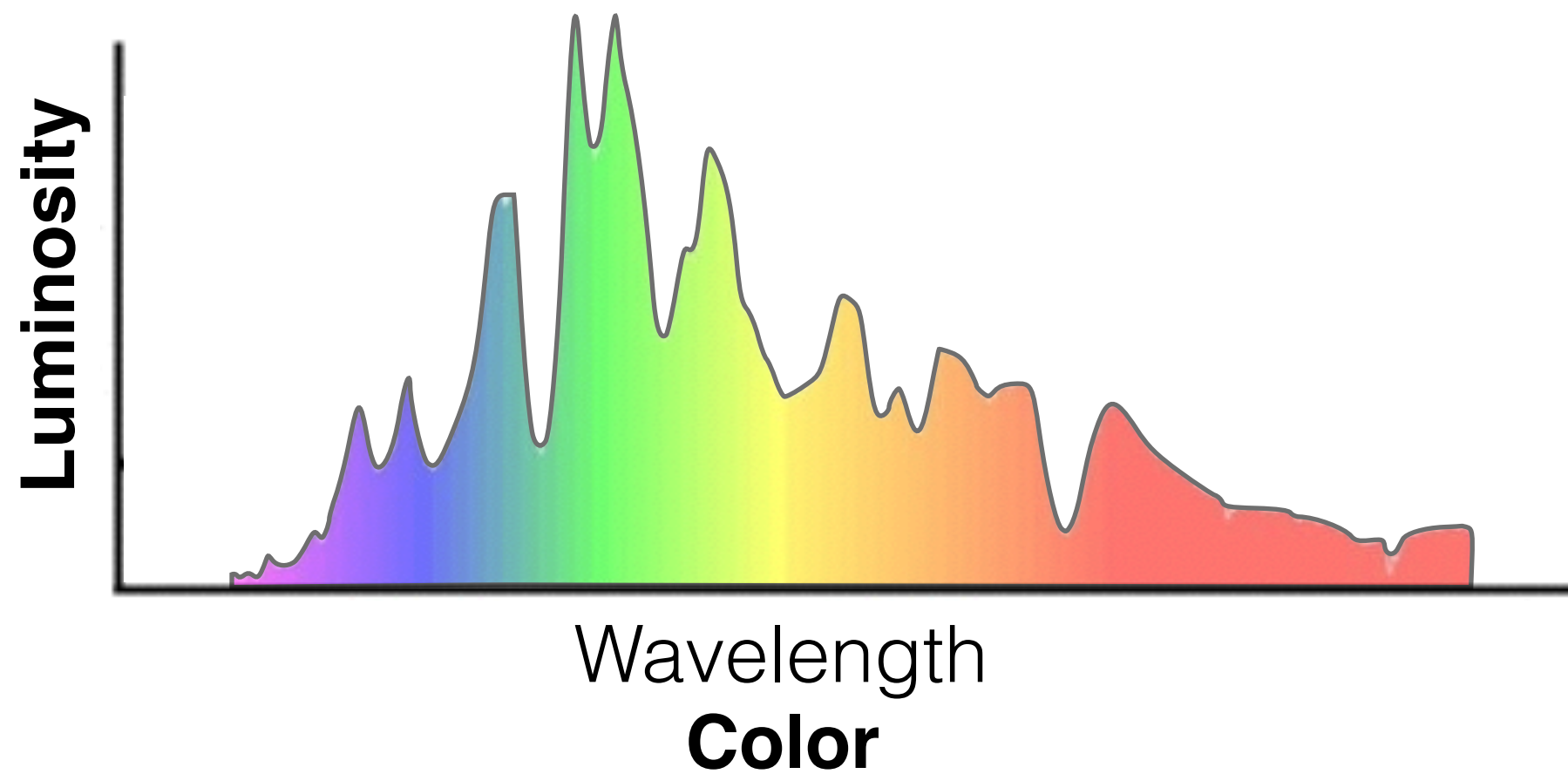
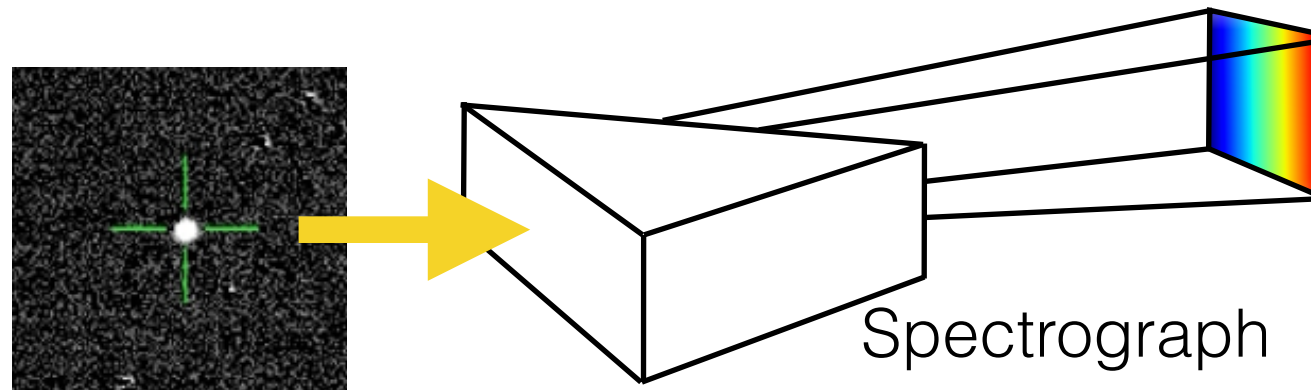
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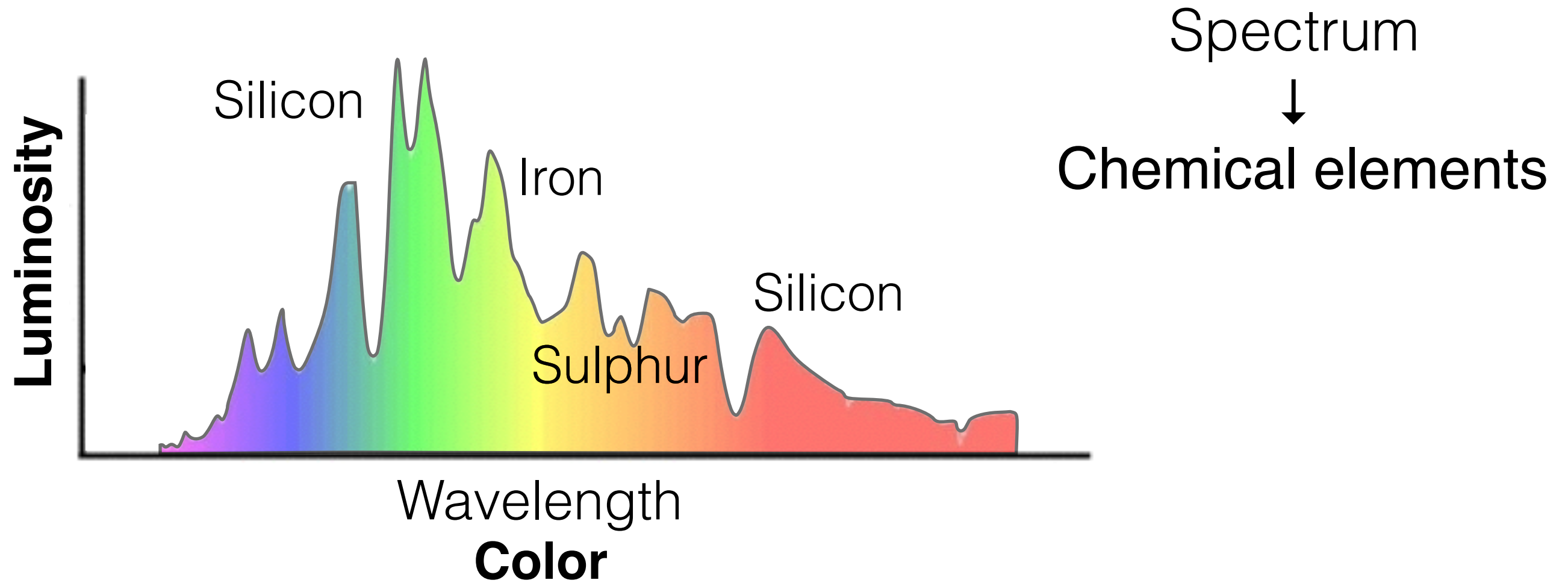
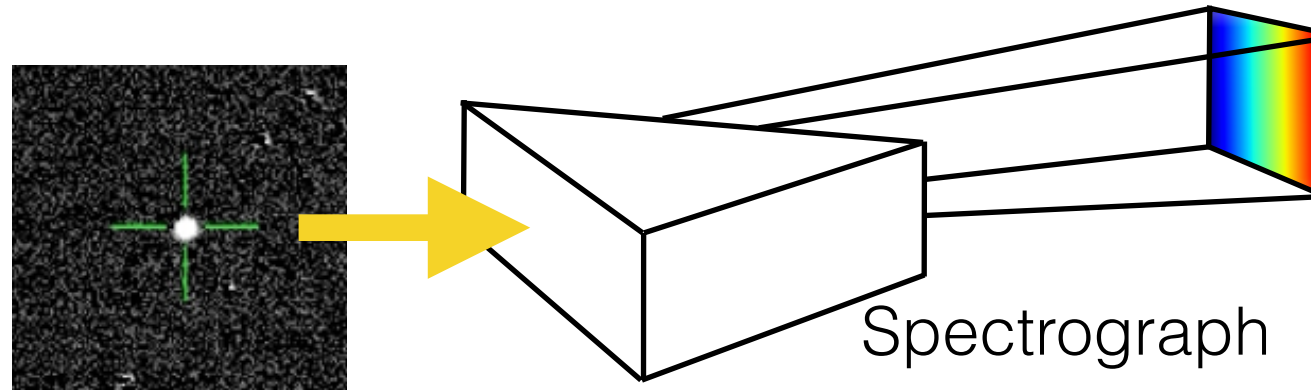


# Imaging —> **Spectroscopy**

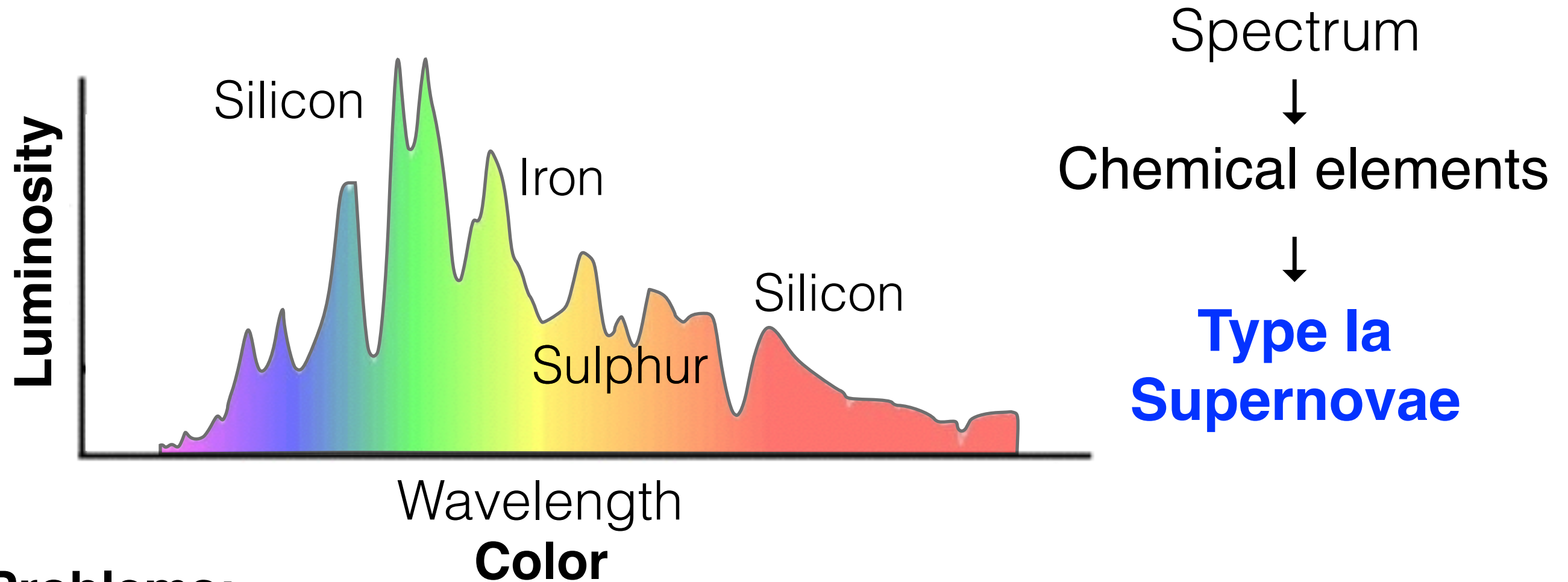
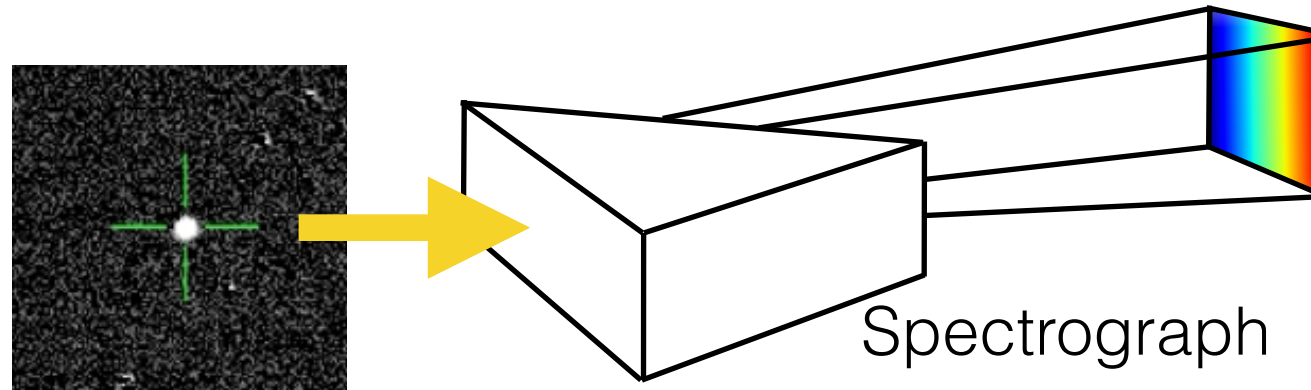




# Imaging —> Spectroscopy



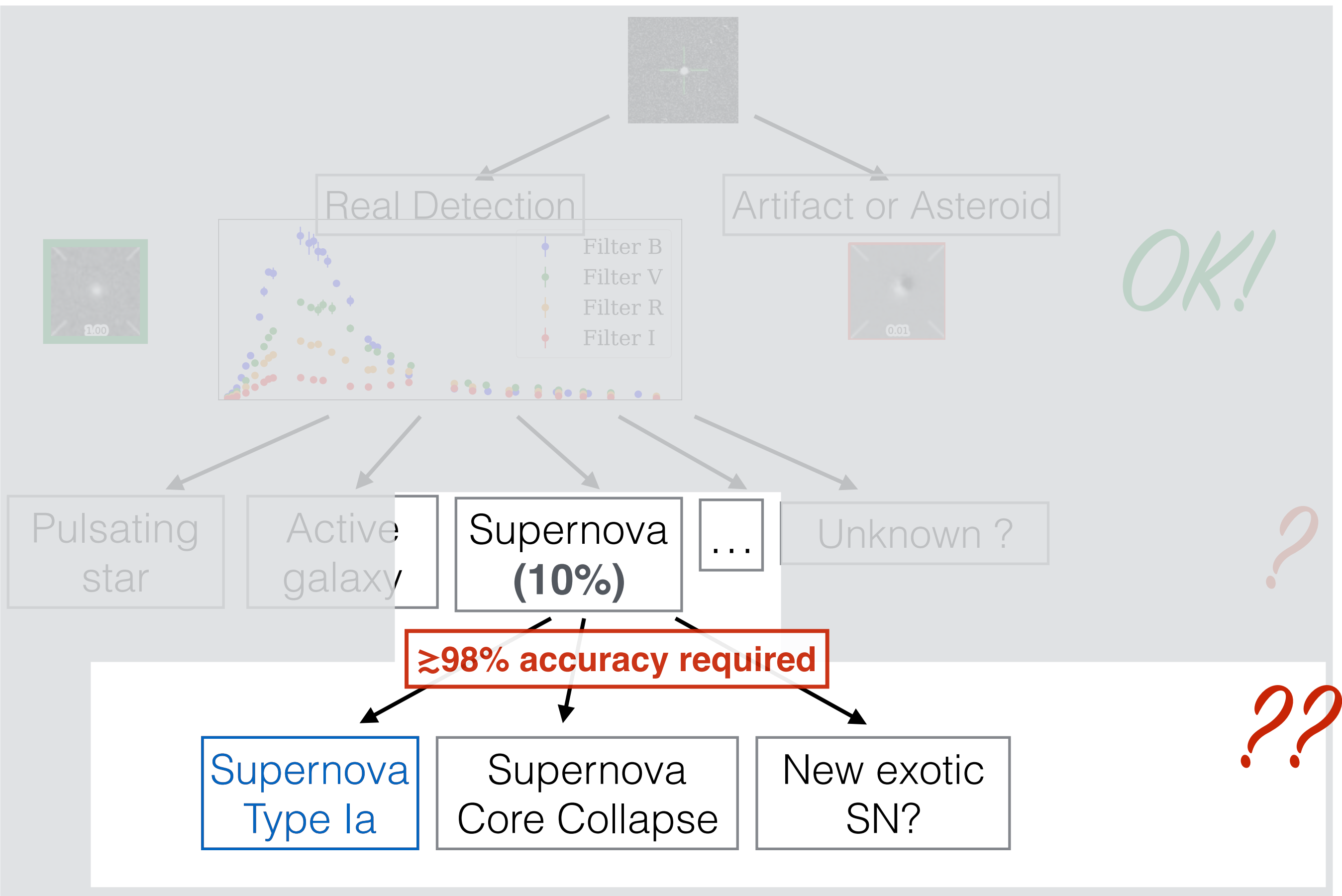
# Imaging —> Spectroscopy



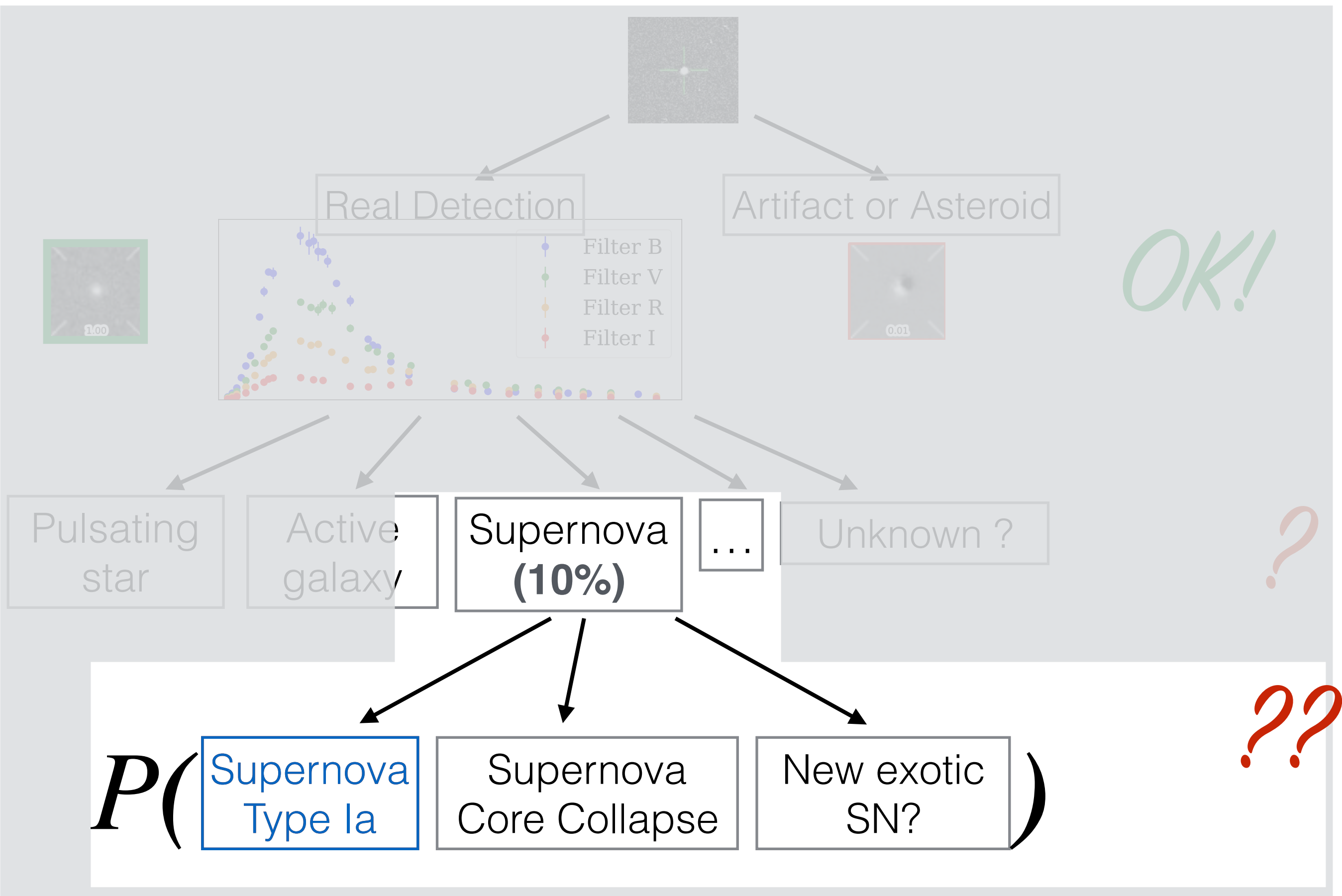
## Problems:

- Only 10% of the sample can be scanned with spectrograph
- Training sample: bias towards brighter objects (i.e. SNe Ia)

# How this works in practice



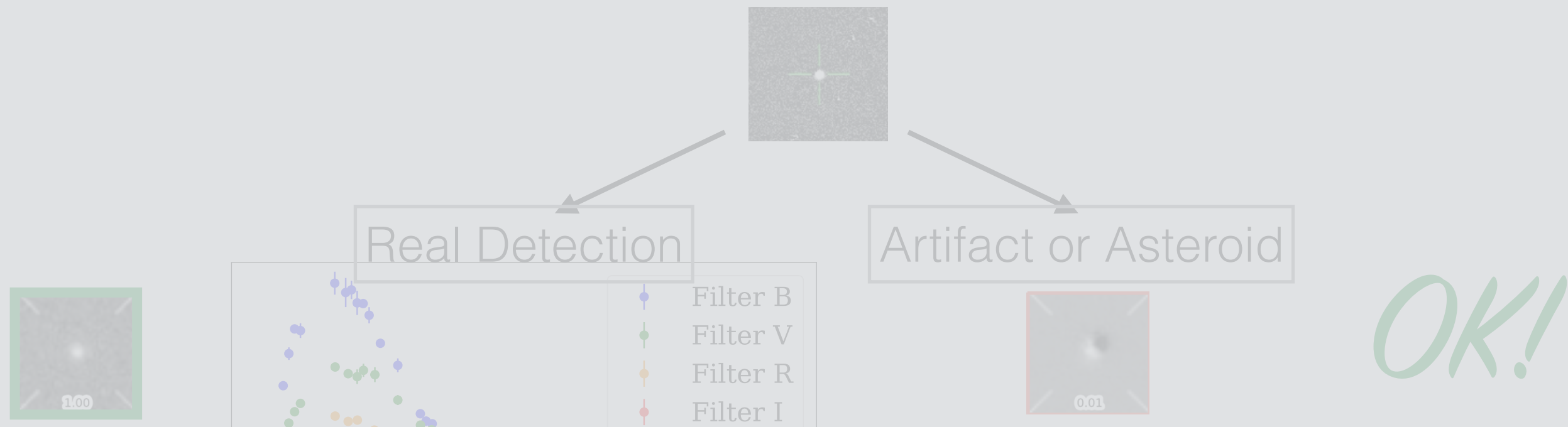
# How this works in practice



# **Challenges to the community of astronomers and data scientists**

**SN Photometric Classification Challenge,  
SNPhotCC (2010)**

**Photometric Classification Challenge for LSST,  
PLAsTiCC (2018)**



## SN Photometric Classification Challenge, SNPhotCC (2010)

Pulsating  
star

Active  
galaxy

Supernova

...

Unknown ?

?

$P(\text{Supernova Type Ia}, \text{Supernova Core Collapse}, \text{New exotic SN?})$

# **SN Photometric Classification Challenge, SNPhotCC (2010)**

Simulations using 3 Classes (SN Ia, 2 types of CC SN)

**Training sample:** 1,103 Supernovae

**Test sample:** 20,216 Supernovae

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## **PSNID**

Template fitting,  
no ML involved

Sako et al. 2008,  
Sako et al. 2014

## **SNmachine**

Feature engineering +  
ML algorithms  
(RF, NB, SVM, BDT,  
ANN)

Lochner et al. 2016



# **SNmachine (Lochner et al. 2016)**

Method (1)

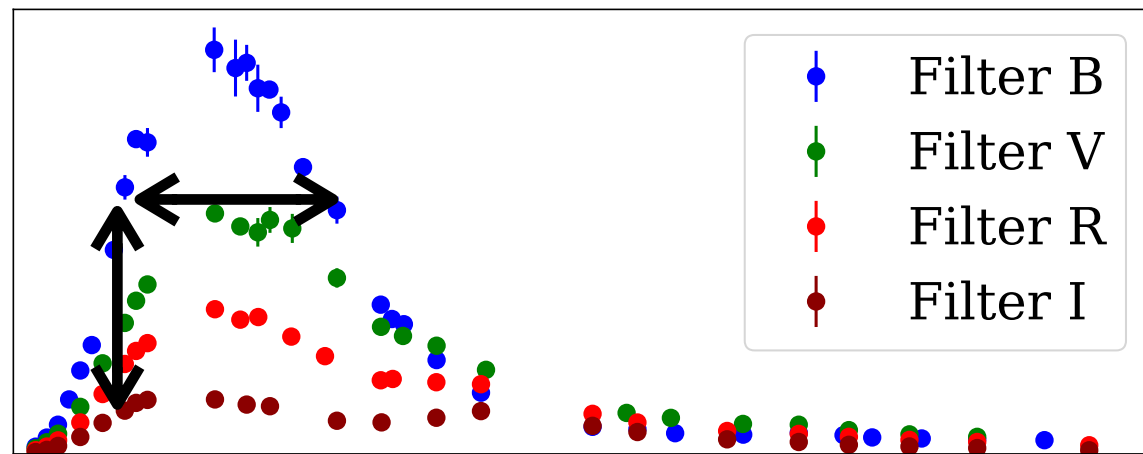
Method (2)

# SNmachine (Lochner et al.2016)

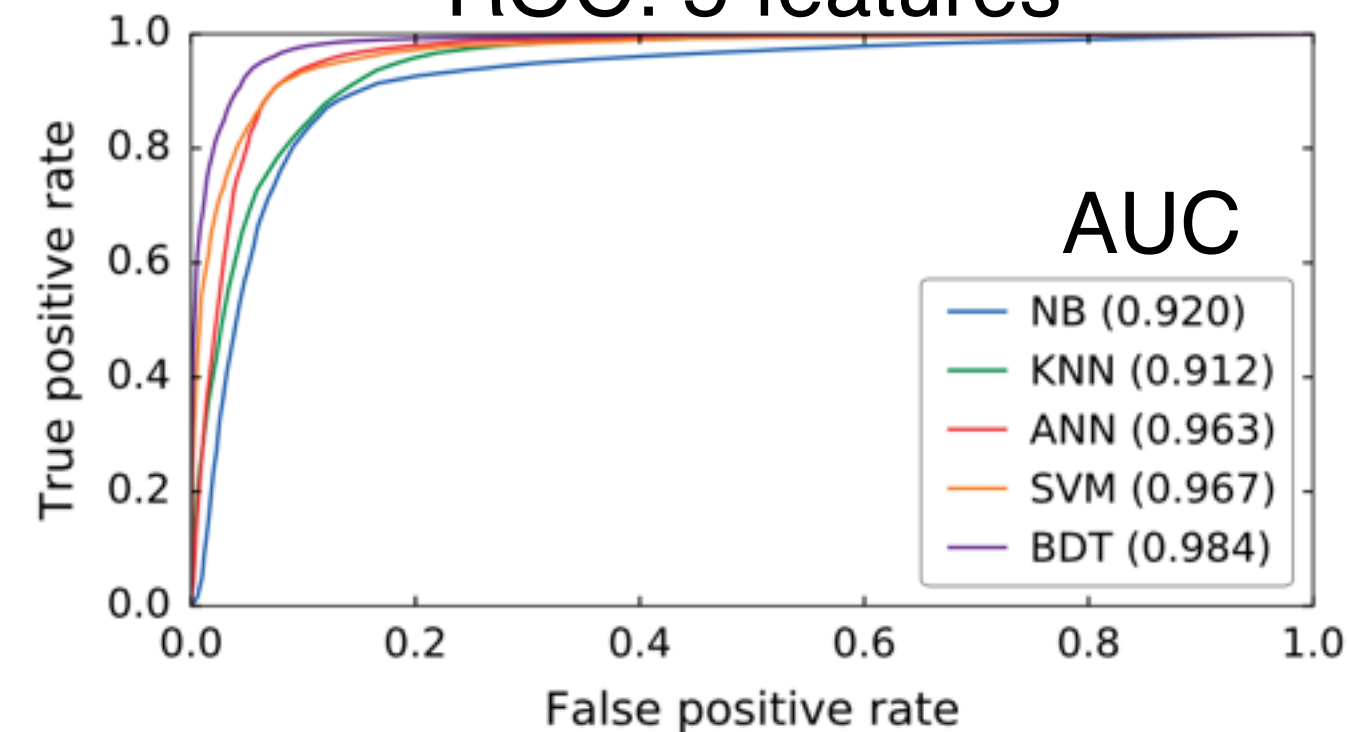
## Method (1)

→ 5 features: width, amplitude, color (B vs V), rise time, galaxy recession velocity

## Method (2)



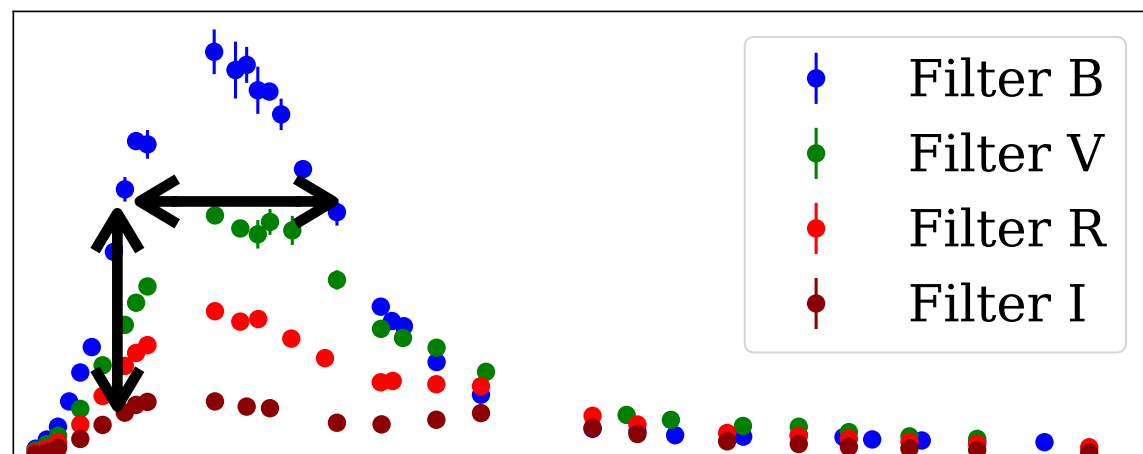
## ROC: 5 features



# SNmachine (Lochner et al.2016)

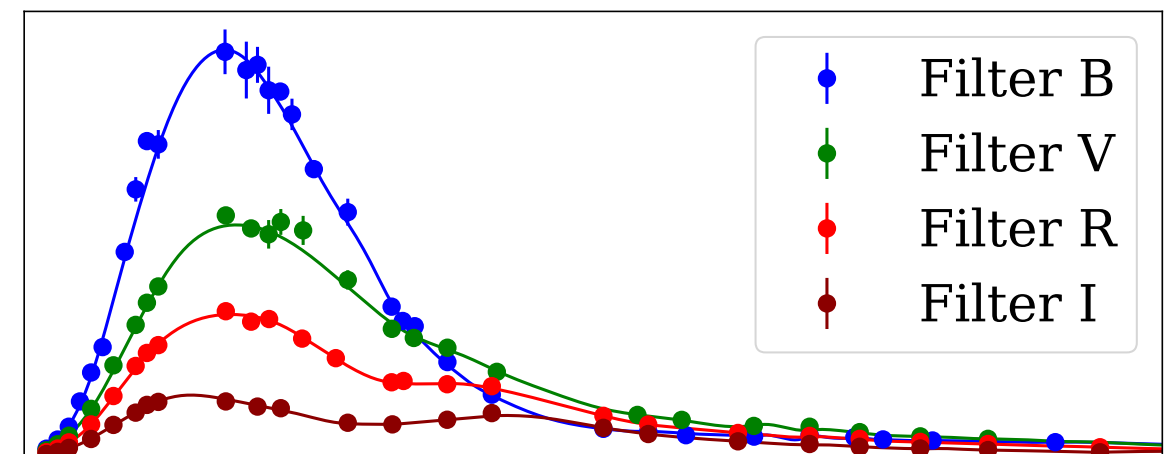
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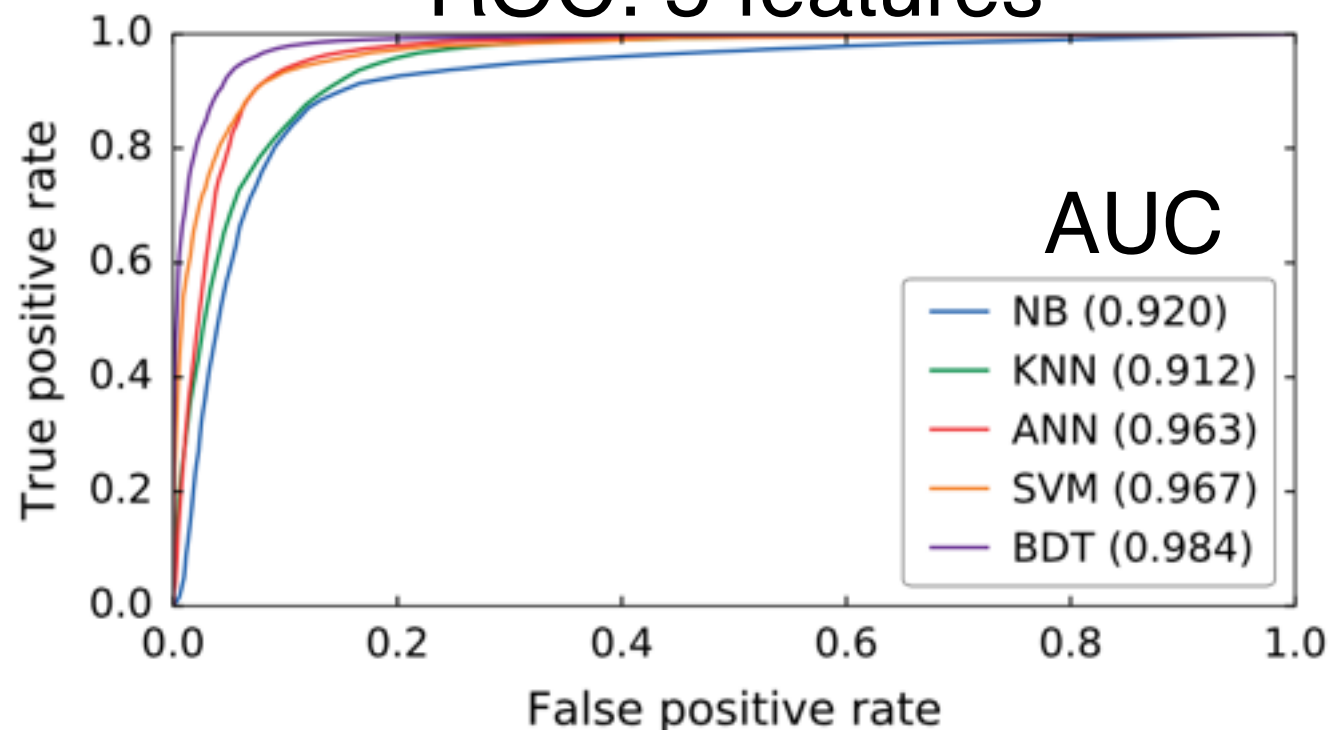


## Method (2)

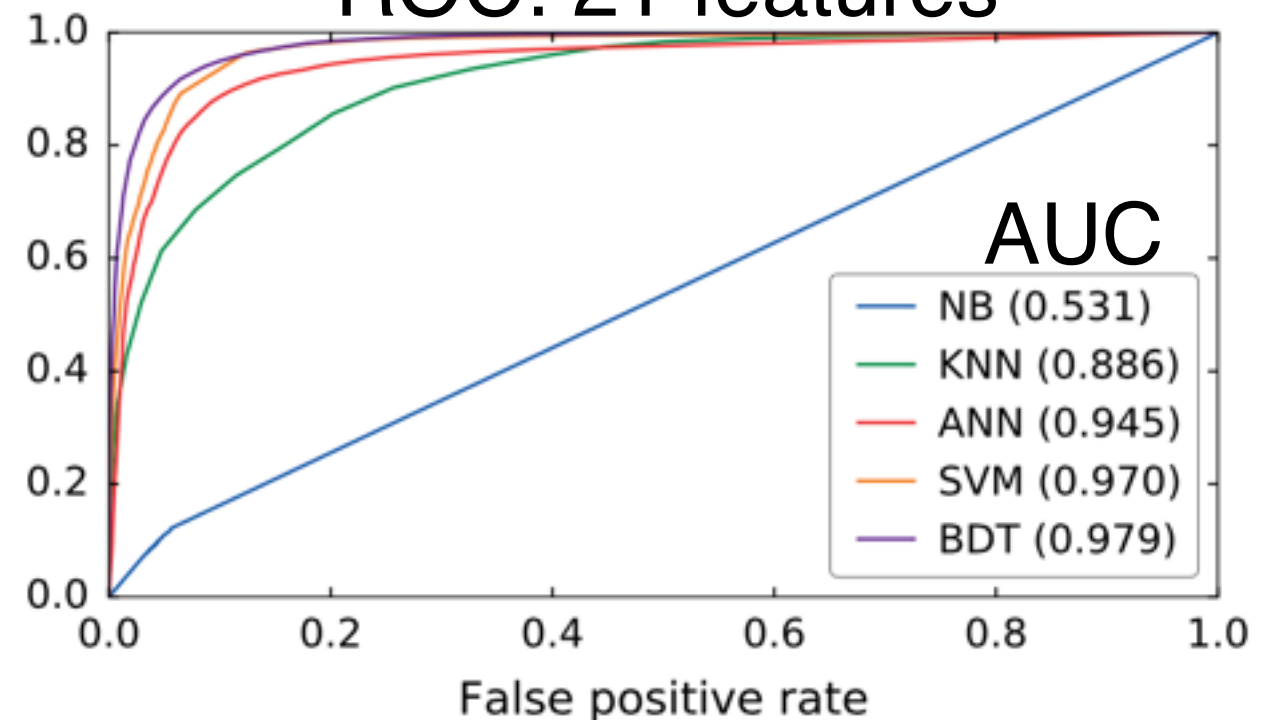
→ 21 features: Gaussian Processes +Wavelet decomposition, galaxy recession velocity



ROC: 5 features



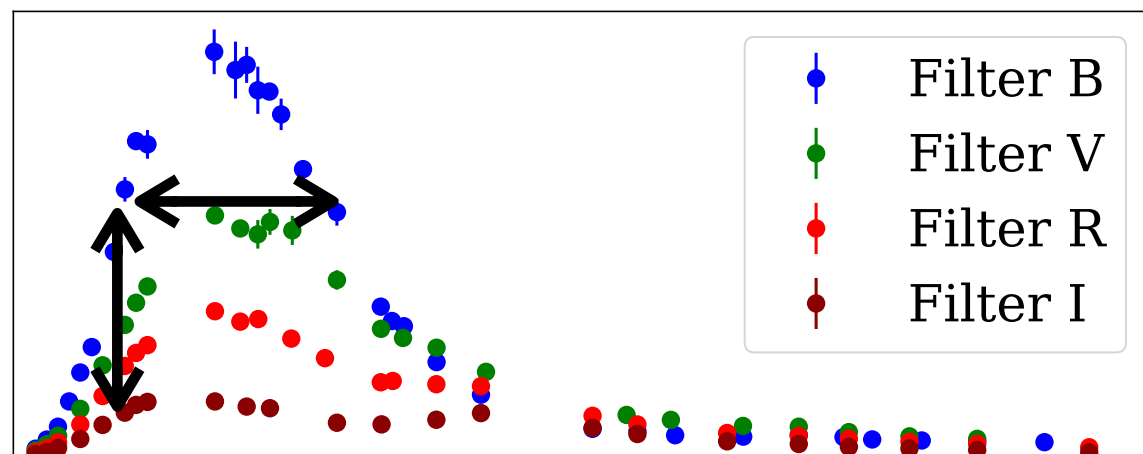
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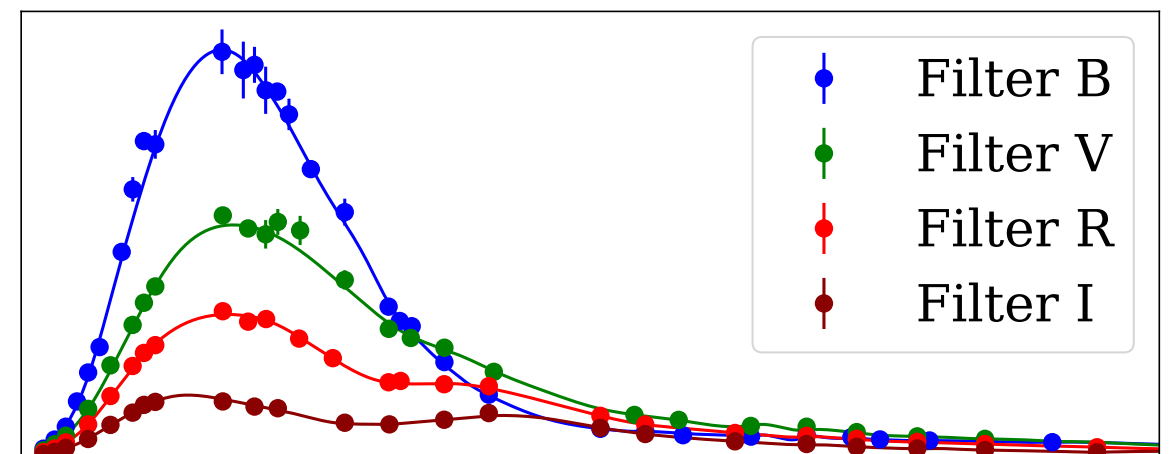
## Method (1)

→ 5 features: width, amplitude, color (B vs V), rise time, galaxy recession velocity



## Method (2)

→ 21 features: Gaussian Processes +Wavelet decomposition, galaxy recession velocity



$AUC < 0.85$  if original training sample  
since this is not representative of the test  
sample.

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Template fitting,  
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Sako et al. 2008,  
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## RNN

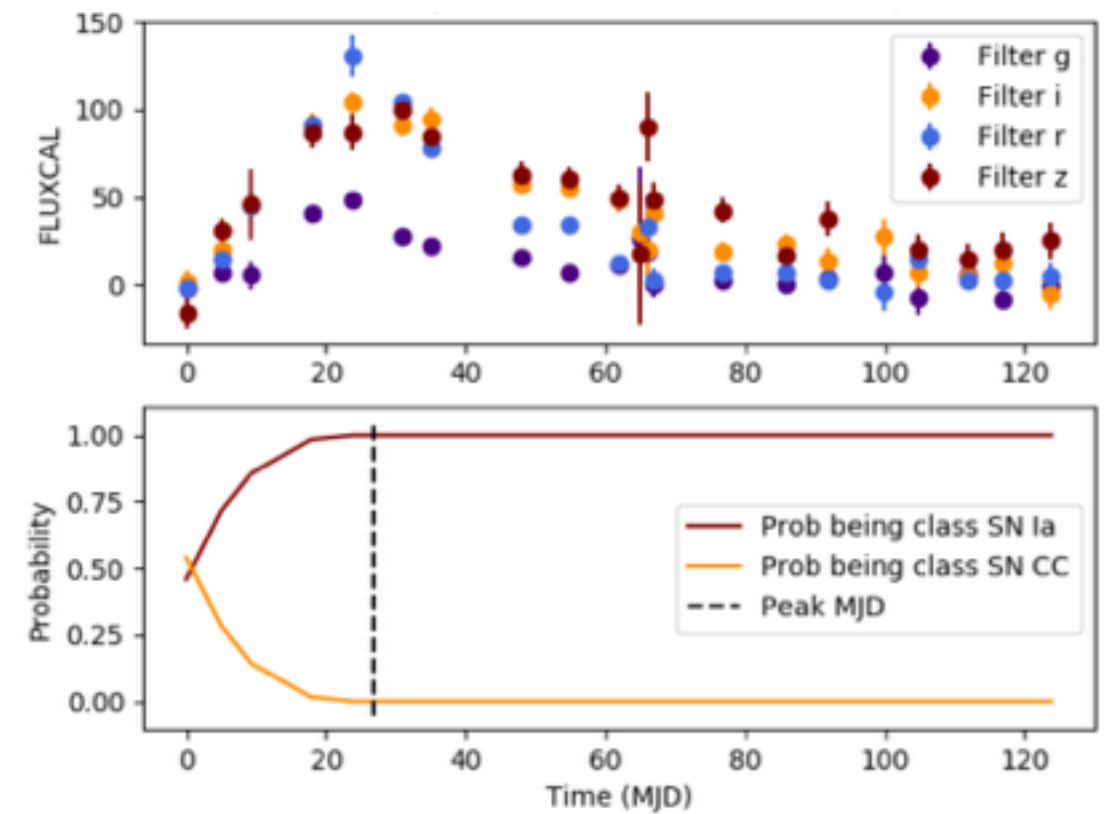
No feature extraction,  
raw data and  
Recurrent NN

Charnock&Moss 2017  
Moller et al. 2019



## Recurrent Neural Networks (Moller et al. 2019)

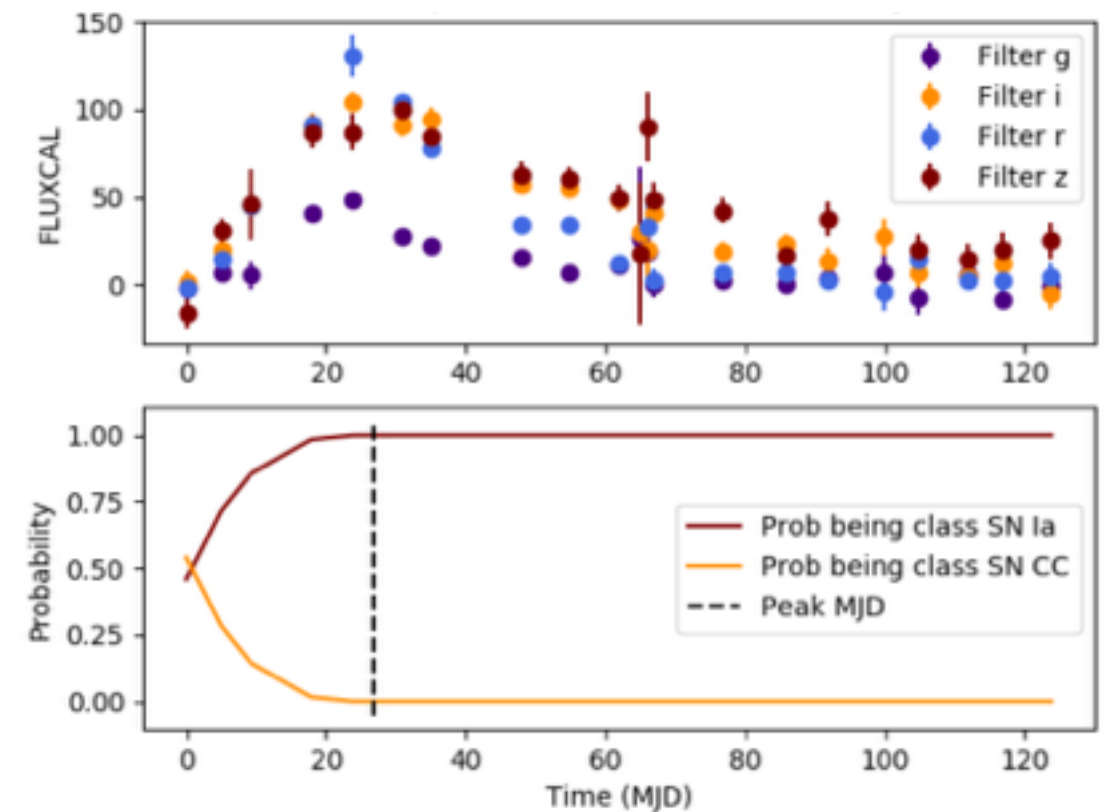
Simulations: 1,983,213 Supernovae





## Recurrent Neural Networks (Moller et al. 2019)

Simulations: 1,983,213 Supernovae



### NON Representative Training Sample (40% Train, 60% Test)

Accuracy (Ia vs CC)

### Representative Training Sample (40% Train, 60% Test)

Accuracy (Ia vs CC)

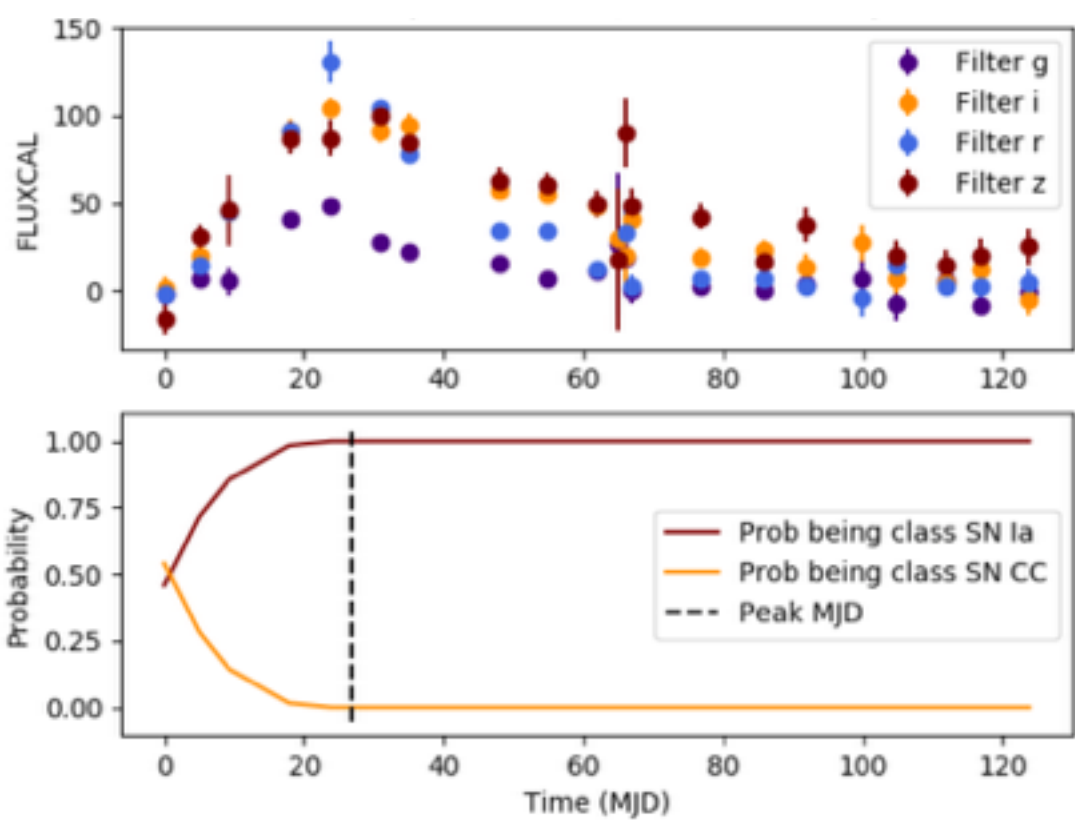
### Training Sample (100%Train, 100%Test)

Accuracy (Ia vs CC)



# Recurrent Neural Networks (Moller et al. 2019)

Simulations: 1,983,213 Supernovae

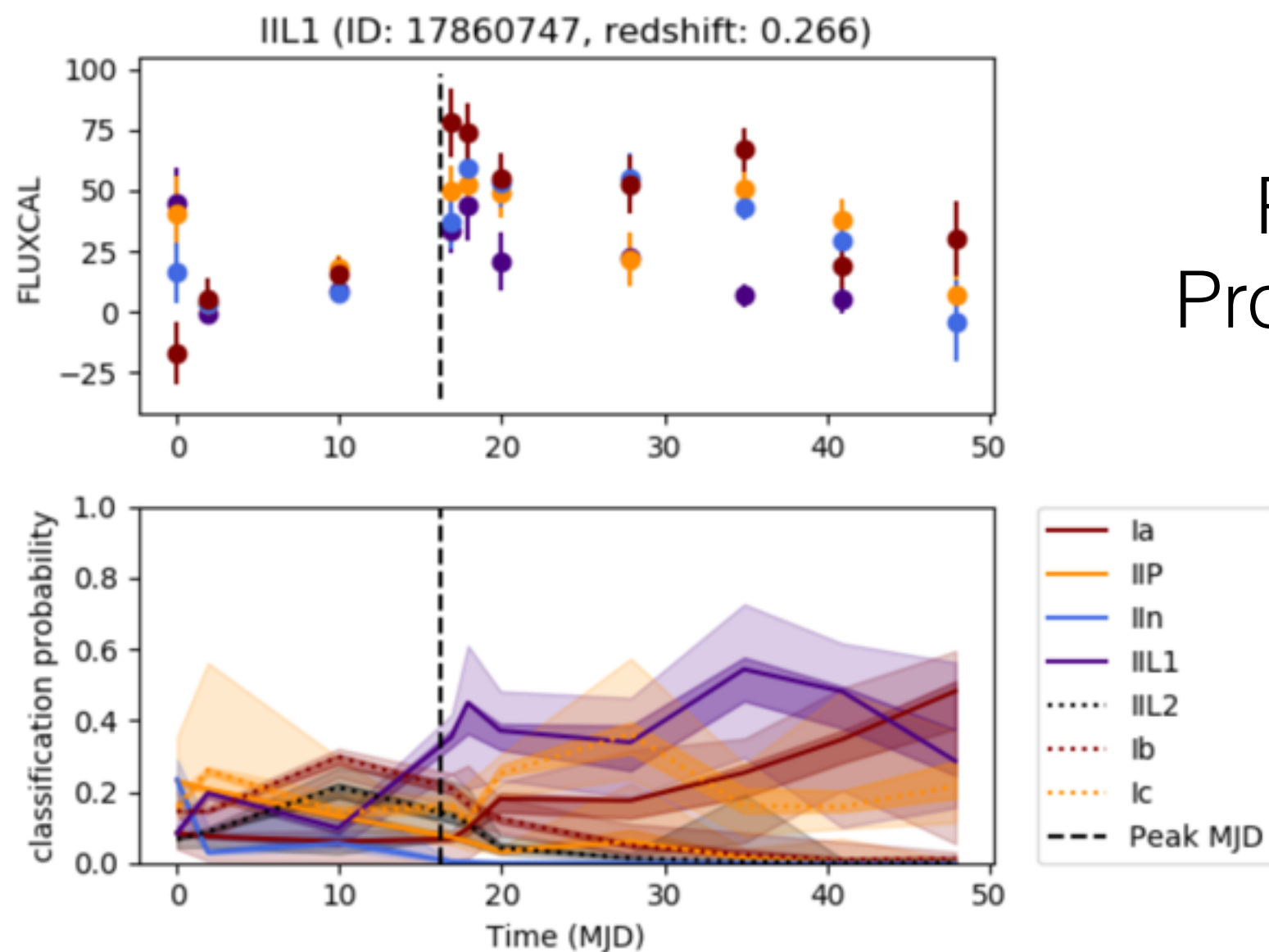


NON Representative Training Sample (40% Train, 60% Test)		
Accuracy (Ia vs CC)	Only first 10 days of data 97.36 ± 0.28	All light curve 99.51 ± 0.08
Representative Training Sample (40% Train, 60% Test)		
Accuracy (Ia vs CC)	92.96 ± 0.77	97.84 ± 0.45
Training Sample (100%Train, 100%Test)		
Accuracy (Ia vs CC)	94.09 ± 0.14	98.43 ± 0.07



## Recurrent Neural Networks (Moller et al. 2019)

Simulations: 1,983,213 Supernovae



Probability errors?  
Probability calibration?

# SN Photometric Classification Challenge, SNPhotCC (2010)

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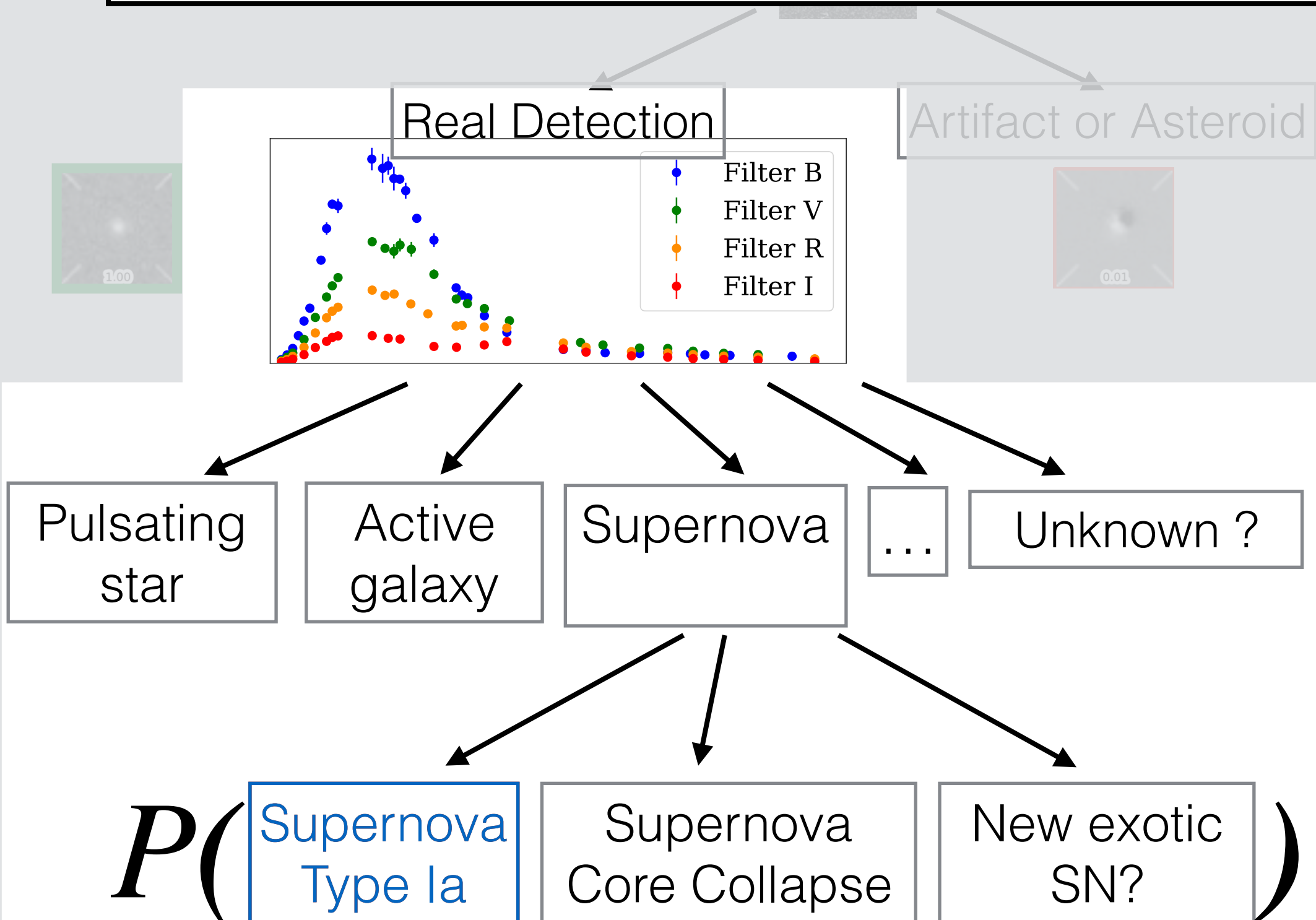
Lochner et al.2016

## RNN

No feature extraction,  
raw data and  
Recurrent NN

Charnock&Moss 2017  
Moller et al. 2019

# Photometric Classification Challenge for LSST, PLAsTiCC (2018)



# Photometric Classification Challenge for LSST, PLAsTiCC (2018)

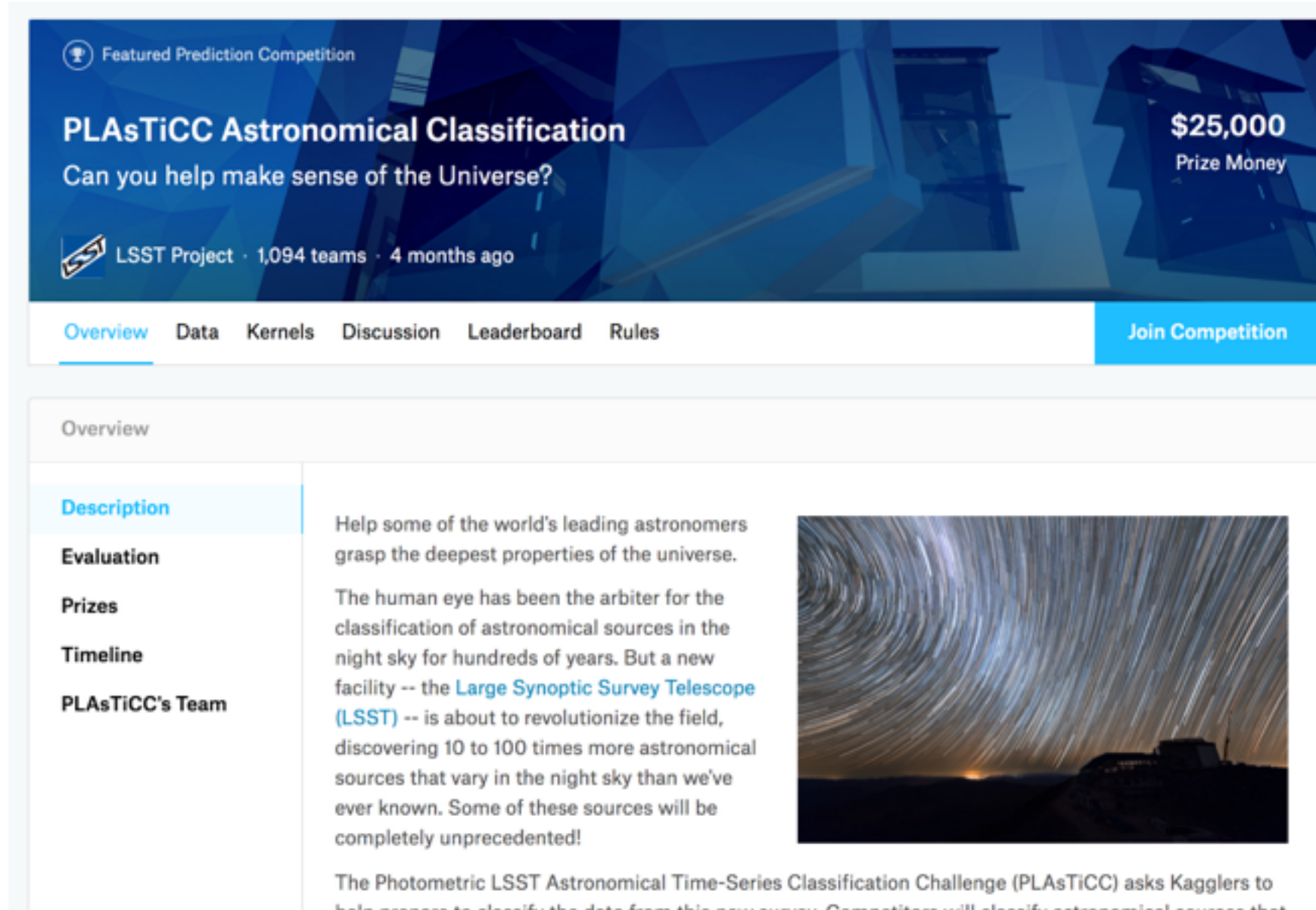
Simulations using 15 classes (6 types of SNe), 14 represented in training sample.

Training: 8000 objects (NON-representative)

Testing: 3.5 million objects

Two challenges:  
Early classification  
Late classification

Performance  
metrics: log-loss



The screenshot shows the Kaggle competition page for PLAsTiCC Astronomical Classification. The header features a blue banner with the competition title, a question "Can you help make sense of the Universe?", and a prize of \$25,000. Below the banner is a navigation bar with links for Overview, Data, Kernels, Discussion, Leaderboard, and Rules, and a "Join Competition" button. The main content area is titled "Overview" and includes a sidebar with links to Description, Evaluation, Prizes, Timeline, and PLAsTiCC's Team. The main text describes the challenge, mentioning the LSST Project and the goal of classifying astronomical sources. A star trail image is shown on the right.

Featured Prediction Competition

## PLAsTiCC Astronomical Classification

Can you help make sense of the Universe?

LSST Project · 1,094 teams · 4 months ago

\$25,000 Prize Money

Overview Data Kernels Discussion Leaderboard Rules Join Competition


### Overview

**Description**

Help some of the world's leading astronomers grasp the deepest properties of the universe.

The human eye has been the arbiter for the classification of astronomical sources in the night sky for hundreds of years. But a new facility -- the [Large Synoptic Survey Telescope \(LSST\)](#) -- is about to revolutionize the field, discovering 10 to 100 times more astronomical sources that vary in the night sky than we've ever known. Some of these sources will be completely unprecedented!

The Photometric LSST Astronomical Time-Series Classification Challenge (PLAsTiCC) asks Kagglers to help prepare to classify the data from this new survey. Competitors will classify astronomical sources that



<https://plasticc.org>

Malz et al. 2018

## What are we learning from these challenges?

- 1) Training samples: representative samples or biased observed samples?
- 2) Probabilities: calibration? statistically meaningful?
- 3) Training and testing is done on simulations, how **realistic** are these simulations?

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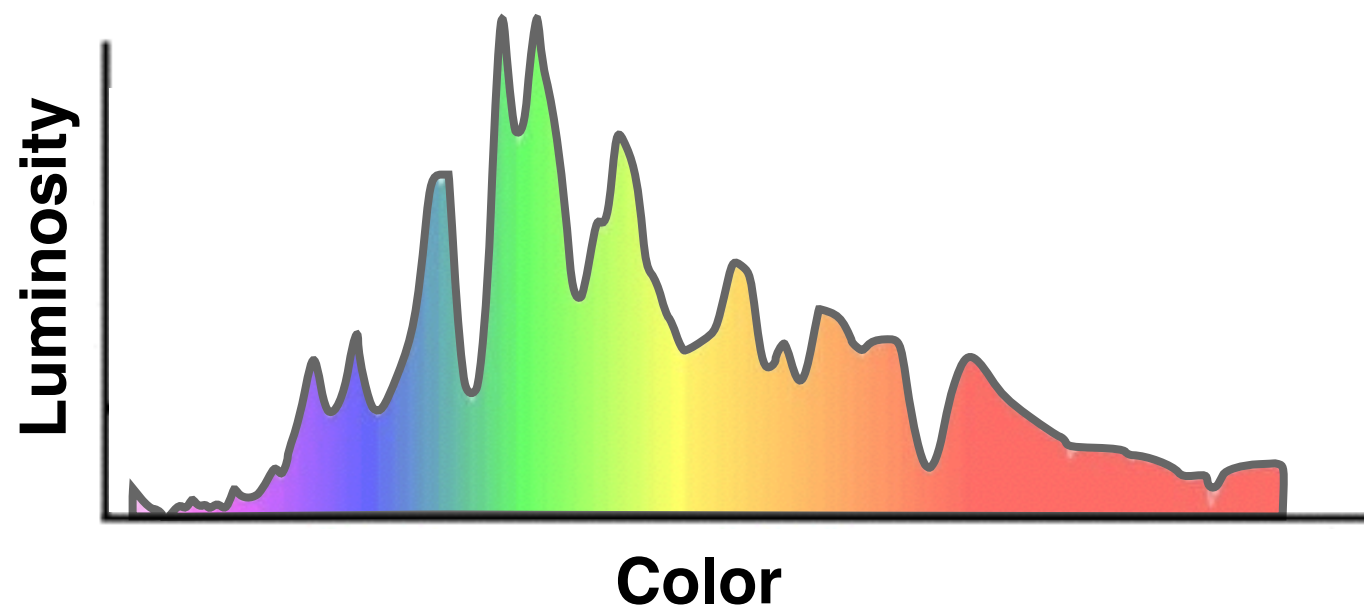
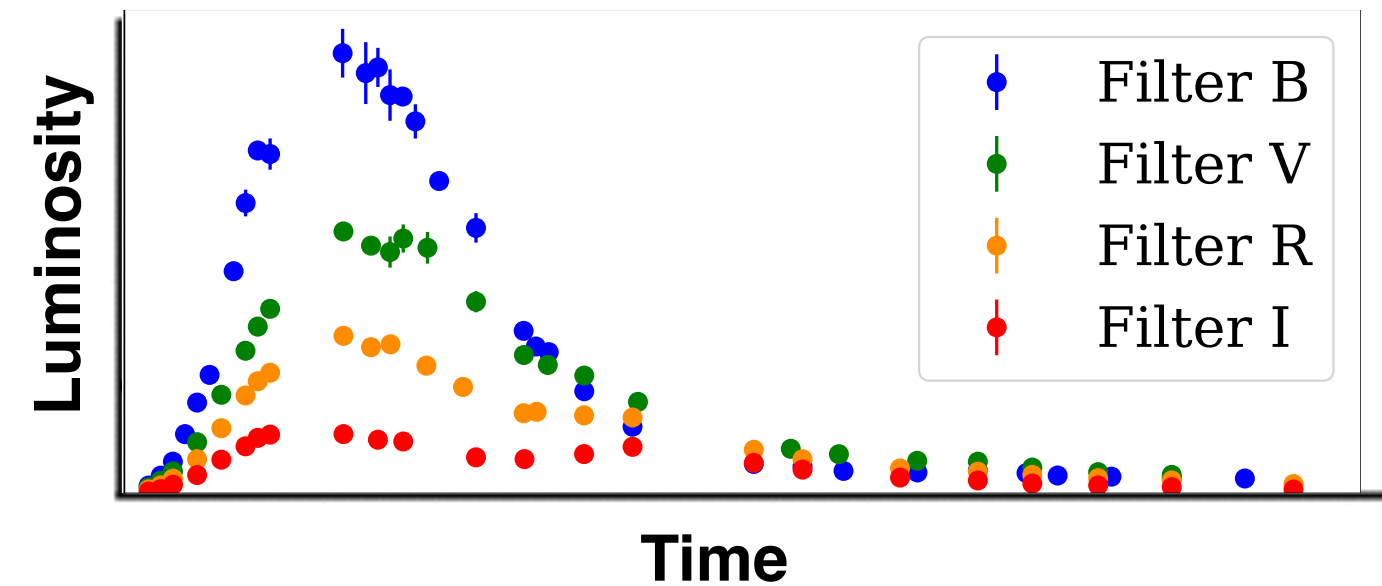
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- 2) Probabilities: calibration? statistically meaningful?
- 3) Training and testing is done on simulations, how **realistic** are these simulations?



**My PhD: new models of Core Collapse Supernovae**

# My PhD: new models of Core Collapse Supernovae

70 well observed Core Collapse Supernovae

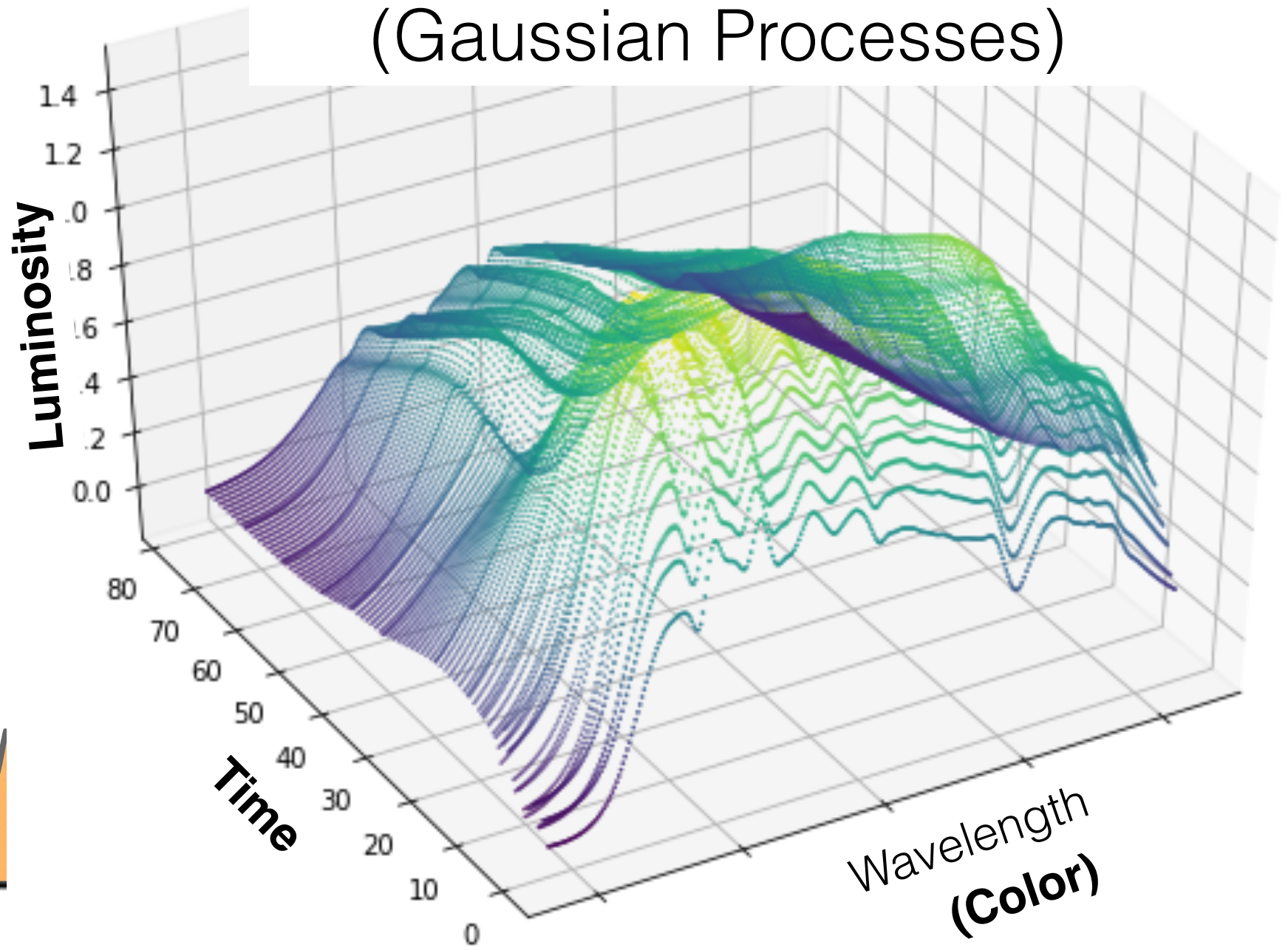
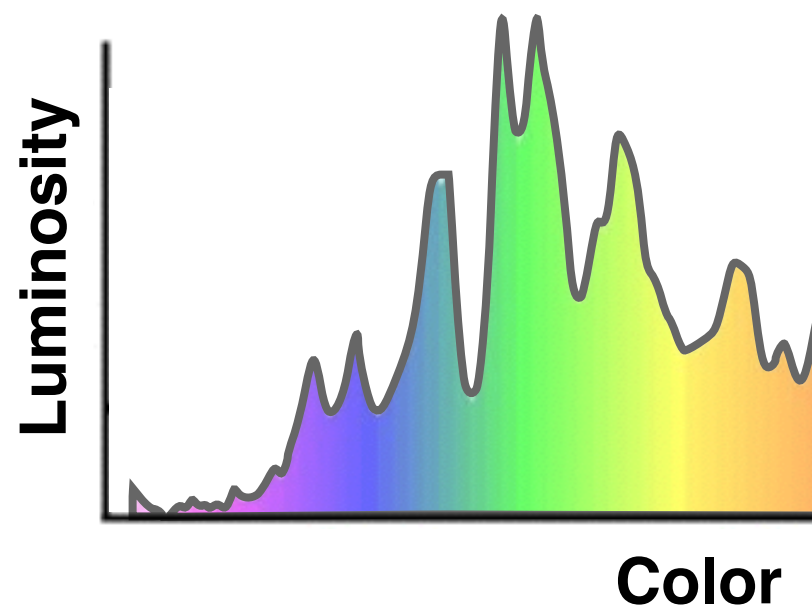
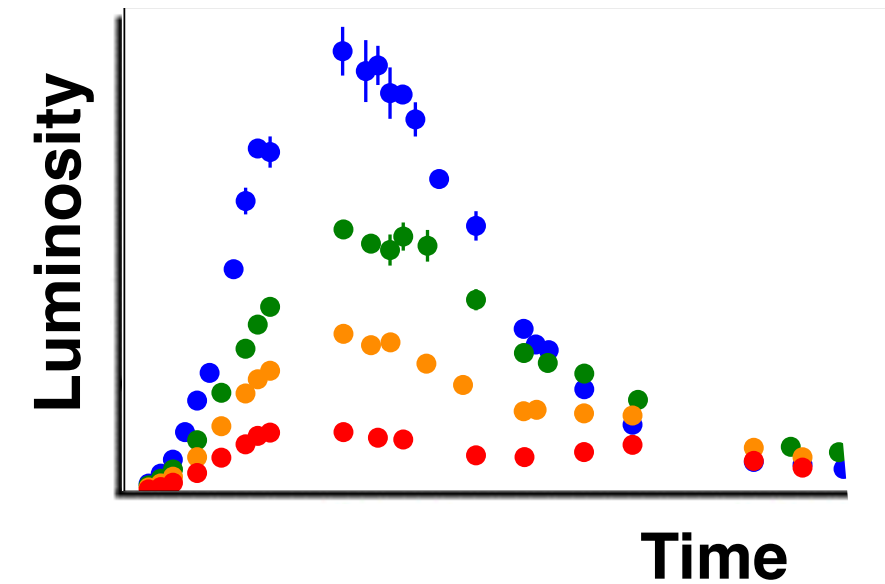




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70 well observed Core Collapse Supernovae

**Time - Color evolution of  
each Supernova**  
(Gaussian Processes)





# My PhD: new models of Supernovae NON Ia

## Previous models

- One “average” spectral template
- Poor “color” coverage

## New Supernova models

- More **diversity**
- More “colors” information (**especially in the UV**)

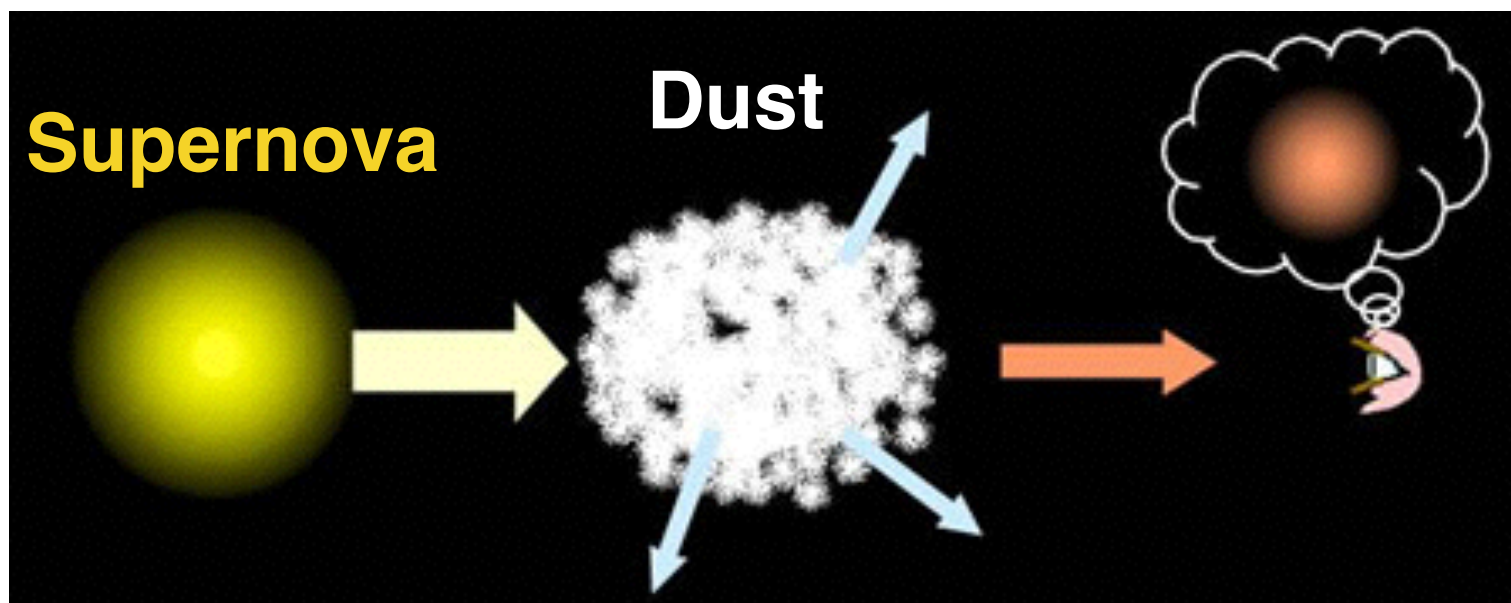
# My PhD: new models of Supernovae NON Ia

## Previous models

- One “average” spectral template
- Poor “color” coverage
- No dust corrections

## New Supernova models

- More **diversity**
- More “colors” information (**especially in the UV**)
- **Dust** taken out



- Dust alter the observation
- It's good for data augmentation!

# Conclusions & What's next?

- **Classification of Type Ia SNe (vs CC SNe)** is one of the crucial challenges for the study of the evolution of the Universe.
- The **PLAsTiCC** challenge is now the ML benchmark. However, it poses a very broad problem. Not optimal for the SNe Ia vs CC SNe problem
- New CC SNe models can help us to improve training sets for ML classifiers.

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**Thank you!**

**Back-up slides**

—> No UV extension

—> **UV extension** for simulations at high redshift

