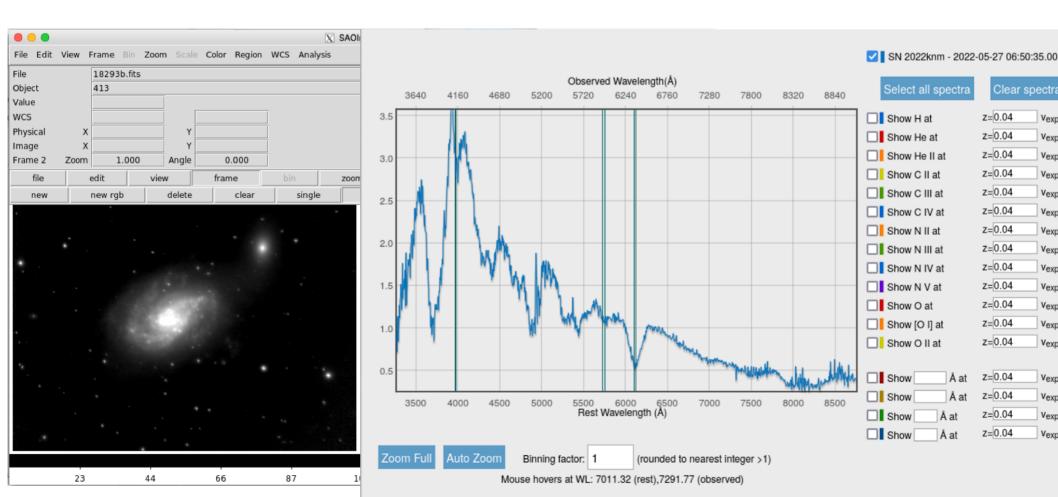
## Astronomical imaging & spectroscopy Seppo Mattila



#### **Course report**

- The minimum length is 9 pages (12 pt font) of text (2 pages based on each of the four practical sessions + 0.5 page introduction + 0.5 page summary) + figures, tables, references
- For reporting the work done in each of the sessions please follow the advice of the teachers
- Keep in mind the learning outcomes (slide 4) when preparing your report
- For writing the report you can use any word processing software that you are familiar with.
   Please, save the report as PDF
- Deadline for handing-in the reports to <u>sepmat@utu.fi</u> on 1st August

#### **Learning outcomes**

After completing the course the students should be able to:

- (1) Describe the principles behind some advanced astronomical imaging techniques and identify suitable topics in astrophysics that can be studies with them;
- (2) Understand the physics behind some of the most important medical imaging modalities and describe their value in clinical applications;
- (3) Identify and discuss the differences and similarities in the challenges faced when analyzing data in these two different disciplines;
- (4) Describe the theoretical basis and suitability of several image/signal processing and analysis methods commonly used in astronomy and medical imaging;
- (5) Identify suitable algorithms and apply them to astronomical and/or medical imaging datasets to enhance their scientific and/or clinical value;
- (6) Produce a written course report

#### **Exercise 1: Convolution**

#### **Convolution**

"real" signal additive noise

$$b(\vec{x}) = f(\vec{x}) * p(\vec{x}) + n(\vec{x})$$

observed signal

**PSF** 

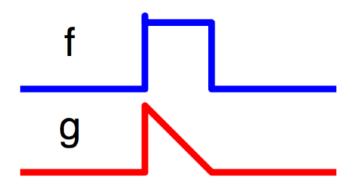
In the case of 1-D functions

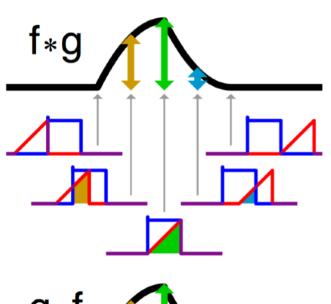
$$(f * g)(x) = \int_{-\infty}^{\infty} f(\tau)g(x - \tau) d\tau$$

In the case of discrete 1-D functions

$$(f * g)_j = \sum_{k=-m/2+1}^{m/2} f_k g_{j-k}$$

#### Convolution





$$(f*g)(x) = \int_{-\infty}^{\infty} f(\tau)g(x-\tau) d\tau$$

$$(f * g)_j = \sum_{k=-m/2+1}^{m/2} f_k g_{j-k}$$



#### **Available Kernels**

AiryDisk2DKernel (radius, **kwargs)	2D Airy disk kernel.							
Box1DKernel (width, **kwargs)	1D Box filter kernel.							
Box2DKernel (width, **kwargs)	2D Box filter kernel.							
CustomKernel(array)	Create filter kernel from list or array.							
Gaussian1DKernel (stddev, **kwargs)	1D Gaussian filter kernel.							
Gaussian2DKernel(x_stddev[, y_stddev, theta])	2D Gaussian filter kernel.							
RickerWavelet1DKernel(width, **kwargs)	1D Ricker wavelet filter kernel (sometimes known as a "Mexican Hat" kernel).							
RickerWavelet2DKernel(width, **kwargs)	2D Ricker wavelet filter kernel (sometimes known as a "Mexican Hat" kernel).							
Model1DKernel (model, **kwargs)	Create kernel from 1D model.							
Model2DKernel (model, **kwargs)	Create kernel from 2D model.							
Moffat2DKernel (gamma, alpha, **kwargs)	2D Moffat kernel.							
Ring2DKernel (radius_in, width, **kwargs)	2D Ring filter kernel.							
Tophat2DKernel (radius, **kwargs)	2D Tophat filter kernel.							
Trapezoid1DKernel (width[, slope])	1D trapezoid kernel.							
TrapezoidDisk2DKernel(radius[, slope])	2D trapezoid kernel.							

#### Gaussian1DKernel ¶

class astropy.convolution. Gaussian1DKernel (stddev, \*\*kwargs) [edit

[edit on github][source]

Bases: astropy.convolution.KernellD

1D Gaussian filter kernel.

The Gaussian filter is a filter with great smoothing properties. It is isotropic and does not produce artifacts.

Parameters: stddev: number

Standard deviation of the Gaussian kernel.

x\_size : odd int, optional

Size of the kernel array. Default = 8 \* stddev

mode: str, optional

One of the following discretization modes:

'center' (default)
 Discretize model by taking the value at the center of the bin.

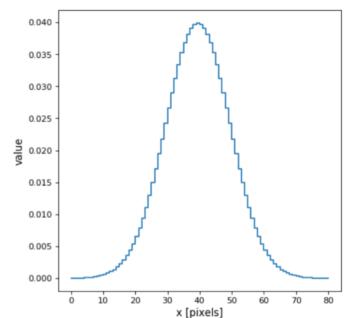


Discretize model by linearly interpolating between the values at the corners of the bin.

- 'oversample'
   Discretize model by taking the average on an oversampled grid.
- 'integrate'
   Discretize model by integrating the model over the bin. Very slow.

factor: number, optional

Factor of oversampling. Default factor = 10. If the factor is too large, evaluation can be very slow.



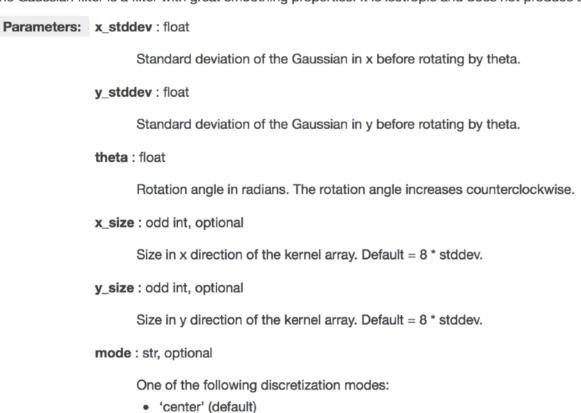
#### Gaussian2DKernel

class astropy.convolution. **Gaussian2DKernel** (x\_stddev, y\_stddev=None, theta=0.0, \*\*kwargs) 1 [edit on github]

Bases: astropy.convolution.Kernel2D

2D Gaussian filter kernel.

The Gaussian filter is a filter with great smoothing properties. It is isotropic and does not produce artifacts.

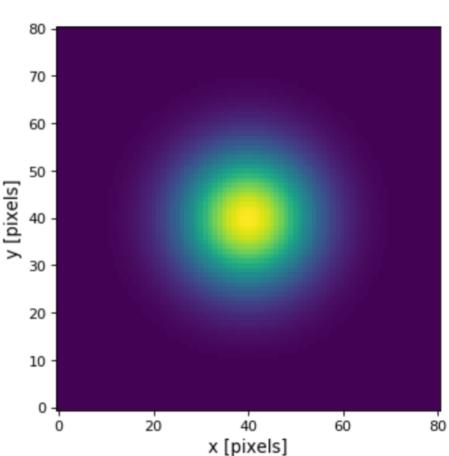


'linear\_interp'
 Discretize model by performing a bilinear interpolation between the values at the corners of the bin.

'oversample'
 Discretize model by taking the average on an oversampled grid.

Discretize model by taking the value at the center of the bin.

'integrate'
 Discretize model by integrating the model over the bin.



#### **Exercise 1: practical work**

Experiment using different types of convolution kernels for 1D or 2D data, present your experiment in the report

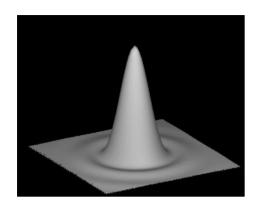
```
Gaussian1DKernel ¶
                                              1.0 -
class astropy.convolution.
                               Gauss
 Bases: astropy.convolution.Kernel1
                                              0.8
 1D Gaussian filter kernel.
 The Gaussian filter is a filter with great smooth
                                              0.6 -
  Parameters: stddev: number
                                              0.4
                      Standard deviation
                x_size : odd int, optional
                                              0.2
                      Size of the kernel ar
                mode: str. optional
                                              0.0
                      One of the following
                                                                    -2
                                                                                0

    'center' (default)

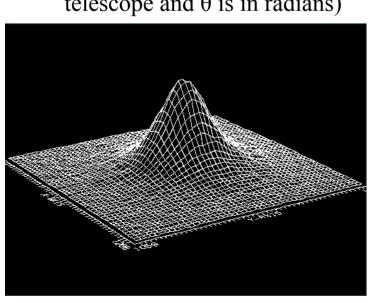
                           Discretize mod
                                        x=3.19355
                                                   y = 0.683779
                                                                        not3@course2021: ~
                       'linear_interp'
                           Discretize mod
                                                                          not3@course2021: ~ 80x15
                           the bin.
                                        >>> import numpy as np
                                       >>> from astropy.modeling.functional models import Lorentz1D
                         'oversample'
                                       >>> from astropy.convolution import convolve, Gaussian1DKernel, Box1DKernel
                           Discretize mod>>> lorentz = Lorentz1D(1, 0, 1)
                                        >>> x = np.linspace(-5, 5, 100)
                                       \Rightarrow data 1D = lorentz(x) + 0.1 * (np.random.rand(100) - 0.5)
                       'integrate'
                                        >>> gauss kernel = Gaussian1DKernel(2)
                           Discretize mod >>> smoothed data gauss = convolve(data 1D, gauss kernel)
                                       >>> import matplotlib.pyplot as plt
                                       >>> plt.plot(x, data 1D, 'r--', x, smoothed data gauss, 'bs')
                factor: number, optional
                                        [<matplotlib.lines.Line2D object at 0x7f975c025ad0>, <matplotlib.lines.Line2D ob</pre>
                                        ject at 0x7f975c025b90>]
                      Factor of oversamp >>> plt.show()
                      be very slow.
```

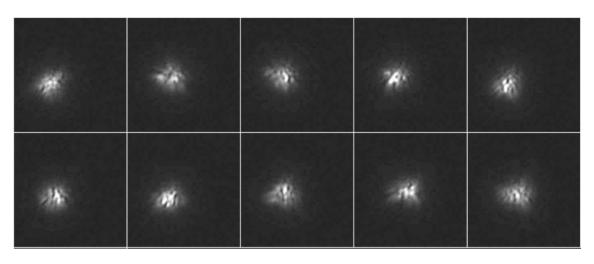
**Exercise 2: image matching and subtraction of astronomical images to detect variability over time** 

### Point spread function (PSF)



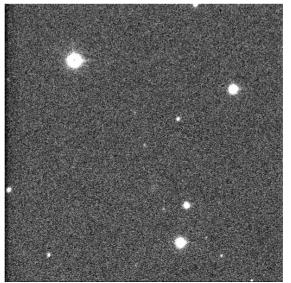
Ideal (diffraction limited) PSF if no atmosphere  $\theta \sim 1.22 \text{ x } \lambda / D$  (where  $\lambda$  is wavelength, D the diameter of the telescope and  $\theta$  is in radians)

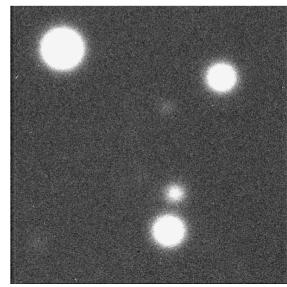




Atmospheric turbulence broadens the PSF resulting in a Gaussian PSF

$$I(r) = I(0) \exp(-r^2/2\sigma^2)$$





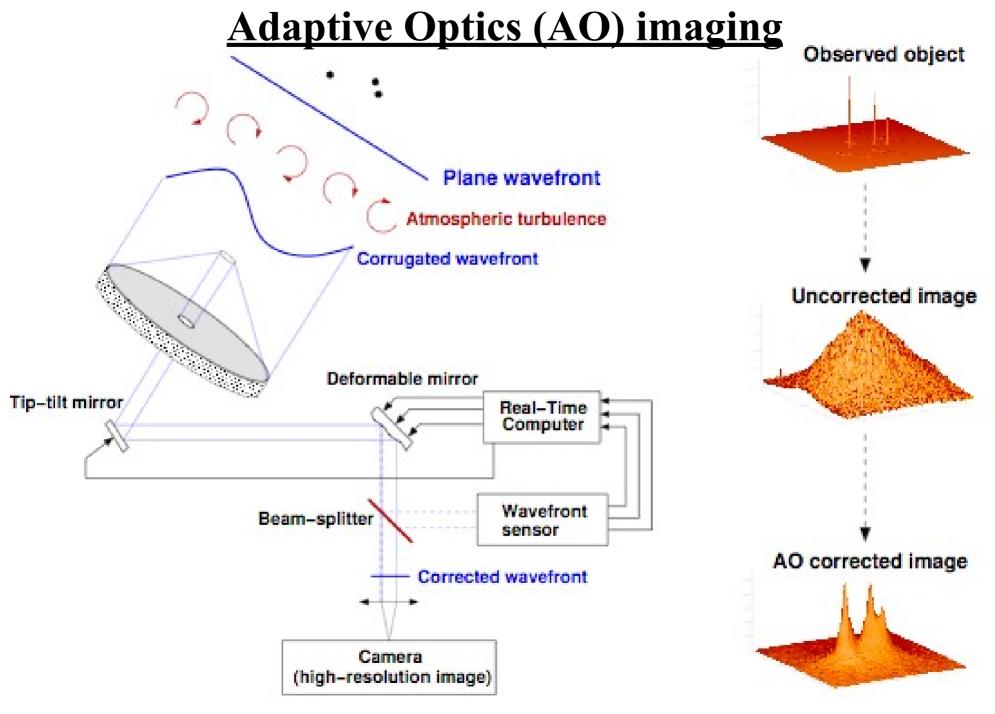
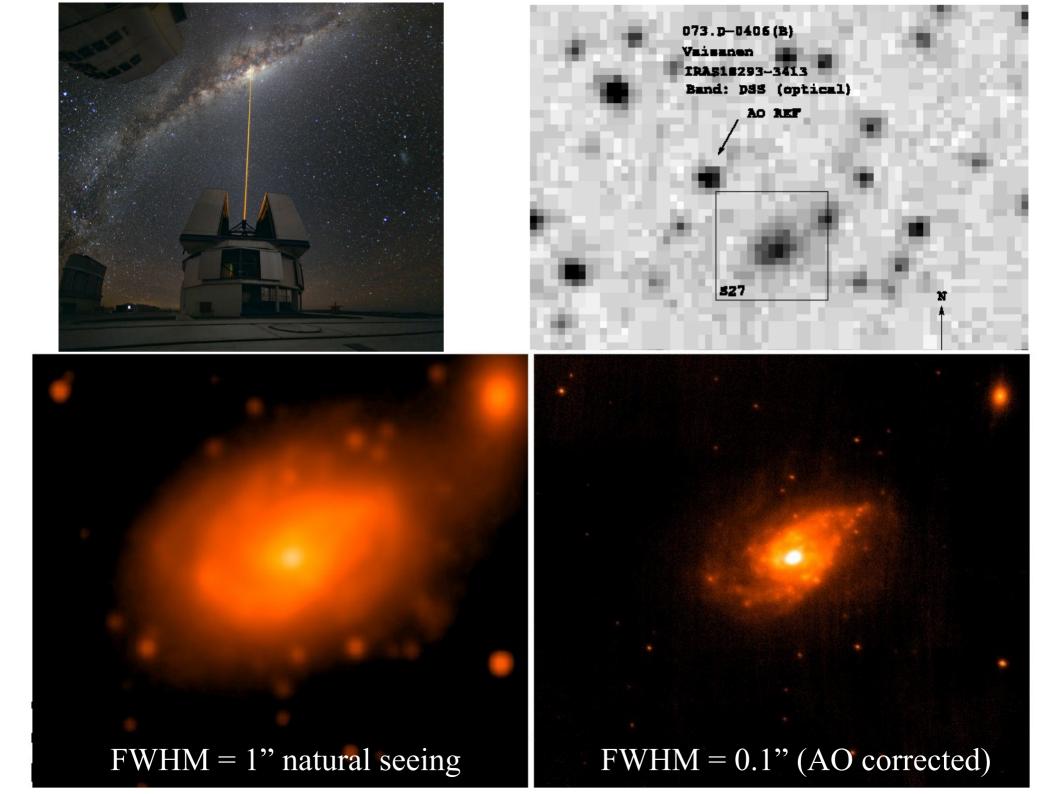


Figure 3-1: Principle of Adaptive Optics

VLT/NACO User manual



### **Convolution of images**

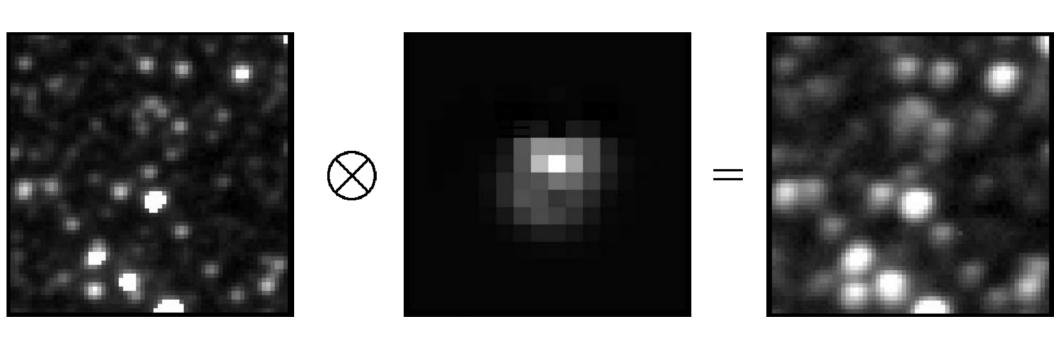
"real" signal

additive noise

$$b(\vec{x}) = f(\vec{x}) * p(\vec{x}) + n(\vec{x})$$

observed signal

**PSF** 



$$ref(x,y) \otimes kernel(x,y,u,v) = im(x,y)$$

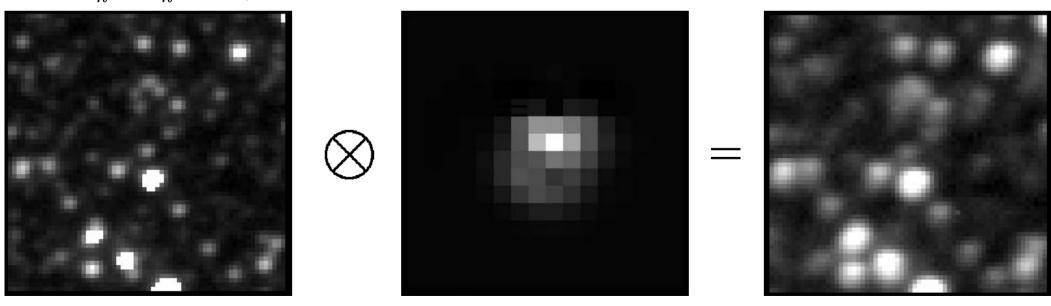
Aland & Lupton 1998: A method for optimal image subtraction, arXiv:astro-ph/9712287

### **Optimal Image Subtraction**

$$ref(x,y) \otimes kernel(x,y,u,v) = im(x,y) + bg(x,y)$$

$$kernel(x, y, u, v) = \sum_{n} \sum_{d_n^x} \sum_{d_n^y} \sum_{\delta^x} \sum_{\delta^y} \left[ a_n \underbrace{x^{\delta^x} y^{\delta^y}}_{3} \underbrace{e^{-(u^2 + v^2)/2\sigma_n^2}}_{1} \underbrace{u^{d_n^x} v^{d_n^y}}_{2} \right]$$

The convolution kernel consists of a set of Gaussian functions (1) which are modified by polynomials (2) and a model for the spatial variations of the kernel (3) where 0  $< d_n^y + d_n^x \le D_n$ , and  $0 < \delta^y + \delta^x \le D^k$ .



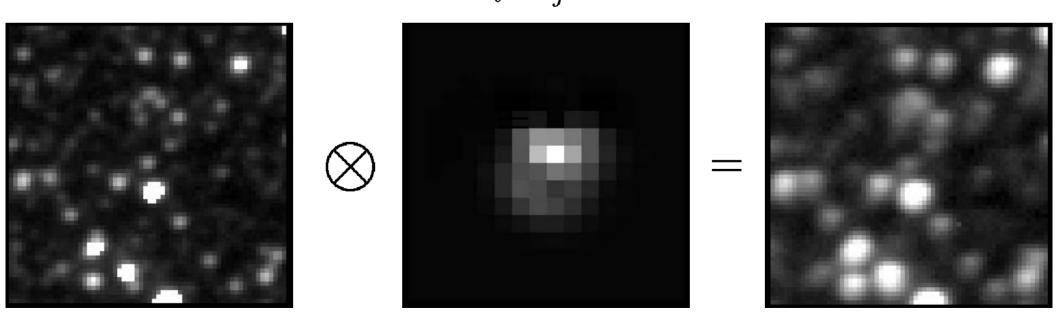
Aland & Lupton 1998: A method for optimal image subtraction, arXiv:astro-ph/9712287

#### **Optimal Image Subtraction**

$$ref(x,y) \otimes kernel(x,y,u,v) = im(x,y) + bg(x,y)$$

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$$bg(x,y) = \sum_{i} \sum_{j} a_{i} x^{i} y^{j}$$



Aland & Lupton 1998: A method for optimal image subtraction, arXiv:astro-ph/9712287

### **Convolution: Optimal Image Subtraction**

$$kernel(x, y, u, v) = \sum_{n} \sum_{d_n^x} \sum_{d_n^y} \sum_{\delta^x} \sum_{\delta^y} \left[ a_n \underbrace{x^{\delta^x} y^{\delta^y}}_{3} \underbrace{e^{-(u^2 + v^2)/2\sigma_n^2}}_{1} \underbrace{u^{d_n^x} v^{d_n^y}}_{2} \right]$$
$$bg(x, y) = \sum_{i} \sum_{j} a_i x^i y^j$$

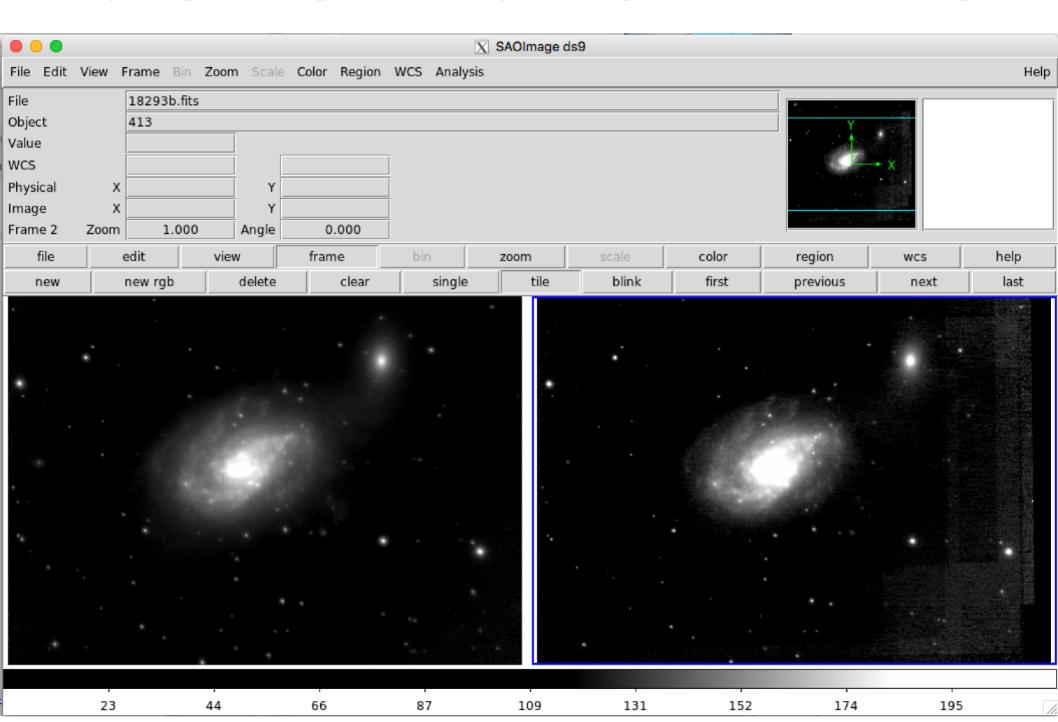
number of Gaussian functions in the kernel n sigmas of the Gaussians  $\sigma_n$ polynomial degrees associated with each of the n gaussians  $D_n$  $D^k$ degree of the polynomial transform for the spatial variations of the kernel  $D^{bg}$ degree of the polynomial used to model the background variations  $N_x$ number of stamps along x-axis number of stamps along y-axis  $N_{\boldsymbol{u}}$  $S_k$ width of the convolution kernel  $S_s$ width of the region used for fitting the background minimum number of counts in the middle of a stamp  $N_c$  $N_{min}$  minimum value of a pixel to be included in the fit maximum value of a pixel to be included in the fit

Aland & Lupton 1998: A method for optimal image subtraction, arXiv:astro-ph/9712287

### **Exercise 2: practical work**

**Experiment with matching and subtraction of AO images** from two different dates present your results in the report

#### Can you spot the supernova? Maybe, image subtraction would help ...

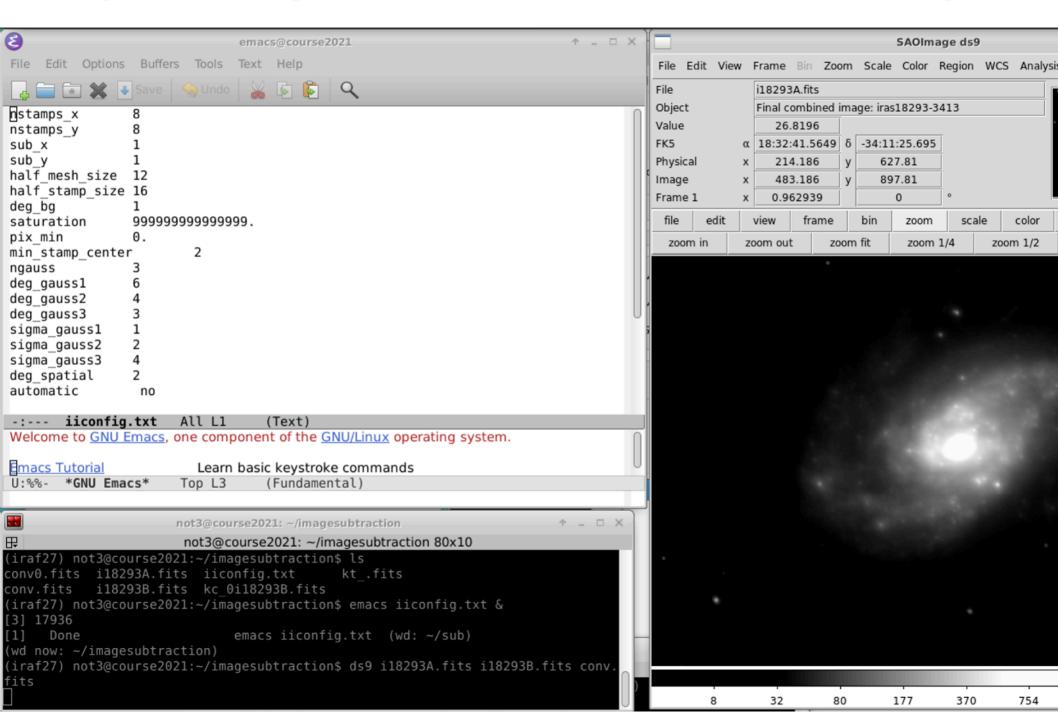


#### image matching and subtraction of astronomical images

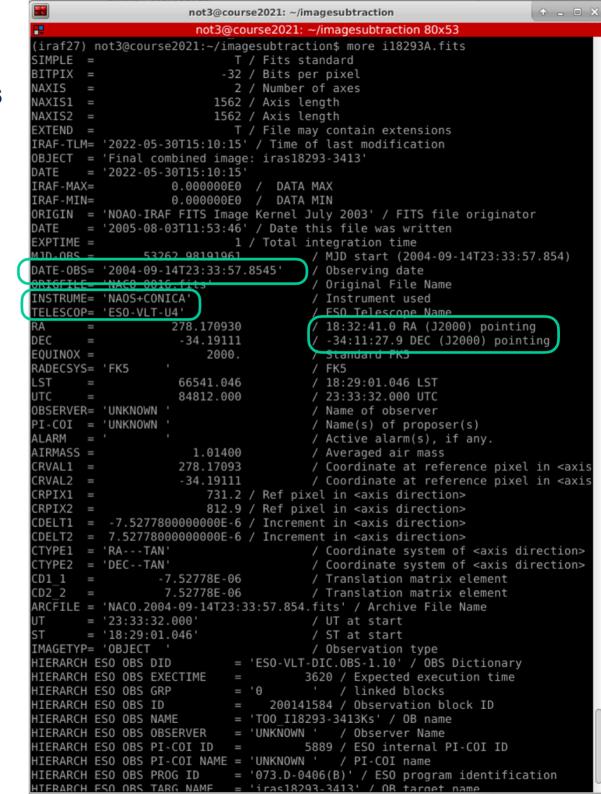
↑ - □ X

```
not3@course2021: ~/imagesubtraction
                             not3@course2021: ~/imagesubtraction 80x7
(iraf27) not3@course2021:~$ mkdir imagesubtraction
(iraf27) not3@course2021:~$ cd imagesubtraction
(iraf27) not3@course2021:~/imagesubtraction$ cp /home/not3/sub/* .
(iraf27) not3@course2021:~/imagesubtraction$ ls
i18293A.fits i18293B.fits iiconfig.txt
(iraf27) not3@course2021:~/imagesubtraction$ mrj phot i18293A.fits i18293B.fits
 c iiconfig.txt
                   not3@course2021: ~/imagesubtraction
                    not3@course2021: ~/imagesubtraction 80x56
Reading Image1
name: i18293A.fits
width: 1562 height: 1562 bitpix: -32 offset header: 46080
name: i18293B.fits
width: 1562 height: 1562 bitpix: -32 offset header: 46080
offsets: 46080 46080
ss: 1 1 1562 1562
ss: 1562 1562 1562 1562
nsx: 8 nsy: 8
mesh size: 25 stam size: 33
ng: 3 6
sq: 0.500000
deg spatial: 2 deg bg: 1
subs: 1562 1562
Allocate: 64
Getting Stamps
bitpix: -32 4
width: 1562 height: 1562 1562 1562
bitpix: -32 4
width: 1562 height: 1562 1562 1562
sub ref: 32.391235 10.000000
Making defect map
Looking for Stamps
nb: 64
Building Zero Order Matrix
Checking Stamps
x: 71 y: 125 -1.375231
```

### image matching and subtraction of astronomical images



extract relevant information from the fits headers incl. dates of the observations, telescope and instrument used, wavelength of the observation, atmospheric conditions?

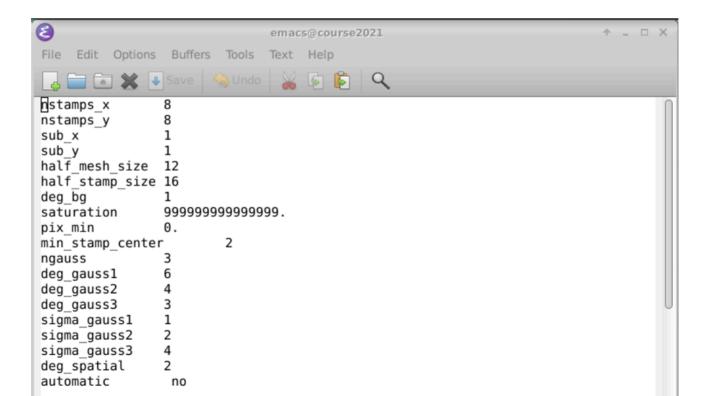


inspect the images using the ds9 tool: different contrast settings, comparison between different images, identifying the subtraction residuals with image sources, astronomical coordinates, estimate the

spatial resolution of the images SAOImage ds9 File Edit View Frame Bin Zoom Scale Color Region WCS Analysis Help i18293A.fits Object Final combined image: iras18293-3413 Value FK5 18:32:41.0238 8 -34:11:27.469 Physical Image 730.92 832.346 SAOImage ds9 2.88469 Frame 1 Frame Bin Zoom Scale Color Region WCS Analysis Help analysis color region i18293A.fits File squared asinh sinh histogram min max Object Final combined image: iras18293-3413 WCS Physical Image 0.721172 0 Frame 1 frame zoor analysis help linea sgrt squared histogram min max zscale File Edit Scale Limits Scope Min Max Parameters Graph Pixel Distribution 1E6 1E5 1E4 1E3 705 1E2 1E1 5000 10000 High 100000 Limits Low 10 Close

#### experiment what happens if we change the subtraction parameters?

```
number of Gaussian functions in the kernel
n
     sigmas of the Gaussians
\sigma_n
     polynomial degrees associated with each of the n gaussians
D_n
D^k
     degree of the polynomial transform for the spatial variations of the kernel
D^{bg}
     degree of the polynomial used to model the background variations
N_r
     number of stamps along x-axis
N_{u}
     number of stamps along y-axis
S_k
     width of the convolution kernel
S_s
     width of the region used for fitting the background
N_c
     minimum number of counts in the middle of a stamp
N_{min} minimum value of a pixel to be included in the fit
     maximum value of a pixel to be included in the fit
```



how does the subtracted image look like? what is causing the different residuals? any real variability between the two images?



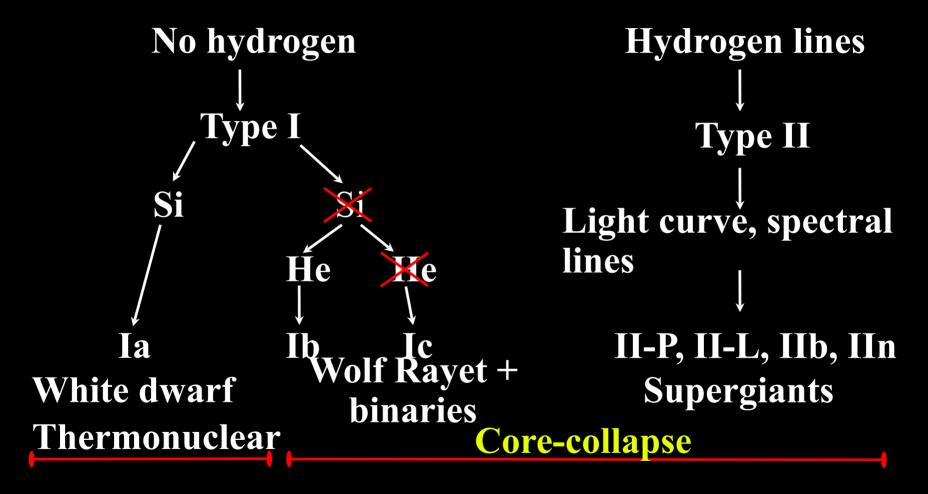
## **Exercise 3: Deep learning for the automated spectral classification of supernovae**

https://github.com/daniel-muthukrishna/DASH

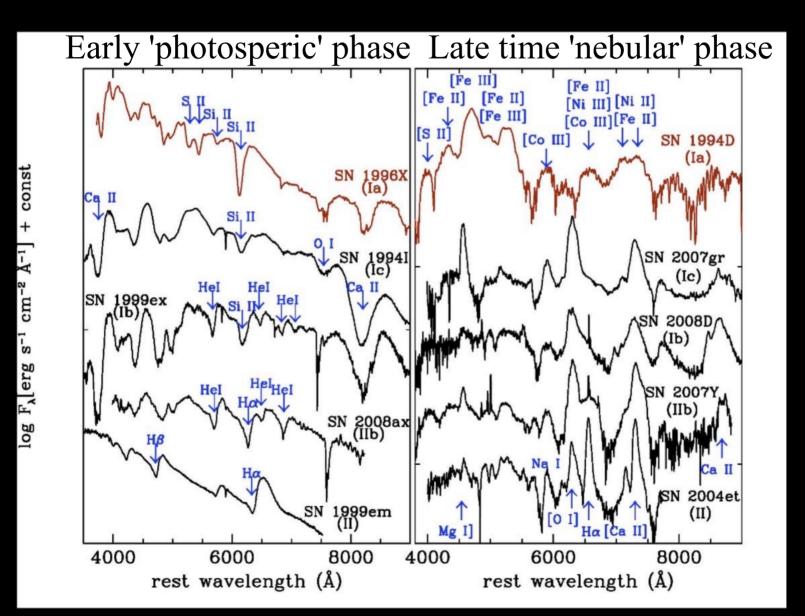
Muthukrishna et al. 2019, ApJ, 885, 18

https://iopscience.iop.org/article/10.3847/1538-4357/ab48f4/pdf

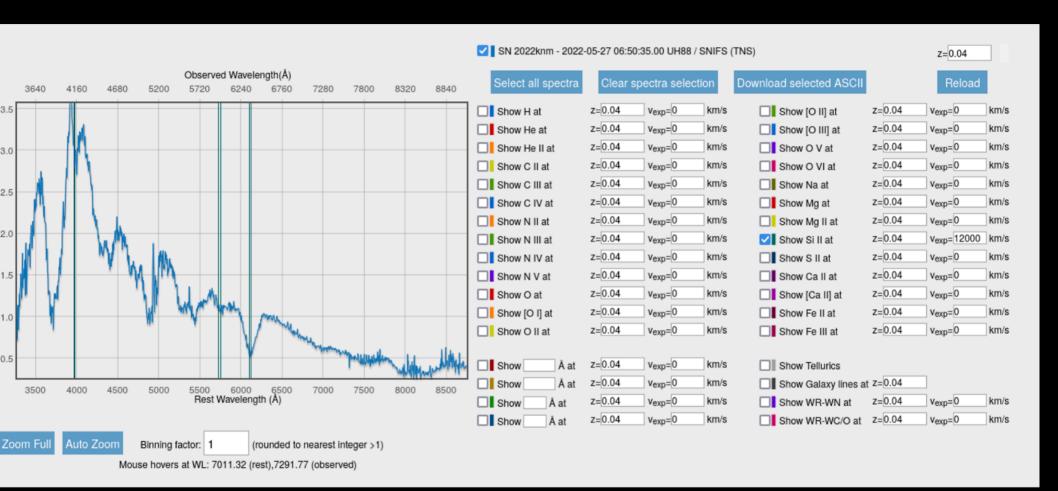
### Supernova types

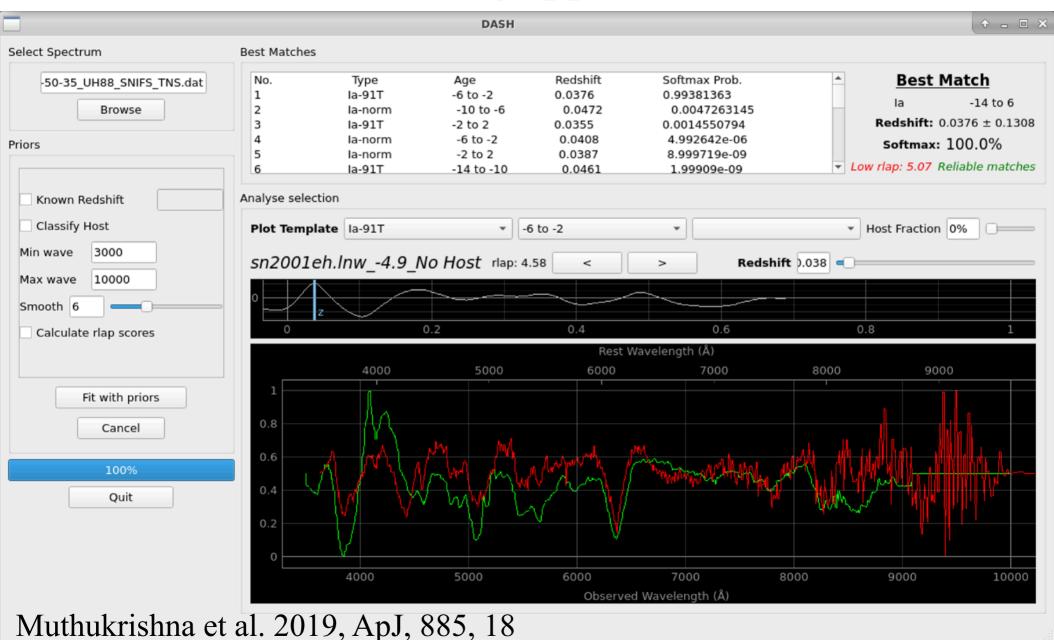


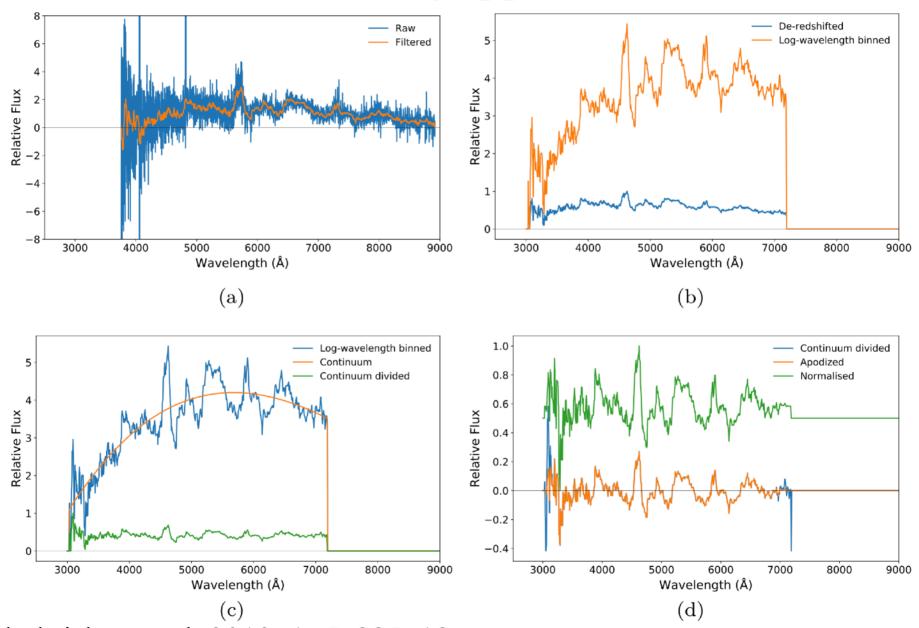
### Supernova types



# Supernova spectral classification by identifying characteristic spectral lines (and elements)

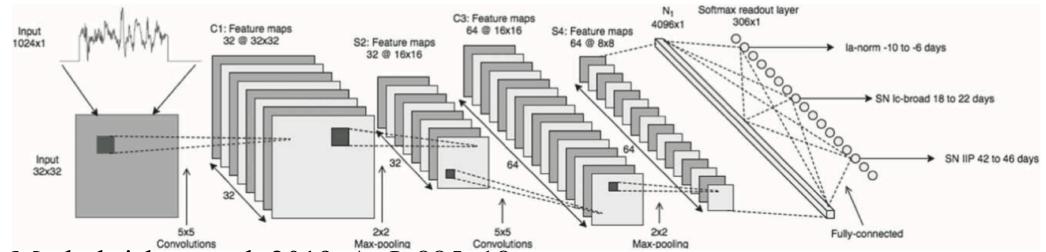






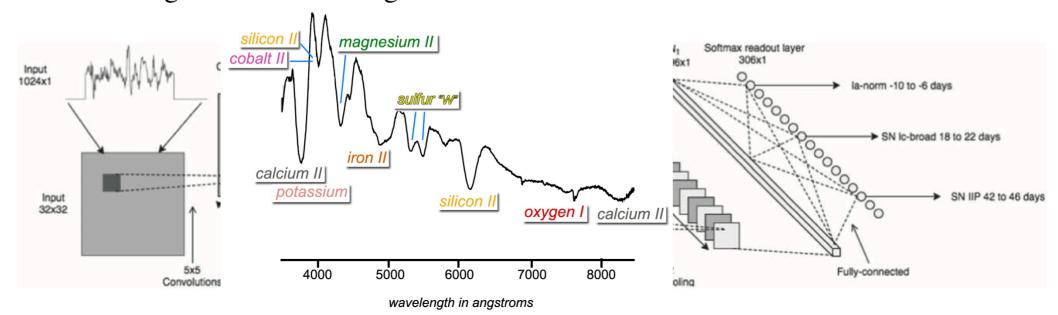
Muthukrishna et al. 2019, ApJ, 885, 18

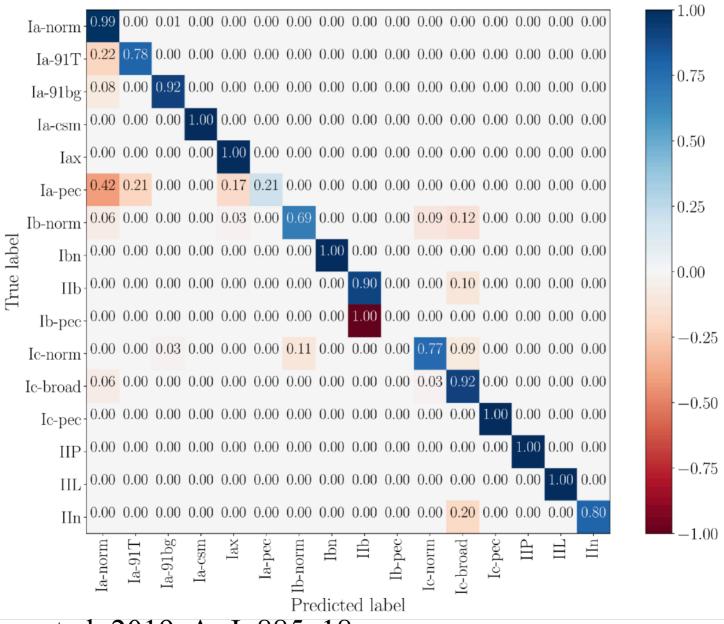
- Developed a convolutional neural network with TensorFlow's Python library
- 1st input layer is made up of 1024 neurons representing fluxes of an input spectrum
- Additional layers captures a more abstract representation of the original input layer
  - •DASH classifies based on spectral features (different SN types & ages)
- Final layer is a 306-point vector, with a score for each SN type and age bin
  - Training + validation using different datasets



Muthukrishna et al. 2019, ApJ, 885, 18

- Developed a convolutional neural network with TensorFlow's Python library
- 1st input layer is made up of 1024 neurons representing fluxes of an input spectrum
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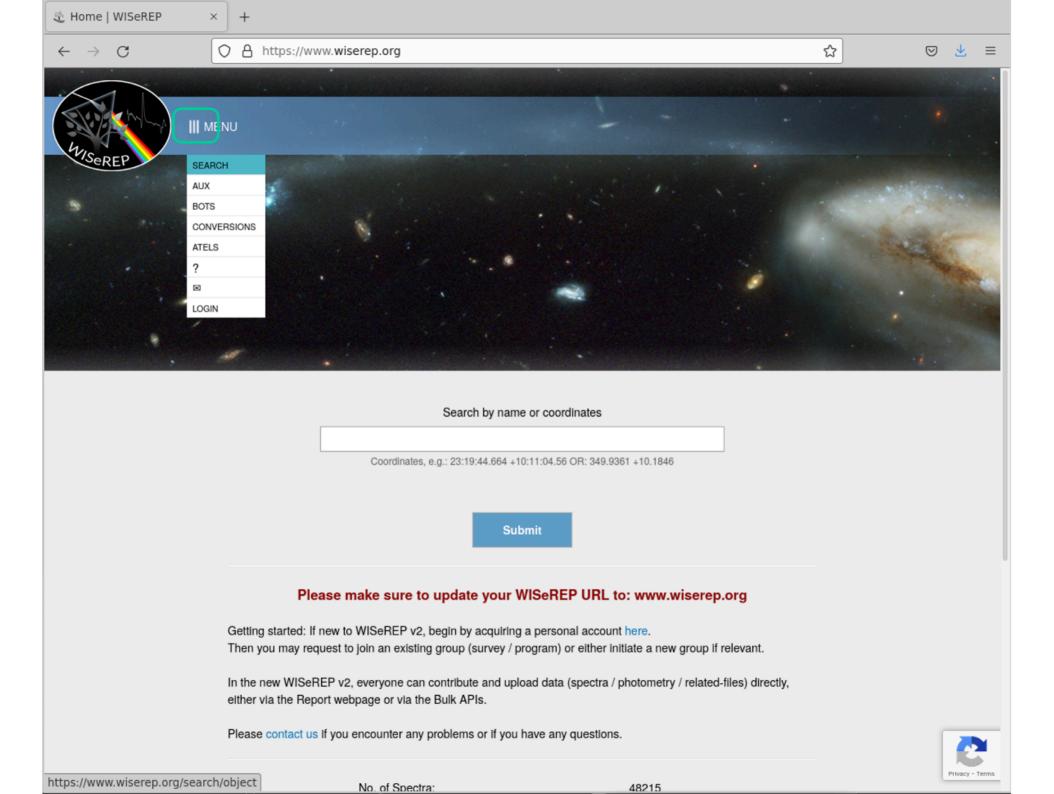




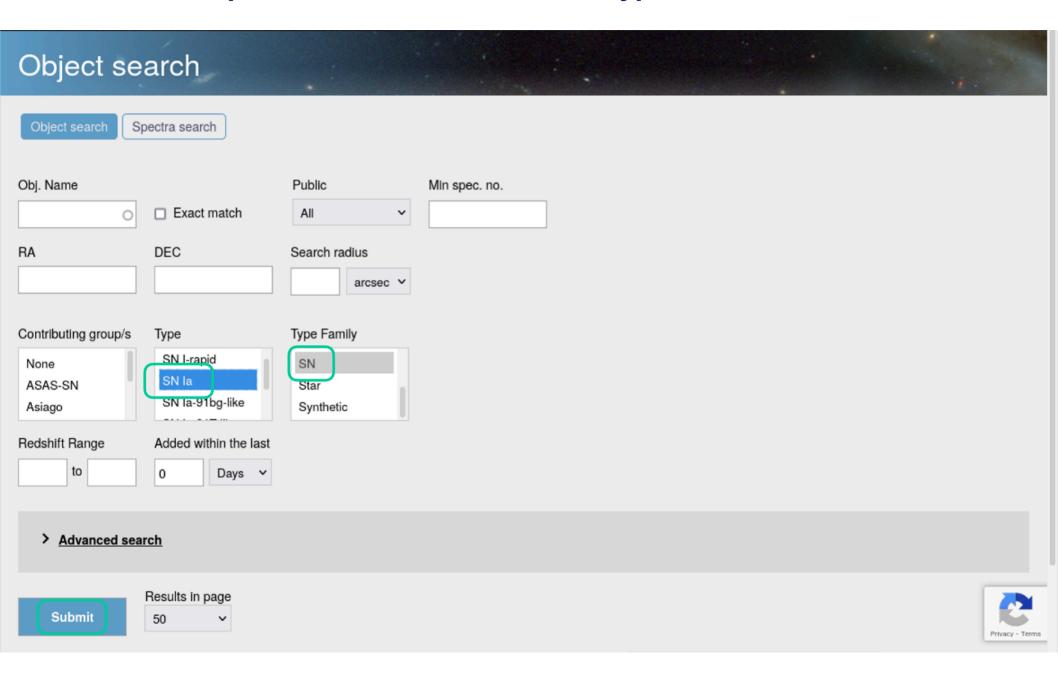
Muthukrishna et al. 2019, ApJ, 885, 18

#### **Exercise 3: practical work**

Experiment with a deep learning based method for supernova classification and present your findings in the report; discuss the pros and cons of the use of machine learning in supernova classification



## select suitable observed supernova spectra from the WISeREP archive, download the spectra, make notes of their types and redshifts



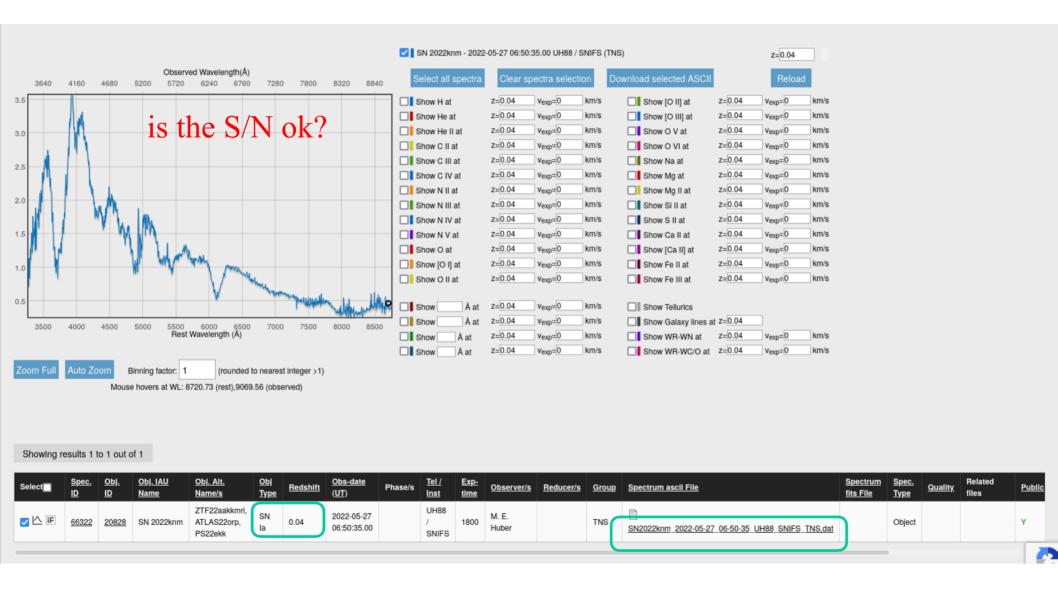
## select suitable observed supernova spectra from the WISeREP archive, download the spectra, make notes of their types and redshifts

Showing results 1 to 50 out of 11031

1 2 3 4 5 6 7 >	>>
-----------------	----

<u>ID</u> ♣	IAU Name	Internal / Alt. Name/s	Obj. Reps		Coords X-Refs	<u>RA</u>	DEC	<u>Type</u>	Redshift	<u>Host</u> <u>Redshift</u>	Host Name	Contributing Group/s	Public	Obj. Spectra	Obj. Phases	Light Curves	Related Files	Created by
20836	<u>SN 2022lax</u>	ZTF22aaldrem	2	0	Coords X-refs	14:24:50.686	-08:45:10.60	SN Ia	0.058			TNS	Υ	1	•			TNS_Bot1
20842	SN 2022kwf	ATLAS22ozp, ZTF22aalfezf	3	o	Coords X-refs	17:36:17.968	+40:08:16.10	SN la	0.0387500003			TNS	Y	1	•			TNS_Bot1
20825	<u>SN 2022kpy</u>	ZTF22aalaajn	2	0	Coords X-refs	00:36:32.281	+19:23:54.61	SN Ia	0.062			TNS	Υ	1	•			TNS_Bot1
20818	<u>SN 2022kpr</u>	ATLAS22ogy	2	0	Coords X-refs	16:26:57.750	+51:07:42.95	SN la	0.08			TNS	Y	1	•			TNS_Bot1
20828	<u>SN 2022knm</u>	ZTF22aakkmri, ATLAS22orp, PS22ekk	4	0	Coords X-refs	13:25:04.348	-24:39:24.80	SN la	0.04			TNS	Y	1	•			TNS_Bot1
20821	<u>SN 2022kmp</u>	ZTF22aakpwof. ATLAS22okr	3	0	Coords X-refs	11:50:24.455	+22:42:48.92	SN la	0.067			TNS	Y	1	•			TNS_Bot1
20839	SN 2022klm	ATLAS22oht	2	0	Coords X-refs	17:33:57.181	+50:33:11.43	SN la	0.07			TNS	Υ	1	•			TNS_Bot1
20806	<u>SN 2022klj</u>	ZTF22aajykxi. PS22eiq	3	0	Coords X-refs	16:18:24.720	+12:28:13.86	SN la	0.085			ePESSTO+, TNS	Y	1	•			WIS_Bot1
20786	SN 2022klh	ATLAS22off	2	0	Coords X-refs	15:21:19.265	+34:17:47.13	SN la	0.031492			TNS	Υ	1	•			TNS
20816	SN 2022klg	ATLAS22ofd	2	0	Coords	13:52:43.849	+59:16:42.91	SN la	0.03			TNS	Υ	1	•			TNS Privacy - Terms

## select suitable observed supernova spectra from the WISeREP archive, download the spectra, make notes of their types and redshifts



## make experiments with DASH for the spectra that you downloaded, do the spectral types agree with previous classifications, are priors needed?

