A deep learning approach to observational cosmology with Supernovae

Johanna Pasquet

Centre de Physique des Particules de Marseille

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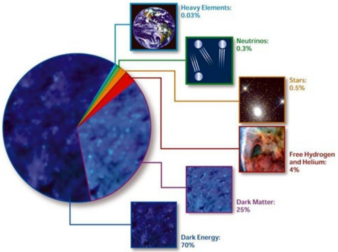
Current cosmology questions



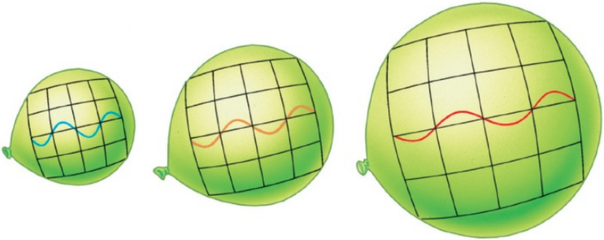
Credit : NASA

- What is the nature of dark matter ?
- What is the nature of dark energy ?
- Is it "dark energy" arising from quantum fluctuations in the vacuum, or is it new gravitational physics ?

Need accurate redshits for cosmology

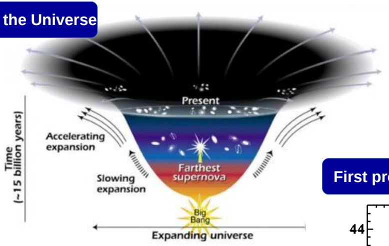
As the universe expands, the radiation is stretched in wavelength

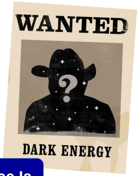
$1 + z = \frac{\lambda_{obs}}{\lambda_{emit}}$



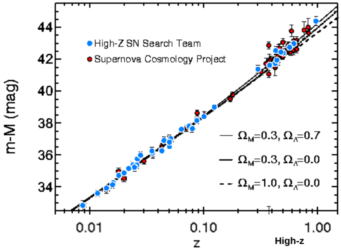
Supernovae Ia as cosmological probe

History of the Universe





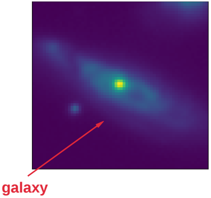
First proof with supernovae Ia



- Dark energy causes the universal expansion to accelerate
- Recent observations of supernovae have produced a value for an acceleration that implies a universe that is about 70 % dark energy

The spectroscopic follow-up to identify SN Ia and measure redshift

Identify and measure the redshift of a galaxy



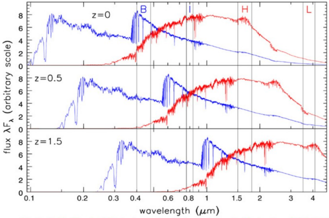
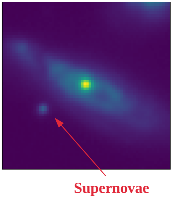
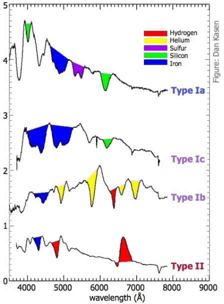


Fig 8.12 (S. Charlot) 'Galaxies in the Universe' Sparke/Gallagher CUP 2007

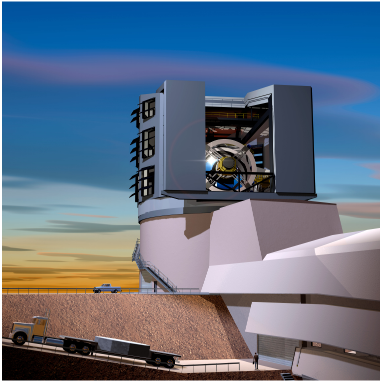
Determine the nature of an observed object





The future image surveys

1. The Large Synoptic Survey Telescope (LSST)

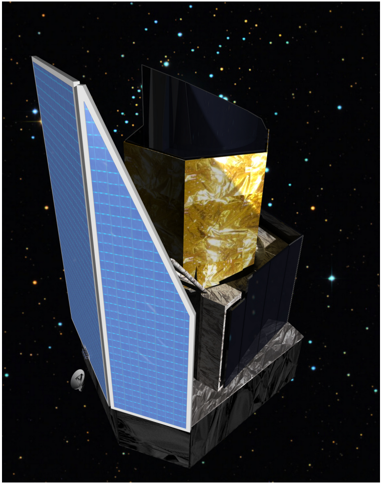


Artist view, Credit : Todd Mason, Mason Productions Inc. / LSST Corporation

- a 10-year survey of the sky
- first light in 2020
- a 8.4-meter special three-mirror design, creating an exceptionally wide field of view, and has the ability to survey the entire sky in only three nights.
- 200 petabyte set of images and data products !

The future image surveys

2. Euclid



- understanding the nature of the source responsible for this acceleration
- slitless spectroscopy
- launch is planned for 2021
- a 6-year survey
- 10 billion sources will be observed !

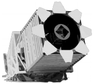
Artist view of the Euclid Satellite -©ESA

The era of Big Data

1924 Henry Drapper Catalog (0.2 Million)

1989 Guide Star Catalog (20 Million)

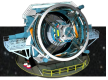
2008 **SDSS (230 Million)**



2018 **Dark Energy Survey (400 Million)**

2027 **Euclid (10 billion)**

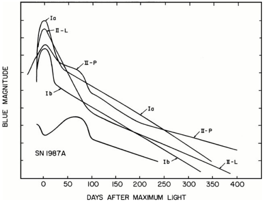
2032 **Large Synoptic Survey Telescope (37 billion)**



A full photometric analysis

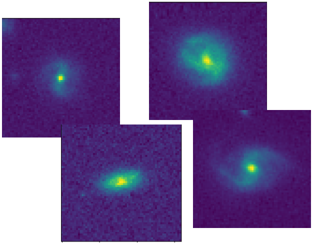
Use all the photometric information in several photometric bands

Light curves of Supernovae



In the LSST context, full photometric SN analyses become crucial

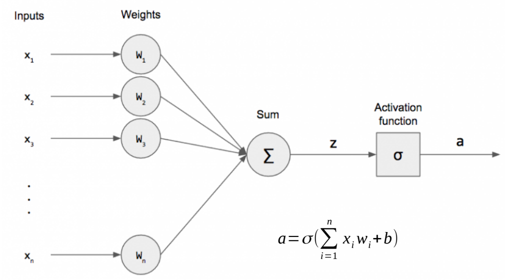
Galaxy images



Outline

History

1957 Perceptron (Rosenblatt)
1986 MLP (Rumelhart et al.)
1998 LeNet (LeCun et al.)
2012 A CNN won ImageNet (Alexnet, Krizhevsky et al.)



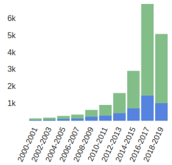
The emergence of artificial intelligence

ads

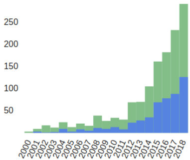
QUICK FIELD: Author First Author Abstract Year Fulltext All Search Terms

machine learning year:2000-2019

General + physics + Astronomy



Astronomy

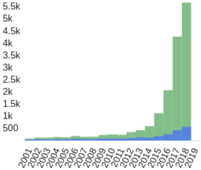


- refereed
- non refereed

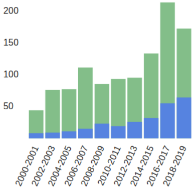
QUICK FIELD: Author First Author Abstract Year Fulltext All Search Terms

deep learning year:2000-2019

General + physics + Astronomy



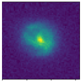
Astronomy



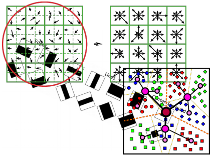
The main property of deep learning

Classical methods

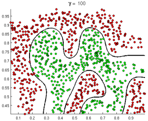
Input data



Feature crafting

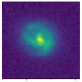


Separation with a classifier

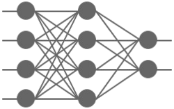


Deep learning

Input data

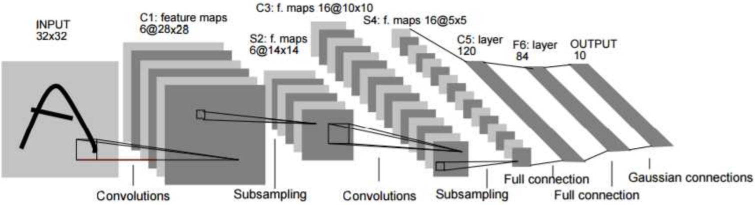


Feature learning



→ The best feature space representation is found by the network

LeNet5



Lecun et al. 1998

3 operations:

- Convolution + non linearity (feature extraction)
- Pooling
- Fully Connected (classification)

Convolutions

An image

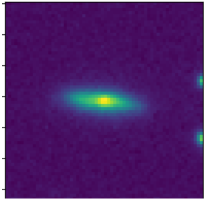
1	1	1	0	0
0	1	1	1	0
0	0	1	1	1
0	0	1	1	0
0	1	1	0	0

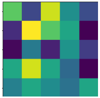
A kernel

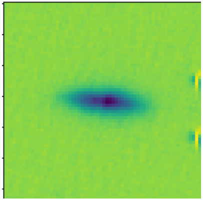
1	1	1
0	1	1
0	0	1

A convolved image

6	5	3
4	6	4
3	4	4

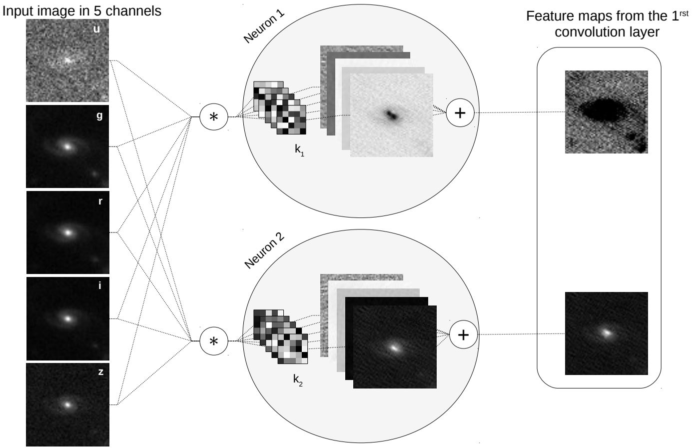






Convolution operation is followed by a non linear function (tanh, ReLu...)

Convolutions



Pooling

A feature map

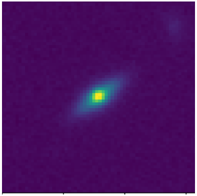
5	1	3	0
0	1	2	7
2	1	1	4
3	1	1	2

Pooling operation

Max in a 2x2 sliding window with a stride of 2

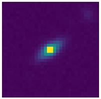
A subsampled feature map

5	7
3	4



64x64

Max in a 2x2 sliding window with a stride of 2



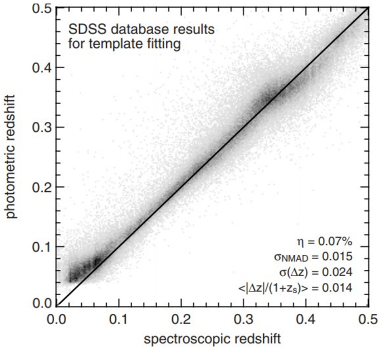
32x32

First step: The estimation of photometric redshift with a deep architecture

J. Pasquet, E. Bertin, M. Treyer, S. Arnouts and D. Fouchez

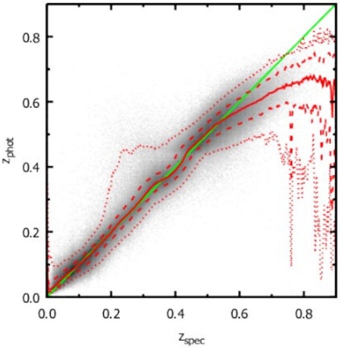
Existing methods

A template fitting method



From Greisel et al. 2013

A machine learning method (KNN)



From Beck et al. 2016

Preliminary results with Deep Learning methods (Hoyle 2016, D'Isanto 2018)

Photometric redshifts from SDSS images using a Convolutional Neural Network (**J. Pasquet**, E. Bertin, M. Treyer, S. Arnouts and D. Fouchez)
A&A, 611 :A97, 2018, **arxiv**: 1806.06607, **code available at**:
https://github.com/jpasquet/Photoz

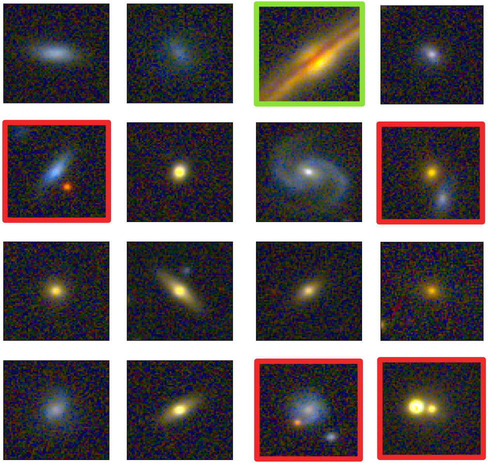
Key elements :

1. A representative and a complete training database with r-band magnitude ≤ 17.8 and redshift, $z \leq 0.4$ (516,525 galaxies)
2. Photoz values + associated Probability Distribution Functions
3. Photoz immune to IQ variations and neighbours contamination
4. A dedicated Neural Network architecture

Results obtained :

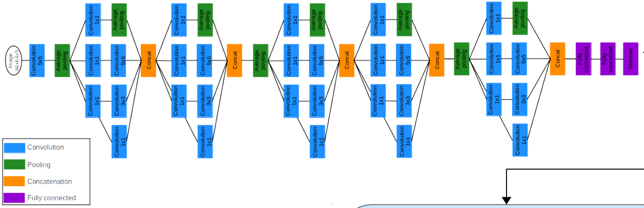
Clear improvements compared to other methods!

Input SDSS galaxy images transmitted to the CNN



– large galaxies — crowded images

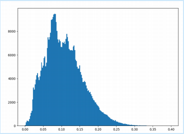
Our architecture



Input images of size 64x64

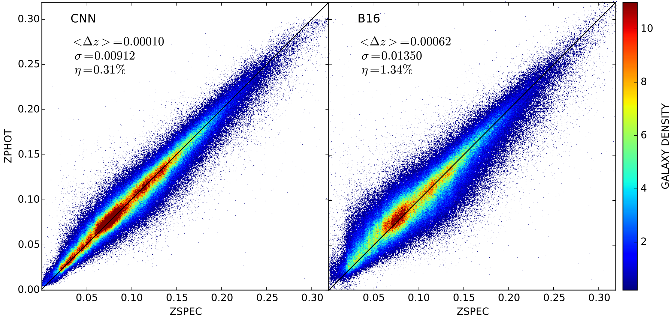
Output probabilities

Vector of posterior probabilities for the galaxy redshift to be in a z-bin



The estimator for z-phot is the centroid of the zPDF

Performance never achieved before!



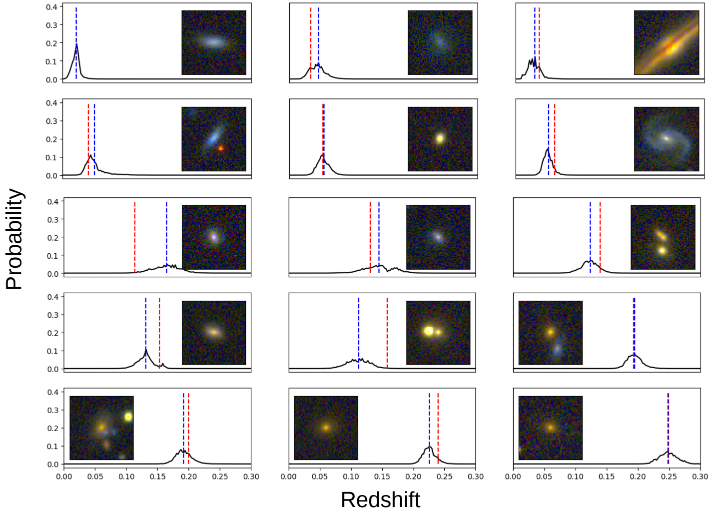
$$\langle \Delta z \rangle = 1.0 \times 10^{-4}$$ ← Factor of 6 improvement $$\langle \Delta z \rangle = 6 \times 10^{-4}$$

$$\sigma = 9.1 \times 10^{-3}$$ ← 30 % improvement $$\sigma = 1.3 \times 10^{-2}$$

$$\eta = 0.31\,\%$$ ← Factor of 4 improvement $$\eta = 1.35\,\%$$

$$\Delta z = (z_{phot} - z_{spec}) / (1 + z_{spec})$$
$$\sigma = 1.4826 \times MAD$$
$$MAD = Median(|\Delta z - Median(\Delta z)|)$$
$$\eta = |\Delta z| > 0.05$$

Examples of PDFs



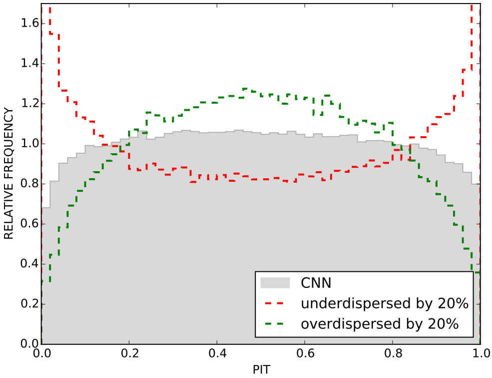
-- Spectroscopic redshift

-- Photometric redshift

Assess the prediction quality of our PDFs

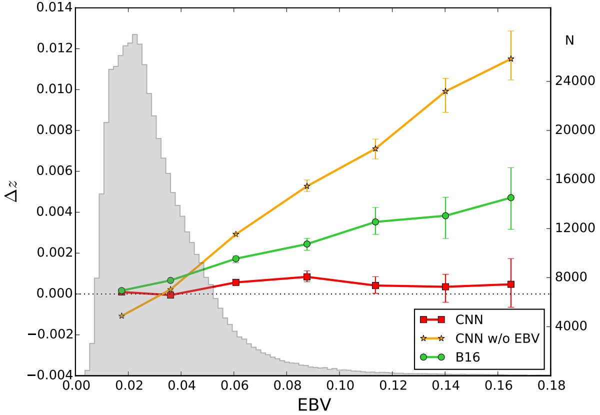
The PIT statistic (Dawid 1984) is based on the histogram of the cumulative probabilities at the true value. For galaxy i with spectroscopic redshift z_i in the test sample :

$$\mathrm{PIT}_i = \int_{-\infty}^{z_i} PDF_i(z)dz$$



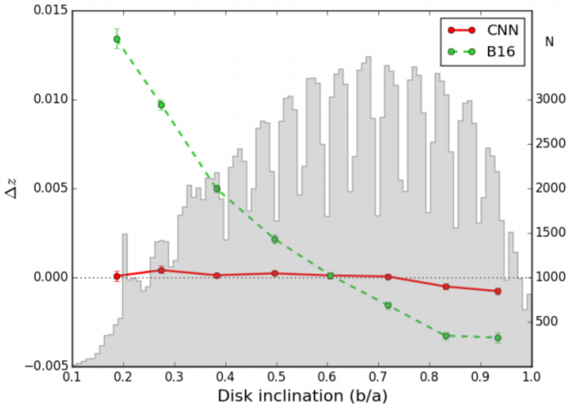
Impact of the extinction of our Galaxy on photometric redshifts

Our method tends to overestimate redshifts in obscured regions (confusing galactic dust attenuation with redshift dimming), unless $E_{(B-V)}$ is used for training



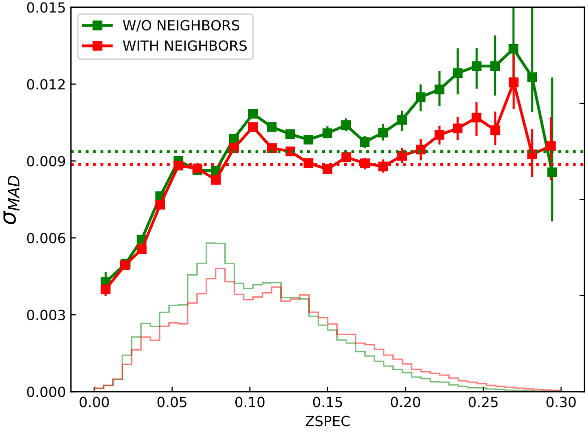
Impact of the disk inclination of galaxies on photometric redshifts

Our method automatically corrects for galactic dust reddening which increases with disk inclination



Neighboring galaxies

The MAD deviation is significantly improved for galaxies with fainter neighbors (43%) compared to those without



Summary results

Trial	training sample size	bias	σ	η
Training with 80% of the dataset	393,219			
Full test sample		**0.00010**	**0.00912**	**0.31**
(B16)		(0.00062)	(0.01350)	(1.34)
Widest 20% of PDFs		**0.00005**	**0.00789**	**0.06**
Stripe 82 only		-0.00009	0.00727	0.34
Stripe 82 with widest 20% of PDFs removed		**0.00004**	**0.00635**	**0.09**
Training with 50% of the dataset★	250,000	0.00007	0.00910	0.29
Training with 20% of the dataset	**99,001**	**-0.00001**	**0.00914**	0.30
Training with 2% of the dataset	10,100	-0.00017	0.01433	1.26
Training and testing on Stripe 82	**15,771**	-0.00002	**0.00795**	0.38

Second step: The classification of light curves of supernovae (SN Ia/ SN Non-Ia)

Johanna Pasquet, Jérôme Pasquet, Marc Chaumont and Dominique Fouchez

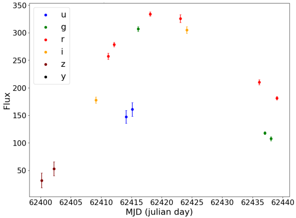
Difficulties for the classification

Many factors degrade the performance of machine learning algorithms:

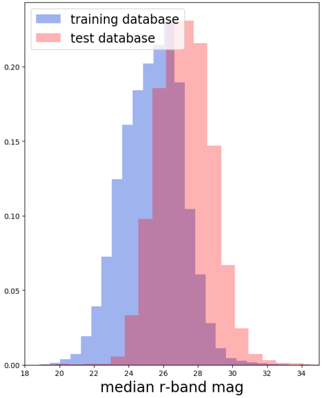
Small training databases

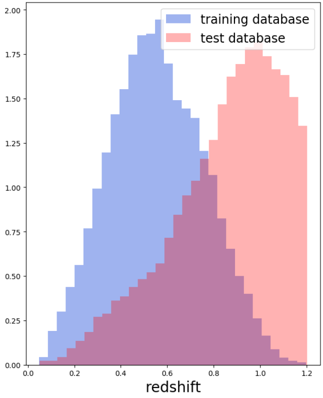
Data can be sparse with an irregular sampling

Non-representativeness between the training and the test databases



Non-representativeness between the training and test databases





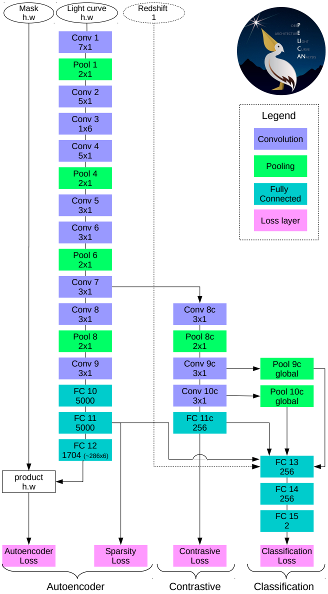
The non-representativeness of the databases, which is a problem of mismatch, is critical for machine learning process.

PELICAN: a deeP architecturE for the LIght Curve ANalysis
(**Johanna Pasquet**, Jérôme Pasquet, Marc Chaumont and Dominique Fouchez, just submitted)

Key elements :

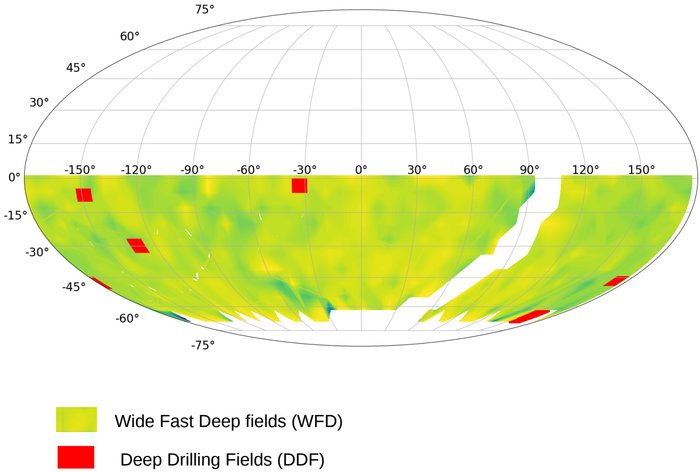
1. a complex Deep Learning architecture to classify light curves of supernovae
2. trained on a small and biased training database
3. overcome the problem of non-representativeness between the training and the test databases
4. deal with the sparsity of data and the difference of sampling and noise

The ability of PELICAN to deal with the different causes of non-representativeness between the training and test databases, and its robustness against survey properties and observational conditions, put it on the forefront of the light curves classification tools for the LSST era.



Mask
h.w
Light curve
h.w
Redshift
1
Conv 1
7x1
Pool 1
2x1
Conv 2
5x1
Conv 3
1x6
Conv 4
5x1
Pool 4
2x1
Conv 5
3x1
Conv 6
3x1
Pool 6
2x1
Conv 7
3x1
Conv 8
3x1
Pool 8
2x1
Conv 9
3x1
FC 10
5000
FC 11
5000
FC 12
1704 (~286x6)
product
h.w
Conv 8c
3x1
Pool 8c
2x1
Conv 9c
3x1
Conv 10c
3x1
FC 11c
256
Pool 9c
global
Pool 10c
global
FC 13
256
FC 14
256
FC 15
2
Autoencoder
Loss
Sparsity
Loss
Contrasive
Loss
Classification
Loss
Autoencoder
Contrastive
Classification
DEEP
ARCHITECTURE
LIGHT
CURVE
ANALYSIS
Legend
Convolution
Pooling
Fully
Connected
Loss layer

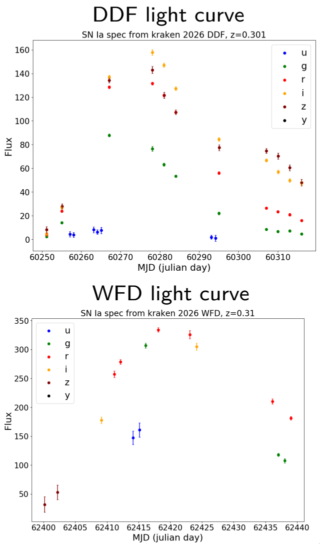
The main survey and the deep fields of LSST



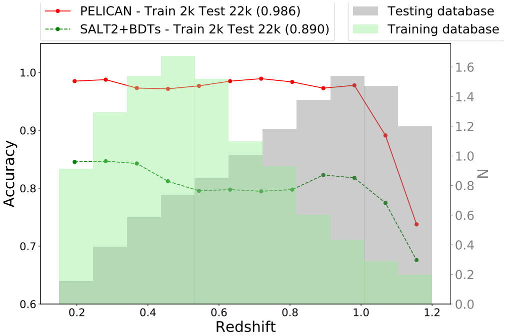
LSST simulated data

Two methodologies:

1. A training and a test on deep fields (DDF)
2. A training on deep fields and a test on the main survey (WFD)

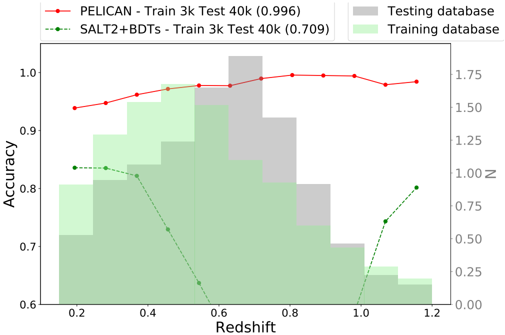


Results on DDF



	Training database (spec only)	Test database (phot only)	Accuracy	Recall_{Ia} Precision_{Ia}>0.95	Recall_{Ia} Precision_{Ia}> 0.98	AUC
DDF	500	1,500	0.849 (0.746)	0.617 (0.309)	0.479 (0.162)	0.937 (0.848)
	2,000	2,000	0.925 (0.783)	0.895 (0.482)	0.818 (0.299)	0.984 (0.882)
	2,000	**22,000**	**0.934 (0.793)**	**0.926 (0.436)**	**0.851 (0.187)**	**0.986 (0.880)**
	10,000	14,000	0.979 (0.888)	0.992 (0.456)	0.978 (0.261)	0.998 (0.899)

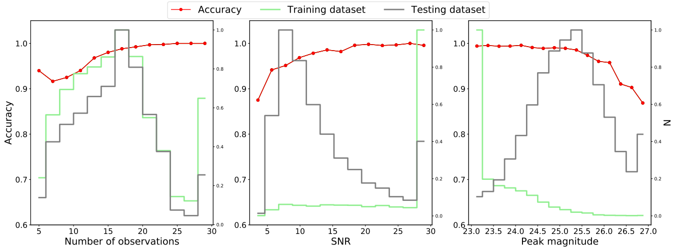
Results on WFD



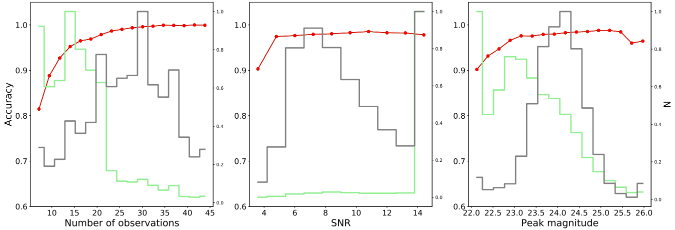
	Training database (spec only)	Test database (phot only)	Accuracy	Recall_{Ia} $\text{Precision}_{Ia} > 0.95$	Recall_{Ia} $\text{Precision}_{Ia} > 0.98$	AUC
WFD	DDF Spec : 2, 000	WFD : 15, 000	0.917 (0.650)	0.857 (0.066)	0.485 (0.000)	0.974 (0.765)
	DDF Spec : 3, 000	**WFD : 40, 000**	**0.940 (0.650)**	**0.939 (0.111)**	**0.729 (0.000)**	**0.984 (0.752)**
	DDF Spec : 10, 000	WFD : 80, 000	0.962 (0.651)	0.977 (0.121)	0.889 (0.010)	0.992 (0.760)

Further analysis of the behaviour of PELICAN

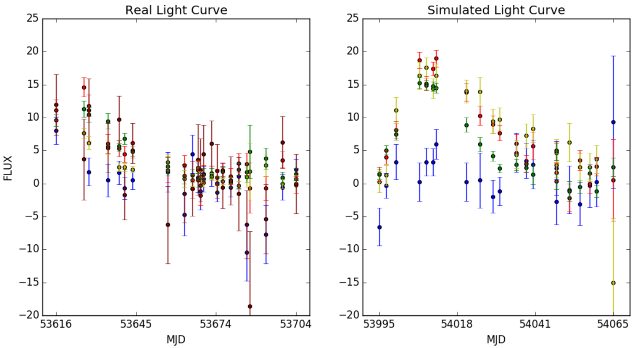
DDF



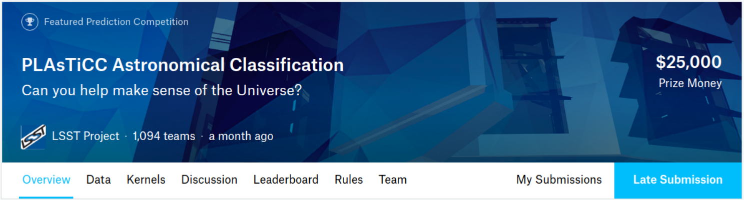
WFD



SDSS data



Training database	test database	Accuracy	AUC
SDSS simulations : 219,362	SDSS-II SN confirmed : 582	0.462	0.722
SDSS simulations : 219,362 SDSS-II SN confirmed : 80	SDSS-II SN confirmed : 582	0.868	0.850



In the money Gold Silver Bronze

#	△pub	Team Name	Kernel	Team Members	Score	Entries	Last
1	—	Kyle Boone			0.68503	104	1mo
2	▲2	Mike & Silogram			0.69933	176	1mo
3	▼1	Major Tom			0.70016	366	1mo
4	▼1	AhmetErdem			0.70423	233	1mo
5	—	SKZ Lost in Translation			0.75229	343	1mo
6	▲2	Stefan Stefanov			0.80173	28	1mo
7	▲3	hklee			0.80836	63	2mo
8	▼1	rapids.ai			0.80905	133	1mo
9	▼3	Three Musketeers			0.81312	313	1mo
10	▲3	J&J			0.81901	246	1mo

Summary

Era of Big data

The future surveys will deliver multi-band photometry for billions of sources

Many issues for the classification algorithms

- Small size of the training database due to the limitation of the spectroscopic follow-up
- Several problems of representativeness
- Nature of data : sparse with an irregular sampling

Promising results for the estimation of photometric redshifts

We developed a CNN used as a classifier to estimate photometric redshifts and their associated PDFs. • Our work shows significant significant improvements for:

- the dispersion of photometric redshifts,
- the PDFs that are well calibrated
- no measurable bias with the reddening and the inclination of galaxies

Summary

New solutions for the classification of light curves

PELICAN obtained the best performance ever achieved with a non-representative training database of the SPCC challenge

PELICAN is able to significantly remove several types of non-representativeness between the training and the test databases due to :

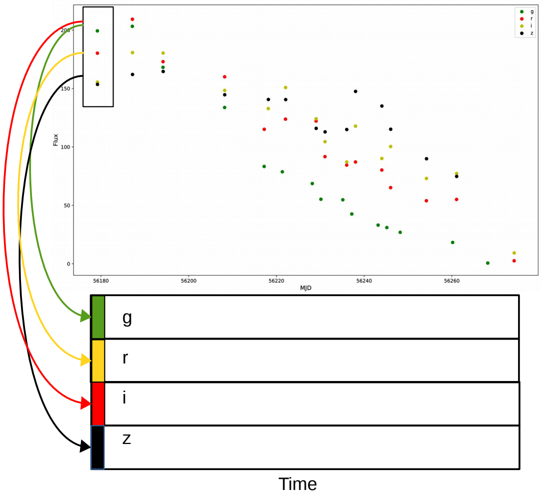
- the limit in brightness and redshift of the spectroscopically confirmed data
- the different observational strategies
- the difficulty of simulated data to reproduce perfectly real data

PELICAN can deal with the data that are sparse, with an irregular sampling

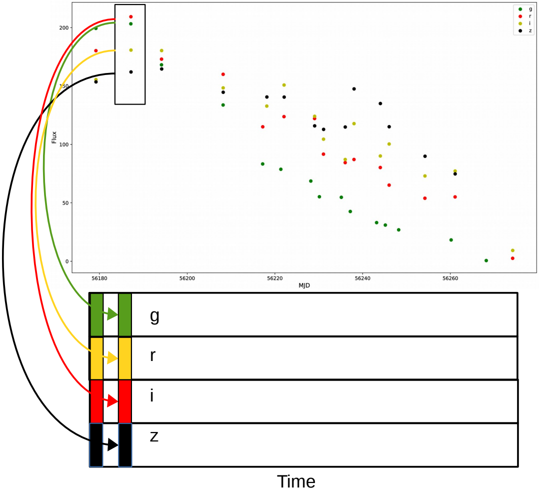
Perspectives

- Estimate photometric redshift from light curves with PELICAN
- Propagation of uncertainties due to the photometric redshift of the supernovae and the host galaxy and the classification errors in the Hubble diagram

The Light Curve Image (LCI)



The Light Curve Image (LCI)



⚠ Overfitting of missing data (zero values)

pact of Signal-to-Noise Ratio (SNR) on widths of PDFs

The Stripe 82 region, which combines repeated observations of the same part of the sky, gives us the opportunity to look into the impact of SNR