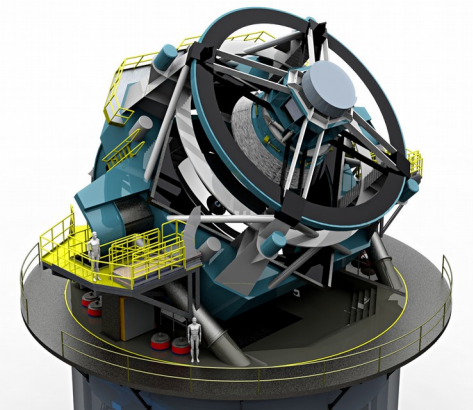




## Exploration des données temporelles transitoires issues des relevés de prochaine génération

E. Gangler (LPC, Clermont-ferrand)



*En collaboration avec*

E. Mephu Nguifo (LIMOS, Clermont-Ferrand)

M. Moniez (LAL, Orsay)

J.-M. Petit, M. Scuturici (LIRIS, Lyon)

S. Lopes, L. Yeh, K. Zeitouni (DAVID, UVSQ)

# Classification des objets

- Données statiques

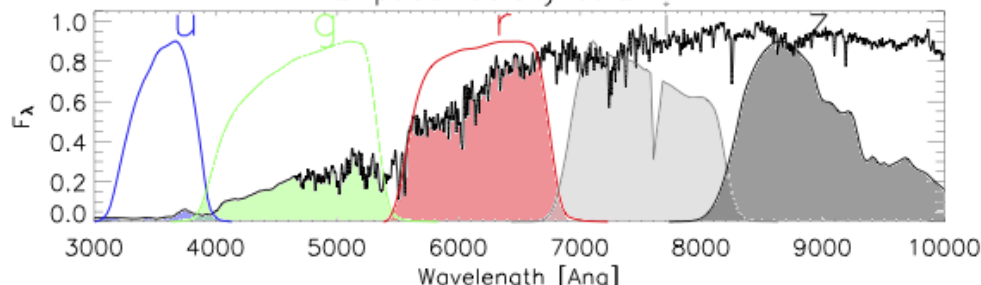


CFHT deep field

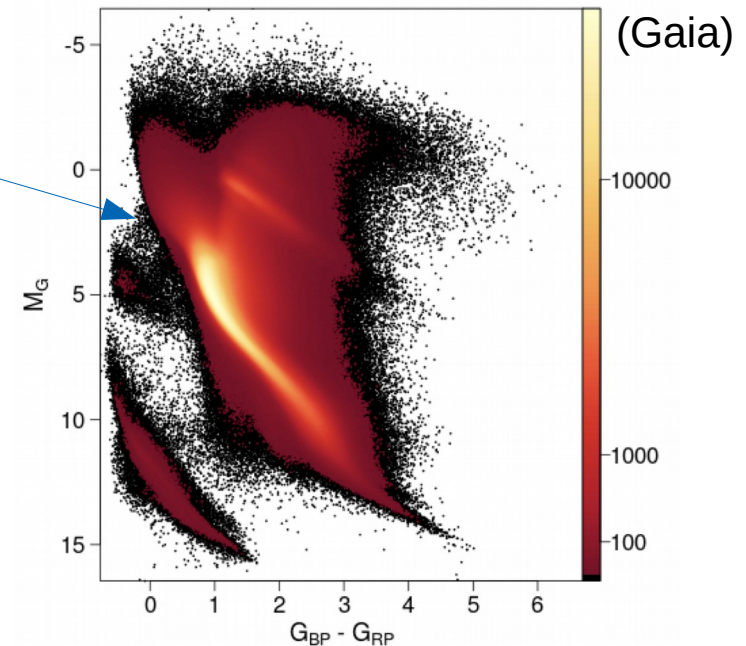
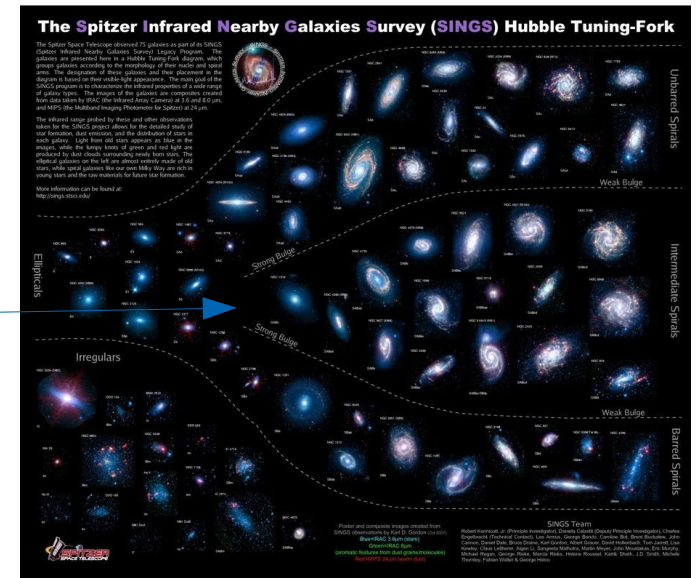
**Morphologie**  
(galaxies)

**Magnitude, Couleur**  
(étoiles, galaxies)

+ **Spectroscopie** complémentaire ...  
Elliptical Galaxy at  $z=0.4$

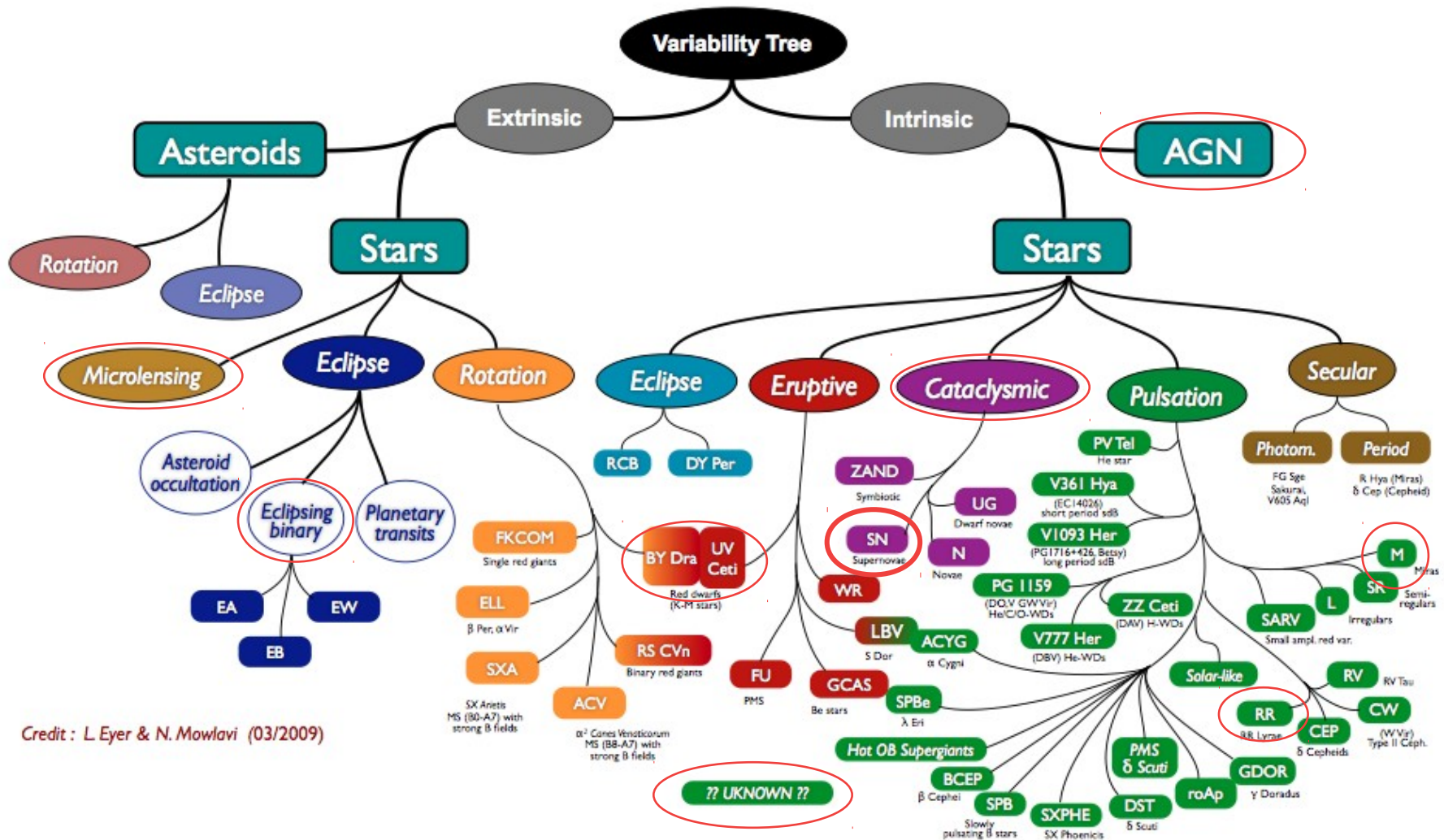


(Spitzer)



# Classification des transitoires

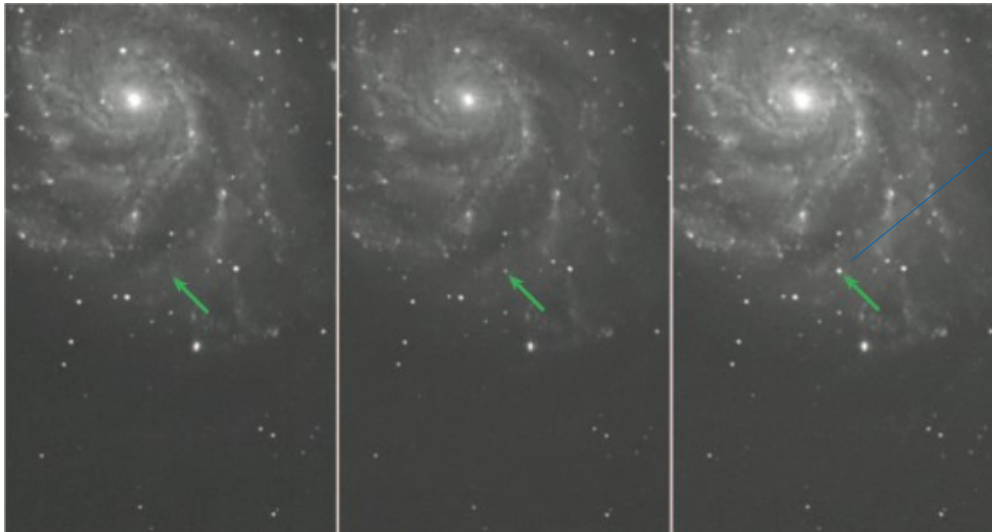
- Une zoologie complexe :





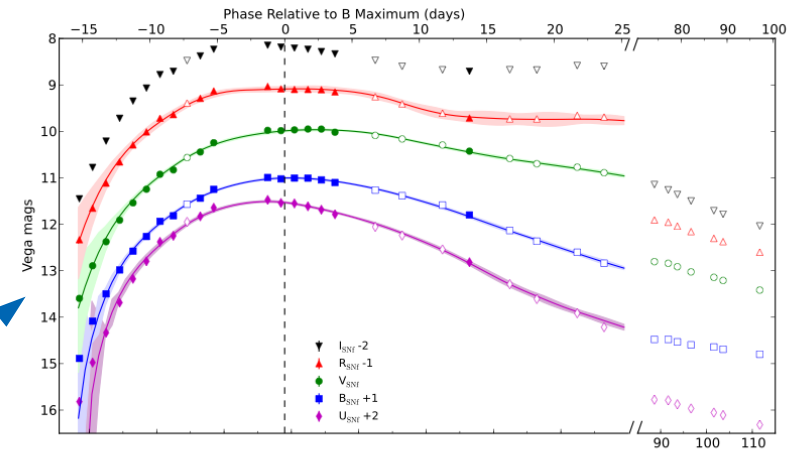
# Classification des objets

- Données temporelles

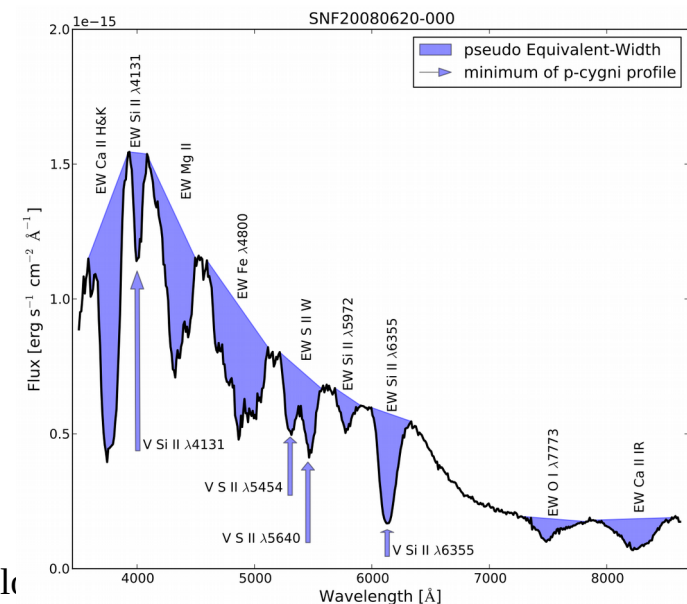


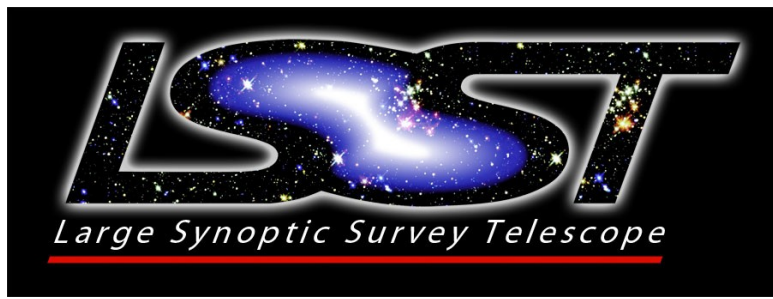
SN 2011 fe

**Spectroscopie** d'identification:  
trop coûteuse  
seuls quelques objets  
→ faible lot d'entraînement



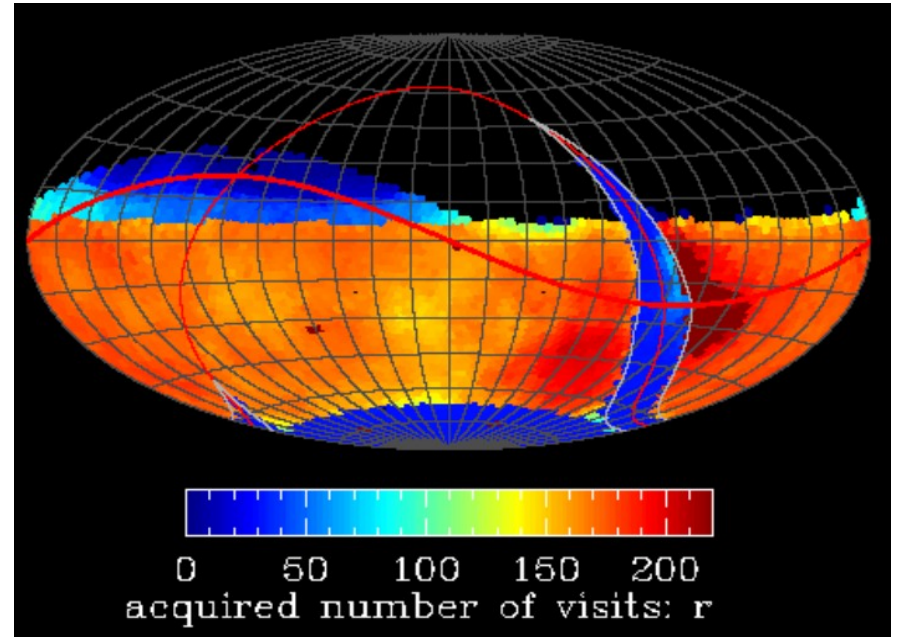
**Courbe de lumière**  
(évolution temporelle du flux en plusieurs bandes)



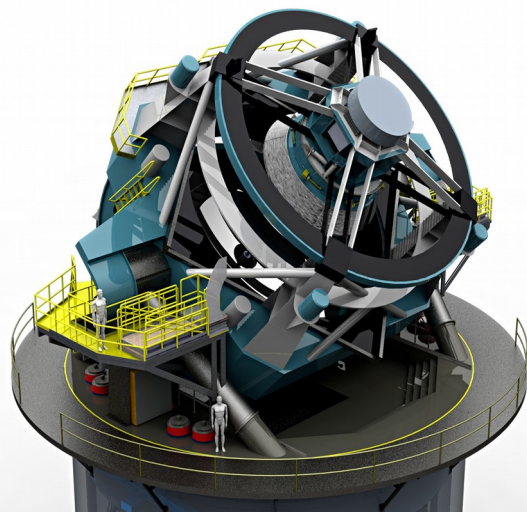


# capabilities :

- A stage-IV survey :
  - 8.4 (6.7) m telescope
  - Cerro Pachon (Chili)
  - 3.2 Gpix 9.6° FoV camera
  - 0.2" pixel / 0.7" median FWHM
  - First light 2020, Survey 2022



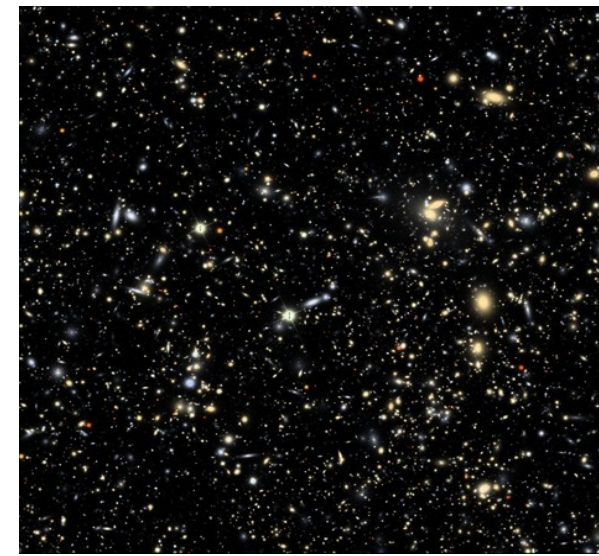
- All visible sky in 6 bands (ugrizy) ( $\sim 18000^\circ$ )
- 2x15 s exposure, 1 visit / 3 days  
 $r \sim 24.4 / \text{visit}$
- During 10 years !  
 $\rightarrow \sim 825 \text{ visits (all bands)}$
- 20TB/day 60 PB/10 years



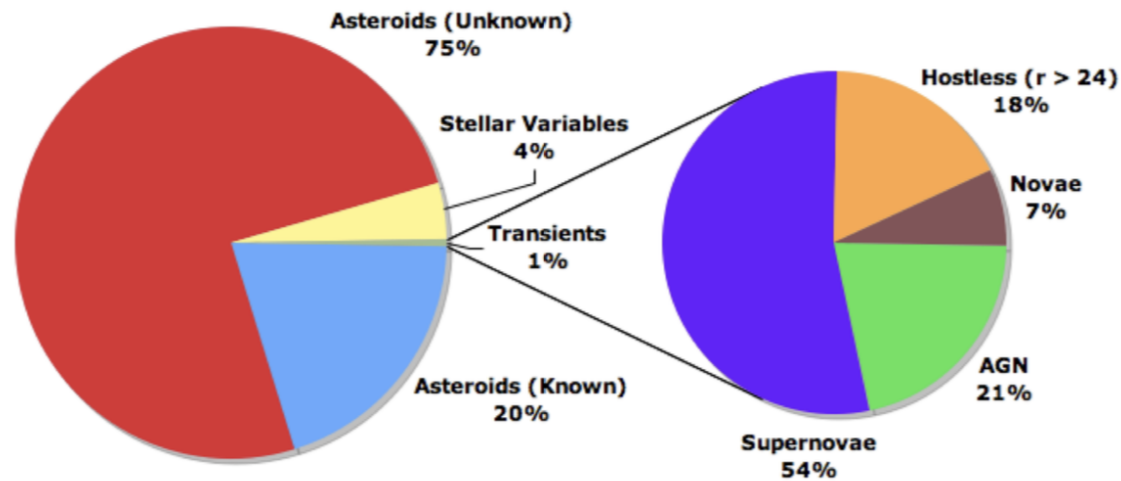
# LSST Data in short

- Huge data flow

- Images : 2x6.4 Gpix/39 seconds
- 20 TB/night, 60 PB image archive
- 40.  $10^9$  objets ( 100-200 TB catalog )
- 5 000.  $10^9$  detections "sources" ( 3-5 PB catalog )
- 32 000.  $10^9$  measurements "forced sources" (1-2 PB catalog)
  - → **Post-observation transients classification**
- Nightly alerts: **10 millions per night**
  - *Live transient classification*



Simulation 1 CCD  
4k x 4k





# https://www.kaggle.com/c/PLAsTiCC-2018

Featured Prediction Competition

## PLAsTiCC Astronomical Classification

Can you help make sense of the Universe?



LSST Project · 1,094 teams · a month ago

1,094

Teams

1,384

Competitors

22,895

Entries

\$25,000

Prize Money

[Overview](#)

[Data](#)

[Kernels](#)

[Discussion](#)

[Leaderboard](#)

[Rules](#)

Launched Sep 28th 2019

Due dec 14th 2019

147 public kernels

279 discussion topics

### Overview

#### Description

#### Evaluation

#### Prizes

#### Timeline

#### PLAsTiCC's Team

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://www.kaggle.com/c/PLAsTiCC-2018>

Featured Prediction Competition

## PLAsTiCC Astron

Can you help make se

LSST Project · 1,094 t

Overview Data Kernels

Overview

Description

Evaluation

Prizes

Timeline

PLAsTiCC's Team →

Tarek Allam Jr.\* (University College of London, UK)

Anita Bahmanyar (University of Toronto, Canada)

Rahul Biswas (Stockolm University, Sweden)

Mi Dai (Rutgers, The State University of New Jersey, USA)

Lluís Galbany (University of Pittsburgh, USA)

Renée Hložek (Univeristy of Toronto, Canada)

Emille E. O. Ishida (CNRS/Universite Clermont Auvergne, France)

Saurabh W. Jha (Rutgers, The State University of New Jersey, USA)

David O. Jones (University of California Santa Cruz, USA)

Michelle Lochner\* (African Institute for Mathematical Sciences, South Africa)

Ashish A. Mahabal (California Institute of Technology, USA)

Alex I. Malz\* (New York University, USA)

Kaisey S. Mandel (Cambridge University, UK)

Juan Rafael Martínez-Galarza (Harvard-Smithsonian Center for Astrophysics, USA)

Jason D. McEwen (University College of London, UK)

Daniel Muthukrishna (Kavli Institute for Cosmology, UK)

Gautham Narayan (Space Telescope Science Institute, USA)

Hiranya Peiris\* (Stockolm University, Sweden)

Christina M. Peters (University of Toronto, Canada)

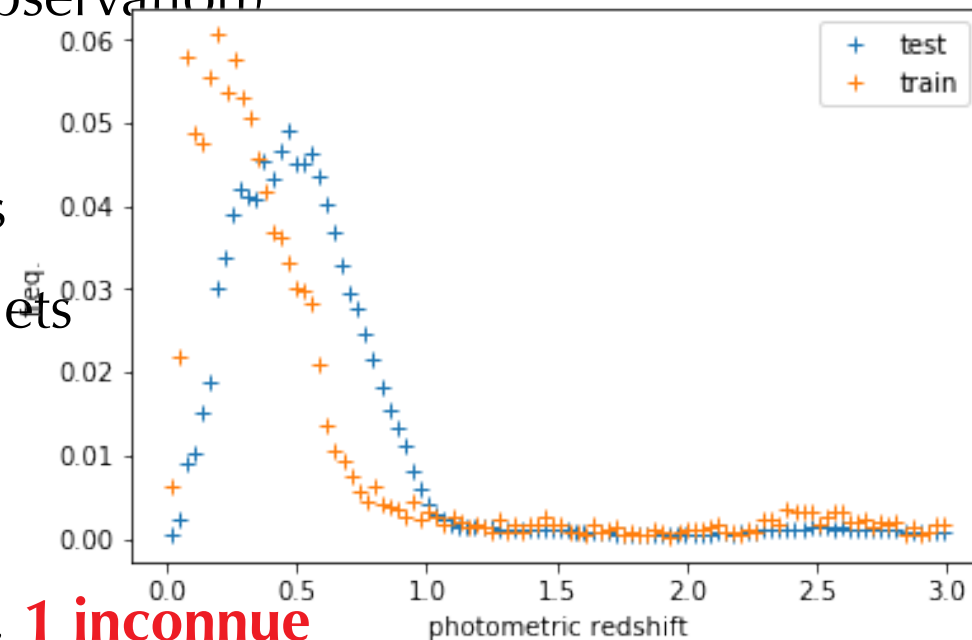
Kara Ponder (University of California Berkeley, USA)

Christian N. Setzer\* (Stockolm University, Sweden)

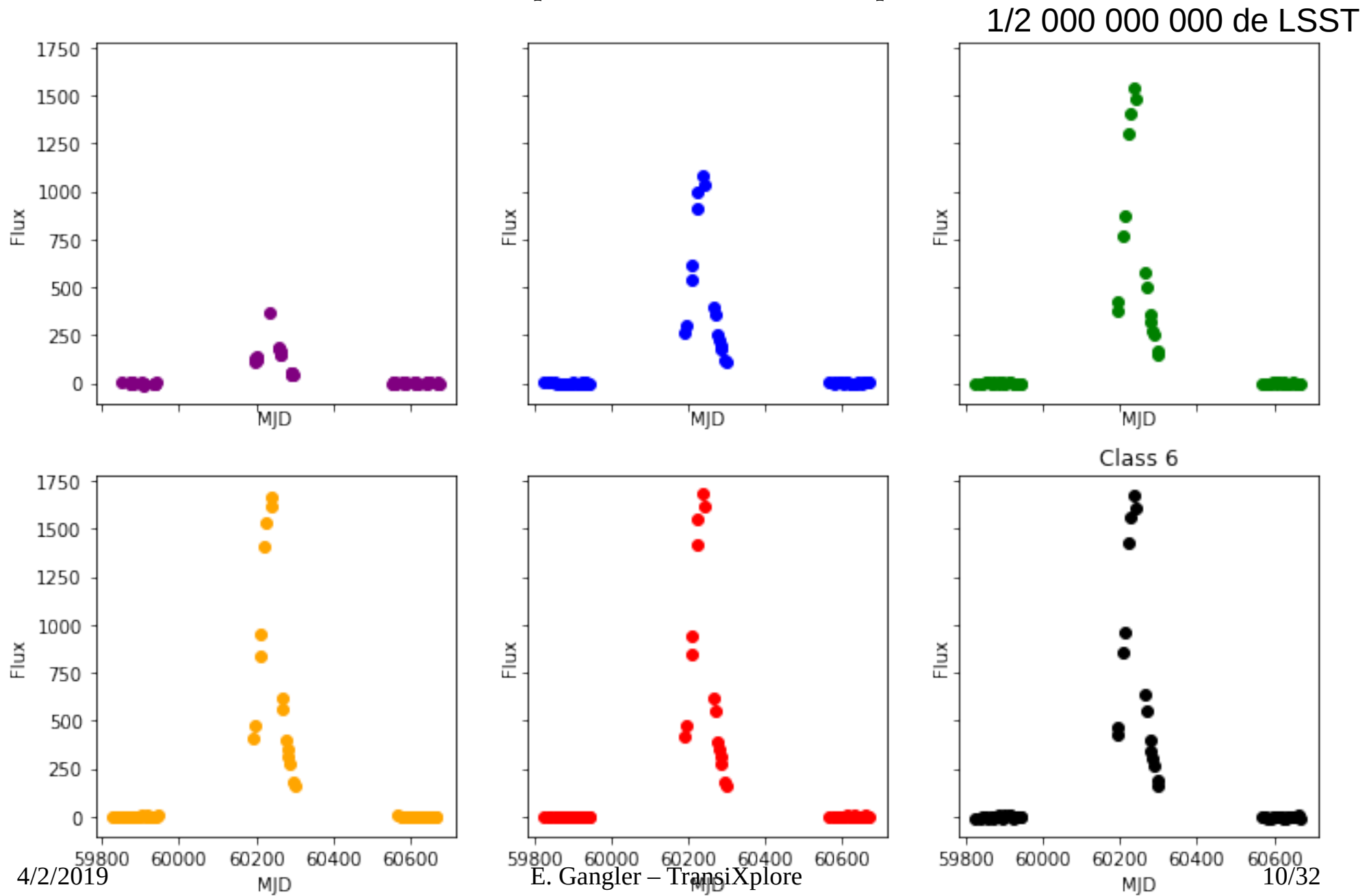


# Données de PLAsTiCC

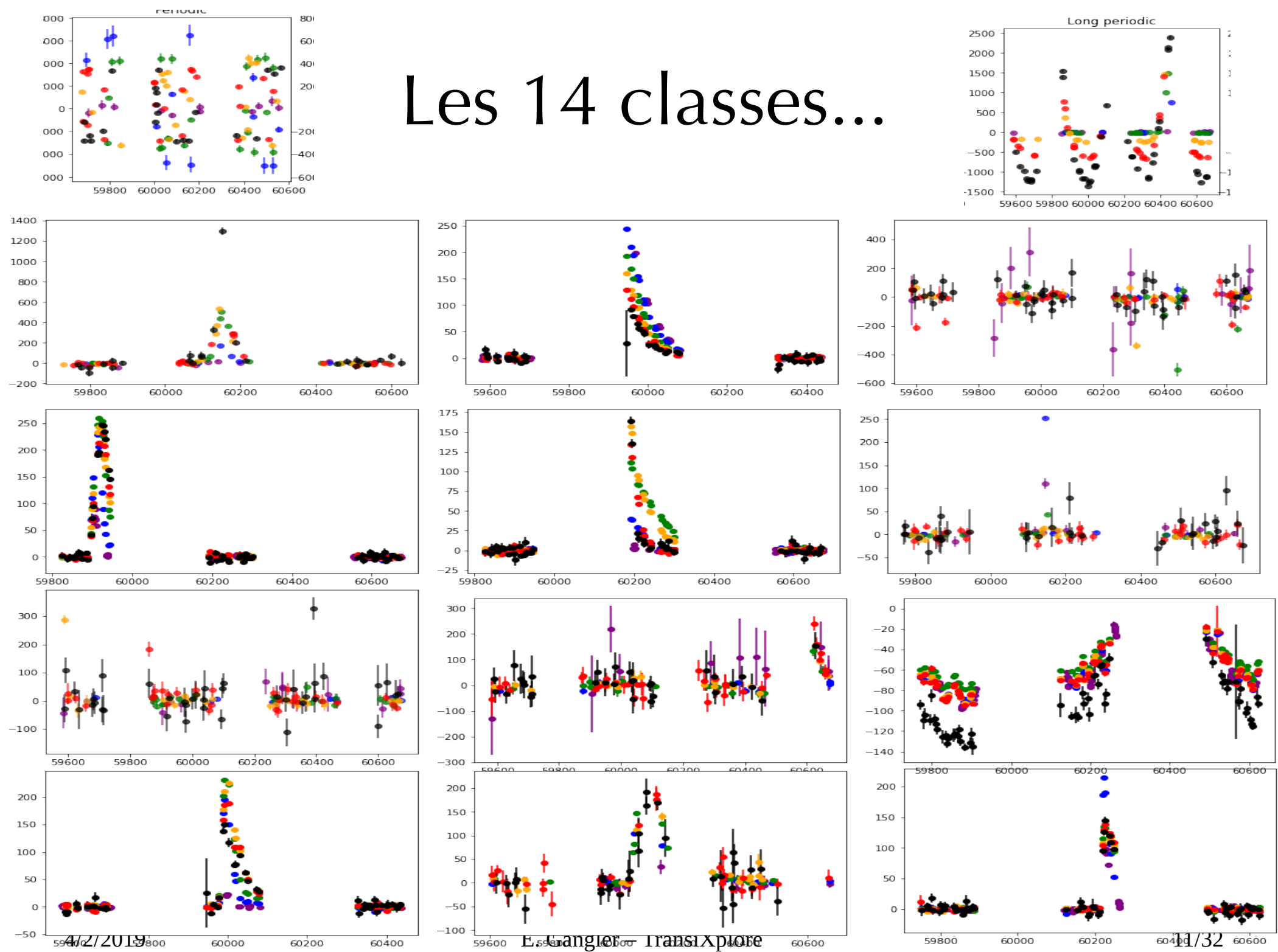
- Données *réalistes* simulées
  - 3 ans de fonctionnement de LSST, 1/150<sup>ème</sup> de l’empreinte
    - **Volume** : ~450 000 000 mesures  
(équivalent à ~7 jours de transitoires hors astéroïdes)
    - Trous dans les séries (saisons d’observation)
  - Problèmes de **représentativité**
    - Lot d’entraînement : 7 848 objets
    - Lot d’application : 3 492 890 objets
    - Entraînement mieux mesuré
  - 15 classes d’objets
    - 5 galactiques, 9 extragalactiques, **1 inconnue**



# Quelques exemples



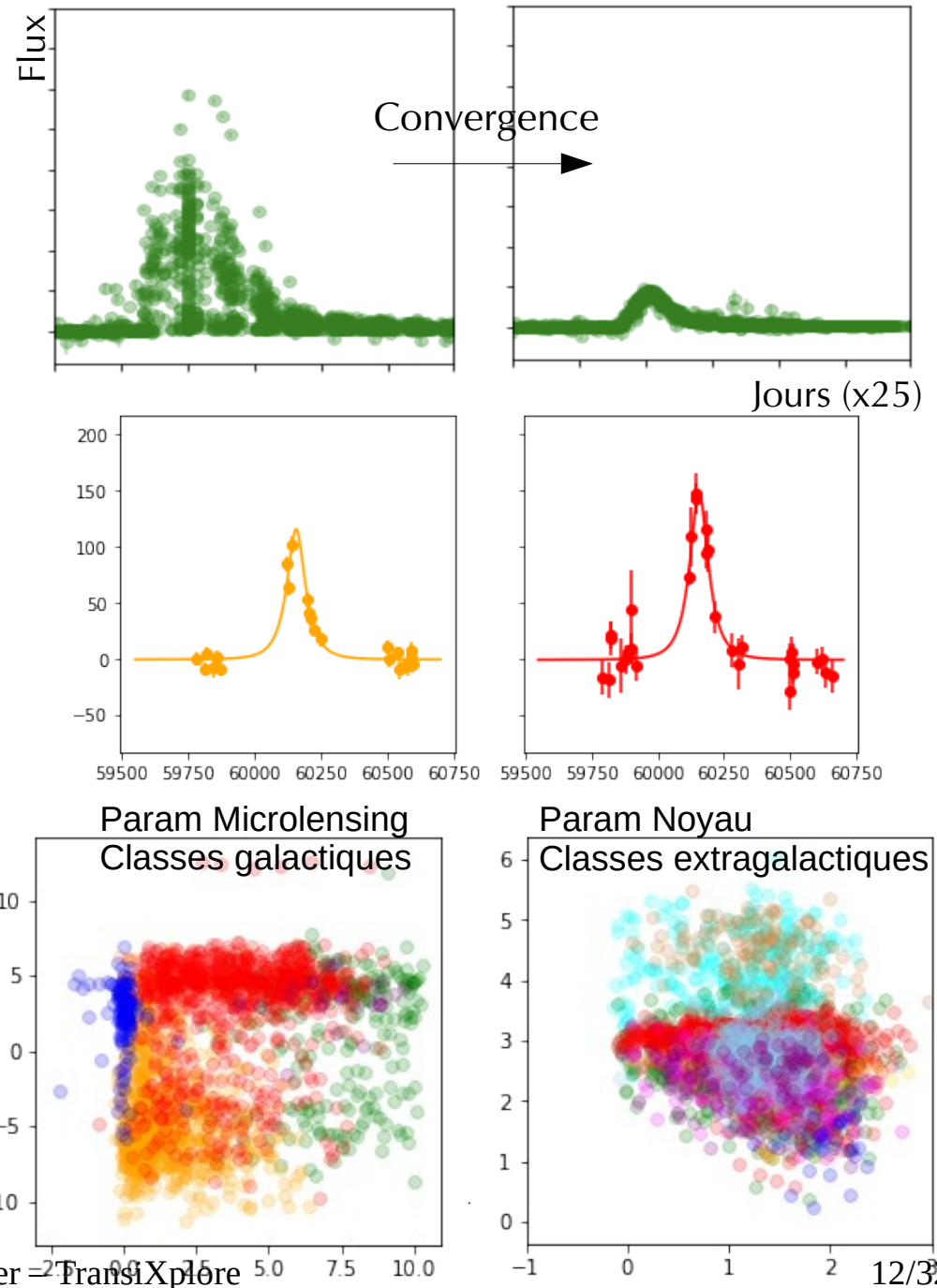
# Les 14 classes...










# Données PLAsTiCC

- *Modèle complet !* (corrélation entre bandes, variabilité interne aux classes)
- Séries longues ; alignement des données → *temps de convergence* du modèle
- Temps de développement...
- *Templates exacts* pour le *microlensing*
  - kernel public, utilisé par les soumissions dans le top #10
- *Extraction de motifs pour les étudiants*
- Code disponible sous [github/TransiXplore](https://github.com/TransiXplore)








# Plasticc : retour sur expérience

1	—	Kyle Boone	Astronomes		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 Stefano
7	▲3	hkleee
8	▼1	rapids.ai
9	▼3	Three Musketeers
10	▲3	J&J

Thx #9 !

Discussions  
Encore un peu actives !

1		Representative light curves for hard classes Raman 4 months ago	last comment by Raman 4mo ago	0
25		Results on the unblinded test set Kyle Boone 9 months ago	last comment by Sergey Zlobin 1mo ago	2
4		Error Importing Sklearn Cross_Validation Danny a year ago	last comment by Misba 1mo ago	22
3		How to install a library in a kernel Manoj 10 months ago	last comment by Mezianek 4mo ago	5
33		20th Place Solution Giba 10 months ago	last comment by Akhilesh 5mo ago	8

- First of all I would like to point to [@manugangler's kernel](#), where he provided a method for fitting light curves to microlensing events. The features obtained from there worked wonderfully for us, especially after taking passband-wise ratios and differences for the microamp and microbase features, respectively. Einstein time is the most important feature of my model.

# Plasticc : retour sur expérience

- Soumission gagnante :

- *Adaptation de domaine et augmentation de données*

- **Processus gaussiens (temps de calcul !)**

- Extraction de motifs

- Classificateur *Light Gradient Boost Model*

Step	Approximate time to run
Augmenting the training set	1 hour
Fitting the GP and calculating features	<b>10 objects/s -&gt; 100 hours for test set</b>
Training the model	20 minutes
Generating predictions	40 minutes

- #2-9 : peu de diversité...

- *Ensemble de classificateurs, 2 RNN*

- #5 : **Ajustement par templates** (sous-optimaux) pour déterminer les motifs

- #10 : PELICAN (Johanna Itam-Pasquet, CPPM, invitée au workshop TransiXplore)

- Autoencodeurs sous-performants → **piste de collaboration**

- **Remarques** :

- Kernels disponibles, beaucoup d'information à exploiter

- « triche » concernant la classe 99

- Résultats tributaires du modèle de photo-redshift

- Notre approche est pertinente vis-à-vis des résultats

**Quid des shapelets ?**

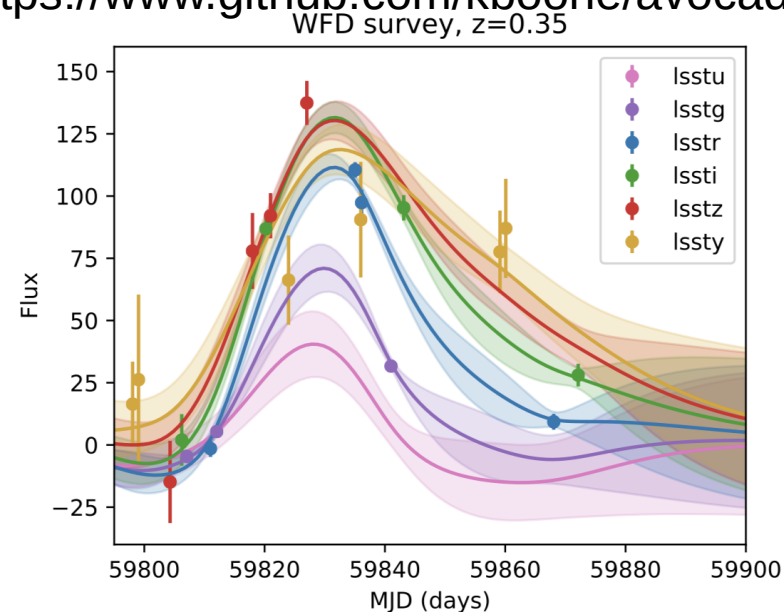
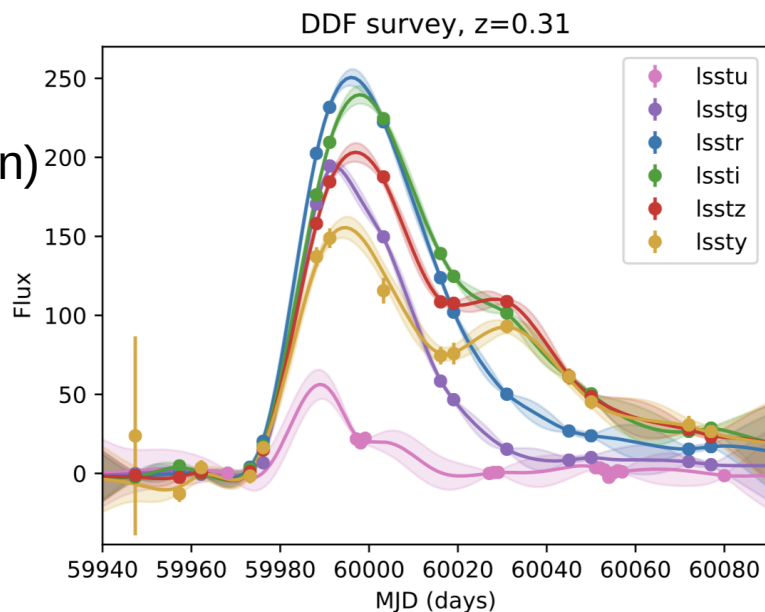


# Avocado (Kyle Boone)

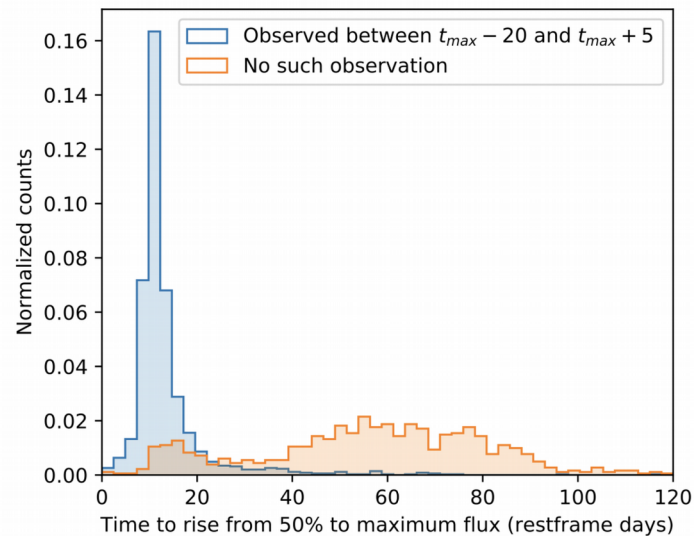
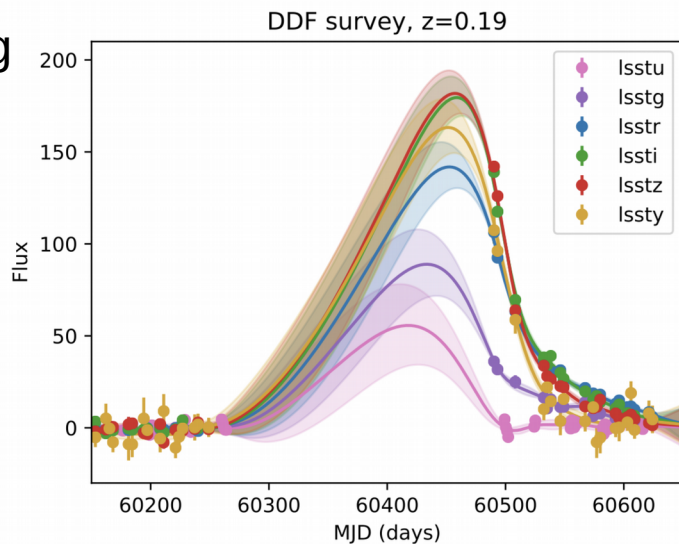
<https://arxiv.org/pdf/1907.04690.pdf>

<https://www.github.com/kboone/avocado>

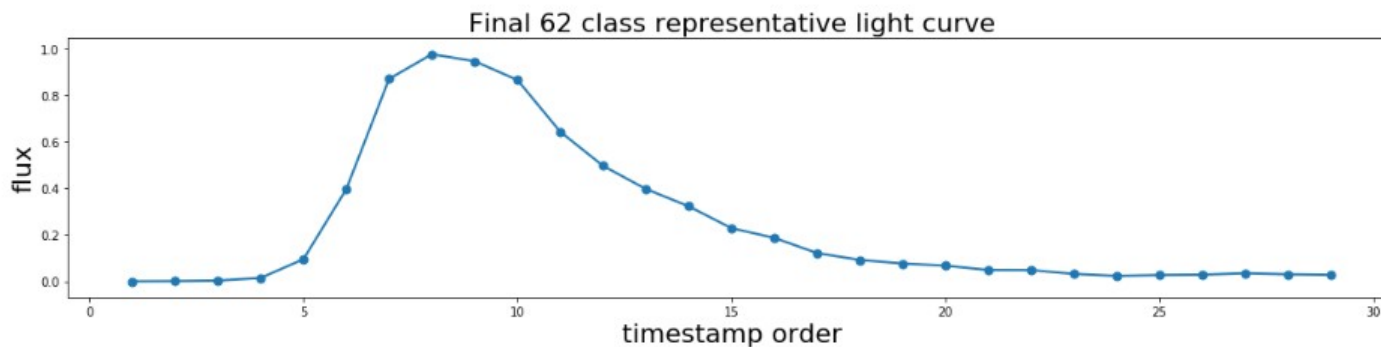
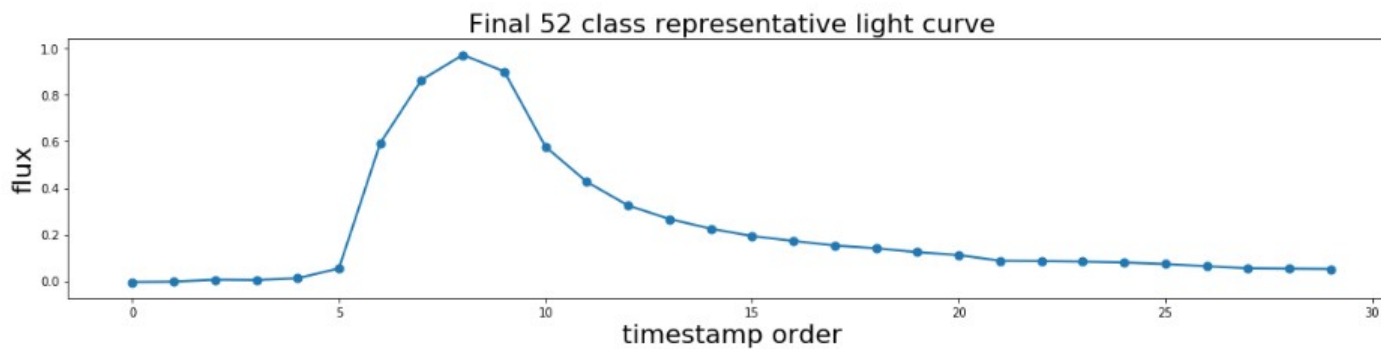
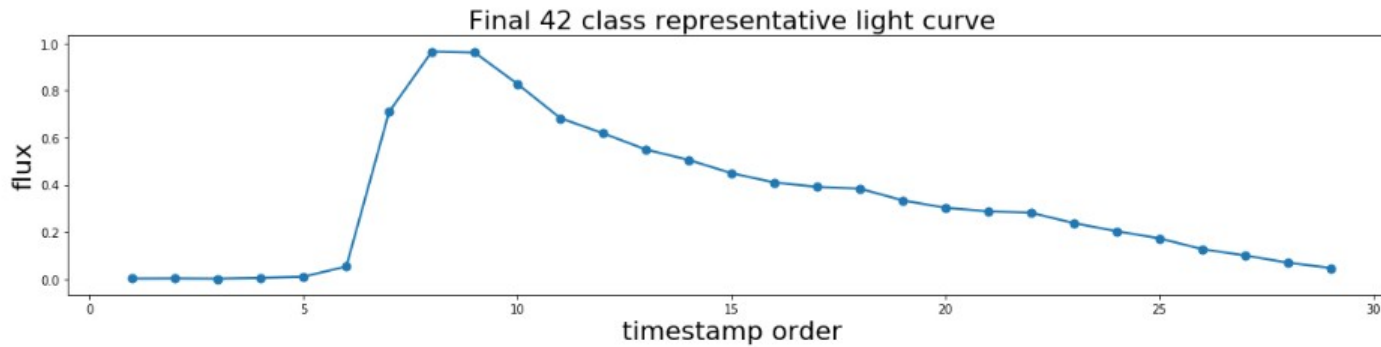
Gaussian processes  
(with band correlation)



Feature engineering  
(data quality)



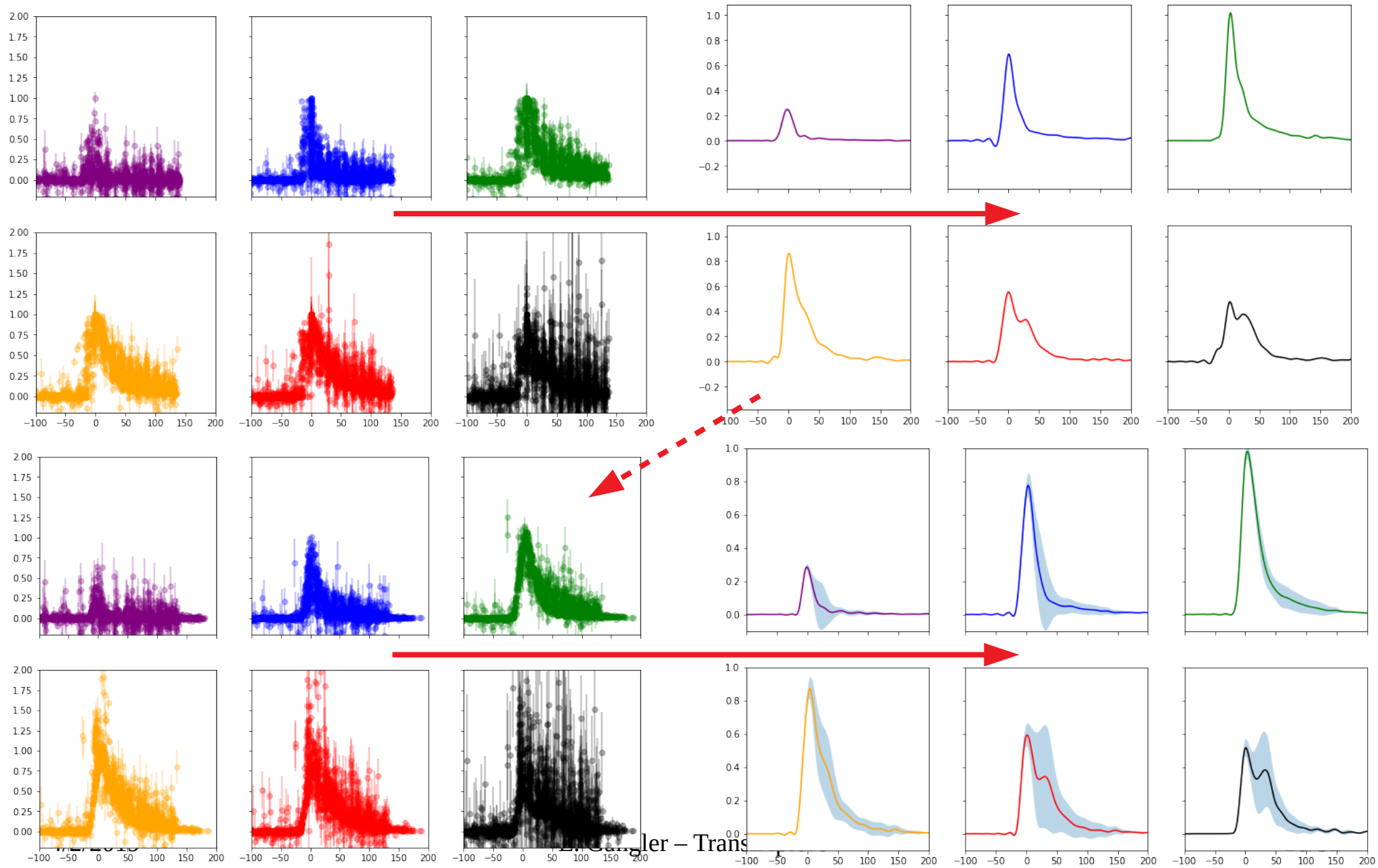
# Templates approaches



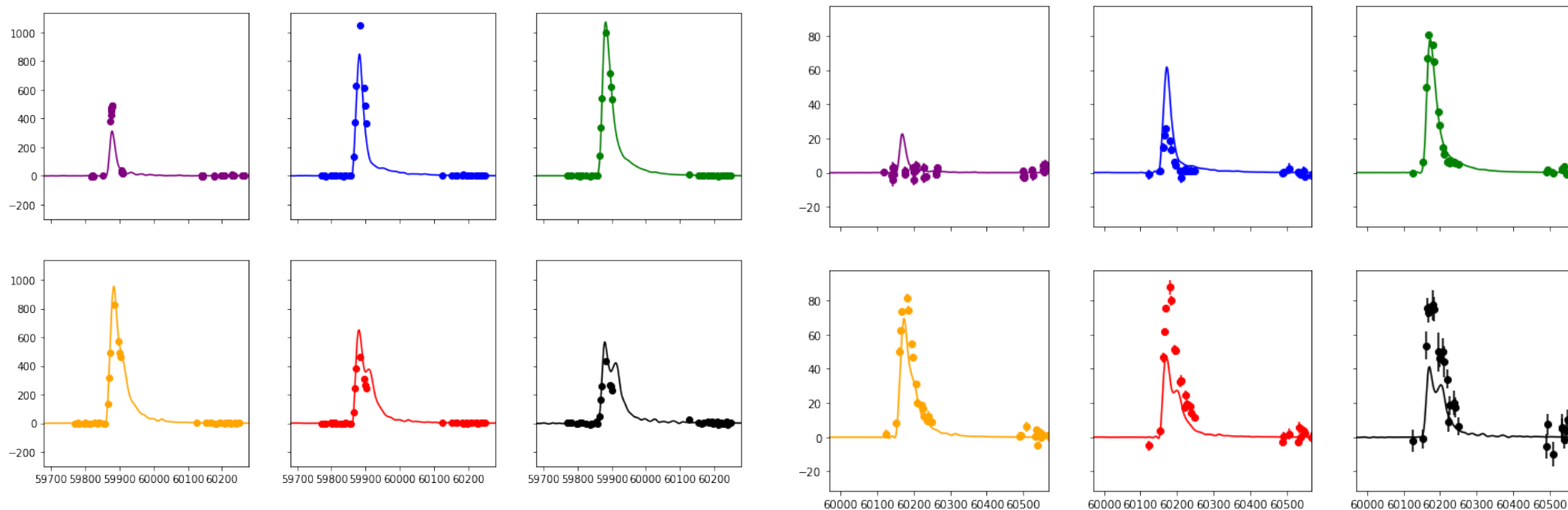
# Template fitting approach

- Time interpolation :
  - → choose a 3rd order B-spline model
  - Fit model by minimizing the distance to data
  - Optimize time step by cross-validation → ~10 days on SNIa
- Initialization and convergence tricky
  - Align on max data for  $t_0$  guess.
  - Best scale approach : initial scale given by maximum → set to 1.
- Convergence
  - Alternate model fitting and object properties fitting
  - 1st step : Fit for  $t_0$ , not Scale (gives good initial template)
  - 2nd step : fit for  $t_0$  and scale → converge the model
  - 3rd step : build an error model, and refit supernovae
    - (not yet done : reconverge the model with error model on!)



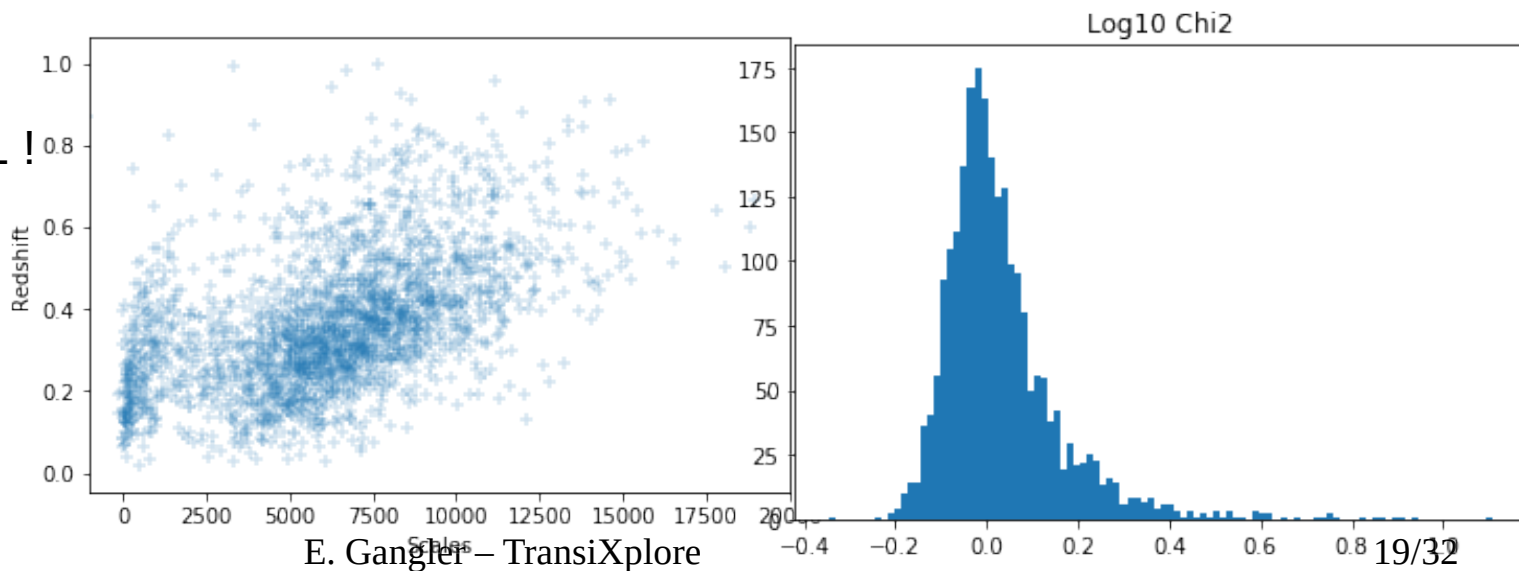


# A few bad fits



Reasons :

- Redshift effect
- Multi-classes in 1 !



# Some conclusions

- Fitting a template :
  - Shared idea in the community
  - Provides restricted set of features : chi2 & scale vs redsfhit
    - Model can be complexified ad lib (variational parameter, K-means based sub-models)
  - But takes time to get good results
  - To come : fit other models
- Goal for december:
  - Compare model-based selection (and models) to output of a shapelet-based approach

# Application aux données SN2010PCC

- *Data challenge précurseur*

- 1100 supernovas
- 2 classes : SNIa et Non Ia

- 2 Patrons

- Discrimination par **rapport de vraisemblances**

- Aucun autre motif utilisé !
- AUC 0.843 : comparable à Lochner 2016

→ **preuve de principe !**

