

References :

- 1-Zachary R. Clayton et al. 2021 :Recovery of TESS Stellar Rotation Periods Using Deep Learning
- 2-Jade Powell et al. 2016 : Classification methods for noise transients in advanced gravitational-wave detectors II: performance tests on Advanced LIGO data.
- 3-Beryl Hovis-Afflerbach et al. 2020 : Identifying and Repairing Catastrophic Errors in Galaxy Properties Using Dimensionality Reduction
- 4-Olaf Ronneberger et al. 2015 : U-Net: Convolutional Networks for Biomedical Image Segmentation

I-Introduction

Systematics, but what kind?

- Noise in measurements : **statistical** and **systematic** noise.
- Statistical noise has its origin in random processes
- **Systematic noise** is caused by **factors that consistently influence** the measurements in a **particular, predictable direction**.
- **Unexpected systematic errors can occur if the factors are not well known**

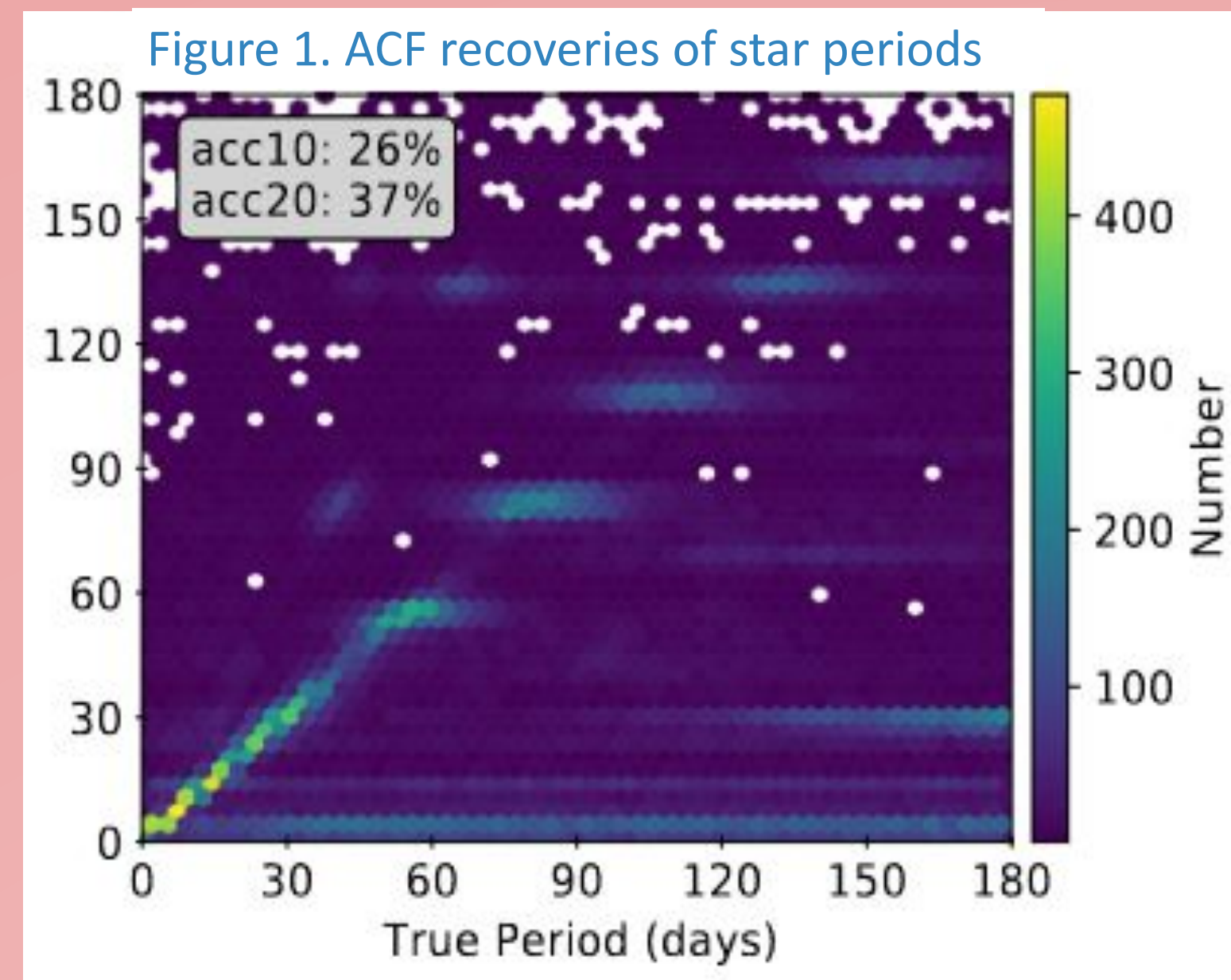
What can we do with such unpredicted, hard to characterize systematics? Is it possible to go beyond these limitations?

→ Example of systematic noise : Periodic systematics parasitizing TESS (Transiting Exoplanet Survey Satellite) data of rotating stars.

→ In order to predict a star's rotation period, the autocorrelation power spectrum of its measured light curve is computed.

→ TESS has a **14 days** rotation period around the earth and a **27 days** segmented observation strategy

→ These systematics are directly seen on figure 1. as well as their aliases.



→ **LiteBIRD** in this story : while the scientific objective is very different, the question of the mission's observation strategy and the impact of systematics on the measured data is essential.

The LiteBIRD simulation framework (https://github.com/litebird/litebird_sim) could provide Time-Ordered Data (TOD) and maps taking into account **realistic noise** and different **scanning strategies** to **test different systematics characterization methods**.

II - Tracking systematics : a Classification Problem

- Identifying and characterizing a systematic error in data can be seen as a **classification problem**.
- Classification is all about **balancing discriminativeness and invariance**
- Very **general** way to formulate this problem : Insights from various approaches to this problem can help
- **Key problem: finding an appropriate space to represent the data in.**

The following examples explore possible methodologies that use the strengths of computer vision to solve classification problems.

III - Augment dimensionality to better reduce it (trust me, it works)

Going back to the **TESS** example, one solution explored to **go beyond the limitations set by the systematics** was to :

- **Transform** the TOD into a **time-period representation** using the Continuous Wavelet Transform (CWT).
- Apply a Convolutional Neural Network (**CNN**) to the obtained 2D "image", having previously trained the CNN on realistic simulations.

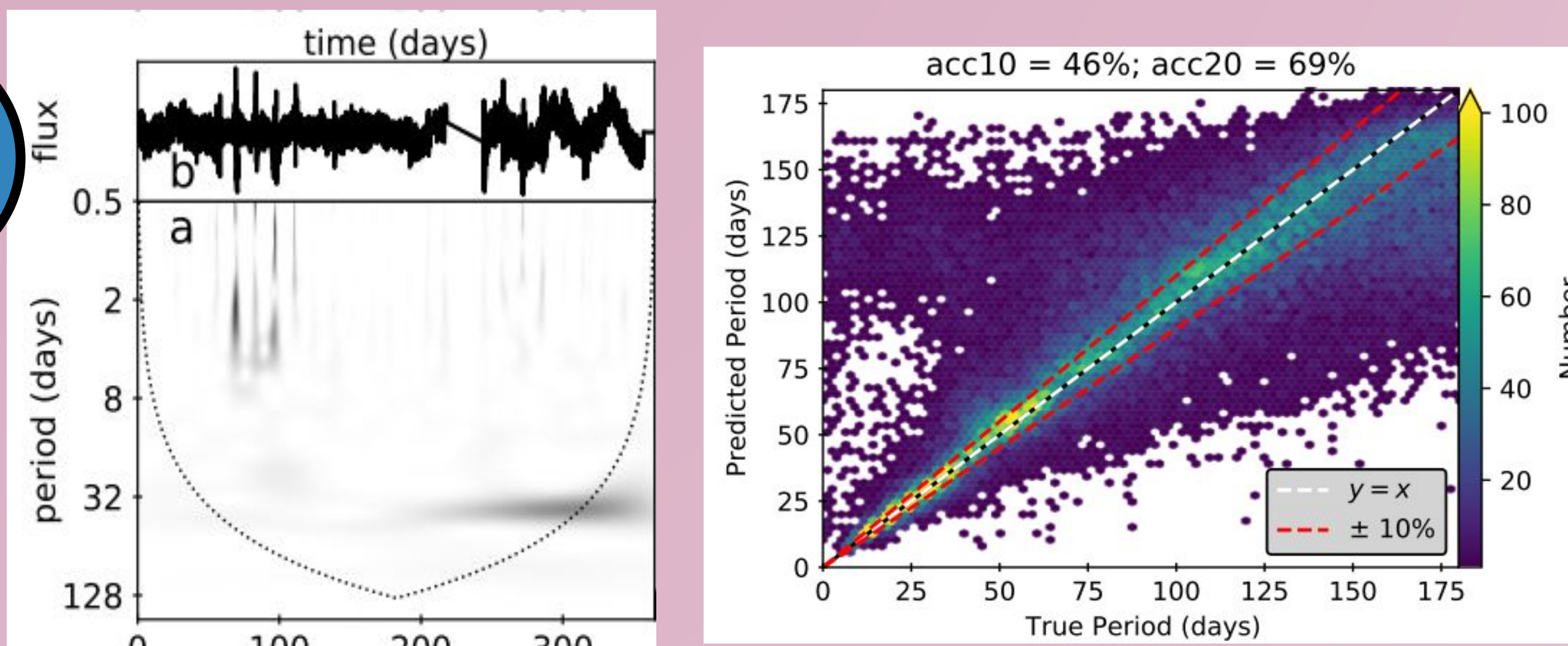


Figure 2. Time-Period representation of the TOD, from its CWT

Figure 3. CNN recoveries of star periods

- The CNN performs better at this task than traditional methods
- **Recognition of Morphological properties** : exactly what computer vision excels at

Gravitational Wave data analysis : classification of transients

- **Hunt for transients** : noise or relevant data?
- Different approaches, some ML based some not

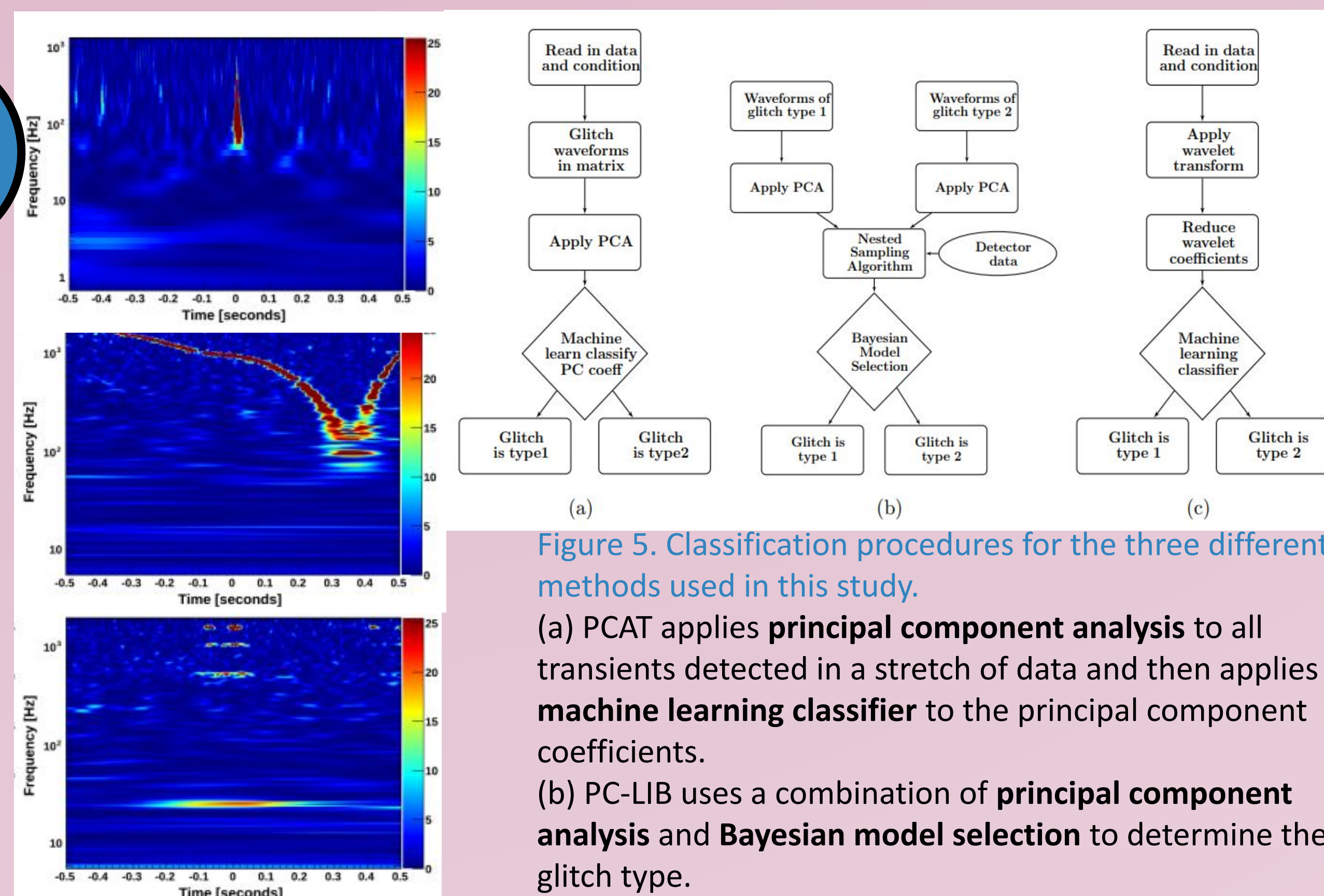


Figure 4. Spectrograms of transients typically found in aLIGO data

Figure 5. Classification procedures for the three different methods used in this study.

- (a) PCAT applies **principal component analysis** to all transients detected in a stretch of data and then applies a **machine learning classifier** to the principal component coefficients.
- (b) PC-LIB uses a combination of **principal component analysis** and **Bayesian model selection** to determine the glitch type.
- (c) WDF-ML applies a **machine learning classifier** to wavelet coefficients obtained by applying a **wavelet transform** to the transients in the data.

IV - Identify and correct Outliers in data : Highlight Invariance to allow Discrimination

- Data with **high dimensionality** : discriminativeness is strongly reduced
- To mitigate this, **dimension-reduction** methods such as t-distributed Stochastic Neighbor Embedding (**t-SNE**) or ML-based **Self Organizing Maps** can be used to plot data points that have very close characteristics as **neighbors in a 2D map**. This can be used to **identify and correct outliers** in measurements, such as in this example of photometric redshift measurements of galaxies.

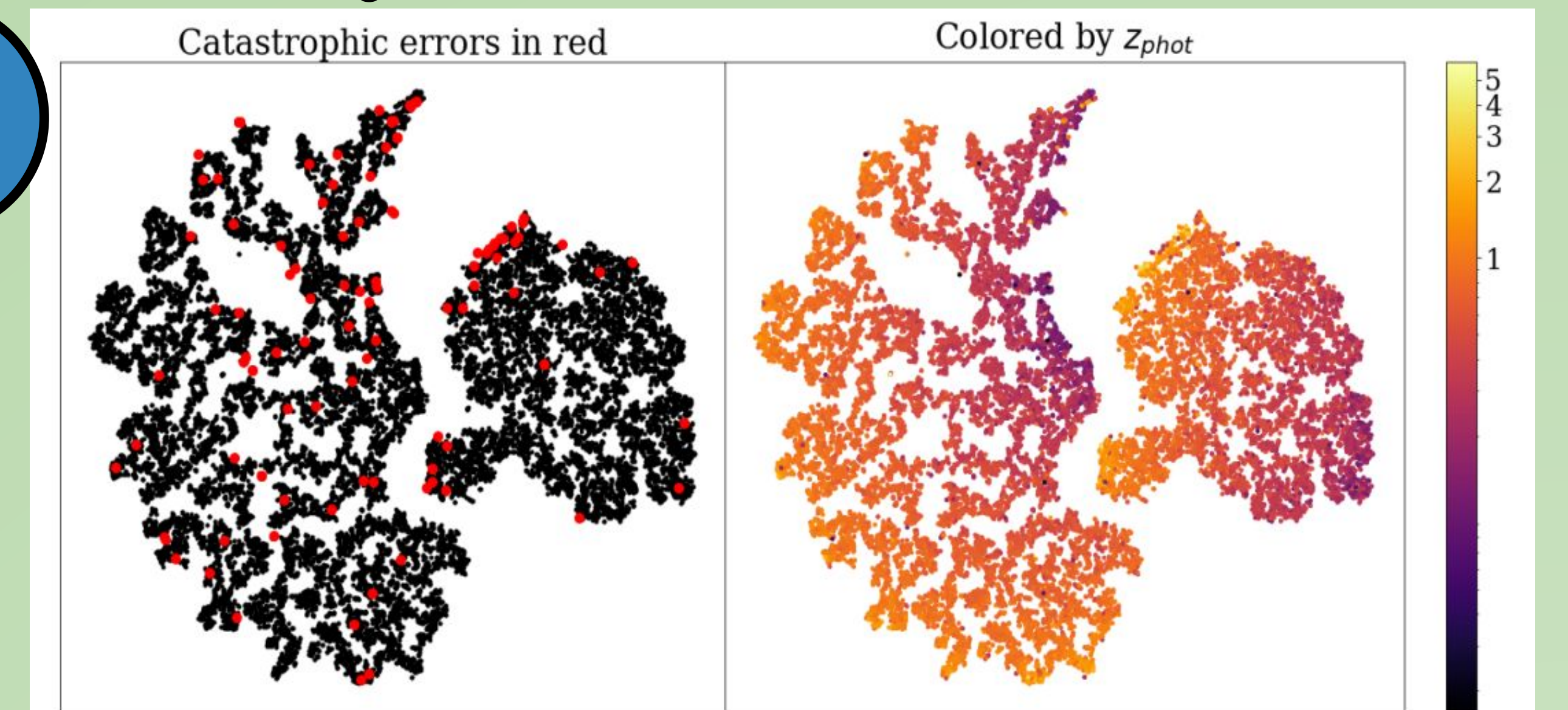


Figure 6. t-SNE maps of "neighbour" galaxies, based on their photometric measurements

- Whatever the dimension, we can think of ways to **transform** the data we're working with to an **appropriately classifying 2D space**
- One issue lies in the **interpretability** as well as the **adaptability** to unexpected systematics of the methods shown here.
- Do this with algorithms that show what they actually discriminate (**U-net** in fig 7). From there, we could even think about using such "blind" discrimination to **define new classes of unexpected systematics**.

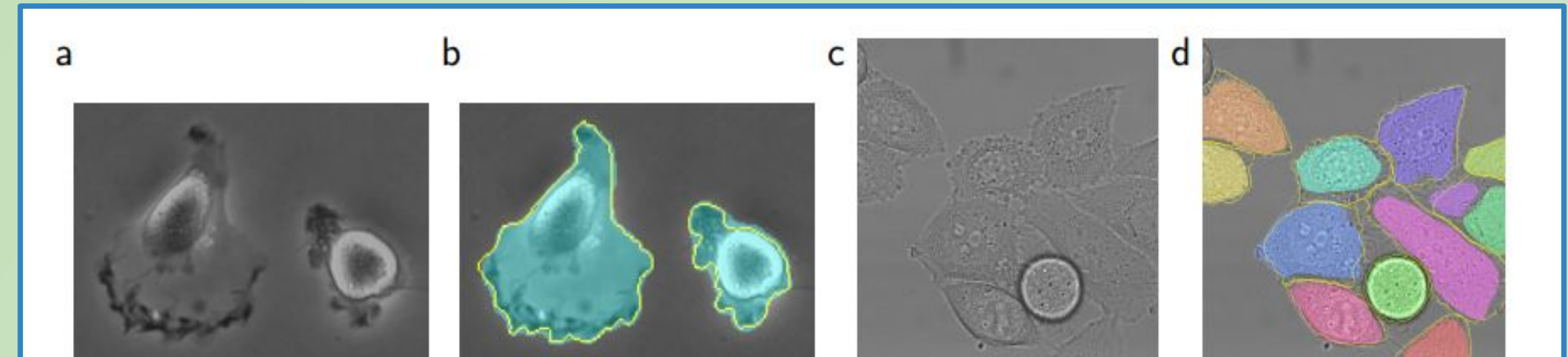


Fig. 7. Result on the ISBI cell tracking challenge. (a) part of an input image of the "PhC-U373" data set. (b) Segmentation result (cyan mask) with manual ground truth (yellow border) (c) input image of the "DIC-HeLa" data set. (d) Segmentation result (random colored masks) with manual ground truth (yellow border).

V - Conclusion

- The **characterization of systematics**, seen as a classification problem, can be **successfully investigated via the approach of computer vision**.
- These **snapshots** from different fields, amongst many others, will be sources of **inspiration for my future work on LiteBIRD systematics**.
- Bridging the gap between the particularities of this experiment and the other showcased here is a challenging yet rewarding challenge I am very excited to be working on for the next 3 years.