Morphologies for the next generation of surveys

Requirements, challenges and opportunities for morphological classification with machine learning in the era of LSST

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Sexten CFA, 04 Feb 2020

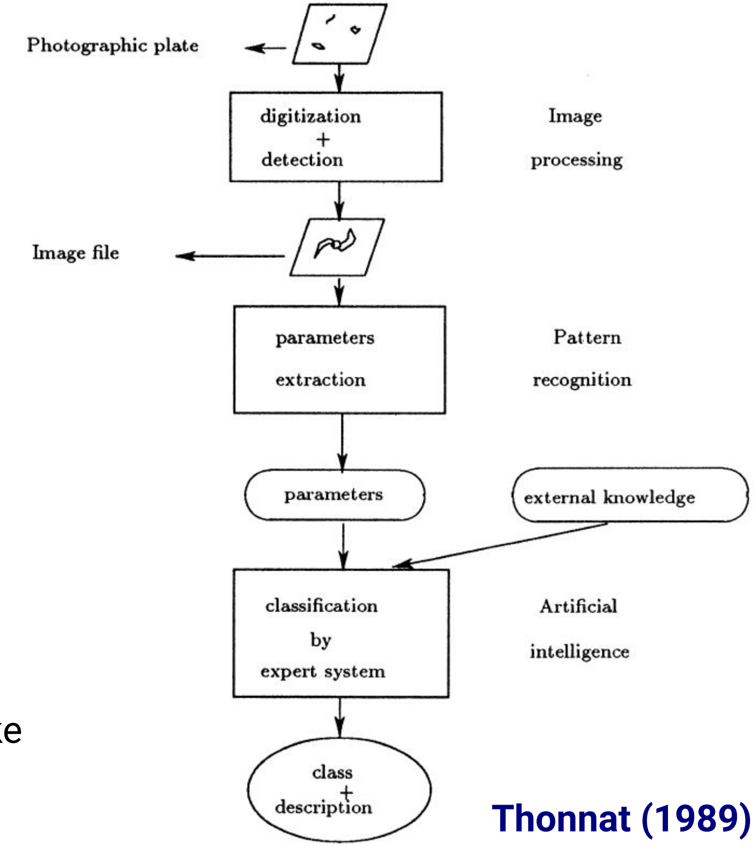
A brief history of ML techniques in astronomy

- Machine learning techniques have been developed for morphological classification since CCDs/plate digitization became widespread in astronomy beginning in the **1980s** e.g. **Kodaira+Watanabe (1984), Thonnat (1989)**.

- At this time, a lack of computer power or sophistication of technique meant that these solutions were **unable to process even the relatively modest data-volumes** seen at this time (< several GB)

- Perhaps the first truly **successful** application of ML to galaxy classification was by **Lahav et al. (1995)**, who were able to efficiently classify ~14000 objects with **similar accuracy to an expert human classifier**

- However, **ML techniques still did not become widespread**, perhaps because did not offer any particular advantage over **expert human classifications** or later **citizen science** efforts like **Galaxy Zoo (Lintott et al., 2008)** , which offer high quality classifications for large numbers of galaxies

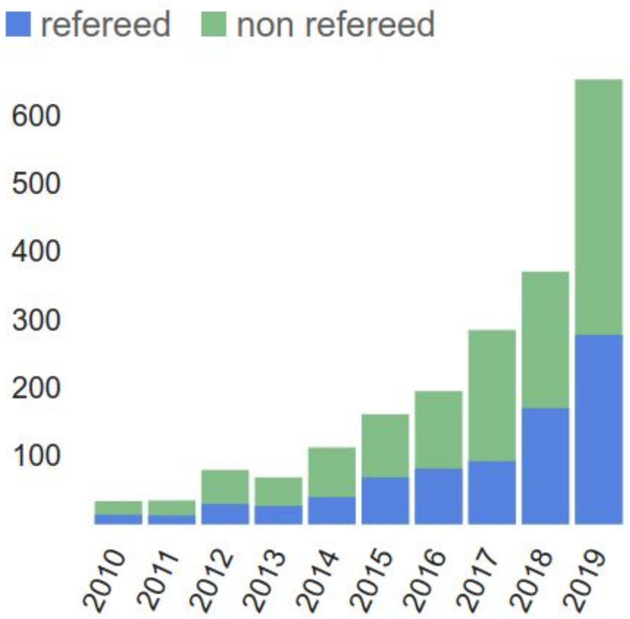


Thonnat (1989)

A brief history of ML techniques in astronomy

As they have become **increasingly necessary due to large data volumes**, a wide range of machine learning solutions have now been applied successfully to problems in astronomy:

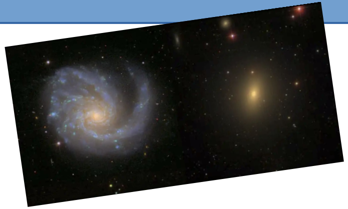
- **Huertas-Company et al. (2015)** convolutional neural networks
- **Ostrovski et al. (2017)** supervised Gaussian mixture models
- **Schawinski et al. (2017)** generative adversarial networks
- **Goulding et al. (2018)** random forest classifier
- **Siudek et al. (2018)** unsupervised Fisher expectation-maximisation
- **Roussi in prep** Siamese networks



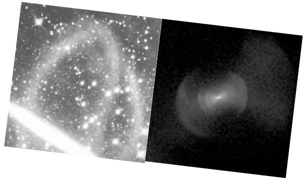
ADS astronomy abstracts referencing "machine learning" by year

The problem

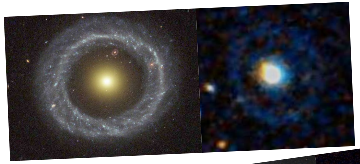
- Morphological classification -- what do our algorithms need to do?:
  - Separation of objects into **Hubble type**



  - Identification of objects of that share **specific features** (e.g. tidal tails, rings, shells and other LSB features)

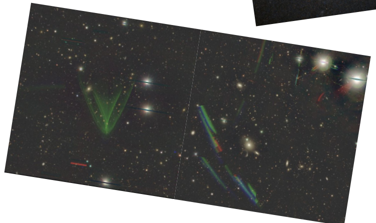


  - Identification of **rare objects, outliers** or objects **that don’t fit into established morphological types** and for which there are no large existing samples (e.g. ring galaxies, certain LSB galaxies)



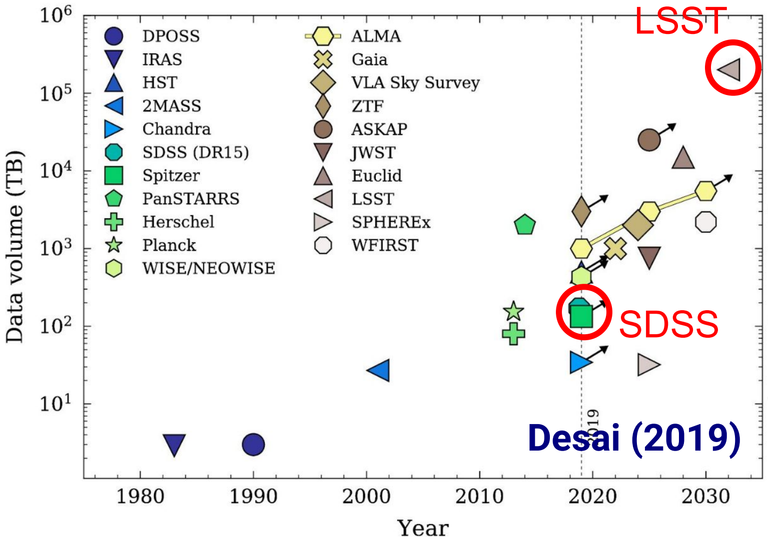
  - Separation of **arbitrary morphologies** and **recovery of blended objects** for which it would not be possible to construct training sets (e.g. low surface brightness objects overlapping other objects)

  - **Identification of ‘junk’** not removed by the pipeline (e.g. satellite trails, ghosts etc), **star / galaxy separation**



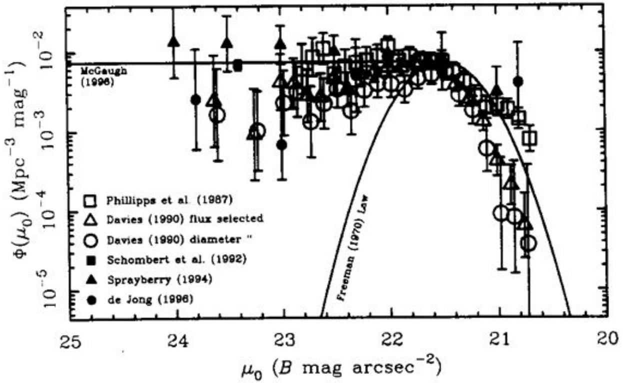
Challenges

- Data volumes **continue to grow** due to the increasing area, depth, resolution and cadence possible with modern survey instruments:
    - Rapidly changing datasets mean we may need to **classify data multiple times**
    - Deep imaging makes **looking for specific types of object laborious**, preventing us from assembling comprehensive samples
    - Large area and higher resolution means **more pixels need to be processed**

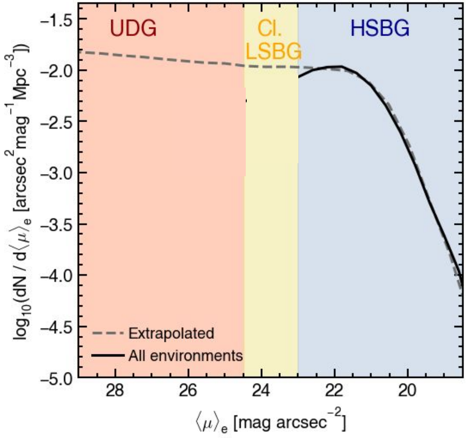


Challenges

This is also regime where we expect a **continuous tail of (resolved) low surface-brightness objects**



(Bothun et al., 1997)



(Martin et al., 2019)

As we probe lower and lower surface brightnesses, there is no indication from <u>observations</u> or <u>simulations</u> that the number of objects will begin to drop

Challenges / requirements

- **Customisable** / general purpose
- And also **efficient and scalable** to large datasets
    - i.e. makes morphological classification feasible and fast for the any given use-case for individual researchers
- Allows for outlier detection
- Ideally applicable to **arbitrary morphologies** without the need for pre-labelled training data
- **Not (too) reliant on human effort**, which can be a significant bottleneck

Solutions

- Human classification will become less and less viable as datasets grow
  - e.g. **billions of individual classifications** required will make it intractable for LSST

- **Machine learning techniques** will soon be the only realistic solution, but face challenges of their own:
  - Repeated construction of **unbiased training sets** for high cadence (rapidly changing) data will be difficult

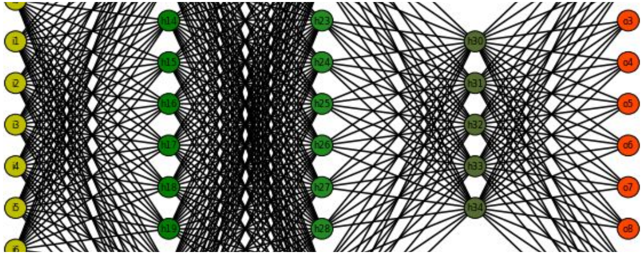
  - The large areas combined with deep imaging will allow the construction of samples of **rare/faint types of object,** but these object **will not have robust training sets** available

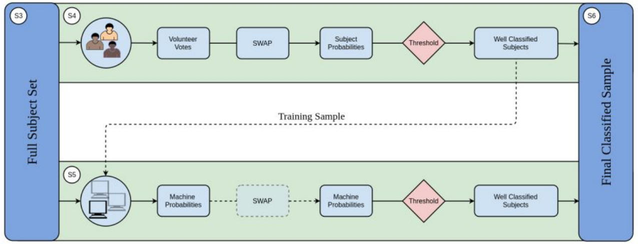
- One solution is to **combine citizen science with machine learning** in order to **continually improve training sets** e.g. **Beck et al. (2018)**, but very large data volumes will continue to be a challenge for any citizen science efforts

THE ZOONIVERSE WORKS

250,469,827

CLASSIFICATIONS SO FAR BY
1,944,912 REGISTERED VOLUNTEERS





Beck et al. (2018)

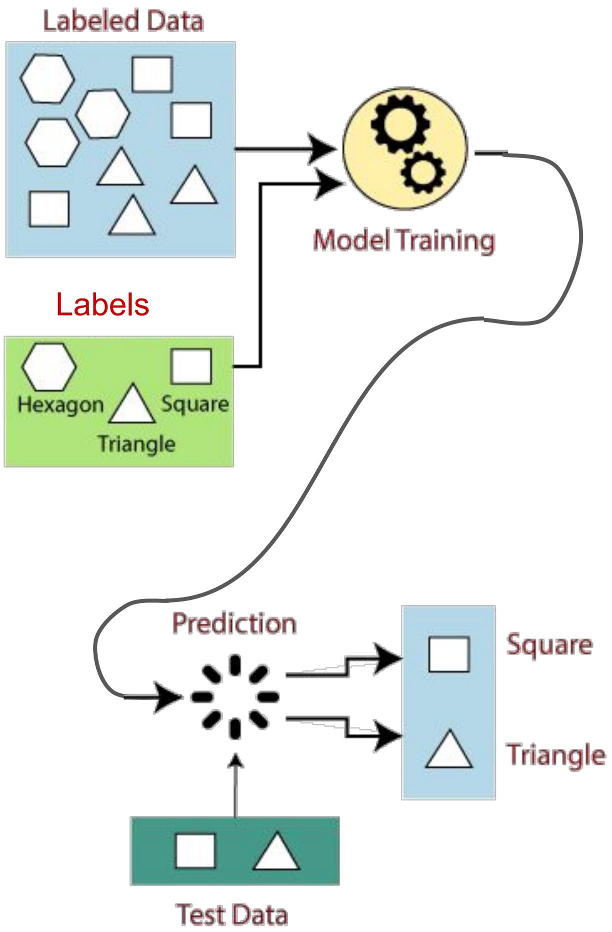
Solutions

- **Supervised machine learning** uses labelled training sets to find a mapping between input and output (e.g. an image of a galaxy and a morphological type).

- Such techniques are **accurate for focussed tasks** (e.g. yes/no classifications, small number of morphological types), but rely on **labelled training data**

- This won't work if we can't **assemble a large enough training set**, which is difficult where very **fine classification** is desired or we are interested in **rare types of object**
  - It is impossible to identify objects for which no training set has been provided

- Since the **assembly of training** sets is now **one of the most significant bottlenecks** for all but the most basic classification tasks, we would ideally want to design a method that requires **minimal human intervention** and can efficiently reduce populations of objects into **arbitrarily fine groups**

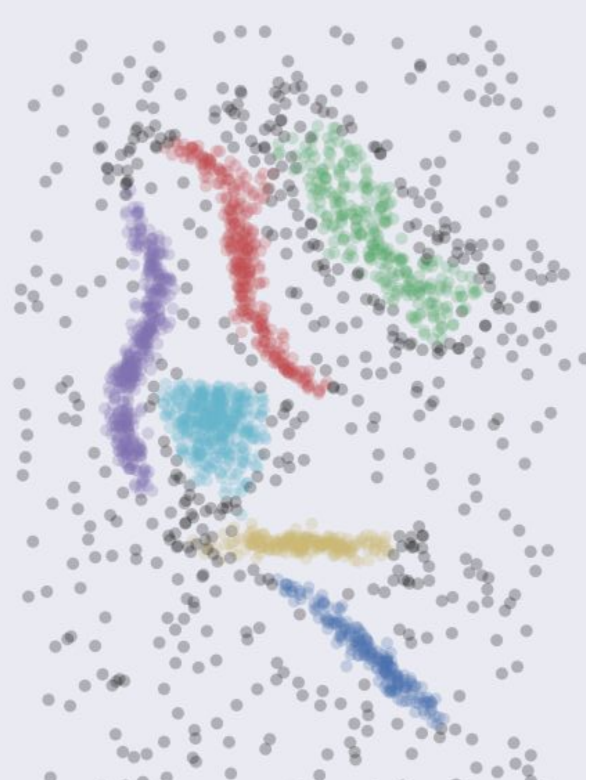


Solutions

- **Deep learning** **(e.g. Barchi et al., 2019)** and **unsupervised** techniques **(e.g. Hocking et al., 2018, Martin et al., 2020)** that can work directly on unlabelled data (**without labelled training sets**) can overcome some of the shortcomings of traditional supervised ML techniques

- Instead of optimising a network to recover provided labels, we try to **find groups of similar objects** within some parameter space

- Importantly, these techniques can be made to be more **general purpose** as they are **not limited to finding only objects in a training set**. They can produce instead **data representations that can be manipulated and used in different ways**



McInnes et al.

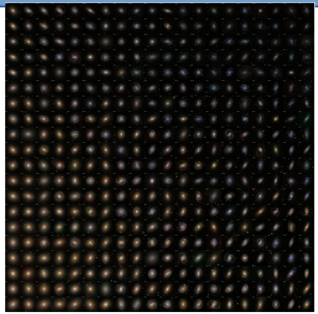
Examples

Labelled

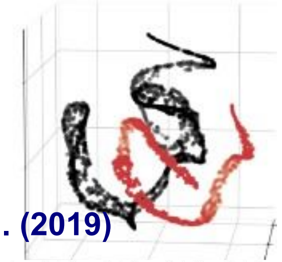
- **Polsterer, Gieseke & Kramer (2012)** -- support vector machines (self organising map method) without feature extraction with limited training sets
- **Dai & Tong (2018)** -- deep convolutional neural networks -- rely on large amounts of training data from galaxy zoo, limited to categories provided by galaxy zoo
- **Kahn et al. (2019)** -- deep learning applied to overlapping SDSS and DES data

Unlabelled

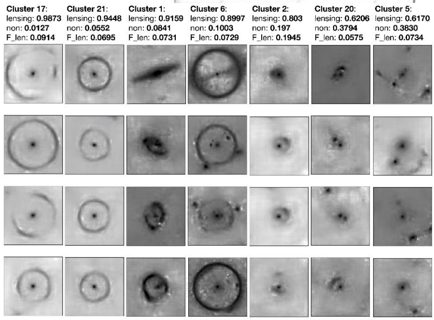
- **Hocking et al. (2018), Martin et al. (2020)** -- Self organising map based unsupervised method
- **Cheng et al. (2019)** -- unsupervised method using convolutional autoencoder for feature extraction rather than engineered features



Polsterer et al. (2012)



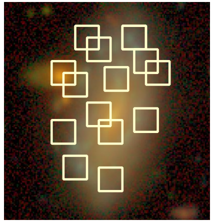
Kahn et al. (2019)



Cheng et al. (2019)

Hocking+ (2018): MNRAS, 473, 1108
Martin+ (2020): MNRAS, 491,1408
(arXiv:1909.10537)

Examples



Convert the survey images into a data matrix
– Extract patches at each non-zero pixel in a multi-band image
– Compute the radial power spectrum to produce rotationally invariant representations of each patch (encodes **intensity**, **colour** and **‘texture’**)

Hocking+ (2018): MNRAS, 473, 1108
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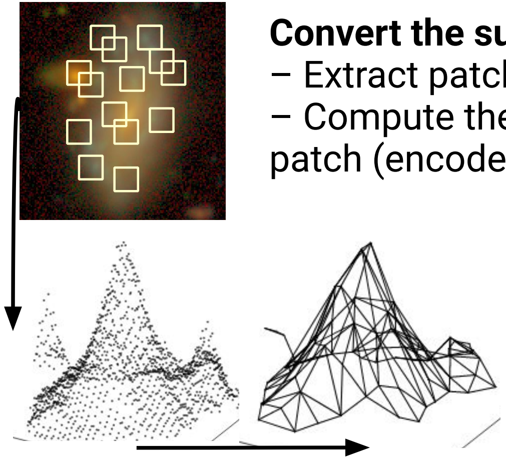
Examples



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Use GNG and HC to produce a condensed version of the original data set
– Using the output patches, iteratively fit the data using growing neural gas to produce a topological map of sample vectors
– Each vector represents a group of similar patches
– By applying hierarchical clustering, we can further reduce the number of groups by reducing them to similar 'types' of patches

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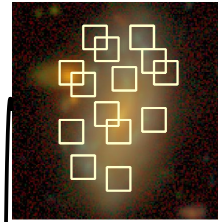

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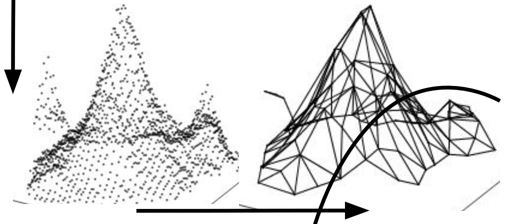

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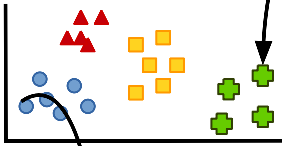

Create object sample vectors corresponding to patch ‘types’
– Identify objects using connected component labelling
– Create a sample vector for each object, represented by a histogram of the different ‘types’ of patches they are formed from
– Grouping similar sample vectors allows us to find visually similar objects

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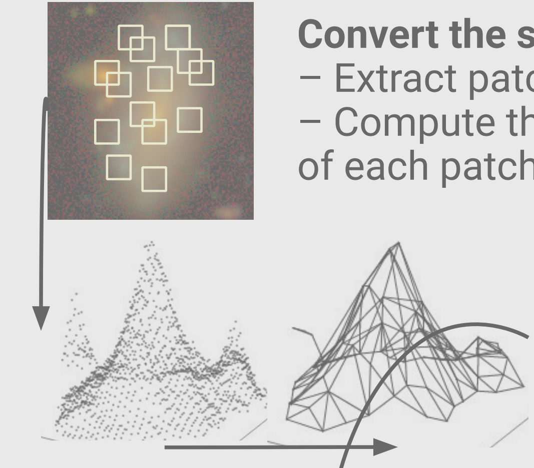
Examples



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– Extract patche
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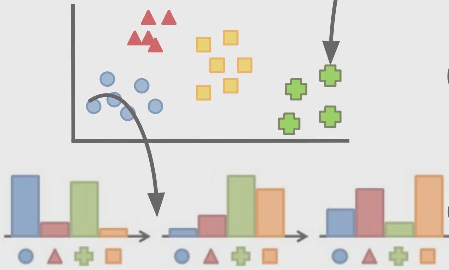


Create c
– Identif
– Create
different 'types' of patches they are formed from
– Sample vectors are weighted by tf*idf (term frequency-inverse document

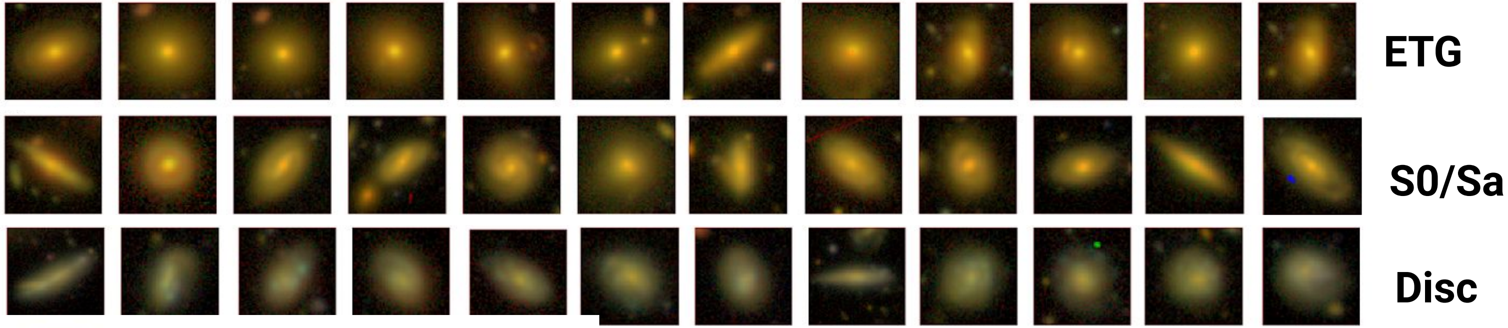
Condensed version:

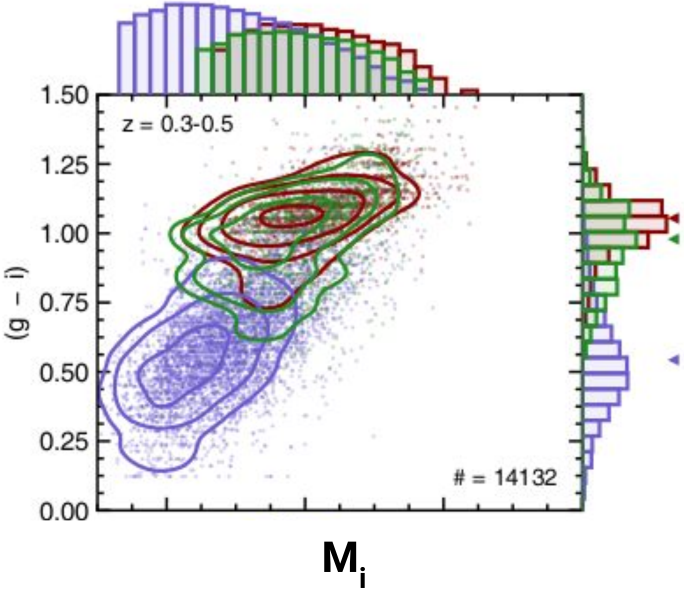
Use clustering techniques (**growing neural gas & hierarchical clustering**) to create a library of pixel 'types' based on colour, intensity and 'texture'

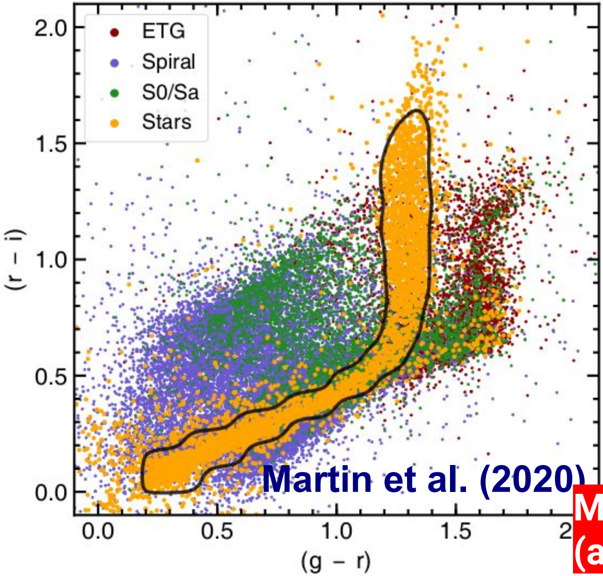
Produce histogram descriptions ('**feature vector**') of objects that describe the frequency of each pixel type in that object

https://github.com/garrethmartin/HSC_UML

Examples - Classification by Hubble type (HSC data)



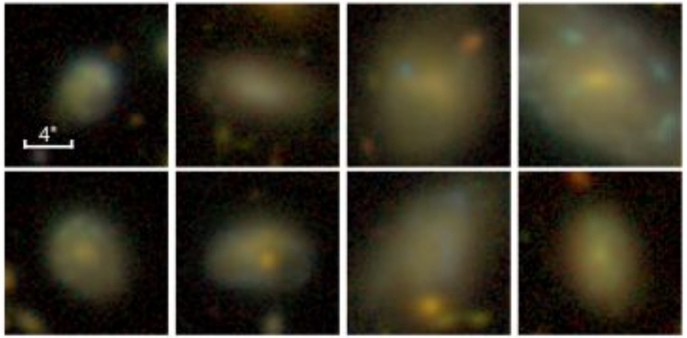




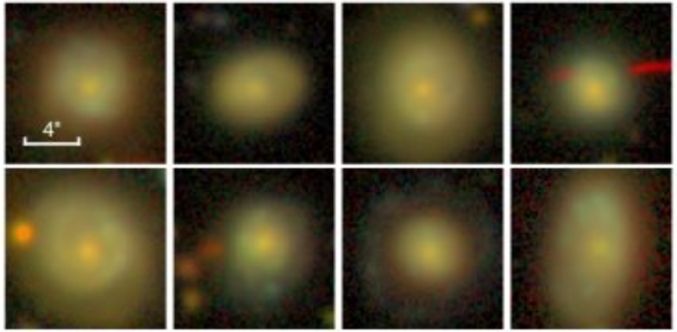
Classifications based on **visual inspection of a small subset** of each group produce expected relations

Martin+ (2020): MNRAS, 491,1408 (arXiv:1909.10537)

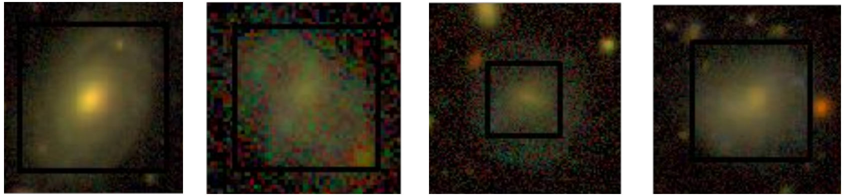
Examples - Arbitrary classification by clustering



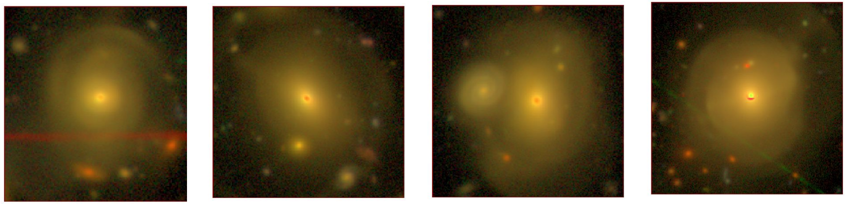
Clumpy discs



Rings / accretion events



LSB discs



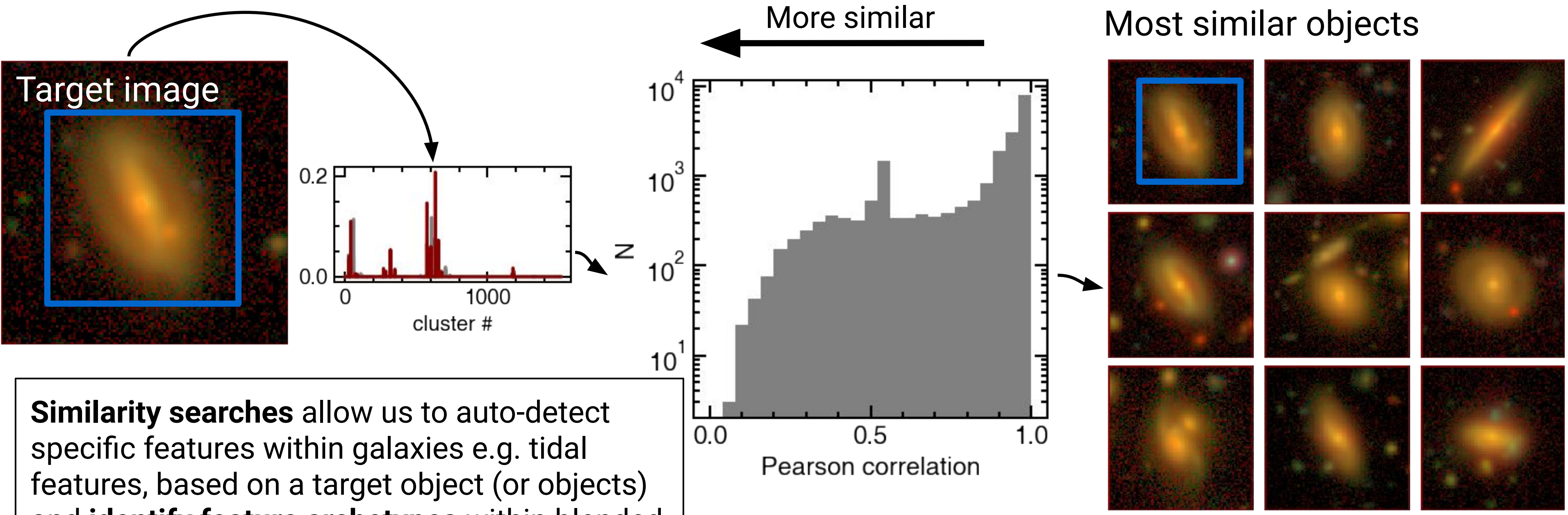
Shells

Some more examples of individual clusters featuring rare/specific types of object

(i.e. groups of object with similar feature vectors)

Martin+ (2020): MNRAS, 491,1408 (arXiv:1909.10537)

Examples - Classification by visual similarity



Similarity searches allow us to auto-detect specific features within galaxies e.g. tidal features, based on a target object (or objects) and **identify feature archetypes** within blended objects

Searching for the nearest feature vectors allows us to produce a library of similar objects

Martin+ in prep.

Summary

- Data volumes **continue to grow** as the area, depth, resolution and cadence of astronomical surveys continues to increase
  - Now becoming **intractable for citizen science** initiatives
- Deep surveys like LSST will allow us to **more finely classify galaxies** than we have been able to before
  - But it will not be possible to produce training sets for every category of object
- For supervised machine learning, the **creation of training sets will be a significant bottleneck**
- Unsupervised machine learning can offer a number of benefits over supervised methods in terms of their **scalability and ability to arbitrarily classify objects** without the need for labelled training data
- Unsupervised techniques do not just produce classifications -- they can also be used to create **usable descriptions** of each object which we can manipulate in various ways **(Martin+ (2020) MNRAS, 491,1408)**