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MACHINE

MACHINE
LEARNING

02.9

MACHINE
LEARNING
IN ASTRONOMY

02.9

02.9

1:10

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11.9



Data in Astronomy

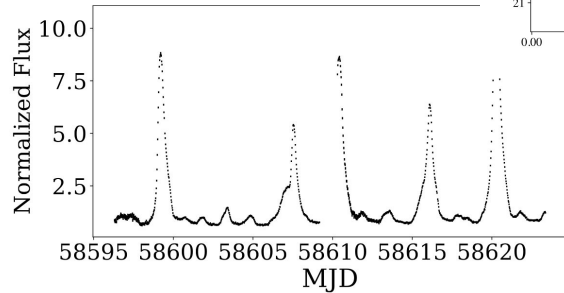
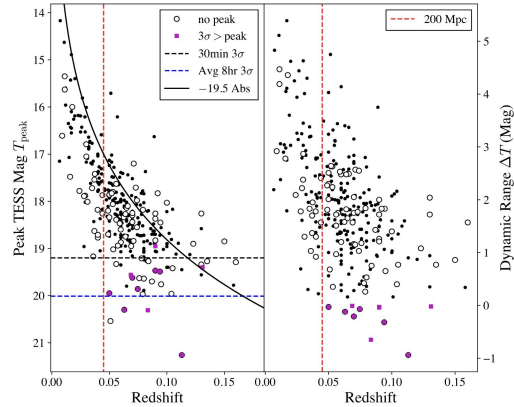
Data in astronomy

Data in astronomy

“Labeled”,
i.e. a defined or measured “target
variable”

Data in astronomy

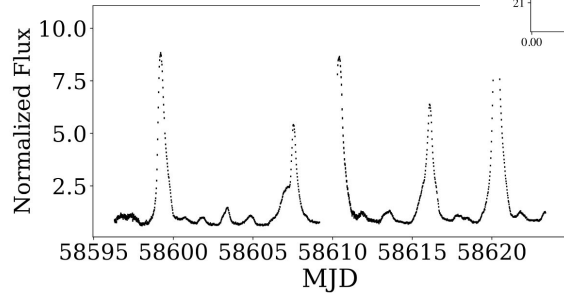
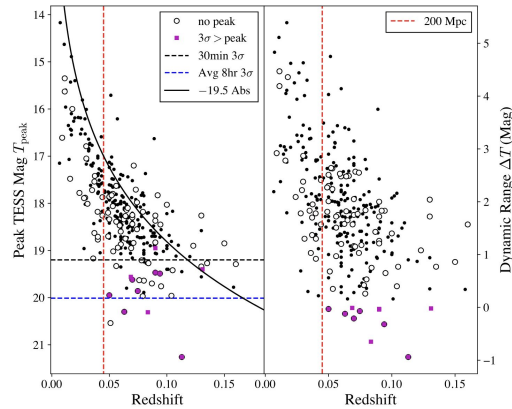
“Labeled”,
i.e. a defined or measured “target variable”



Data in astronomy

“Labeled”,
i.e. a defined or measured “target variable”

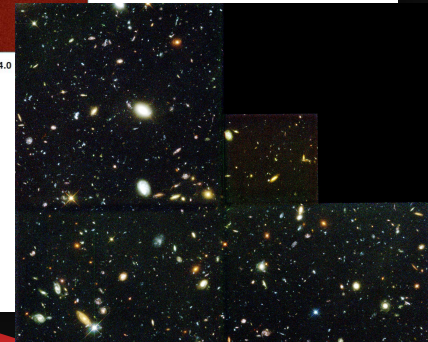
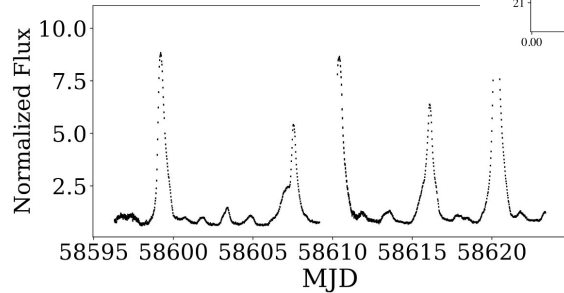
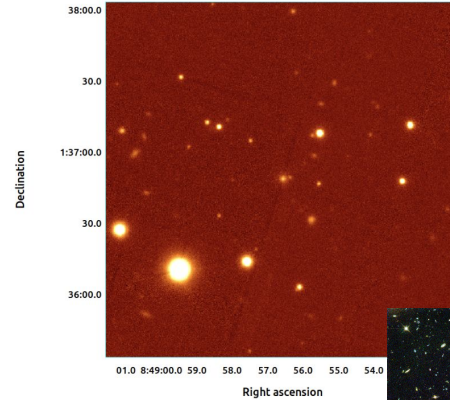
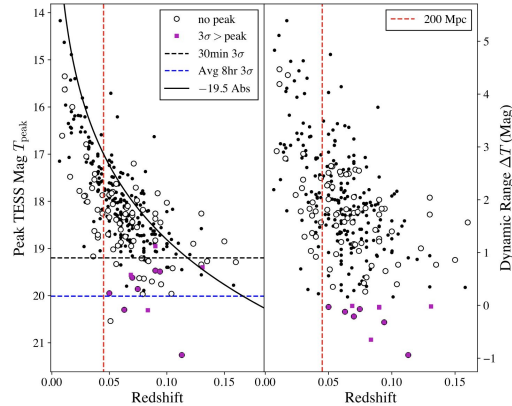
“Unlabeled”,
i.e. no defined “target variable”



Data in astronomy

“Labeled”,
i.e. a defined or measured “target variable”

“Unlabeled”,
i.e. no defined “target variable”





Machine learning methods for astronomical data

Machine Learning methods

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graph TD; A[Machine Learning methods] --> B[Supervised learning]; A --> C[Unsupervised learning]; B --> B1[Support vector machines.]; B --> B2[Decision trees and random forests.]; B --> B3[Neural networks (logistic, convolutional, etc.)]; C --> C1[Clustering.]; C --> C2[Dimensionality reduction.]; C --> C3[Neural networks (auto-encoders, GANs, etc.)]; C --> C4[Anomaly/outlier detection.]
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Supervised learning

- Support vector machines.
- Decision trees and random forests.
- Neural networks (logistic, convolutional, etc.).

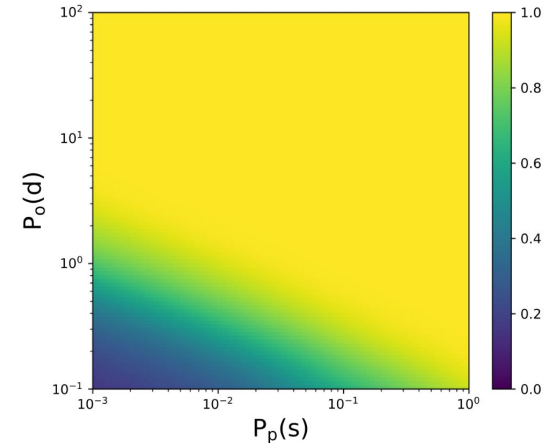
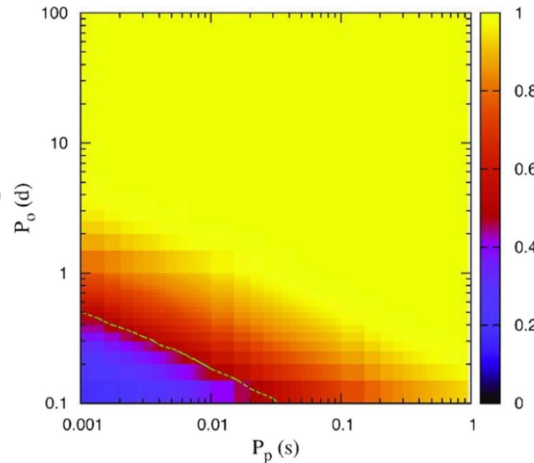
Unsupervised learning

- Clustering.
- Dimensionality reduction.
- Neural networks (auto-encoders, GANs, etc.).
- Anomaly/outlier detection.

Supervised learning: Dense neural network regression

- Used a neural network to calculate the orbital degradation factor in the search for binary pulsars in radio data.
- Once trained, NN provides incredibly fast calculations, which are required in population synthesis studies.

$$\gamma_{2m}(\alpha_a, \alpha_v, T) = \frac{1}{T} \left| \int_0^T \exp \left[\frac{im\omega_p}{c} (r_l - r_{l0} - \alpha_a t^2 - \alpha_v t) \right] dt \right|$$



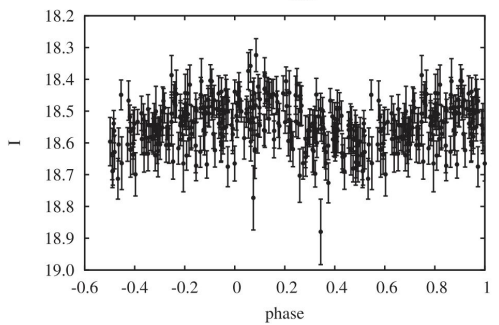
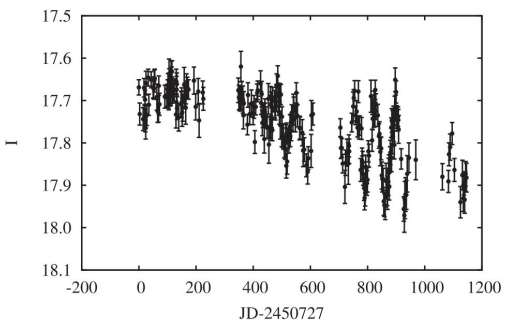
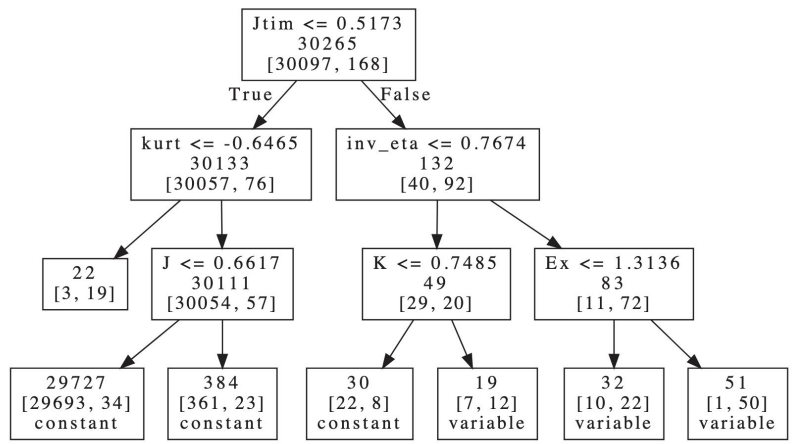
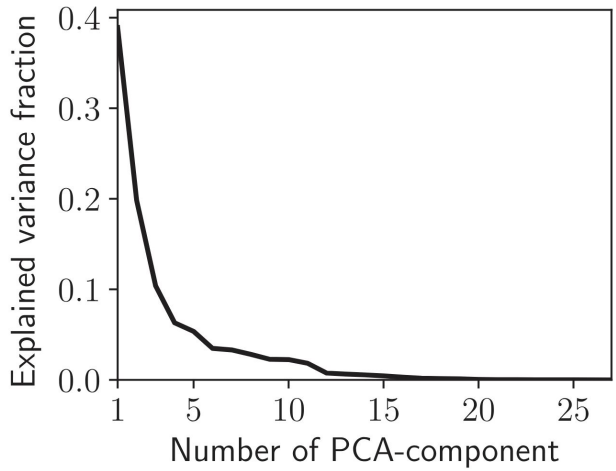
Machine learning search for variable stars

- Trained a broad range of ML algorithms on 168 objects (OGLE) using 18 variability indices.
- OGLE-II results: 205 candidates, of which 178 are real, and 13 are new discoveries.

Type	LMC_SC19	LMC_SC20
Eclipsing binaries	36	54
Variable red giants (L/M/SR/ELL)	54	52
RR Lyrae-type variables	56	26
Cepheids (classical and Type II)	17	20
Blue irregular variables (GCAS/BE/QSO)	22	13
δ Scuti stars	1	3
Total	186	168

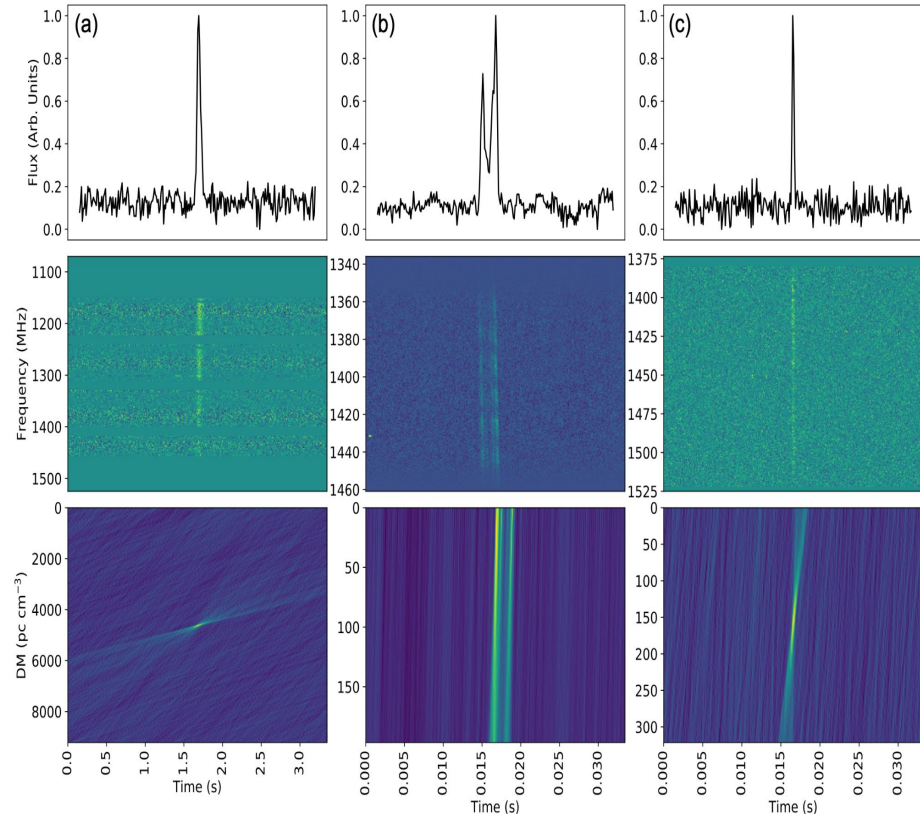
Index	Reference
Weighted standard deviation – σ	Kolesnikova et al. (2008)
<i>Clipped</i> $\sigma - \sigma_{\text{clip}}$	Appendix A1
<i>Median abs. deviation</i> – MAD	Zhang et al. (2016)
Interquartile range – IQR	Sokolovsky et al. (2017)
Reduced χ^2 statistic – χ_{red}^2	de Diego (2010)
Robust median statistic – RoMS	Rose & Hintz (2007)
Norm. excess variance – σ_{NXS}^2	Nandra et al. (1997)
Norm. peak-to-peak amp. – ν	Sokolovsky et al. (2009)
<i>Autocorrelation</i> – I_1	Kim et al. (2011)
Inv. von Neumann ratio – $1/\eta$	Shin et al. (2009)
Welch–Stetson index – I_{WS}	Welch & Stetson (1993)
Flux-independent index – I_{fi}	Ferreira Lopes et al. (2015)
Stetson’s J index	Stetson (1996)
Time-weighted Stetson’s J_{time}	Fruth et al. (2012)
<i>Clipped Stetson’s</i> J_{clip}	Appendix A2
<i>Stetson’s</i> L index	Stetson (1996)
<i>Time-weighted Stetson’s</i> L_{time}	Fruth et al. (2012)
<i>Clipped Stetson’s</i> L_{clip}	Appendix A2
<i>Consec. same-sign dev.</i> – CSSD	Shin et al. (2009)
S_B statistic	Figuera Jaimés et al. (2013)
Excursions – E_x	Parks et al. (2014)
Excess Abbe value – \mathcal{E}_A	Mowlavi (2014)
Stetson’s K index	Stetson (1996)
Kurtosis	Friedrich, Koenig & Wicencec (1997)
Skewness	Friedrich et al. (1997)

Machine learning search for variable stars

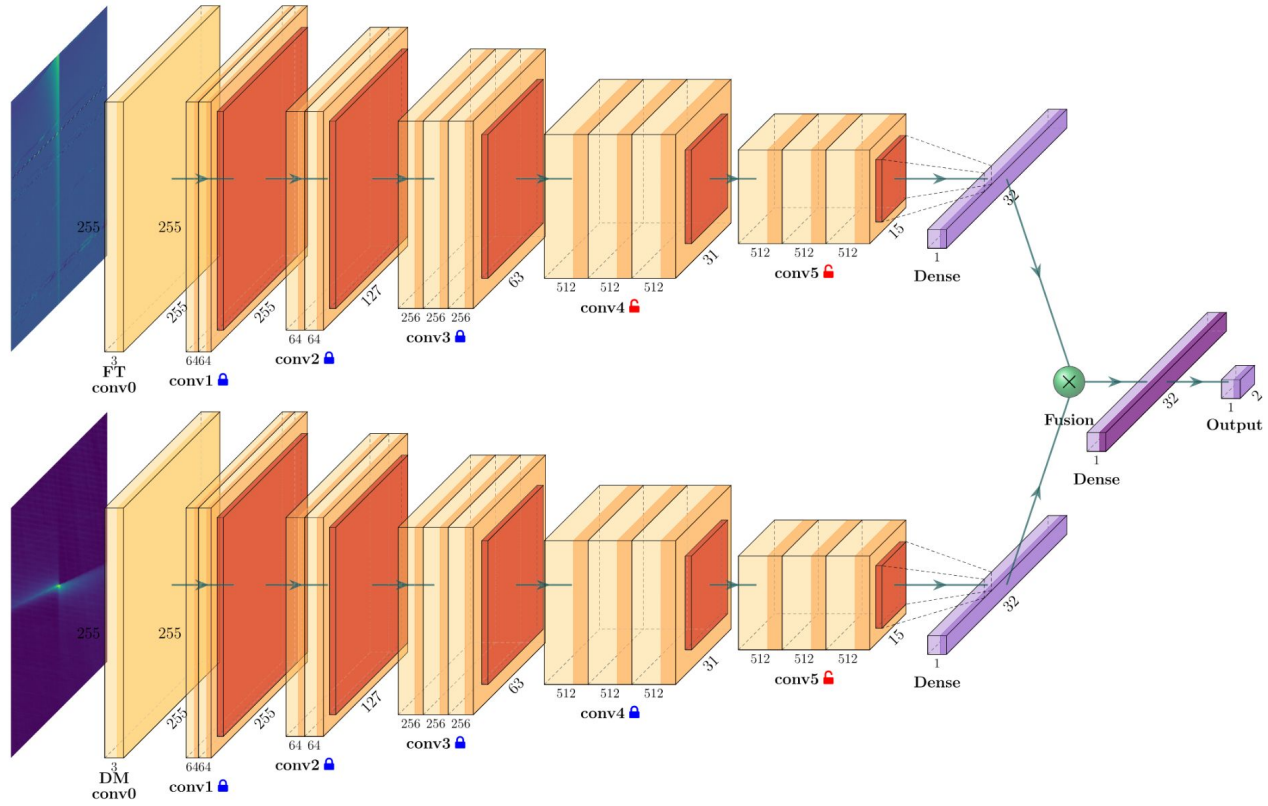


Transfer learning for classification

- Train a deep convolutional neural network to detect fast radio bursts, a class of radio transients.
- Bulk of neural network design leveraged image classifiers pre-trained on ImageNet like *ResNet50*, *VGG16*, *DenseNet*.

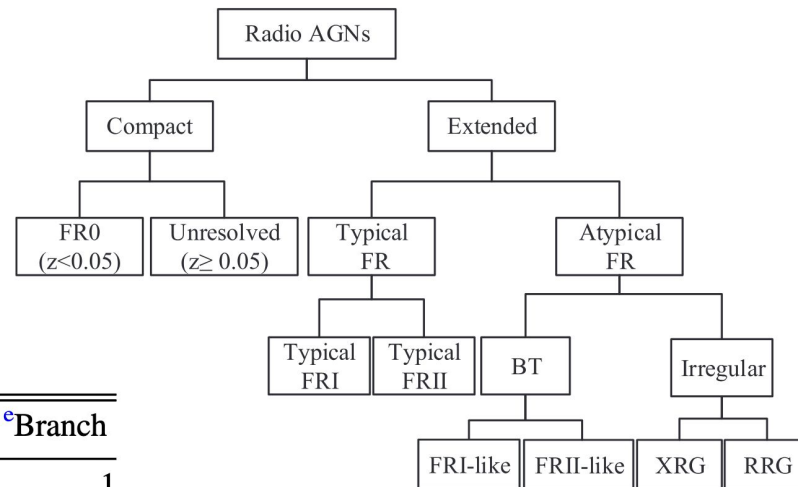


Transfer learning with classification



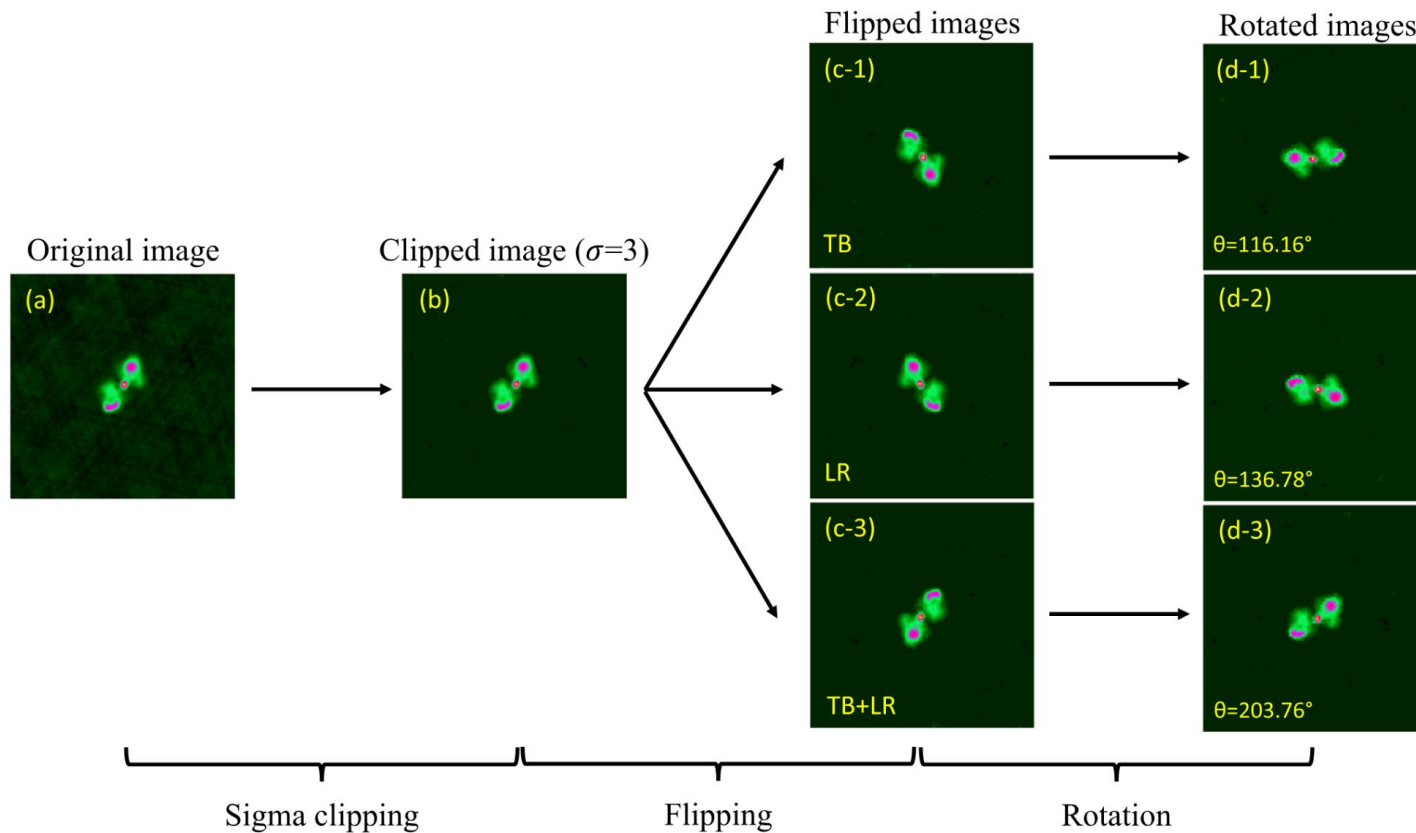
Classification with autoencoders

- Design a convolutional auto-encoder to classify radio AGN into six types: FR I/II, FR I/II-like bent-tailed, X-shaped, ring-like
- Clever use of augmentation to increase their training set.

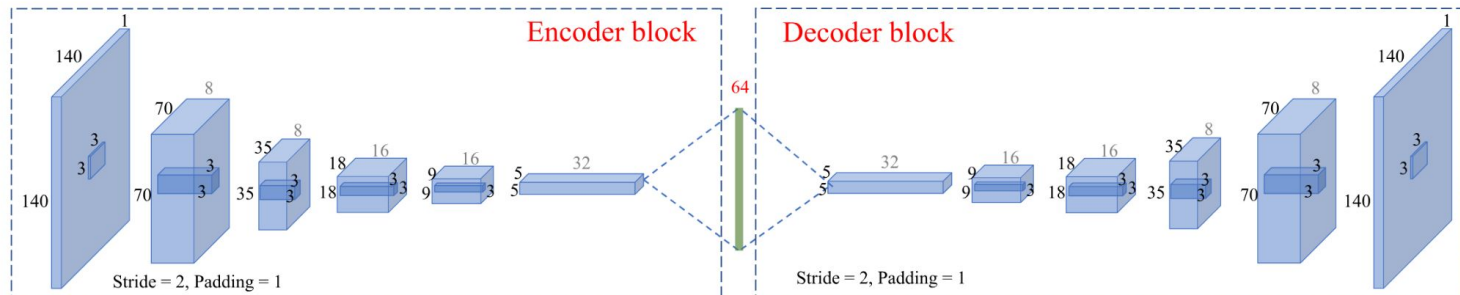


AGN Type	Label	^a $N_{\text{Trn+Val}}$	^b N_{Tst}	^c R_{Aug}	^d N_{Aug}	^e Branch
compact	1	302	75	64	19,328	1
FRI	2	169	42	29	4901	1, 2, 3
FRII	3	345	86	14	4830	1, 2, 3
BT	4	245	62	20	4900	1, 2, 4, 5
XRG	5	67	17	37	2479	1, 2, 4, 6
RRG	6	26	6	94	2444	1, 2, 4, 6
Total	...	1154	288	...	38,882	...

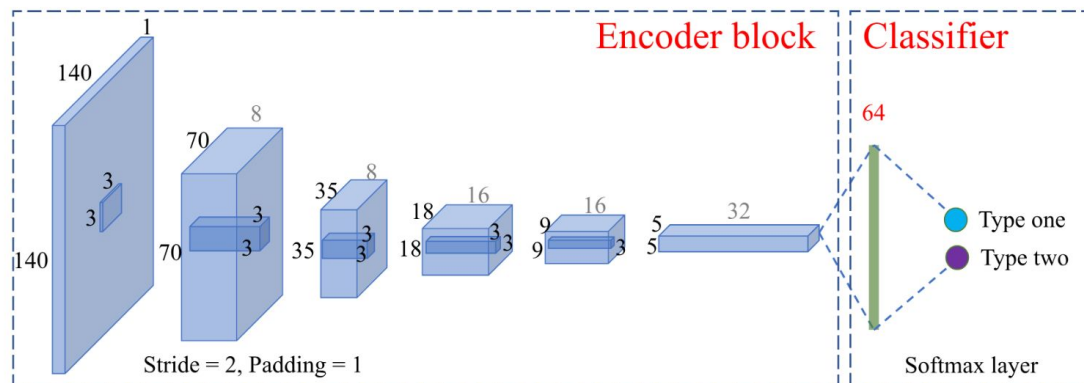
Classification with autoencoders



Classification with autoencoders



(a)



More interesting applications of ML to astronomy:

- More applications:
 - [Bayesian neural networks](#)
 - [Distribution learning with normalizing flows.](#)
 - [Time series analysis with neural networks.](#)
 - LLMs in astronomy? [AstroLlama](#), [Slack chatbots grounded in arXiv](#), [survey of ChatGPT and LLM use by astronomers](#). (also: next week's colloquium speaker)
 - [Outlier detection](#)
- Many algorithms already available in Python:
 - [Scikit-learn](#)
 - [Tensorflow](#)
 - [Keras for deep learning.](#)