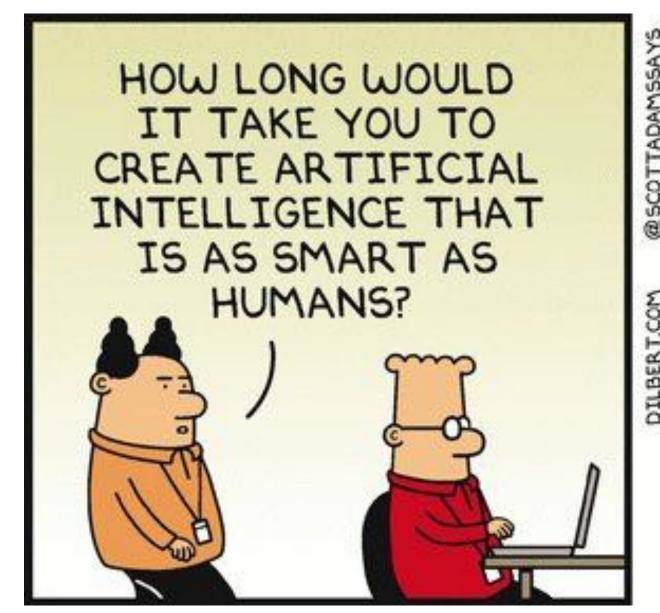
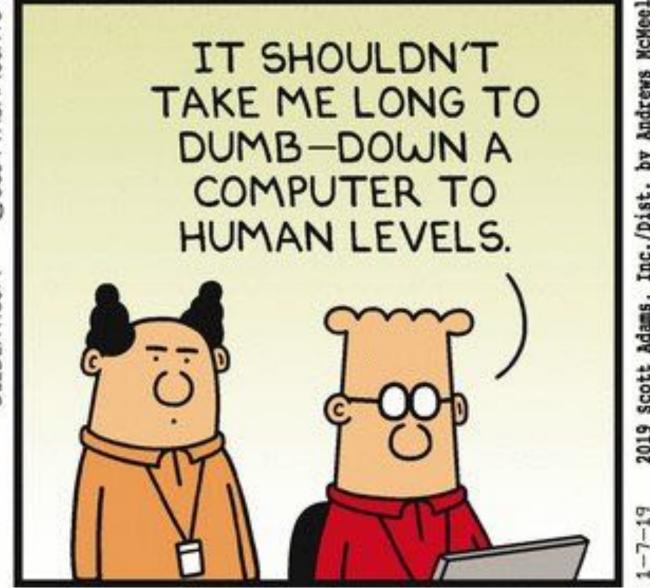
Status of Machine Learning in Astronomy

Nikhel Gupta

CSIRO Future Science Platform for MLAI CSIRO Space & Astronomy



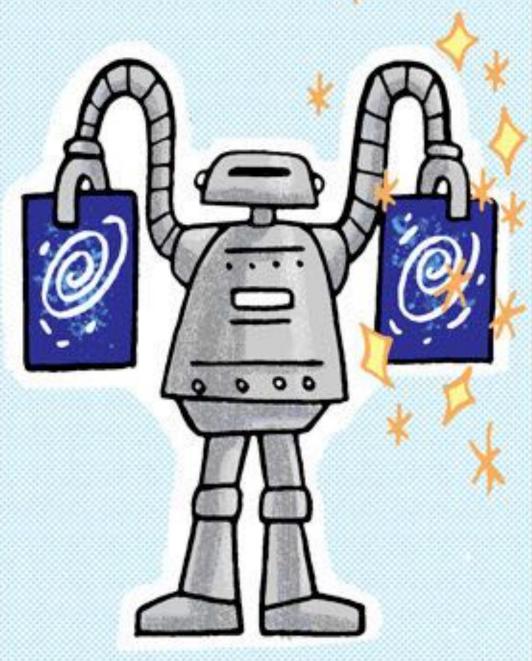




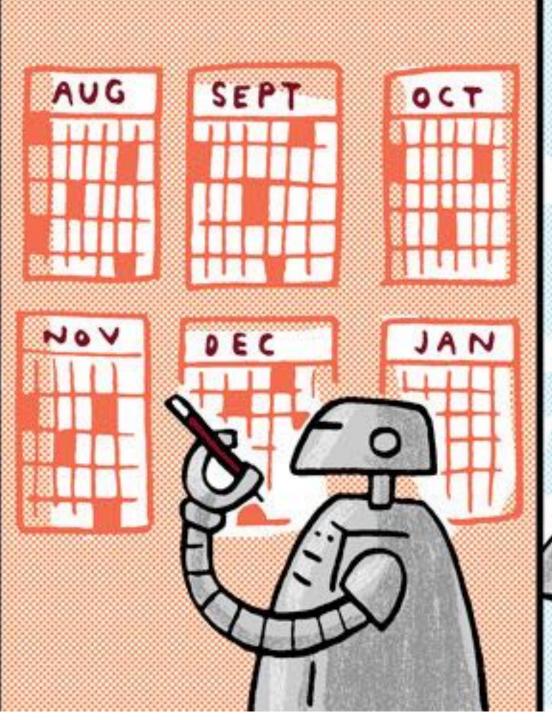


MACHINE LEARNING HELPS OUT

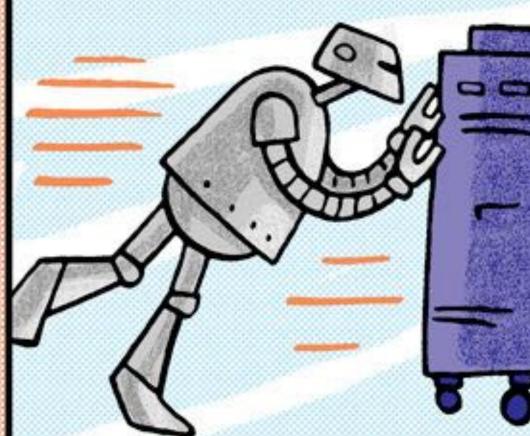
OBJECT DETECTION CLASSIFICATION CLEANING

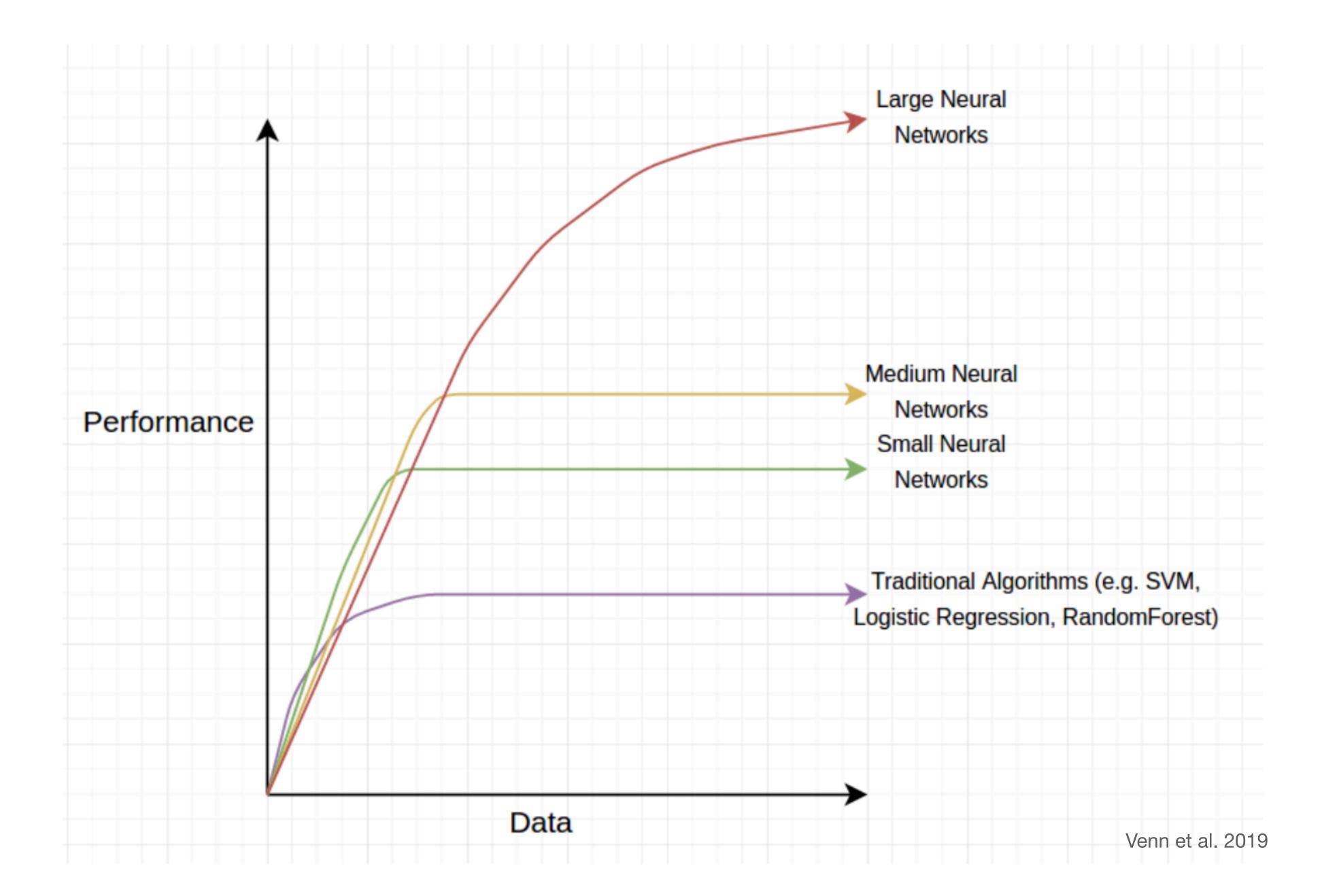


MAKING SCHEDULES

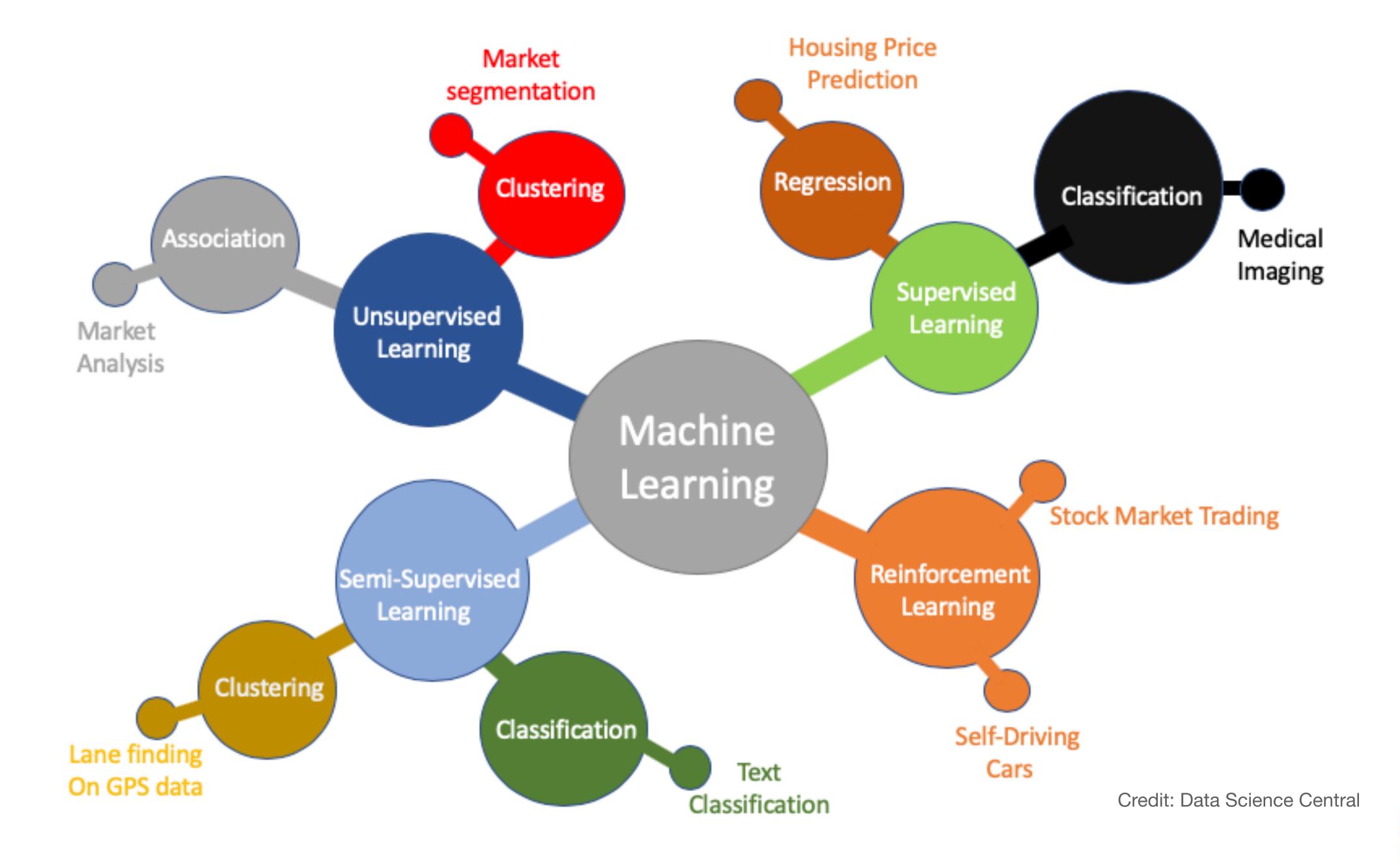


MAKING SIMULATIONS GO FASTER









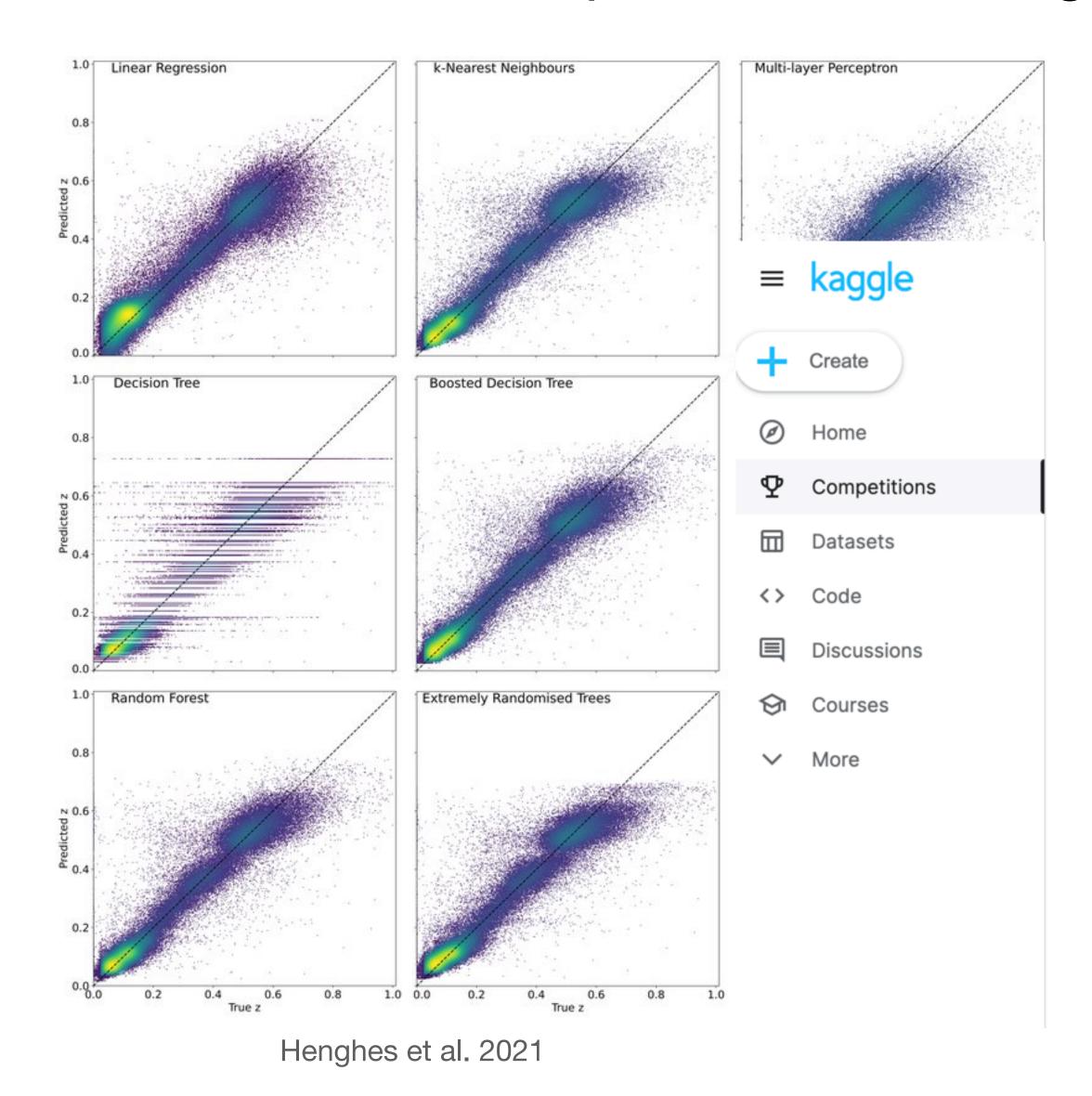




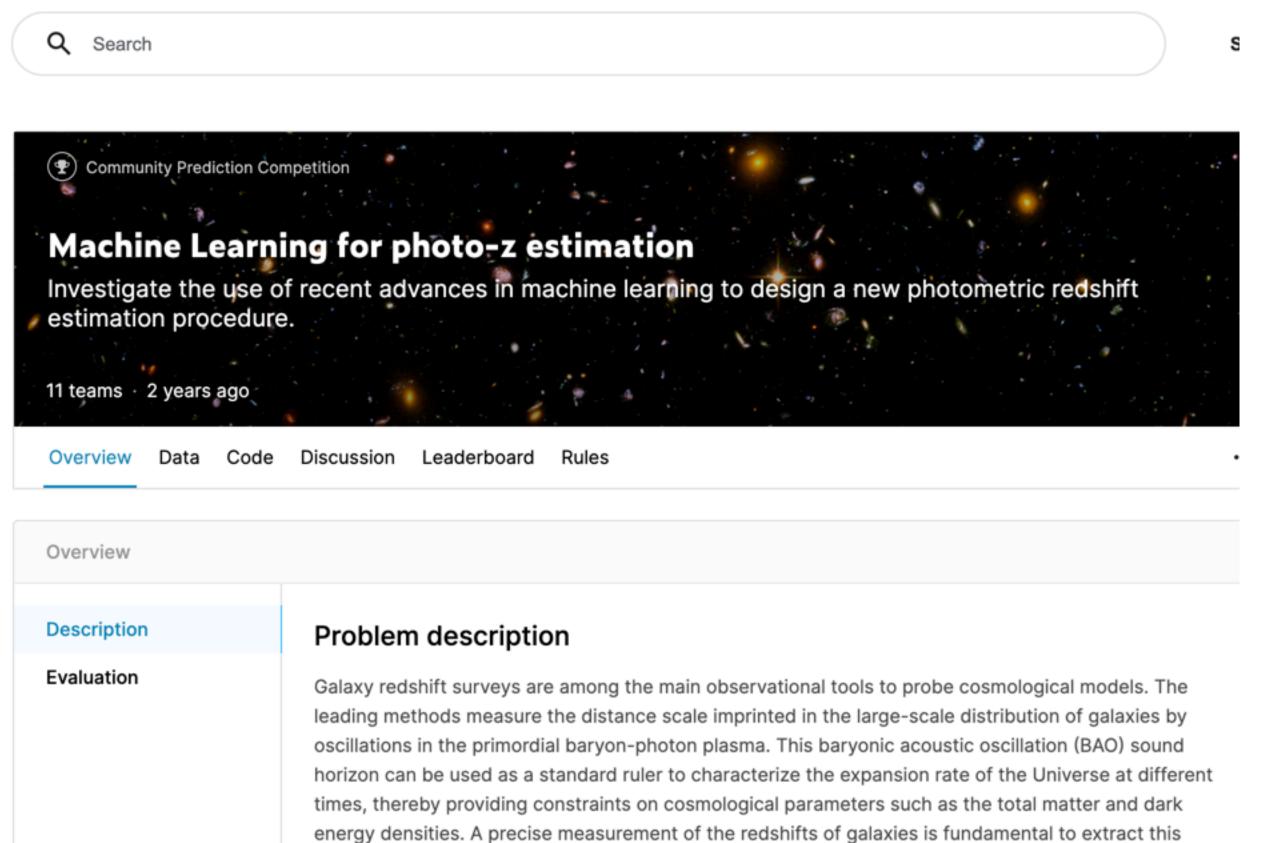
Credit: Data Science Central



Supervised Learning in Astronomy Examples



Redshift estimations Catalog space i.e. using tables

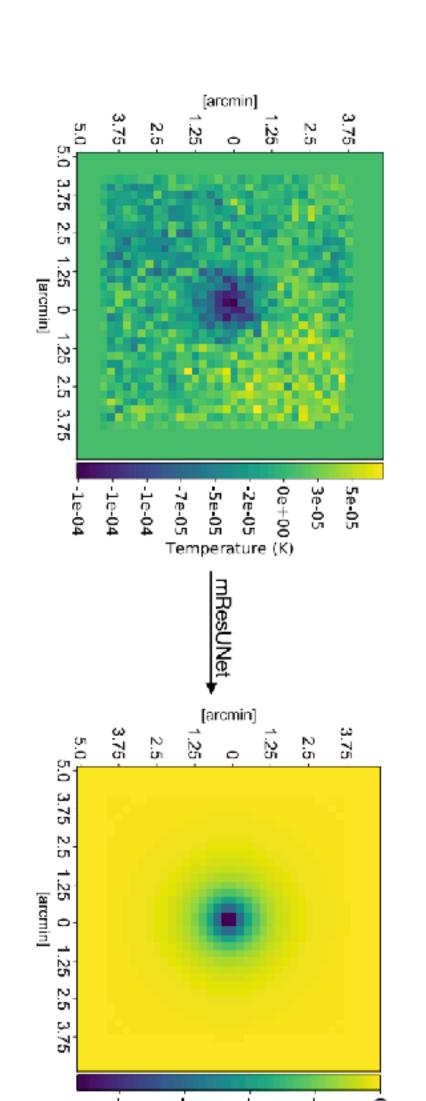


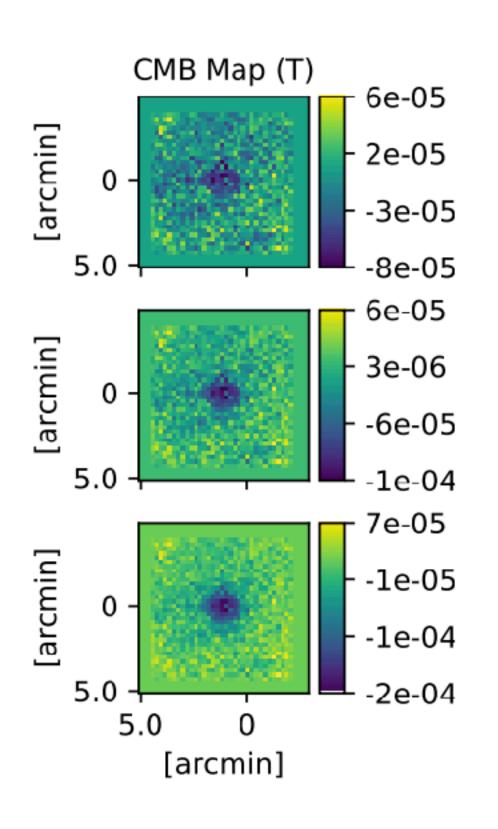


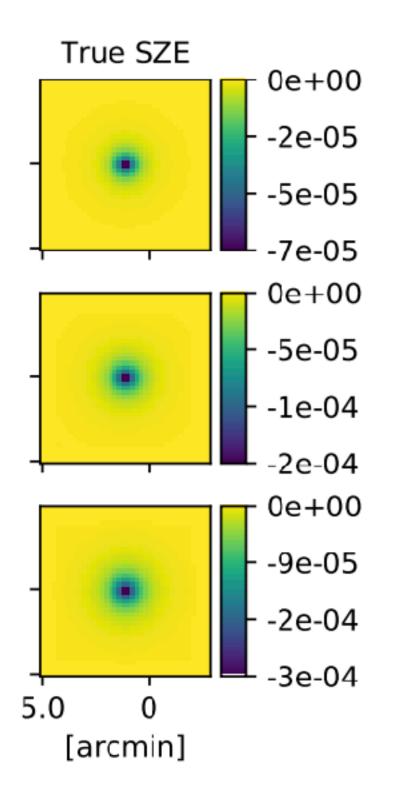
Supervised Learning in Astronomy Examples

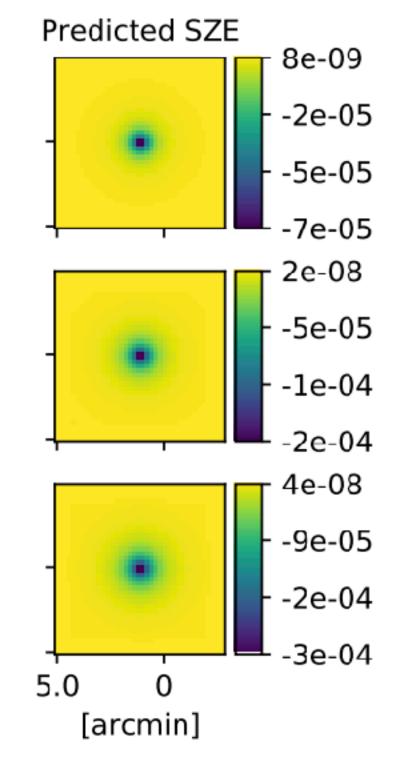
Mass Estimatation (Image Space)

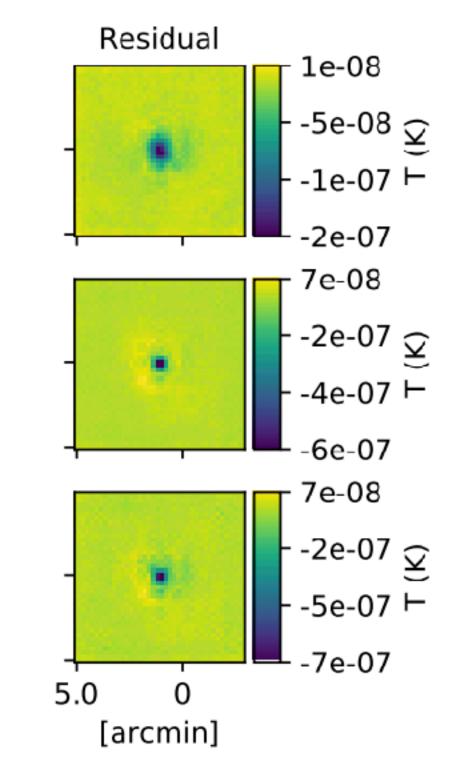
Gupta et al. 2020, 2021











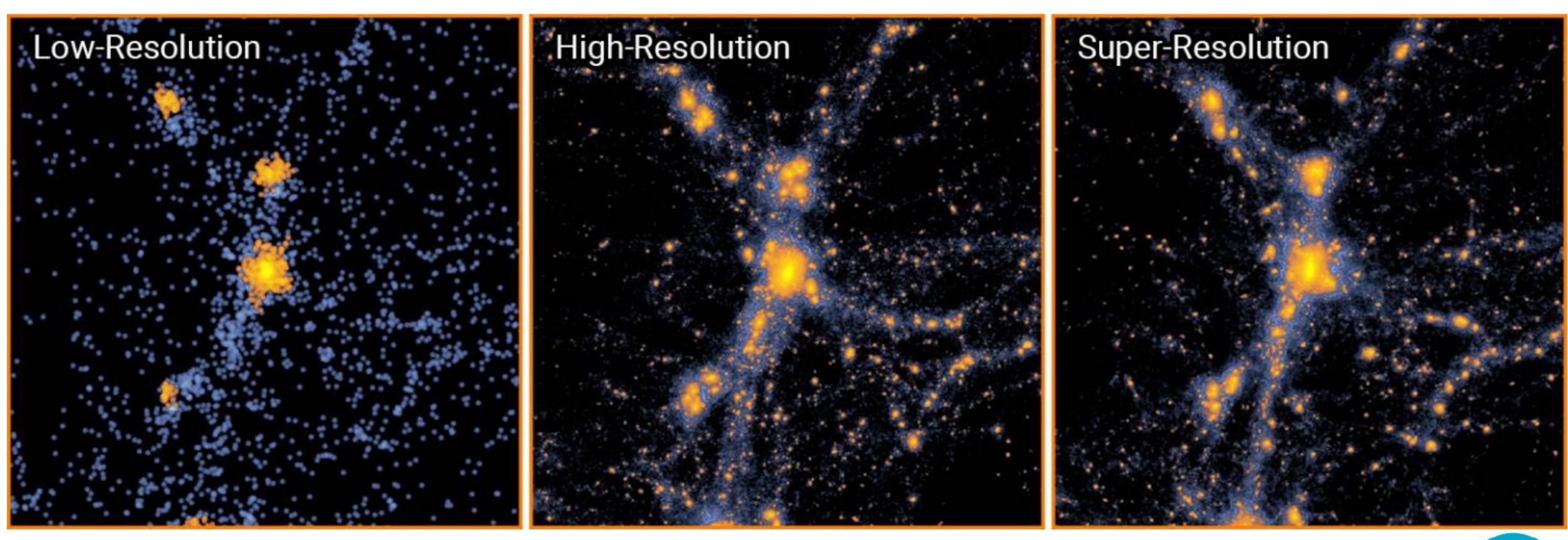


Temperature (K)

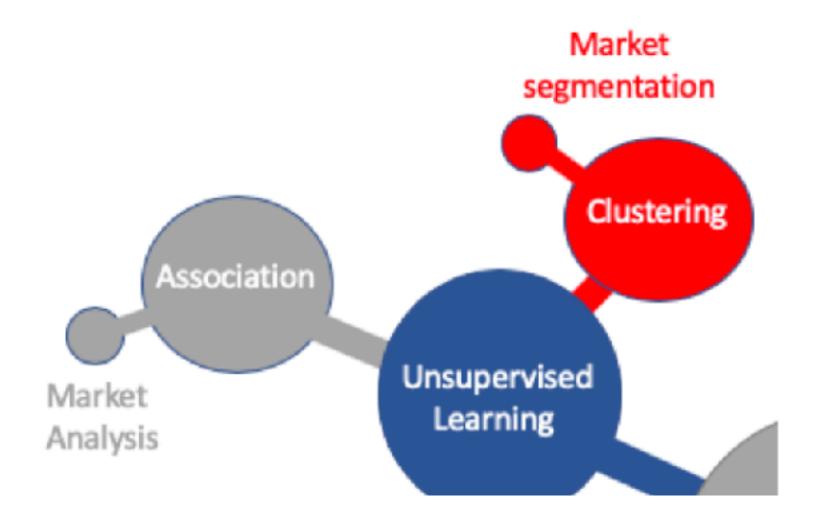
Supervised Learning in Astronomy Examples

Making simulations fast (Image Space)

Y. Li et al. 2021





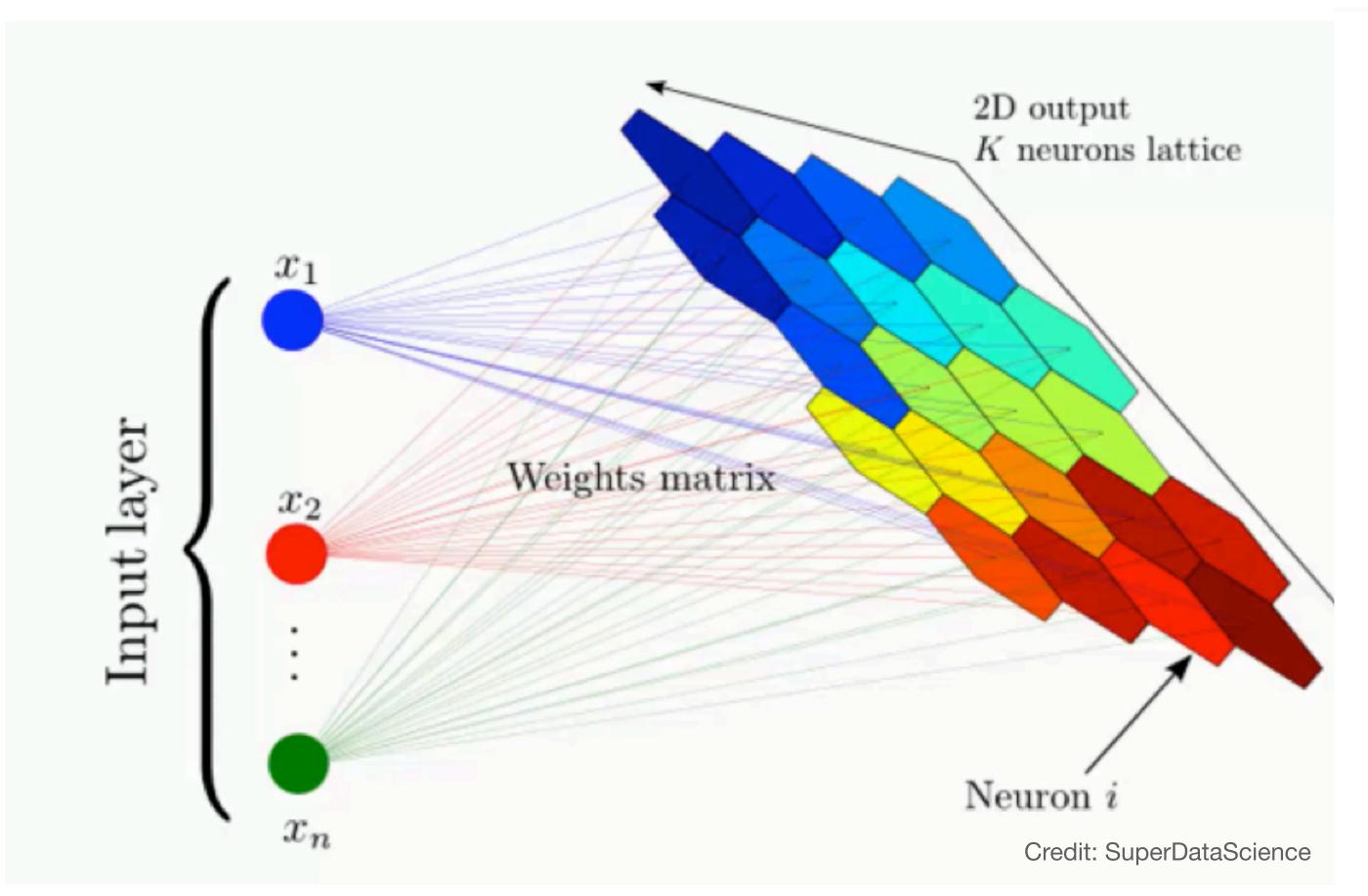




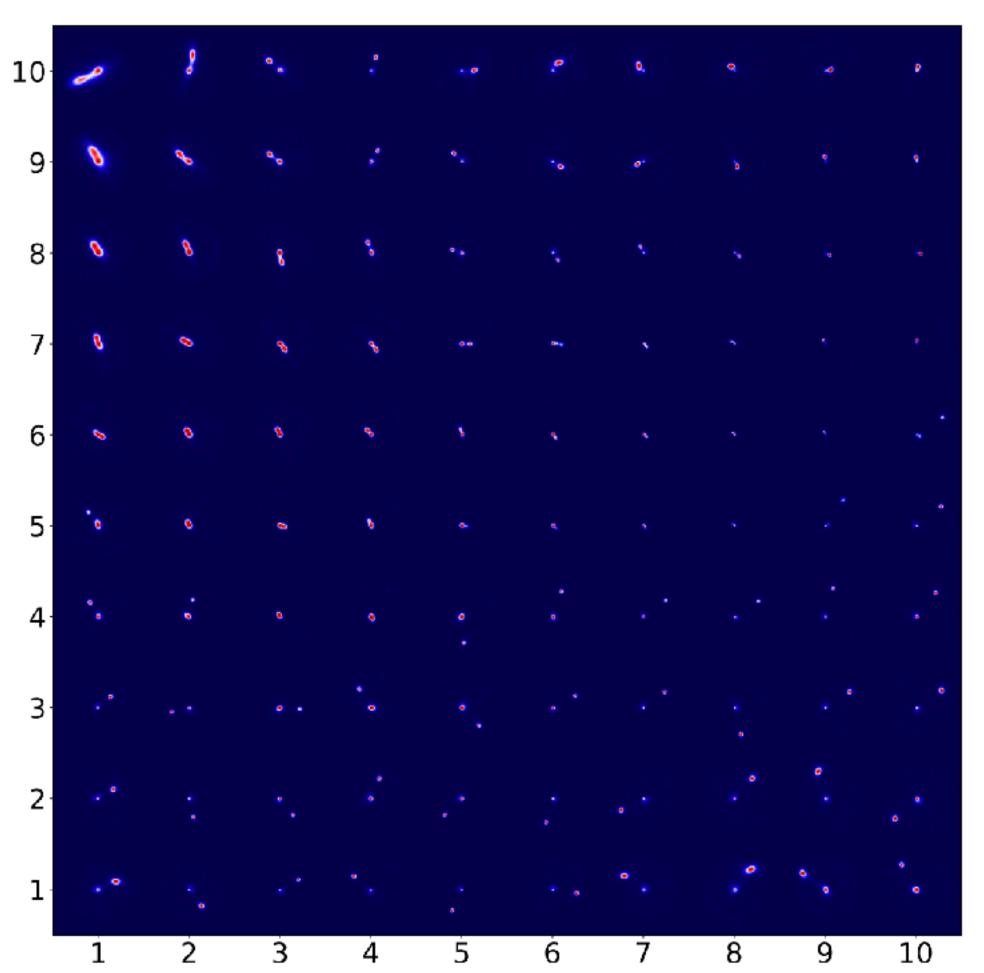


Un-supervised Learning in Astronomy Examples

(1) feature extraction, (2) clustering, (3) visual representation



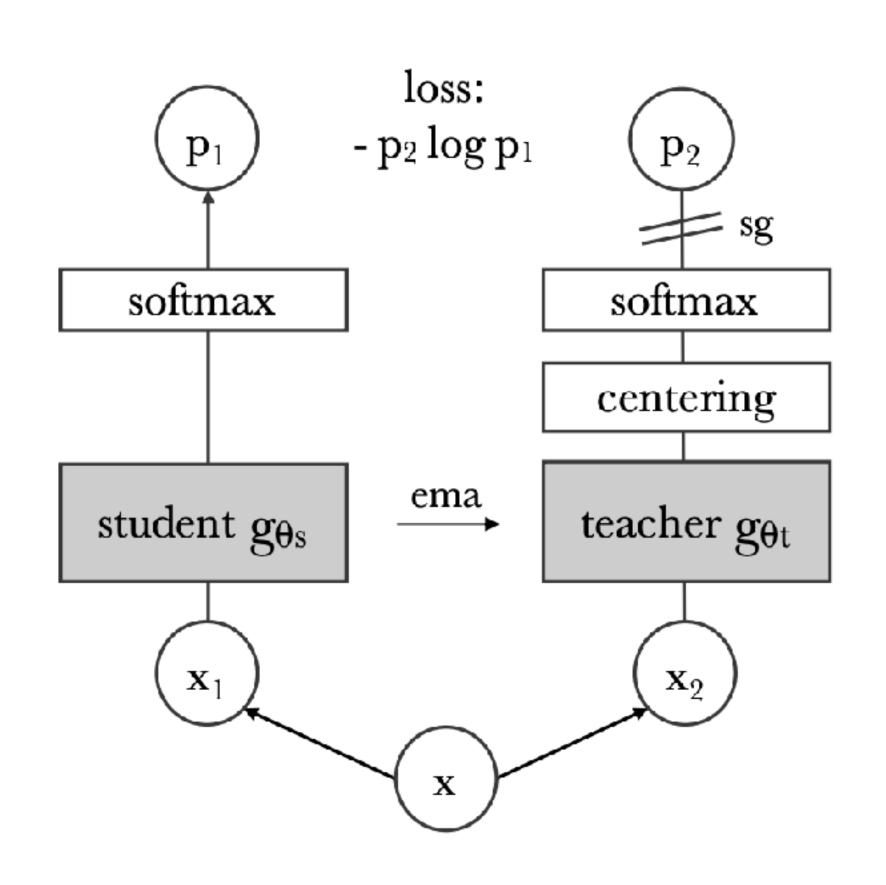
Self Organising Maps



CSIRO

Un-supervised Learning in Astronomy Examples

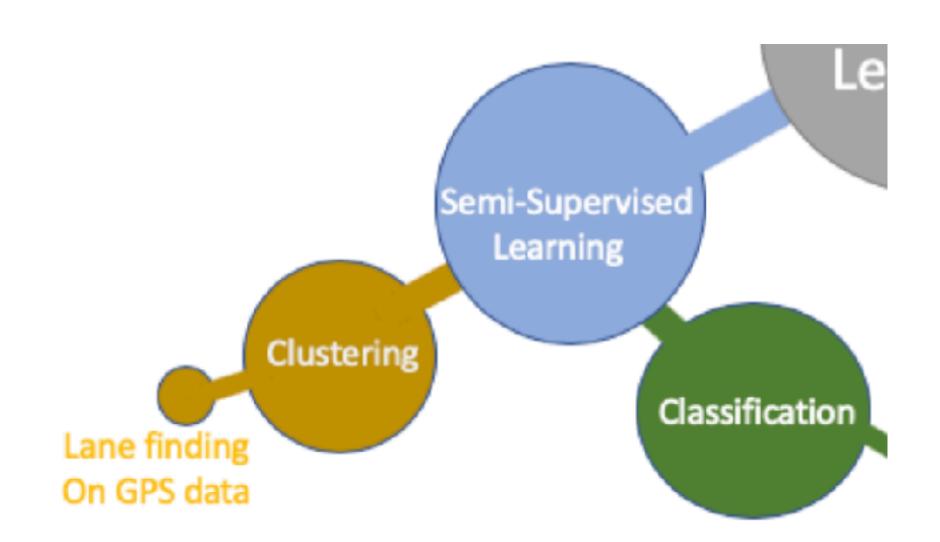
(1) feature extraction, (2) clustering, (3) visual representation



Student Teacher self-supervised networks



Webb et al. 2020

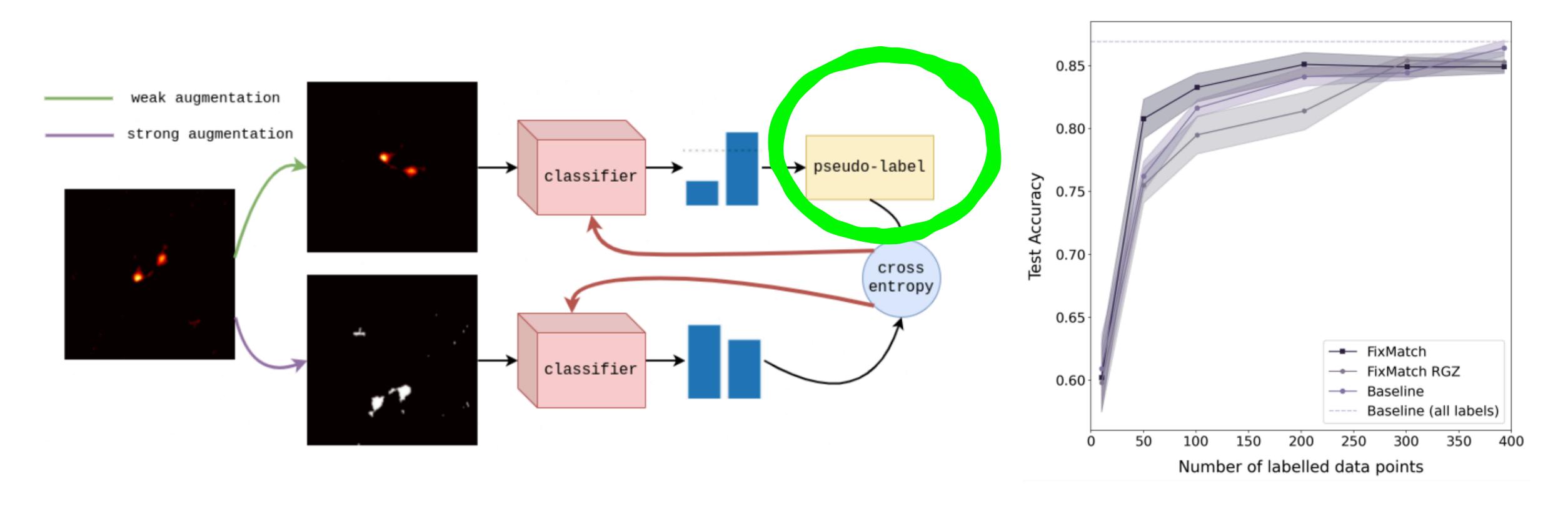


Credit: Data Science Central



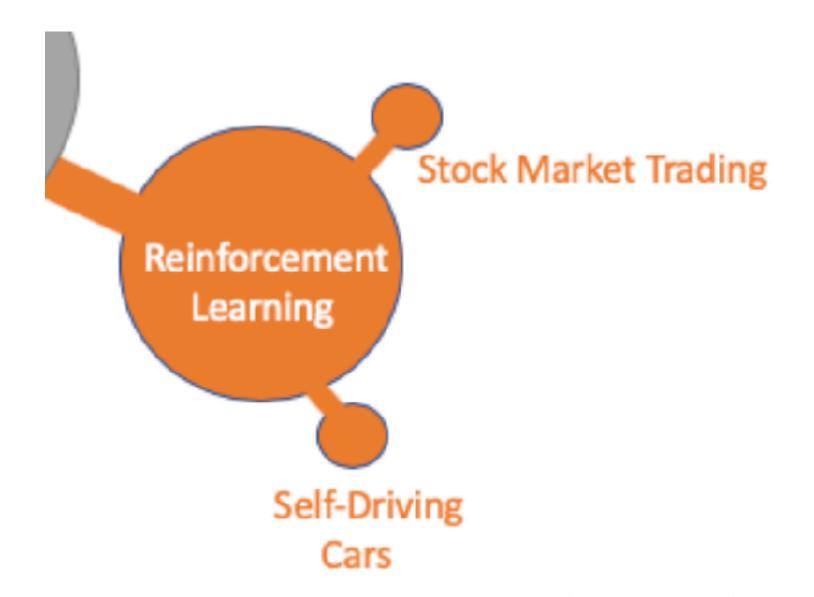
Semi-supervised Learning in Astronomy Examples

(1) feature extraction, (2) clustering/classification (few labels), (3) visual representation



Slijepcevic et al. 2021





Credit: Data Science Central



Reinforcement Learning in Astronomy Examples

Deep reinforcement learning for smart calibration of radio telescopes

Sarod Yatawatta^{1*} and Ian M. Avruch[†]

¹ASTRON, Oude Hoogeveensedijk 4, 7991 PD Dwingeloo, The Netherlands

13 May 2021

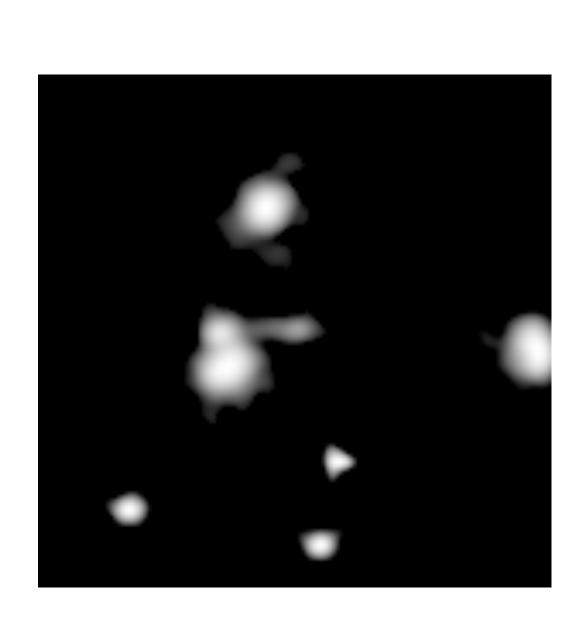
ABSTRACT

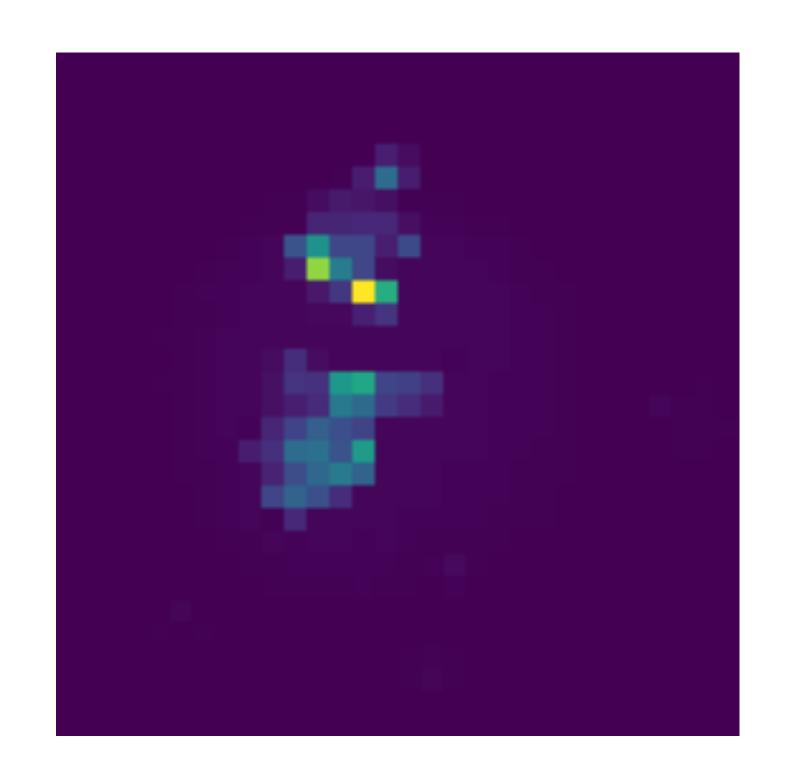
Modern radio telescopes produce unprecedented amounts of data, which are passed through many processing pipelines before the delivery of scientific results. Hyperparameters of these pipelines need to be tuned by hand to produce optimal results. Because many thousands of observations are taken during a lifetime of a telescope and because each observation will have its unique settings, the fine tuning of pipelines is a tedious task. In order to automate this process of hyperparameter selection in data calibration pipelines, we introduce the use of reinforcement learning. We test two reinforcement learning techniques, twin delayed deep deterministic policy gradient (TD3) and soft actor-critic (SAC), to train an autonomous agent to perform this fine tuning. For the sake of generalization, we consider the pipeline to be a black-box system where the summarized state of the performance of the pipeline is used by the autonomous agent. The autonomous agent trained in this manner is able to determine optimal settings for diverse observations and is therefore able to perform *smart* calibration, minimizing the need for human intervention.

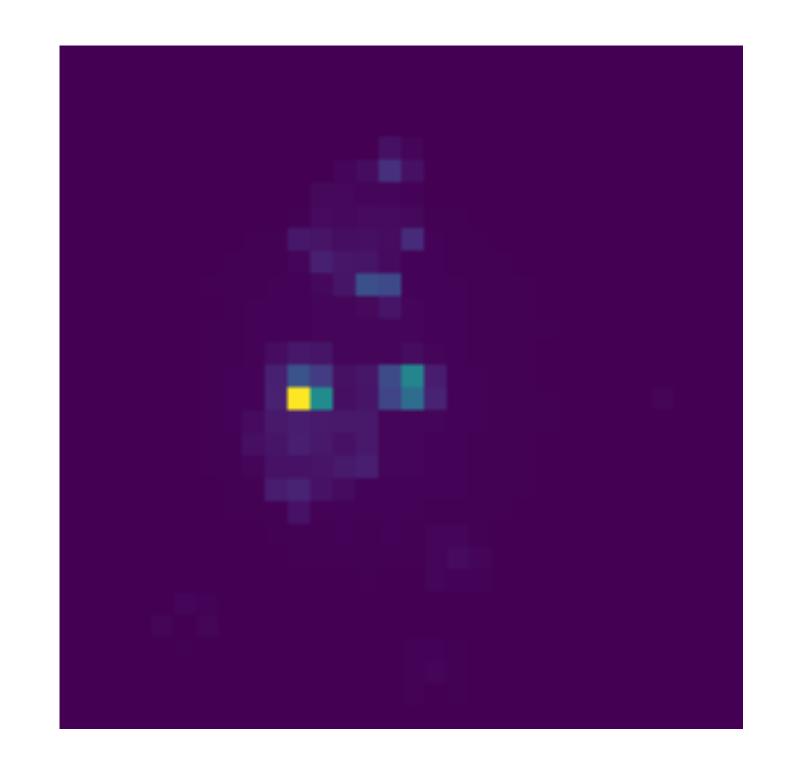
Key words: Instrumentation: interferometers; Methods: numerical; Techniques: interferometric



New Networks other than Convolutional Neural Network



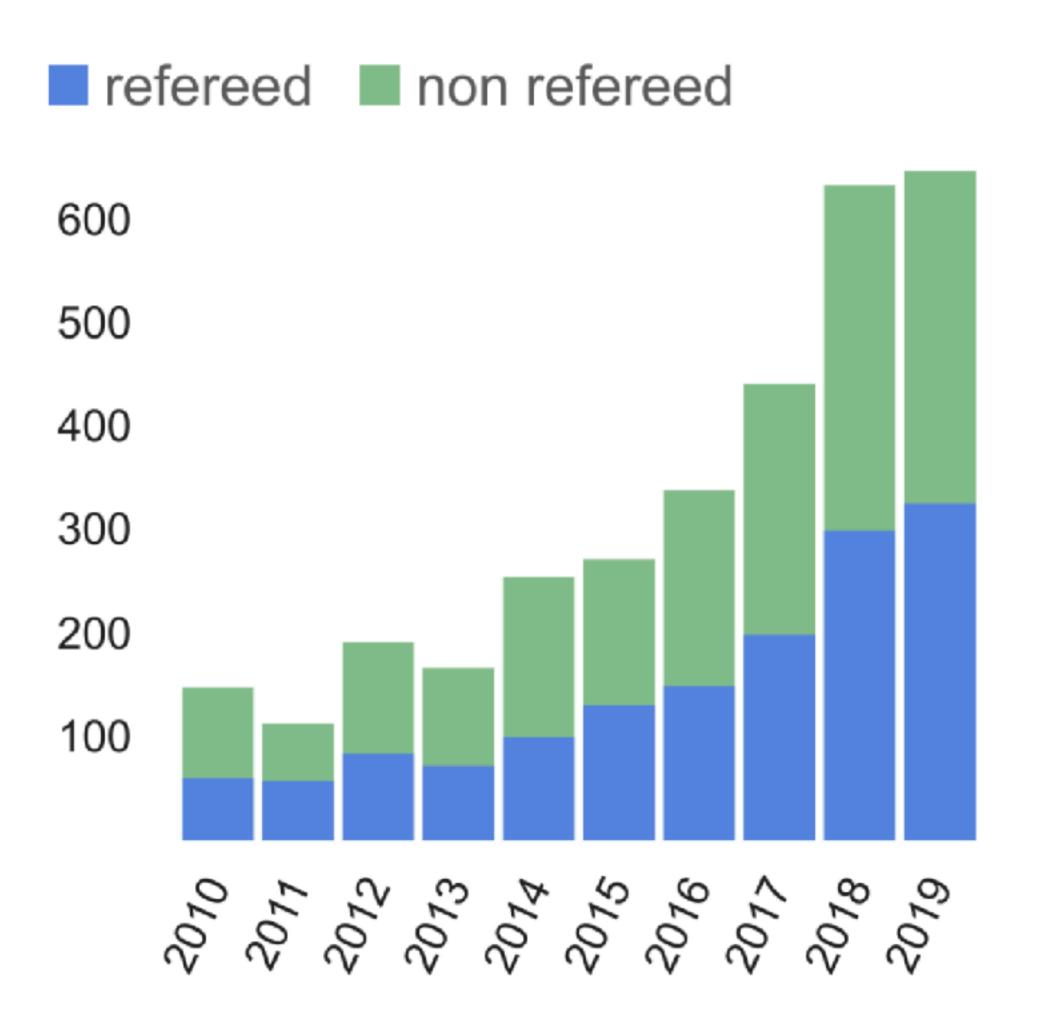




Vision Transformers with Attention Layers instead of Convolutional Layers



Astronomy papers that include machine learning methods in the abstract or title!



Source ADS, Venn et al. 2019

