Today, there are many astronomy datasets provided by various top research groups and companies. Each dataset can be unimodal including images, various natural measures like spectrum, radio waves, redshift, stellar mass, etc, or can be multimodal containing various pairs of unimodal E.g. image-spectrum, image-redshift, etc. Technologies cause datasets to grow drastically, and consequently, working on these datasets is more challenging.

Common deep-learning approaches are based on data that are labeled by humans. This is so time-consuming, and due to the size of the data, it may not be possible to prepare labeled datasets. In this regard, new methods are proposed to take advantage of many available unlabeled datasets. Self-supervised learning tries to generate pseudo-labels from the unlabeled datasets, and train models supervisely. Some self-supervised learning approaches are contrastive learning, mask autoencoders, etc.

Models proposed for astronomy are so task-specific. It means that each of them cannot be utilized for other tasks or data, and they lack generality. Instead of putting time and effort into training task-specific models, we can train a larger model that can be employed for many tasks with only small modifications. This is the main concept of the foundation model, and also the goal that we desire to reach it.

In the proposed foundation model for the galaxy morphology, several tasks like galaxy classification, similarity search, and natural measures prediction like stellar mass, and redshift, applying the foundation model for unseen new data can be employed, and be compared with other proposed foundation models.

Different possible models:

* Propose new foundation models based on unimodal and multi-modal datasets using mask autoencoder, combinations of the mask autoencoder, and contrastive learning, applying some possible modifications to the available methods.
* Propose a larger foundation model using pre-trained models based on ensemble learning methods.
* Applying different fine-tuning approaches to new and previous models and investigating their effectiveness.

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Chapters 6, 11, and 12 of AI for Science Book [(Alok Choudhary, Geoffrey Fox, Tony Hey 2023)](https://paperpile.com/c/f2CY2t/FJSWX)

Foundation models across disciplines [ScienceFMHub](http://sciencefmhub.org) [(“ScienceFMHub Portal for Science Foundation Model Community” 2023)](https://paperpile.com/c/f2CY2t/U7l7x) include related science image applications in remote sensing and climate science.

**Research**

**Datasets** datasets that use imaging surveys

* [Astroinformatics of galaxies and quasars: a new general method for photometric redshifts estimation](https://arxiv.org/abs/1107.3160)  (Laurino et al 2011) discusses about applying an innovative weak-gated attention mechanism for CNN’s for the SDSS DR-7 dataset.
* [Attention-gating for improved radio galaxy classification](https://arxiv.org/abs/2012.01248) [(Bowles et al. 2020)](https://paperpile.com/c/f2CY2t/5U5d) focuses on building CNN’s that use attention mechanisms for the VLA Sky Survey dataset.
* [Classifying Radio Galaxies with Convolutional Neural Network](https://arxiv.org/pdf/1705.03413.pdf) [(Aniyan and Thorat 2017)](https://paperpile.com/c/f2CY2t/DwpV) uses CNN for classifying radio images from the Fanaroff-Riley, Very Large Array, and Fain Images of the Radio Sky at Twenty Centimeters survey.
* [Deep Learning Approach to Photometric Redshift Estimation](https://arxiv.org/pdf/2310.16304.pdf) [(Chunduri and Mahesh 2023)](https://paperpile.com/c/f2CY2t/BlhP) testing a fully connected neural network and decision tree for SDSS dataset.
* [Deep learning based detection of cosmological diffuse radio sources](https://academic.oup.com/mnras/article-pdf/480/3/3749/25519514/sty2102.pdf) [(C. Gheller, Vazza, and Bonafede 2018)](https://paperpile.com/c/f2CY2t/IXjF) using a CNN for detecting extragalactic radio sources for surveys such as LOFAR and SKA.
* [Fanaroff-Riley classification of radio galaxies using group-equivariant convolutional neural networks](https://arxiv.org/pdf/2102.08252.pdf) [(Scaife and Porter 2021)](https://paperpile.com/c/f2CY2t/SQNO) uses the LeNet CNN Architecture to classify images from the MiraBest Dataset.
* [New Approaches to Object Classification in Synoptic Sky Surveys](https://arxiv.org/pdf/0810.4945.pdf) [(Donalek et al. 2008)](https://paperpile.com/c/f2CY2t/FALx) uses a multilayer perceptron to classify images from the Palomar-Quest Survey.
* [Photometric redshifts for Quasars in multi band Surveys](https://arxiv.org/pdf/1305.5641.pdf) [(Brescia et al. 2013)](https://paperpile.com/c/f2CY2t/EfZt) uses multilayer perceptron trained by learning rule from Quasi Newton Algorithm on the SDSS, GALEX, UKDSS, and WISE datasets.

**Techniques** that could be used for multi-modal datasets

* [Convolutional Deep Denoising Autoencoders for Radio Astronomical Images](https://arxiv.org/abs/2110.08618) [(Claudio Gheller and Vazza 2021)](https://paperpile.com/c/f2CY2t/dUjs) applying Convolutional Denoising Autoencoder to denoise synthetic images of radio telescopes.
* [Deep-Learnt Classification of Light Curves](https://arxiv.org/pdf/1709.06257.pdf) [(Mahabal et al. 2017)](https://paperpile.com/c/f2CY2t/zbq2) transformed the time series from Catalina Real Time Transient Survey to two-dimensional light curve representations for convolutional neural networks.
* [Deeply Uncertain: Comparing Methods of Uncertainty Quantification in Deep Learning Algorithms](https://arxiv.org/pdf/2004.10710.pdf) [(Caldeira and Nord 2020)](https://paperpile.com/c/f2CY2t/JjG5) uses deep ensembles, bayesian neural networks, and concrete dropouts in comparison with other standard error propagation techniques in regards to calculating aleatoric, epistemic, statistical, and systematic uncertainty.
* [Deep Probabilistic Imaging: Uncertainty Quantification and Multi-modal Solution Characterization for Computational Imaging](https://arxiv.org/abs/2010.14462) [(Sun and Bouman 2020)](https://paperpile.com/c/f2CY2t/9tZD) uses deep generative models to learn reconstructed image’s posterior distribution and variational Bayesian method for predicting a distribution.
* [Density of States Prediction of Crystalline Materials via Prompt-guided Multi-Modal Transformer](https://arxiv.org/pdf/2311.12856.pdf) [(Lee et al. 2023)](https://paperpile.com/c/f2CY2t/UWHo) uses a transformer to predict the DOS of a material using GNN’s, cross-attention layers of multi-modal transformers, and a decoder.
* [Detecting Tidal Features using Self-Supervised Representation Learning](https://arxiv.org/pdf/2311.12856.pdf) [(Desmons, Brough, and Lanusse 2023)](https://paperpile.com/c/f2CY2t/sSg8) uses Nearest Neighbor Contrastive Learning self-supervised learning algorithms as a process for detecting tidal features.
* [Gravity Spy: Integrating Advanced LIGO Detector Characterization, Machine Learning, and Citizen Science](https://arxiv.org/pdf/1611.04596.pdf) [(Zevin et al. 2017)](https://paperpile.com/c/f2CY2t/RAb3) combines crowdsourcing and machine learning in order to categorize glitches into morphological classes.
* [Image as First-order Norm+Linear Autoregression: Unveiling Mathematical Invariance](https://arxiv.org/pdf/2305.16319.pdf) [(Chen et al. 2023)](https://paperpile.com/c/f2CY2t/Cgbd) uses FINOLA (First-Order Norm + Linear Autoregression) to classify images.
* [Machine Learning for the Zwicky Transient Facility](https://arxiv.org/ftp/arxiv/papers/1902/1902.01936.pdf) [(Mahabal et al. 2019)](https://paperpile.com/c/f2CY2t/a4TD) uses real vs. bogus classifier and uses random forest and CNN architecture for the Zwicky Transient Facility dataset.
* [Model-Aware Contrastive Learning: Towards Escaping Uniformity-Tolerance Dilemma in Training](https://arxiv.org/pdf/2207.07874.pdf) [(Huang et al. 2022)](https://paperpile.com/c/f2CY2t/mRqt) used techniques such model temperature strategy and others to fix uniformity-tolerance dilemma and gradient reduction dilemma.
* [ParSNIP: Generative Models of Transient Light Curves with Physics-Enabled Deep Learning](https://arxiv.org/pdf/2109.13999.pdf) [(Boone 2021)](https://paperpile.com/c/f2CY2t/7Sbz) uses a generative model with a variational autoencoder for the Pan-STARRS1 and PLAsTiCC datasets.
* [Pulsar Candidate Identification using Semi-Supervised Generative Adversarial Networks](https://arxiv.org/pdf/2010.07457.pdf) [(Balakrishnan et al. 2020)](https://paperpile.com/c/f2CY2t/5l9U) uses a semi-supervised GAN model for the HTRS-Survey dataset. Primarily on medlat and hilate data.
* [Quantifying Uncertainty in Deep Learning Approaches to Radio Galaxy Classification](https://arxiv.org/pdf/2201.01203.pdf) [(Mohan et al. 2022)](https://paperpile.com/c/f2CY2t/Aj0Y) uses variational inference for the MiraBest Dataset.

**Astroclip** multi-band imaging and optical spectra.

* [AstroCLIP: Connecting Diverse Observational Modalities in Astrophysics](https://polymathic-ai.org/blog/astroclip/) [(Polymathic 2023, n.d.)](https://paperpile.com/c/f2CY2t/xtbgu+UZsLN)
* AstroCLIP: Cross-Modal Pre-Training for Astronomical Foundation Models, [(Lanusse et al. 2023)](https://paperpile.com/c/f2CY2t/YYHUO)
* [Self-supervised similarity search for large scientific datasets](https://arxiv.org/pdf/2110.13151.pdf) [(Stein et al. 2021)](https://paperpile.com/c/f2CY2t/7nHGe) analysis that was used by Astroclip for image modality. Uses Contrastive loss

**Radio Galaxy Zoo** ResNet107893 images; 1256 fine-tuning

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* [Classification of Astronomical Bodies by Efficient Layer Fine-Tuning of Deep Neural Networks](https://ieeexplore.ieee.org/iel7/9672322/9672339/09672430.pdf?casa_token=1ajTnZylzWcAAAAA:r2B7Crg6drIdJ-lTmZK0DWnMWWVOf2z509EfUNVJ_nWgpPHJmlIYD5ovuW8MF_RZz6w4Rxxm) [(Ethiraj and Bolla 2021)](https://paperpile.com/c/f2CY2t/Uqahk)
* [Galaxy Morphological Classification with Efficient Vision Transformer](https://arxiv.org/abs/2110.01024) [(Lin et al. 2021)](https://paperpile.com/c/f2CY2t/t7ebX)
* [[2205.01677] ASTROMER: A transformer-based embedding for the representation of light curves](https://arxiv.org/abs/2205.01677) [(Donoso-Oliva et al. 2022)](https://paperpile.com/c/f2CY2t/OmrTd)
* [Radio Galaxy Zoo: Leveraging latent space representations from variational autoencoder](https://arxiv.org/pdf/2311.08331.pdf) [(Andrianomena and Tang 2023)](https://paperpile.com/c/f2CY2t/kujy) uses very deep variational autoencoder (VDVAE) using SimCLR contrastive learning for the Radio Galaxy Zoo DR-1, MiraBest, and FR-Deep NVSS.
* [Radio Galaxy Zoo: Towards building the first multi-purpose foundation model for radio astronomy with self-supervised learning](https://arxiv.org/abs/2305.16127) [(Slijepcevic et al. 2023)](https://paperpile.com/c/f2CY2t/MJVdr) uses BYOL (Bootstrap Your Own Latent) self-supervised learning algorithm for the MiraBest dataset.
* [Separation of Pulsar Signals from Noise Using Supervised Machine Learning Algorithms](https://arxiv.org/pdf/1704.04659.pdf) [(Bethapudi and Desai 2017)](https://paperpile.com/c/f2CY2t/tJRh) uses ANN, AdaBoost, Gradient Boosting Classifier, and Xtreme Gradient Boosting on the HTRU Survey and SMOTE Dataset.
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* [VoLTA: Vision-Language Transformer with Weakly-Supervised Local-Feature Alignment](https://arxiv.org/pdf/2210.04135.pdf) [(Pramanick et al. 2022)](https://paperpile.com/c/f2CY2t/BRjy) uses the VoLTA model which achieved fine-grained region-level image understanding, good low-level matching criterion, and effective on wide range of course- and fine-grained tasks.’
* [Weight Pruning and Uncertainty in Radio Galaxy Classification](https://arxiv.org/pdf/2111.11654.pdf) [(Mohan and Scaife 2021)](https://paperpile.com/c/f2CY2t/RMHC) uses LeNet-5 architecture and variational inference approach using Adam optimizer on the MiraBest dataset.

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