

SummerSOC 2025

📍 Crete, Greece

# Uncertainty-Aware Machine Learning for Astronomical Data Analysis

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Computer Science Department, University of Crete



Funded by  
the European Union

# SPL at a glance



2006



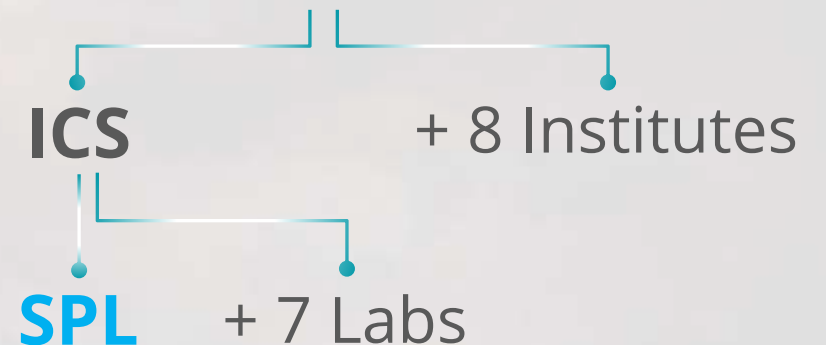
4 Researchers/Academics (permanent)  
1 Postdoctoral Researchers  
12 Postgraduate Students  
2 Research Engineers



> 10M€ (PI/co-PI in EU & national projects)



**FORTH**



## Research Institutes



Electronic Structure  
& Laser



Molecular Biology &  
Biotechnology



Computer Science



Applied and  
Computational  
Mathematics



Mediterranean  
Studies



Chemical  
Engineering  
Sciences



Astrophysics



Geoenegy



Biomedical  
Research

# Collaborators & Funding



**Panos Tsakalides**  
**Signal Processing lab**  
**FORTH**



**TITAN**

ARTIFICIAL INTELLIGENCE  
IN ASTROPHYSICS



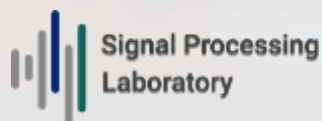
**Jean-Luc Starck**  
**CosmoStat lab**  
**CEA, France**

**CALCHAS**

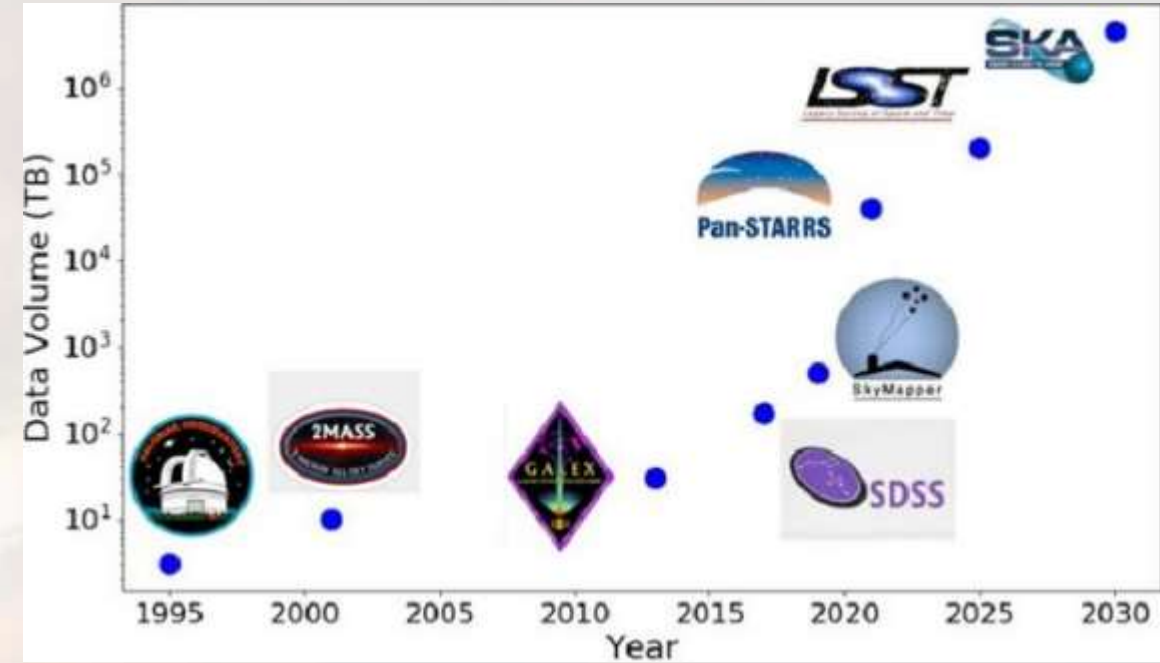
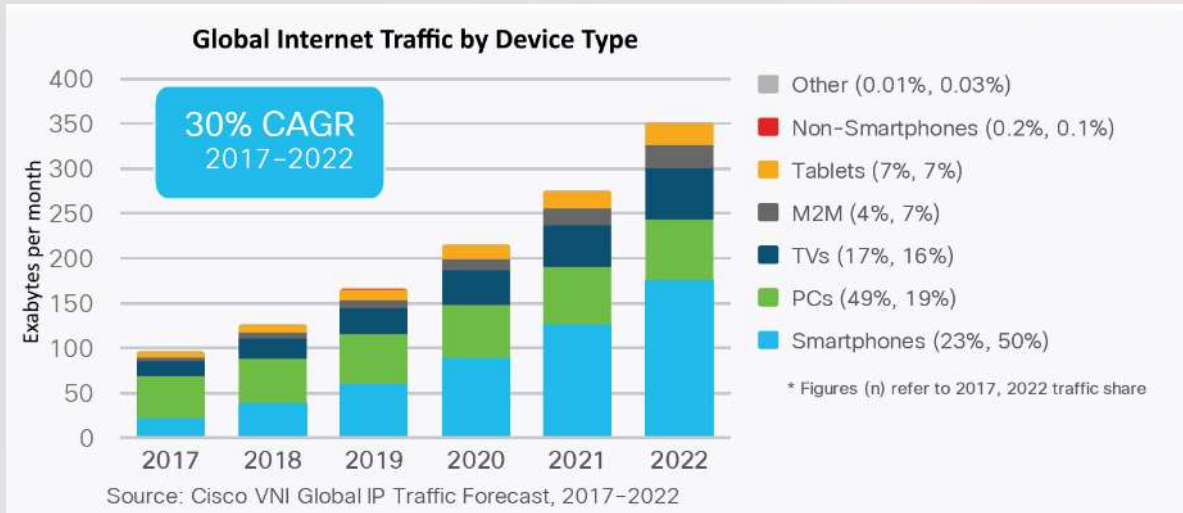
*Computational Intelligence for Multi-  
Source Remote Sensing Data Analytics*



**Mahta Moghaddam**  
**MiXIL lab**  
**USC**

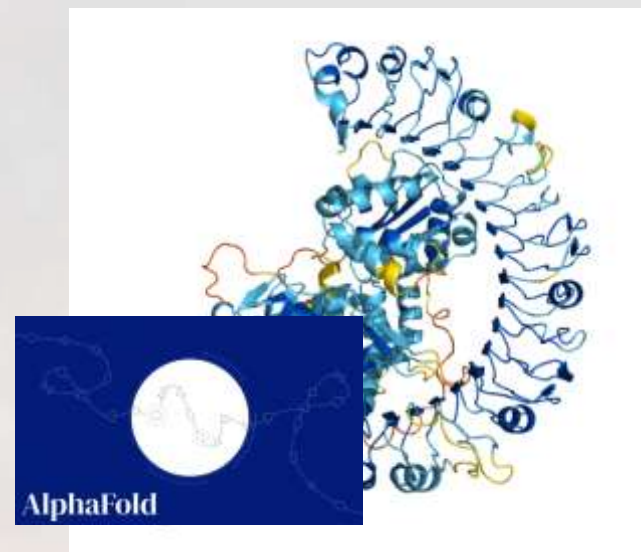
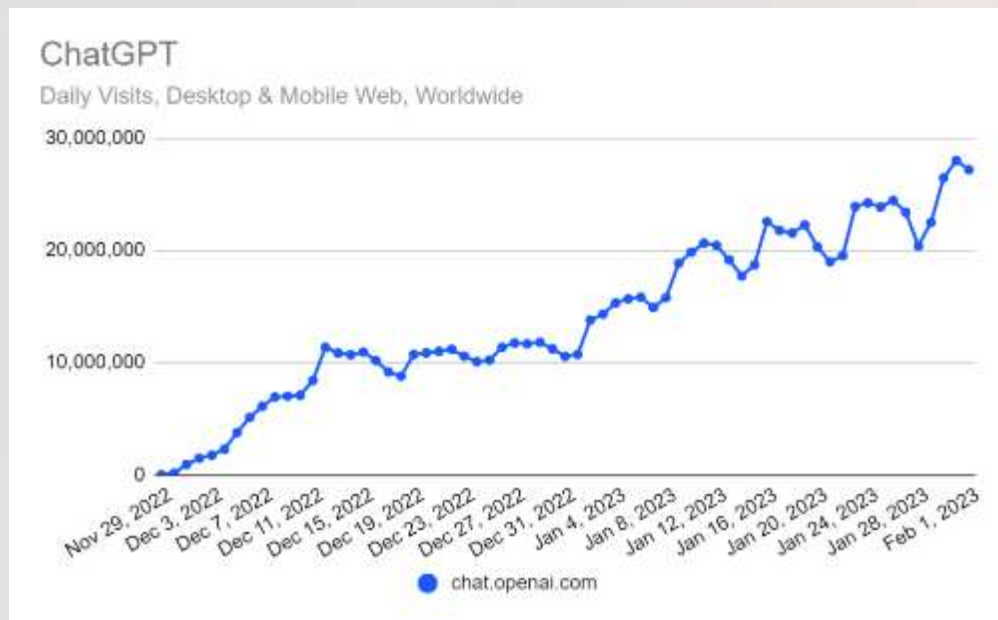


# The Big Data Revolution





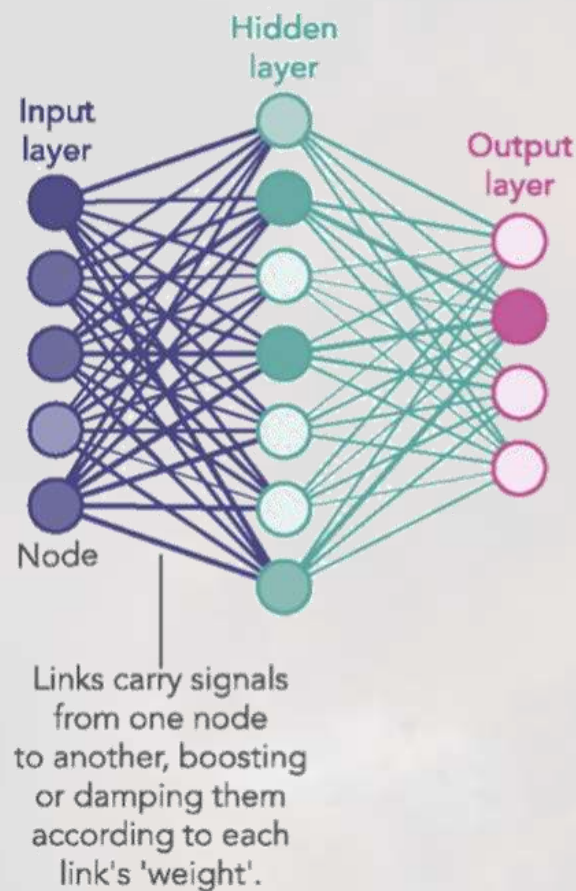
# The AI Revolution



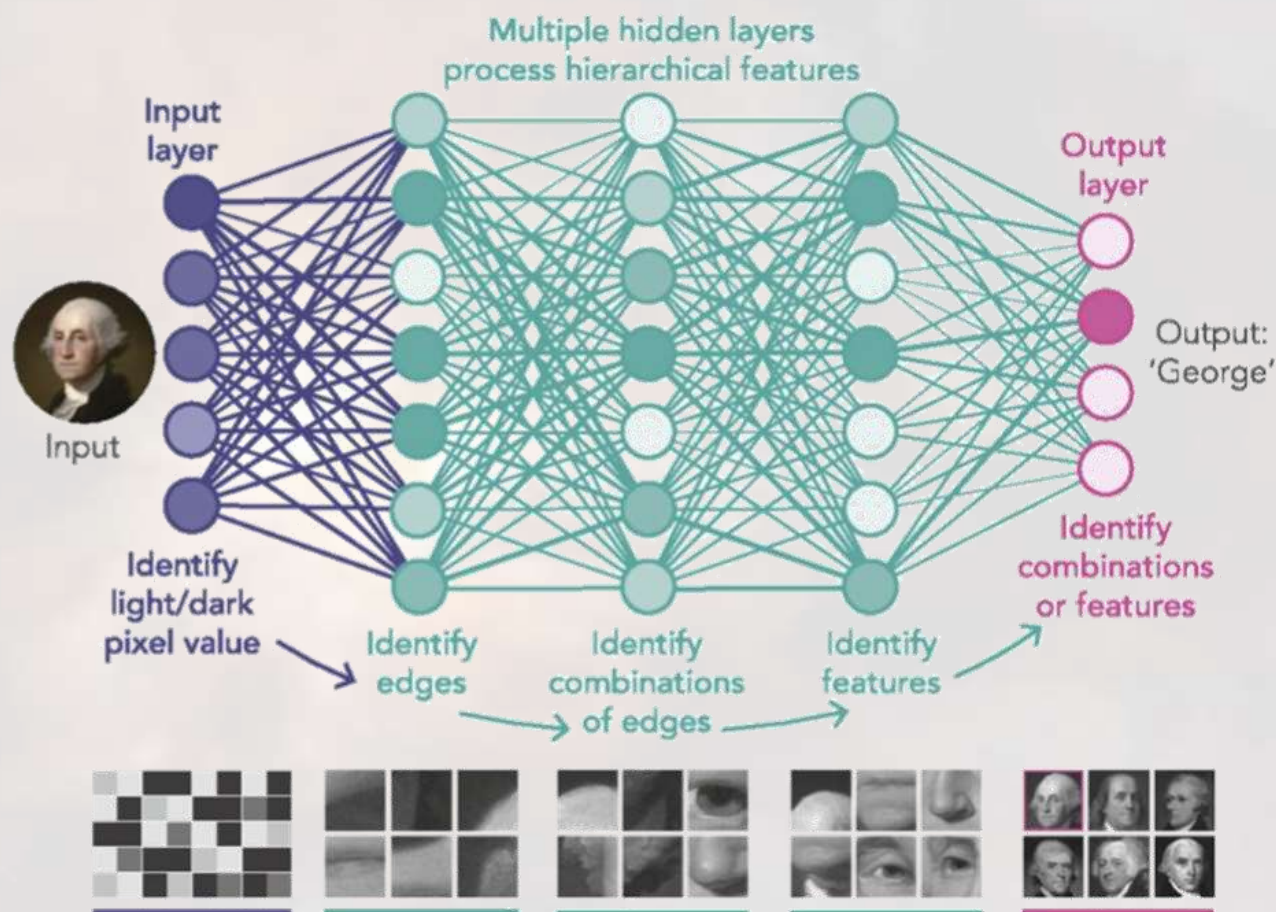
Jumper, John, et al. "Highly accurate protein structure prediction with AlphaFold." *Nature*. 2021.

# Deep Learning

1980S-ERA NEURAL NETWORK



DEEP LEARNING NEURAL NETWORK



# State-of-the-art in DL

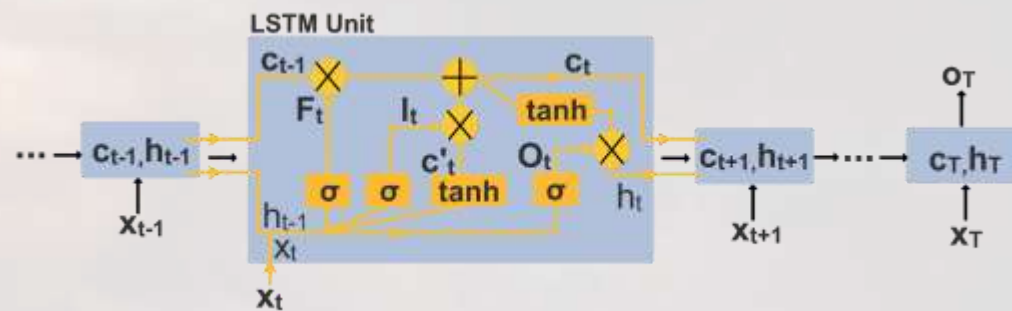
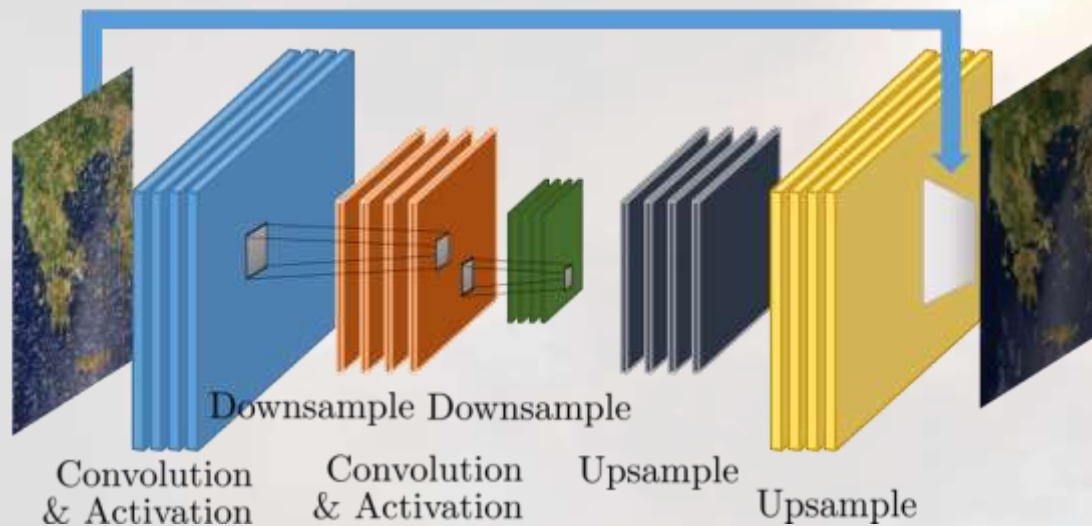
CNNs



RNN/LSTMs



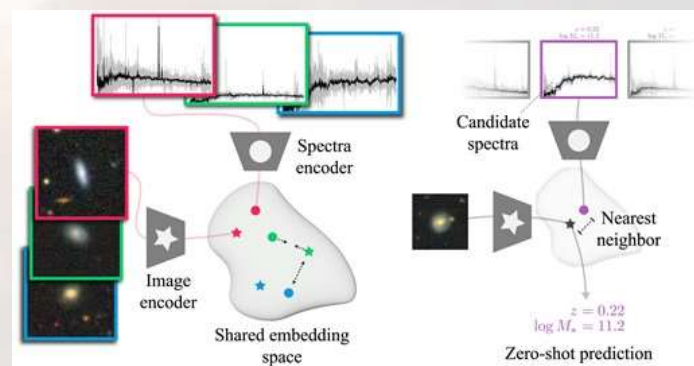
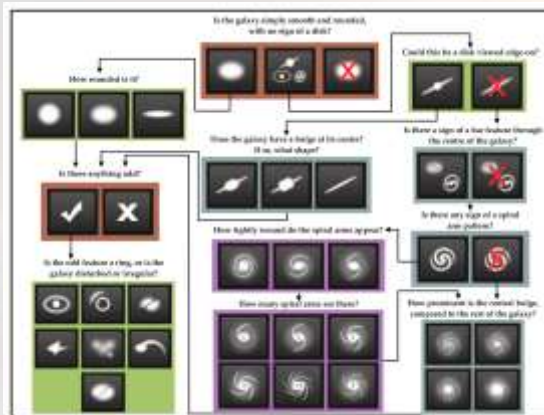
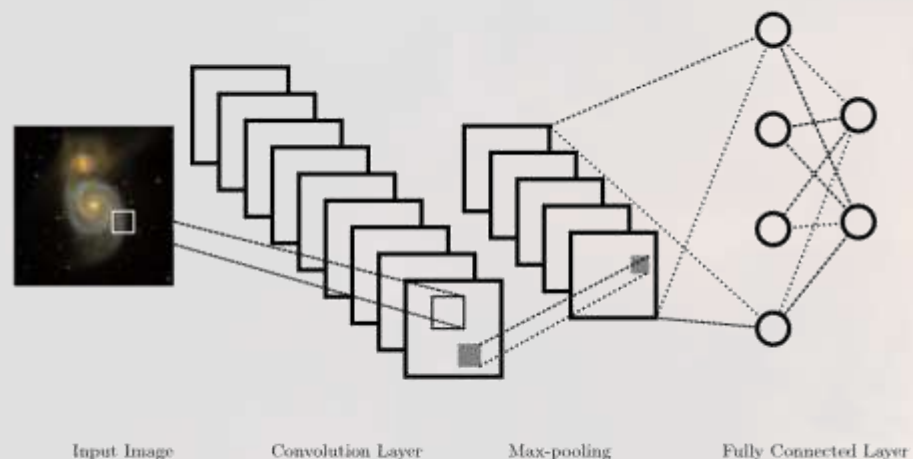
Residual



Transformers



# Deep Learning in Astronomy





# Uncertainty (model)



alaskan malamute



siberian husky



siberian husky

## Epistemic Uncertainty:

- Due to lack of knowledge about a system or process.
- Can be reduced as more knowledge is gained.

# Uncertainty (data)



cat



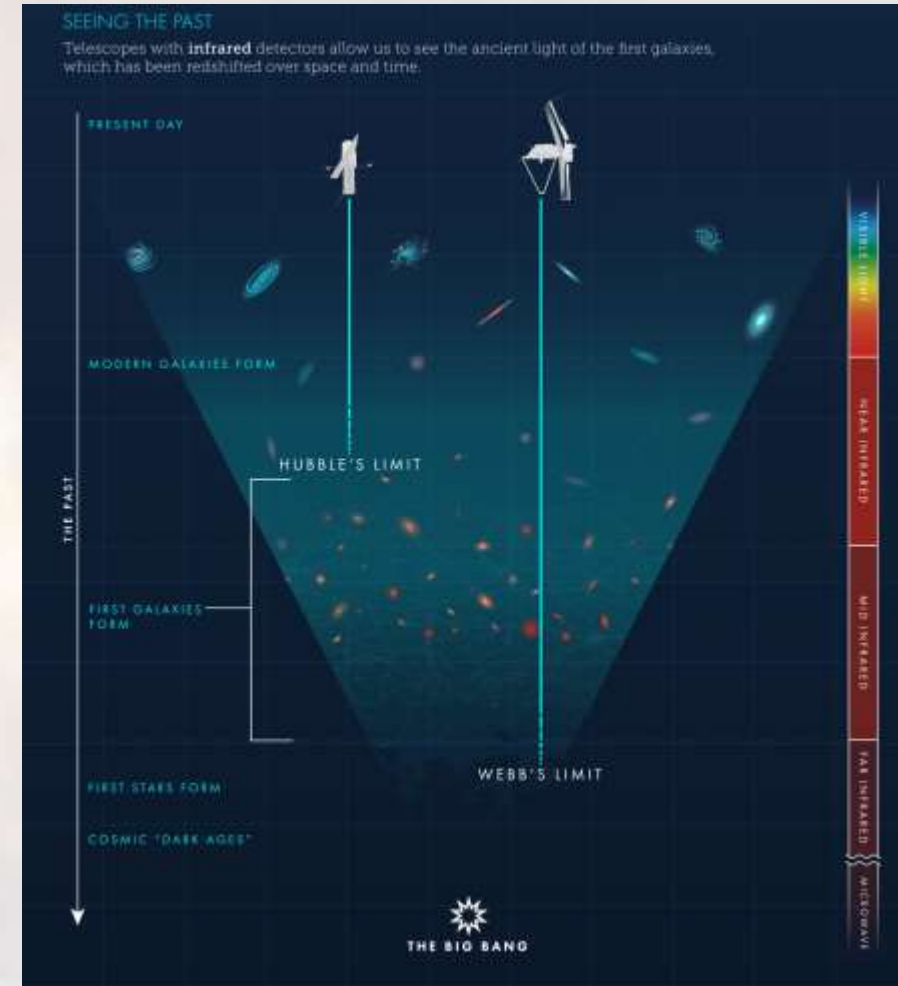
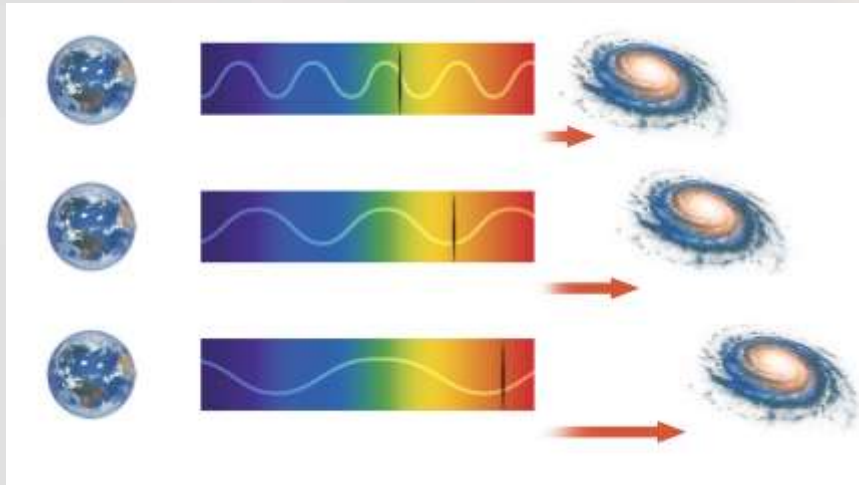
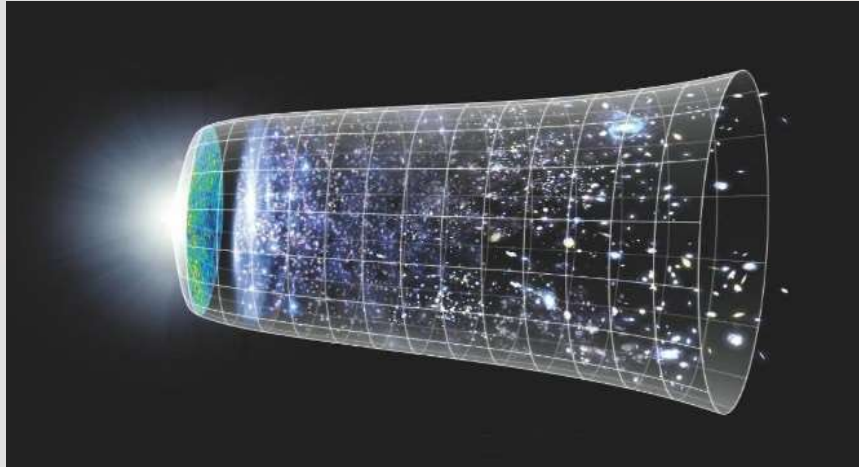
dog



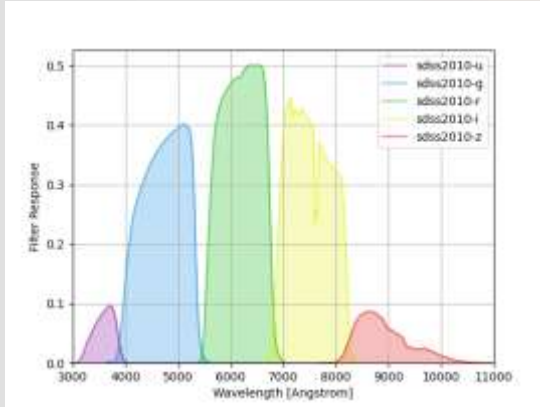
## Aleatoric Uncertainty:

- inherent randomness in a system or process (flipping a coin)
- cannot be reduced with more information or knowledge about the system.

# Redshift estimation

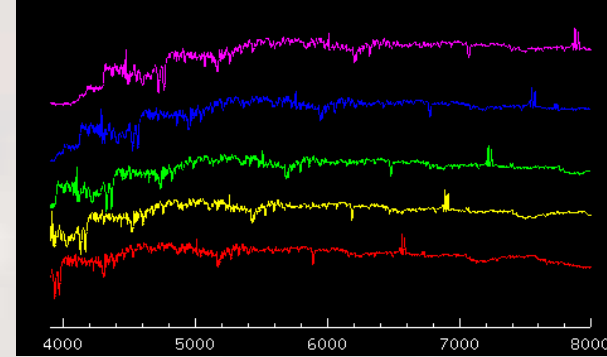


# Observations for Redshift estimation



## Photometric

- 3-4 broad bands
- Cheap
- Inaccurate

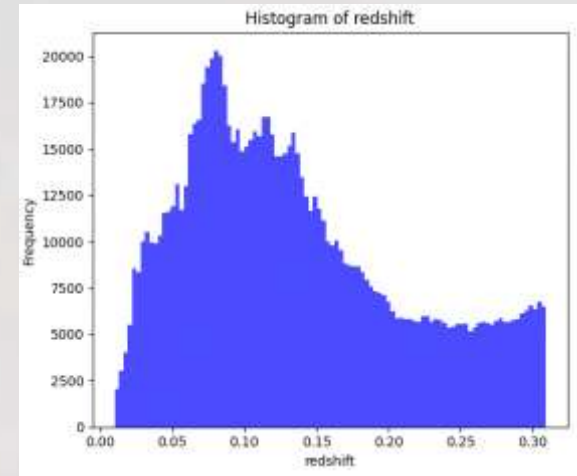
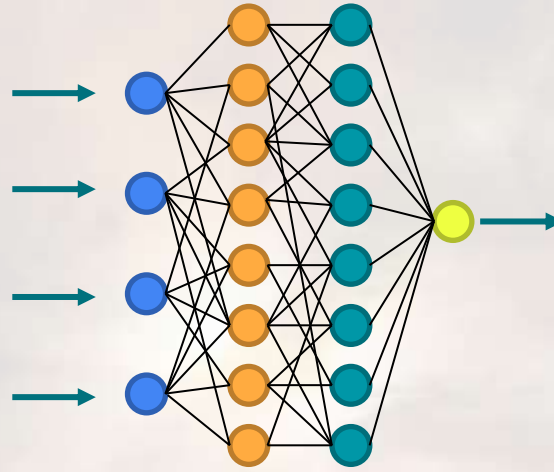
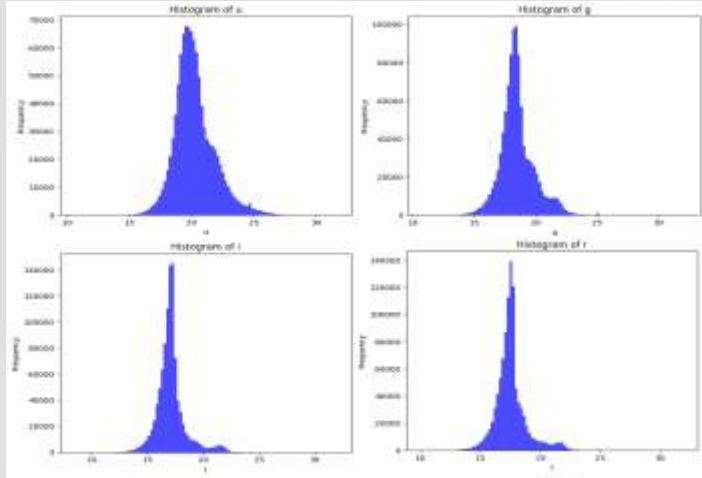


## Spectroscopic

- Extended spectral range
- Expensive
- Accurate



# ANNs for Photometric Redshift Estimation

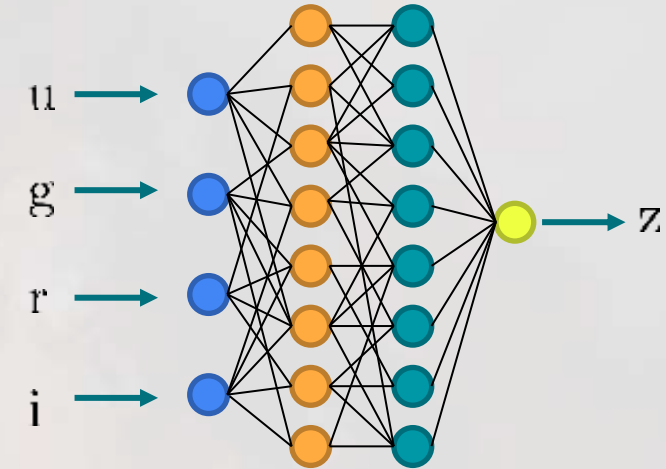


# ANN - Regression

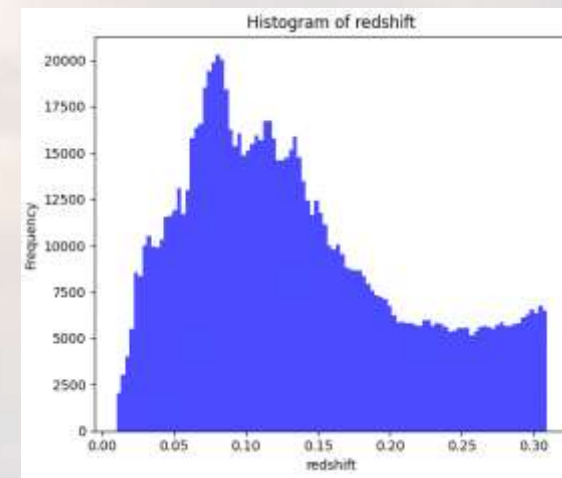
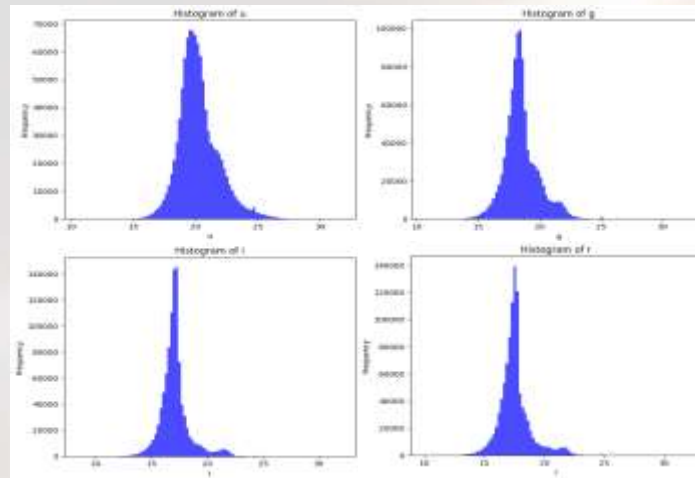
Baseline regression model  $\hat{y}_i = f(x_i; \mathbf{w})$  where:

- $f(x_i; \mathbf{w})$  is the prediction for the  $i$ -th observation,
- $y_i$  is the actual value for the  $i$ -th observation

Loss function:  $\text{MSE} = \frac{1}{n} \sum_{i=1}^n (f(x_i; \mathbf{w}) - y_i)^2$



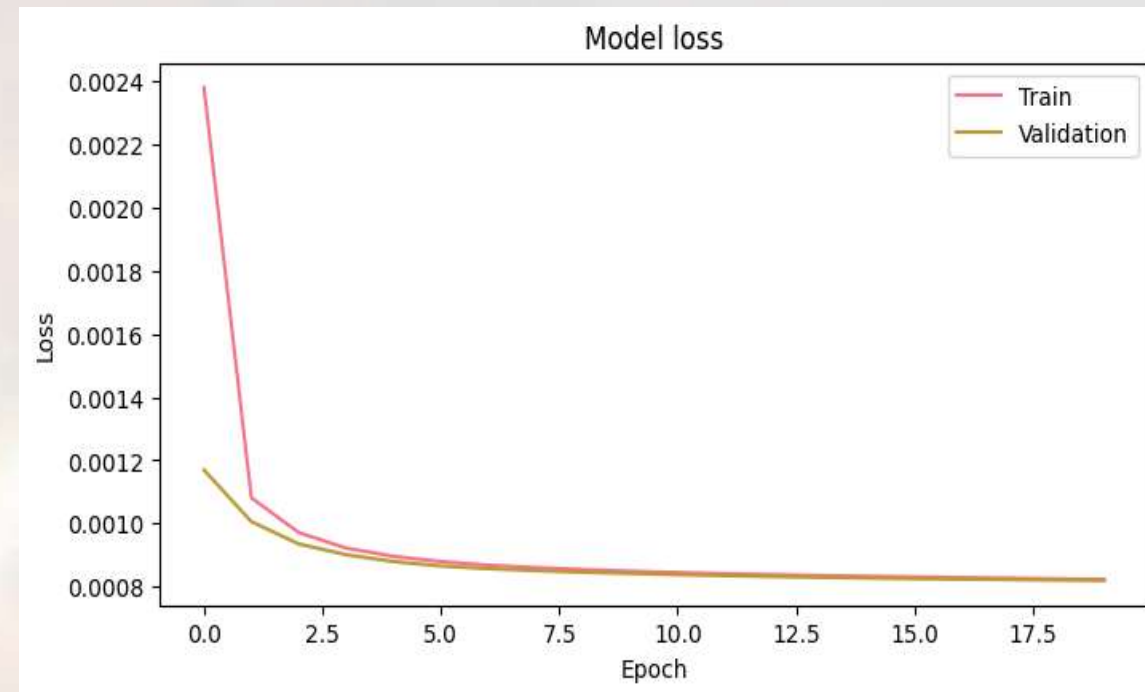
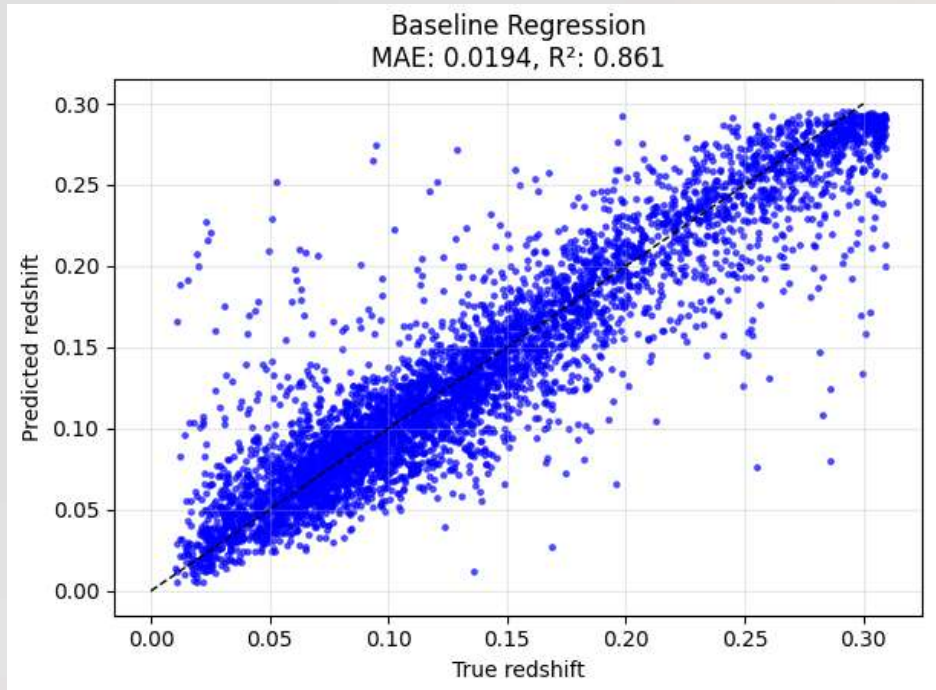
## Dataset



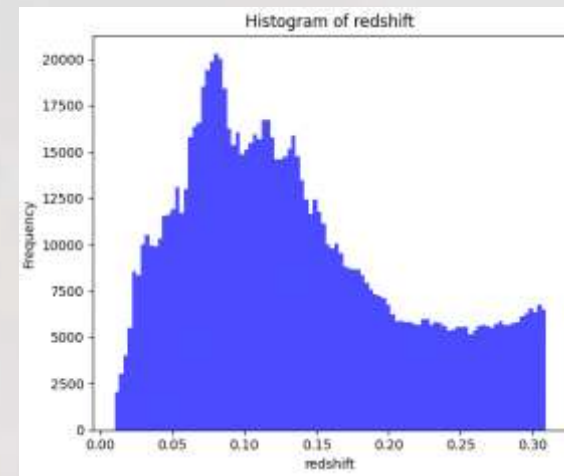
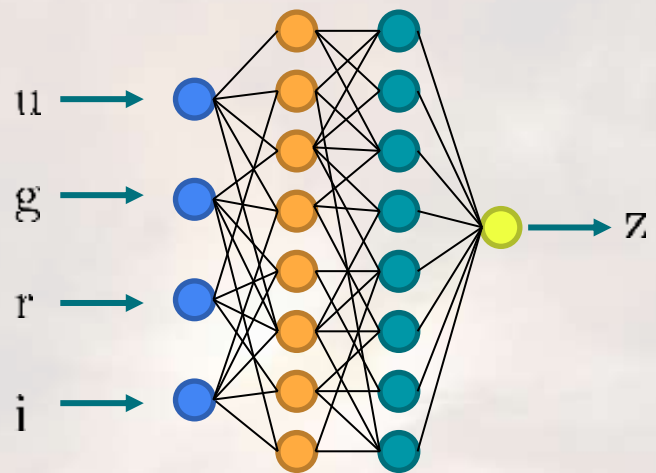
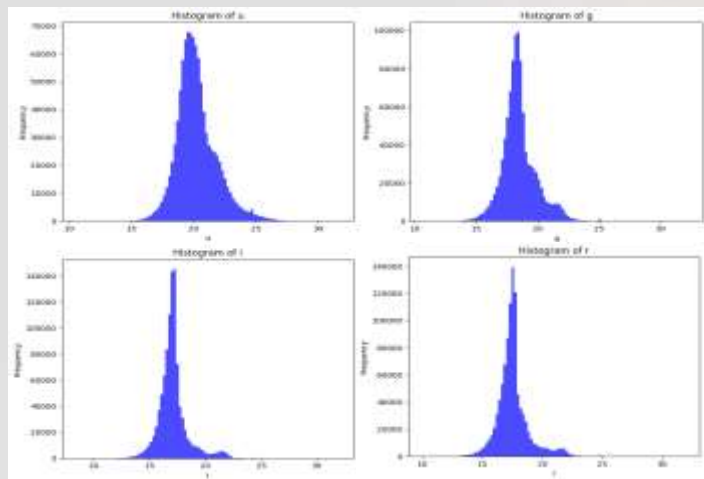
Training: 800K

Testing: 200K

# Baseline model & Data

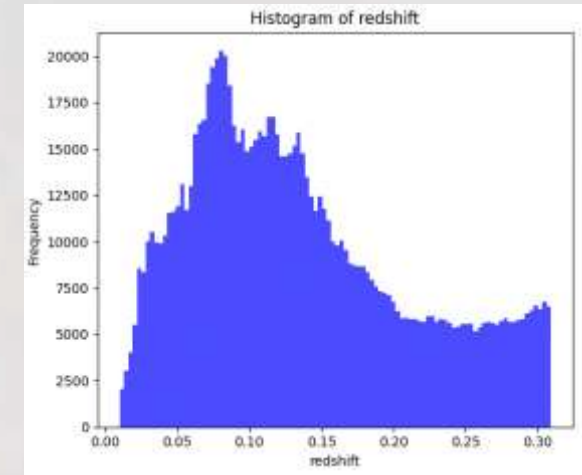
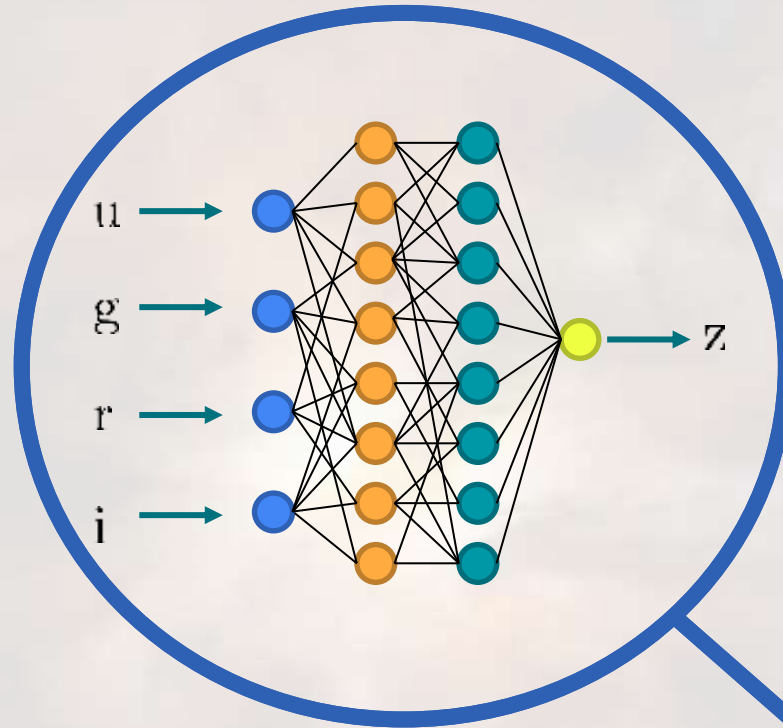
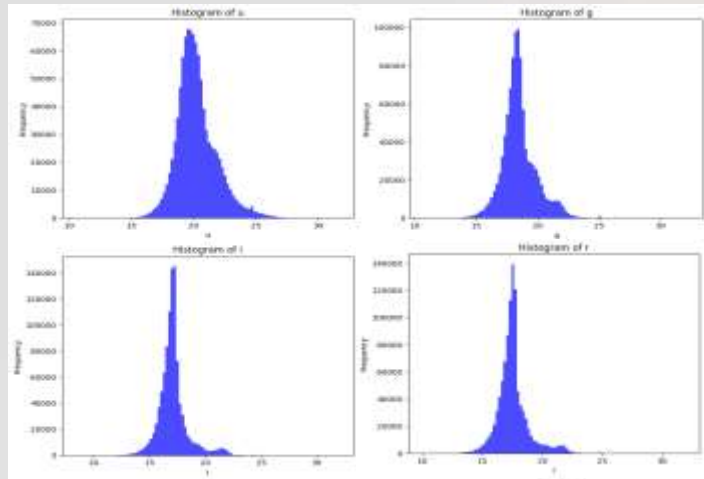


# Uncertainties





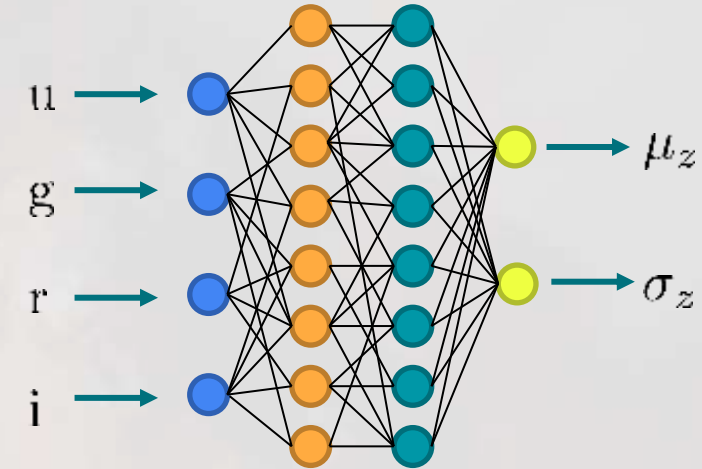
# Uncertainties (model)



# Gaussian Regression via ANN

- The target variable  $y_i \sim \mathcal{N}(f(x_i; \mathbf{w}), \sigma^2)$
- The likelihood for each observation is:

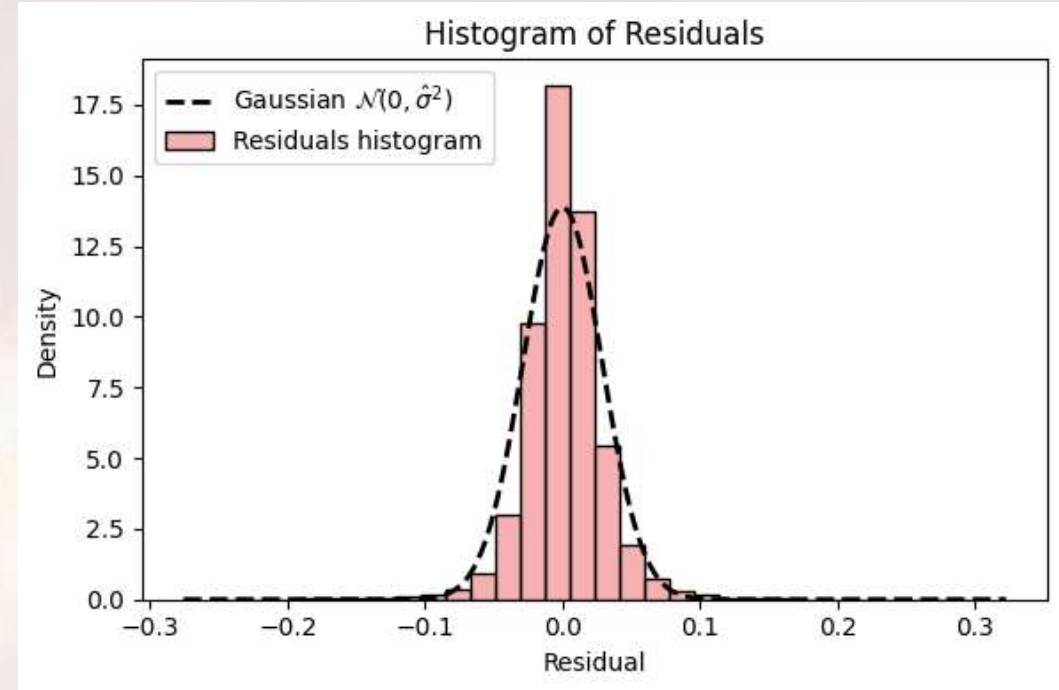
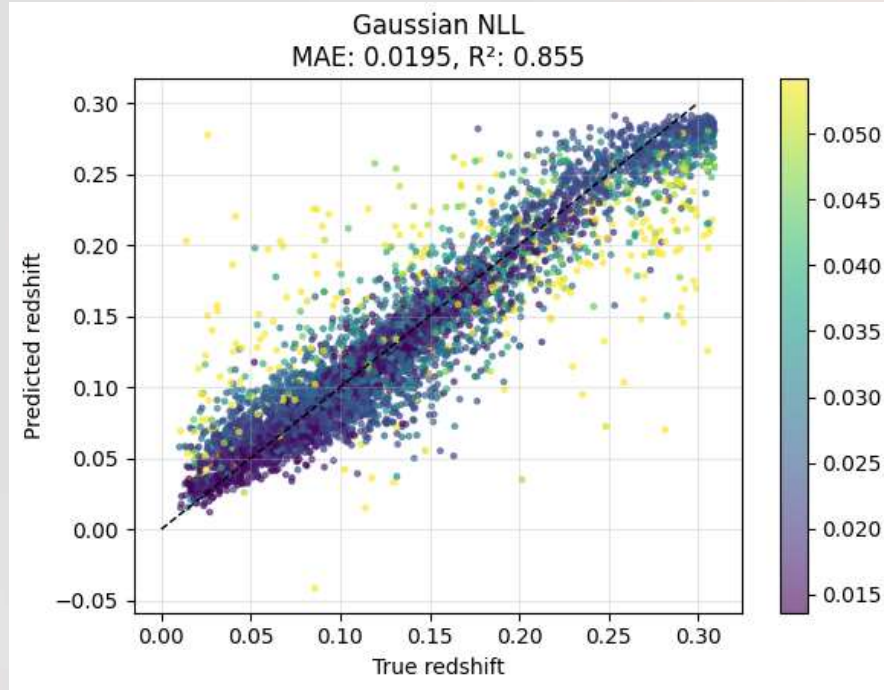
$$p(y_i | x_i, \mathbf{w}) = \frac{1}{\sqrt{2\pi\sigma^2}} \exp \left( -\frac{(y_i - f(x_i; \mathbf{w}))^2}{2\sigma^2} \right)$$



**Loss:** Negative Log-Likelihood (NLL) for  $N$  observations is:

$$\begin{aligned} \mathcal{L}(\mathbf{w}) &= - \sum_{i=1}^N \log p(y_i | x_i; \mathbf{w}) \\ &= \frac{N}{2} \log(2\pi\sigma^2) + \frac{1}{2\sigma^2} \sum_{i=1}^N (y_i - f(x_i; \mathbf{w}))^2 \end{aligned}$$

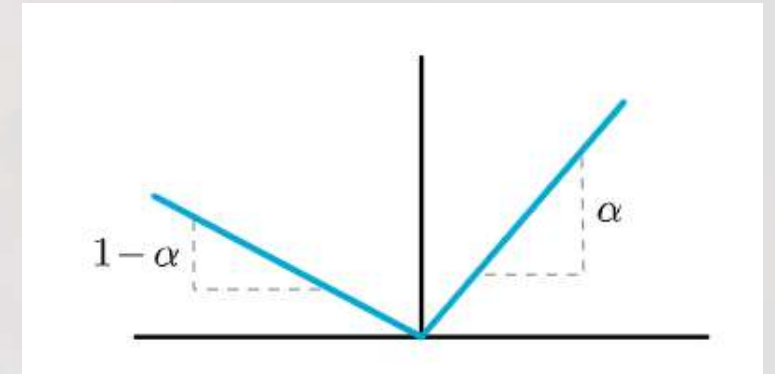
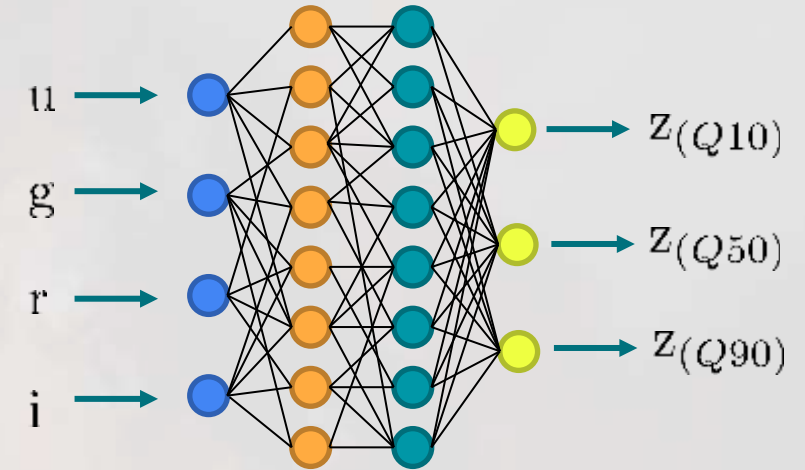
# Gaussian Regression via ANN



# Quantile Regression

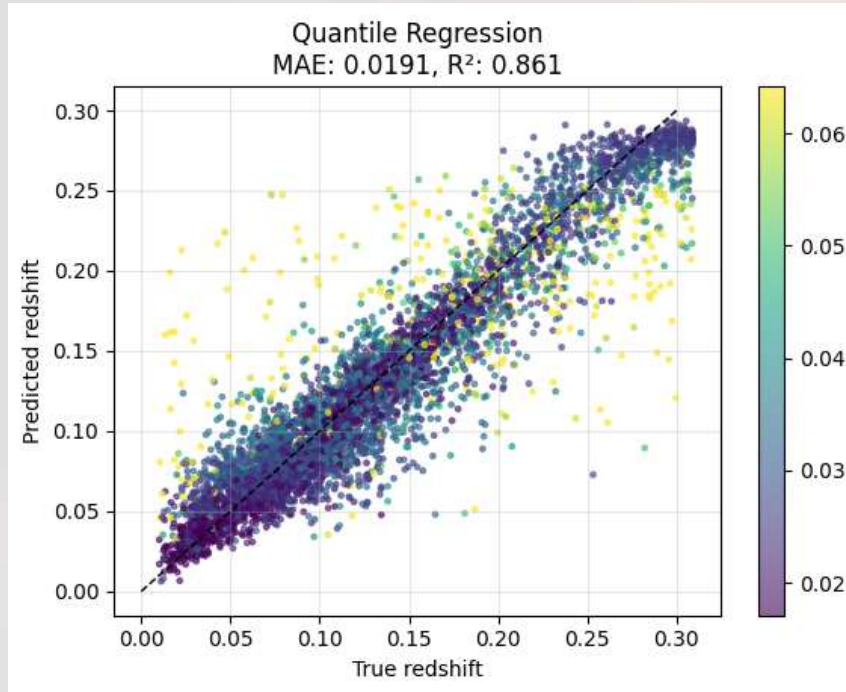
- Assume a set of target quantiles  $\{\alpha_k\}_{k=1}^K$ .
- $\hat{\mathbf{y}}_i = f(x_i; \mathbf{w}) = (\hat{y}_{i,\alpha_1}, \hat{y}_{i,\alpha_2}, \dots, \hat{y}_{i,\alpha_K})$
- *Mean pinball loss* ( $n$  samples,  $K$  quantiles):

$$L_\alpha(y, f(x)) = \begin{cases} \alpha |y - f(x)|, & y \geq f(x), \\ (1 - \alpha) |y - f(x)|, & y < f(x). \end{cases}$$



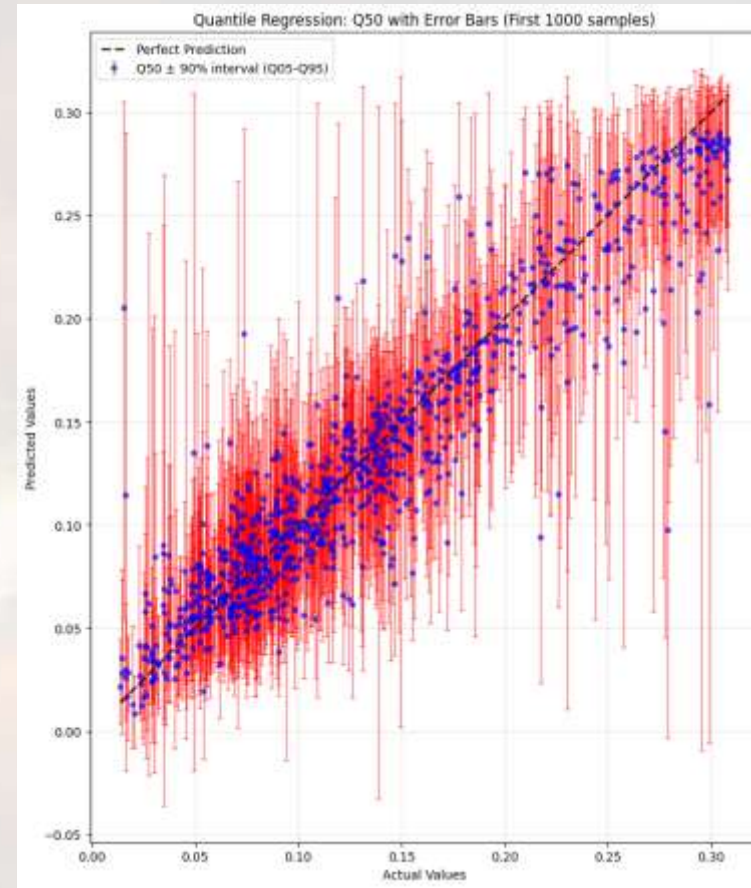


# Quantile Regression



90% Coverage: 0.922

IQR  $[Q_{0.75}(z) - Q_{0.25}(z)]$ : 0.0319



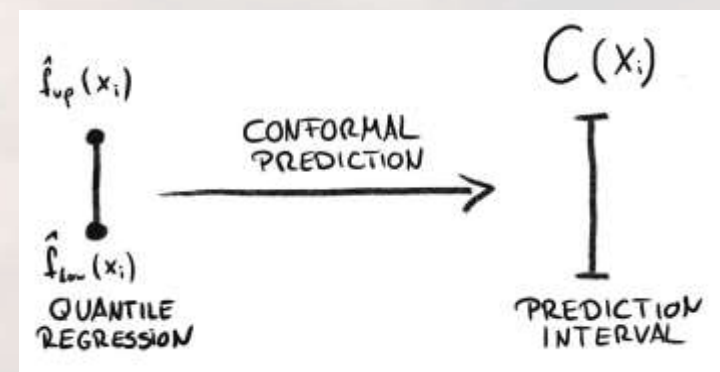
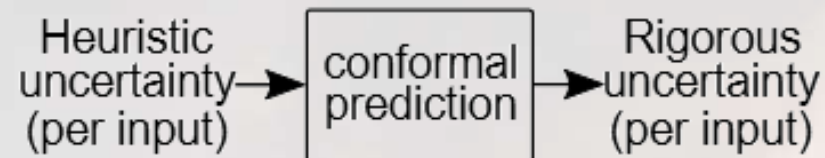
# Conformal Prediction



Regression task: age estimation

Model prediction: 24

MAPIE prediction interval: [20, 29]  
(with 90% confidence)



# Conformal Prediction

1. Split training data to *proper training set* and *calibration*
2. Train lower and upper-quantile regressors  $\hat{Q}^{\alpha/2}, \hat{Q}^{1-\alpha/2}$
3. On the calibration set, compute

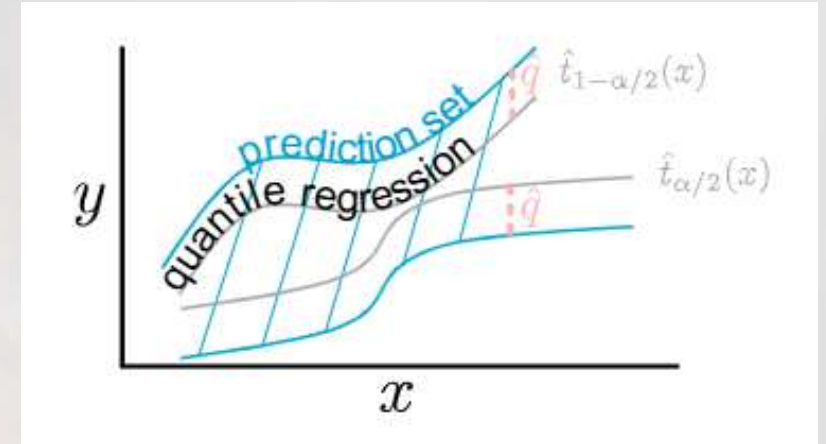
$$s_i^{\text{CQR}} = \max \left\{ y_i^c - \hat{Q}^{1-\alpha/2}(x_i^c), \hat{Q}^{\alpha/2}(x_i^c) - y_i^c \right\}.$$

4. Compute the empirical  $(1 - \alpha)$ -th quantile of the scores:

$$\hat{q}^{\text{CQR}} = \begin{cases} s_{[(1-\alpha)(n^c+1)]}^{\text{CQR}}, & \text{if } \alpha \geq \frac{1}{n^c + 1}, \\ \infty, & \text{otherwise.} \end{cases}$$

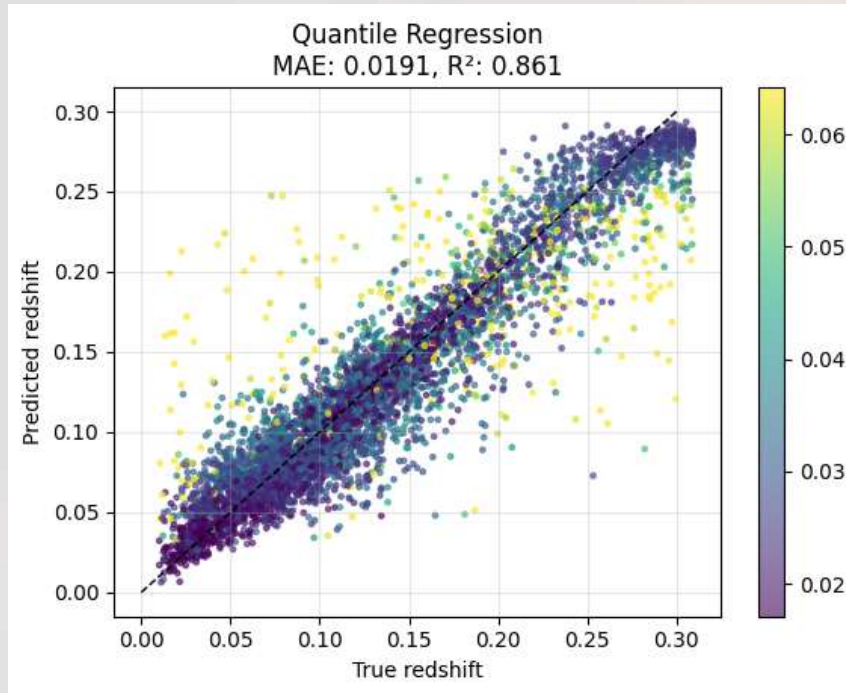
5. Output the coverage interval:

$$\mathcal{C}^{\text{CQR}}(x) = \left[ \hat{Q}^{\alpha/2}(x) - \hat{q}^{\text{CQR}}, \hat{Q}^{1-\alpha/2}(x) + \hat{q}^{\text{CQR}} \right]$$

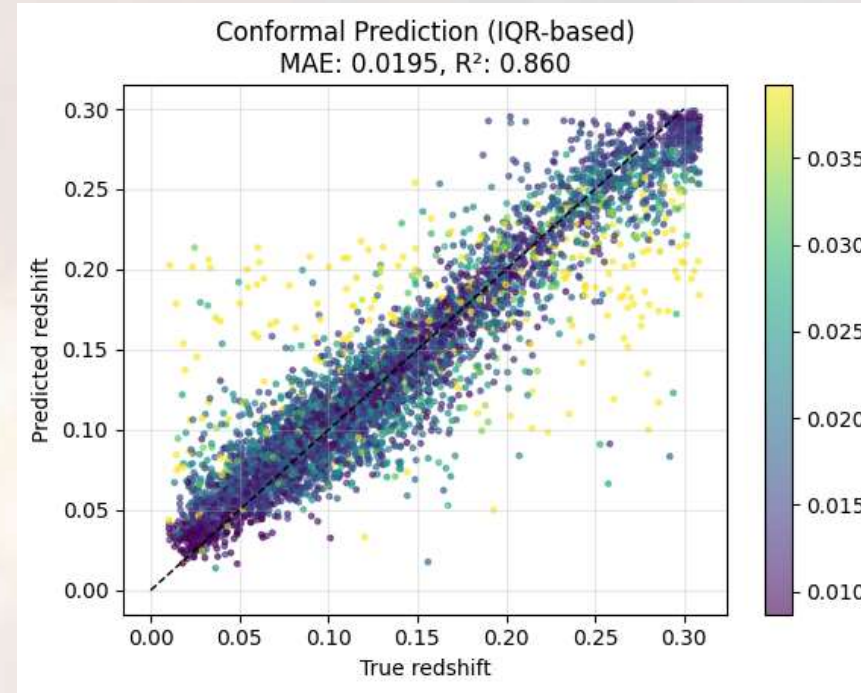


Romano, Y., Patterson, E., & Candes, E.  
Conformalized quantile regression.  
*NeurIPS 2029.*

# Conformal Prediction



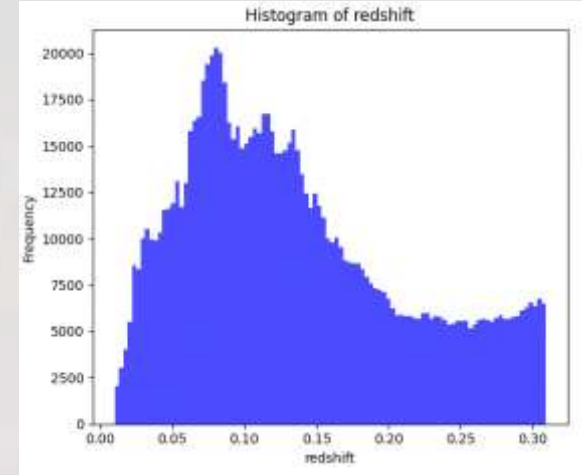
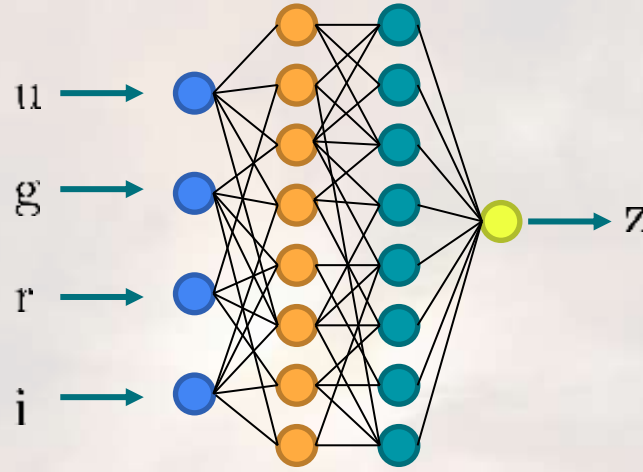
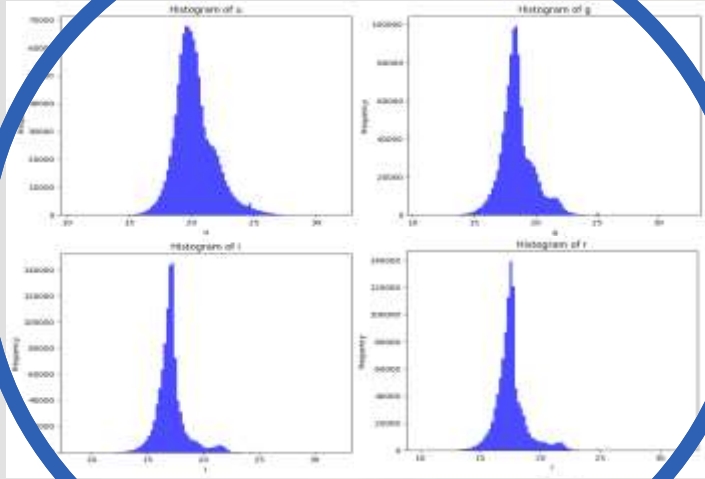
90% Coverage: 0.922  
IQR: 0.0319



90% Coverage: 0.900  
IQR: 0.0184



# Uncertainties (data)

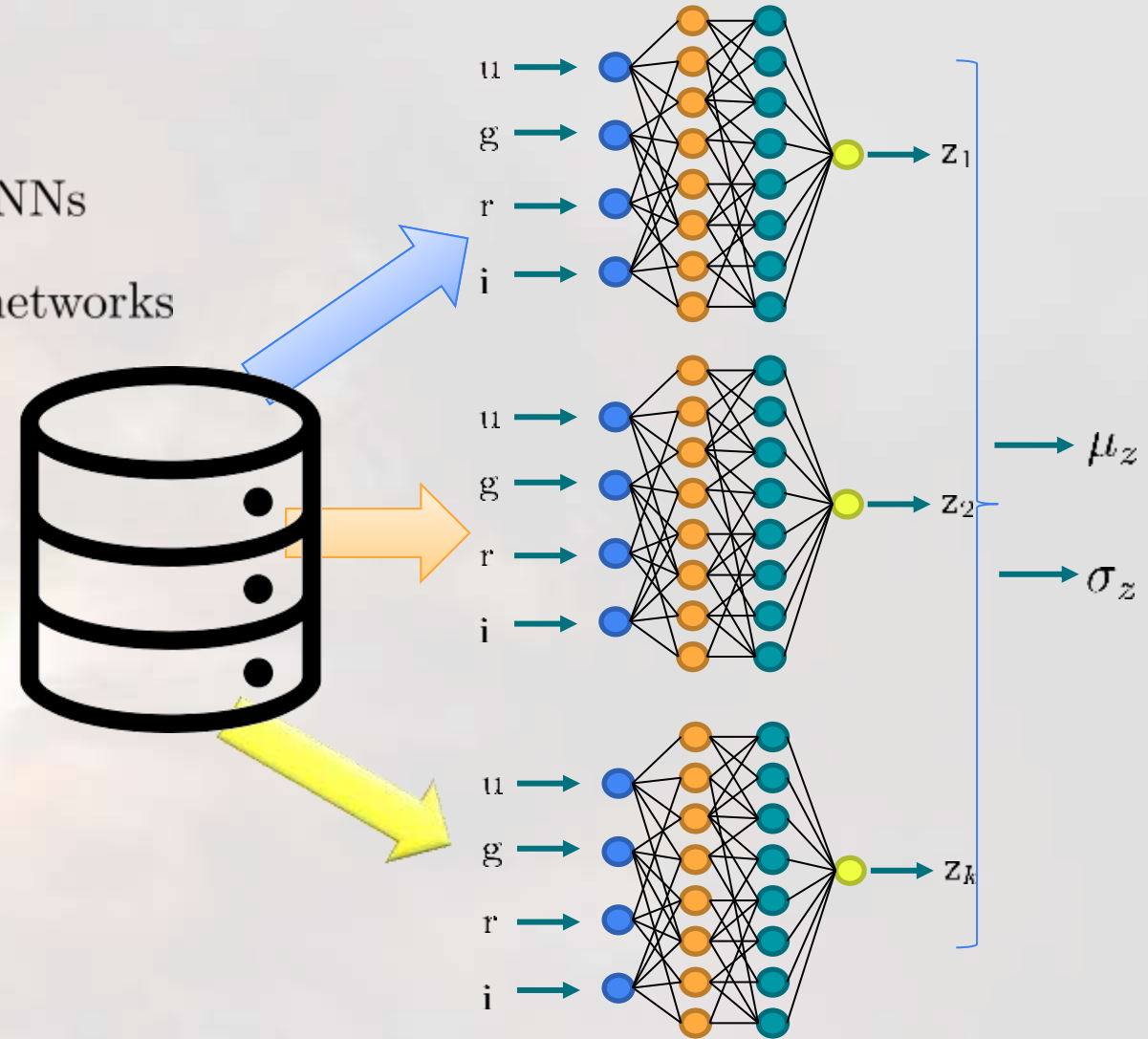


# Ensembles

- Let  $f^{(m)}(\cdot; \mathbf{w}^{(m)})$  be  $M$  independently trained ANNs
- During inference, forward-propagate through all networks

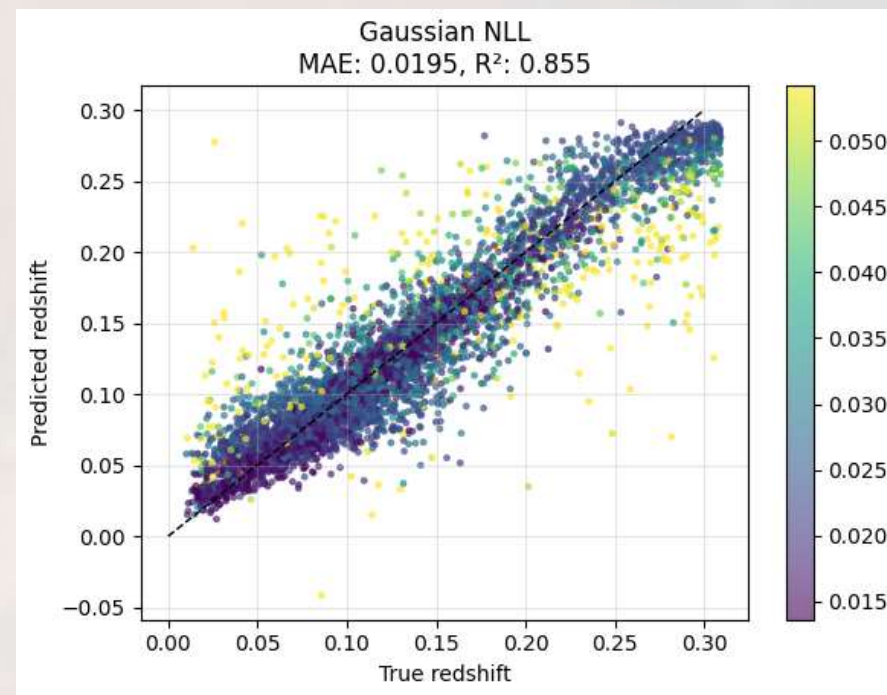
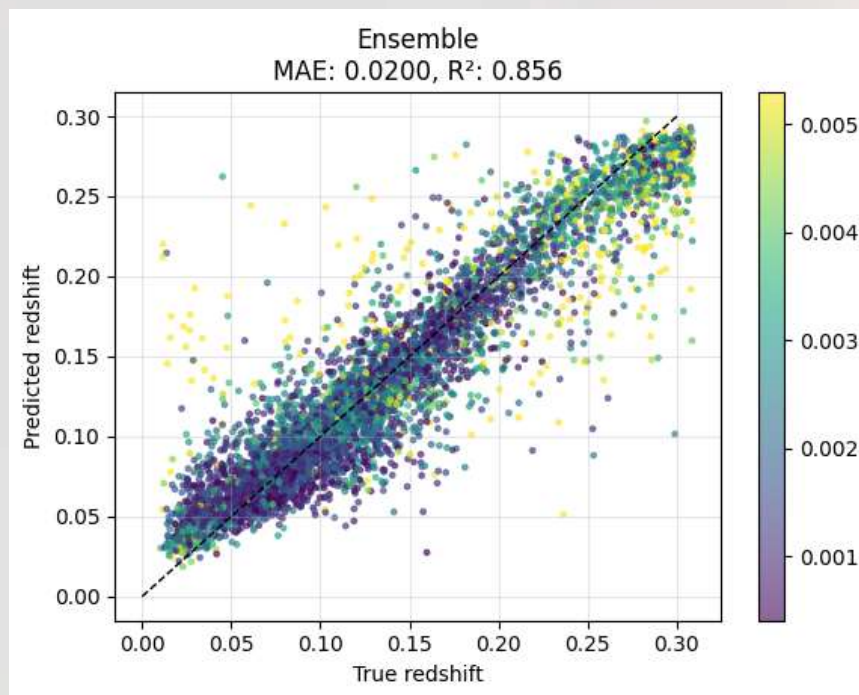
$$\mathbb{E}[y | x] \approx \bar{y}(x) = \frac{1}{M} \sum_{m=1}^M \hat{y}^{(m)}$$

$$\text{Var}[y | x] \approx \frac{1}{M} \sum_{m=1}^M (\hat{y}^{(m)})^2 - \bar{y}(x)^2$$



# Ensemble approach

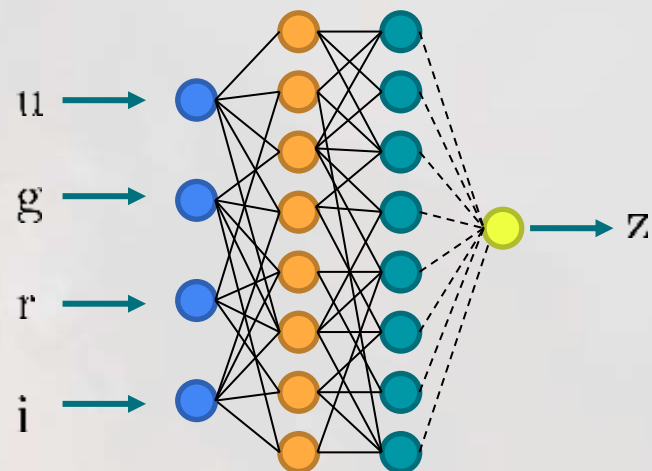
5 Models



# MCDropout

Apply *dropout* to forward pass

$$\hat{y}_i = f(x_i; \mathbf{w} \odot \mathbf{z}_i), \quad \mathbf{z}_i \sim \text{Bernoulli}(p),$$



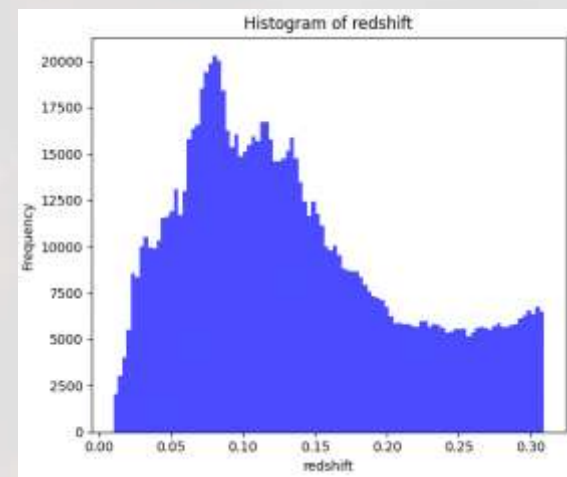
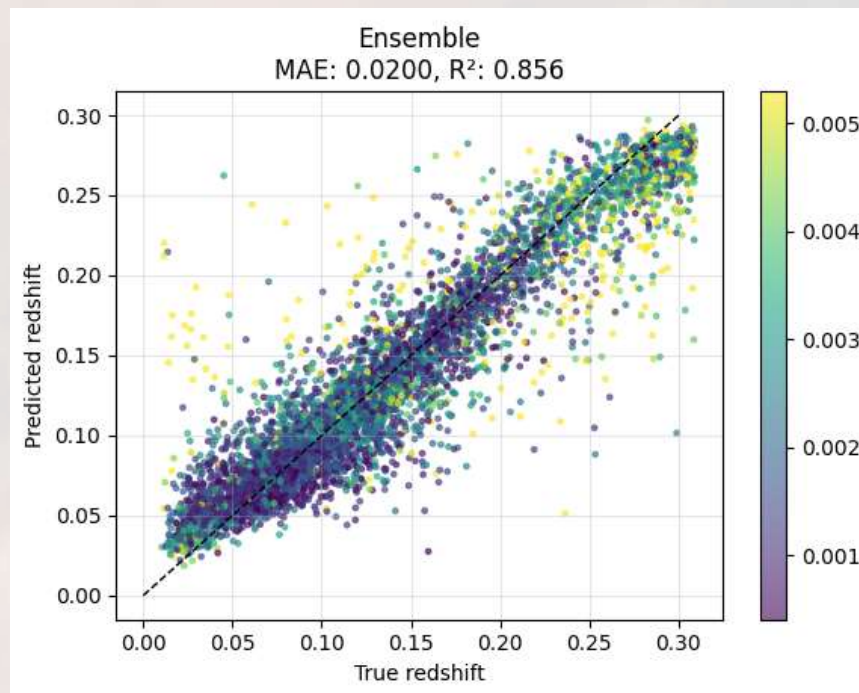
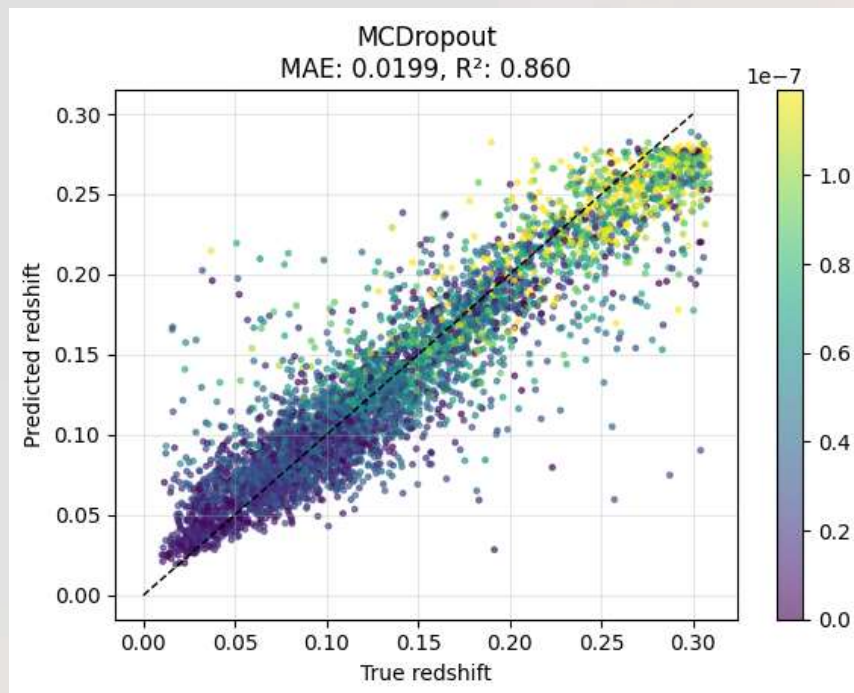
## Predictive mean and variance

At test time keep dropout *on* and run  $S$  stochastic forward passes  $\hat{y}^{(s)} = f(x; \mathbf{w} \odot \mathbf{z}^{(s)})$ ,  $s = 1, \dots, S$ . The predictive posterior moments are approximated by

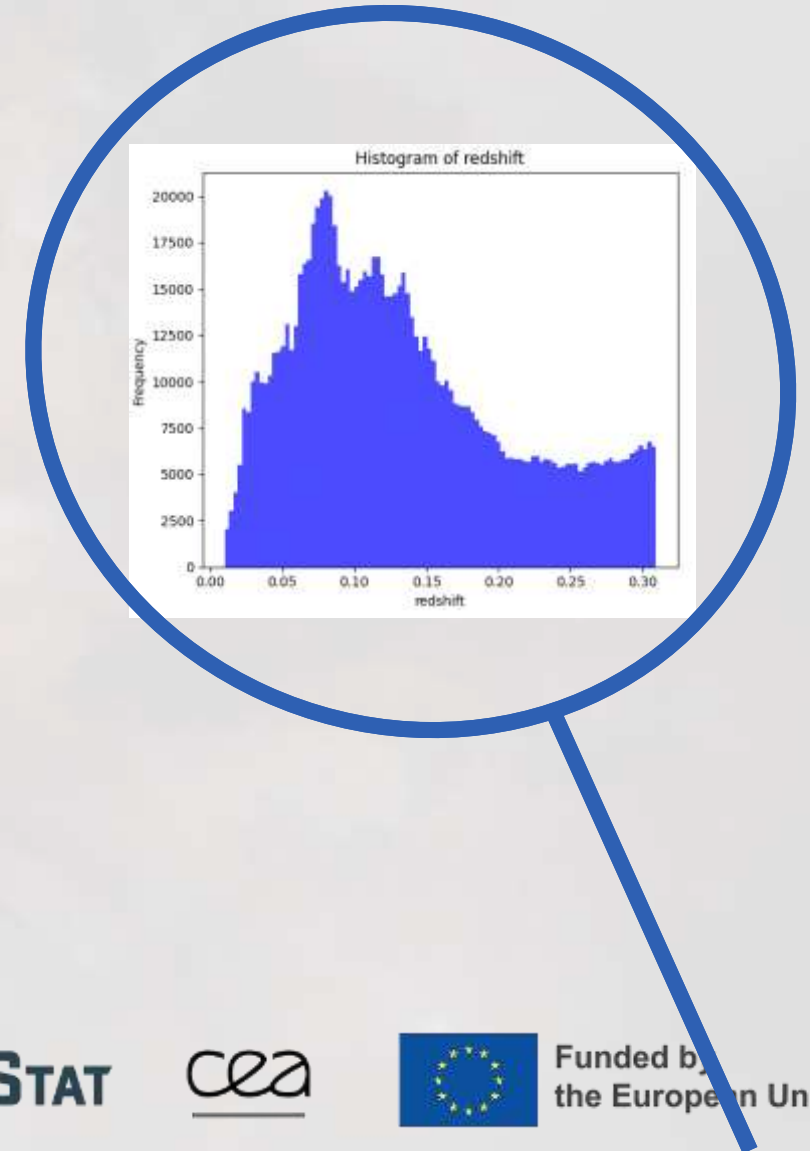
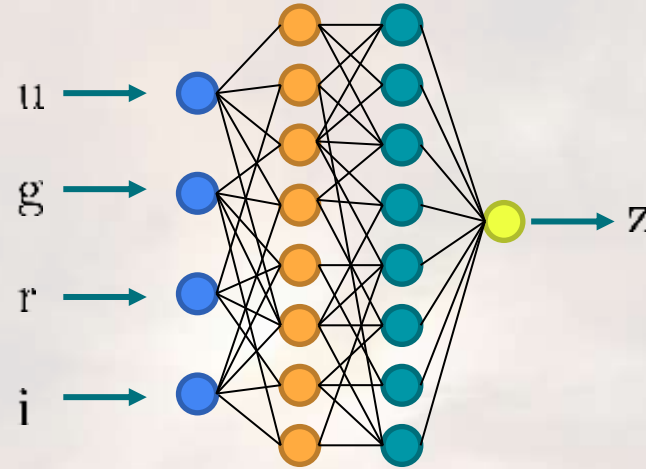
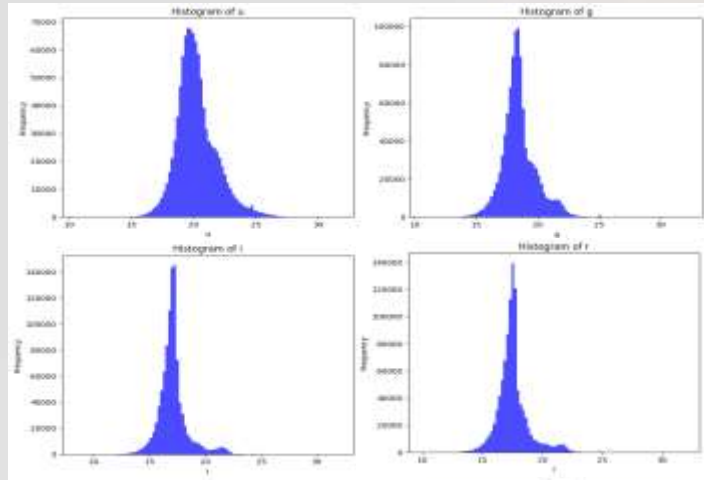
$$\mathbb{E}[y | x] \approx \bar{y} = \frac{1}{S} \sum_{s=1}^S \hat{y}^{(s)}, \quad \text{Var}[y | x] \approx \frac{1}{S} \sum_{s=1}^S (\hat{y}^{(s)})^2 - \bar{y}^2 + \tau^{-1}.$$



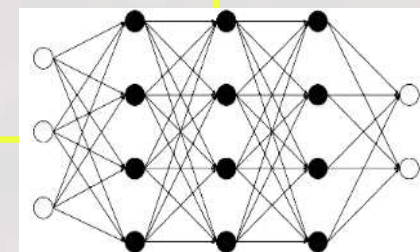
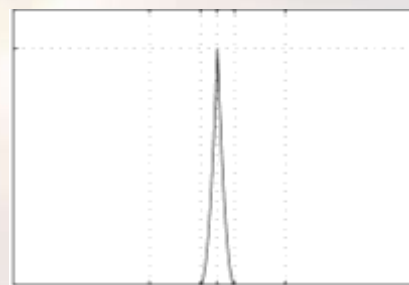
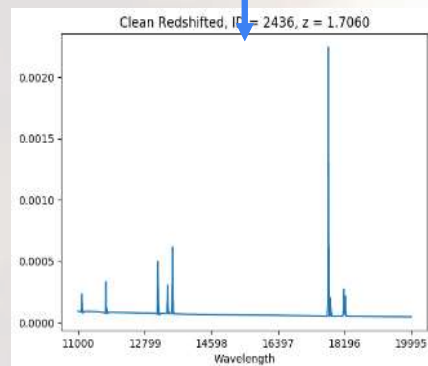
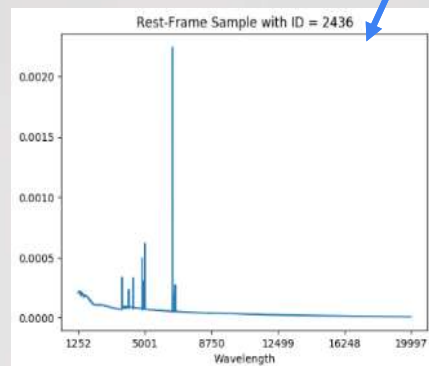
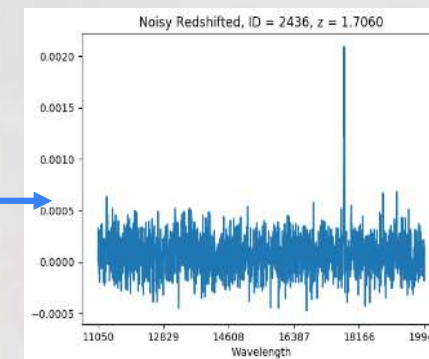
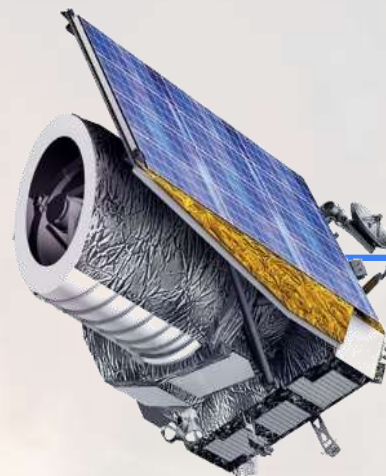
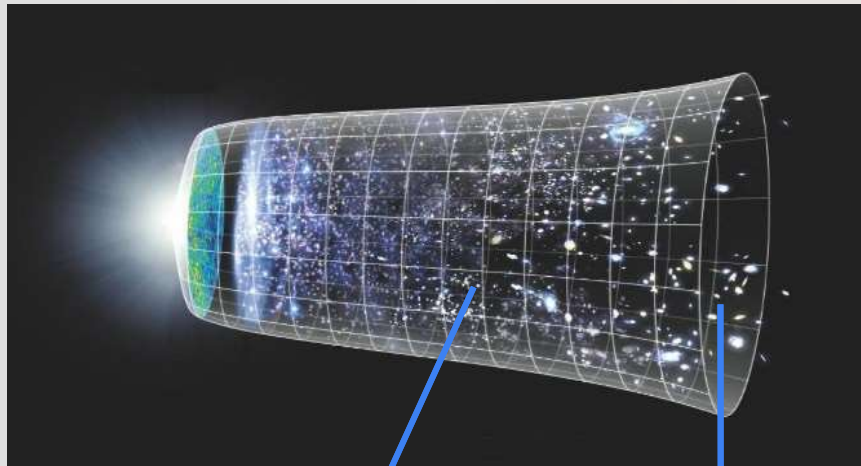
# MCDropout



# Uncertainties (labels)



# Spectroscopic Red-Shift Estimation



# Predictive model

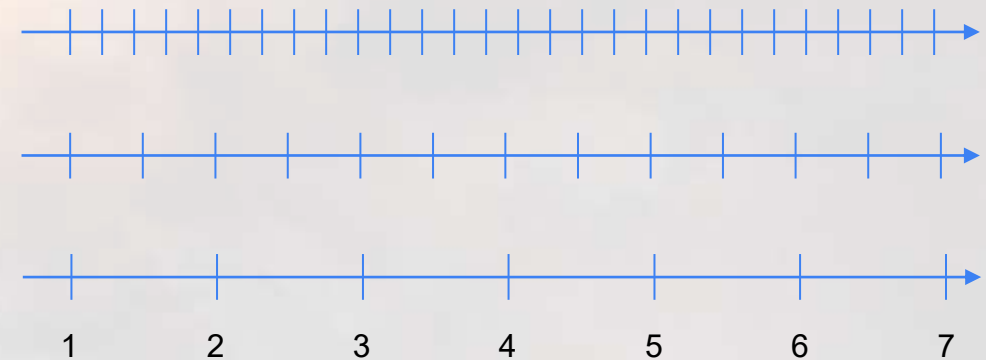
## Redshift Estimation

Real-valued, non-negative number ( $z$ )

Regression Analysis

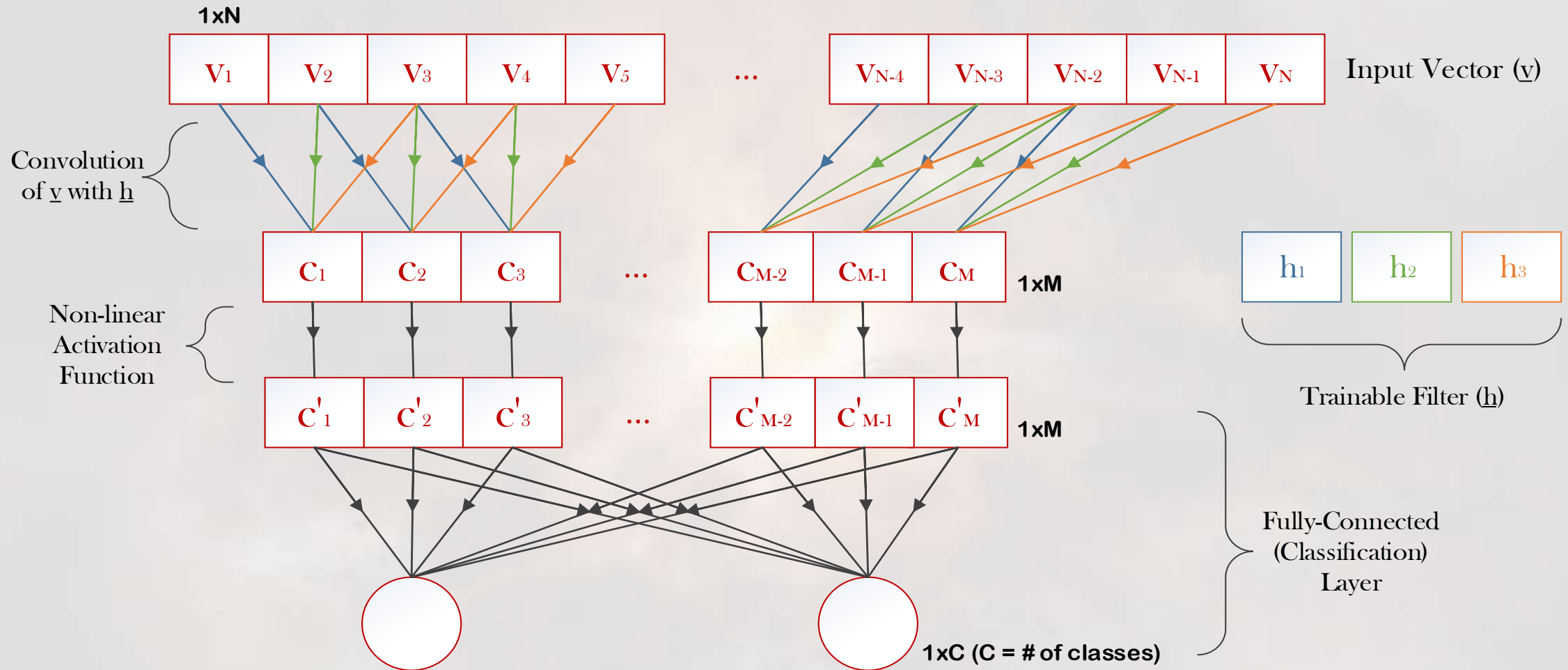
Split the examined redshift interval into ordinal classes, based on Euclid's characteristic resolution

Classification Problem



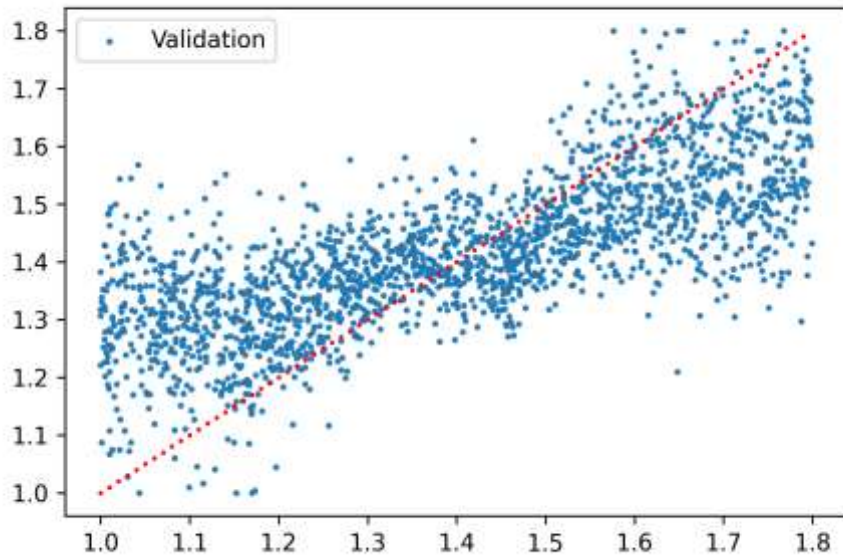


# 1-Dimensional CNN - Classification

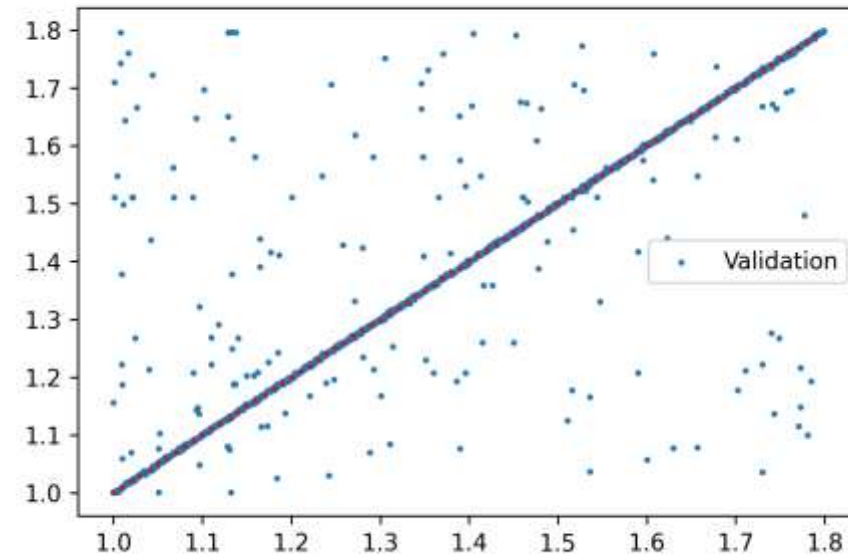


# Regression

# Classification (800 classes)

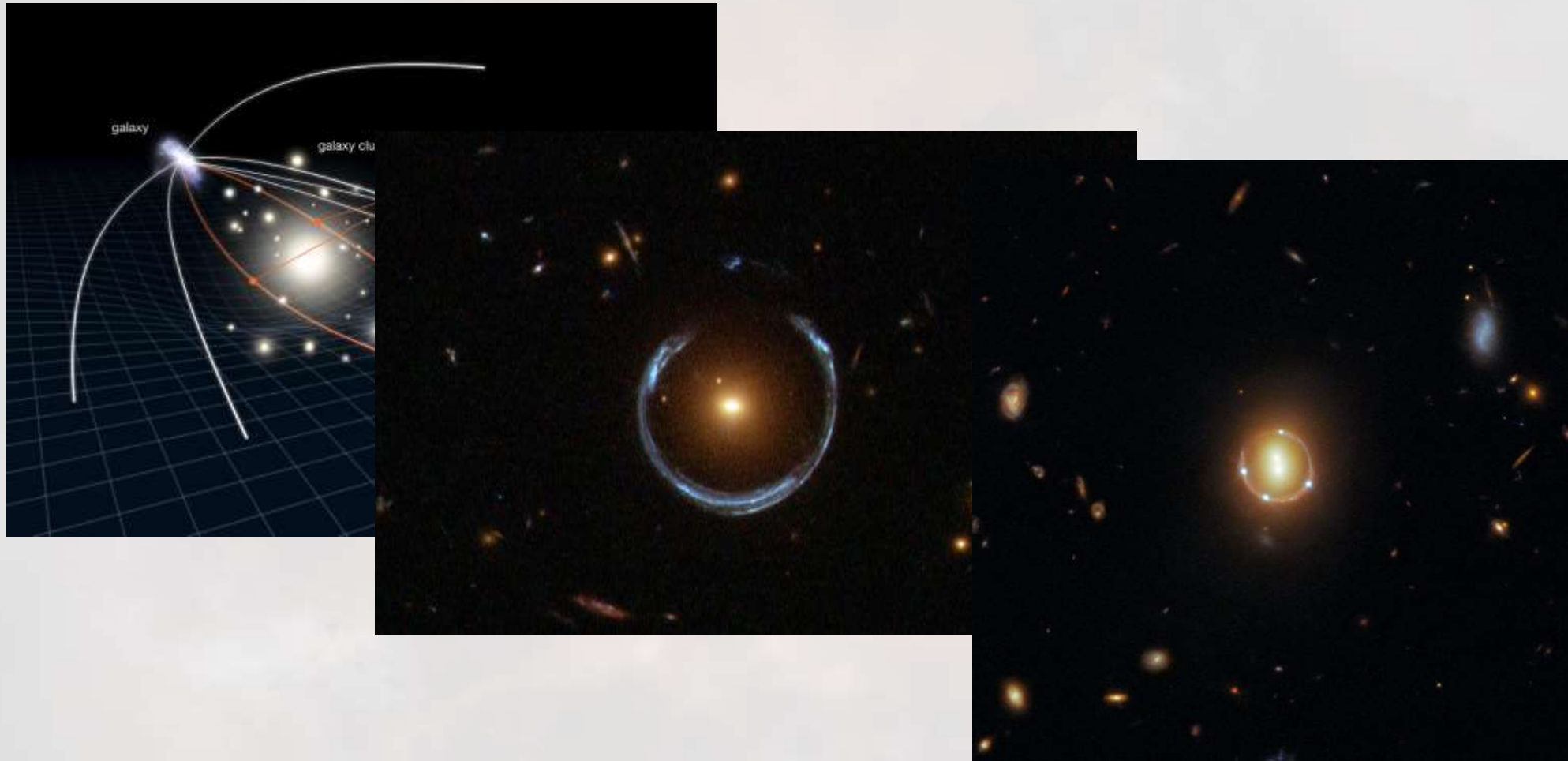


MSE 0.03811  
MAE 0.16469  
 $R^2$  0.28188

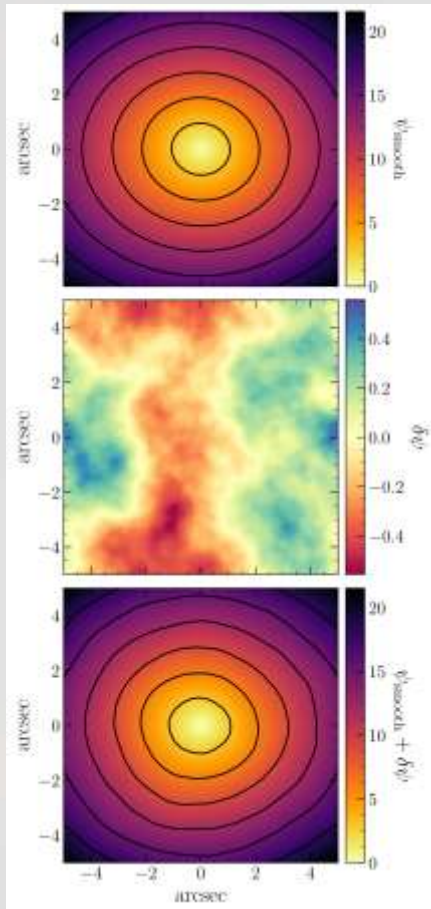


MSE 0.00791  
MAE 0.02325  
 $R^2$  0.85082

# Gravitational Lensing



# Modeling with uncertain labels



Singular Isothermal Ellipsoid parametric model

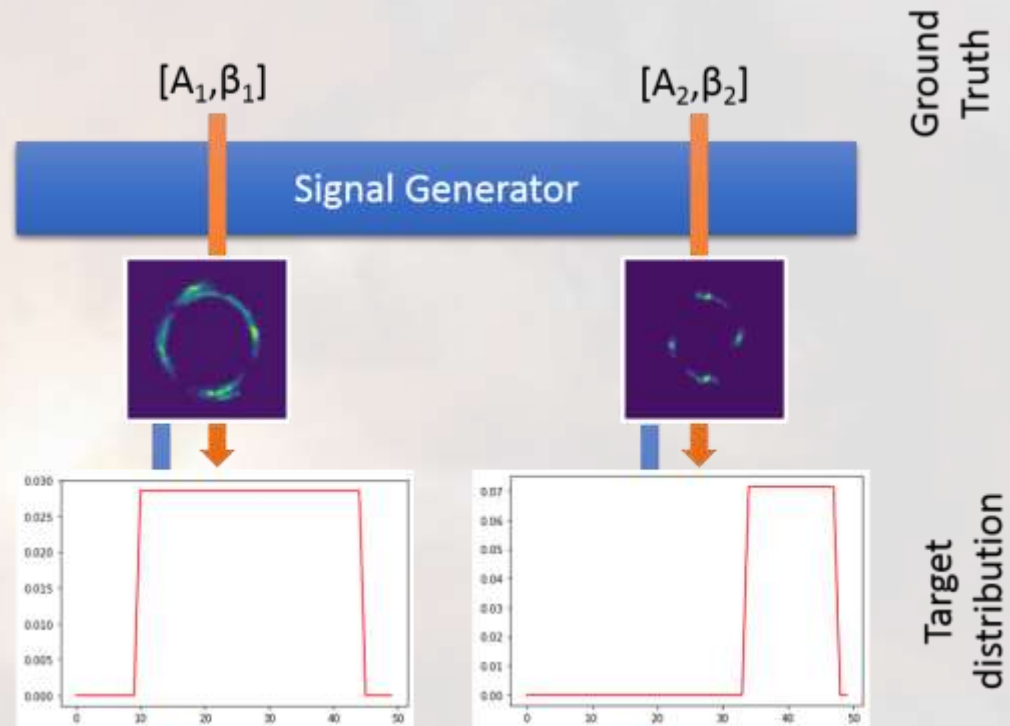
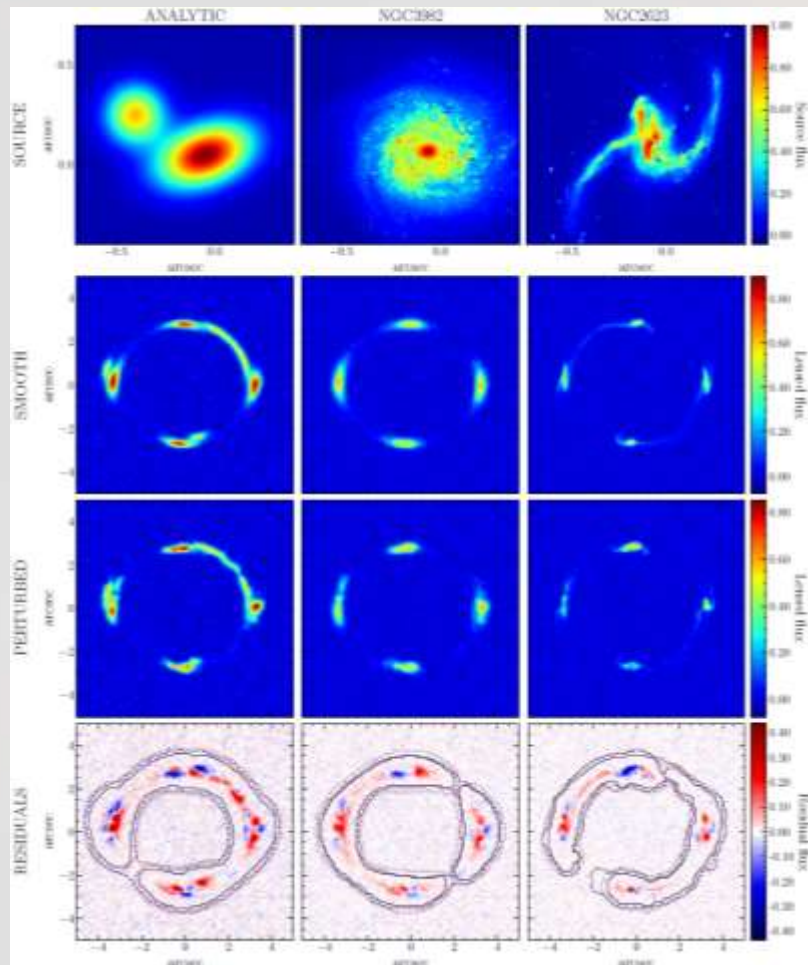
Realization of Gaussian Random Field perturbations

Perturbed lens potential

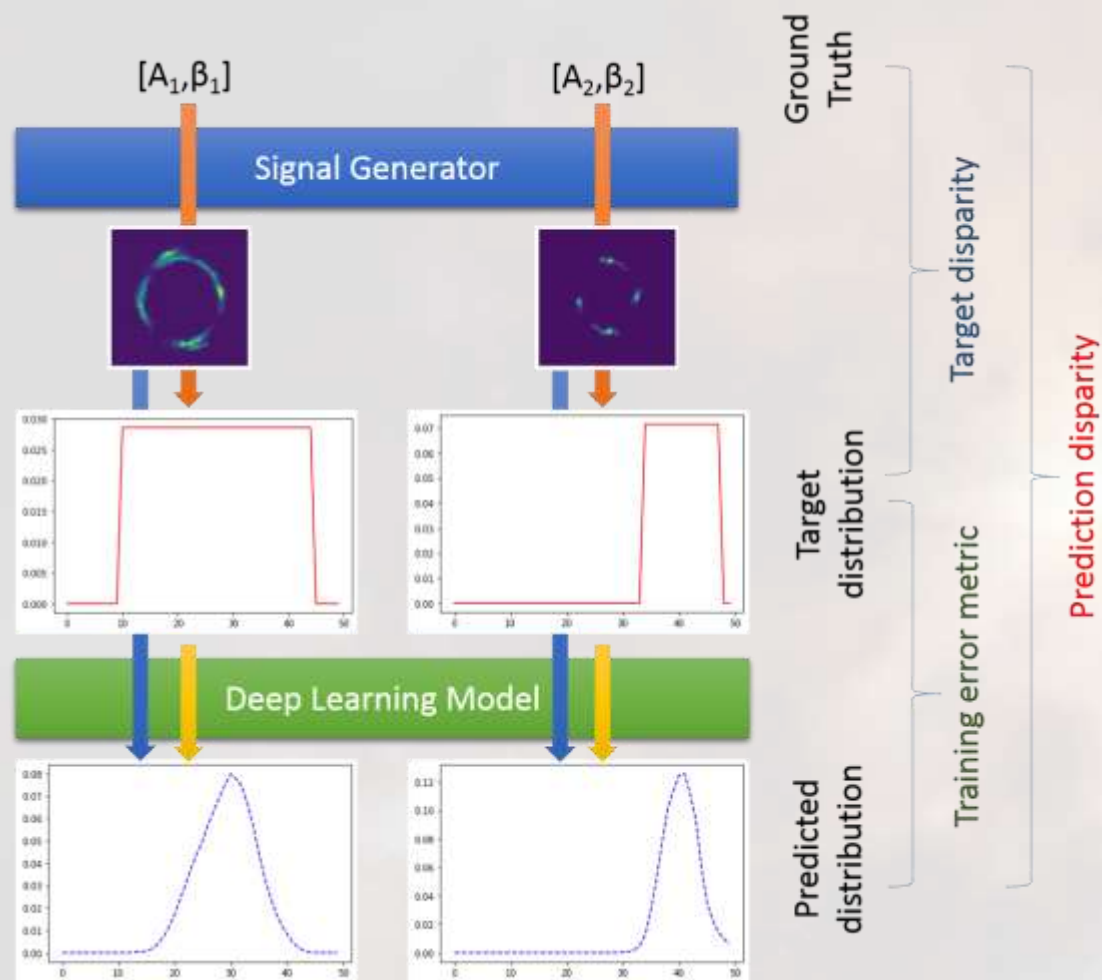
G. Vernardos, G. Tsagkatakis, and Y. Pantazis. "Quantifying the structure of strong gravitational lens potentials with uncertainty-aware deep neural networks." MNRAS. 2020.



# Label uncertainty



# Modeling with uncertain labels



# Modeling with uncertain labels

Given the predicted distribution  $P$  and the target distribution  $Q$ , the Jensen-Shannon divergence is defined by:

$$JS(Q, P) = \frac{1}{2}KL(P\|M) + \frac{1}{2}KL(Q\|M), M = \frac{1}{2}(P + Q)$$

Formally, the entropy of the predicted distribution  $H(P)$  is given by:

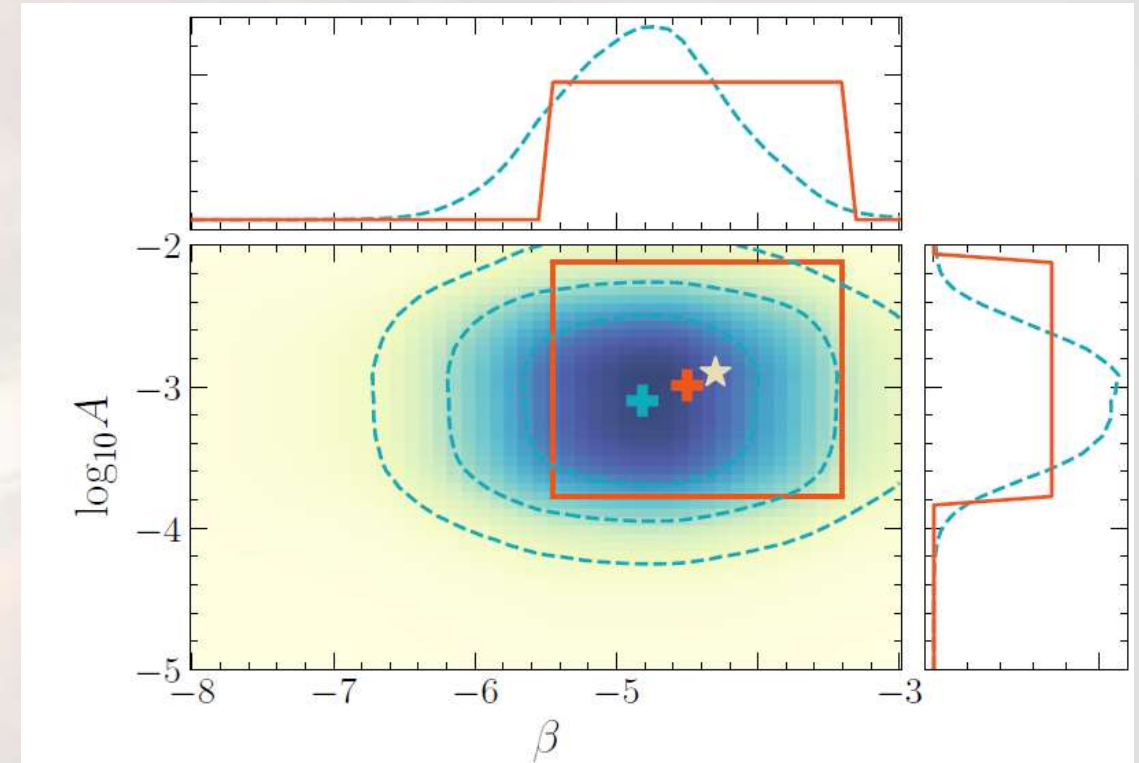
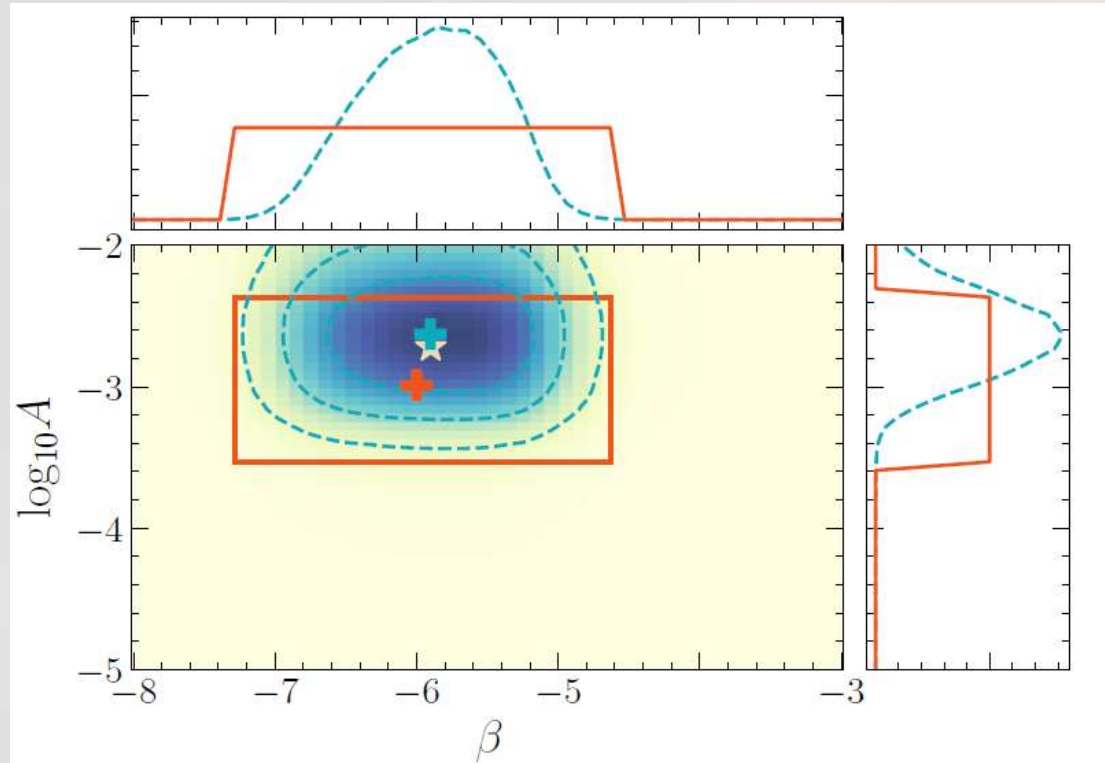
$$H(P) = - \sum_{x \in \mathcal{X}} P(x) \log(P(x)).$$

Entropy-regularized version of the JS divergence and is given by:

$$\mathcal{L}(P, Q) = \lambda_1 JS(P, Q) + \lambda_2 H(P),$$

where  $\lambda_1$  and  $\lambda_2$  control the impact of the two terms.

# “Label-super-resolution”





# Take-home messages

- Many flavors of uncertainty (decoupling, Bayesian, ordinal regression)
- “Limited” investigation in scientific data analysis
- The case of time-domain astronomy
- The case of spatially resolved observations
- The promise of multi-modality

A visualization of the cosmic web, showing a dense network of filaments and clusters of galaxies. The filaments are colored in vibrant green, red, and purple, set against a dark blue background filled with numerous small, bright yellow and white stars or distant galaxies.

# Thank you



**MINOAS** – Machine Intelligence for iNverse imaging,  
Observation Analysis and Sensing Workshop

**Dates:** 24-26 September 2025

**Location:** FORTH, Crete