

Estimating photometric redshifts using Deep Learning

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A dark blue diagonal gradient bar that starts from the bottom left and extends towards the top right, covering the lower half of the slide.

Why photo-z ?

Spectroscopic Redshifts	Photometric Redshifts
More accurate	Comparatively less accurate
More expensive	Way less expensive
Far more telescopic time	Way less telescopic time

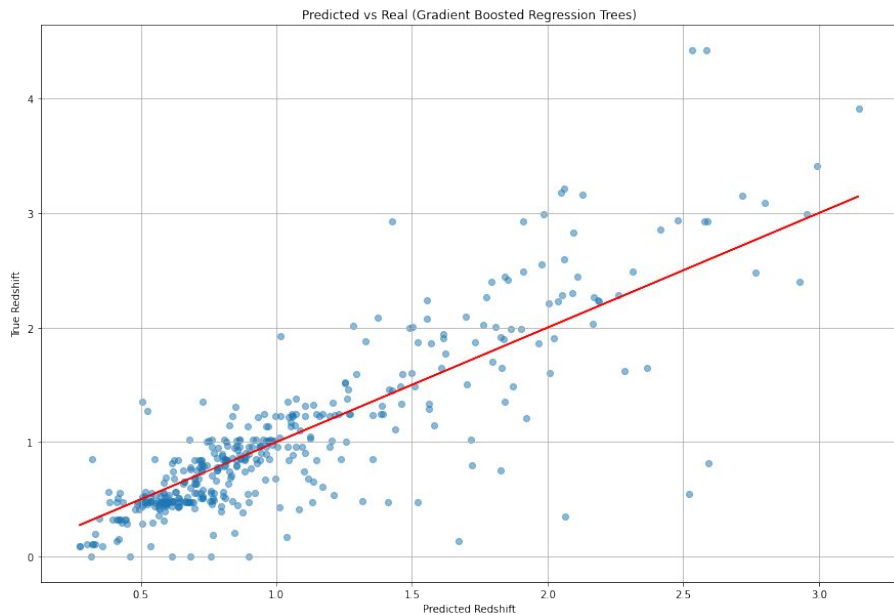
Photo-z measurement techniques

1. Direct Shift Measurement: [Baum\(1962\)](#)
2. Color-color diagrams: [Koo \(1985\)](#)
3. Template Fitting: [Loh & Spiller \(1986\)](#)
4. Machine Learning (using regression)

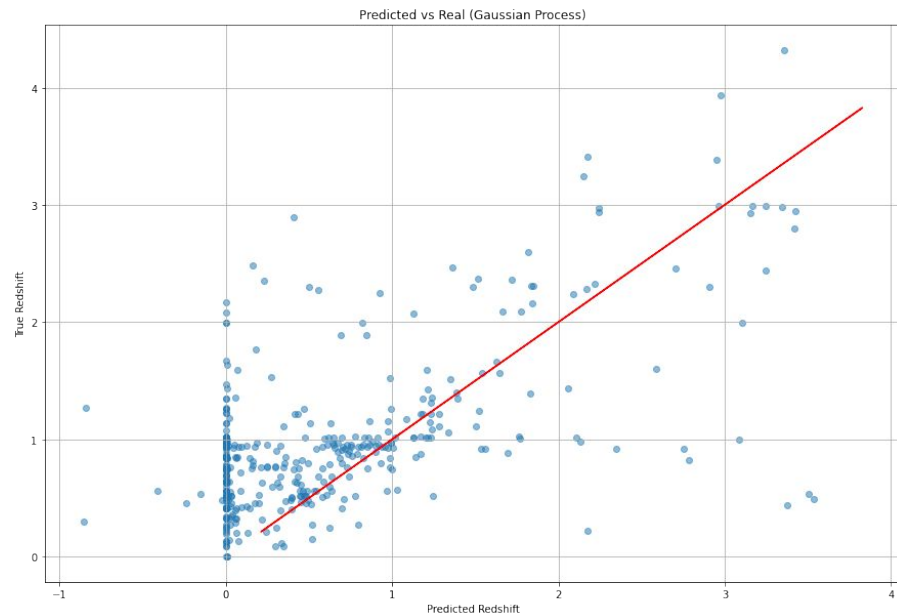
Machine Learning

- **Dataset:** Hubble Deep Survey (GOODS- North) from Barro(2019)
- **Input:** Multiband fluxes from 500 nm to 941 nm
- **Output:** Photometric redshifts
- **Comparison Metric:** Mean-squared error

Classical ML Algorithms

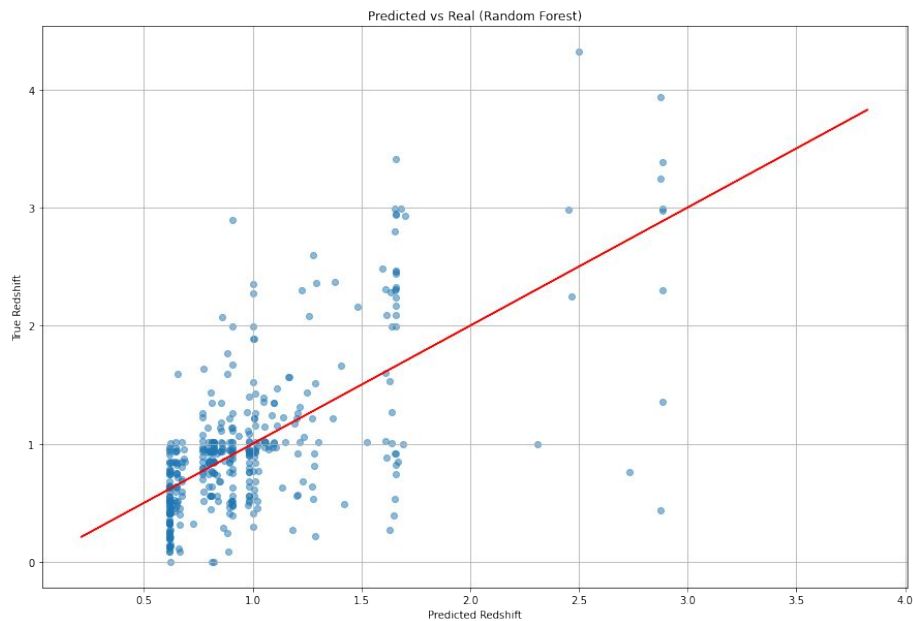


Gradient Boosted Regression Trees
(MSE = 0.154)

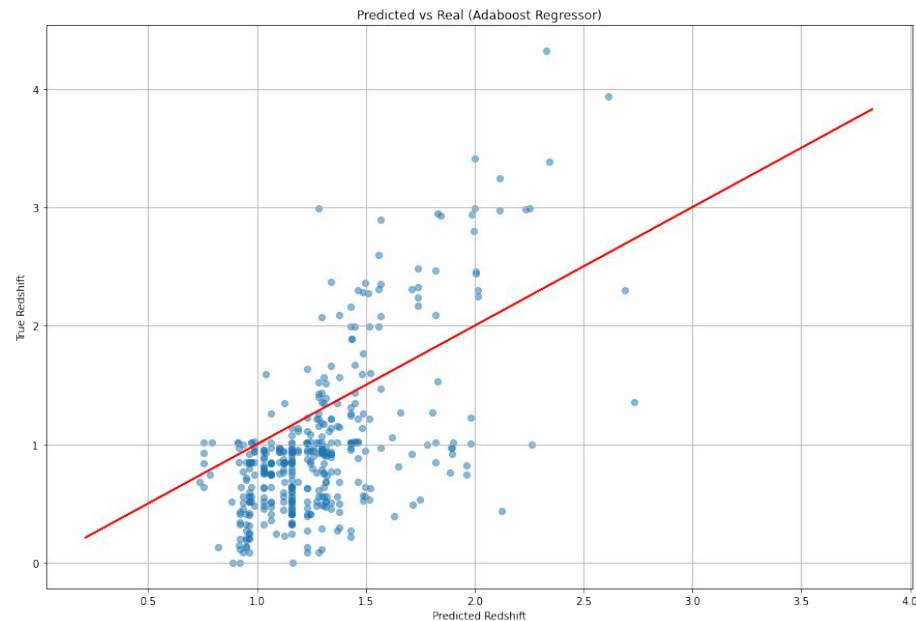


Gaussian Processes
(MSE = 0.584)

Classic ML Algorithms

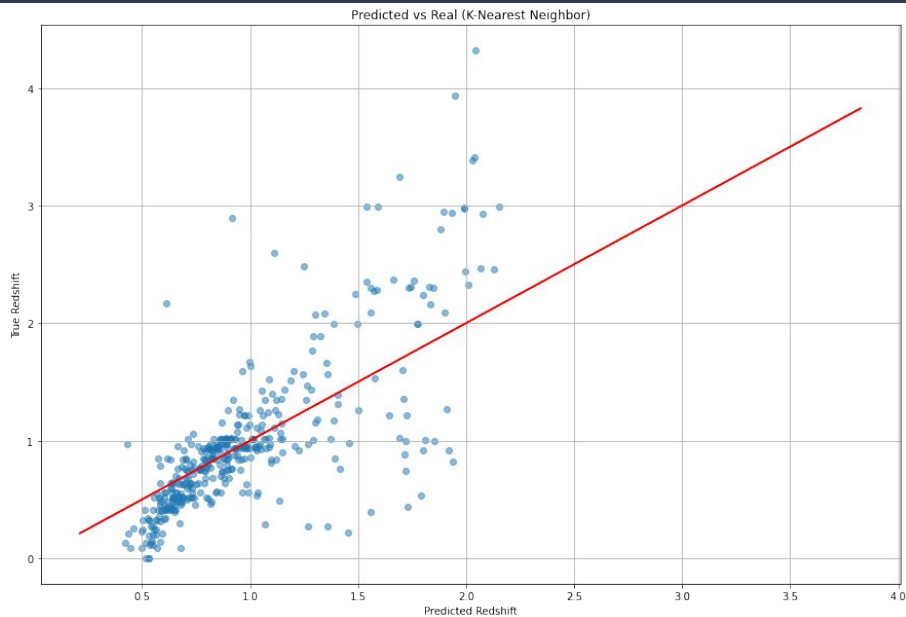


Random Forests
(MSE = 0.242)

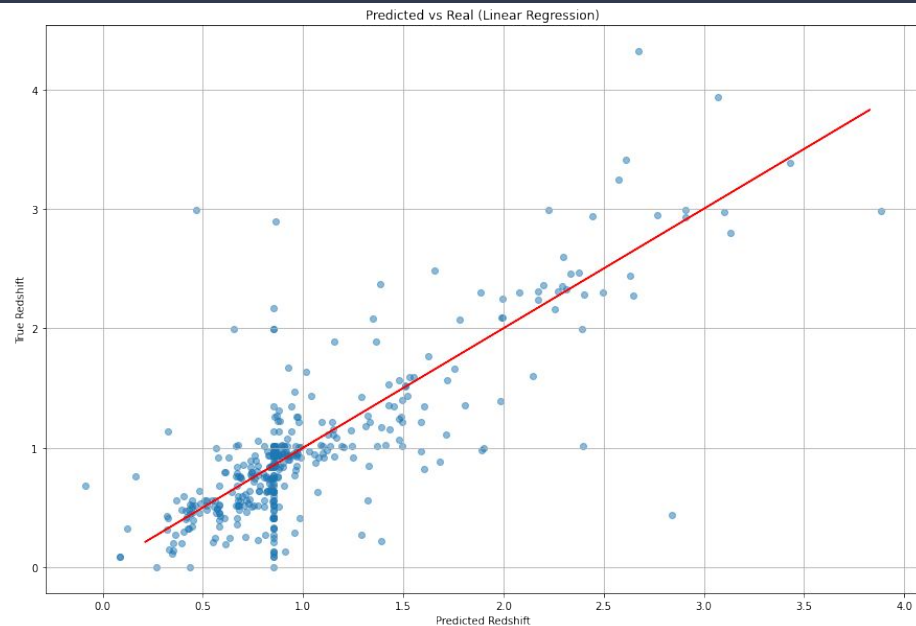


Adaboost Regressor
(MSE = 0.359)

Classic ML Algorithms

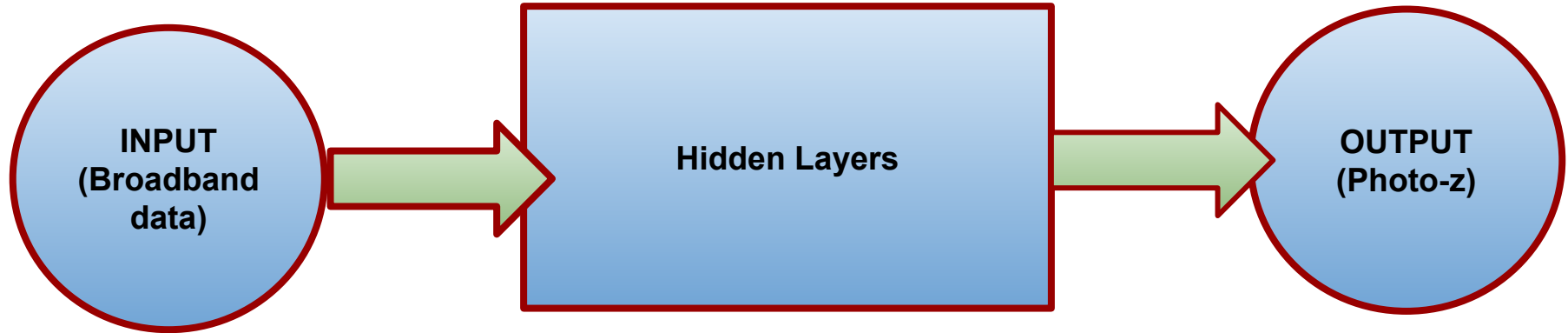


K-Nearest Neighbor
(MSE = 0.189)

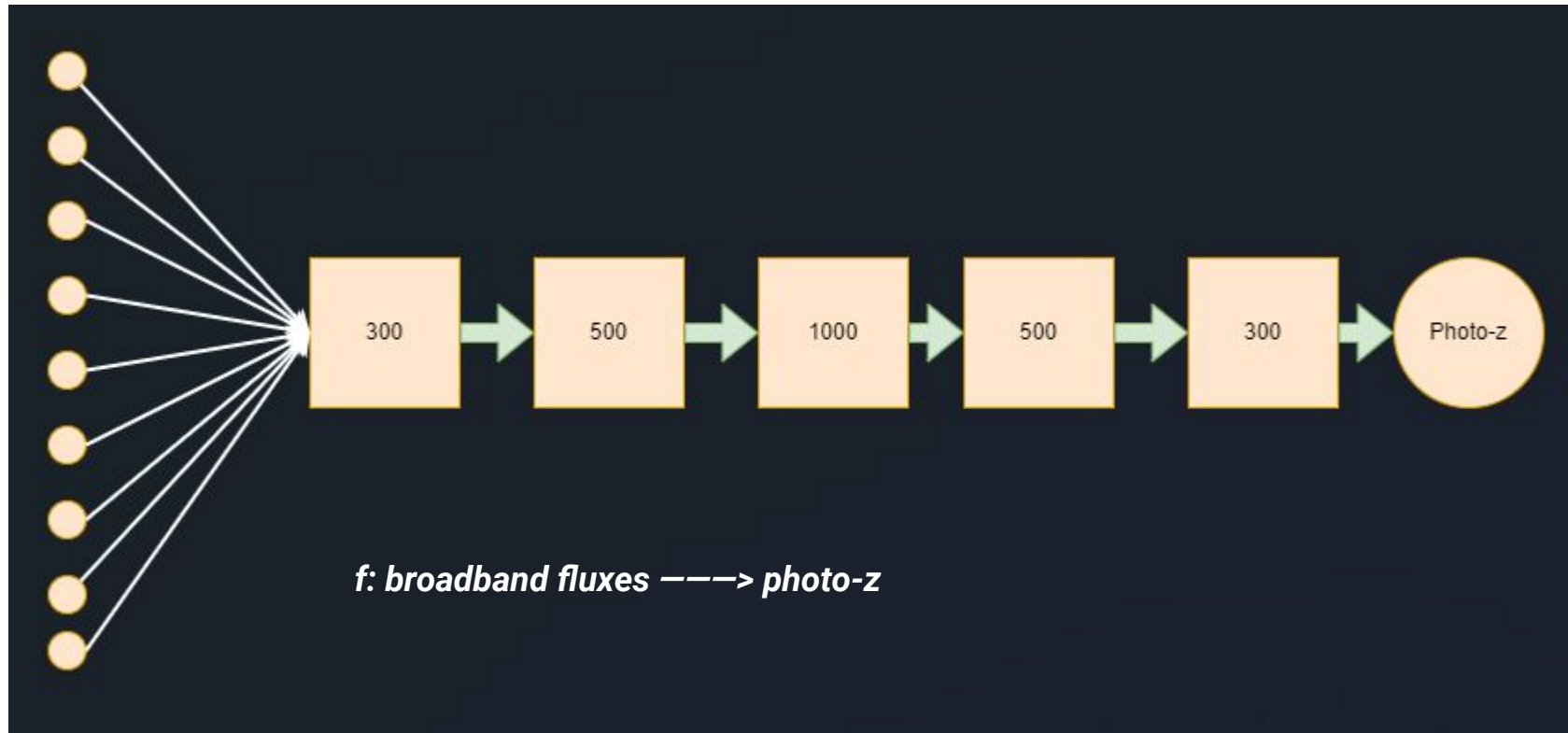


Support Vector Machines
(MSE = 0.156)

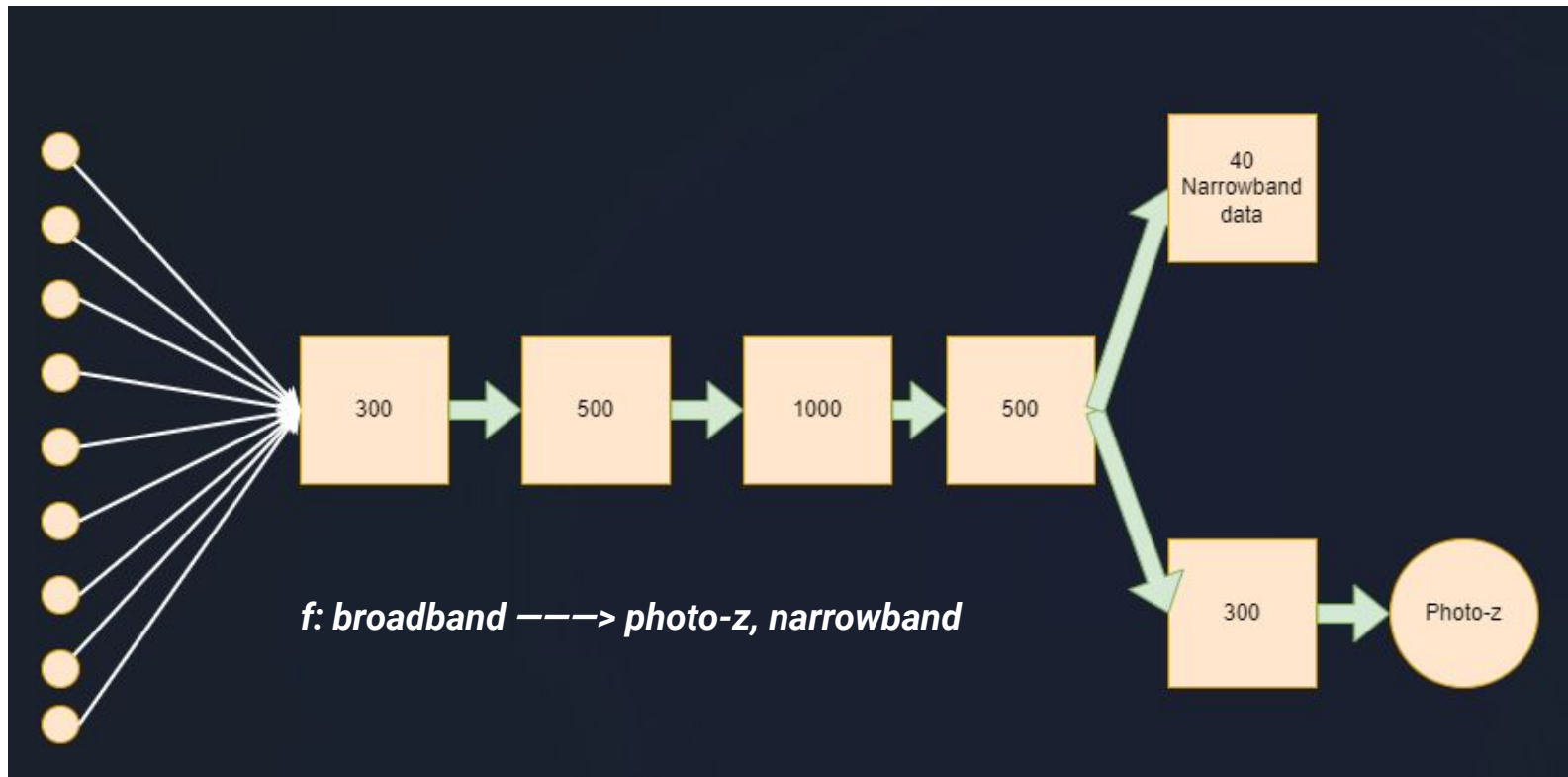
Neural Networks



Baseline network



Multitask Network



Network features

- **Dataset:** PAU Survey Catalogue
- **Broadband data:** 9 bands from u,b,v,g,r,z,i,j,k bands (fluxes in Janskys)
- **Narrowband data:** 40 bands from 455 nm to 845 nm
- **Redshift output**

Comparison Metrics

- **Dispersion:** $\sigma_{68} := \frac{1}{2} [Q_{84}(\Delta z) - Q_{16}(\Delta z)]$

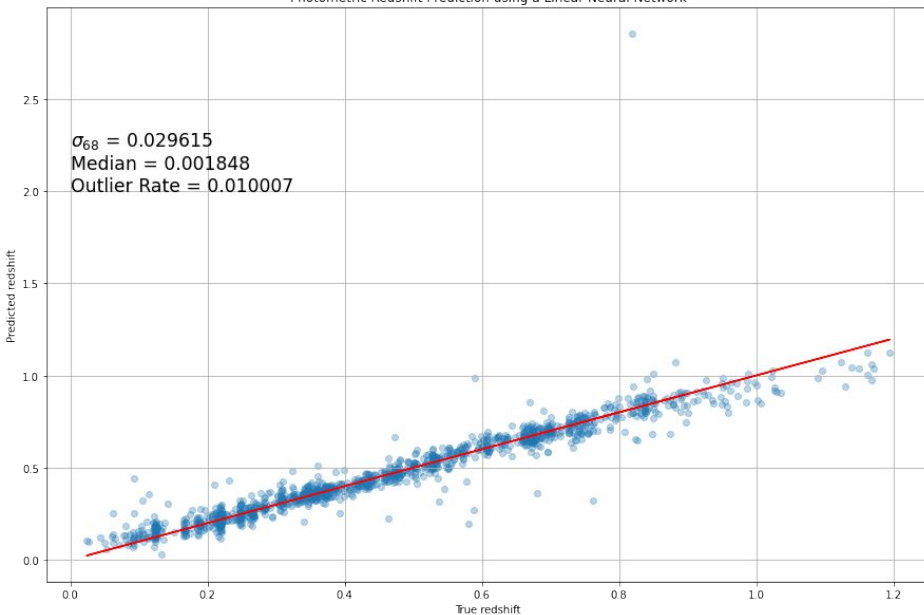
where,

$$\Delta z := (z_p - z_t) / (1 + z_t)$$

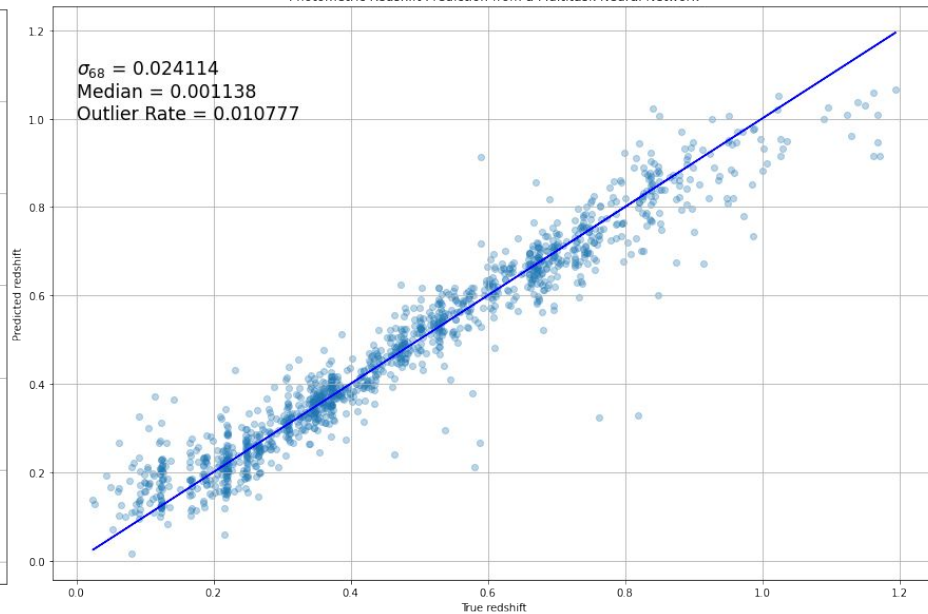
- **Outlier:** $|z_p - z_t| / (1 + z_t) > 0.15$

Results

Photometric Redshift Prediction using a Linear Neural Network



Photometric Redshift Prediction from a Multitask Neural Network



CONCLUSION

