



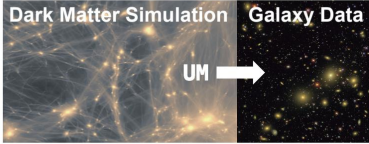
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SUMMARY

- The UNIVERSEMACHINE (UM) is a cosmological model that links *dark matter halos* to *galaxies* [1].
- UM is massively parallel and takes over 2M CPU hours to optimize; deep learning captures the model accurately and efficiently.

DATASET

- Halo data: 10^6 halos from Bolshoi-Planck cosmological dark matter simulation [2]; 4 features per halo (3D position + V_{peak}).
- Galaxy data: UM-predicted galaxy number density in 32 mass bins.



METHOD

- Segment simulation into 3D boxes; bin halos by position; feed binned halo properties into convolutional ResNet; predict SMF.

$$\mathcal{L} = -\langle (\log \phi_*^{\text{obs}} - \log \phi_*^{\text{pred}}) \Sigma^{-1} (\log \phi_*^{\text{obs}} - \log \phi_*^{\text{pred}}) \rangle$$

- ϕ_*^{obs} (ϕ_*^{pred}): observed (predicted) SMF
- Σ : observational covariance matrix
- $\langle \dots \rangle$: average over stellar mass bins

ARCHITECTURE AND OPTIMIZATION

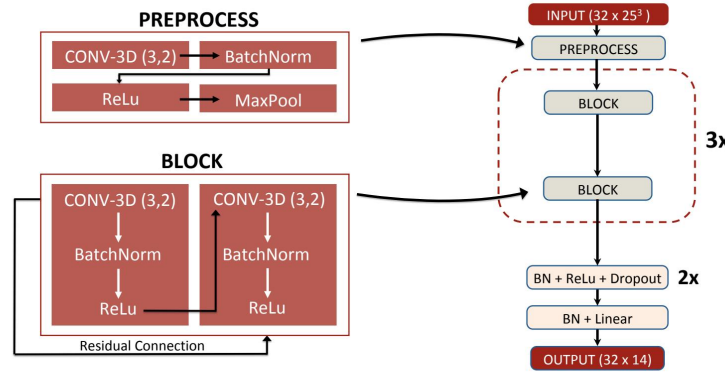
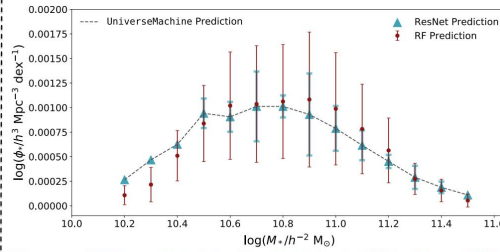


Figure: Convolutional ResNet architecture for our single-snapshot halo \rightarrow galaxy model.

SINGLE-SNAPSHOT RESULTS

- Loss on training and validation set plateaus after ~ 5 training epochs.
- ResNet reproduces UM-predicted SMF at a single snapshot.



Figures: SMF predicted by ResNet (blue), RF (red), and UM (gray); loss vs. training epoch.

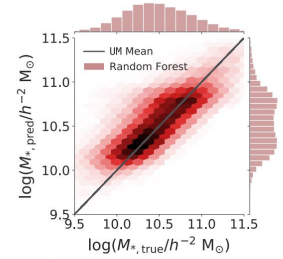
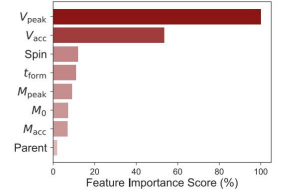
OPTIMIZATION

- Scan over architecture hyperparameters:

N_{channels}	$\langle \mathcal{L} \rangle$
20	135
100	93
200	84

FEATURE SELECTION

- Use random forest to test for importance of other halo features.



Figures: Feature importances and predicted galaxy mass.

FUTURE WORK

- Connect halos across time by simultaneously predicting SMF at different simulation snapshots.
- Run trained model on independent simulation to test generality of halo \rightarrow galaxy mapping.

REFERENCES

- Behroozi et al. 2018, arXiv 1806.07893
- Klypin et al. 2016, MNRAS 457, 4340