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Max-Planck-Institut für Astrophysik

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GalaxyNet: Connecting galaxies and DM haloes with neural networks and reinforcement learning

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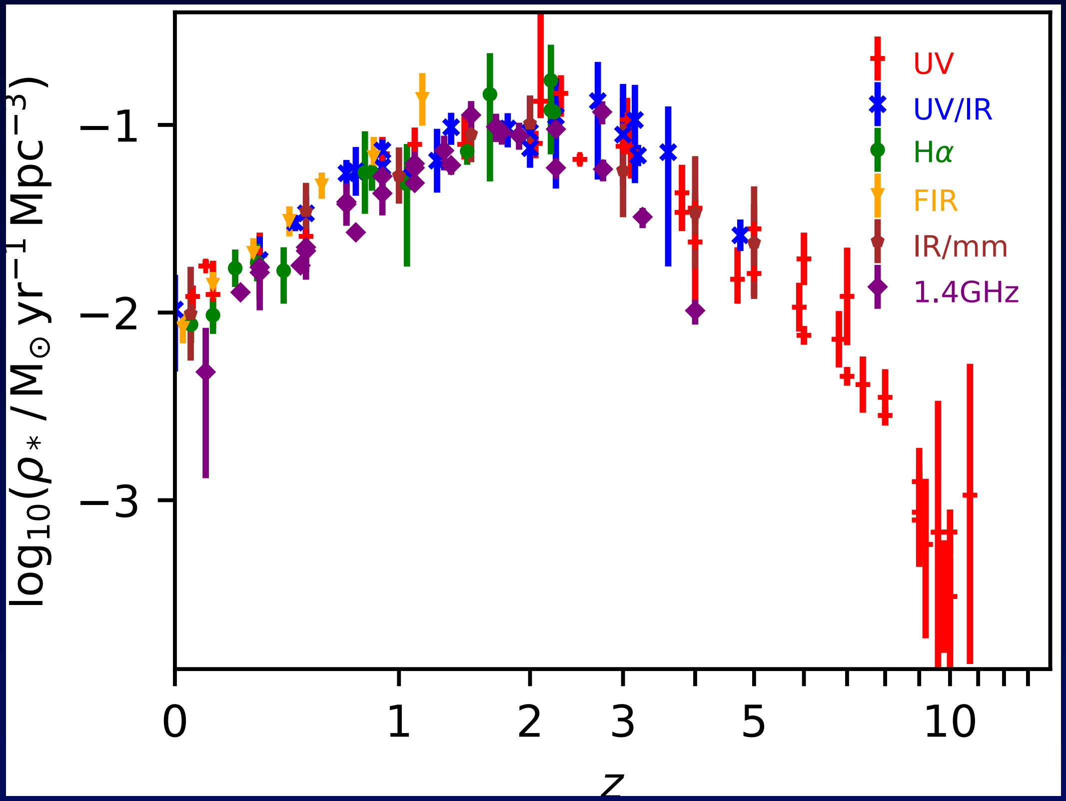
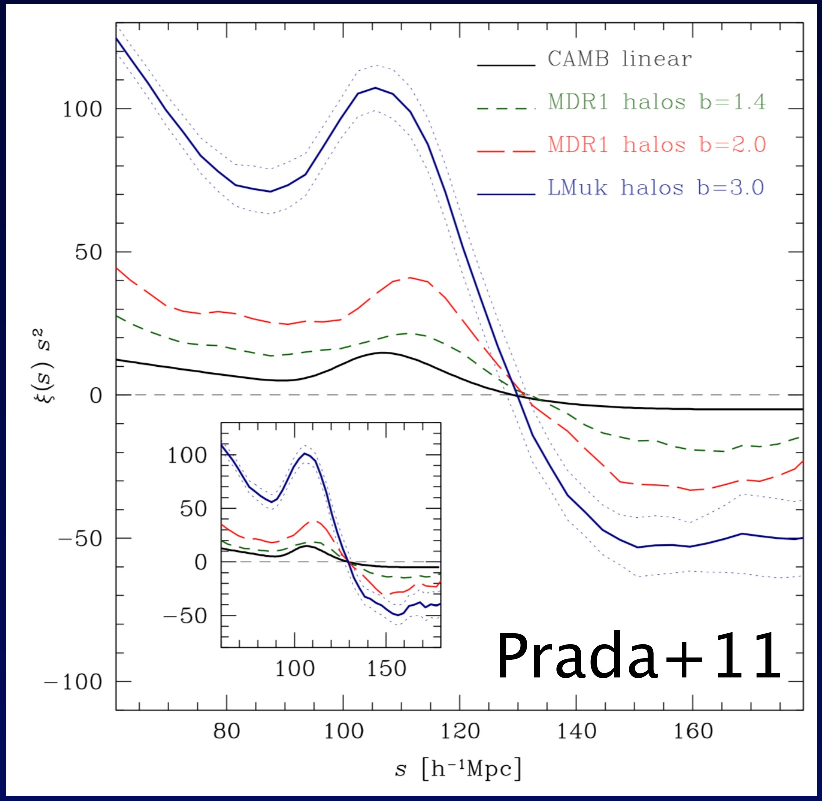
How do galaxies form in the Universe?

- Large amount of observed data: mass, SFR, size, clustering…
- Observations just ‘snapshots’ - no time evolution

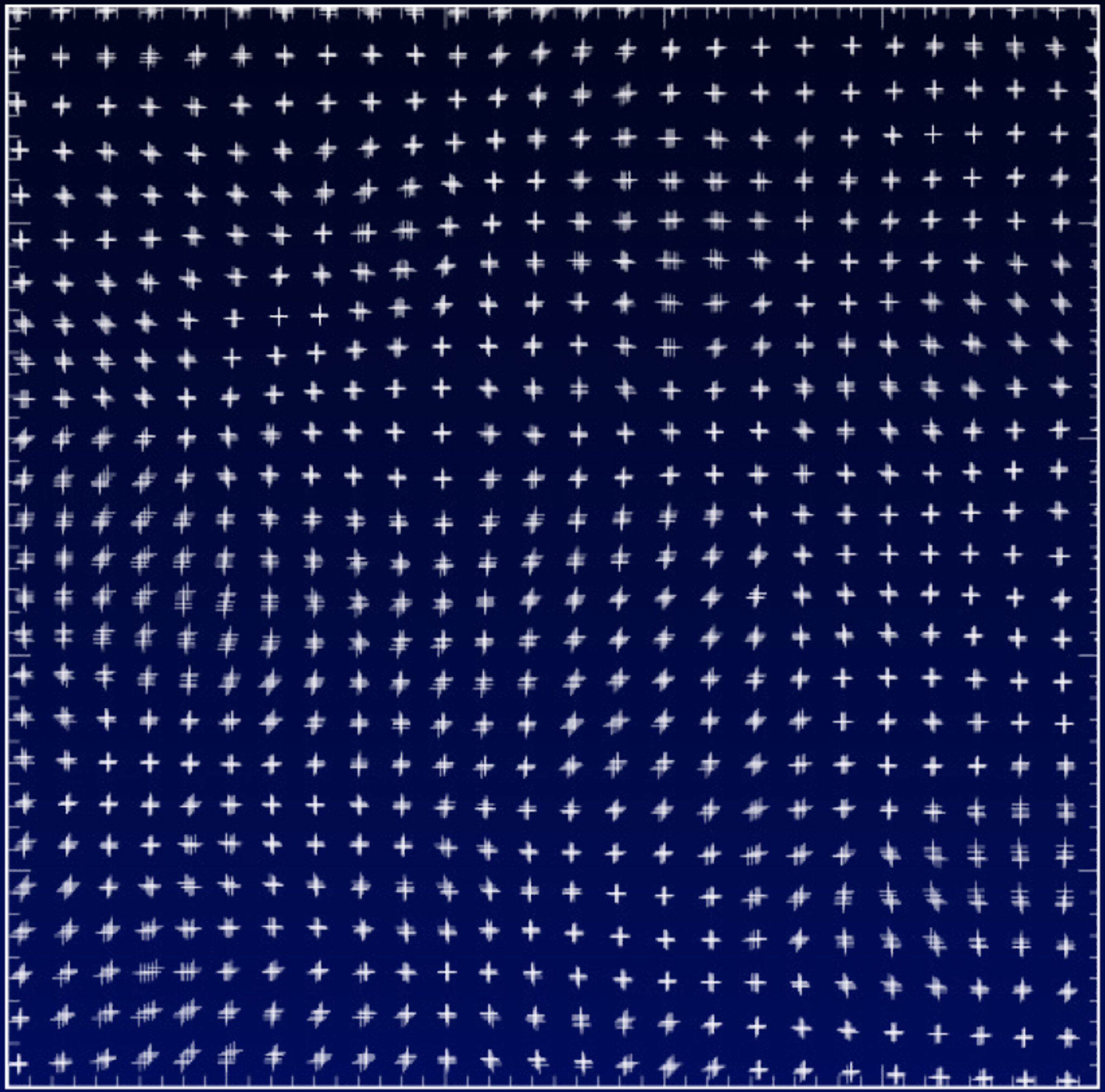
- How do galaxies assemble in dark matter haloes?
- What sets galaxy properties (e.g. SFR) and scatter?
- What does LSS tell us about cosmology?





Cosmological simulations

- Initial conditions measured very accurately (WMAP, Planck)
- Simulations of Dark Matter are numerically converged



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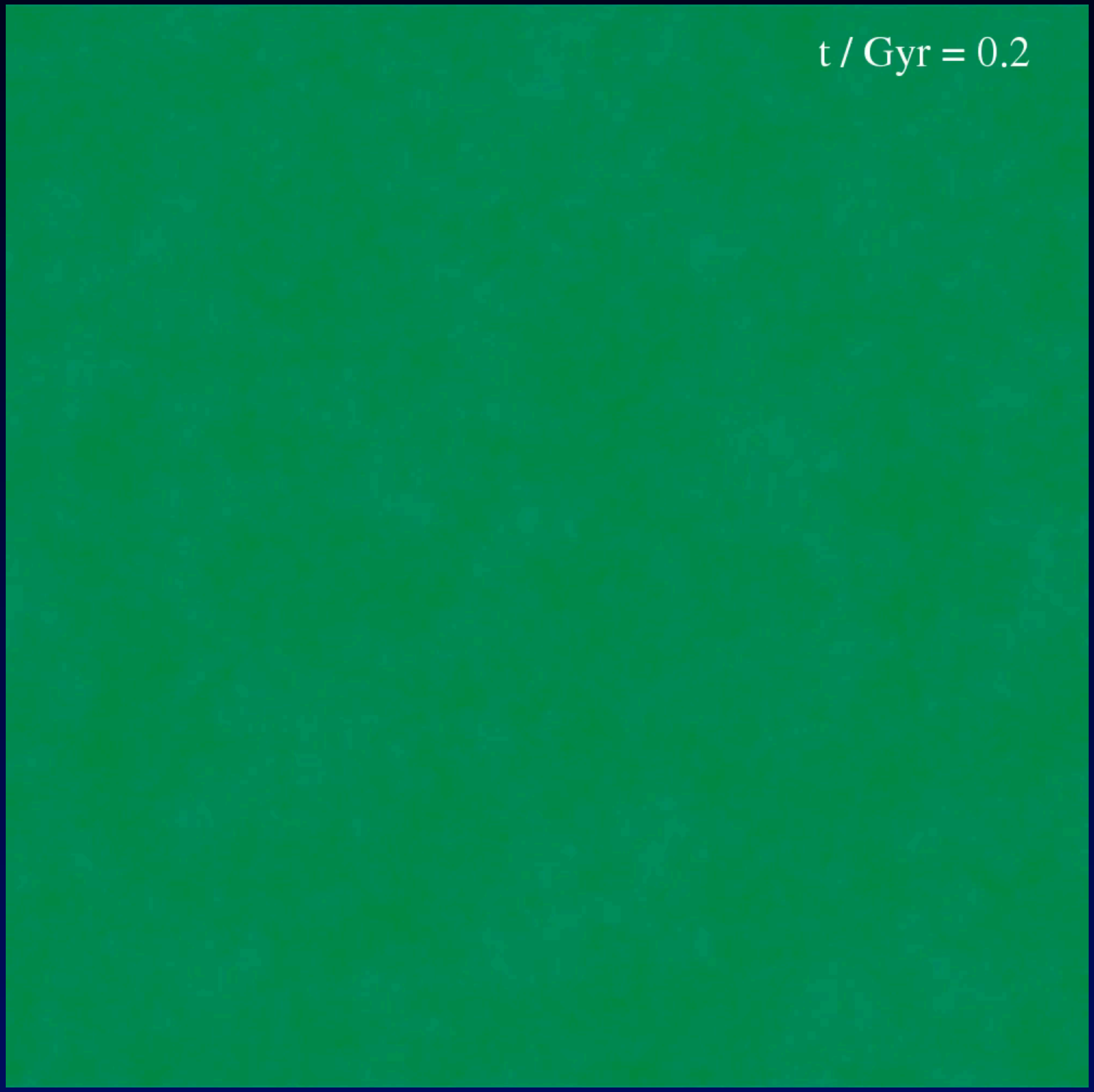
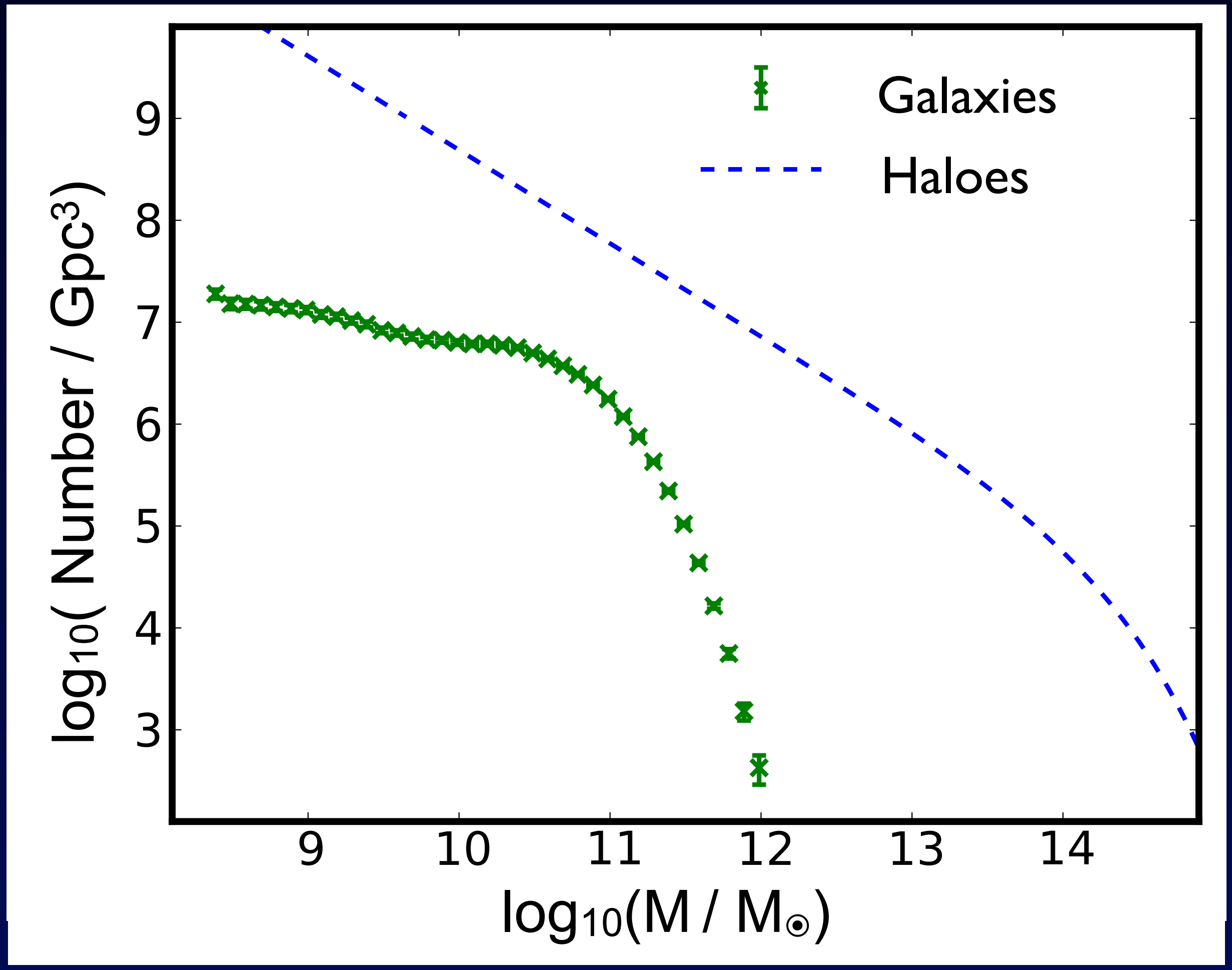
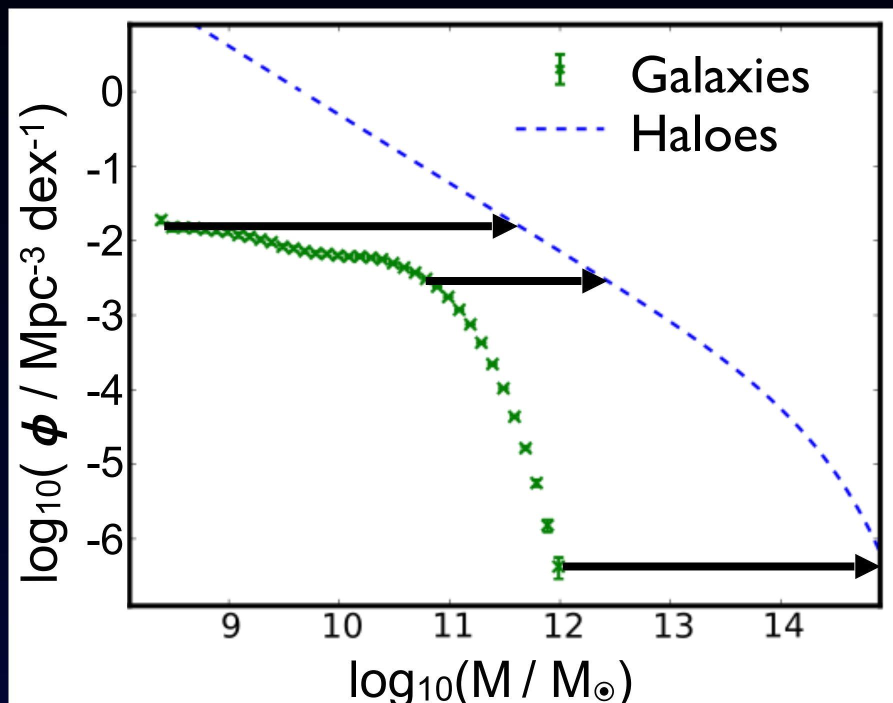
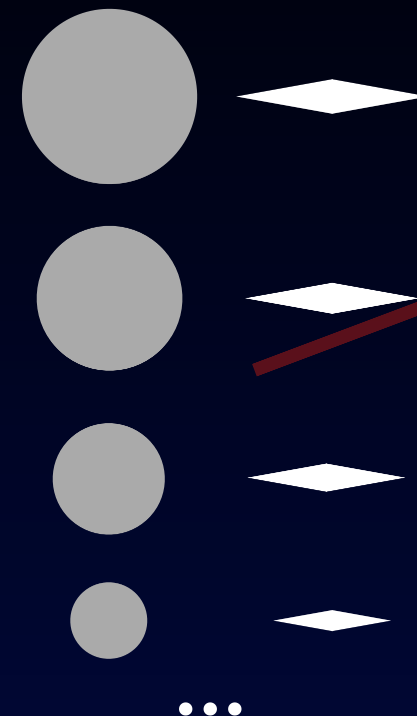
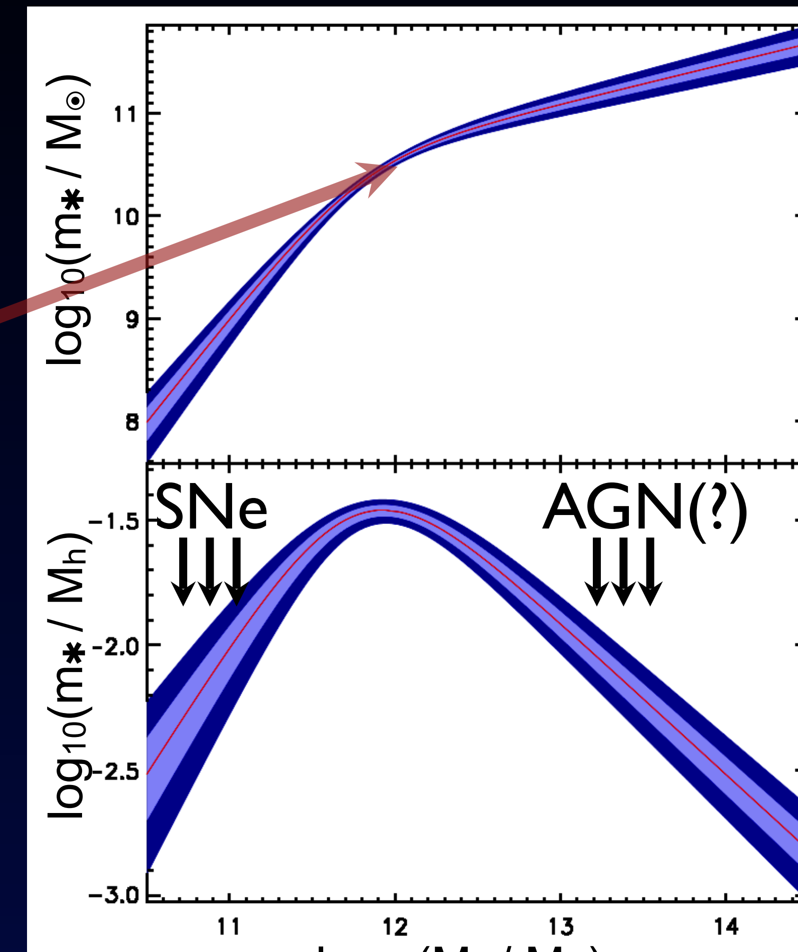




Abundance matching and variants



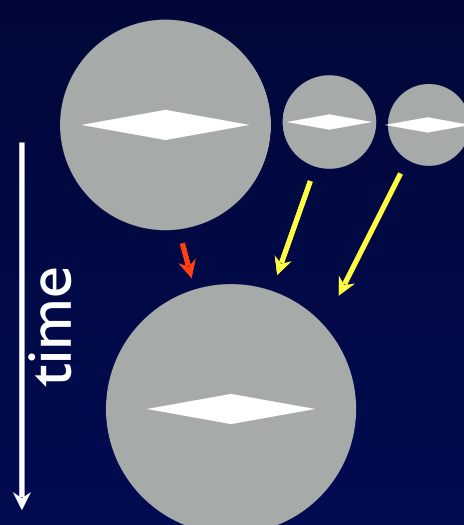


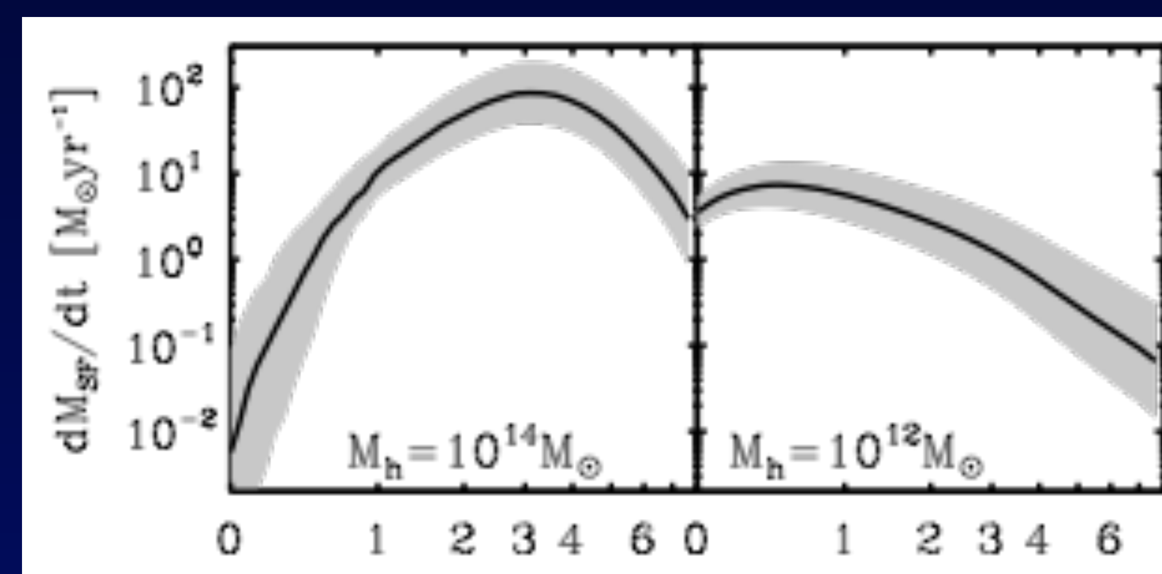


BPM+(2010)

- Populate halo merger trees

- infer SF & accretion rates





BPM, Naab, White (2013)

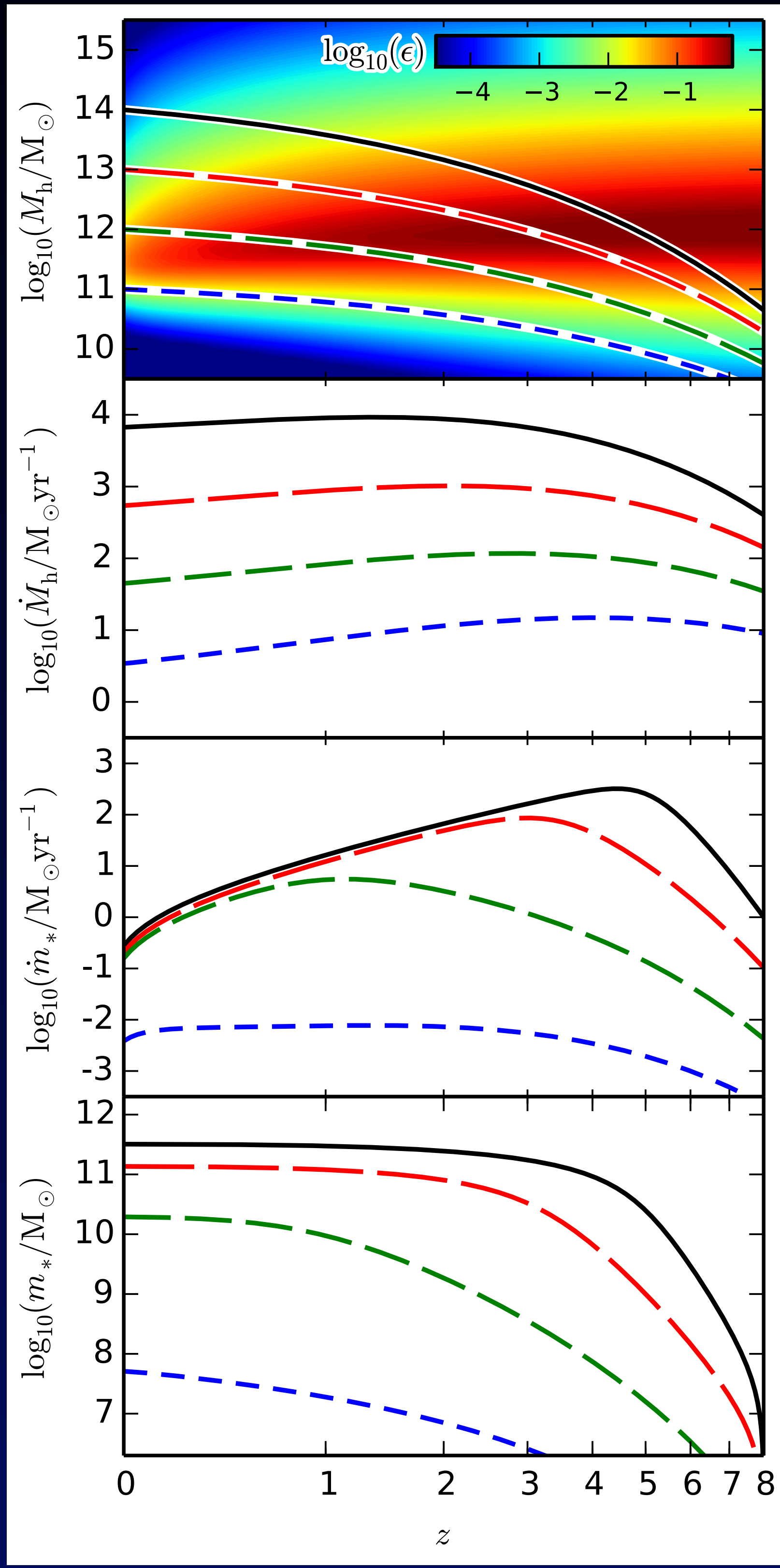
Models for individual haloes

- Abundance matching:
  average relation between m_* and M_h
- EMERGE has individual growth histories
  $\dot{m}_* / \dot{M}_h = \varepsilon_{\mathrm{instant}} (M_h, z)$
- Stellar mass increases as
  $\Delta m_* = \varepsilon \cdot \Delta M_h = \varepsilon \, M_h \, \Delta t$

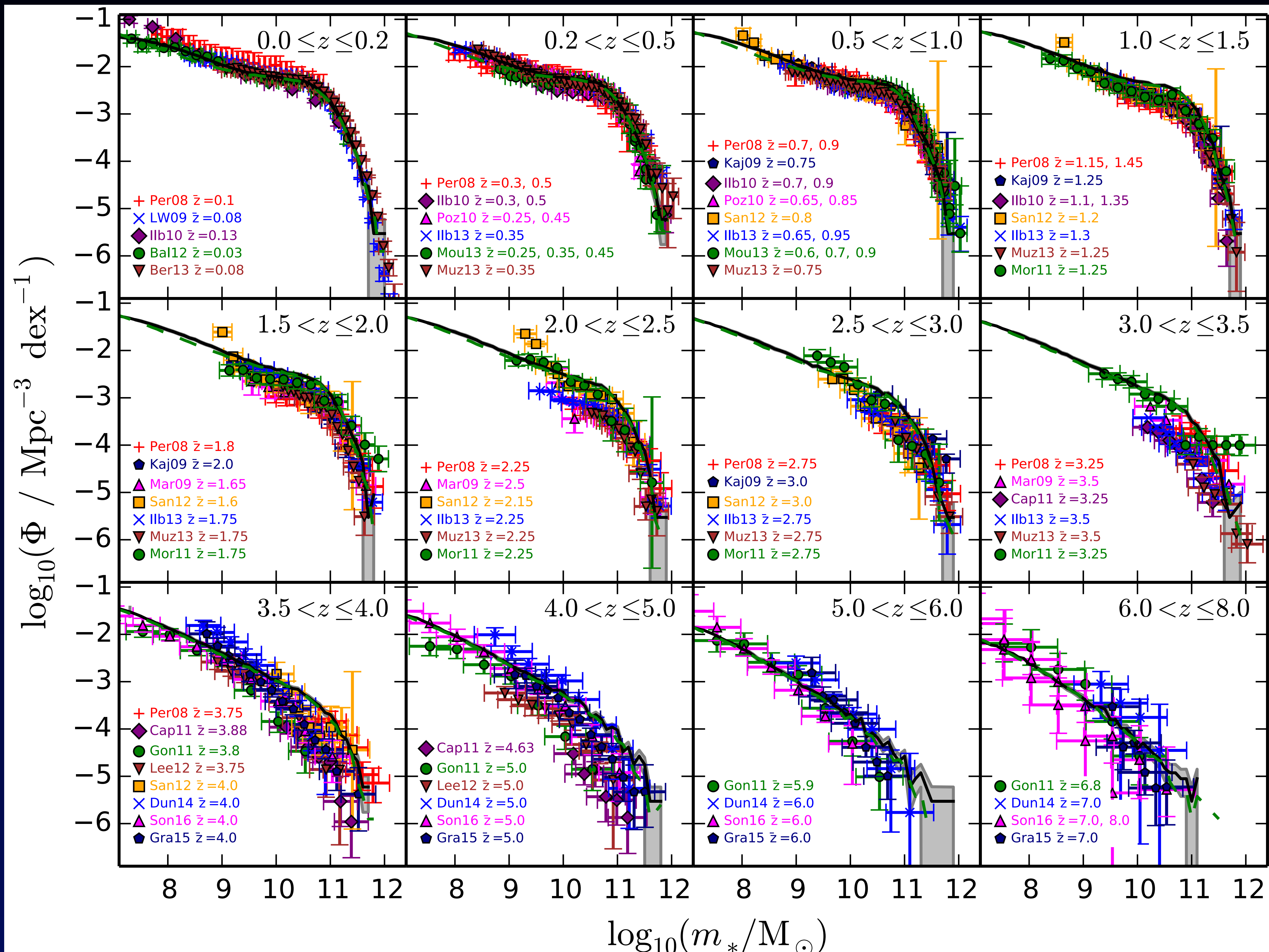
Material becoming available

Conversion efficiency

- Additionally for satellite galaxies:
  delayed quenching, stripping, merging
- Parameterised model (11 free parameters)



Statistical galaxy properties up to high redshift

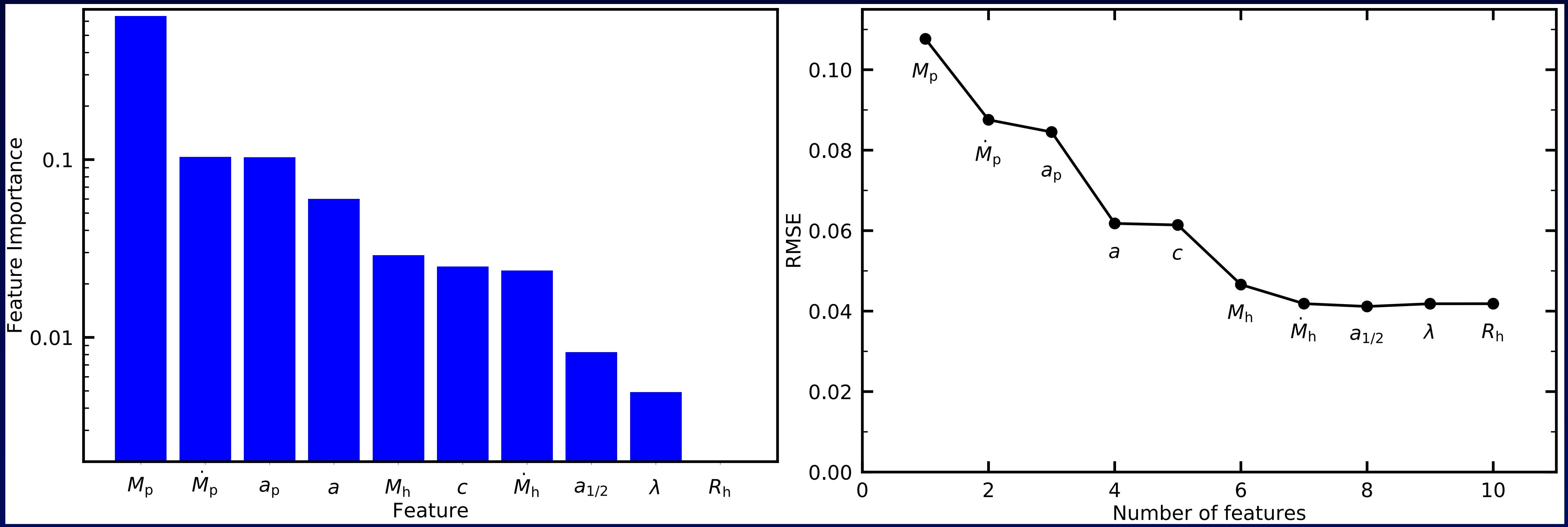


Galaxy formation modelling with AI

- Model & quality of fit is determined by selected relations
  Form of these relations not clear a priori!

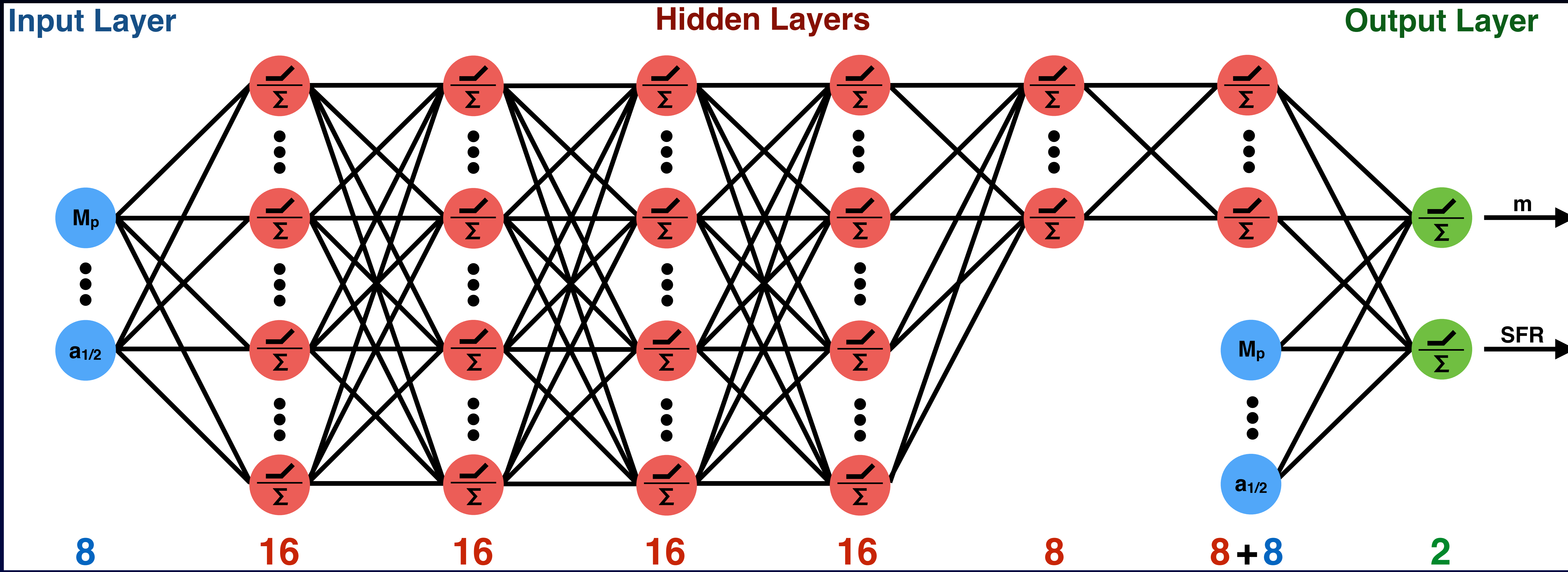
- How can we find sensible empirical relations between galaxy and halo properties? ➞ Machine Learning

- Use Random Forests to find most important halo properties



Wide & Deep Neural Network

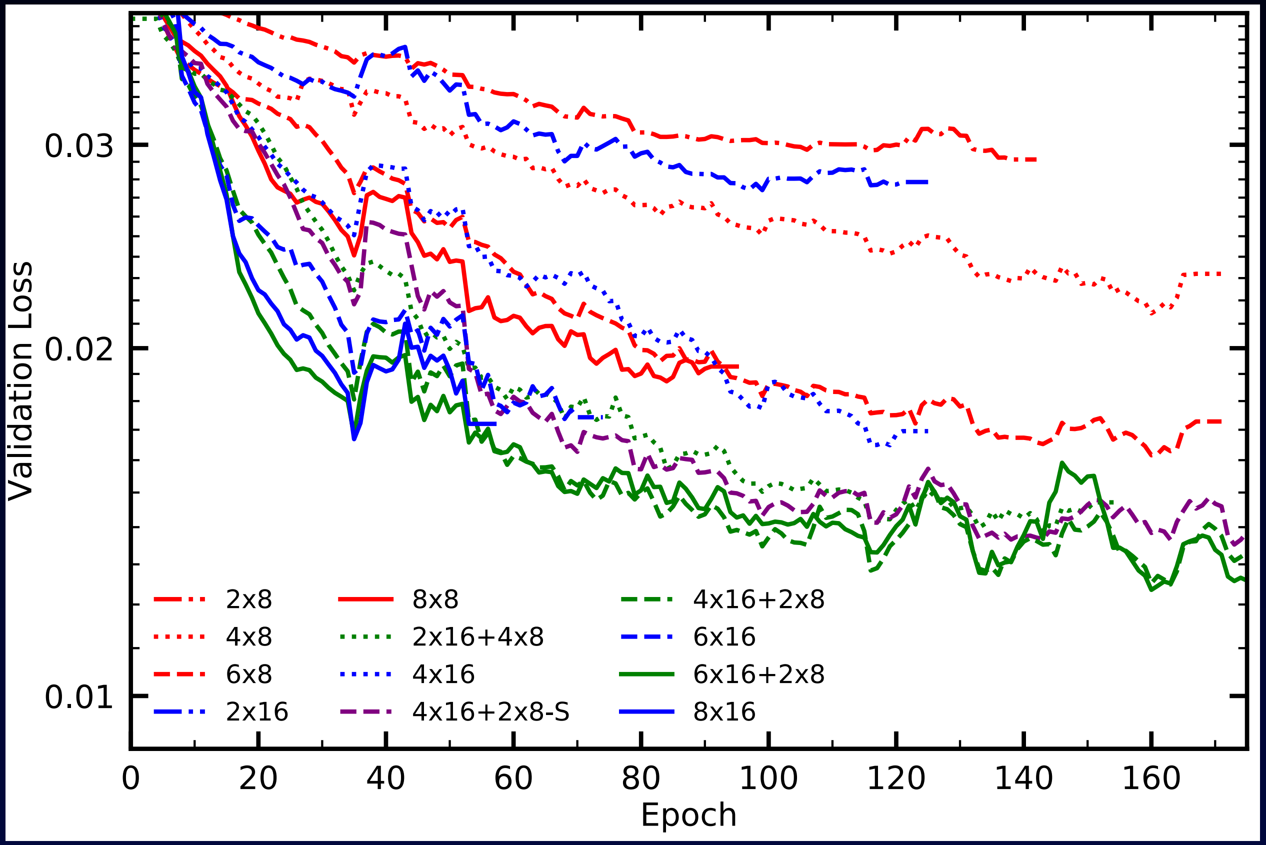
- Wide & deep neural network to model Galaxy-Halo connection

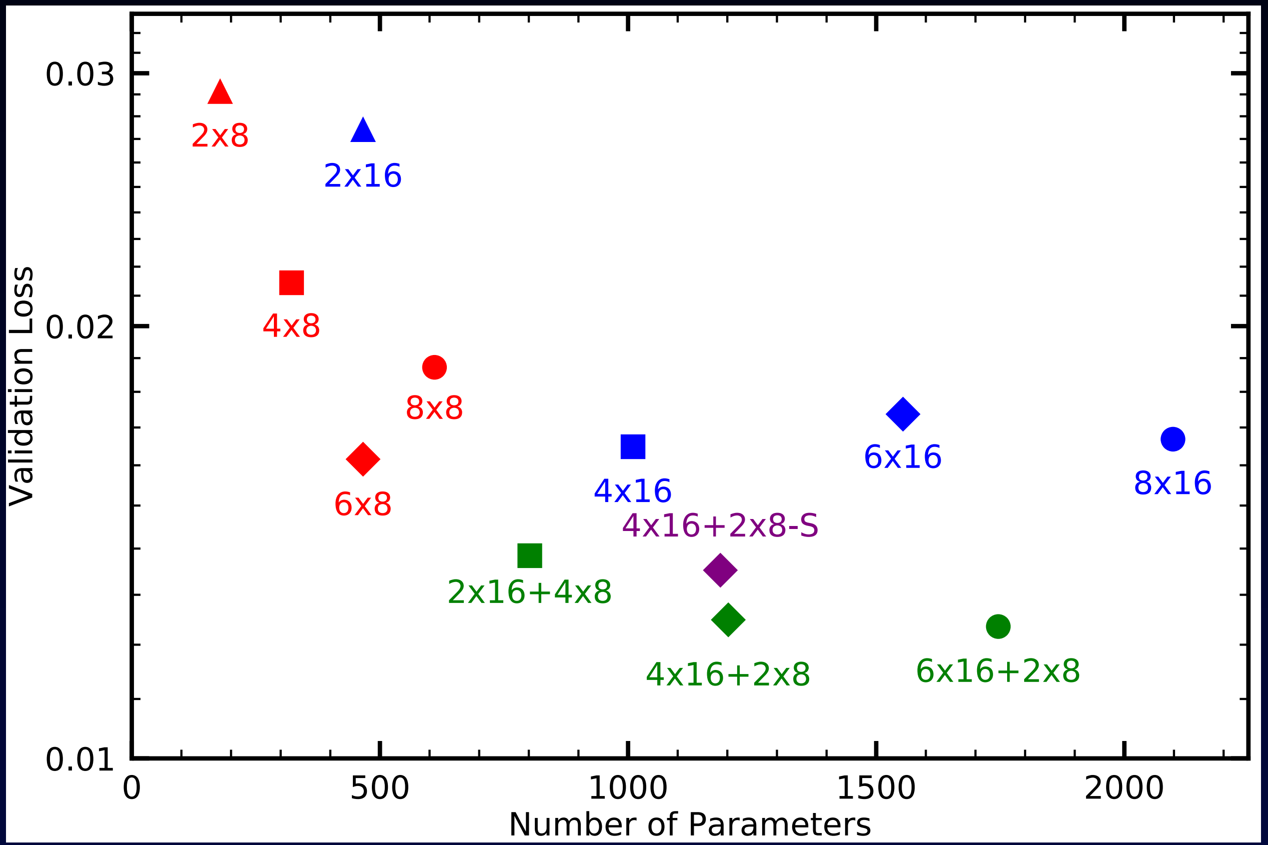


- Train GalaxyNet with supervised learning and Emerge data first
- Prediction of GalaxyNet for each galaxy (m*, SFR) is compared to Emerge → Adjust weights to minimise difference

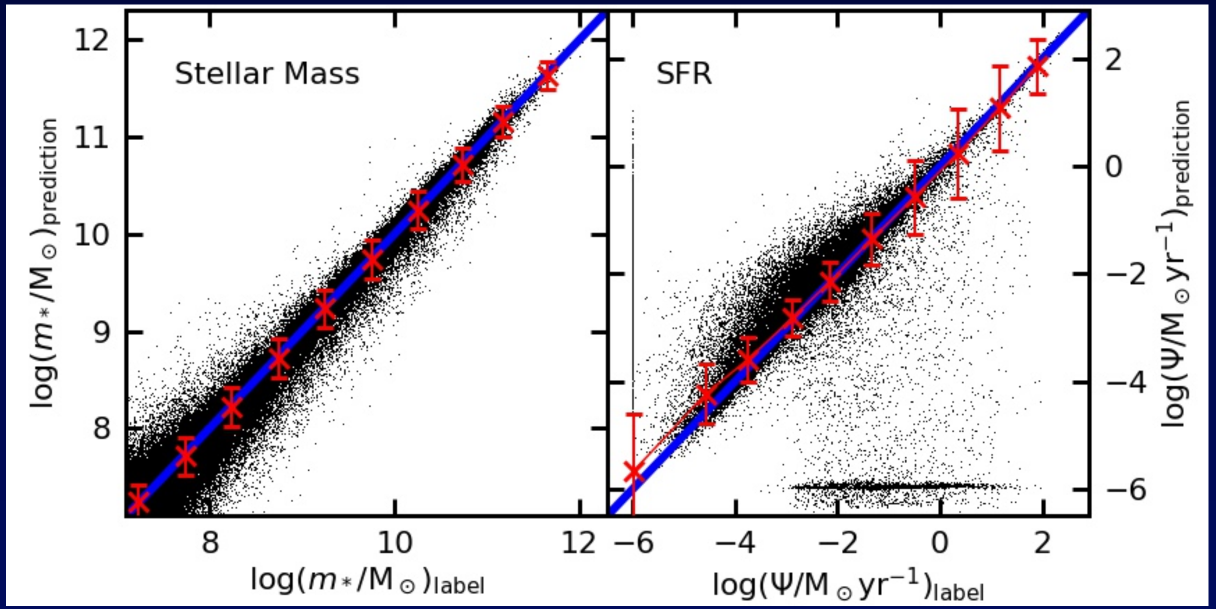
Wide & Deep Neural Network

- Test different architectures and stop training early

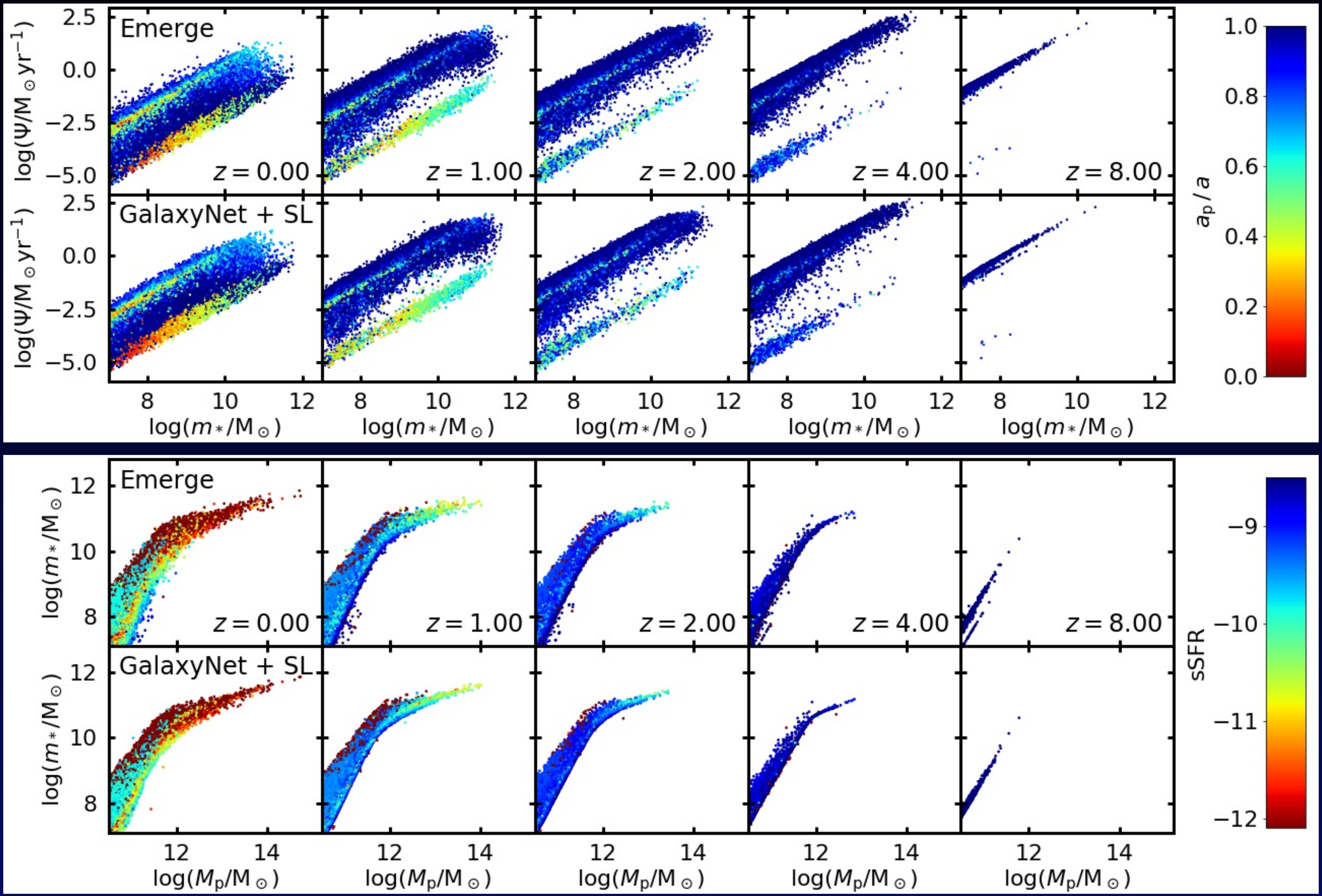




- Best network has 4 layers w/ 16 nodes + 2 layers w/ 8 nodes
- Reproduce validation data well

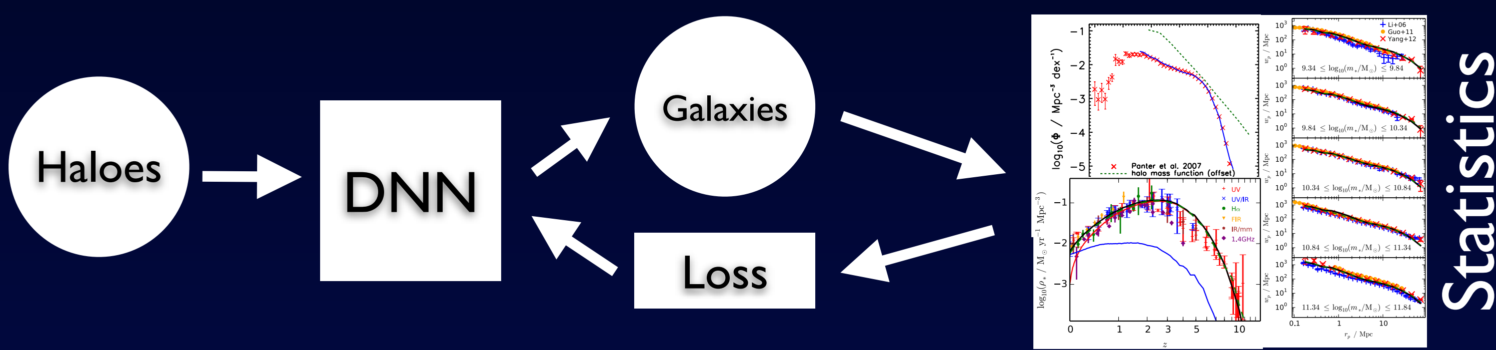


Supervised Learning results using Emerge data

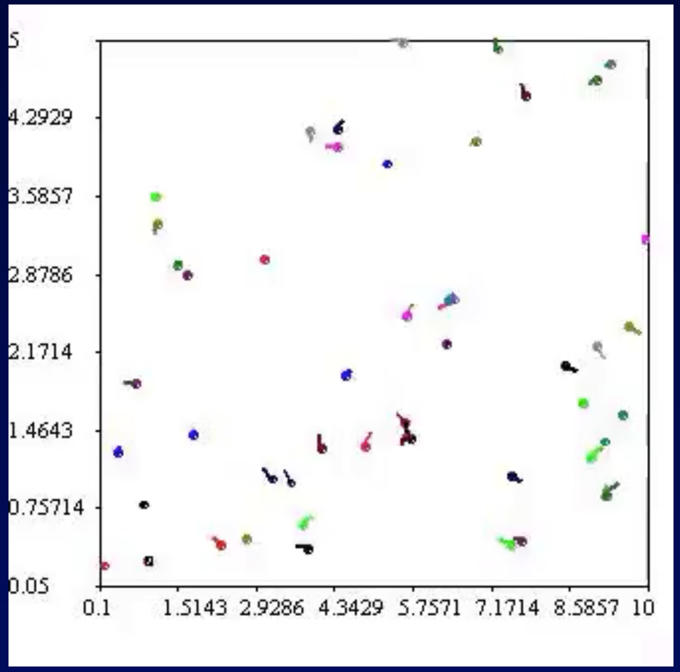


Reinforcement Learning with PSO

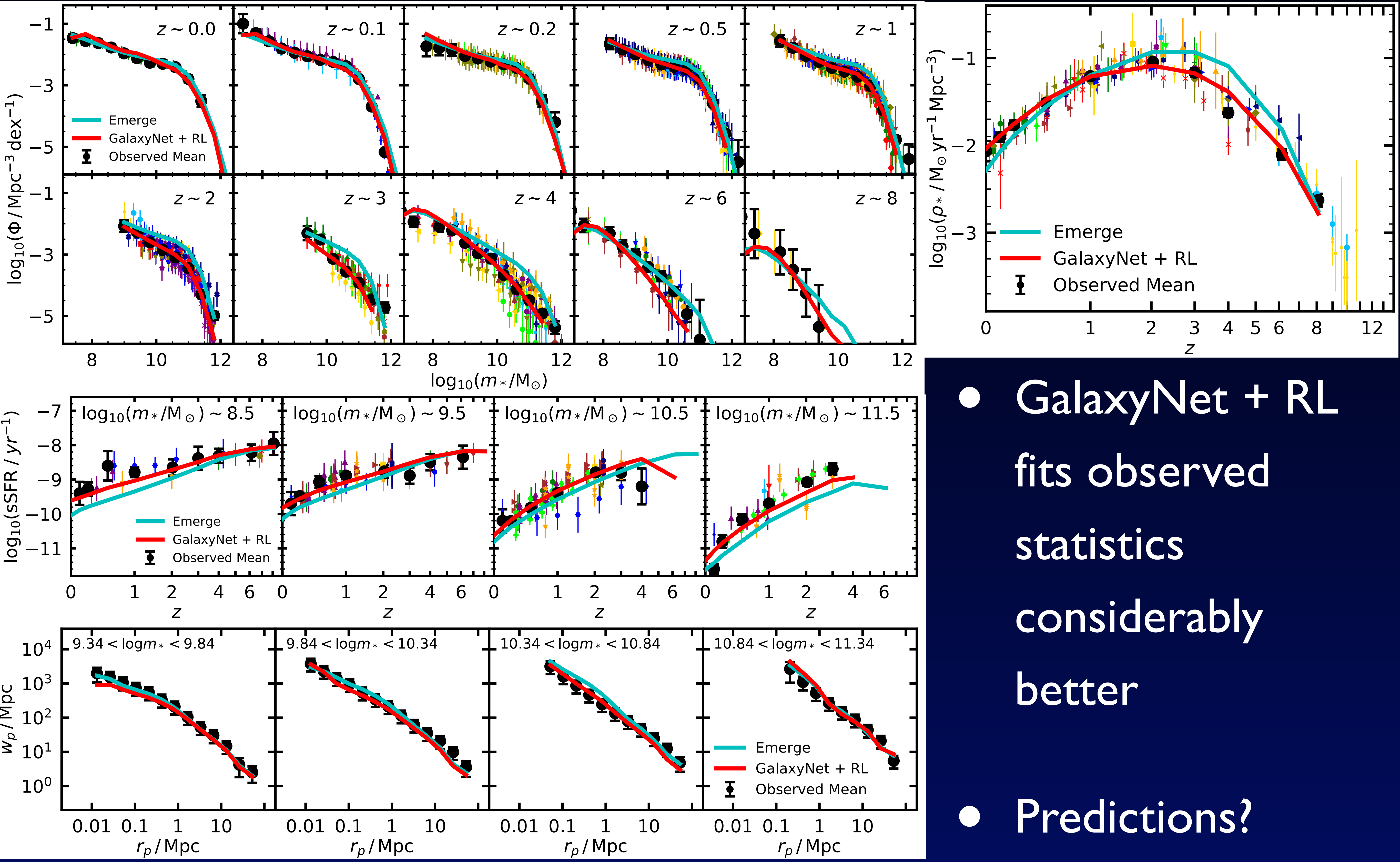
- Best possible result with supervised learning is to reproduce Emerge (training data), which we *already* have
- Better option: train network directly with observations using a reinforcement learning approach!



- Use particle swarm optimisation to find best parameters (network weights / biases)
- Very efficient to probe high-D space

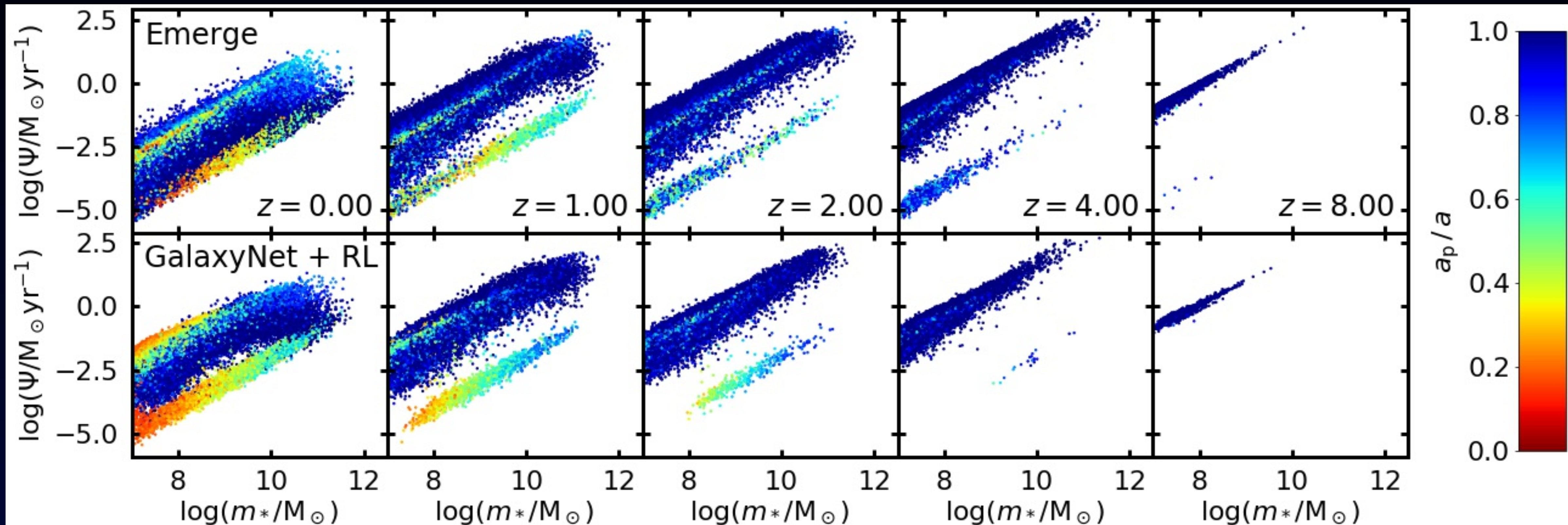


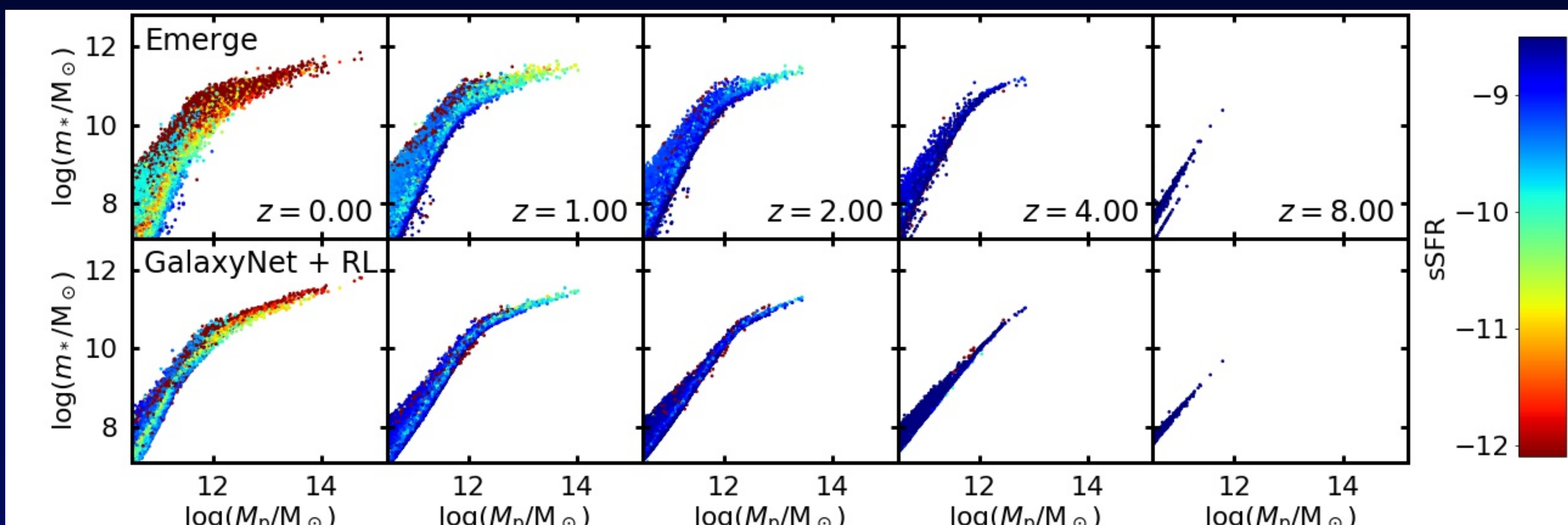
Results from Reinforcement Learning



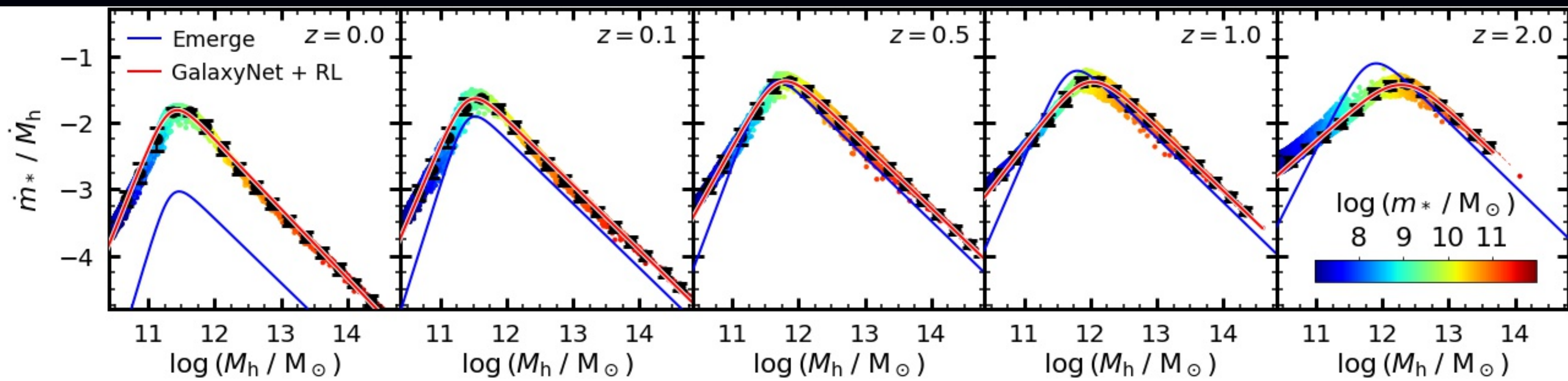
- GalaxyNet + RL fits observed statistics considerably better
- Predictions?

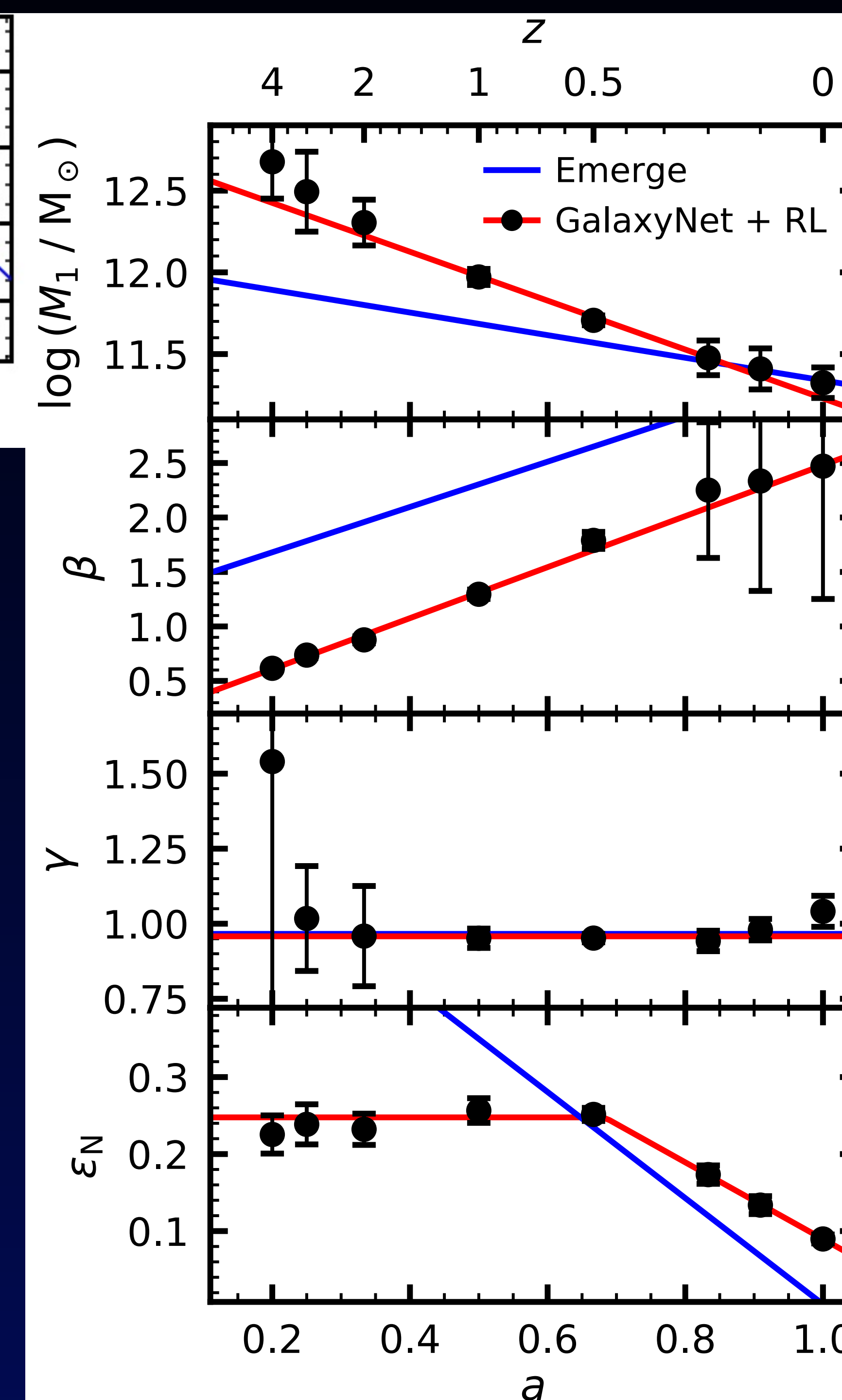
Results from Reinforcement Learning





What do we learn about the conversion efficiency?

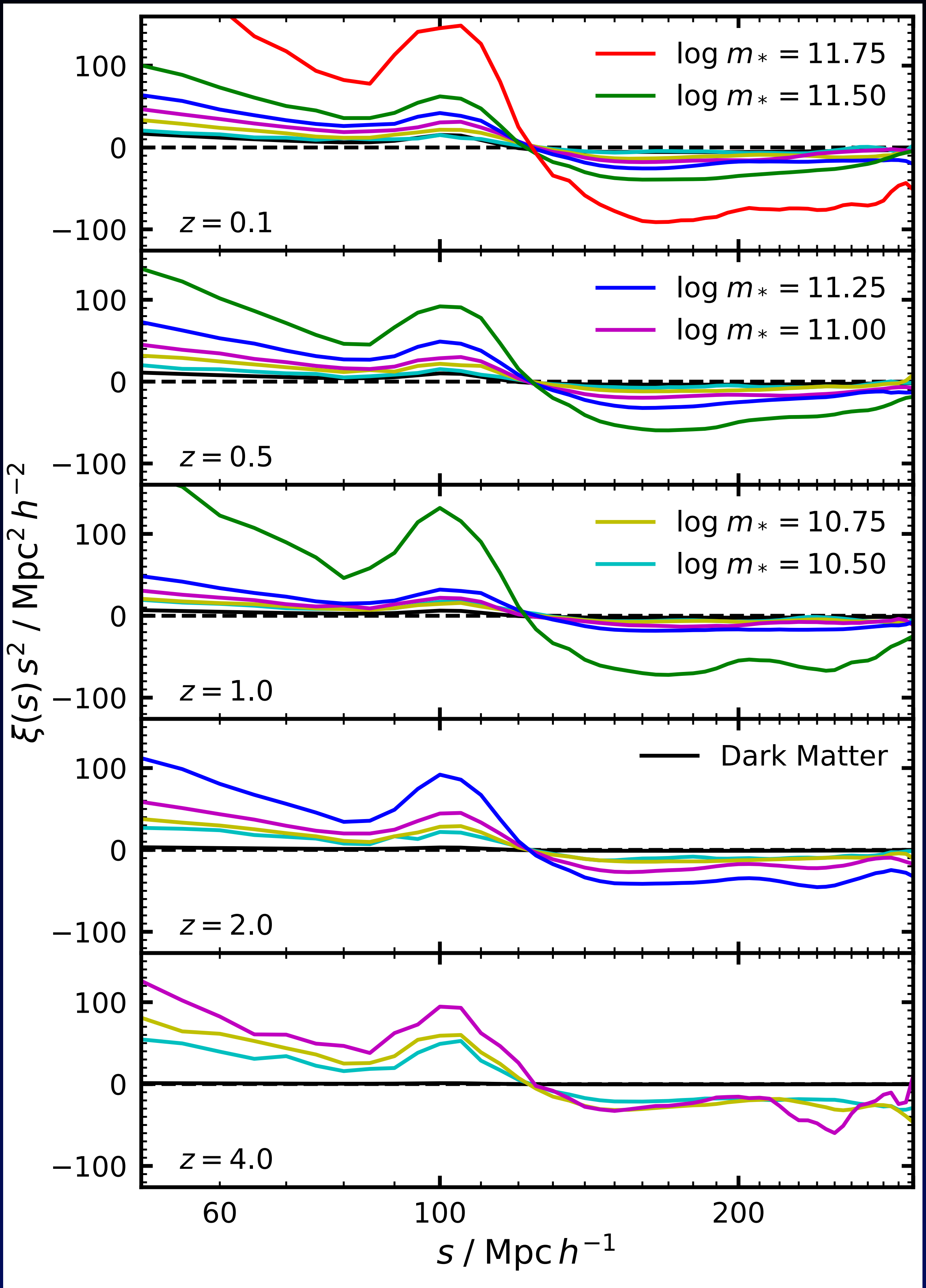




- Take central galaxies and plot instant. conversion efficiency ($\dot{m}_*/\dot{M}_\mathrm{h}$) vs M_h
- Fit double-power-law at each redshift and study evolution of parameters
- All parameters show linear evolution with scale factor *a* as assumed in EMERGE
- Exception: normalisation! Constant at high z, then decreasing!

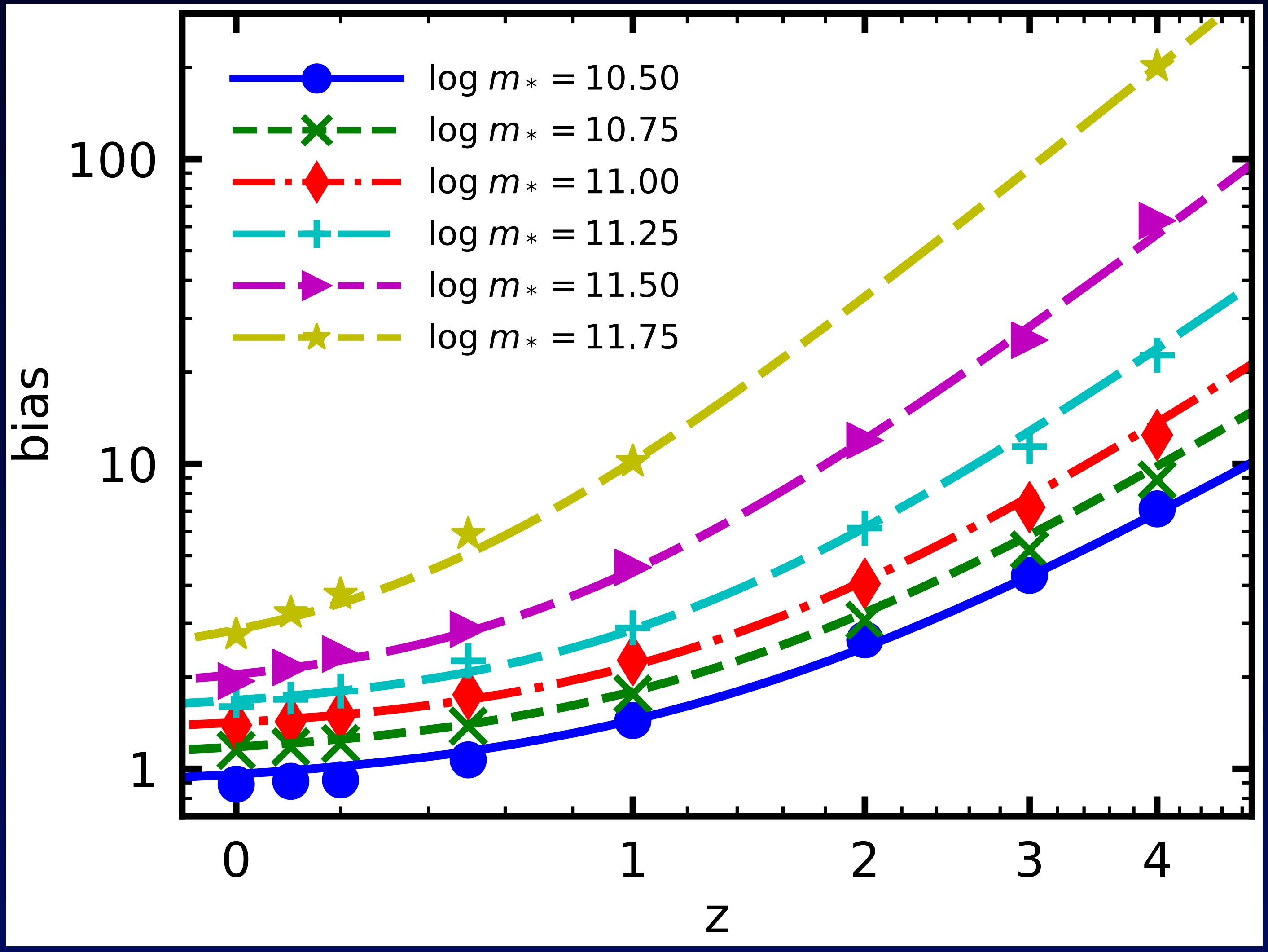
LS - Clustering at high redshift

- In large volume simulations, low-mass haloes unresolved → problem for Emerge, SAMs,…
- Apply GalaxyNet to HugeMDPL DM simulation (L = 4 Gpc/h)
- Predict BAO signal and zero-crossing for different stellar mass bins up to z ~ 4



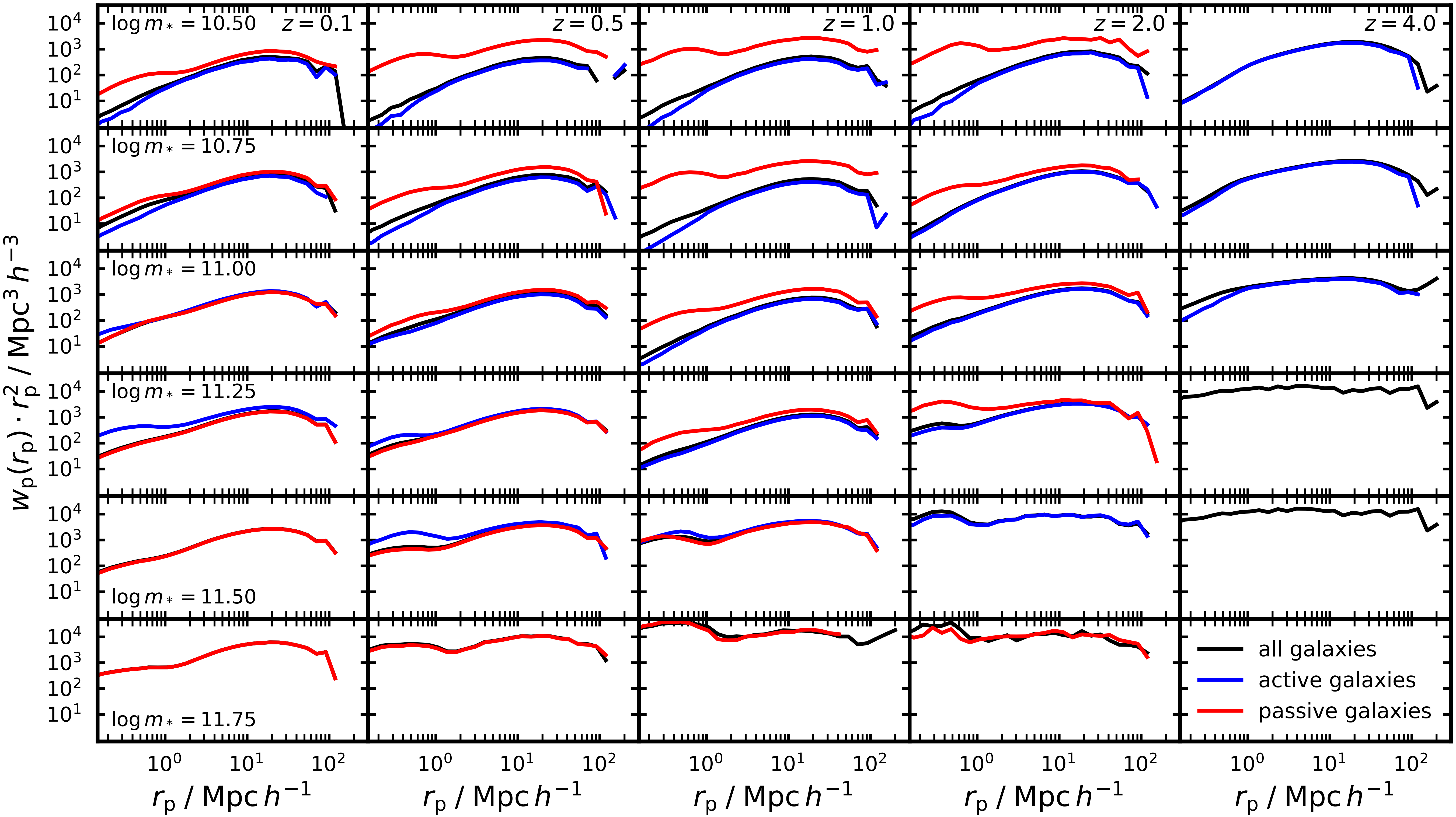
LS - Clustering at high redshift

- Predict galaxy bias at 8 Mpc/h for different stellar mass bin
- Simple scaling law $b = b_0(m_*)\,[\,(z+1)^{b_1} + b_2\,]$
- Can be used to infer cosmic variance for high-z surveys



LS - Clustering at high redshift

- Predict projected correlation function up to high redshift



Conclusions

- Self-consistent cosmological framework
  → connect observed galaxies to simulated DM haloes
  Model individual haloes/galaxies with conversion efficiency

- Relations between galaxy and halo properties are not always clear
  → Use Wide & Deep NN with a reinforcement learning approach
  → Galaxy-Halo Connection without imposed relations

- Can fit observations even better than empirical models
  However, not self-consistent between m and SFR (yet).

- Use GalaxyNet to get better parameterisation for EMERGE

- Apply GalaxyNet to huge DM sims to get (clustering) predictions