





# A Forward Modeling Approach to Understanding the Light from Galaxies

2023/10/10

BCCP/Cosmology Seminar

# Suchetha Cooray

Nagoya U. Doctor of Science 2023 JSPS Postdoctoral Fellow at NAOJ



- Understanding galaxy formation using ML with simulations and observations
- Some interests are;
  - Forward modeling all galaxy observables within cosmological structure formation
  - Learning latent representations of galaxies
- Soccer, music, and socializing over drinks...
- In the job market & open for collaborations!





Galaxy Observation

# Talk Outline

- ► Why study galaxies?
- ► What is empirical forward modeling for galaxy formation?
- Challenges with current approaches to studying galaxies
- Proposed solution (field-level inference)
- Future of empirical forward modeling for galaxy formation and cosmology



Mock universe with UM

# Why study galaxies in the Universe?



# Difficulty in Understanding Galaxies



- Gas flows/IGM/CGM
- Dust/ISM
- Blackholes/AGNs
- Supernovae/Stellar evolution
- Chemical evolution
- Magnetic fields
- Cosmic rays
- Reionization
- And so on...

# Difficulty in Understanding Galaxies

# The key driver of galaxy formation, i.e., star formation, is a multi-scale process



Large-scale physics

**Small-scale physics** 

# Difficulty in Understanding Galaxies

#### Physics and their times scales regulating star formation histories



# Galaxies in the Cosmology Context



# Galaxies in the Cosmology Context



# Galaxies in the Cosmology Context



**Smoothed DM Distribution** 

**Smoothed Galaxy Distribution** 

# Significant Progress in Simulations!







Magneticum

CAMELS

#### We just don't know if they are right!

Suchetha Cooray

SIMBA

# Can we Learn Galaxy Formation from the Universe?



#### High Res. DM Distribution

Galaxy Formation

Challenging!



15

**Galaxy Distribution** 



Construct a model that is flexible to be able to capture the real galaxy formation physics while being physically consistent (e.g, conservation)

=> Let the machine learn!



Wechsler & Tinker 2018

# **Combining Various Observations**



# **Combining Various Observations**



# Our Approach



Approaches to modeling the galaxy-halo connection

physical models			empirical models	
Hydrodynamical Simulations	Semi-analytic Models	Empirical Forward Modeling	Subhalo Abundance Modeling	Halo Occupation Models
Simulate halos & gas; Star formation & feedback recipes	Evolution of density peaks plus recipes for gas cooling, star formation, feedback	Evolution of density peaks plus parameterized star formation rates	Density peaks (halos & subhalos) plus assumptions about galaxy—(sub)halo connection	Collapsed objects (halos) plus model for distribution of galaxy number given host halo properties

UniverseMachine (Behroozi+19) is an empirical galaxy  $\succ$ formation model that has been constrained on the latest observations and produces consistent galaxy growth histories from z=10 to z=0



18

# Key Concepts - HMF



# Key Concepts - SMF



# Key Concepts - SMHM Relation



# **Empirical Galaxy Formation Models**



## UniverseMachine Procedure



Minimal Galaxy Formation Model

 $SFR = f(M_h, \dot{M}_h, z)$ 





**Populated Dark Matter Merger Trees** 

# UniverseMachine Procedure



Constrain based on observed stellar mass functions, SFRs (specific and cosmic), quenched fractions, ultraviolet (UV) luminosity functions, UV–stellar mass relations, IRX–UV relations, auto- and cross-correlation functions (including quenched and star-forming subsamples), and quenching dependence on environment

### UniverseMachine Results - Observational Constraints

![](_page_21_Figure_1.jpeg)

# Uncertainties in the Galaxy-Halo Connection

# Challenge of Extracting Galaxy Physical Properties

- Main source of uncertainty is in galaxy property measurements!
- Degeneracy between effects of redshift, star formation history, dust, and metallicities on the SED (e.g., Calzetti et al. 2001)
- Recovered galaxy physical properties are significantly and systematically affected by modeling assumptions

![](_page_23_Figure_4.jpeg)

SED Modeling Assumption	Stellar Mass Error*	
Star Formation Histories	~0.2 dex	
Dust	~0.2 dex	
Metallicity	~0.1 dex	
Photometric Redshifts	~0.1 dex	
Stellar Population Synthesis	~0.1 dex	
Total (in quadrature)	~0.35 dex	

# Physical Properties from Observations

Most galaxy properties should be determined from observed fluxes of galaxies!

![](_page_24_Figure_2.jpeg)

# Recovery of Simulated SFHs

![](_page_25_Figure_1.jpeg)

![](_page_25_Figure_2.jpeg)

Suchetha Cooray

Cooray+ in prep.

# Generative Models as a New SFH Model

Generative models are machine learning (ML) algorithms that can generate new data instances from a learnt data distribution

![](_page_26_Figure_2.jpeg)

We try to train a model with simulated galaxy SFHs and the model can learn characteristics and the diversity of simulated SFHs

Provo late in procession

#### Generated SFHs follows the original data (simulated SFH) distributions and thus produce physically-motivated SFHs to fit real galaxies

# Latent Space of GalGen-UM

Log  $M_{*,z=0} = 9.00$ 

![](_page_27_Figure_2.jpeg)

Ф

 $\theta$ 

![](_page_27_Figure_3.jpeg)

Cooray+ in prep.

35

6

11

SFR (z)

Log

# Example SED fit of the GalGen model Preliminary!

![](_page_28_Figure_1.jpeg)

# Recovery of Simulated SFHs

 $\begin{array}{c|cccc} & 10^{12} \ M_{\odot} \\ \hline & 10^{11} \ M_{\odot} \\ \hline & 10^{10} \ M_{\odot} \\ \hline & 10^{9} \ M_{\odot} \end{array}$ 

37

![](_page_29_Figure_2.jpeg)

## Better way to do it?

Forward model galaxy formation up to SEDs and match all SEDs simultaneously!

![](_page_31_Picture_1.jpeg)

Constrain based on observed multi wavelength color distributions, ultraviolet (UV) luminosity functions, auto- and cross-correlation functions

![](_page_32_Picture_1.jpeg)

Constrain based on observed multi wavelength color distributions, ultraviolet (UV) luminosity functions, auto- and cross-correlation functions

![](_page_33_Figure_1.jpeg)

Constrain based on observed multi wavelength color distributions, ultraviolet (UV) luminosity functions, auto- and cross-correlation functions

![](_page_34_Figure_1.jpeg)

#### **Benefits**:

- A maximum likelihood solution of the population instead of individual galaxies
- Self-consistent evolution solves much of the degeneracy in SED
- Encodes the environmental information
- Population-level SED fitting code that is both consistent with the population as well as individual!

# Matching Observed Color Distributions

![](_page_35_Figure_1.jpeg)

Matching SDSS optical photometry, more coming soon

- Requires careful modeling of selection function, metallicity (w/ scatter), dust attenuation (w/scatter), and photometric errors, etc.
- Arbitrary bands can be implemented

Suchetha Cooray

#### Stay tuned!

# **Expected Outcomes**

- A fully physical, self-consistent picture of galaxy stellar masses, star formation histories, metallicity histories, and dust from z = 0 to 15
- Significantly reduced systematic uncertainties in the extracted galaxy physical properties.
- Mock catalogs for arbitrary current and future surveys that simultaneously match currently observed galaxy number densities, colors, and clustering.
- Better photometric redshifts

![](_page_36_Figure_5.jpeg)

# Should we stop here?

# Forward model up to the image level!

# Generative Models for Mock Observations

- ➤ We should be able to simulate observations!
- ► Can we simulate the image domain?

![](_page_38_Picture_3.jpeg)

![](_page_38_Figure_4.jpeg)

![](_page_38_Picture_5.jpeg)

![](_page_38_Picture_6.jpeg)

#### High dimensional space

# From SEDs to Galaxy Images with Generators!

![](_page_39_Figure_1.jpeg)

Conditional information from UM

47

21

Feat. 2

# From SEDs to Galaxy Images

#### SDSS-like images generated with a denoising diffusion model

![](_page_40_Picture_2.jpeg)

Cooray+ in prep.

Suchetha Cooray

21

# Galaxy Properties to Galaxy Images

SDSS-like images generated with a conditional diffusion model

![](_page_41_Picture_2.jpeg)

## Mock universes as telescope-level images **Preliminary!**

50

![](_page_42_Picture_1.jpeg)

SDSS-like survey field. The colors and the color-dependent spatial information come from the empirical forward model. A conditional diffusion model trained on SDSS images and photometry generated individual galaxy image patches. Relative sizes come from the size-mass relation (Mawla\_2019).

# Mock Universes with Empirical Modeling

# Parameters of cosmology and galaxy formation

Forward modeling

![](_page_43_Picture_3.jpeg)

51

# Mock Universes with Empirical Modeling

# Forward modeling

## Parameters of cosmology and galaxy formation

![](_page_44_Picture_3.jpeg)

![](_page_44_Picture_4.jpeg)

![](_page_44_Figure_5.jpeg)

# **Expected Outcomes**

# Field-level (pixel-level) inference, maximizing the information from galaxy surveys

- Data-driven model of galaxy morphologies with data from multiple telescopes
- Constraints on galaxy size evolution
- Observationally indistinguishable mock images

# The way forward for galaxy formation

- Increase model complexity
  - Add other physical processes: blackholes (Zhang et al. 2023), gas (Hong et al. 2023), Metals (Ishigaki et al. in prep.)
- Distribution of light with distribution of DM
  - Model light and mass profiles with DM profiles
- ► Latent representations
  - Fundamental parameters
- ► Causality
  - Go beyond correlations
- Bayesian optimization approach for designing new surveys
  - Maximize science outcome while balancing costs

![](_page_46_Picture_11.jpeg)

Mock universe with UM

54

# The way forward for cosmology

- Mock catalogs
  - End-to-end tests of pipelines
- Cosmology + galaxy formation joint analysis
  - Benefits more for galaxy formation?
- Field-level inference for initial condition reconstructions
  - Differentiable codes

![](_page_47_Picture_7.jpeg)

Mock universe with UM

# Summary

- I am building a field-level (pixel-level) inference machine for galaxy formation
- Will combine all observations to simultaneously derive constraints on SFR, SM, dust, metallicity evolution and its connection to halos from z=0-15
- Some topics I am interested in include;
  - Learning physically meaningful representations and dimensionality reduction
  - Signal processing
  - Faraday tomography
  - Anything cosmology, galaxy formation, ML, etc.

![](_page_48_Picture_8.jpeg)

Mock universe with UM

56

# Thank you!

And to Peter Behroozi, Risa Wechsler, Andrew Hearin, Tsutomu Takeuchi, Daichi Kashino, Kartheik Iyer, Sultan Hassan, and many more!

Web: https://suchethac.github.io/