

# From Far-Ultraviolet to Far-Infrared: Multi-wavelength Spectra of Galaxies at $z=0$ in the L-Galaxies Model—Postprint

**Authors:**

**Date:** 2024-10-15T09:46:43+00:00

## Abstract

Semi-analytic models of galaxy formation are important tools for studying galaxy formation. Current mainstream semi-analytic models can not only reproduce many observed galaxy properties, but also be used to predict results of future large-scale survey observations. Using the L-Galaxies semi-analytic model to generate galaxy star formation histories, considering dust absorption and re-emission, and combining with the machine learning model starduster based on the SKIRT (Stellar Kinematics Including Radiative Transfer) radiative transfer process, we predict the multi-band spectral energy distribution of galaxies. The results show that the dust extinction of the starduster model is slightly insufficient, leading to luminosities slightly higher than observational data in the ultraviolet and optical bands. In the longer infrared bands, starduster reproduces the number of galaxies at the bright end well, but is somewhat deficient at the faint end. At the same time, combining empirical dust extinction with infrared spectral energy templates as an empirical model also yields luminosity functions from far-ultraviolet to far-infrared. The empirical model demonstrates good dust extinction effects, and its total infrared luminosity function matches observational results. Although due to limitations of the template observational data, it cannot fully reproduce the number of faint-end galaxies, the empirical model can better predict luminosity functions in various infrared bands.

## Full Text

### Preamble

Vol. 65 No. 5

Sept., 2024

*Acta Astronomica Sinica*

## From the Far-Ultraviolet to the Far-Infrared: Multi-Wavelength Spectra of Galaxies in the L-Galaxies Model at $z = 0$

Wei Liping<sup>1</sup>, Luo Yu<sup>2, 3†</sup>, Kang Xi<sup>1, 2</sup>

(1 Institute for Astronomy, School of Physics, Zhejiang University, Hangzhou 310058)

(2 Purple Mountain Observatory, Chinese Academy of Sciences, Nanjing 210023)

(3 National Basic Discipline Public Science Data Center, Beijing 100190)

### Abstract

Semi-analytical models of galaxy formation are important tools for studying galaxy evolution. Current mainstream semi-analytical models can not only reproduce many observed galaxy properties but also predict results for future large-scale surveys. In this work, we use the L-Galaxies semi-analytical model to generate galaxy star formation histories, consider dust absorption and re-radiation, and combine this with the machine learning model starduster—based on SKIRT (Stellar Kinematics Including Radiative Transfer) radiative transfer simulations—to predict the multi-band spectral energy distributions (SEDs) of galaxies. Our results show that the dust extinction in the starduster model is slightly insufficient, causing galaxies to be somewhat brighter than observational data in the ultraviolet and optical bands. At longer infrared wavelengths, starduster reproduces the number counts at the bright end reasonably well but slightly underpredicts the faint end. Meanwhile, using empirical dust extinction combined with infrared SED templates as an empirical model also yields luminosity functions from the far-ultraviolet to the far-infrared. The empirical model demonstrates good dust extinction effects, and its total infrared luminosity function matches observations well. Although the template's observational data limitations prevent a complete reproduction of faint galaxy numbers, the empirical model can predict infrared band luminosity functions reasonably well.

**Keywords:** galaxies: dust attenuation, multi-wavelength, luminosity function, spectral energy distribution

### 1. Introduction

The deployment of increasingly numerous observational facilities has greatly expanded our ability to obtain multi-wavelength spectral energy distribution (SED) data for galaxies. For example, the Galaxy Evolution Explorer (GALEX) in the ultraviolet (UV), the Sloan Digital Sky Survey (SDSS) in the optical, the Two Micron All Sky Survey (2MASS) in the near-infrared (NIR), the Spitzer Space Telescope and James Webb Space Telescope (JWST) in the mid-infrared (MIR), the Herschel Telescope in the far-infrared (FIR), and the James Clerk Maxwell Telescope (JCMT) at submillimeter wavelengths have provided observational data on cosmic evolution for different materials and at different epochs.

Observational studies of galaxy multi-wavelength SEDs are becoming increas-

ingly common, such as GAMA (Galaxy And Mass Assembly survey) in the nearby universe and COSMOS (Cosmic Evolution Survey), CANDELS (The Cosmic Assembly Near-infrared Deep Extragalactic Legacy Survey), and DEVIIS (The Deep Extra-galactic VIvisible Legacy Survey) at high redshift. These works attempt to explain galaxy evolution through multi-wavelength SEDs (see Conroy's 2013 review on galaxy SEDs for details). For instance, at  $z = 0$ , galaxies bright from UV to optical wavelengths have relatively vigorous star formation activity, while at high redshift, bright red galaxies dominate. Through different wavelength spectra of galaxies, we can infer the physical properties of various material components in galaxies. Therefore, in theoretical simulations, calculating the spectrum of each galaxy becomes particularly important. Conversely, rich observational data on galaxy spectra can also constrain theoretical models.

To date, most theoretical models have focused on describing galaxy physical properties in the optical band, partly because most galaxy surveys are conducted in the optical, and partly because dust absorption and re-radiation models are either too crude or computationally expensive. Galaxy formation semi-analytical models (SAMs) provide an excellent description of galaxy formation and evolution within the  $\Lambda$  cold dark matter ( $\Lambda$ CDM) framework, offering a series of physical properties and evolutionary histories for galaxies, such as stellar mass, bulge mass, bulge scale, gas mass, gas disk radius, star formation history (SFH), metal enrichment history, supernova feedback, and merger processes. Using these results—primarily the star formation and metal enrichment histories—combined with stellar population synthesis (SPS) models like the classic work of Bruzual & Charlot (2003), one can calculate the intrinsic (unattenuated) SED of a galaxy's starlight for a given initial mass function (IMF) and specified stellar population age and metallicity. If dust extinction is then incorporated, the galaxy's luminosity function from UV to optical wavelengths can be obtained. However, calculating the energy absorbed at corresponding wavelengths and how this energy is re-radiated in the infrared has become the key difficulty in successfully predicting galaxy multi-wavelength SEDs.

Currently, there are two approaches to predict galaxy multi-wavelength SEDs. The first involves considering the specific distribution and properties of galactic dust and calculating the radiative transfer process in detail. Dust radiative transfer (RT) models have made substantial progress in the past two decades. If the specific distributions of stars, dust, and gas in a galaxy are known, one can calculate dust absorption of radiation, dust heating, and subsequent emission to obtain the galaxy's SED from UV to infrared. However, unlike hydrodynamical simulations of galaxy formation, semi-analytical models cannot accurately provide specific galaxy geometric structures, so we need a corresponding modeling process, for which many excellent attempts have been made.

The second method uses empirical extinction curves to estimate the attenuated starlight SED and calculates the energy absorbed by dust, assuming this energy is completely re-radiated in the infrared band. One can then use observation-

ally derived or calibrated SED templates to describe the dust emission portion. Many SAMs in the past, based on empirical extinction curves and assuming optical depth depends on galaxy metallicity, viewing angle, and other parameters, have obtained UV-to-optical SEDs. Observationally, there is a relationship between galaxy luminosity in a given band and total infrared luminosity, and these templates establish a spectral library based on total infrared luminosity—that is, the total infrared luminosity determines the shape of the infrared SED. Both methods can predict galaxy multi-wavelength SEDs reasonably well. Fontanot et al. (2009) applied the first method to the MORGANA SAM and found that statistical results such as luminosity functions compared well with those from Silva et al. (1998), who used the GRASIL RT method.

The goal of this paper is to predict luminosity functions from far-ultraviolet to far-infrared using SAMs. To this end, we use the L-Galaxies semi-analytical model to obtain the intrinsic luminosity distribution of galaxies (without dust absorption and re-radiation) and employ two different models to simulate dust extinction and re-radiation. In the first model, we use the starduster machine learning model, based on SKIRT radiative transfer simulations, to generate multi-wavelength SEDs. This model uses machine learning methods to reduce computational cost while achieving good agreement with observational data. In the second model, we use empirical dust extinction curves in the UV and optical bands and SED templates for the infrared portion to predict complete multi-wavelength luminosity functions as an empirical model for comparison with starduster. Section 2 introduces the semi-analytical model we use and our methods for calculating extinction and dust re-radiation. Section 3 presents the luminosity functions in different bands and comparisons with observations. Sections 4 and 5 provide discussion and summary, respectively.

## 2.1 Galaxy Formation and Stellar Population Synthesis Model

We use the 2015 release of the L-Galaxies semi-analytical model for galaxy formation. L-Galaxies includes many evolutionary processes such as gas radiative cooling, star formation, supernova feedback, AGN feedback, galaxy mergers, metal enrichment in the interstellar medium (ISM) and intracluster medium (ICM), and stellar population evolution. Here we only briefly describe the physical processes and parameters used in the model; details can be found in the series of works on L-Galaxies.

The L-Galaxies model is built upon dark halo merger trees from large-scale N-body cosmological simulations. First, a certain proportion of baryonic matter is assigned to each collapsed dark matter halo, which varies with redshift and halo mass considering the effects of cosmic reionization. These baryons are then shock-heated to the virial temperature as they collapse with the dark matter, subsequently cooling radiatively and falling to the center of the dark halo potential well to form a cold gas disk. The cold gas disk provides fuel for star formation. Supernovae from massive stars release enormous energy and heavy

elements into the surrounding medium. This energy can reheat cold gas and may eject some gas to the outskirts of the halo, which will later cool and fall back. The supermassive black hole at the galaxy center grows primarily through accretion of cold gas during mergers and through static accretion of hot gas, releasing energy that can suppress hot gas cooling. This form of AGN feedback ultimately reduces star formation in massive galaxies. When satellite galaxies enter the virial radius of the central galaxy, tidal forces strip hot gas, cold gas, and stars, while ram pressure stripping can also remove some gas. These environmental effects suppress star formation in satellite galaxies, particularly in massive groups and clusters. Additionally, as dark matter halos merge, their corresponding galaxies also merge after a certain time delay. If a subhalo is completely disrupted, its galaxy will merge into the central galaxy after a dynamical friction time, triggering a starburst and producing a bulge at the galaxy center. Furthermore, if a galaxy disk becomes large enough to be dynamically unstable, the galaxy will also form a bulge through long-term evolution.

Stellar population synthesis models are crucial components of galaxy formation theory because they connect predicted stellar masses, ages, and metallicities to observable radiation at various wavelengths. In this paper, we adopt the Bruzual & Charlot (2003) stellar population synthesis model. For each galaxy, we divide its stellar component into disk and bulge, tracking stellar mass at different ages and metallicities. We then convolve this distribution with the SPS model to obtain the galaxy's intrinsic SED.

In this work, we apply L-Galaxies to the dark halo merger trees from the Millennium Simulation. The Millennium Simulation is a large-scale pure dark matter N-body simulation that tracks the evolution of dark matter in a standard  $\Lambda$ CDM cosmology within a cubic volume of side length  $500 h^{-1}$  Mpc (Hubble constant  $H_0 = h \times 100 \text{ km s}^{-1} \text{ Mpc}^{-1}$ ). The cosmological parameters are:  $\Omega = 0.272$ ,  $\Omega_\Lambda = 0.728$ , Hubble constant  $H_0 = 70.4 \text{ km s}^{-1} \text{ Mpc}^{-1}$ , using the Chabrier (2003) IMF.

## 2.2 Machine Learning Model with Dust Radiative Transfer

The machine learning model starduster uses results from semi-analytical models such as star formation histories, given galaxy geometric parameters, and employs the SKIRT radiative transfer code to simulate the physical processes of dust attenuation and re-radiation, generating training data for the neural network. It can then predict galaxy multi-wavelength SEDs based on galaxy geometric parameters and star formation histories. Since semi-analytical models cannot accurately provide internal galaxy structures, we assume an idealized geometry consisting of a disk, a bulge, and a dust disk. For radiative transfer simulations, the galaxy density distribution is given by the following parametric forms:

$$\begin{aligned}\rho_{\text{disk}}(r, z) &\propto \exp\left(-\frac{r}{r_{\text{disk}}}\right) \text{sech}^2\left(\frac{z}{h_{\text{disk}}}\right) \\ \rho_{\text{bulge}}(r, z) &\propto \exp\left[-\left(\frac{\sqrt{r^2 + z^2}}{r_{\text{bulge}}}\right)^{1/n_s}\right] \\ \rho_{\text{dust}}(r, z) &\propto \exp\left[-\left(\frac{\sqrt{r^2 + z^2}}{r_{\text{dust}}}\right)^{1/n_s}\right]\end{aligned}$$

where  $r$  and  $z$  are polar coordinates,  $\rho_{\text{disk}}$ ,  $\rho_{\text{bulge}}$ , and  $\rho_{\text{dust}}$  are the density distributions of the galaxy disk, bulge, and dust disk, respectively,  $r_{\text{disk}}$ ,  $r_{\text{bulge}}$ , and  $r_{\text{dust}}$  are the radii of the disk, bulge, and dust disk,  $h_{\text{disk}}$  and  $h_{\text{dust}}$  are the heights of the galaxy disk and dust disk,  $n_s$  is the Sérsic index, and  $q$  and  $b$  are appropriate parameters corresponding to the effective radius of the dust disk.

Dust mass can be obtained through additional dust evolution models or from observed dust-to-metal ratios. In this paper, we adopt the assumption from Lacey et al. (2016) that dust mass  $M_{\text{dust}}$  is proportional to the metal mass in cold gas  $M_{\text{metal-cold-gas}}$ , i.e.,  $M_{\text{dust}} = 0.334 \times M_{\text{metal-cold-gas}}$ . The dust mass from this model as a function of galaxy stellar mass  $M_*$  is almost consistent with the median result at  $z = 0$  from Popping et al. (2017), who used a semi-analytical simulation to track dust evolution [Figure 1: see original paper]. This indicates our dust mass assumption is reasonable. Additionally, since dust is dispersed in cold gas, we assume the dust disk radius  $r_{\text{dust}}$  is consistent with the cold gas half-mass radius obtained from the semi-analytical model. The physical results from the semi-analytical model plus dust mass and dust disk size parameters serve as inputs to the starduster machine learning model, allowing us to predict multi-wavelength SEDs.

## 2.3 Empirical Model

Our other model uses results from the semi-analytical model such as star formation histories, combined with empirical dust extinction curves, to predict the attenuated UV-to-optical SED. From this, we calculate the energy absorbed by dust, which is then assumed to be re-radiated in the infrared, combined with infrared SED templates to obtain the galaxy infrared luminosity function. We call this the empirical model, which serves as a comparison to starduster.

### 2.3.1 Dust Extinction

In this paper, we adopt parameterized dust extinction from previous works to obtain the attenuated SED. This extinction method combines the assumption of a uniform ISM from Devriendt et al. (1999) with the “two-component” model from Charlot & Fall (2000, hereafter CF2000). The optical depth of the interstellar medium in galaxy disks is assumed to vary with wavelength as:

$$\tau_{\text{ISM},\lambda} = (1+z)^{-1} \tau_{\text{ISM},\lambda_0} \left( \frac{\lambda}{5500\text{\AA}} \right)^{-s} \left( \frac{Z_{\text{gas}}}{Z_{\odot}} \right) \left( \frac{\langle N_H \rangle}{2.1 \times 10^{21} \text{atoms cm}^{-2}} \right) A_V$$

where the dust attenuation parameter is defined as the ratio between the attenuated luminosity  $L_{\lambda}$  and the intrinsic luminosity  $L_{\lambda}^0$ , i.e., the difference between the attenuated and intrinsic magnitudes  $m_{\lambda}$  and  $m_{\lambda}^0$ , typically denoted as  $A_{\lambda}$ :

$$A_{\lambda} = m_{\lambda} - m_{\lambda}^0 = -2.5 \log_{10} \left( \frac{L_{\lambda}}{L_{\lambda}^0} \right)$$

$A_V$  represents the dust attenuation parameter at wavelength 5500 Å. The mean hydrogen column density is defined using the gas fraction  $f_{\text{gas}}$ :

$$\langle N_H \rangle = 6.8 \times 10^{21} f_{\text{gas}} \text{atoms cm}^{-2} = 6.8 \times 10^{21} \frac{M_{\text{gas}}}{M_{\text{gas}} + M_{*}} \text{atoms cm}^{-2}$$

Some works have updated the mean hydrogen column density to be proportional to cold gas mass divided by the square of the gas scale:

$$\langle N_H \rangle = \frac{M_{\text{cold}}}{1.4 m_p \pi (a R_{\text{gas},d})^2}$$

where  $R_{\text{gas},d}$  is the half-mass radius of cold gas, 1.4 accounts for helium,  $m_p$  is the proton mass, and  $a = 1.68$  is chosen so that  $\langle N_H \rangle$  represents the mass-weighted mean column density of an exponential disk. Following Guiderdoni et al. (1987), the extinction curve in the optical depth calculation depends on gas metallicity  $Z_{\text{gas}}$ , based on interpolation between the solar neighborhood and the Large and Small Magellanic Clouds: for  $\lambda < 2000$  Å,  $s = 1.35$ ; for  $\lambda > 2000$  Å,  $s = 1.6$ . The solar metallicity extinction curve is taken from Cardelli et al. (1989).

Based on the CF2000 two-component model, young stars in birth clouds (BCs) experience additional attenuation. Stars younger than the finite lifetime of birth clouds (assumed to be  $10^7$  yr) are affected by a different mean vertical optical depth  $\tau_{\text{BC},\lambda}$  that varies with wavelength:

$$\tau_{\text{BC},\lambda} = \tau_{\text{ISM},\lambda_0} \left( \frac{\lambda}{5500\text{\AA}} \right)^{-1.3} \left( \frac{\langle N_H \rangle}{2.1 \times 10^{21} \text{atoms cm}^{-2}} \right) \mu$$

where  $\mu$  is given by a random Gaussian deviation with mean 0.3 and standard deviation 0.2, truncated at 0.1 and 1. Finally, to calculate actual dust extinction, each galaxy is assigned a random inclination angle  $i$ :

$$A_{\text{ISM},\lambda}(\theta) = -2.5 \log_{10} \left[ \frac{1 - \exp(-\tau_{\text{ISM},\lambda} \sec \theta)}{\tau_{\text{ISM},\lambda} \sec \theta} \right]$$

For young stars (age  $< 10^7$  yr), dust extinction uses:

$$A_{\text{BC},\lambda}(\theta) = -2.5 \log_{10} \left[ \frac{1 - \exp(-\tau_{\text{BC},\lambda} \sec \theta)}{\tau_{\text{BC},\lambda} \sec \theta} \right]$$

For old stars (age  $> 10^7$  yr), dust extinction uses the ISM formula. Additionally, since the SFH from L-Galaxies contains very few young stars, we do not consider birth clouds in this work.

### 2.3.2 Dust Re-radiation

As mentioned, after estimating the energy absorbed by dust, this energy is re-radiated in the infrared (neglecting scattering) according to energy conservation. Based on the assumption that total infrared luminosity determines the shape of the infrared spectrum, we can use infrared SED templates to describe the luminosity function in the dust emission bands.

There are two basic approaches to construct infrared spectral templates. The first uses numerical or analytical solutions of dust models and the standard radiative transfer equation to create template libraries, calibrated against observations of the nearby universe. This approach was pioneered by Desert et al. (1990) and subsequently developed by many researchers. Desert et al. (1990) proposed three main sources of dust radiation: polycyclic aromatic hydrocarbons (PAHs), very small grains, and large grains. Grains consist of graphite and silicate, with thermal properties determined by size distribution and thermodynamic state. Assuming large grains are near thermal equilibrium, their radiation can be described as a modified blackbody spectrum. Small grains and PAHs may exist in an intermediate state between thermal equilibrium and single-photon heating, are susceptible to temperature fluctuations, and have much broader radiation spectra than modified blackbody spectra. Detailed size distributions are modeled with free parameters calibrated by matching observational constraints such as extinction curves, observed infrared colors, and infrared spectra of local galaxies.

The second method directly uses observed SED templates of galaxies. These templates construct detailed SEDs based on published ISO (Infrared Space Observatory), IRAS (Infrared Astronomical Satellite), and NICMOS (Near Infrared Camera and Multi-Object Spectrometer) data, along with previously unpublished IRAC (Infrared Array Camera), MIPS (Multi-Band Imaging Photometer for Spitzer), and IRS (InfraRed Spectrograph) data, modeling the far-infrared SED based on single blackbodies with wavelength-dependent emissivity. Table 1 summarizes the wavelength coverage and infrared luminosity ranges for several different SED templates.

Figure 2 [Figure 2: see original paper] compares different templates for a given total infrared luminosity (solid black line for Chary & Elbaz 2001, dashed black line for Dale & Helou 2002, solid gray line for Rieke et al. 2009, dotted black line for Safarzadeh et al. 2016), along with 10 randomly selected SEDs from starduster simulations (colored solid lines). The starduster SEDs were randomly selected near specified total infrared luminosity values. Figure 2 shows that before 100  $\mu\text{m}$ , the three main radiation sources (PAHs, large grains, and small grains) are included, and differences in how each SED template treats these sources lead to variations in the SED before 100  $\mu\text{m}$ . Taking Rieke et al.'s template as an example, both PAH and near-infrared radiation (before  $\sim 17 \mu\text{m}$ ) are relatively low, becoming more pronounced at brighter total infrared luminosities. Brighter infrared luminosity means brighter UV, indicating active star formation, which is accompanied by PAH spectral features. This suggests that Rieke's template differs significantly from other templates in its treatment of star-forming galaxies in the infrared. For starduster, at  $\lambda < 10 \mu\text{m}$  it clearly overestimates the corresponding luminosity compared to other templates, underestimates it at 10–100  $\mu\text{m}$ , and is slightly higher than other templates at  $\lambda > 100 \mu\text{m}$ . This can be understood as starduster's dust temperature being slightly lower than the effective dust temperature set in the SED templates, since hotter dust components enhance the overall mid-infrared dust SED and help shift the radiation peak to shorter wavelengths.

### 3.1 Ultraviolet to Optical Bands

We first present the luminosity functions in the rest frame at  $z = 0$  from far-ultraviolet (FUV) to near-infrared (NIR). Figure 3 [Figure 3: see original paper] shows the luminosity functions for GALEX FUV and NUV, SDSS u, g, r, i, z bands, 2MASS Ks band, and total infrared as labeled.

Overall, the empirical model agrees very well with observational data, only slightly overestimating the number of faintest galaxies in GALEX FUV and NUV bands. The starduster model clearly overestimates galaxy numbers at the bright end in UV bands, apparently due to insufficient dust extinction, which is also evident in the infrared luminosity function where the total infrared luminosity is significantly lower than observed. The dust extinction in starduster is based on Trayford et al. (2020), so we compare the V-band (5500  $\text{\AA}$ ) extinction value as a function of dust surface density ( $\Sigma_{\text{dust}} = M_{\text{dust}} / (\pi r_{\text{dust}}^2)$ , where  $r_{\text{dust}}$  is the dust disk radius) with their simulated median values [Figure 4: see original paper]. If we view all galaxies edge-on, the extinction parameter distribution matches the simulation, indicating sufficient extinction, but this is obviously unrealistic. With random viewing angles, the extinction is slightly lower than the simulated values.

Note that starduster is slightly brighter than the unattenuated empirical model in Figure 3. This is because the two models differ in their treatment of stellar ages when inputting star formation histories into the population synthesis model, resulting in slightly different galaxy spectra. In short, L-Galaxies records

each galaxy's SFH as the stellar mass  $\{m_1, m_2, \dots\}$  at different ages  $\{t_1, t_2, \dots\}$ , while starduster adds an initial age  $\{t_0, t_1, t_2, \dots\}$  when calculating galaxy spectra, meaning a mass  $m_1$  of stars is uniformly distributed between ages  $t_0$ – $t_1$ , and so on. Compared to the empirical model's approach, this results in more young stars, making starduster somewhat brighter.

Nevertheless, starduster has more physically self-consistent IR luminosity functions than the empirical model because starduster's IR represents the energy intrinsically absorbed by dust, independent of galaxy inclination changes, providing more accurate physical interpretation. The empirical model's absorbed energy (i.e., total infrared luminosity) is inclination-dependent, as evident from equation (9).

### 3.2 Infrared Bands

This section presents infrared luminosity functions after dust re-radiation. Figures 5 [Figure 5: see original paper] and 6 show our model predictions for luminosity functions at  $z = 0$  in the rest frame for Spitzer IRAC 3.6, 4.5, 5.8, 8  $\mu$ m bands, JWST MIRI 11, 15, 21  $\mu$ m bands, Spitzer MIPS 24  $\mu$ m, Herschel PACS 70, 100, 160, 250, 350, 500  $\mu$ m bands, and JCMT 850  $\mu$ m band. The solid gray lines show starduster results, while other colored lines show empirical model results using different infrared SED templates.

In the empirical model for IRAC 3.6, 4.5, 5.8  $\mu$ m bands, using Chary et al.'s template agrees well with observations, only underpredicting faint galaxy numbers. Dale et al.'s template underestimates galaxy numbers overall at 3.6 and 4.5  $\mu$ m and slightly underpredicts the faint end at 4.5 and 8  $\mu$ m. At longer far-infrared wavelengths, the empirical model's SED templates perform similarly, matching observations well at intermediate and bright ends except for the faint end, while Dale et al.'s template overestimates galaxy numbers at 850  $\mu$ m overall. The small differences in luminosity functions from different infrared SED templates correspond to the SED differences shown in Figure 2. Taking Dale et al.'s template as an example, Figure 2 shows that for a given total infrared luminosity  $L_{\text{IR}} < 10^{11} L_{\odot}$ , the luminosity is lower at  $\lambda < 5 \mu$ m, corresponding to the underestimation of faint galaxy numbers at 3.6 and 4.5  $\mu$ m in Figure 5. At  $\lambda \sim 1000 \mu$ m, the luminosity is always slightly higher than other templates, corresponding to the overall overestimation of galaxy numbers at 850  $\mu$ m in Figure 6 [Figure 6: see original paper].

The starduster model's luminosity functions show overall trends consistent with observations. From Figure 2 and previous analysis, for a given total infrared brightness, starduster overestimates luminosity at  $\lambda < 10 \mu$ m, underestimates it at 20–100  $\mu$ m, and shows little difference from other templates at  $\lambda > 100 \mu$ m. Therefore, in the infrared luminosity functions (Figure 5), starduster is similar to other templates at IRAC bands, only slightly higher at the bright end. At JWST mid-infrared bands around 20  $\mu$ m, starduster's luminosity functions are always lower than templates. At 25–70  $\mu$ m, we can reasonably infer that star-

duster's luminosity functions remain lower than templates, but the gap narrows with increasing wavelength. At Herschel bands, starduster differs little from other templates, only being slightly lower at the knee. However, starduster's predictions deviate somewhat from observations at the faint end. At 850  $\mu$ m, starduster is similar to Dale's template, with slightly higher luminosity near  $\lambda \sim 1000 \mu$ m, corresponding to an overall overestimation of galaxy numbers compared to observations.

Guiderdoni et al. (1998) were the first to combine semi-analytical models with dust extinction and re-radiation modeling in the  $\Lambda$ CDM framework. In subsequent studies, Fontanot et al. (2007) combined the GRASIL model, whose advantage is that the dust re-radiation SED is self-consistently calculated based on assumed dust properties and the predicted radiation field. Devriendt et al. (1999) and Somerville et al. (2012) combined simple geometric models with dust infrared/submillimeter SED templates.

However, templates have disadvantages: (1) they are derived or calibrated from observations of the nearby universe, and (2) their shape depends on total infrared luminosity. This makes templates less applicable to high-redshift universes. If we continue to explore multi-wavelength functions of galaxies at high redshift and better understand which physical processes affect infrared spectral shapes, we can proceed in two ways: first, by combining radiative transfer models from hydrodynamical simulations such as SKIRT and SUNRISE; second, by applying templates with richer observational data covering higher redshifts and more galaxy types.

Baugh et al. (2005) found that semi-analytical models combined with GRASIL failed to reproduce sufficient numbers of bright submillimeter galaxies (SMGs). Therefore, they modified previous models to improve this: (1) adopting constant star formation timescales to produce more gas in high-redshift galaxies, and (2) implementing efficient starburst modes in major and minor mergers. However, Somerville et al. (2001) noted that this would produce many bright starburst galaxies at high redshift. Additionally, Baugh et al. adopted a top-heavy IMF in starbursts, which would produce more UV, metals, and dust per unit mass of star formation. The results showed that reproducing SMG number densities required combining these modifications to simultaneously reproduce UV and optical luminosity functions at high redshift. Lacey et al. (2008, 2010) also argued that a top-heavy IMF was needed to reproduce Spitzer mid-infrared luminosity functions.

In our work, we do not adopt a variable IMF but use the standard Chabrier (2003) IMF, which can reproduce the total infrared luminosity function but underestimates faint galaxy numbers in infrared bands. We suspect this is related to insufficient simulation resolution, which leads to an underabundance of low-mass galaxies and consequently insufficient faint-end galaxy numbers. Improving simulation resolution would allow semi-analytical models to better capture the formation and evolution of faint-end galaxies, yielding more accurate predictions.

Cosmological hydrodynamical simulations themselves often do not include dust treatment (e.g., EAGLE). Camps et al. (2016) and Trayford et al. (2017) added dust post-processing to simulation results, predicting galaxy UV-to-submillimeter luminosities after considering dust absorption, scattering, and re-radiation, and studied optical colors at low redshift and FIR colors. Baes et al. (2019) combined the SKIRT radiative transfer model with EAGLE and found that EAGLE underestimates dust attenuation in the FUV band, possibly due to constant dust-to-metal ratios or overly simplistic spherical geometry assumptions for galaxies and dust, as well as limitations in subgrid treatment of star-forming regions in the EAGLE-SKIRT post-processing.

In this paper, starduster also adopts a constant dust-to-metal ratio. Although the dust-to-stellar mass distribution matches simulations, it similarly underestimates extinction, consistent with Baes et al. (2019). Li et al. (2019) used the SIMBA hydrodynamical simulation to predict dust evolution in galaxies from  $z = 0$  to 6, finding good agreement with observations for the dust mass function at  $z = 0$ . They found that galaxy dust-to-metal ratios are not constant, with dust-to-gas ratios positively correlated with metallicity in star-forming galaxies but not in quenched galaxies. We speculate that if we could track dust formation and destruction processes in semi-analytical models, the predicted dust masses might better match observations. Popping et al. (2017) used a semi-analytical model to track dust evolution and obtained results showing that dust-to-metal ratios are closely related to galaxy properties and gas states. Therefore, we need to further improve the model to obtain more accurate dust mass predictions.

Furthermore, Salim et al. (2020) noted that simple geometric assumptions produce steep dust attenuation curves, while complex geometries with clumpy dust produce flatter curves. We suspect that changing the dust density distribution to isotropic might improve the final extinction results compared to current assumptions. Moreover, in real galaxies, galaxy and dust geometries are not ideal spherically symmetric structures, and limited spatial resolution leads to systematic errors in our description of interstellar medium distribution.

In summary, so far we can obtain consistent results with observations from UV to infrared in multi-wavelength SED modeling, but we face some difficulties in reproducing the faint-end numbers of SMGs.

## 5 Summary and Outlook

In this work, we demonstrate how to predict the spectral energy distribution of galaxies from far-ultraviolet to far-infrared at  $z = 0$ . Our predictions are based on the L-Galaxies semi-analytical model of galaxy formation, which includes gas cooling, star formation, supernova feedback, metal enrichment, AGN feedback, and other physical processes, from which we obtain galaxy physical properties such as star formation histories, metal enrichment histories, bulge/disk scales, and masses. We first use the Bruzual & Charlot (2003) spectral library to predict galaxy intrinsic spectra, then employ two simple but physically clear

methods to predict galaxy luminosity functions from UV to infrared in the rest frame at  $z = 0$  after dust extinction.

In the starduster machine learning model, we assume a fixed dust-to-metal gas mass ratio equal to the solar value to obtain dust mass [Figure 1: see original paper]. Assuming dust is dispersed in gas, we take the cold gas half-mass radius as the dust disk radius as part of the model input. Considering the physical characteristics of dust attenuation and re-radiation, we simulate dust radiative transfer to predict multi-wavelength SEDs based on galaxy geometric parameters and star formation histories.

In the empirical model, based on the CF2000 two-component model, young stars are covered by dense birth clouds while older stars are in more diffuse ISM, meaning dust attenuation depends on stellar age. Additionally, following Guiderdoni et al. (1987), we make dust optical depth depend on galaxy metallicity and mean hydrogen column density, obtaining attenuated UV-to-optical luminosity functions. We assume energy absorbed by dust is completely re-radiated in the infrared, and since total infrared luminosity determines infrared SED shape, we use various infrared spectral templates to predict infrared luminosity functions.

Figure 2 compares the empirical model's SED templates at given total infrared luminosities, with differences mainly in the near-infrared due to different treatments of radiation components. Figure 2 also shows SEDs randomly selected from starduster predictions at given total infrared luminosities, which overestimate luminosity at  $\lambda < 10 \mu\text{m}$ , underestimate it at  $10\text{--}100 \mu\text{m}$ , and are slightly higher at  $\lambda > 100 \mu\text{m}$  compared to templates—effectively shifting rightward at  $\lambda > 10 \mu\text{m}$ . These differences affect infrared luminosity functions as shown in Figures 5–6.

We find that starduster requires enhanced extinction to match UV observations [Figure 3: see original paper]. Since starduster's dust extinction curve data is similar to Trayford et al. (2020), we compare their V-band extinction values as a function of dust surface density [Figure 4: see original paper], again finding starduster needs enhanced extinction. The consequence of insufficient extinction is evident in its total infrared luminosity predictions being systematically low [Figure 3: see original paper]. We will improve the dust distribution in future work, which should improve dust extinction. The empirical model performs well in UV and optical bands, reproducing these luminosity functions [Figure 3: see original paper].

For infrared luminosity functions, the empirical model's total infrared luminosity combined with different infrared SED templates shows little variation across infrared bands except for insufficient faint-end galaxy numbers. Notably, Chary et al.'s template matches observations relatively well across infrared bands [FIGURE:5–6]. Although starduster underestimates total infrared luminosity, this does not affect its overall infrared trends. Apart from similarly underestimating faint-end galaxy numbers, it can reasonably predict galaxy number densities at the knee and bright end across infrared bands [FIGURE:5–6]. In future

work, we will further improve both the semi-analytical model and starduster's extinction component to more accurately predict galaxy multi-wavelength SEDs.

## Acknowledgments

We thank the referee for valuable suggestions that significantly improved the paper. We also thank Yi-Sheng Qiu, Yao-Xin Chen, and Xing-Pao Suo for many helpful discussions.

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