

Monte Carlo Simulation of a Globular Cluster

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Abstract

The goal of this project is to simulate a Globular Cluster population using Monte Carlo methods. This is done to visualize the properties of main-sequence and white dwarf stars. Using this method, the mass distribution, star temperature, and luminosity relationships can be observed from the simulation for different cluster ages. From these values, the percentage of white dwarfs, main-sequence, neutron stars, and black holes can be obtained, comparing them to their respective ages. It can also be determined the MSTO, or main-sequence turn-off, for each age. From this, it can then be analyzed, how sensitive the main sequence track is to the change of variables, in particular, the minimum star mass. This is what we hope to observe.

1 Introduction

Based on the age and mass of stars, a wide range of properties can be observed. With this in mind, we can perform a simulation using the Initial Mass Function (IMF) to generate a population of stars in order to estimate these aforementioned properties, such as luminosity, effective temperature (T_{eff}), and cooling times.

2 Methodology

Using a population of $N = 1000$ stars using a random sampling method based on the IMF. The conditions, inputs, and guidelines for the simulation can be seen in the following.

1. Minimum and maximum masses: $0.1 M_{\odot}$ to $100 M_{\odot}$.
2. Cluster age, t_{cluster} : 8, 10, and 12 Gyr.
3. Born age, t_{born} , according to a constant SFR with a burst of $\Delta t = 1.0$ Gyr.
4. Luminosity, radius, and T_{eff} computed using standard stellar models.
5. Main sequence mass, M_{ms} , following the IMF of Salpeter (1995) with standard slope $\alpha = -2.35$ and a range of masses

$0.1 < M/M_{\odot} \leq 100$ with a relationship of:

$$\phi(M) = (M/M_{\odot})^{\alpha}$$

6. For main sequence luminosities, from Salaris & Cassisi (2005):

$$\frac{L}{L_{\odot}} = \begin{cases} 0.23M^{2.3} & \text{if } M \leq 0.43M_{\odot} \\ M^4 & \text{if } 0.43 < M \leq 2M_{\odot} \\ 1.4M^{3.5} & \text{if } 2 < M \leq 5M_{\odot} \\ 32000M & \text{if } M > 5M_{\odot} \end{cases}$$

7. For the main sequence life-time:, t_{MS} , from Iben & Laughlin (1989):

$$t_{\text{MS}} = 10 \left(\frac{M_{\text{MS}}}{M_{\odot}} \right)^{-3.5} \text{ Gyr}$$

8. Progenitors, or stars with $M < 10M_{\odot}$ evolve into white dwarfs. Stars with $M > 10M_{\odot}$ form neutron stars or black holes.

9. White dwarf mass, m_{WD} , from Iben & Laughlin (1989):

$$M_{\text{WD}} = 0.49 \exp(0.095M_{\text{MS}})$$

10. White dwarf cooling age:

$$t_{\text{cool}} = t_{\text{cluster}} - t_{\text{born}} - t_{\text{MS}}$$

11. White dwarf cooling model follows the Mestel law: $t_{\text{cool}} = CL^{-5/7}$, which gives

$$-\log \left(\frac{L}{L_{\odot}} \right) = \frac{7}{5} \log(t_{\text{cool}}) + 3$$

12. Effective temperature from the Stefan-Boltzmann law:

$$L = 4\pi R^2 \sigma T_{\text{eff}}$$

13. Main-sequence star radii:

$$R_{\text{MS}}/R_{\odot} = \begin{cases} 100.66 \log(M/M_{\odot}) + 0.05 & \text{if } M \geq 1.12M_{\odot} \\ M/M_{\odot} & \text{if } M \leq 1.12M_{\odot} \end{cases}$$

14. White dwarf radii:

$$R_{\text{WD}}/R_{\odot} = C \left(\frac{M_{\text{WD}}}{M_{\odot}} \right)^{1/3}, C = 0.0101$$

15. $L = 3.827 \times 10^{26} \text{ W}$

16. $R = 6.969 \times 10^8 \text{ m}$.

The simulation is implemented in Python, and the core code is appended in appendix A, below.

3 Results

3.1 Mass Distribution

The stellar mass distribution can be seen below for 10 Gyrs. A similar graph could be generated for other values of age; however, they all follow the same distribution. It can be observed that most stars have low masses, consistent with the IMF.

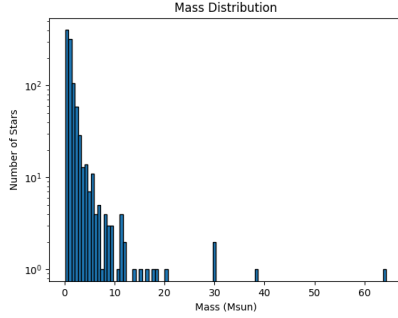


Figure 1: Mass distribution of simulated stars for 10 Gyrs (logarithmic scale).

3.2 Star Formation Ages (t_{born})

The t_{born} distribution for 10 Gyrs. can be seen below. Again, this can also be generated for different ages. However, for the sake of brevity, an age of 10 Gyrs is shown below, while other ages produce a similar result. It can be seen that random birth ages are uniformly distributed over the lifetime of the cluster.

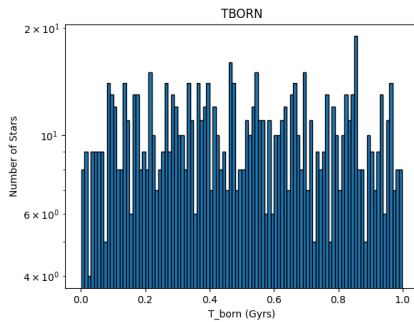


Figure 2: Distribution of star formation ages for 10 Gyrs. (t_{born}).

3.3 Temperature vs Luminosity

The relationship between T_{eff} and luminosity for main-sequence and white dwarf stars is

shown in the following figures for 8, 10, and 12 Gyrs., respectively.

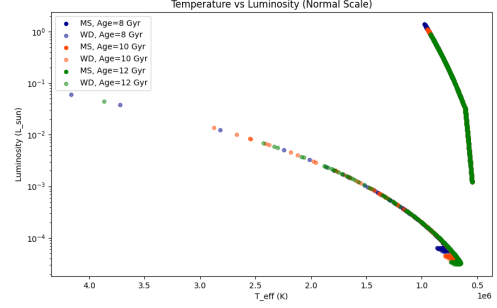


Figure 3: Temperature (T_{eff}) vs Luminosity for main sequence (blue) and white dwarf (orange) stars for 8 Gyrs.

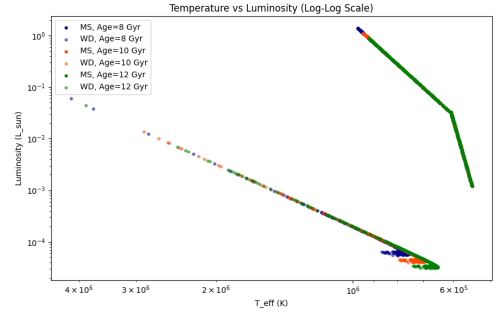


Figure 4: Log-log plot of T_{eff} vs Luminosity for 12 Gyrs.

3.4 Temperature and Luminosity with Noise

The following figures incorporate a 10% Gaussian noise, providing a visualization of the scatter in observed stellar populations. The following figures are again generated for 8, 10, and 12 Gyrs.

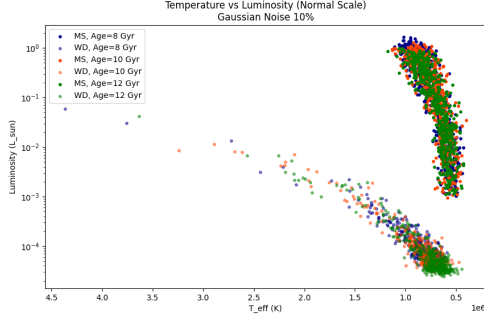


Figure 5: Noisy temperature (T_{eff}) vs Luminosity for main sequence (blue) and white dwarf (orange) stars for 8 Gyrs.

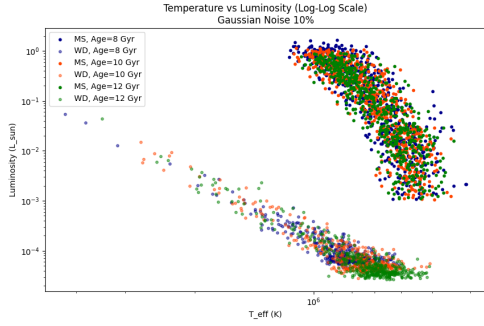


Figure 6: Temperature (T_{eff}) vs Luminosity for main sequence (blue) and white dwarf (orange) stars with 10% Gaussian noise using log-log axis for 8 Gyrs.

3.5 Percentage of WD, MS, NS, and Black Holes per age

Cluster Age (Gyr)	8 Gyr	10 Gyr	12 Gyr
Percentage of Black Holes/Neutron Stars	1.7%	1.7%	1.7%
Percentage of White Dwarfs	36.4%	40.3%	43.9%

Table 1: Percentage of Black Holes/Neutron Stars and White Dwarfs for Different Cluster Ages

3.6 Main-sequence Turn-off and Sensitivity (MSTO)

The main-sequence turn-off refers to the point at which MS stars begin to leave the MS, normally due to fuel exhaustion. We can modify the code slightly in order to find this point, while simultaneously running the simulation for multiple values of minimum star masses to analyze how sensitive the main

sequence track is to a change in variables. Table 2: MSTO Properties for $\text{min_mass} = 0.1 M_{\odot}$:

Age (Gyr)	MSTO Mass (M_{\odot})	T_{eff} (K)	Luminosity (L_{\odot})
8	1.03	5843.82	1.11
10	0.96	5636.55	0.83
12	0.43	3803.18	0.04

Table 3: MSTO Properties for $\text{min_mass} = 0.3 M_{\odot}$:

Age (Gyr)	MSTO Mass (M_{\odot})	T_{eff} (K)	Luminosity (L_{\odot})
8	0.91	5496.08	0.68
10	0.78	5098.98	0.37
12	0.81	5192.38	0.43

Table 4: MSTO Properties for $\text{min_mass} = 0.5 M_{\odot}$:

Age (Gyr)	MSTO Mass (M_{\odot})	T_{eff} (K)	Luminosity (L_{\odot})
8	0.72	4902.14	0.27
10	0.58	4405.37	0.12
12	0.53	4183.75	0.08

The tables above give numerical values for the relationship the minimum mass has with parameters such as MSTO, effective temperature, and luminosity. We see that there is an inverse relationship between the minimum star mass and the main sequence track in general. We can also plot these values to obtain visual representations of what is happening here:

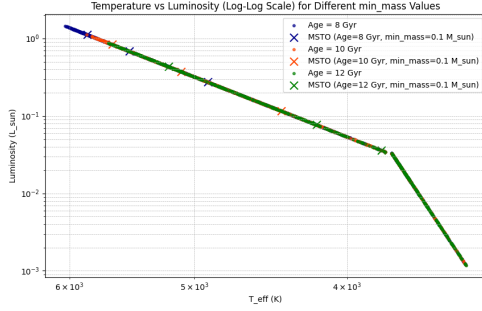


Figure 7: Temperature (T_{eff}) vs Luminosity and MSTOs for different values of minimum mass

We can see above the difference in the MSTOs as the age increases, as well as the difference in T_{eff} and Luminosity. It should be noted that because of the scale, the difference between the effective temperature and luminosity is not as apparent as when the graphs are separated. I have not included the separate graphs as we have numerical data and for the sake of brevity.

4 Conclusions

Throughout the various simulations, we were able to see the various mass distributions of simulated stellar systems, the relationships between effective temperature and luminosity over certain values of years, what these systems would look like with a 10% Gaussian noise, and finally were able to analyze the effects that the minimum solar mass has on the main sequence and Main-sequence Turn-off values.

While most of the values and simulations above seem to be accurately modeling the expected results of these systems, there are some values that should be addressed in this report. First of all, the values in section 3.6 are mostly correct, following an inverse trend with time. However, in table 3, there seems to be an anomaly where the values for MSTO, T_{eff} , and Luminosity drop unexpectedly. From what we expect, this should not be the case. We should see a consecutive decrease between the three.

While we could be attribute this to many things, this could be due to inconsistencies in the initial mass function (IMF), or perhaps something to do with a large distribution of

low-mass stars. Because MSTO is largely impacted by stars with greater mass, this could potentially impact our results. In fact, we can see a more desirable result when we plot a population of just $N = 10$:

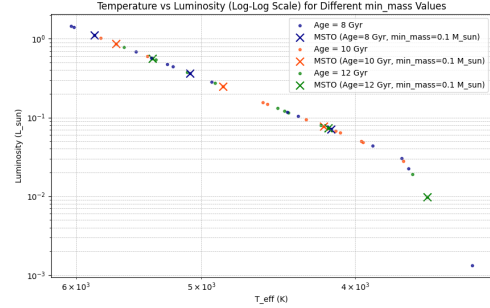


Figure 8: Temperature (T_{eff}) vs Luminosity and MSTOs for $N = 10$

This could signify that there might be an over-population of smaller-mass stars skewing the MSTO points.

Besides this being said, we have managed to produce the desired results for our stellar simulation. From here, future steps could be taken to expand on the basis we have formed. Some examples could be adding realistic error to the luminosity and temperature, computing the luminosity function, building a spatial distribution of the objects in the cluster, or even adding a binary population. Along with all of these things come many more possibilities, made possible by the flexibility of our software.

However, we can simply add a small amount of code to model a 2d HR-Diagram to visualize a Density Map using the Seaborn library. This gives us a beautiful looking graph:

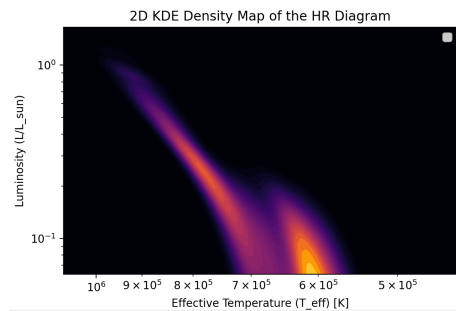


Figure 9: Temperature (2D HR-Diagram)

A Appendix: Python Code

```
182 import numpy as np
183 import matplotlib.pyplot as plt
184 import seaborn as sns
185
186
187 np.random.seed(9)
188
189 # Create variables
190 N = 1000 # Number of objects
191 # t_cluster = 10 # Cluster age
192 t_born = [] # Born age
193 t_ms = [] # Main Sequence Temperature
194 t_cool = [] # T_cool temperatures
195 dt = 1 # Timestep
196 alpha = 2.35 # IMF constant
197 min_mass = 0.1 # Minimum Star Mass
198 max_mass = 100 # Maximum Star Mass
199 mass_ms = [] # Main Sequence Mass Array
200 mass_wd = [] # White Dwarf Mass Array
201 num_wd = 0 # White Dwarf Count
202 num_bh = 0 # Black Holes and Neutron Star count
203 lum_ms = [] # Main Sequence Luminosity Array
204 lum_wd = [] # White Dwarf Luminosity Array
205 t_eff = [] # Main Sequence Effective Temperature
206 t_eff_wd = [] # White Dwarf Effective Temperature
207 R_ms = [] # Main Sequence Radius
208 R_wd = [] # White Dwarf Radius
209 sigma = 5.67e-8 # W/m^2 K^4
210 C = 0.0101 # Constant
211 R_solar = 6.969e8 # Solar Radius
212 L_solar = 3.827e26 # Solar Luminosity
213
214
215
216 # Define cluster ages
217 cluster_ages = [8, 10, 12]
218
219 # Store results for different cluster ages
220 all_lum_ms = [] # Main sequence luminosities
221 all_t_eff = [] # Main sequence effective temperatures
222 all_lum_wd = [] # White dwarf luminosities
223 all_t_eff_wd = [] # White dwarf effective temperatures
224
225 # Simulate for each cluster age
226 for t_cluster in cluster_ages:
227
228     np.random.seed(9) # Ensure reproducibility for each age
229
230     # Initialize lists for combined graphs
231     mass_ms, t_ms, t_born, t_cool = [], [], [], []
232     lum_ms, lum_wd, t_eff, t_eff_wd = [], [], [], []
233     num_wd, num_bh = 0, 0
234
235     # Monte Carlo Simulation
236     while len(mass_ms) < N:
237
238         # Generate random number for comparison between 1 and 0
239         rand_y = np.random.uniform(0,1)
240
241         # Generate IMF with random mass vector between min-max mass
242         rand_mass = np.random.uniform(min_mass, max_mass)
```

```

243     mass_i = (rand_mass)**(-alpha) # Use mass_i as the probability function
244     of acceptance
245
246
247     # Accept Reject Method
248     if rand_y < mass_i:
249         # ACCEPT
250         mass_ms.append(rand_mass) # Accept the random mass in between min
251 and max, not mass_i
252     else:
253         # REJECT
254         continue
255
256
257 # Create T_ms and T_i arrays
258 for i in range(N):
259     # Calculate t_ms
260     t_msi = 10 * mass_ms[i] ** -3.5
261     t_ms.append(t_msi)
262
263     # Calculate t_born
264     t_i = dt * np.random.uniform(0, 1)
265     t_born.append(t_i)
266
267     # Calculate t_cool
268     t_cool_i = t_cluster - t_born[i] - t_ms[i]
269     t_cool.append(t_cool_i)
270
271 # Finding luminosity and temperature, etc. for MS and WD
272 for i in range(N):
273
274     mass = mass_ms[i]
275
276     # MAIN SEQUENCE CONDITIONS
277     if t_cool[i] <= 0:
278         # Calculate Luminosity based on mass ranges
279         if mass > 55:
280             lum_i = 32000 * mass
281         elif 2 < mass <= 55:
282             lum_i = 1.4 * mass ** 3.5
283         elif 0.43 < mass <= 2:
284             lum_i = mass ** 4
285         elif mass <= 0.43:
286             lum_i = 0.23 * mass ** 2.3
287         lum_ms.append(lum_i)
288
289     # Main Sequence Radius
290     if mass >= 1.12:
291         R_i = 10 ** (0.66) * np.log(mass) + 0.5
292     else:
293         R_i = mass
294     R_ms.append(R_i)
295
296     # Main Sequence Effective Temperature
297     t_eff_i = (lum_i * L_solar / (4 * np.pi * R_i**2 * R_solar * sigma))
298 ** (1 / 4)
299     t_eff.append(t_eff_i)
300
301     # print(f"mass[{i}] = {mass}, t_cool[{i}] = {t_cool[i]}, lum[{i}] =
302 {lum_i}, R[{i}] = {R_i}, T_eff[{i}] = {t_eff_i}")
303
304
305     # WHITE DWARF CONDITIONS

```



```

306     elif t_cool_i > 0:
307         if mass_ms[i] < 10:
308             num_wd += 1 # White Dwarf
309
310             # White Dwarf Mass
311             mass_wd_i = 0.49 * np.exp(0.095 * mass_ms[i])
312             mass_wd.append(mass_wd_i)
313
314             # White Dwarf Radius
315             R_wd_i = C / mass_wd_i**(1/3)
316             R_wd.append(R_wd_i)
317
318             # White Dwarf Luminosity
319             lum_wd_i = 10**(-3) / t_cool[i]**(7/5)
320             lum_wd.append(lum_wd_i)
321
322             # White Dwarf T_eff
323             t_eff_wd_i = (lum_wd_i * L_solar / (4 * np.pi * R_wd_i**2 *
324 R_solar * sigma)) ** (1 / 4)
325             t_eff_wd.append(t_eff_wd_i)
326
327             # Black Hole or Neutron Star
328         elif mass_ms[i] > 10:
329             num_bh += 1 # Black Hole or Neutron Star
330
331     # Store results for this cluster age
332     all_lum_ms.append(lum_ms)
333     all_t_eff.append(t_eff)
334     all_lum_wd.append(lum_wd)
335     all_t_eff_wd.append(t_eff_wd)
336
337     print(f'Number of Black Holes/Neutron Stars for Age: {t_cluster} = {num_bh}
338 ')
339     print(f'Number of Black White Dwarfs for Age: {t_cluster} = {num_wd}')
340
341
342
343     # -----
344     # Individual Plots:
345     # Un-comment for individual plots
346     # -----
347
348     # # Create Gaussian Noise Main Sequence
349     # lum_noisy = lum_ms * (1 + np.random.normal(0, 0.1, size=len(lum_ms)))
350     # temp_noisy = t_eff * (1 + np.random.normal(0, 0.1, size=len(t_eff)))
351
352     # # Create Gaussian Noise White Dwarf
353     # lum_wd_noisy = lum_wd * (1 + np.random.normal(0, 0.1, size=len(lum_wd)))
354     # temp_wd_noisy = t_eff_wd * (1 + np.random.normal(0, 0.1, size=len(
355 t_eff_wd)))
356
357     # # Debug, Masses from largest to smallest
358     # # sorted_arr = sorted(mass_ms, reverse=True)
359     # # print("Sorted array from largest to smallest:", sorted_arr)
360
361     # # Print Number of Black Holes and Neutron Stars, as well as White Dwarfs
362     # print(f"Number of Black Holes or Neutron Stars: {num_bh}")
363     # print(f"Number of White Dwarfs: {num_wd}")
364
365     # # Plot Original Mass
366     # plt.hist(mass_ms, bins=100, log=True, edgecolor='black')
367     # plt.xlabel('Mass (Msun)')
368     # plt.ylabel('Number of Stars')

```

```

369 # plt.title('Mass Distribution')
370 # plt.show()
371
372 # # Plot t_born
373 # plt.hist(t_born, bins=100, log=True, edgecolor='black')
374 # plt.xlabel('T_born (Gyrs)')
375 # plt.ylabel('Number of Stars')
376 # plt.title('TBORN')
377 # plt.show()
378
379 # # Plot Main Sequence Luminosity vs T_eff
380 # plt.scatter(t_eff, lum_ms, color='#00008B')
381
382 # # Plot White Dwarf Luminosity vs T_eff_wd
383 # plt.scatter(t_eff_wd, lum_wd, color='#FFA500')
384 # plt.yscale('log')
385 # plt.xlabel('T_eff')
386 # plt.ylabel('Luminosity')
387 # plt.title('Plot of Temperature vs Luminosity')
388 # plt.gca().invert_xaxis()
389 # plt.show()
390
391 # # Plot White Dwarf / Main Sequence Luminosity vs T_eff_wd LOG-LOG
392 # plt.scatter(t_eff, lum_ms, color='#00008B')
393 # plt.scatter(t_eff_wd, lum_wd, color='#FFA500')
394 # plt.yscale('log')
395 # plt.xscale('log')
396 # plt.xlabel('T_eff')
397 # plt.ylabel('Luminosity')
398 # plt.title('Plot of Temperature vs Luminosity')
399 # plt.gca().invert_xaxis()
400 # plt.show()
401
402 # # Plot with 10% Gaussian Noise
403 # plt.scatter(temp_noisy, lum_noisy, s=2, color='#00008B')
404 # plt.scatter(temp_wd_noisy, lum_wd_noisy, s=2, color='#FFA500')
405 # plt.yscale('log')
406 # plt.xlabel('T_eff')
407 # plt.ylabel('Luminosity')
408 # plt.title('Plot of Temperature vs Luminosity')
409 # plt.gca().invert_xaxis()
410 # plt.show()
411
412 # # Plot with 10% Gaussian Noise LOG-LOG
413 # plt.scatter(temp_noisy, lum_noisy, s= 2, color='#00008B')
414 # plt.scatter(temp_wd_noisy, lum_wd_noisy, s = 2, color='#FFA500')
415 # plt.yscale('log')
416 # plt.xscale('log')
417 # plt.xlabel('T_eff')
418 # plt.ylabel('Luminosity')
419 # plt.title('Plot of Temperature vs Luminosity')
420 # plt.gca().invert_xaxis()
421 # plt.show()
422
423 #-----
424 # Combined Plots
425 #-----
426
427 # Plot Main Sequence and White Dwarfs for all ages (normal scale)
428 plt.figure(figsize=(10, 6))
429 colors = ['#00008B', '#FF4500', '#008000'] # Colors for ages
430 for i, age in enumerate(cluster_ages):
431     plt.scatter(all_t_eff[i], all_lum_ms[i], s=20, color=colors[i], label=f'MS,

```

```

432     Age={age} Gyr')
433     plt.scatter(all_t_eff_wd[i], all_lum_wd[i], s=20, color=colors[i], alpha
434     =0.5, label=f'WD, Age={age} Gyr')
435
436 plt.yscale('log')
437 plt.xlabel('T_eff (K)')
438 plt.ylabel('Luminosity (L_sun)')
439 plt.title('Temperature vs Luminosity (Normal Scale)')
440 plt.gca().invert_xaxis()
441 plt.legend()
442 plt.show()
443
444 # Plot Main Sequence and White Dwarfs for all ages (log-log scale)
445 plt.figure(figsize=(10, 6))
446 for i, age in enumerate(cluster_ages):
447     plt.scatter(all_t_eff[i], all_lum_ms[i], s=10, color=colors[i], label=f'MS,
448     Age={age} Gyr')
449     plt.scatter(all_t_eff_wd[i], all_lum_wd[i], s=10, color=colors[i], alpha
450     =0.5, label=f'WD, Age={age} Gyr')
451 plt.xscale('log')
452 plt.yscale('log')
453 plt.xlabel('T_eff (K)')
454 plt.ylabel('Luminosity (L_sun)')
455 plt.title('Temperature vs Luminosity (Log-Log Scale)')
456 plt.gca().invert_xaxis()
457 plt.legend()
458 plt.show()
459
460 # Plot Gaussian Noise for all ages (normal scale)
461 plt.figure(figsize=(10, 6))
462 for i, age in enumerate(cluster_ages):
463     # Create Gaussian Noise Main Sequence
464     lum_noisy = all_lum_ms[i] * (1 + np.random.normal(0, 0.1, size=len(
465     all_lum_ms[i])))
466     temp_noisy = all_t_eff[i] * (1 + np.random.normal(0, 0.1, size=len(
467     all_t_eff[i])))
468
469     # Create Gaussian Noise White Dwarf
470     lum_wd_noisy = all_lum_wd[i] * (1 + np.random.normal(0, 0.1, size=len(
471     all_lum_wd[i])))
472     temp_wd_noisy = all_t_eff_wd[i] * (1 + np.random.normal(0, 0.1, size=len(
473     all_t_eff_wd[i])))
474
475     # Plot Main Sequence and White Dwarfs with noisy data
476     plt.scatter(temp_noisy, lum_noisy, s=10, color=colors[i], label=f'MS, Age={
477     age} Gyr')
478     plt.scatter(temp_wd_noisy, lum_wd_noisy, s=10, color=colors[i], alpha=0.5,
479     label=f'WD, Age={age} Gyr')
480
481 plt.yscale('log')
482 plt.xlabel('T_eff (K)')
483 plt.ylabel('Luminosity (L_sun)')
484 plt.title('Temperature vs Luminosity (Normal Scale)\nGaussian Noise 10%')
485 plt.gca().invert_xaxis()
486 plt.legend()
487 plt.show()
488
489 # Plot Gaussian Noise for all ages (log-log scale)
490 plt.figure(figsize=(10, 6))
491 for i, age in enumerate(cluster_ages):
492     # Create Gaussian Noise for Main Sequence
493     lum_noisy = all_lum_ms[i] * (1 + np.random.normal(0, 0.1, size=len(
494     all_lum_ms[i])))

```

```

495     temp_noisy = all_t_eff[i] * (1 + np.random.normal(0, 0.1, size=len(
496     all_t_eff[i])))
497
498     # Create Gaussian Noise for White Dwarf
499     lum_wd_noisy = all_lum_wd[i] * (1 + np.random.normal(0, 0.1, size=len(
500     all_lum_wd[i])))
501     temp_wd_noisy = all_t_eff_wd[i] * (1 + np.random.normal(0, 0.1, size=len(
502     all_t_eff_wd[i])))
503
504     # Plot Main Sequence and White Dwarfs with gaussian noise
505     plt.scatter(temp_noisy, lum_noisy, s=10, color=colors[i], label=f'MS, Age={
506     age} Gyr')
507     plt.scatter(temp_wd_noisy, lum_wd_noisy, s=10, color=colors[i], alpha=0.5,
508     label=f'WD, Age={age} Gyr')
509
510     plt.xscale('log')
511     plt.yscale('log')
512     plt.xlabel('T_eff (K)')
513     plt.ylabel('Luminosity (L_sun)')
514     plt.title('Temperature vs Luminosity (Log-Log Scale)\nGaussian Noise 10%')
515     plt.gca().invert_xaxis()
516     plt.legend()
517     plt.show()
518
519
520     #-----
521     # Adding 2d HR Diagram
522     #-----
523
524
525     # Combine Main Sequence and White Dwarf Data
526     t_eff_combined = np.concatenate(all_t_eff)
527     lum_combined = np.concatenate(all_lum_ms)
528     t_eff_combined_wd = np.concatenate(all_t_eff_wd)
529     lum_combined_wd = np.concatenate(all_lum_wd)
530
531     plt.figure(figsize=(10, 6))
532
533     # Create a KDE plot (Main Sequence + White Dwarfs)
534     sns.kdeplot(x=t_eff_combined, y=lum_combined, cmap='inferno', fill=True, thresh
535     =0, levels=30, label='Main Sequence')
536     sns.kdeplot(x=t_eff_combined_wd, y=lum_combined_wd, cmap='coolwarm', fill=True,
537     thresh=0, levels=30, label='White Dwarfs')
538
539     plt.xlabel('Effective Temperature (T_eff) [K]')
540     plt.ylabel('Luminosity (L/L_sun)')
541     plt.title('2D KDE Density Map of the HR Diagram')
542     plt.xscale('log')
543     plt.yscale('log')
544     plt.gca().invert_xaxis()
545     plt.legend()
546     plt.show()

```

Listing 1: Python Code for Stellar Population Simulation

```

547 import numpy as np
548 import matplotlib.pyplot as plt
549
550 # Constants
551 np.random.seed(9)
552
553 N = 1000          # Number of stars
554 dt = 1            # Timestep
555 alpha = 2.35      # IMF constant

```

```

556 max_mass = 100      # Maximum star mass
557 sigma = 5.67e-8     # Stefan-Boltzmann constant (W/m^2 K^4)
558 C = 0.0101         # White Dwarf constant
559 R_solar = 6.969e8    # Solar radius (m)
560 L_solar = 3.827e26   # Solar luminosity (W)
561
562 # Cluster ages and minimum mass values
563 cluster_ages = [8, 10, 12]
564 min_mass_values = [0.1, 0.3, 0.5] # Chosen as solar masses
565
566 # Main code but split into definitions to simplify
567 def generate_masses(min_mass, max_mass, alpha, N):
568     masses = []
569     while len(masses) < N:
570         rand_y = np.random.uniform(0, 1)
571         rand_mass = np.random.uniform(min_mass, max_mass)
572         mass_i = (rand_mass) ** (-alpha)
573         if rand_y < mass_i:
574             masses.append(rand_mass)
575     return masses
576
577 def main_sequence_luminosity(mass):
578     if mass > 55:
579         return 32000 * mass
580     elif 2 < mass <= 55:
581         return 1.4 * mass ** 3.5
582     elif 0.43 < mass <= 2:
583         return mass ** 4
584     elif mass <= 0.43:
585         return 0.23 * mass ** 2.3
586
587 def main_sequence_radius(mass):
588     if mass >= 1.12:
589         return 10 ** 0.66 * np.log(mass) + 0.5
590     else:
591         return mass
592
593 def effective_temperature(lum, radius):
594     return (lum * L_solar / (4 * np.pi * radius ** 2 * R_solar ** 2 * sigma))
595     ** (1 / 4)
596
597 def calculate_msto(cluster_age, masses, t_ms):
598     # MSTO is the biggest star that is still on main sequence
599     for i, age in enumerate(t_ms):
600         if cluster_age - age <= 0:
601             return i, masses[i]
602     return len(masses) - 1, masses[-1] # Default to least massive star if no
603     MSTO
604
605 # Create figure for combined plot
606 plt.figure(figsize=(10, 6))
607
608 # Loop through all min_mass values and ages, and plot the data (COMBINED)
609 colors = ['#00008B', '#FF4500', '#008000']
610 labels = ['min_mass = 0.1 M_sun', 'min_mass = 0.3 M_sun', 'min_mass = 0.5 M_sun']
611
612
613 for idx, min_mass in enumerate(min_mass_values):
614     print(f"Analyzing for min_mass = {min_mass} M_sun")
615
616     all_lum_ms, all_t_eff, all_msto = [], [], []
617
618     for age_idx, t_cluster in enumerate(cluster_ages):

```

```

619     # Generate initial star parameters
620     masses = generate_masses(min_mass, max_mass, alpha, N)
621     t_ms = [10 * mass ** -3.5 for mass in masses]
622     t_born = [dt * np.random.uniform(0, 1) for _ in range(N)]
623     t_cool = [t_cluster - t_born[i] - t_ms[i] for i in range(N)]
624
625     # Separate stars into MS and WD
626     lum_ms, t_eff_ms = [], []
627     for i, mass in enumerate(masses):
628         if t_cool[i] <= 0:
629             lum = main_sequence_luminosity(mass)
630             radius = main_sequence_radius(mass)
631             t_eff = effective_temperature(lum, radius)
632             lum_ms.append(lum)
633             t_eff_ms.append(t_eff)
634
635     # Calculate MSTO
636     msto_index, msto_mass = calculate_msto(t_cluster, masses, t_ms)
637     msto_lum = main_sequence_luminosity(msto_mass)
638     msto_radius = main_sequence_radius(msto_mass)
639     msto_t_eff = effective_temperature(msto_lum, msto_radius)
640     all_msto.append((msto_mass, msto_t_eff, msto_lum))
641
642     # Append data
643     all_lum_ms.append(lum_ms)
644     all_t_eff.append(t_eff_ms)
645
646     # Print MSTO details
647     print(f"Age: {t_cluster} Gyr, MSTO Mass: {msto_mass:.2f} M_sun, "
648           f"T_eff: {msto_t_eff:.2f} K, Luminosity: {msto_lum:.2f} L_sun")
649
650     # Plot all MS stars and MSTO stars for this min_mass
651     for i, age in enumerate(cluster_ages):
652         plt.scatter(all_t_eff[i], all_lum_ms[i], s=10, color=colors[i], alpha
653 =0.7, label=f'Age = {age} Gyr' if idx == 0 else "")
654         msto_mass, msto_t_eff, msto_lum = all_msto[i]
655         plt.scatter(msto_t_eff, msto_lum, s=100, edgecolor='black', color=
656 colors[i], marker='x', label=f'MSTO (Age={age} Gyr, min_mass={min_mass}
657 M_sun)' if idx == 0 else "")
658
659 # Plotss
660 plt.xscale('log')
661 plt.yscale('log')
662 plt.xlabel('T_eff (K)')
663 plt.ylabel('Luminosity (L_sun)')
664 plt.title('Temperature vs Luminosity (Log-Log Scale) for Different min_mass
665 Values')
666 plt.grid(True, which="both", linestyle="--", linewidth=0.5)
667 plt.gca().invert_xaxis()
668 plt.legend()
669 plt.show()

```

Listing 2: Python Code for Combined MSTO Analysis