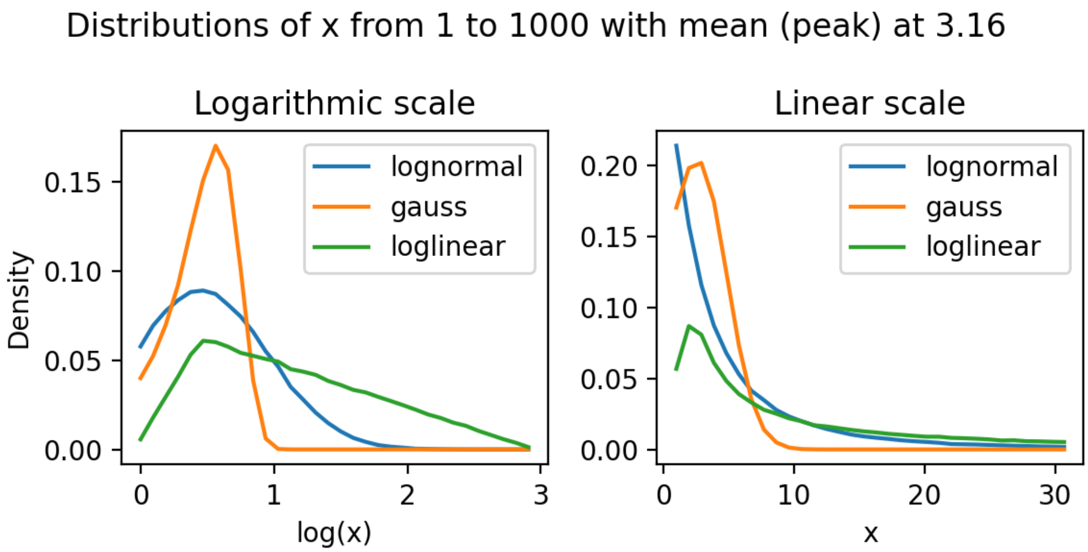
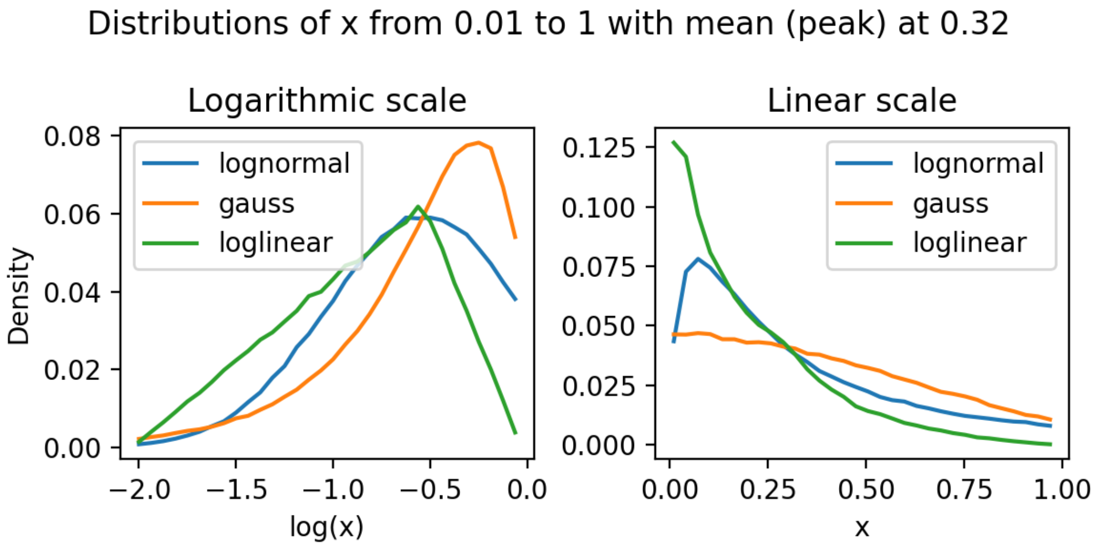
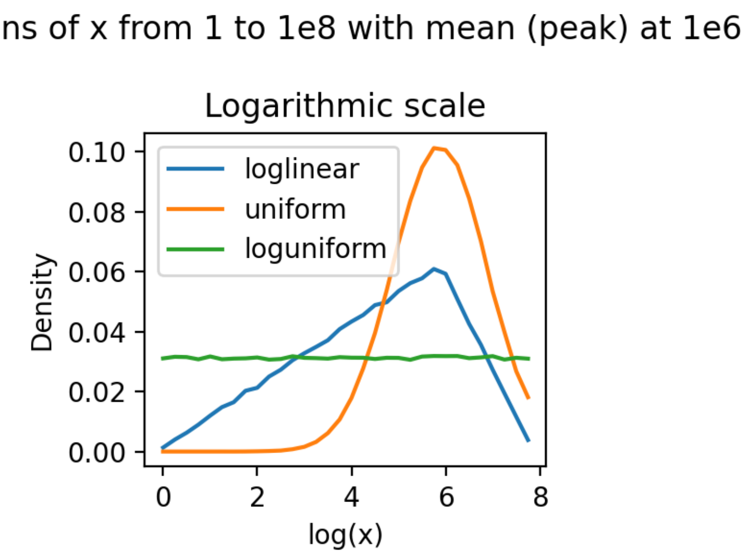
supermodel

December 22, 2021

[1]:
```
from pca import cluster
import numpy as np
import matplotlib.pyplot as plt
import pandas as pd
import warnings
warnings.filterwarnings("ignore")

# primeri vseh treh porazdelitev v primeru povprečja večjega in manjšega od 1,
# ob tem so najprej predstavljene porazdelitve za N v primeru večje možnosti
# za širitev na druge planete
```



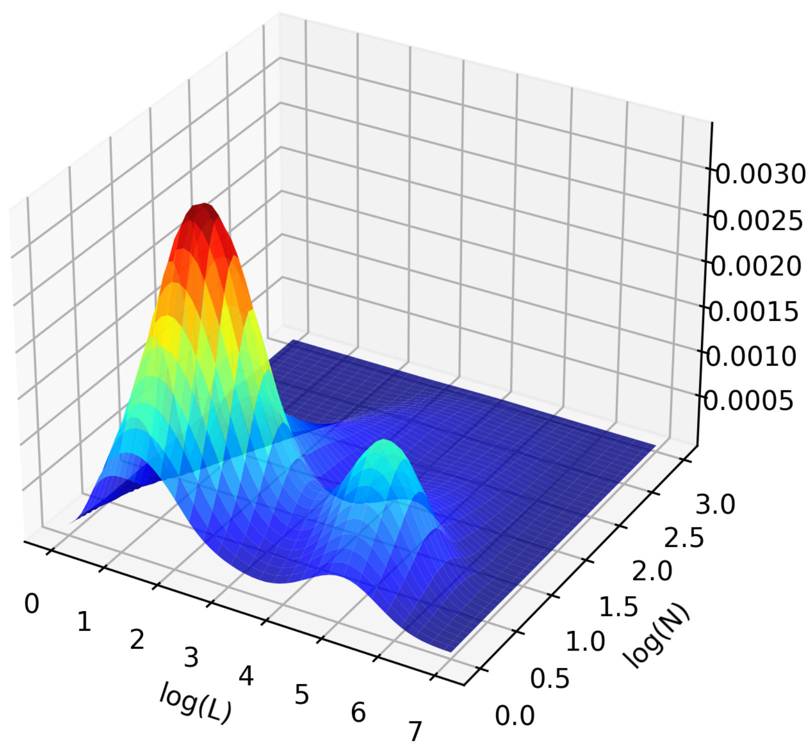


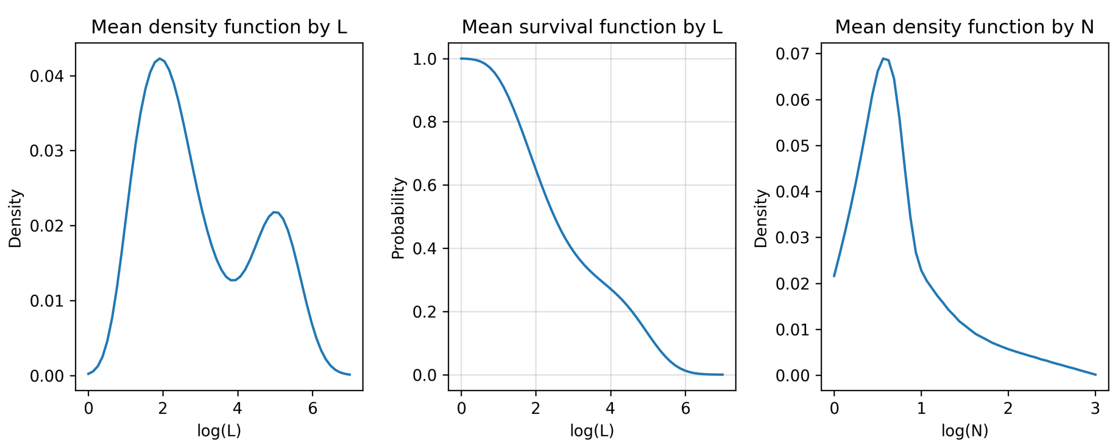


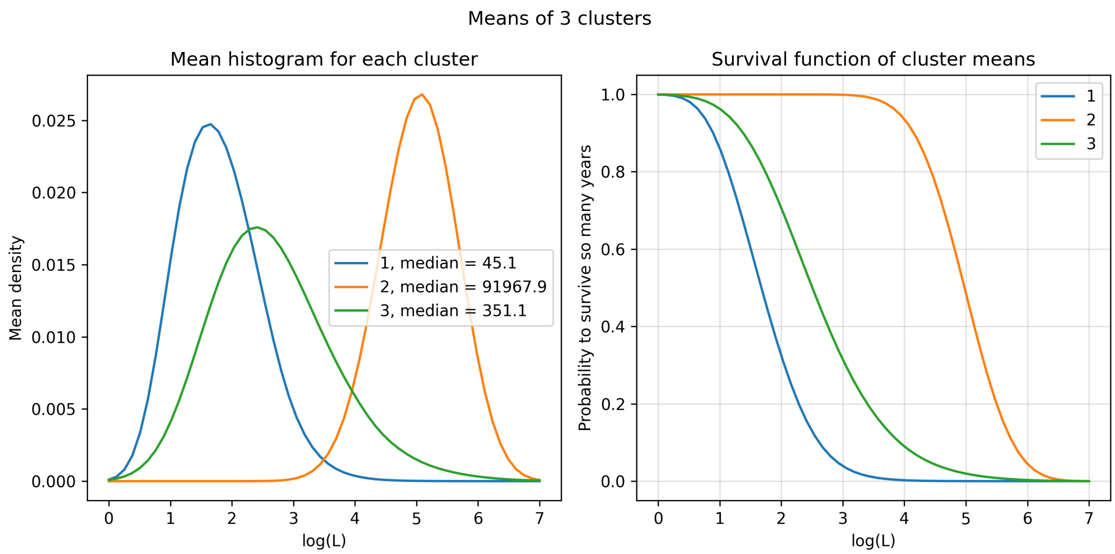
[2]:
```
cluster(model=0, ks=[3, 5], supermodel=1)  # supermodel
cluster(model=0, ks=[5], supermodel=2)  # supermodel 2
cluster(model=0, ks=[5], supermodel=3)  # supermodel 3
```

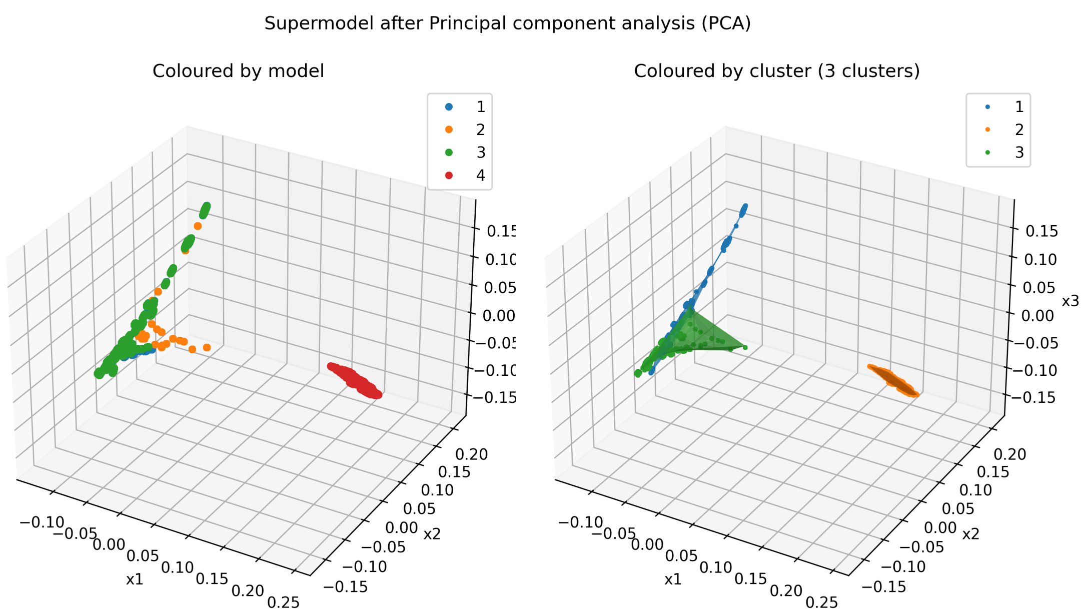
Supermodel

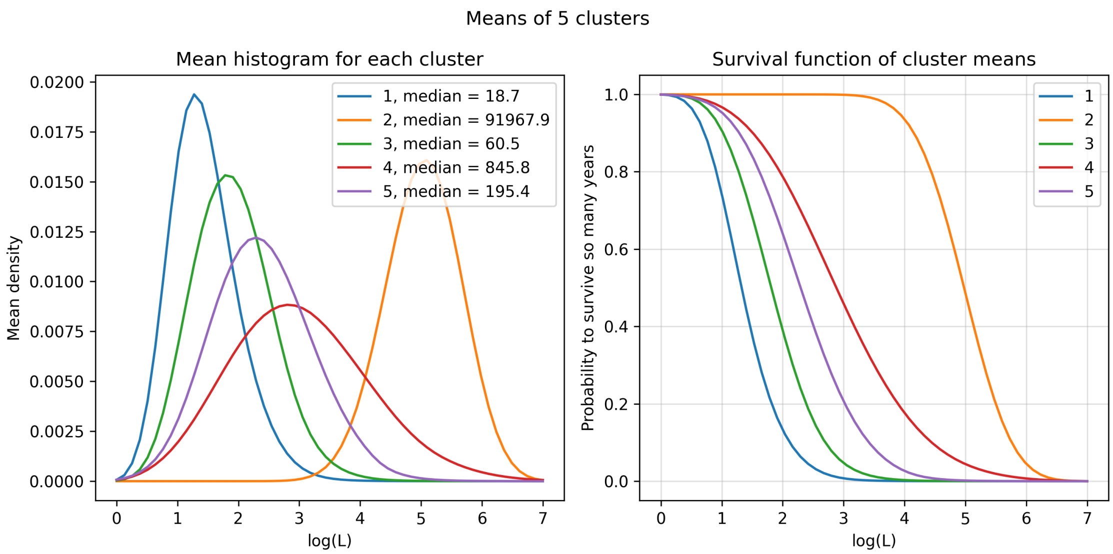
Mean density



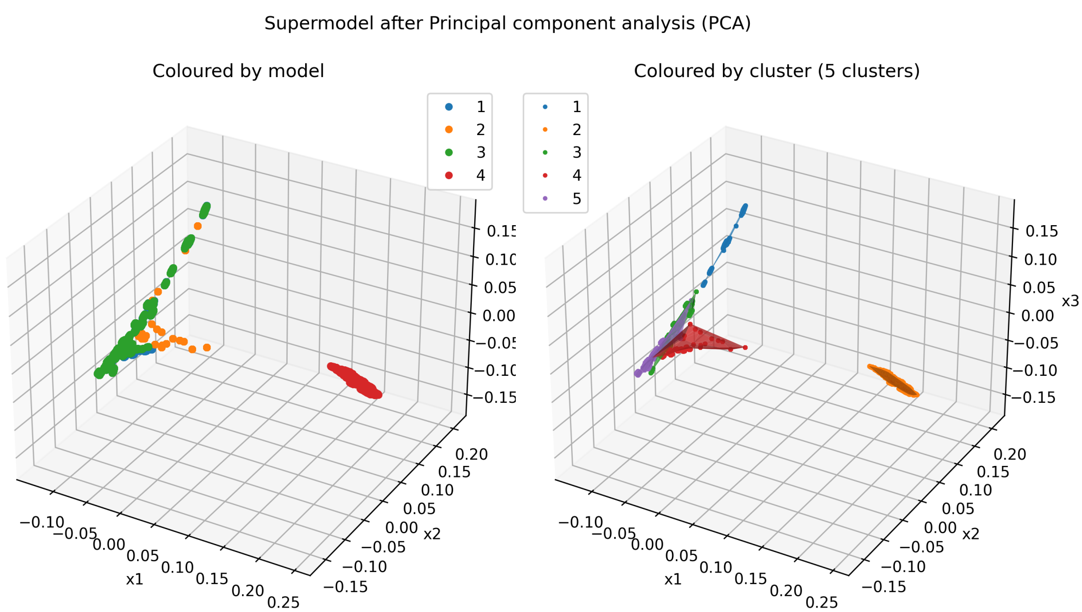



Means of 3 clusters
Mean histogram for each cluster
Mean density
log(L)
1, median = 45.1
2, median = 91967.9
3, median = 351.1
Survival function of cluster means
Probability to survive so many years
log(L)
1
2
3

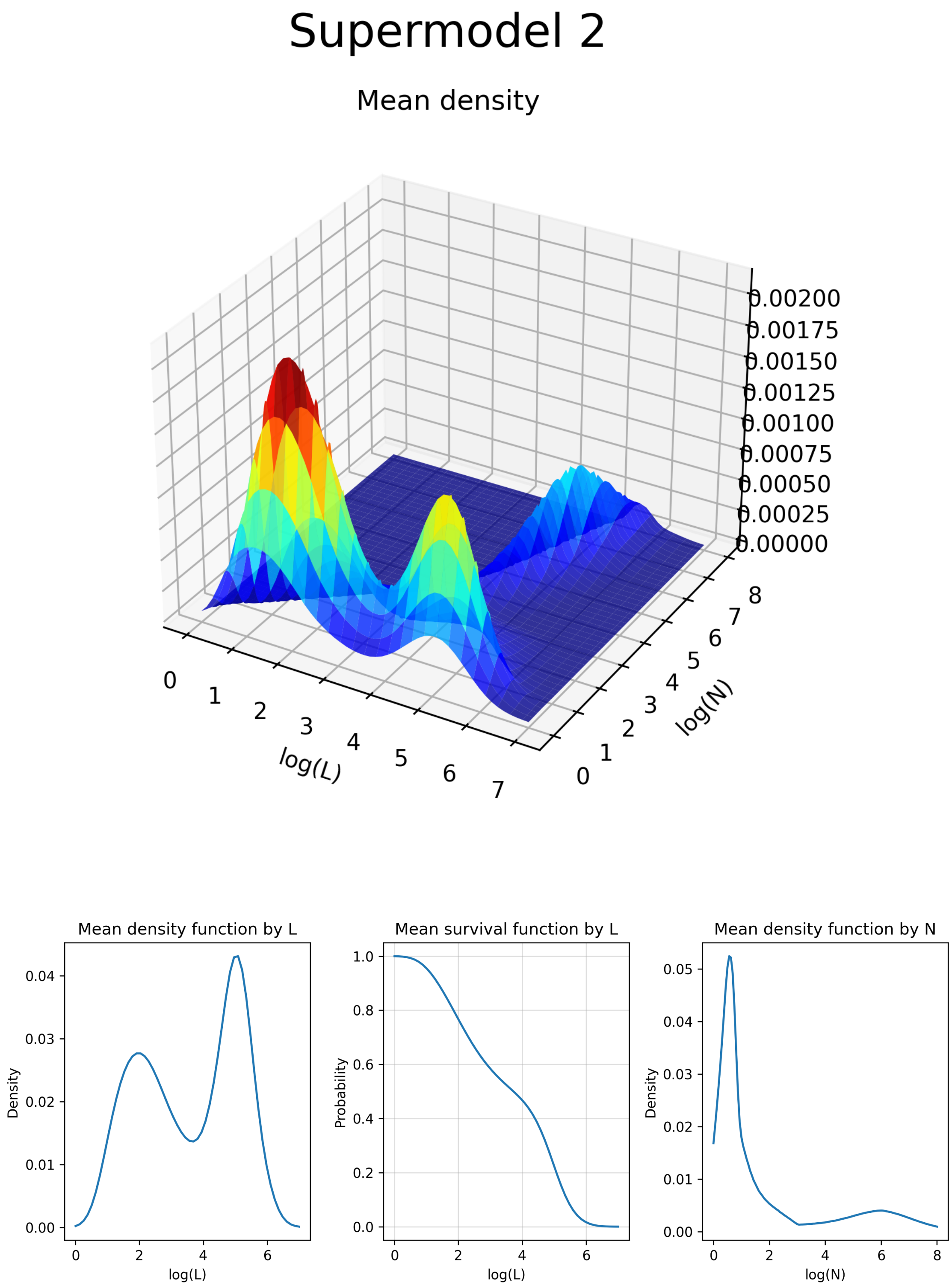

Supermodel after Principal component analysis (PCA)
Coloured by model
1
2
3
4
x1
x2
Coloured by cluster (3 clusters)
1
2
3
x1
x2
x3



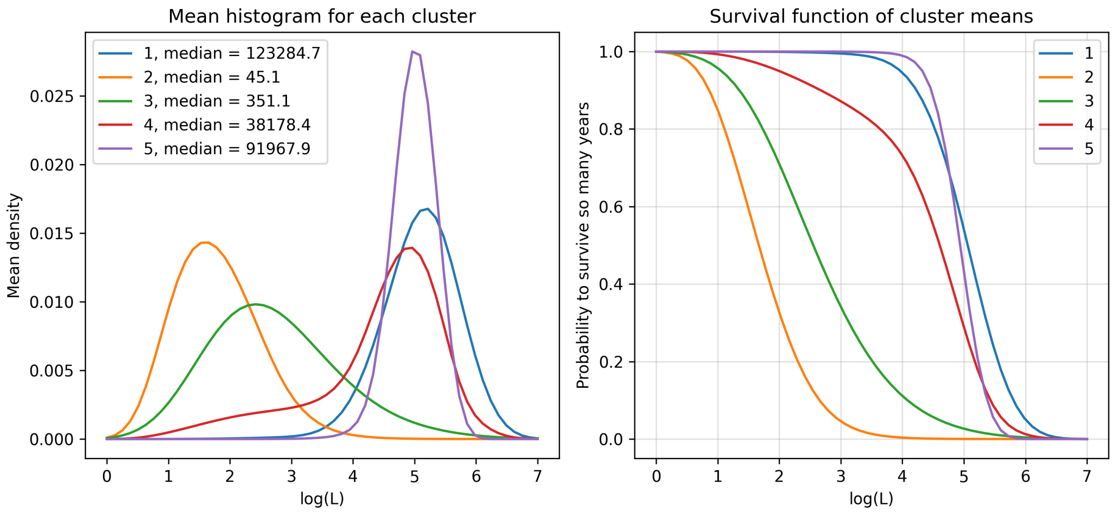
Means of 5 clusters
Mean histogram for each cluster
1, median = 18.7
2, median = 91967.9
3, median = 60.5
4, median = 845.8
5, median = 195.4
Mean density
log(L)
Survival function of cluster means
Probability to survive so many years
log(L)



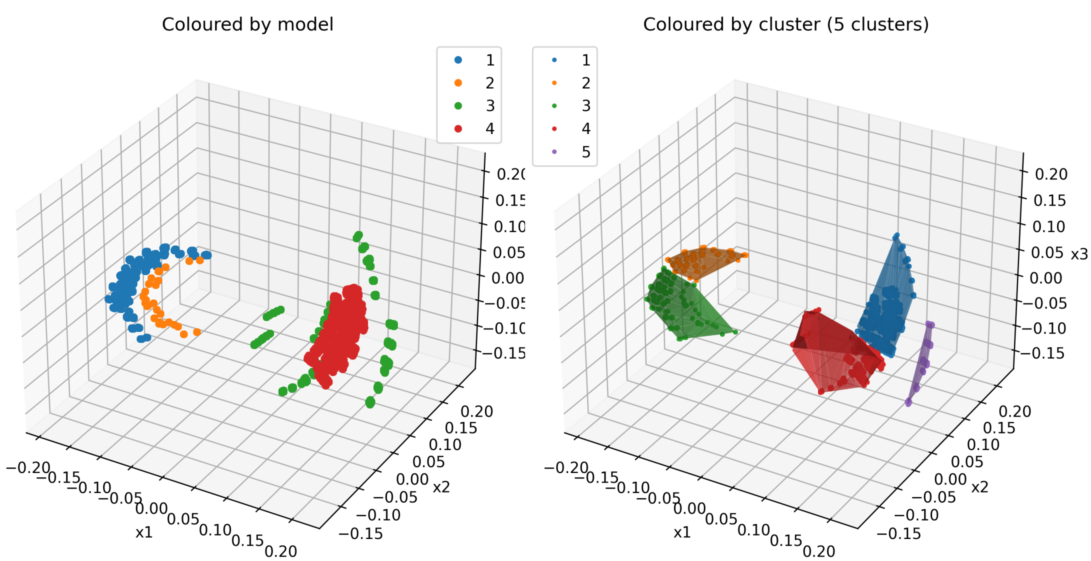
Supermodel after Principal component analysis (PCA)
Coloured by model
Coloured by cluster (5 clusters)
x1
x2
x3


Supermodel 2
Mean density
log(L)
log(N)
Mean density function by L
Density
log(L)
Mean survival function by L
Probability
log(L)
Mean density function by N
Density
log(N)

Means of 5 clusters

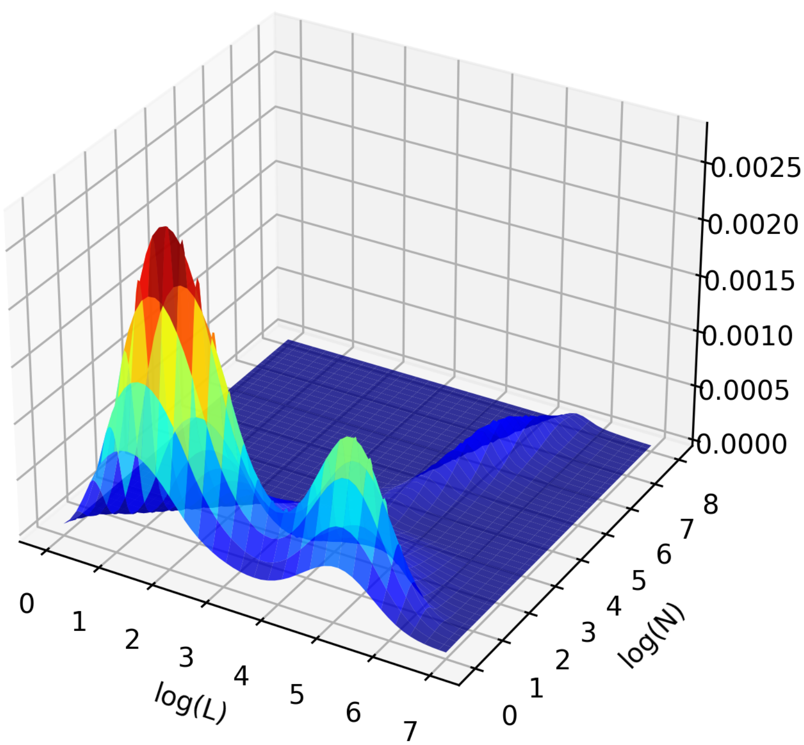


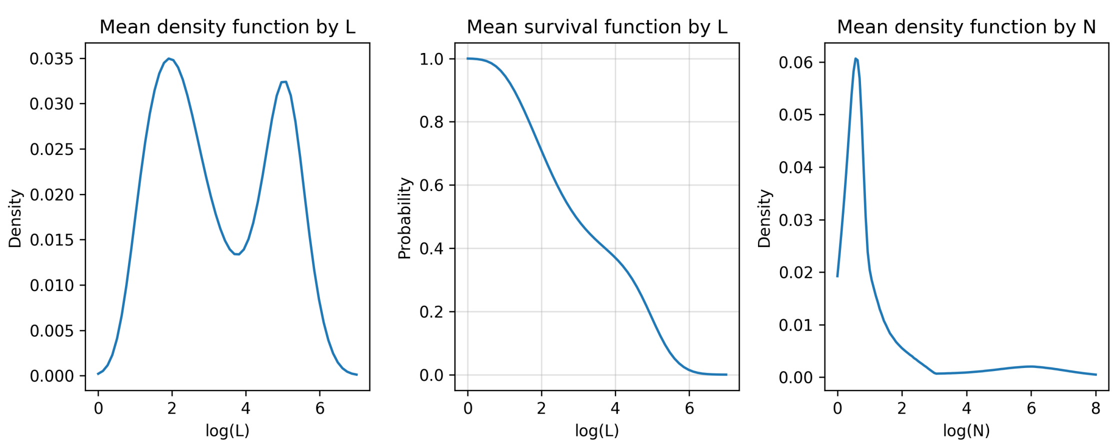
Supermodel 2 after Principal component analysis (PCA)

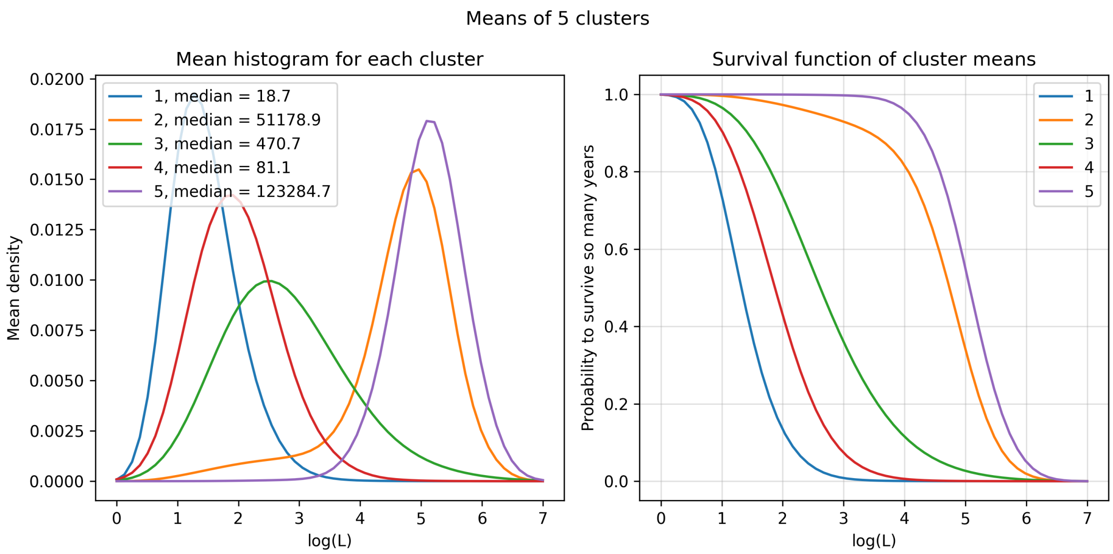


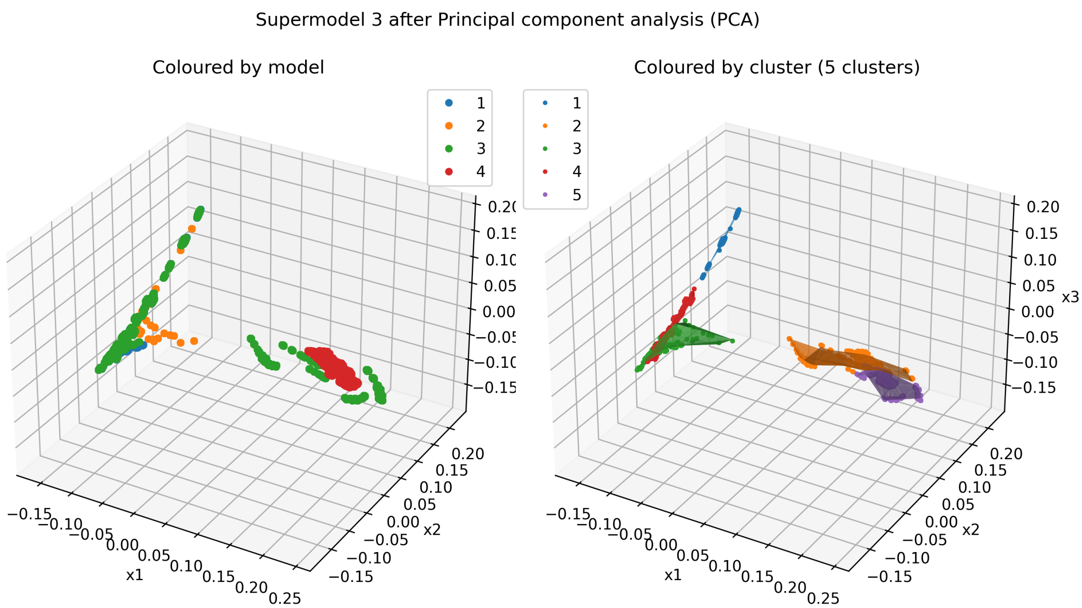
Supermodel 3

Mean density



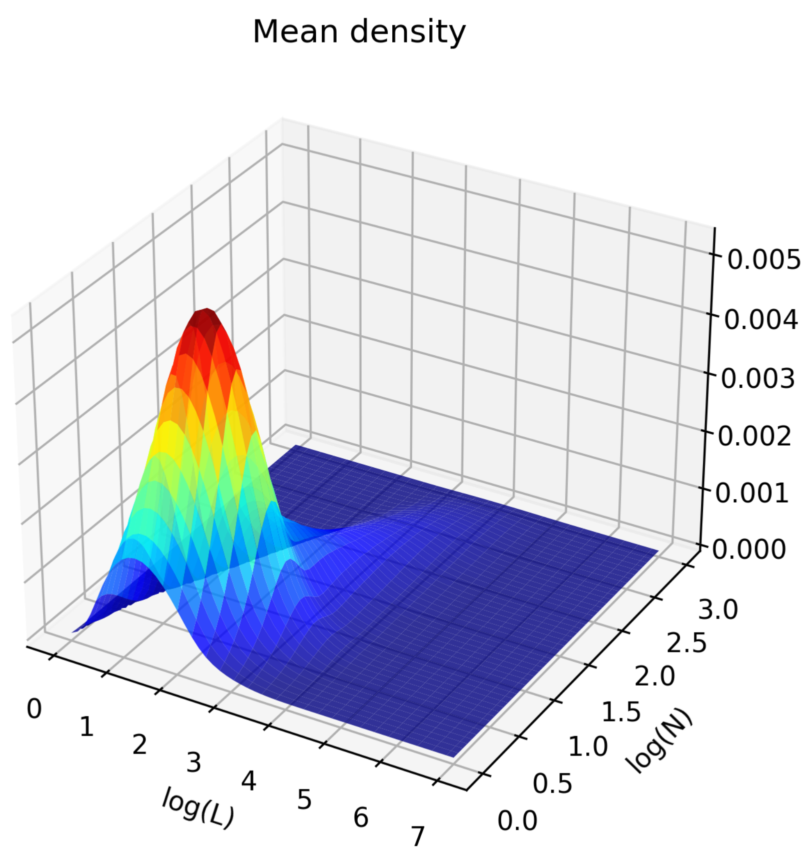


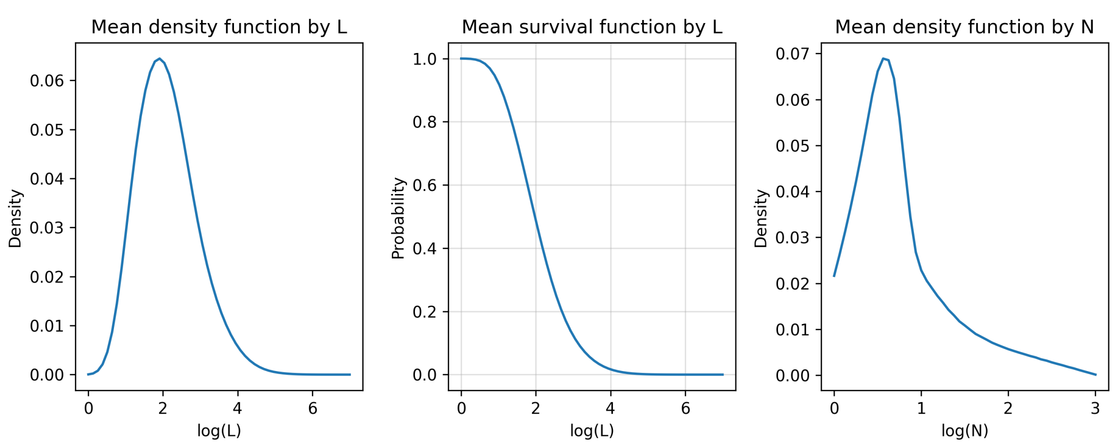


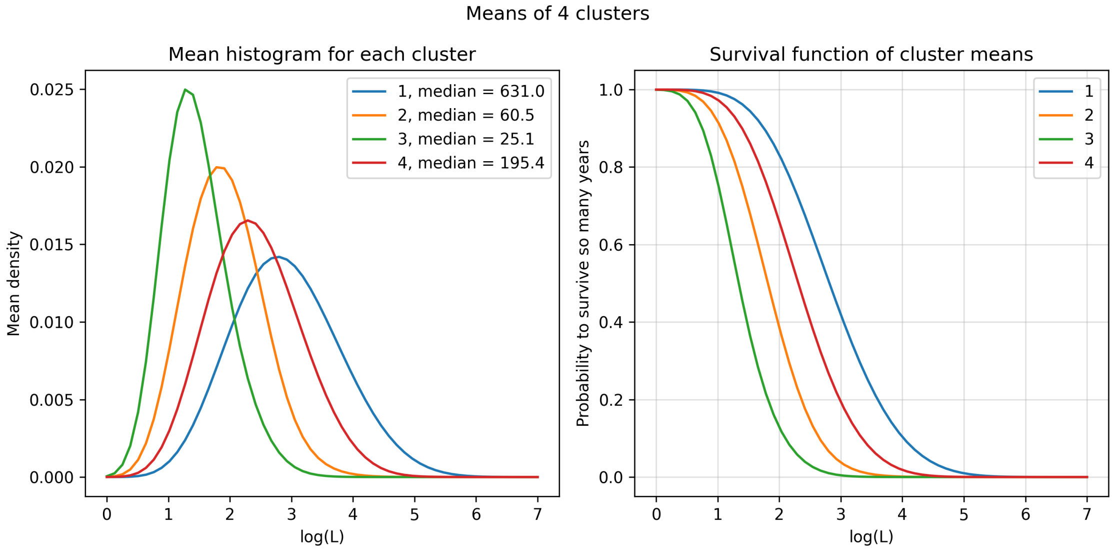



```
[3]: cluster(model=1, ks=[4])  # model 1
```

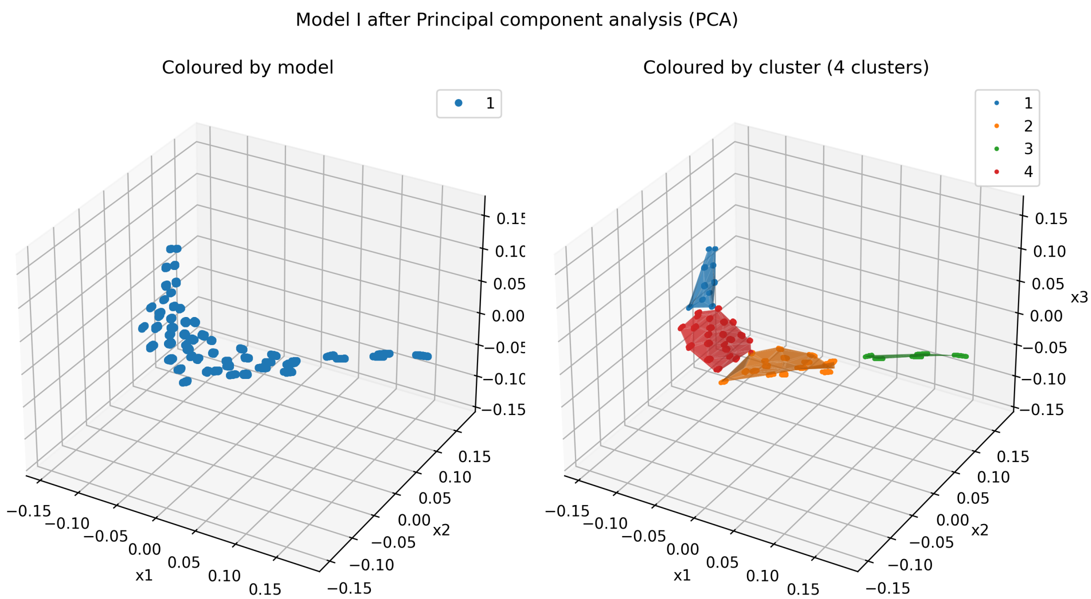
Model I


Mean density
0.005
0.004
0.003
0.002
0.001
0.000
0
1
2
3
4
5
6
7
log(L)
0.0
0.5
1.0
1.5
2.0
2.5
3.0
log(N)

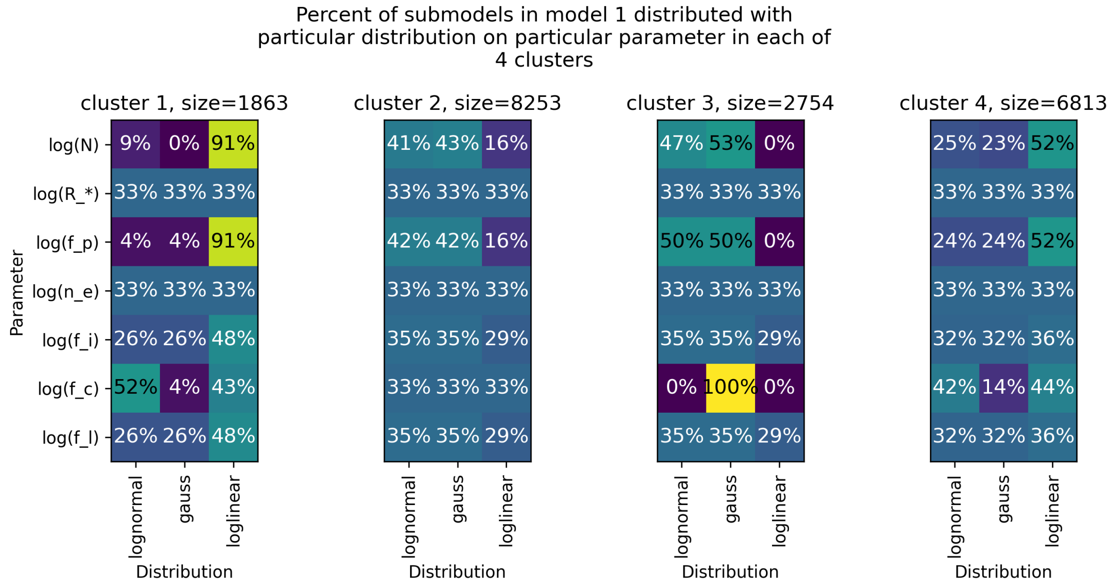

Mean density function by L
Density
log(L)
Mean survival function by L
Probability
log(L)
Mean density function by N
Density
log(N)

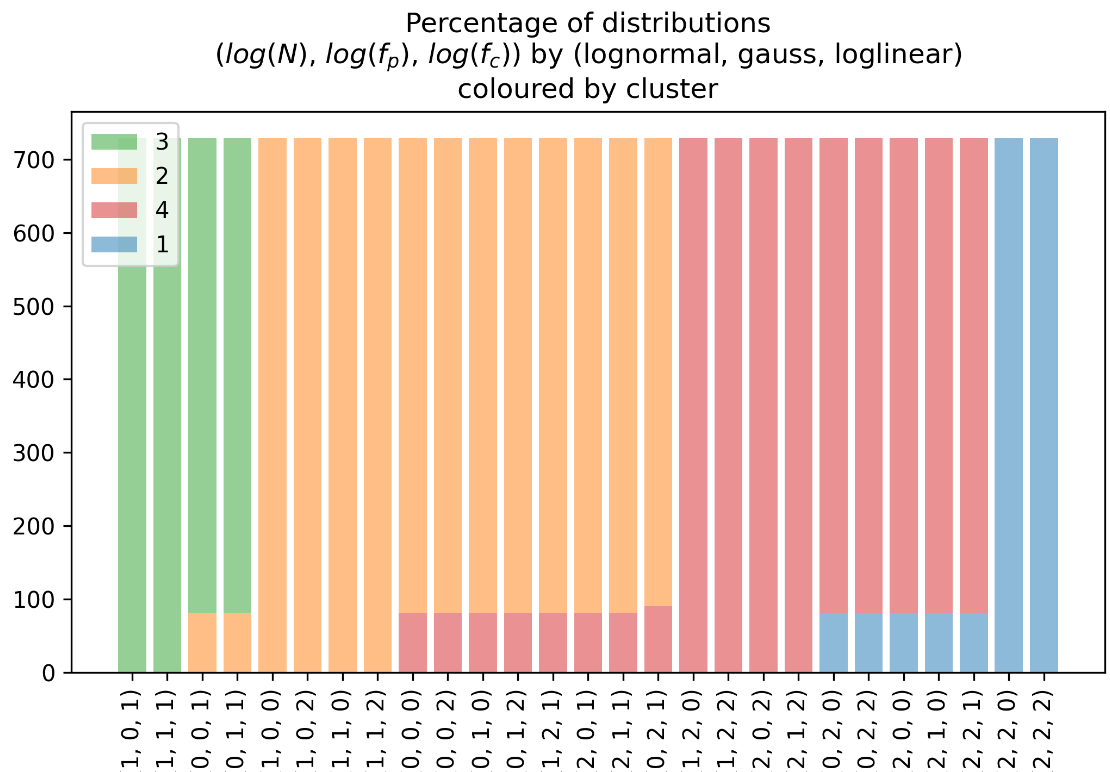


Means of 4 clusters
Mean histogram for each cluster
1, median = 631.0
2, median = 60.5
3, median = 25.1
4, median = 195.4
Mean density
log(L)
Survival function of cluster means
Probability to survive so many years
log(L)



Model I after Principal component analysis (PCA)
Coloured by model
Coloured by cluster (4 clusters)
x1
x2
x3



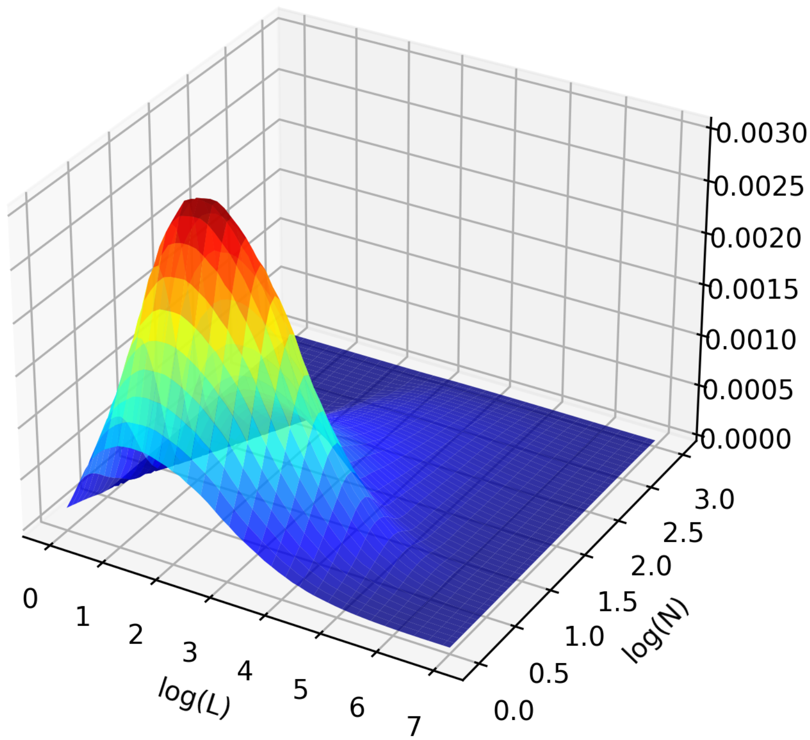


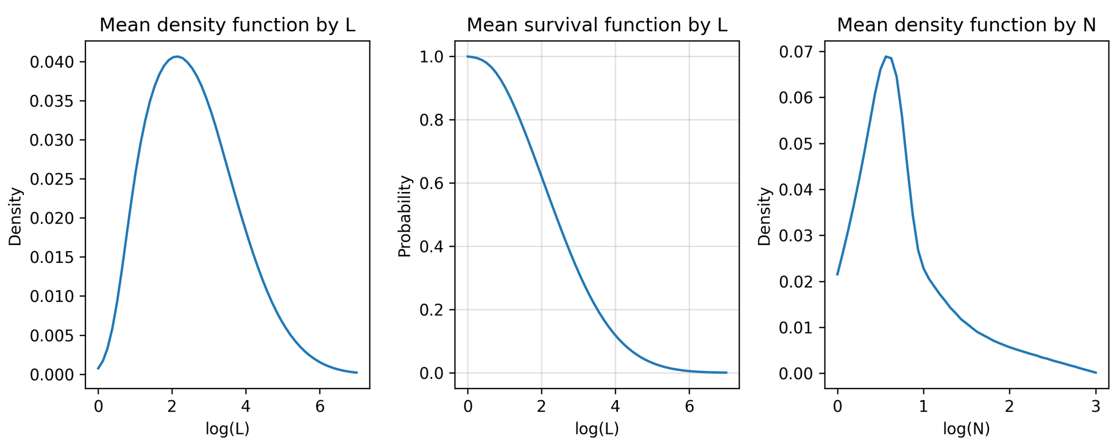
[4]:

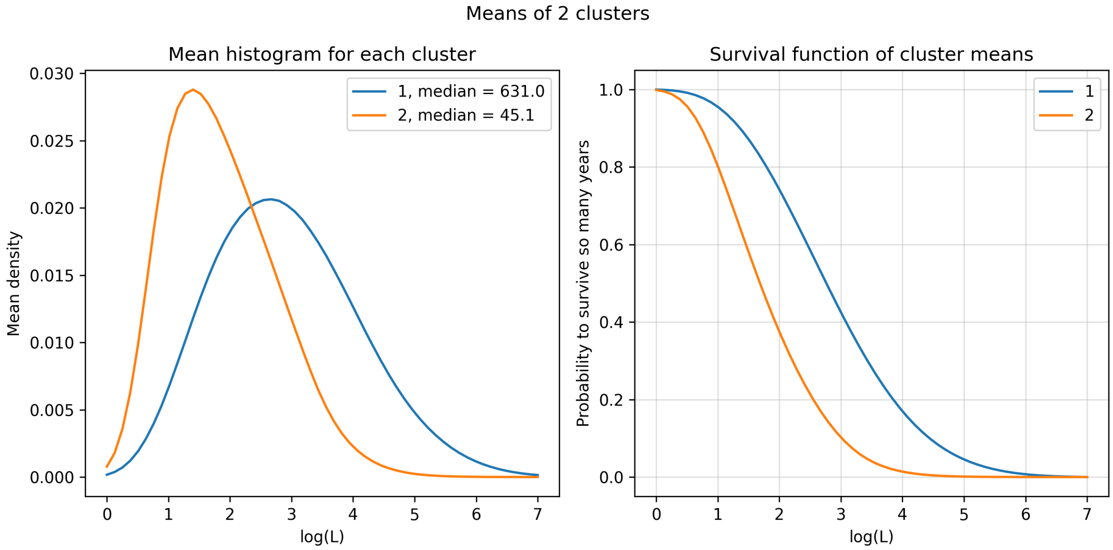
```
cluster(model=2, ks=[2])  # model 2
```

Model II

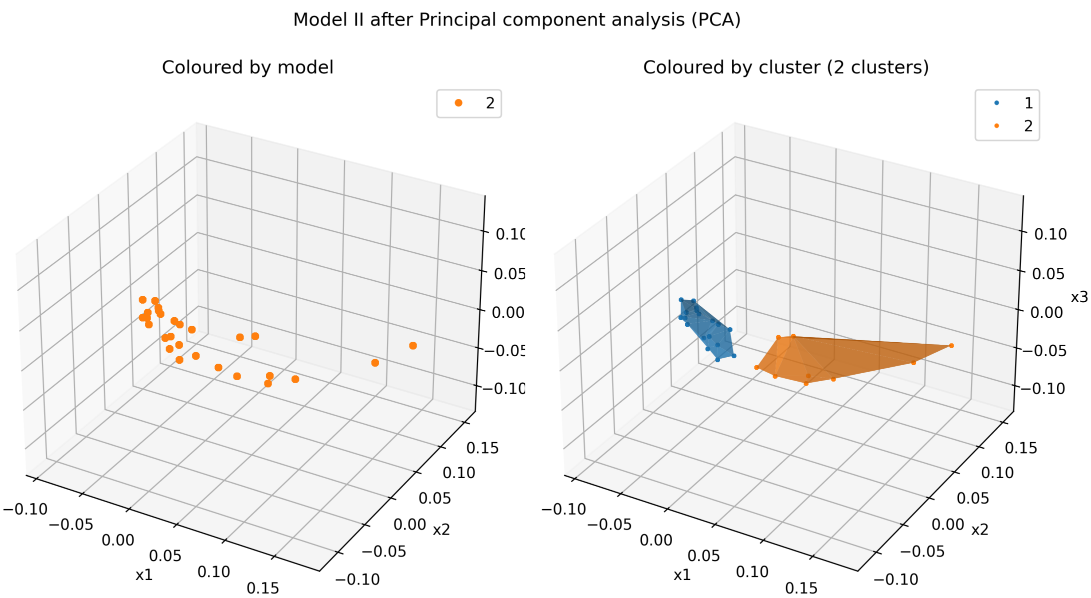
Mean density



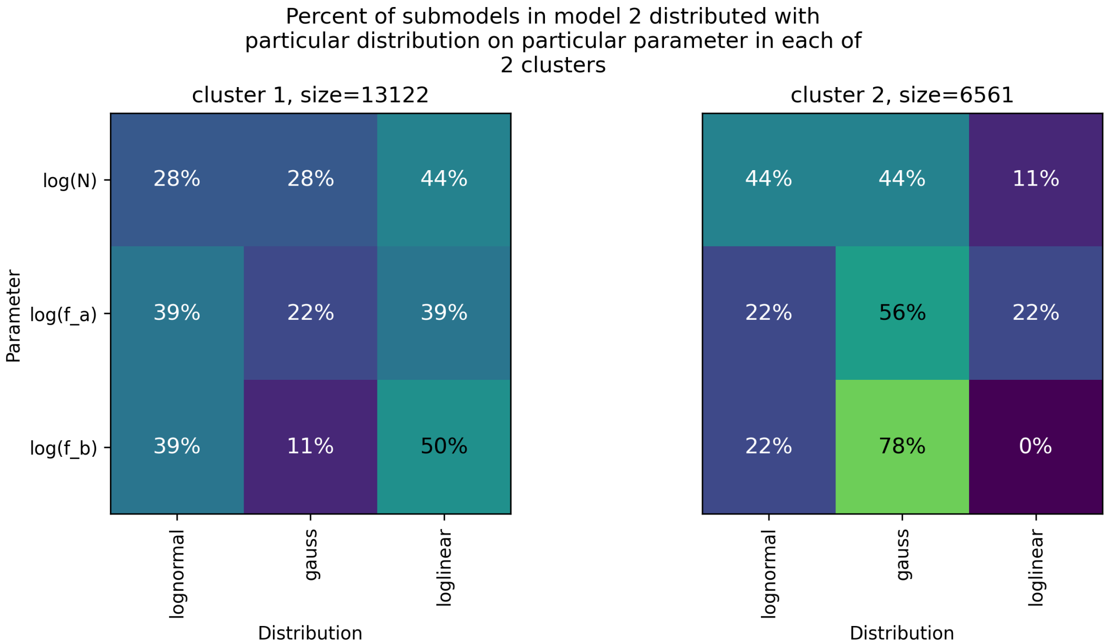


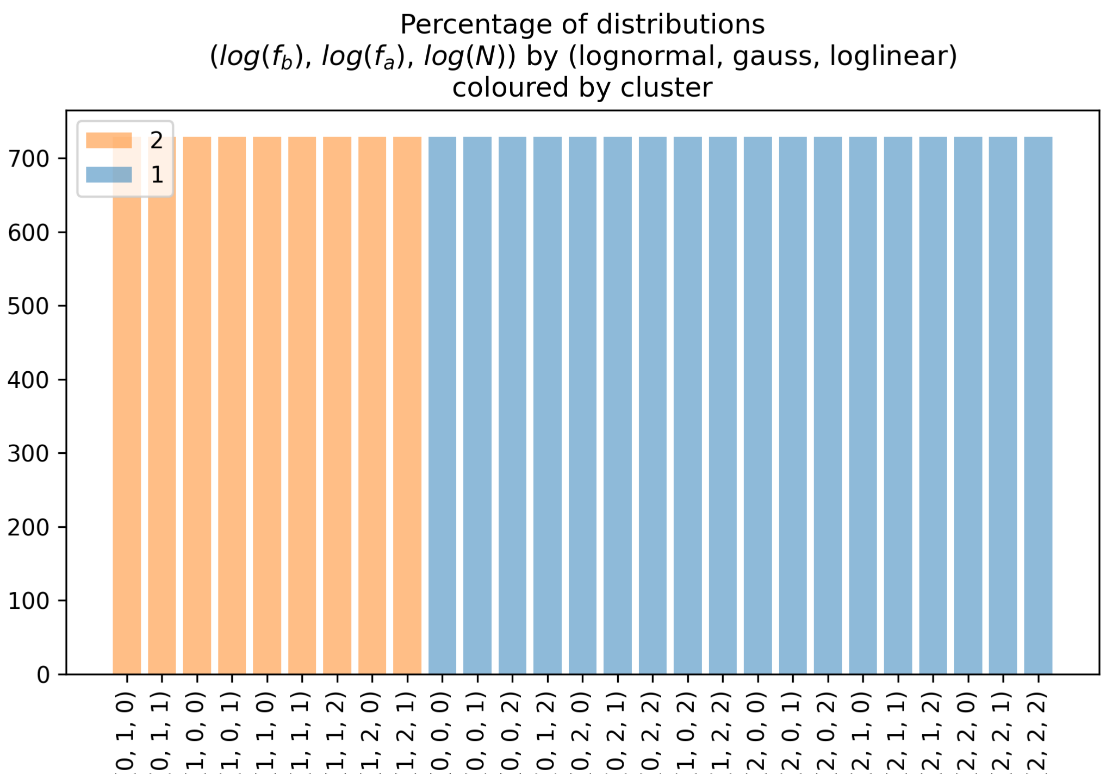


Means of 2 clusters
Mean histogram for each cluster
1, median = 631.0
2, median = 45.1
Mean density
log(L)
Survival function of cluster means
Probability to survive so many years
log(L)

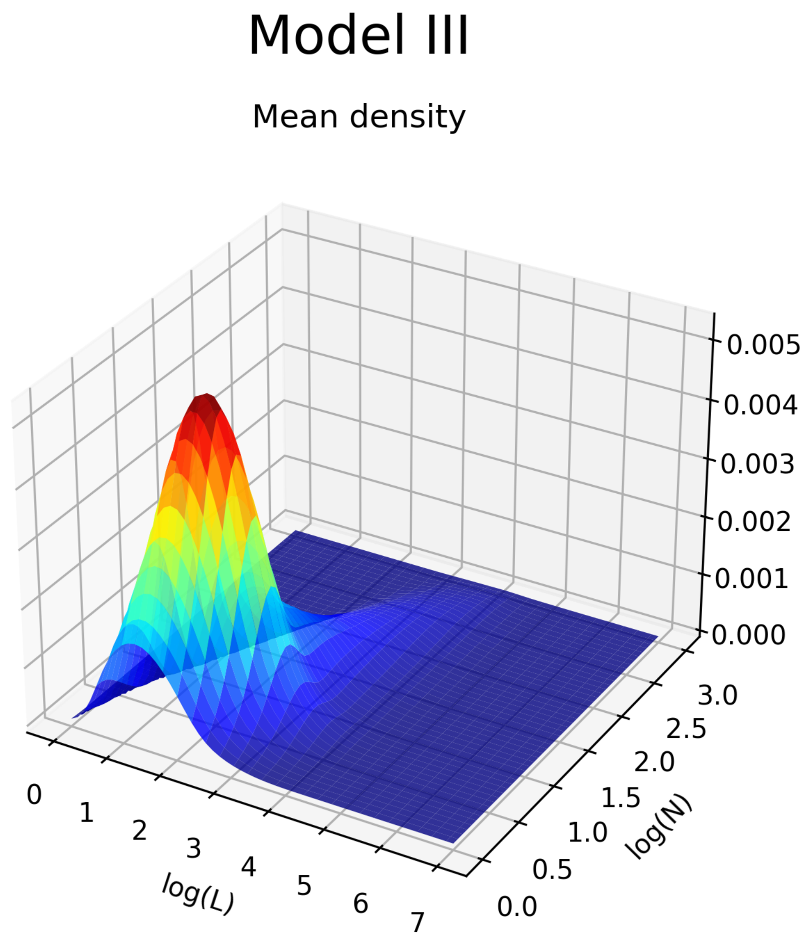


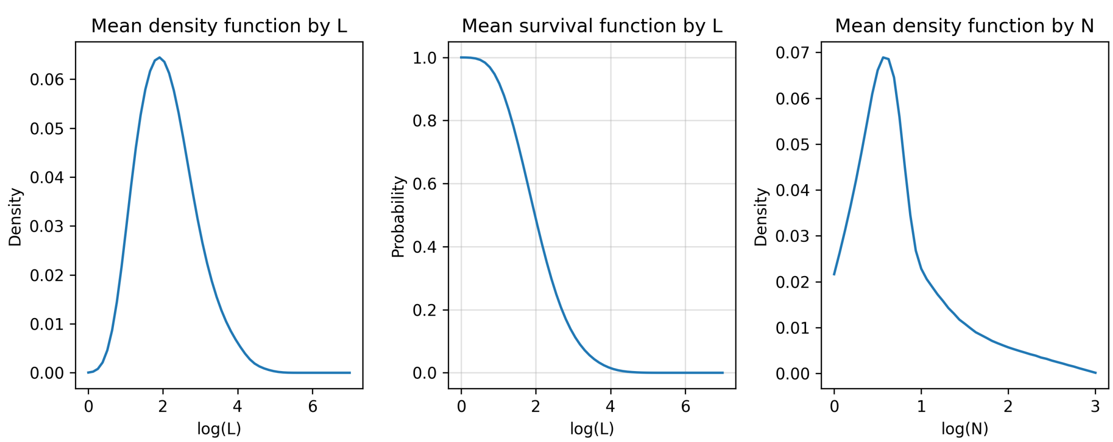
Model II after Principal component analysis (PCA)
Coloured by model
Coloured by cluster (2 clusters)
x1
x2
x3

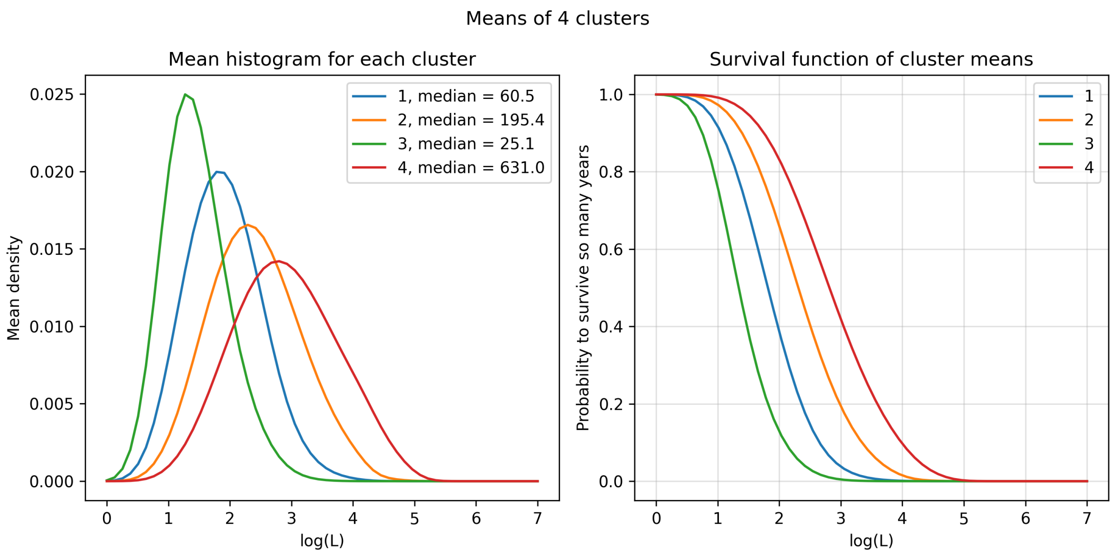

Percent of submodels in model 2 distributed with
particular distribution on particular parameter in each of
2 clusters
cluster 1, size=13122
cluster 2, size=6561
log(N)
log(f_a)
log(f_b)
Parameter
28%
28%
44%
39%
22%
39%
39%
11%
50%
44%
44%
11%
22%
56%
22%
22%
78%
0%
lognormal
gauss
loglinear
Distribution


Percentage of distributions
($log(f_b)$, $log(f_a)$, $log(N)$) by (lognormal, gauss, loglinear)
coloured by cluster
2
1
0
100
200
300
400
500
600
700
(0, 1, 0)
(0, 1, 1)
(1, 0, 0)
(1, 0, 1)
(1, 1, 0)
(1, 1, 1)
(1, 1, 2)
(1, 2, 0)
(1, 2, 1)
(0, 0, 0)
(0, 0, 1)
(0, 0, 2)
(0, 1, 2)
(0, 2, 0)
(0, 2, 1)
(0, 2, 2)
(1, 0, 2)
(1, 2, 2)
(2, 0, 0)
(2, 0, 1)
(2, 0, 2)
(2, 1, 0)
(2, 1, 1)
(2, 1, 2)
(2, 2, 0)
(2, 2, 1)
(2, 2, 2)

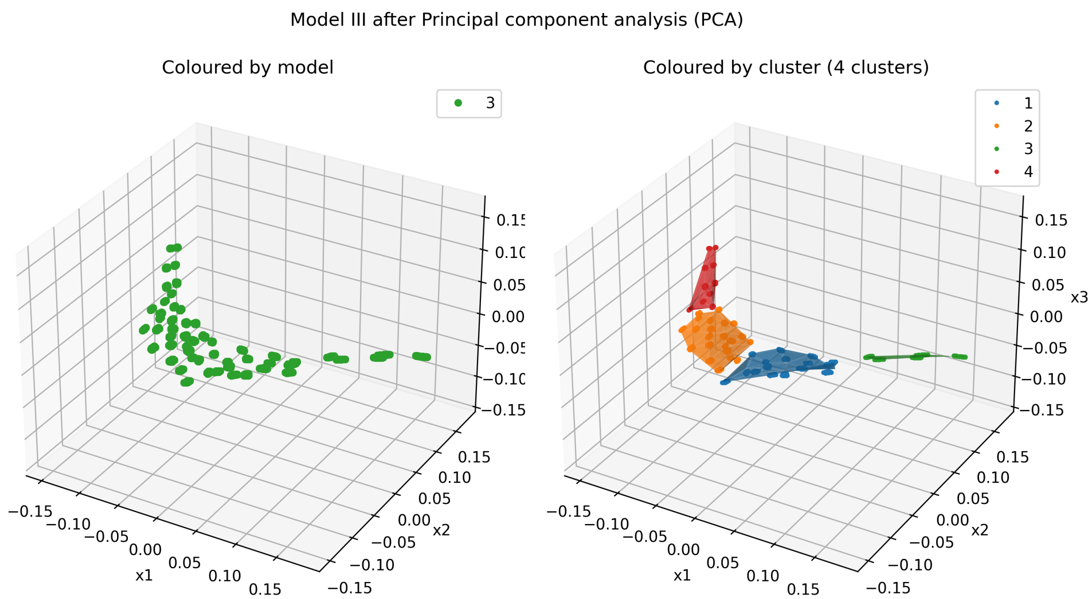
```
[5]: for s in [1, 2, 3]:
         cluster(model=3, ks=[4], supermodel=s)  # model 3
```



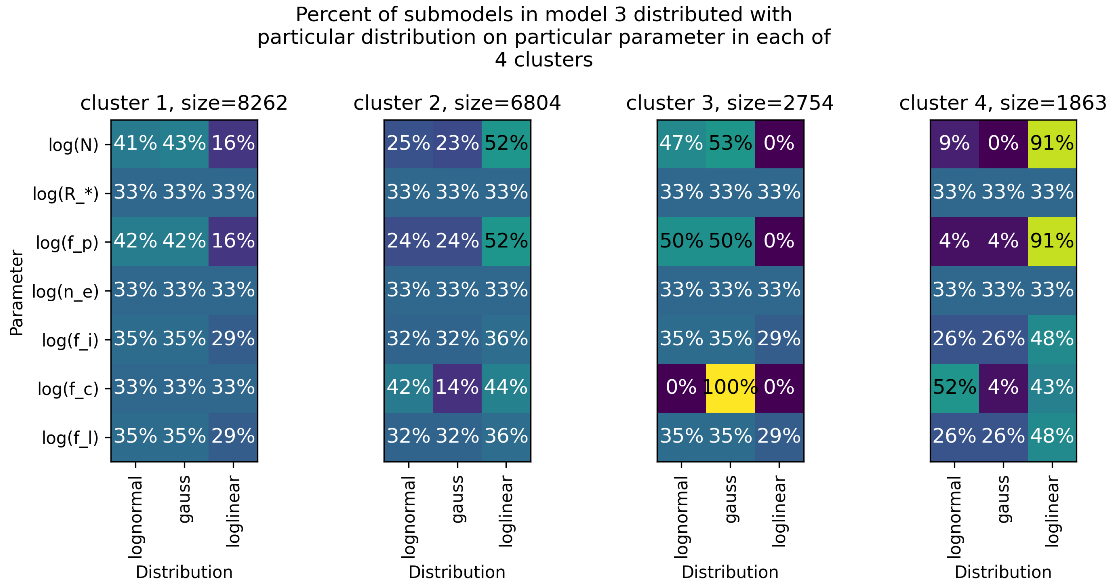


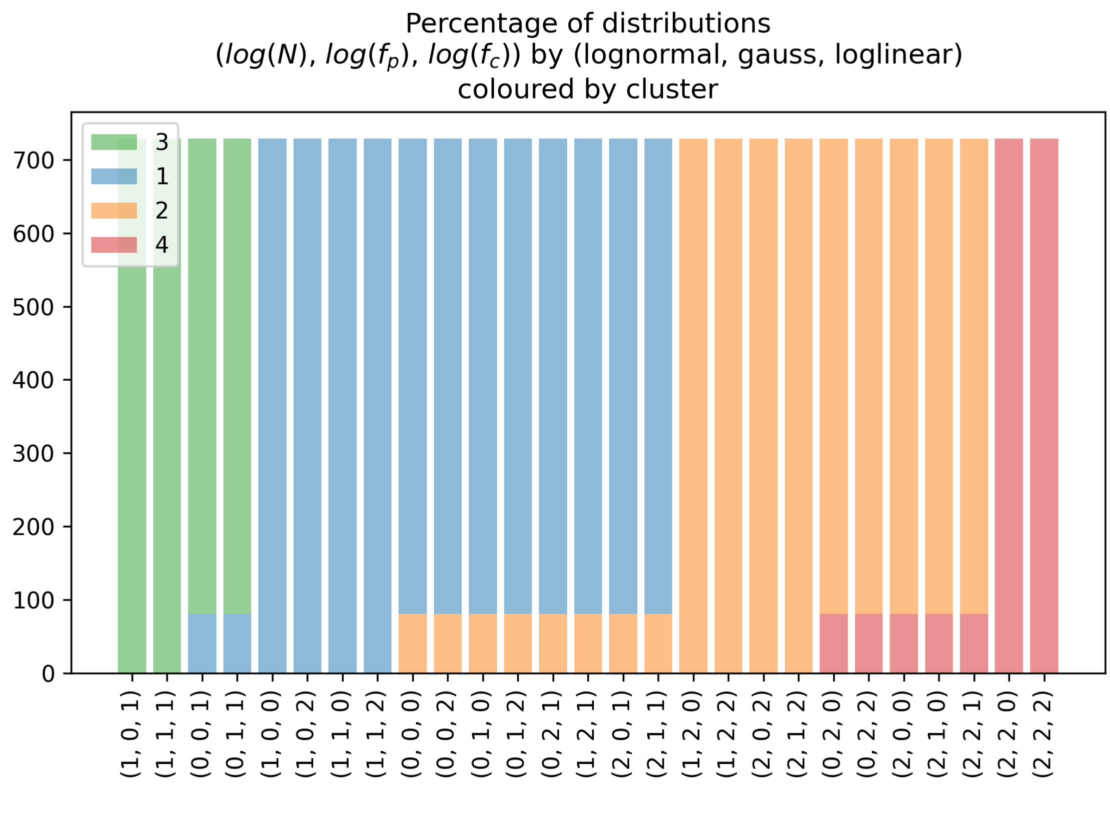


Means of 4 clusters
Mean histogram for each cluster
Survival function of cluster means
1, median = 60.5
2, median = 195.4
3, median = 25.1
4, median = 631.0
Mean density
Probability to survive so many years
log(L)

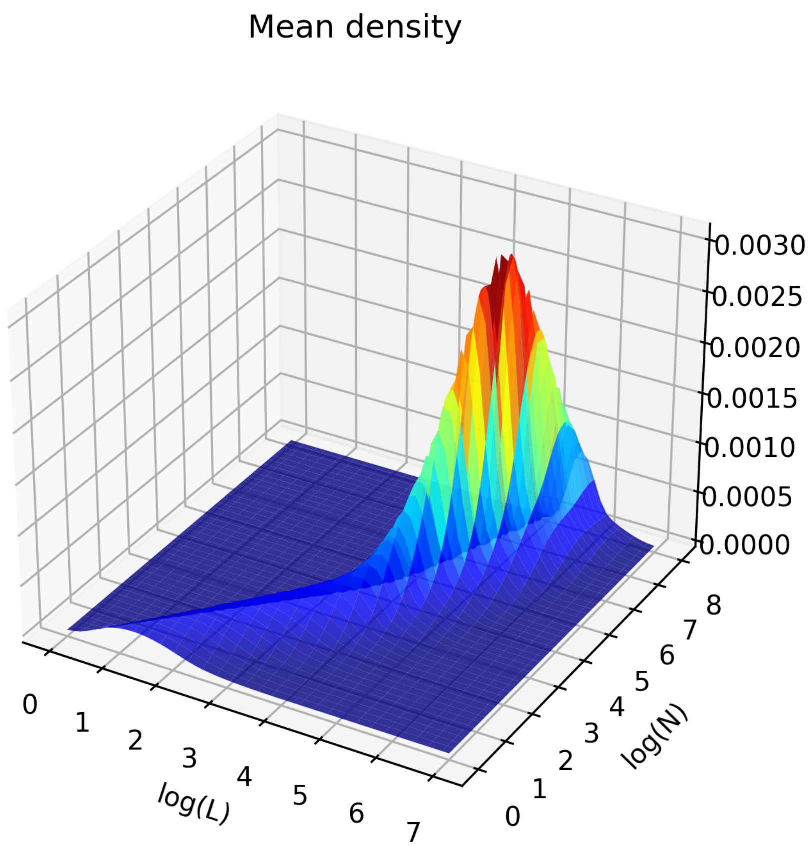


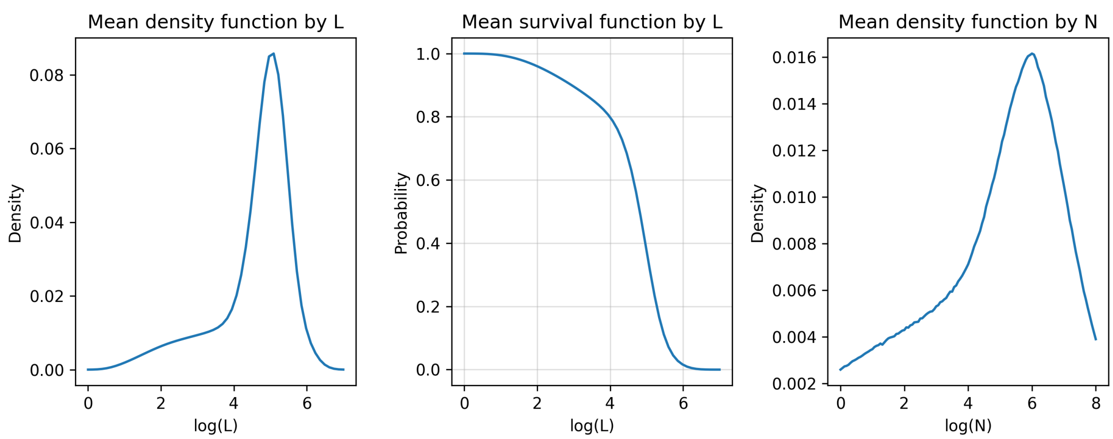
Model III after Principal component analysis (PCA)
Coloured by model
Coloured by cluster (4 clusters)
x1
x2
x3

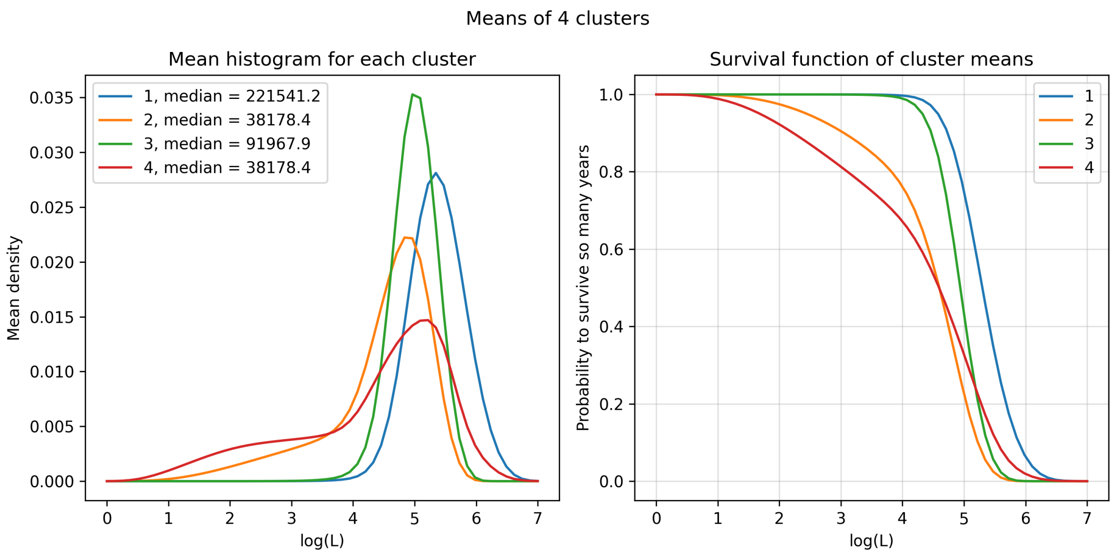

Percent of submodels in model 3 distributed with particular distribution on particular parameter in each of 4 clusters
cluster 1, size=8262
cluster 2, size=6804
cluster 3, size=2754
cluster 4, size=1863
Parameter
log(N)
log(R_*)
log(f_p)
log(n_e)
log(f_i)
log(f_c)
log(f_l)
lognormal
gauss
loglinear
Distribution
41% 43% 16%
33% 33% 33%
42% 42% 16%
33% 33% 33%
35% 35% 29%
33% 33% 33%
35% 35% 29%
25% 23% 52%
33% 33% 33%
24% 24% 52%
33% 33% 33%
32% 32% 36%
42% 14% 44%
32% 32% 36%
47% 53% 0%
33% 33% 33%
50% 50% 0%
33% 33% 33%
35% 35% 29%
0% 100% 0%
35% 35% 29%
9% 0% 91%
33% 33% 33%
4% 4% 91%
33% 33% 33%
26% 26% 48%
52% 4% 43%
26% 26% 48%

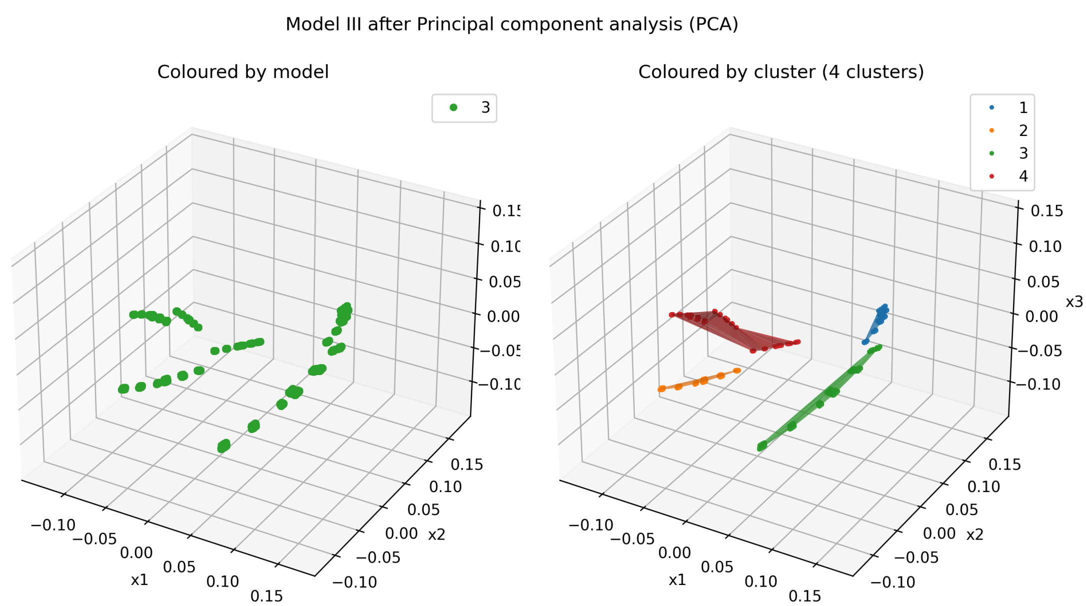

Percentage of distributions
($log(N)$, $log(f_p)$, $log(f_c)$) by (lognormal, gauss, loglinear)
coloured by cluster
3
1
2
4
0
100
200
300
400
500
600
700
(1, 0, 1)
(1, 1, 1)
(0, 0, 1)
(0, 1, 1)
(1, 0, 0)
(1, 0, 2)
(1, 1, 0)
(1, 1, 2)
(0, 0, 0)
(0, 0, 2)
(0, 1, 0)
(0, 1, 2)
(0, 2, 1)
(1, 2, 1)
(2, 0, 1)
(2, 1, 1)
(1, 2, 0)
(1, 2, 2)
(2, 0, 2)
(2, 1, 2)
(0, 2, 0)
(0, 2, 2)
(2, 0, 0)
(2, 1, 0)
(2, 2, 1)
(2, 2, 0)
(2, 2, 2)

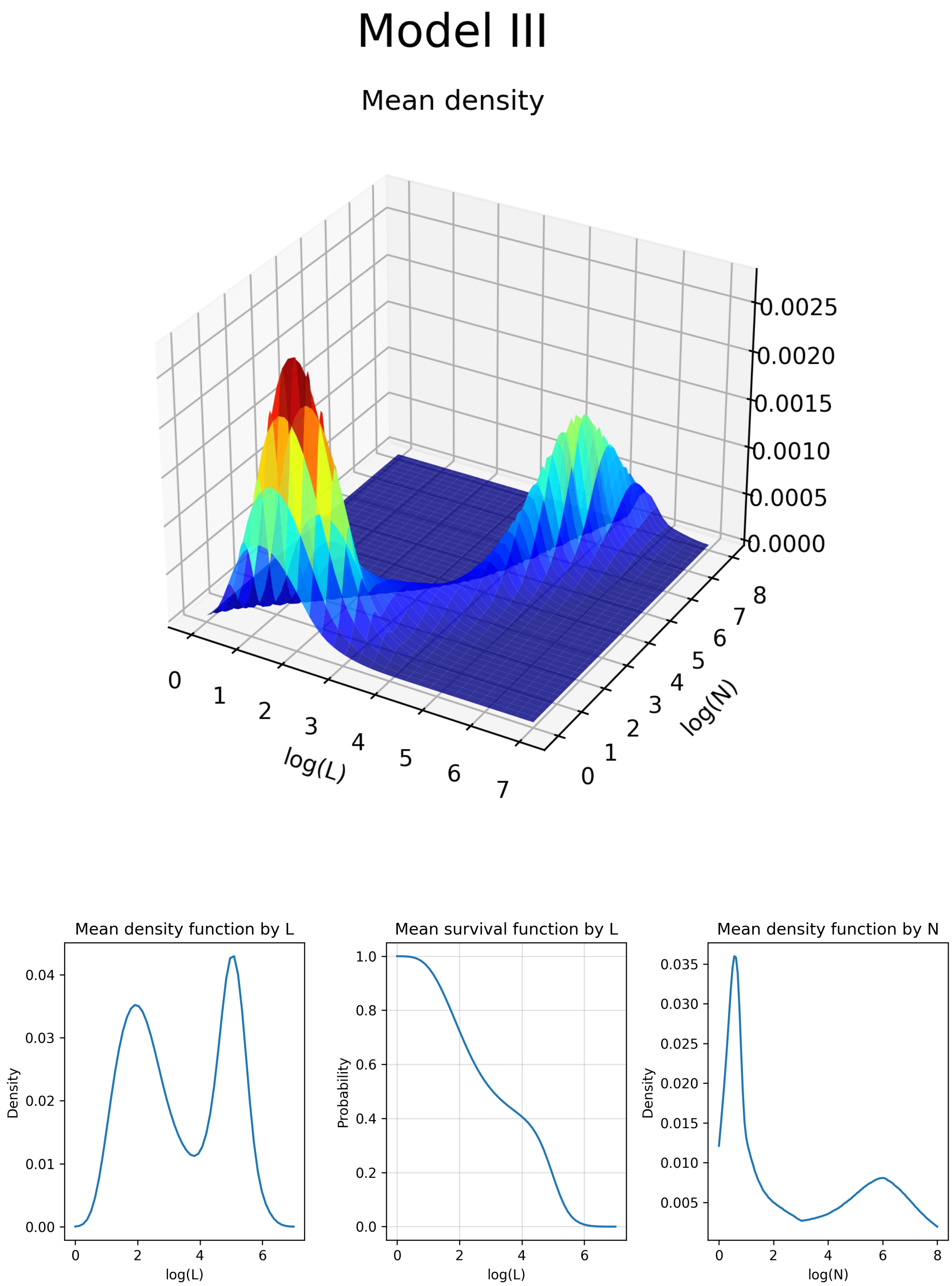
Model III

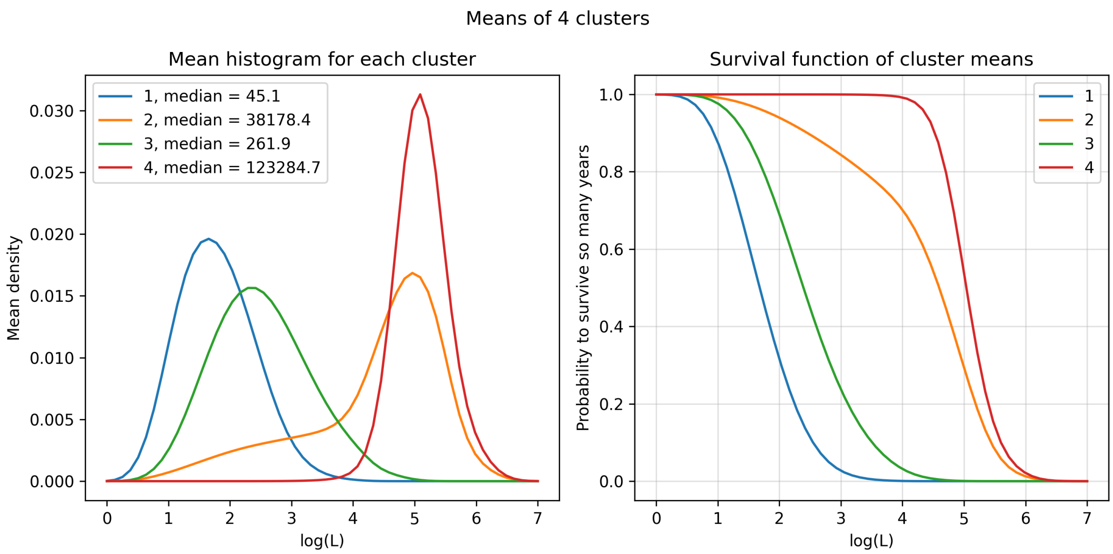

Mean density
log(L)
log(N)
0.0000
0.0005
0.0010
0.0015
0.0020
0.0025
0.0030

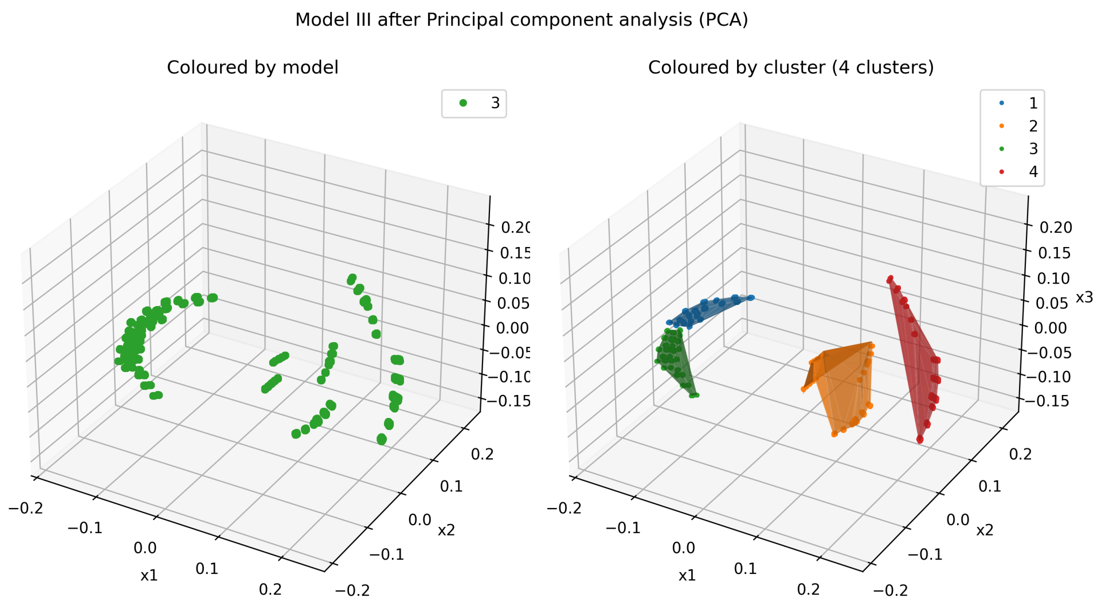

Mean density function by L
Density
log(L)
Mean survival function by L
Probability
log(L)
Mean density function by N
Density
log(N)


Means of 4 clusters
Mean histogram for each cluster
1, median = 221541.2
2, median = 38178.4
3, median = 91967.9
4, median = 38178.4
Mean density
log(L)
Survival function of cluster means
Probability to survive so many years
log(L)


Model III after Principal component analysis (PCA)
Coloured by model
Coloured by cluster (4 clusters)
x1
x2
x3

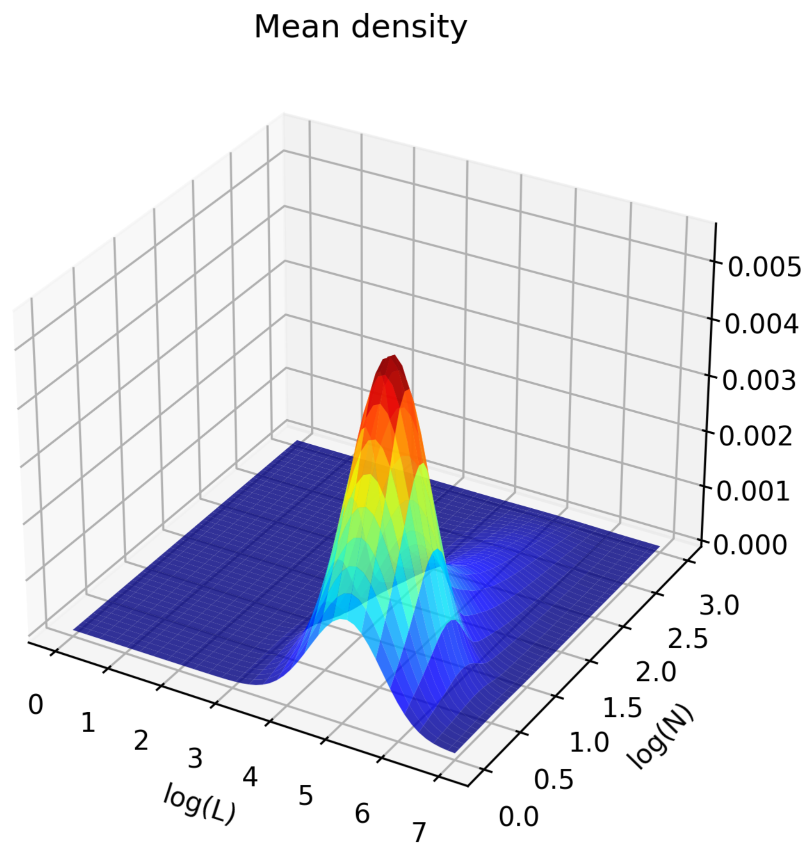

Model III
Mean density
0.0025
0.0020
0.0015
0.0010
0.0005
0.0000
log(L)
log(N)
Mean density function by L
Density
log(L)
Mean survival function by L
Probability
log(L)
Mean density function by N
Density
log(N)

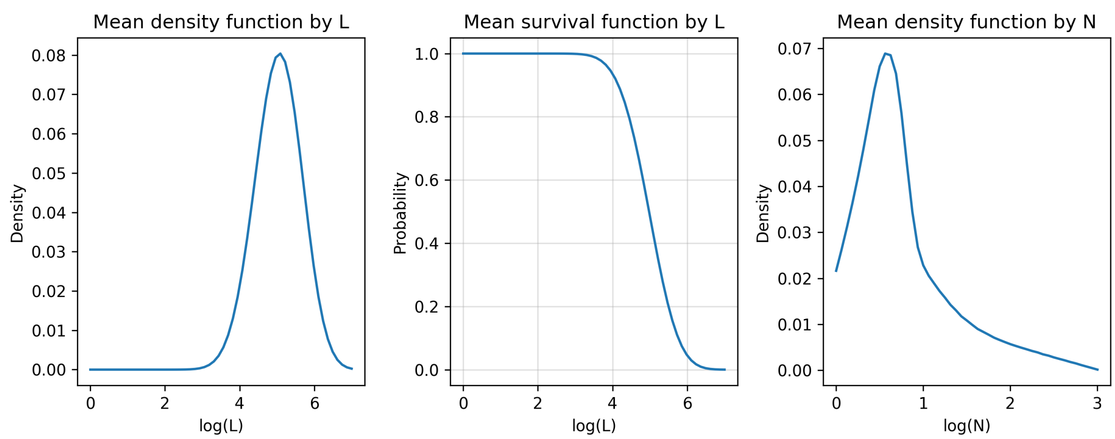


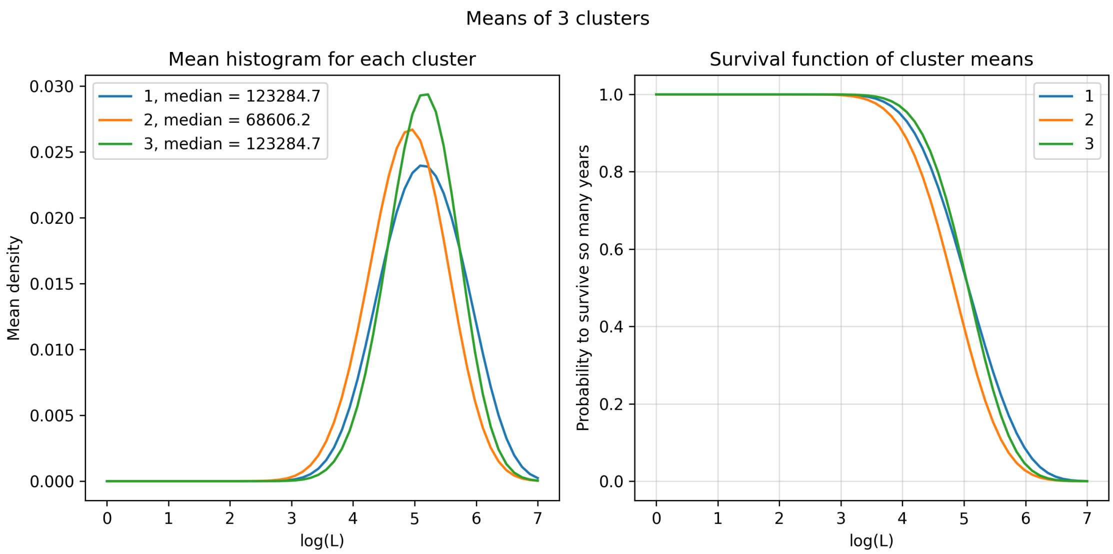



```
[6]: cluster(model=4, ks=[3])  # model 4
```

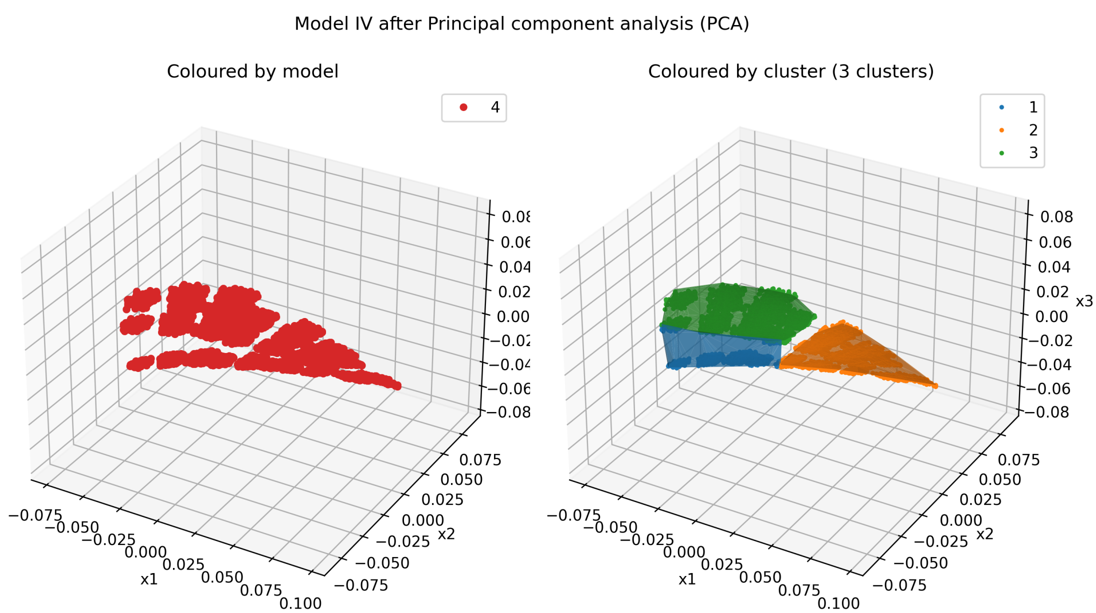
Model IV


Mean density
0.005
0.004
0.003
0.002
0.001
0.000
0 1 2 3 4 5 6 7
log(L)
0.0 0.5 1.0 1.5 2.0 2.5 3.0
log(N)

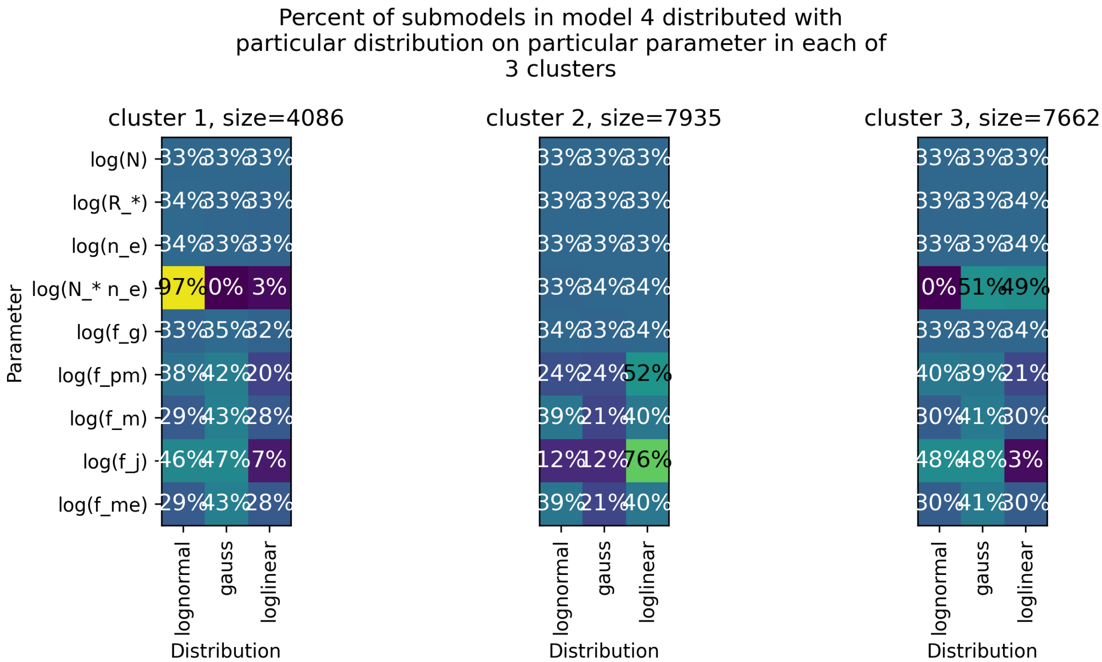

Mean density function by L
Density
log(L)
Mean survival function by L
Probability
log(L)
Mean density function by N
Density
log(N)

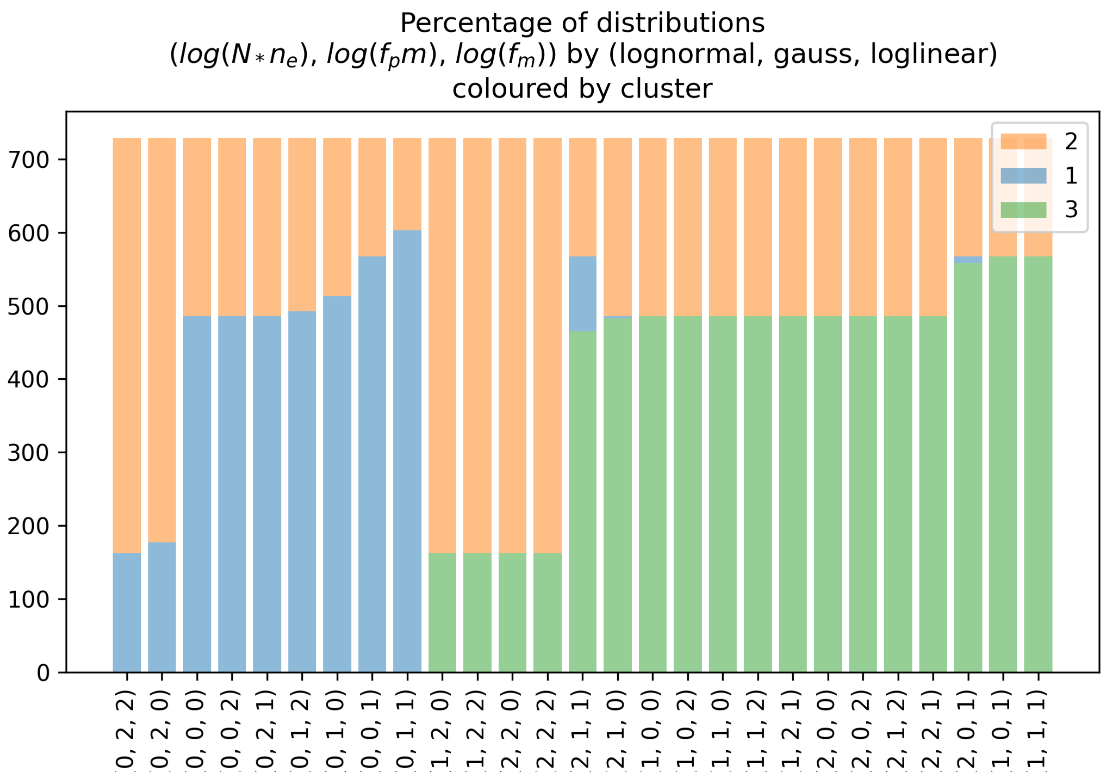


Means of 3 clusters
Mean histogram for each cluster
1, median = 123284.7
2, median = 68606.2
3, median = 123284.7
Mean density
log(L)
Survival function of cluster means
Probability to survive so many years
log(L)

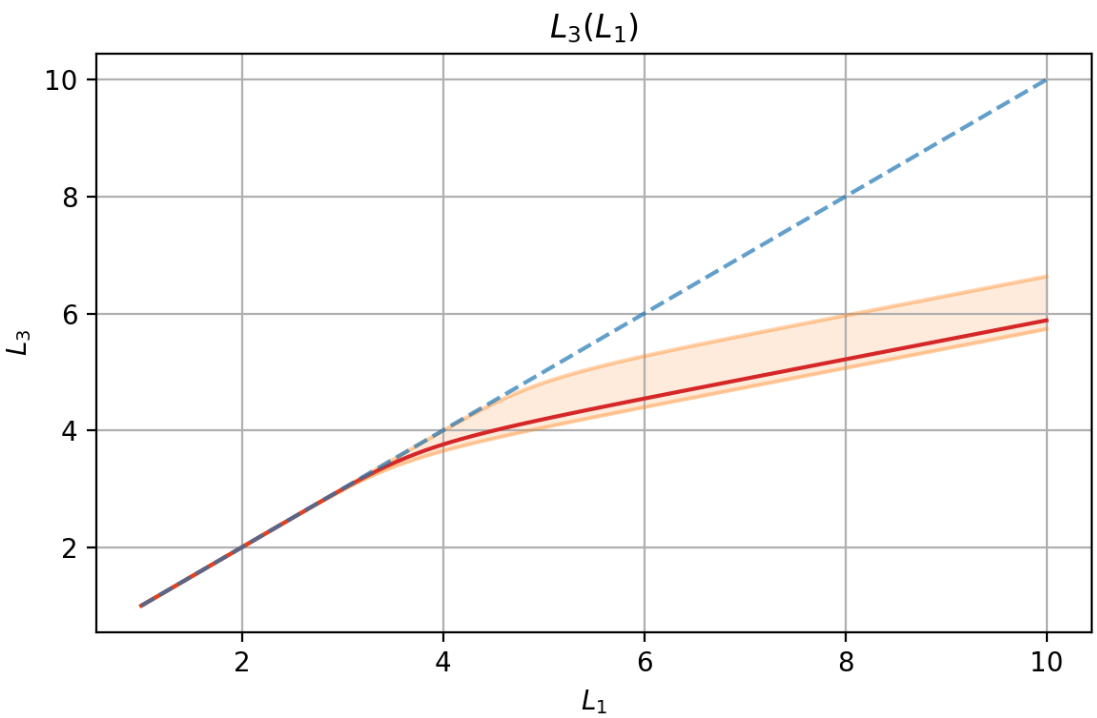


Model IV after Principal component analysis (PCA)
Coloured by model
Coloured by cluster (3 clusters)
x1
x2
x3

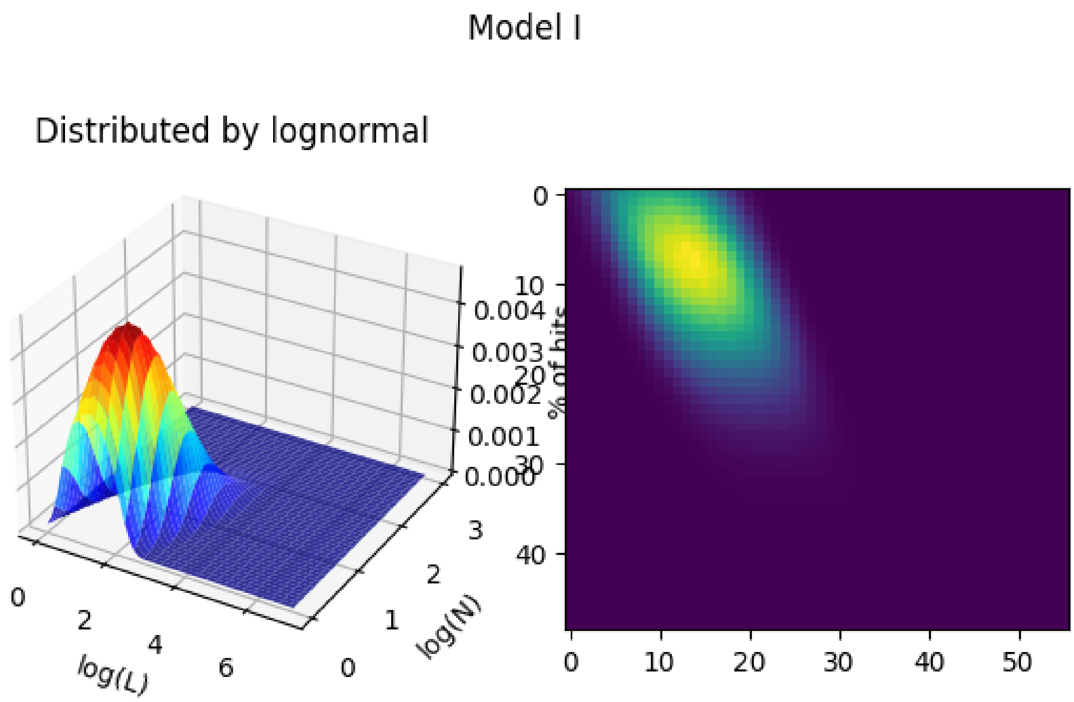

Percent of submodels in model 4 distributed with
particular distribution on particular parameter in each of
3 clusters
cluster 1, size=4086
cluster 2, size=7935
cluster 3, size=7662
Parameter
log(N)
log(R_*)
log(n_e)
log(N_* n_e)
log(f_g)
log(f_pm)
log(f_m)
log(f_j)
log(f_me)
lognormal
gauss
loglinear
Distribution

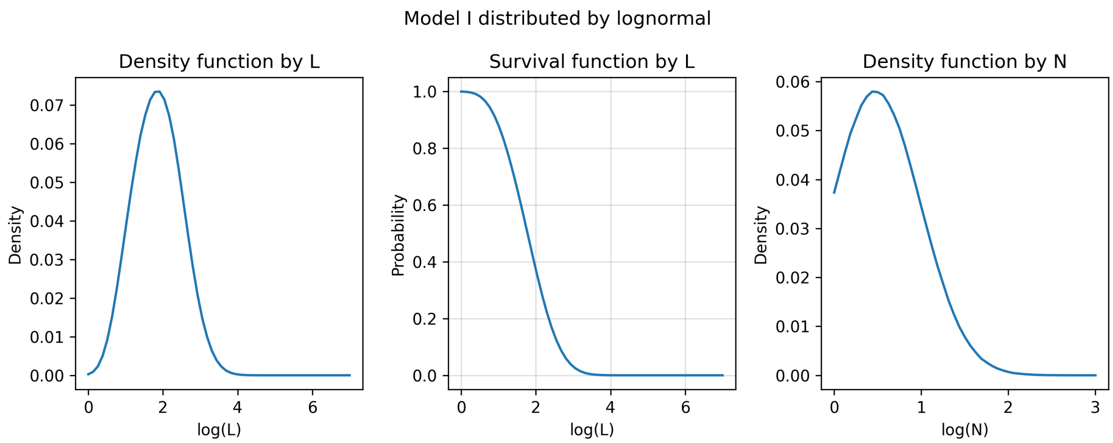

Percentage of distributions
($log(N_* n_e)$, $log(f_pm)$, $log(f_m)$) by (lognormal, gauss, loglinear)
coloured by cluster

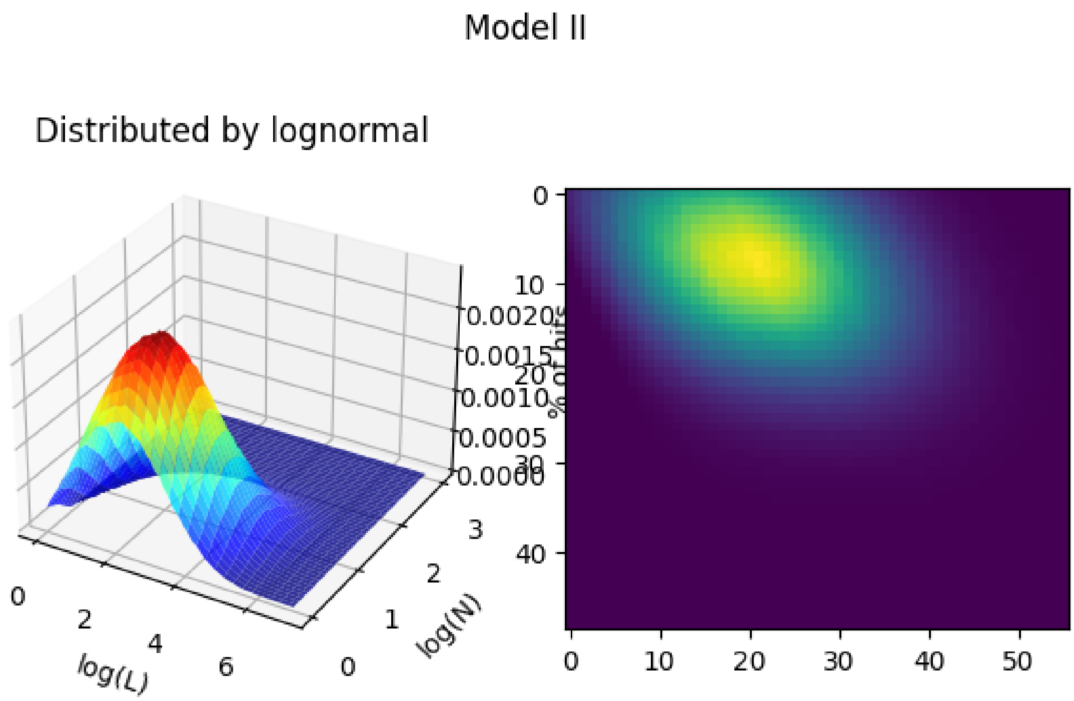
[7]:
```python
def polyDeltaL(logL1):
    minP, meanP, maxP = -2, np.log10(1.8), np.log10(5)
    L1 = 10 ** logL1
    a1 = 10 ** (9 - np.array([minP, meanP, maxP]) - np.log10(np.pi * 4))
    a1 = [np.roots([1, 3 * L1, 3 * L1 ** 2 + a, L1 ** 3]) for a in a1]
    return [- min(a, key=lambda x: np.abs(x.imag)).real for a in a1]


xi = np.linspace(1, 10, 100)
xi3 = np.array([xi, xi, xi]).T
h = np.array([polyDeltaL(x) for x in xi])
ca = [("tab:orange", 0.3), ("tab:red", 1), ("tab:orange", 0.3)]

for ylab, ydat in [("L_3", np.log10(np.abs(10 ** xi3 - h)))]:
    plt.figure(figsize=(6, 4), dpi=200, tight_layout=True)
    plt.fill_between(xi, ydat[:, 0], ydat[:, 2],
                     color=ca[0][0], alpha=ca[0][1] / 2)
    for i in range(3):
        plt.plot(xi, ydat[:, i], color=ca[i][0], alpha=ca[i][1])
    if "L_1" not in ylab:
        plt.plot(xi, xi, "--", alpha=0.7)
    plt.title(f"${ylab}(L_1)$")
    plt.xlabel("$L_1$")
    plt.ylabel(f"${ylab}$")
    plt.grid()
    plt.show()
```

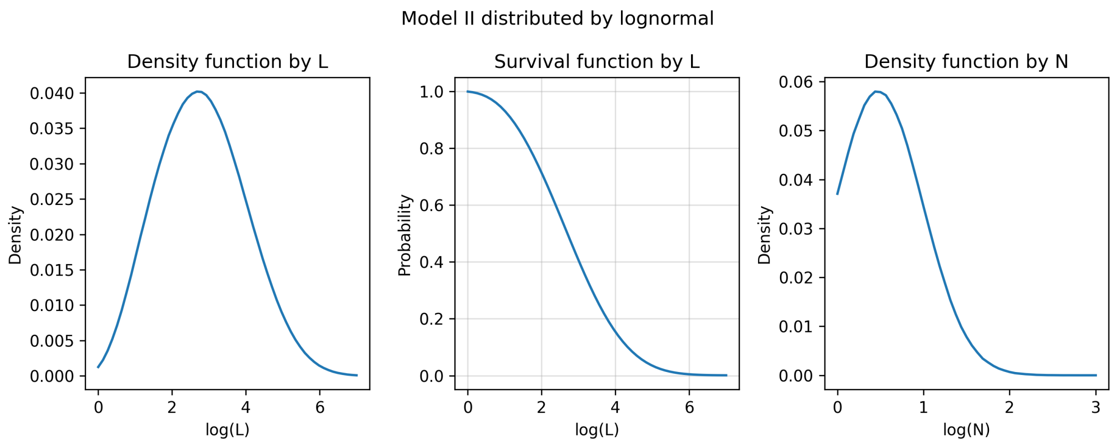


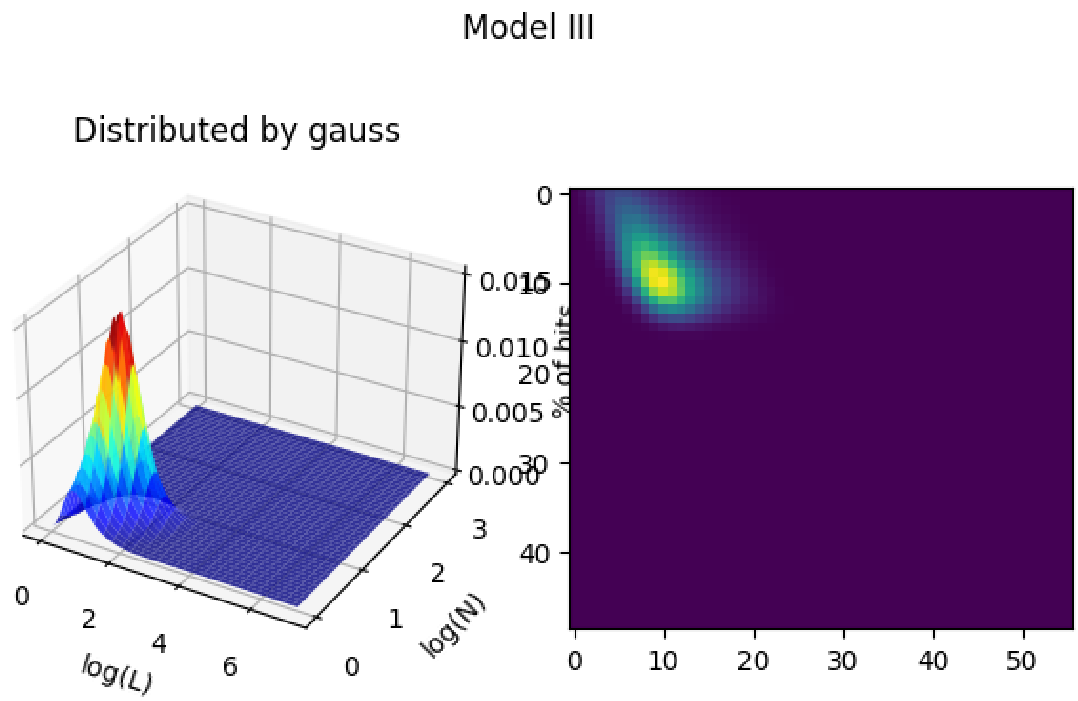
[8]:
```
from plot3D_L import draw_histograms3D
draw_histograms3D(model=1, distribution=tuple(0 for _ in range(6)),␣
 ↪supermodel=1)
draw_histograms3D(model=2, distribution=tuple(0 for _ in range(2)),␣
 ↪supermodel=1)
draw_histograms3D(model=3, distribution=tuple(1 for _ in range(6)),␣
 ↪supermodel=1)
draw_histograms3D(model=4, distribution=tuple(0 for _ in range(8)),␣
 ↪supermodel=1)
plt.show()
```

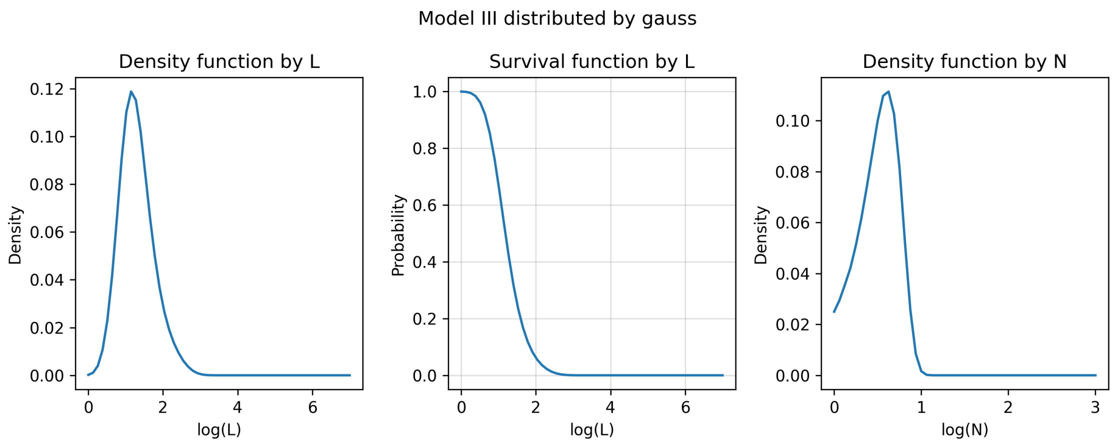


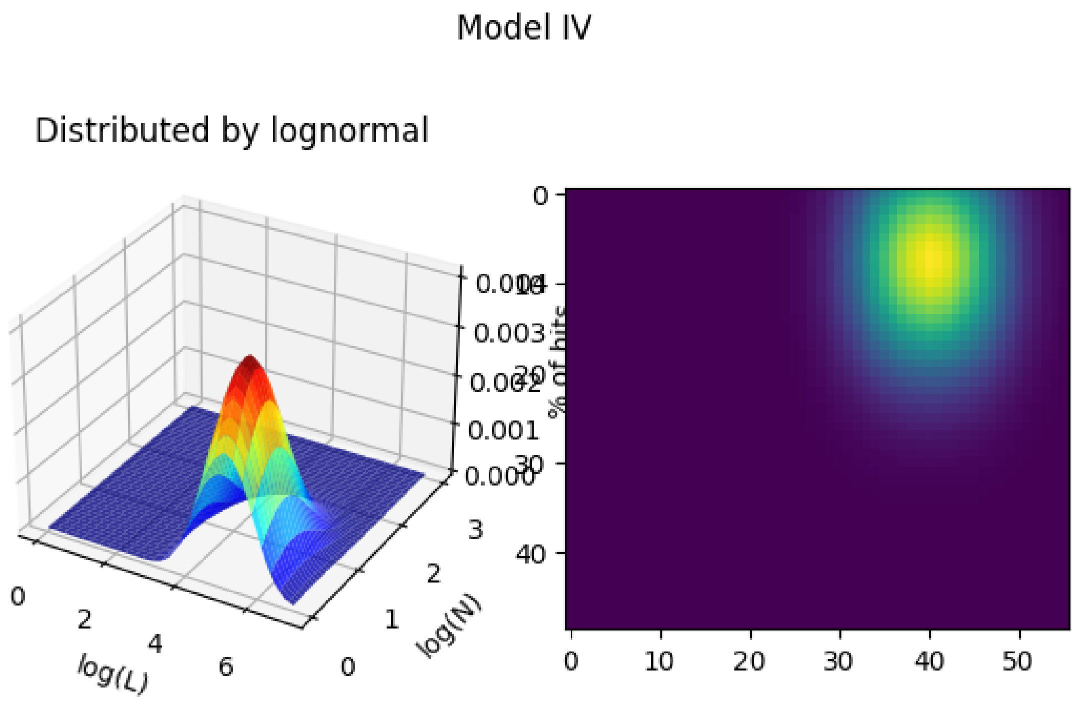

Model I distributed by lognormal
Density function by L
Density
log(L)
Survival function by L
Probability
log(L)
Density function by N
Density
log(N)

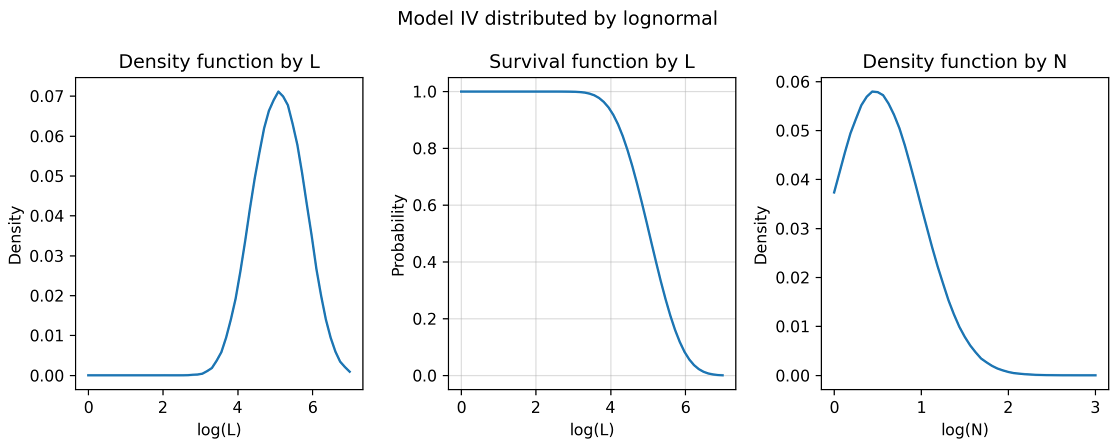

Model II
Distributed by lognormal
log(L)
log(N)
% of hits


Model II distributed by lognormal
Density function by L
Survival function by L
Density function by N
Density
Probability
log(L)
log(N)


Model III
Distributed by gauss
log(L)
log(N)


Model III distributed by gauss
Density function by L
Density
log(L)
Survival function by L
Probability
log(L)
Density function by N
Density
log(N)


Model IV
Distributed by lognormal
log(L)
log(N)
% of hits




```
[ ]: from tabela_napake_p import modeli_napake
     e = modeli_napake()
```

1 Pravila

Pomembne so pomembnosti parametrov (koliko vpliva vrednost) in v katero smer vpliva (+/- v formuli). Pravila ne povejo nič dodatnega, nepričakovanega. Opazimo, da je za prvi model najpomembnejši N, nato f_p in tretji je f_c, potem se N spet ponovi. Vpliv vrednosti pa je pričakovan izformule modela (N pozitivno vpliva in f_c negativno). Torej nič zanimivega, česar nam ne bi povedala že pomembnost parametrov in predznak pred parametrom v formuli. So pa pravila v regresijskem modelu nekoliko daljša kot v klasifikacijskem, kar je posledica enostavnejšega problema.

1.1 Model Drake

log(L):

- $(log(N) <= 0.9) \wedge (log(f_c) > -1.1) \wedge (log(f_p) > -0.7) \wedge (log(f_c) <= -0.7) \Rightarrow 1.0$
- $(log(N) <= 0.9) \wedge (log(f_c) > -0.9) \wedge (log(f_p) > -0.5) \wedge (log(f_c) > -0.5) \Rightarrow 0.4$
- $(log(N) <= 0.9) \wedge (log(f_c) > -0.9) \wedge (log(f_p) <= -0.7) \wedge (log(f_p) <= -1.2) \Rightarrow 2.1$
- $(log(N) <= 0.9) \wedge (log(f_c) > -0.9) \wedge (log(f_p) <= -0.5) \wedge (log(f_p) > -1.2) \Rightarrow 1.4$
- $(log(N) <= 0.9) \wedge (log(f_c) <= -0.9) \wedge (log(f_p) > -0.5) \wedge (log(f_c) <= -1.4) \Rightarrow 1.9$
- $(log(N) <= 0.9) \wedge (log(f_c) <= -0.9) \wedge (log(f_p) > -0.5) \wedge (log(f_c) > -1.4) \Rightarrow 1.4$
- $(log(N) > 0.9) \wedge (log(f_c) > -0.9) \wedge (log(N) <= 1.7) \wedge (log(f_p) > -0.6) \Rightarrow 1.5$

L < 1000:

- $(log(N) > 1.8) \wedge (log(f_c) <= -0.8) \Rightarrow 0.2$
- $(log(N) > 1.8) \wedge (log(f_c) > -0.8) \Rightarrow 0.9$
- $(log(N) <= 1.8) \wedge (log(f_p) <= -1.6) \Rightarrow 0.5$

- $(log(N) <= 1.8) \wedge (log(f_p) <= -1.2) \wedge (log(f_c) <= -0.8) \Rightarrow 0.4$
- $(log(N) <= 1.8) \wedge (log(f_p) <= -1.2) \wedge (log(f_c) > -0.8) \Rightarrow 0.9$
- $(log(N) <= 1.8) \wedge (log(f_p) > -1.2) \wedge (log(f_c) <= -1.8) \wedge (log(N) <= 0.7) \Rightarrow 1.0$

L < 10 000:

- $(log(f_p) > -1.6) \wedge (log(N) > 2.4) \Rightarrow 0.9$
- $(log(f_p) <= -1.2) \wedge (log(N) <= 1.1) \Rightarrow 1.0$
- $(log(f_p) <= -1.2) \wedge (log(N) > 1.1) \Rightarrow 0.6$
- $(log(f_p) <= -1.6) \Rightarrow 0.8$
- $(log(N) <= 2.4) \wedge (log(f_p) > -1.2) \Rightarrow 1.0$
- $(log(N) > 2.4) \Rightarrow 0.8$

1.2 Model Expand

log(L):

- $(log(N) <= 1.2) \wedge (log(f_c) > -0.8) \wedge (log(f_p) > -0.7) \wedge (log(N) > 0.6) \Rightarrow 0.9$
- $(log(N) <= 1.2) \wedge (log(f_c) > -0.8) \wedge (log(f_p) > -0.7) \wedge (log(N) <= 0.6) \Rightarrow 0.4$
- $(log(N) <= 1.2) \wedge (log(f_c) > -1.1) \wedge (log(f_p) > -0.7) \wedge (log(f_c) > -0.6) \Rightarrow 0.6$
- $(log(N) <= 1.2) \wedge (log(f_c) > -1.1) \wedge (log(f_p) > -0.7) \wedge (log(f_c) <= -0.6) \Rightarrow 1.1$
- $(log(N) <= 1.2) \wedge (log(f_c) > -0.8) \wedge (log(f_p) <= -0.7) \wedge (log(N) <= 0.5) \Rightarrow 1.3$
- $(log(N) <= 1.2) \wedge (log(f_c) <= -1.1) \wedge (log(f_p) > -0.5) \wedge (log(N) <= 0.8) \Rightarrow 1.5$
- $(log(N) <= 1.2) \wedge (log(f_c) <= -1.1) \wedge (log(f_p) > -0.5) \wedge (log(N) > 0.8) \Rightarrow 2.1$
- $(log(N) <= 1.2) \wedge (log(f_c) <= -0.8) \wedge (log(f_p) > -0.5) \wedge (log(f_c) <= -1.2) \Rightarrow 1.8$
- $(log(N) <= 1.2) \wedge (log(f_c) <= -0.8) \wedge (log(f_p) > -0.5) \wedge (log(f_c) > -1.2) \Rightarrow 1.3$
- $(log(N) <= 1.2) \wedge (log(f_c) <= -0.8) \wedge (log(f_p) <= -0.5) \wedge (log(N) > 0.6) \Rightarrow 2.7$

L < 1000:

- $(log(N) > 1.8) \wedge (log(f_c) <= -1.1) \Rightarrow 0.2$
- $(log(N) > 1.8) \wedge (log(f_c) > -1.1) \wedge (log(N) <= 2.2) \Rightarrow 0.9$
- $(log(N) > 1.8) \wedge (log(f_c) > -1.1) \wedge (log(N) > 2.2) \Rightarrow 0.6$
- $(log(N) > 1.8) \wedge (log(f_c) > -1.1) \wedge (log(f_c) > -0.6) \Rightarrow 0.9$
- $(log(N) > 1.8) \wedge (log(f_c) > -0.9) \Rightarrow 0.8$
- $(log(N) <= 1.8) \wedge (log(f_p) <= -1.3) \wedge (log(f_c) > -0.7) \Rightarrow 0.9$
- $(log(N) <= 1.8) \wedge (log(f_p) <= -0.8) \wedge (log(f_c) <= -1.2) \Rightarrow 0.5$
- $(log(N) <= 1.7) \wedge (log(f_p) <= -1.4) \Rightarrow 0.6$

1.3 Model Simplified

log(L):

- $(log(f_b) <= -1.8) \wedge (log(f_a) > -0.1) \wedge (log(f_b) > -2.5) \wedge (log(N) > 1.1) \Rightarrow 3.1$
- $(log(f_b) <= -1.8) \wedge (log(f_a) > -0.1) \wedge (log(f_b) > -2.5) \wedge (log(N) <= 1.1) \Rightarrow 2.1$

L < 1000:

- $(log(f_b) <= -2.2) \wedge (log(f_a) > 0.3) \wedge (log(N) > 1.1) \Rightarrow 0.1$
- $(log(f_b) <= -2.2) \wedge (log(f_a) > 0.2) \wedge (log(N) <= 1.1) \wedge (log(f_b) > -3.0) \Rightarrow 0.9$
- $(log(f_b) <= -2.2) \wedge (log(f_a) > 0.2) \wedge (log(N) <= 1.1) \wedge (log(f_b) <= -3.0) \Rightarrow 0.3$
- $(log(f_b) <= -2.5) \wedge (log(f_a) > 0.6) \wedge (log(N) <= 0.8) \Rightarrow 0.7$
- $(log(f_b) <= -2.2) \wedge (log(f_a) <= 0.2) \wedge (log(N) <= 0.5) \Rightarrow 0.2$
- $(log(f_b) <= -2.2) \wedge (log(f_a) <= 0.2) \wedge (log(f_a) > -0.2) \Rightarrow 0.2$
- $(log(f_b) > -2.2) \wedge (log(f_a) <= -1.2) \wedge (log(f_b) <= -0.7) \wedge (log(N) > 0.7) \Rightarrow 0.0$
- $(log(f_b) > -2.2) \wedge (log(f_a) <= -0.9) \wedge (log(f_b) <= -1.1) \wedge (log(f_b) <= -1.4) \Rightarrow 0.0$
- $(log(f_b) > -2.2) \wedge (log(f_a) <= -0.9) \wedge (log(f_b) > -1.1) \wedge (log(N) <= 0.9) \Rightarrow 0.9$

L < 10 000:

- $(log(f_b) > -2.5) \wedge (log(f_a) > -0.9) \wedge (log(N) > 2.2) \Rightarrow 0.7$
- $(log(f_b) > -2.5) \wedge (log(f_a) > -0.9) \wedge (log(N) <= 2.2) \wedge (log(f_b) > -2.2) \Rightarrow 1.0$
- $(log(f_b) <= -2.5) \wedge (log(f_a) > -0.1) \wedge (log(N) <= 1.2) \wedge (log(f_b) > -3.5) \Rightarrow 1.0$
- $(log(f_b) <= -2.2) \wedge (log(f_a) > -0.5) \wedge (log(N) > 1.3) \Rightarrow 0.2$
- $(log(f_b) <= -2.2) \wedge (log(f_a) <= -0.5) \wedge (log(f_a) <= -0.9) \Rightarrow 0.0$
- $(log(f_b) <= -2.5) \wedge (log(f_a) <= -0.1) \wedge (log(f_b) <= -3.0) \Rightarrow 0.0$
- $(log(f_b) <= -2.2) \wedge (log(f_a) <= -0.5) \wedge (log(N) > 0.7) \Rightarrow 0.0$

L < 100 000:

- $(log(f_b) <= -3.0) \wedge (log(f_a) <= -0.5) \Rightarrow 0.1$
- $(log(f_b) <= -3.0) \wedge (log(f_a) > -0.5) \Rightarrow 0.9$
- $(log(f_b) > -3.0) \wedge (log(N) <= 1.7) \wedge (log(f_a) <= -1.8) \Rightarrow 0.9$

1.4 Model Rare Earth

log(L):

- $(log(N_* n_e) <= 11.8) \wedge (log(N_* n_e) <= 11.2) \wedge (log(f_p m) > -1.2) \wedge (log(f_m e) > -2.0) \Rightarrow 4.4$
- $(log(N_* n_e) <= 11.8) \wedge (log(N_* n_e) <= 11.2) \wedge (log(f_p m) > -1.2) \wedge (log(f_m e) <= -2.0) \Rightarrow 3.9$
- $(log(N_* n_e) <= 11.8) \wedge (log(N_* n_e) > 11.2) \wedge (log(f_p m) > -1.2) \wedge (log(f_m) <= -1.9) \Rightarrow 4.5$

- $(log(N_*n_e) <= 11.6) \wedge (log(f_pm) > -1.2) \wedge (log(f_me) <= -2.0) \wedge (log(N_*n_e) > 11.2) \Rightarrow 4.3$
- $(log(N_*n_e) <= 11.6) \wedge (log(f_pm) > -1.2) \wedge (log(f_me) <= -2.0) \wedge (log(N_*n_e) <= 11.2) \Rightarrow 3.8$
- $(log(N_*n_e) > 11.6) \wedge (log(f_pm) <= -1.2) \wedge (log(f_m) <= -2.0) \wedge (log(f_me) > -1.9) \Rightarrow 4.6$
- $(log(N_*n_e) > 11.6) \wedge (log(f_pm) <= -1.2) \wedge (log(f_m) <= -2.0) \wedge (log(f_me) <= -1.9) \Rightarrow 4.2$
- $(log(N_*n_e) > 11.8) \wedge (log(f_m) <= -1.9) \wedge (log(f_pm) > -1.2) \wedge (log(N_*n_e) > 12.2) \Rightarrow 5.5$
- $(log(N_*n_e) > 11.8) \wedge (log(f_m) <= -1.9) \wedge (log(f_pm) > -1.2) \wedge (log(N_*n_e) <= 12.2) \Rightarrow 5.0$
- $(log(N_*n_e) > 11.8) \wedge (log(f_m) <= -1.9) \wedge (log(f_pm) <= -1.2) \wedge (log(f_me) <= -1.8) \Rightarrow 4.4$

L < 10 000:

- $(log(N_*n_e) > 11.2) \wedge (log(f_pm) > -1.2) \wedge (log(f_j) > -0.6) \Rightarrow 0.0$
- $(log(N_*n_e) > 11.2) \wedge (log(f_pm) > -1.2) \wedge (log(f_j) <= -0.6) \wedge (log(N_*n_e) <= 11.8) \Rightarrow 0.4$
- $(log(N_*n_e) > 11.2) \wedge (log(f_pm) > -1.2) \wedge (log(f_j) <= -0.6) \wedge (log(N_*n_e) > 11.8) \Rightarrow 0.0$
- $(log(N_*n_e) > 11.2) \wedge (log(f_pm) <= -1.2) \wedge (log(f_m) > -2.0) \wedge (log(N_*n_e) > 11.6) \Rightarrow 0.0$
- $(log(N_*n_e) > 11.2) \wedge (log(f_pm) <= -1.2) \wedge (log(N_*n_e) > 11.6) \wedge (log(f_m) > -2.0) \Rightarrow 0.0$
- $(log(N_*n_e) > 11.2) \wedge (log(f_pm) <= -1.2) \wedge (log(N_*n_e) > 11.6) \wedge (log(f_m) <= -2.0) \Rightarrow 0.3$
- $(log(N_*n_e) <= 11.2) \wedge (log(f_pm) <= -1.2) \wedge (log(R_*) <= 0.3) \Rightarrow 0.5$
- $(log(N_*n_e) <= 11.2) \wedge (log(f_pm) <= -1.2) \wedge (log(R_*) > 0.3) \wedge (log(f_me) <= -2.0) \Rightarrow 1.0$

L < 100 000:

- $(log(N_*n_e) > 11.8) \wedge (log(f_m) <= -1.9) \wedge (log(f_pm) > -1.2) \wedge (log(N_*n_e) > 12.1) \Rightarrow 0.2$
- $(log(N_*n_e) > 11.8) \wedge (log(f_m) <= -1.9) \wedge (log(f_pm) > -1.2) \wedge (log(N_*n_e) <= 12.1) \Rightarrow 0.6$
- $(log(N_*n_e) > 11.8) \wedge (log(f_m) <= -1.9) \wedge (log(f_pm) <= -1.2) \wedge (log(f_me) > -1.8) \Rightarrow 0.5$
- $(log(N_*n_e) > 11.8) \wedge (log(f_m) <= -1.9) \wedge (log(f_pm) <= -1.2) \wedge (log(f_me) <= -1.8) \Rightarrow 0.9$
- $(log(N_*n_e) > 11.8) \wedge (log(f_m) > -1.9) \wedge (log(f_pm) <= -1.4) \Rightarrow 0.6$
- $(log(N_*n_e) > 11.8) \wedge (log(f_m) > -1.9) \wedge (log(f_pm) > -1.4) \wedge (log(f_j) > -0.4) \Rightarrow 0.1$
- $(log(N_*n_e) <= 11.8) \wedge (log(f_m) <= -1.9) \wedge (log(f_me) <= -1.8) \wedge (log(n_e) > 0.2) \Rightarrow 1.0$
- $(log(N_*n_e) <= 11.8) \wedge (log(N_*n_e) > 11.3) \wedge (log(f_m) <= -2.0) \wedge (log(f_me) <= -1.8) \Rightarrow 1.0$
- $(log(N_*n_e) <= 11.8) \wedge (log(N_*n_e) > 11.3) \wedge (log(f_m) > -2.0) \wedge (log(f_pm) > -1.1) \Rightarrow 0.4$
- $(log(N_*n_e) <= 11.8) \wedge (log(N_*n_e) > 11.3) \wedge (log(f_m) > -2.0) \wedge (log(f_pm) <= -1.1) \Rightarrow 0.8$

1.5 Super Model

log(L):

- $(log(f_m) > -0.8) \wedge (log(f_b) > -1.8) \wedge (log(N) <= 1.2) \wedge (log(f_c) > -1.1) \Rightarrow 1.0$
- $(log(f_m) > -0.8) \wedge (log(f_b) > -1.8) \wedge (log(N) <= 1.2) \wedge (log(f_c) <= -1.1) \Rightarrow 1.8$

- $(log(f_m) > -0.8) \wedge (log(f_b) > -1.8) \wedge (log(N) > 1.2) \wedge (log(N) > 1.8) \Rightarrow 3.0$
- $(log(f_m) > -0.8) \wedge (log(f_b) > -1.8) \wedge (log(N) > 1.1) \wedge (log(N) <= 1.8) \Rightarrow 2.1$
- $(log(f_m) > -0.8) \wedge (log(f_b) <= -1.8) \wedge (log(f_a) <= -0.1) \Rightarrow 4.3$
- $(log(N_*n_e) <= 5.3) \wedge (log(f_b) > -1.8) \wedge (log(N) <= 1.1) \wedge (log(f_c) <= -1.1) \Rightarrow 1.8$
- $(log(N_*n_e) <= 5.3) \wedge (log(f_b) > -1.8) \wedge (log(N) <= 1.1) \wedge (log(f_c) > -1.1) \Rightarrow 1.0$

L < 10 000:

- $(log(N_*n_e) > 11.1) \wedge (log(N_*n_e) <= 11.4) \wedge (log(f_pm) <= -1.1) \Rightarrow 0.5$
- $(log(N_*n_e) > 11.1) \wedge (log(N_*n_e) <= 11.4) \wedge (log(f_pm) > -1.2) \Rightarrow 0.2$
- $(log(N_*n_e) > 10.8) \wedge (log(N_*n_e) > 11.2) \wedge (log(f_pm) <= -1.2) \wedge (log(f_m) > -2.0) \Rightarrow 0.1$
- $(log(N_*n_e) <= 11.1) \wedge (log(f_b) <= -2.2) \wedge (log(f_a) > 0.3) \Rightarrow 0.9$
- $(log(N_*n_e) <= 11.1) \wedge (log(f_b) <= -2.2) \wedge (log(f_a) <= -0.1) \Rightarrow 0.2$
- $(log(N_*n_e) <= 11.1) \wedge (log(f_b) <= -2.5) \Rightarrow 0.6$
- $(log(N_*n_e) <= 10.8) \wedge (log(f_b) > -2.5) \wedge (log(f_a) <= -0.9) \Rightarrow 0.8$

L < 100 000:

- $(log(N_*n_e) <= 11.7) \wedge (log(N_*n_e) > 11.3) \wedge (log(f_pm) <= -1.1) \Rightarrow 0.9$
- $(log(N_*n_e) <= 11.7) \wedge (log(N_*n_e) > 11.3) \wedge (log(f_pm) > -1.1) \Rightarrow 0.6$
- $(log(N_*n_e) <= 11.4) \wedge (log(f_b) <= -3.0) \Rightarrow 0.7$
- $(log(N_*n_e) <= 11.4) \wedge (log(f_b) > -3.0) \Rightarrow 0.9$
- $(log(N_*n_e) > 11.7) \wedge (log(f_m) > -1.9) \wedge (log(f_me) <= -2.0) \Rightarrow 0.5$
- $(log(N_*n_e) > 11.7) \wedge (log(f_m) > -1.9) \wedge (log(f_me) > -2.0) \wedge (log(N_*n_e) > 11.9) \Rightarrow 0.1$
- $(log(N_*n_e) > 11.7) \wedge (log(f_m) <= -1.9) \wedge (log(f_pm) <= -1.1) \wedge (log(f_me) > -1.9) \Rightarrow 0.7$
- $(log(N_*n_e) > 11.7) \wedge (log(f_m) <= -1.9) \wedge (log(f_pm) <= -1.1) \wedge (log(f_me) <= -1.9) \Rightarrow 0.9$
- $(log(N_*n_e) > 11.7) \wedge (log(f_m) <= -1.9) \wedge (log(f_pm) > -1.2) \wedge (log(f_me) > -1.9) \Rightarrow 0.3$

[ ]:
```
models = []
labels = []
results = {}
with open("ML_tabele.txt", "r") as f:
    lines = f.readlines()
    for i in range(len(lines) // 13 + 1):
        part_lines = lines[i * 13:(i+1) * 13 - 1]
        model = part_lines[-2][:-1].replace("_", " ")
        label = part_lines[-1][:-1]
        if model not in models:
            models.append(model)
        if label not in labels:
```

```
            labels.append(label)
        col_names = part_lines[0][:-1].split(" ")[1:]
        row_names = [l[:-1].split(" ")[0][:13]
                     for l in part_lines[1:-2] if "error" not in l]
        part_lines = [[round(float(n), 4) for n in l[:-1].split(" ")[1:]]
                      for l in part_lines[1:-2] if "error" not in l]
        results[(model, label)] = pd.DataFrame(part_lines,
                                               index=row_names,␣
↪columns=col_names)
```

[ ]:
```
pd.set_option('display.width', 82)
pd.set_option('display.max_columns', None)
for model in models:
    print("\n  " + "="*60 + "\n")
    print(" "*5 + "-"*20 + " "*3 + model + " "*3 + "-"*20 + "\n")
    a = pd.concat({k[1]: l for k, l in results.items() if model in k and "<" in␣
↪k[1]}, 1)
    a.columns = a.columns.swaplevel()
    a.name = label
    a = a[sorted(a.columns, key=lambda x: (x[0], x[1].replace(" 0", "0")))]
    print(a)
    a.style.background_gradient(cmap="Blues")
    # from IPython.display import display
    # display(a.style.background_gradient(cmap="Oranges"))
```

[ ]:
```
pd.set_option('display.width', 72)
pd.set_option('display.max_columns', None)

for label in labels:
    print("\n  " + "="*60 + "\n")
    print(" "*5 + "-"*20 + " "*3 + label + " "*3 + "-"*20 + "\n")
    a = pd.concat({k[0].replace("Model ", ""): l for k, l in results.items() if␣
↪label in k}, 1)
    a.columns = a.columns.swaplevel()
    a.name = label
    a = a[sorted(a.columns)]
    if "100 " in label:
        pd.set_option('display.width', 62)
    print(a)
    a.style.background_gradient(cmap="Blues")
    # from IPython.display import display
    # display(a.style.background_gradient(cmap="Oranges"))
```