GroupModels

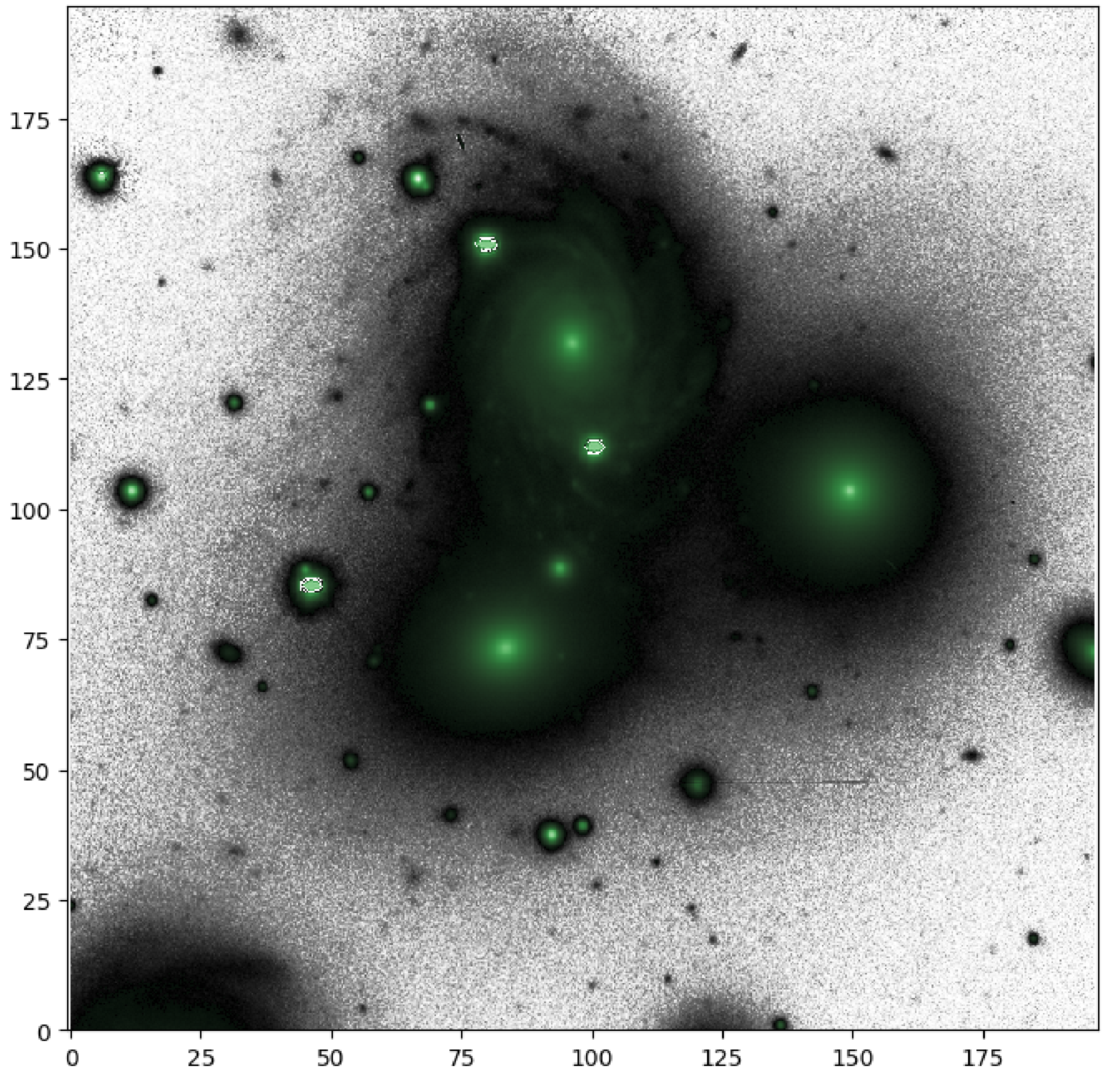
June 10, 2023

1 Group Models

Here you will learn how to combine models together into a larger, more complete, model of a given system. This is a powerful and necessary capability when analysing objects in crowded environments. As telescopes achieve ever deeper photometry we have learned that all environments are crowded when projected onto the sky!

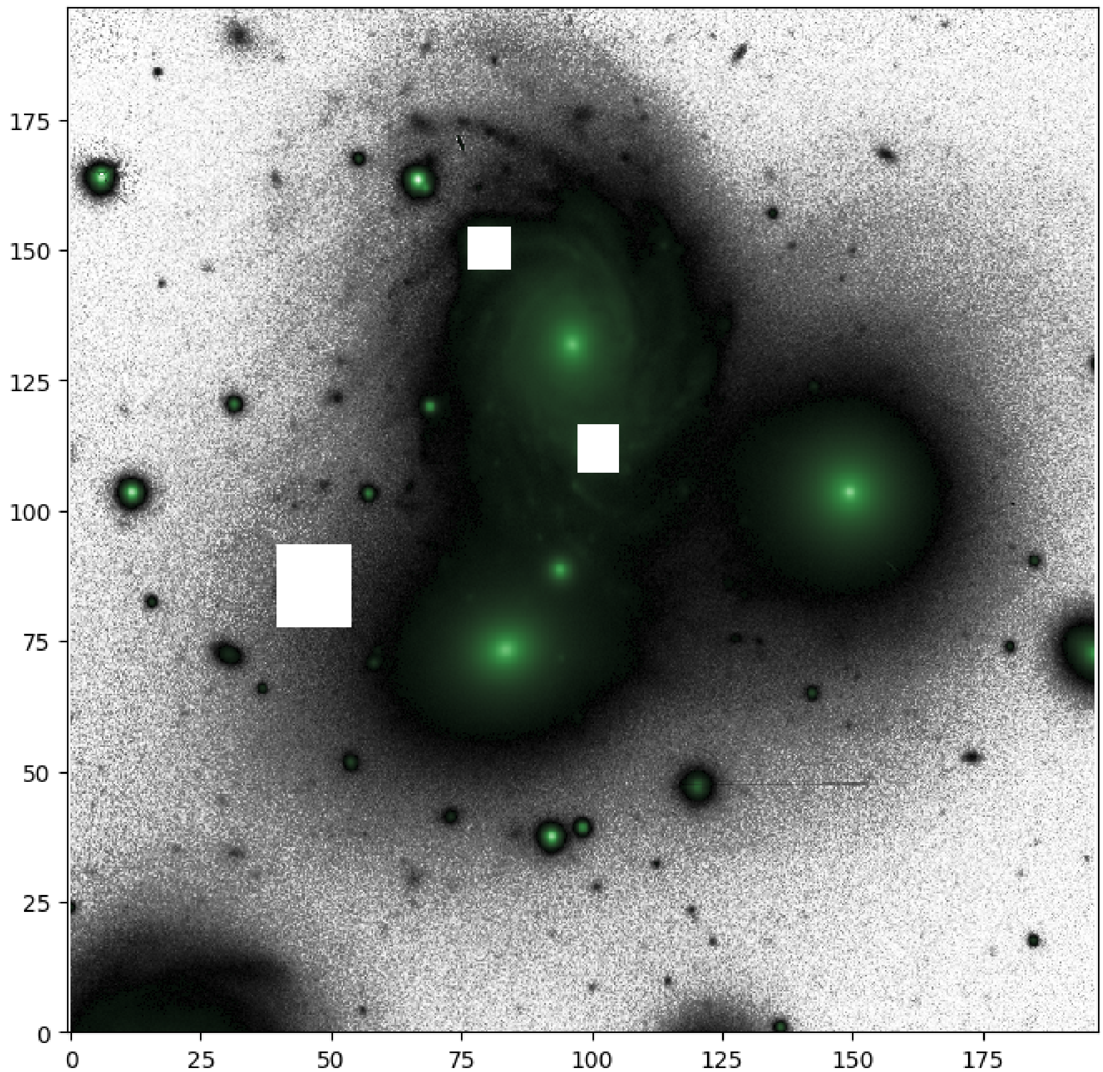
[1]:
```
import autoprof as ap
import numpy as np
import torch
from astropy.io import fits
import matplotlib.pyplot as plt
from scipy.stats import iqr
```

[2]:
```
# first let's download an image to play with
hdu = fits.open("https://www.legacysurvey.org/viewer/fits-cutout?ra=4.
↪5934&dec=30.0702&size=750&layer=ls-dr9&pixscale=0.262&bands=r")
target_data = np.array(hdu[0].data, dtype = np.float64)

target1 = ap.image.Target_Image(
    data = target_data,
    pixelscale = 0.262,
    zeropoint = 22.5,
)

fig1, ax1 = plt.subplots(figsize = (8,8))
ap.plots.target_image(fig1, ax1, target1)
plt.show()
```



[3]:
```
# We can see that there are some blown out stars in the image. There isn't much␣
↪that can be done with them except
# to mask them. A very careful modeller would only mask the blown out pixels␣
↪and then try to fit the rest, but
# today we are not very careful modellers.
mask = np.zeros(target_data.shape, dtype = bool)
mask[410:445,371:402] = True
mask[296:357 ,151:206] = True
mask[558:590,291:322] = True
# Note that it is also possible to set a mask just for an individual model.␣
↪Simply create a mask in the same way as
# above. Just note that the mask should have the same shape as the model window␣
↪instead of the whole image.
```

```
pixelscale = 0.262
target2 = ap.image.Target_Image(
    data = target_data,
    pixelscale = pixelscale,
    zeropoint = 22.5,
    mask = mask, # now the target image has a mask of bad pixels
    variance = 0.001*np.abs(target_data + iqr(target_data,rng=[16,84])/2), # we
  ↪create a variance image, if the image is in counts then variance image =
  ↪image, in this case the sky has been subtracted so we add back in a certain
  ↪amount of variance
)

fig2, ax2 = plt.subplots(figsize = (8,8))
ap.plots.target_image(fig2, ax2, target2)
plt.show()
```

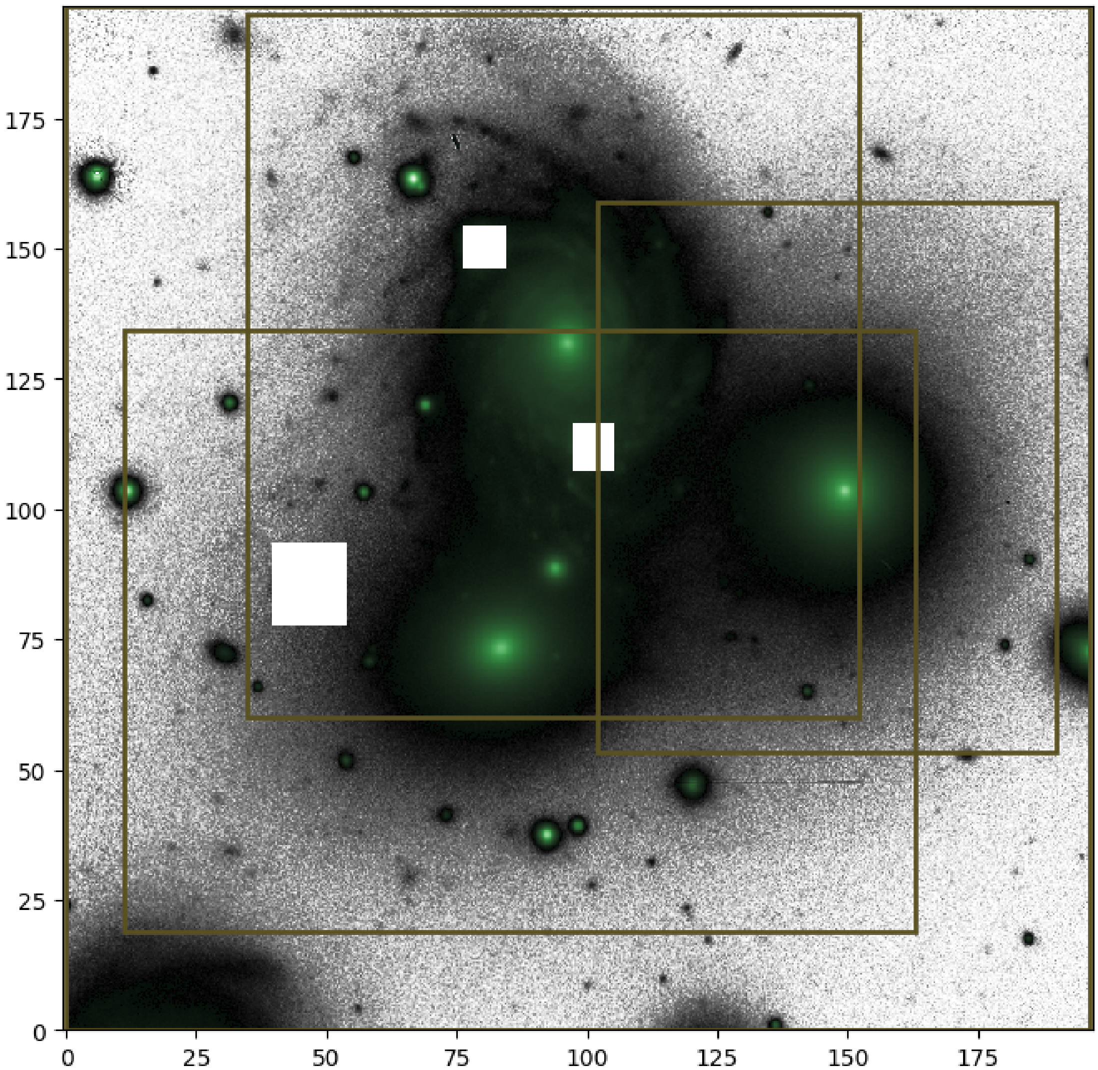


1.1 Group Model

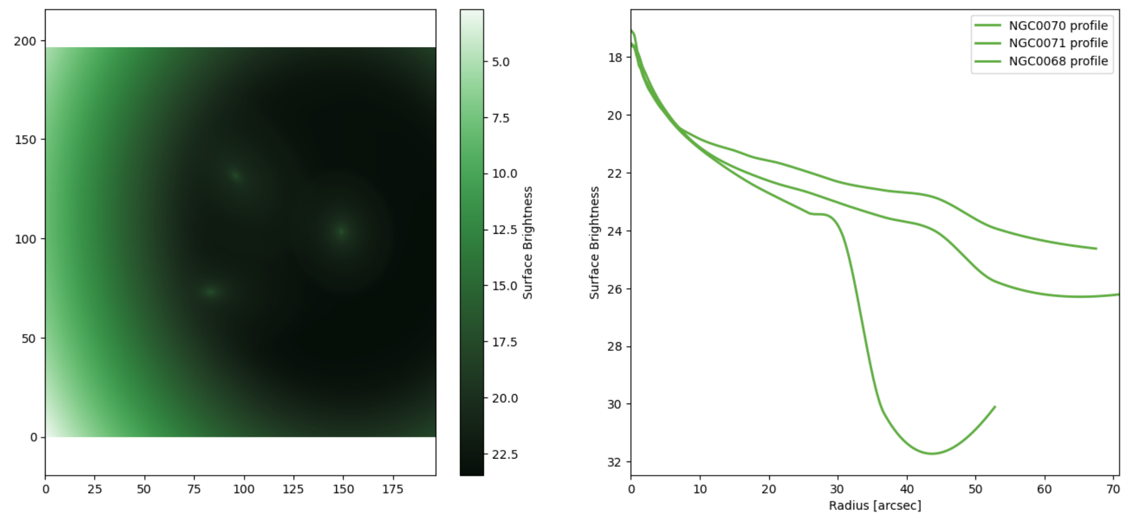
A group model takes a list of other AutoProf_Model objects and tracks them such that they can be treated as a single larger model. When "initialize" is called on the group model, it simply calls "initialize" on all the individual models. The same is true for a number of other functions like finalize, sample, and so on. For fitting, however, the group model will collect the parameters from all the models together and pass them along as one group to the optimizer. When saving a group model, all the model states will be collected together into one large file.

The main difference when constructing a group model is that you must first create all the sub models that will go in it. Once constructed, a group model behaves just like any other model, in fact they are all built from the same base class.

[4]:
```
# first we make the list of models to fit

# Note that we do not assign a target to these models at construction. This is␣
↪just a choice of style, it is possible
# to provide the target to each model separately if you wish. Note as well that␣
↪since a target isn't provided we need
# to give the windows in arcsec instead of pixels, to do this we provide the␣
↪window in the format (xmin,xmax,ymin,ymax)
model_kwargs = [
    {"name": "sky", "model_type": "flat sky model", "window": np.
↪array([0,0,750,750])*pixelscale},
    {"name": "NGC0070", "model_type": "spline galaxy model", "window": np.
↪array([133,229,581,744])*pixelscale},
    {"name": "NGC0071", "model_type": "spline galaxy model", "window": np.
↪array([43,72,622,513])*pixelscale},
    {"name": "NGC0068", "model_type": "spline galaxy model", "window": np.
↪array([390,204,726,607])*pixelscale},
]

model_list = []
for M in model_kwargs:
    model_list.append(ap.models.AutoProf_Model(target = target2, **M))

VV166Group = ap.models.AutoProf_Model(name = "VV166 Group", model_type = "group␣
↪model", models = model_list, target = target2)

fig3, ax3 = plt.subplots(figsize = (8,8))
ap.plots.target_image(fig3, ax3, VV166Group.target)
ap.plots.model_window(fig3, ax3, VV166Group)
plt.show()
```



[5]:
```
# See if AutoProf can figure out starting parameters for these galaxies
VV166Group.initialize()

# The results are reasonable starting points, though far from a good model
fig4, ax4 = plt.subplots(1,2,figsize = (16,7))
ap.plots.model_image(fig4, ax4[0], VV166Group)
for M in VV166Group.models.values():
    if M.name == "sky": continue
    ap.plots.galaxy_light_profile(fig4, ax4[1], M)
plt.legend()
plt.show()
```



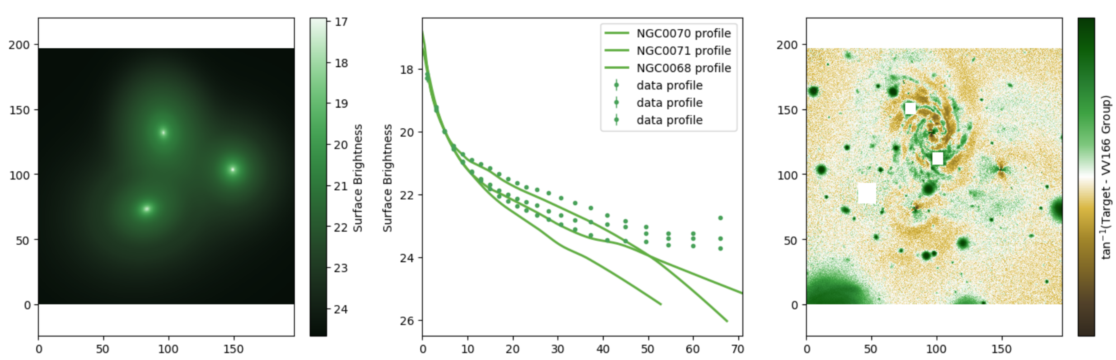
[6]:
```
# Allow AutoProf to fit the target image with all 3 models simultaneously. In
↪total this is about 80 parameters!
result = ap.fit.LM(VV166Group, verbose = 1).fit()
print(result.message)
```

```
L: 1.0
---------init---------
LM loss: 9.530863296542552
max grad 192605.5960084294
L: 1.0
---------iter---------
LM loss: 7.902843356196168
accept
max grad 101159.37200881244
L: 0.1111111111111111
---------iter---------
LM loss: 18898.377842047463
reject
L: 1.2222222222222222
---------iter---------
LM loss: 7.279457255093016
accept
max grad 67850.79777293086
L: 0.13580246913580246
---------iter---------
LM loss: 6.85152268547747
accept
max grad 35189.9489833552
L: 0.015089163237311385
---------iter---------
```

```
LM loss: 6.598676257868404
accept
max grad 23717.34757652277
L: 0.0016765736930345982
---------iter---------
LM loss: 6.5892785492017785
accept
max grad 4336.864243638984
L: 0.00018628596589273313
---------iter---------
LM loss: 6.589007534644504
accept
max grad 1180.5381024597718
L: 2.0698440654748124e-05
---------iter---------
LM loss: 6.588984802645844
accept
max grad 280.222059218564
success
```

[7]:

```python
# Now we can see what the fitting has produced
fig5, ax5 = plt.subplots(1,3,figsize = (17,5))
ap.plots.model_image(fig5, ax5[0], VV166Group)
for M in VV166Group.models.values():
    if M.name == "sky": continue
    ap.plots.galaxy_light_profile(fig5, ax5[1], M)
    ap.plots.radial_median_profile(fig5, ax5[1], M)
ax5[1].legend()
ap.plots.residual_image(fig5, ax5[2], VV166Group)
plt.show()

# we can also see that the data profiles which just take a median for all␣
 ↪pixels at a given radius are no longer
# helpful when we have overlapping systems. The medians are biased high by the␣
 ↪neighboring galaxies
```



[8]:

```
# To access parameters in a group model you use the same syntax as usual, but␣
↪with the model name as well:
print(VV166Group["NGC0070:PA"])
print(VV166Group["NGC0071:PA"])
```

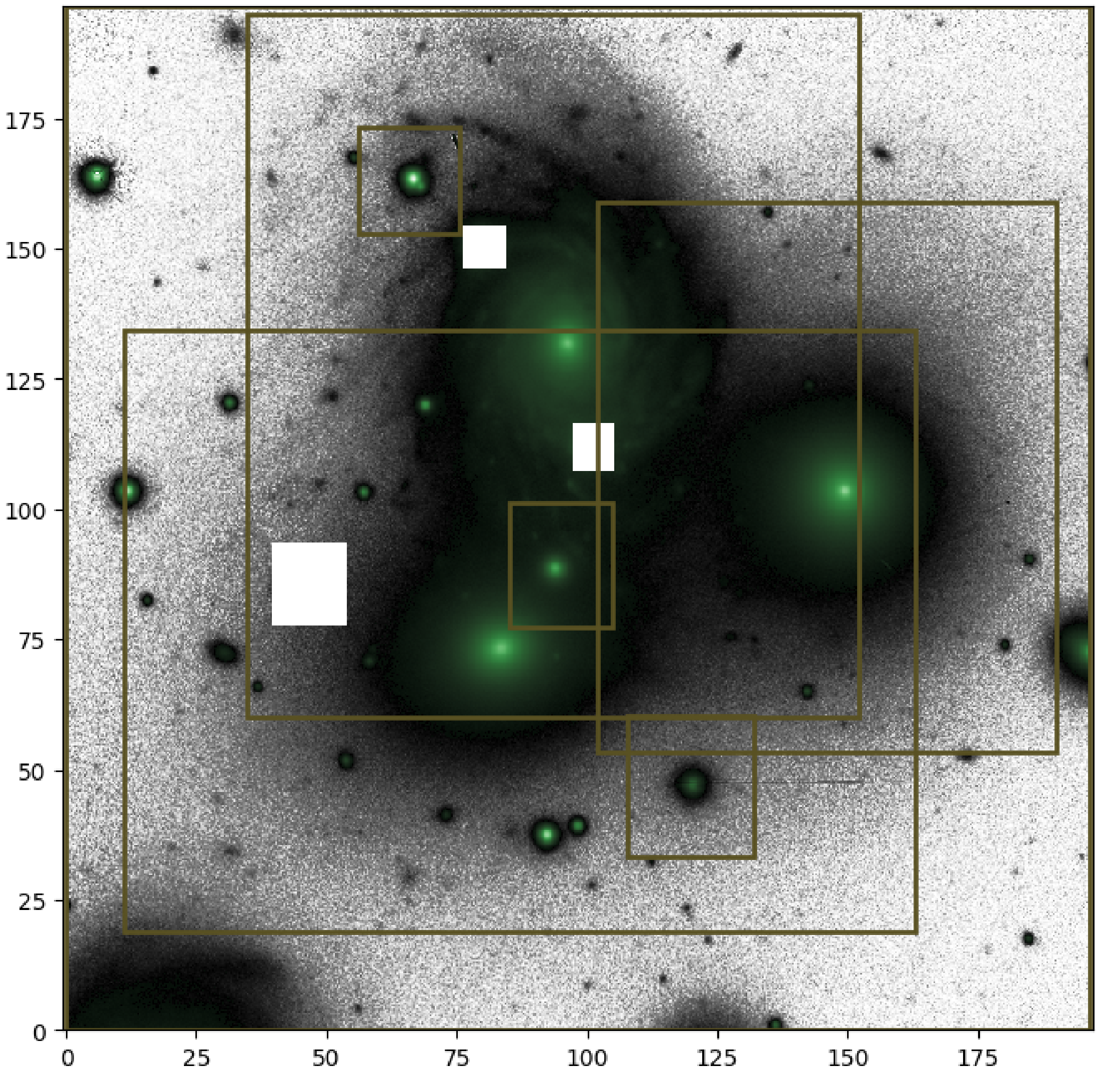
```
PA: 0.11271372919767558 +- 0.06 [radians, (tensor(0., dtype=torch.float64),
tensor(3.1416, dtype=torch.float64)), cyclic]
PA: 1.9034205936803075 +- 0.06 [radians, (tensor(0., dtype=torch.float64),
tensor(3.1416, dtype=torch.float64)), cyclic]
```

[9]:

```
# The model will improve the more galaxies in the system we include
# By adding models now, we keep the fitted parameters from before.
VV166Group.add_model(ap.models.AutoProf_Model(name = "litte 1", model_type =␣
↪"sersic galaxy model", target = target2, window = [[325,400],[295,386]]))
VV166Group.add_model(ap.models.AutoProf_Model(name = "litte 2", model_type =␣
↪"sersic galaxy model", target = target2, window = [[412,504],[127,231]]))
VV166Group.add_model(ap.models.AutoProf_Model(name = "litte 3", model_type =␣
↪"sersic galaxy model", target = target2, window = [[214,288],[583,662]]))
```

[10]:

```
fig6, ax6 = plt.subplots(figsize = (8,8))
ap.plots.target_image(fig6, ax6, VV166Group.target)
ap.plots.model_window(fig6, ax6, VV166Group)
plt.show()
```



[11]:
```
# Initialize will only set parameter values for the new models, the old ones␣
↪will just be skipped
VV166Group.initialize()
```

[12]:
```
result = ap.fit.LM(VV166Group, verbose = 1).fit()
print(result.message)
```

```
L: 1.0
---------init---------
LM loss: 5.382884295346622
max grad 321659.17679281754
L: 1.0
---------iter---------
LM loss: 51637794846989.76
```

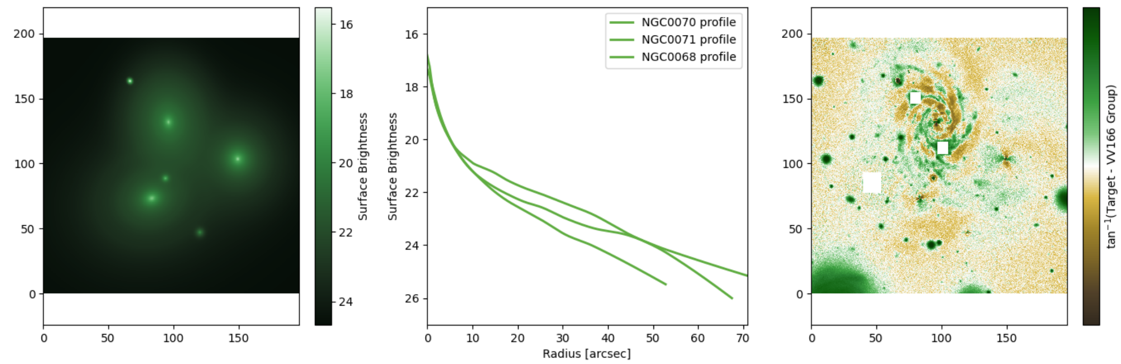
```
reject
L: 11.0
---------iter---------
LM loss: 21.90145148686181
reject
L: 121.0
---------iter---------
LM loss: 5.368805210244601
accept
max grad 318327.9666471579
L: 13.444444444444445
---------iter---------
LM loss: 5.113995555102579
accept
max grad 291059.48707666754
L: 1.4938271604938271
---------iter---------
LM loss: 5.028489686037363
accept
max grad 170004.05677977862
L: 0.16598079561042522
---------iter---------
LM loss: 5.166313969218832
reject
L: 1.8257887517146774
---------iter---------
LM loss: 4.943879803420671
accept
max grad 114974.0898438092
L: 0.20286541685718637
---------iter---------
LM loss: 5.092457249462326
reject
L: 2.23151958542905
---------iter---------
LM loss: 4.9187425770410425
accept
max grad 79314.39974263587
L: 0.2479466206032278
---------iter---------
LM loss: 4.879963322280563
accept
max grad 56045.02546996206
L: 0.027549624511469757
---------iter---------
LM loss: 4.8503002290472805
accept
max grad 14159.764451472083
```

```
L: 0.003061069390163306
---------iter---------
LM loss: 10.466773310002024
reject
L: 0.033671763291796365
---------iter---------
LM loss: 4.836168524461978
accept
max grad 7500.034989278659
L: 0.0037413070324218184
---------iter---------
LM loss: 8.698952460644822
reject
L: 0.04115437735664
---------iter---------
LM loss: 8.953291661615554
reject
L: 0.45269815092304
---------iter---------
LM loss: 9.964316716358283
reject
L: 4.97967966015344
---------iter---------
LM loss: 4.829695801508422
accept
max grad 6591.019775403669
L: 0.5532977400170489
---------iter---------
LM loss: 9.77524595678537
reject
L: 6.086275140187538
---------iter---------
LM loss: 4.855659874891515
reject
L: 66.94902654206291
---------iter---------
LM loss: 4.829042522326352
accept
max grad 6650.941137241782
L: 7.438780726895879
---------iter---------
LM loss: 4.806548361114496
accept
max grad 7087.583170286509
L: 0.8265311918773199
---------iter---------
LM loss: 4.8220719509084145
reject
```

```
L: 9.091843110650519
---------iter---------
LM loss: 4.802634739664198
accept
max grad 7305.736855662983
L: 1.01020479007228
---------iter---------
LM loss: 4.781766455401287
accept
max grad 7302.46372927319
L: 0.11224497667469777
---------iter---------
LM loss: 4.776207366383345
accept
max grad 4750.437478997691
L: 0.012471664074966419
---------iter---------
LM loss: 4.772640296183216
accept
max grad 3674.575515317525
L: 0.0013857404527740464
---------iter---------
LM loss: 4.771859725421297
accept
max grad 1854.6818854715425
L: 0.00015397116141933385
---------iter---------
LM loss: 4.771781658082509
accept
max grad 252.7461175453955
L: 1.7107906824370942e-05
---------iter---------
LM loss: 4.77177517791931
accept
max grad 100.62778086481264
success
```

[13]:
```
# Now we can see what the fitting has produced
fig7, ax7 = plt.subplots(1,3,figsize = (17,5))
ap.plots.model_image(fig7, ax7[0], VV166Group)
# let's just plot the 3 main object profiles
for M in VV166Group.models.values():
    if not "NGC" in M.name: continue
    ap.plots.galaxy_light_profile(fig7, ax7[1], M)
ax7[1].legend()
ax7[1].set_ylim([27,15])
ap.plots.residual_image(fig7, ax7[2], VV166Group)
```

```
plt.show()
```



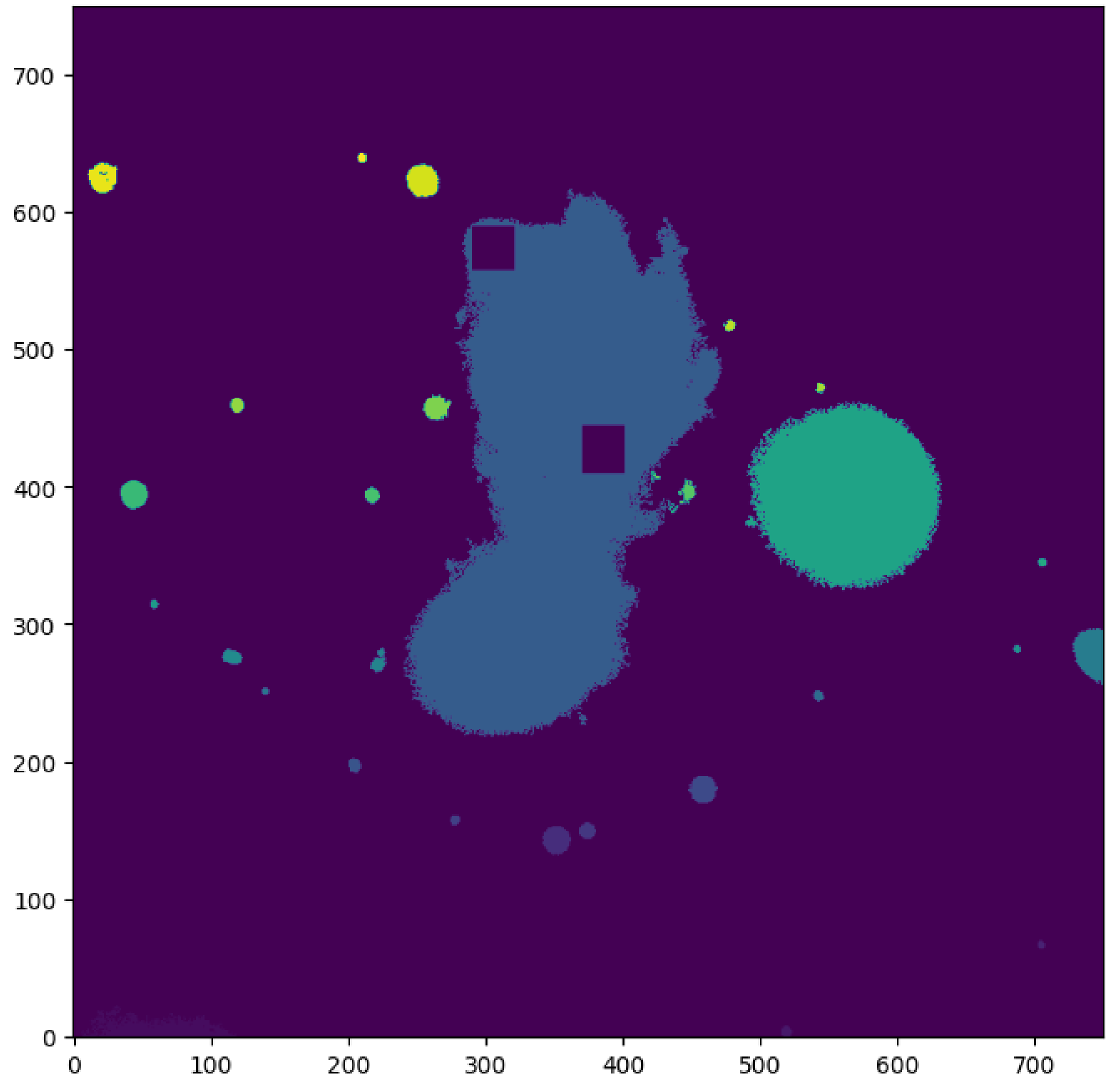
Which is even better than before. As more models are added, the fit should improve. In principle one could model eventually add models for every little smudge in the image. In practice, it is often better to just mask anything below a certain size.

1.2 Working with segmentation maps

A segmentation map provides information about the contents of an image. It gives the location and shape of any object which the algorithm was able to separate out and identify. This is exactly the information needed to construct the windows for a collection of AutoProf models.

Photutils provides an easy to use segmentation map implimentation so we use it here for simplicity. In many cases it may be required to use a more detailed segmentation map algorithm such as those implimented in Source Extractor and ProFound (among others), the principle is the same however since the end product for all of them has the same format.

[14]:
```
#########################################
# NOTE: photutils is not a dependency of AutoProf, make sure you run: pip install photutils
# if you dont already have that package. Also note that you can use any segmentation map
# code, we just use photutils here because it is very easy.
#########################################
from photutils.segmentation import detect_sources
segmap = detect_sources(target_data, threshold = 0.1, npixels = 20, mask = mask) # threshold and npixels determined just by playing around with the values
fig8, ax8 = plt.subplots(figsize=(8,8))
ax8.imshow(segmap, origin = "lower")
plt.show()
```



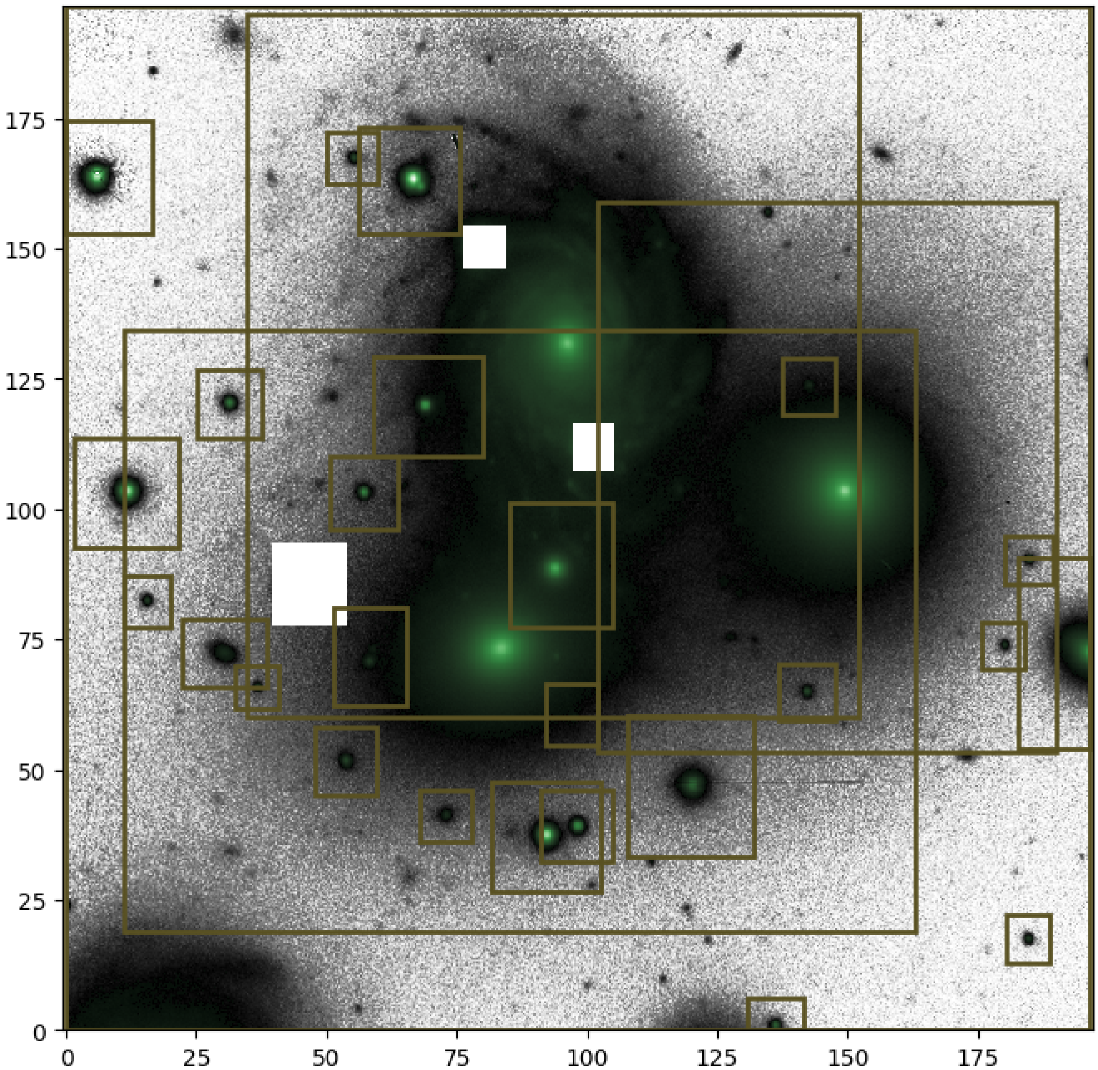
[15]:
```
# This will convert the segmentation map into boxes that enclose the identified
 ↪pixels
windows = ap.utils.initialize.windows_from_segmentation_map(segmap.data)
# Next we filter out any segments which are too big, these are the NGC models
 ↪we already have set up
windows = ap.utils.initialize.filter_windows(windows, max_size = 100)
# Next we scale up the windows so that AutoProf can fit the faint parts of each
 ↪object as well
windows = ap.utils.initialize.scale_windows(windows, image_shape = target_data.
 ↪shape, expand_scale = 3, expand_border = 10)

del windows[20] # this is a segmented chunk of spiral arm, not a galaxy
del windows[23] # this is a segmented chunk of spiral arm, not a galaxy
```

```
del windows[24] # this is a segmented chunk of spiral arm, not a galaxy
del windows[28] # this is a segmented chunk of spiral arm, not a galaxy
del windows[29] # this is a repeat of little 2
del windows[7] # this is a repeat of little 3
print(windows)
```

```
{2: [[499, 540], [0, 24]], 3: [[689, 721], [49, 84]], 4: [[312, 392], [102,
182]], 5: [[348, 401], [123, 176]], 6: [[259, 297], [138, 176]], 8: [[183, 227],
[172, 222]], 10: [[352, 390], [209, 253]], 11: [[522, 563], [227, 268]], 12:
[[124, 156], [235, 267]], 13: [[697, 750], [206, 346]], 14: [[196, 249], [238,
309]], 15: [[85, 147], [251, 301]], 16: [[671, 703], [264, 299]], 17: [[42, 77],
[295, 333]], 19: [[688, 723], [327, 362]], 21: [[6, 83], [354, 434]], 22: [[193,
243], [367, 420]], 25: [[225, 305], [420, 494]], 26: [[96, 143], [434, 484]],
27: [[525, 563], [451, 492]], 30: [[0, 63], [583, 666]], 31: [[191, 229], [620,
658]]}
```

[16]:
```
# Now we use all the windows to add to the list of models
seg_models = []
for win in windows:
    seg_models.append({"name": f"minor object {win:02d}", "window":
↪windows[win], "model_type": "sersic galaxy model", "target": target2})

# we make a new set of models for simplicity
for M in seg_models:
    VV166Group.add_model(ap.models.AutoProf_Model(**M))

VV166Group.initialize()
```

[17]:
```
fig9, ax9 = plt.subplots(figsize = (8,8))
ap.plots.target_image(fig9, ax9, VV166Group.target)
ap.plots.model_window(fig9, ax9, VV166Group)
plt.show()
```



[18]:
```
# This is now a very complex model composed of about 30 sub-models! In total␣
↪253 parameters! While it is
# possible for the AutoProf Levenberg-Marquardt (LM) algorithm to fully␣
↪optimize this model, it is faster in this
# case to apply an iterative fit. AutoProf will apply LM optimization one model␣
↪at a time and cycle through all
# the models until the results converge. See the tutorial on AutoProf fitting␣
↪for more details on the fit methods.
result = ap.fit.Iter(VV166Group, verbose = 1).fit()
print(result.message)

# Other technqiues that can help for difficult fits:
# - Try running some gradient descent steps (maybe 100) before doing LM
```

```
# - Try changing the initial parameters. AutoProf seeks a local minimum so make␣
↪sure its the right one!
# - Fit the large models in the frame first, then add in the smaller ones␣
↪(thats what we've done in this tutorial)
# - Fit a simplier model (say a sersic or exponential instead of spline) first,␣
↪then use that to initialize the complex model
# - Mix and match optimizers, if one gets stuck another may be better suited␣
↪for that area of parameter space
```

```
--------iter-------
sky
max grad -49545.18682506749
max grad -24589.84129888739
max grad -2572.8075115521933
max grad -33.34677569651103
max grad -0.04602840103325434
NGC0070
max grad 4379.9707759372905
max grad 3185.6583495174345
max grad 846.057939131596
max grad 410.3683067723414
max grad 92.05209128420938
max grad 256.1448842934816
NGC0071
max grad 3621.553001631422
max grad 2968.8371611974544
max grad 829.1326060188702
max grad 152.78805835405092
max grad 92.96433392251363
NGC0068
max grad 4760.992828924123
max grad 2538.9593003979576
max grad 345.5004936156106
max grad 26.710648417807306
max grad 18.45416419016182
max grad 18.097865063730968
max grad 17.81623938111646
max grad 17.59214109414048
max grad 17.412863345304796
max grad 17.26882641813251
max grad 17.15270409239023
litte 1
max grad 99.07943509388917
max grad 88.81521310800144
max grad 68.20198544352024
max grad 18.05500656164122
max grad 1.53939381053533
```

```
litte 2
max grad 1330.0668061441547
max grad 157.74295379549957
max grad 108.68321721941274
max grad 44.722065347993535
max grad 3.607615688807943
max grad 0.1399111790901877
max grad 0.017373857374600732
litte 3
max grad 25.576911760199437
max grad 100.95743456942182
max grad 54.02299264730027
max grad 7.9779124204305845
max grad 2.6638713235042815
minor object 02
max grad 6.8729047202217775
max grad 18.491485615435714
max grad 50.93690781449264
max grad 102.67881143318299
max grad 155.5292632906589
max grad 245.45418018083876
max grad 2224.2548755888392
max grad 2975.9219590277016
max grad 6648.100628880853
max grad 1700.9725425540105
max grad 1103.7883857944432
max grad 690.8537217237949
max grad 1.074016037320085
max grad 15.95197055390549
max grad 262.1036294340969
max grad 234.62162660374506
max grad 144.6975582071602
max grad 162.00285035217007
max grad 150.4565314242428
max grad 154.86301971954833
max grad 517.3834533890977
max grad 137.5843465784398
max grad 5.968028342382384
max grad 2.837372957871729
max grad 1.1018972210278957
minor object 03
max grad 1203.319805189652
max grad 369.9306808085763
max grad 307.5819272176718
max grad 74.61271642258636
max grad -1.6521471021278555
max grad -0.8326686639294478
max grad 0.09833059704678693
```

```
max grad 0.19469731168929627
max grad 0.01217909569457909
minor object 04
max grad 69505.81758329709
max grad 61806.71001613771
max grad 71485.82998010621
max grad 58282.97645051972
max grad 46739.82170637584
max grad 17519.1417375323
max grad 79.51226264252261
max grad 629.5780677264247
max grad 625.5996272722241
max grad 622.3059966987703
max grad 593.0427346799634
max grad 569.834611235714
max grad 550.5084769307214
max grad 430.5306021918623
max grad 176.55210608674133
max grad 175.57939652945834
max grad 174.7919979077119
minor object 05
max grad 20729.22068187171
max grad 10188.901387766771
max grad 2870.2561513255123
max grad 367.81043921333094
max grad 16.247828807988753
max grad 4.111511125607905
max grad 0.8267761406181933
minor object 06
max grad 966.585762787294
max grad 445.347337121775
max grad 304.5383981383317
max grad 235.7328722038983
max grad 111.1803292458253
max grad 16.315294699833856
max grad 0.2501920017197401
max grad 0.03475980465909512
minor object 08
max grad 3734.4336871804535
max grad 3798.318637933001
max grad 3599.4043600387154
max grad 604.653084296649
max grad 561.8924354536007
max grad 563.9749331571013
max grad 62.625039245234916
max grad 12.447463939089808
max grad 1.3585230833524875
max grad 0.01781474058303445
```

```
max grad 0.007094808297743782
minor object 10
max grad 34.73496520882661
max grad 29.68072948536487
max grad 14.552406735396243
max grad 2.6357371459992756
max grad 1.4241545531846889
max grad 0.14462406161799513
max grad 0.39821073791718664
max grad 0.05434739699068081
minor object 11
max grad 3274.484566492625
max grad 1741.1505376448322
max grad 392.2434195830481
max grad 198.70956074194999
max grad 54.64866525119895
max grad 44.379304421744294
max grad 41.02537334735382
max grad 116.22963029118117
max grad 48.93886175980617
max grad 6.055664073979223
max grad 2.418926737566693
max grad 0.9809671824892519
max grad 0.3575247419983967
minor object 12
max grad 1146.3856574006195
max grad 566.5928463208297
max grad 17.439732841481906
max grad 14.273847010059258
max grad 0.07837243679989214
max grad 0.060761822611123506
max grad 0.00023684997126727225
minor object 13
max grad 7.945103018530757
max grad 25.501402693859585
max grad 116.80326613516404
max grad 255.7901351046222
max grad 432.7576738975687
max grad 10220.891620684642
max grad 8725.034256180375
max grad 13605.438890333664
max grad 14388.083923674385
max grad 57612.17853094972
max grad 75431.19007244654
max grad 14169.514047959432
max grad 15812.031002689206
max grad 17699.903182687332
max grad 66501.11127696517
```

```
max grad 15046.811565122884
max grad 56717.77787954836
max grad 6997.729818259654
max grad 11038.694003981826
max grad 6325.256693535708
max grad 2338.1625135528966
max grad 2234.920063358945
max grad 1372.438714954426
max grad 1047.6001490856374
max grad 1045.2455827933206
max grad 1043.419718258393
max grad 1043.754181415767
max grad 1016.9177524481394
max grad 1010.0174034792246
max grad 922.4459687521924
max grad 918.2367315957907
max grad 914.1676012631598
max grad 885.6899561235188
minor object 14
max grad 55.496624576499194
max grad 185.91348420645696
max grad 289.0857757797863
max grad -10.501291141569407
max grad 965.6667722059707
max grad 1236.9009515256987
max grad 50.82658166317777
max grad 98.6694816466177
max grad 167.6587986814474
max grad 26.60771748669253
max grad 13.298232002726884
max grad 1.5845555061059287
max grad 0.1994256793649276
max grad 0.0739514124662346
minor object 15
max grad 6548.861235659131
max grad 6434.7812330440265
max grad 6015.235673863977
max grad 549.513868871122
max grad 1446.4831294437452
max grad 3328.4041412108163
max grad 0.6136026957522613
max grad 1.3878082367494287
max grad 0.10045363180451616
max grad 0.25388831640122866
max grad 0.012174379200406094
minor object 16
max grad 823.9024423229132
max grad 732.9665307404678
```

```
max grad 315.15372831410605
max grad 3.1498270925229357
max grad 1.368840073554253
max grad 0.49373625241096164
max grad 0.03647952312784675
max grad 0.002344999926766178
minor object 17
max grad 2289.7636761041413
max grad 2327.470800826045
max grad 2246.347637000258
max grad 651.7608680321939
max grad 1123.4595565683157
max grad 51.084989390652886
max grad 16.379919748106992
max grad 1.2360201692260766
max grad 0.14415974740521875
max grad 0.009739109955042125
minor object 19
max grad 2223.4486782863614
max grad 1061.569287132338
max grad 178.436336336335
max grad 36.5611011390242
max grad 13.778064190108445
max grad 0.19171645642544632
max grad 0.012439205002474196
minor object 21
max grad 116728.63213491857
max grad 66949.7663846768
max grad 82873.63710616974
max grad 54329.05973851528
max grad -225.20967429796667
max grad -25.541048359054862
max grad -4.180505872125671
max grad -1.1448639913001557
max grad -0.3736745171275828
max grad -0.07207764631948521
minor object 22
max grad 9429.689991448427
max grad 20262.018310372398
max grad 4791.299330346183
max grad 1717.5433297932373
max grad 592.3515960774088
max grad 180.3160258263946
max grad 23.32389650646705
max grad 2.6365185192936877
max grad 0.4461080816869867
max grad 0.07578198910287881
minor object 25
```

```
max grad 18465.679561972305
max grad 9219.791337290464
max grad 1889.9051961370114
max grad 1187.5010429173071
max grad 157.1128980141707
max grad 7.688377426635135
max grad 2.9440400208013386
max grad 0.9514710073834394
max grad 0.3427710137519284
minor object 26
max grad 10695.321354074656
max grad 3993.920571951191
max grad 4634.499414001168
max grad 453.9091095038748
max grad 17.6300961276105
max grad 6.556592590950359
max grad 1.6582016947241556
max grad 0.1418922060729244
max grad 0.026099864863894595
minor object 27
max grad 220.33430784732195
max grad 110.55852392894437
max grad 134.8973585114151
max grad 10.159329956389954
max grad 23.334653953338908
max grad 1.0912288227492182
max grad 0.44705975682853083
max grad 0.13769332060666217
max grad 0.01808236903681948
minor object 30
max grad 45.89201619615576
max grad 17186.981092220474
max grad 99005.84189097708
max grad 16826.646857634172
max grad 35688.33923786396
max grad 31659.976430277427
max grad 40075.23595732986
max grad 21799.18120079246
max grad 21929.80619605813
max grad 19018.67193402887
max grad 20022.010322213115
max grad 22554.634460220594
max grad 23790.49539521009
max grad 24485.818339862017
max grad 53871.911115607356
max grad 29940.931673085805
max grad 15804.698148157782
max grad 6885.852637108223
```

```
max grad 5377.866460222028
max grad 3564.9444237254165
max grad 1992.4112187605078
max grad 1130.148788671363
max grad 604.3546898501127
max grad 401.32369593638396
max grad 268.5375496572433
max grad 338.57215930819075
minor object 31
max grad 3829.190546088572
max grad 1638.1997493171289
max grad 72.27304612586178
max grad 670.241797548237
max grad 171.58580145882632
max grad 69.85599245541687
max grad 58.208288853666176
max grad 56.11430620785406
max grad 55.322749399459546
max grad 290.81819175915257
max grad 85.09846977553232
max grad 6.3051617624978284
max grad 2.790078154573486
max grad 0.9878802739873258
max grad 0.3806106703126986
Update Chi^2 with new parameters
Loss: 2.022545541412988
--------iter-------
sky
max grad -25820.266579948395
max grad -12857.560227875336
max grad -1318.6718288146367
max grad -16.617762347246753
max grad -0.022853330476209 52
NGC0070
max grad 5565.887277069065
max grad 1958.416179293521
max grad 329.02806802310624
max grad 101.54999535301613
max grad 68.09444299978335
max grad 66.57078352947995
max grad 66.45783755840773
max grad 66.44943857489007
max grad 66.44256796493704
max grad 66.43694742534481
max grad 66.432349391468
NGC0071
max grad 6926.373521392877
max grad 3541.8103365197558
```

```
max grad 297.0353373974376
max grad 144.86881678133614
max grad 80.09451441359604
NGC0068
max grad 1492.4717849693334
max grad 347.3273165621058
max grad 324.3423756756165
max grad 65.82319666212167
max grad 85.84865625529203
litte 1
max grad 54.20380573711543
max grad 31.670511241378676
max grad 12.111614857653592
max grad 5.4788663060605245
max grad 2.0217287678666196
litte 2
max grad 204.30353042406995
max grad 20.564063718389658
max grad 10.292292346319414
max grad 2.800808145725835
max grad 0.19148654529649178
litte 3
max grad 29.00127750300817
max grad 6.958426428156599
max grad 2.8502179790092157
max grad 1.4414313588116272
max grad 0.531457682174107
minor object 02
max grad 32.10919445446547
max grad 3.883679002567204
max grad 3.561356114525866
max grad 3.039860559178525
max grad 1.6421139018507471
minor object 03
max grad 16.203208298230194
max grad 1.438104243005192
max grad 0.7886091829866615
max grad 0.09434611533826676
max grad 0.004128084311957991
minor object 04
max grad 55.12014188808371
max grad 54.761818386950836
max grad 51.743669489468175
max grad 51.51734692006448
max grad 51.331259714494536
max grad 51.17877271647194
max grad 51.053964139507116
max grad 49.97441414309333
```

```
max grad 49.89097134867825
max grad 49.822902504607555
max grad 49.198162832261005
minor object 05
max grad 5.2363076961820525
max grad 85.19772565151209
max grad 51.05313527173041
max grad 7.345001117001175
max grad 0.6047647581169713
minor object 06
max grad 12.723163667898518
max grad 6.409933562169373
max grad 1.4211702963778965
max grad 0.20156644700436743
max grad 0.025797920180025802
minor object 08
max grad 82.36925723372019
max grad 8.941691900846788
max grad 5.2485599420421885
max grad 2.2231519920015685
max grad 0.41638405675732315
max grad 0.05043981043154133
minor object 10
max grad 2.677498386967392
max grad 0.7222461389364623
max grad 0.2732312270326205
max grad 0.033150205528710286
max grad 0.04360408949371242
minor object 11
max grad 42.83210884568453
max grad 5.384994839699594
max grad 4.054116833994435
max grad 3.019398106165184
max grad 1.5188259457198114
max grad 0.62407765610822
minor object 12
max grad -0.010639737329431131
max grad 1.333304396791522
max grad 1.0168965181535472
max grad 0.2028448604368691
max grad 0.007306254730315764
minor object 13
max grad 882.1331806542534
max grad 791.0563481984091
max grad 737.8093987017232
max grad 723.359417757014
max grad 717.5073007459918
max grad 672.0455439263952
```

```
max grad 669.8540692769682
max grad 667.8490915304241
max grad 666.0953554072125
max grad 656.0330124910263
max grad 654.0395176716767
minor object 14
max grad 141.96638619612804
max grad 14.174069248550888
max grad 9.099257614900495
max grad 7.175834681215807
max grad 2.5646605139633976
max grad 0.8868481599367746
max grad 0.2422315465890197
minor object 15
max grad 227.75848541434166
max grad 15.347311682521616
max grad 6.659514283617861
max grad 0.5323191084001344
max grad 0.015963806108285183
max grad 0.005369642156837884
minor object 16
max grad 47.13812997146118
max grad 4.941103726090454
max grad 2.945604868208946
max grad 0.7841487172781747
max grad 0.07734040697508426
max grad 0.002912852241323094
minor object 17
max grad 12.431858958343241
max grad 1.3397571630842844
max grad 0.831921439463887
max grad 0.2640840103006692
max grad 0.03422549409393483
minor object 19
max grad 32.29616262362659
max grad 3.3677063178898266
max grad 2.0354746686361693
max grad 0.6123054408258017
max grad 0.48594843766176865
max grad 0.43813304915907914
max grad 0.4106029173414676
max grad 0.3918852136723512
max grad 0.37822940829919816
max grad 0.3678940253339089
max grad 0.3598944100891508
minor object 21
max grad 17.282808811142786
max grad 6.385117523784174
```

```
max grad 3.6855746641695077
max grad 0.6213198297818963
max grad 0.04630560917848925
minor object 22
max grad 23.082723917702594
max grad 68.39199121688986
max grad 43.71257634542124
max grad 7.1449458501652146
max grad 0.86881305316453
max grad 0.1631606148563094
minor object 25
max grad 2.093709611012173
max grad 41.574201838841645
max grad 29.57338292121267
max grad 6.057128278731511
max grad 0.6598927007854343
minor object 26
max grad 0.3978258112470172
max grad 12.531223757264343
max grad 7.800630060757953
max grad 8.192449287299837
max grad 8.164498072511492
max grad 8.139064111233552
max grad 8.136946326174098
max grad 8.135199001714795
max grad 8.133757533873336
max grad 8.132568143276785
max grad 8.13158622411106
minor object 27
max grad -0.00792044599887165
max grad 2.0324459631645
max grad 1.2306704786700706
max grad 0.17524184316229174
max grad 0.015236222153825807
minor object 30
max grad 333.9219200450025
max grad 220.83416762560228
max grad 422.30177642334456
max grad 287.83266552445275
max grad 154.64160791133327
minor object 31
max grad 0.30506497048560277
max grad 2.021792391658238
max grad 1.690195460618412
max grad 0.43252972561032266
max grad 0.7869674024044997
max grad 0.8188662758708318
max grad 0.8188550500533864
```

```
max grad 0.8188406650670572
max grad 0.8188241975435062
max grad 0.8188064188782107
max grad 0.8188303382280679
Update Chi^2 with new parameters
Loss: 2.0211784059732576
--------iter-------
sky
max grad -8970.093517457426
max grad -4478.501537282718
max grad -451.96458953896945
max grad -5.5756357131758705
max grad -0.007648026308743283
NGC0070
max grad 1887.1521819719037
max grad 503.5500002255849
max grad 124.13738689361382
max grad 121.33628957493197
max grad 119.07633289960026
max grad 117.24968632904212
max grad 115.77065041653086
max grad 114.57112852727528
max grad 113.59690291278349
max grad 112.80468088367519
max grad 112.15978509794205
NGC0071
max grad 1246.9565839203506
max grad 392.9665259947379
max grad 164.374852770394
max grad 49.41075987735176
max grad 105.38187326365568
max grad 102.93485414665184
max grad 100.97707462039061
max grad 99.40426957292965
max grad 98.13649751479426
max grad 97.11180292118084
max grad 96.2817298159355
NGC0068
max grad 109.15278073302319
max grad 67.47535388297165
max grad 28.68944978148159
max grad 26.047756193785077
max grad 23.96667917549553
max grad 22.34375500669061
max grad 21.069894721230582
max grad 20.958644166982108
max grad 20.867750335301903
max grad 20.860889689833684
```

```
max grad 20.855277342568957
litte 1
max grad 0.08719713176583133
max grad 11.693768251748224
max grad 7.846881980685794
max grad 1.7372111048730403
max grad 0.11230539415510066
litte 2
max grad 29.873171036527197
max grad 2.6806578653205015
max grad 1.5993669784141105
max grad 0.4619776381966858
max grad 0.030724337742476848
litte 3
max grad 0.0073029323957598535
max grad 14.155955903754148
max grad 7.593232311501197
max grad 1.1188686081950436
max grad 0.3654932621138869
minor object 02
max grad 11.209437928577074
max grad 1.840634584538714
max grad 1.8203163343605464
max grad 1.5668016177266129
max grad 0.8559723368538563
minor object 03
max grad 5.75983788988998
max grad 0.5103546756111186
max grad 0.28048594842250196
max grad 0.036042547041326145
max grad 0.0010378660184429123
minor object 04
max grad 50.83911438890482
max grad 50.50130919794128
max grad 50.22162888659659
max grad 49.99270559212982
max grad 49.76436428880288
max grad 47.806599907120926
max grad 47.65704208256602
max grad 47.53519848768974
max grad 47.43580527649192
max grad 46.54646147180074
max grad 46.48165798589616
minor object 05
max grad 0.9566995561052067
max grad 2.814397831407291
max grad 1.530056565274208
max grad 0.20941860487880604
```

```
max grad 0.017476953507980397
minor object 06
max grad 0.003081452320553568
max grad 0.20732897078130996
max grad 0.13069587230485347
max grad 0.019425462499491175
max grad 0.002601578042009667
minor object 08
max grad 0.02794675932885493
max grad 0.16235968299594106
max grad 0.10441873534877288
max grad 0.019028640090581916
max grad 0.0007218491680731631
minor object 10
max grad 0.0632367689089548
max grad 0.03493188622479093
max grad 0.0388873546534656
max grad 0.0043104618238404835
max grad 0.006966772426149959
minor object 11
max grad 0.14629904028859642
max grad 0.08142225650701107
max grad 0.12649599249913024
max grad 0.11960537260152648
max grad 0.06021236127733687
minor object 12
max grad 0.9166979913711653
max grad 0.06886259302998798
max grad 0.03564781182481802
max grad 0.01472785065369564
max grad 0.0031179431045158523
minor object 13
max grad 653.0629226537937
max grad 466.27489691507265
max grad 429.09057197344345
max grad 420.4398942954807
max grad 416.6903894464774
max grad 414.31145045545895
max grad 394.0116115424595
max grad 393.2092386268928
max grad 392.462536145797
max grad 391.78371516521383
max grad 391.1858481470716
minor object 14
max grad 0.6009701624324428
max grad 0.885184515968632
max grad 0.6307694123424525
max grad 0.15923597381863175
```

```
max grad 0.008283480423173728
minor object 15
max grad 16.33682471366786
max grad 1.1369764845091517
max grad 0.49732713984728605
max grad 0.039375143872915075
max grad 0.0012494318162836748
minor object 16
max grad 5.1331257454454535
max grad 0.524888057264322
max grad 0.3187744332721838
max grad 0.0958950976715709
max grad 0.008031888697257017
minor object 17
max grad 0.7195137066487405
max grad 0.08880169041581176
max grad 0.05635981385523969
max grad 0.018177320721688872
max grad 0.00242426612911828
minor object 19
max grad 4.535683541425136
max grad 0.9082463258458979
max grad 0.581663563009192
max grad 0.16656770587028902
max grad 0.015958519522351722
minor object 21
max grad 17.096400496744536
max grad 1.6266255058854995
max grad 2.7834336500783365
max grad 1.5103798674679183
max grad 0.5318351114902953
minor object 22
max grad 1.282774032295663
max grad 11.149365173919307
max grad 7.107906627132905
max grad 1.163901457280403
max grad 0.13673437020345602
minor object 25
max grad 1.761761789411139
max grad 12.82187876333478
max grad 8.863172292263812
max grad 1.8017261206992998
max grad 0.19567619228088518
minor object 26
max grad 9.241601600056242
max grad 9.194980423723223
max grad 9.157530300096596
max grad 9.127345340774013
```

```
max grad 9.102949431496995
max grad 9.083188509602678
max grad 9.067153169072412
max grad 9.067045253543256
max grad 9.066083038995089
max grad 9.066075600848308
max grad 9.066069478284248
minor object 27
max grad 0.02691874697743657
max grad 0.6958886202501304
max grad 0.42246940195501637
max grad 0.05881420965860329
max grad 0.005041461394460711
minor object 30
max grad 153.00490343699494
max grad 79.38131431126385
max grad 67.33237709584546
max grad 57.50652836085055
max grad 55.21379271187857
max grad 53.758937914955595
max grad 52.55594913384675
max grad 52.42678527748012
max grad 52.32204838796133
max grad 52.23691275614374
max grad 52.16759262186679
minor object 31
max grad 0.11332485787651336
max grad 4.57658926195257
max grad 3.5782276801419783
max grad 0.8950336337164799
max grad 0.1535716885748819
Update Chi^2 with new parameters
Loss: 2.021059626464757
--------iter-------
sky
max grad -6326.076543508898
max grad -3159.7455146881257
max grad -318.0457455262658
max grad -3.910509591398295
max grad -0.005361906543839723
NGC0070
max grad 585.157390784525
max grad 186.5597230347703
max grad 93.3191365810639
max grad 93.03924294109201
max grad 92.81110559600623
max grad 92.6250248640895
max grad 92.47316169026885
```

```
max grad 91.14196630356778
max grad 91.13293457487222
max grad 91.12554593271685
max grad 91.11950132991514
NGC0071
max grad 1245.266102489867
max grad 339.29586722367276
max grad 41.088365228437915
max grad 95.1386410267189
max grad 66.71299200338225
max grad 57.04263812546742
max grad 56.23979297149786
max grad 55.58992291199485
max grad 55.06285434219162
max grad 54.63470019525965
max grad 54.28644315874609
NGC0068
max grad 419.0276489081534
max grad 113.32531588329948
max grad 26.816908397855318
max grad 4.70267338320321
max grad 0.618231728383762
max grad 0.11799748195880966
litte 1
max grad 0.02823069286175106
max grad 9.961233397580145
max grad 7.793951841205853
max grad 2.1934012453161813
max grad 0.15817904192499554
litte 2
max grad 13.970633053226493
max grad 1.1653644637753615
max grad 0.697651482573292
max grad 0.211769719345682
max grad 0.014344347782127898
litte 3
max grad 9.49369868641952
max grad 0.8646872257543237
max grad 1.415182554494919
max grad 0.7173688657254331
max grad 0.2610595655208954
minor object 02
max grad 8.033751495001269
max grad 1.1969168044990965
max grad 1.1624209615033099
max grad 1.0019954046394322
max grad 0.5508956240426262
minor object 03
```

```
max grad 4.0960948175042375
max grad 0.36266621171673563
max grad 0.19952665042558237
max grad 0.02574633742139376
max grad 0.0006953542466376916
minor object 04
max grad 46.60060389027876
max grad 46.28235033829287
max grad 46.01851967874154
max grad 45.80258377208975
max grad 43.955421386641774
max grad 43.81346424745743
max grad 43.698045714057116
max grad 43.604013289297654
max grad 43.52732071139508
max grad 42.83342208045178
max grad 42.30807986547234
minor object 05
max grad 2.4457503039342328
max grad 0.3039579768031686
max grad 0.2573293924274651
max grad 0.09860110435073466
max grad 0.02136210666225935
minor object 06
max grad 1.2886642343412547
max grad 0.11339728574719032
max grad 0.055693961471091846
max grad 0.004610668322182931
max grad 0.003157971218548994
minor object 08
max grad 2.393137940070446
max grad 0.2693959824949701
max grad 0.1747340854622479
max grad 0.07653565692050535
max grad 0.01522199620183784
minor object 10
max grad 0.07897124843183123
max grad 0.016557557074662776
max grad 0.010413950409050132
max grad 0.0012231519494662058
max grad 0.0018979096063331813
minor object 11
max grad 0.14460711024709383
max grad 1.017251134592101
max grad 0.8408525704093677
max grad 0.22346686346298839
max grad 0.03834778767659941
minor object 12
```

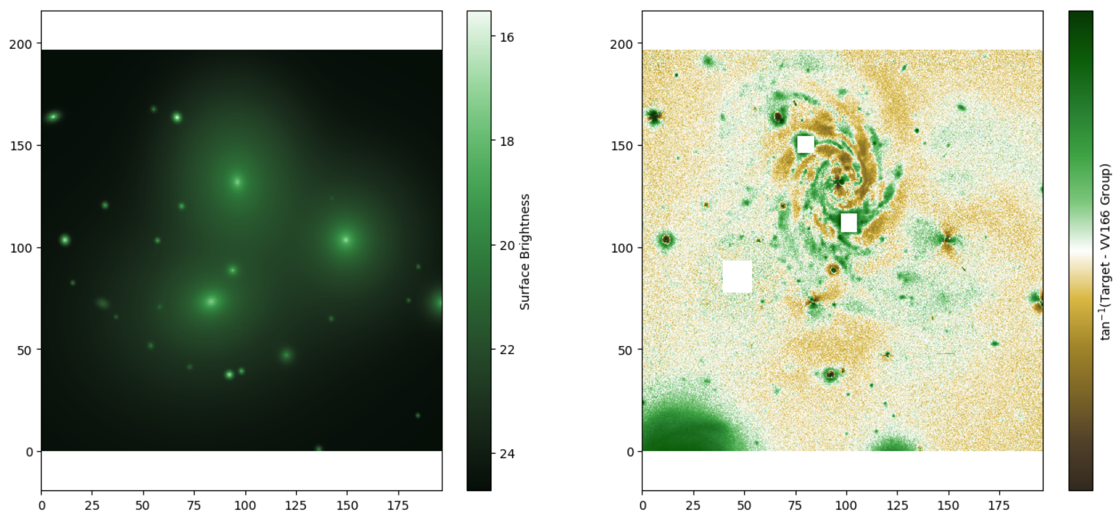
```
max grad 0.765345149389538
max grad 0.07913680106141019
max grad 0.048243563544879464
max grad 0.020622858636047958
max grad 0.00436793764435528
minor object 13
max grad 390.46792475857376
max grad 190.27303111704356
max grad 166.4748890033993
max grad 161.84251530041382
max grad 160.0426227878728
max grad 158.99033595415798
max grad 149.6264923483708
max grad 149.58424572497125
max grad 149.4797909284291
max grad 149.35255004518018
max grad 152.22877256983347
minor object 14
max grad 0.8238612196614454
max grad 0.05900868196948661
max grad 0.03915281023063777
max grad 0.029507628806628716
max grad 0.011192709987663196
minor object 15
max grad 4.873135501319801
max grad 4.728549980361947
max grad 4.61291329428439
max grad 4.520075455639315
max grad 4.445313277331497
max grad 4.440112122318126
max grad 4.435898707772484
max grad 4.432486580542854
max grad 4.399662163304427
max grad 4.397437193500501
max grad 4.3972880020427745
minor object 16
max grad 1.49382444372546
max grad 1.0048963991007787
max grad 0.6941507913062059
max grad 0.6744490858836816
max grad 0.6731741268403191
max grad 0.6721550019902951
max grad 0.6713418150028305
max grad 0.6706939568848433
max grad 0.6701784464692828
max grad 0.6645306949415231
max grad 0.6645078960108401
minor object 17
```

```
max grad 0.06996684983896984
max grad 0.008395244830198934
max grad 0.0054280686142185175
max grad 0.0017646551536145694
max grad 0.00023572468155741433
minor object 19
max grad 2.016235753237602
max grad 0.2126104741483772
max grad 0.13064721761922904
max grad 0.03914478285375722
max grad 0.00384819337760689
minor object 21
max grad 13.187777082236607
max grad 1.3877124095281488
max grad 2.316540984063977
max grad 1.2408698827770195
max grad 0.4370686690904222
minor object 22
max grad 0.22448507377544047
max grad 2.219683292390414
max grad 1.3995740498953069
max grad 0.2281419034823955
max grad 0.02647712876311914
minor object 25
max grad 0.4618477319631893
max grad 2.4542558046322256
max grad 1.652885506798043
max grad 0.333239268676607
max grad 0.035868403559021544
minor object 26
max grad 10.112677612953007
max grad 9.28573585037634
max grad 8.745195840632164
max grad 8.375120820861866
max grad 8.350096384177846
max grad 8.32983384085503
max grad 8.328352849820021
max grad 8.327144646916622
max grad 8.326159145149632
max grad 8.325355424829809
max grad 8.32470004298159
minor object 27
max grad 0.02004410167105597
max grad 0.18423980059724165
max grad 0.10518195799004282
max grad 0.014750251414563209
max grad 0.001274745508721864
minor object 30
```

```
max grad 61.841085177714604
max grad 61.56584533439377
max grad 61.345339750182575
max grad 61.16799815215063
max grad 61.024920526055666
max grad 60.909189662899735
max grad 60.81538231375225
max grad 60.73921527691073
max grad 60.67728496929499
max grad 60.62687294655552
max grad 60.585798760066155
minor object 31
max grad 1.6436998031018248
max grad 0.14792991791122745
max grad 0.043994164152593385
max grad 0.005534089346298288
max grad 0.0007953360584309621
Update Chi^2 with new parameters
Loss: 2.0210125260050624
success
```

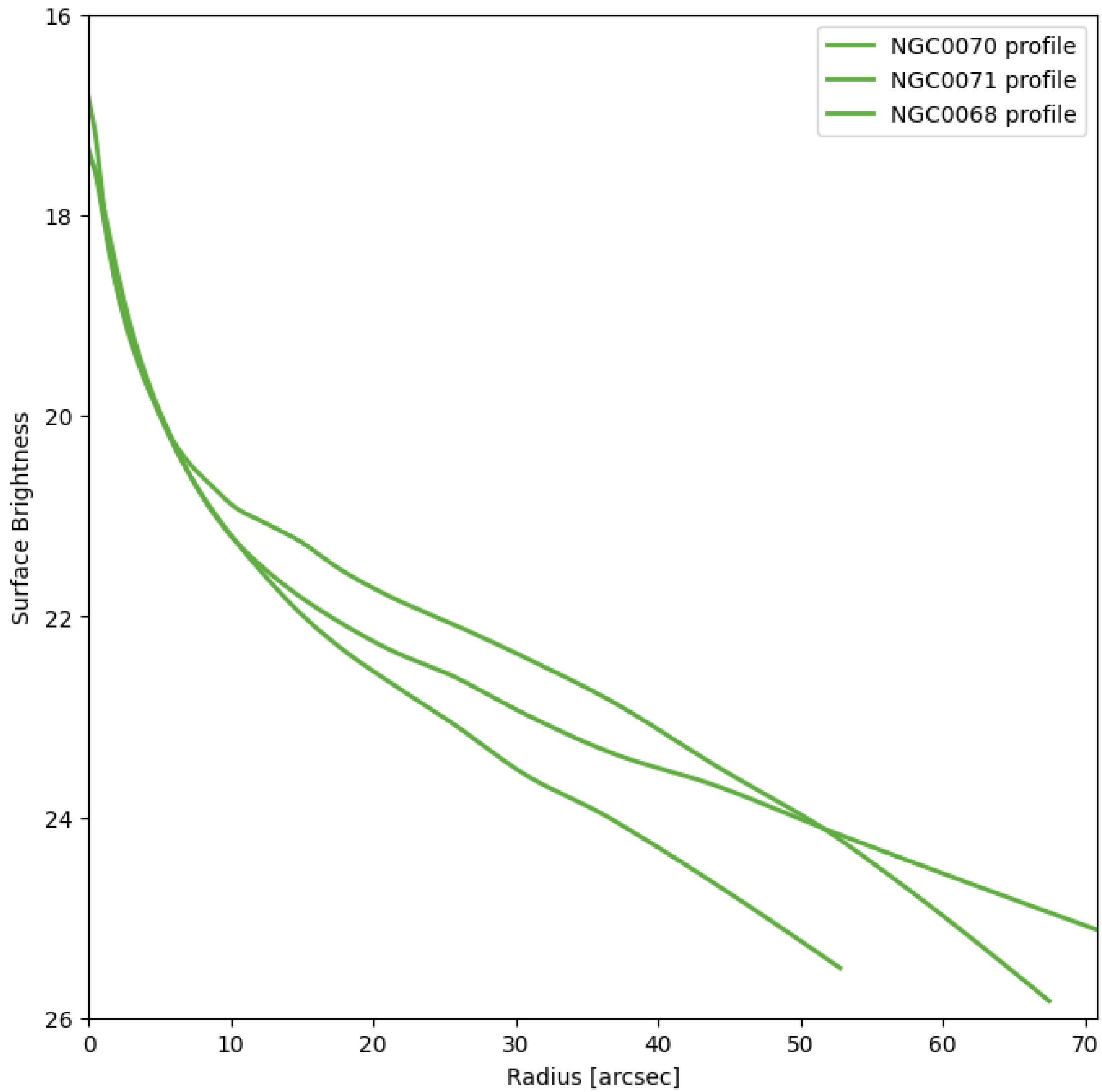
[19]:

```python
# Indeed the fit converges successfully! These tricks are really useful for complex fits.

# Now we can see what the fitting has produced
fig10, ax10 = plt.subplots(1,2,figsize = (16,7))
ap.plots.model_image(fig10, ax10[0], VV166Group)
ap.plots.residual_image(fig10, ax10[1], VV166Group)
plt.show()
```



Now that's starting to look like a complete model, and the Chi^2/ndf is much lower! And all for very little effort considering the level of detail. Looking at the residuals there is a clear improvement from the other attempts, that said there is a lot of structure in the residuals around the small objects, suggesting that a sersic alone is not the best model for these galaxies. That's not too surprising, at the very least we should apply PSF convolution to the models to get the proper blurring. PSF convolution is very slow though, so it would be best to do on a GPU, which you can try out if you have access to one! Simply set psf_mode = "full" and run fit again. For now though, we'll forgo the PSF convolution in the interest of time.

[20]:
```
# and we can also take a look at the three main object profiles

fig8, ax8 = plt.subplots(figsize = (8,8))
# let's just plot the 3 main object profiles
for M in VV166Group.models.values():
    if not "NGC" in M.name: continue
    ap.plots.galaxy_light_profile(fig8, ax8, M)
ax8.legend()
ax8.set_ylim([26,16])
plt.show()
```



NGC0070 profile
NGC0071 profile
NGC0068 profile
Surface Brightness
Radius [arcsec]
16
18
20
22
24
26
0
10
20
30
40
50
60
70

[ ]: