CustomModels

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0.1 Custom model objects

Here we will go over some of the core functionality of AutoProf models so that you can make your own custom models with arbitrary behavior. This is an advanced tutorial and likely not needed for most users. However, the flexibility of AutoProf can be a real lifesaver for some niche applications! If you get stuck trying to make your own models, please contact Connor Stone (see GitHub), he can help you get the model working and maybe even help add it to the core AutoProf model list!

0.1.1 AutoProf model hierarchy

AutoProf models are very much object oriented and inheritence driven. Every AutoProf model inherits from `AutoProf_Model` and so if you wish to make something truly original then this is where you would need to start. However, it is almost certain that is the wrong way to go. Further down the hierarchy is the `Component_Model` object, this is what you will likely use to construct a custom model as it represents a single "unit" in the astronomical image. Spline, Sersic, Exponential, Gaussian, PSF, Sky, etc. all of these inherit from `Component_Model` so likely that's what you will want. At its core, a `Component_Model` object defines a center location for the model, but it doesn't know anything else yet. At the same level as `Component_Model` is `Group_Model` which represents a collection of model objects (typically but not always `Component_Model` objects). A `Group_Model` is how you construct more complex models by composing several simpler models. It's unlikely you'll need to inherit from `Group_Model` so we won't discuss this any further (contact the developers if you're thinking about that).

Inheriting from `Component_Model` are a few general classes which make it easier to build typical cases. There is the `Galaxy_Model` which adds a position angle and axis ratio to the model; also `Star_Model` which simply enforces no psf convolution on the object since that will be handled internally for anything star like; `Sky_Model` should be used for anything low resolution defined over the entire image, in this model psf convolution and integration are turned off since they shouldn't be needed. Based on these low level classes, you can "jump in" where it makes sense to define your model. Of course, you can take any AutoProf model as a starting point and modify it to suit a given task, however we will not list all models here. See the documentation for a more complete list.

0.1.2 Remaking the Sersic model

Here we will remake the sersic model in AutoProf to demonstrate how new models can be created

[1]:
```
import autoprof as ap
import torch
from astropy.io import fits
```

```python
import numpy as np
import matplotlib.pyplot as plt
ap.AP_config.set_logging_output(stdout = True, filename = None) # see GettingStarted tutorial for what this does
```

[2]:

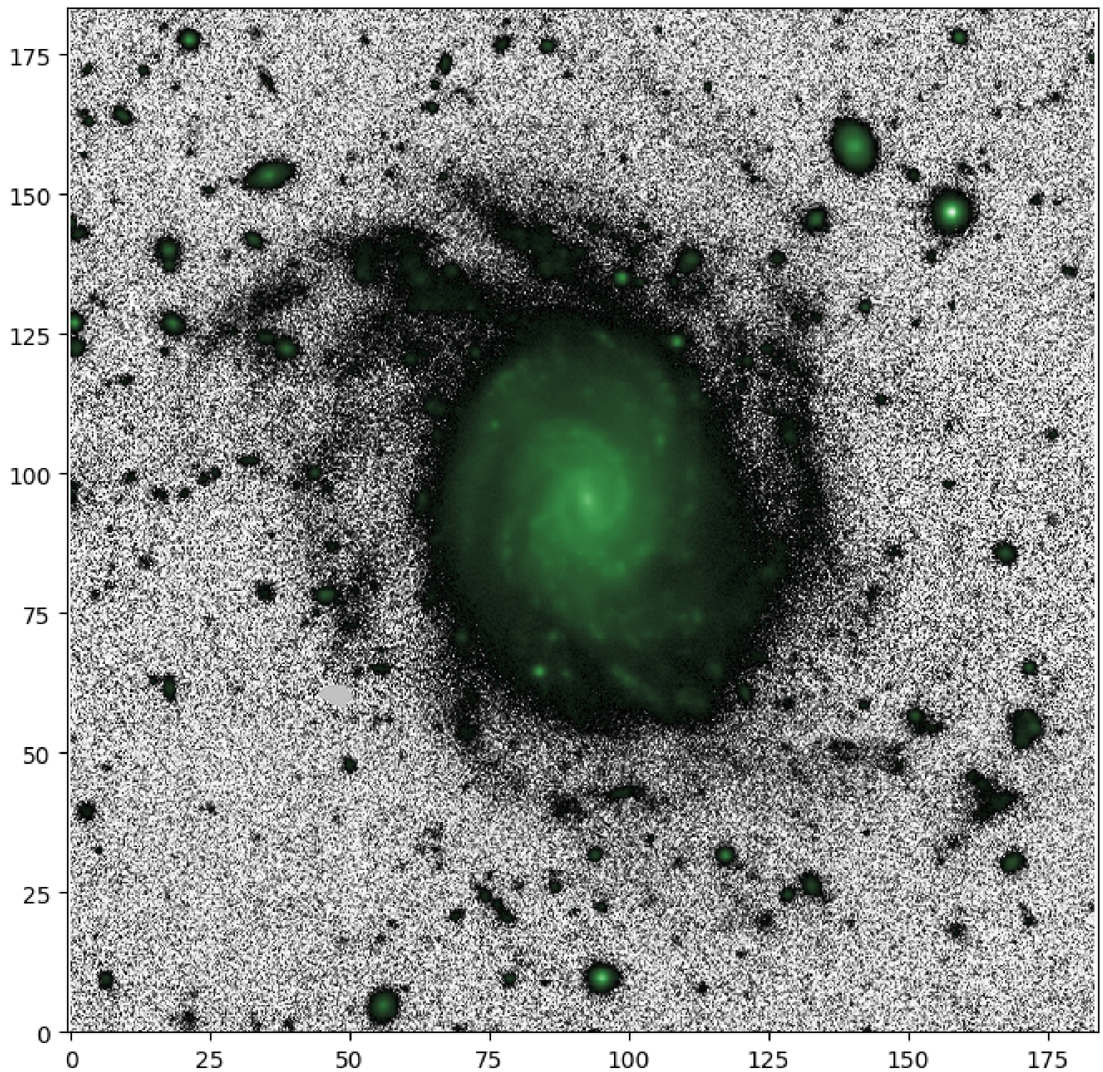
```python
class My_Sersic(ap.models.Galaxy_Model):
    """Let's make a sersic model!
    """

    model_type = f"mysersic {ap.models.Galaxy_Model.model_type}" # here we give a name to the model, the convention is to lead with a new identifier then include the name of the inheritance model
    parameter_specs = {
        "my_n": {"limits": (0.36,8)}, # our sersic index will have some default limits so it doesn't produce weird results
        "my_Re": {"limits": (0,None)}, # our effective radius must be positive, otherwise it is fair game
        "my_Ie": {}, # our effective surface density could be any real number
    }
    _parameter_order = ap.models.Galaxy_Model._parameter_order + ("my_n", "my_Re", "my_Ie") # we have to tell AutoProf what order to access these parameters, this is used in several underlying methods

    def radial_model(self, R, image = None, parameters = None): # by default a Galaxy_Model object will call radial_model to determine the flux at each pixel
        bn = ap.utils.conversions.functions.sersic_n_to_b(parameters["my_n"].value) # AutoProf has a number of useful util functions, though you are welcome to use your own
        return parameters["my_Ie"].value * (image.pixel_area) * torch.exp(-bn * ((R / parameters["my_Re"].value)**(1. / parameters["my_n"].value) - 1)) # this is simply the classic sersic profile. more details later.
```

Now lets try optimizing our sersic model on some data. We'll use the same galaxy from the GettingStarted tutorial. The results should be about the same!

[3]:

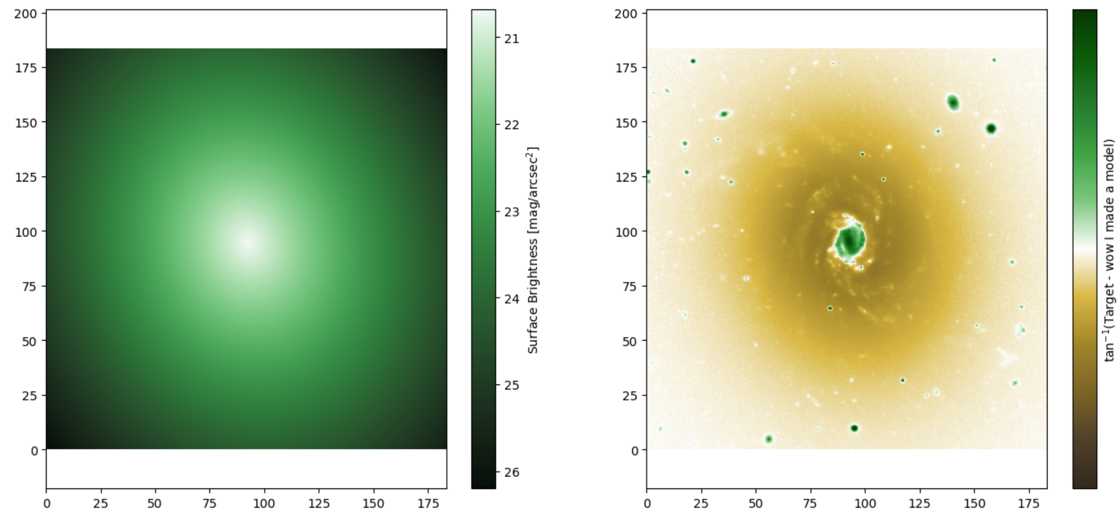
```python
hdu = fits.open("https://www.legacysurvey.org/viewer/fits-cutout?ra=36.3684&dec=-25.6389&size=700&layer=ls-dr9&pixscale=0.262&bands=r")
target_data = np.array(hdu[0].data, dtype = np.float64)

# Create a target object with specified pixelscale and zeropoint
target = ap.image.Target_Image(
    data = target_data,
    pixelscale = 0.262, # Every target image needs to know it's pixelscale in arcsec/pixel
    zeropoint = 22.5, # optionally, you can give a zeropoint to tell AutoProf what the pixel flux units are
```

```
)

# The default AutoProf target plotting method uses log scaling in bright areas
↪and histogram scaling in faint areas
fig, ax = plt.subplots(figsize = (8,8))
ap.plots.target_image(fig, ax, target)
plt.show()
```



[4]:
```
my_model = My_Sersic( # notice we are now using the custom class
    name = "wow I made a model",
    target = target, # now the model knows what its trying to match
```

```
    parameters = {"my_n": 1., "my_Re": 50, "my_Ie": 1.}, # note we have to give␣
↪initial values for our new parameters. We'll see what can be done for this␣
↪later
)

# We gave it parameters for our new variables, but initialize will get starting␣
↪values for everything else
my_model.initialize()

# The starting point for this model is not very good, lets see what the␣
↪optimizer can do!
fig, ax = plt.subplots(1, 2, figsize = (16,7))
ap.plots.model_image(fig, ax[0], my_model)
ap.plots.residual_image(fig, ax[1], my_model)
plt.show()
```



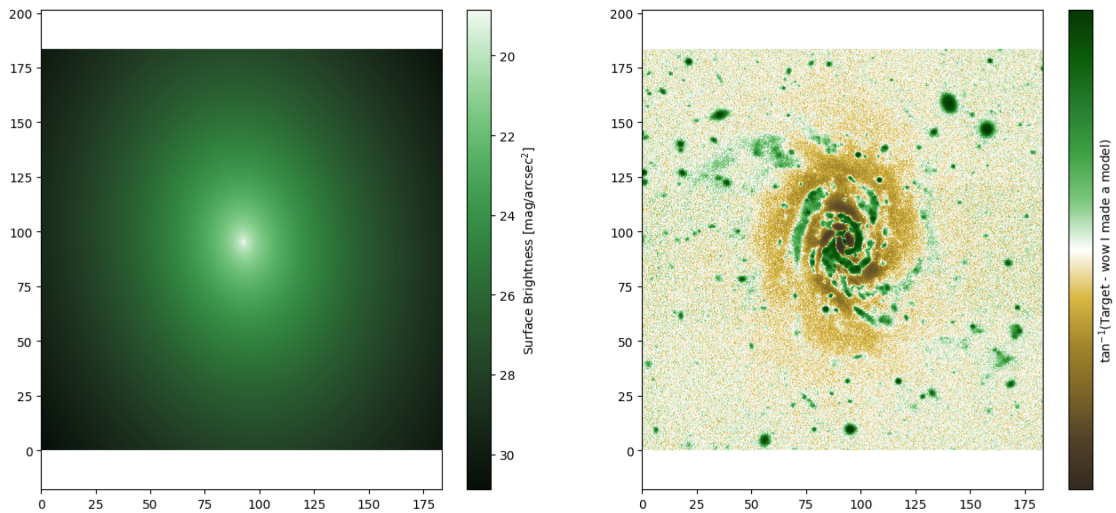
[5]:
```
result = ap.fit.LM(my_model, verbose = 1).fit()
print(result.message)
```

```
L: 1.0
---------init---------
LM loss: 0.007109751126274875
L: 1.0
---------iter---------
LM loss: 0.005143727869357506
accept
L: 0.1111111111111111
---------iter---------
LM loss: 0.03893428826188387
reject
```

```
L: 1.2222222222222222
---------iter---------
LM loss: 0.006403603082445545
reject
L: 13.444444444444443
---------iter---------
LM loss: 0.0050355741084663974
accept
L: 1.493827160493827
---------iter---------
LM loss: 0.004619861396437552
accept
L: 0.16598079561042522
---------iter---------
LM loss: 0.004435851872105284
accept
L: 0.01844231062338058
---------iter---------
LM loss: 0.004355903933502252
accept
L: 0.0020491456248200642
---------iter---------
LM loss: 0.004322354319306442
accept
L: 0.00022768284720222937
---------iter---------
LM loss: 0.004313105326024137
accept
L: 2.529809413358104e-05
---------iter---------
LM loss: 0.004312869422955362
accept
L: 2.810899348175671e-06
---------iter---------
LM loss: 0.0043128644520618155
accept
success
```

[6]:

```
fig, ax = plt.subplots(1, 2, figsize = (16,7))
ap.plots.model_image(fig, ax[0], my_model)
ap.plots.residual_image(fig, ax[1], my_model)
plt.show()
```



Success! Our "custom" sersic model behaves exactly as expected. While going through the tutorial so far there may have been a few things that stood out to you. Lets discuss them now:

- What was "sample_image" in the radial_model function? This is an object for the image that we are currently sampling. You shouldn't need to do anything with it except get the pixelscale.
- what else is in "ap.utils"? Lots of stuff used in the background by AutoProf. For now the organization of these is not very good and sometimes changes, so you may wish to just make your own functions for the time being.
- Why the weird way to access the parameters? The self["variable"].value format was settled on for simplicity and generality. it's not perfect, but it works.
- Why is "sample_image.pixel_area" in the sersic evaluation? it is important for AutoProf to know the size of the pixels it is evaluating, multiplying by this value will normalize the flux evaluation regardless of the pixel sizes.
- When making the model, why did we have to provide values for the parameters? Every model can define an "initialize" function which sets the values for its parameters. Since we didn't add that function to our custom class, it doesn't know how to set those variables. All the other variables can be auto-initialized though.

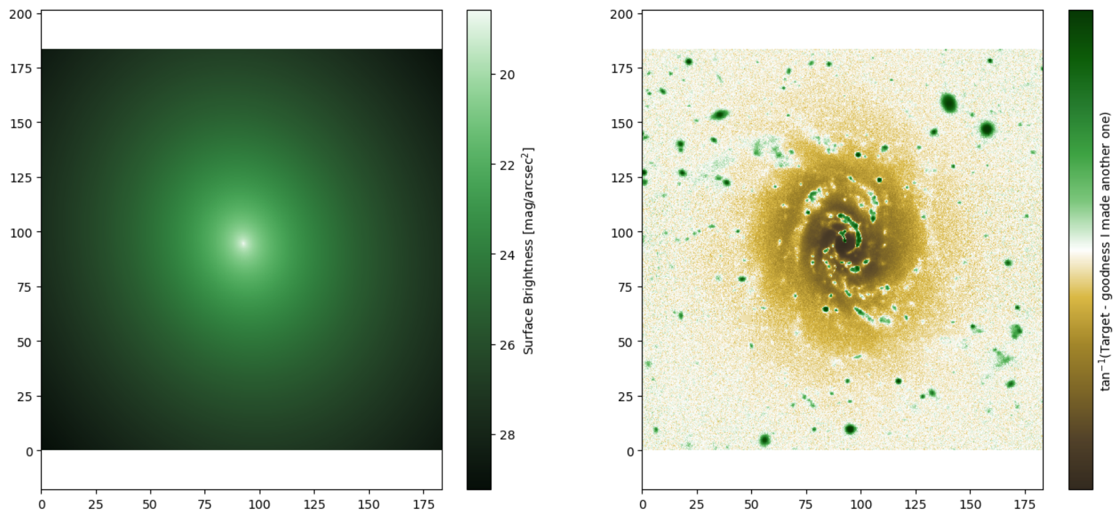
0.1.3 Adding an initialize method

Here we'll add an initialize method. Though for simplicity we wont make it very clever. It will be up to you to figure out the best way to start your parameters. The initial values can have a huge impact on how well the model converges to the solution, so don't underestimate the gains that can be made by thinking a bit about how to do this right. The default AutoProf methods have reasonably robust intiializers, but still nothing beats trial and error by eye to get started.

[7]:
```
class My_Super_Sersic(My_Sersic): # note we're inheriting everything from the My_Sersic model since its not making any new parameters
    model_type = "super awesome sersic model" # you can make the name anything you like, but the one above follows the normal convention
```

```
    def initialize(self,target = None, parameters = None):
        if target is None: # good to just use the model target if none given
            target = self.target
        if parameters is None:
            parameters = self.parameters
        super().initialize(target=target, parameters=parameters) # typically␣
↪you want all the lower level parameters determined first

        target_area = target[self.window] # this gets the part of the image␣
↪that the user actually wants us to analyze

        if self["my_n"].value is None: # only do anything if the user didn't␣
↪provide a value
            parameters["my_n"].set_value(2., override_locked = True) # make an␣
↪initial value for my_n. Override locked since this is the beginning
            parameters["my_n"].set_uncertainty(0.1, override_locked = True) #␣
↪make sure there is a starting point for the uncertainty too

        if self["my_Re"].value is None: # same as my_n, though in general you␣
↪should try to do something smart to get a good starting point
            parameters["my_Re"].set_value(20., override_locked = True)
            parameters["my_Re"].set_uncertainty(0.1, override_locked = True)

        if self["my_Ie"].value is None: # lets try to be a bit clever here
            small_window = self.window / 5. # This creates a window 5x smaller,␣
↪but still centered on the same point
            parameters["my_Ie"].set_value(torch.
↪median(target_area[small_window].data)/target_area.pixel_area,␣
↪override_locked = True) # this will be an average in the window, should at␣
↪least get us within an order of magnitude
            parameters["my_Ie"].set_uncertainty(0.1, override_locked = True)
```

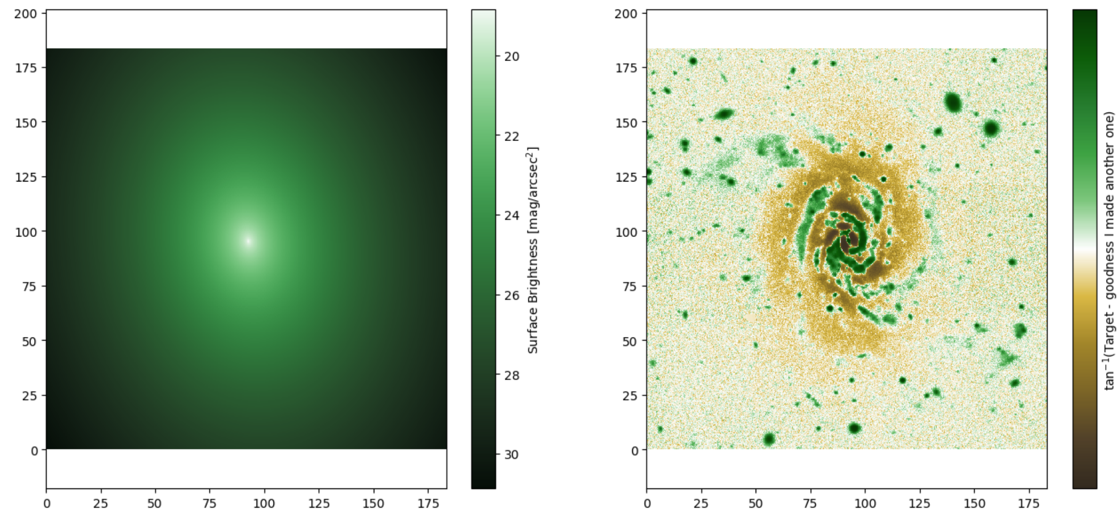
[8]:
```
my_super_model = My_Super_Sersic( # notice we switched the custom class
    name = "goodness I made another one",
    target = target,
) # no longer need to provide initial values!

my_super_model.initialize()

# The starting point for this model is still not very good, lets see what the␣
↪optimizer can do!
fig, ax = plt.subplots(1, 2, figsize = (16,7))
ap.plots.model_image(fig, ax[0], my_super_model)
ap.plots.residual_image(fig, ax[1], my_super_model)
plt.show()
```




```
[9]: # We made a "good" intializer so this should be faster to optimize
     result = ap.fit.LM(my_super_model, verbose = 1).fit()
     print(result.message)
```

```
L: 1.0
---------init---------
LM loss: 0.004501723356449894
L: 1.0
---------iter---------
LM loss: 0.004328692438256 15
accept
L: 0.1111111111111111
---------iter---------
LM loss: 0.0043139255902297545
accept
L: 0.012345679012345678
---------iter---------
LM loss: 0.004313061130247116
accept
L: 0.0013717421124828531
---------iter---------
LM loss: 0.004312883954846044
accept
L: 0.00015241579027587256
---------iter---------
LM loss: 0.004312865093292262
accept
success
```

[10]:
```
fig, ax = plt.subplots(1, 2, figsize = (16,7))
ap.plots.model_image(fig, ax[0], my_super_model)
ap.plots.residual_image(fig, ax[1], my_super_model)
plt.show()
```



Success! That covers the basics of making your own models. There's an infinite amount of possibility here so you will likely need to hunt through the AutoProf code to find answers to more nuanced questions (or contact Connor), but hopefully this tutorial gave you a flavour of what to expect.

0.2 Models from scratch

By inheriting from `Galaxy_Model` we got to start with some methods already available. In this section we will see how to create a model essentially from scratch by inheriting from the `Component_Model` object. Below is an example model which uses a $\frac{I_0}{R}$ model, this is a weird model but it will work. To demonstrate the basics for a `Component_Model` is actually simpler than a `Galaxy_Model` we really only need the `evaluate_model` function, it's what you do with that function where the complexity arises.

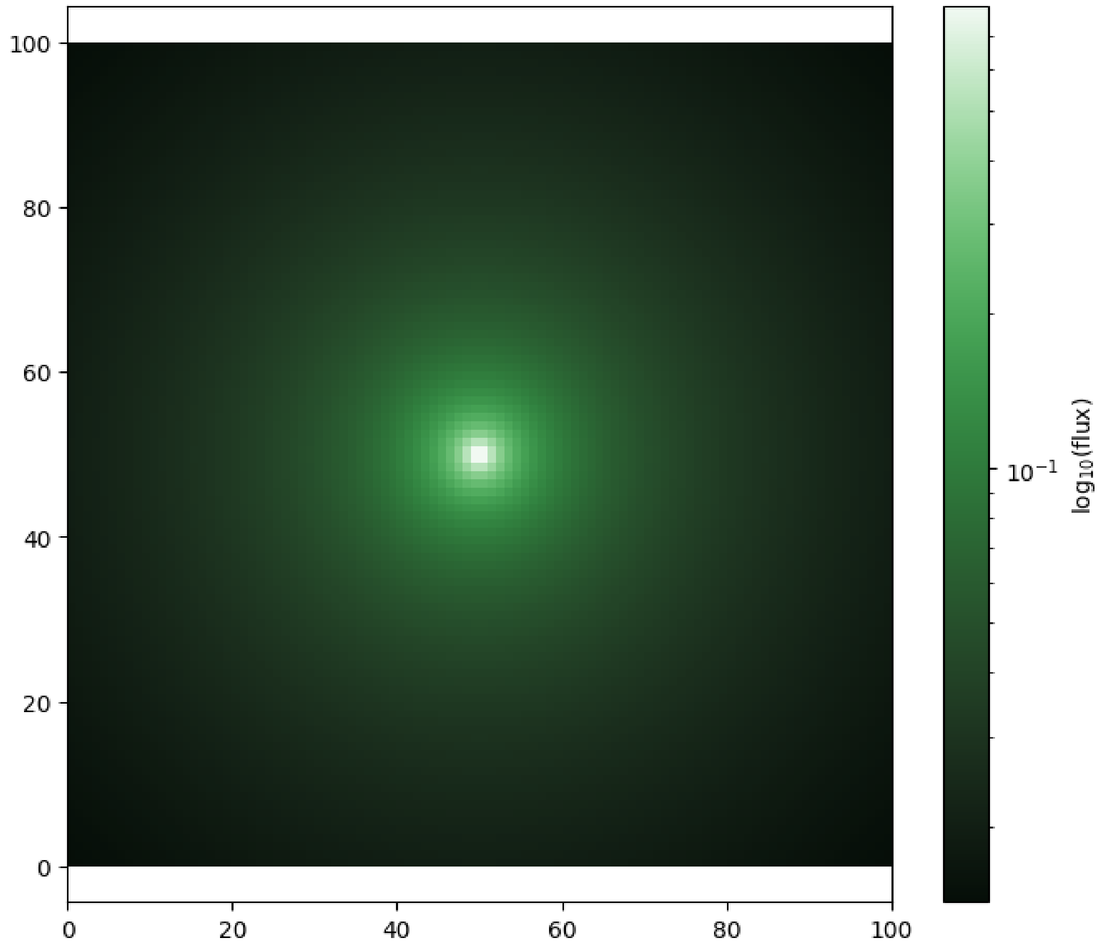
[11]:
```
class My_InvR(ap.models.Component_Model):
    model_type = "InvR model"

    parameter_specs = {
        "my_Rs": {"limits": (0,None)}, # This will be the scale length
        "my_I0": {}, # This will be the central brightness
    }
    _parameter_order = ap.models.Component_Model._parameter_order + ("my_Rs", "my_I0") # we have to tell AutoProf what order to access these parameters, this is used in several underlying methods
```

```
    epsilon = 1e-4 # this can be set with model.epsilon, but will not be fit␣
↪during optimization
    def evaluate_model(self, X = None, Y = None, image = None, parameters =␣
↪None):
        if X is None or Y is None:
            Coords = image.get_coordinate_meshgrid()
            X, Y = Coords - parameters["center"].value[...,None,None]
        return parameters["my_I0"].value * image.pixel_area / torch.sqrt(X**2 +␣
↪Y**2 + self.epsilon)
```

See now that we must define a `evaluate_model` method. This takes coordinates, an image object, and parameters and returns the model evaluated at the coordinates. No need to worry about integrating the model within a pixel, this will be handled internally, just evaluate the model at the center of each pixel. For most situations this is made easier with the `get_coordinate_meshgrid_torch` method that all AutoProf `Target_Image` objects have. We also add a new value `epsilon` which is a core radius in arcsec. This parameter will not be fit, it is set as part of the model creation. You can now also provide epsilon when creating the model, or do nothing and the default value will be used.

From here you have complete freedom, it need only provide a value for each pixel in the given image. Just make sure that it accounts for pixel size (proportional to pixelscale^2). Also make sure to use only pytorch functions, since that way it is possible to run on GPU and propogate derivatives.

[12]:
```
simpletarget = ap.image.Target_Image(data = np.zeros([100,100]), pixelscale = 1)
newmodel = My_InvR(name = "newmodel", epsilon = 1, parameters = {"center":␣
 ↪[50,50], "my_Rs": 10, "my_I0": 1.}, target = simpletarget)

fig, ax = plt.subplots(1, 1, figsize = (8,7))
ap.plots.model_image(fig, ax, newmodel)
plt.show()
```


100
80
60
40
20
0
0
20
40
60
80
100
10^{-1}
$\log_{10}$(flux)

```
[ ]:
```