HW8-RyanSponzilli

October 28, 2024

1 ASTR 310 HW 8

1.0.1 1. Making a contour plot with annotations

a) Create a contour plot of the function

$$z(x, y) = \frac{1}{|y| + 1} \sin(x^2 + y^2)\, e^{-x^2}$$

containing 15 contour levels equally spaced between the global minimum and maximum of the function within the domain $[-\pi, \pi] \times [-\pi, \pi]$. [5 pts]

b) Find all the local minima and maxima of z. Indicate positions of the minima with circles and positions of the maxima with $\times$'s. Finding local extrema is nontrivial, so there are two ways you might do this task. The easy but inelegant way is to loop over all the pixels of z and check whether they are larger or smaller than all of their neighbors. The more elegant way is to use tests like `(z >= np.roll(z, -1, axis=0))` to eliminate the loop. [10 pts]

c) Create a legend that shows that circles indicate minima and that $\times$'s indicate maxima. Be sure to include an appropriate title and labels for the x and y axes. [5 pts]

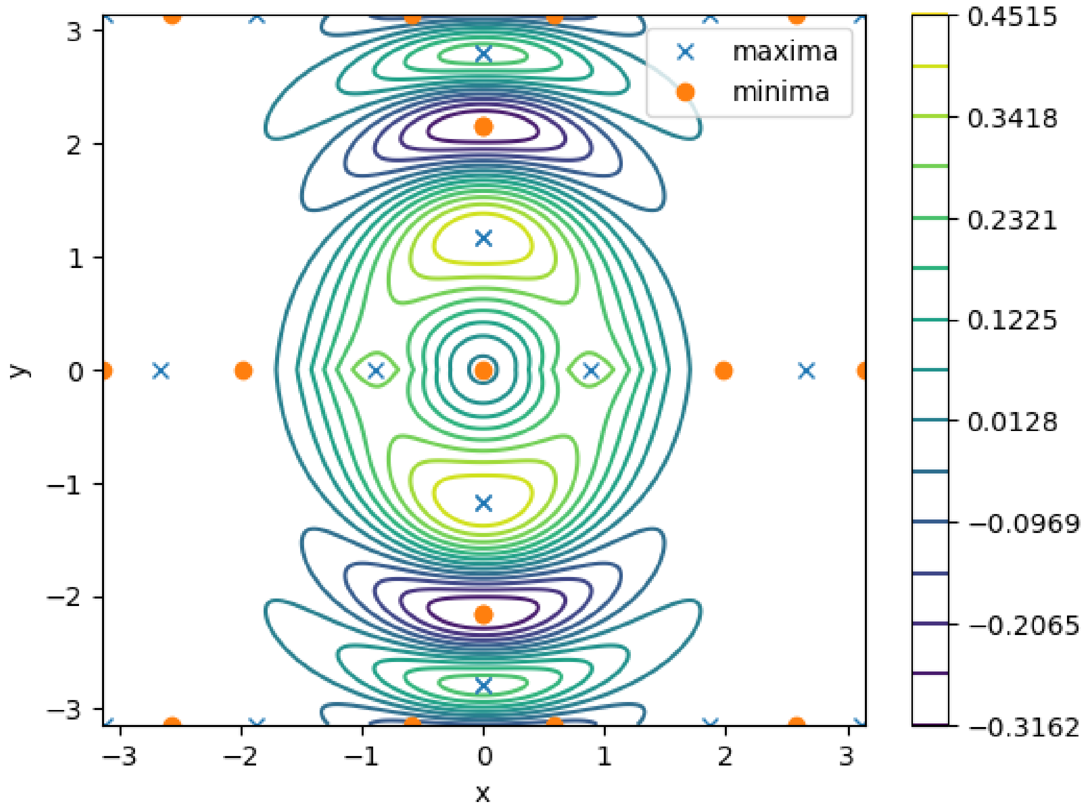
[503]:
```
import numpy as np
import matplotlib.pyplot as plt
import astropy.io.fits as fits
import astropy.table as table
from matplotlib.patches import Ellipse
```

[504]:
```
x = np.linspace(-np.pi, np.pi, 1000)
y = np.linspace(-np.pi, np.pi, 1000)

xx, yy = np.meshgrid(x, y)

z = (1 / (np.abs(yy) + 1)) * np.sin(xx**2 + yy**2) * np.exp(-(xx**2))
levels = np.linspace(np.min(z), np.max(z), 15)
plt.contour(xx, yy, z, levels=levels, extent=[-np.pi, np.pi, -np.pi, np.pi])
plt.xlabel("x")
plt.ylabel("y")
plt.colorbar()
maxima = (z >= np.roll(z, 1, axis=0)) & (z >= np.roll(z, -1, axis=0)) & (z >=␣
 ↪np.roll(z, 1, axis=1)) & (z >= np.roll(z, -1, axis=1))
```

```
minima = (z <= np.roll(z, 1, axis=0)) & (z <= np.roll(z, -1, axis=0)) & (z <=
    np.roll(z, 1, axis=1)) & (z <= np.roll(z, -1, axis=1))
plt.plot(xx[maxima], yy[maxima], 'x', label="maxima")
plt.plot(xx[minima], yy[minima], 'o', label='minima')
plt.legend()
plt.show()
```



1.0.2 2. Reading and working with data in a FITS file

Download the file `acisf26248N001_evt2.fits` from the course website. This is an X-ray photon event file from a 25 ksec (25,120 seconds) Chandra ACIS-I observation of the supernova remnant Cassiopeia A (Cas A). In X-rays most astronomical sources are faint enough that we receive one photon at a time. Thus, detectors usually don't record an image with intensities in an array of pixels. They usually produce files giving information about the arrival of each photon, including its position in the focal plane and its energy.

In this problem you will read in, analyze, and plot results from this file. The file contains an empty primary HDU and two binary table extension HDUs. Each row of the first binary table (EVENTS) corresponds to a single X-ray photon. The table columns that we care about (see the header for the full list) are X, Y, and ENERGY. (X,Y) is the pixel location of the photon in a plane tangent to the sky. See the EVENTS header for the values of X and Y axis reference pixel [TCRPX11 and

TCRPX12], sky coordinate value of reference pixel [TCRVL11/12], and pixel size needed to derive sky positions from table values [TCDLT11/12]). ENERGY is the energy of the photon in electron volts (eV).

Note: we are going to skip some of the standard X-ray data analysis steps, such as limiting counts to time intervals considered to produce reliable observations and accounting for the detector response matrix.

a) Write code to read the file and select the data by photon energy so that you have a NumPy record array containing (X,Y) positions for photons with energies between 2.0 and 9.5 keV. You will need to convert the (X,Y) positions from the file into sky coordinates (RA, Dec) in degrees in the following way. Note that TCDLT11/12 and TCRVL11/12 are given in degrees. Since the NumPy trig functions take arguments in radians, and the inverse trig functions return results in radians, you will need to supply the appropriate conversion factors between radians and degrees.

$$\begin{aligned}
\xi &= \mathrm{TCDLT11} \cdot (\mathrm{X} - \mathrm{TCRPX11}) \\
\eta &= \mathrm{TCDLT12} \cdot (\mathrm{Y} - \mathrm{TCRPX12}) \\
\alpha_0 &= \mathrm{TCRVL11} \\
\delta_0 &= \mathrm{TCRVL12} \\
\mathrm{RA} &= \alpha_0 + \tan^{-1}\left(\frac{\xi}{\cos\delta_0 - \eta\sin\delta_0}\right) \\
\mathrm{Dec} &= \sin^{-1}\left(\frac{\sin\delta_0 + \eta\cos\delta_0}{\sqrt{1+\xi^2+\eta^2}}\right)
\end{aligned}$$

Use Astropy commands to get the necessary header information from the file; do not hard-code the values.

[10 pts]

[505]:
```
hdulist = fits.open("acisf26248N001_evt2.fits")
x_ref = hdulist[1].header['TCRPX11']
y_ref = hdulist[1].header['TCRPX12']
x_ref_coord = hdulist[1].header['TCRVL11']
y_ref_coord = hdulist[1].header['TCRVL12']
x_pix_size = hdulist[1].header['TCDLT11']
y_pix_size = hdulist[1].header['TCDLT12']
```

[506]:
```
data = table.Table(hdulist[1].data)
data = data[['x', 'y', 'energy']]
data = data[(data['energy'] >= 2000) & (data['energy'] <= 9500)]
```

[507]:
```
rads = np.pi/180
degs = 180/np.pi
e = x_pix_size*rads * (data['x'] - x_ref)
n = y_pix_size*rads * (data['y'] - y_ref)
```

```
data['ra'] = x_ref_coord + np.arctan2(e, (np.cos(y_ref_coord * rads) - n * np.
    ↪sin(y_ref_coord * rads))) * degs
data['dec'] = np.arcsin((np.sin(y_ref_coord * rads) + n * np.cos(y_ref_coord *␣
    ↪rads)) / np.sqrt(1 + e**2 + n**2)) * degs
data
```

[507]:
```
<Table length=1441507>
    x         y       energy      ra       dec
 float32   float32   float32   float32   float32
--------- --------- --------- --------- ---------
4811.3877 4734.3164 3473.9565  350.7389  58.85262
 4632.411  4789.352  4602.755 350.78616 58.860188
 4683.042  4609.748 2309.4846  350.7729  58.83564
4549.8853 4702.1343 4365.5337   350.808  58.84829
4520.6055 4693.7485  2694.231 350.81577 58.847157
4588.8105 4628.2705  4471.224 350.79776 58.838196
4400.3096  4768.022 2492.6804  350.8475  58.85733
4490.0435 4693.3823 3946.0737 350.82382 58.847107
 4566.478 4624.5293 5225.1846 350.80368 58.837673
      …         …         …         …         …
 4114.135  4346.734 2458.3508 350.92316  58.79978
   4154.6  4312.702 3434.5913 350.91248 58.795124
4037.6182  4399.676 2220.8901 350.94333 58.807014
  4195.94 4270.2637 3019.2092 350.90158 58.789337
  4268.78 4208.0664   2428.81 350.88235 58.780815
4166.4307 4287.7295 2398.4297 350.90936 58.791706
4147.9766 4280.8496 2666.0254  350.9142 58.790764
4075.5295 4226.5605  4035.601 350.93332  58.78336
3987.7861 4148.7236 2314.9414 350.95645  58.77272
3886.3574 4229.5215 2140.3892 350.98322 58.783752
```

b) Write code to construct an image array from this selection; that is, produce a 2D mesh covering the region of sky from which photons were received, and set the array values equal to the number of photons that fell within each mesh cell. Use 128^2 mesh cells. You can use `np.histogram2d` or you can do the gridding yourself by hand.

If you do the gridding by hand, loop over all the photons and increment the cell count of the pixel where each photon landed. Note two things: (a) You should index your mesh using the $y-$index first; that is, if a photon's X-coordinate places it in the *ith* mesh column and the Y-coordinate places it in the *jth* mesh row, you should allocate it to the [j,i] index of your 2D count array. (b) RA increases eastward (leftward when looking out at the celestial sphere), while column numbers will increase toward the right when we plot the array.

Divide the photon counts by the area of each cell in square arcseconds, the effective area of the detector (assume it to be 600 cm^2; in reality it varies with photon energy and position), and the "live time" of the observation. (Use the LIVETIME keyword in the EVENTS header to get this information.) At the end of this operation you will have an image array containing values in units of photons $arcsec^{-2}\ cm^{-2}\ sec^{-1}$.

[7 pts]

[508]:
```
livetime = hdulist[1].header['LIVETIME']
livetime
```

[508]:
```
24778.918026537
```

[509]:
```
cell_area = 600 / 128**2
```

[510]:
```
grid, bins1, bins2 = np.histogram2d(data['ra'], data['dec'], bins=128)
grid
```

[510]:
```
array([[0., 0., 0., …, 0., 0., 0.],
       [0., 0., 0., …, 0., 0., 0.],
       [0., 0., 0., …, 0., 0., 0.],
       …,
       [0., 0., 0., …, 0., 0., 0.],
       [0., 0., 0., …, 0., 0., 0.],
       [0., 0., 0., …, 0., 0., 0.]])
```

[511]:
```
grid = grid / cell_area / livetime
grid
```

[511]:
```
array([[0., 0., 0., …, 0., 0., 0.],
       [0., 0., 0., …, 0., 0., 0.],
       [0., 0., 0., …, 0., 0., 0.],
       …,
       [0., 0., 0., …, 0., 0., 0.],
       [0., 0., 0., …, 0., 0., 0.],
       [0., 0., 0., …, 0., 0., 0.]])
```

c) Use the image array to produce a color image plot. The plot should have appropriate axis ranges (remember units!) and labels and a title, and a color bar legend should be included. Use whatever color palette you like. By default `imshow` assumes the [0,0] element of the array is at the top left; use the `origin="lower"` argument to override this behavior. Also, since Cas A is at a high Declination, to get the image to look square you will need to specify `aspect=R`, where R is (width in RA)/(width in Dec). This scaling accounts for the fact that longitude lines get closer together towards the pole.

You might want to "stretch" the image to make faint features more visible by plotting, e.g., the logarithm of the counts. If you do so, be sure to use the "unstretched" data in the following steps.

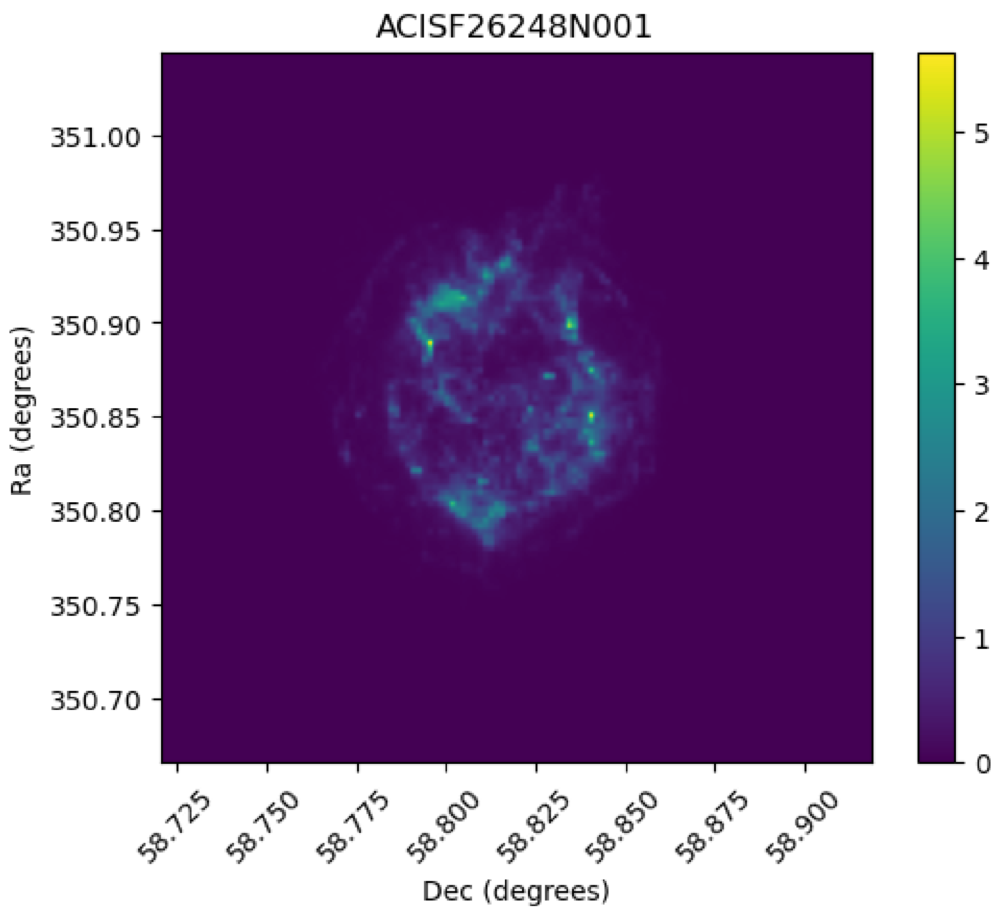
The pdf version of this assignment has an example of what your figure should look like, if you want to check yourself.

[8 pts]

[512]:
```
extent = [bins2[0], bins2[-1], bins1[0], bins1[-1]]
R = (bins2[-1] - bins2[0]) / (bins1[-1] - bins1[0])
plt.imshow(grid, origin='lower', extent=extent, aspect=R)
```

```
plt.colorbar()
plt.xlabel("Dec (degrees)")
plt.ylabel("Ra (degrees)")
plt.title("ACISF26248N001")
plt.xticks(rotation=45)
```

[512]:
```
(array([58.7  , 58.725, 58.75 , 58.775, 58.8  , 58.825, 58.85 , 58.875,
        58.9  , 58.925]),
 [Text(58.7, 0, '58.700'),
  Text(58.725, 0, '58.725'),
  Text(58.75, 0, '58.750'),
  Text(58.775000000000006, 0, '58.775'),
  Text(58.800000000000004, 0, '58.800'),
  Text(58.825, 0, '58.825'),
  Text(58.85, 0, '58.850'),
  Text(58.875, 0, '58.875'),
  Text(58.900000000000006, 0, '58.900'),
  Text(58.925000000000004, 0, '58.925')])
```



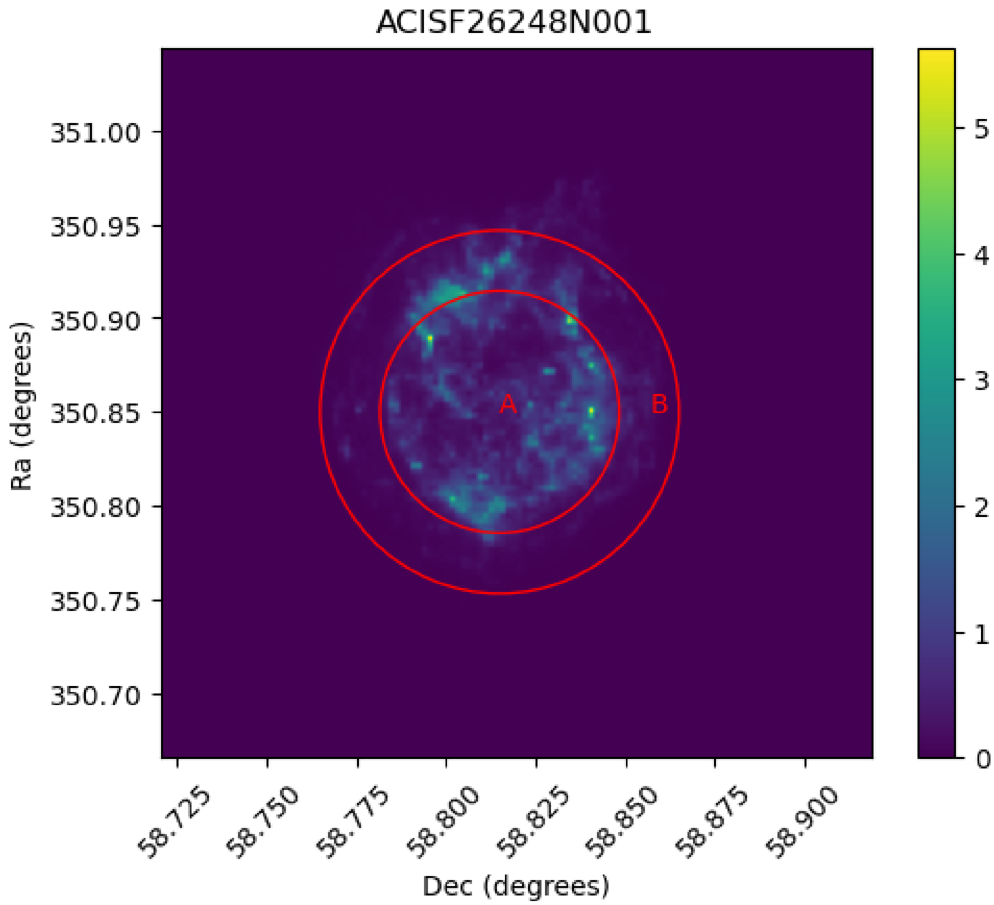
d) Designate two special regions "A" and "B" on the map. The "A" region should be a circle of radius 2' centered on J2000 coordinates 23h23m24s, +58d48m54s. (Convert these to decimal degrees to compare to photon positions.) The "B" region should be an annulus centered on the same point with an inner radius of 2' and an outer radius of 3'. Have your code draw the outline of each region on the image and label the outlines appropriately ("A", "B"). Because of the aspect ratio mentioned in (c), to make your circles look circular you will need to plot them as ellipses. For example, for region "A" you would use an ellipse of width 2 x 2'/cos δ_0 and height 2 x 2'.

[5 pts]

[513]:
```
ra = (23 + (23/60) + (24/3600))*15
dec = 58 + (48/60) + (54/3600)

plt.imshow(grid, origin='lower', extent=extent, aspect=R)
plt.colorbar()
plt.xlabel("Dec (degrees)")
plt.ylabel("Ra (degrees)")
plt.title("ACISF26248N001")
plt.xticks(rotation=45)
ax = plt.gca()
ax.add_patch(Ellipse((dec, ra), height=2*2/60/np.cos(dec*rads), width=2*2/60,␣
 ↪facecolor='none', edgecolor='red'))
ax.add_patch(Ellipse((dec, ra), height=2*3/60/np.cos(dec*rads), width=2*3/60,␣
 ↪facecolor='none', edgecolor='red'))
ax.text(dec, ra, "A", color ='red')
ax.text(dec + 2.5/60, ra, "B", color='red')
```

[513]:
```
Text(58.85666666666666, 350.85, 'B')
```



1.0.3 Extra credit

e) Return to the original file data and select photons by position so that you have two NumPy record arrays, one containing photon energies for photons arriving in region "A" and the other containing energies for photons in region "B." Apart from using the positions to select photons from the two regions we will now be interested only in their energies. Hint: you can use the coordinates of each photon to create a SkyCoord object and compute its distance to the center – see Reading 14 again.

You might think that, since we have a position and energy for each photon, we could make a spectrum for each image pixel. However, remember that we are dealing with a limited number of photons. The number of photons needed to get a statistically reliable estimate of the radiation intensity is considerably smaller than the number needed to get a temperature or a spectrum. So usually we have to accumulate photons from a larger region of sky to construct a spectrum. That's why we're considering the two regions "A" and "B".

Write code to create a second plot showing spectra for the two regions (two curves on one plot). The spectra should be shown as "step"-type histograms of photon counts per cm^2 per second per keV versus photon energy in keV. Both x and y axes should be logarithmic, with ranges chosen to allow the curves to fill most of the plot. Include a legend, appropriate axis labels (remember units!), and an appropriate title. In choosing the bin size for each curve (they do not have to be the same), ensure that at least 10 photons contribute to each bin. You will need to experiment with the bin size to find the appropriate value.

When constructing photon energy histograms, keep in mind that the NumPy or Matplotlib histogram routines will return data that are effectively in units of photons per bin. So to get the spectra in the desired units you need to divide the histograms by effective area in cm^2, live time in seconds, and bin width in keV.

[20 pts]

[ ]:
```

```

[ ]:
```

```

[ ]:
```

```