Source finding demo

1. Initialisation

imports:

In [1]:
```
%matplotlib ipympl
from matplotlib import pyplot as plt
from matplotlib import colors
import numpy as np
from astropy.io import fits
#from astropy.table import QTable
from numba import njit
from photutils import segmentation as segm
from scipy.spatial import ConvexHull
```

2. Read data

select one dataset:

In [2]:
```
dataset = 2
```

Images:

In [3]:
```
if dataset == 1:
    hdu = fits.open('data/hcg44_cube_R.fits')
    data = hdu[0].data[69]*1.  # to make sure it's converted to float
    #data = hdu[0].data[:, 270, :]*1.
    #data = hdu[0].data[:, 170, :]*1.
    #data = hdu[0].data[99]*1.
```

In [4]:
```
if dataset == 2:
    hdu = fits.open('data/CIG_335.fits')
    data = hdu[0].data[3000:4000, 1500:2500] * 1.  # to make sure it's converted to float
```

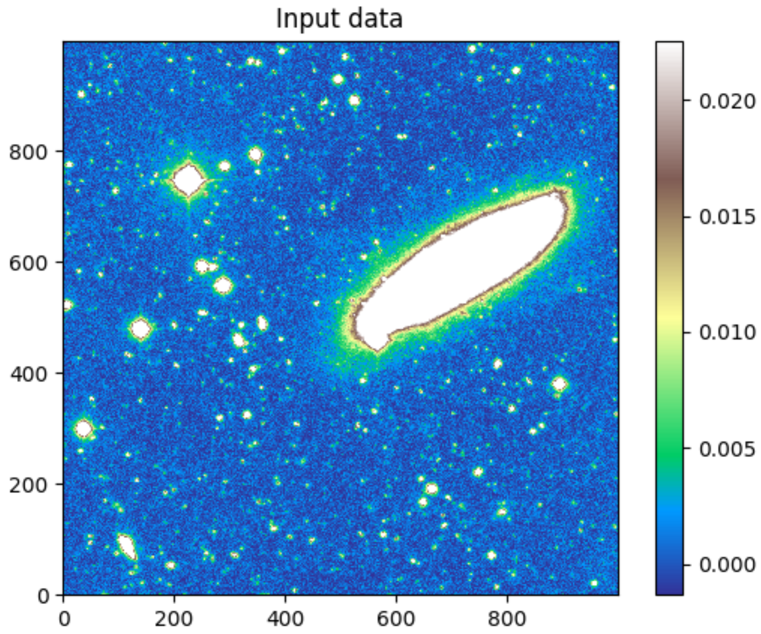
Datacubes:

---

visual inspection:

In [5]:
```
# fig, ax = fm.select('data', nrows=1, ncols=3, sharex=True, sharey=True, figsize=(10, 3))
#fig, ax = fm.select('data')
plt.close('data')
fig = plt.figure('data')
ax = fig.subplots()

im = ax.imshow(data,
               interpolation='nearest', origin='lower', cmap='terrain',
               vmin=np.nanpercentile(data, 5), vmax=np.nanpercentile(data, 95),
              )
ax.set_title('Input data')
cb = fig.colorbar(im, ax=ax)
```

data



3. Find mode

cumulative mass:

In [6]:

```
sorted_by_data = np.argsort(data.flatten())
sorted_data = data.flatten()[sorted_by_data]
```

Allow for statistical weights:

In [7]:

```
weights = np.ones_like(data)
sorted_weight = weights.flatten()[sorted_by_data]
```

In [8]:

```
cumulative_mass = np.nancumsum(sorted_weight)
sorted_weight /= cumulative_mass[-1]
cumulative_mass /= cumulative_mass[-1]
```

density peak (mode of the probability distribution):

Here we have a couple of free parameters:

In [9]:

```
delta = .5  # relative size of the smoothing kernel (delta <= 1)

# mass fractions to be tested:
m = np.linspace(delta**2,  # somewhat arbitrary :^(
                1/(1+delta),  # do not overshoot
                int(np.sqrt(data.size)) # a reasonable number of trials
               )
```

Find maximum:

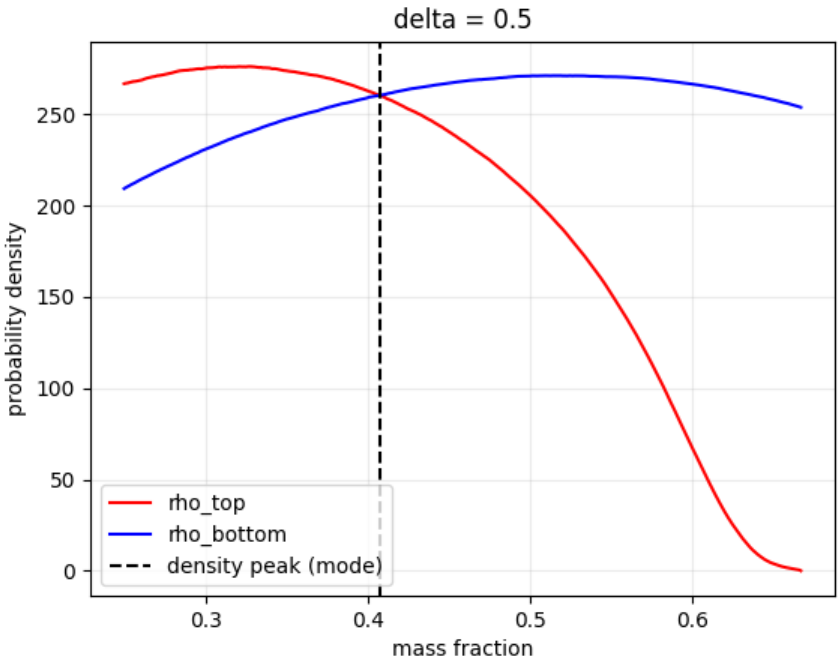
In [10]:

```
x_top = np.interp((1+delta)*m, cumulative_mass, sorted_data)
x_mid = np.interp(m, cumulative_mass, sorted_data)
x_bot = np.interp((1-delta)*m, cumulative_mass, sorted_data)
rho_top = delta * m / (x_top - x_mid)
rho_bot = delta * m / (x_mid - x_bot)
peak = np.nanargmin((rho_top - rho_bot) ** 2)
data_mode = x_mid[peak]
```

In [11]:
```
plt.close('density')
fig = plt.figure('density')
ax = fig.subplots()

ax.plot(m, rho_top, 'r-', label='rho_top')
ax.plot(m, rho_bot, 'b-', label='rho_bottom')
ax.axvline(m[peak], c='k', ls='--', label='density peak (mode)')

ax.grid(alpha=.25)
ax.legend()
ax.set_xlabel('mass fraction')
ax.set_ylabel('probability density')
ax.set_title(f'delta = {delta}')
```

Out[11]:
```
Text(0.5, 1.0, 'delta = 0.5')
```

density



estimate source threshold:

In [12]:
```
m_background = 2 * m[peak]
m_signal = 1 - m_background
threshold_guess = np.interp(m_background, cumulative_mass, sorted_data)

m_above = 1 - cumulative_mass
m_symmetric_above = np.interp(2 * data_mode - sorted_data, sorted_data, cumulative_mass, left=0.)
left = np.where(sorted_data < data_mode)
m_symmetric_above[left] = m_background - cumulative_mass[left]
m_signal_above = m_above - m_symmetric_above
purity = m_signal_above / (m_above+1e-30)
purity[-1] = 1
```

In [13]:
```
print(f'data_mode = {data_mode}')
print(f'threshold_guess = {threshold_guess}, m_signal = {m_signal}')
```

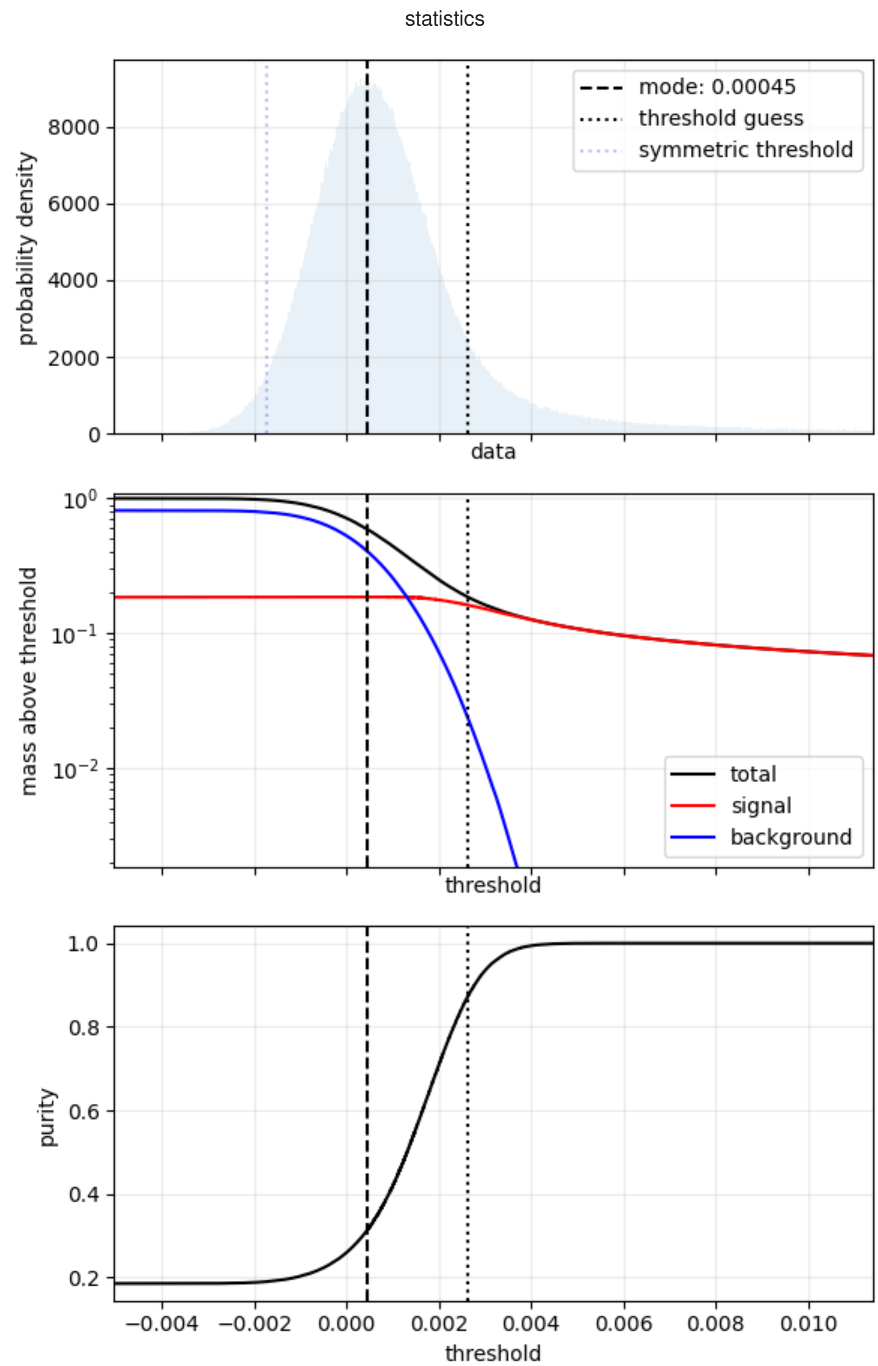
```
data_mode = 0.0004482927539949746
threshold_guess = 0.0026369258242411905, m_signal = 0.1855188521855189
```

In [14]:

```
L = max(data_mode-sorted_data[0], threshold_guess-data_mode)

plt.close('statistics')
fig = plt.figure('statistics', figsize=(6, 9))
fig.set_tight_layout(True)
ax = fig.subplots(nrows=3, sharex=True)

# density:

ax[0].hist(sorted_data, bins=np.linspace(sorted_data[0], data_mode + 5*L, int(np.sqrt(data.size))), al
ax[0].axvline(data_mode, c='k', ls='--', label=f'mode: {data_mode:.2g}')
ax[0].axvline(threshold_guess, c='k', ls=':', label='threshold guess')
ax[0].axvline(2*data_mode-threshold_guess, c='b', ls=':', alpha=.25, label='symmetric threshold')

ax[0].grid(alpha=.25)
ax[0].legend()
ax[0].set_xlabel('data')
ax[0].set_ylabel('probability density')

# mass:

ax[1].plot(sorted_data, m_above, 'k-', label='total')
ax[1].plot(sorted_data, m_signal_above, 'r-', label='signal')
ax[1].plot(sorted_data, m_symmetric_above, 'b-', label='background')
ax[1].axvline(data_mode, c='k', ls='--')
ax[1].axvline(threshold_guess, c='k', ls=':')

ax[1].grid(alpha=.25)
ax[1].legend(loc='lower right')
ax[1].set_xlabel('threshold')
#ax[1].set_xlim(sorted_data[0], data_mode + 5*L)
ax[1].set_ylabel('mass above threshold')
ax[1].set_yscale('log')
ax[1].set_ylim(1e-2*m_signal, 1.1)

# purity:

ax[2].plot(sorted_data, purity, 'k-')
ax[2].axvline(data_mode, c='k', ls='--')
ax[2].axvline(threshold_guess, c='k', ls=':')

ax[2].grid(alpha=.25)
#ax[2].legend()
ax[2].set_xlabel('threshold')
ax[2].set_ylabel('purity')

ax[0].set_xlim(sorted_data[0], data_mode + 2*L)
```

Out[14]:

```
(-0.0050287372432649136, 0.011402352748514751)
```



3. Hierarchical Overdensity Tree (HOT)

routine definition:

In [15]:

```
@njit
def hot(data, threshold=-np.inf):
    """Hierarchical Overdenity Tree (HOT)"""

    flat_data = data.flatten()
    strides = np.array(data.strides)//data.itemsize

    label = np.zeros(data.size, dtype=np.int64)
    n_labels = 0
    parent = np.zeros(data.size, dtype=np.int64)
    area = np.zeros(data.size, dtype=np.int64)
    max_value = np.zeros_like(flat_data)
    saddle_value = np.full_like(max_value, threshold)
    saddle_area = np.zeros(data.size, dtype=np.int64)

    for pixel in np.argsort(flat_data)[::-1]:  # decreasing order
        pixel_value = flat_data[pixel]
        if np.isnan(pixel_value):
            continue
        if pixel_value < threshold:
            break

        neighbour_parents = []
        for stride in strides:
            if pixel >= stride:
                p = label[pixel-stride]
                while p > 0:
                    pp = parent[p]
                    if pp == p:
                        break
                    else:
                        p = pp
                if p > 0 and p not in neighbour_parents:
                    neighbour_parents.append(p)
            if pixel+stride < flat_data.size:
                p = label[pixel+stride]
                while p > 0:
                    pp = parent[p]
                    if pp == p:
                        break
                    else:
                        p = pp
                if p > 0 and p not in neighbour_parents:
                    neighbour_parents.append(p)

        neighbour_parents = np.array(neighbour_parents)
        n_parents = neighbour_parents.size
        if n_parents == 0:
            n_labels += 1
            selected_parent = n_labels
            parent[n_labels] = n_labels
            max_value[n_labels] = pixel_value
        elif n_parents == 1:
            selected_parent = neighbour_parents[0]
        else:
            selected_parent = neighbour_parents[np.argmax(area[neighbour_parents])]
            for p in neighbour_parents:
                parent[p] = selected_parent
                if saddle_area[p] == 0:
                    saddle_value[p] = pixel_value
                    saddle_area[p] = area[p]+1
            #saddle_area[selected_parent] -= 1

        label[pixel] = selected_parent
        area[selected_parent] += 1
        #saddle_area[selected_parent] += 1
        if saddle_area[selected_parent] == 0:
            saddle_value[selected_parent] = pixel_value

    n_src = np.count_nonzero(label)
    indep = np.where(parent[:n_labels+1] == np.arange(n_labels+1))
    print(f'{n_labels} overdensities found:',
          f'{n_src} "pixels" ({int(100*n_src/data.size)}%),',
          f'{indep[0].size -1} independent regions')
    area[0] = saddle_area[0] = data.size-n_src
    saddle_area[indep] = area[indep]
    max_value[0] = saddle_value[0] = threshold
    catalog = (parent[:n_labels+1],
               area[:n_labels+1],
               max_value[:n_labels+1],
               saddle_value[:n_labels+1],
               saddle_area[:n_labels+1],
              )
```

```
    return label.reshape(data.shape), catalog
```

normal and inverted catalogues:

In [16]:

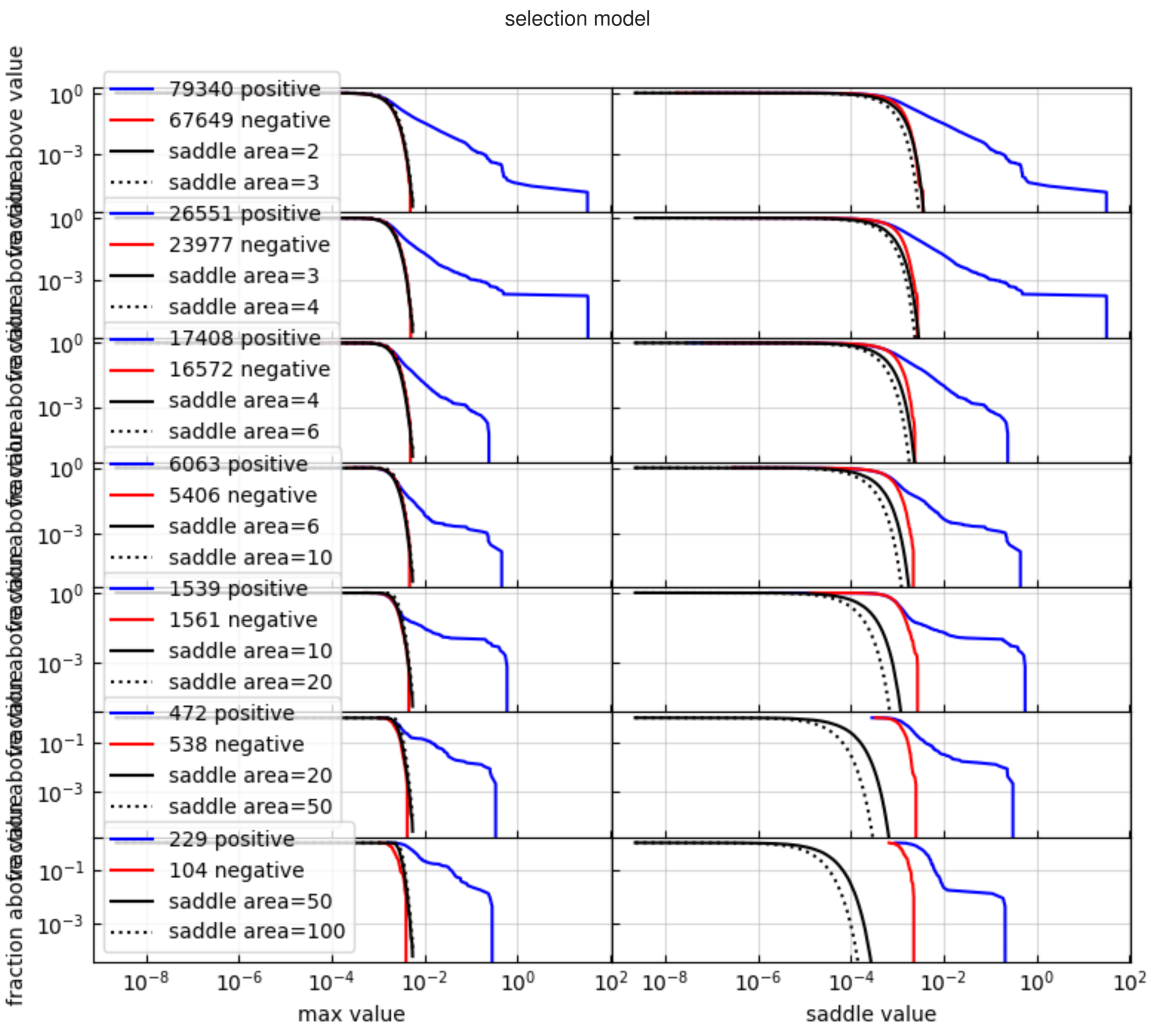
```
label, catalog = hot(data-data_mode, 0)
segmentation = segm.SegmentationImage(label)
parent = catalog[0]
area = catalog[1]
max_value = catalog[2]
saddle_value = catalog[3]
saddle_area = catalog[4]

label_inv, catalog_inv = hot(data_mode-data, 0)
segmentation_inv = segm.SegmentationImage(label_inv)
parent_inv = catalog_inv[0]
area_inv = catalog_inv[1]
max_value_inv = catalog_inv[2]
saddle_value_inv = catalog_inv[3]
saddle_area_inv = catalog_inv[4]
```

```
152109 overdensities found: 592760 "pixels" (59%), 43525 independent regions
135667 overdensities found: 407240 "pixels" (40%), 38478 independent regions
```

I tried to predict the probability distribution of max_value and saddle value, given saddle_area. In the former, I more or less succeeded...

In [17]:

```
#'''
plot_areas_edges = [2, 3, 4, 6, 10, 20, 50, 100]
x_bg = np.sort(data_mode-data[data < data_mode])
P_bg = (np.arange(x_bg.size)+.5)/x_bg.size

plt.close('selection model')
fig = plt.figure('selection model', figsize=(8, 4+np.sqrt(len(plot_areas_edges))))
ax = fig.subplots(nrows=len(plot_areas_edges)-1, ncols=2, squeeze=False,
                  sharex=True, sharey='row',
                  gridspec_kw={'hspace': 0, 'wspace': 0})
for axis in ax.flatten():
    axis.tick_params(which='both', direction='in')
    axis.grid(alpha=.5)
fig.set_tight_layout(True)


for i in range(len(plot_areas_edges)-1):
    ax[i, 0].set_ylabel('fraction above value')
    ax[i, 0].set_yscale('log')

    n0 = plot_areas_edges[i]
    n1 = plot_areas_edges[i+1]
    selected_regions = np.where((saddle_area >= n0) & (saddle_area < n1))
    seleced_max = np.sort(max_value[selected_regions])
    seleced_saddle = np.sort(saddle_value[selected_regions])
    selected_regions_inv = np.where((saddle_area_inv >= n0) & (saddle_area_inv < n1))
    seleced_max_inv = np.sort(max_value_inv[selected_regions_inv])
    seleced_saddle_inv = np.sort(saddle_value_inv[selected_regions_inv])

    f = np.arange(seleced_max.size)[::-1]/seleced_max.size
    ax[i, 0].plot(seleced_max, f, 'b-', label=f'{seleced_max.size} positive')
    f = np.arange(seleced_max_inv.size)[::-1]/seleced_max_inv.size
    ax[i, 0].plot(seleced_max_inv, f, 'r-', label=f'{seleced_max_inv.size} negative')
    ax[i, 0].plot(x_bg, 1-P_bg**n0, 'k-', label=f'saddle area={n0}')
    ax[i, 0].plot(x_bg, 1-P_bg**n1, 'k:', label=f'saddle area={n1}')

    f = np.arange(seleced_saddle.size)[::-1]/seleced_saddle.size
    ax[i, 1].plot(seleced_saddle, f, 'b-', label='positive')
    f = np.arange(seleced_saddle_inv.size)[::-1]/seleced_saddle_inv.size
    ax[i, 1].plot(seleced_saddle_inv, f, 'r-', label='negative')
    ax[i, 1].plot(x_bg, (1-P_bg)**n0, 'k-', label=f'saddle area={n0}')
    ax[i, 1].plot(x_bg, (1-P_bg)**n1, 'k:', label=f'saddle area={n1}')

    ax[i, 0].legend(loc='lower left')
    #ax[i, 0].set_ylim(1/n_regions, 1)

ax[-1, 0].set_xlabel('max value')
ax[-1, 1].set_xlabel('saddle value')
ax[-1, 0].set_xscale('log')
#ax[-1, 0].set_xlim(x_bg[-1]/100, x_bg[-1])
#'''
```



4. Object selection

estimate thresholds:

Compute upper hulls in log(max_value) and log(saddle_value) as a funtion of log(saddle area) for the "inverted" data:

In [18]:

```python
def upper_hull(x, y):
    """Compute upper hull"""

    points = np.array([x, y]).T
    hull = ConvexHull(points)
    i_max = np.argmax(x[hull.vertices])
    i_min = np.argmin(x[hull.vertices])
    if i_min > i_max:
        i = hull.vertices[i_max:i_min+1]
    else:
        i = np.concatenate([hull.vertices[i_max:], hull.vertices[:i_min+1]])
    srt = np.argsort(x[i])
    return x[i[srt]], y[i[srt]]


log_sarea_inv = np.log(saddle_area_inv[1:])
log_max_inv = np.log(max_value_inv[1:])
log_svalue_inv = np.log(saddle_value_inv[1:])
max_hull_x, max_hull_y = upper_hull(log_sarea_inv, log_max_inv)
saddle_hull_x, saddle_hull_y = upper_hull(log_sarea_inv, log_svalue_inv)
```

Let's go for a more aggressive threshold:

In [19]:

```
log_sarea = np.log(saddle_area)
log_max = np.log(max_value)
log_svalue = np.log(saddle_value)

max_cut = np.interp(log_sarea, max_hull_x, max_hull_y)
max_cut_inv = np.interp(log_sarea_inv, max_hull_x, max_hull_y)
saddle_cut = np.interp(log_sarea, saddle_hull_x, saddle_hull_y)
saddle_cut_inv = np.interp(log_sarea_inv, saddle_hull_x, saddle_hull_y)

cut_bins = np.linspace(0, 1, 101)
cut_mid = (cut_bins[1:] + cut_bins[:-1]) / 2

max_hist, cut_bins = np.histogram(np.exp(log_max-max_cut), bins=cut_bins, density=True)
max_hist_inv, cut_bins = np.histogram(np.exp(log_max_inv-max_cut_inv), bins=cut_bins, density=True)
max_threshold = np.max(cut_mid[max_hist < 3*max_hist_inv])
print(f'select objects above {100*max_threshold:.1f}% of max_value upper hull')

saddle_hist, cut_bins = np.histogram(np.exp(log_svalue-saddle_cut), bins=cut_bins, density=True)
saddle_hist_inv, cut_bins = np.histogram(np.exp(log_svalue_inv-saddle_cut_inv), bins=cut_bins, density
saddle_threshold = np.max(cut_mid[saddle_hist < 3*saddle_hist_inv])
#saddle_threshold = 1
print(f'select objects above {100*saddle_threshold:.1f}% of saddle_value upper hull')
```

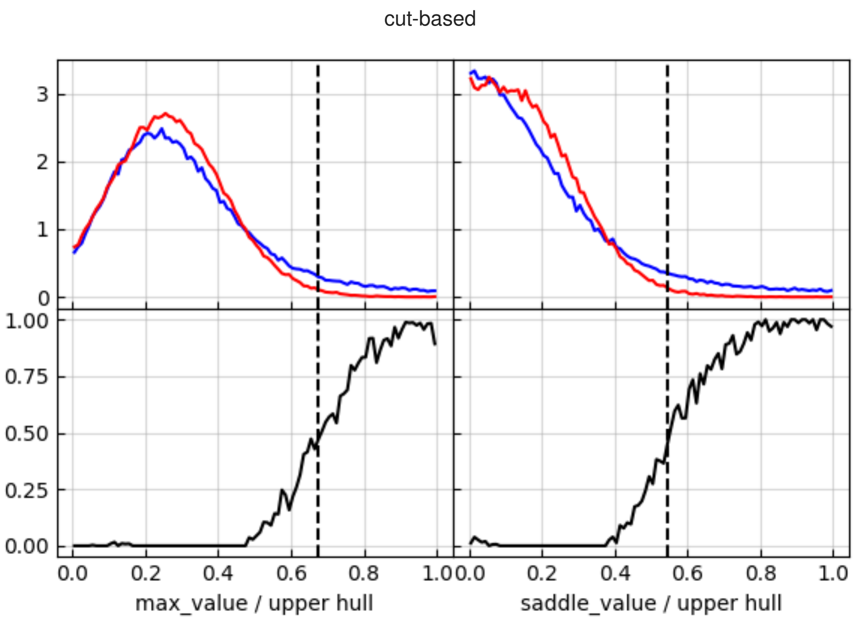
```
select objects above 67.5% of max_value upper hull
select objects above 54.5% of saddle_value upper hull
/tmp/ipykernel_12997/3953992399.py:2: RuntimeWarning: divide by zero encountered in log
  log_max = np.log(max_value)
/tmp/ipykernel_12997/3953992399.py:3: RuntimeWarning: divide by zero encountered in log
  log_svalue = np.log(saddle_value)
```

In [20]:

```
plt.close('cut-based')
fig = plt.figure('cut-based', figsize=(6, 4))
ax = fig.subplots(nrows=2, ncols=2, squeeze=False,
                  sharex=True, sharey='row',
                  gridspec_kw={'hspace': 0, 'wspace': 0})
for axis in ax.flatten():
    axis.tick_params(which='both', direction='in')
    axis.grid(alpha=.5)
fig.set_tight_layout(True)


ax[0, 0].plot(cut_mid, max_hist, 'b-')
ax[0, 0].plot(cut_mid, max_hist_inv, 'r-')
ax[0, 0].axvline(max_threshold, c='k', ls='--')

ax[1, 0].plot(cut_mid, np.clip(max_hist-max_hist_inv, 0, np.inf)/(max_hist+max_hist_inv), 'k-')
ax[1, 0].axvline(max_threshold, c='k', ls='--')


ax[0, 1].plot(cut_mid, saddle_hist, 'b-')
ax[0, 1].plot(cut_mid, saddle_hist_inv, 'r-')
ax[0, 1].axvline(saddle_threshold, c='k', ls='--')

ax[1, 1].plot(cut_mid, np.clip(saddle_hist-saddle_hist_inv, 0, np.inf)/(saddle_hist+saddle_hist_inv),
ax[1, 1].axvline(saddle_threshold, c='k', ls='--')

ax[1, 0].set_xlabel('max_value / upper hull')
ax[1, 1].set_xlabel('saddle_value / upper hull')
```

Out[20]:

```
Text(0.5, 0, 'saddle_value / upper hull')
```



apply threshod-based selection criteria:

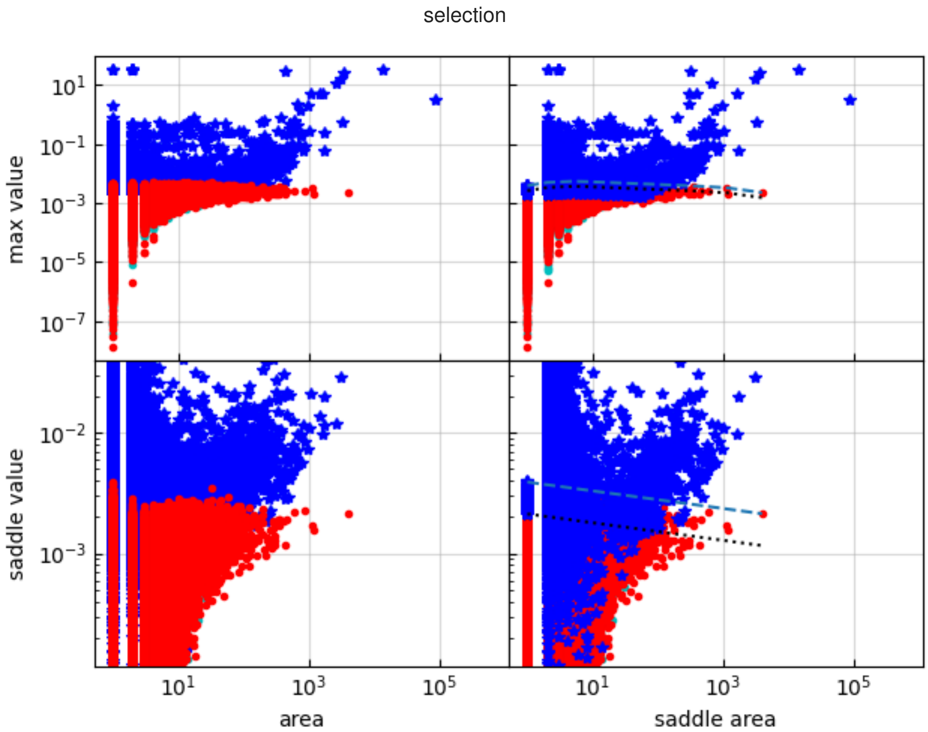
In [21]:

```
selected = np.where(
    (log_max > np.log(max_threshold) + max_cut)
    |
    (log_svalue > np.log(saddle_threshold) + saddle_cut)
)
print(f'{selected[0].size} overdensities pass the selection criteria')

valid_labels = -np.arange(parent.size)
valid_labels[selected] = 0
valid_labels += np.arange(parent.size)
valid_labels = valid_labels[label]
thresold_selection = segm.SegmentationImage(valid_labels)
```

```
22663 overdensities pass the selection criteria
```

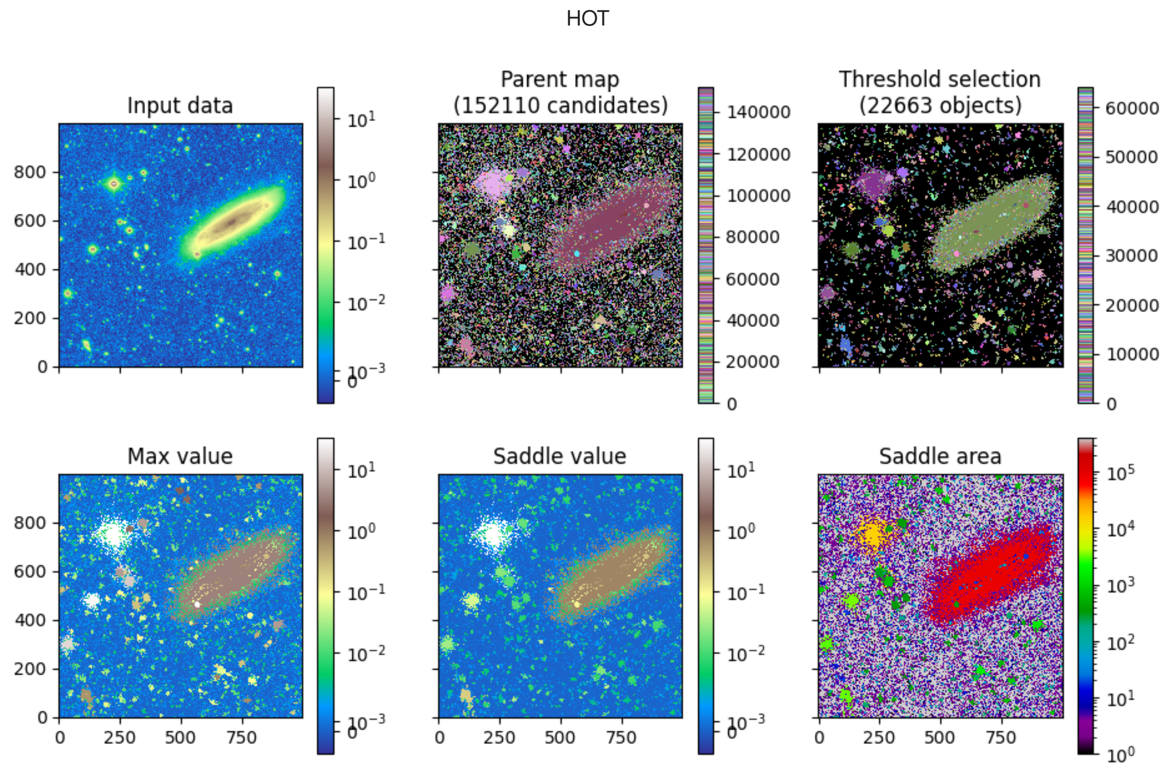
In [22]:

```
plt.close('selection')
fig = plt.figure('selection')
ax = fig.subplots(nrows=2, ncols=2, squeeze=False,
                  sharex=True, sharey='row',
                  gridspec_kw={'hspace': 0, 'wspace': 0})
for axis in ax.flatten():
    axis.tick_params(which='both', direction='in')
    axis.grid(alpha=.5)
fig.set_tight_layout(True)

ax[0, 0].set_ylabel('max value')
ax[0, 0].set_yscale('log')
ax[0, 0].plot(catalog[1], catalog[2], 'c.')
ax[0, 0].plot(catalog[1][selected], catalog[2][selected], 'b*')
ax[0, 0].plot(catalog_inv[1], catalog_inv[2], 'r.')

ax[1, 0].set_ylabel('saddle value')
ax[1, 0].set_yscale('log')
ax[1, 0].plot(catalog[1], catalog[3], 'c.')
ax[1, 0].plot(catalog[1][selected], catalog[3][selected], 'b*')
ax[1, 0].plot(catalog_inv[1], catalog_inv[3], 'r.')

ax[-1, 0].set_xlabel('area')
ax[-1, 0].set_xscale('log')


ax[0, 1].plot(catalog[4], catalog[2], 'c.')
ax[0, 1].plot(catalog_inv[4], catalog_inv[2], 'r.')
ax[0, 1].plot(catalog[4][selected], catalog[2][selected], 'b*')
ax[0, 1].plot(np.exp(max_hull_x), np.exp(max_hull_y), '--')
ax[0, 1].plot(np.exp(max_hull_x), max_threshold*np.exp(max_hull_y), 'k:')

ax[1, 1].plot(catalog[4], catalog[3], 'c.')
ax[1, 1].plot(catalog_inv[4], catalog_inv[3], 'r.')
ax[1, 1].plot(catalog[4][selected], catalog[3][selected], 'b*')
#ax[1, 1].plot(nn, cut_saddle, 'k--')
ax[1, 1].plot(np.exp(saddle_hull_x), np.exp(saddle_hull_y), '--')
ax[1, 1].plot(np.exp(saddle_hull_x), saddle_threshold*np.exp(saddle_hull_y), 'k:')
ax[1, 1].set_ylim(.1*saddle_threshold*np.exp(np.min(saddle_hull_y)), 10*np.exp(np.max(saddle_hull_y)))

ax[-1, 1].set_xlabel('saddle area')
ax[-1, 1].set_xscale('log')
```



In [23]:

```
plt.close('HOT')
fig = plt.figure('HOT', figsize=(9.5, 6))
fig.set_tight_layout(True)
ax = fig.subplots(nrows=2, ncols=3, sharex=True, sharey=True)
delta = threshold_guess-data_mode

ax[0, 0].set_title('Input data')
im = ax[0, 0].imshow(
    data-data_mode,
    interpolation='nearest', origin='lower', cmap='terrain',
    norm = colors.SymLogNorm(vmin=-delta, linthresh=3*delta, vmax=np.max(data-data_mode)),
    )
cb = fig.colorbar(im, ax=ax[0, 0])

ax[0, 1].set_title(f'Parent map\n({parent.size} candidates)')
im = ax[0, 1].imshow(
    segmentation,
    interpolation='nearest', origin='lower', cmap=segmentation.make_cmap(seed=123),
    )
cb = fig.colorbar(im, ax=ax[0, 1])

ax[0, 2].set_title(f'Threshold selection\n({selected[0].size} objects)')
im = ax[0, 2].imshow(
    thresold_selection,
    interpolation='nearest', origin='lower', cmap=thresold_selection.make_cmap(seed=123),
    )
cb = fig.colorbar(im, ax=ax[0, 2])

ax[1, 0].set_title('Max value')
im = ax[1, 0].imshow(
    max_value[label],
    interpolation='nearest', origin='lower', cmap='terrain',
    norm = colors.SymLogNorm(vmin=-delta, linthresh=3*delta, vmax=np.max(data-data_mode)),
    )
cb = fig.colorbar(im, ax=ax[1, 0])

ax[1, 1].set_title('Saddle value')
im = ax[1, 1].imshow(
    saddle_value[label],
    interpolation='nearest', origin='lower', cmap='terrain',
    norm = colors.SymLogNorm(vmin=-delta, linthresh=3*delta, vmax=np.max(data-data_mode)),
    )
cb = fig.colorbar(im, ax=ax[1, 1])

ax[1, 2].set_title('Saddle area')
im = ax[1, 2].imshow(
    saddle_area[label],
    interpolation='nearest', origin='lower', cmap='nipy_spectral', norm=colors.LogNorm(),
    )
cb = fig.colorbar(im, ax=ax[1, 2])
```



5. Mode filter

In [24]:
```
@njit
def mode_filter(data):
    flat_data = data.flatten()
    mode = np.empty_like(flat_data)
    count = np.empty_like(flat_data)
    strides = np.array(data.strides)//data.itemsize
    neighbours = np.empty(2*len(strides)+1, dtype=np.int64)
    counts = np.empty_like(neighbours)
    n_changes = 0

    for pixel in range(flat_data.size):
        #print('>', pixel)
        neighbours[0] = flat_data[pixel]
        counts[0] = 1
        n_neighbours = 1
        for stride in strides:
            if pixel >= stride:
                #print(-stride)
                value = flat_data[pixel-stride]
                n = 0
                while True:
                    if value == neighbours[n]:
                        counts[n] += 1
                        break
                    else:
                        n += 1
                        if n == n_neighbours:
                            neighbours[n] = value
                            counts[n] = 1
                            n_neighbours += 1
                            break
            if pixel+stride < flat_data.size:
                value = flat_data[pixel+stride]
                #print(stride, value)
                n = 0
                while True:
                    if value == neighbours[n]:
                        counts[n] += 1
                        break
                    else:
                        n += 1
                        if n == n_neighbours:
                            neighbours[n] = value
                            counts[n] = 1
                            n_neighbours += 1
                            break
        best = np.argmax(counts[:n_neighbours])
        if counts[best] == counts[0]: # just in case
            best = 0
        else:
            n_changes += 1
        #print(f'> pixel {pixel} moves from {neighbours[0]} to {neighbours[best]} (out of {n_neighbour
        mode[pixel] = neighbours[best]
        count[pixel] = counts[best]

    return mode.reshape(data.shape), count.reshape(data.shape), n_changes
```

In [26]:
```
filtered_labels = np.copy(valid_labels)
n_old = 0
n = filtered_labels.size
while n != n_old:
    n_old = n
    filtered_labels, c, n = mode_filter(filtered_labels)
    print(n, 'changes')
```

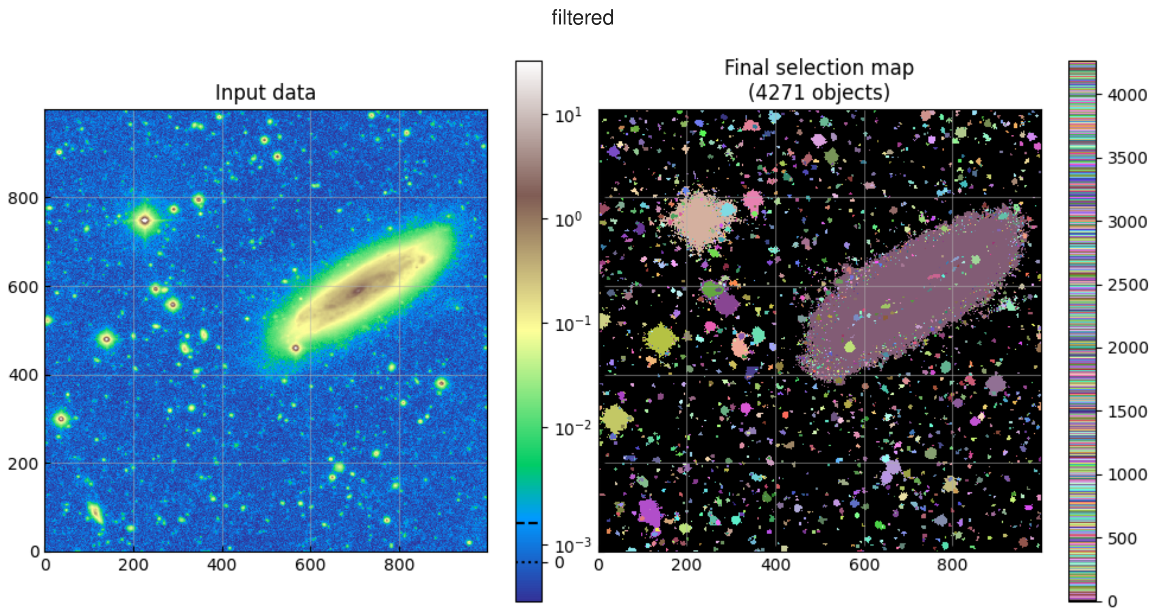
```
85612 changes
22109 changes
6211 changes
1899 changes
643 changes
255 changes
120 changes
71 changes
55 changes
52 changes
50 changes
48 changes
47 changes
47 changes
```

In [27]:

```
final_labels = np.copy(filtered_labels)
unique_labels = np.unique(filtered_labels)
n_final_labels = unique_labels.size
for i, lbl in enumerate(unique_labels):
    final_labels[final_labels == lbl] = i
final_selection = segm.SegmentationImage(final_labels)
```

In [28]:

```
plt.close('filtered')
fig = plt.figure('filtered', figsize=(10, 5))
ax = fig.subplots(nrows=1, ncols=2, squeeze=False,
                  sharex=True, sharey='row',
                  gridspec_kw={'hspace': 0, 'wspace': 0})
for axis in ax.flatten():
    axis.tick_params(which='both', direction='in')
    axis.grid(alpha=.5)
fig.set_tight_layout(True)

ax[0, 0].set_title('Input data')
im = ax[0, 0].imshow(
    data-data_mode,
    interpolation='nearest', origin='lower', cmap='terrain',
    norm = colors.SymLogNorm(vmin=-delta, linthresh=3*delta, vmax=np.max(data-data_mode)),
    )
cb = fig.colorbar(im, ax=ax[0, 0])
cb.ax.axhline(0, c='k', ls=':')
cb.ax.axhline(threshold_guess-data_mode, c='k', ls='--')

ax[0, 1].set_title(f'Final selection map\n({n_final_labels} objects)')
im = ax[0, 1].imshow(
    final_selection,
    interpolation='nearest', origin='lower', cmap=final_selection.make_cmap(seed=123),
    )
cb = fig.colorbar(im, ax=ax[0, 1])
```



In [ ]: