Photometry

This notebook goes through photometry on multiple images that are aligned.

In [1]:
```
%matplotlib inline
import numpy as np
import pylab as pl
pl.rcParams['image.origin'] = 'lower'
pl.rcParams['image.interpolation'] = 'none'
from astropy.io import fits
from astropy import stats
from scipy import ndimage
from astropy.table import Table, Column
from astropy import table
pl.style.use('dark_background')
from astropy.stats import mad_std
```

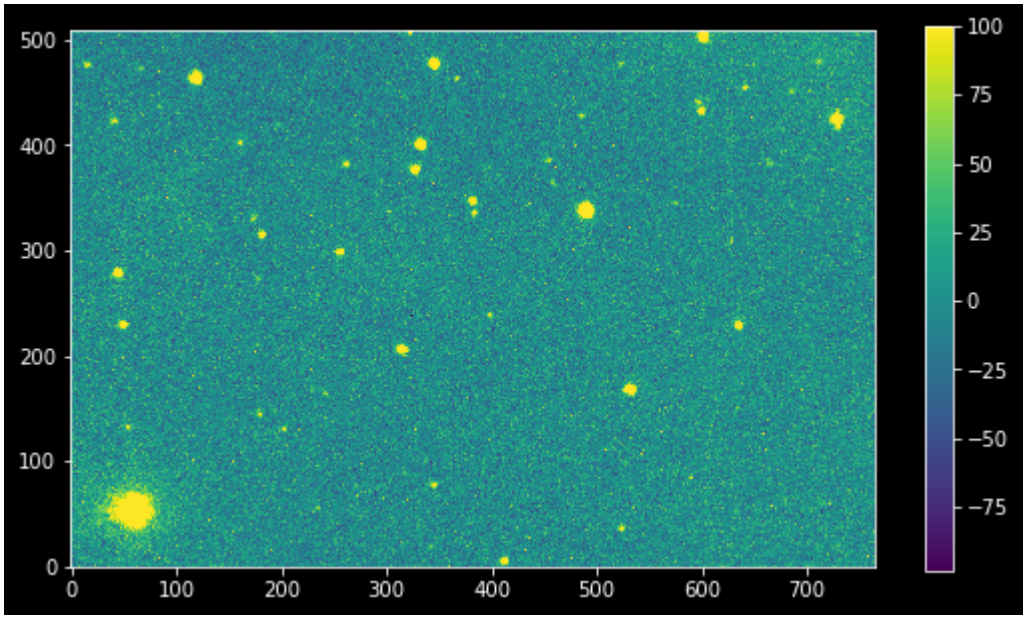
In [2]:
```
from photutils.detection import DAOStarFinder
from photutils.aperture import aperture_photometry, CircularAperture
```

We're going to use both our combined, aligned images (you should use your final reduced, combined images here) and uncertainty frames:

In [3]:
```
fh = fits.open('NGCSomething_median_combined_V.fits')
background = np.median(fh[0].data)
bgsub_V = fh[0].data - background
uncertainty_V = fits.getdata('NGCSomething_uncertainty_V.fits')
```

In [4]:
```
pl.figure(figsize=(9,5))
pl.imshow(bgsub_V, vmax=100)
pl.colorbar()
```

Out[4]:
```
<matplotlib.colorbar.Colorbar at 0x2a005577ac0>
```



We need to estimate the background noise level to give to our photometry routine (you need this no matter which photometry routine you use)

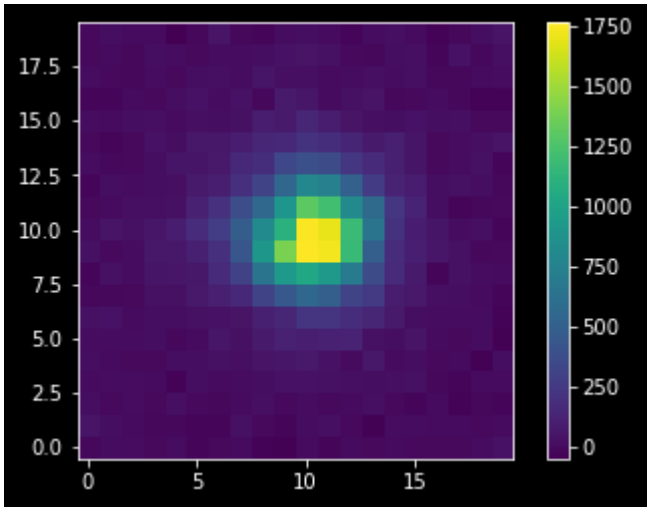
In [5]:
```
# estimate the background noise
# two ways to do this are to take the std dev of the background:
background_stddev = mad_std(bgsub_V)
# or to take the mean or median of the uncertainty image:
background_stddev = np.median(uncertainty_V)
background_stddev
```

Out[5]:
```
21.35337138135146
```

We then need to cut out a star and measure its FWHM, because we need to give a FWHM guess to DAOPhot.

In [6]:
```
cx,cy = 532,168
star_cutout = bgsub_V[cy-10:cy+10, cx-10:cx+10]
pl.imshow(star_cutout); pl.colorbar()
yc, xc = np.indices(star_cutout.shape)
mom1_x = (xc * star_cutout).sum() / star_cutout.sum()
mom1_y = (yc * star_cutout).sum() / star_cutout.sum()
mom2_x = ((xc - mom1_x)**2 * star_cutout).sum() / star_cutout.sum()
mom2_y = ((yc - mom1_y)**2 * star_cutout).sum() / star_cutout.sum()
sigma_x, sigma_y = mom2_x**0.5, mom2_y**0.5
sigma_to_fwhm = np.sqrt(8*np.log(2))
fwhm_x, fwhm_y = sigma_x*sigma_to_fwhm, sigma_y*sigma_to_fwhm
avg_fwhm = (fwhm_x*fwhm_y)**0.5
print(f"FWHM average, in pixels: {avg_fwhm}")
```

```
FWHM average, in pixels: 6.146991971581738
```



We then run DAOPhot to automatically extract the stars from the image.

In [7]:
```
# 4.5-sigma threshold was determined by guess-and-check
daofind = DAOStarFinder(fwhm=avg_fwhm, threshold=4.5*background_stddev)
sources_V = daofind(bgsub_V)
```

In [8]:
```
sources_V
```

Out[8]: *Table length=47*

id	xcentroid	ycentroid	sharpness	roundness1	
int32	float64	float64	float64	float64	
1	412.32226091327726	4.454417657783118	0.4678626911464587	0.1166919283575839	-0.146
2	524.395650698649	36.60810298623848	0.4585280906290881	-0.04895156548733161	-0.088
3	62.80152680553008	52.14099586749775	0.41214645451875603	-0.025467892478472757	-0.159
4	234.90047245197448	55.652266592823885	0.5686032046267451	0.1350415316667007	0.10
5	346.1218232081367	77.49393628138374	0.6761398068532941	0.21735072612549658	-0.2
6	589.1243749929839	84.07776588611777	0.3958372644383514	0.4647156709626752	-0.174
7	661.0501077366088	111.11060435833711	0.2681131516191789	0.3328481843884077	0.77
8	202.5924437202105	130.83069655924731	0.2730024310425074	-0.0781729430962552	0.0100
9	55.614882744991434	132.4025657548193	0.4461109832616089	-0.4541918397431229	-0.016
10	180.07996968558814	144.69365293589797	0.3150598384333698	-0.06984938614467898	-0.257
...	...	...	...	...	
38	641.293423135761	454.6413399255095	0.35976734440691366	0.3424675129886484	-0.055
39	120.18011137831861	463.2623882696433	0.432071611699966	-0.03907358230929629	-0.19
40	367.63439643172757	463.44023201770244	0.5383338590904929	0.40997384414855587	0.078
41	66.56375543669016	472.6070482902853	0.30417058585862045	-0.1795497916991123	-0.409
42	16.56458729224963	476.4027894311309	0.6403139410686233	-0.173248135046169	-0.215
43	346.30843955662135	477.01898483124825	0.4459194060719733	-0.01971308899285296	-0.197
44	711.274454832441	479.8177992717391	0.5328754805487258	0.18383460256078143	-0.107
45	602.2580557775832	502.8318525535556	0.4397403032477437	0.03440967627965608	-0.154
46	192.81681157661131	508.11347945937047	0.7478881815532088	-0.3617102567351843	-0.496
47	322.76146070390644	507.80605263368716	0.6056815515061421	0.011426522630284932	-0.33

We then do *aperture photometry* to get the fluxes and uncertainties per star.

Aperture photometry is just taking the sum of the flux within a region, in this case, within a circle centered on the star with radius equal to the FWHM of the star.

In [9]:
```
positions = np.transpose((sources_V['xcentroid'], sources_V['ycentroid']))
apertures_V = CircularAperture(positions, r=avg_fwhm)
phot_table_V = aperture_photometry(bgsub_V, apertures_V, error=uncertainty_V)
for col in phot_table_V.colnames:
    phot_table_V[col].info.format = '%.3g'  # "%.3g" will print only 3 values, sc
phot_table_V
```

Out[9]: *QTable length=47*

id	xcenter	ycenter	aperture_sum	aperture_sum_err
	pix	pix		
int32	float64	float64	float64	float64
1	412	4.45	7.85e+03	232
2	524	36.6	3.8e+03	235
3	62.8	52.1	2.77e+06	989
4	235	55.7	1.41e+03	234
5	346	77.5	3.42e+03	235
6	589	84.1	2.06e+03	234
7	661	111	614	233
8	203	131	2.83e+03	235
9	55.6	132	2.77e+03	235
...	...	...	...	...
38	641	455	3.6e+03	235
39	120	463	5.55e+04	269
40	368	463	1.92e+03	234
41	66.6	473	1.11e+03	233
42	16.6	476	3.28e+03	235
43	346	477	5.17e+04	267
44	711	480	3.4e+03	235
45	602	503	3.98e+04	260
46	193	508	788	187
47	323	508	3.2e+03	194

ASIDE:

Aperture Photometry is basically the same thing we've been doing!

If we use our previous photometry tool:

In [10]:
```
def calculate_star_flux_and_error(cutout_star, cutout_uncertainty, sky_stddev):

    mask = cutout_star > 2*sky_stddev
    masked_star_sum = cutout_star[mask].sum()
    masked_star_sum_error = ((cutout_uncertainty[mask]**2).sum() + sky_stddev**2*

    return masked_star_sum, masked_star_sum_error
```

we could calculate similar flux values by looping over each star:

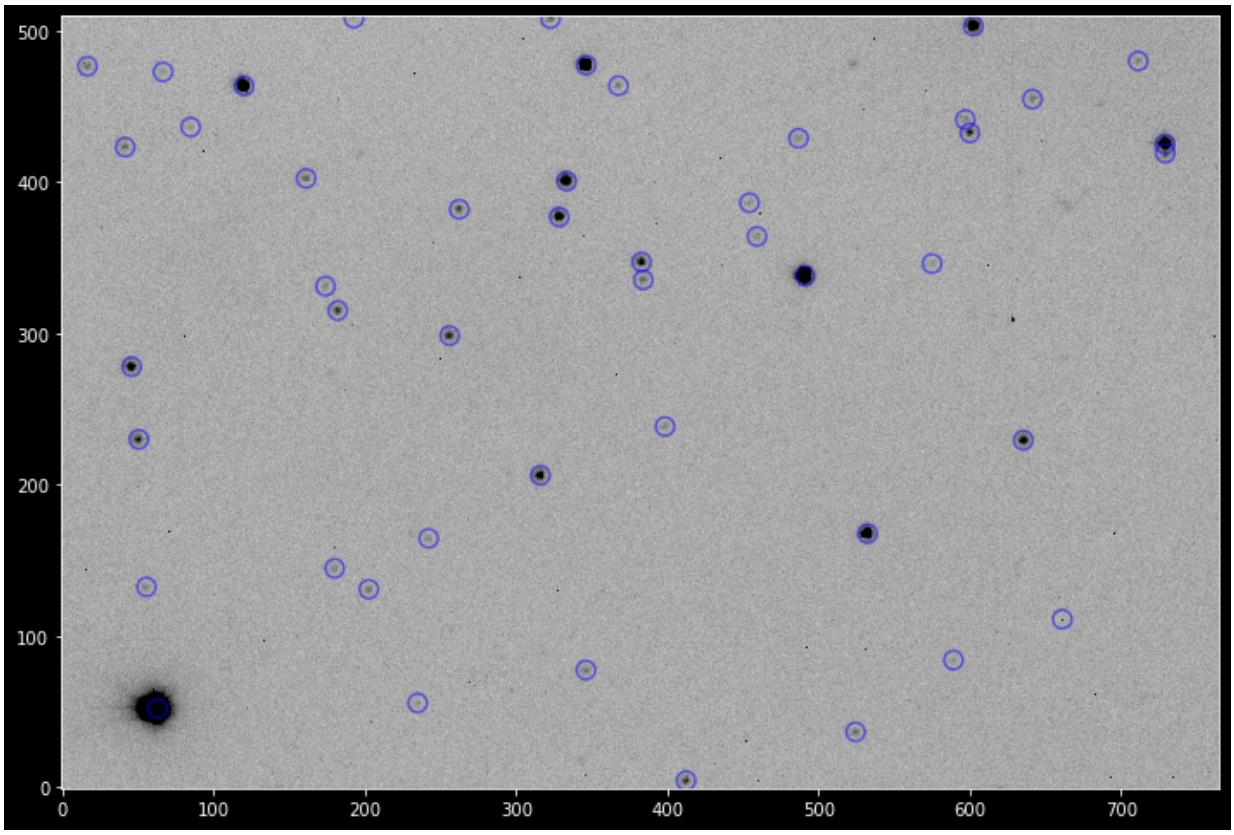
In [11]:
```
# equivalent to: aperture_photometry(bgsub_V, apertures_V, error=uncertainty_V)
threshold_aperture_fluxes = []
threshold_aperture_errors = []
for row in sources_V:
    xcen,ycen = row['xcentroid'], row['ycentroid']
    cutout = bgsub_V[int(row['ycentroid']-10):int(row['ycentroid']+10),
                     int(row['xcentroid']-10):int(row['xcentroid']+10),
                    ]
    uncertainty_cutout = uncertainty_V[int(row['ycentroid']-10):int(row['ycentroi
                                       int(row['xcentroid']-10):int(row['xcentroi
                                      ]
    starsum, starerror = calculate_star_flux_and_error(cutout, uncertainty_cutout
    threshold_aperture_fluxes.append(starsum)
    threshold_aperture_errors.append(starerror)
```

The DAOPhot apertures are doing *nearly* the same thing, but with a little bit less bookkeeping work and a little more robustness (for example, our version doesn't work very well if the star is at the edge of the image).

END ASIDE

We can show the apertures on the image to prove that we found reasonable stars and used reasonable apertures:

In [12]:
```
pl.figure(figsize=(12,12))
pl.imshow(bgsub_V, cmap='gray_r', origin='lower', vmax=400, vmin=-200)
_=apertures_V.plot(color='blue', lw=1.5, alpha=0.5)
```



We then combine the "source" table, which had the coordinates, with the aperture photometry table.:

In [13]:
```
# rename the phot_tbl columns to indicate they're V-band
for colname in phot_table_V.colnames:
    phot_table_V.rename_column(colname, "V_"+colname)
mtbl_V = table.hstack([sources_V, phot_table_V])
mtbl_V
```

Out[13]: *QTable length=47*

id	xcentroid	ycentroid	sharpness	roundness1	
int32	float64	float64	float64	float64	
1	412.32226091327726	4.454417657783118	0.4678626911464587	0.1166919283575839	-0.146
2	524.395650698649	36.60810298623848	0.4585280906290881	-0.04895156548733161	-0.088
3	62.80152680553008	52.14099586749775	0.41214645451875603	-0.025467892478472757	-0.159
4	234.90047245197448	55.652266592823885	0.5686032046267451	0.1350415316667007	0.10
5	346.1218232081367	77.49393628138374	0.6761398068532941	0.21735072612549658	-0.2
6	589.1243749929839	84.07776588611777	0.3958372644383514	0.4647156709626752	-0.174
7	661.0501077366088	111.11060435833711	0.2681131516191789	0.3328481843884077	0.77
8	202.5924437202105	130.83069655924731	0.2730024310425074	-0.0781729430962552	0.0100
9	55.614882744991434	132.4025657548193	0.4461109832616089	-0.4541918397431229	-0.016
...	...	...	...	...	
38	641.293423135761	454.6413399255095	0.35976734440691366	0.3424675129886484	-0.055
39	120.18011137831861	463.2623882696433	0.432071611699966	-0.03907358230929629	-0.19
40	367.63439643172757	463.44023201770244	0.5383338590904929	0.40997384414855587	0.078
41	66.56375543669016	472.6070482902853	0.30417058585862045	-0.1795497916991123	-0.409
42	16.56458729224963	476.4027894311309	0.6403139410686233	-0.173248135046169	-0.215
43	346.30843955662135	477.01898483124825	0.4459194060719733	-0.01971308899285296	-0.197
44	711.274454832441	479.8177992717391	0.5328754805487258	0.18383460256078143	-0.107
45	602.2580557775832	502.8318525535556	0.4397403032477437	0.03440967627965608	-0.154
46	192.81681157661131	508.11347945937047	0.7478881815532088	-0.3617102567351843	-0.496
47	322.76146070390644	507.80605263368716	0.6056815515061421	0.011426522630284932	-0.33

This is a pretty good catalog, based on the image above.

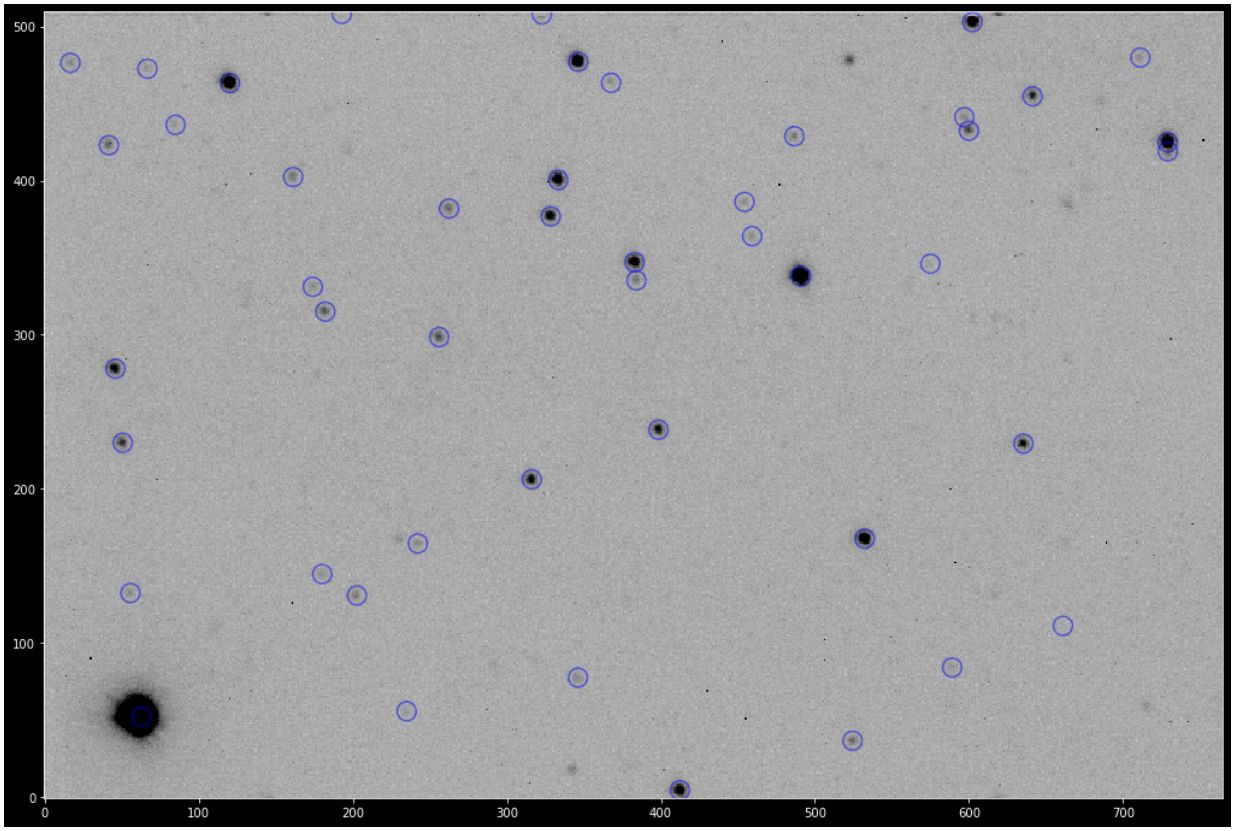
Now we do the same thing on the I-band image, except we're going to use the same apertures as in the V-band - this way, we know we're using the exact same stars!

Note that this step requires that the images are well-aligned!

In [14]:
```
fh_I = fits.open('NGCSomething_median_combined_I.fits')
background_I = np.median(fh_I[0].data)
bgsub_I = fh_I[0].data - background_I
uncertainty_I = fits.getdata('NGCSomething_uncertainty_I.fits')
```

If we overlay our V-band catalog on the I-band image,

In [15]:
```
pl.figure(figsize=(20,12))
pl.imshow(bgsub_I, cmap='gray_r', origin='lower', vmax=400, vmin=-200)
_=apertures_V.plot(color='blue', lw=1.5, alpha=0.5)
```

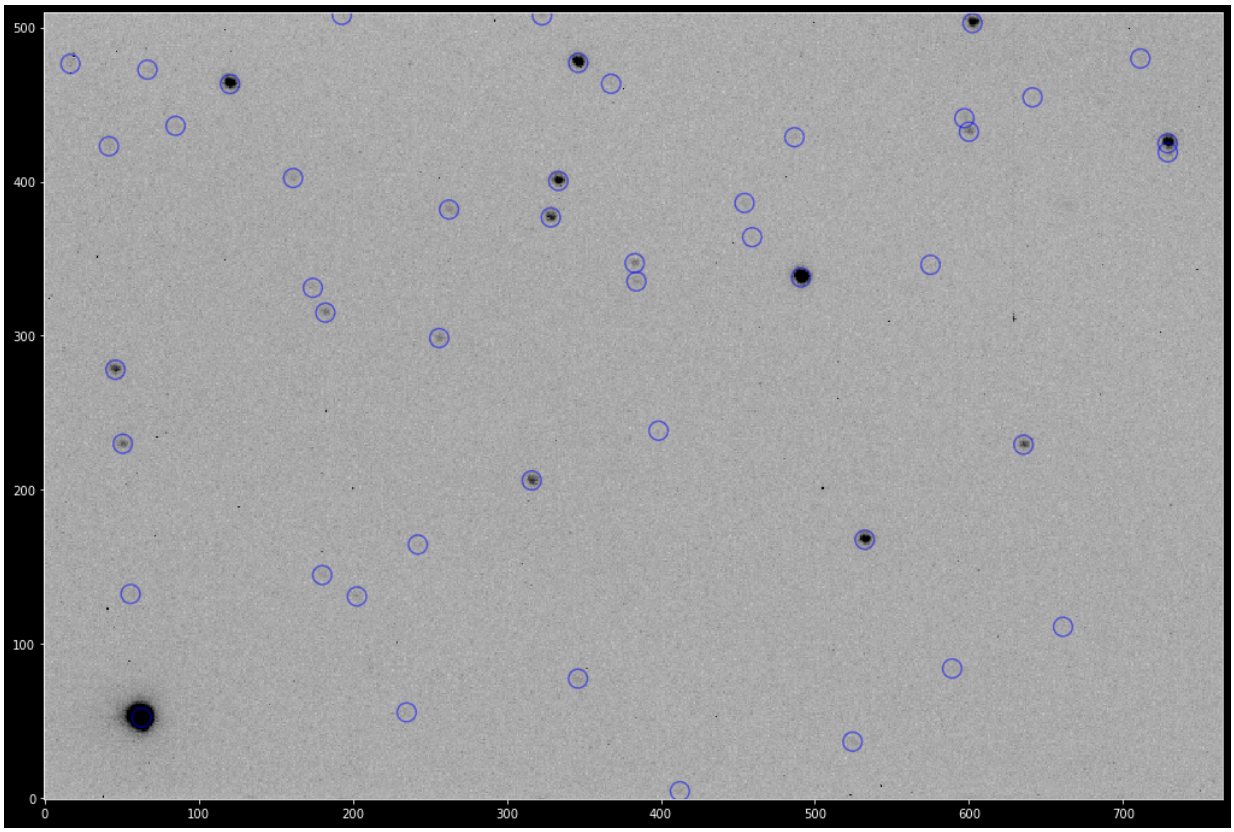


We can see in the above image that most of the stars are the same!

Let's do B too:

In [16]:
```
fh_B = fits.open('NGCSomething_median_combined_B.fits')
background_B = np.median(fh_B[0].data)
bgsub_B = fh_B[0].data - background_B
uncertainty_B = fits.getdata('NGCSomething_uncertainty_B.fits')
```

In [17]:
```
pl.figure(figsize=(20,12))
pl.imshow(bgsub_B, cmap='gray_r', origin='lower', vmax=400, vmin=-200)
_=apertures_V.plot(color='blue', lw=1.5, alpha=0.5)
```



In the B-filter, we can see that there are several stars that aren't detected.

Nonetheless, *if* the images are well-aligned, as they are in this case, we can use the V-band apertures to extract fluxes from the I- and B-bands.

Then, we do the same column-renaming as before, and we combine all the tables into one:

In [18]:
```
phot_table_I = aperture_photometry(bgsub_I, apertures_V, error=uncertainty_I)
for colname in phot_table_I.colnames:
    phot_table_I.rename_column(colname, "I_"+colname)
phot_table_B = aperture_photometry(bgsub_B, apertures_V, error=uncertainty_B)
for colname in phot_table_B.colnames:
    phot_table_B.rename_column(colname, "B_"+colname)
```

In [19]:
```
full_table = table.hstack([sources_V, phot_table_V, phot_table_B, phot_table_I])
full_table
```

Out[19]: *QTable length=47*

id	xcentroid	ycentroid	sharpness	roundness1	
int32	float64	float64	float64	float64	
1	412.32226091327726	4.454417657783118	0.4678626911464587	0.1166919283575839	-0.146
2	524.395650698649	36.60810298623848	0.4585280906290881	-0.04895156548733161	-0.088
3	62.80152680553008	52.14099586749775	0.41214645451875603	-0.025467892478472757	-0.159
4	234.90047245197448	55.652266592823885	0.5686032046267451	0.1350415316667007	0.10
5	346.1218232081367	77.49393628138374	0.6761398068532941	0.21735072612549658	-0.2
6	589.1243749929839	84.07776588611777	0.3958372644383514	0.4647156709626752	-0.174
7	661.0501077366088	111.11060435833711	0.2681131516191789	0.3328481843884077	0.77
8	202.5924437202105	130.83069655924731	0.2730024310425074	-0.0781729430962552	0.0100
9	55.614882744991434	132.4025657548193	0.4461109832616089	-0.4541918397431229	-0.016
...	...	...	...	...	
38	641.293423135761	454.6413399255095	0.35976734440691366	0.3424675129886484	-0.055
39	120.18011137831861	463.2623882696433	0.432071611699966	-0.03907358230929629	-0.19
40	367.63439643172757	463.44023201770244	0.5383338590904929	0.40997384414855587	0.078
41	66.56375543669016	472.6070482902853	0.30417058585862045	-0.1795497916991123	-0.409
42	16.56458729224963	476.4027894311309	0.6403139410686233	-0.173248135046169	-0.215
43	346.30843955662135	477.01898483124825	0.4459194060719733	-0.01971308899285296	-0.197
44	711.274454832441	479.8177992717391	0.5328754805487258	0.18383460256078143	-0.107
45	602.2580557775832	502.8318525535556	0.4397403032477437	0.03440967627965608	-0.154
46	192.81681157661131	508.11347945937047	0.7478881815532088	-0.3617102567351843	-0.496
47	322.76146070390644	507.80605263368716	0.6056815515061421	0.011426522630284932	-0.33

The table above is our final photometry table!

For display purposes, we can modify it a bit, though:

In [20]:
```
for col in full_table.colnames:
    full_table[col].info.format = '%.3g'  # "%.3g" will print only 3 values, so t
full_table
```

Out[20]: *QTable length=47*

id	xcentroid	ycentroid	sharpness	roundness1	roundness2	npix	sky	peak	flux
int32	float64	float64	float64	float64	float64	int32	float64	float64	float64
1	412	4.45	0.468	0.117	-0.146	49	0	319	5.02
2	524	36.6	0.459	-0.049	-0.0883	49	0	160	2.58
3	62.8	52.1	0.412	-0.0255	-0.16	49	0	9.98e+04	1.68e+03
4	235	55.7	0.569	0.135	0.105	49	0	73.4	1.1
5	346	77.5	0.676	0.217	-0.288	49	0	152	1.84
6	589	84.1	0.396	0.465	-0.174	49	0	73.1	1.35
7	661	111	0.268	0.333	0.776	49	0	33.1	1.06
8	203	131	0.273	-0.0782	0.0101	49	0	97.9	2.24
9	55.6	132	0.446	-0.454	-0.0162	49	0	100	1.64
...	...	...	...	...	...	...	...	...	...
38	641	455	0.36	0.342	-0.0557	49	0	114	1.99
39	120	463	0.432	-0.0391	-0.199	49	0	2.07e+03	33.9
40	368	463	0.538	0.41	0.0784	49	0	130	2.08
41	66.6	473	0.304	-0.18	-0.409	49	0	54.7	1.24
42	16.6	476	0.64	-0.173	-0.216	49	0	164	2.08
43	346	477	0.446	-0.0197	-0.197	49	0	1.97e+03	31.4
44	711	480	0.533	0.184	-0.107	49	0	113	1.57
45	602	503	0.44	0.0344	-0.155	49	0	1.5e+03	24.7
46	193	508	0.748	-0.362	-0.496	49	0	78.5	1.02
47	323	508	0.606	0.0114	-0.332	49	0	224	3.47

If we want to show only a subset of the columns, we can do that too:

In [21]:
```
full_table['id',
           'V_aperture_sum', 'V_aperture_sum_err',
           'B_aperture_sum', 'B_aperture_sum_err',
           'I_aperture_sum', 'I_aperture_sum_err'].show_in_notebook()
# .pprint(max_lines=1000, max_width=1000)
```

Out[21]:

QTable length=47

Show 50 entries Search:

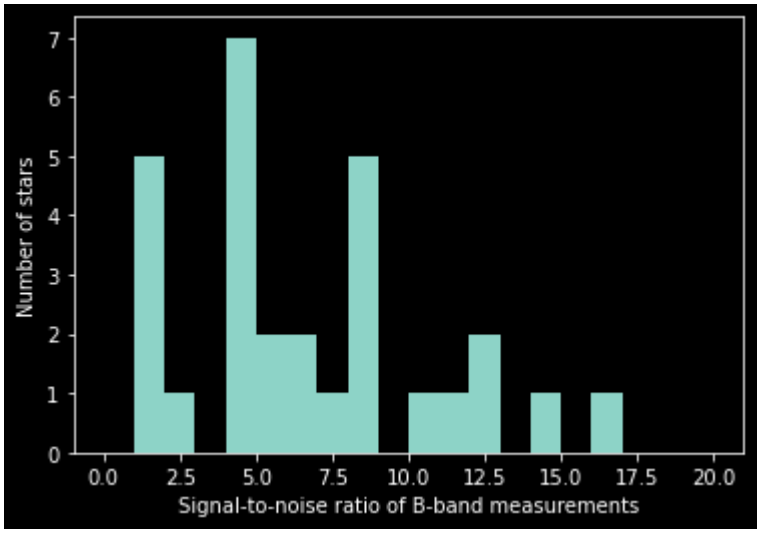
idx	id	V_aperture_sum	V_aperture_sum_err	B_aperture_sum	B_aperture_sum_err	I_aperture_sum
0	1	7.85e+03	232	864	193	2.78e+04
1	2	3.8e+03	235	1.37e+03	199	4.72e+03
2	3	2.77e+06	989	1.18e+06	656	3.03e+06
3	4	1.41e+03	234	924	198	1.3e+03
4	5	3.42e+03	235	2.01e+03	199	3.08e+03
5	6	2.06e+03	234	824	198	2.13e+03
6	7	614	233	279	198	165
7	8	2.83e+03	235	1.59e+03	199	3.69e+03
8	9	2.77e+03	235	1.44e+03	199	2.7e+03
9	10	2.9e+03	235	1.7e+03	199	2.16e+03
10	11	2.1e+03	234	979	198	2.31e+03
11	12	4.2e+04	261	1.94e+04	213	3.61e+04
12	13	1.94e+04	246	1e+04	206	1.55e+04
13	14	1.59e+04	244	7.2e+03	203	1.42e+04
14	15	1.18e+04	241	6.01e+03	203	1.04e+04
15	16	2.9e+03	235	-78.9	197	1.5e+04
16	17	2.01e+04	247	1.04e+04	206	1.78e+04
17	18	8.98e+03	239	4.1e+03	201	8.44e+03
18	19	7.04e+03	238	4.05e+03	201	7.09e+03
19	20	2.38e+03	234	1.63e+03	199	3.05e+03
20	21	5.16e+03	236	2.57e+03	200	5.16e+03
21	22	1.55e+05	325	7.41e+04	252	1.21e+05
22	23	1.4e+03	234	324	198	847
23	24	1.28e+04	242	3.28e+03	200	2.75e+04
24	25	2.02e+03	234	319	198	2.08e+03
25	26	2.25e+04	248	1.06e+04	206	1.85e+04
26	27	5.73e+03	237	2.95e+03	200	6.01e+03
27	28	2.03e+03	234	879	198	1.85e+03
28	29	3.62e+04	257	1.67e+04	211	2.93e+04
29	30	4.2e+03	236	2.45e+03	200	4.74e+03
30	31	3.27e+04	255	1.19e+04	207	2.66e+04

idx	id	V_aperture_sum	V_aperture_sum_err	B_aperture_sum	B_aperture_sum_err	I_aperture_sum
31	32	4.22e+03	236	1.6e+03	199	6.76e+03
32	33	6.04e+04	272	2.65e+04	219	5.31e+04
33	34	2.69e+03	235	276	198	3.54e+03
34	35	1.01e+04	240	4.36e+03	201	8.41e+03
35	36	1.02e+03	233	1.08e+03	198	2e+03
36	37	4.27e+03	236	1.78e+03	199	3.93e+03
37	38	3.6e+03	235	307	198	1.13e+04
38	39	5.55e+04	269	2.71e+04	219	4.77e+04
39	40	1.92e+03	234	836	198	2.1e+03
40	41	1.11e+03	233	955	198	1.49e+03
41	42	3.28e+03	235	2.3e+03	199	2.83e+03
42	43	5.17e+04	267	2.5e+04	218	3.98e+04
43	44	3.4e+03	235	1.35e+03	199	2.7e+03
44	45	3.98e+04	260	1.76e+04	212	3.12e+04
45	46	788	187	359	159	429
46	47	3.2e+03	194	877	163	1.15e+03

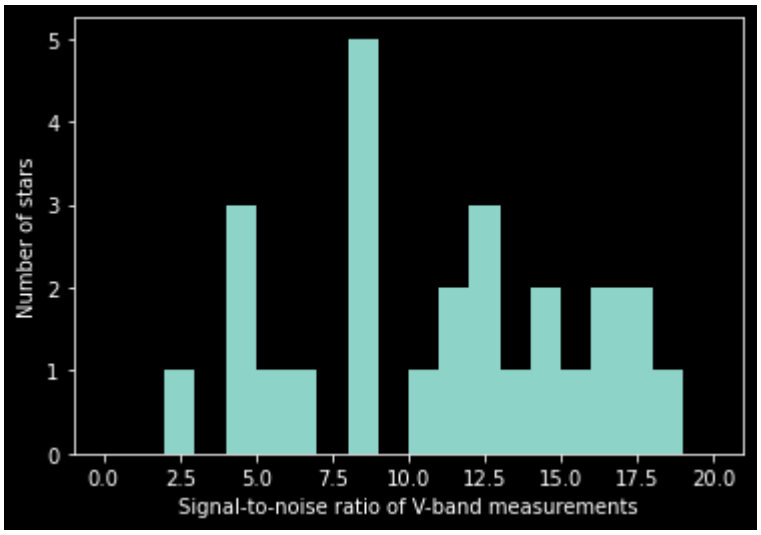
Showing 1 to 47 of 47 entries First Previous 1 Next Last

Some of the data have low signal-to-noise, and therefore we'll want to ignore them. Objects with SNR < 5 are generally not well-measured:

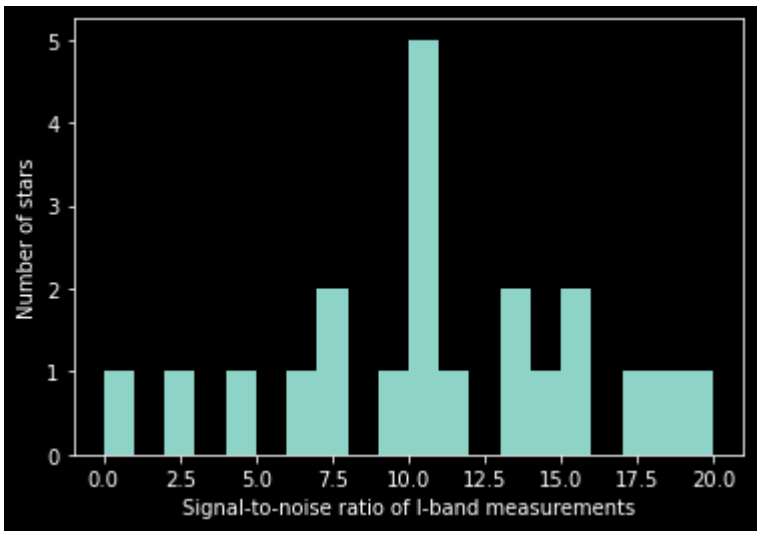
In [22]:
```
SNR_B = full_table['B_aperture_sum']/full_table['B_aperture_sum_err']
_=pl.hist(SNR_B, bins=np.linspace(0,20,21))
_=pl.xlabel("Signal-to-noise ratio of B-band measurements")
_=pl.ylabel("Number of stars")
```



In [23]:
```
SNR_V = full_table['V_aperture_sum']/full_table['V_aperture_sum_err']
_=pl.hist(SNR_V, bins=np.linspace(0,20,21))
_=pl.xlabel("Signal-to-noise ratio of V-band measurements")
_=pl.ylabel("Number of stars")
```



In [24]:
```
SNR_I = full_table['I_aperture_sum']/full_table['I_aperture_sum_err']
_=pl.hist(SNR_I, bins=np.linspace(0,20,21))
_=pl.xlabel("Signal-to-noise ratio of I-band measurements")
_=pl.ylabel("Number of stars")
```



It is best to use only stars with SNR > 5

In [25]:
```
high_snr = (SNR_B > 5) & (SNR_V > 5) & (SNR_I > 5)
high_snr.sum()
```

Out[25]: 32

In [26]:
```
full_table['id',
           'V_aperture_sum', 'V_aperture_sum_err',
           'B_aperture_sum', 'B_aperture_sum_err',
           'I_aperture_sum', 'I_aperture_sum_err'][high_snr].show_in_notebook()
```

Out[26]:

QTable length=32

Show 50 entries Search:

idx	id	V_aperture_sum	V_aperture_sum_err	B_aperture_sum	B_aperture_sum_err	I_aperture_s
0	2	3.8e+03	235	1.37e+03	199	4.72e
1	3	2.77e+06	989	1.18e+06	656	3.03e
2	5	3.42e+03	235	2.01e+03	199	3.08e
3	8	2.83e+03	235	1.59e+03	199	3.69e
4	9	2.77e+03	235	1.44e+03	199	2.7e
5	10	2.9e+03	235	1.7e+03	199	2.16e
6	12	4.2e+04	261	1.94e+04	213	3.61e
7	13	1.94e+04	246	1e+04	206	1.55e
8	14	1.59e+04	244	7.2e+03	203	1.42e
9	15	1.18e+04	241	6.01e+03	203	1.04e
10	17	2.01e+04	247	1.04e+04	206	1.78e
11	18	8.98e+03	239	4.1e+03	201	8.44e
12	19	7.04e+03	238	4.05e+03	201	7.09e
13	20	2.38e+03	234	1.63e+03	199	3.05e
14	21	5.16e+03	236	2.57e+03	200	5.16e
15	22	1.55e+05	325	7.41e+04	252	1.21e
16	24	1.28e+04	242	3.28e+03	200	2.75e
17	26	2.25e+04	248	1.06e+04	206	1.85e
18	27	5.73e+03	237	2.95e+03	200	6.01e
19	29	3.62e+04	257	1.67e+04	211	2.93e
20	30	4.2e+03	236	2.45e+03	200	4.74e
21	31	3.27e+04	255	1.19e+04	207	2.66e
22	32	4.22e+03	236	1.6e+03	199	6.76e
23	33	6.04e+04	272	2.65e+04	219	5.31e
24	35	1.01e+04	240	4.36e+03	201	8.41e
25	37	4.27e+03	236	1.78e+03	199	3.93e
26	39	5.55e+04	269	2.71e+04	219	4.77e
27	42	3.28e+03	235	2.3e+03	199	2.83e
28	43	5.17e+04	267	2.5e+04	218	3.98e
29	44	3.4e+03	235	1.35e+03	199	2.7e
30	45	3.98e+04	260	1.76e+04	212	3.12e

idx	id	V_aperture_sum	V_aperture_sum_err	B_aperture_sum	B_aperture_sum_err	I_aperture_s
31	47	3.2e+03	194	877	163	1.15e

Showing 1 to 32 of 32 entries First Previous 1 Next Last

We calculate the magnitude and calibrate the data:

In [27]:
```
# we measure the magnitude zeropoints earlier...
I_magzero = 20.2
V_magzero = 20.1
B_magzero = 19.5

Imag = -2.5 * np.log10(full_table['I_aperture_sum']) + I_magzero
Vmag = -2.5 * np.log10(full_table['V_aperture_sum']) + V_magzero
Bmag = -2.5 * np.log10(full_table['B_aperture_sum']) + B_magzero

eImag = 1.09 * full_table['I_aperture_sum_err']/full_table['I_aperture_sum']
eVmag = 1.09 * full_table['V_aperture_sum_err']/full_table['V_aperture_sum']
eBmag = 1.09 * full_table['B_aperture_sum_err']/full_table['B_aperture_sum']
```

```
<ipython-input-27-9b35c003feab>:8: RuntimeWarning: invalid value encountered in
log10
  Bmag = -2.5 * np.log10(full_table['B_aperture_sum']) + B_magzero
```

We can add these columns to the table:

In [28]:
```
full_table.add_column(Imag, name='M_I')
full_table.add_column(eImag, name='eM_I')
full_table.add_column(Vmag, name='M_V')
full_table.add_column(eVmag, name='eM_V')
full_table.add_column(Bmag, name='M_B')
full_table.add_column(eBmag, name='eM_B')
for col in full_table.colnames:
    full_table[col].info.format = '%.3g'  # "%.3g" will print only 3 values, so i
```

In [29]:
```
full_table['id',
           'M_I', 'eM_I',
           'M_V', 'eM_V',
           'M_B', 'eM_B'][high_snr].show_in_notebook()
```

Out[29]:

QTable length=32

Show 50 entries Search:

idx	id	M_I	eM_I	M_V	eM_V	M_B	eM_B
0	2	11	0.0461	11.2	0.0675	11.7	0.158
1	3	4	0.000369	3.99	0.000389	4.32	0.000609
2	5	11.5	0.0701	11.3	0.0749	11.2	0.108
3	8	11.3	0.0586	11.5	0.0904	11.5	0.136
4	9	11.6	0.0799	11.5	0.0925	11.6	0.151
5	10	11.9	0.0998	11.4	0.0883	11.4	0.127
6	12	8.81	0.00678	8.54	0.00677	8.78	0.012
7	13	9.72	0.0147	9.38	0.0138	9.5	0.0224
8	14	9.82	0.0159	9.59	0.0167	9.86	0.0308
9	15	10.2	0.0215	9.92	0.0223	10.1	0.0367
10	17	9.58	0.0129	9.34	0.0134	9.46	0.0216
11	18	10.4	0.0262	10.2	0.029	10.5	0.0534
12	19	10.6	0.031	10.5	0.0368	10.5	0.054
13	20	11.5	0.0709	11.7	0.107	11.5	0.133
14	21	10.9	0.0422	10.8	0.0499	11	0.0847
15	22	7.49	0.00253	7.12	0.00228	7.33	0.00371
16	24	9.1	0.00864	9.83	0.0206	10.7	0.0666
17	26	9.53	0.0124	9.22	0.012	9.44	0.0213
18	27	10.8	0.0364	10.7	0.045	10.8	0.0738
19	29	9.03	0.00816	8.7	0.00775	8.94	0.0138
20	30	11	0.0459	11	0.0612	11	0.0886
21	31	9.14	0.00888	8.81	0.0085	9.31	0.0189
22	32	10.6	0.0325	11	0.0609	11.5	0.135
23	33	8.39	0.00486	8.15	0.00492	8.44	0.00901
24	35	10.4	0.0263	10.1	0.0259	10.4	0.0503
25	37	11.2	0.0551	11	0.0601	11.4	0.122
26	39	8.5	0.00532	8.24	0.0053	8.42	0.00881
27	42	11.6	0.0761	11.3	0.0781	11.1	0.0946
28	43	8.7	0.00622	8.32	0.00563	8.5	0.00947
29	44	11.6	0.0799	11.3	0.0755	11.7	0.16
30	45	8.96	0.00771	8.6	0.00711	8.89	0.0131
31	47	12.6	0.154	11.3	0.0659	12.1	0.203

Showing 1 to 32 of 32 entries First Previous 1 Next Last

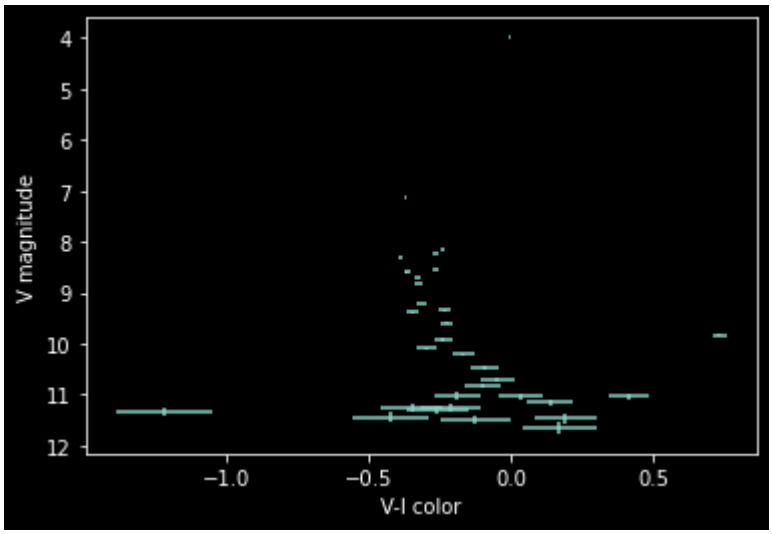
In [30]:
```
full_table.write('NGCSomething_photometry_table.fits', overwrite=True)
```

```
WARNING: VerifyWarning: Keyword name 'aperture_photometry_args' is greater than
8 characters or contains characters not allowed by the FITS standard; a HIERARC
H card will be created. [astropy.io.fits.card]
```

Now we can make a color-magnitude diagram:

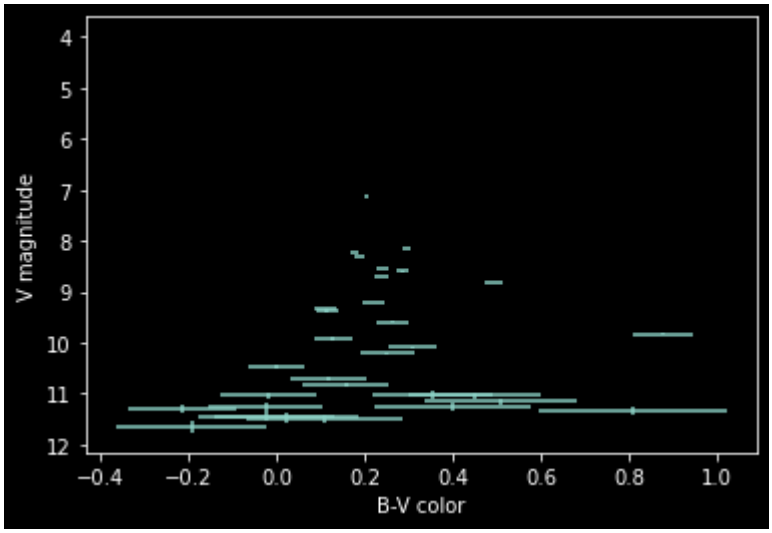
In [31]:
```
pl.errorbar((Vmag-Imag)[high_snr], Vmag[high_snr],
            xerr=((eImag**2+eVmag**2)**0.5)[high_snr],
            yerr=eVmag[high_snr], linestyle='none')
pl.gca().invert_yaxis()
pl.xlabel("V-I color")
pl.ylabel("V magnitude")
```

Out[31]:
```
Text(0, 0.5, 'V magnitude')
```



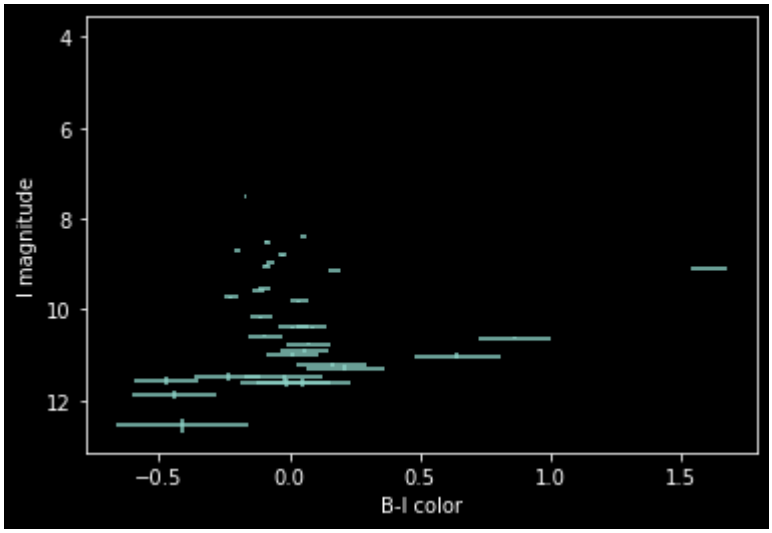
In [32]:
```
pl.errorbar((Bmag-Vmag)[high_snr], Vmag[high_snr],
            xerr=((eBmag**2+eVmag**2)**0.5)[high_snr],
            yerr=eVmag[high_snr], linestyle='none')
pl.gca().invert_yaxis()
pl.xlabel("B-V color")
pl.ylabel("V magnitude")
```

Out[32]: Text(0, 0.5, 'V magnitude')



In [33]:
```
pl.errorbar((Bmag-Imag)[high_snr], Imag[high_snr],
            xerr=((eBmag**2+eImag**2)**0.5)[high_snr],
            yerr=eImag[high_snr], linestyle='none')
pl.gca().invert_yaxis()
pl.xlabel("B-I color")
pl.ylabel("I magnitude")
```

Out[33]: Text(0, 0.5, 'I magnitude')



We can look at which stars are red by selecting those stars that are redder than average. For magnitudes, B-I or B-V colors with *larger* values are *redder*.

We select these by creating a mask, then overlay them on the image below.

In [34]:
```
red_stars = (Vmag-Imag) > 0.3
```

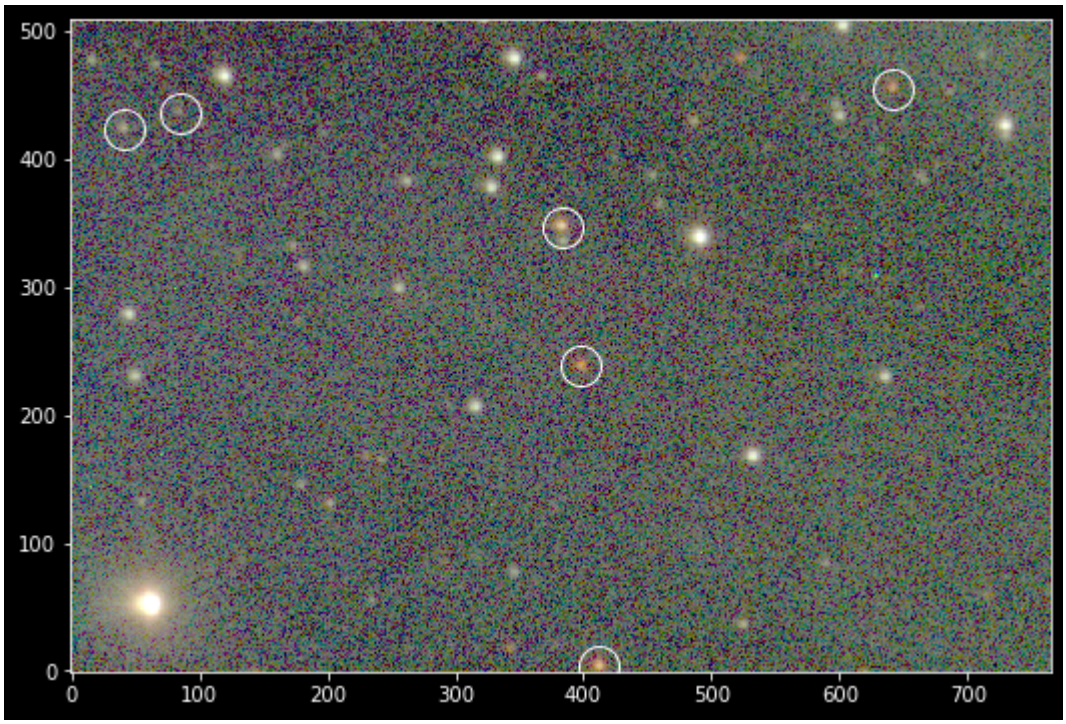
In [35]:
```
# we make an RGB image...
rgb_image = np.array([bgsub_I, bgsub_V, bgsub_B]).T.swapaxes(0,1)
rgb_image = (rgb_image - np.percentile(rgb_image, 10, axis=(0,1)))
rgb_image = np.log10(rgb_image)
rgb_image[np.isnan(rgb_image)] = 0
rgb_image /= np.percentile(rgb_image, 99.95)
```

```
<ipython-input-35-877518f59634>:4: RuntimeWarning: invalid value encountered in
log10
  rgb_image = np.log10(rgb_image)
```

In [36]:
```
pl.figure(figsize=(10,6))
pl.imshow(rgb_image)
pl.plot(full_table[red_stars]['xcentroid'], full_table[red_stars]['ycentroid'], '
```

```
Clipping input data to the valid range for imshow with RGB data ([0..1] for flo
ats or [0..255] for integers).
```

Out[36]:
```
[<matplotlib.lines.Line2D at 0x2a0058d7970>]
```



In [ ]:
```
```

What's in a color-magnitude diagram?

Color-magnitude diagrams are the tools we use to make Hertzsprung-Russell diagrams, i.e., plots that tell us stars' temperatures and luminosities.

To interpret them, we use models of stellar evolution. We show *isochrones*, which are models where all the stars are the same age - so the most massive stars may be dead, but the lowest-mass stars are on the *main sequence*. You should recall these terms and concepts from AST 3018/3019!

These isochrones include predictions of the stars' *absolute magnitudes*, which you should recall are the magnitude if the star is at a distance of 10 parsecs.

We will plot the isochrone at the appropriate distance using the *distance modulus*. H and Chi Persei are at a distance of about 2.3 kpc, or distance modulus

$$\mu = 5\log(d) - 5$$

In [37]:
```
distance_modulus = 5 * np.log10(2300) - 5
distance_modulus
```

Out[37]:
```
11.808639180087965
```

In [41]:
```
isochrone1 = Table.read('isochrone.dat', format='ascii', header_start=12, data_st
isochrone1.sort('Vmag')
```

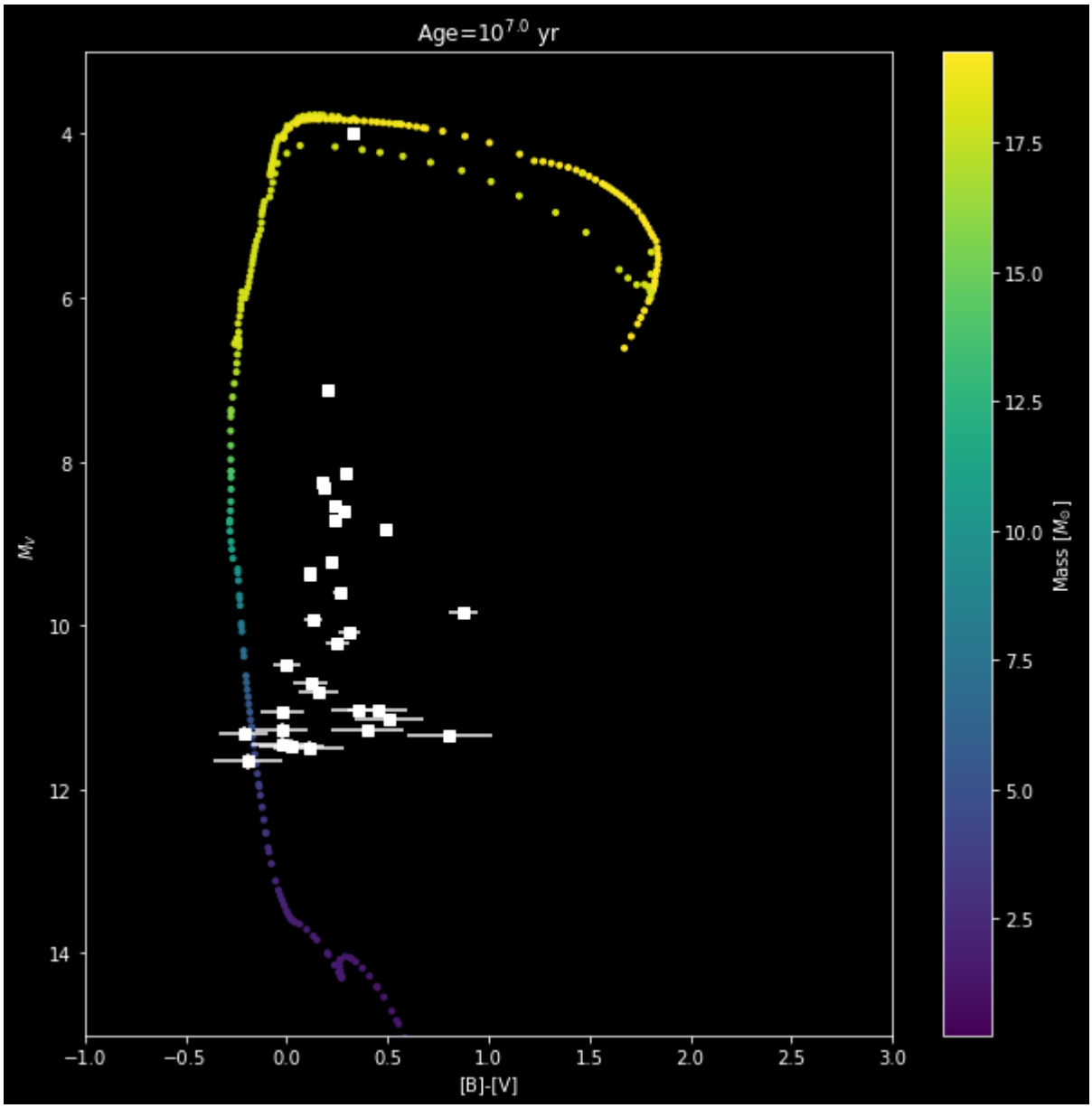
We plot the isochrone color-magnitude diagram by adding the distance modulus to the V-magnitude. The color remains unchanged because color is independent of distance (because $B - \mu - (V - \mu) = B - V$).

```
pl.scatter(isochrone1['Bmag'] - isochrone1['Vmag'],
           isochrone1['Vmag'] + distance_modulus)
```

We will colorize the isochrone by the mass.

Then, we overplot our measurements:

In [42]:
```
pl.figure(figsize=(10,10))
pl.scatter(isochrone1['Bmag'] - isochrone1['Vmag'],
           isochrone1['Vmag'] + distance_modulus,
           c=isochrone1['Mini'],
           marker='.')
pl.errorbar((Bmag-Vmag)[high_snr], Vmag[high_snr],
            xerr=((eBmag**2+eVmag**2)**0.5)[high_snr],
            yerr=eVmag[high_snr], linestyle='none', color='w', marker='s')
pl.ylim(15,3); pl.ylabel("$M_V$")
pl.xlim(-1,3); pl.xlabel("[B]-[V]")
pl.title(f'Age=$10^{{{isochrone1["logAge"][0]}}}$ yr')
cb = pl.colorbar()
cb.set_label("Mass [$M_{\odot}$]")
```



If our measurements are good, and we have the distance right, and all the stars are in the cluster, and we know the age of the cluster, we can use the isochrone model to determine the stars' masses!

The misalignment between our measurements and the isochrone is probably because of *interstellar extinction*, which blocks some of the starlight and changes stars' colors. We won't worry about that further in this class, though.

That's a lot of caveats, but this is how we measure star cluster ages and star masses.

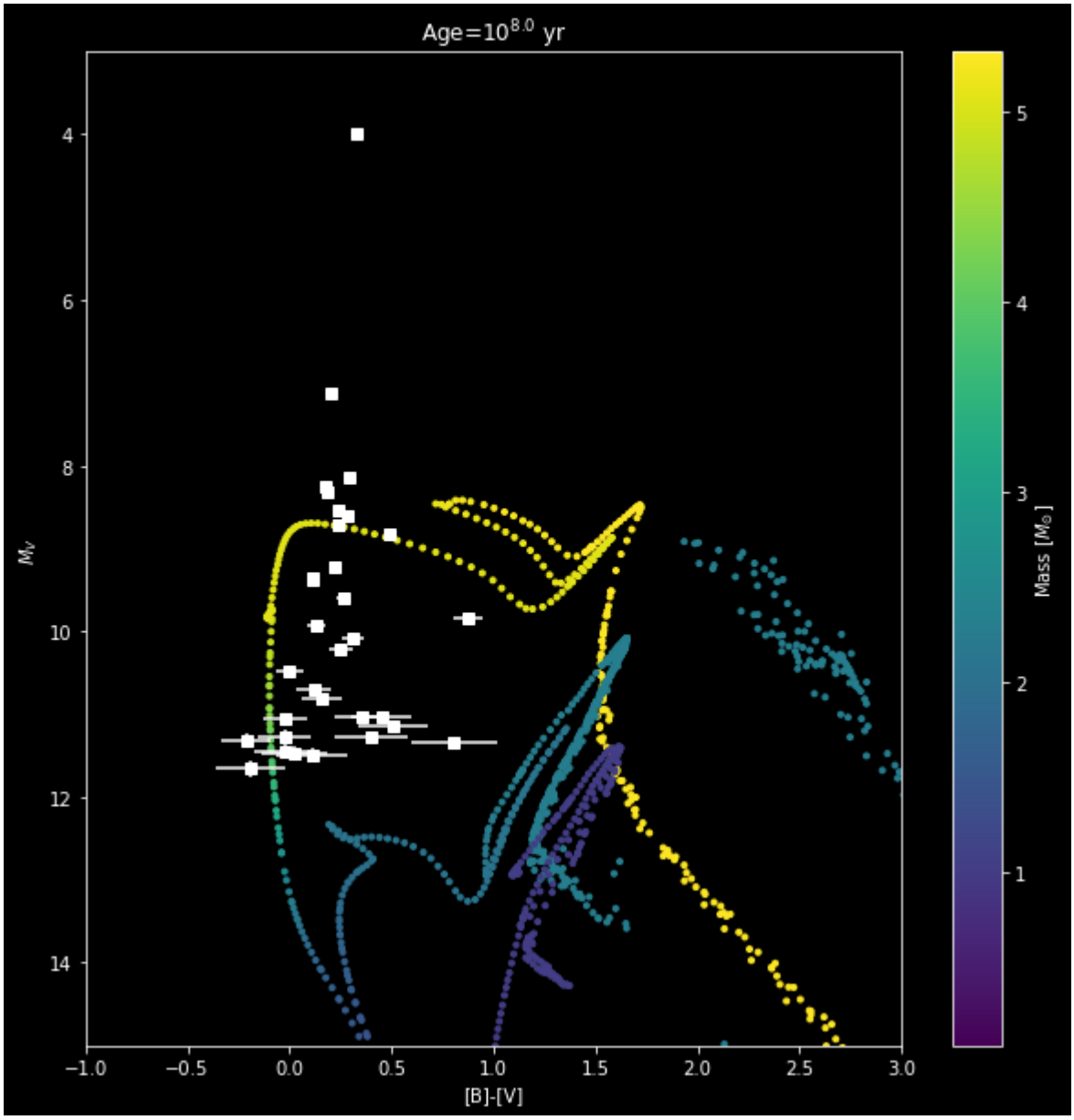
Exercise: Overplot different isochrones on the data

I have obtained several additional isochrones from http://stev.oapd.inaf.it/tmp/output518100630565.dat (http://stev.oapd.inaf.it/tmp/output518100630565.dat) for you to compare to your cluster data.

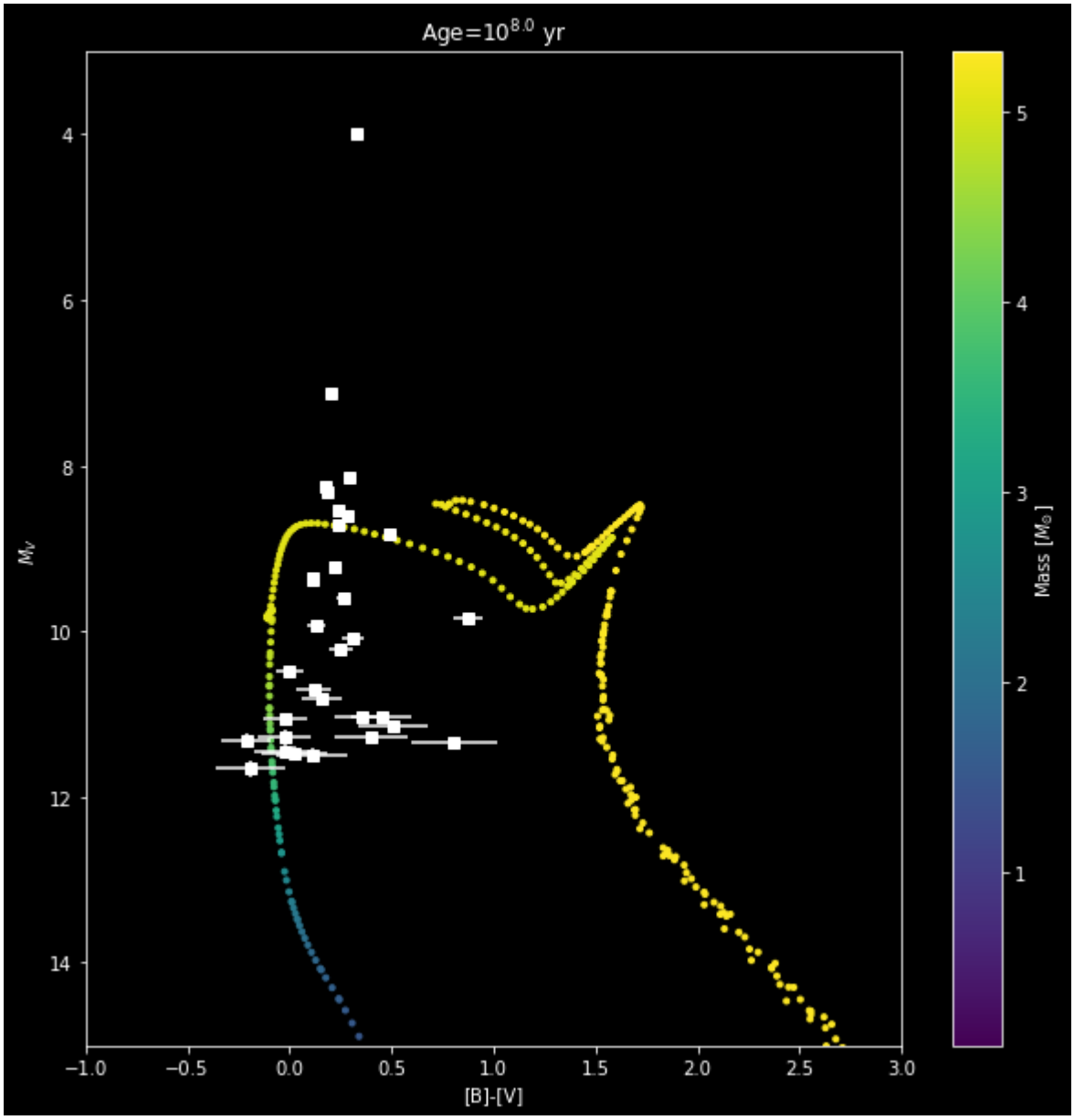
To start, though, let's compare these isochrons to the CMD you just derived. Overplot the different age isochrones on the data above:

In [46]:
```
isochrone2 = Table.read('isochrones.dat', format='ascii')
isochrone2.sort('logAge')
isochrone_100Myr = isochrone2[isochrone2['logAge'] == 8]
isochrone_1Gyr = isochrone2[isochrone2['logAge'] == 9]
isochrone_10Gyr = isochrone2[isochrone2['logAge'] == 10]
```

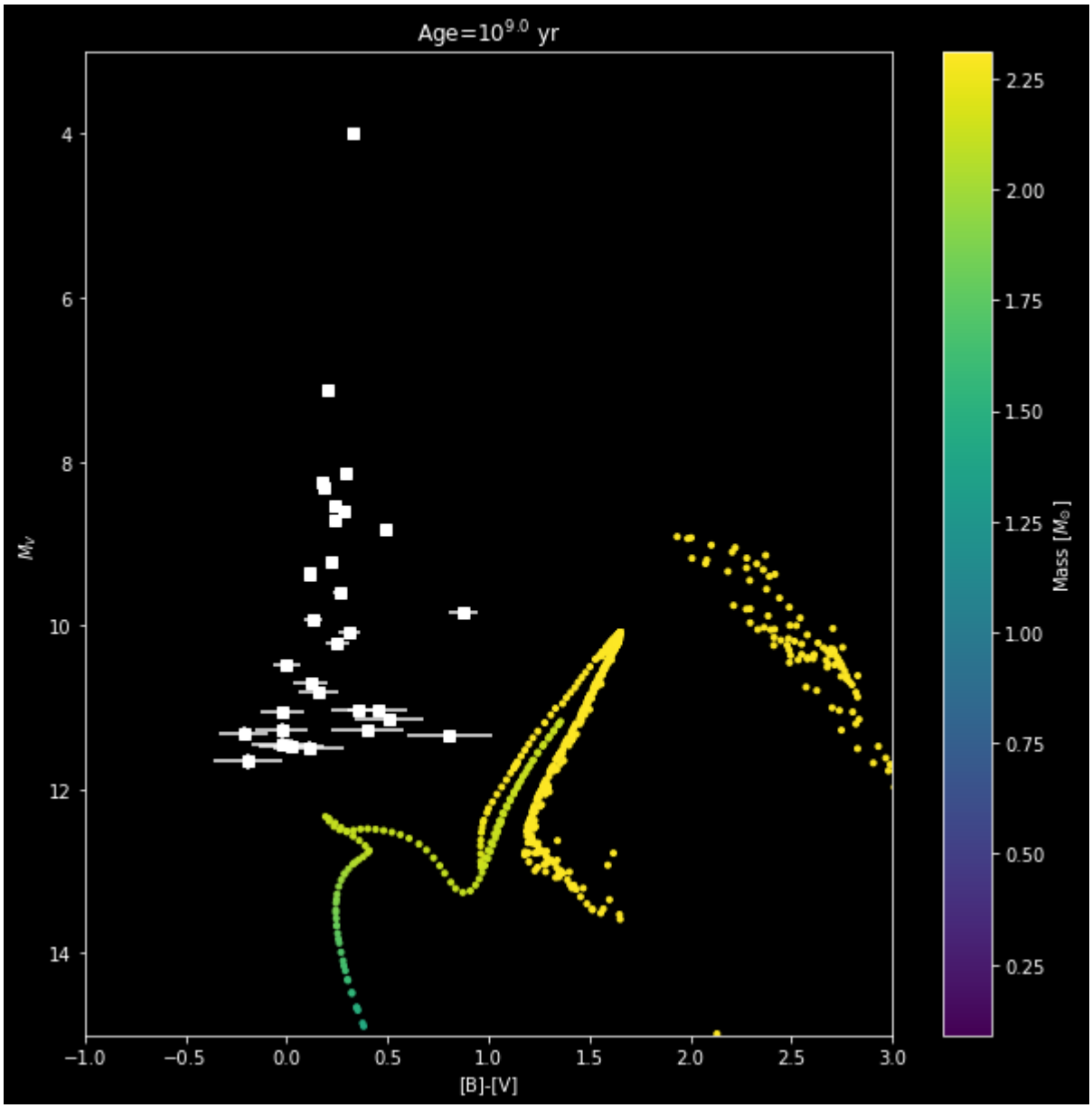
In [48]:
```
pl.figure(figsize=(10,10))
pl.scatter(isochrone2['Bmag'] - isochrone2['Vmag'],
           isochrone2['Vmag'] + distance_modulus,
           c=isochrone2['Mini'],
           marker='.')
pl.errorbar((Bmag-Vmag)[high_snr], Vmag[high_snr],
            xerr=((eBmag**2+eVmag**2)**0.5)[high_snr],
            yerr=eVmag[high_snr], linestyle='none', color='w', marker='s')
pl.ylim(15,3); pl.ylabel("$M_V$")
pl.xlim(-1,3); pl.xlabel("[B]-[V]")
pl.title(f'Age=$10^{{{isochrone2["logAge"][0]}}}$ yr')
cb = pl.colorbar()
cb.set_label("Mass [$M_{\odot}$]")
```



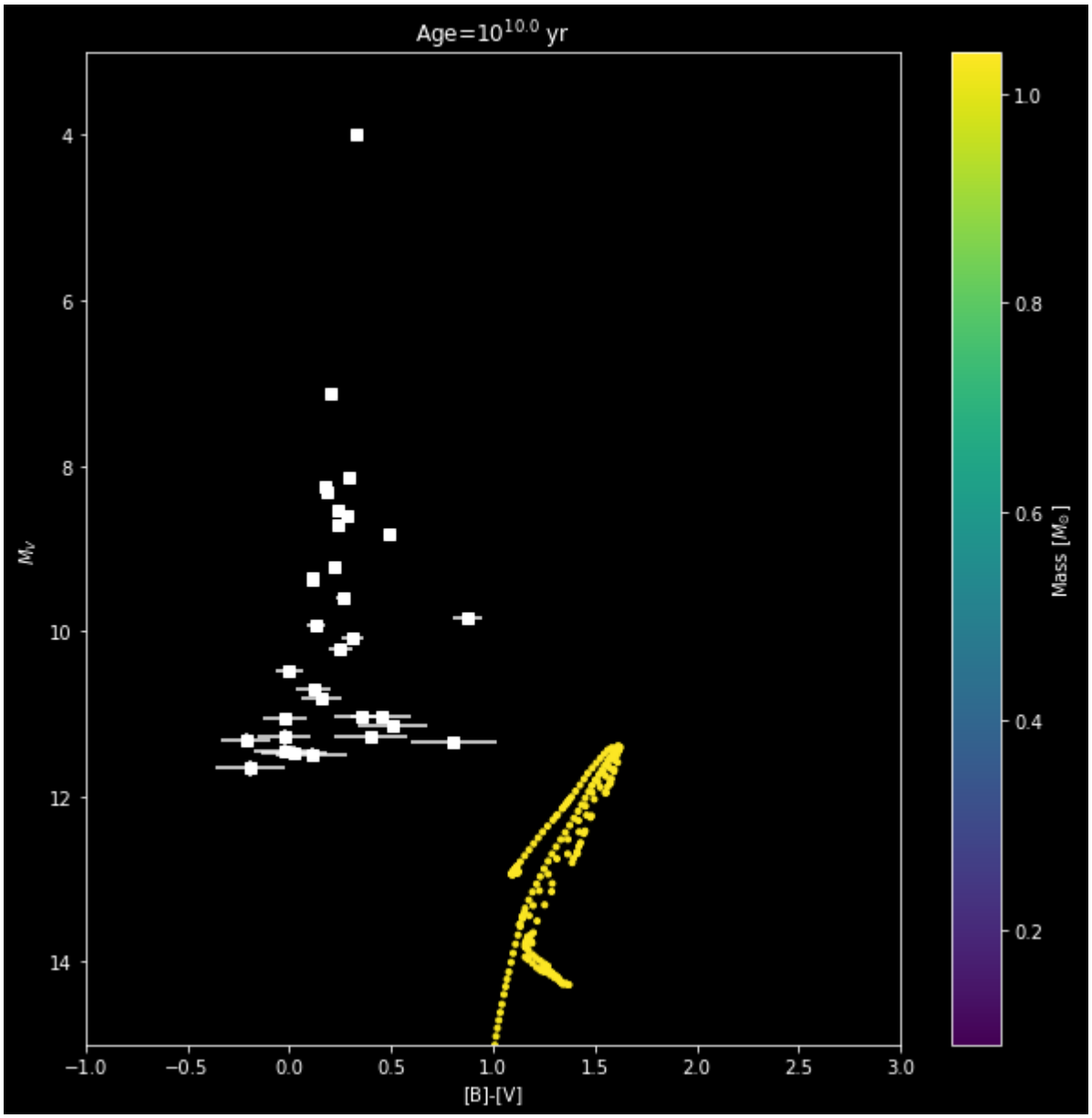
In [49]:
```
pl.figure(figsize=(10,10))
pl.scatter(isochrone_100Myr['Bmag'] - isochrone_100Myr['Vmag'],
           isochrone_100Myr['Vmag'] + distance_modulus,
           c=isochrone_100Myr['Mini'],
           marker='.')
pl.errorbar((Bmag-Vmag)[high_snr], Vmag[high_snr],
            xerr=((eBmag**2+eVmag**2)**0.5)[high_snr],
            yerr=eVmag[high_snr], linestyle='none', color='w', marker='s')
pl.ylim(15,3); pl.ylabel("$M_V$")
pl.xlim(-1,3); pl.xlabel("[B]-[V]")
pl.title(f'Age=$10^{{{isochrone_100Myr["logAge"][0]}}}$ yr')
cb = pl.colorbar()
cb.set_label("Mass [$M_{\odot}$]")
```



In [50]:
```
pl.figure(figsize=(10,10))
pl.scatter(isochrone_1Gyr['Bmag'] - isochrone_1Gyr['Vmag'],
           isochrone_1Gyr['Vmag'] + distance_modulus,
           c=isochrone_1Gyr['Mini'],
           marker='.')
pl.errorbar((Bmag-Vmag)[high_snr], Vmag[high_snr],
            xerr=((eBmag**2+eVmag**2)**0.5)[high_snr],
            yerr=eVmag[high_snr], linestyle='none', color='w', marker='s')
pl.ylim(15,3); pl.ylabel("$M_V$")
pl.xlim(-1,3); pl.xlabel("[B]-[V]")
pl.title(f'Age=$10^{{{isochrone_1Gyr["logAge"][0]}}}$ yr')
cb = pl.colorbar()
cb.set_label("Mass [$M_{\odot}$]")
```



In [51]:
```
pl.figure(figsize=(10,10))
pl.scatter(isochrone_10Gyr['Bmag'] - isochrone_10Gyr['Vmag'],
           isochrone_10Gyr['Vmag'] + distance_modulus,
           c=isochrone_10Gyr['Mini'],
           marker='.')
pl.errorbar((Bmag-Vmag)[high_snr], Vmag[high_snr],
            xerr=((eBmag**2+eVmag**2)**0.5)[high_snr],
            yerr=eVmag[high_snr], linestyle='none', color='w', marker='s')
pl.ylim(15,3); pl.ylabel("$M_V$")
pl.xlim(-1,3); pl.xlabel("[B]-[V]")
pl.title(f'Age=$10^{{{isochrone_10Gyr["logAge"][0]}}}$ yr')
cb = pl.colorbar()
cb.set_label("Mass [$M_{\odot}$]")
```



Once you've done this, assess: Can you say anything about the observed cluster's age?

The cluster has an age of around 100Myr because our data points match most closely and show most prominently on he first graph. Extenction causes the data to not show as well as it would otherwise. Since the 100Myr fit doesn't fit very well, we can probably sat that the cluster is younger than 100 Myr because as you go forward in time, the fit gets worse.