Lab 6 - Exoplanet Detection

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Abstract

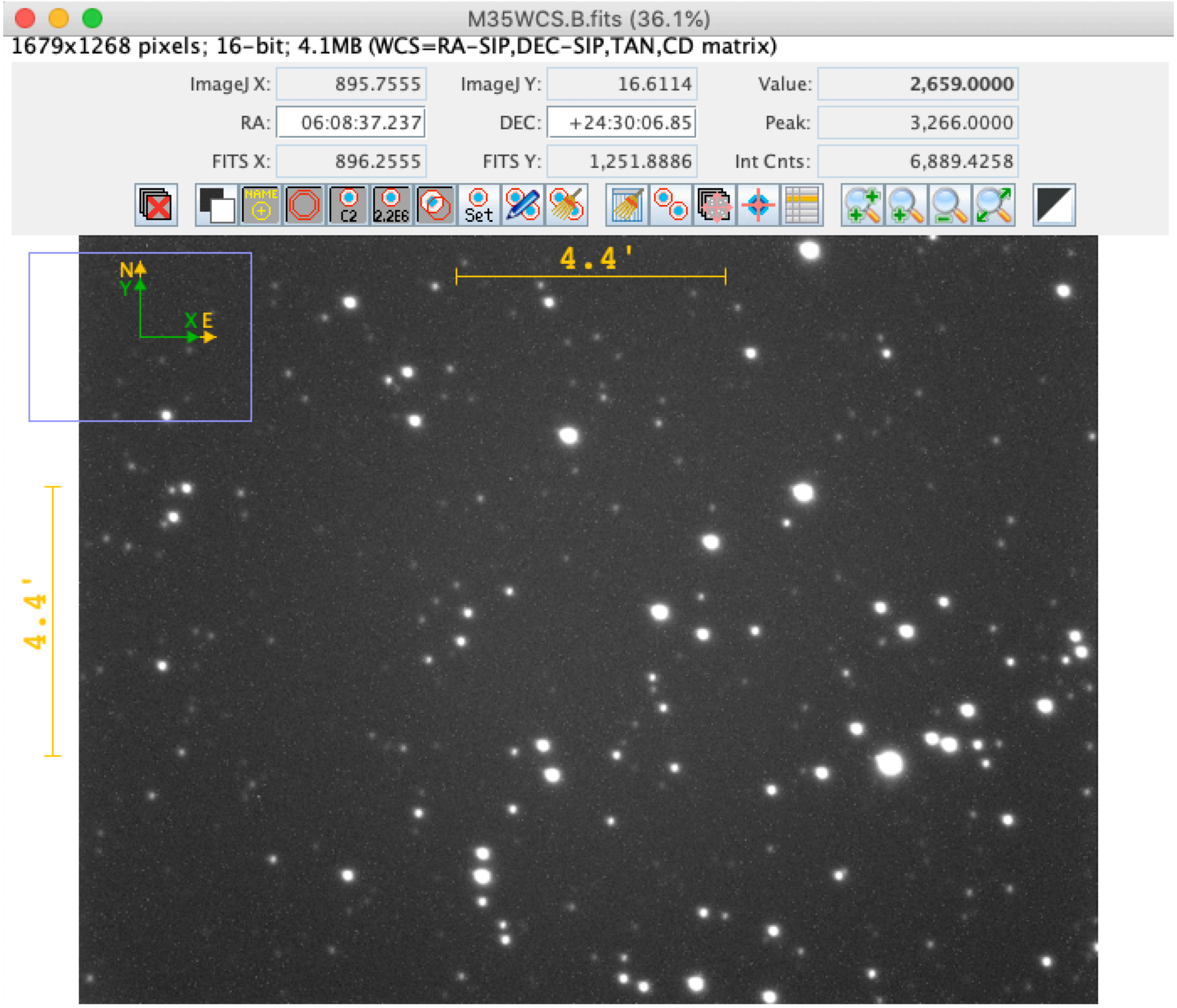
Based on the signal to noise ratio we are able to achieve with our telescope and camera and the demographics of the exoplanets that are suitable for ground based detection an assessment was made to verify quanitatively that it is possible to detect exoplanet transits.

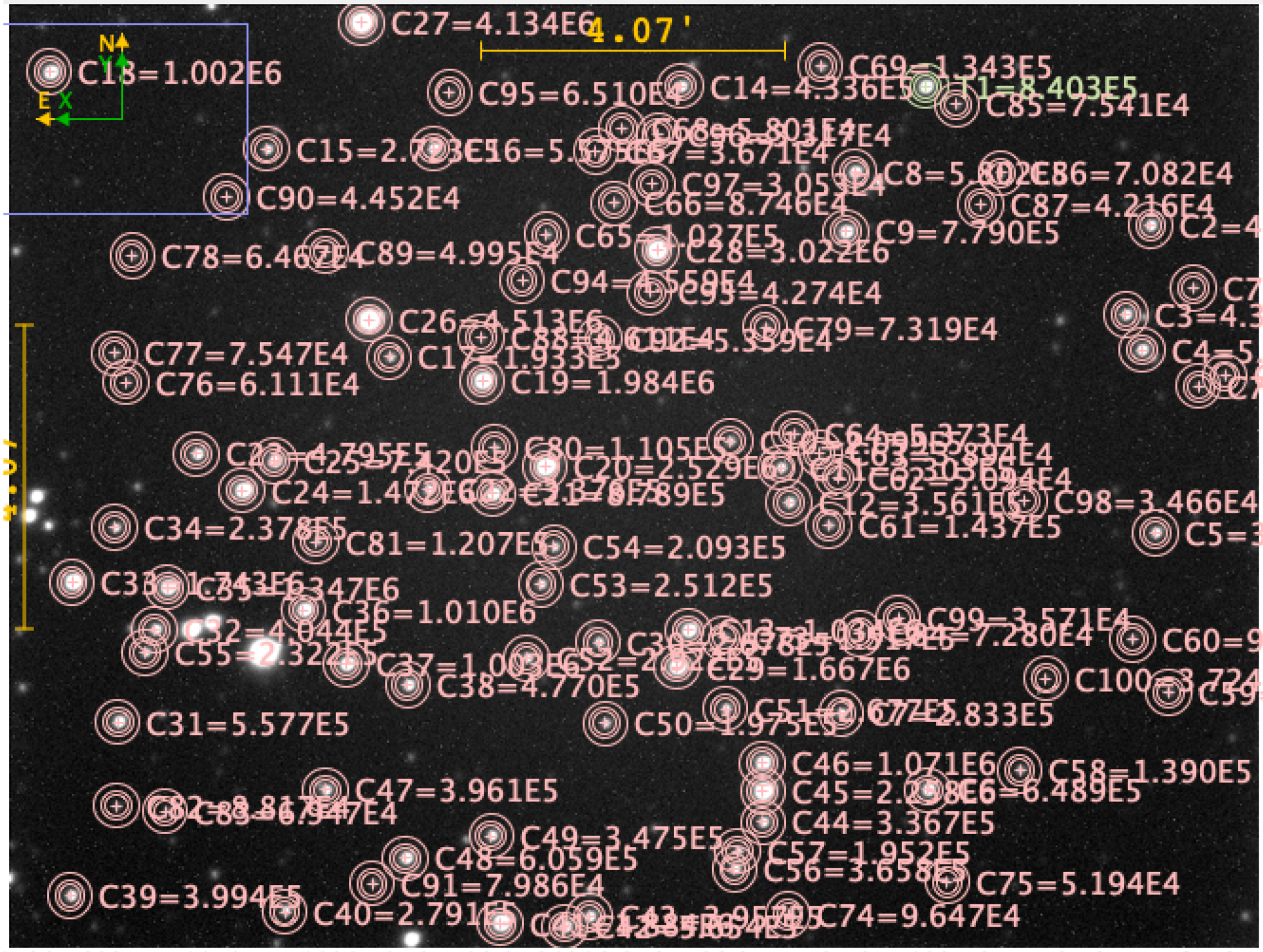
Signal to Noise Ratio

Data was taken from observations previously made of open clusters in B and R filters. The clusters observed were selected based on monthly recommendations from SkyMaps.com. The observations were made on 2/27/2020 and 2/28/2020 with the UWM 14" telescope and CCD camera. Astrometry.net was used to obtain astrometric solutions for each image.

AstroImageJ (AIJ) was used extensively to calibrate the images with bias, dark and flat field images. AIJ also created a Seeing Profile where the FWHM was found to be 9.18 pixels or 5.49 arcsec. AIJ's Multi-Aperature functionality was used to select stars to analyze and plot on the diagram.

A pair of images from the M35 cluster in each filter was then analyzed and flux measurements taken. The flux error measurements were also recorded and output with the measurement table for one hundred stars. From these a profile of the signal to noise ratio as a function of magnitude was produced. A curve was fit to this data so that the signal to noise ratio could be predicted for stars of any magnitude.


M35WCS.B.fits (36.1%)
1679x1268 pixels; 16-bit; 4.1MB (WCS=RA-SIP,DEC-SIP,TAN,CD matrix)
ImageJ X: 895.7555
ImageJ Y: 16.6114
Value: 2,659.0000
RA: 06:08:37.237
DEC: +24:30:06.85
Peak: 3,266.0000
FITS X: 896.2555
FITS Y: 1,251.8886
Int Cnts: 6,889.4258
NAME
C2
2.2E6
Set
4.4'
N
Y
X
E
4.4'



Python code

In [16]:

```
from astropy.io import fits
from os import walk
from matplotlib import pyplot as plt

import numpy as np
from scipy import stats
```

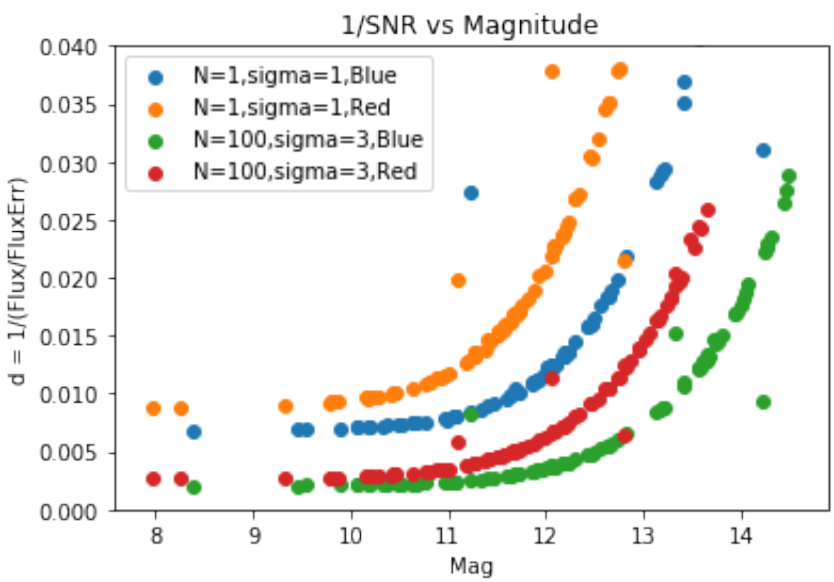
In [17]:

```
data = np.genfromtxt(fname="100MeasurementsM35Br.tsv", delimiter="\t

print(data.shape)  # (200,100)
```

(2, 717)

In [18]:

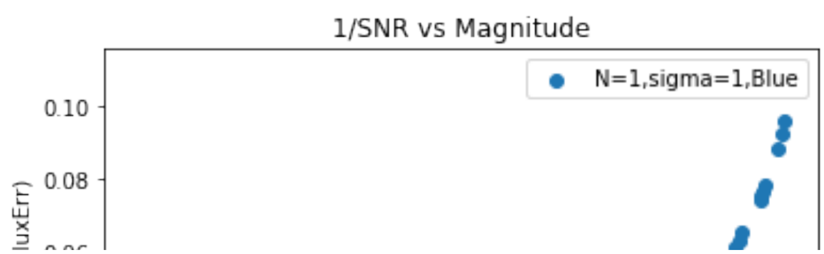
```
FluxB = (data[0,15:115])
FluxErrB = (data[0,115:215])
Fluxr = (data[1,15:115])
FluxErrr = (data[1,115:215])
#print(FluxB,FluxErrB)
#plt.scatter(FluxB,FluxErrB)
#plt.scatter(Fluxr,FluxErrr)
#plt.show()

MagRefB = (data[0,217])
MagRefB = np.append(MagRefB,data[0,223:716:5])
MagRefr = (data[1,217])
MagRefr = np.append(MagRefr,data[1,223:716:5])

plt.scatter(MagRefB,(FluxErrB/FluxB),label='N=1,sigma=1,Blue')
plt.scatter(MagRefr,(FluxErrr/Fluxr),label='N=1,sigma=1,Red')
plt.scatter(MagRefB,((FluxErrB/FluxB)/np.sqrt(100)*3),label='N=100,s
plt.scatter(MagRefr,((FluxErrr/Fluxr)/np.sqrt(100)*3),label='N=100,s
plt.ylim(0,0.04)
plt.title('1/SNR vs Magnitude')
plt.xlabel('Mag')
plt.ylabel('d = 1/(Flux/FluxErr)')
plt.legend()
plt.show()
```

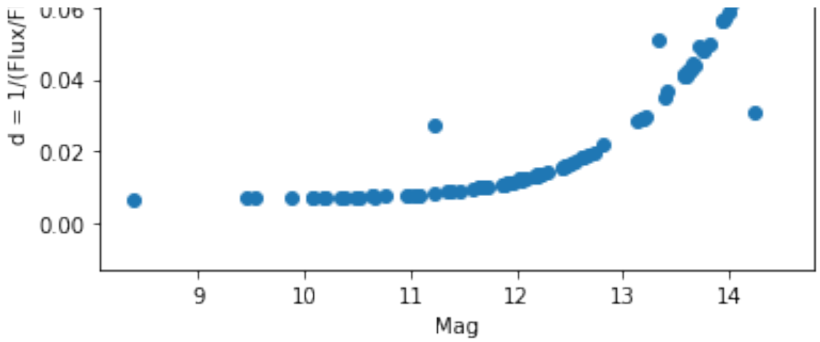


In [19]:

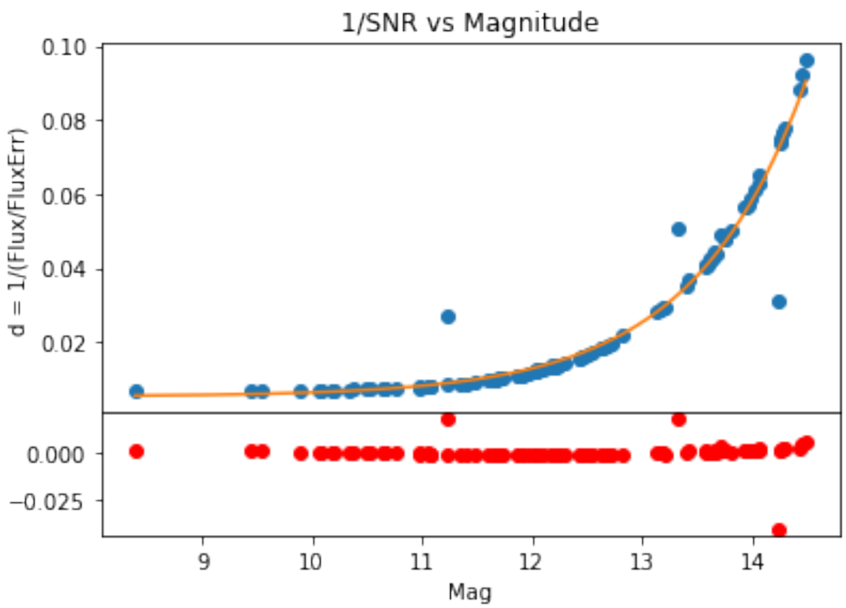
```
import numpy as np
import matplotlib.pyplot as plt
import scipy as scypy
from astropy.stats import sigma_clipped_stats
from scipy import stats

def exponential(x, a, k, b):
```

```
    return a*np.exp(x*k) + b

plt.scatter(MagRefB,(FluxErrB/FluxB),label='N=1,sigma=1,Blue')
plt.title('1/SNR vs Magnitude')
plt.xlabel('Mag')
plt.ylabel('d = 1/(Flux/FluxErr)')
plt.legend()
plt.show()

fig = plt.figure()

x = MagRefB
y = (FluxErrB/FluxB)

mean, median, std = sigma_clipped_stats(y)

popt_UncVsD, pcov_UncVsD = scypy.optimize.curve_fit(exponential, x,
perr_UncVsD = np.sqrt(np.diag(pcov_UncVsD))
print ("Exponential on the raw data")
#print (popt_exponential, pcov_exponential)
print ("pre-exponential factor = %0.10f (+/-) %0.10f" % (popt_UncVsD
print ("rate constant = %0.4f (+/-) %0.4f" %(popt_UncVsD[1], perr_Un
print ("yintercept = %0.4f (+/-) %0.4f" %(popt_UncVsD[2], perr_UncVs

xtest = np.linspace(min(x),max(x),3969)
testy = (popt_UncVsD[0]*np.exp(xtest*popt_UncVsD[1]) + popt_UncVsD[2
diffy = (popt_UncVsD[0]*np.exp(x*popt_UncVsD[1]) + popt_UncVsD[2])

#plt.subplot(2, 2, 1)
frame1=fig.add_axes((.1,.3,.8,.6))
plt.plot(x, y, linestyle = 'None', marker = 'o')
plt.plot(xtest,testy)
plt.title('1/SNR vs Magnitude')
plt.ylabel('d = 1/(Flux/FluxErr)')

#Residual plot
difference = y - diffy
frame2=fig.add_axes((.1,.1,.8,.2))
plt.plot(x,difference,'or')
plt.xlabel('Mag')
plt.show()
```






```
Exponential on the raw data
pre-exponential factor = 0.0000000654 (+/-) 0.0000107066
rate constant = 0.9718 (+/-) 11.3949
yintercept = 0.0054 (+/-) 0.2309
```



Exoplanet Data

A list of exoplanets suitable for ground based observation was obtained from the AAVSO website, https://www.aavso.org/exoplanet-section (https://www.aavso.org/exoplanet-section).

According to the AAVSO this target list was derived using the following criteria for each exoplanet:

```
It is a confirmed, transiting exoplanet.

It is the first planet discovered in a multi-planetary system (i
.e., with the suffix “b”);

Its orbital period is less than three (3) days.

Its V magnitude is brighter than magnitude 14.

Its transit depth is greater than 0.5% (i.e., 5 parts-per-thousa
nd, or 5 mmag).
```

Based on the magnitude the exoplanet the single observation signal to noise ratio was calulated. The single exposure signal to noise ratios were calculated based on the blue filter as it had slightly better performance than the red. Based on the duration of the transit this SNR ratio was divided by the square root of the number of exposures possible to obtain the transit's signal to noise ratio. A two minute exposure was assumed based on experience with the typical observation and seeing conditions.

Number of exposures

The number of exposures, $NumExp$, was calculated as follows:

$$NumExp = Duration * 60 \text{ minutes / 2 minutes per exposure}$$

Transit Signal to Noise Ratio

The Transit Signal to Noise Ratio, $SNR_{Transit}$, was calculated as follows:

$$SNR_{Transit} = SNR_{Exposure}/\sqrt{NumExp}$$

In [ ]:

```
1
```

Python Code

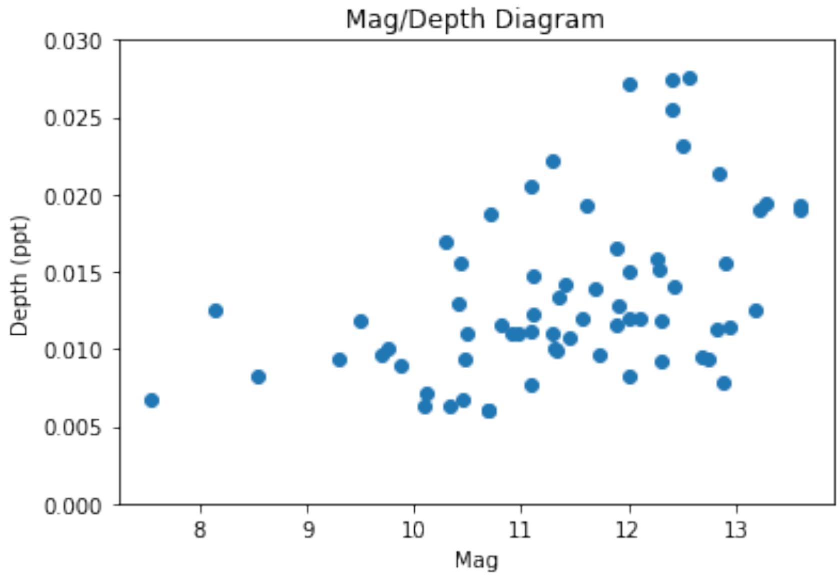
In [20]:
```
import fileinput

data = np.genfromtxt(fname="addAAVSOTargetList.tsv", delimiter="\t",

print("Catalog data shows",data.shape[0],"exoplanets.")


Header = np.array([0])
UncDat = (popt_UncVsD[0]*np.exp((data[:,3])*popt_UncVsD[1]) + popt_U
UncDat = np.append(Header, UncDat)

for fl, line in zip(UncDat, fileinput.input(['addAAVSOTargetList.tsv
    print(line.strip() + '\t' + str(fl))
fileinput.close()
#Header = np.array([0])
ExpDat = (data[:,8]*60)/2
numExp = np.append(Header, ExpDat)

for fl, line in zip(numExp, fileinput.input(['addAAVSOTargetList.tsv
    print(line.strip() + '\t' + str(fl))
fileinput.close()
#Header = np.array([0])
UncTst = ((popt_UncVsD[0]*np.exp((data[:,3])*popt_UncVsD[1]) + popt_
UncTst = np.append(Header, UncTst)

for fl, line in zip(UncTst, fileinput.input(['addAAVSOTargetList.tsv
    print(line.strip() + '\t' + str(fl))
fileinput.close()
#Header = np.array([0])
UncVsD = ((data[:,10]/1000)/((popt_UncVsD[0]*np.exp((data[:,3])*popt_
UncVsD = np.append(Header, UncVsD)

for fl, line in zip(UncVsD, fileinput.input(['addAAVSOTargetList.tsv
    print(line.strip() + '\t' + str(fl))

fileinput.close()
```

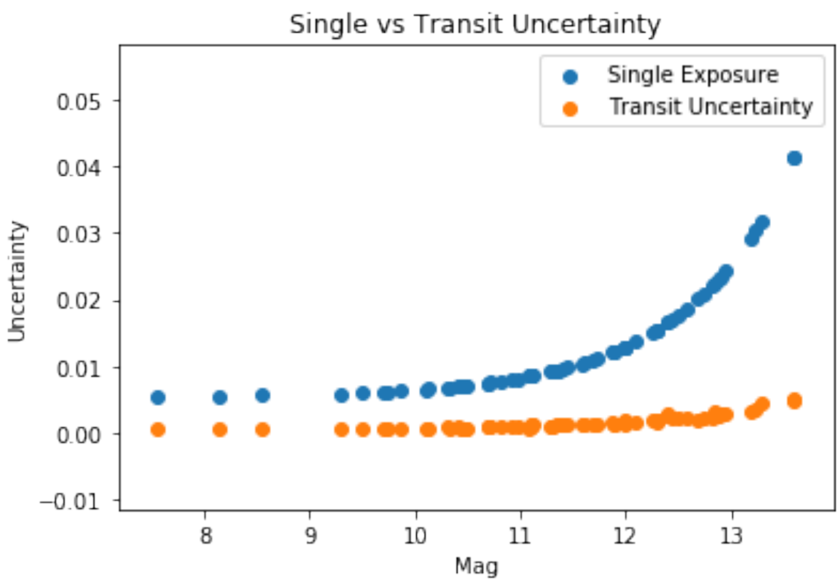
```
Catalog data shows 68 exoplanets.
```

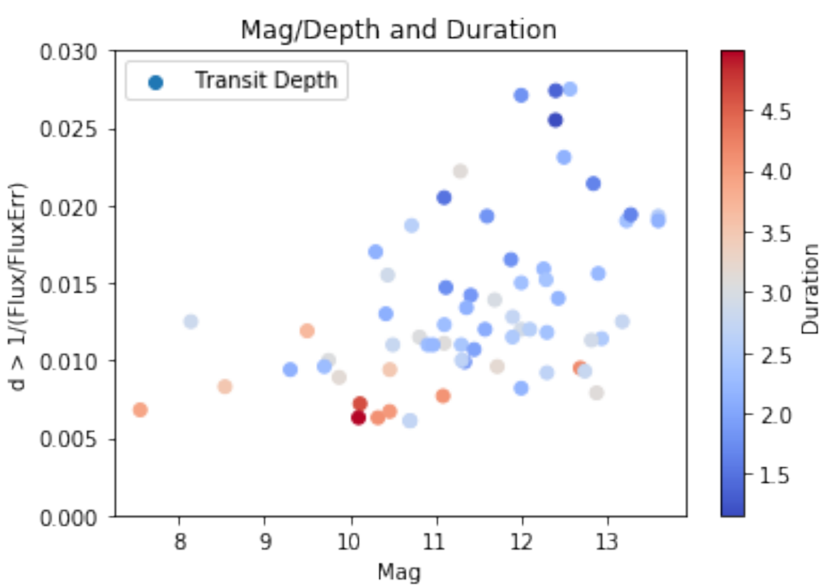
In [23]:
```
adta = np.genfromtxt(fname="addAAVSOTargetList.tsv", delimiter="\t",

print(adta.shape)  # (200,100)
#print(data)

#cata = np.genfromtxt(fname="M35Catalog.tsv", delimiter="\t", skip_h

```

```
print("Catalog data shows",adta.shape[0],"stars in this field.")

deladray = (adta[:,10])/1000
Magadray = (adta[:,3])
Duradray = (adta[:,8])
Uncadray = (adta[:,11])
UncTdray = (adta[:,13])
UncVdray = (adta[:,14])
#YErrArray = (data[2:1767,14])
#plt.scatter(b_vArray,MagArray)
plt.scatter(Magadray,deladray)
#plt.errorbar(delArray,MagArray,xerr=XErrArray, yerr=YErrArray, fmt=
#plt.errorbar((-2.5*np.log10((1-(delArray))/1000000)),MagArray,xerr=
#print(MagArray, delArray),
#print(YErrArray, XErrArray),
#plt.gca().invert_yaxis()
#plt.xlim(-.01,.2)
#plt.ylim(16,4)
plt.title("Mag/Depth Diagram")
plt.ylabel("Depth (ppt)")
plt.xlabel("Mag")
plt.ylim(0,0.03)
plt.savefig("ExoMagDepth.png")
plt.show()

#plt.scatter(MagRefB,(FluxErrB/FluxB),label='N=1,sigma=1,Blue')
plt.scatter(Magadray,Uncadray,label='Single Exposure')
plt.scatter(Magadray,UncTdray,label='Transit Uncertainty')
plt.title("Single vs Transit Uncertainty")
plt.ylabel("Uncertainty")
plt.xlabel("Mag")
#plt.ylim(0,0.03)
plt.savefig("ExoMagDepth.png")
plt.legend()
plt.show()

#plt.scatter(MagRefB,(FluxErrB))
#plt.scatter(Magadray,UncTdray,label='Transit Uncertainty')
#plt.scatter(Magadray,UncVdray,label='AAVSO exoplanets')
graduration = plt.scatter(Magadray,deladray,label='Transit Depth',c=
plt.colorbar(graduration, label = 'Duration')
plt.title("Mag/Depth and Duration")
plt.xlabel('Mag')
plt.ylabel('d > 1/(Flux/FluxErr)')
plt.ylim(0,.03)
plt.legend(loc = 'upper left')
plt.show()
```

```
(68, 15)
Catalog data shows 68 stars in this field.
```


Mag/Depth Diagram
Depth (ppt)
Mag
0.030
0.025
0.020
0.015
0.010
0.005
0.000
8
9
10
11
12
13


Single vs Transit Uncertainty
Single Exposure
Transit Uncertainty
Uncertainty
Mag
0.05
0.04
0.03
0.02
0.01
0.00
−0.01
8
9
10
11
12
13

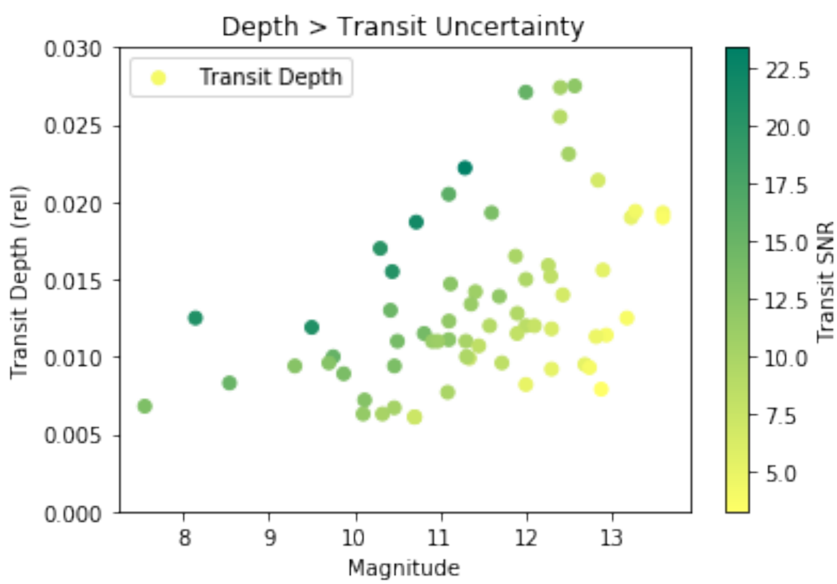

Mag/Depth and Duration
Transit Depth
d > 1/(Flux/FluxErr)
Mag
Duration
0.030
0.025
0.020
0.015
0.010
0.005
0.000
8
9
10
11
12
13
4.5
4.0
3.5
3.0
2.5
2.0
1.5

Depth versus Transit Uncertainty

Comparing the transit depths to the transit uncertainty shows that the majority of these exoplanets can be detected with a high degree of confidence. The primary factors are the magnitude of the star and the depth of the transit. To a much lesser extent the duration of the transit is also a factor.

In [25]:

```
gradient = plt.scatter(Magadray,deladray,label='Transit Depth',c=Unc
plt.colorbar(gradient, label = 'Transit SNR')

#ax1.scatter(Magadray,UncTdray,label='Transit Uncertainty')
plt.title("Depth > Transit Uncertainty")
plt.ylabel("Transit Depth (rel)")
plt.xlabel("Magnitude")
plt.ylim(0,.03)
plt.savefig("DepthVsTstUnc.png")
plt.legend(loc = 'upper left')
plt.show()


```



In [ ]:

```

```