Extinction Law

Let's take a look at the extinction laws that we can use to de-redden the young stars in Cep Ob3b. The three main laws are the Rieke and Lebofsky (1985), the Cardelli, Clayton, and Mathis (1989), and Allen et al. (2014) link. The spectra used in Allen et al. (2014) were recently calssified visually and many that were used as K5 background giants have been retyped. We will explore here how reasonable the (???) law is.

We will make use of the reticulate package. Note, we are defining the python engine in the R setup chunk.

```
\#devtools::install\_github("rstudio/reticulate")
library(reticulate)
use_python("/anaconda3/bin/python")
library(readr)
library(dplyr)
##
## Attaching package: 'dplyr'
## The following objects are masked from 'package:stats':
##
##
       filter, lag
##
  The following objects are masked from 'package:base':
##
       intersect, setdiff, setequal, union
library(ggplot2)
```

We read in the data set. Here we will start with the full.df.csv dataset. For details about this data set see the data documentation. We are interested in the spectral typing of the stars with *Hectospec* spectra.

```
data_path <- "/Users/thomasallen/cep_ob3b/cepr/data/"</pre>
data path2 <- "/Users/thomasallen/cep ob3b/data/"</pre>
#full.df.csv
full.df <- read_csv(paste(data_path2, "full.df.csv", sep=""))</pre>
## Warning: Missing column names filled in: 'X1' [1]
## Parsed with column specification:
## cols(
##
     .default = col_double(),
##
     X1 = col_integer(),
     bmag = col_character(),
##
##
     berr = col_character(),
     vmag = col_character(),
##
##
     verr = col_character(),
##
     imag = col_character(),
##
     ierr = col_character(),
##
     cluster = col character(),
##
     cloud = col_character(),
##
     disk = col_character(),
##
     xray = col_character(),
##
     acis = col_character(),
     spec = col_character(),
##
```

```
##
     chelle = col_character(),
##
     spt = col_character(),
##
     spterr = col_character(),
     tio = col_character(),
##
##
     tior = col_character(),
     cah = col_character(),
##
     cahr = col character()
     # ... with 28 more columns
##
## )
## See spec(...) for full column specifications.
#head(full.df)
gsdss.df <- read_csv(paste(data_path, "gsdss.csv", sep=""))</pre>
## Parsed with column specification:
## cols(
##
    mag = col_double(),
##
     err = col_double()
## )
rsdss.df <- read_csv(paste(data_path, "rsdss.csv", sep=""))</pre>
## Parsed with column specification:
## cols(
##
    mag = col_double(),
##
     err = col_double()
## )
full.df <- full.df %>%
    mutate(gmag=gsdss.df$mag,gerr=gsdss.df$err) %>%
    mutate(rmag=rsdss.df$mag,rerr=rsdss.df$err)
full.df <- full.df %>%
    mutate(bmag=as.numeric(bmag)) %>%
    mutate(berr=as.numeric(berr)) %>%
    mutate(vmag=as.numeric(vmag)) %>%
    mutate(verr=as.numeric(verr)) %>%
    mutate(imag=as.numeric(imag)) %>%
    mutate(ierr=as.numeric(ierr))
```

We want the objects that have spectral types. These will be rows where the columns spt, the spectral type as classified by eye, and spt_old, the spectral type as classified by regression.

Lets make a column that tells us which stars we classified as probable background giants.

##

Х1

ra

```
full.df <- full.df %>%
    mutate(giant = ifelse(cagiant == "giant" | nagiant == "giant", "giant", "unclassified"))

spt.df <- full.df %>%
    filter(is.na(spt)==FALSE & is.na(spt_old)==FALSE)

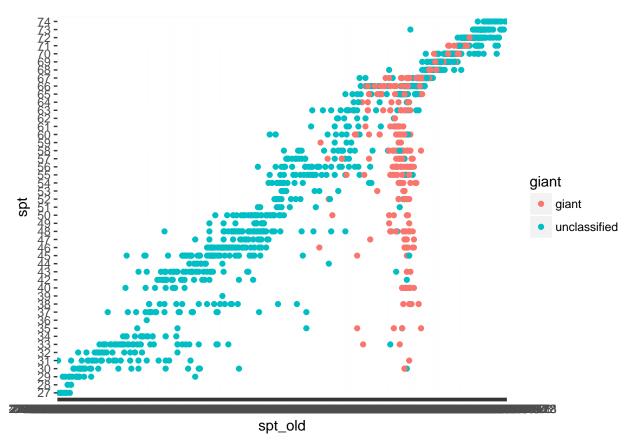
head(spt.df)

## # A tibble: 6 x 93
```

jerr hmag

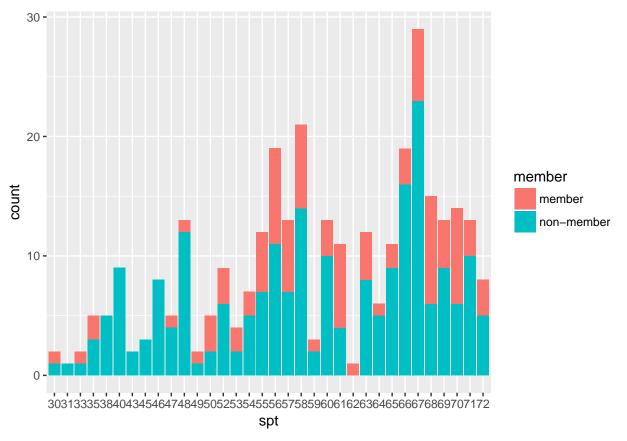
dec bmag berr vmag verr imag ierr jmag

```
<int> <dbl> <
## 1
           343.
     4666
                  62.4
                                                            13.8 0.025
                          NA
                                 NA
                                       NA
                                             NA
                                                   NA
                                                         NA
                                                                           12.4
                                                             13.8 0.025
## 2
      4760
           344.
                  62.3
                          NA
                                 NA
                                       NA
                                             NA
                                                   NA
                                                                           13.1
## 3
      4925
           343.
                  62.4
                          NA
                                NA
                                       NA
                                                             14.8 0.046
                                                                           13.7
                                             NA
                                                   NA
                                                         NA
## 4
      5949
            343.
                  62.4
                          NA
                                 NA
                                       NA
                                             NA
                                                   NA
                                                         NA
                                                             15.3 0.0580
                                                                           14.2
## 5
      6017
                  62.4
                          NA
                                 NA
                                       NA
                                             NA
            344.
                                                   NA
                                                         NA
                                                            13.6 0.035
                                                                           13.0
      7049
           344.
## 6
                  62.4
                          NA
                                 NA
                                       NA
                                             NA
                                                   NA
                                                         NA
                                                             13.0 0.023
                                                                           12.6
## #
     ... with 81 more variables: herr <dbl>, kmag <dbl>, kerr <dbl>,
## #
       c1mag <dbl>, c1err <dbl>, c2mag <dbl>, c2err <dbl>, c3mag <dbl>,
## #
       c3err <dbl>, c4mag <dbl>, c4err <dbl>, m24mag <dbl>, m24err <dbl>,
## #
       cluster <chr>, cloud <chr>, disk <chr>, xray <chr>, acis <chr>,
## #
       spec <chr>, chelle <chr>, spt <chr>, spterr <chr>, tio <chr>,
## #
       tior <chr>, cah <chr>, cahr <chr>, spt_old <chr>, spterr_old <chr>,
## #
       nagiant <chr>, cagiant <chr>, minxray.ra <int>, minxray.dec <int>,
## #
       minxray.id <chr>, minxray.rcnts <int>, minxray.ncnts <int>,
## #
       minxray.npflux <int>, minxray.npfluxerr <int>, minxray.nh <int>,
## #
       minxray.nherr <int>, minxray.kt1 <int>, minxray.kt1err <int>,
## #
       minxray.aflux <int>, minxray.uflux <int>, minxray.rchi <int>,
## #
       medxray.ra <dbl>, medxray.dec <dbl>, medxray.id <chr>,
## #
       medxray.rcnts <int>, medxray.ncnts <dbl>, medxray.npflux <dbl>,
## #
       medxray.npfluxerr <dbl>, medxray.nh <dbl>, medxray.nherr <dbl>,
## #
       medxray.kt1 <int>, medxray.kt1err <int>, medxray.aflux <dbl>,
## #
       medxray.uflux <dbl>, medxray.rchi <dbl>, maxxray.ra <dbl>,
## #
       maxxray.dec <dbl>, maxxray.id <chr>, maxxray.rcnts <int>,
## #
       maxxray.ncnts <dbl>, maxxray.npflux <dbl>, maxxray.npfluxerr <dbl>,
## #
       maxxray.nh <dbl>, maxxray.nherr <dbl>, maxxray.kt1 <dbl>,
## #
       maxxray.kt1err <dbl>, maxxray.aflux <dbl>, maxxray.uflux <dbl>,
       maxxray.rchi <dbl>, lbol.teff.sa.lbol <chr>, lbol.teff.sa.teff <chr>,
## #
## #
       lbol.teff.sa.sa <chr>, member <chr>, gmag <dbl>, gerr <dbl>,
## #
       rmag <dbl>, rerr <dbl>, giant <chr>
plot1 <- spt.df %>% ggplot(aes(x=spt_old,y=spt,color=giant)) +
    geom_point()
plot1
```



It looks like many of the stars classified as K5/K6 background giants have the wrong spectral classification. Lets look at the distibution of visually determined spectral types of these "background giants".

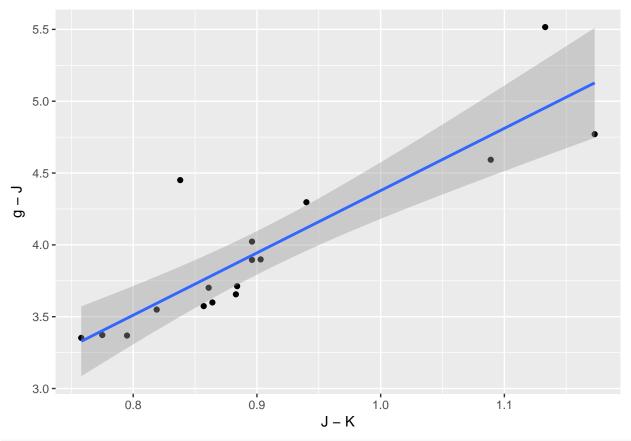
```
spt.df %>%
  filter(giant=="giant") %>%
  ggplot(aes(x=spt,fill=member)) + geom_bar()
```



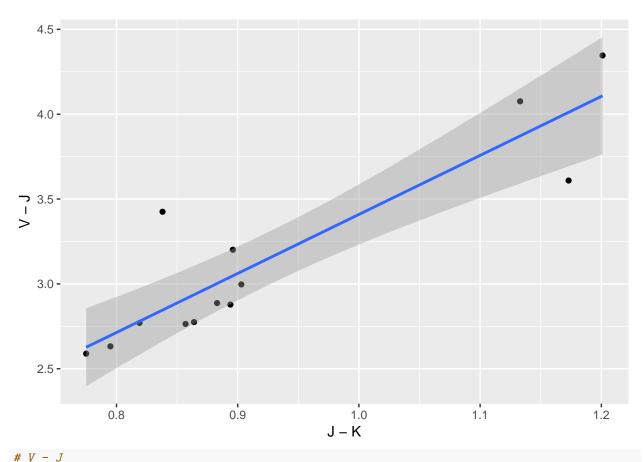
Ok, so after removing potential members, there are about 25 K5/K6 stars that still remain, and over 20 K7s.

```
ext_cc_plot_fit <- function(df,c1=vmag,c2=jmag,c3=kmag,xtitle="J - K",ytitle="V - J") {</pre>
    \# Plots X - J vs. J - K and fits a linear model
    # Slope of linear model is used to derive Ax/Aj extinction coefficient
   c1<-enquo(c1)
   c2<-enquo(c2)
   c3<-enquo(c3)
   df.plot <- df %>%
       filter(giant=="giant") %>%
       filter(member=="non-member") %>%
       filter(is.na(!!c2)==FALSE & is.na(!!c3)==FALSE & is.na(!!c1)==FALSE) %>%
       filter(spt==65 | spt==66) %>% # / spt==67)
        #mutate(c1=as.numeric(c1)) %>%
       mutate(x=!!c2 - !!c3,y= !!c1 - !!c2) %>%
        select(x,y)
    #filter(jmk < 1.75)
   plot <- df.plot %>%
        ggplot(aes(x=x,y=y)) +
        geom_point() +
```

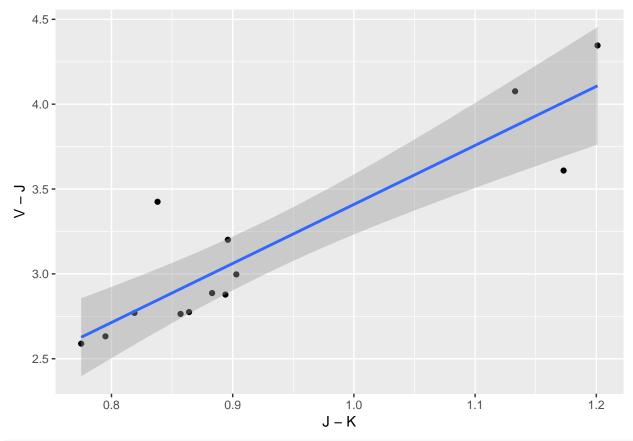
```
geom_smooth(method='lm') +
        labs(x=xtitle,y=ytitle)
    fit \leftarrow lm(y \sim x, data = df.plot)
    print(summary(fit))
    #print(plot)
    return(plot)
}
\# g - J
spt.df %>% ext_cc_plot_fit(c1=gmag,ytitle="g - J")
##
## Call:
## lm(formula = y ~ x, data = df.plot)
##
## Residuals:
##
       \mathtt{Min}
                 1Q Median
## -0.35719 -0.17104 -0.05845 0.02387 0.77533
##
## Coefficients:
               Estimate Std. Error t value Pr(>|t|)
##
                           0.55792 0.076
## (Intercept) 0.04265
               4.33510
                           0.61231 7.080 3.75e-06 ***
## x
## ---
## Signif. codes: 0 '***' 0.001 '**' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.2926 on 15 degrees of freedom
## Multiple R-squared: 0.7697, Adjusted R-squared: 0.7543
## F-statistic: 50.12 on 1 and 15 DF, p-value: 3.747e-06
```



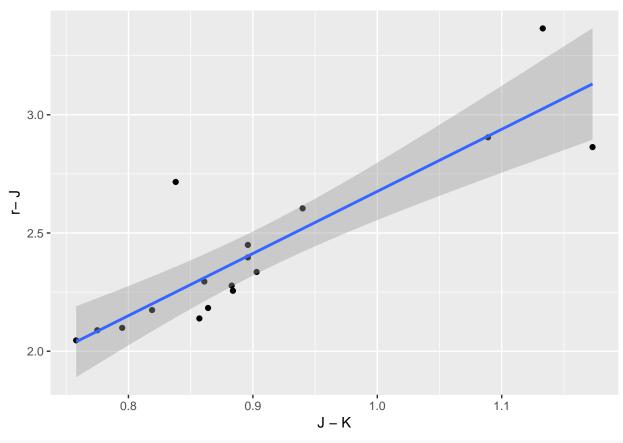
```
\# V - J
spt.df %>% ext_cc_plot_fit(c1=vmag,ytitle="V - J")
##
## Call:
## lm(formula = y ~ x, data = df.plot)
##
## Residuals:
       Min
                 1Q Median
                                   3Q
## -0.40187 -0.14781 -0.06417 0.15355 0.57927
##
## Coefficients:
##
              Estimate Std. Error t value Pr(>|t|)
## (Intercept) -0.06887
                          0.47660 -0.144
                                             0.888
                          0.50926
                                  6.830 2.84e-05 ***
## x
               3.47804
## ---
## Signif. codes: 0 '***' 0.001 '**' 0.05 '.' 0.1 ' ' 1
## Residual standard error: 0.2554 on 11 degrees of freedom
## Multiple R-squared: 0.8092, Adjusted R-squared: 0.7918
## F-statistic: 46.64 on 1 and 11 DF, p-value: 2.84e-05
```



```
# Filter outlier
spt.df %>%
   filter(jmag - kmag < 1.75) %>%
   ext_cc_plot_fit(c1=vmag,ytitle="V - J")
##
## Call:
## lm(formula = y ~ x, data = df.plot)
## Residuals:
                 1Q
                     Median
                                   3Q
## -0.40187 -0.14781 -0.06417 0.15355 0.57927
##
## Coefficients:
              Estimate Std. Error t value Pr(>|t|)
## (Intercept) -0.06887
                          0.47660 -0.144
                                             0.888
## x
               3.47804
                          0.50926
                                  6.830 2.84e-05 ***
## ---
## Signif. codes: 0 '***' 0.001 '**' 0.05 '.' 0.1 ' ' 1
## Residual standard error: 0.2554 on 11 degrees of freedom
## Multiple R-squared: 0.8092, Adjusted R-squared: 0.7918
## F-statistic: 46.64 on 1 and 11 DF, p-value: 2.84e-05
```



```
# r - J
spt.df %>% ext_cc_plot_fit(c1=rmag,ytitle="r- J")
##
## Call:
## lm(formula = y ~ x, data = df.plot)
##
## Residuals:
                 1Q Median
       \mathtt{Min}
                                   3Q
## -0.26718 -0.09085 -0.01599 0.00600 0.46569
##
## Coefficients:
##
              Estimate Std. Error t value Pr(>|t|)
## (Intercept) 0.04814
                          0.34434
                                   0.140
                                             0.891
                          0.37791
                                    6.953 4.63e-06 ***
## x
               2.62776
## ---
## Signif. codes: 0 '***' 0.001 '**' 0.05 '.' 0.1 ' ' 1
## Residual standard error: 0.1806 on 15 degrees of freedom
## Multiple R-squared: 0.7632, Adjusted R-squared: 0.7474
## F-statistic: 48.35 on 1 and 15 DF, p-value: 4.627e-06
```



```
alam <- function(slope) {
    alam <- slope * (1 - 0.397) + 1
    return(alam)
}
alam(4.3)</pre>
```

[1] 3.5929

alam(3.5)

[1] 3.1105

alam(2.6)

[1] 2.5678

Allen, T. S., J. J. Prchlik, S. T. Megeath, R. A. Gutermuth, J. L. Pipher, T. Naylor, and R. D. Jeffries. 2014. "An Anomalous Extinction Law in the Cep OB3b Young Cluster: Evidence for Dust Processing During Gas Dispersal." $|Apj\>786\>({\rm May}): 113.$ doi:10.1088/0004-637X/786/2/113.

Cardelli, J. A., G. C. Clayton, and J. S. Mathis. 1989. "The Relationship Between Infrared, Optical, and Ultraviolet Extinction." |Apj| 345 (October): 245–56. doi:10.1086/167900.

Rieke, G. H., and M. J. Lebofsky. 1985. "The Interstellar Extinction Law from 1 to 13 Microns." Apj 288 (January): 618-21. doi:10.1086/162827.