IoA internship record

Local measurements of the Hubble constant: Type 1a supernova systematics

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July/August 2021

1 Week beginning 05/07/2021

Monday: Installed SnooPy on my desktop inside an anaconda environment in ubuntu. Read through SnooPy documentation again and familiarised myself with the package's basic commands.

Tuesday: Configured my SnooPy installation to work in Jupyter notebook. Met with Suhail to discuss initial project tasks and questions I had about SnooPy. Continued learning to use SnooPy in Jupyter notebook and how to load files into python, specifically .txt files, individually as well as multiple .txt files in a directory.

Wednesday: Continued getting used to SnooPy, lookng at different models and fitting parameters. Wrote code that tabulates the filters in a given SN file, alongside the number of observations for the respective filter. Looped this for all SN in DR3 to give a .txt file for DR3 which tabulates this. I also created an excel file for ease of use and visualisation. Used the .txt file to plot bar charts of the number of observations for a given filter for all SN.

Thursday: Plotted histograms of the number of observations for the IR filters Y, J and H, with the Ydw and Jrc2 variants included as part of Y and J respectively.

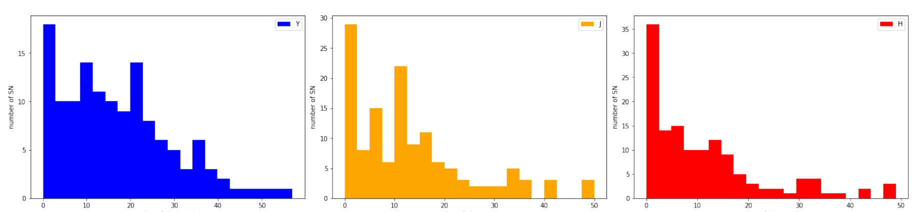


Figure 1: Histograms of IR band observations for DR3

Then I read through the Burns 2018 paper again to understand how they were getting from their SN to the DM values. I deduced the conditions used in the analysis and set up SnooPy in python to use these conditions in simple terms. This consisted of using all available filters, choosing EBVmodel 2 with the fitting parameter as Sbv. I chose which DM calculator to use and then applied this fitting to all SN in DR3 minus the 14 removed in Burns 2018. The fitting in all but 19 of these terminated successfully, yielding DM and Sbv values which I stored alongside the SN. Learnt how to read a http file in python since I needed the data from Burns 2018 on DM. Sorted the http webpage into the 101 DM measurements in the correct order. Plotted an initial scatter plot of Burns 2018 vs my data.

Friday: Repeated the plot with the error in DM from Burns 2018. This allowed me to include a line of best fit which assumed that my data was identical to Burns 2018, as well as a residual plot and histogram of the distribution of these.

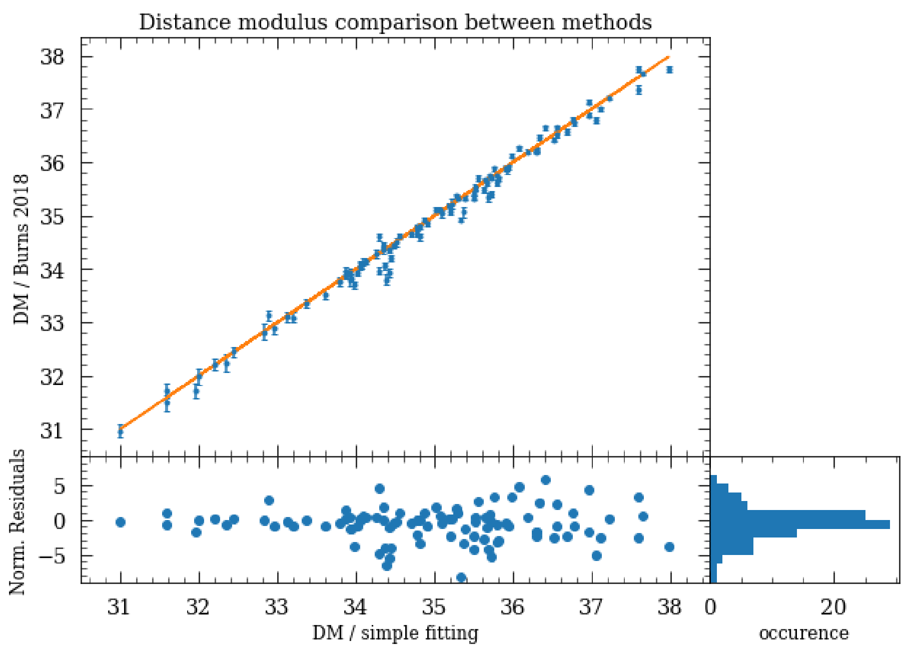


Figure 2: Distance modulus comparison between Burns 2018 paper and my fits

Investigated why 19 SN in DR3 didn't fit properly. These fell into three categories: A filter was listed in the .txt file but had no data, all weights for a filter were zero, or m¿k in the fitting. I tabulated these SN with the 14 SN not in Burns 2018 from DR3, with the reason for not being used. I worked out which SN had residuals greater than 5, i.e. where my fitting was massively in disagreement with Burns 2018, for the worst one; SN2009I with an std err of 8.1 my fitting was:

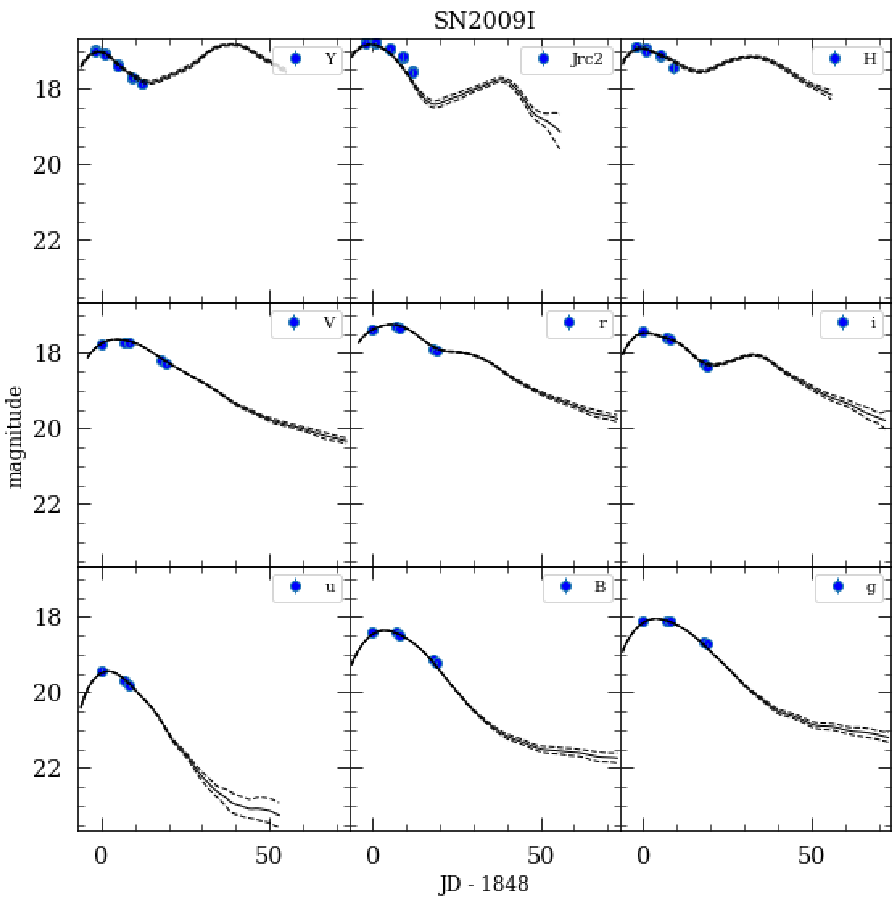


Figure 3: My fitting for SN2009I

2 Week beginning 12/07/2021

Monday: Read up on reddening corrections Rv and more on the differences between SnooPy's models. Tried fitting light curves using the EBVmodel with specific Rv values but this didn't work as Rv was not recognised as a parameter in EBVmodel. Therefore we moved on to the colour model instead. Initially looked at how different Rv values affected the fitting from the colour model, comparing Rv=2 and Rv=3. Then started fitting the colour model for all SN in DR3 that were not removed in Burns 2018 or produced an error when fitting.

Two additional SN were erroneous (SN2008bi and SN2009I) on top of the erroneous ones removed last week on Thursday, both caused by the fitting weights being zero for the u band data, leaving 99 SN in the dataset. The colour model fitting was kept default apart from a Rv=2 or 3 argument in the s.fit() function. Each text file was loaded into SnooPy, fitted and then saved as a .snpy file to be loaded later. The code iterated through all 99 .txt files. The same process was applied for the .snpy fitted light curves, with two separate files for each SN, one for Rv=2 and the other for Rv=3. Once loaded each of the Sbv values and their associated errors were stored in arrays.

Tuesday: After solving problems related to the order in which python loads files I could correctly plot Sbv for Rv=2 against Sbv for Rv=3 since Sbv is an important parameter in the model function for the colour model and thus affected by Rv. It was also included in Burns 2018 table 2, which would be useful later.

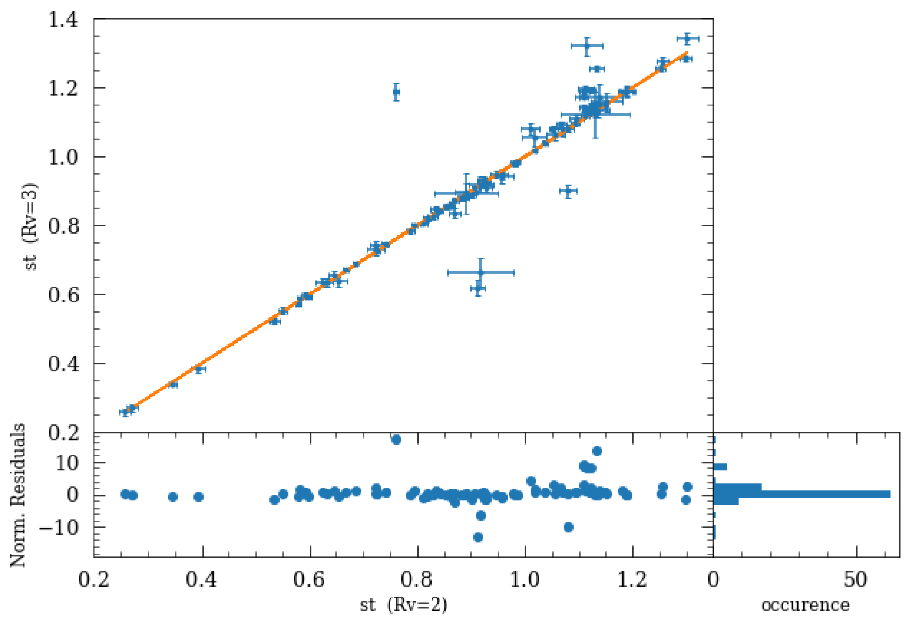


Figure 4: color-stretch parameter comparison from reddening correction values

On the whole the different Rv values fit the light curves similarly as they mostly follow a perfect fit where the Sbv values are equal however there are a few outliers. I then loaded the Sbv values from Burns 2018 with the errors and plotted my Sbv values against theirs.

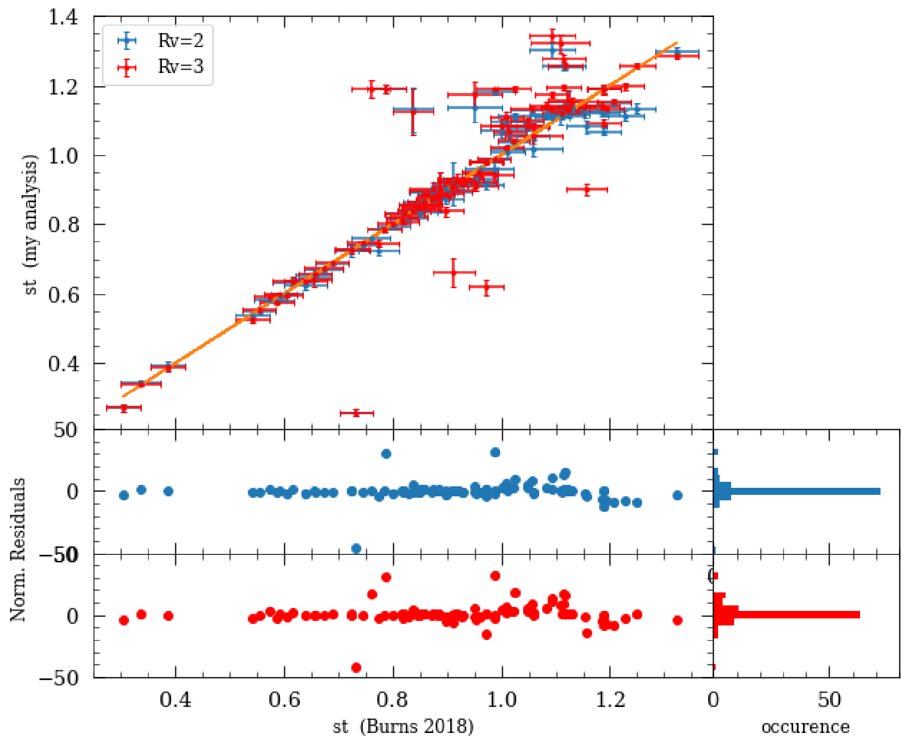


Figure 5: color-stretch parameter compared to Burns 2018

As can be seen, there are a few outliers for Rv=3 that agree with Burns 2018 for Rv=2. I worked out which SN these were coming from. E.g. the outlier for Rv=3 at 0.76 on the x-axis is SN2008fl and has a normalised residual value of 11. I then investigated the affect of removing cases where E(B-V) is greater than 0.5 and observing the effect on the plots. These SN from Burns 2018 were tabulated and four remained in the dataset.

While this did show that the Rv=2 fittings were better for this case only two of these SN displayed a significant difference between the fittings. I then made a dataset of all SN in DR3 from Burns 2018 with J or Jrc2 filter data that produced fits without an error for the max model. This consisted of 97 SN. I tabulated the removed SN with the reason for removal.

Wednesday: I fitted the light curves using the max model for all the SN that didn't produce an error, this totalled to 79. The remaining 55 were divided into: having no Jband filter (including Jrc2), being peculiar according to Burns 2018

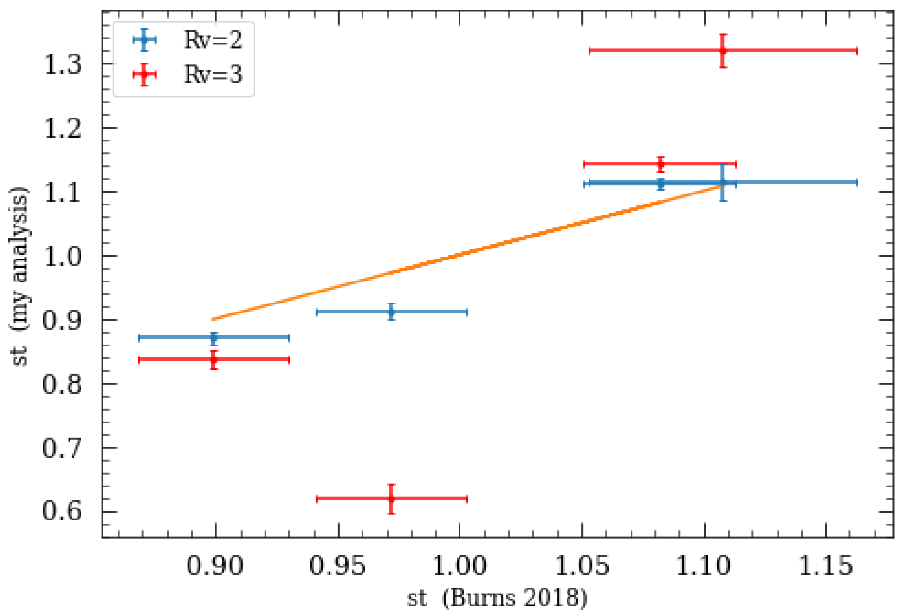


Figure 6: colour-stretch parameter comparison between reddening values for SN with E(B-V) greater than 0.5

and producing errors when fitting, these were then tabulated. To maximise the sample size we searched for ways to mitigate the errors in the fitting. This mainly consisted of fitting the light curves only in the Jband to avoid errors arising from fittings in other bands. I also edited some of the raw SN files to stop an error caused by the formatting. I built code using the s.restbands command, to deal with the different combinations of J and Jrc2 data. Sometimes this included using only one of J or Jrc2 even though both were available, due to errors in the fitting. In total this amounted to a sample size of 94. During the day I also met on zoom with Suhail to discuss progress made and the next steps to take.

Thursday: With the larger sample size fitted, I loaded the .snpy files created and used them to plot the redshift against the maximum J band magnitude, using the s.Jmax command in SnooPy. On the plot I overlaid the model function for Jmax against z given in Suhail et al (2018). This fitted the data well, which validated my analysis. Creating the model in functional form allowed me to change the three constants aj, j0 and q0, and observe the effect on the best fitting line compared to my data.

I also loaded data from Burns 2018 table 2 to divide the SN into specific cases. SN2005ke was included separately as it does not appear in the residual plot, since the residual value of 145 would have obscured the other points. Suhail and I looked at the 3 cases which still gave errors and why that might be. Some of them were spectroscopically peculiar e.g. SN2007N and there weren't enough

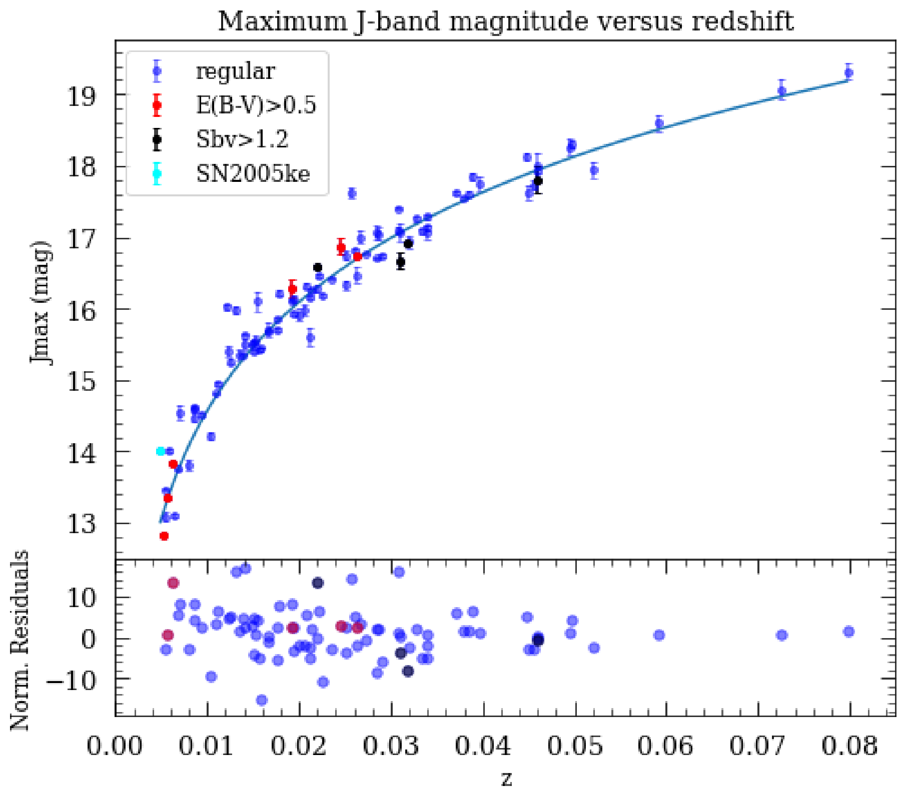


Figure 7: Maximum Jband magnitude against redshift for non-peculiar supernova in DR3.

data points for others, e.g. SN2009al. SN2005hj was an example of where the data points in the Jband were too close together in time to accurately fit the light curve.

I then repeated the Jband fitting but using the Tmax from fitting only B band data, as a constraint in the fitting for J. This was especially relevant when there wasn't enough data to only use J for the fitting. This gave 5 SN which outputted errors from the fitting. Some simply couldn't be fit still, while others were fitting but clearly not accurately to the data. There were also a couple of special cases where the Bband data wasn't sufficient so another filter was used. In this case I always tried to fit with the V band where possible. In order to compare the two methods I plotted the Jmax values against each other.

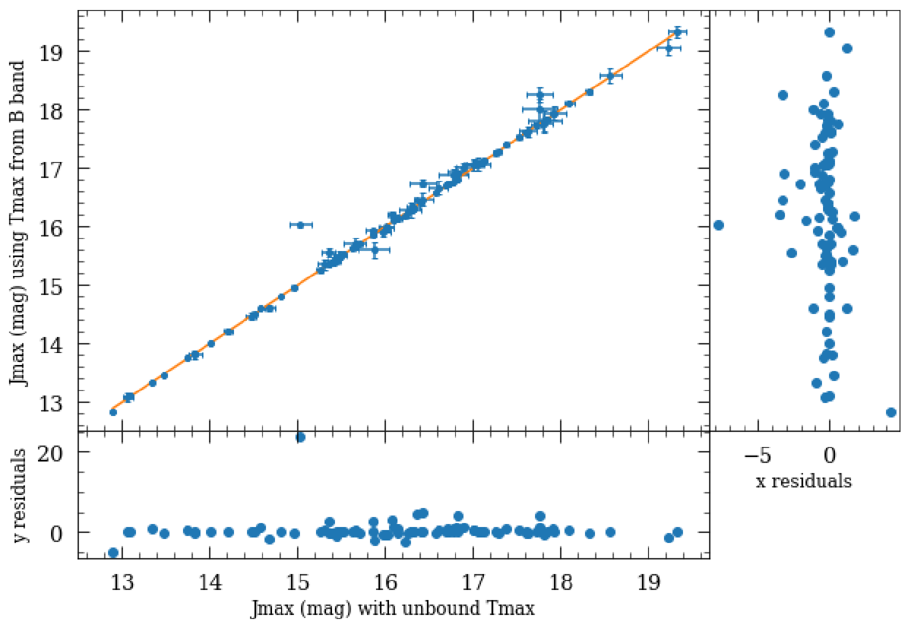


Figure 8: Comparison between maximum J band magnitudes from bound and unbound Tmax values. Subplots of the normalised residuals from the horizontal and vertical axes are also included.

I then used the number of observations record created in the first week to plot the difference between the two values against the number of observations.

The plot shows that on the whole, the two techniques differ more when there are less J band observations, meaning that the Tmax constraint likely has a greater influence on Jmax in this case. That said it could also be that there are generally less B band observations when J band observations are low.

Friday: I repeated the analysis by fitting only for the J band from the outset. Before this, I would fit for all bands and then try fitting only in the J band when an error occured in the fitting. This produced fits for 79 SN, significantly less

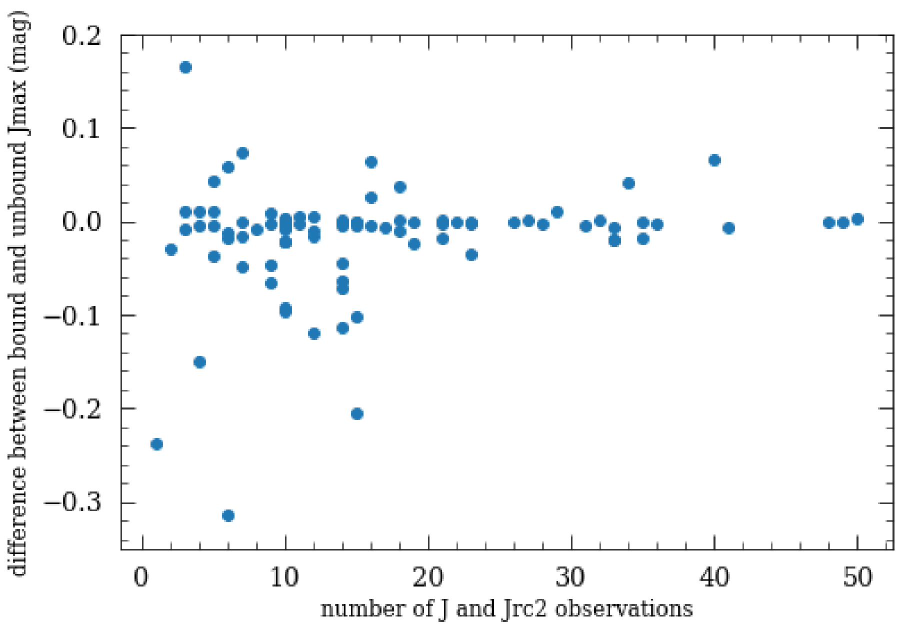


Figure 9: Number of observations against the difference between the bound and unbound Jmax values. This is a zoomed in version to see the distribution around zero more easily.

than the other methods since only the J band data was used, and sometimes this was not enough to fit the light curves properly. The 19 SN that couldn't be fitted were tabulated with their reason for not fitting, and then plotted in a histogram according to the number of J band observations.

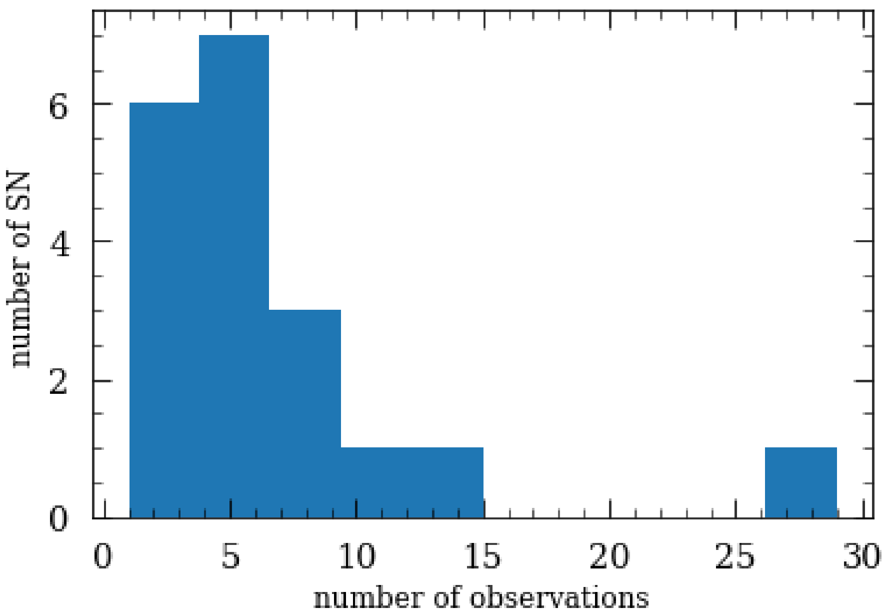


Figure 10: Histogram of the number of observations for the 19 SN that couldn't be fitted.

As seen from the graph most of these SN had few observations. While SN2008ff had 29 observations, many of which occured very close together in time, which is probably why the fit didn't work.

I then repeated the above analysis by constraining Tmax using a B band light curve fitting, as done previously. This worked for 92 SN, while there was not enough J band data for the 5 other SN. When the initial B band fitting failed I used the same process as yesterday, such as trying to fit in the V band first. I was now able to create a summary .txt file which recorded the number of SN sampled for each of the four max model J band methods, with a list of the SN that failed for each and their reason for failing.

I tabulated the SN from Burns 2018 that had an Sbv less than 0.5 and added this to my plot for the 92 SN just sampled.

I conducted chi-squared analysis on the 92 fits to compare to the idealised line of best fit. Setting the 3 parameters q0, j0 and aj as free variables wouldn't terminate so I kept q0 and j0 equal to their ideal constants and only allowed aj to vary. This give 5aj as 2.723 mag, within 5 standard errors from the model value. I plotted the curve using this value of aj in the above plot for comparison.

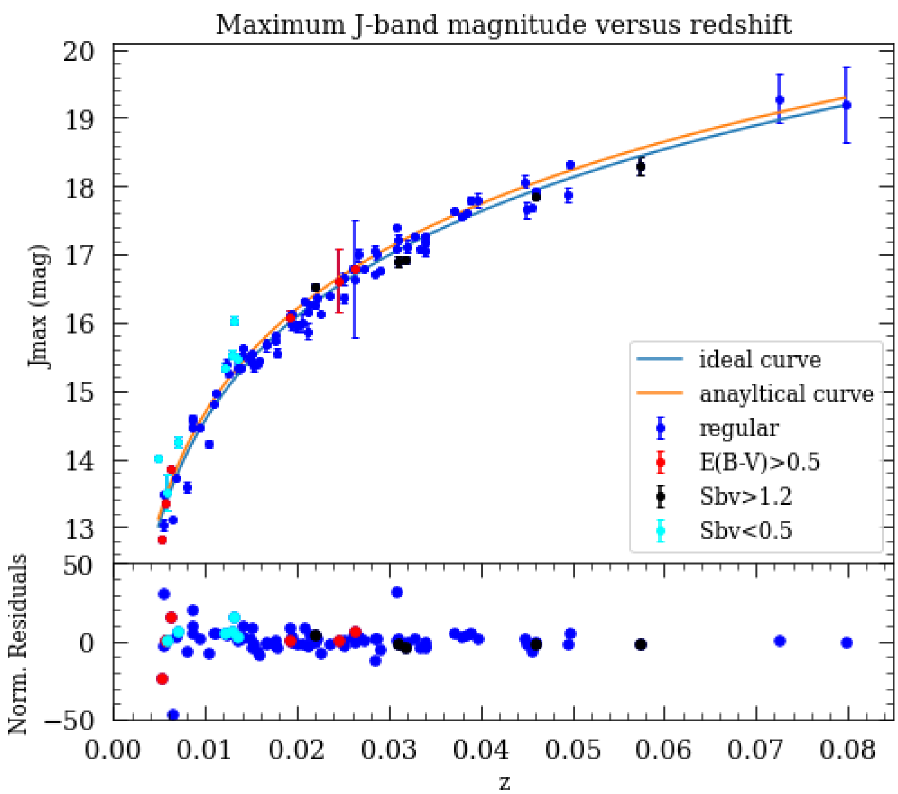


Figure 11: Redshift verses maximum J band magnitude for 92 SN fitted using Tmax from the B band data and light curve fittings solely for the J band. Idealised line of best fit from Suhail et al 2018 and an analytical fitting line using a single parameter chi-squared analyis of the intercept.

I also computed the standard deviations of the difference between my Jmax values and the idealised values. These varied between 0.19 and 0.30 depending on the different combinations of data groups used, e.g. for cases where E(B-V) was less than 0.5.

3 Week beginning 19/07/2021

Monday: I repeated the chi-squared analysis with an additional 'sigma-int' term, and varied this term such that the chi-squared analysis indicated a good fit. I also included an error based on the peculiar velocities of the SN according to Dhawan et al 2018, which reduced sigma-int from 0.19 mag to 0.15 mag. I divided this analysis into the 'quiet' and 'loud' models of the universe's local structure by using sigma-pec values of 150kms-1 and 250kms-1 respectively. This allowed me to replot z against jmax for the max model, with lines of best fit that apply various conditions overlaid. The initial value for sigma-int of 0.15 mag is considered large, and Suhail and I explored why this might be the case. Suhail suggested that the Gaussian likelihood contains a normalisation term in the chi-squared fitting which cannot be ignored when adding terms in the errors, and that this might cause the value to be so large. During the day I also attended a meeting with Kaisey Mandel and Stephen Thorp. I showed them some of my initial graphs and Stephen explained to me the work he was doing for his PhD, building an analysis tool similar to SnooPy.

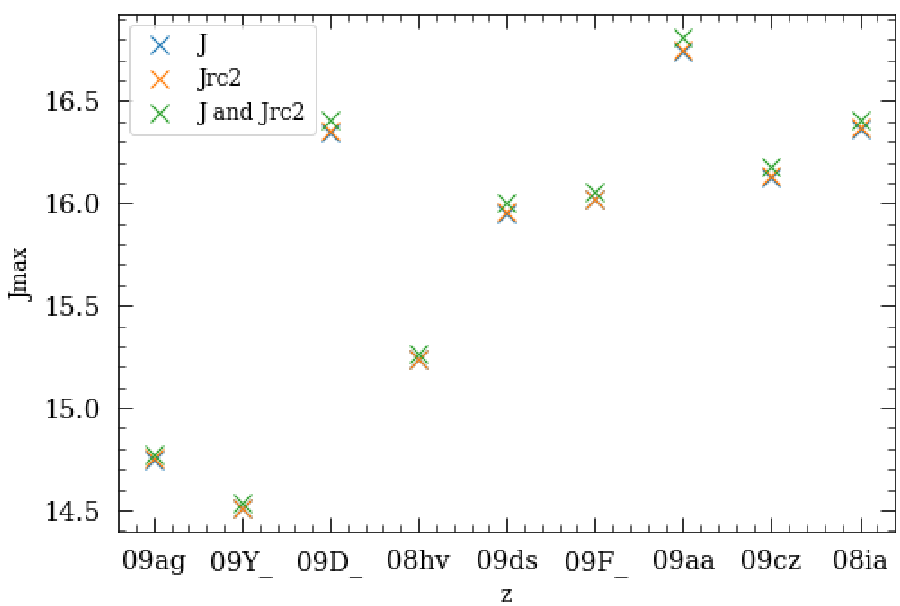


Figure 12: Comparison between max J-band magnitudes values from SN with J and Jrc2 data.

Tuesday: I tabulated my chi-squared statistics including the parameter values and their errors for q0, j0 and aj where necessary. I started to repeat the light curve fitting with the EBVmodel2 but realised the command for Jmax I used previously wouldn't work for EBVmodel2. Suhail and I investigated the difference in SNooPy between s.Jmax and s.get-max(["J"]) in cases for J-band data with and without Jrc2 data. We concluded that I should use s.get-max(["J"]) for all analysis. I tabulated the SN with both J-band and Jrc2 observations to compare the values of get-max(["J"]), get-max(["Jrc2"]) and get-max(["J","Jrc2"]). The graph shows that the values are very similar. It suggests that J is always the lowest value, followed by only Jrc2 and then both. Generally the individual ones are a much closer magnitude than using J and Jrc2 together. I decided to use all the data from both bands where possible.

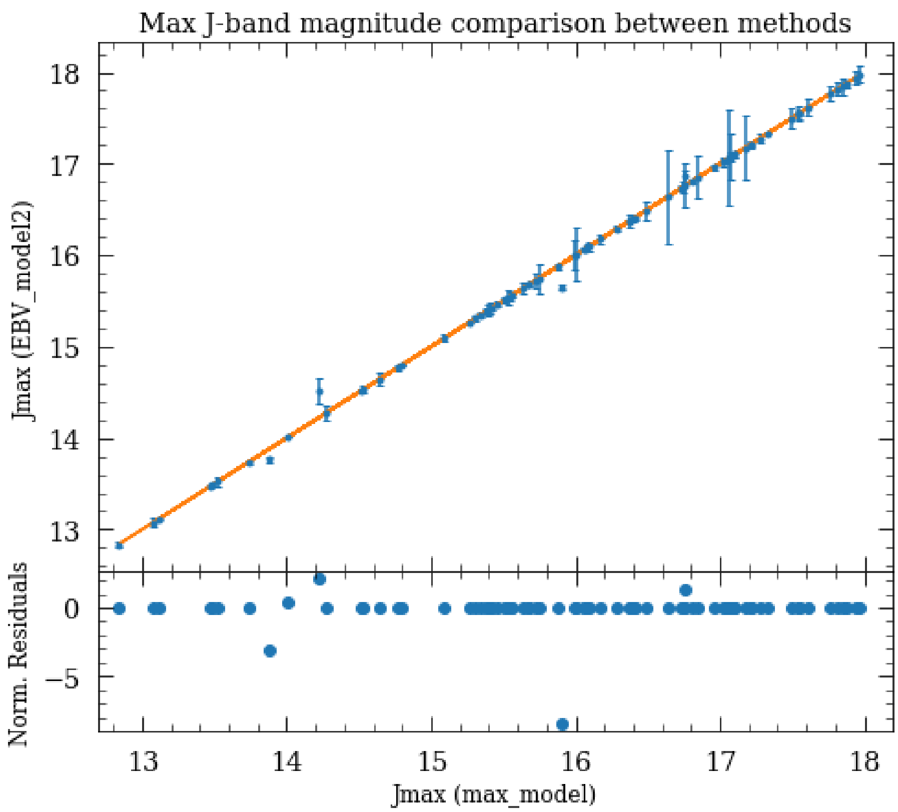


Figure 13: Comparison between max J-band magnitudes values from fitting with the EBVmodel2 and the max model.

The initial z against Jmax plot for the EBVmodel2 had extremely large errors on a lot of the SN. For each one I plotted the fit and in most cases the number of observations around the peak (or at all) was very small (or not over a large enough time) and so the SN was removed from the plot. In some cases such as SN2006mr, the intial fittinf was Tmax for B was the problem so V-band observations were used instead.

I also looked into how to proceed from the z against Jmax plot to get to a value for the Hubble constant. I imported the Cepheid variable distance modulus data from Burns 2018 into python and cross-referenced this with my dataset. However there were only two SN in both groups, so I would need to obtain more distance modulus estimates elsewhere.

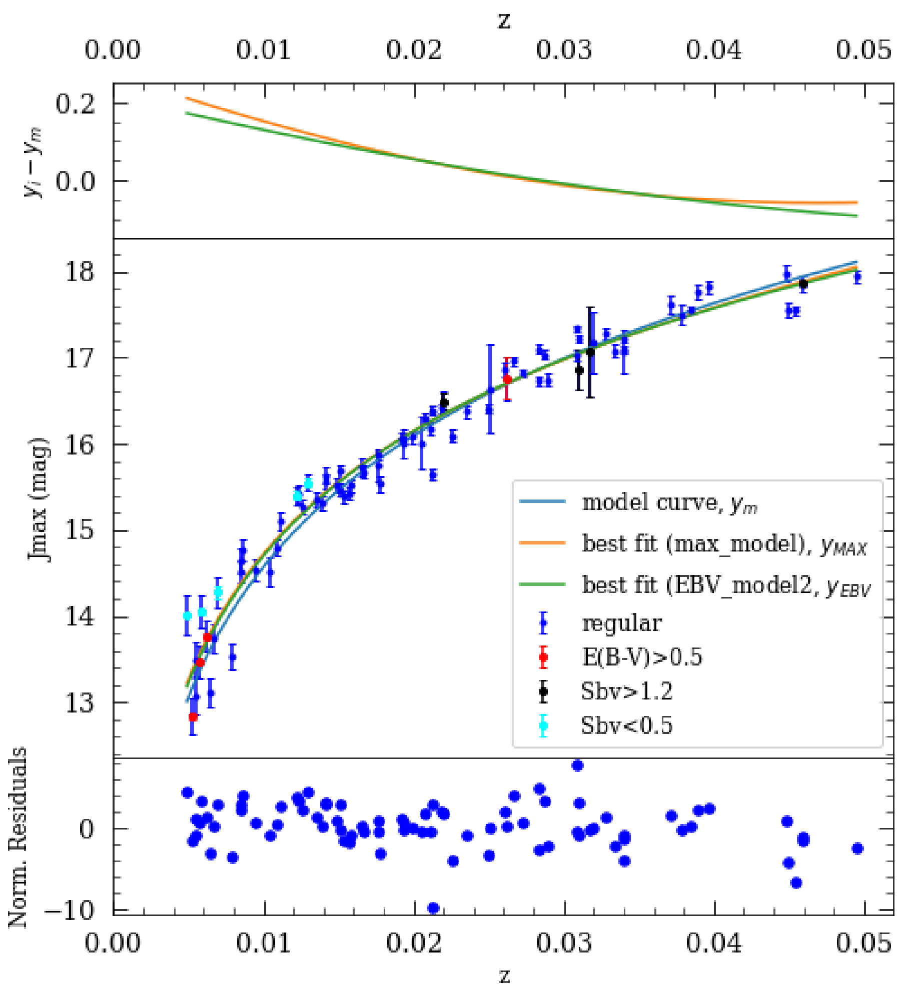


Figure 14: Maximum J-band magnitude against redshift for SN fitted according to the EBVmodel2, with best fitting lines from EBVmodel2 and max model.

Wednesday: I continued to look at the fits for the SN which large errors in the Jmax versus z plot. To help with this I plotted the Jmax values from the EBVmodel2 data against the max model data, SN with large discrepancies between the models indicated a poor fitting. On the remaining SN I applied chi-squared statistics once more with sigma-int and peculiar velocities error. I plotted these results alongside the same best fitting curve from the max-model.

I tabulated the chi-squared statistics for the new modelling and updated the max model statistics from switching to the get-max() for J-band magnitudes. This included sigma-int terms which were very similar between models, as well as the peculiar velocity errors.

I then continued to analyse the fitting discrepancies between the max-model and the EBV-model2 fittings by looking back at the plot in figure 13. For the SN with the largest normalised residuals I looked at the plots of the light curve fittings for each model. Most of the time one of the model simply fit the data better than the other and EBV-model2 was usually the culprit for poor fitting. In this case I repeated the fittings with an initial filter that wasn't B (I always tried the V-band first), and observed how this would affect the fittings. When another filter significantly improved the fitting to the data I noted this down and adjusted the plot to see the result on the residuals. Overall, I was able to get all Jmax values bar one to differ by no more than 1 error for all SN that could be fitted successfully by both models. SN2008ar differed by 1.4 errors but there was no legitimate reason to remove it since it had good J-band coverage around the peak and the light curve visually fitted the data well for both models.

Thursday: I read through suhail's 2018 paper to understand how to get from the Hubble plot to a value for Hubble constant. I then took the distance modulus values from Cepheid variables in Burns 2018. Only two SN were still in my dataset for each model. I followed the analysis in Dhawan 2018 and calculated the error propagations to calculate H0 for the max-model and EBV-model2. However the final value must be kept blind before any analysis is done to avoid bias. Consequently I removed the H0 calculation from my analysis after realising this.

I briefly explored GitHub repo's and then met with Suhail. We discussed when we would install SnooPy from source, GitHub repo's including Suhail's own one for the 2018 paper as well as the next steps for the project. After the meeting I spent the rest of the day cleaning up my code and making it more function orientated.

Friday: I went through the questionable fittings from both models very carefully and kept track of the different categories that the SN fell into. I carried on changing the programming methodology, especially looking into improving the way I handle cuts in the sample. E.g. plotting SN with high EBV. I automated this to make this clear and easier to use. With the improved code I made Hubble plots for each model that included the poorly fitting SN, as well as other criteria.

Table 1: The number of SN in various cuts of the SN in CSP DR3.

	max-model	EBV-model 2
Total SN fitted	97	97
fitting worked	92	91
Visually poor	7	10
non B-band	5	4
$EBV > 0.5$	6	6
$sBV > 1.2$	5	5
$sBV < 0.5$	8	7

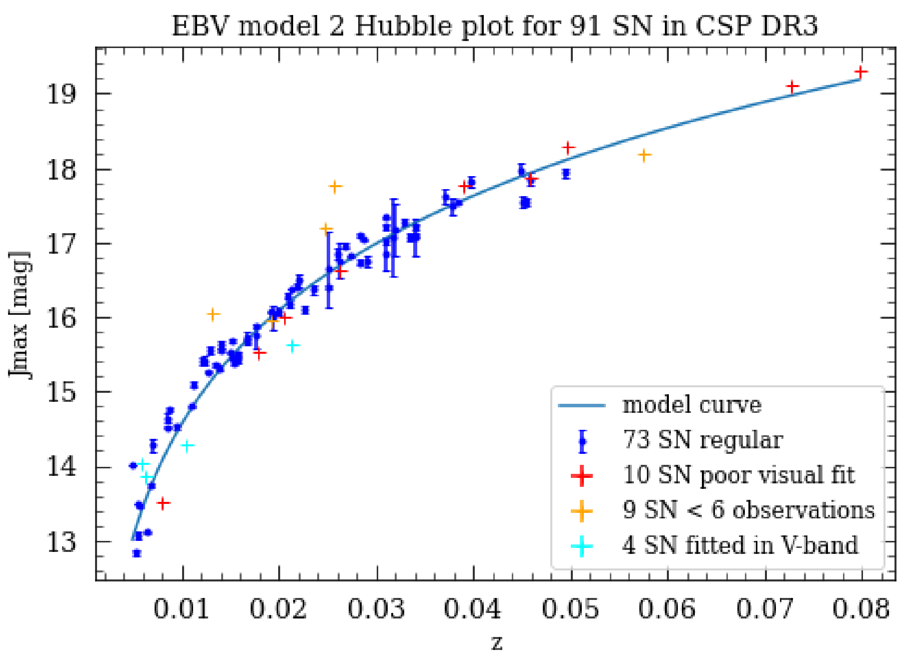


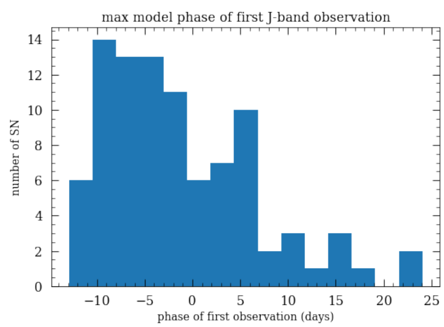
Figure 15: Hubble plot for the EBV-model2 with all non error SN included. The non-regular SN are shown without error-bars since some of these exceed the plotting area.

Table 2: The number of SN with observations before 5 and 10 days after Tmax.

	max-model	EBV-model 2
SN fitted	92	91
phase < +5	74	75
phase < +10	82	81

4 Week beginning 26/07/2021

I calculated the time of the first observation for each SN and by subtracting Tmax from this to calculate the phase. I plotted this for each model, with the max model plots shown. The histogram shows that the majority of the SN have observations before Tmax. The SN with observations before Tmax tend to have smaller errors in Jmax, as seen in the scatter plot. I explored the SN with errors above 0.2 mag, of which there were 6 SN in EBV-model2. For some of these SN I plotted the fitted light curves in an effort to understand the reasons for the large error. In most cases the observations were either very close together or not many at all.



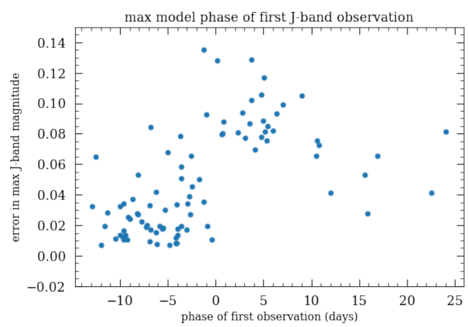


Figure 16: Left: Histogram of phase for SN that were fit in DR3. Right: phase plotted against the error in maximum J-band magnitude.

I then calculated the number of SN with first detection less than 5 and 10 days after Tmax, and added this to the summary file.

Tuesday: I explored the emcee analysis tool by investigating the example given in the online documents. I then applied this to the Hubble plot using a model function given by equation 6 in Dhawan 2018, that included an intrinsic scatter error called sigma-int. After a few problems with the form of the likelihood function I managed to get the mcmc analysis to work and produce parameter values for aj and sigma-int that made sense. I tabulated the parameter values for lots of combinations of cuts and conditions. I was now able to plot Hubble diagrams using model curves from mcmc fitting instead of chi-squared analysis.

Table 3: Parameter values and errors for EBV-model 2 Hubble plot model function parameters from mcmc fitting.

	num of SN	5aj	sigma
all fitted SN (LM)	91	2.776(+30/-30)	0.236(+26/-23)
all fitted SN (QM)	91	2.770(+31/-31)	0.261(+25/-23)
- <6 obs and poor fits (LM)	77	2.797(+27/-26)	0.175(+24/-21)
- <6 obs and poor fits (QM)	77	2.781(+27/-27)	0.210(+24/-21)
- sBV<0.5 as well (LM)	72	2.816(+25/-25)	0.164(+23/-20)
- sBV<0.5 as well (QM)	72	2.809(+25/-26)	0.187(+22/-19)
- EBV>1.2 as well(LM)	68	2.818(+24/-26)	0.165(+23/-19)
- EBV>1.2 as well(QM)	68	2.812(+26/-26)	0.187(+22/-19)

Table 4: Table displaying parameter values and errors for max model Hubble plot model function parameters from mcmc fitting.

	num of SN	5aj	sigma
all fitted SN (LM)	92	2.771(+29/-30)	0.244(+26/-23)
all fitted SN (QM)	92	2.763(+30/-30)	0.270(+26/-22)
- <6 obs and poor fits (LM)	80	2.795(+26/-25)	0.186(+25/-22)
- <6 obs and poor fits (QM)	80	2.778(+27/-28)	0.226(+24/-22)
- sBV<0.5 as well (LM)	74	2.826(+22/-22)	0.148(+21/-19)
- sBV<0.5 as well (QM)	74	2.818(+23/-22)	0.172(+20/-18)
- EBV>1.2 as well(LM)	69	2.830(+23/-22)	0.152(+22/-19)
- EBV>1.2 as well(QM)	69	2.821(+23/-23)	0.176(+21/-19)

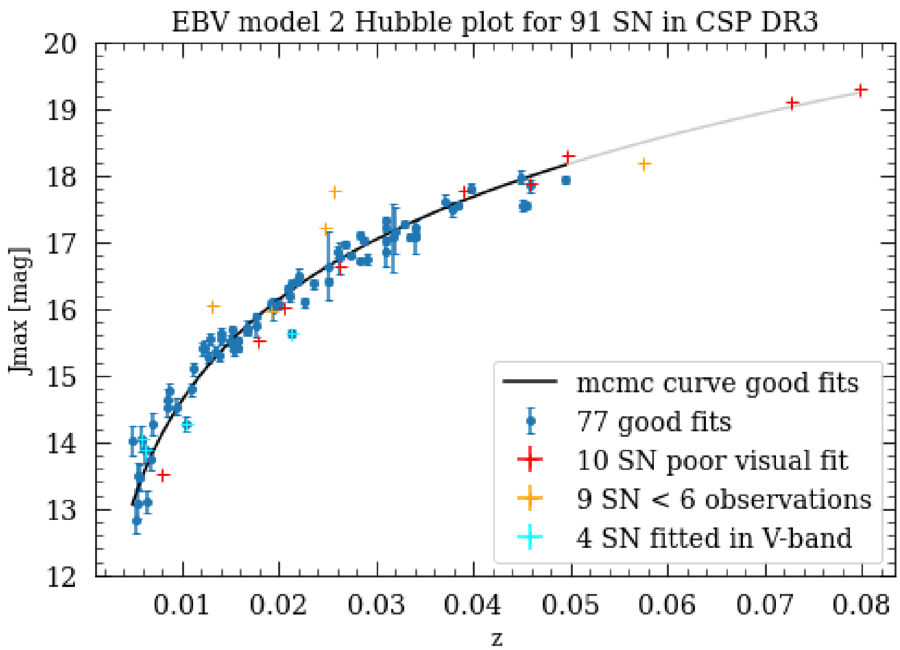


Figure 17: Left: Hubble plot for the EBV-model2 fittings with mcmc analysis conducted on the 77 so called 'good fits'.

Wednesday: I repeated the fittings in the H-band instead of the J-band for EBV-model2 and max-model. I kept a record of the SN that couldn't be fit, as well as the different categories of the fittings. I also tabulated the phase of the observations similarly to J-band observations.

Thursday: I plotted the values of aj from the mcmc fitting against the number of SN in the cut for the J-band data. I explored NASA's NED database, looking at redshift errors. I then tried to install SNooPy from source on my laptop and desktop. Both didn't work but I made good progress in the installation process.

Friday: I met with Suhail, he sent me the calibrator SN data and he helped me install SnooPy from source. We changed the filter system to recognise non CSP DR3 filters and discussed how to use MCMC fitting to fit for Hubble's constant and the absolute magnitude immediately from the Hubble plot and the calibrator distance moduli.

I tabulated the filter names for the B-band and J-band for the calibrator SN. I then fit these SN for the max-model and EBV-model2 using the same conditions as before except with the respective filter name. I had a few issues withe the fittings, particularly with SnooPy not recognising some of the filter names and

Table 5: The number of SN in various cuts of the SN in CSP DR3 from H-band fittings.

	max-model	EBV-model 2
Total SN fitted	94	94
fitting worked	87	86
Visually poor	>3	>1
non B-band	7	4
phase < +5	65	66
phase < +10	77	79

then recognising them after restarting the kernel. 5 of the 21 calibrator SN had no J-band data while SN2007sr and SN2007af were already in CSP DR3 so in total there were 16 SN with distance moduli data, 14 of which were new SN. 3 of these SN showed reasonably poor visual fits (SN1981B, SN2003du, SN2007sr) particularly for max-model. I added these to the Hubble Plot for comparison, it is standard to not include these in the Hubble plot but it shows how low redshift the calibrator SN are, which is a result of Cepheid's only being detectable out to about 30Mpc, corresponding to a redshift of about 0.007.

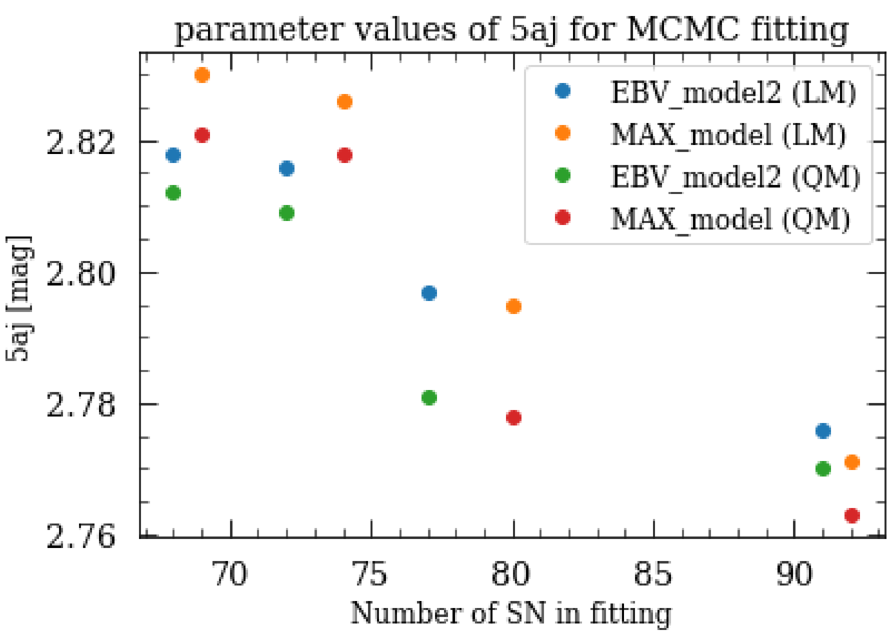


Figure 18: Value of parameter value 5aj for different cuts and models.

5 Week beginning 2/08/2021

Monday: I tabulated the distance moduli values and their errors for the calibrator SN, first from Burns et al 2018 and then from Freedman et al 2019, the latter has the most recent distance measurements. I carefully looked through Suhails notebook 'full-analysis' in conjunction with the Dhawan 2018 paper to understand the process by which MCMC is used to fit for H0, Mj, aj and sigma instantaneously. I drafted code in my notebook that followed this process. I used pretty much the same prior and likelihood functions, only for the above parameters, and then adapted Suhail's code for the parameters and error propagation. After some troubleshooting I managed to obtain sensible values, sample plots and corner plots. A sample plot for sigma is included.

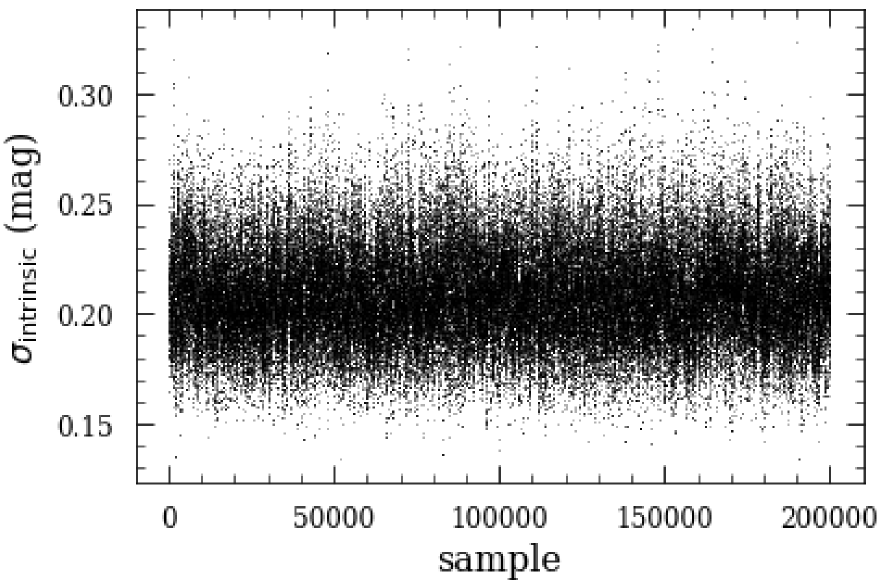


Figure 19: Sample plot for the intrinsic scatter value from MCMC fitting.

Tuesday: I compared the new MCMC fitting of Mj and H0 with the previous MCMC fitting of only aj. As an example, for the max-model Loud model with sBV < 0.5 removed 5aj=2.826(+0.022/-0.022) [mag] and 5aj=2.821(+0.022/-0.021) [mag] for the previous and new techniques respectively. This shows good agreement between the two fitting methods and validates sequentially fitting Mj and H0 alongside aj. I then added a cut for all SN with z < 0.01 to account for the fact that the local peculiar velocities can't be trusted for nearby SN. This removed all 16 calibrator SN and around 10 additional SN depending on what cuts had already been made. I explored the effect this cut had on the terminating parameter values, these are tabulated and the corner plot with the low redshift SN removed is included.

Table 6: Comparison of parameter values for fittings with and without low redshift SN included. For max-model LM with sBV < 0.5 removed.

	z < 0.01 removed	z < 0.01 included	z < 0.01 included + corr
Mj	-18.471(+45/-46)	-18.470(+46/-47)	-18.484(+47/-46)
5aj	2.833(+22/-23)	82.821(22)	82.824(22)
sigma	0.148(+19/-17)	0.153(+19/-17)	0.153(+19/-17)

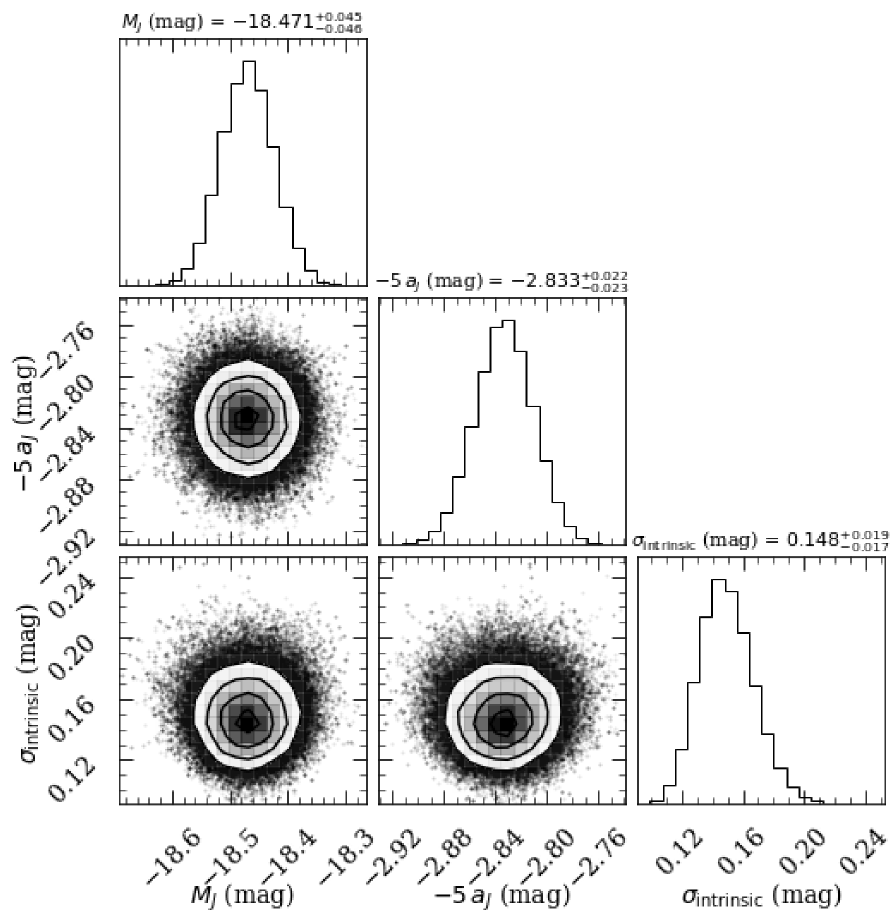


Figure 20: Corner plot for max-model with z < 0.01 SN removed.

Table 7: MCMC fitting Parameter values for various lowest redshift cutoffs.

z cutoff	Num of SN	Mj [mag]	5aj [mag]	sigma [mag]
0.0000	88	-18.482(47)	2.824(22)	0.153(+18/-17)
0.0025	85	-18.482(+46/-47)	2.825(22)	0.152(+19/-17)
0.0050	80	-18.484(47)	2.830(+22/-21)	0.152(+19/-17)
0.0075	68	-18.484(46)	2.824(22)	0.151(+19/-17)
0.0100	63	-18.484(+46/-45)	2.834(23)	0.150(+18/-17)
0.0125	59	-18.484(+46/-45)	2.836(23)	0.149(+19/-17)
0.0150	53	-18.485(46)	2.847(+24/-25)	0.151(+20/-17)
0.0175	46	-18.485(+49/-47)	2.842(+27/-27)	0.159(+21/-19)
0.0200	39	-18.484(51)	2.845(30)	0.169(+24/-21)
0.0225	33	-18.483(+48/-49)	2.841(+31/-32)	0.160(+24/-21)
0.0250	31	-18.484(+49/-47)	2.833(+33/-32)	0.161(+25/-21)

I met with Suhail and talked about how to correct for the supernova restframe and also for the milky way extinction. I was given some more data and we discussed the next steps. I then added these corrections to my code but couldn't get the restframe=1 (this corrected for the supernova restframe) term in the get-max() command to work for multiple filters at once. However this made me realise that I am not using get-max() for multiple filters quite correctly, since the value of Jmax depends on the order of the filters specified. Since this was only important in the CSP DR3 data for SN with J and Jrc2 measurements I decided to only use Jrc2 data for Jmax values since in almost all cases where there were Jrc2 measurements, there were more Jrc2 observations than J observations. This also allowed the restframe term to be added without producing an error. As well as this I also subtracted $0.81 * s.EBVgal$ from the value of Jmax to account for the milky way extinction. The effect this had on the parameter values from the fitting is also included in table 6. The main effect this has is decreasing the absolute magnitude (brighter) which would be expected since the milky way extinction correction decreases the apparent peak J-band magnitude.

Wednesday: I wrote some code to quickly cut SN from the sample that had a redshift lower than a given value. I then conducted mcmc fittings on the sample using a lowest possible redshift from 0.000 to 0.0250 with 0.0025 increments. I tabulated the parameter values of aj, Mj and sigma.

The table shows that adjusting the lowest redshift cutoff significantly decreases the sample size, with less than 40% of the SN left when a lower bound of $z = 0.025$ is used. The values of Mj are largely unchanged and while aj and sigma vary these changes are within their error bars so any conclusions are insignificant.

Thursday: I unpacked the RATIR data and loaded it into python. SnooPy wasn't able to recognise most of the filters used in the RATIR sample that do not appear in CSP data sets. I explored this issue but Suhail pointed out that this was an issue to do with the directory path to the filters, which I then solved. Most of the filters were now recognised, except, P48 filters and rc filters. The

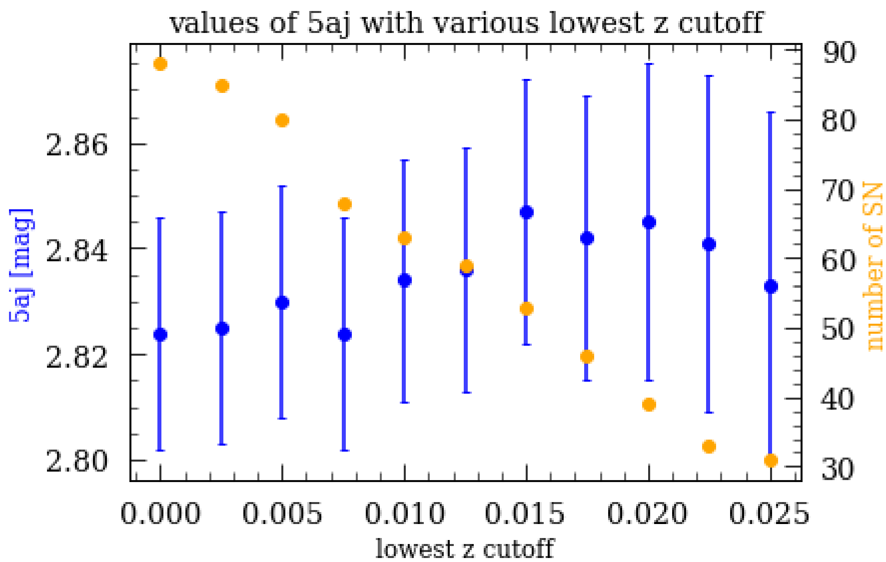


Figure 21: 5aj parameter values for various lowest redshift cutoffs, with the number of SN in the sample plotted.

rc filters only appeared in one SN, which didn't have J-band data so these were ignored. The P48 filters were fixed by changing the filters.dat file to match the filter names in the SN.dat files.

I also loaded the file for the host masses into python and wrote code to read the masses for a list of SN. I tested this on the CSP DR3 and then split the Hubble plot into SN with host masses above and below $10^{10} M_o$.

Friday/Weekend: Due to the large numbers of different filters in the RATIR sample my previous method for fitting the SN automatically wouldn't work. Consequently I iterated through the sample to find all the B-band and J-band filters that appeared. I made lists for these and then my code iterated through each SN to see if each filter was in the sample. It then fitted the SN with whatever B-band (and then J-band) filters appeared. However due to the SN being at different redshifts some filters appeared were actually observing different restbands. E.g. B60 sometimes appeared in restband Bs as well as u. However removing these filters from my list would have unnecessarily dropped the fitting data for many SN so these filters were kept in. Of the 44 SN in RATIR I fitted the 38 which had J-band data. Of these, 30 SN were able to be fit, with 8 not being able to fit. In all cases this was caused by poor J-band coverage. Some erroneous SN were still able to be fit; when the B-band coverage was poor the r-band was chosen. This differed to previously where the V-band was used, however the V-band usually had similarly few observations as the B-band whereas the r-band typically had lots of data.

Tuesday: I finished off the fittings for RATIR and plotted the Hubble plots

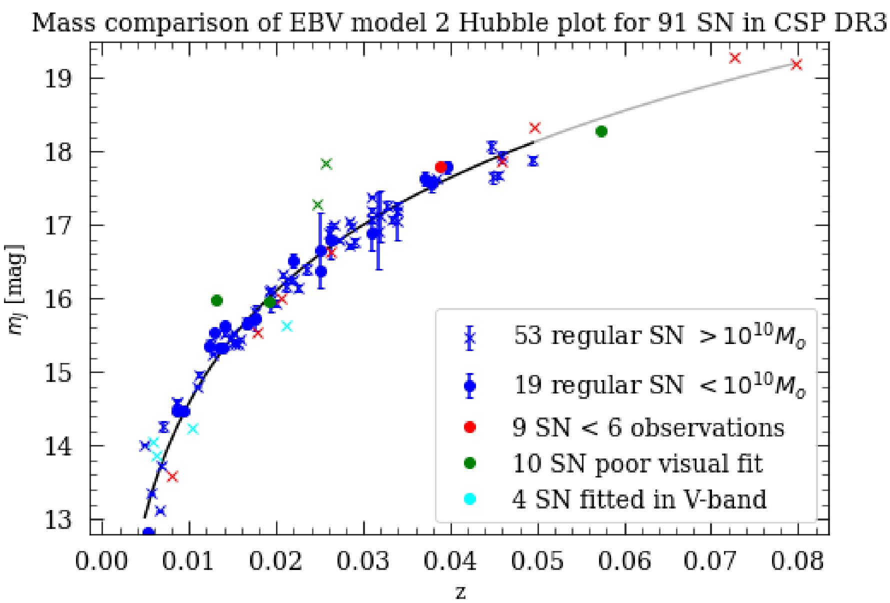


Figure 22: Hubble plot for CSP DR3 with masses split between symbols.

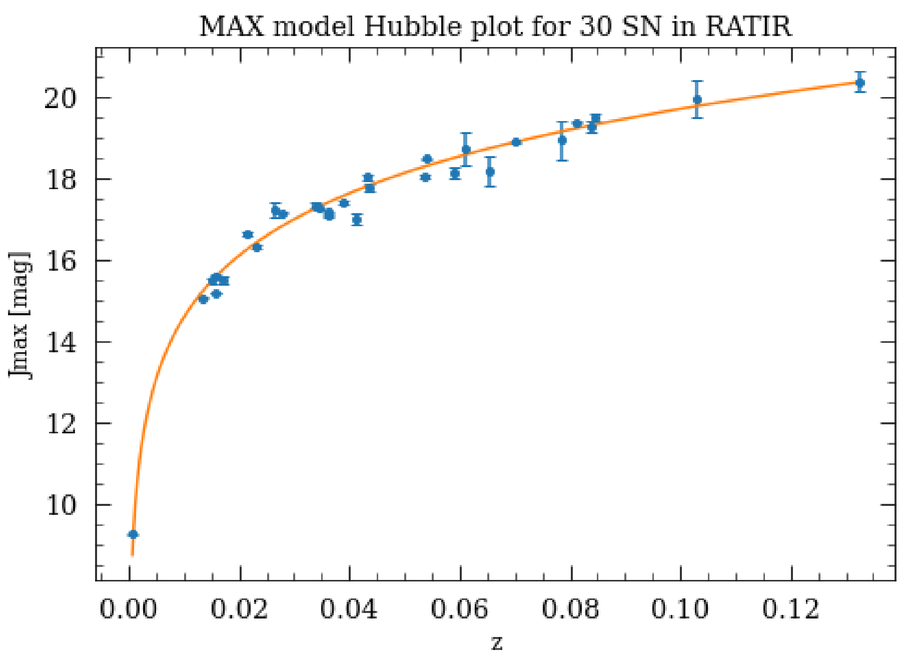


Figure 23: Hubble plot for CSP DR3 with masses split between symbols.

for both models. The MAX model plot is shown. The EBV model 2 plot has a few SN with significantly large errors, which was also the case for CSP DR3 and must be indicative of the model fitting. I also used code to record the number of J-band observations for the SN in RATIR. 59% (26/44) of all the SN in RATIR had 0-5 J-band observations, while 40% (12/30) of the successfully fitted SN were also in this category. In the CSP data these were removed but due to the large fraction this cannot be the case for RATIR. I also compared the max

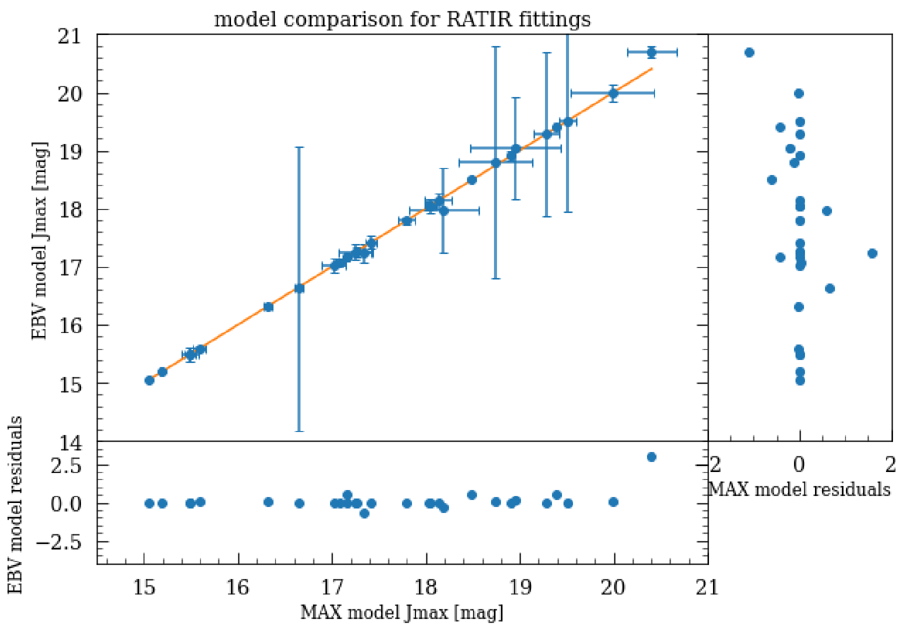


Figure 24: Histogram of the number of J-band observations across all J-band filters for the SN in RATIR. This excludes SN2014J which has 59 observations.

model Jmax values with that of EBV model 2 by plotting them against each other, alongside their residuals. Unlike CSP DR3, the RATIR sample had no SN with residual differences between the two models of more than 3 errorbars. This indicated that the models generally agreed on the Jmax values and that the errors were not hugely underestimated.

Wednesday: I added a $z < 0.01$ cut to the sample. This removed SN2014J. The 8 fits identified as being questionable were kept in to maintain sample size in later cuts. A $sbv < 0.5$ cut was also added. These values were taken from the EBV-model2 sbv values produced in the fitting. A $EBV > 0.5$ cut was also included. This couldn't be taken from the EBV-model2 fits since EBVhost=0 was applied to allow fitting in single bands. Consequently a separate all band fitting was undertaken on the RATIR SN. Originally I wanted to use the color-model for this but too many fittings were erroring so the EBV-model2 was used. The EBV values were calculated, resulting in SN2014aje and SN2013ahk being removed. I tabulated the SN with $sbv > 1.2$ of which there were 6. Most of these had either questionable fits or large Jmax errors.

I added the mass splitting code for RATIR and passed the RATIR SN through the host-masses file. I had to alter a few of the SN labels to match up with the formatting of the host-masses file. This allowed me to conduct MCMC analysis on different mass cuts for RATIR. The parameter values are included in table 8. My additional categories were: all mass values, high mass values ($> 10^{10}M_o$) and low mass values ($< 10^{10}M_o$). For all the following parameter values the quiet model (sigma-pec=150kms-1). I combined these with the SN from CSP DR3 to produce a Hubble plot.

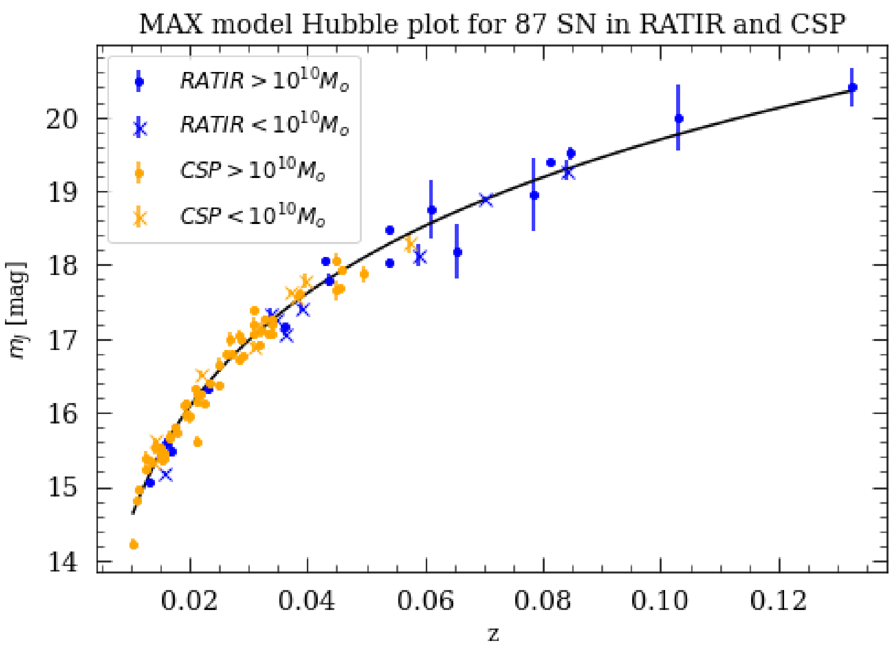


Figure 25: Hubble plot for CSP DR3 and RATIR with masses split between symbols.

Thursday: I repeated the mass splits for CSP DR3 separately and then with CSP and RATIR combined. I exported all the corner plots and from this the 5aj values are tabulated in table 8 alongside the std deviation values. These represent the discrepancy of 5aj from the equivalent all masses value divided by the error on the parameter. The variation of 5aj with different mass cuts can clearly be seen in the parameter plot. Interestingly RATIR and CSP disagree on the parameter value variation from high and low masses. And while MAX model and EBV model 2 do yield similar results, the MAX model points agree more closely.

I then setup my github repo and cleaned up the code for RATIR with CSP,

Table 8: MCMC fitting values of 5aj for RATIR and CSP mass splits.

SN sample	model	masses	num of SN	5aj [mag]	std dev
RATIR+CSP	MAX	all	87	2.845(+21/-20)	
RATIR+CSP	EBV	all	86	2.842(22)	
RATIR+CSP	MAX	high	69	2.849(22)	+0.18
RATIR+CSP	EBV	high	69	2.838(24)	-0.17
RATIR+CSP	MAX	low	17	2.856(+52/-51)	+0.22
RATIR+CSP	EBV	low	16	2.857(60)	+0.25
CSP	MAX	all	61	2.836(+22/-23)	
CSP	EBV	all	60	2.826(25)	
CSP	MAX	high	53	2.850(+25/-24)	+0.58
CSP	EBV	high	53	2.842(27)	+0.59
CSP	MAX	low	8	2.747(+73/-75)	-1.22
CSP	EBV	low	7	2.701(+82/-83)	-1.52
RATIR	MAX	all	26	2.870(+46/-45)	
RATIR	EBV	all	26	2.887(+50/-49)	
RATIR	MAX	high	16	2.851(+58/-60)	-0.33
RATIR	EBV	high	16	2.825(+63/-64)	-0.98
RATIR	MAX	low	9	2.952(+72/-70)	+1.17
RATIR	EBV	low	9	2.992(+80/-79)	+1.33

including the MCMC fitting, before adding this to the repo and making it public.

Friday: I continued to add files and folders to the github repo, including the raw SN .txt or .dat files, as well as the light curved fitted SN .snpy files. I also improved the distance modulus data importing method in the notebook from a list to a .dat file that I imported in python.

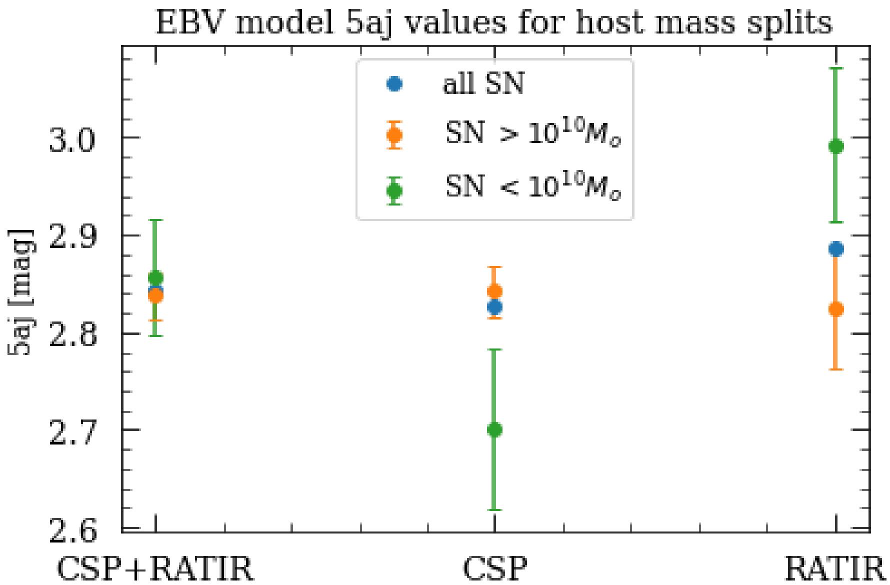


Figure 26: Plot of 5aj for different mass splits using EBV-model2.

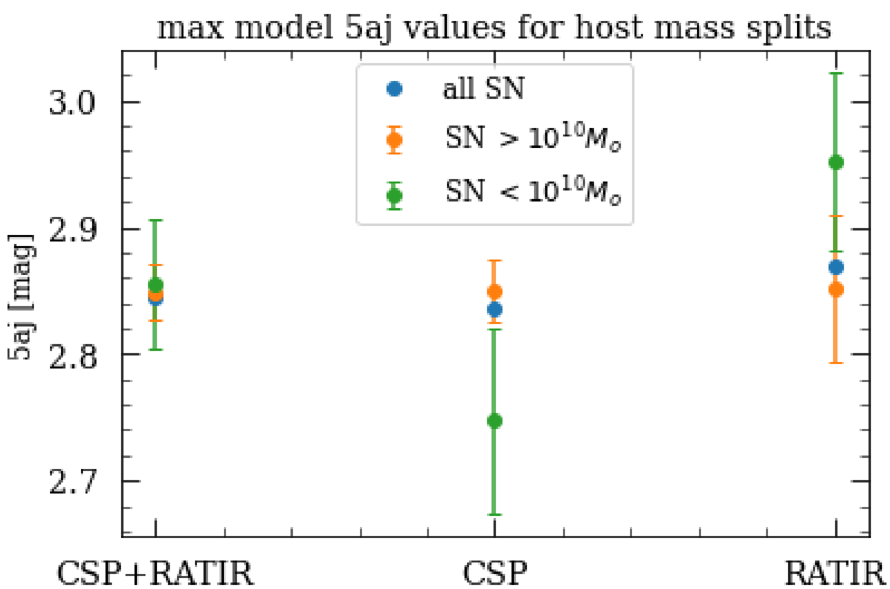


Figure 27: Plot of 5aj for different mass splits using MAX-model.