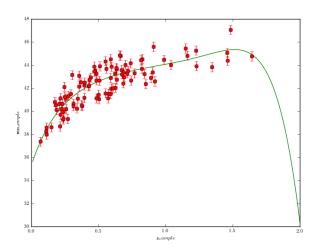
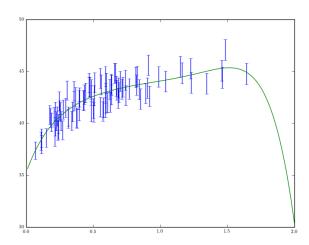
1 Problem 2

1.1 PartI Polyfit

This is part 1 diagram 6th order polynomial fit using polyfit with 1-sigma error bar. This is the result of code I wrote myself.



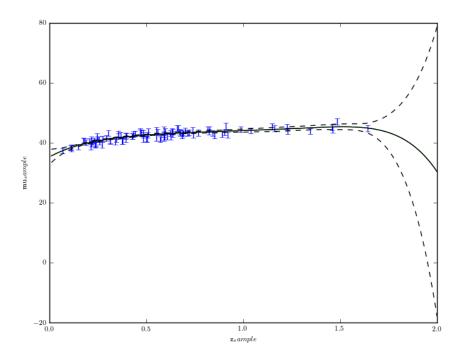
This is what I use your code for the same part1.



1.2 PartII Frequestist

This diagram is Frequentist case for 6th order polynomials fit with 90percent confidence error bars. I did not able to shade using fill-between command. I will learn it soon. But

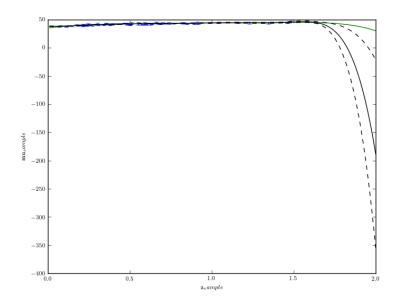
right now I was unable to write code that show shade for 1 sigma confidence intervals.In this dashed code line showing 90 percent confidence interval: The routine for error bars I use yhat +1.6sigma and yhat -1.6sigma, where sigma is sqaureoot or standard deviations obtained from diagonals of inverse covariance matrix. In I-python notebook I mention the expression for error bars



This is the line for errornbars in the code.

```
plt.plot(z, yhat + 1.645*np.sqrt(sigma_yhat_2),'k--') #90% confidence error bars
plt.plot(z, yhat - 1.645*np.sqrt(sigma_yhat_2),'k--')
```

Now for change in the basis I am not sure how to code up this but I know Instead of polynomial we can define say cosine function or for Chebyshev the third column of design matrix F will be replace by 2nd degree Chebyshev polynomial which is $2x^2$ -1. I changed my basis as coskx type. The result of that change in basis is this.

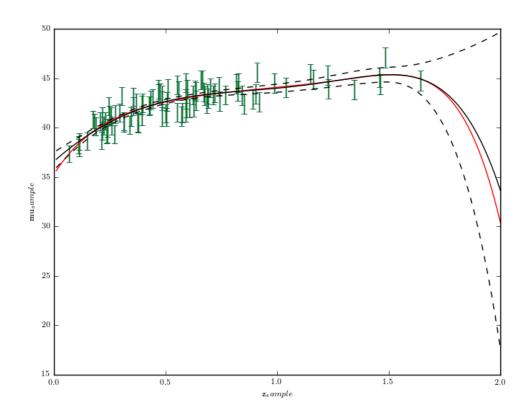


So I think there will be change once we change basis.

1.3 PartIII Bayesian

This is Bayesian case. So for prior I use the definition given that is all the diagonals for n>2 is $\frac{1}{2^k}$. This is my matrix form for prior.

So for Bayesian case I got this graph.



1.4 PartIV Smoothness Prior

This is L=1 smoothness prior case. First of I use math mathematica to get these expression to figure out the Inverse covariance matrix from

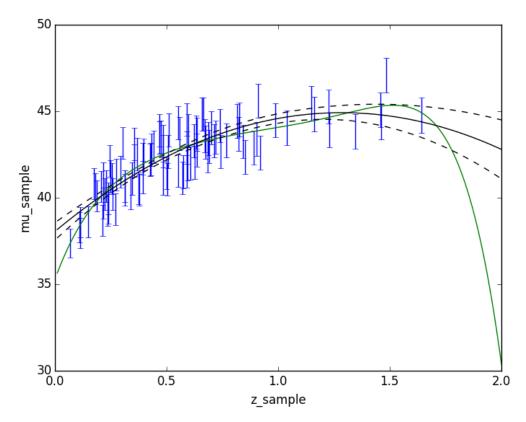
$$p(\lambda) \propto \exp{-L^5 \int_0^2 dz} (\sum_{lpha} F_{lpha}^{\prime\prime\prime} \lambda_{lpha})^2$$
 :

It turns out that using equation the polynomial coefficient of powers and products of parameters gives the components of inverse covariance prior matrix. e.g for Γ_{12} we can use coefficient of $\lambda_1 * \lambda_2$. So This is what I did in mathematica

```
P = 6 * a * 24 * x * b * 60 * x^2 * c * 120 * x^3 * d
6 a * 24 b x * 60 c x^2 * 120 d x^3
PP = Expand[P*P]
36 a^2 * 288 a b x * 576 b^2 x^2 * 720 a c x^2 * 2880 b c x^3 * 1440 a d x^3 * 3600 c^2 x^4 * 5760 b d x^4 * 14400 c d x^5 * 14400 d^2 x^6
Integrate[PP, \{x, 0, 2\}]
72 a^2 * 576 a b * 1536 b^2 * 1920 a c * 11520 b c * 23040 c^2 * 5760 a d * 36864 b d * 153600 c d * \frac{1843200 d^2}{7}
```

and than perform equating coefficient to get this matrix.

So adding this prior smoothness to bayesian case I got this graph. For L=1 case



For L=1 case

1.4.1 Comparison

So the graphs for 6th order fit using frequentist, Basiyan and Smoothness prior is.

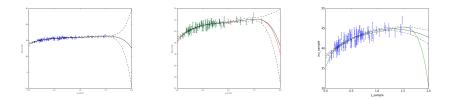


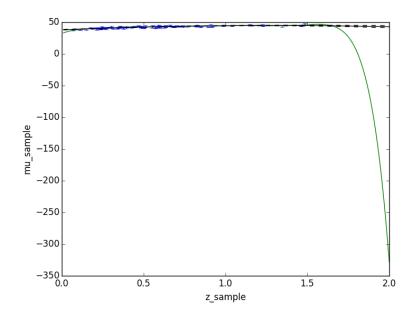
Figure 1: This is combine figure side by side. left Freq, Middle, Bay, Right, smooth

So there is clearly a difference at higher redshift. For smoothing prior there is change from 1.5 to 1.7 redshift and even after that due to smoothness. There is clear change in

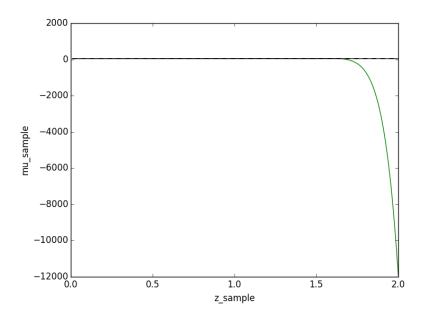
smoothness prior fit. Also sparse of points occur at higher up redshift after say z>0.9.

1.4.2 Increasing Order L= 1

Now For L=1but parameter =9 we got



Now For L=1but parameter =12 we got



We see clear difference when we increase number of parameter. Prior smoothness is change dramatically and affected by increasing parameters. There is comparison for all three L=1 with 6th, 9th and 12th order.

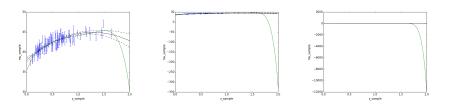


Figure 2: For L=1, Prior smooth left 6th, middle 9th, right 12th order cases

We can compare Frequentist, Bayesian and Prior smooth L=1 at higher order say for 12 parameters so comparison can be made as shown in figure

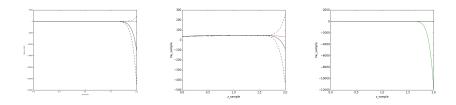
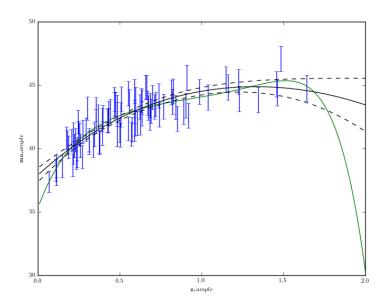


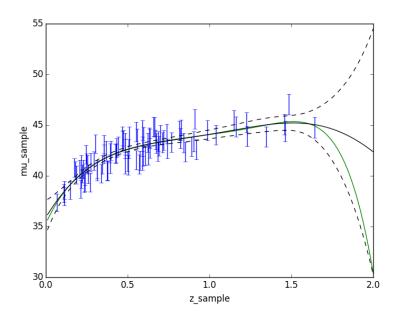
Figure 3: For 12 parameters. left Freq, Middle, Bay, Right, smooth

1.4.3 For Changing L at 0.5 and 0.1 case

Now, Lets Decrease L by 0.5. Then we need to modify Prior so I got for L=0.5 and 6th order.



Now, Decrease L by 0.1 . Then we need to modify Prior so I got for L=0.1 and 6th order.



So combining L=1, L=0.5 and L= 0.1 cases for the 6th order we have shown the graph below that there is a change for changing the L as well in the prior smooth function. Which is more at high redshifts.

How ever for higher order say 12 we have same kind of change. This is the Comparison

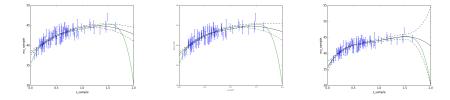


Figure 4: For 6 parameters. left L at 1, Middle L at 0.5, Right L at 0.1

when L is 1,0.5 and 0.1 For 12 parameters.

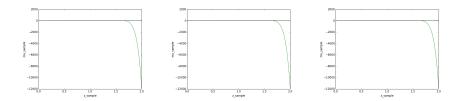
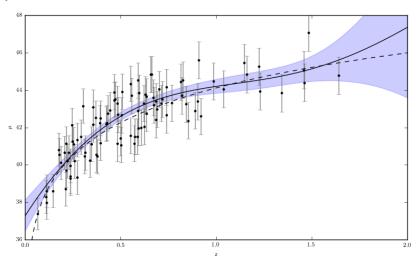


Figure 5: For 12 parameters. left L at 1, Middle L at 0.5, Right L at 0.1

At large parameter both Value of L and Parameters produce affects.

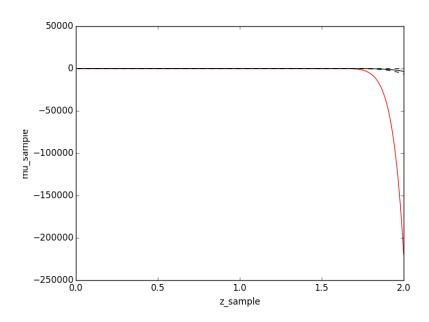
1.5 PartV Gaussian

I did not know how to fit band-width h to be unity. In figure 8.9 they define data and in Kernel by putting h=1. But in our case data is different and I do not know where h can be fixed. I used code for figure 8.10. They use cross validation for BANDWIDTH. In book the band width is said to be nearly unity. But I could not figure out how I can make it to unity in this code. Here is the result.



1.6 PartVI Large n ill condition Bayesian

I use part c Bayesian fit for n = 15, There are the result clearly showing offset.

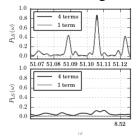


2 Problem 3

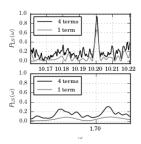
2.1 Multiterm-Periodogram with LombScragle

Firstly I use figure 10.17 to get data. I also use the same code to compute Omega the best frequency. Then I use the code of figure 10.18 and compute the periodogram for 1 term and 4 term. So these are the result.

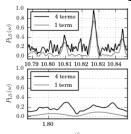
For 1009459 I got this



For 10022663 I got this



For 10022663 I got this



Below I use a fastLombscragle code to compute the periodogram but still I did not know how to change number of terms in this code. Here are the result for given data sets.

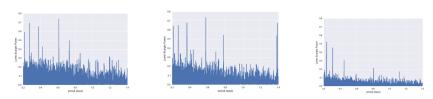


Figure 6: For 4 term Periodogram. left 1009459, Middle 18525697, Right 10025796