# Assignment 3: Data Estimation REPORT

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### 1 Introduction

Planck's law describes the spectral radiance of electromagnetic radiation emitted by a black body in thermal equilibrium at a given temperature T. The formula is:

$$S(\lambda, T) = \frac{2hc^2}{\lambda^5} \cdot \frac{1}{\exp\left(\frac{hc}{\lambda k_B T}\right) - 1}$$

Where:

- $S(\lambda, T)$  is the spectral radiance (the power emitted per unit area, per unit solid angle, per unit wavelength).
- $\lambda$  is the wavelength of the radiation.
- T is the absolute temperature of the black body in kelvins.
- h is Planck's constant  $(6.626 \times 10^{-34} \, \mathrm{Js})$ .
- c is the speed of light in a vacuum  $(3.0 \times 10^8 \,\mathrm{m/s})$ .
- $k_B$  is the Boltzmann constant  $(1.38 \times 10^{-23} \, \text{J/K})$ .

The objective of this assignment is to take the constants as unknown parameters and optimize them, given a dataset of spectral radiance and wavelength values.

#### 2 How to Run

- Download the .ipynb file on a jupyter server or another environment that supports ipympl to show interactive plots in the notebook.
- Run the code blocks cell by cell, or press run all to see the outputs.
- You can then see the markdown and outputs to go through my approach.

• The last code block generates a lot of plots, so I have kept it commented out, as I thought it didn't provide any necessary additional information. If you want to run it it should be uncommented.

Note: I made the .ipynb file in VSCode after pip installing ipython and ipympl, and the jupyter notebook extansion and was able to view the ipympl plots properly.

# 3 Approach

• I have a class 'Data' to hold all data related to a given file so that I can perform certain operations easily over a list of different files.

It expects a file containing x and y coordinates data separated by commas.

It stores these values when initialized with a file.

Once 'fit()' is called on an instance of 'Data' with a model function and a List of initial guesses for unknown parameters of the model function, it estimates those parameters and stores them.

We can plot the fitted curve along with the raw data using 'plot\_data\_and\_fitted\_curve()'. It has parameters to customize the plot.

 $Note: \ `plot\_data\_and\_fitted\_curve()` \ must \ be \ called \ only \ once \ `fit()` \ has \ been \ called$ 

Note: The reason behind requiring initial guesses is that if data ranges from highly negative to highly positive powers of 10, the calculations can easily cause overflows. I wasn't able to avoid overflow without a very good initial guess.

```
# Define a class Data with an initializer
class Data:
    ''' Holds all data related to a given file \n
    '''

def __init__(self, filename: str):
    '''When initialized with a file name, loads a 2D
        numpy array with co-ordinates \n
Creates two numpy arrays to hold x and y values
        separately \n
    '''

self.points = np.loadtxt(filename, float,
        delimiter=',') # Loads coordinates as 2-D
    numpy array

self.x_values = self.points[:, 0] # All rows,
    first column (x values)
```

```
self.y_values = self.points[:, 1] # All rows,
11
               second column (y values)
12
       def fit(self, function: Callable, initial_guesses:
13
           List):
            '','Fits curve for a model function and a List
14
               containing initial guesses \n
           Returns optimized parameters (Array)\n
15
            # This function must take x_values as first
17
               argument
            self.model_function = function
18
19
            # Using curve_fit() function from scipy.optimize
20
            self.popt, self.pcov = curve_fit(function, self.
21
               x_values, self.y_values, p0=initial_guesses)
22
            # popt is in the order of next parameters of
               function
           return self.popt
24
25
       def plot_data_and_fitted_curve(self, curve_color:
           str, data_color: str, x_label: str, y_label: str
           ):
            \ref{eq:constraints} , \ref{eq:constraints} Plots the fitted curve along with the raw
27
               data \n
            Returns optimized parameters (Array) and their
28
               covariance matrix (2D Array)\n
29
            # Begin plotting
30
31
           plt.figure()
            # Plot the original data
33
           plt.plot(self.x_values, self.y_values, label='
34
               Data', color=data_color)
35
            # Plot fitted curve using optimized parameters
            self.new_y_values = self.model_function(self.
               x_values, *self.popt)
            plt.plot(self.x_values, self.new_y_values, label
38
               ='Fitted Radiance', color=curve_color)
39
            # Add labels and a legend
           plt.xlabel(x_label)
           plt.ylabel(y_label)
           plt.legend()
44
            # Show the plot
45
           plt.show()
```

- Then, I made a function to find spectral radiance given wavelength, h, c, kb and T, and used it with fit() for the 4 data files given.
- Using very close initial guesses, I was able to get the curve to fit the data pretty well, but the estimated parameters were way off. You can see the plots in the notebook, I have given the optimized parameters below.

| File/Parameter | h                      | c                    | $k_B$                  | T                    |
|----------------|------------------------|----------------------|------------------------|----------------------|
| Initial Guess  | $6 \times 10^{-34}$    | $3 \times 10^{8}$    | $2 \times 10^{-23}$    | $6 \times 10^3$      |
| d1.txt         | $2.05 \times 10^{-33}$ | $1.68 \times 10^{8}$ | $8.28 \times 10^{-24}$ | $1.17 \times 10^4$   |
| d2.txt         | $6.92 \times 10^{-34}$ | $2.36 \times 10^{8}$ | $1.36 \times 10^{-23}$ | $3.61 \times 10^{3}$ |
| d3.txt         | $2.73 \times 10^{-33}$ | $1.44 \times 10^{8}$ | $1.56 \times 10^{-23}$ | $7.07 \times 10^{3}$ |
| d4.txt         | $1.90 \times 10^{-33}$ | $1.72 \times 10^{8}$ | $1.35 \times 10^{-23}$ | $6.64 \times 10^{3}$ |

Table 1: Optimized parameters for different input files

- Then, I made partial application functions where only wavelength, h and T or wavelength, c and T were unknowns, and used them with fit for the 4 data files given.
- Despite using much worse initial guesses, I was able to get quite accurate values of h and c. I have given them below. You can see the plots in the notebook.

| File/Parameter | h                      | T                    |
|----------------|------------------------|----------------------|
| Initial Guess  | $1 \times 10^{-33}$    | $1 \times 10^{4}$    |
| d1.txt         | $6.43 \times 10^{-33}$ | $3.93 \times 10^{3}$ |
| d2.txt         | $4.27 \times 10^{-34}$ | $2.78 \times 10^{3}$ |
| d3.txt         | $6.27 \times 10^{-33}$ | $3.83 \times 10^{3}$ |
| d4.txt         | $6.25 \times 10^{-33}$ | $3.73 \times 10^{3}$ |

Table 2: h values

| File/Parameter | c                    | T                    |
|----------------|----------------------|----------------------|
| Initial Guess  | $1 \times 10^{8}$    | $1 \times 10^{4}$    |
| d1.txt         | $2.95 \times 10^{8}$ | $3.98 \times 10^{3}$ |
| d2.txt         | $2.41 \times 10^{8}$ | $3.46 \times 10^{3}$ |
| d3.txt         | $2.92 \times 10^{8}$ | $3.94 \times 10^{3}$ |
| d4.txt         | $2.91 \times 10^{8}$ | $3.84 \times 10^{3}$ |

Table 3: h values

## 4 Conclusion

• We cannot predict many parameters at once using noisy data, as the parameters cannot always be separated out. For eg: kb and T in planck's

formula appear as a product only.

- By using partial application, we can predict 2 parameters at a time rather reliably.
- Even then, my predicted h and c for d2 showed much greater error than for other files because that file has more noise.