EECS 639
Project Report
Dr. Shontz
12/12/2024

EECS 639 Project

In this report, we seek to pursue a thorough investigation and understanding of interpolation following the guidelines as provided within the assignment instructions.
Our team consists of Dylan Davis, Jason Melton, and Siddarth Dodia, whomst each undertook the following divisions of labor:

Sidd implemented and tested the interpolation functions and parametric curves, Jason and Dylan looked over, understood, and contributed to his work, Jason worked on improving the conditioning of the functions. Everyone agreed on a data set, Jason preprocessed the data. Dylan and Jason determined the most interesting features to interpolate over the questions, defined the real world testing functions, and wrote the report, which Sidd edited.

Contributors:

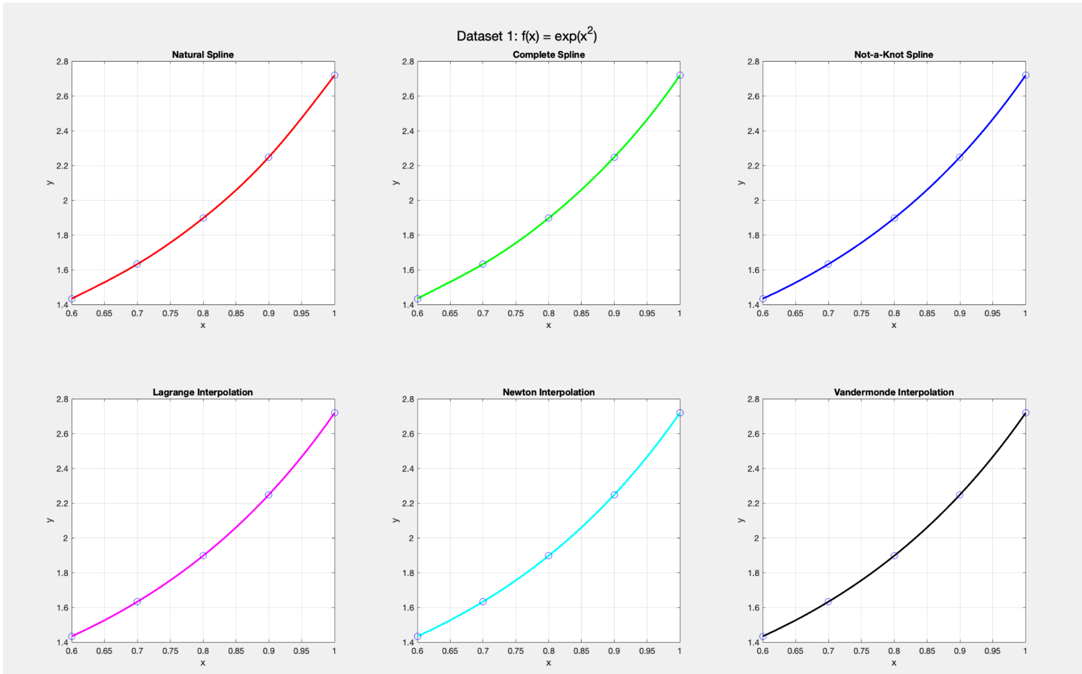
Jason Melton:

Dylan Davis:

Siddarth Dodia:

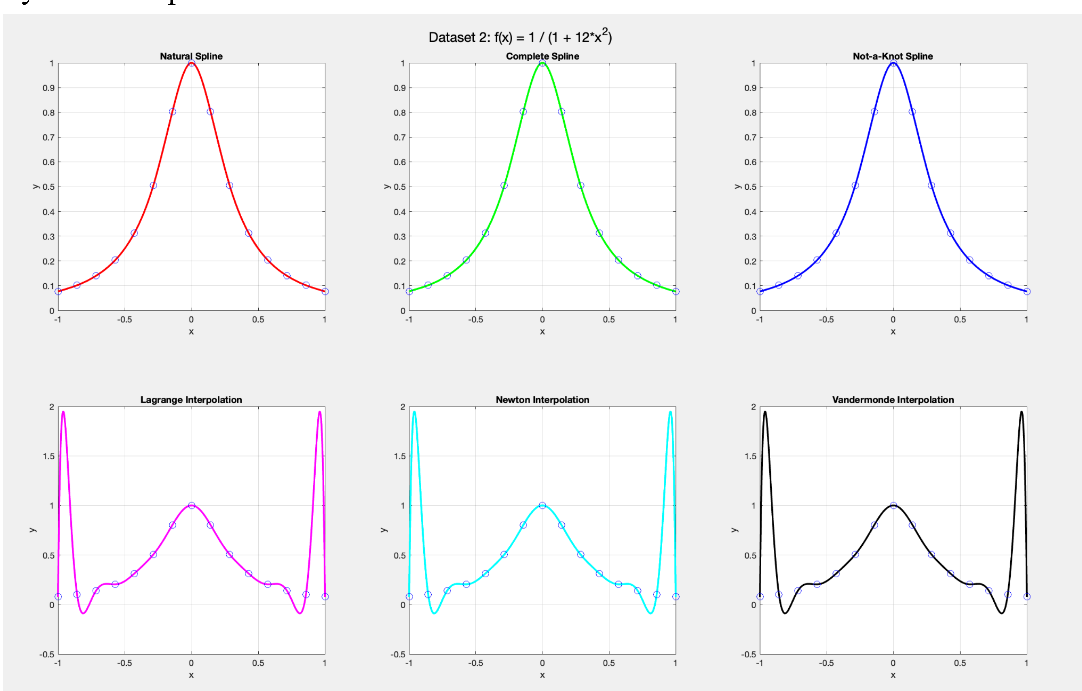
A.) Implementation of methods for Interpolation (zip)

B.) Testing the Interpolants (zip)



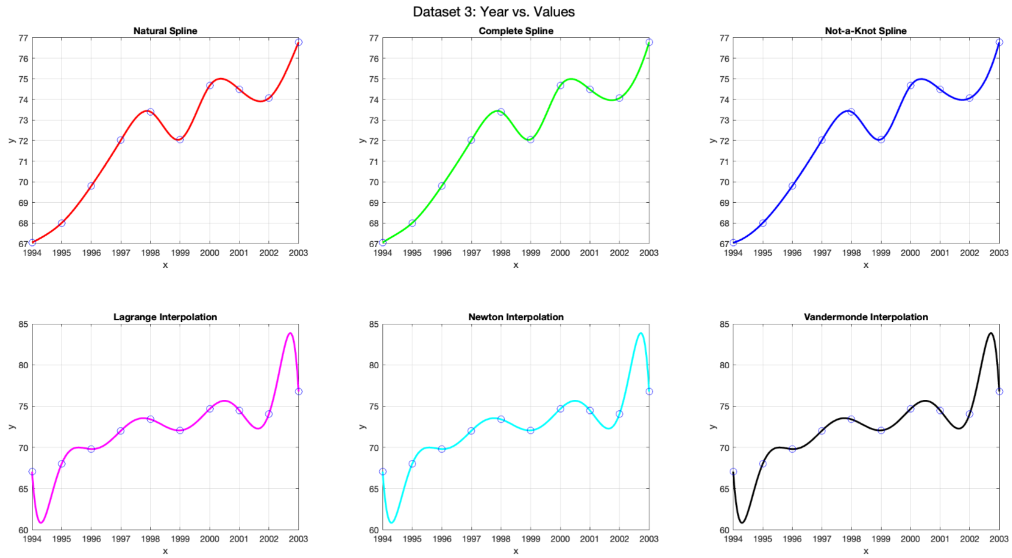
$$f(x) = exp(x^2)$$

The Conditioning for this function is very good across the splines and the interpolants. The accuracy is almost perfect with the function here as well.



$$f(x) = 1/(1 + 12 * x^2)$$

The Conditioning Splines are well conditioned here while the interpolation methods are not. The accuracy is much better for the splines compared to the interpolations. The data fits the splines very well.

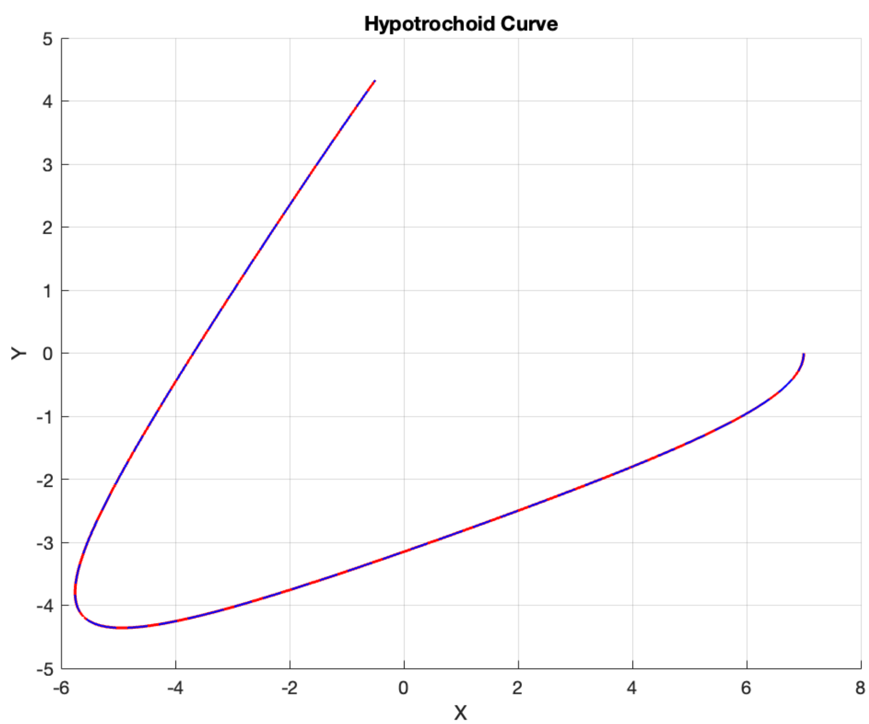


Year Data Set

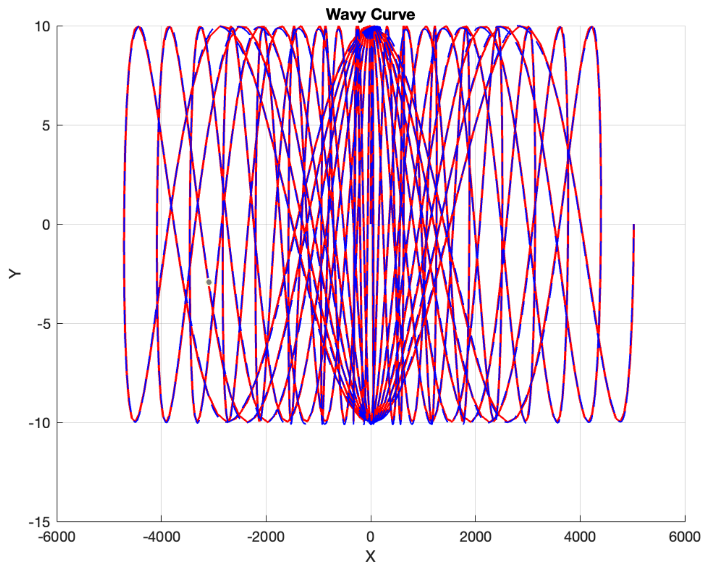
The conditioning and accuracy once again lean towards the splines as they are well conditioned and accurate; However, now the interpolation methods are also decently conditioned and fairly accurate.

C.) Parametric Curves (zip)

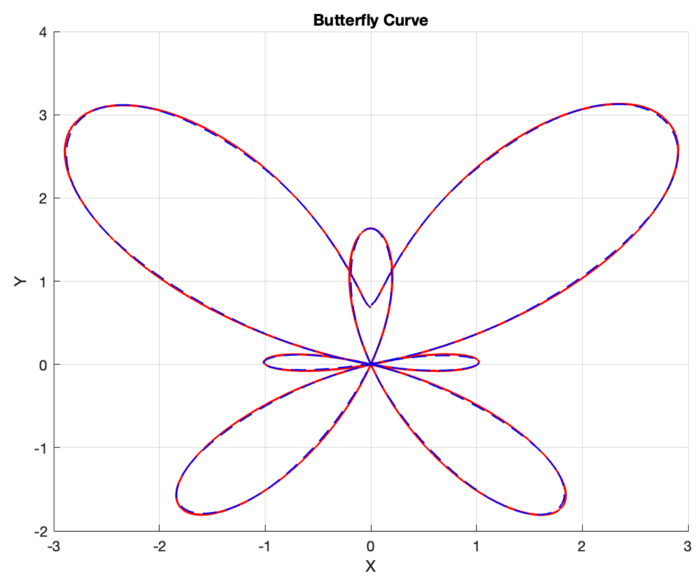
Ellipse Curve



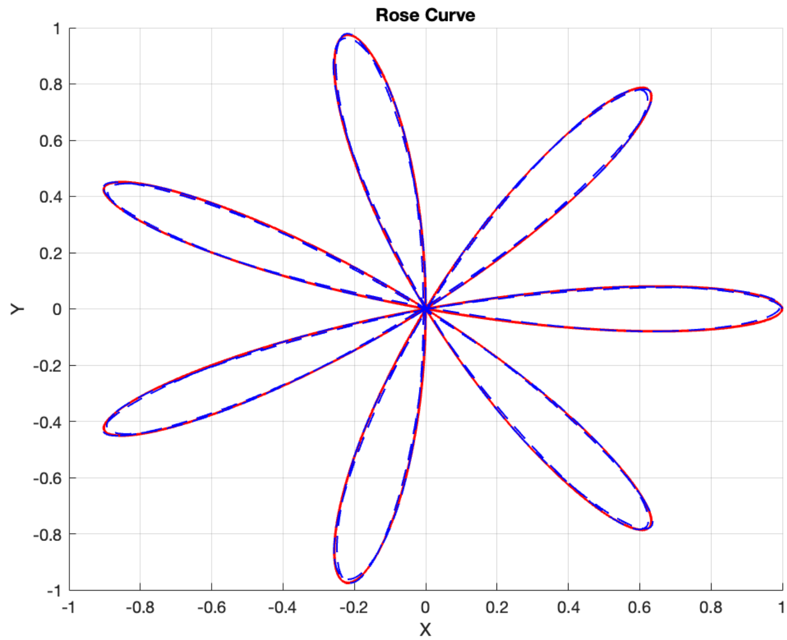
Hypotrochoid Curve



Wavy Curve



ButterFly Curve



Rose Curve

d.)

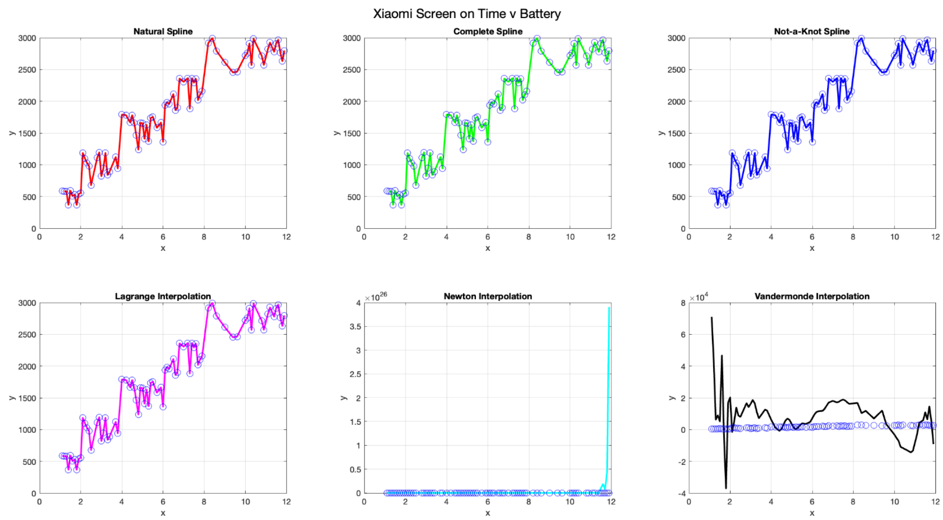
Mobile Devices, Effects on Battery Life

The research was focused on a data set called, “Mobile Device Usage and User Behavior Dataset”[1]. This data set contains seven hundred unique entries. Each of the entries contains user information: User ID, Device Model, Operating System, App Usage Time, Screen On Time, Battery Drain, Number of Apps Installed, Data Usage, Age, Gender, User Behavior Class. The motivation was to determine if there is a difference in battery performance between specific mobile device models. The primary data set was split into different csv files using a python script based on ‘Mobile Device’. The phone models are, Xiaomi, Samsung Galaxy 21, One Plus 9, Iphone 12, Google Pixel 5. The different kinds of splines and interpolations used are: natural, complete, not-a-knot, lagrange, Newton, and Vandermonde. Two features were chosen App Usage Time, and Screen On Time to interpolate over the data. To answer three question:

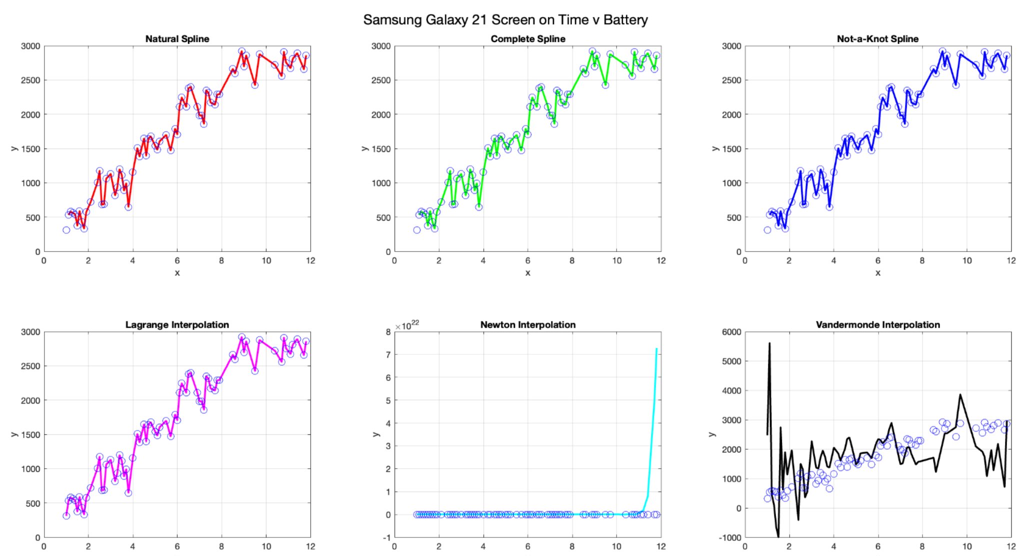
1. Is there a difference in Battery Drain between Device Models given Screen On Time?
2. Is there a difference in Battery Drain between Device Models given App Usage Time?
3. What has a greater effect on battery drain App Usage Time vs Screen on Time and to which model?

[1] https://www.kaggle.com/datasets/valakhorasani/mobile-device-usage-and-user-behavior-dataset

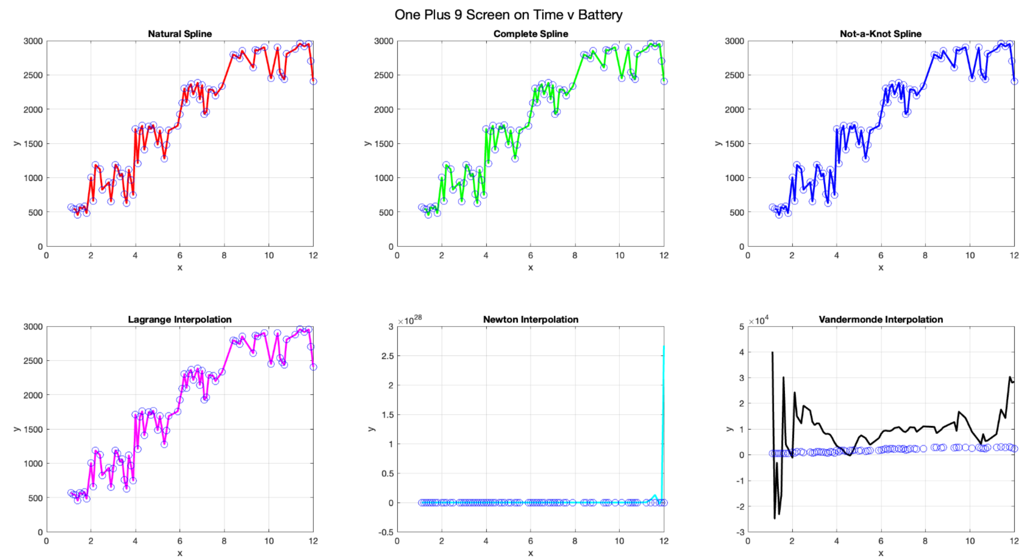
The first question was to determine if there was a difference in Battery Drain on Device Model given Screen On Time. Screen On Time is defined as the average hours per-day the screen is active. To compare the models, an average of battery consumption was taken after 8.5 hours of use. See the figures below.



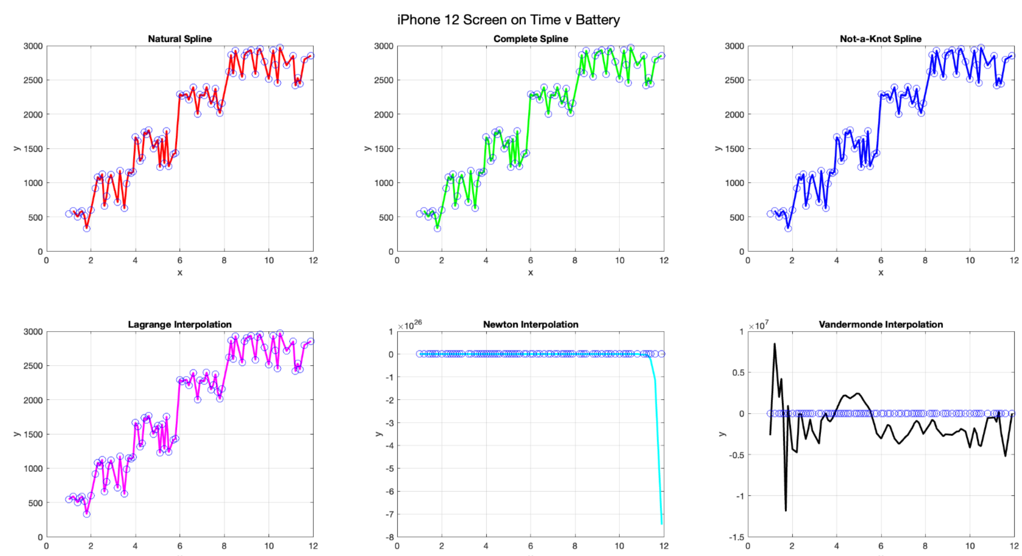
The Xiaomi: avg: 2683.6: Figure 1



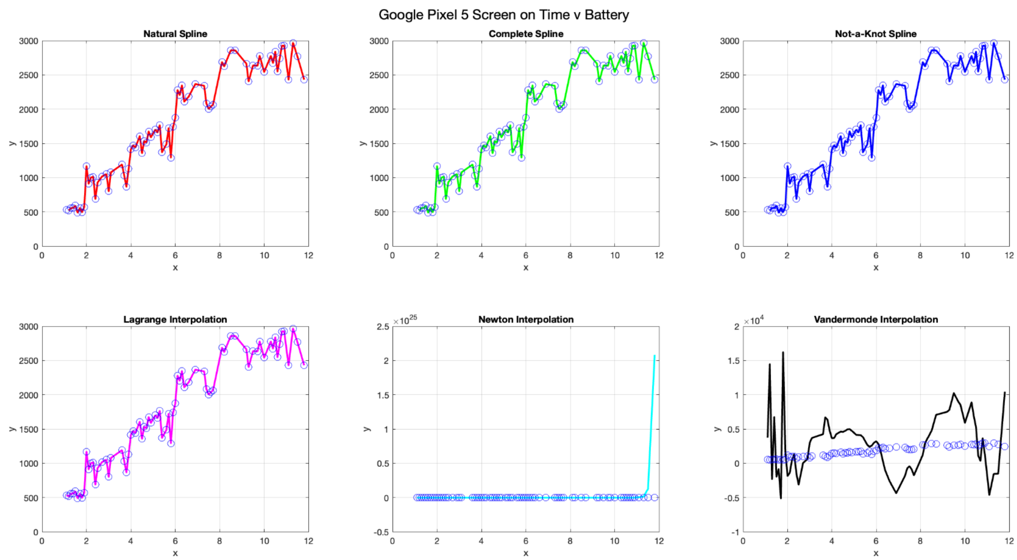
The Samsung Galaxy 21: avg: 2680.62: Figure 2



The One Plus 9: avg: 2717.05: Figure 3



The Iphone 12: avg: 2722.77 : Figure 4



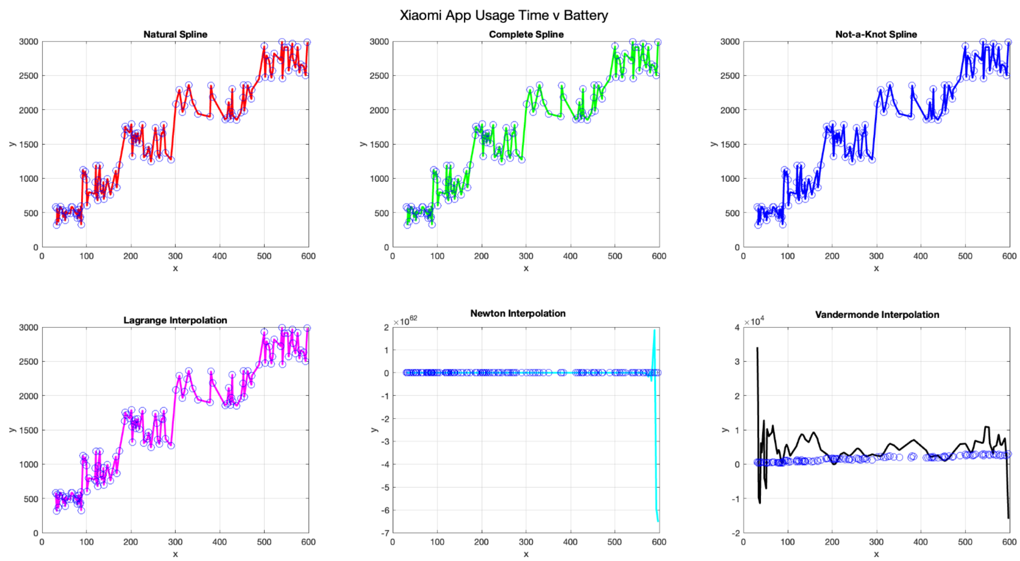
The Google Pixel 5: avg: 2674.26 : Figure 5

On the ‘Y’ axis we have ‘Battery Drain’ which is the daily battery consumption in mAh (milliampere-hour), while ‘Screen on Time’ is on the ‘X’ axis measured in hours per day.

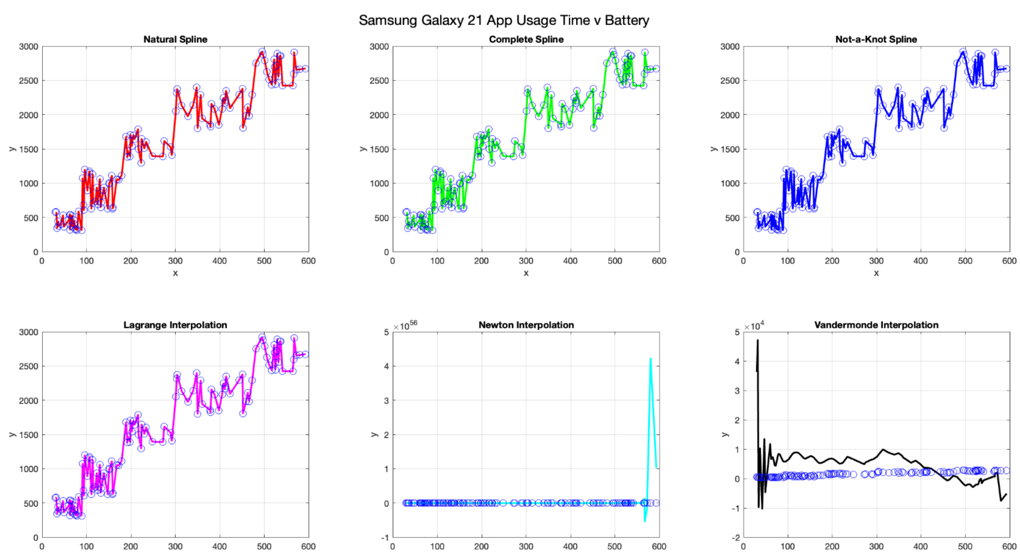
As you can see from the figures, generally as expected when Screen on Time increases so does the drain on battery. Additionally, notice across all the models there is a plateau in battery drain around 2500 mAh, after speculation it was assumed that this is a low power mode, or some other battery preserving built in system. After interpolation it was discovered that Screen on time affects the models similarly, there is a gradual descent until 2500 mAh where the low power mode is activated. The models vary in their descent, but generally follow a logarithmic path. Comparing the average consumption after 8.5 hours: The Google Pixel performs the best with the lowest average consumption of 2674.26 followed by The Samsung Galaxy 21, The Xiaomi, The One Plus 9, and surprisingly the Iphone 12 had the highest with a battery consumption of 2722.77. Out of these models the Google Pixel 5 has the most conservative rate on battery drain that is only increased by the low power mode. An important note is that the Samsung never reaches 3000 mAh.

- Is there a difference in Battery Drain on Device Model given Screen On Time?
    a. Yes, all the phone models react differently, through interpolation we were able generally determine how much battery would be consumed given a mobile phone model. Additionally, we were able to see the Google pixel perform the best.

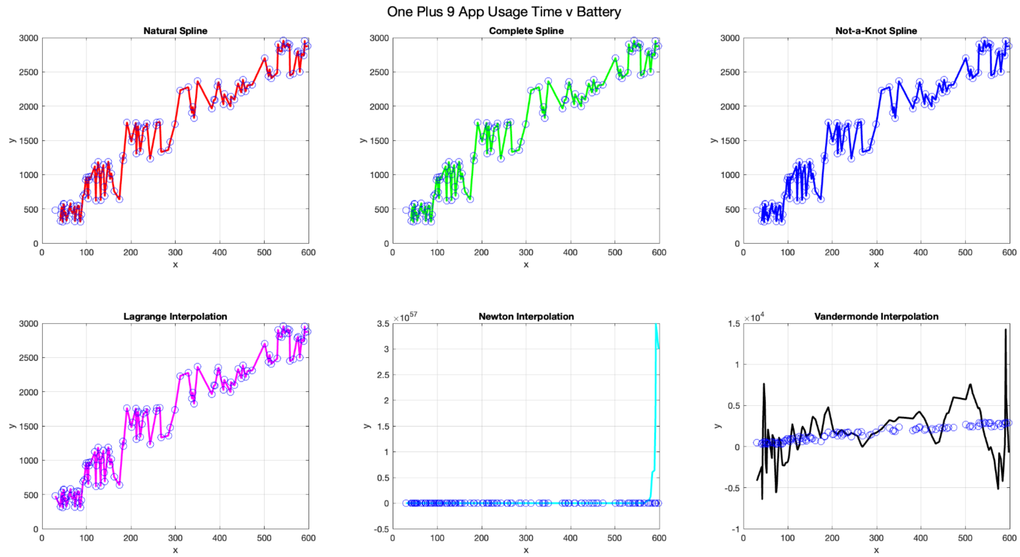
The second question was if App Usage Time had an affect on battery drain on device models. App Usage Time is defined as daily time spent on mobile applications, measured in minutes. To examine the battery consumption an average of the battery consumption was taken after 470 minutes/day.



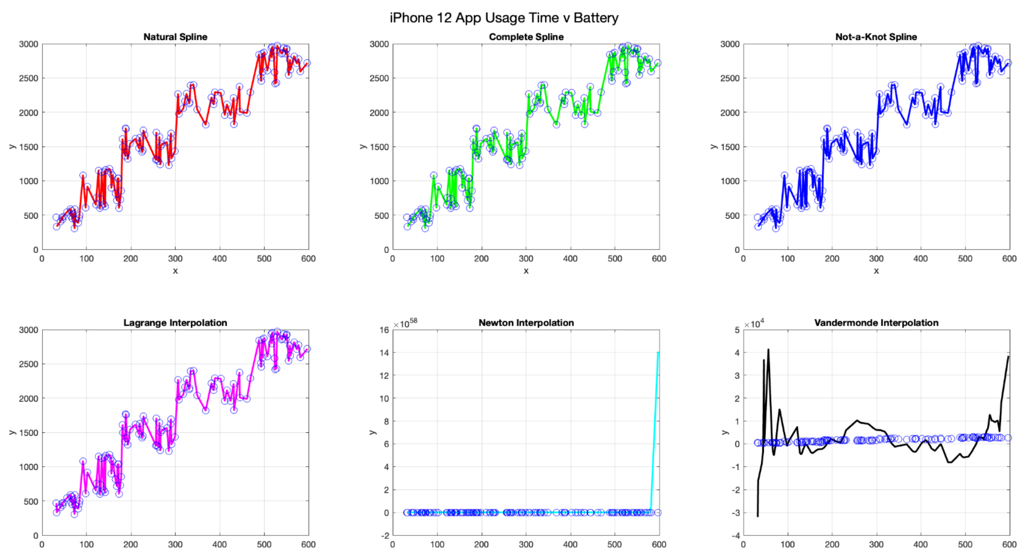
The Xiaomi: 2676.06 mAh/day: Figure 6



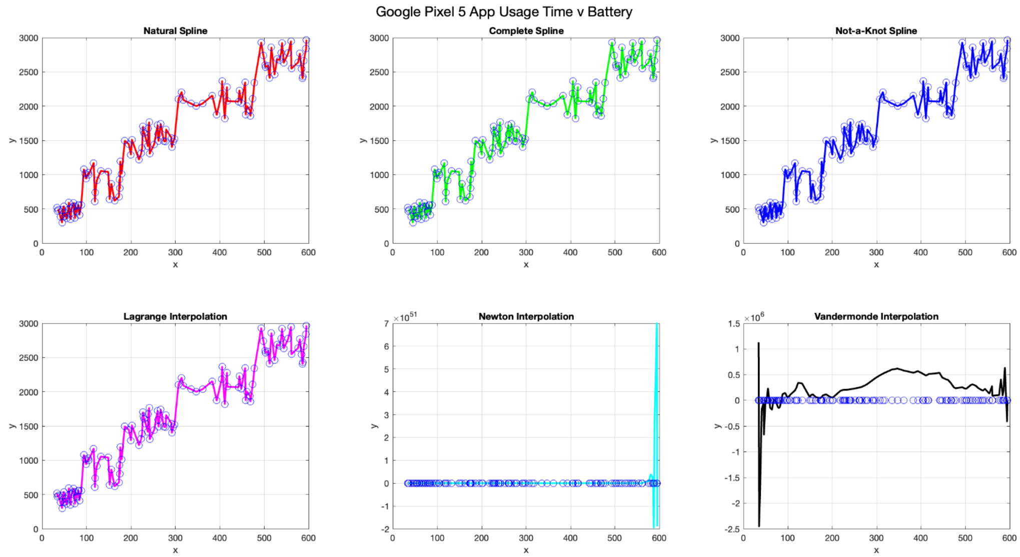
The Samsung Galaxy 21: 2641.12 mAh/day: Figure 7



The One Plus 9: 2691.44 mAh/day: Figure 8



The Iphone 12: 2727.97 mAh/day: Figure 9



The Google Pixel 5: 2645.59 mAh/day: Figure 10

On the ‘Y’ axis we have ‘Battery Drain’ which is the daily battery consumption in mAh (milliampere-hour), while ‘App Usage Time ’ (measured in minutes/day) is on the ‘X’ axis.

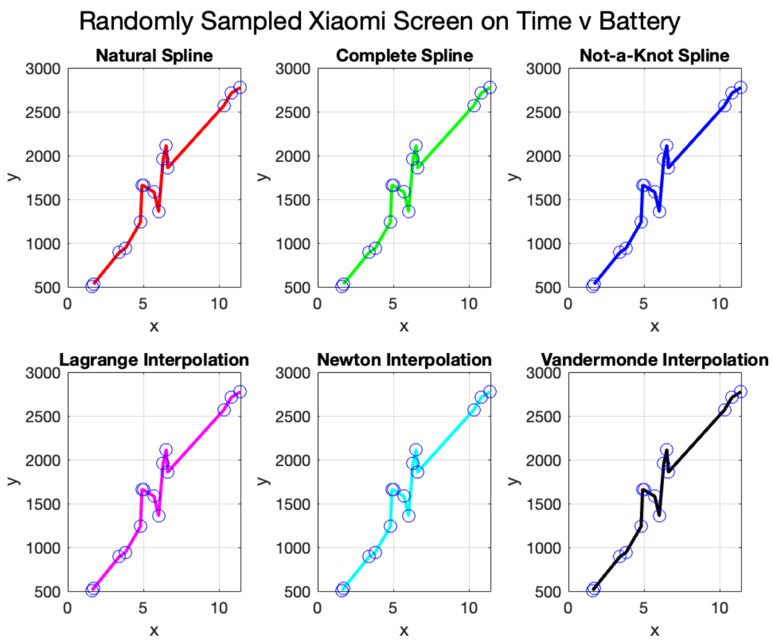
The first thing to notice about the data is that App Usage Time does affect the device models differently than Screen on Time. Once again, as App Usage Time goes up the drain on battery trends upwards as well. This time at a faster rate than Screen on Time, as the Device Models reach 3000 mAh after 600 minutes-10 hours- compared to 12 hours seen before for Screen on Time. The data on the graphs is also far more clumped and dense, indicating with app usage users could experience jumps in consumption of battery, as they use apps for extended periods of time. The phone models perform similarly once again: there is a plateau around 2500 mAh, again assumed to be the build in a low-power mode mentioned earlier. Looking at the average of the battery consumption after 470m of use. The Samsung Galaxy 21 consumes the least with 2641.12 mAh followed by the Google Pixel 5, Xiaomi, One Plus 9, and finally the Iphone with the highest consumption at 2727.97 mAh.

- Is there a difference in Battery Drain on Device Model given App Usage Time?
    a. Yes, there is a difference in battery drain on device models given app usage time, app usage time used mAh faster than Screen on Time. Additionally, we were able to see the Samsung Galaxy performed the best.

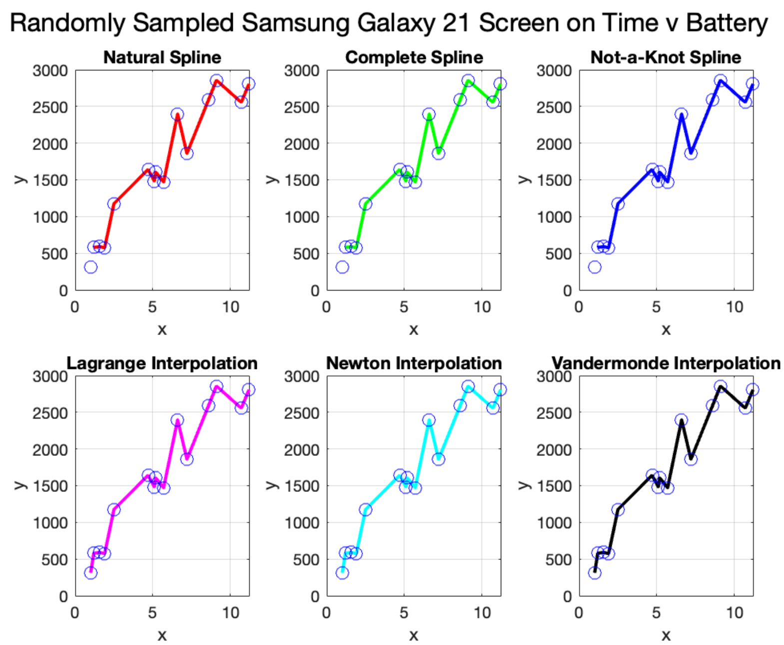
- What has a greater effect on battery drain App Usage Time vs Screen on Time and to which model?
    a. App Usage Time has a greater effect on battery drain than Screen on Time. meaning. Looking at the figures we can see that Screen on time reaches 3000

mAh near 12 hours, meanwhile App Usage Time reaches 3000 mAh near 600 minutes or 10 hours. Indicating a faster burn of battery life if you are using apps on your phone. After examining all the figures App Usage Time affects the models most severely. Additionally, given a scenario of App Usage for a long period of time, the Iphone would tend to reach 3000 mAh consumed before the other models; Additionally, the Iphone 12 consumes the most battery of the models when averaging consumption after use, regardless of App Usage Time or Screen on Time.

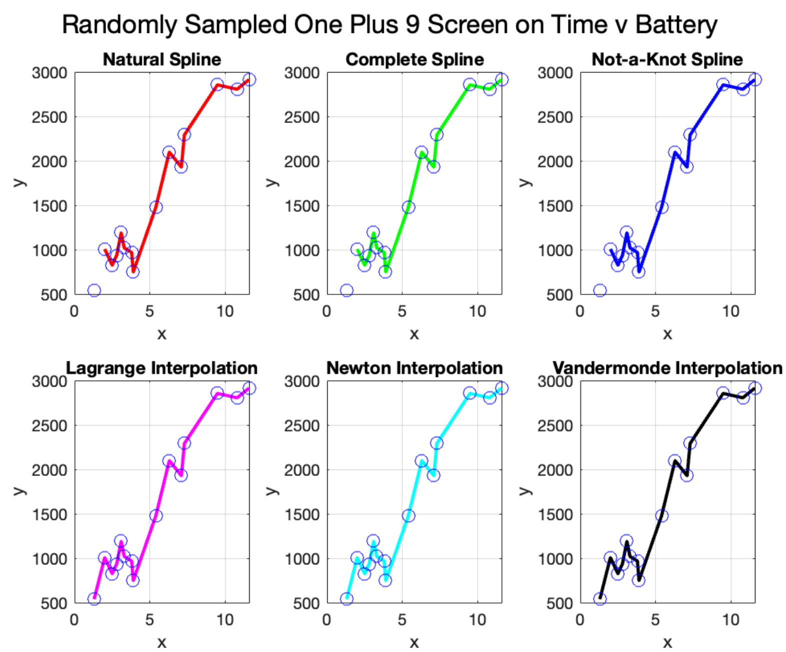
In all of the above graphs which interpolate across the entire data sets, it is clear to see that the Newton and Vandermonde methods of interpolation quickly diverge (and seemingly grow without bound) from the optimal polynomial which would fit the points.
This is in part because the interpolants are ill-conditioned and sensitive, especially to the amount of data points in the data set. To observe and verify this property, 15 points were randomly selected from each Device Model's data set- a significant reduction in the total number of points- and re-interpolated, resulting in the below graphs.



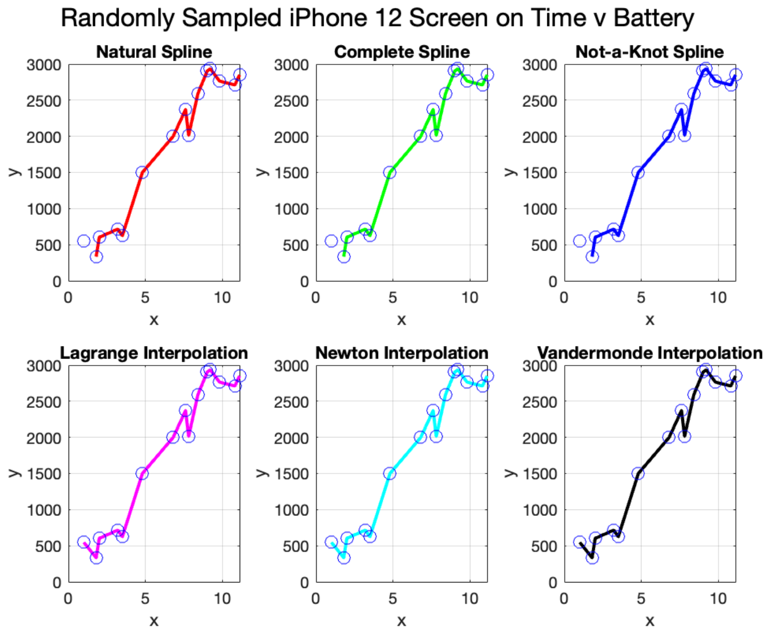
The Xiaomi: Figure 6



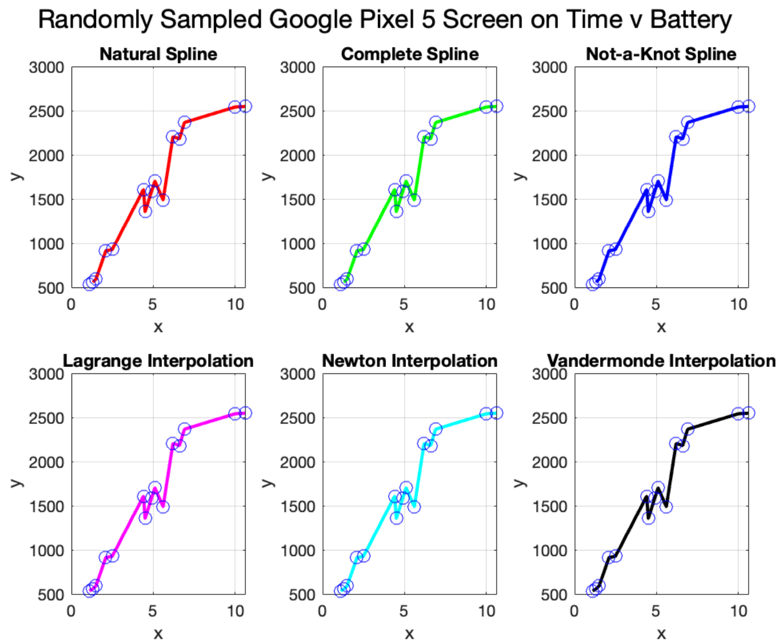
The Samsung Galaxy 21: Figure 7



The One Plus 9: Figure 8

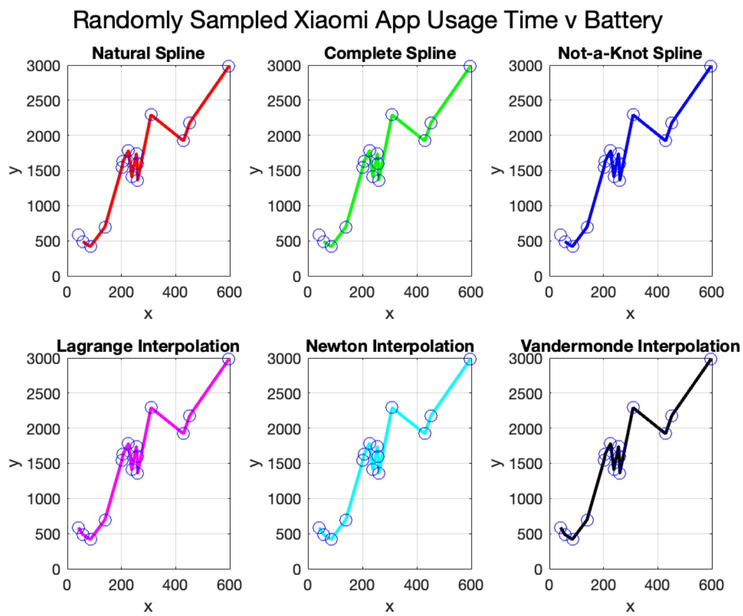


The iPhone 12: Figure 9

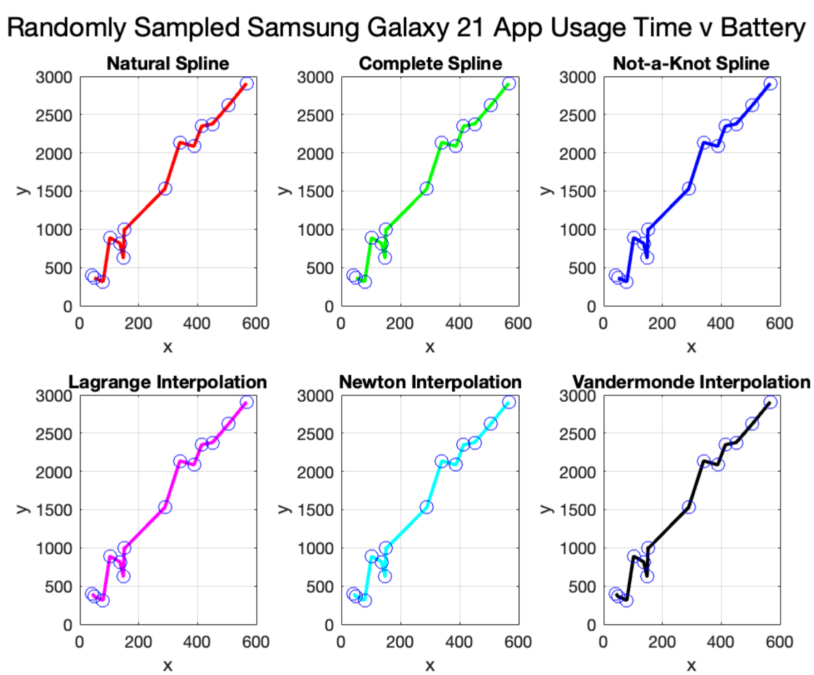


The Google Pixel 5: Figure 10

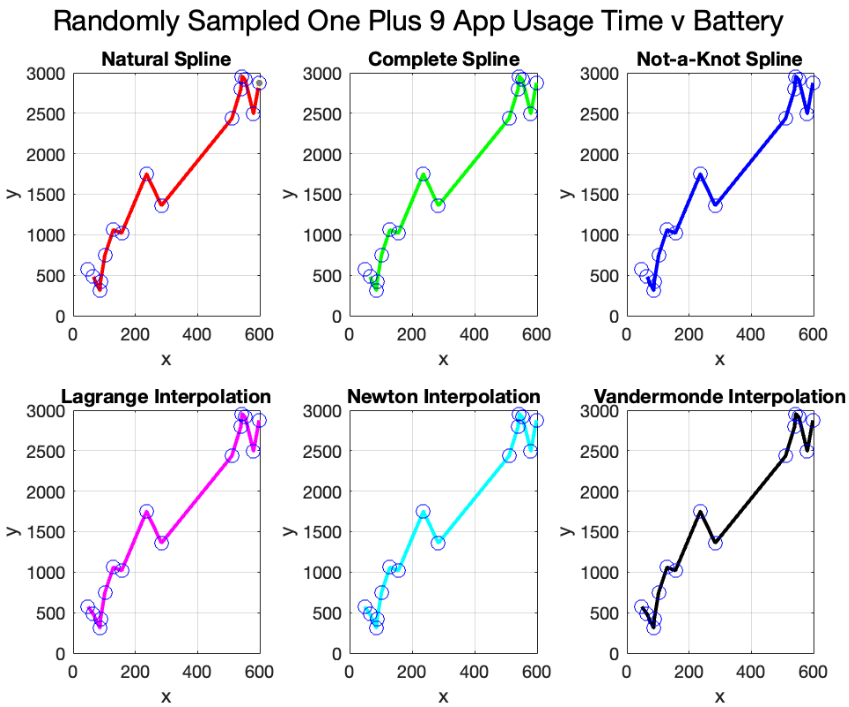
App Usage Time



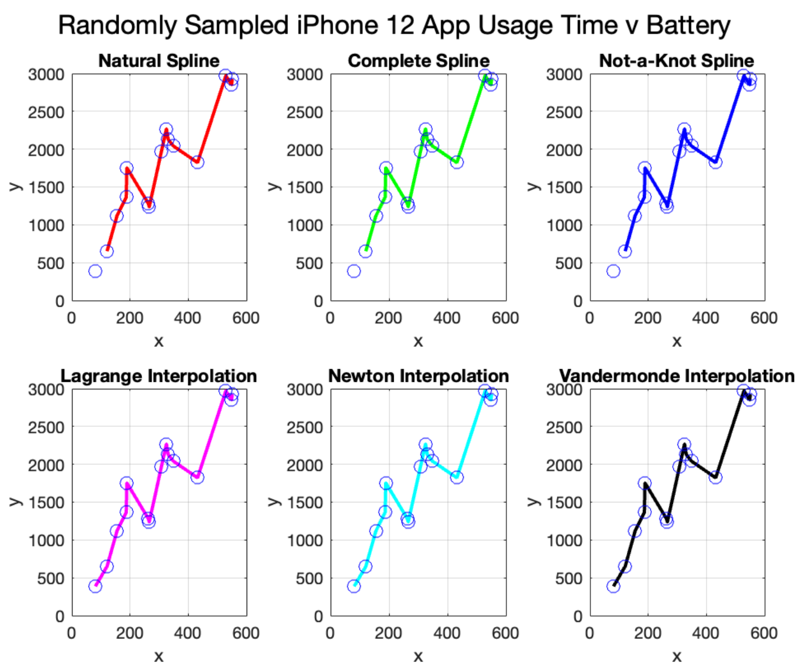
The Xiaomi: Figure 6



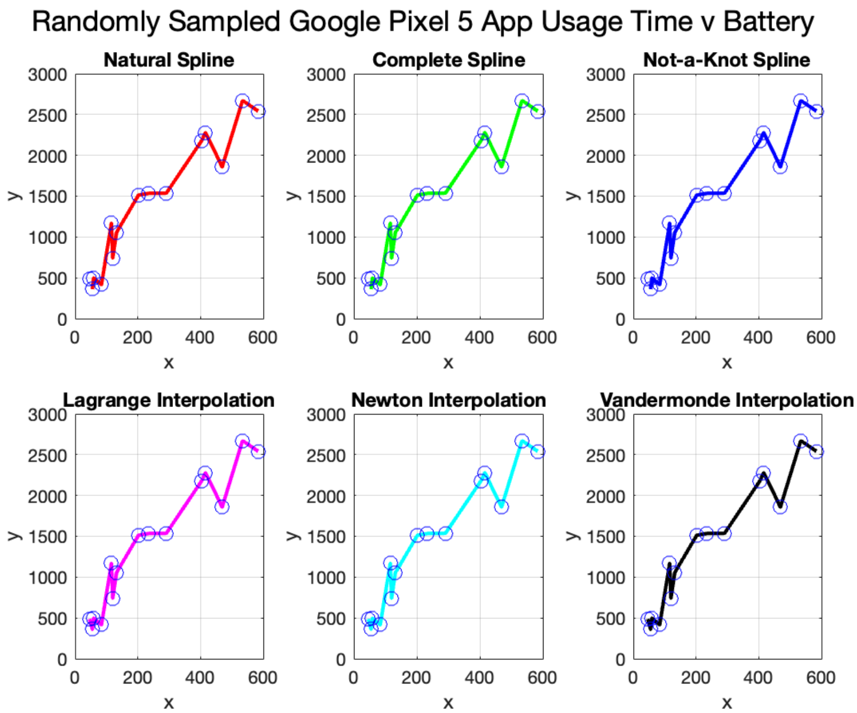
The Samsung Galaxy 21: Figure 7



The One Plus 9: Figure 8



The Iphone 12: Figure 9



The Google Pixel 5: Figure 10

e.) Through this project, we were able to implement six total interpolation methods: three variations of cubic splines (natural, complete, not-a-knot), Lagrange interpolation method, Newton interpolation method, and Vandermonde interpolation method, and interpolate over a sample data set. We selected a real world data set and sought to learn if there was any difference in mobile phone device models when it came to the drain on their battery with respect to App Usage Time (measured in minutes/day) and Screen On Time (measured in hours/day).

Interpolation of the data set in this way enables us to estimate a Battery Consumption (in mAh), of any Device Model present in the data set given either App Usage Time or Screen On Time.

Notably, we discovered that across all Device Models for both App Usage Time and Screen On Time, Battery Consumption tends to increase positively linearly until the limits of the data set was reached, in which the Battery Consumption was trending to plateau in an almost logarithmic degree. Through interpolation we were able to answer our three scientific questions about mobile phone devices and battery drain.

With even relatively small data sets we noted that the Vandermonde and Newton methods of interpolation are very sensitive to the placement of the evaluation points and prone to "diverge" very quickly from the optimal polynomial which fits the data points. The Cubic Splines method of interpolation was undoubtedly the most stable.