

Spring 2017

Project 1 – MSS

Group14

Team: Philip, Elizabeth, Aleita
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Problem Recap

Given an array of small integers $A[1, \dots, n]$, compute $\max_{i \leq j} \sum_{k=i}^j A[k]$, and determine the subarray

For example, $\text{MAXSUBARRAY}([31, -41, 59, 26, -53, 58, 97, -93, -23, 84]) = 187$ with subarray = **[59, 26, -53, 58, 97]**.

Theoretical Run-Time Analysis

Algorithm #1 – Enumeration

Per the instructions, our first algorithm loops over each pair of indices i, j and computes the sum $\sum_{k=i}^j A[k]$. Keeping the best sum found so far.

```

38  vector<int> algorithm1(vector<int> v)
39  {
40      int sum = 0;
41      int maxSum = 0;
42      vector<int> temp;
43      vector<int> maxArr;
44
45      for(int i = 0; i < v.size(); i++)
46      {
47          for(int k=i; k < v.size(); k++) {
48              sum = 0;
49              temp.clear();
50
51              for(int j=i; j < v.size(); j++) {
52                  sum +=v[j];
53                  temp.push_back(v[j]);
54                  if(sum > maxSum) {
55                      maxSum = sum;
56                      maxArr = temp;
57                  }
58              }
59          }
60      }
61      return maxArr;
62  }
```

Algorithm #1 has three “for” loops executing at $O(n)$ time. Therefore, the asymptotic run-time is $O(n^3)$.

Algorithm #2 – Better Enumeration

The enumeration can be computed more efficiently from $\sum_{k=i}^{j-1} A[k]$ in $O(1)$ time:

```

72  vector<int> algorithm2(vector<int> array)
73  {
74      vector<int> temp;
75      vector<int> result;
76      int sum = 0;
77      int maxSum = 0;
78
79      for(int i = 0; i < array.size(); i++) {
80          sum = 0;
81          temp.clear();
82
83          for(int j = i; j < array.size(); j++) {
84              sum = sum + array[j];
85              temp.push_back(array[j]);
86
87              if(sum > maxSum) {
88                  maxSum = sum;
89                  result = temp;
90              }
91          }
92      }
93      return result;
94  }

```

Algorithm #2 improves by only looping twice through the array, each loop executing at $O(n)$ times. The asymptotic run-time is $O(n^2)$.

Algorithm #3 – Divide & Conquer

Algorithm #3 works by dividing the left and right side up into two halves, then respectively dividing each half into more halves until it gets to the smallest element. Then returning in elements. Please see our implementation on the following page.

We determined the asymptotic run time to be $\Theta(n \log n)$ with following analysis:

For base case $n = 0$ or $n = 1$, algorithm #3 runs constant time $\Theta(1)$. For $n > 1$, our algorithm has two recursive calls, for two subproblems of half size and 1 loop through n .

Base Case: $T(n) = \Theta(1)$

For $n > 2$: $T(n) = 2T(n/2) + \Theta(n)$

Using Master Method

$a = 2, b = 2, f(n) = \Theta(n)$

$n^{\log_b(a)} = n^{\log_2(2)} = n^1 = \Theta(n)$

Case 2 applies

$$T(n) = \Theta(n^{\log_2(2)} * \log_2(n))$$

$$T(n) = \Theta(n * \log_2 n)$$

In summary the theoretical run-time for our divide and conquer algorithm is $\Theta(n \log n)$.

Algorithm #3 Code:

```

155  *****/
156  vector<int> algorithm3(vector<int> arrIn, int iLow, int iHigh)
157  {
158      vector<int> resultL;
159      vector<int> resultR;
160      vector<int> resultX;
161      vector<int> result;
162
163
164      int sumL = 0;
165      int sumR = 0;
166      int sumX = 0;
167      int iMid = 0;
168
169      if(iHigh == iLow){
170          result.push_back(iLow);
171          result.push_back(iHigh);
172          result.push_back(arrIn[iLow]);
173          return result;
174      } else {
175          iMid = (iLow+iHigh)/2;
176          resultL = algorithm3(arrIn, iLow, iMid);
177          sumL = resultL[2];
178          resultR = algorithm3(arrIn, iMid+1, iHigh);
179          sumR = resultR[2];
180          resultX=maxXsubArr(arrIn, iLow, iMid, iHigh);
181          sumX = resultX[2];
182      }
183      if((sumL>=sumR)&&(sumL>=sumX))
184          return resultL;
185      else if((sumR>=sumL)&&(sumR >=sumX))
186          return resultR;
187      else
188          return resultX;
189  }
190

```

Algorithm #4 – Linear Time

Algorithm # 4 determines the maximum subarray of the form $A[i..j+1]$ in constant time based on knowing a maximum subarray ending at index j . We then use those index positions to create a vector of the subarray values to be returned to the main function.

```

188 vector<int> algorithm4(vector<int> array)
189 {
190     int n = array.size(); //# of elements in array/vector
191     int max_sum = array[0];
192     int current_sum = 0;
193     int right = 0;
194     int left = 0;
195     int temp_left = 0;
196     vector<int> maxArr;
197
198     //calculate max sum & subarray positions
199     for(int i = 0; i < n; i++) {
200         current_sum = max((current_sum + array[i]), array[i]);
201         if(current_sum > max_sum) {
202             max_sum = current_sum;
203             right = i;
204             left = temp_left;
205         }
206         if( current_sum == array[i]) {
207             temp_left = i;
208         }
209     }
210
211     //create vector based on positions calculated above
212     for(int j = left; j <= right; j++) {
213         maxArr.push_back(array[j]);
214     }
215     return maxArr;
216 }

```

The main portion of algorithm #4, which determines the maximum subarray sum and elements make up that subarray (identified by starting and stopping position), iterates through the given array only once. The second is a utility loop to convert the solution into a vector that be easily returned. Given those complexities, $T(n) = 2n$, the asymptotic run-time is $O(n)$.

Testing

To test our algorithms “correctness” we created the main program in the separately attached file. We used the provided test set to compare our input & output results and we are confident that there no problems with our algorithms. We also created our own test sets and manually checked.

Based on our testing we are confident in the results provided in MSS_Results.txt.

Experimental Analysis

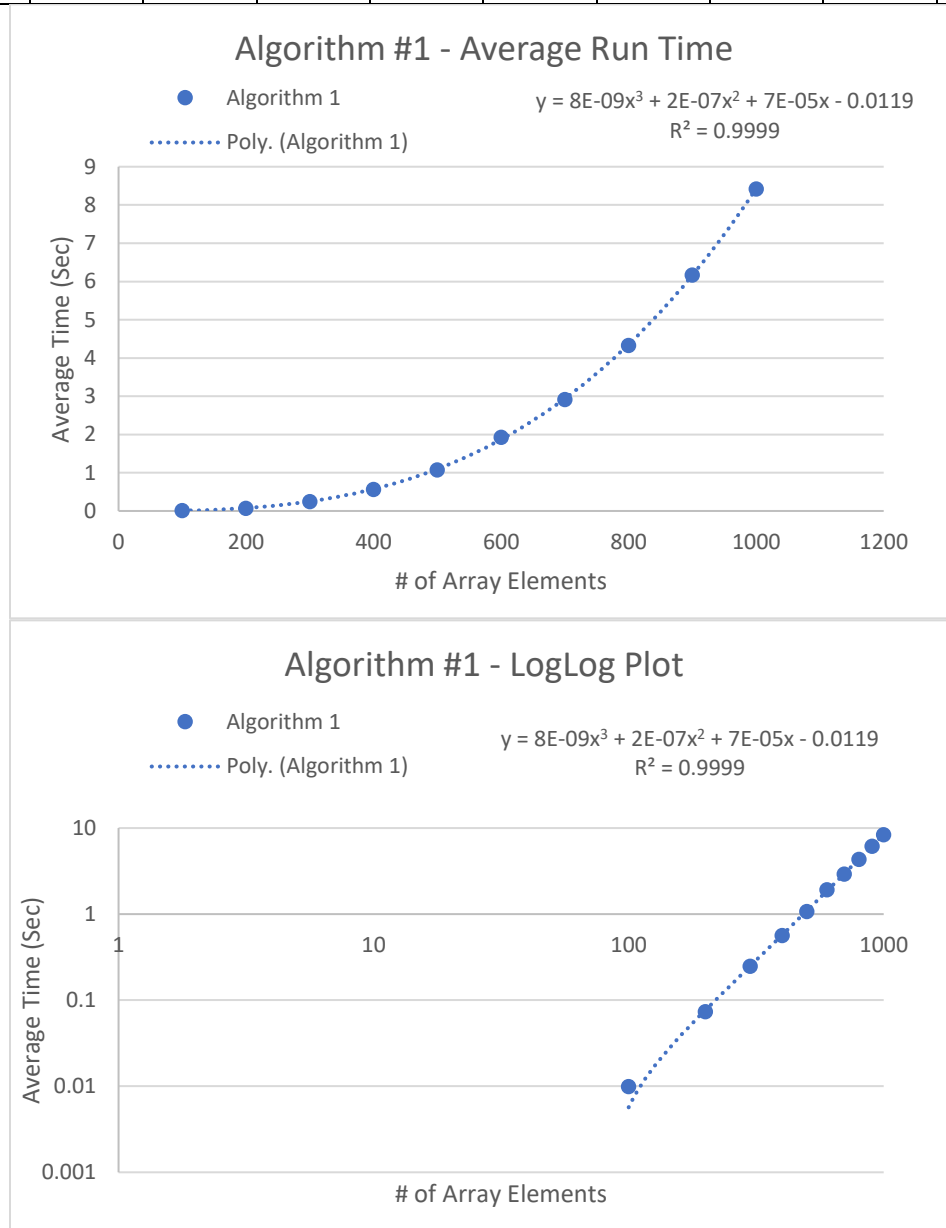
In this section you will find average run time charts and plots, regression modeling, log-log plots, and any deviation analysis, for each of the four algorithms. We then use our models to determine the maximum size of each array that can be processed in 5, 10, and 60 seconds.

Each average run time is based on 10 experimental times for each (n) number of elements.

Algorithm #1 – Enumeration

Average Run Times

N:	100	200	300	400	500	600	700	800	900	1000
Sec:	0.009	0.074	0.247	0.563	1.075	1.931	2.919	4.330	6.167	8.423



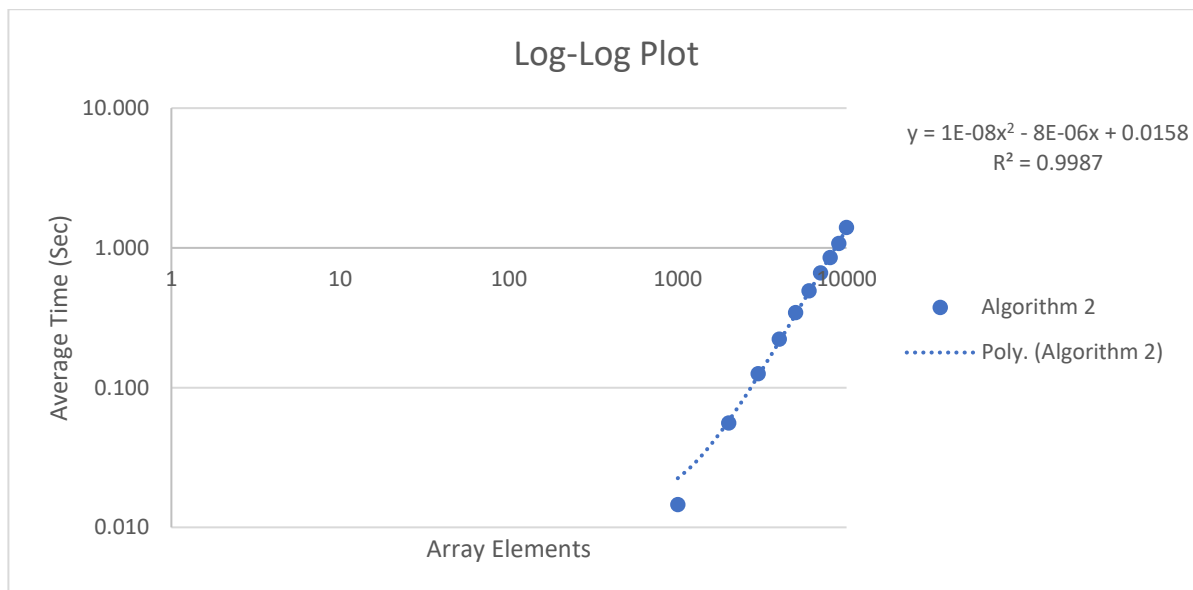
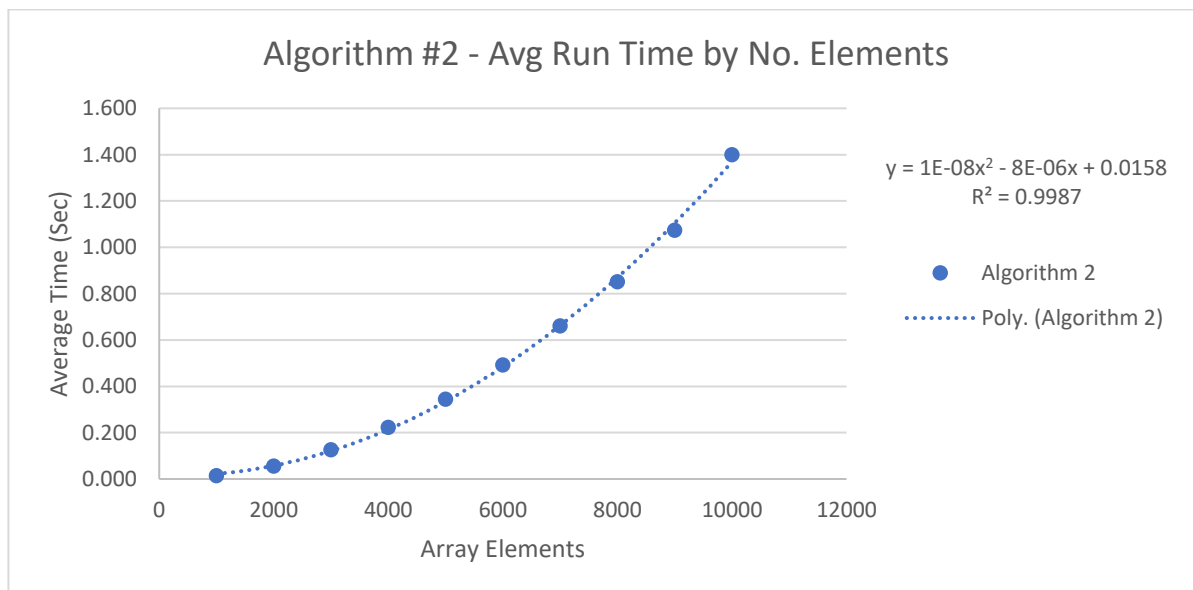
Our algorithm #1 experiment results matched our theorized run time expectations of a polynomial trend n^3 . Based on the regression model function: $y = 8E-09x^3 + 2E-07x^2 + 7E-05x - 0.0119$ we estimate the maximum array sizes processed to be:

Time:	5 seconds	10 seconds	60 seconds
Max N:	844.038	1,066.69	1,947.78

Algorithm #2 – Better Enumeration

Average Run Times:

N:	1000	2000	3000	4000	5000	6000	7000	8000	9000	10000
Sec:	0.015	0.056	0.126	0.223	.344	0.492	0.661	0.852	1.074	1.400



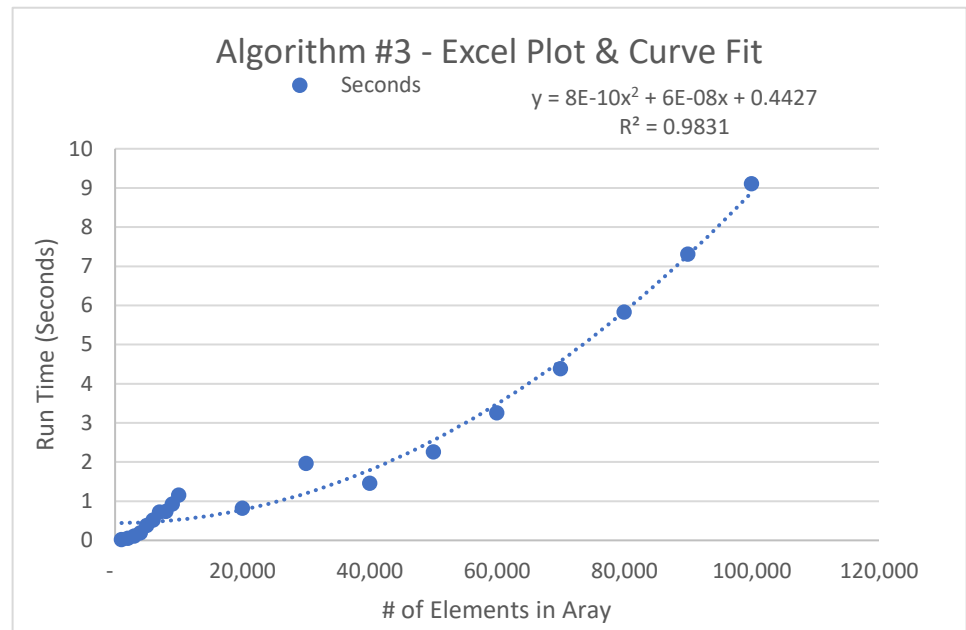
Algorithm #2 experimental run times demonstrate no discrepancies. Based on the regression model function:
 $y = 1E-08x^2 - 8E-06x + 0.0158$ we estimate the maximum array sizes processed to be:

Time:	5 seconds	10 seconds	60 seconds
Max N:	22,728.9	32,000.3	77,050.5

Algorithm #3 – Divide & Conquer

Average Run Times:

N	Seconds
1,000	0.0141
2,000	0.0495
3,000	0.1111
4,000	0.1925
5,000	0.3748
6,000	0.5201
7,000	0.7239
8,000	0.7403
9,000	0.9286
10,000	1.1519
20,000	0.817
30,000	1.959
40,000	1.458
50,000	2.254
60,000	3.253
70,000	4.38
80,000	5.829
90,000	7.31
100,000	9.106



MATLAB Custom Fit :

General model:

$$f(x) = a \cdot x \cdot \log(x)$$

Coefficients (with 95% confidence bounds):

$$a = 6.51e-06 \text{ (5.845e-06, 7.174e-06)}$$

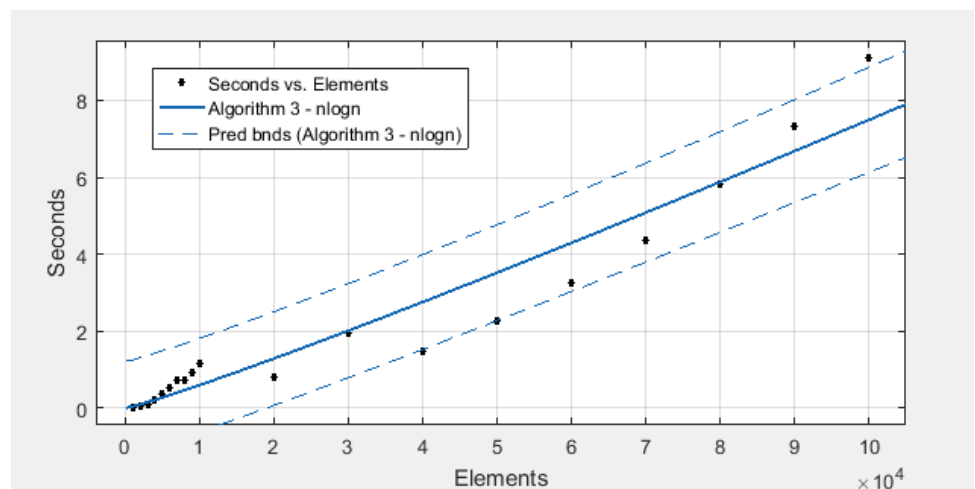
Goodness of fit:

SSE: 8.79

R-square: 0.9304

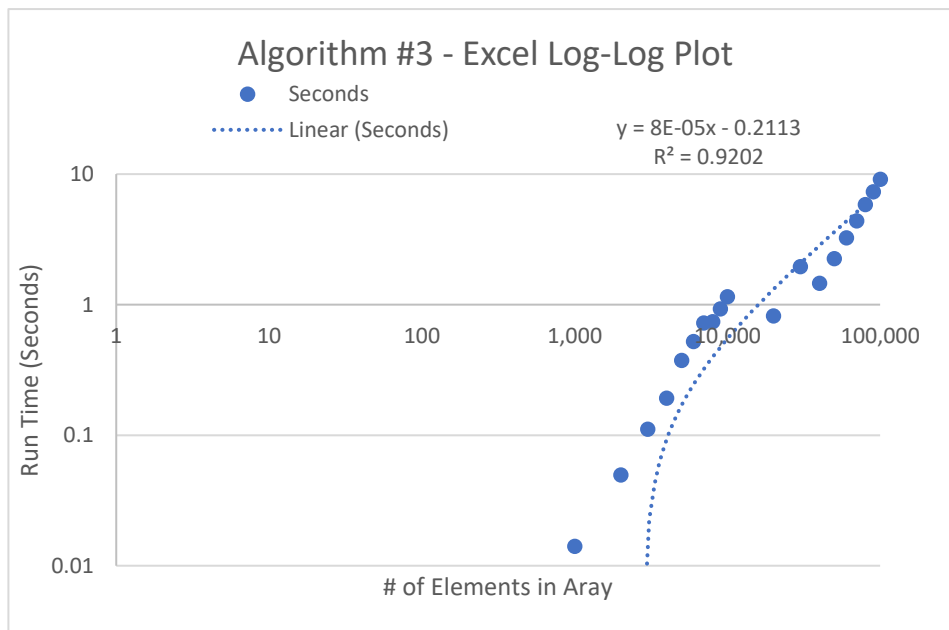
Adjusted R-square: 0.9304

RMSE: 0.6988



Using MatLab to custom curve fit found that while the experimental run times of algorithm #3 have the best R value, “fit”, to a polynomial function, they are also within statistical range of the anticipated $n \cdot \log(n)$. Our experiment results fall within 90% predictive bounds of the theorized run-time.

Still, we did not expect our run-times to be a perfect fit due to variations in our code implementation and systems. For example, we removed the cross over function from the main algorithm and had it separate from the main recursive call.

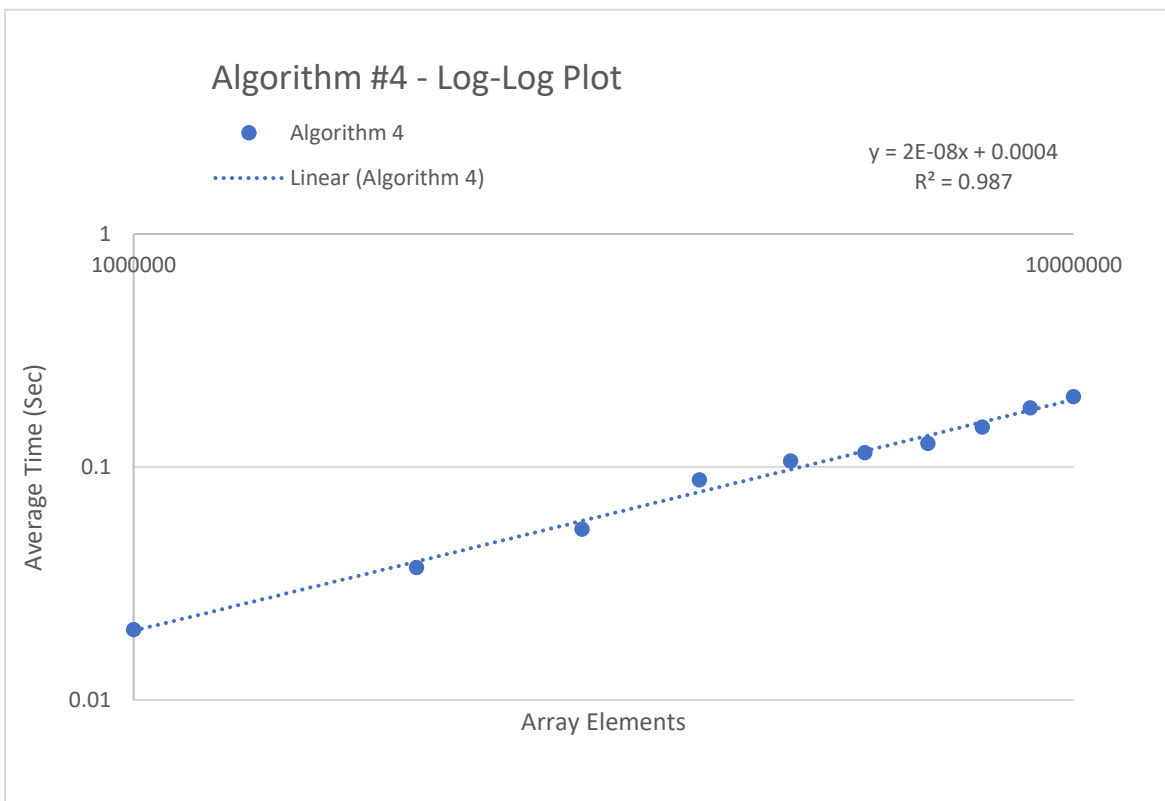
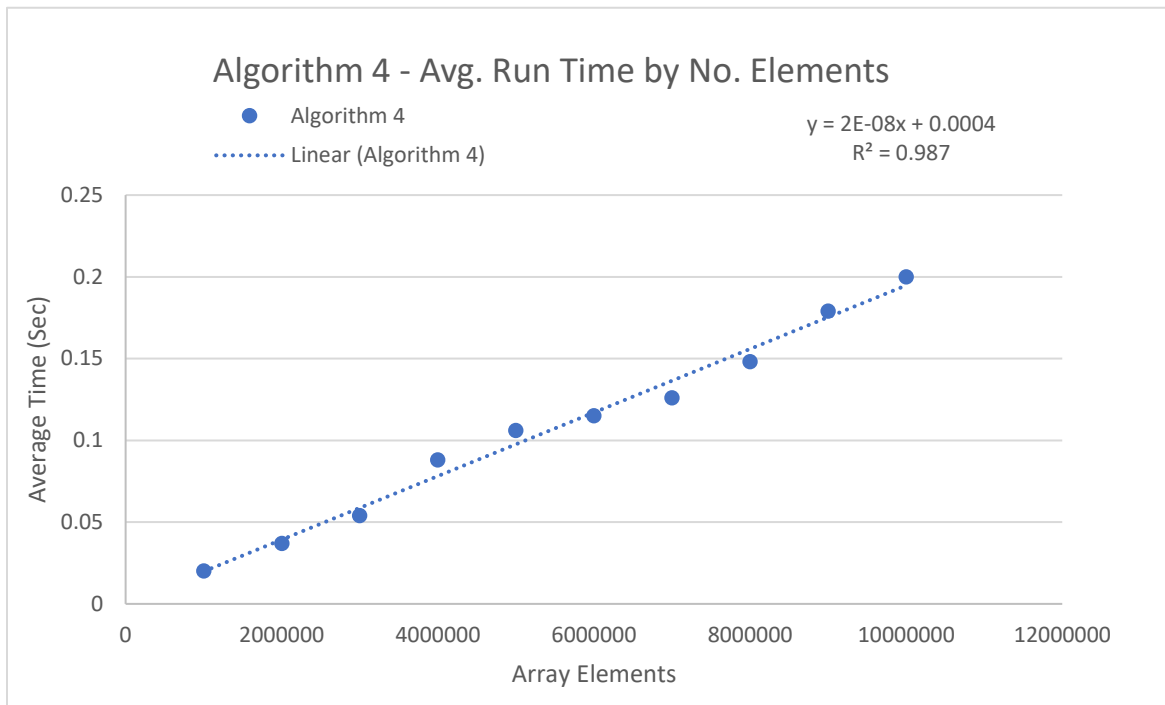


Based on the regression model function: $y = 8E-10x^2 + 6E-08x + 0.4427$ we estimate the maximum array sizes processed to be:

Time:	5 seconds	10 seconds	60 seconds
Max N:	75,438.5	109,263	272,812

Algorithm #4 – Average Run Times

There were no discrepancies with our experiment results.



Based on the regression model function: $y = 2E-08x + 0.0004$ we estimate the maximum array sizes processed to be:

Time:	5 seconds	10 seconds	60 seconds
Max N:	249,980,000	~499,980,000	2,999,980,000

Algorithm Comparison Graph

