## Analysis of addInt, multInt, divInt, addDoub, multDoub, and divDoub

Generally, into should be more efficient than doubles in terms of both time and memory since int uses less space than doubles. However, the difference in efficiency, especially in terms of time, is so small that it cannot be observed by using such simple operations from this lab.

Looking at the different operations that were performed, theoretically, addition should take the least amount of time. However, similar to above, the difference is so trivial that it cannot really be observed. There are some discrepancies between the operations as seen on the figures attached on the next page but due to the unreasonable nature of these fluctuations in the data where there seem to be no certain pattern nor explanations, it is safe to conclude that these fluctuations are happening because of the hardware, other programs occupying processing block, and/or other reasons that's preventing the program from utilizing the constant resources throughout the lab.

One thing that is certain as observed from the box plots is that as n becomes larger, the confidence of the data increases, meaning that the variance of the data for each of the operations decreases. By comparing the box plot when n = 10 to any other box plot, it is clear that the variance of data when n = 100 is far greater than any other. The size and the range of the box and whisker is far larger when n is small. This occurs because as the number of times increases, the accuracy of the runtime becomes more precise as outliers have diminished effect on the averaged runtime.

## Analysis of sine, pwr, and print

All three of these operations take considerable more time to run than the operations discussed above. This is mostly due to the fact that these operations are not simple addition, multiplication, and division.

Although the computational operations between sine and power functions are not too discernible in the numpy library, the reason power function takes slightly longer than the sine function is that the power function has two inputs instead of one as done for sine function. In fact, the power function has to take two numbers into consideration when running and these numbers affect each other (one is the base while the other is the power) compared to the sine function where it's just one input that runs through the sine function. Print, on the other hand, is a completely different story. Print itself takes quite a long time (compared to other operations used in this lab) and the fact that there is a loop (although it is a simple one) that involves two runs of the print operation adds considerable time to the runtime.

As mentioned above, as n increases, the precision of the data also improves. This is shown for these three operations too with the exception of print for n = 5000. The only explanation for this is that there is a big outlier or multiple outliers in the data that is skewing the shape of the box plot. As n increases, the box plots for all three operations grow smaller and smaller in size indicating that the data is becoming more accurate.

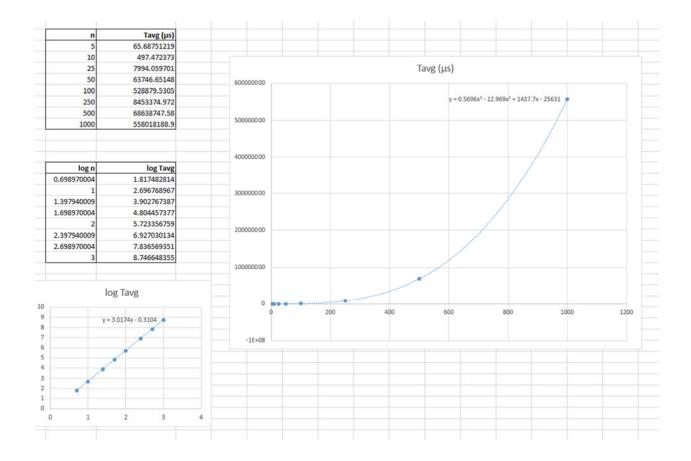
## Gauss Analysis

Theoretically, the runtime of Gaussian Elimination with Pivoting is  $O(n^3)$ . Looking at the algorithm step by step, let's say n = 6 (six columns and five rows). The algorithm first makes 5 comparisons to figure out the largest absolute value of the first column by going through the 5 rows. Then the algorithm swaps the rows. This swapping does not take too much time to run but rather consumes memory by creating a temp variable (memory is not a concern for this lab). The algorithm then goes to the rows below the first row and adds/subtracts after calculating the ratio that would make that row's first element 0 for every single row below the first. The entire process of this is then repeated 4 times so that a triangular matrix is outputted. To simply the algorithm further, there are 3 for-loops which results in a cubic runtime.

Plotting the log-log of the n vs runtime for Gaussian algorithm, the slope of the line is approximately 3. By fitting a cubic polynomial trendline on the actual data, it is clear to see that the trendline fits the data well. This confirms the fact that Gaussian algorithm has a cubic runtime. The coefficients, however, are fairly small. This can be explained by how the algorithm does not have a full cubic runtime. In fact, even though n = 6, the 3 for-loops are running 5 times (going through the 5 rows), 5 times (doing 5 compares of the absolute values), and 4 times (adding/subtracting the remaining rows to zero out the elements). To be clearer, the runtime should be O((n-1)(n-2)(n-2)). Because the runtime is O((n-1)(n-2)(n-2)) instead of O((n)(n)(n)), the coefficients for the cubic trendline are relatively small.



n=1000 function Q3	addint1 (ns) 0.677249364			multint2 (ns) 0.677249364	divint1 (ns) 0.677249368	divint2 (ns) a 0.677249364		) addDoub2 0 0.67724		ub1 (ns) r	multDoub2 (ns) d 0.677249364	divDoub1 (ns) d	fivDoub2 (ns 0.6772493		ne (ns) pr 681.9901062	owr (ns) p	print (ns) 65124.2989
Max	1.354498732	1.35449873		2.70899746	1.354498728	2.031748092	2.03174809			1748096	2.031748096	2.031748092	1.3544987		713.8208264	1384.2977	65657.294
Min	0	0	0	0	0	0		0	0	0	0	0		0	677.2493606	1357.884975	55684.797
Q1	0	0	0	0	0	0		0	0	0	0	0		0	679.2811087	1359.239474	64566.922
			n = 10	000							= 1000					n = 1000	
	addInt1, 2,	multint1, 2, d	fivInt1, 2, add	Doub1, 2, mu	ltDoub1, 2, di	vDoub1,				sin	ne, pwr					print	
			2					1600						68000	9		
3																	
								1400						66000	9		
2.5																	0
2.5								1200						54000	0		
														62000	,		
2								1000						0200			
														60000	2		
1.5								800									
	1 1			1						_				58000	0		
								600									
1														56000	0		
	<u> </u>		<b>+</b> +			, 4		400						54000	,		
0.5														5400			
						1 📕 🖟		200						52000	)		
0																	
	dint1 addint2 m		ivint1 (ns) divint2 (ns)					0						50000	0		
()	ns) (ns)	(ns) (ns)		(ns) (ns)	(ns) (ns)	) (ns) (n	15)		sine (ns)	)		pwr (ns)				print (ns)	
=5000																	
unction					divint1 (ns)	divInt2 (ns) a						divDoub1 (ns)					print (ns)
unction Q3	0.135449875	0.135449875	0.135449869	0.135449864	0	0	0.13544987	75 0.13544	9875 0.13	35449875	0.135449875	0.135449864	0.135449	9864	678.0620173	1356.124035	53391.36
unction Q3 Max	0.135449875 0.541799494	0.135449875 0.406349619	0.135449869 0.406349619	0.135449864 0.406349614	0.27089975	0.406349614	0.13544987	75 0.13544 14 0.40634	9875 0.13 9614 0.40	35449875 06349625	0.135449875 0.27089975	0.135449864 0.27089975		9864 9614	678.0620173 687.6789583	1356.124035 1362.35473	53391.36 53977.04
unction 23 Max Min	0.135449875 0.541799494 0	0.135449875 0.406349619 0	0.135449869 0.406349619 0	0.135449864 0.406349614 0	0 0.27089975 0	0 0.406349614 0	0.13544987 0.40634961	75 0.13544 14 0.40634 0	9875 0.13 9614 0.40 0	35449875 06349625 0	0.135449875 0.27089975 0	0.135449864 0.27089975 0	0.135449 0.406349	9864 9614 0	678.0620173 687.6789583 677.249318	1356.124035 1362.35473 1354.904986	53391.36 53977.04 49766.04
unction 23 Max Min	0.135449875 0.541799494	0.135449875 0.406349619	0.135449869 0.406349619 0	0.135449864 0.406349614	0.27089975	0.406349614	0.13544987 0.40634961	75 0.13544 14 0.40634	9875 0.13 9614 0.40	35449875 06349625	0.135449875 0.27089975 0	0.135449864 0.27089975 0	0.135449 0.406349	9864 9614	678.0620173 687.6789583	1356.124035 1362.35473	53391.36 53977.04 49766.04
unction 23 Max Min	0.135449875 0.541799494 0	0.135449875 0.406349619 0	0.135449869 0.406349619 0	0.135449864 0.406349614 0 0	0 0.27089975 0	0 0.406349614 0	0.13544987 0.40634961	75 0.13544 14 0.40634 0	9875 0.13 9614 0.40 0	35449875 06349625 0 0	0.135449875 0.27089975 0 0	0.135449864 0.27089975 0	0.135449 0.406349	9864 9614 0	678.0620173 687.6789583 677.249318 677.5202178	1356.124035 1362.35473 1354.904986 1355.175886	53391.36 53977.04 49766.04
unction 23 Max Min	0.135449875 0.541799494 0 0	0.135449875 0.406349619 0	0.135449869 0.406349619 0 0	0.135449864 0.406349614 0 0	0.27089975 0 0	0 0.406349614 0 0	0.13544987 0.40634961	75 0.13544 14 0.40634 0	9875 0.13 9614 0.40 0	35449875 06349625 0 0	0.135449875 0.27089975 0 0	0.135449864 0.27089975 0	0.135449 0.406349	9864 9614 0	678.0620173 687.6789583 677.249318 677.5202178	1356.124035 1362.35473 1354.904986 1355.175886	53391.36 53977.04 49766.04
unction 23 Max Min 21	0.135449875 0.541799494 0 0	0.135449875 0.406349619 0	0.135449869 0.406349619 0	0.135449864 0.406349614 0 0	0.27089975 0 0	0 0.406349614 0 0	0.13544987 0.40634961	75 0.13544 14 0.40634 0 0	9875 0.13 9614 0.40 0	35449875 06349625 0 0	0.135449875 0.27089975 0 0	0.135449864 0.27089975 0	0.135449 0.406349	9864 9614 0	678.0620173 687.6789583 677.249318 677.5202178	1356.124035 1362.35473 1354.904986 1355.175886	53391.36 53977.04 49766.04
unction (3 Max Min	0.135449875 0.541799494 0 0	0.135449875 0.406349619 0	0.135449869 0.406349619 0 0	0.135449864 0.406349614 0 0	0.27089975 0 0	0 0.406349614 0 0	0.13544987 0.40634961	75 0.13544 14 0.40634 0	9875 0.13 9614 0.40 0	35449875 06349625 0 0	0.135449875 0.27089975 0 0	0.135449864 0.27089975 0	0.135449 0.406349	9864 9614 0	678.0620173 687.6789583 677.249318 677.5202178	1356.124035 1362.35473 1354.904986 1355.175886	53391.36 53977.04 49766.04
unction (3 Max Min	0.135449875 0.541799494 0 0	0.135449875 0.406349619 0	0.135449869 0.406349619 0 0	0.135449864 0.406349614 0 0	0.27089975 0 0	0 0.406349614 0 0	0.13544987 0.40634961	75 0.13544 14 0.40634 0 0	9875 0.13 9614 0.40 0	35449875 06349625 0 0	0.135449875 0.27089975 0 0	0.135449864 0.27089975 0	0.135449 0.406349	9864 9614 0 0	678.0620173 687.6789583 677.249318 677.5202178	1356.124035 1362.35473 1354.904986 1355.175886	53391.36 53977.04 49766.04
unction 13 4ax 4in 11	0.135449875 0.541799494 0 0	0.135449875 0.406349619 0	0.135449869 0.406349619 0 0	0.135449864 0.406349614 0 0	0.27089975 0 0	0 0.406349614 0 0	0.13544987 0.40634961	75 0.13544 14 0.40634 0 0	9875 0.13 9614 0.40 0	35449875 06349625 0 0	0.135449875 0.27089975 0 0	0.135449864 0.27089975 0	0.135449 0.406349	9864 9614 0 0	678.0620173 687.6789583 677.249318 677.5202178	1356.124035 1362.35473 1354.904986 1355.175886	53391.36 53977.04 49766.04
unction 33 Max Min 21	0.135449875 0.541799494 0 0	0.135449875 0.406349619 0	0.135449869 0.406349619 0 0	0.135449864 0.406349614 0 0	0.27089975 0 0	0 0.406349614 0 0	0.13544987 0.40634961	75 0.13544 14 0.40634 0 0	9875 0.13 9614 0.40 0	35449875 06349625 0 0	0.135449875 0.27089975 0 0	0.135449864 0.27089975 0	0.135449 0.406349 5500	9864 9614 0 0	678.0620173 687.6789583 677.249318 677.5202178	1356.124035 1362.35473 1354.904986 1355.175886	53391.36 53977.04 49766.04
unction 33 Aax Min 21	0.135449875 0.541799494 0 0	0.135449875 0.406349619 0	0.135449869 0.406349619 0 0	0.135449864 0.406349614 0 0	0.27089975 0 0	0 0.406349614 0 0	0.13544987 0.40634961	75 0.13544 14 0.40634 0 0	9875 0.13 9614 0.40 0	35449875 06349625 0 0	0.135449875 0.27089975 0 0	0.135449864 0.27089975 0	0.135449 0.406349	9864 9614 0 0	678.0620173 687.6789583 677.249318 677.5202178	1356.124035 1362.35473 1354.904986 1355.175886	53391.36 53977.04 49766.04
unction 33 Aax Min 21	0.135449875 0.541799494 0 0	0.135449875 0.406349619 0	0.135449869 0.406349619 0 0	0.135449864 0.406349614 0 0	0.27089975 0 0	0 0.406349614 0 0	0.13544987 0.40634961	75 0.13544 14 0.40634 0 0 1500	9875 0.13 9614 0.40 0	35449875 06349625 0 0	0.135449875 0.27089975 0 0	0.135449864 0.27089975 0	0.135449 0.406349 5500 5400	9864 9614 0 0	678.0620173 687.6789583 677.249318 677.5202178	1356.124035 1362.35473 1354.904986 1355.175886	53391.36 53977.04 49766.04
unction 33 Aax Min 21	0.135449875 0.541799494 0 0	0.135449875 0.406349619 0	0.135449869 0.406349619 0 0	0.135449864 0.406349614 0 0	0.27089975 0 0	0 0.406349614 0 0	0.13544987 0.40634961	75 0.13544 14 0.40634 0 0	9875 0.13 9614 0.40 0	35449875 06349625 0 0	0.135449875 0.27089975 0 0	0.135449864 0.27089975 0	0.135449 0.406349 5500	9864 9614 0 0	678.0620173 687.6789583 677.249318 677.5202178	1356.124035 1362.35473 1354.904986 1355.175886	53391.36 53977.04 49766.04
unction 23 Max Min 21 0.5	0.135449875 0.541799494 0 0	0.135449875 0.406349619 0	0.135449869 0.406349619 0 0	0.135449864 0.406349614 0 0	0.27089975 0 0	0 0.406349614 0 0	0.13544987 0.40634961	75 0.13544 14 0.40634 0 0 0 1600 1400 1200 1200 1200 1200	9875 0.13 9614 0.40 0	35449875 06349625 0 0	0.135449875 0.27089975 0 0	0.135449864 0.27089975 0	0.135449 0.406349 5500 5400 5300	9864 9614 0 0 0	678.0620173 687.6789583 677.249318 677.5202178	1356.124035 1362.35473 1354.904986 1355.175886	53391.36 53977.04 49766.04
unction 23 Max Min 21 0.5	0.135449875 0.541799494 0 0	0.135449875 0.406349619 0	0.135449869 0.406349619 0 0	0.135449864 0.406349614 0 0	0.27089975 0 0	0 0.406349614 0 0	0.13544987 0.40634961	75 0.13544 14 0.40634 0 0 1500	9875 0.13 9614 0.40 0	35449875 06349625 0 0	0.135449875 0.27089975 0 0	0.135449864 0.27089975 0	0.135449 0.406349 5500 5400	9864 9614 0 0 0	678.0620173 687.6789583 677.249318 677.5202178	1356.124035 1362.35473 1354.904986 1355.175886	53391.36 53977.04 49766.04
unction 23 Max Min 21 0.5	0.135449875 0.541799494 0 0	0.135449875 0.406349619 0	0.135449869 0.406349619 0 0	0.135449864 0.406349614 0 0	0.27089975 0 0	0 0.406349614 0 0	0.13544987 0.40634961	75 0.13544 14 0.40634 0 0 0 1500 1500 1500 1500 1500 1500 150	9875 0.13 9614 0.40 0	35449875 06349625 0 0	0.135449875 0.27089975 0 0	0.135449864 0.27089975 0	0.135449 0.406349 5500 5400 5300 5100	9864 9614 0 0 0 00 00	678.0620173 687.6789583 677.249318 677.5202178	1356.124035 1362.35473 1354.904986 1355.175886	53391.36 53977.04 49766.04
unction	0.135449875 0.541799494 0 0	0.135449875 0.406349619 0	0.135449869 0.406349619 0 0	0.135449864 0.406349614 0 0	0.27089975 0 0	0 0.406349614 0 0	0.13544987 0.40634961	75 0.13544 14 0.40634 0 0 0 1600 1400 1200 1200 1200 1200	9875 0.13 9614 0.40 0	35449875 06349625 0 0	0.135449875 0.27089975 0 0	0.135449864 0.27089975 0	0.135449 0.406349 5500 5400 5300	9864 9614 0 0 0 00 00	678.0620173 687.6789583 677.249318 677.5202178	1356.124035 1362.35473 1354.904986 1355.175886	53391.36 53977.04 49766.04
unction 23 Max Min 21 0.5	0.135449875 0.541799494 0 0	0.135449875 0.406349619 0	0.135449869 0.406349619 0 0	0.135449864 0.406349614 0 0	0.27089975 0 0	0 0.406349614 0 0	0.13544987 0.40634961	75 0.135444 0.40634 0.406	9875 0.13 9614 0.40 0	35449875 06349625 0 0	0.135449875 0.27089975 0 0	0.135449864 0.27089975 0	0.135449 0.406349 5500 5400 5300 5100 5000	000 000 000 000	678.0620173 687.6789583 677.249318 677.5202178	1356.124035 1362.35473 1354.904986 1355.175886	53391.36 53977.04 49766.04
unction 23 Max Win 21 0.6 0.5 0.4 0.3 0.2	0.135449875 0.541799494 0 0	0.135449875 0.406349619 0	0.135449869 0.406349619 0 0	0.135449864 0.406349614 0 0	0.27089975 0 0	0 0.406349614 0 0	0.13544987 0.40634961	75 0.13544 14 0.40634 0 0 0 1500 1500 1500 1500 1500 1500 150	9875 0.13 9614 0.40 0	35449875 06349625 0 0	0.135449875 0.27089975 0 0	0.135449864 0.27089975 0	0.135449 0.406349 5500 5400 5300 5100	000 000 000 000	678.0620173 687.6789583 677.249318 677.5202178	1356.124035 1362.35473 1354.904986 1355.175886	53391.36 53977.04 49766.04
unction 23 Max Win 21 0.6 0.5 0.4 0.3 0.2	0.135449875 0.541799494 0 0	0.135449875 0.406349619 0	0.135449869 0.406349619 0 0	0.135449864 0.406349614 0 0	0.27089975 0 0	0 0.406349614 0 0	0.13544987 0.40634961	75 0.135444 0.46634 0.46634 0.1600 11000 1200 1200 1000 1000 1000 1000	9875 0.13 9614 0.40 0	35449875 06349625 0 0	0.135449875 0.27089975 0 0	0.135449864 0.27089975 0	0.135449 0.406349 5500 5400 5300 5100 5000 4900	000 000 000 000 000 000	678.0620173 687.6789583 677.249318 677.5202178	1356.124035 1362.35473 1354.904986 1355.175886	53391.360 53977.04
unction 23 Max Win 21 0.6 0.5 0.4 0.3 0.2	0.135449875 0.541799494 0 0	0.135449875 0.406349619 0	0.135449869 0.406349619 0 0	0.135449864 0.406349614 0 0	0.27089975 0 0	0 0.406349614 0 0	0.13544987 0.40634961	75 0.135444 0.40634 0.406	9875 0.13 9614 0.40 0	35449875 06349625 0 0	0.135449875 0.27089975 0 0	0.135449864 0.27089975 0	0.135449 0.406349 5500 5400 5300 5100 5000	000 000 000 000 000 000	678.0620173 687.6789583 677.249318 677.5202178	1356.124035 1362.35473 1354.904986 1355.175886	53391.36 53977.04 49766.04
unction  33  Max  Min  21  0.6	0.135449875 0.541799494 0 0	0.135449875 0.406349619 0	0.135449869 0.406349619 0 0	0.135449864 0.406349614 0 0	0.27089975 0 0	0 0.406349614 0 0	0.13544987 0.40634961	75 0.135444 0.40634 0 0 1600 1400 1200 800 600 400	9875 0.13 9614 0.40 0	35449875 06349625 0 0	0.135449875 0.27089975 0 0	0.135449864 0.27089975 0	0.135449 0.406349 5500 5400 5300 5100 4900 4800	00000000000000000000000000000000000000	678.0620173 687.6789583 677.249318 677.5202178	1356.124035 1362.35473 1354.904986 1355.175886	53391.36 53977.04 49766.04
unction 23 wax	0.135449975 0.541799494 0 0 0	0.135449875 0.406349619 0 0 0 nult1Nt1, 2 div	0.135449869 0.406349919 0 0 n = 50	0.135449864 0.406349914 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0	0 0.22089975 0 0	0.406349614 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0	0.135449813 0.40634961	75 0.135444 0.46634 0.46634 0.1600 11000 1200 1200 1000 1000 1000 1000	9875 0.13 9614 0.40 0	35449875 06349625 0 0	0.135449675 0.27089975 0 0 0	0.135449864 0.27089975 0	0.135449 0.406349 5500 5400 5300 5100 5000 4900	00000000000000000000000000000000000000	678.0620173 687.6789583 677.249318 677.5202178	1356.124035 1362.35473 1354.904986 1355.175886	53391.36 53977.04 49766.04



```
lab2.py
# CS 317 Algorithm Anaylsis Lab 2
# Drake Song
# Python 3.6
import numpy as np
import timeit
import os
import pdb
def clear():
    os.system('cls')
def addInt1():
    return 23 + 38
def addInt2():
    return 7261852 + 4917528
def multInt1():
    return 23 * 28
def multInt2():
    return 7261852 * 4917528
def divInt1():
    return 23 / 38
def divInt2():
    return 7261852 / 4917528
def addDoub1():
    return 23.3 + 38.1
def addDoub2():
    return 7261852.6 + 4917528.9
def multDoub1():
    return 23.3 * 38.1
def multDoub2():
    return 7261852.6 * 4917528.9
def divDoub1():
    return 23.3 / 38.1
def divDoub2():
    return 7261852.6 / 4917528.9
```

```
lab2.py
def sine():
    return np.sin(1.23)
def pwr():
    return np.power(3.13, 2.78)
def printStuff():
    for i in range(2):
        print(i)
def runFunction(n, x):
    time = []
   minimum = 0
    q1 = 0
    q3 = 0
    maximum = 0
    for i in range(n):
        for j in range(21):
            tic = timeit.default_timer()
            toc = timeit.default_timer()
            time.append((toc-tic)*1000000000)
        sorted time = sorted(time)
        minimum += sorted_time[0]
        q1 += sorted_time[5]
        q3 += sorted_time[15]
        maximum += sorted_time[20]
    minimum /= n
    q1 /= n
    q3 /= n
    maximum /= n
    selected_time = [minimum, q1, q3, maximum]
    print(selected_time)
def runPrintStuff(n):
    time = []
    minimum = 0
    q1 = 0
    q3 = 0
    maximum = 0
    for i in range(n):
        for j in range(21):
            tic = timeit.default_timer()
            printStuff()
```

```
lab2.py
            toc = timeit.default timer()
            time.append((toc-tic)*1000000000)
        sorted_time = sorted(time)
        minimum += sorted_time[0]
        q1 += sorted_time[5]
        q3 += sorted_time[15]
        maximum += sorted_time[20]
    clear()
    minimum /= n
    q1 /= n
    q3 /= n
    maximum /= n
    selected_time = [minimum, q1, q3, maximum]
    runFunction(n, addInt1)
    runFunction(n, addInt2)
    runFunction(n, multInt1)
    runFunction(n, multInt2)
    runFunction(n, divInt1)
    runFunction(n, divInt2)
    runFunction(n, addDoub1)
    runFunction(n, addDoub2)
    runFunction(n, multDoub1)
    runFunction(n, multDoub2)
    runFunction(n, divDoub1)
    runFunction(n, divDoub2)
    runFunction(n, sine)
    runFunction(n, pwr)
    print(selected_time)
n = int(input("Please enter a positive integer: "))
runPrintStuff(n)
```

```
gauss.py
# CS 317 Algorithm Anaylsis Lab 2
# Drake Song
# Python 3.6
import numpy as np
import timeit
import os
os.system('cls')
time = []
ans = []
n = int(input("Enter a number greater than 2: "))
matrix = np.random.randint(-100, 100, size=(n-1, n)).tolist()
# print("\nInitial matrix:")
# print(np.matrix(matrix))
for a in range(5):
    tic = timeit.default_timer()
    for k in range(n-2):
        largest = 0
        row = 0
        for i in range(k, n-1):
            if np.absolute(matrix[i][k]) > largest:
                largest = np.absolute(matrix[i][k])
                row = i
        temp = matrix[k]
        matrix[k] = matrix[row]
        matrix[row] = temp
        # print("\nMatrix after swap:")
        # print(np.matrix(matrix))
        for i in range(k+1, n-1):
            ratio = matrix[i][k]/matrix[k][k]
            temp = [np.absolute(matrix[k][j]*ratio) for j in range(n)]
            if matrix[i][k] > 0:
                matrix[i] = [matrix[i][j] - temp[j] for j in range(n)]
            else:
                matrix[i] = [matrix[i][j] + temp[j] for j in range(n)]
        # print("\nMatrix after subtraction:")
        # print(np.matrix(matrix))
    toc = timeit.default_timer()
    time.append((toc-tic)*1000000)
```

print(sum(time)/5)