EECS 469/569: Homework 3 Submission

Multi-Node Performance of Roaring Thunder

Due: Tuesday, Nov. 1 *before* midnight

(Optional this time) Sign-up for a grading period here.

$Main\ Takeaway$

MPI provides a more flexible way to implement parallel computing. MPI is more difficult to implement than openMP, it requires coder to think in paralle and have plans for all the ranks, but it is more flexible on each rank and more effecient than opnemp.

Another take away is that with MPI, there are algorithms based on paralle computing, and they can be done through MPI, and not openMP

$Work\ load\ distribution$

We worked together at all times in person during our meetings, we set up a github forfile sharing. For different parts, we did the same thing individually and discussed our findings. Lastly, wefinalized the submission on Chen-Wei's machine.

Name 1: Chen-Wei Hung

Name 2: Matthew Dentlinger

Checklist

1. Other Deliverables
    A. Sign up for grading slot (Optional, but encouraged)
    B. Email team to Dr. Hansen
    C. Write a couple of paragraphs on main takeaways and how you worked together
2. MPI Overhead
    A. ping pong overhead (single node, two nodes)
    B. collective communication overhead
3. MPI I/O
    A. MPI write speed
    B. MPI read speed
4. MPI Linear Algebra
    A. matrix-multiply speedup

B. matrix-vector and dot-product speedup

5. Other MPI Accelerations

   A. description of your solved problem and how you solved it, discussion of another group

Submission Instructions

Follow all instructions within `hw03.ipynb` . To submit the homework assignment, put **only relevant files (including this notebook)** in a folder. Zip the folder (e.g., using 7-zip) and send one email to Dr. Hansen (CC your partner) with the zipped folder. **Do not include the benchmark files, they are not relevant.** Print a .pdf of this (completed) Jupyter notebook and submit it to D2L before the deadline (`CTRL+P` $\rightarrow$ `Save as PDF` in Google Chrome).

It is your responsibility that all of the figures, plots, source code, etc. properly appear in the submitted notebook **and .pdf**.

Other Deliverables

∞.1 FIRST DELIVERABLE (-5 points if not on time): ***By class on Monday, Oct. 17,*** email Dr. Hansen (CC your group) who you will be working with for this homework.

∞.2 FINAL DELIVERABLE (3 points): ***After*** you have completed the entire assignment, write a few paragraphs on your main takeaways from the assignment. **Clearly state** how the work was split up between each of your group members.

1. MPI Overhead

Required SLURM Batch Submissions:

- pingpong with 1 node 2 processes
- pingpong with 2 nodes 1 process per node
- collectives with 4 nodes and 32 processes per node

Datasets: link your datasets here with a couple word description of each:

- example link
-

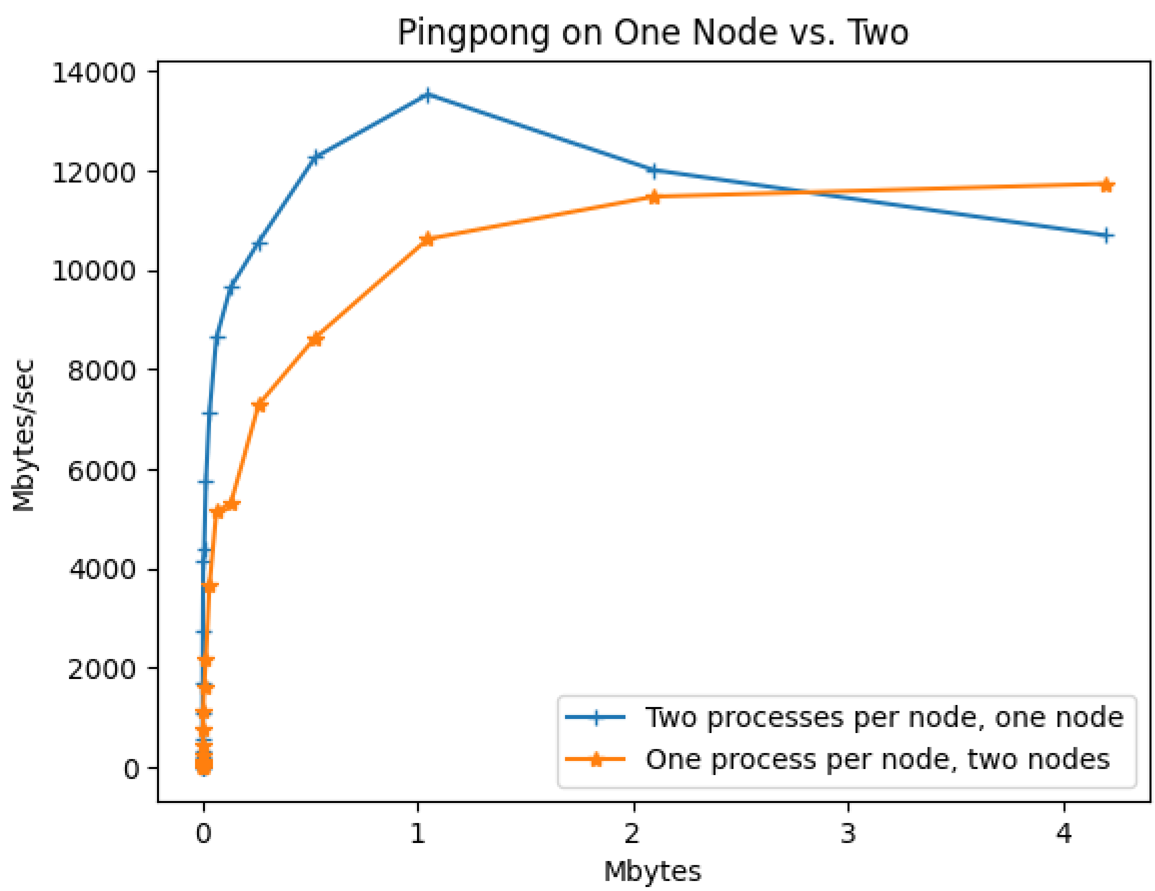
1.1 DELIVERABLE (8 points): Collect the output of the pingpong into a .csv file (or other data format to be used for plotting). You will need the following: number of Bytes, MBytes/sec. Plot two lines on the same graph:

1. pingpong on one node, MBytes/s (y-axis) vs. Bytes (x axis)
2. pingpong on two nodes, MBytes/s vs. Bytes

Be sure to add a legend and clearly identify which line is which. Discuss the difference in results for the pingpong benchmark for the two cases. What is different between the two cases, and why does that impact the transfer speed?

In [ ]:

```
# plot of pingpong MBytes/s vs Bytes

import matplotlib.pyplot as plt
import numpy as np
import pandas as pd

#create a dataframe
dataFrame_n1p2 = pd.read_csv("n1p2_pp.csv")
dataFrame_n2p1 = pd.read_csv("n2p1_pp.csv")

#plot
plt.plot(dataFrame_n1p2['#bytes']/(1e6),dataFrame_n1p2['Mbytes/sec'], marker='+', label
plt.plot(dataFrame_n2p1['#bytes']/(1e6),dataFrame_n2p1['Mbytes/sec'], marker='*', label
plt.xlabel('Mbytes')
plt.ylabel('Mbytes/sec')
plt.legend()
plt.title("Pingpong on One Node vs. Two")
plt.show()
```



Discussion: On paper, the pingpong on the same node with tow processes should be faster than two nodes with one processor each, because the communcation and send/receive between two nodes is slower than on one node. This is true for our result for upto 1MB. And for some reason, the two processors on the same node gets slower than the other one, and we are unsure why.

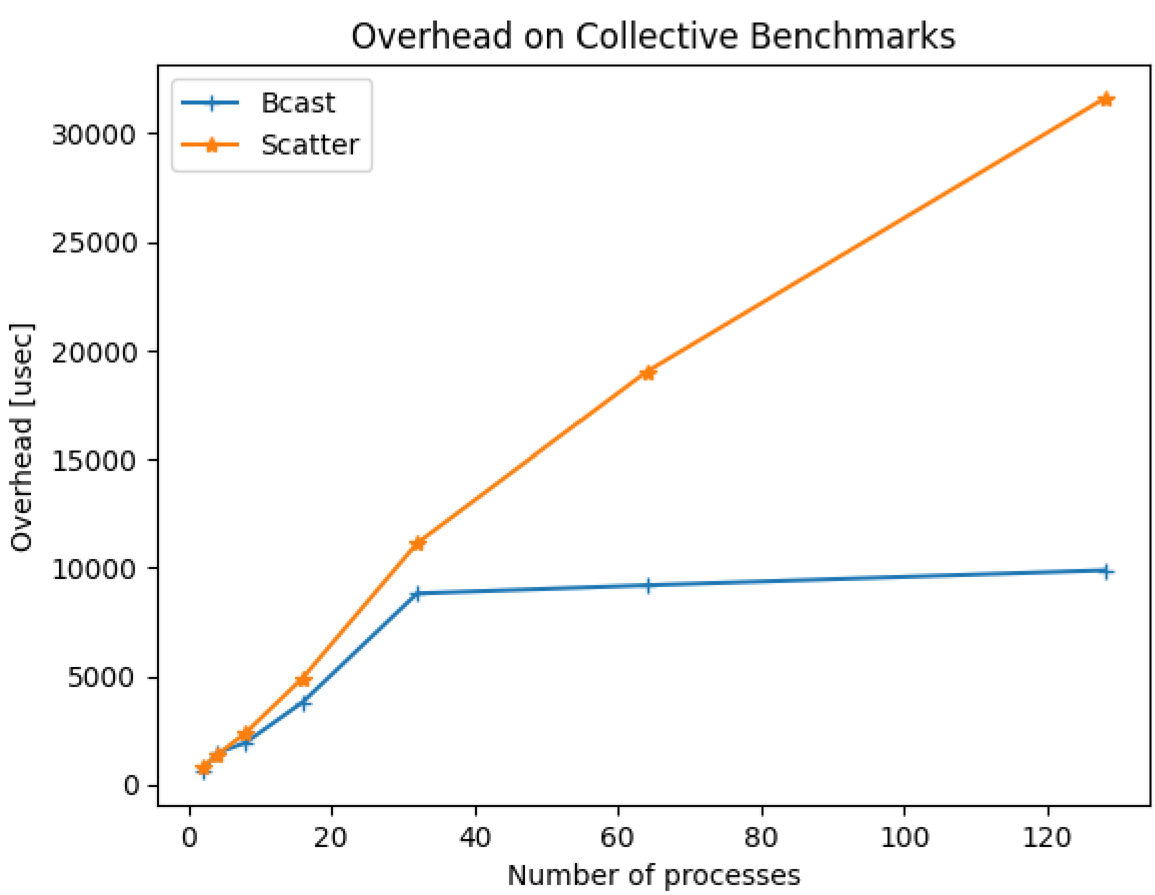
1.2 DELIVERABLE (12 points): Create three figures:

1. two line plots for two benchmarks: overhead [t_avg] vs. number of processes
2. one line plot for one benchmark: overhead [t_avg] vs. number of Bytes

3. eight box-whiskers (one for each benchmark) comparing the overhead of each collective communication.
    - you can approximate the true dataset by using a Normal distribution with mean [t*avg] and std. dev. $(t*{max}-t_{min})/4$.

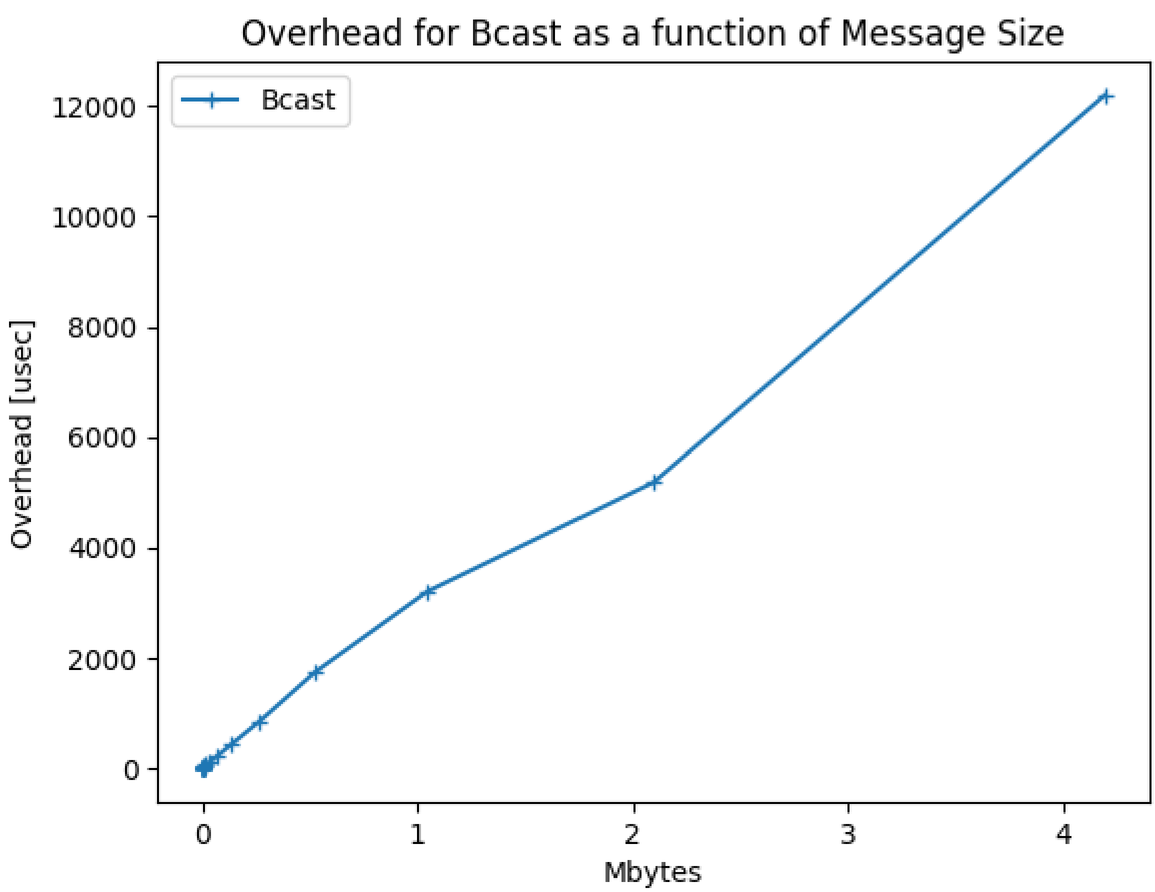
For the collective communication operations, discuss how they compare in terms of communication overhead. Spend time discussing how each scale as a function of the number of processes, as well as the size of the message. Do you notice anything in particular as the messages go across nodes?

In [ ]:
```python
# plot overhead for two benchmarks here

import matplotlib.pyplot as plt
import numpy as np
import pandas as pd

#create a dataframe
dataFrame_bcast = pd.read_csv("bcast.csv")
dataFrame_scatter = pd.read_csv("scatter.csv")

#plot
plt.plot(dataFrame_bcast['proc'],dataFrame_bcast['t_avg[usec]'], marker='+', label = "B
plt.plot(dataFrame_scatter['proc'],dataFrame_scatter['t_avg[usec]'], marker='*', label
plt.xlabel('Number of processes')
plt.ylabel('Overhead [usec]')
plt.legend()
plt.title("Overhead on Collective Benchmarks")
plt.show()
```



In [ ]:

```python
# plot the overhead for one benchmark here as a function of message size

import matplotlib.pyplot as plt
import numpy as np
import pandas as pd

#create a dataframe
dataFrame_bcast128 = pd.read_csv("bcast_128.csv")

#plot
plt.plot(dataFrame_bcast128['#bytes']/(1e6),dataFrame_bcast128['t_avg[usec]'], marker='
plt.xlabel('Mbytes')
plt.ylabel('Overhead [usec]')
plt.legend()
plt.title("Overhead for Bcast as a function of Message Size")
plt.show()
```



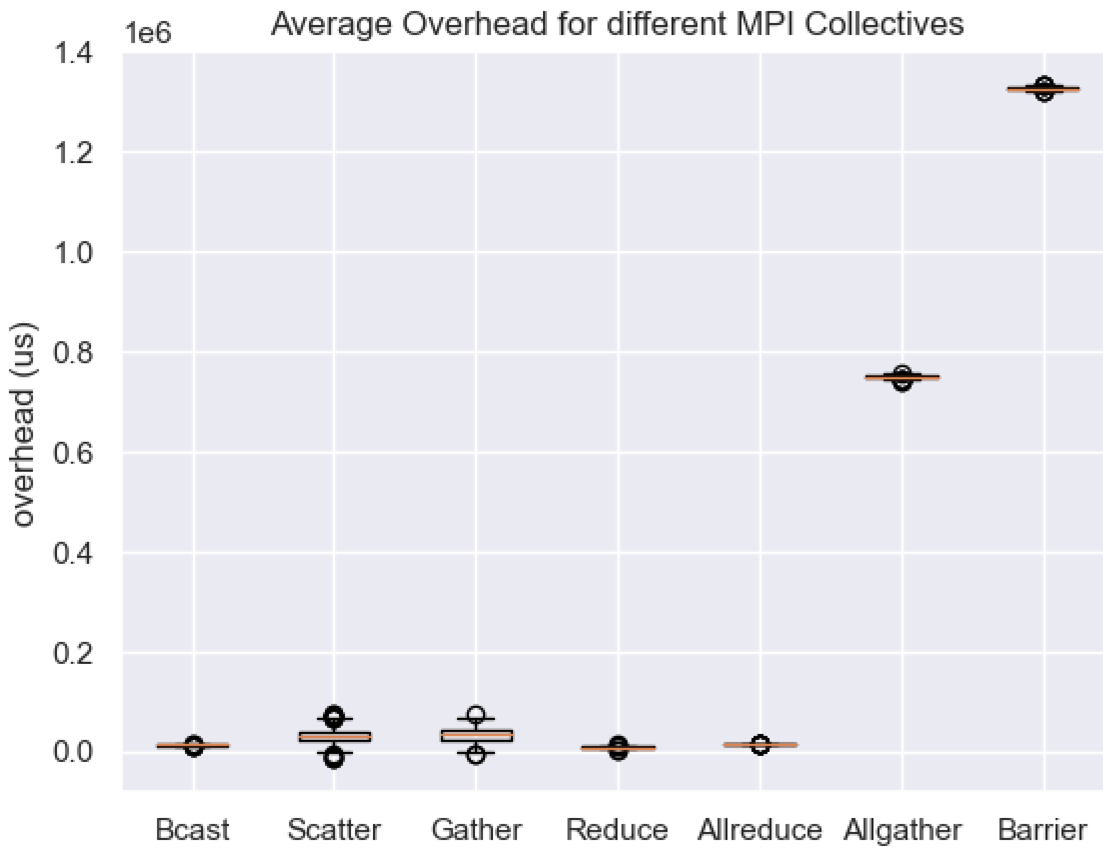
In [ ]:

```python
# plot the box-whiskers plot here

import matplotlib.pyplot as plt
import seaborn as sns
import numpy as np
import pandas as pd

sns.set()

#get random number generator from numpy
rng = np.random.default_rng()

#create a dataframes
```

```
dataFrame_allcollective = pd.read_csv("all_128.csv")

#defining min, maxes, and averages
bcast_min = dataFrame_allcollective["t_min[usec]"][0]
scatter_min = dataFrame_allcollective["t_min[usec]"][1]
gather_min = dataFrame_allcollective["t_min[usec]"][2]
reduce_min = dataFrame_allcollective["t_min[usec]"][3]
allreduce_min = dataFrame_allcollective["t_min[usec]"][4]
allgather_min = dataFrame_allcollective["t_min[usec]"][5]
barrier_min = dataFrame_allcollective["t_min[usec]"][6]

bcast_max = dataFrame_allcollective["t_max[usec]"][0]
scatter_max = dataFrame_allcollective["t_max[usec]"][1]
gather_max = dataFrame_allcollective["t_max[usec]"][2]
reduce_max = dataFrame_allcollective["t_max[usec]"][3]
allreduce_max = dataFrame_allcollective["t_max[usec]"][4]
allgather_max = dataFrame_allcollective["t_max[usec]"][5]
barrier_max = dataFrame_allcollective["t_max[usec]"][6]

bcast_avg = dataFrame_allcollective["t_avg[usec]"][0]
scatter_avg = dataFrame_allcollective["t_avg[usec]"][1]
gather_avg = dataFrame_allcollective["t_avg[usec]"][2]
reduce_avg = dataFrame_allcollective["t_avg[usec]"][3]
allreduce_avg = dataFrame_allcollective["t_avg[usec]"][4]
allgather_avg = dataFrame_allcollective["t_avg[usec]"][5]
barrier_avg = dataFrame_allcollective["t_avg[usec]"][6]

bcast_stdev = (bcast_max - bcast_min)/4
scatter_stdev = (scatter_max-scatter_min)/4
gather_stdev = (gather_max-gather_min)/4
reduce_stdev = (reduce_max-reduce_min)/4
allreduce_stdev = (allreduce_max-allreduce_min)/4
allgather_stdev = (allgather_max-allgather_min)/4
barrier_stdev = (barrier_max-barrier_min)/4

y_bcast = rng.normal(bcast_avg,bcast_stdev, size = 1000)
y_scatter = rng.normal(scatter_avg,scatter_stdev,size=1000)
y_gather = rng.normal(gather_avg,gather_stdev,size=1000)
y_reduce = rng.normal(reduce_avg,reduce_stdev,size=1000)
y_allreduce = rng.normal(allreduce_avg,allreduce_stdev,size=1000)
y_allgather = rng.normal(allgather_avg,allgather_stdev,size=1000)
y_barrier = rng.normal(barrier_avg,barrier_stdev,size=1000)


names = ['Bcast','Scatter','Gather','Reduce','Allreduce','Allgather','Barrier']

plt.boxplot([y_bcast,y_scatter,y_gather,y_reduce,y_allreduce,y_allgather,y_barrier],lab
plt.ylabel('overhead (us)')
plt.title("Average Overhead for different MPI Collectives")
```

Out[ ]:

```
Text(0.5, 1.0, 'Average Overhead for different MPI Collectives')
```



discussion: Barrier has the most overhead, because barier waits for all processes to finish. It is more sensitive to the slowest thread. Allgather has the second most overhead by significance. The reason is because allgather is a two way communication on all the nodes. But allreduce being another two way communication, it has way less overhead thatn allgather, we think its becuase the data size all reduce move around is much smaller than allgather.

We also noticed that broadcast's overhead caps after 32 processes, but the scatter's overhead grows almost linearly.

When looking at the relationship of message size and overhead, broadcast's overhead increases linearly with the grow of message size.

2. MPI I/O

Required SLURM Batch Submissions:

- MPI Write (5 each): P = 2, 4, 8, 16, 32, 64
- MPI Read (5 each): P = 2, 4, 8, 16, 32, 64

Code and Datasets: link your code and datasets here with a couple word description of each:

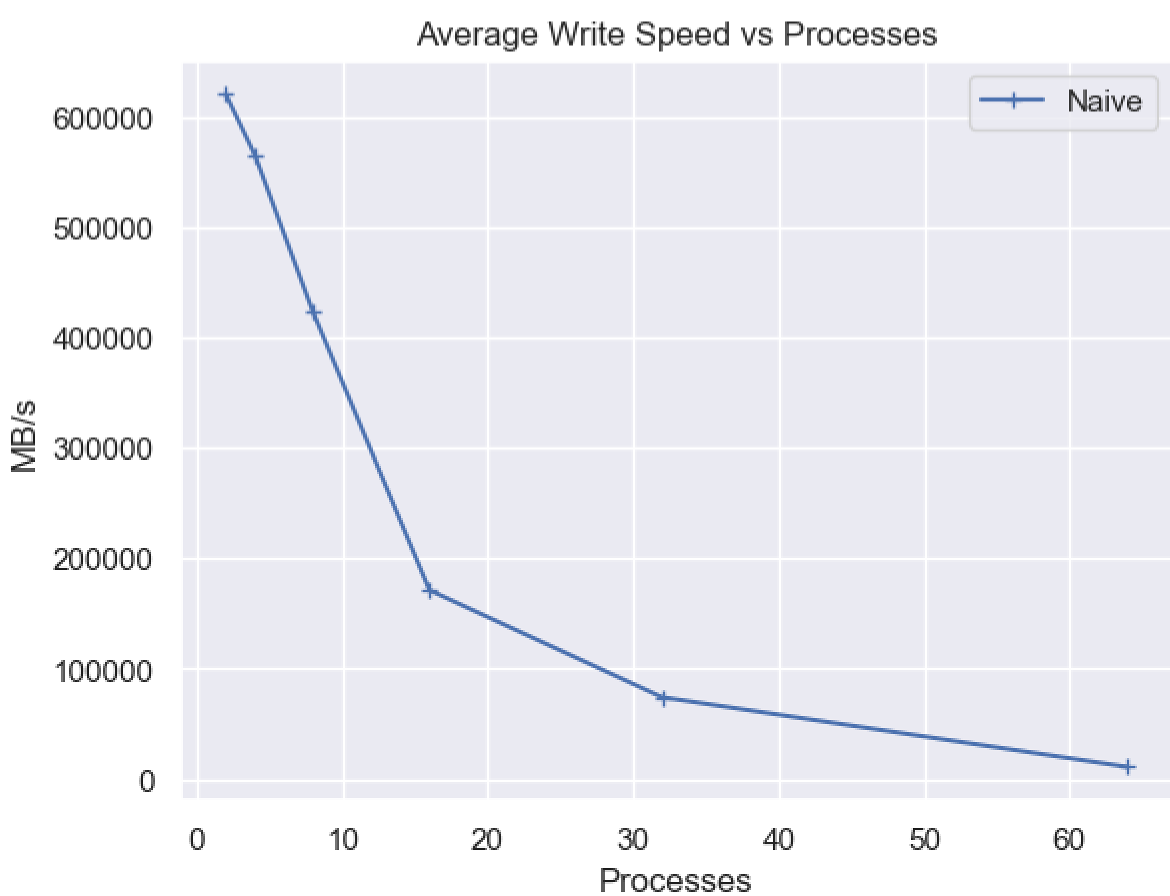
- example link
- mpi_read
- mpi_write

2.1 DELIVERABLE: Plot the average write speed (MB/s or other SI prefix) vs. P. Analyze and discuss your results (2-3 sentences).

Discussion: The write speed decreases as the processes number increases. We are guessing the file I/O is extremely fast, at the size of 10G file the overhead from MPI only slows it down.

In [ ]:

```
# plot average write speed vs. P

import matplotlib.pyplot as plt
import numpy as np
import pandas as pd

#create a dataframes
dataFrame_write = pd.read_csv("mpi_write.csv")

#group the data by processes
averages_write = dataFrame_write.groupby('P',as_index=False)['MB/s'].mean()


#plot
plt.plot(averages_write['P'],averages_write['MB/s'], marker='+', label = "Naive")
plt.xlabel('Processes')
plt.ylabel('MB/s')
plt.legend()
plt.title("Average Write Speed vs Processes")
plt.show()
```

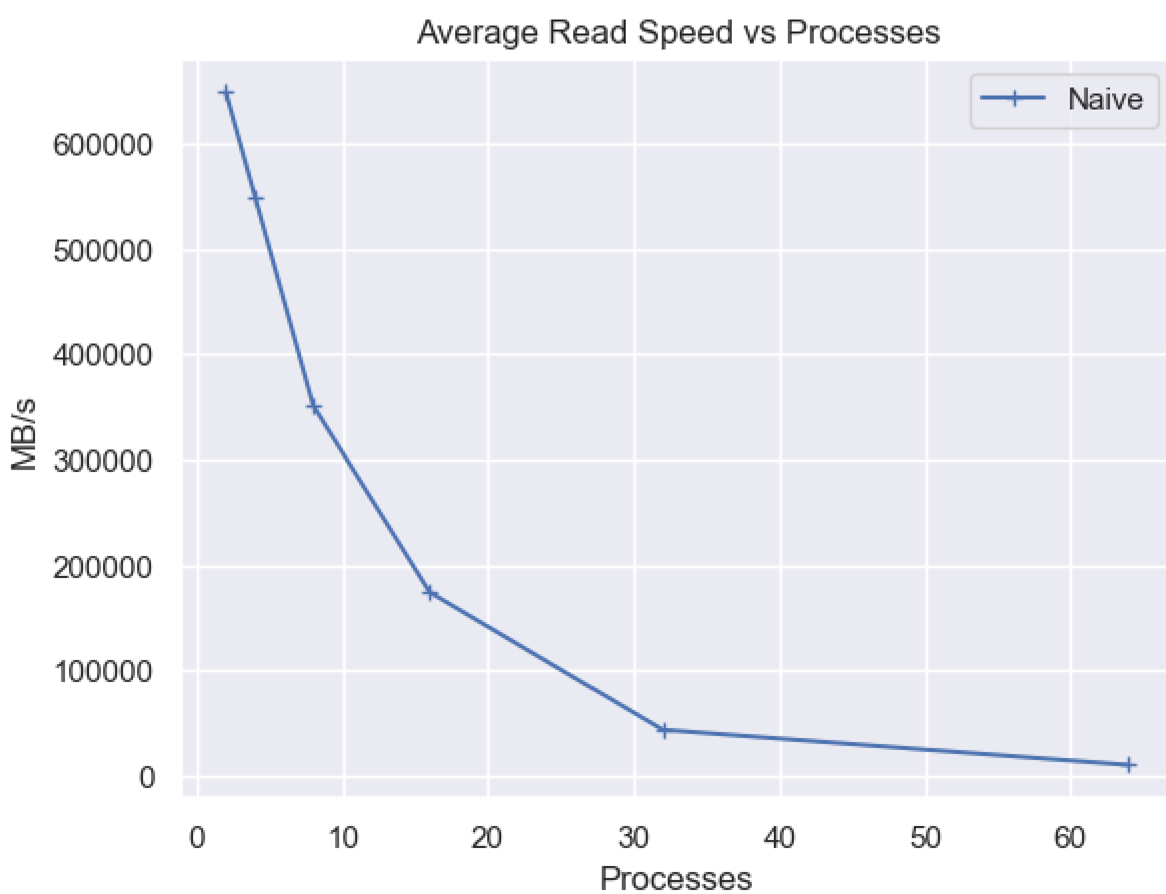


2.2 DELIVERABLE: Plot the average read speed (MB/s or other SI prefix) vs. P. Analyze and discuss your results (2-3 sentences).

Discussion: The read speed decreases as the processes number increases. We are guessing the file I/O is extremely fast, at the size of 10G file the overhead from MPI only slows it down.

In [ ]:

```
# plot average read speed vs. P


import matplotlib.pyplot as plt
import numpy as np
import pandas as pd

#create a dataframes
dataFrame_read = pd.read_csv("mpi_read.csv")

#group the data by processes
average_read = dataFrame_read.groupby('P',as_index=False)['MB/s'].mean()


#plot
plt.plot(average_read['P'],average_read['MB/s'], marker='+', label = "Naive")
plt.xlabel('Processes')
plt.ylabel('MB/s')
plt.legend()
plt.title("Average Read Speed vs Processes")
plt.show()
```



2.3 DELIVERABLE: Create a box-whiskers plot that compares the read/write speed of the cluster for the P that had the highest performance (make sure that each has the same P). Add two additional box-whiskers for the sequential read/write results that you obtained in HW1.

What are the key takeaways of parallel I/O vs. serial I/O?

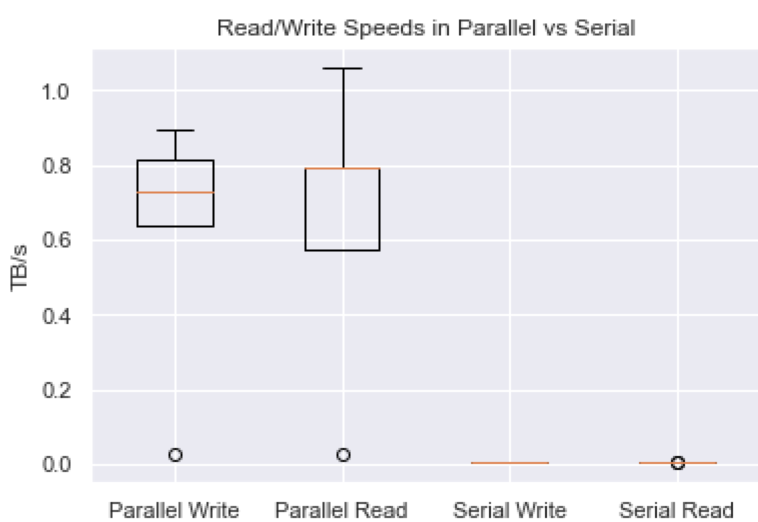
Discussion: Our takeaways are that two proceses can do I/O way faster than serial, but as the processes increases after two, the speed decreases instead. We think it is because spreading the cursor in the file causes alot of overhead.

In [ ]:

```
# plot box-whiskers here

import matplotlib.pyplot as plt
import seaborn as sns
import numpy as np
import pandas as pd

sns.set()

#create a dataframes
dataFrame_mpi_write = pd.read_csv("mpi_write.csv")
dataFrame_mpi_read = pd.read_csv("mpi_read.csv")
dataFrame_serial_write = pd.read_csv("fwrite_new.csv")
dataFrame_serial_read = pd.read_csv("fread_new.csv")

mpi_write = np.array(dataFrame_mpi_write["MB/s"].tolist()[0:5]) / (1e6)
mpi_read = np.array(dataFrame_mpi_read["MB/s"].tolist()[0:5])/(1e6)
serial_write = np.array(dataFrame_serial_write["MB/s"].tolist()[80:90])/(1e6)
serial_read = np.array(dataFrame_serial_read["MB/s"].tolist()[80:90])/(1e6)

names = ['Parallel Write','Parallel Read','Serial Write','Serial Read']
plt.boxplot([mpi_write,mpi_read,serial_write,serial_read],labels=names)
plt.ylabel('TB/s')
plt.title("Read/Write Speeds in Parallel vs Serial")
```

Out[ ]:

```
Text(0.5, 1.0, 'Read/Write Speeds in Parallel vs Serial')
```



3. MPI Linear Algebra

Required SLURM Batch Submissions:

- Matrix-Matrix Multiply, $N = 4096$ (5 each): $P = 4, 16$

    - (20 times) $P = 64$
- Matrix-Vector Product (5 each): $P = 1, 2, 4, 8, 16, 32$
    - (20 times) $P = 64$
- Dot Product (5 each): $P = 1, 2, 4, 8, 16, 32$
    - (20 times) $P = 64$

Code and Datasets: link your code and datasets here with a couple word description of each:

- mpi_matrix_matrix
- mpi_matrix_vector
- mpi_dot_product

3.1 DELIVERABLE: Create three figures that have P on the x-axis, and on the y-axis:

- average parallel speedup (Use a $T = 1$ time from Homework 1 or 2 from the serial version of the matmul code.)
- average floating point operations per second (FLOPs)
- average execution time

USE AN APPROPRIATE SI PREFIX FOR YOUR Y-AXES!

BONUS (5 points): extend your method to not need a square power-of-2 number of processes and also analyze $P = 8, 32, 80$

Discuss in a few sentences per figure the impact of MPI and the number of processes on algorithm performance. ***WHY*** do you think you are seeing the results you are?

Discussion: On the compaison between our actual paralle speedup results and ideal results, they are pretty close. We think it is because at N=4069, the overhead from MPI isnt significant enough.

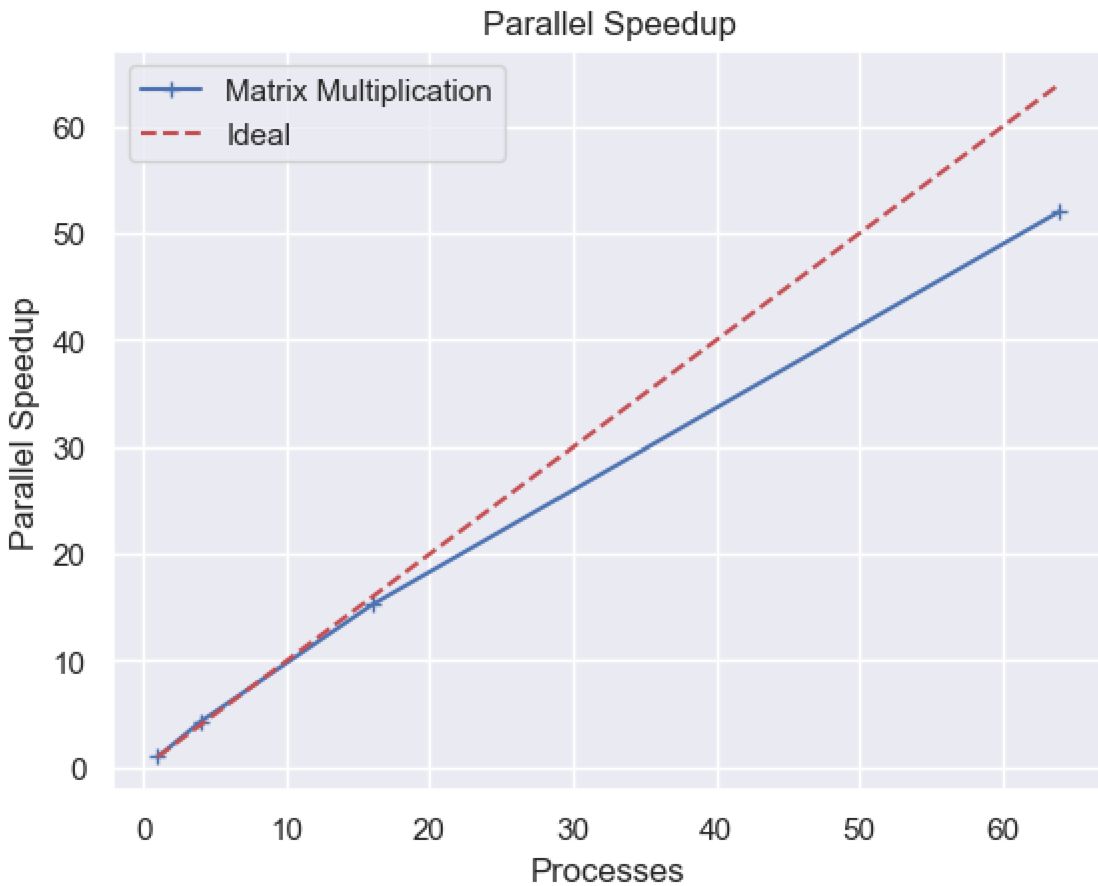
For average Flops, it grows linearly with the number of processes, this is similar to paralle speed up result with low overhead.

The ave. exe. time drops steeply with the numbers of processes, especially under 10 processes. And after 16 processes, the decrease in exe. time flattened out.

In [ ]:

```
#plot average parallel speedup versus P

import matplotlib.pyplot as plt
import numpy as np
import pandas as pd

#create a dataframe
dataFrame_mat_mat = pd.read_csv("mpi_matrix_multiply.csv")

#group the data by N
groups_mat_mat = dataFrame_mat_mat.groupby(' P',as_index=False)[' s']

#average each group
averages = groups_mat_mat.mean()

sequential_time = np.array(averages[" s"].tolist()[0:1])
```

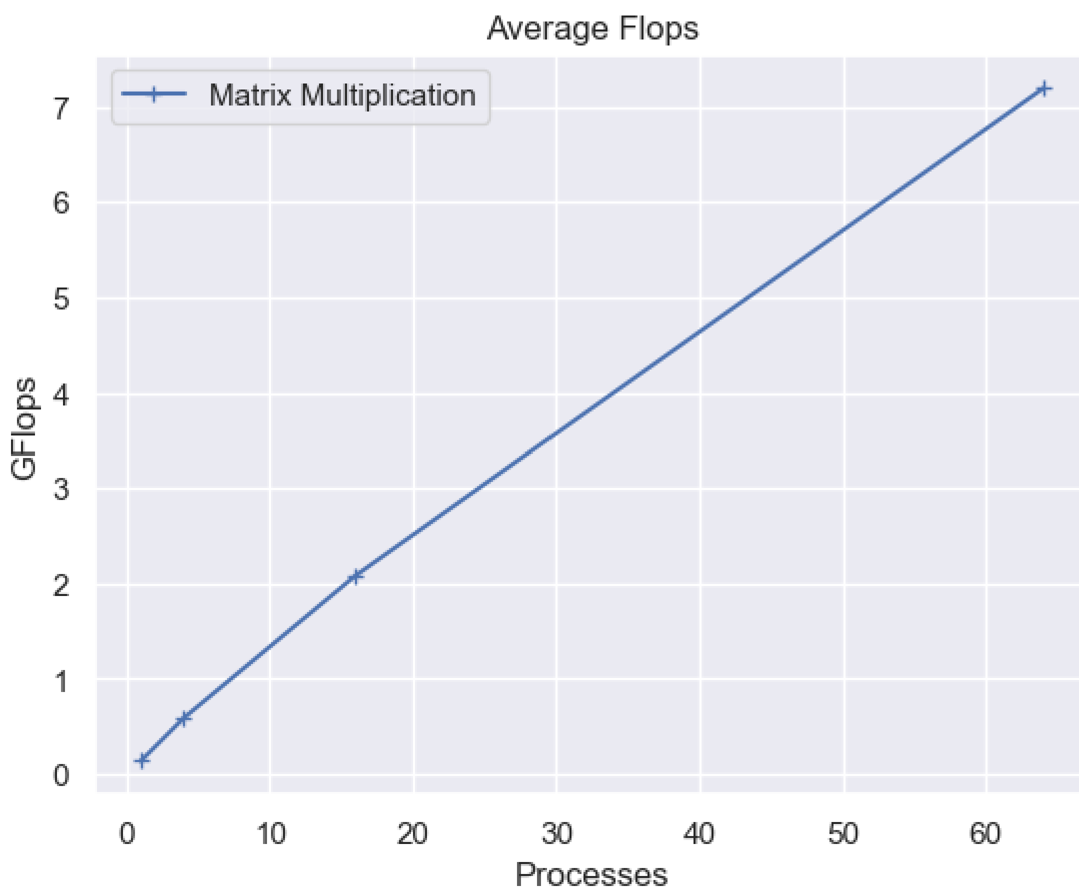
```
parallel_times = np.array(averages[" s"].tolist()[0:4])

parallel_speedup = sequential_time/parallel_times
threads = [1, 4, 16, 64]

#plot
plt.plot(threads,parallel_speedup, marker='+', label = "Matrix Multiplication")
plt.plot(threads,threads, 'r--', label = "Ideal")
plt.xlabel('Processes')
plt.ylabel('Parallel Speedup')
plt.legend()
plt.title("Parallel Speedup")
plt.show()
```



In [ ]:

```
#plot average FLOPs versus P

import matplotlib.pyplot as plt
import numpy as np
import pandas as pd

#create a dataframe
dataFrame_mat_mat = pd.read_csv("mpi_matrix_multiply.csv")

#group the data by N
groups_mat_mat = dataFrame_mat_mat.groupby(' P',as_index=False)[' Flops']

#average each group
averages = groups_mat_mat.mean()

Flops = np.array(averages[" Flops"].tolist()[0:4])/(1e9)
```

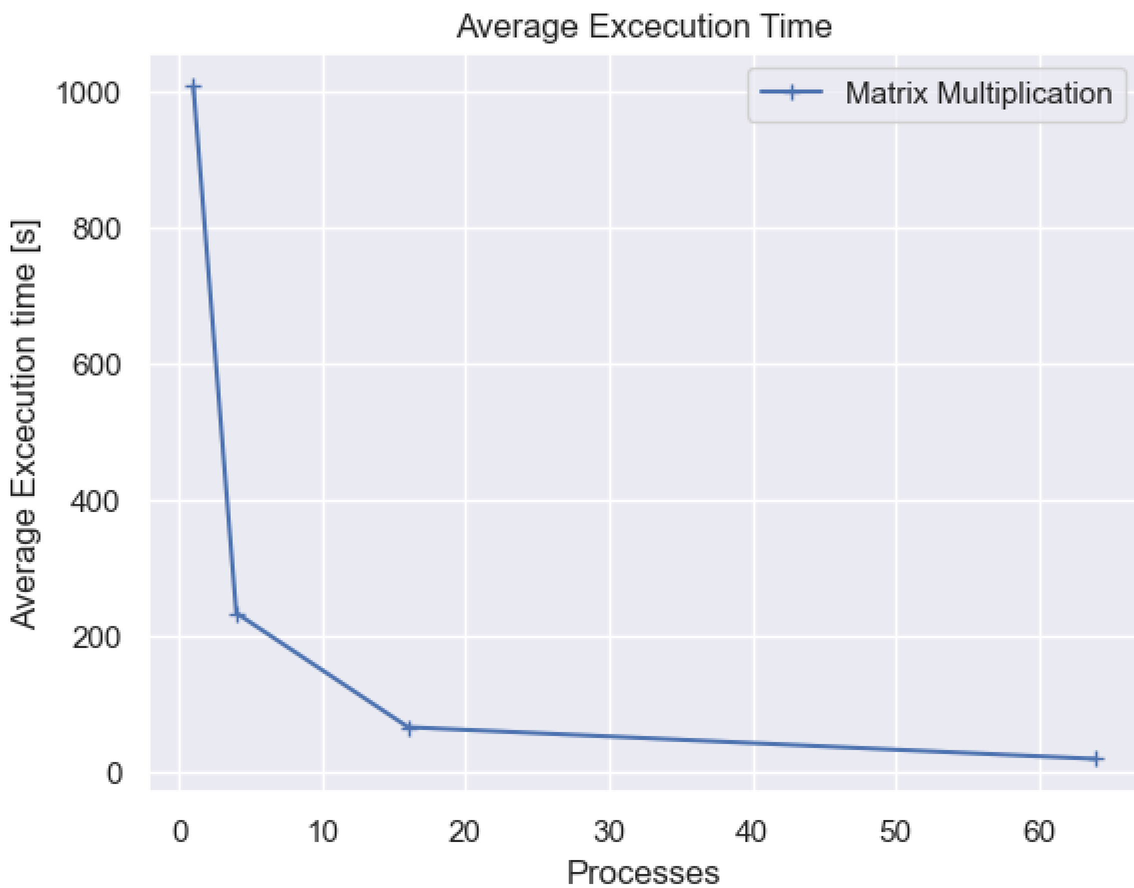
```python
threads = np.array(averages[" P"].tolist()[0:4])


#plot
plt.plot(threads,Flops, marker='+', label = "Matrix Multiplication")
plt.xlabel('Processes')
plt.ylabel('GFlops')
plt.legend()
plt.title("Average Flops")
plt.show()
```



In [ ]:

```python
#plot average execution time versus P

import matplotlib.pyplot as plt
import numpy as np
import pandas as pd

#create a dataframe
dataFrame_mat_mat = pd.read_csv("mpi_matrix_multiply.csv")

#group the data by N
groups_mat_mat = dataFrame_mat_mat.groupby(' P',as_index=False)[' s']

#average each group
averages = groups_mat_mat.mean()

Flops = np.array(averages[" s"].tolist()[0:4])
threads = np.array(averages[" P"].tolist()[0:4])
```

```
#plot
plt.plot(threads,Flops, marker='+', label = "Matrix Multiplication")
plt.xlabel('Processes')
plt.ylabel('Average Excecution time [s]')
plt.legend()
plt.title("Average Excecution Time")
plt.show()
```



3.2 DELIVERABLE: Create two figures that show the scaling of OpenMP versus MPI with P (or T) on the x-axis, and on the y-axis:

1. one plot each for OpenMP/MPI with parallel speedup (**include the ideal speedup as a third plot**)
2. one plot each for OpenMP/MPI with FLOPs

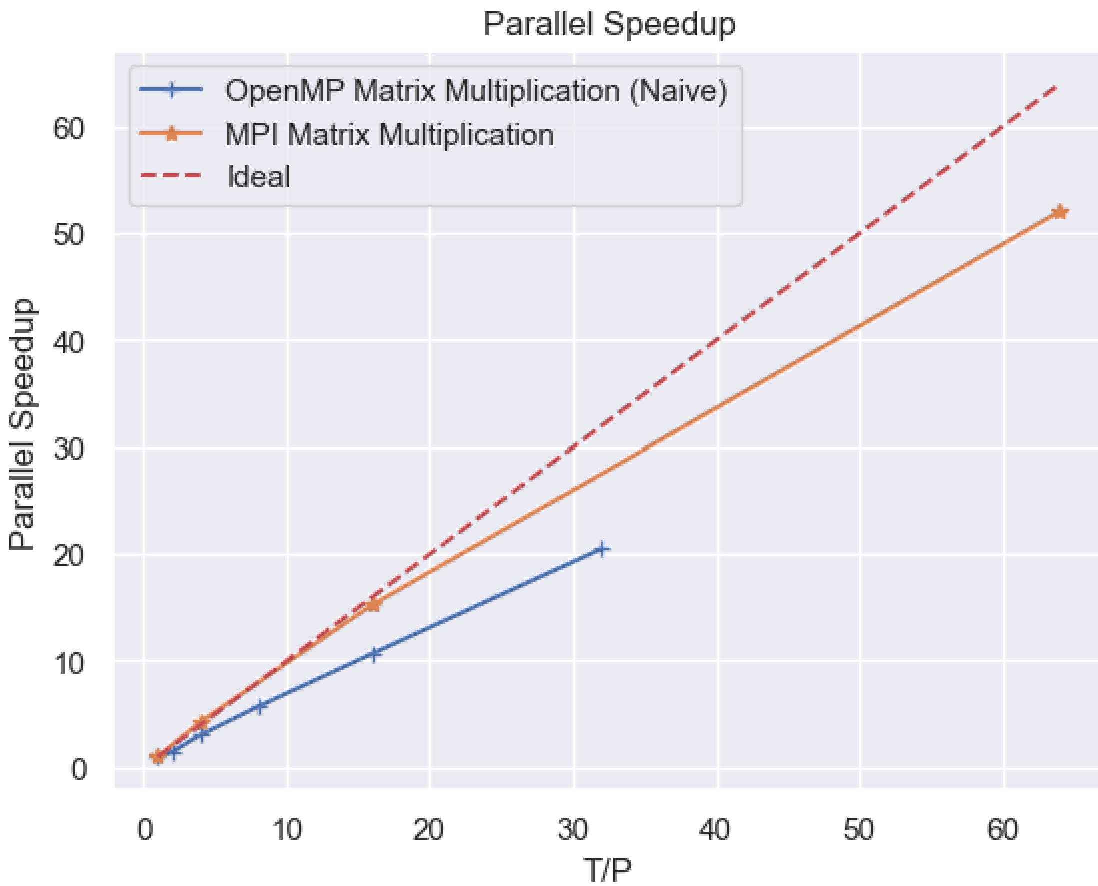
Discuss how the two parallel frameworks scale.

Discussion: The MPI has better performance in general with more speedup and more flops, we think its because with MPI, we can manaully manipulate each rank, and we cant do that with openMP.

In [ ]:

```
#plot MPI and OpenMP: average parallel speedup versus P/T (include ideal speedup) WITH

import matplotlib.pyplot as plt
import numpy as np
import pandas as pd
```

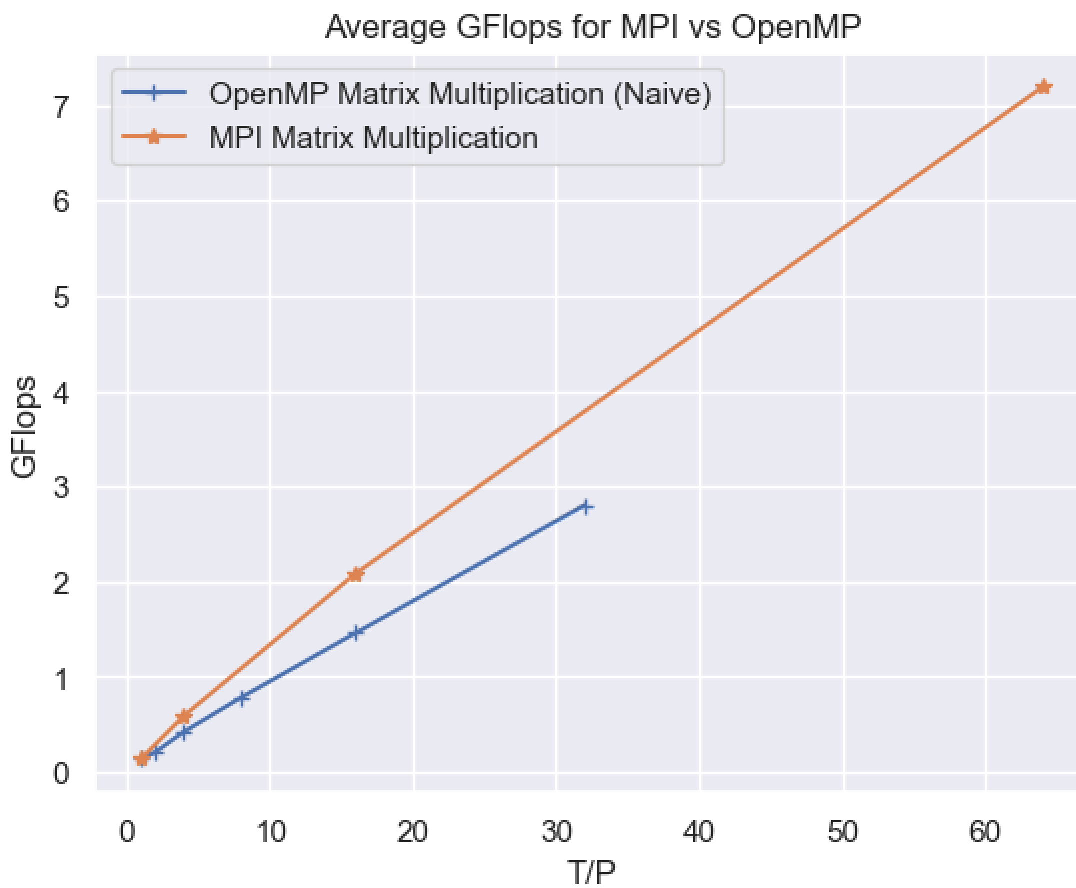
```
#create a dataframe
dataFrame_openmp = pd.read_csv("matrix_multiply_serial_naive.csv")
dataFrame_mpi = pd.read_csv("mpi_matrix_multiply.csv")

#group the data by N
groups_openmp = dataFrame_openmp.groupby('T',as_index=False)['s']
groups_mpi = dataFrame_mpi.groupby(' P',as_index=False)[' s']

#average each group
averages_openmp = groups_openmp.mean()
averages_mpi = groups_mpi.mean()

#print(averages_openmp)

seq_openmp = np.array(averages_openmp["s"].tolist()[0:1])
par_openmp = np.array(averages_openmp["s"].tolist()[0:6])
seq_mpi = np.array(averages_mpi[" s"].tolist()[0:1])
par_mpi = np.array(averages_mpi[" s"].tolist()[0:7])

ps_openmp = seq_openmp/par_openmp
threads_openmp = np.array(averages_openmp["T"].tolist()[0:6])

ps_mpi = seq_mpi/par_mpi
threads_mpi = np.array(averages_mpi[" P"].tolist()[0:7])

#plot
plt.plot(threads_openmp,ps_openmp, marker='+', label = "OpenMP Matrix Multiplication (N
plt.plot(threads_mpi,ps_mpi, marker='*', label = "MPI Matrix Multiplication")
plt.plot(threads_mpi,threads_mpi, 'r--', label = "Ideal")
plt.xlabel('T/P')
plt.ylabel('Parallel Speedup')
plt.legend()
plt.title("Parallel Speedup")
plt.show()
```



In [ ]:

```
#plot MPI and OpenMP: average FLOPs versus P/T WITH legend

import matplotlib.pyplot as plt
import numpy as np
import pandas as pd

#create a dataframe
dataFrame_openmp = pd.read_csv("matrix_multiply_serial_naive.csv")
dataFrame_mpi = pd.read_csv("mpi_matrix_multiply.csv")

#group the data by N
groups_openmp = dataFrame_openmp.groupby('T',as_index=False)['Flops']
groups_mpi = dataFrame_mpi.groupby(' P',as_index=False)[' Flops']

#average each group
averages_openmp = groups_openmp.mean()
averages_mpi = groups_mpi.mean()

#print(averages_openmp)

flops_openmp = np.array(averages_openmp["Flops"].tolist()[0:6])/(1e9)
flops_mpi = np.array(averages_mpi[" Flops"].tolist()[0:7])/(1e9)

threads_openmp = np.array(averages_openmp["T"].tolist()[0:6])
threads_mpi = np.array(averages_mpi[" P"].tolist()[0:7])

#plot
plt.plot(threads_openmp,flops_openmp, marker='+', label = "OpenMP Matrix Multiplication
plt.plot(threads_mpi,flops_mpi, marker='*', label = "MPI Matrix Multiplication")
plt.xlabel('T/P')
```

```
plt.ylabel('GFlops')
plt.legend()
plt.title("Average GFlops for MPI vs OpenMP")
plt.show()
```



3.3 DELIVERABLE:

Create two figures that have P on the x-axis (including $T = 1$), and on the y-axis:

1. average parallel speedup versus the sequential time (plot the ideal speedup on the same graph)
2. average floating point operations per second (FLOPs)

Each figure should have three plots: one for the dot product, one for the matrix-vector product, and one for the matrix-matrix product. The two plots should have distinct colors and lines (e.g., solid verus dashed). Add a legend that clearly identifies which plot is which.

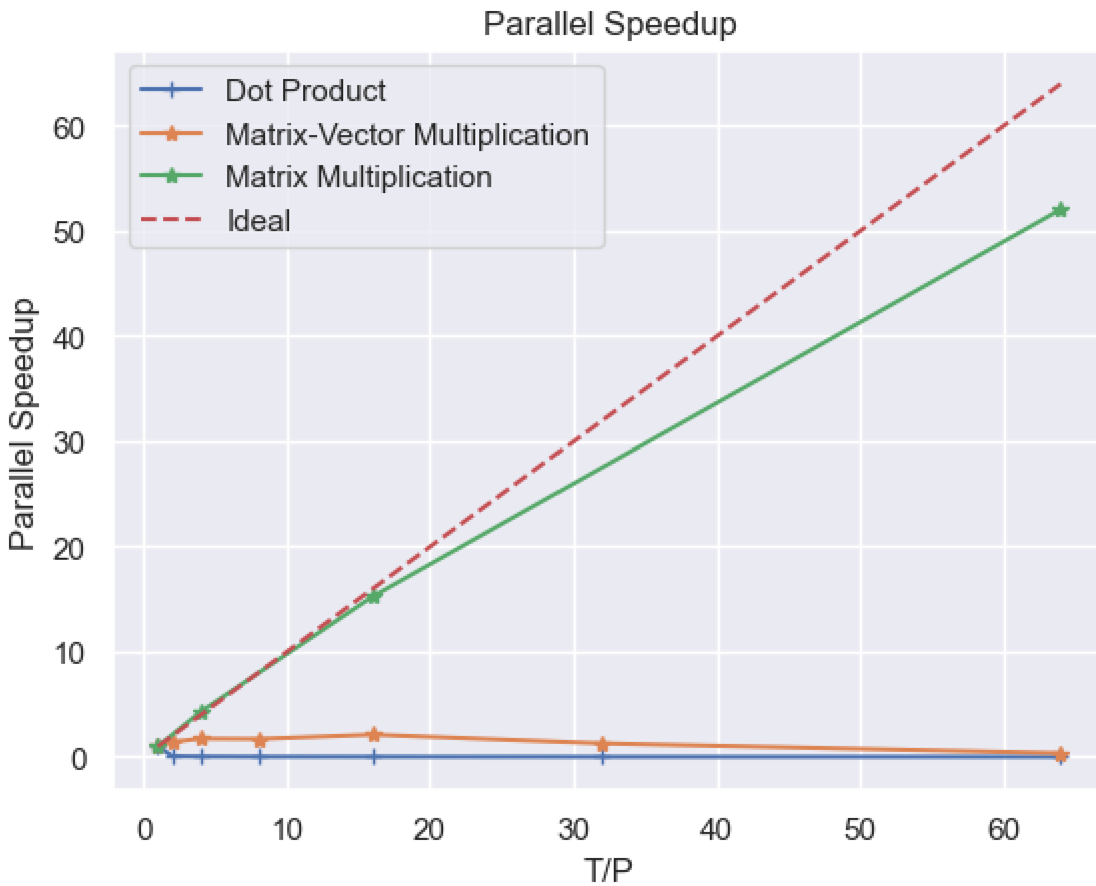
Create a box-whiskers plot that shows the FLOPs performance compared between the matrix-matrix product, matrix-vector product, and dot-product for $P = 64$. **Include both the MPI and OpenMP ($T = 32$) results.** Discuss the results and make note of the performance between the OpenMP and MPI.

Discussion:

$$waiting\ the\ right\ result\ from\ cluster$$

In [ ]:

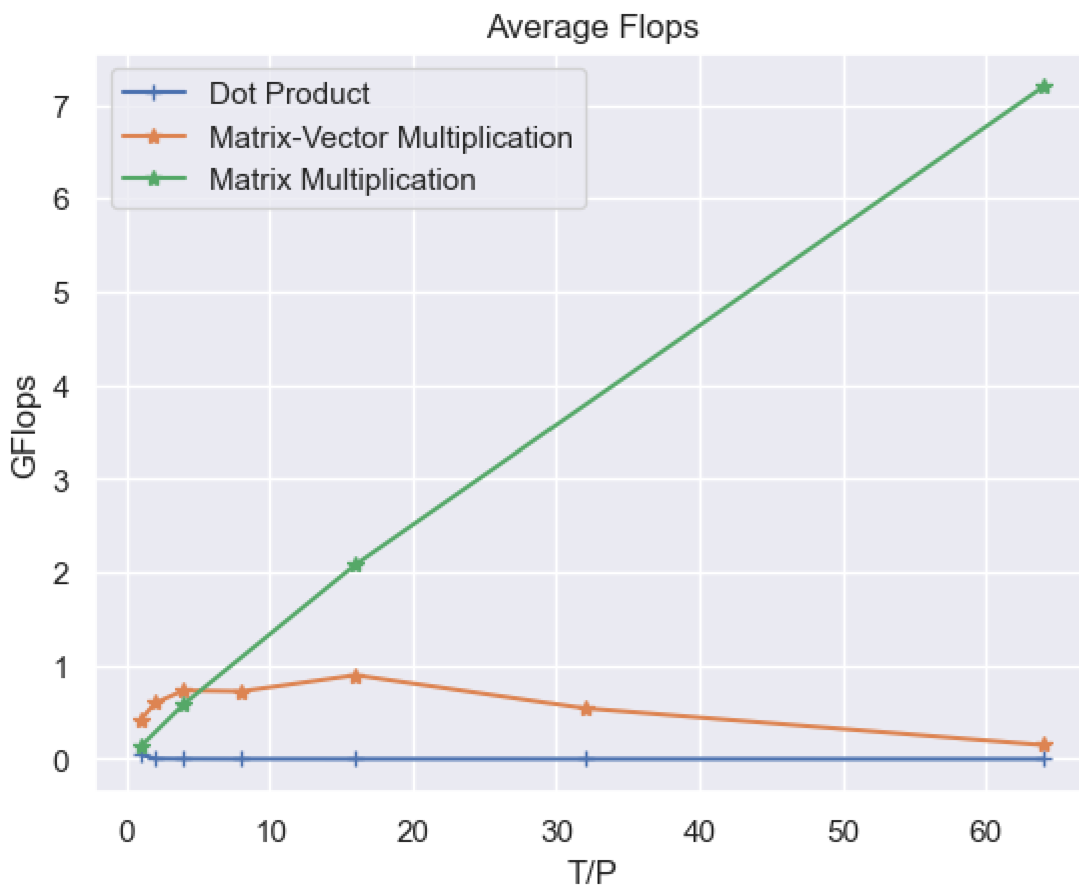
```python
# average parallel speedup versus the sequential time (plot the ideal speedup on the sa
# three plots: one for the dot product, one for the matrix-vector product, and one for

import matplotlib.pyplot as plt
import numpy as np
import pandas as pd

#create a dataframe
dataFrame_dot = pd.read_csv("mpi_dot_product.csv")
dataFrame_vec = pd.read_csv("mpi_matrix_vector.csv")
dataFrame_mat = pd.read_csv("mpi_matrix_multiply.csv")

#group the data by N
groups_dot = dataFrame_dot.groupby(' P',as_index=False)[' s']
groups_vec = dataFrame_vec.groupby(' P',as_index=False)[' s']
groups_mat = dataFrame_mat.groupby(' P',as_index=False)[' s']

#average each group
averages_dot = groups_dot.mean()
averages_vec = groups_vec.mean()
averages_mat = groups_mat.mean()

#print(averages_mat)

seq_dot = np.array(averages_dot[" s"].tolist()[0:1])
par_dot = np.array(averages_dot[" s"].tolist()[0:7])
seq_vec = np.array(averages_vec[" s"].tolist()[0:1])
par_vec = np.array(averages_vec[" s"].tolist()[0:7])
seq_mat = np.array(averages_mat[" s"].tolist()[0:1])
par_mat = np.array(averages_mat[" s"].tolist()[0:4])

ps_dot = seq_dot/par_dot
ps_vec = seq_vec/par_vec
ps_mat = seq_mat/par_mat

threads_dot = np.array(averages_dot[" P"].tolist()[0:7])
threads_vec = np.array(averages_vec[" P"].tolist()[0:7])
threads_mat = np.array(averages_mat[" P"].tolist()[0:4])

#plot
plt.plot(threads_dot,ps_dot, marker='+', label = "Dot Product")
plt.plot(threads_vec,ps_vec, marker='*', label = "Matrix-Vector Multiplication")
plt.plot(threads_mat,ps_mat, marker='*', label = "Matrix Multiplication")
plt.plot(threads_mat,threads_mat, 'r--', label = "Ideal")
plt.xlabel('T/P')
plt.ylabel('Parallel Speedup')
plt.legend()
plt.title("Parallel Speedup")
plt.show()
```



In [ ]:

```
# average floating point operations per second (FLOPs) versus the sequential time (plot
# three plots: one for the dot product, one for the matrix-vector product, and one for

import matplotlib.pyplot as plt
import numpy as np
import pandas as pd

#create a dataframe
dataFrame_dot = pd.read_csv("mpi_dot_product.csv")
dataFrame_vec = pd.read_csv("mpi_matrix_vector.csv")
dataFrame_mat = pd.read_csv("mpi_matrix_multiply.csv")

#group the data by N
groups_dot = dataFrame_dot.groupby(' P',as_index=False)[' Flops']
groups_vec = dataFrame_vec.groupby(' P',as_index=False)[' Flops']
groups_mat = dataFrame_mat.groupby(' P',as_index=False)[' Flops']

#average each group
averages_dot = groups_dot.mean()
averages_vec = groups_vec.mean()
averages_mat = groups_mat.mean()

#print(averages_mat)

flops_dot = np.array(averages_dot[" Flops"].tolist()[0:7])/(1e9)
flops_vec = np.array(averages_vec[" Flops"].tolist()[0:7])/(1e9)
flops_mat = np.array(averages_mat[" Flops"].tolist()[0:4])/(1e9)

threads_dot = np.array(averages_dot[" P"].tolist()[0:7])
threads_vec = np.array(averages_vec[" P"].tolist()[0:7])
```

```
threads_mat = np.array(averages_mat[" P"].tolist()[0:4])

#plot
plt.plot(threads_dot,flops_dot, marker='+', label = "Dot Product")
plt.plot(threads_vec,flops_vec, marker='*', label = "Matrix-Vector Multiplication")
plt.plot(threads_mat,flops_mat, marker='*', label = "Matrix Multiplication")
plt.xlabel('T/P')
plt.ylabel('GFlops')
plt.legend()
plt.title("Average Flops")
plt.show()
```



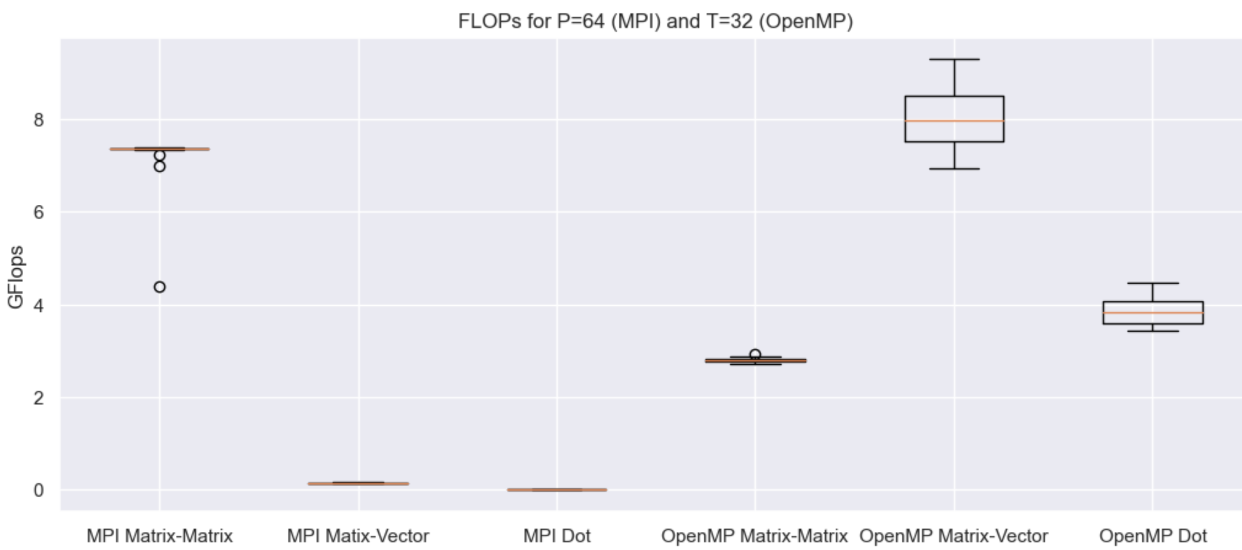
In [ ]:

```
#box-whiskers of FLOPs for P=64 (MPI) and T=32 (OpenMP)
#6 plots: MPI matrix-matrix product, MPI matrix-vector product, MPI dot-product
#         OpenMP matrix-matrix product, OpenMP matrix-vector product, OpenMP dot-produc

import matplotlib.pyplot as plt
import seaborn as sns
import numpy as np
import pandas as pd

sns.set()
plt.figure(figsize=(12.5, 5))

#create a dataframes
dataFrame_mpi_mat = pd.read_csv("mpi_matrix_multiply.csv")
dataFrame_mpi_vec = pd.read_csv("mpi_matrix_vector.csv")
dataFrame_mpi_dot = pd.read_csv("mpi_dot_product.csv")
dataFrame_openmp_mat = pd.read_csv("matrix_multiply_serial_naive.csv")
dataFrame_openmp_vec = pd.read_csv("matrix_vector_serial.csv")
```

```
dataFrame_openmp_dot = pd.read_csv("dot_product_serial.csv")

mpi_mat = np.array(dataFrame_mpi_mat[" Flops"].tolist()[15:35])/(1e9)
mpi_vec = np.array(dataFrame_mpi_vec[" Flops"].tolist()[30:50])/(1e9)
mpi_dot = np.array(dataFrame_mpi_dot[" Flops"].tolist()[30:50])/(1e9)
openmp_mat = np.array(dataFrame_openmp_mat["Flops"].tolist()[25:45])/(1e9)
openmp_vec = np.array(dataFrame_openmp_vec["Flops"].tolist()[25:45])/(1e9)
openmp_dot = np.array(dataFrame_openmp_dot["Flops"].tolist()[25:45])/(1e9)

names = ['MPI Matrix-Matrix','MPI Matix-Vector','MPI Dot','OpenMP Matrix-Matrix','OpenM
plt.boxplot([mpi_mat,mpi_vec,mpi_dot,openmp_mat,openmp_vec,openmp_dot],labels=names)
plt.ylabel('GFlops')
plt.title("FLOPs for P=64 (MPI) and T=32 (OpenMP)")
```

Out[ ]:

```
Text(0.5, 1.0, 'FLOPs for P=64 (MPI) and T=32 (OpenMP)')
```



4. Other MPI Accelerations

Required SLURM Batch Submissions:

- solve your chosen problem (same as OpenMP) for $P = 1, 32, 64$
- choose one:
  - parallel sort (5 each), $P = 1, 2, 4, 8, 16, 32, 64$
  - Cannon's algorithm: (5 each) $P = 4, 16$; (20 times) $P = 64$

Code and Datasets: link your datasets here with a couple word description of each:

- mpi_prime

4.1 DELIVERABLE: Describe what problem you chose and how you accelerated it using MPI; how does this differ from the OpenMP version? Prove that the parallel version is thread safe (same answer as non-threaded) and show the parallel speedup.

Discuss your problem with another group and describe their problem in a few sentences, and which group (by name of team members).

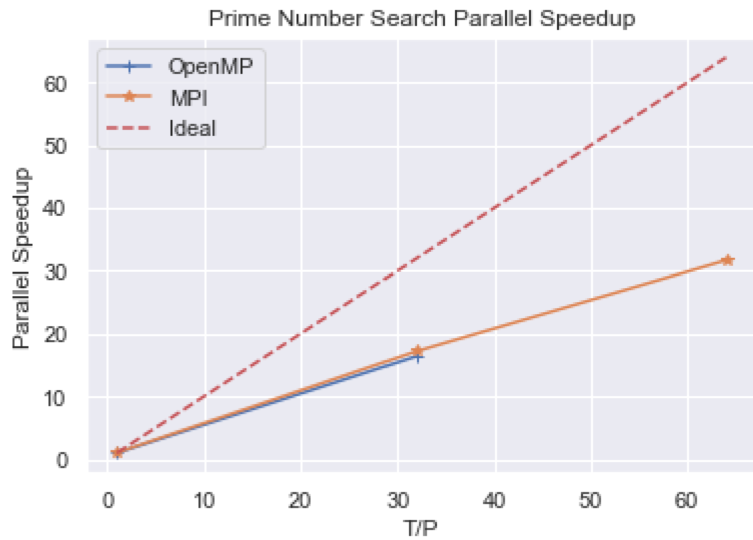
Discussion of problem and MPI vs. OpenMP: We choose the prime number search problem, we used MPI to break the iteration into sub-iteration based on MPI_size to have each processes look for number of primes in their own range. Once all rank is done, we used MPI_reduction to sum up the number of primes from each processes.

With OpenMP, we simply put in an omp parallel for on the for loops, also used reduction to ensure the thread safety to get the sum of number of primes from each thread. Compared with MPI, OpenMP is more restrictive, because it does not allow you to allocate each rank like MPI.

Discussion with another group: We talked with Mose and Zac, and they had the similar approach with ours. They also break the for loop iteration into smaller chunks and have different processes execute them.

In [ ]:

```
#plot or present any supporting evidence of your MPI acceleration (vs sequential and Op

import matplotlib.pyplot as plt
import numpy as np
import pandas as pd

#create a dataframe
dataFrame_openmp = pd.read_csv("prime_omp.csv")
dataFrame_mpi = pd.read_csv("prime_mpi.csv")

#group the data by N
groups_openmp = dataFrame_openmp.groupby('T',as_index=False)['s']
groups_mpi = dataFrame_mpi.groupby('P',as_index=False)['s']

#average each group
averages_openmp = groups_openmp.mean()
averages_mpi = groups_mpi.mean()

#print(averages_openmp)

seq_openmp = np.array(averages_openmp["s"].tolist()[0:1])
par_openmp = np.array(averages_openmp["s"].tolist()[0:2])
seq_mpi = np.array(averages_mpi["s"].tolist()[0:1])
par_mpi = np.array(averages_mpi["s"].tolist()[0:3])

ps_openmp = seq_openmp/par_openmp
threads_openmp = np.array(averages_openmp["T"].tolist()[0:2])

ps_mpi = seq_openmp/par_mpi
threads_mpi = np.array(averages_mpi["P"].tolist()[0:3])

#plot
plt.plot(threads_openmp,ps_openmp, marker='+', label = "OpenMP")
plt.plot(threads_mpi,ps_mpi, marker='*', label = "MPI")
plt.plot(threads_mpi,threads_mpi, 'r--', label = "Ideal")
plt.xlabel('T/P')
plt.ylabel('Parallel Speedup')
plt.legend()
plt.title("Prime Number Search Parallel Speedup")
plt.show()
```



4.2 DELIVERABLE *only perform the deliverable that goes with your chosen problem*

Parallel Sort:

1. Plot average parallel speedup vs. P (include the ideal speedup)
2. Plot average execution time vs. P

Discuss the scaling of this algorithm in a few sentences. Describe how you parallelized the sort. If you have time, you may also want to fix P and vary N to see how the algorithm scales as $\mathcal{O}(N)$. Bonus points may be in order.

Discussion:

$waiting\ the\ right\ result\ from\ cluster$

In [ ]:

```
# Plot average parallel speedup vs. P (include the ideal speedup)
```

In [ ]:

```
# Plot average execution time vs. P
```

4.2 DELIVERABLE *only perform the deliverable that goes with your chosen problem*

Cannon's Algorithm:

Compare the performance of Cannon's to the other MPI implementation and OpenMP. Create two figures that have P on the x-axis (including $T = 1$), and on the y-axis:

1. average parallel speedup versus the sequential time (plot the ideal speedup on the same graph)
2. average floating point operations per second (FLOPs)

Each figure should have three plots: one for OpenMP, one for original MPI, and one for Cannon's. Add a legend that clearly identifies which plot is which.

Create a box-whiskers plot that shows the FLOPs performance compared between the three matrix multiply implementations. Discuss the results.

Discussion:

In [ ]:

```
# average parallel speedup (plot the ideal speedup on the same graph)
# three plots: one for OpenMP, one for original MPI, and one for Cannon's
```

In [ ]:

```
# average FLOPs (plot the ideal speedup on the same graph)
# three plots: one for OpenMP, one for original MPI, and one for Cannon's
```

In [ ]:

```
# box-whiskers plot of FLOPs
# three plots: OpenMP, MPI original, Cannon's
```