EECS 469/569: Homework 1 Submission

Serial Performance of Roaring Thunder

Due: Sunday, Sep. 11 *before* midnight

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Take away: This homeworks gave us the the ability to navigate with linux system using commnad lines, and instroduced us to the slurm job scheduling with slurm on roaring thunder. It was interesting to see how different algorithms affect the execution performance, even though they all produced the same results. And we are also instroduced with plotting in Python and some basic data processing.

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

Submission Instructions

Follow all instructions within `hw01.ipynb` . To submit the homework assignment, put **only relevant files (including this notebook)** in a folder. Zip the folder (e.g., using [7-zip (https://www.7-zip.org/)](https://www.7-zip.org/)) and send one email to Dr. Hansen (CC your partner) with the zipped folder. Print a .pdf of this (completed) Jupyter notebook and submit it to D2L before the deadline (`CTRL+P → 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.

FINAL DELIVERABLE (5 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 you and your partner.

1. Basic Unix Commands

1.1 DELIVERABLE (3 points): Include a screenshot of your terminal after executing the Bash commands on the Roaring Thunder, and write a few sentences describing what the commands did.

chung@rtlogin:~

```
[chung@rtlogin ~]$ pwd
/home/chung
[chung@rtlogin ~]$ ls
biofilm  cavityico  eecs569  percavity  PINNs
[chung@rtlogin ~]$ ls -la
total 144
drwx------  14 chung domain users  4096 Sep  1 18:17 .
drwxr-xr-x 400 root  root         16384 Aug 26 11:57 ..
-rw-------   1 chung domain users  5476 Aug 29 14:55 .bash_history
-rw-------   1 chung domain users    18 Sep 23  2021 .bash_logout
-rw-------   1 chung domain users   193 Sep 23  2021 .bash_profile
-rw-------   1 chung domain users   247 Sep 23  2021 .bashrc
drwxr-xr-x   5 chung domain users  4096 Sep 23  2021 biofilm
drwxr-xr-x   4 chung domain users  4096 Feb 23  2022 .cache
drwxr-xr-x  97 chung domain users  4096 Jan 25  2022 cavityico
drwxr-xr-x   3 chung domain users  4096 Feb 23  2022 .config
drwx------   2 chung domain users  4096 Sep  1 18:17 eecs569
-rw-------   1 chung domain users   334 Sep 23  2021 .emacs
drwxr-xr-x   2 chung domain users  4096 Feb 23  2022 .keras
-rw-------   1 chung domain users   172 Sep 23  2021 .kshrc
drwxr-xr-x   3 chung domain users  4096 Feb 22  2022 .lmod.d
drwxr-xr-x   7 chung domain users  4096 Nov  3  2021 percavity
drwxr-xr-x   7 chung domain users  4096 Feb 22  2022 PINNs
drwxr-----   3 chung domain users  4096 Sep 23  2021 .pki
drwx------   2 chung domain users  4096 Feb 24  2022 .ssh
-rw-------   1 chung domain users  6456 Feb 24  2022 .viminfo
drwxr-xr-x   5 chung domain users  4096 Aug 29 13:59 .vscode-server
[chung@rtlogin ~]$ ls -a
.               .bash_logout   biofilm    .config  .keras   percavity  .ssh
..              .bash_profile  .cache     eecs569  .kshrc   PINNs      .viminfo
.bash_history   .bashrc        cavityico  .emacs   .lmod.d  .pki       .vscode-server
[chung@rtlogin ~]$ ls -l
total 0
drwxr-xr-x  5 chung domain users 4096 Sep 23  2021 biofilm
drwxr-xr-x 97 chung domain users 4096 Jan 25  2022 cavityico
drwx------  2 chung domain users 4096 Sep  1 18:17 eecs569
drwxr-xr-x  7 chung domain users 4096 Nov  3  2021 percavity
drwxr-xr-x  7 chung domain users 4096 Feb 22  2022 PINNs
[chung@rtlogin ~]$ ls
biofilm  cavityico  eecs569  percavity  PINNs
[chung@rtlogin ~]$ cd eecs569/
[chung@rtlogin eecs569]$ cd ..
[chung@rtlogin ~]$ ls
biofilm  cavityico  eecs569  percavity  PINNs
[chung@rtlogin ~]$
```

```
pwd: show working directory
man pwd %'spacebar' to page down, 'q' to quit: man show the manual of a command
ls: list file
ls -al: -la is the list/all flag
ls -a: -a is a flag, stands for all
ls -l: -l is a flag, stands for list
man head: show the manual of head command, and head print the first part of a file
mkdir eecs569: make a directory call eecs569
chmod 700 eecs569: Protects a file against any access from other users, while the
 issuing user still has full access
cd eecs569: change the pwd to eecs569
pwd: show working directory
cd: change the homedirectory
pwd: present working directory
```

1.2 DELIVERABLE (2 points): Take a screenshot of the output of hello_world and the files in your directory (use `ls -al`) and paste here. Write a couple sentences about modules and the gcc compiler.

chung@rtlogin:~/eecs569/hw1

```
[chung@rtlogin hw1]$ clear
[chung@rtlogin hw1]$ gcc hello_world.c
[chung@rtlogin hw1]$ ./a.out
hello world!
[chung@rtlogin hw1]$ ls -la
total 10851648
drwxr-xr-x 3 chung domain users        4096 Sep 11 16:17 .
drwx------ 4 chung domain users        4096 Sep  2 13:25 ..
-rwxr-xr-x 1 chung domain users        8280 Sep 11 16:17 a.out
-rw-r--r-- 1 chung domain users         920 Sep  8 20:04 block.csv
-rwxr-xr-x 1 chung domain users         243 Sep  5 18:56 cheesecakeread.sh
-rwxr-xr-x 1 chung domain users         245 Sep  1 20:00 cheesecake.sh
-rw-r--r-- 1 chung domain users        1776 Aug 25 17:50 file_read.c
-rw-r--r-- 1 chung domain users        2051 Sep  2 10:53 file_write.c
-rwxr-xr-x 1 chung domain users        8824 Sep  5 18:07 fread
-rw-r--r-- 1 chung domain users        3400 Sep  5 18:17 fread_new.csv
-rwxr-xr-x 1 chung domain users       13000 Sep  1 20:02 fwrite
-rw-r--r-- 1 chung domain users         988 Sep  1 19:56 fwrite.csv
-rw-r--r-- 1 chung domain users        6789 Sep  5 18:16 fwrite_new.csv
-rw-r--r-- 1 chung domain users          97 Sep  1 18:40 hello_world.c
-rw-r--r-- 1 chung domain users         730 Sep  5 19:11 hw1.slurm
drwxr-xr-x 2 chung domain users        4096 Sep  1 20:25 .ipynb_checkpoints
-rw-r--r-- 1 chung domain users         189 Sep  8 15:36 .log
-rwxr-xr-x 1 chung domain users       13128 Sep  8 14:35 matmul
-rwxr-xr-x 1 chung domain users       13144 Sep  8 16:02 matmulb
-rw-r--r-- 1 chung domain users         814 Sep  5 20:06 matmul.csv
-rwxr-xr-x 1 chung domain users       13128 Sep 11 15:26 matmullporder
-rwxr-xr-x 1 chung domain users       13128 Sep 11 15:24 matmulo
-rwxr-xr-x 1 chung domain users       13128 Sep  8 14:41 matmult
-rwxr-xr-x 1 chung domain users         730 Sep  8 16:04 matrix_block.slurm
-rw-r--r-- 1 chung domain users        3661 Sep  8 15:57 matrix_multiply_blockin
g.c
-rw-r--r-- 1 chung domain users           0 Sep  5 19:22 matrix_multiply_loopord
er.c
-rw-r--r-- 1 chung domain users        3228 Sep  8 14:35 matrix_multiply_naive.c
-rw-r--r-- 1 chung domain users        3172 Sep  8 14:41 matrix_multiply_transpo
se.c
-rw-r--r-- 1 chung domain users          94 Sep 11 15:26 options]
-rw-r--r-- 1 chung domain users 10000000000 Sep  5 18:16 out2500000000.dat
-rw-r--r-- 1 chung domain users  1000000000 Sep  5 18:11 out250000000.dat
-rw-r--r-- 1 chung domain users   100000000 Sep  5 18:10 out25000000.dat
-rw-r--r-- 1 chung domain users    10000000 Sep  5 18:10 out2500000.dat
-rw-r--r-- 1 chung domain users     1000000 Sep  5 18:10 out250000.dat
-rw-r--r-- 1 chung domain users      100000 Sep  5 18:10 out25000.dat
-rw-r--r-- 1 chung domain users       10000 Sep  5 18:10 out2500.dat
-rw-r--r-- 1 chung domain users        1000 Sep  5 18:10 out250.dat
-rw-r--r-- 1 chung domain users         100 Sep  5 18:10 out25.dat
-rw-r--r-- 1 chung domain users        4868 Sep  5 20:12 out-2715349-node057.log
-rw-r--r-- 1 chung domain users        5146 Sep  8 20:04 out-2715606-node057.log
```

modules are programms that can be loaded and used my the user, and gcc is one of the example. And gcc compiles C code

2. Memory Input/Output (I/O) Performance

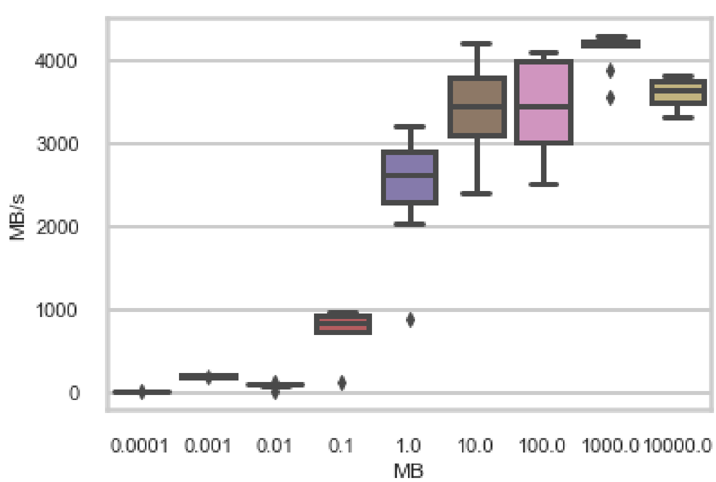
2.1 DELIVERABLE (10 points): Test the write performance of the cluster by timing the output of writing 10^{-4} to 10^{4} MB. Plot your results using a statistical method (i.e., run multiple times per filesize, and plot the distributions). Discuss in one paragraph the write performance of the Roaring Thunder cluster and any key takeaways you notice.

Link to your dataset here: [write data CSV (fwrite_new.csv)]

Discussion The write performance increases as the data size increases, but it hit a maximum of speed about 4000MB/s after the data file grows to 100MB. For smaller data sizes, the slow speed can be attributed to the overhead of initialization. So the key take away is the performance peaks at about 4000MB/s.

In [1]:
```
# put your write speed plotting code here
# I recommend using matplotlib.pyplot and seaborn
import matplotlib.pyplot as plt
import numpy as np

#optional, load seaborn for nicer looking plots
import seaborn as sns
'''
This breaks for versions of seaborn < 0.11.0. Google Colab has latest version.
To install in Anaconda, use "conda install seaborn=0.11.2"
'''
sns.set_theme(style="whitegrid",context="poster", font_scale=0.5)

#load column headers into array
data = np.genfromtxt('fwrite_new.csv', delimiter=',', names=True)

## create figure
# f,ax = plt.subplots()
# ax.set(xscale='log',xlim=(0.00005,1500),ylabel='MB/s',xlabel='MB')
# plt.plot(data['MB'],data['MBs'],marker='.')

# put your read speed plotting code here
data = np.genfromtxt('fwrite_new.csv', delimiter=',', names=True)

f,ax = plt.subplots()
ax.set(ylabel='MB/s',xlabel='MB')

sns.boxplot(x=data['MB'],y=data['MBs'])
```

Out[1]: `<AxesSubplot:xlabel='MB', ylabel='MB/s'>`



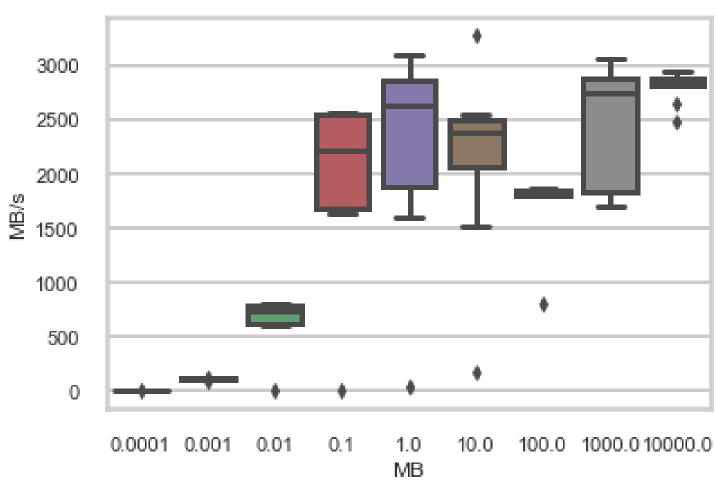
2.2 DELIVERABLE (10 points): Test the read speed of the cluster by timing the read of the files you created in the previous section from 10^{-4} to 10^{4} MB. Plot your results using a statistical method (i.e., run multiple times per filesize, and plot the distributions). Discuss in one paragraph the write performance of the Roaring Thunder cluster and any key takeaways you notice. How does the read speed compare to the write speed?

Link to your dataset here: [read data CSV (fread_new.csv)]

Discussion: The read speed peaks at about 3000MB/s, which is slower than write speed's 4000MB/S.

In [2]:
```
# put your read speed plotting code here
# todo
# put your write speed plotting code here
# I recommend using matplotlib.pyplot and seaborn
import matplotlib.pyplot as plt
import numpy as np

#optional, load seaborn for nicer looking plots
import seaborn as sns
'''
This breaks for versions of seaborn < 0.11.0. Google Colab has latest version.
To install in Anaconda, use "conda install seaborn=0.11.2"
'''
sns.set_theme(style="whitegrid",context="poster", font_scale=0.5)

#load column headers into array
data = np.genfromtxt('fread_new.csv', delimiter=',', names=True)

#create figure
# f,ax = plt.subplots()
# ax.set(xscale='log',xlim=(0.00005,1500),ylabel='MB/s',xlabel='MB')
# plt.plot(data['MB'],data['MBs'],marker='.')

# put your read speed plotting code here
data = np.genfromtxt('fread_new.csv', delimiter=',', names=True)

f,ax = plt.subplots()
ax.set(ylabel='MB/s',xlabel='MB')

sns.boxplot(x=data['MB'],y=data['MBs'])
```

Out[2]:
```
<AxesSubplot:xlabel='MB', ylabel='MB/s'>
```



3. Sequential Linear Algebra

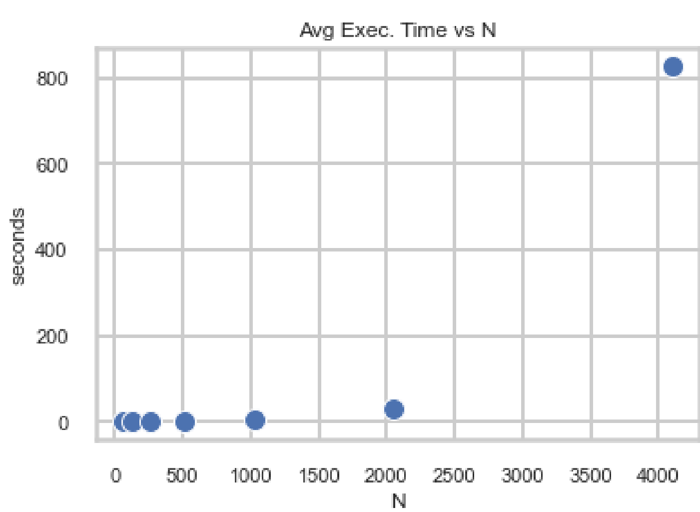
3.1 DELIVERABLE (10 points): Using a dedicated node via SLURM, determine the execution time and Flops for the naive matrix matrix multiplication using $N = 2^k$ with $k = 6, \ldots, 12$. Plot (i) execution time (s) vs. N, and (ii) Flops vs. N. Average each size at least 5 times. Plot a statistical distribution of Flops for $N = 2^{12} = 4096$. Discuss the scaling of matrix-matrix product using the naive algorithm.

Link your dataset(s) here: naive mat-mat CSV (matmul_naive.csv)

Discussion: In naive matrix multiplication, the flops did not scale well as it decreased drastically as the N increased, which resulted in longer execution time. The reason behind the slow execution is that the CPU needs to read the memories that are far away from other memories in one flop>

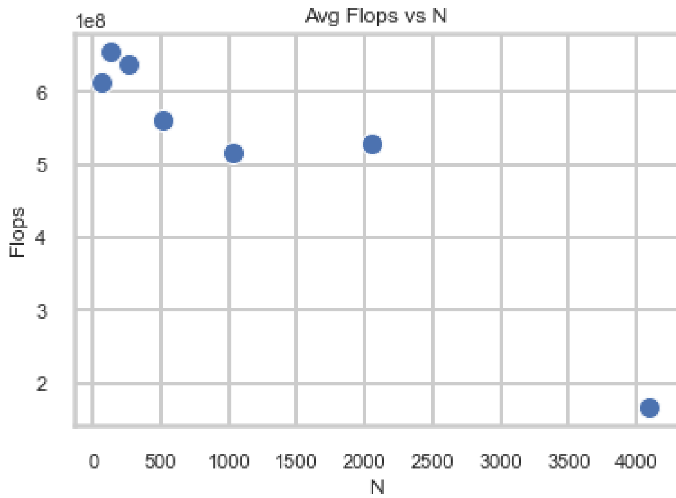
In [3]:
```
# plot code: average execution time vs N plot
from turtle import title
import matplotlib.pyplot as plt
import numpy as np
import seaborn as sns
import pandas as pd


sns.set_theme(style="whitegrid",context="poster", font_scale=0.5)

#load column headers into array
# data = np.genfromtxt('matmul_naive.csv', delimiter=',', names=True)

dataFrame = pd.read_csv("matmul_naive_ave.csv")

#create figure

sns.scatterplot(dataFrame['N'],dataFrame['s'])
plt.xlabel("N")
plt.ylabel("seconds")
plt.title("Avg Exec. Time vs N")
plt.show()

## plot naive n vs time
# f,ax = plt.subplots()
# ax.set(xscale='log',ylim=(0, 1000),ylabel='Time(s)',xlabel='N')
# plt.title("Naive N vs Time")
# plt.plot(data['N'],data['s'],marker='.')

# put your read speed plotting code here

# data = np.genfromtxt('matmul_naive.csv', delimiter=',', names=True)

# # plot naive n vs time
# f,ax = plt.subplots()
# ax.set(ylabel='Time(s)',xlabel='N', title="Naive N vs time")
# sns.boxplot(x=data['N'],y=data['s'])
```

```
C:\Users\lucky\anaconda3\lib\site-packages\seaborn\_decorators.py:36: FutureWarning: Pass
the following variables as keyword args: x, y. From version 0.12, the only valid positiona
l argument will be `data`, and passing other arguments without an explicit keyword will re
sult in an error or misinterpretation.
  warnings.warn(
```



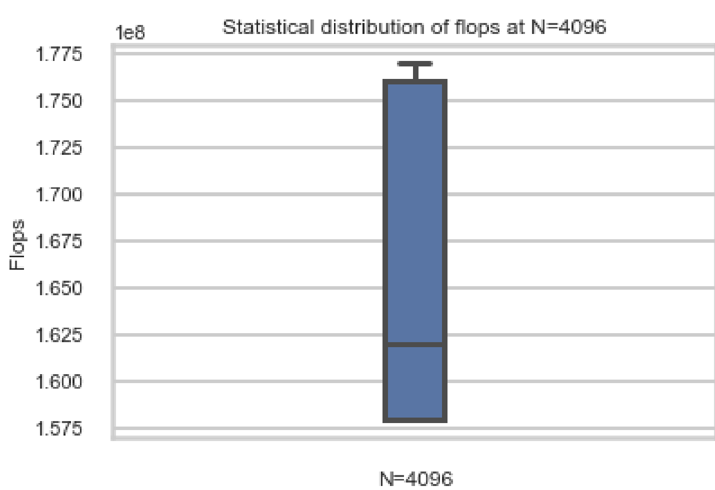
In [4]:
```python
# # plot code: average Flops vs N plot

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


sns.set_theme(style="whitegrid",context="poster", font_scale=0.5)

#load column headers into array
# data = np.genfromtxt('matmul_naive.csv', delimiter=',', names=True)

dataFrame = pd.read_csv("matmul_naive_ave.csv")

#create figure

sns.scatterplot(dataFrame['N'],dataFrame['Flops'])
plt.xlabel("N")
plt.ylabel("Flops")
plt.title("Avg Flops vs N")
plt.show()

# import matplotlib.pyplot as plt
# import numpy as np

# #optional, load seaborn for nicer looking plots
# import seaborn as sns
# '''
# This breaks for versions of seaborn < 0.11.0. Google Colab has latest version.
# To install in Anaconda, use "conda install seaborn=0.11.2"
# '''
# sns.set_theme(style="whitegrid",context="poster", font_scale=0.5)

# #load column headers into array
# data = np.genfromtxt('matmul_naive.csv', delimiter=',', names=True)

# #create figure
# f,ax = plt.subplots()
# ax.set(xscale='log',ylim=(100_000_000, 800_000_000),ylabel='Flops',xlabel='N')
# plt.title("Flops vs N")
# plt.plot(data['N'],data['Flops'],marker='.')

# # put your read speed plotting code here
# data = np.genfromtxt('matmul_naive.csv', delimiter=',', names=True)

# f,ax = plt.subplots()
# ax.set(ylabel='Flops',xlabel='N', title="Flops vs N")

# sns.boxplot(x=data['N'],y=data['Flops'])
```

```
C:\Users\lucky\anaconda3\lib\site-packages\seaborn\_decorators.py:36: FutureWarning: Pass
the following variables as keyword args: x, y. From version 0.12, the only valid positiona
l argument will be `data`, and passing other arguments without an explicit keyword will re
sult in an error or misinterpretation.
  warnings.warn(
```


Avg Flops vs N
1e8
6
5
4
3
2
Flops
0
500
1000
1500
2000
2500
3000
3500
4000
N

In [5]:
```python
# plot code: statistical plot of Flops at N=4096
from cgitb import text
import matplotlib.pyplot as plt
import numpy as np

#optional, load seaborn for nicer looking plots
import seaborn as sns
'''
This breaks for versions of seaborn < 0.11.0. Google Colab has latest version.
To install in Anaconda, use "conda install seaborn=0.11.2"
'''
sns.set_theme(style="whitegrid",context="poster", font_scale=0.5)

#load column headers into array
data = np.genfromtxt('matmul_naive.csv', delimiter=',', names=True)

# #create figure
# f,ax = plt.subplots()
# ax.set(xscale='log',ylim=(100_000_000, 200_000_000),ylabel='Flops',xlabel='N=4096 indexin
# plt.title("Flops at N=4096")
# plt.plot(data['Flops'][-6:],marker='.')

# put your read speed plotting code here
data = np.genfromtxt('matmul_naive.csv', delimiter=',', names=True)

f,ax = plt.subplots()
ax.set(ylabel='Flops',xlabel='N=4096',title="Statistical distribution of flops at N=4096")
f.text(.5, -0.07, "Statistical distribution of Flops for N = 4096 using matrix-matrix produ
sns.boxplot(y=data['Flops'][-5:], width=0.1)
```

Out[5]:
```
<AxesSubplot:title={'center':'Statistical distribution of flops at N=4096'}, xlabel='N=409
6', ylabel='Flops'>
```



Statistical distribution of Flops for N = 4096 using matrix-matrix product naive algorithm.

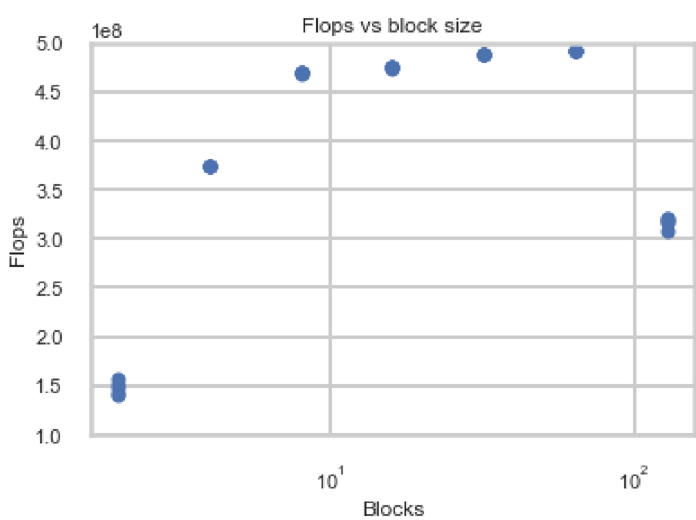
3.2.1 DELIVERABLE (15 points): Using a dedicated node via SLURM, for $N = 2^{12} = 4096$, create a plot of Flops versus block size ($T = 2, 4, 8, 16, 32, 64, 128$) for the `matrix_multiply_blocking.c` code. What is the impact of block size on performance? Cite all external material you used to implement the algorithm.

Link your dataset here: [blocking CSV (block.csv)](block.csv)

Link your **commented** `matrix_multiply_blocking.c` code here: [matrix_multiply_blocking.c (matrix_multiply_blocking.c)](matrix_multiply_blocking.c)

Discussion: as the block size increases, the performace also increases, until the performance peaked at block size of 64

In [6]:
```
# plot code: Flops vs block size
# put your read speed plotting code here
# todo
# put your write speed plotting code here
# I recommend using matplotlib.pyplot and seaborn
import matplotlib.pyplot as plt
import numpy as np

#optional, load seaborn for nicer looking plots
import seaborn as sns
'''
This breaks for versions of seaborn < 0.11.0. Google Colab has latest version.
To install in Anaconda, use "conda install seaborn=0.11.2"
'''
sns.set_theme(style="whitegrid",context="poster", font_scale=0.5)

#load column headers into array
data = np.genfromtxt('block.csv', delimiter=',', names=True)

#create figure
f,ax = plt.subplots()
ax.set(xscale='log',ylim=(100000000, 500000000),ylabel='Flops',xlabel='Blocks')
plt.scatter(data['B'],data['Flops'],marker='.')
plt.title("Flops vs block size")
plt.show()

# # put your read speed plotting code here
# data = np.genfromtxt('block.csv', delimiter=',', names=True)

# f,ax = plt.subplots()
# ax.set(ylabel='Flops',xlabel='Blocks', title="Flops vs block size")

# sns.boxplot(x=data['B'],y=data['Flops'])
```



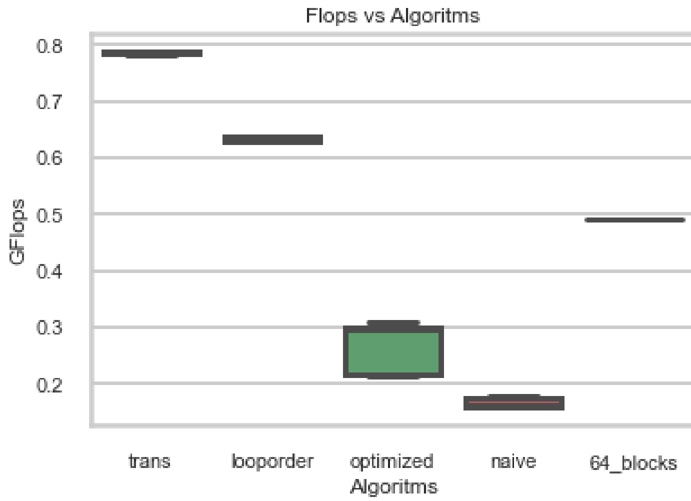
3.2.2 DELIVERABLE (20 points): Using a dedicated node via SLURM, for $N = 2^{12} = 4096$ create a statistical plot that compares (i) the Flops (use a proper SI prefix, such as GFlops) and (ii) execution time between the naive method (you should already have these numbers) and the four new adjustments. Properly label each algorithm. Discuss the impact of each matrix multiply method.

- Link your **commented** `matrix_multiply_transpose.c` code: [matrix_multiply_transpose.c (matrix_multiply_transpose.c)]
- Link your **commented** `matrix_multiply_looporder.c` code: [matrix_multiply_looporder.c (matrix_multiply_flipped.c)]

Discussion: the transposed method is the fastest as the memory allocation of transposed matrix is optimal for CPU's memory access, becuase each cell of memories are closer to each other. Loop order also increased the speed significally compared to naive method, due the similar cause of tranposed matrix. Optimized method also increased the speed, but its not as consistent and faster compared to transpose and looporder. We picked the block size of 64 as it is the fastest among all blocks, and its improvement is slightly less than the loop order method.

In [7]:
```python
# plot code: statistical Flops based on algorithm
from operator import delitem
import matplotlib.pyplot as plt
import numpy as np

#optional, load seaborn for nicer looking plots
import seaborn as sns
'''
This breaks for versions of seaborn < 0.11.0. Google Colab has latest version.
To install in Anaconda, use "conda install seaborn=0.11.2"
'''
sns.set_theme(style="whitegrid",context="poster", font_scale=0.5)

#load column headers into array
trans_data = np.genfromtxt('matmul_transpose.csv', delimiter=',', names=True)
trans_flops_4096 = trans_data["Flops"] / 10**9

looporder_data = np.genfromtxt('matmul_flipped.csv', delimiter=',', names=True)
looporder_flops_4096 = looporder_data["Flops"]/ 10**9

optimized_data = np.genfromtxt('matmul_optimized.csv', delimiter=',', names=True)
optimized_flops_4096 = optimized_data["Flops"]/ 10**9

naive_data = np.genfromtxt('matmul_naive.csv', delimiter=',', names=True)
naive_flops_4096 = naive_data["Flops"][-5:]/ 10**9

block_data = np.genfromtxt("block.csv", delimiter=',', names=True)
block_flops_4096 = block_data["Flops"][-10:-5]/ 10**9

x_axis = []
x_axis.extend("trans" for i in range(5))
x_axis.extend("looporder" for i in range(5))
x_axis.extend("optimized" for i in range(5))
x_axis.extend("naive" for i in range(5))
x_axis.extend("64_blocks" for i in range(5))
y_axis_flops = []
y_axis_flops.extend(trans_flops_4096)
y_axis_flops.extend(looporder_flops_4096)
y_axis_flops.extend(optimized_flops_4096)
y_axis_flops.extend(naive_flops_4096)
y_axis_flops.extend(block_flops_4096)

#create figure
f,ax = plt.subplots()
ax.set(ylabel='GFlops',xlabel='Algoritms', title="Flops vs Algoritms")

sns.boxplot(x=x_axis,y=y_axis_flops)
```

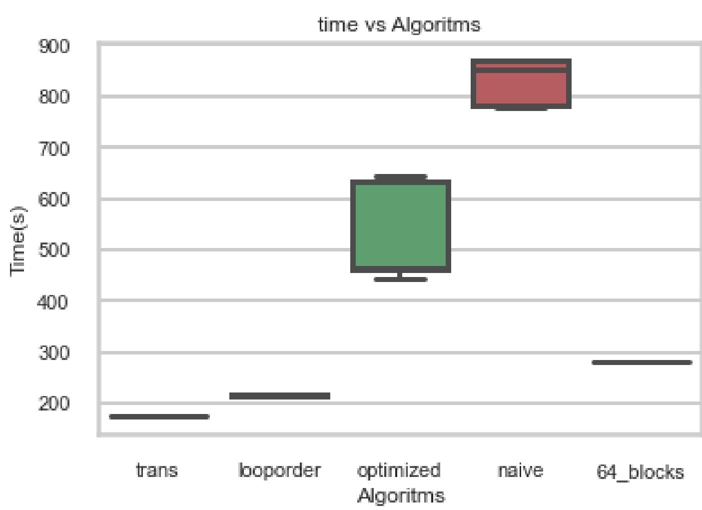
Out[7]:
```
<AxesSubplot:title={'center':'Flops vs Algoritms'}, xlabel='Algoritms', ylabel='GFlops'>
```



Flops vs Algoritms
0.8
0.7
0.6
0.5
0.4
0.3
0.2
GFlops
trans
looporder
optimized
naive
64_blocks
Algoritms

In [8]:
```python
# plot code: statistical execution time based on algorithm
trans_time_4096 = trans_data['s']

looporder_time_4096 = looporder_data['s']

optimized_time_4096 = optimized_data['s']

naive_time_4096 = naive_data['s'][-5:]

block_time_4096 = block_data["s"][-10:-5]

y_axis_time = []
y_axis_time.extend(trans_time_4096)
y_axis_time.extend(looporder_time_4096)
y_axis_time.extend(optimized_time_4096)
y_axis_time.extend(naive_time_4096)
y_axis_time.extend(block_time_4096)


#create figure
f,ax = plt.subplots()
ax.set(ylabel='Time(s)',xlabel='Algoritms', title="time vs Algoritms")

sns.boxplot(x=x_axis,y=y_axis_time)
```

Out[8]: <AxesSubplot:title={'center':'time vs Algoritms'}, xlabel='Algoritms', ylabel='Time(s)'>



3.2.3 DELIVERABLE (5 points): Report in a markdown table the cache-misses and instructions per cycle between the five versions of the algorithm. You only need to report these for one run per algorithm. How do they compare and correlate with the timing information above?

Algorithm	Cache Misses	Instructions Per Cycle
Naive	1278	0.67
O3	859	0.71
Transpose	948	0.70
Loop Order	871	0.71
Blocking	798	0.75

Discussion: the naive method has the highest cache misses and lowest instruction per cycle as expected due to its poor memory allocation. and we did not see significant difference between other optimzed method on terms of caches misses and instructions per cycle, but they are still much imporved than naive method.

3.3.1 DELIVERABLE (15 points): On a dedicated SLURM node, using the same N as the matrix multiply section, plot (i) execution time (s) vs. N, and (ii) Flops vs. N for the two algorithms.

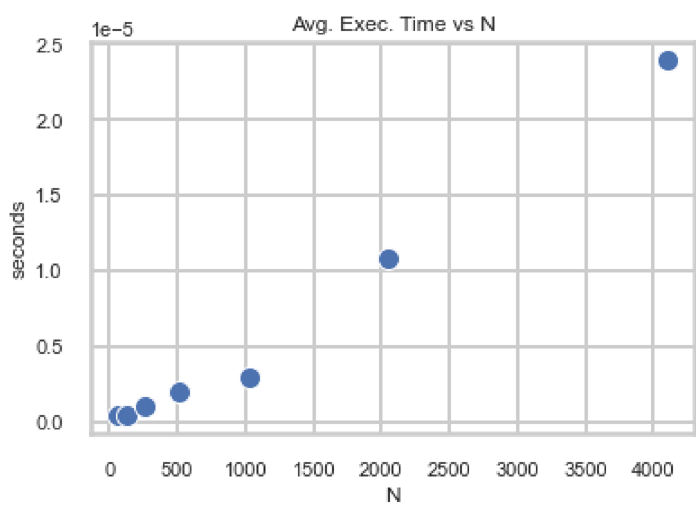
Link to your dot product dataset: [dotproduct.csv (dotproduct.csv)](dotproduct.csv)

Link to your matrix-vector product dataset: [matrixvector.csv (matrixvector.csv)](matrixvector.csv)

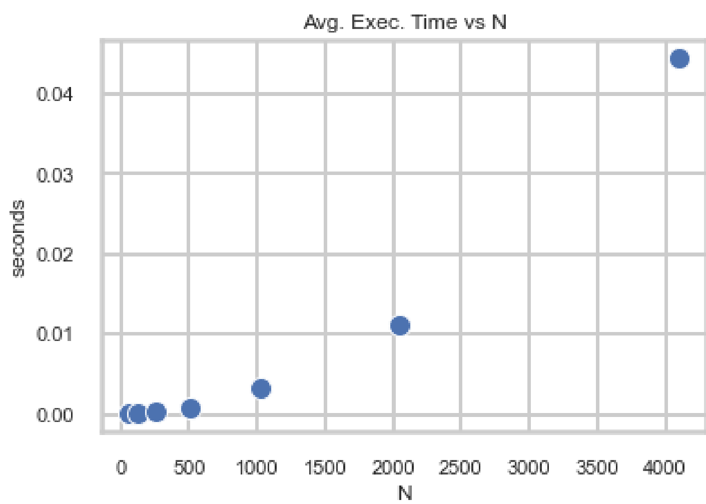
Link to your **commented** dot product code: [dot_product_naive.c (dot_product_naive.c)](dot_product_naive.c)

Link to your **commented** matrix-vector product code: [matrix_vector_product_naive.c (matrix_vector_product_naive.c)](matrix_vector_product_naive.c)

In [9]:
```
# plot code: average execution time vs N plot (dot product)

import matplotlib.pyplot as plt
import numpy as np
import seaborn as sns
import pandas as pd
import warnings
warnings.filterwarnings('ignore')

dataFrame = pd.read_csv("dotproduct_ave.csv")

sns.scatterplot(dataFrame['N'],dataFrame['s'])

plt.xlabel("N")
plt.ylabel("seconds")
plt.title("Avg. Exec. Time vs N")
plt.show()
```

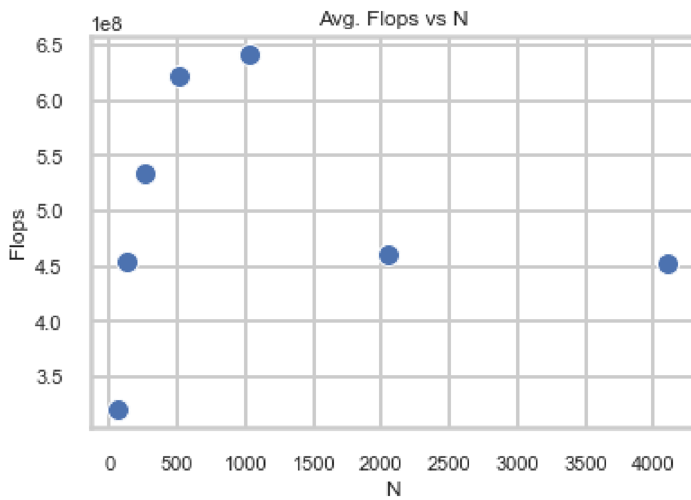


In [10]:
```
# plot code: average execution time vs N plot (matrix-vector product)

import matplotlib.pyplot as plt
import numpy as np
import seaborn as sns
import pandas as pd
import warnings
warnings.filterwarnings('ignore')

dataFrame = pd.read_csv("matrixvector_ave.csv")

sns.scatterplot(dataFrame['N'],dataFrame['s'])

plt.xlabel("N")
plt.ylabel("seconds")
plt.title("Avg. Exec. Time vs N")
plt.show()
```

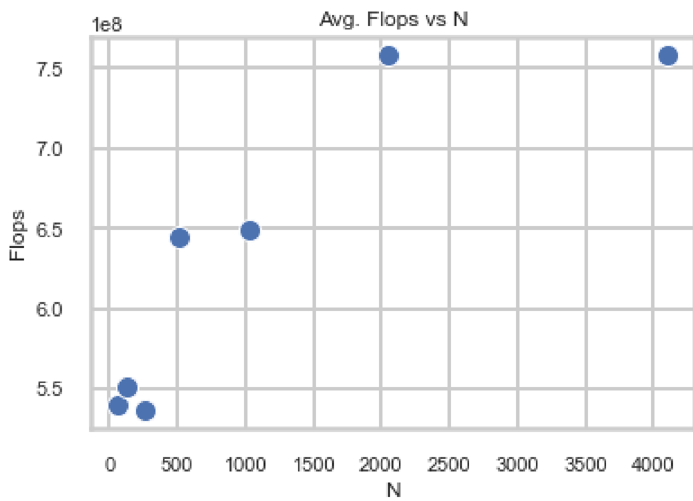


In [11]:

```python
# plot code: average Flops vs N plot (dot product)

import matplotlib.pyplot as plt
import numpy as np
import seaborn as sns
import pandas as pd
import warnings
warnings.filterwarnings('ignore')

dataFrame = pd.read_csv("dotproduct_ave.csv")

sns.scatterplot(dataFrame['N'],dataFrame['Flops'])

plt.xlabel("N")
plt.ylabel("Flops")
plt.title("Avg. Flops vs N")
plt.show()
```



In [12]:
```
# plot code: average Flops vs N plot (matrix-vector product)

import matplotlib.pyplot as plt
import numpy as np
import seaborn as sns
import pandas as pd
import warnings
warnings.filterwarnings('ignore')

dataFrame = pd.read_csv("matrixvector_ave.csv")

sns.scatterplot(dataFrame['N'],dataFrame['Flops'])

plt.xlabel("N")
plt.ylabel("Flops")
plt.title("Avg. Flops vs N")
plt.show()
```

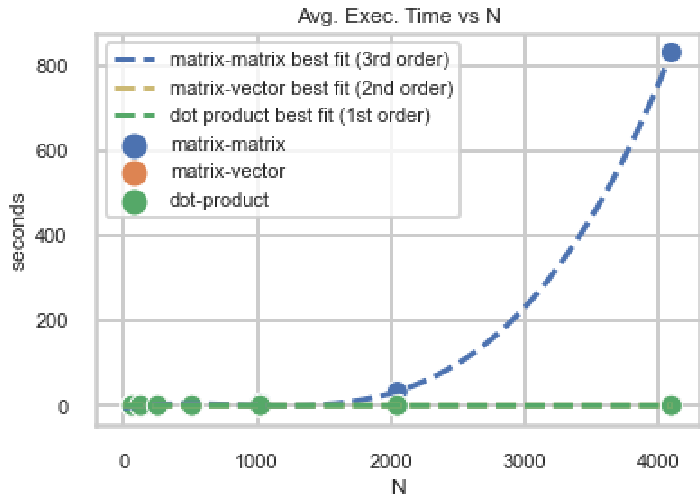


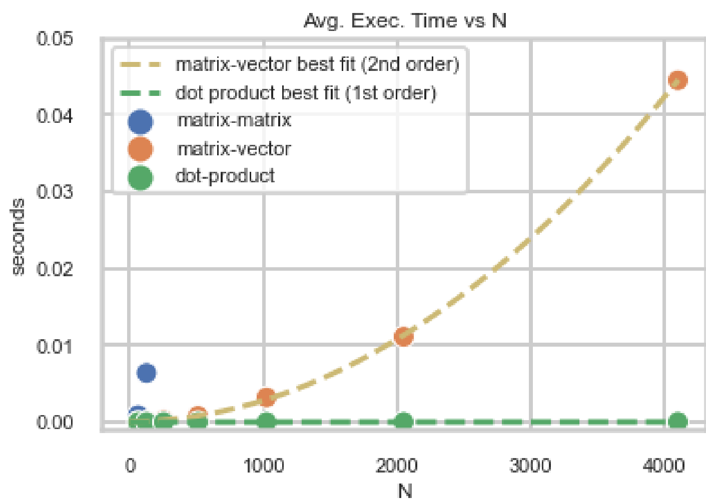
3.3.2 DELIVERABLE (5 points): Create a plot that compares the execution time of matrix-matrix, matrix-vector, and dot products. Validate that the algorithms scale linearly, quadratically, and cubicly. You may need to have a second plot with a scaled Y-axis to see all three plots clearly. Try to fit a linear, quadratic, and cubic polynomial to the three datasets.

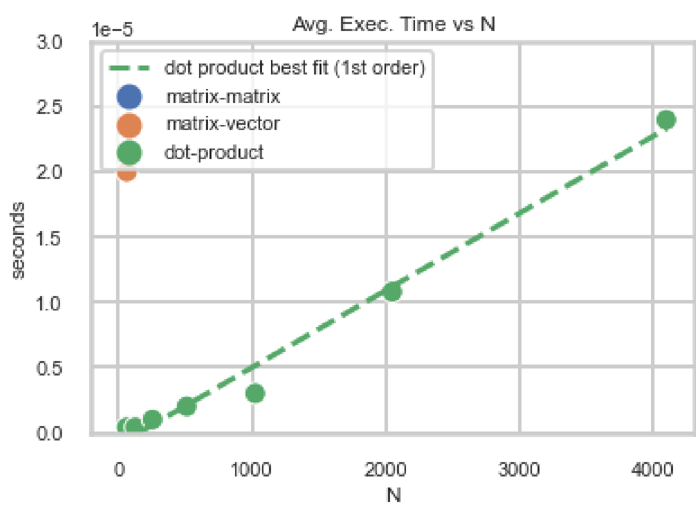
Discuss the scaling of the three algorithms.

In [13]:

```
# plot code: execution time vs. N for all three algorithms

import matplotlib.pyplot as plt
import numpy as np
import seaborn as sns
import pandas as pd
import warnings
warnings.filterwarnings('ignore')

dataFrame = pd.read_csv("matrix_vector_dot.csv")
dataFrame_matmul = pd.read_csv("matmul_naive_ave.csv")
dataFrame_matvec = pd.read_csv("matrixvector_ave.csv")
dataFrame_dot = pd.read_csv("dotproduct_ave.csv")

z_dot = np.polyfit(dataFrame_dot['N'],dataFrame_dot['s'],1)
z_matvec = np.polyfit(dataFrame_matvec['N'],dataFrame_matvec['s'],2)
z_matmul = np.polyfit(dataFrame_matmul['N'],dataFrame_matmul['s'],3)

x_plot = np.linspace(0,4100,100000)
y_dot = z_dot[0] * x_plot + z_dot[1]
y_matvec = z_matvec[0] * pow(x_plot,2) + z_matvec[1] * x_plot + z_matvec[2]
y_matmul = (z_matmul[0] * pow(x_plot,3) + z_matmul[1] * pow(x_plot,2) +
            z_matmul[2] * x_plot + z_matmul[3])

sns.scatterplot(dataFrame['N'],dataFrame['s'], hue=dataFrame['kind'])

plt.xlabel("N")
plt.ylabel("seconds")
plt.title("Avg. Exec. Time vs N")
plt.plot(x_plot, y_matmul, 'b--', label = "matrix-matrix best fit (3rd order)")
plt.plot(x_plot, y_matvec, 'y--', label = "matrix-vector best fit (2nd order)")
plt.plot(x_plot, y_dot, 'g--', label = "dot product best fit (1st order)")
plt.legend()
plt.show()

sns.scatterplot(dataFrame['N'],dataFrame['s'], hue=dataFrame['kind'])

plt.xlabel("N")
plt.ylabel("seconds")
plt.title("Avg. Exec. Time vs N")
plt.ylim(-0.001,0.05)
plt.plot(x_plot, y_matvec, 'y--', label = "matrix-vector best fit (2nd order)")
plt.plot(x_plot, y_dot, 'g--', label = "dot product best fit (1st order)")
plt.legend()
plt.show()

sns.scatterplot(dataFrame['N'],dataFrame['s'], hue=dataFrame['kind'])

plt.xlabel("N")
plt.ylabel("seconds")
plt.title("Avg. Exec. Time vs N")
plt.ylim(-0.0000001,0.00003)
plt.plot(x_plot, y_dot, 'g--', label = "dot product best fit (1st order)")
plt.legend()
plt.show()


print(f"Dot product best fit line: y = {z_dot[0]}*x + {z_dot[1]}")
print(f"Matrix-vector product best fit line: y = {z_matvec[0]}*x^2 + {z_matvec[1]}*x + {z_m
print(f"Matrix-matrix product best fit line: y = {z_matmul[1]}*x^3 + {z_matmul[1]}*x^2 {z_m
```








```
Dot product best fit line: y = 5.919936193320662e-09*x + -9.310344827586255e-07
Matrix-vector product best fit line: y = 2.611974293816255e-09*x^2 + 1.4682514170282202e-0
7*x + 5.944222553402844e-05
Matrix-matrix product best fit line: y = -6.36872953958494e-05*x^3 + -6.36872953958494e-05
*x^2 0.04415154129957325*x + -5.1241824642859415
```

In [ ]: