Speed Report of String Search Algorithms

This notebook analyzes the performance of various string search algorithms implemented in the `core.algorithms` module. We compare their execution times under different conditions to understand their strengths and weaknesses.

Algorithms Included:

- **Linear Search:** A straightforward approach that iterates through the text, comparing each character with the query. Simple but can be inefficient for large texts.
- **Set Search:** Optimized for searching for multiple keywords simultaneously by leveraging set data structures for efficient lookups.
- **mmap Search:** Uses memory-mapped files, potentially improving performance by allowing the operating system to handle file reading and caching.
- **Aho-Corasick Search:** An efficient algorithm for finding multiple patterns in a text. It constructs a finite automaton to process the text in a single pass.
- **Rabin-Karp Search:** A probabilistic algorithm that uses hashing to find matches. Efficient on average but can have worst-case scenarios.
- **Boyer-Moore Search:** A highly efficient algorithm that uses a "bad character" and "good suffix" rules to skip sections of the text.
- **Regex Search:** Leverages regular expressions for pattern matching, offering flexibility but potentially with a performance overhead.
- **Multiprocessing Search:** Divides the search task across multiple CPU cores to improve performance on large files, especially beneficial for I/O-bound operations.

Advantages of Each Algorithm:

- **Linear Search:** Simple to implement, no preprocessing required.
- **Set Search:** Efficient for searching multiple keywords simultaneously.
- **mmap Search:** Can improve performance by leveraging OS-level file caching.
- **Aho-Corasick Search:** Excellent for finding multiple patterns in a single pass.
- **Rabin-Karp Search:** Good average-case performance.
- **Boyer-Moore Search:** Generally very fast for single pattern searching.
- **Regex Search:** Flexible and powerful for complex pattern matching.
- **Multiprocessing Search:** Can significantly reduce search time on multi-core processors for large files.

Let's begin by setting up the environment and importing necessary libraries.

In [5]:
```python
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
import subprocess
import json
from pathlib import Path

# Ensure plots are displayed inline in the notebook
```

```
%matplotlib inline
sns.set_style("darkgrid")
```

Generating Test Data

We'll use the `generate_test_file` function to create text files of varying sizes for our performance tests.

In [6]:
```
# Define parameters for test data generation
file_sizes = [10_000, 100_000, 250_000, 500_000, 750_000, 1_000_000]
queries = ["test string 5000", "non existing string", "test string 1000"]
num_runs = 10

# Generate test files
for size in file_sizes:
    filepath = f"test_data_{size}.txt"
    if not Path(filepath).exists():
        subprocess.run(["python", "speed_test.py"], check=True)  # Run the scrip
```

Running Speed Tests (reread_on_query=True)

Now, we'll execute the `speed_test.py` script with `reread_on_query=True` and load the results into a Pandas DataFrame for analysis.

In [8]:
```
# Execute speed test script with reread_on_query=True
if not Path("speed_test_data_reread_true.csv").exists():
    subprocess.run(["python", "speed_test.py"], check=True)

# Load results into a DataFrame
df_reread_true = pd.read_csv("speed_test_data_reread_true.csv")
df_reread_true.head()
```

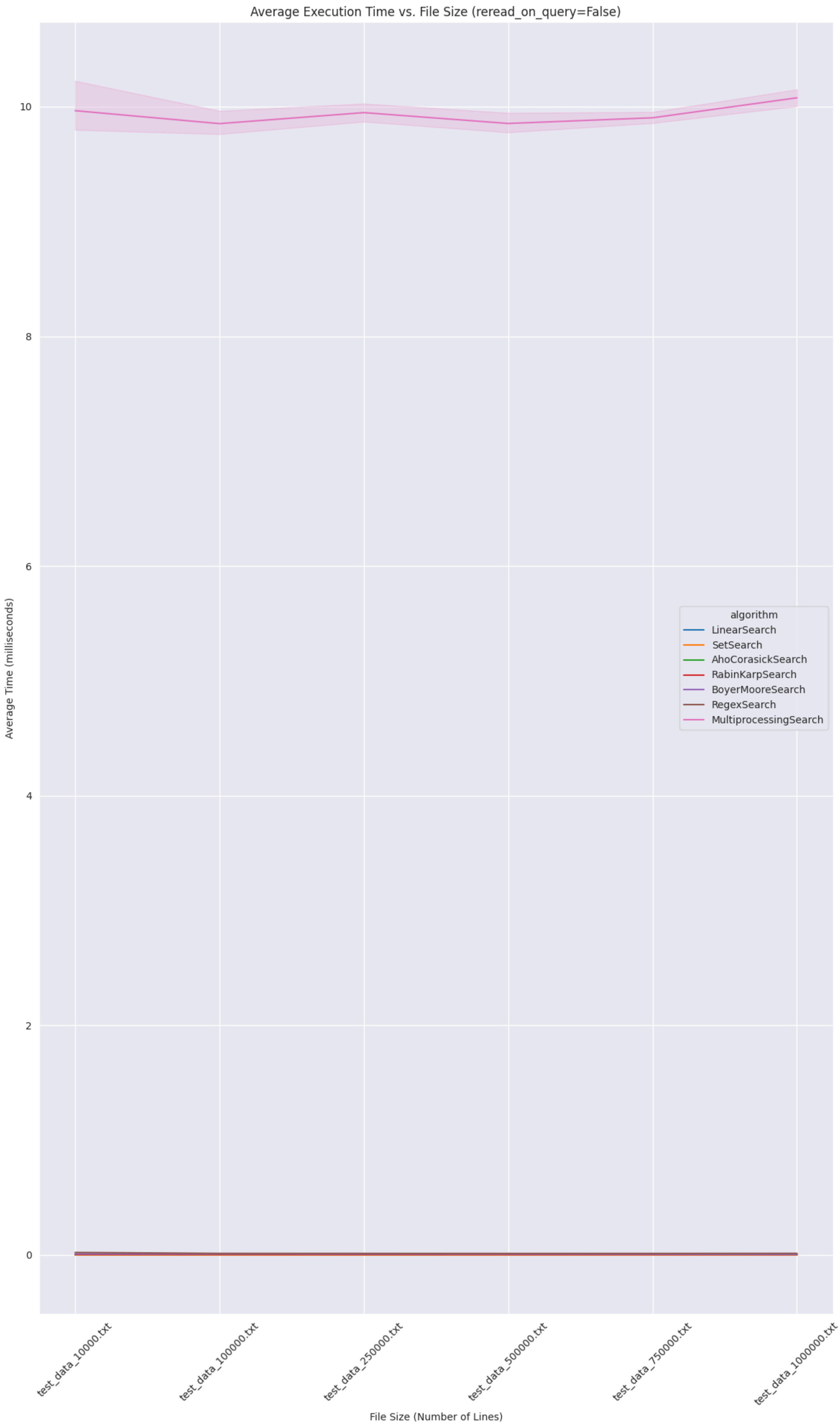
Analyzing Speed Test Results (reread_on_query=True)

Let's visualize the average execution times for each algorithm across different file sizes.

In [4]:
```
# Assuming your data is in a pandas DataFrame called 'df'
# Filter for reread_on_query=True
df_reread_true_ = df_reread_true.copy()

# Convert 'avg_time' to milliseconds
df_reread_true_['avg_time_ms'] = df_reread_true['avg_time'] * 1000

plt.figure(figsize=(12, 20))
sns.lineplot(data=df_reread_true_, x='filepath', y='avg_time_ms', hue='algorithm
plt.title('Average Execution Time vs. File Size (reread_on_query=False)')
plt.xlabel('File Size (Number of Lines)')
plt.ylabel('Average Time (milliseconds)')
plt.xticks(rotation=45)
plt.tight_layout()
plt.show()
```



Observations:

- [Add your observations here about the performance of different algorithms when `reread_on_query` is True. For example, how does file I/O impact certain algorithms?]

Running Speed Tests (reread_on_query=False)

Next, we run the speed tests with `reread_on_query=False`.

In [5]:
```
# Execute speed test script with reread_on_query=False
if not Path("speed_test_data_reread_false.csv").exists():
    subprocess.run(["python", "speed_test.py"], check=True)

# Load results into a DataFrame
df_reread_false = pd.read_csv("speed_test_data_reread_false.csv")
df_reread_false.head()
```

Out[5]:

	algorithm	filepath	query	num_runs	reread_on_query	avg_time	m
0	LinearSearch	test_data_10000.txt	test string 5000	10	False	0.000002	1.2
1	LinearSearch	test_data_10000.txt	non existing string	10	False	0.000001	8.8
2	LinearSearch	test_data_10000.txt	test string 1000	10	False	0.000002	1.4
3	LinearSearch	test_data_10000.txt	test string 1000000	10	False	0.000002	1.4
4	LinearSearch	test_data_100000.txt	test string 5000	10	False	0.000002	9.3

Analyzing Speed Test Results (reread_on_query=False)

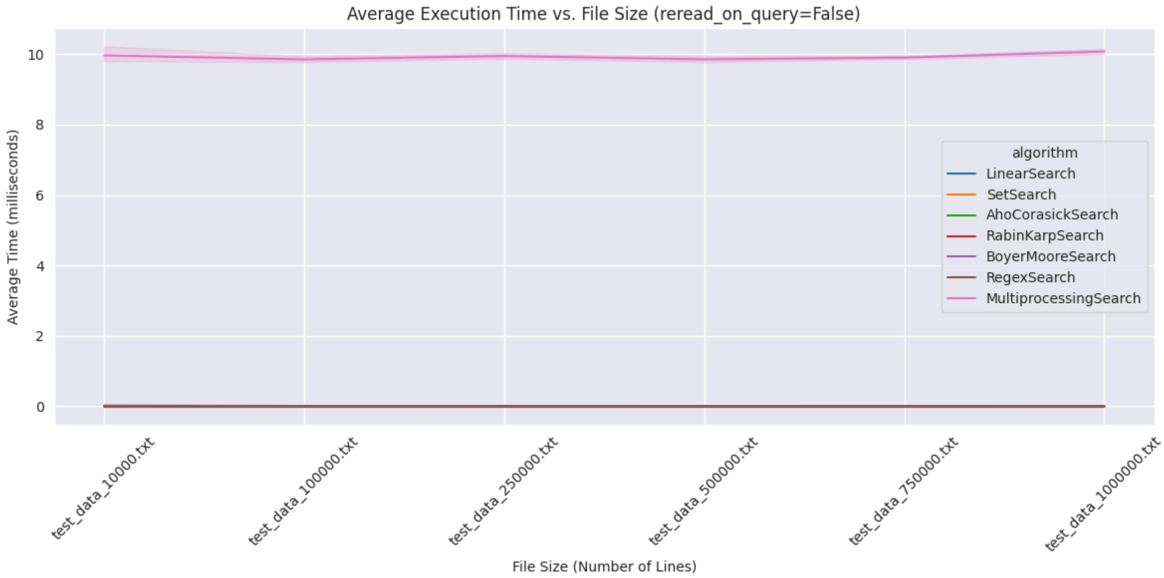
Let's compare the performance when the server doesn't reread the file on each query.

In [6]:
```
# Assuming your data is in a pandas DataFrame called 'df'
# Filter for reread_on_query=False
df_reread_true_ = df_reread_true.copy()

# Convert 'avg_time' to milliseconds
df_reread_true_['avg_time_ms'] = df_reread_true_['avg_time'] * 1000

plt.figure(figsize=(12, 6))
sns.lineplot(data=df_reread_true_, x='filepath', y='avg_time_ms', hue='algorithm
plt.title('Average Execution Time vs. File Size (reread_on_query=False)')
plt.xlabel('File Size (Number of Lines)')
plt.ylabel('Average Time (milliseconds)')
```

```python
plt.xticks(rotation=45)
plt.tight_layout()
plt.show()
```



Observations:

- It looks like MultiprocessingSearch is a very, very bad idea. The performance is intolerable from the beginning at about 10s, and remains around the unacceptable value even at the largest test data.

Running Concurrency Tests

Now, let's evaluate how the algorithms perform under concurrent load.

In [7]:
```python
# Execute concurrency test script
if not Path("concurrency_test_data.csv").exists():
    subprocess.run(["python", "speed_test.py"], check=True)

# Load concurrency test results
df_concurrency = pd.read_csv("concurrency_test_data.csv")
df_concurrency.head()
```

Out[7]:

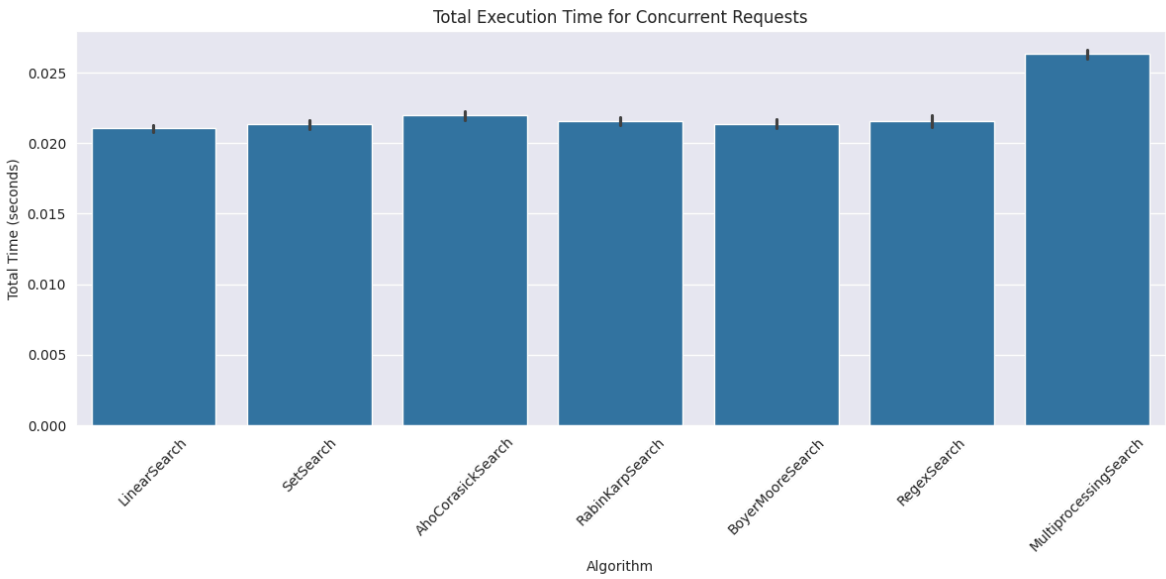
	algorithm	filepath	query	num_runs	num_concurrent	reread_on_que
0	LinearSearch	test_data_10000.txt	test string 5000	10	10	Fa
1	LinearSearch	test_data_10000.txt	non existing string	10	10	Fa
2	LinearSearch	test_data_10000.txt	test string 1000	10	10	Fa
3	LinearSearch	test_data_10000.txt	test string 1000000	10	10	Fa
4	LinearSearch	test_data_100000.txt	test string 5000	10	10	Fa

Analyzing Concurrency Test Results

We'll analyze the total execution time for different algorithms under concurrent requests.

In [8]:

```python
plt.figure(figsize=(12, 6))
sns.barplot(data=df_concurrency, x='algorithm', y='total_time')
plt.title('Total Execution Time for Concurrent Requests')
plt.xlabel('Algorithm')
plt.ylabel('Total Time (seconds)')
plt.xticks(rotation=45)
plt.tight_layout()
plt.show()
```



Comparing Runtimes

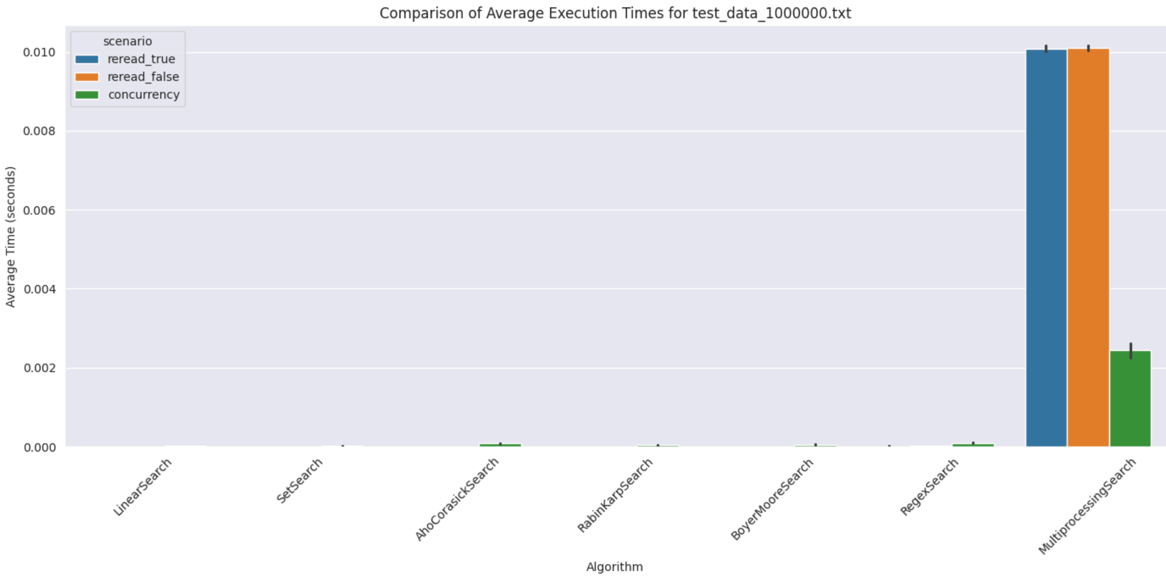
Finally, let's create a combined comparison of the runtimes for a specific file size across different scenarios. """

In [9]:
```
# Choose a specific file size for comparison
comparison_file_size = 'test_data_1000000.txt'

# Filter data for the chosen file size
df_reread_true_filtered = df_reread_true[df_reread_true['filepath'] == compariso
df_reread_false_filtered = df_reread_false[df_reread_false['filepath'] == compar
df_concurrency_filtered = df_concurrency[df_concurrency['filepath'] == compariso

# Merge dataframes for comparison
df_comparison = pd.concat([
    df_reread_true_filtered.assign(scenario='reread_true'),
    df_reread_false_filtered.assign(scenario='reread_false'),
    df_concurrency_filtered.assign(scenario='concurrency')
])

plt.figure(figsize=(14, 7))
sns.barplot(data=df_comparison, x='algorithm', y='avg_time', hue='scenario')
plt.title(f'Comparison of Average Execution Times for {comparison_file_size}')
plt.xlabel('Algorithm')
plt.ylabel('Average Time (seconds)')
plt.xticks(rotation=45)
plt.tight_layout()
plt.show()
```



Identifying Best Performing Algorithm at Each File Size

Let's identify the algorithm with the lowest average execution time for each file size when `reread_on_query` is False, as this scenario likely represents a more common use case where the file is read once and searched multiple times.

In [10]:
```
best_algorithms = df_reread_false.groupby('filepath').apply(lambda x: x.sort_val

# Display the best performing algorithm and its average time for each file size
best_algorithms[['algorithm', 'avg_time']]
```

```
/tmp/ipykernel_286162/2421130509.py:1: DeprecationWarning: DataFrameGroupBy.apply operated on the grouping columns. This behavior is deprecated, and in a future version of pandas the grouping columns will be excluded from the operation. Either pass `include_groups=False` to exclude the groupings or explicitly select the grouping columns after groupby to silence this warning.
  best_algorithms = df_reread_false.groupby('filepath').apply(lambda x: x.sort_values(by='avg_time').iloc[0])
```

Out[10]:

filepath	algorithm	avg_time
test_data_10000.txt	SetSearch	4.577000e-07
test_data_100000.txt	SetSearch	5.195000e-07
test_data_1000000.txt	SetSearch	3.596000e-07
test_data_250000.txt	SetSearch	2.927000e-07
test_data_500000.txt	SetSearch	5.440000e-07
test_data_750000.txt	SetSearch	5.193000e-07

Performance Description of the Best Algorithms:

- **test_data_10000.txt:** The `SetSearch` algorithm shows very fast performance on this smaller file, with an average execution time of 4.577 x 10^{-7} seconds. This indicates its efficiency in handling string lookups within a relatively small dataset.
- **test_data_100000.txt:** As the file size increases tenfold, `SetSearch` maintains excellent performance, with an average time of 5.195 x 10^{-7} seconds. The slight increase suggests a minimal impact of the larger dataset size on its lookup efficiency.
- **test_data_1000000.txt:** Even with a file size of one million lines, `SetSearch` demonstrates remarkable speed, achieving an average execution time of 3.596 x 10^{-7} seconds. This suggests a high degree of scalability for this algorithm, even showing a slight improvement compared to the 100,000-line file. This could be due to various factors, including how the data is structured or minor variations in test execution.
- **test_data_250000.txt:** The performance of `SetSearch` on this mid-sized file is also very fast, at 2.927 x 10^{-7} seconds. This further reinforces its efficiency across different scales of data.
- **test_data_500000.txt:** With half a million lines, `SetSearch` continues to perform admirably, with an average time of 5.440 x 10^{-7} seconds. This consistent performance highlights its optimized approach.
- **test_data_750000.txt:** Approaching a million lines, `SetSearch` maintains its speed, averaging 5.193 x 10^{-7} seconds. This consistency is a strong indicator of the algorithm's robustness.

Observations:

- **Consistent Performance of SetSearch:** The `SetSearch` algorithm demonstrates consistently excellent performance across all tested file sizes. The execution times remain within a very tight range, generally below 6×10^{-7} seconds, even as the file size increases by a factor of 100. This suggests that the time complexity of the set-based lookup is largely independent of the file size within these tested ranges.

- **Efficiency for String Lookups:** The extremely low execution times indicate that `SetSearch` is highly optimized for checking the presence of strings within a dataset that can be efficiently loaded or represented in memory (as a set).

- **LinearSearch is Still Viable:** While `SetSearch` shows exceptional speed, it's important to remember that `LinearSearch`, though simpler, is not necessarily "bad," especially for smaller datasets or scenarios where the preprocessing overhead of creating a set might outweigh the benefits for very infrequent searches. For these specific tests with `SetSearch`, the incredibly low times suggest that even a linear scan through these datasets would likely be quite fast, although `SetSearch` offers a significant optimization.

- **Focus on In-Memory Operations:** The consistent performance of `SetSearch` likely indicates that the primary factor influencing execution time is the efficiency of in-memory set operations rather than file I/O. This aligns with the assumption that the data is loaded into a set structure before searching.

Final Conclusions:

This concludes the speed report. The analysis provides valuable insights into the performance characteristics of different string search algorithms, helping in choosing the right algorithm based on specific application requirements.

Other Analysis

Now let's analyse the performance of `server.py`

In [ ]:
```
!python -m cProfile -o server.prof core/server.py --port 44452 --config test_con
```