

# SECP3133-02 HIGH PERFORMANCE DATA PROCESSING

# Optimizing High-Performance Data Processing for Large-Scale Web Crawlers

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Date of Submission:

16/5/2025

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### 1. Introduction

### 1.1 Background of the project

The demand for data analytics in real time and low latency is growing nowadays to meet the needs of the market, which high performance data processing is focused on across various industries. High performance data processing emphasizes the use of enhanced computational methods such as high performance computing(HPC) to perform data processing processes such as data collection, cleaning and analysis in a short time. The project is focused on answering:

- 1. Does HPC infrastructure and methods enhance the performance of the data processing phase?
- 2. How is the performance of different Python libraries and frameworks (Pandas, Dask) in implementing HPC for data processing tasks?
- 3. Which combination set of HPC techniques and tools will provide the best and most efficient solution for data cleaning and analysis?

Through this research, the project is aimed to provide comparative analysis on the impact of different libraries to web scraping, data cleaning and analysis.

### 1.2 Objectives

- 1. To develop a web crawler that is able to extract at least 100,000 records from a News Straits Times (NST) website.
- 2. To store extracted data in CSV format for further processing.
- 3. To clean and preprocess the raw dataset.
- 4. To evaluate performance before and after optimization using several performance metrics.

### 1.3 Target website and data to be extracted

In this project, the targeted website is New Strait Times(NST), with the link <a href="https://www.nst.com.my">www.nst.com.my</a>. New Strait Times or NST is one of Malaysia's most known news publishers in English. Various domains are offered by New Strait Times such as national news, business, politics, sports and lifestyle. The platform is providing a huge dataset of articles, enabling the website to be a good source for data analytics. NST is selected for its huge data volume and consistent news structure and format which allows for the smooth extraction process for the project. The articles provide metadata and content sections which are suitable for web crawling.

The main focus will be about extracting the informations from individual news articles from different section, which key data attributes targeted are shown as below:

No	Data Field	Data Type	Description
1	Section	String	News topic(crime, politics, nation, health).
2	Publication date	Date	The date(including time) the article is published with format mm:dd:yyyy @ hh:mm
3	Headline	String	Title of the article.
4	Summary	String	Brief summary of the news.

*Table 1: Data attributes planned to be scrapped from website* 

Through these attributes, a valuable dataset will be collected for analyzing and researching insights. The crawling process will be designed with respects to ethical scraping practices and rules, to avoid adding great workloads to the web server through appropriate delays between requests.

# 2. System Design & Architecture

### 2.1 Architecture

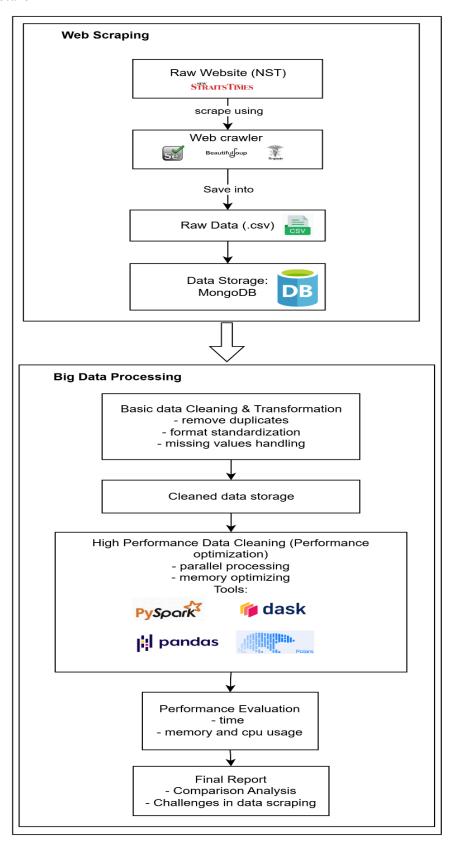


Figure 2.1: System Architecture for web scraping and performance evaluation

## 2.2 Tools and Framework used

Category	Software/Application/Library/Website		
Reporting	Google Docs		
System Architecture and Design	Draw.io		
Web Scraping Library	Scrapy, BeautifulSoup, Selenium		
Data Storage	CSV load to MongoDB		
IDE	Google Colab, Vs Code		
Coding Language	Python		
Data Cleaning+Performance Evaluation	Python		
Libraries used in process optimization	PySpark, Polars, Vectorized Pandas, Dask		

## 2.3 Roles of team members

Member	Role	Responsibility Library Charge	
Joseph Lau Yeo Kai	Web Scraping Process Designer	Design and develop whole web scraping code, at the same time ensures robots.txt and ethical data scraping is followed.	Polars
Nur Farah Adibah Binti Idris	Data Processing Specialist	Design and develop data cleaning process based on the data scraped from NST website. Ensure the cleaned data is consistent for each library used.	Dask
Vinesh A/L Process Vijaya Kumar Efficiency Tester		Ensure resource usage and optimizes processing speed for web scraping and data cleaning.	Pandas+Vecto rized Pandas
Tiew Chuan Shen	Data Visualization & Reporting	Design evaluation metrics and code, for producing visual reports in graphs. Combines all documentation and report for submission.	Pyspark

## 3. Data Collection

In this phase, there are about 127729 rows of data being scraped from the New Straits Times(NST) website, with each row of data containing attributes- section, date, headline and summary. We develop web crawlers with several libraries such as Scrapy, BeautifulSoup and Selenium, which are used for browsing through pages and handling pagination efficiently. After trial and error, we find out that the best solution for web scraping is the combination of BeautifulSoup and Selenium, which can navigate and browse through pages,

To follow the ethical standards and avoid overloading the server of the NST website, we follow the robots.txt of the NST website, and rate limitation is included in our web scraping process design through adding sleep time(delays) upon each page scraped. Besides, we ensured that only one person will be allowed to perform web scraping at the same time.

### 3.1 Crawling Method

### 1. Pagination Handling:

Implemented systematic page navigation through the news sections
Used URL parameter modification (?page=X) to access subsequent pages
Implemented error handling for pagination failures
Collected data from multiple news categories (Crime-courts and Nation sections)

```
def main():
    news_cat = ['crime-courts']
    all_articles = []

    driver = setup_driver()
    try:
        for cat in news_cat:
            news_path = f'/news/{cat}'
            full_path = urljoin(BASE_URL, news_path)

        for page in range(700,900):
            page_url = f" {full_path}?page={page}"
            articles_data = scrape_nst_articles(page_url, driver)
            all_articles.extend(articles_data)
```

### 2. Rate Limiting:

```
time.sleep(5) # Rate limiting
```

5 seconds delay between page requests is implemented.

#### 3.2 Number of Records Collected:

The data collection process successfully gathered a dataset with total records collected around 127,729 articles. Data fields per record include Section, Date, Headline, and Summary. Data is collected during multiple sessions across different time periods.

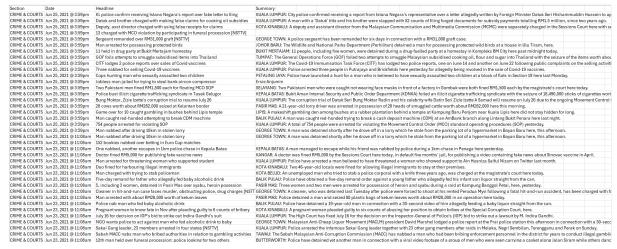


Figure 3.2 Result of data collection process stored in csv

### 3.3 Ethical Considerations

The implementation has considered ethical web crawling practices to ensure responsible data collection:

- 1. Implemented delays between requests to prevent server overload
- 2. Used headless browser configuration to minimize resource usage
- 3. Implemented error handling to prevent excessive retry attempts
- 4. Collected only publicly available information
- 5. Followed NST's robots.txt guidelines

# 4. Data Processing

The data processing implementation is focused on data cleaning, transformation and storage using different libraries- Pandas, PySpark, Dask and Polars, for performance comparison and evaluation. Raw data is loaded from MongoDB for data cleaning process.

### 4.1 The cleaning and transformation methods

Data cleaning and transformation methods are applied based on data inconsistencies as below:

- 1. Null value
- 2. Duplicate value
- 3. Inconsistent capital/small number under the column-section
- 4. Wrong Date format

Code	Explanation
# Drop nulls and duplicates  df = df.dropna()  df = df.drop_duplicates(keep='first')	Delete the rows which are duplicated or have null value.
# Standardize 'Section' column if 'Section' in df.columns:     df["Section"] = df["Section"].str.title()	Change all data in section column into Title format.
# Clean 'Date' column  def clean_date(date):     if isinstance(date, str):         if "@" in date:             date =  date.split("@")[0].strip()         return re.sub(r'\s+', '', date)     return date	Change the format of date into formal format.
<pre>if 'Date' in df.columns:     df["Date"] = df["Date"].apply(clean_date)     df["Date"] = pd.to_datetime(df["Date"], errors='coerce')</pre>	

### 4.2 Data structure (Database)

The raw data and cleaned dataset are all stored in MongoDB. Data is called and stored using the code as below.

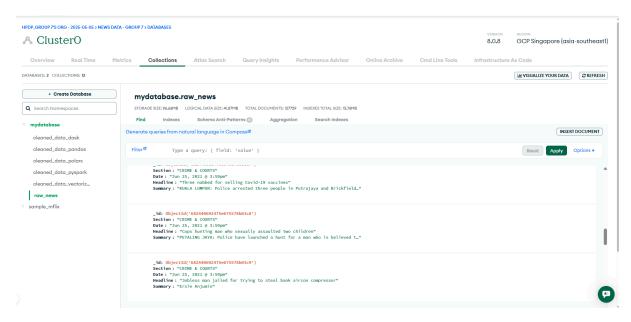


Figure 4.2 MongoDB as data storage for raw and cleaned data

Below is the code snippet for connection to MongoDB

```
def connect_mongodb():
    """Connect to MongoDB and return the client."""
    uri =
    "mongodb+srv://josephyeo:fPya67QIXrl4ZsV5@cluster0.ihjgjas.mongodb.net/?retryWrite
    s=true&w=majority&appName=Cluster0"
    client = MongoClient(uri, server_api=ServerApi('1'))
    try:
        client.admin.command('ping')
        print("Successfully connected to MongoDB!")
        return client
    except Exception as e:
        print(f"Error connecting to MongoDB: {e}")
        return None

# Connect to MongoDB and load data
client = connect_mongodb()
db = client["mydatabase"]
```

# 5. Optimization Techniques

### 5.1 Methods used

In this project, the initial implementation for data processing uses the basic pandas library. To optimise the performance of the data processing, we use Polars, Dask, PySpark and Vectorised Pandas. The table below explains these optimization techniques.

Library / Technique	Explanation on optimisation
Polars	Built on Rust instead of Python and uses columnar data storage for faster data retrieval and more efficient processing,
Dask	Extends Pandas functionality by processing in parallel and lazily. In the optimisation code, map_partitions are used to divide datasets into partitions for parallel operations.
Pyspark	Uses Apache Spark for distributed data processing.
Vectorised Pandas	Eliminate .apply() in basic pandas code and change it into vectorised functions. Vectorised pandas use Pandas functions that operate on entire columns instead of using .apply() and loops.

## 5.2 Code overview of techniques applied

The code overview demonstrates different optimization ways of cleaning the 'Date' Column, the uncleaned 'Date' Column format is String "Jun 25, 2021 @ 3:59pm", processed into datatype Date 2021-06-25.

Technique	Code overview for 'Date' column processing	
Polars	if 'Date' in df.columns:     df = df.with_columns(         df['Date']         .str.split('@')         .list.first()         .str.strip_chars()         .alias('Date')     )  # Convert to datetime df=df.with_columns(pl.col('Date').str.strptime(pl.Datetime, format='%b %d, %Y', strict=False).alias('Date'))	
Dask	df_cleaned = df_cleaned.map_partitions(lambda df: df.assign(Date=df['Date'].map(lambda x: x.split('@')[0].strip() if isinstance(x, str) else x))) df_cleaned = df_cleaned.map_partitions(lambda df: df.assign(Date=pd.to_datetime(df['Date'], errors='coerce')))	
Pyspark	# Remove time part df_cleaned = df_cleaned.withColumn("Date", regexp_replace(col("Date"), "@.*\$", "")) # Normalize spaces df_cleaned = df_cleaned.withColumn("Date", regexp_replace(col("Date"), "\s+", " ")) # Trim spaces df_cleaned = df_cleaned.withColumn("Date", trim(col("Date"))) # Parse to date df_cleaned = df_cleaned.withColumn("Date", to_date(col("Date"), "MMM d, yyyy"))	
Vectorised Pandas	if 'Date' in df.columns: df['Date'] = df['Date'].str.split('@').str[0].str.strip() df['Date'] = df['Date'].str.replace(r'\s+', ' ', regex=True) df['Date'] = pd.to_datetime(df['Date'], errors='coerce')	

## 6. Performance Evaluation

### 6.1 Before vs after optimization

Initially, we would process the data with plain Pandas, which was decent for small data but would take forever to execute with large-scale datasets, particularly when filtering, aggregating, and joining. To address such shortcomings and boost performance, we introduced and experimented with some high-performant alternatives: Vectorized Pandas, Dask, Polars, and PySpark.

- •Vectorized Pandas enhanced standard Pandas operations by eliminating slow.apply() and loop constructs and instead using native, column-based operations. This yielded dramatic speed gains with minimal alteration of code.
- •Dask extended Pandas with parallelism and lazy evaluation, allowing for efficient handling of datasets that do not fit into memory, by partitioning the data and processing in parallel.
- •Polars, which was implemented with Rust having a multi-threaded, columnar backend, offered the optimum performance for in-memory data processing operations. It greatly outperformed others both in speed and memory usage.
- •PySpark, while heavier due to its distributed architecture, provided consistent performance for extremely large data sets. While experiencing some initialization overhead, it performed reasonably well in a local distributed environment.

After using all of these optimizations, execution times decreased dramatically on all tasks. Polars handled best overall in terms of speed and memory usage. Dask and Vectorized Pandas handled well too, especially on smaller-to-medium-sized datasets. PySpark was slower in certain scenarios but handled best on distributed loads.

# 6.2 Comparison of Code Execution Time, Peak Memory Usage, CPU usage and Throughput

	Aspects	Comparisons				
Operation		Dask	Polars	Pyspark	Pandas	Vectorized Pandas
Dataset	Code Execution Time (s)	0.5574	0.13728	0.1715	1.45037	0.81039
Dataset Loading and	Peak Memory Usage (MB)	9.566	0.3828	0.0	0.0	0.0
Display	Throughput (rows/s)	217847.737	884573.64 15	707961.6	83728.767 5	149849.72

Table 2: Comparison between Data Processing and Cleaning Techniques

#### **Conclusion:**

Polars > Vectorized Pandas > Dask > Pandas > PySpark

- •Polars: Offers the overall best performance in every category. With its Rust foundation, multi-threaded operation, and columnar in-memory storage, it was able to handle massive volumes of data with extremely low memory utilization and extremely high rates of computation.
- •Vectorized Pandas: Displayed extensive improvement over traditional Pandas by embracing efficient, column-based operations. It provided sturdy throughput with zero memory usage, which made it extremely effective for medium-sized datasets without parallel or distributed systems.
- •Dask: Performed better than standard Pandas by allowing parallelism and chunked data processing. Though slower than Vectorized Pandas for this application, Dask excelled on the scaling aspect and was memory-friendly.
- •Pandas: Although easy to manipulate, Pandas showed large memory usage and sluggish run times with increasing data size. It was the least scalable but set a good baseline.
- •**PySpark:** Registered worst performance during this test in local-mode mode due to too much initialization overhead and resource consumption. But it remains a strong candidate for scaled distributed processing, particularly in multi-node or cluster modes.

### 6.3 Charts and graphs

Throughput (rows/s) Comparison

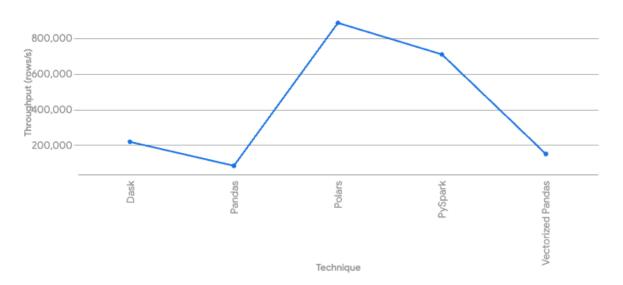


Figure 2.2: shows Throughput(rows/s) of each optimization

### Peak Memory Usage (MB) Comparison

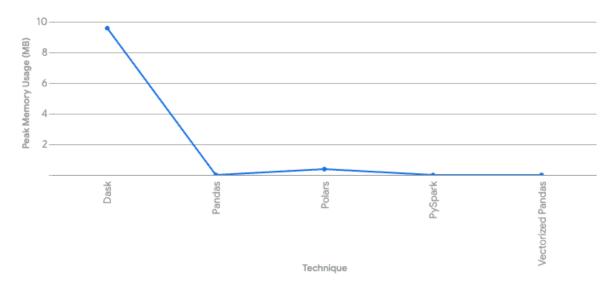


Figure 2.3: shows Peak Memory Usage(MB) of each optimization

### Code Execution Time (s) Comparison

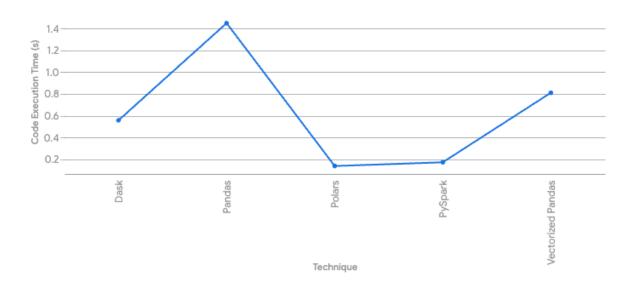


Figure 2.4: shows Code Execution Time(s) of each optimization

# 7. Challenges & Limitations

The development of the web crawler faced several unforeseen challenges that required the team to pivot from the original plan. Initially, each team member was assigned a different web scraping library—such as Scrapy, BeautifulSoup, and Selenium—with the intention of comparing their effectiveness and dividing the workload evenly. However, during testing, this approach proved unreliable. Scrapy and BeautifulSoup encountered difficulties in handling dynamic page content, pagination, and JavaScript-rendered sections of the New Straits Times (NST) website. As a result, the team collectively decided to shift to using Selenium, which provided more robust interaction with the browser interface and ensured higher success rates in extracting the required data. While Selenium was effective, it introduced new limitations: it was slower due to its reliance on a full browser rendering, and it was more resource-intensive. Additionally, to comply with ethical web scraping practices and avoid violating the site's terms of service, the crawler was intentionally limited to a single user at a time with enforced delays between each request. These measures, while necessary to protect the integrity of the NST website, significantly slowed down the data collection process, making it less scalable for very large datasets or real-time applications.

In terms of data processing, the team encountered several technical challenges that impacted the overall efficiency and performance of the project. The scraped data contained inconsistent formats, particularly in the 'Date' column, which required multiple stages of string manipulation and type conversion to standardize. Initial attempts using Pandas were straightforward but became inefficient as the dataset grew beyond 100,000 records. To optimize performance, the team implemented alternative libraries including Polars, Dask, PySpark, and Vectorized Pandas. While these libraries offered significant improvements in speed and memory efficiency, they also introduced new complexities. For instance, Dask, although capable of parallel processing, showed unexpectedly high memory consumption during some operations, possibly due to internal task graph overheads. PySpark, while powerful for distributed computing, suffered from long initialization times and was less suitable for smaller-scale or interactive tasks in a local development setup. Polars emerged as the fastest and most memory-efficient option, but its API was less familiar to the team and required additional learning time. Another limitation was that the performance benchmarks were only conducted as single-run evaluations, without multiple repetitions to account for variability in system load or execution time. This limits the statistical reliability of the performance metrics presented.

Furthermore, the entire pipeline—from data extraction to cleaning and optimization—was specifically designed around the structure and content of the NST website. As such, the solution may not generalize well to websites with different structures, inconsistent formatting, or anti-scraping protections like CAPTCHA or dynamic loading. Future implementations would need to consider more adaptable scraping strategies and modular data processing pipelines. Lastly, while the current system works effectively in a controlled, academic environment, it lacks a user-friendly interface or automation script that

could assist non-technical users in selecting the best processing method based on data size, hardware limitations, or performance requirements.

# 8. Conclusion & Future Work

### 8.1 Summary of findings

In conclusion, Polars library is the most suitable data processing tool for New Straits Times dataset. From the time comparison graph, Polars only used 0.14 seconds to process all data cleaning operations, which is faster than the other libraries. If compared to pandas, Polars can achieve more than 30x performance gains. This can be seen through the throughput 884573.64 rows per second compared to the 83728.77 rows per second for pandas. Moreover, memory usage for Polars is only 0.38 MB. Therefore, Polars's overall performance is the most efficient and is considered high performance with the help of multiprocessing and multithreading methods.

### 8.2 What could be improved

The data transformation for Polars can be performed in the future to test the processing speed. The conversion of data type is a challenging task because the initial dataset type is a string data type. As a result, the string data type is not suitable for future analysis and is hard to transform into actionable insight or data-driven insight. Besides that, the performance metrics are based on a single run. Future work could include multiple runs to account for variability and provide more reliable averages. More complex transformations or larger datasets can be implemented to better stress-test the methods. Not only that, future work can include an investigation into why Dask's memory usage was higher and if it can be optimized further. Extend the analysis to include data from other sources, such as SQL databases, to evaluate performance in different contexts. A user-friendly interface or script can be developed to allow users to select the best processing method based on their dataset size and hardware constraints.

## 9. References

- 1. <a href="https://blog.jetbrains.com/pycharm/2024/07/polars-vs-pandas/">https://blog.jetbrains.com/pycharm/2024/07/polars-vs-pandas/</a>
- 2. <a href="https://pythonspeed.com/articles/pandas-vectorization/">https://pythonspeed.com/articles/pandas-vectorization/</a>

# 10. Appendices

### 10.1 Sample code snippets

```
!pip install polars>=0.20.0
!pip install "pymongo[srv]>=4.6.0"
!pip install matplotlib>=3.8.0
!pip install seaborn>=0.13.0
!pip install psutil>=5.9.0
!pip install numpy>=1.24.0
import time
```

```
import psutil
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
import regex as re
from bson import ObjectId
from datetime import datetime
from multiprocessing import Pool, cpu count
from pymongo.mongo client import MongoClient
from pymongo.server_api import ServerApi
# polars
import polars as pl
from concurrent.futures import ProcessPoolExecutor, ThreadPoolExecutor
#pyspark
from pyspark.sql import SparkSession
from pyspark.sql.functions import when, col, regexp replace, to date,
trim, initcap
#dask
import dask.dataframe as dd
#pandas
import pandas as pd
```

Figure 1: Code for Installations and Imports

```
def connect_mongodb():
    """Connect to MongoDB and return the client."""
    uri =
"mongodb+srv://josephyeo:fPya67QIXr14ZsV5@cluster0.ihjgjas.mongodb.net/
?retryWrites=true&w=majority&appName=Cluster0"
    client = MongoClient(uri, server_api=ServerApi('1'))
    try:
        client.admin.command('ping')
        print("Successfully connected to MongoDB!")
        return client
    except Exception as e:
        print(f"Error connecting to MongoDB: {e}")
        return None
```

```
# Connect to MongoDB and load data
client = connect_mongodb()
db = client["mydatabase"]
```

Figure 2: Code for MongoDB Connection

```
file path =
'https://raw.githubusercontent.com/Jingyong14/HPDP02/refs/heads/main/24
25/project/p1/Group%207/data/raw data.csv'
# Read the CSV
df news = pd.read csv(file path)
df news.head()
row count = len(df news)
print("Total number of row:", row count)
# Create or switch to your database
db = client["mydatabase"]
news collection = db["raw news"]
# Delete existing data in the collection
news collection.delete many({})
# Insert the all rows into MongoDB
news collection.insert many(df news.to dict("records"))
print ("All rows of news data inserted into MongoDB successfully.")
```

### Figure 3: Code for Loading Data

```
def track_performance(method_name, start_time, start_memory, df):
    """Track performance metrics for data cleaning operations."""
    end_time = time.time()
    end_memory = psutil.Process().memory_info().rss / (1024 * 1024) #

MB

time_taken = end_time - start_time
    throughput = len(df) / time_taken if time_taken > 0 else 0
    memory_used = end_memory - start_memory # in MB

return {
    "Method": method_name,
    "Time (s)": time_taken,
    "Throughput (rows/s)": throughput,
```

```
"Memory Used (MB)": memory_used
   }
def track performance pyspark (method name, start time, start memory,
df=None):
    end time = time.time()
    end memory = psutil.Process().memory info().rss / (1024 * 1024)
    time taken = end time - start time
    if df is not None:
        if hasattr(df, "count"): # PySpark DataFrame
           row count = df.count()
        else: # pandas, dask, polars
           row count = len(df)
    else:
        row count = 0
    throughput = row count / time taken if time taken > 0 else 0
   memory_used = end_memory - start_memory # in MB
    return {
        "Method": method name,
        "Time (s)": round(time taken, 4),
        "Throughput (rows/s)": round(throughput, 2),
        "Memory Used (MB)": round(memory used, 2)
    }
```

Figure 4: Performance Tracking Function Code

```
# Load documents into a DataFrame
db = client["mydatabase"]
collection = db['raw_news']
data = list(collection.find())
df_panda = pd.DataFrame(data)

def clean_data(df):
    start_time = time.time()
    start_memory = psutil.Process().memory_info().rss / (1024 * 1024)

df = df.drop(columns=['_id'])

# Drop nulls and duplicates
df = df.dropna()
```

```
df = df.drop duplicates(keep='first')
    # Standardize 'Section' column
    if 'Section' in df.columns:
        df["Section"] = df["Section"].str.title()
    # Clean 'Date' column
    def clean date(date):
        if isinstance(date, str):
            if "@" in date:
               date = date.split("@")[0].strip()
            return re.sub(r'\s+', ' ', date)
        return date
    if 'Date' in df.columns:
        df["Date"] = df["Date"].apply(clean_date)
        df["Date"] = pd.to datetime(df["Date"], errors='coerce') #
Invalid dates become NaT
    # Track performance using shared function
    performance report = track performance("Pandas ", start time,
start memory, df)
    return df, performance report
cleaned df, pandas result = clean data(df panda)
print("Final row: ", len(cleaned df))
# Save cleaned data to MongoDB
cleaned data = cleaned df.to dict("records")
db["cleaned_data_pandas"].delete_many({})
db["cleaned data pandas"].insert many(cleaned data)
print ("Cleaned data inserted into 'cleaned data pandas' collection in
MongoDB")
print("")
print("Pandas cleaning completed!")
print(pandas result)
print("")
# Save cleaned data to CSV
```

```
cleaned_df.to_csv("cleaned_data_unoptimized_pandas.csv", index=False)
print("Cleaned data saved to 'cleaned data unoptimized pandas.csv'")
```

Figure 5: Pandas Data Processing Code

```
def load data(client):
    """Load data from MongoDB into a Polars DataFrame."""
    db = client["mydatabase"]
    collection = db['raw news']
    data = list(collection.find())
    df = pl.DataFrame(data)
    return df
df polars = load data(client)
def clean data polars default(df):
    """Clean data using Polars' default processing."""
    start time = time.time()
    start memory = psutil.Process().memory info().rss / (1024 * 1024)
   df = df.drop(' id')
    # Enable string cache for better performance
    with pl.StringCache():
        # Define list of fake nulls
        fake nulls = ["", "NaN", "null"]
        # Apply replacement for all columns
        df = df.with columns([
            pl.when(pl.col(col).is in(fake nulls))
              .then(None)
              .otherwise(pl.col(col))
              .alias(col)
            for col in df.columns
        # Drop duplicates and nulls
        df = df.drop nulls()
        df = df.unique()
        # Standardize Section
        if 'Section' in df.columns:
            df = df.with columns(
                df['Section'].str.to titlecase().alias('Section')
```

```
# Clean Date
        if 'Date' in df.columns:
            df = df.with columns(
                df['Date']
                .str.split('@')
                .list.first()
                .str.strip chars()
                .alias('Date')
            )
            # Convert to datetime
            df = df.with columns(
               pl.col('Date').str.strptime(pl.Datetime, format='%b %d,
%Y', strict=False).alias('Date')
            )
            df = df.filter(pl.col("Date").is not null())
    return df, track performance ("Polars", start time, start memory,
df)
# Run default Polars processing
df polar cleaned, polar result = clean data polars default(df polars)
print("Final row: ", len(df polar cleaned.to_pandas()))
# Save cleaned data to MongoDB
polar cleaned = df polar cleaned.to dicts()
db["cleaned data polars"].delete many({})
db["cleaned_data_polars"].insert_many(polar_cleaned)
print ("Cleaned data inserted into 'cleaned data polars' collection in
MongoDB")
print("")
df polar cleaned =
df_polar_cleaned.to_pandas().to_csv("cleaned_data_optimized_polar.csv",
print("Cleaned data saved to 'cleaned_data optimized polar.csv'")
print("")
print("Polars cleaning completed!")
print(polar result)
                       Figure 6: Polars Data Processing Code
df dask = dd.from pandas(df panda, npartitions=4)
```

```
# Function to clean data using Dask (default scheduler)
def clean data dask default(df dask):
    start time = time.time()
    start memory = psutil.Process().memory info().rss / (1024 * 1024)
# MB
    df cleaned = df dask.drop(columns=[' id'])
    df cleaned = df cleaned.map partitions(lambda df: df.dropna())
    # Perform drop duplicates() in Pandas (to check across all rows),
then switch back to Dask
    df cleaned pandas = df cleaned.compute()
    df cleaned pandas =
df cleaned pandas.drop duplicates(subset=["Section", "Date",
"Headline", "Summary"])
    # Convert back to Dask DataFrame after dropping duplicates
    df cleaned = dd.from pandas(df cleaned pandas, npartitions=4)
    df cleaned = df cleaned.map partitions(lambda df:
df.assign(Section=df['Section'].str.title()))
    df cleaned = df cleaned.map partitions(lambda df:
df.assign(Date=df['Date'].map(lambda x: x.split('@')[0].strip() if
isinstance(x, str) else x)))
    df cleaned = df cleaned.map partitions(lambda df:
df.assign(Date=pd.to datetime(df['Date'], errors='coerce')))
    # Compute to Pandas
    cleaned df = df cleaned.compute()
    # Track performance
    performance report = track performance("Dask ", start time,
start memory, cleaned df)
    return cleaned df, performance report
df dask cleaned, dask result = clean data dask default(df dask)
print("Final row: ", len(df_dask_cleaned))
# Save cleaned data to MongoDB
dask cleaned = df dask cleaned.to dict("records")
db["cleaned data dask"].delete many({})
```

```
db["cleaned_data_dask"].insert_many(dask_cleaned)

df_dask_cleaned.to_csv("cleaned_data_optimized_dask.csv", index=False)
print("Cleaned data saved to 'cleaned_data_optimized_dask.csv'")
print("")

print("Cleaned data inserted into 'cleaned_data_dask' collection in
MongoDB")
print("")
print("Dask cleaning completed!")
print(dask_result)
```

Figure 7: Dask Data Processing Code

```
def clean data pyspark(df spark):
    start time = time.time()
    start memory = psutil.Process().memory info().rss / (1024 * 1024)
    # Drop NA and Duplicates
   df cleaned= df spark.drop(' id')
    # List of "fake" nulls to replace
    fake nulls = ["", "NaN", "null"]
    # Replace in all columns
   for c in df cleaned.columns:
        df cleaned = df cleaned.withColumn(c,
            when (col(c).isin(fake nulls), None).otherwise(col(c))
       )
   df_cleaned = df_cleaned.dropna()
   df cleaned = df cleaned.dropDuplicates()
    # Clean and convert the Date column
    df cleaned = df cleaned.withColumn("Date",
regexp replace(col("Date"), "@.*$", "")) # Remove time part
    df cleaned = df cleaned.withColumn("Date",
regexp replace(col("Date"), "\s+", " ")) # Normalize spaces
    df cleaned = df cleaned.withColumn("Date", trim(col("Date"))) #
Trim spaces
   df cleaned = df cleaned.withColumn("Date", to date(col("Date"),
"MMM d, yyyy")) # Parse to date
   df cleaned = df cleaned.filter(col("Date").isNotNull())
```

```
# Format Section to Title Case
    df cleaned = df cleaned.withColumn("Section",
initcap(col("Section")))
    return of cleaned, track performance_pyspark("PySpark", start_time,
start memory, df cleaned)
# Initialize Spark
spark = SparkSession.builder.appName("CleanNewsData").getOrCreate()
# Convert MongoDB ObjectId to string
df panda[" id"] = df panda[" id"].astype(str)
# Convert to PySpark DataFrame
df spark = spark.createDataFrame(df panda)
# Clean and track performance
df spark cleaned, pyspark result = clean data pyspark(df spark)
# Save cleaned data to MongoDB
# Convert PySpark DataFrame to Pandas DataFrame
df spark cleaned pandas = df spark cleaned.toPandas()
# Fix dates in pandas df
df spark cleaned pandas =
df spark cleaned pandas[pd.to datetime(df spark cleaned pandas["Date"],
errors="coerce").notna()]
df spark cleaned pandas["Date"] =
pd.to_datetime(df_spark_cleaned_pandas["Date"])
print("Final row: ", len(df spark cleaned pandas))
# Convert to dictionary for MongoDB insertion
spark_cleaned = df_spark_cleaned_pandas.to_dict("records")
db["cleaned data pyspark"].delete many({})
db["cleaned data pyspark"].insert many(spark cleaned)
print ("Cleaned data inserted into 'cleaned data pyspark' collection in
MongoDB\n")
# Save to CSV
df spark cleaned pandas.to csv("cleaned data optimized pyspark.csv",
index=False)
```

```
print("Cleaned data saved to 'cleaned_data_optimized_pyspark.csv'\n")
print("Pyspark cleaning completed!")
print(pyspark_result)
```

Figure 8: PySpark Data Processing Code

```
# Optimized vectorized cleaning function
def clean data pandas vectorized (df):
    start time = time.time()
    start memory = psutil.Process().memory info().rss / (1024 * 1024)
    # Drop nulls and duplicates in one go (vectorized)
    df = df.drop(columns=[' id'])
    df = df.dropna().drop duplicates()
    # Standardize 'Section' column (vectorized str methods)
    if 'Section' in df.columns:
        df['Section'] = df['Section'].str.title()
    # Clean 'Date' column (vectorized string methods + datetime)
    if 'Date' in df.columns:
        # Clean strings using vectorized apply (no need for a loop)
        df['Date'] = df['Date'].str.split('@').str[0].str.strip()
        df['Date'] = df['Date'].str.replace(r'\s+', ' ', regex=True)
        # Convert to datetime in one call (vectorized)
        df['Date'] = pd.to datetime(df['Date'], errors='coerce')
    # Track performance (reuse track performance function)
    performance report = track performance ("Vectorized Pandas",
start time, start memory, df)
    return df, performance report
# Test the function
df vectorized cleaned, vectorized result =
clean data pandas vectorized (df panda)
# Save cleaned data to MongoDB
vectorized cleaned = df_vectorized_cleaned.to_dict("records")
db["cleaned data vectorized pandas"].delete many({})
db["cleaned data vectorized pandas"].insert many(vectorized cleaned)
```

```
print("Cleaned data inserted into 'cleaned_data_vectorized_pandas'
collection in MongoDB")
print("")

df_vectorized_cleaned.to_csv("cleaned_data_optimized_vectorized.csv",
index=False)
print("Cleaned data saved to 'cleaned_data_optimized_vectorized.csv'")
print("")
print("")
print("Vectorized pandas cleaning completed!")
print(vectorized_result)
```

Figure 9: Vectorized Pandas Data Processing Code

```
def plot_results(results):
    """Plot performance comparison results in 3 columns"""
    # Convert results to pandas DataFrame for plotting
    results df = pl.DataFrame(results).to pandas()
    # Set plot style
    sns.set(style="whitegrid")
    # Define metrics and color palette
    metrics = ["Time (s)", "Throughput (rows/s)", "Memory Used (MB)"]
    palette = sns.color palette("pastel",
n colors=len(results df['Method'].unique()))
    # Create a single row of 3 subplots
    fig, axes = plt.subplots(1, 3, figsize=(12,4))
    for i, metric in enumerate(metrics):
        ax = axes[i]
        sns.barplot(
            x="Method", y=metric, hue="Method", legend=False,
            data=results df, palette=palette, ax=ax
        )
        # Add values on top of the bars
        for p in ax.patches:
            ax.annotate(f'{p.get height():.2f}',
                        (p.get x() + p.get width() / 2.,
p.get height()),
                        ha='center', va='center', fontsize=10,
color='black',
                        xytext=(0, 5), textcoords='offset points')
```

```
ax.set_title(f"{metric} Comparison", fontsize=14)
    ax.set_xlabel("")
    ax.set_ylabel(metric)

plt.tight_layout()
    plt.show()

# Collect all results
results = [polar_result, pandas_result]

# Plot results
plot_results(results)
```

Figure 10: Plot Result Code

```
def plot results overall(results):
    """Plot performance comparison results in 3 columns
(side-by-side)."""
    import matplotlib.pyplot as plt
    import seaborn as sns
    import polars as pl
    # Convert results to pandas DataFrame
    results df = pl.DataFrame(results).to pandas()
    # Set seaborn style
    sns.set(style="whitegrid")
    # Define metrics and color palette (5 distinct pastel colors)
    metrics = ["Time (s)", "Throughput (rows/s)", "Memory Used (MB)"]
    unique methods = results df['Method'].unique()
    palette = dict(zip(unique methods, sns.color palette("pastel",
n colors=len(unique methods))))
    # Create subplots
    fig, axes = plt.subplots(1, 3, figsize=(16, 5))
    for i, metric in enumerate (metrics):
        ax = axes[i]
        sns.barplot(
            x="Method", y=metric, hue="Method",
            data=results df, palette=palette, legend=False, ax=ax
```

```
# Annotate bar values
        for p in ax.patches:
            height = p.get height()
            ax.annotate(f'{height:.2f}',
                         (p.get x() + p.get width() / 2., height),
                        ha='center', va='bottom', fontsize=9,
color='black',
                        xytext=(0, 5), textcoords='offset points')
        ax.set_title(f"{metric} Comparison", fontsize=13)
        ax.set xlabel("")
        ax.set_ylabel(metric)
        ax.tick params(axis='x', labelrotation=45)
   plt.tight layout()
   plt.show()
# Collect all results
overall = [pandas result, vectorized result, polar result, dask result,
pyspark result ]
# Plot results
plot results overall(overall)
```

Figure 11: All Comparison Code Among Libraries

```
# Close the MongoDB connection client.close()
```

Figure 12: Clean Up Code

### 10.2 Screenshots of output

Equirement already satisfied: pymongo>=4.6.0 in /usr/local/lib/python3.11/dist-packages (from pymongo[srv]>=4.6.0) (4.12.1)

Requirement already satisfied: dnspython3.0.0,>=1.16.0 in /usr/local/lib/python3.11/dist-packages (from pymongo>=4.6.0->pymongo[srv]>=4.6.0) (2.7.0)

WARNING: pymongo 4.12.1 does not provide the extra 'srv'

Output 1: Installations complete

Successfully connected to MongoDB!

# Total number of row: 127729 All rows of news data inserted into MongoDB successfully.

### Output 3: Data insertion into MongoDB

```
Final row: 121437
Cleaned data inserted into 'cleaned_data_pandas' collection in MongoDB

Pandas cleaning completed!
{'Method': 'Pandas', 'Time (s)': 1.450361728668213, 'Throughput (rows/s)': 83728.76752029915, 'Memory Used (MB)': 0.0}

Cleaned data saved to 'cleaned_data_unoptimized_pandas.csv'
```

### Output 4: Pandas Data Processing

```
Final row: 121437
Cleaned data inserted into 'cleaned_data_polars' collection in MongoDB

Cleaned data saved to 'cleaned_data_optimized_polar.csv'

Polars cleaning completed!
{'Method': 'Polars', 'Time (s)': 0.1372830867767334, 'Throughput (rows/s)': 884573.6415986606, 'Memory Used (MB)': 0.3828125}
```

### Output 5: Polars Data Processing

```
cipython-input-143-fedb2e56790b>:19: UserWarning: Could not infer format, so each element will be parsed individually, falling back to 'dateutil'. To ensure parsing is consistent and a df_cleaned_map_partitions(lambda df: df.assign(Date=pd.to_datetime(df['Date'], errors='coerce')))
final row: 121437
Cleaned data saved to 'cleaned_data_optimized_dask.csv'
Cleaned data inserted into 'cleaned_data_dask' collection in MongoDB

Dask cleaning completed!
{"Method': 'Dask', 'Time (s)': 0.5574398040771484, 'Throughput (rows/s)': 217847.7373015931, 'Memory Used (MB)': 9.56640625}
```

### Output 6: Dask Data Processing

```
Final row: 121437
Cleaned data inserted into 'cleaned_data_pyspark' collection in MongoDB

Cleaned data saved to 'cleaned_data_optimized_pyspark.csv'

Pyspark cleaning completed!
{'Method': 'Pyspark', 'Time (s)': 0.1715, 'Throughput (rows/s)': 707961.62, 'Memory Used (MB)': 0.0}
```

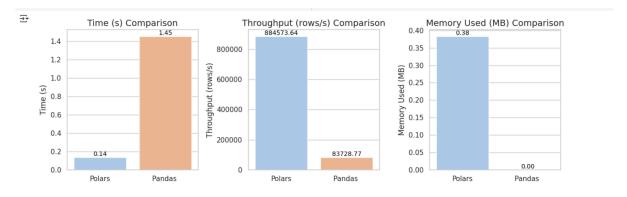
### Output 7: PySpark Data Processing

```
Cleaned data inserted into 'cleaned_data_vectorized_pandas' collection in MongoDB

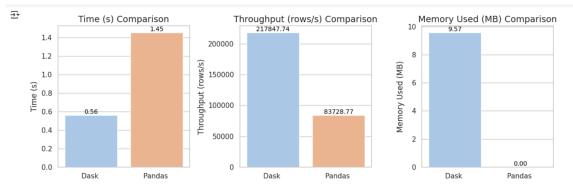
Cleaned data saved to 'cleaned_data_optimized_vectorized.csv'

Vectorized pandas cleaning completed!
{'Method': 'Vectorized Pandas', 'Time (s)': 0.810391902923584, 'Throughput (rows/s)': 149849.72031667858, 'Memory Used (MB)': 0.0}
```

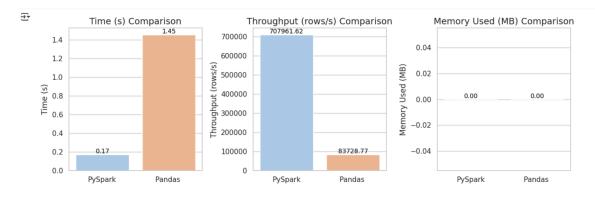
Output 8: Vectorized Pandas Data Processing



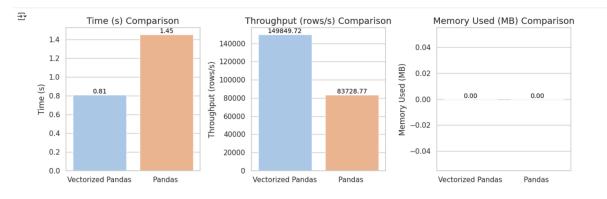
Output 9: Graph of Polars vs Pandas



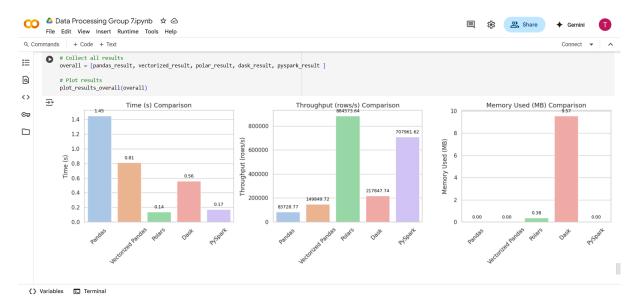
Output 10: Graph of Dask vs Pandas



Output 11: Graph of PySpark and Pandas



Output 12: Graph of Vectorized Pandas vs Pandas



Output 13: All Graphs Compared with Pandas

### 10.3 Links to full code repo or dataset

### Raw Dataset link:

https://github.com/Jingyong14/HPDP02/blob/main/2425/project/p1/Group%207/data/raw\_data.csv Data Processing File Link:

 $\underline{https://colab.research.google.com/drive/1khMiYXUq926IHhzo20M8q18WZEOx\_QCy?usp=sharing\#scrollTo=w1RDQKQkfQYt}$